

Distilling a Small Utility-Based Passage Selector to Enhance Retrieval-Augmented Generation

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Abstract

Retrieval-augmented generation (RAG) enhances large language models (LLMs) by incorporating retrieved information. Standard retrieval process prioritized relevance, focusing on topical alignment between queries and passages. In contrast, in RAG, the emphasis has shifted to utility, which considers the usefulness of passages for generating accurate answers. Despite empirical evidence showing the benefits of utility-based retrieval in RAG, the high computational cost of using LLMs for utility judgments limits the number of passages evaluated. This restriction is problematic for complex queries requiring extensive information. To address this, we propose a method to distill the utility judgment capabilities of LLMs into smaller, more efficient models. Our approach focuses on utility-based selection rather than ranking, enabling dynamic passage selection tailored to specific queries without the need for fixed thresholds. We train student models to learn pseudo-answer generation and utility judgments from teacher LLMs, using a sliding window method that dynamically selects useful passages. Our experiments demonstrate that utility-based selection provides a flexible and cost-effective solution for RAG, significantly reducing computational costs while improving answer quality. We present the distillation results using Qwen3-32B as the teacher model for both relevance ranking and utility-based selection, distilled into RankQwen_{1.7B} and UtilityQwen_{1.7B}. Our findings indicate that for

complex questions, utility-based selection is more effective than relevance ranking in enhancing answer generation performance. We will release the relevance ranking and utility-based selection annotations for the MS MARCO dataset, supporting further research in this area. Our code and datasets can be found at <https://github.com/Trustworthy-Information-Access/UtilitySelection>.

CCS Concepts

• **Information systems** → **Question answering**; **Novelty in information retrieval**; **Top-k retrieval in databases**.

Keywords

Relevance Ranking, Utility-based Selection, RAG

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1 Introduction

Retrieval-augmented generation (RAG) leverages retrieved information as external knowledge to empower large language models (LLMs) to answer questions. The criterion for measuring whether a result is helpful for RAG has shifted from relevance to utility [13, 29, 41, 43]. Relevance typically focuses on the topical matching between a query and retrieved passages [27, 28]. Utility, in contrast, emphasizes the usefulness of a passage in facilitating the generation of an accurate and comprehensive answer to the question [42]. Empirical results demonstrate that using retrieval results judged as having utility by LLMs in RAG can enhance the quality of subsequent answer generation [41, 43].

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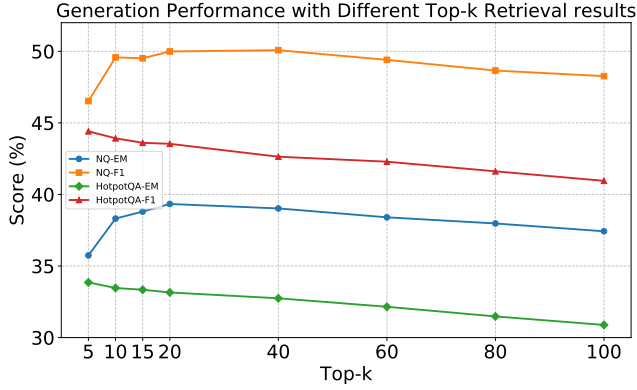


Figure 1: Different answer generation performance (generator: Llama-3.1-8B-Instruct) directly with different top- k retrieval results (retriever: BM25).

Due to the high computation cost, using LLMs for utility judgments usually takes 10 to 20 passages as context [41, 43]. This is insufficient for weaker retrievers that rank useful passages at lower positions, and when complex questions require many useful documents to generate comprehensive answers. Although it is promising to scale utility judgments to a large number of candidate passages for RAG, using LLMs to do so is cost-prohibitive. Therefore, we propose to distill the utility judgment capability of LLMs to smaller models that are efficient to do so.

In this paper, we focus on utility-based selection rather than ranking when distilling smaller models. There are two reasons: 1) Ke et al. [13] find that for effective RAG, the ranking of input passages is less critical than effectively filtering out low-quality passages. 2) The number of passages that should be selected for different questions can vary. As shown in Figure 1, the optimal number of passages used for simple questions (i.e., in NQ) and complex questions (i.e., in HotpotQA) is different. If we conduct utility ranking, a fixed threshold is usually used, which introduces a hyperparameter to tune and can be suboptimal. In contrast, utility-based selection mechanisms can dynamically determine how many passages to retain. Consequently, our goal is to distill a small utility-based selector from LLMs that are competent in zero-shot utility-based selection.

There have been several studies on distilling the zero-shot listwise ranking capability of LLMs (e.g., ChatGPT, GPT-4) into smaller efficient rankers [16, 21–23, 31], such as RankVicuna [21] and RankMistral [16]. The distilled student rankers ingest a large number of retrieval results using a sliding window-based bubble sort approach. The window is moved from lower to higher positions, popping the most relevant results to the head, until all the results are ranked. This approach, however, cannot be applied to utility-based selection due to the inherent differences. State-of-the-art (SOTA) utility judgment methods are based on pseudo answers that are generated from a group of input documents [41, 43]. This requires the student model to also inherit the answer generation capability from the teacher model. Moreover, to ensure decent pseudo-answer quality, results that are more likely to be useful are needed, indicating that the initial passages fed to the model should be of high ranks.

This argues for a dedicated approach for distilling small utility-based passage selectors and utility judgments of a large number of passages.

