Erler at the NTCIR-13 OpenLiveQ Task

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Introduction

What problem do we have to solve?

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Introduction

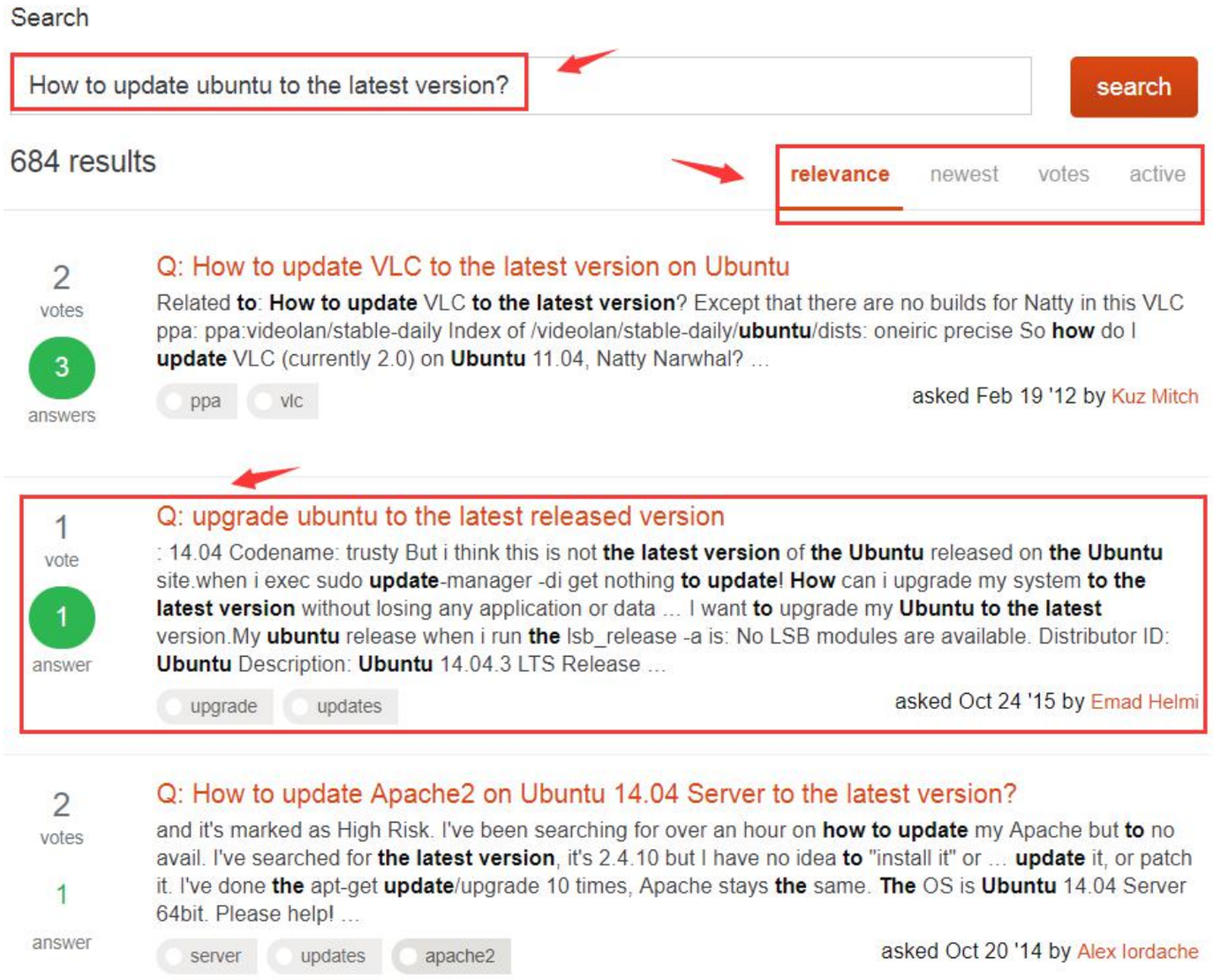

Figure 1: An example of Question Retieval

Task:

The task was simply defined as: given a query and a set of questions with their answers, return a ranked list of questions.

Challenge:

People expresses similar meanings through different words.

Example:

update/upgrade

更改/更新

We need to model the relationship between different terms to improve the retrieval model.

