RAGServe: Fast Quality-Aware RAG Systems with Configuration Adaptation

Siddhant Ray, Rui Pan*, Zhuohan Gu, Kuntai Du, Ganesh Ananthanarayanan†, Ravi Netravali*, Junchen Jiang
University of Chicago †*Microsoft Research* **Princeton University*

Abstract

RAG (Retrieval Augmented Generation) allows LLMs (large language models) to generate better responses with external knowledge, but using more external knowledge often improves generation quality at the expense of response delay. Prior work either reduces the response delay (through better scheduling of RAG queries) or strives to maximize quality (which involves tuning the RAG workflow), but they fall short in optimizing the *tradeoff* between the delay and quality of RAG responses. This paper presents RAGServe, the first RAG system that *jointly* schedules queries and adapts the key RAG configurations of each query, such as the number of retrieved text chunks and synthesis methods, in order to balance quality optimization and response delay reduction. Using 4 popular RAG-QA datasets, we show that compared with the state-of-the-art RAG optimization schemes, RAGServe reduces the generation latency by $1.64-2.54\times$ without sacrificing generation quality.

1 Introduction

Retrieval-augmented generation (RAG) is a popular LLM inference technique that augments an LLM inference query with relevant text chunks, or "context", *retrieved* from a large corpus. **RAG systems**, which include retrieval and LLM inference[1], have found many use cases in QA tasks, personal assistants, chatbots, and LLM-powered search [10,55]. While RAG can enhance the quality (accuracy and relevance) of LLM-generated responses [7, 47, 52, 80, 85], RAG queries are inherently slow as they need more compute and memory resources to process long input contexts to answer a query [6,15,39]. Thus, it is essential to balance *high response quality* and *low response delays* in RAG inference systems.

Past research efforts have optimized RAG, regarding either response quality or response delay, but they fall short in optimizing the **quality-delay tradeoffs** of RAG. One line of prior work focuses on reducing response delay through better query scheduling (*e.g.,* GPU allocation and inference batching) for RAG queries [2, 40, 62, 66], without changing the RAG queries themselves. An alternate line of work focuses on maximizing generation quality by tuning the configuration of RAG queries [31,67,73], but this is often done at the cost of longer response delay.

[1]In the literature and industry lingo, RAG sometimes refers to the retrieval step, but in this work, RAG systems include both retrieval and LLM inference based on the retrieved texts, and we aim to optimize the whole pipeline.

The RAG configuration *simultaneously* affects generation quality and response delay. Unlike traditional data queries (*e.g.,* SQL) which specify the inputs and operators, RAG queries are inherently *under*-specified as they contain only a short question written in natural language [27,31,51,57]. The RAG system needs to first determine the *RAG configuration*, such as how many text chunks to retrieve (more in §2) [63,69,73]. For instance, retrieving too many chunks for a simple RAG query may unnecessarily inflate delay without increasing quality.

Moreover, *multiple* configuration knobs can be tuned to optimize delay-quality tradeoffs. For instance, besides how many chunks to retrieve, *how* to use them in the LLM's input involves two design choices—should the chunks be processed by the LLM jointly, and should the text chunks be summarized first before being fed into the LLM together (and how long should a summary be). Some recent works also tune RAG configuration [31, 67], but they focus on tuning individual knobs and only maximize quality at the cost of higher delay.

What's more, the RAG configuration should be tuned *jointly* with scheduling. Consider two configurations: *A* feeds all retrieved text chunks in one LLM input, and *B* summarizes first each chunk with an LLM and then feeds the summaries to an LLM input for a final generation. While *A* (which calls the LLM once) is seemingly faster than *B* (which calls the LLM multiple times), *A* could be slower as it requires more GPU memory than *B* and thus could be delayed in the scheduler queue. Without making batching and configuration selection jointly, it would be difficult to avoid such pitfalls.

Finally, the impact of RAG configurations on quality-delay tradeoffs also varies *significantly* with queries. For example, to answer *"In which country is the Kimbrough Memorial Stadium located?"*, the RAG may retrieve and analyze one text chunk about the stadium. In contrast, to answer *"Compare NVIDIA's operating cost over the first three quarters of 2022 and identify the highest one"*, the RAG may need multiple chunks, each containing the operating cost for a quarter, and process these chunks together, instead of reading them separately. Empirically, we show that picking RAG configuration *per-query* achieves $12-15\%$ higher quality and $2.5-3\times$ lower delay than using any fixed configuration across all queries in a dataset (§5). Thus, RAG configurations should be adapted on a *per-query* basis. Yet, existing RAG systems, which hand-pick a *static* configuration offline based on a few example queries [1,21,36,75], lose out on quality or response time.

This paper presents RAGServe, the *first* RAG system that adapts multiple configuration knobs on a per-query basis and jointly makes configuration selections and scheduling decisions (*i.e.,* which LLM inference in a batch) to optimize the delay-quality tradeoffs for RAG.

At first, this would require solving a joint combinatorial problem for every query, which can be prohibitively expensive (§3). RAGServe tackles the challenge by a two-step approach.

First, RAGServe *prunes* the massive configuration space for each received query to a smaller yet promising one that contains configurations that likely yield high-quality output for the query at hand. Specifically, RAGServe uses a separate LLM to estimate the query's *profile*, including how many pieces of information is required to answer the query and whether joint reasoning is likely required across these pieces of information (more details in §4.1). The intuition of the query profiles is that they can effectively filter out undesirable RAG configurations. For the earlier query example "*Compare NVIDIA's operating cost over the first three quarters of 2022 and identify the highest one*," the estimated profile would suggest that it involves at least three separate pieces of information, so the number of chunks (one of the configuration knobs) should be at least three. It should be noted that the LLM-based profiler is an extra overhead in RAGServe, but fortunately, its input only contains the RAG query itself and the metadata of the RAG database, which are orders of magnitude shorter than the long contexts in RAG, so the estimation can be relatively *fast*, about 1/10 of the delay of the execution of the RAG query.

Then, using the narrower configuration space, RAGServe reduces the RAG response delays by *jointly* deciding the per-query configuration and query scheduling (batching) based on available resources (§4.3). The insight is that with the pruned configuration space, the scheduler can pick the optimal configuration and batching decisions without exploring the original, large configuration space and the implication on quality.

In short, RAGServe's two-level design *loosely* decouples the problem into (1) pruning configuration space to a smaller yet promising range of configurations, which focuses solely on keeping the accuracy high, and (2) jointly optimizing configuration (within the narrowed range) and scheduling to optimize response delay by choosing configurations which best-fit into the GPU memory.

We evaluate RAGServe across four RAG datasets with diverse query profiles (*e.g.,* reasoning vs. domain-specific QA). Figure 1 shows a preview of our results. Our key takeaways are as follows. When achieving the same or higher quality than the baselines, RAGServe reduces the response delay by $1.6-2.8\times$ compared to the latest vLLM (a state-of-the-art serving engine), Parrot (the latest LLM query-scheduling method), as well as AdaptiveRAG (the latest RAG configuration-tuning method). RAGServe also achieves

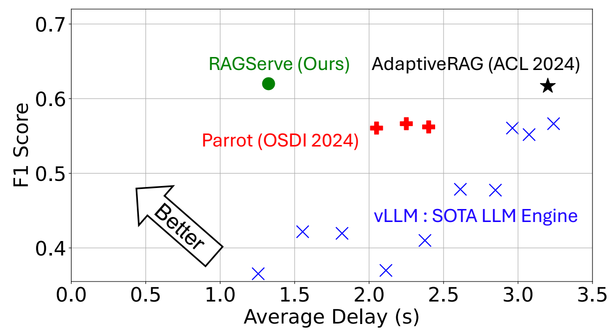


Figure 1: Performance of RAGServe on the KG RAG FinSec [45] dataset compared to the baselines. Full results shown in §7.

