

An Analysis of Hyper-Parameter Optimization Methods for Retrieval Augmented Generation

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Abstract

Optimizing Retrieval-Augmented Generation (RAG) configurations for specific tasks is a complex and resource-intensive challenge. Motivated by this challenge, frameworks for RAG hyper-parameter optimization (HPO) have recently emerged, yet their effectiveness has not been rigorously benchmarked. To fill this gap, we present a comprehensive study involving five HPO algorithms over five datasets from diverse domains, including a newly curated real-world product documentation dataset. Our study explores the largest RAG HPO search space to date that includes full grid-search evaluations, and uses three evaluation metrics as optimization targets. Analysis of the results shows that RAG HPO can be done efficiently, either greedily or with random search, and that it significantly boosts RAG performance for all datasets. For greedy HPO approaches, we show that optimizing model selection first is preferable to the common practice of following the RAG pipeline order during optimization.

1 Introduction

In the **Retrieval-Augmented Generation (RAG)** paradigm, a generative LLM answers user questions using a retrieval system which provides relevant context from a corpus of documents (Lewis et al. 2020; Huang and Huang 2024; Gao et al. 2024; Wang et al. 2024b). By relying on a dedicated retrieval component, RAG solutions focus LLMs on grounded data, reducing the likelihood of dependence on irrelevant preexisting knowledge.

The popularity of RAG is largely thanks to its modular design, allowing full control over which data sources to pull data from and how to process that data. While advantageous, this modularity also means that practitioners are faced with a wide array of decisions when designing their RAG pipelines. One such choice is which generative LLM to use; other choices pertain to parameters of the retrieval system, such as how many items to retrieve per input question, how to rank them, and so forth.

Furthermore, evaluating even a single RAG configuration is costly in terms of time and funds: the embedding step as part of corpus indexing is compute-intensive; generating answers using LLMs is also a demanding task, especially for large benchmarks; and evaluation with LLM-as-

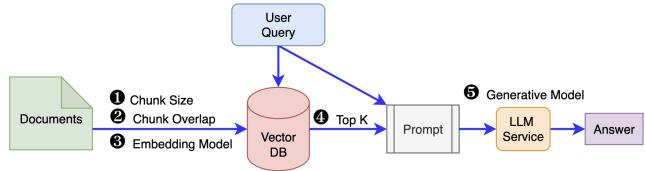


Figure 1: We study hyper parameter optimization over a RAG pipeline with 5 parameters. The explored search space includes 162 RAG configurations formed from combinations of the depicted hyper parameters.

a-Judge (LLMaaJ) adds another costly round of inference. As a result, exhaustively exploring the exponential search space of RAG parameters is prohibitively expensive. At the same time, suboptimal parameter choices may significantly harm result quality.

A promising approach to this challenge is **hyper-parameter optimization (HPO)** for RAG (Fu et al. 2024; Kim et al. 2024), which aims to identify high-performing configurations by systematically evaluating a subset of the search space. Existing methods range from established HPO algorithms to simple random sampling. Importantly, despite growing interest, the effectiveness of HPO in realistic RAG scenarios has not been rigorously tested.

Our work addresses this gap through a comprehensive study of HPO for RAG in a setup that mirrors real-world usage, where a dataset is provided up front for experimentation, and unseen queries arrive after deployment. The best RAG configuration is therefore selected by development set performance and evaluated on held out test data. To the best of our knowledge, this is the first study that considers RAG HPO in such a setup.

The scope of our experiments includes multiple datasets, evaluation metrics and algorithms. To represent diverse use cases, we evaluate across several domains: scientific (Eibich, Nagpal, and Fred-Ojala 2024), biomedical (Krithara et al. 2023), Wikipedia (Rosenthal et al. 2024; Smith, Heilman, and Hwa 2008) and a newly curated enterprise product documentation dataset that we open-source as part of this work.¹ Additionally, recognizing that different applications prioritize distinct performance metrics – such as answer correct-

¹<http://huggingface.co/datasets/ibm-research/watsonxDocsQA>

ness or faithfulness – our study evaluates multiple RAG optimization objectives, implemented through two alternative approaches: lexical overlap metrics and LLMaJ.