Introduction

Task

Question retrieval is an important task for Community Question Answering services.

Challenge

The lexical gap, the word mismatch between queries and candidate questions.

Solution

We propose a retrieval model based on Translation Model and Topic Model.

Example

“I need a music sharing website.”
“Where can I listen to rock for free online?”

Introduction

Word	Translation probability	Word	Translation probability
あり	0.026	設備	0.008
よう	0.015	電気工事	0.008
電力	0.013	冷蔵庫	0.007
機械	0.011	電	0.007
用	0.011	配線	0.007
物	0.011	工事	0.006
エアコン	0.010	これから	0.006
工学部	0.009	節約	0.006
家	0.009	電子	0.006
暖房	0.009	ブレーカー	0.005

Table 1: An example of Translation Model (source word is “電気”)

Solution:

- We utilize Translation Model to model the relationship between different words;
- we use **translation probability** concretely.

Introduction

Topic 1		Topic 2	
する	0.014324	大学	0.047982
家	0.012173	就職	0.013081
あり	0.011606	高校	0.012793
い	0.011130	合格	0.010597
いる	0.010675	受験	0.009892
工事	0.009775	偏差値	0.009028
部屋	0.009184	学科	0.008651
業者	0.008671	学生	0.008585
電気	0.007376	者	0.008320
設置	0.007285	進学	0.007968

Table 2: An example of Topic Model

Solution:

- Similarly, we can use **word topic distribution probability** from Topic Model.
- The two words get a **higher correlation** if they have higher probabilities of distributions under a certain topic.

Our Model

How to combine Translation Model and Topic Model to improve retrieval model?

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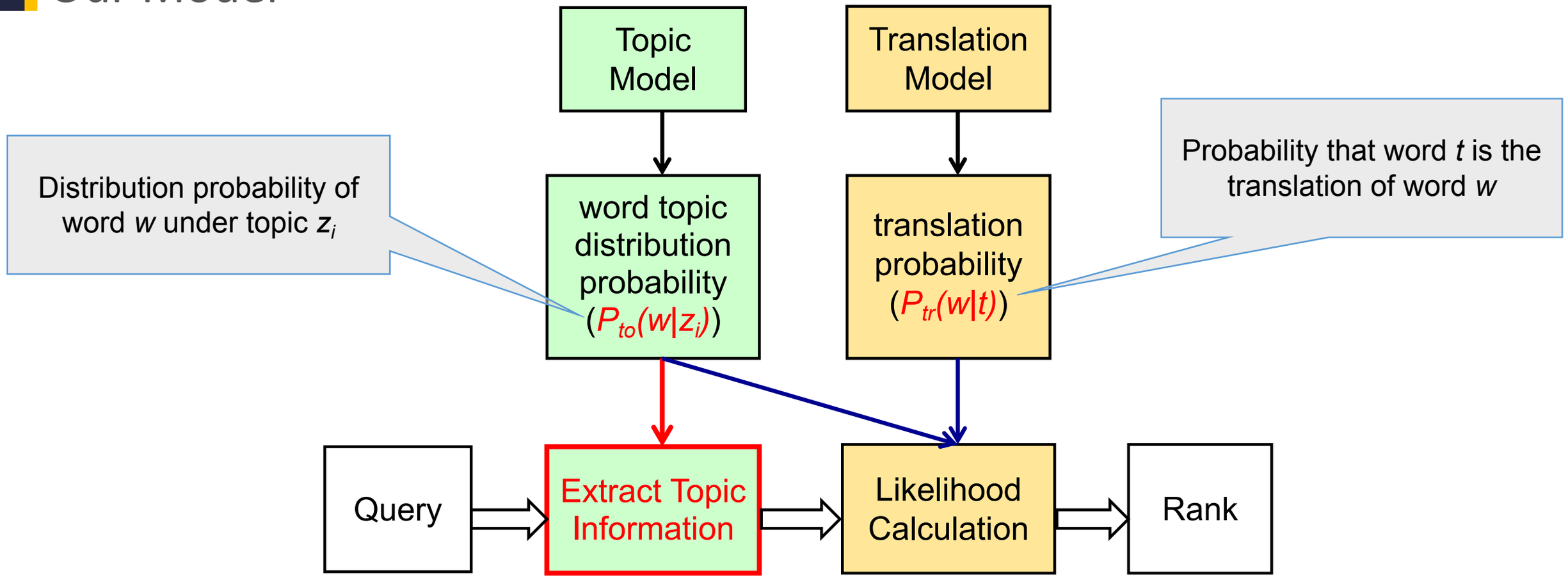
Our Model



Ming Chen, Lin Li, Qing Xie, Translation Language Model Enhancement for Community Question Retrieval Using User Adoption Answer, ***APWEB-WAIM 2017***: 251-265.

