

GRIPRANK: Bridging the Gap between Retrieval and Generation via the Generative Knowledge Improved Passage Ranking

Jiaqi Bai
School of Cyber Science
and Technology, Beihang
University
Beijing, China
bjq@buaa.edu.cn

Hongcheng Guo
State Key Lab of Software
Development Environment,
Beihang University
Beijing, China
hongchengguo@buaa.edu.cn

Jiaheng Liu
State Key Lab of Software
Development Environment,
Beihang University
Beijing, China
liujiaheng@buaa.edu.cn

Jian Yang
DAMO Academy,
Alibaba Group
Beijing, China
jiaya@buaa.edu.cn

Xinnian Liang
State Key Lab of Software
Development Environment,
Beihang University
Beijing, China
xnliang@buaa.edu.cn

Zhao Yan
Tencent Cloud AI
Beijing, China
zhaoyan@tencent.com

Zhoujun Li*
State Key Lab of Software
Development Environment,
Beihang University
Beijing, China
lizj@buaa.edu.cn

ABSTRACT

Retrieval-enhanced text generation has shown remarkable progress on knowledge-intensive language tasks, such as open-domain question answering and knowledge-enhanced dialogue generation, by leveraging passages retrieved from a large passage corpus for delivering a proper answer given the input query. However, the retrieved passages are not ideal for guiding answer generation because of the discrepancy between retrieval and generation, i.e., the candidate passages are all treated equally during the retrieval procedure without considering their potential to generate a proper answer. This discrepancy makes a passage retriever deliver a sub-optimal collection of candidate passages to generate the answer. In this paper, we propose the **GeneRative Knowledge Improved Passage Ranking (GRIPRANK)** approach, addressing the above challenge by distilling knowledge from a generative passage estimator (GPE) to a passage ranker, where the GPE is a generative language model used to measure how likely the candidate passages can generate the proper answer. We realize the distillation procedure by teaching the passage ranker learning to rank the passages ordered by the GPE. Furthermore, we improve the distillation quality by devising a curriculum knowledge distillation mechanism, which allows the knowledge provided by the GPE can be progressively distilled to the ranker through an easy-to-hard curriculum, enabling the passage ranker to correctly recognize the provenance of the answer from many plausible candidates. We conduct extensive experiments

on four datasets across three knowledge-intensive language tasks. Experimental results show advantages over the state-of-the-art methods for both passage ranking and answer generation on the KILT benchmark.

CCS CONCEPTS

• **Information systems** → **Retrieval models and ranking.**

KEYWORDS

Knowledge-intensive language tasks; Retrieval-enhanced text generation; Passage ranking; Knowledge distillation

ACM Reference Format:

Jiaqi Bai, Hongcheng Guo, Jiaheng Liu, Jian Yang, Xinnian Liang, Zhao Yan, and Zhoujun Li. 2023. GRIPRANK: Bridging the Gap between Retrieval and Generation via the Generative Knowledge Improved Passage Ranking. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management (CIKM '23)*, October 21–25, 2023, Birmingham, United Kingdom. ACM, New York, NY, USA, 11 pages. <https://doi.org/XXXXXXX.XXXXXXX>

1 INTRODUCTION

Knowledge-intensive language tasks, including open-domain question answering, knowledge-grounded conversation, and fact verification, pose a challenge for retrieving passages most likely to be the provenance of the target answer from a large passage corpus (e.g., Wikipedia). One of the most successful paradigms to deal with these tasks is retrieval-enhanced text generation [17, 23, 31, 59]. It first trains a passage retriever (e.g., DPR [27] and GTR [37]) to collect passages relevant to the input query. Then, it uses a generative language model (e.g., BART [30] and T5 [45]) to generate the answer grounding on the retrieved passages and the input query.

Ideally, a passage retriever with good retrieval capability can provide passages more likely to be the provenance of the golden answer. Some efforts have been made toward this goal by improving the relevance of the retrieved passages to the input query. For

*Corresponding Author

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
CIKM '23, October 21–25, 2023, Birmingham, United Kingdom
© 2023 Copyright held by the owner/author(s). Publication rights licensed to ACM.
ACM ISBN 979-8-4007-XXXX-X/23/10...\$15.00
<https://doi.org/XXXXXXX.XXXXXXX>

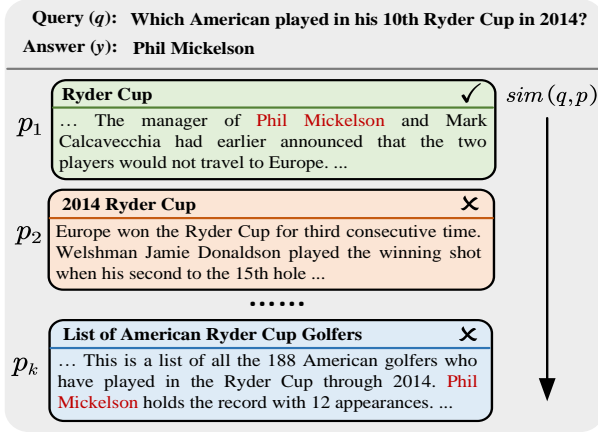


Figure 1: An example taken from the TriviaQA dataset [26] standardized by the KILT benchmark [41]. We show that the golden answer hides in the passage which is not highly relevant to the input query. The $sim(q, p)$ with the down arrow denotes the passages are ranked in descending order according to the similarity with the input query q . The “✓” and “✗” denote the passage is annotated as golden and non-golden for answer generation, respectively.

example, mining the candidate passages to serve as hard negatives [15, 18, 27, 60] or leveraging a passage ranker to improve the ranking quality of the candidates selected by the passage retriever [13, 16, 19, 21]. These methods demonstrate the importance of enhancing the relevancy between the input query and the selected candidates from different perspectives. However, they ignore that the golden answer may hide in the passages which are not highly relevant to the input query. As shown in Figure 1, we present the passages retrieved by DPR according to the input query, sorting in descending order regarding the predicted similarity score. In this case, the golden passage p_1 is correctly retrieved at the top from the passage corpus, while another reasonable passage p_k that contains the golden answer is ranked at the tail of the candidate passage pool, which will be ignored during the answer generation. One of the main reasons for the above challenge is that the candidate passages are all treated equally during the retrieval procedure without considering their potential to generate the golden answer. Moreover, the deficiency of such critical knowledge will result in the retriever being hard to correctly recognize the provenance of the golden answer from many plausible candidate passages.

Some pioneering work tried to handle the above challenges. A solution that would at first glance seem obvious is end-to-end training of the passage retriever and the answer generator [17, 31], in which both components are optimized to generate the correct answer regardless of the golden passage label. However, this resolution lacks a mechanism to explicitly measure how likely the selected passages can be used to generate the correct answer, which may damage the performance of the passage retriever when there are too many plausible candidates to distinguish provenance from them correctly [47], resulting in the golden passage being ignored during the answer generation. Another line of work approaches the posterior information during the passage retrieval procedure [33, 39, 48], where

the posterior information can be incorporated into a teacher model like a pre-trained passage retriever or a passage ranker. However, this line of work only considers the posterior information from the encoder part, which lacks a mechanism to explicitly measure how likely the retrieved passages can be used to generate the golden answer autoregressively.