To this end, we propose a distilling approach that jointly learn pseudo-answer generation and utility judgments from teacher LLMs. For utility judgments with the student selector on a long initial ranking list, we propose a sliding window method that moves from higher to lower positions. At each step, the selector generates pseudo answers based on the selected useful results, and slides to the next window, which is comprised of the so-far selected useful results and the unseen passages. New selected useful results will be prepended to the selected result pool, and duplicates in the pool will be deleted, maintaining an ordered list of selected useful results. This process is repeated until all the candidate results are judged. This process ensures that the final selected useful results are based on the information of the entire candidate results. It also incurs a smaller cost than the above-mentioned ranking distillation due to smaller overlap between windows.

Following the current works for relevance ranking distillation [16, 22, 31], we also utilize the dataset of 100k queries, sampled from the MS MARCO training set by [31] for training. We employ Qwen3-32B [33] as teacher model to generate both relevance ranking and utility-based selection outputs. These outputs are then distilled into Qwen3-1.7B, yielding RankQwen_{1.7B} (for relevance ranking) and UtilityQwen_{1.7B} (for utility-based selection). To evaluate RAG performance, we utilize two QA datasets from BEIR [34]: NQ [14], and HotpotQA [40], on two kinds of top-100 initial candidate passages retrieved by two retrievers, i.e., BM25 [25] and BGE-base-en-v1.5 [39]. Following extensive experimentation, we found that: (1) For simple questions, such as those in the NQ dataset, relevance ranking (by adjusting various thresholds) demonstrated no statistically significant difference in optimal answer generation performance compared to directly using utility-based selection. (2) However, for complex questions, exemplified by the HotpotQA dataset, relevance ranking proved insufficient; utility-based selection was more effective in helping large language models (LLMs) identify document sets pertinent to answering the query. (3) Our utility-based selection method adaptively determines the number of useful passages based on the query and the passages. A key consequence is that selecting fewer documents per query enables more unprocessed passages to be handled within each sliding window iteration. This results in fewer window iterations for utility-based selection compared to relevance ranking, dramatically reducing the computational cost of LLM inference. Using merely 30% of the computational time, this approach yields higher-quality passages and, consequently, superior answers. Additionally, we will release the Qwen3-32B relevance ranking and utility-based selection annotations for the 100k MS MARCO dataset, providing a high-quality dataset for future research in relevance ranking and utility-based selection.

2 Related Work

In this section, we briefly review existing studies on LLM-based ranking and utility in Retrieval-Augmented Generation (RAG).

2.1 LLM-based Ranking

Ranking models frequently utilize a cross-encoder architecture, enabling fine-grained, token-level interactions between the query and the document text. Ranking approaches are categorized based on how they model the relationship between a query and documents: pointwise [18, 19], pairwise [4, 19, 20], and listwise [5, 9, 38, 44]. In the era of pre-trained language models (PLMs), owing to input length constraints, listwise ranking methods are typically implemented using pointwise inputs during training while employing listwise loss functions. This approach cannot be considered authentic listwise learning, as it inherently fails to capture query-document interactions during inference. The widespread adoption of Large Language Models (LLMs) has spurred significant advancements within the ranking domain, especially zero-shot listwise ranking [16, 22–24]. RankVicuna [21] and RankGPT [31] pioneered the application of using LLMs for zero-shot listwise ranking. RankZephyr [22] explored distilling the powerful listwise ranking capabilities of high-performing LLMs into smaller, more efficient models. Currently, the primary distillation signal involves relevance ranking sequence generated by LLM. Unlike these works, this work explores novel methods to distill utility-based selection capability of LLMs into smaller models.

2.2 Utility in RAG

Retrieval-Augmented Generation (RAG) typically involves two stages: retrieval and generation. While relevance serves as the primary optimization objective for the retriever, the ultimate goal in RAG shifts towards optimizing end-task question answering (QA) performance using outputs from effective retrievers, with less direct emphasis on retrieval metrics themselves [42]. Consequently, significant research has focused on the importance of retrieval utility – the measure of a passage’s contribution to generating a correct answer – within RAG systems [11, 29, 41–43]. Zhang et al. [43] was the first to propose directly using large language models (LLMs) to judge the utility of retrieved passages, demonstrating that LLM-generated pseudo-answers can effectively assist utility assessment. Zhang et al. [41] further introduced an approach based on Schutz’s theory of relevance to iteratively enhance LLM-based utility judgments. However, these methods are constrained by their reliance on utility judgments for only a small number of retrieval candidates per query. In contrast, Shi et al. [29] proposed quantifying utility score probabilistically, using either the likelihood of the ground-truth answer or performance differences on downstream tasks. This probabilistic approach, however, relies heavily on the availability of ground-truth answers. In this work, we extend utility-based selection to a significantly larger scale of retrieval candidates.

