

### PERSONALIZED SEARCH: POTENTIAL AND PITFALLS

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#### 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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#### CIKM

#### **Conference on Information and Knowledge Management**

The Conference on Information and Knowledge Management (CIKM) provides an international forum for presentation and discussion of research on information and knowledge management, as well as recent advances on data and knowledge bases. The purpose of the conference is to identify challenging problems facing the development of future knowledge and information systems, and to shape future directions of research by soliciting and reviewing high quality, applied and theoretical research findings. An important part of the conference is the Workshops program which focuses on timely research challenges and initiatives.

In 1995, CIKM is sponsored by ACM (through SIGART and SIGIR, and in cooperation with SIGLINK), and held in cooperation with AAAI and the University of Maryland Baltimore County. The 1995 conference will be held at the Omni Inner Harbor Hotel, in Baltimore, Maryland from November 29 through December 2.

The <u>CIKM 95 Brochure (34k postsvirity) is new evolution</u>. That document includes information on the todasised program, hotel rates, and related information. Then, you can download and fill out the <u>CIKM 95 conference registration form (53k)</u>, and fax it back to us at (<u>410)455-1075</u> (you can't print these postscript files, call (<u>410)455-2336</u> and we'n tax three to you

Papers were due May 1, 1995. See the <u>1995 Call for Papers</u> or the <u>Postscript version of the CIKM 95 Call for Papers</u> for more information on the 1995 conference. The program from CIKM 94 is still available.

Three post-conference workshops are scheduled:

- <u>Advances in Geograph</u> fill out the <u>CIKM 95 conference registration form (53k)</u>,
   <u>Intelligent Information Agents</u> and fax it back to us at (410)455-1074.
- New Paradigms in Information Visualiz

The material from the CIKM 94 Workshop on Intelligent Information Agents is still available. There is also information available on some related conferences.

The topics of interest include, but are not limited to the following areas:

- · Application of knowledge representation techniques to semantic modeling
- Development and management of heterogeneous knowledge bases
- Automatic acquisition of data and knowledge bases (especially raw text)
- Object-oriented DBMS
   Optimization techniques
- Optimization techniques
   Transaction management
- High performance OLTP systems



# 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

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Find:	Go Get It
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PeopleFind . Point Review . Ro	ad Maps . Software . About Lycos . Club Lycos . Help
	Add Your Site to Lycos

## 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

sigir

bing

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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**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 <u>single ranking</u> for everyone, in every context, at every point in time, <u>limits how well a search engine can do</u>

#### **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

**PNav** 

**PSearch** 

Short/Long

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

### 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 -> <u>www.facebook.com</u>
  - 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.) -> <u>www.sigir.mil</u>

		Repeat Click	New Click
Repeat Query	33%	29%	4%
New Query	<b>67</b> %	10%	57%
		<b>39</b> %	61%



## Personal Navigation Details

#### Large-scale log analysis (offline)

Identifying personal navigation queries

- Use consistency of queries & clicks within an individual
- 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<sup>st</sup> query, can only use historical
  - By 3<sup>rd</sup> 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") New Session 2:

Dentistry ("root canal") Dentistry ("dental implant") Healthcare ("dental implant recovery")

#### $\square \sim 6\%$ 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	1.64	1.07	1.43
shakers		( <b>34%</b> )	( <b>13%</b> )
Food	1.51	1.38	1.19
(Boston)		( <b>9%</b> )	( <b>22%</b> )
Food	1.58	1.28	1.26
(Seattle)		( <b>19%</b> )	( <b>20%</b> )

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.





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

#### André et al., CHI 2009, C&C 2009

# Serendipity and Novelty



Does personalization mean the end of serendipity?

Actually, it can improve it!

□ Experiment on Relevance vs. Interestingness

- Personalization finds more <u>relevant</u> results
- Personalization also finds more <u>interesting</u> 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: <u>http://research.microsoft.com/~sdumais</u>

#### 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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