In this paper, we propose the **GeneRative Knowledge Improved Passage Ranking (GRIPRANK)** approach by distilling knowledge from a generative passage estimator (GPE) to a passage ranker. The GPE is a generative language model [30, 55], which explicitly measures how likely a candidate passage can be used to guide the generation of the golden answer. We train a GPE by feeding the concatenation of the query and the golden passage, generating the golden answer autoregressively. Once the training is finished, we freeze the entire GPE, taking the concatenation of the query and the candidate passage as input, leveraging the cross-entropy loss between the predicted and the golden answer to measure how likely a candidate passage can be the provenance. The distillation procedure can be realized by teaching a student learning to rank the passages ordered by the GPE. Compared to the work that distills knowledge from the encoder-only architecture [39, 48], the generative framework provides fine-grained knowledge to measure the relevance between the candidate passages and the golden answer in an autoregressive manner. However, there can be one-to-many relations between the golden answer and the selected passages in the real-world scenario [9, 26, 28], especially when the passage corpus is large (e.g., Wikipedia), which may result in the golden passage out-of-recall in the top-ranked candidates. To enforce that the golden passage always ranks at the top of the output distribution estimated by the GPE, we devise a label rectification method by introducing a balanced term between the golden passage label and the output distribution. Furthermore, to make the ranker better distinguish the provenances of the golden answer from many plausible candidates, we devise a novel curriculum knowledge distillation mechanism to progressively distill knowledge from the GPE to the ranker, which is realized by dynamically controlling the difficulty of the sampled passages from the candidate passage pool through an easy-to-hard curriculum [4]. We conduct experiments on four datasets across three tasks standardized by the KILT benchmark, including ZSRE [29] (zero-shot slot filling task), TriviaQA [26] and Natural Questions [28] (open-domain question answering task), and Wizard of Wikipedia [9] (Knowledge-enhanced dialogue generation task). Experimental results show the superior performance of the proposed GRIPRANK over the previous state-of-the-art for both passage ranking and answer generation. Further analysis demonstrates the effectiveness of the proposed approach.

Our contributions are three-fold: **i)** We introduce GRIPRANK, the first generative knowledge improved passage ranking approach for improving the answer generation in knowledge-intensive language tasks. **ii)** We propose a novel curriculum knowledge distillation mechanism for better distilling the generative knowledge to a passage ranker. **iii)** Extensive experiments and thorough analysis demonstrate the effectiveness of our proposed approach. We present that distilling knowledge from a generative passage estimator to a passage ranker effectively narrows the gap between passage retrieval and answer generation.

2 RELATED WORK

2.1 Knowledge-Intensive Language Tasks

Knowledge-Intensive Language Tasks (KILT) are a collection of tasks that require a system to produce a proper answer according to the input query by accessing external knowledge sources (e.g., Wikipedia). For example, the zero-shot slot-filling task [29] aims to recognize a set of relations for a given entity and use them to populate structures [15]. Open-domain question answering [12, 26, 28, 58] aims to produce the correct answer for a given question by accurately locating the provenance from knowledge sources. Knowledge-enhanced dialogue generation [2, 9] aims to generate the proper response for the given dialogue history by considering knowledge relevant to the dialogue context.

There is plenty of datasets have been proposed for KILT tasks [1, 10, 29]. While these datasets always have different input formats and evaluation schemes. Moreover, they always access knowledge from different knowledge sources. To facilitate the comparison among these tasks, a benchmark named KILT [41] was introduced to unify these tasks. All tasks in KILT are formulated into a unified interface and grounded in the same snapshot of Wikipedia. In this work, we focus on three tasks standardized by the KILT benchmark, including zero-shot slot-filling, open-domain question answering, and knowledge-enhanced dialogue generation.

2.2 Retrieval-Enhanced Text Generation

Retrieval-enhanced text generation aims to produce a proper answer for the input query by leveraging a retrieval component to collect evidence from large knowledge sources, which achieves competitive performance across many knowledge-intensive language tasks [5, 16, 21, 35, 42]. It has been demonstrated that the passage retrieval performance significantly impacts the quality of the final generated answer. Following this intuition, researchers attempt to incorporate the posterior information into the passage retrieval procedure [33, 39, 51] or leverage a passage ranker to further boost the ranking quality of the candidates retrieved by a passage retriever [11, 16, 48]. For example, Ren et al. [48] introduced a joint training approach to jointly optimize the retriever and re-ranker by distilling knowledge from each other. Glass et al. [16] employed a passage ranker with cross-encoder architecture to improve the passage retrieval capability and achieved state-of-the-art results on the KILT benchmark. Paranjape et al. [39] incorporated the posterior information into the passage retrieval procedure. They leverage an additional passage retriever as a teacher, which takes the golden answer as input and uses the output distribution of the teacher to supervise the learning of the student.

We follow the line of research that uses the passage ranker to enhance the ranking quality of the collected candidate passages by passage retriever. However, we focus on leveraging a passage ranker to mitigate the discrepancy between retrieval and generation by distilling the knowledge from a generative language model.

2.3 Knowledge Distillation

Knowledge distillation [20] aims to transfer knowledge from a stronger pre-trained teacher model to a compact student model.

One of the key ideas of knowledge distillation is to inject the posterior knowledge (e.g., the provenance of the golden answer) into the teacher, and the student is supervised by matching the output distribution of the teacher during the training procedure.

Conventional methods conduct knowledge distillation by minimizing the Kullback-Leibler divergence loss (KLD loss) between the output distribution of the teacher model and the student model [8, 20, 25, 56]. Recent studies treat knowledge distillation as a learning-to-rank problem [6, 46, 57]. Thus, the distillation process can be regarded as a teacher teaching a student how to order the top-ranked candidates correctly. Another line of work improves the distillation performance by progressively distilling knowledge from a teacher model to a student model. For example, Lin et al. [33] proposed a progressive distillation approach for dense passage retrieval, which gradually improves the capability of teachers and students through both model and data perspectives. Li et al. [32] enhanced the distillation performance by progressively increasing the learning difficulty of the student. They realized the progressive distillation by controlling the distillation temperature [20] in an easy-to-hard curriculum [3, 4], where the distillation temperature is a hyper-parameter that controls the smoothness of probability distributions and can faithfully determine the difficulty level of the distillation process [7, 34].

In contrast to the above work, we train a generative passage estimator as a teacher and distill the ranking order estimated from it to the student, which allows the student to learn how to order the top-ranked passages. Moreover, we realize the knowledge distillation in an easy-to-hard manner by progressively increasing the difficulty of the sampled candidate passages for training the student, which enables the student progressively learn to distinguish the provenance of answers from many plausible candidates.

3 METHODOLOGY

3.1 Problem Formalization

Knowledge-intensive NLP tasks aim to generate answer y given input query x with the usage of a list of retrieved passages \mathbf{P} , where $\mathbf{P} = \{p_1, \dots, p_{|\mathbf{P}|}\}$ is related to the input query x and retrieved from a large passage corpus such as Wikipedia.

A popular solution to deal with these tasks employs a retrieval-enhanced text generation framework (e.g., FiD [23], RAG [31] and REALM [17]). These architectures typically consist of two components: a passage retriever Q and an answer generator \mathcal{G} . The passage retriever $Q(\mathbf{P}|x; \theta_Q)$ with parameters θ_Q is trained to retrieve a list of passages $\mathbf{P} = \{p_1, \dots, p_{|\mathbf{P}|}\}$ with the $|\mathbf{P}|$ most relevant scores for input query x . The answer generator $\mathcal{G}(y_i|x, \mathbf{P}, y_{1:i-1}; \theta_{\mathcal{G}})$ parameterized by $\theta_{\mathcal{G}}$ is then trained to generate answer y token by token, given the input query x and retrieved passages \mathbf{P} .

Usually, the relevance between the retrieved passages and the ground-truth answer significantly impacts the correctness of the generated results. Because the more passage relevant to the input query, the more likely it contains the provenance of the answer. With this intuition, we aim to leverage a passage ranker $\mathcal{R}(\mathbf{P}'|x, \mathbf{P}; \theta_{\mathcal{R}})$ parameterized by $\theta_{\mathcal{R}}$, to improve the ranking order of passages in \mathbf{P} given input query x , gathering a list of re-ordered passages $\mathbf{P}' = \{p'_1, \dots, p'_{|\mathbf{P}|}\}$ for answer generation.

