

Best Practices for Distilling Large Language Models into BERT for Web Search Ranking

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Abstract

Recent studies have highlighted the significant potential of Large Language Models (LLMs) as zero-shot relevance rankers. These methods predominantly utilize prompt learning to assess the relevance between queries and documents by generating a ranked list of potential documents. Despite their promise, the substantial costs associated with LLMs pose a significant challenge for their direct implementation in commercial search systems. To overcome this barrier and fully exploit the capabilities of LLMs for text ranking, we explore techniques to transfer the ranking expertise of LLMs to a more compact model similar to BERT, using a ranking loss to enable the deployment of less resource-intensive models. Specifically, we enhance the training of LLMs through Continued Pre-Training, taking the query as input and the clicked title and summary as output. We then proceed with supervised fine-tuning of the LLM using a rank loss, assigning the final token as a representative of the entire sentence. Given the inherent characteristics of autoregressive language models, only the final token </s> can encapsulate all preceding tokens. Additionally, we introduce a hybrid point-wise and margin MSE loss to transfer the ranking knowledge from LLMs to smaller models like BERT. This method creates a viable solution for environments with strict resource constraints. Both offline and online evaluations have confirmed the efficacy of our approach, and our model has been successfully integrated into a commercial web search engine as of February 2024.

1 Introduction

Relevance ranking is a paramount challenge in web search systems. The objective of relevance ranking is to rank candidate documents based on their pertinence to a specified inquiry. These documents are usually culled from an extensive corpus by a retrieval module. Of late, the integration of pre-trained language models (PLMs) such as

BERT(Devlin et al., 2018), along with industry giants like Google¹, Bing², and Baidu(Zou et al., 2021; Liu et al., 2021), has been massively adopted within industry web search systems, yielding commendable results(Zhuang et al., 2023). BERT models are adept at considering the entire context of a word by examining adjacent words, which is particularly beneficial for discerning the intent of search queries. The efficacy of IR dictates the system’s response time to inquiries of users, which predominantly contingent on the performance of ranking model

The recent triumphs LLMs(Brown et al., 2020) in natural language processing have ignited interest in their application to text ranking. Researchers have delved into prompting LLMs to undertake zero-shot unsupervised ranking employing pointwise(Wang et al., 2023; Sachan et al., 2023), pairwise(Sachan et al., 2022), or listwise approaches(Sun et al., 2023b). Although these have made notable strides, they have yet to fully harness the potential of LLMs. Moreover, there have been initiatives to train pointwise rankers in supervised settings, utilizing LLMs, as exemplified by RankLLaMA(Ma et al., 2023a). Despite the SOTA performance yielded by LLM rank models in experimental settings, their direct application in real-world search engines is impractical.

To overcome the challenges of deploying LLMs online, this paper introduces a novel Rank Distillation framework (DisRanker) that combines the capabilities of LLMs with the agility of BERT. Distillation is renowned for enhancing the efficiency of various neural ranking models(Hofstätter et al., 2020). Simultaneously, knowledge distillation facilitates the transfer of discerning skills from the teacher model to more compact models, signifi-

¹<https://blog.google/products/search/search-language-understanding-bert/>

²<https://azure.microsoft.com/en-us/blog/bing-delivers-its-largest-improvement-in-search-experience-using-azures-gpus/>

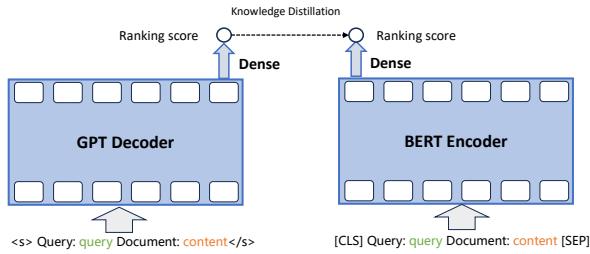


Figure 1: The overview of Rank Distillation from LLM Decoder to BERT Encoder.

