PERSONALIZED SEARCH: POTENTIAL AND PITFALLS

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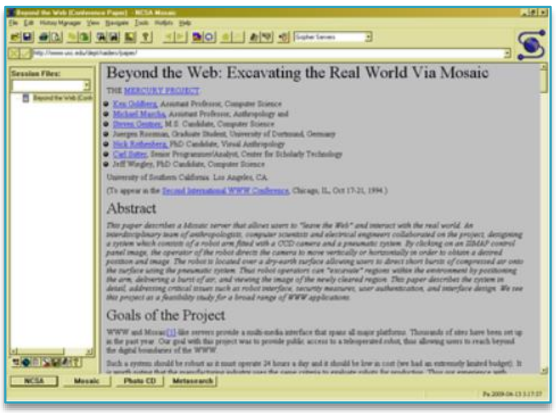
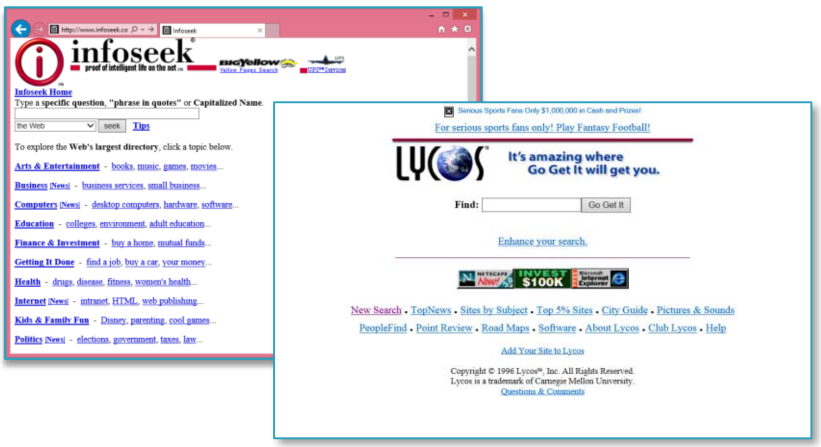
Overview

- Context in search
- “Potential for personalization” framework
- Examples
  - Personal navigation
  - Client-side personalization
  - Short- and long-term models
  - Personal crowds
- Challenges and new directions

20 Years Ago … In Web Search

- NCSA Mosaic graphical browser 3 years old, and web search engines 2 years old





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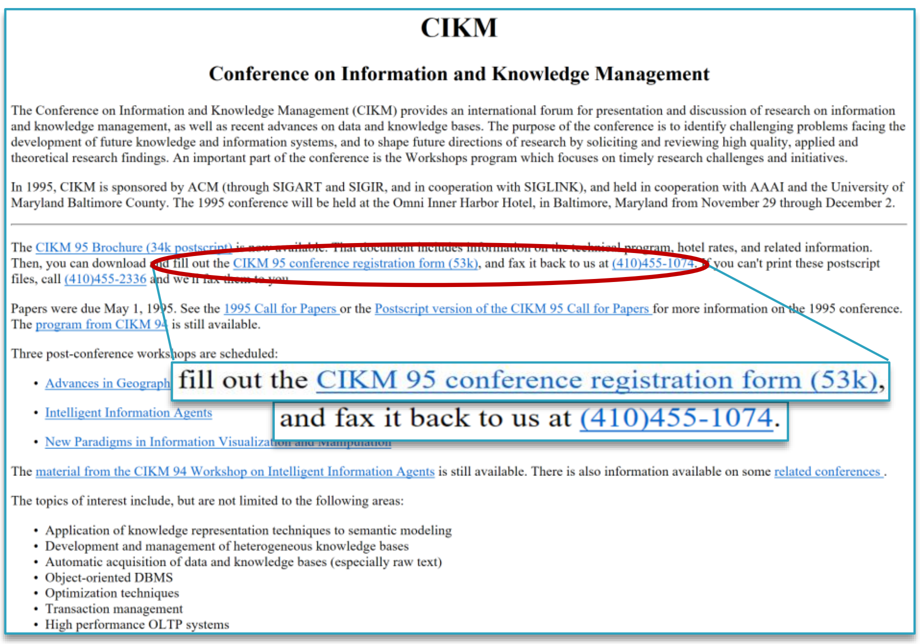
  - Online presence ~1996



