Deep Reinforced Query Reformulation for Information Retrieval

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ABSTRACT

Query reformulations have long been a key mechanism to alleviate the vocabulary-mismatch problem in information retrieval, for example by expanding the queries with related query terms or by generating paraphrases of the queries. In this work, we propose a deep reinforced query reformulation (DRQR) model to automatically generate new reformulations of the query. To encourage the model to generate queries which can achieve high performance when performing the retrieval task, we incorporate query performance prediction into our reward function. In addition, to evaluate the quality of the reformulated query in the context of information retrieval, we first train our DRQR model, then apply the retrieval ranking model on the obtained reformulated query. Experiments are conducted on the TREC 2020 Deep Learning track MSMARCO document ranking dataset. Our results show that our proposed model outperforms several query reformulation model baselines when performing retrieval task. In addition, improvements are also observed when combining with various retrieval models, such as query expansion and BERT.

1 INTRODUCTION

Vocabulary mismatch is an inherent problem in information retrieval (IR) tasks, due to the possible inconsistency between the way users express their information needs and the manner in which relevant content is described in the documents. In order to alleviate this vocabulary mismatch problem in IR, many approaches have been proposed. For instance, in relevance feedback, additional terms identified from known relevant documents are added to the original user's query; pseudo-relevance feedback (PRF) is the name given to the automatic process, where the original query is reformulated (typically expanded) using terms occurring in the pseudo-relevant set of documents – typically the top-ranked documents in response to the initial query [10].

More recently, there has been a move towards addressing more complex information needs where the user queries are often expressed as questions rather than "keywords". Indeed, recent context-aware neural ranking techniques such as BERT have been shown to be effective over question-like queries [12]. The research by participants in the recent TREC 2019 Deep Learning track [9] exemplifies recent work in this direction. To address the vocabulary mismatch for question-like queries, we are inspired by the work of Zerveas et al. [44], who aimed to learn how to generate paraphrases (alternative question formulations) of queries using a deep learned text generation model called query2query.

Indeed, in recent years, deep neural networks have played an important role in text processing-related tasks. For instance, sequence to sequence (seq2seq) models (based on recurrent neural networks, RNNs) have demonstrated an ability to learn the meaning of a sentence. Seq2seq models have been extensively used, for instance, to generate paraphrases of an input sentence [42]; to simplify natural language queries into a keyword query [22] or to extract the key phrases of a given input document [7, 43].

However, the traditional sequence to sequence (seq2seq) model suffers from two problems: the exposure bias and the inconsistency between the train and test measurement metrics [18, 31]. To address these problems, reinforcement learning has been applied to sequence to sequence modelling, such that the RNN-based seq2seq model is regarded as an agent, while an action is generated by a stochastic policy based on the reward given by the reward function [18, 31]. In this work, we propose the Deep Reinforced Query Reformulation (DRQR) model, which is a deep reinforcement learning-based seq2seq model that can automatically generate query reformulations for a given input query. The reward function in our reinforcement learning setup is inspired by previous work in selective pseudo-relevance feedback [15]: indeed, the effectiveness of pseudo-relevance feedback is sensitive to the quality of the initial retrieval results [5], and therefore query performance predictors [4, 14] can be used to identify when it suitable to apply PRF [15]. Similarly, we use query performance predictors within the reinforcement reward function to select high quality paraphrases – in doing so, the predictors help the learning algorithm to produce paraphrases that are predicted to be effective, and helps to bridge the gap between sequence prediction (the training task) and retrieval effectiveness (the ultimate “test” task).

In summary, this paper provides three contributions: (1) We employ a reinforcement learning technique within our query reformulation model to generate query reformulations; (2) the model incorporates the query performance prediction into our reward function to direct the learning towards good query reformulations; (3) We demonstrate the effectiveness of our reinforcement learning-generated query paraphrases within a state-of-the-art BERT ranking model upon the TREC 2019 Deep Learning track test collection.

The remainder of this paper is structured as follows: In Section 2, we position our model with respect to the related work. Section 3 presents our proposed deep reinforcement learning model. Research questions and experimental setup are described in Sections 4 & 5. Results analysis and conclusions respectively follow in Sections 6 & 7.
2 RELATED WORKS

We consider two aspects of related work, namely, a review of relevant information retrieval (IR) approaches addressing the vocabulary mismatch problem, query performance predictors, and work related to text generation models.

2.1 Paraphrasing Queries

Many approaches have been proposed to alleviate the vocabulary mismatch problem by adjusting the formulation of the query, including automatic pseudo-relevance feedback techniques, ranging from Rocchio’s algorithm [34] to the DFR relevance feedback approaches [1] through relevance models such as RM3 [20]. Such query expansion approaches typically reweight the query terms, such that new query terms may be added with non-binary weights.

Alternatively, generating paraphrases of user queries has been proposed to address the "lexical chasm" problem. Many studies have employed lexical paraphrases of queries to expand the original query thus improving the retrieval performance. For instance, Zukerman et al. used an iterative process to identify similar phrases to a query based on WordNet [45]. However, static resources such as WordNet may not be able to address the changing nature of search, for example the new words. One recent branch of work involves considering previous user queries for sources of reformulations. For instance, Jones et al. generated candidate substitutions for phrases of the input query based on logs of previous user queries [17]. Later, Statistical Machine Translation (SMT) techniques were employed to expand the query by first generating the phrase-level paraphrases of the query, then selecting terms from the n-best paraphrases queries as expanded terms [33]. For instance, a query such as “paint a house” is rephrased as “decorate a room”, where the terms “decorate” and “room” can be used to expand the original query. However, these methods are not neural models-based and require extensive efforts on users to select from the rephrased phrases.

