Accelerating Iterative Retrieval-augmented Language Model Serving with Speculation

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Abstract

This paper introduces RaLMSpec, a framework that accelerates iterative retrieval-augmented language model (RaLM) with *speculative retrieval* and *batched verification*. RaLMSpec further introduces several important systems optimizations, including prefetching, optimal speculation stride scheduler, and asynchronous verification. The combination of these techniques allows RaLMSPec to significantly outperform existing systems. For document-level iterative RaLM serving, evaluation over three LLMs on four QA datasets shows that RaLMSpec improves over existing approaches by 1.75-2.39×, 1.04-1.39×, and 1.31-1.77× when the retriever is an exact dense retriever, approximate dense retriever, and sparse retriever respectively. For token-level iterative RaLM (KNN-LM) serving, RaLMSpec is up to 7.59× and 2.45× faster than existing methods for exact dense and approximate dense retrievers, respectively.

1. Introduction

Recent advancements in large language models such as LLaMA-2, GPT-3, and PaLM have shown promising results in diverse NLP tasks (Touvron et al., 2023; Brown et al., 2020; Chowdhery et al., 2022). However, encoding a massive amount of knowledge into a fully parametric model requires excessive effort in both training and deployment. The situation can be further exacerbated when the foundation model is required to adapt to new data or various downstream tasks (Asai et al., 2023). To address this challenge, recent work introduces *retrieval-augmented* language models (RaLM), which integrate the parametric language model with a non-parametric knowledge base through retrieval augmentation (Khandelwal et al., 2019; Shi et al., 2023; Ram et al., 2023; Khattab et al., 2022).

Existing RaLM methods can be categorized into two classes based on the interaction between the knowledge base and language model. First, *one-shot* RaLM performs retrieval *once* for each request and combines the retrieved documents with the original request to assist generation. On the other hand, *iterative* RaLM enables iterative interactions between the language model and knowledge base for a request so that the language model can opportunistically query the knowledge base to retrieve more relevant documents during generation. Compared to iterative RaLM, one-shot RaLM introduces less retrieval overhead but is inherently limited when the required information varies from time to time during the generation process. On the other hand, iterative RaLM achieves better generative performance while suffering from frequent retrievals and, thus, high retrieval overhead. This paper answers the following research question: *can we reduce the overhead of iterative RaLM without affecting generative quality?*

We propose RaLMSpec, a framework that employs *speculative retrieval* with *batched verification* to reduce the serving overhead for iterative RaLM while provably preserving the model output. A critical bottleneck of existing iterative RaLM methods is the inefficiency of retrieval. In particular, due to the auto-regressive nature of generative language models, the retrieval step is usually performed with a single query summarizing the current context. As shown in Figure 1(a), existing iterative RaLM approaches interleave the retrieval step and the generation step by constantly retrieving from the knowledge base with the latest context-dependent queries (i.e., q_0, q_1, and q_2). The corresponding retrieved contents (A, B, C) can then assist the generation process by contributing relevant information to the language model through a prompt or attention-level combination. However, issuing these queries for knowledge base retrieval *sequentially* is inefficient.

The idea of speculative retrieval is conceptually similar to speculative execution from the computer architecture literature (Burton, 1985). More specifically, RaLMSpec replaces

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the expensive, iterative retrieval steps of existing RaLM methods with more efficient but less accurate speculative retrieval steps. Consequently, RaLMSpec uses a *batched verification* step to correct any incorrect speculation result and preserve the model's generative quality. More precisely, after several speculative retrieval steps, RaLMSpec initiates a verification step by performing a batched retrieval (i.e., ⑥ in Figure 1(b)), where the queries in the batch are the corresponding queries in the speculative retrieval steps. If there is a mismatch between the speculated documents and the ground truth documents retrieved in the verification step, RaLMSpec automatically corrects the mismatch by rolling back to the first mis-speculated position and rerunning language model decoding using the ground truth documents. As a result, a subpar speculation method with an early mismatch can result in additional overhead. In observing that the same or consecutive entries can be repetitively retrieved from the knowledge base when generating the response (i.e., temporal and spatial locality), RaLMSpec maintains a *local retrieval cache* to store past documents for each request, and performs speculative retrieval by retrieving from the local cache instead of the knowledge base. RaLMSpec updates the local cache by directly adding the same or consecutive documents retrieved from the knowledge base in each verification step. Figure 1(c) shows a timeline comparison between RaLMSpec and existing iterative RaLM methods. RaLMSpec's latency saving is obtained through efficient batched retrieval, i.e., retrieving from the knowledge base with n batched queries is more efficient than executing n retrievals sequentially. We show evidence of the above claim in Appendix A.1.

Besides maintaining a local cache for speculative retrieval, we propose three additional techniques to further reduce RaLM serving latency. First, RaLMSpec can support *cache prefetching* by updating the local cache with the top-k retrieved documents from the knowledge base to boost RaLMSpec's speculative performance. Second, RaLMSpec enables an *optimal speculation stride scheduler* that dynamically adjusts the speculation stride (i.e., the number of consecutive speculation steps between two verification steps) to minimize the speculation overhead. Third, RaLMSpec can exploit concurrency by allowing *asynchronous verification*, which enables an extra speculation step to be performed asynchronously with a verification step.

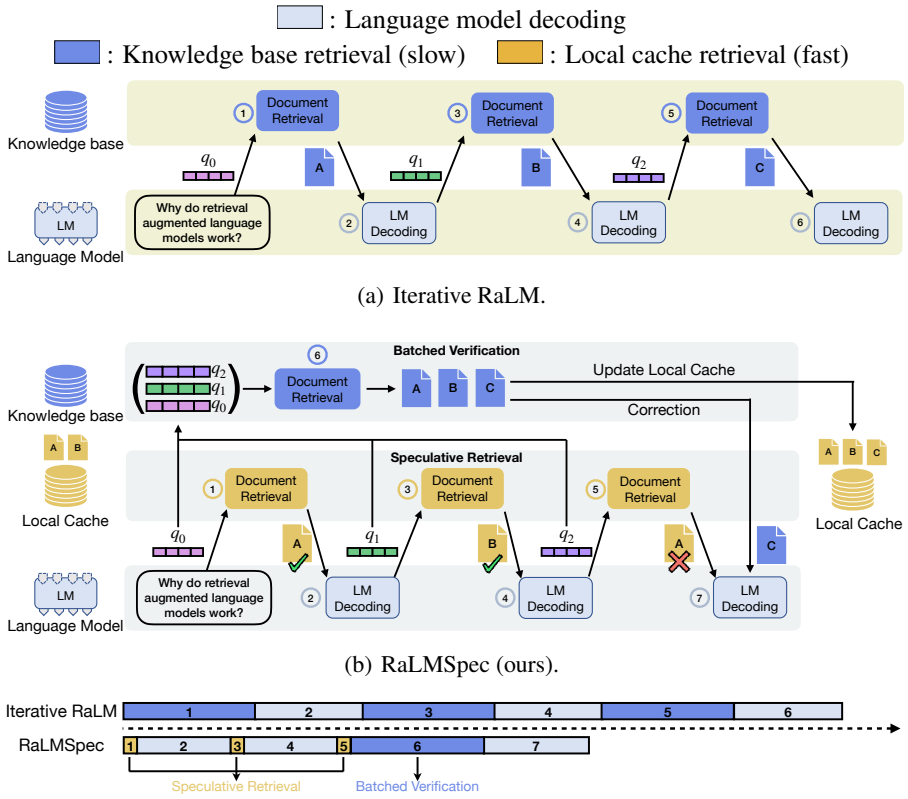
We test RaLMSpec against two serving tasks: document-level and token-level iterative RaLM serving. For document-level iterative RaLM serving, extensive evaluation of RaLMSpec over the Wiki-QA (Yang et al., 2015), Web Questions (Berant et al., 2013), Natural Questions (Kwiatkowski et al., 2019), and Trivia QA (Joshi et al., 2017) datasets on the GPT-2, OPT, and LLaMA-2 models show that RaLMSpec can automatically adapt the speculation configuration and reduce the serving latency of the baseline implementation by up to $2.4\times$, $1.4\times$, $1.8\times$ with an exact dense, approximate dense, and sparse retriever, respectively. For token-level iterative RaLM (KNN-LM) serving, RaLMSpec can achieve a speed-up ratio up to $7.59\times$ and $2.45\times$ when the retriever is an exact dense retriever and approximate dense retriever, respectively.

Contributions. This paper makes the following contributions:

- We propose RaLMSpec, a framework that reduces the serving latency of generic iterative RaLM approaches while preserving the same model outputs.
- Technically, by leveraging the temporal/spatial locality of the retrieved documents, RaLMSpec uses a caching-based speculative retrieval mechanism with batched verification to reduce the retrieval overhead. We propose three additional techniques to reduce RaLM serving latency: cache prefetching, asynchronous verification, and optimal speculation stride scheduling.
- Empirically, we validate that RaLMSpec achieves significant RaLM serving latency reduction across different tasks, datasets, language models, and retriever types. These results indicate RaLMSpec can be a generic acceleration framework for serving iterative RaLMs.

