METIS: Fast Quality-Aware RAG Systems with Configuration Adaptation

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Abstract

RAG (Retrieval Augmented Generation) allows LLMs (large language models) to generate better responses with external knowledge, but using more external knowledge causes higher response delay. Prior work focuses either on reducing the response delay (*e.g.,* better scheduling of RAG queries) or on maximizing quality (*e.g.,* tuning the RAG workflow), but they fall short in systematically balancing the *tradeoff* between the delay and quality of RAG responses. To balance both quality and response delay, this paper presents METIS, 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. Using four popular RAG-QA datasets, we show that compared to the state-of-the-art RAG optimization schemes, METIS 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.[1] **RAG systems**, which include retrieval and LLM inference[2], have found many use cases in QA tasks, personal assistants, chatbots, and LLM-powered search [10, 62]. While RAG can enhance the quality (accuracy and relevance) of LLM-generated responses [7, 53, 58, 91, 96], RAG queries are inherently slow as they need more compute and memory resources to process the long input context to answer a query [6, 15, 42]. 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. RAG queries have an associated *RAG configuration* which describes how and how much data to input for the query (more in §2) [72, 79, 83]. 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, 44, 45, 70, 76], without adapting the RAG configuration themselves. An alternate line of work focuses on maximizing generation quality by tuning the configurations of RAG queries [32, 77, 83], but this is often done at the cost of longer response delay.

The RAG configuration *simultaneously* affects generation quality and response delay (*e.g.,* retrieving too many chunks for a simple RAG query may unnecessarily inflate delay without increasing quality). Unlike traditional data queries (*e.g.,* SQL) which specify the inputs and operators, RAG queries are inherently *under*-specified as they consist of a text query written in natural language [27, 32, 57, 64] and do not directly specify the exact RAG configuration of its execution.

Moreover, *multiple* configuration knobs can influence the 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, or should the chunks be summarized first before being fed into the LLM together (and how long should a summary be). Recent works also attempt to tune RAG configuration [32, 77], but they focus on either tuning individual knobs or maximizing quality at the cost of higher delay. However, tuning configurations across multiple knobs quickly hits a *prohibitive* combinatorial space (more in §3) and requires optimizations to reduce the search cost.

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

[1] RAG vs. long-context models is an active field of research, with the industry widely deploying RAG for its task-focused model inference quality and better resource-sharing capabilities [68].

[2] Though RAG sometimes refers to the retrieval step, in this work, a RAG system includes both retrieval and LLM inference based on the retrieved texts, and we aim to optimize the whole pipeline.

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 2024 and identify the highest one"*, the RAG may need multiple chunks, each containing the quarter's operating cost, and process these chunks jointly, instead of reading them separately. The above examples illustrate queries differ in *complexity* (more in §4), leading to needing different configurations per-query for optimal quality-delay tradeoffs. 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, 39, 85], lose out on quality or response time.

This paper presents METIS, 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.

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

First, METIS *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 given query. Specifically, METIS uses a separate LLM to estimate the query's *profile*, including how many pieces of information are required to answer the query and whether joint reasoning is likely required across these pieces of information (more 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 2024 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 METIS, 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.

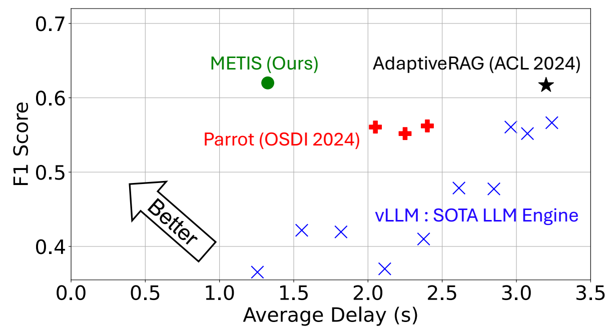


Figure 1. Performance of METIS on the KG RAG FinSec [50] dataset compared to the baselines. Full results shown in §7.

Using the narrowed configuration space, METIS reduces the RAG response delays by *jointly* deciding the per-query configuration and query scheduling based on available resources (§4.3). The insight is that within the pruned configuration space, the scheduler can make optimal configuration decisions without exploring the original, large configuration space and the implications on quality.

In short, METIS'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 METIS 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, METIS 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). METIS also achieves $1.8-4.5\times$ higher throughput compared to these baselines when achieving the same response delay and same/higher quality.

The general concept of using LLMs to guide system tuning is not exactly new [60, 88], but our key contribution lies in applying the concept to RAG systems, through joint scheduling with resource-aware configuration selection, leading to significantly better resource sharing (§4.2, §4.3).