Our Model

- ✓ Translation Model
  - Statistical Machine Translation
  - The Noisy Channel Model
  - Expectation Maximization (EM) Algorithm
  - Translation probability $P_{tr}(w|t)$
  - Monolingual Parallel Corpus
- ✓ Topic Model
  - Latent Dirichlet Allocation (LDA) Model
  - Word topic distribution probability $P_{to}(w|z_i)$

Our Model

Likelihood Calculation

Query likelihood is a generative model that assumes that the question answer pair *(q, a)* is a sample of a multinomial distribution of terms. We estimate this probability by interpolating the term distribution in the *(q, a)* with the term distribution in the collection:

$$P(query|(q,a)) = \prod_{w \in query} \left(\frac{|(q,a)|}{|(q,a)|+1} P((w,query)|(q,a)) + \frac{1}{|(q,a)|+1} P_{ml}(w|C) \right)$$

Here $P_{ml}(w|C)$ is the distribution of word w in C.

C is the training collection.

We use length of (q, a) as a smoothing parameter.

Our Model

Likelihood Calculation

Translation Model

$$P((w,query)|(q,a)) = \mu_1 P_{ml}(w|q) + \mu_2 \sum_{t \in q} \left(P_{tr}(w|t) P_{ml}(t|q) \right)$$

$$+ \mu_3 \sum_{t \in q} \left(\sum_{i=1}^{K} \left(P(query|z_i) P_{to}(w|z_i) P_{to}(t|z_i) \right) P_{ml}(t|q) \right) + \mu_4 P_{ml}(w|a)$$

Topic Model

Here $P_{ml}(w|q)$ is the distribution of word w in q.

We use μ_1, μ_2, μ_3 and μ_4 balance the impact of each component and $\mu_1 + \mu_2 + \mu_3 + \mu_4 = 1$.

Example:

w = “A”; q = (“A”, “B”, “C”); $P_{ml}(w|q)$ = 1/3

Our Model

Extract Topic Information of a Query

For different queries we can get different weights of each topic as follows:

$$P(query \mid z_i) = \frac{\prod_{w \in query} P_{to}(w \mid z_i)}{\sum_{j=1}^{K} \prod_{w \in query} P_{to}(w \mid z_j)}$$

K is the number of topics.

To balance the impact of each topic, which is different from traditional model.

Example:

query = (“大学”, “偏差値”)

$$P(\text{query} \mid \text{Topic1}) = \frac{0.047982 \times 0.009028}{0.047982 \times 0.01918 + 0.009028 \times 0.006282} \approx 0.7824$$

Word	Topic 1	Topic 2
大学	0.047982	0.01918
偏差値	0.009028	0.006282

Experiments

How do we conduct experiments?

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Experiments

Baselines

TM (Topic-based Model)

Wei, W., Croft, W.B.: LDA-based document models for ad-hoc retrieval. In: Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 178–185 (2006)

TLM (Translation-based Language Model)

Xue, X., Jeon, J., Croft, W.B.: Retrieval models for question and answer archives. In: Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 475–482 (2008)

