FlashRAG: A Modular Toolkit for Efficient Retrieval-Augmented Generation Research

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Abstract

With the advent of Large Language Models (LLMs), the potential of Retrieval Augmented Generation (RAG) techniques have garnered considerable research attention. Numerous novel algorithms and models have been introduced to enhance various aspects of RAG systems. However, the absence of a standardized framework for implementation, coupled with the inherently intricate RAG process, makes it challenging and time-consuming for researchers to compare and evaluate these approaches in a consistent environment. Existing RAG toolkits like LangChain and LlamaIndex, while available, are often heavy and unwieldy, failing to meet the personalized needs of researchers. In response to this challenge, we propose FlashRAG, an efficient and modular open-source toolkit designed to assist researchers in reproducing existing RAG methods and in developing their own RAG algorithms within a unified framework. Our toolkit implements 12 advanced RAG methods and has gathered and organized 32 benchmark datasets. Our toolkit has various features, including customizable modular framework, rich collection of pre-implemented RAG works, comprehensive datasets, efficient auxiliary preprocessing scripts, and extensive and standard evaluation metrics. Our toolkit and resources are available at https://github.com/RUC-NLPIR/FlashRAG.

1 Introduction

In the era of large language models (LLMs), retrieval-augmented generation (RAG) [1, 2] has emerged as a robust solution to mitigate hallucination issues in LLMs by leveraging external knowledge bases [3]. The substantial applications and the potential of RAG technology have attracted considerable research attention. With the introduction of a large number of new algorithms and models to improve various facets of RAG systems in recent years, comparing and evaluating these methods under a consistent setting has become increasingly challenging.

Many works are not open-source or have fixed settings in their open-source code, making it difficult to adapt to new data or innovative components. Besides, the datasets and retrieval corpus used often vary, with resources being scattered, which can lead researchers to spend excessive time on preprocessing steps instead of focusing on optimizing their methods. Furthermore, due to the complexity of RAG systems, involving multiple steps such as indexing, retrieval, and generation, researchers often need to implement many parts of the system themselves. Although there are some existing RAG toolkits like LangChain [4] and LlamaIndex [5], they are typically large and cumbersome, hindering researchers from implementing customized processes and failing to address the aforementioned issues.

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Thus, a unified, researcher-oriented RAG toolkit is urgently needed to streamline methodological development and comparative studies.

To address the issue mentioned above, we introduce FlashRAG, an open-source library designed to enable researchers to easily reproduce existing RAG methods and develop their own RAG algorithms. This library allows researchers to utilize built pipelines to replicate existing work, employ provided RAG components to construct their own RAG processes, or simply use organized datasets and corpora to accelerate their own RAG workflow. Compared to existing RAG toolkits, FlashRAG is more suited for researchers. To summarize, the key features and capabilities of our FlashRAG library can be outlined in the following four aspects:

Extensive and Customizable Modular RAG Framework. To facilitate an easily expandable RAG process, we implemented modular RAG at two levels. At the component level, we offer comprehensive RAG components, including 13 components across four major categories: judger, retriever, refiner, and generator. These components can be used individually in one's code or combined to form a cohesive pipeline. At the pipeline level, after reviewing the current state of RAG development, we implemented 8 common RAG processes. Based on this framework, existing methods can be easily replicated, and RAG processes can be run and evaluated under different settings.

Pre-Implemented advanced RAG algorithms. To our knowledge, the implementation of existing work provided by FlashRAG is the most extensive. So far, based on our framework, we have implemented 12 advanced RAG algorithms, such as Self-RAG and FLARE, covering Sequential RAG, Conditional RAG, Branching RAG, and Loop RAG categories. These methods have been evaluated under a unified setting, and a benchmark report is available. With our framework, researchers can easily evaluate these methods under various settings and fairly compare them with their own methods, enhancing overall reproducibility. More methods are planned to be incorporated into our library.

Comprehensive benchmark datasets. To improve the consistency and reusability of datasets in RAG research, we have compiled 32 common RAG benchmark datasets and preprocessed them into a unified format. Some of these datasets, such as asqa and wikiasp, have undergone specific adjustments for RAG scenarios to ensure consistency. We have hosted these datasets on the Hugging Face platform for easy access and use.

