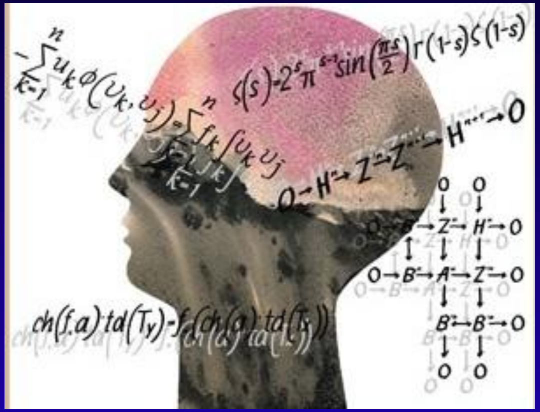
Artificial Intelligence in the Open World

Eric Horvitz

Presidential Address
July 2008

Rich Intellectual History of AI



18th - **Julien Offray de La Mettrie**

***L'homme machine* (1747)**

19th - **Charles Babbage**

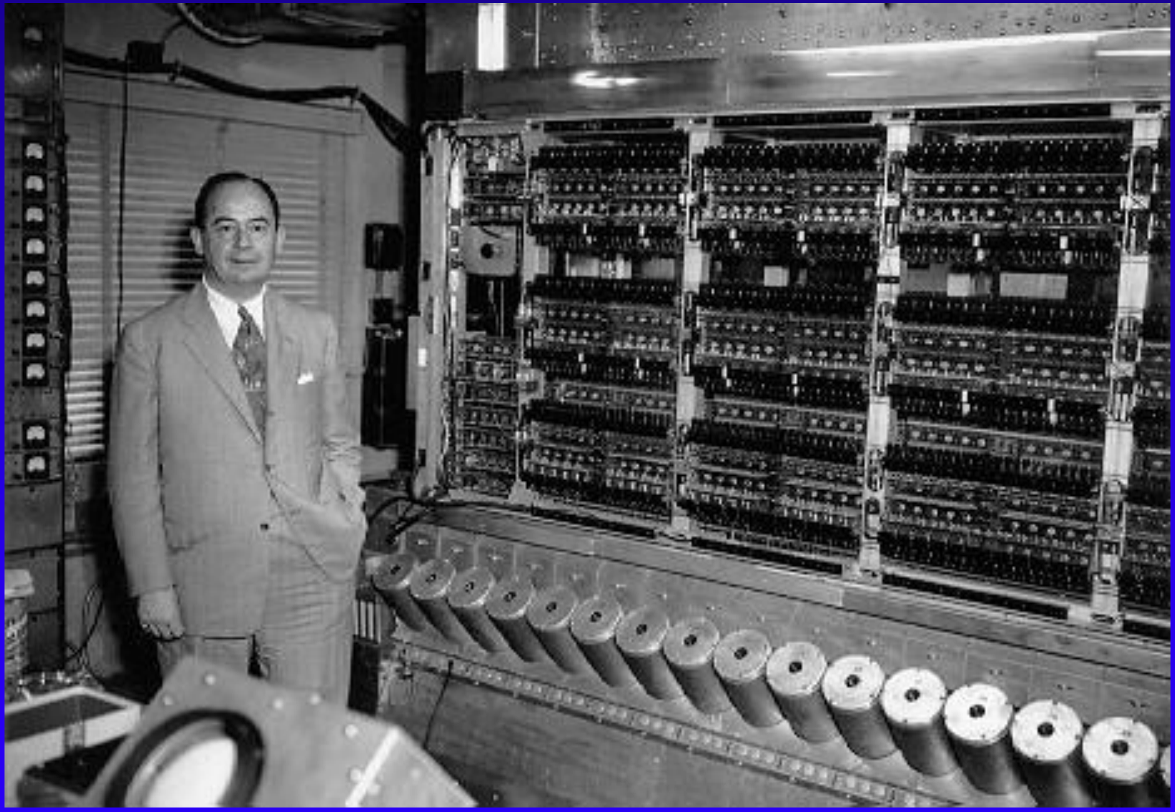
Difference Machine, Analytical Engine

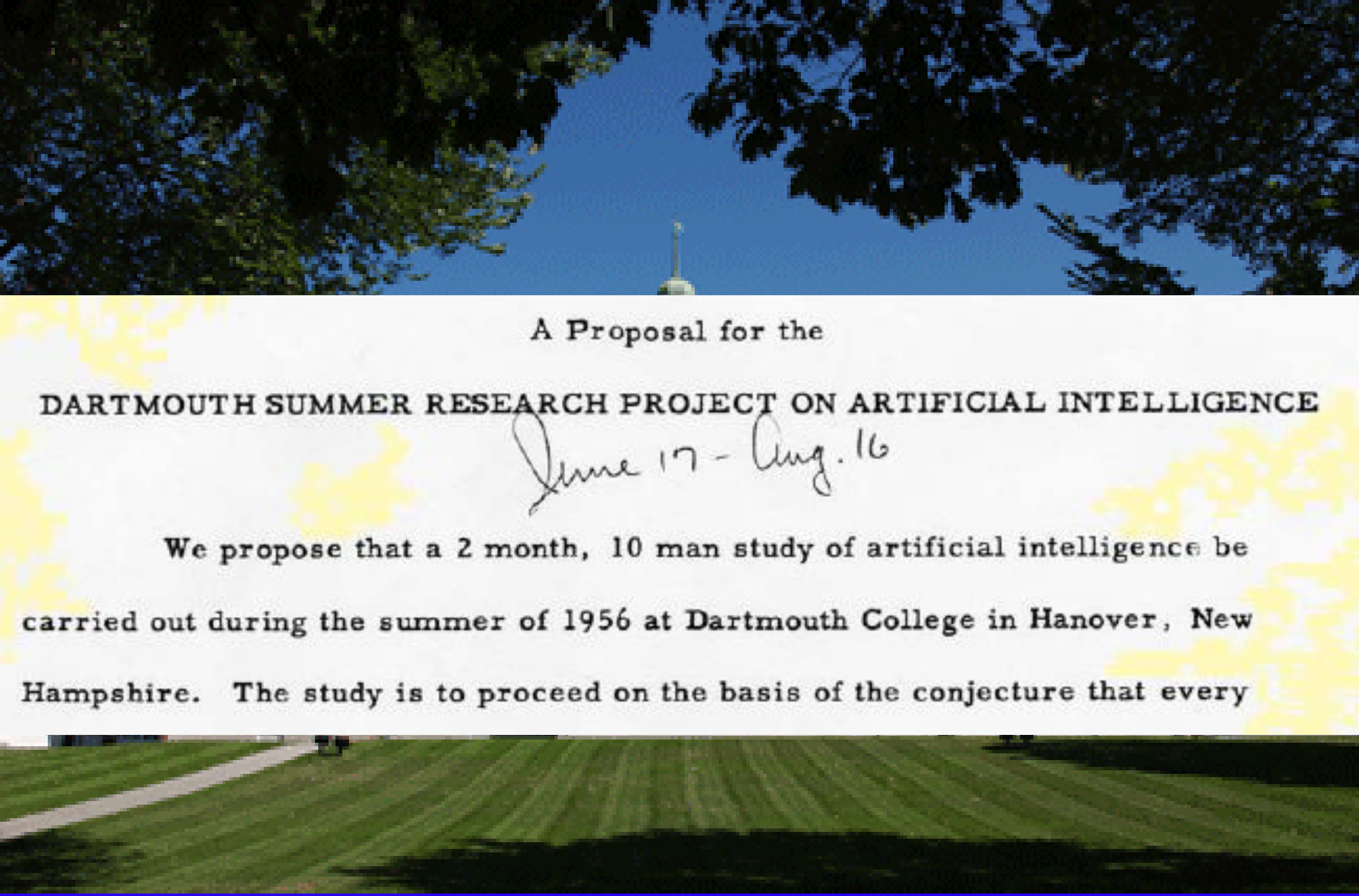
20th - **Turing, von Neumann, Weiner, *et al.***

- **Newell, Simon, Rochester, McCarthy, *et al.***

Computation as Basis of Thought & Intelligent Behavior

- Theories of computability
- General purpose computer





A Proposal for the

DARTMOUTH SUMMER RESEARCH PROJECT ON ARTIFICIAL INTELLIGENCE

June 17 - Aug. 16

We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every

Dartmouth Meeting

- Machine methods of forming abstractions from sensory and other data
- Carrying out activities which may best be described as self-improvement
- Manipulating words according to rules of reasoning and rules of conjecture
- Developing a theory of the complexity for various aspects of intelligence

Paradigms of Computational Intelligence

"AI"

Decision sciences / OR

Optimization

Logic

Computability

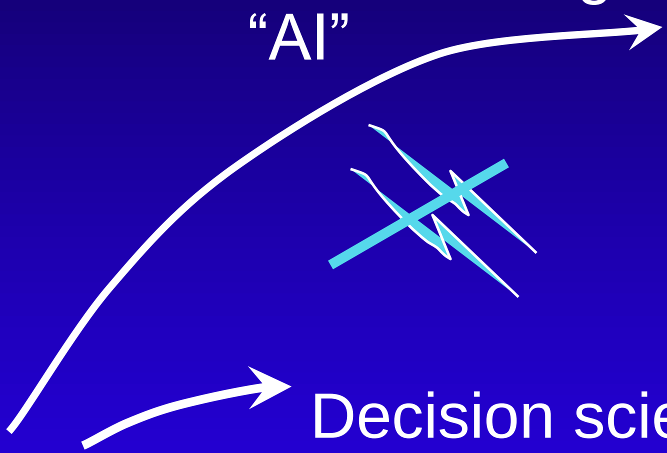
General purpose computer

Paradigms of Computational Intelligence

Satisficing

High-level symbols

Logic



Decision sciences / OR

Optimization

Logic

Computability

General purpose computer

Grappling with Incompleteness in an Open World

Grappling with Incompleteness in an Open World

Grappling with Incompleteness in an Open World

Bounded rationality (Simon, *et al*).

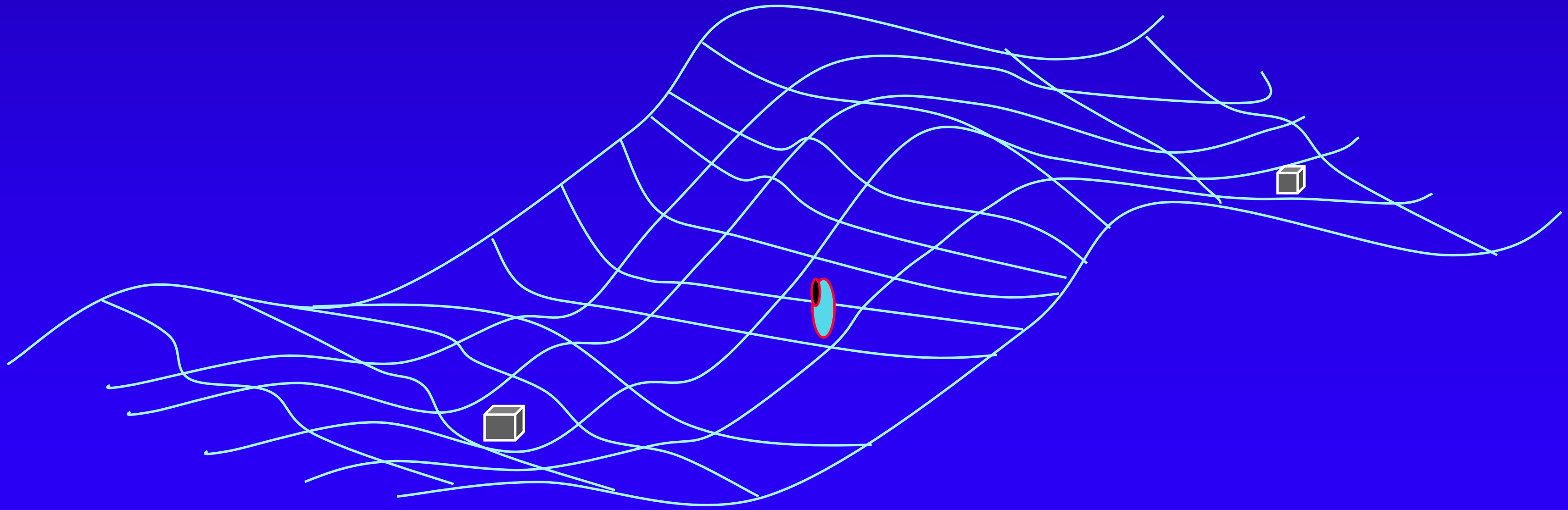
Hopelessly incomplete knowledge of …

- Preferences
- State of world
- Outcomes of action

Enduring Perspective: Intelligence amidst Inescapable Incompleteness

Limited agents immersed in complex universes

- **Limited representations**
- **Limited time and memory**



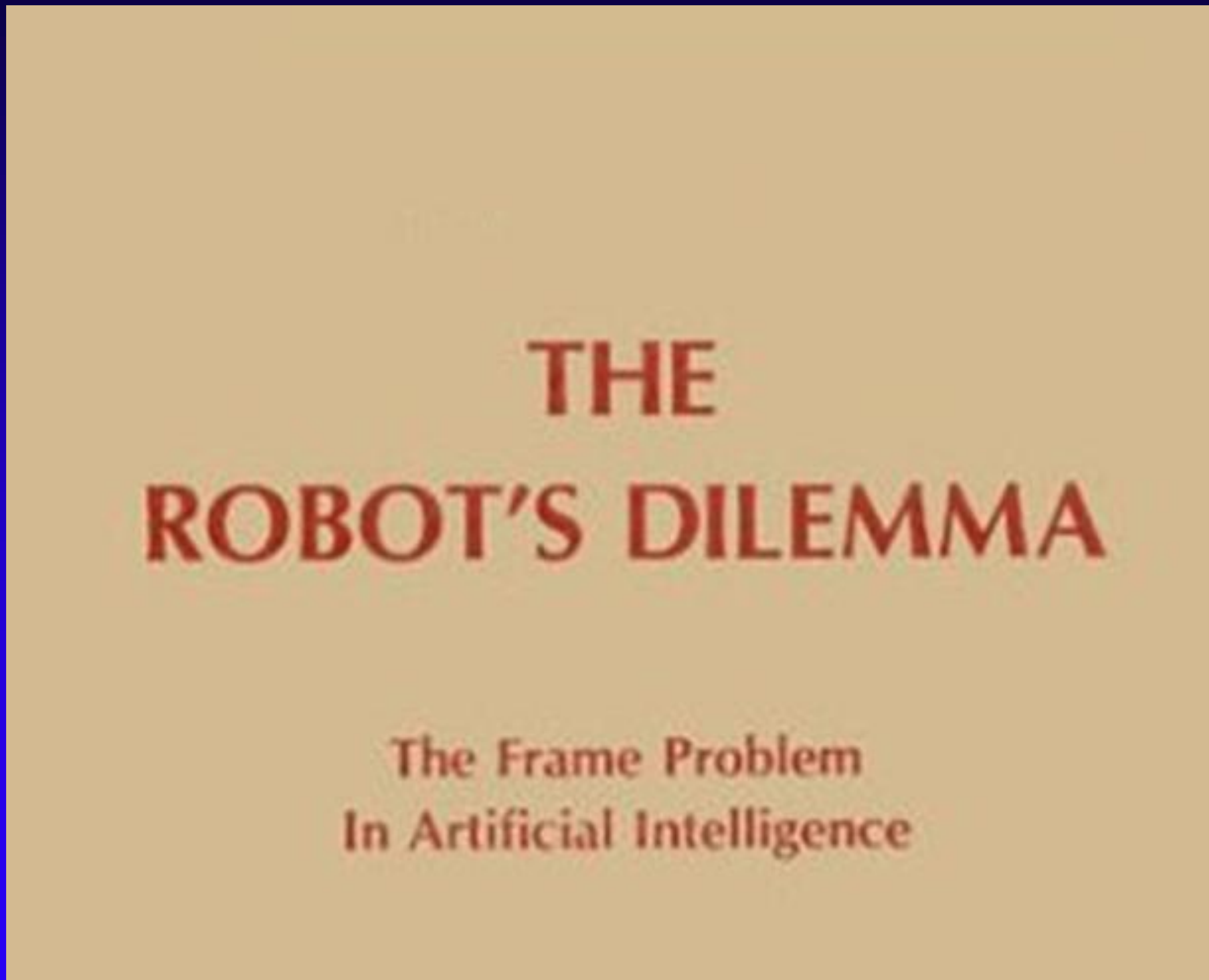
Stepping into the Open World

- Key technical challenges
- AI moving into the world
- AI research community

Stepping into the Open World

- Key technical challenges
- AI moving into the world
- AI research community

Stepping into the Open World



Stepping into the Open World

Relevance & Attention in Open Worlds

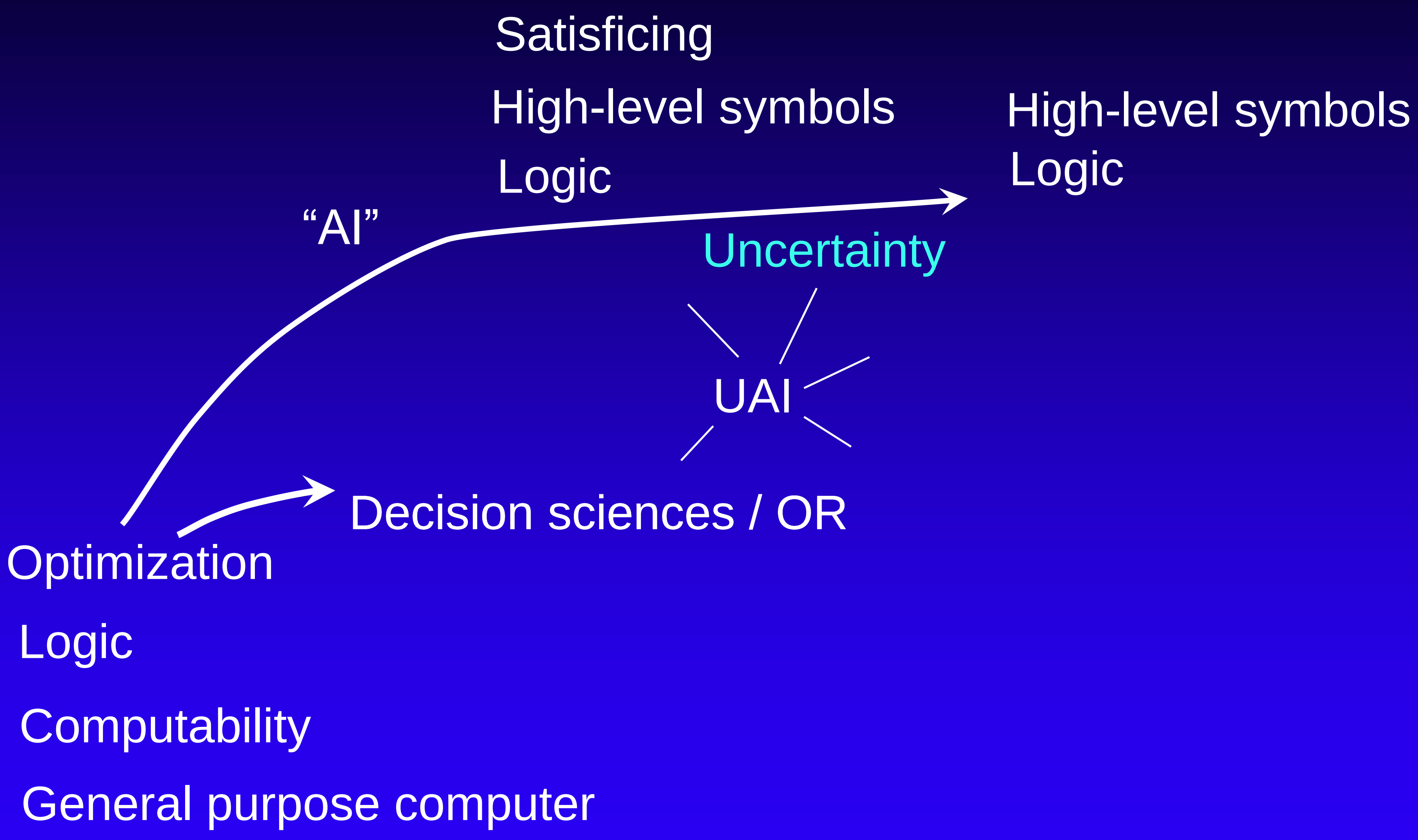
- Frame problem

  How to limit the scope of the reasoning required to derive the consequences of an action?

  - Qualification problem
    - *All preconditions required for actions to have intended effects*
  - Ramification problem
    - *All effects of action*

Nonmonotonic logics, representation of fluents

Paradigms of Computational Intelligence



Paradigms of Computational Intelligence

Satisficing

High-level symbols

Logic

Optimization

High-level symbols

Logic

"AI"

Probability

Utility

MEU

UAI

Decision sciences / OR

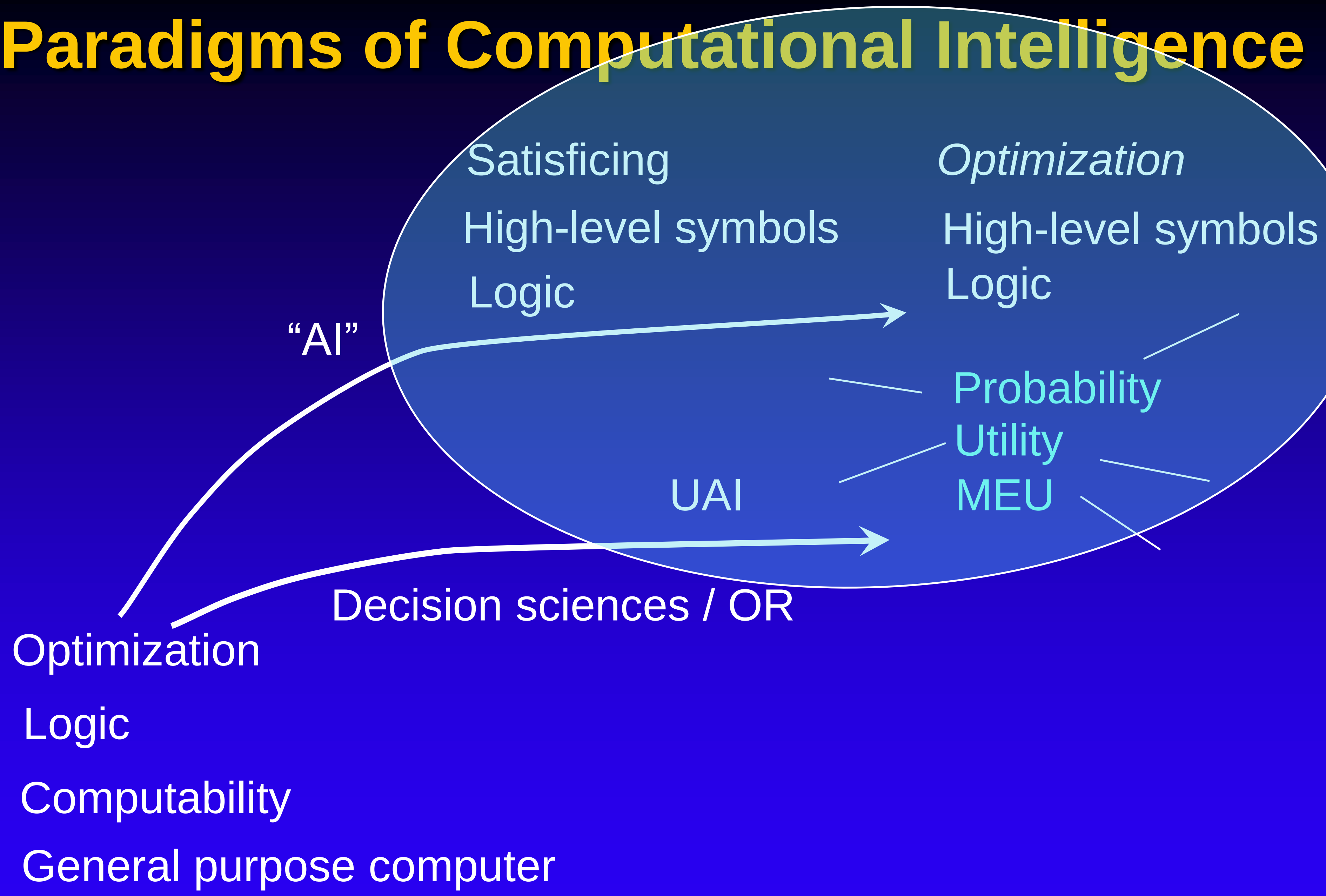
Optimization

Logic

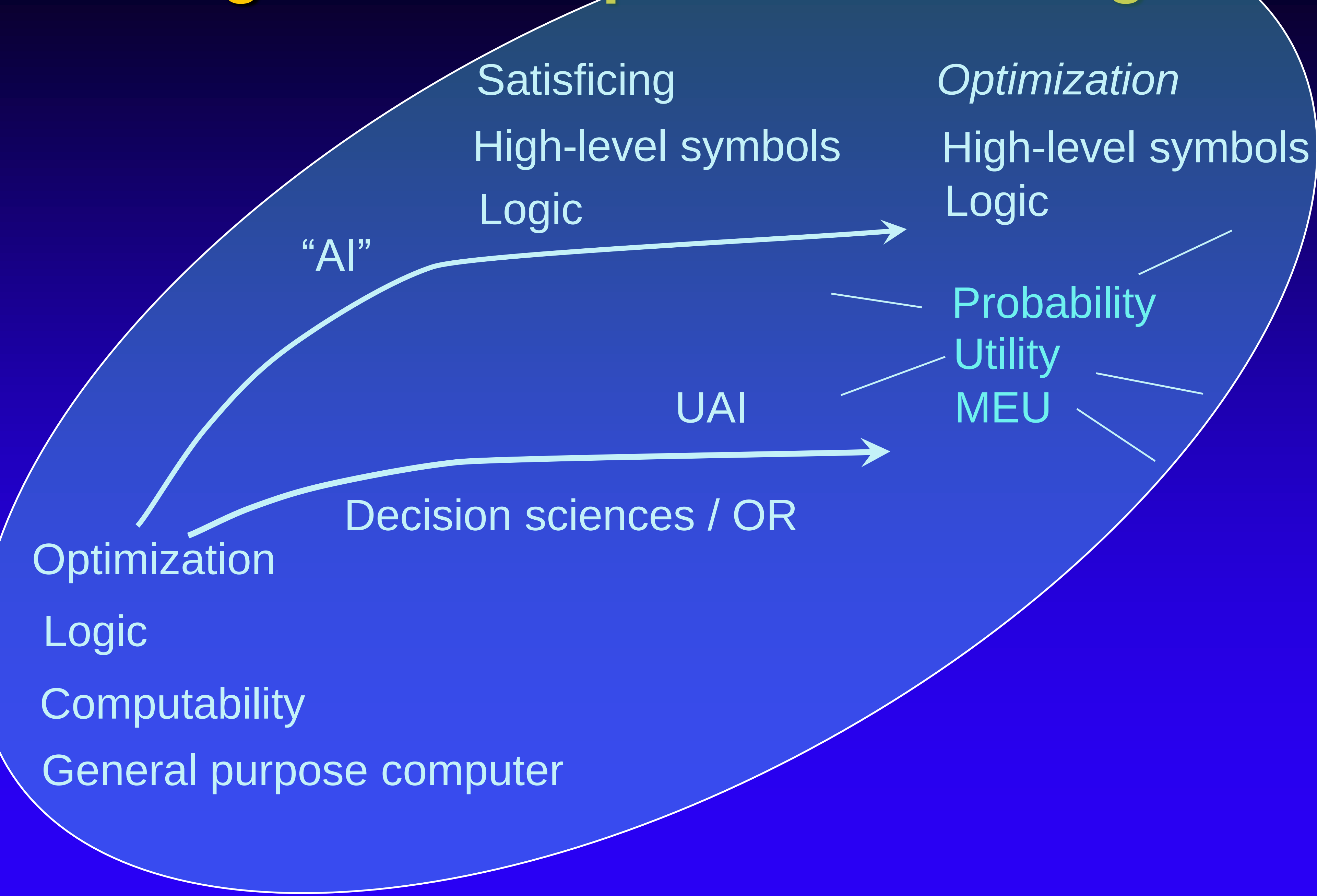
Computability

General purpose computer

Paradigms of Computational Intelligence



Paradigms of Computational Intelligence



Uncertainty as Organizing Principle

- Incompleteness is inescapable
- Uncertainty is ubiquitous
  - State of world
  - Outcome of action
  - Problem solving itself

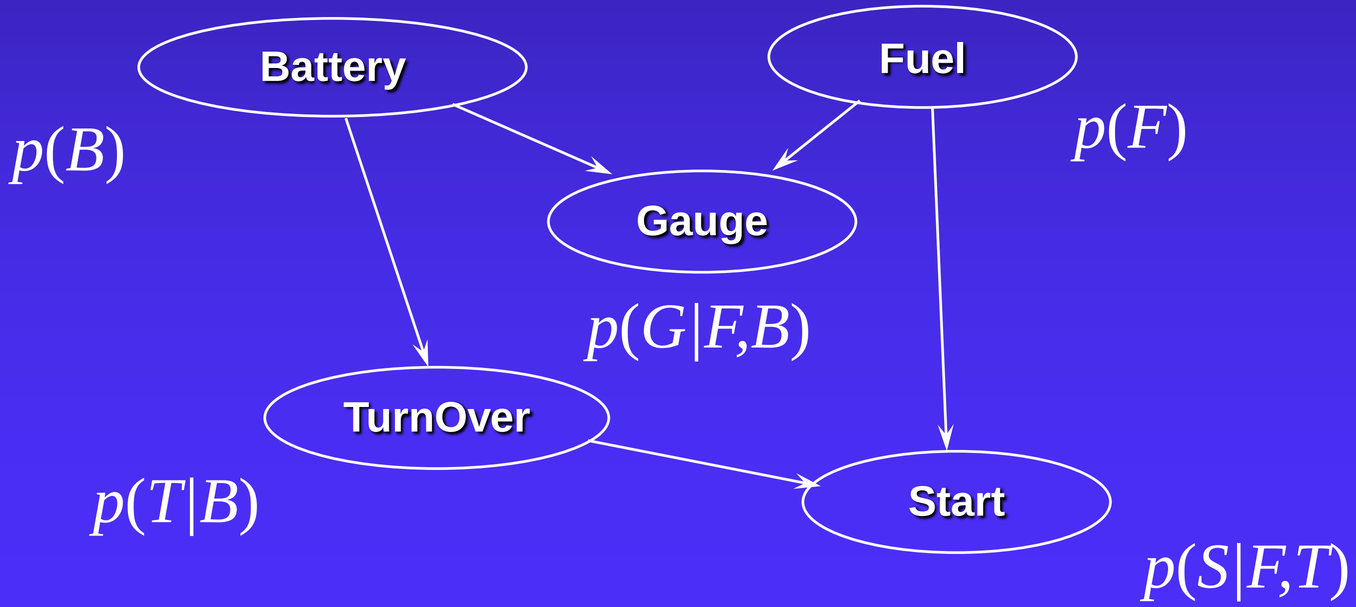
Push unknown & unrepresented details into probabilities and propagate

Uncertainty as Organizing Principle

➔ ***Machinery for handling <u>uncertainty</u> & <u>resource limitations</u> foundational in intelligence***

Expressive Representations of Uncertainty

- **Graphical models for representing beliefs**
  - *d*-separation
  - Sound and complete algorithm for identifying all independencies entailed by the graph.

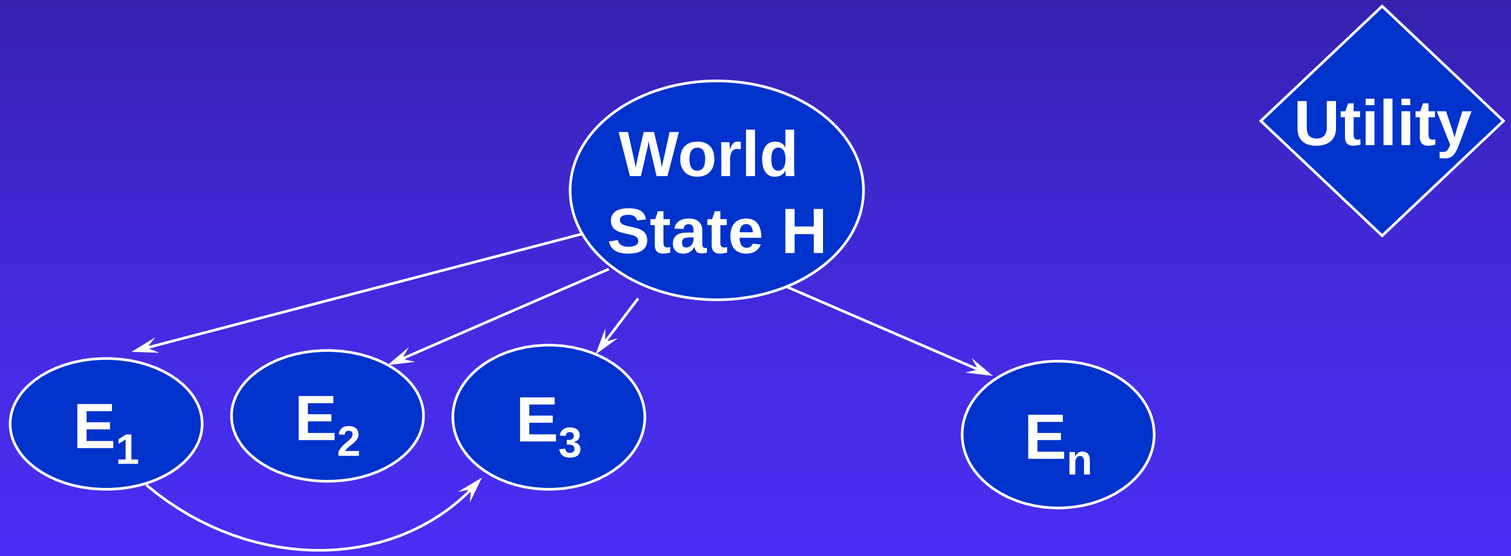


Representing Problems of Action

- **Maximum expected utility (MEU)**
- **Influence diagrams (Howard & Matheson, 1975)**

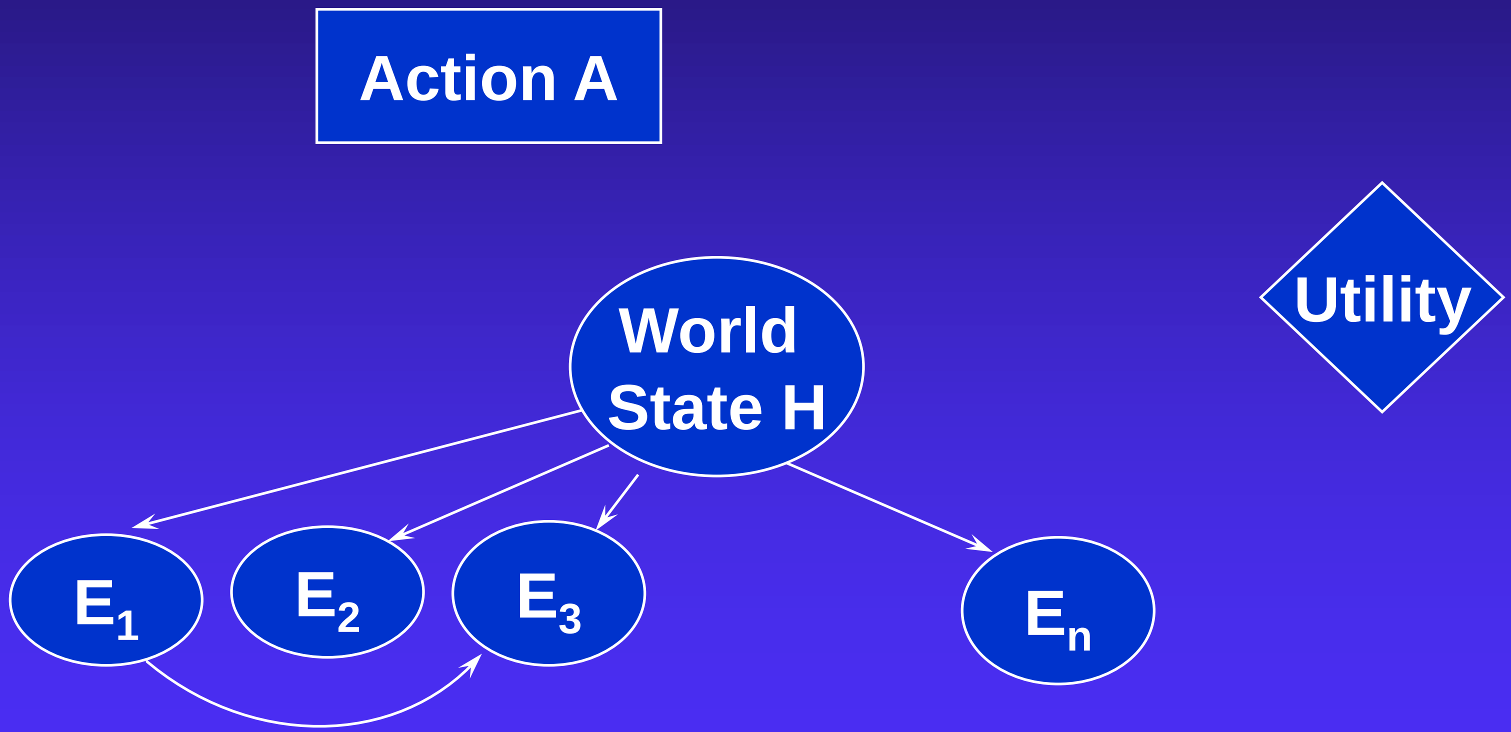
Representing Problems of Action

- **Maximum expected utility (MEU)**
- **Influence diagrams** (Howard & Matheson, 1975)



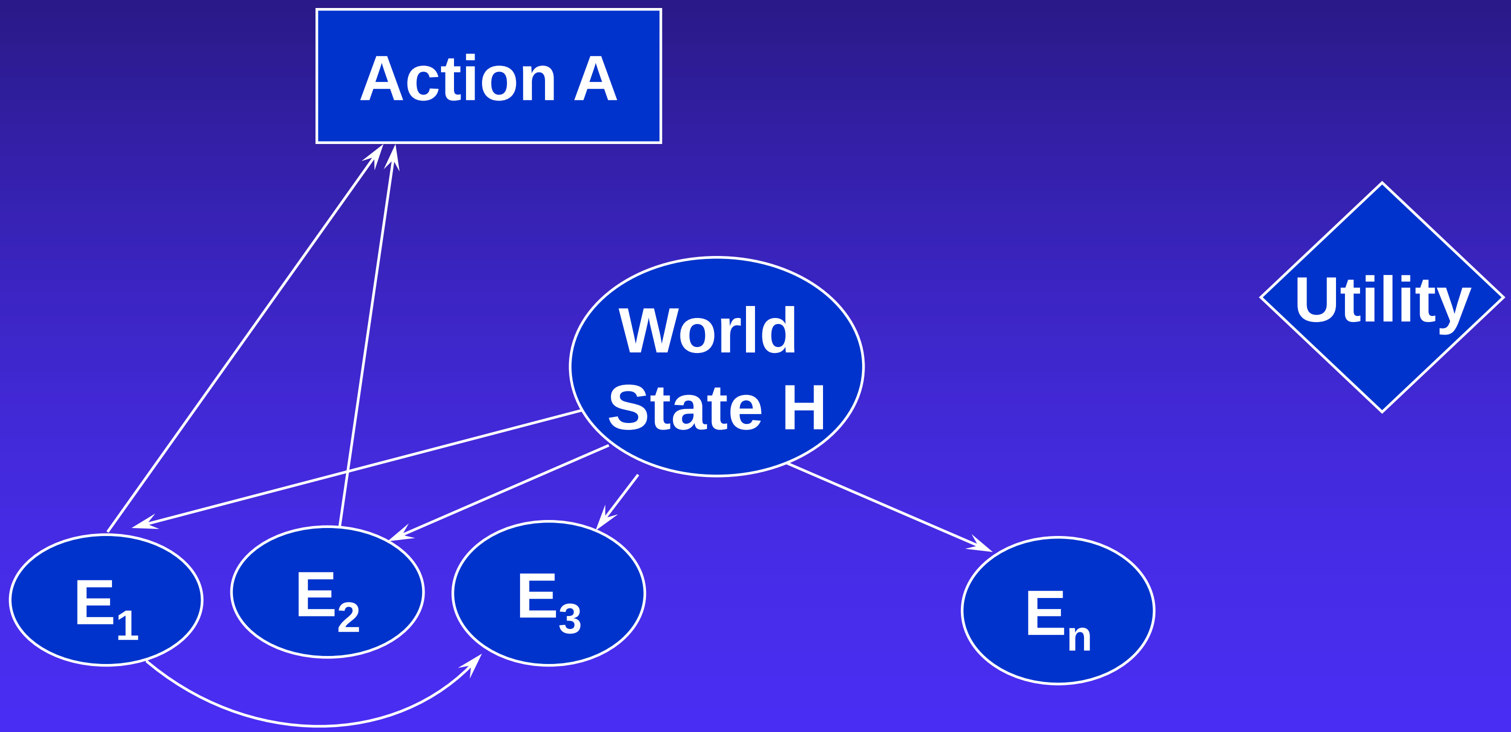
Representing Problems of Action

- **Maximum expected utility (MEU)**
- **Influence diagrams** (Howard & Matheson, 1975)



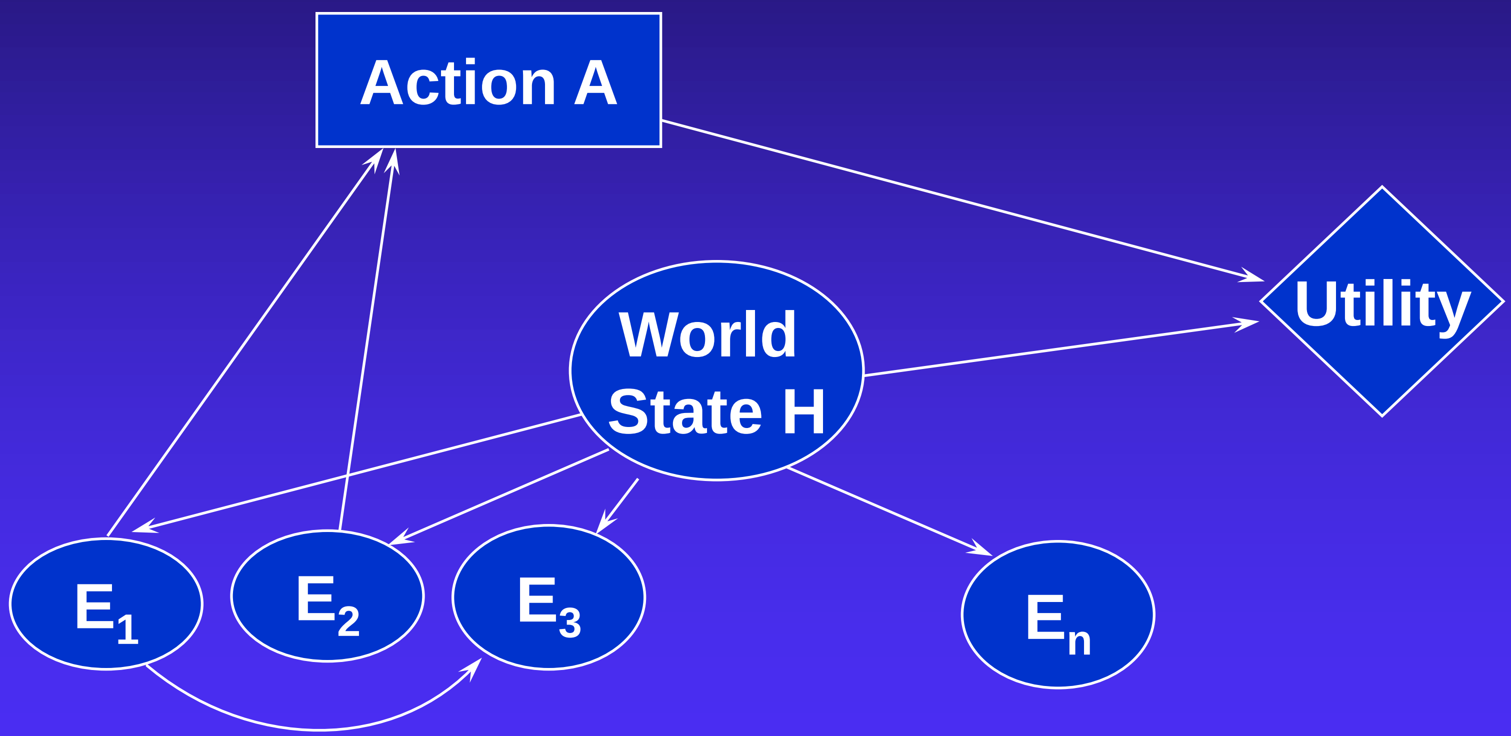
Representing Problems of Action

- Maximum expected utility (MEU)
- Influence diagrams (Howard & Matheson, 1975)