Our evaluation compares five HPO algorithms: Tree-Structured Parzen Estimators (TPE) (Watanabe 2023), three greedy variants, and random search. Also included are baseline grid search results for both the development and test sets, over the full search space.² These are crucial for establishing upper bounds on HPO performance for RAG, and understanding its generalization capability.

While the inclusion of grid search enables a comparison to the best possible result, it poses computational constraints on the size of the explored search space. Nonetheless, our search space is the largest considered for RAG HPO to date while still including a comparison to full grid search.

The search space comprises of 162 RAG configurations derived from five core RAG parameters (see Figure 1): chunk size and overlap, which control how documents are split, the embedding model used to encode chunks in a vector database, the number of retrieved chunks included as context when answering a question, and the generative model that produces the answer. Exploring an expanded search space introduced by more complex RAG pipelines, such as agentic workflows, poses significant computational challenges for exhaustive grid search. Consequently, this aspect is deferred to future work.

Our evaluation addresses multiple aspects of HPO for RAG, including the convergence properties of the algorithms, the impact of the objective metric on the best configuration, and an analysis of HPO overall cost. We also explore reducing that cost through development set sampling.

In summary, our main contributions are as follows: (i) comprehensive benchmarking of RAG HPO in a realistic generalization setup, over the largest search space with full grid-search evaluations to-date, showing that RAG HPO can be done efficiently, either greedily or with simple random search, and that it significantly boosts RAG performance for all datasets; (ii) a detailed analysis of the results, exploring the connections between the optimized parameters, the dataset and the optimization objective. For greedy HPO approaches, we show that the order in which the parameters are optimized is of great importance; (iii) new open-source resources: the full grid search results of our experiments, and an enterprise product documentation RAG dataset.

2 Related Work

Within the open-source community, several tools offer out-of-the-box HPO algorithms for RAG. AutoRAG (Kim et al. 2024) adopts a greedy approach, optimizing one RAG parameter at a time following the sequential pipeline order.³ RAGBuilder employs TPE for HPO.⁴ Additionally, RAG-centric libraries such as LlamaIndex⁵ support HPO by integrating general-purpose optimization frameworks like Ray-

²The grid results are at <https://github.com/IBM/rag-hpo-bench>.

³<https://github.com/Marker-Inc-Korea/AutoRAG>

⁴<https://github.com/KruxAI/ragbuilder>

⁵<https://www.llamaindex.ai/>

Tune (Liaw et al. 2018), optuna (Akiba et al. 2019) and hyperopt (Bergstra, Yamins, and Cox 2013).

Other works investigate the impact of RAG hyper-parameters without automated optimization. For example, Lyu et al. (2024) and Wang et al. (2024c) focus on manual tuning of RAG hyper-parameters, while Zhu et al. (2024) evaluates multiple configurations via grid search. Their studies highlight the critical role of hyper-parameter tuning in RAG and motivate the need for automated RAG HPO.

Another interesting line of work (Fu et al. 2024) is motivated by a setting of online feedback from users. It describes an online HPO algorithm that iteratively updates the reward for the various RAG parameters based on small batches of queries. In contrast, our work addresses offline HPO, where optimization is performed on full benchmark datasets prior to best configuration deployment.

More recently, Barker et al. (2025) introduced multi-objective HPO for RAG. The studied methods select a set of RAG configuration deemed Pareto-optimal by multiple metrics. Choosing the best configuration from this set remains an open challenge. Our study instead focuses on single-objective HPO returning a single configuration as output.

Despite these efforts, still missing is a systematic evaluation of HPO algorithms across diverse datasets under realistic conditions where optimized configurations are tested on held-out sets. This gap is the primary focus of our work. Building upon existing approaches, our evaluation prioritizes HPO algorithms already considered in the context of RAG, over introducing alternatives such as BOHB (Falkner, Klein, and Hutter 2018) or SMAC (Lindauer et al. 2022). Specifically, the greedy algorithms we explore resemble those used by Kim et al. (2024), and the TPE algorithm we assess is the same one used by RAGBuilder.

