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Abstract

We explore the use of state of the art query expansion techniques combined with a new family of ranking functions which can take into account some semantic structure in the query. This structure is extracted from Wordnet similarity measures. Our approach produces improvements over the baseline and over query expansion methods for a number of performance measures including GMAP.

Categories and Subject Descriptors

H.3 [**Information Storage and Retrieval**]: H.3.1 Content Analysis and Indexing; H.3.3 Information Search and Retrieval

General Terms

Natural Language Processing, Information Retrieval, Robust Retrieval

Keywords

Query expansion, semantic expansion

1 Introduction

Exploiting semantic information for information retrieval is known to be very hard. One of the problems, in our opinion, is the term independence hypothesis. A second problem is that of query-dependant semantics: two terms semantically related in a query may not be so in the next. We try to address these two problems. We propose to make explicit some of the term dependence information using a form of structured query (which we call query clauses), and to use a ranking function capable of taking the structure information into account. We combine the use of query expansion techniques and semantic disambiguation to construct the structured queries that are both semantically rich and focused on the query.

1.1 Ranking Function

Our baseline will be the BM25 ranking function[9]:

$$R(q,d) = \sum_{t\ en\ q} \frac{tf_t^d}{k_1((1-b)+b*\frac{l_d}{avl_d})+tf_t^d} * idf_t \tag{1}$$

$$idf_t = \frac{N - df(t) + 0.5}{df(t) + 0.5} \tag{2}$$

For all our experiments we used Lucene[1], modifying the raking functions as needed.

[1] http://lucene.apache.org

1.2 Query Expansion Algoritms

Our first approach is to apply state of the art query expansion methods. We selected two methods which we find very effective.

1.3 Information-theoretic approach

One of the most interesting approaches based on term distribution analysis has been proposed by C. Carpineto et. al. [2], and uses the concept the Kullback-Liebler Divergence [3] to compute the divergence between the probability distributions of terms in the whole collection and in the top ranked documents obtained for a first pass retrieval using the original user query. The most likely terms to expand the query are those with a high probability in the top ranked set and low probability in the whole collection. For the term t this divergence is:

$$w(t) = P_R(t)\log\frac{P_R(t)}{P_C(t)} \tag{3}$$

where $P_R(t)$ is the probability of the term t in the top ranked documents, and $P_C(t)$ is the probability of the term t in the whole collection.

1.4 Divergence From Randomness for Query Expansion

The Divergence From Randomness (DFR) [1] term weighting model infers the informativeness of a term by the divergence between its distribution in the top-ranked documents and a random distribution. The most effective DFR term weighting model is the *Bo1 model* that uses the Bose-Einstein statistics [8, 6]:

$$w(t) = \mathrm{tf}_x \log_2(\frac{1+P_n}{P_n}) + \log(1+P_n) \tag{4}$$

where tf_x is the frequency of the query term in the x top-ranked documents and P_n is given by $\frac{F}{N}$, where F is the frequency of the query term in the collection and N is the number of documents in the collection.

We have used the first document retrieved for term extraction. The number of terms used to expand the original query has been 40.

1.5 Methods for Reweighting the Expanded Query Terms

After the list of candidate terms has been generated by one of the methods described above, the selected terms which will be added to the query must be re-weighted. Different schemas have been proposed for this task. We have compared these schemas and tested which is the most appropriate for each expansion method and for our combined query expansion method.

The classical approach to term re-weighting is the Rocchio algorithm [10]. In this work we have used Rocchio's beta formula, which requires only the β parameter, and computes the new weight qtw of the term in the query as:

$$qt_w = \frac{qtf}{qtf_{max}} + \beta\frac{w(t)}{w_{max}(t)} \tag{5}$$

where $w(t)$ is the original expansion weight of term t, $w_{max}(t)$ is the maximum $w(t)$ of the expanded query terms, β is a parameter, qtf is the frequency of the term t in the query and qtf_{max} is the maximum term frequency in the query q. In all our experiments, β is set to 0.3.

1.6 Query Performance Prediction

Query expansion is known to degrade the performance of some queries. In order to alleviate this problem we experimented with query quality predictors [4]. For efficiency reasons we only consider pre-retrieval methods. In particular, we used the AvICTF predictor proposed by [5]:

$$AvICTF = \frac{\log_2 \prod_{t \in Q} ICTF}{ql} = \frac{\log_2 \prod_{t \in Q} \frac{token_c}{F}}{ql} \tag{6}$$

The predictor is used as follows. We compute the AcICTF value of the expanded query. If this value is above a certain threshold (9.0) we will use the expanded query. Otherwise we use the original query.

