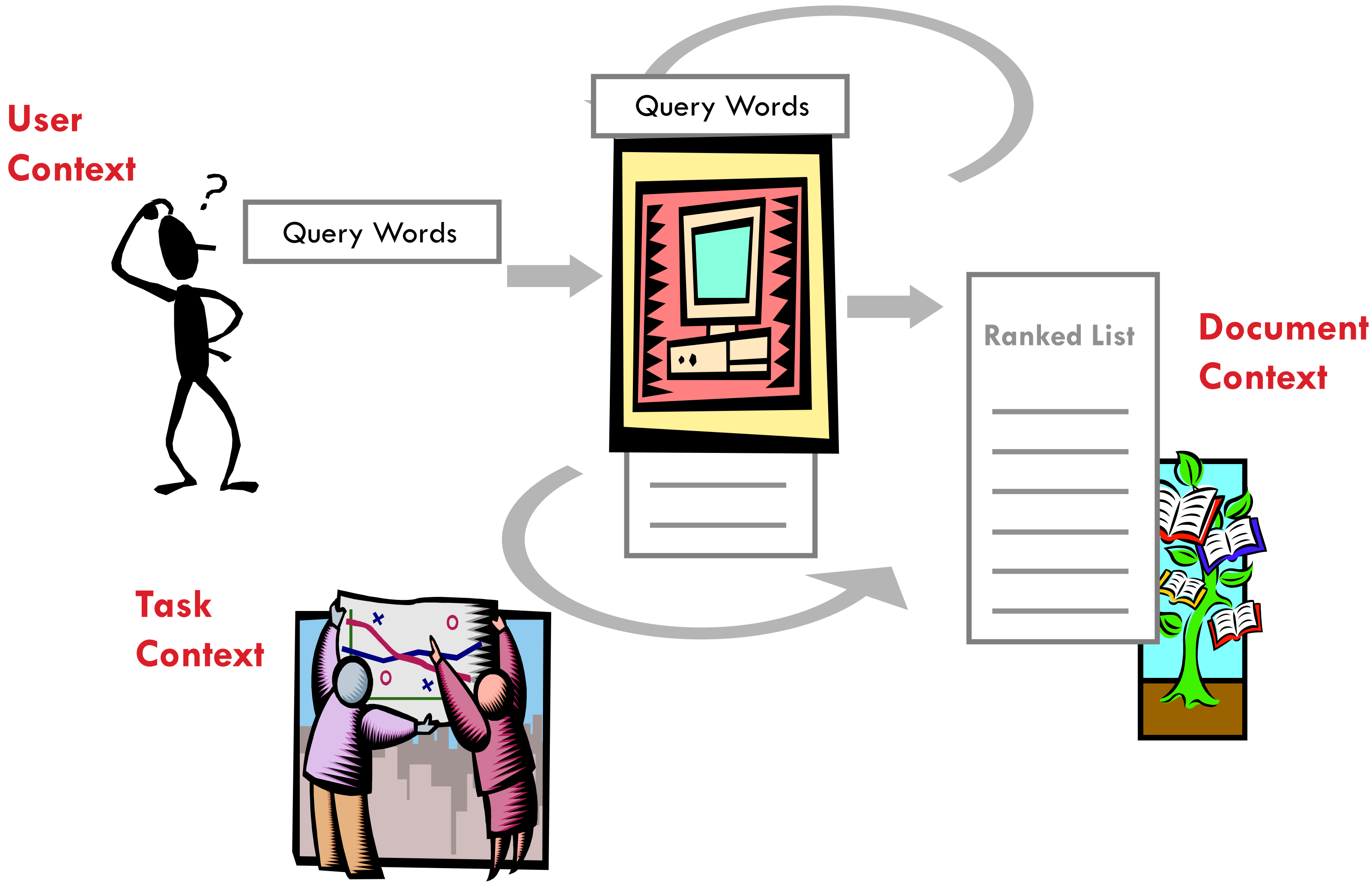
PERSONALIZED SEARCH: POTENTIAL AND PITFALLS

Susan Dumais, Microsoft Research

Overview

- Importance of context in search
- Potential for personalization framework
- Examples
  - Personal navigation
  - Client-side personalization
  - Short- and long-term models
  - Temporal dynamics
- Challenges and new directions

Search and Context



Context Improves Query Understanding

- Queries are difficult to interpret in isolation

- Easier if we model: who is asking, what they have done in the past, where they are, when it is, etc.