cantly reducing computational costs during online inference. Initially, we utilize clickstream data to propagate domain knowledge through Continued Pre-Training (CPT)(Gupta et al., 2023), using queries as inputs to generate titles and summaries that have captured user interest. In a process similar to question-answering, the LLM develops a detailed understanding of the interaction between queries and documents. We then refine the LLM using a pairwise rank loss, employing the end-of-sequence token, $</s>$, to represent query-document pairs. While previous research on neural rank models primarily used a bidirectional encoder-only model like BERT, interpreting the [CLS] token as a comprehensive representation of the text input, the autoregressive nature of LLMs prompts us to introduce an end-of-sequence token for the input query and document to structure the input sequence. The latent state from the final layer corresponding to this token is considered the embodiment of the query and document relationship. Consequently, we integrate a dense layer to act as a relevance adjudicator, applying pairwise rank loss to fine-tune the LLM. The deployment of LLMs for ranking tasks still faces practical challenges, particularly regarding application efficacy and output consistency. In the next phase, we employ a hybrid approach using Point-MSE(Qin et al., 2021) and Margin-MSE(Hofstätter et al., 2020) losses to distill the LLM. Point-MSE calculates the absolute difference between the LLM teacher and the BERT student, while Margin-MSE introduces a form of regularization and encourages the student model to learn the relative ranking from the teacher. This approach prevents overfitting by not requiring the student model to exactly match the teacher’s scores but to maintain the order of the scores, which is essential for ranking tasks. Thus, the student model learns to emulate the teacher’s ranking behavior while being more lightweight and efficient, making it better

suit for deployment in resource-constrained environments. The main contributions of this paper can be summarized as follows:

- We present **DisRanker**, a novel Rank Distillation pipeline that seamlessly integrates LLM with BERT to enhance web search ranking. A comprehensive suite of offline and online evaluations substantiates the efficacy of DisRanker.
- We propose a domain-specific continued pre-training methods which is beneficial for enhancing the performance of LLMs on text ranking tasks. Additionally, we contribute a hybrid approach that employs Point-MSE and Margin-MSE loss to refine the distillation of LLM.

2 Related Work

2.1 LLM for Text Ranking

Large language models have been increasingly harnessed for relevance ranking tasks in search engines(Sachan et al., 2023; Muennighoff, 2022; Wang et al., 2023). These methodologies primarily bifurcate into two streams: one is the prompt approach(Qin et al., 2023; Zhuang et al., 2024; Ma et al., 2023b), and the other is the supervised fine-tuning technique(Zhang et al., 2023b; Ma et al., 2024; Zhang et al., 2023a). In the realm of prompts, rankGPT(Sun et al., 2023b) has unveiled a zero-shot permutation generation method, which incites LLMs to directly generate the ranking order. Remarkably, its performance eclipses that of supervised models, particularly when utilizing GPT-4(Achiam et al., 2023). In the domain of supervised fine-tuning, RankLLaMA(Ma et al., 2023a) injects a prompt that includes the query-document pair into the model, subsequently refining the model using a point-wise loss function. TSRankGPT (Zhang et al., 2023a) advocates for a progressive, multi-stage training strategy tailored for LLMs. Indeed, while these methodologies have achieved commendable results, few have delved into how to enhance the performance of LLM models through continued pre-training, or how to effectively harness rank loss to bolster ranking capabilities.

2.2 Knowledge Distillation for Text Ranking

Knowledge Distillation in text ranking(Reddi et al., 2021; Formal et al., 2022; Zhuang et al., 2021; Cai

et al., 2022) indeed centers on minimizing the discrepancy between the soft target distributions of the teacher and the student(Tang and Wang, 2018). The overarching goal of distillation methods is to condense the model size and curtail the aggregate inference costs, which encompasses both memory requirements and computational overhead(Gao et al., 2020; He et al., 2022). The student model is then trained on this enriched dataset using a specialized loss function known as Margin MSE(Hofstätter et al., 2020). Instruction Distillation(Sun et al., 2023a) proposes to distill the pairwise ranking ability of open-sourced LLMs to a simpler but more efficient pointwise ranking. This paper primarily investigates the methodology of distilling the ranking capabilities of a LLM Decoder into a BERT Encoder.