2. Related Work

Retrieval-augmented language models. Since Guu et al. (2020) first proposed to provide relevant information to the language model with retrieved documents from an external knowledge base, numerous works have started to leverage retrieval to improve the language model generation quality (Shi et al., 2023; Park et al., 2023; Wang et al., 2023a; Zhu et al., 2023; Rubin & Berant, 2023; Wang et al., 2023b; Zhou et al., 2023). As these works only perform retrieval once before the language model generation starts, we refer to them as one-shot RaLM. Besides one-shot RaLM approaches, another line of work performs retrieval regularly when serving a single request. Ram et al. (2023); Lewis et al. (2020); Jiang et al. (2023); Borgeaud et al. (2022); Khattab et al. (2022); Shao et al. (2023) retrieve constantly from the external database with the latest context and leverage the retrieved documents to improve the generation quality either through direct concatenation or intermediate layer cross-attention, which we refer to as document-level iterative RaLM approaches. K-Nearest Neighbour Language Models (KNN-LM), on the other hand, produce the next token distribution by interpolating between a weighted distribution over k retrieved documents and the language model output (Khandelwal et al., 2019; Drozdov et al., 2022), which we refer to as token-level iterative RaLM approaches. Compared with



(a) Iterative RaLM.

(b) RaLMSpec (ours).

(c) Timeline comparison.

Figure 1. $\{q_0, q_1, q_2\}$ denotes context-dependent query embeddings and A, B, C are document entries. Figure 1(a) shows the workflow of existing iterative RaLM, which suffers from high retrieval overhead. Figure 1(b) shows an overview of RaLMSpec, which enables faster speculative retrieval steps (①, ③, ⑤) followed by a batched verification step (⑥) to guarantee correctness (we leave out the cache initialization phase for better illustration). Consequently, RaLMSpec achieves a lower latency while preserving model quality as shown in Figure 1(c).

one-shot RaLM, iterative RaLM methods have been shown to provide higher quality responses at the cost of excessive latency overhead (Khandelwal et al., 2019; Drozdov et al., 2022; Ram et al., 2023). For instance, Khandelwal et al. (2019) retrieves up to 1024 documents for each token generated, which results in unaffordable serving overhead in practice. Reducing the serving overhead of iterative RaLM methods while preserving its high-quality output is thus the core of our work.

Retrievers for RaLM. Different retrievers have different tradeoffs between retrieval overheads and retrieval accuracy when serving RaLMs. Instead of using conventional sparse retrievers such as TF-IDF or BM25 (Ramos et al., 2003; Robertson et al., 2009), Karpukhin et al. (2020) trains a dense retriever particularly for RaLM. Similarly, Izacard et al. (2021) proposes to train a dense retriever by unsupervised contrastive learning. Later work further explores the possibility of end-to-end pretraining, where the retriever and language model are trained collaboratively (Izacard et al., 2022; Zhong et al., 2022; Khattab & Zaharia, 2020; Santhanam et al., 2021). Exact dense retrievers are inefficient but accurate, while approximate retrievers are fast to query but less accurate (He et al., 2021; Xiong et al., 2020). To demonstrate the generality of our design, we experiment RaLMSpec with different retrievers (sparse, exact dense, and approximate dense retrievers).

Iterative RaLM serving. As for efficient iterative RaLM serving approaches, the work most relevant to ours is Alon et al. (2022). By using a pre-computed automaton state when a complete retrieval for the KNN-LM is unnecessary, Alon et al. (2022) can reduce the number of calls to the external knowledge base and thus save latency. However, Alon et al. (2022) is not guaranteed to preserve the same model output and hence might compromise model generation quality. To this end, our goal is to achieve generic and efficient serving for existing iterative RaLM approaches while guaranteeing to preserve model quality. To the best of our knowledge, RaLMSpec is the first work that achieves inference time speed-up for generic iterative RaLM approaches without compromising model output. The key intuition behind RaLMSpec is speculative retrieval and batched verification. Speculation has a long history in the computer architecture

field (Burton, 1985). Recent works further bring the concept of speculative decoding into Large Language Models (LLM) serving, which essentially reduces serving latency (Leviathan et al., 2022; Stern et al., 2018; Chen et al., 2023; Miao et al., 2023; Xia et al.; Joao Gante, 2023; Yang et al., 2023; Cai et al., 2024). However, as far as we know, RaLMSpec is the first work that incorporates the concept of speculative retrieval in RaLM serving and is orthogonal to the speculative inference technique for large language models (LLMs).

3. RaLMSpec

A key observation that motivates the design of RaLMSpec is that the *same or consecutive* documents in a knowledge base can be retrieved multiple times during the iterative retrievals of a generative task (e.g., the sequence of the retrieved documents can be A, B, A, B, C), also known as the temporal/spatial locality in the system domain. Leveraging this observation, RaLMSpec enables a caching-based mechanism for *speculative retrieval*. Combined with *batched verification*, RaLMSpec can thus reduce the serving latency of iterative RaLM while provably preserving its generative quality. We describe the pipeline of RaLMSpec in Algorithm 1.

Algorithm 1 RaLMSpec Pipeline.

Input: Input tokens $X = \{x_0, x_1, \cdots, x_{t-1}\}$, external corpus $\mathcal{C}$, language model $f(\cdot)$
Output: RaLM generated outputs
Initialize local cache $Q = \{\}$, speculation stride s, model generation stride k
$q = \text{encode}(X), Q.\text{insert}(\mathcal{C}.\text{retrieve}(q))$ ▷ cache prefetching
while EOS not in X **do**
  for $i = 1$ **to** s **do**
    $q_i = \text{encode}(X), \hat{d}_i = Q.\text{retrieve}(q_i)$ ▷ speculative retrieval
    $\hat{X}_i = f(X, \hat{d}_i, k)$ ▷ model generation step that generates k new tokens
    $X = [X, \hat{X}_i]$
  end for
  $d_1, \cdots, d_s = \mathcal{C}.\text{retrieve}(q_1, \cdots, q_s)$ ▷ batched verification
  $m = \arg\min_i \hat{d}_i \neq d_i$
  if $m \leq s$ **then** ▷ do correction if needed
    Roll X back to the m-th speculation step
    $\hat{X} = f(X, d_i, k)$
    $X = [X, \hat{X}]$
  end if
end while

Speculative retrieval. For speculative retrieval, we maintain a local cache for each new request to store retrieved documents. As shown in Figure 2, RaLMSpec utilizes the local cache as a "retrieval" cache instead of a typical exact match cache in the system literature, where a local cache retrieval is performed similarly to a knowledge base retrieval except for the number of documents in the local cache is far less. As there is no entry in the local cache at the start of the process, we perform a retrieval from the knowledge base using the initial query and populate the local cache with the retrieved key and value pairs. The key is usually a vectorized representation of the retrieved documents for dense retrievers or a set of local information (e.g., word level frequency) for sparse retrievers, while the value is the retrieved documents. For a retrieval step, instead of retrieving from the knowledge base, RaLMSpec retrieves from the local cache speculatively. However, the speculative retrieval results might deviate from the actual retrieval results. To guarantee correctness, a verification step is required for every s consecutive number of speculative retrieval steps performed. We refer to s as the speculation stride. For instance, $s = 3$ in the example in Figure 1(b).

A fundamental property that ensures the effectiveness of leveraging a local cache for speculative retrieval is that for most dense and sparse retrievers, relative ranking between documents is preserved between the local cache and the knowledge base. More importantly, if the top-ranked entry in the knowledge base is present in our local cache for a given query, the same entry is guaranteed to be ranked at the top when retrieving from our local cache using the same retrieval metric for this query. For most dense retrievers, this property can be naturally satisfied as the distance metric used by the dense retrievers can be locally computed. For sparse retrievers like BM25 (Robertson et al., 2009), we store the corpus-related information throughout the generation process so that the score can be locally computed on the fly. Thus, combined with the temporal locality of the retrieved documents, leveraging a local cache for speculative retrieval can significantly boost the speculation success rate.

Batched verification. During a verification step, we verify the speculated results with a batched retrieval from the knowledge base. For instance, as Figure 1(b) shows, with a speculation stride $s = 3$, the corresponding queries and cache-retrieved documents for the three consecutive speculative retrieval steps (①, ③, ⑤) are $q_0 \to q_1 \to q_2$ and A→B→A, respectively. During the verification process, we will retrieve from the external knowledge base with the batched query $\{q_0, q_1, q_2\}$. Suppose the documents retrieved from the knowledge base are {A, B, C} for the verification step[1].

[1]Note that we actually don't need to perform the last speculative retrieval step. We show it in our toy example only to demonstrate the verification process.

We can then validate that the third speculative retrieval step mismatches with the ground truth results. In case of a mismatch, the generation process will roll back to the first mismatch position in the sequence and redo the generation with the correct value (i.e., replacing the third speculated document A with the ground truth document C and continuing generation for the request). In the meantime, we can populate the local cache with the documents retrieved during the verification step. Aside from the *top-1 cache update* approach, RaLMSpec also supports *top-k cache update* as demonstrated in Figure 2. Similar to the concept of prefetching, the top-k cache update aims to fetch more relevant entries to the local cache per verification step to further boost the speculation success rate.

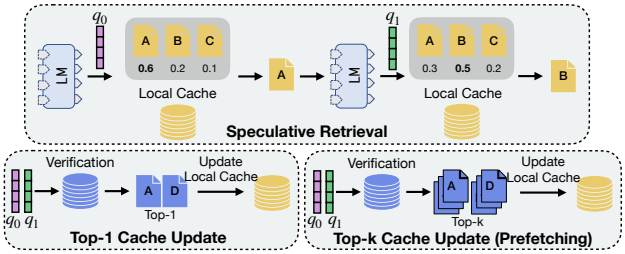


Figure 2. For speculative retrieval, we maintain a local cache for each request and use the same scoring metric as the original retriever to rank the entries within the local cache for a given query. In the verification step, we populate the local cache with either the top-1 or top-k retrieved documents from the knowledge base, where the latter one is referred to as *prefetching*.

