Personalized Question Routing via Heterogeneous Network Embedding

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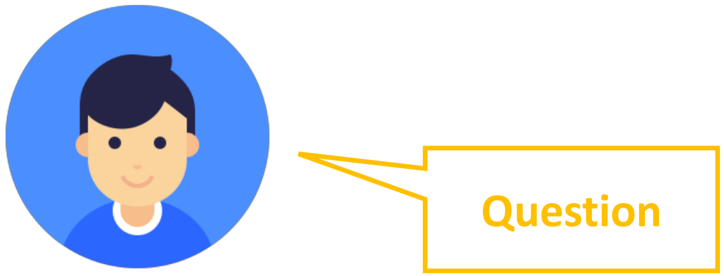
Community-based Question Answering

- Community-based Question Answering (CQA)
  - sharing knowledge and experience
  - accessible to everyone
  - gaining popularity
  - Examples:
    - Stack Overflow
    - Quora
    - Yahoo! Answers

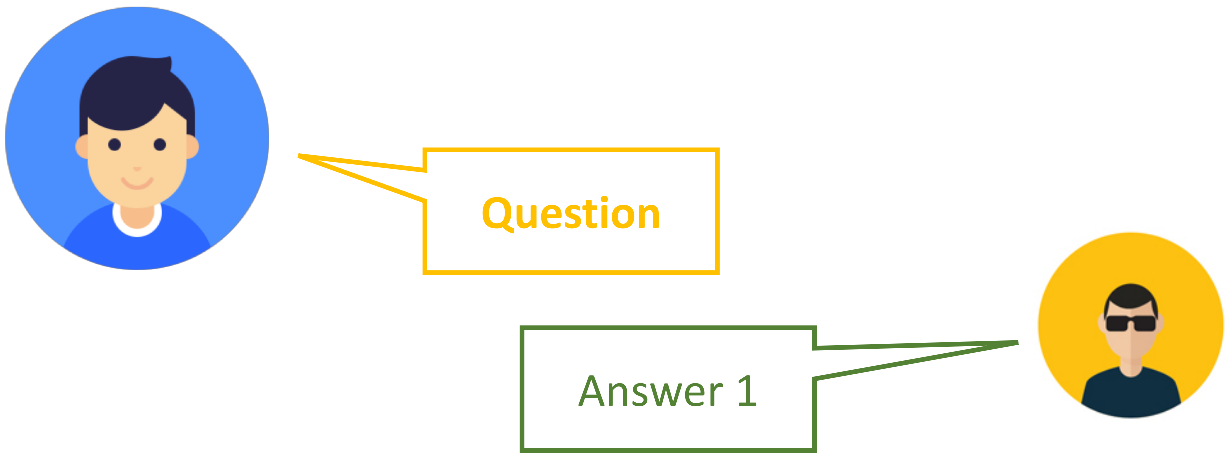
Examples of CQA

What is Question Routing?



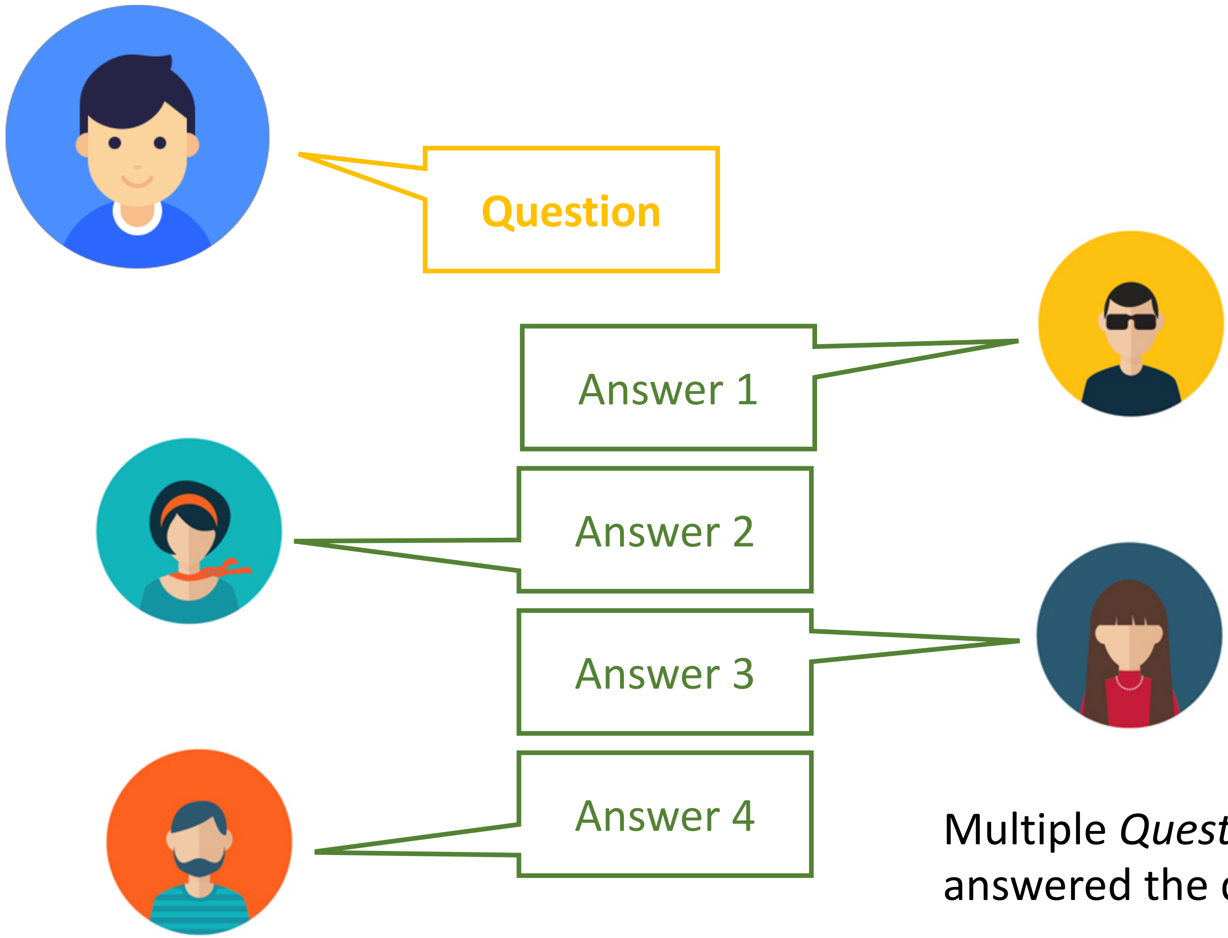
Question Raiser asked a question.