Another promising approach is to expand the original query by generating the query-level paraphrases at once while preserving the meaning of the original query. For example, “do goldfish grow” and “how long does a goldfish grow” form a pair of paraphrases. Zerveas et al. [44] proposed a query2query method based on the Transformer model to generate three rephrased queries given the input query. Then the three generated paraphrases together with the original query can be used to retrieve relevant documents, with the aim of enhancing the retrieval effectiveness. However, Zerveas et al. did not intervene in the process of generating the paraphrases, meaning that their paraphrase generation model failed to consider the generated paraphrases’ retrieval effectiveness. In this work, our model takes the query retrieval performance into consideration while generating the paraphrases of a given query.

2.2 Query Performance Prediction

A risk when generating paraphrases of queries is that they might not be of high quality, and lead to degraded retrieval effectiveness. To address this, in this paper, we make use of query performance predictors (QPP). The goal of query performance prediction is to predict the search effectiveness for a given query in advance, without any relevance information provided by humans. Query performance prediction has been used to apply different retrieval approaches for queries that are predicted to be difficult – for instance, selective query expansion exploits query performance predictors to decide whether to expand the original query or not [11, 15]. Furthermore, Lv et al. [24] suggested to use query performance prediction to decide the number of additional terms to expand a given query with when performing pseudo relevance feedback. However, both of these approaches using query performance predictors are more focused on expanding the original query with additional terms rather than generating an entire paraphrase of the query at once, as we apply in our work.

Query performance prediction approaches can mainly be categorised as being pre-retrieval and post-retrieval in nature, where pre-retrieval predictors only exploit the raw query and statistics of the query terms, as recorded at indexing time. In contrast, post-retrieval predictors analyse the retrieved documents, in terms of score distributions and/or content. Based on this, our work uses pre-retrieval predictors as a reward signal to generate query paraphrases that are expected to be effective.

2.3 Text Generation Models

Neural text generation models have achieved outstanding performances in many applications. In this paper, we cast our query reformulation task as a form of text generation task, which can be addressed using sequence-to-sequence models (seq2seq). Below, we review seq2seq models and discuss how they can be enhanced using reinforcement learning.

2.3.1 seq2seq models. Sequence to sequence models [37] generally consist of an RNN-based encoder and decoder. The encoder encodes the input sequence into a fixed-size hidden vector, based on which the decoder generates the predicted sequence. However, an information bottleneck can form when trying to encode all the information of the source sequence into a single vector. Later, an attention mechanism was proposed by Bahdanau et al. [2] and Loung et al. [23] to allow the decoder to build a direct connection with the encoder and to focus on a particular part of the source sequence at each decoding step. Later, Gu et al. [13] proposed the copy mechanism, which is a mixture of generating a token from the vocabulary or copying a token from the source sequence. The copying mechanism enables a seq2seq model to generate out-of-vocabulary words in the target, by selecting words from the source sequence.

The sequence to sequence models have been used for a variety of IR tasks. For instance, Sordoni et al. applied a hierarchical RNN-based model to generate query suggestions [35]. Liu et al. transformed the natural language query into the keyword query [22] with the aim to improve the retrieval effectiveness of term-matching IR models. In addition, in the work of He et al. [16], a seq2seq model is trained to reformulate the input queries, and the beam search technique is employed to generate multiple query reformulations as candidates, from which good reformulations are selected by a candidate ranking process. Considering that time-complexity is increased by beam search, in our work, we build our query reformulation model based on a seq2seq model that includes both attention and the copy mechanism. To encourage our reformulation model to reformulate the original query using different words, we adopt the one2many technique in Catseq [43]. The Catseq model has been
originally designed to deal with the keyphrase generation problem by generating multiple keyphrases conditioned on the input text. Instead of using the above generation technique, for example, the beam search technique, the Catseq model concatenates multiple generated phrases into a sequence as output to achieve the diversity goal. We build our proposed model based on Catseq, where each word of the ground-truth paraphrase is regarded as a one-word keyphrase and the input query is regarded as the input text.

2.3.2 Reinforcement learning for text generation. While traditional sequence to sequence models are trained using the word-level cross-entropy loss function, their usefulness may only be determined for some information retrieval tasks, which would be evaluated using different metrics. Indeed, in our query reformulation task, we may consider reformulation success in terms of retrieval effectiveness, but typical retrieval metrics are not differentiable with respect to the model parameters, and hence cannot be considered within the seq2seq learning process. Further, traditional sequence to sequence models suffer from exposure bias, in that during training they are fed the ground truth tokens one at a time – this creates models that are conditioned based on the correct words [31], and as a results produce less accurate generations at test time.