3 Utility-based Selection Distillation

Unlike relevance emphasizes topical matching between query and passage, utility focuses on the usefulness in generating an answer, which is more important in RAG. However, directly using powerful LLMs to judge the utility of large-scale passages is computationally expensive. Moreover, ranking approach needs a threshold to determine the number of passages to generate an answer, which is not query-specific. Therefore, we propose a novel utility-based

selection distillation approach. Specifically, utility-based distillation approach trains student selectors to learn pseudo-answer generation and utility judgment from teacher LLMs jointly. After distillation, the student model employs a front-to-back sliding window strategy to dynamically select optimal passage sets from large-scale candidates, which accounts for the dependency of pseudo-answers on input passages.

```

<system>You are the utility selector, an intelligent assistant that can select the passages that
have utility in answering the question.
<assistant> Yes, I am the utility selector.
<user>I will provide you with {num} passages, each indicated by number identifier [].
Select the passages that have utility in answering the question: {query}.
<assistant>Okay, please provide the passages.
<user> [1] {content}
<assistant>Received passage [1].
...
<user> [20] {content}
<assistant>Received passage [20].
<user> Question: {query}

Utility Requirement: A passage has utility only if it is both relevant to the question
AND useful for generating a correct and reasonable answer.

Firstly, provide the answer to the question based on the provided {num} passages or your
own knowledge without sources, which can help judge passages utility. Then, select the
passages that have utility in answering the question.

Output Format STRICTLY:

Answer: [Your generated answer here]

My selection: [[i],[j],...]

Only respond to the answer and the selected list, do not say any word or explain.

```

Figure 2: The prompt for utility-based selection. The bold is the special part for utility-based selection compared to relevance ranking.

3.1 Prompt Design

Figure 2 shows the prompt utilized for utility-based selection. The relevance ranking prompt is the same as Sun et al. [31].

3.2 Sliding Window for Utility-Based Selection

To overcome LLM token limitations during passage re-ranking, prior work often employs a sliding window strategy processed in back-to-front order [31], as shown in Figure 3 (a). This approach typically starts re-ranking the last w passages (window size), then slides backwards by stride size s , re-ranking passages from position $(M - w - s)$ to $(M - s)$ and repeats until reaching the beginning of the list, where M is the number of candidate passages. This back-to-front progression is effective for relevance permutation generation.

However, utility-based selection presents a distinct challenge: the generation of high-quality pseudo-answers, essential for estimating passage utility, is sensitive to the quality of the input passages provided to the LLM. Feeding lower-quality passages in the process can degrade pseudo-answer generation and subsequent utility judgments for all passages. To address this dependency and ensure robust pseudo-answer generation, we propose a forward-propagating sliding window strategy, processing passages from front to back.

As depicted in Figure 3 (b), our method operates as follows: For the first window (positions 1 to w), the LLM judges the utility of the w passages within the current window and selects passages

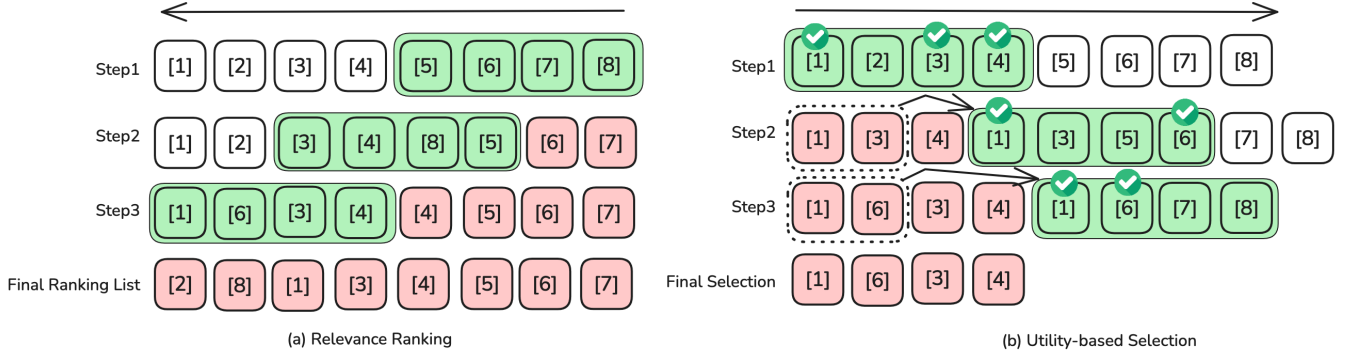


Figure 3: This diagram depicts an 8 passage selection ($M = 8$) process using a sliding window $w = 4$, stride $s = 2$: (a) relevance ranking and (b) utility-based selection. Greed part means the windows, and the arrow indicates the direction of the window sliding. Passages shown in red are those that have undergone re-ranking or preselected passages. White passages denote unprocessed passages. For utility-based selection, s documents (within the dashed-border box) from the preselected queue are placed into the processing window for utility-based selection. Documents selected within the current window are prepended to the head of the preselected queue.

that have utility. Selected passages are prepended to the preselected queue. The original queue content is duplicated and positioned after the new selections. The window slides forward by a stride size s . Specifically, the first s passages from the current preselected queue are carried forward as input into the next window, which propagates high-utility context in the sequence. The next window now consists of these first s propagated passages from the preselected queue, followed by the next $w - s$ unprocessed passages from the original list (maintaining their sequence). The LLM then performs utility-based selection within this new window context. Repeat until all M passages have been processed. The final preselected queue represents the utility-based selection results.

4 Experiment Setup

We distill the relevance ranking and utility-based selection capabilities from larger 32B LLMs into compact 1.7B models, yielding RankQwen_{1.7B} and UtilityQwen_{1.7B}. We conduct comparative analyses of both RankQwen_{1.7B} and UtilityQwen_{1.7B} on Retrieval-Augmented Generation (RAG) datasets. Additionally, we evaluate RankQwen_{1.7B} in established experiments to compare its ranking performance with prior works [17, 18, 25, 26, 39]. This section introduces the datasets and implementation details used in this work.

