Distillation versus Contrastive Learning: How to Train Your Rerankers

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Abstract

Training effective text rerankers is crucial for information retrieval. Two strategies are widely used: contrastive learning (optimizing directly on ground-truth labels) and knowledge distillation (transferring knowledge from a larger reranker). While both have been studied extensively, a clear comparison of their effectiveness for training cross-encoder rerankers under practical conditions is needed.

This paper empirically compares these strategies by training rerankers of different sizes and architectures using both methods on the same data, with a strong contrastive learning model acting as the distillation teacher. Our results show that knowledge distillation generally yields better in-domain and out-of-domain ranking performance than contrastive learning when distilling from a larger teacher model. This finding is consistent across student model sizes and architectures. However, distilling from a teacher of the same capacity does not provide the same advantage, particularly for out-of-domain tasks. These findings offer practical guidance for choosing a training strategy based on available teacher models. We recommend using knowledge distillation to train smaller rerankers if a larger, more powerful teacher is accessible; in its absence, contrastive learning remains a robust baseline.

1 Introduction

Modern information retrieval (IR) systems often rely on a two-stage process: an initial retriever quickly finds candidate texts, and a more powerful reranker re-orders them by relevance to improve the final ranking quality (Schütze et al., 2008; Ma et al., 2023; Asai et al., 2024; Singh et al., 2025, *inter alia*). This reranking stage, which involves scoring and sorting texts by their relevance to a given query, commonly employs powerful cross-encoders (Yates et al., 2021; Zhuang et al., 2024b).

Effective training is key to building a high-performing cross-encoder reranker. Two main strategies have emerged for this purpose. The first, contrastive learning (CL), trains the model directly using ground-truth relevance labels, learning to distinguish positive (relevant) examples from negative (irrelevant) ones (Oord et al., 2018; Gao et al., 2021; Ma et al., 2023). The second, knowledge distillation (KD), instead involves training a smaller "student" model to replicate the outputs of a larger, more capable "teacher" model (Buciluǎ et al., 2006; Hinton et al., 2015; Hofstätter et al., 2020; Schlatt et al., 2025). This method is often employed to create efficient models that can approximate the performance of larger ones.

Both strategies are widely used to train rerankers. But for practical deployments, is one preferable to the other? Prior work has explored related, but distinct, questions. For instance, Hofstätter et al. (2020) explored distilling from rerankers to retrievers; while Baldelli et al. (2024) and Schlatt et al. (2025) focused on training rerankers via distilling from large language models (LLMs) like GPT-4 (Achiam et al., 2023). However, there is no direct comparison of these two strategies.

In this paper, we address this gap. We present an empirical comparison of contrastive learning and knowledge distillation as training strategies for cross-encoder rerankers. To this end, we conduct a suite of controlled experiments. We train cross-encoder models of various sizes (0.5B, 1.5B, 3B, 7B) and different architectures (Transformer and Recurrent) using both strategies. For knowledge distillation, we employ a performant 7B Qwen2.5 model (Yang et al., 2024) trained with contrastive learning as the teacher. We focus on modern decoder-only models, as recent works have reported their effectiveness over smaller encoder-based models like BERT (Ma et al., 2023; Muennighoff et al., 2024a; Zhang et al., 2025, *inter alia*). We train all models on the same dataset

and evaluate their ranking performance on standard in-domain and out-of-domain benchmarks.

Our findings consistently show that training with knowledge distillation yields better ranking performance than direct contrastive learning when the student model is smaller than the teacher. For instance, distilling from our 7B teacher significantly improved the performance of 0.5B, 1.5B, and 3B student models on both in-domain and out-of-domain benchmarks compared to training them with contrastive learning. This advantage holds across both Transformer and Recurrent model architectures. However, this benefit diminishes when the student and teacher have the same capacity; distilling from a 7B teacher to a 7B student yielded no significant improvements and, in some cases, harmed out-of-domain generalization (Gou et al., 2021; Gholami and Omar, 2023). To further test the robustness of our conclusions, we conduct an additional experiment where models are trained on a diverse, multi-domain dataset RLHN (Thakur et al., 2025) instead of only on hard negatives mined from a single source. In this setting, knowledge distillation again proves to be the more effective strategy, confirming its advantage even when the reranker's training data is decoupled from the first-stage retriever. Together, these findings position knowledge distillation as a powerful and robust strategy for training smaller rerankers, provided a strong, larger teacher is available. In its absence, we find contrastive learning remains a strong baseline.

2 Methodology

Training strategy is critical for cross-encoder reranker's ranking performance. Two primary strategies have been extensively studied in the literature: (1) direct optimization on ground-truth labels via contrastive learning (Gao et al., 2021; Yates et al., 2021; Ma et al., 2023), and (2) knowledge transfer from a larger model via knowledge distillation (Hofstätter et al., 2020; Schlatt et al., 2025, *inter alia*).

> **Objective:** This paper aims to empirically compare contrastive learning and knowledge distillation for training cross-encoder rerankers. We aim to elucidate their respective strengths and provide clear guidance on which strategy is preferable under different practical constraints.

