Evaluating Retrieval over Sessions: The TREC Session Track 2011–2014

Ben Carterette
University of Delaware,
Newark, DE, USA
carteret@cis.udel.edu

Paul Clough
University of Sheffield,
Sheffield, UK
p.d.clough@sheffield.ac.uk

Mark Hall
Edge Hill University, Ormskirk,
UK
hallmark@edgehill.ac.uk

Evangelos Kanoulas
University of Amsterdam,
Amsterdam, The Netherlands
e.kanoulas@uva.nl

Mark Sanderson
RMIT University, Melbourne,
Australia
mark.sanderson@rmit.edu.au

ABSTRACT

Information Retrieval (IR) research has traditionally focused on serving the best results for a single query—so-called ad hoc retrieval. However, users typically search iteratively, refining and reformulating their queries during a session. A key challenge in the study of this interaction is the creation of suitable evaluation resources to assess the effectiveness of IR systems over sessions. This paper describes the TREC Session Track, which ran from 2010 through to 2014, which focussed on forming test collections that included various forms of implicit feedback. We describe the test collections; a brief analysis of the differences between datasets over the years; and the evaluation results that demonstrate that the use of user session data significantly improved effectiveness.

1. INTRODUCTION

One of the commonest IR system evaluation methodologies is the Cranfield approach [4] using test collections to conduct controlled, systematic, and repeatable evaluations [7]. The focus of such evaluation is on how well an IR system can locate and rank relevant documents from a single query. In practice, however, users typically reformulate queries in response to search results or as their information need alters over time [9]. Retrieval evaluation should compute system success over multiple query-response interactions [10].

The TREC Session Track1 was an attempt to evaluate IR systems over multi-query sessions. In 2010, the track produced test collections and evaluation measures for studying retrieval over sessions [11]; from 2011 on [12, 13, 1, 2], the track focused more on providing participants with user data with which to improve retrieval. The resulting collections consist of document collections, topics, and relevance assessments, as well as log data from user sessions.

The track’s test collections are described here and compared: including studying the effects of the search engines used to build the collections, user variability, and topic analysis. Participant results indicate that certain types of search benefit significantly from exploiting session information.

2. SESSION TRACK OVERVIEW

The aim of the track was to test if the retrieval effectiveness of a query could be improved by using previous queries, ranked results, and user interactions. We constructed four test collections comprising N sessions of varying length, each the result of a user attempting to satisfy one of T pre-defined topics. Each session numbered 1…N consisted of:

• $m_i$ blocks of user interactions (the session’s length);
• the current query $q_m$, in the session;
• $m_i - 1$ blocks of interactions in the session prior to the current query, composed of:
  1. the user queries in the session, $q_1, q_2, ..., q_{m_i-1}$;
  2. the ranked list of URLs seen by the user for each of those queries;
  3. the set of clicked URLs/snippets.

Ranking algorithms were evaluated on the current query under two conditions: A one-off ad hoc query; or a query using some or all of the prior logged data. The latter condition had several different sub-conditions that varied year to year: (*RL* refers to Ranked List):

• RL1: The baseline condition: an ad hoc query
• RL2-1: RL1 plus previous session queries
• RL2-2: RL2-1 plus rankings (URLs, titles, snippets)
• RL2-3: RL2-2 plus user data (clicks, dwell times)
• RL3: Using all data in the session log (in particular, other sessions on the same topic)

The focus of the track was on the degree to which a group improved their retrieval system’s baseline effectiveness (RL1) by incorporating some or all of the additional log data.

3. TEST COLLECTIONS

Table 1 shows statistics of the Session track collections. The ClueWeb09 collection was used in 2011 and 2012, and the ClueWeb12 collection in 2013 and 2014.

Topics: While not a part of a true log of user search activity, we felt it was important to define topic descriptions for overall sessions so as to make relevance assessing

1http://ir.cis.udel.edu/sessions/
Table 1: Four years of TREC Session Track test collections and evaluations