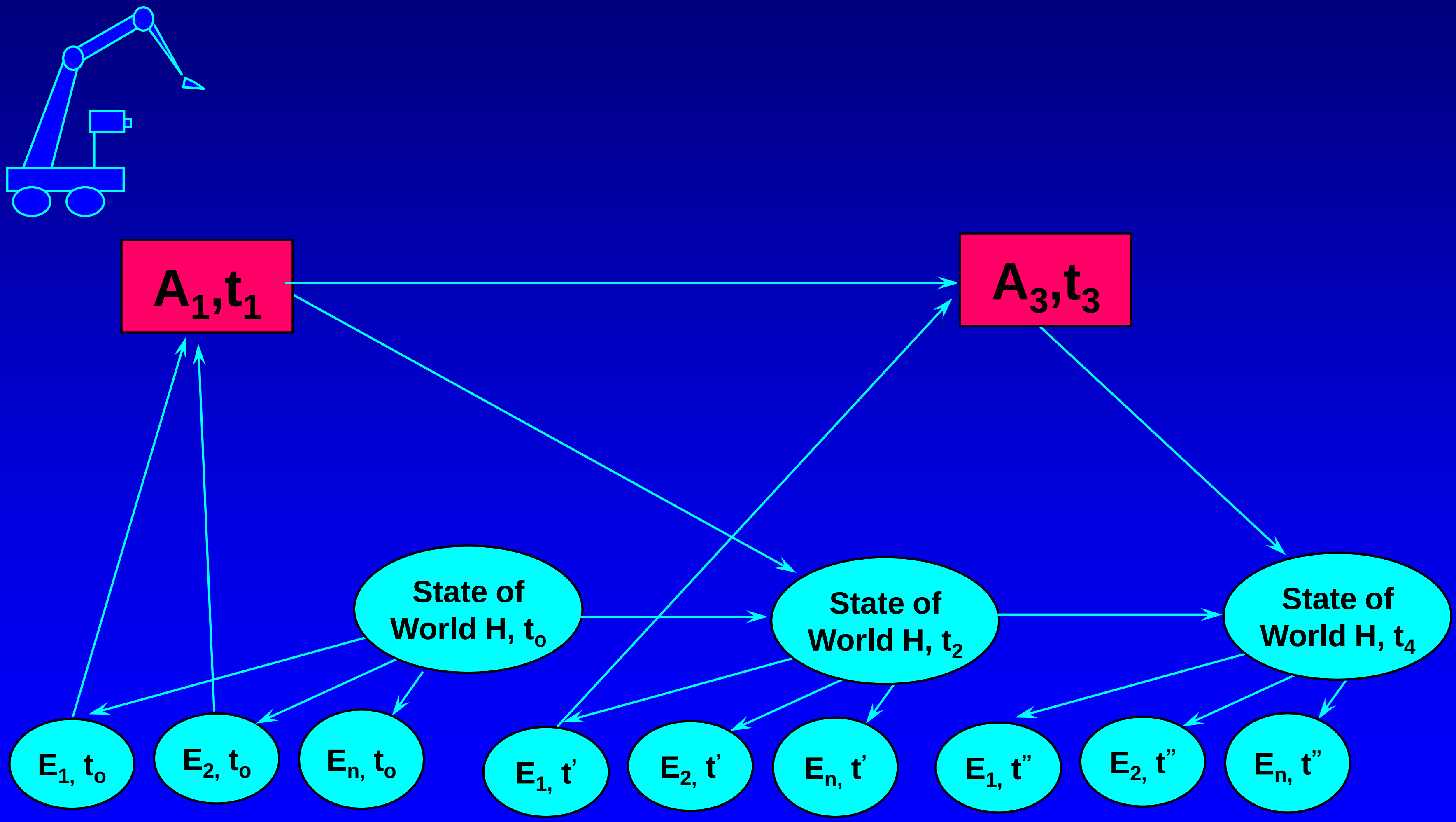


Representing Problems of Action

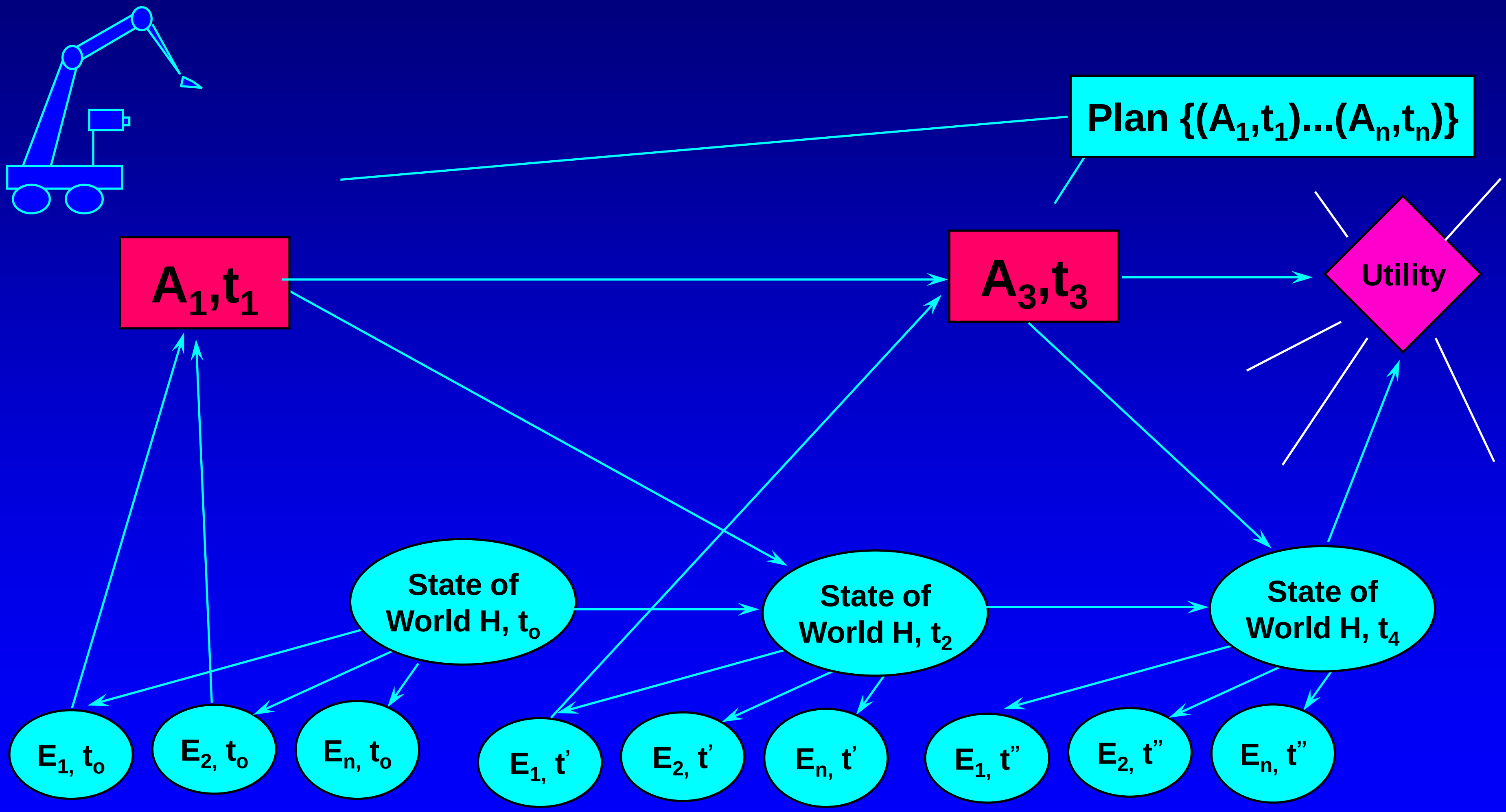
- **Maximum expected utility (MEU)**
- **Influence diagrams** (Howard & Matheson, 1975)



Reasoning about Beliefs and Actions over Time

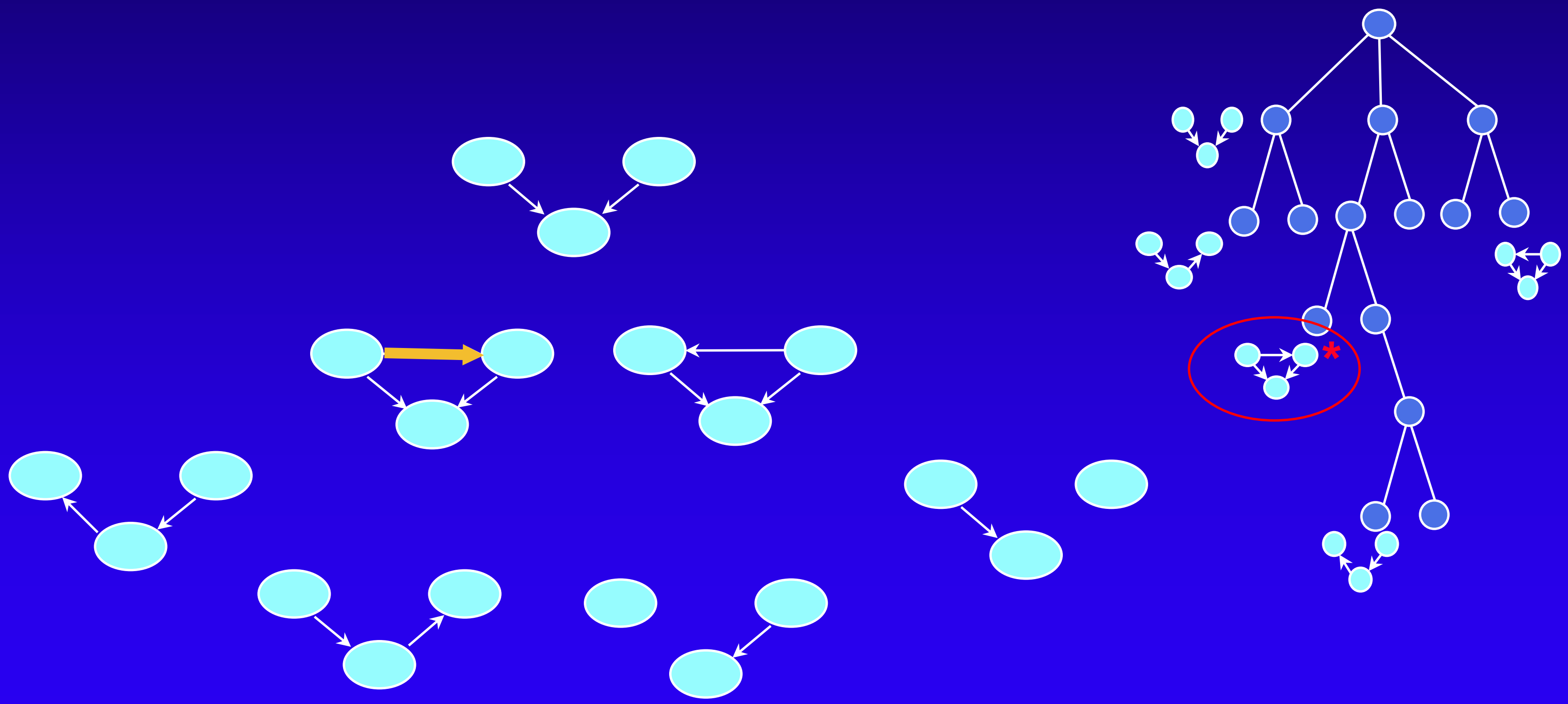


Reasoning about Beliefs and Actions over Time



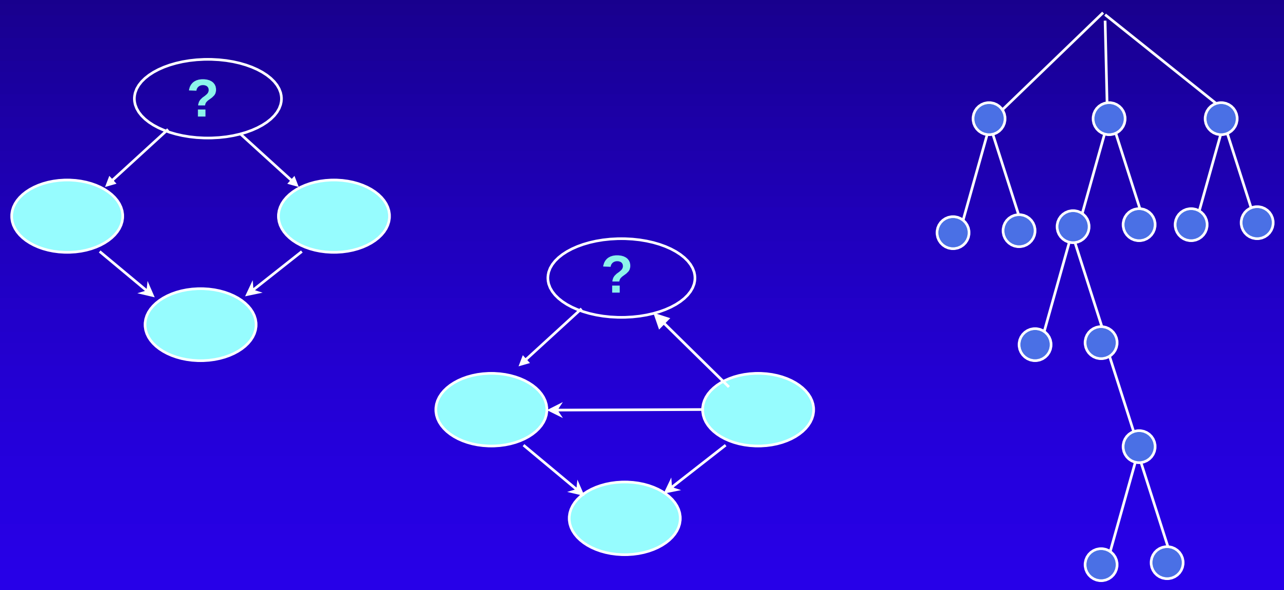
Acceleration of Machine Learning: Discovering Structure and Concepts

- *e.g.,* Structure search
- Measure of model likelihood



Identification of Hidden Variables

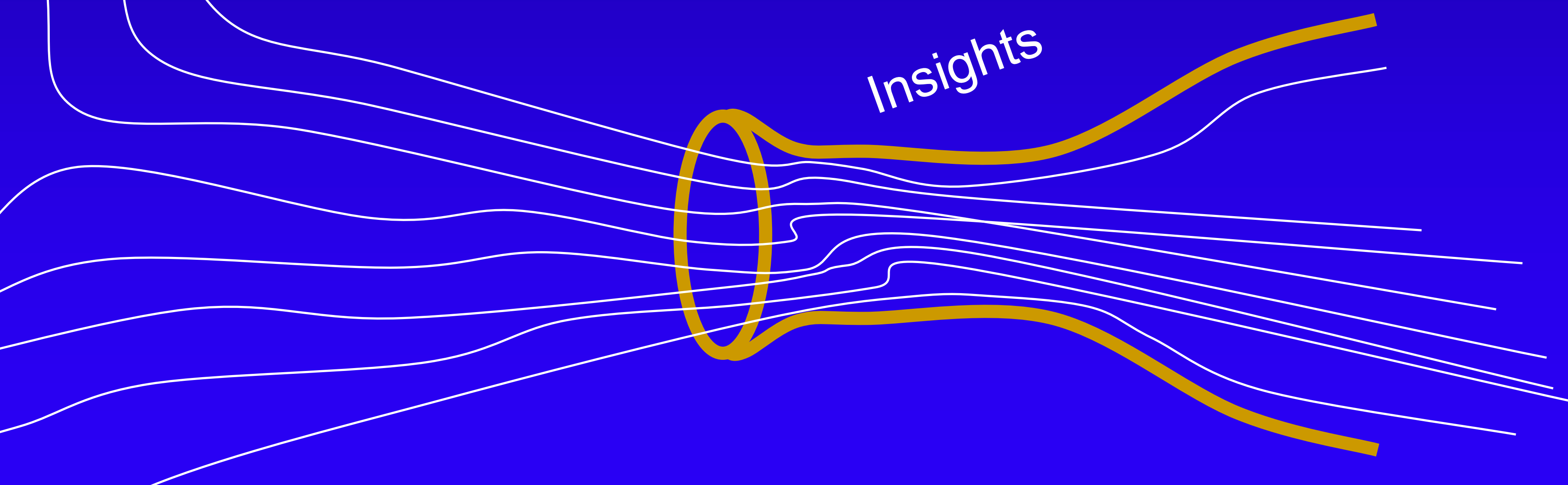
- "Unknown" variables discovered



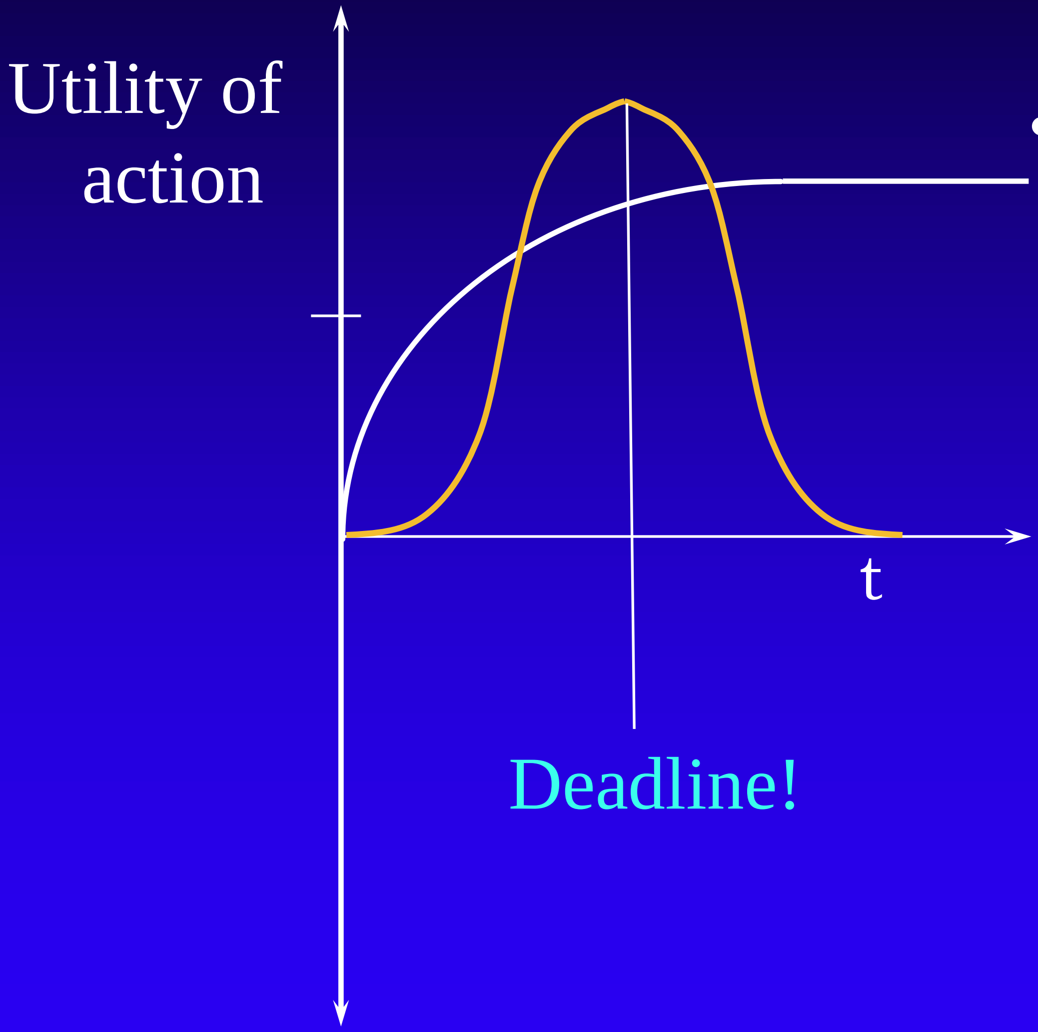
Beauty …and the Bottleneck

Insights arising in tight situations

- **Bounded rationality → *Bounded optimality***
- **Economics of computation**
- **Flexible computational strategies**
- **Principles of reflection**

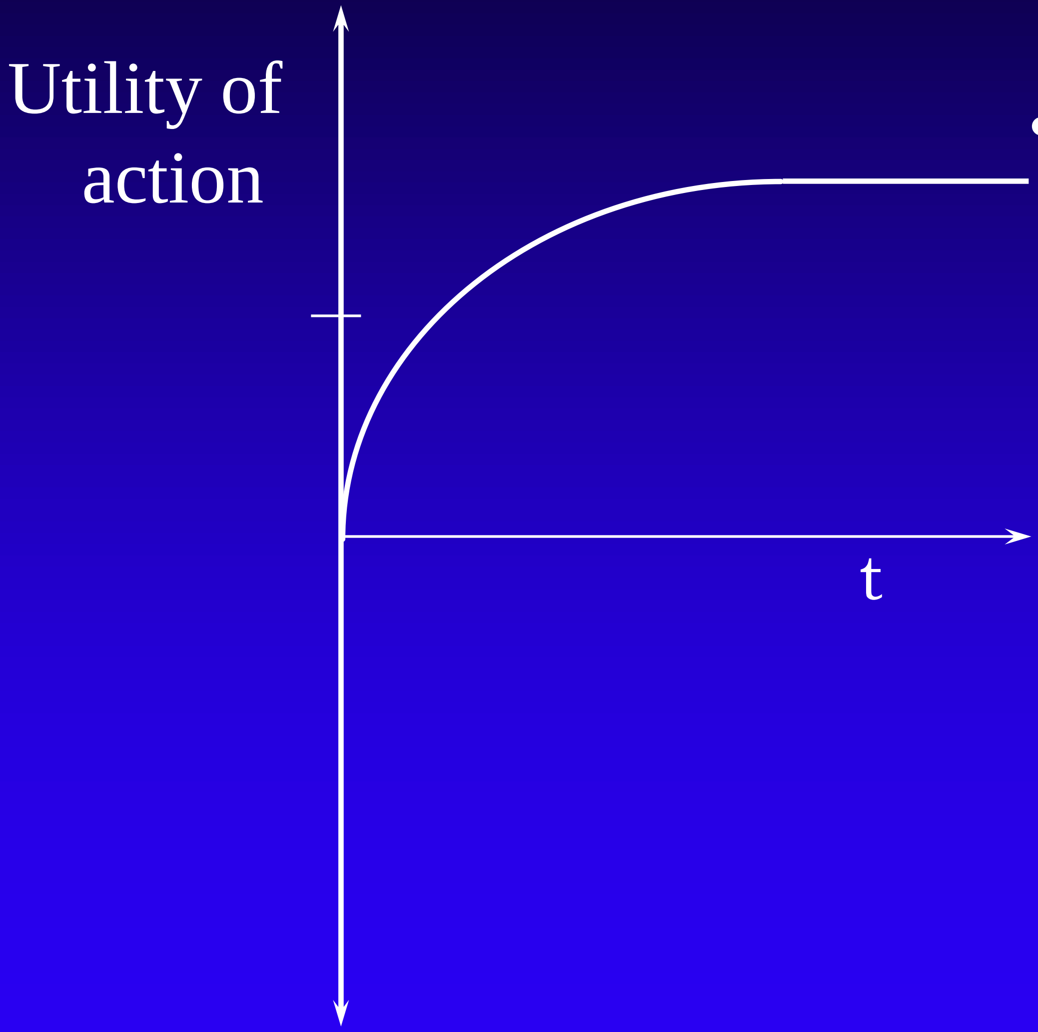


Economics of Flexible Computation



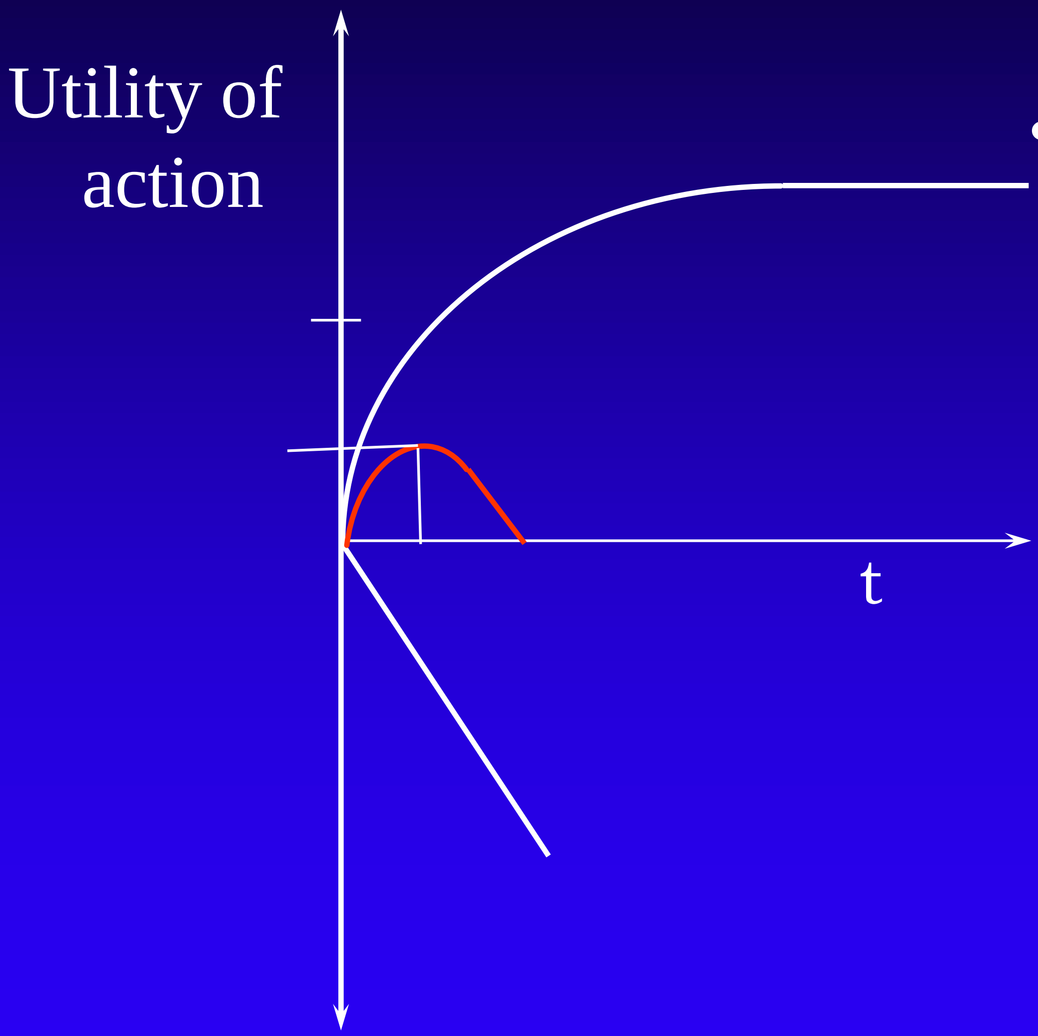
- Immediate value of result

Economics of Flexible Computation



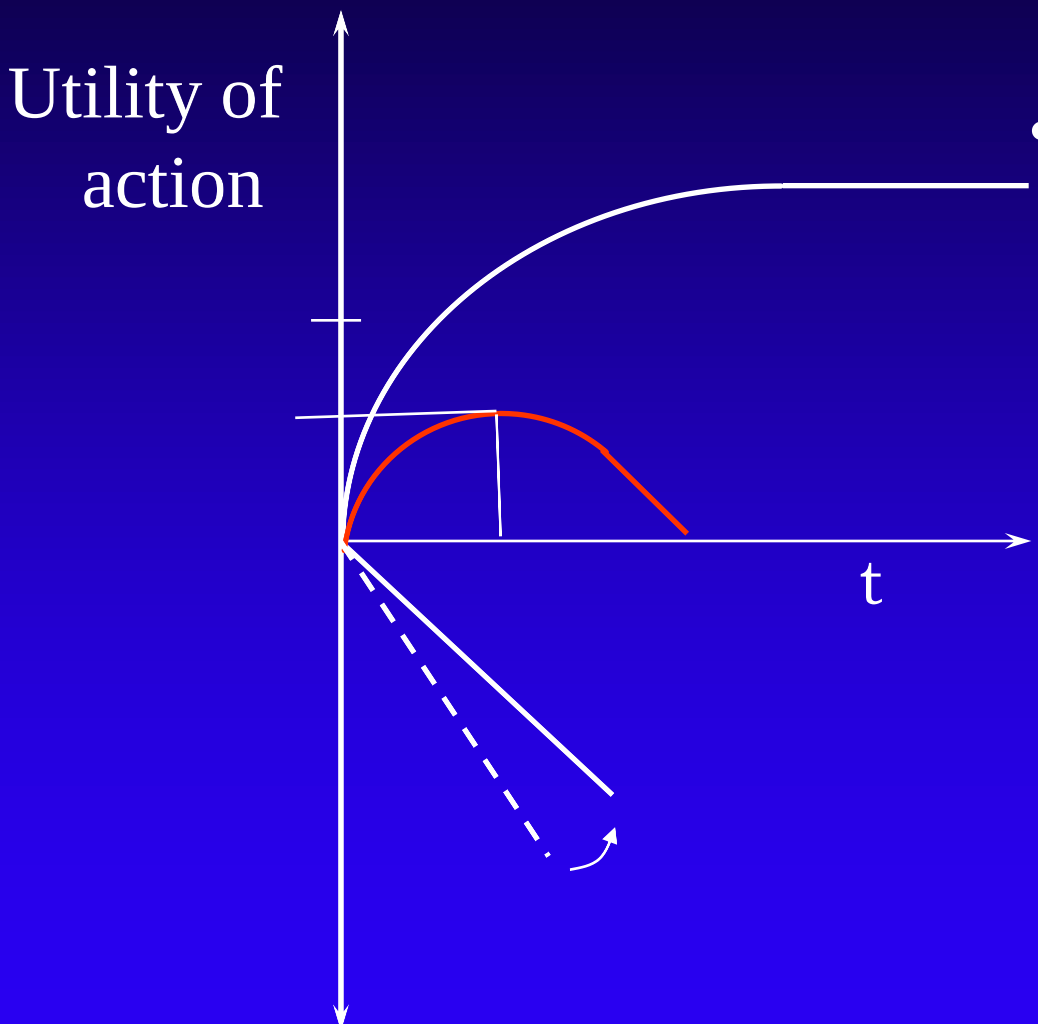
- Immediate value of result

Economics of Flexible Computation



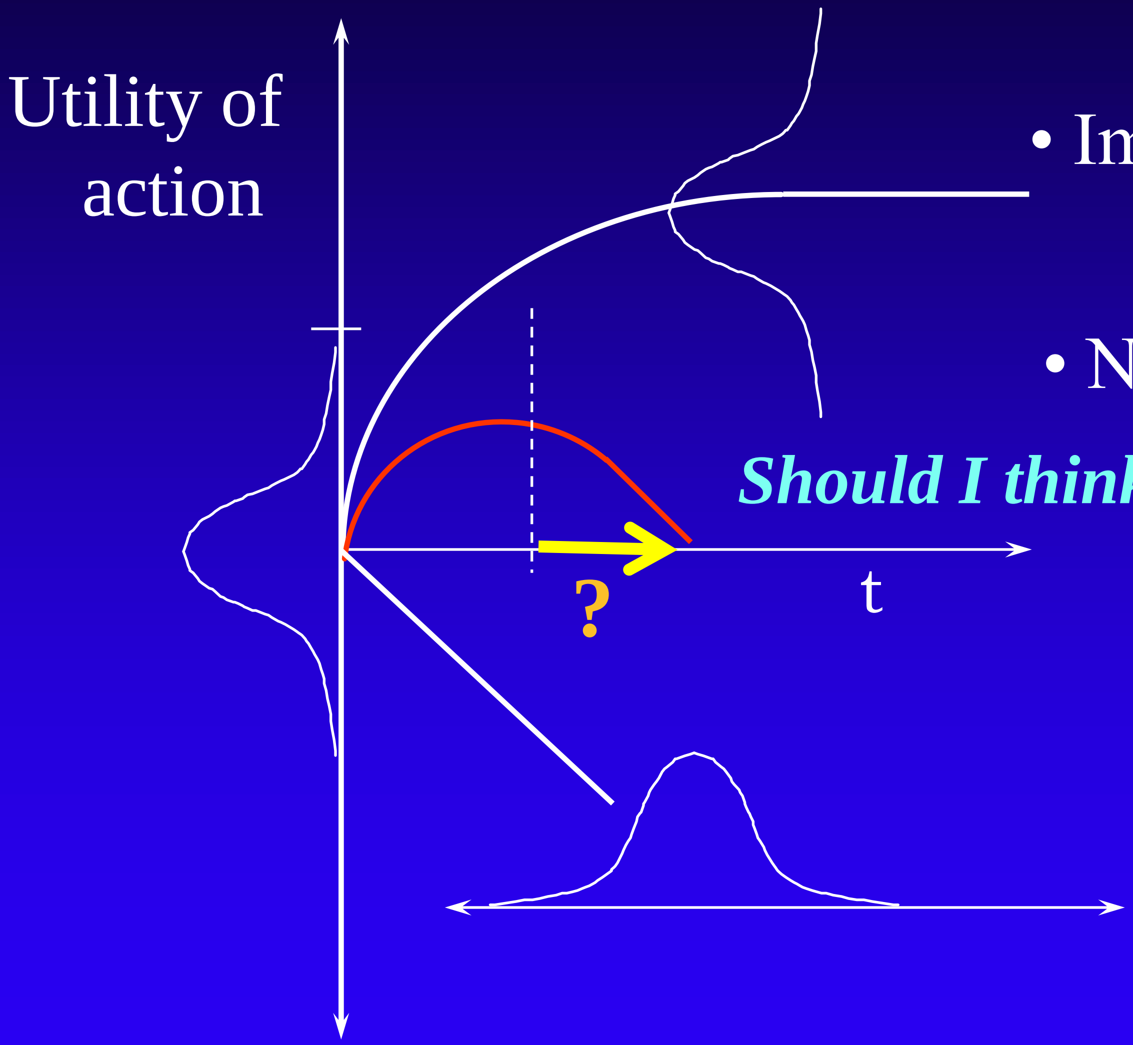
- Immediate value of result
- Net value of result
- Cost of delay

Economics of Flexible Computation



- Immediate value of result
- Net value of result
- Cost of delay

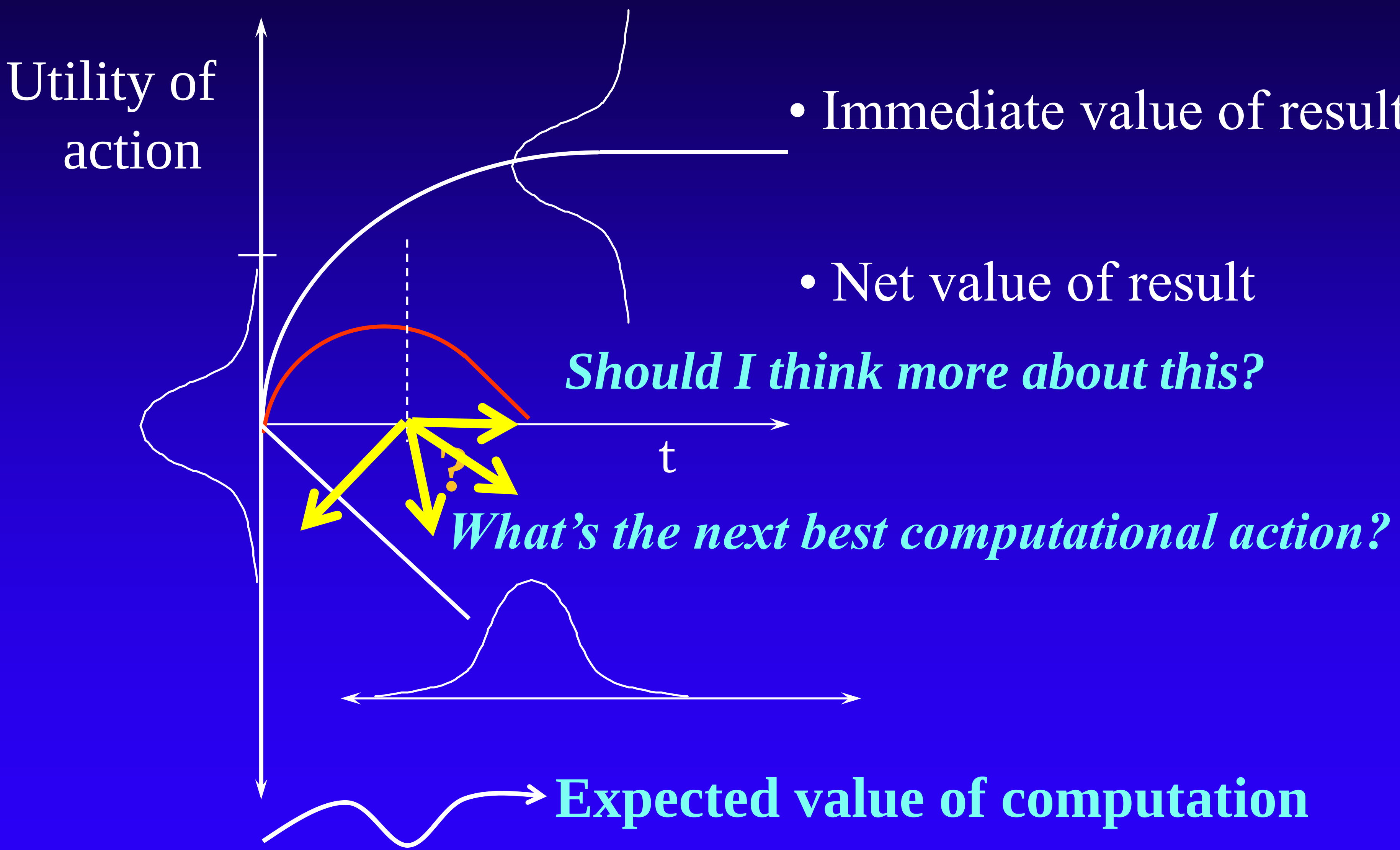
Flexible Procedures



- Immediate value of result
- Net value of result

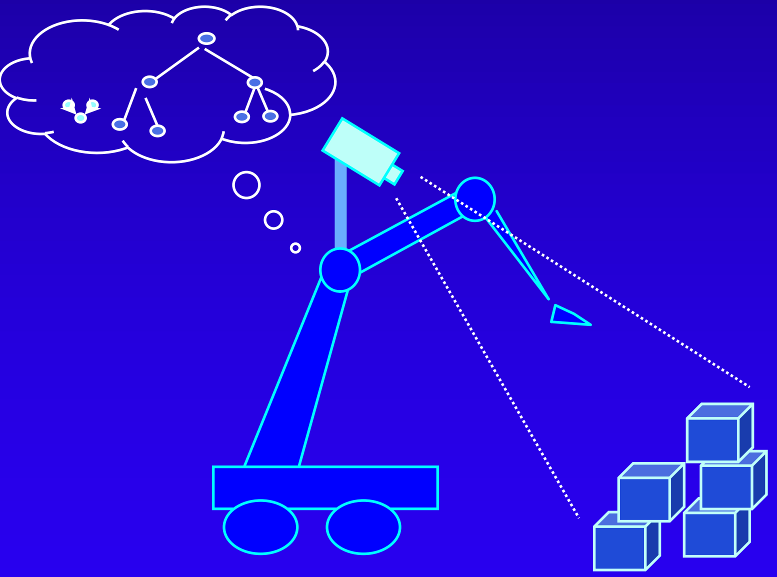
Should I think more about this?

