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## ＊Framework Overview

$>$ 4－step framework in query understanding subtask
$>$ Candidate mining，candidate clustering，candidate ranking and vertical predicting．

＞Disambiguation Items from Wikipedia，Baidu Baike and Hudong Baike．
＞Query Facets：Query Completions and Query Suggestions
$>$ Query Reformulations extracted from SogouT
$>$ Query Recommendations from Sogou Search Engine

## ＊Candidate Clustering with K－Means

$>$ Goal：Find diversified candidates
$>$ Cluster candidates with K－means algorithm
$>$ Query vector representation
$>$ Word embedding trained based on SogouT dataset
＞Long query candidate：average word embedding of the words
$>$ Cluster candidates into n clusters
$>\mathrm{n}=5$ or 10
$>$ Candidate evaluation
＞Clusters

$$
c_{1}, c_{2}, c_{3}, \cdots, c_{n}
$$


＞Inner distance

$$
S_{\text {inner }}(q)=\frac{\sum_{q_{k} \epsilon c_{i}, q_{k} \neq q} \operatorname{dist}\left(q, q_{k}\right)}{\left|c_{i}\right|-1}, q \epsilon c_{i}
$$

＞Outer distance

$$
S_{\text {outer }}(q)=\min \left\{\frac{\sum_{q_{k} \epsilon c_{i}} \operatorname{dist}\left(q, q_{k}\right)}{\left|c_{i}\right|}\right\}(j=1,2, \cdots, n, j \neq i), q \epsilon c_{i}
$$

$>$ Candidate score

$$
S(q)=\frac{S_{\text {outer }}(q)-S_{\text {inner }}(q)}{\max \left\{S_{\text {outer }}(q), S_{\text {inner }}(q)\right\}}
$$

## ＊Candidate Ranking with Learning to Rank

$>$ Goal：Find high quality subtopic candidates
$>$ Rank candidates with Learning To Rank algorithm （RankBoost）
＞Features：
Text similarity：length difference，Jaccard similarity，edit distance．．． Word embedding：average，medium，top 3 average of cosine similarities

Search Result Similarity：number of shared results．．．
＞Metric to optimize：NDCG＠10

## ＊Vertical Predicting

$>$ Training query
＞Seed Urls generated from an Open Directory Project
$>$ Random walk on a click－through bipartite graph
$>$ Vertical Distribution
$>$ Vertical information collected from search result pages

$$
\mathrm{P}-\text { score }=\frac{1}{\log \left(1+R_{i}\right)}
$$

$>$ Model Construction
＞Logistic Regression
$>$ Word embedding query representation
$>$ Six prediction models for each type of verticals
$>$ Vertical Diversification
$>$ Empirical rules
$>$ Replace the top 3 Web intent with corresponding vertical intent
$>$ The top vertical result is chosen to be the vertical intent if there are more than two verticals in the top 3 positions

## ＊Experimental Results

| RUNNAME | SYSTEM DESC． | D\＃－ <br> nDCG | V－ <br> score | QU－ <br> score |
| :---: | :---: | :---: | :---: | :---: |
| THUIR－QU－ <br> 1A | Cluster all subtopic candidates into 10 clusters <br> and select the candidate with the highest $\mathrm{S}(\mathrm{q})$ <br> from each cluster． | 0.5204 | 0.5579 | 0.5392 |
| THUIR－QU－ <br> 2A | Cluster all subtopic candidates into 5 clusters <br> and select two candidates with the highest two <br> S（q）from each cluster． | 0.5550 | 0.5506 | 0.5528 |
| THUIR－QU－ <br> 1B | Rerank the 10 subtopics generated by THUIR－ <br> QU－1A with learning to rank algorithm． | 0.5368 | 0.5763 | 0.5565 |
| THUIR－QU－ <br> 2B | Rerank the 10 subtopics generated by THUIR－ <br> QU－2A with learning to rank algorithm． | 0.5436 | 0.5686 | 0.5561 |
| THUIR－QU－ | Cluster all subtopic candidates into 5 clusters <br> and select the candidate with the highest ten <br> 3A | 0.4973 | 0.5942 | 0.5458 |

## ＊Retrieval Models

＞Probabilistic model based on BM25 and our previous proposed word pair model．
$>$ Relevance score for subtopic $>R(q, D)=W_{B M 25}+\alpha \cdot W_{w p}$ $>W_{B M 25}=\sum_{i=1}^{m} \log \frac{N-n\left(q_{i}\right)+0.5}{n\left(q_{i}\right)+0.5} \cdot \frac{f\left(q_{i}, D\right) \cdot\left(k_{1}+1\right)}{f\left(q_{i}, D\right)+k_{1} \cdot\left(1-b+b \cdot \frac{|D|}{a v g d l}\right)}$ $>W_{w p}=\sum_{i=1}^{m} \log \frac{N-n\left(q_{i} q_{i+1}\right)+0.5}{n\left(q_{i} q_{i+1}\right)+0.5} \cdot \frac{f\left(q_{i} q_{i+1}, D\right) \cdot\left(k_{1}+1\right)}{f\left(q_{i} q_{i+1}, D\right)+k_{1} \cdot\left(1-b+b \cdot \frac{\mid D D}{\text { avgdl }}\right)}$
$>$ Relevance score for query
$>R(Q, D)=\sum_{i=1}^{10} R\left(q_{i}, D\right) \times S\left(q_{i}\right)$
$>$ Vertical importance based on subtopic candidate score $>I(v)=\alpha \cdot S-\operatorname{score}(v)$
$>$ Combination of $R(Q, D)$ and $\mathrm{I}(v)$

## ＊Experimental Results

| RUNNAME | D\＃－nDCG <br> （unclear topics） | nDCG <br> （clear topics） | D\＃－nDCG＋nDCG <br> （all topics） |
| :---: | :---: | :---: | :---: |
| THUIR－QU－ <br> 1A | 0.6677 | 0.5756 | 0.6594 |
| THUIR－QU－ <br> 2A | 0.6664 | 0.5652 | 0.6573 |
| THUIR－QU－ <br> 1B | 0.6594 | 0.5416 | 0.6488 |
| THUIR－QU－ <br> 2B | 0.6632 | 0.5442 | 0.6525 |
| THUIR－QU－ <br> 3A | 0.6429 | 0.5506 | 0.6346 |

$>$ Training set：Ranked Subtopics from NTCIR－11 Imine