$1.8-4.5\times$ higher throughput compared to these baselines when achieving the same response delay and same/higher quality.

2 RAG systems and configurations

As an LLM often does not have domain-specific or up-to-date knowledge, LLM applications commonly employ RAG to supplement LLM inference with external knowledge to generate high-quality responses. Before processing queries, a RAG system organizes background documents by splitting them into chunks (each with a fixed number of tokens), embedding each chunk using models like Bert [12, 19], and storing the embeddings with the chunks in a vector database.

Processing a RAG query involves two main steps:

- *Retrieval:* The RAG system retrieves one or more relevant context chunks from the database by comparing the query's embedding, computed using the same embedding model during database indexing, with the stored embeddings.
- *Synthesis:* After retrieving the relevant chunks, the RAG system combines these chunks and the RAG query to form an LLM call or multiple LLM calls to generate the answer for that query.

Retrieval is computationally lightweight and much faster than synthesis, so the response delay is typically dominated by the synthesis step [79].

RAG configuration: This work focuses on optimizing three configuration **knobs**, illustrated in Figure 2, which are derived from key design questions that affect RAG performance in terms of response delay and quality:

- *How many chunks to retrieve* (`num_chunks`): The number of context chunks directly affects the delay of the synthesis step, with more computation needed to process the longer sequences from using more chunks. In the meantime, retrieving too few chunks risks low response quality if the retrieved chunks do not contain enough useful information.
- *How to synthesize* (`synthesis_method`): If more than one chunk is retrieved, then two underlying questions determine

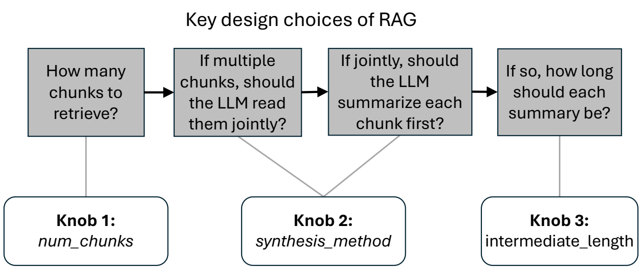


Figure 2: The configuration knobs adapted by RAGServe are derived from key design choices of RAG systems.

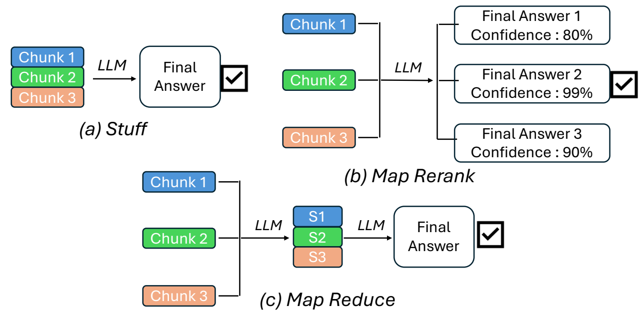


Figure 3: Illustration of different RAG synthesis methods, which have various LLM reasoning capabilities.

the choice of the synthesis method (illustrated in Figure 3). First, should the LLM read the chunks separately? If so, RAG uses the LLM to generate one answer for the query using each chunk separately and picks the output with the highest confidence, which is called `map_rerank`. This often incurs the least computation but can cause low quality if the useful information is scattered in different chunks, in which case the LLM should read the chunks jointly. The RAG system can choose to feed these chunks in the LLM input directly by concatenating them within a single prompt (referred to as `stuff`) or to create a shorter summary for each chunk first before feeding the summaries and the query into the LLM to generate the final response (referred to as `map_reduce`). `stuff` needs less computation than `map_reduce`, but risks degraded output quality for long inputs due to the lost-in-the-middle problem [42].

- *How long is each summary* (`intermediate_length`): Finally, if the LLM produces the summary for each chunk based on the user query, the length of each summary greatly affects the quality and response of `map_reduce`—shorter summaries yield lower delay but also risk not feeding enough information to the final LLM inference.

While other tunable knobs exist (*e.g.,* chunk size, embedding model, or LLM), tuning them requires costly reindexing of the data store or changes to the underlying embedding model or final LLM. In contrast, our configuration knobs only change the input of these two modules and thus require almost no code change to existing RAG systems.

Performance metrics: We evaluate the performance of a RAG system using two metrics:

- *Response quality* calculates the F1 score of the generated response against the ground truth. This metric is widely used in prior works [10, 61, 63].
- *Response delay* measures the time elapsed from when the RAG system receives a RAG request to when it completes generating the response.

Next, we will show that these knobs need to be properly tuned on a per-query basis to achieve optimal tradeoff between quality and delay in §3.

3 Towards better quality-delay tradeoffs

Prior work on RAG either optimizes for lower delay or higher quality, but not the tradeoff between quality and delay. The first direction picks static configurations and focuses on reducing the delay by smart scheduling and resource allocation [40, 62, 66]. The second direction picks RAG configurations to maximize quality without regard to resource usage or delay [31, 67, 73]. For the first time, we explore the potential of optimizing the ***quality-delay tradeoffs*** for RAG.

To improve the delay-quality tradeoff, our insight is that quality and delay should jointly be optimized in this large tradeoff space created by the choice of RAG configuration knobs. Importantly, the configurations with better quality-delay tradeoffs *vary* significantly across queries.

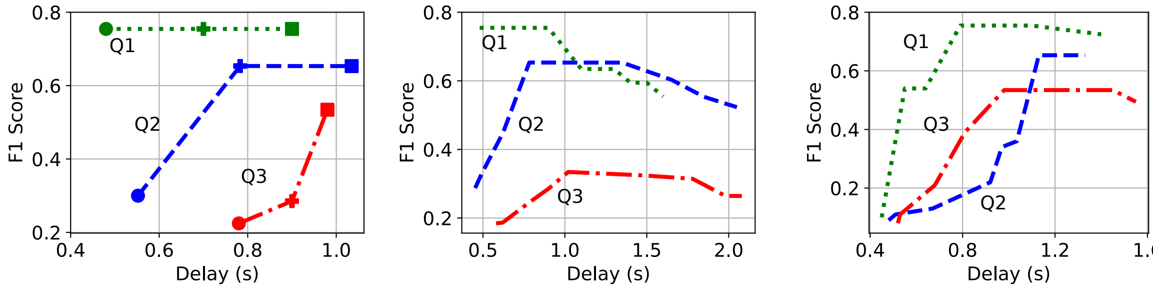
To showcase this observation, we use three queries selected from Musique [68], a popular reasoning QA dataset (§7.1).

- **Q1:** *"In what county was William W. Blair's born?"*
- **Q2:** *"Are Alison Skipper, Diane Gilliam Fisher, and Rachel McAdams from the same country?"*
- **Q3:** *"When and why did the Voyager 1, the spacecraft that detected storms on Neptune, leave our solar system?"*

We chose queries with different natural language complexity and reasoning, Q1 being relatively less complex than Q2 and Q3. Then, we adjust the value of each configuration knob in order to quantify **each knob's impact on the quality-delay tradeoffs** in each of the three queries.

Impact of synthesis method: Figure 4 (a) changes the synthesis method and shows its effect on the quality-delay tradeoff, while keeping the other RAG configuration knobs constant. We vary the synthesis method as `map_rerank`, `stuff`, and `map_reduce` from left to right. The insight is that the optimal synthesis method that strikes the best quality-delay tradeoff (closest to the top left corner) differs significantly across the different queries.

