

My Background

- Mathematics & Psychology
- Bell Labs
 - Vocabulary mismatch
 - Rich aliasing, adaptive indexing, latent semantic indexing (LSI)
 - Modeling vocabulary acquisition
- Microsoft Research
 - Text classification (e.g., spam filter)
 - Context & search (e.g., re-finding, personalization, task support)
 - Personal web of information
- Evolution of search
- Better together

My Background

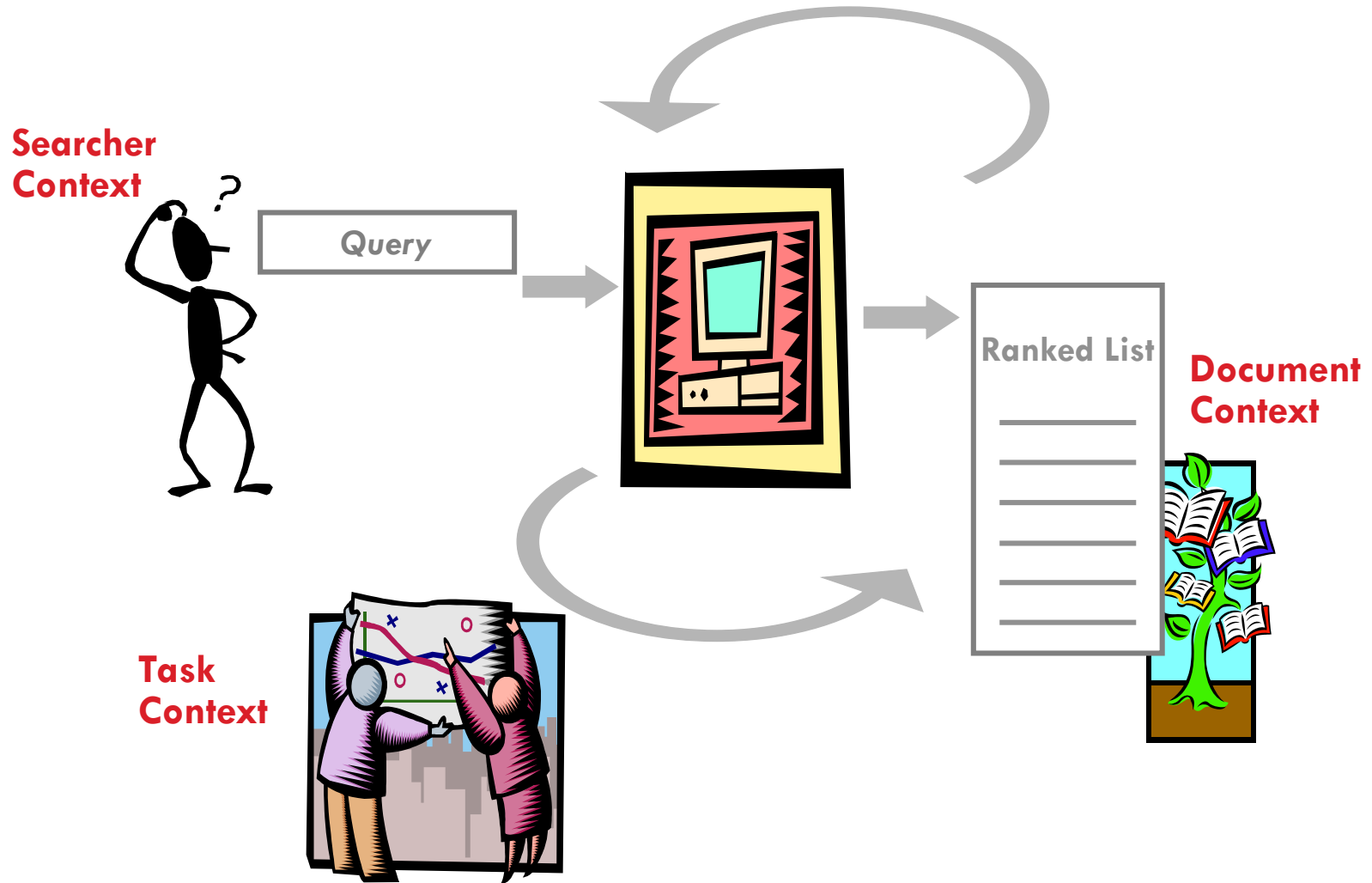
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 - Personal web of information
- Evolution of search
- Better together: *If search doesn't work for people, it doesn't work!*

