Enterprise and Desktop Search

Lecture 2: Searching the Enterprise Web

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Germany
Outline

• Searching the Enterprise Web
  – What works and what doesn’t (Fagin 03, Hawking 04)

• User Feedback in Enterprise Web Search
  – Explicit vs Implicit feedback (Joachims 02, Radlinski 05)
  – User Annotations (Dmitriev 06, Poblete 08, Chirita 07)
  – Social Annotations (Millen 06, Bao 07, Xu 07, Xu 08)
  – User Activity (Bilenko 08, Xue 03)
  – Short-term User Context (Shen 05, Buscher 07)
Searching the Enterprise Web
Searching the Workplace Web

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• How is Enterprise Web different from the Public Web?
  – Structural differences

• What are the most important features for search?
  – Use Rank Aggregation to experiment with different ranking methods and features
Enterprise Web vs Public Web: Structural Differences

Structure of the Public Web [Broder 00]
Enterprise Web vs Public Web: Structural Differences

!! Structure of Enterprise Web [Fagin 03] !!

- Implications:
  - More difficult to crawl
  - Distribution of PageRank values is such that larger fraction of pages has high PR values, thus PR may be less effective in discriminating among regular pages
Rank Aggregation

• Input: several ranked lists of objects

• Output: a single ranked list of the union of all the objects which minimizes the number of “inversions” wrt initial lists

• NP-hard to compute for 4 or more lists
• Variety of heuristic approximations exist for computing either the whole ordering or top k [Dwork 01, Fagin 03-1]

Rank Aggregation can also be useful in Enterprise Search for combining rankings from different data source
What are the most important features?

- Create 3 indices: Content, Title, Anchortext (aggregated text from the <a> tags pointing to the page)
- Get the results, rank them by tf-idf, and feed to the ranking heuristics
- Combine the results using Rank Aggregation
- Evaluate all possible subsets of indices and heuristics on very frequent (Q1) and medium frequency (Q2) queries with manually determined correct answers
## Results

$I_{Ri}(a)$ is “influence” of the ranking method $a$

### Observations:

- Anchortext is by far the most influential feature
- Title is very useful, too
- Content is ineffective for $Q1$, but is useful for $Q2$
- PR is useful, but does not have a huge impact

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$I_{R1}(\alpha)$</th>
<th>$I_{R3}(\alpha)$</th>
<th>$I_{R5}(\alpha)$</th>
<th>$I_{R10}(\alpha)$</th>
<th>$I_{R20}(\alpha)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ti</td>
<td>29.2</td>
<td>13.6</td>
<td>5.6</td>
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<td>An</td>
<td>24.0</td>
<td>47.1</td>
<td>58.3</td>
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</tr>
<tr>
<td>Co</td>
<td>3.3</td>
<td>-6.0</td>
<td>-7.0</td>
<td>-4.4</td>
<td>-2.7</td>
</tr>
<tr>
<td>Le</td>
<td>3.3</td>
<td>4.2</td>
<td>1.8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>De</td>
<td>-9.7</td>
<td>-4.0</td>
<td>-3.5</td>
<td>-2.9</td>
<td>-4.0</td>
</tr>
<tr>
<td>Wo</td>
<td>3.3</td>
<td>0</td>
<td>-1.8</td>
<td>0</td>
<td>1.4</td>
</tr>
<tr>
<td>Di</td>
<td>0</td>
<td>-2.0</td>
<td>-1.8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PR</td>
<td>0</td>
<td>13.6</td>
<td>11.8</td>
<td>7.9</td>
<td>2.7</td>
</tr>
<tr>
<td>In</td>
<td>0</td>
<td>-2.0</td>
<td>-1.8</td>
<td>1.5</td>
<td>0</td>
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<tr>
<td>Da</td>
<td>0</td>
<td>4.2</td>
<td>5.6</td>
<td>4.6</td>
<td>0</td>
</tr>
</tbody>
</table>

### Inference 1.

- Title index improves the accuracy of the top $k$ by nearly 100%.