What is Question Routing?



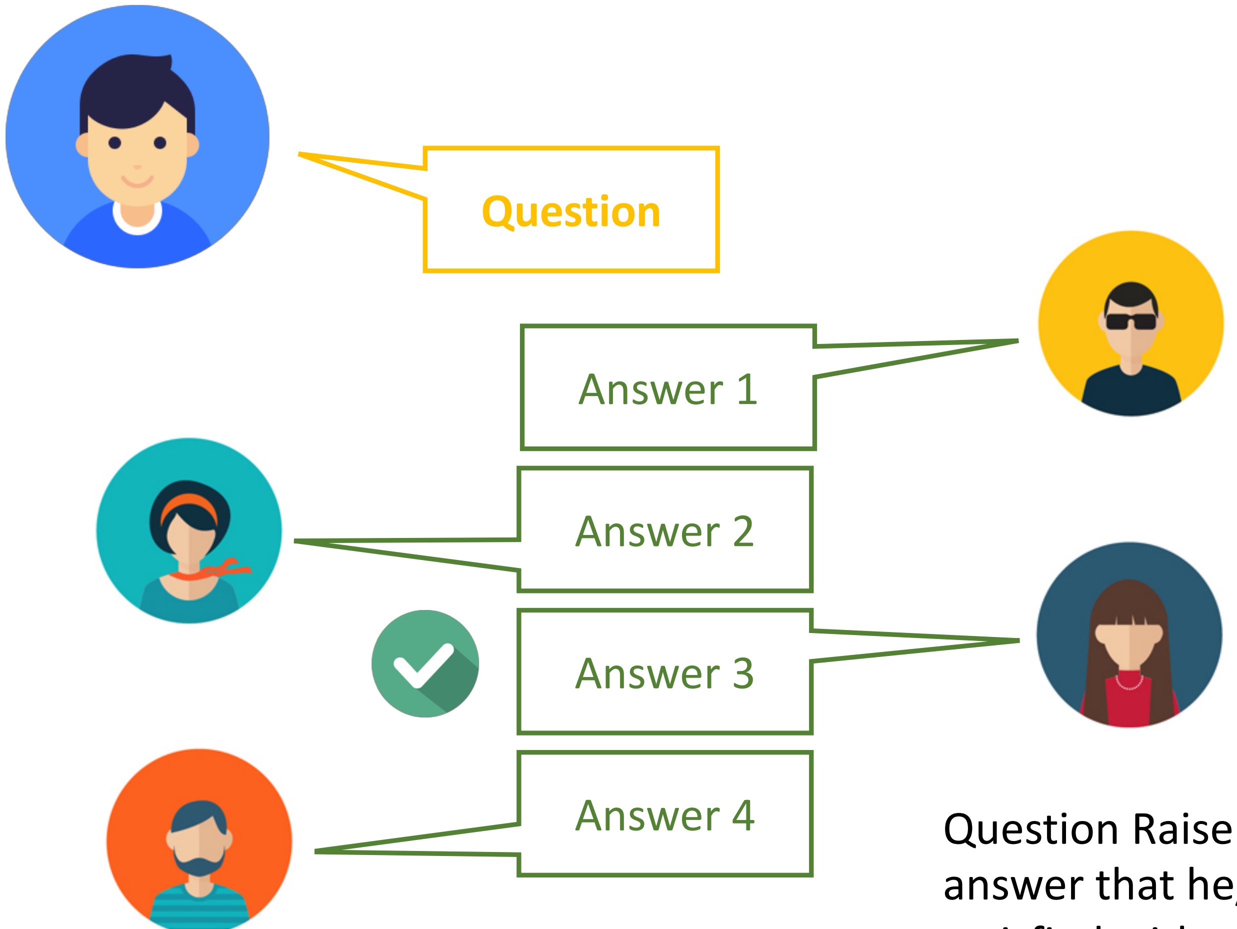
One *Question Answerer* answered the question.

What is Question Routing?



Multiple *Question Answerers* answered the question.

What is Question Routing?