Searcher: (*SIGIR* | Susan Dumais … an information retrieval researcher)
vs. (*SIGIR* | Stuart Bowen Jr. … the Special Inspector General for Iraq Reconstruction)

Previous actions: (*SIGIR* | information retrieval)
vs. (*SIGIR* | U.S. coalitional provisional authority)

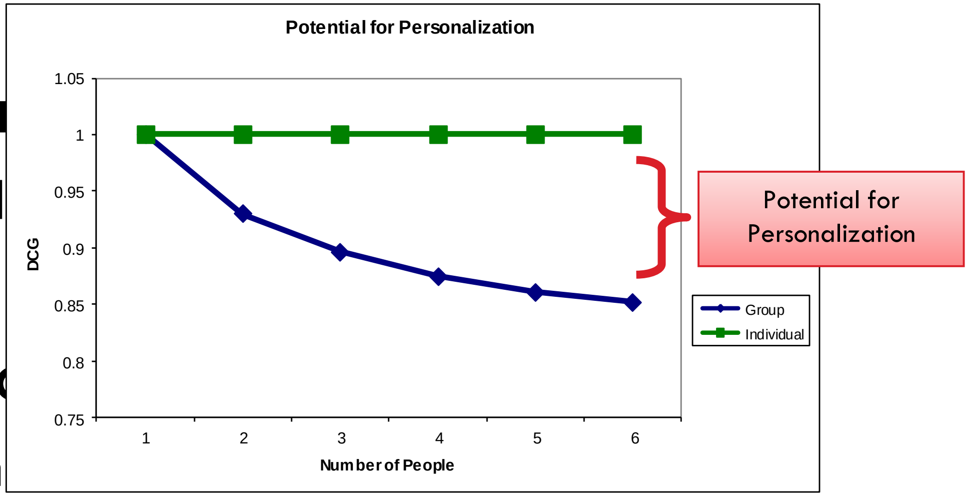
Location: (*SIGIR* | at SIGIR conference) vs. (*SIGIR* | in Washington DC)

Time: (*SIGIR* | Jan. submission) vs. (*SIGIR* | Jul. conference)

- Using a single ranking for everyone, in every context, at every point in time, limits how well a search engine can do

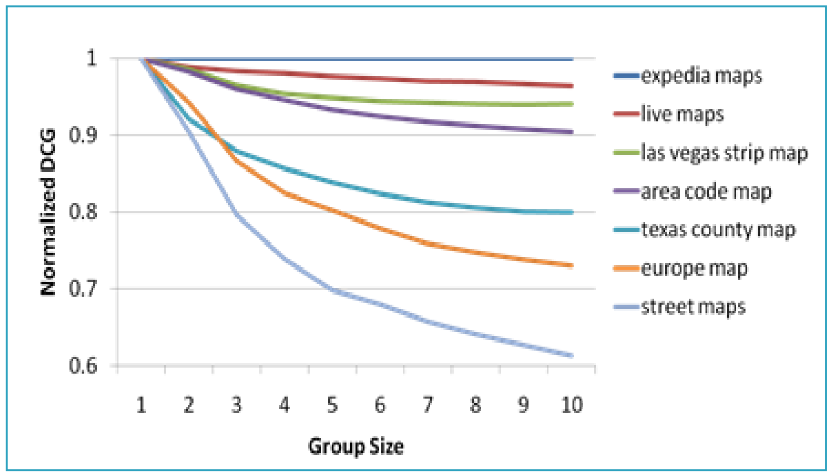
Potential For Personalization

- A single ranking for everyone limits search quality
- Quantify the variation in individual relevance for the same query
- Different ways to mea
  - Explicit judgments from d
  - Implicit judgments (clicks,
- Personalization can le
  - Study with explicit judgm
  - 46% gain with single ranking
  - 72% gain with personalized ranking

