Modeling User Behavior and Interactions

Lecture 1: Modeling Searcher Behavior

Eugene Agichtein
Emory University
Overview of the Course

• Lecture 1: Modeling searcher behavior

• Lecture 2: Interpreting behavior ➞ relevance

• Lecture 3: Using behavior data ➞ ranking

• Lecture 4: Personalizing search with behavior

• Lecture 5: Search user interfaces
Lecture 1: Models of Search Behavior

• Understanding user behavior at micro-, meso-, and macro- levels

• Theoretical models of information seeking

• Web search behavior:
  – Levels of detail
  – Search Intent
  – Variations in web searcher behavior
  – Click models
Levels of Understanding User Behavior

[Daniel M. Russell, 2007]

- **Micro (eye tracking):**
  least level of detail, milliseconds

- **Meso (field studies):**
  mid-level, minutes to days

- **Macro (session analysis):**
  millions of observations, days to months
Models of Information Seeking

- “Information-seeking ... includes recognizing ... the information problem, establishing a plan of search, conducting the search, evaluating the results, and ... iterating through the process.” - Marchionini, 1989
  - Query formulation
  - Action (query)
  - Review results
  - Refine query

Adapted from: M. Hearst, SUI, 2009
Key Concept: Relevance

- Intuitively well understood
  - same perception globally – “y’know”
  - a “to” and context always present
- Relevance:
  - a relation between objects P & Q along property R
  - may also include a measure S of the strength of connection
- Example: topical relevance (document on the correct topic)
Relevance clues

• What makes information or information objects relevant? What do people look for in order to infer relevance?
  – Topicality (subject relevance)
  – Extrinsic (task-, goal- specific)

• Information Science “clues research”:
  – uncover and classify attributes or criteria used for making relevance inferences
IR Relevance Models

- All IR and information seeking models have relevance at their base
- Traditional IR model has most simplified (topic) version of relevance (topical)
  - Enough to make progress
- Variety of integrative models have been proposed
  - more complex models = increased challenge to evaluation and implementation in practice
Cognitive Model of Information Seeking

• Static Info Need
  – Goal
  – Execution
  – Evaluation
Relevance dynamics

• Do relevance inferences and criteria change over time for the same user and task, and if so, how?

• As user progresses through stages of a task:
  – the user’s cognitive state changes
  – the task changes as well
Dynamic “Berry Picking” Model

• Information needs change during interactions

Information Foraging Theory

**Goal:** maximize rate of information gain.

Patches of information → websites

**Basic Problem:** should I continue in the current patch or look for another patch?

*Expected gain* from *continuing* in current patch, *how long* to continue searching in that patch
Hotel Search

Goal: Find cheapest 4-star hotel in Paris.

Step 1: pick hotel search site

Step 2: scan list

Step 3: goto 1
Example: Hotel Search (cont’d)
Charnov’s Marginal Value Theorem

Diminishing Returns Curve; 80% of users don’t scan past the 3rd page of search results

\[ R^* = \text{steepest slope from origin} = \text{tangent from origin} \]

If \( t_b \) is low, then people tend to switch more easily. (web snacking)
Browsing vs. Search

• Recognition over recall (I know it when I see it)
• Browsing hierarchies/facets more effective than querying
Orienteering

• Searcher issues a quick, imprecise to get to approximately the right information space region
• Searchers follow known paths that require small steps that move them closer to their goal
• Expert searchers starting to issue longer queries
Information Scent for Navigation

• Examine clues where to find useful information

The Bureau of Labor Statistics is an agency within the U.S. Department of Labor. Search results listings must provide the user with clues about which results to click.

