A METHOD FOR THE CONSTRUCTION AND APPLICATION OF THE TERM HIERARCHY RELATIONSHIP RESIDING IN RELEVANCE FEEDBACK

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Abstract

In the field of information retrieval, the information of term frequency contained in relevance feedback has been widely used. However, the analysis and application of term frequency does not cover the semantic meaning of the terms, which could make the retrieval results deviate from the user's searching goal. Consider the semantic meaning of the terms, Wille (1992) had proposed a structured view in the dealing with the term relationships of the terms in the retrieval documents. To enhance the effectiveness of information retrieval by the dealing with the mentioned information of term hierarchy relationship, this study has developed a method of query expansion to extract and apply this information contained in relevance feedback first, and then conducted some formal tests to verify the efficiency of the method in the re-ranking of the retrieved documents. The results of the formal tests show that the proposed method of query expansion is more effective than the Rocchio's query expansion algorithm. The contribution of this study is the disclosure of the applicability of the information of term hierarchy relationship contained in relevance feedback, and the demonstration of the application of this information.

Keywords: Term hierarchy, Semantic analysis, Query expansion, Relevance feedback, Document re-ranking, Information retrieval

1 INTRODUCTION

In information retrieval, the document processing and analysis are usually based on the terms in documents. The terms are utilized to identify the relevance of documents and to judge the user's satisfactions of documents. However, how to select suitable terms in the document is difficult, and it dependents on user's descriptions on the query terms. A user can't obtain needed retrieval results when she/he can't make suitable descriptions to the query (Furnas et al. 1987).

One important strategy of solving above problem is to utilize the information of relevance feedback. Relevance feedback contains the information which can be utilized to improve the information retrieval. In the application relevance feedback, Rocchio's method is the best known one (Rocchio 1971). It mainly exploits the term frequency information (TF-IDF) of relevant and irrelevant documents to expand the query and to modify the new query's weights, which make the new query move towards the relevant document vectors and far away from the irrelevant document vectors.

As above-mentioned, the applications of relevance feedback focus on the information of term frequency and term appearance in conventional studies. However, there is other information contained in relevance feedback that could be useful to improve information retrieval. For example, the terms with high appearances in the documents or the terms with low appearances in the documents could be an important key in searching. Another example is the relationships among terms. The term semantics figures the term relationships and contains important information for information retrieval. Wille (1992) proposed a structure view based on the relationships among terms, and it generated term hierarchical information based on the semantics.

To understand and apply the term hierarchical information based on semantics, this study aims to develop a method, which analyzes and extracts the information of term hierarchy and semantics in relevance feedback. Then, it applies the information to query expansion for document re-ranking in the TREC6 collection. In the query expansion, this study applies the term semantic relationship in addition to term frequency information. We utilized WordNet as the semantic analysis toolkit, which identifies and computes the semantic level between the original query and relevant terms, and removes the non-representative terms for query expansion to improve the effectiveness of document re-ranking.

2 RELATED STUDIES

2.1 Relevance Feedback

In 1960, Salton and McGill proposed the concept of relevance feedback (Salton & McGill 1986). Relevance feedback is the process that user judges the initial retrieved results and feedback the results to the information system. Relevance feedback exactly improves the performances of information retrieval. In small data collection experiments, such as SMART information system (Salton 1971), relevance feedback obtains good improvements. There are three main modes in relevance feedback, including: (1) explicit relevance feedback, which the information system shows the retrieved results to user, and receives user's judgments and feedbacks; (2) pseudo relevance feedback, which the information system uses the top ranked retrieved results as user's feedbacks; (3) implicit relevance feedback (Xu & Croft 1996), which the information system judges the relevance of documents by user's browsing times, click times, and other behaviors.