### Inference 2.

- Table 1 also shows that the title index is the single largest improvement for the top $k$. Interestingly, the title index is very useful, too.

### Inference 3.

- While PageRank is uniformly good, contrary to its important role on the Internet, it does not add much value. Its value is more evident when we consider different perForems.

# Table 2: Influences of various ranking heuristics on recall

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$I_{R1}(\alpha)$</th>
<th>$I_{R3}(\alpha)$</th>
<th>$I_{R5}(\alpha)$</th>
<th>$I_{R10}(\alpha)$</th>
<th>$I_{R20}(\alpha)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ti</td>
<td>6.7</td>
<td>8.7</td>
<td>3.4</td>
<td>3.0</td>
<td>0</td>
</tr>
<tr>
<td>An</td>
<td>23.1</td>
<td>31.6</td>
<td>30.4</td>
<td>21.4</td>
<td>15.2</td>
</tr>
<tr>
<td>Co</td>
<td>-6.2</td>
<td>-4.0</td>
<td>3.4</td>
<td>0</td>
<td>5.6</td>
</tr>
<tr>
<td>Le</td>
<td>6.7</td>
<td>-4.0</td>
<td>0</td>
<td>0</td>
<td>-5.3</td>
</tr>
<tr>
<td>De</td>
<td>-18.8</td>
<td>-8.0</td>
<td>-10</td>
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<td>-7.9</td>
</tr>
<tr>
<td>Wo</td>
<td>6.7</td>
<td>-4.0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Di</td>
<td>-6.2</td>
<td>-4.0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PR</td>
<td>6.7</td>
<td>4.2</td>
<td>11.1</td>
<td>6.2</td>
<td>2.7</td>
</tr>
<tr>
<td>In</td>
<td>-6.2</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Da</td>
<td>14.3</td>
<td>4.2</td>
<td>3.4</td>
<td>0</td>
<td>2.7</td>
</tr>
</tbody>
</table>
Challenges in Enterprise Search

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This study confirms most of the findings if [Fagin 03] on 6 different Enterprise Webs (results for 4 datasets are shown)

- Anchortext and title are still the best
- Content is also useful
Summary

• Enterprise Web and Public Web exhibit significant structural differences

• These differences result in some features very effective for web search not being so effective for Enterprise Web Search
  – Anchortext is very useful (but there is much less of it)
  – Title is good
  – Content is questionable
  – PageRank is not as useful
Using User Feedback in Enterprise Web Search
Using User Feedback

• One of the most promising directions in Enterprise Search
  – Can trust the feedback (no spam)
  – Can provide incentives
  – Can design a system to facilitate feedback
  – Can actually implement it

• We will look at several different sources of feedback
  – Clicks (very briefly)
  – Explicit Annotations
  – Queries
  – Social Annotations
  – Browsing Traces
Sources of Feedback in Web Search

• Explicit Feedback
  – Overhead for user
  – Only few users give feedback
    => not representative

• Implicit Feedback
  – Queries, clicks, time, mousing, scrolling, etc.
  – No Overhead
  – More difficult to interpret

[Joachims 02, Radlinski 05]
Using Click Data to Improve Search

• Very active area of research in both academia and industry, mostly in the context of Public Web search, but can be applied to Enterprise Web search as well

• The idea is treat clicks as relevance votes ("clicked"="relevant"), or as preference votes ("clicked page" > "non-clicked page"), and then use this information to modify the search engine’s ranking function

Explicit and Implicit Annotations
Using Annotations in Enterprise Search

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• Anchortext is the most important ranking feature for Enterprise Web Search
• But the quantity of the anchortext is very limited in the Enterprise
• Can we use user annotations as a substitute for anchortext?
Explicit Annotations

• Create a Toolbar to allow users annotate pages they visit

• Provide incentives to annotate:
  – Personal annotation appears in the toolbar every time user visits the page
  – Aggregated annotations from all users appear in search engine results
## Examples of Explicit Annotations