Flexible Procedures



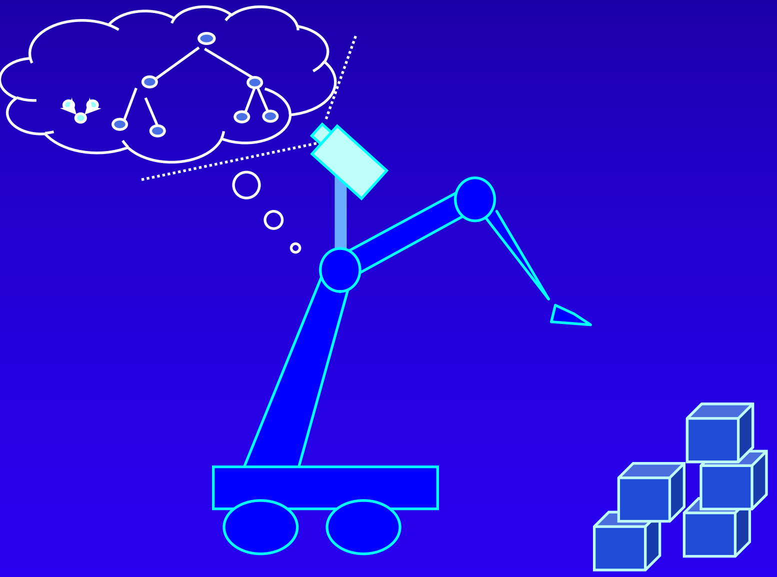
Foundations of Reflection

Expected value of computation



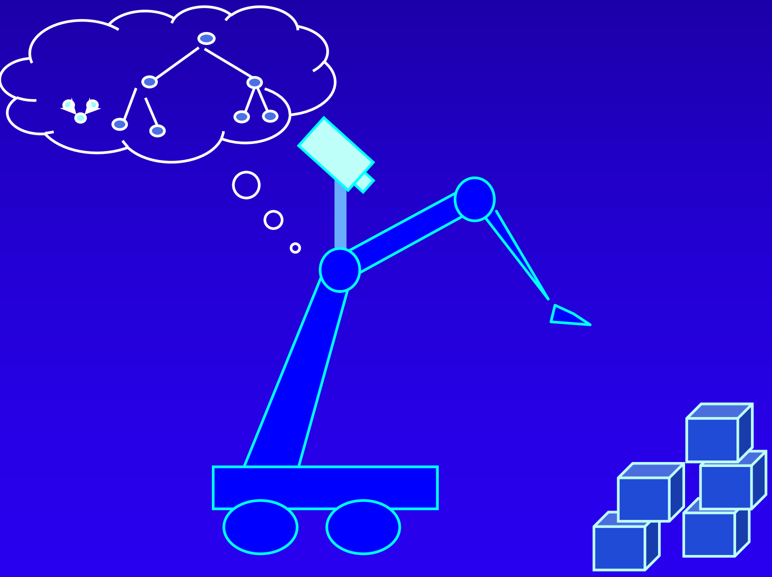
Foundations of Reflection

Expected value of computation



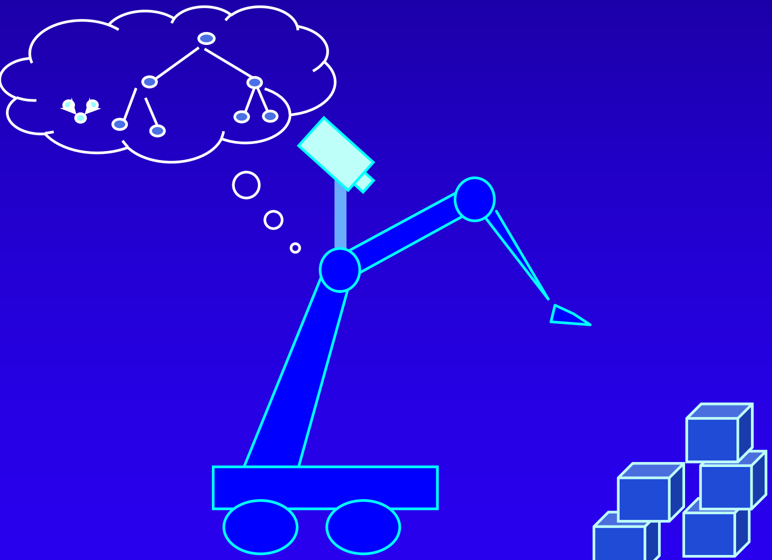
Foundations of Reflection

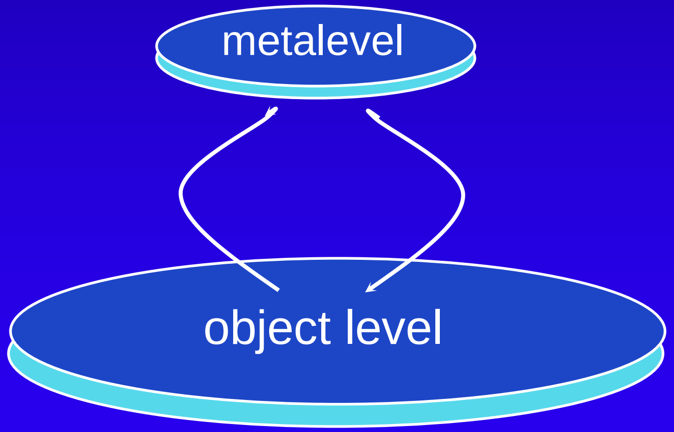
Expected value of computation



Foundations of Reflection

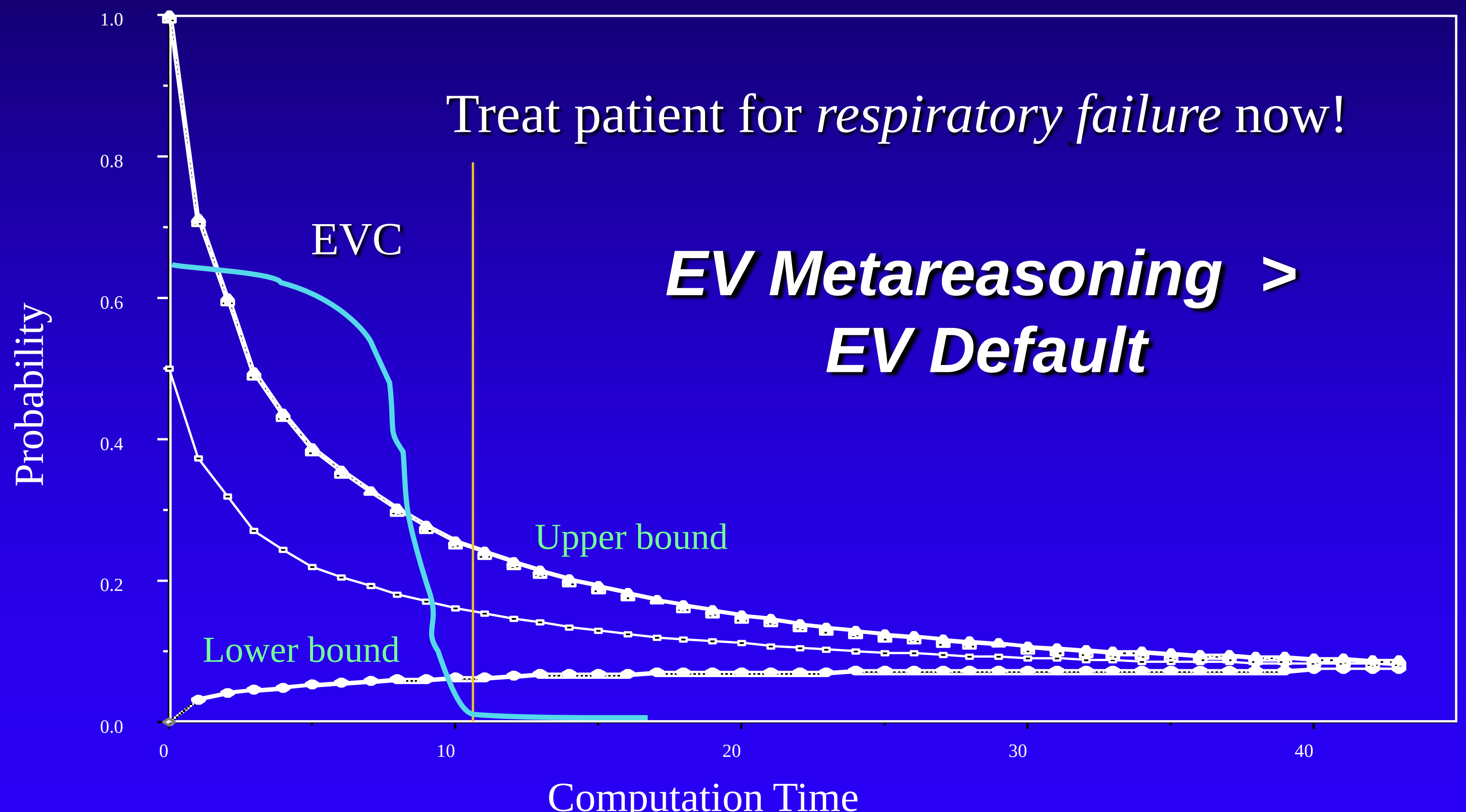
Expected value of computation





Real-World: Uncertain performance & Cost of Delay

Tractable EVC in time-critical medical decisions

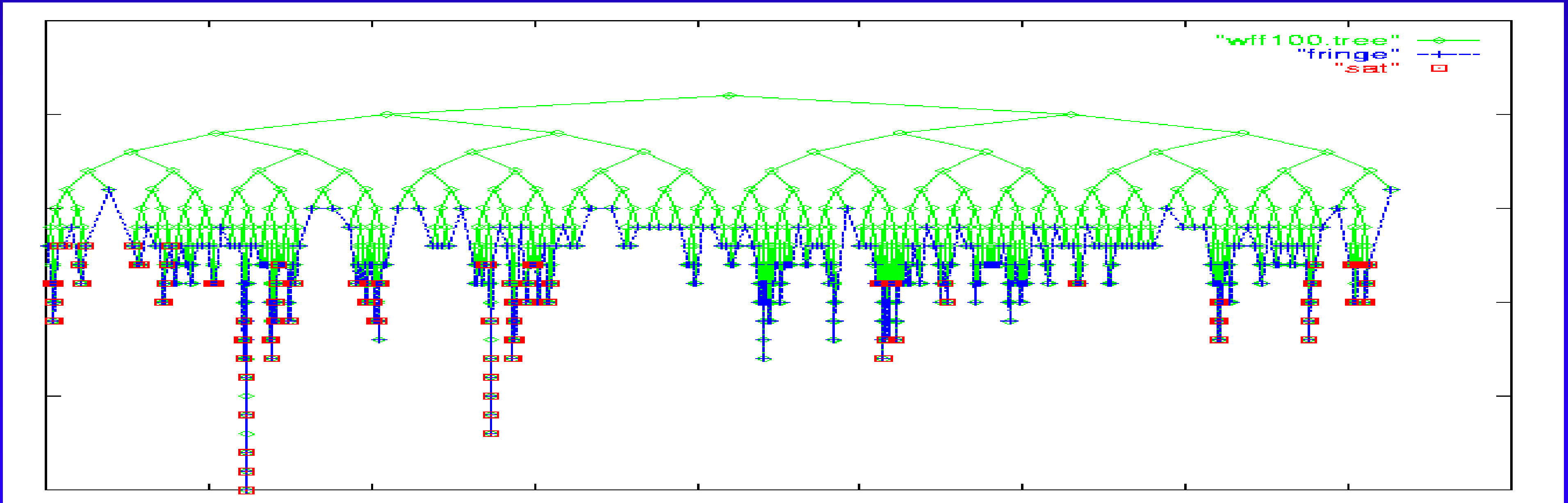


Learning about Instances & Reasoning from a Stream of Problems

e.g., **Machine learning & SAT solvers**

- **Grappling with long tails**
- **Dynamic restart policy in SAT solvers** (Kautz, et al)

$$(a \vee \neg b \vee c) \wedge (\neg b \vee d) \wedge (b \vee c \vee e) \wedge \ \ldots$$



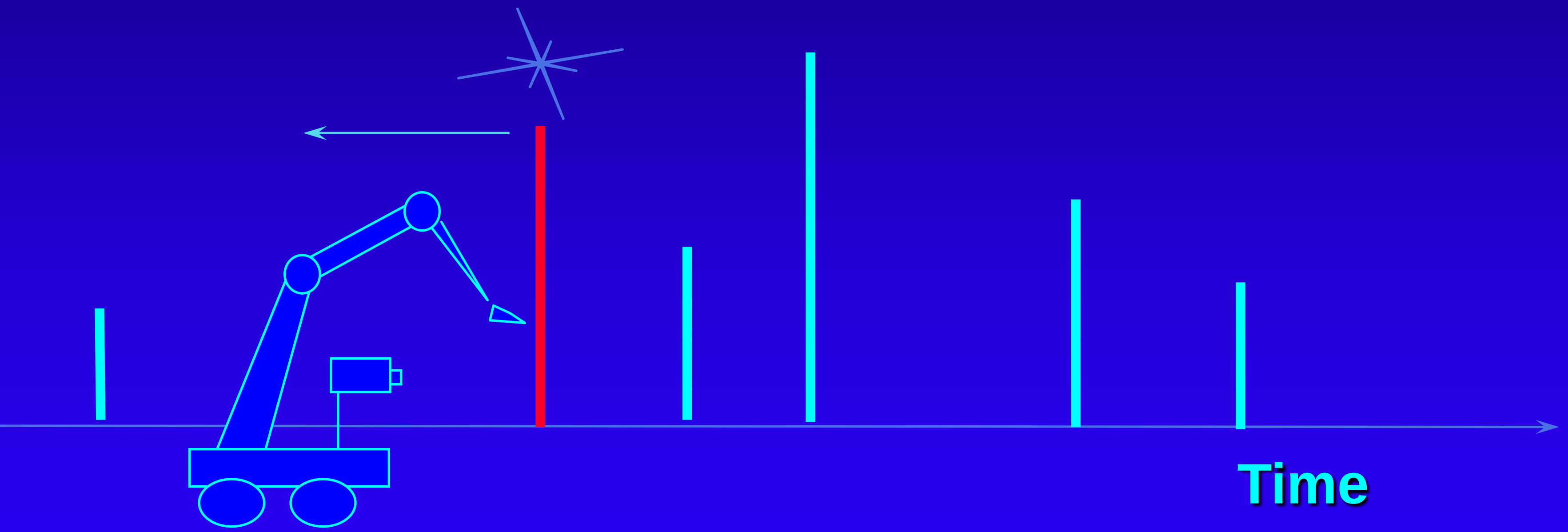
Open-World AI

Toward Situated, Flexible, Long-Lived Open-World Systems

Flexible adaptation to varying & dynamic situations

- **Streams of observations and challenges over different time frames**
- **Broad variation, uncertainty in goals, time criticality, available actions**
- **Learning about new objects, predicates, goals, preferences**

…and about perception & reasoning

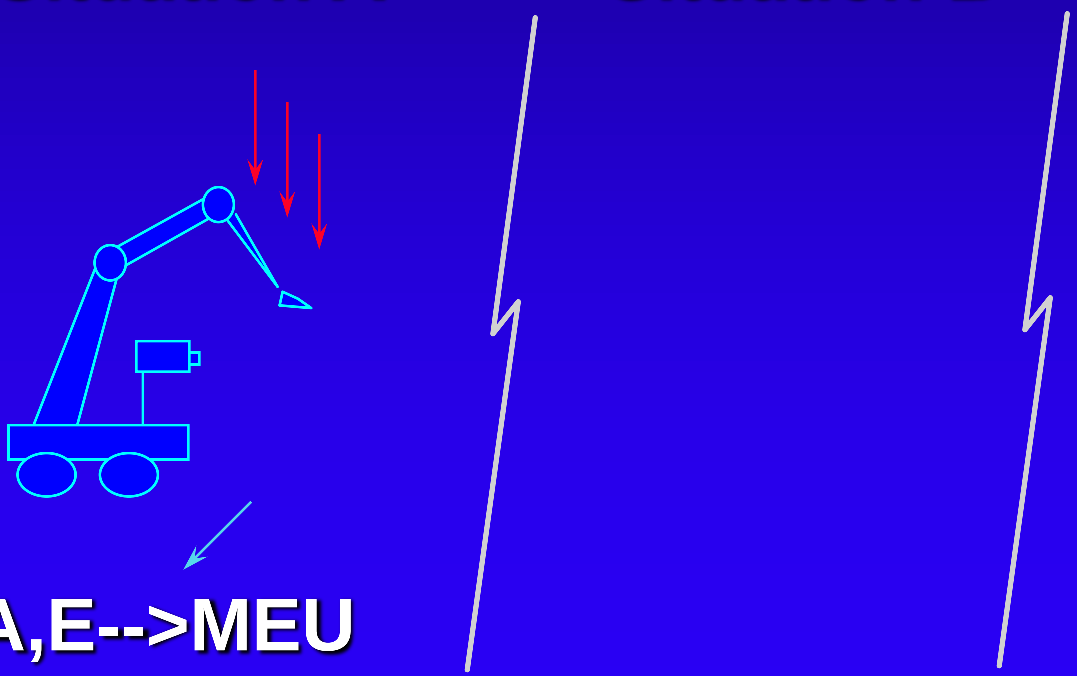

Time

Flexible adaptation to varying tasks, situations, environments

Situation A

Situation B

Situation C



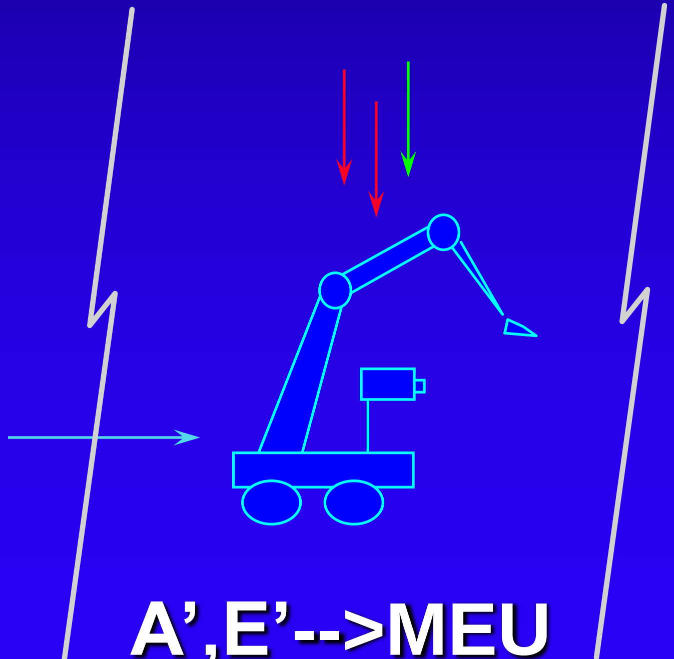
A,E-->MEU

Flexible adaptation to varying tasks, situations, environments

Situation A

Situation B

Situation C



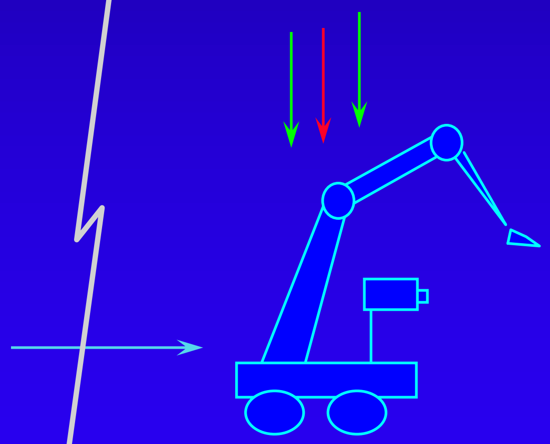
A',E'-->MEU

Flexible adaptation to varying tasks, situations, environments

Situation A

Situation B

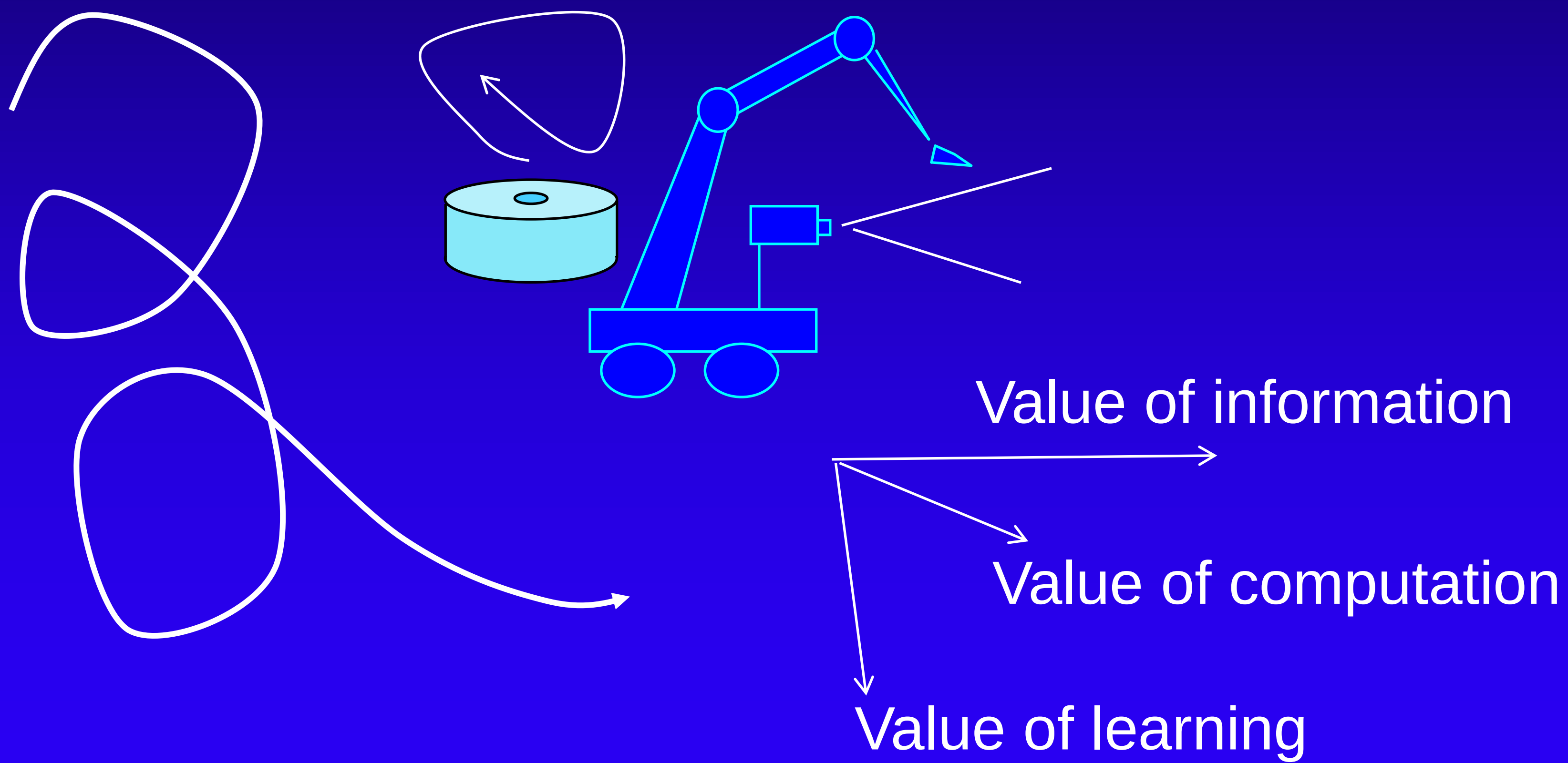
Situation C



A”,E”-->MEU

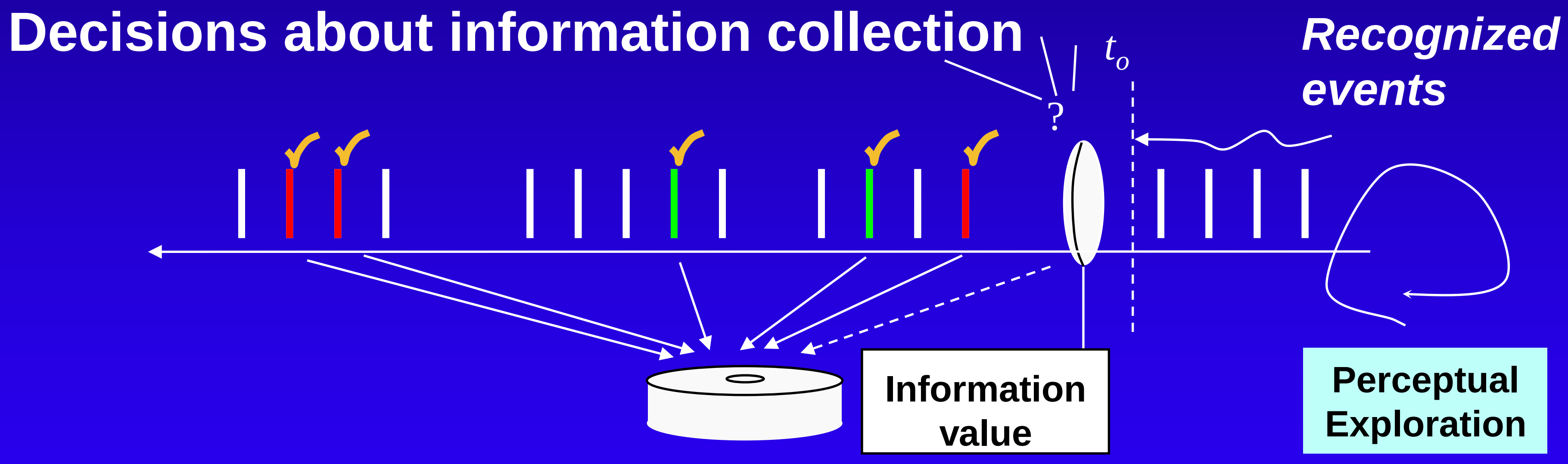
Attentional Challenge: Coordinate Sensing, Reflection, Action, Learning

Standing challenge…



Challenge: Lifelong Learning

- **Tradeoff local costs of exploration, labeling for long-term gains**

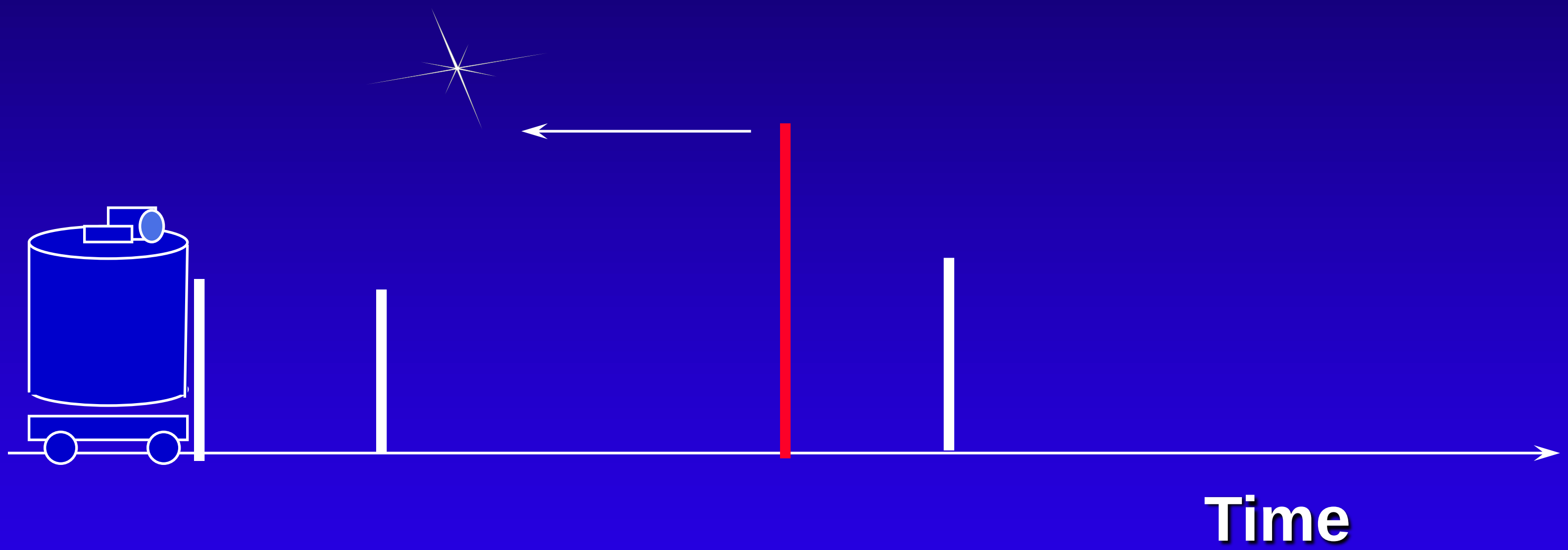


Challenge: Handle Streams of Problems

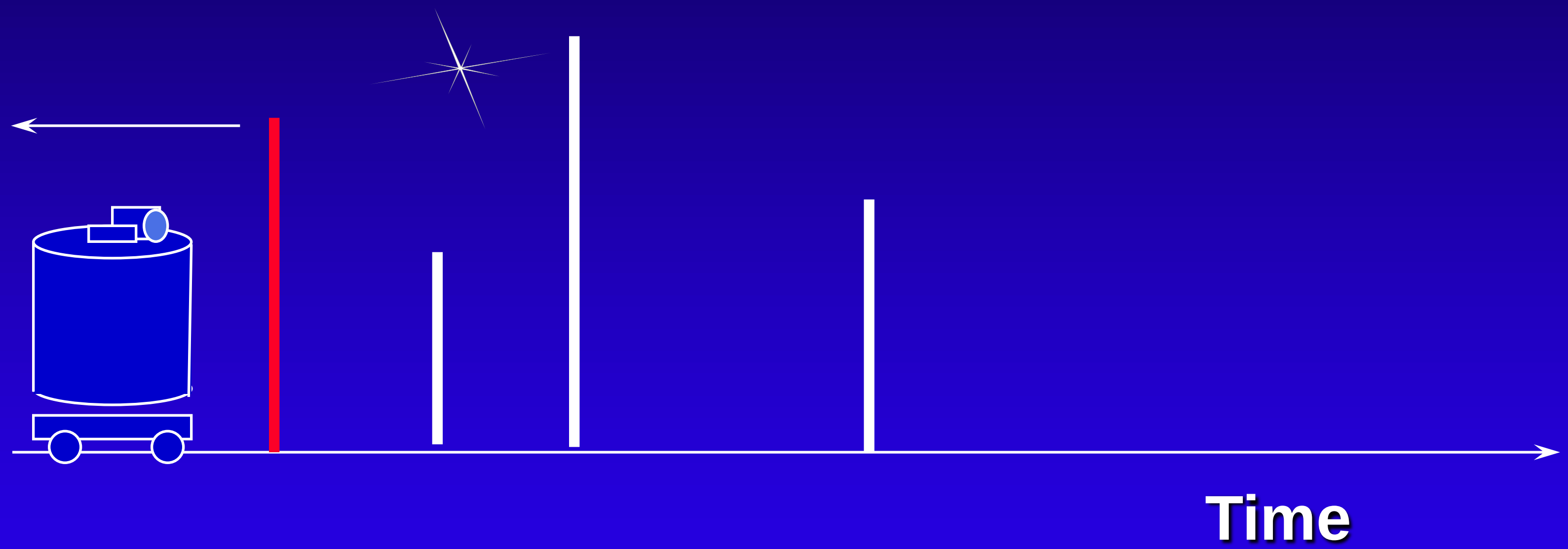
- Policies for using all time…incl. *idle* time

- How to best use available time to solve future problems?
- How to trade current problem solving for solving future problems?

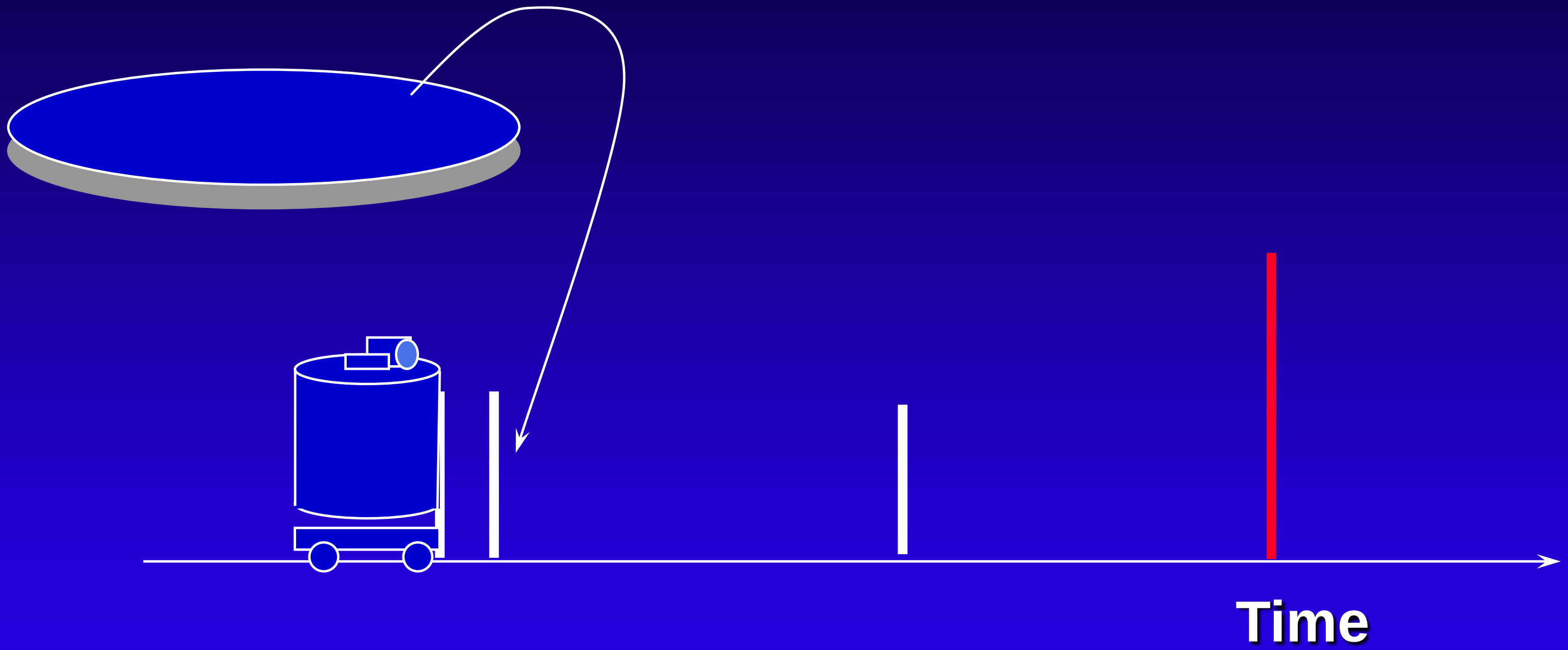
Stream of Problem Instances



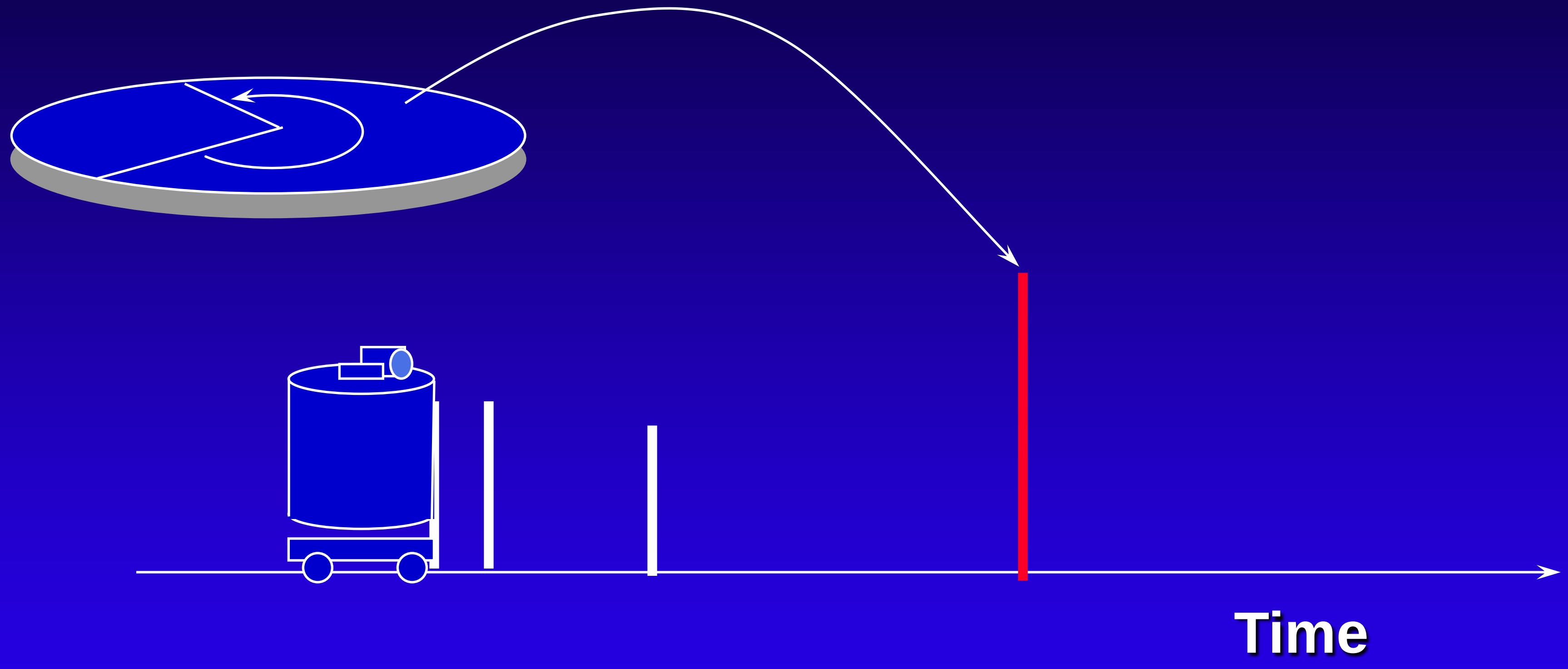
Stream of Problem Instances



Trading Off Present for Future



Trading Off Present for Future



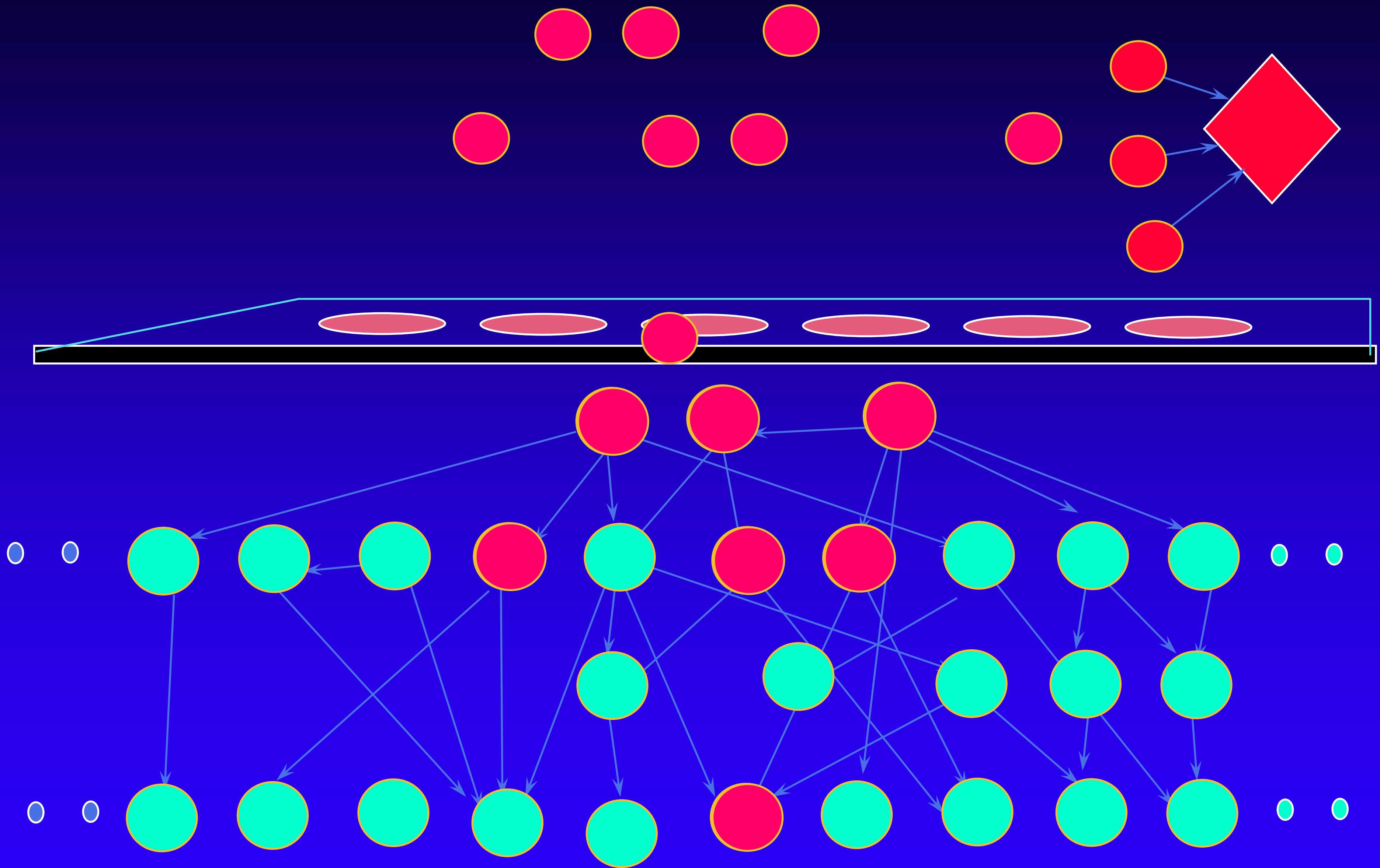
Challenge:
Frame – and Framing Problem

- What goals, preferences, …objects, predicates, relationships should be in a decision model?

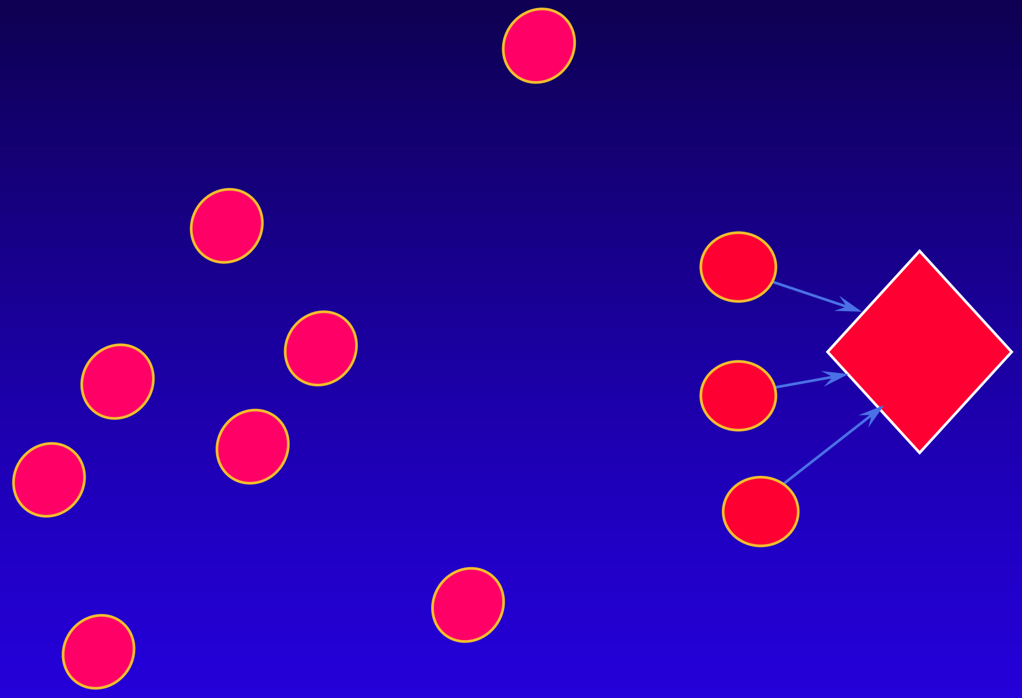
- How can tractable, relevant models be constructed automatically?

- How can the system learn about the frame?

