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Fourth Workshop on Human-Computer Interaction and Information Retrieval

When we held the first HCIR workshop in 2007, the idea of uniting the fields of Human-Computer Interaction (HCI) and Information Retrieval (IR) was a battle cry to move this research area from the fringes of computer science into the mainstream. Three years later, as we organize this fourth HCIR workshop on the heels of a highly successful HCIR 2009 in Washington, DC we see some of the fruits of our labor. Topics like interactive information retrieval and exploratory search are receiving increasing attention, among both academic researchers and industry practitioners.

But we have only begun this journey. Most of the work in these two fields still stays within their silos, and the efforts to realize more sophisticated models, tools, and evaluation metrics for information seeking are still in their early stages.

In this year's one-day workshop, we will continue to explore the advances each domain can bring to the other.

New this year, we also ran the HCIR Challenge. Six teams participated. The aim of the challenge was to encourage researchers and practitioners to build and demonstrate effective information access systems. Challenge participants had no-cost access to a large collection of almost two million newspaper articles with rich metadata from The New York Times, generously provided for use in the challenge by the Linguistic Data Consortium. The focus of participation was on building systems (or using existing ones) to help people search the collection interactively. Entries were be evaluated by the workshop organizers based on HCIR criteria (specifically: effectiveness, efficiency, control, transparency, guidance, fun) and will also be judged by workshop attendees.

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VISTO for Web Information Gathering and Organization

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ABSTRACT
This paper presents a VIsual Search Task Organizer (VISTO). VISTO is a visual tool with effective information gathering task capabilities for the Web. In this prototype system, the task of Web information gathering is taken into consideration with respect to how user locate information for the task, organize task information, preserve and re-find task information, and compare information for effective reasoning and decision making. VISTO was designed and built based on recommendations from previous studies in a larger research. The prototype is ready to be evaluated in the next step of the research.

Categories and Subject Descriptors
H.3.3 [**Information Search and Retrieval**]: Clustering, Search Process.
H.1.2 [**User/Machine Systems**]: Human Factors
H.5.2 [**User Interfaces**]: User Centered Design.

General Terms
Human Factors, Theory, Measurement.

Keywords
Information retrieval, Web search, user tasks, Web information gathering, Web information organization and management

1. INTRODUCTION
Web information retrieval has been studied in the light of request-response for a relatively significant period of time. The user submits a query trying to convey their information need to the Web and in return, they receive a response from the search engine in the form of document hits. In many occasions, a search activity may require that the user continues interacting with the search engine to achieve a higher-level Web task [15]. Research has studied user tasks in order to identify a task framework that would help with understanding user interactions with the Web. Web tasks have been classified into fact finding, navigation, performing a transaction, and information gathering [7, 14]. The latter type accounts for a large portion of the overall tasks on the Web, representing between 51.7% [7] and 61.5% [19].

A Web information gathering task is a composite of subtasks/activities users perform while interacting with the Web for accomplishing a goal described in the task. User activities during Web information gathering may involve finding sources of Web information (Web documents), searching for information on the sources located for the task, finding related information to the already located sources and information, comparing information for reasoning and decision making, organizing task information, and preserving and re-finding information [2]. Figure 1 shows these subtasks in the Web information gathering task. For example, when planning for a trip to a foreign country for the first time, one has to gather different kinds of information to accomplish the goal of the trip. The plan may include looking for sources of information regarding currency exchange rates, flight rates, hotel rates, and so on. While trying to find information regarding each criterion, locating further information and comparing information are possible activities. Re-finding information during the process of information accumulation is an activity that may occur at any time. Moreover, information organization in addition to reasoning and decision making are required for ensuring the validity of the information located for the task and the degree to which the task goal is satisfied.

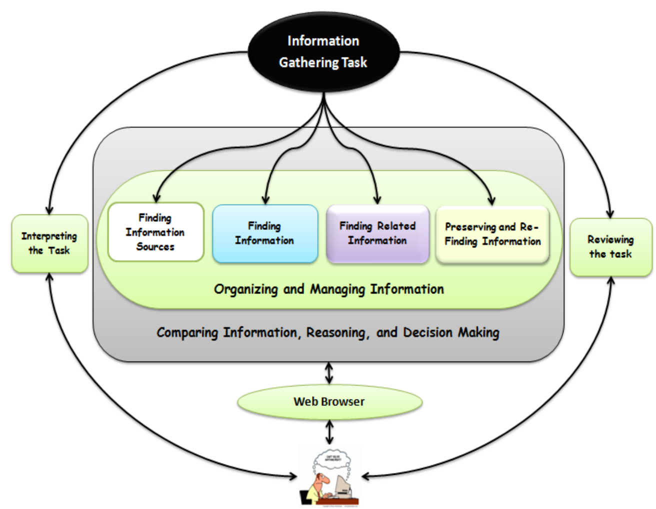

Figure 1. The Web information gathering task [2]

Since information mismatching and overloading are two significant problems regarding the way search engines gather and present information [23], it becomes the user's role to locate, compare, and manage the required information in the task. A Web search engine sees the sequences of a task as separate interaction steps. It also provides no means for re-finding information, which is an activity that represents one third of the user interactions during information gathering tasks according to Kellar and Watters [13]. Moreover, search engines do not usually provide support for representing task results according to the type of information being sought in the task. Consequently, there is a very limited understanding by the design of current Web search models of the fact that a search activity may not be only a one-time query, but rather a more complete and sophisticated task.

With regard to information gathering tasks, there has been no specific focus in the literature on the effects of visualization, clustering, and the concepts of information re-finding and information organization on the effectiveness of users performing Web tasks for information gathering. Visualization and clustering have been investigated for improving the effectiveness of Web search techniques in general. In addition, re-finding is a factor that has been studied in isolation, and there are several techniques intended for improving re-finding of information on the Web either locally on the Web browser or, sometimes, on the entire Web through the use of a search engine. However, information organization is barely studied in the context of the Web. In this article, a Web information gathering and organization prototype (VISTO) is presented. VISTO exploits visualization, visual clustering, and several Web information preserving, re-finding, and organization strategies for Web information gathering tasks. The paper is presented as follows. Section 2 discusses related research work. Section 3 presents principles and motivations for the design of VISTO. Section 4 describes VISTO in details. Section 5 discusses further research directions. Section 6 concludes the paper.

2. RESEARCH RATIONALE

2.1 Visualizing Web Information

Visualization is a concept that has been in focus for research in information retrieval [15, 20]. Information visualization is suggested to improve users' performance by harnessing their innate abilities for perceiving, identifying, exploring, and understanding large volumes of data. There are several visualization-based prototypes that have been investigated for improving the effectiveness of Web search [5, 6, 20]. For example, Teevan et al. [23] investigated the use of visual snippets in Web search results presentation and compared the effectiveness of this approach to the conventional text snippets provided by search engines such as Google. In addition, Bonnel et al. [6] showed that users favored visual clustering in a *3D City Metaphor*. Visual thumbnails of Web search results that accompany textual presentations were also shown to be effective in searching the Web for revisiting [22].

There are several search tools on the Web that use visualization such as the search engines Gceel (www.Gceel.com), Nexplore (www.nexplore.com), and Viewz (www.viewzi.com). Visualization of Web search results has also been investigated in several layouts including the use of *hyperbolic trees*, *Scatterplots, Self-Organizing Maps*, and *thematic maps* such as in the visual search engine *Kartoo* (www.kartoo.com). Most of these approaches were intended for improving how users find sources of Web information. Exploring multiple features of Web documents such as their content similarities, page thumbnails, URLs, and document summaries in a visualized approach should be exploited in Web information gathering tasks. These features—when visualized properly—can help users find sources of information on the Web, find information in such sources, compare information, and make more effective and efficient decisions during the task accomplishment process.

2.2 Clustering Web Information

Clustering is intended for grouping together items that share similar characteristics and attributes. In Web information retrieval, clustering is meant for grouping similar documents [18]. The use of clustering has been widely investigated in Web information retrieval [18]. Clustering is usually intended to provide overviews of information categories (topics) in the result set. Hence, efficient subtopic retrieval is anticipated with the use of clustering in Web search results presentations [8]. When more than one topic is desired while gathering information on the Web, clustering may provide effective topic exploration in the high-level views of the result hits. Clustering can also decrease the need for scrolling over multiple pages of results and motivate users to look beyond the first few hits, resulting in more effective and efficient user performance.

In Web information retrieval, clustering has been investigated in several prototypes such as in the work of Alhenshiri et al. [1]. Clustering has also been implemented in conventional search engines such as Clusty (www.clsuty.com), Gceel (www.Gceel.com), and Google (in their "*see similar*" feature and *Google Wonder Wheel*). Although the performance of users with row presentations of Web documents is comparable to their performance with clustering-based presentations, user preference usually comes in favor of clustering-based methods [8]. In addition, there are indications that clustering can even be more effective [24]. With the variety of information that is gathered on the Web, clustering can play a significant factor in Web information gathering tasks. Clustering should be investigated with regard to finding related information to the task during the gathering process.

2.3 Preserving and Re-finding Web Information

Research has focused on enhancing re-finding Web information locally on the Web browser. However, re-finding strategies such as the back button, favorites, and bookmarks can maintain limited numbers of information sources. In addition, the use of those strategies is limited to pages and sites of interest during particular Web sessions. Therefore, searching the Web for re-finding, also known as re-searching [22], has been studied for assisting users in locating results of interest that were found interesting in previous sessions. Research shows that a great deal of Web search visitations is for revisiting [22]. Consequently, Re-finding is a common activity in Web information gathering tasks accounting for (53.27%) according to Mackay and Watters [17]. For information gathering tasks of multi-session nature, which may require multi-topic search, re-finding can play a significant role in the effectiveness of tools designed for this type of task. Re-finding should be focused not only on preserving active Web pages in the browser but also on Web search results. In addition, research should further explore the role of re-finding in the context of a complete information gathering task.

2.4 Organizing and Managing Web Information

Research has focused on investigating how users manage their information for re-finding [9, 10, 16]. Important reasons behind giving up on certain personal information management tools were discussed in the work of Jones et al. [11]. Strategies users follow to manage Web information in order to be able to relocate and reuse previously found information are discussed in the work of Jones et al. [10]. Their work shows that users—while gathering Web information—follow different preserving strategies to re-find and compare information. Most users gather information over multiple sessions [17], which indicates the need for management strategies for preserving and re-finding such information for reuse. The variety of finding, re-finding, organizing, and management strategies and approaches users follow while seeking and gathering Web information can be related to the fact that current Web tools lack important reminding, integration, and organization schemes.

Research has had little consideration to factors that would improve how Web users collect, manage, compare, and organize information for gathering tasks. On the Web, research has only considered the case of managing and organizing information for re-finding [10]. How users organize and manage information during Web information gathering has had little consideration. Since Web information gathering tasks may take several sessions, involve looking at information from different sources, and require comparing information that may belong to varied topics, investigating organizational and management strategies users follow on the Web is necessary.

3. VISTO Principles and Motivations

To further exploit the concepts of information visualization, visual clustering, re-finding, and organization, VISTO was designed. The prototype offers the following features for supporting information gathering tasks:

a. Effective visualized search.

b. Intuitive visualized clustering.

c. Effective Web information organization.

d. Effective preserving and re-finding strategies.

VISTO was designed based on the recommendations drawn from the studies in [1, 2, 3, 10, 23]. Research has studied visualization and clustering for improving the effectiveness of general Web search tasks. In addition, re-finding has been investigated for providing effective techniques that allow users to relocate previously preserved Web documents. What is lacking in research regarding Web information gathering tasks is threefold. First, visualization and clustering should be investigated for improving the process of accomplishing the whole task. VISTO attempts to utilize visualization and clustering to allow users to find, compare, and relate information to the already located sources of information more effectively.

Second, re-finding has been studied only for permitting users to effectively and efficiently re-find Web documents that were preserved in previous sessions. VISTO attempts to create a more effective storing and re-finding environment. This is done by allowing users to store individual documents as well as complete sessions. In addition, re-finding is done not only by searching a list of documents, but also by using keyword search to re-find individual documents, sessions, and whole tasks previously preserved by the user. Third, Information organization has been studied in the desktop environment for personal information management. The Web has had little consideration except in the case of information management for re-finding [10].VISTO takes a step further and attempts to provide effective organizational schemes for information during information gathering tasks.

4. VISTO Design

The VISTO interface was designed using Java swing components and the *prefuse* visualization toolkit (http://prefuse.org/). A snapshot of the VISTO interface is shown in Figure 2. There are four different models, shown in Figure 3, employed in the design of the VISTO interface as follows:

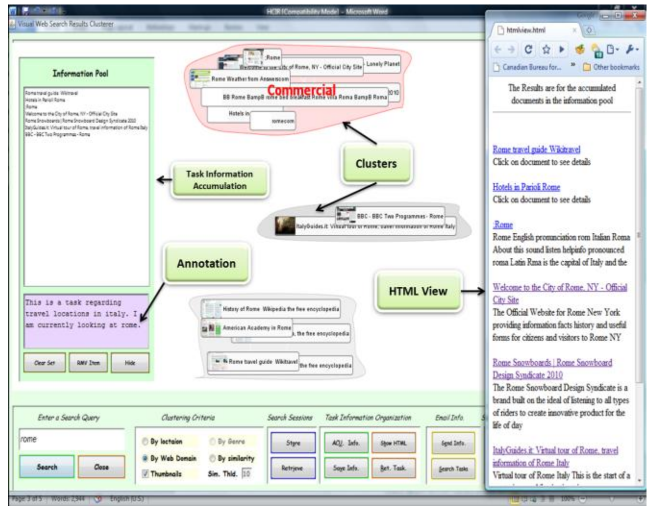

Figure 2. VISTO interface

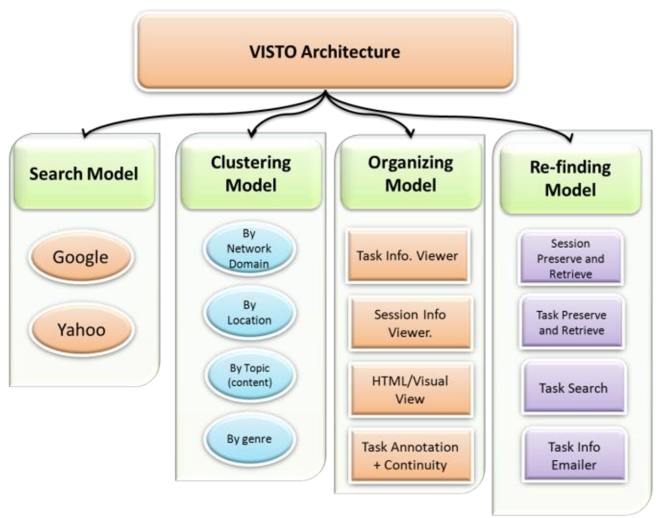

Figure 3. VISTO architecture

4.1 Search Model

VISTO provides search services to users gathering Web information. It combines the powers of Google and Yahoo Web search engines. When a user submits a query, VISTO uses Google's spell correction service and then submits the query to both search engines. VISTO eliminates repeated hits and prepares the results for display. Three main features are provided to the user in results displayed by VISTO. First, *context* is provided by presenting document titles on visual glyphs. Document glyphs are clustered so that relations among search results are conveyed to the user. Second, *look-ahead* is provided by VISTO. The user can see the document thumbnail and summary to predict the page content. Third, focus is provided to the user by hovering over the visual glyphs. The hover-over feature narrows the focus of the user to the specific cluster/document so that the user can see the document summary and URL. Moreover, the user can eliminate clusters and individual glyphs from the display for reducing clutter and achieving more focus.

4.2 Clustering Model

VISTO uses intuitive visual clustering to render its search results and its preserved task and session documents. Clustering is performed based on one of four criteria. First, network domain clustering permits the user to see visual clusters of Web documents categorized based on network domains such as commercial, organizational, and educational domains. Second, the user can select clustering by location in which documents are categorized based on the country of origin. Third, VISTO permits for clustering by content similarity (*topical clustering*) in which similar documents are grouped together. Clusters are labeled using *cluster-internal labeling* [18]. The title of the document closest to the centroid of the cluster is used as the label of the cluster. Last, VISTO provides clustering by genre. Documents that belong to the same genre are grouped together. Currently, VISTO uses 17 of the 25 genre types described in the work of Santini et al. [21]. For computing genre-based similarity, the structure and the content of the documents are taken into account.

4.3 Organizing Model

To assist users with organizing task information, VISTO uses different strategies. Based on the study described in [3], users find it hard to keep track of task information especially in multi-session information gathering tasks. Therefore, VISTO allows the user to store partial information during a task by preserving current session information. This is done by either preserving active visual views of the current display or by selectively preserving particular documents among the search results. Preserved documents are grouped under a task title (name) and sorted by date for later retrieval. The user can continue working on the same task over multiple sessions while adding and eliminating documents. The user can add annotations to the preserved task information along the way towards completing the task. To further assist users with organizing the task information and making effective decisions regarding the task, two different views of the task gathered information are available in VISTO. Search results and accumulated task information (documents) can be viewed either visually or in HTML format. The study in [1] showed that users prefer to have both views during information gathering. VISTO provides continuous task information accumulation strategy so that users do not lose track of their information.

4.4 Re-finding Model

Re-finding is a heavily studied subject in Web information retrieval. In VISTO, re-finding for information gathering and organization is emphasized best. VISTO allows users to store complete sessions and individual documents for re-finding. It also allows search within sessions and within tasks by either selecting from a list of tasks/sessions or by keyword search to further assist the user. The keyword search matches the task name given previously by the user and the annotations preserved alongside the task. Moreover, VISTO allows users to email task information including accumulated documents, task subject and date, and task annotations. The emailing strategy was recommended in the work of Jones et al. [10]. However, VISTO adds the organization of a task to the subject matter by submitting all the aforementioned information items. With VISTO, the user can follow the preserving and re-finding strategy that suits their needs and accommodates the task requirements.

5. Discussion

VISTO is a prototype system ready to be tested on the Web for information gathering tasks. A complete factorial study will be conducted for evaluating the efficiency, effectiveness, and engagement of VISTO in performing Web information gathering tasks. In this study, participants will be asked to perform the tasks using VISTO and other Web tools. The study will evaluate effectiveness with respect to the relevancy and accuracy of task information, the number of queries required for the task, the number of sequences/steps needed during the task, and the completeness of the task requirements. Efficiency will also be measured with regard to the time on task. User engagement will be measured using the user confidence in the task results, their interest in the tool, and other self-reported comments. The results of the study will provide practical research recommendations for Web tools intended for Web information gathering tasks.

6. Conclusion

This paper presented VISTO, a prototype system for improving the effectiveness of gathering and organizing Web information. The current state in Web information gathering necessitates studying challenges users encounter during this type of tasks. Based on three previous studies [1, 2, 3], VISTO was designed. Our previous studies revealed several questions regarding which visualization, clustering, re-finding, and organizing factors would improve the process of Web information gathering. The research will continue with a user study to evaluate VISTO.

7. REFERENCES

[1] Alhenshiri, A., Brooks, S., Watters, C., and Shepherd, M. 2010. Augmenting the Visual Presentation of Web Search Results. In proceedings of the 5th International Conference on Digital Iformation Management, Thunder Bay, ON, Canada, (to appear).

[2] Alhenshiri, A., Shepherd, M., Watters, C. 2010. Web Information Gathering Tasks: A Framework and Research Agenda. Paper accepted at the International Conference on Knowledge Discovery and Information Retrieval (KDIR2010), Valencia, Spain, (to appear).

[3] Alhenshiri, A., Shepherd, M., Watters, C. 2010. User Behaviour during Web Search as a Part of Information Gathering. In Proceedings of the Hawaii International Conference on System Sciences (HICSS 2011), Hawaii, USA, (to appear).

[4] Alonso, O., and Baeza-Yates, R. 2003. Alternative Implementation Techniques for Web Text Visualization. In Proceedings of the 1st Latin American Web Congress, California, USA, 202-204.

[5] Bonnel, N., Cotarmanac'h A., and Morin, A. 2005. Meaning Metaphor for Visualizing Search Results. In Proceedings of the 9th International Conference on Information Visualization, London, England, 467-472.

[6] Bonnel, N., Lemaire, V., Cotarmanac'h, A., and Morin, A. 2006. Effective Organization and Visualization of Web Search Results. In Proceedings of the 24th IASTED International Multi-Conference on Internet and Multimedia Systems and Applications, Innsbruck, Austria.209-216.

[7] Broder, A. 2002. A Taxonomy of Web Search. ACM SIGIR Forum, vol. 36, issue 2, 2-10.

[8] Carpineto, C., Osiński, S., Romano, G., and Weiss, D. 2009. A Survey of Web Clustering Engines. ACM Computing Surveys, vol. 41, issue 3, Article No. 17.

[9] Elsweiler, D., and Ruthven, I. 2007. Towards Task-based Personal Information Management Evaluations. In proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Amsterdam, The Netherlands, 23-30.

[10] Jones, W., Bruce, H., and Dumais, S. 2003. How do People Get Back to Information on the Web? How Can They Do It Better? In Proceedings of the 9th IFIP TC13 International Conference on Human-Computer Interaction, Zurich, Switzerland.

[11] Jones, E., Bruce, H., Klasnja, P., and Jones, W. 2008. I Give Up! Five Factors that Contribute to the Abandonment of Information Management Strategies. In proceedings of the 68th Annual Meeting of the American Society for Information Science and Technology, Columbus, OH, USA.

[12] Karim, J., Antonellis, I., Ganapathi, V., and Garcia-Molina, H. 2009. A Dynamic Navigation Guide for Web Pages. In CHI 2009.

[13] Kellar, M., and Watters, C. 2006. Using Web Browser Interactions to Predict Task. In Proceedings of the 15th International Conference on World Wide Web, Edinburgh, Scotland, 843-844.

[14] Kellar, M., Watters, K., and Shepherd, M. 2007. A Field Study Characterizing Web-based Information-Seeking Tasks. Journal of the American Society for Information Science and Technology, vol. 58, issue 7, 999-1018.

[15] Kules, W., Wilson, M. L., Schraefel, M. C., and Shneiderman, B. 2008. From Keyword Search to Exploration: How Result Visualization Aids Discovery on the Web. Technical Report, School of Electronics and Computer Science, University of Southampton.

[16] Mackay, B., Kellar, M., and Watters, C. 2005. An Evaluation of Landmarks for Re-finding Information on the Web. In Proceedings of the 2005 ACM Conference on Human Factors in Computing Systems, Portland, Oregon, USA, 1609 - 1612.

[17] Mackey, B., and Watters, C. 2008. Exploring Multi-session Web Tasks. In Proceedings of the 2008 ACM Conference on Human Factors in Computing Systems, Florence, Italy, 4273-4278.

[18] Manning, C. D., Raghavan, P., and Schütze, H. 2008. Introduction to Information Retrieval. Cambridge University Press.

[19] Rose, D., and Levinson, D. 2004. Understanding User Goals in Web Search. In Proceedings of the 13th International Conference on World Wide Web, New York, NY, USA, 13-19.

[20] Suvanaphen, E., and Roberts, J. C. 2004. Textual Difference Visualization of Multiple Search Results Utilizing Detail in Context. Theory and Practice of Computer Graphics Conference, Bournemouth, UK, 2-8.

[21] Santini, M. 2006. Interpreting Genre Evolution on the Web . EACL 2006 Workshop, Trento, 32-40.

[22] Teevan, J. 2008. How People Recall, Recognize, and Reuse Search Results. ACM Transactions on Information Systems, vol. 26, issue 4. Article No. 19.

[23] Teevan, J., Cutrell, E., Fisher, D., Drucker, S. M., Ramos, G., Andre, P., and Hu, C. 2009. Visual Snippets: Summarizing Web Pages for Search and Revisitation. In Proceedings of the 27th International Conference on Human Factors in Computing Systems, Boston, MA, USA, 2023-2032.

[24] Turetken, O., & Sharda, R. (2005). Clustering-based Visual Interfaces for Presentation of Web Search Results: An Imperical Investigation. Information Systems Frontier, 7(3), 273-297.

Time-Based Exploration of News Archives

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ABSTRACT

In this paper, we present NEAT, a prototype system that provides an exploration interface to news archive search. Our prototype visualizes search results making use of two kinds of temporal information, namely, news articles' publication dates but also their contained temporal expressions. The displayed timelines are annotated with major events, harvested using crowdsourcing, to make it easier for users to put the shown search results into context. The prototype has been fully implemented and deployed on the New York Times Annotated Corpus.

Categories and Subject Descriptors

H.3.1 [**Content Analysis and Indexing**]: Linguistic processing; D.5.2 [**Information Interface**]: User Interfaces

General Terms

Design, Experimentation, Human Factors

Keywords

Crowdsourcing, timelines, exploration, news archives

1. INTRODUCTION

News archives keep growing in volume and coverage as fresh content is published and old content is being digitized. The New York Times (NYT), as one example, allows users to search and access all of its contents published since 1851. The archive of the British newspaper The Times, as a second example, even goes back until 1785.

When searching news archives, presenting users with a ranked list of few search results is insufficient, as it does not reflect how relevant news articles are spread in the time dimension and thus fails to display the course of history. Instead, it forces users to sift through a large number of relevant news articles and painstakingly piece together how real-world events unfolded.

In this paper, we describe our **N**ews **E**xploration **A**long **T**ime (NEAT) prototype that provides an exploration interface to search news archives. NEAT has been deployed on the New York Times Annotated Corpus [3], as a real-world news archive, and combines several novel features including:

- **Use of Richer Temporal Information**: News articles come with different kinds of temporal information. This includes their publication dates that are typically readily available. However, within the news articles' contents there is often more temporal information hidden. For example, a news article on oil spills published on February 3rd 1991 may contain the following sentences: *"By contrast, the spill caused by the Exxon Valdez* ***in 1989*** *contained almost 11 million gallons..."* and *"**Nearly three years later**, he said, young trees are growing in the mangrove..."*. Temporal expressions (e.g., ***in 1989***) are another kind of temporal information that can be extracted from the news articles' contents.
- **Snippets with Temporal Information**: NEAT leverages both kinds of temporal information mentioned above. Relevant news articles are anchored on a timeline based on their publication date. Beyond that, NEAT shows relevant snippets that contain temporal expressions and anchors them accordingly. In doing so, NEAT facilitates gaining an understanding of *when relevant news articles were published* but also *which times relevant news content refers to.*
- **Semantic Temporal Anchors**: To aid users in contextualizing the displayed news articles and snippets, our system shows a set of major events that serve as semantic temporal anchors. Examples of such major events include *"Building of Berlin Wall"* (for the year 1961), *"Challenger Disaster"* (for January 1986), and *"Woodstock"* (for the year 1969). We harvest a large collection of such semantic temporal anchors using the crowdsourcing platform Amazon Mechanical Turk. Note that temporal anchors can easily be personalized - users could thus have local libraries of personal anchors (e.g., including their day of birth or wedding day), making it even easier for them to contextualize search results.

Organization. Related work is discussed in Section 2. Section 3 gives details on NEAT's exploration interface. In Section 4, we describe the gathering of timeline annotations using crowdsourcing. NEAT's implementation is subject of Section 5. Finally, in Section 6, we conclude this work and outline next steps.

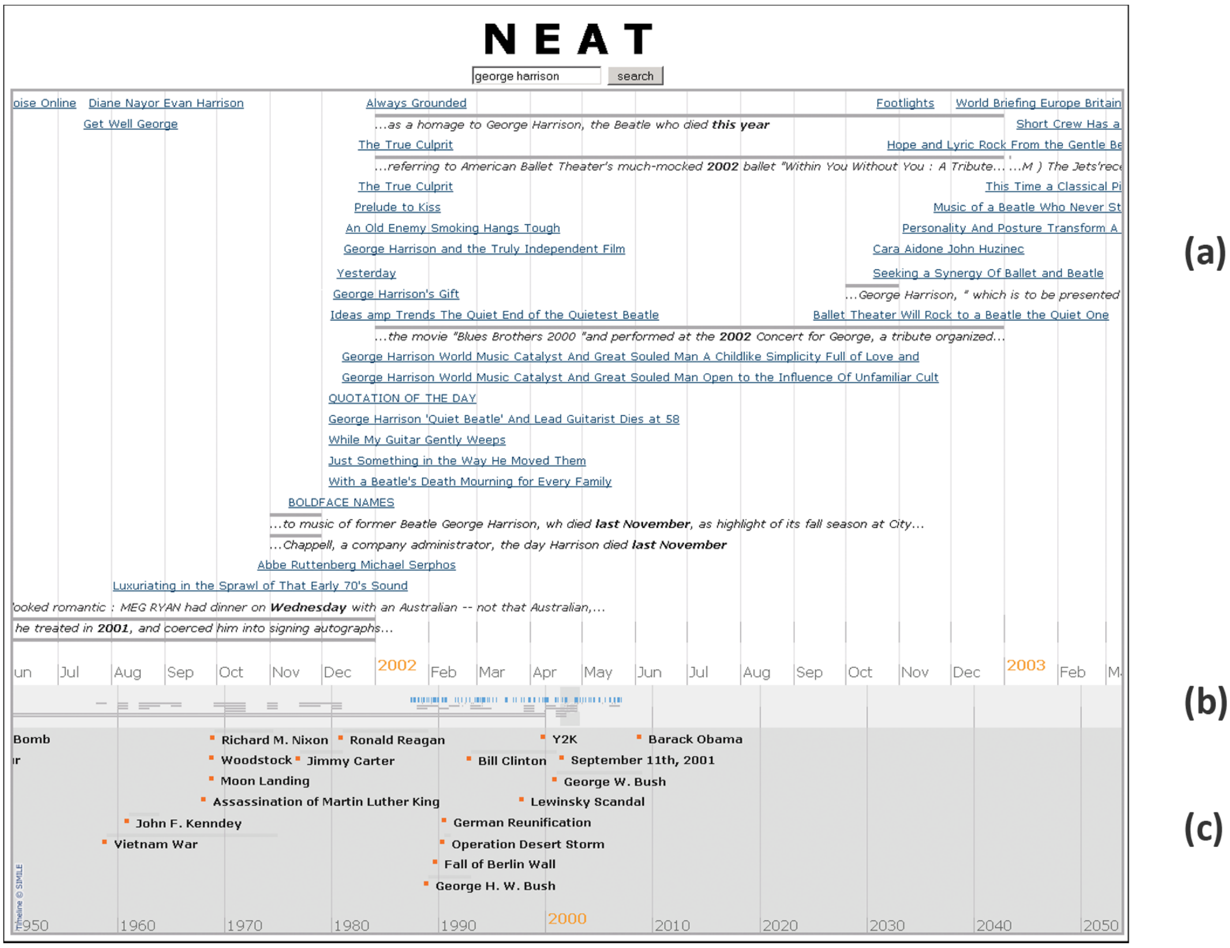

Figure 1: NEAT screenshot for the query george harrison showing (a) main timeline with relevant news articles and relevant temporal snippets, (b) overview timeline, and (c) major events as semantic temporal anchors.

2. RELATED WORK

We now put the present work in context with existing prior research. The "Stuff I've Seen" system described by Dumais et al. [9] and similar approaches such as Ringel et al. [13] also make use of temporal information to facilitate information access. However, in their setting, typically only publication dates or timestamps of documents, emails, etc. are considered. In addition we exploit temporal expressions contained in news articles' contents in our work. The Time Frames system described by Koen and Bender [11] is similar to our work, since it also uses temporal expressions contained in news articles. Their main focus, though, is on supporting users in reading news articles, but not on search and exploration.

Our own earlier work is also related but focuses on different aspects. Alonso et al. [7] present an approach for clustering and exploring search results in timelines. Berberich et al. [8] describe a model for temporal information needs that makes use of temporal expressions. Both approaches use crowdsourcing for their respective evaluations.

Other related research includes the recently proposed Memetracker system [12] that tracks the mutational flow of so-called memes over time. Their system, though, focuses on pre-identified memes and does not support arbitrary ad-hoc queries. Jones and Diaz [10] show that the temporal profile of a query, determined based on the publication dates of relevant documents, is useful in query classification. Swan and Allan [15], as an early piece of research, focus on automatically generating overview timelines for a collection of documents. Wang and McCallum [17] is a more recent, more sophisticated approach along similar lines. It is conceivable to augment NEAT with such topical overviews.

Google has recently added the `view:timeline` feature to display search results along a timeline. Similarly, Google News Archive Search [2] also visualizes the query results as a temporal frequency distribution of relevant documents. While such visualization provides a high-level view of the topical popularity, they do not makes use of temporal expressions contained in documents and thus do not provide interesting snippets corresponding to a time period. Finally, TimeSearch [5], another related prototype, also makes use of temporal expressions contained in relevant documents.

3. TEMPORAL EXPLORATION

We now describe NEAT's exploration interface in more detail. Figure 1 shows a screenshot of the interface when displaying results for the query george harrison. In detail, the interface consists of the following timelines:

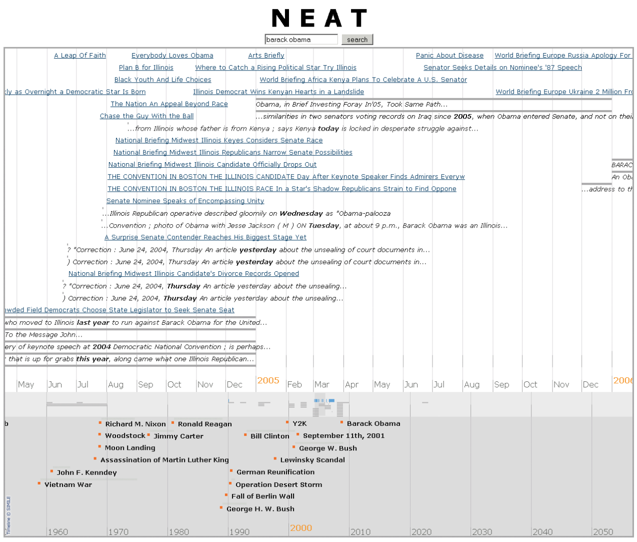

Figure 2: Results for barack obama around *2005*

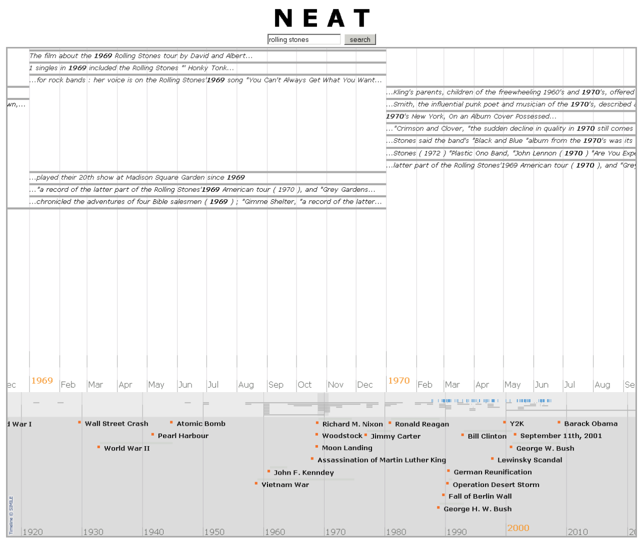

Figure 3: Results for rolling stones around *1970*

(a) **Main timeline** showing titles of relevant news articles (e.g., "The True Culprit") placed according to their publication date and relevant temporal snippets (e.g., "*...as a hommage to George Harrison, the Beatle who died this year*") placed according to their contained temporal expressions.

(b) **Overview timeline** summarizing relevant news articles and temporal snippets shown in (a) at a coarser temporal granularity.

(c) **Major events**, gathered using crowdsourcing as described in more detail in Section 4, that serve as semantic temporal anchors for the users.

Notice that the timelines are synchronized, so that navigating in one will automatically adjust the others.

We distinguish two time dimensions in NEAT, namely, publication time and reference time. By placing titles of relevant news articles on the timelines based on their publication time (i.e., when they were published), we provide users with an overview of relevant news articles and the order of real-world events behind them. Reference time, as the second time dimension considered, reflects which times relevant news content refers to. To illustrate the difference between publication time and reference time, consider an article published in June 2010 that compares this year's FIFA World Cup against earlier instances of the tournament. Whereas the article's title would be placed on the day of its publication in June 2010 according to publication time, parts of its content, so-called temporal snippets, would be placed, for instance, at the years 2006, 2002, 1998 etc. depending on which earlier FIFA World Cup they talk about. As the example suggests, in order to get a hold on the reference-time dimension, we must identify the times that an article's content refers to. This can be accomplished using existing tools for identifying and interpreting temporal expressions, such as TARSQI [16] or TimexTag [6], that are readily available. By showing relevant temporal snippets, we provide the user with a means to explore the content of many documents at once, which is less time-consuming than sifting through each of them separately.

Figure 2 and 3 show two more anecdotal examples of NEAT in action. As shown in Figure 2, for the query barack obama, it is apparent from the overview timeline that there is little relevant content before 2005 – the year when Barack Obama became United States Senator. For the query rolling stones, as our second example shown in Figure 3, we see that, by showing relevant temporal snippets, NEAT offers insights into the rock band's activities during the 1970s, which is long before the publication dates of news articles in the New York Times Annotated Corpus. Apart from that, for both examples, the major events shown provide an interesting political and societal context.

4. TIMELINE ANNOTATION USING CROWDSOURCING

An important item that arises when working with timelines is the selection of the main events and how they should be presented. In the particular case of a newspaper like NYT that contains a wealth of information, how do we select the most representative events? An obvious approach would be to select the events based on coverage or popularity. However, the quality of the timeline in this case would be purely based on the newspaper's content. Instead, we took a "wisdom of the crowd" approach. The idea is to annotate the timeline based on collective human knowledge. We model this as a bipartite graph where we want to match a temporal expression to an event. We believe this may provide a more realistic representation of major events. We gathered temporal annotations at large-scale using Amazon Mechanical Turk (AMT) [1]. In a series of experiments, each HIT (Human Intelligence Task) on AMT consists of a request to expand a temporal expression with an entity (e.g., a person, country, or organization) or event. Based on the agreement level among workers, we derive key entities for constructing a semantic temporal annotation layer on top the timeline. The outcome is a manually annotated timeline that helps users in contextualizing anchor search results. We paid $0.01 per assignment and each task was completed by five different workers. We manually created a set of 50 temporal expressions that represent time at different granularities as follows:

- Dates (e.g., ***9/1/1939*** or ***4/4/1968***)
- Relative (e.g., ***last year***, ***next year***, or ***tomorrow***)
- Weekdays (e.g., ***Monday*** or ***Tuesday***)
- Months (e.g., ***January*** or ***February***)
- Years (e.g., ***1492***, ***1945***, or ***1970***)
- Decades (e.g., ***60s***, ***70s***, or ***80s***)
- Centuries (e.g., ***19th*** or ***20th***)

We ran the experiment for different categories (politics, sports, culture, world affairs, movies, and music) using the same set of temporal expressions. By analyzing the data we can see that an explicit temporal expression tends to have a clear annotation as we see in the following examples verbatim. In the case of "1492", the workers wrote: America, Christopher Columbus, Columbus, Columbus discovers America, France. For relative expressions, the annotation tends to be of less value. For the temporal expression "4pm", we have: Afternoon, Bakers, Mauritius, Oprah Winfrey, TED. Going at a higher level than year, decades also provide interesting information. For example, for "70s", we have: disco, oil shocks, Richard Nixon, usa, Watergate. Months provide a mix of typical calendar events with some other observations. For "March", workers wrote: Brutus killed Julius Caesar on the ides, caesar, Easter, saint patrick, St. Patrick's Day. The next step is to get a consensus among workers and select one or two significant events for that particular temporal expression. Examples of annotations produced by crowdsourcing are (1969: Woodstock, Moon landing), (1970: Nixon), and (2003-2009: Iraq war) to name a few with different time granularities. It is not always possible to get consensus on an <event, temporal expression> pair. An interesting example is the year "1982", where the crowd annotated: Ronald Reagan, Spain World Cup, Charles & Lady Di wedding, and Falklands War. These are all valid events and probably interesting on their own, but we were not able to find consensus on one or two.

5. IMPLEMENTATION

We now provide some details on the implementation of our NEAT prototype. Prior to indexing the dataset using our prototype, we annotated temporal expressions using TARSQI [16]. To implement the user interface, shown in Figure 1, we make use of the timeline visualization provided as part of the SIMILE project [4]. When the user issues a query, a request is sent to a Java servlet. This Java servlet, running in the backend, then processes the user query by retrieving a fixed number of relevant documents and a fixed number of relevant temporal snippets. Notice that the retrieved temporal snippets are independent from the retrieved relevant documents, thus fostering diversity of displayed information. To retrieve relevant documents and temporal snippets, the servlet accesses two inverted indexes, one for documents and one for snippets, that are implemented using an Oracle 11g database. To determine the relevance of news articles and temporal snippets, we employ Okapi BM25 [14] as a retrieval model. For temporal snippets, we slightly modify the retrieval model, using the number of temporal expressions contained in a snippet as a multiplicative boosting factor. Finally, before sending a response, the servlet looks up metadata for the identified documents and phrases (e.g., their URLs and publication dates), and adds markup to highlight query terms and temporal expressions.

6. CONCLUSIONS AND FUTURE WORK

We presented NEAT, a working prototype for exploring news along timelines. We used the New York Times Annotated Corpus to show the features of our system. The prototype is easy to use and the authors found it interesting to navigate to the past when issuing queries about current world affairs.

Future work includes a user study of the user interface to get a better idea (and metrics) about the prototype. Previous research [7] has shown that users like to see information in time, so we would to explore this in more detail. The annotation of timelines by major events gathered using crowdsourcing looks very promising. A limitation is that the annotation depends a lot on the quality of the workers and, in our experience, the annotations seemed to have an American flavor instead of being world representative. We plan to keep working on this aspect.

7. REFERENCES

[1] Amazon Mechanical Turk `http://www.mturk.com`.

[2] Google News Archive Search `http://news.google.com/archivesearch`.

[3] New York Times Annotated Corpus `http://corpus.nytimes.com`.

[4] SIMILE TimeLine Visualization. `http://simile.mit.edu/timeline/`.

[5] TimeSearch History `http://www.timesearch.info`.

[6] D. Ahn et al. A Cascaded Machine Learning Approach to Interpreting Temporal Expressions. *HLT-NAACL* 2007.

[7] O. Alonso et al. Clustering and exploring search results using timeline constructions. *CIKM* 2009.

[8] K. Berberich et al. A Language Modeling Approach for Temporal Information Needs. *ECIR* 2010.

[9] S. T. Dumais et al. Stuff I've seen: a system for personal information retrieval and re-use. *SIGIR* 2003.

[10] R. Jones and F. Diaz. Temporal profiles of queries. *ACM TOIS* 2007.

[11] D. B. Koen and W. Bender. Time frames: Temporal augmentation of the news. *IBM Systems Journal* 2000.

[12] J. Leskovec et al. Meme-tracking and the dynamics of the news cycle. *KDD* 2009.

[13] M. Ringel et al. Milestones in Time: The Value of Landmarks in Retrieving Information from Personal Stores. *INTERACT* 2003.

[14] S. E. Robertson and S. Walker. Okapi/keenbow at trec-8. 1999.

[15] R. Swan and J. Allan. Automatic generation of overview timelines. *SIGIR* 2000.

[16] M. Verhagen et al. A. Rumshisky, J. Phillips, and J. Pustejovsky. Automating Temporal Annotation with TARSQI. *ACL* 2005.

[17] X. Wang and A. McCallum. Topics over time: a non-Markov continuous-time model of topical trends. *KDD* 2006.

Combining Computational Analyses and Interactive Visualization to Enhance Information Retrieval

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ABSTRACT

Exploratory search and information-seeking support systems attempt to go beyond simple information retrieval and assist people with exploration, investigation, learning and understanding activities on document collections. In this work we integrate several computational text analysis techniques, including document summarization, document similarity, document clustering, and sentiment analysis, within the interactive visualization system Jigsaw in order to provide a flexible and powerful environment for people to examine sets of documents. Our focus is not on cutting edge algorithms for computational analysis but rather on the process of integrating automated analyses with interactive visualizations in a smooth and fluid manner. We illustrate this integration through an example scenario of a consumer examining a collections of car reviews in order to learn more about the car and understand its strengths and weaknesses.

Keywords

exploratory search, information seeking, sense-making, visualization, visual analytics

1. INTRODUCTION

We have been developing new interfaces and systems for information retrieval, in particular, for retrieval of collections of documents with a goal of understanding the many different dimensions and contents of those documents. Sometimes called Exploratory Search [11, 5], Information Seeking Support [6], or Sense-making [4], these processes go beyond the initial retrieval of data by providing environments in which a person can browse, explore, investigate, discover, and learn about the topics, themes, and concepts within the documents.

More specifically, the following situations provide examples of the types of processes we seek to support:

- A police investigator has a collection of case reports, evidence reports, and interview transcripts and seeks to "put the pieces together" to identify the culprits behind a crime.

- An academic researcher moves into a new area and seeks to understand the key ideas, topics, and trends of the area, as well as the set of top researchers, their interests, and collaborations.

- A consumer wishes to buy a new digital camera but encounters a large variety of possible models to choose from, each of which with supporting documentation and consumer reviews.

- A family learns that their child may have a rare disease and they scour the web for documents and information about the condition.

Our approach combines two main components: automated computational analysis of the documents and interactive visualizations of the documents themselves and of the results of the analysis. Such a combination is described as a *visual analytics* approach [9, 3] and it attempts to leverage the strengths of both the human and the computer. Humans excel at the interactive dialog and discourse of exploration and discovery. They develop new questions and hypotheses as more and more information is uncovered. The computer excels at complicated analyses of large data collections to determine metrics, correlations, connections, and statistics about the document collection.

Relatively few systems to date, however, have smoothly incorporated both automated computational analysis and interactive visualization while providing a tight coupling between the two. It is more common to encounter systems focused on one of the two capabilities that also add a few elements from the other capability. For instance, computational analysis tools sometimes provide rudimentary user interfaces to access analysis capabilities. Alternatively, interactive visualization systems may provide a few simple techniques such as filtering or statistical analysis of the data.

The system through which we have been exploring this coupling is Jigsaw [8], a tool for helping people explore document collections. Jigsaw is a relatively mature prototype system, and has seen initial use in the field by clients from law enforcement, investigative reporting, fraud detection, and academic research, among others. An initial user study with the system showed its potential in helping investigators and supporting different analysis strategies [2].

Until now, Jigsaw has provided more in the way of interactive visualization support of document exploration. In particular, Jigsaw visualizes connections between entities across documents to help investigators follow trails of information. Recently, we added enhanced computational analysis to the system. Jigsaw now also provides capabilities such as analysis of document similarity, document sentiment, document clusters by theme or content, and document summarization through a few words or sentences.

Our focus has not been about developing innovative new algorithms for computational analysis, however. Instead, we have been exploring methods for smoothly integrating the computational analyses into an interactive visual interface in a seamless manner that would provide a natural and fluid user experience.

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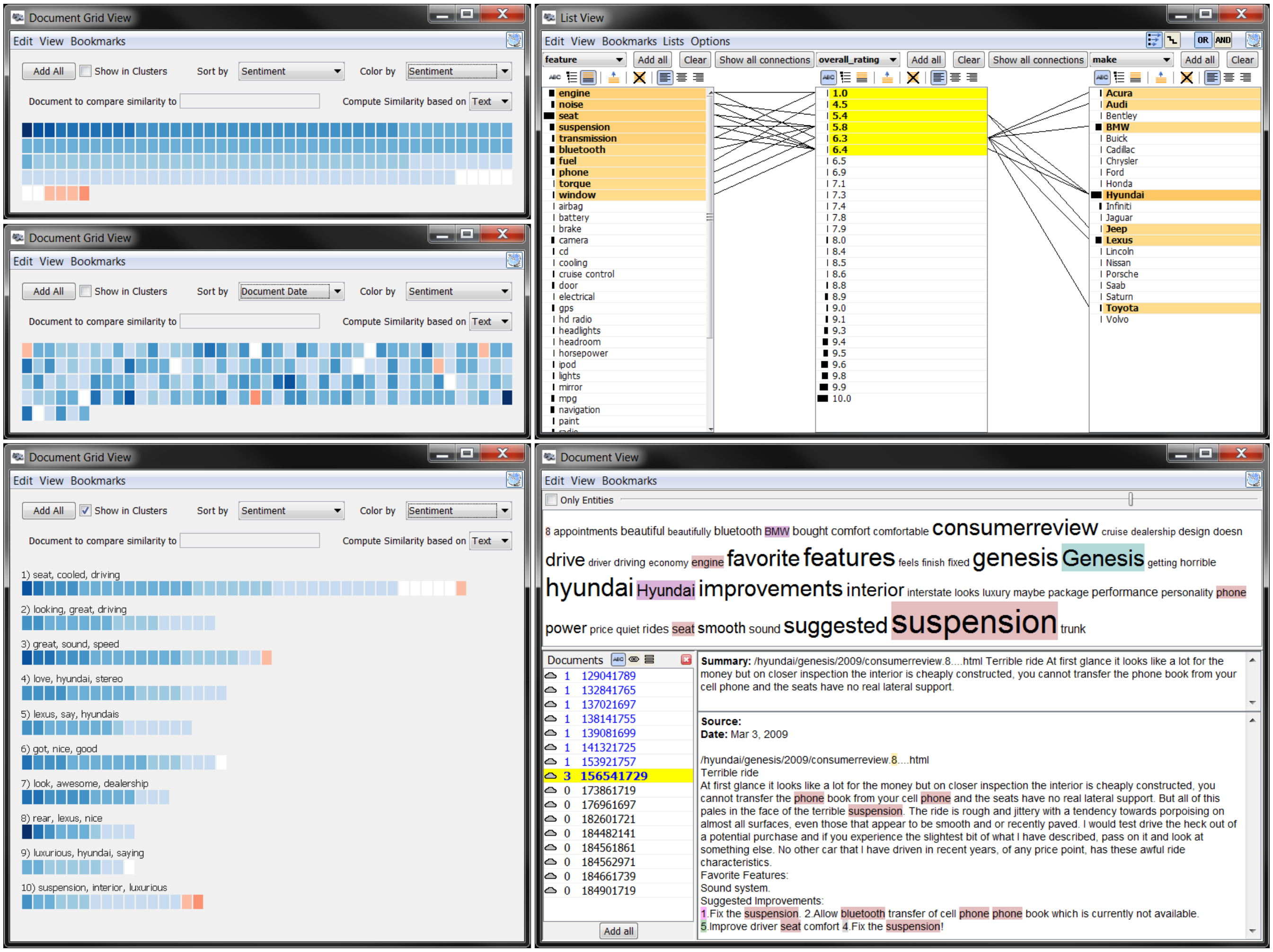

Figure 1: Jigsaw's Document Grid Views, List View, and Document View showing connections in and statistics of car reviews about the 2009 Hyundai Genesis retrieved from the edmunds.com website.

2. AN EXAMPLE INVESTIGATIVE SCENARIO: CAR REVIEWS

Jigsaw is a system for helping analysts with different kinds of investigative and sensemaking scenarios based on textual documents. It is a multi-view system, including a number of different visualizations of the documents in the collection and the entities (e.g., people, places, organizations, etc.) within those documents. Figure 1 shows some of the visualizations. Initially developed for use in intelligence and law enforcement scenarios, more recently Jigsaw has seen increased use in other domains and for many different kinds of document collections. More detail about Jigsaw can be found in [8].

To help illustrate how computational analyses and interactive visualization combine in Jigsaw, we present an example investigative scenario in which an example consumer, Mary, is shopping for a new car. To help her learn about a particular car, the 2009 Hyundai Genesis, that she is considering, Mary examines a document collection consisting of 178 reviews of the car from the edmunds.com website. She could, of course, examine these reviews sequentially from the website in the manner that anyone would do when exploring a topic using a collection of consumer reviews or webpages retrieved from a search engine. That can, however, be slow and not well illuminate the key themes and connections across the reviews.

For illustrating Mary's use of Jigsaw in this scenario, we scraped the 178 reviews from the edmunds.com website and imported them into Jigsaw. Each review is modeled as a document. The main textual content of the review is the text of the document. The document's entities include various rating scores (e.g., exterior design, fuel economy, overall, etc.) that the review author explicitly designated, and other car makes and models mentioned in the review's text. Additionally, we added an entity type "feature" for which we defined about 40 general terms about cars such as seat, trunk, and engine, and we look for mention of those terms in the review text. Figure 1 presents several Jigsaw views from the exploration session that will be used throughout our discussion.

To get an overview of the reviews, Mary begins her investigation by invoking the Document Cluster View (Figure 2) and examining the different key concepts across the reviews. The Cluster View shows each document as a small rectangle and it includes commands to cluster the documents based on either the document text or on the entities connected to a document. Here, Mary chose full document text as the basis for the clustering to achieve the broadest interpretation. Jigsaw then reorganizes the display and positions the documents into clusters based on the analysis. Mary notices clusters around concepts such as the sound system, the ride, fuel economy, and seating.

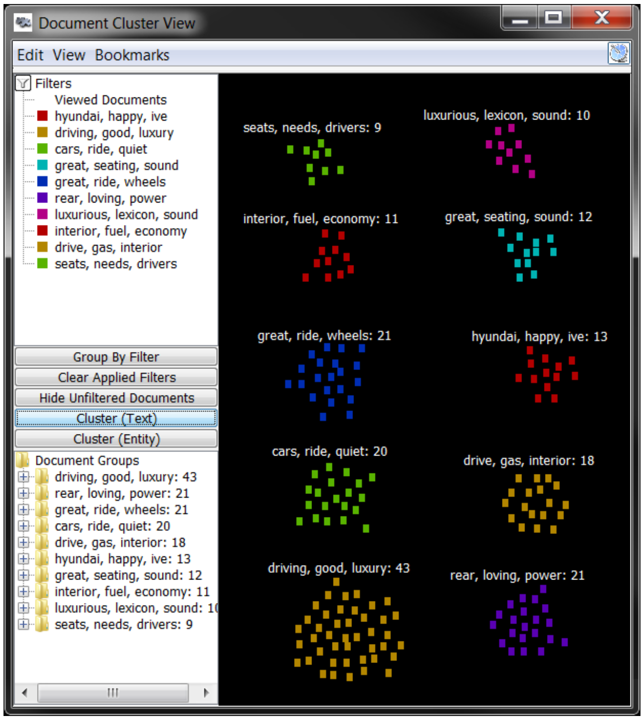

Figure 2: Jigsaw's Document Cluster Views showing clusters of car reviews about the 2009 Hyundai Genesis retrieved from the edmunds.com website.

Next, Mary wants to learn about the subjective opinions of the reviewers, so-called sentiment analysis [1], so she examines the Document Grid View. It displays all the documents as a grid of rectangles where the order and color/shading of the documents in the grid reflect different document metrics. Mary orders and colors the reviews by sentiment calculated by Jigsaw (see Document Grid View at the top left in Figure 1). Positive reviews are colored blue, neutral reviews are colored white, and negative reviews are colored red. Darker shades of blue and red indicate stronger positive and negative sentiment, respectively. At first glance, the reviews for the Genesis appear to be quite positive overall; there are only four negative reviews.

To double check the sentiment, Mary examines in the List View the connections of those four documents to the overall rating given by the reviewer and the car features mentioned by the reviewer. The List View organizes different types of entities into different lists and visually presents connections between entities through orange shading and connecting lines. Two entities are considered to be "connected" if they occur in at least one document together. The List View shows that those four reviews are indeed very negative. The consumers who wrote them assigned overall ratings of 1.0, 4.5, 5.8, and 6.5, respectively, far below the average rating of 9.4. The List View also shows that the features *phone*, *seat*, and *suspension* are most strongly connected to the four negative reviews.

Mary now changes the order of the reviews in the Document Grid View to be sorted by date (see the middle left in Figure 1). The most recent review from 09/28/2009 is the leftmost document in the first row, and the oldest review from 06/26/2008 is the rightmost document in the last row. This view indicates that the earlier reviews were slightly more positive than the more recent reviews. The strong positive reviews (dark blue) are in the lower rows, while most of the the neutral reviews (white) and three of the four negative reviews (red) are in the upper rows. This might indicate that some issues with the car were not apparent when it came out but were revealed over the course of the first year of use.

To learn more about the car's potential weaknesses, Mary displays features and overall ratings in the List View and selects all ratings with a score below 6.5. The terms *engine*, *noise*, *seat*, *suspension*, and *transmission* appear as the features most connected to the negative reviews (see List View in Figure 1, upper right). To put these results in context, Mary switches back to the Document Grid View and displays the reviews in ten clusters based on the review text as calculated by Jigsaw (see Document Grid View at the bottom left in Figure 1). The clusters are labeled with three descriptive keywords and the documents within each cluster are ordered and colored by their sentiment. Two of the four negative reviews are in cluster 10 mentioning *suspension* as a keyword. Cluster 1, mentioning *seat* as a keyword, also contains one negative and most of the neutral reviews. This suggests that the suspension and the seats may be weaker points of the 2009 Hyundai Genesis. Interestingly here, even though Jigsaw only performs document level sentiment analysis, the system also effectively presents a type of feature-level sentiment simply through its multiple views and brushing across views.

To examine more closely the reviews in cluster 10 containing two of the four negative reviews, Mary displays these reviews in the Document View (see Document View in Figure 1, lower right). The view shows a word cloud (at the top) of the loaded documents that helps the viewer to quickly understand the main themes and concepts within the documents by presenting the most frequent words across the documents. The number of words shown can be adjusted interactively with the slider above the cloud. Here, the word cloud shows that the suspension is indeed mentioned frequently in these reviews. Browsing through the reviews and reading their summaries reveals that the suspension is often described in a negative context, as shown in the selected review in the figure. To help with fast triage of a large set of documents, the Document View provides a one sentence summary (most significant sentence) of the currently displayed document above its full text. This one sentence summary of a document is available in all other Jigsaw views as well and can be displayed through a tooltip wherever a document is presented.

To learn more about the ride quality of the car, Mary displays the Word Tree [10] View for "ride" (Figure 3). A Word Tree shows all occurrences of a word or phrase from the reviews in the context of the words that follow it. The user can navigate through the tree by clicking on its branches. The Word Tree in Figure 3 shows that reviewers have different opinions about the quality of the ride, ranging from "a little bumpy" and "rough and jittery" to "comfortable and quiet" and "most impressive".

Not shown in this scenario is the document similarity computation and display within Jigsaw. Document similarity can be measured relative to complete document text or just to the entities connected to a document. These different similarity measures are of particular interest for semi-structured document collections, such as publications, in which metadata-related entities (e.g. authors or conferences) are not mentioned in the actual document text. The Document Grid View (top left in Figure 1) can provide an overview of all the documents' similarity (relative to a selected document) via the order and color of the documents in the grid representation. In all other views, the five most similar documents can be retrieved with a right mouse button command on a document representation.

Jigsaw also includes a Calendar View that presents documents and entities within the context of a calendar so that an investigator can see patterns, trends, and temporal orderings and a Graph

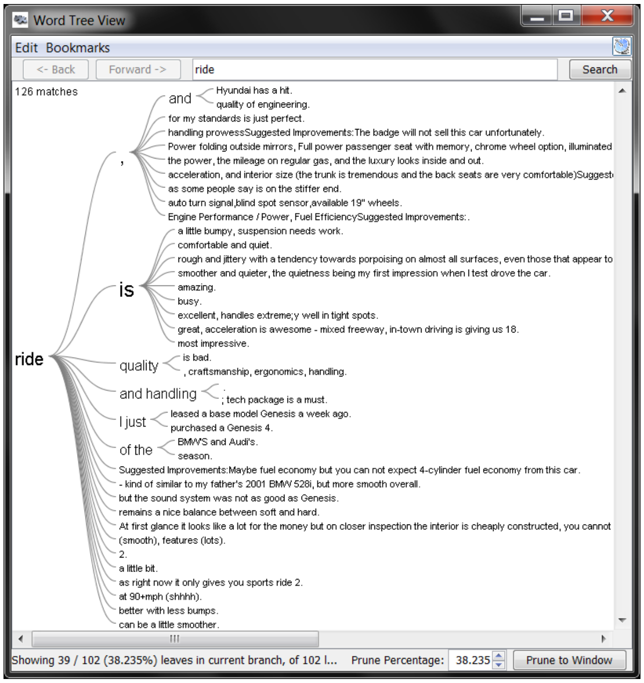

Figure 3: Jigsaw's Word Tree View showing sentences using the word "ride" in car reviews about the 2009 Hyundai Genesis retrieved from the edmunds.com website.

View that shows a node-link network representation of documents and the entities within them. Investigators can choose two or more entities within the Graph View and Jigsaw will compute "related" entities, that is, entities in the local neighborhood of the selected ones, and it will show the shortest paths between all these entities.

All the Jigsaw views discussed above primarily assist investigators with "information foraging" activities, the first half of the investigative process model proposed by Pirolli and Card [7]. In this respect, we believe that Jigsaw is most useful in helping people determine which document(s) they should read next. To assist investigators with "sense-making" activities, the second half of the Pirolli-Card model, we have recently added a new window called the Tablet to Jigsaw. The Tablet functions much like an electronic notebook in which an investigator can drop in entities, documents, snapshots of views, or manually-generated notes and content. These items within the Tablet also can be connected with edges to help create structures like social networks or the items can be positioned along timelines. Essentially, the Tablet helps investigators to organize their thoughts, gather evidence, take notes, and develop ideas.

3. CONCLUSION

Helping investigators to explore a document collection is more than just retrieving the "right" set of documents. In fact, all the documents retrieved or examined may be important, and so the challenge becomes how to give the analyst fast and yet deep understanding of the contents of those documents.

We speculate that simply performing rich computational analysis of the documents may not be sufficient – The analyst inevitably will think of some question or perspective about the documents that is not illuminated by the computational analysis. We also speculate that interactive visualization of the documents itself also may not be sufficient – As the size of the document collection grows, interactively exploring the individual characteristics of each document simply may take too much time. Thus, through the combination of these two technologies, so-called visual analytics, we can develop systems that provide powerful exploratory, investigative capabilities that were unavailable before.

In this research, we have illustrated methods for doing just that: integrating automated computational analysis with interactive visualization for text- and document-based exploration, investigation, and understanding. We integrated a suite of textual analysis techniques into the Jigsaw system, showing how the analysis results can be combined with existing and new visualizations. Further, we provided an example analysis scenario that shows both the methodology and the utility of these new capabilities. Although the computational analysis techniques are not new, we have integrated them with interactive visualization in new manners to provide a system that we feel provides innovative and powerful exploratory search and sense-making capabilities.

4. ACKNOWLEDGMENTS

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5. REFERENCES

[1] M. Gregory, N. Chinchor, P. Whitney, R. Carter, E. Hetzler, and A. Turner. User-directed sentiment analysis: Visualizing the affective content of documents. In *Workshop on Sentiment and Subjectivity in Text*, pages 23–30, 2006.

[2] Y. Kang, C. Görg, and J. Stasko. The evaluation of visual analytics systems for investigative analysis: Deriving design principles from a case study. In *IEEE VAST*, pages 139–146, Oct. 2009.

[3] D. Keim, G. Andrienko, J.-D. Fekete, C. Görg, J. Kohlhammer, and G. Melançon. Visual analytics: Definition, process, and challenges. *Information Visualization: Human-Centered Issues and Perspectives*, pages 154–175, 2008.

[4] G. Klein, B. Moon, and R. Hoffman. Making sense of sensemaking 1: alternative perspectives. *IEEE Intelligent Systems*, 21:70–73, 2006.

[5] G. Marchionini. Exploratory search: From finding to understanding. *Communications of the ACM*, 49(4):41–46, Apr. 2006.

[6] G. Marchionini and R. W. White. Information-seeking support systems. *IEEE Computer*, 42(3):30–32, Mar. 2009.

[7] P. Pirolli and S. Card. The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In *International Conference on Intelligence Analysis*, May 2005.

[8] J. Stasko, C. Görg, and Z. Liu. Jigsaw: supporting investigative analysis through interactive visualization. *Information Visualization*, 7(2):118–132, 2008.

[9] J. J. Thomas and K. A. Cook. *Illuminating the Path*. IEEE Computer Society, 2005.

[10] M. Wattenberg and F. B. Viégas. The Word Tree, an Interactive Visual Concordance. *IEEE Transactions on Visualization and Computer Graphics*, 14(6):1221–1228, 2008.

[11] R. W. White, B. Kules, S. M. Drucker, and M. C. Schraefel. Supporting exploratory search. *Communications of the ACM*, 49(4):36–39, Apr. 2006.

Impact of Retrieval Precision on Perceived Difficulty and Other User Measures

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ABSTRACT

When creating interactive retrieval systems, we want to reduce the perceived difficulty of finding relevant documents. We conducted a user study that controlled retrieval precision. We found that a higher retrieval precision caused a reduction in perceived difficulty compared to a lower retrieval precision. We also found that higher precision increases enjoyment and has some influence on ability to concentrate, but we found no evidence that precision keeps the user engaged vs. bored with the search.

1. INTRODUCTION

In this paper, we examine whether or not the user perceives any differences in the search experience given a change in precision. In other words, does retrieval precision affect how a user feels about a search for relevant documents? We certainly expect the topic to have significant impact on the degree to which a search seems difficult or enjoyable, but does precision?

To answer this question, we utilize data collected as part of larger user study that we conducted to examine the relationship between retrieval precision and human performance [5]. In that study, we examined the effect of two levels of precision on the performance of users. We looked at search results with a uniform precision at rank N of 0.3 and 0.6. Users were to find as many relevant documents as possible within 10 minutes. We asked the users to work quickly and to balance their speed with accuracy. We found that precision is strongly related to performance for the interfaces and tasks of our study.

While the two levels of precision resulted in different levels of human performance, did the retrieval precision affect the users' perception of search difficulty? We can improve user performance as measured by some metric of our choosing, but if users do not notice this measured performance improvement, then we may need to reexamine our conception of performance. We found that:

- Retrieval precision has a statistically significant effect on the perceived difficulty of finding relevant documents ($p = 0.006$) as well on the enjoyability of the search experience ($p = 0.016$).
- The user's ability to concentrate is somewhat impacted by retrieval precision ($p = 0.079$).
- The mood of the user (bored or engaged) is not affected by retrieval precision ($p = 0.341$).

These results add support to results of Bailey, Kelly, and Gyllstrom [3] who found that their estimate of topic difficulty correlated with perceived difficulty of finding relevant documents. Bailey et al. estimated a topic's difficulty for users by using a collection of existing user queries for the topic and measuring the average nDCG of these queries.

There are many ways to describe topic difficulty. For example, a topic could be hard for users to understand and distinguish relevant from non-relevant documents. Conversely, a topic could be easy to understand, but the topic could require careful inspection of documents for relevance if there are many requirements attached to what makes a document relevant. Users can vary greatly in their familiarity of a topic, and these differences in familiarity could affect the user's perception of the topic difficulty. Another notion of topic difficulty may be to consider easier topics to be those topics that allow more relevant documents to be found in a given amount of time than harder topics.

Rather than attempt to define topic difficulty and determine its affect on various user measures, we control the precision of retrieval results for a set of topics. Many of the ways to describe topic difficulty are likely independent of the precision of the results the user is examining. Our primary contribution in this paper is that we show evidence that precision causes changes in perceived difficulty. While we believe that Bailey et al. also found that that users perceive it easier to find relevant documents the higher the retrieval precision, they did not directly control the retrieval precision nor did they vary precision across a set of topics.

2. METHODS AND MATERIALS

In this section, we briefly describe our user study. Details can be found in our earlier publication [5].

We conducted a two phase user study. 48 users participated in the study. The same users participated in both phases of the study. For each phase, users completed 4 search tasks. A task corresponded to searching for documents relevant to a given TREC topic. Each task took 10 minutes. In total, we used 8 topics from the 2005 TREC Robust track, which are shown in Table 1. The 2005 Robust track used the AQUAINT collection of 1,033,461 newswire documents.

Each phase used a different user interface. Figure 1 shows the user interfaces. In the first phase, users judged the relevance of document summaries and full documents. Users saw one summary or document at a time and had to judge

Fourth Workshop on Human-Computer Interaction and Information Retrieval (HCIR'10), August 22, 2010, New Brunswick, NJ, USA.