Overview

- Personalized search perspectives
 - ▣ Context in search
 - ▣ Potential for personalization framework
- Examples
 - ▣ Personal navigation
 - ▣ Client-side personalization
 - ▣ Short- and long-term models
 - ▣ Spatio-temporal contexts
 - ▣ Personal crowds
- Challenges and new directions

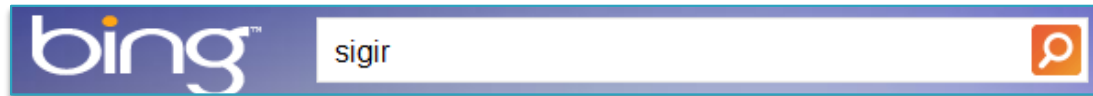
Context & Potential for Personalization

Search in Context



Context Improves Query Understanding

- Queries are difficult to interpret in isolation



- Easier if we can 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* | Aug. conference)

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

SIGIR

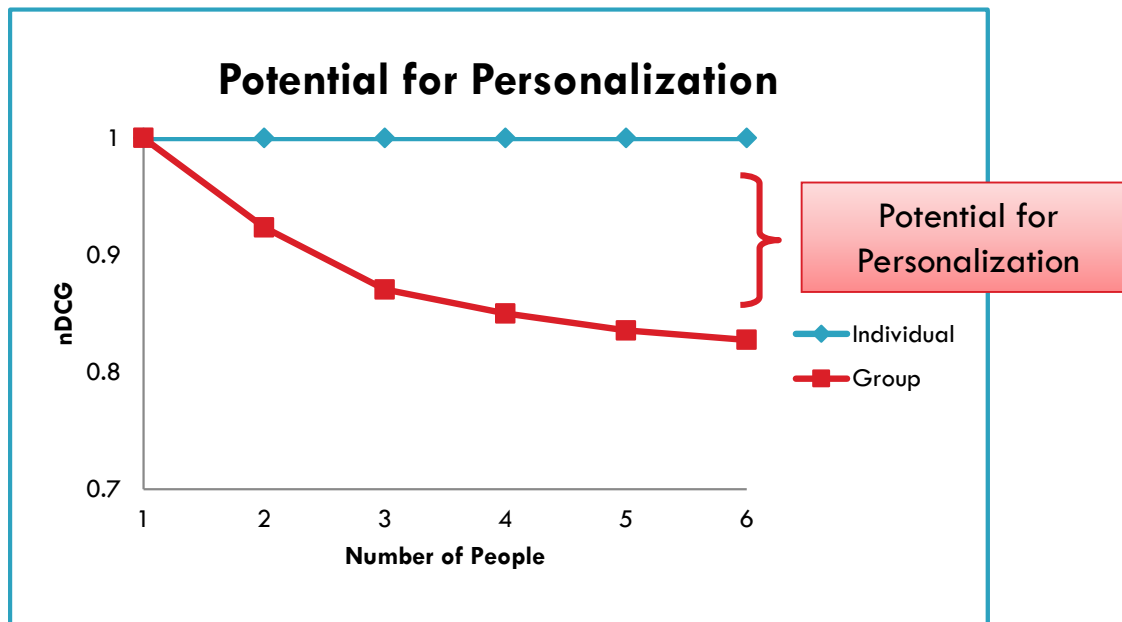


SIGIR



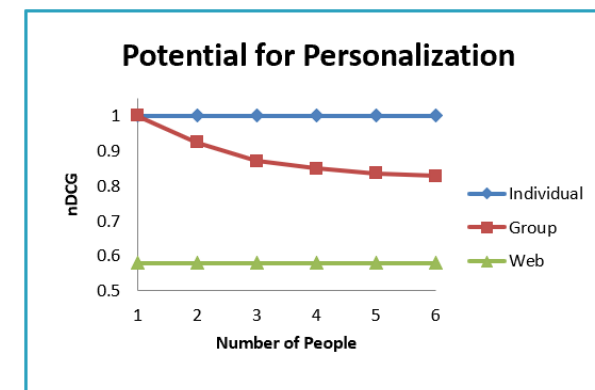
Potential For Personalization

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



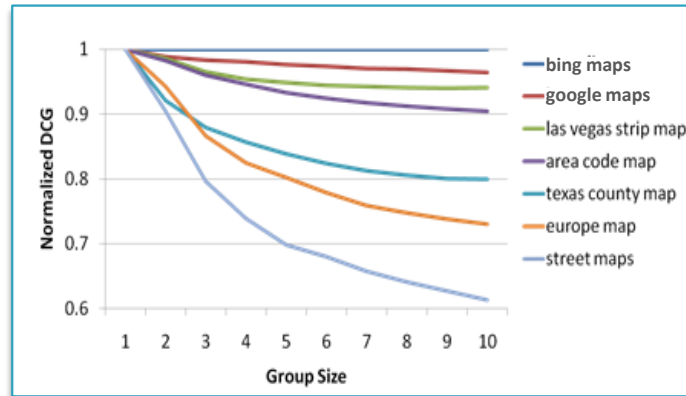
Potential For Personalization

- 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

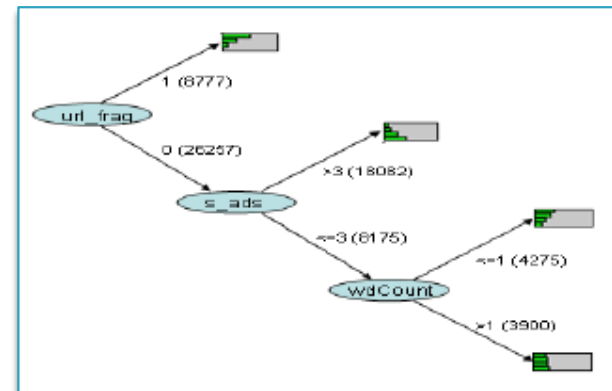


Potential For Personalization

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

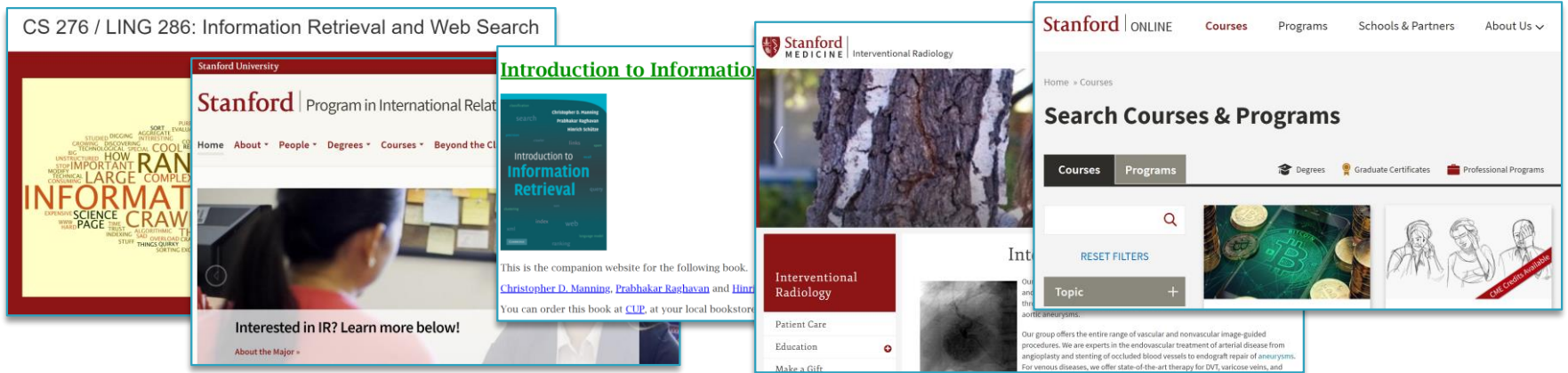


- Learn when to personalize



Potential for Personalization

- ❑ Query: *Stanford IR course*
- ❑ What is the “potential for personalization”?



- ❑ How can you identify different intents?
 - ▣ Past behavior - Current session, Longer history of actions and preferences
 - ▣ Contextual metadata – Location, Time, Device, etc.

User Models

□ Constructing user models

▣ Sources of evidence

- Content: Queries, content of web pages, desktop index, etc.
- Behavior: Explicit feedback, implicit feedback, visited web pages
- Context: Location, time (of day/week/year), device, etc.

▣ Time frames: Short-term, long-term

PNav

▣ Who: Individual, group

PSearch

□ Using user models

▣ Where resides: Client, server

Short/Long

▣ How used: Ranking, query support, presentation, etc.

▣ When used: Always, sometimes, context learned

A horizontal bar at the top of the slide, divided into a red section on the left and a teal section on the right. The text "Examples Methods & Applications" is centered in the teal section.

Examples Methods & Applications

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., *new york times* -> www.nytimes.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
 - SIGIR (for Bowen Jr.) -> www.sigir.mil

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

WEB IMAGES VIDEOS MAPS MORE

sigir

448,000 RESULTS

SIGIR Conference is on Sunday, Aug tomorrow.

ACM SIGIR Special Interest Group on Information Retrieval ...