Efficient Helping Scripts for RAG. To minimize the setup time in RAG experiments, we offer a comprehensive suite of helping scripts, including downloading and slicing Wikipedia for corpus creation, building indexes for retrieval, and prepare retrieval results in advance. These steps are important for the subsequent process, but they are often tedious and can take up a lot of time. Our user-friendly scripts are designed to be intuitive, ensuring researchers can easily navigate the preparatory stages of RAG-related research.

2 Related work

The RAG process often involves various components and complex preliminary handling (such as constructing corpus and building indexes). Due to the lack of a dedicated RAG library for research, most open-source codes tend to use their preferred implementation and entail intricate environment configurations. Therefore, it is often time-consuming to run others' code and difficult to migrate to your own settings. Simultaneously, the processing and use of datasets and corpus lack standardization, enhancing the challenge of making a fair comparison between oneself and existing methods.

In recent years, numerous open-source toolkits pertaining to RAG have been developed, providing rich RAG components. Langchain [4], LlamaIndex [5], and Haystack [6] are among the widely adopted works. These libraries provide a range of advanced APIs related to LLM, such as vector databases and embedding models, which greatly streamline the interaction with LLM and facilitate running a RAG process effortlessly. Despite the many advantages, these libraries lack support for researchers. On one hand, they tend to overlook the implementation of existing works including methods, widely used retrieval corpus, and benchmark datasets. On the other hand, they are often too hefty and heavily encapsulated, obscuring operational details or necessitating complex document searches, thereby lacking flexibility for customization.

Given these issues, several specialized toolkits for RAG have been introduced that are lighter and more customizable. For instance, FastRAG [7] optimizes based on Haystack's api and provides a

Table 1: Comparison with other RAG toolkits. *Modular Component* refers to whether the toolkit is composed of modular components. *Automatic Evaluation* indicates if the toolkit provides automated evaluation capabilities to assess the performance of various datasets. *Corpus Helper* shows if the toolkit offers auxiliary tools for processing corpus, including cleaning and chunking.

Toolkit	Modular Component	Automatic Evaluation	Corpus Helper	# Provided Dataset	# Support Work
Langchain [4]	1	X	✓	-	2
LlamaIndex [5]	1	1	1	-	2
Haystack [6]	1	1	×	-	-
FastRAG [7]	1	×	×	2	1
LocalRQA [8]	X	1	X	3	-
AutoRAG [9]	1	1	×	4	-
FlashRAG (ours)	1	1	1	32	12

limited number of support methods and benchmark datasets. LocalRQA [8] focuses on the training stage in the RAG process, providing comprehensive scripts for training various components (such as retrievers, generators) that might be involved in the RAG process during research. AutoRAG [9] adopts a similar design philosophy to ours, implementing modular RAG process. This library represents each component in RAG as a node, and the RAG process is achieved by connecting the nodes. Although AutoRAG encompasses a variety of evaluation metrics and benchmarks, it falls short concerning the direct implementation of existing works. Therefore, in our library, we have not only designed an exhaustive assortment of RAG components to implement a wide array of RAG processes but also implemented various RAG works so that the effects of existing works under various settings can be replicated directly with a few lines of code. Furthermore, we offer a wealth of resources, including a large number of processed datasets, scripts for obtaining and pre-processing widely-used corpus, among others, to expedite researchers' preparation time as much as possible.

3 The Toolkit: FlashRAG

The FlashRAG is designed to facilitate RAG-related research for researchers. As depicted in Figure 1, the overall structure of the FlashRAG toolkit comprises three hierarchical modules: the environment module, the component module, and the pipeline module. The environment module is fundamental to the toolkit, establishing the requisite datasets, hyperparameters, and evaluation metrics necessary for experimentation. Building upon the environment module, the component module consists of various RAG components, each endowed with its specific role (e.g., retrieval and generation). The pipeline module synthesizes an assortment of component modules with the purpose of effectuating a complete RAG process. In this paper, we will introduce the component and pipeline modules. Additional details are available in the documentation of our library.