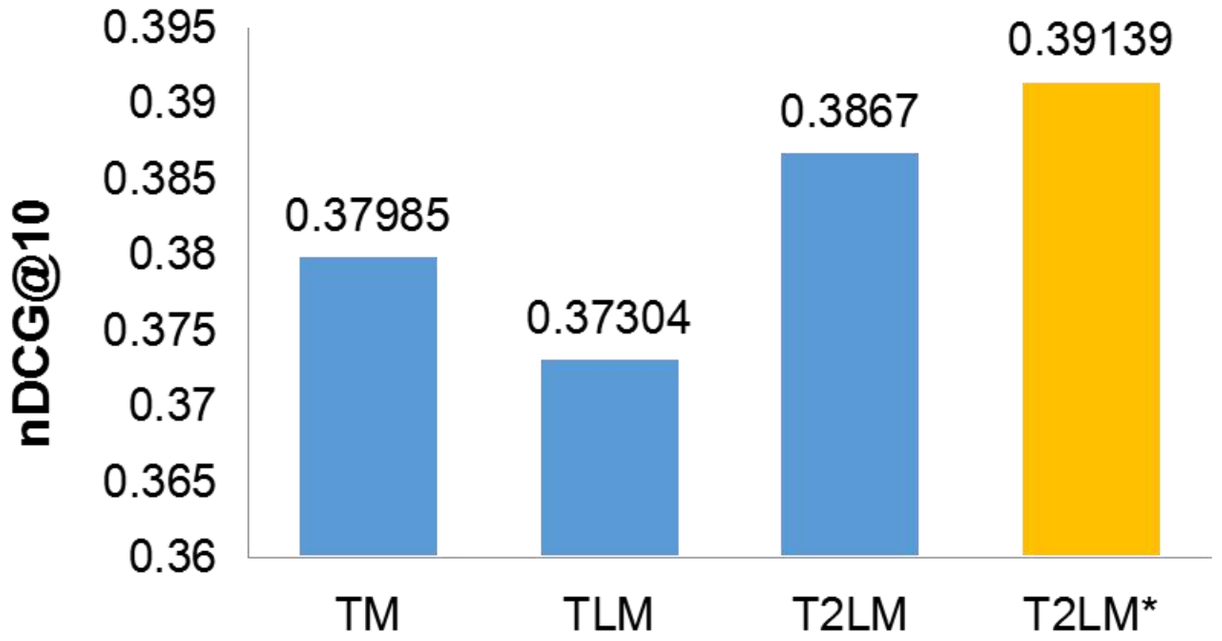
T^2LM (Topic Inference-based Translation Language Model)

Zhang, W.N., Zhang, Y., Liu, T.: A topic inference based translation model for question retrieval in community-based question answering services. Chin. J. Comput. 38(2), 313–321 (2015)

Experiments

Experimental results

In terms of nDCG@10, T^2LM^* performs best among traditional topic and translation models.

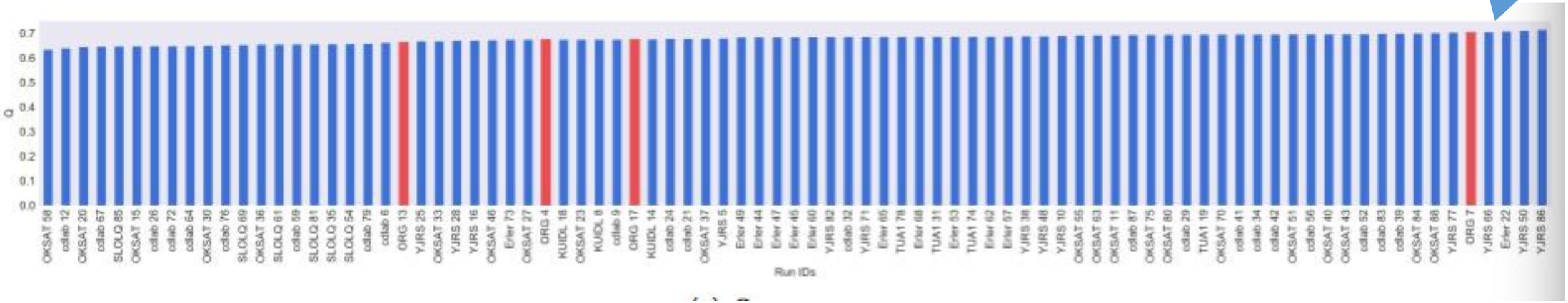


Offline Test Results

Experiments

Experimental results

Better than baseline in terms of Q measure.