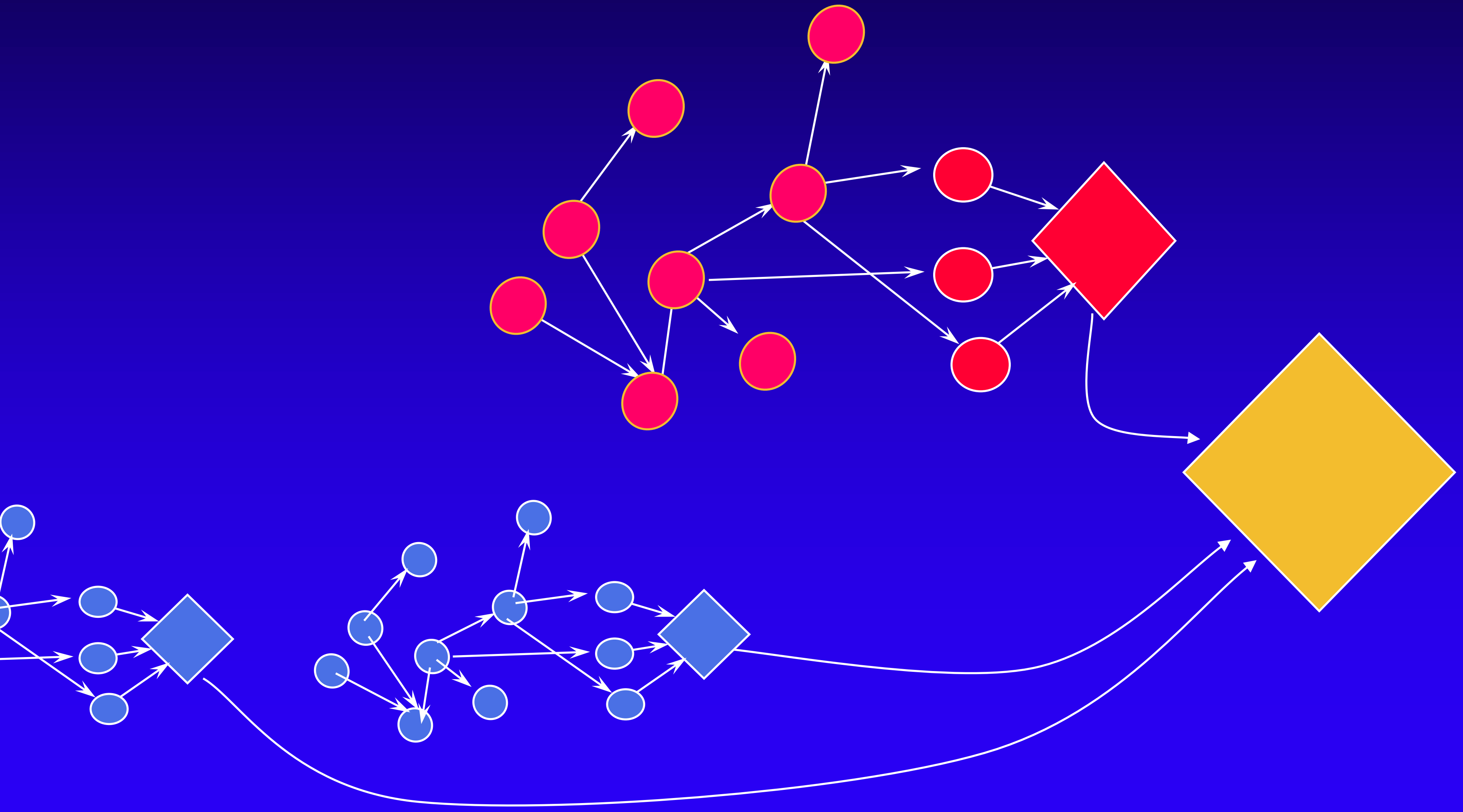
Automated Framing & Execution of Local Decision Problems

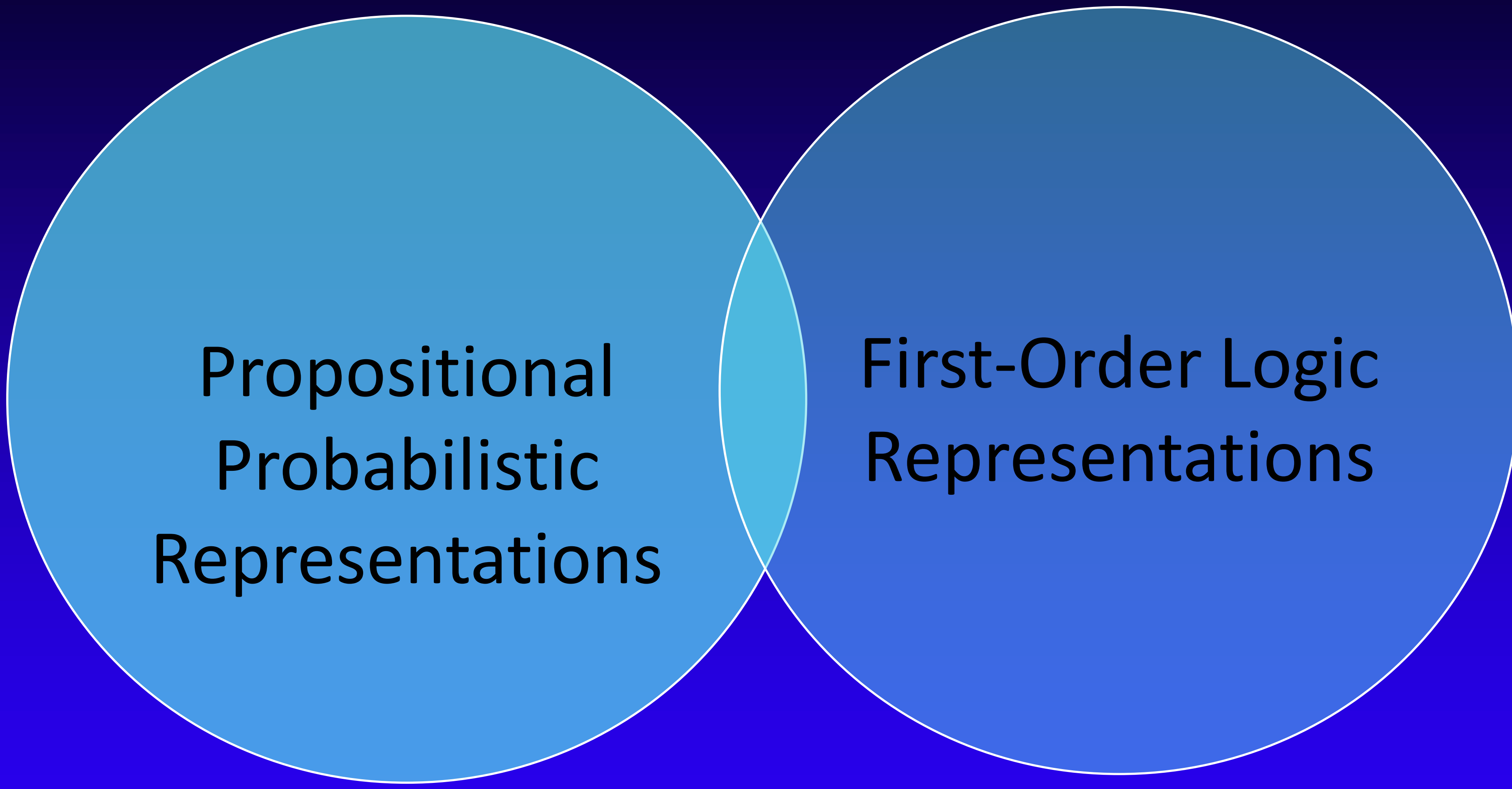


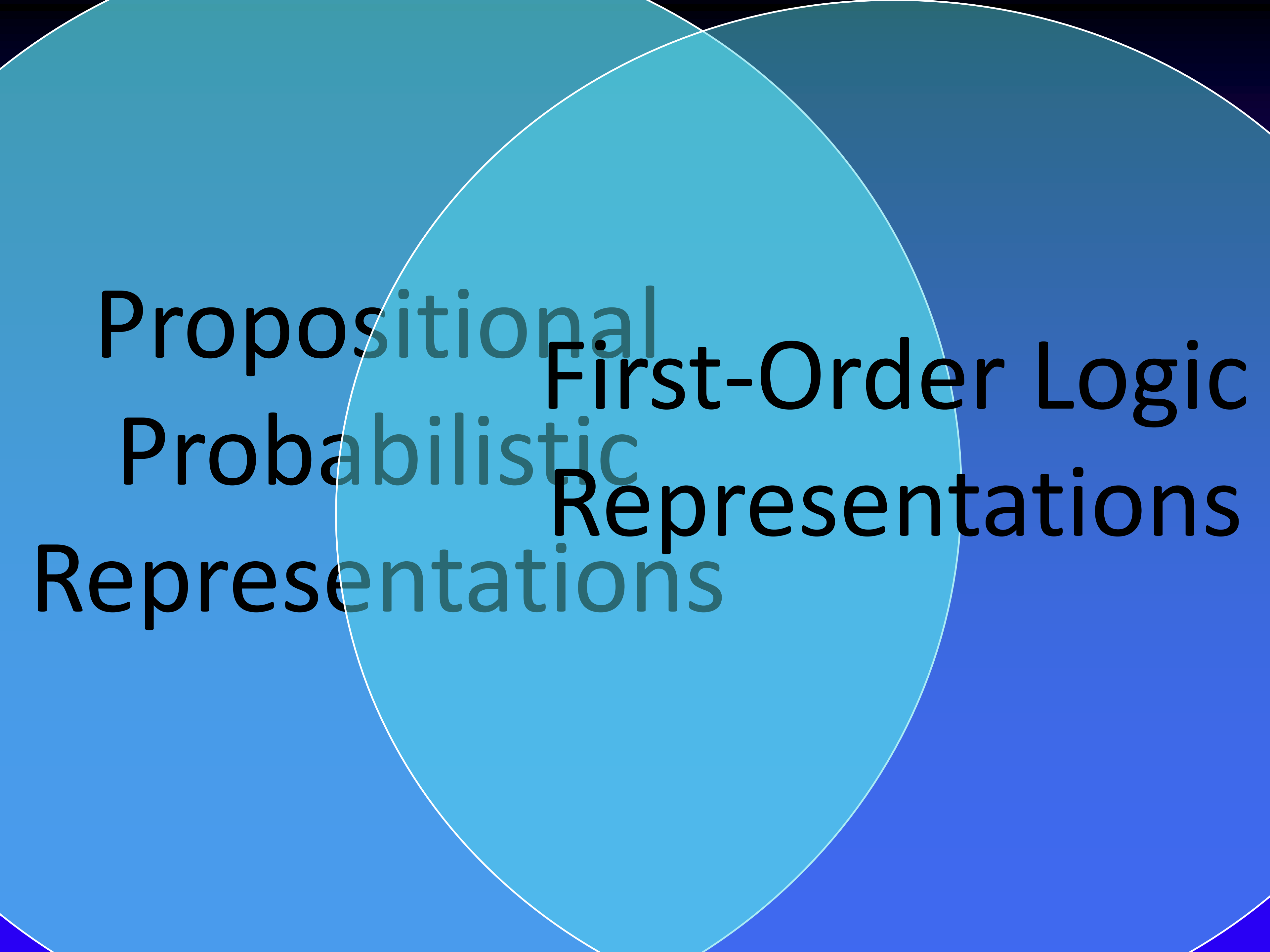
Automated Framing & Execution of Local Decision Problems



Automated Framing & Execution of Decision Problems

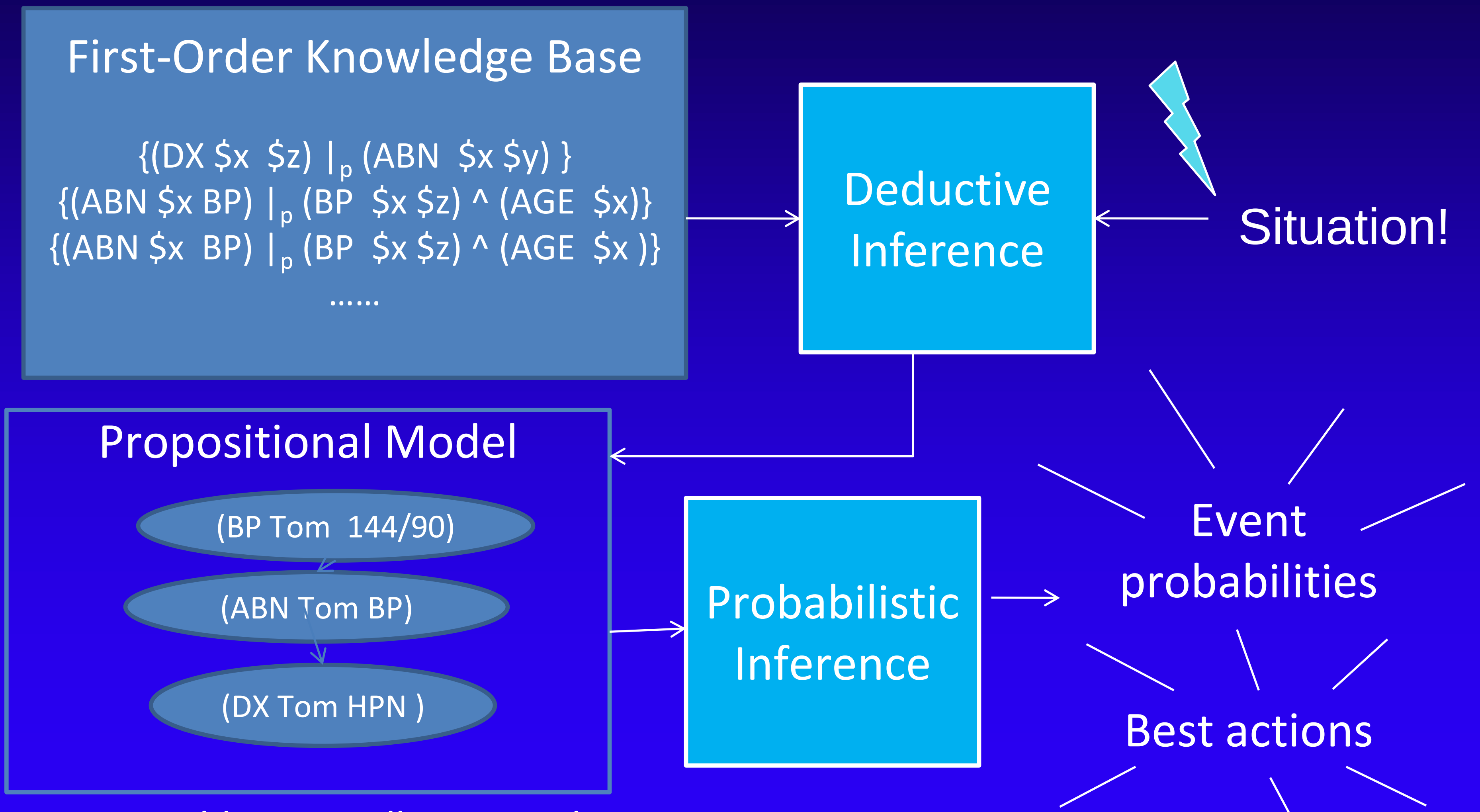



Propositional Probabilistic Representations
First-Order Logic Representations


Propositional
Probabilistic
Representations
First-Order Logic
Representations

Knowledge-Based Model Construction

Context-sensitive propositional models from first-order knowledge base



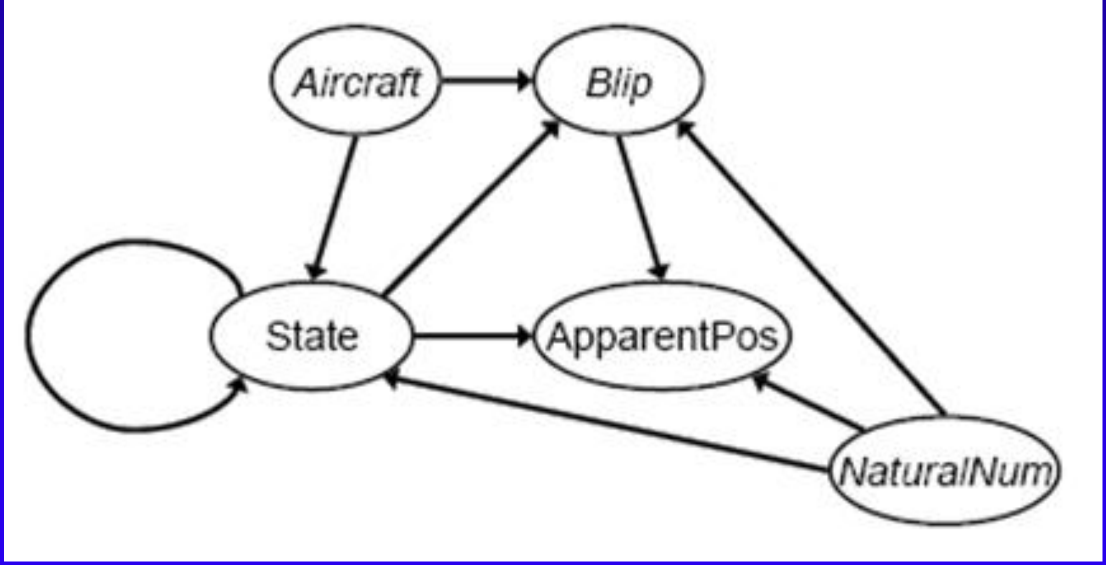
Breese, Goldman, Wellman, *et al.*

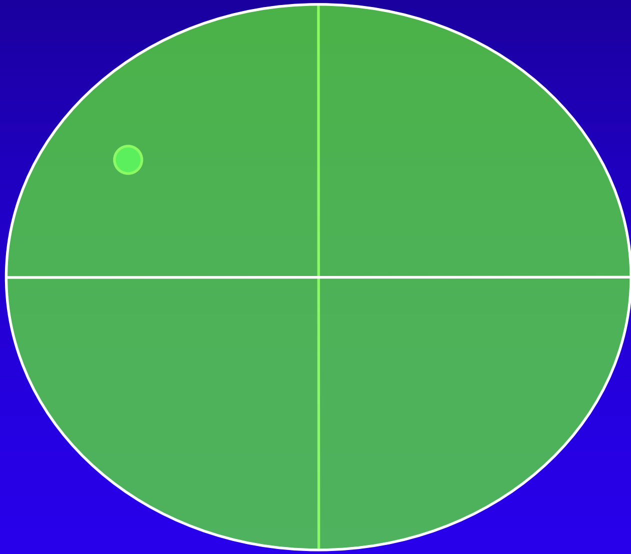
Learning & First-Order Probabilistic Representations

- Generate objects, relations, models
  - *Plan recognition networks*
  - *Probabilistic relational models*
  - *Markov logic networks*
  - *BLOG: Probabilistic models with unknown objects*

Reasoning about …and Expecting the Unknown

Probabilistic Models with Unknown Objects

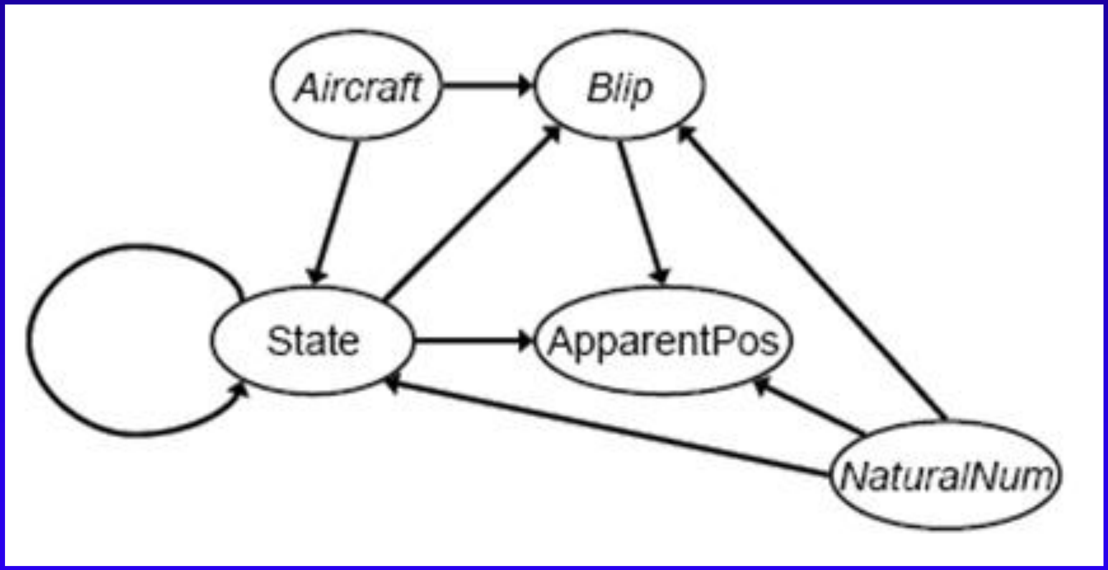


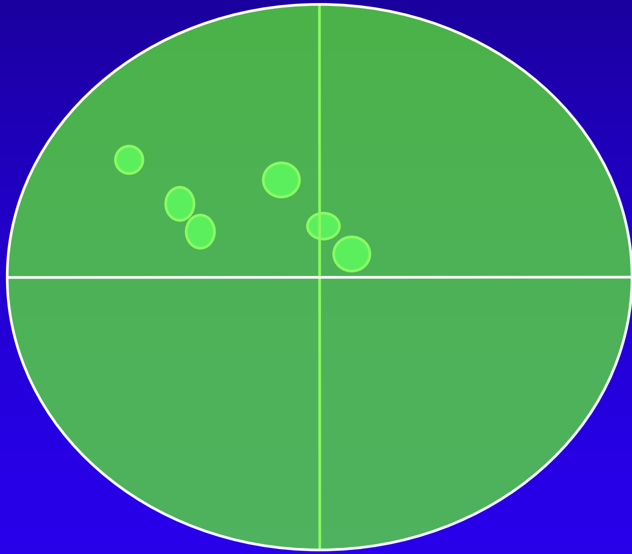


Brian Milch, *et al.*

Reasoning about …and Expecting the Unknown

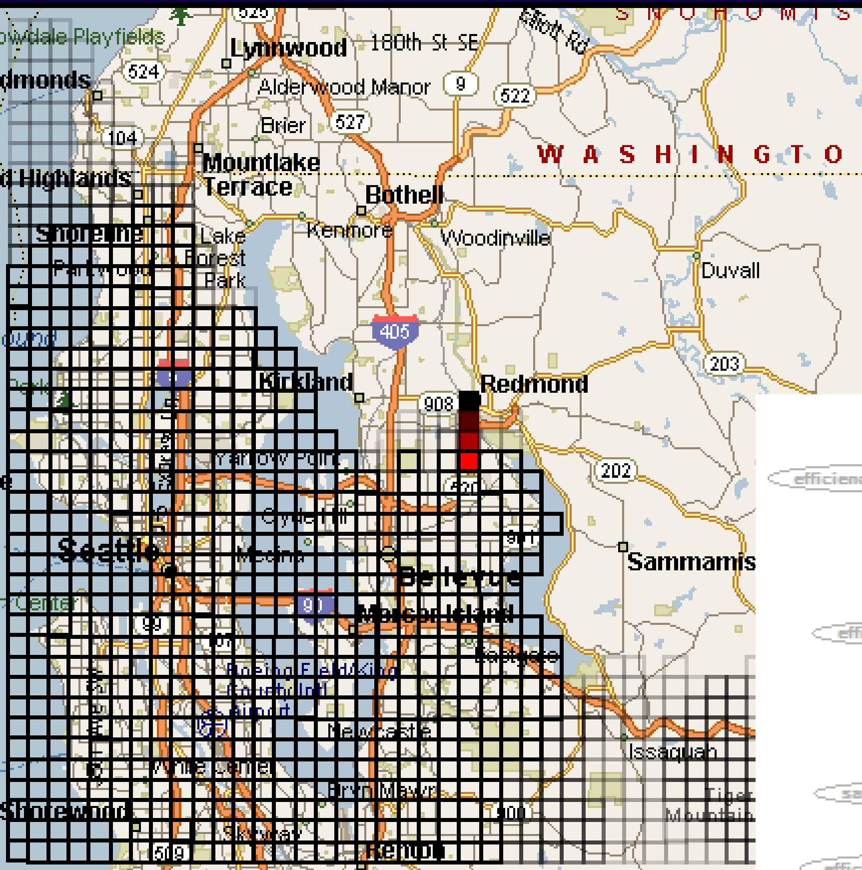
Probabilistic Models with Unknown Objects

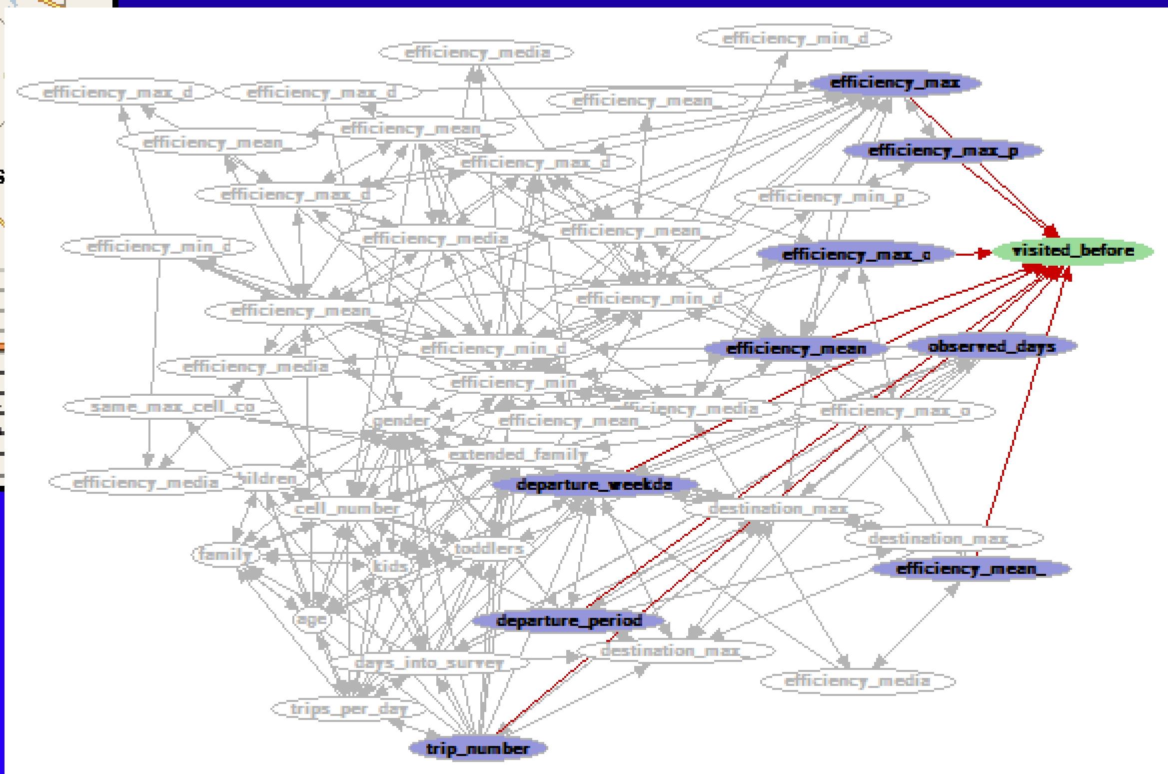




Brian Milch, *et al.*

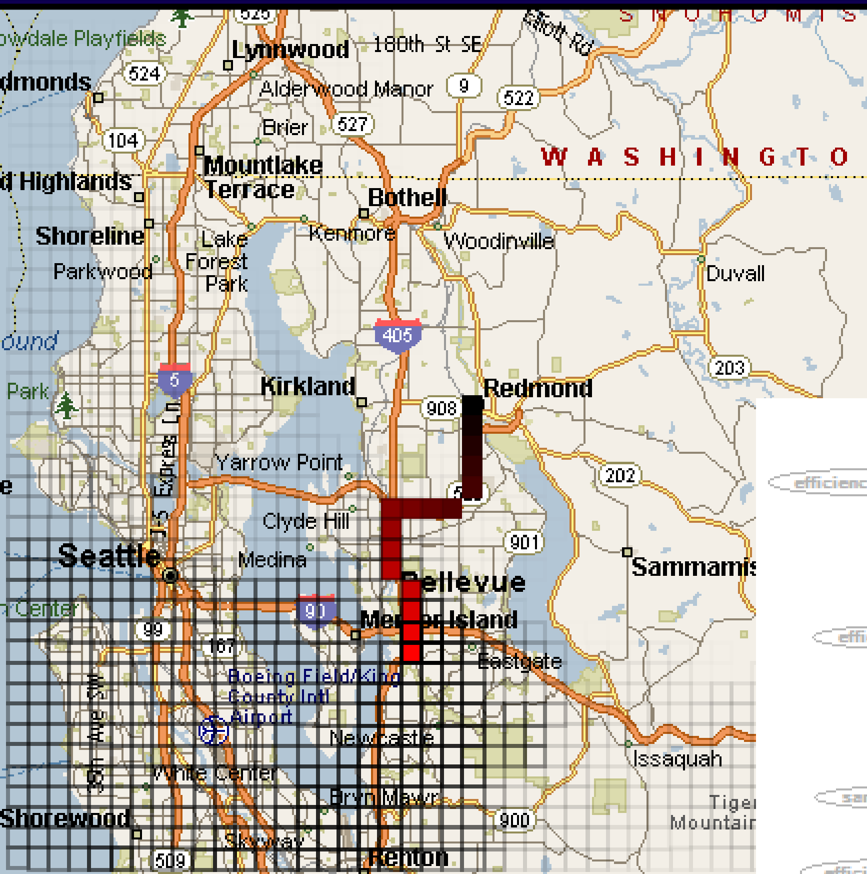
Reasoning about …and Expecting the Unknown

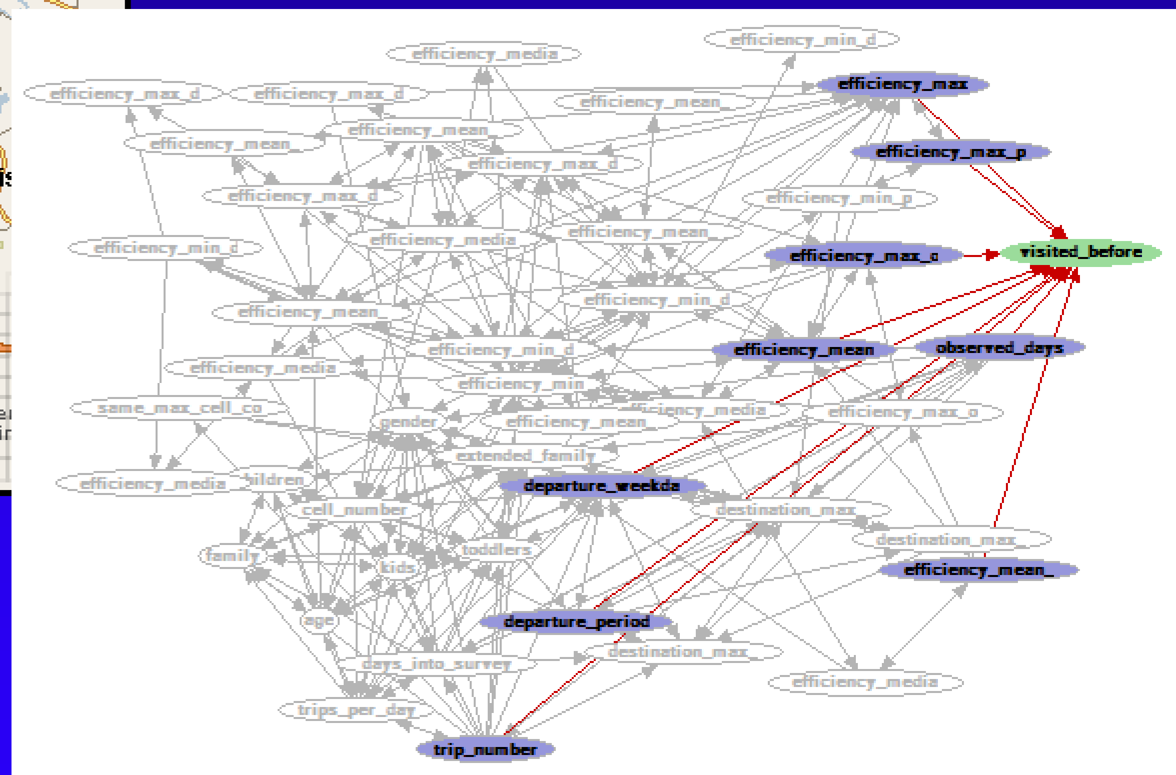




Krumm, H., et al.

Reasoning about …and Expecting the Unknown

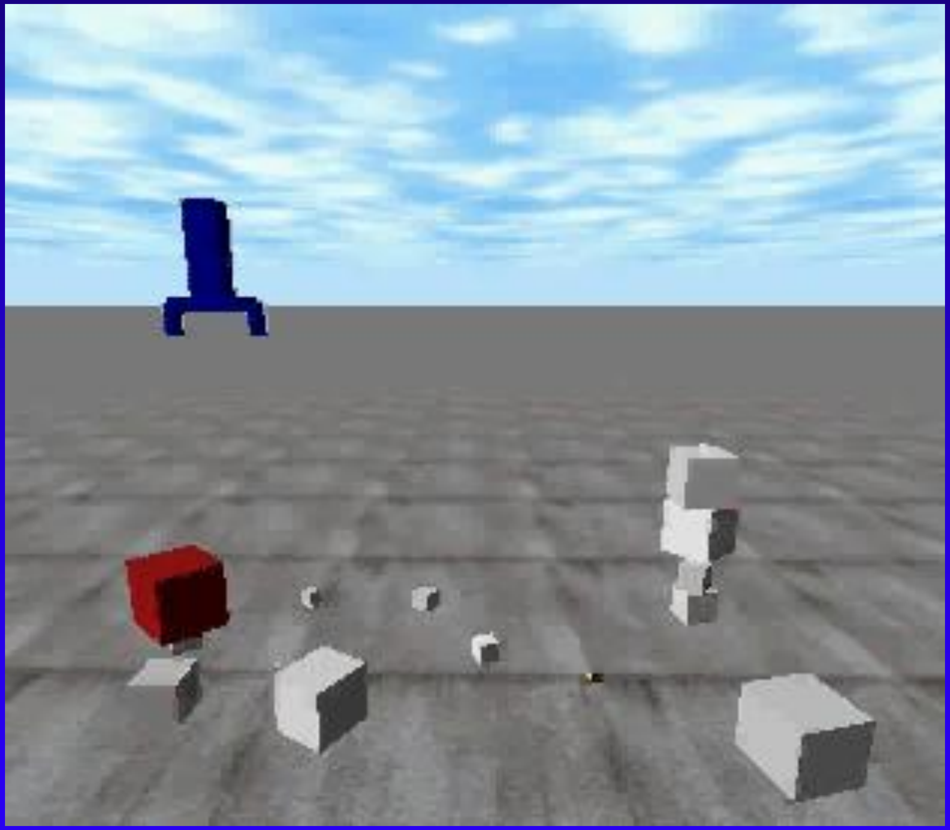




Krumm, H., et al.

Extending Proficiency in a Messy World

- Assume *unmodeled* objects, relations, noise
- Continue to extend models with experiences

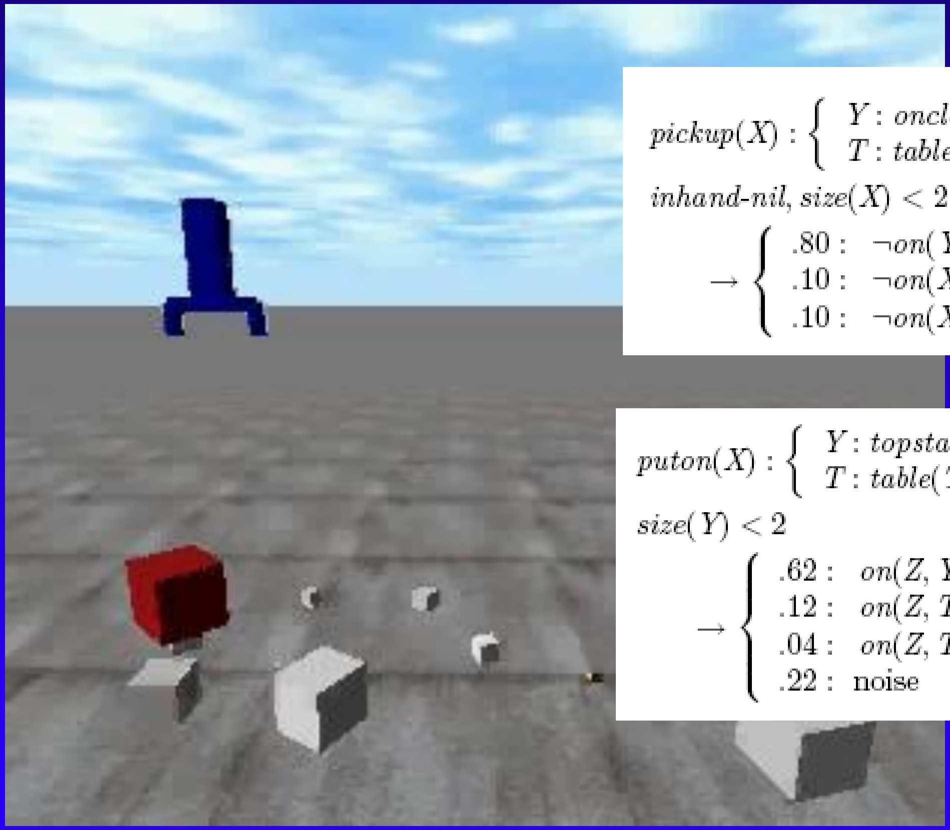


(video)

Pasula, Zettlemoyer, Kaelbling

Extending Proficiency in an Open World

- Assume *unmodeled* objects, relations, noise
- Continue to extend models with experiences



$$pickup(X) : \left\{ \begin{array}{l} Y : onclear(X, Y),\ Z : on(Y, Z), \\ T : table(T) \end{array} \right\}$$

$$inhand\text{-}nil,\ size(X) < 2$$

$$\rightarrow \left\{ \begin{array}{ll} .80 : & \neg on(Y, Z) \\ .10 : & \neg on(X, Y) \\ .10 : & \neg on(X, Y), on(Y, T), \neg on(Y, Z) \end{array} \right.$$

$$puton(X) : \left\{ \begin{array}{l} Y : topstack(Y, X),\ Z : inhand(Z), \\ T : table(T) \end{array} \right\}$$

$$size(Y) < 2$$

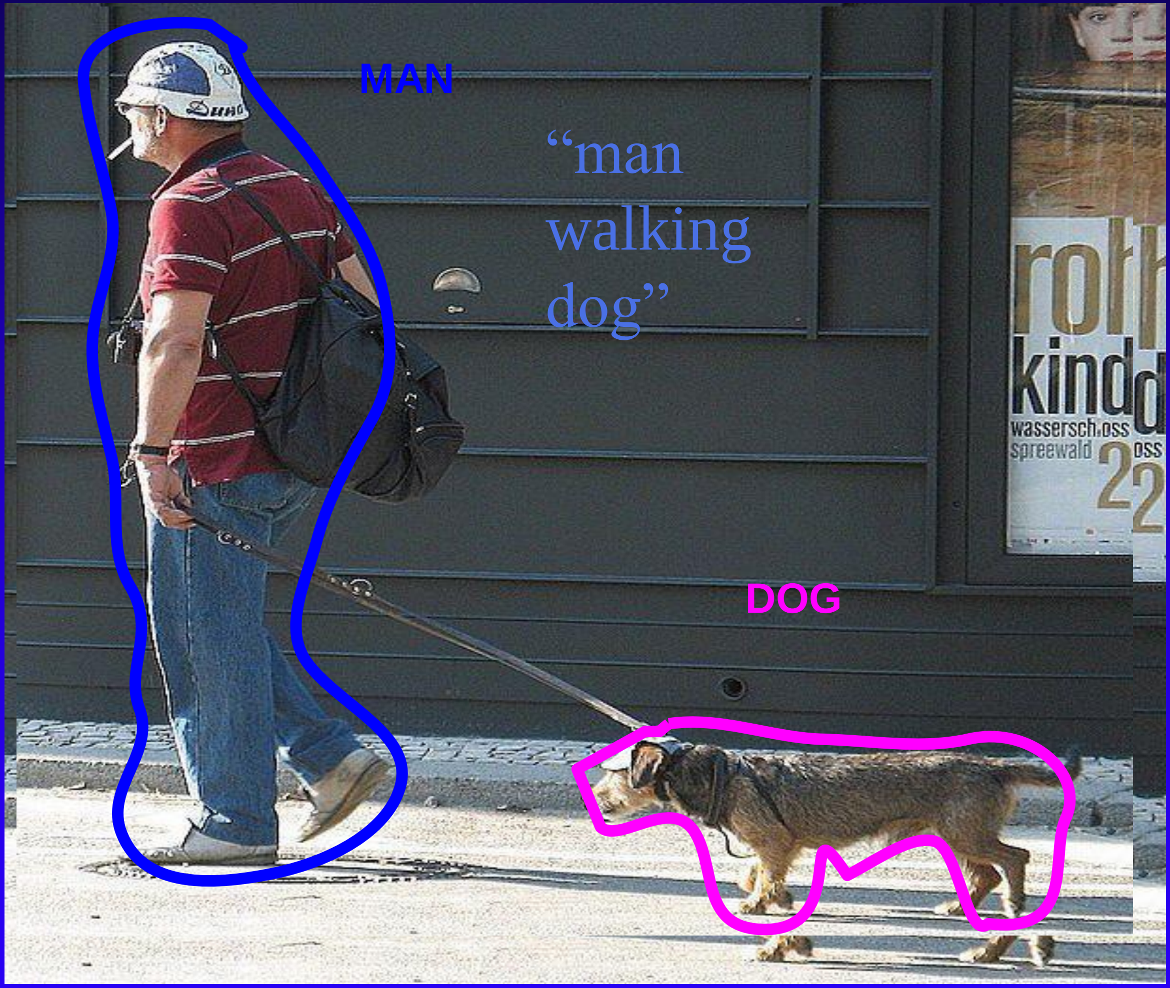
$$\rightarrow \left\{ \begin{array}{ll} .62 : & on(Z, Y) \\ .12 : & on(Z, T) \\ .04 : & on(Z, T), on(Y, T), \neg on(Y, X) \\ .22 : & \text{noise} \end{array} \right.$$

Pasula, Zettlemoyer, Kaelbling

Extending Perceptual Proficiency with Shape Prototypes and Deformations

G. Elidan, G. Heitz, and D. Koller

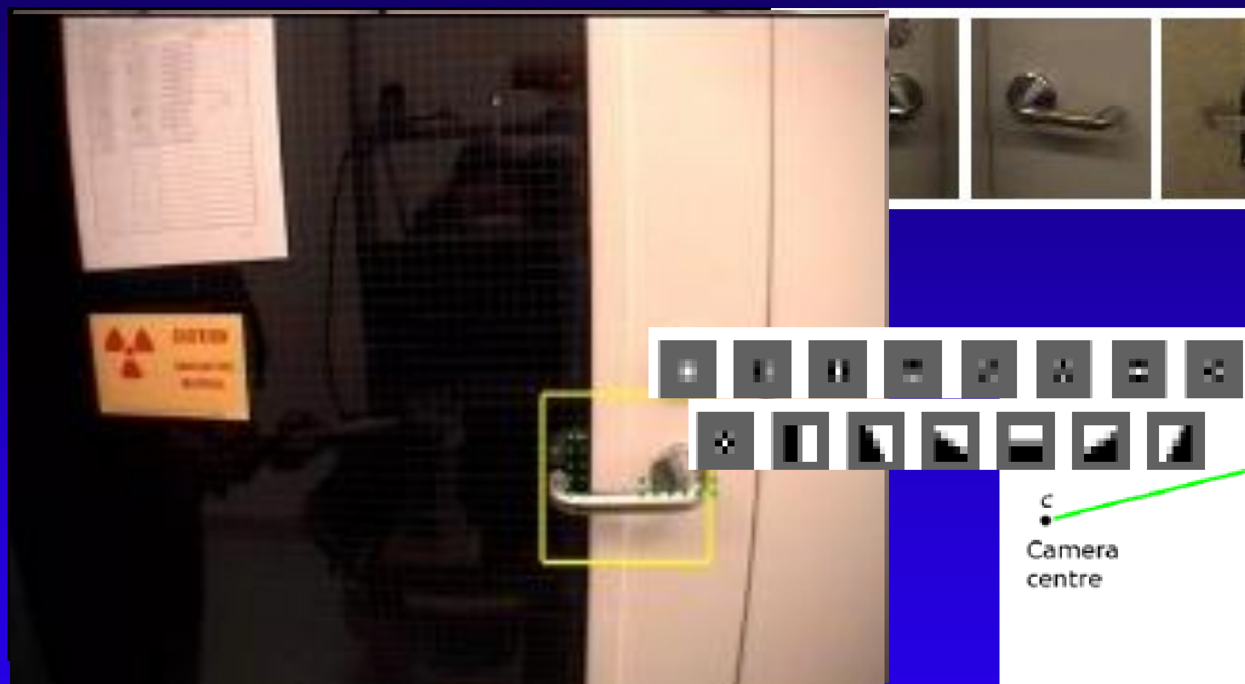
Extending Perceptual Proficiency with Shape Prototypes and Deformations

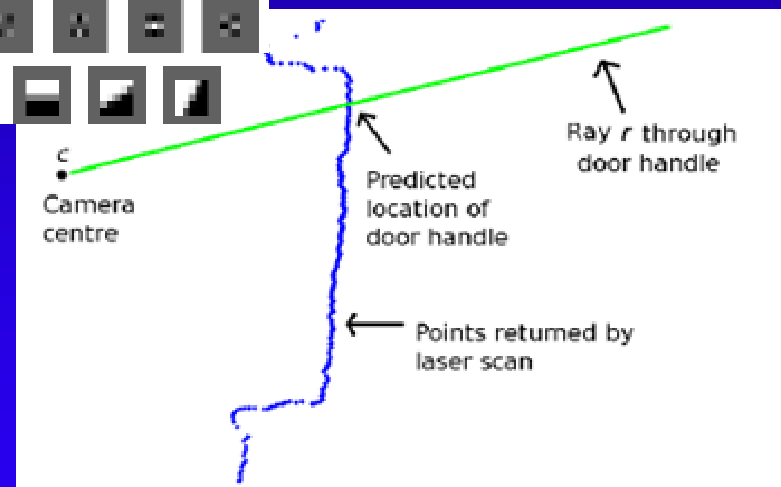


G. Elidan, G. Heitz, and D. Koller

Proficiency via Transfer in Open Worlds

- **Transferring prior knowledge to new situations**





Klingbeil, Saxena, Ng, *et al.*

Proficiency via Transfer in Open Worlds

- **Transferring prior knowledge to new situations**

(video)

Klingbeil, Saxena, Ng, *et al.*

Prospering in the Open World

To know that you do not know is the best.