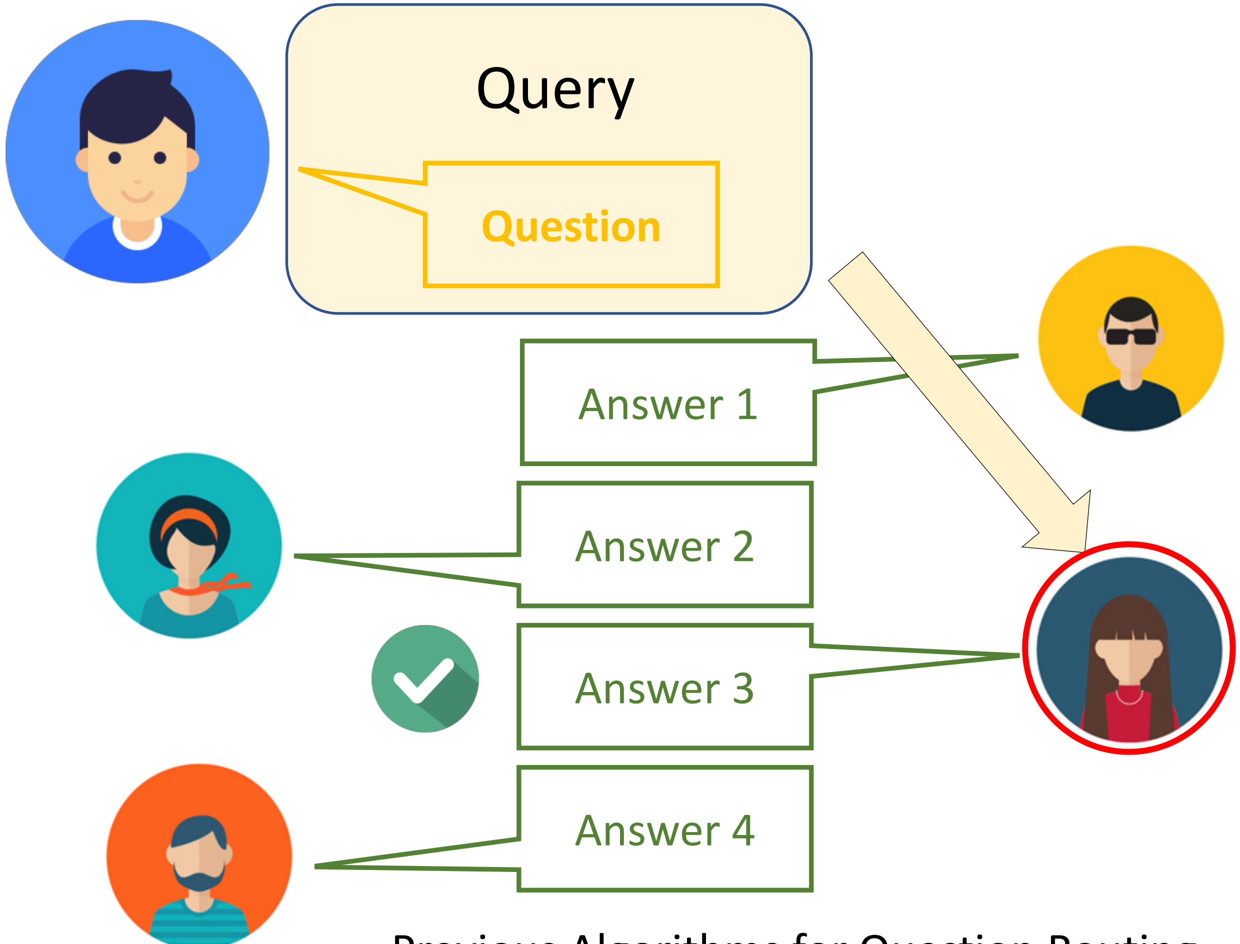
Question Raiser select the answer that he/she is most satisfied with as the "**accepted answer**"!

What is Question Routing?

Challenge:
Collecting answers can be time consuming.

What is Question Routing?

