Learning to Expand: Reinforced Pseudo-relevance Feedback Selection for Information-seeking Conversations

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ABSTRACT

Intelligent personal assistant systems for information-seeking conversations are increasingly popular in real-world applications, especially for e-commerce companies. With the development of research in such conversation systems, the pseudo-relevance feedback (PRF) has demonstrated its effectiveness in incorporating relevance signals from external documents. However, the existing studies are either based on heuristic rules or require heavy manual labeling. In this work, we treat the PRF selection as a learning task and proposed a reinforced learning based method that can be trained in an end-to-end manner without any human annotations. More specifically, we proposed a reinforced selector to extract useful PRF terms to enhance response candidates and a BERT based response ranker to rank the PRF-enhanced responses. The performance of the ranker serves as rewards to guide the selector to extract useful PRF terms, and thus boost the task performance. Extensive experiments on both standard benchmark and commercial datasets show the superiority of our reinforced PRF term selector compared with other potential soft or hard selection methods. Both qualitative case studies and quantitative analysis show that our model can not only select meaningful PRF terms to expand response candidates but also achieve the best results compared with all the baseline methods on a variety of evaluation metrics. We have also deployed our method on online production in an e-commerce company, which shows a significant improvement over the existing online ranking system.

CCS CONCEPTS

• Applied computing → Electronic commerce; • Information systems → Retrieval models and ranking.

KEYWORDS

Pseudo-relevance feedback selection, Reinforcement learning, BERT, Info-seeking conversations

1 INTRODUCTION

Intelligent personal assistant systems or chatbots such as Microsoft’s XiaoIce, Apple’s Siri, Google’s Assistant have boomed during the last few years. It brings the interests from both academia and industry on information-seeking conversational search systems, where the end-users could access information with conversation interactions.

Previous studies on such conversational systems mostly can be categorized into three types of methods, i.e., retrieval-based [35, 46, 48, 49, 51, 56], generation-based [23, 27, 31, 39] and hybrid retrieval-generation based methods [33, 50]. Comparing with generation-based methods, retrieval-based methods can produce more informative, relevant, fluent, and controllable responses, which is the key factor for conversational information-seeking systems. The recent advance of retrieval-based methods are based on external knowledge incorporation, i.e., Pseudo-relevance Feedback (PRF) expansion [2, 12, 16, 29, 51, 53, 54]. The basic idea is to retrieve some relevant documents and extract PRF terms from them to improve the original query representation, which has shown to provide effective relevance signals for retrieval-based systems [2, 12, 16, 29, 53, 54]. It has also shown to be beneficial for the multi-turn scenario, as the context is usually longer than the response, thus external PRF expansion for the response can help to better understand the response [51].

Some studies [51] for PRF term expansion do not take PRF terms selection as a learning procedure and simply use all the selection results as additional inputs. However, as shown in [2], some of the retrieved PRF terms identified by these approaches are unrelated to the query, thus not helpful for the retrieval process. Other studies [2] treat the PRF terms selection as a supervised classification problem. However, its applicability is limited, as manually labeling the useful PRF terms from the long context and external documents is costly and non-trivial. In this paper, we consider the problem of expanding the response as a learning task and seek a more effective way to guide the selection without requiring explicitly labeled signals.

To this end, we consider Reinforcement Learning (RL) for our task, due to its effectiveness in exploration with implicit feedback [4–6, 21, 41, 44]. We model the problem as a Markov Decision Process (MDP) and propose a general framework to jointly learn a reinforced selector with a response ranker. The selector acts on all the external documents to extract PRF terms and feed them to the ranker, and the ranker updates its model and provides feedback to help the selector. More specifically, we treat the reinforced PRF term selector as the agent that takes the actions to select a subset of PRF terms based on
the state representation. These selected PRF terms will be further fed into the ranking module together with the conversation context and the response. The ranking module and the validation data play a role of an environment and output rewards for those selection actions. The resulting rewards can guide the reinforced selector to generate higher-quality PRF terms to improve the ranking results.

In this paper, we adopt BERT [3] as the pre-trained language encoder of our response ranker. Recently, the emergence of language models pre-trained on large unsupervised corpora [3, 15, 22, 25] has demonstrated stunning success in natural language processing (NLP). Task-specific fine-tuning of those pretrained language models such as BERT [3] further pushes the performance of a variety of NLP tasks [9, 20, 22, 38, 47, 52]. We adopt the original BERT architecture but a different input format to incorporate the context of the conversation, the candidate response, and the selected PRF terms. The resulting BERT response ranker is shown to have better performance than the competing response rankers. Furthermore, the reinforced selector and BERT response ranker are jointly optimized as they interact with each other closely during training. We refer to our proposed whole model as "PRF-RL".

The model overview is outlined in Figure 1. Clearly, the reinforced selector selects useful PRF terms to help the ranker, and in turn, the ranker provides helpful feedback to guide the selector. Together these two modules improve the task performance. The benefits for such an RL-based approach lie in two aspects: (1) the joint learning process can guide the reinforced selector to choose those PRF terms that can directly improve the ranking quality; (2) the feedback provided by the ranking model serves as implicit rewards to guide the selector without requiring human annotations.