Observe that batched retrieval is more efficient by exploiting parallelism, and the speculative retrieval latency is negligible compared to retrieving from the knowledge base. Consequently, in the former toy example, we complete three retrieval steps with only one batched knowledge base retrieval, while a naive implementation requires three knowledge base retrievals. Note that if there is an early mismatch for the speculative retrieval steps, we will incur additional speculation overhead for generating extra tokens. As a result, the speculation stride is a crucial parameter exploiting the trade-off between speculation overhead and retrieval saving. We will elaborate more on choosing an optimal speculation stride s in Section 4.

In addition to a single-thread implementation, RaLMSpec also considers *asynchronous verification*. Instead of stalling the speculation step during verification, we can launch an extra speculation step asynchronously while the verification of the previous step occurs. This *asynchronous verification* technique is especially beneficial when the verification latency is smaller than the language model's decoding latency as shown in Figure 3. In fact, in this case, *asynchronous verification* with a speculation stride $s = 1$ is the optimal strategy for speculative retrieval. Intuitively, since the verification results can be returned before a speculative retrieval and language model decoding step is completed, we can always hide the latency of a verification step behind a speculation step if the speculation succeeds. More specifically, if the verification succeeds, the model can continue the generation process, saving the verification latency. On the other hand, as soon as the verification fails, the model can regenerate the output based on the corrected information, which falls back to the naive implementation with no speculation overhead.

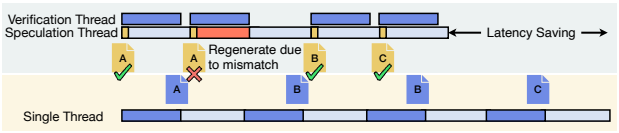


Figure 3. Asynchronous verification obtains latency saving by hiding the verification latency behind a valid speculation step. In case a mismatch is detected between the speculated document and ground truth document, the language model will regenerate outputs using the ground truth document.

4. Optimal Speculation Stride Scheduler

RaLMSpec uses *speculation stride* s (defined in Section 3) as a hyperparameter to control the number of speculation steps performed before a verification step. It plays a crucial role in our system due to its effect on the trade-off between speculation overhead and latency saving. Too large a speculation stride would incur high speculation overhead if verification fails early in the stage, while too small a speculation stride does not exploit the benefits of speculation to the fullest. Additionally, depending on different language models, retrieval methods, and speculation accuracy, the optimal choice of the speculation stride varies across diverse setups.

Instead of hand-tuning the speculation stride, we propose the Optimal Speculation Stride Scheduler (OS^3), which formalizes this trade-off into an objective function and solves an optimal speculation stride across different configurations adaptively. Given that the goal is to correctly verify a fixed number of documents with minimal latency, we formulate our objective function as the expected number of documents verified successfully per unit time. The goal is therefore to maximize the objective function by optimizing speculation stride s.

More precisely, let a denote the latency of a speculation step (speculative retrieval + language model decoding), b denote the latency of a verification step, d_i be the ground truth documents retrieved from the corpus, and $\hat{d}_i$ be the speculated documents retrieved from the local cache. If we define $\gamma(X) = P(d_i = \hat{d}_i \mid X), \forall i \in [s]$ as the

speculation accuracy given the current context X, then the expected number of verified documents is given by $\frac{1-\gamma(X)^s}{1-\gamma(X)}$ with a speculation stride s. We include the derivation in Appendix A.2. For synchronous verification, the latency is calculated as $sa + b$. For asynchronous verification, if all speculated documents match with the ground truth documents in the verification step with a probability of $\gamma(X)^s$, we can benefit from the asynchronous verification with a latency of $(s-1)a + \max(a, b)$. Otherwise, with probability $1 - \gamma(X)^s$, we incur a mismatch, so asynchronous verification brings no gain at all with a latency of $sa + b$. Therefore, the expected latency is $[\gamma(X)^s((s-1)a + \max(a, b)) + (1 - \gamma(X)^s)(sa + b)]$ for asynchronous verification. By defining the objective function as $\frac{1-\gamma(X)^s}{(1-\gamma(X))(sa+b)}$ for synchronous verification or $\frac{1-\gamma(X)^s}{(1-\gamma(X))[\gamma(X)^s((s-1)a+\max(a,b))+(1-\gamma(X)^s)(sa+b)]}$ for asynchronous verification, we can adaptively solve for the optimal s with an estimation of $a, b, \gamma(X)$. Appendix A.2 describes how we estimate $a, b, \gamma(X)$.

5. Evaluation

5.1. Experimental Setups

We describe our experimental setups in this section, including language models, downstream datasets, retrievers, and the implementation details of the baseline, as well as our approach. Evaluation code is publicly available at https://github.com/JackFram/ralm-sys

Language Models. To demonstrate the effectiveness of our framework with different language models, we select models from three standard natural language generation (NLG) model classes, namely GPT2, OPT, and LLaMA-2 (Radford et al., 2019; Zhang et al., 2022; Touvron et al., 2023). More specifically, we choose GPT2-medium, OPT-1.3B, and LLaMA-2-7/13/70B, which are commonly used as base language models in RaLM and, at the same time, span across different model sizes. For KNN-LM serving, we use the same language model as in Khandelwal et al. (2019), which is a 16-layer decoder-only transformer model that has 247M trainable parameters.

Datasets. For the downstream workload, we mainly focus on the knowledge-intensive open-domain question-answering tasks. We thus include four QA datasets in our experiments: Wiki-QA, Web Questions, Natural Question, and Trivia-QA (Yang et al., 2015; Berant et al., 2013; Kwiatkowski et al., 2019; Joshi et al., 2017). For all QA datasets, we use the Wikipedia corpus as our external knowledge base (Chen et al., 2017). For the KNN-LM evaluation, we use the same WikiText-103 dataset (Merity et al., 2016) as the corpus following the original KNN-LM work (Khandelwal et al., 2019) and test the results over the Wiki-QA dataset.

Retrievers. To demonstrate the consistency of our approach, we test our method against both dense retrievers (vector-based) and sparse retrievers (bag-of-words-based). For dense retrievers, we further experiment with the exact and approximate methods, where the approximate method is much faster but less accurate. We use the Dense Passage Retriever (DPR) (Karpukhin et al., 2020) as the exact dense retriever (EDR), and its approximate version DPR-HNSW as the approximate dense retriever (ADR) (Malkov & Yashunin, 2018). For the sparse retriever (SR), we use the BM25 retriever (Robertson et al., 2009). We use the implementation from Pyserini (Lin et al., 2021) for all dense and sparse retrievers, where the dense retrievers are built on top of the standard FAISS library (Johnson et al., 2019).

Baseline. For document-level iterative RaLM serving, we follow directly from the implementation as in Ram et al. (2023); Jiang et al. (2023); Shao et al. (2023) when applicable. The latest retrieved document chunk is directly prepended to the prompt and replaces previous documents. We use RaLMSeq to denote the baseline implementation for iterative RaLM serving. For KNN-LM serving, we use the implementation from Khandelwal et al. (2019) as the baseline, where retrieval is performed for every token generated.

Implementation Details. For both RaLMSpec and RaLMSeq, we set the maximum input prompt length to be 512 tokens and the maximum generation length to be 128 tokens. For document-level iterative RaLM serving, the maximum length of the retrieved document chunk is set to 256 as in Ram et al. (2023). When OS^3 is disabled, RaLMSpec uses a constant speculation stride $s = 3$. Whenever OS^3 is enabled, RaLMSpec initializes the speculation stride with $s = 1$ and lets the scheduler adapt onwards. In all our experiments, we set the window size $w = 5$ and $\gamma_{\text{max}} = 0.6$ for estimating γ. For prefetching, we use a prefetch size of 20. We also test with a prefetch size of 256 for the ablation study. Due to the existence of Global Interpreter Lock (GIL) in Python, the potential of asynchronous verification cannot be fully realized. Thus, for asynchronous verification only, we use a simulated latency by calculating the ideal running time without additional overhead[2]. Except for asynchronous verification, all latencies are measured in wall-clock time, including the cache initialization phase. We want to note that asynchronous verification is not a significant factor contributing to the speed-up; details are provided in the ablation study in Section 5.2. For simplicity, we don't enable asynchronous verification in RaLMSpec for KNN-LM serving and leave it as future work. All implementations are written in Python. We use the VM.GPU.A10 instance on the Oracle cloud, which contains one A10 GPU and 15 CPUs for models that can fit into a single device. For larger models

[2]Enabling an asynchronous verification only requires two parallel threads (one thread for model generation and one thread for retrieval), thus the overhead should be minimal.