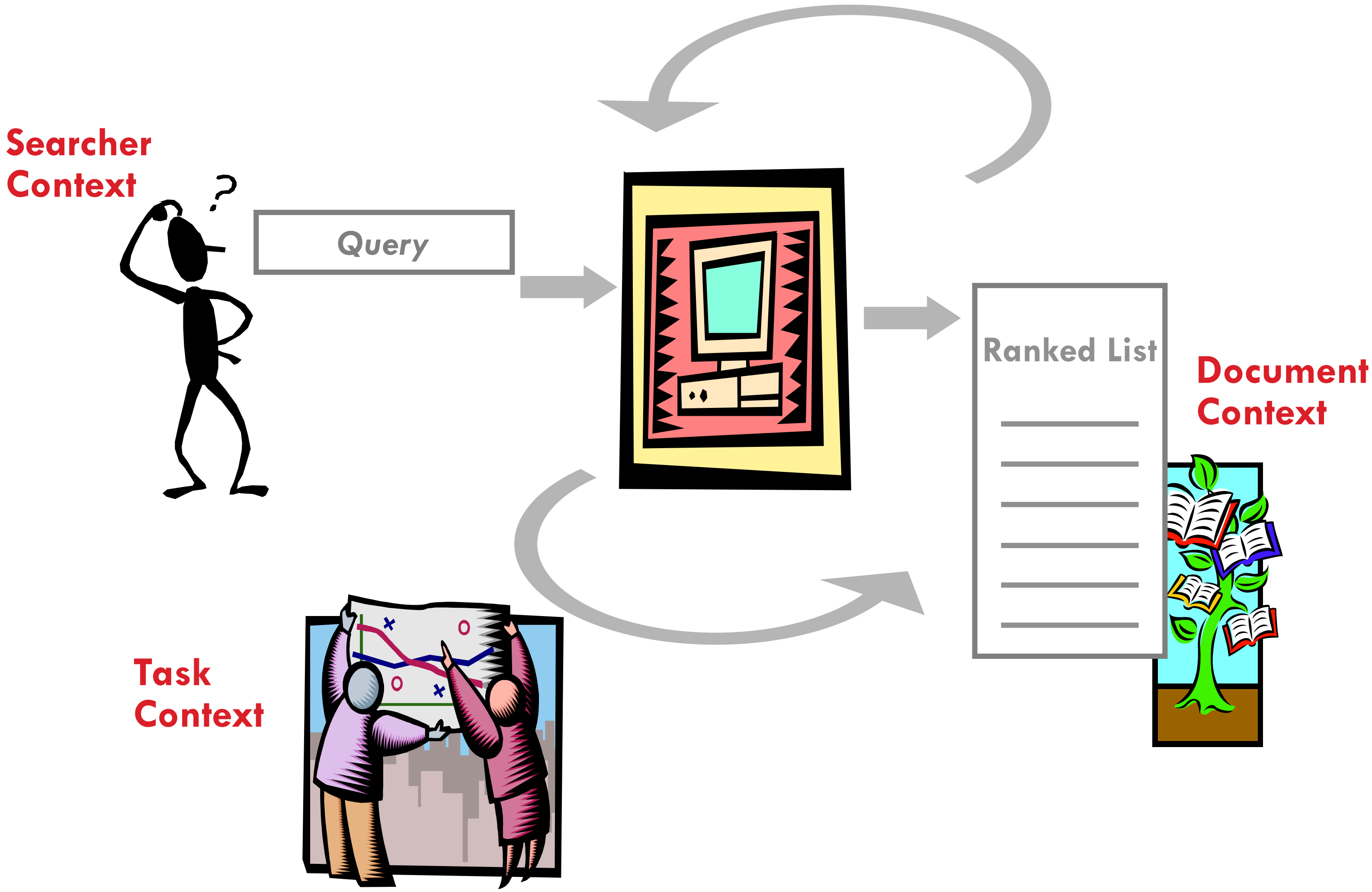
20 Years Ago … In Web Search

- NCSA Mosaic graphical browser 3 years old, and web search engines 2 years old
  - Online presence ~1996
- Size of the web
  - # web sites: 2.7k
- Size of Lycos search engine
  - # web pages in index: 54k
- Behavioral logs
  - # queries/day: 1.5k
  - Most search and logging client-side