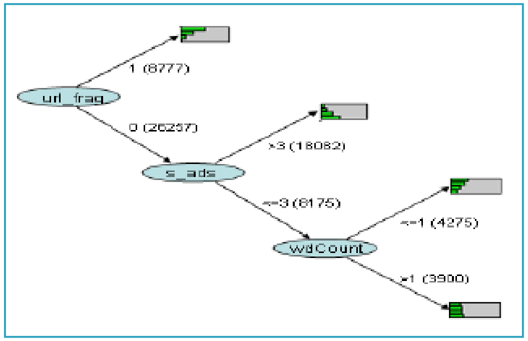


Potential For Personalization

- Not all queries have high potential for personalization
  - E.g., facebook vs. sigir
  - E.g., * maps



- Learn when to personalize



User Models

- Constructing user models
  - Sources of evidence
    - Content: Queries, content of web pages, desktop index, etc.
    - Behavior: Visited web pages, explicit feedback, implicit feedback
    - Context: Location, time (of day/week/year), device, etc.
  - Time frames: Short-term, long-term
  - Who: Individual, group
- Using user models
  - Where resides: Client, server
  - When used: Always, sometimes, context learned
  - How used: Ranking, query support, presentation, etc.

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PNav

PSearch

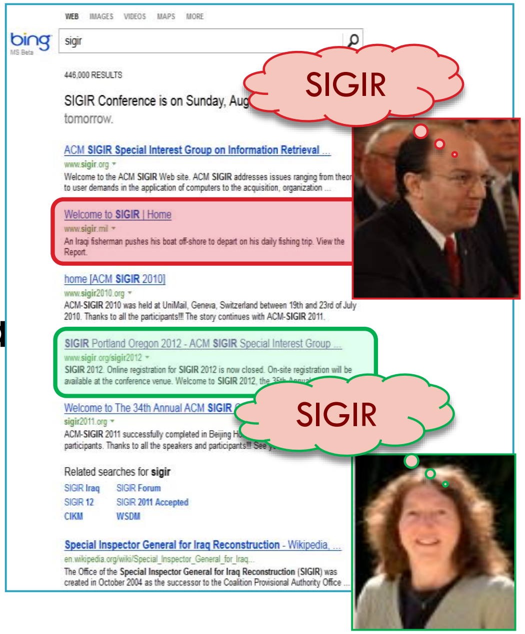
Short/Long

Time

Example 1: Personal Navigation

- Re-finding is common in Web search
  - 33% of queries are repeat queries
  - 39% of clicks are repeat clicks
- Many of these are navigational queries
  - E.g., *facebook* -> www.facebook.com
  - Consistent intent across individuals
  - Identified via low click entropy
- "Personal navigational" queries
  - Different intents across individuals, but consistently the same intent for an individual
    - *SIGIR* (for Dumais) -> www.sigir.org/sigir2013
    - *SIGIR* (for Bowen Jr.) -> www.sigir.mil

