Multi-Task Learning for Document Ranking and Query Suggestion

Objectives

Understanding users' information need is essential for a search engine to provide relevant search results. As a user's click behavior and query reformulation are driven by the shared underlying search intent, we argue that jointly modeling both tasks can benefit each other. We model search context within a session via a recurrent latent state in a deep neural network to guide the following:

- The generation of clicks for the current query
- The formation of the next query

Motivation

To understand the user's intent accurately, user's previously submitted queries can be utilized.

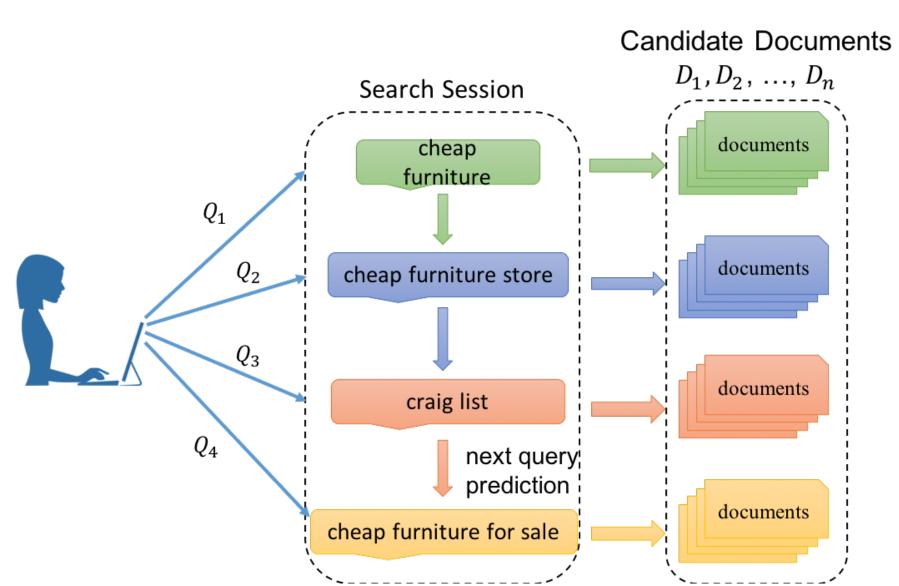


Figure 1: A user with intent of buying "cheap furnitures" is searching for relevant documents in web.

- For the query, "craig list", we can better server the user by promoting documents related to furnitures.
- The user's next query, "cheap furniture for sale" can be better inferred if previous in-session queries are taken into account.

Major Components

• Document Ranker: ranks a list of candidate documents given current query and previous queries.

$$P(D_j|Q_i, S_{i-1}) = \sigma(D_j^T \tanh(W_r[Q_i, S_{i-1}] + b_r))$$

• Query Recommender: generates next query in a sequence-to-sequence fashion following [1].

 $P(Q_i|Q_{1:i-1}) = \prod_{t=1}^q P(w_i^t|w_i^{1:t-1}, Q_{1:i-1})$

Wasi Uddin Ahmad[†], Kai-Wei Chang[†], and Hongning Wang^{*}

[†]Department of Computer Science, University of California, Los Angeles *Department of Computer Science, University of Virginia

Our Contribution

Multi-task learning of document ranking and query suggestion benefits each other. Our proposed framework is generalizable and shows improvement when adapted to other exsiting neural IR models.