<table>
<thead>
<tr>
<th>Annotation</th>
<th>Annotated Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>change IBM passwords</td>
<td>Page about changing various passwords in IBM intranet</td>
</tr>
<tr>
<td>stockholder account access</td>
<td>Login page for IBM stock holders</td>
</tr>
<tr>
<td>download page for Cloudscape and Derby</td>
<td>Page with a link to Derby download</td>
</tr>
<tr>
<td>ESPP home</td>
<td>Details on Employee Stock Purchase Plan</td>
</tr>
<tr>
<td>EAMT home</td>
<td>Enterprise Asset Management homepage</td>
</tr>
<tr>
<td>PMR site</td>
<td>Problem Management Record homepage</td>
</tr>
<tr>
<td>coolest page ever</td>
<td>Homepage of an IBM employee</td>
</tr>
<tr>
<td>most hard-working intern</td>
<td>an intern’s personal information page</td>
</tr>
<tr>
<td>good mentor</td>
<td>an employee’s personal information page</td>
</tr>
</tbody>
</table>
Implicit Annotations

• Mine annotations from query logs
  – Treat queries as annotations for relevant pages
  – While such annotations are of lower quality, a large number of them can be collected easily

```
LogRecord ::= <Query> | <Click>
Query ::= <Time>\t<QueryString>\t<UserID>
Click ::= <Time>\t<QueryString>\t<URL>\t<UserID>
```

• How to determine “relevant” pages? [Joachims 02, Radlinski 05]
Strategy 1

• Assume every clicked page is relevant
  – Simple to implement
  – Produces a large number of annotations
  – But may attach an annotation to an irrelevant page
Strategy 2

• *Session* = time ordered sequence of clicks a user makes for a given query

• Assume only the last click in the session is relevant
  – Produces less annotations
  – Avoids assigning annotations to irrelevant pages
Strategies 3 & 4

• *Query Chain* = time ordered sequence of queries executed over a short period of time

• Strategy 3: Assume every click in the query chain is relevant

• Strategy 4: Assume only the last click in the last session of the query chain is relevant
Experimental Results

- Dataset: 5.5M index of IBM intranet
- Queries: 158 test queries with manually identified correct answers
- Evaluation was conducted after 2 weeks since starting collecting the annotations

<table>
<thead>
<tr>
<th>Baseline</th>
<th>EA</th>
<th>IA 1</th>
<th>IA 2</th>
<th>IA 3</th>
<th>IA 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.9%</td>
<td>13.9%</td>
<td>8.9%</td>
<td>8.9%</td>
<td>9.5%</td>
<td>9.5%</td>
</tr>
</tbody>
</table>

Table 2: Summary of the results measured by the percentage of queries for which the correct answer was returned in the top 10. EA = Explicit Annotations, IA = Implicit Annotations.
P-TAG: Large Scale Automatic Generation of Personalized Annotation TAGs for the Web

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²National University of Ireland / DERI, IDA Business Park, Lower Dangan, Galway, Ireland
Siegfried.Handschuh@deri.org

• Want to generate personalized web page annotations based on documents on the user’s Desktop

• Suppose we have an index of Desktop documents on the user’s computer (files, email, browser cache, etc.)
Extracting tags from Desktop documents

• Given a web page to annotate, the algorithm proceeds as follows:
  – Step 1: Extract important keywords from the page
  – Step 2: Retrieve relevant documents using the Desktop search
  – Step 3: Extract important keywords from the retrieved documents as annotations

• Users judged 70%-80% of annotations created using this algorithm as relevant
Query-Sets: Using Implicit Feedback and Query Patterns to Organize Web Documents

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Ricardo Baeza-Yates  
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Barcelona Media Innovation Center  
Barcelona, Spain  
ricardo@baeza.cl

• When have lots of annotations for a given page, which ones should we use?
• This paper proposes to perform frequent itemset mining to extract recurring groups of terms from annotations
  – Show that this type of processing is useful for web page classification
  – May also be useful for improving search quality by eliminating noisy terms
Summary

• User Annotations can help improve search quality in the Enterprise

• Annotations can be collected by explicitly asking users to provide them, or by mining query logs and users’ Desktop contents

