P³ Ranker: Mitigating the Gaps between Pre-training and Ranking Fine-tuning with Prompt-based Learning and Pre-finetuning

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ABSTRACT

Compared to other language tasks, applying pre-trained language models (PLMs) for search ranking often requires more nuances and training signals. In this paper, we identify and study the two mismatches between pre-training and ranking fine-tuning: the training schema gap regarding the differences in training objectives and model architectures, and the task knowledge gap considering the discrepancy between the knowledge needed in ranking and that learned during pre-training. To mitigate these gaps, we propose Pre-trained, Prompt-learned and Pre-finetuned Neural Ranker (P³ Ranker). P³ Ranker leverages prompt-based learning to convert the ranking task into a pre-training like schema and uses pre-finetuning to initialize the model on intermediate supervised tasks. Experiments on MS MARCO and Robust04 show the superior performances of P³ Ranker in few-shot ranking. Analyses reveal that P³ Ranker is able to better accustom to the ranking task through prompt-based learning and retrieve necessary ranking-oriented knowledge gleaned in pre-finetuning, resulting in data-efficient PLM adaptation. Our code is available at https://github.com/NEUIR/P3Ranker.

CCS CONCEPTS

• Information systems → Information retrieval.

KEYWORDS

Prompt-based Learning; Pre-finetuning; Few-shot Ranking

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1 INTRODUCTION

Recent research applies pre-trained language models (PLMs) for ad hoc search through fine-tuning with plenty of human-annotated relevance pairs [6, 16, 20]. Attaining outstanding results in data-sufficient scenarios, however, PLMs often showcase poor performance in search ranking scenarios where training labels are limited [25, 32], in contrast to their strong few-shot ability in NLP tasks. As shown in Figure 1, when trained with ~ 2⁶ instances, RoBERTa achieves less than 1% of the performance of the full data fine-tuned model on the ranking task MS MARCO [2] but over half of the performance of the full data fine-tuned model on the NLP task MNLI [29]. The inability of adapting PLMs into few-shot ranking hinders PLM’s application in many real-world search scenarios where relevance labels are expensive to accumulate.

In this paper, we argue that the less optimal few-shot performance of PLM-based ranking models may reside in the unfilled gaps between pre-training and search ranking. Typical PLMs are not tailored for text ranking, leading to two potential gaps. First, there is a training schema gap: pre-training typically uses token-level objectives like masked language modeling (MLM), but ranking fine-tuning uses a sequence-pair level classification objective and needs to learn a new MLP head from scratch. Second, there also exists a task knowledge gap: The knowledge and signals gleaned...
from unsupervised LM pre-training may not benefit the ranking task, which needs to extract the underlying relevance signals on the \((q, d)\) pairs [3, 14, 30]. The two gaps, one from the schema perspective and another from the knowledge perspective, challenge PLMs’ adaptation into ranking tasks in few-shot scenarios.

This work mitigates the gaps with a Pre-trained, Prompt-learned and Pre-finetuned Neural Ranker (P³ Ranker). P³ Ranker uses the prompt-based learning technique, casting the input into a "prompt" and obtaining output from token predictions [4, 7, 10, 12]. This ensures a consistent input/output form and maintains the same model architecture as pre-training during ranking fine-tuning, closing the training schema gap. Using prompt-based learning, as depicted in Figure 1, boost the performance on MS MARCO, but still can’t match the few-shot advantage on MNLI. We argue that the remaining discrepancy results from the lack of ranking knowledge in PLMs, i.e. the existence of the task knowledge gap. To mitigate the gap, we introduce pre-finetuning to warm up the model on intermediate NLP tasks before final fine-tuning. The pre-finetuning stage serves as a "bridge" between unsupervised pre-training and ranking fine-tuning where the model can learn useful knowledge for ranking.

Experiments on ad hoc ranking benchmarks MS MARCO [2] and Robust04 [8] show that P³ Ranker has strong advantages in few-shot ranking. On MS MARCO, when trained on only 5 queries, P³ Ranker retains 45% of the performance of full-data fine-tuning, greatly outperforming vanilla pre-training/fine-tuning baselines. Analyses find that both prompt-based learning and pre-finetuning contribute to P³ Ranker’s effectiveness. By closely resembling the pre-training form, prompt-based learning methods better unleash the power of PLMs for search ranking, narrowing the training schema gap. Pre-finetuning, on the other hand, offers ranking-oriented knowledge which can be easily transformed and leveraged in few-shot scenarios, narrowing the task knowledge gap.