Today … Search is Everywhere

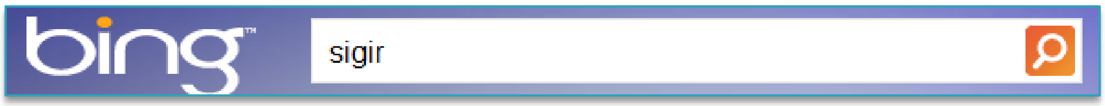
- A billion web sites
- Trillions of pages indexed by search engines
- Billions of web searches and clicks per day
- Search is a core fabric of everyday life
  - Diversity of tasks and searchers
  - Pervasive (web, desktop, enterprise, apps, etc.)
- Understanding and supporting searchers more important now than ever before

Search in Context



Context Improves Query Understanding

- Queries are difficult to interpret in isolation



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

Searcher: (*SIGIR* |Susan Dumais … an information retrieval researcher)

vs. (*SIGIR* |Stuart Bowen Jr. … the Special Inspector General for Iraq Reconstruction)

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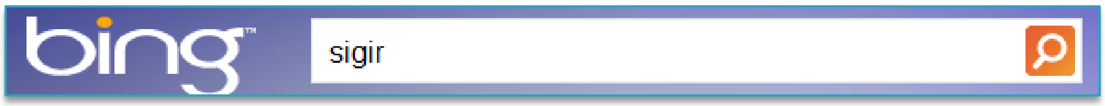

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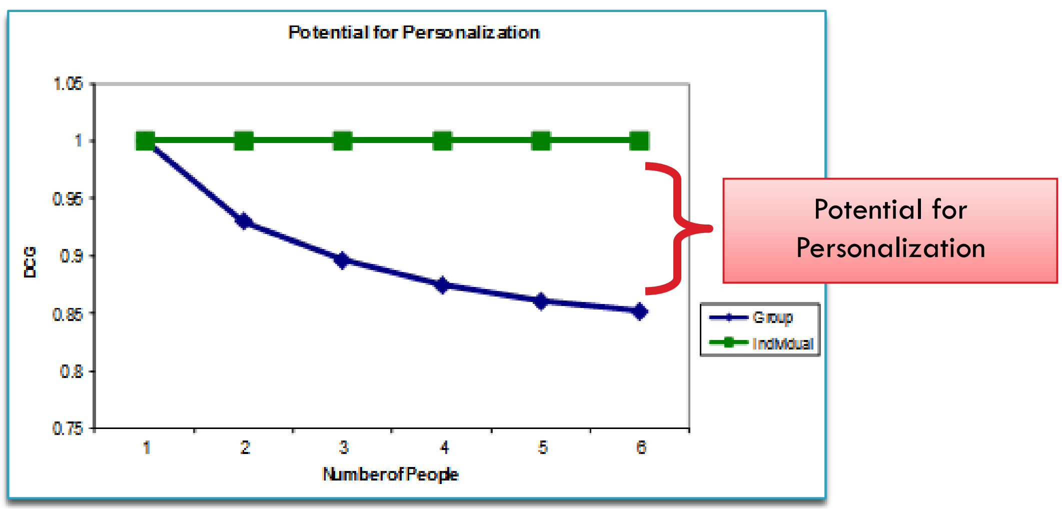
  Searcher: (*SIGIR* | Susan Dumais … an information retrieval researcher)
  vs. (*SIGIR* | Stuart Bowen Jr.
  Previous actions: (*SIGIR* | information retrieval)
  vs. (*SIGIR* | U.S. coalitional provisional authority)
  Location: (*SIGIR* | at SIGIR conference) vs. (*SIGIR* | in Washington DC)
  Time: (*SIGIR* | Jan. submission) vs. (*SIGIR* | Aug. conference)

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

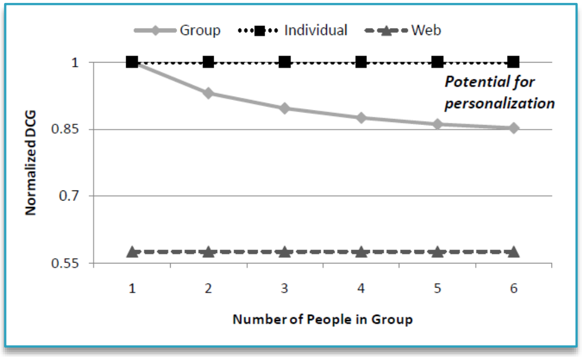
Potential For Personalization

- A single ranking for everyone limits search quality
- Quantify the variation in relevance for the same query across different individuals