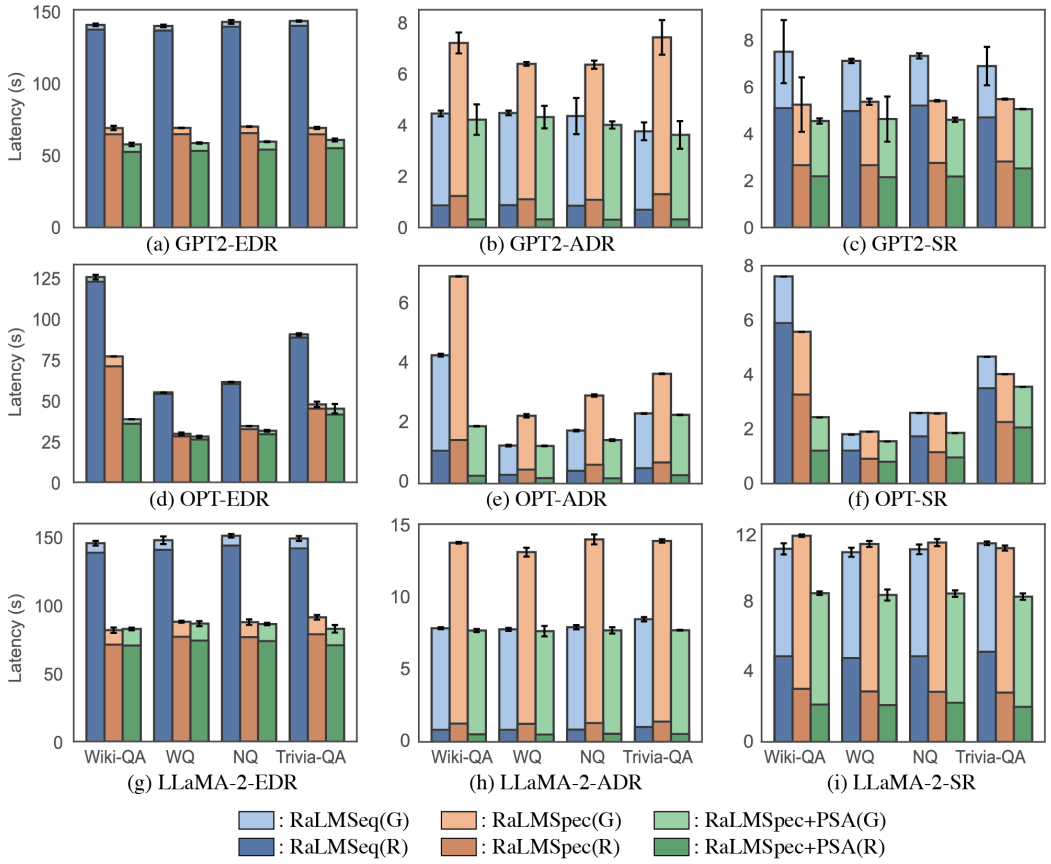


Figure 4. Latency comparison between RaLMSeq, RaLMSpec, and RaLMSpec+PSA on GPT2-medium, OPT-1.3B, and LLaMA-2-7B over four QA datasets with three different types of retrievers, where EDR, ADR, SR stand for exact dense retriever, approximate dense retriever, and sparse retriever respectively. We decompose the overall latency into the language model generation latency (G) and retrieval latency (R) to demonstrate the trade-off.

(LLaMA-2-70B) we use instances with four A100-80G and 20 CPUs.

5.2. Document-Level Iterative RaLM Serving

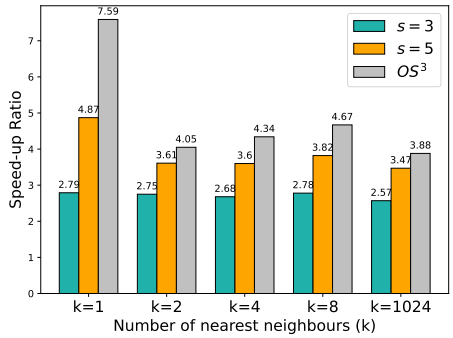
In this section, we empirically verify our approach against diverse language models, retrievers, and downstream datasets. We demonstrate our main results in Figure 4. RaLMSpec+P denotes RaLMSpec with prefetching enabled, RaLMSpec+S denotes RaLMSpec with the optimal speculation stride scheduler (OS^3) enabled, and RaLMSpec+A denotes RaLMSpec with asynchronous verification enabled. RaLMSpec+PSA indicates RaLMSpec with all three components enabled. We randomly select 100 questions from each dataset to test the latency results with RaLMSeq and RaLMSpec. We plot the mean and standard deviation over five independent runs for each setup to show the confidence interval. With the exact dense retriever (EDR), RaLMSpec+PSA can reduce the latency by $2.39\times$ for GPT2, $2.33\times$ for OPT, and $1.75\times$ for LLaMA-2 compared with RaLMSeq. With the approximate dense retriever (ADR), RaLMSpec+PSA can reduce the latency by $1.05\times$ for GPT2, $1.39\times$ for OPT, and $1.04\times$ for LLaMA-2 compared with RaLMSeq. With the sparse retriever (SR), RaLMSpec+PSA can reduce the latency by $1.53\times$ for GPT2, $1.77\times$ for OPT, and $1.31\times$ for LLaMA-2 compared with RaLMSeq. We include the full results in Appendix A.7.

In order to demonstrate the effectiveness of RaLMSpec on larger language models as well as more diverse workloads. We also include the evaluations of RaLMSpec+S and RaLMSpec+PSA on LLaMA-2-70B over the wiki QA dataset in Appendix A.3 and LLaMA-2-7B over the wiki QA dataset for the iter-retgen (Shao et al., 2023) and FLARE (Jiang et al., 2023) workloads in Appendix A.4.

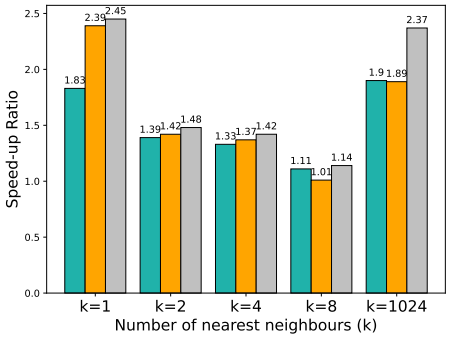
Analysis. As shown in Figure 4, RaLMSpec+PSA achieves the best performance consistently across all scenarios. However, the most significant speed-up ratio is achieved when the retriever is the exact dense retriever. This is because our approach can only optimize for the retrieval latency (R), not the language model generation latency (G).

Thus, our speed-up is intrinsically bottlenecked by the ratio of the retrieval latency over the end-to-end latency. When we use the approximate dense or sparse retriever, the naive implementation of RaLMSpec performs worse than the baseline for some cases. This relates to a constant speculation stride being used, and consequently, the trade-off between the speculation overhead and gain might not be optimal. More specifically, as the language model decoding step latency outweighs the retrieval latency, being too optimistic in the speculation stride can result in excessive speculation overhead due to an early mismatch in the verification step. On the other hand, if we enable the optimal speculation stride scheduler (OS^3), we can resolve this issue as the speculation stride can then be optimally adapted. Combined with prefetching and asynchronous verification, RaLMSpec+PSA achieves the best speed-up ratio performance consistently and automatically across all scenarios.

5.3. Token-Level Iterative RaLM (KNN-LM) Serving



(a) Exact dense retriever.



(b) Approximate dense retriever

Figure 5. Speedup Ratio Results for RaLMSpec on kNN-LMs over Wikipedia-QA. k stands for the number of nearest neighbors in kNN-LMs, s stands for stride size, and OS^3 stands for optimal scheduler stride.

We further evaluate our approach against a retrieval-intensive workload KNN-LM (Khandelwal et al., 2019). For KNN-LM, the knowledge base is constructed for each training token, with the key being the embedding of its leftward context and the value being the token itself. Instead of relying on a single language model to generate the subsequent token sampling distribution, KNN-LM retrieves k closest entries in a knowledge base along with their target tokens using an embedding of the current context. A distribution over these k target tokens is then computed based on their distance with respect to the current context embedding. The distribution is then interpolated with the original language model distribution to get the next token sampling distribution. Khandelwal et al. (2019) indicates KNN-LM can improve the perplexity of the base language model to state-of-the-art without extra training. While effective, the inference overhead of KNN-LM models is prohibitive as retrieval will be performed for every token generation step. To this end, we are interested in testing our system against the KNN-LM models. Different from the original speculation cache design, we cannot populate the cache by adding the same documents, as it will likely not be retrieved again in future decoding steps. However, for speculation, we can populate the cache with the following n entries directly after the currently retrieved item (due to observed spatial locality). In our experiments, we use an $n = 10$. In addition, instead of defining a successful speculation step as retrieving the same set of items that should have been retrieved, we identify that equivalency can be preserved as long as the speculated next token matches the ground truth next token. This relaxation is critical when k is large, e.g., $k = 1024$. Matching all 1024 entries with the ground truth one is exponentially hard, but matching the ground truth decoded token can be more accessible.

By modifying the cache update rule and verification protocol as above, we can achieve significant speed-up ratios compared with the naive implementation as shown in Figure 5. We have verified our approach against different k values ranging from 1 to 1024. When the retriever is an exact dense retriever, RaLMSpec can achieve up to $7.59\times$ acceleration rate with the optimal speculation stride scheduler (OS^3) and even $3.88\times$ acceleration rate when $k = 1024$. When the retriever is an approximate dense retriever, RaLMSpec can achieve up to $2.45\times$ acceleration rate with the optimal speculation stride scheduler (OS^3) and even $2.37\times$ acceleration rate when $k = 1024$. The reason why RaLMSpec can achieve a more significant speed-up for the exact dense retriever is due to its higher retrieval overhead. We have further experimented with different speculation stride sizes to have some ablation studies on the importance of the stride. The results show that a larger stride is consistently better for the exact dense retriever but not for all choices of k when we use the approximate dense retriever. However, enabling the optimal speculation stride scheduler can achieve the best performance consistently across all scenarios.

6. Conclusion

In this work, we introduce RaLMSpec, a speculation-inspired framework that accelerates the serving of generic retrieval augmented generation approaches that suffer from frequent retrieval-generation interactions. By leveraging the temporal and spatial locality of retrieved documents, we enable a request-level local cache for speculative retrieval and a batched verification step to guarantee correctness. In addition, we introduce cache prefetching, an optimal speculation stride scheduler, and asynchronous verification to boost the speculation performance further. The effectiveness of RaLMSpec has been verified empirically against different tasks, language models, retrievers, and downstream datasets. The results demonstrate that RaLMSpec can have substantial speed-ups consistently in all scenarios compared with the baseline.