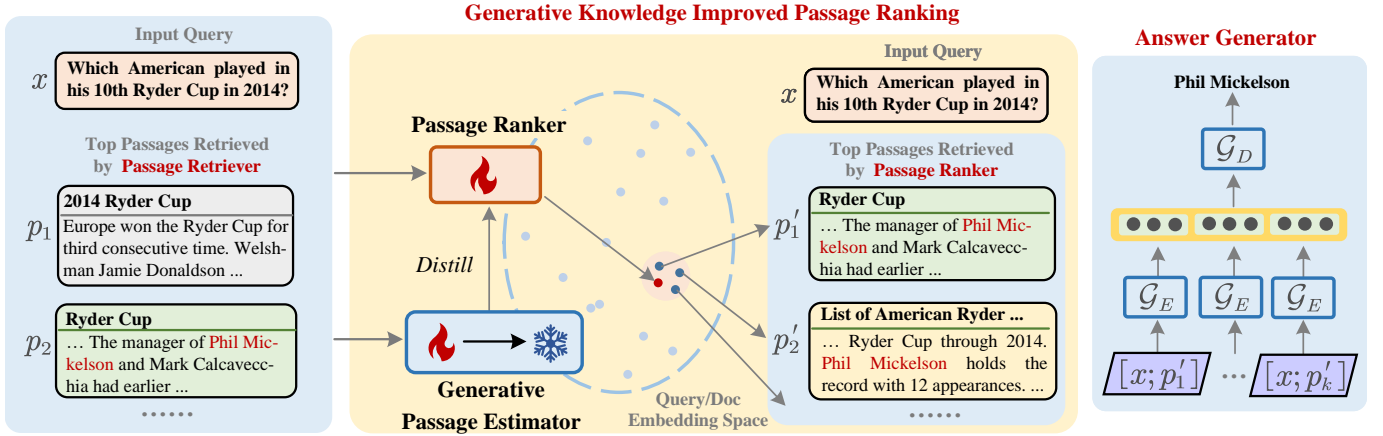


Figure 2: The architecture of our proposed GRIPRANK. We train a generative passage estimator (GPE) under the supervision of the golden answer, taking the concatenation of the query and golden passage as input. Once the GPE finishes training, we freeze the entire GPE and the passage ranker learns to rank the candidate passages ordered by the GPE. Each top-ranked passage is then concatenated with the input query for answer generation.

3.2 Method Overview

We improve the conventional retrieval augmented generation framework by introducing a ranker to enhance the ranking order of passages collected from the passage retriever. Thus, a passage retriever is trained to first retrieve candidate passages according to the given input query. Then, the ranker further ranks retrieved candidates, exploring the most relevant passages to the golden answer.

The architecture of our proposed method is shown in Figure 2. Different from previous work [16, 48], we improve the passage ranker by distilling knowledge from a generative passage estimator (GPE), which is trained to estimate how likely the provided candidate passages can generate the ground-truth answer by combining the input query. Once the distillation process is finished, the ranker re-ranks the candidate passages retrieved from the passage retriever, aiming to collect the most relevant passages for generating the golden answer.

3.3 Passage Ranker

Given an input query x , and a list of candidate passages \mathbf{P} retrieved by the passage retriever \mathcal{Q} , a vanilla passage ranker aims to enhance the relevance level of a candidate passage p_k ($p_k \in \mathbf{P}$) to the input query x . We implement the passage ranker with cross-encoder architecture [38, 43], as it can better capture the semantic interactions between the passage and the query. To compute the relevance score $z_k \propto \text{sim}(x, p_k)$, we concatenate x and p_k separated by a special token [SEP], prepending a [CLS] token to the beginning of the sequence. The z_k can be collected by the output representation at the [CLS] token encoded by \mathcal{R} . Generally, we use the negative of the summed log-likelihood for the relevance score of the golden passage z_g as the loss function:

$$\mathcal{L}_{NLL} = -\log \frac{e^{(z_g)}}{\sum_j |\mathbf{P}| e^{(z_j)}} \quad (1)$$

3.4 Improving Passage Ranker with Generative Passage Estimator

Different from the previous work [16, 48] only employs the ranker to enhance the relevance between the retrieved passages and the source input. We improve the passage ranker by distilling the knowledge from a generative passage estimator (GPE), where the GPE is trained to measure how likely the retrieved passages can be used to generate a correct answer autoregressively.

3.4.1 Generative Passage Estimator. The GPE can be arbitrary generative language models, such as BART [30] and T5 [45]. We train a GPE by taking the concatenation of input query x and the golden passage p_g as input, generating the golden answer y token-by-token. Once the training is finished, we freeze the parameters of the GPE and ask it to generate golden answer y given the input query x concatenated with a candidate passage p_k ($p_k \in \mathbf{P}$). We employ the normalized sentence-level cross-entropy loss of y to measure how likely the candidate passage p_k can be used to generate the golden answer y , which is formalized as follows:

$$z_k = \frac{\sum_j |\mathbf{P}| \sum_t |y| \log p(y_t | y_{<t}, x, \hat{p}_j)}{\sum_t |y| \log p(y_t | y_{<t}, x, \hat{p}_k)} \quad (2)$$

$$r_k = \frac{e^{(z_k)}}{\sum_j |\mathbf{P}| e^{(z_j)}} \quad (3)$$

Intuitively, a large value of r_k (i.e., lower cross-entropy loss for candidate passage \hat{p}_k) indicates that the candidate passage \hat{p}_k is more likely to be a provenance of the golden answer.

In practice, the sorting results of GPE may result in the golden passage out-of-recall in the top-ranked candidates. Because there exist some reasonable potential resolutions which are not labeled as golden passages when the passage corpus is large. To overcome this issue, we devise a *label rectification* method to enforce the golden passage always ranked at the top of the output distribution

estimated by the GPE:

$$r \leftarrow \varepsilon \cdot q + (1 - \varepsilon) \cdot r \quad (4)$$

where ε is a rectified term to balance the probability distribution r predicted by GPE and the one-hot label q labeled by human annotators. To enable the golden passage p_g always receive the largest probability in r , one reasonable solution is to ensure $\varepsilon = (1 - \varepsilon) \max(r_{\#q_{p_g}})$, where $\max(r_{\#q_{p_g}})$ is the maximum probability for non-golden passages in r . Thus, we have to enforce the ε meets the following equation:

$$\varepsilon = \frac{\max(r_{\#q_{p_g}})}{1 + \max(r_{\#q_{p_g}})} \quad (5)$$

3.4.2 Distilling Knowledge from the Passage Estimator to the Passage Ranker. During training, the ranker is supervised by the estimation results of the trained GPE. Therefore, the order of the candidate passages measured by GPE serves as a teacher and the ranker is a student. We employ ListMLE loss [54] to enforce the ranker learning the ranking order from GPE:

$$\mathcal{L}_{ListMLE} = - \sum_{k=1}^{|P|} \log \frac{e^{(r_{o_k})}}{\sum_{i=k}^{|P|} e^{(r_{o_i})}} \quad (6)$$

where o_i is the relevance order of the i -th candidate passage measured by GPE. The overall loss to optimize the ranker is the sum of the NLL loss (equation 1) and the ListMLE loss formulated as:

$$\mathcal{L} = \mathcal{L}_{NLL} + \mathcal{L}_{ListMLE} \quad (7)$$

Once the ranker is finished training, we re-rank the candidate passages in P sorted by the passage retriever and output them into the re-ordered candidate sentence pool P' .

3.4.3 Curriculum Knowledge Distillation. The selection of candidate passages has a significant impact on the distillation quality for a passage ranker. One of the alternative approaches is to mind candidate passages serving as hard negatives [15, 16, 27] for improving the ranking capability. However, in human education, teachers always train students starting with basic (easy) curricula, and then progressively exposure to more advanced (hard) curricula along with students growing up. Students will learn much better if the curricula are organized in a reasonable order.

Inspired by curriculum learning [4], we propose a curriculum knowledge distillation mechanism for better distilling the knowledge from GPE to ranker. Concretely, we devise a *curriculum passage sampling* strategy to realize the knowledge distillation in a curriculum manner, which is achieved by gradually increasing the difficulty of the sampled candidate passages during the distillation procedure. Thus, it challenges the passage ranker to distinguish and order the passages in an easy-to-hard curriculum progressively.

Difficulty Measurement. We define the difficulty of a candidate passage p_j ($j \neq g, p_j \in P$) as its similarity to the input query x , where the similarity is the normalized dot-product score predicted by the pre-trained passage retriever Q . We sort the passages according to the similarity in ascending order, obtaining a sorted passage pool $P_{sort} = \{\tilde{p}_1, \dots, \tilde{p}_{|P_{sort}|}\}$. Thus, a higher rank of passage means it is more similar to the input query x , indicating that it is more

difficult for the passage ranker to distinguish it from the golden provenance p_g .

