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

Ranked List

Document Context

Task 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?

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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
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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

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Personalized ranking model

- Score: Weighted combination of personal and global web features
  \[ Score(result_i) = \alpha PersonalScore(result_i) + (1 - \alpha) WebScore(result_i) \]
- 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, 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

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Example 3: Short + Long

- **Short-term context**
  - Previous actions (queries, clicks) within current session
    - (Q=\textit{sigir} | information retrieval vs. \textit{iraq} reconstruction)
    - (Q=\textit{ego} | id vs. dangerously in love vs. \textit{eldorado gold corporation})
    - (Q=\textit{acl} | computational linguistics vs. knee injury vs. \textit{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
Atypical Sessions

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

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

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

- ~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
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.

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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:
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References

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  - P. André et al., CHI 2009. *From x-rays to silly putty via Uranus: Serendipity and its role in Web search.*

- **Long-term models**
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  - Teevan et al., TOCHI 2010. *Potential for personalization.*
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- **Temporal models**