For simple queries like Q1 (green), quality plateaus for more complex synthesis methods (`stuff` and `map_reduce`). Because it only needs a single piece of context, `map_rerank` that processes chunks in isolation suffices, whereas cross-chunk reasoning (`stuff` and `map_reduce`) adds undue delay



(a) Change: synthesis method from map_rerank (*circle*) , stuff (*plus*) and map_reduce (*square*)

(b) Change: number of chunks from 1 to 35 with stuff

(c) Change: intermediate length from 1 to 100 with map_reduce

Figure 4: Varying each RAG configuration knob leads to different quality-latency tradeoffs, and these tradeoffs differ across queries (Q1 in green, Q2 in blue, and Q3 in red).

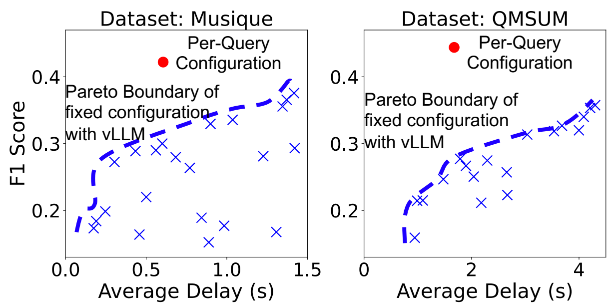


Figure 5: Per-query configuration can achieve significantly better quality-delay tradeoffs across queries compared to every fixed configuration choice.

($2\times$) without improving quality.

In contrast, for queries such as Q2 (blue) that require *cross-chunk* reasoning, `stuff` and `map_reduce` provide significant quality improvements (35% increase) as they process all retrieved chunks jointly.

For even more complex queries, such as Q3 (red), which require even more reasoning and information (why Voyager 1 left has multiple reasons), methods like `map_reduce` improve quality (30% increase) by removing unnecessary text in the mapper phase, to help the LLM focus on the relevant content.

Impact of the number of retrieved chunks: Figure 4 (b) fixes the synthesis method (`stuff`) and shows the impact of the number of retrieved chunks (1 to 35) on quality and delay.

Simple queries, like Q1 (green), can often be answered using just one or two chunks (needs only birth county). For more complex queries, Q2 (blue) and Q3 (red), increasing the number of chunks from 1 to 15 improves the likelihood of retrieving all relevant context and improves quality.

Blindly retrieving more chunks than necessary risks diluting the relevance of actual important information, due to commonly known problems such as "lost-in-the-middle" [42]. In all three queries, retrieving more chunks beyond a point harms the quality (up to 20% drop) and unnecessarily inflates delay (up to $3\times$). Hence we have a quality-delay tradeoff where increasing chunks up to a point helps quality but beyond that increases delay while degrading quality.

Impact of the intermediate output length: Figure 4 (c) shows the impact of our third configuration knob, varying the intermediate output length (1-100) for `map_reduce` synthesis methods on the quality-delay tradeoff. For simple queries like Q1 (green), short amounts of intermediate length are enough to answer the query (10-20 words). For more complex queries Q2 (blue) and Q3 (red), increasing the amount of intermediate length (70-100 words) provided helps the model with enough information to answer the query.

Overall, we see that RAG queries naturally vary in complexity, requiring differing levels of reasoning between chunks and varying numbers of context chunks. More complex queries, which require more reasoning and context, benefit from increased LLM computation, which can come at the cost of increased delay. Adding more context chunks helps to a point beyond which it harms the output quality and delay.

Thus, **adapting RAG configuration on a *per-query* basis is crucial.**

Figure 5 uses queries from two datasets (Musique and QMSUM, see §7.1) and shows that picking the best configuration for each query (the best configuration is the one with the lowest delay that achieves less than 2% drop than the highest achievable quality) achieves superior quality-delay tradeoff than picking any static configuration for all queries. Specifically, choosing the configuration per-query allows up to $3\times$ delay saving compared to static configurations which are the closest in quality. Every single static configuration choice that achieves comparable delay has at least a 10% quality drop.

In spite of the potential benefits, however, per-query configuration adaptation faces challenges that hinder their real-world adoption. Each RAG query comes in plain text with practically no RAG configurations associated with it. Moreover, the space of configurations grows exponentially with multiple knobs. For example, for a `map_reduce` configuration, having 30 values for `num_chunks` and 50 values for `intermediate_length` leads to 1500 configurations for a query. To enable per-query configuration selection, we cannot exhaustively profile all configurations for every query and choose the best.

Alternatively, if we profile periodically, we lose out on the potential configuration selection for *each* query, as variance in query profile leads to different quality-delay tradeoffs. Profiling cost is also *prohibitively* expensive as the LLM needs to be run with many synthesis methods, number of chunks *etc.,* which require high GPU usage. Additionally, the delay of profiling can be $\sim$100$\times$ the inference delay due to multiple LLM calls during profiling. Online RAG queries have stringent requirements for GPU resource usage and end-to-end delay [62, 66]. This makes it hard to systematically decide what an optimal per-input configuration should be.

To truly achieve the benefit of per-query configuration adaptation, we need a *smart system* to *drastically* reduce the configuration space to useful ones, in a *fast* and *cheap* manner.

4 RAGServe: Enabling per-query configuration adaptation for RAG

We present RAGServe, a novel system for serving RAG queries with an emphasis on high generation quality and minimal delay. RAGServe is a RAG controller with two main components:

- *Pruning configuration space*: For each query, it first reduces the RAG configuration space to a smaller yet promising one that still yields high generation quality based on the profile of the query.
- *RAG scheduler*: It then chooses the best configuration jointly with available system resource to reduce the delay while preserving quality.

The overall pipeline for RAGServe (Figure 6) is as follows: on the arrival of a RAG query, we prune the configuration space by first estimating the query's profile (§4.1) and then mapping the profile to a pruned configuration space (§4.2). This reduces the possible configurations from 1500 down to about 50. With the pruned configuration space for the query, RAGServe's scheduler then choose the best configuration for the query that achieves the best quality-latency trade-off based on the available system resource (§4.3).

Once the configuration is chosen, the RAG system executes the query using the chosen configuration—retrieving the selected number of chunks and uses the selected synthesis method to feed the retrieved chunks in the LLM's input. RAGServe focuses on achieving the best quality-latency trade-off by choosing an appropriate number of chunks to retrieve.

4.1 Estimating a query's profile

Query profile: To choose the correct RAG configurations, the first step of RAGServe is to create the profile of the query (as we see in Figure 7) by querying an LLM (we call this LLM *query profiler*). We ask the query profiler to estimate four high-level dimensions for each query.

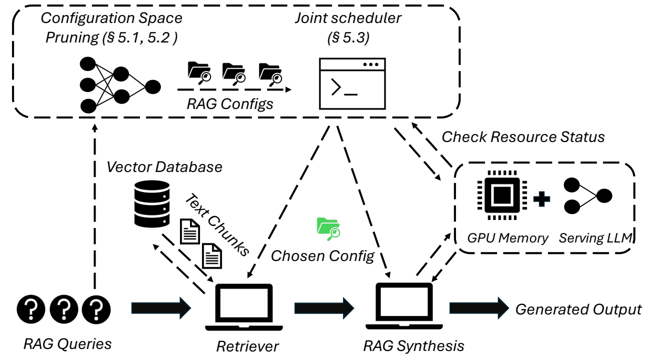


Figure 6: RAGServe consists of a RAG controller which performs configuration space pruning and joint scheduling.