2 RELATED WORK

This section reviews previous studies on PLM-based search ranking, prompt-based learning and pre-finetuning.

**PLM-based Search Ranking.** Search ranking models have been developed and thrived on plenty of NLP tasks, e.g., question answering [5, 9, 21] and fact verification [13]. Recent models are usually based on pre-trained language models (PLMs) [6, 16–18, 20]. In a typical reranking setting, every candidate \((q, d)\) pair from a first-stage retrieval system is concatenated and fed into a PLM, which outputs a relevance score for ranking. Though PLMs have significantly improved ranking performance with large amounts of data, they tend to be less competitive with traditional lexical models in few-shot ranking scenarios [25, 32].

**Prompt-based Learning.** Recently, prompt-based learning [4, 11] is proposed to adapt language model to downstream tasks. Unlike traditional fine-tuning, prompt-based learning reformulates model input to make downstream task closer to pre-training through a template. A template consists of a series of prompt words for the model to understand the task, typically defined manually [23] or generated automatically [7, 24]. The model learns to fill label words in the reserved blank in the template as output. Thanks to prompt-based learning, PLMs can easily adapt to downstream tasks and achieve admirable performance with few labeled data on a wide range of NLP tasks [7, 23, 24]. Nevertheless, it is still unclear whether it can benefit PLM-based ranking models and alleviate the gaps between language model pre-training and ranking fine-tuning.

**Pre-finetuning.** Researchers have explored the idea of pre-finetuning on single/multiple supervised intermediate task(s) in order to improve the downstream performance of PLMs [1, 19, 26–28]. Pre-finetuned models generally show better performance on downstream tasks and are more data-efficient [1, 27]. However, the criteria for selecting intermediate tasks remain unclear, and unsuitable ones can bring negative impacts [19]. Inspired by previous research, our work explores the effectiveness of pre-finetuning on search ranking together with prompt-based learning.

3 METHODOLOGY

The ad hoc ranking task is to estimate a relevance score \(P(y|q, d)\) for a user query \(q\) and a document \(d\) from a document collection.

Recent ranking models follow the pre-training/fine-tuning paradigm, encoding the query and document together and adding a layer on the top to perform classification. Those models rely highly on the in-domain relevance labels for training, limiting the performance in few-shot scenarios. To mitigate the transfer gaps, we propose P³ Ranker to start from a pre-trained model and then use the method of prompt-based learning (Section 3.1) to perform pre-finetuning (Section 3.2) and final fine-tuning.

3.1 Prompt-based Learning for Search Ranking

P³ Ranker alleviates the training schema gap between pre-training and fine-tuning by using prompt-based learning methods. This is done with a predefined template \(T\) and a verbalizer \(M\).

**Building Input with a Template.** A template consists of slots for input data and several prompt tokens serving as hints to the PLM. P³ Ranker is based on the encoder-decoder model T5 [22]. We follow Nogueira et al. [17] to reformulate a \((q, d)\) pair with the following template:

\[
T(q, d) = \text{Query: } [q]\text{ Document: } [d]\text{ Relevant: },
\]

where \([q], [d]\) are slots for the query and document. The \((q, d)\) pair is filled in and then fed into the model.

**Obtaining Output from Label Words.** P³ Ranker sniffs the output directly from output label words. To achieve this, a verbalizer \(M(y)\) is used to establish the mapping from the task label space \(Y\) to the label word space \(\mathcal{V}\). The verbalizer of P³ Ranker maps relevant \((y=1)\) to "true" and irrelevant \((y=0)\) to "false". The final prediction is based on the softmax over the set of label words:

\[
P(y|q, d) = P(t = M(y)) = \frac{\exp(w_t^T M(y) h_t)}{\sum_{y' \in \mathcal{Y}} \exp(w_{M(y')} h_t)},
\]

where \(t, h_t\) denote the first token from the decoder and its hidden representation. \(w\) is the corresponding vector in the language modeling head. During training, we use the cross entropy (CE) loss.