We conduct extensive experiments on both public and industrial datasets, i.e., the MSDial dataset [24] that contains customer service dialogs from Microsoft Answers community and the AliMeCQA dataset [14] collected from the chat logs between the customers and the service assistant agent in an e-commerce app. We compare our method with various baselines, such as traditional retrieval models, neural ranking models, a strong multi-turn conversation response ranking baseline [57] and pre-trained language model based methods. Our method outperforms all the baseline methods on a variety of evaluation metrics. Besides, to demonstrate the effectiveness of our reinforced PRF term selector, we also compare our model with other potential PRF selection methods, including the rule-based selection method mentioned in [51], soft and hard selection by gate functions such as tanh or Gumbel softmax trick [11]. Both the numerical results and case studies show the superiority of our proposed reinforced selector. Moreover, we have deployed our proposed "PRF-RL" model into an e-commerce information-seeking conversational search system. We deploy our proposed "PRF-RL" model into an online information-seeking system on a real e-commerce production AliMe. The online A/B test results show that our model can significantly outperform the existing online ranking system.

In a nutshell, our contributions can be summarized as follows:

1. We conduct extensive experiments on both public and industrial datasets and show that our methods outperform various baselines and show that our reinforced PRF terms selector is superior to other competing PRF term selection mechanisms. We have also deployed our method on an online chatbot system in an e-commerce company.

Our method consists of two modules: i) a reinforced selector to extract useful PRF terms, and ii) a BERT response ranker with PRF. To the best of our knowledge, it is the first work that employs an RL-based strategy to select high-quality PRF terms for response ranking in the information-seeking systems.

2. Experimental results on both public and industrial datasets show that our methods outperform various baselines and show that our reinforced PRF terms selector is superior to other competing PRF term selection mechanisms. We have also deployed our method on an online chatbot system in an e-commerce company.

2 OUR APPROACH

2.1 Problem definition

We formulate the problem of response ranking with pseudo-relevance feedback as follows. Given an information-seeking conversation dataset \( \mathcal{D} = \{ (\mathcal{U}, r_i, y_i) \}_{i=1}^N \), where \( \mathcal{U} = \{ u_1, u_2, ..., u_m \} \) is a \( m \)-turns dialog context, \( u_i = \{ w_{i,1}^{(u)}, w_{i,2}^{(u)}, ..., w_{i,L_u}^{(u)} \} \) is the utterance in the \( i \)-th turn of this dialog and \( L_u \) is the number of sub-tokens of this utterance. \( r = \{ w_1^{(r)}, w_2^{(r)}, ..., w_m^{(r)} \} \) is a response candidate and \( y \in \{ 0, 1 \} \) is the corresponding label. When the pseudo-relevance feedback information is incorporated, for each response \( r \), we have PRF term set \( \mathcal{P} = \{ p_1, p_2, ..., p_k \} \) and \( p_i = \{ w_{i,1}^{(p)}, w_{i,2}^{(p)}, ..., w_{i,L_p}^{(p)} \} \) is an \( i \)-th PRF term and \( L_p \) is the number of sub-tokens of this PRF term. The task is to learn a model which has two sub-modules: (1) a selection module \( f(\cdot) \) to select a meaningful subset \( \mathcal{P}' \subseteq \mathcal{P} \) of PRF terms and (2) a ranking module \( g(\cdot) \) with \( \mathcal{D} \) and \( \mathcal{P}' \) as inputs to rank the responses. Given \( \mathcal{U} \) and \( \mathcal{P} \), the model should be able to generate a prediction \( \hat{y} \) for response \( r \) for ranking with other candidate responses.

2.2 Model overview

In the following sections, we describe our proposed model for response ranking with pseudo-relevance feedback. Given a set of retrieved PRF terms, we first propose a reinforced PRF term selector to select a subset of the PRF terms, and feed them into a BERT-based response ranking model, which outputs the final predictions. In this section, we will first briefly introduce how the BERT response ranker works and then leave more space to introduce our proposed reinforced PRF term selector in detail. Figure 1 presents an overview of the proposed method.
2.3 BERT response ranker

As mentioned above, once we have a context \( U \), a response \( r \) and a set of PRF terms \( \mathcal{P} \), we can concatenate them with the following specific format as the input of BERT \( x = \{ [\text{CLS}], u_1, [\text{EOT}], u_2, [\text{EOT}], ..., u_m, [\text{SEP}], r, [\text{SEP}], p_1, [\text{SEP}], p_2, [\text{SEP}], ..., p_k \} \). Here we use [EOT] to separate the multiple turns of the dialog and use [SEP] to separate different PRF terms since they are independent with each other. After multiple standard BERT layers, we can get a contextual representation \( T_{[\text{CLS}]} \) of [CLS] token. We then feed the contextual representation into an extra feed forward network with sigmoid activation function to predict the ranking score of \( r \) given \( U \) and \( \mathcal{P} \), illustrated as follows:

\[
T_{[\text{CLS}]} = \text{BERT}(x). \tag{1}
\]

\[
g = g(U, \mathcal{P}, r) = \sigma(T_{[\text{CLS}]}) + b. \tag{2}
\]

The overview of the ranker is illustrated in Figure 2. The response ranking model can be optimized by gradient descent based methods and the cross-entropy loss is applied as follows.

\[
\text{Loss} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \tag{3}
\]

2.4 Reinforced PRF term selector

The PRF term selection process can be viewed as a sequential decision-making problem and modeled as a Markov Decision Process, which can be further solved by reinforcement learning. Under the reinforcement setting, the PRF term selector serves as the agent and interacts with the environment consisting of the BERT response ranker and a utility evaluation dataset. With the help of a learnable policy network, the agent takes the actions of selecting or dropping a given PRF term, where the decision is based on a state representation of each candidate term. Then the BERT response ranker takes the selected PRF terms as one of the inputs and further provides rewards for guiding the agent. The overview of the reinforced PRF term selector is shown in Figure 3.