• Post-processing the resulting annotations may help to improve the search quality
Social Annotations
Tagging

• Easy way for the users to annotate web objects
• People do it (no one really knows why)
Tagging

• Very popular on the Web, becoming more and more popular in the Enterprise
  – Users add tags to objects (pages, pictures, messages, etc.)
  – Tagging System keeps track of <user, obj, tag> triples and mines/organizes this information for presenting it to the user (more in Lecture 3)

• In this lecture we will see how tags can be used to improve search in enterprise web
Using Tagging to Improve Search

- Approach 1: Merge tags with content or anchortext
- Approach 2: Keep tags separate and rank query results by
  \[ \alpha \times content\_match + (1 - \alpha) \times tag\_match \]
- Other approaches: explore the social/collaborative properties of tags
  - Give more weight to some users and tags vs others
  - Compute similarities between tags and documents and incorporate it into ranking
Optimizing Web Search Using Social Annotations
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{feiben, suzhong}@cn.ibm.com

- **Observation**: similar (semantically related) annotations are usually assigned to similar (semantically related) web pages
  - The similarity among annotations can be identified by similar web pages they are assigned to
  - The similarity among web pages can be identified by similar annotations they are annotated with
- Proposed iterative algorithm to compute these similarities and use them to improve ranking
Algorithm 1: SocialSimRank (SSR)

Step 1  **Init:**  Let $S^0_A (a_i, a_j) = 1$ for each $a_i = a_j$ otherwise 0

$$S^0_P (p_i, p_j) = 1$$ for each $p_i = p_j$ otherwise 0

Step 2  **Do** { 

*Similarity of annotations*  $a_i$ and $a_j$ 

For each annotation pair $(a_i, a_j)$ do

$$S_{A}^{k+1} (a_i, a_j) = \frac{C_A}{|P(a_i)||P(a_j)|} \sum_{m=1}^{P(a_i)} \sum_{n=1}^{P(a_j)} \frac{\min(M_{AP}(a_i, p_m), M_{AP}(a_j, p_n))}{\max(M_{AP}(a_i, p_m), M_{AP}(a_j, p_n))} S_{P}^{k} (p_m(a_i), p_n(a_j))$$  \hspace{1cm} (2)

*Similarity of pages*  $p_i$ and $p_j$ 

For each page pair $(p_i, p_j)$ do

$$S_{P}^{k+1} (p_i, p_j) = \frac{C_P}{|A(p_i)||A(p_j)|} \sum_{m=1}^{A(p_i)} \sum_{n=1}^{A(p_j)} \frac{\min(M_{AP}(a_m, p_i), M_{AP}(a_n, p_j))}{\max(M_{AP}(a_m, p_i), M_{AP}(a_n, p_j))} S_{A}^{k+1} (a_m(p_i), a_n(p_j))$$  \hspace{1cm} (3)

} Until $S_A(a_i, a_j)$ converges.

Step 3  **Output:** $S_A(a_i, a_j)$
Using Annotation Similarity for Ranking

- Given a query \( q = \{q_1, \ldots, q_n\} \), a page \( p \), and a set of annotations \( A(p) = \{a_1, \ldots, a_m\} \), “social similarity” of \( q \) and \( p \) can be computed as follows:

\[
\text{sim}_{SSR} \left(q, p \right) = \sum_{i=1}^{n} \sum_{j=1}^{m} S_A(q_i, a_j)
\]

- Combine different ranking features using RankSVM (Joachims 02)

<table>
<thead>
<tr>
<th>DocSimilarity</th>
<th>Similarity between query and page content</th>
</tr>
</thead>
<tbody>
<tr>
<td>TermMatching (TM)</td>
<td>Similarity between query and annotations using the term matching method.</td>
</tr>
<tr>
<td>SocialSimRank (SSR)</td>
<td>Similarity between query and annotations based on SocialSimRank.</td>
</tr>
</tbody>
</table>

*See (Xu 07) for how to use annotation similarity in a Language Modeling framework*
Experimental Results

