ABSTRACT
This paper reports the use of a document distance-based approach to automatically expand the number of available relevance judgements when these are limited and reduced to only positive judgements. This may happen, for example, when the only available judgements are extracted from a list of references in a published review paper. We compare the results on two document sets: OHSUMED, based on medical research publications, and TREC-8, based on news feeds. We show that evaluations based on these expanded relevance judgements are more reliable than those using only the initially available judgements, especially when the number of available judgements is very limited.

Categories and Subject Descriptors
H.2.4 [Systems]: Textual databases; H.3.4 [Systems and Software]: Performance evaluation

Keywords
Information Retrieval, Evaluation, Relevance Judgements Expansion

1. INTRODUCTION
An important bottleneck in the development of information retrieval (IR) systems is their evaluation. Generating human-produced judgements is expensive and time-consuming, and it is not always possible to produce a large set of relevance judgements (qrels henceforth).

We envisage a scenario where the only available qrels are the list of references of a survey paper. For example, within the area of Evidence Based Medicine (EBM), clinical systematic reviews provide the key published evidence that is relevant to a specific clinical query, together with a list of references that backs up the clinical evidence. This list of references, however, covers only a small sample of all relevant references. Furthermore, only a fraction of the documents of a systematic review can be retrieved after performing exhaustive searches, mostly due to the fact that there are complex queries and several document repositories. Another problem with using the list of references as the only qrels is that negative qrels, that is, judgements about non-relevant documents, are not included. Any attempts to develop IR systems for such a scenario will need to supplement the list of references with something else. In this paper we propose to automatically expand the qrels by finding similar documents.

2. RELATED WORK
Using document distance as a criterion to expand a list of qrels sounds intuitive. The approach is related to the well-known cluster hypothesis: “closely associated documents tend to be relevant to the same requests” [9]. This hypothesis has been typically used to improve the quality of the retrieval of documents but there is very limited past work using the cluster hypothesis to improve the quality of the evaluation.

Previous work on the expansion of an initial set of document assessments include the use of Machine Learning. For example, Büttcher et al. [1] trained over a subset of qrels in order to expand the set of qrels. They showed that evaluation results with the expanded set of qrels had better quality than using the source subset of qrels. Quality of the evaluation was measured by ranking a set of IR systems according to the new expanded qrels, and comparing it against the system ordering produced by the original qrels. In the clinical domain, Martinez et al. [6] explored the use of re-ranking methods based on reduced judgements, and found that the use of automatic classifiers would allow to considerably reduce the time required for clinicians to identify a large portion (95%) of the relevant documents. Both of these articles reported limitations of the classifiers when the initial number of documents was small. Furthermore, in the scenario that we contemplate, where we rely on the list of references of a systematic review as the set of qrels, we do not have information about negative qrels, and therefore a classifier-based approach to expand the set of relevant documents would have to deal with this issue.

More recent work [8] has shown that by relying on documents retrieved frequently by a diverse set of systems, it is
section

| BM25 | BM25 | DFR | DLH |
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| DFR  | DFR  | InL2| DLH |
| expB2| expC2| Pl2 | TF  |
| LGO | Hiemstra_L-M | InL2 | TF_JDF |

Table 1: List of 16 runs from the terrier package

possible to build relevance assessments automatically, and achieve high correlation with manually judged data. However, this approach has been tested by building on a set of competing runs from different research groups, which is not always available; and this method does not benefit from existing qrels.

Prior work using document distance criteria for expanding the qrels includes [7], who suggests that this approach may work for a document collection within the medical domain. In this paper we show that this approach improves the quality of evaluation both for medical and news reports, and we therefore add further evidence of the plausibility of this method.

Our work complements that of related work on the study of the impact of the number of topics and relevance judgements in IR evaluation [2].

3. DATA SETS

We use the OHSUMED collection of medical research publications, and the TREC-8 collection of news feeds.

The OHSUMED collection [4] is a corpus containing clinical queries and assessments. We focus on the set of 63 queries that was used in the TREC-9 Filtering Track. The OHSUMED queries were generated to address actual information needs for clinicians, and the assessed documents were retrieved in two iterations, by relying on the MEDLINE search interface and the SMART retrieval system respectively. The retrieved documents were judged by a separate group of domain experts to the group performing the search. As document collection we rely on the 1988-91 subset of MEDLINE that was released as test data for the TREC-9 challenge, which contains 293,856 documents. The judgment set has an average of 50.87 judgements per query, all of them positive. Since the original runs of the systems participating in the TREC-9 challenge are not available, for evaluation we created 16 IR systems implemented with the Terrier 3.5 open source package [5]. Table 1 lists the settings of the Terrier package used for our runs, which are the same settings used by [7].

Each document of the OHSUMED collection contains bibliographical data (title, authors, etc) plus the abstract. For the experiments reported in this paper we used only the contents of the abstract.

The TREC-8 collection [10] comprises disks 4 and 5 of the TREC collection, excluding the Congressional Record sub-collection. We used the test set, which has 50 queries with an average of 1,736 qrels per query. Of these, since we want to model a scenario where only positive judgements are used, we use only the positive qrels, which average 94.56 positive qrels per query. The qrels were generated using the pooling method, taking the top 100 documents retrieved by the systems participating in the ad-hoc task of TREC-8. For evaluation we used the results of the original systems that participated in the ad-hoc track of TREC-8.

Each document of the TREC-8 collection contains various XML markups. Given that each of the multiple sources had a different XML tag set, for the experiments reported in this paper simply we ignored all lines that had an XML markup. The remaining lines consisted mostly of the main text, but there were still a few lines left that had meta-data.