To be specific, we formulate the learning framework as follows. Given a response \( r \) and the corresponding PRF terms set \( \mathcal{P} = \{ p_i \}_{i=1}^{k_1} \), where \( k_1 \) is the number of PRF terms before selection. We can apply a state representation network \( z(s_i) \) for each PRF term \( p_i \) to obtain states \( S = \{ s_i \}_{i=1}^{k_1} \) and feed each \( s_i \) into the policy network \( \pi(s_i) \). According to the policy, the agent takes the corresponding actions \( A = \{ a_1, a_2, ..., a_{k_1} \} \), where \( a_i \in \{0, 1\} \). The selected subset of PRF terms \( \mathcal{P}' = \{ p_i | \forall p_i \in \mathcal{P}, a_i = 1 \} \), together with \( U \) and \( r \), are then fed into the response ranker to output a prediction. The parameters of the response ranker will be updated with label \( y \) and a reward \( r \) will be produced after evaluating the ranker's performance on a held-out validation data.

2.4.1 State representation. The state \( s_i = z(r, p_i) \) of given response \( r \) and a PRF term \( p_i \) is a \( d \)-dimension continuous real valued vector. We use attention mechanism between token embeddings of \( r \) and \( p_i \) to obtain a contextual vector as follows.

With the WordPiece embeddings [45], we can represent tokens of \( r \) and \( p_i \) as:

\[
E_r = \{ e_{w_1}^{(r)}, e_{w_2}^{(r)}, ..., e_{w_n}^{(r)} \}, \tag{4}
\]

\[
E_{p_i} = \{ e_{v_1}^{(p_i)}, e_{v_2}^{(p_i)}, ..., e_{v_{n_{p_i}}}^{(p_i)} \}. \tag{5}
\]

We first use max-pooling to get a \( d \)-dimension vector \( h_i = \text{maxpool}(E_{p_i}) \) to represent the PRF term and obtain the attended weighted context as follows:

\[
h'_i = \sum_{j=1}^{n} \frac{\exp(h_{ij} \cdot e_{w_j}^{(r)})}{\sum_{k=1}^{n} \exp(h_{kj} \cdot e_{w_k}^{(r)})} e_{w_j}^{(r)}. \tag{6}
\]

Finally we get the state representation as \( s_i = h_i + h'_i \).

2.4.2 Policy network and actions. The agent (i.e., the reinforced selector) takes actions to decide whether to select the PRF...
where \( N \) is the number of batches in this episode, \( r \) is the reward discount factor.

\[ r_b = L_{b-1} - L_b, \]  \( \text{(8)} \)

where \( L_b \) and \( L_{b-1} \) are the cross-entropy losses on the validation data for the current batch and the previous batch respectively. The intuition is that if the current loss is smaller than the previous loss, we encourage the selector to follow the current policy by giving it a positive reward. Other metrics generated on the validation data could also be incorporated. To enable fast training, we obtain the reward by evaluating a subset of the validation data. This subset is referred to as the reward set, which is randomly sampled from the validation data and changed at the end of every episode.

Furthermore, we compute the future total reward for each batch after an episode since the decisions of the agent not only have a direct impact on the immediate rewards but also have long-term influence. The amended reward \( r' \) is formulated as follows.

\[ r'_b = \sum_{k=0}^{N_b-1} \gamma^k r_{b+k}, \]  \( \text{(9)} \)

where \( N_b \) is the number of batches in this episode, \( r'_b \) is the future total reward for batch \( b \), and \( \gamma \) is the reward discount factor.

### 2.4.4 Optimization

We use a policy gradient method, i.e., REINFORCE [43] to optimize our proposed reinforced PRF Term selector. For a given episode, our goal is to maximize the expected total reward, which can be formulated as follows:

\[ J(\Theta) = E_{\tau_B}[\sum_{b=1}^{N_b} r_b], \]  \( \text{(10)} \)

where the policy network \( \pi_\Theta \) is parameterized by \( \Theta \). The policy network can be updated by the gradient as follows:

\[ \Theta \leftarrow \Theta + \alpha \frac{1}{B} \sum_{i=1}^{B} r_i \nabla_\Theta \log \pi_\Theta(S_i). \]  \( \text{(11)} \)

Here, \( \alpha \) is the learning rate, \( B \) is the batch size.