• Data from Delicious: 1,736,268 pages, 269,566 different annotations

Example:
Top 4 related annotations for different categories

<table>
<thead>
<tr>
<th>Technology related:</th>
</tr>
</thead>
<tbody>
<tr>
<td>dublin</td>
</tr>
<tr>
<td>debian</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Economy related:</th>
</tr>
</thead>
<tbody>
<tr>
<td>adsense</td>
</tr>
<tr>
<td>800</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Entertainment related:</th>
</tr>
</thead>
<tbody>
<tr>
<td>album</td>
</tr>
<tr>
<td>chat</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Entity related:</th>
</tr>
</thead>
<tbody>
<tr>
<td>einstein</td>
</tr>
<tr>
<td>christian</td>
</tr>
</tbody>
</table>
Experimental Results

• Two query sets:
  – MQ50: 50 queries manually generated by students
  – AQ3000: 3000 queries auto-generated from ODP

• Measure NDCG and MAP:

<table>
<thead>
<tr>
<th>Method</th>
<th>MQ50</th>
<th>AQ3000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.4115</td>
<td>0.1091</td>
</tr>
<tr>
<td>Baseline +TM</td>
<td>0.4341</td>
<td>0.1128</td>
</tr>
<tr>
<td>Baseline +SSR</td>
<td>0.4697</td>
<td>0.1147</td>
</tr>
</tbody>
</table>
What about PageRank?

• **Observation**: popular web pages attract hot social annotations and bookmarked by up-to-date users

• Use these properties to estimate popularity of pages (SocialPageRank)
Algorithm 2: SocialPageRank (SPR)

Step 1

Input:
Association matrices $M_{PU}$, $M_{AP}$, and $M_{UA}$ and the random initial SocialPageRank score $P_0$

Step 2

Do:

Page-User association matrix $\rightarrow U_i = M_{PU}^T \cdot P_i$ (5.1)

User-Ann. association matrix $\rightarrow A_i = M_{UA}^T U_i$ (5.2)

Ann.-Page association matrix $\rightarrow P_i' = M_{AP} A_i$ (5.3)

$A_i' = M_{AP} \cdot P_i'$ (5.4)

$U_i' = M_{UA} \cdot A_i'$ (5.5)

$P_{i+1} = M_{PU} \cdot U_i'$ (5.6)

Until $P_i$ converges.

Step 3:

Output:

$P^*$: the converged SocialPageRank score.
Experimental Results

- Using SocialPageRank significantly improves both MAP and NDCG measures:
Exploring Folksonomy for Personalized Search

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- **Observation**: social annotations characterize well topics of pages and interests of users

- Rank query results for query $q$, page $p$, user $u$ as follows:

  $$r(u, q, p) = \gamma \cdot r_{term}(q, p) + (1 - \gamma) \cdot r_{topic}(u, p)$$

- Compute $r_{topic}(u, p)$ as cosine similarity between annotations of $u$ and annotations of $p$
Experimental Results

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Num. Users</th>
<th>Max. Tags</th>
<th>Min. Tags</th>
<th>Avg. Tags</th>
<th>Max. Pages</th>
<th>Min. Pages</th>
<th>Avg. Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delicious</td>
<td>9813</td>
<td>2055</td>
<td>1</td>
<td>56.04</td>
<td>1790</td>
<td>1</td>
<td>40.35</td>
</tr>
<tr>
<td>Dogear</td>
<td>5192</td>
<td>2288</td>
<td>1</td>
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<td>4578</td>
<td>1</td>
<td>46.78</td>
</tr>
<tr>
<td>DEL.gt500</td>
<td>31</td>
<td>1133</td>
<td>74</td>
<td>464.42</td>
<td>1790</td>
<td>506</td>
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<td>100</td>
<td>80</td>
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<td>1</td>
<td>18.53</td>
<td>10</td>
<td>5</td>
<td>7.44</td>
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<td>999.04</td>
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<td>80</td>
<td>89.32</td>
</tr>
<tr>
<td>DOG.5-10</td>
<td>100</td>
<td>41</td>
<td>2</td>
<td>16.11</td>
<td>10</td>
<td>5</td>
<td>6.99</td>
</tr>
</tbody>
</table>