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. Despite the growth of model context length, using RAG to pinpoint the relevant context is still significantly cheaper in terms of *resource cost* (GPU requirement), *latency*, and *memory consumption* (KV Cache size). For general-purpose QA pipelines, RAG is cost-efficient with retrieving targeted chunks based on semantic similarity to the query. Using LLMs with long-context documents in contrast has much higher GPU memory usage and delay [43, 45, 71].

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, (using the same embedding model as for database indexing), with the stored embeddings.
- *Synthesis:* After retrieving the relevant chunks, the RAG system combines these chunks and the RAG query to form a single/multiple LLM call(s) to generate the response.

Retrieval is computationally lightweight and much faster than synthesis (> 100×), so the response delay is typically dominated by the synthesis step [90].

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 with 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 the LLM should read the chunks separately, 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 feed these chunks in the LLM input directly by concatenating them within a single prompt (called `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 (called `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 [47].
- *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.

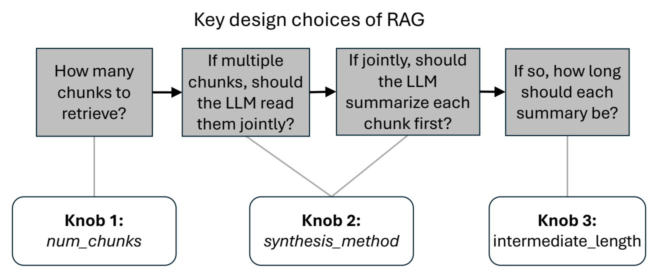


Figure 2. The configuration knobs adapted by METIS are derived from key design choices of RAG systems.

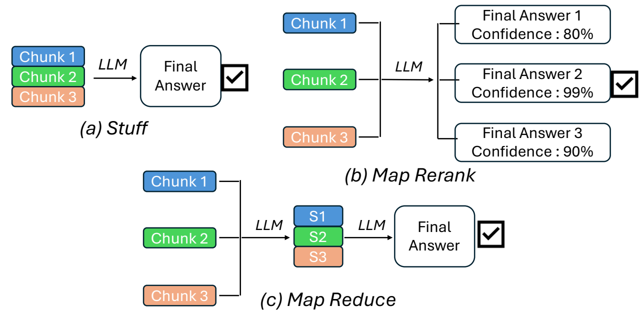


Figure 3. Illustration of different RAG synthesis methods, which have various LLM reasoning capabilities.

In this work, while we focus on universal RAG knobs which affect quality and delay common to *all* RAG systems, METIS can be extended to other tunable knobs (*e.g.,* some RAG system may dynamically choose the embedding model, retrieval index or serving LLM). METIS' design is extensible to any RAG configuration knob based on the query profile.

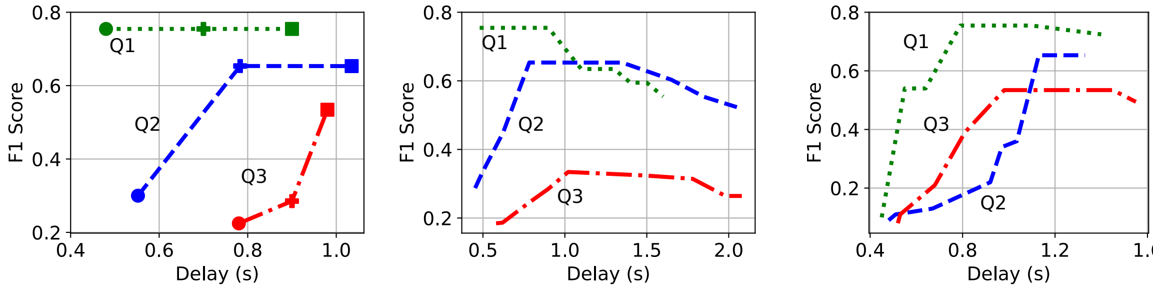
Performance metrics: We evaluate the performance of a RAG system using two metrics:

- *Response quality* calculates the F1 score of the generated response against the ground truth. The F1 score is the harmonic mean of precision (# correctly generated words) and recall (# of correct words successfully generated). This metric is widely used in prior works [10, 69, 72].
- *Response delay* measures the time elapsed from when the RAG system receives a RAG request to when it completes generating the response.

Next, we 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, *i.e.,* the first picks static configurations and focuses on reducing the delay by smart scheduling and resource allocation [44, 70, 76] and the second picks RAG configurations to maximize quality without regard to resource usage or delay [32, 77, 83]. For the first time, we explore the potential of optimizing the ***quality-delay tradeoffs*** for RAG.



(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).

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 from Musique [78], 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 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` which processes chunks in isolation suffices, whereas cross-chunk reasoning (`stuff` and `map_reduce`) adds undue delay (2×) without improving quality.

For queries such as Q2 (blue) that require *cross*-chunk reasoning, `stuff` and `map_reduce` provide significant quality improvements (35% increase) by processing chunks jointly.

