## **THUIR at NTCIR-9 INTENT Task**

IR Group of Tsinghua University

Yufei Xue, Fei Chen, Tong Zhu, Chao Wang, Zhichao Li, Yiqun Liu, Min Zhang, Yijiang Jin, Shaoping Ma

# Outline

- Overview
- Subtopic Mining
  - Extracting Subtopics from Web Resrouces
  - Mining Subtopics from Clickthrough Data
  - Re-ranking Based on Clicked Titles and Snippets
  - Removing reduplicate subtopics
- Document Ranking
  - Retrieval Models
  - Result Re-ranking with HITS
  - Documents Duplication Elimination
  - Novelty-Result Selection algorithm
  - D#-nDCG-based Selection algorithm

## Overview

- THUIR's first experience of NTCIR
- Participate in INTENT task
  - Both Subtopic Mining and Document Ranking
  - Focus on Chinese topics only
- Methods
  - Minig subtopics from different resources (search engines, Wikipedia, Clickthrough data)
  - Diversifying search results with different algorithms (traditional and D#-measure oriented diversifying methods)

# Subtopic Mining

#### • 5 runs submitted

Runs	Data	
THU-S-C-1	Web resources:	
THU-S-C-2	Query recommendations of search engines &	
THU-S-C-3	Wikipedia items	
THU-S-C-4	Clickthrough data: SogouQ	
THU-S-C-5	Clickthrough data: Sogou web search log in about 1 year.	

#### Minig subtopics from search engines

- Commercial search engines usually suggest related search queries in SERPs.
- Most of the suggested queries are specializations of the previous query.

#### Minig subtopics from search engines

- Crawl the suggested related queries of each topic in different search engines.
- Use the search engines to vote for all related queries and get a ranked subtopic list.

Search Engine	Weight
Google	1
Baidu	1
Bing	1
Sogou	1
Soso	0.5
Youdao	0.5

<b>Fable</b>	1:	The	search	engines	and	their	weights
--------------	----	-----	--------	---------	-----	-------	---------

# Mining subtopics from Wikipedia

• Disambiguation pages in Wikipedia



# Mining subtopics from Wikipedia

- Besides disambiguation pages, we can get more subtopics from the items in Wikipedia.
- We extract all the items with an INTENT subtopic as its substring.
- For the topic "巧克力" (Chocolate), there are items
  - 白巧克力(White chocolate)
  - 热巧克力(Hot chocolate)
  - 巧克力棒(Chocolate candy bar)

— .....

# Mining subtopics from Wikipedia

• Make Wikipedia join the vote of search engines.

Resource	Weight of vote	
	Google	1
Query recommendation of	Bing	1
	Baidu	1
	Sogou	1
	Youdao	0.5
	Soso	0.5
Mikinadia Itam fram	Disambiguition Page	0.9
wikipedia item from	Other	0.4

Mining subtopics from clickthrough data

- The queries and clicked URLs are often presented in a bipartite gr
- For q and  $q_i$ , define  $Score(q, q_i) = \sum_j \frac{W(q, U_j)}{\sum_k W(q, U_k)} \times \frac{W(q_i, U_j)}{\sum_k W(q_i, U_k)}$ 
  - Score(q, qi) is the probability that user clicks the same URL when searching different query q and q<sub>i</sub>.
  - Show the relevance of two queries.

Mining subtopics from clickthrough data

- To ensure q<sub>i</sub> is a subtopic of given query, we filter out a query q<sub>i</sub> if:
  - -q is a substring of  $q_i$ , or
  - $-q_i$  has no common items with q

## Submitted Runs

Runs	Data	Postprocessing	D#-nDCG@10
THU-S-C-1		Removing duplicate ones	0.5921
THU-S-C-2	Query recommendations & Wikipedia items	Removing duplicate ones; Re-ranking based on snippets	0.5993
THU-S-C-3			0.5967
THU-S-C-4	Clickthrough data: SogouQ		0.3347
THU-S-C-5	Clickthrough data: Sogou web search log in about 1 year.		0.3672

- Titles and snippets are the only contents that users can see before they click on search results.
- Clicked titles and snippets contain a lot of information about users' needs and intents.
- With the clicked titles and snippets, we try to find which subtopics are more important.

• Step 1:

For a topic, analyze all the clickthrough data of the topic and gather the title and snippet texts of each click into a "snippet document"



 Step 2: Get term frequencies of snippet document.



• Step 3: Assign a weight to each term according to the rank.

![](_page_15_Figure_2.jpeg)

 Step 4: Look back into the subtopic list. If any term in the ranked term list appears in a subtopic, we add the weight of the term to the score of the subtopic.

• Step 5: Re-rank the subtopics by the updated score.