3.1 Component Module

The Component Module consolidates all elements involved in the RAG process into a unified framework. Each component is equipped with autonomous functionality, enabling standalone application. Currently, the Component Module encompasses five main components: Judger, Retriever, Reranker, Refiner, and Generator.

Judger functions as a preliminary component that assesses whether a query necessitates retrieval. Given the limited work and models in this domain, we presently offer a judger based on the SKR [10] method, which determines the necessity of retrieval using a curated set of LLM self-knowledge data.

Retriever implementations are extensively covered by our toolkit. For sparse retrieval, we have integrated the Pyserini library [11] to facilitate the BM25 method. For dense retrieval, we provide support for various BERT-based embedding models such as DPR [12], E5 [13] and BGE [14]. FlashRAG also support models based on the T5 architecture like ANCE [15]. We employ FAISS [16, 17] for vector database computations to ensure retrieval efficiency and utilize the HuggingFace's datasets library to enhance corpus loading speed.

To enhance the reusability of retrieval results and accommodate non-open source retrievers, our library supports the use of pre-retrieved results termed "retrieval cache". During each retrieval instance, the system automatically searches the retrieval cache for relevant results using the current query, presenting them as the return value. Using our retrievers, user can set automatic saving of retrieval

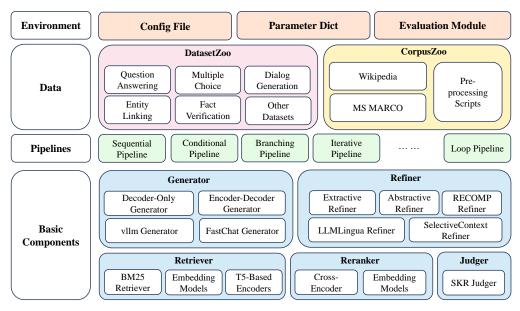


Figure 1: An overview of the FlashRAG toolkit.

caches as JSONL files for future use. For non-open source retrievers, user can format the retrieval results to fit our cache structure for loading.

Reranker aims at refining the order of results returned by the retriever to enhance retrieval accuracy. Currently, FlashRAG supports a variety of widely-used Cross-Encoder models, such as the bgereranker and jina-reranker. In scenarios where embedding models are used for reranking (e.g., employing BM25 as the retriever), we also facilitate the use of Bi-Encoder models like E5 as rerankers. In practice, the reranker is integrated into the retriever's retrieval function via a decorator, enabling seamless combination with any retriever. Users can assemble any retriever and reranker with just one line of code.

Refiner refines the input text for generators to reduce token usage and reduce noise from retrieved documents, improving the final RAG responses. Serving as an essential part of the RAG process, various studies focus on developing superior refinements. We have reviewed the existing literature and implemented four types of refiners, each performing differently in handling retrieved documents. The Extractive Refiner employs an embedding model to extract semantic units, like sentences or phrases, from the retrieved text that hold higher semantic similarity with the query. The Abstractive Refiner utilizes a seq2seq model to directly summarize the retrieved text, supporting dedicated models like RECOMP [18], as well as the general summarizer models with similar structures available on HuggingFace. Furthermore, we also facilitate the use of LLMLingua [19, 20] Refiner and Selective-Context [21] Refiner, both perplexity-based refiners.

Generator is the final component in the RAG process, thoroughly covered within our toolkit. In the generator module, we've integrated two leading LLM acceleration libraries, vllm [22] and FastChat [23], hence, a myriad of mainstream LLMs are supported. Furthermore, we provide the native interface of the Transformers library [24] to enhance robustness. We also support various encoder-decoder models, such as Flan-T5 [25]. For these models, we facilitate the use of Fusion in Decoder (FiD) techniques [26], further optimizing efficiency when dealing with retrieved documents.

