Query Chains: Learning to Rank from Implicit Feedback

Filip Radlinski, Thorsten Joachims
KDD’05

CSE 450 Web Mining Seminar
Jian Wang
Roadmap

- **Analysis of User Behavior**
- Analysis of Implicit Feedback
- Learning Ranking Functions
- Conclusion and Future Work

- Reference: Accurately Interpreting Clickthrough Data as Implicit Feedback, Thorsten Joachims, Laura Granka, BingPan, Helene Hemebrooke & Geri Gay, SIGIR’05
Analysis of User Behavior

- Which links do users view and click

Figure 1: Percentage of times an abstract was viewed/clicked depending on the rank of the result.
Analysis of User Behavior (contd)

- Do users scan links from top to bottom

Figure 2: Mean time of arrival (in number of previous fixations) depending on the rank of the result.
Analysis of User Behavior (contd)

- Which links do users evaluate before clicking

Table 2: Percentage of times the user viewed an abstract at a particular rank before he clicked on a link at a particular rank.

<table>
<thead>
<tr>
<th>Viewed Rank</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>90.6%</td>
<td>76.2%</td>
<td>73.9%</td>
<td>60.0%</td>
<td>54.5%</td>
<td>45.5%</td>
</tr>
<tr>
<td>2</td>
<td>56.8%</td>
<td>90.5%</td>
<td>82.6%</td>
<td>53.3%</td>
<td>63.6%</td>
<td>54.5%</td>
</tr>
<tr>
<td>3</td>
<td>30.2%</td>
<td>47.6%</td>
<td>95.7%</td>
<td>80.0%</td>
<td>81.8%</td>
<td>45.5%</td>
</tr>
<tr>
<td>4</td>
<td>17.3%</td>
<td>19.0%</td>
<td>47.8%</td>
<td>93.3%</td>
<td>63.6%</td>
<td>45.5%</td>
</tr>
<tr>
<td>5</td>
<td>8.6%</td>
<td>14.3%</td>
<td>21.7%</td>
<td>53.3%</td>
<td>100.0%</td>
<td>72.7%</td>
</tr>
<tr>
<td>6</td>
<td>4.3%</td>
<td>4.8%</td>
<td>8.7%</td>
<td>33.3%</td>
<td>18.2%</td>
<td>81.8%</td>
</tr>
</tbody>
</table>

Figure 3: Mean number of abstracts viewed above and below a clicked link depending on its rank.
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Analysis of Implicit Feedback

- Does relevance influence user decisions

- Are clicks absolute relevance judgments
  - Trust bias
  - Quality bias
Analysis of Implicit Feedback (contd)

<table>
<thead>
<tr>
<th>Click ( q ) Skip Above</th>
<th>Click ( q ) No-Click Second</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q )[q]</td>
<td>( q )[q]</td>
</tr>
<tr>
<td>( x )([x]q)</td>
<td>( x )([x]q)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Click ( q' ) Skip Above</th>
<th>Click ( q' ) No-Click Second</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q' )([q']q)</td>
<td>( q' )([q']q)</td>
</tr>
<tr>
<td>( x )([x]q')</td>
<td>( x )([x]q')</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Click ( q' ) Skip Earlier Query</th>
<th>Click ( q' ) Top Two Earlier Query</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q' )([q']q) ( x )([x]q')</td>
<td>( q' )([q']q) ( x )([x]q')</td>
</tr>
</tbody>
</table>

\[
\begin{align*}
\frac{q_1}{d_1} & \quad \frac{q_2}{d_4 \times} \\
\frac{d_2 > q_1}{d_1} & \quad \frac{d_4 > q_2}{d_5} \\
\frac{d_3}{d_6} & \quad \frac{d_4 > q_1 d_1}{d_4 > q_1 d_3}
\end{align*}
\]
Analysis of Implicit Feedback (contd)

- How accurately do clicks correspond to explicit judgment of a document?

