BEIJING UNIVERSITY OF POSTS AND TELECOMMUNICATIONS

Enhanced User Interest and Expertise Modeling for Expert Recommendation

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OUTLINE

- Motivations
- **E**nhanced **U**ser **I**nterest and **E**xpertise **M**odeling for Expert Recommendation (EUIEM)
- Experiment:
- Conclusions & Future Work

Motivations

User Interest
User Expertise

Key

Expert
Recommendation

Handcrafted features:

question features,

user features,

user feedback features

Deep learning methods:

high-level semantics

end to end learning

But

- Statistics features
- Low-level representation

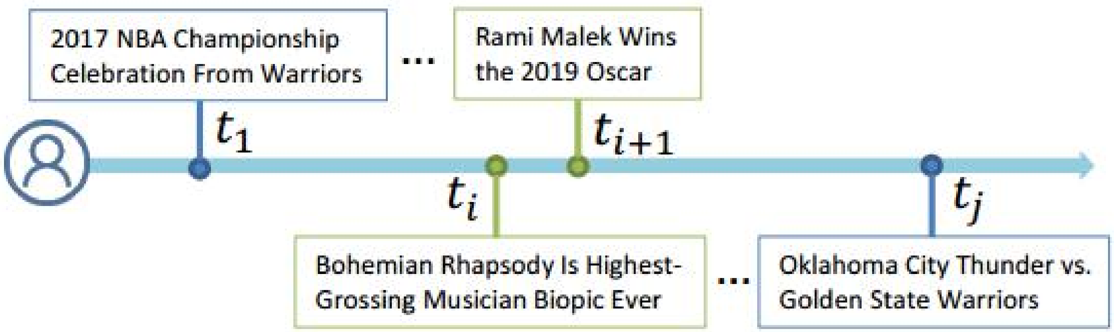
But

- Static representation for user interest
- Implicit representation for User Expertise

Thus, a learning framework that captures user interest dynamicly and models user expertise explicitly is badly needed.

Motivations

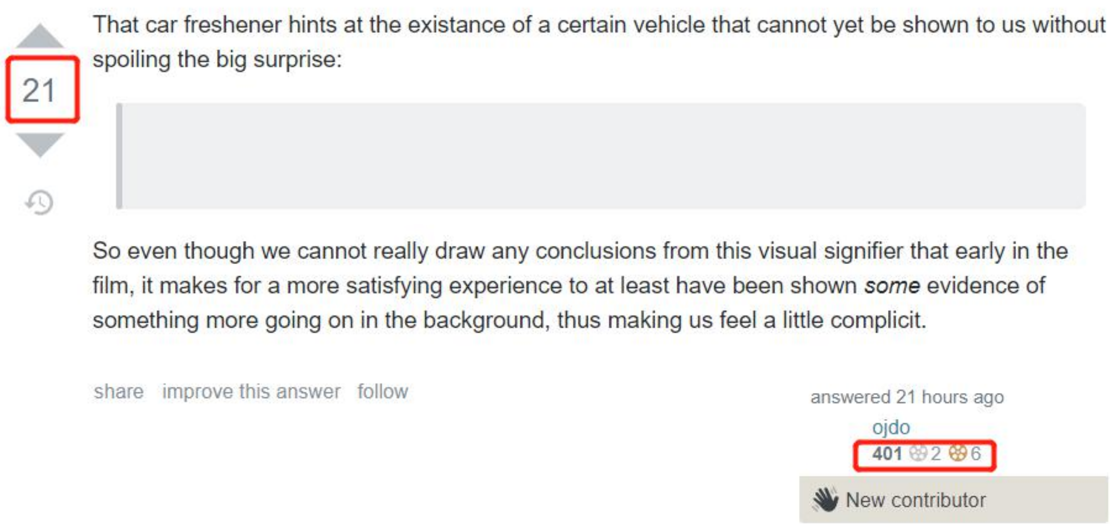
In the real-world CQA websites, **users' interest** is **changing over time**. A user may not answer the question because his current interest is not in this question domain even if he has high expertise on it.



Thus:
1. capture users' short-term interests
2. combine short-term and long-term interests

Motivations

The feedback information(votes) from users' answering questions can reflect the expertise of users in this question field.



Thus:

1. learn the expertise embedding and interest embedding respectively.
2. use the feedback to learn the expertise embedding.