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Impact Statement

This paper presents work whose goal is to advance the field of iterative retrieval augmented language model serving. There are many potential societal consequences of our work; for instance, latency savings can result in energy savings, thus reducing CO2 emissions.

References

Alon, U., Xu, F., He, J., Sengupta, S., Roth, D., and Neubig, G. Neuro-symbolic language modeling with automaton-augmented retrieval. In *International Conference on Machine Learning*, pp. 468–485. PMLR, 2022.

Asai, A., Min, S., Zhong, Z., and Chen, D. Acl 2023 tutorial: Retrieval-based language models and applications. *ACL 2023*, 2023.

Berant, J., Chou, A., Frostig, R., and Liang, P. Semantic parsing on Freebase from question-answer pairs. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pp. 1533–1544, Seattle, Washington, USA, October 2013. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/D13-1160.

Borgeaud, S., Mensch, A., Hoffmann, J., Cai, T., Rutherford, E., Millican, K., Van Den Driessche, G. B., Lespiau, J.-B., Damoc, B., Clark, A., et al. Improving language models by retrieving from trillions of tokens. In *International conference on machine learning*, pp. 2206–2240. PMLR, 2022.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33: 1877–1901, 2020.

Burton, F. W. Speculative computation, parallelism, and functional programming. *IEEE Transactions on Computers*, 100(12):1190–1193, 1985.

Cai, T., Li, Y., Geng, Z., Peng, H., Lee, J. D., Chen, D., and Dao, T. Medusa: Simple llm inference acceleration framework with multiple decoding heads. *arXiv preprint arXiv:2401.10774*, 2024.

Chen, C., Borgeaud, S., Irving, G., Lespiau, J.-B., Sifre, L., and Jumper, J. Accelerating large language model decoding with speculative sampling. *arXiv preprint arXiv:2302.01318*, 2023.

Chen, D., Fisch, A., Weston, J., and Bordes, A. Reading wikipedia to answer open-domain questions. In *55th Annual Meeting of the Association for Computational Linguistics, ACL 2017*, pp. 1870–1879. Association for Computational Linguistics (ACL), 2017.

Chowdhery, A., Narang, S., Devlin, J., Bosma, M., Mishra, G., Roberts, A., Barham, P., Chung, H. W., Sutton, C., Gehrmann, S., et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.

Drozdov, A., Wang, S., Rahimi, R., McCallum, A., Zamani, H., and Iyyer, M. You can't pick your neighbors, or can you? when and how to rely on retrieval in the k nn-lm. *arXiv preprint arXiv:2210.15859*, 2022.

Guu, K., Lee, K., Tung, Z., Pasupat, P., and Chang, M. Retrieval augmented language model pre-training. In *International conference on machine learning*, pp. 3929–3938. PMLR, 2020.

He, J., Neubig, G., and Berg-Kirkpatrick, T. Efficient nearest neighbor language models. *arXiv preprint arXiv:2109.04212*, 2021.

Izacard, G., Caron, M., Hosseini, L., Riedel, S., Bojanowski, P., Joulin, A., and Grave, E. Unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118*, 2021.

Izacard, G., Lewis, P., Lomeli, M., Hosseini, L., Petroni, F., Schick, T., Dwivedi-Yu, J., Joulin, A., Riedel, S., and Grave, E. Few-shot learning with retrieval augmented language models. *arXiv preprint arXiv:2208.03299*, 2022.

Jiang, Z., Xu, F. F., Gao, L., Sun, Z., Liu, Q., Dwivedi-Yu, J., Yang, Y., Callan, J., and Neubig, G. Active retrieval augmented generation. *arXiv preprint arXiv:2305.06983*, 2023.

Joao Gante. Assisted generation: a new direction toward low-latency text generation, 2023. URL https://huggingface.co/blog/assisted-generation.

Johnson, J., Douze, M., and Jégou, H. Billion-scale similarity search with GPUs. *IEEE Transactions on Big Data*, 7 (3):535–547, 2019.

Joshi, M., Choi, E., Weld, D., and Zettlemoyer, L. triviaqa: A Large Scale Distantly Supervised Challenge Dataset for Reading Comprehension. *arXiv e-prints*, art. arXiv:1705.03551, 2017.

Karpukhin, V., Oğuz, B., Min, S., Lewis, P., Wu, L., Edunov, S., Chen, D., and Yih, W.-t. Dense passage retrieval for open-domain question answering. *arXiv preprint arXiv:2004.04906*, 2020.

Khandelwal, U., Levy, O., Jurafsky, D., Zettlemoyer, L., and Lewis, M. Generalization through memorization: Nearest neighbor language models. *arXiv preprint arXiv:1911.00172*, 2019.

Khattab, O. and Zaharia, M. Colbert: Efficient and effective passage search via contextualized late interaction over bert. In *Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval*, pp. 39–48, 2020.

Khattab, O., Santhanam, K., Li, X. L., Hall, D., Liang, P., Potts, C., and Zaharia, M. Demonstrate-search-predict: Composing retrieval and language models for knowledge-intensive nlp. *arXiv preprint arXiv:2212.14024*, 2022.

Kwiatkowski, T., Palomaki, J., Redfield, O., Collins, M., Parikh, A., Alberti, C., Epstein, D., Polosukhin, I., Devlin, J., Lee, K., et al. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466, 2019.

Leviathan, Y., Kalman, M., and Matias, Y. Fast inference from transformers via speculative decoding. *arXiv preprint arXiv:2211.17192*, 2022.

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., Küttler, H., Lewis, M., Yih, W.-t., Rocktäschel, T., et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474, 2020.

Lin, J., Ma, X., Lin, S.-C., Yang, J.-H., Pradeep, R., and Nogueira, R. Pyserini: A Python toolkit for reproducible information retrieval research with sparse and dense representations. In *Proceedings of the 44th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2021)*, pp. 2356–2362, 2021.

Malkov, Y. A. and Yashunin, D. A. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs. *IEEE transactions on pattern analysis and machine intelligence*, 42(4):824–836, 2018.

Merity, S., Xiong, C., Bradbury, J., and Socher, R. Pointer sentinel mixture models, 2016.

Miao, X., Oliaro, G., Zhang, Z., Cheng, X., Wang, Z., Wong, R. Y. Y., Chen, Z., Arfeen, D., Abhyankar, R., and Jia, Z. Specinfer: Accelerating generative llm serving with speculative inference and token tree verification. *arXiv preprint arXiv:2305.09781*, 2023.

Park, J. S., O'Brien, J. C., Cai, C. J., Morris, M. R., Liang, P., and Bernstein, M. S. Generative agents: Interactive simulacra of human behavior. *arXiv preprint arXiv:2304.03442*, 2023.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I., et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.

Ram, O., Levine, Y., Dalmedigos, I., Muhlgay, D., Shashua, A., Leyton-Brown, K., and Shoham, Y. In-context retrieval-augmented language models. *arXiv preprint arXiv:2302.00083*, 2023.

Ramos, J. et al. Using tf-idf to determine word relevance in document queries. In *Proceedings of the first instructional conference on machine learning*, volume 242, pp. 29–48. Citeseer, 2003.

Robertson, S., Zaragoza, H., et al. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends® in Information Retrieval*, 3(4):333–389, 2009.

Rubin, O. and Berant, J. Long-range language modeling with self-retrieval. *arXiv preprint arXiv:2306.13421*, 2023.

Santhanam, K., Khattab, O., Saad-Falcon, J., Potts, C., and Zaharia, M. Colbertv2: Effective and efficient retrieval via lightweight late interaction. *arXiv preprint arXiv:2112.01488*, 2021.

Shao, Z., Gong, Y., Shen, Y., Huang, M., Duan, N., and Chen, W. Enhancing retrieval-augmented large language models with iterative retrieval-generation synergy. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 9248–9274, 2023.

Shi, W., Min, S., Yasunaga, M., Seo, M., James, R., Lewis, M., Zettlemoyer, L., and Yih, W.-t. Replug: Retrieval-augmented black-box language models. *arXiv preprint arXiv:2301.12652*, 2023.

Stern, M., Shazeer, N., and Uszkoreit, J. Blockwise parallel decoding for deep autoregressive models. *Advances in Neural Information Processing Systems*, 31, 2018.

Touvron, H., Martin, L., Stone, K., Albert, P., Almahairi, A., Babaei, Y., Bashlykov, N., Batra, S., Bhargava, P., Bhosale, S., et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Wang, G., Xie, Y., Jiang, Y., Mandlekar, A., Xiao, C., Zhu, Y., Fan, L., and Anandkumar, A. Voyager: An open-ended embodied agent with large language models. *arXiv preprint arXiv:2305.16291*, 2023a.

Wang, W., Dong, L., Cheng, H., Liu, X., Yan, X., Gao, J., and Wei, F. Augmenting language models with long-term memory. *arXiv preprint arXiv:2306.07174*, 2023b.

Xia, H., Ge, T., Chen, S.-Q., Wei, F., and Sui, Z. Speculative decoding: Lossless speedup of autoregressive translation.

Xiong, L., Xiong, C., Li, Y., Tang, K.-F., Liu, J., Bennett, P., Ahmed, J., and Overwijk, A. Approximate nearest neighbor negative contrastive learning for dense text retrieval. *arXiv preprint arXiv:2007.00808*, 2020.

Yang, N., Ge, T., Wang, L., Jiao, B., Jiang, D., Yang, L., Majumder, R., and Wei, F. Inference with reference: Lossless acceleration of large language models. *arXiv preprint arXiv:2304.04487*, 2023.

Yang, Y., Yih, W.-t., and Meek, C. WikiQA: A challenge dataset for open-domain question answering. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 2013–2018, Lisbon, Portugal, September 2015. Association for Computational Linguistics. doi: 10.18653/v1/D15-1237. URL https://aclanthology.org/D15-1237.