- Observed 75%-250% improvement in MAP for all datasets
- Improvement is larger for the datasets where users who own less bookmarks, because typically their annotations are semantically richer
Summary

• Social Annotations (tags) can help improve search quality in the Enterprise

• While they can be directly used as features for the ranking function, exploiting their collaborative properties helps to further improve search quality

• Annotations can also be used to infer users’ interests and provide personalized search results
Users’ Browsing Traces
Mining the Search Trails of Surfing Crowds: Identifying Relevant Websites From User Activity

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- Observe users’ browsing behavior after entering a query and clicking on a search result
- Rank web sites for a new query based on how heavily they were browsed by users after entering same or similar queries
- Use it as a feature in search ranking algorithm
Search Trails

- Start with a search engine query
- Continue until a terminating event
  - Another search
  - Visit to an unrelated site (social networks, webmail)
  - Timeout, browser homepage, browser closing
Using Search Trails for Ranking

- **Approach 1: Adapt BM25 scoring function**

\[
wd_{i,t_j} = QTF_{i,j} \cdot IQF_j = \frac{(\lambda + 1)n(d_i, t_j)}{\lambda((1 - \beta) + \beta \frac{n(d_i)}{n(d)})} \cdot \log \frac{N_d - n(t_j) + 0.5}{n(t_j) + 0.5}
\]

Instead of term frequency in a document use sum of logs of dwell times on \(d_i\) from queries containing \(t_j\)

Instead inverse doc frequency use #docs for which queries leading to them include \(t_j\)

- **Approach 2: Probabilistic model**

\[
Rel_P(d_i, \hat{q}) = p(d_i|\hat{q}) = \sum_{\hat{t}_j \in q} p(\hat{t}_j|\hat{q})p(d_i|\hat{t}_j)
\]
Experimental Results

• Dataset: 140 million search trails; 33,150 queries with 5-point scale human judgments (site gets highest relevance score of all its pages)

• Add the web site rank feature to RankNet (Burges 05)

• Measure improvement in NDCG
Implicit Link Analysis for Small Web Search

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• Use all users’ browsing traces to infer “implicit links” between pairs of web pages
• Intuitively, there is an implicit link between two pages if they are visited together on many browsing paths
• Construct a graph with pages as nodes and implicit links as edges and use it to calculate PageRank
Implicit Link Generation

• Use gliding window to move over each browsing path generating all ordered pairs of pages and counting occurrence of each pair

\[(w_{i1}, w_{i2}, w_{i3}, \ldots, w_{ik})\]

\[(i1, i2), (i1,i3), \ldots, (i1, ik), (i2,i3), \ldots, (i2, ik), \ldots\]

• Select pairs which have frequency > \(t\) as implicit links
Using Implicit Links in Ranking

- Calculate PageRank based on the web graph with implicit links
- Combine PageRank and content-based similarity using a weighted linear combination
- Approach 1: use raw scores
  \[ Score(w) = \alpha Sim + (1 - \alpha) PR \quad (\alpha \in [0, 1]) \]
- Approach 2: use ranks instead of scores
  \[ Score(w) = \alpha OSim + (1 - \alpha) OPR \quad (\alpha \in [0, 1]) \]
Experimental Results

• Dataset: 4-months logs from [www.cs.berkeley.edu](http://www.cs.berkeley.edu) (300,000 traces; 170,000 pages; 60,000 users)
• 216,748 explicit links; 336,812 implicit links (11% are common to both sets)
• 10 queries; volunteers identify relevant pages and 10 most authoritative pages for each query out of top 30 results
• Measure “Precision @ 30” and “Authority @ 10”
Experimental Results
Summary

• User browsing traces can be collected easily in the Enterprise

• Two types of traces:
  – Traces starting from search engine queries
  – Arbitrary traces

• Traces are very useful for calculating authoritativness of web pages and web sites, and can be successfully used to improve search ranking
Short-term User Context and Eye-tracking based Feedback
Context-Sensitive Information Retrieval Using Implicit Feedback

- Two types of user context information:
  - Short-term context
  - Long-term context

- Long-term context:
  - User’s topics of interest, department and position, accumulated query history, desktop context, etc.