Curriculum Passage Sampling. To realize curriculum knowledge distillation, we sample passages from the sorted passage pool P_{sort} by progressively increasing the difficulty of sampled candidates. Concretely, we adjust the scale φ ($\varphi \leq |P_{sort}|$) of the sampling space ρ_{sort} from which the candidate passages are sampled, where $\rho_{sort} = \{\tilde{p}_1, \dots, \tilde{p}_\varphi\}$ is a subset of P_{sort} (i.e., $\rho_{sort} \in P_{sort}$). The sampling scale φ can be determined as follows:

$$\varphi = \begin{cases} N_0 & t \leq T_0 \\ N_0 + \lfloor \frac{t-T_0}{T-T_0} (|P_{sort}| - N_0) \rfloor & T_0 < t \leq T \\ |P_{sort}| & t > T \end{cases} \quad (8)$$

where N_0 ($N_0 \in \mathbb{N}, N_0 \leq |P_{sort}|$) is the scale of warm-up passage pool. T_0 and T are warm-up steps and total curriculum steps, respectively. $\lfloor \cdot \rfloor$ denotes the fraction rounded down.

Intuitively, when the current training steps t satisfy $t \leq T_0$, the candidate passages are sampled from the set $\{\tilde{p}_1, \dots, \tilde{p}_{N_0}\}$. Thus, we only use N_0 easiest candidates for knowledge distillation to warm up the ranker. Once the warm-up stage is finished, we progressively expand the sampling scale φ with the training process going on ($T_0 < t \leq T$). The ranker is exposed to harder candidates, requiring a strong ranking capability for distinguishing the provenance from each plausible candidate. When $t > T$, the ranker approaches the entire passage pool P_{sort} and randomly samples the candidates in P_{sort} to distill knowledge from GPE to ranker.

3.5 Ranker-Augmented Answer Generator

During answer generation, we first select the k most relevant passages ranked at the top by the passage ranker. Then, we concatenate the input query x with each selected passage p'_m ($m \leq k$) and independently feed them into the encoder of the generator (\mathcal{G}_E), similar to the implementation of FiD [23], formulating as:

$$e_m = \mathcal{G}_E ([\text{query} : x; \text{passage} : p'_m]) \quad (9)$$

where $[\cdot; \cdot]$ denotes the concatenation operation. Each encoded representation e_m is concatenated into a long sequence and fed through the decoder of the generator (\mathcal{G}_D), generating the answer sequence \hat{o} token-by-token:

$$\hat{o} = \mathcal{G}_D ([e_1; e_2; \dots; e_k]) \quad (10)$$

The generator is optimized by minimizing the cross-entropy loss between the predicted answer \hat{o} and the golden answer o in training.

4 EXPERIMENTAL SETTINGS

4.1 Datasets

We conduct our experiment on four datasets, across three tasks in the KILT benchmark, including zero-shot slot filling, open-domain question answering, and knowledge-enhanced dialogue generation.

- **Zero-Shot Slot Filling** We use the ZSRE (Zero-Shot Relation Extraction) [29] to evaluate our method on the zero-shot slot filling. The ZSRE is originally designed for relation extraction. The KILT casts it as a zero-shot slot-filling task, where a head entity and a relation are regarded as input

Table 1: The number of samples in the dataset standardized by the KILT benchmark.

Dataset	Train	Dev	Test
<i>Zero-Shot Slot Filling</i>			
Zero Shot Relation Extraction (ZSRE) [29]	147,909	3,724	4,966
<i>Open-Domain Question Answering</i>			
TriviaQA [26]	61,844	5,359	6,586
Natural Questions (NQ) [28]	87,372	2,837	1,444
<i>Knowledge-Enhanced Dialogue Generation</i>			
Wizard of Wikipedia (WoW) [9]	63,734	3,054	2,944

for the system and the system is expected to output the tail entity for slot-filling.

- **Open-Domain Question Answering** We use the TriviaQA [26] and NQ (Natural Questions) [28] to evaluate our method on the open-domain question-answering task. Both datasets are a collection of question-answer-evidence triples, and the relevant Wikipedia page for each sample can be explicitly found by a retrieval step.
- **Knowledge-Enhanced Dialogue Generation** We use the Wizard of Wikipedia (WoW) [9] to evaluate our method on the knowledge-enhanced dialogue generation task. The input for this task is a dialogue history ending with the information seeker’s turn. The output is a response to the mentioned content grounded on a relevant Wikipedia page.

The statistic of each dataset is shown in Table 1. Unlike the previous work [21, 22] that trains the model on the training and passage sets filtered from the original dataset. We train our model on the dataset standardized by the KILT, facilitating a fair comparison with other work.

4.2 Evaluation Metrics

For all tasks in KILT, a system is expected to correctly retrieve the provenance of golden answers from the KILT knowledge sources, and then ground on the retrieved evidence to guide the generation of the answer. Following previous work [35, 41], we use R-Precision (R-Prec) and Recall@5 (R@5) to measure the correctness of the retrieved provenance, where R-Prec and Recall@5 figure out how many retrieved results meet that ground-truth provenance appears in the top-1 and top-5 passages retrieved by the system, respectively. We use the F1 score to measure the correctness of the generated output at the unigram level for all tasks. In addition, we use accuracy (ACC), Rouge-L (R-L) [50], and exact match (EM) as indicative metrics to evaluate the specific task accordingly. Moreover, we use the KILT version of these metrics [41] to indicate the correctness of the output when provenance is ranked at the top in predictions.

4.3 Baselines

We compare our approach with a set of competitive baselines:

- **KGI** [15] trains the DPR and the RAG models in a task-specific manner. They constructed hard negatives by fetching the candidate passages from the pre-trained DPR, which boosts the retrieval results by a significant margin and, subsequently, the performance of downstream tasks.

- **KILT-WEB 2** [42] created a new knowledge source SPHERE and conducted experiment over it. They employ the conventional retrieve-then-generate approach to achieve the KILT tasks, where BM25 or DPR is employed first to retrieve relevant passages. Then they use FiD [23] as a reader component to produce answers.
- **Hindsight** [39] proposed leveraging an additional retriever that can approach the posterior information to guide the training of the passage retriever, which achieves competitive performance on the WoW dataset.
- **SEAL** [5] introduced a novel generative approach for text retrieval. It can generate any strings that appeared in the dataset with the FM-index [14], and then map the generated contents to passages.
- **Re²G** [16] employed a passage re-ranker with cross-encoder architecture to improve the ranking quality of the candidate passages retrieved by the passage retriever. They achieved state-of-the-art performance on four tasks over the KILT benchmark.

4.4 Implementation Details

4.4.1 Model Settings. The passage retriever is in a dual-encoder architecture. Both encoders use BERTBASE as the backbone, each with 110M parameters. We initialize the passage retriever from Dense Passage Retriever (DPR) [27] from HuggingFace [53], and train it with hard negatives fetched from BM25 [49], similar to the implementation in Glass et al. [15, 16]. The passage ranker is in a cross-encoder architecture, which is composed of a single Transformer encoder enabling interactively models of queries and passages. We use ELECTRABASE (110M) pre-trained on MS MARCO dataset [36] as the backbone of the passage ranker. Both the generative passage estimator (GPE) and the answer generator are trained to do sequence-to-sequence generation with encoder-decoder architecture, which is initialized from BARTLARGE (406M) on HuggingFace.

4.4.2 Hyper-parameter Settings. There are four components in our model, i.e., passage retriever, passage estimator, passage ranker, and answer generator. We set the learning rate to 5e-5 for the passage retriever, and 3e-5 for the other three components. We use a linear learning rate scheduler for all components, with 10% of the total steps for warmup updates. The batch size is set to 128 for the passage retriever and the answer generator, and 32 for the passage estimator and the passage ranker. We train all components with up to 5 epochs. Moreover, we set the scale of the warm-up passage pool N_0 , the warm-up steps T_0 , and the curriculum steps T to 5, 500, and 1000 for all datasets during passage ranking, respectively. During the inference stage, we set the number of passages utilized for the answer generator to 15 and the beam size to 3. We use Pytorch [40] and Huggingface [52] to implement our model, and conduct training and inference on four Tesla V100 machines.