3.2 Pipeline Module

Building on the diverse components outlined earlier, we are able to decouple the algorithmic flow of the RAG process from the specific implementations of each component, facilitating the assembly of the entire pipeline. The entire pipeline processes the dataset provided by the user, executes the corresponding RAG process on it, and delivers both the final evaluation outcomes and intermediate results. In constructing the pipeline, one only needs to consider which components are required for the entire RAG process and the logic of data flow between these components. Specifically, within

each pipeline, it is necessary to load the required components in the init(.) function and implement the corresponding logic in the run(.) function according to each component's interface.

To systematically execute the operational logic of various RAG tasks, we conducted an in-depth survey of RAG-related literature. Drawing on the summaries from the RAG survey [27], we categorized all RAG process flows into four types: Sequential, Branching, Conditional, and Loop. So far, we have implemented 8 different pipelines, covering a range of advancing RAG works.

Sequential Pipeline implements a linear execution path for the query, formally represented as query -> retriever -> post-retrieval (reranker, refiner) -> generator. Once the user has configured their settings, the library automatically loads the necessary components along with their corresponding process logic.

Branching Pipeline executes multiple paths in parallel for a single query (often one path per retrieved document) and merges the results from all paths to form the ultimate output. Currently, our library supports two advancing branching methods: REPLUG pipeline [28] and SuRe pipeline [29]. The REPLUG pipeline processes each retrieved document in parallel and combines the generation probabilities from all documents to produce the final answer. The SuRe pipeline generates a candidate answer from each retrieved document and then ranks all candidate answers. In implementing SuRe, we adhere to the original paper's prompt and processing flow to ensure accuracy and comparability of the results.

Conditional Pipeline utilizes a judger to direct the query into different execution paths based on the judgement outcome. In the current framework, queries deemed in need of retrieval are sent into the normal sequential process, while the rest bypass retrieval and proceed directly to generation. We offer utility functions to split and merge the input dataset based on the judger's determination, ensuring that all processing can be conducted in batches, which enhances the efficiency of the pipeline. Moreover, the conditional pipeline supports integration with various types of pipelines, meaning it can execute different pipelines for queries based on different judger outcomes.

Loop Pipeline involves complex interactions between retrieval and generation processes, often encompassing multiple cycles of retrieval and generation. Compared to the previous three types of pipelines, this type offers greater flexibility and improved outcomes. We support four widely recognized methods, including Iterative [30, 31], Self-Ask [32], Self-RAG [33], and FIARE [34]. For each of these methods, we support flexible adjustments to the retrievers and generators to test their performances in different scenarios.

3.3 Datasets and Corpus

3.3.1 Datasets

As shown in Table 2, we collects and pre-processes 32 benchmark datasets, covering the majority of the datasets utilized in RAG works. We researched and listed the sources of answers in each dataset for reference. For most datasets, the knowledge comes from Wikipedia, underscoring its importance in RAG tasks. All datasets have been formatted into a unified JSONL structure, typically encapsulating four fields: ID, question, golden answer, and metadata. For multiple-choice datasets like MMLU [35, 36] and OpenBookQA [37], an additional "choices" field is provided as options. We have hosted the processed datasets on HuggingFace for easy access. Details on dataset processing can be found in the appendix.

Besides the datasets, we offer a variety of dataset filtering tools for user to filter the entire dataset. For instance, user can choose a certain number of samples from the entire dataset, either randomly or sequentially for evaluation, or select a subset of the dataset through the dataset's metadata. These methods are unified within a dataset loading function, which is accessible through a standard interface. Users are also allowed to implement their own filtering functions.

3.3.2 Corpus

Besides datasets, the corpus used for retrieval, also known as the knowledge base, is another vital preparation of experiments. In various research works, the following two types of corpus are often used: Wikipedia dump and MS MARCO passage.

