KECIR at the NTCIR-10 INTENT Task

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ABSTRACT

This paper describes the approaches and results of our system for the NTCIR-10 INTENT task. We present some methods for Subtopic Mining subtask and Document Ranking subtask. In the Subtopic Mining subtask, we employ a voting method to rank candidate subtopics and semantic resource HowNet was used to merge those candidate subtopics which may impact diversity. In the Document Ranking Subtask, we also employ a voting method based on the mined subtopics. In the Chinese subtopic mining, our best values of I-rec@10, D-nDCG@10 and D#-nDCG@10 were separately 0.3743, 0.3965 and 0.3854. In the Document Ranking subtask, they were separately 0.6366, 0.3998 and 0.5182.

Experimental Results

RunID	Description	D# -nDCG
KECIR-S-C-1B	The baseline method, use FSM Algorithm to get subtopics.	0.3570
KECIR-S-C-2B	Base on KECIR-S-C-1B, use the first method in section 2.2	0.3854
KECIR-S-C-3B	Base on KECIR-S-C-1B, employ the second method in section 2.2	0.3116
KECIR-S-C-4B	Base on KECIR-S-C-1B, use the third method in section 2.2	0.3001

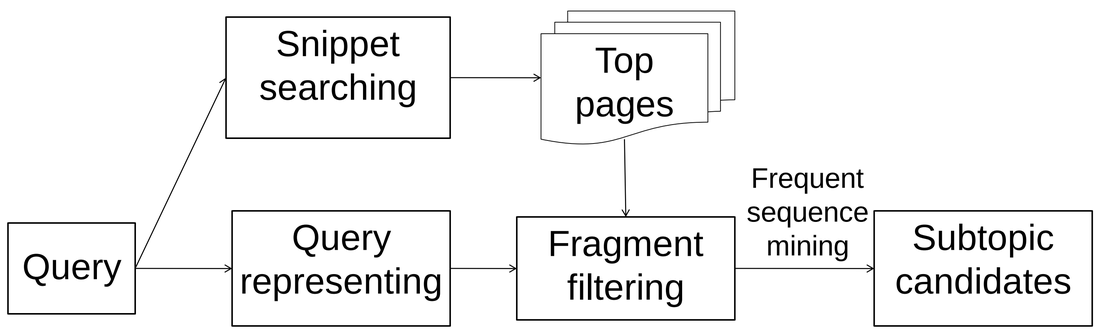
Subtopic Mining

Assumption

a) A subtopic should be the most frequent sequence which contains the key words vector of original query.
b) The more a frequent sequence contains others the less likely it is to be selected as a subtopic. And on the contrary, the more a frequent sequence is contained in others the more likely it is to be selected as a subtopic.

Modeling

➢ *Candidates Subtopics Mining*



➢ *Subtopics Clustering and Ranking*

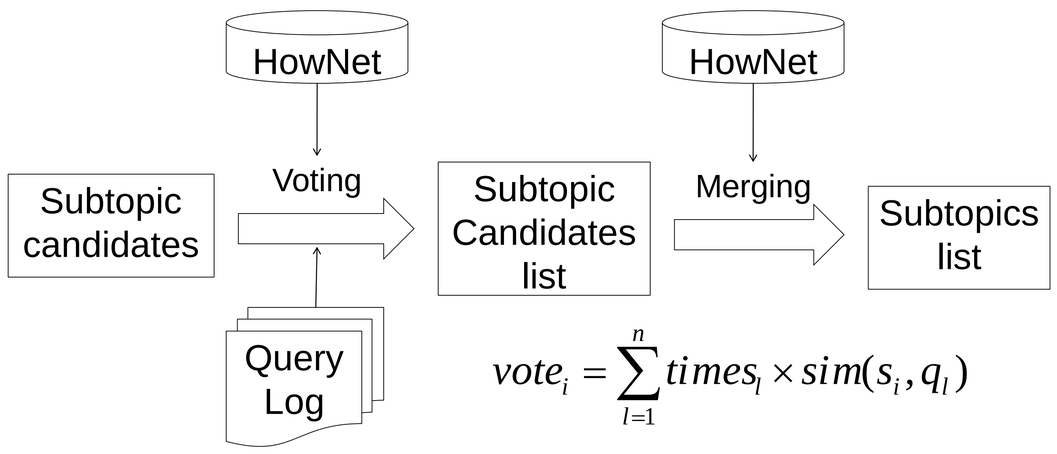
✓ **Semantic similarity**

$$Sim(phrase_a, phrase_b) = \frac{1}{n_a \times n_b} \sum_{i=1}^{n_a} \sum_{j=1}^{n_b} Similarity(c_i^a, c_j^b)$$

✓ **Merging based on the DEF**

In this method , we cluster and rank the subtopics based on finding the same DEF in HowNet of the representative words .

✓ **Voting**



$$vote_i = \sum_{l=1}^{n} times_l \times sim(s_i, q_l)$$

where $times_l$ refers to the frequency of $query_l$ in log file; $sim(s_i; q_l)$ is the similarity between $subtopic_i$ and $query_l$, here we use semantic resource HowNet to compute semantic similarity.

Document Ranking

➢Score Documents Directly

✓***Just considering the coverage of subtopics in documents.***

✓***Considering the coverage and the position of subtopics***

$$Score(document) = \sum_{i=1}^{n} Score(subtopic_i)$$

$$Score(subtopic_i) = \frac{\sum subtopic_T}{Pos(subtopic_i)}$$

where $subtopic_i$ is the subtopic the document contains, and $Score(subtopic_i)$ is the score the $subtopic_i$ gets. $\sum subtopic_T$ is the sum of subtopics that topic T owns, and $Pos(subtopic_i)$ is the position of subtopic i in the topic T ranking list.

➢Map Back to Snippets

✓***If one document snippet contains a subtopic, the document will get a vote.***

✓***Based on the above method, we add the location information of the subtopics. The Score(snippet-document)is defined as:***

$$Score(snippet - document) = \sum_{i=1}^{n} \frac{2^{score(subtopic_i)} - 1}{\log_2(1+i)}$$

where n refers the subtopic numbers of the snippet contains, and $score(subtopic_i)$ is the $subtopic_i$ original score in the ranking list.

Experimental Results

RunID	Description	D# -nDCG
KECIR-D-C-1B	Based on the baseline result and appearances of subtopics in the snippets.	0.5005
KECIR-D-C-2B	Based on the similarity result and appearances of subtopics in the htmls.	0.3938
KECIR-D-C-3B	Based on the similarity result and appearances of subtopics in the snippets.	0.5182
KECIR-D-C-4B	Based on the query log result and appearances of subtopics in the snippets.	0.5005
KECIR-D-C-5B	Based on the query log and HowNet results, also cumulative gain of subtopics in the snippets.	0.4942