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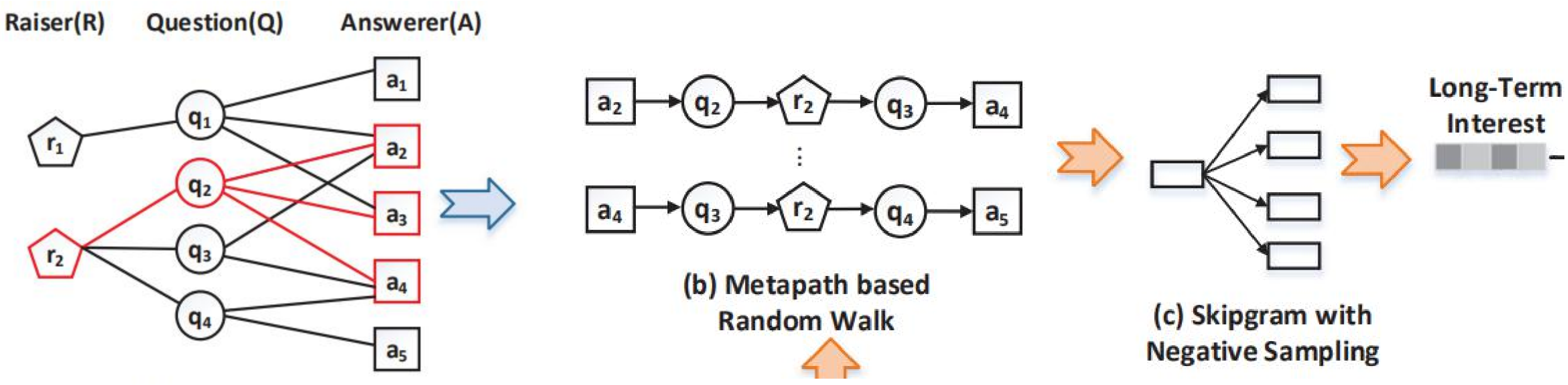
- To capture the long-term interests, we use metapath based random walk and skipgram algorithm for superiority in dealing with sparsity.



(a) CQA Network
(b) Metapath based Random Walk
(c) Skipgram with Negative Sampling

- To capture the short-term interests, we input user's recent behavior into LSTM due to its remarkable ability in processing sequential data.

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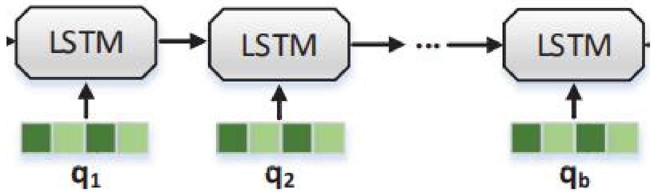
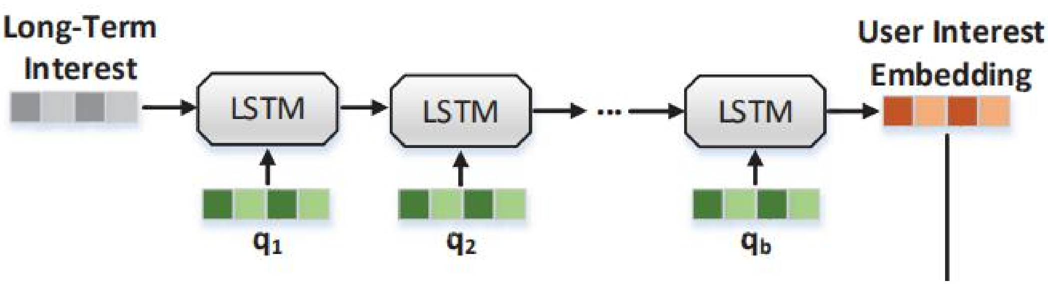


(d) Short-Term Interest Modeling

- In order to combine the long-term interest and short-term interest more naturally, we use the long-term interest to initialize the first hidden state of the LSTM, So that the last hidden state is a combination of short-term and long-term interest and we use it as users’ interest embedding.