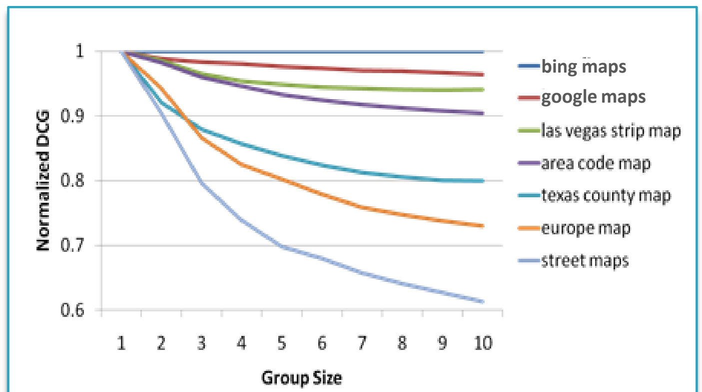
Potential For Personalization

- A single ranking for everyone limits search quality
- Quantify the variation in relevance for the same query across different individuals
- Different ways to measure individual relevance
  - Explicit judgments from different people for the same query
  - Implicit judgments from click entropy or content analysis
- Personalization can lead to large improvements
  - Study with explicit judgments
  - 46% improvements for core ranking
  - 70% improvements with personalization

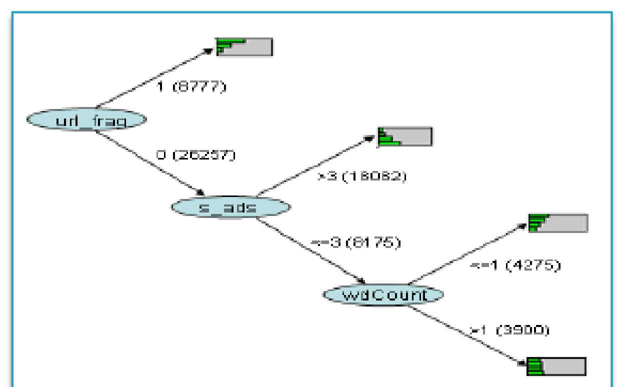


Potential For Personalization

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

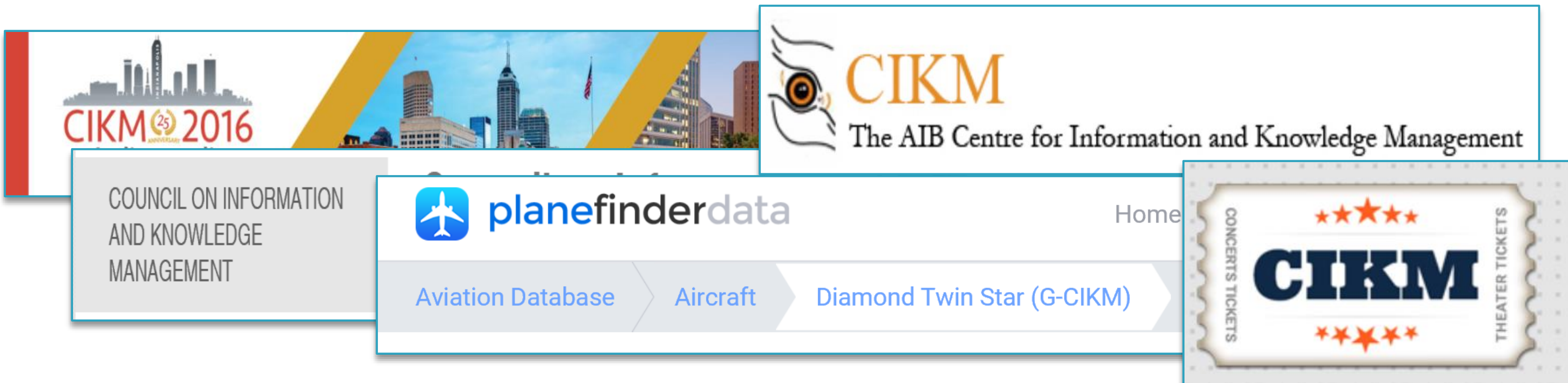


- Learn when to personalize



Potential for Personalization

- Query: *CIKM*
- What is the "potential for personalization"?