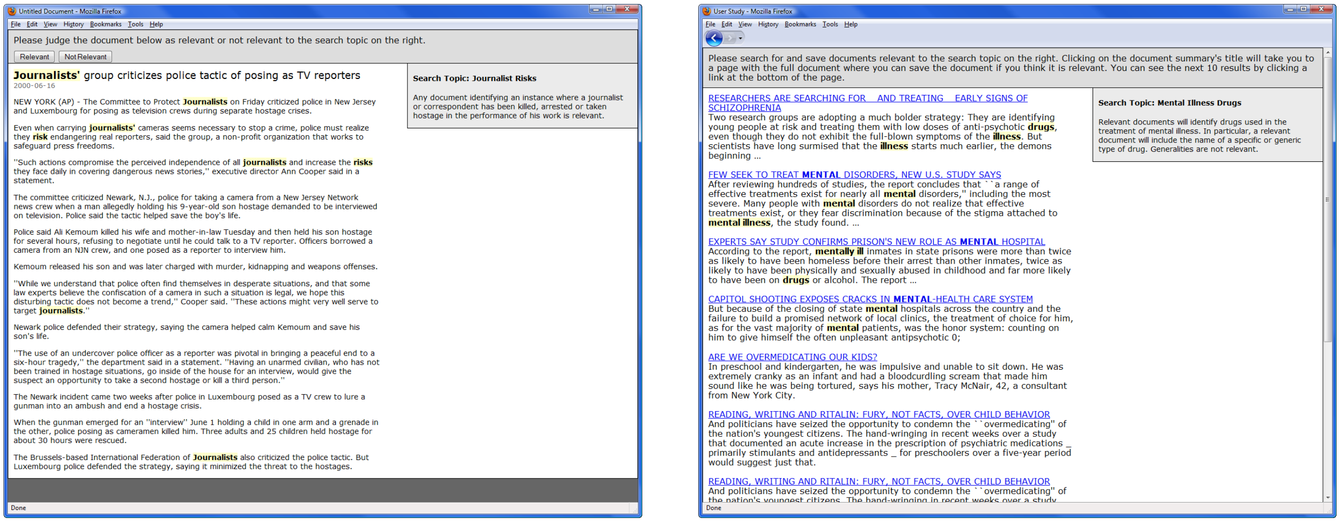


Figure 1: The left screenshot shows the user interface (UI) for phase 1 with a full document. Participants in phase 1 also judged document summaries in the same way. The right screenshot shows the phase 2 UI with query-biased document summaries shown. Clicking on a summary took the user to a page with the full document. This page, similar to the phase 1 document judging UI on the left, allowed the user to save the document as relevant, but did not require a relevance judgment be made.

Number	Topic Title	Relevant
310	Radio Waves and Brain Cancer	65
336	Black Bear Attacks	42
362	Human Smuggling	175
367	Piracy	95
383	Mental Illness Drugs	137
426	Law Enforcement, Dogs	177
427	UV Damage, Eyes	58
436	Railway Accidents	356

Table 1: Topics used in the study and the number of NIST relevant documents for each topic.

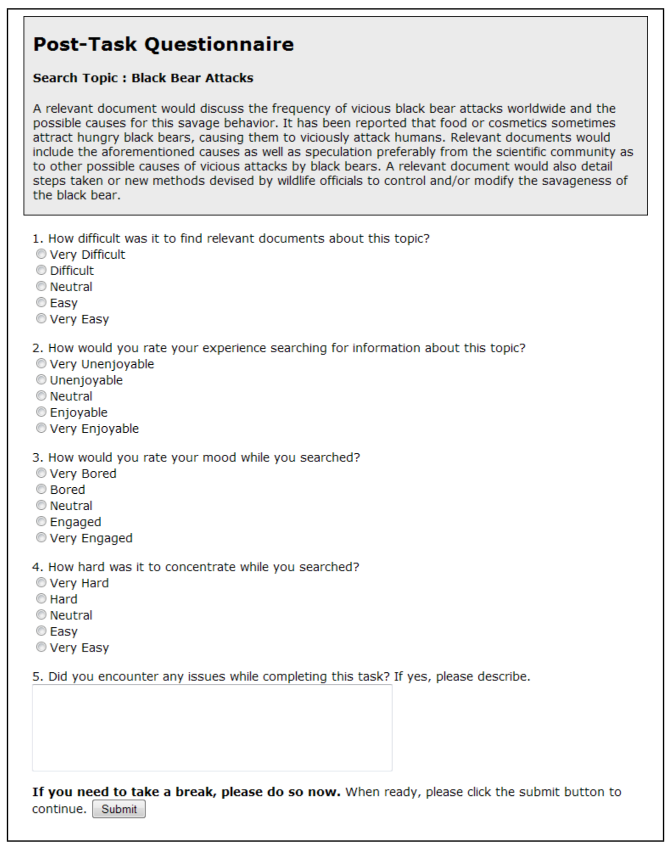
the document to see the next document. Summaries and documents alternated.

In the second phase, the user interface was similar to today's web search engines that display 10 query-biased summaries in response to a user's search query. Clicking on a summary showed the user the full document, and the user could choose to save the document if it was relevant. If the user believed the document was non-relevant, or did not want to take further action on this document, the user would click the web browser's back button to return to the search result summaries. Query reformulation was not possible. While phase 1 restricted users to making judgments in the order of the search results, phase 2 made no such restriction.

As part of the study, the users answered a questionnaire after each task. For the questionnaire, we used the same 4 questions as used by Bailey et al. [3] in their work:

1. How difficult was it to find relevant documents about this topic?

2. How would you rate your experience searching for information about this topic?



Post-Task Questionnaire

Search Topic : Black Bear Attacks

A relevant document would discuss the frequency of vicious black bear attacks worldwide and the possible causes for this savage behavior. It has been reported that food or cosmetics sometimes attract hungry black bears, causing them to viciously attack humans. Relevant documents would include the aforementioned causes as well as speculation preferably from the scientific community as to other possible causes of vicious attacks by black bears. A relevant document would also detail steps taken or new methods devised by wildlife officials to control and/or modify the savageness of the black bear.

1. How difficult was it to find relevant documents about this topic?
- Very Difficult
- Difficult
- Neutral
- Easy
- Very Easy

2. How would you rate your experience searching for information about this topic?
- Very Unenjoyable
- Unenjoyable
- Neutral
- Enjoyable
- Very Enjoyable

3. How would you rate your mood while you searched?
- Very Bored
- Bored
- Neutral
- Engaged
- Very Engaged

4. How hard was it to concentrate while you searched?
- Very Hard
- Hard
- Neutral
- Easy
- Very Easy

5. Did you encounter any issues while completing this task? If yes, please describe.

If you need to take a break, please do so now. When ready, please click the submit button to continue. Submit

Figure 2: Post-task questionnaire.

Post-Task Question	p-values of Experiment Factors User	Topic	Precision	Phase	Task
Finding Relevant Docs (Difficult - Easy)	0.000	0.000	0.006	0.893	0.444
Experience (Unenjoyable - Enjoyable)	0.000	0.049	0.016	0.003	0.345
Mood (Bored - Engaged)	0.000	0.047	0.341	0.005	0.383
Ability to Concentrate	0.000	0.025	0.079	0.630	0.260

Table 2: Analysis of variance results for all factors.

Post-Task Question	P@N = 0.3	P@N = 0.6	p-value
Finding Relevant Docs (Difficult - Easy)	2.84 ± 0.08	3.13 ± 0.08	0.006
Experience (Unenjoyable - Enjoyable)	2.97 ± 0.06	3.16 ± 0.07	0.016
Mood (Bored - Engaged)	3.09 ± 0.07	3.17 ± 0.07	0.341
Ability to Concentrate	3.21 ± 0.06	3.34 ± 0.07	0.079

Table 3: Average and standard error of users' responses given the precision of the results.

3. How would you rate your mood while you searched?

4. How hard was it to concentrate while you searched?

Figure 2 shows the user interface for the post-task questionnaire. In our analysis, we mapped the 5 point Likert scale for each question to the values 1 through 5 with the most negative response mapped to 1, e.g. "Very Difficult", and the most positive response mapped to 5, e.g. "Very Easy", and the neutral response mapped to 3.

2.1 Experiment Factors

The factors of our experiment include the phase of the study, the task order, the topic, the user, and the precision of the ranked list. The responses that we examine are the 4 post-task questions that we asked of each user.

Phase The experiment had two phases, phase 1 and 2, as described above. The phase of the experiment contains a possible order effect. Phase 1 of the experiment always occurred before phase 2. The user interface was tied to the phase of the experiment.

Task Users completed two 1 hour sessions. A session corresponded to a phase of the experiment, and each session included 4 tasks. We number the tasks 1 through 4. Search topics and precision levels were rotated across tasks and balanced across all other factors. Of the eight topics, users would complete 4 of the 8 in phase 1 and the remaining 4 in phase 2.

Topic As described above, the experiment used the 8 topics shown in Table 1.

User We continued to recruit participants until after data cleaning [5] we had a completely balanced experiment with 48 users. Each user completed both phases.

Precision We looked at two levels of precision. For a given topic, users would receive either the higher or lower precision ranked list of documents. We carefully constructed the ranked lists of documents to produce near uniform levels of precision at rank N. As such, the ranked lists have near equal precision at N, mean average precision (MAP), and R-precision (precision at the number of known relevant documents, R). The lower level of precision was 0.3 and the higher level of precision was 0.6. We choose these levels of precision based on the range of precision at 10 for the runs without obvious errors submitted to the TREC 2005 Robust track.

3. RESULTS AND DISCUSSION

For each of the post-task questions, we performed an analysis of variance (AOV) with the question as the response. As can be seen in Table 2, precision has a statistically significant impact on perceived difficulty of finding relevant documents ($p = 0.006$). Table 3 reports the average response and AOV p-value for each question given the two levels of precision. As expected, the user and topic also have a significant impact on perceived difficulty and all other responses. The user interface (phase) and task order did not impact perceived difficulty. The task order had no significant effect on any of the responses.

Precision also had a statistically significant effect on the enjoyability of the search experience ($p = 0.049$). It appears that users felt that their concentration was better with higher precision ($p = 0.079$), but this effect was not as strong as for difficulty or enjoyability. There is no evidence that precision affected the mood (engagement) of the users ($p = 0.341$).

The phase did have a significant effect on both the enjoyability ($p = 0.003$) and mood ($p = 0.005$) of the users. Users enjoyed and felt more engaged with phase 2 than with phase 1, but because the user interface was not rotated across phases, we cannot draw any conclusion about the effect of the user interface on the user. We hypothesize that the web-like interface of phase 2 was the cause of the improved enjoyability and mood. There is no evidence of either phase making the user feel as though it was easier to find relevant documents ($p = 0.893$).

To give some sense of the variability in the topics, Figure 3 shows the user performance for both phases and topics. Of the many possible ways to define and measure topic difficulty, one objective measure is the number of documents found relevant by the user in 10 minutes.

Of note, for the results shown in Figure 3, precision is a controlled variable. With an actual retrieval system, users might be able to easily obtain high precision results for one topic but not for the other. For example, Bailey et al. [3] found topics 336 and 367 to be "easy" topics based on the nDCG scores for queries obtained from users. Topic 336 is certainly not "easy" if we take the number of relevant documents found in 10 minutes as our measure of topic difficulty. For phase 2, topic 336 was one of the more difficult topics as measured by number of documents saved as relevant. Topic

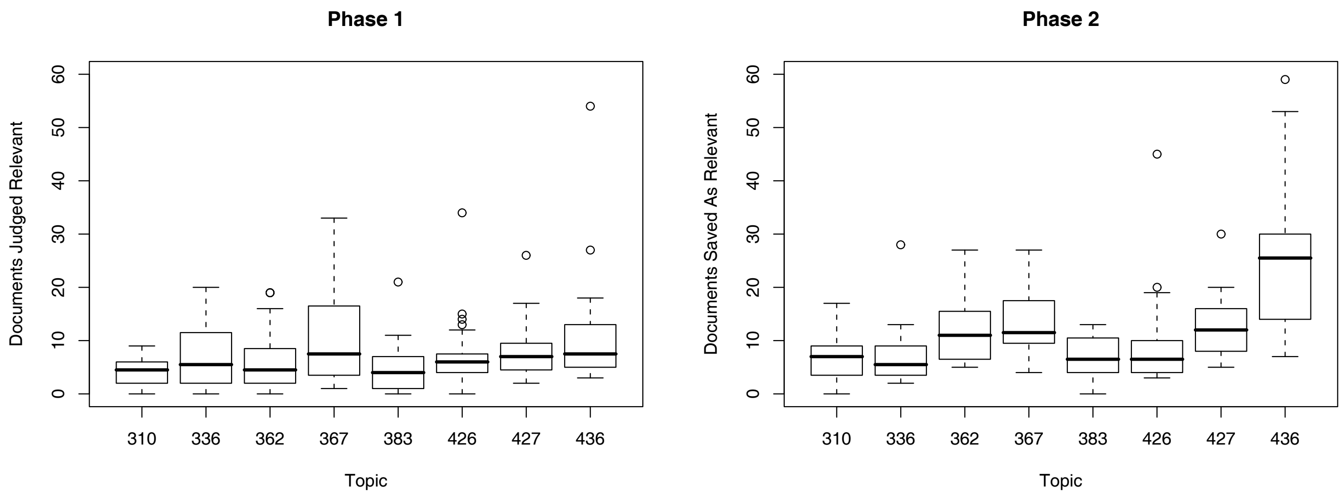


Figure 3: Number of documents judged as relevant (phase 1) and saved as relevant (phase 2) per topic. Each topic represents 24 users' data. The median is the heavy line inside the box. The box represents the data from the 1st quartile to the 3rd quartile, i.e. 50% of the values fall within the box.

367 does appear to be one of the easier topics. All the topics shown in Figure 3 have an equal number of users searching the same result lists of controlled levels of precision. Our control of precision across topics is one of the differences between our and Bailey et al.'s work.

4. RELATED WORK

There has been quite a bit of research looking at retrieval precision and its effect on user performance and satisfaction. We limit our review here to a few papers on precision's effect on perceived difficulty and satisfaction. We have already discussed the work of Bailey et al. [3] whose questions we used for our work.

Most similar to our user study is the work of Kelly, Fu, and Shah [4] who controlled the quality of the search results and asked users to evaluate the quality of the retrieval system. Kelly et al. found that higher precision resulted in better evaluation scores for the system. Their study differed from ours in that while we were primarily concerned with user performance, they were concerned with users' evaluations of the search engines. It may be that users consider retrieval quality to be the same as their difficulty with finding relevant documents, but we think Bailey et al.'s question about perceived difficulty is directed at the user's personal assessment of their search and not directed towards the search engine. Unfortunately we only had one question about difficulty. Multiple questions would have helped us target some questions towards the user and some towards the retrieval system. In addition to their own work, Kelly et al. provide an extensive and excellent review of related literature.

Al-Maskari, Sanderson, and Clough have studied the relationship between retrieval quality and user satisfaction [2]. They found a strong correlation between user satisfaction, precision, and cumulated gain, but a weaker correlation with discounted cumulative gain, and little correlation with nDCG. There may be an interesting difference between *satisfaction* and *difficulty with finding relevant documents*. Recall that Bailey et al. [3] found a correlation between nDCG and perceived difficulty. In another experiment, Al-Maskari and Sanderson [1] again report that system effectiveness, as measured by mean average precision, is positively correlated with user satisfaction as is user effectiveness and user effort.

5. CONCLUSION

We conducted a two phase user study that controlled retrieval precision. Across search topics, user performance differed greatly with some topics being much easier than others to find relevant documents. We found that retrieval precision had a statistically significant effect on perceived difficulty of finding relevant documents. In addition, we found that the higher level of precision produced more enjoyment and somewhat increased concentration, but we found no evidence that precision affected engagement with the search.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] A. Al-Maskari and M. Sanderson. A review of factors influencing user satisfaction in information retrieval. *JASIST*, 61(5):859–868, 2010.

[2] A. Al-Maskari, M. Sanderson, and P. Clough. The relationship between IR effectiveness measures and user satisfaction. In *SIGIR'07*, pages 773–774. 2007.

[3] E. W. Bailey, D. Kelly, and K. Gyllstrom. Undergraduates' evaluations of assigned search topics. In *SIGIR'09*, pages 812–813, 2009.

[4] D. Kelly, X. Fu, and C. Shah. Effects of position and number of relevant documents retrieved on users' evaluations of system performance. *TOIS*, 28(2):1–29, 2010.

[5] M. D. Smucker and C. Jethani. Human performance and retrieval precision revisited. In *SIGIR'10*. 2010.

Exploratory Searching As Conceptual Exploration

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ABSTRACT

The aim of this paper is to analyze the characteristics of exploratory searching for inferring ideas on how to evaluate exploratory search systems. Exploratory searching is defined as conceptual exploration. Information search process is divided into major stages. Goals, criteria and measures of attaining goals in explicating information need and formulating search are proposed. They can be applied for evaluating search systems aiming at supporting these two stages in searching.

Categories and Subject Descriptors

H.3.3 [Information Search and Retrieval]

General Terms

Measurement, Performance, Human Factors.

Keywords

Exploratory Search Systems, Search Process, Outcomes, Evaluation

1. INTRODUCTION

Studies on exploratory searching have gained popularity in recent years, although the same phenomenon has been studied earlier by other names like information search process [6] or task-based searching [13; 14]. Exploratory searching is understood here as searching for learning or investigative activities as defined in [8].

If learning is the ultimate goal of the activity generating searching it is evident that the paradigmatic model of evaluating interactive information retrieval [2; 4; 15] is not sufficient for evaluating exploratory searching. It focuses too much on assessing the output of the search system, not sufficiently observing the outcome of the system. Outputs are the products delivered by a system, whereas outcomes are the benefits the system produces to its users [11]. Typical output in IIR evaluation is the number of relevant items retrieved. The outcome of searching like growing understanding of the topic or to which extent the system supports searchers reaching their goals at various stages of search process is typically left without notice [cf. 14]. There is a need to develop ideas for evaluating exploratory search systems based on a deeper understanding of exploratory searching [cf. 15].

The aim of this paper is to analyze exploratory searching for creating ideas on how to evaluate exploratory search systems. First, the nature of activities leading to exploratory searching is discussed briefly. Based on that, information search process is conceptualized as representations of concepts and their relations in humans and documents [4]. After that exploratory searching is analyzed and ideas for evaluating search systems are introduced consisting of goals, evaluation criteria and their measures for the beginning stages of searching.

2. EXPLORATORY ACTIONS

A common feature of actions leading to exploratory searching is that the actor has insufficient information for solving an ill-structured problem for proceeding in her task [6; 13; 15]. This situation is called e.g. anomalous state of knowledge (ASK) [2] or uncertainty [6]. It is typical that the actor has problems to explicitly express her information need. This kind of ill-structured problems 1) begin with a lack of information necessary to develop a solution or even precisely define the problem, 2) have no single right approach for solution, 3) have problem definitions that change as new information is gathered, and 4) have no identifiable 'correct' solution [3]. Creating a solution is a gradual learning process, which implies integrating new information into existing mental models [3; 5].

Understanding learning as conceptual change [10] allows us to conceptualize mental models as consisting of concepts and their relations. This notion matches with the cognitive view of information retrieval, which conceptualizes information as knowledge structures both in humans and documents [4]. Exploratory searching is generated in situations, when actors' mental models lack concepts and relations between concepts for accurately representing the task. They have insufficient concepts and insufficient relations in their knowledge structure [12]. We claim that exploring concepts and their relations is a major characteristic of exploratory searching. Thus, we may say, that actors search information for obtaining concepts and their relations in order to understand, structure and represent their task more validly for proceeding in its performance.

In an ASK when actors have insufficient conceptual understanding, the goal of information searching is to help to understand and structure their task. By implication, the goal of exploratory search systems is to support the search process so that the searchers' understanding of their task grows and becomes more structured, and therefore produces more useful information items. Consequently, the evaluation of exploratory search systems includes both to which extent they support the search process, and produce useful information items [cf. 2].

3. EVALUATION

Evaluation begins typically by analyzing what is the goal of the system, process or service to be evaluated. It is assessed to what extent the object of evaluation attains the goals defined [11]. This requires that we have an understanding of which factors are associated in reaching the goal, i.e. what means are used to attaining it. In evaluation a distinction is made between outputs and outcomes. Outputs are the products delivered by a system, whereas outcomes are the benefits the system produces to its users [11]. Therefore, in evaluating exploratory search systems, one has to focus on the benefits the system produces to users during the search process, and on benefits the information items retrieved produce to the searchers' task.

For analyzing the outcomes of the system to users, we divide the search process into three main stages: explicating information need, search formulation, and evaluating search results. Search formulation can be divided into two elements; term selection and query formulation [1]. The former means expressing information need in search terms, and the latter combining terms for formulating a query. In this paper we focus on explicating information need and search formulation.

4. EXPLICATING INFORMATION NEED

4.1 Measuring conceptual constructs

The goal of explicating information need is to articulate it so that the actor has a growing understanding of the task for proceeding in its performance. Information need refers to insufficient conceptual construct (mental model) representing the task, which lacks necessary concepts and relations [12].

If the actor does not know much about her task, there may be alternative ways of conceptualizing the task and proceeding in its performance. A predefined, given conceptual structure to be used does not exist. The actor has to construct it incrementally while proceeding in the task. Kuhlthau's model indicates how the actor's understanding of a topic changes from vague to clear by formulating a focus [6], i.e. by constructing a necessary conceptual representation. Thus, the conceptual construct representing the task can be reconstructed only afterwards.

The actor's knowledge structure can be measured by observing the number of concepts and their relations that it consists of. Changes in the conceptual construct indicate to which extent the actor has been successful in explicating her information need.

If the goal of an exploratory search system is to help the searcher to express information need by explicating the concepts and relations it consists of, then the degree to which the articulation covers these concepts and their interrelations is the criterion of success.

This criterion is easy to apply to the given search tasks (topics) in retrieval experiments, because they contain the description of the information needs (topics). They are predefined, known in advance and do not change during the search process [4]. Thus, success can be measured by the proportion of articulated concepts of all concepts the topic consists of.

In tasks generated by actors the application of previous criterion is possible only afterwards. In an ASK it is not possible to know in advance the exact conceptual structure of information need [cf. 2]. However, there is some evidence of how conceptual construct changes when actors' understanding grows. In general, it changes from vague to precise [6; 13]. The extension of concepts decreases, the number of sub-concepts increases, and the number of connections between the concepts increases [5; 10]. This hints, that growth of understanding consists of an increasing number of concepts and their relations, and of the specificity of conceptual construct. Thus, increase in the number of concepts and in the number of interrelations between these concepts, as well as in the specificity of conceptual construct are the criteria for success of explicating information need for searching. Specificity is reflected in the actors' ability to differentiate a concept into sub-concepts. This can roughly be measured by the proportion of sub-concepts of all concepts the conceptual construct consists of [cf. 9]. Measures and criteria of success are presented in table 1.

Table 1. Measures of success in explicating information need

Measure	Criteria of success
Exhaustivity = # of concepts articulated	Increase in the # of concepts articulated *in ASK*, or Increase in the proportion of concepts articulated *in given topics*
Specificity = the proportion of sub-concepts of all concepts articulated	Increase in the proportion of sub-concepts of all concepts articulated
Combined measure	Increase in the # of concepts added by the increase in the number of specified concepts (greater weight)
Conceptual integration = # number of links expressed between concepts	Increase in the # links between concepts

4.2 Measuring conceptual change

Explication of information need for constructing a focus, i.e. when is it fully represented as concepts, may require several iterations within a search session or even several sessions. In the following we focus on changing information needs [cf. 4] for presenting criteria of success in explicating them after the initial search.

If the information need is vague after the initial search, the actor continues explicating it. We may distinguish between two types of conceptual changes. The first one is conceptual continuity, which is based on the concepts explicated in the initial search. Conceptual change refers to the situation when the actor replaces at least an existing concept in the conceptual construct by a new concept with differing extension.

In conceptual continuity new explication includes either new concepts or specifications of the concepts explicated in the initial search or both. The specification of a concept means that its extension is smaller than the original one, but it belongs mainly to original extension. It is a class inclusion. An example of this is the specification of the concept "information seeking" as "information retrieval". Introducing new concepts or specifying old ones is likely to lead to a more specific articulation of information need. As stated earlier the increase in the number of concepts and their interrelations in explicating information need are the criteria of success. Also the proportion of sub-concepts of all concepts explicated can be used as a measure of the specificity of the conceptual construct (table 1). An additional measure of the specificity could be the proportion of concepts in the initial search (previous iteration) specified in the next iteration.

It is possible to form a combined measure for the success of explicating information need after the initial search. For each new concept that is introduced in the conceptual construct the weight of e.g. 1 is given, and for each old concept specified e.g. the weight 1.5. The greater weight is assigned to specification, because it adds value to the original concept by limiting its extension. The measure is the sum of the values of the new and specified concepts. This combined measure gives a rough estimate in the increase of the articulation of information need.

In conceptual change at least one old concept in the information need is replaced by a new one with differing extension. Other concepts may be unchanged or specified. It is difficult to infer, how replacing concepts increases the actor's understanding of information need. In which cases it is justified to claim that the replacing of concepts has increased the understanding of information need?

If a concept or concepts are replaced without specifying the remaining ones, it is likely that the actor is surveying the conceptual space of the information need not being able to decide how to specify it. She may be looking for alternative explications among which to choose. We call this activity as conceptual mapping. It resembles Bates' vary tactics replacing an existing search term by another [1]. In our case, it is likely that the actor's information need has not become more specific, but it has changed on the same level of specificity.

Introducing new concepts in the conceptual construct typically includes creating new relationships between the new and old ones. These relationships contribute to the meaning of the construct [5]. If the actor specifies at least one of the remaining concepts when replacing one or more concepts, this hints that the relations to the new, replacing concepts have helped her to specify the original concept. The meanings of the replacing concepts have contributed in specifying the meaning of the original concept. Thus, at least in part of the specified concept the information need is more specifically articulated. This specification hints also that the replacing concepts are in some way more specific than the replaced concepts, implying that the explication of the whole information need is more specific.

We may measure the success of explicating conceptually changing information need as follows. In replacing concepts, the number of concepts does not increase, and thus the understanding has not grown in the sense of a more specific information need. However, replacing may lead to selecting a conceptual alternative among the surveyed concepts, and help the searcher to articulate information need. Therefore, only the concept, which is selected after varying concepts, will receive the weight (e.g. 1). If replacement is associated with the specification of at least one original concept, then each specified concept is assigned the weight 1.5.

5. SEARCH FORMULATION

Search formulation is divided into term selection for representing search concepts, and query formulation for combining search terms as a query [1]. We discuss first about term selection, and then query formulation.

5.1 Term selection

For evaluating exploratory search system providing support in term selection, we have to define the goal of term selection in order to be able to infer criteria of success. This goal can be understood from the angle of expressing information need or from the angle of information retrieval.

Term selection based on information need requires that an actor is able to express the concepts it consists of as search terms. The goal of term selection is thus to express the concepts of information need. The exhaustivity of query refers to the extent to which the concepts of information need are expressed in the query [7]. Thus, the more exhaustive the query, the more successful term selection is from the angle of expressing the information need.

From the angle of information retrieval it has been typical to reduce the success in term selection to the number of relevant items retrieved based on new terms in the query, and inferred measures like precision or recall. Depending on whether the goal of searching is recall or precision, there are known procedures to aim at those goals. Other factors controlled, increasing the exhaustivity and specificity of query increases precision, whereas increasing the extent of the query (# of terms per concept) increases recall [7].

In exploratory searching the actor does not know exactly the concepts her information need consists of, but she tries to articulate them. How would measures like precision or recall reflect to which extent the actor has been successful in articulating the information need and expressing it by search terms? It seems that those measures are not very meaningful in estimating the success of those activities and the help provided by the system.

However, it is suggested that investigative searching is more concerned about recall (maximizing the number of possible relevant objects) than precision (minimizing the number of possibly irrelevant objects) [8]. When actors are exploring possible conceptualizations of their topic in order to formulate a focus, they are typically confused and overwhelmed with information. Information seems inconsistent and incompatible with their prior conceptual constructs [6]. In a situation like this, it is not likely that actors are concerned with recall, but precision. They are not interested in finding most of the documents, which would provide them with ideas in structuring the topic, but a sufficient number for formulating a focus. When the information need is structured containing all the necessary concepts, i.e. when it is stable [4], then it is likely that actors are concerned with recall and aim at comprehensive searches on the topic. Thus, in pre-focus stage, searching is precision oriented, whereas in post-focus stage it is recall oriented.

If searching aims at precision in pre-focus stage, then most productive in term selection is to express all the concepts of information need in search terms. As known, increasing exhaustivity increases precision [7].

5.2 Query formulation

Broadening the view from term selection to query formulation may be a more fruitful approach to evaluate search success. In exploratory searching query formulation is open due to the fact that not all concepts in information need are known. The actor aims at finding documents, which would provide her with ideas of how to structure her topic. She tries to find conceptual alternatives within the scope of her information need, and to compare those alternatives [cf. 8; 9]. It is a question about finding connections between concepts, i.e. finding propositions which connect concepts in a meaningful way. A proposition asserts something about two or more concepts and their relations [10].

As stated earlier, growth of understanding is characterized by the increasing number of concepts and their interrelations (i.e. propositions), and by the specificity of concepts. In order to structure information need, the actor should use search tactics that would help her in exploring document space accordingly. A typical way of expanding and mapping conceptual structure is by adding a concept in a query and replacing it by another one leading to vary tactics [1]. Empirical findings confirm, that vary tactics are used for mapping conceptually the search topic [9]. The same study also showed, that searchers quite systematically chunked the search topic into conceptually smaller fields by using successive facets for inspecting the items retrieved [9].

A means of specifying concepts is to provide an actor with the sub-concepts of the concepts in her information need [cf. 1]. E.g. if one is interested in evaluating information searching, it would be beneficial, if the system could provide her with sub-concepts like process evaluation and product evaluation, or efficiency and effectiveness. This is likely to help in specifying her information need.

The discussion above hints that structuring searching conceptually both in expressing information need and formulating search would be beneficial in exploratory searching. Consequently, exploratory search systems should provide actors with tools that help them conceptually map and structure the topic of their information need and formulating search tactics accordingly. Distinction between expressing information need and selecting search terms is an analytical one. In searching actors engage in both activities simultaneously. Therefore, it is important that querying facility in exploratory search systems helps searchers to explicitly structure their search formulation conceptually, and that it also provides them with a tool for specifying their search terms e.g. into hierarchically narrower terms.

6. CONCLUSIONS

We have explicated the major stages in exploratory searching, and suggested some criteria for evaluating exploratory search systems especially at the early stages in exploration. Our ideas extend the evaluation paradigm from a focus only on the output of the system onto the whole search process.

In evaluation of systems and services, the point of departure is to assess to which extent the goal of the system is achieved [11]. It seems that one of the major limitations in interactive evaluation has been to focus on only one goal of information retrieval, optimizing the output in terms of the number of relevant items retrieved. Although this is a necessary condition for a successful information retrieval, the search process is in its turn a necessary condition for a good retrieval result. Therefore, in evaluating search systems, it is important to assess to what extent the search process variables reach their objectives, and through those objectives contribute to retrieval effectiveness [cf. 2].

A major implication of our analysis is that in system evaluation it is critical to define the goals of the tools assessed in improving human performance in information searching. Without reflecting and defining the objectives of the system it is difficult to infer appropriate evaluation criteria. This is of special importance in evaluating tools for supporting exploratory searching. In exploration it is as critical to support the search process and structuring of the topic, as it is to retrieve relevant items [13; 15]. Surveying information space with appropriate tools is likely to contribute to structuring the topic and expressing the information need as search terms leading to growing understanding of the topic and as a consequence, more useful search results. Thus, the exploratory search system should help the user to attain several search goals from explicating the information need to finding documents conceptually matching that need [8; 15]. It is important to assess to which extent the system attains these various goals.

We have excluded from the analysis of search process the evaluation of search results. Our next step is to analyze assessing retrieval results as conceptual exploration. We seek to infer measures of success in this activity understood as conceptual correspondence between searcher's conceptual construct and author's conceptual construct in the document retrieved [12]. It is possible to extend this conceptualization also to cover the benefits information retrieval systems produce to task performance, the ultimate goal of these systems. By representing task as a conceptual construct it is possible to relate task performance process to search process as we have described it in this study. This procedure implies that we are able to model and assess how the search process and the use of information in the items retrieved contribute to task performance.

7. REFERENCES

[1] Bates, M.J. 1979. Information search tactics. *JASIS* 30, 205-214.

[2] Belkin, N. J. 1993. Interaction with texts: information retrieval as information-seeking behavior. In *Information Retrieval ´93*. Konstanz: Universitetsverlag Konstanz, 55-66.

[3] Gallagher, S., Sher, B., Stepien, W. and Workman, D. 1995. Implementing problem-based learning in science classrooms. *School Sci. and Math.* 95, 136-140.

[4] Ingwersen, P. and Järvelin, K. 2005. *The Turn: Integration of Information Seeking and Retrieval in Context*. Springer, Dordrecht.

[5] Kintsch, W. 1998. *Comprehension. A paradigm for cognition*. Cambridge UP, Cambridge.

[6] Kuhlthau, C. 1993. *Seeking Meaning*. Ablex, Norwood, N.J.

[7] Lancaster, W. and Warner, A. 1993. *Information retrieval today*. Information Resources Press, Arlington, VA.

[8] Marchionini, G. 2006. Exploratory search. *Comm. ACM* 49, 41-46.

[9] Pennanen, M. and Vakkari, P. 2003. Students' conceptual structure, search process and outcome while preparing a research proposal. *JASIST* 54,759-770.

[10] Rebich,S. and Gautier, C. 2005. Concept mapping to reveal prior knowledge and conceptual change in a mock summit course on global climate change. *J. Sci. Educ.* 53, 355-365.

[11] Rossi, P., Lipsey, M. and Freeman, H. 2004. *Evaluation. A systematic approach*. 7th ed. Sage, Thousand Oaks.

[12] Vakkari, P. 1999. Task complexity, problem structure and information actions. *IP&M* 35, 819-837.

[13] Vakkari, P. 2001. A Theory of the task-based information retrieval process. *J. Doc.* 57, 44-60.

[14] Vakkari, P. 2003. Task-based information searching. In *ARIST* 37 (B. Cronin, Ed.) Information Today, Medford, NJ., 413-464.

[15] White, R.W. and Roth, R. 2009. *Exploratory search*. Morgan & Claypool.

Casual-leisure Searching: the Exploratory Search scenarios that break our current models

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ABSTRACT

In trying to understand Exploratory Search, the community has focused on users who are working towards an information need, but who are unclear of their goal, technology, or domain of information. Our recent research, however, suggests that this definition misses perhaps the most exploratory search scenario of all - scenarios where the goal is not information-oriented. We present combined evidence from two on-going research projects, which demonstrates that such situations occur regularly within casual-leisure situations. We use our findings to characterise such tasks and suggest that casual-leisure search scenarios deserve more focus as we work towards supporting exploratory search.

Keywords

Exploratory Search, Information Needs, Casual Search

1. INTRODUCTION

In trying to understand Exploratory Search, the community has focused on users who are working towards solving an information need, but who are unclear of their goal, technology, or domain of information. Exploratory searches typically involve learning or investigating. Similarly, Information Seeking typically presumes the resolution of an information need. In two separate research projects, however, we have recorded several examples of real-life information behaviours that are outside of our definition of Exploratory Search, and do not fit the model of 'Work Tasks' at home. Although neither project was focused on exploratory search, both revealed novel scenarios that we believe need more focus in our community. These novel scenarios include users with no explicit information need to solve and where the act of searching is often of greater importance than the content found. Such scenarios, which occur regularly in casual-leisure situations [12], are often more exploratory than the notions of learning and investigation that we currently work with, and are sometimes performed for much longer periods of time.

In the following sections we first summarise important information seeking and exploratory search research, and discuss related work from leisure-studies, which frames our recent findings. We then provide an overview of our two research projects, highlighting the findings on casual-leisure information behaviours. We conclude by presenting an initial definition of casual-leisure searching and discuss the impact that our results may have on how we define and study exploratory search.

2. RELATED WORK

Our models of Information Retrieval (IR), Information Seeking (IS), Exploratory Search(ES) and Sensemaking are all typically information focused. IR is well established as the more technical returning of relevant documents or information in relation to a specific given query. IS is more behaviour-oriented, describing the resolution of an information need [8]. ES is defined as trying to resolve an information need when the searcher has limited knowledge of their goal, domain, or search system [13], normally involving some kind of learning or investigating behaviour [9]. Sensemaking has been described as bridging a knowledge gap [2]. Each of these definitions underlines the assumption that searching occurs to find information (or media, etc).

Investigations have revealed that these situations are often motivated by work tasks [6], where one or more information seeking episodes help resolve a higher level need. It is typical within the IS community to consider that Exploratory Search or Sensemaking occurs in order to write a report, and that as part of IS process, IR is performed to find references. Included in the definition of 'Work Tasks' is the notion of personal work tasks, such as buying a car or booking a holiday (e.g. [10]).

Despite including "personal tasks", most of the models underpinning the mentioned research stem from library and information science, which has historically focused on work contexts. However, technological advances and cultural changes mean that information now pervades peoples' everyday lives and non-work scenarios have become increasingly important with respect to information behaviour research [5, 4]. Stebbins [12] characterises non-work or leisure activities as hedonic in nature, the benefits of which include 1) Serendipity; 2) Edutainment; 3) Regeneration or re-creation; 4) Maintenance of interpersonal relationships; and 5) Well-being. Stebbins distinguishes between 3 different leisure situations: *Serious leisure*, e.g. serious hobbies or volunteer activities; *Project-based leisure* e.g. planning a holiday or car purchase; and *Casual leisure* short, pleasurable activities requiring little or no special training to enjoy.

It is within the third space, casual-leisure, where least information seeking research has been performed and has been the focus of our research. Our work has highlighted specific examples of search behaviours that we believe are of interest to the exploratory search community. Below, we characterise these situations as found in our two studies and provide an initial definition of casual-leisure search behaviours for the community to work with.

3. TV-BASED CASUAL INFORMATION BEHAVIOURS

In recent work [3], we performed a diary study with a heterogeneous population (n=38) to learn about information needs in the context of television viewing. An inductive grounded theory approach was taken by four researchers on both the needs recorded and motivating factors to produce affinity diagrams and a final coding scheme for both needs and reasons. The final coding schemes can be found in [3]. Here we focus on then novel scenarios relating to exploratory search behaviours.

We found many examples of standard information needs that fit into the information-oriented models of how we search; example quotes are shown in Table 1. Participants noted, for example, wishing to know the name of an actor, or finding the time that a specific show was going to begin. These tasks involve an information need, and the goals are not satisfied until the information was found. Others involved making viewing decisions, and depended on multiple factors such as obtaining a plot summary of a film in order to decide if they had seen it before. These are good examples of needs with complex and multiple dependencies – the kind typically investigated in ES.

(a) Need:	How old was Tina Turner when that concert was filmed?
(b) Need:	[I would like] a list of interesting films / documentaries showing, from 7 or 8pm
(c) Need:	"[I am looking for] up-to-date news; [I need to know the] channel and time of broadcast"

Table 1: Example tasks recorded in diary entries: (a) a simple information-based need, (b) a fuzzy information-based need, and (c) a complex information-based need.

Many of the motivations recorded were not information-oriented, as shown in Table 2. At the highest level, we saw participants wishing to 'kill time', while others noted wishing to find something to distract their attention or provide something entertaining to support a laborious task like ironing. In each of these cases, the answer or information found was not of critical importance. When looking for edutainment the participants' needs were mostly non-specific in nature with participants noting a desire for something "interesting", "sophisticated" or "challenging" and not on a particular topic or domain as would be typical of work-based tasks. Participants often reported satisficing for the first appropriate result they found, regularly not being bothered to check if there was a better or more appropriate option available.

From analysing the motivating reasons, we recorded examples of users wishing to enhance or change their mood, by finding something relaxing, thrilling, entertaining, or simply new. We also saw people finding something to watch

Need:	[I want an] entertaining programme, something funny, to distract me
Reason:	Stressful day!
Need:	[I want] something interesting, distracting, informative, cultured such as a travel report or history programme
Reason:	I need to iron and at the same time i like to watch tv - it takes my mind off the chore
Reason:	Stressful day!
Need:	[I'm looking for] short entertainment during dinner
Reason:	[I have a] little time to waste
Need:	Channel hopping
Reason:	I'm bored

Table 2: Example entries where the information need is secondary to the experience of searching.

because they could not sleep, or because they were feeling curious. Again, in these situations, people aimed primarily to achieve a hedonistic goal, where success in their search was more closely tied to achieving this primary aim than finding a specific show to watch. The last example in Table 2, the oft recorded "need" to channel hop, which was regularly motivated by a short period of free time or boredom, particularly highlights the importance of experience over information found.

This investigation of information needs in the context of a particular casual-leisure activity has provided novel insights into how and why people search, but it is not clear how these generalise into other casual-leisure situations e.g. online shopping. Our second project, discussed below, has begun to demonstrate that these kinds of scenarios do pervade both our physical and digital worlds.

4. HARVESTING REAL SEARCH TASKS

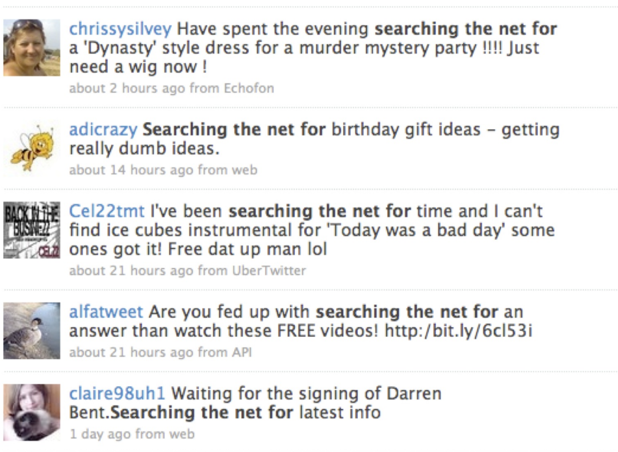

Figure 1: Example tweets about real information needs and searching behaviours.

In the second study, Twitter [1] was used as a data source to learn about casual-leisure information behaviour in a wide variety of situations. Twitter provides a public forum where people discuss a broad range of everyday life experiences, including search behaviours [14]. We collected a corpus of 2.4M unique tweets over 5 months by accessing and storing tweets containing search-oriented keywords like 'browse',

[1]http://www.twitter.org

'explore', and 'search' in their past, present, and future tenses. 12 seed-terms were used to query Twitter each hour, with the 100 newest tweets being stored each time. Our corpus contains information about hundreds of thousands of real human searching scenarios and information needs, some examples are shown in Figure 1.

To investigate the information behaviours described in the corpus, we embarked on a large-scale qualitative, inductive analysis of these tweets using a grounded theory approach. With the aim of building a taxonomy of searching scenarios and their features, we have so far coded 2500 tweets in approx. 40 hrs of manual coding time. Already, we have begun to develop a series of dimensions and learned, ourselves, a great deal about the kinds of search scenarios that people experience in both the physical and digital domains.

To date, we have identified 10 dimensions within our taxonomy, 6 of which were common in the dataset and have become fairly stable. We will present this taxonomy in future work, when more tweets have been coded and the taxonomy is complete. Further, once the taxonomy is stable and has been tested for validity, we will use alternative automatic or crowd-sourcing techniques to gain a better idea of how important the factors are and how they relate. Here, however, we will highlight some of the casual-leisure search behaviours documented so far.

4.1 Need-less browsing

Much like the desire to pass time at the television, we saw many examples (some shown in Table 3) of people passing time typically associated with the 'browsing' keyword.

1) ... I'm not even *doing* anything useful... just browsing eBay aimlessly...
2) to do list today: browse the Internet until fasting break time..
3) ... just got done eating dinner and my family is watching the football. Rather browse on the laptop
4) I'm at the dolphin mall. Just browsing.

Table 3: Example tweets where the browsing activity is need-less.

From the collected tweets it is clear that often the information-need in these situations are not only fuzzy, but typically absent. The aim appears to be focused on the activity, where the measure of success would be in how much they enjoyed the process, or how long they managed to spend 'wasting time'. If we model these situations by how they manage to make sense of the domain, or how they progress in defining their information-need, then we are likely to provide the wrong types of support e.g these users may not want to be supported in defining what they are trying to find on eBay, nor be given help to refine their requirements. We should also point out, however, that time wasting browsing was not always associated with positive emotions (Table 4).

1) It's happening again. I'm browsing @Etsy. Crap.
2) browsing ASOS again. tsk.
3) hmmm, just realizd I've been browsing ted.com for the last 3 hours.

Table 4: Example tweets where the information-need-less browsing has created negative emotions.

The addictive nature of these activities came through repeatedly and suggests perhaps that support is needed to curtail exploration when it is not appropriate.

4.2 Exploring for the experience

Mostly related to the exploration of a novel physical space, we saw many people exploring *with* family and friends. The aim in these situations (see Table 5) is often not to find specific places, but to spend time with family.

1) exploring the neighbourhood with my baby!
2) What a beautiful day to be outside playing and exploring with the kids:)
3) Into the nineties and exploring dubstep [music] while handling lots of small to-dos

Table 5: Example tweets where the experience outweighs the things found.

In these cases, the goal may be to investigate or learn about the place, but the the focus of the activity is less on the specific knowledge gained than on the experience itself. Another point of note is that in these situations people regularly tried to behave in such a way that accidental or serendipitous discoveries were engendered. While examples 1) and 2) are physical-world examples, it is easy to image digital world equivalents, such as exploring exploring the Disney website with your children.

Below we attempt to combine the characteristics we have discovered to create an initial definition of what we refer to as casual search.

5. CASUAL SEARCH

We have seen many examples of casual information behaviours in these recent projects, but here we highlight the factors that make them different from our understanding of Information Retrieval, Information Seeking, Exploratory Search, and Sensemaking. First, we should highlight that it is not specifically their information-need-less nature that breaks the model of exploratory search, although some examples were without an information need entirely. The differentiators are more in the motivation and reasoning for searching, where all of our prior models of search are typically oriented towards finding information, but casual search is typically motivated by more hedonistic reasons. We present the following defining points for casual search tasks:

- In Casual search the information found tends to be of secondary importance to the experience of finding.
- The success of Casual search tasks is usually not dependent on actually finding the information being sought.
- Casual search tasks are often motivated by being in or wanting to achieve a particular mood or state. Tasks often relate at a higher level to quality of life and health of the individual.
- Casual search tasks are frequently associated with very under-defined or absent information needs.

These defining points break our models of searching in several ways. First, our models focus on an information need, where casual search often does not. Second, we measure success in regards to finding the information rather than the experience of searching. Third, the motivating scenarios we use are work-tasks, which often is not appropriate in casual search.

5.1 Discussion

In many ways, we are typically aware of these casual information behaviours in everyday life. Most of us have ourselves wasted time, either intentionally or accidentally, endlessly following links in Wikipedia or watching related movies on youtube. Similarly, services like flickr are for sharing and discovering interesting photographs, where trying to find suitable images for a work task is only one identifiable use of the system.

Yet our investigations into Exploratory Search, for example, typically focus on whether people were able to find what they wanted. In evaluating the MrTaggy interface [7], for example, the amount learned was measured by the quality of subsequent report writing and level of cognitive load. Yet systems built with social tags are often designed to help people discover interesting content. It may be also interesting, therefore, to measure how long a user wants to continue an exploratory search task or the affects the task has on his mood or state. Capra et al [1] chose specifically not to use time as a metric for ES, noting that a good ES system may encourage people to search for longer. Their tasks, however, had information-oriented learning goals, and so increased time would not have been a suitable measure in their case either. More appropriate measures of casual search are beginning to arrive. O'Brien et al [11], for example, have designed a measure of Engagement, identifying how long people remain engaged in an activity, and what factors influence their prolonged engagement. Our work supports the use of this kind of metric for casual search scenarios.

Beyond challenging the way we measure the success of exploratory search tasks, we must also consider the way we define exploratory search tasks. Currently, we design tasks that have information-oriented Work Tasks, such as trying to buy a new piece of technology or writing a report. We must consider how we can, with high ecological validity, create studies where users are provided with hedonistically motivated tasks. Studies could be designed, for example, where users are told that there is a unforeseen delay and told they may use a computer while they wait. Then, when they appear to be bored, or after a reasonable amount of time, the faux-study continues.

We believe these insights into *casual search* are particularly important for the study of Exploratory Search, where our working definition of Exploratory Search does not include searchers with non-information oriented goals. Further, these activities are important to health and wellbeing [3]. Some of the casual information behaviours we have identified motivate people to explore for websites for hours, but our definition of exploratory search does not cover them all. The community will struggle to design effective support for these lengthy casual search scenarios, or indeed the short hedonistically motivated searches, if continuing focusing on systems that help build knowledge or refine information needs.

6. SUMMARY

In this paper we have presented initial evidence, from two recent and on-going research projects, towards a notion of *casual search*. We believe that *casual search* is not properly covered by existing definitions of information seeking and exploratory search, but is perhaps one of the more exploratory scenarios discovered so far. People engaged in casual search are typically not trying to resolve an information need, and their objective is not to learn or investigate. Instead casual search involves hedonistically motivated scenarios which involves, for example, searching to be entertained and satisficing for any result that, in this case, enjoyable. Consequently, the models and measures we have for exploratory search may not be sufficiently inclusive, and may need redefining. Instead, we may wish to focus on measures of maintained engagement (e.g. [11]) for how well a search system supports need-less exploration.

7. REFERENCES

[1] R. Capra, G. Marchionini, J.S. Oh, F. Stutzman, and Y. Zhang, *Effects of structure and interaction style on distinct search tasks*, Proc. JCDL'07, ACM Press, 2007, pp. 442–451.

[2] B. Dervin and M. Frenette, *Sense-making methodology: communicating communicatively with campaign audience*, Sense-Making Methodology reader: selected writings of Brenda Dervin (Brenda Dervin, Lois Foreman-Wernet, and Eric Lauterbach, eds.), Hampton, Cresskil, NJ, 2003, pp. 233–249.

[3] D. Elsweiler, S. Mandl, and B. Kirkegaard-Lunn, *Understanding casual-leisure information needs: a diary study in the context of television*, Proc. IIiX 2010, 3rd Symposium on Information Interaction in Context, 2010.

[4] C. Fulton, *Quid pro quo: information sharing in leisure activities*, Library Trends **57** (2009), no. 4, 753–768.

[5] J. Hartel, *The serious leisure frontier in library and information science: hobby domains*, Knowledge Organization **30** (2003), no. 3-4, 228–238.

[6] K. Järvelin and P. Ingwersen, *Information seeking research needs extension towards tasks and technology*, Information Research **10** (2004), no. 1.

[7] Y. Kammerer, R. Nairn, P. Pirolli, and E. H. Chi, *Signpost from the masses: learning effects in an exploratory social tag search browser*, Proc. CHI '09 (New York, NY, USA), ACM Press, 2009, pp. 625–634.

[8] G. Marchionini, *Information Seeking in Electronic Environments*, Cambridge University Press, 1995.

[9] G. Marchionini, *Exploratory search: from finding to understanding*, Commun. ACM **49** (2006), no. 4, 41–46.

[10] M. R. Morris, *A survey of collaborative web search practices*, Proc. CHI '08 (New York, NY, USA), ACM, 2008, pp. 1657–1660.

[11] H. L. O'Brien and E. G. Toms, *What is user engagement? a conceptual framework for defining user engagement with technology*, JASIST **59** (2008), no. 6, 1–18.

[12] R. A. Stebbins, *Leisure and its relationship to library and informations science: bridging the gap*, Library Trends **57** (2009), no. 4, 618–631.

[13] R. W. White, B. Kules, S. M. Drucker, and m.c. schraefel, *Introduction*, Commun. ACM **49** (2006), no. 4, 36–39.

[14] M. L. Wilson, *Using twitter to assess information needs: Early results*, Proc. HCIR'09, 2009, pp. 109–112.

Search for journalists: New York Times challenge report

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ABSTRACT

We investigate how a user-centred design to search can improve the support of user tasks specific to journalism. Illustrated by example information needs, sampled from our own exploration of the New York Times annotated corpus, we demonstrate how domain specific notions rooted in a field theory of journalism can be transformed into effective search strategies. We present a method for search-context aware classification of authorities, witnesses, reporters and columnists. A first search strategy supports the journalistic task of investigating the trustworthiness of a news source, whereas the second search strategy supports assessments of the objectivity of an author. In principle, these strategies can exploit the semantic annotations in the corpus; however, based on our preliminary work with the corpus, we conclude that straightforward full-text search is still a crucial component of any effective search strategy, as only recent articles are annotated, and annotations are far from complete.

Keywords

journalism, faceted search, interactive IR

1. INTRODUCTION

> A rhetoric is a social invention. It arises out of a time and place, a peculiar social context, establishing for a period the conditions that make a peculiar kind of communication possible and then is altered or replaced by another scheme. [1]

The particular context where a textual document has been written, the audience an author appeals to, and the goals she wants to achieve shape argumentation and the rules a written text has to comply with in order to be considered for publication. Conversely, understanding the features of a rhetoric shades some light on the context of a document and on its correct interpretation by a reader.

Journalism is one peculiar discursive practice, which fits what, in an attempt to establish a theory of journalism, Andrew R. Cline referred to as an *epistemological field* [2]. This model for the domain of journalism contains a characterisation of 1) what can and cannot be known, 2) the nature of the knower, 3) the nature of the relationships among the knower, the known, and the audience, and 4) the nature of language. Legitimate questions within this domain are "how to correctly represent a fact?", "why should I trust a certain source?" or "who's opinion does a certain text represents?". We believe that the richness of the semantics provided by the New York Times (NYT) annotated collection allows to specify search strategies in these domain specific terms, which are highly abstract from an information system perspective, but nevertheless most familiar to our target end user: a journalist in the process of writing an article. This is the main intuition behind our contribution to the New York Times challenge organised at HCIR2010.

The collection as a whole can be thought of as an implicit definition of a dominant journalistic field: through a careful process of editing and verification only an article that complies with all the requirements of this domain will appear in the newspaper. Our aim is to support a journalist in accessing the NYT collection by means of domain specific concepts, providing a highly inclusive system, which is intuitive, effective and entertaining to use.

In order to demonstrate our approach, we focus on two of what perhaps are the most important elements in any theory of journalism, writers and sources: "it is the curious relationship between the reporter as knower and the source as knower that creates much of what we understand as journalism. The reporter shifts between the roles of knower and conduit of the known."[2]. We built a search engine to retrieve sets of documents which support an end user in charting the entangled relationship between authors of an article and their sources, showing that abstract concepts can be translated to possibly very complex search strategies.

In the next section, after briefly discussing how authors and sources are understood in the domain theory of journalism that inspired our design, we introduce four important typifications into which, according to this theory, authors and sources can be classified. An author can aim to produce journalistic knowledge and be a Reporter or to express a private opinion and be a Columnist. A source on the other hand, that is a person who is mentioned in an article as in-

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formed about the facts, can derive her trustworthiness on a given issue in force of the circumstance that she was on the scene when a news event happened, being for that event a Witness, or because she is an expert on that matter, being then an Authority. Experts on journalism claim that it is of paramount importance, in order to evaluate any document on a given issue, to know who wrote the document and how information has been gathered on the field.

Section 3 explains how the four typifications can be translated into partitions of the search space: evidence to support belonging to one of the four categories here above can be gathered by means of different search strategies fired onto the NYT annotated corpus. Each strategy, which can be interactively tuned by a user, allows these abstract categories to be mapped onto faceted search processes. Finally, the last section summarises the main conclusions with respect to the specific challenge requirements.

2. AUTHORS AND SOURCES

According to the theories of rhetoric [1] and of journalism [2] that we considered, journalistic knowledge relies on inductive reasoning upon most often only indirect experience of events. The goal of a journalist is to collect and present different and possibly incompatible views on how events have been, leaving to a reader the burden of interpretation. While a Reporter must at least in principle abstain herself from commenting on the facts, a Columnist is sought after just because of her opinions: while both Reporters and Columnists write about facts, a competent reader is able to discern whether the focus is on a description of a fact or on a description of its possible meanings. Both rhetoric and visual cues contribute to allow a reader to establish memberships to one or another category. While a more rigid article structure is a common feature of a Reporter's work and the position of an article within the printed newspaper may also be used to determine an author's status, it is most often an author's reputation that affords a reader to either believe in the author's impartiality of to let her concentrate on the author's personal view on the facts.

Since a writer's experience on a fact is mostly mediated by an interpretation given by a source, evaluation of what has been written heavily depends on whether a source can be trusted on a particular issue. Readers mostly rely on their own background knowledge in order to evaluate a source's trustworthiness. Authorities derive their legitimacy to speak about a certain topic by virtue of being member of an official organisation, of academic or social achievements, or because of a past demonstration of their skills. When a reader does not have the necessary prior knowledge, she will typically rely on the information provided by the author, in order to determine a source's trustworthiness.

This is often the case for Witnesses, who's competence scope does not exceed a particular event: since a reader does not generally have much prior information about an event she is reading about, otherwise she would probably skip the article, trustworthiness of a Witness depends on the guarantees that a writer can provide in a reader's eyes. Reporters and Columnists will be given different weights when deciding on the sources they are quoting. The relationship between authors and sources, once an interpreting reader is included into the picture may become increasingly complex.

The system that we propose aims to extend the background knowledge that a reader commonly employs to assess both authors and sources, by letting the semantic annotations provided with the collection act as additional cues, allowing an end user to still be competent in evaluating this complicated relationship between authors and sources onto the much larger scale of the entire NYT collection.

3. SEARCH STRATEGIES

This is the core part of this report. Here we explain how the treatment of the two concepts of authors and sources in the domain theory of journalism can be translated to search strategies and how the documents within the annotated NYT corpus jointly with the search strategies support a user in making sense of those concepts. We used both the Apache Solr[1] and the Spinque[2] search servers to test informally the applicability of our proposed approach. Solr represents a classic text retrieval case, where the newspaper archive can be searched by ranking the full-text of the articles on their content. Spinque's *Strategy Builder* is a prototype environment where search processes are divided into two phases: search strategy definition, and the actual search. Search strategies are visually defined data-flows consisting of query terms, documents and named entities. While not the topic of this paper, the probabilistic database back-end on which search strategies are executed provides the flexibility needed to allow full exploration of the data space spanned by articles and their semantic annotations.

We think the level of control provided by the strategy builder provides to a user very powerful primitives for exploratory search. In our approach there is no set of documents that can be thought of as the denotation of the high level concepts: meaning arise from the act of exploring the collection and defining a search strategy as well as from reading the retrieved documents. Since with Spinque there is, even for a less experienced user, a clear division of meaning making labour between a visual development of a search strategy, faceted browsing of (intermediate) results and strategy refining, we expect further work on this subject to be carried forth in the form of 'search by strategy' processes.

3.1 Reporters and Columnists

In a first search task we suppose that, possibly as part of another search process, a user, in order to make sense of some document (Δ) that she retrieved, wants to collect evidence in favour or against its author being likely to deliver journalistic knowledge or rather personal opinions, although possibly very well motivated. The following semantic annotations are relevant to this task:[3] `taxonomicClassifiers`, `columnName`, `featurePage`, `authorBiography`, `body`, `byline`, and `people`.

The set of all `taxonomicClassifiers` forms a directed graph within the space of the whole collection: each document can be thought of as occupying a particular node of the graph and therefore a document's classification **C** can be defined as a set of nodes that contain a certain document. The search strategy to perform this task is an interactive and iterative process starting with a user, who must select for the document Δ a partition of the classifications **C**, `columnName` and `featurePage` that she would consider definitely supporting the assertion that articles with those characteristic have been written by either a Reporter or a Columnist.

[1]http://lucene.apache.org/solr/

[2]http://www.spinque.com/

[3]Unless otherwise specified, a use of a fixed font refers to the scheme for Solr that has been provided with the NYT collection.

The system should be instructed on how to deal with borderline cases, whether to exclude them from search or to consider these features as supporting both cases.

The `authorBiography` and `byline` fields are used to query the `body` and, respectively, the `people` fields of documents in the collection. The results can again be partitioned by classifications **C**, `columnName` and `featurePage` and, if deemed necessary, the search process can continue, by applying the same strategy to any of the documents in the result set. Typically one step only is sufficient to complete the task, which can also be repeated by modifying the search strategy in any of its components.

Example.

Is the article "CELEBRATION; Chicago" an Opinionist's work?[4]
Its classification **C** is:

<Top, Features; Features, Travel; Travel, Columns; Columns, Celebration; Travel, Sophisticated Traveler Magazine; Features, Magazine; Top, Classifieds; Classifieds, Job Market; Job Market, Job Categories; Job Categories, Hospitality; Hospitality, Restaurant and Travel; Travel, Guides; Guides, Destinations; Destinations, North America; North America, United States; United States, Illinois; Illinois, Chicago; Travel, Guides; Guides, Destinations; Destinations, North America; North America, United States>

which contain elements from both partitions: the node `<Columns, Celebration>` is typical of a Columnist's contribution, while `<Job Market, Job Categories>` more of a Reporter and `<Illinois, Chicago>` is neutral.

Using the annotations `byline: By Stephen McCauley` and `authorBiography: Stephen McCauley's most recent novel is "True Enough" (Simon & Schuster).` to query the collection, allow to retrieve *'True Enough': Just So-So Stories* [5], a review of McCauley's novel *True Enough*, which has been published in the Sunday Book Review.

By examining this evidence a user can conclude that the original article Δ should be regarded as a type Columnist's work. When necessary this process can continue, by using the `<str name="authorBiography">Louis Bayard's most recent novel is "Endangered Species."</str>` as the input of a second iteration step. It is important to notice that our proposed system does not provide a direct answer to the high level question of whether or not Stephen McCauley should be considered a Columnist in this case, but only the means for a user to make sense of this situation. The datum of a certain person being named in an article, which is also a book's review, licenses the statement that Stephen McCauley should be considered a Columnist only upon an autonomous interpretation by a user, who decides that the book is not written by a journalist, but by a novelist.

3.2 Authorities and Witnesses

Designing search strategies for Authorities and Witnesses is slightly more complicated as they require to detect events first: an Authority should be trusted because there is a set of past events in which the same person served as a source of reliable information, while a Witness should be trusted because many articles published around a certain event count her as a source. In addition to what we already used in the previous case, the following semantic annotations are also relevant to this task: `taxonomicClassifiers`, `publicationDate`, `locations`, `dateline`, and `text`.

The set of all `taxonomicClassifiers` forms again a directed graph, which can be used in the same way as in the previous case to partition the search space. Documents are moreover thought of as occupying the spatio-temporal space **S** defined by the `locations`, `dateline` and `publicationDate` fields.

[4] www.nytimes.com/2002/03/03/magazine/celebration-chicago.html
[5] www.nytimes.com/2001/08/05/books/review/05BAYARDTw.html

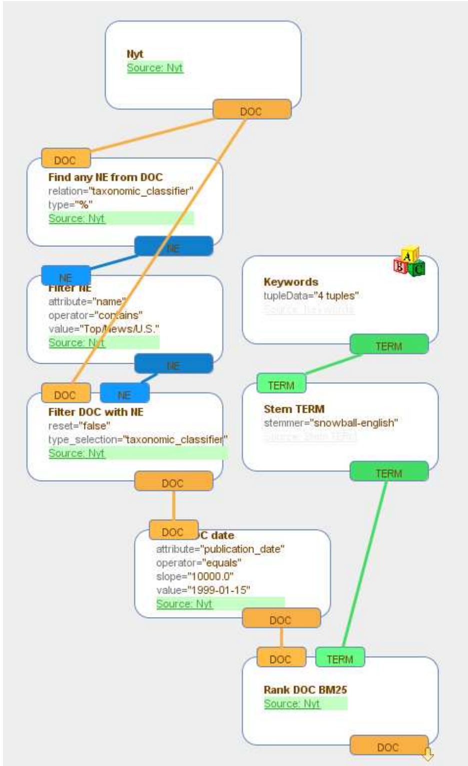

Figure 1: A Spinque strategy, consisting of connected building blocks, depicting a search approach taken to find the document set for Search A, in which the filter on date is a vague predicate. (no. results 30043)

A user may define an event for which she wants to determine which Authorities or Witnesses are potentially reliable source in the form of a set of documents, that, in order for the system to perform correctly, should occupy a narrow portion of the spatio-temporal space: most likely an event will be defined by onlya few documents, as we tested in these pilot experiments.

Provided that we can find an interval of area δ such that the intersection between a space **S** and a part of the taxonomy graph contains δ relevant documents about a given issue, while only $\frac{A}{\delta}$ relevant documents are outside the interval, for some positive constant A, we can define the same issue to denotate an event. Intuitively, many news articles have been published about the event around the same time and featuring the same places and names as the event: outside this local regularity the number of relevant documents decrease in measure of A.

Evidence for a person being a Witness can be presented to a user by collecting the documents which mention that person in their `text` fields and for which there are much less documents around other events. Conversely, evidence for Authorities, can be presented by collecting relevant document in more that one event.

Example.

Is justice Antonin Scalia an Authority? We first define an event as a non-empty partition of the search space (Search A):

<keywords: newcomers state welfare policy>,<approx 1999-01-14>,<C=Top/News/U.S.>

contains amongst others 3 documents that rank high (using a custom Spinque search strategy) and are about the same event, see Fig.3.2:

- Supreme Court Hears Welfare Case (NYT, Jan 14, 1999)
- January 10-16; A New Look At the Right to Move (NYT, Jan 17, 1999)
- THE SUPREME COURT: CITIZENS' RIGHTS; Newcomers to States Have Right To Equal Welfare, Justices Rule (NYT, Jan 18, 1999)

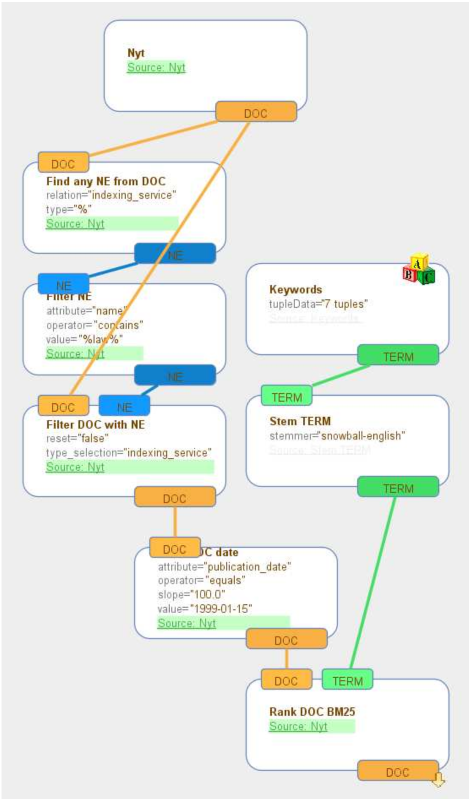

Figure 2: A Spinque strategy depicting a possible search approach taken to find the document set for Search B. (no. results: 16106.)

The same three documents could also have been found by a different search (using again a Spinque search strategy, Search B, see Fig.3.2):

> <keywords: individual rights equal citizen state supreme court>,<approx 1999-01-14>,<C≐Law>

Imagine the user of the system would have flagged these three documents, and would like to know more about their content. Two of these documents mention justice Antonin Scalia. The question of whether he is or not an authority on the issue depends on the search context. In the first search Antonin might not be regarded as an authority, as not many documents in the total result set (even if the date-filter is left out) are about him. He is not likely to be a Witness either as there are many documents about him outside this search result set. In the second search Antonin would very likely be an authority, as in many documents of the result set his name will be annotated, as he is a long serving supreme court member.

Notice that, again, we stress the importance of letting meaning arise from both an examination of the documents *and* from the search strategy that produced those documents: the event defined by the partition is a different event, albeit it contains the same documents as the previous one. When more events are generated in this way, adding multiple overlaps as in Fig.3.2, and upon examination of the evidence presented by the system, a user

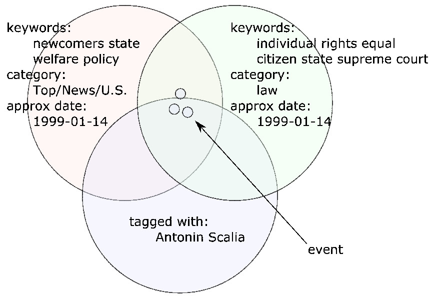

Figure 3: Events as overlapping partitions of the search space.

will probably conclude that the referent of `<str name="people"> Scalia, Antonin</str>` is an Authority, and possibly on the topic of 'Law and Legislation'. Notice that the amount of overlap of the second event can also trigger the conclusion that Antonin Scalia is also a Witness for that particular event. Albeit sentences of a court are generally easier events to detect, because they usually show a sharp temporal localisation, that is the day a sentence has been issued and a sharp spatial localisation as well, always Washington in case of the supreme court, we believe that this approach can be extended to more difficult cases where a user may require several steps, not only to establish membership to the classes of Authorities or Witness, but also to select appropriate events to initiate the task.

4. CONCLUSIONS

In this challenge report we explained how a system that allows end users to interactively map high level concepts to search strategies could be useful to make sense of those notions within a large and possibly unfamiliar repository. Motivated by an analysis of the available theories that have been developed by the same community to which our target users belong, we selected two abstract and deeply intertwined notions, that of author and source, that are difficult to approach using standard retrieval tools. The complexity of these notions and the open issue on whether or not any straightforward definition is possible or even desirable, calls for facilities to let users explore these notions, without taking an overly narrow stance on the issue.