Zhang, S., Roller, S., Goyal, N., Artetxe, M., Chen, M., Chen, S., Dewan, C., Diab, M., Li, X., Lin, X. V., Mihaylov, T., Ott, M., Shleifer, S., Shuster, K., Simig, D., Koura, P. S., Sridhar, A., Wang, T., and Zettlemoyer, L. Opt: Open pre-trained transformer language models, 2022.

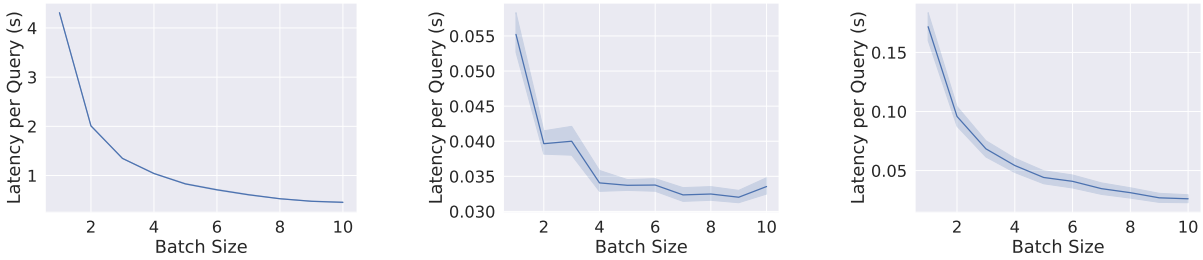
Zhong, Z., Lei, T., and Chen, D. Training language models with memory augmentation. *arXiv preprint arXiv:2205.12674*, 2022.

Zhou, W., Jiang, Y. E., Cui, P., Wang, T., Xiao, Z., Hou, Y., Cotterell, R., and Sachan, M. Recurrentgpt: Interactive generation of (arbitrarily) long text. *arXiv preprint arXiv:2305.13304*, 2023.

Zhu, X., Chen, Y., Tian, H., Tao, C., Su, W., Yang, C., Huang, G., Li, B., Lu, L., Wang, X., et al. Ghost in the minecraft: Generally capable agents for open-world enviroments via large language models with text-based knowledge and memory. *arXiv preprint arXiv:2305.17144*, 2023.

A. Appendix

A.1. Batched Retrieval



(a) Exact dense retriever. (b) Approximate dense retriever (c) Sparse retriever

Figure 6. Effect of batch size on latency per query for three different types of retrievers. 95% confidence bands for the true mean latency are included.

We demonstrate the benefit of batched retrievals by examining the latency per query for increasing batch sizes. For all three retrieval methods, latency per query decreases with increasing batch size. This is most noticeable with the exact dense retriever and sparse retriever, where total retrieval time was essentially constant across all batch sizes. The approximate dense retriever exhibited latency that scaled linearly with batch size; however, there was a significant intercept term in the linear relationship. With batch retrievals, repeated incurrences of this latency under individual retrievals are saved. The result is less latency per query for approximate dense retrievers as well, though not to the extent of exact dense retrievers or sparse retrievers.

A.2. Detailed Derivations

Expected matching length. Given a speculation accuracy of $\gamma(X) \in [0, 1]$ for single-step speculation, the expected number of matched documents with a speculation stride s can be calculated as:

$$\begin{aligned}
\mathbb{E}\left[\#\text{ of verified documents} \mid X, s\right] &= 1 + \sum_{i=1}^{s-2} i\gamma(X)^i(1-\gamma(X)) + (s-1)\gamma(X)^{(s-1)} \\
&= 1 + \sum_{i=1}^{s-2} i\gamma(X)^i - \sum_{i=1}^{s-1}(i-1)\gamma(X)^i + (s-1)\gamma(X)^{(s-1)} \\
&= \sum_{i=0}^{s-1} \gamma(X)^i \\
&= \frac{1-\gamma(X)^s}{1-\gamma(X)}
\end{aligned}$$

Parameter estimation for OS^3 To get an optimal stride s, we need to adaptively estimate $a, b, \gamma(X)$. For a, b, we directly estimate their value with the profiling results from the most recent steps. For the exact dense retriever and sparse retriever, we observe that the latency of batched retrieval with a batch size smaller than 10 is nearly constant, while for the approximate dense retriever, the latency is surprisingly linear to the batch size but with a large intercept (batch retrieval is still more efficient due to the intercept is non-zero). We include the batched retrieval latency analysis for three different retrievers in Appendix A.1. For $\gamma(X)$, we use the maximum log-likelihood estimation within a specific window size w so that the estimated $\hat{\gamma}$ can have both locality and less variance. More specifically, denoting $s(t), t \in [w]$ as the speculation stride (also the batch size) in the t-th most recent verification step, $M(s(t), X)$ as the corresponding number of matched documents, we estimate $\gamma(X)$ with

$$\hat{\gamma}(X) = \frac{\sum_t M(s(t), X)}{\sum_t M(s(t), X) + \sum_t \mathbb{1}(M(s(t), X) < s(t))}$$

where $\mathbb{1}(\cdot)$ is the indicator function. To prevent the over-optimistic estimation and division-by-zero error when $\hat{\gamma}$ approaches probability 1 in some cases, we further set a constant upper bound γ_{max} and truncate $\hat{\gamma}$ accordingly.

A.3. LLaMA-2-13/70B Serving Evaluation

Table 1. RaLMSpec+PSA speed-up ratio compared against the baseline on LLaMA-2-13B over four downstream datasets (Wiki QA, Web Questions, Natural Questions, and Trivia-QA).

Retriever	Wiki QA	Web Questions	Natural Questions	Trivia-QA
EDR	$1.70\times$	$1.85\times$	$1.73\times$	$1.78\times$
ADR	$1.03\times$	$1.04\times$	$1.02\times$	$1.03\times$
SR	$1.18\times$	$1.21\times$	$1.22\times$	$1.26\times$

Table 2. RaLMSpec+S and RaLMSpec+PSA speed-up ratio compared against the baseline on LLaMA-2-70B over Wiki QA.

Method	EDR	ADR	SR
RaLMSpec+S	$1.29\times$	$1.00\times$	$1.02\times$
RaLMSpec+PSA	$1.44\times$	$1.03\times$	$1.11\times$

To demonstrate the effectiveness of RaLMSpec, we further evaluate RaLMSpec with the LLaMA-2-13B model over the Wiki QA, Web Questions, Natural Questions, and Trivia-QA and present the results in Table 1 and LLaMA-2-70B model over the Wiki QA in Table 2. We can still observe RaLMSpec+PSA can achieve up to $1.85\times$ speed-up for LLaMA-2-13B and $1.44\times$ speed-up for LLaMA-2-70B compared against RaLMSeq when the retriever is the exact dense retriever. We observe marginal improvement for the approximate dense retriever because language model generation latency has far outweighed the retrieval latency. Thus, the retrieval latency saving is amortized within the end-to-end latency saving.

A.4. Diverse Workload Evaluation

In order to show the effectiveness of our method over more diverse workloads, we further conduct experiments on two iterative RaLM workloads iter-retgen (Shao et al., 2023) and FLARE (Jiang et al., 2023), where the retrieval operation is triggered on demand. The results are in Table 3 and Table 4 respectively.

Table 3. RaLMSpec+S and RaLMSpec+PSA speed-up ratio compared against the baseline on LLaMA-2-7B over Wiki QA for the Iter-RetGen workload.

Method	EDR	ADR	SR
RaLMSpec+S	$1.53\times$	$1.00\times$	$1.09\times$
RaLMSpec+PSA	$1.68\times$	$1.08\times$	$1.16\times$

Table 4. RaLMSpec+S and RaLMSpec+PSA speed-up ratio compared against the baseline on LLaMA-2-7B over Wiki QA for the FLARE workload.

Method	EDR	ADR	SR
RaLMSpec+S	$1.27\times$	$1.01\times$	$1.11\times$
RaLMSpec+PSA	$1.41\times$	$1.07\times$	$1.07\times$

We can see that RaLMSpec with the optimal speculation stride scheduler (RaLMSpec+S) and RaLMSpec+PSA can still

achieve reasonable speed-ups in both the iter-retgen and FLARE workloads due to the locality. Though the speed-ups brought by RaLMSpec are less significant for an RAG workload, RaLMSpec still demonstrates its effectiveness on the iterative RAG workload.

Table 5. Ablation results of speed-up ratio compared with baseline of each component. P stands for prefetching, S stands for optimal speculation stride scheduler and A stands for asynchronous verification. $(*)$ and $(**)$ denote the most speed-up and the second most speed-up respectively.