3.2 Pre-finetuning for Search Ranking

To mitigate the task knowledge gap, we introduce an additional pre-finetuning process in P³ Ranker between LM pre-training and fine-tuning. By pre-finetuning, we expect P³ Ranker to inherit the
knowledge from the massive labels of other supervised NLP tasks, serving as a complement to the scarce labels in few-shot ranking scenarios. Starting from a PLM, we continuously train the model on language understanding tasks using prompt-based learning with manually defined task-specific templates and verbalizers. Then the pre-trained and pre-finetuned model is ready for final prompt-based fine-tuning on ranking datasets.

4 EXPERIMENTAL METHODOLOGY

This section describes our experimental settings and implementation details.

Datasets and Metrics. We train and evaluate our models on MS MARCO Passage [2] and Robust04 [8]. MS MARCO is a large-scale IR dataset containing 530k training queries. The evaluation of MS MARCO is on the official dev set and the evaluation metric is MRR@10. Robust04 contains TREC-style fine-grained annotations on 249 queries and we use NDCG@20 as the evaluation metric.

Few-Shot Configurations. To simulate different training scenarios, we partition the training data according to training queries on MS MARCO and relevance labels on Robust04: On MS MARCO, for there just exists 1 relevant passage per query, we sample [5, 50, 1k, 530k (all)] training queries from the training set, each paired with a relevant passage and an irrelevant passage returned by BM25. On Robust04, for there are far more than 1 relevance label (often >1k) per query, we directly sample [0.2%, 2%, 100%] relevance labels.

Baselines. We compare $P^3$ Ranker to vanilla fine-tuning models BERT and RoBERTa as well as monoT5 [17] in our main experiments. MonoT5 is a T5-based ranker trained with manually defined prompts, but it does not have the pre-finetuning process. To have a fair comparison, monoT5 is initialized with the vanilla pre-trained version (denoted as T5 (Vanilla)), i.e. the one that is pre-trained solely on the unsupervised denoising objective [22]. We also compare our model with PROP [14], a ranking-oriented pre-training model. For lexical retrieval models, we report Anserini BM25 [31] on MS MARCO and SDM [15] on Robust04.

Implementation Details. In our main experiments, we initialize $P^3$ Ranker with T5 (Vanilla) and pre-finetune it on MNLI [29] for 12k steps with batch size set to 32. The batch size of the fine-tuning process is set to 8 when there are less than 50 queries on MS MARCO and 2% labels on Robust04, and 32 for remaining cases. During inference, we rerank top 1000 passages from Anserini BM25 on MS MARCO and top 100 passages from SDM on Robust04. We do five-fold cross-validation on Robust04. In both the pre-finetuning and fine-tuning stages we use Adam as the optimizer with the initial learning rate set to 2e-5 and linear decay.

5 EVALUATION RESULTS

In this section, we present overall results and the analyses of prompt-based learning and pre-finetuning.

5.1 Overall Results

The results on MS MARCO and Robust04 are presented in Table 1. $P^3$ Ranker demonstrates strong few-shot ability on MS MARCO: It can acquire basic search ranking ability with only 5 training queries, outperforming all neural baselines among all data sizes. On Robust04, the large version of $P^3$ Ranker also outperforms neural baselines by large margins in few-shot scenarios.

A usable neural ranker should be able to improve over traditional lexical retrieval models. To achieve this goal, $P^3$ Ranker only needs to use 50 queries on MS MARCO or 2% relevance labels on Robust04, whereas baseline models require much more data. That makes $P^3$ Ranker applicable to special ranking domains where relevance labels are difficult to accumulate.

5.2 Effectiveness of Prompt-based Learning

To have a thorough understanding of the effectiveness of prompt-based learning on mitigating the training schema gap, in this experiment, we compare BERT, RoBERTa, and T5 with different prompt schemes as well as vanilla fine-tuning. The prompt schemes that we consider include manually designed and automatically designed prompts. For manually designed prompts (“Manual Prompt”), the template is manually defined according to human understanding of the task. For automatically designed prompts (“Auto Prompt”), we borrow the methods from LM-BFF [7], which utilizes T5 to automatically generate prompts. Results are presented in Table 2.