### 2.5 Training process

The selector and the ranker modules are learned jointly as they interact with each other closely during training. For each batch, the PRF term selector selects a subset of PRF terms \( P' \) from the input PRF term set \( P \). Then the BERT response ranker uses \( P' \) together with the context \( U \) and the response \( r \) as inputs to output the predictions. To optimize the BERT response ranker, we use a standard gradient descent method to minimize the loss function in Eq. 3. The reinforced PRF selector intervenes before every iteration of the ranker update by selecting helpful PRF terms to augment the candidate responses. Such an intervention process has a direct impact on the gradient computed for the ranker update. The BERT response ranker provides a reward in turn to evaluate the utility of the selected PRF terms. After each episode, the policy network of the selector is updated with the policy gradient algorithm with the stored (states, actions, reward) triples. A detailed description of our algorithm is shown in Algorithm 1.

### 3 EXPERIMENTS

#### 3.1 DataSet Description

We evaluated our method and the competing methods with two info-seeking conversation datasets: MSDialog dataset and AliMe-CQA dataset as used in [51].

##### 3.1.1 MSDialog

The MSDialog dataset is a labeled dialog dataset of question answering (QA) interactions between information seekers and answer providers from an online forum on Microsoft products [24]. Previous works [51] have a preprocessed version which is suitable for experimenting with conversation response ranking models. The ground truth responses returned by the real agents are the positive response candidates, and negative sampling has been adopted to create nine negative response candidates for each context query. We only removed some common prefixes such as “\text{\textit{<AGENT}}}” and use WordPiece [45] to tokenize the context and the response candidates for further modeling.

##### 3.1.2 AliMe-CQA Data

We collected the multi-turn question answering chat logs between customers and a chatbot from AliMe Conversation System\(^3\). This chatbot is built based on a question-to-question matching system [14], where for each query, it finds the

\(^3\)https://ciir.cs.umass.edu/downloads/msdialog/

\(^4\)https://www.aliexpress.com/


Algorithm 1 Training Procedure

Require:
Training data \( D_{train} = \{(U_i, r_i, y_i)\}_{i=1}^N \); 
Validation data \( D_{val} = \{(U_i, r_i, y_i)\}_{i=1}^{N'} \); 
Episode \( N_e \), validation sample rate \( q \);

1: Initialize the pre-trained BERT response ranker \( g(\cdot) \);
2: Initialize the policy network \( \pi_B \) as PRF term selector;
3: for episode \( e \) \( \in \{1, \ldots, N_e\} \) do 
4: Obtain the random batch \( D'_{train} = \{X_b\}_{b=1}^B \);
5: Obtain the reward set \( D_{reward} \) by random sampling from \( D_{val} \) with rate \( q \);
6: for each \( X_b \) in \( \{X_b\}_{b=1}^B \) do 
7: Obtain state \( S_b \) by \( z(r_b, \mathcal{P}_b) \); 
8: Sample action \( \mathcal{A}_b \) according to policy \( \pi(S_b) \); 
9: Obtain PRF subset \( \mathcal{P}_b' \) according to \( \mathcal{A}_b \); 
10: Update the ranker \( g(\cdot) \) by \( X'_{b} = \{(U_i, r_i, \mathcal{P}_b', y_i)\}; 
11: Obtain the reward \( r_b' \) on \( D_{reward} \);
12: Store \( (S_b, \mathcal{A}_b, r_b) \) to an episode history \( \mathcal{H} \); 
end for

end for
4: for each \( (S_b, \mathcal{A}_b, r_b) \) in \( \mathcal{H} \) do
5: Obtain the future total reward \( r_b'' \) as in Eq. 10;
6: Update the policy network \( \pi_B \) following Eq. 11;
end for
8: Empty \( \mathcal{H} \);
19: end for

most similar candidate question in a QA database and returns its answer as the reply. To form an information-seeking conversation QA dataset, we firstly select more than 3k multi-turns context to form queries and apply this conversation system to retrieve the top-15 most similar candidate questions as the “response” in our setting. A group of the business analyst is asked to annotate the candidate “response”. If the “response” is similar to the input query (context), the label will be positive, otherwise negative. In the process of annotation, if the confidence score of answering a given query (context) is low, the system will prompt three top related questions (response candidates) for users to choose. We collected such user click logs as our external data, where we treat the clicked question as positive and the others as negative. We have collected about 50k Context-response pairs from this annotation process and remove all of the contexts that have zero positive candidate responses. The language of the context and response is Chinese and we use character-level tokenization for further modeling.

The statistics of these two datasets is shown in Table 1.

3.2 Experimental Setup

3.2.1 Baselines. We explore different baselines lying on four categories, including traditional retrieval models, neural ranking models, a strong multi-turn conversation response ranking method, pre-trained language model based models as follows:

BM25 [28] is a traditional retrieval model, which uses the dialog context as the query to retrieve response candidates for response ranking.

ARC-II [10], MV-LSTM [40], DRMM [8], DUET [17] are neural ranking models proposed in recent years for ad-hoc retrieval and question answering. MV-LSTM is a representation focused model and ARC-II, DRMM are interaction focused models. Duet is a hybrid method of both representation focused and interaction-focused models.

DAM [57] is a strong baseline model for response ranking in multi-turn conversations. DAM also represents and matches a response with its multi-turn context usingdependency information learned by Transformers.