To avoid these problems, reinforcement learning has been applied to a wide array of text generation tasks, including, keyphrase generation [6], summarisation [29] and paraphrasing [21]. Buck et al. proposed a question reformulation model based on seq2seq trained using reinforcement learning for the QA task [3]. The reward is calculated based on the returned answer in response to the reformulated question. Different from their work, our target is document retrieval rather than question-answering. In addition, Nogueira et al. [27] proposed a reinforcement learning-based query reformulation model that selects expansion terms from the top-ranked documents returned by the initial retrieval. Their reward function is designed to leverage recall when conducting retrieval on the predicted query sequence at the end of each episode. However, similar to pseudo-relevance feedback, the model is sensitive to the initial retrieval performance. In addition, due to the use of recall in their reward function, the need to retrieve at each iteration means it takes a considerable time to train the RL model – indeed, they report training for 8-10 days.

In our work, we cast our query reformulation learning task as a reinforcement learning problem and employ the policy gradient algorithm REINFORCE [40]. Concretely, we adopt the Self-Critic (SC) [32] REINFORCE model to reduce its high-variance. The goal of our proposed model is to improve the effectiveness of the retrieval task. However, different from existing work, our RL approach incorporates the rewards not only from the lexical match between the generated sequence and the source sequence but also from a retrieval-related reward, obtained from the query performance predictors. Indeed, by using query performance predictors to guide the paraphrase generation instead of retrieval recall (as used by Nogueira et al. [27]), this results in faster training time, as the predictors only require collection statistics.

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**Figure 1: Architecture of our proposed Deep Reinforced Query Reformulation (DRQR) model.**

3 A DEEP REINFORCED QUERY REFORMULATION MODEL

In this section, we describe our Deep Reinforced Query Reformulation (DRQR) model in detail. We first formally define our problem in Section 3.1 and the detailed training process is explained in Section 3.2. Our reward function is specified in Section 3.3.

3.1 Query Reformulation Problem Definition

Formally, the task performed by the DRQR model can be described as follows: given a pair of input user query \( X = [x_1, x_2, ..., x_N] \) of \( N \) terms length and a paraphrase of that query \( \hat{Y} = [y_1, y_2, ..., y_M] \) with length \( M \), the model is trained to produce a reformulation \( \hat{Y} = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_M] \). This predicted query \( \hat{Y} \) should aid a retrieval system to identify documents that are relevant to the original query \( X \).

3.2 Training Process

In this section, we describe the training process of our DRQR model. Figure 1 presents the architecture of our model, which consists of two parts: The left part is the query reformulation model, which is trained using the REINFORCE algorithm. After the query reformulation model is trained, the obtained reformulated query together with the original query form an augmented query. The right part is the retrieval pipeline, which scores the documents based on the augmented query. We first introduce the backbone text generation models: a seq2seq model with an attention and copy mechanisms, then the reinforced learning process.

3.2.1 Encoder-decoder model. Our query reformulation model adopts the recurrent neural network (RNN)-based encoder-decoder framework. Generally speaking, the encoder encodes the input sequence into a fixed-length vector representation, then the decoder decodes it back into a variable-length sequence. We adopt bi-directional gated recurrent units (GRU-RNN) as the encoder [8], which reads each word, then updates the hidden state:

\[
 h_n = \text{GRU}_{encoder}(h_{n-1}, x_n)
\]

Thus the encoder converts the input sequence into a sequence of real-valued vectors: \( H_e = [h_1, h_2, ..., h_N] \).

The decoder is an uni-directional GRU model, which is trained to generate the current hidden state conditioned on the current word \( y_m \) and the previous hidden state:

\[
 s_m = \text{GRU}_{decoder}(s_{m-1}, y_m)
\]

An Attention mechanism [2] is used to determine the importance of each word from the source sequence given the current decoder
hidden state $s_m$ when generating token $y_m$. At each decoder step $t \in [1, M]$, we have the encoder hidden states $H_e = \{h_1, h_2, \ldots, h_N\}$ and the current decoder hidden state $s_t$, then we get the attention scores by applying a single-layer feed forward attention function:

$$e^t = [s^T_t h_1, \ldots, s^T_t h_N]$$

(3)

To address the importance of each word from the input sequence, the softmax function is applied to the obtained attention scores. Then we get the attention distribution $a^t$, which is the probability distribution of the input sequence, as follows:

$$a^t = \text{softmax}(e^t)$$

(4)

Finally, the attention weights are used to represent the encoder hidden states as a context vector:

$$c_t = \sum_{i=1}^{N} a^t_i h_i$$

(5)

Next, an effective query reformulation often involves using at least one of the input query words appearing in the reformulated query. This contrasts with other conventional seq2seq tasks, such as machine translation, where it is rarer for the same words to appear in both input and output. To address such a need, Gu et al. [13] proposed a copy mechanism, which we also adopt in this work. At each generation step $t$, the copy mechanism decides to switch between generating words from the vocabulary or copying words from the input source sequence.