For 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 (1-35) 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 (1-15) 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" [28, 47]. In all three queries, retrieving more chunks beyond a point harms the quality (up to 20% drop) and unnecessarily inflates delay (up to 3×). Hence we have a quality-delay tradeoff where increasing chunks up to a point helps quality but beyond that it 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 inter-chunk reasoning 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.** Figures 2, 3, 4 *illustrate* tuning most popular RAG configuration knobs, however the tuning extends to more RAG configurations with richer tradeoff spaces (§4.2).

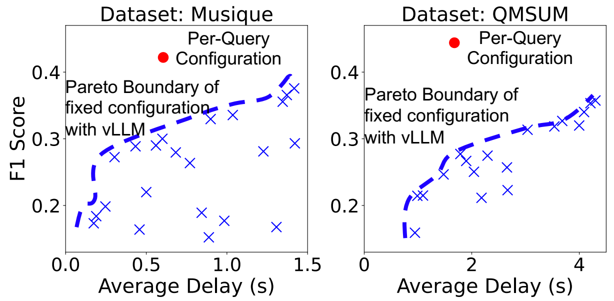


Figure 5. Per-query configuration can achieve significantly better quality-delay tradeoffs across queries compared to every fixed configuration choice.

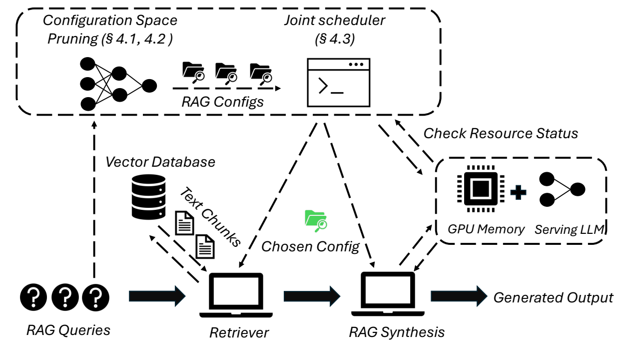


Figure 6. METIS consists of a RAG controller which performs configuration space pruning and joint scheduling.

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. Choosing the configuration per-query allows up to 3× 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, per-query configuration adaptation faces challenges that hinder their real-world adoption. Each RAG query comes in plain text with practically no associated RAG configurations. Moreover, the space of configurations grows *exponentially* with multiple knobs. For example, for a `map_reduce` configuration, with 30 values for `num_chunks` and 50 values for `intermediate_length` leads to 1500 configurations for a query. Exhaustively profiling all configurations per-query and choosing the best is infeasible.

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 ∼100× 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 [70, 76]. 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 to a useful configuration space, in a *fast* and *cheap* manner.

4 METIS: Enabling per-query configuration adaptation for RAG

We present METIS, a novel system for serving RAG queries focusing on high generation quality and minimal delay. METIS is a RAG controller (Figure 6) with two main components:

- *Pruning configuration space*: We estimate each query's profile (§4.1) and reduce the RAG configuration space to a smaller yet promising one that still yields high generation quality (§4.2) (leading to a 50-100× reduction).
- *RAG scheduler*: Within the pruned configuration space for the query, METIS' scheduler chooses the best configuration for the query to achieve the best quality-latency trade-off based on the available system resources (§4.3).

Once the configuration is chosen, the METIS' executes the query using the chosen configuration—retrieving the selected number of chunks and uses the selected synthesis method to feed into the LLM's input.

4.1 Estimating a query's profile

Query profile: To choose the correct RAG configurations, the first step of METIS 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.

- *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 1-10.

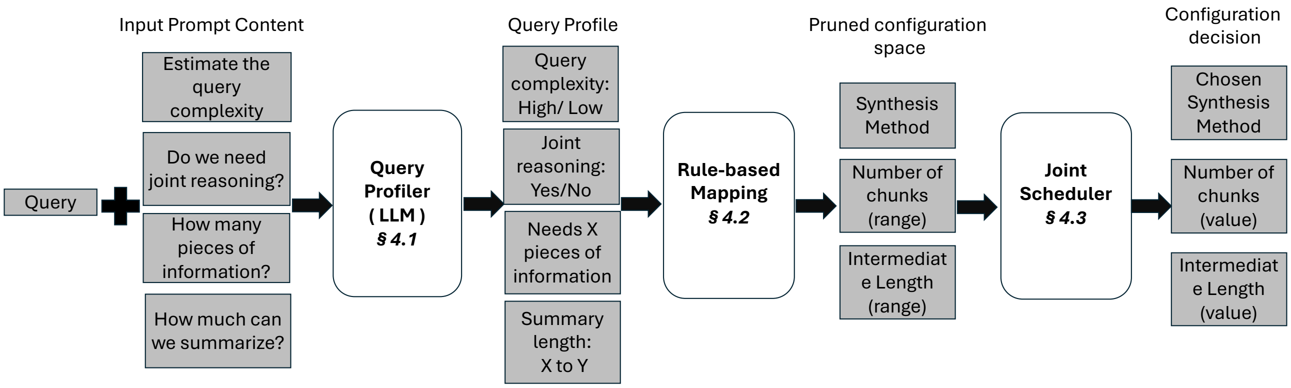


Figure 7. METIS RAG configuration selection workflow.