Welcome to the ACM SIGIR Web site. ACM SIGIR addresses issues ranging from theoretical to user demands in the application of computers to the acquisition, organization, and use of information.

Welcome to SIGIR! Home

An Iraqi fisherman pushes his boat off-shore to depart on his daily fishing trip. View the Report.

home | ACM SIGIR 2010

ACM-SIGIR 2010 was held at UnMail, Geneva, Switzerland between 19th and 23rd of July 2010. Thanks to all the participants! The story continues with ACM-SIGIR 2011.

SIGIR Portland Oregon 2012 - ACM SIGIR Special Interest Group

SIGIR 2012. Online registration for SIGIR 2012 is now closed. On-site registration will be available at the conference venue. Welcome to SIGIR 2012, the 33rd Annual SIGIR Conference.

Welcome to The 34th Annual ACM SIGIR Conference

ACM-SIGIR 2011 successfully completed in Beijing. Thanks to all the speakers and participants!

Related searches for sigir

SIGIR Iraq SIGIR Forum SIGIR 12 SIGIR 2011 Accepted SIGIR WSDM

Special Inspector General for Iraq Reconstruction - Wikipedia

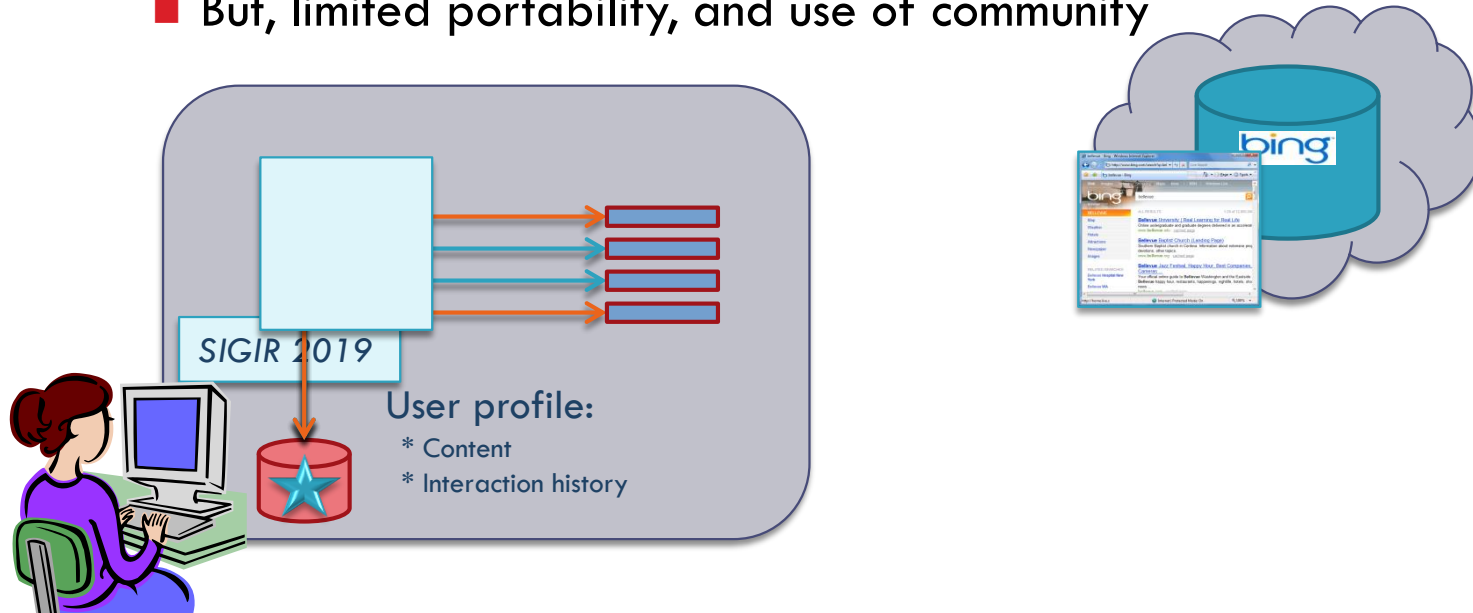
The Office of the Special Inspector General for Iraq Reconstruction (SIGIR) was created in October 2004 as the successor to the Coalition Provisional Authority Office.