BERT-CLF is a general classification framework proposed in BERT [3] paper. It uses [SEP] and segment embedding to separate the query and answer, and incorporates a pre-trained language model for contextual representation. The predictions are based on the contextual vector of [CLF] token.

PRF-RL is our proposed model consisting of a reinforced PRF term selector and a BERT response ranker.

3.2.2 Evaluation Methodology. For evaluation metrics of both MSDialog and AliMe-CQA, we adopted mean average precision (MAP) and Recall@k which is the recall at top k ranked responses from n available candidates for a given conversation context. Following previous related works [57], here we reported Recall@1, Recall@2, and Recall@5 on both two datasets. For AliMe-CQA, we reported an extra metric Precision@1 for further exploration, since there are multiple positive candidates of a given query. One should also notice that for the MSDialog dataset, the value of precision@1 is equal to the recall@1 since there is only one positive candidate for each query in this dataset.

3.2.3 Experimental Settings. The four neural ranking models are experimented using the MatchZoo toolkit. We use the code released by [57] to tune the DAM model on our datasets. We use the pytorch version of BERT model to implement BASE-BERT classifier. We choose the BERTBASE \((L=12, H=768, A=12)\) as our pre-trained BERT encoder for both BERT-CLF and PRF-RL. We now introduce some hyper-parameters and training process of BERT-CLF and PRF-RL.

### Table 1: The statistics of experimental datasets, where C denotes context and R denotes response. # Cand. per C denotes the number of candidate responses per context. Note that we didn’t filter any stop words or words with low frequency when we computed the average length of contexts or responses.

| Items | MSDialog | AliMe-CQA |
|-------|----------|-----------|
| # C-R pairs | 173k | 32k | |
| # Cand. per C | 10 | 2 | |
| # + Cand. per C | 1 | 1 | 1 |
| Min # turns per C | 2 | 2 | 2 |
| Max # turns per C | 11 | 11 | 11 |
| Avg # turns per C | 5.0 | 4.9 | 4.4 |
| Avg # words per C | 451 | 435 | 375 |
| Avg # words per R | 106 | 107 | 105 |

5https://github.com/NTMC-Community/MatchZoo
6https://github.com/baidu/Dialogue/tree/master/DAM
7https://github.com/huggingface/transformers
For the MSDialog dataset, the context length is truncated by 384 and the response length is truncated by 96. The batch size is set to 12. We use Adam optimizer with linear decay for both two models. The learning rate for BERT-CLF is set to 3e-5 following the previous works. For PRF-RL, we firstly pre-trained the BERT response ranker without PRF term selection of learning rate 3e-5 for 1000 steps, and then jointly trained the reinforced PRF term selector and the BERT response ranker with learning rate 1e-4, 5e-6 respectively. For reinforcement learning, the number of the episode is set to 100, the reward discount reward factor is set to 0.3, and the reward set is randomly sampled from 0.5% of the validation dataset considering the trade-off of quality and efficiency of training.

For the AliMe dataset, the context length is truncated by 100 and the response length is truncated by 50. The batch size is set to 32. We again use Adam optimizer with linear decay for both two models. The learning rate for BERT-CLF is set to 3e-5. For PRF-RL, we firstly pre-trained the BERT response ranker with learning rate 3e-5 for 200 steps, and then jointly trained the reinforced PRF term selector and the BERT response ranker with learning rate 1e-4, 5e-6 respectively. The number of the episode is set to 10 and the reward discount reward factor is set to 0.3, and the reward set is randomly sampled from 1% of the validation dataset.

### 3.3 Comparison with the Baselines

We present evaluation results over different methods on MSDialog and AliMe-CQA in Table 2.

| Methods | MSDialog | AliMe-CQA |
|---------|-----------|-----------|
| BM25 [28] | Recall@1 0.2626, Recall@2 0.3933, Recall@5 0.6329, MAP 0.4387 | Recall@1 0.5811, Recall@2 0.2012, Recall@5 0.3201, MAP 0.6310 |
| ARC-IT [10] | Recall@1 0.3189, Recall@2 0.5413, Recall@5 0.8662, MAP 0.5398 | Recall@1 0.6075, Recall@2 0.1717, Recall@5 0.3027, MAP 0.6841 |
| MV-LSTM [40] | Recall@1 0.2768, Recall@2 0.5000, Recall@5 0.8516, MAP 0.5059 | Recall@1 0.5925, Recall@2 0.1657, Recall@5 0.3194, MAP 0.6813 |
| DRMM [8] | Recall@1 0.3507, Recall@2 0.5854, Recall@5 0.9003, MAP 0.5704 | Recall@1 0.6868, Recall@2 0.2194, Recall@5 0.3563, MAP 0.7048 |
| Duet [17] | Recall@1 0.2934, Recall@2 0.5046, Recall@5 0.8481, MAP 0.5158 | Recall@1 0.6679, Recall@2 0.1920, Recall@5 0.3408, MAP 0.6302 |
| DAM [57] | Recall@1 0.7012, Recall@2 0.8527, Recall@5 0.9715, MAP 0.8150 | Recall@1 0.7558, Recall@2 0.2472, Recall@5 0.3969, MAP 0.7773 |
| BERT-CLF | Recall@1 0.7667, Recall@2 0.8926, Recall@5 0.9852, MAP 0.8580 | Recall@1 0.8476, Recall@2 0.2968, Recall@5 0.4622, MAP 0.7263 |
| PRF-RL | Recall@1 0.7872, Recall@2 0.9032, Recall@5 0.9792, MAP 0.8700 | Recall@1 0.8717, Recall@2 0.3181, Recall@5 0.4868, MAP 0.7576 |