- Short-term context:
  - Queries and clicks in the same session, the text user has read in the past 5 min, etc.
Problem of Context-Independent Search
 Putting Search in Context

**Apple software**

**Search**

Web Results 1 - 10 of about 18,700,000 for Jaguar

**Jaguar**
Official worldwide web site of Jaguar Cars.
www.jaguar.com - Similar pages

**Jaguar Cars**
Click here to be redirected to www.jaguar.com.
www.jaguar.comcars.com/-1k - May 21, 2005 - Cached - Similar pages

**Apple - Mac OS X**
The Apple Mac OS X product page. Describes features in the current version of Mac OS X, a screenshot gallery, latest software downloads, and a directory of ...
www.apple.com/macosx/-33k - May 21, 2005 - Cached - Similar pages

**Jaguar**
General information and facts from Big Cats Online.
dspace.dial.pipex.com/Jaguar/Jaguar.htm - 12k - May 21, 2005 - Cached - Similar pages

**Jaguar UK - R is for Racing**
... Le Mans winning C-TYPE - the first car ever to have disc brakes - Jaguar’s racing technology has been bred into the bloodline of every Jaguar, ...
www.jaguar-racing.com/-19k - Cached - Similar pages

**Jaguar US - home**
... Sales Satisfaction. Jaguar provides the most exquisite sales experience. ... The Answer is Jaguar. Why is Jaguar the superior choice? ...
www.jaguarusa.com/-24k - Cached - Similar pages

**Jaguar AU - Jaguar Cars**
Information on new, preowned, services and news on models.
www.jaguar.com.au/-36k - May 21, 2005 - Cached - Similar pages

**Schrödinger -> Site Map**
... Jaguar, Publications, Brochure, Liaison, Brochure, LiaPrep, Brochure, MacroModel, Publications, Brochure, Maestro, Brochure, Phase, Brochure ...
www.schrodinger.com/SiteMap.php?mid=3&sid=0&cid=0 - 62k - May 21, 2005 - Cached - Similar pages

Other Context Info:
- Dwelling time
- Mouse movement
- Clickthrough
- Query History

Hobby...
Short-term Contexts

• Will look at 2 types of short-term contexts:
  – *Session Query History*: preceding queries issued by the same user in the current session
  – *Session Clicked Summary*: concatenation of the displayed text about the clicked urls in the current session

• Will use language modeling framework to incorporate the above data into the ranking function
Using Short-term Contexts for Ranking

• Basic Retrieval Model:
  – For each document $D$ build a unigram language model $\theta_D$, specifying $p(\omega | \theta_D)$
  – Given a query $Q$, build a query language model $\theta_Q$, specifying $p(\omega | \theta_Q)$
  – Rank the documents according to the KL divergence of the two models:
    \[
    D(\theta_Q \parallel \theta_D) = \sum_{\omega} P(\omega | \theta_Q) \log \frac{P(\omega | \theta_Q)}{P(\omega | \theta_D)}
    \]

• Assuming user already issued $k-1$ queries $Q_1, \ldots, Q_{k-1}$, want to estimate the “context query model” $\theta_k$ specifying $p(\omega | \theta_k)$ for the current query $Q_k$ to use instead of $\theta_Q$
Using Short-term Contexts for Ranking

- **Fixed Coefficient Interpolation:**

  \[
  p(w|Q_i) = \frac{c(w, Q_i)}{|Q_i|}
  \]

  \[
  p(w|H_Q) = \frac{1}{k-1} \sum_{i=1}^{i=k-1} p(w|Q_i)
  \]

  \[
  p(w|C_i) = \frac{c(w, C_i)}{|C_i|}
  \]

  \[
  p(w|H_C) = \frac{1}{k-1} \sum_{i=1}^{i=k-1} p(w|C_i)
  \]

  \[
  p(w|H) = \beta p(w|H_C) + (1 - \beta)p(w|H_Q)
  \]

  \[
  p(w|\theta_k) = \alpha p(w|Q_k) + (1 - \alpha)[\beta p(w|H_C) + (1 - \beta)p(w|H_Q)]
  \]
Using Short-term Contexts for Ranking