Motivation – Existing Algorithms

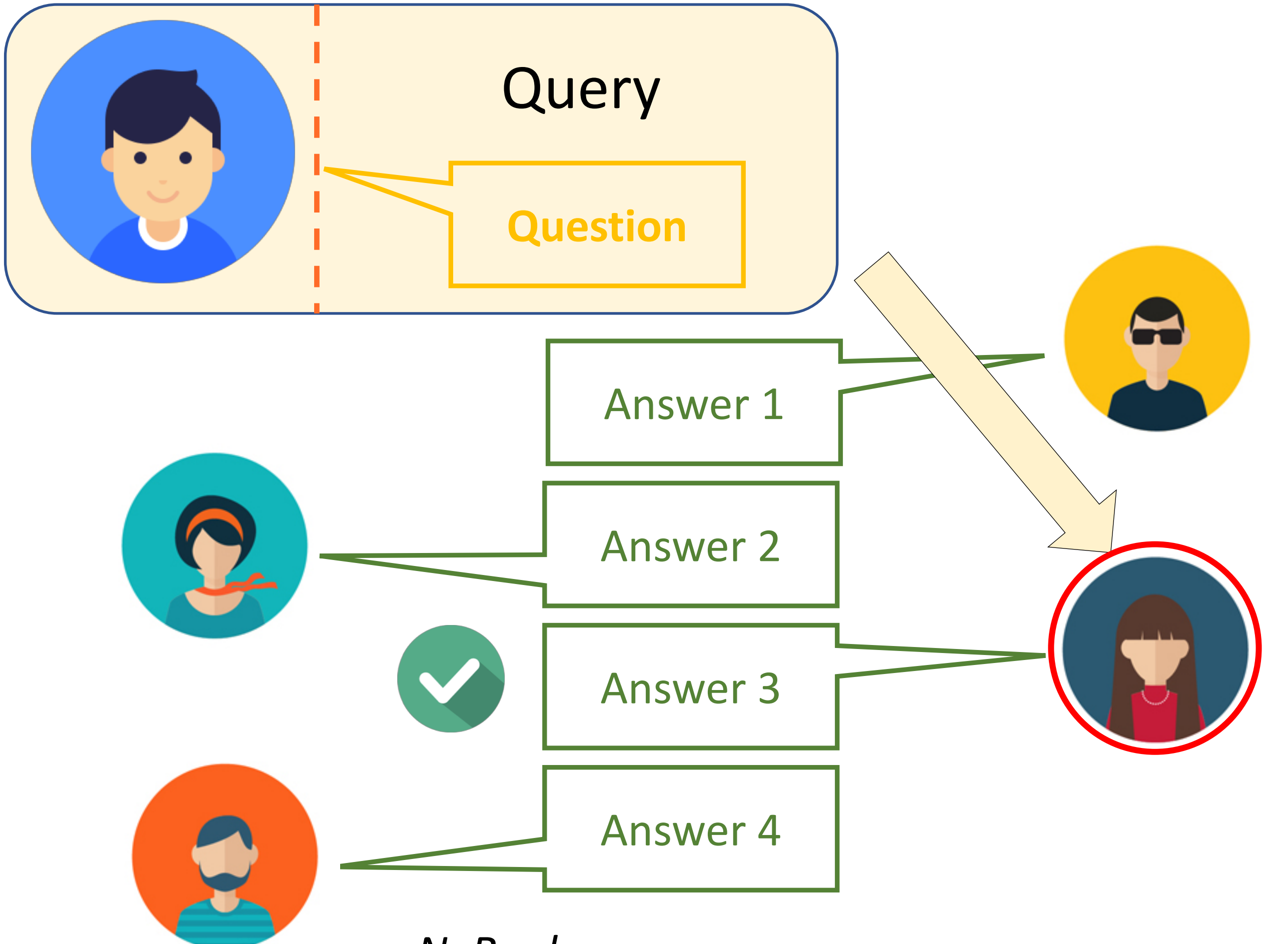


Previous Algorithms for Question Routing:
Recommend answerers based on *Question*.
`Query: {question content} → answerers`

Motivation – Limitations

- Limitations of existing QR Algorithms:
  - Lack of personalization
    - Prior algorithms are unable to customize recommendations to suit user's (diverse) characteristics.
  - Lack of quantitative ranking scores
    - Prior algorithms generate the rankings directly from the features without using explicit ranking scores.
  - Lack of mechanism to capture deep non-linear semantics of questions.
    - Prior algorithms interpret questions by language models and topic models.

Motivation – Our Algorithm

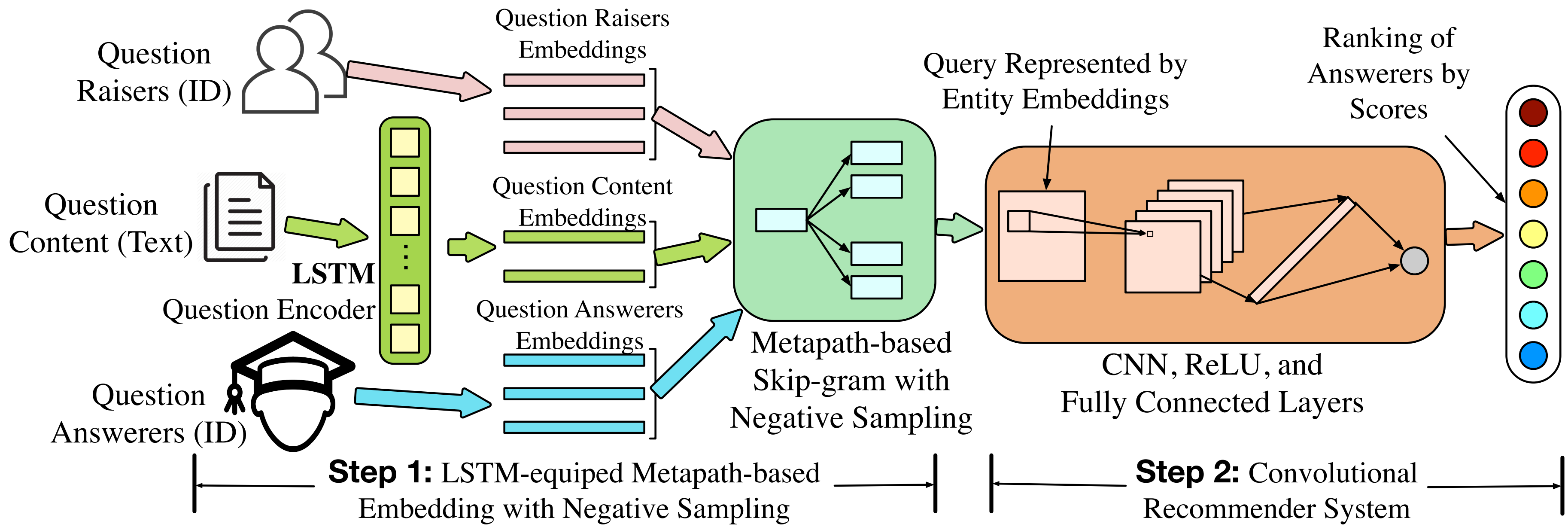


NeRank:
Assess the “personalized authority” of answerers.
Query: {question content, question Raiser} → answerers