4.1 Datasets and Evaluation

RAG. We use the two subsets of BEIR, i.e., NQ [14], which consists of real questions issued to the Google search engine, and HotpotQA [40], which consists of 7405 QA pairs requiring multi-hop reasoning gathered via Amazon Mechanical Turk. We used the queries with ground truth answers from queries on NQ and then filtered 2,255 queries for RAG evaluation. We process the top-100 candidate documents retrieved by two retrievers, i.e., BM25 [25] and BGE-base-en-v1.5 [39] through distinct pathways: 1) Re-ranking via our RankQwen_{1.7B} model; 2) Utility-based selection via our UtilityQwen_{1.7B} model. Subsequently, the top- k passages from the re-ranked list and all passages selected by the UtilityQwen_{1.7B} served as evidence for answer generation using the same underlying generator. RAG performance was evaluated on two aspects: 1)

Evidence Selection: Measured by recall, precision, and micro-F1 score. 2) **Answer Generation:** Measured by Exact Match (EM) and F1 score.

Ranking. We adopt consistent datasets and metrics with Sun et al. [31] for ranking performance. Specifically, we leveraged test collections from the TREC 2019 and 2020 Deep Learning Tracks [7]. These tracks employed the MS MARCO v1 passage corpus [1], comprising approximately 8.8 million passages. To further evaluate RankQwen’s generalization capability beyond the MS MARCO v1 dataset, we assessed it on the BEIR benchmark [34] following Sun et al. [31]: TREC-COVID [36], NFCorpus [3], Touche [2], DBpedia [10], SCIDOCs [6], SciFact [37], TREC-News [30], Rousust04 [35]. All ranking models re-rank the top-100 passages retrieved by BM25 using pyserini¹ and use nDCG@10 as evaluation metrics.

4.2 Implementation Details

LLMs. We employ the state-of-the-art open-source Qwen3-32B [33] model as the teacher for both relevance ranking and utility-based selection functions. Through generative distillation, we transfer these capabilities to a compact Qwen3-1.7B student architecture, yielding the specialized models RankQwen_{1.7B} and UtilityQwen_{1.7B}. In our RAG pipeline, we integrate the distilled models with two distinct generators to examine robustness: Llama-3.1-8B-Instruct [8] and Qwen2.5-7B-Instruct [32]. To ensure reproducibility, the temperature for all LLMs in this study was set to 0.

Teacher Model Annotation. We employed Qwen2.5-32B as annotators for relevance ranking and utility-based selection. The annotated queries were derived from 100K training queries sourced from the MS MARCO v1 passage ranking dataset, originally curated by Sun et al. [31]. For each query, the top 20 candidate passages were retrieved using BM25 via Pyserini [15]. Qwen3-32B then re-ranked these passages to generate teacher orderings and select passages with utility according to the prompt in Figure 2, which were later distilled into smaller ranker and selector, respectively. Following RankZephyr [22], we also enhanced the relevance ranking annotations’ quality and robustness by excluding malformed generations

¹<https://github.com/castorini/pyserini>

from the training data. This exclusion targeted examples exhibiting improper list formatting, missing document identifiers, or repetitive elements.

Distillation Training Details. Using the axolotl library² on eight NVIDIA A800 80GB GPUs, we trained the 1.7B parameter Qwen 3 model [33] for three epochs on both ranking and selection data generated by Qwen3-32B. Training employed bfloat16 precision, an effective batch size of 64, and a learning rate of 5×10^{-6} . Mirroring RankZephyr [22], we also incorporated noisy embeddings, a method demonstrated to enhance instruction fine-tuning [12].

Inference Details. For both relevance ranking and utility-based selection tasks, we employed two retrievers, BM25 [25] and BGE-base-en-v1.5 [39], to retrieve the initial top-100 ($M = 100$) candidate lists. During inference, two sliding window strategies were applied to both tasks, respectively. The window size was set to 20 ($w = 20$), with a stride size of 10 ($s = 10$).

5 Experimental Results

We propose a novel utility-based selection distillation approach to transfer the capability for utility judgment into smaller, more efficient models, and conducted a comparative analysis between relevance ranking (top- k passages are used to answer generation) and utility-based selection for answer generation on RAG. The RAG performance, presented comprehensively in Table 1, reveal four key insights: (i) Evidence performance: Our utility-based selection achieves best performance among different generators and different initial retrieval candidate lists. (ii) Answer generation performance: For simple questions, such as those in the NQ dataset, relevance ranking (by adjusting various thresholds) demonstrated no statistically significant difference in optimal answer generation performance compared to directly using utility-based selection. However, for complex questions, exemplified by the HotpotQA dataset, relevance ranking proved insufficient; utility-based selection was more effective in helping large language models (LLMs) identify document sets pertinent to answering the query. This substantial improvement stems from the inherent requirement of multi-hop reasoning: generating an answer often necessitates identifying a set of complementary passages, i.e., set-based utility-based selection, that collectively provide the necessary evidence, which is beyond relevance. (iii) With a better initial retrieval candidate, such as BGE, the UtilityQwen_{1.7B} model shows a larger performance margin compared to RankQwen_{1.7B}. This improvement may be because better initial retrieval candidates enable UtilityQwen to generate higher-quality pseudo-answers, which further enhances its utility judgment performance. (iv) Given the same re-ranked results, Llama-3.1-8B-Instruct achieves peak performance using only the top 5 passages. Conversely, Qwen2.5-7B-Instruct performs optimally across various top- k values, indicating potentially distinct passage digestion capabilities. Crucially, utility-based selection demonstrates superior robustness. It consistently outperforms fixed top- k approaches across diverse generators, datasets, and initial retrieval lists. Therefore, our approach provides a robust alternative by dynamically selecting the most useful passages. It achieves answer quality comparable to or exceeding the best-performing fixed top- k cutoff for any given configuration, while entirely eliminating

the need for manual k -selection. These findings demonstrate that UtilityQwen_{1.7B} offers a superior and more adaptable paradigm for passage selection in RAG, particularly for complex information needs, by explicitly optimizing for the collective utility of passages in supporting accurate answer generation.