In the rest of this section, we first formally define the text reranking problem and our notation (§ 2.1). We then provide detailed technical descriptions of the training process using contrastive learning (§ 2.2) and knowledge distillation (§ 2.3).

2.1 The Text Reranking Problem

Modern IR systems often employ a two-stage retrieval-and-rerank pipeline (Schütze et al., 2008; Zhang et al., 2021; Asai et al., 2024, *inter alia*). An efficient first-stage retriever initially fetches a broad set of candidate texts. Subsequently, a more powerful reranker refines this initial list to optimize ranking metrics. Reranking is the task of ordering texts (e.g., passages or documents) by their relevance to a given query.

Let q be an input query, and d be a text from a corpus $\mathcal{D}$. We define a reranking model $f_\theta(q, d)$, parameterized by θ, which computes a scalar relevance score. This model is typically a cross-encoder: the query q and text d are concatenated and fed into a transformer-based language model, whose output is passed through a linear layer to produce the final score (Yates et al., 2021; Nogueira et al., 2019; Boytsov et al., 2022; Ma et al., 2023; Xu, 2024; Xu et al., 2025b, *inter alia*).

2.2 Training with Contrastive Learning

Contrastive learning is one strategy for learning representations (Oord et al., 2018; Weng, 2021). Its application to reranking builds on the principle of the InfoNCE loss (Oord et al., 2018), which is derived from Noise-Contrastive Estimation (Gutmann and Hyvärinen, 2010).

The general goal is to learn a model that distinguishes a "positive" data sample from a set of "negative" (or noise) samples, given a certain context. Denote a context vector $\mathbf{c}$, and consider a set of N samples $X = \{\mathbf{x}_i\}_{i=1}^N$, where one sample $\mathbf{x}_{\text{pos}}$ is a positive sample drawn from the conditional distribution $p(\mathbf{x}|\mathbf{c})$, and the $N-1$ negative samples are drawn from a proposal distribution $p(\mathbf{x})$. Using Bayes' rule, the probability that a sample $\mathbf{x}_i$ is the positive one is:

$$p(C = \text{pos}|X, \mathbf{c}) = \frac{p(\mathbf{x}_{\text{pos}}|\mathbf{c}) \prod_{i \neq \text{pos}} p(\mathbf{x}_i)}{\sum_j \left[p(\mathbf{x}_j|\mathbf{c}) \prod_{i \neq j} p(\mathbf{x}_i) \right]}$$
$$= \frac{p(\mathbf{x}_{\text{pos}}|\mathbf{c})/p(\mathbf{x}_{\text{pos}})}{\sum_j p(\mathbf{x}_j|\mathbf{c})/p(\mathbf{x}_j)} = \frac{f(\mathbf{x}_{\text{pos}}, \mathbf{c})}{\sum_j f(\mathbf{x}_j, \mathbf{c})}$$

We can define the scoring function that is proportional to the density ratio $f(\mathbf{x}, \mathbf{c}) \propto \frac{p(\mathbf{x}, \mathbf{c})}{p(\mathbf{c})}$. The

InfoNCE loss optimizes the negative log probability of classifying the positive sample correctly:

$$\mathcal{L}_{\text{InfoNCE}} = -\mathbb{E}\Big[\log \frac{f(\mathbf{x}, \mathbf{c})}{\sum_{\mathbf{x}' \in \mathbf{X}} f(\mathbf{x}', c)}\Big] \quad (1)$$

We map the abstract concepts to our reranking task:

- The context $\mathbf{c}$ is the query q_i.

- The positive sample $\mathbf{x}_{\text{pos}}$ is the relevant document d_i^+.

- The negative samples $\{\mathbf{x}_k\}$ are a set of irrelevant documents D_i^-.

- The scoring function f is the parameterized reranker model f_θ.

For a training instance consisting of a query q_i, a positive document d_i^+, and a set of negative documents D_i^-, the loss is:

$$-\frac{1}{|\mathcal{S}|} \sum_{(q_i, d_i^+) \in \mathcal{S}} \log \frac{\exp f_\theta(q_i, d_i^+)}{\exp f_\theta(q_i, d_i^+) + \sum_{j \in \mathcal{D}_i^-} \exp f_\theta(q_i, d_i^-)}$$

The total loss is averaged over all training instances. Following common practice (Gao et al., 2021; Xu, 2024), the negative documents are often "hard negatives" — documents that the first-stage retriever ranked highly but are not labeled as relevant. In practice, training instances are grouped into mini-batches, and the parameters θ are optimized jointly.

2.3 Training with Knowledge Distillation

Knowledge distillation (KD) is a technique for training a smaller, efficient "student" model by transferring knowledge from a larger, more capable "teacher" model (Hinton et al., 2015; Gou et al., 2021). In IR, KD is used to create fast rerankers that approximate the performance of slower, larger models, which is critical for production systems (Hofstätter et al., 2020; Santhanam et al., 2022, *inter alia*).