5 EXPERIMENTAL RESULTS

We conduct extensive experiments to answer the following research questions:

Table 2: Performance on the KILT test set. We report results on the KILT Leaderboard. Bold and underline indicate the best and second best approach respectively. “K.-” is the KILT score for the corresponding metric. “R-P” and “R@5” denotes the R-precision and Recall@5, respectively. All models apart from the KILT-WEB-2 employ BART_{LARGE} as the backbone of the answer generator.

Models	Zero-Shot Relation Extraction				Wizard of Wikipedia				Natural Questions				TriviaQA			
	R-P	R@5	ACC (K.-)	F1 (K.-)	R-P	R@5	R-L (K.-)	F1 (K.-)	R-P	R@5	EM (K.-)	F1 (K.-)	R-P	R@5	EM (K.-)	F1 (K.-)
KGI ₀	94.2	95.2	69.0 (68.3)	74.5 (73.5)	55.4	78.5	16.4 (10.4)	18.6 (11.8)	63.7	70.2	45.2 (36.4)	53.4 (41.8)	60.5	63.5	61.0 (42.9)	66.6 (46.1)
KGI ₁	<u>98.5</u>	99.2	72.6 (72.3)	77.1 (76.7)	-	-	-	-	-	-	-	-	-	-	-	-
KILT-WEB-2	89.6	97.9	74.0 (67.2)	78.4 (71.0)	41.5	68.3	13.9 (6.6)	15.7 (7.6)	59.8	71.2	51.6 (35.3)	60.8 (40.7)	58.9	71.6	72.7 (45.6)	79.5 (49.6)
HindSight	-	-	-	-	56.1	74.3	<u>17.1 (11.9)</u>	<u>19.2 (13.4)</u>	-	-	-	-	-	-	-	-
SEAL	98.0	<u>99.3</u>	<u>74.6 (73.2)</u>	<u>79.7 (78.1)</u>	57.6	79.0	16.7 (10.5)	18.3 (11.6)	63.2	68.2	<u>53.7 (38.8)</u>	<u>62.2 (44.4)</u>	68.4	<u>76.4</u>	70.9 (50.1)	77.3 (55.0)
Re ² G	-	-	-	-	<u>60.1</u>	80.0	16.8 (11.4)	18.9 (13.0)	70.8	<u>76.6</u>	51.7 (43.6)	61.0 (<u>49.8</u>)	<u>72.7</u>	74.2	<u>76.3 (57.9)</u>	<u>81.4 (61.8)</u>
GRIPRANK	99.3	99.7	74.7 (74.3)	80.3 (79.9)	63.5	<u>79.3</u>	18.1 (12.9)	20.5 (14.7)	<u>70.2</u>	77.6	54.0 (43.6)	63.2 (50.3)	73.0	78.8	77.9 (58.2)	83.3 (62.4)

- **RQ1:** How does the proposed GRIPRANK perform compared with the state-of-the-art retrieval-enhanced text generation models?
- **RQ2:** Is the proposed GRIPRANK really narrowing the gap between retrieval and generation?
- **RQ3:** Is the proposed Curriculum Knowledge Distillation beneficial to help the ranker distinguish the provenance from many plausible candidates?
- **RQ4:** How do different generative language models impact the distillation quality of the generative passage estimator?
- **RQ5:** Can we better understand how different models perform via some case studies?

5.1 Performance Comparison

To answer **RQ1**, we report the results of each model on ZSRE (zero-shot slot filling task), WoW (knowledge-enhanced dialogue generation task), NQ and TriviaQA (open-domain question answering) in Table 2.

Generally, the proposed GRIPRANK outperforms the previous state-of-the-art methods for both passage ranking and answer generation. For example, compared to SEAL, one of the strongest baselines on these four datasets, the GRIPRANK achieves around 7.3% and 4.7% relative improvements on average according to R-precision and Recall@5 respectively, indicating the superior performance of our method on passage ranking. With regard to answer generation, the GRIPRANK improves SEAL by around 5.5% and 13.9% according to F1 and KILT-F1 on average respectively, indicating that the better passage ranking performance of GRIPRANK further improves the quality of generated answers. The above observation is still consistent in contrast to the best baselines on each dataset according to the corresponding metric. For example, the GRIPRANK outperforms the previous state-of-the-art on each dataset according to R-precision and F1 by around 1.5% and 2.9% relative improvements on average, respectively.

Interestingly, compared with other baselines, we observe that the GRIPRANK shows potential in correctly predicting the answer

no matter if the golden passage ranks at the top. For example, on the ZSRE dataset, the GRIPRANK outperforms one of the strongest baselines SEAL by around 1.1 and 1.8 points in terms of KILT-ACC and KILT-F1 respectively, even though they perform comparably according to ACC and F1 score. While on the NQ and TriviaQA dataset, the GRIPRANK outperforms one of the strongest baselines Re²G by around 2.0 and 2.1 points on average in terms of EM and F1 respectively, even though they perform comparably according to the counterpart of the KILT metrics. It indicates the superiority of the proposed ranking strategy, which enhances the answer generation by making better use of the golden passage with the help of other top-ranked candidates for generating correct answers.

5.2 Effect of Passage Ranking

To answer **RQ2**, we consider the following variants to conduct ablation: **i) w/o Ranker:** We remove the passage ranker from the proposed GRIPRANK. Thus, only the top-ranked passages fetched from the passage retriever (i.e., DPR) are used to guide the answer generation. **ii) w/o Distill:** We only use NLL loss (defined in Eq. 1) to supervise the training of the passage ranker without distilling knowledge from teacher models. **iii) w/ Encoder Distill:** We replace the generative passage estimator (GPE) with an encoder-only teacher model, which shares the same architecture with the passage ranker but additionally considers the golden answer as input. The student passage ranker is under posterior-guided training from the teacher model. **iv) w/ KL Distill:** We replace the *ListMLE* loss defined in equation 6 with *Kullback-Leibler Divergence* loss (KLD loss), supervising the passage ranker to learn the output distribution of the GPE.

Table 3 shows the ablation results, from which we have the following observations: First, the passage ranker plays a significant role in both passage retrieval and answer generation. Results over all of the metrics degrade significantly when the passage ranker is removed from the proposed approach. Second, all distillation strategies are beneficial to answer generation. For example, the variant *w/ Encoder Distill* and the variant *w/ KL Distill* outperform

Table 3: Ablation results on the KILT validation set.

Models	ZSRE			WoW			TriviaQA			NQ		
	R-prec	ACC	KILT-ACC	R-prec	F1	KILT-F1	R-prec	EM	KILT-EM	R-prec	EM	KILT-EM
GRIPRANK	99.0	73.8	73.5	58.5	20.2	14.3	74.3	76.8	58.2	72.0	57.3	46.4
w/o Ranker	92.8	66.4	65.0	51.2	18.6	12.8	62.2	61.7	45.6	66.0	50.1	39.5
w/o Distill	98.2	72.0	71.5	57.0	19.2	13.4	73.8	74.3	56.8	71.6	55.7	45.1
w/ Encoder Distill	99.4	72.5	72.3	<u>57.6</u>	<u>19.4</u>	<u>13.6</u>	74.8	75.2	57.4	72.3	56.1	45.6
w/ KL Distill	98.6	<u>73.0</u>	<u>72.5</u>	57.0	<u>19.4</u>	13.4	73.5	<u>75.6</u>	<u>58.0</u>	71.0	<u>56.4</u>	<u>45.9</u>

the baseline without distillation (i.e., *w/o Distill*) in terms of the metric to measure generated answers (e.g., ACC, F1, and EM). Third, the proposed GRIPRANK outperforms the variant *w/ KL Distill*, indicating that the ranker trained by distilling the order knowledge from the GPE outperforms its counterpart distilling whole output distribution. We speculate that the output distribution of GPE may be too complex for the ranker to learn accurately.

More importantly, distilling the knowledge from GPE to the ranker narrows the gap between retrieval and generation. As shown in Table 3, the proposed GRIPRANK outperforms one of the competitive variants *w/ Encoder Distill* according to the metrics to evaluate answer generation (e.g., EM and KILT-EM for open-domain question answering), despite the fact that the latter presents a superior performance in passage retrieval in terms of *R-prec*. It indicates that simply improving the ranking capability of the ranker will not be beneficial to narrow the gap between retrieval and generation without explicitly considering how likely the candidate passages can be used to generate the target answer.