Retriever	Method	GPT2	OPT	LLaMA-2
EDR	RaLMSpec	$2.04\times$	$1.76\times$	$1.70\times$
	RaLMSpec+P	$2.10\times$	$2.16\times(**)$	$1.75\times(**)$
	RaLMSpec+S	$2.26\times(**)$	$2.15\times$	$1.69\times$
	RaLMSpec+A	$2.03\times$	$1.74\times$	$1.74\times$
	RaLMSpec+PSA	$2.39\times(*)$	$2.32\times(*)$	$1.75\times(*)$
ADR	RaLMSpec	$0.62\times$	$0.61\times$	$0.58\times$
	RaLMSpec+P	$0.59\times$	$0.76\times$	$0.58\times$
	RaLMSpec+S	$0.92\times(**)$	$1.17\times(**)$	$1.01\times(**)$
	RaLMSpec+A	$0.66\times$	$0.46\times$	$0.55\times$
	RaLMSpec+PSA	$1.05\times(*)$	$1.39\times(*)$	$1.04\times(*)$
SR	RaLMSpec	$1.34\times$	$1.18\times$	$0.97\times$
	RaLMSpec+P	$1.39\times$	$1.42\times$	$0.98\times$
	RaLMSpec+S	$1.32\times$	$1.52\times(**)$	$1.05\times(**)$
	RaLMSpec+A	$1.41\times(**)$	$1.27\times$	$1.01\times$
	RaLMSpec+PSA	$1.53\times(*)$	$1.77\times(*)$	$1.31\times(*)$

A.5. Ablation Study on Different System Components

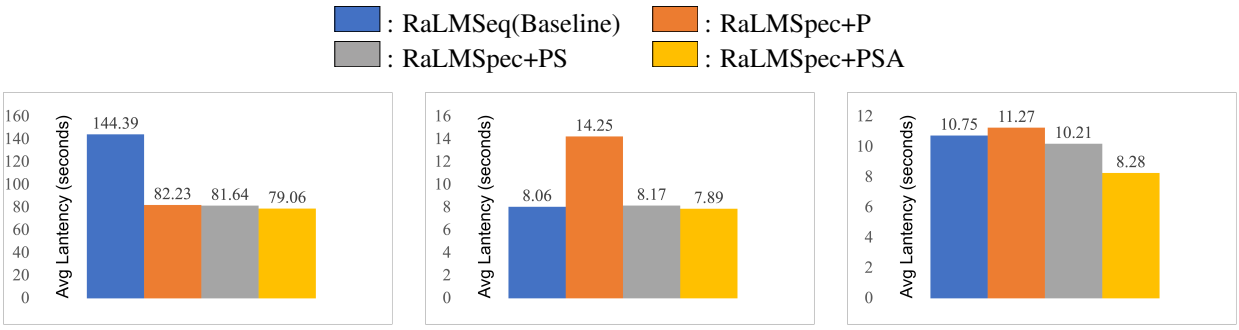
We further present the contribution of each component (prefetching, OS^3, and asynchronous verification) in Table 5 on GPT2, OPT, and LLaMA-2 with the exact dense retriever (EDR), approximate dense retriever (ADR), and sparse retriever (SR). The speed-up ratio is compared against the baseline (RaLMSeq) and averaged over the four datasets. In most cases, enabling OS^3 brings the most significant gain among the three components, while combining all three elements achieves the best performance consistently. This reflects that controlling the trade-off between speculation overhead and latency reduction with the speculation stride is critical for achieving the optimal speed-up under various scenarios. The results demonstrate that OS^3 can find a better stride scheduling solution than the naive hand-tuned constant speculation stride in most cases. Prefetching can also improve performance by caching more entries in the local cache to obtain a higher speculation accuracy. However, increasing a prefetching size can introduce higher retrieval overhead. As shown in Table 6, when we increase the prefetching size from 20 to 256, the performance decreases in most cases due to the diminished prefetching gain and increased retrieval overhead. Asynchronous verification improves the performance by introducing an extra speculation step when doing verification. However, if the verification fails at an earlier stage, the benefit of doing asynchronous verification cannot be realized. As prefetching, OS^3, and asynchronous verification compensate one another, combining all of them fully realizes our approach's potential.

Table 7. Speed-up contribution of different combinations of prefetching (P), optimal speculation stride scheduler (S), and asynchronous verification (A). We report the average serving latency over 100 requests evaluated over LLaMA-2-7B and the Wiki QA dataset.

Retriever	B	P	S	A	PS	SA	PA	PSA
EDR	144.39s	82.23s	85.19s	90.49s	81.64s	85.13s	**81.60s**	**79.06s**
ADR	8.06s	14.25s	8.14s	13.90s	8.17s	**7.83s**	12.84s	**7.89s**
SR	10.75s	11.27s	10.38s	10.88s	10.21s	**8.26s**	10.61s	**8.28s**

Table 6. Ablation results of speed-up ratio of different prefetching size compared with the baseline.

Retriever	Method	GPT2	OPT	LLaMA-2
EDR	RaLMSpec+P(20)	2.10×	**2.16**×	**1.75**×
	RaLMSpec+P(256)	**2.15**×	1.72×	1.63×
ADR	RaLMSpec+P(20)	0.59×	**0.76**×	**0.58**×
	RaLMSpec+P(256)	**0.67**×	0.25×	0.34×
SR	RaLMSpec+P(20)	**1.39**×	**1.42**×	**0.98**×
	RaLMSpec+P(256)	1.02×	0.93×	0.84×



(a) Exact dense retriever. (b) Approximate dense retriever (c) Sparse retriever

Figure 7. Ablation study on the contribution of the prefetching (P), optimal speculation stride scheduler (S), and asynchronous verification (A) components.

To demonstrate the effect of different component groups, we have evaluated all combinations among prefetching (P), optimal speculation stride scheduler (S), and asynchronous verification (A) with the LLaMA-2-7B model on the Wiki QA dataset and presented the results in Table 7 and Figure 7. When the retriever is the exact dense retriever, prefetching can improve more effectively than the optimal speculation stride scheduler and asynchronous verification. In addition, prefetching+asynchronous verification can even outperform RaLMSpec+PSA. This is due to the prefixed stride (s=3) for the exact dense retriever is already near-optimal, and the optimal speculation stride scheduler needs a warm-up phase at the start to adapt to the optimal stride, thus incurring some additional overheads. We can observe that the optimal speculation stride scheduler is the most crucial component for the approximate dense and sparse retriever and achieves the best performance when combined with asynchronous verification. Prefetching can even affect performance negatively because the overhead of prefetching outweighs its gain. To sum up, enabling the optimal speculation stride scheduler for all workloads can help achieve a near-optimal stride adaptively. For workloads where retrieval dominates most of the latency, enabling prefetching can further improve the serving latency while the contribution of asynchronous verification is marginal. For workloads where retrieval is not the most time-consuming step, asynchronous verification can benefit the serving latency while prefetching's overhead can outweigh its benefit if the prefetching size has not been chosen properly.

A.6. Ablation Study on Speculation Stride

Table 8. Ablation results on different speculation strides (S=2,4,8) and the optimal speculation stride scheduler (OS^3). We report the average serving latency over 100 requests evaluated over LLaMA-2-7B and the Wiki QA dataset.

Retriever	S=2	S=4	S=8	OS^3
EDR	92.17s	**81.06s**	81.90s	85.19s
ADR	9.86s	14.93s	25.88s	**8.14s**
SR	10.65s	12.48s	16.66s	**10.38s**

To demonstrate the effect of the optimal speculation stride scheduler, we have conducted ablation studies on different fixed speculation strides (s=2, 4, 8) with LLaMA-2-7B over the Wiki QA dataset. The results are presented in Table 8. We can observe from the results that a larger speculation stride is better when the exact dense retriever is used. This is because the retrieval latency is much larger for the exact dense retriever and way exceeds the language model generation latency. Thus, an aggressive speculation stride will incur little overhead while having the opportunity for a longer match. On the other hand, the approximately dense and sparse retrievers prefer a smaller speculation stride because the retrieval is more efficient, and the cost-performance ratio for doing more speculations is low. Thus, the optimal speculation stride scheduler is designed to tackle this dynamism and can achieve near-optimal stride scheduling in all scenarios. OS^3 performs slightly worse than $s = 4, 8$ in the case of EDR because a warm-up phase is required for OS^3 to start its adaptation, i.e., we initialize s=1 when we enable OS^3. Thus, the warm-up phase can introduce non-optimal strides and, thus, slightly worse performance.

A.7. Additional Experimental Results

This section presents the full evaluation results with GPT2, OPT, and LLaMA-2 over Wiki QA, Web Questions, Natural Questions, and Trivia-QA against the exact dense, approximate dense, and sparse retriever.

Table 9. Averaged latency measured in seconds over GPT-2. OPT and LLaMA-2 with the exact dense retriever.