- *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.

METIS is not the first to use query profile as a metric for deciding RAG configurations, it extends upon methods like AdaptiveRAG [32] which have used LLM's to estimate query profile but they only focus on one dimension (the number of chunks to retrieve). In Section 7, we show the impact of each dimension on the overall improvement.

Why the query profile *could* be estimated: Estimating the aforementioned query profile is feasible, not only because of the reasoning power of LLMs[3] in analyzing natural language queries, but also because we provide sufficient information to the LLM-based profiler. METIS 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`). Specifically, 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 [50] 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/how much reasoning is required. We give details on the prompt and the intuition to generate metadata for new datasets in Appendix §A.

It is important to acknowledge that for highly under-specified 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.[4]

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 used by RAG. Yet, the embedding models perform similarly overall across queries and datasets under our consideration. This explains their limited contribution to the profiler, though more future work is needed to understand the wider implications.

4.2 Mapping query profiles to RAG configurations

After METIS obtains the query profile using the LLM, it performs rule-based mapping to generate values for RAG configuration knobs (*e.g.,* `synthesis_method` etc. introduced in §2). based on the query profiler's outputs.

How we map and why the profile helps: To understand the role of query profiles, consider the following examples:

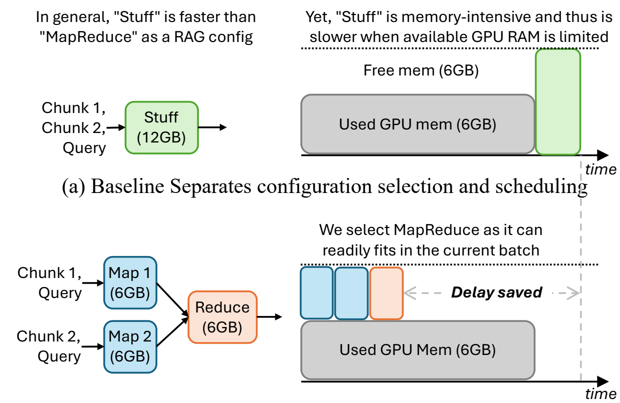
- *"Who is the current CEO of NVIDIA?"* This query is not complex and does not require joint reasoning. Due to the query being simple with no reasoning required and one piece of information (name of CEO).
- *"Which month had the highest NVIDIA's stock price the six months from January to June 2024?"* This query is simple but still needs to read information jointly, specifically six pieces of information (stock price for every month)
- *"What are the reasons for NVIDIA's month-on-month stock price change from January to June 2024"* This query is complex and needs to read multiple pieces of information jointly (stock prices, reasons for change etc.) As multiple reasons need to be analyzed here, summarizing all of the information first helps narrow down to relevant information and perform clearer reasoning (why the prices changed).

[3]We have tested both GPT and Llama models as the profile query-profiler, and they yield similarly impressive results (§7).

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

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. METIS joint schedules RAG configurations with available GPU memory (chosen example - `map_reduce`)

Algorithm 1 outlines the rule-based mapping process. This mapping is significantly helpful, it improves upon raw profiler outputs and converts them to usable RAG configurations. It reduces the cost of the profiler LLM by restricting it to provide short binary decisions only.

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". 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 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 `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)[5] 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 from the "summary length" estimate, which is already a value range (derived from the query, metadata and chunk size).

Algorithm 1 is *central* to METIS' design to reduce to the space to our useful RAG configurations and this is *extendable* to other RAG configurations. For instance, a particular RAG pipeline might use an external re-ranker [23, 52], query rewriter [36, 51] or perform an external web-search [73] along with database retrieval. The mapping algorithm can map the profiling LLM's output (*e.g.,* of *Query complexity*) and be used to guide such decisions for these newer RAG configurations.

Additionally, such mapping algorithms greatly reduce the overall inference cost of RAG inference. Attempting to use the LLM profiler to directly provide the exact RAG configuration values does not work. For this, the LLM needs to be regularly retrained for this task to adapt to new configurations and will require significantly greater system resources (*e.g.,* GPUs blocked for this). In contrast, METIS uses the LLM to only analyze natural language properties and provide binary decisions, which the mapping algorithm translates to useful configurations with a significantly lower cost.