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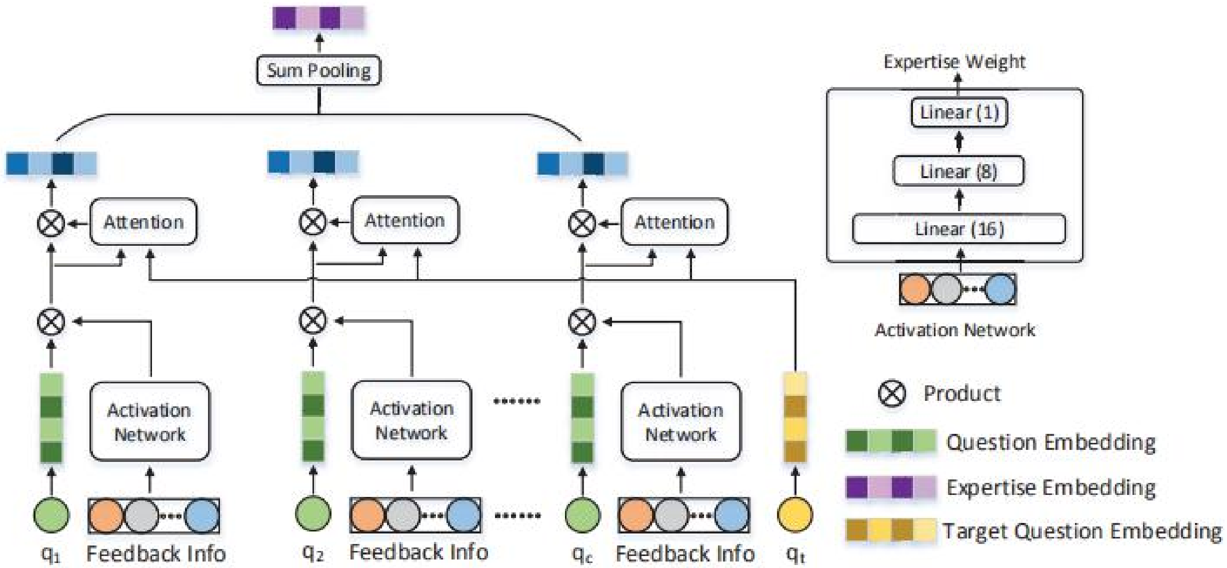
- We mine user history answers and feedback to model user expertise explicitly.



We construct several statistics of the feedback and put them into a feed-forward network to get the expertise weight. We also use attention mechanisms to pay more attention to the answers which are related to the target quesiton.

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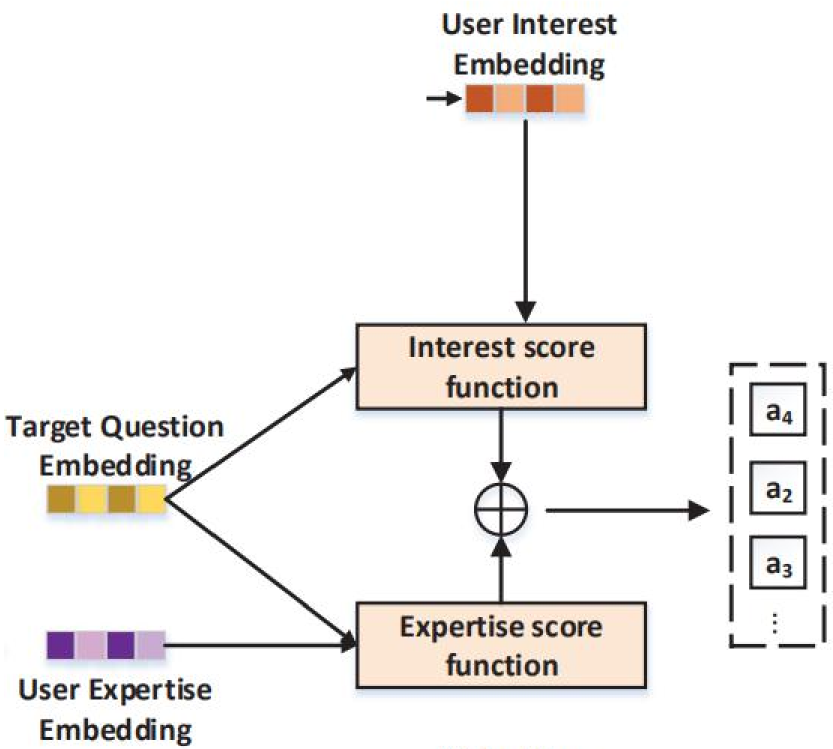
- We introduce the relative rank to model the score. Given the votes of the answers, we design the following rules:

(1)Answerers with higher vote score higher than those with lower vote.
(2) Answerers who answered question score higher than those who did not.