Lao Tzu

Prospering in the Open World

To know that you do not know is the best.

Lao Tzu

- **Modeling model competencies, limitations, extensions**
- **Context-sensitive failures & successes**
- **Models of anomaly & surprise**
- **Value of prototypes, analogy, transfer**
- **Learning objects, predicates, preferences, goals in noisy environments**

Value of Open-World Challenges

- **AAAI / CVPR Semantic Robot Vision Challenge**
  - **Robots must perform a scavenger hunt in a *previously-unknown* indoor environment.**

-e.g.,

- scientific calculator

- Ritter Sport Marzipan

- DVD “Shrek”

- DVD “Gladiator”

- CD “Hey Eugene”

- electric iron

.

.

.

Web access

Value of Open-World Challenges

2004 DARPA Challenge: Sandstorm

- Closed world vs open world model
  - **Model of anomaly, surprise**
  - **Thinking out of the box?**

DARPA GRAND CHALLENGE

Where there's Smoke…

(video)

Stepping into the Open World

- Key technical challenges
- AI moving into the world
- AI research community

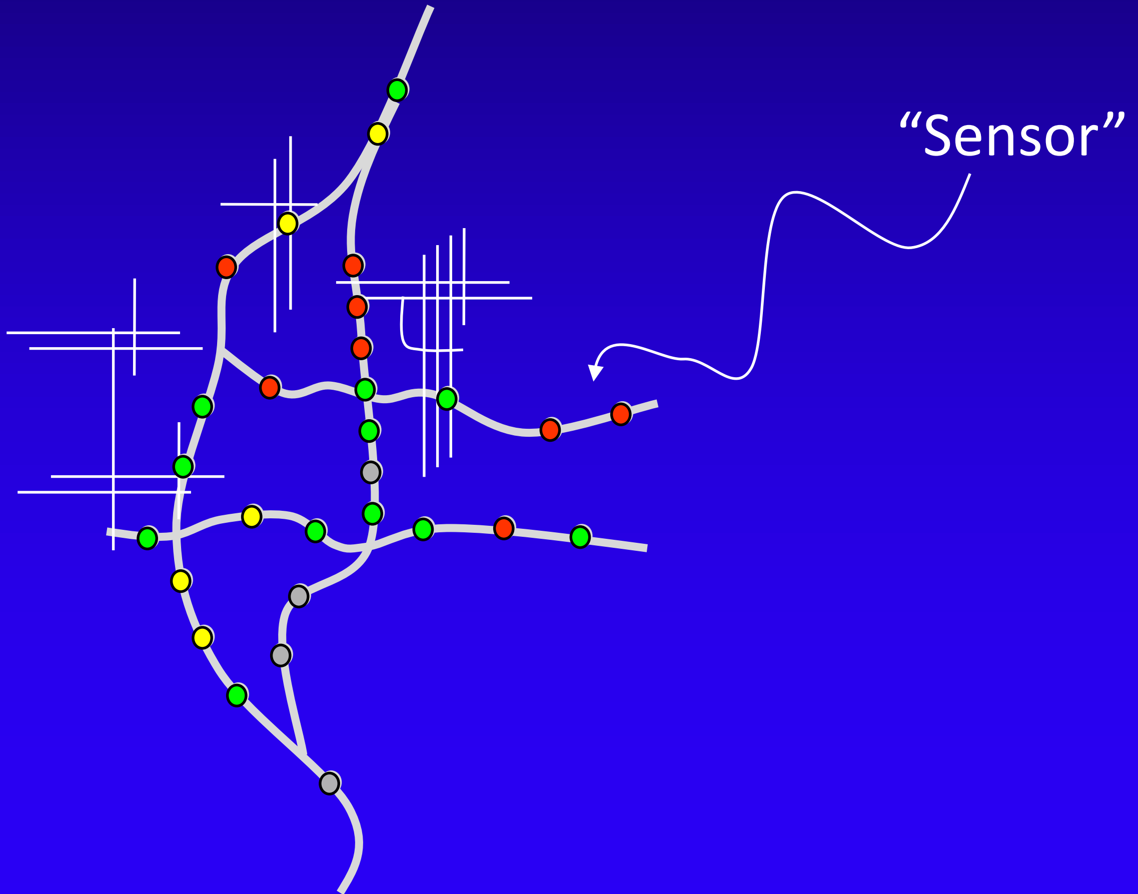
AI Moving into the World: Trends & Directions

- Robust services in dynamic settings
- Human-computer collaboration
- Integrative intelligence
- Sciences
- Harnessing web

Robust Services in Dynamic Settings

- **Context-sensitive competencies & policies**

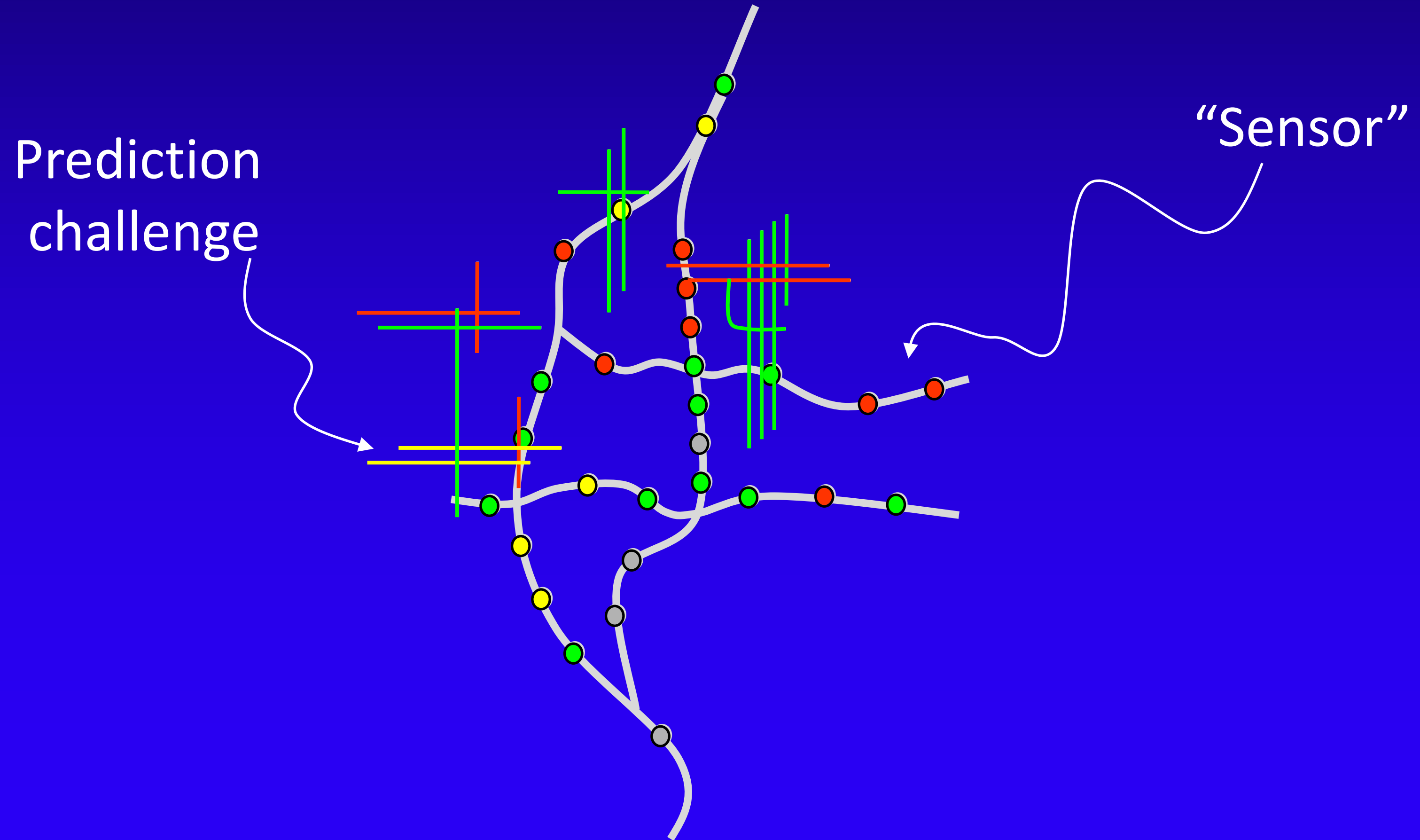
Example: Traffic prediction & routing



Robust Services in Dynamic Settings

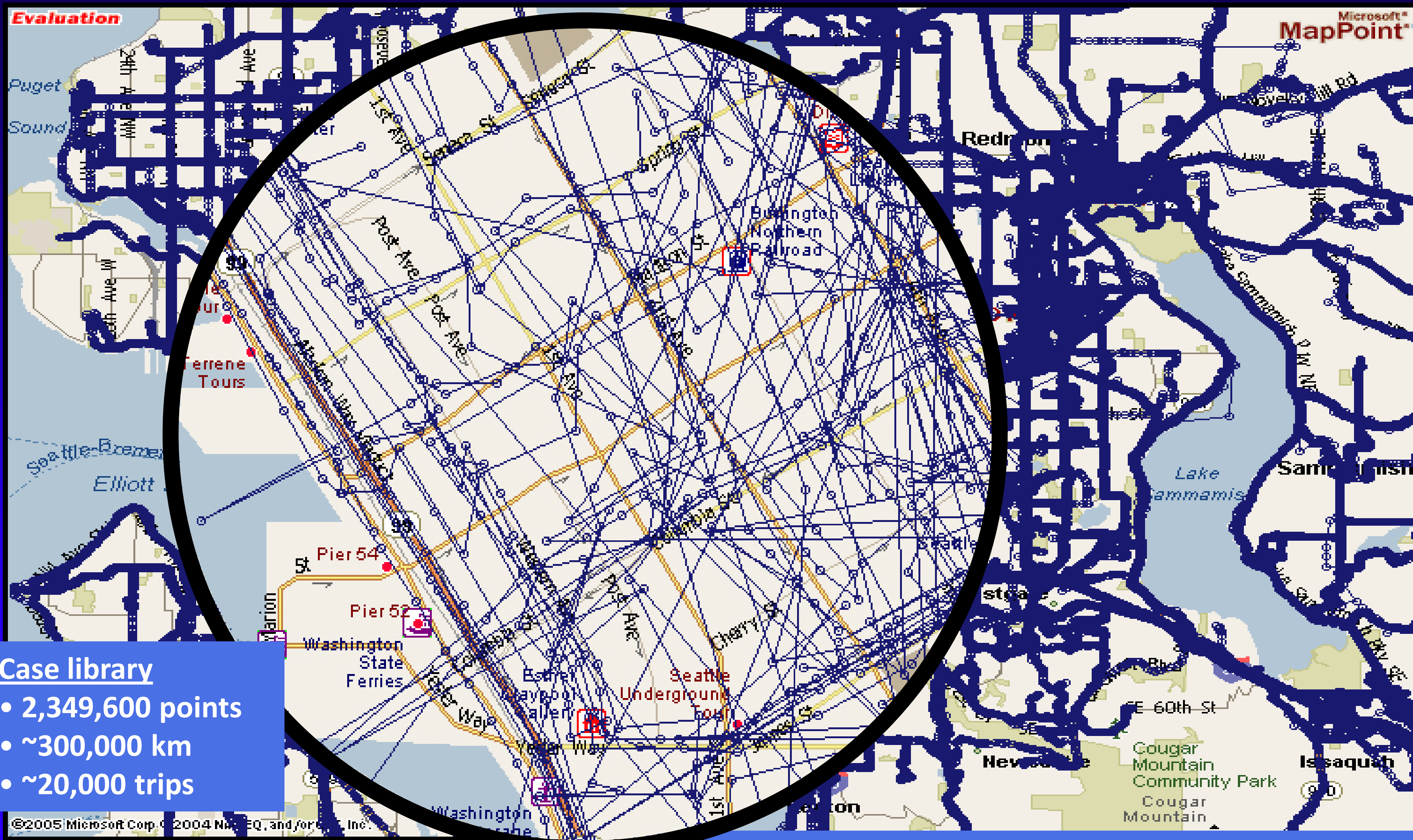
- Context-sensitive competencies & policies

Example: Traffic prediction & routing

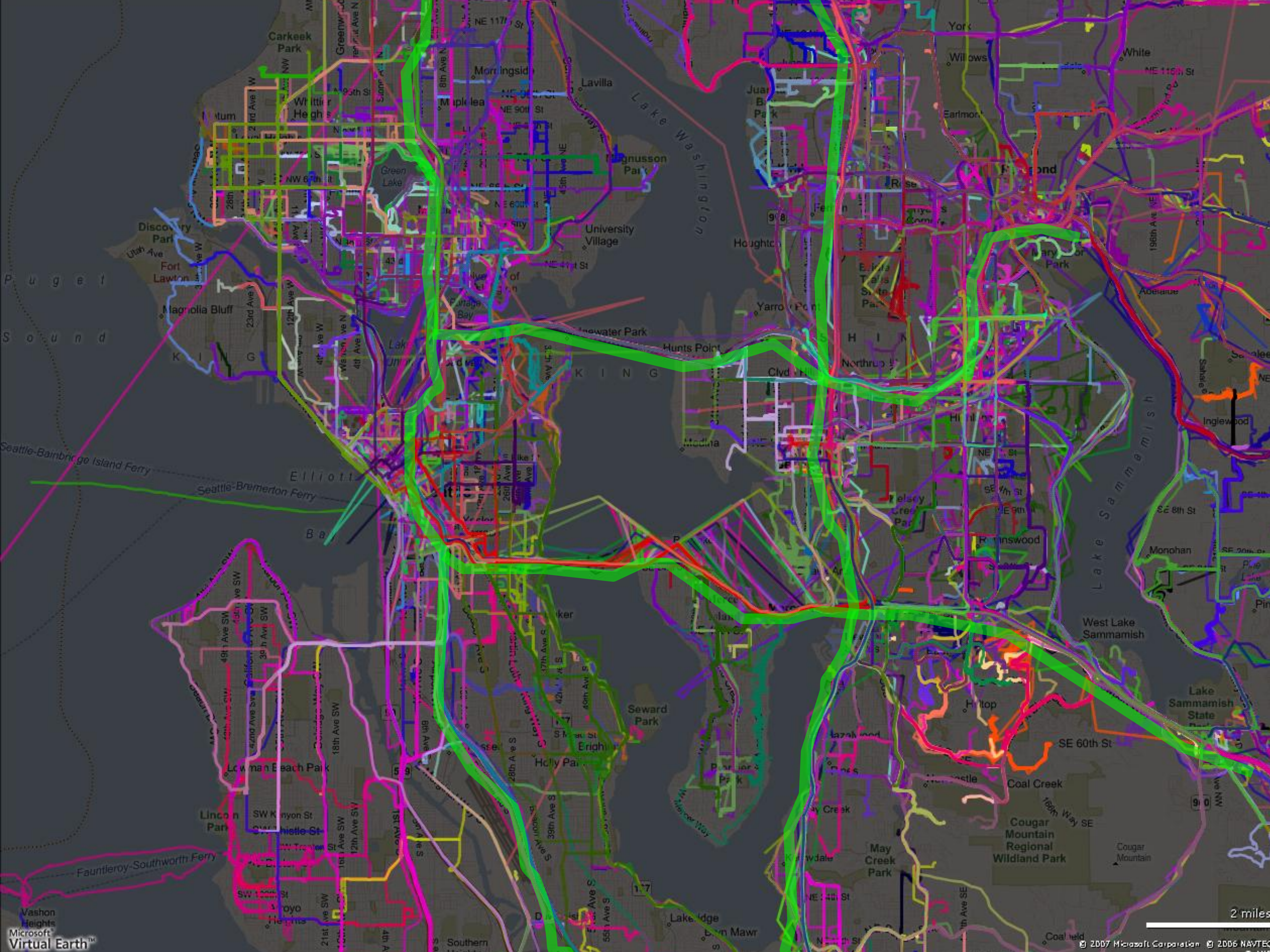


Multiuser Location Survey

~4.5 years of data collection



Case library
- 2,349,600 points
- ~300,000 km
- ~20,000 trips


Carkeek Park
Lavilla
Lake Washington
Magnusson Park
Green Lake
University Village
Discovery Park
Fort Lawton
Magnolia Bluff
Puget Sound
Seattle-Bainbridge Island Ferry
Elliott Bay
Seattle-Bremerton Ferry
Hunts Point
Yarrow Point
Houghton
Medina
Northrup
Willows
White
York
Earlmont
Marymoor Park
Adelaide
Inglewood
Lake Sammamish
West Lake Sammamish
Monohan
Lake Sammamish State Park
Seward Park
Holly Park
Lowman Beach Park
Lincoln Park
Fauntleroy-Southworth Ferry
Vashon Heights
Coal Creek
Cougar Mountain Regional Wildland Park
Cougar Mountain
May Creek Park
SE 60th St
Hilltop
Southern
Lakeridge
Bryn Mawr
Coalfield
2 miles
NE 117th St
NE 90th St
NE 41st St
NE 8th St
SE 8th St
SE 20th St
NE 116th St
SW Kenyon St
SW 106th St
Microsoft Virtual Earth
© 2007 Microsoft Corporation © 2006 NAVTEQ

ClearFlow

- **Fielded in 72 cities in North America (April 2008)**
- **Roads speeds assigned to ~60 million streets across North America *every few minutes***

Pittsburgh
Louisville
Philadelphia
Norfolk
Dallas/Ft. Worth
Columbus
Detroit
Charlotte
Houston
Hartford
Los Angeles
Raleigh-Durham
New York
Richmond
San Francisco
Tulsa
Chicago
Albany

Baltimore
Jacksonville
Boston
Greensboro
Washington, D.C.
Nashville
Miami
West Palm Beach
Tampa
New Orleans
Orlando
Tucson
San Diego
Albuquerque
Minneapolis
Colorado Springs
St. Louis
Allentown

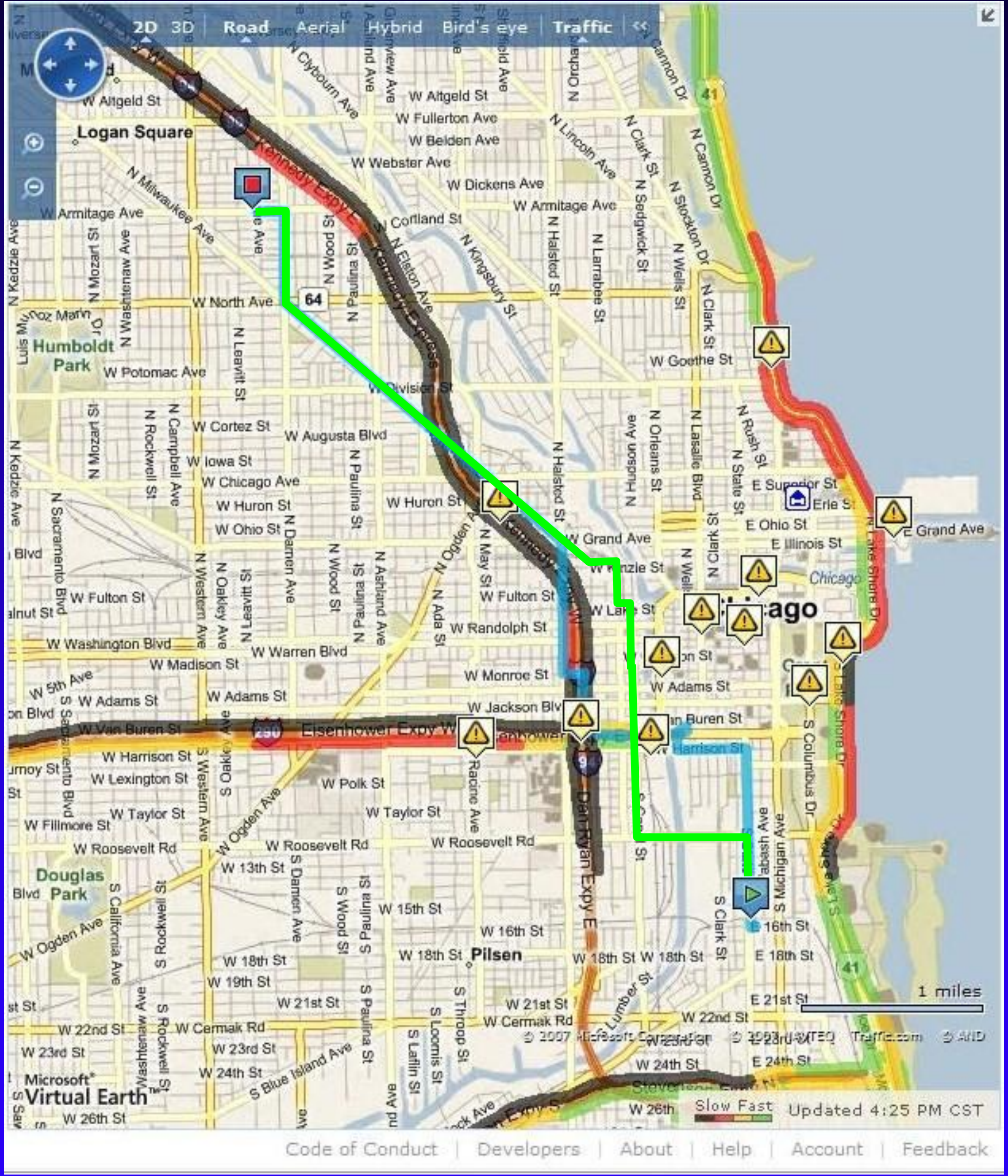
Denver
Harrisburg
Cleveland
Wilkes-Barre
Portland
Buffalo
Sacramento
Dayton
Seattle
Fresno
Atlanta
Grand Rapids
Birmingham
Toledo
Indianapolis
Greenville
Las Vegas
Memphis

Oklahoma City
Lincoln
Phoenix
Omaha
Providence
Little Rock
Salt Lake City
Mobile
Cincinnati
Portsmouth-Manchester
San Antonio
Rochester
Milwaukee
Syracuse
Austin
Spokane
Kansas City
Toronto

Chicago

Default

Chicago



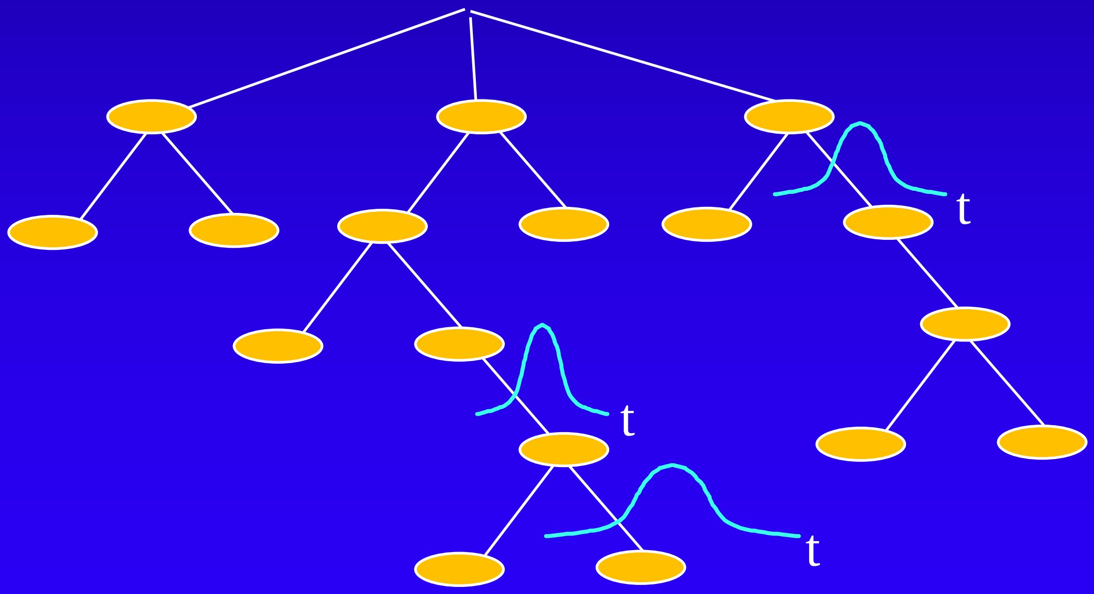
Clearflow

Planning while the Sands are Shifting

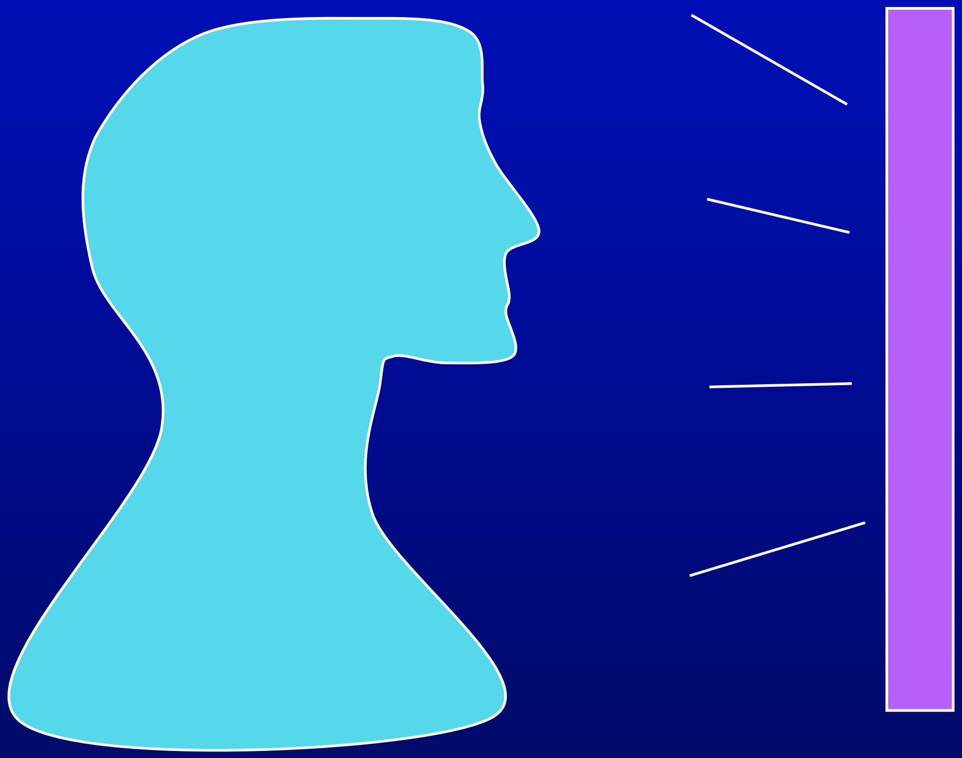
- Lab: Temporal models forecast future speeds and uncertainties

- Path planning with changing situation
- Variances, robustness, flexibility

  … finding paths with contingencies

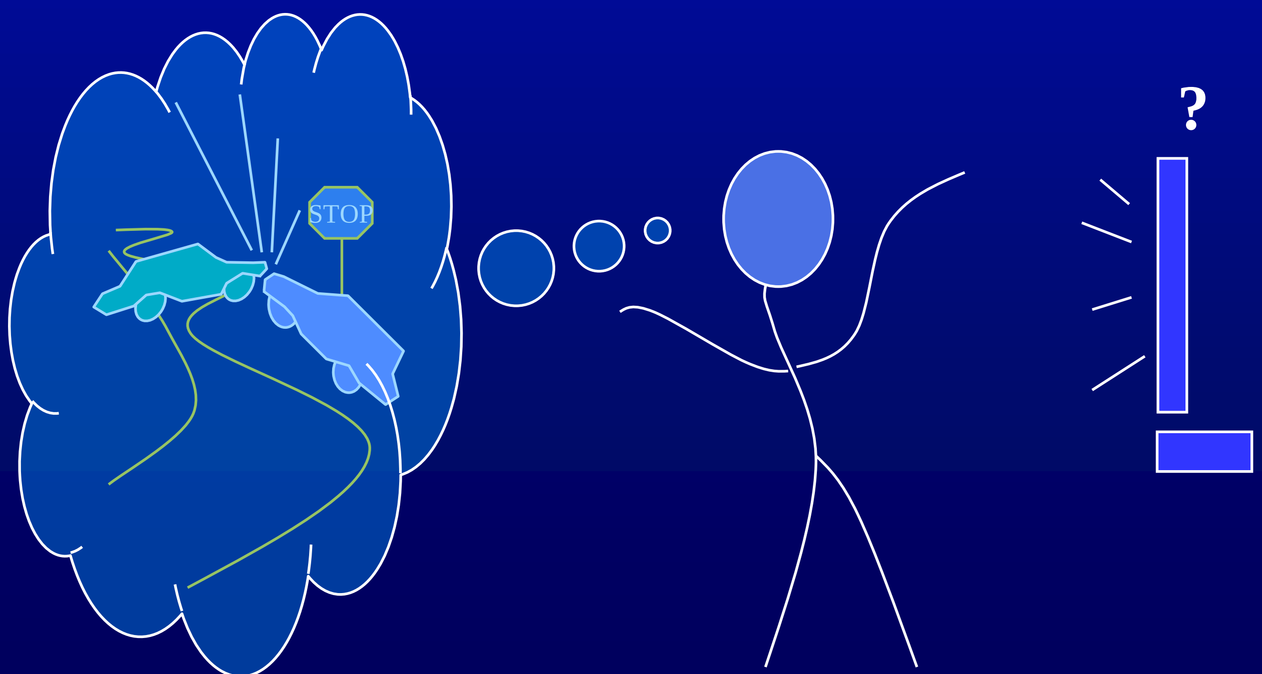


Human-Computer Collaboration in Open Worlds



Grounding

Converging on shared references, beliefs, and intentions

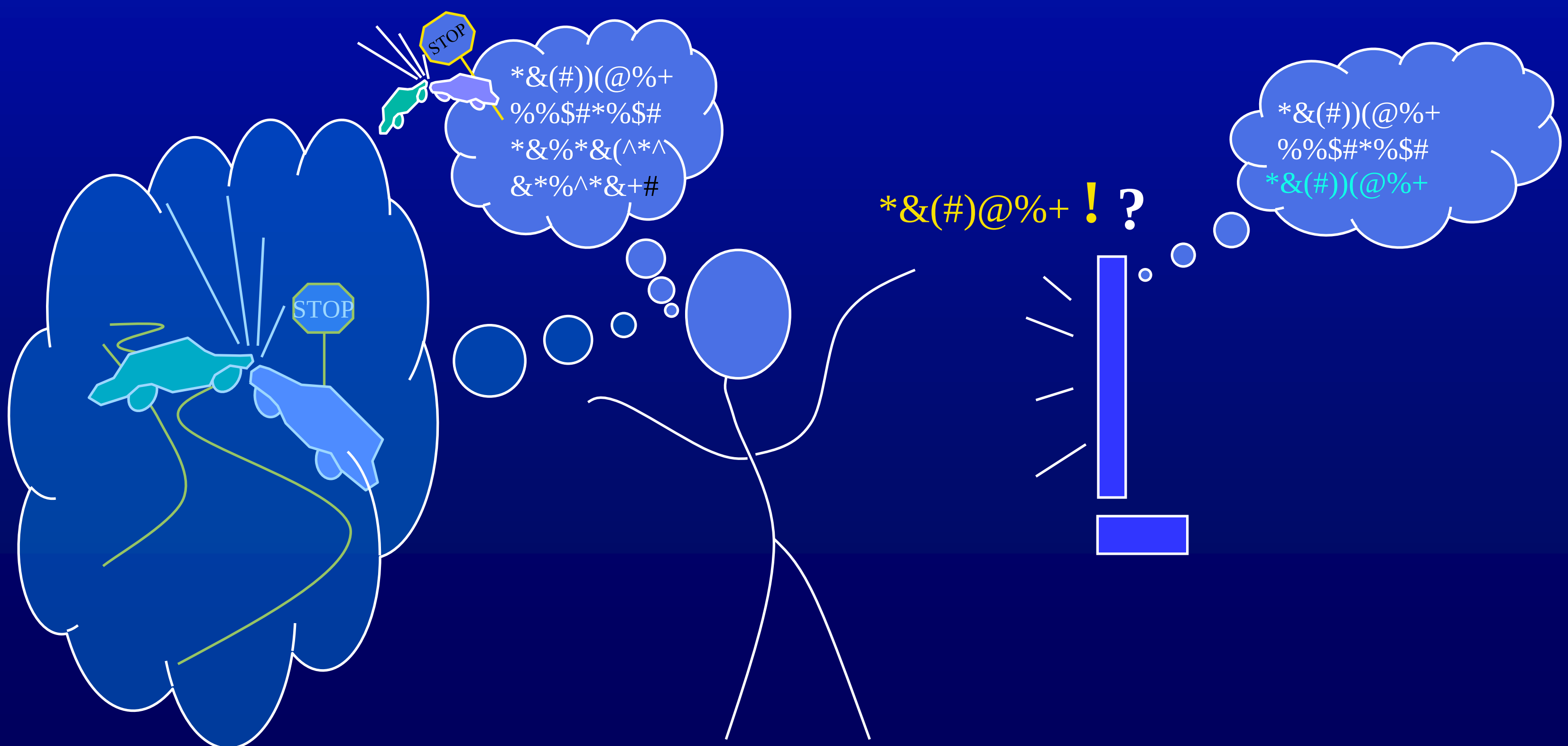


Grounding

Converging on shared references, beliefs, and intentions

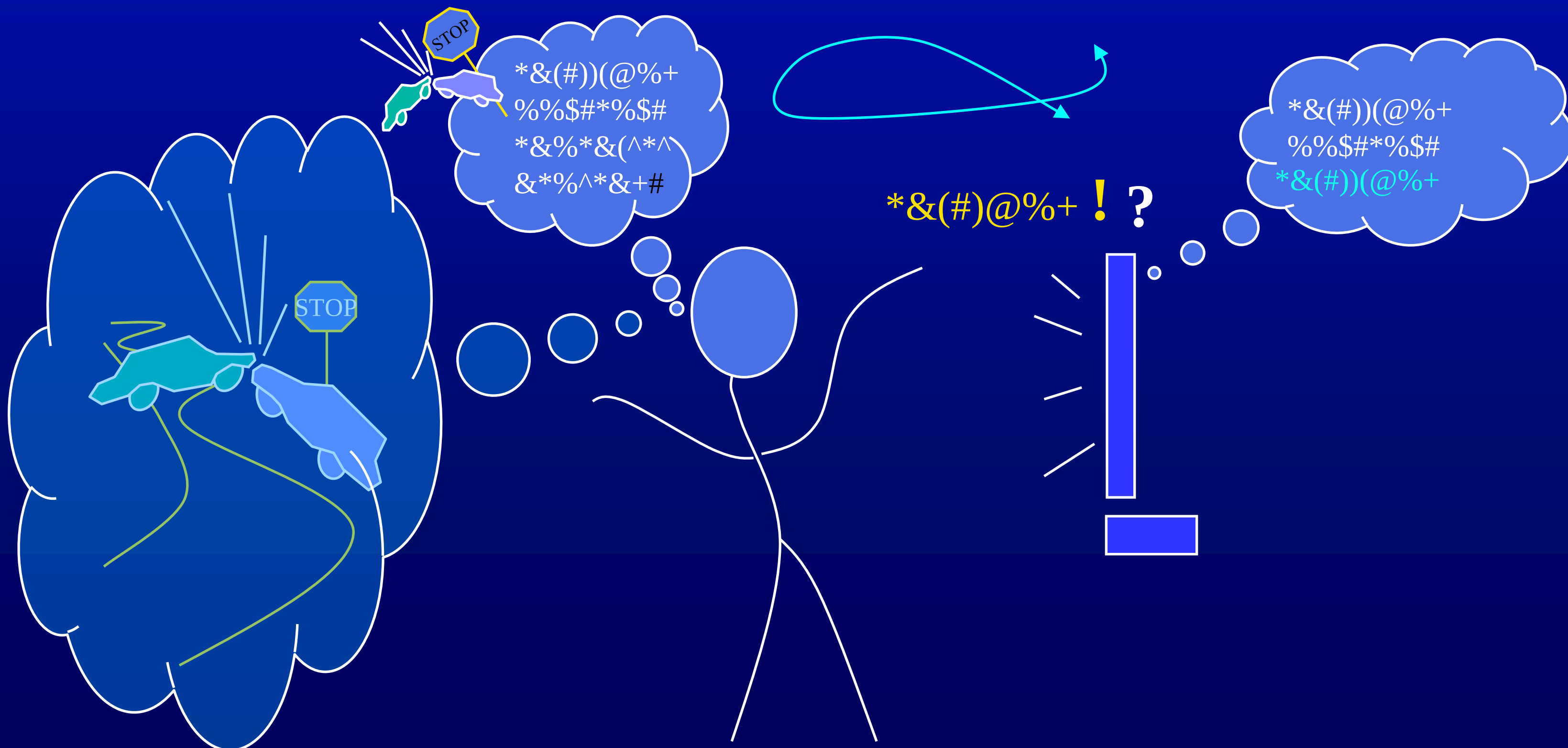
Grounding

Converging on shared references, beliefs, and intentions



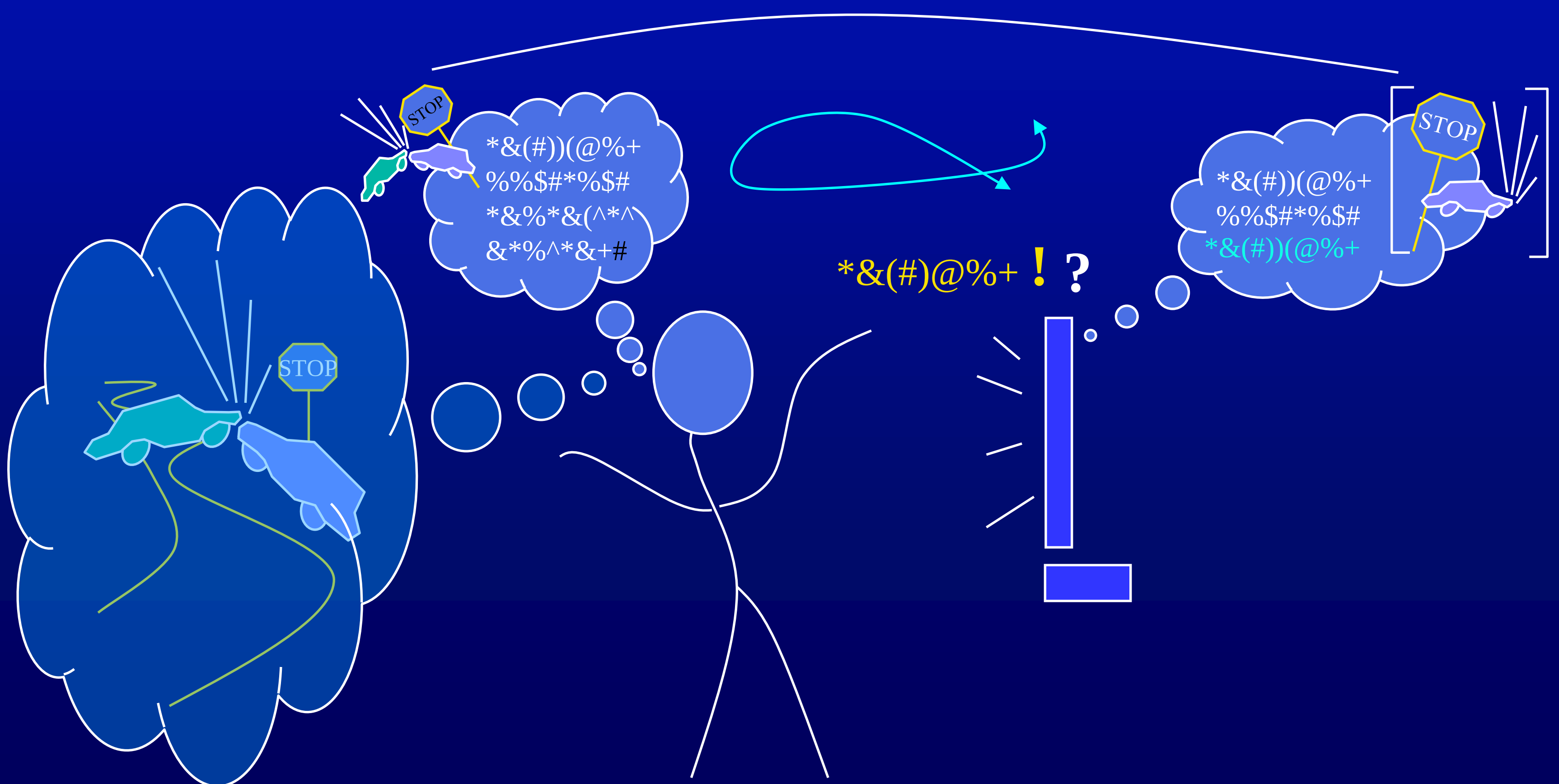
Grounding

Converging on shared references, beliefs, and intentions

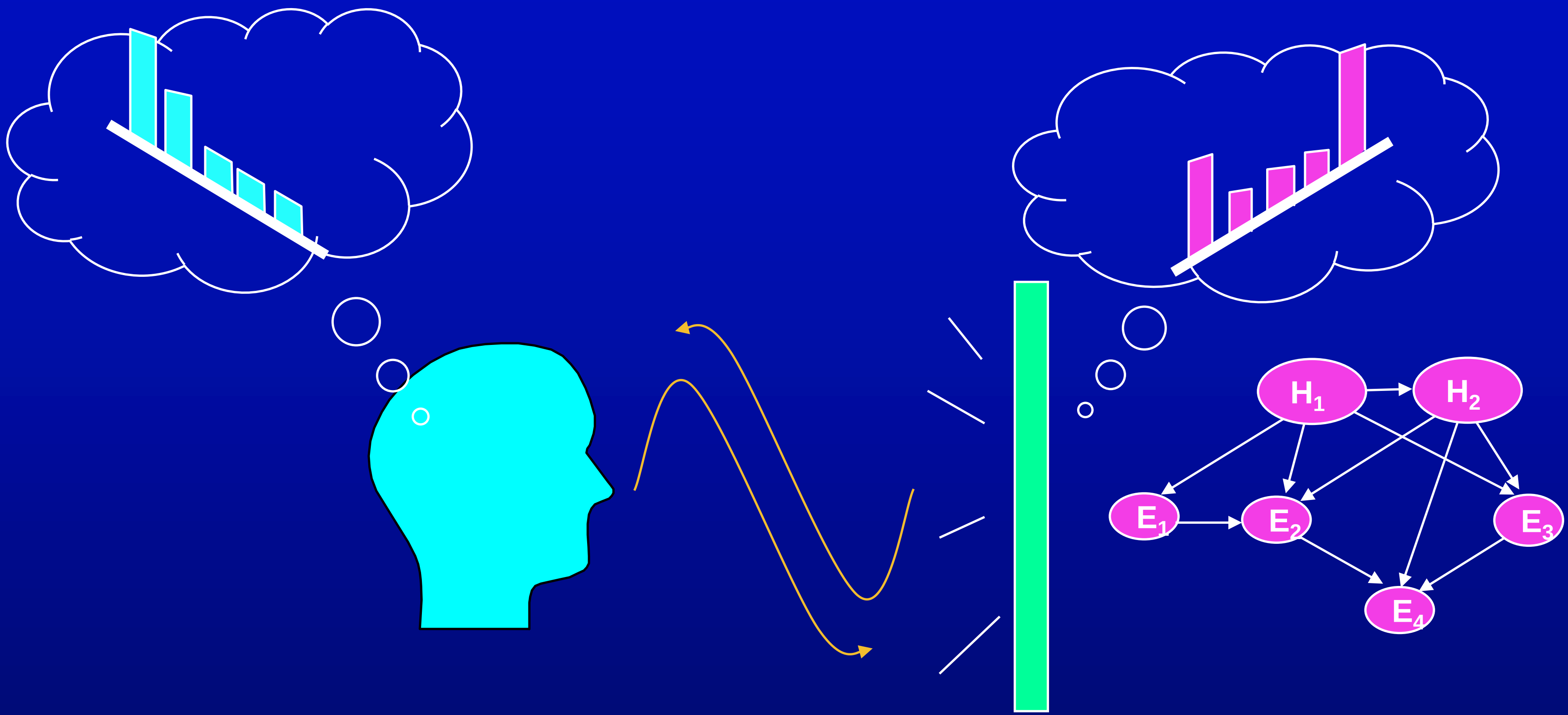


Grounding

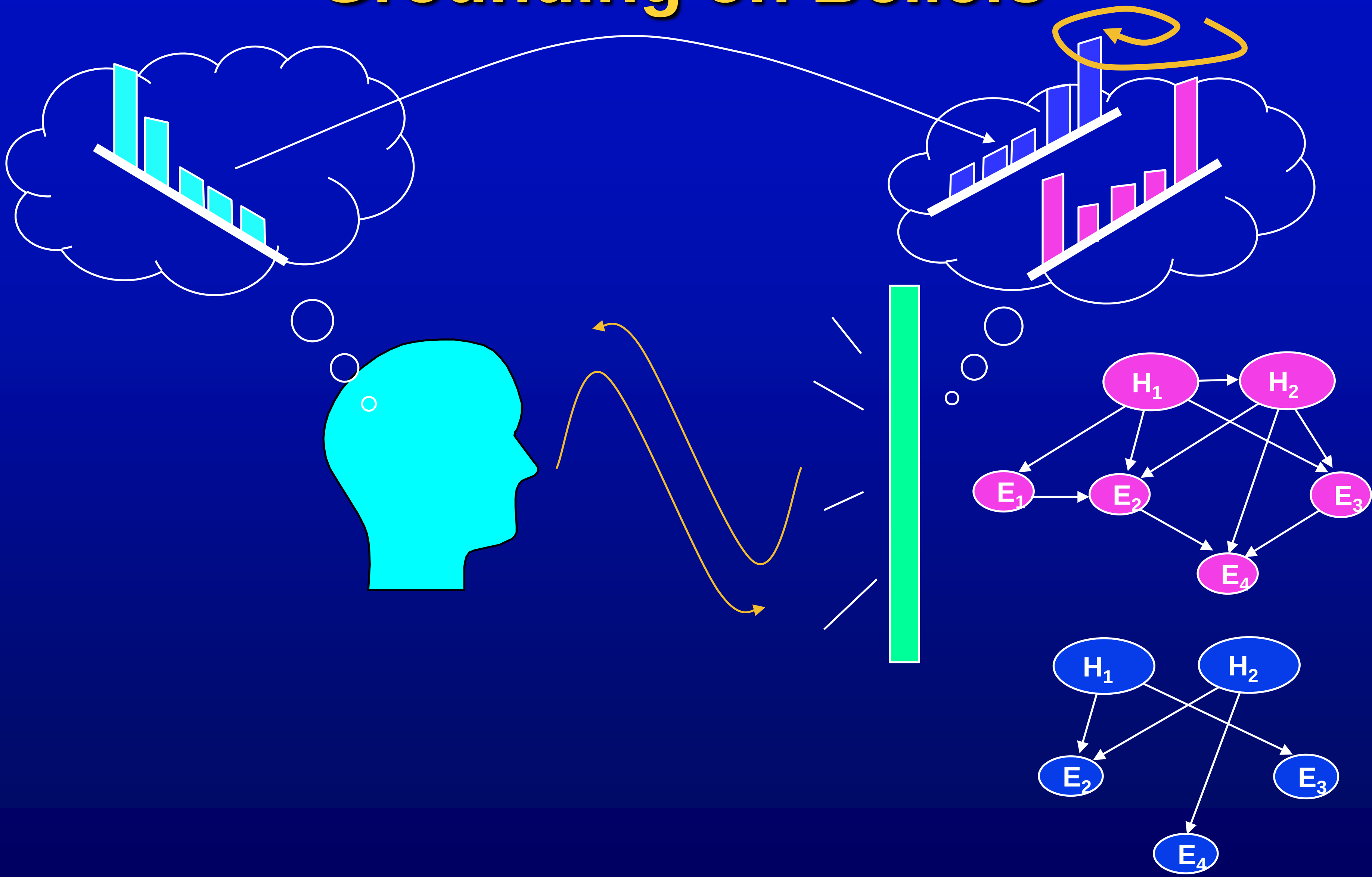
Converging on shared references, beliefs, and intentions