5.3 Effect of Curriculum Knowledge Distillation

To answer RQ3, we use different strategies to fetch n candidates¹ from the 100 most relevant passages collected by the passage retriever for training the ranker. We consider three fetching strategies: i) *Random*: We randomly select n candidates from the top 100 passages retrieved by the passage retriever. ii) *TopN*: We select n most relevant passages ranked at the top by the passage retriever. iii) *CPS*: We sample n candidates by our proposed Curriculum Passage Sampling strategy. Furthermore, we investigate how each strategy impact passage ranking in distinguishing the relevant passages from many plausible candidates by progressively expanding the candidate passage pool during validation. We evaluate the performance of each variant through two indicative metrics for passage ranking, i.e., *R-prec* and *Recall@5*.

Figure 3 shows the impact of different passage fetching strategies on the passage ranker, from which we have the following observations: i): All variants performed on WoW and NQ datasets lose the retrieval accuracy with the growing size of the candidate passage pool in terms of *R-prec*. It indicates there are a growing number of plausible candidates with the expansion of the candidate passage pool, challenging the passage ranker to distinguish the provenance from them correctly. More importantly, the proposed CPS drops the most slightly compared with two other variants, indicating the effectiveness of our proposed approach in distinguishing the answer provenance from many plausible candidates. ii): Both CPS

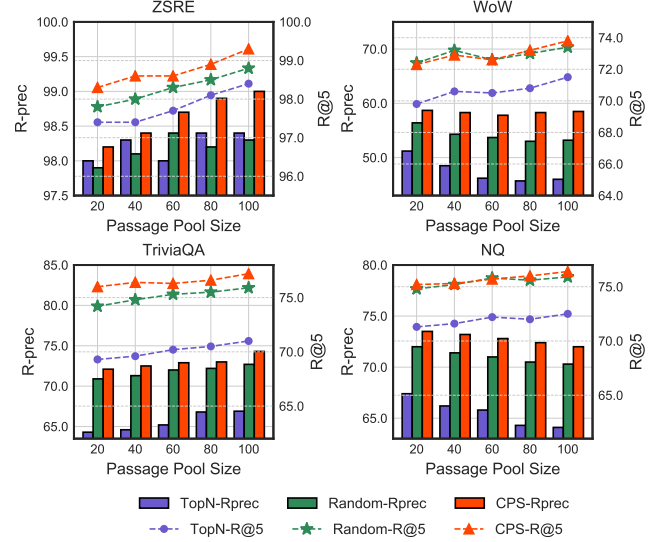


Figure 3: The impact of different passage fetching strategies on the passage ranker. We report *R-prec* and *Recall@5* on the validation set of each dataset.

and *Random* fetching strategies outperform *TopN* fetching strategy according to *R-prec* and *Recall@5*, which indicates that simply fetching the top-ranked candidates as hard negatives may be too hard for the passage ranker to distinguish the answer provenance, thus hinder the learning of the passage ranker. iii): The proposed CPS outperforms *Random* fetching strategy across all datasets according to *R-prec*, indicating the effectiveness of the proposed curricula in boosting the ranking capability of the passage ranker.

5.4 Impact of Different Passage Estimators

To answer RQ4, we employ different generative pre-trained language models, including BART [30], T5 [45] and GPT2 [44], to serve as the generative passage estimators. Table 4 reports the results, from which we have two main observations: i): To the same backbone model, the larger model has a stronger capability in ranking the candidate passages into the correct order. For example, the BART-Large outperforms BART-Base by around 1.2 points on average over all datasets in terms of *R-Prec*, which subsequently improves the generation performance further. ii): To the different backbone models, the BART-Large achieves comparable performance with T5-Large with fewer parameters used. While both the

¹We set $n = 5$ for all fetching strategies to facilitate a fair comparison.

Table 4: Impact of using different generative language models as the generative passage estimator (GPE).

GPEs	Params	ZSRE			WoW			TriviaQA			NQ		
		R-prec	ACC	KILT-ACC	R-prec	F1	KILT-F1	R-prec	EM	KILT-EM	R-prec	EM	KILT-EM
GPT2-medium	345M	97.2	72.7	72.4	57.1	19.5	13.7	73.4	75.3	57.0	69.8	55.7	45.2
GPT2-large	774M	97.7	73.2	72.8	57.6	19.9	14.0	73.8	76.0	<u>58.0</u>	70.5	56.1	45.5
T5-base	220M	98.0	73.0	72.7	57.4	19.8	14.2	73.5	75.9	57.8	70.8	56.6	45.7
T5-large	770M	<u>98.6</u>	74.4	74.2	<u>58.0</u>	20.5	14.6	74.3	<u>76.4</u>	57.9	<u>71.5</u>	<u>56.9</u>	<u>46.3</u>
BART-base	139M	97.8	72.9	72.6	57.1	19.6	13.8	73.2	75.5	57.5	71.1	56.5	45.9
BART-large	406M	99.0	<u>73.8</u>	<u>73.5</u>	58.5	<u>20.2</u>	<u>14.3</u>	74.3	76.8	58.2	72.0	57.3	46.4

Table 5: Cases from the ZSRE and the WoW validation set. Blue boldface is the essential associated with the golden answer.

	Knowledge-Enhanced Dialogue Generation (WoW)	Zero-Shot Slot Filling (ZSRE)
<i>Input Query:</i>	Do you ever enjoy listening to gospel music?	Badrock [SEP] from fictional universe
<i>Answer Provenance:</i>	Gospel music is a genre of Christian music... Gospel music usually has dominant vocals (often with strong use of harmony) with Christian lyrics. Gospel music can be traced to the early 17th century, with roots in the black oral tradition...	Being one of the most popular members of Youngblood (both in the fictional Image Universe and with real-life comic readers), Badrock starred in more spin-off comics than any other member of the team. Many of Badrock’s non-Youngblood adventures...
KGI₀:	I do! I like the music from the 1940s and 1950s.	The Flintlockers
SEAL:	I do! I love the music that is composed and performed for many purposes, including aesthetic pleasure, religious or ceremonial purposes.	Youngblood
GRIPRANK:	I do! I like the music of the early 17th century, with roots in the black oral tradition.	Image Universe
Golden Answer:	I listen to a bit of Christian music , but I don’t really like the genre of Gospel music . I prefer Christian music with a more popular genre.	Image Universe

T5-Large and the BART-Large outperform GPT2-Large on both passage retrieval and answer generation. We suspect it may be attributed to the difference in the pre-training data and tasks used for these generative language models.

5.5 Case Study

To answer **RQ5**, we take input queries from the WoW validation set (knowledge-enhanced dialogue generation task) and the ZSRE validation set (zero-shot slot filling task), and show the generated results from our proposed GRIPRANK and two other competitive baselines, i.e., KGI₀ and SEAL.

As shown in Table 5, we have two main observations: i): In the case of WoW, the responses generated by KGI₀ and SEAL deliver no essentials evidenced by the answer provenance. In contrast, the GRIPRANK generates a response that is faithful to the provenance. It incorporates evidence snippets relevant to the dialogue context into the generated response, considering both knowledgeability and conversational ability. ii): In the case of ZSRE, both KGI₀ and SEAL produce incorrect answers. Specifically, the KGI₀ suffers from the extrinsic hallucination problem [24], which generates an answer “*The Flintlocker*” that is not mentioned in the provenance. We suspect it is because the provenance is out-of-recall from the candidates retrieved by KGI₀. In particular, both SEAL and the proposed GRIPRANK deliver an answer that appears in provenance, while the GRIPRANK shows a better ability to make better use of

the retrieved passages for generating the correct answer, benefiting from its superior passage ranking capability.

6 CONCLUSIONS

In this paper, we focus on narrowing the gap between retrieval and generation for retrieval-enhanced text generation methods. We propose GRIPRANK, a novel approach to improve the passage ranking capability by distilling knowledge from a generative passage estimator to the passage ranker. We evaluate our approach on diverse knowledge-intensive language tasks, including zero-shot slot filling, open-domain question answering, and knowledge-enhanced dialogue generation. Experimental results show that the proposed GRIPRANK presents advantages over previous state-of-the-art approaches. Further analysis demonstrates the effectiveness of our proposed approach in narrowing the gap between passage retrieval and answer generation.