3 Method

3.1 Preliminaries

Text Rank. Given a query Q and a candidate documents $D = \{d_1, d_2, \dots, d_n\}$, the task of text ranking is to compute a relevance score $S(q, d_i)$ for each document d_i in D . The relevance labels of candidate documents with regard to the query are represented as $Y_i = (y_{i1}, \dots, y_{im})$ where $y_{ij} > 0$. We aim to optimize the ranking metrics after we sort the documents d_i for each query q_i based on their ranking scores. \mathcal{L} is the loss function.

$$\mathcal{L} = \sum_{q \in Q} (l(Y_{D_q}, S(q, D_q)))$$

Knowledge Distillation. Given a large teacher model T finetuned well in advance and a small student S , the task of knowledge distillation is to transfer T to S by minimizing the difference between them which can be formulated as:

$$\mathcal{L}_{KD} = \sum_{x \in \mathcal{D}} \mathbf{M}(f_T(x), f_S(x))$$

where \mathcal{D} denotes the training dataset and x is the input sample, $f_T(x), f_S(x)$ represents scores of teacher and student models, and $\mathbf{M}(\cdot)$ is a loss function to measure the difference between their behaviors.

3.2 Domain-Continued Pre-Training

The pre-training task for LLMs is centered on next-token prediction, which primarily imparts general knowledge but does not inherently capture explicit signals that delineate the correlation between

queries and documents. To address this, we introduce an additional phase of continue d pre-training that leverages search data to endow the model with a more refined comprehension of such relationships. Specifically, we have curated a collection of high-quality clickstream data formatted as [Query, Title, Summary]. The task of LLM is then to generate a Title and corresponding Summary based on the query, akin to a question-answering format, thereby stimulating the model’s capacity to model relevance. During this stage, the tokenized raw texts of the query serve as the input.

$$\mathcal{L}_{cpt} = - \sum_j \log(T_j, S_j | P(q), q < j)$$

3.3 Supervised Fine-Tuning

Although LLMs have instigated a paradigm shift in natural language processing with their remarkable performance, there remains a discernible gap between the pre-training task of next-token prediction and the fine-tuning objectives. To bridge this, we append an end-of-sequence token, $</s>$, to the input query-document sequence to represent the entirety. Due to the autoregressive nature of the LLM model, only the final token can observe the preceding tokens, which is a distinction from BERT’s approach. Concurrently, we have constructed a dense layer that maps the last layer representation of the end-of-sequence token to a scalar value.

input = $<\text{s}>$ query : title : summary $</\text{s}>$

$$f(Q, D) = \text{Dense}(\text{Decoder}(\text{input})[-1])$$

$$\text{Loss} = \text{Max}(0, f(q, d^+) - f(q, d^-), \mathcal{T})$$

3.4 Knowledge Distillation with Rank Loss

Following the supervised fine-tuning of LLM, we conducted predictions on a large corpus of unlabeled data, then utilized the score of teacher to distill knowledge into the student models. We employed a hybrid approach of pointwise and Margin MSE loss for distillation. Considering a triplet of queries q , a relevant document d^+ , and a non-relevant document d^- , we use the output margin of the teacher model as a label to optimize the weights of the student model as Margin MSE loss, and the output score of the teacher model as a label to optimize the weights of the student model as pointwise MSE loss.