Reformulating the task into a prompt format helps minimize the training schema gap for RoBERTa but not for BERT. The contrasting results may stem from the different pre-training schemes – RoBERTa is just pre-trained with MLM whereas BERT has an extra pre-training scheme, Next Sentence Prediction (NSP). In addition, RoBERTa is pre-trained with MLM for much longer steps than BERT, having the potential to better understand the clues in the prompt. Compared to manually designed prompts, automatically designed prompts seem to be more effective for RoBERTa.

Different from BERT and RoBERTa, T5 processes pre-training and all downstream tasks in a unified text-to-text framework with manually designed prompts, thus there is no training schema gap during its downstream adaption. We compare the performance of manual prompt with a “No-word Prompt” version, where all prompt words are removed from the input. As shown in Table 2, the performance downgrades greatly after removing prompt words. Maintaining a proper form of prompts is beneficial for the model to understand the task, leading to better performance.

5.3 Effectiveness of Pre-finetuning

In this experiment, we study the effectiveness of pre-finetuning on mitigating the task knowledge gap by investigating the performance of pre-finetuning on different tasks and steps. To better showcase how well the ranking-oriented knowledge is learned during pre-finetuning, we present model performance with “prompt tuning” [10], where we fix all the parameters of the PLM and only tune a few continuous token embeddings, which account for less than 1% of total parameters. In this way, adapting to the downstream knowledge
Table 1: Overall results on MS MARCO official Dev set and Robust04 under different training data sizes. We sample training data based on the numbers of queries on MS MARCO and relevance labels on Robust04. See Section 4 for more details. †, ‡, §, and ¶ indicate statistically significant improvements over Lexical, BERT, RoBERTa, and monoT5, respectively.

| Model | MS MARCO MRR@10 | Robust04 NDCG@20 |
|-------|------------------|------------------|
|       | 5 Queries | 50 Queries | 1k Queries | All Queries (530k) | 0.2% Labels | 2% Labels | All Labels (100%) |
| Lexical | 0.1874 (BM25) | 0.4269 (SDM) |

| Base Models |
|-------------|
| BERT | 0.0038†‡ | 0.1035‡§ | 0.2210 †§ | 0.3518 † | 0.2563¶§ | 0.3178¶ | 0.4625†¶ |
| RoBERTa | 0.0011 | 0.0064†¶ | 0.1771 | 0.3471†§ | 0.2054 | 0.2171 | 0.4634†¶ |
| monoT5 [17] | 0.0009 | 0.0037 | 0.0157 | 0.3351† | 0.1645 | 0.1669 | 0.2269 |
| PROP [14] | 0.1199‡§ | 0.1656‡§ | 0.2098 †§ | 0.3519 † | 0.3484‡¶ | 0.3967¶§ | 0.4569¶ |
| P³ Ranker | 0.0525‡§ | 0.0949‡§ | 0.2027 †§ | 0.3311† | 0.2410¶§ | 0.3292¶ | 0.4403¶ |

| Large Models |
|--------------|
| BERT | 0.0245†‡ | 0.1296† | 0.2259†¶ | 0.3520† | 0.3196¶¶ | 0.3801¶§ | 0.4888¶ |
| RoBERTa | 0.0017 | 0.0053 | 0.2570†‡¶ | 0.3475†¶ | 0.2089¶ | 0.1933¶ | 0.5086¶ |
| monoT5 [17] | 0.0029§ | 0.1117‡¶ | 0.1616 | 0.3496†¶ | 0.1386 | 0.1424 | 0.2271 |
| P³ Ranker | 0.1659‡§ | 0.1943‡¶ | 0.2876‡¶ | 0.3645‡¶ | 0.3787¶¶ | 0.4321¶§ | 0.5213¶¶ |

Table 2: Comparison of prompt-based methods and vanilla fine-tuning. All experiments are conducted using the large models on MS MARCO. The evaluation metric is MRR@10.