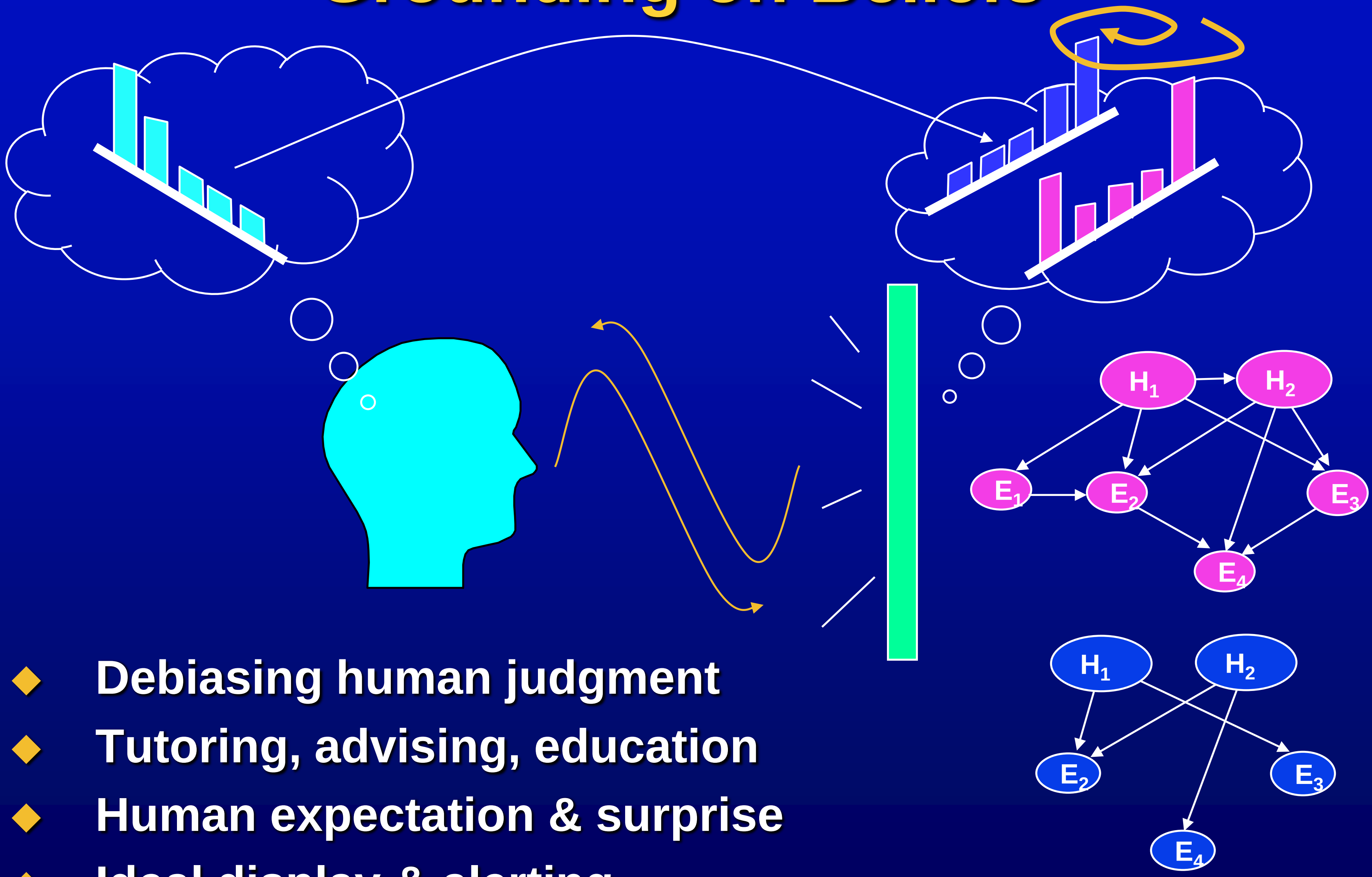
Grounding on Beliefs



Grounding on Beliefs



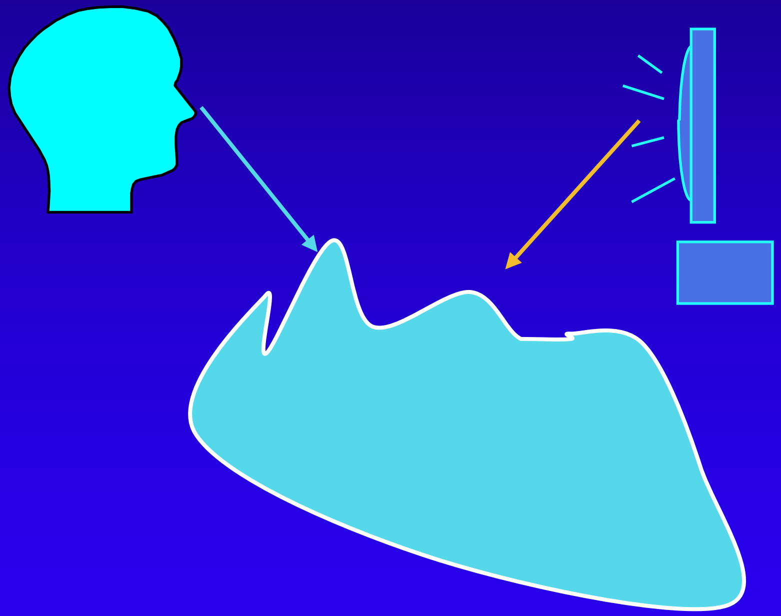
Grounding on Beliefs



- Debiasing human judgment
- Tutoring, advising, education
- Human expectation & surprise
- Ideal display & alerting

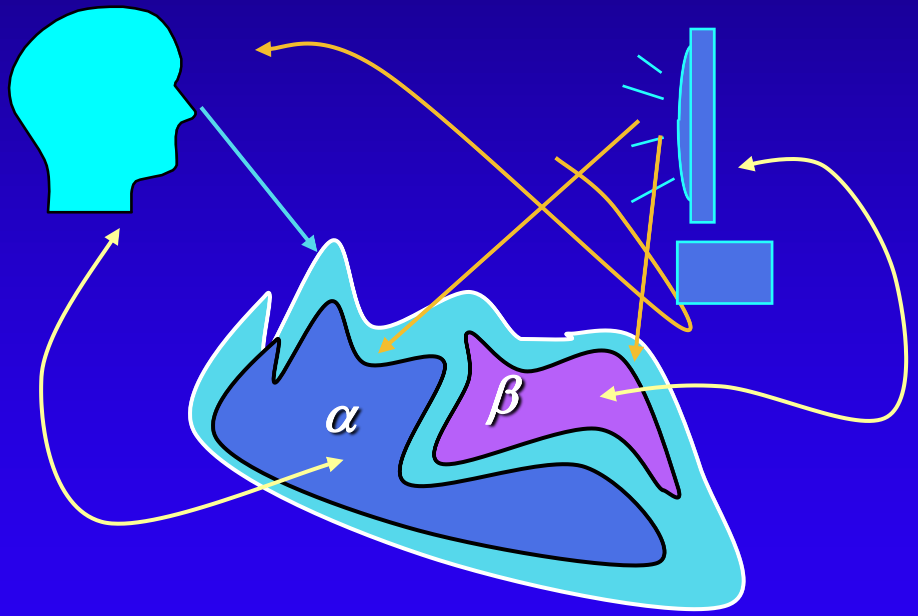
Mixed-Initiative Collaboration

- Interleaving of contributions from machine and human to jointly solve problems.
  - Problem recognition, decomposition, coordination



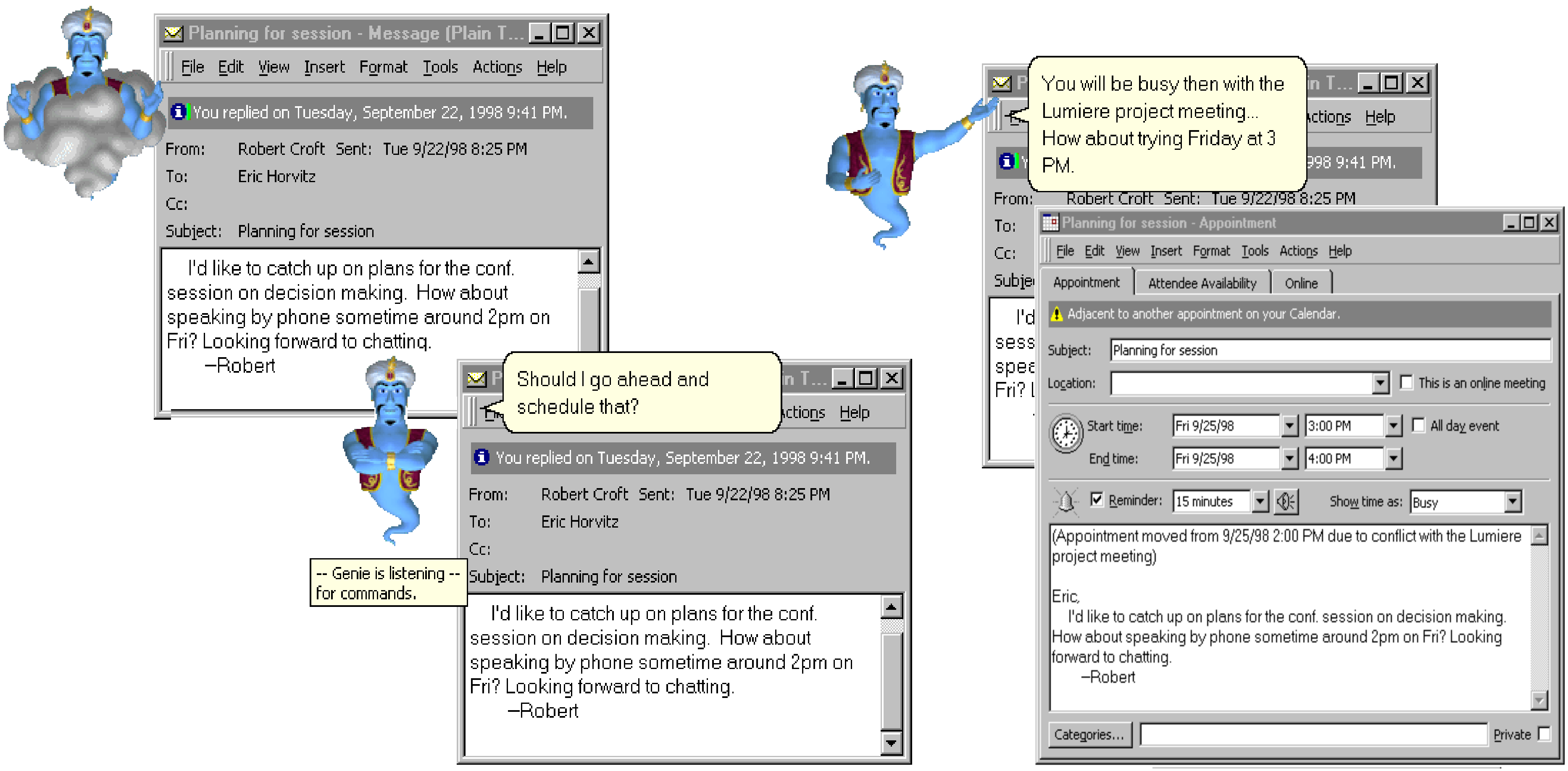
Mixed-Initiative Collaboration

- Interleaving of contributions from machine and human to jointly solve problems.
  - Problem recognition, decomposition, coordination



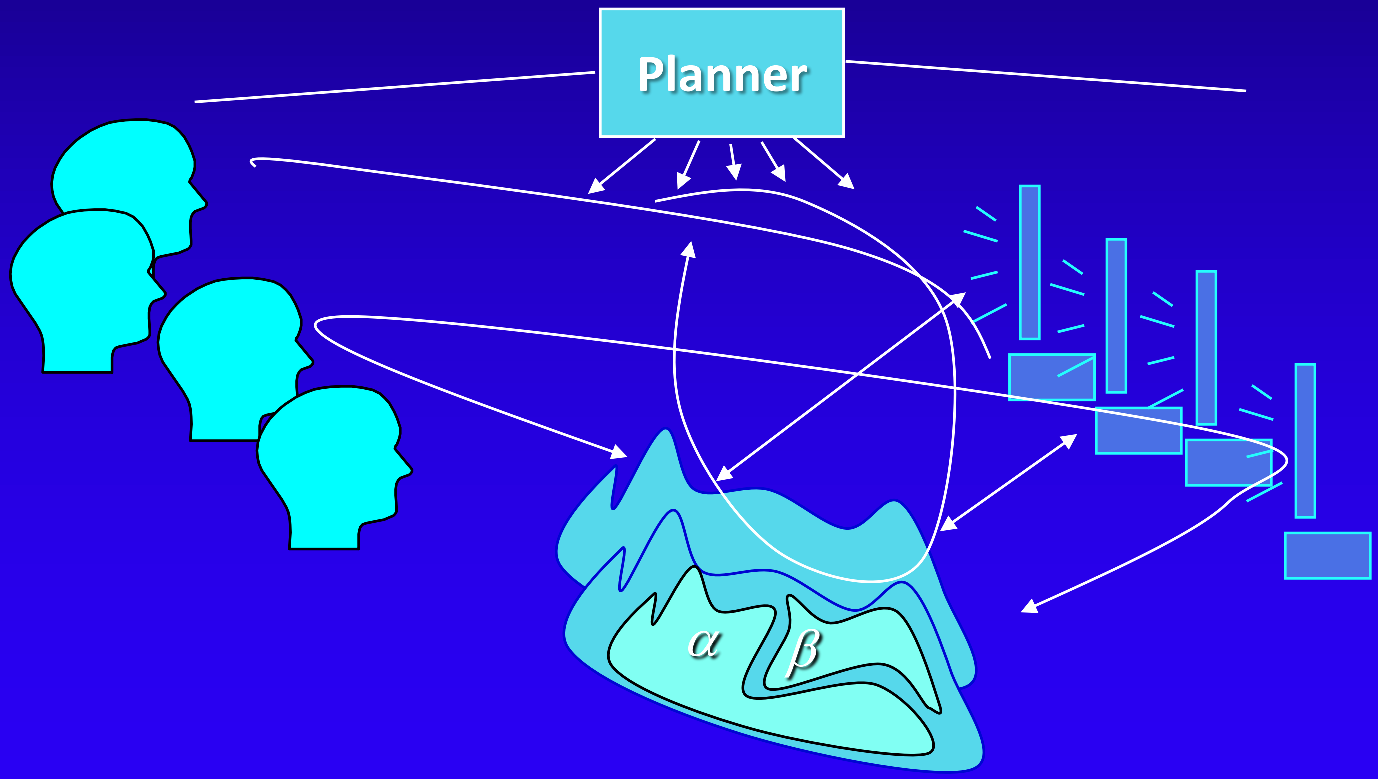
Mixed-Initiative Collaboration

- Interleaving of contributions from machine and human to jointly solve problems.



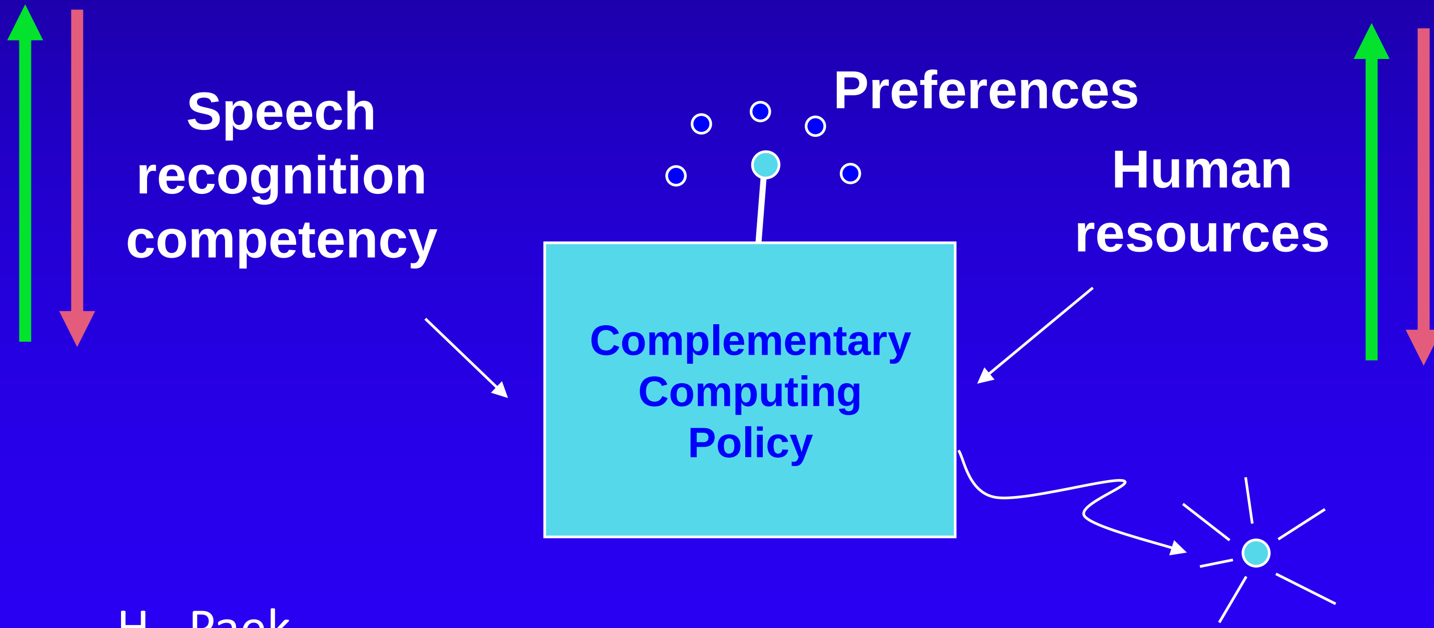
Complementary Computing

- **Consider systems of people & computation**
- **Policies for coordinating contributions**
- ***Task markets* for humans, computers, sensors, effectors**



Example: Adaptive Policies in an Automated Reception System

- Changing dialog competencies
- Changing load on staff

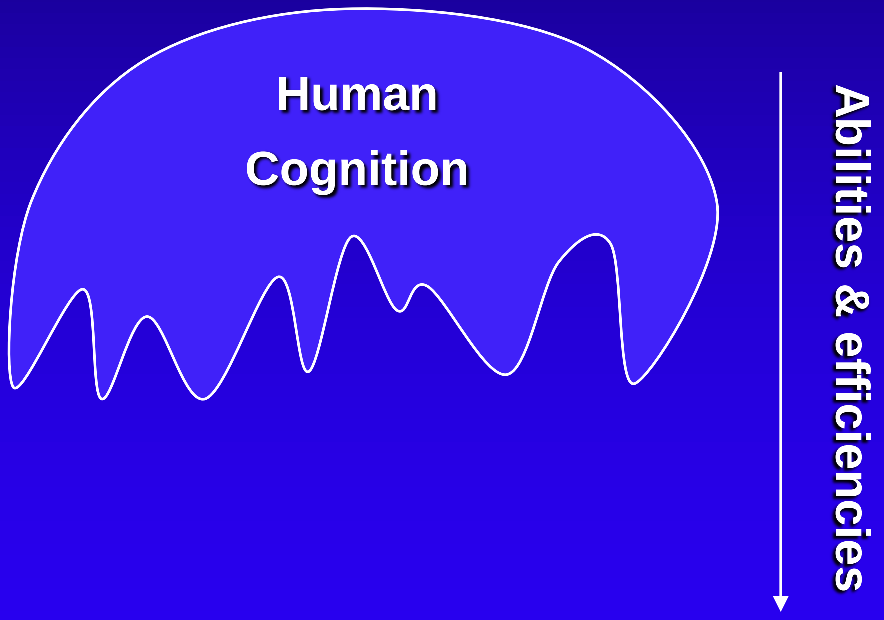


H., Paek

Learning about Human Cognition for Augmenting Human Abilities

20^{th} Century cognitive psychology:

Characterizable limitations & bottlenecks

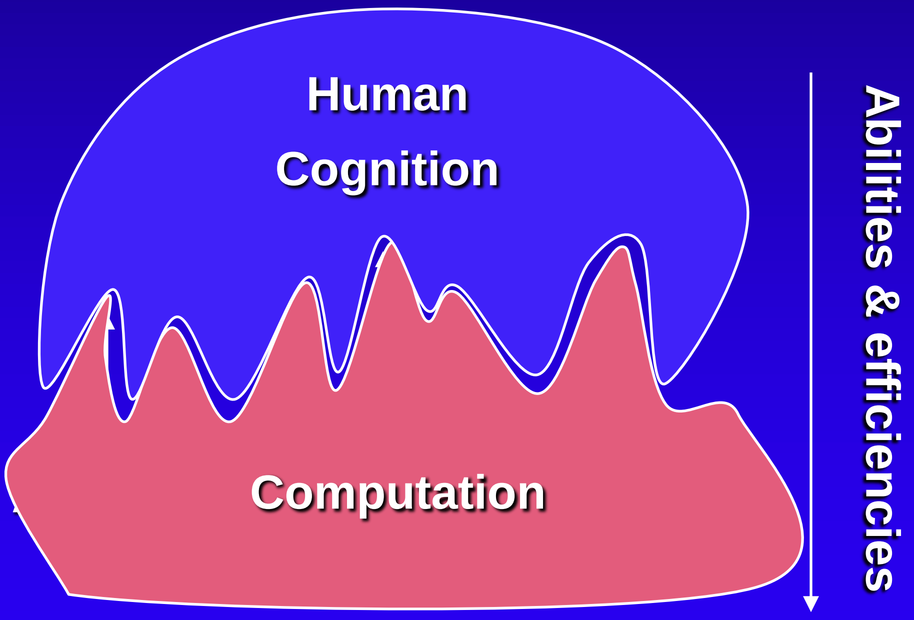


Learning about Human Cognition for Augmenting Human Abilities

20th Century cognitive psychology:

Characterizable limitations & bottlenecks

Promise of sensing & reasoning

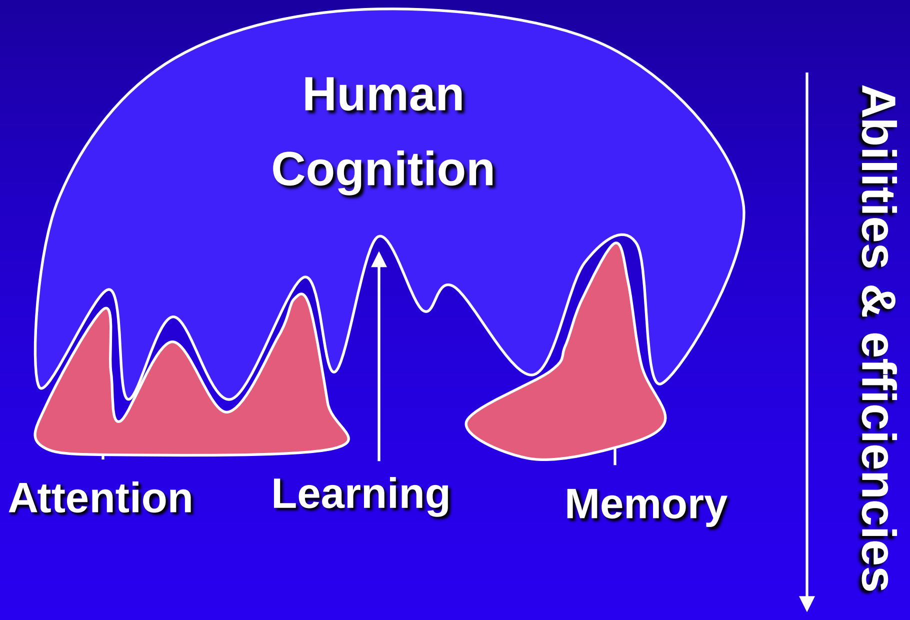


Learning about Human Cognition for Augmenting Human Abilities

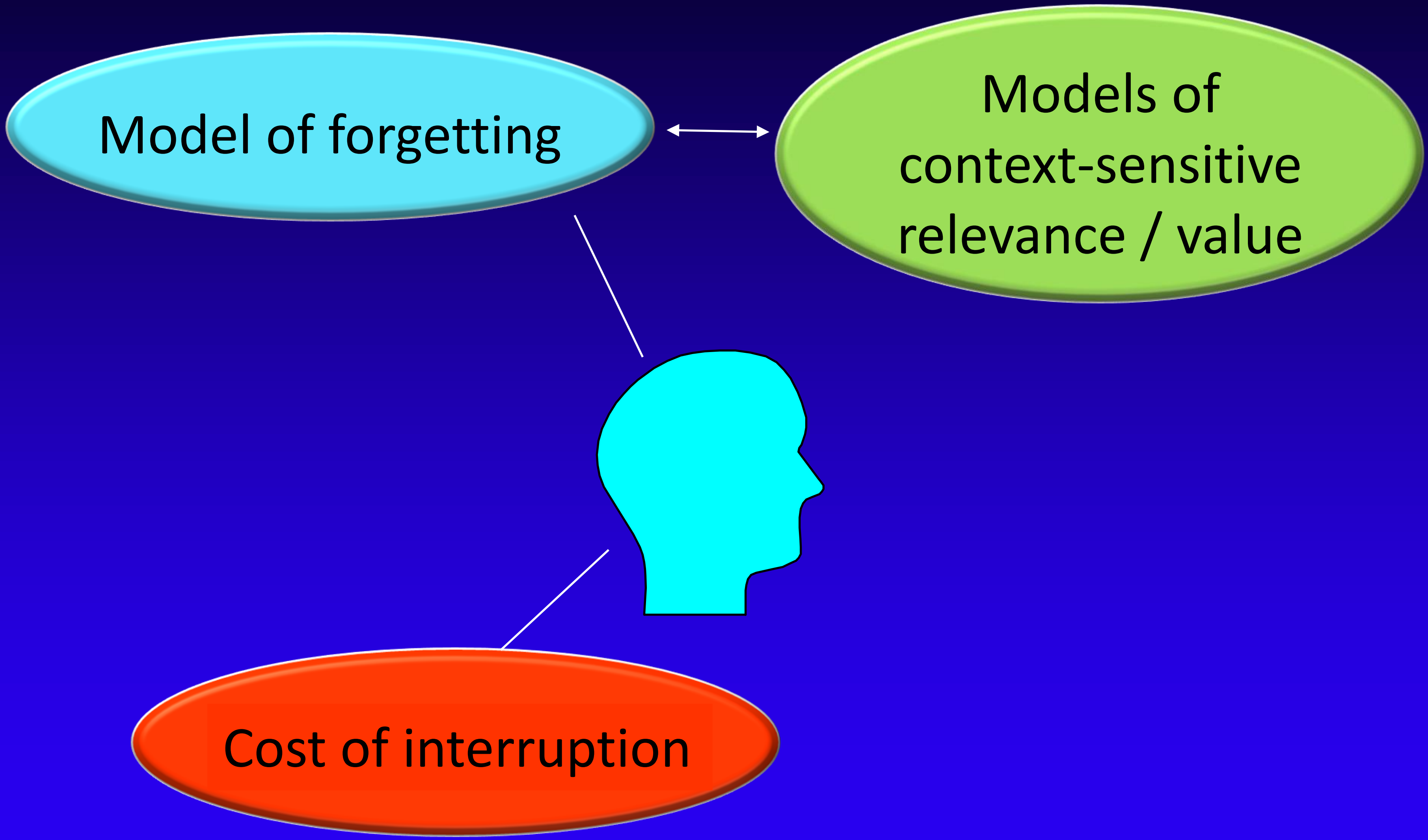
20th Century cognitive psychology:

Characterizable limitations & bottlenecks

Promise of sensing & reasoning

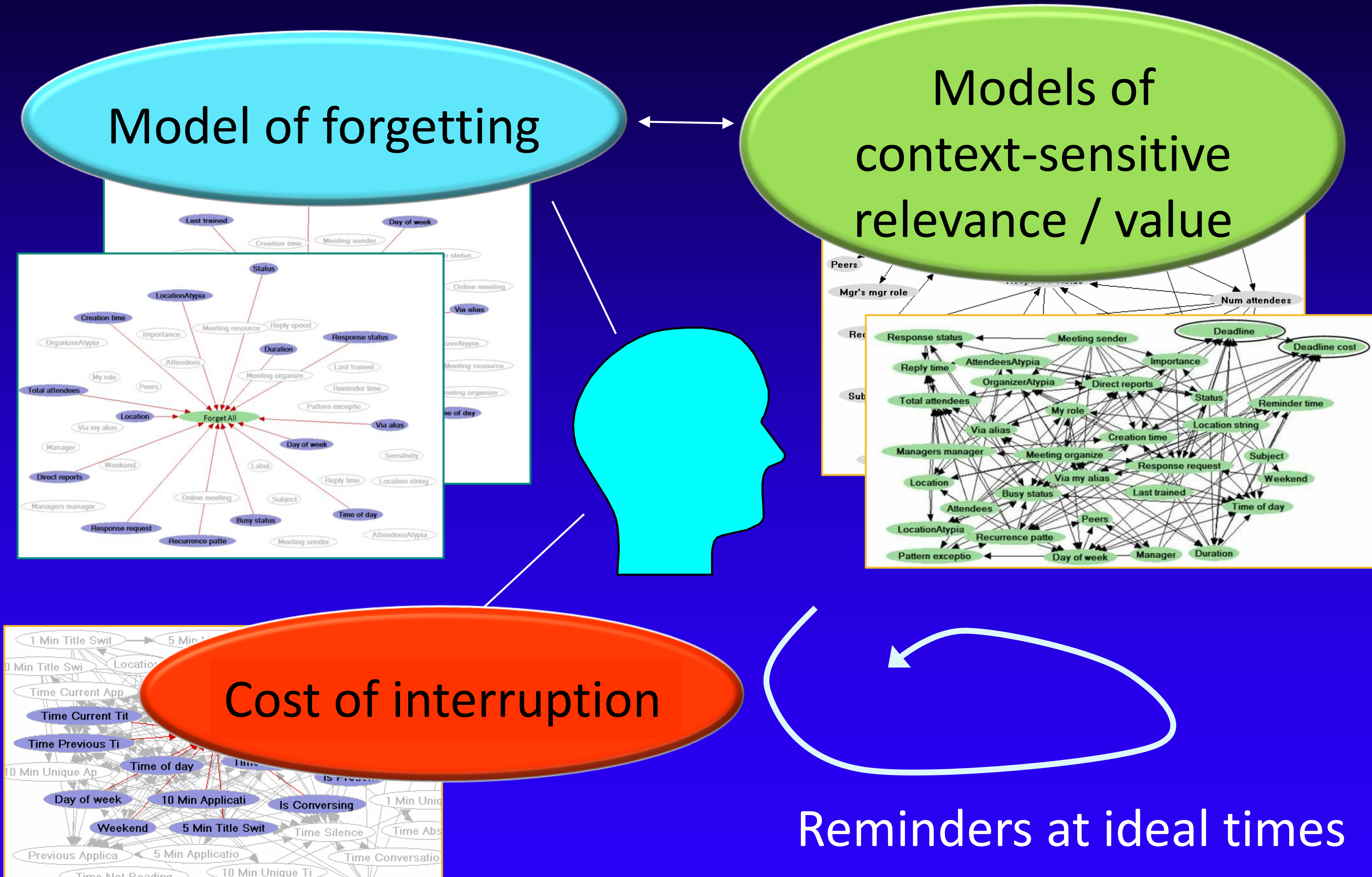


Models of Memory in Reminding



Kamar, H.