2.2 Query Expansion

Query expansion is the modification of the initial query by adding meaningful terms to the query and the process of reformulate the query (Vechtomova & Wang 2006). Query expansion improves the effectiveness of information retrieval (Abberley et al. 1999). The process includes user's query and query term expansion in order to obtain more relevant documents. There are four key important technologies, such as (1) synonyms expansion, which selects the same meaning terms in natural language to expand the initial query; (2) stemming, which finds the general terms by the of stems of terms; (3) spelling error fixing, which fixes the spelling errors and raises suggestions to the user base on user's initial query; (4) query term weights modification, which gives weights to initial query terms to present the importance, and formulates the expanded query, for example, Rocchio's method.

The key advantage of query expansion is to increase the effectiveness of retrieval by adding more expanded terms. However, it also causes the drawback, which adds the probability of finding irrelevant documents. It is on the horns of a dilemma. Harman's study (1992) shows that selecting representative terms improves the performances of information retrieval. Consequently, improving the expanded term quality is more important than adding more expanded term to the initial query (Sihvonen & Vakkari 2004).

2.3 Rocchio's method

Rocchio's query expansion (Rocchio 1971) is utilized broadly in the research area of relevance feedback with the vector space model. In 1970, SAMRT information system exploited Rocchio's method to apply the information of term frequency, and it obtained good performances in information retrieval. Rocchio's method exploits the term frequency information in relevant documents $\overrightarrow{D_j}$ and irrelevant documents $\overrightarrow{D_k}$ to modify the query vector $\overrightarrow{Q_o}$. This makes the query vector $\overrightarrow{Q_o}$ move towards the relevant document vectors and far away from the irrelevant document vectors. According to the query vector modification to achieve the query expansion, the expanded query is more suitable for user's needs. Eq. 1 shows Rocchio's method.

$$\overrightarrow{Q_m} = \left(a \cdot \overrightarrow{Q_o}\right) + \left(b \cdot \frac{1}{|D_r|} \cdot \sum_{\overrightarrow{D_j} \in D_r} \overrightarrow{D_j}\right) - \left(c \cdot \frac{1}{|D_{nr}|} \cdot \sum_{\overrightarrow{D_k} \in D_{nr}} \overrightarrow{D_k}\right) \tag{1}$$

|Dr|: the number of relevant documents |Dn|: the number of irrelevant documents

a、b、c：the modified weights

2.4 The semantic relationships between two terms on WordNet

There are two methods to compute the semantic relationships between two terms, such as (1) term glosses, and (2) term distance. Term glosses is to compute the numbers of term duplication to measure the term relationship (Banerjee & Pedersen 2003). Term distance is to utilize the relationship pointer in WordNet to find the path between the two terms in the term hierarchy, and is to evaluate the semantic distance. The distance is the value between 0 and 1, which the smaller value presents more better relevance between the two terms.

3 METHOD

Because WordNet obtains well-known effectiveness in document classification and the semantic technology is useful in the improving of information retrieval, this study aims to develop a method (denoted by THSI), which combines term hierarchy information on WordNet and semantic information from relevance feedback, to improve the performances of query expansion. The advances of WordNet and semantic information are utilized to extract the information of semantic relationships among terms.

This study mainly extracts and applies the term hierarchy based on semantics to develop a method, which expands the query to re-rank documents. Figure 3-1 shows the flow of the proposed method, which is composed of 7 steps, including relevant term identification, lexical category identification, term hierarchy distance computing, hierarchical term combination, semantic selection, semantic term combination, and query term formulation.