		Repeat Click	New Click
Repeat Query	33%	29%	4%
New Query	67%	10%	57%
		39%	61%



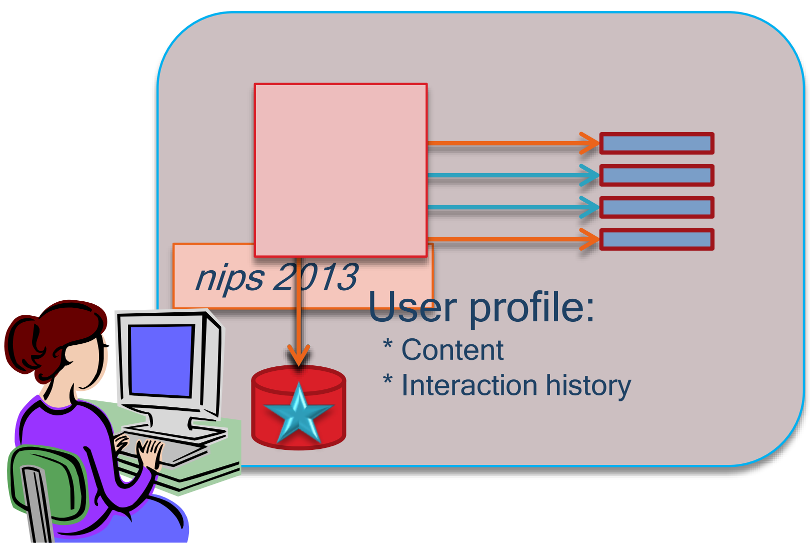
Personal Navigation Details

- Large-scale log analysis
  - Identifying personal navigation queries
    - Use consistency of clicks <u>within an individual</u>
    - Specifically, the last two times a person issued the query, was there a unique click on same result?
    - Behavior consistent over time
  - Coverage and accuracy
    - Many such queries: ~12% of queries
    - Prediction accuracy high: ~95% accuracy
    - High coverage, low risk personalization
- Can be used to re-rank, or augment presentation
- Online evaluation

Example 2: PSearch

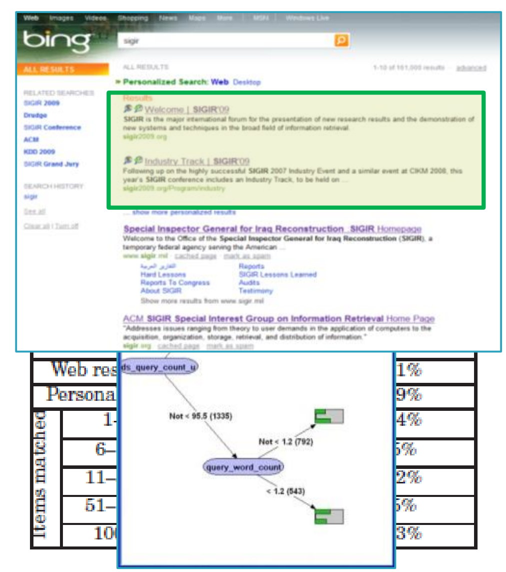
- Rich client-side model of a user's interests
  - Model: Content from desktop search index & Interaction history

    Rich and constantly evolving user model
  - Client-side re-ranking of (lots of) web search results using model
  - Good privacy (only the query is sent to server)
    - But, limited portability, and use of community



PSearch Details

- Ranking Model
  - Score: Weighted combination of personal and global scores
    - $Score(result_i) = \alpha PersonalScore(result_i) + (1 - \alpha)WebScore(result_i)$
  - Personal score: Content and interaction history features
    - Content score - log odds of term in personal vs. web content
    - Interaction history score - visits to the specific URL, with backoff to domain
- Evaluation
  - Offline evaluation, using explicit judgments
  - Online evaluation, using PSearch prototype
    - Internal deployment; 225+ people for several months
    - Coverage: Results personalized for 64% of queries
    - Effectiveness:
      - CTR 28% higher, for personalized results
      - CTR 74% higher, when personal evidence is strong
    - Learned model for when to personalize