It is important to note that the concept of METIS belongs to an active research trend in the ML and systems community that leverages LLM outputs and mapping functions to guide real system decisions and optimizations, an example of which is *LLM routing* [13, 31, 56, 59]. While current LLM routers use trained LLMs to map decisions from query complexity to only 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.

Like these prior efforts, METIS is 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.

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 a 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 queuing delay waiting for the GPU memory to free up.

We have METIS'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.

[5]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, 55].

Why 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 for 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) does not 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`, METIS can choose to use `map_reduce` (based on the current GPU memory available).

By doing so, METIS can start putting the mappers which fit in memory, into the current `running_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.

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

Jointly choosing the configuration knobs: METIS first provides us with a pruned range of configurations. A *strawman* solution is to pick a constant value from the across queries. (*e.g.,* the median value of the `num_chunks`). 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 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* from the pruned space that fits into the GPU. METIS defines the best configuration as the one with overall highest memory requirement, from all which fit in memory. The insight here is that within the reduced range of good quality configurations, higher memory configurations correspond to expensive configurations (e.g. more number of chunks, higher intermediate length). In general, these configurations should lead to *slightly higher quality* in the reduced space. For example, if the pruned space says `num_chunks` is 5-10 and the `synthesis_method` is stuff and both 5 or 6 chunks can fit in memory, we choose 6 chunks. We don't pick a configuration that doesn't fit in GPU, so we would never choose more than 6 chunks. If we do that, the system will *queue* the request inflating the delay.

After choosing the configuration that fits into the current `running_batch`, 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 inflates the queuing delay. Jointly scheduling RAG configurations enables efficient resource usage, which cannot be obtained by only relying on the output of the LLM profiler.

What if none of the configurations fit in the GPU? A main insight for METIS's design comes from the observation that in general, the RAG-specific focused configurations can be *loosely-decoupled* from the scheduling-specific configurations. METIS 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 currently available 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 instance, if the query doesn't require joint reasoning, we can pick a `map_rerank` configuration with as many chunks that fit into the current GPU memory, ignoring the remaining pruned spaces. 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.

5 Refinements to METIS

In spite of it all, it is possible for the profiler to (sometimes) fail and in such cases, it is important to detect if METIS'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 METIS to improve.

When is the quality profile reliable? METIS uses LLM to generate the quality profile. Inspired by recent work in use

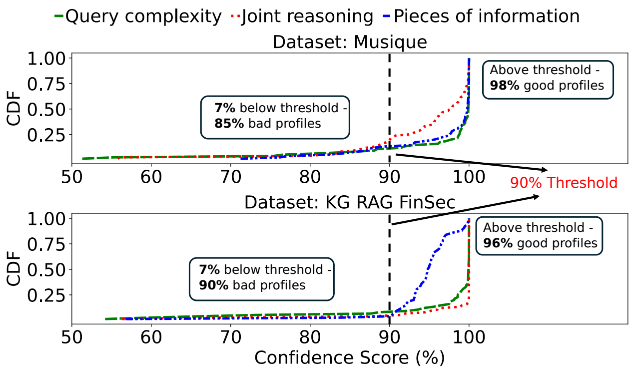


Figure 9. Confidence score threshold for different profiler outputs is used to decide when not to use the profiler output.

of model confidence [20, 25, 84] as a quality metric, we use confidence scores for METIS'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%* , METIS will fall back to the pruned configuration space of recent 10 queries.

How to improve the profiler over time? METIS improves the query profiler LLM by profiling extra feedback prompt to this LLM. We generate this feedback prompt by 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* and thus can be used to further improve its decision.

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

The cost of METIS' LLM quality profiler: For the profiler LLM, we use a larger LLM as compared to the serving LLM (7B parameters). Using this has minimal cost, as METIS *only runs it on the query* itself and in METIS as the query is at least $100\times$ shorter than the context. Using this approach, METIS still saves cost as opposed to using a large LLM for inference (as shown in Section 7). We also show that METIS can use different closed and open-source LLMs as the profiler LLM for pruning and can still provide impressive delay reduction without hurting the accuracy in Section 7.

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.

6 Implementation

We implement METIS in about 2K lines of code in Python on top of the state-of-the-art popular LLM serving engine vLLM [41]. For the profiler used for configuration space pruning, we define a class `LLMProfiler` inheriting OpenAI's Chat Completion API [61] interface (to invoke GPT-4o) and HuggingaceAPI [81] (to invoke LLama-3.1-70B) as models to profile the queries.

We use `Cohere-embed-v3.0` [4] as a state-of-the-art embedding method. We construct a FAISS [16] index using the `IndexFlatL2` interface and perform L2-distance similarity search with `index.search(query_embedding, top_k)` on the chunk embeddings to retrieve for RAG inference. We use the `LLMChain` interface from Langchain [8] in order to build efficient implementations of multiple synthesis methods.