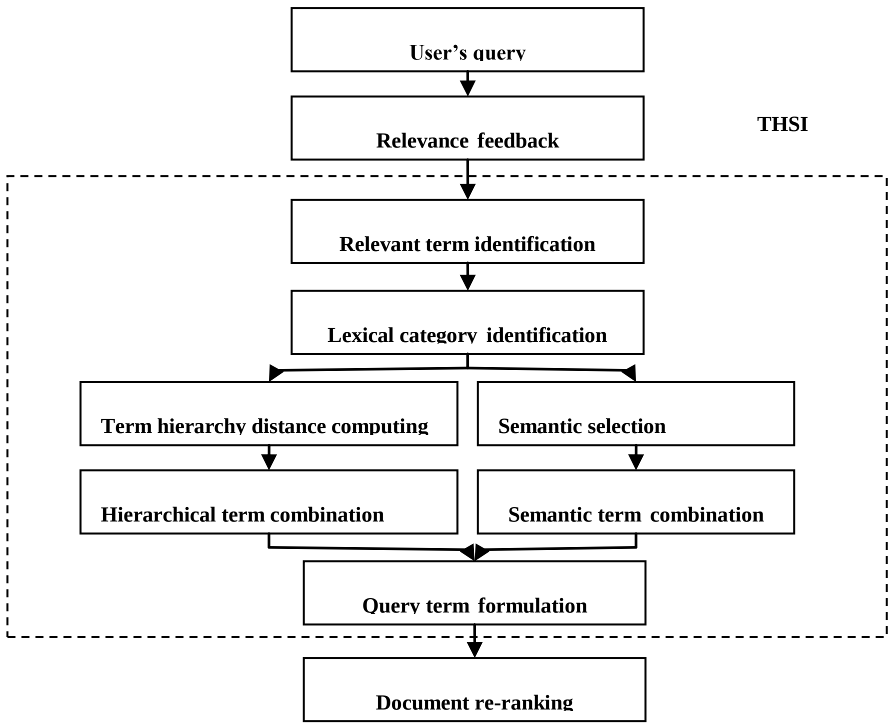

Figure 3-1. The flow of application of THSI

3.1 Relevant term identification

In the relevance feedback, there are two categories documents, relevant documents and irrelevant documents. Terms obtains categorical attributes according to the category of documents containing the terms. This classifies terms into two categories, relevant terms and irrelevant terms. The relevant term appears in the relevant document; the irrelevant term appears in the irrelevant documents. In order to simulate the semantics of user's feedback, the relevant terms were selected for next steps.

3.2 Lexical category identification

In the relevant terms, the word classes of a term contain different meanings, and the noun of a term implies the usability. In our previous studies, we obtained which the word class is useful to find the usability of terms. The adjective, verb, and noun contain the different usability and are most suitable for application. Therefore, we adopted adjectives, verbs, and nouns in the relevant terms, which WordNet judged the word classes for next steps.

3.3 Term hierarchical distance computing

In the step, WordNet was utilized to compute the term hierarchical distance and to select suitable terms by the threshold of term hierarchical distance. Figure 3-2 shows a sample of term hierarchical architecture. As Figure 3-2 shown, we can compute the distances between the terms "document" and "sacred_text". we first computed the distances between the selected terms and the query terms, and second computed the distances between the selected terms and the terms in relevant documents. Finally, we selected the terms, which the distance lower than the threshold. The two term sets were formed in this step and utilized in next steps.