$$p(y_t) = q_t \cdot p_p(y_t) + (1 - q_t) \cdot p_g(y_t)$$

(6)

where $q_t$ is conditioned on the context vector and the decoder hidden state and decides to switch between the generation or copying modes. We employed the teacher forcing algorithm [41] to train the model using the ground-truth $Y = \{y_1, y_2, \ldots, y_M\}$. The maximum-likelihood training objective can be described as:

$$L(\theta)_{ML} = -\sum_{i=1}^{M} \log p(y_i | y_1, \ldots, y_{i-1}; \theta)$$

(7)

where $\theta$ denotes the parameters of the seq2seq models. However, as mentioned in Section 2.3.2, minimising the maximum-likelihood loss function may not necessarily lead to generated query reformulations that are effective in nature. Thus, there is a discrepancy between the training objective and the overall objective. In addition, due to the use of teacher forcing during the training phase, the model is exposed to the ground-truth word when generating the next word at each time step. However, since there is no ground-truth provided in the testing time, the model generates the next word conditioned on its own previous predicted word. If this is incorrect, it may deviate the whole generated sequence from the actual sequence [31]. This scenario is called exposure bias. To address these issues, we employ a reinforcement learning algorithm that can directly optimise over the discrete evaluation metric and not rely on the ground truth during training.

3.2.2 Reinforcement learning training process. We formulate our query reformulation task as a reinforcement learning problem and employ the REINFORCE [40] algorithm in this work. The sequence to sequence model acts as the agent, the parameter $\theta$ of the agent is regarded as the policy $\pi_\theta$ and an action $\hat{y}_t$ refers to the prediction of the next word at each time step $t \in [0, M]$. A reward $r(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_M)$ is observed at the end of the sequence but is set to zero when selecting a word within the sequence. The goal of the training is to optimise the policy by maximising the expected reward or minimising the negative expected reward:

$$L(\theta)_{RL} = -\mathbb{E}_{\hat{Y}} \cdot \pi_\theta(\hat{Y}) r(\hat{Y})$$

(8)

where $\hat{Y} = [\hat{y}_1, \ldots, \hat{y}_M]$ is the predicted sequence and $r(\hat{Y})$ is the observed reward given by the reward function. The gradient of Equation (8) is provided as follows:

$$\nabla_\theta L(\theta)_{RL} = -\mathbb{E}_{\hat{Y} \sim \pi_\theta(\hat{Y})} [r(\hat{Y}) \nabla_\theta \log p_\theta(\hat{Y})]$$

(9)

In practice, the expectation is estimated using a single sample sequence from the distribution of actions produced from the agent. However, this would cause a high-variance for the model. Hence, a baseline $r_b$ reward is used to encourage the model to select a sequence with reward $r > r_b$ and discourage those action sequences with reward $r < r_b$. The gradient of the loss function is as follows:

$$\nabla_\theta L(\theta)_{RL} = -\mathbb{E}_{\hat{Y} \sim \pi_\theta(\hat{Y})} [\nabla_\theta \log \pi(\hat{Y})(r(\hat{Y}) - r_b)]$$

(10)

where $r_b$ is the baseline reward. The baseline $r_b$ can be any estimator that is independent of the action, thus it can reduce the variance of the gradient loss without changing the gradient value (since the second component of Equation (10) can be proven to be zero [32]). In this work, we adopt the Self-Critic [32] REINFORCE model, which produces a baseline based on the output at the time of inference rather than estimating the baseline using samples from the current model. Another problem for training the RL model is that the action space is very big thus making the model difficult to learn with an initial random policy. To avoid starting with an initial random policy, we train the model using the combination of the $L(\theta)_{ML}$ and $L(\theta)_{RL}$ loss function, as follows:

$$L_{train} = N_{ML} L(\theta)_{ML} + N_{RL} L(\theta)_{RL}$$

(11)

where we first train the model using $L(\theta)_{ML}$ for $N_{ML}$ epochs, then train $N_{RL}$ epochs using $L(\theta)_{RL}$ [7].

3.3 Reward Function

To force our model to learn how to reformulate the input queries into a form that would perform well in the retrieval task, at the end of each predicted sequence, we give a reward through the reward function. The reward function for our model is the weighted sum of two components namely, the F1 reward and the QQP reward.

3.3.1 F1 reward. To encourage the model to generate an accurate reformulated query, our reward function encapsulates sequence classification accuracy, specifically an F1 reward, therefore encapsulating both recall and precision for the correct terms. Recall measures how well the agent could generate identical terms with the ground-truth reformulation, and precision measures how well the agent rejects incorrect words. In short, the F1 reward encourages the model to generate the correct form of a reformulated query compared to the ground-truth paraphrased query. However, in our initial experiments, we observed that seq2seq tends to generate repeated words for our task. Thus, we adopt the technique from [7] to penalise the generated sequence by replacing the repetitive words with the (PAD) token. Thus the duplicated words are treated as an incorrect generation.
3.3.2 QPP reward. While the F1 reward aims to encourage the model to generate a reformulated query that is close to the ground truth examples (c.f. instances in Y) in the training dataset, we also want the learned model to generate queries that are likely to be effective in nature. To this end, we propose the integration of a query performance predictor into the reward function, as a signal to encourage the model to reformulate the query from the perspective of improving the retrieval effectiveness. Depending on the deployed predictor, this may guide the reward function to avoid words that are too non-informative.