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



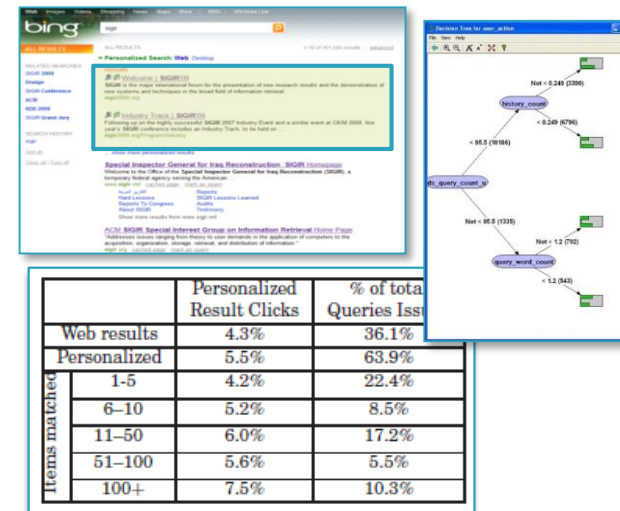
PSearch Details

□ Personalized ranking model

- Score: Weighted combination of personal and global web features
 - $Score(result_i) = \alpha WebScore(result_i) + (1 - \alpha) PersonalScore(result_i)$
- 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, and back off to site

□ Evaluation

- Offline evaluation, using explicit judgments
- *In situ* evaluation, using PSearch prototype
 - 225+ people for several months
 - CTR 28% higher, for personalized results
 - CTR 74% higher, when personal evidence is strong
 - Learned model for when to personalize

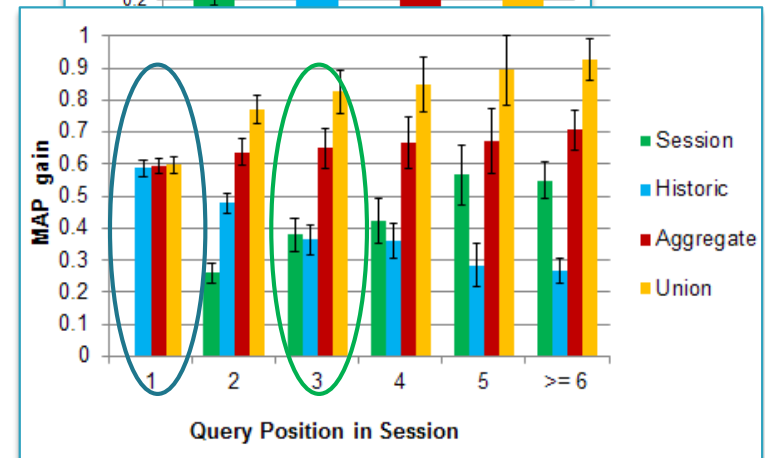
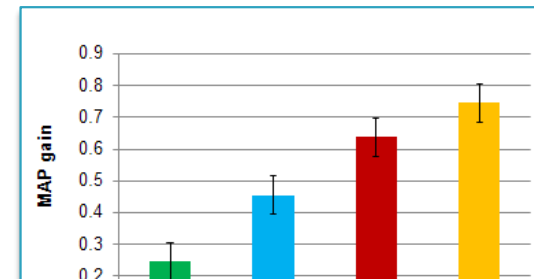
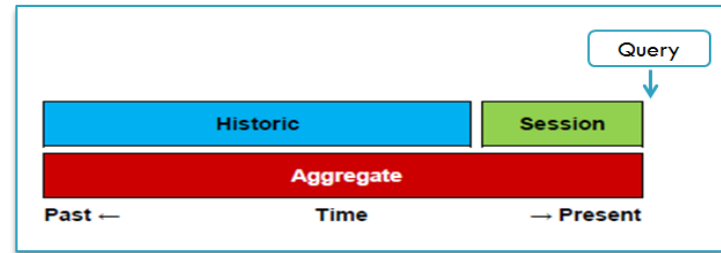


Example 3: Short + Long

- Long-term preferences and interests
 - ▣ Content: Language models, topic models, etc.
 - ▣ Behavior: Specific queries, URLs
- 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=*Stanford IR course* | *CS276* vs. *intl relations* vs. *radiology*)
 - (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?
 - ▣ 1st 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 family”, “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

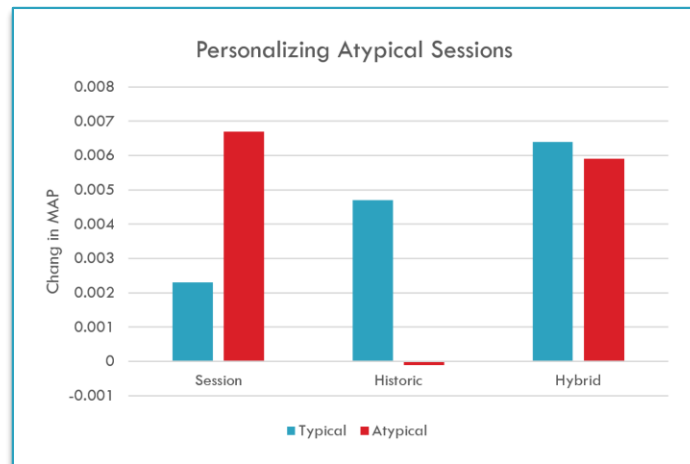
New Session 2:
Dentistry (“root canal”)
Dentistry (“dental implant”)
Healthcare (“dental implant recovery”)