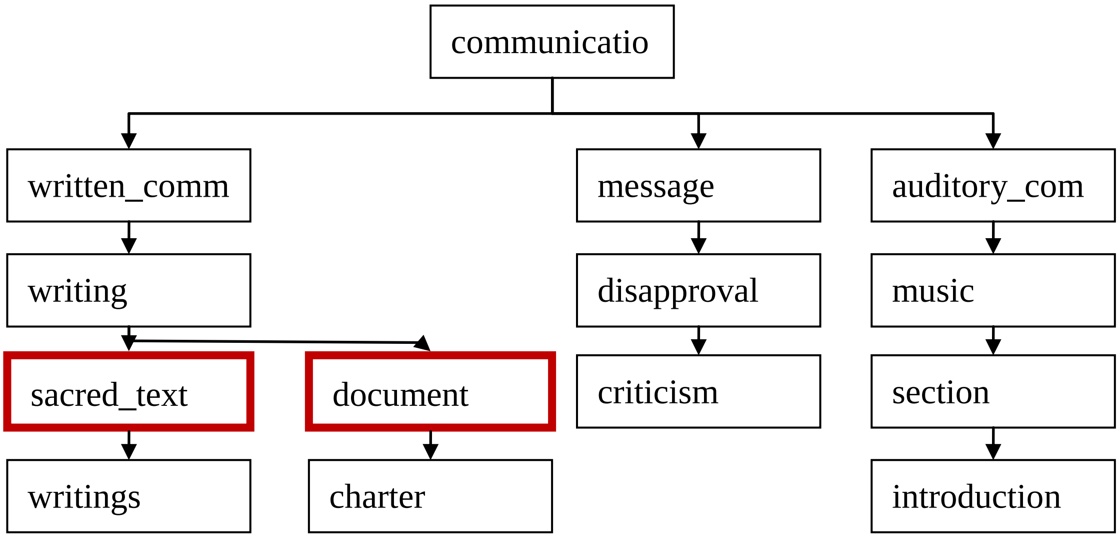

Figure 3-2. The architecture of term hierarchy distance (source: http://www.dh2012.uni-hamburg.de/wp-content/uploads/2012/07/img172-2.jpg)

3.4 Semantic selection

In this step, we utilized the WordNet to measure the term relationships by computing the term duplication in the term explanations in the query results on WordNet (Banerjee & Pedersen 2003). The relevance between two terms increases when the term duplication increases. Figure 3-3 shows the term explanations on WordNet. We first measured the relationships between the selected terms and query terms, and second measured the relationships between the selected terms and the terms in the relevant documents. Finally, we selected the terms which the value of relationship is lower than the threshold. The two term sets were formed in this step and utilized in next steps.

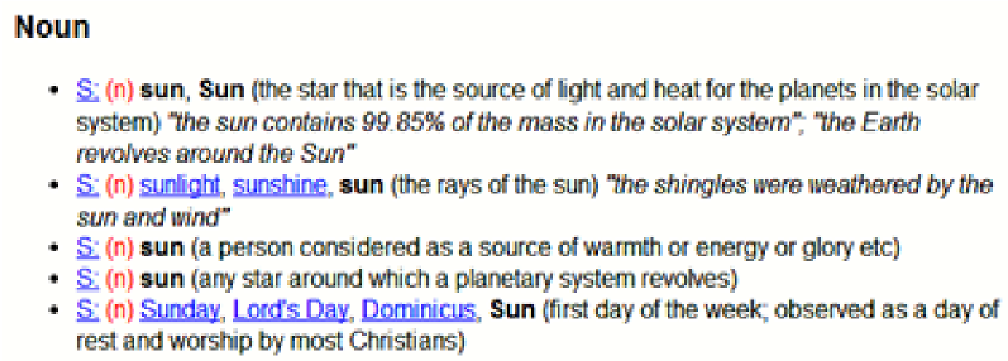

Figure 3-3. The term explanations on WordNet

3.5 Term combination

3.5.1 Hierarchical term combination

After term hierarchical distance computing, the two term sets contains the selected terms, in which some are the same, but some are not the same. Therefore, we utilized the two term sets to form a union of semantic hierarchical terms, and each term appears only once in the new term set.

3.5.2 Semantic term combination

After semantic selection, the two term sets contains the selected terms, in which some are the same, but some are not the same. Therefore, we combined the two term sets to form a union of semantic terms, in which each term appears only once in the new term set. This step is like to the hierarchical term combination, but it needs to handle independently to avoid the term meaning confusion.

3.6 Query term formulation

In this step, we combined the initial query and the two term sets formed in 3.5.1 and 3.5.2 to generate the new query for document re-ranking. Figure 3-4 shows the new query is formed by the three term sets, including the original query, the hierarchical terms (3.5.1), and the semantic terms (3.5.2). We adopted two strategies to formulate new query, including term set combination (TSC), and term set union (TSU).