Let f_t denote the teacher reranker and f_s denote the student reranker. For a given query q and a list of candidate texts $\mathcal{D}_q = \{d_1, d_2, \ldots, d_k\}$, we first compute relevance scores from both models. This yields two score vectors (logits):

$$\mathbf{z}_t = [f_t(q, d_1), f_t(q, d_2), \ldots, f_t(q, d_k)]$$
$$\mathbf{z}_s = [f_s(q, d_1), f_s(q, d_2), \ldots, f_s(q, d_k)]$$

The student model f_s is trained to mimic the teacher's output distribution over the candidate texts. This is achieved by minimizing the Kullback-Leibler (KL) divergence between the two softened probability distributions:

$$\mathcal{L}_{\text{KD}} = D_{\text{KL}} \left(\text{softmax}\left(\frac{\mathbf{z}_t}{T}\right) \Big| \text{softmax}\left(\frac{\mathbf{z}_s}{T}\right) \right)$$

where T is the temperature hyperparameter. A higher temperature creates a softer probability distribution, which can help in transferring more nuanced information from the teacher. In practice, T is often set to 1 (Hinton et al., 2015).

Whereas contrastive learning optimizes a model on ground-truth labels, knowledge distillation mimics the outputs of a more capable teacher. The central goal of this paper is to empirically compare these distinct paradigms for training cross-encoder rerankers under controlled settings, which we detail in the following section.

3 Experimental Setup

Training setup. We construct our training set based on the well established MS MARCO passage retrieval dataset (Bajaj et al., 2016). The official training set contains 532k training pairs, and the corpus contains 8.8M passages. For first stage retriever, we reproduce the RepLlama experiment (Ma et al., 2023), but replace the Llama-2-7B backbone model (Touvron et al., 2023) with stronger Qwen2.5-7B model (Yang et al., 2024). The retriever — named RepQwen — is trained on `Tevatron/MSMARCO-passage-aug`[1] trainset, which consists of 486k (q_i, d_i^+) pairs with hard negatives mined from BM25 and CoCondenser (Gao and Callan, 2022).

To construct the training set for the rerankers, we follow the same strategy as Ma et al. (2023) to mine hard negatives from the first stage retriever. Specifically, for each (q_i, d_i^+) pair, we randomly sample k negatives from top-200 passages retrieved by the retriever, excluding d_i^+. As shown in the experimental results (§ 4), the models trained using this constructed dataset achieves on par or improved performance over RankLlama2 (Ma et al., 2023), suggesting the correctness of the pipeline. We did not further investigate hard negative mining strategies like prior works (Yu et al., 2024; Thakur et al., 2025; Lee et al., 2025) as they are orthogonal to the goal of this paper.

The (q_i, d_i^+) pairs, together with the mined hard negatives are then used to train rerankers

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[1] https://huggingface.co/datasets/Tevatron/msmarco-passage-aug

with contrastive learning. We first train the most capable reranker — named RankQwen-7B — with Qwen2.5-7B backbone using contrastive learning. This RankQwen-7B is then used as the teacher model to label $\mathcal{D}_i = \{d_i^+, D_i^-\}$ to be subsequently used to train student rerankers. This way, we create a controlled experiment as the rerankers trained with contrastive learning and knowledge distillation are trained on the same $(q, d, \mathcal{D}^-)$ triples, and the only difference is the training strategy.

Evaluation setup. We evaluate the reranking performance following prior works' practices (Ma et al., 2023; Xu et al., 2025c, *inter alia*). For in-domain evaluation, we use MS MARCO passage dev set, which includes 6,980 queries. We also include TREC DL19 and DL20 (Craswell et al., 2020, 2021) consisting of 43 and 54 queries respectively. For out-of-domain evaluation, we adopt BEIR benchmark (Thakur et al., 2021). We evaluate performances on 13 subsets that are publicly available. Refer to Appx. A for details of datasets.

We report the official evaluation metrics for all benchmarks, i.e., MRR@10 for MS MARCO passage dev, NDCG@10 for DL19 and DL20, NDCG@10 for BEIR benchmarks.

Models used. Our main experiments are based on RepQwen, the retriever with a Qwen2.5-7B backbone following the RepLlama (Ma et al., 2023) training strategy. We also report the performance of a retriever with a Llama-3.1-8B backbone.

The objects of our study are reranker models. We evaluate Qwen2.5 models of different sizes, including 0.5B, 1.3B, 3B and 7B, to allow us to observe the scaling trend. For each model size, we train two reranker models: one via direct contrastive learning and one via distillation; we denote with CL/KD suffix, e.g., RankQwen-0.5B-CL means 0.5B model trained with contrastive learning. For knowledge distillation training, we distil from the RankQwen-7B-CL teacher.

We also experiment with RecurrentGemma (De et al., 2024), a recurrent language model based on the Griffin architecture instead of quadratic complexity Transformers (Vaswani et al., 2017). We use the 2B variant and refer to the trained model as RankRGemma-2B. Recent works have explored recurrent language models' efficacy for IR tasks, such as state space models like Mamba (Gu and Dao, 2023; Dao and Gu, 2024) for retrieval (Zhang et al., 2024) and reranking (Xu, 2024; Xu et al., 2025c). We follow this direction to examine re-

current language models' efficacy under different training strategies.