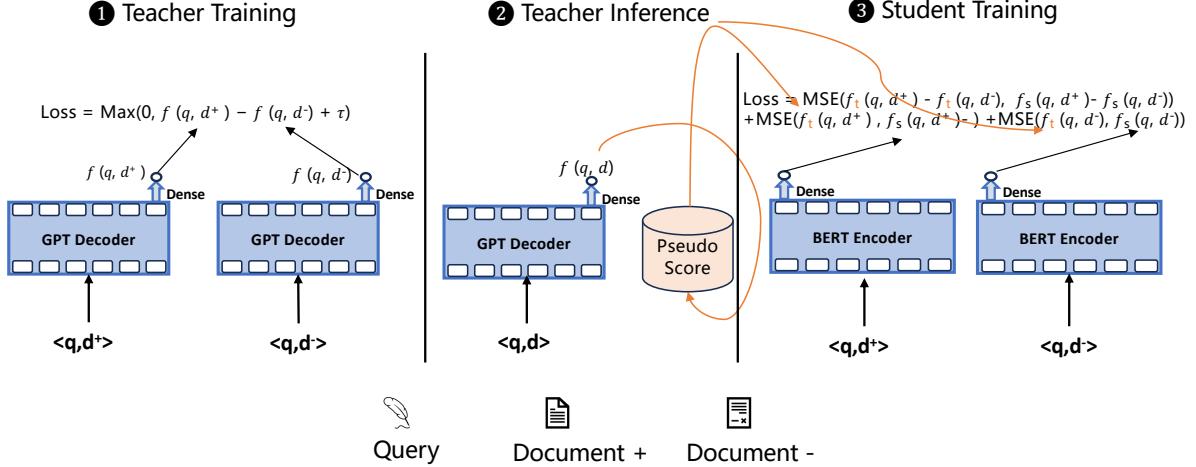


Figure 2: Illustration of the knowledge distillation process: Step 1: Performing supervised fine-tuning of LLM using a ranking loss. Step 2: Utilizing LLM to score unlabeled data. Step 3: Employing hybrid rank loss to distill the knowledge into the BERT model.

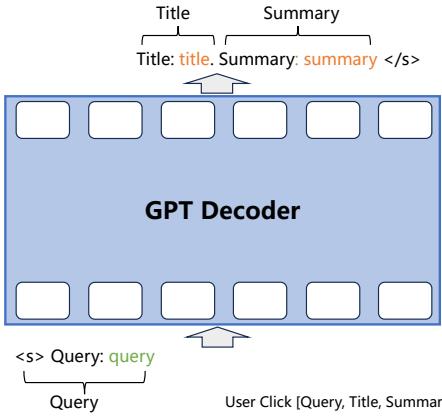


Figure 3: Illustration of domain continued pre-training. The task is to generate a clicked title and summary based on a given query.

$$\mathcal{L}_{Point} = MSE(Sim_T(q, d^+), Sim_S(q, d^+)) + MSE(Sim_T(q, d^-), Sim_S(q, d^-))$$

$$\mathcal{L}_{Margin} = MSE(Sim_T(q, d^+) - Sim_T(q, d^-), Sim_S(q, d^+) - Sim_S(q, d^-))$$

$$\mathcal{L}_{hybrid} = \mathcal{L}_{Point} + \beta * \mathcal{L}_{Margin}$$

where β is a scalar to balance the pointwise and Margin loss.

4 Experiments

4.1 Dataset and Metrics

The datasets employed for the Continued Pre-Training(CPT), Supervised Fine-Tuning(SFT), Knowledge Distillation(KD), and test are sourced from a commercial web search engine. In the SFT phase, queries and documents extracted from search engine workflows were meticulously annotated by professionals. For the Knowledge Distillation phase, we gathered an extensive dataset from anonymous search logs, which includes 46,814,775 query-document pairs. The dataset information is summarized in Table 1.

Data Type	Queries	Q-D Pairs
CPT	10,468,974	59,579,125
KD	5,939,563	46,814,775
SFT Data	106,496	796,095
Test Data	13,094	104,960

Table 1: Statistics of datasets.

In our experiments, we employed the Positive-Negative Ratio (PNR)(Ye et al., 2024) and Normalized Discounted Cumulative Gain (NDCG) as our principal evaluation metrics. PNR gauges the concordance between the definitive labels and the predictive scores generated by the models. NDCG, a metric ubiquitously utilized in the industry, appraises the efficacy of search engine result rankings.

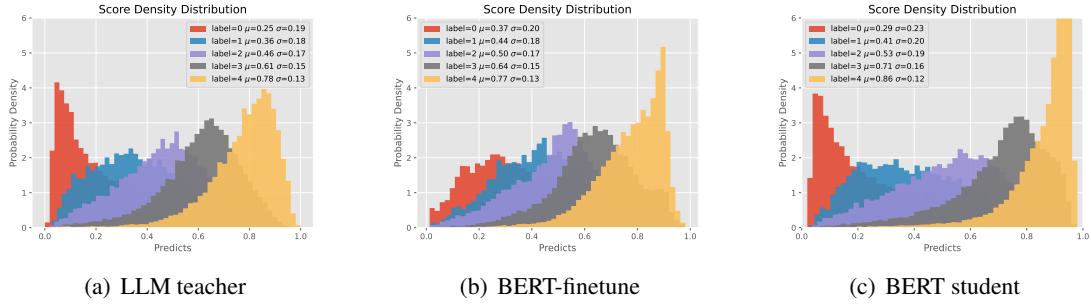


Figure 4: The output score distribution of the LLM teacher, BERT student, and BERT-finetune models on test datasets.