3.3.1 Performance Comparison on MSDialog. From the results on the MSDialog dataset, we have the following findings. First, the transformer-based models (DAM, BERT-CLF, PRF-RL) show significant improvements compared with traditional retrieval models and other neural ranking models, which further proves the powerful representation capabilities of the Transformer. Second, compared with the DAM model, when the pre-trained language model BERT is incorporated, the performance also has a good improvement. Last but not least, our model performs the best over all the other baselines on Recall@1, Recall@2, and MAP, which we can see that incorporating external knowledge via pseudo-relevance feedback could improve the performance of the BERT-based response ranking models by large margins. Specifically, compared with BERT-CLF, our proposed PRF-RL model has a comparable result in terms of Recall@5, but an improvement of 2.05% for Recall@1, 1.06% for Recall@2, 1.20% for MAP. This shows the benefits of considering PRF selection.

3.3.2 Performance Comparison on AliMe-CQA. After comparing our PRF-RL model with other baselines on the AliMe-CQA dataset in Table 2, we find those similar findings as using MSDialog. First, our model achieves the best performance against all the baselines in terms of all evaluation metrics. Specifically, for precision-based metrics, our model achieves 2.41% and 1.62% improvements compared with the strongest baseline BERT-CLF in terms of Precision@1 and MAP; And for recall-based metrics, our model achieves improvements of 2.13% for Recall@1, 2.46% for Recall@2 and 3.13% for Recall@5. Second, Compared with the MSDialog dataset, the absolute values of Recall@k are lower. This phenomenon comes from multiple positive candidates given one query, in such case, a lower recall comparing with MSDialog dataset does not necessarily mean the method has lower performance. In practice, for info-seeking conversation systems, Precision@1 is the most important metric as only the top-1 response will be returned to the customer. In this metric, all the methods on AliMe-CQA tend to have better performance than MSDialog.

In all, our proposed method has a clear advantage over all the competing methods in both datasets, which demonstrates the usefulness of our method for info-seeking conversations.

3.4 Comparison with other PRF methods

To further explore how well our reinforced PRF term selector contributes to the overall model, we build several baseline methods that use different ways to incorporate the information of pseudo-relevance feedback. Here we have:

- **RULE-PRF** is a simple method to feed the PRF terms filtered by term frequencies, which is introduced in [51].

- **PRF-ML-Tanh** is a soft selection method which outputs a score \( p_i = \tanh(s_i) \), and before the embedding of PRF terms \( p_i \) is feed into BERT, the embedding will first be scaled by this score \( q_p \). It’s more like a gate function to ensure the gradients can be back-propagated into the selector.

- **PRF-ML-Sig** is a similar soft selection method which replace \( \tanh \) function with \( \text{sigmoid} \) function.
PRF-ML-Gumb is a method that can not only produce a hard selection decision but also can be optimized by gradient descent based algorithms. It uses a categorical reparameterization trick with Gumbel softmax [11] that enables the model to sample discrete random variables in a way that is differentiable. Specifically, it first defines a categorical variable \( z \) with class probabilities \( \pi_1, \pi_2, \ldots, \pi_k \), then adds random samples to draw samples \( z \) from a categorical distribution with class probabilities \( \pi \):

\[
q_i = \frac{\exp \left( \log(\pi_i) + g_i \right)/\tau}{\sum_{j=1}^{k} \exp \left( \log(\pi_j) + g_j \right)/\tau}, \quad \forall i = 1, \ldots, k
\]  

(12)

Where \( g_1, \ldots, g_k \) are i.i.d samples drawn from Gumbel(0, 1) distribution and \( \tau \) is the softmax temperature \( \tau \).

Table 3: Comparison of different models over MSDialog and AliMe-CQA datasets. Numbers in bold font mean the result is the best compared with other models. Here “P” means precision and “R” means recall. The Precision@1 results on MSDialog dataset are omitted since it is equal to Recall@1.