We believe to have demonstrated the feasibility of our approach, meeting the main requirements of the challenge, for that we take advantage, when possible, of the extended semantic annotations, relying on text retrieval only when the annotations are unavailable of incomplete. The system we propose is effective mostly because the tasks are based on a domain model for exactly that particular class of users that we aim to support. It is also efficient, for that upon examination of only one set of documents a user is able to decide whether one of the two concepts apply. While guidance is still limited, as we do not yet provide any facility to determine how a modification in a search strategy affects its results, we claim to be successful in providing an application that is both transparent and fun to use. Because of the graphic interface of both the strategy builder and the graph exploration tool, which is currently under development, a user is able to identify which components and facets are being used at any moment and to very intuitively modify on the fly a search strategy.

5. REFERENCES

[1] J. A. Berlin. *Writing instruction in nineteenth-century American colleges / James A. Berlin ; with a foreword by Donald C. Stewart*. Southern Illinois University Press, Carbondale :, 1984.

[2] A. R. Cline. Toward a field theory of journalism, July 2010.

Exploring the New York Times Corpus with NewsClub

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ABSTRACT

In this HCIR 2010 challenge paper, I report on the evaluation of the NewsClub information retrieval system on the New York Times corpus.

1. INTRODUCTION

Keyword queries are still the easiest and common way to start a search in an information retrieval system. However, in many cases these queries can be over- or underspecified, and so the quality of the returned results is strongly dependent on the quality of the specified terms. As a complementary feature to unstructured text queries ("is there a document containing the keyword K?"), structured classifications (complex taxonomies or orthogonal, faceted categories) can help the user to choose the right document features to quickly drill-down to a particular aspect within the whole result set, such that only specifically relevant documents are returned. Additionally, the proposed classifications themselves may satisfy the user's information need, especially when looking for aggregate information or when just checking for the presence of a particular classification ("which *authors* wrote the most articles concerning X?", "is there a *book* about Y written by author Z in *2010*?").

However, maintaining a structured classification system requires a substantial, continuous effort, deep domain knowledge and preferably control over the document creation process to ensure a somewhat complete and valid classification, as incomplete or wrong classifications may drastically deteriorate the search experience (especially for the aggregate queries described above). In any case, especially with growing collections such as in the news domain, it will in any case be no perfect or concluded labeling.

In this paper, I present my information retrieval system *NewsClub*, which provides, in addition to keyword queries and faceted search, a third way to explore the set of retrievable documents: relevant terms and phrases. For example, when querying for "terrorism", the system determines *Al Qaeda* and *Osama bin Laden* as highly relevant terms. These n-grams are relatively easy to determine from any unstructured text, do not need any manual processing and yet provide a surprisingly high utility for search. In combination with keyword and faceted search, this allows a very quick and efficient navigation within the result set.

In addition to just showing the most relevant terms and phrases for a query, NewsClub can also visualize term associations (i.e., determine words that deal with different aspects of terrorism, for example: *Afghanistan/Taliban* vs. *Palestina/Hamas*) and find contrasting terms which best match individual sub-queries, i.e.., terrorism w.r.t. Israel/Palestina (*Gaza strip, Intifada*), Afghanistan (*bin Laden*, *Taliban*), Iraq (*Saddam, Zarqawi*) or the USA (*Oklahoma*, *Littleton*). The sub-queries may represent any other typical keyword or classification feature and thus are easy to specify.

While the NewsClub platform has initially been targeted mainly at analyzing news, it is also being deployed in different scenarios. A publicly available system is *NewsClub im Bundestag*[1], which monitors the plenary sessions in the German Parliament. It allows to drill-down by speaker, party, role and legislative period and provides the very same text-analytics features described above.

2. USER INTERFACE

UI Fundamentals. NewsClub's Web-based user interface has been designed for the curious searcher who wants to interact with the system, but it also allows for fast ad-hoc queries. The AJAX application has been built using the Google Web Toolkit, designed for low-latency and high extensibility. The fundamental UI structure was inspired by the Eclipse platform, which allows to have different tabbed panes in one perspective; NewsClub's search perspective consists of a keyword query box and a set of tabs, each containing a different view on the query or the results. The tabs are grouped into the two parts of a horizontally-split pane, a wide pane on the left, and a tall pane on the right, thus allowing the user to activate two different tabs at once, a large one and a small one. Currently, the user can choose from the following tabs. *Left*: Search results, Associator, Contrastor, Time Window and Detail view. *Right*: Facets, Term Stack, Sub-queries (see Figure 4).

Search results. In this view, individual search results are shown (very much like in traditional search engines). The only notable difference is that NewsClub's view supports continous scrolling (one can actually scroll through all retrievable results). Clicking on a result will open the original URL in another window or the locally stored information in the **Detail** view. The **Facets** view contains a tree panel containing all possible facet dimensions, the categories and the corresponding number of matching documents for the current query. By clicking on a category, one can narrow the search to only those documents that are labeled with the

[1] `http://newsclub.de/bundestag`

selected category (the query box is extended by an appropriate button to indicate the drill-down). The **Term Stack** view contains a set of relevant terms and phrases that are matched in the documents retrieved for the query. The relevance of a term is determined by a measure based on the Shannon entropy, not by absolute frequency. The *stack* differs from a typical *cloud* in the fact that the terms are first grouped by importance (only changes in the order of magnitude are considered), then alphabetically. This allows a much faster reception of the most important terms, as they will always appear first (and larger than the other terms). **Associator.** For ambiguous queries, this view helps clustering the relevant terms and phrases into distinct subgraphs. The graph can be zoomed and the terms can be added to the keyword search by clicking them. Using the **Time Window** view one can narrow the search to items of a particular time span. The view contains calendars for start and end date as well as a graph depicting the absolute number of items per date. The values can be smoothed using an arbitrary sliding average and can thus also be used for a rough trend analysis (also see Figure 1). In the **Sub-queries** view the user may specify additional queries that are evaluated with respect to the main query. Generally, sub-queries may be utilized in any other view, but currently, this is only used for the **Contrastor** view. Here, the user can re-arrange the top-500 relevant terms and phrases with respect to relevance to the main query, to the subset of results that also match each sub-query as well as to the variance between the individual sub-queries.

3. EVALUATION ON THE NYT CORPUS

In this section, I report on how one can conduct searches in NewsClub for the task scenarios described in the HCIR2010 challenge call.

Subway crime. We start by selecting "Crime and Criminals" in the "Descriptors" facet, "New York City" at "Locations" and enter "subway OR metro" as the keyword query. We switch to the sub-queries tab, enter the article years 1987 to 2007 and then open the *Contrastor* view. The unfiltered top-10 terms for each year are shown in Table 1. From these terms, we see for example that there was a shooting involving a person called "goetz" in 1987, which we can confirm by adding "goetz" as an additional keyword, switching to the search results view and examining the 27 matching articles (Bernhard H. Goetz was accused for shooting four black youths on a subway train). As another example, in 1990, Brian Watkins, a tourist from Utah, has been murdered and robbed in the subway (first, second and eigth term matched). We may also drill deeper into each year's terms by switching to the *Associator* view. Here, for example, we find out that in 1987 there are many terms around the Goetz case, but that there also was also homeless man being pushed in front of a subway and that a subway token booth has been attacked and one clerk has been shot and critically wounded.

Development of pizza prices. NewsClub currently does not analyze numbers, so this is out of scope at the moment. However, we can search for "pizza" and analyze the Associator graphs (see for example Figure 2). Apparently, some restaurants are famous, some had to be closed due to bad hygienic conditions, and there also is a Mafia connection.

Rent Control. We start a new search for *rent control* with facet "Location:New York" and the sub-queries "pro", "against" and "pros and cons". For *pro*, we find terms like *fund hotel, pro-landlord* and *cloward and piven.* The last term refers to two authors of a study, pro-landlord leads us (via the Associator) to the related terms "pro tenant" and "rent control regulations", and finally "fund hotel" refers to the phrase "hedge fund hotel" (finding one article, where *rent* and *control* are not referring to a phrase). For the sub-query *against*, we find terms like "luxury decontrol" and "vacancy decontrol", and for the sub-query *"pros and cons"* we get "landlord-tenant", "Lansco" (a brokerage firm specializing in retailing properties, according to a snippet summary in the search view), "bedroom apartments", "one-bedroom", and "commercial space".

Adding one or more of these terms to the keyword query finally yields few, highly relevant documents. For example, "rent control 'pro-landlord' 'pro-tenant"' yields 3 results, including "*A Landlord's Lot Is Sometimes Not an Easy One*" and *"Raising the Rent, and Raising the Roof"*, which provide some of the desired arguments pro and against rent control.

Clinton Impeachment. We could start our search the same way like for *Rent Control*, but this time we look at the Term Stack (Figure 3). Without knowing the background of the impeachment, we see that Monica Lewinsky and Paula Jones were involved in a Clinton scandal, that the president lied and that there was the question of "crime or misdemeanor". We also find other persons involved, e.g,. Kenneth Starr and other scandals such as "filegate" and "travelgate", which we may use to further explore the result set by adding one or more of these terms to the query.

Free Concerts in New York City. Let us try searching for "concert ('free admission' OR 'no admission charge' OR 'admission: free')" and narrow to facet Location: New York City. Of the 25 documents we found, 15 have been annotated for the "Organizations" facet, which we can simply open and read the matching terms (see Table 2). We would now have to check each organization by inspecting the search results to determine whether they really offer free concerts.

Member of the Communist party. This task requires a join over the *People* facet, between search results for "Communist party" and "(legislative OR executive)" (both restricted to "Location: New York State"). Matching people are likely to answer the question (but still need to be reviewed). NewsClub currently does not support joins, but luckily, we only get eight labels in "people" for the query "Communist party", which we can manually join with the second query (see Table 3). We can check the remaining five people by again switching to the "Communist party" results (three documents only!). For Governor Mario Cuomo, we see that he only visited a member of the communist party on a diplomatic mission, so we can exclude him from the candidate list. On further reading, we find an article ("*Cardinal and Mayor: Excerpts From Book*") containing a book excerpt by Edward Koch who stated that there indeed was a New York legislator who was an active member of the Communist party and sat on the executive board of a local Communist organization (Koch probably knows what the name of the mentioned legislator is; I do not know).

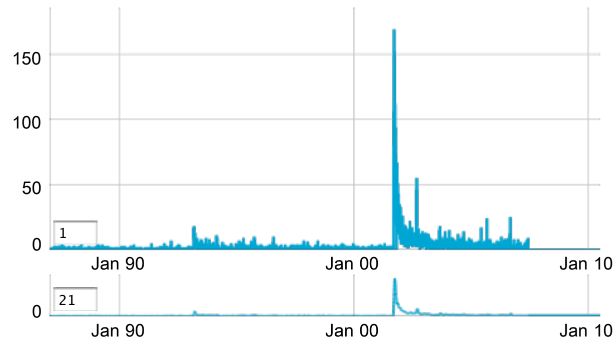

Figure 1: Time Window: "*World Trade Center*"

4. REMARKS, CONCLUSIONS AND FURTHER WORK

The HCIR 2010 challenge is a great opportunity to evaluate the NewsClub information retrieval system on the New York Times corpus. I was able to show that NewsClub can deliver (at least approximate) results for all demanded tasks, without much preparation. The data was loaded into the system basically without any post-processing, reasoning on facet dimensions etc. Indeed, there are some problems with the NYT classification that should be fixed for a production system. For example, there is a change from all-uppercase names to regular case in 1996, which would require special alignment to unify pre- and post-1996 labels. The classification also lacked proper aggregate information/meronym-relations, which would have helped in the task scenarios (for example, it would be good to know that New York City is part of New York State).

On the other hand, also the terms that NewsClub automatically determined relevant appear unfiltered and sometimes cannot be understood without specific knowledge (e.g., person names). A pre-processing using a part-of-speech tagger or a thesaurus would have been helpful.

Moreover, the subway crime task has shown that if we really only want to evaluate specific terms (in our case: a finite set of subway crime words), we would need the ability to specify these terms in the Contrastor. This features is currently being developed, but was unfortunately not ready for this report.

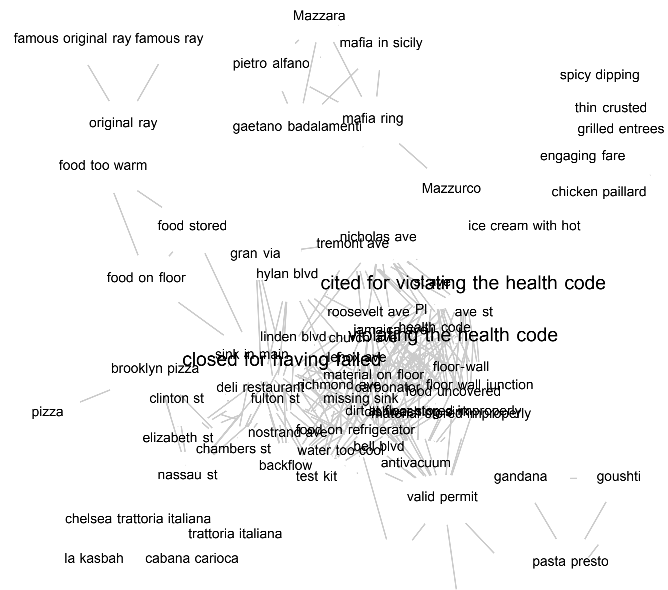

Figure 2: Associator graph for "Pizza" in New York from 1987 to 1996

Figure 3: Term Stack for "*Impeachment Clinton*"

Table 1: *Subway crime.* Top-10 words and phrases for years 1987 to 2007.

1987: DelCastillo, goetz shot, crime at kennedy, disrupted subway, woman eight, bernhard h, berhard goetz, professor kaufman, downtown irt, goetz verdict. **1988:** vincent del, albert o, bmt station, del castillo, transit patrolmen, debra elisa, Moraff, rider-advocacy, stranger-to-stranger, fatally burned. **1989:** sergeant galea, miss honig, reported in new york city rose, Decepticons, jackie peterson, sergeant keaveny, Nero-like, abandonned, citing a sharp, neck-bending. **1990:** tourist from utah, brian watkins, Gosso, men commit, larcenies, arrested teen, civilianized, utah tourist, non-negligent, anti-crime. **1991:** token-booth, token booth clerk, pickpocketing, subway tracking, thomas reppetto, toughest mayor on crime, Debhasis, Dettman, Onionhead, Rettler. **1992:** fare-evasion, Cantius, Taneka, Gasparik, Pecola, stage-prop, chain snatching, eexit gate, Tirsa, abuna paulos. **1993:** ted husted, Ficaro, Kowslowsky, Unick, gerry griffin, nostaglic, co owner of la, convering, jamican drug, kevin jett. **1994:** Del-Debbio, peter del debbio, desmond robinson, Darnal, shaul linyear, peter del, hate to hate, Coplen, robbery on feb, allyn winslow. **1995:** appeared in news, questioned the veracity, Brahmbhatt, phenemenon, Lanzman, Maioglio, pushed in front of a subway train, Bonina, joseph castellano, copulated. **1996:** violent and property, Elmer-DeWitt, Maxian, the merger of the transit, single-officer, car-window, solo patrol, strongest democratic, two-officer, murder of brian. **1997:** larcenies, transit division, convicted of the misdemeanor, Vimala, armed teen, survey-research, overall crime, Ceasia, mood-shifting, sergeant miranda said. **1998:** bap bap, captain, phipps, th street and roosevelt, murder or rape, Kolden, Petracco, cab watch, DeMarion, crime has dropped. **1999:** misdaemeanor criminal, Ciraolo, bat as a weapon, Lombardino, fare gates, throat-grabbing, fare beating, danied that the department, fordham students, domestic-relations. **2000:** max fine, Haly, subject to sexual, credit-taking, struggling-artist, murder-conspiracy, Kelling, Jaycor, older-brother, professor at the university of california in los angeles. **2001:** alibi statement, pre-arraignment, wwwnytimescom/metro, open-aired, spokeswoman for the new york city law department, Calik, Gulsen, Huascar, resulting emotional, multiborough. **2002**: murder nine, John/Jane, half-green, Eksi, st precinct station, leave-me-alone, drug-drenched, stuff of hollywood, unusually loud, exxon gas. **2003:** nd street and seventh, william glaberson, trial of peter, deserted station, Cassarino, assemblyman ivan, peter gotti, frederic block, DeFede, crime-reduction. **2004:** captain matusiak, Facciolo, Wolfrom, assassination-style, Stacy-Ann, pimple-facet, twice-broken, Fanale, dead-on-arrive, phone for hours, rape and beating of a jogger in central. **2005:** Kneafsey, contact with the homeless, metrocard vending, living in the subway, chambers street subway station, digitalize, trust necessary, theft-deterrent, Wastberg, madrid train bombing. **2006:** jersey trucking, courtroom space, citing continuing, lag times, sentenced yesterday in federal district, arrest-to-arrignment, councilman peter, spokesman for mayor michael r, turnstiles. **2007:** mappelle, Lucyna, producing the latest, palazzolike, security is concerned, crime and vandalism, behind the crime, Karnen, Eterno, urinators.

Table 2: *Free Concerts.* Retrieved organizations from NYT facet classification.

92d Street Y, Brooklyn Children's Museum, Fogg Art Museum (Cambridge, Mass), Gardner, Isabella Stewart, Museum (Boston), Halle Orchestra, Liberty Science Center (Jersey City, NJ), Long Island Rail Road Co, Lower Manhattan Development Corporation (NYC), Museum of Fine Arts (Boston), Museum of the City of New York, NYC-TV (Cable Station), New York Botanical Garden, Newark Museum (NJ), Queens Wildlife Center, World Trade Center Memorial Foundation

Table 3: *Communist Party/Legislative or executive post*: People

"Communist Party": *Cuomo, Mario M (Gov); Dionne, E J Jr.; Jackson, Jesse L (Rev); Kazakov, Vasily (Deputy Chmn); Koch, Edward I (Mayor); Mailer, Norman; Schmalz, Jeffrey; Vinogradov, Vladimir M (Min)*
"Legislative OR executive" *Cuomo, Mario M (Gov); Dionne, E J Jr.; Jackson, Jesse L (Rev); Koch, Edward I (Mayor); Schmalz, Jeffrey*

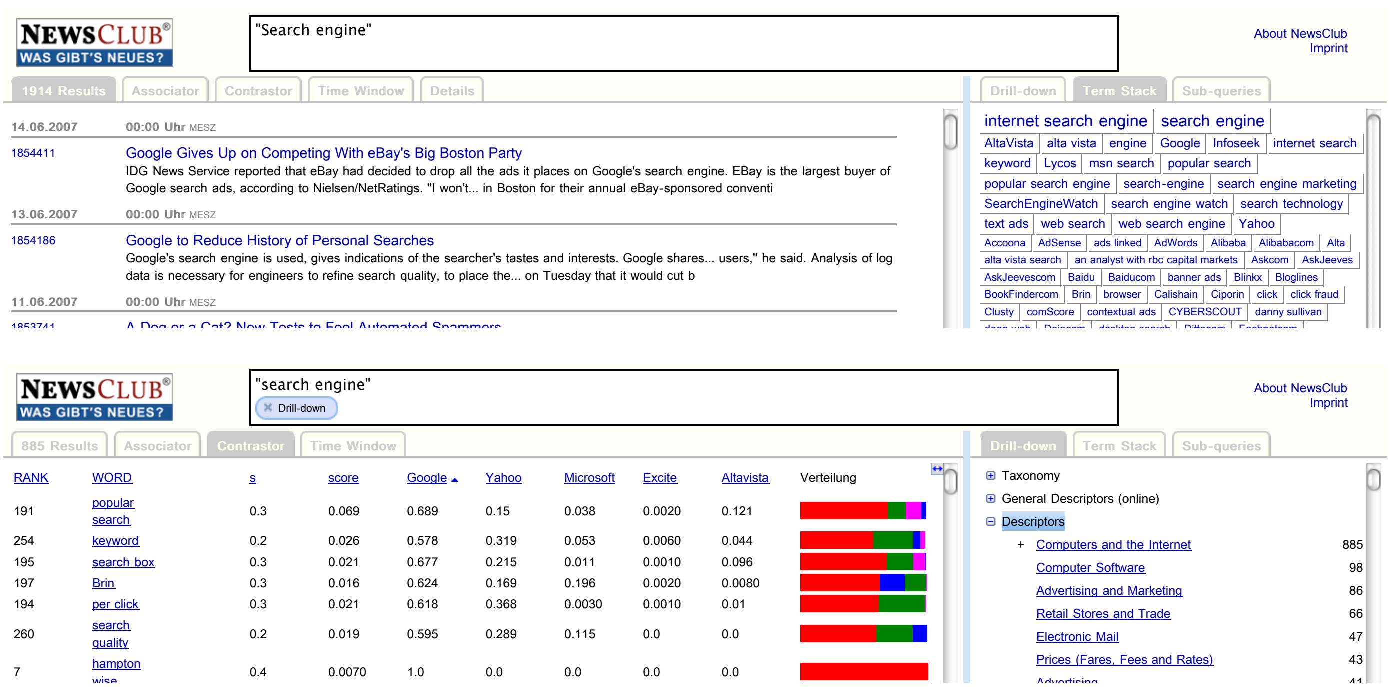

Figure 4: NewsClub's search perspective. Showing the *Search Results* and *Term Stack* tabs (top) and the *Contrastor and Drill-down* Tabs, restricted to "Descriptors: Computers and the Internet (bottom)

Searching through time in the New York Times

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ABSTRACT

In this paper we describe the Time Explorer, an application designed for analyzing how news changes over time. We extend on current time-based systems in several important ways. First, Time Explorer is designed to help users discover how entities such as people and locations associated with a query change over time. Second, by searching on time expressions extracted automatically from text, the application allows the user to explore not only how topics evolved in the past, but also how they will continue to evolve in the future. Finally, Time Explorer is designed around an intuitive interface that allows users to interact with time and entities in a powerful way. While aspects of these features can be found in other systems, they are combined in Time Explorer in a way that allows searching through time in no time at all.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Entity Ranking, Information Retrieval

1. INTRODUCTION

The role of time is critical to understanding the news. In current news search engines, time is primarily used to boost the relevance of the most recent stories. While useful when users are interested in the latest news, it may hinder the search experience of those interested in a broader understanding of a particular news story. These users may benefit from a transversal organization of the topic across time so as to better view how the story has evolved and which people and places have shaped the evolution. Furthermore, these users may equally benefit from predictions on how the story might evolve into the future. When searching about a regional conflict, for example, a user should be able to identify what factors lead to the conflict, which people where most influential and when, and how the conflict is likely to evolve in the future. In the following paper, we present Time Explorer[1], a system that has been designed specifically to answer these types of questions. We begin by presenting related work followed by a discussion of the New York Times (NYT) document collection and corpus preparation. We then present the user interface and finally discuss conclusions and ideas for future work.

2. BACKGROUND AND RELATED WORK

Time has long been an integral part of search engine ranking with most major search engine giving a ranking boost for recently published documents, particularly in the news domain. However, recent work [2, 5] has suggested that the time dimension can be further exploited by automatically creating timelines from temporal information extracted from documents both from metadata such as the publication date, but also from temporal expressions found in the text. In recent years, the importance of timelines has been further evidenced as search engines including Google[2] and Cuil[3] have started incorporating timelines into their search results. Work by Baeza-Yates [3] and later by Jatowt et al [6] focus, in particular, on mining collections for statements about future events and provide frameworks for searching into the future. In addition to searching the time dimension, there has been much work in entity search which has the goal returning the entities, such as people and locations, that are most related to a query [4, 1, 7]. As with time search, entity search requires that the entities are either provided as metadata or extracted automatically using named-entity recognition techniques. The primary contribution of our work is to combine these technologies into a working system with an intuitive user interface that allows users to explore the evolution of topics and entities over time in a powerful way.

3. TIME EXPLORER

3.1 Corpus Preparation

The Time Explorer application has been built as part of the European project LivingKnowledge[4] which aims to

[1]Firefox,http://fbmya01.barcelonamedia.org:8080/future/
[2]http://www.google.com/
[3]http://www.cuil.com/
[4]http://livingknowledge-project.eu/

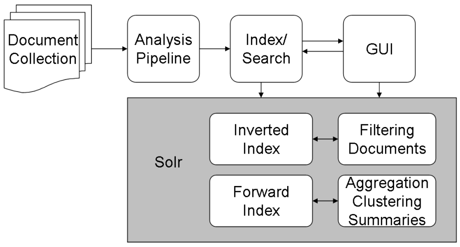


Figure 1: Testbed Architecture

make diversity of knowledge an asset in search applications. The goal is to provide tools that allow exploring knowledge from all points of view and crucially to see how knowledge evolves over time. At the core project is the LivingKnowledge testbed, a planned open source toolkit that allows for annotating document collections with a wide range natural language processing and image analysis tools and provides methods for indexing, searching, and visualizing these annotations using the Solr search engine[5].

The NYT collection of 1.8M news articles from 1987 to 1997 is publicly available, clean, and enriched with high-quality hand-annotated data all of which make it an ideal document collection for evaluating Time Explorer. Though Time Explorer will ultimately aim to incorporate all aspects of diversity covered by LivingKnowledge, the application described here is focused on understanding the time dimension. We have used a subset of the analysis tools available in the testbed including OpenNLP[6] (for tokenization, sentence splitting and part-of-speech tagging, and shallow parsing), the SuperSense tagger[7] (for named entity recognition) and TARSQI Toolkit[8] (for annotating document with TimeML[9]). The resulting analysis is used to extract from each document all of the person, location and organization entities and all time expressions that can be resolved to a specific day, month or year. The time expressions extracted are both explicit as in "September 2010" and relative as in "next month". The relative dates are resolved based on the **publication date** of the article and all dates are associated as **event dates** with the corresponding documents. In addition, simple heuristics are used to assign **keywords** to the document that represent the most important concepts contained in the document, and finally, all of the metadata provided in the NYT collection is associated with each document. From these extractions, two indices are created, one for each document in the collection and one for each sentence in the collection. For the sentence level index, a **content date** is computed as one or more of the **event dates** found in the document or the **publication date** if there are no event dates.

For example, given the following hypothetical document with publication date in May 1^{st}, 1999:

> Slobodan Milošević became president of Yugoslavia in 1997. Slobodan Milošević will run for president again next year.

[5]http://lucene.apache.org/solr/
[6]http://opennlp.sourceforge.net/
[7]http://sourceforge.net/projects/supersensetag/
[8]http://www.timeml.org/site/tarsqi/
[9]http://www.timeml.org/site/index.html

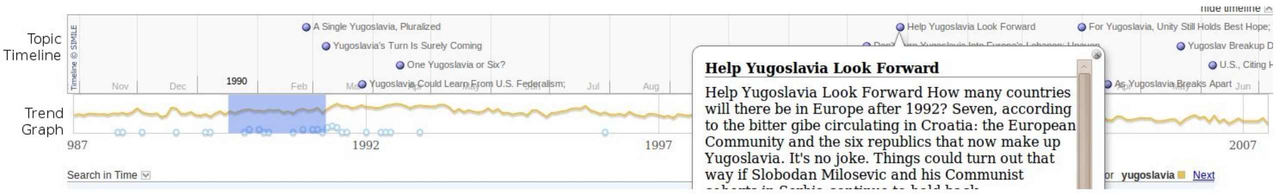
Two sentences will be found. *Slobodan Milošević* will be extracted as a person in both sentences and *Yugoslavia* will be extracted as a location in first sentence. *1997* will be extracted as a time expression in the first sentence and *next year* will be extracted as an expression in the second sentence and resolved to 2000. The **publication date** for both sentences will be May 1^{st}, 1999 while the **content date** of the first sentence will be 1997 and the **content date** of the second sentence will be 2000.

The resulting indices allow for a wide range of queries including: 1) return the documents that contain the word Yugoslavia, 2) return a list of people most related to the query Yugoslavia, 3) return the number of documents containing Yugoslavia that were published in each month, 4) return documents that contain the query Yugoslavia and mention the person Slobodan Milošević, 5) return documents containing the query Yugoslavia that were published in 1999 and 6) return documents containing the query Yugoslavia with events in 2000. These queries and the combinations of them are very powerful but it is unlikely that a user will be able to express the queries in a meaningful way. Therefore defining an intuitive user interface is extremely important.

3.2 User Interface

The focus of this application in understanding how topics evolve over time and thus, not surprisingly, the core of the user interface is a timeline. Though there are many timelines available, including Google trends[10] and Google timeline[11] and many derived from the Simile Timeline widget[12], we attempt to improve on these implementations by combining many of the best features. Figure 2(a) displays the timeline produced for the query "Yugoslavia". The timeline is split between two bands - the bottom band, we call the **trend graph**, shows how the frequency of documents containing Yugoslavia changes over the 20 years covered by the NYT collection while the top band, called the **topic timeline** uses the Simile widget to display the titles of the top ranked articles. As shown, the user can click on the title of the articles to get a document summary. Furthermore, the user is able to scroll through the articles that are displayed in the top window by moving the highlight box with the mouse. Circles indicate which documents are immediately available for viewing. The number of results available for viewing initially is configurable by the application with a trade-off between response time and coverage on the timeline. However, one can easily view more documents for a particular time period by using the mouse to move the highlighted region to a particular point in time and the mouse button to trigger a search. For example, clicking the mouse with the highlight region over the start of the timeline will populate the topic timeline with documents from that time period as shown in Figure 2(b). In this case, this quickly helps one discover that before the conflict started, published articles were dominated by stories of both ethnic and economics problems. When a time period has been selected, the time frame is automatically displayed below the timeline and standard user interface features are used to indicate to the user that they can remove the time range by clicking on the close button, or change the time range manually by entering the dates directly in date fields and selecting search.

[10]http://www.google.com/trends
[11]http://www.google.com/
[12]http://www.simile-widgets.org/timeline/



(a) Basic Timeline

(b) Time period Selection

(c) Timeline with Entity trends

Figure 2: Timeline Control

In addition to seeing the articles, an entity list panel displays the entities most associated with the query as shown in Figure 3. The user can view all documents that contain the entity by clicking on the entity, but can also use a menu to choose to exclude documents containing the entity, submit the entity as a stand alone query and also see a definition of the entity, currently using a simple Wikipedia lookup. These advanced features are only displayed if the user specifically moves the mouse over the icon next to the entity thus keeping the interface simple for the basic user, but still providing useful features in a straightforward manner to the more experienced user.

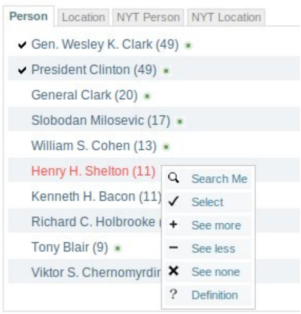


Figure 3: Entity Selection

An additional feature of the entity filter is to provide a trend line for the entity on the trend graph. Figure 2(c) demonstrates this feature. *President Clinton* and *General Wesley Clark* have been selected as entities. The trend lines makes it easy to see when these entities were important with respect to Yugoslavia. *President Clinton* became important when he became president and *General Clark* when he became commander of the NATO forces. Again, there are visual clues as to which entities have been selected and how to remove them from the query if desired. Similar visual clues are also displayed in the entity list as previously shown in Figure 3. The entity list is modified as the query is refined allowing the user to easily see how the important entities change over time for a given query. For Yugoslavia, before the conflict many sports figures were highly associated with query, but, as the conflict progressed, world leaders became much more relevant. Using a similar technique, an evolving relationship was found between Slobodan Milošević and Saddam Hussein. At first, the relationship was largely based on people comparing the relatively unknown Milošević with Hussein and at the end, the relationship was that both were on trial for war crimes. In between, however, a directly relationship was found where Yugoslavia was selling arms to Iraq. In the above scenarios, the timeline is centered around the **publication date** of the articles. However, it is also possible to use the **content date** as the driving date which has the advantage of allowing searching into the future. Figure 4, shows the results for a search on *Iraq*. Using the timeline, it is quick to look into predictions such as the one shown suggesting that Iraq could develop missiles capable of hitting the U.S by 2015. Other predictions include details about the expected cost of the war as well as pre-

Figure 4: Searching the Future

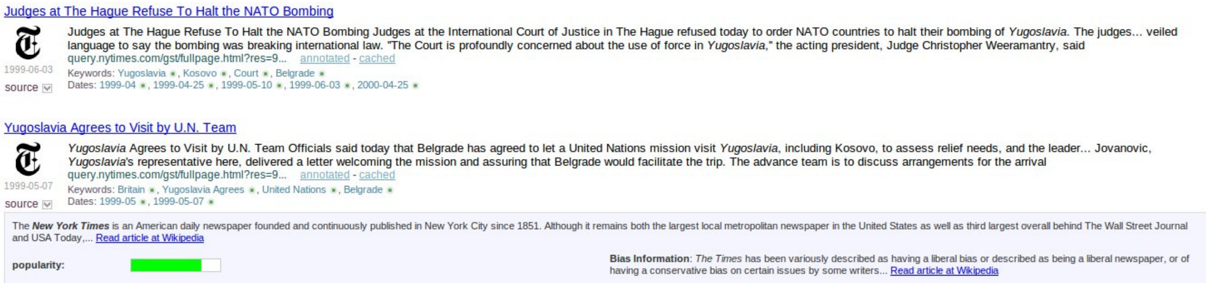


Figure 5: Results

dictions about the success and/or failure on future dates. Using the **content date**, it is also possible to look for articles making predictions about the current date that were made in the past. For example, we were able to look at predictions that were made about 2010 in the articles from the NYT collection. Some results were accurate such as articles discussing a possible 2010 UK election between Gordon Brown and David Cameron, which did take place. Others were amusing like the one from Al Gore during the run-up to the 2000 US presidential election suggesting that his budget proposal would still leave some room for a budget surplus in 2010 - far different from the half-trillion dollar budget deficit actually faced today.

Though the user can learn quite a great deal from the timeline alone, there are also some features in the document snippet shown in Figure 5 that can further assist the user. In addition to the standard highlighted snippet text, there are lists of both the most important keywords associated with the document and the most important dates. These serve to both better summarize the document and to provide an additional mechanism for refining the search. In addition, clicking on the source gives details about the source of the article. In the NYT collection, this is obviously limited to the New York Times, but other collections will include additional news sources and possibly well known authors and bloggers.

4. CONCLUSIONS AND FUTURE WORK

In conclusion, the system presented is an effective tool for analyzing how news topics evolve over time. The application includes many features that, in combination, we believe improve upon what is currently available in news search. Most notably, the tight integration between the trend graph, the topic timeline, and the entity list and the ability to search into the future, but also a user interface which allows for easy query refinement while still providing visual clues that allow the user to understand how he arrived at the current state. In the future, we plan on integrating LivingKnowledge work on opinion mining and bias detection. The search for the future of Iraq, for example, would be greatly improved if we visualize whether the opinions concerning Iraq are positive or negative and how these opinions change over time and also by visualizing the bias of the opinion holders. We also plan on evaluating the system in a realistic setting to confirm that the system does provide advantages over current technologies.

5. REFERENCES

[1] Overview of the inex 2008 entity ranking track. In *Focused Access to XML Documents: INEX 2008 Dagstuhl Castle, Germany*, 2008.

[2] O. Alonso, M. Gertz, and R. Baeza-Yates. Clustering and exploring search results using timeline constructions. In *CIKM '09*, pages 97–106, New York, NY, USA, 2009. ACM.

[3] R. Baeza-Yates. Searching the future. In *SIGIR Workshop MF/IR*.

[4] K. Balog, A. P. de Vries, P. Serdyukov, P. Thomas, and T. Westerveld. Overview of the trec 2009 entity track. In *TREC 2009 Working Notes*. NIST, November 2009.

[5] R. Catizone, A. Dalli, and Y. Wilks. Evaluating automatically generated timelines from the web. In *LREC 2006*, 2006.

[6] A. Jatowt, K. Kanazawa, S. Oyama, and K. Tanaka. Supporting analysis of future-related information in news archives and the web. In *JCDL '09*, pages 115–124, New York, NY, USA, 2009. ACM.

[7] H. Zaragoza, H. Rode, P. Mika, J. Atserias, M. Ciaramita, and G. Attardi. Ranking very many typed entities on wikipedia. In *CIKM '07*. ACM, 2007.

News Sync: Three Reasons to Visualize News Better

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ABSTRACT

News consumption patterns are changing, but the tools to view news are dominated by portal and search approaches. We suggest using a mix of search, visualization, natural language processing, and machine learning to provide a more captivating, sticky news consumption experience. We present a system that was built for three scenarios where a user wants to catch up on news from a particular time period, location, or topic. The results cover key events from that time period and are prioritized based on the user's interests. Further, users can interact with and explore stories of interest. An initial prototype is currently being piloted.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering, selection process.*

General Terms

Algorithms, Human Factors.

Keywords

News summarization, clustering, news adaptation, news exploration, news interfaces.

1. INTRODUCTION

The news landscape has undergone major changes with the advent of online media. While the readership of traditional newspapers has declined over the past few years, the consumption of news over the Internet has increased significantly. In a March 2010 survey of US Internet users [1] on the primary source used to find news, it was found that the Web/Internet is by far the most popular source (49%) as compared to Television (32%) and Newspapers (9%). As with other kinds of online information, the dominant mode of assessing news online is through search. According to a Pew Research survey conducted over Apr–Jun 2008 [5], 83% of those going online for news use search engines to find stories of interest. So, even though there are several dedicated news portals, consumption of news is triggered primarily through queries. Search engines today address this user behavior by integrating relevant news results with Web search results for news-related queries and provide news verticals and topic-specific news pages.

HCIR'10, August 22, 2010, New Brunswick, NJ, USA.

However, the presentation of news is not optimal on these sites. Even as news is shifting online, the presentation of news is still driven by the print media. There is limited real estate on the search result pages to display news, and many news articles do not get surfaced on the site. Finding relevant news is more than just retrieving news results or restricting the search based on keyword queries over the news domain. Presentation of news needs to cater to specific user needs. We propose a use-case or scenario driven approach to selecting relevant news stories and presenting these appropriately to the user. Further, users should be able to explore the news landscape – getting to other related news articles, visualizing the connections between stories, getting background information on relevant people and concepts, commenting on and annotating stories, and sharing interesting items with friends.

In this paper, we present our system, called *News Sync*, which was developed to enable such enhanced news experience. The system is built over the New York Times Corpus released as part of HCIR Challenge. In Section 2, we present the motivation for this system with the help of three use-cases, and list key features that must be present in such a system in Section 3. In Section 4, we present our solution in detail and show how these use-cases can be addressed by the system. We conclude in Section 5 with related work and future steps.

2. NEWS EXPLORATION SCENARIOS

In this section, we present three specific scenarios for a user-driven news digest to illustrate our ideas. We propose techniques to select and present news according to user needs and preferences. While the techniques used may not be new, we suggest that the integration we propose will lead to a better news experience.

2.1 Scenario 1: Catching up on News

Consider the following scenario: Katie is an avid news reader who tracks news on a daily basis, often following up on specific news events several times a day. At times, Katie may be cut off from news, for example, when she goes on a long vacation. When she is back online, she may want to know what happened while she was away. She may want to skim through the major news stories that took place, including updates on the news she was following regularly before going on vacation.

This caters to a common, specific need of a news consumer wanting to catch up on news.

2.2 Scenario 2: Diaspora Digest

It has become fairly common for people to migrate to another country or city for work or studies. Though most of these expatriates try to keep abreast with the news from the country of origin, they lose touch with traditional sources of news. They visit news websites from the home country periodically to do so. If

Katie is from Berlin and residing in the US, she might not be interested in local news bulletin from Berlin, but might be interested in a summarized view of key events in Germany from the past week. She might be interested in the country's soccer team's performance round the year and also country-wide soccer competitions such as the German Cup.

This need caters not only to expatriates living in another country but also people migrating to other cities within a country.

2.3 Scenario 3: Following Celebrities

A longitudinal look at news is of great value for specific needs, such as following the activities of celebrities. Assume Katie is an admirer of Princess Diana and she wants to get a perspective of Princess Di's life history as described in the news. She would be interested in key events such as her marriage, her time as the princess, her divorce, and her death and subsequent investigations. The key idea here is that the user gets a historic perspective on celebrities using archival news content.

3. REQUIREMENTS FOR *News Sync*

To address the above scenarios, we propose a system we call *News Sync*. This allows Katie and similar news consumers to get adaptive, personalized news digests covering a period of time, a region, a topic, or a combination of these.

We list the following requirements for *News Sync*, a modified version of the requirements we presented in [13]:

1. **Control over news categories, topics, and sources:** The user should be able to specify the time period of interest. In addition, the user may specify if she is interested in news from particular sources, specific news categories, locations/regions, and/or specific topics.
2. **Personalized news feed:** The system should identify stories that are currently the most relevant to the user, based on past user behavior and user preferences.
3. **Variety in news content:** The system should show a variety of content across diverse categories, instead of, say, returning a list of ten "most popular" news links which may be restricted to one or two topics. Users can thus get an overall picture of key events first, before they delve into specific stories.
4. **Adaptive and integrated news presentation:** The news interface needs to be adaptive to the category of news and presence of multiple modes of news content. For example, news about Harry Potter over Summer 2007 should include, among other stories, the trailers from the movie "Harry Potter and the Order of Phoenix" (video), book reviews of "Harry Potter and the Deathly Hallows" (text, blogs) – which were both released in July 2007 – along with pictures and news about the Harry Potter theme park announced in May 2007 (images).
5. **Interactive and exploratory user interface:** The user should be able to interactively and directly modify time, location, and other parameters and have the system respond immediately with updated views of relevant news.
6. **Parameterized interface design:** Users should be able to set system parameters to get results at different specificities.
7. **Support source-tracing and finding related news:** The system should allow users to go from any news summaries to the original news articles. Further, the system should suggest other related news articles based on the news items viewed.
8. **Ability to share news:** Users should be able to comment on and share interesting news articles over their social network.
9. **Support news analyses by sentiment and points of view:** Users should be able to view stories pivoted/summarized on sentiment or different points of view.
10. **Keep the familiar list-view as back-off:** Even as the news interface gets a facelift, it may be prudent to maintain the list-based view as a back-off option to take advantage of familiarity with the concept.

Such a system would help frequent travellers, business customers who need to know the impact of ongoing news on their business, and avid news followers who spend a lot of time with news.

4. THE *News Sync* SYSTEM

In this section, we present a brief description of *News Sync*, the system we developed based on requirements listed in Section 3.

4.1 System Description

Figure 1 gives a schematic diagram of the *News Sync* system.

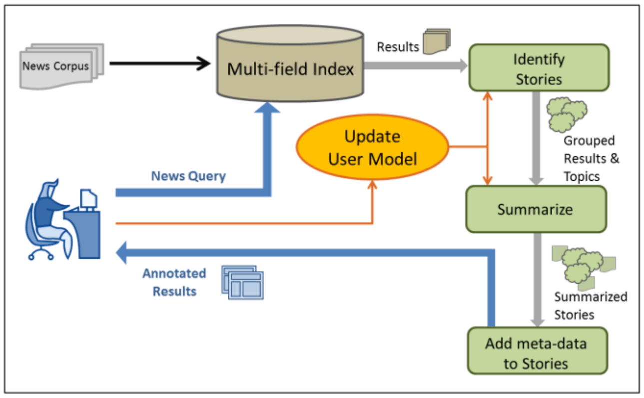

Figure 1. Schematic Diagram of *News Sync*

The key steps in the system are:

1. **Collecting a news corpus:** Our first step is to get access to the news articles for the time period of interest to the user population. Articles are processed with a named entity recognizer, to identify key concepts. In this prototype, we use the New York Times corpus, released as part of the HCIR 2010 Challenge. In addition to all articles published (or posted online) by New York Times from 1987 to 2007, the corpus also contains rich meta-data such as normalized list of people, locations, and organizations found in the articles.
2. **Indexing the corpus:** The New York Times corpus was indexed using Lucene.Net [3], such that each field can be queried individually. This involved removing frequently occurring words (stop words) and spurious characters, and additional pre-processing to normalize some fields, such as publication date, to make them searchable.

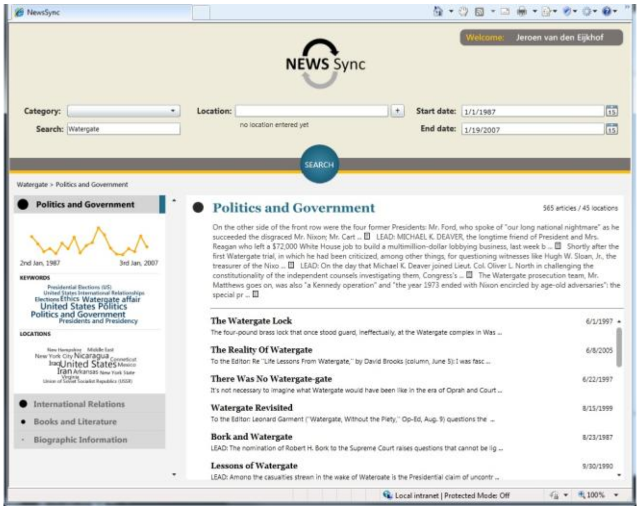

Figure 2. Screenshot of *News Sync* showing results for the query "Watergate" in the catching-up scenario.

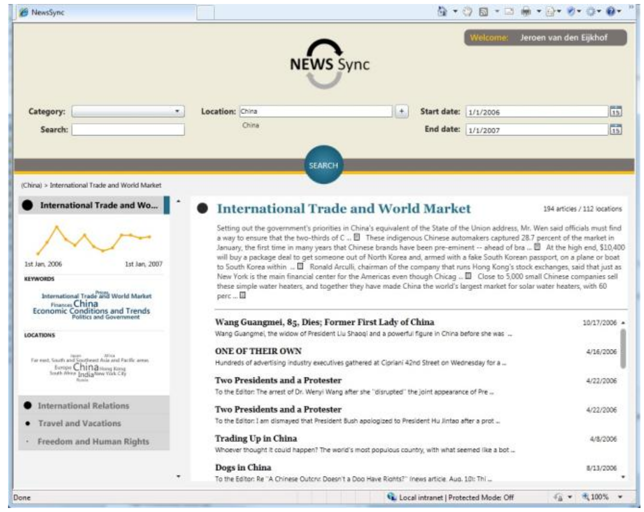

Figure 3. Screenshot of *News Sync* showing results for the diaspora query about *China*.

3. **Retrieving relevant news results:** When the user issues a query for news, the system converts the query to an appropriate Lucene [2] query. If the category or location is specified, they must appear in the document. If a date range is specified, only results from that date range are retrieved.

4. **Grouping news articles:** News needs to be presented in a manner that is easy to consume. This involves selecting the content to present and deciding how best to present it. In this work, we cluster articles to find related groups of articles. Each group may not be a single story thread, but this dimension reduction by clustering offers a more structured view into the articles. Recursive clustering can help us get to news stories, which are collections of tightly related articles. These news clusters may be adapted to the user model (user profile, explicit user preferences, and implicit interest tracking). We currently cluster on key concepts from articles, including named entities, descriptors, categories, and section headings obtained from article meta-data.

5. **Summarizing news clusters:** We adaptively summarize the clusters, to provide some insight into the articles in a cluster. Summarization is performed using a modified version of SumBasic [9].

6. **Add aggregated meta-data about the clusters:** Each news cluster is annotated with additional meta-data such as the news timeline, relevant categories, locations, and key concepts from the articles.

7. **Presenting and visualizing news:** Once the news clusters are annotated, they are presented to the user along with relevant meta-data. The meta-data, presented in the form of sparklines and tag clouds, can be used to further refine and explore news clusters.

The system is developed in C#. The interface is developed using Microsoft Silverlight [4], since it gives us access to animation and interactivity, and provides browser independence.

4.2 User Interaction

We now sketch the interaction flow for the system:

1. **Providing search parameters:** When Katie logs in, she is shown a tag cloud of key topics from the corpus. She can browse for news by providing one or more of four input parameters – the news category, topics of interest (keywords), location(s), and a date range of interest.

2. **Viewing news clusters:** When Katie enters a news query, consisting of one or more of the parameters, she is shown dynamically generated clusters of related articles. Figure 2 shows a screenshot of the results for the catching-up scenario query "Watergate". The left panel of the result screen lists clusters, ordered by popularity and relevance. The top-most cluster is highlighted and the left panel displays additional properties about the selected cluster, such as key concepts and locations mentioned in the news articles. A sparkline shows the distribution of articles with time.

   The right panel gives additional information about the highlighted cluster. It shows a brief summary, followed by the list of relevant articles. The list shows the date of publication, headline, and lead paragraph for each article.

   Figure 3 shows a similar screen for the diaspora scenario, where the user is looking for information about *China*.

3. **Browsing news results:** Katie can either explore the articles in the current cluster or can look into other clusters from the left panel. If she clicks on the article headline, the article and all relevant meta-data is displayed (see Figure 4). If she clicks on another cluster from the left panel, the section with additional properties on the first story shrinks, and the newly selected cluster expands to show its properties. Katie can also select a portion of the timeline; as the date range is varied, the articles from that date range are highlighted in real-time. This allows Katie to zoom into news from a specific time period. If Katie is interested in exploring a particular topic further, she can select a topic and choose to dig deeper. A new query is then issued based on the chosen topic and the original query to get a refined search experience.

4. **Sharing results:** The interface also allows Katie to share the summary, articles, or stories with her friends on popular social networking sites. She can also save the query/results.

5. **Following user actions:** As Katie interacts with the system, her actions, queries, and parameter settings are stored. When Katie reads articles and shares it with her friends, the key concepts from the article are recorded in user models maintained per

user. The ranking and summarization of clusters are continuously adapted based on the user model.

Katie can also explicitly restrict her results to be from particular regions or categories. These customization preferences are recorded and subsequent results are tuned to these preferences.

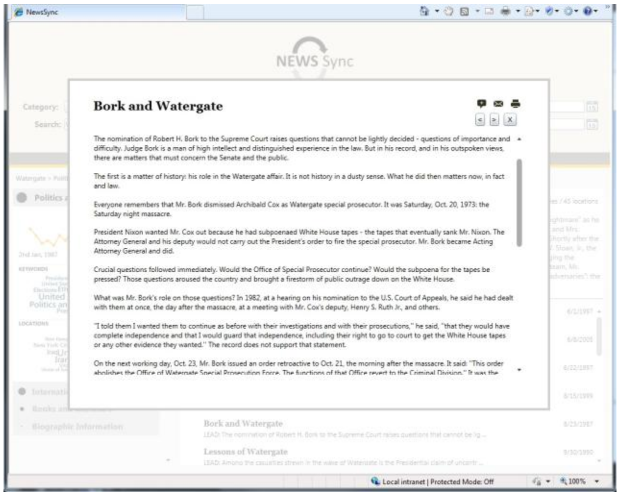

Figure 4. *News Sync* article obtained after clicking an article in the summary view shown in Figure 2.

4.3 Evaluation

We are currently piloting an initial prototype of *News Sync*. We are deploying it to a small user-base to understand how users interact with the system, using implicit and explicit feedback. We are also conducting a survey to understand usage patterns and features that are popular.

5. RELATED WORK

Past literature has looked into generating a personalized webpage of news relevant to the user based on the topics of interest. Kamba et al. [8] conducted one of the early studies on presenting an interactive newspaper on the Web. They propose a system that builds web pages dynamically as the user browses the newspaper. Anderson and Horvitz [6] developed a personalized web page as a montage of links of frequently viewed pages that changes dynamically with the time at which the page is viewed. The system learns which pages are viewed regularly at certain time periods and presents content based on the user's interests and browsing pattern. For example, a user might be shown weather forecasts and key news in the morning; the stock price ticker and work-related resources during the day; and traffic pattern and TV listings in the evening.

There has also been work in providing personalized newsfeeds. Gabrilovitch et al. [7] analyzed inter-/intra-document differences and similarities to recognize novel content in articles and how the information has evolved over time. This helps them develop measures to rank news by novelty, and pick the best (most novel) update to send to the user as a newsfeed. Other researchers, such as Tintarev and Masthoff [12] have studied different measures of similarity of news headlines to improve news recommendation.

There is a lot of relevant work in the realm of interface design. For example, Shneiderman [10] suggests use of dynamic queries to update the search results as users adjust sliders and other UI elements. Teitler et al. [11] suggest NewsStand, which proposes using geographic information in news articles to overlay news on a map. This presents users with a geographic perspective of where the news comes from and helps them cluster and explore news based on location.

Some news ranking sites are able to show "popular" news for particular days or months, based on how many users clicked on or shared a news article.

6. CONTRIBUTIONS AND CONCLUSION

In this paper, we propose an approach to providing a captivating, sticky news consumption experience, using techniques from search, language processing, visualization and learning. We listed requirements for three news exploration scenarios. We presented our prototype, called News Sync, which is currently being piloted.

In the News Sync prototype, we provide controls to users to explore news by specifying topics, a time range, and/or locations of interest. We react immediately to user inputs to show not just the relevant articles, but additional information including clusters and summaries, tag clouds of locations and key concepts and a sparkline to show temporal trends. We also adapt results based on user preferences and a model of the user acquired over time, to ensure that the user gets maximally relevant content.

In this work, we have relied on news only from a single source, namely the New York Times. We hope to extend this to multiple sources, deal with different points of view and sentiments, and work with live news streams.

7. REFERENCES

[1] Gather: The Changing Face of News Media, May 25th, 2010, www.emarketer.com

[2] Lucene. http://lucene.apache.org/java/docs/index.html

[3] Lucene.Net. http://lucene.apache.org/lucene.net/

[4] Microsoft Silverlight. http://www.silverlight.net/

[5] Pew Research Center for the People and the Press, 2008. Key News Audiences Now Blend Online and Traditional Sources – Audience Segments in a Changing News Environment. *Pew Research Center Biennial News Consumption Survey*. http://people-press.org/reports/444.pdf

[6] Corin R. Anderson and Eric Horvitz. 2002. Web Montage: A Dynamic Personalized Start Page. In *WWW*.

[7] Evgeniy Gabrilovich, Susan Dumais, and Eric Horvitz. 2004. NewsJunkie: Providing Personalized Newsfeed via Analysis of Information Novelty. In *WWW*.

[8] Tomonari Kamba, Krishna Bharat, and Michael C. Albers. 1993. The Krakatoa Chronicle - An Interactive, Personalized, Newspaper on the Web. In *WWW*.

[9] Ani Nenkova and Lucy Vanderwende. 2005. The Impact of Frequency on Summarization. MSR-TR-2005-101.

[10] Ben Shneiderman. 1994. Dynamic Queries for Visual Information Seeking. In *IEEE Software*, 11(6), 70-77.

[11] Benjamin E. Teitler, Michael D. Lieberman, Daniele Panozzo, Jagan Sankaranarayanan, Hanan Samet, and Jon Sperling. 2008. NewsStand: A New View on News. In *Proceedings of the 16th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS)*.

[12] Nava Tintarev and Judith Masthoff. 2006. Similarity of news recommender systems. In *Workshop on Recommender Systems and Intelligent User Interfaces*, G. Uchyigit (Ed).

[13] V.G.Vinod Vydiswaran and Raman Chandrasekar. 2010. Improving the Online News Experience. In *HCIR*.

Custom Dimensions for Text Corpus Navigation

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ABSTRACT
We report on our Custom Dimension search application, built for HCIR Challenge on the basis of the New York Times annotated corpus, Endeca structureless database, and WordNet semantic network.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering, query formulation, retrieval models, search process, selection process*. I.2.4 [**Artificial Intelligence**]: Knowledge Representation Formalisms and Methods – *semantic networks*.

General Terms
Algorithms, Design, Experimentation.

Keywords
Faceted search, user interfaces, refinements, semantic networks.

1. INTRODUCTION
The power of faceted search comes from facets: navigable and summarizable properties, tagged onto the records in the system. The problems with facets are: they have to be created in advance (usually, during data pre-processing), are inflexible (cannot be modified), and might not suit the particular search intent of a given user. While this does apply to numerical properties, the recent advances in analytics allow rapid computation of derived metrics, thus somewhat alleviating the problem (see "Dynamic Facets" section in [1]). With topical (keyword) properties, such as salient natural language terms, the issues above present real problems. A text corpus that has been parsed and tagged with typed entities of Person, Organization, and Location type might not suit the needs of a user who is interested in navigating the dimensions of car parts or exploring noteworthy neighborhoods of New York City.

Prior work exists [2, 4, 5] that combines pre-extracted salient terms into topical dimensions; the work in [3] detects particular dimensions that the systems considers useful as leading to potential refinements. We, however, posit the need of a system that is capable of creating such topical dimensions with no pre-processing required whatsoever.

2. PROTOTYPE
We have created a prototype application that allows new dimensions to be created at query-time, combining Endeca (http://endeca.com/) structureless database with WordNet semantic network (http://wordnet.princeton.edu/), and applied the resulting application to the New York Times annotated corpus (http://corpus.nytimes.com/). In our interface, the user can enter at query time a seed topic for the automated creation of an additional dimension. This topic term is queried against WordNet, retrieving all its senses (e.g., 1: "New York" as a city, and 2: "New York" as a state). For each sense, the application retrieves all related terms by following the meronym, holonym, and hyponym network edges. The results are considered as candidates for our refinements. As the last step, the candidates are checked against the corpus (of course, it is also possible to check the candidates against the current search result / navigation state), by measuring their precision and recall relative to the topic term. The candidates that have sufficiently high f-measures are returned to the user as refinements, along with the counts of matching documents. After experimenting with several variations on the f-measure, we ended up simply using the frequency of the candidate term in the entire corpus as the sole relevance criterion. When the user clicks on a refinement, the system performs search for the text of the refinement term on the body of the articles.

The algorithm is fast and has the added advantage of providing multiple senses of the topic term, as long as the semantic network contains them. In our application, we intentionally disabled all other refinements in order to showcase the power of custom dimensions.

We would be glad to present a live demo at HCIR if invited.

3. RESULTS
The custom dimensions interface shares two key properties with other faceted search interfaces: (1) it provides an overview of current result set, while (2) offering ways to refine it. To our surprise, the interface is useful in a third way: it helps the users to reconsider their initial assumptions, thus allowing broadening of the search intent / task. As an example, see Figure 1, where we display custom dimensions for the term "continent". One would expect to see "Africa" and "Asia"; one is less likely to expect seeing "Gondwanaland" and "Pangea" on the same list. In our (informal) usability study, we found this property of the interface repeatedly affecting the users' information retrieval process.

continent

Africa (38516)
Antarctica (1561)
Asia (31110)
Australia (20557)
Eurasia (263)
Europe (86318)
Gondwanaland (14)
North America (14305)
Pangaea (47)
South America (6711)

Figure 1. Custom dimensions for "continent"

Figure 2 displays the dimensions for the user topic "New York". Here, the system detected two senses (New York as the city vs. New York as the state) and created corresponding refinements.

new york

Bronx (54398)
Brooklyn Bridge (3409)
Brooklyn (106862)
Columbia University (24009)
Cooper Union (1700)
East River (5397)
Empire State Building (2439)
George Washington Bridge (1664)
Greenwich Village (14266)
ground zero (4347)
Harlem River (724)
Manhattan (186163)
New Amsterdam (1091)
Queens (64548)
Queensboro Bridge (645)
Staten Island (18027)
Verrazano Narrows (924)
Verrazano-Narrows Bridge (839)
World Trade Center (15684)

Adirondacks (1391)
Albany (22638)
Allegheny (1372)
Binghamton (2902)
Buffalo (19965)
Catskills (2457)
Cooperstown (1379)
Cornell University (7827)
Delaware (12308)
Hudson (33891)
Ithaca (2909)
Kingston (2778)
Long Island (55957)
New York (588553)
Newburgh (1074)
Niagara Falls (1250)
Niagara (2573)
Rochester (10601)
Saratoga Springs (1164)
Schenectady (1654)
Syracuse (12039)
Utica (1532)
Watertown (1122)
West Point (2902)

Figure 2. Custom dimensions for "New York"

Figure 3 displays the dimensions for "science"; its child, "linguistics"; and its child, "semantics", illustrating the possibility of creating custom hierarchies.

science

agronomy (101)
cognitive science (114)
cryptography (246)
informatics (68)
information processing (279)
information science (154)
IP (297)
linguistics (926)
math (11014)
mathematics (6928)
metallurgy (241)
natural history (5698)
natural science (261)
nutrition (6075)
psychology (12454)
social science (1021)
systematics (72)
tectonics (204)

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nose (17352)
virtuosity (3365)

linguistics

computational linguistics (12)
descriptive linguistics (1)
dialect geography (1)
etymology (360)
historical linguistics (15)
neurolinguistics (3)
pragmatics (20)
semantics (552)
sociolinguistics (8)
structural linguistics (8)
structuralism (106)

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dialectology (3)
lexicology (2)

semantics

deixis (1)
lexical semantics (1)

Figure 3. Custom dimensions for "science" and its children

4. CONCLUSIONS

The main issue with using the custom dimensions application is the polysemic nature of language: when performing text search for a term, it is not guaranteed the system will return only the documents where this term is used in the sense that corresponds to the given dimension topic; for example, selecting "Queens" from the "New York" dimension (Figure 2) will also return documents that refer to monarchy. Restricting matches to proper nouns (possibly even pre-extracted with a Location entity extractor) will solve this particular issue, but will not help with the case of "Syracuse" being not only a city in the state of New York, but also a town in Sicily. A possible solution is a reduced-recall, increased-precision replacement: instead of searching for the refinement term, the application can perform the search for the term as well as the text of the topic seed.

The possibility of limiting refinement to pre-extracted salient terms likewise remains a promising venue of investigation.

The author would like to thank The New York Times for providing the corpus, and Adam Ferrari for his assistance with data wrangling.

5. REFERENCES

[1] O. Ben-Yitzhak et al. Beyond Basic Faceted Search. WSDM 2008. DOI: http://doi.acm.org/10.1145/1341531.1341539

[2] W. Dakka, R. Dayal, P. Ipeirotis. Automatic Discovery of Useful Facet Terms. *Proceedings of the ACM SIGIR '06 Workshop on Faceted Search*, 2006.

[3] C. Li, N. Yan, S. B. Roy, L. Lisham, G. Das. Facetedpedia: Dynamic Generation of Query Dependent Faceted Interfaces for Wikipedia. *International World Wide Web Conference*, Raleigh, North Carolina, USA, 2010. DOI: http://doi.acm.org/10.1145/1772690.1772757

[4] E. Stoica, M. Hearst. Demonstration: Using WordNet to Build Hierarchical Facet Categories. ACM SIGIR Workshop on Faceted Search, August, 2006.

[5] K. Yang, E. Jacob, A. Loehrlein, S. Lee, N. Yu. Organizing the Web: semi-automatic construction of a faceted scheme. *IADIS International Conference WWW/Internet*, Madrid, Spain, 2004.

A Retrieval System based on Sentiment Analysis

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ABSTRACT

The aim of HCIR Challenge is to encourage systems that can help users to quickly find the needed information and understand the meanings of the retrieval results. We participated in the second task of HCIR Challenge that helps users understand the competing perspectives on controversial queries. The reason for us to choose this task is that users need to know the different opinions on the controversial queries while it is difficult for them to get the information in traditional retrieval systems that just return a list of documents without further analyzing the knowledge in these documents. We develop a system that returns documents based on their sentiments and topics given the query. The system retrieves documents given the original query and displays the topics in the results that are for or against the query. It then connects the pair of similar topics belonging to the for and against categories. Therefore, users can easily know the perspectives in the query and compare the positive and negative arguments discussing these perspectives in our system instead of reading all the returned documents and summarize those information by themselves in traditional retrieval systems.

1. INTRODUCTION

The HCIR Challenge encourages the novel systems that give users more guidance to quickly find the needed information and get more knowledge from the retrieval results. It has three tasks that include learning about the topic having a long history, understanding the controversial perspectives on the controversial query and answering the question requiring looking at more than one document. We participated in the second task because users need to understand the retrieval results and know different arguments in the results while they cannot easily get these information from the traditional retrieval systems that simply return a list of documents as the results without giving any further knowledge of the results. Therefore, it is necessary to re-organize the retrieval results and provide facilities for users to understand the results.

We developed a system that returns documents given the query according to their sentiments and topics. It not only returns relevant documents but also displays the perspectives in the query and different arguments in each perspective. The system was based on the Lemur toolkit which we added a re-organizing component to. The system retrieves the documents given the query with Lemur and classifies the returned documents to the categories that are for or against the query according to their sentiments analysis results using the toolkit OpinionFinder. It then uses the probabilistic latent semantic analysis (PLSA) [1] algorithm to extract the topics in the documents of each category and displays the topics with both the topic descriptions and the documents belonging to the topics. We also connect the similar pair of topics belonging to different categories. Each pair of similar topics corresponds to a perspective of the query and each topic correspond to the arguments for or against that query perspective. The result of the system allows user to easily know the perspectives in the query and compares the opinions in each perspective by reading the arguments of the perspective.

The paper is organized as follows. We describe the framework of the system in Section 2 and show the system interface and results in Section 3. We then conclude in Section 4.

2. THE SYSTEM FRAMEWORK

As shown in Figure 1, the steps of the system are listed as follows:

1. Retrieving documents. We use the Lemur toolkit to build the index of New York Time corpus and retrieve documents with Dirichlet prior retrieval function.

2. Analyzing the sentiment of the returned documents. We use the OpinionFinder toolkit to analyze the sentiments in the documents returned in the above step and classify the documents into categories that are for or against the query.

3. Mining the topics of documents in each category. We extract the topics of documents in each category with PLSA topic modeling method using Lemur toolkit. Each document and term is assigned to the topic in which they have the highest probabilities. The number of topics in each category is set to be 5.

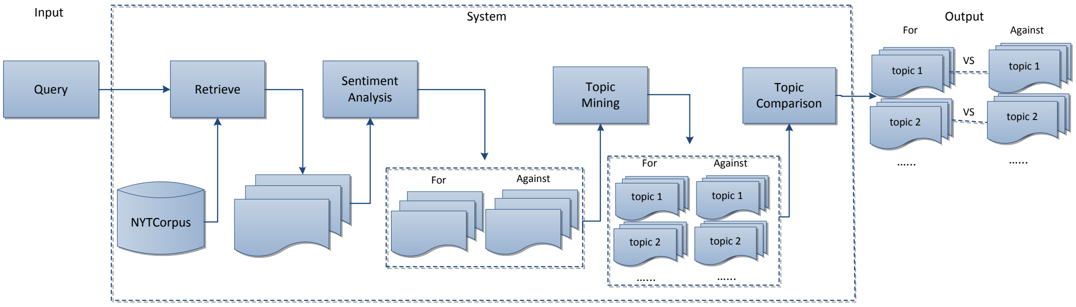

Figure 1: the architecture of our system

4. Comparing topics belonging to different category. After modeling the topics in the for and against category, we use cosine similarity method to compute the similarity between topics using their terms. The pair of topics belonging to different categories is judged to be similar and correspond to one perspective of the query if their similarity is larger than a threshold which is set to be 0.2.

3. THE SYSTEM INTERFACE

Figure 2 shows the retrieval results of the query *rent control in New York*. The system uses PLSA algorithm to extract the topics in the documents of each category. The default number of topics is set to be 5. The interface displays the top ranked terms of the topics and the information of related documents in each topic. We also build connections between the similar topics belonging to different categories and use *VS* to show that two topics are discussing the same query perspective but expressing different opinions. As shown in Figure 2, topic 0-3 in the *FOR* and *AGAINST* categories are discussing the same perspectives while topic 4 in the two categories are discussing different perspectives. We can see some encouraging results in the topics. For example, the topic 0 of *FOR* and topic 0 of *AGAINST* are different opinions about the influence of the rent control to the rent market, and topic 1 on both sides are about the change of the rent cost.

Users can check the detail results of each topic when clicking the *detail* button. The table in each topic shows the ID and title information of the documents. Users can see the original document with highlighted topic terms, as shown in Figure 3, when clicking the row of the document.

4. CONCLUSION

The traditional retrieval systems just return a list of documents for users to read. It is difficult for users to know all the perspectives in the query. We developed a system that returns documents based on their sentiments and topics. Therefore, users can easily know the topics that are for or against the query when reading the topic description and related documents. They can also compare different arguments on the same perspective when comparing the similar topics displayed in the system. There are some interesting future works for the system. First, we can analyze the documents in each sentiment category to automatically decide the number of subtopics. Second, we can extract the terms that express the common meaning of the pair of similar topics as the description of that pair and use terms expressing opposite opinions as the description of the individual topic in the topic pair.