<table>
<thead>
<tr>
<th>topic properties</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>topic set size</td>
<td>62</td>
<td>48</td>
<td>61</td>
<td>60†</td>
</tr>
<tr>
<td>topic cat. dist.</td>
<td>known-item‡</td>
<td>10 exploratory,</td>
<td>10 exploratory,</td>
<td>15 exploratory,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>6 interpretive,</td>
<td>9 interpretive,</td>
<td>15 interpretive,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 known-item,</td>
<td>32 known-item,</td>
<td>15 known-item,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>12 known-subj</td>
<td>10 known-subj</td>
<td>15 known-subj</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>session properties</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>user population</td>
<td>U. Sheffield</td>
<td>U. Sheffield</td>
<td>U. Sheffield + IR researchers</td>
<td>MTurk</td>
</tr>
<tr>
<td>search engine</td>
<td>BOSS+CW09 filter</td>
<td>BOSS+CW09 filter</td>
<td>indri</td>
<td>indri</td>
</tr>
<tr>
<td>total sessions</td>
<td>76</td>
<td>98</td>
<td>133</td>
<td>1,257</td>
</tr>
<tr>
<td>sessions per topic</td>
<td>1.2</td>
<td>2.0</td>
<td>2.2</td>
<td>21.0</td>
</tr>
<tr>
<td>mean length (in queries)</td>
<td>3.7</td>
<td>3.0</td>
<td>3.7</td>
<td>3.7</td>
</tr>
<tr>
<td>median time between queries</td>
<td>68.5s</td>
<td>66.7s</td>
<td>72.2s</td>
<td>25.6s</td>
</tr>
<tr>
<td>topics judged</td>
<td>62</td>
<td>48</td>
<td>49</td>
<td>51</td>
</tr>
<tr>
<td>total judgments</td>
<td>19,413</td>
<td>17,861</td>
<td>13,132</td>
<td>16,949</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>evaluation by nDCG@10</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean RL1</td>
<td>0.3015</td>
<td>0.1847</td>
<td>0.1373</td>
<td>0.1719</td>
</tr>
<tr>
<td>mean RL2-1</td>
<td>0.3083</td>
<td>0.1950</td>
<td>0.1373</td>
<td>0.1719</td>
</tr>
<tr>
<td>mean RL2-2</td>
<td>0.2941</td>
<td>0.2140</td>
<td>0.1832</td>
<td>0.1885</td>
</tr>
<tr>
<td>mean RL2-3</td>
<td>0.3077</td>
<td>0.2303</td>
<td>0.2303</td>
<td>0.2303</td>
</tr>
<tr>
<td>mean RL3</td>
<td></td>
<td></td>
<td>0.1834</td>
<td>0.2002</td>
</tr>
<tr>
<td>max RL* - RL1</td>
<td>0.1800</td>
<td>0.1770</td>
<td>0.1230</td>
<td>0.1507</td>
</tr>
</tbody>
</table>

† 2011 topics were not categorized, but a retrospective analysis suggests most of them fit the “known-item” label best.
‡ 2014 topics were reused 2012 and 2013 topics.
§ The RL2-1 and RL2-2 conditions were eliminated for 2013 and 2014; the RL3 condition was introduced in 2013.

simpler. The challenge was to construct topics that were likely to require multiple query reformulations. In 2011, we did this by adapting multi-faceted TREC 2007 Question Answering track topics. Because of the nature of the QA track, many topics modelled “fact-finding” tasks answerable by a single document. In 2012-2013, we developed topics according to a task categorization scheme [15] with four classes: known-item; known-subject; interpretive; and exploratory. In 2014, we reused topics from 2012-2013 selecting fifteen topics from the four categories, biasing selection to topics that had longer user sessions and more clicks.

Sessions: Assessing the impact of session data on retrieval effectiveness required capturing user-system interactions, including queries, rankings, and clicks. We describe the users and search engines employed to generate the data.

Users: In 2011-2013, the primary user group were staff and students at the University of Sheffield. Using a university-wide email, we invited participants to search on as many topics as they had time for. In 2013 we solicited additional participants from the Session Track and SIG-IRList mailing lists. In 2014 we used a crowdsourcing platform (Mechanical Turk) taking a similar approach to past work for crowdsourcing interactions [18].

Search process: Users were shown a topic description, a search box for entering queries, and a list of ten ranked results with a pagination control to navigate to further results. Each retrieved item was represented by its title, URL, and snippet. Additionally, there was a “Save” button that users were instructed to use to collect those documents that helped them satisfy their information need. We experimented with additional components, such as a list of queries issued, but did not observe a difference in users’ behaviour.