4.2 Baselines and Settings

We conduct several comparison experiments on the following baselines. For Unsupervised LLM Rankers: Pointwise(Sun et al., 2023b), Pairwise(Qin et al., 2023), Listwise(Ma et al., 2023b). For Supervised Rankers: RankLLaMA(Ma et al., 2023a), TSRankGPT(Zhang et al., 2023a), LLM2Vec(BehnamGhader et al., 2024). In addition, we also used a fully domain-trained BERT as a baseline. For supervised rankers, we adopt LLaMA 2(Jiang et al., 2023) 7B as base model. For unsupervised LLM rankers, we use GPT4. In the distillation experiment, we employed LLM³ as the teacher model, while BERT-6L⁴ was utilized for the student model. For hyperparameter, we set $\mathcal{T} = 0.1$, $\beta = 0.4$.

4.3 Offline Results

Model	PNR	nDCG@5
BERT-Base	3.252	0.8336
BERT-large	3.426	0.8412
GPT4-Pointwise	3.01	0.8251
GPT4-Pairwise	3.14	0.8273
GPT4-Listwise	3.19	0.8299
TSRankGPT	3.475	0.8505
RankLLaMA	3.514	0.8611
LLM2Vec	3.496	0.8604
DisRanker-Teacher with CPT	3.546	0.8709
	3.643	0.8793

Table 2: Offline comparison of LLM ranker performance on test sets.

Unsupervised LLM rankers generally do not outperform BERT models that have been comprehen-

sively trained within a specific domain. When compared with zero-shot methods, BERT-Base gets 3.252 on PNR but unsupervised pointwise zero-shot ranker gets 3.01. Listwise ranker achieved better results, but still can't beat BERT-Base.

Fine-tuning LLMs with rank loss significantly enhances their ranking capabilities. When compared with zero-shot methods, the NDCG@5 of RankLLaMA improve from 0.8251 to 0.8505. RankLLaMA and DisRanker are better than TSRankGPT, which underscores the effectiveness of selecting the </s> token as the representation of the query-document pair. Compared to RankLLaMA, PNR of DisRanker has increased from 3.514 to 3.546, indicating that LLM can benefit from rank loss.

Continued Pre-Training (CPT) further benefits LLM for web search ranking. The PNR improved from 3.546 to 3.643, and the NDCG increased from 0.8709 to 0.8793, which indicates that Continued Pre-Training with large-scale behavioral data substantially improves the performance of the ranking model, likely by aligning the model more closely with the specific domain and user interaction patterns.

Distill Strategy	PNR	nDCG@5
BERT-large distill	3.352	0.8367
Instruction distillation	3.538	0.8464
Point-wise	3.534	0.8496
Margin-wise	3.554	0.8460
Hybrid-loss	3.593	0.8536

Table 3: Rank distill loss function ablation results on test sets. The student is a 6-layer BERT.

The hybrid distillation loss enable LLM to achieve better results. Compared to using only point-wise or only margin loss, there is an improve-

³<https://huggingface.co/mistralai/Mistral-7B-v0.1>

⁴<https://huggingface.co/google-bert/bert-base-multilingual-cased>

ment of 1.6% and 1.1% on PNR, respectively. This suggests that both the absolute scores from the teacher model and the pairwise differences provide distinct and valuable information to the student models. Furthermore, the margin MSE loss appears to be particularly effective on PNR while less help for nDCG, which may be due to its focus on the relative ranking of documents rather than absolute score predictions. Instruction distillation(Sun et al., 2023a) also achieved comparable results.

4.4 Online A/B Test

The online A/B test results for DisRanker, as shown in Table 4, are quite promising. Our online baseline is a 6-layer BERT obtained by distilling a 24-layer BERT. Deploying DisRanker to the live search system and comparing it with the baseline model over the course of one week has yielded the following statistically significant improvements: PageCTR has increased by 0.47%. The average post-click dwell time, which suggests how long users stay on the page after clicking a search result, has gone up by 1.2%. UserCTR has increased by 0.58%.