For all the models used in our experiments, we use the pretrained base models.

Baselines. Our baselines are prior results under the same training setting. RepLlama and RankLlama (Ma et al., 2023) are the closest baselines which use the same trainset for contrastive learning, using Llama-2 backbone (Touvron et al., 2023). CSPLADE (Xu et al., 2025a) is a learned sparse retrieval model with Llama-3-8B backbone (Dubey et al., 2024), and achieves competitive performance compared to dense retrieval models. RankMamba-2 (Xu et al., 2025c) trains Mamba-2-based rerankers for passage reranking, though their results are based on BGE retriever (Xiao et al., 2023). We compare against the original numbers reported by the authors.

Implementation details. Our implementation is based on packages including PyTorch, Huggingface Transformers and Tevatron-v2 (Ma et al., 2025). For all our models, we train with LoRA (Hu et al., 2021) to balance in-domain and out-of-domain performance and reduce overfitting. For scalable training, we use DeepSpeed stage 2 (Aminabadi et al., 2022), activation checkpointing, FlashAttention-2 (Dao, 2024), mixed precision and gradient accumulation. Appx. B gives details about hyperparameters.

4 Results and Analysis

4.1 Main Results

In-domain results. Table 1 reports the reranking performance on MS MARCO Dev and DL19+DL20. We observe our trained retrieval models, i.e., RepLlama3 and RepQwen performs on par or better than RepLlama2 and CSPLADE, the two models trained with same trainset. Similarly, RankQwen-7B-CL is comparable to RankLlama2-7B, suggesting the correctness of our training pipeline.

We now compare performances between rerankers trained with contrastive learning, and rerankers trained with knowledge distillation, with RankQwen-7B-CL as teacher. We notice that with the same model sizes, knowledge distillation achieves better ranking performance compared to contrastive learning. For example, RankQwen-0.5B-KD achieves 43.5 MRR@10 on Dev, and average 75.8 NDCG@10 on DL19+20's 97 queries,

| Model | Size | Source | | DEV | DL19 | DL20 |
		prev.	top-k	MRR@10	NDCG@10	
Retrieval						
BM25 (Lin et al., 2021)	-	-	$|\mathcal{D}|$	18.4	50.6	48.0
CoCondenser (Gao and Callan, 2022)	110M	-	$|\mathcal{D}|$	38.2	71.7	68.4
RepLlama2 (Ma et al., 2023)	7B	-	$|\mathcal{D}|$	41.2	74.3	72.1
CSPLADE (Xu et al., 2025a)	8B	-	$|\mathcal{D}|$	41.3	74.1	**72.8**
RepQwen♣	7B	-	$|\mathcal{D}|$	42.2	73.2	72.5
RepLlama3♣	8B	-	$|\mathcal{D}|$	**42.6**	**74.4**	**72.8**
Reranking						
cross-SimLM (Wang et al., 2022a)	110M	bi-SimLM	200	43.7	74.6	72.7
RankT5 (Zhuang et al., 2023)	220M	GTR	1000	43.4	-	-
RankMamba (Xu et al., 2025c)	1.3B	BGE	100	38.6	75.8	74.0
RankLlama-7B (Ma et al., 2023)	7B	RepLlama2	200	**44.9**†	75.6	**77.4**†
RankQwen-7B-CL♣	7B	RepQwen	200	44.8‡	**77.4**	77.1
Contrastive Learning						
RankQwen-0.5B-CL	0.5B	RepQwen	200	42.1	75.7	72.9
RankQwen-1.5B-CL	1.5B	RepQwen	200	43.5	75.8	**75.4**
RankQwen-3B-CL	3B	RepQwen	200	**43.9**	**76.8**	**75.4**
RankRGemma-2B-CL	2B	RepQwen	200	43.0	76.0	74.7
Knowledge Distillation						
RankQwen-0.5B-KD	0.5B	RepQwen	200	43.5	76.1	75.5
RankQwen-1.5B-KD	1.5B	RepQwen	200	43.9	76.1	76.8
RankQwen-3B-KD	3B	RepQwen	200	**44.7**	77.4	**77.1**‡
RankQwen-7B-KD	7B	RepQwen	200	**44.7**	**77.5**†‡	77.0
RankRGemma-2B-KD	2B	RepQwen	200	43.6	76.1	75.0

Table 1: Results for passage reranking in-domain evaluation. We mark best results in each section bold; † indicates the overall best result and ‡ indicates the best result among our trained models; for models in *Retrieval* and *Reranking* baseline sections, ♣ denotes the model we trained. Note RankQwen-7B-CL♣ is used as the teacher for distillation.

improving over RankQwen-0.5B-CL's 42.1 and 74.1. The similar observation applies for 1.5B and 3B scale Qwen models as well as RankRGemma — the recurrent model with Griffin architecture. These observations suggest the efficacy of knowledge distillation: the performance improvement is consistent across different model sizes (0.5B, 1.5B, 3B) and model architectures (Transformer, Griffin).