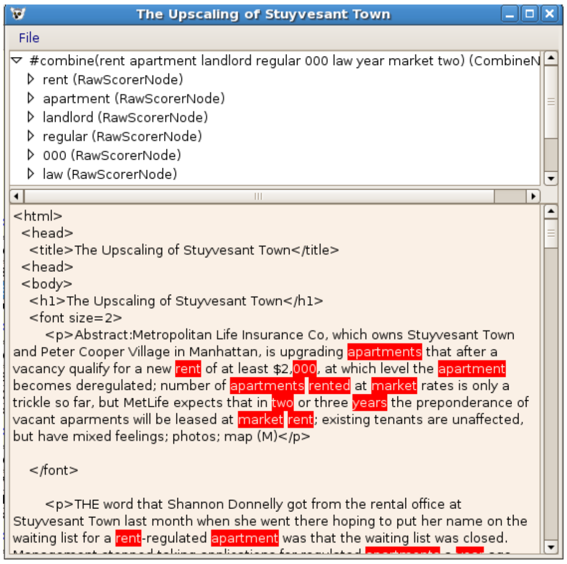

Figure 3: The display of the original document

5. REFERENCES

[1] T. Hofmann. Probabilistic latent semantic analysis. In *Proceedings of UAI'99*, 1999.

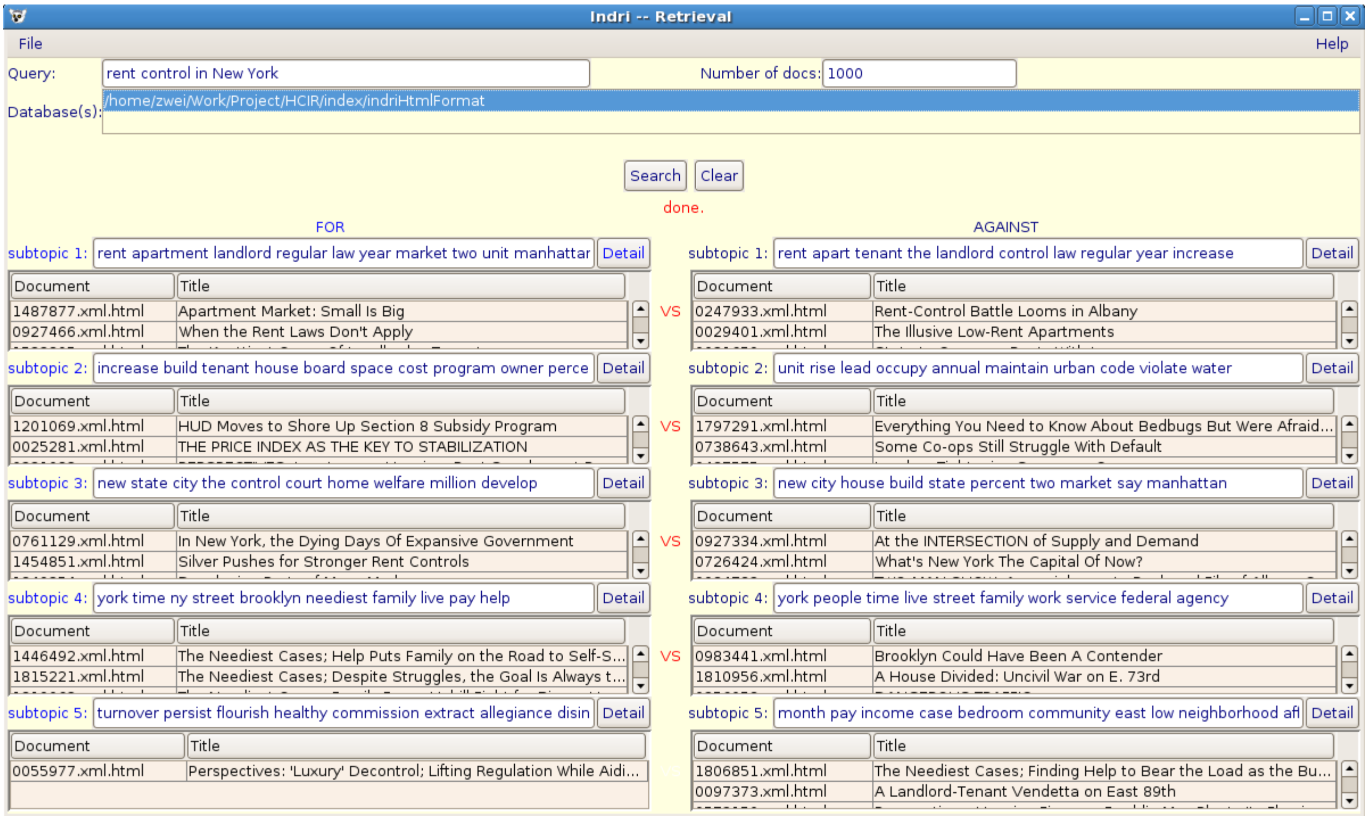

Figure 2: The retrieval results

Improving Web Search for Information Gathering: Visualization in Effect

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ABSTRACT

The nature of the Web implies heterogeneity, large volumes, and varied structures. Hence, finding results that best suit the needs of every individual in every type of Web task is a very challenging problem. This research presents an interactive Visual Search Engine (VSE) in which both query reformulation and results presentation are visualized. The paper presents the results of a user study in which the effectiveness of the VSE compare to Google is evaluated. The VSE was shown to be effective with respect to Web information gathering tasks.

Categories and Subject Descriptors

H.3.3. [**Information Search and Retrieval**]: Search process, query formulation, clustering

General Terms

Measurement, Performance, Design, Experimentation, Human Factors

Keywords

Web information retrieval, relevancy, information gathering, search tasks, query reformulation, visual search, visual rendering.

1. INTRODUCTION

The process of results presentation in most conventional search engines presents few links per display with textual content attached to each link. The user may have to perform scrolling over multiple pages to find relevant results [11]. However, it has been shown that the majority of Web search users do not look beyond the first three results [5, 11]. At which point, users either modify the search query or switch to a different search tool [1].

Information visualization is suggested to improve users' performance by harnessing their innate abilities for perceiving, identifying, exploring, and understanding large volumes of data [3, 4]. Consequently, visualization has become of interest to researchers in Web information retrieval due to the large numbers of documents the Web contains in addition to the often overwhelming resultant matches of Web search results. Visualization may permit the display of more results with connectivity features. Integrating visualization in Web search aims to combine computation and high bandwidth human perception [13, 14].

In previous works [5, 6], several visualization aspects were investigated in Web information search and retrieval. Some of the visualization research either achieved certain levels of success while being evaluated using search queries or usability case studies, or suffered from issues of delay and scalability concerns due to the user of sophisticated 3D visualizations. Evaluating visualization and clustering-based search interfaces may reveal different finding in the case of using the context of a complete task. The presented VSE aims to utilize the user’s visual abilities to improve query reconstruction and search results exploration. The improvement is intended for the case of information gathering tasks in which uses locate, compare, and further locate Web documents for satisfying criteria described in the task [7].

2. DESIGN AND IMPLEMENTATION

The VSE uses Google as its underlying search service provider. Hence, the VSE is a visualized layer built on top of Google as a search interface with which the user interacts to submit and reformulate queries and also to explore search results. The VSE presents results as glyphs on an interactive interface. Each glyph contains the document title and a snapshot of the Web page as recommended in the work of Teevan et al. [12]. Edges between visualized glyphs represent content similarity between connected documents. The interactive interface of the VSE permits the user to see document statistics such as document size, Google’s PageRank value, and documents’ last updates. Along with the user original query, the VSE uses alternate queries provided by the semantic network WordNet [8, 9] for single term user queries and by randomly reordering query terms for multiple-term queries.

The VSE permits its users to reconstruct subsequent queries from a query reconstruction area on the display. The query reconstruction area contains terms and phrases inferred from the top documents retrieved for the current query. The aim of this design is to assist users with perceiving more relevant results and related search queries. Figure 1 shows the interface of the VSE. A user study was conducted to evaluate the effectiveness of the VSE as reported in the following Section.

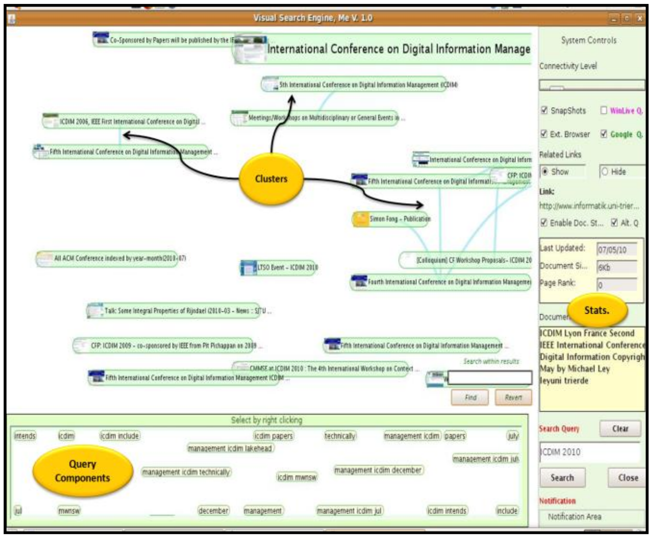

Figure 1. The VSE interface

3. EVALUATION

Fourteen participants took part in the study to evaluate the VSE by comparing it to Google. The type of Web tasks intended to be evaluated was information gathering since it represents approximately 61.5% of the overall Web tasks [10]. Information gathering tasks involve collecting information possibly of different types from different sources to achieve an overall goal identified in the task [7]. Hence, this type of task was considered for evaluation in this project. The other two types of search tasks (navigational and transactional according to Border [2]) imply seeking more specific results. Consequently, they were not considered in the study. An example of the information gathering tasks that were used in the study is the following.

> *"Use the given search engine to gather webpages that include information about how to use the java programming language in transforming html documents into images. The pages you find should give someone a good idea about the task's topic. You can submit up to five queries only, and you should not go beyond viewing one page of results for each query you submit. You can still view results of webpages in the Web browser".*

In the evaluation study, users were asked to perform two information gathering tasks both on Google and the VSE. The study design was complete factorial within-subjects and counterbalanced. After finishing each task on either search tool, the study asked participants to complete a post-task questionnaire in which they stated their confidence in the results in addition to other self-reported engagement measures. Study data included machine logged data in addition to data accumulated in the questionnaires. The study took under 30 minutes and was preceded by a short training session on the VSE. Participants were computer science students from Dalhousie University.

4. RESULTS AND DISCUSSION

Although the study was intended to evaluate only the effectiveness of the VSE compared to Google, the VSE was found to also be more efficient in performing searches for information gathering with an average time on task of 6.5 minutes compared to Google with 8.2 minutes. However, the difference was not significant in this case.

Regarding effectiveness, the VSE—compared to Google—required submitting fewer queries, opening fewer pages on the Web browser, and permitted its users to discover more relevant pages with closer numbers of types of information to the types required in the tasks. Google, on the other hand, required the participants to submit more queries, open more pages on the browser to locate fewer relevant results for the tasks. By comparing the study results, the t-test revealed significant differences between the VSE and Google with $F = 45$, and $\alpha < 0.003$ with respect to above criteria. The quantitative results are shown in Table 1. For further illustration, a comparison of the VSE and Google with respect to the number of pages participants had to open on the Web browser to accomplish their tasks is shown in Figure 2. Figure 3 shows the difference between the two search tools regarding the number of queries used for achieving the tasks.

Table 1. Quantitative results

Where, (μ) is the Mean, and (σ) is the Standard Deviation.

	System	**VSE**	**Google**
	Time (Mean)	*6.5*	*8.2*
Submitted Queries	μ	2.5	3.5
	σ	1.5	1.6
Pages opened on the browser	μ	2.1	9
	σ	1.5	11
Relevant pages found	μ	6.5	4.5
	σ	2.7	2.1
Covered topics	μ	3	2
	σ	1.4	1.3

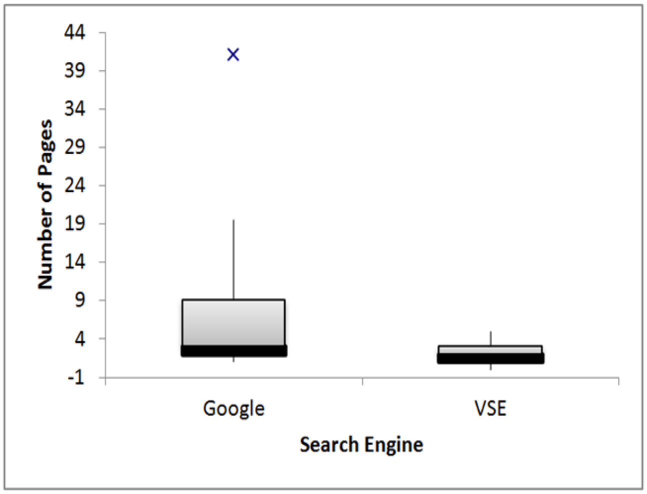

Figure 2. Pages browsed by participants

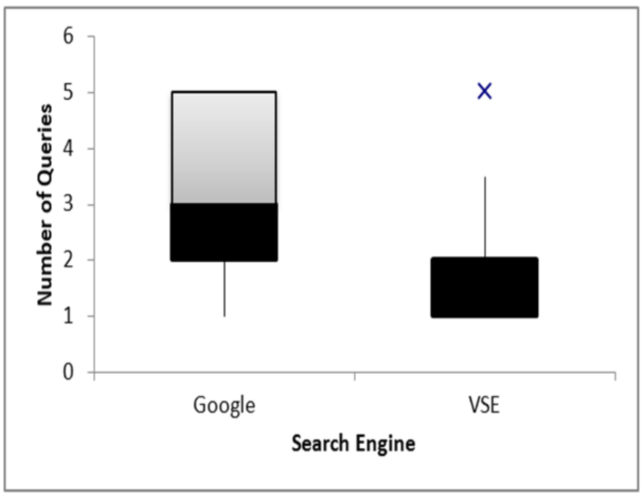

Figure 3. Queries submitted by participants

Analyzing the results of the questionnaires showed that the VSE was considered better for information gathering than Google by the participants in the study. In addition, the VSE was regarded as more effective in reconstructing queries and more helpful in finding relevant documents. Figure 4 shows the results of the analysis of the post-study questionnaires. However, the one-tail z-test shows no significance difference between the two proportions of participants ($z = 1.42,\ \alpha = 0.08$). In addition, the user qualitative comments are shown in Figure 5. Generally, 80% of the comments about the VSE were positive. According to the one-tail z-test, there was a significance difference between the two proportions of comments ($z = 2.79,\ \alpha < 0.004$). Furthermore, the user confidence with the located results for the search tasks with both the VSE and Google is shown in Figure 6.

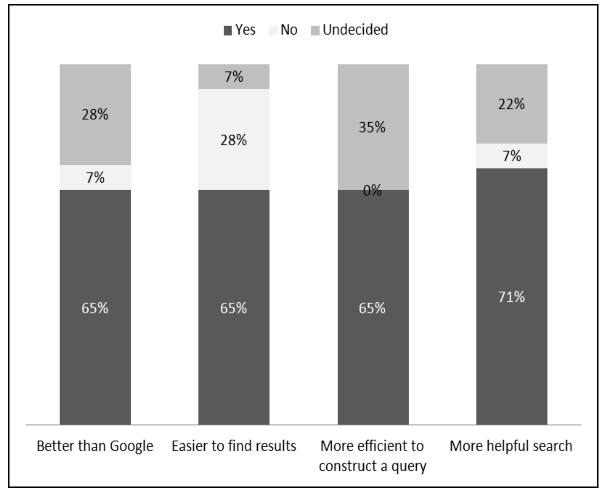

Figure 4. Post-study questionnaire ratings of the VSE compared to Google

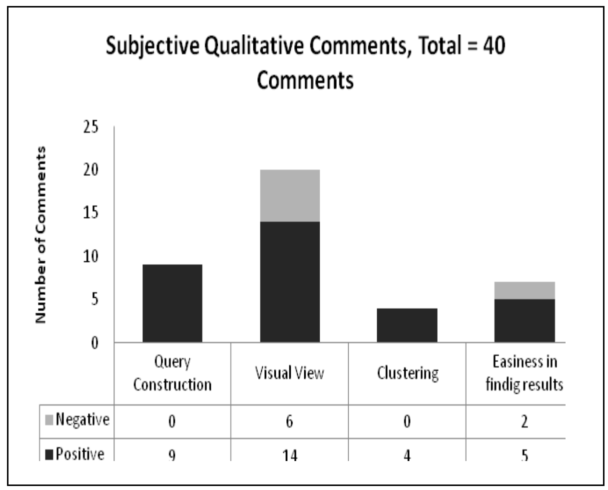

Figure 5. Subjective self-reported comments

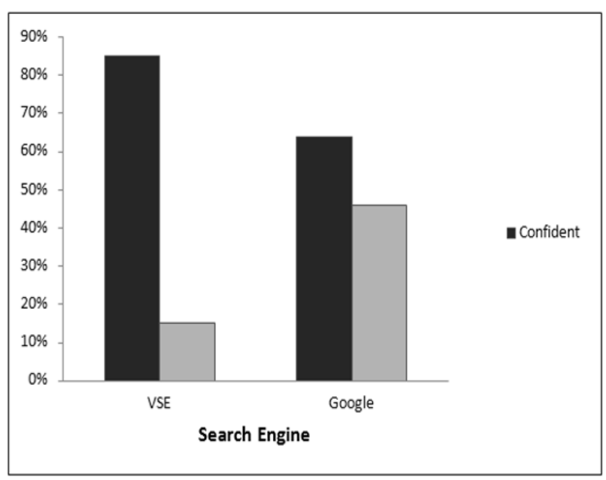

Figure 6. User confidence in the located results

Minor concerns were raised about the slow movement of the glyphs on the display. However, the study showed that the current Web search model suffers from ineffectiveness with regard to how search queries are reformulated and how search results are presented to the user. In the case of Web information gathering tasks, the limited document attributes shown by the search engine, the current approach for submitting and reformulating search queries, and the way search results are presented for comparing Web information and making decisions regarding the task requirements need further investigations.

5. FUTURE WORK

For information gathering tasks, users usually need to explore more results per session and to effectively perceive more features of the presented documents to be able to make effective decisions regarding the information gathered for the task requirements. In further research, different layouts will be evaluated for search results presentation. In addition, different clustering criteria will be investigated in information gathering with the use of visualization. The concepts of re-finding and Web information organization for information gathering will also be investigated.

6. CONCLUSION

The VSE demonstrated that exclusive textual presentations of Web search results would benefit from our visualizations. The VSE may help Web search users with finding relevant documents in the case of information gathering tasks. Future work will focus on this type of task by emphasizing its underlying subtasks for investigation.

7. REFERENCES

[1] Alhenshiri, A. and Solis-Oba, R. 2007. Improving Results for Short Web Queries Using Preserved Query Knowledge. In proceedings of the 1st international Conference on Digital Communications and Computer Applications, Amman, Jordan, 634-649.

[2] Border, A. 2002. A Taxonomy of Web Search. ACM SIGIR Forum. Vol. 36, Issue 2, 2-10.

[3] Card, S., K., Mackinlay J. D., and Shneiderman B., Readings in Information Visualization. 1999. Using Vision to Think. Morgan Kaufman Publishers, San Francisco, CA, USA.

[4] Friendly, M. 2008. Milestones in the History of Thematic Cartography, Statistical, Graphics, and Data Visualization. York University Archives, Ca*na*da. http://www.math.yorku.ca/SCS/Gallery/milestone/

[5] Hoeber, O., and Yang, X. D. 2007. Visual Support for Exploration within Web Search Results Lists. In Conference Compendium of the IEEE Information Visualization Conference (October 28- November 01, Sacramento, California, USA), 157-167.

[6] Jacso P.: SAVVY SEARCHING.2007. Clustering Search Results. Part I: Web-wide Search Engines, Online Information Review, 31(1), 85-91.

[7] Kellar, M., Watters, K., and Shepherd, M. 2007. A Field Study Characterizing Web-based Information-Seeking Tasks. Journal of the American Society for Information Science and Technology, 58(7), 999-1018.

[8] Miller G., A. 1990. WordNet: An On-line Lexical Database. International Journal of Lexicography, 3(4), 285-303.

[9] Moldovan, D., and Mihalcea, R.2000. Using WordNet and Lexical Operators to Improve Internet Searches. IEEE Internet Computing, 4(1), 34-43.

[10] Rose, D., E., and Levinson, D. 2004. Understanding User Goals in Web Search. In Proceedings of the 13th International Conference on World Wide Web (May 19-21, New York, NY, USA), 133-142.

[11] Spink, A., Wolfram, D., Jansen, M., and Saracevic, T. 2001. Searching the Web: The Public and Their Queries. Journal of the American Society for Information Science and Technology, 52(3), 226-234.

[12] Teevan, J., Cutrell, E., Fisher, D., Drucker, S. M., Ramos, G., André, P. and Hu, C. 2009. Visual Snippets: Summarizing Web Pages for Search and Revisitation. In Proceedings of the 27th International Conference on Human Factors in Computing Systems (April 04-09, Boston, MA, USA).

[13] Vincente, K., J., Rasmussen, J.1990. The Ecology of Human Machine Systems: Ii. Mediating "Direct Perception" in Complex Domain, Journal of Ecological Psychology, 2(3), 207-207.

[14] Youssefi, A., Duke, D., Zaki, M. 2004. Visual Web Mining. In Proceedings of 13th International World Wide Web Conference on Alternate Track Papers and Posters (May 19-21, New York, NY, USA), 394-395.

User-Oriented and Eye-Tracking-Based Evaluation of an Interactive Search System

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ABSTRACT

We report on experiences and challenges we faced during an user-oriented eye-tracking-based evaluation of an interactive search system. Furthermore, some exemplary analyses were performed. Finally, we specify requirements for the design and architecture of search systems amenable for eye-tracking.

Categories and Subject Descriptors

H.3.3 [**Information Systems**]: Information Storage and Retrieval—*Information Search and Retrieval*
; H.3.4 [**Information Systems**]: Information Storage and Retrieval—*Systems and Software*

General Terms

Interactive Retrieval

Keywords

interactive retrieval, eye-tracking, evaluation, INEX iTrack

1. INTRODUCTION AND RELATED WORK

The INEX Interactive Track (iTrack) is a cooperative research effort run as part of the INEX Initiative for the Evaluation of XML retrieval[1]. The overall goal of the iTrack is to investigate how users behave in interactive search systems. In the 2009 run of this track[2] the focus was on what aspects of documents the users are interested in, how they make use of various search tools, and finding out new challenges for the next iTracks [7]. We created a collection based on a crawl of 2.7 million records from the book database of the online bookseller *Amazon.com*, consolidated with corresponding bibliographic records from the cooperative book cataloging web site *LibraryThing*.

[1]http://www.inex.otago.ac.nz/
[2]http://itrack09.is.inf.uni-due.de

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Using eye-tracking in retrieval evaluations is a demanding challenge [5]. The study design has to be developed carefully to cope with many parameters that are difficult to control. Joachims et al. [4] examined the reliability of click-through data for implicit relevance feedback of a web search engine by comparing them to eye-tracking data. A faceted search interface was evaluated with exploratory and known-item working tasks by Kules et al [6]. The result area and the facet area were used most frequently. Cutrell and Guang [2] used eye-tracking to explore the effects of different presentations of search results.

In addition to the standard experiments in the iTrack we also performed eye-tracking-based evaluations. In this paper we report on our experiences and the problems we faced.

2. SYSTEM DESCRIPTION

The search system (see figure 1) was developed at the University of Duisburg-Essen and partially at the Distance University of Hagen (see [7] and [1] for a more detailed description). It is based on the digital library front-end systems *Daffodil*[3] [3] and *ezDL*[4]. The retrieval component was implemented using Apache Solr[5].

The **search tool** offers a Google-like search field as well as advanced search fields for title, author and year. A combo box allows the user to select the aspects he wants to search in. Below this query panel the user can select fields for sorting and the display style of the result list. The lower half of the search tool contains the result list. The default result list view shows the title, authors, year, publisher, average customer rating and a thumbnail of the book cover. Each page of the result list contains 20 result items. The user can use the buttons at the bottom to navigate to following or previous pages of the result list.

A double-click on a result item shows book details in the **detail tool**. Users can indicate the relevance of an examined book as either *relevant*, *partially relevant*, or *not relevant*, by clicking markers at the bottom of the tool. A second tab shows reviews of the selected book.

Users can mark any book as part of the answer to the search task by moving it to the **basket tool**. This can be performed either via drag-and-drop or by clicking the *add to basket* button next to the relevance buttons.

[3]http://www.is.inf.uni-due.de/projects/daffodil/
[4]http://www.is.inf.uni-due.de/projects/ezdl/
http://www.ezdl.de/
[5]http://lucene.apache.org/solr/

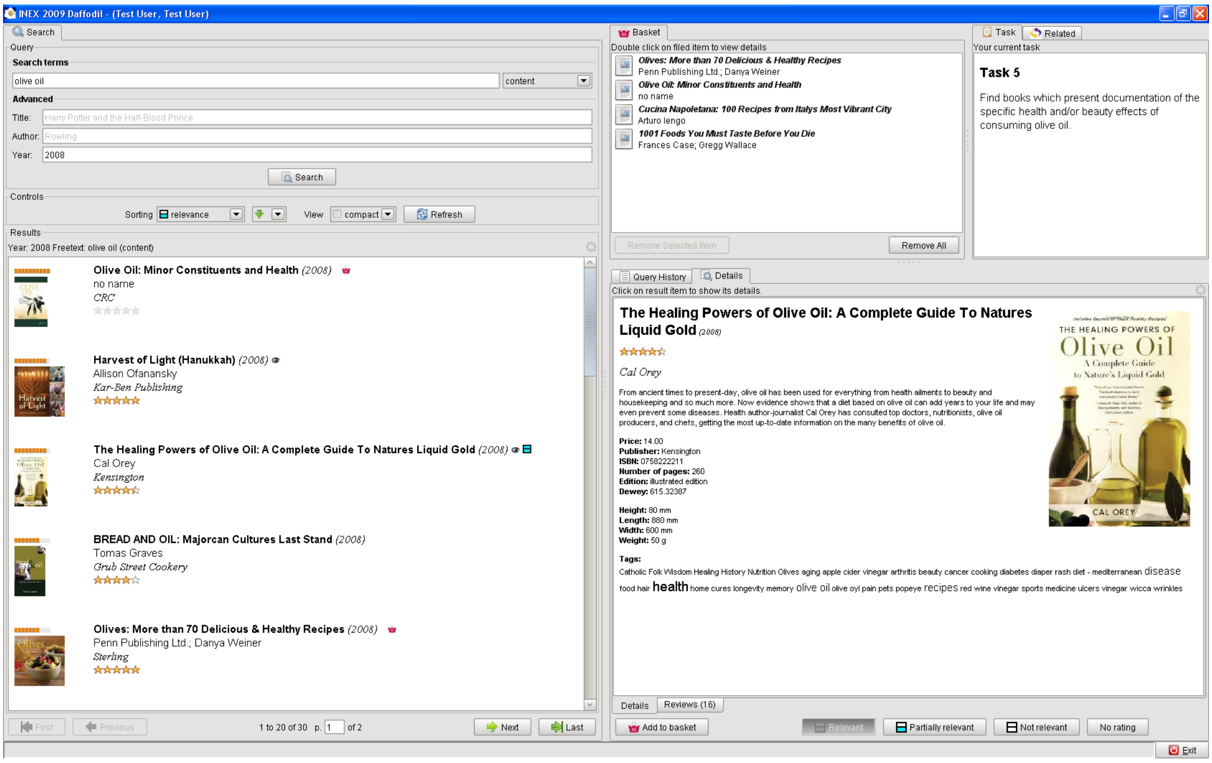

Figure 1: The user interface of the search system

A history of performed search queries is provided by in the **query history tool**. The **related terms tool** presents terms related to those used in the search query. A search for related terms can also be triggered manually by the user. Finally, the **task tool** shows the current working task.

3. EVALUATION DESIGN

There were three different task groups, namely *broad tasks* (I), that require exploratory search behaviour, *narrow tasks* (II), that are about a relatively narrow topic, and a *self-selected* (III) task about finding a single book for a course the volunteers were currently attending. The first two task groups consisted of three concrete working tasks from which one had to be chosen by the participant. A detailed description of the working tasks the users worked on is provided by Pharo et al [7].

For the study 12 volunteers were recruited from students of computer science, cognitive and communication science and some other fields. 6 of them were male and 6 of them female. Their average age was 23.84, having used the Internet for 9.5 years on average. All had experiences with web search engines, searching in Digital Libraries or digital bookstores. The participation was on a voluntary basis, with a compensation in form of a voucher for an online bookstore.

4. SETUP AND EYE-TRACKING

For our experiments we used the eye-tracker *RED*[6] by *SensoMotoric Instruments* (SMI). Both the stimulus as well as the eye-tracking data recording was done on a computer running Windows XP (Intel 3 GHz CPU, 4 GB RAM).

With the recording and experiment software (*iView X* and *Experiment Center*) by SMI we collected

- the actual eye-tracking data,
- the screen of the search system including user actions and
- a video of the user herself (by a standard webcam).

The screen recording requires substantial hardware resources (at least a quad-core CPU with 3+ GHz).

The experiments were performed under equal conditions. The lighting in the lab was kept under control. The participants had to sit on a non-rotatable chair to prevent them from moving too much during the experiments. In general, participants wearing eyeglasses posed no problem for the eye-tracking system. Only for very few users the system was not able to recognize their eyes, so they could not participate in the experiment.

Before each working task the eye-tracking systems was calibrated. Therefore, the participants had to follow a moving point on the screen with their eyes (overall 9 steps). Afterwards, the participants started working on the tasks. In addition to the eye-tracking and video data, the user interaction with the search system was logged (see [7] and [1]). Furthermore, the participants had to fill out questionnaires (pre-experiment, pre-task, post-task and post-experiment).

An observer was present during the time of the experiments to ensure that the data recording was working without any problems. Also, the data recording had to be started and stopped for each of the three working tasks by the observer since the above mentioned eye-tracking software does not support a fully automated experiment flow.

[6] http://www.smivision.com/en/gaze-eye-tracking-systems/products/red-red250.html

5. ANALYSIS AND RESULTS

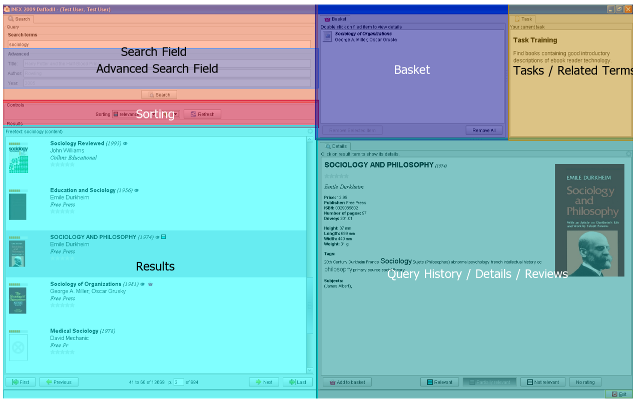

Figure 2: Areas of Interest (AOIs) of the search system interface

For analysing the eye-tracking data, the user interface of the system (see figure 1) was divided into so called Areas of Interests (AOIs) (see figure 2). AOIs define larger and logically connected gaze areas. These areas are used to capture not only fixations, but also more peripheral perceptions. Since some of the tools in the search system are on top of other tools, it would have been necessary to record the visibility information of tools to create dynamic AOIs automatically. The manual creation of AOIs would have taken too much time, thus we could not perform certain analyses. In future versions of the front-end of our digital library access system *ezDL*, we will implement automatic logging of screen positions of displayed objects, thus supporting dynamic AOIs.

The eye-tracker analysis software BeGaze provides multiple possibilities for investigating the recorded eye-tracking data:

- Gaze Plots (Gaze Replay, Bee Swarm, Scan Path)
- Attention Maps (Heat Map and Focus Map)
- Quantitative Information (Key Performance Indicators, Gridded AOIs, AOI Sequence Chart, Binning Chart, Event Statistics and Line Graph)

In our analysis we focused on attention maps and quantitative information because the gaze plots offer only a weak aggregation of the eye-tracking data. Figure 3 shows the heat map of the topically broad working task group I in comparison to the narrow self-selected working task group III. In both heat maps, the participants focused on the left side of the result list. The right part of this heated area is frayed which means that the participants were particularly interested in the title of the search results. The other main attention area is the upper and left part of the detail tool which contains the detail information and the reviews (if available) of a selected book as well as the rarely used query history tool.

In working task group III, the participants were less interested in the thumbnails of the book covers. There is no heated area on the very left side of the result list. Also, the lower right part of the detail tool/query history tool was used more frequently. At this place on the screen, the subjects and user-generated tags were shown most of the time. The area of the task tool/related terms tool was used less frequently than in the topically broader task group I. This

Area of Interest	I	III
Search Field	6%	7%
Advanced Search Field	2%	3%
Sorting	2%	2%
Results	35%	31%
Basket	3%	5%
Task/Related Terms	5%	3%
Details/Query History	33%	39%

Table 1: Relative dwell times in AOIs

is not very surprising because it seems obvious that users have to take a look at the working task description during the search session to recapitulate the actual task. Also, the related terms tool can provide users with useful suggestions or ideas for new search queries.

Table 1 lists the dwell times of the users' eyes in the AOIs. The result area and the details area were looked at most frequently while the participants dwelled in other areas for a much shorter time. For task group III, the participants focused longer on the detail area and shorter on the result area. We explain this observation by the fact that the exploratory working tasks (I) require more interaction with the result list. The self-selected working tasks (III) required the choice of a single book. Consequentially, the participants spent more time in the detail area to assess the relevance. Likely because of the limited number of participants (12), the differences are not statistically significant (p-value of student's t-test: 0.16 and 0.12 respectively) though.

Figure 4 shows the binning chart of the sessions of task group I in comparison with the sessions of task group III. A binning chart visualizes the relative dwell time over the duration of the search sessions. The different colors of the bins correspond with the colors of the defined AOIs (see figure 2). Both charts are decreasing because the sessions have different lengths. The task/related terms tools area is used more often in exploratory tasks (task group I) than in the topically narrow self-selected tasks (task group III). This area is not used continuously but only occasionally during the sessions. The participants presumably consulted the tasks description or the search for related terms during search queries to remind of the actual working tasks or to get new ideas for new search queries.

For lack of space we do not describe task group II more detailed. An overview of the results based on questionnaires and system logs is presented by Beckers et al [1].

6. CONCLUSION AND OUTLOOK

User-oriented and eye-tracking-based evaluations of interactive search systems pose a highly complex challenge. We reported on such an evaluation that was performed in the context of the INEX iTrack 2009. Eye-tracking-based evaluation studies can provide insightful information that cannot be captured with usual data such as questionnaires and system logs. The most important question is how systems and user interfaces have to be constructed so that useful analyses can be performed. In our case the system should e. g. be able to collect data that allows analyzing how users make use of different document aspects. So far, we are only able to make conclusions primarily about the use of the book cover and the title.


Figure 3: The heat maps of task group I and III respectively

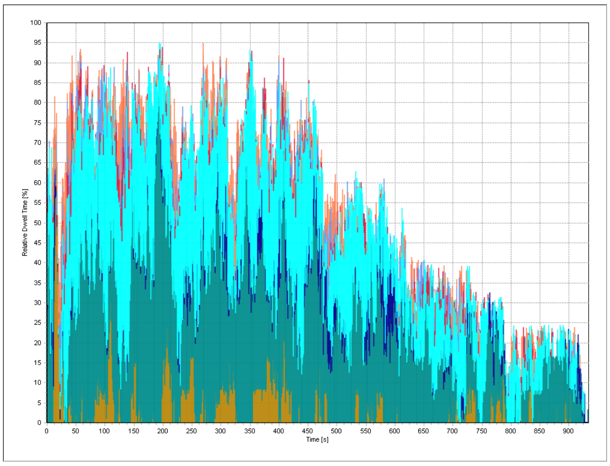
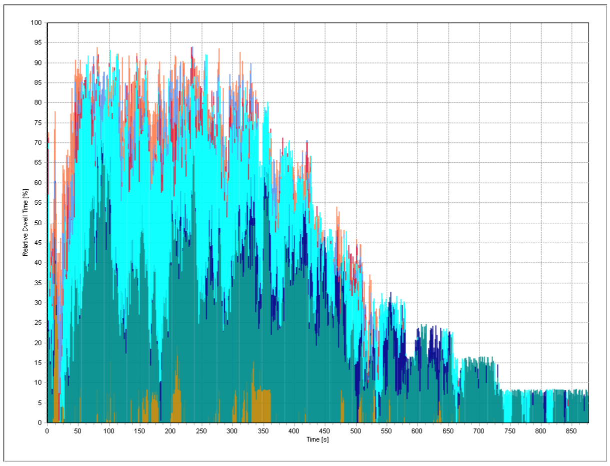

Figure 4: The binning charts of task group I and III respectively

As mentioned in the previous section, it is important for search systems that do not have a solely static user interface to record the actual screen position of certain elements. We plan to implement such a recording of visible components on the screen in *ezDL* to find out more about the actual use of various components of search interfaces.

Most of the working tasks have been too easy for the participants to work on. The related terms tool, the query history tool and the reviews of the detail tool have been used less often than we expected. Thus, we plan to create new working tasks for the next run of the iTrack that focus less on well-known metadata, such as title and author but also more on e. g. reviews or book covers. Also, the book data is to be cleaned-up to increase the homogeneity, that is, entries with sparse metadata will be removed from our collection.

7. REFERENCES

[1] T. Beckers, N. Fuhr, N. Pharo, R. Nordlie, and K. N. Fachry. Overview and results of the INEX 2009 Interactive Track. In *14th European Conference on Research and Advanced Technology for Digital Libraries (ECDL 2010)*, 2010.

[2] E. Cutrell and Z. Guan. What are you looking for?: An eye-tracking study of information usage in web search. In *CHI '07: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 407–416, New York, NY, USA, 2007. ACM.

[3] N. Fuhr, C.-P. Klas, A. Schaefer, and P. Mutschke. Daffodil: An integrated desktop for supporting high-level search activities in federated digital libraries. In *Research and Adv. Technology for Digital Libraries. ECDL 2002*, pages 597–612, Heidelberg et al., 2002.

[4] T. Joachims, L. Granka, B. Pan, H. Hembrooke, F. Radlinski, and G. Gay. Evaluating the accuracy of implicit feedback from clicks and query reformulations in web search. *ACM Transactions on Information Systems*, 25(2), 2007.

[5] M. Jordan, S. Dungs, M. Kamsu, R. Planert, T. V. Tran, and N. Fuhr. Challenges and perspectives of eyetracker-based evaluation of interactive retrieval. In *WIR 2009 – Workshop Information Retrieval 2009*, 2009. in German.

[6] B. Kules, R. Capra, M. Banta, and T. Sierra. What do exploratory searchers look at in a faceted search interface? In *Proceeding of the Joint Conference on Digital Libraries*, June 2009.

[7] N. Pharo, R. Nordlie, N. Fuhr, T. Beckers, and K. N. Fachry. Overview of the inex 2009 interactive track. In *Proceedings of the 8th International Workshop of the Initiative for the Evaluation of XML Retrieval (INEX 2009)*, 2010.

Exploring Combinations of Sources for Interaction Features for Document Re-ranking

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ABSTRACT

The behavior of the user when interacting with a result page or the corresponding landing documents is a possible source of evidence that Information Retrieval (IR) systems can exploit to assist the user when searching for information. Interaction features can be adopted as evidence to model the user behavior, thus making it usable to assist relevance prediction. One issue when dealing with interaction features is the selection of the sources from which these features are distilled. Individual users and group of users which perform a similar task or look for information matching the same query are possible sources. This paper will focus on these two sources, particularly investigating group of users searching for the same topic as source for interaction features to be used as an alternative to, or in combination with, individual users. The objective of this work is to investigate the impact of diverse combinations of these sources on the retrieval effectiveness, specifically when interaction features are used as evidence to support document re-ranking.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Relevance feedback, Search Process.

General Terms

Experimentation, Human Factors.

Keywords

Interaction Features, Implicit Relevance Feedback.

1. INTRODUCTION

A potential source of evidence to support IR systems when predicting relevance is the behavior of the user when interacting with result pages or the documents which results refer to. Implicit Feedback techniques [1] exploit features that can be gathered by monitoring the user behavior, e.g. interaction features, as indicators of the user interests or intents.

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Interaction feature values can be distilled from diverse sources, and the selection of the source for features can affect the effectiveness of implicit feedback techniques. Individual users and group of interrelated users are possible sources from which interaction feature values can be observed. These sources have been investigated as alternative choices or used in combination because of their impact on the reliability and the availability of implicit features. For instance, in [2] the authors investigated display-time thresholds as implicit indicator of relevance. The obtained results showed that display-time, when considered in isolation and with regard to an individual user, may be hardly usable to support prediction; differently, it was a more consistent indicator when the threshold was learned from multiple subjects sharing a common task. In [3] user behavior models to support web search were learned by exploiting simultaneously feature values derived from the individual's behavior and those aggregated across all the users and search session for each query-URL pair, thus reducing the impact of individual variation in behavior. In [4] the authors investigated the impact of aggregating personalized scores per group formed according to diverse criteria on personalization algorithms when a small amount of personal data is available.

This work considers the scenario where a user interacts with some of the results obtained by a first search. The features gathered from this interaction can be exploited to obtain a representation of the information need which refines and complement the initial one, e.g. a textual query, as a new *dimension* of the user need representation. This dimension can be then adopted for document re-ranking. Beside the representation for the dimension, also documents need to be described in terms of the features observed from the user behavior. Two sources of evidence have been considered in the research work reported in this paper: individual users and groups of users. Since two source for features are considered, and a representation both for the dimension and the documents is required, that leads to different possible source combinations. For instance, the dimension can be modeled by the features gathered from the individuals, thus obtaining a personal user behavior model, and documents can be represented in terms of group data; this combination makes possible a representation in terms of interaction features for documents unseen by the individual users from which the evidence cannot be observed. Since other combinations are possible, this paper investigates the following research question: *Which is the best combination of source of features for modeling and exploiting the user behavior dimension for document re-ranking in terms of retrieval effectiveness?*

2. METHODOLOGY

2.1 Methodology Description

The methodology adopted in this paper to exploit user interaction features for document re-ranking represents the user behavior dimension and the documents as vector subspaces according to the formalism proposed in [5]. The basic rationale is to map the collected data, prepared in a matrix, in a new vector space basis. The vector subspace spanned by this basis is the model of the dimension. The mapping is a matrix transformation technique which extracts information about our dimension from the collected data. For instance, if our hypothesis is that a dimension of the user information need can be represented by the correlation among interaction features, a technique like Principal Component Analysis (PCA) can be adopted. This is actually the approach proposed in [6] and adopted in this paper.

Also the documents to be re-ranked need to be described as subspaces; in this work they are represented as one dimensional subspaces, namely vectors, of the interaction feature values distilled from the users or the user groups behavior.

Once a representation in terms of subspaces has been built both for the dimension and the documents, the distance among the subspaces provides a measure of the degree to which the documents, represented with regard to the source, e.g. the user behavior, satisfy the dimension of the information need representation corresponding to that source.

Differently from [6] where user behavior models were used to support query expansion, we will focus on the impact of the diverse source combinations on document re-ranking.

2.2 Combinations of Sources for Features

The adopted methodology requires a representation both for the dimension of the information need and for the documents to re-rank with regard to the considered source. Since we are considering two distinct sources for features and two representations are required, this leads to four possible combinations of sources `X/Y`, where `X` denotes the source for the dimension and `Y` that for document representation – `X` or `Y` is either `P` (personal) or `G` (group). The `P/P` combination refers to the case where the features gathered from the individual user – i.e. its *personal data* – when searching for a specific topic are adopted both for modeling the dimension and for representing documents. The `P/G` combination refers to the case where personal data are adopted for modeling the dimension, while the data gathered from a group of users searching for the considered topic are adopted for documents representation. The remaining two combinations have analogous meaning.

The experiments reported in the next section aim at investigating the impact of the above source combinations on the retrieval effectiveness, specifically when they are adopted to support user behavior-based document re-ranking.

3. EXPERIMENTS

3.1 Evaluation Methodology

The basic rationale underlying the methodology to investigate the above research question was to observe the behavior of the user when visiting the first n results, and then use this evidence to model it, specifically as a vector subspace; this subspace representation was then used for re-ranking the top m documents provided by the baseline.

In particular, the evaluation methodology consisted of the following steps, that were performed for each topic-user pair:

1. Selection of the combination of the source for features, that is `P/P`, `P/G`, `G/P`, or `G/G`.
2. Collection of the features from the first $n = 3$ visited documents[1]. The collected features are prepared in a matrix $F \in \mathbb{R}^{n \times k}$, where k is the number of features collected from the n visited documents.
3. Modeling the dimension of the information need representation by extracting possible behavioral patterns by applying PCA on F. The result of the application of this technique is an orthonormal basis – one basis vector $\mathbf{b}$ for each pattern. Patterns, namely eigenvectors, associated to non-null eigenvalues are tested one at a time as possible models for the dimension – the model of the dimension is the subspace $L(\{\mathbf{b}\})$ spanned by $\{\mathbf{b}\}$, namely a one-dimensional subspace.
4. Representation of the documents in terms of features gathered from the source selected at step 1. Each document is represented as a vector $\mathbf{y}$ of k features.
5. Re-ranking of the top $m = 10$ results of the baseline list according to the measure $m_{\mathbf{b}}(\mathbf{y}) = \mathbf{y}^T \cdot \mathbf{P}_{L(\{\mathbf{b}\})} \cdot \mathbf{y}$, where $\mathbf{P}_{L(\{\mathbf{b}\})} = \mathbf{b} \cdot \mathbf{b}^T$ is the projector onto $L(\{\mathbf{b}\})$. $m_{\mathbf{b}}(\mathbf{y})$ provides a measure of the degree to which the document representation satisfies the dimension model.
6. Computation of the NDCG@10 for the new result list obtained after document re-ranking using the gains provided by the user for the considered topic[2].

When the *group* was adopted as source for features for modeling the dimension, namely in the `G/·` or `·/G` combinations, the value $f^G_{i,u',d,t}$ of a feature i for a specific user-topic-document (u', t, d) triple was computed as

$$f^G_{i,u',d,t} = \frac{1}{|G| - 1} \sum_{u \in G \text{ and } u \neq u'} f^I_{i,u,d,t}$$

where G denotes the group constituted by all the users which visited the document d with regard to the topic t and $f^I_{i,u,d,t}$ the feature value observed for a specific individual u with regard to (d, t). In other words the group value of a feature for a specific user u' was obtained as the average value of the feature values observed for the other users in G. The reason for this choice was to test if the evidence gathered from users in G other than u' can "substitute" the feature values for the document unseen by the user.

3.2 Dataset

Addressing the considered research question requires a dataset constituted by a set of topics, the properties of the results and the documents to re-rank for each topic, the features when interacting with them, and finally explicit judgments of the users for each topic-document pair.

[1]The order in which the users visited the documents in the study described in Section 3.2 was not necessarily the displayed order, so the visited order is adopted.

[2]DCG is computed according to the alternative formulation reported in [7], namely $\sum_i (2^{r(i)} - 1)/\log(i + 1)$, where $r(i)$ is the relevance of the document at position i. The normalization factor is the DCG of the perfect ranking.

Difficulty	# of Relevant Docs	Topics
High	1/2	506 - 517 - 518 - 543 - 546
Medium	3/4/5	501 - 502 - 504 - 536 - 550
Low	6/7/8/9/10	509 - 510 - 511 - 544 - 549

Table 1: Topic bins.

Feature	Description
Features observed from document/browser window	
query terms in title	number of topic terms displayed in the title of the corresponding result
ddepth	depth of the browser window when examining the document
dwidth	width of the browser window when examining the document
doc-length	length of the document (number of terms)
Features observed from the user behavior	
display-time	time the user spent on the page in its first visit
scroll-down	number of actions to scroll down the document performed both by page down and mouse scroll
scroll-up	number of actions to scroll up the document performed both by page up and mouse scroll
sdepth	maximum depth of the page achieved by scrolling down, starting from ddepth

Table 2: Features adopted to model the *user behavior* dimension and to represent documents.

A dataset with this information has been gathered through a user study which involved fifteen people which were asked to assess the top 10 retrieved results in response to assigned topics and to assess their relevance with a four-graded scale. We adopted the WT10g test collection and the ad-hoc topics of the TREC 2001 Web Track. The collection was indexed by the Lemur Toolkit[3]; english stop-words were removed and the Porter stemmer was adopted. Kullback-Leibler (KL) Divergence was adopted to rank documents because of its effectiveness in the TREC 2001 Web Track [8]. Then the top 10 documents were considered for each topic. A subset of the fifty topics were adopted in the study: topics were divided in three bins according to their difficulty – see Table 1 – where the measure of difficulty was the number of relevant documents in the top 10 – here relevance refers to the judgments provided by TREC assessors. We randomly selected five topics per bin, thus obtaining fifteen distinct topics; then three distinct groups of nine queries were built and distributed among the users; each user was asked to assess topics in one group.

The assessment was performed by a web application which displayed for each topic its description, the list of the titles of top 10 results for that topic, and when a result title was clicked by the user, the content of the document corresponding to that title. Both client-side and server-side functionalities were adopted to gather features, specifically those reported in Table 2 – these features are those adopted to prepare the matrix F in step 2 of Section 3.1.

To gather explicit judgments beside each title a drop down menu was available to select the relevance degree of the document corresponding to that title – these judgments are those used in step 6 of Section 3.1. Some users did not assess all the documents in the result list for some topics. For this reason, in regard to the objective of this paper, only the user behavior of thirteen among the fifteen users were considered in this work, for a total of 79 (user,topic) pairs and 790 entries where each entry refers to the visit of a specific user to a particular document with regard to a topic.

[3]`http://www.lemurproject.org/lemur/`

4. RESULTS

Table 3 reports the average and the median NDCG@10 computed over all the entries for the different combinations. There is no significant difference among the contributions of the diverse combinations. This is confirmed by the Wilcoxon signed rank test performed – with a 95% confidence interval – between the NDCG values obtained using the different source combinations. The Wilcoxon signed rank test was adopted since the Shapiro-Wilk test showed that normality cannot be assumed for the NDCG's values obtained by the different combinations.

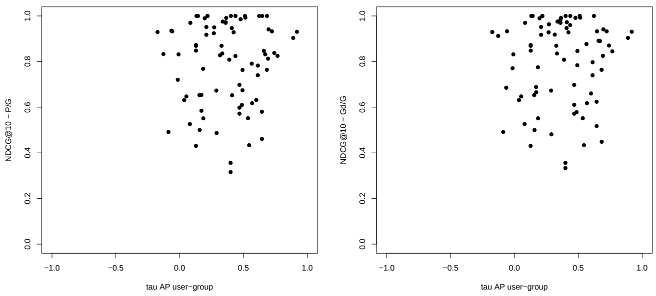
The `G/-` combinations (`G/P` and `G/G`) performed worse than the correspondent `P/-` combinations (`P/P` and `P/G`). A possible reason for the low performance of `G/-` was the adoption of the average values of the features over the group to model the dimension. In order to investigate this hypothesis we considered another combination labeled as `Gd/G`. In this combination, as for the other `-/G` cases, the evidence adopted to represent the documents with regard to a topic is obtained by computing the average values of the features over all the users other than the user under consideration that assessed that topic. The `Gd` label denotes that the model was obtained by applying PCA to a document-by-feature matrix where the documents of the diverse users were considered as distinct evidence. For instance, if the system was supporting user1 when searching for topic 502, the feature matrix adopted as evidence was $F \in \mathbb{R}^{(n \cdot 5) \times k}$, where k is the number of features, n is the number of visited documents, and 5 is the number of users other than user1 that searched for topic 502 in the collected dataset.

The average and the median NDCG@10 values for the `Gd/G` combination computed over all the users and all the topics was higher than that obtained for the other combinations. The Wilcoxon signed rank test showed that the improvement `Gd/G` respect to `P/G`, `G/P` and `G/G` was significant with a 95% confidence interval – ($V = 399$, p-value $= 0.002$) for `P/G`, ($V = 1746.5$, p-value $= 0.03$) for `G/P`, and ($V = 560$, p-value $= 0.00001$) for `G/G`. This result confirms the negative impact of using average feature values to prepare the matrix F. The best performance achieved by the `Gd/G` case may be also due to the larger amount of data adopted for modeling the dimension: the PCA-based approach seems to benefit from a larger number of observations. Moreover, the better results obtained for the `P/G` and the `Gd/G` cases suggest that group behavior features can substitute personal features for document representation, thus making personalized IRF feasible despite the data sparsity observed when the interaction features are collected on a per-user basis.

The results observed for `P/G` and `Gd/G` could be due to the level of agreement between what the user and the group perceived as relevant. In order to investigate this hypothesis, the NDCG@10's for these combinations were plotted against the τ_{AP} [9] computed between the ideal individual ranking and the ideal group ranking for each (user,topic) pair. The ideal ranking for a user was obtained by ranking documents by the gain he provided. For the group ideal ranking, the gain of each document was obtained as the sum of the gains provided for that document by the users in the group, as proposed in [10] to compute NDCG for a group of users.

NDCG@10	Baseline	Source combinations				
	`KL`	`P/P`	`P/G`	`G/P`	`G/G`	`Gd/G`
Average	0.765	0.765	0.791	0.759	0.777	0.797
Median	0.838	0.817	0.832	0.799	0.825	0.869

Table 3: Average and median NDCG@10 computed over all the (user,topic) pairs.



(a) `P/G` (b) `Gd/G`

Figure 1: NDCG@10 for the `P/G` (Fig. 1a) and the `Gd/G` (Fig. 1b) combination compared with τ_{AP} between user and group (not including the user) gains.

User	Baseline	Source combinations		Increment (%)	
	`KL`	`P/G`	`Gd/G`	$\Delta_{\texttt{PG}-\texttt{KL}}$	$\Delta_{\texttt{GdG}-\texttt{KL}}$
user1	0.760	0.766	0.810	0.784	6.520
user2	0.688	0.844	0.885	22.662	28.744
user3	0.726	0.729	0.747	0.445	2.949
user5	0.798	0.798	0.803	0.054	0.671
user7	0.775	0.823	0.699	6.283	-9.700
user8	0.737	0.758	0.766	2.853	3.942
user9	0.792	0.759	0.770	-4.134	-2.724
user10	0.850	0.886	0.847	4.314	-0.341
user11	0.799	0.776	0.776	-2.825	-2.825
user12	0.866	0.756	0.767	-12.681	-11.381
user13	0.676	0.839	0.849	24.103	25.552
user15	0.839	0.820	0.849	-2.302	1.102
user16	0.670	0.733	0.745	9.284	11.147

Table 4: NDCG@10 per user

The scatter-plots depicted in Figure 1a and Figure 1b, which refer respectively to the `P/G` and the `Gd/G` case, suggest that the agreement did not impact of the performance of the two combinations.

When compared with the baseline, the diverse combinations did not provide a significant improvement respect to the baseline `KL` – the best performing combination `Gd/G` provided an improvement of 4.18% and 3.70% (V = 1698, p-value = 0.07) respectively in terms of average and median NDCG@10. Table 4 reports the average NDCG@10 value for each user with regard to the baseline and the two best performing combinations. The improvement is not consistent among the users, and for some of them, e.g. user12, the user behavior-based re-ranking negatively affected the initial ranking. These results suggests that further research work is needed to understand why and when these features are an usable source for improving retrieval effectiveness.

5. CONCLUDING REMARKS

This paper has investigated the impact of the selection of the source for interaction features on document re-ranking, when those features are used to obtain a usable representation of the information need and of the documents.

The results of the experiments carried out in this work showed that the contribution of the diverse combinations is comparable, although the combinations where group data were adopted for document representation performed slightly better. In particular, significant difference with the other combinations was observed only for the combination where the model was learned from feature values of the individuals constituting the group considered as individual entries. These results suggest that group data can be a good source for document representation, thus making possible a representation also for documents unseen by the individual users.

Since groups were constituted by users assessing the same topic, we investigated if the comparable results obtained for individual and group-based representations were due to the agreement between individual's and group gains, but no relationship between NDCG's and agreement was found.

Future investigation will be focused on more realistic grouping criteria than considering users with the same information need – the entire topic description was shown to the users.

The strategy adopted in this paper to extract behavioral patterns requires the manual selection of the best performing pattern. Although this approach was appropriate for exploring source combinations, different techniques are needed and will be investigated to automatically support individual's.

6. REFERENCES

[1] D. Kelly and J. Teevan. Implicit feedback for inferring user preference: a bibliography. *SIGIR Forum*, 37(2):18–28, 2003.

[2] R. W. White and D. Kelly. A study on the effects of personalization and task information on implicit feedback performance. In *Proceedings of CIKM '06*, pages 297–306, New York, NY, USA, 2006. ACM.

[3] E. Agichtein, E. Brill, S. Dumais, and R. Ragno. Learning user interaction models for predicting web search result preferences. In *Proceedings of SIGIR '06*, pages 3–10, New York, NY, USA, 2006. ACM.

[4] J. Teevan, M. Ringel Morris, and S. Bush. Discovering and using groups to improve personalized search. In *Proceedings of WSDM '09*, Barcelona, Spain, 2009.

[5] M. Melucci. A basis for information retrieval in context. *ACM TOIS*, 26(3):1–41, 2008.

[6] M. Melucci and R. W. White. Utilizing a geometry of context for enhanced implicit feedback. In *Proceedings of CIKM 2007*, Lisbon, Portugal, 2007.

[7] W. B. Croft, D. Metzler, and T. Strohman. *Search Engines: Information Retrieval in Practice*. Addison Wesley, 2009.

[8] P. Ogilvie and J. Callan. Experiments using the Lemur toolkit. In *Proceedings of TREC-10*, Gaithersburg, MD, USA, 2001.

[9] E. Yilmaz, J. A. Aslam, and S. Robertson. A new rank correlation coefficient for information retrieval. In *Proceedings of SIGIR '08*, pages 587–594, New York, NY, USA, 2008. ACM.

[10] J. Teevan, S. T. Dumais, and E. Horvitz. Potential for personalization. *ACM TOCHI*, 17(1):1–31, 2010.

Extracting expertise to facilitate exploratory search and information discovery: Combining information retrieval techniques with a computational cognitive model

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ABSTRACT

We compared and combined the traditional information retrieval (IR) methods of expert identification with a computational cognitive model to test their effectiveness in facilitating exploratory search performance using a data set from a large-scale social tagging system. We found that the two methods of expert identification, although based on different assumptions, were in general consistent in extracting useful structures for exploratory search. The methods, however, did show systematic differences in their effectiveness to guide users to find popular vs less popular topics. The findings have important implications on presentations of information cues that facilitate interactive IR and discovery.

Categories and Subject Descriptors

H.5.3 Group and Organization Interfaces: Collaborative computing. H5.4. Information interfaces and presentation (e.g., HCI): Hypertext/Hypermedia.

General Terms

Performance, Design, Human Factors, Theory

Keywords

SNIF-ACT, Knowledge exploration, knowledge exchange, social tagging, Expert Identification

1. INTRODUCTION

The Web has become a participatory social-computational systems that allow people to explore, learn, and share information with others. A good example is social bookmarking systems such as del.icio.us, CiteULike.org, and Bibsonomy.org, which allow users to annotate, organize and share their web-based resources using short textual labels called tags. Many have argued that social tagging systems can provide navigational cues or "way-finders" to facilitate exploratory search and information discovery [8-9]. The notion is that, given that social tags are labels that users create to represent topics extracted from Web documents, interpretation of these tags should allow other users to better predict and evaluate relevance of documents in interactive search.

Many researchers have argued that the openness of social tagging systems may result in a large number of low-quality tags that are not meaningful to other users. Although many methods have been proposed to distinguish between indices and contents contributed by experts and novices, there is still a lack of systematic evaluation on how the extracted expertise could be utilized to facilitate knowledge exploration by others. The goal of this position paper is to demonstrate how a computational cognitive model of Web search could be utilized to complement existing data-mining techniques to predict the usefulness of different presentations of expert-generated indices and contents extracted by different methods in facilitating exploratory search.

Research has shown that the definition of expertise can be *referential* or *representational*. In the referential definition, experts are individuals who are recognized and referred to by others. The idea is that the more a person is being referred to, the more likely that others will follow and regard the person as an expert. Many information retrieval (IR) methods rely on this definition of expertise. Typically, the referential method identifies experts based on the hubness or authoritativeness of the source by analyzing the link structures in the system [10]. In contrast, in the area of HCI or cognitive sciences, definition of expertise is often representational [3]: experts tend to show better search performance or have better domain knowledge. Methods based on the representational definition of expertise use certain forms of semantic representations to extract structures and indices in Web resources and to identify users who share similar semantic representations [1, 7]. This method, compared to the referential method, has the advantage of being able to measure how well users can *interpret* and *represent* different topics by tags in a social tagging system, but may not capture as much the "social" aspect of the definition of expertise as in IR methods.

2. The simulations

2.1 The Database

We used the database dump provided by Bibsonomy on January 1st of 2009, which contains 3859 users, 201,189 tags, 543,43 resources, and are connected by 1,483,767 tag assignments. We selected the most recent 6 months of tag assignments in our simulations, which contained data from 537 users, 18,278 tags, 52,098 resources, and connected by 101, 428 tag assignments.

2.2 Expert identification by Link Structures

We chose to identify experts using the SPEAR algorithm [10], which used mutual reinforcement to generate the lists of experts and quality resources in the folksonomies. Following Noll et al. [10], the lists were represented as two vectors: E represented the vector of expertise scores of users, i.e., $E = (e_1; e_2; \ldots; e_M)$, and Q represented the vector of quality resources, i.e., $Q = (q_1; q_2; \ldots; q_N)$, where M and N were the total number of users and resources in the set respectively. Mutual reinforcement was implemented by preparing an adjacency matrix A of size M x N, where $A_{ij} = 1 + k$ if user i had assigned a tag to document j, and k users had assigned tags to document j after user i, and $A_{ij} = 0$ otherwise. Thus, if user i was the first to tag resource j, A_{ij} would be set to the total number of users who tag resource j; but if user i was the last one, then A_{ij} would be set to 1. This effect of this was to create a bias to those users who discovered quality resources. Following Noll et al., in order to balance the impact of the discovery and hubness effect, the value of A_{ij} was adjusted by the square root function, such that $A_{ij}' = \sqrt{A_{ij}}$. Based on this adjacency matrix, the calculations of expertise and quality scores followed an iterative process similar to that of the HITS algorithm. However, because the SPEAR algorithm also took into account the time of tagging as a factor that influenced expert identification, it was less susceptible to spammers (who typically give a lot of tags to a wide range of resources, but are less likely to be the first to identify quality resources). Specifically, in each iteration, E and Q were updated as:

$$E' = Q \times AT \text{ and } Q' = E \times A$$

The final lists of E and Q would represent the expertise and quality scores of the users and resources, which could be sorted to identify the top experts and resources in the system.

2.3 Identifying semantic structures

To study the differences in the semantics structures of the resources tagged by experts and non-experts, we extracted topics from the resources using the LDA model [1]. However, because topic extraction is computationally extensive, we selected the top 5,000 quality resources identified by the SPEAR algorithm, and then randomly sampled another 5,000 resources from the resources located in the bottom half of the quality vector Q. We called these the *high-quality* and *low-quality* sets of resources. In addition, we identified the first 50 experts from the SPEAR algorithm, and then randomly sampled another 50 users in the bottom half of the expert vector E. We extracted the resources tagged by these experts and non-experts to form the *expert* and *non-expert* sets of resources. We then processed the HTML files based on the URLs of the resources in the database. We filtered out any non-English pages and pages that contained fewer than 50 words, and eventually obtained 5000 usable resources from each of the four sets. We performed the topic extraction algorithm derived from the standard LDA model on each set of resources.

We were interested in how tags given by experts and non-experts and those on low and high quality resources could serve as good navigational cues for the users. To measure this, we assumed that users would adopt a tag-based topic inference process [5-6], which allowed them to predict whether the tagged resource would contain topics that they were interested in. This value could be calculated by the posterior probability $p(c_j|tags)$, where c_j is the topic of interest. For the current purpose, it was useful to compare the predictive distribution of tags in each set of resources to compare the usefulness of the tags. This empirical distribution $P(tag_i|c_j)$ could be derived from the LDA model, but due to space limitation the exact derivation is not given here. The predictive distribution of tags in each topic will show whether there are differences in the predictive power of tags in each set. The assumption is that the higher the predictive power, the more likely users would be able to use the assigned tags to infer what topics can be found in the resources, and thus the more useful will be the tags in guiding users to find relevant information in the system. In other words, the predictive probability of tags reflected the quality of tags for knowledge exploration

Another useful measure for understanding the semantic structures in the different sets of resources is to compare the predictive distributions of *topics* in the different set of resources. This probability $P(c_j)$ can also be estimated empirically based on the LDA model. The predictive distributions of topics reflected how likely certain topics could be found in a resource. Comparing the predictive distributions of topics between the set of resources would therefore show how the distributions of popular or "hot" topics would correlate with the experts and quality resources identified by the SPEAR algorithm.

2.4 Simulating search by computational cognitive models

To simulate exploratory search, we first randomly pick a topic (represented as a topic-word distribution) and a random tag, and calculate average performance of the model-searcher in different search environments through repeated simulations. The model-searchers were developed based on previous research, and due to space limitation we could not repeat the details here [4-5], but they were developed based on the cognitive mechanisms that were shown to match well with actual users as they performed Web search. The model-searcher would navigate in the folksonomies and collect resources that were relevant to the topic of interest. Topical relevance of a resource was calculated by Kullback–Leibler (KL) divergence between the desired and the best matching topic-word distribution in the resource. If the KL divergence reached the threshold, the resource was considered relevant. To measure exploratory search performance, we limited each model-searcher to perform 1000 steps of "clicking" to count the number of relevant resources it could find. In other words, we assumed that the average number of relevant resources found within 1000 transitions in the hypergraph reflected how well the environment could support exploratory search conducted by the model-searcher. We also randomly selected the topic of interest based on the predictive probabilities of topics, such that half of the simulations were looking for popular topics, the other half were looking for less popular topics. We could then compare how different model-searchers would perform differently when searching for popular or less popular topics.

We also created a number of search environments by ranking different navigational cues based on the predictive probabilities of the tags, experts, and resources. For example, in a "tag" environment, all tags were ranked according to $p(c_j)$ calculated by the LDA model, in a resource/experts environment, resources/experts were ranked by the quality/experts scores calculated by the SPEAR algorithm. Simulations results would therefore allow comparisons of how these cues generated by the IR techniques and the LDA model were *utilized by real users* to demonstrate their usefulness in facilitating exploratory search.

3. Results

3.1 Topics distributions

Figure 1 shows the mean predictive probabilities of topics (top) and tags (bottom) against the ranked list of resources in the expert and non-expert sets of resources (left) and against the ranked list of experts in the high- and low-quality sets of resources (right). These probability distributions show that the semantic structures in each set of the resources identified by the referential method had very different properties. In terms of the predictive probabilities of topics, low-ranking resources found by experts tended to contain more "popular" topics than non-experts, but this difference seemed to diminish quickly as the resource quality rank increased (top-left of Figure 1). On the other hand, comparing the sets of high and low quality resources identified by the referential method, there seemed to be consistently more popular topics in the high quality resources than low equality resources, and this difference seemed to be relatively insensitive to the rank of experts within the sets (top-right of Figure 1).

The predictive probabilities of tags also showed interesting difference between the sets of resources. In general, resources tagged by experts contained more predictive tags compared to those by non-experts, and this difference was relatively stable across the set of resources (bottom-left of Figure 1). Similarly, the predictive probabilities of tags between the high and low quality sets of resources also showed differences, but this difference diminished quickly as the expert rank increased.

To summarize, results implied that while following the list of high quality resources would allow users to discover mostly "hot" topics, following the list of experts would allow users to sometimes discover "cold" topics (but could be useful for a subgroup of users) in the folksonomies

3.2 Tag Distributions

Figure 1 (bottom) also shows that while tags created by experts were in general predictive, not all tags in the high quality resources were predictive. To confirm these differences, we compared the empirical probability distribution functions (PDF) of the predictive probabilities of topics and tags in each sets of resources (see Figure 2). One could see that the topic distributions between experts and non-experts were indeed less distinguishable than those between low and high quality resources (top-left of Figure 2), but the reverse was true for the tag distributions (bottom-left of Figure 2). This suggested that quality of resources were in general better at predicting "hot" topics; but high quality resources did not necessarily contain fewer "hot" topics. Rather, expert-generated tags tended to be more predictive of "cold" topics than resource quality.

It was quite possible that, because the SPEAR algorithm (and the referential method in general) primarily determined the quality of a resource based on the number of times the resource was identified by experts, resources that contained popular topics were more likely reckoned high quality. As popularity of topics in a folksonomy tended to correlate with frequencies of occurrence of corresponding real-world events, ranking of resources based on the referential method would therefore likely benefit users who were interested in following "hot" topics. On the other hand, although experts identified by the referential method were users who frequently tag the high quality resources, they were also users who tend to tag many resources, and many of these resources were not tagged by other experts. We therefore see that rankings by resources tended to be generally better at distinguishing "hot" from "cold" topics than by the distinction between experts and non-experts.