Models of Memory in Reminding



Integrative Intelligence

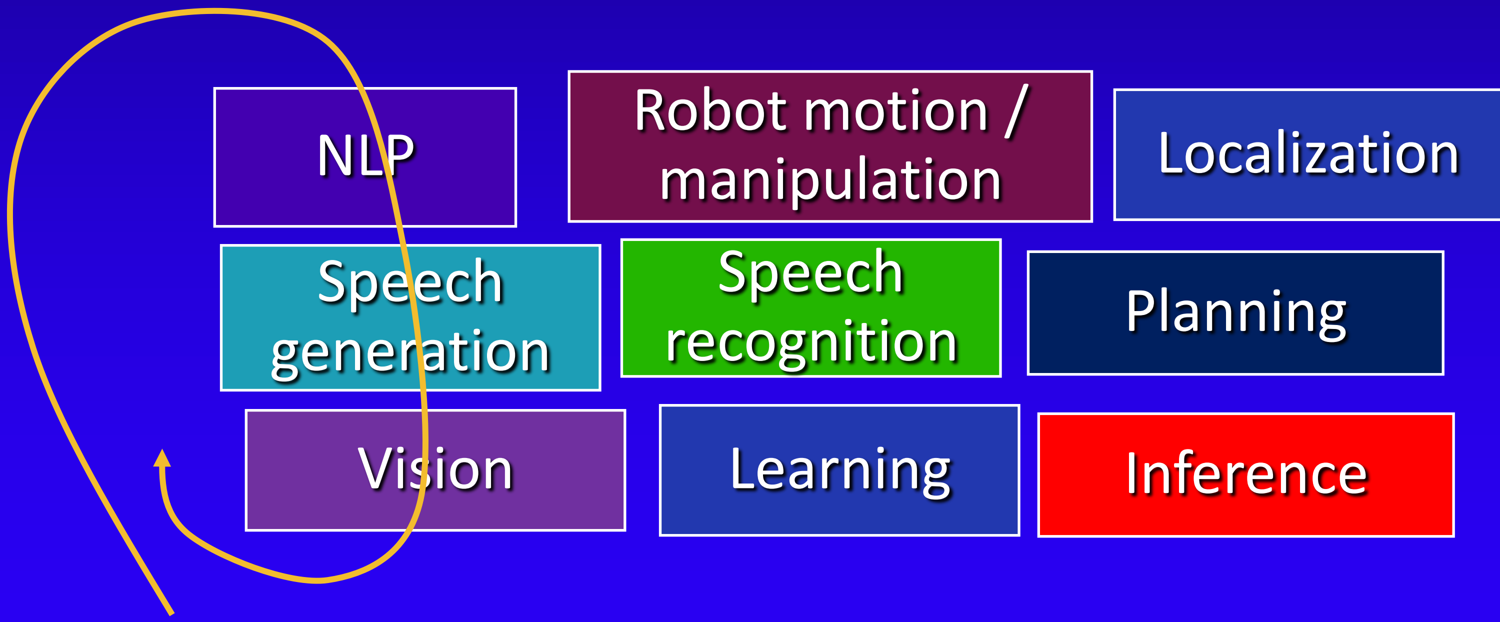
Opportunity: More comprehensive, “integrative intelligences,” probing open world

- Sensing & symbols
- Goals & preferences
- Action execution, monitoring
- Learning, semi- and unsupervised
- Interaction of components

Integrative Intelligence

Opportunity: More comprehensive, "integrative intelligences," probing open world

- **Weaving together components that have been developed separately**



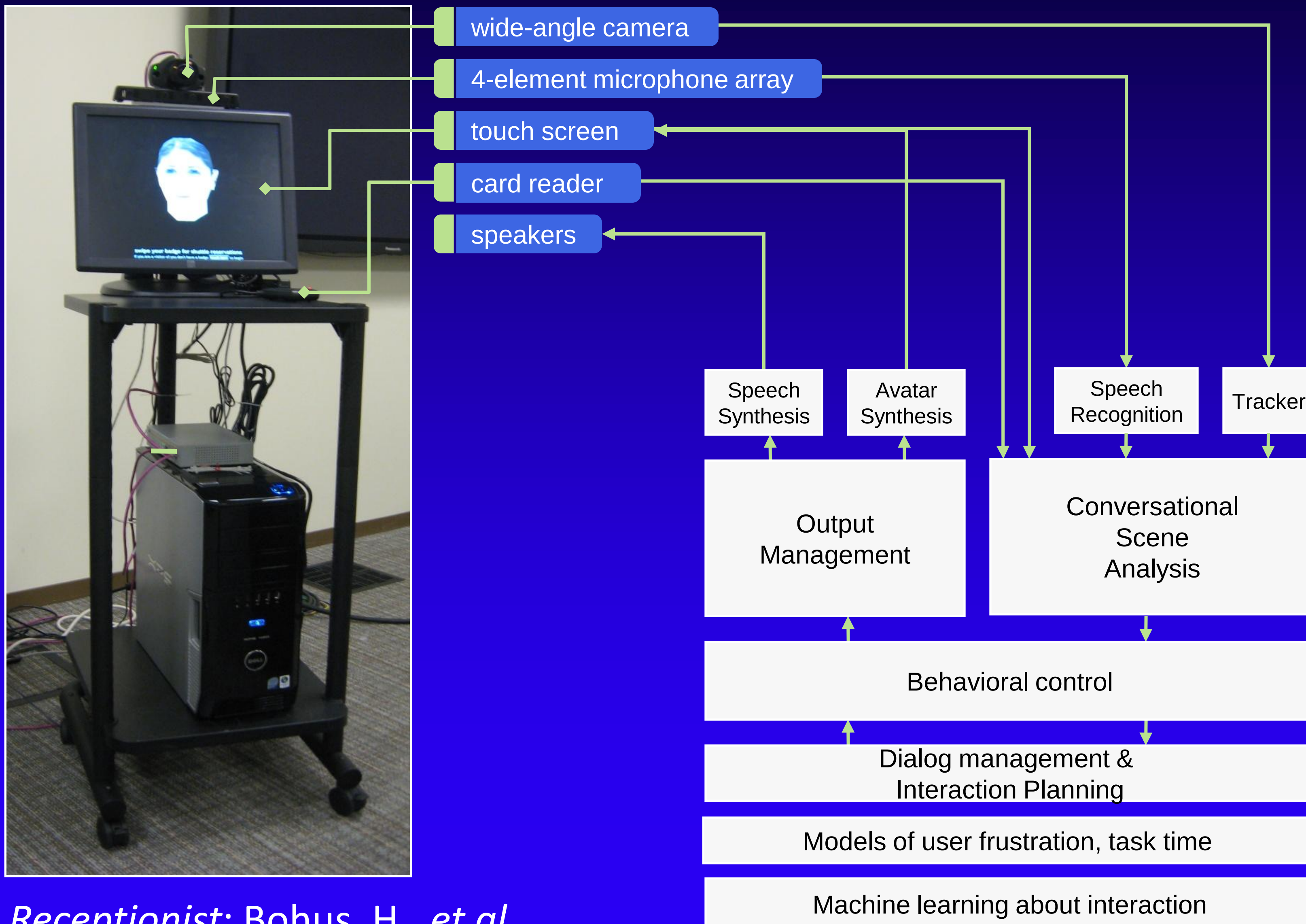
Integrative Intelligence

- Vision, manipulation, navigation, learning

(video)

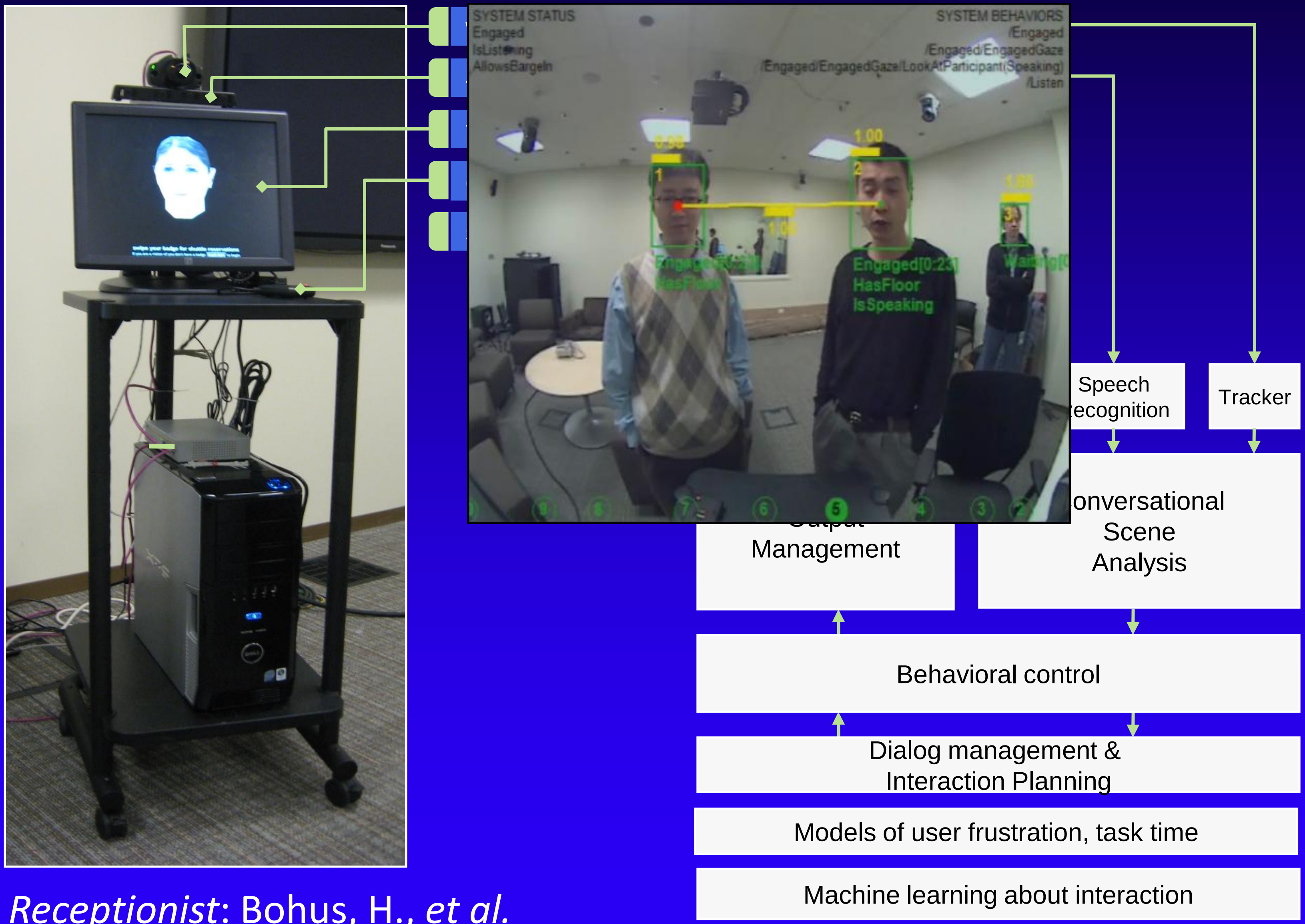
STAIR, Ng, *et al.*

Integrative Intelligence



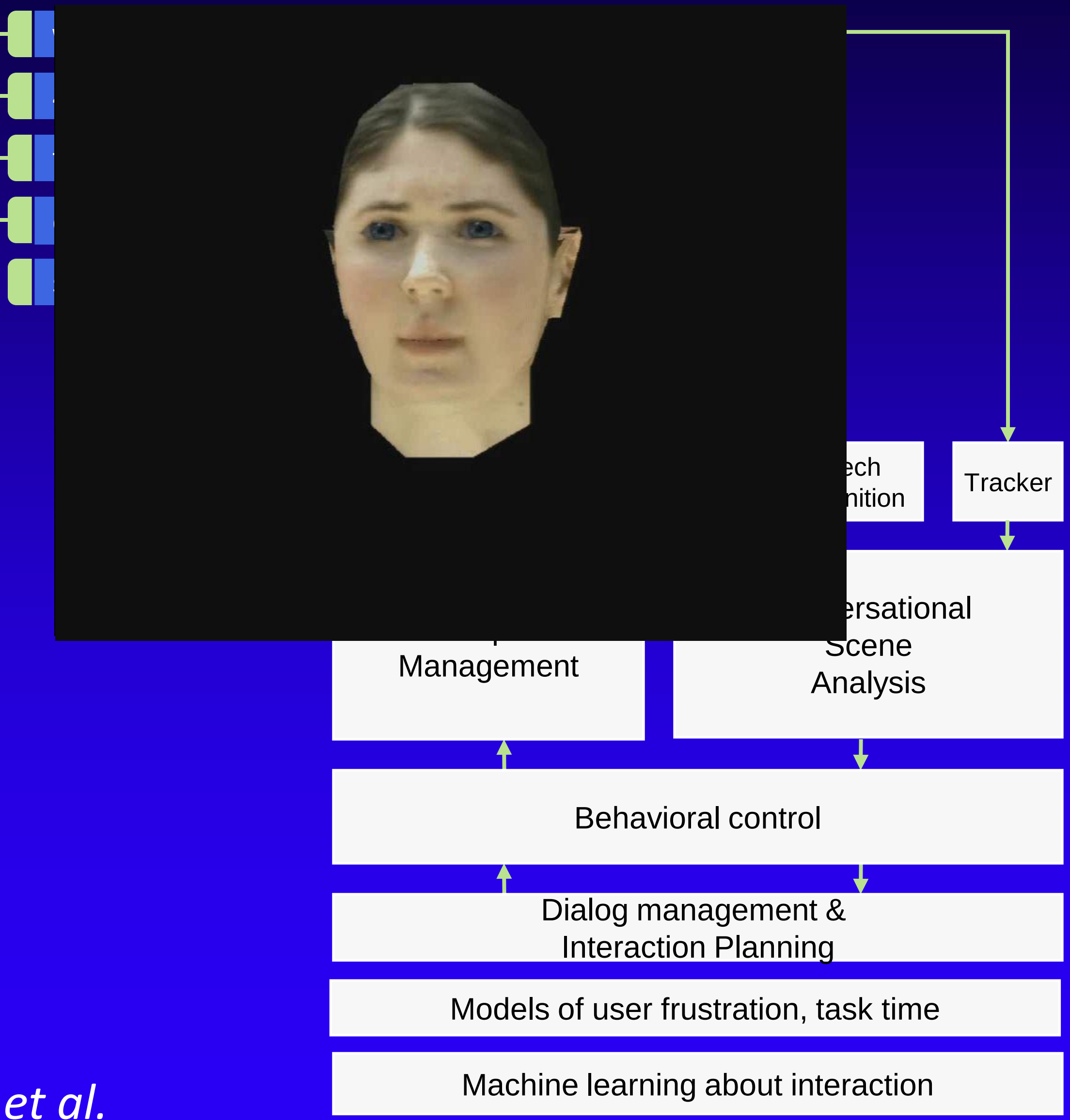
Receptionist: Bohus, H., *et al.*

Integrative Intelligence



Receptionist: Bohus, H., *et al.*

Integrative Intelligence



Receptionist: Bohus, H., *et al.*

Integrative Intelligence

(video)

Transformation of Science

- Scientific discovery & confirmation
- Learning & inference
- Triage of experimentation

Dendral

Planner, hypothesis generator, confirmation

Rule 74:

```
IF    The spectrum for the molecule has two peaks
      at masses X1 and X2 such that:
          X1 + X2 = M + 28
              and
          X1 - 28 is a high peak
              and
          X2 - 28 is a high peak
              and
          at least one of X1 or X2 is high
THEN The molecule contains a ketone group
```

Rule 75:

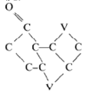
```
IF     There is a high peak at mass 71
           and
       There is a high peak at mass 43
           and
       There is a high peak at mass 86
           and
       There is a high peak at mass 58

THEN   There must be an N-propyl-ketone3 structure
```

#DRAW ATNAMED 1

[Comment: The following is a sample structure in which Z has been imbedded. Note that V's are not yet imbedded.]

#1:



#IMBED

[Comment: The V's will now be imbedded.]
SUPERATOM: **V**
NUMBER TO BE IMBEDDED: **2**
THE 'EXPANDED' FORMULA IS O 1 C 12 H 14
CONSTRAINT: **SUBSTRUCTURE CH0 EXACTLY 2**
[C7: we must end up with exactly two quaternary carbons.]
CONSTRAINT: **RING 3 NONE** [C9]
CONSTRAINT: **RING 4 NONE** [C9]
CONSTRAINT:

#.#.#.#..#..#..#..#..#..#..#..#..#.#.#.#..#.#..

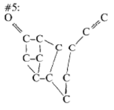
#.#..#.#..#..#...#..#..#.#.#.#..

47 STRUCTURES WERE OBTAINED

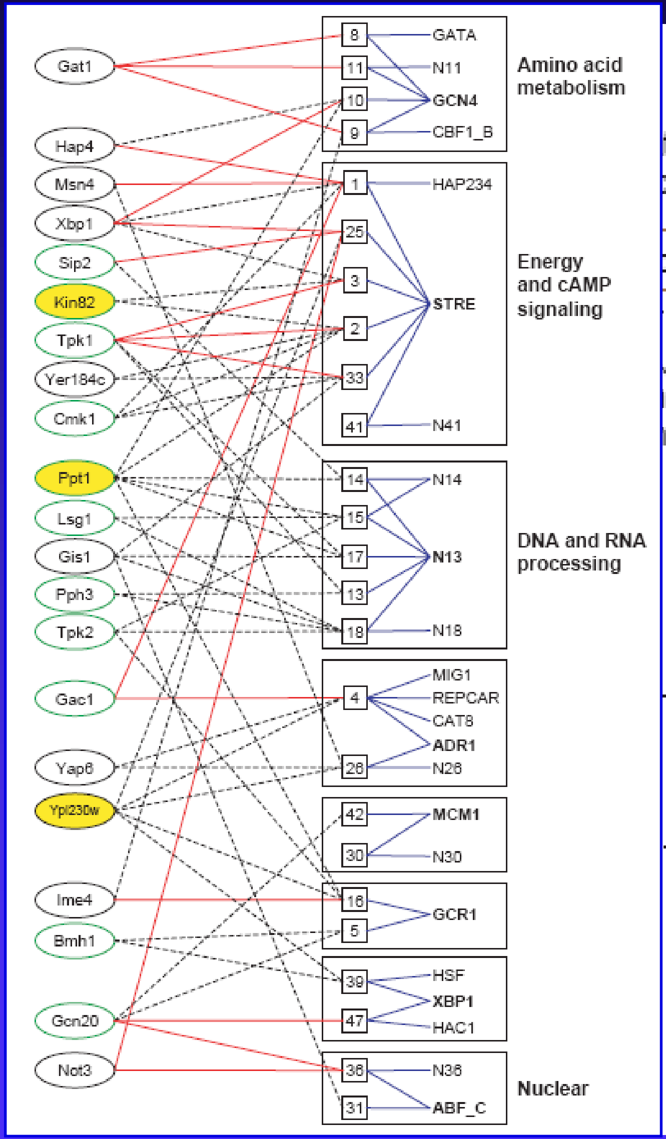
#DRAW ATNAMED (5 6)

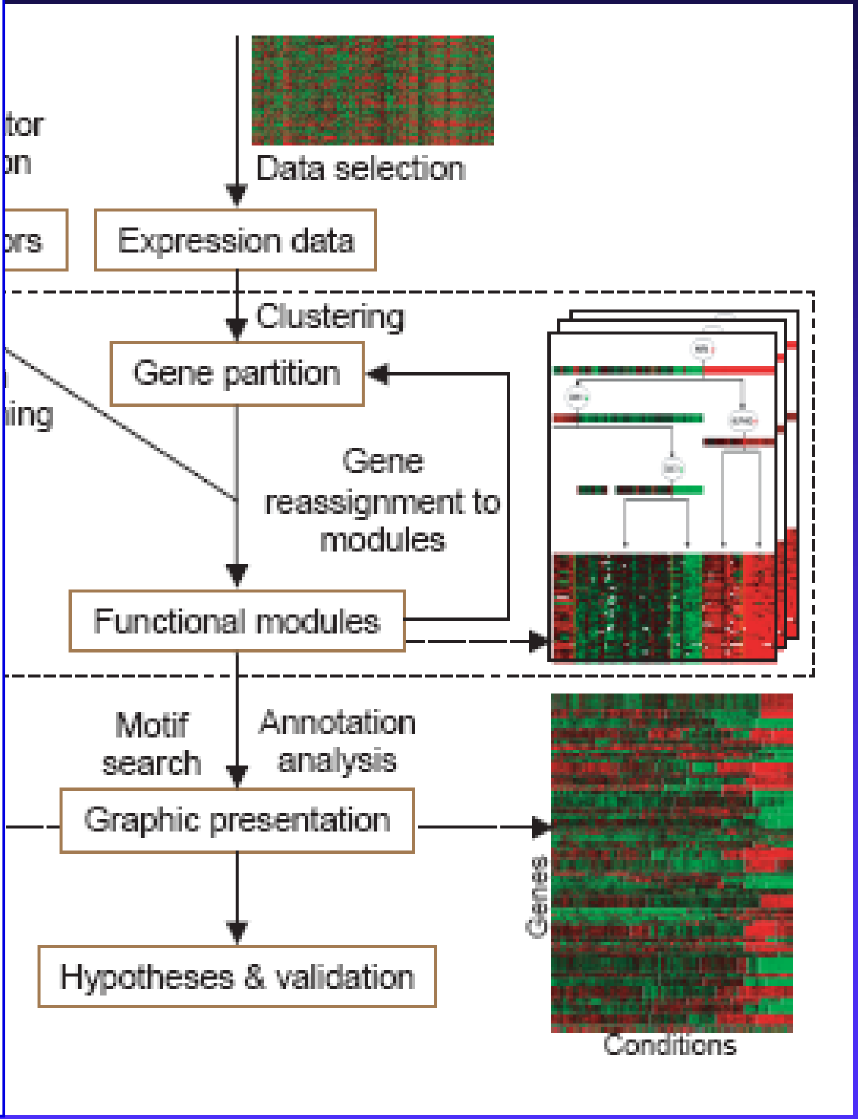
[Comment: The following is a selection of final structures 5, 6.]

#5:



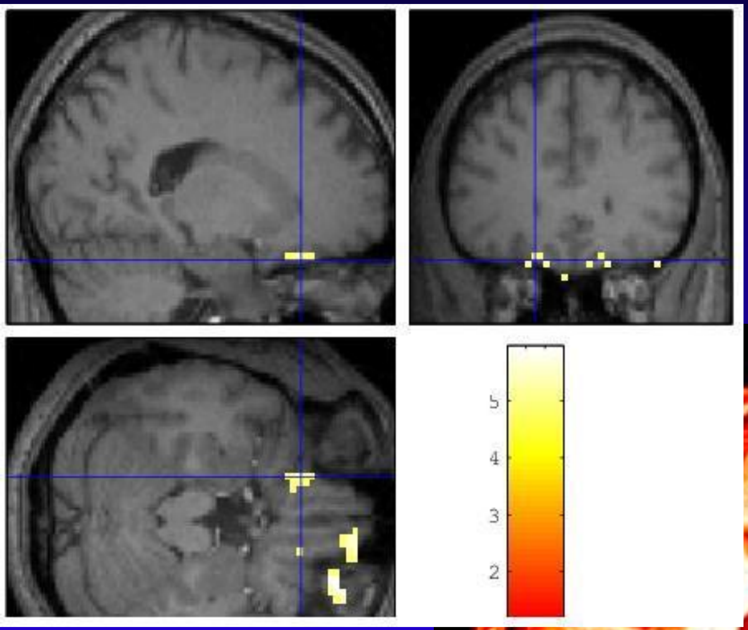
Learning about Structure & Function

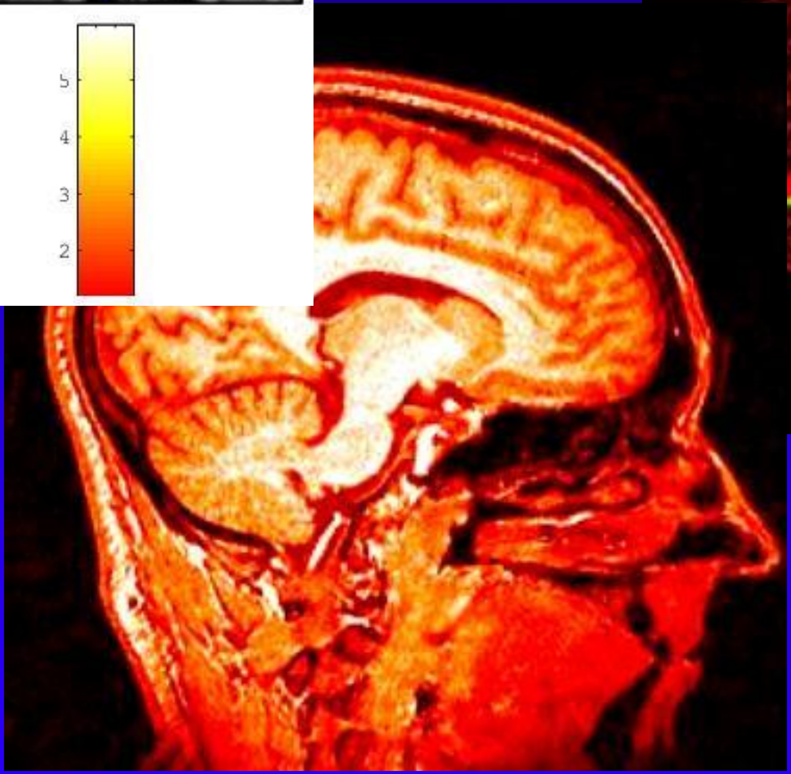


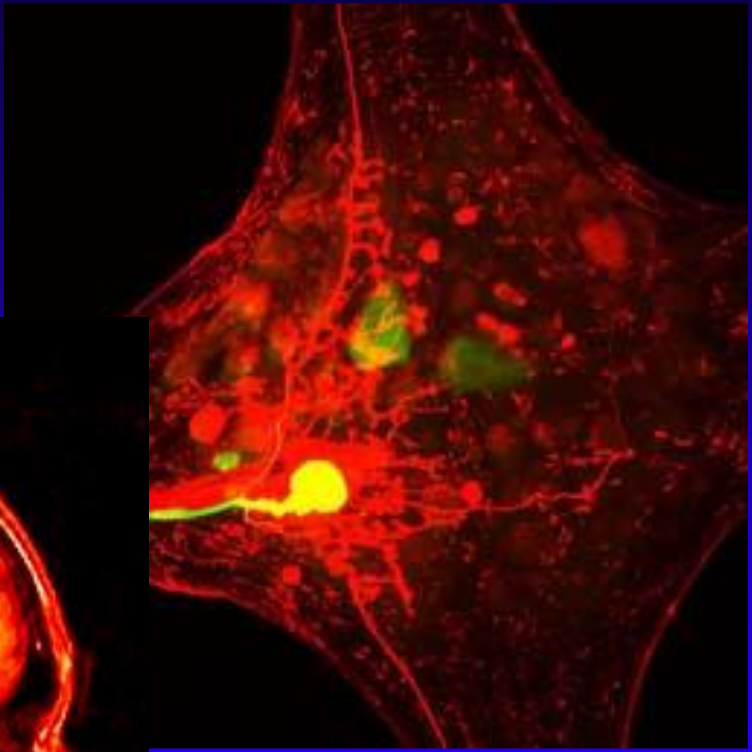


Segal, Pe'er, Regev, Koller, Friedman, *et al.*

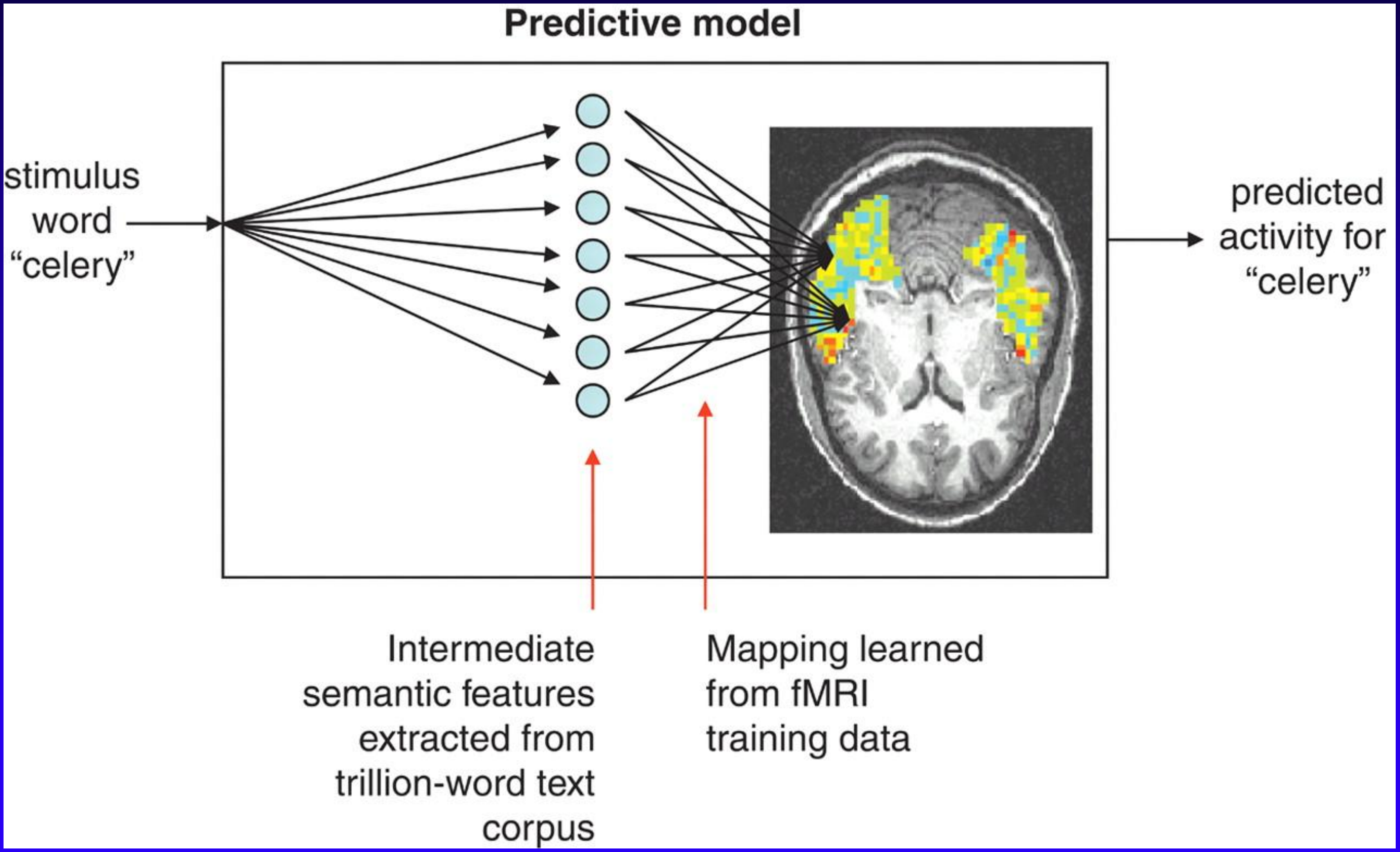
Insights From & About Neurobiology





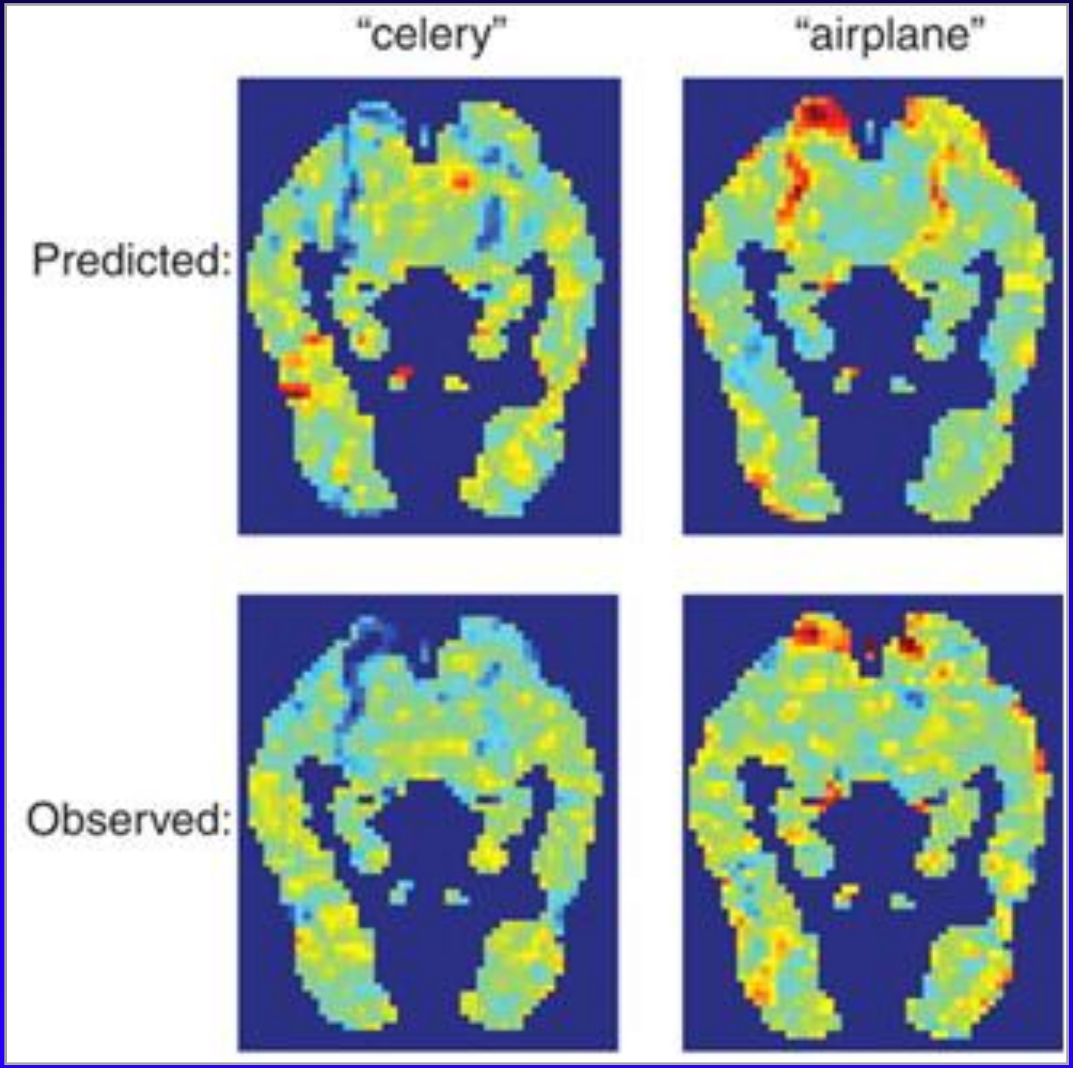


A Study in Representation



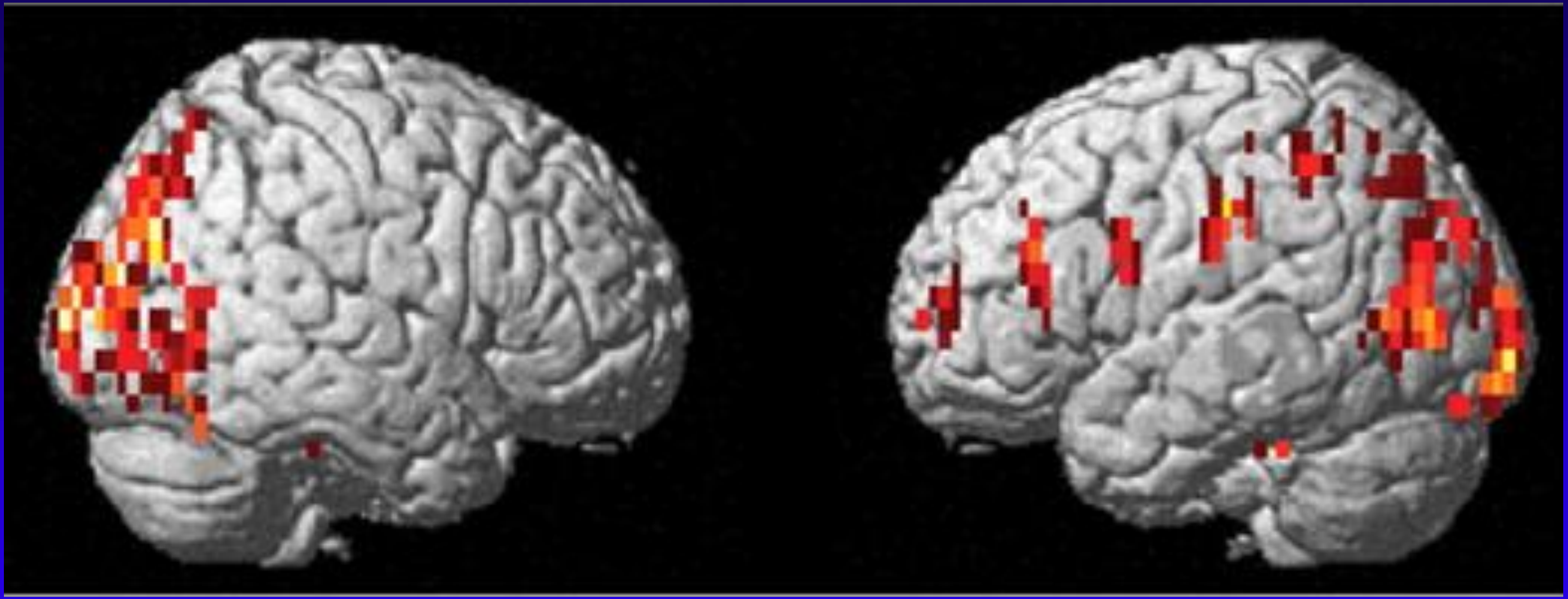
Mitchell, *et al.*

A Study in Representation



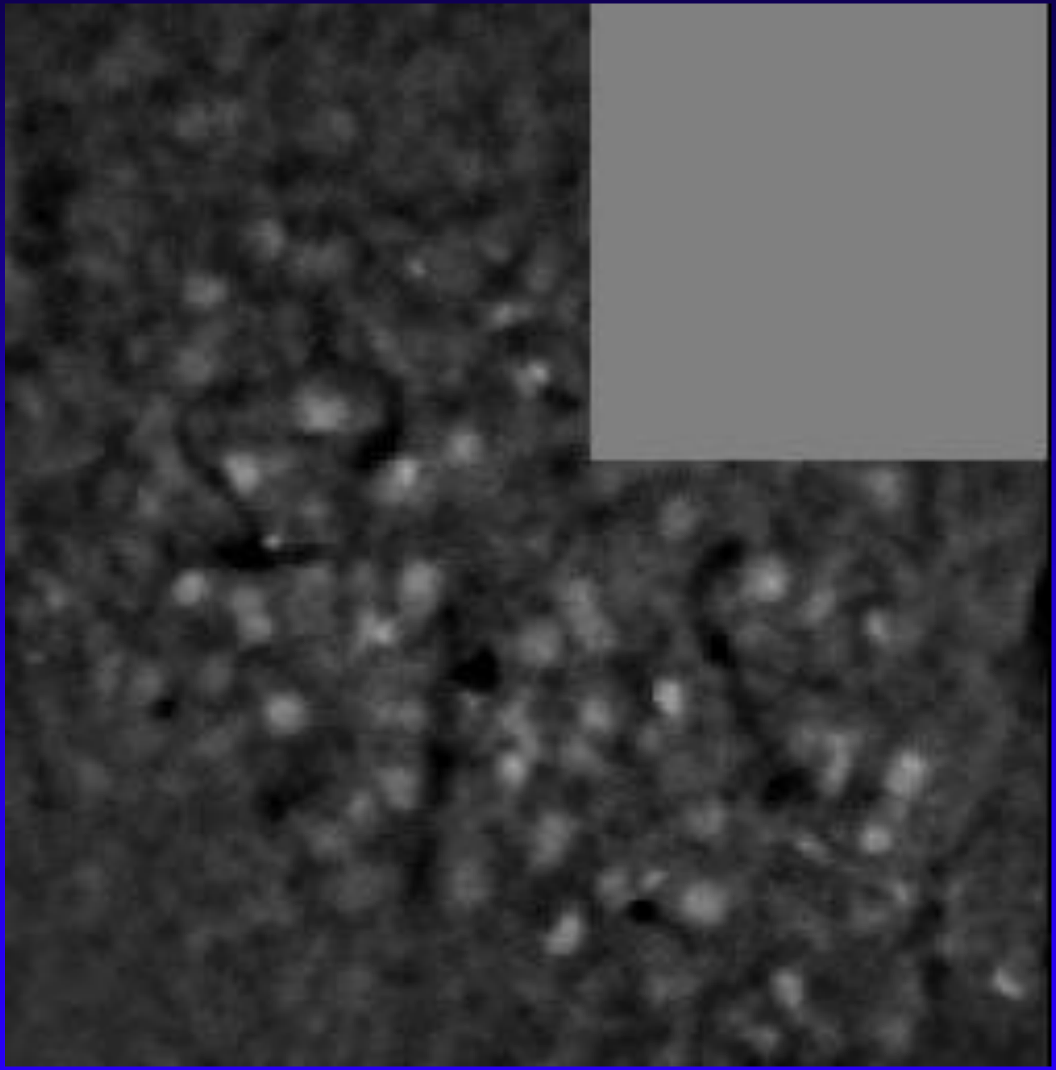
Mitchell, *et al.*

A Study in Representation



Mitchell, *et al.*

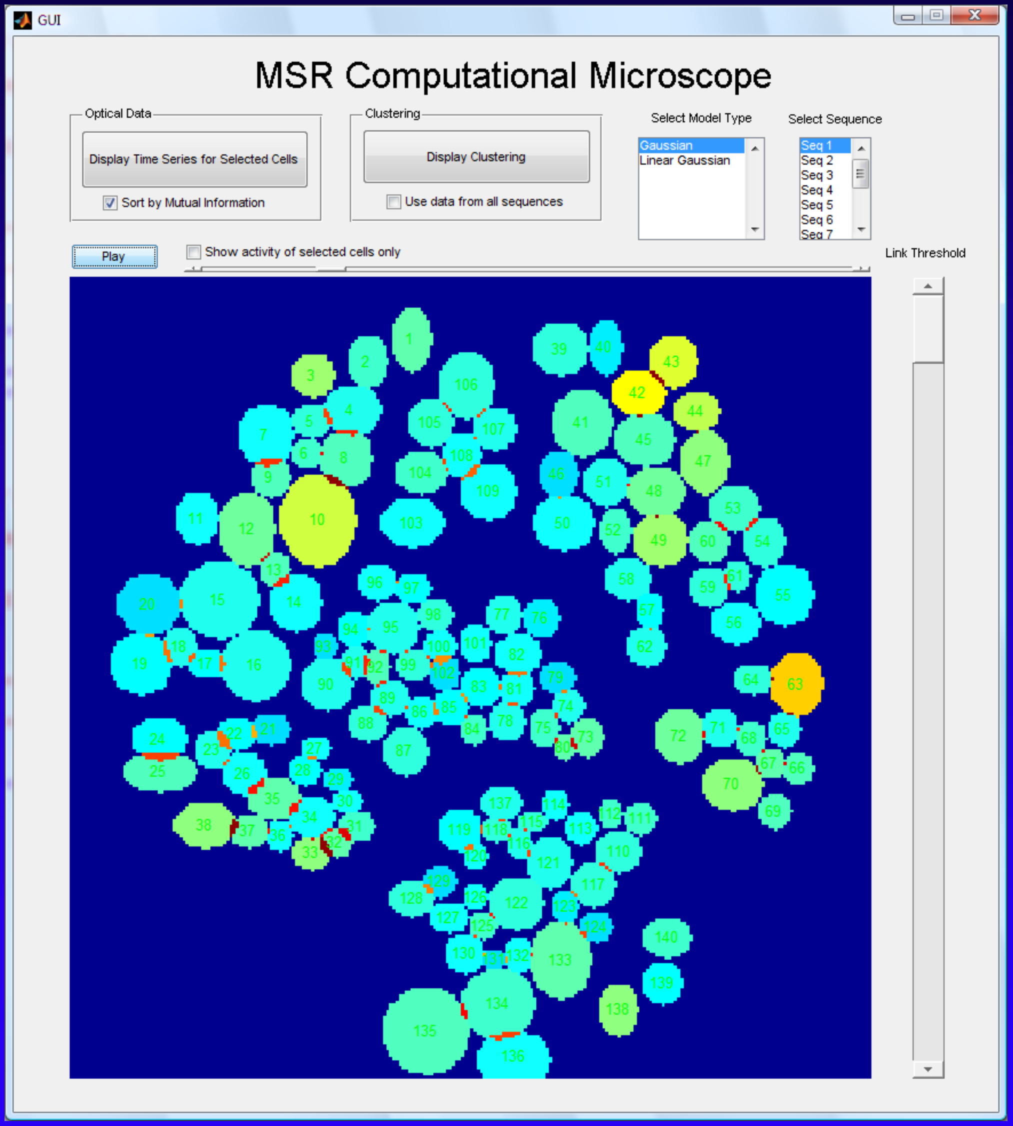
Coming Era of Neuroinformatics



(video)

Reid, *et al.*

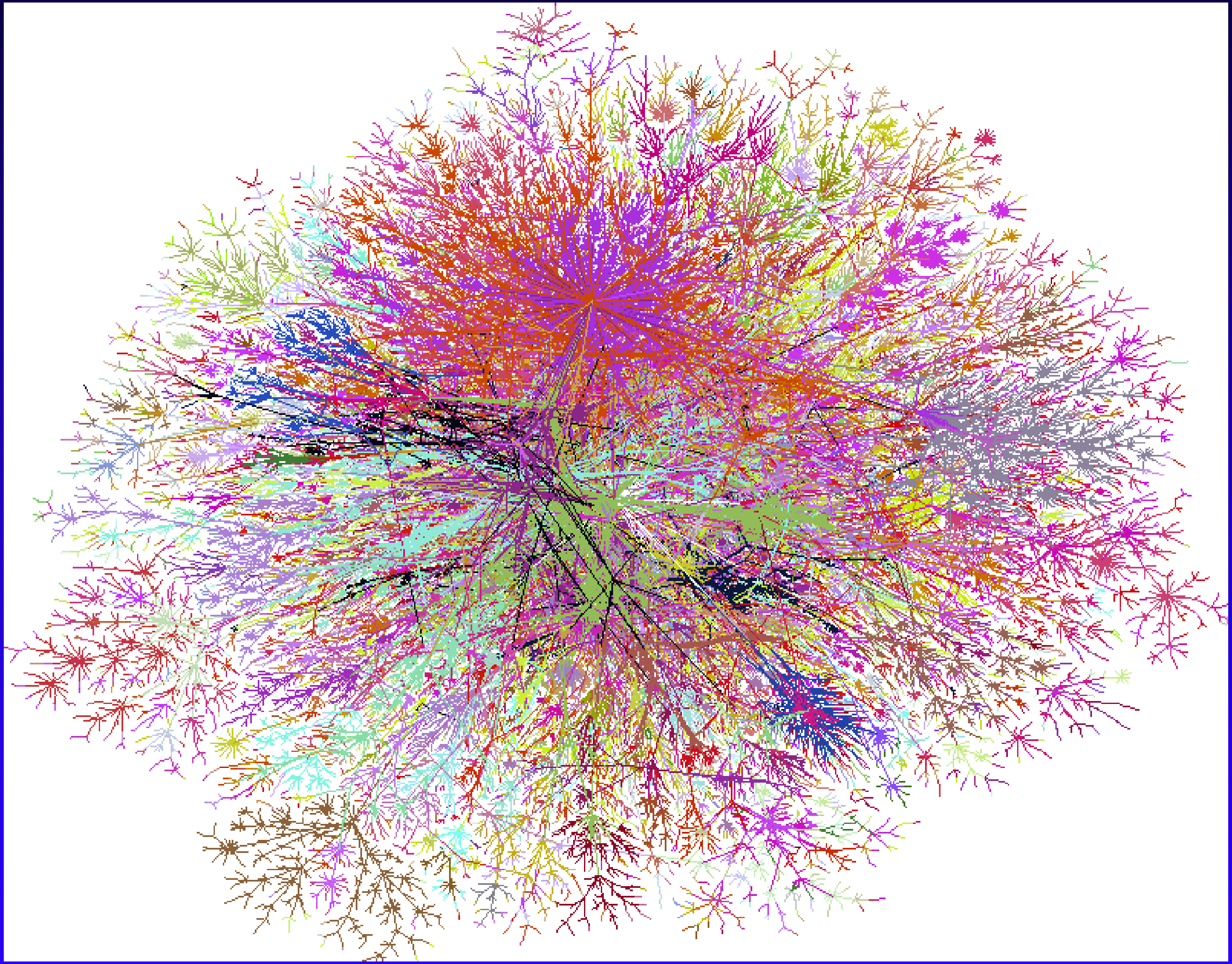
Toward a Computational Microscope



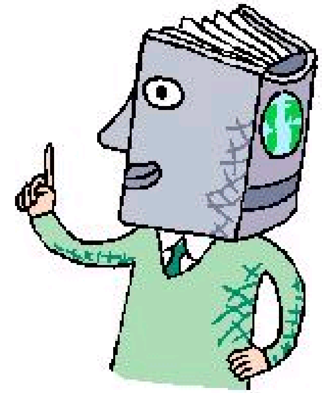
(video)

Kapoor, H., *et al.*

Learning to Harness the Web



Learning to Harness the Web



University of Washington

Department of Computer Science & Engineering

KnowItAll

CSE Home | About Us | Search

Demonstrations

- TextRunner
- Opine

People

- Oren Etzioni
- Stephen Soderland
- Matt Broadhead
- Michele Banko
- Michael Cafarella
- Doug Downey
- Ana-Maria Popescu
- Mausam
- Marcus Sammer
- Michael Schmitz
- Alex Yates

- **How can a computer accumulate a massive body of knowledge?**
- **What will Web search engines look like in ten years?**

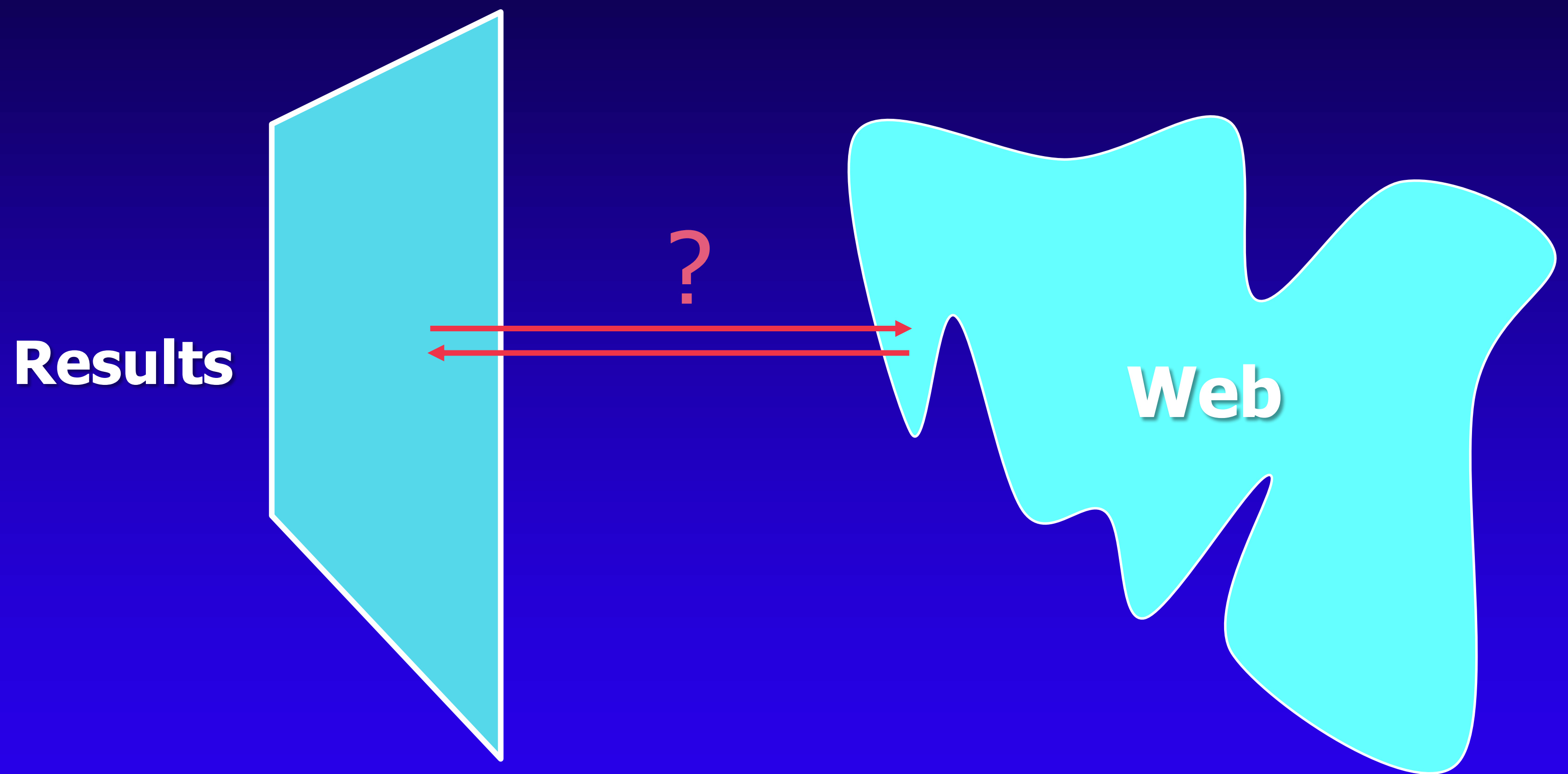
To address these questions, the **KnowItAll** project has been developing a variety of doma systems that extract information from the Web in an autonomous, scalable manner.