It would be possible to integrate a retrieval component into the reward function, and therefore calculate post-retrieval query performance predictors, which are known to be more accurate [4]. However, repeated invocation of the search engine would dramatically slow down the training process. For this reason, we focus on pre-retrieval predictors. We discuss the used predictors later in Section 5.4. Our final reward function is therefore a linear combination of F1 (representing the paraphrase accuracy) and query performance prediction (representing the likelihood that the generated query will be useful to the search engine):

\[
r(\hat{Y}) = \lambda r_{F1} + (1 - \lambda) r_{QPP}
\]

where \(\lambda \in [0, 1]\) is a tunable hyper-parameter that adjusts the importance of the QPP values within the reward function. We assume a default value of \(\lambda = 0.5\), but investigate the impact of this setting later in Section 6.

4 RESEARCH QUESTIONS
In this work, we address four research questions. Firstly, one of our key contributions is the introduction of pre-retrieval query performance predictors (QPPs) for use within the reinforcement learning reward function. In doing so, we assume that they can differentiate between high and low quality query reformulations, to guide the learning process. However, no work has yet investigated QPPs on the MSMARCO dataset, where the queries are question-like in nature. For this reason, we pose our first research question as:

**RQ1**: How accurate are pre-retrieval query performance predictors on the MSMARCO dataset at (a) discriminating between easy and hard queries, and (b) discriminating between high and low quality query reformulations?

Secondly, we investigate the effectiveness of our proposed DRQR model, as follows:

**RQ2**: Do queries reformulated using our RL model result in effectiveness improvements over text generation baselines for generating query reformulations?

Thirdly, we examine how the effectiveness of the used retrieval approach impacts the effectiveness of our RL model, as follows:

**RQ3**: Does our DRQR model result in further improvements when combined with other enhanced retrieval approaches such as QE or BERT?

5 EXPERIMENTAL SETUP
In the following, we describe the used MSMARCO dataset in Section 5.1. We discuss our experimental setup for seq2seq and retrieval pipeline in detail in Section 5.2 and Section 5.3. The descriptions of the seven deployed query performance predictors and that of the four baseline reformulation models are provided in Section 5.4 and Section 5.5, respectively. Finally, the measures used in our experiments are detailed in Section 5.6.

5.1 Dataset
All of our experiments are conducted using the MSMARCO document ranking dataset\(^2\), in the setting of the TREC 2019 Deep Learning (DL) track [9]. In particular, in the TREC DL setting, the corpus is composed of \(\sim 3.2\text{M}\) documents, along which are provided \(\sim 367\text{k}\) training queries with one or two known relevant documents. In order to train the model to learn how to reformulate queries, we use the training corpus for identifying pairs of queries. In particular, following Zerveas et al. [44], we find that some documents are labeled as relevant for multiple queries. We assume that the information needs for such pairs of queries sharing a relevant document are close enough that they can be considered as paraphrases. We identified 188,292 pairs of such rephrased queries. We sample 90% of the generated pairs as training data, while the remainder 10% is taken as a validation dataset.

Finally, to test retrieval effectiveness, we use the 43 new test queries from the TREC Deep Learning Track 2019, which were the object of deep pooling and relevance assessments with an average of 153.4 relevant documents per query.

5.2 Seq2Seq Setup
For the implementation of the sequence to sequence query reformulation model, we follow the setting of Chen et al. [7], where the hidden size of the encoder and decoder is set as 300. The parameters of the model are initialised using a uniform distribution – i.e. we do not use any trained embedding representation. In the training process, the dropout rate is 0.1 and a gradient clipping of 1.0 is used. In the maximised-likelihood training process, teacher-forcing is applied and the Adam optimiser with a learning rate of \(1 \times 10^{-3}\) and a batch size of 12 is used. We also employ the early stopping mechanism, if there are no validation improvements for three consecutive epochs.

After obtaining the pre-trained ML model, we use it for training our DRQR model. The Adam optimiser with a batch size of 32 and a learning rate of \(5 \times 10^{-3}\) is used to train the model. A similar early-stopping mechanism used in seq2seq setup is used to early terminate the training. In the decoding phase, we use the greedy search algorithm to generate the reformulated query. Before obtaining the evaluation scores of F1, we remove all the duplicated terms from the prediction sequence [7]. For calculating the pre-retrieval query performance predictor scores, we apply the Porter Stemmer to each token since the index we are using is a stemmed MSMARCO index. For the implementation of the Transformer model, we employ the OpenNMT [19] platform.

5.3 Retrieval Pipeline Setup
We index MSMARCO using the Terrier IR platform [28], removing standard stopwords and applying Porter stemming. For the retrieval experiments, we make use of the recent Python bindings for Terrier, namely PyTerrier\(^3\). Our ranking pipeline incorporates DPH as well as a BERT re-ranker from the CEDR toolkit [12]. Following the experimental setup of Su et al. [36], we train the BERT model using

\(^2\) https://microsoft.github.io/msmarco/ \(^3\) https://github.com/terrier-org/pyterrier
where \( Pr \) is the probability of a query term in the collection \( D \), \( N \) is the number of documents in the whole collection and \( N_t \) is the number of documents containing the query term \( t \).

**Inverse Collection Term Frequency (ICTF).** Similar to IDF, the inverse collection term frequency measures the relative importance of a query term in the collection \( D \), as follows:

\[
ictf(t) = \log \left( \frac{|D|}{tf(t,D)} \right)
\]

where \( |D| \) is the number of terms in the collection \( D \) and \( tf(t,D) \) is the number of occurrences of term \( t \) in the whole collection \( D \).