In addition to these user action metrics, expert assessments were also conducted. Expert manual evaluations of 200 random queries revealed a distribution of Good vs. Same vs. Bad at 54:116:30. This expert feedback is crucial as it provides a more nuanced understanding of where the model excels and where it may require further refinement.

Metric	Δ Gain	P value
PageCTR	+0.47% \uparrow	0.025
UserCTR	+0.58% \uparrow	0.018
Change Query Ratio	-0.38% \downarrow	0.026
Dwell time	+1.2% \uparrow	0.016
Δ_{GSB}	+12% \uparrow	0.002

Table 4: Online A/B test results of DisRanker. The p-value is less than 0.05

4.5 Runtime Operational Improvement

To provide a description of runtime operational improvement, we conduct an experiment comparing the LLM Teacher and the BERT student regarding throughput and cost savings. Our experiment was conducted on Nvidia A10, with the batch size set to 48. The data in Table 5 show that the LLM model consumes a considerable amount of time, which is intolerable for time-sensitive web search engines. Through distillation, we are able to conveniently

transfer the capabilities of LLM to BERT, while ensuring that there is no increase in online latency.

Models	Params	Latency
LLM	7B	\approx 100ms
BERT-12	0.2B	\approx 20ms
BERT-6	0.1B	\approx 10ms

Table 5: Latency between LLM teacher and BERT student. The max sequence length is set to 256.

4.6 Score Distribution Analysis

To better understand the hybrid distillation loss, we analyze the output score distribution of the LLM teacher, BERT student, and BERT-finetuned models in Figure 4. We observe that the score patterns between the LLM decoder and the BERT encoder models are distinct, especially at the lower and higher ends of the scoring spectrum. This discrepancy may stem from the difference in model parameter sizes, with the LLM model exhibiting higher confidence levels compared to the BERT model (Xiong et al., 2023). Employing only point-wise soft labels could potentially lead to overfitting in student models, as they might learn to replicate the teacher’s output too closely without generalizing effectively. On the other hand, the margin loss introduces a form of regularization. It not only encourages the student model to learn the relative ranking from the teacher but also maintains a margin between the scores of different classes or examples.

5 Conclusion

In this paper, we introduce DisRanker, an innovative distillation ranking pipeline designed to harness the capabilities of LLMs for BERT. To bridge the gap between pre-training for next-token prediction and downstream relevance ranking, we initially engage in domain-specific Continued Pre-Training, using the query as input and the relevant document as output. Subsequently, we conduct supervised fine-tuning of the LLM using a ranking loss, employing the end-of-sequence token, $</s>$, to represent the query and document sequence. Finally, we adopt a hybrid approach of point-wise and margin MSE as our knowledge distillation loss to accommodate the diverse score output distributions. Both offline and online experiments have demonstrated that DisRanker can significantly enhance the effectiveness and overall utility of the search engine.

Ethics Statement

The primary objective of this paper is to explore the transfer of LLM model's ranking capability to a smaller BERT model, aiming to enhance the search service provided to users. During the model training process, we have anonymized the data to ensure the protection of user privacy, without collecting any personally identifiable information.

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A Appendix

A.1 Industry Datasets

The industry datasets are collected from the search pipelines and manually labeled on the crowdsourcing platform, where a group of hired annotators assigned an integer label range from 0 to 4 to each query document pair, representing their relevance as {bad, fair, good, excellent, perfect}.

A.2 Evaluation Metrics

$$\Delta_{GSB} = \frac{\#Good - \#Bad}{\#Good + \#Same + \#Bad}$$

where $\#Good$ (or $\#Bad$) donates the number of queries that the new (or base) model provides better ranking results. and $\#Same$ for the number of results that having same quality.

$$PNR = \frac{\sum_{i,j \in [1,N]} \mathbf{I}\{y_i > y_j\} \mathbf{I}\{f(q, d_i) > f(q, d_j)\}}{\sum_{i,j \in [1,N]} \mathbf{I}\{y_i > y_j\} \mathbf{I}\{f(q, d_i) < f(q, d_j)\}}$$

where the indicator function $\mathbf{I}(y_i > y_j)$ takes the value 1 if $y_i > y_j$ and 0 otherwise.