NeRank – Overview

- Objectives
  - Personalization: Question answerers are preferable to share similar "background" to that of the question raiser.
  - Expertise: The recommended answerers are knowledgeable in the question domain.
- Proposed Solutions
  - To model user similarity: Heterogeneous Information Network (HIN) embedding. [DCS, KDD2017]
  - To capture user expertise: Convolutional recommender system.

NeRank – Pipeline



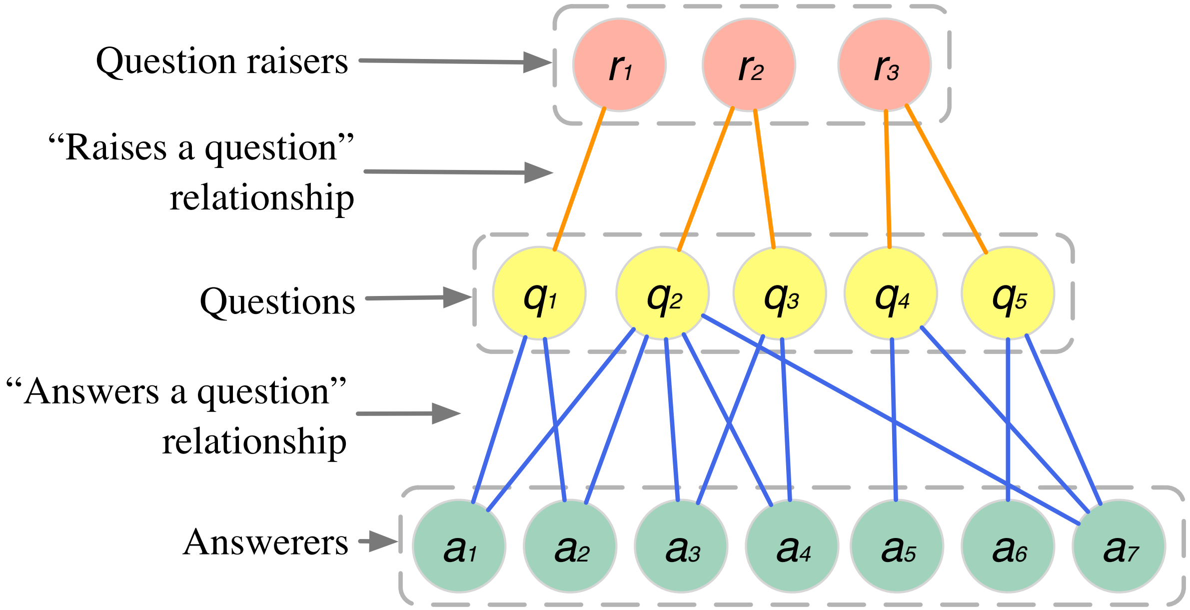
Two Major Components:

(1) LSTM-equipped Metapath-based HIN Embedding with Negative Sampling

(2) Convolutional Recommender System

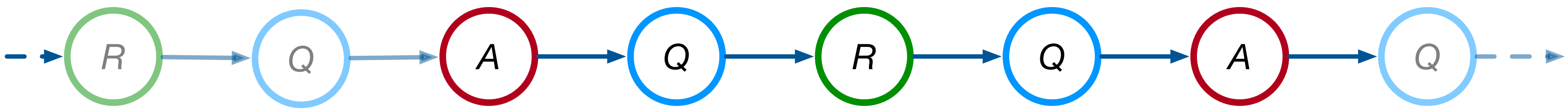
NeRank – HIN Embedding

- CQA Network
  - Three types of entities: Question Raiser, Question Content, Question Answerer.
  - Two types of relationships: “Raises a question”, “Answers a question”.