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. Particularly, we use *pynvml* to construct `get_free_memory()` with its interfaces of `nvmlDeviceGetHandleByIndex` and `nvmlDeviceGetMemoryInfo` to measure the amount of GPU memory available. We measure the current `num-seqs` and `num-batched-tokens` within vLLM to calculate which configuration can be fit into the current batch, based on the GPU availability and the request's memory requirement.

7 Evaluation

The key takeaways from the evaluation are

- *Lower delay* : Across 4 task representative datasets for RAG QA, METIS achieves $1.64 - 2.54\times$ lower response delay compared to fixed configurations of comparable quality.
- *Higher throughput* : METIS achieves $1.8 - 4.5\times$ higher throughput than RAG serving systems which use fixed configurations reaching similar quality.

- *Negligible overhead* : METIS' profiler's delay is negligible compared to the overall delay of the LLM's RAG inference.

7.1 Setup

Models and hardware: : We evaluate METIS 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 with various query profiles, in order to have task-representative workloads. Table 1 summarizes their input-output statistics.

- Squad [66]: Squad is a single-hop reading comprehension dataset, consisting of questions on articles, where the answer to every question is a segment from the corresponding reading passage.
- Musique [78]: Musique is a multihop QA dataset with reasoning-based questions. It is designated to test LLM's reasoning ability where one reasoning step critically relies on information from another.
- KG RAG FinSec [50]: 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 [93]: QMSUM is a human-annotated query-based multi-domain meeting summarization benchmark designed to test LLM's reasoning-based summarization capabilities. This dataset contains multiple meeting transcripts and queries to summarize relevant spans of meetings.

We build a retrieval database database by splitting the queries' contexts into fixed-sized chunks using Langchain [8] for the database, with `Cohere embed-v3.0` [4] embeddings and FAISS [16] L2-distance similarity search in order to retrieve relevant chunks for RAG inference. To simulate a real RAG workload, we create a mix of queries from each dataset, and send them to METIS 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 METIS's serving model's generated response (defined in §2) It is the most widely adopted metric for evaluating RAG QA tasks [10, 69, 72]

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 system metric similar to other RAG serving papers [44, 70, 76]
- *Dollar Cost* is used to measure the lower cost of using METIS's profiler as compared to using larger serving models with fixed configurations having the closest accuracy.

Baselines: We compare METIS with the following baselines.

- *vLLM*: We serve RAG with vLLM with multiple static configurations across different queries.
- *Parrot**: We implement Parrot's [44] 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.
- *AdaptiveRAG**: We implement AdaptiveRAG's [32], query complexity-based RAG-configuration selection and choose the configuration which maximizes the F1-score, without considering the system resource cost.

7.2 Overall improvement

Lower delay without sacrificing generation quality: Figure 10 shows METIS 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*, METIS achieves $12-18\%$ higher F1-score.

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

Understanding METIS' improvement: METIS's gains come from jointly selecting the configuration based on the available resource, along with performing scheduling. METIS achieves higher quality than the fixed-config baselines as it is adapts the RAG-configuration per query. It reduces delay by resource-aware scheduling, making it better than fixed configurations which achieve closest quality.

METIS 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 RAG-configurations and cannot benefit from delay achieved by adapting the configuration like METIS. *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 METIS

Delay saving: Figure 12 shows the contribution of every component of METIS. We compare with vLLM's fixed configuration, which achieves the highest quality (blue bar). Using the profiler's outputs and choosing the median value every time (orange bar), we achieve $1.4-1.68\times$ reduction in delay. Next, we see the effect of batching (like Parrot*), by choosing the median value configuration and batching, we achieve $1.1-1.2\times$ reduction in delay. Finally, METIS achieves even greater delay reduction by $1.45-1.75\times$ by adapting the configuration based on available GPU memory with batching.

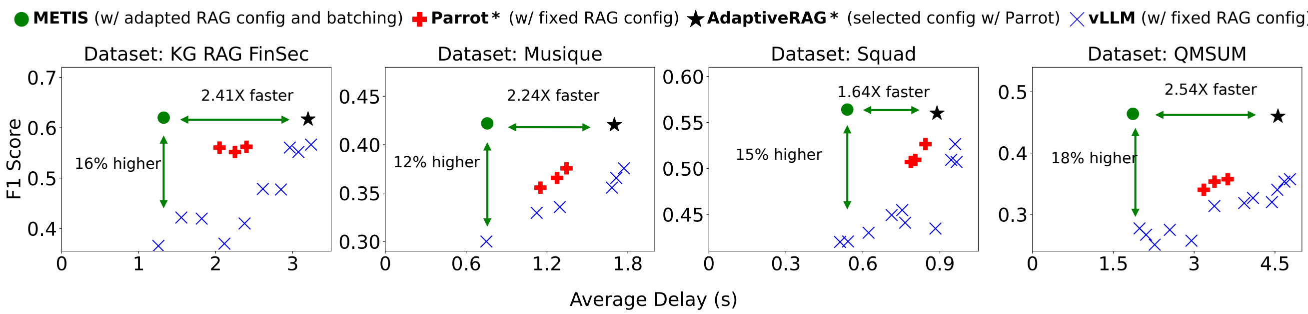


Figure 10. METIS achieves $1.64 - 2.54\times$ lower delay compared to both best fixed configuration baselines and quality-optimized RAG configuration without sacrificing generation quality.