**Simplified Clarity Score (SCS).** The simplified clarity score measures the Kullback-Leibler Divergence (KL divergence) between the distribution of the term in the query and in the collection \( D \):

\[
SCS(q) = \sum_{t \in q} Pr(t|q) \log \left( \frac{Pr(t|q)}{Pr(t|D)} \right)
\]

where \( Pr(t|q) = \frac{tf(t,q)}{|q|} \) is the probability of a query term in the query, and \( Pr(t) = \frac{tf(t,D)}{|D|} \) is the probability of a query term in the whole collection \( D \).

**Collection Query Similarity (SCQ).** The collection query similarity measures the query similarity to the collection. A higher similarity potentially indicates more relevant documents.

\[
SCQ(t) = (1 + \log(tf(t,D))) \cdot idf(t)
\]

In particular, the MaxSCQ, AvgSCQ and SumSCQ scores are calculated by respectively taking the maximum, average or summation of the SCQ scores over the query terms.

**Query Length.** The number of tokens of a given query. The premise is that longer queries are better specified, and hence are likely to have a higher effectiveness.

Since \( idf(t) \) and \( ictf(t) \) as well as \( SCQ(t) \) are term-level statistics, to obtain query-level effectiveness predictions, we take the average of the statistics over the query terms, and denote these as AvgIDF, AvgICTF and AvgSCQ. Moreover, following [4], we also calculate MaxSCQ and SumSCQ.

### 5.5 Baseline Reformulation Models

In order to test the effectiveness of our DRQR model in generating reformulated queries, we compare our model with various reformulation baselines, namely:

**Transformer.** The transformer model is proposed by Vaswani et al. [39]. Following the setup of Zerveas et al. [44], we use the OpenNMT platform [19]. In [44], the authors generated three rephrased queries and concatenated these to the original query to form a new query. We apply the Transformer model with one, three and five generated paraphrases obtained using the Beam Search technique in the decoding phase. These are denoted as Transformer1, Transformer3 and Transformer5, respectively.

**CatseqML Model.** Compared to the previous model, CatseqML adds the copy mechanism (Equation (6)). CatseqML is trained using the maximum-likelihood loss function [43]. In this baseline, the original query is regarded as the input source text, the ground-truth paraphrase is taken as a set of one-word keyphrases.

**CatseqRL Model.** Compared to CatseqML, CatseqRL is trained using reinforcement learning [7]. The reward only uses the F1 score calculated from the predicted sequence and input sequence. Hence, this model is identical to Equation (12) with \( \lambda = 1 \), i.e. without considering any query performance predictors in the reward function. As for CatseqNL, the ground-truth paraphrase is regarded as a set of one-word keyphrases extracted from the input text.

### 5.6 Measures

Our experiments encapsulate two types of measurements, as follows: for measuring retrieval effectiveness; and for measuring the accuracy of the query performance predictors. In particular, for measuring effectiveness we make use of mean average precision (MAP) and normalised discounted cumulative gain (NDCG@10), which were the official measures reported in the TREC 2019 Deep Learning track overview [9]. We use the paired t-test for testing significant differences between effectiveness values.

For measuring the QPP accuracy, we rank queries based on the QPP values, as well as by retrieval effectiveness, and then compute rank correlation coefficients. In particular, following [4], we compute Spearman’s \( \rho \) correlation and Kendall’s \( \tau \) rank correlation – a high absolute correlation for a given predictor indicates that the predictor accurately predicts the performance. To determine if a
correlation is significant, we perform a permutation test; we determine if the differences between two correlations are significantly different using a Fisher-\(z\) transform.

6 RESULTS

In the following, we present our findings for RQ1 concerning the QPP accuracy in Section 6.1. Findings for the effectiveness of DRQR viz. RQ2 and RQ3 are reported in Sections 6.2 and 6.3 respectively.

6.1 RQ1: Query Performance Predictors

In this section, we investigate the accuracy of the pre-retrieval query performance predictors on the MSMARCO document ranking dataset, both for predicting the effectiveness of queries, as well as for different reformulations.

Firstly, to illustrate the correlation between a particular QPP predictor and an IR effectiveness metric, e.g. NDCG@10, Figure 2 contains a scatter plot showing how the predictions of the AvgSCQ QPP scores are correlated with the NDCG@10 retrieval effectiveness. Each point denotes a particular query among the N = 43 TREC queries. The x-axis of each point is the calculated QPP predictor value for the query, while the y-axis of the point is the value of its NDCG@10 performance. The more that the points fall on the principal diagonal, the stronger the correlation between the predictor and the NDCG@10 performance. In contrast, irregular and other dispersed points denote a weak correlation. To quantify the observed correlation, the left hand side of Table 1 contains the Spearman’s \(\rho\) and Kendall’s \(\tau\) correlations between different QPP predictors and ranking effectiveness metrics (namely mean average precision and NDCG@10). All correlations are calculated on the N = 43 TREC queries. In the table, the highest correlations in each column are emphasised, and significant correlations are denoted with *.

To establish the best QPP predictor for each reformulation model, we take the QPP values for each query reformulation instance; we obtain the predictors’ values for each reformulation instance, and measure the correlation with the effectiveness of the reformulation. The results are presented in the right hand side of Table 1.