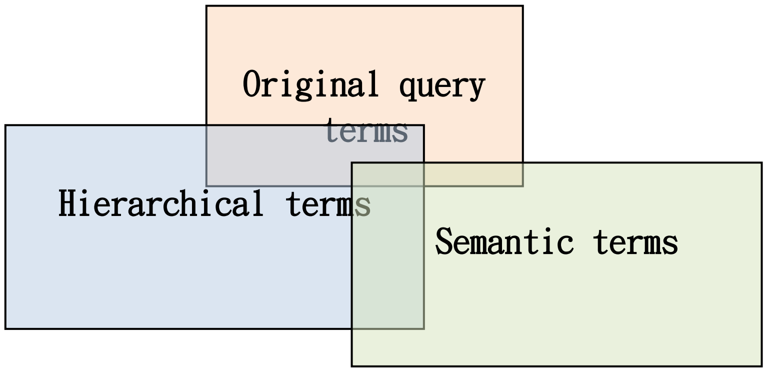

Figure 3-4. The term categories in new query terms

3.6.1 Term set combination

In term set combination (TSC), each term is not the same important so that the appearance of the term is to set as sum of the appearances in both term sets. The feature of this strategy represents more dimension connections and term importance modifications in vector space model. Figure 3-5 shows an example, DIST denotes the hierarchical term set, EXP denotes the semantic term set, and COMB_SET denotes the union set formed by above two sets. Our proposed method with term set combination strategy is denoted by THSI-TSC.

DIST = {apple, book, cherry, dictionary, element}
EXP = {cherry, dictionary, element, fresh, good}
COMB_SET = {apple, book, cherry, cherry, dictionary, dictionary, element, element, fresh, good}

Figure 3-5. Term set combination

3.6.2 Term set union

In term set union (TSU), each term is the same important so that the appearance of a term is to set as one. The feature of this strategy represents more dimension connection in vector space model. Figure 3-6 shows an example, DIST denotes the hierarchical term set, EXP denotes the semantic term set, and UNION_SET denotes the union set formed by above two sets. Our proposed method with term set union strategy is denoted by THSI-TSU.

DIST = {apple, book, cherry, dictionary, element}
EXP = {cherry, dictionary, element, fresh, good}
UNION_SET = {apple, book, cherry, dictionary, element, fresh, good}

Figure 3-6. Term set union

4 EXPERIMENT

In this section, we conducted experiments of document re-ranking to evaluate performances of our proposed method with two strategies (THSI-TSC and THSI-TSU). The experiments utilized three measures, such as mean average precision (MAP), precision at top N documents (P@N, N=5, 10, 100, and 500), and precision-recall curve, for comparing performances between Rocchio's method and our proposed method with two strategies. MAP (Eq. 2) is calculated by the average of average precisions (AP) in the query results, and it represents the performances of whole system. P@N (Eq. 3) evaluates the number of relevant documents in the top N ranked documents in each topic. The top N documents evaluation is fitted most real life situation. Also, in the Internet browsing, most users only pay attentions on the ranked list in the first page (Olson & Delen 2008). In order to simulate the real query usage, we adopted P@5, P@10, P@100,and P@500 to our experiment evaluations. Precision-recall curve (Eq. 4 and Eq. 5) computes the precision with each new incoming result to see if the document is relevant. The precision and recall raise when the document is relevant, but the precision decreases when the document is irrelevant (Everingham et al. 2010). In the experiments with specific parameters, the similarity between query vector and document vector is computed by the cosine similarity (Eq. 6).

$$\mathrm{MAP} = \frac{\sum_{q=1}^{Q} \mathrm{AveP(q)}}{Q} \qquad (2)$$

$$\mathrm{P@N} = \sum_{i=1}^{N} \frac{rel(Si)}{N} \qquad (3)$$

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|} \qquad (4)$$

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|} \qquad (5)$$

$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}} \qquad (6)$$

The global parameters utilized in the experiments are listed in Table 4.1. Lemur information system is utilized to document pre-processing, document retrieval, document re-ranking and Rocchio's method. TREC6 is selected as the document collection. The topics in TREC6 are filtered by the two conditions which the number of relevant documents is fewer than 30 and the number of relevant terms obtained from relevant documents is fewer than 30. Then, the topics 301, 307, 324, 331, 332, 335, and 347 are exploited in the document retrieval, Rocchio's method and our proposed method with two strategies. In the document retrieval of each selected topic, the number of retrieved document is 1000, and the top 20 relevant documents are selected as user's feedback simulation so that the remaining 980 documents are re-ranked by Rocchio's method and our proposed method with two strategies in the documents re-ranking.