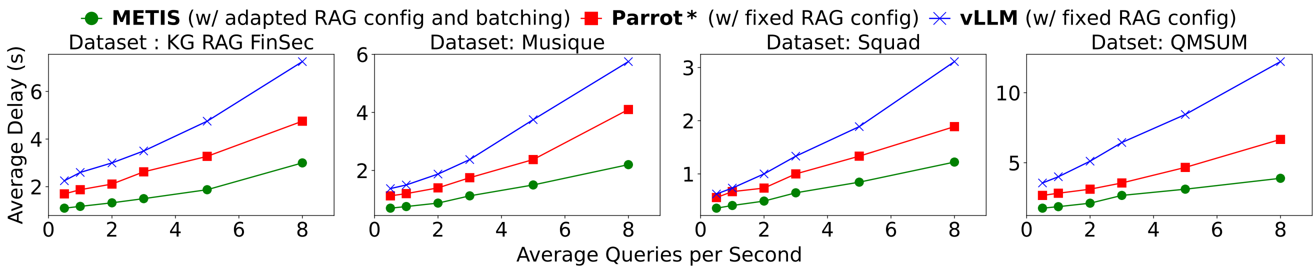


Figure 11. METIS achieves $1.8 - 4.5\times$ higher throughput (at 1.8 seconds) than baselines which use fixed configurations of closest (not higher) quality.

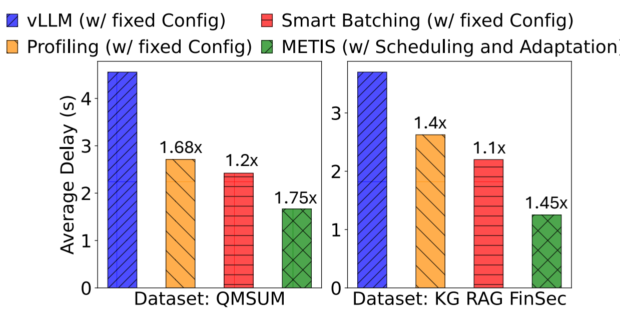


Figure 12. Understanding the delay improvement in METIS

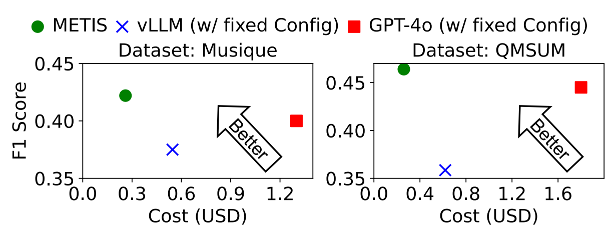


Figure 13. Even with increasing the inference model size, fixed configurations have $2.38 - 6.8\times$ higher cost and lower quality compared to METIS.

Cost saving: Figure 13 shows METIS (including its profiler) has significant lower dollar cost 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

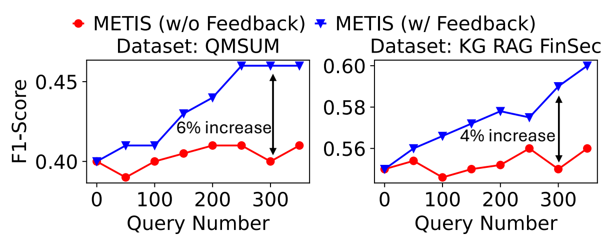


Figure 14. Improvement for METIS using feedback from the output helps improve the F1-score by $4 - 6\%$.

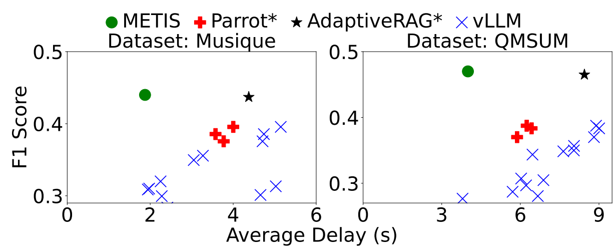


Figure 15. METIS achieves lower delay by $2.1 - 2.4\times$ at the same quality even with a larger inference LLM.

is higher by $2.38\times$ times while also having a lower F1-score of 6.5% times across datasets. Even more powerful inference 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