(f) Ranking

Model Training

- The ranking loss:

$$Obj_{rank} = \sum_{(i,j,q_t,r)\in D_1} S(\mathbf{p}_i^a, \mathbf{e}_i^a, \mathbf{q}_t, \mathbf{p}^r) - S(\mathbf{p}_j^a, \mathbf{e}_j^a, \mathbf{q}_t, \mathbf{p}^r) + \sum_{(y,z,q_t,r)\in D_2} S(\mathbf{p}_y^a, \mathbf{e}_y^a, \mathbf{q}_t, \mathbf{p}^r) - S(\mathbf{p}_z^a, \mathbf{e}_z^a, \mathbf{q}_t, \mathbf{p}^r)$$

We alternatively maximize the two objective functions

$$\log p(j|i) = \log \sigma(u_i^T v_j) + \sum_{l=1}^{k} \mathbb{E}_{j' \sim P(j')}[\log \sigma(-u_i^T v_{j'})]$$

$$Obj_{rank} = \sum_{(i,j,q_t,r)\in D_1} S(\mathbf{p}_i^a, \mathbf{e}_i^a, \mathbf{q}_t, \mathbf{p}^r) - S(\mathbf{p}_j^a, \mathbf{e}_j^a, \mathbf{q}_t, \mathbf{p}^r) + \sum_{(y,z,q_t,r)\in D_2} S(\mathbf{p}_y^a, \mathbf{e}_y^a, \mathbf{q}_t, \mathbf{p}^r) - S(\mathbf{p}_z^a, \mathbf{e}_z^a, \mathbf{q}_t, \mathbf{p}^r)$$

Experiments: dataset

Stack Exchange Dataset:

we choose two sub-dataset: Biology and English

Dataset	# of users	# of r	# of q	# of a	# of a/q	# of p/a
Biology	5858	4176	8296	2429	6.8	3.4
English	41013	22229	42972	23123	7.6	5.6

Experiments

Q1: How does the proposed EUIEM perform comparing with other state-of-the-art methods?

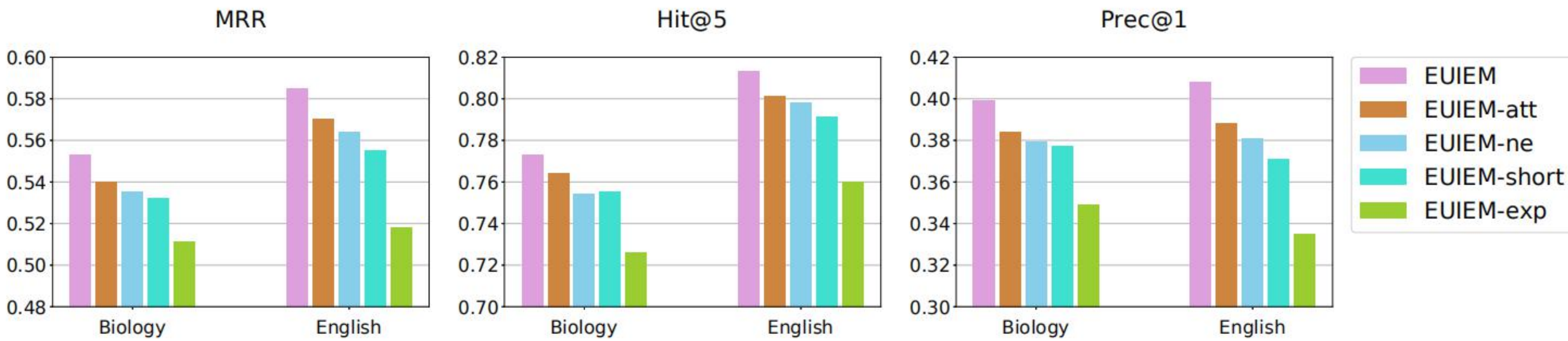
- Compared Methods:
- Metric
- Results

Method	T=2019-01-01						T=2018-10-01					
	Biology			English			Biology			English		
	MRR	Hit@5	Prec@1	MRR	Hit@5	Prec@1	MRR	Hit@5	Prec@1	MRR	Hit@5	Prec@1
Similarity	0.211	0.387	0.102	0.225	0.406	0.097	0.216	0.374	0.100	0.218	0.398	0.099
GBDT	0.329	0.491	0.203	0.372	0.612	0.188	0.301	0.483	0.185	0.362	0.600	0.192
ConvNCF	0.392	0.611	0.274	0.417	0.668	0.245	0.366	0.601	0.277	0.422	0.669	0.246
RMNL	0.483	0.697	0.315	0.491	0.717	0.336	0.488	0.691	0.317	0.492	0.708	0.331
NeRank	0.518	0.737	0.351	0.528	0.775	0.343	0.501	0.730	0.337	0.515	0.766	0.341
EUIEM	**0.553**	**0.773**	**0.399**	**0.585**	**0.813**	**0.408**	**0.541**	**0.765**	**0.389**	**0.572**	**0.797**	**0.403**

Experiments

Q2: How does the proposed EUIEM perform comparing with its variants?

- Compared variants
- Metric
- Results



Future work

- the profile of user such as user personal description should be considered to solve cold-start problem,
- the dynamic modeling of expertise can

be applied since user expertise keeps improving over time.

Thanks!

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