- *Query complexity* refers to the intricacy of the query itself. Queries with less complexity are more like simple yes/no questions, while queries with high complexity are more like why questions, which require deeper reasoning than yes/no questions. As a result, it requires more LLM computation to correctly answer complex queries. The output for this dimension is binary "High/Low"
- *Joint reasoning requirement* describes whether multiple pieces of information are needed to answer the query. Even relatively simple queries may require joint reasoning (*e.g.,* checking whether the annual income from two years is the same). The output for this dimension is binary "Yes/No"
- *Pieces of information required* refers to the distinct, standalone pieces of information required to fully answer the query (*e.g.,* the annual income from how many years is required to draw the trend of annual income). The output for this dimension is a number from 1-6.
- *The length of the summarization:* If the query is complex and needs a lot of different information, it is often necessary to first summarize the relevant information chunks first (to reduce the noise inside these chunks) and then generate the final answer from these summaries. The output for this dimension is a number from 30-200.

We should note that RAGServe is not the first to use query profile as a metric for deciding RAG configurations. Methods like AdaptiveRAG [31] have used LLM's to estimate query profile but they only focus on one dimension (the number of chunks to retrieve).

Why the query profile *could* be estimated: Estimating the aforementioned query profile is feasible, not only because of the reasoning power of LLMs[2] in analyzing natural language queries, but also because we provide sufficient information to the LLM-based profiler. RAGServe feeds the profile estimator with not only the query, but also a *metadata* of the database that contains the background document.

The metadata is a short description about the type of content in the database and its data size (`chunk_size`). Specifi-

[2]We have tested both GPT-4o and Llama-70b as the profile query-profiler, and they yield similarly impressive results (§7).

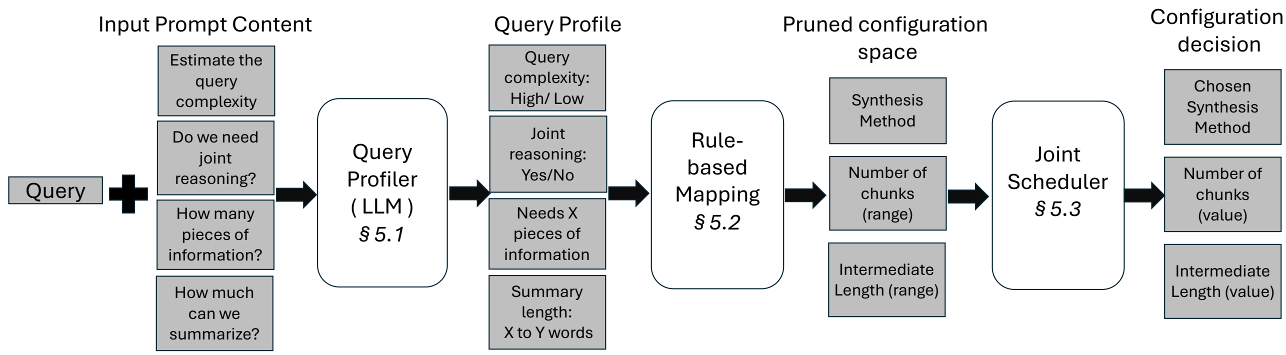


Figure 7: RAGServe RAG configuration selection workflow.

cally, we use a single-line summaries already attached to the original source datasets as the metadata of the dataset. For example, the metadata for the KG RAG Finsec's database [45] contains quarterly financial reports and questions of Fortune 500 companies with a `chunk_size` of 1000. It describes the content topics of the chunks with information such as revenue growth indicators, product release information, sales *etc.,*. When presented with a query on financials of such a company, the LLM can use the metadata to decide questions like how much to summarize and how much reasoning is required. We give the details of the used metadata and how we generate the metadata in §A.

It is important to acknowledge that for highly underspecified queries, it is hard for any model (even human) to reasonably estimate the query's profile. For an example query "Compare current US Stock Market trends," the query profile here does not provide enough information (*e.g.,* how many years should the trend be derived from). To answer such highly under-specified queries, more information about the dataset will unlikely help.[3]

Moreover, we observed that extra information does not significantly improve the profiler's estimates. For instance, in theory, it helps to know the embedding algorithm and the LLM used by RAG. Yet, the embedding model and the LLM perform similarly overall across queries and datasets under our consideration. This explains their limited contribution to the profiler, though more future work will be needed to understand the wide implications.

4.2 Mapping query profile to reduced RAG configuration space

First, RAGServe obtains the query profile using the LLM. It then performs rule-based mapping to generate values for RAG configuration knobs (`synthesis_method`, `num_chunks`, and `intermediate_length` introduced in §2). To do so, we perform a subsequent rule-based mapping from the query profiler's outputs to RAG configuration knobs.

[3]Maybe some chat history from the same user will help, but that is beyond the scope of this work.

How the profile helps: To understand the importance of the query profiles further, let's consider the following examples:

- *"Who is the current CEO of NVIDIA?"* This query is not complex and does not require joint reasoning. Due to the query being simple with no reasoning required and one piece of information (name of CEO), this query can be mapped to `map_rerank` as we should only need a few chunks (1-2).
- *"Which month had the highest NVIDIA's stock price the six months from January to June 2024?"* This query is simple but needs to read information jointly (different stock prices). We need six pieces of information (stock price for every month). Due to the need for multiple pieces with reasoning, this query can be mapped to `stuff` with at least 6 chunks.
- *"What might be the reasons for NVIDIA's month-on-month stock price change from January to June 2024"*

  This query is complex, needs a lot of information, and needs to read information jointly. We need multiple pieces of information (stock prices, reasons for change, revenue, etc.) As multiple reasons need to be analyzed and compared here, summarizing all of the information first helps narrow it down to relevant information.

  Due to the needing multiple pieces with deep reasoning on why the prices changed, this query can be mapped to `map_reduce` with summarization with at least 6 chunks.

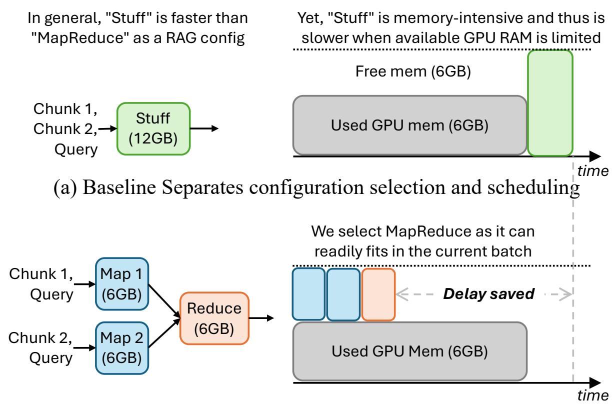
Algorithm 1 outlines this rule-based mapping process. This mapping is significantly helpful, it improves upon raw profiler outputs and converts them to usable RAG configurations. We use query complexity and whether joint reasoning is needed to determine the `synthesis_method`. Simple queries that don't need any reasoning can answered with `map_rerank` while queries that require joint reasoning need `stuff` or `map_reduce`.

We decide the range of `synthesis_method` selections based on two of the profile dimensions estimated in §4.1, *i.e.,* the "Query complexity" and the "Joint reasoning requirement". We then decide the range of values for `num_chunks` based on the profile dimension of the "Pieces of information required", *i.e.,* n—specifically, we set the range of

Algorithm 1: Rule based mapping algorithm

Input: *Query complexity*, *Joint reasoning required*
Input: *Pieces of information* , *Summarization length range*
Result: synthesis_method, num_chunks, intermediate_length

if *Joint reasoning required* == *“no”* **then**
  synthesis_method = `map_rerank`
else
  if *Query complexity* == *“low”* **then**
    synthesis_method = `stuff`
  else
    synthesis_method = `stuff`, `map_reduce`
num_chunks = [*Pieces of information* , 3× *Pieces of information*]
intermediate_length_range = *Summarization length range*



(a) Baseline Separates configuration selection and scheduling

(b) Ours performs configuration selection and scheduling jointly

Figure 8: RAGServe joint schedules RAG configurations with available GPU memory

`num_chunks` to be $1-3$ times of n. We do not directly set `num_chunks` at n, because it (1) gives some leeway for the retrieval logic (*e.g.,* typically Bert-embedding-based)[4] to find necessary information, and (2) provides the room for the scheduler to select the configuration that fits in available memory. Finally, we get the `intermediate_length` range directly from the “summary length” estimate, which is already a value range.

