SEARCH AND CONTEXT
Overview

- Importance of context in information retrieval
- “Potential for personalization” framework
- Examples with varied user models and evaluation methods
  - Personal navigation
  - Client-side personalization
  - Short- and long-term models
  - Time-aware models
- Challenges and new directions
Search and Context

User Context

Query Words

Task Context

Ranked List

Document 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
CLEF 2014

- Have you searched for CLEF 2014 recently?
- What were you looking for?

SDumais - CLEF 2014, Sept 16 2014
Potential For Personalization

- A single ranking for everyone limits search quality
- Quantify the variation in individual relevance for the same query
- Different ways to measure individual relevance
  - Explicit judgments from different people for the same query
  - Implicit judgments (search result clicks, 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
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
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
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/sigir2014
    - SIGIR (for Bowen Jr.) -> www.sigir.mil
Personal Navigation Details

- Large-scale log analysis & online A/B evaluation
- Identifying personal navigation queries
  - Use consistency of 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
    - Consistent over time
  - High coverage, low risk personalization
- Used to re-rank results, and augment presentation
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

User profile:
- Content
- Interaction history
PSearch Details

- **Personalized ranking model**
  - Score: Weighted combination of personal and global web features
    - \( \text{Score}(\text{result}_i) = \alpha \text{PersonalScore}(\text{result}_i) + (1 - \alpha) \text{WebScore}(\text{result}_i) \)
  - 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
    - 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 context**
  - Previous actions (queries, clicks) within current session
    - (Q=\textit{sigir} | information retrieval vs. iraq reconstruction)
    - (Q=\textit{ego} | id vs. dangerously in love vs. elдорado gold corporation)
    - (Q=\textit{acl} | computational linguistics vs. knee injury vs. country music)

- **Long-term preferences and interests**
  - Behavior: Specific queries/URLs
    - (Q=\textit{weather}) -> weather.com vs. weather.gov vs. intellicast.com
  - Content: Language models, topic models, etc.

- Learned model to combine both
Short + Long Details

- User model (content)
  - Specific queries/URLs
  - Topic distributions, using ODP

- Which sources are important?
  - Session (short-term): +25%
  - Historic (long-term): +45%
  - Combinations: +65-75%

- What happens within a session?
  - 60% sessions involve multiple queries
    - 1st query, can only use historical
    - By 3rd query, short-term features more important than long-term

- User model (temporal extent)
  - Session, Historical, Combinations
  - Temporal weighting

SDumais - CLEF 2014, Sept 16 2014
Atypical Sessions

- Example user model
  - 55% Football ("nfl","philadelphia eagles","mark sanchez")
  - 14% Boxing ("espn boxing","mickey garcia","hbo boxing")
  - 09% Television ("modern familiy","dexter 8","tv guide")
  - 06% Travel ("rome hotels","tripadvisor seattle","rome pasta")
  - 05% Hockey("elmira pioneers","umass lax","necbl")

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

New Session 1:
  - Boxing ("soto vs ortiz hbo")
  - Boxing ("humberto soto")

New Session 2:
  - Dentistry ("oral sores")
  - Dentistry ("aphthous sore")
  - Healthcare ("aphthous ulcer treatment")
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

- Accuracy by similarity of session to user model
Example 4: 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 2014 vs. in 2013
  - E.g., US Open 2014 … in May (golf) vs. in Sept (tennis)
  - E.g., US Tennis Open 2014 …
    - 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
Challenges in Personalization

- User-centered
  - Privacy
  - Transparency and control
  - Serendipity

- Systems-centered
  - Evaluation
    - Measurement, experimentation
  - System optimization
    - Storage, run-time, caching, etc.
Privacy

- User profile and content need to be in the same place

- Local profile (e.g., PSearch)
  - Local profile, local computation
  - Only query sent to server

- Cloud profile (e.g., Web search)
  - Cloud profile, cloud computation
  - Transparency and control over what’s stored

- Other approaches
  - Light weight profiles (e.g., queries in a session)
  - Public or semi-public profiles (e.g., tweets, Facebook status)
  - Matching to a group vs. an individual
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

- External judges, e.g., “assessors”
  - Lack diversity of intents and realistic context
  - Crowd workers may help some

- 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 … not directly repeatable; requires production-level code; mistakes costly; biased toward what is presented; etc.

- Diversity of methods important
  - User studies, log analysis, and A/B testing
Summary

- Queries difficult to interpret in isolation
- Augmenting query with context helps
  - Who, what, where, when?
- Potential for improving search using context is large
- Examples
  - PNav, PSearch, Short/Long, Time
- Challenges and new directions
  - Spatio-temporal especially in mobile, social, proactive
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 Radinsky, Jon Elsas, Sarah Tyler, Alex Kotov, Anagha Kulkarni, Paul André, Carsten Eickhoff
References

- **Short-term models**
  - Eickhoff et al., WSDM 2013. *Personalizing atypical search sessions.*
  - P. André et al., CHI 2009. *From x-rays to silly putty via Uranus: Serendipity and its role in Web search.*

- **Long-term models**
  - Teevan et al., SIGIR 2005. *Personalizing search via automated analysis of interests and activities.* *
  - Teevan et al., SIGIR 2008. *To personalize or not: Modeling queries with variations in user intent.* *
  - Teevan et al., TOCHI 2010. *Potential for personalization.* *
  - Teevan et al., WSDM 2011. *Understanding and predicting personal navigation.* *
  - Bennett et al., SIGIR 2012. *Modeling the impact of short- & long-term behavior on search personalization.* *

- **Temporal models**
  - Elsas & Dumais, WSDM 2010. *Leveraging temporal dynamics of document content in relevance ranking.* *
  - Radinsky et al., TOIS 2013. *Behavioral dynamics on the web: Learning, modeling and predicting.* *