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Summary of Models

• Many cognitive models proposed

• Classical IR Systems research mainly uses the simplest form of relevance (topicality)

• Open questions:
  – How people recognize other kinds of relevance
  – How to incorporating other forms of relevance (e.g., user goals/needs/tasks) into IR systems
Lecture 1: Models of Search Behavior

• Understanding user behavior at micro-, meso-, and macro- levels

✓ Theoretical models of information seeking

 предост. Web search behavior:
  – Levels of detail
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  – Variations in web searcher behavior
  – Click models

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Web Searcher Behavior

- **Meso-level**: query, intent, and session characteristics

- **Micro-level**: how searchers interact with result pages

- **Macro-level**: patterns, trends, and interests
Web Search Architecture
[from Baeza-Yates and Jones, WWW 2008 tutorial]

Example centralized parallel architecture

Diagram showing the components of a web search architecture including:
- Crawlers
- Indexing
- Searching
- Ranking
- Visual Interface
- User
- Query Operations
Information Retrieval Process (User view)

Source Selection

Query Formulation

Search

Ranked List

Selection

Examination

Documents

Delivery

Resource

Query

Documents

source reselection

query reformulation,

vocabulary learning,

relevance feedback
Some Key Challenges for Web Search

• Query interpretation (infer intent)

• Ranking (high dimensionality)

• Evaluation (system improvement)

• Result presentation (information visualization)
User intent taxonomy (Broder 2002)

- **Informational** – want to learn about something (~40% / 65%)
  
  - History nonya food

- **Navigational** – want to go to that page (~25% / 15%)
  
  - Singapore Airlines

- **Transactional** – want to do something (web-mediated) (~35% / 20%)
  
  - Jakarta weather
  
  - Kalimantan satellite images
  
  - Nikon Finepix

- Gray areas
  
  - Find a good hub
  
  - Exploratory search “see what’s there”
Web Search Queries

• Cultural and educational diversity
• Short queries and impatient interaction
  – Few queries posed and few answers seen (first page)
  – Reformulation common
• Smaller and different vocabulary
  – Not “expert” searchers!
  – “Which box do I type in?”
Classified Queries

[from SIGIR 2008 Tutorial, Baeza-Yates and Jones]
People Look at Only a Few Results

“When you perform a search on a search engine and don’t find what you are looking for, at what point do you typically either revise your search, or move on to another search engine? (Select one)”

- 27% After reviewing more than 3 pages
- 25% After reviewing the first 3 pages
- 20% After reviewing the first 2 pages
- 16% After reviewing the first page
- 12% After reviewing the first few entries

(Source: iprospect.com WhitePaper_2006_SearchEngineUserBehavior.pdf)
Snippet Views Depend on Rank

Mean: 3.07 Median: 2.00
Snippet Views and Clicks Depend on Rank

![Graph showing the percentage of fixations and clicks for different ranks of abstracts.](image)

**Figure 1:** Percentage of times an abstract was viewed/clicked depending on the rank of the result.

[from Joachims et al, SIGIR 2005]

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“Eyes are a Window to the Soul”

- **Eye tracking** gives information about search interests:
  - Eye position
  - Pupil diameter
  - Seekads and fixations

Eugene Agichtein, Emory University, IR Lab

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Micro-level: Examining Results

- Users rapidly scan the search result page.
- What they see in lower summaries may influence judgment of higher results.
- Spend most time scrutinizing top results.
  - Trust the ranking.

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Result Examination (cont’d)

• Searchers might use the mouse to focus reading attention, bookmark promising results, or not at all.

• Behavior varies with task difficulty and user expertise

Macro-Level (Session) Analysis

- Can examine theoretical user models in light of empirical data:
  - Orienteering?
  - Foraging?
  - Multi-tasking?

- Search is often a multi-step process:
  - Find or navigate to a good site ("orienteering")
  - Browse for the answer there: [actor most oscars] vs. [ oscars]

- Teleporting
  - "I wouldn’t use Google for this, I would just go to…"

- Triangulation
  - Draw information from multiple sources and interpolate
  - Example: “how long can you last without food?”
Users (sometimes) Multi-task

[Daniel M. Russell, 2007]