| Model  | Training Schema | # Training Queries |
|--------|-----------------|--------------------|
|        | 5q | 50q | 1k q | All q |
| BERT   | Vanilla Fine-tune | 0.0245 | 0.1296 | 0.2259 | 0.3526 |
|        | Manual Prompt | 0.0038 | 0.0085 | 0.2181 | 0.3413 |
|        | Auto Prompt | 0.0043 | 0.0289 | 0.2218 | 0.3471 |
| RoBERTa | Vanilla Fine-tune | 0.0017 | 0.0053 | 0.2570 | 0.3475 |
|        | Manual Prompt | 0.0043 | 0.1025 | 0.2547 | 0.3439 |
|        | Auto Prompt | 0.0062 | 0.1806 | 0.2789 | 0.3412 |
| monoT5 | No-word Prompt | 0.0020 | 0.0111 | 0.0775 | 0.3470 |
|        | Manual Prompt | 0.0029 | 0.1117 | 0.1616 | 0.3496 |

Task introduces little additional knowledge. Thus better prompt tuning performance indicates more ranking-oriented knowledge learned during pre-finetuning. To distinguish, the method that we use normally to train P³ Ranker is referred to as “model tuning”.

Performance Gains from Pre-finetuning. As shown in Figure 2, we compare the performance of P³ Ranker to monoT5 initialized from three officially released pre-trained T5 checkpoints: T5 (Vanilla), T5 (LM-Adapt) and T5 (Multi-task). T5 (LM-Adapt) is pre-finetuned using the prefix LM objective [10] and T5 (Multi-task) is pre-trained in a multi-task manner [22]. As shown in Figure 2a, P³ Ranker shows on-par performance with monoT5 (Multi-task), and it greatly outperforms other models in few-shot scenarios. MonoT5 (Multi-task) benefits from knowledge of multiple task sources, but with an overhead of extensive pre-training on various tasks with careful mixing techniques. Compared to monoT5 (Multi-task), P³ Ranker is simpler and more efficient for it only needs pre-finetuning on one task for only several thousands of steps. In the case of prompt tuning, as shown in Figure 2b, P³ Ranker still yields results close to monoT5 (Multi-task). By pre-finetuning on a single task, though keeping the parameters of the PLM fixed, P³ Ranker is still able to rank documents through exploiting the knowledge obtained during pre-finetuning, which monoT5 (LM-Adapt) and monoT5 (Vanilla) are unable to leverage in few-shot scenarios.

Task and Model Selection for Pre-finetuning. As shown in Figure 3, we compare the performance of P³ Ranker pre-finetuned with other tasks and under varying steps. We introduce a pre-finetuning task on Natural Questions (NQ) to predict the answerability of a passage given a question. We also conduct multi-task learning on an equal mixture of the MNLI and NQ task. We find that using a single task, either MNLI or NQ, can effectively narrow the knowledge gap. The NQ-pre-finetuned version tends to yield better performance; The answerability-checking task NQ seems to be more similar to ranking, a relevance checking task, than the entailment prediction task MNLI. The mixture of the two tasks doesn’t bring significant improvements. Multi-task pre-finetuning for ranking needs further study.

5.4 Knowledge Transfer

In this experiment, we study the embeddings of the token used for prediction to figure out how the knowledge gleaned in pre-finetuning is transferred into search ranking. In Figure 4, we plot the t-SNE visualizations of the embeddings produced by P³ Ranker and monoT5 (Vanilla). Without pre-finetuning, the embeddings from monoT5 (Vanilla) distribute randomly, and the positive/negative
Both models are trained with prompt tuning on 50 queries. The distributions of the relevance scores produced by the two models are presented in Figure 5. MonoT5 (Vanilla) yields similar scores for the pos/neg pairs, whilst P\textsuperscript{3} Ranker learns to assign scores with a large gap with the help of pre-finetuning knowledge.

### 6 Conclusion

In this paper, we present a few-shot ranking model for search ranking, P\textsuperscript{3} Ranker. P\textsuperscript{3} Ranker narrows the training schema gap and task knowledge gap between pre-training and ranking fine-tuning by using prompt-based learning and pre-finetuning. Our experiments show that P\textsuperscript{3} Ranker can effectively learn to rank documents in few-shot scenarios. We present analyses on the prompt-based learning and pre-finetuning, and find that both of them contribute to mitigating the gaps, leading to a strong overall performance.

