Learning to Rank Search Results for Time-Sensitive Queries

Nattiya Kanhabua
L3S Research Center
Leibniz Universität, Hannover, Germany
kanhabua@L3S.de

Kjetil Nørvåg
Department of Computer Science
Norwegian University of Science and Technology
Trondheim, Norway
noervaag@idi.ntnu.no

Problem Statement
• Searching temporal collections, e.g., news archives or blogs, is difficult because relevant documents/queries are time-dependent.
  - Documents are about events happening at particular time.
  - Queries contain temporal information needs, e.g., Indian Ocean tsunami 2004, Germany FIFA World Cup, or US Presidential Election 2008.
• Taking into account the time dimension in ranking can significantly improve the effectiveness of time-sensitive queries [1,2,3,4,5,6].
• Previous time-aware ranking models follow two main approaches:
  (1) a mixture model linearly combining textual and temporal similarity
  (2) a probabilistic model generating a given query from the textual and the temporal parts of documents independently

Contributions
• We propose a novel time-aware ranking model based on learning-to-rank techniques and two classes of features extracted from annotated documents: entity-based features and temporal features.
• Extensive experiments using the New York Times Annotated Corpus, and temporal queries and relevance assessments from [4].

Document Model
• A temporal collection consists of unstructured textual documents.
• A document $d$ is composed of a bag of words $d_{text}$ and time:
  - $PubTime(d)$, the publication date of $d$
  - $ContentTime(d)$, temporal expressions mentioned in $d$
• Annotated document $d'$ is composed of:
  - Named entities $d'_e = \{e_1, \ldots, e_n\}$
  - Temporal expressions $d'_t = \{t_1, \ldots, t_m\}$
  - A set of annotated sentences $d'_s = \{s_1, \ldots, s_z\}$

Temporal Query Model
• A temporal query $q$ is composed of keywords $q_{text}$ and temporal expressions $q_{time}$ which can be explicitly provided as part of a query, or have temporal intent implicitly provided [5].

Time-aware Ranking Model
• A learning-to-rank model is trained using labeled query/document pairs by different learning algorithms, e.g., SVM$^{MAP}$ and RankSVM.
• Given an unseen document/query pair $(d', q')$, a document $d'$ will be ranked according to a weighted sum of its feature scores:

\[
\text{score}(d', q') = \sum_{i=1}^{N} w_i \times x_i^{d'}
\]

Temporal Features
• $LMT$ [4] measures the temporal similarity between $q$ and $d$ by considering $ContentTime(d)$, but ignore time uncertainty.
• $LMTU$ [4] uses temporal expressions mentioned in a document $ContentTime(d)$, and take into account time uncertainty.
• $TS$ [5] is computed similarly to $LMT$, but $PubTime(d)$ is used instead of the content time of a document.
• $TSU$ employs $PubTime(d)$ not the content time, and captures time uncertainty using an exponential decay function.
• $FuzzySet$ [3] exploits $PubTime(d)$ and captures time uncertainty between $q$ and $d$ using a fuzzy membership function.

Experimental Results

<table>
<thead>
<tr>
<th>Model</th>
<th>P@10</th>
<th>P@50</th>
<th>P@100</th>
<th>MRR</th>
<th>MAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tfidf</td>
<td>0.375</td>
<td>0.415</td>
<td>0.410</td>
<td>0.562</td>
<td>0.460</td>
</tr>
<tr>
<td>LatIN</td>
<td>0.500</td>
<td>0.570</td>
<td>0.579</td>
<td>0.625</td>
<td>0.478</td>
</tr>
<tr>
<td>LaoEX</td>
<td>0.415</td>
<td>0.405</td>
<td>0.408</td>
<td>0.588</td>
<td>0.447</td>
</tr>
<tr>
<td>LaoQU</td>
<td>0.475</td>
<td>0.490</td>
<td>0.493</td>
<td>0.639</td>
<td>0.475</td>
</tr>
<tr>
<td>LaoUX</td>
<td>0.520</td>
<td>0.520</td>
<td>0.520</td>
<td>0.570</td>
<td>0.500</td>
</tr>
<tr>
<td>LatKSM</td>
<td>0.550</td>
<td>0.550</td>
<td>0.550</td>
<td>0.691</td>
<td>0.576</td>
</tr>
<tr>
<td>SQSVM</td>
<td>0.575</td>
<td>0.575</td>
<td>0.575</td>
<td>0.700</td>
<td>0.584</td>
</tr>
<tr>
<td>PegasosSVM</td>
<td>0.550</td>
<td>0.540</td>
<td>0.540</td>
<td>0.690</td>
<td>0.595</td>
</tr>
<tr>
<td>PA-precision</td>
<td>0.475</td>
<td>0.475</td>
<td>0.475</td>
<td>0.630</td>
<td>0.460</td>
</tr>
<tr>
<td>FuzzySet</td>
<td>0.495</td>
<td>0.495</td>
<td>0.495</td>
<td>0.665</td>
<td>0.565</td>
</tr>
</tbody>
</table>

| Table 2: Feature analysis.

<table>
<thead>
<tr>
<th>Feature</th>
<th>P@10</th>
<th>P@50</th>
<th>P@100</th>
<th>MRR</th>
<th>MAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>timeSim</td>
<td>0.100</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>querySim</td>
<td>0.200</td>
<td>0.400</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
</tr>
<tr>
<td>docSim</td>
<td>0.300</td>
<td>0.500</td>
<td>0.600</td>
<td>0.600</td>
<td>0.600</td>
</tr>
<tr>
<td>entitySim</td>
<td>0.400</td>
<td>0.600</td>
<td>0.700</td>
<td>0.700</td>
<td>0.700</td>
</tr>
</tbody>
</table>

References