2 Standard Query Expansion Results

In table 1 we report results on the baseline and query expansion for several evaluation measures, including GMAP which is perhaps the most interesting in the context of robust retrieval.

	MAP	GMAP	R-PREC	P@5	P@10
BM25 (baseline)	.3614	.1553	.3524	.4325	.3663
BM25 + KLD	.3833	.1527	.3647	.4575	.3869
BM25 + Bo1	.3835	.1528	.3615	.4613	.3844
BM25 + Bo1 + AvICTF	.3811	.1518	.3587	.4550	.3831

Table 1: Evaluation for different expansion methods.

As we can see, the query expansion methods obtain some improvement over the baseline, for all linear average measures, but not for GMAP. As it is usually the case, the query expansion methods are hurting the performance of the hardest queries. AvICTF it is helping somewhat but not enough to improve over the baseline.

3 Structured Query Expansion

Simply adding terms to a query may not be the best way to enrich them. We believe that adding related terms worsens the term independence hypothesis. In this section we explore an alternative family of ranking functions that addresses this issue. These ranking functions and their motivation were described in more detail in [7]. Here we will give only a brief description.

Related terms are grouped in sets called clauses, and queries are defined as sets of clauses. Terms within the clauses and clauses themselves may be weighted. Each clause is considered as a pseudo term with each own tf and idf:

$$score(d, qc) = \sum_{i=1}^{n} eIDF(c_i) \cdot \frac{f(c_i, d)}{k_1 \cdot (1 - b + b \cdot \frac{|d|}{avgdl}) + f(c_i, d)} \tag{7}$$

where qc is the expanded query with clauses, and c_i is the ith clause, $eIDF(c_i)$ is the expected idf of the clause, described below, and c_i the defined as:

$$c_i = \sum_{t \in c_i} tf_t \tag{8}$$

where tf_t is the term frequency of the terms that belong to the clause c_i

The expected IDF $eIDF$ formulation or IDF per clause is defined as:

$$icf_{\mathsf{E}}(d,c) = \frac{1}{ctf(d,c)} \sum_{(t,w)\in c} w_t \cdot tf(d,t) \cdot idf(t) \tag{9}$$

where:

w_t can be defined using Rocchio weight or other weighting schema and IDF_t is the IDF of the term t in the collection $IDF_t = \frac{N}{df_t}$ where N is the number of documents in the collection and df_t is the number of documents in the collection that contains the term t.

This function provides a method to introduce into the ranking function the expanded terms without the need of Rochio. The question remains how to construct the clauses. This is described in the next section.

Our hypothesis is that semantically related terms should be grouped in clauses. The CLEF corpus is ideal to test this hypothesis since all the terms in it have be annotated with their corresponding synset in Wordnet

4 Claused Query Expansion

We report here results on the semantic clause method described above.

Table 2: Results for claused queries using different similarity thresholds in Wordnet.

	MAP	GMAP	R-PREC	P@5	P@10
BM25 (baseline)	.3614	.1553	.3524	.4325	.3663
BM25 + Bo1	.3835	.1528	.3615	.4613	.3844
BM25 + Bo1 + Clauses ($\alpha > 0.0$)	.3937	**.1620**	.3735	.4600	.3869
BM25 + Bo1 + Clauses ($\alpha > 0.3$)	.3935	.1613	.3726	.4563	.3869
BM25 + Bo1 + Clauses ($\alpha > 0.6$)	.3926	.1606	.3737	.4600	.3906
BM25 + Bo1 + Clauses ($\alpha > 0.9$)	**.3957**	.1618	**.3772**	**.4625**	**.3975**

We can see that the proposed method improves results over the baseline and over query expansion, for all relevance measures including GMAP. This is very encouraging because it is one of the few results to our knowledge that show that semantic disambiguation can be used to improve retrieval in an open domain.

In our opinion a bottleneck to further improve performance is the difficulty of creating good query clauses. Wordnet Similarity methods tend to produce noisy clauses, often putting in correspondence terms that are not related in the context of the query.

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