3.3 Exploratory search performance

Figure 3 shows the number of relevant resources found by three model-searchers in the exploratory search simulations. The position-searcher always followed the ranking of cues during evaluation, the topic-satisficer combined ranking and topical relevance of the cues during evaluation (see [4] for details), and the perfect-searcher always picked the cue that had the highest topical relevance (with respect to the topic that it was searching). Comparisons of the three model-searcher would therefore reveal the effects of position and topical relevance of cues on search performance.

As shown in Figure 3, the general uptrend from all four figures suggested that the addition of more rankings of tags, experts, and resources had led to better exploratory performance. Interestingly, for popular topics, rankings of users and resources seemed to lead to slightly better results than the ranking of tags. Consistent with previous results, this could be attributed to the fact that the rankings of users and resources were based on the referential method that were in general better at predicting hot topics. In contrast, ranking of tags was based on their predictability of topics, which depended, to a large extent, on the likelihood that the tags were uniquely associated with the different topics. Given that hot (popular) topics tended to be associated with semantically general tags that appeared in multiple topics [2], the general predictability of tags for popular topics were therefore lower than the rankings derived from link structures.

Compared to the position-searcher, the topic-satisficer in general found more relevant resources, suggesting that the process of sequential topic evaluation improved exploratory search performance. Similar to the position-searcher, however, tag ranking was slightly less useful for exploring for hot topics compared to expert and resource rankings. On the other hand, the combination of tag and expert or tag and resource rankings did significantly improve performance. Performance of the topic-satisficer in the all-ranking environment was almost the same as

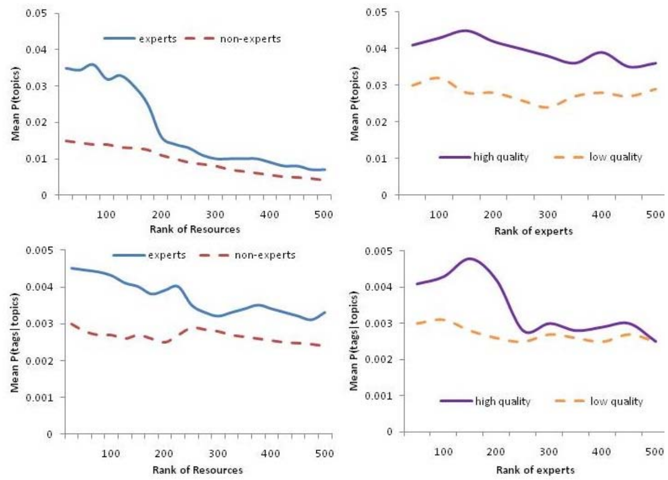

Figure 1. Predictive distributions of topics (top) and tags (bottom) plotted against ranks of resources and experts (lower rank is better) in the sets of resources tagged by experts and non-experts (left) as identified by the algorithm, and the sets of resources identified as high and low quality by the algorithm (right).

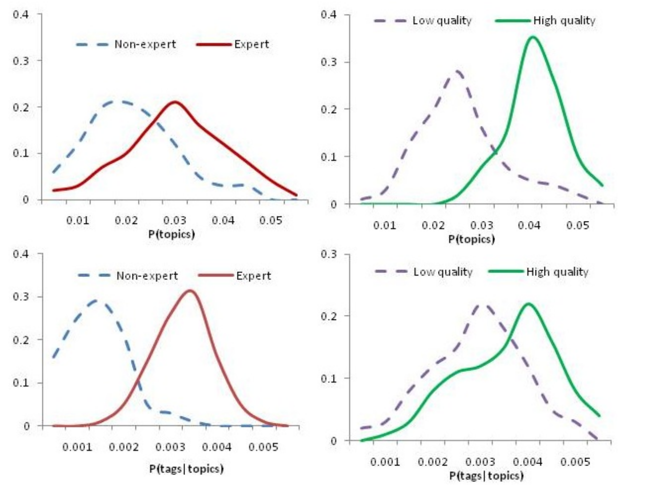

Figure 2. The empirical PDF for the predictive probabilities of topics and tags in each of the four sets of resources.

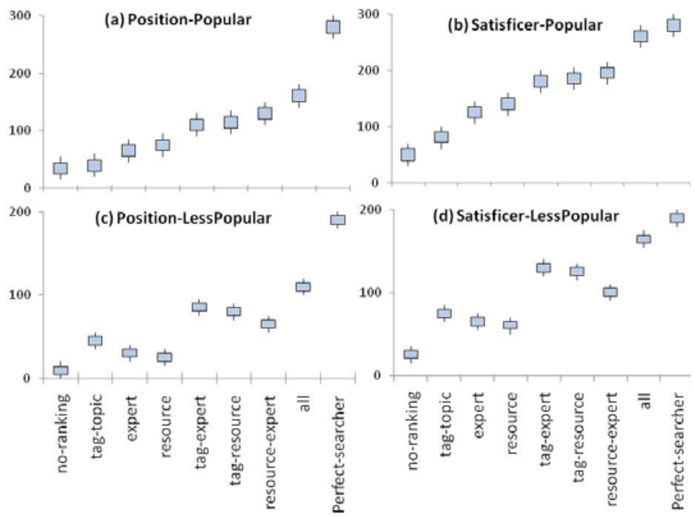

Figure 3. Exploratory search performance of the position-searcher (left) and the topic-satisficer (right) when the topics of interest were popular (top) and not popular. (bottom).

the perfect-searcher, which always picked the most predictive nodes in every transition.

When the model-searchers explored for less popular topics, the results were similar but did show differences (bottom of Figure 3) when compared to exploration for hot topics. In particular, while the addition of rankings improved performance, but for both model-searchers, *tag ranking* in general led to better exploratory performance than expert and resource rankings. This could be attributed to the fact that for cold topics, the predictive power of tags was higher than that by expert and resource rankings (see top two graphs of Figure 1). Following the tags therefore led to a higher chance of discovering cold topics than by following expert and resource rankings.

In summary, the patterns of simulation results showed not only that expertise rankings could improve exploratory performance, but it also showed that different expert identification methods could have systematic differences in their influence on exploratory performance. In particular, we found that while expert and resource rankings based on the referential method could facilitate exploration of hot topics, ranking of tags based on the probabilistic topic extraction method could facilitate discovery of cold topics. In our simulations, a combination of the two methods seemed to lead to the best overall result in providing effective navigational cues that facilitate knowledge exploration. Future research should focus on how to adapt the presentation of these cues based on interaction patterns of the user to allow the user to select different cues for exploration of cold or hot (or both) topics.

4. Conclusion and General Discussion

The current results provide support to the promising aspect of using expertise in social tags to facilitate exploratory search. Specifically, our results showed that (1) the method based on the referential definition of expertise was more useful for generating rankings that facilitate search for popular topics, while the method based on the representational definition of expertise was more useful for generating rankings that facilitate search for less popular topics, (2) rankings of tags based on their predictive probabilities of topics could facilitate search of less popular topics, and (3) combinations of referential and representational methods of expert identification could facilitate knowledge exploration of both popular and less popular topics.

We have shown how IR methods can be combined with semantic and mechanistic models of exploratory search to understand how different interface representations could impact overall utilities of the system. Our results highlight the importance of including realistic assumption of the users to evaluate the functional utilities of structures extracted from different data-mining methods. In general, we believe that it is useful to investigate the dynamics between how individual users will actually *utilize* information cues or structures extracted from a social information system, and how they would in turn influence the computational properties of the system itself.

5. REFERENCES

[1] Blei, D. *et al.*, “Latent Dirichlet Allocation,” *Journal of Machine Learning Research*, vol. 3, pp. 993-1022, 2003.

[2] Ericsson, K. A., and J. Smith, eds., “Toward a general theory of expertise: Prospects and limits,” Cambridge, MA: Cambridge University Press, 1991

[3] Fu, W.-T. *et al.*, "A Semantic Imitation Model of Social Tag Choices. ," *Proceedings of the IEEE conference on Social Computing*, pp. 66-72, Vancouver, BC, 2009.

[4] Fu, W.-T., and P. Pirolli, “SNIF-ACT: A cognitive model of user navigation on the World Wide Web,” *Human-Computer Interaction, vol. 22*, pp. 355-412, 2007.

[5] Fu, W.-T. *et al.*, “Semantic Imitation in Social Tagging,” *ACM Transactions on Computer-Human Interaction*, in press.

[6] Kang, R. et al., "Exploiting Knowledge-in-the-head and Knowledge-in-the-social-web: Effects of Domain Expertise on Exploratory Search in Individual and Social Search Environments," Proceedings of the ACM Conference on Computer-Human Interaction, Atlanta, GA, 2010.

[7] Landauer, T. K., and S. T. Dumais, “A solution to Plato's problem: The Latent Semantic Analysis theory of the acquisition, induction, and representation of knowledge,” Psychological Review, vol. 104, pp. 211-240, 1997.

[8] Marchionini, G., “Exploratory search: from finding to understanding,” Commun. ACM, vol. 49, no. 4, pp. 41-46, 2006.

[9] Millen, D. R. et al., "Social bookmarking and exploratory search."

[10] Noll, M. G. et al., "Telling experts from spammers: Expertise ranking in folksonomies," Proceedings of the ACM conference on Information Retrieval (SIGIR), pp. 612-619, MA: Boston, 2009.

[11] Russell, D. M. et al., “The cost structure of sensemaking,” in Proceedings of the INTERACT '93 and CHI '93 conference on Human factors in computing systems, Amsterdam, The Netherlands, 1993

An Architecture for Real-time Textual Query Term Extraction from Images

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ABSTRACT

This paper presents an approach that generates a set of search queries from a user's query image. The approach provides the ability to query one's environment in real-time, effectively allowing a user to ask *"What is that?"*. This is achieved by capturing the user's context through a geo-tagged photograph, and using it to filter a community image collection, for example Flickr, to retrieve a set of descriptive tags; these tags are processed and used as query terms. Having discussed the role of context in the application and the service's architecture, an initial study of the benefits of this approach will be presented.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval—*information filtering, query formulation*; H.3.5 [**Information Storage and Retrieval**]: On-line Information Services—*web-based services*

General Terms

Human Factors

Keywords

Query-by-image, mobile search, context-in-search, location based search

1. INTRODUCTION

When we are in an unfamiliar place, we often query our environment - through a friend or guide - by pointing and asking *"What is that?"*. When we are alone, we look up a guidebook for the area. These are usually organized by location; on examining the section for the searcher's current location, a set of photographs and maps is examined until the subject in question is found; this process uses the visitor's current context as a means of querying an information source. By combining inputs from smart-phones and shared community images (and their associated tags), the results of the latter technique can be achieved with the ease of use of the former. The phone (in particular its camera), equipped with a wide range of sensors, provides a context for the user; this can be used to filter an image collection and retrieve a set of tags that describe the subject of interest. These are then used to query some information source.

This type of application is called augmented reality (AR); these are programs that embellish a view of the physical world with digital information. Many of these are based on a browsing metaphor; information is serendipitously discovered by the user. Layar[1], for example, provides a framework to place icons representing geo-tagged digital artifacts; each icon represents a piece of information related to the searcher's environment, for example, youtube videos, or tweets. Recently, research has begun to explore how search might work with AR; applications such as Google Goggles[2] and the work of Gammeter et al[1] have enabled users to query their environment - in both of those cases through images. While the goals of these contributions are similar in intent to that described herein, they have focussed on creating extensive searchable indices. This paper focusses on how context can be used to rationalize the search space *on the fly*. A relatively small subset of candidate images and their associated tags are retrieved and processed in real-time from the image-base, substantially reducing the need to implement expensive hardware and software infrastructures.

Having examined the role of context, the remainder of this paper will describe the service's architecture before presenting the results of an evaluation of its performance and accuracy.

2. THE ROLE OF CONTEXT

The accuracy of the system described herein is achieved by using both the user's context and that of those contributing knowledge to the community image-base. The seeker's context encapsulates the circumstance of an information seeking task, capturing the relationship and impact of the task being undertaken, the system being used and the user's existing knowledge that can influence his use of the search system[2]; it is this final component of context that is weakest when trying to formulate a query about an unfamiliar scene. Research mentioned in Section 4 suggests that a stranger to an area will typically describe a building, or some other point of interest, in terms of its physical characteristics and any location information.

[1] http://www.layar.com/
[2] http://www.google.com/mobile/goggles/

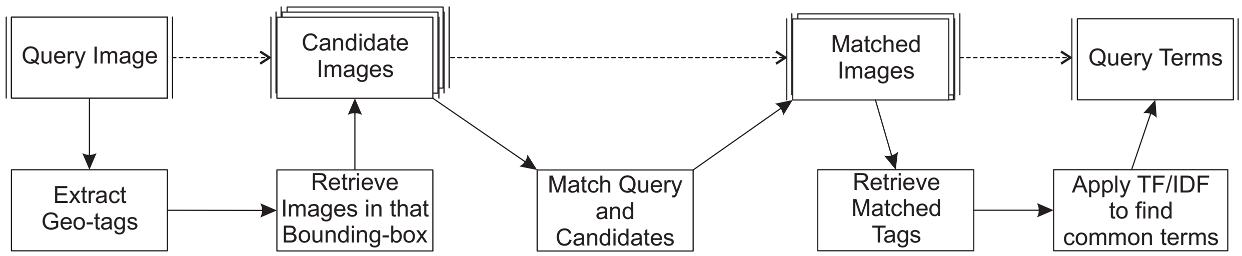

Figure 1: Service Architecture.

Smart-phones capture numerous facets of their users' context. When taking a photograph, the iPhone embeds the location and time, along with a host of camera specific attributes. This contextual information can be used to query that of others.

In creating a set of query terms, the application seeks to capture *the power of the crowds* through tags that contributors associate with their photographs in community image databases, for example, Flickr[3] or Panoramio[4]. While individuals' reasons for posting a photograph of a place vary - that variance is reflected in the tags they select to describe a subject - a subset of the tags are common across most users; this subset captures a social description of that location; in addition to naming a location, these can include historic and functional information. Determining which tags are significant requires applying a set of filters to the tagset. These include determining which tags are user specific and ensuring that the tags apply to the subject of the query photograph. The contributors' context is also important; research undertaken during the development of the service has shown that local photographers' tags are more accurate and revealing. The paper will now describe how these findings were used when implementing the system.

3. IMPLEMENTATION

Producing a list of terms that describe an object in a query photograph was accomplished by taking fast image matching algorithms and combining them with the power of social networks and smart-phones. The results of the service provide an information seeker with an entry point to conduct information seeking about a photographed object. Some restrictions apply - the object has to have a fixed position, for example, a building or statue and the object must be of interest enough to have been photographed and tagged a-priori. In addition, the camera that takes the query image must be capable of geo-tagging the image; many smartphones are capable of this. These devices are also capable of uploading the image to the service, and provide a means of viewing results. This set of abilities allows a seeker to use their smart-phone to resolve serendipitous curiosities and explore their environment in-situ.

The process that translates a photograph to a set of terms is shown in Figure 1. In summary, the service takes an uploaded query image, extracts its geographical metadata and uses this to retrieve a set of images from an image-base. Because photographs of several objects of interest may be returned by the image-base, quick image matching is conducted to find a set of matching images. Tags associated with these images are then retrieved and ranked. These textual tags can then be used to query an information source. The authors will now examine each of these steps in greater detail.

Several metadata standards exist; the iPhone (the target device for the prototype client for this service) uses Exchangeable Image File Format (EXIF). Many attributes are recorded in this metadata when a photograph is taken on the iPhone, including the longitude and latitude of the device taking the photograph, the date when the photograph was taken and other camera attributes such as aperture and focal length. This admits many dimensions across which exploration can occur. Many smart-phones use a combination of signal triangulation and GPS (Global Positioning Service) to determine what position is recorded. While it is generally accurate, there are circumstances under which it is not. In addition, it is the location of the device is recorded when a photograph is taken; if the photographed object is large, this position might be some distance from the object. To account for these potential errors, images are retrieved from an area 100 meters square centered on the recorded location. This bounding box is submitted to several image-bases including Flickr and Panoramio and a set of candidate images are retrieved.

This set of candidate images may contain photographs whose subject is something other than that of the query photograph's. To ensure that only the query image's subject is considered, the candidates are filtered using an implementation of the Scale Invariant Feature Transform (SIFT) image matching algorithm[3]. The algorithm uses distinctive invariant features in an image to match against different views of a scene. It is an efficient approach, robust to distortion, scale and noise. Once this step has executed, the set of candidate images is reduced to a set of matching images.

Once a set of matching images has been found, tags associated with these images are retrieved from the image-base. While tags include descriptions of the location, they often reflect the personal context of the user including their names, details of the camera used and the occasion on which the photograph was taken; the tags describing the photograph should reflect generic information and filter out those that reflect personal context. After analysis of the tagging habits of users, it was determined that tags that describe personal contexts are common across numerous photographs, though they are unique to the photographer. As a result, tags were grouped into meta-documents on a per-user basis, and the TF/IDF statistical information retrieval technique[4] was

[3]http://www.flickr.com
[4]http://www.panoramio.com/

Figure 2: The Quad, University College Cork. The service returned 'University College Cork', 'Cork', 'Ireland', 'UCC', 'Cork City' as descriptive tags.

Figure 3: St. Donat's Church, Zadar, Croatia. The service returned 'Zadar', 'Croatia', 'Zadarska', 'Donat', 'Church' as descriptive tags.

applied to these. This resulted in terms that were common across the collection of documents (and thus users) emerging; these are ranked by popularity. While some relevant terms' significance was easily determined, there were others that were ranked lower, but were considered very descriptive. A second pass of relevance measurement is completed to capture these terms. For each of these terms, a Yahoo! Boss[5] query is formed by *AND*-ing each term with the significant terms, and measuring the number of documents that are returned. While tags that describe personal context are rarely associated with the significant descriptive tags, minor descriptive terms appear in many documents with the significant terms. A list of the top ten descriptive terms is returned by the service. This list can be used to form queries to an information source; this can be a general source, Google or Wikipedia, or a custom information source.

The implementation of the service instance used during the evaluation was architected thus; a service mediator marshaled each request; it was responsible for accepting requests, making the initial request to the image-base (Flickr), sending requests for work to distributed agents and processing their responses into a query. The distributed agents, reserved lab machines, were responsible for processing each candidate image and its tags. Both the mediator and ten agents were Apple iMac *2.66 GHz* Intel Core Duo machines running *2GB* of RAM. The distributed network was enabled using XServe.

4. RESULTS

During development of the service, a simple iPhone client was developed and deployed to several devices. This application allowed a user to take a query image, upload it to the service server and displayed the set of query tags that were returned for the query. Two examples are shown, one instance from Ireland (Figure 2), and one instance that was submitted when visiting Croatia (Figure 3). When the returned terms are AND-ed and submitted to Google, the first page of results contains Wikipedia articles about each location. The service was formally evaluated based on its ability to efficiently produce an accurate query. The quality of the service's queries were also evaluated by comparing their precision to those created by human 'visitors' to a location.

Performance

Queries executed with an average time of 9.1 seconds. This time is reduced as more distributed agents are attached to the service. The greatest limiter to performance was the XML handling that resulted from interactions with the image-bases. This code is currently not fully optimized so performance gains are expected.

Quality

During the development of this service, the authors sought to understand how users would formulate a query when tasked with identifying a building. Using the crowd-sourcing tool, Amazon mTurk[6], a series of ten images of local landmarks were presented along with their general location (Cork City, Ireland). Two hundred participants we asked to provide the initial query they would use to identify the building.

When these queries were submitted to Google's search engine, 40% of queries returned a site on the first page of re-

[5]http://developer.yahoo.com/search/boss/

[6]https://www.mturk.com/mturk/welcome

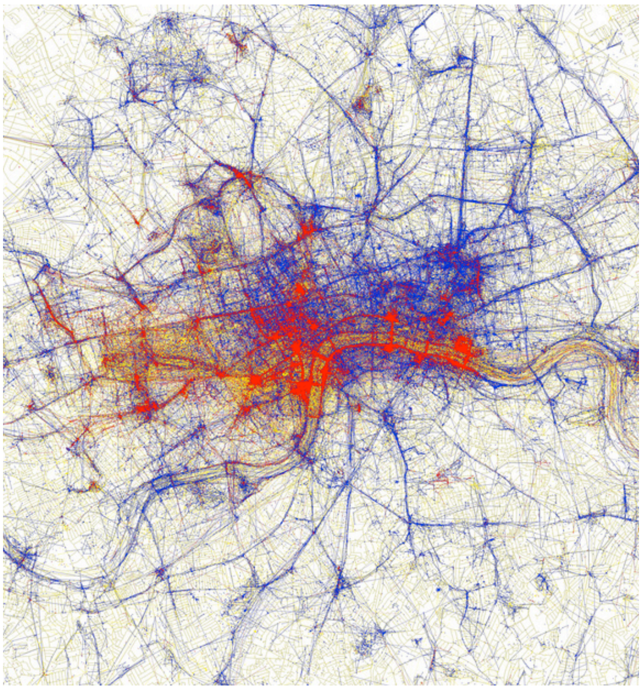

Figure 4: A portion of one of Eric Fischer's Geotaggers World Atlas Maps - showing London. Locals' images are in blue, visitors in red

sults that contained the answer. When queries formed from the generated terms were submitted, 100% of first pages returned an a result that contained the answer.

Unsuccessful queries tended to use the location information provided and combined it with descriptions of the physical features of the building (e.g. Cork, waterfront, stone, building and glass, modern, Cork). Successful queries tended to use terms that categorized the building (e.g. historical places in Cork City of Ireland and high rise buildings in Cork City of Ireland). This reflects the tendency of those writing articles to describe the physical appearance of a building by including imagery. This suggested that users might have better results for their queries when presented with images from the articles. The queries were resubmitted to test if these physical descriptions fared better when conducting an image search on Google. However, there was only a marginal improvement to 52% of queries, resulting in a matching image on the first page of results. This suggests that when faced with an image matching task, the descriptive tags associated with images of a scene by previous explorers far out perform textual descriptions provided by visitors who are beginning to learn about a location.

5. CONCLUSIONS AND FUTURE WORK

This paper has introduced a service that provides accurate query terms for photographed subjects that have a fixed location. An initial evaluation showed that these generated query terms provided results of greater precision than those created by simulated visitors to a location. The work, while promising, is embryonic; more complete evaluations must be conducted. This is hampered by the provision of independent test collections suited to the tasks being examined.

Development testing exposed some interesting social habits. It demonstrated a tendency towards a *social curiosity*. While testers did try to foil the service by submitting images of buildings that caused no social interest, they admitted that when a location caused a genuine curiosity, the service would respond with an accurate set of query terms. This is borne out by the work of Eric Fischer[7]. The images he created, one of which is shown in Figure 4 (reproduced under the terms of the creative common's license[8]), shows the locations of geo-tagged photographs taken in the Greater London area; images taken by local people are shown in blue, those by visitors are shown in red and those of an indeterminate providence are shown in yellow. Red clusters visibly demonstrate that there is a natural tendency for visitors' photographs to cluster around popular tourist locations. This is also apparent for locals, though their range of locations is much wider. The authors' own research has shown that tags generated by local photographers tend to demonstrate greater precision. The role that context - both the user's and contributor's - has in improving the precision and accuracy must also be investigated; initial evaluations suggest that tags generated by local contributors are superior to those of visitors. This observation might be used to weight the terms when determining those of greater descriptive significance.

Finally, the application currently does not examine the context of the location. It too has a story to tell, for instance a location's history and its association with historical events; already others have begun to provide a historic context for photographs[9]. Community image-bases also provide sufficient metadata to implement this type of exploration.

6. REFERENCES

[1] S. Gammeter, L. Bossard, T. Quack, and L. V. Gool. I know what you did last summer: object-level auto-annotation of holiday snaps. In *ICCV 2009*, September 2009.

[2] P. Ingwersen and K. Jarvelin. *The Turn: Integration of Information Seeking and Retrieval in Context.* Springer-Verlag New York, Secaucus, NJ, 2005.

[3] D. G. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110, 2004.

[4] G. Salton and C. Buckley. Term-weighting approaches in automatic text retrieval. *Information Processing & Management*, 24(5):513–523, 1998.

[7]http://www.flickr.com/photos/walkingsf/4671589629/in/set-72157624209158632/

[8]http://creativecommons.org/licenses/by-sa/2.0/

[9]http://www.historypin.com

Transaction Log Analysis of User Actions in a Faceted Library Catalog Interface

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ABSTRACT
In this paper, we report preliminary findings from an analysis of searcher actions in a faceted library catalog. In this comparative laboratory study (N=18) searchers were asked to conduct exploratory searches. For the control group facet use accounted for approximately 14% of logged actions. For participants who were shown a 60 second video about how to use facets, facet use accounted for approximately 21% of actions. We also observed differences in sequences of actions that participants undertook during their searches that suggest that searchers who watched the facet training video used facets at key points in their search process such as just after issuing a search and just before adding an item to their "book bag".

INTRODUCTION
Faceted search interfaces (Tunkelang, 2009; Yee et al., 2003) are commonly used to support users' needs to conduct iterative, exploratory searches (White et al. 2006). Search interfaces with hierarchical facets are often found on shopping and entertainment websites where users are likely to be familiar with the metadata used for the facet values, such as clothing styles or movie genres. Recently, libraries have started incorporating faceted search features into their on-line public access catalogs (OPACs) using facets such as Library of Congress subject headings and other metadata.

Previous research on facet use in OPACs indicates their usefulness. Lown and Hemminger (2009) examined log data from a four month period of real-world use of North Carolina State University's OPAC and found that facets were used to refine the results of searches in 34% of the sessions. They also found that facet refinement of a search made up 18% of the overall log requests. In our work using eye-tracking to investigate faceted OPAC use, we have found that users do spend considerable time looking at the facets (Kules et al., 2009; Kules and Capra, 2010) suggesting that they play an important role in the search process.

The research presented here focuses on how users interact with faceted OPAC interfaces to conduct exploratory searches. Specifically, we are interested in improving our understanding of how faceted interfaces affect searcher actions and tactics.

The research questions investigated in this study address aspects of these objectives:

1. How often do searchers use facets for exploratory search in a library catalog?
2. Do searcher actions differ when training is provided?
3. What sequences of actions are used, and do they differ when training is provided?

METHOD
To examine the research questions, we conducted a laboratory study in which participants were given representative search tasks and asked to conduct searches using a custom-built, Web-based, faceted OPAC interface.

Participants
The study was conducted at Catholic University using an IRB approved protocol. Eighteen (18) undergraduate students were recruited as participants (8 male, 10 female). Participants represented 11 different major areas of study. Eleven participants were 20 or under; seven were 21-30. Most participants (15) conducted a web search at least every day and fourteen (14) conducted a library catalog search at least once per month. Participants were provided a small honorarium for participation.

Study Design
The data presented here was collected as part of a broader study designed to investigate aspects of how facets are used in exploratory search and the effects of different training conditions on the use of the interface. Two methods of data collection were used while participants completed the search tasks: 1) user actions with the interface were logged, and 2) users' eye movements were tracked using a Tobii eye-tracking system. In this paper, we describe the overall study design, but only present preliminary results from analysis of the log of user actions.

Participants were assigned to one of three training conditions: a control group with no training, a group that was shown a short training video about facet use, and a group who did not see the video, but was given an interface that included help links labeled "What's This". There were six participants in each group. All participants conducted the same six searches based on representative task scenarios. Search task orders were counterbalanced within each training condition. Searches were conducted in a quiet

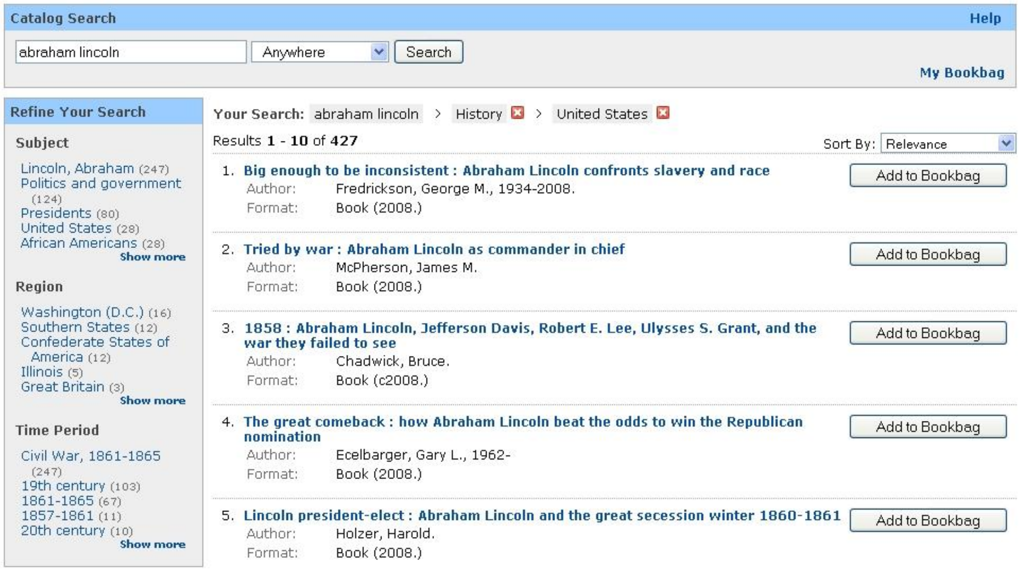

Figure 1. Faceted OPAC Interface

room using a Web browser (Internet Explorer 7) running on a Windows XP computer attached to the eye-tracker. After each search, participants completed a brief questionnaire.

The six search tasks were designed to be relevant to an undergraduate student doing research for an academic paper. For example, one task was:

"Imagine you are taking a class called 'Feminism in the United States'. For this class you need to write a research paper on some aspect of the U.S. feminist movement, but have yet to decide on a topic. Use the catalog to find two possible topics for your paper. Then use the catalog to find three books for each topic so that you might make a decision as to which topic to write about."

Procedure

Participants were greeted, given a brief introduction to the study and asked to sign an informed consent form. Next, all participants were shown a 60 second video that described how to complete the tasks by placing selected items in the "book bag" Participants in the facet training video group were shown an additional 60 seconds of video that explained how to use the facets. After watching the videos, the eye-tracker was calibrated and participants began the six search tasks. After each task, participants answered a questionnaire about their experience. After completing all six tasks, a retrospective interview was conducted. Overall, the sessions lasted about one and a half hours from start to finish.

Analysis

As users interacted with the faceted library interface using the Web browser, a back-end PHP script logged a variety of user actions. The summary counts and statistics presented in this paper were generated by parsing these log files and tallying recorded actions. Actions logged are described in Table 1.

Table 1. Description of Actions Logged

SEARCH	user submitted a query via the search box at the top of the page
BOOKBAGADD BOOKBAGREMOVE	user added/removed an item in their bookbag via its corresponding button
ITEMCLICK	user clicked an item's title on the search results page, which will render the item's detail page
FACETADD	user clicked a facet, which will apply the facet to the current results set
FACETREMOVE	user clicked the "x" link to remove a facet from the results set
FACETEXPAND	user clicked the "Show more", which will display more facet values
FACETCOLLAPSE	user clicked the "Show less" link to return a facet to show five values
PAGE	user clicked a paging link to move to a different page of search results
SORT	user chose a sort option from the "Sort By:" dropdown
BOOKBAGVIEW	user clicked "My Bookbag" link at the top part of the page
RETURNTORESULTS	user clicked "Back to Search Results" link
HELPVIEW	user clicked the "Help" link

RESULTS

In this section, we present preliminary results of descriptive statistics about overall frequencies of logged actions and about pairwise sequences of actions (i.e. transitions from one action to another).

Overall Actions

The 18 participants each completed six tasks for a total of 108 task instances. Table 1 summarizes descriptive statistics about the top actions recorded in the logs for the 108 task instances.

Table 2. Summary of Logged Actions for all Task Instances

Action	Count	% total	Avg per task instance
BOOKBAGADD	965	29%	8.9
FACETADD	536	16%	5.0
PAGE	487	15%	4.5
SEARCH	459	14%	4.3
FACETREMOVE	192	6%	1.8
Other actions	683	21%	6.3
Total of all actions	3322	100%	30.8

Adding an item to the book bag made up 29% of the overall actions and on average, participants added 8.9 items to their book bag per task. Participants also added on average 5.0 facets per task and used moved to a new page of results about 4.5 times per task. Searches made up about 14% of the overall actions and there were on average 4.3 searches per task. These results indicate that participants were engaged with the tasks and did make use of the features provided in the interface.

Figure 2 shows a comparison of the five actions for each interface condition. Each bar in the chart represents data from the six participants in that condition completing the six tasks (a total of 36 task instances per bar). As can be seen in the chart, the training video condition had higher use of facets (e.g. FACETADD and FACETREMOVE) than the other two conditions. The results also suggest that the training video condition had slightly less use of search and paging actions.

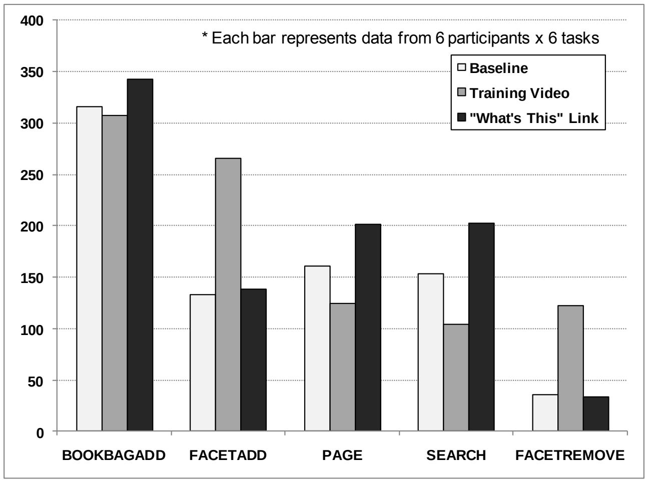

Figure 2. Summary Counts of Top Five Actions Overall

Adding facets to refine a search made up 14% of the total logged actions for the baseline condition, 21% for the training video condition, and 13% for the "What's This" help link condition. Issuing a search accounted for 16%, 8%, and 19% of the actions in each condition, respectively.

Pairwise Sequences of Actions

Figure 3 shows a summary of the top 10 pairwise sequences of actions (transitions) overall. As with the individual actions, for each interface condition, we tallied the logged actions for the six participants in that condition and present the top 10 pairs of actions overall as bars in Figure 3. These represent approximately 55% of all pairs. The chart shows that the BOOKBAGADD-BOOKBAGADD pair is most common, with an average of 126 occurrences, or 3.5 per search session. The four next most common pairs, BOOKBAGADD-PAGE, PAGE-PAGE, PAGE-BOOKBAGADD, and FACETADD-BOOKBAGADD occur 61-64 times each, or on average 1.7-1.8 per session. The remaining five pairs, FACETADD-FACETADD, SEARCH-SEARCH, SEARCH-BOOKBAGADD, SEARCH-FACETADD, and SESSIONSTART-SEARCH, occur 36-48 times, or on average 1.0-1.3 times per search session. Note that the SESSIONSTART-SEARCH pair represents the first query submitted at the beginning of each search session.

The prevalence of the BOOKBAGADD-BOOKBAGADD pairs suggests that searchers marked potential items in a "bursty" manner. That is, they would add multiple items to the bookbag one after another with no intervening logged action. We note that the three pairs of actions involving facets were more common in the training condition and that the five pairs that do not involve facets were more prevalent in the non-training conditions. This suggests that searchers in the training condition were more likely use the facets in the course of their exploration. For example, in the training condition, searchers were less likely to issue a query followed immediately by adding a book (SEARCH-BOOKBAGADD) and more likely to follow a query with a facet (SEARCH-FACETADD) and a facet with a book add (FACETADD-BOOKBAGADD).

Limitations

The results we present here are preliminary in nature. We mainly present summary count statistics of logged actions. These counts and comparisons provide insights into the data, but more rigorous comparative analysis will be needed to assess and establish statistically significance differences.

One limitation of this analysis is that the data does not capture use of the Back button, because this was logged at the server. The tasks we gave participants were grounded in actual search data and framed in a familiar context of writing an undergraduate research paper. However, these type of task represent a fairly narrow slice of the overall space of exploratory search tasks that might be done with a faceted OPAC interface. A broader range of task scenarios, perhaps including participant-motivated searches would be useful to explore.

DISCUSSION AND CONCLUSION

Using facets to refine search results made up 16% of the overall actions logged in this study. Although the data are not directly comparable due to differences in methods and data collection, Lown and Hemminger (2009) reported facet refinement made up 18% of the overall actions logged in a study of four months of data from the "live" OPAC and NCSU. Taken together, we believe that the results of these studies indicate the important role that facets play in the searching for information in a library OPAC.

We also found evidence that even simple training on the use of facets may increase their use. Participants in our study who received 60 seconds of video training on facet use made greater use of facets in conducting their searches than those participants who did not receive the training. While it is possible this was due to an experimentation effect, it suggests strategies for provide training to library patrons.

Investigation of pairwise sequences of actions suggests that participants who received training used facets at key points in their searches where participants in the non-training conditions issued additional search or paging actions. For example, participants in the training condition used facets more often just after issuing a search and just before adding an item to their "book bag". This suggests that these participants were using facets as an additional search refinement tactic at their disposal.

ACKNOWLEDGEMENTS

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REFERENCES

Kules B. & Capra, R. (submitted 2010). The influence of search stage on gaze behavior in a faceted search interface.

Kules, B., Capra, R., Banta, M., and Sierra, T. (2009). What Do Exploratory Searchers Look at in a Faceted Search Interface? In Proceedings of the 9th ACM/IEEE-CS Joint Conference on Digital Libraries (JCDL '09), Austin, TX, June 15 - 19, 2009.

Lown, C. and Hemminger, B. (2009). Extracting User Interaction Information from the Transaction Logs of a Faceted Navigation OPAC. Code4Lib Journal, 7(2009-06-26). http://journal.code4lib.org/ articles/1633

Tunkelang, D. (2009). Faceted Search. Synthesis Lectures on Information Concepts, Retrieval, and Services, 1(1), 1-80. Morgan & Claypool.

White, W. Kules, B., Drucker, S., schraefel, m.c. (2006). Introduction. *Commun. ACM* 49(4): 36-39.

Yee, K.-P., Swearingen, K., Li, K., & Hearst, M. (2003). Faceted metadata for image search and browsing. In *Proc. SIGCHI*, Ft. Lauderdale, FL (pp. 401-408). New York: ACM Press.

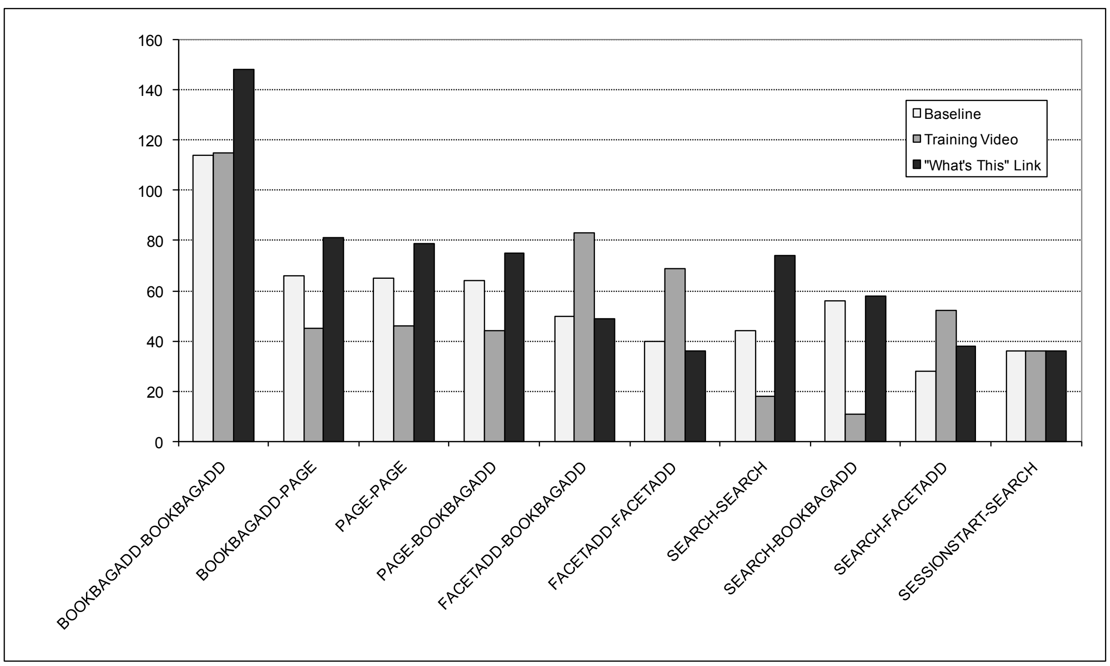

Figure 3. Pairwise Sequences of Actions (transitions)

Context in Health Information Retrieval: What and Where

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ABSTRACT

Researchers are aware that context affects information retrieval in general. The health area is no exception and is particularly rich in terms of context. To understand how context is used in health information research, we collected a sample of health information research papers that use context features. Papers were analyzed and classified according to the type of context features and to the stage of the retrieval process into which they were incorporated. Further, we also identified the specific context features used in each category of features and each stage of the process. Results show a weaker use of interaction context features than we expected and, as supposed, a large use of collective features. A considerable number of papers use context to query related activities. We also found that research is mainly aimed at health professionals, suggesting a gap in health consumers research that should be explored.

Categories and Subject Descriptors

H.3.3 [**[Information Storage and Retrieval]**]: Information Search and Retrieval

General Terms

Human Factors

Keywords

Context, Information Retrieval, Survey, Health

1. INTRODUCTION

Health Information Retrieval (HIR) focus on the application of IR concepts and techniques to the domain of healthcare. This field has largely evolved in the last few years. Habits of health professionals and consumers (patients, their family and friends) have been changing as a result of several factors like the increasing production of information in a digital format [27], the greater availability and the easier access to health information.

Several authors agree that context, often ignored, might be used to improve the retrieval process [21, 2]. A contextualised Information Retrieval (IR) could allow IR systems to learn and predict what information a searcher needs, learn how and when information should be displayed, present how information relates to other information that has been seen and how it relates to other tasks the user was engaged in and decide who else should be informed about new information.

According to Lin and Fushman, "the domain of clinical medicine is very well-suited for experiments in building richer models of the information seeking process" [23]. In fact, it's not difficult to foresee context features in this domain that could enrich HIR models. Similarly to any visit to the doctor, where the patient doesn't just say "itch", but explains the context of the "itch" to the doctor, context is relevant to HIR. Other examples of context features that can be used are the search scenario [24] and its specificities (e.g.: treatment of a disease), the searcher's personal health record, the clinical case in hands and the searcher's knowledge in the health domain.

We have done a review on the definition of context in a previous work [25]. To this work, context is considered an interactional problem, as defined by Dourish [8]. It not only includes the environmental features surrounding the user and his activities, but also the interaction in which he is involved. We believe context is dynamic and might change each time a new search is made, a new set of results is reviewed or a new document is viewed [14].

To understand how context is being used in health information research, we gathered a set of HIR research papers that use any kind of context features. These papers were analyzed and classified according to the type of used context features and to the stage of the retrieval process into which they were incorporated. Further, we also identified the specific features used in each context category and each stage of the process.

The following section presents the adopted methodology, specifying how the papers were selected and describing the taxonomies used in the classification. Section 3 presents the classification of the research papers and enumerates the specific context features used in each category and stage. Finally, in Section 4 we report the main conclusions of this analysis.

2. METHODOLOGY

To define the sample of papers, we considered all the documents classified with the tags context and health in CiteU-

Like[1], a social web service for management of bibliographic references. From this set we excluded papers not related with IR and papers in which IR was not the main focus. For example, papers on Information Extraction and papers proposing readability formulas for health documents were excluded from this analysis. In addition, papers without an innovative contribution (e.g.: literature reviews or comparisons of IR systems) were also excluded. The final set was composed of 27 papers.

To classify the research papers according to the used context features, we adopted the Ingwersen and Järvelin's nested model of contexts for Information Seeking and Retrieval (IS&R) [20] that is described in the next subsection. To analyze the usage given to the context features we adopted a taxonomy similar to the one defined by Lopes [25] for the "uses of context".

2.1 Nested model of contexts for IS&R

The first version of Ingwersen and Järvelin's nested model of contexts has 6 dimensions [20]. The first and second dimensions represent the intra and inter object contexts and are the central component of the cognitive IS&R framework, proposed by the authors. The other four dimensions are: the interaction (session) context; the context provided by the remaining components of the framework; the societal infrastructures and, across the stratification, the historic context of all actors' experience. Later, and by the same authors, the social/organizational/cultural context dimension was divided in two subdimensions: an individual and a collective one [19].

This model may be centered on the information space, on the cognitive author (e.g.: searcher), on the interface, on the information technology (engines, logics, algorithms) or on the social/organizational/cultural context. This choice will affect the nature of the interaction context and the context of the individual and collective dimensions.

In this classification we decided to center the model on the information space as can be seen in Figure 1. The cognitive actor was another potential alternative but we felt the specificities of the information space in the health domain would be better described if placed in the first two dimensions of the model. Searcher's context is therefore included in the fourth dimension. We also felt the choice of the cognitive actor as the core would result in a more ambiguous model. In fact, depending on the use given to context features, the cognitive actor could be the searcher or another actor (e.g.: person contributing to the indexing process).

2.2 Uses of context taxonomy

To analyze how the context features are used, we adopted four categories, similar to the four top categories of the *uses of context* taxonomy proposed by Lopes [25]: Indexing and Searching, Query Operations, Ranking and Interface. The Query Operations category is more comprehensive than the *Relevance Feedback and Query Expansion* category initially proposed in Lopes's work because, in the health domain, it is frequent to have systems that generate queries and gather information resources from other systems. With this modification, papers describing this kind of research can fit into this category.

[1] http://www.citeulike.org/search/all?q=tag\%3Acontext+\%26\%26+tag\%3Ahealth

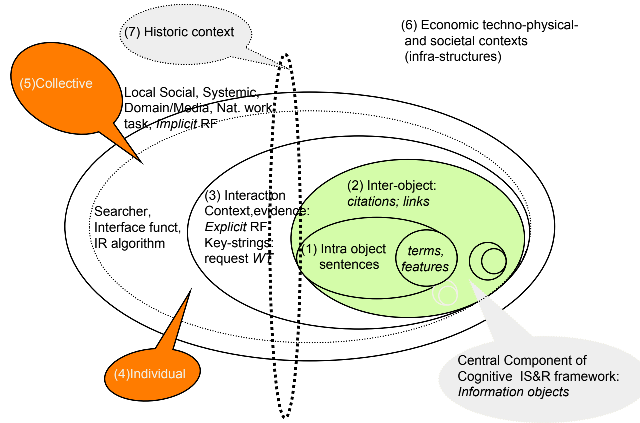

Figure 1: Ingwersen and Järvelin's nested model of contexts [20] with the information space as the central component.

In the IR process, the ranking phase is usually straight connected to the searching phase. Yet, we prefered to keep them as two distinct categories to help differentiate systems that have their own index and implement a retrieval model from systems that just reorder existing result sets based on some specific criteria.

3. RESEARCH ANALYSIS

The results of our analysis are presented in Figure 2 with the distribution of papers by categories. For convenience of representation, we switched the initial order [25] of the interface and ranking categories. Each paper is represented by its bibliographic reference and a letter (P, C or B) that represents the type of users to whom the system is targeted: professionals, consumers or both.

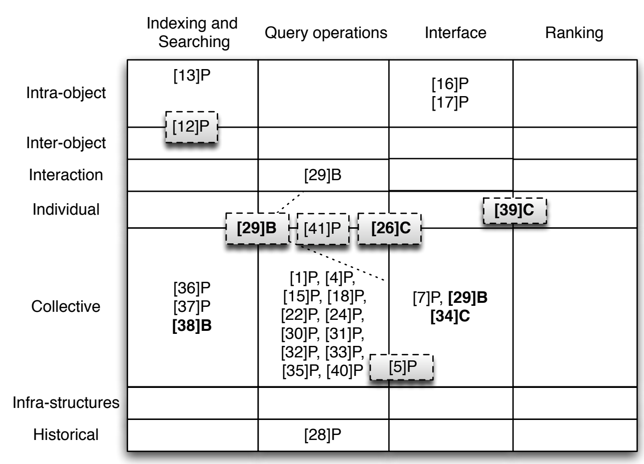

Figure 2: Classification based on the used context features and their specific use.

When a paper crosses more than one category, its reference is represented in the categories' intersection area. In some cases, it may also be connected with a dotted line to another cell of the matrix. For example, paper with refer-

Table 1: **Context Features used in CHIR.**

	Indexing and Searching	Query Operations	Interface	Ranking
Intra-Object	Document contents and structure (e.g. abstract, conclusions, title, HTML structure).		Document images and captions.	
Inter-Object	Links between documents.			
Interaction		Browsing behavior.		
Individual	Authoring context.	Searcher's clinical data and user interest.	Searcher's clinical data and PHR.	PHR.
Collective	UMLS, domain categories, tasks, ontologies, taxonomies and patient data (age, sex and clinical context).	UMLS, MeSH, domain questions and terminologies, clinical practice guidelines, retrieval feedback, task context and patient data (clinical data, consult reports, exam reports, EHR).	UMLS, MeSH, domain questions, Gene Ontology and patient data (clinical data, EHR).	
Infrastructures				
Historical		Search history.		

ence [29] uses interaction, individual and collective context features in Indexing and Searching, Query operations and Interface stages.

Figure 2 shows that research is more intense on Query Operations using mainly context features from the individual and collective dimensions. We were surprised with the weak use of the interaction context. This might be explained by the preference to use context features more related to the health domain. Typically, interaction context is more generic and not so health-related as individual and collective context features. On the other hand, we already expected to have a large number of papers using collective context features since this category is exhaustive, covering the characteristics of all the components from the cognitive framework that are not at the center of the model.

In Figure 2 we highlight the papers dedicated to research on health consumers systems (letters C or B). As can be seen, research is mostly dedicated to health professionals. The small number of consumer dedicated research papers use interaction, individual and collective context features.

To show which exact context features are used, we built Table 1 where we included the features in a structure similar to the one in Figure 2. In this table, EHR stands for Electronic Health Record and PHR for Personal Health Record, to distinguish institutional data from the records managed by the patient. UMLS is a project from the National Library of Medicine (NLM) of the United States composed of three knowledge sources: the Metathesaurus, the Semantic Network and the SPECIALIST Lexicon and Tools. MeSH is also an NLM thesaurus.

As can be seen in the collective dimension of Table 1, the health domain is very rich in structured information. This dimension mainly consists of terminologies, thesaurus and ontologies. Note that in IR systems used by health professionals, the EHR and patient's clinical data is part of the professional work task. Therefore, in professional systems, these context features incorporate the collective dimension of context. In IR systems designed for patients, the use of clinical data or PHR about the searcher is considered individual context.

4. CONCLUSIONS

Most researchers are aware that context affects information retrieval. The health area is no exception, being particularly rich in terms of context. Results presented in the previous section show a weaker use of interaction context features than we expected. Also, research makes an extensive use of collective features. This was not a surprise because this dimension is very comprehensive, including several types of context features. In addition, it is the dimension where all the health-related structured knowledge sources (e.g.: thesaurus) are included. A considerable number of papers use context to query related activities.

We have noticed that research has been more focused on health professionals than on consumers. Of the 27 papers analyzed, only 3 are dedicated to health consumers and 2 are dedicated to both professionals and consumers. This difference may be explained by the longer tradition of information retrieval in health professionals when compared to consumers. Only recently, with the advent of the Web, has search become more popular among health consumers. Other possible reasons include the large number of medical knowledge sources, the possibilities open by the integration of search systems with clinical systems and the difficulties associated with user studies in consumer health retrieval.

The lack of research on the use of context in health IR by consumers, the growing number of health searches (61% of the American adults look online for health information [11] and so does 19,6% of the Portuguese population aged 15 or more [9]) and the importance of well-informed patients [10] suggest the importance of focusing research on health consumers.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

[1] A. R. Aronson and T. C. Rindflesch. Query expansion using the UMLS Metathesaurus. *Proceedings of the AMIA Annual Fall Symposium*, pages 485–489, 1997.

[2] R. Bierig and A. Göker. Time, location and interest: an empirical and user-centred study. In *IIiX: Proceedings of the 1st international conference on Information interaction in context*, pages 79–87, New York, NY, USA, 2006. ACM.

[3] J. J. Cimino. Linking patient information systems to bibliographic resources. *Methods of information in medicine*, 35(2):122–126, June 1996.

[4] J. J. Cimino, A. Aguirre, S. B. Johnson, and P. Peng. Generic queries for meeting clinical information needs. *Bulletin of the Medical Library Association*, 81(2):195–206, April 1993.

[5] J. J. Cimino, S. B. Johnson, A. Aguirre, N. Roderer, and P. D. Clayton. The MEDLINE button. In *Proc Annu Symp Comput Appl Med Care*, pages 81–85, 1992.

[6] J. J. Cimino and J. Li. Sharing infobuttons to resolve clinicians' information needs. In *AMIA Annu Symp Proc.*, page 815, 2003.

[7] A. Doms and M. Schroeder. GoPubMed: exploring PubMed with the Gene Ontology. *Nucl. Acids Res.*, 33(suppl_2):W783–786, July 2005.

[8] P. Dourish. What we talk about when we talk about context. *Personal Ubiquitous Comput.*, 8(1):19–30, February 2004.

[9] R. Espanha and F. Lupiáñez Villanueva. Health and the Internet: Autonomy of the User. Technical report, LINI - Lisbon Internet and Networks, 2008.

[10] T. Ferguson. e-patients - how they can help us save health care. Technical report, e-patients scholars working group, 2007.

[11] S. Fox and S. Jones. The social life of health information. Technical report, Pew Internet & American Life Project, June 2009.

[12] M. E. Frisse. Searching for information in a hypertext medical handbook. In *HYPERTEXT '87: Proceedings of the ACM conference on Hypertext*, pages 57–66, New York, NY, USA, 1987. ACM.

[13] C. W. Gay, M. Kayaalp, and A. R. Aronson. Semi-automatic indexing of full text biomedical articles. *AMIA Annual Symposium Proceedings*, pages 271–275, 2005.

[14] D. J. Harper and D. Kelly. Contextual relevance feedback. In *IIiX: Proceedings of the 1st international conference on Information interaction in context*, pages 129–137, New York, NY, USA, 2006. ACM Press.

[15] Z. Hashmi, T. Zrimec, and A. Hopkins. CQGF: Context specific query generation framework from computerized clinical practice guidelines. In *Second International Conference on the Applications of Digital Information and Web Technologies - ICADIWT '09*, pages 288–293, October 2009.

[16] M. A. Hearst, A. Divoli, H. Guturu, A. Ksikes, P. Nakov, M. A. Wooldridge, and J. Ye. Biotext search engine: beyond abstract search. *Bioinformatics*, 23(16):2196–2197, August 2007.

[17] M. A. Hearst, A. Divoli, J. Ye, and M. A. Wooldridge. Exploring the efficacy of caption search for bioscience journal search interfaces. In *BioNLP '07: Proceedings of the Workshop on BioNLP 2007*, pages 73–80, Morristown, NJ, USA, 2007. Association for Computational Linguistics.

[18] W. Hersh, S. Price, and L. Donohoe. Assessing thesaurus-based query expansion using the UMLS metathesaurus. *AMIA Annual Symposium Proceedings*, pages 344–348, 2000.

[19] P. Ingwersen. Context in information interaction revisited 2006. Presentation at Prolissa 2006: Proceedings of the Fourth Biennial DISSAnet Conference, 2006.

[20] P. Ingwersen and K. Järvelin. *The Turn: Integration of Information Seeking and Retrieval in Context (The Information Retrieval Series)*. Springer, 1 edition, September 2005.

[21] P. Ingwersen, K. Jelin, and N. Belkin, editors. *Proceedings of the ACM SIGIR 2005 Workshop on Information Retrieval in Context (IRiX)*, Royal School of Library and Information Science. Denmark., August 2005.

[22] L. C. Kingsland, A. M. Harbourt, E. J. Syed, and P. L. Schuyler. Coach: applying UMLS knowledge sources in an expert searcher environment. *Bull Med Libr Assoc.*, 81(2):178–183, April 1993.

[23] J. Lin and D. D. Fushman. Representation of information needs and the elements of context: A case study in the domain of clinical medicine. In *ACM SIGIR 2005 Workshop on Information Retrieval in Context (IRiX)*, 2005.

[24] Liu, Zhenyu, Chu, and Wesley. Knowledge-based query expansion to support scenario-specific retrieval of medical free text. *Information Retrieval*, 10(2):173–202, April 2007.

[25] C. T. Lopes. Context features and their use in information retrieval. In *Third BCS-IRSG Symposium on Future Directions in Information Access*, September 2009.

[26] G. Luo and C. Tang. On iterative intelligent medical search. In *SIGIR '08: Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval*, pages 3–10, New York, NY, USA, 2008. ACM.

[27] P. Lyman and H. R. Varian. How much information. Available from: http://www.sims.berkeley.edu/how-much-info-2003 [cited 2008-07-10], 2003.

[28] R. S. Marcus. An experimental comparison of the effectiveness of computers and humans as search intermediaries. *Journal of the American Society for Information Science. American Society for Information Science*, 34(6):381–404, November 1983.

[29] D. S. Martins, L. H. Z. Santana, M. Biajiz, Antonio, and W. L. de Souza. Context-aware information retrieval on a ubiquitous medical learning environment. In *SAC '08: Proceedings of the 2008 ACM symposium on Applied computing*, pages 2348–2349, New York, NY, USA, 2008. ACM.

[30] S. M. Maviglia, C. S. Yoon, D. W. Bates, and G. Kuperman. Knowledgelink: Impact of context-sensitive information retrieval on clinicians' information needs. *J Am Med Inform Assoc*, 13(1):67–73, Jan 2006.

[31] E. A. Mendonça, J. J. Cimino, S. B. Johnson, and Y. H. Seol. Accessing heterogeneous sources of evidence to answer clinical questions. *Journal of biomedical informatics*, 34(2):85–98, April 2001.

[32] R. A. Miller, F. M. Gieszczykiewicz, J. K. Vries, and G. F. Cooper. CHARTLINE: providing bibliographic references relevant to patient charts using the UMLS Metathesaurus Knowledge Sources. *Proceedings of the Annual Symposium on Computer Application in Medical Care.*, pages 86–90, 1992.

[33] S. M. Powsner and P. L. Miller. Linking bibliographic retrieval to clinical reports: Psychtopix. In *Proc Annu Symp Comput Appl Med Care*, November 1989.

[34] W. Pratt, M. A. Hearst, and L. M. Fagan. A knowledge-based approach to organizing retrieved documents. In *AAAI '99/IAAI '99: Proceedings of the sixteenth national conference on Artificial intelligence and the eleventh Innovative applications of artificial intelligence conference innovative applications of artificial intelligence*, pages 80–85, Menlo Park, CA, USA, 1999. American Association for Artificial Intelligence.

[35] S. L. Price, W. R. Hersh, D. D. Olson, and P. J. Embi. Smartquery: context-sensitive links to medical knowledge sources from the electronic patient record. *Proc AMIA Symp*, pages 627–631, 2002.

[36] G. P. Purcell, G. D. Rennels, and E. H. Shortliffe. Development and evaluation of a context-based document representation for searching the medical literature. *International Journal on Digital Libraries*, 1(3):288–296, December 1997.

[37] G. Quellec, M. Lamard, L. Bekri, G. Cazuguel, B. Cochener, and C. Roux. Multimedia medical case retrieval using decision trees. In *IEEE Engineering in Medicine and Biology Society*, volume 2007, pages 4536–4539, ENST Bretagne, GET-ENST, Brest, F-29200 France. gwenole.quellec@enst-bretagne.fr, 2007.

[38] S. Sakji, A. D. D. Dibad, I. Kergourlay, S. Darmoni, and M. Joubert. Information retrieval in context using various health terminologies. In *Research Challenges in Information Science, 2009. RCIS 2009. Third International Conference on*, pages 453–458, 2009.

[39] J. M. Silva and J. Favela. Context aware retrieval of health information on the Web. In *LA-WEB '06: Proceedings of the Fourth Latin American Web Congress (LA-WEB'06)*, pages 135–146, Washington, DC, USA, 2006. IEEE Computer Society.

[40] P. Srinivasan. Retrieval feedback in MEDLINE. *Journal of the American Medical Informatics Association : JAMIA*, 3(2):157–167, 1996.

[41] Q. Zeng and J. J. Cimino. Linking a clinical system to heterogeneous information resources. In *Proc AMIA Annu Fall Symp.*, pages 553–557, 1997.

[42] Q. Zeng-Treitler, S. Goryachev, T. Tse, A. Keselman, and A. Boxwala. Estimating consumer familiarity with health terminology: A context-based approach. *J Am Med Inform Assoc*, 15(3):349–356, May 2008.

Tactics for Information Search in a Public and an Academic Library Catalog with Faceted Interfaces

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ABSTRACT

This study examined a large number of searches conducted when the users are interacting with two Endeca-based faceted library catalogs (University of North Carolina at Chapel Hill [UNC] Library catalog and Phoenix Public Library [PPL] catalog). The goal is to investigate people's search tactics with the faceted catalogs in an academic library and a public library environment. Two large data sets (with 504,142 logs for 40 days, and 1,010,239 logs for 60 days respectively) are analyzed. State transition analysis and maximal repeating patterns [MRP] analysis are conducted to identify the search tactics and action patterns. The results have both implications for designers in developing faceted library catalogs, and methodological contributions to the empirical research on faceted search systems.

1. INTRODUCTION

In recent years, faceted navigation has grown to be a well-accepted approach. It has been applied as a standard technique on commercial Web sites for a number of years (Breeding, 2007). Since the adoption of the faceted search in some university libraries, it has become adopted by to many academic and public libraries. Many librarians and IT professionals take it for granted that the categorized labels will help people find what they want. However, little has been known about how people are searching through these faceted systems. While significant work has examined the usability of facets (for example, Antelman et al., 2006; Lown, 2008), few investigated the sequences of moves, i.e., search tactics, made by searchers in order to understand the cognitive process when they are interacting with a faceted search system.

The current paper tackles this problem by examining the tactics of users searching two faceted library catalogs—University of North Carolina at Chapel Hill (UNC) Library catalog and Phoenix Public Library (PPL) catalog, focusing on the comparison between the academic library and the public library.

The two library catalogs, catering to different audiences, represent faceted OPACs in leading research universities and leading public libraries respectively. UNC library catalog (http://search.lib.unc.edu/), implemented faceted search on top of their original catalog system in 2008 to enhance the search ability. PPL's catalog (http://www.phoenixpubliclibrary.org/default.jsp), , has excellent facet implementation added on its traditional ILS system. The commonality of the two catalogs is both are using the commercial Endeca search engine to implement faceted navigation. However, for UNC catalog, facets are primarily serving the purpose of narrowing down a search, rather than browsing the collection. In contrast, for PPL catalog, facets are supporting browsing as well as refining a search.

2. BACKGROUND

Bates in her paper (1979) first introduces the concept of the search tactic as moves to further a search in information seeking context, as compared to the search strategy which focuses on the plan of the whole search. Since then, a few studies have examined search tactics adopted by users in various search systems. According to Wildemuth (2004), a search tactic is a set of search moves that are temporally and semantically related in order to accomplish a search goal. In her study, she investigated the effects of domain knowledge on search tactic formulation, and found that the search tactics changed over time as the students' domain knowledge changed. Qiu (1993) used a regression model to examine the fit of Markov models to search tactics in a hypertext system. It was found that a second-order Markov model best fit the data. Chen and Cooper (2002) studied users' moves of a library catalog through semi-Markov chains and identified six different usage groups with distinct patterns of system usage. Kiestra, Stokmans, and Kamphuis (1994) derived that the minimum "meaningful unit" of search behavior consisted of three consecutive actions, therefore analyzed these fragments of move sequence, and discovered 65 commonly used patterns. Jansen, Spink, and Saraevic (2000) conducted transaction log analysis for over 50,000 Web search engine queries and found that only 22% queries were modifications of a previous query. They also analyzed search moves of 191 search sessions and concluded that the most common session was "a unique query followed by a request to view the next page of results."

Although the analyses were similar in each of these studies, it is difficult to draw general conclusions due to different search move definitions, and different search systems. In addition, none of this study investigated the search tactics through a faceted search system—almost a standard feature for today's commercial search engines.

3. RESEARCH PROBLEM

This study addresses two research questions. First, it examines the tactics actually used by users to understand how they formulate and reformulate their cognitive process and search strategies when they are searching the faceted library catalogs. Second, it focuses on differences in these tactics that might be attributable to differences between an academic and a public library setting.

4. METHODS

4.1 Data Extracting and Processing

The transaction log datasets in this study are from UNC OPAC and PPL OPAC servers. Description of the two datasets is summarized in Table 1. The data are extracted and coded using Perl scripts and MySQL database. Details about analyzing the data have been elaborated elsewhere (Niu, Lown, & Hemminger, 2009; Lown, 2008). Table 2 below summarizes the available action codes and their descriptions.

Table 1. Description of transaction log datasets

Log Dataset	Time Frame	Size	Available Fields
UNC library Apache server logs	40 days 1/1/2010—2/9/2010	491M raw data 504,142 useful records	IP address /data,time/URL/ reference URL/user agent
PPL Apache server logs	2 month 3/1/2010—4/30/2010	371M raw data 1,010,239 useful records	IP address /data,time/URL/ reference URL/user agent

4.2 State Transition Matrix

A Markov model is a stochastic process with the Markov property which means that the description of the present state fully captures all the information that could influence the future evolution of the process. Future states will be reached through a probabilistic process instead of a deterministic one. The order of Markov models means how many previous states (including the current state) influence the choice of the next state probabilistically. The simplest form of a Markov model is called a zero-order model. It is simply the frequency with which each state occurred. The first-order Markov model, also called a state transition matrix, reports the probability of the transition from all the possible current states to all the possible future states. First-order Markov models are the types of models most frequently found in the ILS literature (Wildemuth, 2009). In this paper, first-order Markov model is adopted to report the frequency of each transition. A graphical representation of the most frequent state transitions is to be created by linking together these individual transitions.

4.3 Maximal Repeating Pattern (MRP)

Previous literature indicates that people's information behavior varies greatly from one person to another. It is helpful to find patterns that are frequently adopted by searchers. Siochi and Ehrich's (1991) algorithm for identifying maximal repeating patterns (MRPs) among sequences of behavior is applied to serve this purpose. They defined an MRP as "a repeating pattern that is as long as possible, or is an independently occurring substring of a longer pattern" (Siochi & Ehrich, 1991). Thus, the algorithm systematically identifies those sequences of events that occur repeatedly within the data set. In this study, each of the two data sets is analyzed with the MRP software. Any frequently occurring fragment strings are selected for further analysis. Selected MRPs are then grouped into families of patterns. Each family could be summarized using a regular expression and exemplified with two most frequent sequences.

5. RESULTS

The results from each library are reported separately and include both the state transition analysis and maximal repeating pattern (MRP) analysis.

5.1 Results From UNC Library Catalog

After processing the UNC data, 1243 search sessions, composed of 6416 moves, are identified. The most frequent state transitions among those moves are illustrated in Figure 1.

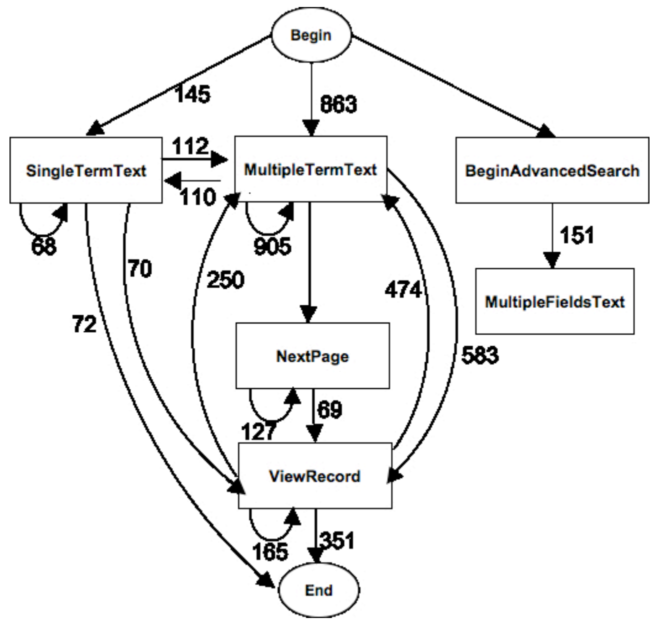

Figure 1. State transition network of search tactics for UNC (1243 search sessions, 6416moves), the numbers only include the transitions > 1% of total.