On analysis of the right hand side of Table 1, we observe that, in general, the QPPs are able to differentiate between good and bad reformulations, since significant correlations under the permutation test are observed, which are only slightly lower than those observed in the left hand side of the table. Moreover, the four best predictors from the left hand side of the table, namely AvgIDF, SCS, AvgSCQ and AvgICTF, are still the best predictors using the reformulations, and are statistically indistinguishable among each other. The low-performing predictors from the left-hand side of Table 1, namely SumSCQ, MaxSCQ, QueryLength, remain inaccurate. This answers RQ1(b) that the pre-retrieval predictors can distinguish between high and low quality query reformulations. For this reason, we take forward these four predictors into our experiments for research question RQ2.

6.2 RQ2: DRQR vs. reformulation baseline models?

Next, we examine the effectiveness of the text generation query reformulation models, including our proposed DRQR model, and those listed in Section 5.5. Table 2 presents the effectiveness of the different reformulation models, when applied to either the DPH or BM25 retrieval models. In this table, DRQR uses the AvgSCQ predictor, along with the default reward tradeoff parameter \(\lambda = 0.5\) in Equation (12) – later, we revisit each of these choices. Further, for each reformulation model, we append the generated query reformulations with the corresponding original query – as the reformulated query alone is not sufficiently effective [44]. Within Table 2, the best result in each column is highlighted in bold and the symbol * denotes a significant degradation of the best result, according to the paired t-test for \(p < 0.05\).

On analysis of Table 2, we observe that the baseline reformulation models, namely the Transformers models, as well as seq2seq
Table 1: Correlation between different QPP predictors and the retrieval evaluation measures. The strongest correlation is emphasised. The * symbol denotes a significant correlation between the predictor and the retrieval measure (p < 0.05), while the < symbol denotes a significant degradation from the best predictor in that column (p < 0.05), according to a Fisher-z transform. The left-hand side of the table presents the correlation analysis conducted on the 43 TREC queries, while the right-hand side is the correlation analysis conducted on the 4*43 reformulated queries obtained from four query reformulation baselines.

| QPP predictors | Queries (N = 43) | Query Reformulations (N = 43 + 4 = 172) |
|----------------|-----------------|----------------------------------------|
|                | Spearman’s ρ    | Kendall’s τ | Spearman’s ρ    | Kendall’s τ |
|                | MAP             | NDCG@10     | MAP             | NDCG@10     |
| AvgIDF         | 0.431*          | 0.318*      | 0.348*          | 0.318*      |
| SCS            | 0.442*          | 0.318*      | 0.348*          | 0.318*      |
| AvgSCQ         | 0.464*          | 0.324*      | 0.360*          | 0.324*      |
| AvgICTF        | 0.443*          | 0.185      | 0.204          | 0.185      |
| MaxSCQ         | 0.211           | 0.110      | 0.0742         | 0.110      |
| SumSCQ         | 0.157           | 0.129      | 0.139          | 0.139      |
| QueryLength    | -0.0162         | -0.0114    | -0.0131        | -0.00358   |

Table 2: Comparison between the DRQR model and the query reformulation baselines. The symbol * denotes a significant difference between the current query reformulation model and the query reformulation model that achieves the best performance with the same ranking model and the same effectiveness metric (paired t-test, p < 0.05).

| Query Reformulation Model | Ranking Model | MAP  | NDCG@10 |
|---------------------------|---------------|------|---------|
| Transformer1              | DPH           | 0.2378* | 0.3712* |
|                           | BM25          | 0.2467* | 0.3438* |
| Transformer3              | DPH           | 0.1806* | 0.2613* |
|                           | BM25          | 0.1648* | 0.2471* |
| Transformer5              | DPH           | 0.1287* | 0.2065* |
|                           | BM25          | 0.1363* | 0.1983* |
| Seq2seqattention          | DPH           | 0.2907* | 0.4557* |
|                           | BM25          | 0.2907* | 0.4550* |
| CatseqML                  | DPH           | 0.2999* | 0.4795* |
|                           | BM25          | 0.3160 | 0.4754* |
| CatseqRL                 | DPH           | 0.3125 | 0.5156  |
|                           | BM25          | 0.3465 | 0.5018  |
| DRQR (AvgSCQ)            | DPH           | 0.3293 | 0.5516  |
|                           | BM25          | 0.3316 | 0.5467  |

with attention, and CatseqML or CatseqRL, do not generate effective reformulations. Indeed, recall that Transformer3 corresponds to the existing approach of Zerveras [44]. In contrast, our proposed DRQR model outperforms these models in terms of both MAP and NDCG@10. These improvements are significant (paired t-test, p < 0.05) over all reformulation models except CatseqRL (one exception being CatseqML for BM25 on MAP). The effectiveness of CatseqRL over the other models supports the benefit of reinforcement learning to avoid the exposure bias problem (discussed earlier in Section 2.3.2).

Furthermore, our approach exhibits marked but not significant improvements over CatseqRL – for instance, DRQR exhibits a 6.9% improvement in NDCG@10 for DPH (0.5156 → 0.5516). We argue that this is because our model has the ability to avoid generating queries that are predicted not to be effective, while traditional text generation models are focused instead on generating correct paraphrases, where they may consequently exhibit a topical drift away from the user’s original information need, thereby damaging effectiveness.