Model	Method	Wiki QA	WQ	NQ	Trivia QA
GPT2	Baseline	142.14 ± 0.96	141.38 ± 1.50	144.22 ± 1.17	144.82 ± 0.96
	RaLMSpec	69.82 ± 0.22	69.88 ± 0.52	70.79 ± 1.27	69.83 ± 0.28
	RaLMSpec+P(20)	68.22 ± 0.18	68.09 ± 0.18	68.06 ± 0.37	68.14 ± 0.06
	RaLMSpec+P(256)	66.14 ± 0.39	65.22 ± 0.79	67.10 ± 0.59	66.64 ± 0.23
	RaLMSpec+S	62.72 ± 0.48	62.43 ± 0.19	63.48 ± 0.69	64.63 ± 0.44
	RaLMSpec+A	69.92 ± 1.06	69.36 ± 0.60	71.00 ± 0.74	70.40 ± 0.78
	RaLMSpec+P(20)SA	58.35 ± 0.31	59.24 ± 0.46	60.21 ± 0.78	61.39 ± 0.99
	RaLMSpec+P(256)SA	$\mathbf{53.95 \pm 0.72}$	$\mathbf{53.36 \pm 1.08}$	$\mathbf{56.26 \pm 0.95}$	$\mathbf{56.95 \pm 1.34}$
OPT	Baseline	126.86 ± 1.39	55.60 ± 0.08	62.02 ± 0.11	91.50 ± 0.01
	RaLMSpec	77.81 ± 0.84	29.99 ± 0.54	34.75 ± 0.19	48.20 ± 0.09
	RaLMSpec+P(20)	40.37 ± 0.07	29.09 ± 0.07	33.79 ± 0.60	52.09 ± 0.11
	RaLMSpec+P(256)	72.68 ± 0.75	31.94 ± 1.16	39.90 ± 3.18	50.24 ± 0.02
	RaLMSpec+S	40.77 ± 0.52	29.49 ± 0.53	35.13 ± 0.10	50.82 ± 0.49
	RaLMSpec+A	77.76 ± 4.99	30.28 ± 0.59	36.16 ± 1.18	47.83 ± 0.03
	RaLMSpec+P(20)SA	$\mathbf{39.00 \pm 0.58}$	28.31 ± 0.62	31.88 ± 1.67	45.51 ± 2.93
	RaLMSpec+P(256)SA	59.21 ± 0.04	$\mathbf{27.79 \pm 0.11}$	$\mathbf{30.02 \pm 0.01}$	$\mathbf{45.13 \pm 0.04}$
LLaMA	Baseline	144.39 ± 1.71	146.52 ± 1.92	149.76 ± 0.95	147.76 ± 2.80
	RaLMSpec	81.05 ± 0.78	87.20 ± 1.83	86.92 ± 1.30	90.44 ± 2.01
	RaLMSpec+P(20)	83.94 ± 1.11	$\mathbf{84.23 \pm 0.37}$	84.74 ± 0.47	81.86 ± 0.76
	RaLMSpec+P(256)	82.23 ± 1.95	94.15 ± 1.60	97.14 ± 1.89	85.65 ± 1.46
	RaLMSpec+S	85.19 ± 2.26	88.95 ± 0.99	89.45 ± 1.28	84.28 ± 2.93
	RaLMSpec+A	90.49 ± 6.12	85.74 ± 1.94	$\mathbf{84.37 \pm 0.62}$	77.39 ± 1.11
	RaLMSpec+P(20)SA	81.94 ± 0.91	85.81 ± 1.82	85.47 ± 1.70	82.03 ± 2.73
	RaLMSpec+P(256)SA	$\mathbf{79.06 \pm 3.61}$	87.34 ± 4.63	95.54 ± 3.36	$\mathbf{73.64 \pm 0.80}$

Table 10. Averaged latency measured in seconds over GPT-2. OPT and LLaMA-2 with the approximate dense retriever.

Model	Method	Wiki QA	WQ	NQ	Trivia QA
GPT2	Baseline	4.48 ± 0.11	4.50 ± 0.41	4.38 ± 0.60	3.78 ± 0.10
	RaLMSpec	7.26 ± 0.07	6.44 ± 0.44	6.41 ± 0.71	7.47 ± 0.16
	RaLMSpec+P(20)	6.92 ± 0.10	7.38 ± 0.56	7.37 ± 0.58	7.28 ± 0.28
	RaLMSpec+P(256)	6.65 ± 0.07	5.97 ± 0.46	5.64 ± 0.74	6.96 ± 0.63
	RaLMSpec+S	4.59 ± 0.28	4.77 ± 0.32	4.65 ± 0.61	4.51 ± 0.45
	RaLMSpec+A	6.50 ± 0.54	6.49 ± 0.38	5.70 ± 0.70	6.94 ± 0.84
	RaLMSpec+P(20)SA	4.24 ± 0.14	4.34 ± 0.35	4.03 ± 0.68	$\mathbf{3.64 \pm 0.54}$
	RaLMSpec+P(256)SA	$\mathbf{4.01 \pm 0.21}$	$\mathbf{3.81 \pm 0.02}$	$\mathbf{3.40 \pm 0.01}$	3.86 ± 0.31
OPT	Baseline	4.43 ± 0.05	1.31 ± 0.01	1.83 ± 0.01	2.42 ± 0.03
	RaLMSpec	7.15 ± 0.06	2.34 ± 0.01	3.04 ± 0.03	3.79 ± 0.04
	RaLMSpec+P(20)	3.44 ± 0.02	2.34 ± 0.01	2.70 ± 0.06	4.66 ± 0.03
	RaLMSpec+P(256)	16.03 ± 0.03	6.06 ± 0.01	7.06 ± 0.04	10.17 ± 0.01
	RaLMSpec+S	2.21 ± 0.01	1.47 ± 0.01	1.88 ± 0.05	2.97 ± 0.05
	RaLMSpec+A	7.55 ± 0.05	2.25 ± 0.01	5.41 ± 1.32	6.20 ± 0.02
	RaLMSpec+P(20)SA	$\mathbf{1.98 \pm 0.03}$	$\mathbf{1.30 \pm 0.01}$	$\mathbf{1.50 \pm 0.01}$	$\mathbf{2.37 \pm 0.01}$
	RaLMSpec+P(256)SA	9.41 ± 0.66	4.14 ± 0.02	4.31 ± 0.02	6.19 ± 0.02
LLaMA	Baseline	8.06 ± 0.07	7.97 ± 0.06	8.11 ± 0.11	8.68 ± 0.10
	RaLMSpec	14.10 ± 0.31	13.44 ± 0.37	14.35 ± 0.15	14.23 ± 0.35
	RaLMSpec+P(20)	14.25 ± 0.39	13.45 ± 0.28	14.08 ± 0.32	14.21 ± 0.30
	RaLMSpec+P(256)	20.63 ± 0.48	26.44 ± 3.11	27.38 ± 3.39	21.04 ± 0.43
	RaLMSpec+S	8.14 ± 0.19	8.08 ± 0.07	8.08 ± 0.07	8.16 ± 0.09
	RaLMSpec+A	13.90 ± 0.36	13.28 ± 0.17	13.72 ± 0.14	18.35 ± 1.11
	RaLMSpec+P(20)SA	$\mathbf{7.89 \pm 0.22}$	$\mathbf{7.84 \pm 0.15}$	$\mathbf{7.90 \pm 0.12}$	$\mathbf{7.91 \pm 0.03}$
	RaLMSpec+P(256)SA	14.06 ± 0.08	14.96 ± 1.34	14.59 ± 2.04	12.94 ± 0.03

Table 11. Averaged latency measured in seconds over GPT-2. OPT and LLaMA-2 with the sparse retriever.

Model	Method	Wiki QA	WQ	NQ	Trivia QA
GPT2	Baseline	7.41 ± 1.34	7.03 ± 1.15	7.23 ± 0.11	6.80 ± 0.09
	RaLMSpec	5.18 ± 0.13	5.30 ± 0.95	5.34 ± 0.11	5.40 ± 0.03
	RaLMSpec+P(20)	5.23 ± 0.23	4.58 ± 0.01	5.17 ± 0.05	5.50 ± 0.04
	RaLMSpec+P(256)	6.88 ± 0.66	7.16 ± 1.34	6.76 ± 0.27	6.91 ± 0.13
	RaLMSpec+S	5.62 ± 0.96	5.03 ± 0.68	5.24 ± 0.13	5.61 ± 0.11
	RaLMSpec+A	5.34 ± 0.89	4.99 ± 0.86	4.76 ± 0.14	5.04 ± 0.12
	RaLMSpec+P(20)SA	$\mathbf{4.49 \pm 0.09}$	$\mathbf{4.57 \pm 0.81}$	$\mathbf{4.54 \pm 0.02}$	$\mathbf{4.99 \pm 0.01}$
	RaLMSpec+P(256)SA	6.66 ± 1.25	6.50 ± 1.39	5.54 ± 0.02	5.91 ± 0.03
OPT	Baseline	7.68 ± 0.01	1.83 ± 0.01	2.62 ± 0.01	4.71 ± 0.02
	RaLMSpec	5.63 ± 0.01	1.93 ± 0.01	2.60 ± 0.01	4.07 ± 0.02
	RaLMSpec+P(20)	3.00 ± 0.01	2.06 ± 0.01	2.50 ± 0.02	4.27 ± 0.01
	RaLMSpec+P(256)	7.13 ± 0.01	2.45 ± 0.01	3.22 ± 0.01	5.24 ± 0.02
	RaLMSpec+S	2.79 ± 0.01	1.69 ± 0.01	2.32 ± 0.01	4.27 ± 0.01
	RaLMSpec+A	5.27 ± 0.02	1.86 ± 0.01	2.28 ± 0.01	3.82 ± 0.02
	RaLMSpec+P(20)SA	$\mathbf{2.46 \pm 0.01}$	$\mathbf{1.57 \pm 0.01}$	$\mathbf{1.88 \pm 0.01}$	$\mathbf{3.59 \pm 0.01}$
	RaLMSpec+P(256)SA	6.37 ± 0.01	1.92 ± 0.04	2.44 ± 0.02	4.53 ± 0.01
LLaMA	Baseline	10.75 ± 0.32	10.55 ± 0.07	10.72 ± 0.10	11.06 ± 0.25
	RaLMSpec	11.47 ± 0.17	11.02 ± 0.31	11.10 ± 0.27	10.79 ± 0.20
	RaLMSpec+P(20)	11.27 ± 0.14	11.04 ± 0.22	10.69 ± 0.15	10.66 ± 0.23
	RaLMSpec+P(256)	12.83 ± 0.21	13.35 ± 0.81	12.48 ± 0.22	12.60 ± 0.36
	RaLMSpec+S	10.38 ± 0.28	10.19 ± 0.19	9.95 ± 0.04	10.18 ± 0.08
	RaLMSpec+A	10.88 ± 0.26	10.66 ± 0.12	10.56 ± 0.20	10.16 ± 0.18
	RaLMSpec+P(20)SA	$\mathbf{8.28 \pm 0.18}$	$\mathbf{8.18 \pm 0.10}$	$\mathbf{8.26 \pm 0.14}$	$\mathbf{8.09 \pm 0.18}$
	RaLMSpec+P(256)SA	9.46 ± 0.17	10.42 ± 0.74	9.64 ± 0.08	9.36 ± 0.16