As shown in Figure 1, the most common transitions during a search are *MultipleTermText* to *MultipleTermText*, *Begin* to *MultipleTermText*, and *MultipleTermText* to *ViewRecord.* These transitions account for over 1/3 of the total transitions. It suggests that a number of searchers of the UNC library catalog adopt rather simple strategies, searching similarly with this faceted catalog as they did in a traditional catalog. "Advanced" features, like facet operations, sorting the result, are not as often used as expected.

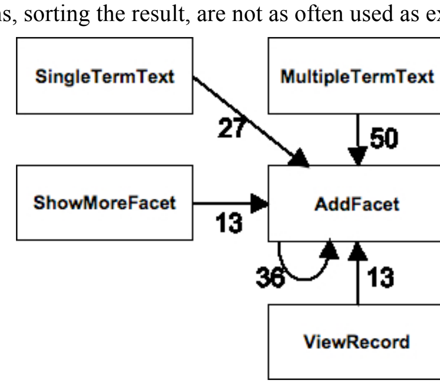

Figure 2. state transition network of facet operations for UNC (only illustrates the top 5 transitions).

Table 2 Action codes

UNC action code	Description	PPL action code
SingleTermText	Submit a single word query in the text search box	SingleTermText
MultipleTermText	Submit a multiple-word query in the text search box	MultipleTermText
SwitchTextField	Switch the search field (e.g. author, title) using the same text query as before	SwitchTextField
MultipleFieldsText	Submit a query in a multiple search boxes in different fields, typically in the advanced search page	MultipleFieldsText
EmptyTextSearch	Submit a empty query in the search box	EmptyTextSearch
BooleanTextSearch	Submit a query in the Boolean search box	
AddFacet	Click a facet value to incorporate it to the current search. For UNC library, AddFacet is only for refining the search. For PPL, could be either refining the search or browsing the collection	Refine Browse
RemoveFacet	Click "x" next to the already chosen facet value to take off it	RemoveFacet
ShowMoreFacet	Click "more" under a facet group to show more values	ShowMoreFacet
RefineYears	Under "Publication Year" facet group, manually type the starting and ending years and submit	N/A
OpenFacet	Click the "+" next to a facet group to show the values of the facet	N/A
CloseFacet	Click the "-" next to a facet group to hide the values of the facet	N/A
BeginSimpleTextSearch	Open the "Search" tab to begin a simple text search	N/A
BeginAdvancedSearch	Open the "Advanced Search" tab to begin a multiple fields text search	N/A
BeginCallNumberSearch	Open the "Browse by Call Number" tab to begin a call number search	N/A
BeginNewTitlesSearch	Open the "Browse New Titles" tab to begin a new title search	N/A
N/A	Open the "books" tab to search in the book collection	BookSearch
N/A	Open the "movies" tab to search in the movie collection	MoviesSearch
N/A	Open the "music" tab to search in the music collection	MusicSearch
N/A	Open the "downloadables" tab to search in the media collection	DownloadablesSearch
N/A	Open the "magazines & newspapers" tab to search in the book collection	MagNewsSearch
ViewRecord	Click through a record link to view details about the record	ViewRecord
NextPage	Click a page number or next button in the result page to view what in next page	NextPage
SortResult	Choose the options (relevance, publication year …) from the "Sort by" drop down menus to sort the result list	SortResult
N/A		SaveItem
FollowupAction	Click a link provided within a record to find the related records	FollowupAction
Refresh	Click refresh button of the browser	Refresh

Figure 2 above represents the state transition network of most frequently occurring facet operations for the UNC catalog. The degree of involvement for each action in this network indicates that the most used facet operation is *AddFacet.* Facets are typically added following a text search with either single term or multi term query. Most likely, these facets are serving the purpose of refining the previous text search. Sometimes, *AddFacet* is followed by another *AddFacet*. Compare to Figure 1, the numbers are much smaller, suggesting less usage in facets.

Focusing on the search sessions having at least one facet operation which are called faceted search sessions, MRP analysis was conducted The result indicates that there are three distinct families of patterns for the tactics frequently adopted by the UNC catalog searchers.

Table 3 Maximal repeating patterns for UNC catalog

Family of Pattern	Examples
F+V*	AddFacet>AddFacet>ViewRecord ShowMoreFacet>AddFaccet>ViewRecord
T+F+V*	MultipleTermText>MultipleTermText>ShowMoreFacet>AddFacet MultipleTermText>AddFacet>ViewRecord>ViewRecord
T*F+V*T+F*V*	AddFacet>ViewRecord>MultipleTermText>AddFacet MultipleTermText>AddFacet>SingleTermText

F denotes facet operations; V denotes viewing an item; T denotes text search
\+ denotes occurring one or more times; * denotes occurring any time

The family patterns are summarized using regular expressions shown in the left column of Table 3. The examples in the right column are the two most frequent individual patterns of that family. Even for the most frequent individual patterns, they only account for approximately 1% of all the possible patterns, which are over 1 thousand identified through MRP analysis. This indicates that search tactics are rather idiosyncratic with much difference that can be attributed to individuals.

5.2 Results From Phoenix Public library catalog

428 search sessions with 6987 moves are extracted from the PPL data. The average number of actions per search triples that of UNC (1243 sessions with 6416 moves). It's probably because of the public library setting or the different implementation of the library catalog. The frequent state transitions among those moves are demonstrated in Figure 3.

The most common transitions happen between *MultipleTermText* and *ViewRecord*, or self-repetitions of *ViewRecord. Begin* to *MultipleTermText* is relatively less than that of the UNC data, due to more choices offered by Phoenix Public Library, rather than just text querying to start a search. In addition to typing a text query, users may browse the collection or select an appropriate tab to begin a search. One remarkable thing is that *Refine*, as one way of adding a facet, appears in the network as one of the frequent states. It implies a boost of facet usage compared to the UNC catalog. *Refine* is typically followed by *MultipleTermText*, and leads to either *ViewRecord* or a repetition of itself. Focusing on the transitions among facet operations (Figure 4), in addition to *Refine*, *ShowMoreFacet* and *Browse* are also the top used facet moves. They are most likely to follow or to be followed by an identical move.

The result from MRP analysis suggests 4 families of patterns, as illustrated in Table 4.

Table 4 Maximal repeating patterns for PPL catalog

Family of Pattern	Examples
F+V*	Refine>Refine>ViewRecord ShowMoreFacet>Refine
T+F+V*	MultipleTermText>ShowMoreFacet>Refine MultipleTermText>Refine>ViewRecord>ViewRecord
T*F+V*T+F*V*	Refine>ViewRecord>MultipleTermText>Refine MultipleTermText>Refine>SingleTermText
B+N*V*	Browse>Browse>Browse>Browse>ViewRecord Browse>Browse>NextPage>NextPage

F denotes facet operations; V denotes viewing an item; T denotes text search; B denotes browsing; N denotes viewing next page
+ denotes occurring one or more times; * denotes occurring any time

Of these four families of patterns, the first three are the same with those of the UNC data. The last one is the unique pattern for the PPL data. The PPL searchers take advantage of the offered browsing features and tend to continue browsing before getting to a reasonable result set.

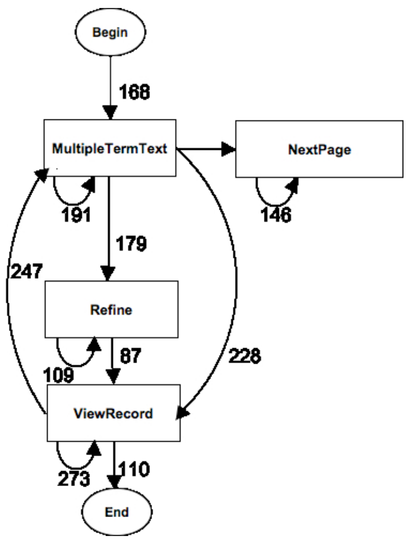

Figure 3. State transition network of search tactics for PPL (428 search sessions, 6987 moves), the numbers only include the transitions > 1% of total.

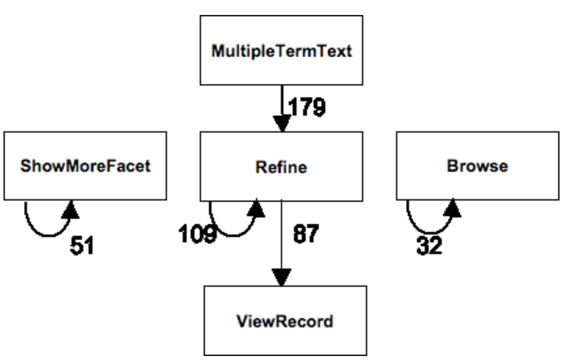

Figure 4. state transition network of facet operations for PPL (only illustrates the top 5 transitions).

6. CONCLUSION

A catalog search is made up of a sequence of temporally and semantically related moves as a search tactic. This study examines a large number of searches conducted when the searchers are interacting with two faceted library catalogs. An analysis of the search moves indicates that the most common tactics across the two environments are text querying followed by viewing result items. This is similar to what the searchers have done through the traditional OPAC without facet features. MRP analysis suggests that search tactics are rather idiosyncratic and users do not have much in common in terms of their search moves. To some extend, a number of searchers are conservative in using facets. They just adopt simple and naïve search strategies. It is unlikely that facets are useful in all types of search situations and for all types of tasks. Facets used by people are primarily for two purposes: refining a search and browsing the collection. Facet usage in PPL is much higher than that of UNC. It might be the better support of facet browsing of PPL that cause the boost of its facet usage. Another striking thing about search tactics is that people are likely to repeat what they did in the previous run. For example, adding a facet is high likely to be followed by adding another facet. Browsing is most likely to repeat during the search process.

REFERENCES

[1] Antelman, K., et al. (2006) Toward a Twenty-First Century Library Catalog. Information Technology and Libraries. 25(3) 128-139.

[2] Bates, M. J. (1979). Information search tactics. Journal of the American Society for Information Science, 30(4), 205-214.

[3] Breeding, M. (2007). Introduction [next-generation catalogs] Library Technology Reports 43(4), 5-14.

[4] Chen, H. M., & Cooper, M. D. (2002). Stochastic modeling of usage patterns in a web-based information system. Journal of the American Society for Information Science and Technology, 53(7), 536-548.

[5] Jansen, B.J., Spink, A., & Saracevic, T. (2000). Real life, real users, and real needs: A study and analysis of user queries on the Web. Information Processing & Management, 36(2), 207–228.

[6] Kiestra, M.D., Stokmans, M.J.W., & Kamphuis, J. (1994). End-users searching the online catalogue: The influence of domain and systemknowledge on search patterns. The Electronic Library, 12(6), 335–343.

[7] Lown, C. (2008). A transaction log analysis of NCSU's faceted navigation OPAC. Master's paper.

[8] Niu, X., Lown, C., & Hemminger, B. M. (2009). Log based analysis of how faceted and text based search interact in a library catalog interface. In Proceedings of Third Workshop on Human-Computer Interaction and Information Retrieval.

[9] Qiu, L. (1993). Markov models of search state patterns in a hypertext information retrieval system. Journal of the American Society for Information Science, 44(7)

[10] Siochi, A.C., & Ehrich, R.W. (1991). Computer analysis of user interfaces based on repetition in transcripts of user sessions. ACM Transaction on Information Systems, 9(4), 309 - 335.

[11] Wildemuth, B. M. (2004). The effects of domain knowledge on search tactic formulation. Journal of the American Society for Information Science and Technology, 55(3), 246-258.

[12] Wildemuth, B. (2009). Applications of social research methods to questions in information and library science. Santa Barbara, CA :Libraries Unlimited.

Understanding Information Seeking in the Patent Domain and its Impact on the Interface Design of IR Systems

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ABSTRACT
In this position paper, we highlight the need for understanding and modeling a user's context when designing the user interface of an information retrieval system using the example of the patent domain. Based on fundamental concepts of information seeking and retrieval research, we describe the different contextual factors characteristic for this domain and common task scenarios of patent retrieval. Finally, we outline first starting points for coping with these domain-specific conditions in the interface design of IR systems and discuss future research needs.

Categories and Subject Descriptors
H 1.2 [**User/Machine Systems**]: Human Factors; H.3.3 [**Information Search and Retrieval**]: Search Process. H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *Graphical user interfaces (GUI).*

General Terms
Design, Human Factors, Theory

Keywords
Information seeking; human-computer interaction; patent retrieval; context modeling

1. INTRODUCTION
While in the community of information retrieval (IR) research much effort has been spent on the invention of sophisticated system features and algorithms, the patent or intellectual property domain is still relying on Boolean systems with basic user interfaces. Even though this industry has developed highly sophisticated human strategies to seek for relevant information, one has to wonder why there has been no significant progress in terms of technical support. According to statistics of the World Intellectual Property Organization (WIPO) [14], the total number of patents in force worldwide at the end of 2006 was approximately 6.1 million. This large amount of data indicates that especially in this domain there should be a certain demand for innovative services to support patent users in their retrieval activities. One approach to enhancing information retrieval activities is the design of the IR system and algorithm itself. This important field of research, however, shall not be the focus of this position paper. Another approach is the design of the user interface to match the respective user need in a given context. In order to be able to develop innovative IR interfaces, it is therefore essential to understand the specificity of the domain and its impact on the interface design of IR systems.

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First efforts in the field of information seeking and retrieval (IS&R) research were made. A study in the Swedish Patent and Registration Office (PRV) by Hansen & Järvelin (2005) examined the collaborative character of the patent handling process. They draw the conclusion that "future research should focus on what affects CIR (collaborative IR) processes. Possible research questions could deal with task variation, task complexity or type of task". [7] Recently, Azzopardi et al. [1] published the results of a survey on patent users. They already started to analyze the relationship between the specialties of this kind of users, their search tasks and the functionalities of patent retrieval systems. [1]

In this position paper we would like to discuss different impact factors on information seeking, highlight the domain-specific aspects of patent retrieval, and give a first outlook on how UI design may be adapted according to these considerations.

2. THE FIELD OF IS&R RESEARCH AND ITS RELEVANCE FOR IR SYSTEMS
In the past thirty years of information science the so-called „cognitive turn" [8] has widened the scope of traditional information retrieval (IR) research. It includes not only system-orientated perspectives of IR but also cognitive aspects of the entire process of information seeking (IS). The consideration of the actor and his context of a respective work or search task, lead to new fields of research and a variety of conceptual models on information behaviour. "Information behaviour may be defined as the more general field of investigation (as shown in Figure 1), with information-seeking behaviour being a sub-set of the field, particularly concerned with the variety of methods people employ to discover and gain access to information resources. Information searching behaviour is then defined as a sub-set of information-seeking, particularly concerned with the interactions between information user (with or without an intermediary) and computer-based information systems, of which information retrieval systems for textual data may be seen as one type." [15]

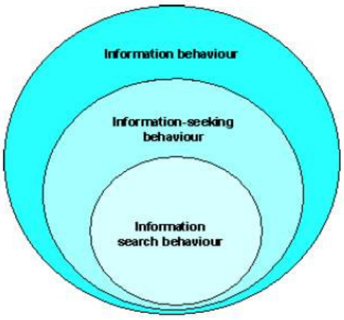

Figure 1 - Wilson's nested model of information behavior

In information seeking (IS) research, the main goal thus is, to model the user's context in order to gain a better understanding of his information needs, seeking, and use (INSU). Therein different types of models have emerged, which may be characterized as either broad or narrow, process or static, abstract or concrete, summary or analytical, general or specific models. [8] While most models of the type narrow, process, abstract, summary, and specific have been widely perceived in information science and adjacent disciplines, other more analytical considerations of the relationships of different concepts, objects, or stakeholders have found less recognition. In order to highlight domain-specific aspects of information seeking, we would like to focus on some of the most relevant findings in this area and aim to promote a deeper understanding of their impact on the design of IR systems and their interface.

In the field of IS research Leckie et al. [10] have taken such an analytical perspective on the information seeking behavior of professionals. Their basic supposition is "that the roles and related tasks undertaken by professionals in the course of daily practice prompt particular information needs, which in turn give rise to an information seeking process. However, information seeking is greatly influenced by a number of interacting variables, which can ultimately affect the outcome." [10] As their model (Fig. 2) reveals, not only the outcome is influenced by the above mentioned factors, but also the way a task and information need are perceived, and what sources of information are consulted or how aware the actor is of certain pieces of information.

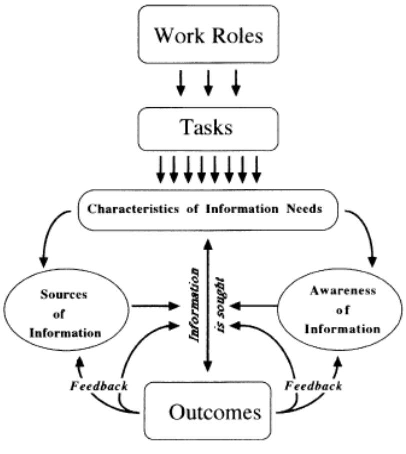

Figure 2 - The information seeking of professionals [10]

They also come to the conclusion that the way information sought is heavily influenced by "the level of complexity, the degree of importance and urgency, and whether the information need is anticipated or unexpected" [10]. The concept of task accordingly arises as central element of these findings. In a recent study by Xie [16] "the relationships between dimensions of work, search tasks, and information-seeking and -retrieving processes, in particular, the extent of planning, the application of different types of information-seeking strategies, and shifts in search-task-related goals" could be validated. Byström and Järvelin [5] also introduce the concepts of task complexity and types of information as influence factors of an actor's information seeking activities. Since task may be understood as search task as well as work task [4], the domain of work plays an important role. Since different work domains are characterized by very manifold organizational structures, areas of work, and work roles, tasks can be considered highly domain-specific.

Building upon the framework of information seeking above, we would like to highlight the importance of work role and task, and its characteristic in the patent domain in order to discuss possible conclusions for the design of user interfaces of patent retrieval systems.

3. DOMAIN-SPECIFIC ASPECTS AND TASKS OF PATENT RETRIEVAL

3.1 Description of the patent domain

The patent or intellectual property domain is characterized by a variety of domain-specific aspects, which have already been discussed by many scientists. One of these specialties is the patent document itself, because it is rather complex and contains a significant number of vague and general vocabulary [6, 9, 11]. This particularly influences the patent retrieval process, because a precise query is necessary to narrow the search and to finally find relevant documents. Furthermore, the complexity complicates the examination of a patent document, e.g. at the end of the search process. In addition to this document-specific aspect, the intellectual property domain differs from others due to the users consuming patent information. Referring to Tiwana and Horowitz [12], there is a variety of users including e.g. inventors and patent attorneys. With respect to this, Azzopardi et al. (2010) figured out that the majority of patent users are analysts or managers [1]. "In contrast to other domains such as the Web, the vast majority of practitioners of patent related retrieval are professional users." [6] This variety of user groups already implies that there might be different use cases or tasks within the patent domain. Graf and Azzopardi [6] identify the following search tasks:

- **prior art search**
  Prior art search focuses on the state of the art of an invention. It is performed in order to check whether there is any existing invention similar to the one claimed in the patent to be filed (patentability search) or to invalidate a patent (invalidity search) [6]. These two types of prior art search might be seen as two separate use cases.
- **freedom-to-operate search**
  A Freedom-to-Operate search aims at analyzing whether there is already a granted patent, which might be infringed by a planned product [6].

- **competitive analysis**
  The third common search type is the competitive analysis. In this case, the focus is set on the patents of a competitor and it is performed to find e.g. technical information [6].

With respect to information-seeking behavior, it is recommended to consider the above mentioned use cases, because each of these search types requires a special search strategy. By now, little is known about concrete search strategies, because in the patent domain user observations are nearly impossible. Modeling information-seeking behavior on a theoretical basis can, thus, be advantageous in order to better understand patent searching and human-computer interaction.

3.2 Modeling patent-specific aspects of information seeking

According to the model developed by Leckie et al. [10] (Fig. 2), the information seeking behavior of professionals heavily depends upon the work role of the user, which corresponds to the user types in the patent domain mentioned above. The target group of patent information is already versatile, but can be even more extended. This is done by Tseng and Wu [13], who argue, that the user group can further consist of examiners, researchers and engineers. Comparing the different work roles, we might first summarize, that it can be academic/ scientific (e.g. researcher) on the one hand and purely industrial (e.g. company, experts) on the other hand. Thus, there are two general work roles that need to be considered when modeling information seeking in the patent domain. Referring to the theory of Byström [3], these are characteristic for the domain specificity of work. It should be acknowledged, that the individual role of a patent attorney is a special one, because normally he acts as an intermediary (between inventor and patent office). [11] This fact is confirmed by Azzopardi et al. [1].

Depending on the work context and the individual role of the actor, different search tasks (explained in 3.1) may be performed to fulfill the information need. For example, a competitive analysis might be especially relevant to users being involved in business decision, while an inventor should be most interested in performing a prior art search. In the patent domain, each task is "strongly shaped and driven by judicial and economic requirements" [6]. This fact further implies the influence of external factors on the work task, which in industrial contexts might, in general, be an economic interest. All in all, the patent domain is significantly task-orientated, because each search task is further dominated by the underlying goal to maximize recall and precision [6, 9], which is characteristic for this special domain.

Each search underlies an information need of the user/ actor, which, according to Leckie et al. [10], is conditioned by the defined task. In the intellectual property domain, the difficulty, with respect to the information need, is to translate it into a suitable query. As already mentioned before the language within a patent document is typically vague [6, 9, 11]. This complicates the search, because domain specific knowledge as well as intensive training is necessary to formulate an effective query and to narrow the search results returned by a retrieval system. Most of the queries are significantly complex.

Once the information need is defined, an actor has to decide which information sources to use. Within the patent domain, an information source can be twofold, because the user has to choose between different databases on the one hand and because he has to decide which part of a patent document is most relevant to the task on the other. In case of a prior art search, for example, the claims would be the most interesting part of a patent [6]. Furthermore, to identify the state of the art of an invention, non-patent as well as patent literature should be considered during the search process [6]. These first examples indicate that the choice of information source is also influenced by the task and the information need of the actor in a given domain.

Summarizing, one can state that the patent domain provides a vivid field of application for existing analytical models in IS research and specifically contains the following influence factors on how information is sought:

- Individual work roles
- Underlying work and search tasks
- Situational and organizational factors
- Type of information need
- Task complexity
- Available information sources

4. SUMMARY AND FUTURE RESEARCH

Taking the here described observations of domain specificity in the intellectual property realm into consideration, it may be concluded that the design of the user interface of IR systems needs to account for all of the above mentioned influence factors (s. Fig. 2) in the context of the user. Next to the adaption of retrieval algorithms, the user interface presents a variety of levers to achieve this goal and make patent retrieval more effective, efficient, and more user-friendly.

Regarding the element of available **sources of information** a context-sensitive IR interface could, for example, provide integrated access to different information sources in order to assist prior art searches. Based on automatic context detection, it could also recommend suitable information sources for the different task types.

Considering the **awareness of information** interface elements for supporting query formulation or refinement could be implemented as well as the recommendation of suitable query terms. [13] Integrating query expansion methods is also suitable for narrowing the scope of a search task. With respect to this, Azzopardi et al. figured out that especially analysts would welcome such functionalities [1]. This clearly indicates that different work roles long for discriminative interface solutions.

Finally, the user interface may be designed in order to support the **outcomes** or what is referred to as "post retrieval interaction" [1] by developing innovative document views or other forms of visualizing complex document structures.

These first ideas demonstrate the relevance a deep understanding of concepts and influence factors of information seeking behavior may have on the design of user interfaces of IR systems in a specific domain of use. The cognitive viewpoint, as presented above, acts as integrating element for a variety of areas in information science [2] and has the ability to bring originally separate fields such as human-computer interaction and information retrieval together. Future research will therefore follow the line of argument of this position paper and further analyze the impact of domain-specific factors on information seeking and the interface as well as system design of information retrieval systems. Therefore, the patent domain as well as other information-intensive domains such as the management consulting as well as academic domain will be subject to future studies of information seeking and human-computer interaction in information retrieval.

REFERENCES

[1] Azzopardi, L., Joho, H., & Vanderbauwhede, W. (2010). Report: A Survey on Patent Users Search Behavior, Search Functionality and System Requirements. Available online: www.ir-facility.org/research/technical-reports/files/irf_tr_2010_00001.pdf

[2] Belkin, N. J. (1990). The cognitive viewpoint in information science. *Journal of Information Science, 16*(1), 11–15.

[3] Byström, K. (1999). *Task complexity, information types and information sources: Doctoral Dissertation.* Tampere: University of Tampere (Acta Universitatis Tamperensis 688).

[4] Byström, K., & Hansen, P. (2005). Conceptual Framework for Tasks in Information Studies. *Journal of the American Society for Information Science and Technology, 56*(10), 1050–1061.

[5] Byström, K., & Järvelin, K. (1995). Task complexity affects information seeking and use. *Information Processing & Management, 31*(2), 191–213.

[6] Graf, E., & Azzopardi, L. (2008). A methodology for building a patent test collection for prior art search. *Proceedings of the 2nd International Workshop on Evaluating Information Access (EVIA)*, December 16, 2008, Tokyo, Japan, 60–71.

[7] Hansen, P., & Järvelin, K. (2005). Collaborative information retrieval in an information-intensive domain. *Information Processing and Management, 41*(5), 1101 - 1119.

[8] Ingwersen, P., & Järvelin, K. (2005). *The Turn: Integration of Information Seeking and Retrieval in Context. Springer-11645 /Dig. Serial]: Vol. 18.* Dordrecht: Springer.

[9] Kando, N. (2000). What Shall We Evaluate? - Preliminary Discussion for the NTCIR Patent IR Challenge (PIC) Based on the Brainstorming with the Specialized Intermediaries in Patent Searching and Patent Attorneys. *ACM-SIGIR Workshop on Patent Retrieval*, July 28, 2000, Athens, Greece, 37–42.

[10] Leckie, G. J., Pettigrew, K. E., & Sylvain, C. (1996). Modeling the Information Seeking of Professionals: A General Model Derived from Research on Engineers, Health Care Professionals, and Lawyers. *The Library Quarterly, 66*(2), 161 - 193, from http://www.jstor.org/stable/4309109

[11] Schamlu, M. (1985). *Patentschriften - Patentwesen. Eine argumentationstheoretische Analyse der Textsorte Patent am Beispiel der Patentschriften zu Lehrmitteln.* München: Iudicium.

[12] Tiwana, S., & Horowitz, E. (2009). Extracting Problem Solved Concepts from Patent Documents. *Proceedings of the 2nd ACM workshop on Patent Information Retrieval, PaIR 2009,* November 6, 2009, Hong Kong, China, 43-48.

[13] Tseng, Y., & Wu, Y. (2008). A Study of Search Tactics for Patentability Search: A Case Study on Patent Engineers. In J. Tait (Ed.). *Proceedings of the 1st ACM workshop on Patent Information Retrieval, PaIR 2008*, October 30, 2008, Napa Valley, California, USA, 33-36.

[14] World Intellectual Property Organization (WIPO) (2008): World Patent Report: A statistical review. Geneva: IPstats.

[15] Wilson, T. D. (1999). Models in information behaviour research. *Journal of Documentation, 55*(3), 249–270.

[16] Xie, I. (2009). Dimensions of tasks: influences on information-seeking and retrieving process. *Journal of Documentation, 65*(3), 339–366.

Better Search Applications Through Domain Specific Context Descriptions: a Position Paper

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ABSTRACT

There is a wide agreement that a user centred approach to IR applications design outperforms system centred ones. A classic understanding of this design approach, and specifically of its underlying notion of context, appeared however insufficient to explain the results of a pilot experiment. We recognise the importance of context, but we define context differently by means of a domain theory: a conceptualisation of the domain at hand, preferably developed within the same community which users belong to.

1. INTRODUCTION

We believe that there is a need to escape the narrowness of existing system centred application development and evaluation frameworks, towards designs that are more open and alert to the human user, whose purposes they are supposed to serve. Karen Spärk Jones [10] raised the same issue already in the late Eighties, arguing in favour of lines of research in Information Retrieval (IR) that go beyond probabilistic weighting and of evaluation paradigms that step outside the entrenchment of the laboratory. These are still present day challenges for IR research [4]: IR applications should address a more realistic environment comprising real users with all their expectations, naiveties, affections, clear-cut ideas or just loose or even incoherent judgements.

In IR the most influential and successful attempts to take a user centred stance and to propose an alternative to a classic document space model [14] have been developed from a cognitive perspective [3]. We regard an IR system as supporting a communicative act between an expert on a certain matter, who made information available about her knowledge of the world, and a system's end-user, who at a certain moment became aware of an anomaly in her epistemic state. When a user issues a query onto the system in an effort to eliminate that anomaly [2], we may interpret IR in terms of linguistic interchange. Language is a paradigmatic form of human interaction and several authors describe a cognitive view, "a forceful theoretical foundation for IR interaction and human-computer interaction (HCI) in general" [8] in terms of linguistic notions.

A cognitive view amounts then to recognising that, while a sentence, an image or more generally a *sign* may have many different meanings, interpretation relies on a cognitive process upon receipt of this sign, which is only potentially informative [8]. The goal of search applications upon this view is "to give access to [these] plausible means or values as, given the situation, may entail transformations of a cognitive state, thus providing information in a pragmatic sense via context" [8].

A cognitive view of IR extends therefore the communication system setup of [2], which is inspired by quantitative models of information exchange [16] such as those for transmissions of electrical signals over noisy channels, into a more complex setting where *sender* and *receiver*, or *speaker* and *hearer* in a classical model of linguistic exchange, are turned down in favour of agents, who engage in an interactive game. The focus of this 'linguistic turn' in IR, a shift from considering documents as labels to regarding them to be part of a sense making process is an analysis of a linguistic and behavioural game: a pragmatics of meaning, that is a model of the way signs are used during information exchange. A cognitive approach explicitly takes an internal perspective [1] by addressing the mental states of agents who play the game, with its set of mutually agreed upon rules, strategies that each agent is determined to employ and criteria of assessing a positive conclusion of the game.

Many approaches to design often derive a potential to gather consensus around their underlying notions from common sense intuitions: obvious properties of reality with which everyone is expected to agree. These unquestioned postulates may not fully endure a more thorough analysis and can be challenged by empirical evidence when these general theoretical frameworks are translated into practice. A tacit assumption in a pragmatics of IR is that understanding the process through which a world view mediates interpreta-

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tion amounts to understanding the characteristics of a world where an act of interpretation takes place.

This short position paper reports on how, during the development of a pilot user study designed to improve our knowledge on combining information from different sources, we came to evince a lack of coherence at the very bottom of IR systems design upon a cognitive view. Exchanging a hypothetical external observer monitoring communication for an analysis of a subjective mental representation of how a game of exchange is being played leaves a scientist seeking to develop cognitive models of information exchange in an ambiguous position: those internal mental models are still supposed to be inferred from observed behaviour. A context, which linguistic indexicality refers to, becomes then a comprehensive set of material, social, cultural and psychological characteristics, which deterministically settle observed behaviour.

We believe that this rather implicit assumption of considering mental representations to be observables within a cognitive model is the main motivation of most efforts in developing a wide range of techniques to improve our knowledge of a user's world. Think aloud protocols, ethnographic studies or extrapolations of simulated work tasks [9]: they all aim to carefully charting a user's environment. Provided that we take a sufficiently unbiased view, empirical data are the means to understand user's behaviour. Conversely, our inability to make sense of some experimental result or to deduce a correct set of design requirements for a new application is a consequence of a lack of empirical material or a flaw in our methodological tools. Such ground assumptions, given the weight of these studies in modern IR research, should be investigated.

We are confident that social structures do matter, but we argue that a linguistic interpretation of the cognitive view in IR seems to point against their observability from user performance. While the discourse analysis community recently suggested that "*there is no direct link between situational or social structures and discourse structures*" [5], no comparable paradigm shift has yet emerged in accounts of IR as discursive practice.

IR is a highly technologically advanced linguistic game and we must grant the participants to this game more skills than current accounts do: apart from intuitively grasping the material and social background of linguistic interaction, players are proficient in abstracting on a set of rules by following which a game can be successfully completed. We will suggest to investigate one of these abstract and domain specific models of a particular discourse that happens to underlie our prospective application as the key of a solution to correct interpret the results of our user study.

The following section explains how we designed and performed our pilot user study and how it challenged our views on what should be regarded as context of the linguistic IR performance. Given the limited space that we have, we will not give much details and we will present the experiment as an empirical trigger for a more abstract claim. Section 3 introduces our solution and in the last section we propose some directions to generalise this conclusion to other IR applications. Our central claim is that we should consider, not only analyses of a user's environment as it appears to a computer scientist approaching a new design, but also the different understandings of a domain of interest that were developed in the same community which a user belongs to.

2. STAGING A LINGUISTIC IR GAME

Acknowledging a view that regards HCI and IR as technology enabled linguistic exchanges and at the same time one that considers a cognitive process to provide the main contribution to sense making, amounts to stress the functional role of language, that is how language is used during interactions, rather than its capacity as information carrier: "communication should be grounded in the pragmatic practices by which speakers use language" [12]. Understanding an IR speech act requires to investigate the situation in which this act takes place. Whitin this theoretical framework we developed a user study aiming to understand how to support combined search for documents which contain information from two repositories: one of textual documents and another of images.

Our ground hypothesis was that, because of what Ingwersen termed 'cognitive free fall' [8], syntactic and semantic components of meaning captured by classic text retrieval language models would trigger characteristic pragmatic features of discourse: "*intentionality*, meaning, implicit *context* and potential *informativeness* underlying the generated and communicated message [that] are *immediately lost* [...] have to be rebuilt and recovered" [8]. In order to investigate this reconstruction process, we designed two different algorithms to search onto textual documents contained in the Keesings[1] archive and pictures available in the Spaarnestad[2] collection. The first repository is a Dutch archive of historical chronicles and the second one contains for the largest part press pictures annotated with free text and some labelled entities such as persons and publication date in one XML file. In both algorithms we used the free text annotations to match their correspondent pictures to one textual document. In a first algorithm the PF/Tijah[3] text retrieval software provided a relevance ranking of the annotations to a textual document: the pictures corresponding to the top 5 ranked annotation, provided that they were above a 0.5 threshold, were chosen for the user study. This is a measure of how much a set of pictures are about a certain textual document.

A second, two-step algorithm aimed to incorporate in the 'aboutness' ranking the information available in the textual collection about a picture. First we generated what can be thought of as a picture's representation from the point of view of an external observer, who has complete knowledge of the textual collection. For every picture we extended its annotation with a set of paragraphs from the text collection ranked top 10 by the PF/Tijah software, again provided that they were above a 0.5 threshold, without regard of which particular document they belong to.

A second step is similar to the first algorithm: pictures associated with the top 5 ranked annotations against the complete document collection are considered to match the information contained in a textual document. We invited 4 people, in different extents familiar with the text collection, to participate in a user study. We asked them to arrange a small number of textual documents and pictures, each deemed relevant to the textual document by at least one algorithm, in joint excerpts containing one textual document and at least more than one picture. They have been left free to search with a keyword based search engine onto the

[1] http://www.kha.nl

[2] http://www.spaarnestadphoto.nl

[3] http://dbappl.cs.utwente.nl/pftijah

image repository and compare the quality of the images provided by our two algorithms, discussing the process through which the joint documents were being generated. Because of our assumption on the existence of syntactic and semantic constraints to interpretation, we expected that the two algorithms would trigger different behaviours when employed in a practical search scenario.

As the information in the archive represents a collective effort of many different people, who mediated between issues as different as aesthetic aspects, scientific rigour, economic feasibility or maintenance requirements, we expected that, on average over the different topics and despite of users' different personal backgrounds, one journalist, a historian, a photographer and a member of the Keesings administrative staff, a clear preference for the second algorithm in all sessions would emerge; only this second algorithm was, at least in principle, designed to grasp some contextual features.

3. THE PROBLEM

Users' performances were audio-recorded and analysed. Since methods of investigation depend on prior methodological stances [17] and results on our framing of the user, the importance of making methodological choices accountable should not be underestimated: we selected *practitioner's profiles* [7] as a tool to achieve our goals of putting practical discursive performance centre stage. Interviews with the participants to the user study concentrate on *how* an action is performed rather than on *why*: instead of asking "why are you doing this or that", the interviewer focused on asking "how do you achieve this or that result".

We found that many of these practice narratives exhibited what we termed signposts of experiences: expressions that denote familiarity with a certain topic. "Nobody knows who is he", says one user referring to Brian Epstein when commenting on using a certain picture to illustrate a text about the Beatles, "I believe you want to show that: I can still remember to have seen him cycling" says another user about a very famous Dutch trainer and a not-so-famous professional cyclist himself. Every time we report an occurrence of a signpost we assign a label to the correspondent user: we call 'expert' on a matter a user who speaks out a signpost in agreement with the information that is present in the textual collection; a case of disagreement is labelled as 'non-expert'. It is important to remember that, during analysis these labels simply denote a discursive pattern and the process of inferring users' mental models builds upon it, but it is by no means identified with it. We draw from the same methodological viewpoint, which has already demonstrated its utility in HCI [13], promoting a phenomenological account of social constructions of reality: 'expert' and 'non-expert' are categories in phenomenological sense [11], both a regular pattern of reality and a mental classification at the researcher's side. Actions and discursive evidence were thus mapped to these two categories. We found that 'experts' were showing a preference for the two-steps algorithm while, against also our expectations, 'non-experts' were indifferent to the two algorithms.

Making sense of these tracings of discourse analysis and of the categorisation induced by the two algorithms turned out to be impossible. Data are available to show that users should react differently to the two algorithms, because of the way the algorithms are constructed. Data are also available to show that the categorisation of 'expert' and 'non-expert' corresponds to measured patterns: one can criticise the terms, but must agree on the content, even by assigning more neutral labels such as 'a' and 'b'. We are puzzled by an apparent paradox: we can argue separately in favour of two categorisations, two divisions of the information interaction space, but we cannot explain their combined effect.

Our first reaction was to question the scope of this experiment. Gathering more data or improving our investigation tools leads, so goes the received view, to a secure determination of all the relevant parameters of the cognitive process underlying interpretation. In our case either the algorithms were not grasping any interesting contextual feature, or the collection did not represent a shared knowledge among all our users, or our panel was too limited, or our methods too superficial or some even more dangerous combination of all these factors flawed our judgement. While we recognise that all these issues may have conspired against us and we agree that much more extended experiments may well overturn our results, we suggest that another possibility has been for too long, too easily discounted by information interaction researchers: the possibility that "discourse and actions are not immediately observable at all" [5], that analysis is mediated by a theoretical model and that the validity of a design is only relative to that theoretical model.

4. THE SOLUTION

In this last section we show a positive example in favour of the claim that we can make sense of our results by limiting the scope of our analysis rather than widening it. We take then a step back, recasting this problem in linguistic and cognitive terms in order to find out where we made an unwarranted assumption that generated a paradox.

What we did not justify at any point is why an analysis of the setting of a situation allows a complete understanding of the cognitive process, hence of interpretation in IR: "it is a widespread misconception [...] that social situations and their properties [...] exercise *direct* and unmediated influence on language use" [5]. We can paraphrase this critique: even if improve our investigation techniques, for example exchanging practitioner's profiles for ethnographic or log-data analysis, there is no guarantee that we understand what a user is doing.

Once we recognise this issue, what seemed a puzzle of interpretation of empirical data, becomes a more fundamental and striking impasse. On one side we cannot predict any particular matching from a knowledge, how accurate it may be, of user performance. On the other hand the matchings that are relevant for a task are shared at least within a small community: there is no point in over fitting any algorithm to comply with the requirements of one unique user. Notice that we do not need a cognitive framework to show this particular point: even in a noisy channel account of IR, or for that matters any communication channel, even the most abstract [15], perfect replication of information at the receiver side, that is in IR perfect replication of the information possessed by a knower at the seeker's side, is theoretically untenable: it implies identifying a knower with an information seeker and therefore allowing in our model only users with a perfect knowledge of the system.

There is no hope to resolve this impasse within a cognitive and linguistic model. The subjective construction of interpretation in IR that is modelled as a chain of cognitive state changes during interaction [8] irremediably conflicts with a requirement of any linguistic pragmatics: a totally private use of language must be denied. At a certain point the chain of pragmatic explanations must end [18].

Our suggestion to solve this problem is to adapt an insight from context theory: there are mental interfaces that mediate discursive performance and "what is observably done or said is only the tip of a iceberg of a communicative event" [5]. We also suggest that characterisations of these mental interfaces or context models should be sought within the same community, which users belong to; most often outside computer science. The results we may achieve as computer scientists are therefore sound only with respect to that characterisation.

In our case *remediation* theory, an account of the process "by which new media refashion prior media forms" [6], provides a local solution to the paradox by adding one additional constraint: remediation depends on the existence of a *prior* personal agenda. Those who do not have any background knowledge on the matter at hand, cannot have a personal agenda: interpretation is then based on the information provided by the system at the time the interpretation act is performed. While we witnessed the act of joining different media, only one group, that labelled as 'expert', was performing an act of remediation, because only one group complied with this additional requirement. If we limit the scope of our algorithms to the case of remediation, we then may conclude that the second algorithm performed better. We are not caught into the impasse because we have to accept it as inherent to the process that we want to support as the 'double logic of remediation' [6].

5. CONCLUSIONS

The initial aim of our user study was to develop an application to allow end-users to retrieve joint documents comprising information from two different repositories, one of historical documents and one photo archive. While the cognitive viewpoint in its linguistic interpretation is confirmed as a very powerful approach to design, the key to solve the issues raised by this task is to modify the received notion of context of interpretation: we derive a sharp distinction between social properties of a situation and cognitive processes that unfold during interaction. Interpretation is still "*mediated* by a system of categories or concepts which, for the information-processing device, are a *model* of his *world*" [3, citing De Mey], but a world description, however accurate it may be, is not enough to completely understand this process of mediation. A subjective construction determines the outcome of this communication act.

Working out the consequences of this paradigm shift results in suggesting an alternative design flow for IR applications. Once we abandon a positivistic belief in the direct observability of discourse and action we need other grounds for motivating applications. Once the ideal of investigation methods, which at least in the limit can converge to general solutions is recognised as illusory, researchers are left with a weaker, but more reliable notion: that of a world model as conceptualised by a theory specific to the particular domain which an end-user belongs to. Design should then start with a first, critical step: a choice to employ a domain theory for the particular scenario rooted in the research tradition and in the practice of the domain at hand and engaging its domain specific conceptualisation and even its proper jargon.

6. REFERENCES

[1] B. G. Bara and J. Douthwaite. *Cognitive Pragmatics: The Mental Processes of Communication*. MIT Press, 2010.

[2] N. J. Belkin. Anomalous states of knowledge as a basis for information retrieval/ Etats anomaux des connaissances comme base du repérage de l'information. *The Canadian Journal of Information Science*, 5:133–143, 1980.

[3] N. J. Belkin. The cognitive viewpoint in information science. *J. Inf. Sci.*, 16(1):11–15, 1990.

[4] N. J. Belkin. Some(what) grand challenges for information retrieval. *SIGIR Forum*, 42(1):47–54, 2008.

[5] T. A. v. Dijk. *Society and Discourse: How Social Contexts Influence Text and Talk*. University press, Cambridge, 2009.

[6] A. Erll and A. Rigney. *Mediation, Remediation, and the Dynamics of Cultural Memory*. Walter de Gruyter, 1st edition, 2009.

[7] J. Forester. Exploring urban practice in a democratising society: opportunities, techniques and challenges. *Development of southern Africa*, 23(5), dec 2006.

[8] P. Ingwersen. Cognitive perspectives of information retrieval interaction: elements of a cognitive IR theory. *Journal of Documentation*, 52:3–50, 1996.

[9] P. Ingwersen and K. Järvelin. *The Turn: Integration of Information Seeking and Retrieval in Context*. Springer-Verlag, Secaucus, NJ, USA, 2005.

[10] K. S. Jones. A look back and a look forward. In *SIGIR '88: Proceedings of the 11th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 13–29, New York, NY, USA, 1988. ACM.

[11] K. Kwang-ki and T. Berard. Typification in society and social science: The continuing relevance of Schutz's social phenomenology. *Human Studies*, 32(3):263–289, 2009.

[12] K. B. Ng. The applicability of universal pragmatics in information retrieval interaction: a pilot study. *Inf. Process. Manage.*, 38(2):237–248, 2002.

[13] K. B. Ng. Toward a theoretical framework for understanding the relationship between situated action and planned action models of behavior in information retrieval contexts: contributions from phenomenology. *Inf. Process. Manage.*, 38(5):613–626, 2002.

[14] G. Salton. *Automatic Text Processing: The Transformation, Analysis, and Retrieval of Information by Computer*. Addison-Wesley, 1989.

[15] M. Serres. *Le parasite*. John Hopkins University, London, 1982.

[16] C. Shannon, N. Petigara, and S. Seshasai. A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423, 1948.

[17] T. D. Wilson. Alfred Schutz, phenomenology and research methodology for information behaviour research. In *ISIC 2002*, pages 193–207, Lisbon, Portugal, 2002.

[18] L. Wittgenstein. *Philosophische Untersuchungen - Auf Grundlage der Kritisch-genetischen Edition*, volume 1372. Suhrkamp, Frankfurt a. M., September 1953.

Layered, Adaptive Results: Interaction Concepts for Large, Heterogeneous Data Sets

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ABSTRACT

Some data environments are not well served by current styles of search results presentation. One example of this is large-scale archival, library or museum collections. The range of user goals and interaction needs can be quite broad, and the information itself is highly structured yet very heterogeneous – it spans many subject areas, information types, and presentation/media. Based on the use of semantic web formats for metadata, we believe it is possible to leverage the semantic relationships to drive aspects of results presentation – to change elements of the UI itself in response to the results data. We present these concepts as a catalyst for discussion with the HCIR research community, exploring how semantic structures can support arrangement and components available for refining search results sets, and thus make the interface more responsive to user's goals and needs.

1. INTRODUCTION

Current commercial search tools are primarily instance-driven – they focus the user on specific content items (results lists) and rely on the quality of relevance algorithms to increase the likelihood that information related to a user's goals will be near the top of the results set. While this has successfully addressed some needs in targeted, open world seeking scenarios, limitations have been identified both for exploratory search [1] and in more closed-world situations (e.g. intranets and specific domain searching).

Beyond instance-level lists, facets provide a simple, interactive abstraction of the underlying results set, derived from the attributes of the result instances. However, while they are successful in helping users filter large results sets, they become problematic when the data is very heterogeneous or changes frequently, and thus the available categories for facets are not easily representative of the potential results set. Facet categories can be difficult to establish, and what can be reliably categorized may not map to users' needs.

There are increasing examples of visualization of search results in order to get a meta-level profile of the types of results returned [2, ch.10]. There are also good examples of model-driven interactions with results sets, based on semantic data relationships, where the interaction with the model extends beyond filtering to broader exploration. mSpace[1] and Parallax[2] are two of the best known examples. However, in these cases, the models remain primarily subject-centered, and the UI itself does not adapt to aspects of the model that are mapped to, or present in, the results metadata and content. Fortunately, it's encouraging to see the concept of responsive UIs increasingly discussed in semantic UI and HCIR papers [e.g. 3, 4, 5].

The work described here represents design thinking and data modeling, not yet implementation. Future prototypes and user studies will assess the value of the concepts, identify what metadata refinement is needed, and find performance issues for technical design. In the meantime, this position paper aims to open discussion of the concepts with HCIR researchers.

2. DOMAIN & INFORMATION CONTEXT

The domains where this approach is being considered are not "open world" search domains. Within the archival, library and museum environments, records and artifacts have particular attributes that provide opportunities and challenges [6]:

- Metadata is highly structured, as are hierarchical relationships within sets of information. However, much of this structure is catalog, not subject, related.
- Some subject and entity categorization exists, although often at a higher aggregate level, and it may be inconsistently applied.
- A wide range of subjects can be present in collections, as they come from a wide range of sources.
- Vocabulary changes quite dramatically over time, yet the vocabulary used to describe items must remain appropriate to its period for historical integrity. Classification schemes that aim to capture this vocabulary can become huge themselves, with millions of terms in the most used schemes.
- Not all materials are equally indexable for search – collections include handwritten text, scanned photographs, drawings, encoding-rich databases, statistical data, legalese, and lots of redundant content.
- User needs (and familiarity with archival/research techniques) vary quite widely, from researching all aspects of detailed subjects that span dozens (or hundreds) of years, to finding single specific documents relating to individual personal ancestors.

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[1] http://mspace.fm
[2] http://www.freebase.com/labs/parallax/

While such collections are not open-world, they can't be considered entirely closed world, either. Useful collections from one institution are often cross-referenced and incorporated with specific materials from other sources. Increasing use of shared ontologies and standard classification schemes (such as the Library of Congress Subject Headings[3]) aim to support cross-collection research and search federation. One might consider this a "porous world" scenario for IR purposes.

3. DESIGN DRIVERS IN THE DATA

It is important to identify metadata and classification elements that will provide sufficient leverage to support relevance and usability, and still be consistently available (and reliable) across a wide and rapidly-growing data environment. While the specific leverage elements will be different in various domains and collections, there are a few key "drivers" that appear to be most useful when identifying interaction approaches in the archival environment. The design concepts presented in this paper have focused on:

- **Quantity:** The number of results returned (overall and by type), and balance of attributes in results.
- **User context:** Their search "perspective" (focus on particular content object types), and motivation (depth, breadth, duration of research).
- **Structure:** The relationships between objects (hierarchy of objects and their aggregate descriptions), and object types that can be mapped to interaction components.
- **Subject alignment:** The degree of consistency or variance in returned results.

4. APPROACH

Layering deals with arranging UI components based on the quantity of results, particularly for result sets with strong structure or where large volumes of data are associated with particular terms (searching for things related to "John Kennedy" and "Nuclear" returns large numbers of records for the US President, the aircraft carrier, the space center, along with other non-related records).

Layering aggregates related items so users can survey the results set overall, in order to assess alignment with their expectations/goals. They then progressively explore details from within related sets, as well as remove less relevant sets. It also exploits the blending of search and browse actions over time.

Adaptive aspects of the UI provide users with appropriate controls for the attributes of the results they are exploring at any one time, as well as aligning the UI to their personal situation.

The mix of layering and adaptive approaches may also make the application more scalable over time, because collections could be searchable with less of curators' item-level preparation time.

5. LAYERING

There are two aspects being explored for UI layering: *result item layering* (responding to the structure in results, such as parent-child instances, by collapsing sets of related results), and *containership layering* (responding to quantity of results by organizing information into object type sets).

[3] http://id.loc.gov/

5.1 Result Item Layering

Imagine that a search result set includes 5,000 photographs based on the work of three photographers, as well as individual record-level results from ten databases that return over 1,000 items each. Because of the structure of the metadata, those 15,000 "results" will flood the list, and typical facet categorization will not adequately narrow such similarly-described items. Rather than flat lists of individual instances, a hierarchical representation could look like this:

Figure 1: Layered result with relevant item sets presented together

As the user explores the hierarchal data set, increasingly specific refinement can be available, since the data set is increasingly homogeneous and smaller.

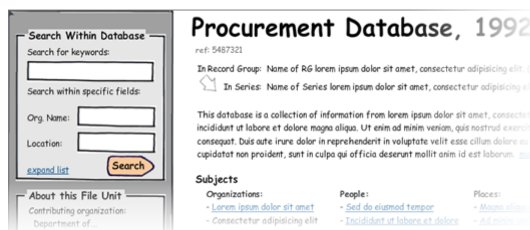

Figure 2: Content display includes "search within" relevance

The underlying semantic model that would be leveraged by the search application would need to look something like this:

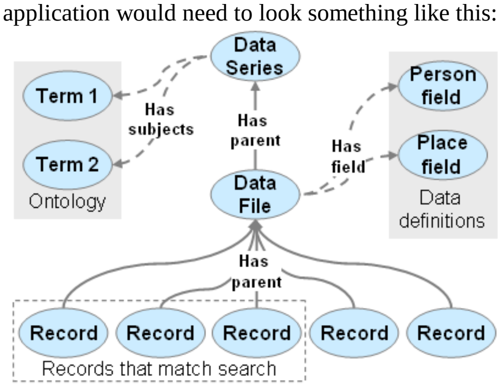

Figure 3: Hierarchy relationship models, with field maps

5.2 Containership Layering

As noted earlier, a search for "John Kennedy" will produce results for a large number of individuals, including the President and his son. It will also include many things named after the President, such as the aircraft carrier, library, performing arts center, space center, and many schools.

The concept of containership layering is to take strong type attributes and use them as a primary grouping mechanism. In small result sets, this can be presented as a primary facet, but as the result set grows the containers can be used differently.

Across many public collections, there is a strong attribute set that may be useful: Organization, Person, Place, Event, Subject. If we consider using these to distinguish particular classes of results, we gain significant leverage in the UI. For example, consider our example search for “John Kennedy,” with increasing results:

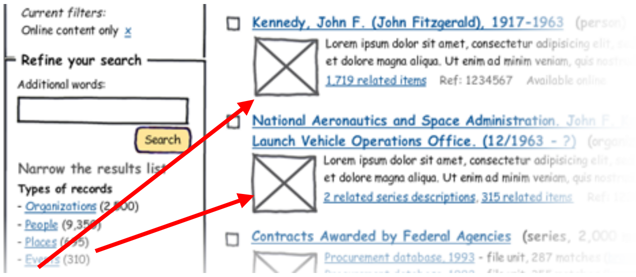

Figure 4: Simple results can use a common facet for a small number of items

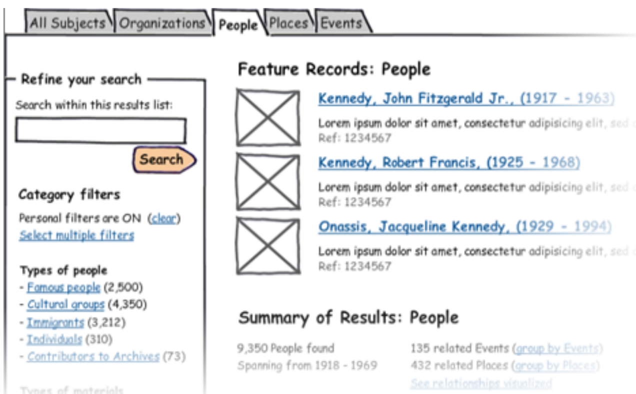

Figure 5: Layered search result, exploiting types as tabs to allow more refinement within focused subsets of results

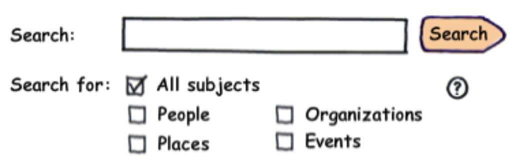

Figure 6: Simple user input as start of search can direct user to the most relevant tab by default

The same effect can help with searching databases, where a large number of results can be returned. For example, searching a large database for “James West” can produce numerous results that include “West Virginia.” It is not practical for curators to map every field and value, then design a model that disambiguates every possible term in a user’s search, but greater disambiguation could be possible from a layered UI – person-related results could flow into the Person tab, where location-related results could appear in the Places tab. An ontology that drives the metadata catalog for the database could help a curator map important specific fields when preparing the content:

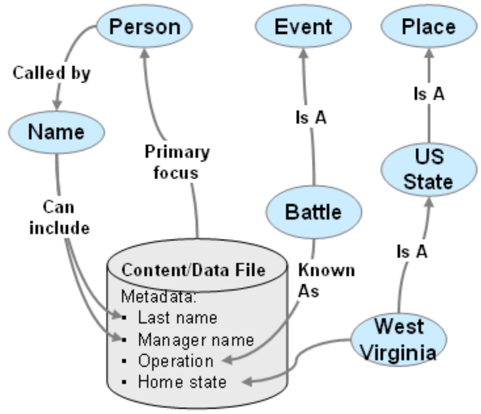

Figure 7: Basic semantic relationships can define containers

6. ADAPTIVE COMPONENTS

The main aspects of adaptive component selection currently being explored are *type-specific interactions* (providing widgets that work on particular data types, like maps and timelines), *quantity-driven interactions* (adding summarization and visualization as quantities of results increase), and *user data management* capabilities (controls for saving, annotating, relating, and organizing personal research activities – this type of adaptivity could also include user view customization).

6.1 Type-Specific Interactions

As part of the use of containership layering, the tab layers offer the benefit of more screen real estate that can be focused on any particular type of result. For example, the John Kennedy “Events” tab could show a timeline of major events to help users focus on particular events or time periods.

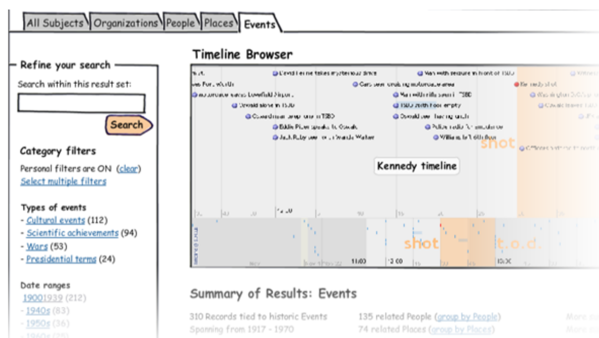

Figure 8: Timeline component mapped to "event" type data

The events on the timeline could be pulled from an ontology, rather than facet/instance data, allowing the events in the timeline to interact with other filters and data applied by users.

In the example of “Person” data, a network diagram (drawn from the underlying RDF graph) could be used to illustrate family relationships between results of prominent/famous people (where such data maps exist in the ontology or name/subject thesaurus).

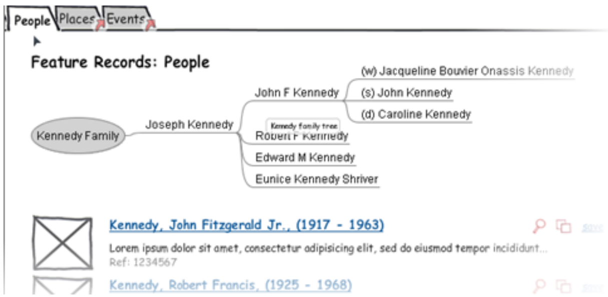

Figure 9: Relationship tree component for "person" type

6.2 Quantity-Driven Interactions

The more potentially relevant information the user needs to sort through and evaluate, the greater the need for different ways of controlling initial search results. Levels of abstraction can help a user identify characteristics (patterns) in the results, including:

- How homogeneous or heterogeneous the result set
- Whether there are clusters or dominant subject areas
- What filters could offer the greatest refinement value

Some of the representations we consider include thesauri maps to provide additional refinement (narrowing or broadening) and visualizations (to support actions like attenuating certain clusters of results, and making sure outliers do not get overlooked).

6.3 User Data Management Capabilities

In section 3, user motivation was mentioned as a driver. For example, a user's expectations are very different when taking 5-10 minutes to look up a photo for a junior high school book report than taking months to research photo composition techniques and subjects for a commercial historical reference book. In these examples, users have said they would value differences in the "directness" of the UI and the level of supporting capabilities available. One idea being explored allows the "motivation" preference to be stated by the user as part of the initial search entry. For multi-session searching, this could even be stored as a default preference in the user's profile.

Another approach is to provide users with options to add useful components and tools for more exploratory or research tasks. These choices could be saved as part of user preferences, and turned off (at least temporarily) when the user's situation is different. For example, the accordion display and editing/control buttons for account holders on the Footnote.com site, when viewing detailed records, is an example of useful additional tools for regular users when doing research.

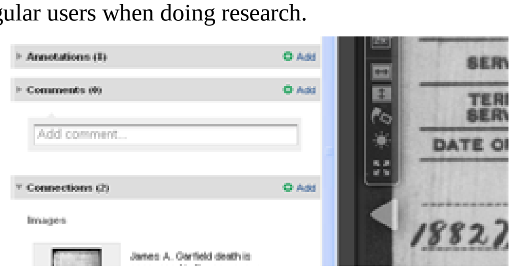

Figure 10: User data entry space and image manipulation controls available via show/hide; www.Footnote.com

The application should also respond differently when faced with different environment variables, such as when used on a mobile device or with an active screen reader employed by a blind user. The more complex the search results controls and representations become, the more they need to be responsive to the device or other environmental conditions brought by each user.

7. CONCLUSION

The layering and adaptive ideas described in this paper are the outcome of exploring user tasks, behaviors, and the particular data relationships found in archival, library or museum environments. Exploring these ideas with the HCIR community helps us consider effects and challenges with various approaches.

The increasing use of semantic web formats in the tools and data make it possible to provide a more dynamic, relevant user experience. Designing UIs based on models that support the user, rather than increase a user's cognitive load, is an important and challenging task. Using the relationship models inherent in the semantics to drive the way the interface itself is presented need to be explored and discussed, in order to overcome some issues with existing results interfaces when faced with large, heterogeneous, and changing data environments.

8. REFERENCES

[1] White, et al. (2006). Supporting exploratory search. Special issue of *Communications of the ACM*. Volume 49, Issue 4, April 2006. http://doi.acm.org/10.1145/1121949.1121978.

[2] Hearst, Marti (2009). *Search User Interfaces*. New York, NY, Cambridge University Press. http://searchuserinterfaces.com/.

[3] Dickinson, Ian (2009). In Favour of (more) Intelligence in the Semantic UI. *Proceedings of the Sixth International Workshop on Semantic Web User Interaction*. Oct 25, 2009. http://ceur-ws.org/Vol-544/dickinson_swui2009.pdf

[4] Dix, Alan, et al., (2010). From the web of data to a world of action. *Web Semantics: Science, Services and Agents on the World Wide Web*, In Press, online May, 5 2010. ISSN 1570-8268, DOI: 10.1016/j.websem.2010.04.007. http://www.sciencedirect.com/science/article/B758F-50106XC-1/2/5c0476c1c3ca9b99df06810ab1f0d17d.

[5] Huynh, David (2009). Freebase Cubed: Text-based Collection Queries for Large, Richly Interconnected Data Sets. In *Proceedings of the Third Workshop on Human-Computer Interaction and Information Retrieval*. October 23, 2009. http://cuaslis.org/hcir2009.

[6] Degler, Duane (2009). Case Study: Archival Information. Prepared for *SWUI 2009: Sharing Ideas for Complex Problems in User Interaction, the Sixth International Workshop on Semantic Web User Interaction*. Oct 25, 2009. http://swui.webscience.org/SWUI2009/archival-casestudy/.

Revisiting Exploratory Search from the HCI Perspective

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ABSTRACT

In this paper, we revisit the definition of Exploratory Search tasks after 4 years of contributions from the Information Seeking and Retrieval community. We consolidate the factors that influence an exploratory search task: objective, search activities, conceptual complexity, and procedural complexity, and introduce a new factor: domain knowledge. We hypothesize that, in order to support Exploratory Search tasks efficiently, we must consider all the factors from an HCI perspective.

1. INTRODUCTION

The concept of a search task is a core component of the Information Science and Retrieval field. Many researchers have distinguished search tasks into two distinct bins: known-item and exploratory search tasks. Despite this binary classification, all search tasks can be seen as being exploratory to some degree [18], and we see that exploratory search tasks can comprise elements of known-item searching. A number of researchers have associated known-item and exploratory search tasks with distinct kinds of search behaviors and activities such as navigation, fact retrieval, learning and investigating [4, 7, 12, 13]. In instances where the searcher is able to adequately specify their information need, we can categorize this type of search as look-up or known-item because of their well-defined information need, and their search task only needing a look-up of a known piece of information. Other researchers have referred to this category as closed tasks [12], information processing tasks [4], simple tasks [5], and specific tasks [15].

The other category of search task, which will be the focus of this paper, is usually motivated by a poor understanding of the search topic, and goes beyond simple fact retrieval. The Information Science and Retrieval community has loosely defined exploratory search tasks as an open-ended, ill-defined and multi-faceted search problem that seeks to foster some knowledge product, or inform some action [13, 14, 18]. Exploratory search tasks are typically detectable from a searcher's:

- Poor familiarity with the domain of their search goal;
- Uncertainty of their search goal;
- Uncertainty in the manner to achieve their goal [19].

Exploratory search tasks are not a new phenomenon by any stretch; they have been referred to by different labels in the last 30 years. Prior to Marchionini's seminal paper on exploratory search [13], this category of search tasks has been referred to as: subject searches [9, 16], general tasks [5, 15], decision tasks [4], and open-ended tasks [12], but they all essentially refer to the same construct.

A number of works has discussed exploratory search tasks from different angles: Byström & Järvelin [4] and Bell and Ruthven [2] discussed it in relation to complexity and uncertainty; Marchionini [13] described the activities involved distinguishing exploratory search tasks from known-item search tasks; Aula and Russell [1] described it according to the number of actions involved; and Kim and Soergel [10], and White and Roth [18] discussed the inherent sensemaking involved, and Kang et al. [8] have discussed the role of domain knowledge and expertise. In this paper, we revisit the existing definition of exploratory search tasks, and put forward a revised explanation, and finally a few ways taking a HCI perspective can address some of the difficulties experienced by exploratory searchers. In section 2, we discuss some of the attributes of exploratory search tasks; in section 3 present a revised definition; in section 4, we bring to attention an overlooked factor in exploratory search tasks; in section 5, we describe how taking a HCI perspective can support exploratory searching; and finally, in section 6 we summarize our work.

2. DEFINING EXPLORATORY SEARCH

Considerable progress has been made in identifying and studying exploratory search tasks by the Information Science and Retrieval community. The body of work describing exploratory search tasks has used factors such as complexity, uncertainty, search objective, motivation, task product, and activities as dimensions to describe them [3, 4, 12, 13, 14]. The factors we discuss below are the most objective and descriptive elements we found in our review, and on occasions we have subsumed factors that greatly overlap.

2.1 Search Objective

The objective of any exploratory search task is typically to create a knowledge product or shape an action through searching, browsing, learning and investigation. Exploratory search tasks are usually abstract, open-ended and multifaceted search problems, where the target information can be poorly-defined [13, 18]. The onus of an exploratory search task is more on the journey the searcher takes to find the required information, rather than the information per se.

2.2 Search Activities

Exploratory search tasks are associated with higher-level search activities like analysis, comparison, comprehension and evaluation as well as more undirected search behaviors like exploratory browsing[1]. There is also a strong element of sensemaking and learning inherent in exploratory search tasks, and according to Marchionini's model of exploratory search tasks [13], these are **core** activities of exploratory search tasks. White and Roth [18] have discussed how more undirected exploratory search behaviors such as exploratory browsing happen in

[1] Though more high-level search activities are associated with exploratory search tasks, directed search activities like look-up are an important part of exploratory search tasks.

conjunction with focused and directed search behaviors like look-up searching.

Exploratory browsing plays an important role in exploratory search tasks: it enables searchers to resolve uncertainty during their search. White and Roth noted this to be a defining characteristic of exploratory search tasks, and ascribe this to the searcher becoming familiar with their search problem and information space [18]. This familiarity with the domain and information space enables the searcher to move further along in their search task, and move from exploratory browsing to more directed and focused searching. But, given the dynamic nature of exploratory search tasks, searchers tend to digress between browsing and searching.

2.3 Conceptual Complexity

The concept of complexity has been described at length by Byström and Järvelin [4] and Bell & Ruthven [2]. Byström and Järvelin have categorized tasks based on *a priori determinability*, or how much of the task's requirements, process and outcomes can be determined beforehand. This is similar to Kuhlthau's concept of uncertainty, where in her work on longitudinal searching [11] she showed that uncertainty decreases with understanding. The uncertainty surrounding exploratory search tasks can be a result of the problem context being under-defined, or the difficulty and complexity of the search task. Byström and Järvelin correlated an increase in uncertainty with the search task becoming more complex and difficult. It is widely accepted that well-defined search tasks like known-item searches have a high level of *a priori determinability* because the searcher is able to determine what information is needed and how they should go about finding it. Whereas for more complex tasks like exploratory search tasks, these factors cannot be *a priori determined* because of the dynamic and transient nature of the searcher's perceived information need and understanding of the problem context. Their uncertainty of the domain and search goal makes the process of searching, browsing and learning undirected to a degree. This has not only been shown to affect the complexity of the search task, and the searcher's information seeking behavior [4], but also increases the uncertainty of the task.

2.4 Procedural Complexity

Complexity has also been used by Aula & Russell [1] to describe search tasks. However, there is a semantic difference in their definition, Aula and Russell [1] denote the number of subtasks and steps involved in a search task, whereas Byström and Järvelin's and Bell and Ruthven's definition refers to the conceptual complexity related to the search task, such as how complex is it to determine the task requirements. Both these definitions of complexity are valid and important in understanding exploratory search tasks, but for clarification we need to delineate these different constructs, and understand the differences between these two perspectives on complexity. To illustrate this point, a search task requiring a searcher to identify CHI best papers for the last 10 years is clear and conceptually very straightforward, but as this search task has a number of steps, it is procedurally complex.