We also note RankQwen-7B-KD achieves similar in-domain performance as RankQwen-3B-KD and the RankQwen-7B-CL teacher, which suggests that the student model is not benefiting from knowledge distillation training when the teacher model is of the same capacity. We will revisit this problem in our discussion of out-of-domain results.

Out-of-domain results. We report the out-of-domain evaluation results in Table 2. The baseline methods' results are deferred to Appx. C.

We note similar observations as in the in-domain setting. Directly comparing contrastive learn-

ing to knowledge distillation, RankQwen-0.5B-KD achieves similar performance as RankQwen-0.5B-CL (53.1 average NDCG@10 v.s. 53.3); while RankQwen-1.5B-KD, RankQwen-3B-KD, RankRGemma-2B have better performance over their contrastive learning counterparts.

Among all models with KD training strategy, RankQwen-3B-KD achieves strong out-of-domain performance, averaging 57.5 NDCG@10 over 13 BEIR datasets, improving over RankQwen-7B-CL teacher. However, we notice that RankQwen-7B-CL's underperformance is mainly due to Quora duplicate question retrieval — a symmetric retrieval task different from the asymmetric MS MARCO trainset. The performance is 55.5 versus 56.2 excluding Quora, suggesting that the student model still cannot improve over the teacher (Gou et al., 2021; Gholami and Omar, 2023).

An important observation is that RankQwen-7B-KD leads to performance degradation in out-of-domain evaluation (55.8 vs RankQwen-3B-KD's

Dataset	Teacher 7B	Contrastive Learning				Knowledge Distillation				
		0.5B	1.5B	3B	2B	0.5B	1.5B	3B	7B	2B
Arguana	55.9	50.6	55.8	**56.2**	52.3	51.3	**57.6†‡**	56.5	55.2	54.7
Climate-FEVER	27.1	23.8	27.6	**30.5†‡**	24.3	23.8	**28.5**	31.6	28.7	26.6
DBPedia	48.7†	44.5	46.3	**48.5‡**	47.0	46.4	47.7	**48.5‡**	48.1	47.6
FEVER	88.2	86.0	86.2	**89.1†**	85.1	86.7	87.3	**88.1**	87.3	86.6
FiQA	45.9	37.9	42.2	43.2	**44.1**	34.7	45.4	**46.6†‡**	44.2	44.7
HotpotQA	76.1	72.5	74.8	**76.2**	74.4	74.4	76.2	**76.7†‡**	72.5	76.6
NFCorpus	31.5	33.0	29.3	25.9	**34.4†‡**	32.2	32.3	33.3	32.3	**34.2**
NQ	65.9†	59.2	63.2	**64.9**	62.8	60.9	64.4	**65.5‡**	64.2	64.2
Quora	79.3	82.3	**84.9†‡**	84.6	79.6	80.2	81.0	**81.9**	78.5	80.3
SCIDOCS	19.1	16.9	16.2	17.3	**18.4**	17.8	**19.2†**	**19.2†‡**	19.1	18.6
SciFact	75.0	72.2	72.1	71.1	**73.7**	75.6	**75.8†‡**	75.5	74.6	75.2
TREC-COVID	85.0	81.9	86.3	**86.8**	85.1	80.7	85.6	86.3	84.7	**87.4†‡**
Touche-2020	36.7	31.9	34.6	**36.5**	36.4	25.9	35.9	**38.6†‡**	35.5	37.8
Average	56.5	53.3	55.3	**56.2**	55.2	53.1	56.7	**57.6†‡**	55.8	56.5
Average w/o Quora	56.2†	50.9	52.9	**53.8**	53.2	50.8	54.6	**55.5‡**	53.9	54.5

Table 2: Results for passage reranking out-of-domain evaluation. 0.5B, 1.5B, 3B, 7B 2B correspond to RankQwen-0.5B, RankQwen-1.5B, RankQwen-3B, RankQwen-7B and RankRGemma-2B, respectively. We also report results without Quora dataset as Quora duplicate question detection is a symmetric retrieval task, not aligning with the asymmetric web search task of the training set. We mark best results in each section bold; † indicates the overall best result including the teacher model, ‡ indicates the best result excluding teacher.

57.6), while their performances on in-domain MS MARCO datasets are comparable. Prior studies have also noted that knowledge distillation suffers from overfitting and poor out-of-domain generalization (Gou et al., 2021; Yuan et al., 2020; Yun et al., 2020). Our experimental results suggest that when distilling from a larger, more capable teacher models (RankQwen-7B-CL in our case), the student still achieve performance improvement compared to contrastive training from scratch.

Scaling model sizes. Scaling has been proven effective in IR tasks (Neelakantan et al., 2022; Muennighoff et al., 2024b; Xu et al., 2025b; Zhu et al., 2023, *inter alia*). We also compare the model size scaling trend between CL versus KD for passage reranking in Fig. 1. We make two observations:

1. We observe that contrastive learning demonstrates a clear scaling trend, i.e., performance improves with increased model size when trained on the same data, as also reported by prior works (Ma et al., 2023; Neelakantan et al., 2022; Muennighoff, 2022; Zhuang et al., 2024a).