ACKNOWLEDGMENTS

We thank all the anonymous reviewers for their insightful comments. This work was supported in part by the National Natural Science Foundation of China (Grant Nos. 62276017, U1636211, 61672081), the 2022 Tencent Big Travel Rhino-Bird Special Research Program, and the Fund of the State Key Laboratory of Software Development Environment (Grant No. SKLSDE-2021ZX-18).

REFERENCES

- [1] Harith Alani, Zhaochen Guo, and Denilson Barbosa. 2018. Robust Named Entity Disambiguation with Random Walks. *Semant. Web* 9, 4 (jan 2018), 459–479.
- [2] Jiaqi Bai, Zhao Yan, Jian Yang, Xinnian Liang, Hongcheng Guo, and Zhoujun Li. 2023. KnowPrefix-Tuning: A Two-Stage Prefix-Tuning Framework for Knowledge-Grounded Dialogue Generation. *CoRR* abs/2306.15430 (2023).
- [3] Jiaqi Bai, Ze Yang, Jian Yang, Hongcheng Guo, and Zhoujun Li. 2023. KINet: Incorporating Relevant Facts Into Knowledge-Grounded Dialog Generation. *IEEE ACM Trans. Audio Speech Lang. Process.* 31 (2023), 1213–1222.
- [4] Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In *Proceedings of the 26th Annual International Conference on Machine Learning, ICML 2009, Montreal, Quebec, Canada, June 14-18, 2009*, Vol. 382. 41–48.
- [5] Michele Bevilacqua, Giuseppe Ottaviano, Patrick Lewis, Scott Yih, Sebastian Riedel, and Fabio Petroni. 2022. Autoregressive Search Engines: Generating Substrings as Document Identifiers. In *Advances in Neural Information Processing Systems*, S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (Eds.), Vol. 35. Curran Associates, Inc., 31668–31683.
- [6] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to rank: from pairwise approach to listwise approach. In *Machine Learning, Proceedings of the Twenty-Fourth International Conference (ICML 2007)*, Corvallis, Oregon, USA, June 20-24, 2007 (ACM International Conference Proceeding Series, Vol. 227). ACM, 129–136.
- [7] Keshigeyan Chandrasegaran, Ngoc-Trung Tran, Yunqing Zhao, and Ngai-Man Cheung. 2022. Revisiting Label Smoothing and Knowledge Distillation Compatibility: What was Missing?. In *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA (Proceedings of Machine Learning Research, Vol. 162)*. PMLR, 2890–2916.
- [8] Yen-Chun Chen, Zhe Gan, Yu Cheng, Jingzhou Liu, and Jingjing Liu. 2020. Distilling Knowledge Learned in BERT for Text Generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*. Association for Computational Linguistics, 7893–7905.
- [9] Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2019. Wizard of Wikipedia: Knowledge-Powered Conversational Agents. In *International Conference on Learning Representations*.
- [10] Hady Elsahar, Pavlos Vougiouklis, Arslan Remaci, Christophe Gravier, Jonathon Hare, Frederique Laforest, and Simperl Elena. 2018. T-Rex : A Large Scale Alignment of Natural Language with Knowledge Base Triples. In *LREC*.
- [11] Martin Fajcik, Martin Docekal, Karel Ondrej, and Pavel Smrz. 2021. R2-D2: A Modular Baseline for Open-Domain Question Answering. In *Findings of the Association for Computational Linguistics: EMNLP 2021*. Association for Computational Linguistics, 854–870.
- [12] Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. 2019. ELI5: Long Form Question Answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 3558–3567.
- [13] Xinyan Fan, Jianxun Lian, Wayne Xin Zhao, Zheng Liu, Chaohuo Li, and Xing Xie. 2022. Ada-Ranker: A Data Distribution Adaptive Ranking Paradigm for Sequential Recommendation. In *SIGIR '22: The 45th International ACM SIGIR Conference on Research and Development in Information Retrieval, Madrid, Spain, July 11 - 15, 2022*. ACM, 1599–1610.
- [14] Paolo Ferragina and Giovanni Manzini. 2000. Opportunistic data structures with applications. In *Proceedings 41st annual symposium on foundations of computer science*. IEEE, 390–398.
- [15] Michael R. Glass, Gaetano Rossiello, Md. Faisal Mahbub Chowdhury, and Alfio Gliozzo. 2021. Robust Retrieval Augmented Generation for Zero-shot Slot Filling. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*, Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (Eds.). Association for Computational Linguistics, 1939–1949.
- [16] Michael R. Glass, Gaetano Rossiello, Md. Faisal Mahbub Chowdhury, Ankita Naik, Pengshan Cai, and Alfio Gliozzo. 2022. Re2G: Retrieve, Rerank, Generate. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL 2022, Seattle, WA, United States, July 10-15, 2022*, Marine Carpuat, Marie-Catherine de Marneffe, and Iván Vladimir Meza Ruiz (Eds.). Association for Computational Linguistics, 2701–2715.
- [17] Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. 2020. REALM: Retrieval-Augmented Language Model Pre-Training. *CoRR* abs/2002.08909 (2020). arXiv:2002.08909
- [18] Huang He, Hua Lu, Siqi Bao, Fan Wang, Hua Wu, Zhengyu Niu, and Haifeng Wang. 2021. Learning to Select External Knowledge with Multi-Scale Negative Sampling. *CoRR* abs/2102.02096 (2021).
- [19] Xingwei He, Yeyun Gong, A-Long Jin, Weizhen Qi, Hang Zhang, Jian Jiao, Bartuer Zhou, Biao Cheng, Sm Yiu, and Nan Duan. 2022. Metric-guided Distillation: Distilling Knowledge from the Metric to Ranker and Retriever for Generative Commonsense Reasoning. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022*. Association for Computational Linguistics, 839–852.
- [20] Geoffrey E. Hinton, Oriol Vinyals, and Jeffrey Dean. 2015. Distilling the Knowledge in a Neural Network. *CoRR* abs/1503.02531 (2015).
- [21] Sebastian Hofstätter, Jiecao Chen, Karthik Raman, and Hamed Zamani. 2022. FiD-Light: Efficient and Effective Retrieval-Augmented Text Generation. *CoRR* abs/2209.14290 (2022).
- [22] Sebastian Hofstätter, Jiecao Chen, Karthik Raman, and Hamed Zamani. 2022. Multi-Task Retrieval-Augmented Text Generation with Relevance Sampling. *CoRR* abs/2207.03030 (2022).
- [23] Gautier Izacard and Edouard Grave. 2021. Leveraging Passage Retrieval with Generative Models for Open Domain Question Answering. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, EACL 2021, Online, April 19 - 23, 2021*, Paola Merlo, Jörg Tiedemann, and Reut Tsarfay (Eds.). Association for Computational Linguistics, 874–880.
- [24] Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. 2023. Survey of Hallucination in Natural Language Generation. *ACM Comput. Surv.* 55, 12, Article 248 (mar 2023), 38 pages.
- [25] Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. 2019. TinyBERT: Distilling BERT for Natural Language Understanding. *CoRR* abs/1909.10351 (2019).
- [26] Mandar Joshi, Eunsol Choi, Daniel S. Weld, and Luke Zettlemoyer. 2017. TriviaQA: A Large Scale Distantly Supervised Challenge Dataset for Reading Comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*. Association for Computational Linguistics, 1601–1611.
- [27] Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick S. H. Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense Passage Retrieval for Open-Domain Question Answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu (Eds.). Association for Computational Linguistics, 6769–6781.
- [28] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural Questions: A Benchmark for Question Answering Research. *Transactions of the Association for Computational Linguistics* 7 (2019), 452–466.
- [29] Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Zettlemoyer. 2017. Zero-Shot Relation Extraction via Reading Comprehension. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, Vancouver, Canada, August 3-4, 2017. Association for Computational Linguistics, 333–342.
- [30] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel R. Tetreault (Eds.). Association for Computational Linguistics, 7871–7880.
- [31] Patrick S. H. Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin (Eds.).
- [32] Zheng Li, Xiang Li, Lingfeng Yang, Borui Zhao, Renjie Song, Lei Luo, Jun Li, and Jian Yang. 2022. Curriculum Temperature for Knowledge Distillation. *CoRR* abs/2211.16231 (2022).
- [33] Zhenghao Lin, Yeyun Gong, Xiao Liu, Hang Zhang, Chen Lin, Anlei Dong, Jian Jiao, Jingwen Lu, Daxin Jiang, Rangan Majumder, and Nan Duan. 2023. PROD: Progressive Distillation for Dense Retrieval. In *Proceedings of the ACM Web Conference 2023, WWW 2023, Austin, TX, USA, 30 April 2023 - 4 May 2023*. ACM, 3299–3308.
- [34] Jihao Liu, Boxiao Liu, Hongsheng Li, and Yu Liu. 2022. Meta Knowledge Distillation. *CoRR* abs/2202.07940 (2022).
- [35] Jean Maillard, Vladimir Karpukhin, Fabio Petroni, Wen-tau Yih, Barlas Oguz, Veselin Stoyanov, and Gargi Ghosh. 2021. Multi-Task Retrieval for Knowledge-Intensive Tasks. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. Association for Computational Linguistics, 1098–1111.
- [36] Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. 2016. MS MARCO: A Human Generated Machine Reading Comprehension Dataset. In *Proceedings of the Workshop on Cognitive Computation: Integrating neural and symbolic approaches 2016 co-located with the*