2.5 Other Attributes

Li and Belkin [14] have collated a comprehensive list of attributes and facets to describe everyday tasks from various studies in Information Science and Retrieval. Their classification provides ample description, but for the purposes of this work some of the facets are redundant, and the search tasks can be better conceptualized by only using a core subset to describe them. For example, attributes relating to the duration, importance and urgency of a task are not considered as core attributes to describe a search task, as we believe these factors do not change the nature of the search task, and whether it is exploratory or not. Our focus has primarily been objective factors such as search motivation and search activities. In the literature, subjective factors such as domain knowledge and search expertise have been overlooked, and excluded in the discussion of exploratory search tasks. These factors play an important role, and affect how information is discovered [8] and how complex a search task is perceived [6, 14, 18].

2.6 Examples of Search Tasks

So far, we have discussed the characteristics that distinguish exploratory tasks; we next provide an example and contrast it with a known-item search task to illustrate these differences.

For the known-item task, searchers would need to identify information to complete the task. In this search task, there is very little uncertainty concerning the information the searcher is looking for, and as it is well-defined they would be able to formulate a definitive judgment on whether they have completed their task or not. In comparison, the exploratory search task requires the user to initially learn about the search topic, and then formulate a decision based on self-defined relevance criteria. This task is not only more difficult and open, but also more engaging, less well-defined, and requires more *a priori* information to be known. The onus therefore is on the searcher to formulate an understanding, and analyze and investigate the information.

Known-item task
Identify three Voice over Internet Protocol (VoIP) telephone services.

Exploratory task
You are considering purchasing a Voice over Internet Protocol (VoIP) telephone. You want to learn more about VoIP technology and providers that offer the service, and select the provider and telephone that best suits you.

Figure 1: An example of known-item and exploratory search tasks.

3. A REVISED DEFINITION

Based on our survey of the literature, we can define exploratory search tasks involving:

- ✓ **Objective:** The purpose of which is to inform a decision or produce some new knowledge;
- ✓ **Search Activities:** Which must involve an element of learning, investigation and discovery;
- ✓ **Conceptual Complexity:** The search steps and target information can be vague;
- ✓ **Procedural Complexity:** The search task must involve a number of search actions;

If we revisit the exploratory search task described above, in light of our criteria for exploratory search tasks, we see that the above example does satisfy these criteria:

- ✓ **Objective:** The intention of the search task is to select a VoIP telephone;
- ✓ **Search Activities:** Learning and investigating is integral to this search task in order to select an appropriate service;
- ✓ **Conceptual Complexity:** How to go about looking for the information, or specific services are unknown;
- ✓ **Procedural Complexity:** The search task requires comparison of several services;

However, if any of these criteria are unmet, this can change the nature of the search task, and can potentially affect which category of search tasks it belongs to. For example, if the search task fails to comprise search activities like learning and investigating, this would mean the search activities for this search task are no longer high-level, and only involve look-up type search behaviours. Because of the absence of higher-level search behaviours, the search task can fall into the known-item search task category.

It should be noted that some factors are more critical to helping us classify a search task than others, for example the procedural and conceptual complexities involved: these criteria only really affect how complex and difficult a search task is perceived, and regardless of whether a search task is more or less procedurally or conceptually complex, it is not critical to defining whether a search task is exploratory or not.

The above criteria are adequate to help us exploratory search tasks based on their description. But, our criteria overlook two very important factors: the searcher's domain knowledge and expertise. As discussed by [8, 6, 17], a searcher's domain knowledge of a search task, and their search expertise can affect how they search and look for information.

4. THE ROLE OF DOMAIN KNOWLEDGE

The role domain knowledge plays in affecting the extent to which a search task is exploratory has received less attention than the factors already mentioned. If we revisit our definition, if a search task involves exploratory search behaviours such as exploration, analysis and synthesis of information, these essentially can be transformed into lower level search behaviours such as look-up and navigation in circumstances when the searcher is familiar with the search topic and has a certain amount of *a priori determinable* knowledge of the information they need for the task. Using the above example of an exploratory search task, what makes this search task exploratory is the search activities involved i.e.:

- Learn
- Explore
- Investigate

This search task is considered exploratory in its current form, but if the searcher has knowledge of VoIP technologies and services, the conceptual and procedural complexity of the search task is reduced. What is also interesting is the search activities that need to be undertaken by the searcher are downgraded from exploration and investigation to look-up. So for a searcher with knowledge in this domain, the search task might look like this:

- What are a few VoIP services
- Which service provides the best quality of service?

Figure 2: What an exploratory search task might look like to a domain expert.

As a result of the searcher's familiarity and knowledge of the domain, the need to learn about VoIP technologies and services is no longer there; instead, they undertake more focused searching. Conversely, for a searcher with little or no domain knowledge in this area, we can expect their search behaviors to include learning, investigating and analysis.

5. HOW HCI CAN HELP

To be able to properly support exploratory searchers, we hypothesize that we need to identify and address each of these four factors from an HCI perspective. It should be the aim to improve the knowledge or search skills of the user, where prior research has shown that both reduces the exploratory nature of the task [19].

5.1 Objectives

Many systems try to help the user identify their needs, by suggesting popular query refinements, for example, or providing auto-completion at query time. Much of the time, systems make assumptions about whether the user is searching broadly or narrowly, and varies the way it presents results. It may perhaps be useful to make these assumptions more transparent in the user interface, and applying the principles of interactive feedback to the objectives the system thinks the user has. If the user is looking to learn about VoIP technology, then the system may present itself differently than when the user is actively deciding on the right service to purchase.

5.2 Search Activities

Many systems try to support users in discovery, especially online retailers that recommend what other customers have also bought. The nature of exploratory search, however, is often improved by understanding. As understanding goes beyond knowledge to knowing the limitations or the counter arguments to knowledge, we believe it may be possible to help users build understanding from the facts presented in a system, where comparison tools, for example, go some way to showing the advantages and disadvantages of different options.

5.3 Conceptual Complexity

Conceptual complexity is perhaps most affected by domain knowledge, where systems should try to introduce users to the factors that are relevant in a domain. Faceted interfaces go some way towards doing this by presenting the types of metadata that are relevant to a current search. eBay, for example, displays different facets depending on the type of product being browsed. Some of our recent work proposed that the interconnectivity displayed in facets may help users in sensemaking [20]. While the search activities above should be oriented towards helping users work within the domain, supporting conceptual complexity involves bringing users up to speed on what they should work on.

5.4 Procedural Complexity

Procedural complexity is the factor that is perhaps most suitably approached by HCI. Procedural complexity can be dramatically reduced by the search functionality provided by the user interface.

A service that provides an easy comparison service for VoIP technology dramatically reduces the task of comparing options. Performing this service directly with a search engine, however, involves many iterative and repeated result viewing, perhaps within multiple tabs.

6. SUMMARY

In this paper, we have put forward a definition of exploratory search tasks that takes into consideration objective and subjective factors. Objective factors like the objective and search activities of a search task determine the category a search task is assigned to. We have discussed how the conceptual and procedural complexity makes a search task more or less difficult, and challenging to undertake. We have also brought to attention subjective factors such as domain knowledge and search expertise which can affect the search activities undertaken by a searcher, and thus how "exploratory" the search task is perceived.

We believe that all four factors identified in our review of exploratory search tasks have to be addressed independently within an exploratory search user interface in order to support searchers effectively. Reduced knowledge of any one of these attributes can turn a normal search task into an exploratory one. We have presented initial ideas for addressing these factors from an HCI perspective and plan to explore these further in the future.

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7. REFERENCES

[1] Aula, A., & Russell, D.M. (2008). Complex and Exploratory Web Search. ISSS: Information Seeking Support Systems Workshop, 23-24.

[2] Bell, D. J., & Ruthven I. (2004). Searcher's Assessments of Task Complexity for Web Searching. ECIR 2004: 57-71

[3] Byström, K., & Hansen, P. (2002). Work tasks as units for analysis in information seeking and retrieval studies. Proc. of the fourth international conference on conceptions of library and information science.

[4] Byström, K., & Järvelin, K. (1995). Task complexity affects information seeking and use. Info. Processing & Management, 31, 191–213.

[5] Campbell, D. J. (1988). Task complexity: A review and analysis. Academy of Management Review, 13(1), 40–52.

[6] Hsieh-Yee, I. (1993). Effects of search experience and subject knowledge on the search tactics of novice and experienced searchers. Journal of ASIS 44(3), 161–174.

[7] Ingwersen, P., & Järvelin, K. (2005). The turn: Integration of information seeking and retrieval in context. Dortrecht, NL: Springer.

[8] Kang, R., Fu, W.-T., & Kannampallil, T. G., (2010) Exploiting knowledge-in-the-head and knowledge-in-the-social-web: effects of domain expertise on exploratory search in individual and social search environments. CHI 2010: 393-402

[9] Kim, K.-S., & Allen, B. (2000). Cognitive and task influences on web searching behavior. Journal of ASIST, 53(2), 109–119.

[10] Kim, S., & Soergel, D. (2005). Selecting and measuring taskcharacteristics as independent variables. Proc. ASIST, 42, Information Today, Medford, NJ.

[11] Kuhlthau, C.C. (1994). Seeking meaning: a process approach to library and information services. Norwood, NJ: Ablex Publishing, 1994.

[12] Marchionini, G. (1989). Information seeking strategies of novices using a full-text electronic encyclopedia. Journal of ASIS, 40(1), 54–66.

[13] Marchionini, G. Exploratory search: From finding to understanding. CACM, 49(4):41–46, 2006

[14] Li, Y., & Belkin, N. J. (2008). A faceted approach to conceptualizing tasks in information seeking. Inf. Process. Manage., 44(6):1822–1837, 2008.

[15] Qiu, L. (1993). Analytical searching vs. browsing in hypertext information retrieval systems. Canadian Journal of Info. and Library Science, 18(4), 1–13.

[16] Walker, G., & Janes, J. (1999). Online retrieval: A dialogue of theory and practice (2nd ed.). Englewood, CO: Libraries Unlimited.

[17] White, R. W., Dumais, S. T., & Teevan, J. (2009). Characterizing the influence of domain expertise on web search behavior. WSDM 2009: 132-141

[18] White, R. W., & Roth, R. (2009) Exploratory Search: Beyond the Query-Response Paradigm, In Morgan & Claypool Series on Information Concepts, Retrieval, and Services.

[19] Wilson, M. L. (2009) An Analytical Inspection Framework for Evaluating the Search Tactics and User Profiles Supported by Information Seeking Interfaces. PhD Thesis, University of Southampton.

[20] Wilson, M. L. & schraefel, m. c. (2009) The Importance of Conveying Inter-Facet Relationships for Making Sense of Unfamiliar Domains. In: *CHI2009 Workshop on Sensemaking*, 2009

Supporting Task with Information Appliances: Taxonomy of Needs

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ABSTRACT
Integrating search systems with task environments to create task-specific information appliances will most likely represent the next wave of technologies. At present, search systems are for the most part isolated from the actual task environment. In this paper we have identified one task environment – that of the student writing a term paper – to propose sets of needs that should to be supported by tools. In addition, the process of completing the task illustrates how search needs change in level of specificity over the life of the task.

Categories and Subject Descriptors
H.3.3 [**Information Search and Retrieval**]: Search Process

General Terms
Design, Human Factors.

Keywords
Task, Information Appliance.

1. INTRODUCTION
As search engine giants such as Yahoo, Google, and Bing fight for market share, their search interfaces are moving away from the original simplicity of the search interface popularized by Google to offer more enhanced search options for users (e.g., filtering, visualizations). However, they still strive to meet the demands of the masses with a "one size fits all" interface and in doing so fail to address the specific, contextual, task-based needs of their users. Essentially, what is missing from the current search engine landscape are task-specific information appliances that embed search as a core function.

The term "information appliance," coined by Raskin in 1978, and popularized by Norman in 1998, is defined as "an appliance specializing in information…designed to support a specific activity" [2]. Information appliances are task-specific tools that support the varied cognitive processes involved in the execution of complex tasks such as patent writing, thesis topic development, environmental decision making and project management. Just as technologies such as the telescope have enabled us to extend our perceptual capacity to make discoveries and cutting edge creativity tools hold the promise of extending our creative abilities [6], information appliances have the potential to support knowledge work in all its stages from idea to outcome, supporting the work *flow* rather than isolated components of the work task.

Norman suggests that "making a proper information appliance has two requirements: the tool must fit the task and there must be universal communication and sharing" [2]. The system needs to integrate multiple activities to support the task as a whole [5]. Search is linked to task-centric processes; yet search is rarely fully integrated as exemplified by the way it is currently included in word processing and email applications. Perhaps the better implementations are within task-centric applications for travel and shopping that support highly structured tasks with very specific goals and known outcomes. However, with student term paper writing, for example, the topic may not be known and the outcome may be only known by its format rather than its content. One of the few to note the close intertwining of search with task was Vakkari [7,8,9] who additionally observed that students needed better support during the various stages of writing a thesis proposal.

Taking but one example from the pool of many task options, how can we support the student who is writing a term paper? In this paper we will outline the processes undertaken by students while writing a paper and illustrate how these processes map to functions and tools needed in an information appliance to support the student writing task.

2. Understanding the Problem
Kuhlthau's [1] model of the search process and Vakkari's [7,8,9] enrichment of the model form the basis for our description of the task which interweaves the search for information with the act of writing a term paper (see column B of Fig 1). Kuhlthau identified six phases of the information search process: 1) task initiation, 2) topic selection, 3) prefocus exploration, 4) focus formulation, 5) information collection and 6) search closure. Each of these phases needs a variety of tools so that the student gets to the final phase. While Kuhlthau stopped at search closure, Vakkari extends it to presentation; the task is not complete and a more iterative process will ensue that

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involves checking and re-finding information sources before the job is done.

Within the task process phases different types of information exploration occur that map to Marchionini's [3] look-up, learn, and investigate (see column A of Fig 1). Look-up encompasses a goal-driven search that may include fact retrieval and retrieval of a known item; learn activities include knowledge acquisition and comparison when the intent is likely to be less specifically defined; and investigate comprises analysis, discovery, and exclusion or negation. These three types of search tasks overlap: look-up activities may be embedded, for example, in learn and investigate activities. Each of the stages in the process will likely have a primary intent, with the other two forming a secondary or tertiary intent. For example, while the primary intent of the prefocus exploration phase is to learn about a topic, this stage may also include look-up and investigate activities. The process moves along a continuum from browse to search.

At the same time, within each phase, a series of needs occur that involve how the user interacts with the information at that stage in the process. Ideally, these needs will be met before the user progresses to the next stage. Those represented in column C (Fig 1) were devised from an earlier work conducted by speculating on the types of tools that are required to facilitate browsing [4]. The list is not meant to be complete but is suggestive; it indicates the types of tools that are required to *use* information. For example, at the prefocus exploration phase when the user is attempting to generate an understanding of the topic, there is a need to define or explain concepts, make connections among a set of information objects, and initiate some organization of the material as the topic unfolds. These are primarily cognitive activities performed by a user, but these are also activities that could be supported by technology.

Column D of Figure 1 identifies a sample of some of the tools that exist today, some of which may support some of the identified needs.

3. Mapping Tools to Process and Needs

To illuminate what an information appliance should be capable of supporting, we examined each phase of the task process, elaborating on the needs at each stage, as well as the types of information search and retrieval that are implicit to each. Figure 1 illustrates the relationships.

3.1 Topic Selection

During the *topic selection* phase, students identify the area and likely scope of the task – they are generating ideas. During this phase, students primarily engage in investigative searches to plan and forecast possible topics and interests. Investigative searches are iterative [3], and learning and look-up searches will be embedded in the process as students expand their knowledgebase and interests.

At this point, students make connections between their knowledge of the topic and the information encountered. Connections allow students to view information objects or topic areas that they may not have known were related; these may be more comprehendible in a visual form. Similarly, suggestions, which provide alternatives based on differing starting assumptions, may augment the available knowledge.

Both Vakkari [8] and Kuhlthau [1] suggest that consulting with mentors is a common strategy during topic selection. Collaboration enables information sharing and communication among students. The ability to discuss potential topics with colleagues can provide insight into which topics have been sufficiently covered and which areas require further exploration. Connected to the function of collaborative tools are discrimination tools which distinguish between desirable and undesirable areas of exploration.

At this point, other needs such as definition rendered by a dictionary define specific terms and how they are used while explanation elaborates on a definition [4], not unlike the role that Wikipedia performs at present. Similarly, simplification, a tool which minimizes complexity in a large body of information [4] can extract core elements that relate to a topic assisting the student in developing a comprehension of the area and additionally highlighting which sources will provide more general information. Students may also benefit from tools that allow them to organize and personalize their information space.

3.2 Prefocus Exploration

Prefocus exploration is conducted when students are attempting to select a focus within their chosen topic. Often, several possible foci will be weighted and decided upon based on personal interest, information available, and relevance to the assignment. Because subject knowledge is minimal, students need general background and theoretical information to move beyond this phase [8]. In order to retrieve general information, students are primarily engaged in learning types of searches for "knowledge acquisition, comprehension of concepts or skills, interpretation of ideas, and comparisons or aggregations of data and concepts" [3]. However, students exhibit difficulty conducting these searches because their limited subject knowledge hinders their ability to express their information needs [7,8]. During this stage students are more likely to have difficulty selecting the appropriate vocabulary and are less able to express their information needs through querying [7,8].

Once students obtain a basic conceptual model of their topic, prefocus exploration can be facilitated by functions which help them gain a deeper understanding of their topic. Various perspectives help students identify information that may come from many different viewpoints [4], and encourage them to think critically about the topic. Similarly, tools that encourage stimulation, divergence, promote idea generation, and enhance students' overall intellectual experience [4] would contribute to the development and refinement of students' mental models. As students' conceptual models of the topics mature, their topical vocabulary grows, and their ability to construct effective queries will develop. The result of this is an increased ability to identify and extract relevant and pertinent information sources [1,9].

3.3 Focus Formulation

During the *focus formulation* phase, students have a greater understanding of their topic and are ready to narrow their focus from a selection of the themes and information they encountered during the prefocus exploration phase. Students often review notes taken while exploring the topic to identify and combine

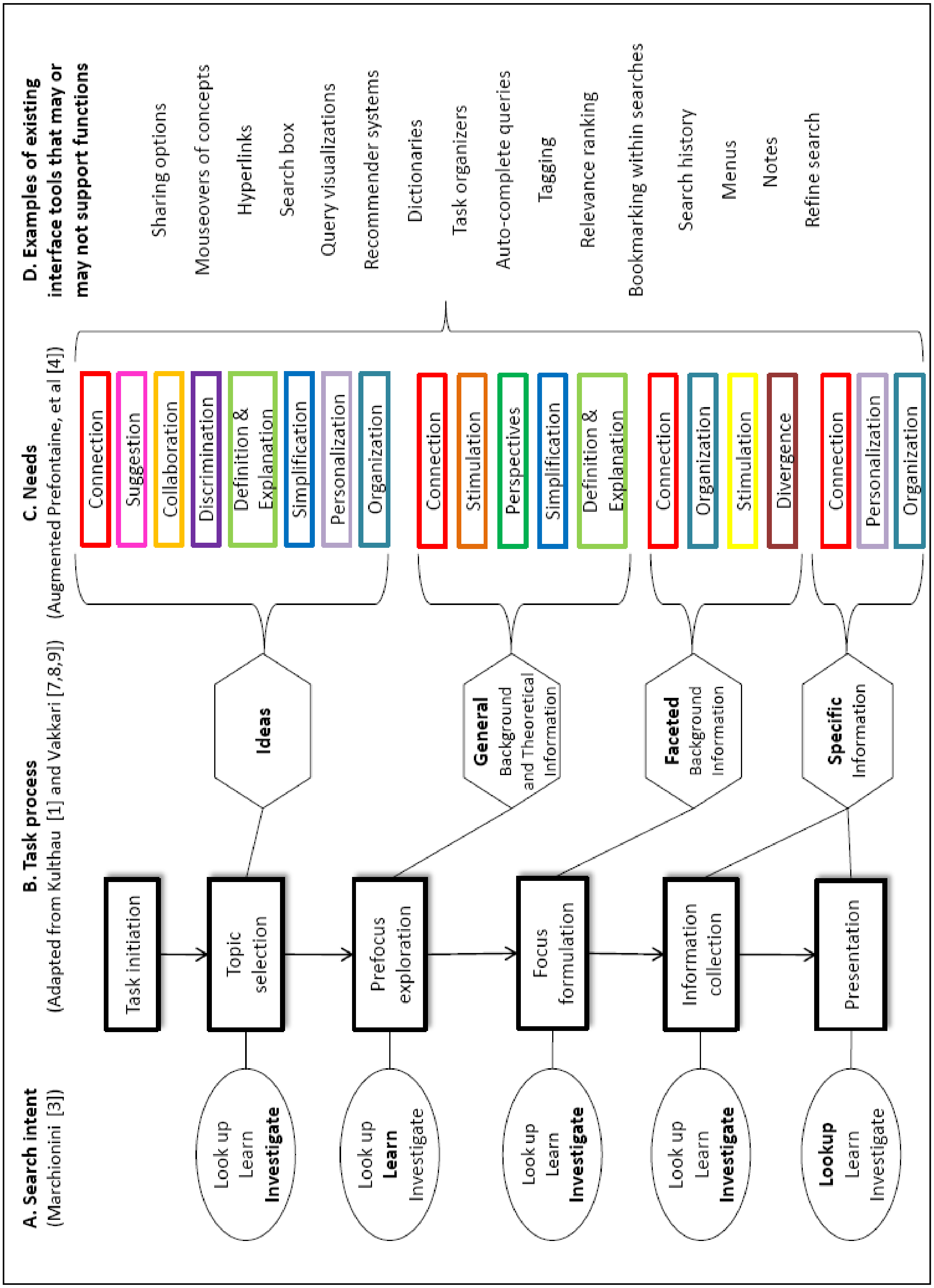

Figure 1 Mapping Tools to Process and Function

themes and ideas [1]. During this phase students need to actualize those "sudden moments of insight" [1] for creativity to be achieved, accomplished by enabling and promoting serendipity, and the making of novel connections.

Students conduct investigative searches to identify research gaps and critically evaluate topical information. During investigative searches, the intent is to maximize recall and retrieve a high number of relevant sources [3]. However, the proportion of non-relevant references increases as the search process matures [8,9] suggesting that the system should be able to manage and present the scope of the material involved in that topic. The general background information reviewed and learned during the previous phases provides students with a greater understanding of the vocabulary associated with the topic, enhancing their ability to use more and more effective querying strategies [7,8]. At the same time their conceptual model is not fully developed, and they continue to seek faceted background information about the broad sub-fields of the topic [8]. While the intent is to retrieve a higher proportion of relevant sources, students have developed a higher standard of relevance criteria. Precision searches, which intend to reduce irrelevant sources [3], are conducted as specificity becomes the dominant requirement.

Note taking and reviewing are core activities during this phase [1]. Organization re-structures information to make it more usable [4] and provides students with the option of organizing their own notes and annotations in a format that they can access and review. Suggestion and stimulation tools can encourage connection-making and focus development.

3.4 Information Collection and Presentation

When a student has decided on a focus, the *information collecting* stage begins. During information collecting, students actively engage in an investigative search for information that will support, define, and extend their selected topic [1]. But they also conduct learning searches to clarify information and expand their knowledgebase. During this stage, students have a more fully developed conceptual model of the topic and no longer need to seek general information; instead, they search for more specific detailed information that uncovers the central variable of the task [1,8]. To obtain specific information, students may once again consult with formal mentors and begin citation chaining. Functions that enable information collection include personalization which may help students find information related to previous search sessions and connection tools can help them relate this information to their current search.

At this stage, students tend to utilize more effective strategies with specific queries that use more synonyms, narrower and related terms, and are more likely to use words that interconnect the concepts such as Boolean operators [7,8]. Formal mentors are still consulted but information systems are heavily relied upon [8]. Students may benefit from organization tools as they make detailed notes, organize citations, arrange their thoughts and theories and synthesize ideas and information [1,8] more formally and likely in writing before and during final *presentation* [7].

4. Conclusion and Future Work

In his description of information appliances, Norman states that: "the primary goal is to design the tool to fit the task so well that the tool becomes part of the task, feeling like a natural extension of the work, a natural extension of the person" [2]. At present, search is just another tool among many and not integrated into a user's task interface as effectively as the functions and tools of a driver's car dashboard. The ultimate goal in most knowledge work is the acquisition of information to create new information or knowledge while enhancing the intellectual capabilities of the individual. This is as true for other types of knowledge workers as it is for students. Our intent is not to automatically generate a paper on a topic; it is about providing a useful tool kit that enables, in the case of our example, a student to learn and produce a product. The first stage in this process is identifying and understanding the process and flow involved in completing the task and determining the needs associated with each phase in the process. From there, an information appliance can be designed to incorporate the needs of the user with functions and tools. The challenge from a development perspective is in controlling the flow and type of information without controlling the user. At the same time, it is about introducing a useful set of tools, pseudo cognitive prostheses, which enhance and augment human capability.

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5. REFERENCES

[1] Kuhlthau, C. C. 1993. *Seeking Meaning: A Process Approach to Library and Information Science*. Norwood, NJ: Ablex Publishing.

[2] Norman, D. A. 1998. *The Invisible Computer*. MIT Press, Cambridge, MA.

[3] Marchionini, G. 2006. Exploratory search: From finding to understanding. *Commun. ACM, 49*(4), 41-46.

[4] Prefontaine, G., Bartlett, J. C. & Toms, E.G. 2001. A taxonomy of browsing facilitators for digital libraries. Paper presented at the CAIS/ACSI 2001 (Québec, CA, May 27-29, 2001).

[5] Puerta Melguizo, M. C., Boves, L., & Ramos, O. M. 2009. A proactive recommendation system for writing: Helping without disrupting. *Int. J. Ind. Ergonomics, 39*(3), 516-523.

[6] Shneiderman, B. 2007. Creativity support tools: Accelerating discovery and innovation. *Commun. ACM, 50*(12), 20-32.

[7] Vakkari, P. 2000. Cognition and changes of search terms and tactics during task performance: A longitudinal study. In *Proceedings of the RIAO 2000 Conference* (Paris, France, April 12-14, 2000).

[8] Vakkari, P. 2001. A theory of the task-based information retrieval process: A summary and generalisation of a longitudinal study. *JDoc, 57*(1), 44-60.

[9] Vakkari, P. 2000. Relevance and contributing information types of searched documents in task performance. In *Proceedings of the 23rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval* (Athens, Greece, July 24-28, 2000).

A Proposal for Measuring and Implementing Group's Affective Relevance in Collaborative Information Seeking

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ABSTRACT
In an interactive information-seeking environment, it is important to consider more user-centric notion of relevance, which includes motivational and affective relevance. In this article we introduce the notion of group's affective relevance for collaborative information seeking. We explore different ways of measuring it and examine how these measures are related to the performance of teams. In addition, we propose a new model for implementing group's affective relevance in information systems that provide support for collaborative information seeking.

Categories and Subject Descriptors
H.5.3 [**Information Interfaces and Presentation**]: Group and Organization Interfaces—*Collaborative computing, Computer-supported cooperative work*

General Terms
Design, Experimentation, Human Factors.

Keywords
Group's affective relevance, Collaborative information seeking.

1. INTRODUCTION
It is generally accepted that relevance means pertinence, indicating usefulness of the object in question in a particular context. In fact, if we look for definitions in common dictionaries we will find explanations like, "Relation to the matter at hand", "Practical and especially social applicability", "pertinence", "the ability (as of an information retrieval system) to retrieve material that satisfies the needs of user" [10]. Although these definitions are just examples, it is very likely that they represent the general meaning that lay people normally ascribe to this concept.

On the other hand, for several years the field of information science has debated about the concept of relevance. To this end, different authors have done extensive reviews of the concept showing its complexity [1]. Indeed, as described by both Saracevic [12] and Mizarro [11], today we do not talk about "relevance"; instead we refer to it as "relevances", reflecting the multidimensionality of the concept.

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In this manner, information scientists today, are able to talk from algorithmic relevance, which is linked to information retrieval systems, to more human versions of the concept, such as motivational and affective relevance. Beyond the various kinds of relevance, none of them consider the dynamic evaluation of information in group contexts, which is the case of collaborative information seeking (CIS) and where the notion of relevance adopts a social dimension. Our interest in this article is to propose and measure a new kind of relevance, namely group's affective relevance (GAR), and also a model for supporting it in CIS environments.

In the following sections we present a brief review of related work, the definition and purpose of groups' affective relevance, the preliminary method we used to evaluate it based on the information collected in previous studies, our observations and corresponding analyses, the model for supporting this kind of relevance in information systems, and finally a general discussion of the results of this work.

2. BACKGROUND
Among the variety of problems and situations studied in the field of information science, relevance is central and probably one of the most important elements. As pointed out above, several authors have studied this concept from different perspective. An important conclusion in this regard is that relevance is more than just a concept with a unique definition; instead, relevance is a multidimensional notion that must be studied carefully based on application domain, goals of an information seeking situation, and related contextual information. For several years the predominant system paradigm established relevance as a central and technical component; however, works such as [4], proposed to shift the focus on the users' perspective, expanding the idea of relevance to new levels. Similarly, Saracevic described a set of relevances that includes system or algorithmic relevance, topical or subject relevance, cognitive relevance or pertinence, situational relevance or utility, and affective relevance [12]. Particularly the latter is considered by different authors as transversal to the other subjective kinds of relevance [1], [3].

It has been assumed in some way that these relevances originally defined for individual information seeking are also applied to more social scenarios, like CIS; nevertheless, few studies have been done for evaluating relevance in this kind of contexts. Zhang for example, proposed the idea of collaborative relevance judgment as a measure of user's search performance [16]. The general idea behind this approach is that certain information is considered more relevant as more users collect it. In the same way and with the aim of exploring relevance and the affective dimension in collaborative settings, we propose group's affective relevance (GAR).

3. GROUP'S AFFECTIVE RELEVANCE

Human beings are able to feel, express, and recognize emotions in their daily lives; particularly when people work together, they share thoughts and opinions in a rational way, but also they are accompanied by emotions. This can be noticed through facial expressions, voice intonation, physiological responses, words, and so on. As reported in [5] and [9], affects may impact either positively or negatively the performance of teams. If these people or groups are working in an information seeking situation, affective dimension may be critical to their collaborative task. Our goal is to understand and evaluate affective relevance for a group in a CIS environment.

Saracevic defined affective relevance as the *"relation between the intents, goals, emotions, and motivations of a user, and information (retrieved or in the systems file, or even in existence)"* [12]. Taking this idea to CIS, we could evaluate the performance of teams in terms of the emotional experiences of their members; but also we could explore how feelings expressed through information judgments, impact the quality and relevance of the information that users gather during the information seeking process (ISP). In addition we could study how users are affected by the judgments of their peers regarding the information they share and how this finally affect to the team as a social system. It is in this sense that we propose group's affective relevance, which we define as the overall emotional experience of each group's member with regard to a specific information object that certain user share with the group. In this sense, group's affective relevance involves a measure and also a model of relevance, whose main idea is that the diversity of both affective-subjective and objective information judgments among collaborators, make possible a better evaluation of the information objects that users collect when they seek information.

In the sections below we present an initial application of the notion of group's affective relevance to a previous study in the context of CIS.

4. METHOD

To commence our investigation on GAR for CIS, we used data previously collected in an experiment of collaborative information seeking [14]. This study involved 42 pairs of remotely located users using a CIS system, called Coagmento [15], in two interactive sessions seeking information on two different exploratory search topics. The participants collected snippets of text from the Web relevant to their tasks. Since the experiment was not originally designed to explore group's affective relevance; we were limited in terms of the data we had to evaluate this idea. As a summary, we had access to chat logs and also to precision (ratio between relevant information and the total amount of information collected. In this formulation, relevant information corresponds to the number of snippets collected by at least two users). With this data, we used the chat logs as a main source to identify affective judgments of information. For this, we coded more than 6000 messages, using two different systems of codes:

1. *Positive, negative, or neutral feeling expressed.*

   Such classification is an adaptation of the affective dimension of speech acts described in [9]. In this sense, messages were classified as positive if they involve pleasant feelings, encouragement, positive judgments, satisfaction, and support, among others; on the other hand, negative messages included opposition, sarcasm, dissatisfaction, and so on. Since the dichotomy positive-negative may not apply to certain messages, especially objective ones (e.g., "Do we have anything showing when social networking started?"), the neutral category was incorporated into the coding system.

2. *Perceived relevance expressed.*

   An interesting aspect of the communication in CIS is that users sometimes report to their peers if they find relevant information according to their own criteria. In this manner, in addition to the categories above, expressions such as: "Hey! Check this article, it is awesome" (*positive*) and "mmm, I don't like the way is written and I don't think it help us to complete our task" (*negative*) in a dialog between users were also coded as reflecting affective relevance.

The coding process was done by two independent coders (the authors) and an inter-rater reliability analysis was performed in order to evaluate the agreement between the judges of the messages. As a result, we found high level of inter-coder reliability with Cohen's kappa = 0.773.

It is worth mentioning that due to the characteristic of the data we had, we studied the overall group's affective relevance of each team without taking in consideration the particular information objects that were collected. The main reason of this is because we did not have access to judgments of each information object that was collected, since participants were not asked to rate such information during the ISP and decide based on the group's evaluation whether or not the information should be collected.

5. OBSERVATIONS AND ANALYSES

One of the main challenges of studying group's affective relevance is the operationalization of the concept. As mentioned above, our affective coding system was inspired in [9]. Hence, chat messages were classified under a dimensional approach of emotions considering positive and negative emotions, but in addition we added neutrality as a way to differentiate objective and subjective messages. In their study, Losada and Heaphy analyzed the dynamics of teams through the ratio between positivity and negativity [9]. In a similar way, we analyzed groups' affective relevance and their performance using this ratio and also a modification of it that incorporates neutrality. Below the two equations we used to compute group's affective relevance:

$$GAR_1(pos, neg) = \frac{\sum pos}{\sum neg}$$

$$GAR_2(pos, neg, neu) = \frac{\sum neu}{\sum pos} + \frac{\sum neu}{\sum neg} + \frac{\sum pos}{\sum neg}$$

Because of our interest is on the performance of teams in terms of the way in which they decide whether certain information is relevant or not, we considered in our analyses only those messages that where coded as affective relevance, which corresponds to 8% of the messages.

Using both ways of measuring group's affective relevance, we studied the correlation with our performance measure (precision). The corresponding dispersion graphs are presented in Figure 1 and Figure 2. We found significant negative correlation between GAR_1 and precision ($r=-0.342$, $p=0.027$) and also between GAR_2 and precision ($r=-0.289$, $p=0.063$); however, the latter was not found to be statistically significant.

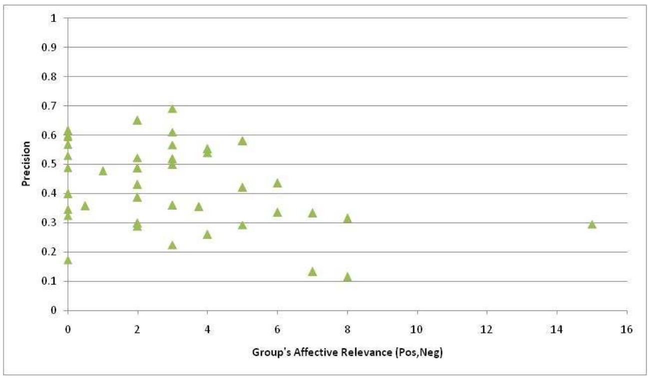

Figure 1: Dispersion Analysis of Precision in terms of GAR using positive and negative information judgments.

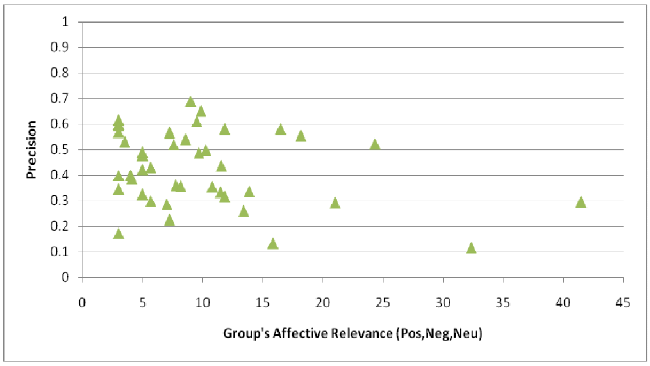

Figure 2: Dispersion Analysis of Precision in terms of GAR using neutral, positive, and negative information judgments.

In addition to the correlation analysis, we also generated clusters using *K-Means* over the number of positive, negative, and neutral information judgments as well as precision as a measure of performance. As a result we found three main clusters, namely low, medium, and high performance teams (Table 1).

Table 1: Clusters features.

	Cluster		
	Low Performance	Medium Performance	High Performance
Positive	10.40	4.57	1.65
Negative	1.60	0.86	0.26
Neutral	23.20	8.29	1.61
Precision	0.33	0.41	0.46

In terms of the characteristics of the clusters, we found that the closer the distance between the number of positive, negative, and neutral information judgments, the higher the performance of teams in terms of precision

6. PROPOSED MODEL

Our goal by introducing group's affective relevance in CIS is to provide better ways of emotional awareness [6,7] to individuals when they work collaboratively. To facilitate this, it is necessary that CIS systems provide ways of communication that allow group members to express and represent what they feel and think about the information they collect and share. Such reactions or impressions could be measured in different ways; some examples are facial expression recognition, linguistic analyses, voice intonation, and galvanic response of the skin. Irrespective of the technical resources that we could use to measure effectively users' feelings, we propose a general model for implementing group's affective relevance as part of the communication channels that individuals use when they seek information collaboratively.

Figure 3 presents an activity diagram from one user's perspective in his/her interaction with the system and his/her collaborators, either synchronously or asynchronously. The hearts in some activities represent the presence, codification, and communication of emotions. Following the flow of activities in the model from its starting point, we have a user that has information need and this lead him/her to initiate the ISP, which could be expressed through the ISP model of Kuhlthau [8].

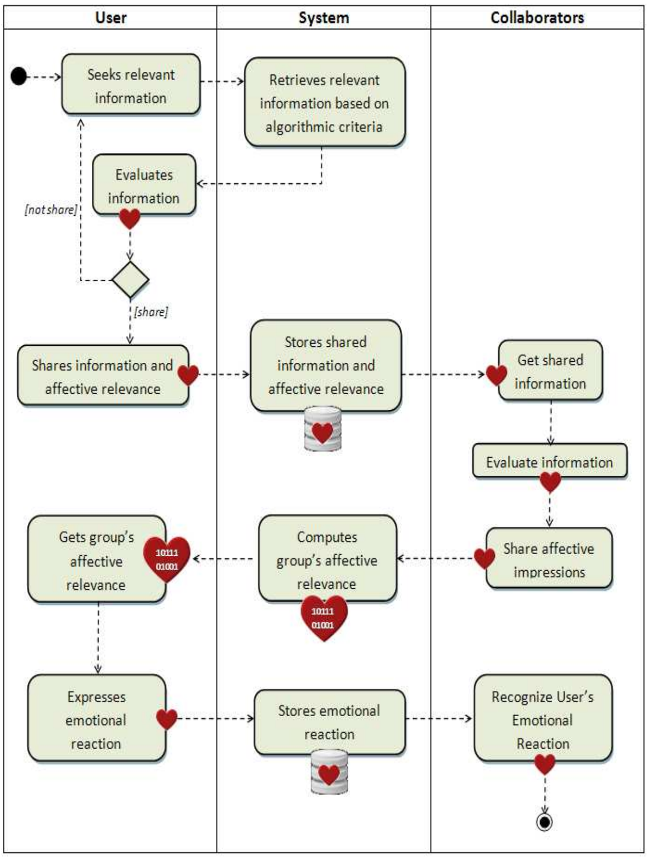

Figure 3: Model for implementing group's affective relevance in system for supporting CIS.

In the interaction with the system, the latter retrieves what according to algorithms is considered relevant. Then the user evaluates the information and selects what according to his/her criteria and affective experience is considered relevant. In this activity the user may react emotionally and this could be reflected either through the body or the language; as a result, the user decides whether share the information or not. In case the user shares the information, this includes his/her emotional response to the information object, that can be classified using either a dimensional or categorical approach of emotions.

As an intermediary, the system stores the information and its associated emotional reaction. Subsequently collaborators get and evaluate such information either objectively or subjectively. Hence, new affective judgments are added to the original information object and this is shared with the rest of the collaborators through the system. On the other hand, the system dynamically computes the group's affective relevance, using formulations similar to the ones presented in the previous section. The result of this is reported to the user who shared the information object, provoking an emotional reaction in him/her that might later be recognized by his/her peers through the system. The entire process is incremental and iterative; so the main idea of implementing this model and use it in experiments is to understand how users are affected by their peers when the information that they consider relevant is criticized either positively or negatively, and how this impacts the information seeking processes of the team.

7. DISCUSSION

Through this paper we proposed a new kind of relevance, namely group's affective relevance (GAR) in the context of collaborative information seeking (CIS). For understanding and evaluating GAR, we used data from a previous study; in particular, chat messages that were code as positive, negative, and neutral. In addition, these messages were classified as exhibiting affective relevance if they included affective judgments of the information that the participants shared. We computed each group's GAR in two different ways (GAR_1 and GAR_2) and tried to link them to groups' performance in terms of precision. Overall, we found a weak and negative correlation using GAR_1, which is based on positivity and negativity. On the other hand, we found three main clusters that characterize teams in terms of the information judgments they reported during the information seeking process (ISP) and the performance they achieved also expressed in terms of precision. A lack of clear correlation could be attributed to the nature of this study, which was not designed to record or evaluate affective relevance. We will address this limitation with the future studies designed specifically for measuring GAR in CIS.

In addition we need to consider additional ways for exploring the emotional dimension of users in the ISP. As we noticed during the coding process, the linguistic approach is limited when used in isolation. To resolve this, in our next study we will examine the same problem under a multimodal approach, which will include the study of emotions using a multiple instruments.

Finally, as expressed in the model above, ideally GAR should be evaluated and studied for each information object that teams collect. Such study design will enable us to look at the dynamics of the teams when they decide whether the information being collected is relevant or not, and how such process affects their overall performance.

8. ACKNOWLEDGMENTS

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9. REFERENCES

[1] Borlund, P. (2003). The concept of relevance in IR. *Journal of the American Society for Information Science and Technology*, 54(10), 913–925.

[2] Budd, J.M. (2004) Relevance: Language, semantics, philosophy. *Library Trends*, 52(3), 447–462.

[3] Cosijn, E., & Ingwersen, P. (2000). Dimensions of relevance. Information Processing and Management, 36(4), 533–550.

[4] Dervin, B. & Nilan, M. (1986). *Information needs and uses*. In M. E. Williams (Ed.), Annual Review of Information Science and Technology 21, 3-33. White Plains, NY: Knowledge Industry Publishers.

[5] Fredrickson, B.L. & Losada, M.F. (2005). The Positive Affect and the Complex Dynamics of Human Flourishing. *American Psychologist*, *60*(7), 678-686.

[6] García, O., Favela, J., & Machorro, R. (1999). Emotional awareness in collaborative systems. In Proceedings of String Processing and Information Retrieval Symposium, 1999 and International Workshop on Groupware (pp. 296-303).

[7] González (2006). Evaluación de la Integración del Darse-Cuenta Emocional en una Aplicación Colaborativa. Master's Thesis, Universidad de Santiago de Chile. Santiago, Chile.

[8] Kuhlthau, C.C. (1991). Inside the search process: Information seeking from the user's perspective. Journal of the American Society for Information Science, 42(5), 361–371.

[9] Losada, M., & Heaphy, E. (2004). The Role of Positivity and Connectivity in the Performance of Business Teams: A Nonlinear Dynamics Model. American Behavioral Scientist, 47(6): 740-765.

[10] Merriam-Webster Online. (2009). Retrieved October 1, 2009, from http://www.merriam-webster.com.

[11] Mizzaro, S. (1997). Relevance: The whole history. *Journal of the American Society for Information Science*, 48(9), 810–832.

[12] Saracevic, T. (1996). Relevance reconsidered '96. Information science: Integration in perspective. In P. Ingewersen & N.O. Pors (Eds.), Proceedings of Second International Conference on Conceptions of Library and Information Science (CoLIS 1996) (pp. 201–218.). Copenhagen: The Royal School of Librarianship.

[13] Saracevic, T. (2007) Relevance: A review of the literature and a framework for thinking on the notion in information science. Part II: Nature and manifestations of relevance. *Journal of the American Society for Information Science and Technology*, 58(13): 1915-1933.

[14] Shah, C. & Marchionini, G. (2009). Query reuse in exploratory search tasks. Poster at Workshop on Human-Computer Interaction and Information Retrieval (HCIR) 2009. Washington, DC: October 23, 2009.

[15] Shah, C. (2010). Coagmento - A Collaborative Information Seeking, Synthesis and Sense-Making Framework. Integrated demo at *CSCW 2010*. Savannah, GA: February 6-11, 2010.

[16] Zhang, X. (2002). Collaborative relevance judgment: A group consensus method for evaluating user search performance. *Journal of the American Society for Information Science and Technology*, *53*(3), 220-231.

Evaluation of Music Information Retrieval: Towards a User-Centered Approach

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ABSTRACT
With the dramatic increase of online digital music, research on Music Information Retrieval (MIR) is flourishing more than ever. However, evaluation in MIR has been focused on system-centered approaches, where systems are evaluated against a pre-built ground truth dataset using system-focused measurements, and little attention has been spent on user experience. In this paper, we argue that MIR evaluation should take users, in addition to systems, into consideration. We suggest that some measures and models in the established area of Interactive IR in the text domain can be applied to the MIR domain. Novel evaluation measures that are unique to MIR are also proposed. The purpose of this paper is to encourage user-oriented, and thus more comprehensive, approaches to evaluating MIR systems.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *search process,* J.5 [**Art and Humanities**] – *Music*

General Terms
Measurement, Performance, Human Factors.

Keywords
evaluation, music information retrieval, user-centered evaluation, usefulness.

1. INTRODUCTION
As a crucial aspect of system development, evaluation of Information Retrieval (IR) systems has attracted continuous attention. Much of this effort can be seen from the annual TREC (Text REtrieval Conference) and the frequent appearance of workshops on IR evaluation at the annual conference of SIGIR. In the text IR area, some evaluation criteria and measurements beyond "relevance" have been proposed and used, and these alternative approaches have addressed many aspects of IR evaluation criteria, including user experiences in the search process, in addition to the well-accepted, system-focused measures such as *precision* and *recall*.

In recent years, with the popularity of digital music, research on Music Information Retrieval (MIR) is flourishing more than ever. The International Society of Music Information Retrieval (ISMIR) will have its 11th annual conference this year. In the last decade, a number of new algorithms and systems have been proposed and developed for a variety of MIR-related tasks: genre classification, artist clustering, music recommendation, playlist generation, etc. While these innovations greatly advance the state of the art of MIR, and some of the systems have been turned into real-world applications, the evaluation of MIR algorithms and systems is not as developed: the current evaluation paradigm is dominated by system-oriented approaches, while users, whom MIR systems serve, have rarely been considered in MIR evaluation frameworks.

During IR processes, users accomplish their tasks by interacting with IR systems. Hence, evaluations of IR systems need to take into account users' interactive processes of information searching and retrieval [2][3][18]. Just as other IR systems, MIR systems do not stand by themselves. The goal of MIR systems is to facilitate users' music information tasks, and thus the evaluation of MIR should inevitably take users into consideration. In this paper, we suggest that along with the maturity of system-centered MIR evaluation, it is needed to bring users into the picture. User-centered evaluation of MIR is grounded in the nature of music information seeking and as such has broad applicability in the evaluation of MIR.

2. RELATED WORK IN THE MIR DOMAIN

2.1 MIR Evaluation
Evaluation of MIR has been dominated by system-centered approaches. Since 2004, the annual event, Music Information Retrieval Evaluation eXchange (MIREX) [13] has become the main venue of system evaluation in the MIR community. MIREX is the counterpart of TREC in the music domain. Just like TREC, there is a variety of MIR *tasks* included in each year's MIREX, such as genre classification, mood classification, cover song identification, audio music similarity and retrieval, melody extraction, etc. For each task, systems developed by participatory research groups around the world are run against pre-built test collections and their performances are compared. The measures used in MIREX are all system-centered, including *accuracy* for classification tasks, *average precision* for retrieval tasks,

variations of *precision/recall* for (key, onset) detection tasks, etc. Unlike TREC, as of the year 2010, there has not been a task in MIREX that considers users' interactions with the systems.

MIR experiments outside MIREX are also primarily evaluated by system-centered approaches, that is, without involving users. Nevertheless, there are a few exceptions. Pauws, S. and Eggen [22] conducted a controlled user experiment to evaluate the quality of playlists generated by the algorithm that the authors proposed. They recruited twenty-two participants, each of whom used the proposed interactive system as well as a control system to generate playlists for two pre-defined situations ("soft music" and "lively music") over four experimental sessions. The researchers then compared the systems using participants' ratings on the resultant playlists. A post-experiment interview was conducted to elicit supplementary findings on the *perceived usefulness* of automatic music compilation. In a similar study, Pauws and van de Wijdeven [23] evaluated their "SatisFly" playlist generation system by conducting a user experiment with twenty-four participants. Each participant rated the playlists generated by the "SatisFly" system and a control system. The measures used in this study included *playlist quality* as calculated by users' ratings, *time spent on the task*, *number of button presses in accomplishing the task*, as well as *perceived usefulness* and *ease-of-use*. On the same line of research, a conclusive user evaluation was conducted in [28] to assess the "similar song" function of the E-Mu jukebox, a music recommendation system. Twenty-two participants used the test system as well as two control systems to perform a playlist generation task where 10 different songs must be chosen for a single imaginary music listening situation. In addition to the measures calculated in [23], this study also measured *the order of participants' preference* among the three systems by asking which system they liked most and least.

These three studies conducted user experiments in evaluation and addressed aspects that by no means can be covered in system-centered approaches. The user-dependent measures are essential for understanding users' experience of MIR systems and for achieving the ultimate goal of MIR systems. Interestingly, these three studies were all on the task of playlist generation, with similar design and scale, were all conducted in the same research lab, Philips Research Laboratories, and were conducted at least five years ago. This indicates that user-oriented evaluation has not been well adopted and has limited influence in MIR.

2.2 User Studies in MIR

Despite of the sparseness of user-centered evaluation, MIR researchers have long paid attention to users. User studies in MIR have primarily focused on identifying users' music information needs and the features users often employed to describe their needs. For example, McPherson and Bainbridge [21] analyzed server logs of the MELDEX digital music library and discovered its usage patterns. Itoh [17] surveyed 21,177 online catalog search logs in an academic music library and identified access points of music scores in online environments. Researchers also analyzed forum postings and requests on Q/A sites (e.g., Google Answers) to identify user needs and information features used in musical queries [1][11][14][19]. Besides these approaches, ethnographic methods (e.g., interviews) and surveys were often used in exploring users' music information seeking behaviors [12][20]. In a study using multiple user study methods, Vignoli [27] conducted interviews, user experiments with existing products, as well as online surveys to investigate how music listeners organize and access their digital music collection.

3. USER-CENTERED EVALUATION IN TEXT IR

In the area of text IR, for the past over three decades, *relevance* [24] has been a major criterion of evaluation and has been overwhelmingly used in TREC practice. However, in recent years, researchers have been arguing that relevance is not sufficient in evaluating IR systems because evaluation studies are routinely pursuing information seeking tasks outside of the traditional, so-called Cranfield paradigm and are taking a broader view of tasks, users, and contexts [15][18]. Relevance-based measures such as *precision* and *recall* are not good for evaluating Interactive Information Retrieval (IIR) systems, because while users may modify or develop search tasks during search processes, the two measures cannot quantify the "informativeness" of interactions [7]. In addition, neither *precision* nor *recall* is a highly significant factor of *user satisfaction* towards a given retrieval system. Depending on their information seeking tasks, users may not be concerned about retrieving all the documents relevant to their search tasks; for many users, they are happy if they can get a good answer in a short amount of time [16]. Further, the purpose of an IR system is to help users accomplish a task, and therefore IR system evaluation should consider both task success as an outcome and the value of support that IR systems provide over the entire information seeking episode as a process [9]. Relevance-based measurements that only focus on topical matches between the documents and the query terms fail to address these requirements.

There have been alternatives to *relevance*, such as *efficiency*, *satisfaction* [26], and *utility* [5][9], to name just a few. Kelly [18] pointed out that very complex IIR activities involving both Behavioral Science and Computer Science require pluralistic approaches and methods, and that "a single, prescribed model would be deleterious" (p. 202). The evaluation methods and measures to be used depend, to a large extent, upon the goal of the evaluation. For example, the evaluation may be used for a system that is able to retrieve relevant documents, or for a system that can help its users accomplish specific tasks.

From a phenomenological perspective and based on the nature of information seeking, Belkin and colleagues [4][9] have recently suggested *usefulness* as a criterion for evaluation of IIR systems. *Usefulness*, as they argues, can be used to evaluate system support from the aspects of both task outcome and task process in the accomplishment of a task. In terms of the measurements under the usefulness framework, *usefulness* itself can be a measurement of how much the search results contribute to task accomplishment. In addition, other measures can include but are not limited to: *task accomplishment* (how well the user finishes the task; how many steps the user goes through; how long it takes) and *support of the system to the information seeking goal* (to the general task and to each possible sub-task; acceptance or rejection to system suggested search strategies and/or query reformulation; usefulness and the use of retrieved documents; recall and precision of single search; etc.). It should be noted that while *usefulness* is an alternative to *relevance*, the authors did not mean to disregard relevance and its measures; instead, relevance measures are part of the usefulness framework. While some of these measures have been used in previous studies, the usefulness framework is not a simple repetition of previous efforts. It suggests that determination of which measures to use in evaluation depends crucially upon the specification of a leading task or goal whose accomplishment itself can be measured. This multiple-measure approach in general echoes Kelly's notion [18] that there is not a single best method in IIR evaluation.

4. PROPOSED MEASURES IN USER-CENTERED MIR EVALUATION

As previously mentioned, while MIR evaluation has been dominated by system-centered approaches which typically measure how well the systems (algorithms) classify music and how relevant their retrieved music was, rare effort has been spent on measuring how well the systems support users' completion of music information seeking tasks or what users' search experiences are like. We believe that the concept of *usefulness* introduced in section 3 could be well applied to MIR system evaluation. We suggest that the measurements of the usefulness framework are applicable to the MIR domain. Further, due to the unique entertaining nature of music that is different from textual information in regular text retrieval, we also suggest additional aspects that are not included in the original usefulness framework proposal, such as *entertainability* and *social life support*. In addition, other IIR measurements such as *learnability* are also important in evaluating MIR systems. Our proposed measures are as follows.

Measure on music information task accomplishment. This measure as Cole et al. [9] proposed in their IIR evaluation framework focuses on search outcome. Since the goal of MIR activities is to support users to fulfill their music information needs represented by their MIR tasks, MIR evaluation can include the measure on task accomplishment in the evaluation as well. This measure can include several points:

- (How) does the user find the desired music?
- How many steps does the user take to find the music?
- How long does the user spend in finding the music?

  This is often referred as *task completion time* or *time lag* and has long been recognized as one of the most important criteria that could be used to evaluate IR systems [8][18][26].

Measure on system support of the music information seeking process. Information seeking is a process instead of just a search outcome [9]. It is often a continuous process instead of a single query-result activity. This is true in the music domain as well. For example, during a music search process, users may modify and refine their queries after listening to part of a retrieved song. Specific points of this measure can include:

- How does the system support identification of and sequence of sub-tasks (if any) toward the completion of the general music information seeking task?
- How useful is the system in querying support (e.g., query reformulation suggestions)?
- How does the system support displaying and playing search results?
- How does the system support saving search results?

  The last two points are very different from text IR. Displaying search results in the music domain is an on-going research question in and of itself. Unlike a text document, a music document (or part of it) has to be played and listened to by the user before he or she can make judgments on its value to the music information needs. Also, due to intellectual property laws, saving a music document is much more complicated than saving a text document, which raises an additional challenge to MIR systems.

Measure on system support of user experience. This aspect includes general rules suggested by experts from Human-Computer Interaction (HCI) and IR areas, as well as our suggested measures that are unique to MIR systems.

- How is the user satisfied with his music finding experience?
- How easy does the user feel the system is to use?
- How much does the system help the user to avoid confusion or "getting lost"?

  These points are frequently seen in system interface evaluation, for example in [25].

- How is the system easy to learn?
- How quickly can a user familiarize himself/herself with the system again after not using it for a while?

  The above two points are on the *learnability* of MIR systems. Researchers have realized the influence of learning in the IR process. For example, Borlund [6] argued that IR evaluation should pay attention to the learning process of users and gauge the *learnability* of an IR system. The issue of *learnability* is even more important in MIR because MIR systems often include multimedia interfaces that are novel and unfamiliar to most users. For instance, McPherson and Bainbridge [21] studied usage patterns of the MELDEX digital music library and found that although the system supported melodic querying, users still preferred issuing textual queries. The overhead of learning how to issue a melodic query had impeded users from taking full advantage of the system.

- How well does the system support entertainment?
- How well does the system support social life?

  The above two points are unique to the MIR domain. Usually, people search music for entertainment purposes, and thus the MIR systems should attempt to support users' general purpose of entertainment. In addition, music is also an aspect of social life. Users often share their favorite music with friends and carefully select certain kinds of music for specific social events and occasions such as weddings, parties, trips or romantic dates. Therefore, it should be a goal of mature MIR systems to support users' music-related social life.

The above proposed measures focus on different aspects of users' interactions with MIR systems. It is desirable to combine multiple measures in evaluation, but the adoption of any of these measures would complement current system-centered approaches.

5. CONCLUSIONS

As the ultimate goal of MIR systems is to help users in seeking music information, the evaluation of MIR systems should take users into consideration. This paper advocates a paradigm shift from system-centered evaluation to user-centered evaluation in

MIR. Interactive IR in the text domain has been an active research area for decades and has plenty to offer to MIR. By applying IIR and HCI evaluation measures to MIR and proposing measures unique to the music domain, this paper aims to elicit more work and attention on user-centered MIR evaluation.

6. REFERENCES

[1] Bainbridge, D., Cunningham, S.J., and Downie, J.S. 2003. How people describe their music information needs: A grounded theory analysis of music queries. In Proceedings of the 4th International Conference on Music Information Retrieval (ISMIR).

[2] Beaulieu, M., Robertson, S. and Rasmussen, E. 1996. Evaluating interactive systems in TREC. Journal of the American Society for Information Science, 47(1): 85-94.

[3] Belkin, N.J. 2008. Some(what) grand challenges for information retrieval. ACM SIGIR. Forum Archive, 42 (1): 47-54.

[4] Belkin, N., Cole, M., and Liu, J. 2009. A model for evaluation of interactive information retrieval. In Proceedings of the SIGIR 2009 Workshop on the Future of IR Evaluation, pp.7-8.

[5] Belkin, N.J. and Vickery, A. 1985. Interaction in Information Systems: A Review of Research from Document Retrieval to Knowledge-Based Systems. Library and Information Research Report 35: The British Library, University Press, Cambridge.

[6] Borlund, P. 2003. The IIR evaluation model: a framework for evaluation of interactive information retrieval systems. Information Research, 8(3), Paper No.152.

[7] Borlund, P. and Ingwersen, P. 1997. The development of a method for the evaluation of interactive information retrieval systems. Journal of Documentation, 53(3): 225-250.

[8] Cleverdon, C. W. and Keen, E.M. 1966. Factors determining the performance of indexing systems. Vol. 1: Design. Vol 2: Results. Cranfield, U.K: Aslib Cranfield Research Project.

[9] Cole, M., Liu, J., Belkin, N.J., Bierig, R., Gwizdka, J., Liu, C., Zhang, J., and Zhang, X. 2009. Usefulness as the criterion for evaluation of interactive information retrieval. In Proceedings of the 3rd Workshop on Human-Computer Interaction and Information Retrieval (HCIR) (pp. 1-4).

[10] Cooper, W.S. 1973. On selecting a measure of retrieval effectiveness, part 1: The “subjective” philosophy of evaluation,” Journal of the American Society for Information Science, 24, 87–100.

[11] Cunningham, S. J., Bainbridge, D. and Falconer, A. 2006. “More of an art than a science”: supporting the creation of playlists and mixes. In Proceedings of the 7th International Conference on Music Information Retrieval (ISMIR).

[12] Cunningham, S.J., Jones, M., and Jones, S. 2004. Organizing digital music for use: an examination of personal music collections. In Proceedings of the 5th International Conference on Music Information Retrieval (ISMIR), pp. 447-454.

[13] Downie, J. S. 2008. The Music Information Retrieval Evaluation eXchange (2005–2007): A window into music information retrieval research. Acoustical Science and Technology, 29(4), 247–255.

[14] Downie, J. S. and Cunningham, S. J. 2002.Toward a theory of music information retrieval queries: System design implications. In Proceedings of the 3rd International Conference on Music Information Retrieval (ISMIR).

[15] Geva, S., Kamps, J., Peters, C., Sakai, T., Trotman, A., and Voorhees, E. (Eds.). 2009. Proceedings of the SIGIR 2009 Workshop on the Future of IR Evaluation. Workshop held at SIGIR 2009, Boston, MA, July 23, 2009.

[16] Hearst, M. 2009. Search User Interfaces. Cambridge University Press.

[17] Itoh, M. 2000. Subject search for music: quantitative analysis of access point selection. In Proceedings of the 1st International Conference on Music Information Retrieval (ISMIR).

[18] Kelly, D. 2009. Methods for evaluating interactive information retrieval systems with users. Foundations and Trends in Information Retrieval, 3(1-2): 1-224.

[19] Lee, J. H., 2010. Analysis of user needs and information features in natural language queries seeking music information. Journal of the American Society for Information Science and Technology, 61 (5): 1025-1045.

[20] Lee, J. H. and Downie, J. S. 2004. Survey of music information needs, uses, and seeking behaviours: preliminary findings. In Proceedings of the 5th International Conference on Music Information Retrieval (ISMIR), pp. 441-446.

[21] McPherson, J.R., and Bainbridge, D. 2001. Usage of the MELDEX digital music library. In Proceedings of the 2nd International Conference on Music Information Retrieval (ISMIR).

[22] Pauws, S. and Eggen, B. 2002. PATS: Realization and evaluation of an automatic playlist generator. In Proceedings of the 3th International Conference on Music Information Retrieval (ISMIR).

[23] Pauws, S. and van de Wijdeven, S. 2005. User evaluation of a new interactive playlist generation concept. In Proceedings of the 6th International Conference on Music Information Retrieval (ISMIR).

[24] Saracevic. T. 1975. Relevance: A review of and a framework for the thinking on the notion in information science. Journal of the American Society for Information Science, 26, 321–343.

[25] Sharp, H., Rogers, Y., & Preece, J. 2007. Interaction Design: Beyond Human-computer Interaction. John Wiley & Sons.

[26] Su, L.T. 1992. Evaluation measures for interactive information retrieval. Information Processing and Management, 28, 503–516.

[27] Vignoli, F. 2004. Digital music interaction concepts: a user study. In Proceedings of the 5th International Conference on Music Information Retrieval (ISMIR).

[28] Vignoli, F. and Pauws, S. 2005. A Music Retrieval System Based on User Driven Similarity and Its Evaluation. In Proceedings of the 6th International Conference on Music Information Retrieval (ISMIR).

Information Derivatives – A New Way to Examine Information Propagation

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ABSTRACT
An increasing amount of information available online is dynamic in nature. That is, it constantly keeps changing with people consuming and adding their own value to it. We propose to study how such information flows from its original source to other locations through the concept of information derivatives. We treat information as an object and consider the original piece of information as the 0^{th} derivative. Any subsequent use of that information produces 1^{st} derivative, 2^{nd} derivative, and so on. We provide a mathematical formulation of this phenomenon and propose a new framework to study information propagation in online sources, and to understand the dynamic nature of information.

Categories and Subject Descriptors
H.1.1 [**Models and Principles**]: Systems and Information Theory—*Information theory*

General Terms
Measurement, Theory.

Keywords
Information propagation, Information derivatives, Information theory, Social media, Network analysis.

1. INTRODUCTION
With the changing ways in which information is stored, retrieved, and shared, it is becoming essential to see information as dynamic and constantly changing with its context and usage. Several works have demonstrated how context could be useful in studying dynamic information (e.g., [8, 11]). Easily creating, sharing, and annotating a piece of information has become largely possible due to the ubiquitous nature of social media sites and services. Examples include YouTube for videos, Flickr for photos, delicious for bookmarks, wordpress for blogs, and Twitter for microblogs.

In this paper we look at information as an object [3] and propose a new method for studying its propagation through various channels on the Web. In order to explain this method, we introduce the notion of information derivatives and propose a new framework for studying the dynamic nature of information through its propagation and derivatives.

2. Information propagation and derivatives
In the field of library and information science (LIS), information is often viewed as an object [3]. Kaye [7] (p.37) stated: *"Library and information professionals, thus have a perception of information as objective matter, defining it instrumentally in terms of data, facts, knowledge and opinion, to be applied to learning, decision making, problem solving and other tasks.*" Rowley [10] also reaffirmed that LIS professionals tend to treat information as an object and create a system's view of information.

There is, however, also other works in the field that treat information as a vehicle for knowledge. For instance, Hill [6] used the term information to mean recordable knowledge, asserting that knowledge is more than information and that information must be recordable and shareable.

2.1 A mathematical view of information derivatives
There are many other views of information, but for the work presented here, we will treat information as a thing, acknowledging that such information is recordable, shareable, and modifiable. We follow Brookes' [2] fundamental equation of information theory:

$$(S) + \Delta I \rightarrow (S + \Delta S) \quad ... \quad (1)$$

Here, S is the knowledge structure that is modified by the information input ΔI to produce a new knowledge structure $(S+\Delta S)$. Instead of knowledge structure, we will focus on changing information itself. In other words, we propose:

$$I + \Delta V \rightarrow (I + \Delta I) \quad ... \quad (2)$$

Here, I is an original piece of information, ΔV is the value added to that information, and $(I+\Delta I)$ is the new information created due to this process. An added value changing the given information is a well-studied concept in information life cycle and related works (e.g., [12]).

Let us consider an example. Using social bookmarking service *delicious*, one could collect bookmarks. Each of these bookmarks is a piece of information (I) to which one adds tags and notes (ΔV)

to create one's own value-added personal information $(I+\Delta I)$. Here, ΔV and ΔI are person and/or context dependent. Continuing this example, these bookmarks could be shared with others over delicious. Those who subscribe to them could create their own versions of the bookmarks, thus adding ΔV to what is already $(I+\Delta I)$. Thus, we can generalize Equation (2) as

$$I^j + \Delta V^j \rightarrow I^{j+1} \quad ... \quad (3)$$

Here, j represents the order or the derivative rank. I with 0th rank (I^0) is the original piece of information (0th derivative). With ΔV^0 added, it transforms to I^1, which is the 1st order derivative.

Let us consider this notion of information derivatives with another example. Stacy uploads a picture that she took at a birthday party on Facebook (0th derivative), in which Mark tags people. This tagged photo is now a 1st derivative information. Others in Stacy's social network could see this value-added information and start commenting on that photo. This creates 2nd derivative information. This can continue, not only on Facebook, but also on other channels such as blogs, creating new derivatives of the original piece of information.

2.2 A graphical view of information derivatives

Information derivatives can be seen as a directed graph,[1] such as the one shown in Figure 1.

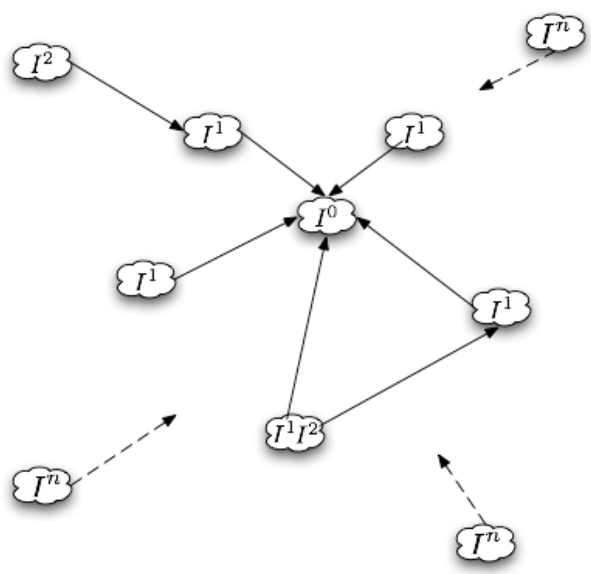

Figure 1: A graphical view of information derivatives.