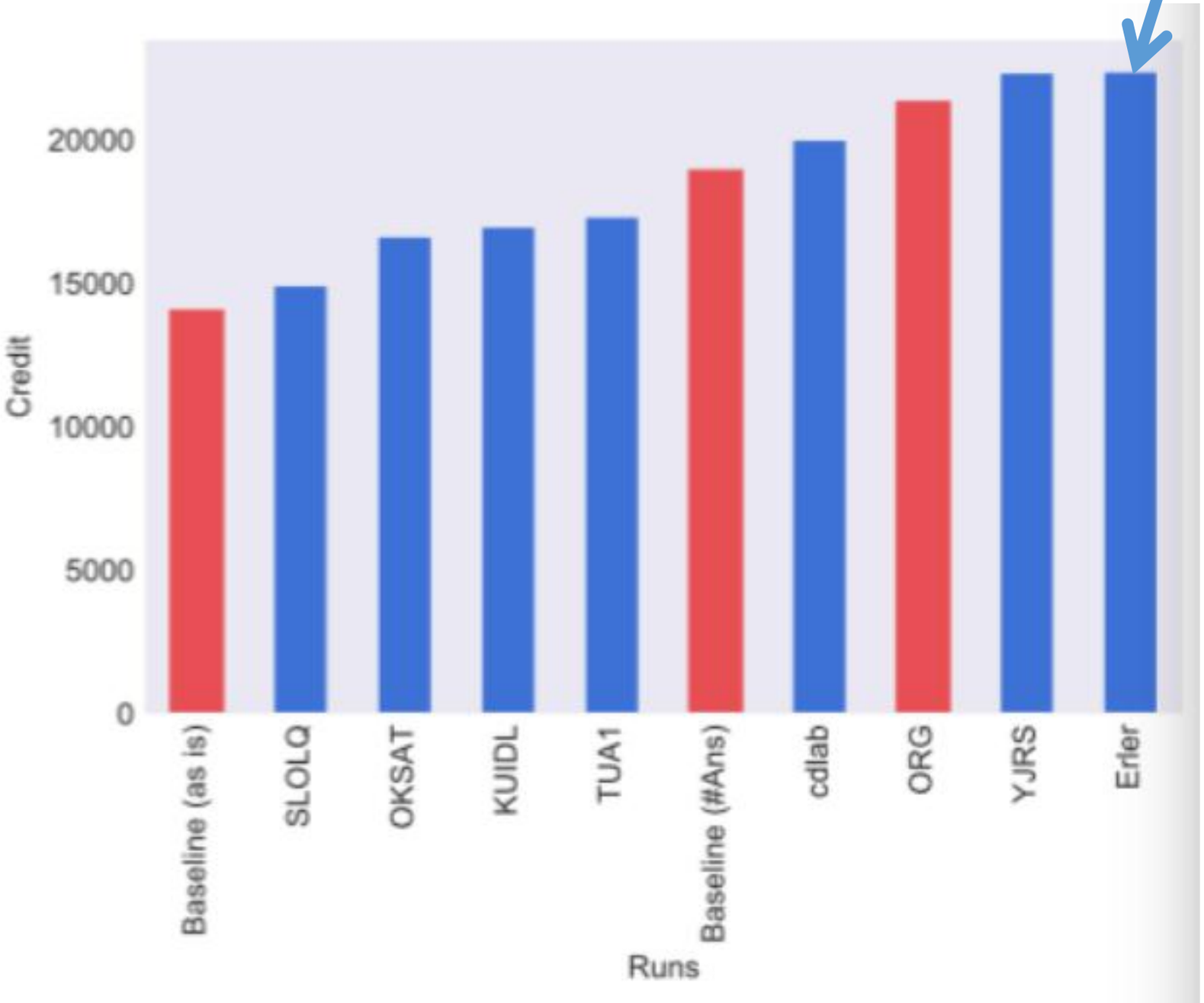


Offline Test Results

Experiments

Experimental results

Cumulated credits in the online evaluation.



Conclusions

What can we get?

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Conclusions

1. We propose a novel approach by using the topic information of a query to improve the likelihood calculation.

2. Experiments on OpenLiveQ task demonstrate the effectiveness of the proposed retrieval model.

3. In the online test, our team and YJRS team have been tied for the first place.

Future Work

1 Integrating other information into our model

- Our model only use the content of the question and its answer.
- Obviously the other information including last update time of the question and the category of a question is helpful to optimize the retrieval results.

2 Looking for better training corpus

- In this task, we use the QA pairs and the answer-question pairs as parallel corpus to train the translation model.
- Training of the translation model in our model can be further optimized.

Thank you for