### **Other Approaches**

- Removing reduplicate subtopics
  - Analyze the clickthrough data of the subtopics.
     If 2 subtopics have more than 5 common clicked URLs, they are considered as reduplicate ones.
  - Merge reduplicate subtopics together, keep the one with higher rank in the list.
- Specificially, we try to recognize the topics with four kinds of common intents:
  - Online Music
  - Online Video
  - Online Novel
  - Encyclopedia.

## Submitted Runs

Runs	Data	Postprocessing	D#-nDCG@10
THU-S-C-1		Removing duplicate ones	0.5921
	Query	ns & Removing ns & duplicate ones; Re-ranking based on snippets	
THU-S-C-2	recommendations & Wikipedia items		0.5993
THU-S-C-3			0.5967
THU-S-C-4	Clickthrough data: SogouQ		0.3347
THU-S-C-5	Clickthrough data: Sogou web search log in about 1 year		0.3672

Table 5. Chinese Subtopic Mining runs ranked by D<sup>#</sup>-nDCG@10.

run name	I-rec@10	D-nDCG@10	D <b>♯-nDCG@1</b> 0
THU-S-C-2	0.4801	0.7186	0.5993
MSINT-S-C-2	0.5130	0.6806	0.5968
THU-S-C-3	0.4828	0.7107	0.5967
THU-S-C-1	0.4946	0.6896	0.5921
ICTIR-S-C-1	0.5161	0.6434	0.5797
uogTr-S-C-5	0.4947	0.6598	0.5772
MSINT-S-C-4	0.4864	0.6604	0.5734
ICTIR-S-C-4	0.5035	0.6417	0.5726
ICTIR-S-C-2	0.4826	0.6576	0.5701
HITIR-S-C-5	0.4936	0.6449	0.5693
ISCAS-S-C-1	0.5022	0.6336	0.5679
ICTIR-S-C-3	0.4808	0.6530	0.5669
HITIR-S-C-1	0.4854	0.6453	0.5653
ISCAS-S-C-3	0.4910	0.6386	0.5648
MSINT-S-C-1	0.5002	0.6240	0.5621
NTU-S-C-2	0.4683	0.6546	0.5615
MSINT-S-C-5	0.4578	0.6543	0.5560
NTU-S-C-3	0.4807	0.6308	0.5558
HITIR-S-C-4	0.4738	0.6291	0.5514
HITIR-S-C-3	0.4738	0.6291	0.5514
HIT2jointNLPLab	0.4596	0.6407	0.5501
-S-C-2			

## **Document Ranking**

- Retrieval Models
- Result Re-ranking with HITS
- Documents Duplication Elimination
- Novelty-Result Selection algorithm
- D#-nDCG-based Selection algorithm

### **Retrieval Models**

• Improved Probabilistic Model  

$$R(Q,D) = W_{BM25} + \alpha_1 \cdot W_{Wp}$$

$$W_{BM25} = \sum_{i=1}^{m} \log \frac{N - n(q_i) + 0.5}{n(q_i) + 0.5} \cdot \frac{f(q_i, D) \cdot (k_1 + 1)}{f(q_i, D) + k_1 \cdot (1 - b + b \cdot \frac{|D|}{avgdl})}$$

$$W_{Wp} = \sum_{i=1}^{m} \log \frac{N - n(q_iq_{i+1}) + 0.5}{n(q_iq_{i+1}) + 0.5} \cdot \frac{f(q_iq_{i+1}, D) \cdot (k_1 + 1)}{f(q_iq_{i+1}, D) + k_1 \cdot (1 - b + b \cdot \frac{|D|}{avgdl})}$$

*N* is the total number of documents, n(q) is the number of documents contain *q*,  $k_1$  and *b* are experimental parameters of BM25 ranking, |D| is the length of document *D*, *avgdl* is the average document length, f(q, D) is the term frequency of *q* in *D*.

## **Result Diversification**

- Result Re-ranking with HITS
  - Top m documents sorted by either Authority or Hub Value are placed up to the front.

$$R_{new} = R_{old} - R_{old} \times (Authority + Hub)$$

where  $R_{new}$  stands for the new rank of the document, and  $R_{old}$  is the old one.

## **Result Diversification**

- Documents Duplication Elimination
  - Calculate the cosine similarity between the current document and the documents before, respectively.
  - If the similarity is greater than the threshold: 0.95, list it in the end.
  - This method is based on HITS.

