The use of WordNet and Automatically Constructed Thesaurus for Query Expansion

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Abstract

This paper describe our method in automatic-adhoc task of TREC-7. We propose a method to improve the performance of information retrieval system by expanded the query using 3 different types of thesaurus. The expansion terms are taken from hand-crafted thesaurus (WordNet), co-occurrence-based automatically constructed thesaurus, and syntactically predicate-argument based automatically constructed thesaurus.

1 Introduction

A critical problem in information retrieval is that the vocabulary that the searchers use is not the same as the one by which the documents have been indexed. The word synonymy is one example of this problem. If a user use a synonym of a word which document has been indexed in his/her query, then that documents could not be retrieved.

Query expansion is one method in information retrieval to avoid this problem. The expansion term can be taken from a thesaurus. There are many research of query expansion using thesaurus in the literature. Briefly there are two types of thesaurus: the hand-crafted thesaurus and automatically constructed thesaurus. WordNet [3] is one example of hand-crafted thesaurus which is publically available in machine readable form.
Corpus-based thesaurus is a thesaurus which is constructed automatically from the corpus without intervention of human. There are two different method to extract thesaural relationships from corpora: predicate-argument (also called head-modifier) method [1, 2] and co-occurrence statistic method [4].

We propose the use of WordNet, co-occurrence-based and predicate-argument-based automatically constructed thesaurus for query expansion in automatic-adhoc task of TREC-7.

2 Method

2.1 Co-occurrence-based Thesaurus

The general idea underlying the use of term co-occurrence data for thesaurus construction is that words that tend to occur together in documents are likely to have similar, or related, meanings. Co-occurrence data thus provides a statistical method for automatically identifying semantic relationships that are normally contained in a hand-made thesaurus. Suppose two words (A and B) occur \( f_a \) and \( f_b \) times, respectively, and cooccur \( f_c \) times, then the similarity between A and B can be calculated using a similarity coefficient such as the Dice Coefficient:

\[
\frac{2 \times f_c}{f_a + f_b}
\]

2.2 Predicate-Argument-based Thesaurus

In contrast with the previous section, this method attempts to construct a thesaurus according to predicate-argument structures. The use of this method for thesaurus construction is based on the idea that there are restrictions on what words can appear in certain environments, and in particular, what words can be arguments of a certain predicate. For example, a cat may walk, bite, but can not fly. Each noun may therefore be characterized according to the verbs or adjectives that it occurs with. Nouns may then be grouped according to the extent to which they appear in similar constructions.

First, all the documents are parsed using the Apple Pie Parser, which is a bottom-up probabilistic chart parser developed by Satoshi Sekine [6]. Its grammar is a semi-
context sensitive grammar and it was automatically extracted from Penn Tree Bank syntactically tagged corpus made at the University of Pennsylvania. Its performance is 0.71 of precision, 0.70 of recall and 3.03 of average crossing.

Using this parser, the following syntactic structures are extracted:

- Subject-Verb
- Verb-Object
- Adjective-Noun

Each noun has a set of verbs and adjective that it occurs with, and for each such relationship, a dice coefficient value is calculated.

- \( C_{\text{sub}}(v_i, n_j) = \frac{2 \times f_{\text{sub}}(v_i, n_j)}{f(v_i) + f_{\text{sub}}(n_j)} \),
  where \( f_{\text{sub}}(v_i, n_j) \) is the frequency of noun \( n_j \) occurring as the subject of verb \( v_i \), \( f_{\text{sub}}(n_j) \) is the frequency of the noun \( n_j \) occurring as subject of any verb, and \( f(v_i) \) is the frequency of the verb \( v_i \)

- \( C_{\text{obj}}(v_i, n_j) = \frac{2 \times f_{\text{obj}}(v_i, n_j)}{f(v_i) + f_{\text{obj}}(n_j)} \),
  where \( f_{\text{obj}}(v_i, n_j) \) is the frequency of noun \( n_j \) occurring as the object of verb \( v_i \), \( f_{\text{obj}}(n_j) \) is the frequency of the noun \( n_j \) occurring as object of any verb, and \( f(v_i) \) is the frequency of the verb \( v_i \)

- \( C_{\text{adj}}(a_i, n_j) = \frac{2 \times f_{\text{adj}}(a_i, n_j)}{f(a_i) + f_{\text{adj}}(n_j)} \),
  where \( f(a_i, n_j) \) is the frequency of noun \( n_j \) occurring as argument of adjective \( a_i \), \( f_{\text{adj}}(n_j) \) is the frequency of the noun \( n_j \) occurring as argument of any adjective, and \( f(a_i) \) is the frequency of the adjective \( a_i \)

We define the object similarity of two nouns with respect to one predicate, as the minimum of each dice coefficient with respect to that predicate, i.e.

\[
SIM_{\text{sub}}(v_i, n_j, n_k) = \min\{C_{\text{sub}}(v_i, n_j), C_{\text{sub}}(v_i, n_k)\}
\]
\[
SIM_{\text{obj}}(v_i, n_j, n_k) = \min\{C_{\text{obj}}(v_i, n_j), C_{\text{obj}}(v_i, n_k)\}
\]
\[
SIM_{\text{adj}}(a_i, n_j, n_k) = \min\{C_{\text{adj}}(a_i, n_j), C_{\text{adj}}(a_i, n_k)\}
\]

Finally the overall similarity between two nouns is defined as the average of all the similarities between those two nouns for all predicate-argument structures.
2.3 Expansion Term Weighting Method

A query $q$ is represented by a vector $\mathbf{q} = (q_1, q_2, ..., q_n)$, where the $q_i$'s are the weights of the search terms $t_i$ contained in query $q$.