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

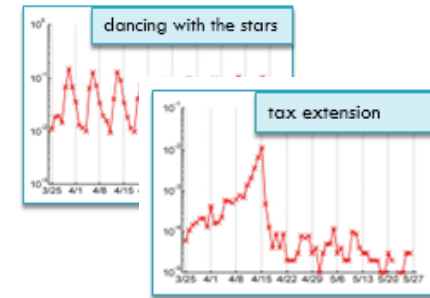
Atypical Sessions Details

- 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



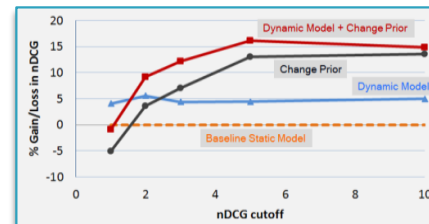
Example: Temporal Dynamics

- Queries are not uniformly distributed over time
 - ▣ Often triggered by events in the world
- What's relevant changes over time
 - ▣ E.g., *US Open* ... in 2019 vs. in 2018
 - ▣ E.g., *US Open 2019* ... in May (golf) vs. in Sept (tennis)
 - ▣ E.g., *US Tennis Open 2019* ...
 - 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

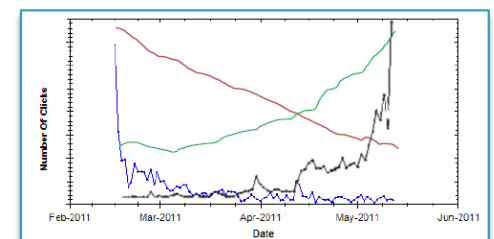


Temporal Dynamics Details

- Develop time-aware retrieval models
- Model content 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



- Model user interactions as a time-series
 - ▣ Model Query and URL clicks as time-series
 - ▣ Enables appropriate weighting of historical interaction data
 - ▣ Useful for queries with local or global trends

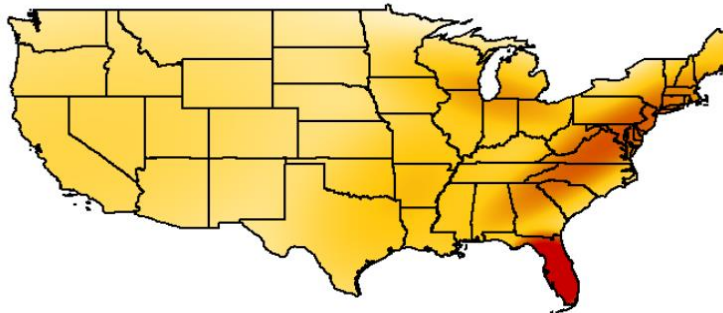


Example: Location Context

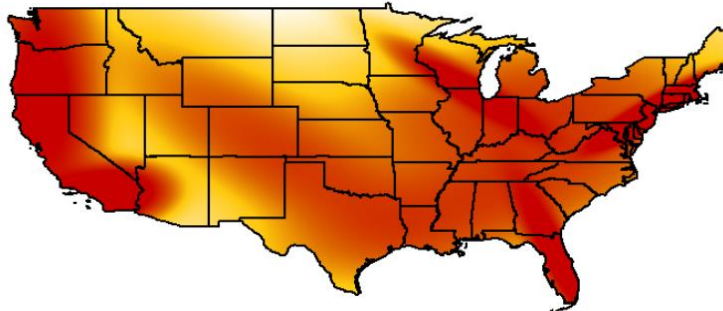
- What's relevant to a query varies by location
 - ▣ E.g., *football* or *jumper* or *chips* [in US vs. UK]
 - ▣ E.g., *library* or *zoo* or *current time* [at state- or city-level]
 - ▣ E.g., *starbucks* or *pizza* [at finer granularity]
- Data: query, URL, location
- Geographic distribution of each URL, query
 - ▣ $P(\text{location} = X \mid \text{URL})$, estimate this using a mixture of Gaussians
 - ▣ $P(\text{location} \mid \text{query})$, estimate this using a mixture of Gaussians
 - ▣ Background model