#### Novelty-Result Selection Algorithm

• Novelty-Result Selection Algorithm

- Novelty function:

$$f(d_i, S) = \frac{|S|}{\sum_{d_j \in S} \alpha_j \cdot \frac{1}{|\omega_i, \omega_j|}}$$
  
the weight parameter  $\alpha_j = \frac{1}{original \ rank \ of \ d_j}$ 

#### Novelty-Result Selection algorithm

- *Set*  $S = \{d_0\}$
- *While*( $||\omega_i|| > 0 \&\&|S| < k$ )
- $\omega_i = \operatorname{argmax} f(d_i, S)$
- Add  $d_i$  to the end of S
- End while
- For i from 1 to n
- If d<sub>i</sub> are not in S
- Add  $d_i$  to the end of S
- End for

#### D#-nDCG-based Selection Algorithm

- Definition
  - Intent probability:

$$p(i|q) = \frac{w_i}{\sum_i w_i}$$

Where  $w_i$  standards for the weight of the *i*th intent.

Document gain:

$$g_i(d) = \begin{cases} 5, & r_d \epsilon [1,5] \\ 4, & r_d \epsilon [6,20] \\ 3, & r_d \epsilon [21,50] \\ 2, & r_d \epsilon [51,100] \\ 1, r_d \epsilon [101,1000] \end{cases}$$

 $r_d$  is the original rank of the document.  $g_i(d)$  is the gain of document d under intent i.

#### D#-nDCG-based Selection algorithm

- Given q, I, D, S
- if |I| > 3 Then
- for every *d* in *D* do
- $GG(d) = \sum_{i} Pr(i|q) g_i(d)$ 
  - $C_i(d) = p(i|q) \cdot \sum_{k=1}^r g_i(d)$
- end for
- while |S| < 1000 do
- for every *d* in *D* do
- $IA O(d) = \sum_{i} g_i(d) \cdot (1 \alpha)^{C_i(r-1)}$
- $D #Value(d) = \gamma IA O(d) + (1 \gamma)GG(d)$
- Add  $max\{D#Value(d)\}$  to S, then delete it in D.
- end for
- end while
- return S
- else
- return D
- Where *I* is the intents collection of *q*. *D* is the searching result of *q*, *S* is the reranked list. IA O(d) stands for the recall how documents in *S* cover the intents *I*.

### **Experiment Results**

Run	Descriptions
THUIR-D-C-1	Documents Duplication Elimination.
THUIR-D-C-2	Novelty-Result Selection algorithm.
THUIR-D-C-3	D # - nDCG-based Selection algorithm.
THUIR-D-C-4	D # - nDCG-based selection + user search log.
THUIR-D-C-5	Result Re-ranking with HITS.
Baseline	The original search result.

	l-rec@10	D-nDCG@10	D#-nDCG@10
THUIR-D-C-1	0.6893	0.4542	0.5717
THUIR-D-C-2	0.6495	0.3853	0.5174
THUIR-D-C-3	0.5979	0.2598	0.4288
THUIR-D-C-4	0.6001	0.2569	0.4285
THUIR-D-C-5	0.6861	0.4573	0.5717
Baseline	0.5157	0.2967	0.4062

## Submitted results

run name	I-rec@10	D-nDCG@10	D <sup>#</sup> -nDCG@10
THUIR-D-C-5	0.6861	0.4573	0.5717
THUIR-D-C-1	0.6893	0.4542	0.5717
uogTr-D-C-5	0.6624	0.4374	0.5499
MSINT-D-C-1	0.7068	0.3854	0.5461
uogTr-D-C-2	0.6600	0.4316	0.5458
MSINT-D-C-4	0.7091	0.3822	0.5456
uogTr-D-C-4	0.6474	0.4423	0.5449
MSINT-D-C-2	0.7003	0.3783	0.5393
uogTr-D-C-3	0.6301	0.4480	0.5390
MSINT-D-C-5	0.6936	0.3783	0.5359
uogTr-D-C-1	0.6406	0.4252	0.5329
THUIR-D-C-2	0.6495	0.3853	0.5174
HIT2jointNLPLab	0.5794	0.3704	0.4749
-D-C-2			
NTU-D-C-1	0.6180	0.3314	0.4747
SJTUBCMI-D-C-2	0.6008	0.3317	0.4663
MSINT-D-C-3	0.5987	0.3222	0.4604
SJTUBCMI-D-C-3	0.5856	0.3288	0.4572
SJTUBCMI-D-C-5	0.6228	0.2816	0.4522
SJTUBCMI-D-C-4	0.6108	0.2756	0.4432
SJTUBCMI-D-C-1	0.6038	0.2654	0.4346
THUIR-D-C-3	0.5979	0.2598	0.4288
THUIR-D-C-4	0.6001	0.2569	0.4285
HIT2jointNLPLab	0.4716	0.3573	0.4144
-D-C-1			
III_CYUT_NTHU	0.4630	0.2040	0.3335
-D-C-1			

#### **THANK YOU! QUESTIONS?**