4.3 Joint configuration-scheduling adaptation

Once provided with the narrowed range of each RAG configuration knob (`synthesis_method`, `num_chunks` and `intermediate_length`), we need to choose the actual RAG configuration, which is aware of the current system resource (GPU memory). If we pick configurations which do not fit in current memory it will lead to additional delay, by waiting for the GPU memory to free up.

We have RAGServe’s pruned configuration space where the quality is high, we now focus on choosing the best configuration which fits in memory, without focusing on quality.

Why do we need to choose the scheduling jointly? We motivate the need for joint scheduling along with the RAG configuration choice in Figure 8.

Consider a setup where we tune only one RAG configuration knob of `synthesis_method`. Other knobs `num_chunks` and `intermediate_length` are fixed at 20 and 100 respectively. Let’s assume both `stuff` and `map_reduce` are present in the pruned space. For the scheduling knob, we consider the amount of GPU memory available in the current batch.

Consider a baseline system which separates the joint decision from the scheduling and picks only the RAG configuration knob (`synthesis_method`). It chooses the `stuff` configuration knob as it has lower compute requirement, so given enough memory it should be fast.

The baseline system in Figure 8 (a) doesn’t consider other jobs in the system and does not evaluate the amount of available resource to make its scheduling decision. Due to its long input length with 20 chunks, `stuff` turns out to be memory-intensive. If the available GPU memory is low, `stuff` doesn’t fit in memory and needs to be queued. This ends up with `stuff` being slow.

Jointly considering the available GPU memory with choosing the RAG configuration knob avoids this pitfall. For example, in Figure 8 (b), if the original configuration was `stuff`, RAGServe can choose to use `map_reduce` (based on the current GPU memory available).

By doing so, RAGServe can start putting the mappers which fit in memory, into the current batch of requests which fits in the GPU. While `map_reduce` requires more compute, in this case, it benefits from being able to start execution much faster, as some of the mappers fit in memory.

RAGServe does not need to wait for the GPU memory to free up and changes the configuration jointly with the system resource, to save delay and achieve a better quality-delay tradeoff.

How do we choose the configuration knob’s value jointly? RAGServe first provides us with a pruned range of configurations. A *straw-man* solution is to pick a constant value from the across queries. (*e.g.,* the median value of the `num_chunks` and `intermediate_length`). While this is better than using one static configuration for all queries, it is still sub-optimal as it does not look at the current system resource availability. This prevents us from exploiting the best quality-delay tradeoff across RAG queries.

We use a *best-fit* algorithm to allow for variation in configurations across queries. We first compute the GPU memory requirement for the RAG query from the RAG configuration knobs (*e.g.,* `num_chunks`) for every configuration in the

[4] A typical RAG retriever these days will have to retrieve 2-3× more chunks than minimally required to provide sufficient information for the LLM inference [24, 49].

pruned space. Then, we measure the current *available memory* on the GPU to see what can fit into the current batch.

We then pick the best configuration (with the highest possible knob value) from the pruned space that fits into the GPU. The insight here is higher values of knobs in the pruned space lead to slightly better quality on average. For example, suppose the pruned space says `num_chunks` is 5-10 and the `synthesis_method` is stuff, and 5 or 6 chunks can both fit in memory, we choose 6 chunks. We don't pick a configuration that doesn't fit, so we would not choose more than 6 chunks. If we do that, the system will *queue* the query, leading to increased delay.

Once the configuration that fits into the current batch is chosen, the vLLM engine is optimized to perform *chunked_prefill*. However, even with *chunked_prefill*, it can only offload parts of long prefill of `stuff` requests which do not fit in the current batch and still cause additional queuing delay.

What if none of the configurations fit in the GPU? A main insight for RAGServe's design comes from the observation that in general, the RAG-specific focused configurations can be *loosely-decoupled* from the scheduling-specific configurations. RAGServe tries to fit the best possible configurations into GPU memory after it gets the profiler's reduced configuration space. It can sometimes happen that the current GPU memory availability is too low and none of the profiler's configurations fit in the current GPU.

One way we handle this is by falling back to a cheaper fixed configuration and choosing to ignore the output of the pruning. As we already have access to the query complexity profile and we can pick cheaper configurations, which would meet the requirement for the current query.

For example, if the query doesn't require any joint reasoning, we can pick a `map_rerank` configuration with as many chunks that fit into the current GPU memory, irrespective of what the pruned spaces says.

If joint reasoning is required, we pick a `stuff` or `map_reduce` configurations with the few chunks that fit into memory. We can choose which synthesis method to use once based on the exact memory availability.

This allows *loose-decoupling* of the RAG configurations into a smaller space and then choosing configurations based on system resource availability. This also allows SLO-based constraints on RAG queries if certain queries have strict budgets on their generation latency.

4.4 RAGServe is just a practical *heuristic*

It is important to notice that the concept of RAGServe belongs to an emerging trend in the ML and systems community that leverages LLM outputs to guide real system decisions and optimizations, an example of which is *LLM routing* [13,30,50,53]. While LLM routers use trained LLMs to map decisions from query complexity to choose from families of inference models (outside the realm of RAG), we differ by mapping the output to the configuration knob we run for the RAG queries.

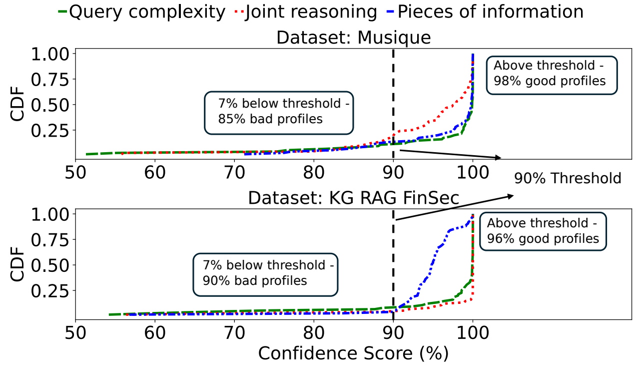


Figure 9: Using a confidence score threshold for different profiler outputs can be used to decide when not to use the output of the profiler.

Like these prior efforts, RAGServe is just a heuristic to best utilize the LLM-generated information to guide system optimizations. While it demonstrates remarkable improvement in practice, more work will be needed to complement it for better interpretability and robustness.

5 Refinements to RAGServe

In spite of it all, it is possible for the profiler to (sometimes) fail and in such cases, it is important to detect if RAGServe's profiler fails on a query in a fast manner to prevent it from leading to bad RAG configurations. Also it is useful to decide how to provide feedback to RAGServe to improve.

When is the quality profile reliable: RAGServe uses LLM to generate the quality profile. Inspired by recent work in use of model confidence [20,25,74] as a quality metric, we use confidence scores for RAGServe's LLM profiler as to measure the reliability of the profile provided. We obtain the confidence scores from the LLM's *log-probs* values on the output (the logarithm of the confidence score, which is directly provided with the output with no extra overhead).

We then threshold the confidence score using a confidence score threshold (90% across different datasets) to predict whether the quality profile derived from the quality profiler LLM is actually good (defined as whether the profile can lead to 10% increase in F1-score or $1.5-2\times$ reduction in delay or both) or not. Such 90% threshold can be tuned for better performance, and we leave it to future work. From Figure 9, we draw two conclusions. First, over 93% of the quality profiles derived from LLM are of high confidence (*i.e.,* over 90%). Further, for those high-confidence profile, over 96% of them are good profiles, meaning that they can be used to improve quality, or reduce latency, or both.