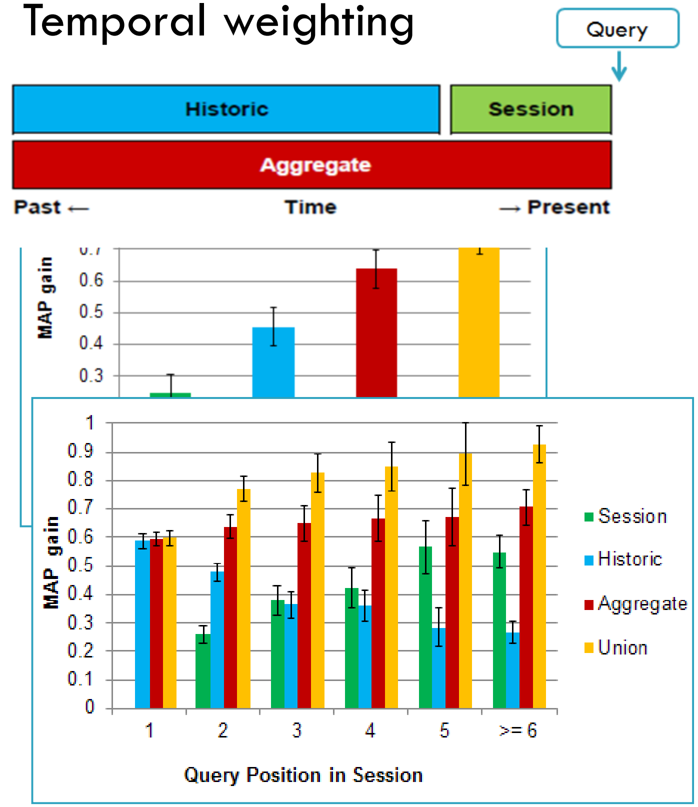


Example 3: Short + Long

- Short-term interests
  - Behavior: Queries, clicks within current session
    - (Q= *sigir* | *information retrieval* vs. *iraq reconstruction*)
    - (Q= *nips* | *icml vs.*
    - (Q= *acl* | *computational linguistics vs.*
  - Content: Language models, topic models, etc.
- Long-term preferences and interests
  - Behavior: Specific queries, clicks historically
    - (Q=*weather*) -> weather.com vs. accuweather.com vs. weather.gov
  - Content: Language models, topic models, etc.
- Developed unified model for both
- Sometimes short-term activity consistent with long-term interests, sometimes not

Short + Long Details

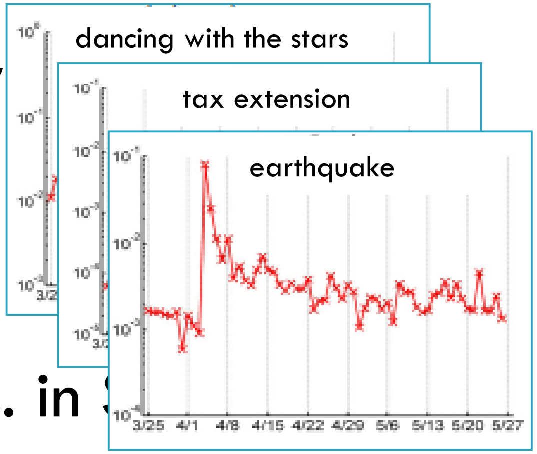
- User model (features)
  - Related queries, clicked URLs
  - Topic distributions, using ODP
- Log-based evaluation, MAP
- Which sources are important?
  - Session (short-term): +25%
  - Historic (long-term): +45%
  - Combinations: +65-75%
- What happens within a session?
  - 60% of sessions involve multiple queries
    - By 3rd query in session, short-term features more important than long-term
    - First queries in session are different – shorter, higher click entropy
- User model (temporal extent)
  - Session, Historical, Combinations
  - Temporal weighting



Elsas & Dumais, *WSDM 2010*
Radinsky et al., *TOIS 2013*

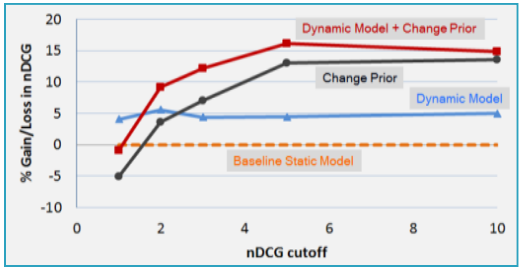
Example 4: Temporal Dynamics

- Queries are not uniformly distributed over time
  - Often triggered by events in the wor
- Relevance changes over time
  - E.g., *US Open* … in 2013 vs. in 2012
  - E.g., *US Open 2013* … in May (golf) vs. in
  - E.g., *US Tennis Open 2013* … before vs. during vs. after
    - Before event: Schedules and tickets, e.g., stubhub
    - During event: Real-time scores or broadcast, e.g., espn
    - After event: General sites, e.g., wikipedia, usta

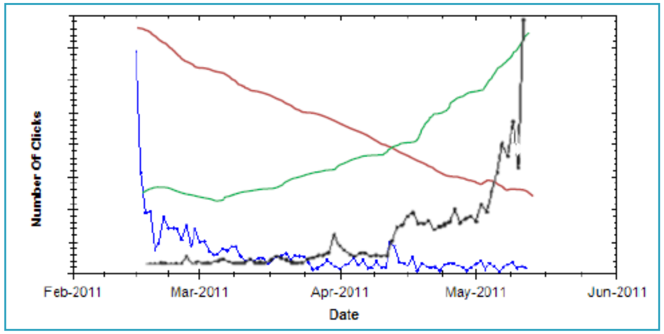


Temporal Dynamics Details

- Develop time-aware retrieval models
- Leverage <u>content</u> change on a page
  - Pages have different *rates of change* (influences document priors, $P(D)$)
  - Terms have different *longevity* on a page (influences term weights, $P(Q|D)$)
  - 15% improvement vs. LM baseline