- 30th Annual Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain, December 9, 2016 (CEUR Workshop Proceedings, Vol. 1773). CEUR-WS.org.
- [37] Jianmo Ni, Chen Qu, Jing Lu, Zhuyun Dai, Gustavo Hernández Abrego, Ji Ma, Vincent Y. Zhao, Yi Luan, Keith B. Hall, Ming-Wei Chang, and Yinfei Yang. 2022. Large Dual Encoders Are Generalizable Retrievers. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7–11, 2022*, Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (Eds.). Association for Computational Linguistics, 9844–9855.
- [38] Rodrigo Frassetto Nogueira and Kyunghyun Cho. 2019. Passage Re-ranking with BERT. *CoRR* abs/1901.04085 (2019).
- [39] Ashwin Paranjape, Omar Khattab, Christopher Potts, Matei Zaharia, and Christopher D. Manning. 2022. Hindsight: Posterior-guided training of retrievers for improved open-ended generation. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25–29, 2022*. OpenReview.net.
- [40] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Z. Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8–14, 2019, Vancouver, BC, Canada*. 8024–8035.
- [41] Fabio Petroni, Aleksandra Piktus, Angela Fan, Patrick S. H. Lewis, Majid Yazdani, Nicola De Cao, James Thorne, Yacine Jernite, Vladimir Karpukhin, Jean Mailard, Vassilis Plachouras, Tim Rocktäschel, and Sebastian Riedel. 2021. KILT: a Benchmark for Knowledge Intensive Language Tasks. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6–11, 2021*. Association for Computational Linguistics, 2523–2544.
- [42] Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Dmytro Okhonko, Samuel Broscheit, Gautier Izacard, Patrick S. H. Lewis, Barlas Oguz, Edouard Grave, Wen-tau Yih, and Sebastian Riedel. 2021. The Web Is Your Oyster - Knowledge-Intensive NLP against a Very Large Web Corpus. *CoRR* abs/2112.09924 (2021).
- [43] Yifan Qiao, Chenyan Xiong, Zhenghao Liu, and Zhiyuan Liu. 2019. Understanding the Behaviors of BERT in Ranking. *CoRR* abs/1904.07531 (2019). arXiv:1904.07531
- [44] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. [n. d.]. Language models are unsupervised multitask learners. ([n. d.]).
- [45] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. *J. Mach. Learn. Res.* 21 (2020), 140:1–140:67.
- [46] Sashank J. Reddi, Rama Kumar Pasumarthi, Aditya Krishna Menon, Ankit Singh Rawat, Felix X. Yu, Seungyeon Kim, Andreas Veit, and Sanjiv Kumar. 2021. RankDistil: Knowledge Distillation for Ranking. In *The 24th International Conference on Artificial Intelligence and Statistics, AISTATS 2021, April 13–15, 2021, Virtual Event (Proceedings of Machine Learning Research, Vol. 130)*. PMLR, 2368–2376.
- [47] Nils Reimers and Iryna Gurevych. 2021. The Curse of Dense Low-Dimensional Information Retrieval for Large Index Sizes. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 2: Short Papers), Virtual Event, August 1–6, 2021*. Association for Computational Linguistics, 605–611.
- [48] Ruiyang Ren, Yingqi Qu, Jing Liu, Wayne Xin Zhao, Qiaobao She, Hua Wu, Haifeng Wang, and Ji-Rong Wen. 2021. RocketQAv2: A Joint Training Method for Dense Passage Retrieval and Passage Re-ranking. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7–11 November, 2021*, Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (Eds.). Association for Computational Linguistics, 2825–2835.
- [49] Stephen E. Robertson and Hugo Zaragoza. 2009. The Probabilistic Relevance Framework: BM25 and Beyond. *Found. Trends Inf. Retr.* 3, 4 (2009), 333–389.
- [50] Lin CY ROUGE. 2004. A package for automatic evaluation of summaries. In *Proceedings of Workshop on Text Summarization of ACL, Spain*.
- [51] Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Rich James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. 2023. REPLUG: Retrieval-Augmented Black-Box Language Models. *CoRR* abs/2301.12652 (2023).
- [52] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, and Jamie Brew. 2019. HuggingFace’s Transformers: State-of-the-art Natural Language Processing. *CoRR* abs/1910.03771 (2019).
- [53] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. Transformers: State-of-the-Art Natural Language Processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, EMNLP 2020 - Demos, Online, November 16–20, 2020*. Association for Computational Linguistics, 38–45.
- [54] Fen Xia, Tie-Yan Liu, Jue Wang, Wensheng Zhang, and Hang Li. 2008. List-wise approach to learning to rank: theory and algorithm. In *Machine Learning, Proceedings of the Twenty-Fifth International Conference (ICML 2008), Helsinki, Finland, June 5–9, 2008 (ACM International Conference Proceeding Series, Vol. 307)*, William W. Cohen, Andrew McCallum, and Sam T. Roweis (Eds.). ACM, 1192–1199.
- [55] Jian Yang, Shuming Ma, Li Dong, Shaohan Huang, Haoyang Huang, Yuwei Yin, Dongdong Zhang, Lijun Yang, Furu Wei, and Zhoujun Li. 2023. GanLM: Encoder-Decoder Pre-training with an Auxiliary Discriminator. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9–14, 2023*. Association for Computational Linguistics, 9394–9412.
- [56] Jian Yang, Yuwei Yin, Shuming Ma, Dongdong Zhang, Shuangzhi Wu, Hongcheng Guo, Zhoujun Li, and Furu Wei. 2022. UM4: Unified Multilingual Multiple Teacher-Student Model for Zero-Resource Neural Machine Translation. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI 2022, Vienna, Austria, 23–29 July 2022*. ijcai.org, 4454–4460.
- [57] Shuo Yang, Sujay Sanghavi, Holakou Rahmanian, Jan Bakus, and Vishwanathan S. V. N. 2022. Toward Understanding Privileged Features Distillation in Learning-to-Rank. In *Advances in Neural Information Processing Systems*, Vol. 35. Curran Associates, Inc., 26658–26670.
- [58] Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Brussels, Belgium, 2369–2380.
- [59] Michihiro Yasunaga, Armen Aghajanyan, Weijia Shi, Rich James, Jure Leskovec, Percy Liang, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. 2022. Retrieval-Augmented Multimodal Language Modeling. *CoRR* abs/2211.12561 (2022).
- [60] Jingtao Zhan, Jiaxin Mao, Yiqun Liu, Jiafeng Guo, Min Zhang, and Shaoping Ma. 2021. Optimizing Dense Retrieval Model Training with Hard Negatives. In *SIGIR ’21: The 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, Virtual Event, Canada, July 11–15, 2021*. ACM, 1503–1512.