- How can you tell different intents apart?
  - Contextual metadata
    - E.g., Location, Time, Device, etc.
  - Past behavior
    - Current session actions, Longer-term actions and preferences

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
  - How used: Ranking, query support, presentation, etc.
  - When used: Always, sometimes, context learned

PNav

PSearch

Short/Long

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, anchor text
- "Personal navigational" queries
  - Different intents across individuals … but consistently the same intent for an individual
    - *SIGIR* (for Dumais) -> www.sigir.org/sigir2017
    - *SIGIR* (for Bowen Jr.) -> www.sigir.mil

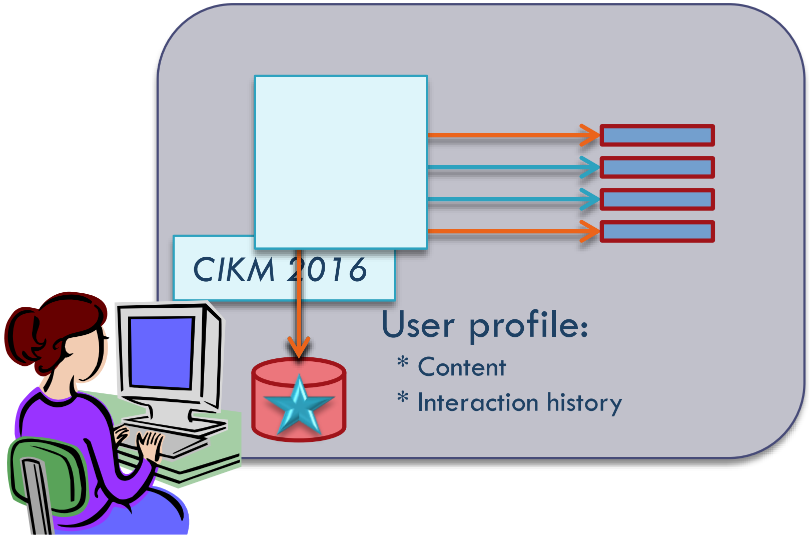
		Repeat Click	New Click
Repeat Query	33%	29%	4%
New Query	67%	10%	57%
		39%	61%

Personal Navigation Details

- Large-scale log analysis (offline)
  - Identifying personal navigation queries
    - Use consistency of queries & clicks <u>within an individual</u>
    - Specifically, the last two times a person issued the query, did they have a unique click on same result?
  - Coverage and prediction
    - Many such queries: ~12% of queries
    - Prediction accuracy high: ~95% accuracy
    - High coverage, low risk personalization
- A/B *in situ* evaluation (online)
  - Confirmed benefits

Example 2: PSearch

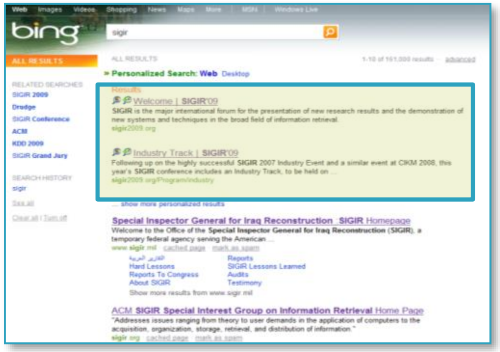
- Rich client-side model of a person's interests
  - Model: Content from desktop search index & Interaction history
    Rich and constantly evolving user model
  - Client-side re-ranking of web search results using model
  - Good privacy (only the query is sent to server)
    - But, limited portability, and use of community



PSearch Details

- Personalized ranking model
  - Score: Global web score + personal score
  - Personal score: Content match + interaction history features
- Evaluation
  - Offline evaluation, using explicit judgments
  - Online *(in situ)* A/B evaluation, using PSearch prototype
    - Internal deployment, 225+ people several months
    - 28% higher clicks, for personalized results

      74% higher, when personal evidence is strong
    - Learned model for when to personalize