Information System	Lemur 4.12
Document collection	TREC CD 4&5
Topic No.	301, 307, 324, 331, 332, 335, 347
Query Terms	Title query
The Number of Relevance Feedback Documents	20
The Number of Documents in Initial Query	1000
The Number of Documents in Document Re-ranking	980
Information Model	Vector Space Model
Rocchio's α	1
Rocchio's β	1
Rocchio's γ	0

Table 4.1 Experimental parameters

4.1 Experimental flow design

The experiments of document re-ranking in the selected topic are conducted by Rocchio's method and our proposed method with two strategies after initial query. Figure 4-1 shows the experiment's flow of document re-ranking. In the user's query, the title query in the judgment file of selected topic is utilized to retrieve top 1000 documents as retrieved results. In the retrieved results, the top 20 relevant documents are selected for user's feedback simulation. For the relevance feedback, the top 20 relevant documents are viewed as user's feedback and prepared for the Rocchio's method and our proposed method with two strategies. Then, the remaining 980 documents are utilized to document re-ranking by both above methods. Finally, for comparing experimental results, the performances of our proposed method with two strategies are compared to the performances of Rocchio's method. (Although the number of remaining documents in topic 324 is 912, topic 324 is still adopted in the experiments.)

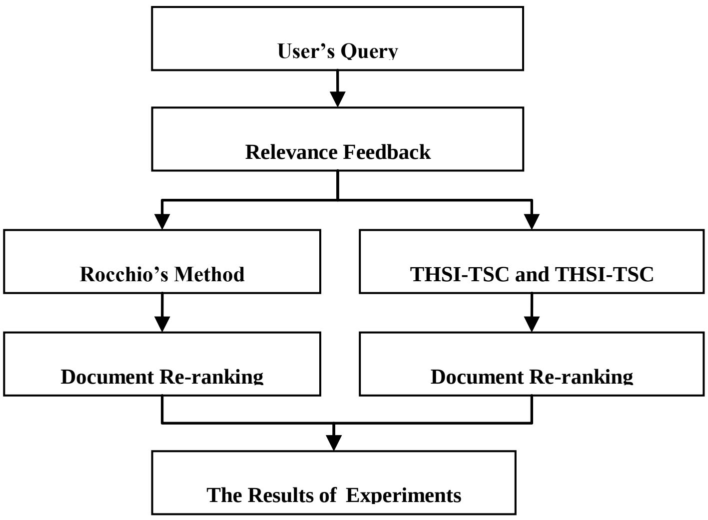

Figure 4-1. The experimental flow of document re-ranking

4.2 Experimental results

For the overall view of re-ranking effectiveness of THSI-TSC and THSI-TSU, the re-ranking performances of Rocchio's method, THSI-TSC and THSI-TSU were compared and measured in MAP, P@N (N = 5, 10, 100, 500), and precision-recall curve. Table 4-2 shows the average performances of all measures between Rocchio's method, THSI-TSC and THSI-TSU. For MAP, THSI-TSC gains an increase of 0.1288, a 74% increase ratio, from the Rocchio's method; THSI-TSU gains an increase of

0.1397, an 80% increase ratio, from the Rocchio's method. For P@5, THSI-TSC gains an increase of 0.0571, a 12% increase ratio, from the Rocchio's method; THSI-TSU gains an increase of 0.1143, a 24% increase ratio, from the Rocchio's method. For P@10, THSI-TSC gains an increase of 0.2286, a 62% increase ratio, from the Rocchio's method; THSI-TSU gains an increase of 0.2571, a 69% increase ratio, from the Rocchio's method. For P@100, THSI-TSC gains an increase of 0.2157, a 135% increase ratio, from the Rocchio's method; THSI-TSU gains an increase of 0.2586, a 162% increase ratio, from the Rocchio's method. For P@500, THSI-TSC gains an increase of 0.0620, a 37% increase ratio, from the Rocchio's method; THSI-TSU gains an increase of 0.0680, a 41% incase ratio, from the Rocchio's method. THSI-TSU is better than the THSI-TSC

	THSI-TSC	THSI-TSU	Rocchio
MAP	0.3031	0.3140	0.1743
P@5	0.5429	0.6000	0.4857
P@10	0.6000	0.6286	0.3714
P@100	0.3757	0.4186	0.1600
P@500	0.2291	0.2351	0.1671

Table 4.2 The average performances of all measures between Rocchio's method, THSI-TSU and THSI-TSC.