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Click (&gt;q) Skip Above</td>
<td>78.2 ± 5.6</td>
</tr>
<tr>
<td>Click First (&gt;q) No-Click Second</td>
<td>63.4 ± 16.5</td>
</tr>
<tr>
<td>Click (&gt;q) Skip Earlier Query</td>
<td>68.0 ± 8.4</td>
</tr>
<tr>
<td>Click (&gt;q) Top Two Earlier Query</td>
<td>84.5 ± 6.1</td>
</tr>
<tr>
<td>Inter-Judge Agreement</td>
<td>86.4</td>
</tr>
</tbody>
</table>

Table 1: Accuracy of the strategies for generating pairwise preferences from clicks. The base of comparison are the explicit page judgments. Note that the first two cases cover two preferences strategies each.
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Reference: Optimizing Search Engines using Clickthrough Data, Thorsten Joachims, SIGKDD’02
• Evaluation Environment
  • Nutch search engine as a starting point
  • Osmot search engine effectively being a wrapper around Nutch

• Detecting query chains
  • Train a number of SVM classifiers with various parameters, with accuracy of 94.3% and precision of 96.5%
  • A simple non-learning strategy, with accuracy and precision of 91.6%
Learning Ranking Functions

\[ d_i >_q d_j \]
\[ \text{rel}(d_i, q) = w \cdot \Phi(d_i, q) \]

- Ranking SVMs

\[ w \cdot \Phi(d_i, q) \geq w \cdot \Phi(d_j, q) + 1 - \xi_{ij} \]
\[ \min_{w, \xi_{ij}} \frac{1}{2} w \cdot w + C \sum_{ij} \xi_{ij} \]
\[ \text{subject to} \quad \forall (q, i, j) : w \cdot \Phi(d_i, q) \geq w \cdot \Phi(d_j, q) + 1 - \xi_{ij} \]
\[ \forall i, j : \xi_{ij} \geq 0 \]

- Retrieval Function Model

\[ \Phi(d, q) = \begin{bmatrix} \phi_{r_{\text{rank}}}^f (d, q) \\ \vdots \\ \phi_{r_{\text{rank}}}^f (d, q) \\ \phi_{\text{terms}} (d, q) \end{bmatrix}, \quad \phi_{r_{\text{rank}}}^f (d, q) = \begin{bmatrix} 1(\text{Rank}(d \text{ in } r^f_0 (d, q)) \leq 1) \\ \vdots \\ 1(\text{Rank}(d \text{ in } r^f_0 (q)) \leq 10) \\ 1(\text{Rank}(d \text{ in } r^f_0 (q)) \leq 15) \\ \vdots \\ 1(\text{Rank}(d \text{ in } r^f_0 (q)) < 100) \end{bmatrix} \]
\[ \phi_{\text{terms}} (d, q) = \begin{bmatrix} 1(d = d_1 \land t_1 \in q) \\ \vdots \\ 1(d = d_M \land t_N \in q) \end{bmatrix} \]
Learning Ranking Functions (contd)

- Adding Prior Knowledge

\[ \forall i \in [1, 28|F|]. \ w^i \geq w_{\text{min}} \]

- Results and Discussion

<table>
<thead>
<tr>
<th>Evaluation Mode</th>
<th>Chains</th>
<th>User Prefers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Other</td>
</tr>
<tr>
<td>( rel_{QC} ) vs. ( rel_0 )</td>
<td>392 (32%)</td>
<td>239 (20%)</td>
</tr>
<tr>
<td>( rel_{QC} ) vs. ( rel_{NC} )</td>
<td>211 (17%)</td>
<td>160 (13%)</td>
</tr>
</tbody>
</table>
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Conclusion and Future Work

• Query chains can be used to extract useful information from search engine

• Tolerance to noise in training data?
• Position of a query within a chain? Position of a click within all clicks?
• Learn personalized ranking functions?
• Alternative learning methods?