| Method       | P@1  | R@1  | R@2  | R@5  | MAP   |
|--------------|------|------|------|------|-------|
| MSDialog     |      |      |      |      |       |
| BERT-CLF     | 0.8476 | 0.7667 | 0.9026 | 0.9852 | 0.8580 |
| RULE-PRF     | 0.7713 | 0.8906 | 0.9826 | 0.8601 |       |
| PRF-ML-Tanh  | 0.7770 | 0.8886 | 0.9815 | 0.8626 |       |
| PRF-ML-Sigmoid | 0.7736 | 0.8906 | 0.9823 | 0.8607 |       |
| PRF-ML-Gumbel| 0.7719 | 0.8946 | 0.9823 | 0.8614 |       |
| PRF-RL       | 0.7872 | 0.9032 | 0.9792 | 0.8700 |       |
| AliMe-CQA    |      |      |      |      |       |
| BERT-CLF     | 0.8476 | 0.2968 | 0.4622 | 0.7263 | 0.8513 |
| RULE-PRF     | 0.8460 | 0.3002 | 0.4785 | 0.7422 | 0.8523 |
| PRF-ML-Tanh  | 0.8604 | 0.3060 | 0.5027 | 0.7631 | 0.8654 |
| PRF-ML-Sigmoid | 0.8340 | 0.3041 | 0.4835 | 0.7362 | 0.8549 |
| PRF-ML-Gumbel| 0.8566 | 0.3084 | 0.4781 | 0.7429 | 0.8554 |
| PRF-RL       | 0.8717 | 0.3181 | 0.4868 | 0.7576 | 0.8675 |

The experimental results are shown in Table 3. By exploring results from two datasets, we have the following findings:

- Overall, the incorporation of pseudo-relevance feedback could improve the performance of the BERT-based response ranking models. The RULE-PRF method without selection achieves improvements of 0.46% for Recall@1 on the MSDialog dataset and 0.34% for Recall@1 on the AliMe-CQA dataset. However, in terms of some metrics such as Recall@2, Recall@5 on MSDialog dataset, and Precision@1 on the AliMe-CQA dataset, adding PRF terms hurt the ranking model’s performance. This means the necessity to implement better ways for PRF term selection.

- For a soft version of machine learning based PRF term selection models, the tanh gating is better than sigmoid gating. Hard version (PRF-ML-Gumb) of machine learning based PRF term selection performance better in terms of Recall@2, Recall@5 on MSDialog Dataset and Recall@1 on AliMe-CQA dataset, which can be concluded that the hard selection has potential to achieve better performance but training hard selection by machine learning is not straightforward and intuitive.

- After incorporating the hard selection by our reinforced PRF term selector, our proposed PRF-RL model achieves the best performance against outperforms all the PRF selection methods. This observation again proves the effectiveness of our framework in PRF term selection.

3.5 Hyper-parameter Sensitivities

In this section, we analyze the hyper-parameter sensitivities on the performance of our proposed reinforced PRF term selector in terms of both the number of episode steps and future reward discount factors.

Figure 4: Performance of PRF-RL with different choices of numbers of episodes over the test partition of MSDialog data. The reward discount factor is set to 0.3 while comparing the different choices of the number of episodes.

We first examine the performance of PRF-RL with different choices of the number of episode steps on the MSDialog dataset. As in Figure 4, we have these observations. First, we find our method is generally not very sensitive to this parameter, although by setting the number of episode steps as 100, our method has a slight improvement.

Second, an interesting observation is that the fluctuation of the performance in terms of Recall@5 is inconsistent with other metrics such as Recall@1 and Recall@2. A good performance in Recall@5 may not come with a good performance in Recall@1 and Recall@2. This means the model optimizes the metrics differently, and may not achieve the best performance on all these metrics. In practice, Recall@1 is more important than Recall@2 or Recall@5. Thus we can set the episode step as 100 as we can achieve the best Recall@1, Recall@2, and MAP.

We then proceed to examine our model performance w.r.t. the future reward discount factors on the MSDialog dataset in Figure 5. In general, the model performance is not very sensitive to this parameter as well, although our method has slightly better performance in terms of Recall@1 and Recall@2 by setting the reward discount factor as 0.3.

From both Figure 4 and Figure 5, we find our method is pretty robust as it is not very sensitive to these parameter settings. But still, by conducting combining the findings in both Figures, we can find a relatively better combination of hyper-parameters for our method.
3.6 Case Study

One of the most interesting features of our model is that it has a certain level of interpretability since the selection process is explicit. We then present a case study to examine whether our selection model can generate meaningful PRF terms for expanding the response candidates.

Figure 6 shows one of the cases generated from the MSDialog dataset. In this case, the user wants to edit and save a “excel notebook” which seems to be protected by multiple formulas and macros. The agent proposes a general solution to the user but not working. So the response might be other solutions or ask the user about more detailed descriptions of the problem he has met. Since the “excel notebook” can be converted to “protected” one through some “macros”, the contextual correlation between “protected excel notebook” with “macros” and “vba” is strong. From the results, we can find the soft selections of ML-Tanh and ML-Sigmoid can confuse the ranking model since they both give more weights on irrelevant terms such as “c” and “active”. ML-Gumbel has the same problem, it selects a general term “using” and dropped the “excel” and “workbook” which are relevant to the response. Our PRF-RL model achieve the best result since it can (1) select the exact match terms such as “excel” and “workbook” in the response, (2) avoid selecting irrelevant or general terms such as “c”, “active” and “using”, (3) select contextually correlated terms such as “macros”, which appears in the context but not in the response, which means it can be used to improve the recall of the response candidate. In all, encouragingly we find the selection process made by the proposed PRF-RL model is insightful and intuitive.

3.7 Online A/B Test

Finally, we deployed the proposed PRF-RL model on an online chatbot engine called AliMe \(^7\) in the e-commerce company Alibaba, and conduct an A/B test on our proposed model and the existing online ranking system without considering external PRF expansion.