Figure 4-2 shows the comparisons of precision-recall curve between Rocchio's method, THSI-TSC and THSI-TSU. For precision-recall, Rocchio's method performs better in recall from 0 to 0.05, but gains poor increases after recall 0.05; THSI-TSC and THSI-TSU perform better after recall 0.05. The effectiveness of both above methods is almost the same, but THSI-TSU is a little better than another one. All measures show that THSI-TSC and THSI-TSU have archived well effectiveness, and THSI-TSU is better than the THSI-TSC.

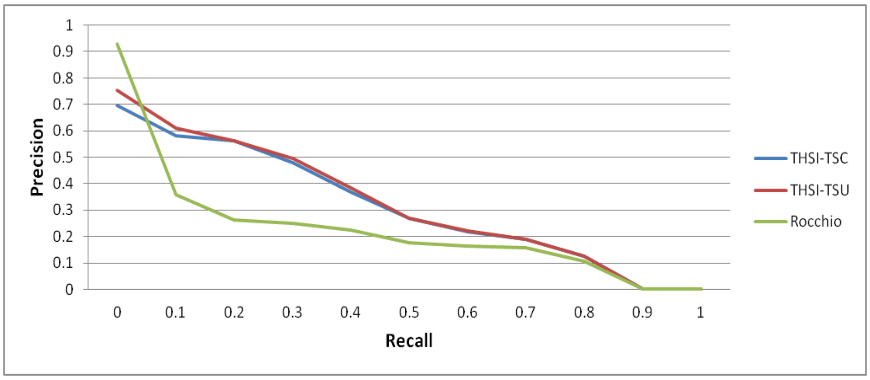

Figure 4-2. Performance comparisons (Precision-Recall Curve)

For the detailed view of re-ranking effectiveness of THSI-TSC and THSI-TSU, the re-ranking performances go into details in MAP and P@10 in each selected topic. Figure 4-3 shows the comparisons of MAP between Rocchio's method, THSI-TSC and THSI-TSU. For MAP, Rocchio's method performs poorly in each topic; THSI-TSC performs better in topics 301, 307, and 324; THSI-TSU performs better in topics 331, 332, and 335. In topic 347, the performances of THSI-TSC and THSI-TSU are the same. For the average comparisons, THSI-TSC and THSI-TSU perform better than Rocchio's method;

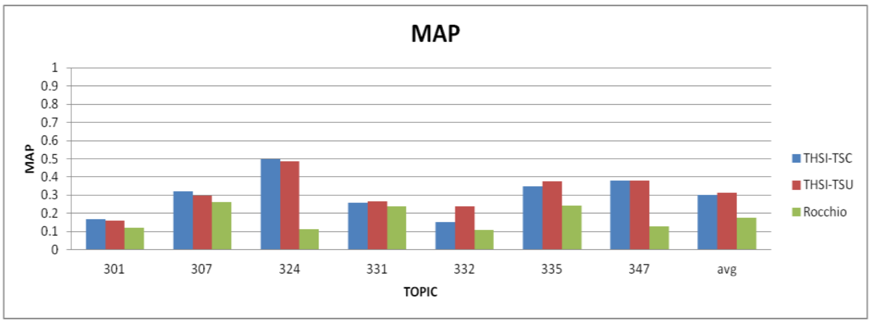

Figure 4-3. Performance comparisons (MAP)

Figure 4-4 shows the comparisons of P@10 between Rocchio's method, THSI-TSC and THSI-TSU. For P@10, Rocchio's method performs better in two topics (307, and 331); THSI-TSC and THSI-TSU perform better in five topics (301, 324, 332, 335, and 347). In topic 335, the performances of THSI-TSC and THSI-TSU are the same. THSI-TSC performs better in topics 301 and 347, and THSI-TSU performs better in topic 324 and 332. For the average comparison, THSI-TSU performs better than Rocchio's method and THSI-TSC.