6 Further Analysis

We further analyze the (1) ranking performance of RankQwen_{1.7B} used in our experiments, (2) the impact of distillation training and the LLM backbone, (3) a statistics study on utility-based selection, and (4) the inference efficiency of both relevance ranking and utility-based selection.

6.1 Ranking Performance

To validate the ranking efficacy of our RankQwen_{1.7B}, we comprehensively compare different ranking model performance across the TREC and BEIR datasets, comprising: (1) Retrievers: BM25 [25] and BGE-base-en-v1.5 [39]; (2) Supervised cross-encoders: monoBERT [17], monoT5 [18], and Cohere Rerank-v2³; (3) Unsupervised cross-encoder: UPR [26]; (4) Zero-shot LLM listwise re-ranking; (5) Relevance ranking distillation, as shown in Table 2. We can observe that: (i) Zero-Shot LLM Superiority: Large language models (LLMs) operating in a zero-shot listwise ranking paradigm (e.g., GPT-4) demonstrably outperform supervised cross-encoder baselines (e.g., monoT5-3B) on both the TREC and BEIR benchmark, indicating the profound semantic understanding capabilities inherent in LLMs, enabling highly effective relevance ranking without task-specific training. (ii) Our distilled model, RankQwen_{1.7B}, notably surpasses the ChatGPT by 5.5% in terms of nDCG@10 on BEIR average. RankQwen_{1.7B} establishes a new state-of-the-art ranker among open source distillation efficient listwise rankers and highlights the exceptional ranking aptitude of the Qwen3 backbone upon which RankQwen_{1.7B} is built. (iii) **Discussion on Reasoning LLMs for Ranking:** Qwen3-series models support an optional reasoning process (thinking) during generation. We conducted relevance ranking annotations under two configurations: 1) Qwen3-32B with reasoning process and 2) Qwen3-32B without reasoning process. For efficiency, we distilled only the final ranking sequences from both configurations into the student ranker, rather than simulating intermediate reasoning steps. Both distilled rankers achieved better ranking performance compared to other rankers. The non-reasoning ranking sequences distillation slightly outperformed the reasoning variant. Based on this efficiency-performance tradeoff, all LLMs in this study operate without reasoning processes unless explicitly noted. In summary, these results provide a robust, high-performance ranking foundation essential for the subsequent in-depth analysis in this work.

6.2 Impact of Distillation Training

To validate the effectiveness of distillation training, we performed utility-based selection on the top-100 BM25 retrieval results for NQ and HotpotQA directly using both the teacher model (Qwen3-32B) and the student model (Qwen3-1.7B) without distillation training. The experimental results are summarized in Table 3. We observe that the student model fine-tuned via generation distillation

²<https://github.com/OpenAccess-AI-Collective/axolotl>

³<https://cohere.com/rerank>

Table 1: Selected evidence performance (%) and answer generation performance (%) using relevance ranking (RankQwen_{1.7B}) and utility-based selection (UtilityQwen_{1.7B}) models with different generators and different Top-100 retrieval results. [†] means that the performance of answer generation corresponding to the passages selected by Top-*k* of RankQwen_{1.7B} is significantly different from that of the passages selected by UtilityQwen_{1.7B} on the paired t-test (p<0.05). “Llama3.1” and “Qwen2.5” are the “Llama3.1-8B-Instruct” and “Qwen2.5-7B-Insrtuct”, respectively. Underline and **Bold indicate the best performance within each group and overall.**