Task	Dataset Name Knowledge Source		# Train	# Dev	# Test
	NQ [38]	Wiki	79,168	8,757	3,610
	TriviaQA [39]	Wiki & Web	78,785	8,837	11,313
	PopQA [40]	Wiki	/	/	14,26
	SQuAD [41]	Wiki	87,599	10,570	/
	MSMARCO-QA [42]	Web	808,731	101,093	/
	NarrativeQA [43]	Books, movie scripts	32,747	3,461	10,55
QA	WikiQA [44]			2,733	6,165
QA	WebQuestions [45] Google Freebase		3,778	/	2,032
	AmbigQA [46, 38] Wiki		10,036	2,002	/
	SIQA [47] -		33,410	1,954	/
	CommenseQA [48] -		9,741	1,221	/
	BoolQ [49]	Wiki		3,270	/
	PIQA [50]	-		1,838	/
	Fermi [51] Wiki		8,000	1,000	1,00
	HotpotQA [52]	Wiki	90,447	7,405	/
Multi-Hop QA	2WikiMultiHopQA [53]	pQA [53] Wiki		12,576	/
Multi-Hop QA	Musique [54]	Wiki	19,938	2,417	/
	Bamboogle [32]	Wiki	/	/	125
Long-Form QA	ASQA [55]	Wiki	4,353	948	/
Long-Form QA	ELI5 [56]	Reddit	272,634	1,507	/
	MMLU [35, 36]	-	99,842	1,531	14,04
	TruthfulQA [57]	Wiki	/	817	/
Multiple-Choice	HellaSwag [58] ActivityNet		39,905	10,042	/
	ARC [59]	-		869	3,548
	OpenBookQA [37]	-	4,957	500	500
Entity-linking	AIDA CoNLL-YAGO [60, 61]	Wiki & Freebase	18,395	4,784	/
Entity-miking	WNED [62, 61]	Wiki	/	8,995	/
Slot filling	T-REx [63, 61]	DBPedia	2,284,168	5,000	/
Slot ming	Zero-shot RE [64, 61]	Wiki	147,909	3,724	/
Fact Verification	FEVER [65, 61]	Wiki	104,966	10,444	/
Dialog Generation	WOW [66, 61]	Wiki	63,734	3,054	/
Open-domain Summarization*	WikiAsp [67]	Wiki	300,636	37,046	37,36

Table 2: Summary of datasets. FlashRAG currently includes a variety of datasets of different tasks. The sample size of each dataset and the knowledge source of the answer are listed as references. "-" indicates that the knowledge source is common sense. The * symbol represents that the task of this dataset has been modified to fit the RAG scene.

Wikipedia passages: The Wikipedia passages comprises a collection of documents from English Wikipedia entries, serving as the knowledge source for many datasets, such as KILT [61]. It was first introduced as a retrieval corpus in DrQA [68], and subsequently utilized in previous works [12, 1, 34]. Acquiring the Wikipedia dump involves a complex process, including downloading Wikipedia snapshots in XML format, cleaning the text to remove redundant HTML tags and extracting the corresponding textual content, and segmenting the entire document text into individual passages for retrieval.

For various reasons, there are several different versions of Wikipedia used in existing work, increasing the difficulty of reproduction. To address this, we provide easy-to-use scripts for automatically downloading and pre-processing any required Wikipedia version. Additionally, we offer various chunking functions to support custom segmentation methods, enabling researchers to align their corpus with others' works or to establish a standard corpus for use. We also provide the widely utilized Wikipedia dump presented by DPR from December 20, 2018, as a fundamental resource.

MS MARCO passages [42]: The MS MARCO passage includes 8.8 million passages, sourced from Bing search engine retrievals. Compared to the Wikipedia dump, it contains fewer passages. Fortunately, this corpus has undergone pre-processing, allowing for its direct use. Since this dataset is already hosted on Hugging Face and matches our required format, we provide its original link for ease of download.

3.4 Evaluation

Our library supports a variety of evaluation metrics to assess the quality of RAG process. Depending on the subject of evaluation, our supporting metrics can be divided into two categories: retrieval-aspect metrics and generation-aspect metrics.

Retrieval-aspect metrics: To evaluate the quality of the retrieval, we support four metrics including recall@k, precision@k, F1@k, and mean average precision (MAP). Unlike assessing standalone retrieval systems, the documents retrieved in the RAG process often lack golden labels (e.g., related or unrelated tags). Therefore, we facilitate these evaluations by considering whether the golden answer is present within the retrieved documents as an indicator of relevance. Other types of metrics can be obtained by inheriting existing metrics and modifying the calculation methods inside.