<table>
<thead>
<tr>
<th>User ID</th>
<th>Query Term</th>
<th>Time (s)</th>
<th>Duration (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>Google Search [free roulette]</td>
<td>4s</td>
<td>78</td>
</tr>
<tr>
<td>102</td>
<td>Google Result 7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>103</td>
<td>Google Result 7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>106</td>
<td>Google Result 8</td>
<td>56s</td>
<td>100</td>
</tr>
<tr>
<td>112</td>
<td>Google Search [shockwave]</td>
<td>4s</td>
<td></td>
</tr>
<tr>
<td>114</td>
<td>Google Result 3</td>
<td>10s</td>
<td></td>
</tr>
<tr>
<td>117</td>
<td>Google Result 5</td>
<td>16s</td>
<td>112</td>
</tr>
<tr>
<td>120</td>
<td>Google Search [free roulette]</td>
<td>3s</td>
<td>78</td>
</tr>
<tr>
<td>122</td>
<td>Google Result 1</td>
<td>15s</td>
<td>DUPE</td>
</tr>
<tr>
<td>124</td>
<td>Google Search [free professional roulette]</td>
<td>2s</td>
<td></td>
</tr>
<tr>
<td>126</td>
<td>Google Search (spell correct)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>128</td>
<td>Google Result 3</td>
<td>5s</td>
<td></td>
</tr>
<tr>
<td>129</td>
<td>Google Result 3</td>
<td>8s</td>
<td>DUPE</td>
</tr>
<tr>
<td>133</td>
<td>Google Result 7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Kinds of Search+Browsing Behavior

[Daniel M. Russell, 2007]

- Short / Nav
- Topic exploration
- Topic switch
- Methodological results exploration
- Query reform

- Multitasking
- Stacking behavior

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Variance in Behavior between Novice and Expert Searchers

[White & Morris, 2007]

• Some people are more expert at searching than others
  – Search expertise, not domain expertise

• Find characteristics of these “advanced search engine users” in an effort to better understand how these users search

• If we can better understand what advanced searchers are doing maybe we can improve the search experience for everyone
Characterizing Advanced Searchers

[White & Morris, 2007]

- Four advanced operators used: +, -, “”, and “site:”
  - ~1% of submitted queries contained at least one operator
  - 51K users (9%) of users used query operators at least once

- \textit{padvanced} used to denote the percentage of a user’s queries that contain advanced operators
  - Non-advanced users (\textit{padvanced} = 0%)
  - Advanced users (\textit{padvanced} > 0%)

- Included users who issued > 50 queries
  - ~38K (20%) advanced users
  - ~151K (80%) non-advanced users
Findings: Query/Result-click

[White & Morris, 2007]

• Factor analysis to study the relationships among the dependent variables

• Factor analysis revealed two factors that could account for ~84% of the variance:
  – Factor A = Querying
    • Query properties associated with position of clicks in result list
  – Factor B = Result-click
    • Querying frequency associated with the likelihood that user will click on a search result and click latency
Search Sessions

[White & Morris, 2007]

• Session
  – Query → Timeout

• Query trail
  – Query → End trail event
    • Another query
    • Type URL
    • Visit homepage
    • Check Web-based online service
    • Close browser
    • Session timeout
Findings – Post-query browsing

Advanced users:
- Traverse trails faster
- Spend less time viewing each Web page
- Follow query trails with fewer steps
- Revisit pages less often
- “Branch” less often

<table>
<thead>
<tr>
<th>Feature</th>
<th>$P_{\text{advanced}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td>Session Secs</td>
<td>701.10</td>
</tr>
<tr>
<td>Trail Secs</td>
<td>205.39</td>
</tr>
<tr>
<td>Display Secs</td>
<td>36.95</td>
</tr>
<tr>
<td>Num. Steps</td>
<td>4.88</td>
</tr>
<tr>
<td>Num. Revisits</td>
<td>1.20</td>
</tr>
<tr>
<td>Num. Branches</td>
<td>1.55</td>
</tr>
<tr>
<td>%Trails</td>
<td>72.14%</td>
</tr>
<tr>
<td>%Users</td>
<td>79.90%</td>
</tr>
</tbody>
</table>

Non-advanced  Advanced  More advanced

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Findings – Post-query browsing

[White & Morris, 2007]

• Greater the proportion of queries with advanced syntax the more focused their search interactions become
  – Shorter query trails
  – Less “branchy” query trails

• Session time increases but search time drops with increases in advanced
  – Perhaps more advanced users are multitasking between search and other activities
Lecture Plan

• Understanding user behavior at micro-, meso-, and macro- levels

• Theoretical models of information seeking

✓ Web search behavior:
  ✓ Levels of detail
  ✓ Search Intent
  ✓ Variations in web searcher behavior
  ➢ Keeping found things found
  – Click models
ReFinding Behavior

