

THUIR_SS at the NTCIR-17 Session Search (SS) Task



Xinyan Han¹, Yiteng Tu², Haitao Li¹, Qingyao Ai¹, Yiqun Liu¹ 1 Department of Computer Science and Technology, Institute for Artificial Intelligence, **Beijing National Research Center for Information Science and Technology**, Tsinghua University, Beijing 100084, China 2 Renmin University of China, Beijing 100872, China

Introduction •••

> We participated in FOSS and POSS subtasks in **NTCIR17 Session Search task.**

POSS Subtask •••

> In POSS subtask, the user interaction information for the last k-n queries is not provided, we just skip the clicked

- \succ In both subtasks, we tried different approaches for feature fusion, including Learning-to-Rank and linearly combination.
- \succ The final report of the SS-2 task demonstrate the effectiveness of our method, significantly outperforming other competitors.

FOSS Subtask •••

> In FOSS subtask, we concatenate all the queries and the first clicked document title of each query except the last one in a session as session context.

> Learning-to-Rank

- \succ In our approaches, we incorporate a total of 11 features which include both term-level features from traditional sparse retrieval methods and semantic-level features obtained through deep neural networks.
- > We choose two classic but effective sparse retrieval methods, BM25 and QLD.
- > We train a dense retrieval model on on TianGong-ST, using the InfoNCE Loss as the loss function.

- document and concatenate query.
- > We use the same method of FOSS subtask to rank documents in POSS subtask.

Submitted Runs and Evaluation

FOSS subtask.

- The preliminary evluation of our runs in FOSS subtask are shown in Table 2.
- \succ The linear combination method using the ad-hoc score of BM25 and the score computed by DCL model achieved the best performance.

Run Name	Description	NDCG@3	NDCG@5	Rank
THUIR_SS-FOSS-NEW-1	learning-to-rank (LightGBM)	0.1547940	0.2038491	5
THUIR_SS-FOSS-NEW-3	linear combination	0.5853154	0.6745773	1
THUIR_SS-FOSS-NEW-4	learning-to-rank (LambdaMART)	0.2506041	0.3309875	4
THUIR_SS-FOSS-NEW-5	RRF	0.3931865	0.4768206	3
THUIR_SS-FOSS-NEW-6	linear combination	0.5643186	0.6569274	2

Table 2: Preliminary Evaluation of Our Runs in FOSS Subtask

- \succ We also train a fine-grained context-aware ranking model, DCL, with a curriculum learning framework.
- ➤ We feed the 11 features (Table 1) into two widely-used learning-to-rank models, LightGBM and LambdaMART.

	feature			
	11 CDM			
1	ad-hoc score of BM25			
2	ad-hoc score of QLD			
3	ad-hoc score of BM25 with RM3			
4	ad-hoc score of QLD with RM3			
5	session score of BM25			
6	session score of QLD			
7	session score of BM25 with RM3			
8	session score of QLD with RM3			
9	ad-hoc score of DR model			
10	session score of DR model			
11	sesion score of DCL model			
Table 1: features of learning-to-rank mode				

> Linearly combination

> POSS subtask.

- > The preliminary evluation of our runs in POSS subtask are shown in Table 3.
- > The linear combination method using the ad-hoc score of QLD and the score computed by DCL model achieved the best performance.

Run Name	Description	RS_DCG	RS_RBP	Rank
THUIR_SS-POSS-NEW-1	learning-to-rank (LightGBM)	0.023533	0.048312	5
THUIR_SS-POSS-NEW-3	linear combination	0.174898	0.367266	2
THUIR_SS-POSS-NEW-4	learning-to-rank (LambdaMART)	0.068510	0.143386	4
THUIR_SS-POSS-NEW-5	RRF	0.136628	0.288760	3
THUIR_SS-POSS-NEW-6	linear combination	0.181201	0.379338	1

Table 3: Preliminary Evaluation of Our Runs in POSS Subtask

- \succ Our learning-to-rank method still has room for improvement.
 - \succ First, more features can be selected to feed into the model, such as user interaction information (clicks and timestamp)
 - \succ Second, we find that sometimes the query at the beginning of a session and the query at the end of a session are not very semantically related. These unrelated queries bring
- \triangleright We use the linear combination of two ad-hoc scores to generate LS score.
- ➤ In THUIR_SS-FOSS-NEW-3 and THUIR_SS-POSS-NEW-3, we choose the ad-hoc score of BM25 as S1 and the score computed by DCL model as S2.
- ➢ In submission THUIR_SS-FOSS-NEW-6 and THUIR_SS-POSS-NEW-6, we replace S1 with QLD ad-hoc score.

> RRF

 \blacktriangleright We sort documents according to the score of 11 features. Then we use all 11 rankings to calculate RRF scores.

noise to our result.

Conclusion & Future work

- > Our team (THUIR_SS) participates in the FOSS and POSS subtask of the NTCIR-17 Session Search (SS) Task.
- > We try learning to rank model, RRF method, and linear combination method.
- \succ The submission using linear combination achieves the best performance in both FOSS and POSS subtasks.

Email: yitengtu16@gmail.com