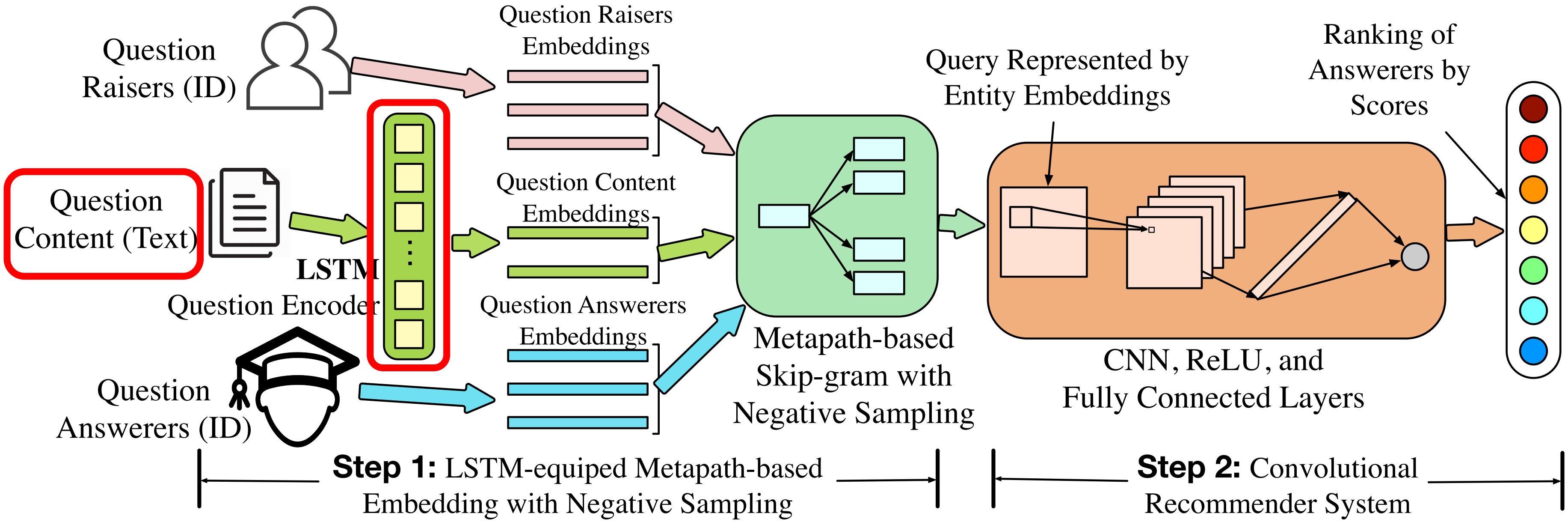
NeRank – HIN Embedding

- CQA Network
- Metapath-based Walk
  - Generate walks on the network following the pattern of a "metapath".
    - E.G. a walk of metapath *"AQRQA"*



  - Conduct Skip-gram on the generated walks.
  - *Use LSTM to learn representations of questions.*

NeRank – HIN Embedding

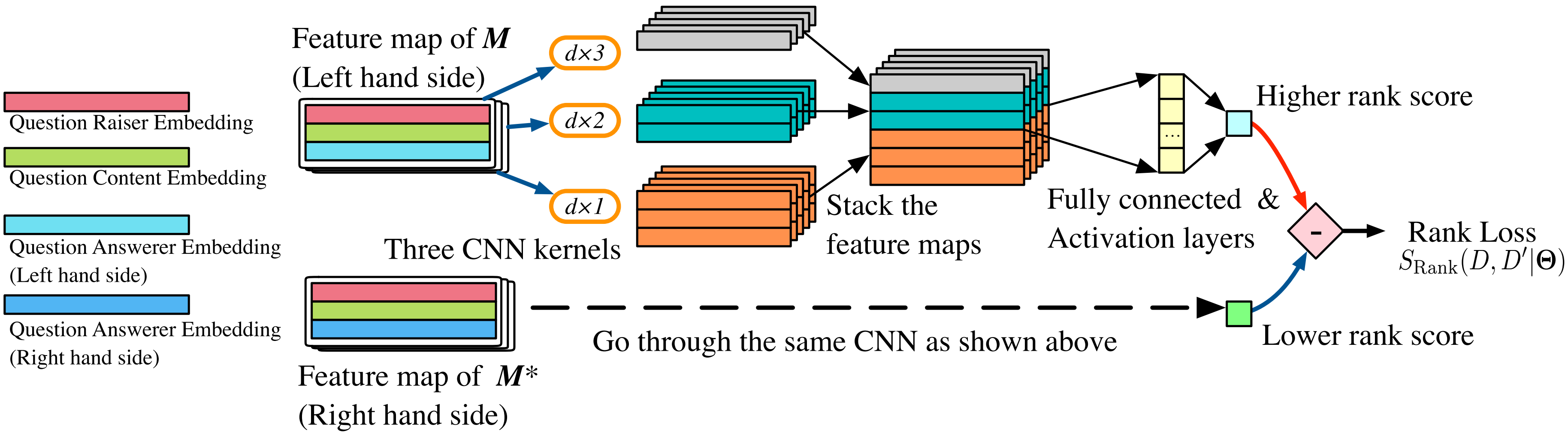


Two Steps for Question Content Representation:

(1) Derive the embedding of text by an LSTM.

(2) Feed the derived representation to Skip-gram for optimization.

NeRank – Conv. Recommender System



Two Partial Order Constraints for Ranking:

(1) The best answerer has the *highest* score among all answerers to the query.

(2) Answerers who answered a question have *higher* scores than those who did not.

NeRank – Optimization

- Embedding Loss and Ranking Loss
- For Embedding Loss:

$$\mathcal{L}(D, D'|\boldsymbol{\Theta}) = \sum_{D} \log(\sigma(v_n \cdot u_c)) + \sum_{D'} \log(-\sigma(v_n \cdot u_c))$$

- For Ranking Loss:

$$\begin{aligned} & S_{\text{Rank}}(D, D'|\boldsymbol{\Theta}) \\ = & \sum_{(a^*,q),(a,q)\in D} (F(v_r, v_q, v_{a^*}) - F(v_r, v_q, v_a)) \\ + & \sum_{(a,q)\in D,(a_n,q)\in D'} (F(v_r, v_q, v_a) - F(v_r, v_q, v_{a_n})) \end{aligned}$$

- They are alternatively optimized using *Adam*.

Experiments – Settings

- Dataset:
  - Two CQA websites under Stack Exchange: Biology (Bio) and English (Eng).
- Metrics
  - Mean Reciprocal Rank (*MRR*)
  - Hit@K:
    - The ground truth has the top-K scores.
  - Precision@1 (*Prec@1*):
    - Special case of Hit@K when K=1.