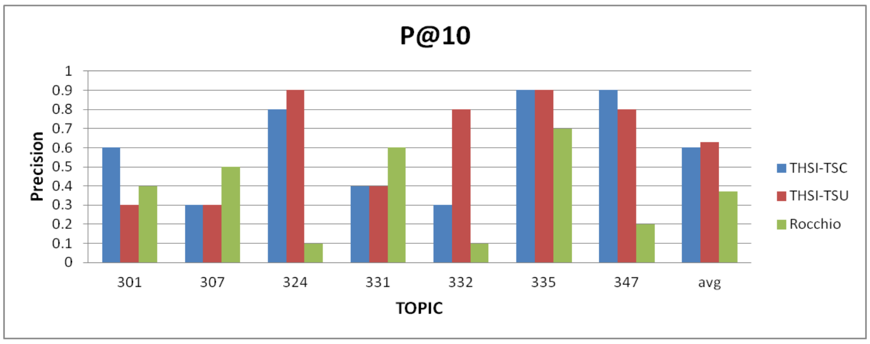

Figure 4-4. Performance comparisons (P@10)

4.3 Discussion

According to the experimental results among Rocchio's method, THSI-TSC and THSI-TSU, the hierarchical information of term semantic is useful to obtain the terms of higher semantic to expand the query terms, and it gains better effectiveness in document re-ranking. We discuss the results below in detail.

In each measure, MAP, P@5, P@10, P@100, and P@500, THSI-TSC and THSI-TSU obtain well effectiveness. The experimental results reveal the semantic and term hierarchy is useful to re-rank relevant documents to higher ranks.

In the comparisons of each topic between Rocchio's method, THSI-TSC, and THSI-TSU, when there are a lot of relevant documents in the ranked list, we can extract enough the information of term hierarchy and semantic. This causes better effectiveness of THSI-TSU and THSI-TSC than Rocchio's method does. Although Rocchio's method performs better in P@5 in topics 301, 307, 331, and 335, it performs poorly in P@10, P@100 and P@500. THSI-TSC and THSI-TSU well achieved the effectiveness in P@5, P@10, P@100, P@500, and MAP. The experimental results show the information of term hierarchy and semantic contains the further usability.

In the comparisons of the number of expanded terms, THSI-TSC and THSI-TSU utilized fewer terms to expand query than Rocchio's method does, and obtained better effectiveness than Rocchio's method in the document re-ranking.

The experimental results show THSI-TSC and THSI-TSU achieved lower effectiveness in the document collection with a lot of proper nouns, for example, personal names and geographical names. THSI-TSC and THSI-TSU are instable in this situation. The reason is WordNet collects fewer proper nouns than the document collection, and this situation causes to ignore the terms. Besides, the attributes of terms also influence performances of THSI-TSC and THSI-TSU.

5 CONCLUSION

This study mainly proposes and evaluates the information of semantic hierarchy in the process of query expansion utilizing relevance feedback. Our proposed method with two strategies utilizes the information of semantic hierarchy, which merges relevance feedback and semantic analysis, and analyzes the information of term hierarchy based on WordNet and relevance feedback for further application. The similarity and relevance of semantics in the semantic hierarchy are exploited to form new query term set with expanded original query. The combination of two term sets with the similar and relevant semantics contains the relationships between the semantic hierarchy of relevance feedback and the semantic hierarchy of the original query, which utilized fewer terms to represent the user's need, and to obtain better results in document re-ranking.

The main contribution of this study is the proposition of the method to extract the information of semantics and semantic hierarchy from relevance feedback for application, and the demonstration of the method's effectiveness in document re-ranking.

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