To handle those cases where the quality profile is of confidence score lower than 90%, RAGServe will fall back to the pruned configuration space of recent 10 queries.

How to improve the profiler over time: RAGServe improve the query profiler LLM by profiling extra feedback prompt to this LLM. We generate this feedback prompt by

Dataset	Task Type	Input	Output
Squad	Single hop QA	0.4K - 2K	5-10
Musique	Multihop QA	1K - 5K	5-20
KG RAG FinSec	Doc Level QA	4K - 10K	20-40
QMSUM	Summarization QA	4K - 12K	20-60

Table 1: Input and output length (# of tokens) distributions of the RAG datasets used in our evaluation.

generating the most accurate output, which is obtained by performing inference on the most resource-demanding configuration (the `map_reduce` configuration with a large number of input chunks (30) and a high value of intermediate length (300 tokens)). And then ask the quality profiler LLM what configuration it should choose based on the query *and* the most accurate answer to that query.

The key insight is that, the most accurate answer to the query provides the quality profiler LLM *extra knowledge* of the knowledge database, and thus can be used to further improve its decision.

To control the cost of generating feedback prompts, RAGServe only generates the feedback prompt once every 30 queries and we only keep the *last four* feedback prompts.

The cost of RAGServe's quality profiler: As for the choice of quality profiler LLM, we mainly use GPT-4o. Though GPT-4o is expensive, as RAGServe only uses it sporadically and only runs it on the *query* itself, the cost of it is marginal in RAGServe and thus RAGServe still saves cost (as shown in Section 7). We also show that RAGServe can use alternative LLMs as the external LLM to provide feedback and still provides delay reduction without hurting the accuracy in Section 7.

6 Implementation

We implement RAGServe in about 1.5K lines of code in Python. We build RAGServe on top of the state-of-the-art popular LLM serving engine vLLM [38]. We also use supporting modules from Langchain [8] in order to have efficient implementations of the multiple synthesis methods. For RAGServe' LLM used for configuration space pruning, we use OpenAI's API [54] to invoke GPT-4o on the RAG queries and HuggingaceAPI [71] to use LLama-3.1-70B as models to profile the queries.

We use a state-of-the-art embedding method `Cohere embed-v3.0` [4] We perform FAISS [16] L2-distance similarity search on the embeddings of the chunks relative to the query, in order to retrieve relevant chunks for RAG inference.

Finally, we use PyTorch's [5] library modules support to perform query-level memory profiling and measurement to implement the best-fit scheduling logic and request batching.

7 Evaluation

The key takeaways from the evaluation are

- *Lower delay* : Across 4 task representative datasets for RAG QA, RAGServe achieves $1.64-2.54\times$ lower response delay compared to fixed configurations of comparable quality.
- *Higher throughput* : RAGServe achieves $1.8-4.5\times$ higher throughput than RAG serving systems which use fixed configurations reaching similar quality.
- *Negligible overhead* : RAGServe' profiler's delay is negligible compared to the overall delay of the LLM's RAG inference.

7.1 Setup

Models and hardware: : We evaluate RAGServe on a popular model for LLM inference, specifically the fine-tuned version of Mistral-7B-v3. We also use Llama3.1-70B for additional experiments. All models are fine-tuned such that they can take long contexts (up to 32K and 128K respectively). We apply AWQ-model quantization both models. We use an NVIDIA A40 GPU server with 2 GPUs to benchmark our results. The server is equipped with 384GB of memory and two Intel(R) Xeon(R) Gold 6130 CPUs with Hyper-threading and Turbo Boost enabled by default. We use 1 GPU to serve Mistral-7B-v3 and 2 GPUs to serve Llama3.1-70B.

Datasets: We use multiple RAG QA datasets which have a variety of different query profiles, in order to have task-representative workloads. Table 1 summarizes their input-output length statistics.

- Squad [59]: Squad is a reading comprehension dataset, consisting of questions on Wikipedia articles, where the answer to every question is a segment of text, or span, from the corresponding reading passage. Squad is classified as a single-hop reasoning dataset.
- Musique [68]: Musique is a multihop QA dataset with reasoning-based questions. It is designated to test LLM's multi-hop reasoning ability where one reasoning step critically relies on information from another.
- KG RAG FinSec [45]: KG RAG Finsec is part of a Knowledge Graph family of RAG datasets and focuses on financial domain questions from Fortune 500 companies. This dataset contains quarterly financial reports and queries need to read information for multiple chunks for answering.
- QMSUM [82]: QMSUM is a human-annotated benchmark for query-based multi-domain meeting summarization that is designed to test LLM's reasoning-based summarization capabilities. This dataset consists of multiple meeting transcripts and the queries are to summarize relevant spans of meetings from them.

For our experiments, we build a retrieval database from all of the datasets. We split the queries' contexts into fixed-sized chunks using Langchain [8] for the database. We use a state-of-the-art embedding method `Cohere embed-v3.0` [4] We perform FAISS [16] L2-distance similarity search on the embeddings of the chunks relative to the query, in order to retrieve relevant chunks for RAG inference.

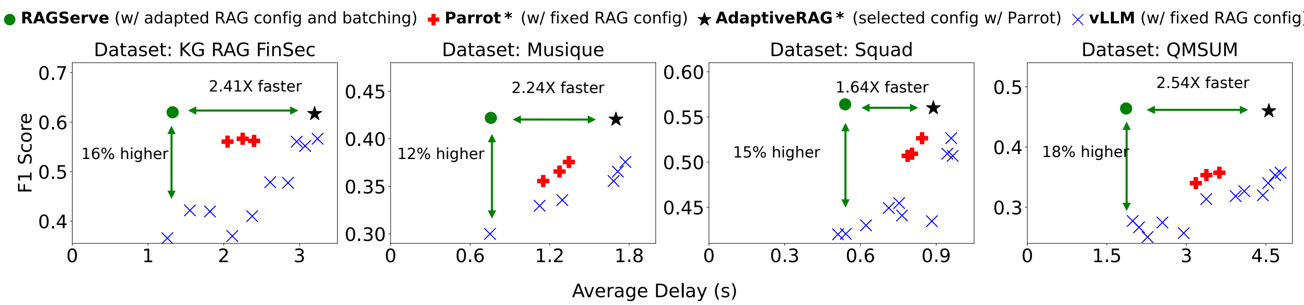


Figure 10: RAGServe achieves $1.64-2.54\times$ lower delay compared to both best fixed configuration baselines and quality-optimized RAG configuration without sacrificing generation quality.

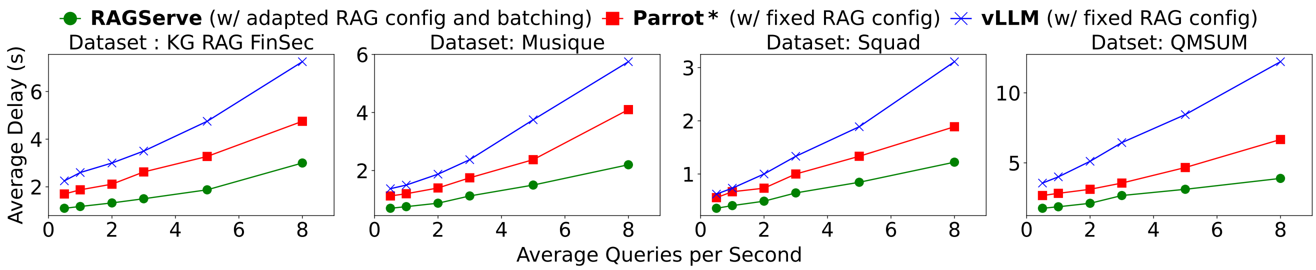


Figure 11: RAGServe achieves $1.8-4.5\times$ higher throughput (at 1.8 seconds) than baselines which use fixed configurations of closest (not higher) quality.