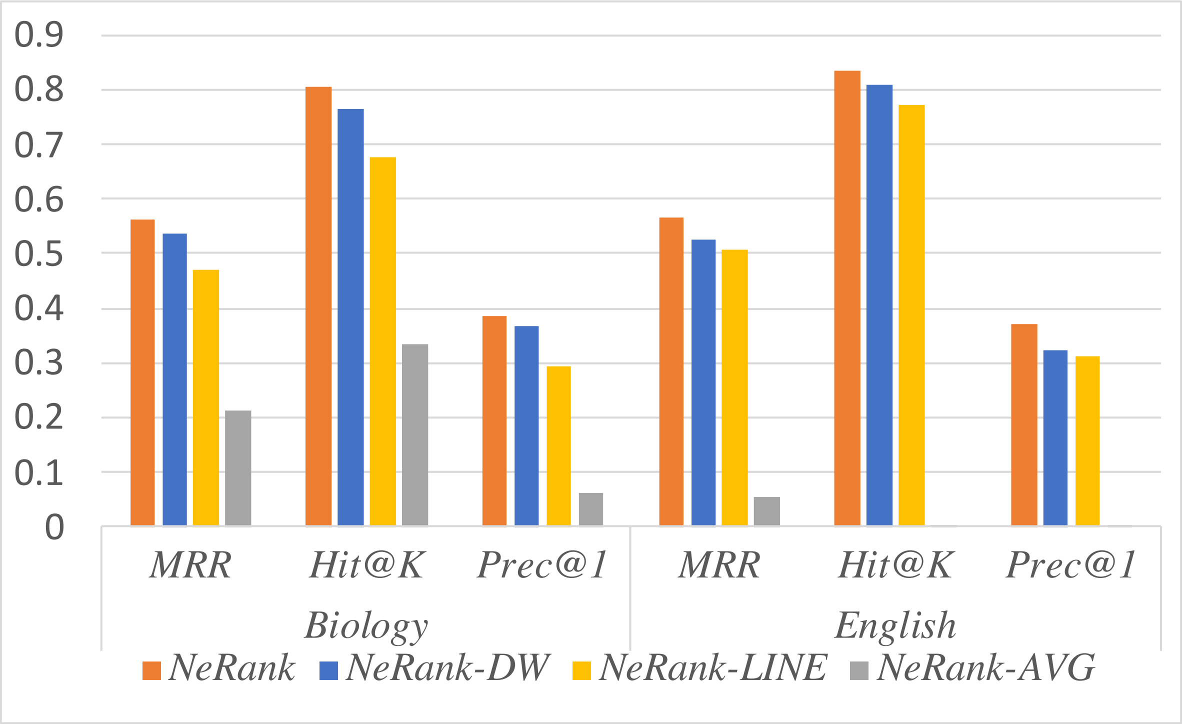
Experiments – Baselines

- Baselines:
  - Score: selecting the one with most accepted answers.
  - NMF: Non-negative Matrix Factorization. (Gemulla et al. 2011)
  - L2R: RankSVM-based QR algorithm. (Ji and Wang 2013)

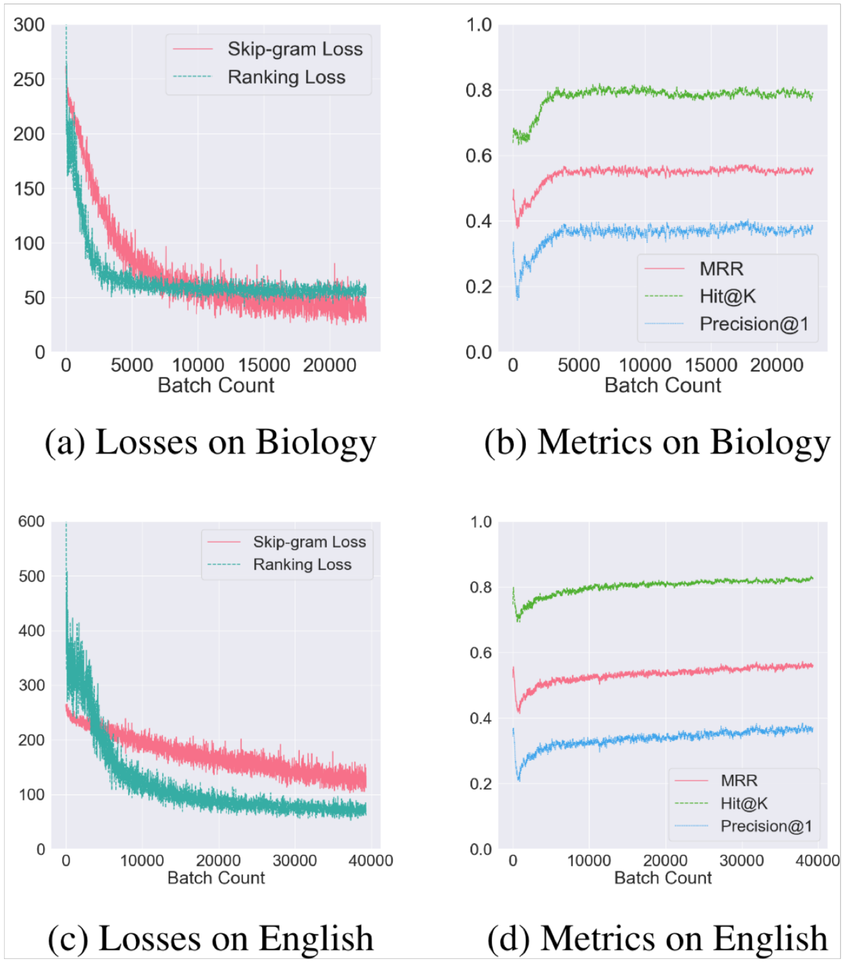
Dataset	Biology			English		
Metric	MRR	Hit@K	Prec@1	MRR	Hit@K	Prec@1
Score	0.27	0.412	0.105	0.203	0.379	0.065
NMF	0.375	0.643	0.177	0.458	0.737	0.225
L2R	0.169	0.158	0.050	0.101	0.058	0.024
NeRank	0.563	0.806	0.387	0.567	0.833	0.372