The KnowItAll project has been sponsored in part by federal research grants from the Nat Foundation and the Office of Naval Research.

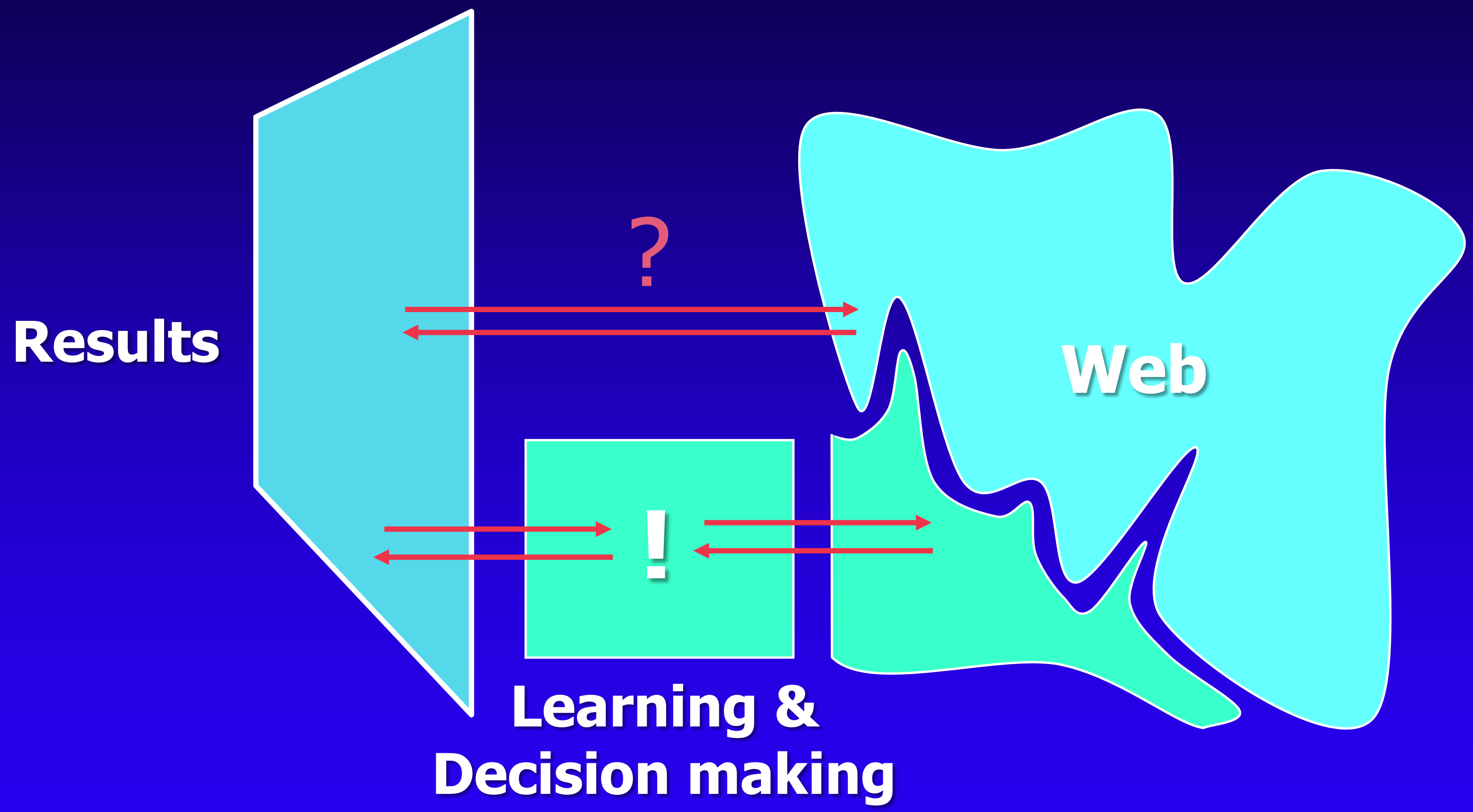
Demos:

- TextRunner: TextRunner searches 77,652,885 tuples extracted on the topic of nutrit the results by probability.
- Opine: Opine is a review mining system which uses KnowItAll-type techniques in or product features and customer opinions from product reviews.

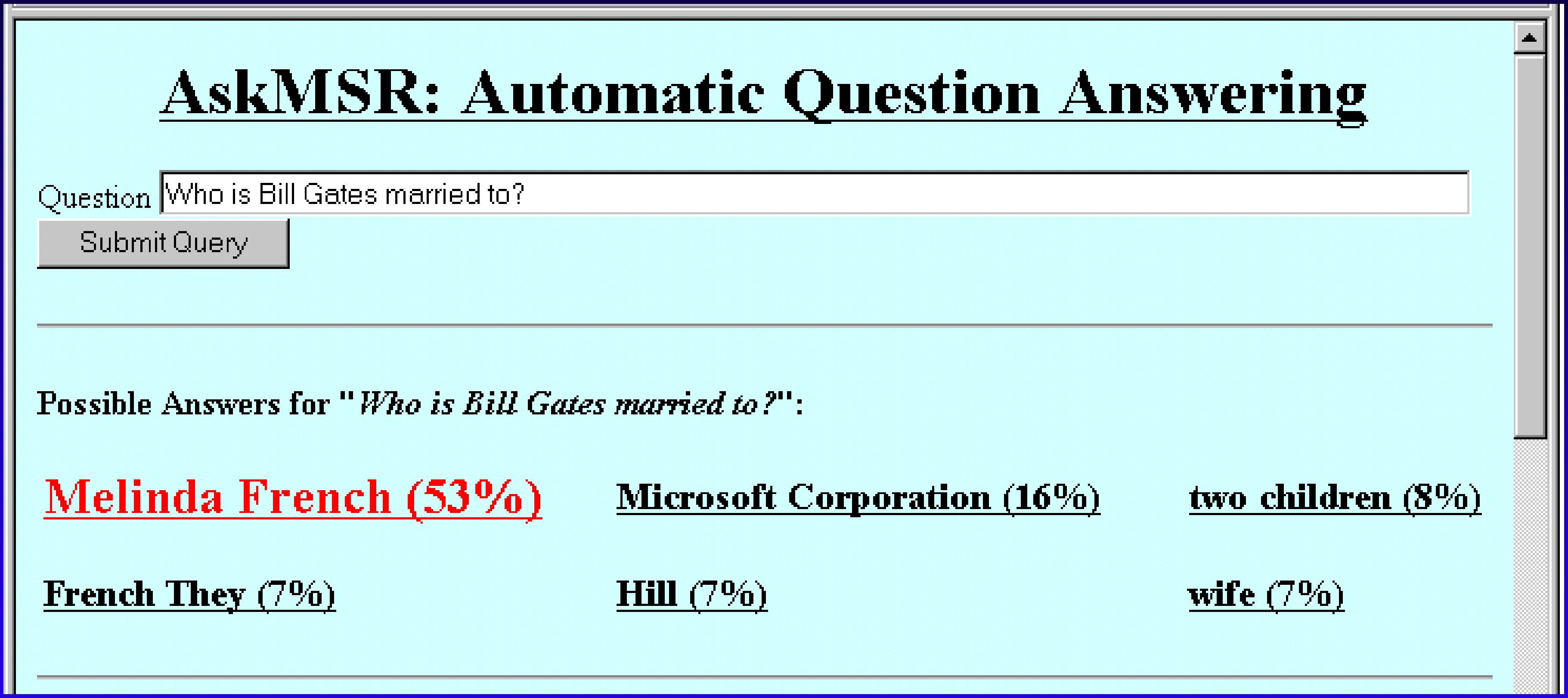
Learning to Harness the Web



Learning to Harness the Web

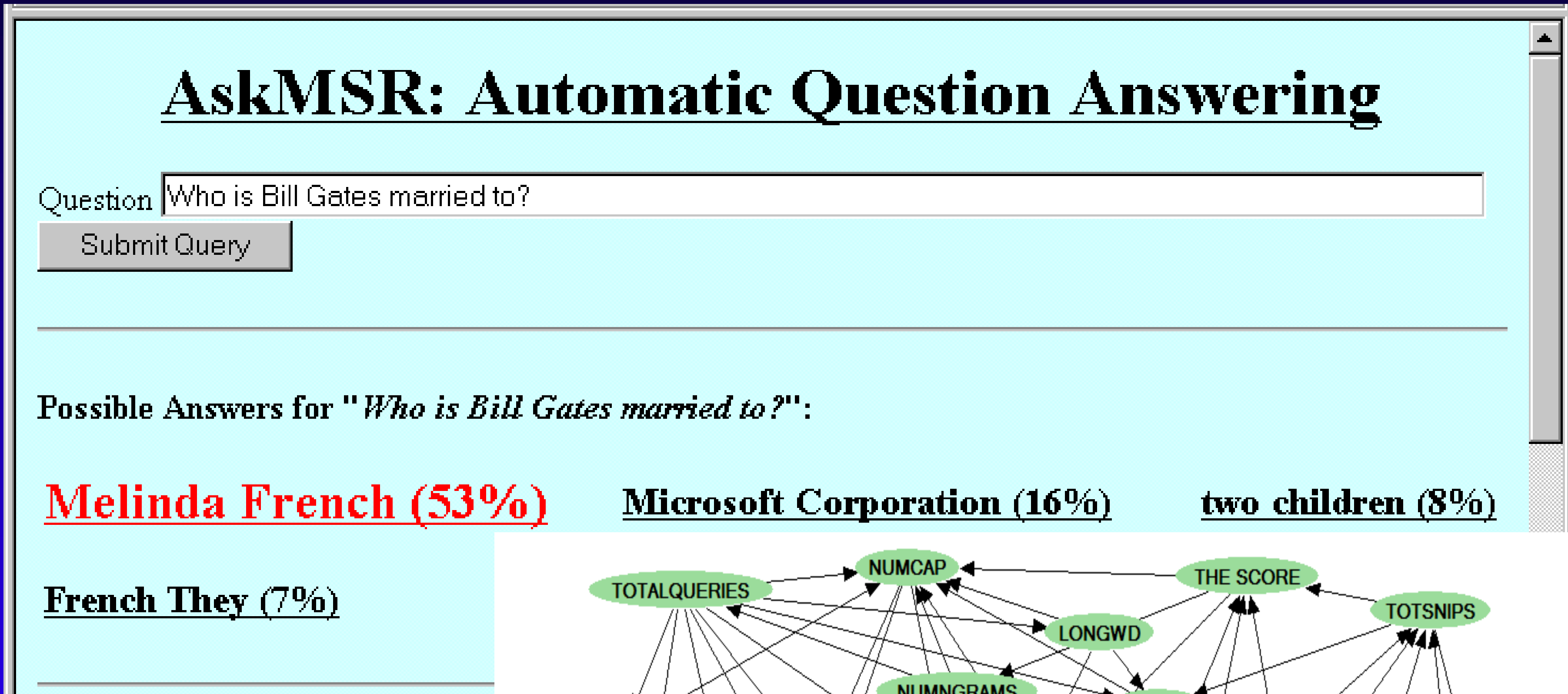


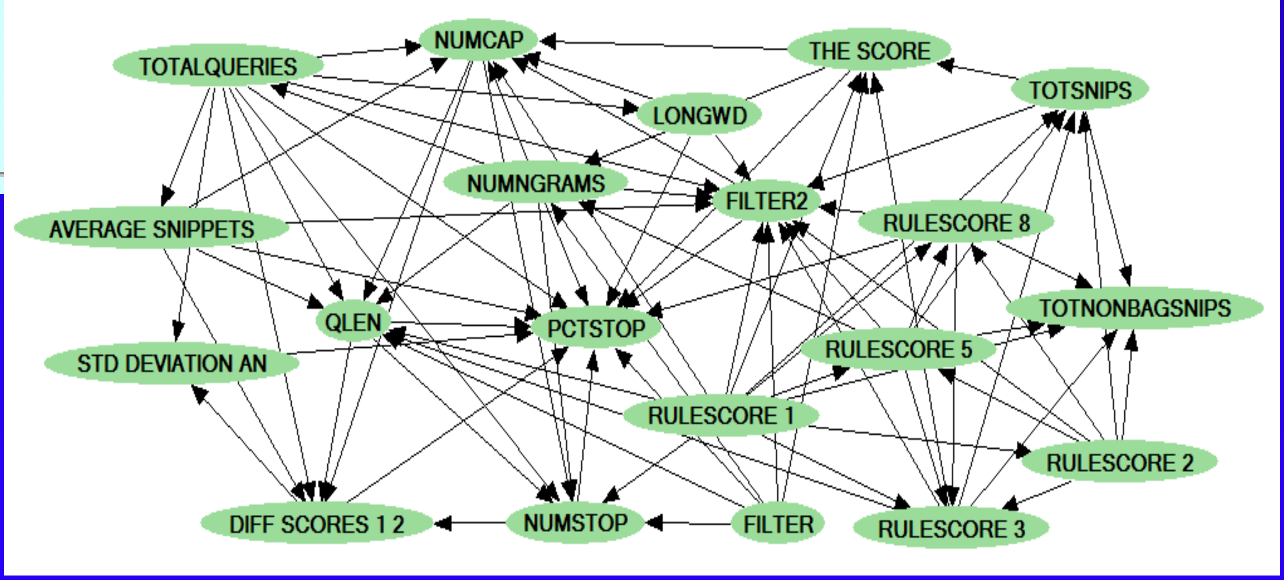
Learning to Harness the Web



Azari, H., Dumais

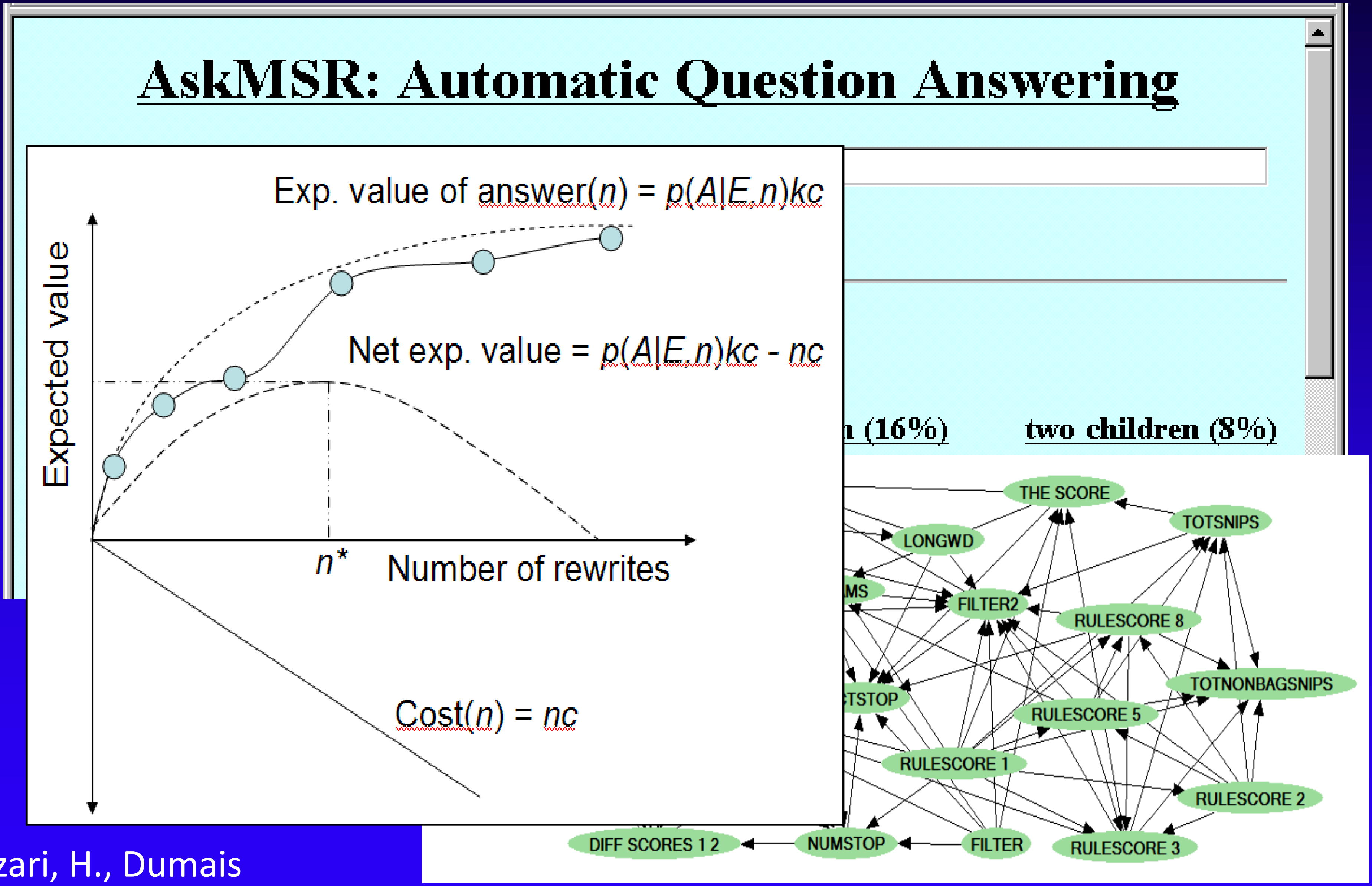
Learning to Harness the Web





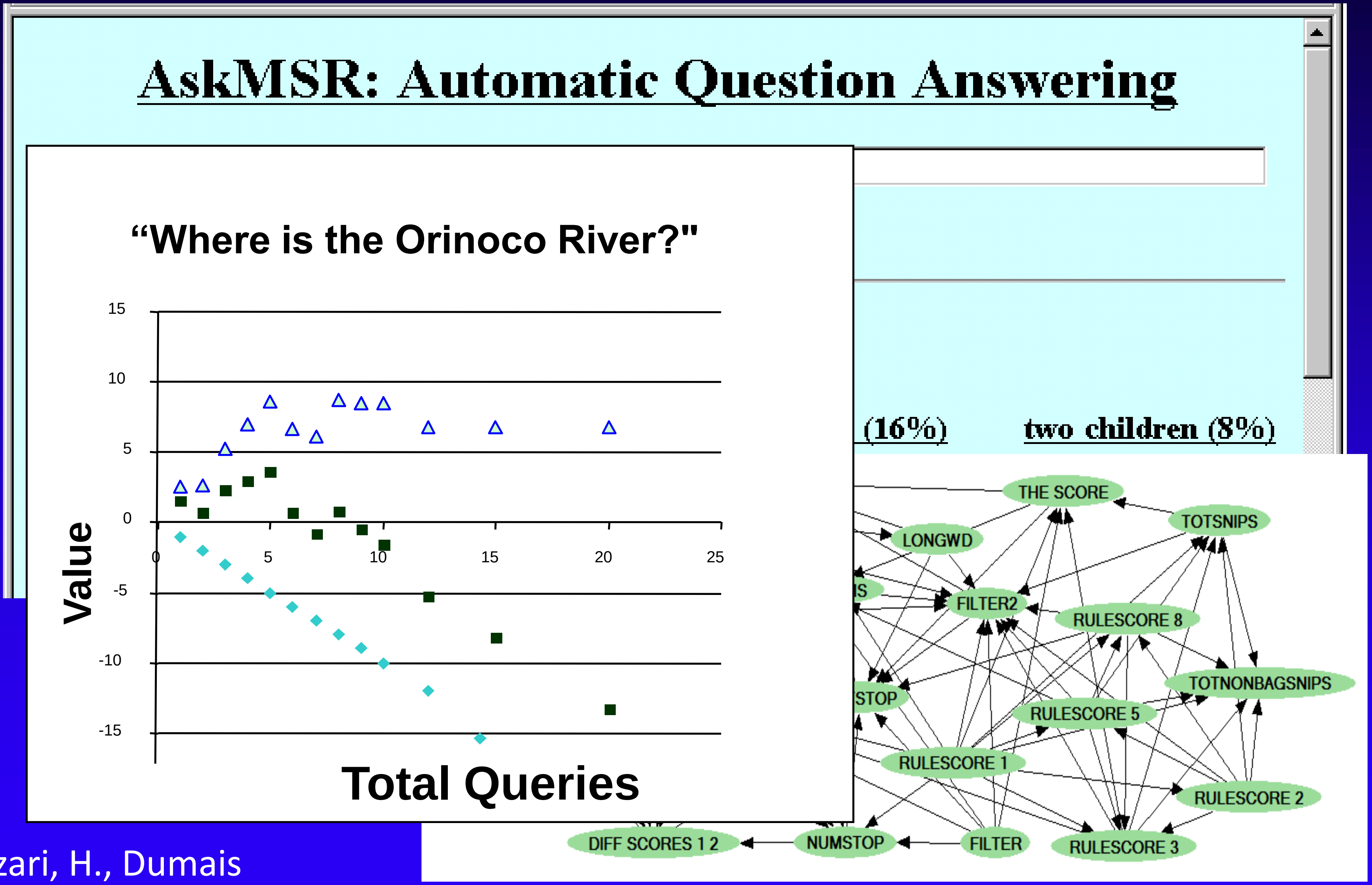
Azari, H., Dumais

Learning to Harness the Web



Azari, H., Dumais

Learning to Harness the Web



Azari, H., Dumais

AI in the Open World: Responsibilities

- Social value & quality of life
- Privacy, democracy, freedom
- Long-term AI futures



AI in the Open World: Responsibilities

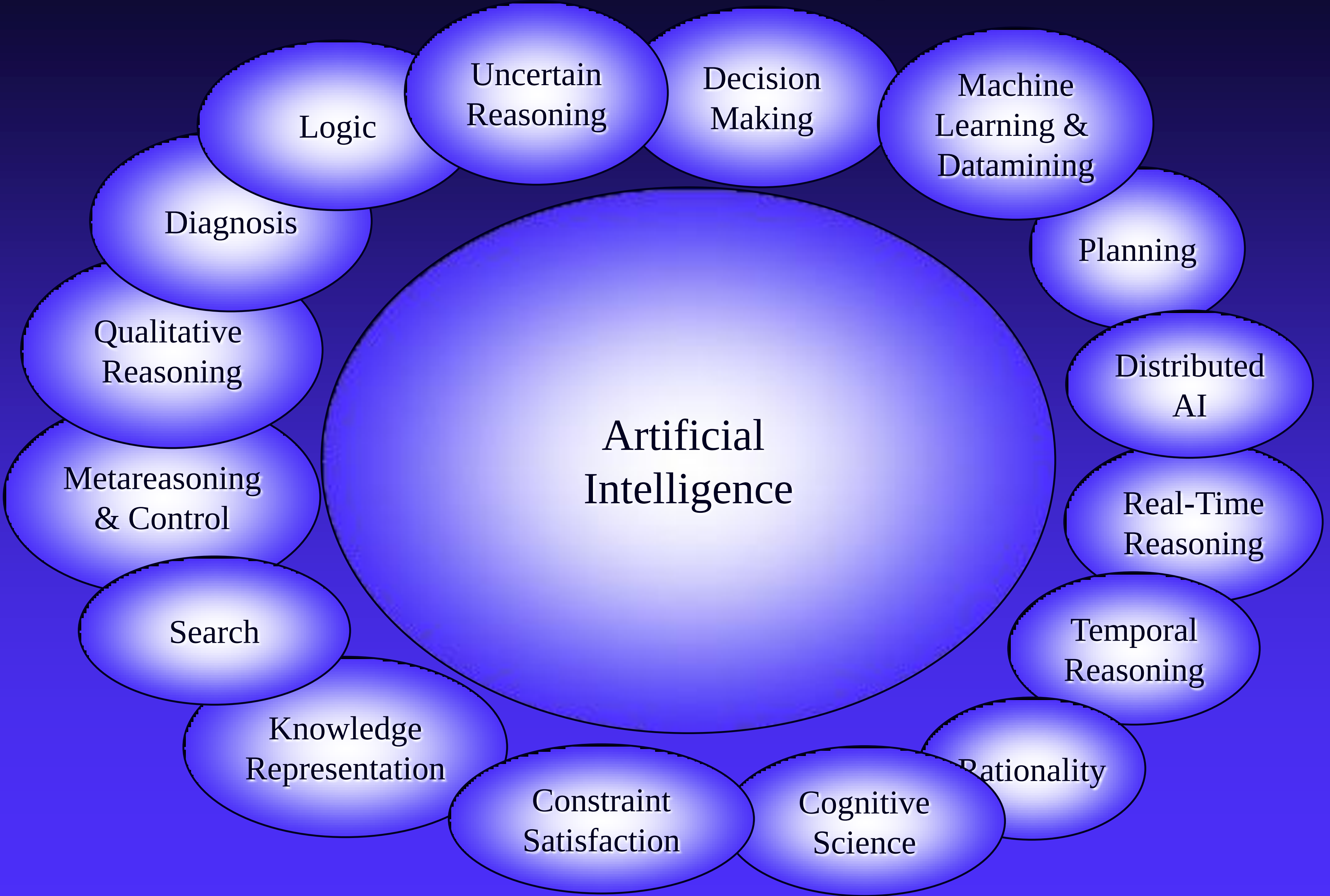
AAAI Presidential Panel on *Long-Term AI Futures*

"…Deliberation will include reflection about concerns about long-term outcomes, and, if warranted, on potential recommendations for guiding research and on creating policies that might constrain or bias the behaviors of autonomous and semi-autonomous systems so as to address the concerns…"

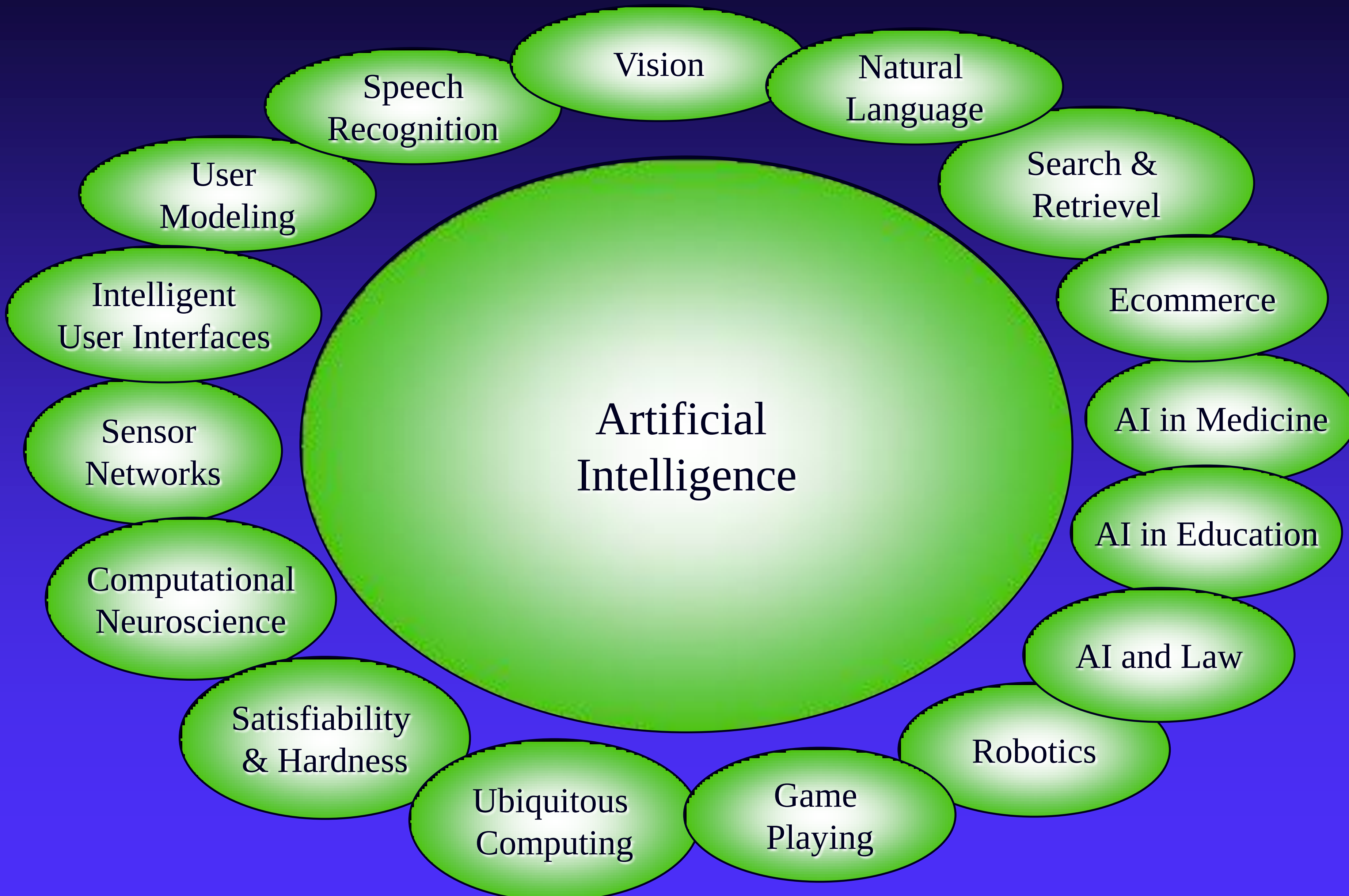
Stepping into the Open World

- Key technical challenges
- AI moving into the world
- AI research community

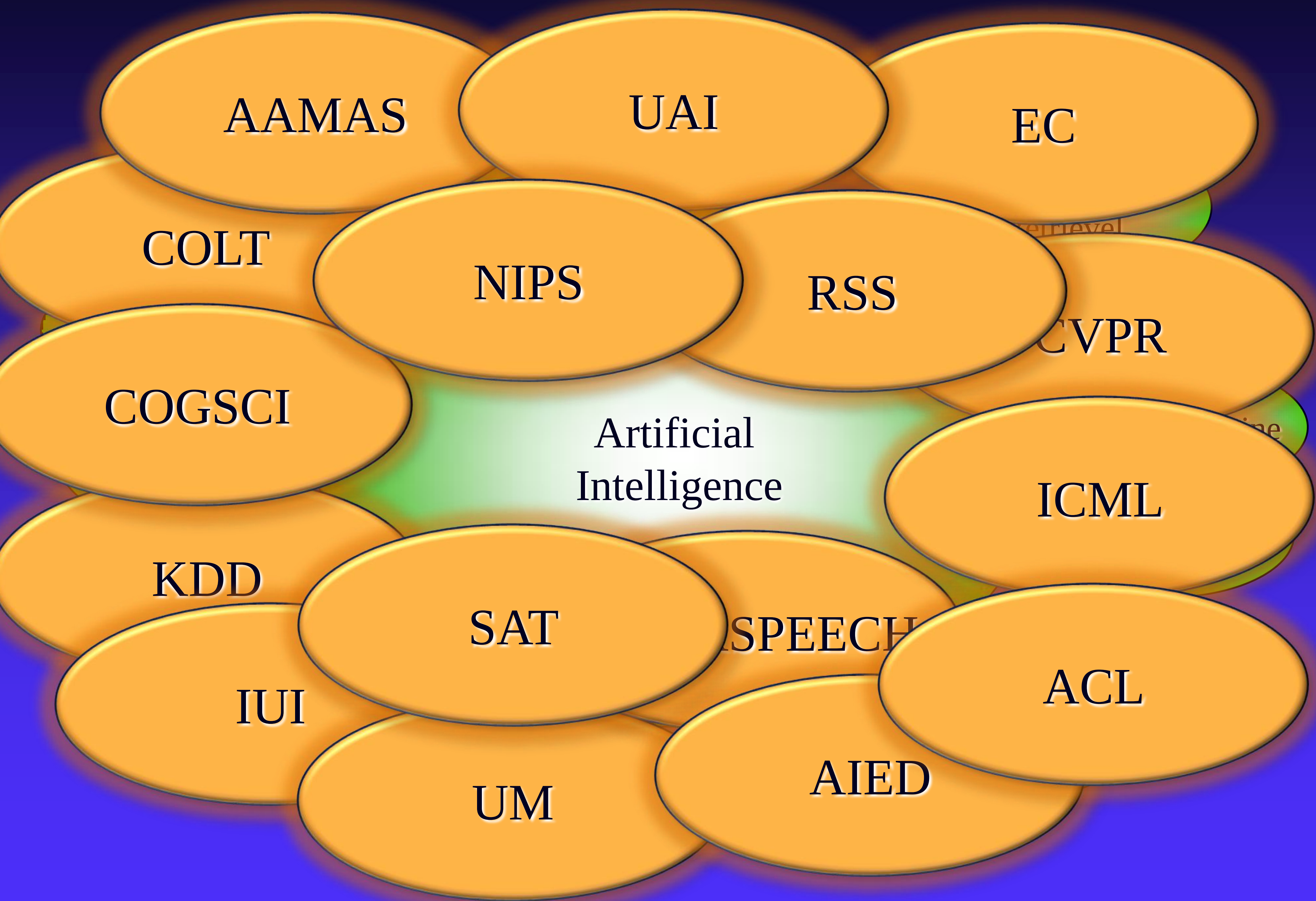
Evolution of Subdisciplines



Evolution of Specialty Areas



Evolution of Communities



Cooperation, Coordination, and Innovation in the Open World

On the Nature of the Organization

Herb Simon, 1947

‘Three bricklayers were asked what they were doing.

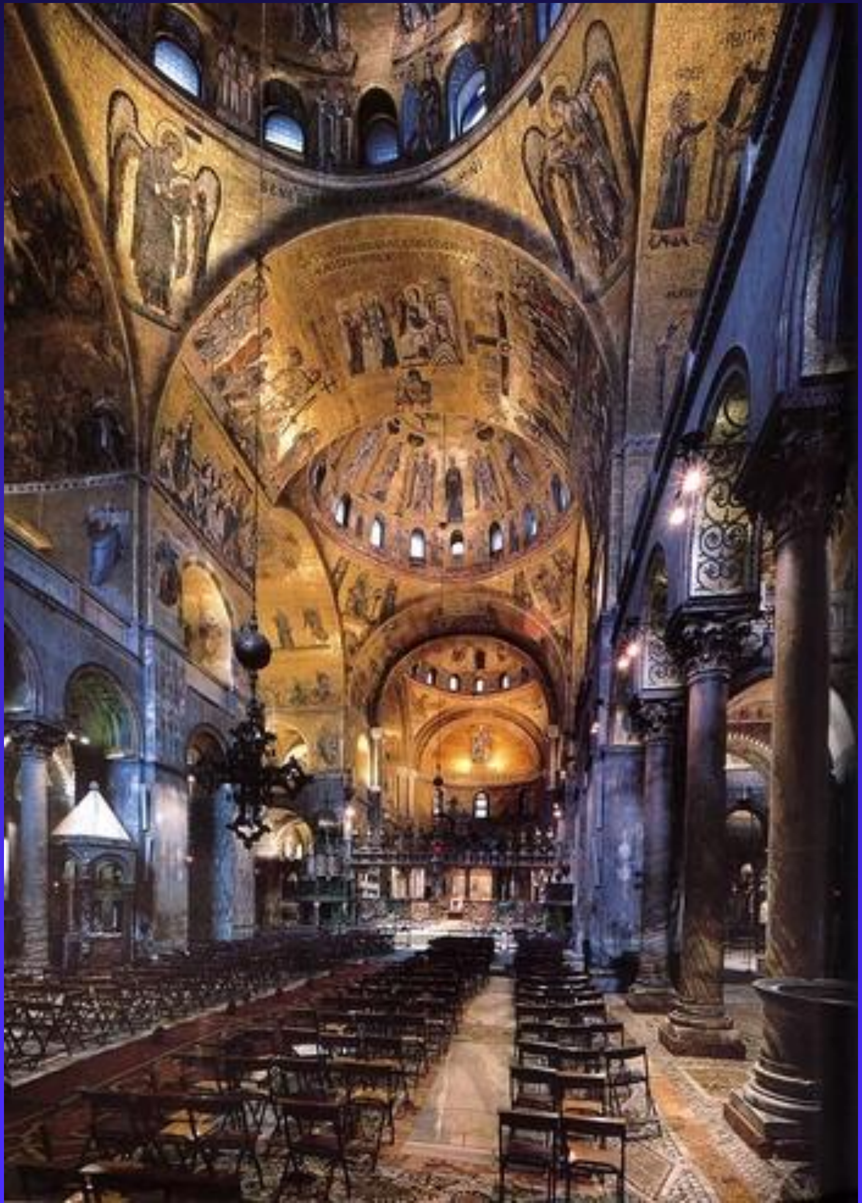
“Laying bricks,”

“Building a wall,”

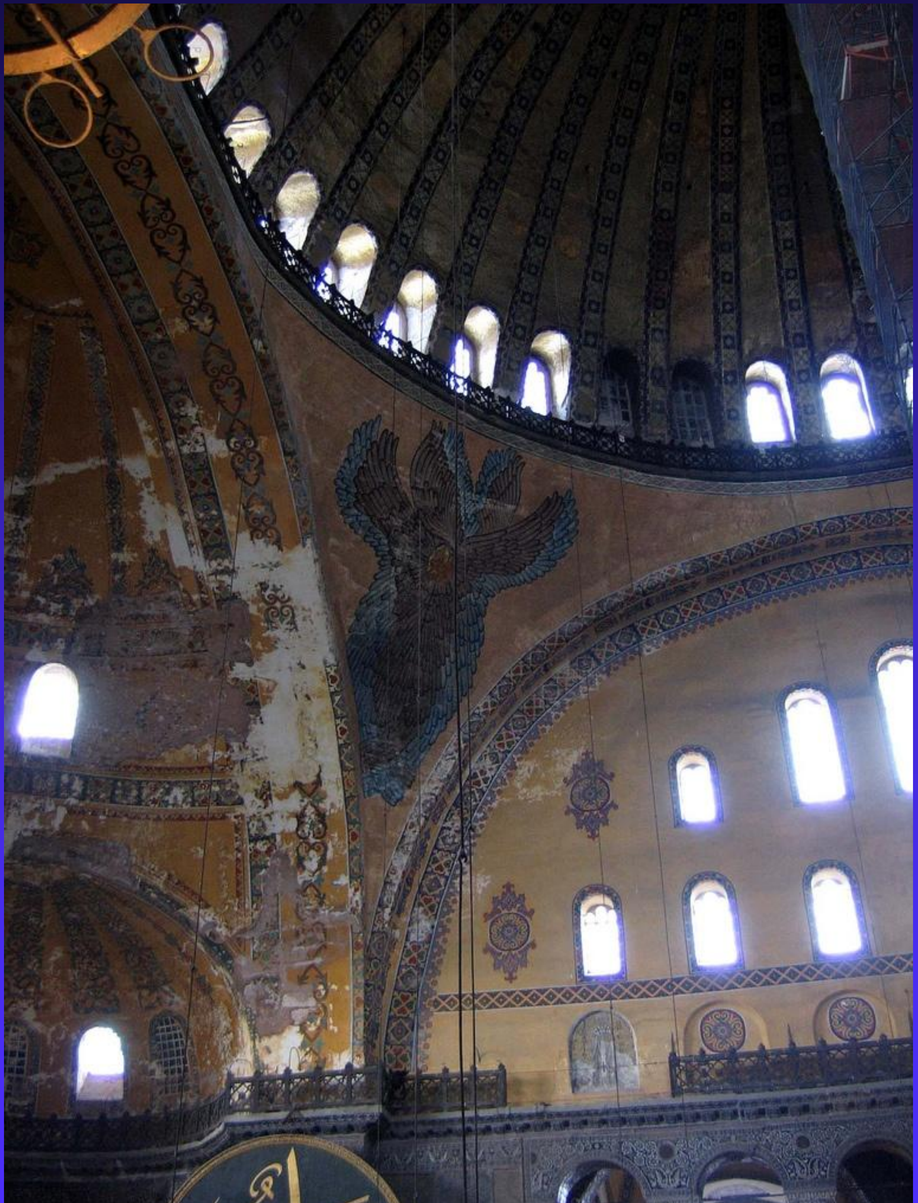
“Helping to build a great cathedral”

…were their respective answers.’

Bricks, Arches, Domes …and Spandrels



Bricks, Arches, Domes …and Spandrels



In the Distance, Through the Mist

In the Distance, Through the Mist