2. We also note that when distilling from a larger, more capable teacher model, knowledge distillation also demonstrates a scaling trend. For example, RankQwen's performance on 12 BEIR datasets (excluding Quora) improves from 50.8

to 54.6, 55.5 when scaling from 0.5B to 1.5B and 3B model sizes.

We hypothesize that with our knowledge distillation training strategy, the passage reranking performance can be further improved by scaling up the student model's model sizes, and distilling from stronger teacher models.

4.2 Scaling Training Data

Experiment setup. In § 4.1, we focus on a controlled experiment with various model sizes. Now we examine the efficacy of knowledge distillation when scaling the axis of training data. Notice that doing so leads to the decoupling of the retriever and reranker as we can no longer mine hard negatives from the retriever on MS MARCO passage trainset. We use a recently released trainset, RLHN (Thakur et al., 2025), which consists of 649K (q, d^+, D^-) training samples pruned from the larger BGE trainset (Xiao et al., 2023). Specifically, RLHN comprises train samples from the following dataset: MS MARCO passage (Bajaj et al., 2016), Arguana (Wachsmuth et al., 2018), FEVER (Thorne et al., 2018), FiQA (Maia et al., 2018), SCIDOCS (Cohan et al., 2020), HotpotQA (Yang et al., 2018) and NQ (Kwiatkowski et al., 2019). In this case, BEIR benchmark as a whole is no longer considered out-of-domain evaluation. We use a lightweight `intfloat/e5-base-v2` re-
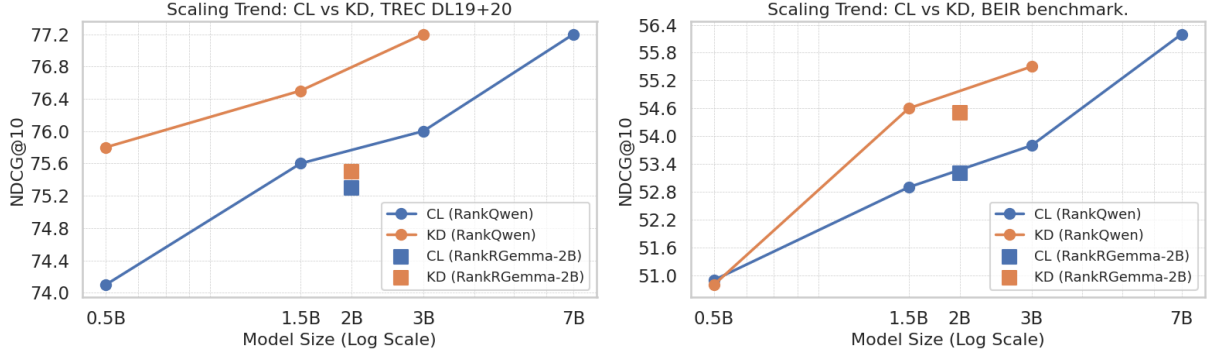
Figure 1: Scaling trend for contrastive learning vs knowledge distillation, for passage reranking. Left figure shows TREC DL19+20 results while right figure shows BEIR results averaged over 12 datasets (excluding Quora). We skip results of RankQwen-7B-KD model.

Dataset	Retriever 110M	Teacher 7B	Contrastive Learning 0.5B	Contrastive Learning 3B	Knowledge Distillation 0.5B	Knowledge Distillation 3B
MSMARCO	42.7	**46.0**	45.5	45.6†	45.3	45.6†
Arguana	44.5	**79.1**	65.2	76.7†	63.7	75.6
Climate-FEVER	26.6	40.5	39.0	40.1	40.2	**42.6†**
DBPedia	42.2	**54.3**	49.9	52.7	50.1	53.7†
FEVER	85.0	94.0	93.6	93.9	93.8	**94.3†**
FiQA	39.9	**55.9**	46.7	55.1†	47.3	54.2
HotpotQA	69.1	**84.8**	82.9	84.7†	82.7	84.6
NFCorpus	35.4	**42.4**	37.0	41.6†	36.8	41.6†
NQ	58.2	**74.5**	67.5	72.8	68.2	73.5†
Quora	86.6	77.6	78.3	78.6	**81.1†**	77.1
SCIDOCS	18.7	**27.1**	22.5	25.7†	22.2	25.7†
SciFact	71.9	**81.9**	78.6	81.3	78.6	81.6†
TREC-COVID	69.5	88.3	85.5	**89.0†**	86.1	88.7
Touche-2020	26.4	32.9	33.1	32.8	35.1	**35.3†**
Average	51.2	**62.8**	58.9	62.2	59.4	62.4†
Average w/o Quora	48.5	**61.7**	57.4	60.9	57.7	61.3†

Table 3: Results with on BEIR benchmark (including MS MARCO passage Dev) with RLHN training mixture. We report NDCG@10 as the performance metric. We mark best result in each row bold; † indicates the overall best result excluding the 7B-sized teacher model.

triever (Wang et al., 2022b) pretrained on unlabeled text pairs, then finetuned with the combined MS MARCO passage and NQ training mixture.