Generation-aspect metrics: For evaluating the quality of generation, we support five metrics including token-level F1 score, exact match, accuracy, BLEU [69], and ROUGE-L [70]. Moreover, we support evaluating the number of tokens used in generation, to facilitate the analysis of the overall process cost.

To accommodate custom evaluation metrics, our library provides a metric template for users to implement. As our library automatically saves intermediate results of the execution, users can conveniently evaluate the outcomes produced by intermediate components. For example, users might compare the number of tokens before and after the refiner runs, or the precision differences between multiple rounds of retrieval results.

4 Experimental Result and Discussion

FlashRAG can enable researchers to benchmark RAG methods, evaluate their own RAG approaches, and conduct investigations within the RAG field. To demonstrate the capabilities of FlashRAG, we conducted several experiments for providing reproducible benchmarks and exploration.

Experimental Setup. In our main experiment, we employed the latest LLAMA3-8B-instruct [71] as the generator and the E5-base-v2 as the retriever, utilizing Wikipedia data from December 2018 as the retrieval corpus. The max input length of generator model is set to 4096. For each query, we retrieved five documents. For approaches not utilizing custom-defined prompts, we applied a consistent default prompt, which is shown in the appendix. Methods requiring specific settings and hyperparameters are marked with asterisks in our tables, with their specific configurations noted in the appendix. All experiments are carried out on 8 NVIDIA A100 GPUs. We conducted experiments on six common datasets: Natural Questions(NQ) [38], TriviaQA [39], HotpotQA [52], 2WikiMultihopQA [53], PopQA [40] and WebQuestions [45]. We use exact match as the metric on NQ, TriviaQA, Web Questions, and token level F1 as the metric on HotpotQA, 2WikiMultihopQA and PopQA.

Methods. We conducted experiments on all supported RAG methods. These methods are categorized based on the RAG component they primarily focused on optimizing: AAR [72] aims at optimizing the retriever; LongLLMLingua [20], RECOMP [18], and Selective-Context [21] focus on the refiner to compress input prompts; Ret-Robust [73] and REPLUG [28] focus on optimizing the generator and its related decoding methods; SKR [10] enhances the judger that decides whether to retrieve for a query; SuRe [29], Self-RAG [33], FLARE [34], Iter-RetGen [30], and ITRG [31] optimize the entire RAG flow, including multiple retrievals and generation processes.

4.1 Main results

The main results of various methods are shown in Table 3. Overall, RAG methods significantly improve compared to the direct generation baseline. Standard RAG, with advanced retrievers and generators, is a strong baseline, performing well across six datasets. AAR improves retrievers by training the contriever model, and get comparable result to the e5 baseline on multiple datasets. For refiners, all three methods show notable improvements. Refiners perform especially well on multi-hop datasets like HotpotQA and 2WikiMultihopQA. This is likely because complex problems lead to less accurate document retrieval, creating more noise and requiring refiner optimization. In generator optimization method, Ret-Robust uses the Llama2-13B model with a lora module, greatly enhancing the generator's understanding of retrieved documents and outperforming other

Table 3: The performance evaluation of RAG methods was carried out on three datasets. *Optimize component* represents the primary component optimized by the method, while *flow* indicates optimization of the entire RAG process. Methods marked with * denote the use of a trained generator.