We further examine the performances on a per-query basis for the Transformer1, Seq2Seqattention, CatseqML, CatseqRL and DRQR models. Figure 3 compares the number of improved, degraded and unchanged queries for the query with and without reformulated queries in terms of NDCG@10 given by the DPH ranking model. In Figure 3, we can see that while our proposed DRQR model does not possess the largest number of improved queries, it has the least number of degraded queries, and many unchanged queries. The reason behind this is that the query performance prediction in our DRQR model has an effect of penalising words that might downgrade the retrieval performance. In addition, Table 4 shows three reformulated queries with improved performances over their corresponding raw query for each query reformulated model. We can see that the paraphrase models tend to reformulate an input query into a question-type query beginning with “what is” or “how”.

Finally, we return to address the choice of query performance predictor within DRQR. Table 3 reports the effectiveness of the DRQR models applying the four best QPPs from Section 6.1. From the table, we observe that while AvgSCQ is the best predictor, there is no significant differences between the effectiveness of the different models, according to a paired t-test. It is also of note that AvgSCQ was the best predictor of reformulation quality in Section 6.1 (see Table 1, right hand side). AvgSCQ considers the similarity between the query terms and the corpus, and hence focuses the DRQR model on generating query terms that are “frequent but not too frequent” in the collection, thereby both preventing too many non-informative terms being added to the query (as AvgICTF and AvgIDF does), but also ensuring that the terms being added to the query have sufficient documents in the collection.

Overall, in response to RQ2, we find that our proposed DRQR model outperforms, significantly, existing text generational models that do not apply reinforcement learning. Moreover, reinforcement learning provides a marked boost in effectiveness, while the introduction of a pre-retrieval query performance predictor to guide the model towards creating queries that appear to be effective, results in further effectiveness improvements.
6.3 RQ3: Does our DRQR approach combine with other enhanced retrieval approaches such as QE or BERT?

In this section, we compare DRQR with other retrieval models, and also experiment to determine if it can be combined with these models. We focus on the parameter-free DPH model, since the observed trends were similar between DPH and BM25 in Section 6.2. In particular, we use DPH, DPH + Bo1 query expansion [1], as well as a BERT re-ranker (as implemented by the CEDR toolkit [25]). Retrieval using the original query is denoted as $q_0$. In this section, both the reformulation weight $\theta$, as well as the reward tradeoff hyperparameter $\lambda$ are trained using the validation set. We again apply AvgSCQ as the QPP in DRQR. Table 5 reports the effectiveness results, comparing DRQR vs. the original query formulation (denoted $q_0$) using different ranking models. From the results, given these experimental settings, we note that DRQR improves NDCG@10 in 3 out of 3 cases, and improves MAP in 2 out of 3 cases. The disparity between MAP and NDCG@10 mirrors some of our earlier findings in [36], where we found that MAP and NDCG@10 responded differently on the MSMARCO dataset. In general, while DRQR is not as effective as query expansion, it can help to enhance the effectiveness of QE.

On the other hand, none of the improvements are significant according to a paired t-test; this is because, as shown in Figure 3, the number of queries altered by DRQR is not sufficiently large; its clear from Figure 3 that the addition of the QPP component makes the RL model more conservative in nature; moreover, from Table 4, both the DRQR and CatseqRL models generate similar reformulations. Indeed, on closer inspection of the generated reformulations for the 43 test queries by each query reformulation model, we find that 35/43 queries for DRQR and 28/43 for CatseqRL are reformulated into queries that start with “what is”, while the proportion is 28/43 for CatseqML, 23/43 for seq2seq with attention model and 17/43 for Transformer1 model. We postulate that this focus on question-like n-grams are due to the absence of any pre-trained term representations for the text generation. We hope to address this in future work.

We now investigate the impact of the reward tradeoff hyperparameter $\lambda$ from Equation (12). We demonstrate its impact on the NDCG@10 performance in Figure 4, while holding $\theta = 1$. From the figure, we observe that $\lambda$ values of 0.5 or 0.3 are the most effective, regardless of the retrieval approach.

Overall, in answer to RQ3, we conclude that our DRQR model demonstrates some promising trends, by improving three different retrieval approaches, albeit not by a significant margin.

7 CONCLUSIONS

In this work, we proposed a deep reinforcement learning text generation model for query reformulation, called DRQR, which includes both an attention and copying mechanisms. DRQR also includes the novel integration an of existing IR technique, through the introduction of pre-retrieval query performance prediction into the reward function. Our experiments on the TREC Deep Learning track test collection demonstrated that pre-retrieval query performance predictors were able to distinguish between both high and
low effectiveness queries on this test collection, as well high and low effectiveness query reformulations. Taking these observations forward, we demonstrated that the use of reinforcement learning results in enhanced query reformulations compared to other classical text generation models, and that query performance predictors further result in more effective reformulations. Finally, we integrated DRQR with various retrieval models, and found that it could enhance retrieval effectiveness, but not by a significant margin.

As future work, we aim to consider the integration of query performance predictors (which are differentiable) as a regularisation directly within non-reinforcement learning models such as CatSeqML, as well as use of pre-trained embeddings model for text generation, such as T5 [30].

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