We use the similar training strategy as § 3 (the only difference is the ranker training data): we first train 7B-scale reranker with Qwen2.5-7B and contrastive learning, then train smaller rerankers with knowledge distillation, with the reranking scores on RLHN dataset labeled by the teacher, as well as the contrastive learning counterparts. We train 0.5B and 3B rerankers, as we notice Qwen2.5-1.5B fail to converge in the contrastive learning setting. We name the trained rerankers as RankQwen-{0.5B, 3B, 7B}-CL-RLHN and RankQwen-{0.5B, 3B}-KD-RLHN, respectively.

Results and analysis. We report the results in Table 3. Compared to Table 2, we notice rerankers trained with RLHN mixture show significant performance boost, suggesting the effectiveness of in-domain training data.

Similar to Table 2, the 7B model achieves the best overall performance, average 62.8 NDCG@10 on 14 BEIR benchmark datasets including MS MARCO Dev. We notice that knowledge distillation still outperforms contrastive learning when distilling from the strong 7B teacher model, though the margin is small (<1%). This observation suggests the robustness of knowledge distillation: it can achieve performance improvement compared to contrastive learning when the reranker training data is not coupled with the retriever.
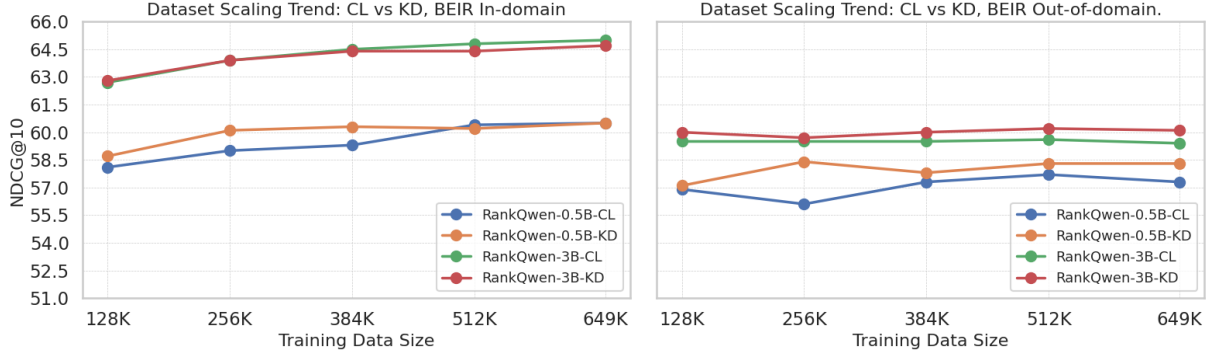
Figure 2: Dataset scaling trend for CL versus KD. Left figure shows average results for 7 in-domain datasets from BEIR benchmark, while the right figure shows average results for 7 out-of-domain datasets.

In Fig. 2 we further analyze BEIR in-domain (7 datasets used in training) and out-of-domain (7 unseen datasets) performance with varying training data sizes. As the amount of training data increases, both CL and KD show improved in-domain performance, with CL eventually outperforming KD. In contrast, KD consistently outperforms CL on the OOD datasets, although the benefits of increasing training data are diminishing. We leave a more in-depth investigation of the in-domain versus OOD performance gap to future work.

5 Related Works

In this paper, we focus exclusively on the architecture of cross-encoder pointwise reranker (Nogueira and Cho, 2019; Nogueira et al., 2020; Zhuang et al., 2024b). The reranker model processes a query and a document simultaneously, allowing the self-attention mechanism to explicitly model the interactions between their tokens throughout the layers. Nogueira and Cho (2019) first demonstrated the efficacy of this approach by fine-tuning BERT as a text pair classifier. The fine-tuning of the BERT-type model as cross-encoder reranker has later been extended to encoder-decoder architectures, such as T5 (Raffel et al., 2020; Nogueira et al., 2020), and decoder-only models like Llama (Touvron et al., 2023; Ma et al., 2023).

The training objective for a cross-encoder is to accurately discriminate between relevant and non-relevant documents for a given query. In practice, the non-relevant documents are usually hard negatives mined from first-stage retrievers (Nogueira et al., 2019; Gao et al., 2021; Boytsov et al., 2022, *inter alia*). Two primary training strategies are widely used to train cross-encoder reranker. The first is contrastive learning, which trains the model directly on ground-truth labels to maximize the distinction between positive and negative exam-

ples (Gao et al., 2021; Zhuang et al., 2023). The second strategy is knowledge distillation, which involves training a student reranker to mimic the behavior and performance of a larger, more capable teacher model (Hofstätter et al., 2020; Baldelli et al., 2024; Schlatt et al., 2025). Knowledge distillation (KD, Buciluǎ et al., 2006; Hinton et al., 2015) facilitates the transfer of knowledge from a large, complex "teacher" model to a smaller, more efficient "student" model. The goal is to enable the student to mimic the teacher's output, thereby inheriting its predictive capabilities at a reduced computational cost. Within the context of training neural IR models, knowledge distillation has been effectively applied to enhance both bi-encoder retriever (Hofstätter et al., 2020; Formal et al., 2021, *inter alia*) and cross-encoder reranker (Baldelli et al., 2024; Schlatt et al., 2025). In this work, we aim to compare these two training strategies in a controlled experimental setting to evaluate their strengths and weaknesses.