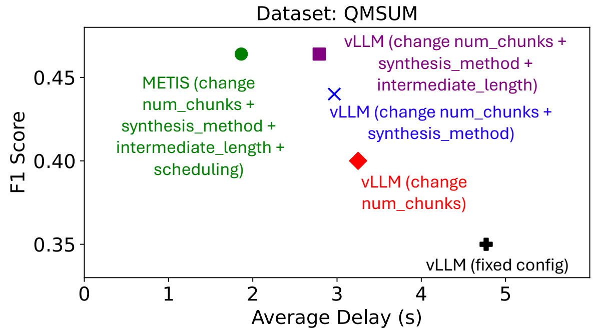


Figure 16. Breakdown analysis: By tuning more knobs in METIS, we can see better quality-delay tradeoffs.

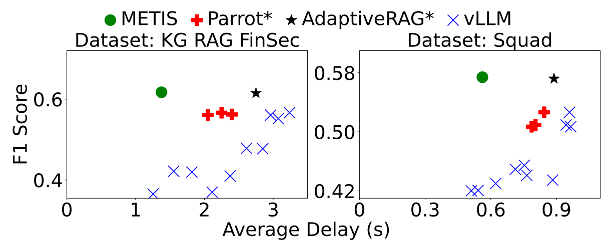


Figure 17. METIS' performance gains remain substantial even with a smaller, open-source LLM profiler.

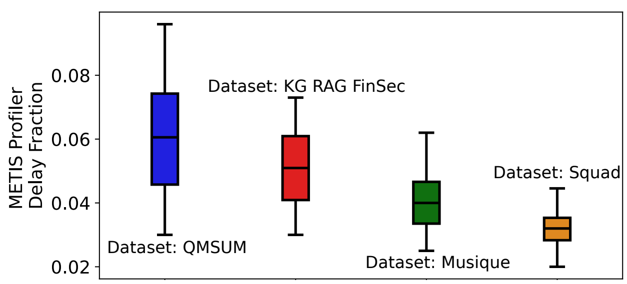


Figure 18. METIS' profiler delay is at most 1/10th of end-to-end response delay across queries from all datasets.

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. We ensure that the feedback mechanism cannot result in the output of very expensive configurations, as METIS' joint scheduler will not pick increasingly expensive configurations based on the GPU resource constraint.

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, METIS 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 tuning knobs in METIS: In Figure 16, we show the benefit we the improvement we get by incrementally adding more knobs to METIS. 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 smaller Llama3.1-70B model. METIS with the new profiler, still achieves $1.4 - 2.1\times$ over *AdaptiveRAG** with a similar F1-score. Static configurations of *Parrot** and *vLLM* which achieve similar delay, METIS achieves $10 - 14\%$ higher F1-score.

Changing the embedding algorithm: METIS picks a state-of-art retrieval algorithm `Cohere-embed-v3.0` [4]. Using two other popular retrieval algorithms `All-mpnet-base-v2` [67] and text-embedding-3-large-256 [18], the F1-score change is within 1%. The delay has no measurable difference as the retrieval is $> 100\times$ faster than LLM synthesis [6].

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

8 Related work

Systems for serving RAG: Several systems have been proposed for RAG [2, 17, 32, 34, 37, 40, 44, 54, 76, 87, 90] which focus on improving retrieval using complex, iterative retrieval algorithms or on serving model selection. METIS can work in conjunction with such systems as METIS focuses on optimizing quality and serving latency, independent of how 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, 29, 33, 41, 46, 48, 49, 63, 75, 86, 92]. METIS 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, 30, 38, 80, 85]. 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 KV 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, 35, 65, 74, 82, 94, 95]. 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. METIS can be applied with such LLM serving systems optimizations.

9 Limitations

METIS is currently designed to work with commonly deployed RAG pipelines. New research directions in RAG [17, 89] have developed further complex pipelines with more agents and stages for deep *chain-of-thought* RAG workloads. These pipelines improve on complex workloads but achieve similar performance on all the commonly used RAG QA workloads we consider [1]. We leave METIS' design extension to *chain-of-thought* pipelines to future work.

10 Conclusion

This paper introduces METIS, 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 METIS 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 METIS' 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.␣
        The␣chunk␣size␣is␣1024␣tokens."
    return metadata
```

The `chunk_size` is chosen based on guidelines RAG literature for different types of RAG tasks [24, 55]. We don't tune this knob as it is fixed when the database is created. Finally in this work, we don't tune the metadata for the dataset, we use the existing summaries.

Today, RAG QA datasets already have summaries present along with the queries and contexts. In future work , it will be interesting to study how to effectively construct such a metadata for newer datasets. One possible solution could be an LLM summarizer on a set of values from the dataset which opens up further avenues to perform joint scheduling and configuration tuning.