Location Context Details

- Location interest model for Q: *smh*

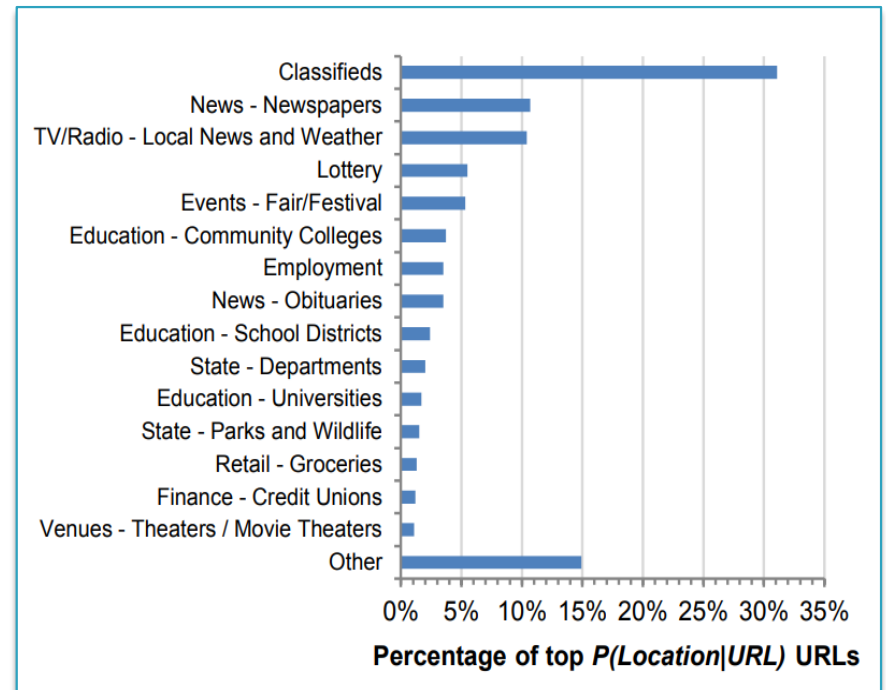


(a) Sarasota Memorial Health, <http://smh.com/>



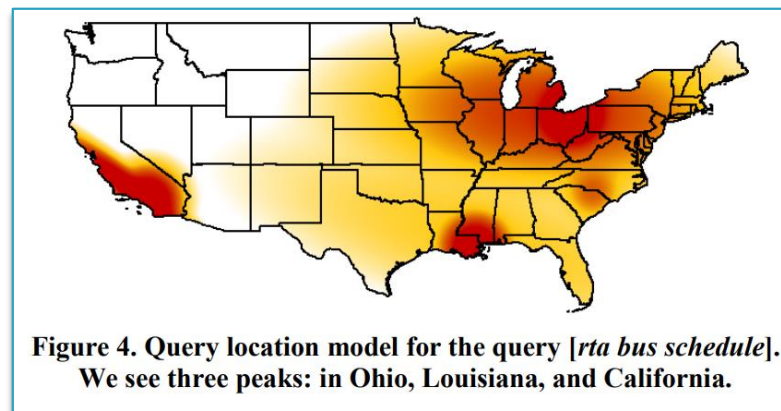
(b) Sydney Morning Herald, <http://smh.com.au/>

- Topics w/ the most location-centric URLs



Location Context Details

- Learn to re-rank using location features
- Important features
 - ▣ Original ranking
 - ▣ $P(\text{URL} \mid \text{searcher location})$
 - ▣ $KL \text{ Div}(\text{URL model}, \text{background model})$
- Query: *rta bus schedule*





Challenges & Opportunities

Challenges in Personalization

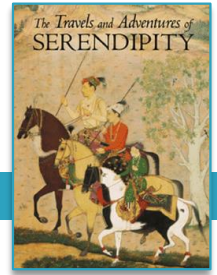
- User-centered
 - ▣ Privacy
 - ▣ Serendipity and novelty
 - ▣ Transparency and control
- Systems-centered
 - ▣ Optimization
 - Storage, run-time, caching, etc.
 - ▣ Evaluation
 - Measurement, experimentation

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/semi-public profiles (e.g., tweets, FB status, blogs, 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



Perspectives

Search: excel flash fill

All Images Videos Maps News Shop | My saves

Microsoft Show business results

What version of Excel are you looking for?

excel 2007 excel 2010 excel 2013 excel 2016

Excel flash fill

The series of entries appear in the new column, literally in a **flash** (thus, the name **Flash Fill**), the moment **Excel** detects a pattern in your initial data entry that enables it to figure out the data you want to copy. The beauty is that all this happens without the need for you to construct or copy any kind of formula.