Experiments – Effectiveness

- Effectiveness of Metapath NE and CNN.
  - Comparing **NeRank** with three variants: Replacing HIN embedding with DeepWalk (**NeRank-DW**) and LINE (**NeRank-LINE**). Replacing CNN ranking scores with average of $(v_r + v_q)$ (**NeRank-AVG**)



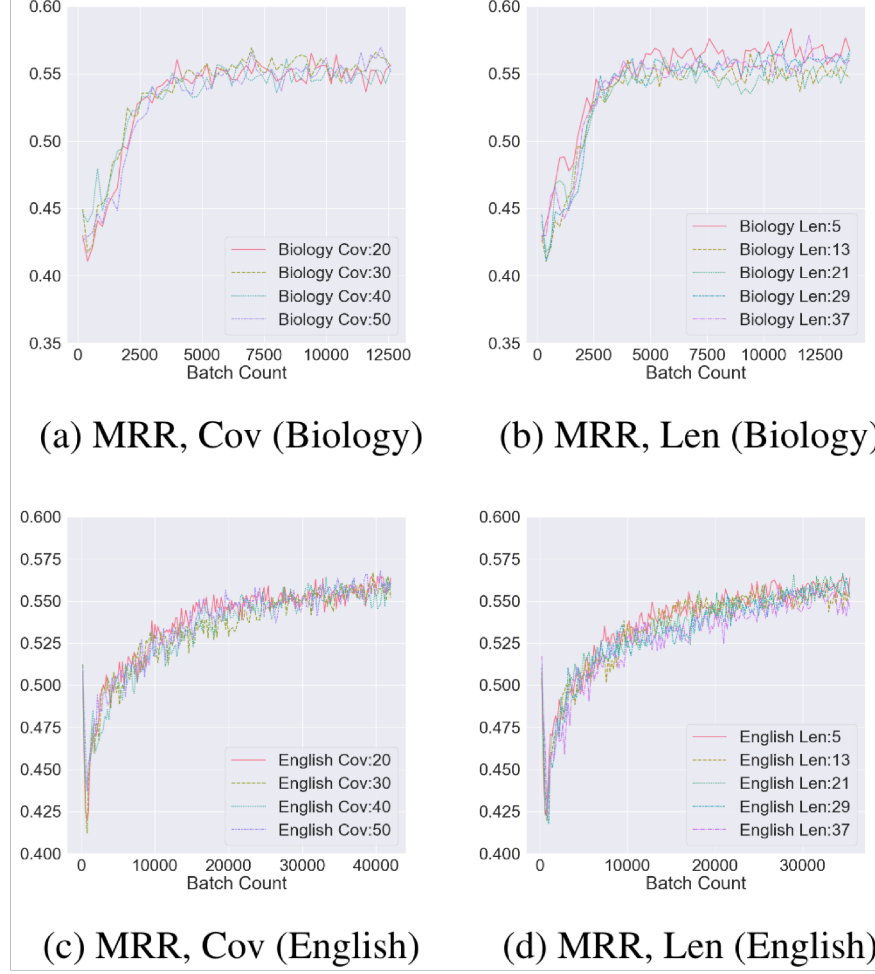
Experiments – Efficiency & Robustness



(a) Losses on Biology (b) Metrics on Biology

(c) Losses on English (d) Metrics on English

Training efficiency



(a) MRR, Cov (Biology) (b) MRR, Len (Biology)

(c) MRR, Cov (English) (d) MRR, Len (English)

Robustness to param change

Conclusion

- We proposed NeRank, a framework for *personalized* Question Routing.
- NeRank learns representations of entities in CQA websites by *HIN embedding and LSTM*.
- Using embeddings, a *convolutional scoring model* generates the ranking.
- Experimental results show that NeRank outperforms the state-of-the-art QR algorithms.

Acknowledgements

Questions?

Jyun-Yu Jiang

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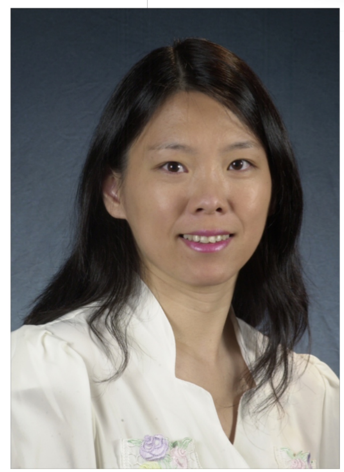

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