[From Teevan et al, 2007]

• 40% of the queries led to a same user had clicked on in a past search session.
  – Teevan et al., 2007

• What’s the URL for this year’s RuSSIR?
  – Does not really matter, it is faster to re-find it

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What Is Known About Re-Finding

[From Teevan et al, 2007]

- Re-finding recent topic of interest
- Web re-visitation common [Tauscher & Greenberg]
- People follow known paths for re-finding
  - Search engines likely to be used for re-finding
- Query log analysis of re-finding
  - Query sessions [Jones & Fain]
  - Temporal aspects [Sanderson & Dumais]
Click on previously clicked results?

[From Teevan et al, 2007]

<table>
<thead>
<tr>
<th></th>
<th>1 click</th>
<th>&gt; 1 click</th>
<th>Click same and different?</th>
<th>Click on different results?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same query issued before?</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Navigational</td>
<td>3100 (24%)</td>
<td>36 (&lt;1%)</td>
<td>635 (5%)</td>
<td>485 (4%)</td>
</tr>
<tr>
<td>Re-finding with different query</td>
<td>637 (5%)</td>
<td>4 (&lt;1%)</td>
<td>660 (5%)</td>
<td>7503 (57%)</td>
</tr>
</tbody>
</table>
How Queries Change
[From Teevan et al, 2007]

• Many ways queries can change
  – Capitalization ("new york" and "New York")
  – Word swap ("britney spears" and "spears britney")
  – Word merge ("walmart" and "wal mart")
  – Word removal ("orange county venues" and "orange county music venues")

• 17 types of change identified
  – 2049 combinations explored
  – Log data and supplemental study
  – Most normalizations require only one type of change
Rank Change Reduces Re-Finding
[From Teevan et al, 2007]

• Results change rank
• Change reduces probability of repeat click
  – No rank change: 88% chance
  – Rank change: 53% chance
• Why?
  – Gone?
  – Not seen?
  – New results are better?
Gone? Not Seen? Better?

[From Teevan et al, 2007]
Change Slows Re-Finding

[From Teevan et al, 2007]

• Look at time to click as proxy for *Ease*
• Rank change $\rightarrow$ slower repeat click
  – Compared with initial search to click
  – No rank change: Re-click is faster
  – Rank change: Re-click is slower
• Changes interferes and stability helps
Helping People Re-Find

• Potential way to take advantage of stability
  – Automatically determine if the task is re-finding
  – Keep results consistent with expectation
  – Simple form of personalization

• Can we automatically predict if a query is intended for re-finding?
Predicting the Query Target

• For simple navigational queries, predict what URL will be clicked
• For complex repeat queries, two binary classification tasks:
  – Will a new (never visited) result be clicked?
  – Will an old (previously visited) result be clicked?
Predicting Navigational Queries

- Predict navigational query clicks using
  - Query issued twice before
  - Queries with the same one result clicked

- Very effective prediction
  - 96% accuracy: Predict one of the results clicked
  - 95% accuracy: Predict first result clicked
  - 94% accuracy: Predict only result clicked
Predicting More Complex Queries

• Trained an SVM to identify
  – If a new result will be clicked
  – If an old result will be clicked

• Effective features:
  – Number of previous searches for the same thing
  – Whether any or the results were clicked >1 time
  – Number of clicks each time the query was issued

• Accuracy around 80% for both prediction tasks
Re-Finding Summary

- Log analysis supplemented by a user study

- Re-finding is very common
  - Navigational queries are particularly common
  - Categorized potential re-finding behavior
  - Explored ways query strings are modified

- Stability of result rank impacts re-finding tasks

- Can identify refinding queries with 80-90% accuracy
Lecture Plan

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✓ Web search behavior:
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  ✓ Variations in web searcher behavior
  ✓ Keeping found things found
  ➢ Click models
Automatic Click models

• Clickthrough and subsequent browsing behavior of individual users influenced by many factors
  – Relevance of a result to a query
  – Visual appearance and layout
  – Result presentation order
  – Context, history, etc.
Hypothesis 1: No Bias

[Crasswell et al., 2008]

• Our baseline

\[ C_{di} = r_d = C_{d} \]