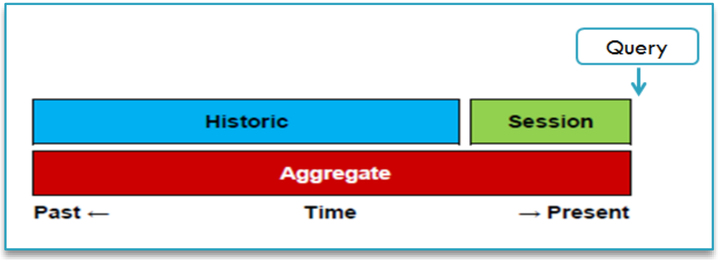


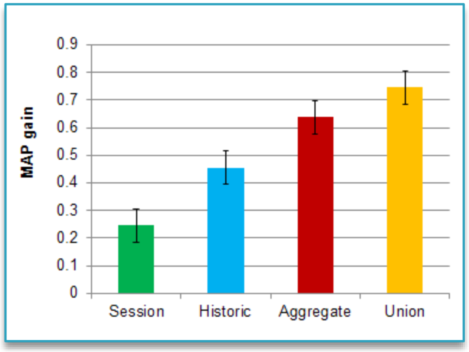
Example 3: Short + Long

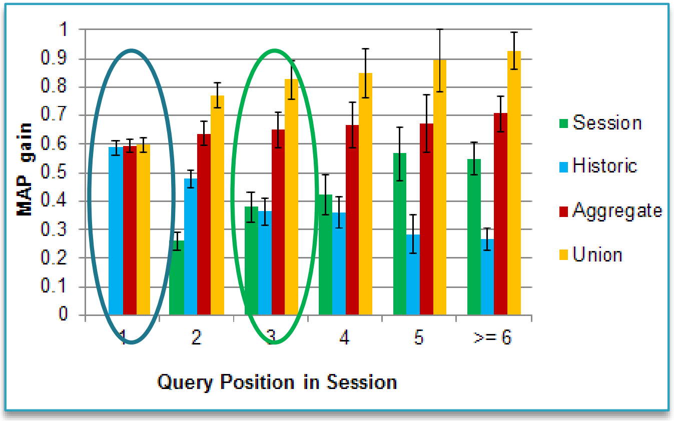
- Long-term preferences and interests
  - Behavior: Specific queries/URLs
  - Content: Language models, topic models, etc.
- Short-term context or task
  - 60% of search session have multiple queries
  - Actions within current session (Q, click, topic)
    - (Q=*sigir* | *information retrieval* vs. *iraq reconstruction*)
    - (Q=*cikm*| *knowledge mgt* vs. *twin star aircraft* vs. *discount tickets*)
    - (Q=*ego* | *id* vs. *eldorado gold corporation* vs. *dangerously in love*)
- Personalized ranking model combines both

Short + Long Details

- User model (temporal extent)
  - Session, Historical, Combinations
  - Temporal weighting
- Large-scale log analysis
- Which sources are important?
  - Session (short-term): +25%
  - Historic (long-term): +45%
  - Combinations: +65-75%
- What happens within a session?
  - 1 st query, can only use historical
  - By 3rd query, short-term features more important than long-term







Atypical Sessions

- Example user model

55% Football (“nfl”,”philadelphia eagles”,”mark sanchez”)
14% Boxing (“espn boxing”,”mickey garcia”,”hbo boxing”)
9% Television (“modern familiy”,”dexter 8”,”tv guide”)
6% Travel (“rome hotels”,“tripadvisor seattle”,“rome pasta”)
5% Hockey (“elmira pioneers”,”umass lax”,”necbl”)

New Session 1:
Boxing (“soto vs ortiz hbo”)
Boxing (“humberto soto”)

Typical

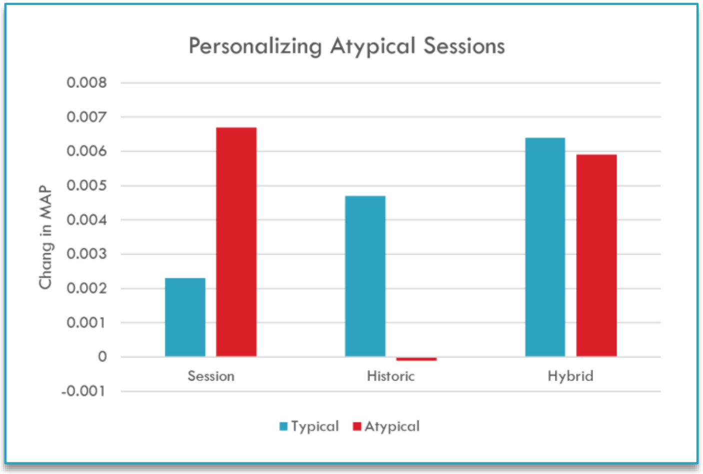
New Session 2:
Dentistry (“root canal”)
Dentistry (“dental implant”)
Healthcare (“dental implant recovery”)