Multi-Task Neural Session Relevance Framework

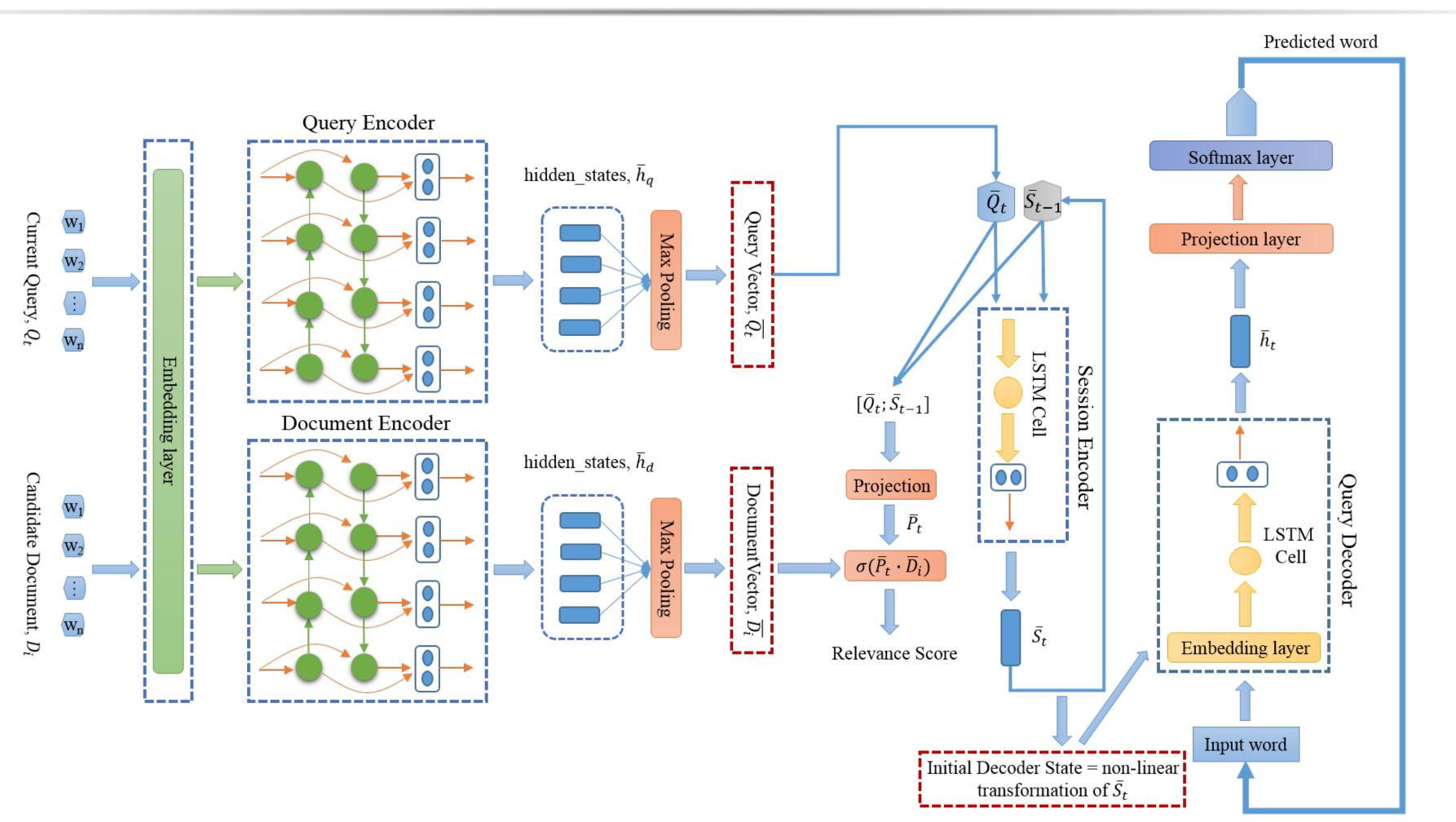


Figure 2: Architecture of the Multi-task Neural Session Relevance Framework (M-NSRF). M-NSRF uses bi-LSTM with max pooling to form query and document representations and use LSTM to gather session-level information. These recurrent states (current query representation and session-level recurrent state, which summarizes all previous queries) are used by query decoder and document ranker for predicting next query and computing relevance scores.

Multi-Task Learning Objective

Our model is trained end-to-end by minimizing the following loss function with regularization.

Binary cross entropy

$$\mathcal{L} \equiv -\frac{1}{m} \sum_{j=0}^{m} o_j \times \log P(D_j | Q_i) + (1 - o_j) \times \log(1 - O_j)$$

Document Ranking Quality

Model Name	MAP	MRR	NDCG			Model Name		BLI		MRR	
			@1	@5	@10	Model Mame	1	2	3	4	
CDSSM	0.465	0.505	0.369	0.482	0.523	Seq2seq	24.5	9.7	4.5	1.9	0.229
Match-Tensor	0.613	0.621	0.568	0.596	0.618	Seq2seq with attention					
NSRF	0.553	0.568	0.481	0.555	0.574	HRED-qs			7.9		
M-NSRF	0.581	0.603	0.523	0.583	0.614	M-NSRF	28.6	16.7	10.2	8.3	0.23
M-Match-Tensor	0.621	0.634	0.572	0.602	0.632	Table 2: Comparison of di	fferent	auerv s	uggesti	on ma	odels

Table 1: Comparison of different document ranking models.

Negative log-likelihood

 $-P(D_{j}|Q_{i})) - \sum_{t}^{q} \log P(w_{i}^{t}|w_{i}^{1:i-1}, Q_{1:i-1})$

Query Suggestion Quality

anson of unicient query suggestion models.

Prev. se

Next us Suggest

Proposed a context-aware multi-task neural session relevance framework and showed that joint training by sharing session recurrent states across document ranking and query suggestion tasks benefits each other.

[1] A. Sordoni, Y. Bengio, H. Vahabi, C. Lioma, J. Grue Simonsen, and J.-Y. Nie. A hierarchical recurrent encoder-decoder for generative context-aware query suggestion. Proceedings of the 24th ACM CIKM, pages 553–562, 2015.

This work was supported in part by National Science Foundation Grant IIS-1760523, IIS-1553568, IIS-1618948, and the NVIDIA Hardware Grant. We would also like to thank ICLR for providing *ICLR* Travel Award to facilitate the participation in this conference.





Qualitative Example

	types of weapons of mass de-
session queries	struction, weapons of mass
	destruction, nuclear weapons
ser query	biological weapons
ted next query	destructive nuclear weapons

Table 3: Examples of next query suggested by M-NSRF given all previous queries in a session.

Ablation Study

• Utilizing contextual information benefits both document ranking and query suggestion tasks. • Attention mechanism improves query suggestion because of high overlapping in real user queries. • Estimating word embeddings based on search log data results in better performance.

Conclusion

References

Acknowledgements