7\(\text{https://www.alixiaomi.com/}\)

Table 4: The performance comparison of our proposed model with the existing ranking system on the online deployment.

| Methods       | Precision@1 | Relative Improv. |
|---------------|-------------|------------------|
| Online system | 0.6031      | N.A.             |
| PRF-RL        | 0.6769      | 12.24\%          |

In the AliMe chatbot engine, for each user query or request, it employs a two-stage model to find a suitable candidate response. It first calls back at most 15 candidate responses from tens of thousands of candidates and then uses a neural ranker to rerank the candidate responses. The engine uses both of the two systems, one is our method and the other is the online method, to rerank the candidates. Note that the online method is a degenerated version of our method without considering PRF expansion. Overall we have randomly selected 13,549 conversational QA-pairs. After filtering out all the context queries that have zero positive responses in the call-back set, we have collected 325 context queries for each system. We then ask a customer agent to annotate the results of both methods. We obtain the number of the hit of the top-1 ranked candidates and compared the precision@1 score. As shown in Table 4, our proposed PRF-RL model has Precision@1 of 67.69%, which has a significant relative improvement (12.24%) compared with the existing online ranking system. Note that, this improvement is considered to be a big improvement for the chatbot engine. This further shows the advantage of our proposed method and the usefulness of the external PRF expansion.

4 RELATED WORK

4.1 Conversational information-seeking systems

Our research is relevant to conversational information-seeking systems, which has drawn significant attention with the emerging of conversational devices. Radlinski and Craswell described the basic features of conversational information-seeking systems [26]. Thomas et al. [36] released the Microsoft Information-Seeking Conversation (MISC) dataset, which contains information-seeking conversations with a human intermediary. Zhang et al. [55] introduced the System Ask User Respond (SAUR) paradigm for conversational search and recommendation. In addition to conversational search models, researchers have also studied the medium of conversational search. Spina et al. [34] studied the ways of presenting search results over speech-only channels to support conversational search. Lv and Zhai [16] compares the ways of presenting search results over speech-only channels to support conversational search [34, 37]. The target of our research is the response ranking of such conversational information-seeking systems, with reinforced pseudo-relevance Feedback Terms selection and pretrained response ranking models.

4.2 Psuedo Relevance Feedback

With the development of research in IR system, the pseudo-relevance feedback (PRF) has been already demonstrated the effectiveness of incorporating relevance signals from top-ranked documents [2, 12, 16, 29, 53, 54]. Cao et al. [2] incorporates multiple manual features to identify useful expanding terms. Lv and Zhai [16] compares methods for estimating query language models with pseudo-relevance
4.3 Reinforcement Learning

Reinforcement Learning is a series of goal-oriented algorithms that have been studied for many decades in many disciplines [1]. The recent development in deep learning has greatly contributed to this area and has delivered amazing achievements in many domains, such as playing games against humans [18, 32]. There are two lines of work in RL: value-based methods and policy-based methods. Value-based methods, including SARSA [30] and the Deep Q Network [19], take actions based on estimations of expected long-term return. On the other hand, policy-based methods such as REINFORCE [43] optimize for a strategy that can map states to actions that promise the highest reward. It is proved that reinforcement learning is effective in data selection problems over many areas, such as active learning [5], co-training [44], and other applications of supervised learning [4, 6, 21, 41]. Our proposed reinforced PRF term selector is trained by the aforementioned REINFORCE methods.

4.4 Neural response ranking

There is growing interest in research about conversation response generation and ranking with deep learning and reinforcement learning [7]. There are two main categories of the previous works, including retrieval-based methods [35, 46, 49, 51, 56] and generation-based methods [23, 27, 31, 39]. Our research work is related to retrieval-based methods. There has been some research on response ranking in multi-turn conversations with retrieval-based methods. Yang et al. [51] studied how to integrate external knowledge into deep neural networks for response ranking in information-seeking conversations. [57] investigated matching a response with conversation contexts with dependency information learned by attention mechanisms of Transformers. The model proposed in this paper incorporating a reinforced PRF terms selection mechanism to select meaningful PRF terms to boost the performance of pretrained model based response ranking model. Recently, language models pretrained on massive unsupervised corpora [3, 15, 22, 25] has achieved a significant improvement in many natural language processing tasks, ranging from syntactic parsing to natural language inference [3, 22], as well as machine reading comprehension [3, 47], information retrieval tasks [20, 52]. The pretrained models such as BERT [3] are also applied to response selection [9, 38, 42]. Our model also applies the general framework of BERT encoder as a part of the response ranker with the response expanded by selected PRF terms.

5 Conclusion

In this work, we propose a principled way to automatically select useful pseudo-relevance feedback terms to help information-seeking conversations. Our method consists of a reinforced PRF term selector
and a BERT response ranker, where the selector interacts with the ranker to generate high-quality pseudo-relevance feedback terms, and the performance of the ranker can help to guide the behaviors of the selector. Extensive experiments have been conducted on both public and industrial datasets, and show our model outperforms the competing models. Experiments and case studies also show that the proposed reinforced PRF term selector is superior to other PRF term selection methods. We have also deployed our proposed model in an online chatbot system and observe a large improvement over the existing online ranking system.

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