Atypical

- ~6% of sessions are atypical
  - Common topics: Medical (49%), Computers (24%)
  - Tend to be more complex, and have poorer quality results
  - What you “need” to do vs. what you “choose” to do

Atypical Sessions Details

- Learn model to identify atypical sessions
  - Logistic regressions classifier
- Apply different personalization models for them
  - If typical, use long-term user model
  - If atypical, use short-term session user model
- Change in precision by typicality of session



Example 4: A Crowd of Your Own

- Personalized judgments from crowd workers
  - Taste “grokking”
    - Ask crowd workers to understand (“grok”) your interests
  - Taste “matching”
    - Find workers who are similar to you (like collaborative filtering)
- Useful for: personal collections, dynamic collections, or collections with many unique items
- Studied several subjective tasks
  - Item recommendation (purchasing, food)
  - Text summarization, Handwriting recognition

A Crowd of Your Own

- "Personalized" judgments from crowd workers

A Crowd of Your Own Details

- Grokking
  - Requires fewer workers
  - Fun for workers
  - Hard to capture complex preferences
- Matching
  - Requires many workers to find a good match
  - Easy for workers
  - Data reusable

	Baseline	Grok	Match
Salt shakers	1.64	1.07 (34%)	1.43 (13%)
Food (Boston)	1.51	1.38 (9%)	1.19 (22%)
Food (Seattle)	1.58	1.28 (19%)	1.26 (20%)

- Crowdsourcing promising in domains where lack of prior data limits established personalization methods

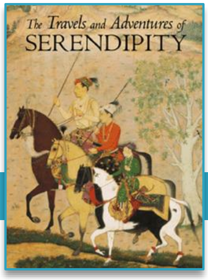
Challenges in Personalization

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

Privacy

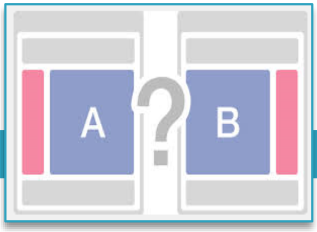
- Profile and content need to be in the same place
- Local profile (e.g., PSearch)
  - Private, only query sent to server
  - Device specific, inefficient, no community learning
- Cloud profile (e.g., Web search)
  - Need transparency and control over what's stored
- Other approaches
  - Public or semi-public profiles (e.g., tweets, public FB status, blog posts, papers)
  - Light weight profiles (e.g., queries in a session)
  - Matching to a group cohort vs. an individual

Serendipity and Novelty



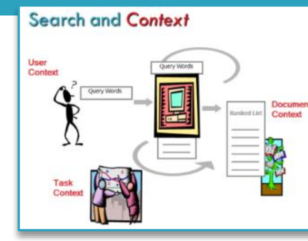
- Does personalization mean the end of serendipity?
  - … Actually, it can improve it!
- Experiment on *Relevance vs. Interestingness*
  - Personalization finds more relevant results
  - Personalization also finds more interesting results
    - Even when interesting results were not relevant
- Need to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

Evaluation

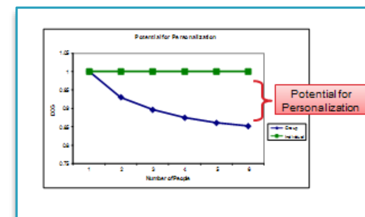


- External judges, e.g., assessors
  - Lack diversity of intents and realistic context
  - Crowdsourcing can help some
- Actual searchers are the "judges"
  - Offline
    - Labels from explicit judgments or implicit behavior (log analysis)
    - Allows safe exploration of many different alternatives
  - Online (A/B experiments)
    - Explicit judgments: Nice, but annoying and may change behavior
    - Implicit judgments: Scalable and natural, but can be very noisy
- Linking implicit actions and explicit judgments

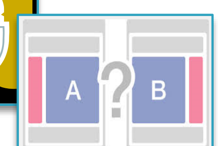
Summary



- Queries difficult to interpret in isolation
  - Augmenting query with context helps
- Potential for improving search via personalization is large



- Examples
  - PNav, PSearch, Short/Long, Crowd
- Challenges
  - Privacy, transparency, serendipity
  - Evaluation, system optimization



- Personalization/contextualization prevalent today, and increasingly so in mobile and proactive scenarios

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, Sarah Tyler, Alex Kotov, Paul André, Carsten Eickhoff, Peter Organisciak

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