Search engine: In 2011-2012 we used Yahoo!’s BOSS (Build your Own Search System) API to search the live web. We filtered URLs returned by BOSS against those in the ClueWeb09 collection so that users would only see pages that were present in the publicly-available corpus. A large number of pages returned by BOSS did not match any URL in ClueWeb09. In 2013-2014, we switched to indri search with a home-built index of ClueWeb12. The indri index included each of the twenty ClueWeb12 segments (ClueWeb12_00 through ClueWeb12_19) indexed using the Krovetz stemmer and no stopword list. The indexes searched contained only text from title fields, anchor text from incoming links ("inlink" text), and page URLs. Each query was incorporated into an indri structured query language template and a retrieval score was computed from a query-likelihood model for the full document representation and three weighted combinations of query-likelihood field models with unordered-window within-field models. The “inlink” model was weighted 50 times higher than the title model, and 100 times higher than the URL model. This query template is the product of manual search and investigation of retrieved results.

The system logged all interactions with the user, including the queries issued, which documents were ranked (including URL, title, and snippet), which documents the user viewed, and which they saved as relevant to the task (note however that the latter are not the relevance judgments). This log data was then used to create the sessions.

4. EVALUATION

We used topical relevance judgments in order to compute measures of effectiveness like nDCG@10 for each topic. Since the Session Track examines whether session log data can be exploited, the evaluation examined the change in effectiveness from the baseline (RL1) to using some data (RL2) to using a full query log (RL3). In addition, since each topic may be the subject of more than one session, and
5. **ANALYSIS**

In this section we perform some basic analysis of the Session Track collections and evaluation results.

**Topic categories:** We investigated the degree to which systems were able to improve effectiveness for each of our four topic classes. We look at the average improvement from the RL1 baseline, and find the maximum average improvement to any other RL condition for each run.

The overall mean improvements are 0.04, 0.07, 0.04, and 0.05 for known-item, known-subject, exploratory, and interpretive respectively, though only the differences between known-subject and the others were statistically significant. This suggests that known-subject topics benefit most from access to session history, but the details are more subtle. Exploratory topics tend to have the largest improvements for individual systems: the five largest improvements in exploratory topics are 5–10% larger than the five largest in known-subject topics. Exploratory topics also show the greatest benefit from the use of more log data: from RL1 to RL2, exploratory topics only increase an average of 0.03 (compare to 0.05 for known-subject topics, the largest improvement), but from RL2 to RL3 they increase by 0.05 (compare to 0.04 for known-subject topics, the second-largest improvement).

**Topic variability:** Most IR test collections have only one instantiation of a topic (an exception is the TREC Query track). Since we may have multiple sessions for any given topic, the Session Track gives us a chance to analyze variability in effectiveness within topics.

Figure 3 shows how much effectiveness varies over the different user sessions of a single topic. Each plot on the y-axis is a topic, the y-axis is a boxplot of the range in nDCG@10 changes from RL1 to any other RL. A taller box means more variability. A point or box plotted further up the y-axis indicates higher average change in nDCG@10 across the sessions.
of a topic. An extreme case is topic 24 from 2012 (the right most topic on the plot); one group improved from 0.00 in RL1 to 0.91 in RL3 on one session, but fell from 0.81 in RL1 to 0.00 in RL2 on another. Many other groups had similarly large differences across sessions on this topic.

The result indicates that there is a substantial variability in topics, separate from the variability in system effectiveness, due to the way the users perform their search and formulates their query. Previous user study showed this as well [14]. It may be beneficial to include multiple versions of the same topic in standard test collections, so as to better capture interactions between topic and system variability.

6. CONCLUSION

This paper describes the four test collections produced for the TREC Session Track that have been used to assess the use of implicit feedback on retrieval performance within sessions. The key result from the track is that aggregate data from all participant submissions shows that retrieval effectiveness was improved for ad hoc retrieval using data based on session history data. It also appears that the more detailed the session data, the greater the improvement.

Through analyzing aspects of the test collections, such as topic categories and variability, we demonstrate how resources can be used to investigate implicit feedback and offer reusable and publicly-accessible resources for evaluating IR systems across sessions.

7. ACKNOWLEDGEMENTS

This work was supported in part by the Australian Research Council’s Discovery Projects scheme (DP130104007), the National Science Foundation (NSF) under grant number IIS-1350799, and the Google Faculty Research Award scheme. Any opinions, findings and conclusions or recommendations expressed in this material are the authors’ and do not necessarily reflect those of the sponsors.

8. REFERENCES