- Leverage time-series modeling of <u>user interactions</u>
  - Model query and URL clicks as time-series
  - Learn appropriate weighting of historical data
  - Useful for queries with local or global trends



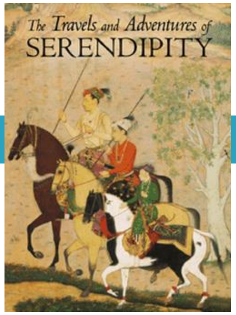
Challenges in Personalization

- User-centered
  - Privacy
  - Transparency and control
  - Serendipity
- Systems-centered
  - Performance/optimization
    - Storage, caching, run-time efficiency etc.
  - Evaluation
    - Measurement, experimentation

Privacy

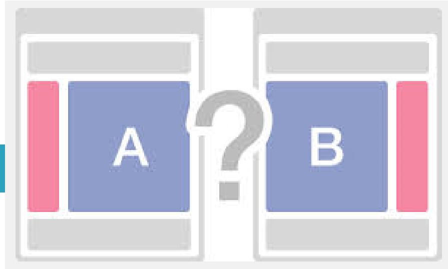
- Profile on client (e.g., PSearch)
  - Profile is private
  - Query to server, many documents returned, local computations
- Profile in cloud
  - Transparency about what's stored
  - Control over what's stored … including nothing
- Other approaches
  - Light weight profiles (e.g., queries in a session)
  - Public or semi-public profiles (e.g., tweets, Facebook status)
  - Matching an individual to group

Serendipity



- Does personalization mean the end of serendipity?
  - … Actually, it can improve it!
- Experiment on Relevance vs. Interestingness
  - Personalization finds more relevant results
  - Personalization also finds more interesting results
  - Even when interesting results were not relevant
- Need to be ready for serendipity
  - … Like the Princes of Serendip

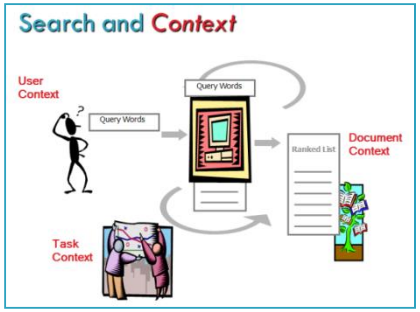
Evaluation and Feedback



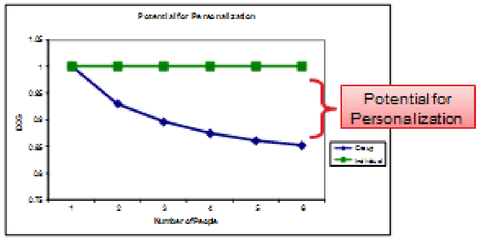
- External judges, e.g., crowdworkers
  - Lack diversity of intents and backgrounds
- Actual searcher
  - Offline
    - Allows safe exploration of many different alternatives
    - Labels can be explicit or implicit judgments (log analysis)
  - Online
    - Explicit judgments: Nice, but annoying and may change behavior
    - Implicit judgments: Scalable, but can be very noisy
    - Note … limited experimental bandwidth; not directly repeatable; requires production-level code; mistakes costly
- Diversity of methods important
  - User studies, log analysis, and A/B testing

Summary

- Queries difficult to interpret in isolation
- Augmenting query with context can help
  - Who, what, where, when?



- Potential for improving search using context is large
- Examples
  - PNav, PSearch, Short/Long, Time



- Challenges and new directions

Thanks!

- Questions?
- More info: http://research.microsoft.com/~sdumais

- Collaborators:
  - Eric Horvitz, Jaime Teevan, Paul Bennett, Ryen White, Kevyn Collins-Thompson, Peter Bailey, Eugene Agichtein, Krysta Svore, Kira Radinski, Jon Elsas, Sarah Tyler, Alex Kotov, Anagha Kulkarni, David Sontag, Carsten Eickhoff

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