4. DISTANCE VERSUS RELEVANCE

We first examined the relation between similarity between qrel candidates, and their relevance. We obtained the candidates by pooling, as explained below for each dataset. For every query and for every qrel candidate in the query, we computed the minimum distance between the qrel candidate and a known positive qrel for the query. The resulting (qrel candidate, query) pairs were sorted by distance and binned into deciles such that the first decile is formed by the top 10% pairs, and so on. Then, within each decile we computed the percentage of qrel candidates that were actually positive qrels. Since the OHSUMED data only had positive qrels, for each query we built the list of qrel candidates by pooling the top 100 documents per run. There was an average of 202.80 qrel candidates per query (12,371 qrel candidates in total), and those that were not in the list of known qrels were tagged as negative judgements. For the TREC data, we used the qrels provided by the organizers of TREC. These qrels had been obtained by pooling the top 100 documents per run and contained positive and negative judgements, with an average of 1,736.60 qrels per query (86,830 qrels in total). Due to time and memory constraints we have used the first 100 qrels of each query, giving a total of 5,000 qrel candidates.

Figure 1 shows the result. The figure shows a clear relation between distance and relevance in both datasets. The relation is not as marked as reported by [7] but, as we will show below, it is sufficient to give an improvement in the evaluation when we expand the original qrels. The reason why the results differ from those of prior work is that the pool of documents in prior work was taken from the global list of known qrels, instead of from the runs of the systems. Our pooling method reflects a more realistic scenario and makes it possible to compare the OHSUMED and the TREC datasets. We observe that, in general, the percentage of relevant candidates drops much quicker in the TREC data than in the OHSUMED data.

For the experiments we used as the distance metric $d(x, y) = 1 - \cos(x, y)$ where $\cos(x, y)$ is the cosine similarity. The vector representations were formed by obtaining the $tfidf$ values of all words after lowercasing and removing stop words, and then taking the top 200 components after performing Principal Component Analysis (PCA) [3] These are the same settings as described by [7].

1http://www.ncbi.nlm.nih.gov/pubmed

2Note that the total number of qrels is slightly lower than 63*202.80=12,777 due to the existence of qrels shared among questions.

3These experiments were carried out in Python and the
4.1 Pseudo-qrels for Evaluation

We expand the original qrels by introducing qrel candidates that are close enough to a known positive qrel. The specific process to rank the candidates is the same as described in Section 3. We then apply a percentile threshold to select the pseudo-qrels. In other words, given the list of pairs (qrel candidate, query) sorted by distance to the closest positive qrel of the query, we select the top $K$% qrel candidates. We will call these added qrel candidates pseudo-qrels.

The process to find the pseudo-qrels uses a threshold that is global to all queries. This means that some queries may receive more pseudo-qrels than others, and a query may receive no pseudo-qrels. As we reduce the threshold, we will find more cases where a query has no additional pseudo-qrels. We thought that using a global threshold is desirable, since if a query only has documents that are relatively far from known qrels, we better not add them as pseudo-qrels.

To test the impact of the number of available qrels, in our experiments we have varied the number of qrels per query, always making sure that each query had at least one qrel. The selected qrels were drawn randomly from the original set of qrels, using the same random seed in all experiments.

4.2 Correlation for ranking IR systems

To determine the quality of the pseudo-qrels, and keeping in mind the scenario envisaged at the introduction, we evaluate and rank the set of runs using the qrels plus pseudo-qrels. The evaluation metric was MAP. We then compare the ranking of systems against another evaluation where we use the complete set of qrels. The system rankings are compared using Kendall’s tau.

We conducted several experiments by varying the percentages of qrels extended with the computed pseudo-qrels. We also included a baseline that does not include the additional pseudo-qrels. The baseline simulates the default case when we only use the available qrels.

The scikit-learn library.

Figure 1: Distance versus relevance in the OHSUMED and TREC-8 test datasets.

Figure 2: Kendall’s tau of system orderings on the OHSUMED data

Figure 3: Kendall’s tau of system orderings on the TREC data

Figure 4 shows the results for the OHSUMED dataset, and Figure 5 shows the results for the TREC dataset. The figures present the results for varying values of $K$ (the percentage of top documents selected as pseudo-qrels). We can observe, as expected, that larger percentages of qrels lead to higher correlation.

In both cases, we observe a gain of Kendall’s tau for small percentages $K$ of the original qrels. The gain is higher in the OHSUMED than the TREC dataset. Figure 6 zooms on the lower values of $K$ for the TREC data. We appreciate a greater gain in some of the smaller values of $K$. Critically, these values represent an original number of qrels that is similar to those encountered in our envisaged scenario.

We observed that selecting a different subset of qrels influences the resulting tau, especially for the smaller percentages of qrels. We tried with several baselines by using different random seeds to select the qrels, and compared them with the expanded versions with the pseudo-qrels. The gain of
5. CONCLUSIONS

We have compared the use of document similarity scores in two datasets, with the aim to compensate for the limited availability of qrels. The advantage of our approach against classification-based approaches such as those of prior work is that our method is applicable even when there are only positive relevance judgements.

The results are particularly encouraging when the number of available relevance judgements is very limited, and they suggest the use of distance-metrics extensions of relevance judgements as a quick and cheap evaluation step during the development stage of information retrieval systems when there are few and only positive relevance judgements. It can therefore be applied for the development of IR systems that search for relevant clinical studies, even when the set of known available relevant documents is just the list of references of a sample clinical systematic review.

Further work includes a more comprehensive study of the thresholds that lead to the best evaluation setting, and the use of variants of distance metrics, other than straight cosine distance over a bag-of-words vector space model. Also, given that the measure of quality used in this study is based on the correlation of rankings with an automated evaluation metric, it is desirable to extend this study with real human judgements.

Finally, note that the present study expands the available qrels with positive judgements only. A further interesting line of research will include the automatic addition of negative judgements.

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