Generator	Evidence	Retriever: BGE						Retriever: BM25					
		HotpotQA			NQ			HotpotQA			NQ		
		Evidence	Answer		Evidence	Answer		Evidence	Answer		Evidence	Answer	
		Micro-F1	EM	F1	Micro-F1	EM	F1	Micro-F1	EM	F1	Micro-F1	EM	F1
Llama3.1	RankQwen _{1.7B} (Top-5)	<u>41.70</u>	<u>38.39</u> [†]	<u>49.68</u> [†]	<u>28.44</u>	<u>48.03</u>	<u>59.93</u>	<u>38.48</u>	<u>37.81</u> [†]	<u>48.97</u> [†]	<u>24.14</u>	45.32	<u>56.61</u>
	RankQwen _{1.7B} (Top-10)	34.55	36.92 [†]	48.21 [†]	23.52	47.72 [†]	59.34 [†]	31.84	36.83 [†]	47.91 [†]	19.71	45.01	56.27
	RankQwen _{1.7B} (Top-15)	29.93	36.81 [†]	48.08 [†]	20.31	47.72 [†]	59.23 [†]	29.29	36.45 [†]	47.65 [†]	16.87	45.14	56.22
	RankQwen _{1.7B} (Top-20)	26.58	36.43 [†]	47.49 [†]	17.97	46.92 [†]	58.30 [†]	24.64	35.84 [†]	46.84 [†]	14.84	44.61	55.35 [†]
	RankQwen _{1.7B} (Top-40)	23.31	35.33 [†]	46.02 [†]	15.67	46.47 [†]	58.16 [†]	20.80	35.69 [†]	46.36 [†]	12.89	43.50	54.27 [†]
	RankQwen _{1.7B} (Top-60)	20.67	34.63 [†]	45.29 [†]	13.83	46.12 [†]	57.43 [†]	17.97	34.31 [†]	44.90 [†]	11.35	41.55 [†]	52.39 [†]
	RankQwen _{1.7B} (Top-80)	18.55	33.71 [†]	44.29 [†]	12.36	45.35 [†]	56.01 [†]	15.83	33.54 [†]	43.99 [†]	10.13	41.02 [†]	51.90 [†]
	RankQwen _{1.7B} (Top-100)	16.83	32.92 [†]	43.62 [†]	11.18	45.59 [†]	56.53 [†]	14.16	32.75 [†]	43.09 [†]	9.15	38.36 [†]	49.57 [†]
	UtilityQwen _{1.7B}	60.58	41.59	53.56	30.54	49.31	60.86	57.03	39.00	50.57	28.80	45.06	56.83
Qwen2.5	RankQwen _{1.7B} (Top-5)	41.70	42.13 [†]	53.98 [†]	<u>28.44</u>	48.03	60.17	38.48	39.97 [†]	51.53 [†]	24.14	44.88	56.61
	RankQwen _{1.7B} (Top-10)	34.55	<u>42.36</u> [†]	<u>54.15</u> [†]	23.52	<u>48.12</u>	60.54	31.84	39.69 [†]	50.98 [†]	19.71	<u>44.97</u>	57.07
	RankQwen _{1.7B} (Top-15)	29.93	42.27 [†]	54.00 [†]	20.31	47.85	<u>60.56</u>	29.29	39.32 [†]	50.70 [†]	16.87	44.70	56.85
	RankQwen _{1.7B} (Top-20)	26.58	42.21 [†]	53.86 [†]	17.97	47.89	60.55	24.64	39.58 [†]	50.87 [†]	14.84	44.52	56.77
	RankQwen _{1.7B} (Top-40)	23.31	42.47 [†]	54.25 [†]	15.67	47.01	59.80	20.80	39.43 [†]	50.80 [†]	12.89	44.21	56.46
	RankQwen _{1.7B} (Top-60)	20.67	41.61 [†]	53.48 [†]	13.83	47.23	59.55 [†]	17.97	38.76 [†]	49.87 [†]	11.35	43.55	55.69
	RankQwen _{1.7B} (Top-80)	18.55	41.22 [†]	52.98 [†]	12.36	46.25 [†]	58.72 [†]	15.83	38.12 [†]	49.14 [†]	10.13	43.10	55.17 [†]
	RankQwen _{1.7B} (Top-100)	16.83	40.53 [†]	52.21 [†]	11.18	46.74 [†]	58.95 [†]	14.16	37.42 [†]	48.24 [†]	9.15	42.26 [†]	53.79 [†]
	UtilityQwen _{1.7B}	60.58	43.59	55.73	30.54	48.07	60.95	57.03	41.00	52.57	28.80	44.61	57.00

Table 2: Results (nDCG@10) (%) on TREC and BEIR. All ranking models re-rank the top-100 BM25 passages. Underline and **Bold indicate the best performance within each group and overall. * means the results are copied from the original paper.**

Method	DL19	DL20	Covid	NFCorpus	Touche	DBPedia	SciFact	Signal	News	Robust04	Avg
BM25* [25]	50.58	47.96	59.47	30.75	<u>44.22</u>	31.80	67.89	<u>33.05</u>	39.52	40.70	43.42
BGE-base-en-v1.5 [39]	<u>70.60</u>	71.70	<u>78.10</u>	<u>37.30</u>	25.70	<u>40.70</u>	<u>74.10</u>	28.90	<u>44.20</u>	<u>44.70</u>	51.60
monoBERT(340M)* [17]	70.50	67.28	70.01	36.88	31.75	41.87	71.36	31.44	44.62	49.35	47.16
monoT5(220M)* [18]	71.48	66.99	78.34	37.38	30.82	42.42	73.40	31.67	46.83	51.72	49.07
monoT5(3B)* [18]	71.83	<u>68.89</u>	80.71	38.97	32.41	<u>44.45</u>	<u>76.57</u>	<u>32.55</u>	<u>48.49</u>	<u>56.71</u>	<u>51.36</u>
Cohere Rerank-v2*	<u>73.22</u>	67.08	<u>81.81</u>	36.36	<u>32.51</u>	42.51	74.44	29.60	47.59	50.78	49.45
UPR(FLAN-T5-XL)* [26]	53.85	56.02	68.11	35.04	19.69	30.91	72.69	31.91	43.11	42.43	42.99
LLM Zero-shot Inference (Permutation generation)											
ChatGPT* [31]	65.80	62.91	76.67	35.62	36.18	44.47	70.43	32.12	48.85	50.62	49.37
GPT-4* [31]	75.59	<u>70.56</u>	85.51	38.47	38.57	47.12	74.95	34.40	52.89	57.55	53.68
Qwen3 _{1.7B}	60.32	55.83	65.65	33.61	45.47	39.05	64.36	32.53	43.29	40.44	45.55
Qwen3 _{32B}	73.33	70.35	85.48	<u>38.77</u>	32.27	44.97	<u>77.71</u>	32.08	50.67	60.65	52.82
LLM Distillation Training											
RankMistral _{7B} * [16]	<u>71.73</u>	68.07	78.00	33.10	27.46	37.71	66.22	30.04	37.10	39.54	43.65
PE-Rank _{7B} * [16]	70.48	63.54	77.72	36.39	33.06	40.05	69.38	33.74	<u>49.70</u>	47.40	48.43
RankQwen _{1.7B} (Teacher: Qwen3-32B w/ think)	70.89	68.83	<u>85.49</u>	<u>38.82</u>	37.63	41.76	74.31	32.98	48.04	56.93	52.00
RankQwen _{1.7B} (Teacher: Qwen3-32B w/o think)	71.36	<u>69.13</u>	83.61	38.19	<u>38.11</u>	<u>42.27</u>	<u>74.64</u>	<u>33.87</u>	48.56	<u>57.64</u>	<u>52.11</u>