Method	Optimize	Pipeline	NQ	TriviaQA	HotpotQA	2Wiki	PopQA	WebQA
Method	component	type	(EM)	(EM)	(F1)	(F1)	(F1)	(EM)
Naive Generation	-	Sequential	22.6	55.7	28.4	33.9	21.7	18.8
Standard RAG	-	Sequential	35.1	58.8	35.3	21.0	36.7	15.7
AAR [72]	Retriever	Sequential	30.1	56.8	33.4	19.8	36.1	16.1
LongLLMLingua [20]	Refiner	Sequential	32.2	59.2	37.5	25.0	38.7	17.5
RECOMP-abstractive [18]	Refiner	Sequential	33.1	56.4	37.5	32.4	39.9	20.2
Selective-Context [21]	Refiner	Sequential	30.5	55.6	34.4	18.5	33.5	17.3
Ret-Robust* [73]	Generator	Sequential	42.9	68.2	35.8	43.4	57.2	9.1
SuRe [29]	Flow	Branching	37.1	53.2	33.4	20.6	48.1	24.2
REPLUG [28]	Generator	Branching	28.9	57.7	31.2	21.1	27.8	20.2
SKR [10]	Judger	Conditional	25.5	55.9	29.8	28.5	24.5	18.6
Self-RAG [*] [33]	Flow	Loop	36.4	38.2	29.6	25.1	32.7	21.9
FLARE [34]	Flow	Loop	22.5	55.8	28.0	33.9	20.7	20.2
Iter-RetGen [30], ITRG [31]	Flow	Loop	36.8	60.1	38.3	21.6	37.9	18.2

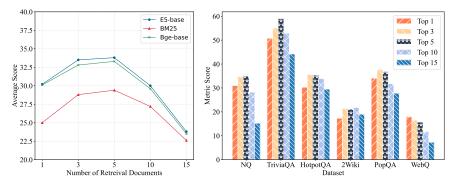


Figure 2: The results of standard RAG process under different number of retrieved documents and retrievers. **Left:** Average results on six datasets using three different retrievers with varying numbers of retrieved documents. **Right:** Individual results on six datasets using E5 as the retriever.

training-free methods. The effectiveness of optimizing the RAG process varies by dataset. On simpler datasets like NQ and TriviaQA, FLARE and Iter-RetGen are on par with or slightly below standard RAG. However, on complex datasets that requiring multi-step reasoning, like HotpotQA, there are significant improvements over the baseline. This suggests adaptive retrieval methods are more suited for complex problems, while on simpler tasks, they may incur higher costs with only modest benefits.

4.2 Impact of Retrieval on RAG

In RAG process, the retriever is a crucial component that significantly impacts the results. The quantity and quality of input retrieved documents determine the final answer. However, due to considerations such as cost, existing research works often employs a fixed retriever and a fixed number of retrieved documents, neglecting exploration in this area. To thoroughly investigate the influence of the retrieval process on overall RAG results, we conducted a series of experiments.

In Figure 2, we present the results for varying numbers of retrieved documents. As shown in the left part of Figure 2, the overall performance is optimal when the number of retrieved documents is 3 or 5. Both an excessive and insufficient number of retrieved documents lead to a significant decrease in performance, with a drop of up to 40%. This trend is consistent across different retrievers, including both dense and sparse retrieval methods. Additionally, we observe that when the number of retrieved documents is large, the results of the three different quality retrievers converge. In contrast, for the top1 results, there is a substantial gap between dense methods (E5, Bge) and BM25, indicating that the fewer documents retrieved, the greater the impact of the retriever's quality on the final result.

In the right part of Figure 2, we plot the impact of the number of retrieved documents on different datasets. It can be seen that on most datasets, using top3 or top5 retrieved results yields the best performance, suggesting that this may represent a good balance between the quality of retrieved documents and noise.

5 Limitations

Our toolkit currently has some limitations, which we plan to gradually improve in the future. (1) Although we strive to encompass many representative RAG methods, due to time and cost considerations, we have not included all existing RAG works. This may require contributions from the open-source community in the future. (2) Our toolkit lacks support for training RAG-related components. We considered training during the initial design, but given the diversity of training methods and the presence of many repositories specifically dedicated to the training of retrievers and generators, we did not include this part. In the future, we may add some helping scripts to provide some assistance for researchers' training needs.

6 Conclusion

To address the challenges researchers face in replicating studies and the high development costs associated with research in the RAG domain, we introduce a modular RAG toolkit. Our toolkit includes comprehensive RAG benchmark datasets, implementations of advanced RAG methods, and code for pre-processing corpus and multiple evaluation metrics. It enable researchers to easily reproduce existing RAG methods, develop new algorithms, and focus on optimizing their research.

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