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A APPENDICES

A.1 Prompt Selection

In this subsection, we describe how we design and generate prompts in our experiments. Given query \( q \) and document \( d \), a prompt, either discrete or continuous, defines the input pattern for pre-trained language models.

**Discrete Prompts.** For monoT5 and P³ Ranker, we use manually designed prompts as described in Section 3.

For encoder-only models (BERT, RoBERTa), we use both manual discrete prompts and automatic discrete prompts, where a \((q,d)\) pair is packed by a template with a [MASK] token into a fill-in-the-blank problem. For manual prompts, we design the template as:

\[
T(q,d) = [q]\text{[MASK]} \text{(relevant/irrelevant) to } [d],
\]

where “relevant” “irrelevant” are label words representing \( y = 1 \) and \( y = 0 \), respectively. The prediction is based on the softmax on the [MASK] token’s logits over the label words:

\[
P(y | (q,d)) = P(t = M(y)) = \frac{\exp(w_M^T \cdot h_t)}{\sum_{y' \in Y} \exp(w_M^T \cdot h_{t}^{y'})},
\]

where \( t \) is the output token located in the [MASK] position, \( h_t \) is its hidden representation, and \( M(y) \) is the verbalizer mapping task labels into corresponding label words. Note that we explicitly specify the label words in the template (Eq. 3) since we find in pilot study that it works better.

We also follow Gao et al. [7] to automatically generate discrete prompts for BERT and RoBERTa. We follow the “Auto T” setting, i.e. fix label words, and use T5 to generate templates. We sample 5 few-shot training datasets (2-way-16-shot) from the official training set. Then use T5-base to generate templates for each few-shot dataset. We manually specify “relevant” and “irrelevant” as our label words, then use beam search (beam width=50) to decode multiple template candidates. Once the template candidates are generated, we perform prompt-based fine-tuning using large models (BERT-large, RoBERTa-large) on every few-shot dataset and rank the templates according to the model’s best performance on the official development set. Then we choose the template with the highest score as our template. The template we choose for BERT is:

\[
T(q,d) = [q] \text{? Is this [MASK] to your situation? [d]},
\]

and for RoBERTa is:

\[
T(q,d) = [q] \text{? Which is [MASK]? [d]}.
\]

**Continuous Prompts.** We follow Lester et al. [10] to conduct prompt tuning on T5 models, which only tunes several tokens’ embeddings while keeping the parameters of the PLM frozen. The template that we use is like below:

\[
T(q,d) = [s_1] [q] [s_2] [d] [s_3],
\]

where \([s_1], [s_2], [s_3]\) are sequences consisting of tunable continuous tokens. In our experiments, \([s_1], [s_2], [s_3]\) are initialized as “Task: Find the relevance between Query and Document. Query:”, “Document:”, and “Relevant:”, respectively.

A.2 Data Partition

In this subsection, we describe how we partition the data to simulate various training scenarios.

**MS MARCO.** For MS MARCO, we partition the data according to the number of training queries. We construct four training scenarios from the official training set, containing [5,50,1k,530k] training queries each. Each query in training set is paired with one relevant passage and one irrelevant passage sampled from top 1000 passages returned by BM25. In every scenario, we sample additional queries from the official training set to set up a development set for model selection. For scenarios in which the number of training queries is no more than 50, queries in the development set keeps a same size as the training set. For scenarios with more than 50 training queries, the number of queries in the development set is fixed at 500 to accelerate validation process. Each query in development set is paired with top 1000 BM25-retrieved passages for reranking.

**Robust04.** We split Robust04 into five folds, each containing 20% of the queries. In each fold, we sample \([0.2%, 2%, 100\%]\) relevance labels. Following Zhang et al. [33], to construct an \( r \)-sampled split under total \( N \) queries and \( M \) associated labels, we iteratively drop a query until there exist less than \( rM \) labels. Then we re-insert the last dropped query, and start to randomly remove a label per query until the number of labels reaches \( rM \).