To simulate a real RAG workload, we create a mix of queries from each dataset, and send the queries to RAGServe using arrival rates that follow a Poisson distribution. We report the results per dataset.

Quality Metric: We adopt the following standard metric to measure the generation quality.

- F1-score is used to evaluate the RAGServe's serving model's response in the datasets. It measures the probability that the generated answer matches the ground-truth answer of the question-answering task. It is the most widely adopted metric for evaluating RAG QA tasks [10, 61, 63]

System Metrics: We adopt the following system metrics:

- *Delay* is used to measure the generation response delay of the model for every RAG query. We choose this metric similar to other RAG serving papers [40, 62, 66]
- *Dollar Cost* is used to measure the lower cost of using RAGServe's profiler as compared to using larger serving models with fixed configurations having the closest accuracy.

Baselines: We compare RAGServe with the following baselines.

- *vLLM*: Every RAG query is served with the same fixed RAG configuration with vLLM and we compare with several such configurations.
- *AdaptiveRAG**: We implement AdaptiveRAG's [31], query complexity-based RAG-configuration choosing, and choose the configuration which maximizes the F1-score.
- *Parrot**: We implement Parrot's [40] configuration-based batching. Parrot* does not adapt the configuration per query. We compare with Parrot* using fixed RAG configurations which achieve the closest quality to us.

7.2 Overall improvement

Lower delay without sacrificing generation quality: Figure 10 shows RAGServe achieves delay reduction $1.64-2.54\times$ over *AdaptiveRAG** with no reduction in F1-score. Over using fixed configurations of similar delay, served with both *Parrot** and *vLLM*, RAGServe achieves $12-18\%$ higher F1-score.

Higher throughput at lower delay: Figure 11 shows RAGServe achieves higher throughput compared to fixed-configuration baselines when they choose the fixed-config which achieves the closest quality. Compared to *Parrot** and *vLLM*, RAGServe achieves $1.8-4.5\times$ times higher throughput.

Understanding RAGServe' improvement: RAGServe's gains come from being able to jointly select the configuration based on the available resource, along with perform batching and scheduling used by existing RAG serving systems. RAGServe achieves higher quality than the fixed-config baselines as it is able to adapt the RAG-configuration per query, focusing on quality. At the same time, it reduces delay by scheduling per-input configurations better than fixed configurations which achieve similar quality.

RAGServe achieves higher throughput due to being able to adapt configurations based on resource availability as compared to the baselines. Both *Parrot** and *vLLM* schedule fixed

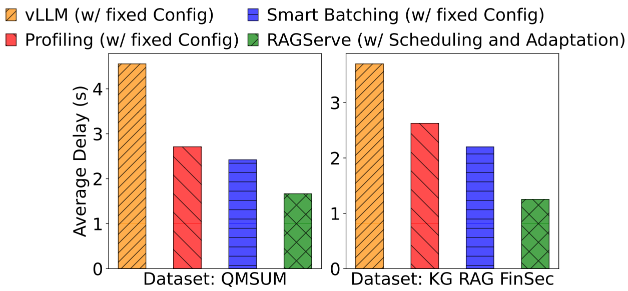


Figure 12: Understanding the reasons for delay improvement in RAGServe.

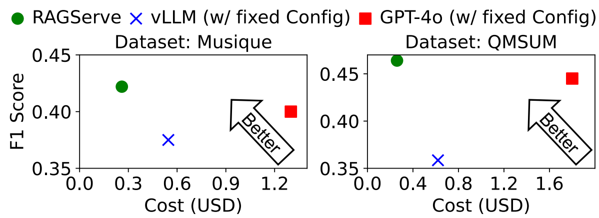


Figure 13: Even with increasing the inference model size, fixed configurations have $2.38-6.8\times$ higher cost and lower quality compared to RAGServe.

RAG-configurations and cannot benefit from delay achieved by adapting the configuration like RAGServe. *Parrot** can improve the delay over using fixed configurations with vLLM by $1.4-1.8\times$ but cannot improve the quality.

7.3 Analyzing the gains from RAGServe

Delay saving: Figure 12 shows the contribution of every component of RAGServe. We compare with vLLM plus a fixed configuration, which achieves the highest quality (orange bar). If we just use the profiler's ranges and naively the fixed median value every time (red bar), we achieve $1.4-1.68\times$ reduction in delay. Further, we see the effect of only batching (like Parrot*), by choosing the median value configuration and batching, we achieve $1.1-1.2\times$ reduction in delay. Finally, RAGServe achieves even greater delay reduction by $1.45-1.75\times$ by adapting the configuration based on available GPU memory along with batching.

Cost saving: Figure 13 shows RAGServe (including its profiler) has significant lower dollar cost saving and higher F1-score, compared to choosing the best fixed configuration, with increasing model complexity. The cost of using a (LLama3-70B) inference model with vLLM and a fixed configuration is higher by $2.38\times$ times while also having a lower F1-score of 6.5% times across datasets. Even more powerful models like GPT-4o fail to achieve the same F1-score with fixed configurations but have a much higher cost of $6.8\times$.

Profiler feedback-based improvement: In Figure 14 we show the effect of the golden-configuration-based feedback to the profiler in order to improve its output. We use a 350 query sample for the QMSUM and KG RAG FinSec dataset as the workload. We see that with the feedback mechanism (blue line), the F1-score improves by $4-6\%$ as compared to not having feedback (red line) from the outputs of the golden configuration. It is important to note that if the feedback mechanism cannot result in the output of very expensive configurations, as RAGServe' joint scheduler will ensure it doesn't pick increasingly expensive configurations based on the GPU resource constraint.

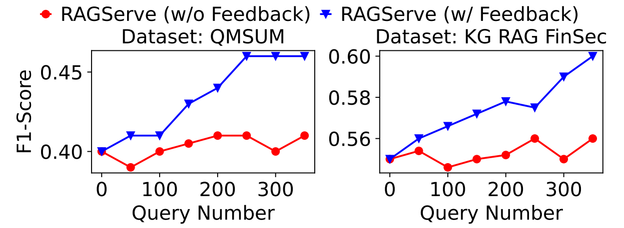


Figure 14: Improvement for RAGServe using feedback from the output helps improve the F1-score by $4-6\%$.

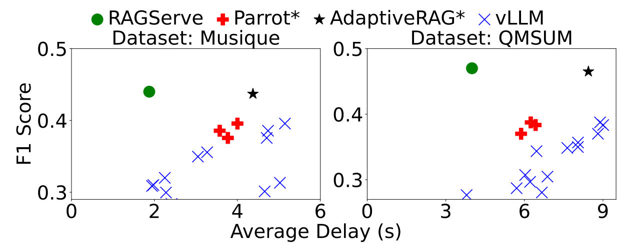


Figure 15: RAGServe achieves lower delay by $2.1-2.4\times$ at the same quality even with a larger inference LLM.

7.4 Sensitivity analysis

Changing the inference LLM: Figure 15 shows the outcome of changing the inference LLM to a larger LLM (Llama3.1-70B) on the Musique and QMSUM datasets. Even with a more powerful LLM, RAGServe achieves $2.1-2.4\times$ lower delay than *AdaptiveRAG** at a similar F1-score. The best fixed-configuration baselines such as *Parrot** and *vLLM* have a lower F1-score of $7-10\%$. In RAG, models mainly rely on the external context to answer the question instead of the model weights and we only get a 2% improvement in F1-score compared to the smaller inference models.