- Problem with Fixed Coefficient Interpolation is that the coefficients are the same for all queries. Want to trust the current query more if it is longer and less if it is shorter.
- Bayesian Interpolation:

\[
p(w|\theta_k) = \frac{c(w, Q_k) + \mu p(w|H_Q) + \nu p(w|H_C)}{|Q_k| + \mu + \nu}
\]

\[
= \frac{|Q_k|}{|Q_k| + \mu + \nu} p(w|Q_k) + \frac{\mu + \nu}{|Q_k| + \mu + \nu} \left[ \frac{\mu}{\mu + \nu} p(w|H_Q) + \frac{\nu}{\mu + \nu} p(w|H_C) \right]
\]

Coefficients depend on the query length.
Experimental Results

• Dataset: TREC Associated Press set of news articles (~250,000 articles)
• Select 30 most difficult topics, have volunteers issue 4 queries for each topic and record query reformulation and clickthrough information
• Measure MAP and Precision@20
Experimental Results

• Results show that incorporating contextual information significantly improves the results

<table>
<thead>
<tr>
<th>Query</th>
<th>FixInt ($\alpha = 0.1, \beta = 1.0$)</th>
<th>BayesInt ($\mu = 0.2, \nu = 5.0$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAP</td>
<td>pr@20docs</td>
</tr>
<tr>
<td>$q_1$</td>
<td>0.0095</td>
<td>0.0317</td>
</tr>
<tr>
<td>$q_2$</td>
<td>0.0312</td>
<td>0.1150</td>
</tr>
<tr>
<td>$q_2 + H_Q + H_C$</td>
<td>0.0324</td>
<td>0.1117</td>
</tr>
<tr>
<td>Improve.</td>
<td>3.8%</td>
<td>-2.9%</td>
</tr>
<tr>
<td>$q_3$</td>
<td>0.0421</td>
<td>0.1483</td>
</tr>
<tr>
<td>$q_3 + H_Q + H_C$</td>
<td>0.0726</td>
<td>0.1967</td>
</tr>
<tr>
<td>Improve</td>
<td>72.4%</td>
<td>32.6%</td>
</tr>
<tr>
<td>$q_4$</td>
<td>0.0536</td>
<td>0.1933</td>
</tr>
<tr>
<td>$q_4 + H_Q + H_C$</td>
<td>0.0891</td>
<td>0.2233</td>
</tr>
<tr>
<td>Improve</td>
<td>66.2%</td>
<td>15.5%</td>
</tr>
</tbody>
</table>

• Additional experiments showed that improvement is mostly due to using Session Clicked Summaries
Attention-Based Information Retrieval

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- Feedback on sub-document level should allow for better retrieval improvements
- Use an eye-tracker to automatically detect which portions of the displayed document were read or skimmed
- Determine which parts of the document are of interest to the user
How can we use this?

• For each page, can aggregate the “visual annotations” across the users of the enterprise
• Can construct a precise short-term user context
Summary

• Using short-term user context to improve search quality is a new and very promising direction of research
• Initial results show that it can be very effective
• Using eye tracking can help to improve the quality and increase the amount of the context data
• Many unexplored applications: on-the-fly reranking, abstract personalization, etc.
Interesting Problems and Promising Research Directions

• Applying the techniques we talked about to improve Enterprise Web search, extending them to better suit Enterprise environment

• Models for the Enterprise Web which take into account its complex structure and allow for expressing different usage data

• Personalization in the Enterprise Web search (usage data + employee personal info)

• Using context (recent history + desktop info) to improve Enterprise Web search
References


• [Hawking 04] Hawking, D. “Challenges in Enterprise Search”. ADC Conference, Dunedin, NZ.


References