6 Conclusion and Future Work

In this paper, we compared the effectiveness of two training strategies, i.e., contrastive learning and knowledge distillation in the context of training text rerankers. With a rigorously controlled experimental setup, we find that when distilling from a larger, more capable teacher model, rerankers trained with knowledge distillation achieve better in-domain and out-of-domain reranking performances compared to contrastive training strategy, and the observation is consistent across different model scales and language model architectures. Our future work will investigate a more optimized way to combine two training strategies, as well as to improve the robustness and out-of-domain generalization of knowledge distillation training.

Limitations

Given the limited computational resources, we are unable to scale the reranker training to >10B models such as Qwen2.5-14B. The observation made in this work may be subject to change for stronger base models. How to improve robustness and out-of-domain generalization of the knowledge distillation training has been extensively investigated by prior works in other NLP domains (Utama et al., 2020; Stacey and Rei, 2024; Wang et al., 2023), we leave investigation for reranking to future works.

This paper focuses on empirical experiments on public benchmarks. We believe this paper do not incur potential risks.

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A Dataset Artifacts and Licenses

Four of the datasets we used in experiments (NF-Corpus (Boteva et al., 2016), FiQA-2018 (Maia et al., 2018), Quora[2], Climate-Fever (Diggelmann et al., 2020)) do not report the dataset license in the paper or a repository. For the rest of the datasets, we list their licenses below:

- MS MARCO (Bajaj et al., 2016): MIT License for non-commercial research purposes.

- ArguAna (Wachsmuth et al., 2018): CC BY 4.0 license.

- DBPedia (Hasibi et al., 2017): CC BY-SA 3.0 license.

- FEVER (Thorne et al., 2018): CC BY-SA 3.0 license.

- HotpotQA (Yang et al., 2018): CC BY-SA 4.0 license.

- NQ (Kwiatkowski et al., 2019): CC BY-SA 3.0 license.

- SCIDOCS (Cohan et al., 2020): GNU General Public License v3.0 license.

- SciFact (Wadden et al., 2020): CC BY-NC 2.0 license.

- TREC-COVID (Voorhees et al., 2021): "Dataset License Agreement".

- Touche-2020 (Bondarenko et al., 2020): CC BY 4.0 license.

B Hyperparameters

For all our training runs, we use a similar set of optimized hyperparameters identified from prior works and our preliminary experiments (Ma et al., 2023; Xu et al., 2025a), only ablating learning rate to reduce the effect of overfitting. We use LoRA rank=16 and α=32. We use AdamW optimizer, learning rate ranging from 3e-5 to 1e-4 with linear warmup and cool down. As we train all models on the train dataset for 1 epoch, we find learning rate is the most important hyperparameter to control

overfitting. We use 8 GPUs with per device batch 4, gradient accumulation steps 4, which leads to a global batch size of 128. For each (q_i, d_i^+) pair, we use $k = 15$ negatives as we find increasing to 31 negatives may lead to instable contrastive learning. For RepQwen training, we use in-batch negatives; while for reranker training, we focus solely on each (q_i, d_i^+) pair's own hard negatives.

C Baseline Results

We report the baseline results in Table 4.

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[2] https://www.kaggle.com/c/quora-question-pairs

Dataset	BM25	GTR-XXL 4.8B	RepLlama2 7B	CSPLADE 8B	RepQwen♣ 7B	RankT5 220M	RankMamba 1.3B	RankLlama2 7B
	-							
Arguana	39.7	54.0	48.6	48.9	54.7	33.0	34.4	56.0
Climate-FEVER	16.5	26.7	31.0	29.4	29.6	21.5	26.2	28.0
DBPedia	31.8	40.8	43.7	44.5	45.2	44.2	45.8	48.3
FEVER	65.1	74.0	83.4	86.5	79.9	83.2	81.9	83.9
FiQA	23.6	46.7	45.8	40.5	45.4	44.5	43.3	46.5
HotpotQA	63.3	59.9	68.5	69.8	68.9	71.0	76.3	75.3
NFCorpus	32.2	34.2	37.8	37.2	38.4	38.1	39.2	30.3
NQ	30.6	56.8	62.4	60.9	62.3	61.4	52.1	66.3
Quora	78.9	89.2	86.8	87.1	87.1	83.1	83.9	85.0
SCIDOCS	14.9	16.1	18.1	17.6	18.3	18.1	19.6	17.8
SciFact	67.9	66.2	75.6	73.9	75.0	75.0	76.8	73.2
TREC-COVID	59.6	50.1	84.7	83.2	85.3	80.7	79.9	85.2
Touche-2020	44.2	25.6	30.5	38.9	36.8	44.0	37.7	40.1
Average	43.7	49.3	55.1	55.3	55.9	53.7	53.6	56.6

Table 4: Baseline results on BEIR datasets. RepQwen♣ is a model we trained.