achieves a substantial improvement in both the quality of the selected passages list and the answer generation performance.

6.3 Impact of LLM Backbone

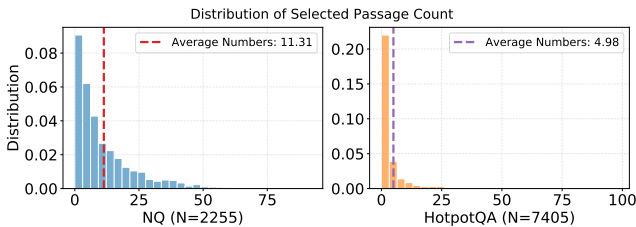
To evaluate the performance ceiling of relevance ranking versus utility-based selection in our experimental setup, we directly employed the teacher model (Qwen3-32B) to perform both relevance

Table 3: Different evidence selection and answer generation performance (%) on the top-100 BM25 retrieval results using utility-based selection approach. The generator is the Llama-3.1-8B-Instruct. Bold represents the best performance.

Model	HotpotQA					NQ				
	Evidence			Answer		Evidence			Answer	
	Recall	Precision	Micro-F1	EM	F1	Recall	Precision	Micro-F1	EM	F1
Qwen3-32B (Teacher Model)	71.37	69.29	70.32	42.55	54.63	68.74	21.50	32.76	46.25	58.74
Qwen3-1.7B (Student Model w/o Distillation)	51.68	39.61	44.85	33.09	43.88	61.42	9.47	16.41	41.91	52.94
UtilityQwen _{1.7B} (Student Model w/ Distillation)	58.68	55.47	57.03	39.00	50.57	67.20	18.32	28.80	45.06	56.83

Table 4: Different evidence selection and answer generation performance (%) on the top-100 BGE retrieval results of the HotpotQA dataset. The generator is the Llama-3.1-8B-Instruct. "Ranking (k)" means the top-k re-ranked documents are used to answer questions. Underline and Bold indicate the best performance within each group and overall. "F1" in evidence evaluation is "Micro-F1".

LLM	Method	Evidence			Answer	
		Recall	Precision	F1	EM	F1
RankQwen _{1.7B}	Ranking (5)	72.97	<u>29.19</u>	<u>41.70</u>	<u>38.39</u>	<u>49.68</u>
	Ranking (10)	75.52	22.40	34.55	36.92	48.21
	Ranking (15)	77.46	18.55	29.93	36.81	48.08
	Ranking (20)	78.83	15.98	26.58	36.43	47.49
	Ranking (40)	80.09	13.64	23.31	35.33	46.02
	Ranking (60)	81.10	11.84	20.67	34.63	45.29
	Ranking (80)	81.91	10.46	18.55	33.71	44.29
	Ranking (100)	<u>82.55</u>	9.37	16.83	32.92	43.62
Qwen3-32B	Ranking (5)	80.91	32.36	46.24	<u>40.12</u>	<u>52.03</u>
	Ranking (10)	82.10	24.51	37.75	39.07	50.70
	Ranking (15)	82.83	20.09	32.33	38.26	49.61
	Ranking (20)	83.31	17.18	28.49	38.07	49.39
	Ranking (40)	83.85	14.61	24.88	37.16	48.44
	Ranking (60)	84.30	12.65	22.00	36.15	47.12
	Ranking (80)	84.67	11.16	19.71	34.83	45.86
	Ranking (100)	84.96	9.98	17.86	34.17	45.24
UtilityQwen _{1.7B}	Selection	63.73	57.73	60.58	41.59	53.56
Qwen3-32B	Selection	78.56	72.18	75.24	46.39	59.20

**Figure 4: Distribution of selected passage count of UtilityQwen_{1.7B} on the NQ and HotpotQA datasets with BM25 retrieval results. "N" means the query numbers of the datasets.**

ranking and utility-based selection on the top-100 BGE-base-en-v1.5 retrieval results for HotpotQA. The selected document sets were then used for downstream answer generation, with results presented in Table 4. Our key observations are: 1) utility-based selection using the teacher model significantly outperforms threshold-based document selection via relevance ranking in terms of answer

Table 5: Analysis of inference efficiency on the HotpotQA datasets with Top-100 BGE retrieval results. "Avg.win_num" represents the average number of windows for each query during the sliding window process. For fair comparison, all the experiments are conducted on eight NVIDIA A800 80GB GPUs. The generator is the Llama-3.1-8B-Instruct.