– cdi is \( P(\text{Click}=\text{True} \mid \text{Document}=d, \text{Position}=i) \)
– rd is \( P(\text{Click}=\text{True} \mid \text{Document}=d) \)

• Why this baseline?
  – We know that rd is part of the explanation
  – Perhaps, for ranks 9 vs 10, it’s the main explanation
  – It is a bad explanation at rank 1 e.g. Eye tracking
Hypothesis 2: Blind Clicks

- There are two types of user/interaction
  - Click based on relevance
  - Click based on rank (blindly)

\[ C_{di} = \lambda r_d + (1 - \lambda) b_i \]

- A.k.a. the OR model:
  - Clicks arise from relevance OR position
Hypothesis 3: Examination

[Crasswell et al., 2008]

- Users are less likely to look at lower ranks, therefore less likely to click

\[ C_{dl} = r_d x_i \]

- This is the AND model
  - Clicks arise from relevance AND examination
  - Probability of examination \( x_i \) does not depend on what else is in the list
Cascade Model Diagram

- Query
- URL1
- URL2
- URL3
- URL4

Relevance:
- \[ r_1 \rightarrow r_2 \rightarrow r_3 \rightarrow r_4 \]

ClickThroughs:
- \[ c_1 \rightarrow c_2 \rightarrow c_3 \rightarrow c_4 \]
Hypothesis 4: Cascade

[Taylor et al., 2008]

• Users examine the results in rank order
• At each document $d$
  – Click with probability $r_d$
  – Or continue with probability $(1-r_d)$

\[
C_{di} = r_d \prod_{j=1}^{i-1} (1 - r_{docinrank:j})
\]
Cascade Model Example

[Craswell et al., 2008]

- 500 users typed a query
- 0 click on result A in rank 1
- 100 click on result B in rank 2
- 100 click on result C in rank 3

- Cascade (with no smoothing) says:
  - 0 of 500 clicked A \( \Rightarrow r_A = 0 \)
  - 100 of 500 clicked B \( \Rightarrow r_B = 0.2 \)
  - 100 of remaining 400 clicked C \( \Rightarrow r_C = 0.25 \)

This may seem different from the formulation on the previous slide, but is precisely equivalent.
Cascade Model Seems Closest to Reality

[Craswell et al., 2008]

<table>
<thead>
<tr>
<th>Model</th>
<th>Cross Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Possible</td>
<td>0.141 ± 0.0055</td>
</tr>
<tr>
<td>Cascade</td>
<td>0.225 ± 0.0052</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.236 ± 0.0063</td>
</tr>
<tr>
<td>Examination</td>
<td>0.247 ± 0.0072</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.250 ± 0.0073</td>
</tr>
</tbody>
</table>

Best possible: Given the true click counts for ordering BA
Problem: Users click based on result “Snippets” [Clarke et al., 2007]
Clickthrough Inversions

[Clarke et al., 2007]
Relevance is Not the Dominant Factor!

[Clarke et al., 2007]

<table>
<thead>
<tr>
<th>Relationship</th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>rel(A) &lt; rel(B)</td>
<td>119</td>
<td>33.5%</td>
</tr>
<tr>
<td>rel(A) = rel(B)</td>
<td>134</td>
<td>37.7%</td>
</tr>
<tr>
<td>rel(A) &gt; rel(B)</td>
<td>102</td>
<td>28.7%</td>
</tr>
</tbody>
</table>

Figure 3: Relevance relationships at clickthrough inversions. Compares relevance between the higher ranking member of a caption pair (rel(A)) to the relevance of the lower ranking member (rel(B)), where caption A received fewer clicks than caption B.
## Snippet Features Studied

[Clarke et al., 2007]