Image: teachucomp.com

Search: stress management

All Images Videos Maps News Shop | My saves

Microsoft Show business results

What do you want to know about this treatment?

breathing exercises doing guided imagery to relax doing meditation practicing yoga

Stress Management: Using Self-Help Techniques for Dealing ...

<https://www.helpguide.org/articles/stress/stress-management.htm>

Overwhelmed by **stress**? You don't have to be. These **stress management** tips can help you drastically reduce your **stress** levels and regain control of your life.

Stress management Stress basics - Mayo Clinic

[www.mayoclinic.org/healthy-lifestyle/stress-management/basics/...](http://www.mayoclinic.org/healthy-lifestyle/stress-management/basics/)

Stress management: Learn why you feel **stress** and how to fight it.

[Stress Relief](#) · [Relaxation Techniques](#)

Stress Management: How To Relax Your Mind and Body

<https://www.webmd.com/balance/stress-management/stress-management...>

Some of the most useful **stress management** skills you can learn are healthy coping strategies. Many of these can be done with little or no instruction. No one strategy ...



Perspectives

is kale good for you

All Images Videos Maps News Shop | My saves

15,400,000 Results Any time ▾

Kale

PERSPECTIVES FROM THE WEB

For a green, kale is unusually high in fiber. This helps create the bulk you need to fill you up and to keep you full for a good amount of time. Kale is also an excellent source of nutrients, especially vitamin A and calcium. With a combination of vitamins, minerals, and phytonutrients, kale is a dieter's dream food.

[Health Benefits of Kale - Kale | HowStuffWorks](https://home.howstuffworks.com)
home.howstuffworks.com

vs

Like spinach, kale contains oxalic acid which can be harmful if consumed to excess. If you are eating a lot of raw foods high in oxalic acid, adding kale to the mix might not be the best idea. On the other hand, kale's oxalic acid content is fairly low, so it is unlikely to be a problem in and of itself.

[4 answers: Is eating raw kale bad for you? - Quora](https://www.quora.com/Is-eating-raw-kale-bad-for-you)
quora.com

facts about kale

All Images Videos Maps News Shop | My saves

Microsoft Show business results ▾

14,200,000 Results Any time ▾

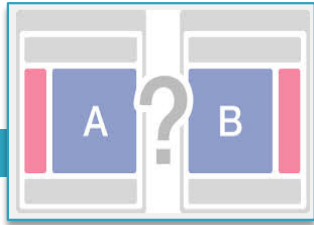
SUMMARIZED FROM 3 SOURCES

- Kale develops large , curly or plain leaves arranged in the form of rosette. Kale produces erect stem that can grow close to the ground or reach the height of 6 to 7 feet , depending on the variety. Leaves can be light or dark green , violet-green or violet-brown colored.[1]
- Kale is popular now , but people have been growing this super food for more than 2,000 years. Popular in Europe during Roman times and the Middle Ages , it arrived in the U.S. in the 17th century.[2]
- Kale or borecole in one of a kind , nutritious leafy greens that are rich in numerous health benefiting polyphenolic flavonoid compounds such as lutein , zeaxanthin , and β - carotene , and vitamins. It is widely cultivated in the Europe , Japan , and the United States for its crispy , “ frilly “ leaves.[3]

Sources: [1] softschools.com · [2] webmd.com · [3] nutrition-and-you.com

7 Fun Healthy Facts about Kale - WebMD
<https://www.webmd.com/diet/features/7-fun-facts-about-kale>
This colorful green brings flavor and nutrition to recipes ranging from kale chips to WebMD's hearty kale soup.

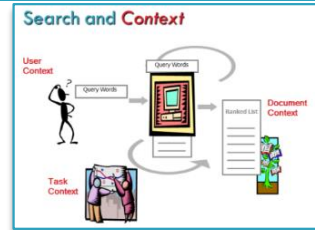
Evaluation



- 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

Personalized Search Recap

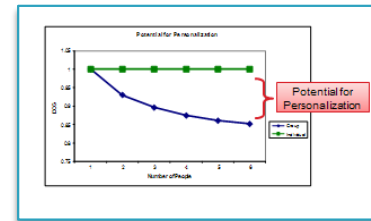
- ❑ Queries difficult to interpret in isolation
 - ▣ Augmenting query with context critical



- ❑ Large potential for improving search via personalization

- ❑ 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

References

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