Method	Avg.win_num	Time	Answer-F1
Qwen3-32B (Ranking)	9.0	23.3h	52.03
Qwen3-32B (Selection)	6.1	6.9h	59.20
RankQwen _{1.7B}	9.0	11.2h	49.68
UtilityQwen _{1.7B}	6.4	3.4h	53.36

generation quality. This further underscores the efficacy of the utility-based approach for evidence selection. 2) The performance gap between utility-based selection and relevance ranking observed with Qwen3-32B is more pronounced than the corresponding gap between UtilityQwen_{1.7B} and RankQwen_{1.7B}. This suggests that utility-based selection benefits more substantially from stronger LLM backbones, indicating its greater potential for improvement in RAG applications compared to traditional ranking methods.

6.4 Statistics of Utility-Based Selection

Figure 4 shows the distribution of passage counts selected as useful by UtilityQwen_{1.7B} from the top-100 BM25 results. UtilityQwen_{1.7B} selects a varying number of useful passages across different queries, with significantly more passages chosen for NQ queries.

We further analyze the distribution of selected passage ranks from the initial retrieval, as shown in Figure 5. Key observations include: (1) Our utility-based selection approach retrieves passages across diverse initial ranks, indicating that useful passages may appear at varying positions. This suggests that a fixed threshold may be suboptimal for handling different queries. (2) The average rank of selected passages is smaller with BGE than with BM25, implying that improved initial ranking (e.g., via BGE) positions utility passages closer to the top.

6.5 Inference Efficiency

Inference efficiency of large language models (LLMs) is a critical practical consideration in RAG deployments. Even after distilling the ranking or selection capabilities from a 32B model to a 1.7B model, the inference latency remains significantly higher than that of a 110M cross-encoder model. Therefore, we conducted a comparative analysis of the inference efficiency between RankQwen_{1.7B} and UtilityQwen_{1.7B}. As shown in the Table 5, we can observe that: (1) **Distillation necessity**: Qwen3-32B incurs significantly higher

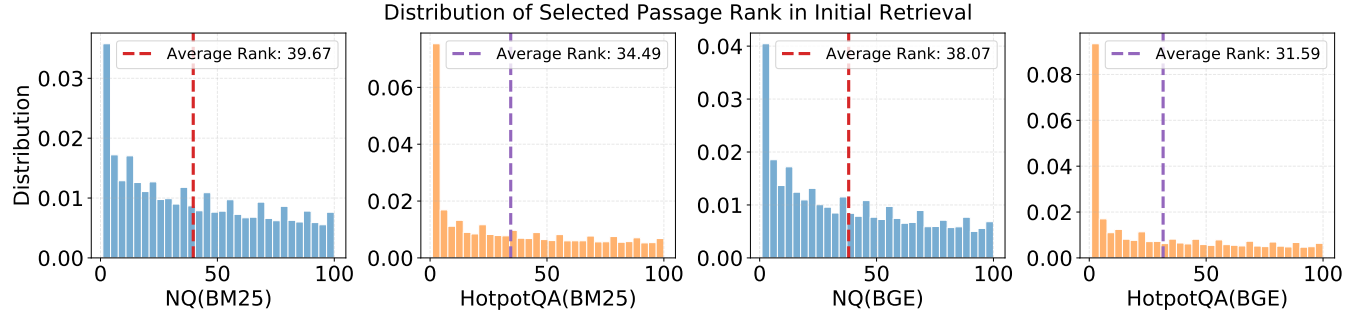


Figure 5: Distribution of selected passage rank in initial retrieval of UtilityQwen_{1.7B} on the NQ and HotpotQA datasets with initial BM25/BGE retrieval results.

costs than Qwen3-1.7B, underscoring the importance of distillation for practical deployment. (2) **Efficiency of utility-based selection:** This approach significantly reduces context window consumption and achieves approximately 30% lower inference latency than relevance ranking. Notably, even Qwen3-32B for utility-based selection requires less computational cost than RankQwen_{1.7B}. Furthermore, utility-based selection demonstrates more stable performance compared to the relevance ranking approach.

7 Conclusion

Retrieval-augmented generation (RAG) demands a paradigm shift from relevance to utility—where passages are valued not merely for topical alignment but for their usefulness to enable complete, accurate answers. Utility-based RAG faces a critical scalability bottleneck: the high cost of using LLMs for utility judgments limits practical deployment to ~20 passages per query, significantly hindering performance over large-scale passages. Since ranking requires a fixed strategy to determine passage count, we propose distilling the utility-based selection capability from larger models into smaller, efficient models. Key contributions and findings: (1) We propose a novel utility-based selection distillation method that trains efficient student models (e.g., Qwen3-1.7B) to jointly learn pseudo-answer generation and utility assessment from teacher LLMs (Qwen3-32B). This bypasses the need for direct LLM inference during deployment. (2) We empirically validate that utility-driven passage selection (unlike traditional relevance ranking) is essential for complex QA tasks (e.g., HotpotQA), where synthesizing information across multiple documents is paramount. (3) Our distilled model employs a front-to-back sliding window strategy to adaptively select minimal high-utility passage sets from large-scale candidates (top-100), dynamically skipping low-utility regions. Adaptive selection yields higher-quality answers with fewer passages, accelerating inference. This reduces computational costs by 70% while improving answer quality. Additionally, we will release the Qwen3-32B relevance ranking and utility-based selection annotations for the 100k MS MARCO dataset, providing a high-quality dataset for future research in relevance ranking and utility-based selection. For future work, extending utility distillation to tasks beyond QA (e.g., summarization, fact verification) is promising in the future.

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