The similarity between a query $q$ and a term $t_j$ can be defined as belows:

$$simqt(q, t_j) = \sum_{t_i \in q} q_i \times sim(t_i, t_j)$$

Where the value of $sim(t_i, t_j)$ can be defined as the average of the similarity values in the three types of thesaurus. Since in WordNet there are no similarity weights, when there is a relation between two terms in WordNet, their similarity is taken from the average of the similarity between those two terms in the co-occurrence-based and in predicate-argument-based thesauri.

With respect to the query $q$, all the terms in the collection can now be ranked according to their $simqt$. Expansion terms are terms $t_j$ with high $simqt(q, t_j)$.

The $weight(q, t_j)$ of an expansion term $t_j$ is defined as a function of $simqt(q, t_j)$:

$$weight(q, t_j) = \frac{simqt(q, t_j)}{\sum_{t_i \in q} q_i}$$

where $0 \leq weight(q, t_j) \leq 1$.

An expansion term gets a weight of 1 if its similarity to all the terms in the query is 1. Expansion terms with similarity 0 to all the terms in the query get a weight of 0. The weight of an expansion term depends both on the entire retrieval query and on the similarity between the terms. The weight of an expansion term can be interpreted mathematically as the weighted mean of the similarities between the term $t_j$ and all the query terms. The weight of the original query terms are the weighting factors of those similarities.

Therefore the query $q$ is expanded by adding the following query:

$$\mathbf{q}_e^r = (a_1, a_2, ..., a_r)$$

where $a_j$ is equal to $weight(q, t_j)$ if $t_j$ belongs to the top $z$ ranked terms. Otherwise $a_j$ is equal to 0.
The resulting expanded query is:

\[ q_{\text{expanded}} = q \circ q_e \]

where the \( \circ \) is defined as the concatenation operator.

The method above can accommodate the polysemous word problem, because an expansion term which is taken from a different sense to the original query term is given very low weight.

### 3 Experiments

As a retrieval engine we used SMART [5] version 11.0. SMART is an information retrieval system based on the vector space model in which term weights are calculated based on term frequency, inverse document frequency, and document length normalization. We used \( lnc \) for document's term weighting and \( ltc \) for query's term weighting.

We ran experiments in the automatic-adhoc task framework using only title, only description, and all terms of the topics. The results are shown belows:

<table>
<thead>
<tr>
<th></th>
<th>Title</th>
<th>Description</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>======</td>
<td>===========</td>
<td>===</td>
</tr>
</tbody>
</table>

Total number of documents over all queries:

- Retrieved: 50000
- Relevant: 4674
- Rel_ret: 2435

Interpolated Recall - Precision Averages:

- at 0.00 0.6957 0.7782 0.8161
- at 0.10 0.4528 0.5643 0.5783
- at 0.20 0.3622 0.4377 0.4511
- at 0.30 0.2864 0.3519 0.3575
- at 0.40 0.2148 0.2981 0.2899
- at 0.50 0.1438 0.2300 0.2177
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<th>0.60</th>
<th>0.70</th>
<th>0.80</th>
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<tbody>
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<td>0.0636</td>
<td>0.0306</td>
<td>0.0054</td>
</tr>
</tbody>
</table>

Average precision (non-interpolated) over all rel docs

0.1898 0.2584 0.2565

Precision:

At 5 docs: 0.4720 0.5840 0.5800
At 10 docs: 0.4260 0.5460 0.5480
At 15 docs: 0.4080 0.5013 0.4973
At 20 docs: 0.3700 0.4640 0.4700
At 30 docs: 0.3320 0.4113 0.4147
At 100 docs: 0.2012 0.2406 0.2484
At 200 docs: 0.1395 0.1771 0.1771
At 500 docs: 0.0791 0.1038 0.1023
At 1000 docs: 0.0487 0.0630 0.0621

R-Precision (precision after R (= num_rel for a query) docs retrieved):

Exact: 0.2403 0.2993 0.2989

4 Discussions of Result

As expected, the performance of retrieval using only title of topics yields a worst performance. The use of only description of topic has a higher retrieval performance than the use of all sections of topic. This can be explained that the narrative section of topics has some negation statements which could not be handled properly by our system yet.
5 Conclusions

We have proposed and experimented a new method for query expansion using WordNet and corpus-based thesaurus. To avoid the wrong expansion terms, a weighting method is utilized whereby the weight of expansion terms depends on the similarity value of those terms in the various thesauri and on the weight of all terms in the original query.

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References