Here, an original piece of information is labeled with I^0, which gets propagated through various channels and becomes I^1. Note that each of the I^1 may be different due to their unique context, usage, and added value. This chain could continue and produce derivatives, I^2, I^3,..., I^n. It is possible that a particular piece of information, for example, I^jI^k is multiple derivatives; that is, it can be produced using derivatives of different lower orders, such as I^p and I^q, where $p=j-1$, $q=k-1$, and $p\neq q$. In other words, such information propagation creates many-to-one mapping of information derivatives. In Figure 1, one of the pieces of information is such derivative, labeled with I^1I^2.

One way of thinking about the information derivatives from this graphical view is to look at how many hops we need to make from a piece of information to I^0. This number indicates the order of that derivative. For instance, for the node labeled with I^1I^2, there are two ways to get to I^0 – one with one hop and the other with two hops. Thus, this piece of information is 1st order as well as 2nd order derivative with respect to the information represented by I^0.

Information propagation through information derivatives can also be represented using other structures, such as tree (Figure 2) and forest, as well. The choice of a structure for portraying and examining information derivatives can depend on the application and the domain in which they are being studied.

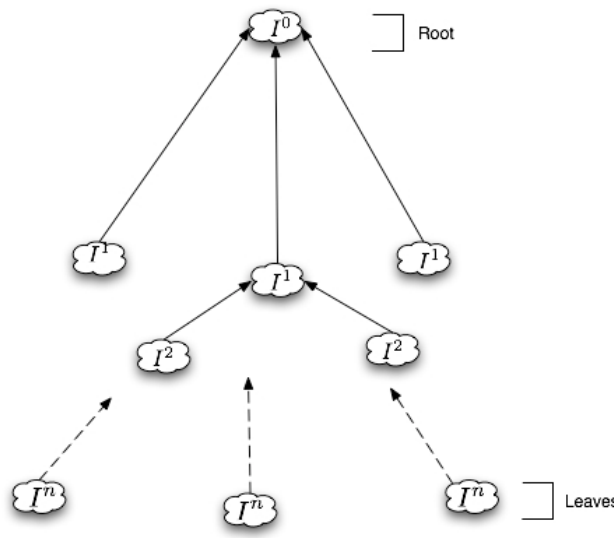

Figure 2: A tree structure for information derivatives.

2.3 Graph-based characteristics of information derivatives

Various structural views of information derivatives provide us an opportunity to define certain characteristics of them based on the structure as well as how different nodes within this structure are defined and linked. Here we present a few important characteristics that will later be useful for our case study.

2.3.1 Diversity or propagation applicability

A given node in the graphical structure could be used multiple times to create information derivatives. The more a piece of information (node) gets used, the higher its propagation applicability. Diversity of a node is determined by the number of unique derivatives created from that node. Thus, diversity of a derivative node can be defined as:

$$\gamma(I^j) = \sum I^k \quad \text{, where } k = j+1 \quad ... \quad (4)$$

[1] Note that the direction of the arrows in this representation may seem opposite of the direction for information propagation, but it clarifies the idea of derivatives or links.

Here, all of I^k are derived from I^j. Note that these I^k come from unique nodes. In case of the Web, these nodes may be different domains.

This characteristic is similar to in-degree of a node in a graph, often used to measure a node's nature as an authority in network analysis [9].

2.3.2 Deriving index

This measures the level of derivation for a piece of information, and is calculated by counting the number of sources it derives. Deriving index is computed as:

$$\theta(I^j) = \sum I^k \quad , \text{where } k = j - 1 \quad ... \quad (5)$$

Here, I^j is derived from I^k.

This characteristic is similar to out-degree of a node in a graph, often used to measure a node's nature as a hub in network analysis [9].

2.3.3 Density

A piece of information may be derived by a single node several times, possibly by different parts of that node. For instance, if a web-domain is considered as a node, its parts are all the webpages in that domain. Density of an information node is computed by dividing the total number of derivations from that node to the number of unique nodes from which those derivations occur. Thus, density:

$$\delta(I^j) = \frac{\sum I^k}{\sum I_p^k} \quad , \text{where } k = j + 1 \quad ... \quad (6)$$

Here, the denominator is the sum of all the unique nodes (e.g., web-domains) that derive from I^j. Note that $\gamma(I^j)$ represents total number of derivations (in-degree) from I^j, whereas $\delta(I^j)$ indicates how spread out those incoming links are among unique sources that derive from it.

3. DISCUSSION

The ways in which people seek, find, and share information have changed considerably in the recent years, and so are the methods for producing and consuming information online. It is not uncommon for one to discover interesting or relevant information from a friend's blog or a Tweet. In this paper we attempted to formalize such information propagation on the Web. We proposed a notion of information derivatives and presented some of their basic characteristics. Our proposal was inspired by some of the classical works on information as an object, information theory, and network analysis.

The framework presented here using information derivatives can be used for examining almost any case of information flow where information can be treated as an object. One of such domains is blogosphere. Similar to the works of Gruhl et al. [5], and Tremayne et al. [13], we can examine information propagation on certain topics within blogosphere using the notions and properties of information derivatives. Such analysis can help us identify and study connectors (high diversity), and authorities (high deriving index) in a given network.

On the theoretical side, the proposed framework can help us classify and explain data, information, and contextual details, similar to Buckland's [4] discussion about the nature of a document. With the same example of antelope that Buckland gave, antelope itself can be treated as the 0^{th} derivative, and the scholarly articles about that antelope can be considered as 1^{st} derivatives.[2] One could imagine applying similar definitions to various artifacts considered for preservation or archiving.

4. ACKNOWLEDGMENTS

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5. REFERENCES

[1] Briet, S. (1951). *Qu'est-ce que la documentation*. Paris: EDIT.

[2] Brookes, B. C. (1974). Robert Fairthorne and the scope of information science. *Journal of Documentation, 30*(2), 139-152.

[3] Buckland, M. K. (1991). Information as Thing. *Journal of the American Society for Information Science, 42*(5), 351-360.

[4] Buckland, M. K. (1997). What is a "Document"? *Journal of the American Society for Information Science, 48*(9), 804-809.

[5] Gruhl, D., Guha, R., Liben-Nowell, D., & Tomkins, A. (2004). Information diffusion through blogspace. In *Proceedings of World Wide Web (WWW) Conference* (p. 491-501). New York, New York, USA: ACM Press.

[6] Hill, M. W. (1982). Information for innovation: a view from the UK. In *Proceedings of ICSU-AS Information for Innovation*. Amsterdam.

[7] Kaye, D. (1995). The nature of information. *Library Review, 44*(8), 37-48.

[8] Lee, C. (2007). Taking Context Seriously: A Framework for Contextual Information in Digital Collections. UNC SILS TR-2007-04.

[9] Park, H. W., & Thelwall, M. (2003). Hyperlink Analyses of the World Wide Web: A Review. *Journal of Computer-Mediated Communication, 8*(4).

[10] Rowley, J. (1998). What is information? *Information Services & Use, 18*(4), 243-254.

[11] Shah, C. (2009). Mining Contextual Information for Ephemeral Digital Video Preservation. *International Journal of Digital Curation (IJDC), 4*(1), 175-192.

[12] Taylor, R. S. (1982). Value-added processes in the information life cycle. *Journal of the American Society for Information Science, 33*(5), 341-346.

[13] Tremayne, M., Zheng, N., Lee, J. K., & Jeong, J. (2006). Issue publics on the web: Applying network theory to the war blogosphere. *Journal of Computer-Mediated Communication, 12*, 290-310.

[2] Briet [1] (p.7-8) recognized a captured antelope as the primary document, and any article written about it as the secondary documents.

Implicit Factors in Networked Information Feeds

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ABSTRACT

In recent years, the development of "News Feed" interfaces have transformed the ways in which individuals seek and encounter information in social network sites. Rather than primarily searching for information, a networked information feed provides a constantly updated stream of information about ongoing activity in the networked community. In the following paper, the components of networked information feeds are examined. Particular attention is paid to the variable forms of content included in networked information feeds, the effects of diversity in network composition on the networked information feed, and the implications of filtering networked information feeds.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information filtering, Selection process; H.5.2 [**User Interfaces**]; H.5.3 [**Group and Organization Interfaces**]: Synchronous interaction

General Terms

Algorithms, Measurement

Keywords

News feeds, information encountering, probability

1. INTRODUCTION

The growth in popularity of networked social interaction, through venues such as social network sites, afford new opportunities for peer-to-peer information sharing. Social network sites provide a set of novel tools that facilitate the disclosure of personal information to a group of alters, or "Friends" [2, 5]. Furthermore, social network sites employ intelligent information-generation techniques that can identify site activity to be shared as actionable information [4, 10]. The end product of social network site use can be thought of as an *activity stream*, a collection of action in a networked system to be shared with alters as part of an ongoing information process.

According to boyd and Ellison, social network sites have three fundamental properties. First, they allow individuals to to "construct a public or semi-public profile within a bounded system." Second, the individual is able to articulate connections to alters in the system. Third, these lists of connections can be "viewed and traversed" by others within the system [2]. Social network sites have traditionally been profile-centric, with information sharing generally occurring within the confines of a profile. In these systems, status updates, wall postings, shared links and pictures and other fundamental activities are centralized on the profile [2].

Ego networks in social network sites are characteristically large, particularly when compared to offline discussion networks [5, 8]. In early iterations of social network sites, "keeping up" with network alters required visiting multiple profiles, an inefficient process. To facilitate awareness of activity streams in the network, Facebook developed the News Feed, which "shows you all the actions your friends are making in real-time[1]." Drawing on design principles of the email inbox and RSS reader, the News Feed is a centralized, real-time networked information feed of the activity streams of connected alters. The Facebook News Feed has proven highly influential, with similar feeds appearing at competing sites, including LinkedIn and Flickr. Furthermore, microblogging networks such as Twitter employ networked information feeds as principle interaction elements.

Situated at the center of a social network, the networked information feed has emerged as an important vehicle for information search and encountering. As networked information feeds are adopted at a wider range of sites, it is important for systems developers, designers, and researchers to understand the set of interactions that produce an individual's networked information feed. The purpose of this paper is to identify and explore the factors that contribute to the production, and differential experience of, a networked information feed.

2. CHARACTERISTICS OF NETWORKED INFORMATION FEEDS

An individual experiences a networked information feed (hereafter, "NIF") by viewing an stream of activity generated in a social network site (See Figure 1[2] for an example). The

[1]http://www.facebook.com/help/?page=408
[2]The image used was provided as an exemplar by Facebook.

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Figure 1: Facebook's News Feed is the canonical example of a networked information feed. "Top News" represents a filtered NIF, whereas "Most Recent" provides an unfiltered NIF.

NIF is a reflection of individual action in the system. For any time period t, let us define the contents of a NIF as the finite sum of content items c shared by alters, where an individual has alters a ($a = 0...n$). An individual's NIF for period t can be represented as:

$$NIF(t) = \sum_{a=0}^{n} c_a \tag{1}$$

where total (t) shared content is a function of network size and alter sharing behavior. An individual's news feed for all periods T (t $= 0...n$) can be represented as:

$$NIF(T) = \sum_{t=0}^{n}\sum_{a=0}^{n} c_a \tag{2}$$

where T is a fixed interval, and a and c are random variables. Therefore, the individual's experience with a NIF is a stochastic process dependent on network size and the content sharing behavior of alters within the system.

In a site such as Twitter, the individual experiences the complete NIF, meaning content is not screened or filtered through any process. In sites where networks are large or multiple opportunities for content creation exist, individuals may be overwhelmed by information in a full NIF. Therefore, sites such as Facebook offer algorithmic filtering of the NIF. We can define the experience of the filtered (f) NIF as the finite sum of content items c shared by alters, where an individual has alters a ($a = 0...n$), and content display is governed by a Binomial variable b. The Binomial variable b has two possible values *0,1* and a probability density function *p(f)* specified by an algorithmic process. The functional form of *NIF(f)* is therefore:

$$NIF(f) = \sum_{a=0}^{n} c_a b \tag{3}$$

In cases of filtered and unfiltered NIF's, the real total of NIF activity can always be described by *NIF(t)* and *NIF(T)*. When the NIF is filtered, however, the displayed total of NIF activity is described by *NIF(f)*. In the next sections, the first principles of content items c and network composition a are be explored. The remainder of the paper focuses on factors of relevance in *p(f)*, the probability function governing the filtering process.

3. NIF PRINCIPLE ELEMENTS

The experience of a networked information feed is dependent on the size of the individual's network of alters, and the content shared by the alters.

3.1 NIF content

In any NIF, there is a diverse range of content that can be shared: status updates, pictures, links, and much more [6, 10]. Within an NIF, there are essentially two types of content shared: that which is *individual-agentic* (c_i), and that which is *system-generated* (c_s). Content which is individual-agentic is intentionally shared by an individual through purposeful action; an example would be the posting of a status update. System-generated content is generally a report of a user's action that is triggered by a system. Examples of system-generated content include NIF notices of "friending" behavior, presentation of third-party conversations, or reports of event attendance (e.g. Figure 1).

Based on the simple ontology I have specified, an alter's NIF content production can be described with the following form:

$$c(alter) = c_i + c_s \tag{4}$$

where c_i is a random variable representing individual-agentic content sharing, and c_s is a random variable representing system-generated content sharing for a finite interval. We expect that both of these variables, c_i and c_s are contingent on u, a random variable describing site use by the alter. Therefore, the function describing total (T) expected alter NIF content production for all periods T (t = *0...n*) can be represented as:

$$c(T) = \sum_{t=0}^{n} \sum_{a=0}^{n} p(c_{it}|u_{at}) + p(c_{st}|u_{at}) \quad (5)$$

That is, the content production in a NIF depends on an alter's actions in a site, which is conditional on site use. It must be noted that while c_i is completely dependent on an alter's actions, it is possible that c_s will contain actions from the alter and the alter's group of contacts. For example, if an alter is tagged in a picture, the system generates activity on behalf of the alter triggered by the actions of a third party. For simplicity's sake, we do not create a third category, instead retaining third-party activity within c_s.

Previous work has identified Pareto, Zipf and exponential distributions for content production in large-scale socio-technical environments [1, 3]. Within the context of individual production, the probability of content creation is better specified with the Poisson distribution, defined as follows:

$$P(c) = \frac{e^{-\lambda}\lambda^{c}}{c!} \quad (6)$$

where c must be a non-negative integer[3]. Using simulation, we can explore potential impact of adding new individuals to the NIF at theoretical lambdas 2,4,6, and 8 (Figure 2). It should be noted that individual content production in NIF may also be well-specified with the Negative Binomial form (in the case of overdispersion). Furthermore, occasional or bursty network use may serve to zero-inflate alter NIF content production over time.

3.2 NIF network properties

The amount of content shared in a NIF is functionally dependent on the size of the alter network. Because we are able to specify an individual probability *p(a)* of content production c by alters a (6), we are able to reasonably estimate the expected impact to an NIF of the addition of alters to the network with the following form:

$$E(c) = \sum_{a=0}^{n} p_a c_a \quad (7)$$

In practice, we find that the composition of an NIF network has a dual form. Similar to the ontology of content production, NIF network membership can either be *explicit* or *system facilitated*. Explicit network membership reflects intentional addition of an alter to a NIF network by an individual. Adding a Facebook friend, or "following" a Twitter user are examples of explicit network additions. System facilitated inclusion in an NIF refer to the penumbra of system-facilitated activities that allow non-members to participate in an individual's NIF. For example, by "Retweeting[4]," the alter employs system functionality to bring a potentially external individual into a NIF. Similarly, a comment left by

[3]It is my belief that the exponential features of power law-type distributions are incompatible with individual behavior, and therefore poorly specify these probabilities.
[4]i.e., hitting the Retweet button.

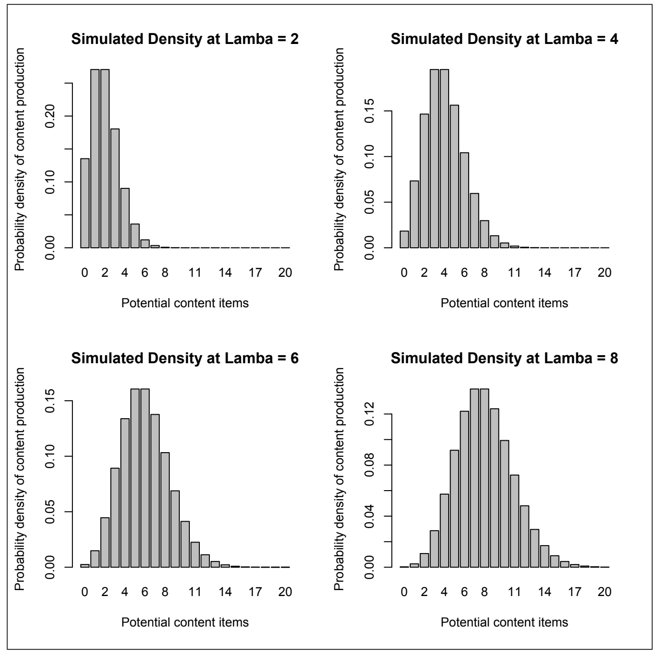

Figure 2: Simulated probability densities for NIF at theoretical lambdas 2, 4, 6, and 8

an alter on a potentially external individual's status update in Facebook may bring the non-member's content into the NIF.

The impact of adding members to an NIF network is more experientially complex than a simple addition of volume. We assume that the individual has relationships with content-producing alters, and therefore evaluates NIF content in light of these relationships. Furthermore, the particular configuration of relationships within an NIF will affect the individual's experience of content. Drawing on theories of tie strength, and empirical models of network configuration, I briefly explore the experiential impact of network configuration.

3.2.1 *Tie strength*

An abundance of literature is devoted to the properties of social ties [7, 9]. The general principle is that each relationship has a certain strength, which is placed on a continuum of weak to strong. Represented mathematically, we can assume that each relationship an individual has with an alter can be represented by the random variable s, with possible values $0 \rightarrow 1$.

Although we are able to place a theoretical value on each relationship within a NIF, it is unwise to assume that "tie strength" always corresponds to a relevance judgment. Early work on tie strength identified the unexpected value of weak ties [7]; in an NIF, a person may allow weak ties into the network to observe ongoing activity, with only a small portion of activity having high relevance. Furthermore, algorithmic identification of relationship strength has proven to be challenging, though there is good work identifying metrics that may be more useful than others for identifying strength [6].

3.2.2 *Network configuration*

Within the bounded network of a social network site, we are able to identify certain characteristics in relationship patterns that may influence the NIF experience. In a network, each vertex (or node) is connected to alters via an edge. The configuration of edges in the network are detectable through graph theoretic techniques, and may be useful for understanding individual experience of the network. Consider a simple measure of graph structure, density:

$$Density(\Delta) = \frac{2E}{v(v-1)} \quad (8)$$

In which the number of incident edges (E) is a proportion of the total vertices (v) possible in the graph [11]. A highly dense graph would indicate a network with many shared connections. A nuclear family, for example, might expect to have a highly dense network when replicated into a NIF. On the other hand, a sparse network indicates a heterogenous mix of connections. A traveling salesperson, for example, may have many connections that do not share network edges. The density of the network, as well as the relative degree density between prominent members of the NIF has implications for the variety, relevance, and actionable nature of the content shared within the network.

Another important factor is the relationship between network configuration and content sharing behavior. When we specifiy the probability of content production (6), we assumed that the lambdas would be (approximately) normally distributed across the population (a safe estimate at large population sizes). At the subgraph level, however, it is possible that lambdas covary with network density, i.e. $cov(\lambda, \Delta) \neq 0$. This is potentially the result of local processes where some networks are incited share more than others as a result of influential, vocal few. Therefore, we assume that certain network configurations have characteristic NIF behavior and should be modeled with group variance.

4. THE FILTERING PARAMETER

Finally, we consider the NIF filtering parameter (3), which governs the display of content in a filtered NIF. As previously discussed, the filtering parameter is a Binomial variable b that has two possible values *0,1* and a probability density specified by an algorithmic process.

It is beyond the scope of this paper to specify potential filtering parameters (see [6] for an extensive list of possibilities). In general, we assume that the designers of NIF filters want to maximize *interest* in the stream. We can therefore define max_i as a locally maximized vector of filtering variables $[f_1, f_2, ..., f_n]$.

In a filtered NIF, we assume that all content items T (2) shared in an individual's NIF have a probability between *0,1* of inclusion in the filtered NIF. Therefore, we define the log odds of inclusion of a content item to be:

$$log\left[\frac{p_i}{(1-p_i)}\right] = \alpha + \beta_t x_{i1} + \beta_n x_{i2} + \beta_{[maxi]} x_{i3} + \beta_k x_{ik} \quad (9)$$

In this simple form, the log odds of content inclusion are a function of individual content production t, network size n, the local maximization vector max_i and a random term k.

5. CONCLUSIONS

Networked information feeds such as the Facebook News Feed are increasingly becoming an important place to both seek and encounter information. Situated in the midst of a social context, the NIF has the potential to continuously deliver relevant information from a large network of connections. This new form of information retrieval poses challenges to designers and researchers. How can the utility and interest of content shared in a NIF be maximized? What variables have the greatest potential to affect experience with the NIF? What factors are most important when filtering NIF's? This paper is the beginning of a research projected aimed at answering these questions, which are of critical interest to industry, academia, and users of networked information feeds.

6. REFERENCES

[1] A. Barabasi, R. Albert, and H. Jeong. Scale-free characteristics of random networks: The topology of the world wide web. *Physica A*, 281:68–77, 2000.

[2] D. Boyd and N. Ellison. Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, 13(1), 2007.

[3] A. Broder, R. Kumar, M. F., P. Raghavan, S. Rajagopalan, R. Stata, A. Tomkins, and J. Wiener. Graph structure in the web. *Computer Networks*, 33(309), 2000.

[4] M. Burke, C. Marlow, and T. Lento. Feed me: motivating newcomer contribution in social network sites. In *CHI '09: Proceedings of the 27th international conference on Human factors in computing systems*, pages 945–954, New York, NY, USA, 2009. ACM.

[5] N. Ellison, C. Steinfield, and C. Lampe. The benefits of facebook "friends:" social capital and college students' use of online social network sites. *Journal of Computer Mediated Communications*, 12(4), 2007.

[6] E. Gilbert and K. Karahalios. Predicting tie strength with social media. In *CHI '09: Proceedings of the 27th international conference on Human factors in computing systems*, pages 211–220, New York, NY, USA, 2009. ACM.

[7] M. Granovetter. The strength of weak ties. *The American Journal of Sociology*, 78(6):1360–1380, 1973.

[8] M. McPherson, L. Smith-Lovin, and M. Brashears. Social isolation in america: Changes in core discussion networks over two decades. *American Sociological Review*, 71(3):353–375, 2006.

[9] R. Putnam. *Bowling Alone : The Collapse and Revival of American Community*. Simon & Schuster, New York, NY, 2001.

[10] E. Sun, I. Rosenn, C. Marlow, and T. Lento. Gesundheit! modeling contagion through facebook news feed. In *Proceedings of the Third International Conference on Weblogs and Social Media*, San Jose, CA, May 2009. AAAI Press, AAAI Press.

[11] S. Wasserman and K. Faust. *Social Network Analysis: Methods and Applications*. Cambridge University Press, New York, 1994.

Improving the Online News Experience

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ABSTRACT

News consumption patterns are changing, but the tools to view news are dominated by portal and search approaches. We suggest using a mix of search, visualization, natural language processing and machine learning to provide a more captivating, sticky news consumption experience. In this position paper, we suggest a design for one specific use-case where a user needs to catch up on news from a particular time period. The results need to cover key events that happened during the time period, but the stories should be prioritized based on the user's interests. Further, users should be able to interact and explore stories of interest. We present the limitations of existing online news sites for such a task and present some ways to address these issues.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering, selection process.*

General Terms

Algorithms, Human Factors.

Keywords

News summarization, news interfaces, news personalization

1. INTRODUCTION

The news landscape has undergone major changes with the advent of online media. While the readership of traditional newspapers has declined over the past few years, the consumption of news over the Internet has increased significantly. As with other kinds of online information, the dominant mode of assessing news online is through search. According to the Pew research conducted over Apr–Jun 2008 [16], 83% of those going online for news use search engines to find stories of interest. So, even though most search engines (and other sources) have dedicated portals for news, consumption of news is triggered primarily through queries. Search engines today address this user behavior by integrating relevant news results with Web search results for news-related queries.

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However, this mode of presentation of news is not optimal. Even as news is shifting online, the presentation of news is still driven by the print media. There is limited real estate on the search result pages to display news, and many news articles do not get surfaced on the site. Finding relevant news is more than just retrieving news results or restricting the search based on keyword queries over the news domain. Presentation of news needs to cater to specific user needs. We propose a use-case driven approach to selecting relevant news stories and presenting these appropriately to the user. Further, users should be able to explore the news landscape – getting to other related news articles, visualizing the connections between stories, getting background information on relevant people and concepts, commenting on and annotating stories, and sharing interesting items with friends.

In this position paper, we survey the existing online news sites in Section 2 and outline their limitations. In Section 3, we present a specific use-case for news consumption, and suggest a design that meets the requirements of this use-case. We conclude with related work and potential directions.

2. SURVEY OF ONLINE NEWS SITES

In this section, we briefly survey different online news sites, and present a summary of some of their features.

2.1 News Aggregators

Traditional search companies form the largest and most frequently visited online news portals. According to the most recent Pew Research biennial news consumption survey [16] conducted in 2008, Yahoo! (28%) and MSN (19%) are the most frequented websites among Web news users, ahead of traditional media outlets, such as CNN (17%). Google was polled at 11%. Other news ranking sites, such as *Digg* [5] and *Reddit* [17], have grown in popularity, but only 5% of Internet news consumers use these to find news stories.

Traditional search engines aggregate news from many sources and categorize them by news categories, such as World, Business, Sports, etc. Aggregating news from multiple sources helps them present a multimodal view of a news story that includes videos, photos, and live feeds. Sites such as *Yahoo! News* [26] prioritize news sources and differentiate news coming from different sources. Users can select the source per category, and the news stories from that source are displayed. Other sites, such as *Bing News* [1] and *Google News* [8], present news stories as clusters across multiple sources. This allows them to also incorporate stories from other sources, such as blogs, *Twitter* [23], and *Wikipedia* [24].

2.2 Traditional News Media Online

While readership and viewership of traditional newspapers and television news diminished over the past decade, their online versions have seen an increase. The average monthly reach of web newspapers among Internet households has increased from 27.4% in 2004 to 40.9% in 2008 [15]. Many television channels now make news clips available online either on their sites or on other video-sharing sites like *YouTube* [27]. Newspapers have augmented their online content with videos and photos to visually appeal to younger readers on the Web (for example, see Figure 1). With the news consumption moving away from print media, some newspapers, such as the *Seattle Post-Intelligencer* [18], have gone web-only, while other news outlets, such as *The Huffington Post* [21], *Newser* [12], and *Seven-Sided Cube* [19], present editorial and blog content as independent news online. In addition, a large section of news is community-generated. Sites such as *Newsvine* [14] and *GlobalReporter* [7] allow users to post (and rate) news local to their community. Other news media outlets, such as *CNN iReport* [3], have also accepted this notion of grass-root journalism and allow users to post news videos.

Figure 1. Print (left) and online (right) versions of *The Washington Post* [22] on June 10th, 2010. Note the integration of (a) video, (b) images, (c) live market feeds, and (d) social networking sites in the online version.

2.3 News On-the-fly

News consumption patterns have also changed over the past decade. Rather than setting apart time to access news, consumption is spread throughout the day. In a recent survey, 73% of all online users say they come across news online when they have been on the Web for another purpose. This is especially true of younger news consumers, who typically follow links to news stories, rather than go to news sources themselves [16].

Social networking sites have played an important role in pushing news content to the web users. Sites such as *StumbleUpon* [20], *Digg* [5], *Reddit* [17], *Yahoo! Buzz* [25], *Delicious* [4], *Facebook* [6], and *Twitter* [23] allow users to tag news stories and recommend or share them with friends on their social network. Such news recommendation services not only rate mainstream news, but also help users stumble upon unique news stories that they may not otherwise have a chance to see. Many traditional news sites have interfaces (plug-ins) to these bookmarking sites to enable readers to share news freely. The bookmarking also helps present "popular" or "upcoming" news, as shown by news ranking sites like *NewsPulse* [13], *BuzzFeed* [2], *Digg*, and *Reddit*.

2.4 Analysis of Online News

As illustrated above, many online news sites augment news with videos, images, and user comments to enrich the news consumption experience. Search-based news aggregator sites cluster and categorize news stories and allow users to customize and personalize what they want to read. Services such as email/mobile news alerts and RSS feeds, and customized web pages, such as *My MSN* [10], *My Yahoo!* [11], and *iGoogle* [9] allows users to get news on demand. Readers are encouraged to share news with others, either in their social network or the online community at large. News ranking sites use these to assess popularity of sites and surface articles that are generating a lot of interest ("buzz").

The algorithmic aggregation of news across sources seems to treat all news sources equally, especially when selecting which news item to show. In addition, recent updates often supersede earlier reports, even if the earlier reports were from reputed sources. However, users may prefer local news sources for local news; or in general, specific news sources for different genres of news. Local news or news from a particular region is often under-represented, because there are fewer sources reporting on regional news. Some sites have space set apart for local news, but this tends to be limited.

The "one size fits all" approach of using keyword query based retrieval is not optimal for news. Query-based triggering is often imperfect, and searching for news using just keyword queries often limits expressivity. News demands a different ranking than web search. News dissemination is more than just selecting a list of news articles about popular events from well-known news sources. Online news must instead cater to specific use-cases and should ideally be personalized to the user.

3. *News Sync*: CATCHING UP ON NEWS

In this section, we present a specific scenario for a user-driven news digest to illustrate our ideas. We propose techniques to select and present news according to user needs and preferences. While the techniques used may not be new, we suggest that the integration we propose will lead to a better news experience.

3.1 Motivation

Consider the following scenario: Katie is an avid news reader who tracks news on a daily basis, often following up on specific news events several times a day. Sometimes Katie may be cut off from news sources, for example, when she goes on a long vacation. When she is back online, she may want to know what happened while she was away. She may want to skim through the major news stories that took place, including updates on the news she was following regularly before going on vacation.

This caters to a common, specific need of a news consumer wanting to catch up on news. The scenario becomes more compelling if Katie migrates to another city or country and loses touch with traditional sources of news. Katie continues to be interested in local news from her place of origin. However, unless she is willing to visit every site regularly, she may not get the news of interest.

We propose a system we call *News Sync*, which allows Katie and similar news consumers to get adaptive, personalized news digests covering a period of time, a region, a topic or a combination of these.

3.2 Requirements for *News Sync*

We list the following requirements for *News Sync*:

1. **Control over news categories, topics, and sources:** The user should be able to specify the time period of interest. In addition, the user may specify if she is interested in news from particular sources, specific news categories, locations/regions, and/or specific topics.
2. **Personalized news feed:** The system should figure out which stories are currently the most relevant to the user, based on past user behavior and user preferences, similar in spirit to work by Billsus and Pazzani [29].
3. **Variety in news content:** The system should show a variety of content across diverse categories, instead of, say, returning a list of ten "most popular" news links which may be restricted to one or two topics. Users can thus get an overall picture of key events first, before they delve into specific stories.
4. **Adaptive and integrated news presentation:** The news interface needs to be adaptive to the category of news and presence of multiple modes of news content. For example, news about Harry Potter over summer 2007 should include, among other stories, the trailers from the movie "Harry Potter and the Order of Phoenix" (video), book reviews of "Harry Potter and the Deathly Hallows" (text, blogs) – which were both released in July 2007 – along with pictures and news about the Harry Potter theme park announced in May 2007 (images).
5. **Interactive and exploratory user interface:** The user should be able to interactively and directly modify time, location, and other news parameters and have the system respond immediately with updated views of relevant news. Further, the system should support browsing related news articles.
6. **Parameterized interface design:** Users should be able to set system parameters to get results at different specificities. For example, a user might ask for news about a specific topic (e.g. "Top Kill" in context of efforts to reduce the oil spill in Gulf of Mexico), or news that is of interest to the user based on search history (e.g. other efforts by BP to reduce the oil spill). The user may also request other related news based on her profile (e.g. news about impact of the oil spill on the marine environment, on the livelihood of people along the Gulf coast, on tourism, or on BP's share price).
7. **Support source-tracing and finding related news:** The system should allow users to go from any news summaries to the original news articles. Further, the system should suggest other related news articles based on the news items viewed.
8. **Ability to share news:** Users should be able to comment on and share interesting news articles over their social network.
9. **Support news analyses by sentiment and points of view:** Users should be able to view stories pivoted/summarized on sentiment or different points of view.

3.3 Key steps in building *News Sync*

We are building a prototype system based on the requirements listed in Section 3.2. To achieve these goals, we propose the following steps:

1. **Collecting a news corpus:** Our first step is to get indexed access to the news articles for the time period of interest to the user population, along with source, location, and date information. In addition, articles are processed with a named entity recognizer, to identify key concepts.
2. **Selecting key news stories:** News stories are then selected based on a number of features, including the content, topic trends, the number of sources covering the news, the number of articles on the news story, the volume of news content, and various aspects of the user model (user profile, explicit user preferences, and implicit interest tracking). The selection criteria also include the time-spread of the news to identify key events that the user should know about.
3. **Selecting relevant threads:** Once the key stories are identified, the relevant individual articles need to be retrieved. This involves filtering based on time and location, and incorporates some of the model preferences described above. The system may choose to ignore or prefer news sources based on the user preference model and granularity of news. Local news sources may be preferred for local news stories, while national mainstream news sources may be preferred for broader scenarios.
4. **Summarizing news stories:** News needs to be presented in a manner that is easy to consume. This involves selecting what content to present and how best to present it. This may involve adaptive summarization across documents based on the user model, and presenting diverse points of view.
5. **Presenting and visualizing news:** News stories may be visualized on a timeline, a map, etc.

Once such a system is developed, it can be evaluated using implicit/explicit feedback and through a survey to understand the usage patterns and the features that are popular.

Such a system would help frequent travellers, business customers who need to know the impact of ongoing news on their business, and avid news followers who spend the most time with the news.

We have developed a prototype of the *News Sync* system as part of this year's HCIR Challenge.

4. RELATED WORK

Past literature has looked into generating a personalized webpage of news relevant to the user based on the topics of interest. Kamba, et al. [31] did one of the early studies on presenting an interactive newspaper on the Web. They propose a system that builds web pages dynamically as the user browses the newspaper. Anderson and Horvitz [28] developed a personalized web page as a montage of links of frequently viewed pages that changes dynamically with the time at which the page is viewed. The system learns which pages are viewed regularly at certain time periods and presents content based on the user interest and browsing pattern. For example, a user might be shown weather forecasts and key news in the morning; the stock price ticker and work-related resources during the day; and traffic pattern and TV listings in the evening. In our system, we propose to follow the users' interests to prioritize the news presented, and also allow users to specify topics or other inputs such as time and location of interest.

There has also been work in providing personalized newsfeeds. Gabrilovitch, et al. [30] analyze inter- and intra-document differences and similarities to recognize novel content in articles and how the information has evolved over time. This helps them develop measures to rank news by novelty, and pick the best (most novel) update to send to the user as a newsfeed. Other researchers, such as Tintarev and Masthoff [34] have studied other measures of similarity of news headlines to improve news recommendation.

There is a lot of relevant work in the realm of interface design. For example, Shneiderman [32] suggests use of dynamic queries to update the search results as users adjust sliders and other UI elements. Teitler, et al. [33] suggest NewsStand, which proposes using geographic information in news articles to overlay news on a map. This presents users with a geographic perspective of where the news comes from and helps them cluster and explore news based on location.

Some news ranking sites are able to show "popular" news for particular days or months, based on how many users clicked on or shared a news article. Figure 2 shows an example that displays the top 10 *dugg* articles for the month of April, 2010. Displays such as these allows for simple presentation of high level summaries.

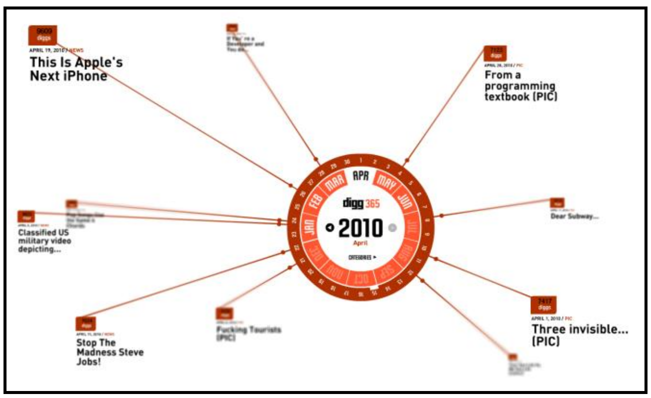

Figure 2. Top 10 *dugg* articles in April 2010. The larger the font size, the more *digg*s the article received.

5. CONCLUSION

In this paper, we propose an approach to providing a captivating, sticky news consumption experience, using techniques from search, language processing, visualization and learning. We listed requirements for a specific use-case of catching up on news. We propose a design for a system to address this use-case. We are working on such a prototype and hope to have the system ready to demo at the workshop.

6. REFERENCES

[1] Bing News. http://www.bing.com/news

[2] BuzzFeed. http://www.buzzfeed.com/

[3] CNN iReport. http://www.ireport.com/

[4] Delicious. http://delicious.com/

[5] Digg. http://digg.com/

[6] Facebook. http://www.facebook.com/

[7] Global Reporter. http://globalreporter.com/

[8] Google News. http://news.google.com/

[9] iGoogle. http://www.google.com/ig

[10] My MSN. http://my.msn.com/

[11] My Yahoo!. http://my.yahoo.com/

[12] Newser. http://www.newser.com/

[13] NewsPulse. http://newspulse.cnn.com/

[14] NewsVine. http://www.newsvine.com/

[15] Nielsen/Net Ratings, MegaPanel Data. http://www.naa.org/TrendsandNumbers/Newspaper-Websites.aspx

[16] Pew Research Center for the People and the Press, 2008. Key News Audiences Now Blend Online and Traditional Sources – Audience Segments in a Changing News Environment. *Pew Research Center Biennial News Consumption Survey*. http://people-press.org/reports/444.pdf

[17] Reddit. http://www.reddit.com/

[18] Seattle Post-Intelligencer. http://www.seattlepi.com/

[19] Seven-Sided Cube. http://www.sevensidedcube.net/

[20] StumbleUpon. http://www.stumbleupon.com/

[21] The Huffington Post. http://www.huffingtonpost.com/

[22] The Washington Post. http://www.washingtonpost.com/

[23] Twitter. http://twitter.com/

[24] Wikipedia. http://en.wikipedia.org/wiki/Main_Page

[25] Yahoo! Buzz. http://buzz.yahoo.com/

[26] Yahoo! News. http://news.yahoo.com/

[27] YouTube. http://www.youtube.com/news

[28] Corin R. Anderson and Eric Horvitz. 2002. Web Montage: A Dynamic Personalized Start Page. In *WWW*.

[29] Daniel Billsus and Michael J. Pazzani. 2000. User modeling for adaptive news access. In *User Modeling and User-Adapted Interaction*, 10(2) pp. 147-180.

[30] Evgeniy Gabrilovich, Susan Dumais, and Eric Horvitz. 2004. NewsJunkie: Providing Personalized Newsfeed via Analysis of Information Novelty. In *WWW*.

[31] Tomonari Kamba, Krishna Bharat, and Michael C. Albers. 1993. The Krakatoa Chronicle - An Interactive, Personalized, Newspaper on the Web. In *WWW*.

[32] Ben Shneiderman. 1994. Dynamic Queries for Visual Information Seeking. In *IEEE Software*, 11(6), 70-77.

[33] Benjamin E. Teitler, Michael D. Lieberman, Daniele Panozzo, Jagan Sankaranarayanan, Hanan Samet, and Jon Sperling. 2008. NewsStand: A New View on News. In *Proceedings of the 16th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS)*.

[34] Nava Tintarev and Judith Masthoff. 2006. Similarity of news recommender systems. In *Workshop on Recommender Systems and Intelligent User Interfaces*, G. Uchyigit (Ed).

Breaking Down the Assumptions of Faceted Search

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ABSTRACT
In this paper, we list several features of faceted search and challenge their implicit assumptions.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering, query formulation, relevance feedback, retrieval models, search process, selection process*. H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *graphical user interfaces (GUI), theory and methods, user-centered design*. I.2.4 [**Artificial Intelligence**]: Knowledge Representation Formalisms and Methods – *semantic networks*.

General Terms
Algorithms, Design, Experimentation, Human Factors.

Keywords
Faceted search, user interfaces, refinements, semantic networks, correlation, fuzzy matching.

1. INTRODUCTION
Faceted search has emerged as one of the most effectice processes for exploratory search and discovery. It allows the user to locate the records of interest by following, in any order, the process of iterative refinement; it also permits discovering unknown data by exposing the sets of data facets that offer both refinement and data-at-a-glance summarization. When even such a change-resistant organization as the U.S. Government embraces faceted search (http://www.whitehouse.gov/search), one can justify considering this process to be the standard way to resolve information retrieval needs.

On one hand, the usage patterns and interface details for faceted search have been ironed out and standardized. Users are starting to use faceted search applications and transferring such acquired knowledge to other applications that utilize the same process [4]. Since faceted search user interfaces exhibit similar look and predictable behavior, the experience of using, for example, HomeDepot.com can be easily replicated at Lowes.com. On the other hand, like every successful idea, faceted search is headed toward the point in its evolution where it is starting to ossify. The main aim of this paper is, in particular, to list several assumptions of the faceted search experience that are ripe for reconsideration; and, more broadly, to suggest that faceted search, however successful its implementations have been, still contains plenty of unexplored possibilities and can support a plethora of novel applications. The first and third ideas below were successfully prototyped; the second one is currently being investigated.

2. CUSTOM DIMENSIONS
The power of faceted search comes, quite (tauto)logically, from facets: navigable and summarizable properties, tagged onto the records in the system. The problem with such facets is that they have to be created in advance (usually, during data pre-processing), are inflexible (cannot be modified), and might not suit the particular search intent of a given user. While this does apply to numerical properties, the recent advances in analytics allow rapid computation of derived metrics, thus somewhat alleviating the problem (see "Dynamic Facets" section in [1]). With topical (keyword) properties, such as salient natural language terms, however, the issues above fully apply. A text corpus that have been parsed and tagged with typed entities of Person, Organization, and Location type might not suit the needs of the user who is interested in navigating the dimensions of car parts or exploring noteworthy neighborhoods of New York City.

Prior work exists [3, 7, 8] that combines pre-extracted salient terms into topical dimensions; the work in [5] detects particular dimensions that the systems considers useful as leading to potential refinements. We, however, posit the need of a system that is capable of creating such topical dimensions with no pre-processing required whatsoever.

We have created a prototype that allows new dimensions to be created at query-time, combining Endeca (http://endeca.com/) structureless database with WordNet semantic network (http://wordnet.princeton.edu/). See Figure 1 for the diagram of the user interface and interaction model. In such an interface, the user can enter at query time a seed topic for the automated creation of an additional dimension. This topic term is queried against WordNet, retrieving all its senses. For each sense, we retrieve all related terms by following the meronym, holonym, and hyponym network edges. The results are considered as candidates for our refinements. As the last step, the candidates are checked against the corpus (of course, it is also possible to check the candidates against the current search result / navigation state), by measuring their precision and recall relative to the topic term. The candidates that have sufficiently high f-measures are returned to the user as refinements, along with the counts of matching documents. When the user clicks on a refinement, the system can perform search for the text of the refinement term – or, if the corpus contains a salient terms dimension and the refinement candidates have been selected from the set of these terms, the action can lead to a traditional dimensional refinement.

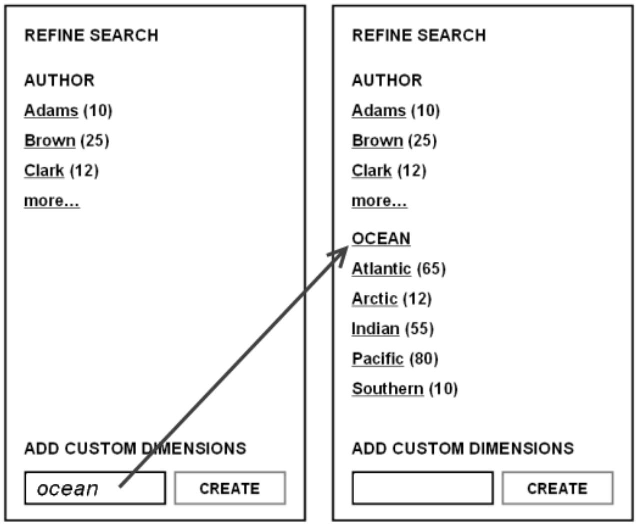

Figure 1. User interface for custom dimensions

The algorithm is fast (O(N), where N is the number of candidate terms) and has the added advantage of providing multiple senses of the topic term, as long as the semantic network contains them.

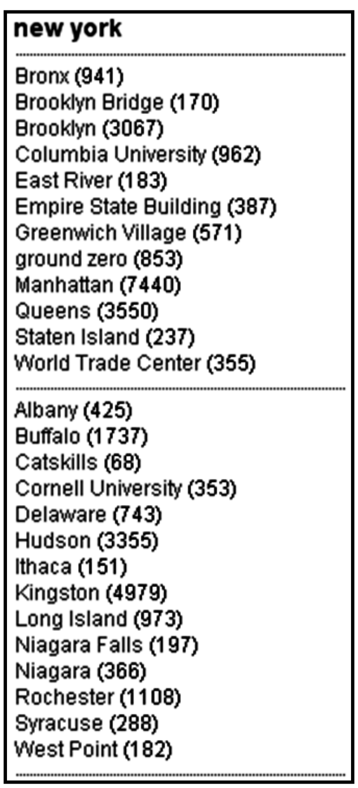

Figure 2. Two clusters of custom dimensions for "New York"

As an example, see Figure 2. For the user topic "New York", the system detected two senses (New York as the city vs. New York as the state) and created corresponding refinements. Naturally, the same system can create hierarchical dimensions by recursively submitting each generated refinement as a topic for generation of child refinements.

We currently plan, time permitting, to apply this system to the NYT corpus for the HCIR challenge.

3. DOUBLE DIMENSION SELECTION

The basic tenet of faceted search is a query-response model, where the user reviews the result set as well as the suggested refinements, selects one, and receives the recomputed result set and a new set of refinements from the system. We question the assumption that the user may select only refinement at a time.

There are cases (such as trade-off analysis), where it is desirable to observe the interplay or correlation of several facets before making a selection. Schneiderman [6] proposes a two-dimensional histogram as an indicator of the regions where an intersection of two dimension values does contain corpus data. We propose the user interface where the main element is a two-dimensional scatter plot, which allows the user to see: (1) the distributions of two dimensions of data; (2) their possible correlation; and (3) data density. Additional interface elaborations, such as providing the details for each particular record on mouse-over, are also possible.

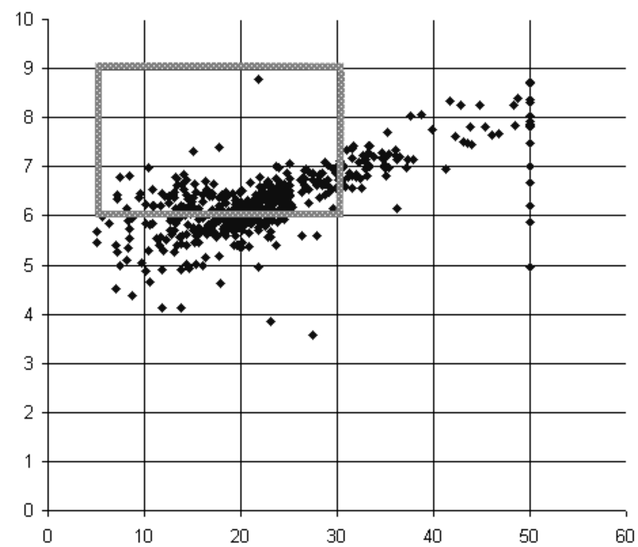

Figure 3. Two-dimensional scatter plot interface

Figure 3 shows the interface, where the data displayed is taken from the well-known 1978 Boston Housing data set (http://lib.stat.cmu.edu/datasets/boston): X axis is the median house price (in tens of thousands of dollars) for a town, while Y axis is the average number of rooms. One can easily observe direct correlation between X and Y. The grey rectangle is the user selection that narrows the data to towns with relatively cheap houses with many rooms. Naturally, the application should restrict such selections to regions that do contain data.

Note that the question of which X and Y should be used in construction of the scatter plot interface raises its own set of challenges. We suggest that a system that calculates either Pearson correlation coefficients or K-L divergence for all pairs of dimensions and suggests highly-correlated (or anti-correlated) pairs would be of interest.

This double dimension selection interface happens to share two key properties with other faceted search interfaces: (1) it provides an overview of current result set, while (2) offering ways to refine it. This duality, by the way, might be yet another assumption of faceted search interfaces that is ripe for re-consideration.

4. FUZZY SELECTIONS

Refinements tend to behave as firm restrictions on the result set: the records that do not satisfy them are not included in the refined set. In some cases, this is not the desired behavior. For example, the user might not be familiar with the data and not sure what refinements are relevant for the given search intent. We suggest that in such scenarios it might be helpful to the user to see what records are not inside the selection but are adjacent to it.

There is considerable amount of research on automatic expansion of text queries (see, for example, [2]); we, however, are concerned with the more general case of: (1) automatically expanding the result set for a broadly defined faceted search, where dimensions might be textual, numerical, or discrete, and (2) suggesting to the user those records that are located inside the expanded set but not in the original one.

We (the author along with user interface expert Blade Kotelly and software architect Maia Hansen) created a prototype that ran on top of a restaurant reviews data set. For a given query (which, in the faceted world, is an intersection of refinements), the application relaxed, one at a time, every refinement. Numerical dimensions were relaxed by considering the union of an interval immediately preceding and immediately succeeding the current selection; thus, a selection of "price: $10-$20" was substituted with "price: $5-$10 OR $20-$30". Discrete dimensions (e.g., "cuisine: Chinese") were replaced with their inverse ("cuisine: NOT Chinese"). If the relaxed set contained fewer results than the original, we returned them as "Also consider..." suggestions.

The experience of using such a prototype delivered a two-fold reaction. On one hand, the system suggesting a highly-rated Turkish restaurant in the same neighborhood where the user was trying to find a good Greek eatery was akin to experiencing mind-reading. On the other hand, some of the suggestions were perceived as having very little in common with the user query.

The issue of "how one can compare average entrée price with the walking distance to the nearest bus stop" still remains open. As the next step, we are considering applying K-L divergence to detect which properties are the most characteristic of the original result set (as differing from the complete set of records in the system). Then the expanded set of "penumbra" records can be filtered to select those that share such characteristic properties but might differ on less relevant ones.

5. CONCLUSION

The three assumptions listed above are meant to be neither an exhaustive list – nor even a coherent one, covering as they do pre-processing, refinement selection, and system's response to selected refinements. They are, however, intended to indicate several ways of breaking down standard assumptions and conventions of the faced search interface. If this paper succeeds in encouraging UX researchers to "think outside the refinement box" and look for under-explored possibilities of faceted search, it will have fulfilled its intended function.

6. REFERENCES

[1] O. Ben-Yitzhak et al. Beyond Basic Faceted Search. WSDM 2008. DOI: http://doi.acm.org/10.1145/1341531.1341539

[2] C. Carpineto, R. de Mori, G. Romano, B. Bigi. An information-theoretic approach to automatic query expansion. *ACM Transactions on Information Systems*, volume 19, 1-27, January 2001. DOI: http://doi.acm.org/10.1145/366836.366860

[3] W. Dakka, R. Dayal, P. Ipeirotis. Automatic Discovery of Useful Facet Terms. *Proceedings of the ACM SIGIR '06 Workshop on Faceted Search*, 2006.

[4] M. Hearst, A. Elliott, J. English, R. Sinha, K. Swearingen, K.-P. Yee. Finding the flow in web site search. *Communications of the ACM*, 45:42-49, September 2002. DOI: http://doi.acm.org/10.1145/567498.567525

[5] C. Li, N. Yan, S. B. Roy, L. Lisham, G. Das. Facetedpedia: Dynamic Generation of Query Dependent Faceted Interfaces for Wikipedia. *International World Wide Web Conference*, Raleigh, North Carolina, USA, 2010. DOI: http://doi.acm.org/10.1145/1772690.1772757

[6] B. Schneiderman, Dynamic Queries for Visual Information Seeking. *IEEE Software*, 11, 70-77, June 1994. DOI: http://doi.acm.org/10.1109/52.329404

[7] E. Stoica, M. Hearst. Demonstration: Using WordNet to Build Hierarchical Facet Categories. ACM SIGIR Workshop on Faceted Search, August, 2006.

[8] K. Yang, E. Jacob, A. Loehrlein, S. Lee, N. Yu. Organizing the Web: semi-automatic construction of a faceted scheme. *IADIS International Conference WWW/Internet*, Madrid, Spain, 2004.

A Survey of User Interfaces in Content-based Image Search Engines on the Web

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ABSTRACT

Content-based image retrieval or CBIR technique has been researched for over a decade, and most researches have been focusing on image matching technologies such as feature extraction and similarity measurement. Recently, there has been an attempt to build content-based image search engines on the web in such a way that they could be as popular as their text-based counterparts. In order to do so, other key issues including user interface should also be explored. This paper presents the user interfaces of current content-based image search engines on the Internet, and analyzes their advantages and disadvantages.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces – *evaluation/methodology, graphical user interfaces (GUI).*

General Terms

Design

Keywords

User Interface, Usability, CBIR, Content-based Image Search Engine

1. INTRODUCTION

Content-based image retrieval or CBIR technique analyzes the actual contents of an image and searches for other images with similar visual features such as colors, shapes, and patterns. CBIR technique has been studied for over a decade [18], and numerous image matching methods and algorithms have been proposed in literature [2, 4, 8, 11, 15]. Content-based image search is useful in many fields including online social networking, E-commerce, E-health, and virtual museums. While the image matching technique is still under improvement, researchers and developers have already started to build content-based image search engines on the web that are expected to be as popular as their text-based counterparts.

The current content-based image search engines on the web can be classified into two broad categories, i.e., domain-specific image search engines and general image search engines. Domain-specific image search engines are designed for a certain purpose within a certain range. For example, Like.com [13] searches for similar looking products from its partner E-commerce websites, and Retrievr [17] allows its users to search and explore in a selection of Flickr [9] (Flickr is an image and video hosting website) images by drawing a rough sketch. Domain-specific image search engines focus either on a specific category like people search or product retrieval, or within a limited range such as a specified image database; thus they are relatively easier to implement.

General image search engines provide their users with the power of searching the same or similar looking images over the whole Internet. For example, both TinEye [19] and GazoPa [10] aim on looking for similar images on the entire web. They provide various ways for image search including searching by query image, searching by keywords, and searching by sketch. General content-based image search engines need to differentiate images by categories and index gigantic number of images (e.g., TinEye has indexed more than 1,500,000,000 images from the web [19]); thus they are much harder to construct than domain-specific ones.

Although the above-mentioned content-based image search engines are available on the web, the total number of such search engines is far less than that of text-based ones. And they are not as widely used as their text-based counterparts. This is due to many reasons including low precision ratio, low recall ratio, and unfriendly user interface.

Low precision ratio is because CBIR is still a young field, and its techniques still have room for improvement. Low recall ratio is due to the terrifying number (billions) of images on the web and this number increases by thousands everyday; therefore it is very difficult to index and store all these images in the database. The above two issues are currently researched by many scholars and developers. This paper concentrates on another important aspect, i.e., usability, especially user interface.

Usability of a system refers to how much effort a user has to take in order to use the system and get results. The usability of a system can be evaluated by user satisfaction, the likelihood of user return, and the frequency of use [16]. It is a comprehensive concept and contains many aspects like system design, user interface, and visualization (searching results display).

User interface decides how users interact with the system and how they feel about the system in terms of outlook and easiness of use. A friendly and artistic user interface would attract and retain users, while an unfriendly or dry one could drive users away. This paper conducts a survey and analyzes the user interfaces of current content-based image search engines on the web.

The rest of this paper is organized as follows. The next section makes a brief review of the previous and current literatures on usability of web-based CBIR systems. Section 3 explores the user

Figure 1. Visual search/ similar image search interface on Like.com

interfaces of the current content-based image search engines. And section 4 concludes the entire paper.

2. BRIEF REVIEW

Usability has also been researched for over a decade, and it is an important part of information systems. Palmer [16] did a thorough survey on how usability was defined in website construction. In [16], it is indicated that website success is significantly associated with factors including navigation, interactivity, and responsiveness. User interface in a large degree decides how users interact with information systems and the easiness of navigation; thus the popularity of a system is significantly affected by its user interface. This is especially the case for online search engines since online users have full freedom of choosing which search engine to use. If they feel one engine is too complicated to use, they will switch to another user-friendly one.

In [7], Datta et al. pointed out that the current need in CBIR area is to establish how CBIR technology can reach out to the common man in the same way text retrieval techniques have. This implies a very important principle of user interface design, i.e., **the design should adapt to users' behavior, not shape users' behavior**. However, the study of users' behavior in content-based image search and how to design user interface accordingly have traditionally had lesser consideration [6].

In current literatures like [14], Massanari discussed three different approaches to system design, i.e., system-centered, user-centered, and user-participated. System-centered design expects users to conform to the system requirements when using the system, user-centered design intends to minimize users' efforts, while user-participated design emphasizes on respecting users' behavior and goals in every detail of system design. The more concerned the system is to its users, the more likely the system will succeed.

As for content-based image search engines on the web, their users are usually web surfers with diverse behavior or goals, e.g., reading online news, visiting web-based social networks, shopping online, or just browsing; thus they are interested in different images such as news image, people's photos, or product pictures. They may want to search for similar looking images to the image in a news report, or the photo in a person's profile, or the picture of a product on an E-commerce website. Then what is the most convenient way for them to conduct similar image search process?

In the next section, different user interfaces of current content-based image search engines on the web are introduced, and their advantages and disadvantages are analyzed. The evaluation of the user interfaces is user-centered, i.e., whether the user interface can best fit users' behavior and goals.

Figure 2. Search-by-keyword interface on like.com

3. USER INTERFACES OF CONTENT-BASED IMAGE SEARCH ENGINES

Although different users are interested in different images as described previously, their expectation of an excellent or successful content-based image search engine is the same. They expect to use the least effort to find the most accurate and complete results. This expectation is natural, and the system design should try to meet it.

The following summary and analysis of the user interfaces in the current content-based image search engines on the web are therefore based on satisfying users' needs.

3.1 Hybrid System is Better

A hybrid CBIR system refers to a CBIR system that allows its users to search by either text or image at any point of the searching process. A hybrid system provides the users with a more flexible and powerful way of searching, and its performance should be at least as good as its text-based counterparts since it can also use keywords to search images. Therefore, a hybrid image search engine would be more powerful and popular than purely text-based or image-based ones.

One example of a hybrid content-based image search engine is Like.com [13]. On Like.com, its users can first search images by using keywords or categories, and then pick an interested image as the query image, and retrieve its similar looking images by clicking on the "VISUAL SEARCH" button under the query image. For example, Figure 1 shows an example of visual search interface/ button on each individual item. And the items in Figure 1 are generated by typing keyword "watch" in the search box on Like.com as depicted in Figure 2. The user can choose one watch image and click the "VISUAL SEARCH" button under that image to find similar looking watches on Like.com's partner websites.

3.2 User Interfaces of Search-by-query-image

Friendly user interface not only means the interface should be as easy as possible to use, but also indicates it can satisfy user's various searching needs.

There is always a tradeoff between the easiness of use and the complexity of the background technology. That is, the easier it is to use a system, the harder it is to implement it or the more complicated the background technology is. In CBIR area, many current content-based image search engines on the web adopted the most convenient way for image searching. This actually challenges the present CBIR technology to be more developed.

The easiest way to search similar images is different under different searching scenarios or users' searching needs; therefore, the corresponding user interfaces should be designed to fit users' various searching needs.

Figure 3. An image uploading interface on Tineye.com

3.2.1 Uploading interface when query image is local

If the query image is local, i.e., on the user's storage devices including hard drive, memory card, and flash drive, then an uploading interface should be provided for the user to upload the image file to the search engine. This uploading interface is standard and it usually contains a search box and a browse/ upload button as shown in Figure 3, which was extracted from TinEye Reverse Image Search [19] website. Once the user clicks the browse/ upload button, a navigation window will be popped up for the user to choose which file to upload. And the search engine will automatically search for similar images once the image file is uploaded.

Some traditional content-based image search engines like ASSERT [1] require users to circle a certain area in the uploaded image before clicking the search button. This way is expected to increase the precision ratio of the searching results, but sometimes, it is not the case, and it significantly increases the users' burden and thus should be avoided as much as possible in user interface design.

3.2.2 What is the best interface for web images

If the query image is on a web page, a friendly image search engine should not ask the user to download the image and then upload it to the search engine for searching purpose. Instead, a more convenient way should be provided. Currently there are at least three ways for this purpose, i.e., copy and paste URL, make bookmarklet, and use plug-in.

Figure 4. Copy and paste URL interface on Tineye.com

Copy and paste URL interface. Figure 4 shows an example of copy and paste URL interface extracted from Tineye.com. The user needs to copy the URL of the web page containing the query image, paste it into the search box, and click the search button. The search engine will then automatically fetch all the images on the pasted URL and present them to the user. The user can then click the interested image to search for its similar images. The inconvenience of this method is that users have to copy and paste the URL and wait for the search engine to fetch all the images from that web page. To avoid copying and pasting URL, bookmarklet is introduced.

Figure 5. A bookmarklet interface on Tineye.com

Bookmarklet interface. Bookmarklet does exactly the same as copying and pasting URL does, but without the need of copying and pasting URL. Bookmarklet is a little script that is run from the browser's bookmark menu or toolbar. To add bookmarklet, users just need to right-click the link or linked button on the search engine website like "TinEye Images" button on TinEye.com as depicted in Figure 5, and select "Bookmark This Link" (on Mac) or "Add to Favorites" (on PC). Then the bookmarlet is added to the browser's bookmark toolbar as shown in Figure 5. The bookmarklet "TinEye Images" looks like a regular bookmark, but when the user clicks it, it will fetch all the images on the current web page, and allow users to click on an interested image to search for similar images. Making bookmarklet saves the step of copying and pasting URL, but users need to add it to their browsers' bookmark menu or toolbar.

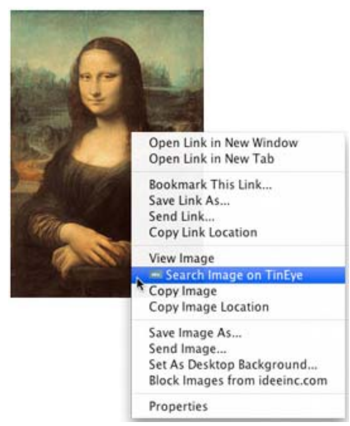

Figure 6. An example of similar image search plug-in

Plug-in interface. Plug-in is a software that users can download and install on their browsers to add more functionalities to the browsers or achieve special presentation effects. Similar image search plug-in is designed for searching similar image purpose. There could be many ways to implement the plug-in user interface. One way is to use right-click menu. That is, once the similar image search plug-in is downloaded and installed, users can right click on any online image, and there will be a new item on the right-click menu like "Search Image on TinEye" in Safari as presented in Figure 6. Then the user can click it to search similar images on the web. Plug-in is direct and easy to use, and saves the time of fetching images compared to the previous two methods. The disadvantage is that some users may not want to install plug-in in their browsers.

Among the above three interfaces, plug-in is the most convenient to users' behaviour and goals. When users intend to search for the similar images of an interested image they came across on the web, the natural way is to directly click/ right-click on the image itself to launch the searching process. Copying and pasting URL puts a heavy load on the users. Even going to the Bookmark or

Favorites toolbar to click on the bookmarklet and waiting for the query images to be loaded are far less convenient than clicking/ right-clicking on the image directly. In addition, many users choose to hide their Bookmark or Favorites toolbars on their browsers, which made bookmarklet less feasible. Therefore, plug-in interface should be the targeted interface when the query image is on a web page.

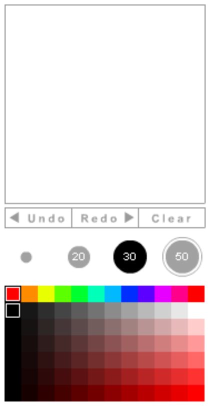

Figure 7. Image search by sketch from Retrievr

3.2.3 Drawing interface for sketch images

Sometimes users want to find people images or artwork pictures similar to a sketch they draw [3, 5, 12], and then the search engine should provide a sketch panel for users to draft. Figure 7 is the search-by-sketch interface extracted from Retrievr [17]. As stated earlier, Retrievr searches images similar to the user's sketch in Flickr image database. In Figure 7, users can pick a certain color and the size of the brush to draw a sketch in the blank panel. Once the user finishes drawing the sketch, Retrievr automatically searches for images similar to the user's sketch and present them to the user. This technique can be used in many practical scenarios including police searching for suspects and people looking for artworks. The hardship of this method is that the sketch drawn on computers is usually rough, and the searching results are thus not quite accurate.

4. CONCLUSION

User interface is an important part of content-based image search engines on the web. Although different user interfaces should be designed for different searching purposes, they follow the same principle of interface design, i.e., the easier it is to use, the more popular it is going to be. The easy-to-use interfaces naturally challenge their background technologies to be more advanced and powerful. This paper conducts a survey on the user interfaces of current content-based image search engines on the Internet and analyzes their advantages and disadvantages. The easy-to-use interfaces are recommended, and it is expected that in the near future, more user-friendly, attractive, and powerful content-based image search engines will be created on the web.

5. REFERENCES

[1] ASSERT demo, http://cobweb.ecn.purdue.edu/~cbirdev/WEB_ASSERT/assert.html

[2] Berretti, S., Del Bimbo, A., and Pala, P. 2000. Retrieval by shape similarity with perceptual distance and effective indexing. *IEEE Trans. Multimed.* 2, 4, 225–239, 2000.

[3] Del Bimbo, A. and Pala, P. 1997. Visual image retrieval by elastic matching of user sketches. *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 19, no. 2, pp. 121-132, Feb. 1997.

[4] Bovis, K. and Singh, S. 2000. Detection of masses in mammograms using texture features. *15th International Conference on Pattern Recognition (ICPR'00)* - Volume 2, 2000.

[5] Chalechale, A., Naghdy, G., and Mertins A. 2005. Sketch-based image matching using angular partitioning. *IEEE Trans. Systems, Man, and Cybernetics*, 35(1):28–41, 2005.

[6] Datta, R., Joshi, D., Li, J., and Wang, J.Z. 2008. Image retrieval: ideas, influences, and trends of the new age. *ACM Computing Surveys*, Vol. 40, No. 2, Article 5, 2008.

[7] Datta, R., Li, J., and Wang, J.Z. 2005. Content-based image retrieval: approaches and trends of the new age. Proceedings *of the 7th ACM SIGMM international workshop on Multimedia information retrieval*, November 10-11, 2005, Hilton, Singapore.

[8] Deng, Y., Manjunath, B.S., Kenney, C., Moore, M.S., and Shin, H. 2001. An efficient color representation for image retrieval. *IEEE Trans. Image Process.* 10, 1, 140–147, 2001.

[9] Flickr, http://www.flickr.com/

[10] GazoPa, http://www.gazopa.com/

[11] Jhanwar, N., Chaudhuri, S., Seetharaman, G., and Zavidovique, B. 2004. Content based image retrieval using motif coocurrence matrix. *Image and Vision Computing*, 22(14), 2004, pp. 1211-1220.

[12] Kato, T., Kurita, T., Otsu, N., and Hirata, K. 1992. A Sketch retrieval method for full color image database—query by visual example. *Proc. ICPR, Computer Vision and Applications*, pp. 530-533, 1992.

[13] Like.com, http://www.like.com/

[14] Massanari, A.L. 2010. Designing for imaginary friends: information architecture, personas and the politics of user-centered design. *New Media & Society*, 12(3), pp 401-416, 2010.

[15] Natsev, A., Rastogi, R., and Shim, K. 2004. Walrus: A similarity retrieval algorithm for image databases. *IEEE Trans. Knowl. Data Eng.* 16, 3, 301–316, 2004.

[16] Palmer, J.W. 2002. Web site usability, design, and performance metrics. *Information Systems Research*, Vol. 13, No. 2, June 2002, pp. 151-167.

[17] Retrievr, http://labs.systemone.at/retrievr/

[18] Smeulders, A. W., Worring, M., Santini, S., Gupta, A., and Jain, R. 2000. Content-based image retrieval at the end of the early years. *IEEE Trans. Pattern Anal. Mach. Intell. 22*, 12, 1349–1380. 2000.

[19] TinEye Reverse Image Search, http://tineye.com/