<table>
<thead>
<tr>
<th>Feature Tag</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MissingSnippet</td>
<td>snippet missing in caption A and present in caption B</td>
</tr>
<tr>
<td>SnippetShort</td>
<td>short snippet in caption A (&lt; 25 characters) with long snippet (&gt; 100 characters) in caption B</td>
</tr>
<tr>
<td>TermMatchTitle</td>
<td>title of caption A contains matches to fewer query terms than the title of caption B</td>
</tr>
<tr>
<td>TermMatchTS</td>
<td>title+snippet of caption A contains matches to fewer query terms than the title+snippet of caption B</td>
</tr>
<tr>
<td>TermMatchTSU</td>
<td>title+snippet+URL of caption A contains matches to fewer query terms than caption B</td>
</tr>
<tr>
<td>TitleStartQuery</td>
<td>title of caption B (but not A) starts with a phrase match to the query</td>
</tr>
<tr>
<td>QueryPhraseMatch</td>
<td>title+snippet+url contains the query as a phrase match</td>
</tr>
<tr>
<td>MatchAll</td>
<td>caption B contains one match to each term; caption A contains more matches with missing terms</td>
</tr>
<tr>
<td>URLQuery</td>
<td>caption B URL is of the form <code>www.query.com</code> where the query matches exactly with spaces removed</td>
</tr>
<tr>
<td>URLSlashes</td>
<td>caption A URL contains more slashes (i.e. a longer path length) than the caption B URL</td>
</tr>
<tr>
<td>URLLenDiff</td>
<td>caption A URL is longer than the caption B URL</td>
</tr>
<tr>
<td>Official</td>
<td>title or snippet of caption B (but not A) contains the term “official” (with stemming)</td>
</tr>
<tr>
<td>Home</td>
<td>title or snippet of caption B (but not A) contains the phrase “home page”</td>
</tr>
<tr>
<td>Image</td>
<td>title or snippet of caption B (but not A) contains a term suggesting the presence of an image gallery</td>
</tr>
<tr>
<td>Readable</td>
<td>caption B (but not A) passes a simple readability test</td>
</tr>
</tbody>
</table>
# Feature Importance

[Clarke et al., 2007]

<table>
<thead>
<tr>
<th>Feature Tag</th>
<th>INV+</th>
<th>INV−</th>
<th>%+</th>
<th>CON+</th>
<th>CON−</th>
<th>%+</th>
<th>$\chi^2$</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>MissingSnippet</td>
<td>185</td>
<td>121</td>
<td>60.4</td>
<td>144</td>
<td>133</td>
<td>51.9</td>
<td>4.2443</td>
<td>0.0393</td>
</tr>
<tr>
<td>SnippetShort</td>
<td>20</td>
<td>6</td>
<td>76.9</td>
<td>12</td>
<td>16</td>
<td>42.8</td>
<td>6.4803</td>
<td>0.0109</td>
</tr>
<tr>
<td>TermMatchTitle</td>
<td>800</td>
<td>559</td>
<td>58.8</td>
<td>660</td>
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Eugene Agichtein
Emory University

RuSSIR 2009: Modeling User Behavior and Interactions
### Important Words in Snippet

[Clarke et al., 2007]

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**Figure 6: Words exhibiting the greatest positive (↑) and negative (↓) influence on clickthrough patterns.**
Click Models Summary

Models proposed to simulate searcher click process

- Increasingly sophisticated and theories
- Assume searcher is rational and consistent

But, searchers are not rational or careful:

- Attracted/repelled by simple features of summaries

Will incorporate summary and browsing info to extract relevance information from clicks (next lecture)
Lecture 1 Summary. Questions?

✓ Understanding user behavior at micro-, meso-, and macro-levels

✓ Theoretical models of information seeking

✓ Web search behavior:
  ✓ Levels of detail
  ✓ Search Intent
  ✓ Variations in web searcher behavior
  ✓ Keeping found things found
  ✓ Click models
References and Further Reading


• **Teevan, J., Adar, E., Jones, R. and Potts, M.** *Information Re-Retrieval: Repeat Queries in Yahoo's Logs*, SIGIR 2007

• **Clarke, C, E. Agichtein, S. Dumais and R. W. White**, *The Influence of Caption Features on Clickthrough Patterns in Web Search*, SIGIR 2007

• **Craswell, N., Zoeter, O., Taylor, M., Ramsey, B.** *An experimental comparison of click position-bias models*, WSDM 2008

• **Dupret, G and Piwowarski, B**: A user browsing model to predict search engine click data from past observations. SIGIR 2008

• **White, R and D. Morris,** *Investigating the Querying and Browsing Behavior of Advanced Search Engine Users*, SIGIR 2007