Adaptive crowdsourcing algorithms for the “bandit survey problem”

Crowdsourcing: multiple-choice questions
E.g.: relevance assessments for Bing
Workers are cheap but less reliable
assume: biased towards the correct answer
Objectives: costs and work quality
Crowd = pool of indistinguishable workers

Single crowd: Adaptive scheme
Two options (A,B), which one is correct?
Each ask: \( \text{Pr[correct]} = \frac{1}{2} + \text{(unknown) bias} \)
Stopping rule: stop if \( |N_A - N_B| > C \sqrt{N} \)
• Cheaper than fixed #trials by 15%-40%
• Increasing \( C \): error rate ↩, costs ↗

Multiple crowds
Two options (A,B), which one is correct?
In each round, pick some crowd \( i \) to ask
\( \text{Pr[correct]} = \frac{1}{2} + \text{(unknown) bias} \) \( b_i \)
Simple algo: round-robin (RR) over crowds
Can we improve costs? Yes!
Learn best crowd! Explore-exploit tradeoff.
We call it the “Bandit survey problem”
NB: algorithm consists of two components: crowd selection and stopping rule
To compare two crowd selection algorithms, use both with the same stopping rule

Index-based crowd selection
Index for crowd \( i \): estimates the total cost of using this crowd only
\[
\text{cost}_i = \sqrt{\left( \frac{|N_{i,A} - N_{i,B}|}{N_i} + \frac{1}{\sqrt{N_i}} \right)^2}
\]
Explore
Exploit
Always ask crowd with smallest index

Alternative interpretation
crowds = different “templates”
e.g. different possible formats, with or without a picture, etc.

Theory: A new explore-exploit problem
\[
\text{cost(\text{IndexBased})} \approx \text{cost(\text{best crowd}) as error rate} \rightarrow 0
\]
\[
\text{cost(\text{RR})} \approx \#\text{crowds} \times \text{cost(\text{best crowd})}, \text{in the worst case}
\]
More algorithms in the paper, incl. Thompson’s sampling

Three options (A,B,C):
A really new twist
Distribution over crowds beats best fixed crowd!
Example with two crowds: (.5, .4, .1) and (.5, .1, .4)
We design algorithms that zoom on (approx) best distribution over crowds (details in the paper)

Ittai Abraham, Alex Slivkins (Microsoft Research Silicon Valley)
Omar Alonso, Vasilis Kandylas (Microsoft Bing)