Incrementally using knobs in RAGServe: In Figure 16, we show the benefit we the improvement we get by incrementally adding more knobs to RAGServe. We measure this for the QMSUM dataset with the original Mistral-7B-v3 model. We first only tune the `num_chunks` (red point). Progressively we tune the RAG-configuration knobs of `synthesis_method` and `intermediate_length` and scheduling. We achieve $5,4,3\%$ higher F1-Score compared to vLLM. Finally, by adding the scheduling, $2.8\times$ lower delay reduction in delay.

Changing the profiler LLM: Figure 17 shows the effect of changing the LLM profiler from GPT-4o to a less powerful,

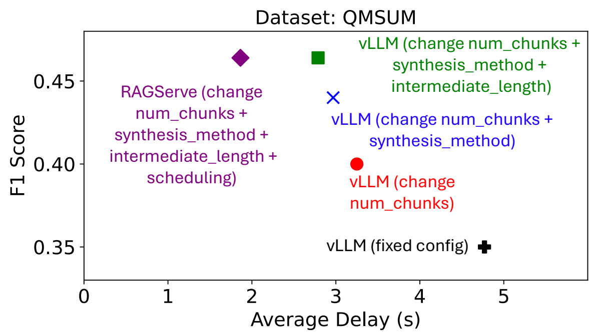


Figure 16: Breakdown analysis: By tuning more knobs in RAGServe, we can see better quality-delay tradeoffs.

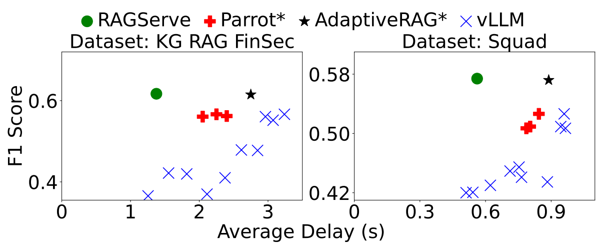


Figure 17: RAGServe' performance gains remain substantial even with a smaller LLM profiler.

Llama3.1-70B model. RAGServe with the new profiler, still achieves $1.4-2.1\times$ over *AdaptiveRAG** with a similar F1-score. Compared to fixed configurations with *Parrot** and *vLLM* which achieve similar delay, RAGServe achieves $10-14\%$ higher F1-score.

Changing the embedding algorithm: RAGServe uses for retrieval on quality. RAGServe picks a state-of-art retrieval algorithm `Cohere embed-v3.0` [4]. When compare with two more popular retrieval algorithms `All-mpnet-base-v2` from SentenceBERT [60] and text-embedding-3-large-256 from OpenAI [18], the F1-score difference is less than 1%, when we use RAGServe' configuration selection. The delay has no measurable difference as the retrieval is $> 100\times$ faster than LLM synthesis [6].

Delay overhead of RAGServe's per-query profiling: We show the negligible delay overhead of using an LLM profiler with RAGServe to serve RAG queries Figure 18 shows the fraction of RAGServe' profiler of the total end-to-end delay. Using the profiler at most adds less 0.1 fraction of the total delay and in the average case, the profiler only adds $0.03-0.06$ fraction across queries from all datasets.

8 Related work

Systems for serving RAG: Several systems have been proposed for RAG [2, 17, 31, 32, 34, 37, 40, 48, 66, 77, 79] which focus on improving retrieval using complex, iterative retrieval algorithms or on serving model selection. RAGServe can work in conjunction with such systems as RAGServe focuses on optimizing quality and serving latency, independent of how

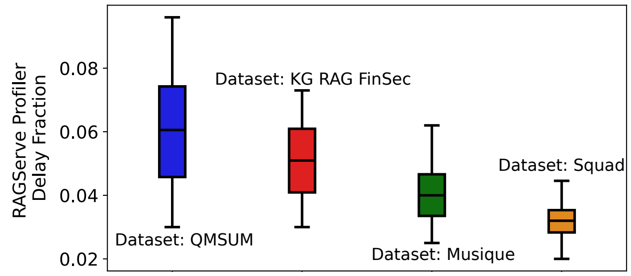


Figure 18: RAGServe' profiler delay is at most 1/10th of end-to-end response delay across queries from all datasets.

the retrieval algorithm identifies chunks for retrieval.

KV cache storage and retrieval: Storing and reusing KV cache across different requests have been commonly studied in recent work [2, 14, 22, 28, 38, 41, 43, 44, 56, 65, 76, 81]. RAGServe can work alongside these systems, where instead of retrieving chunks, it can retrieve the KV Caches for generating the output. In RAG, some additional optimizations are needed to combine KV Caches of different chunks that don't share a common prefix. This is important as the trivial concatenation of KV Caches loses important cross-attention and reasoning between chunks. These optimizations are enabled by KV Cache blending-based approaches [9, 26, 29, 35, 70, 75]. However RAG workloads have a large number of related contexts across queries and storing all the KV Cache is extremely expensive. We do not measure the KC Cache reuse ratio across queries and leave it for future work.

Prefill-Decode Optimizations: Several systems have proposed optimizations to speed-up prefill and decode for LLMs by leveraging unique properties of each phase [3, 11, 33, 58, 64, 72, 83, 84]. Some notable techniques include *chunked-prefill* which allows interleaving prefill and decode requests and *disaggregated prefill* which separates compute nodes for prefill and decode. All of these optimizations enable faster generation speed but don't focus on generation quality. RAGServe is orthogonal to these LLM serving systems optimizations.

9 Limitations

RAGServe is designed to work with commonly deployed RAG pipelines. New research directions in RAG [17, 78] have shown developed more complex pipelines and configuration knobs for deep *chain-of-thought* RAG workloads. While their pipelines improve these on complex workloads, they achieve similar performance on the commonly used RAG workloads we consider [1]. Additionally, some RAG systems use external re-rankers [23, 46] to choose the exact `num_chunks` the model might need. However, for joint scheduling, it is still necessary to have the opportunity to tune this number and RAGServe can be adapted to use a range of chunks from the re-ranker output.

10 Conclusion

This paper introduces RAGServe, the first system that focuses on optimizing the tradeoffs between response delay and generation quality in RAG, by by jointly scheduling RAG queries and adapting key configurations on a per-query basis. Evaluation on four datasets shows that RAGServe outperforms the state-of-the-art, reducing generation latency by $1.64-2.54\times$ without compromising response quality.

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A Appendix

We use a very simple prompt to provide the metadata to RAGServe' LLM profiler. We don't perform any prompt tuning or optimizations.

```

f"""
For the given query = {get.query()}: Analyse
     the language and internal structure of
    the query and provide the following
    information :

    1. Does it needs joint reasoning across
        multiple documents or not.
    2. Provide a complexity profile for the
        query:
        Complexity: High/Low \n \
        Joint Reasoning needed: Yes/No \n "
    3. Does this query need input chunks to
        be summarized and if yes, provide a
        range in words for the summarized
        chunks.
    4. How many pieces of information is
        needed to answer the query?

    database_metadata = {get.metadata()}
    chunk_size = {get.chunk_size()}

Estimate the query profile along with the
    database_metadata and chunk_size to
    provide the output.

"""
```

The metadata is a single line summary of the content of the database. For example, for KG RAG FinSec , the metadata is derived from the dataset definition.

```

def get_metadata():

    metadata = "The␣dataset␣consists␣of␣
        multiple␣chunks␣of␣information␣from␣
        Fortune␣500␣companies␣on␣financial␣
        reports␣from␣every␣quarter␣of␣2023."
    return metadata
```

The `chunk_size` is chosen based on guidelines RAG literature for different types of RAG tasks [24, 49]. We don't tune this knob as it is fixed when the database is created.