3 Experimental Setup

Search space

In our explored RAG pipeline (see Figure 1), processing starts with **chunking** the input documents into smaller chunks, based on two parameters: the *size* of each chunk in tokens, and the *overlap* between consecutive chunks. This is followed by representing each chunk with a dense vector created by an **embedding** model – our third parameter. The vectors are stored in a vector-database,⁶ alongside their original text. Upon receiving a query, the top k relevant chunks are retrieved (**retrieval**); k being our fourth parameter. Lastly, a prompt containing the query and the retrieved chunks is passed to a *generative model* (our fifth parameter) to create an answer (**generation**). Greedy decoding was used throughout all experiments. The prompts were fixed to RAG prompts tailored to each model.⁷

The specific values considered for each of the five hyper-parameters are described in Table 1. In total, the search space has $3 * 2 * 3 * 3 * 3 = 162$ possible **RAG configurations**. Dividing into stages, we get 18 ($3 * 2 * 3$) different configurations for data indexing (chunking and embedding) and 9

⁶Milvus (Wang et al. 2021) with default settings; index type is HNSW (Malkov and Yashunin 2018).

⁷See Appendix G.

Hyper Parameter	RAG step	Values
Chunk Size (# Tokens)	Chunking	256, 384, 512
Chunk Overlap (% Tokens)	Chunking	0%, 25%
Embedding Model	Embedding	<i>multilingual-e5-large</i> (Wang et al. 2024a) <i>bge-large-en-v1.5</i> (Xiao et al. 2023) <i>granite-embedding-125M-english</i> (IBM 2024)
Top-K (# Chunks to retrieve)	Retrieval	3, 5, 10
Generative Model	Generation	<i>Llama-3.1-8B-Instruct</i> (AI 2024) <i>Mistral-Nemo-Instruct-2407</i> (AI and NVIDIA 2024) <i>Granite-3.1-8B-instruct</i> (Granite Team 2024)

Table 1: The hyper parameters explored in our search space, and their values.

Dataset	Domain	#Doc	#Dev	#Test
AIArxiv	Papers	2673	41	30
BioASQ	Biomedical	40181	1000	150
MiniWiki	Wikipedia	3200	663	150
ClapNQ	Wikipedia	178890	1000	150
WatsonxQA	Business	5534	45	30

Table 2: Properties of the RAG Datasets in our experiments: the number of documents within the corpus (**#Doc**), and counts of QA pairs in the **#Dev** and **#Test** sets.

($3 * 3$) different configurations for answering (retrieval and generation). The values chosen for the chunk size, overlap, and top-k reflect common practices (see Appendix B for details). Popular open source models were selected as options for the embedding and generative models. We opted to focus on LLMs that are similar in size, since otherwise an obvious strategy is to simply discard the smaller less capable models from the search.

Our experiments involve performing a full grid search – i.e., evaluating all possible configurations – in order to establish upper bound baselines for the optimization strategies. Hence, due to computational constraints we avoid using an even larger search space, and choose a set of moderately sized LLMs as our generators. Still, to the best of our knowledge, our search space is the largest considered to date that compares to full grid-search.

Datasets

Each RAG dataset is comprised of a corpus of documents and a benchmark of QA pairs, with most also annotating the document(s) with the correct answer. Below are the RAG datasets we used:

AIArxiv This dataset was derived from the ARAGOG benchmark (Eibich, Nagpal, and Fred-Ojala 2024) of technical QA pairs over a corpus of machine learning papers from ArXiv.⁸ As gold documents are not annotated in ARAGOG dataset, we added such labels where they could be found, obtaining 71 answerable QA pairs out of 107 in the original benchmark.

⁸<https://huggingface.co/datasets/jamescalam/ai-arxiv2>

BioASQ (Krithara et al. 2023) A subset of the BioASQ Challenge train set.⁹ Its corpus contains 40200 passages extracted from clinical case reports. The corresponding benchmark of 4200 QA pairs includes multiple gold documents per question.

MiniWiki A benchmark of 918 QA pairs over Wikipedia derived from Smith, Heilman, and Hwa (2008).¹⁰ The contents are mostly factoid questions with short answers. This dataset has no gold document labels.

ClapNQ (Rosenthal et al. 2024) A subset of the Natural Questions (NQ) dataset (Kwiatkowski et al. 2019) on Wikipedia pages, of questions that have long answers. The original benchmark contains both answerable and unanswerable questions. For our analysis we consider only the former. ClapNQ dataset consists of 178890 passage texts generated from 4293 pages. These passages constitute the input to the pipeline.

WatsonxQA (ProductDocs) A new open-source dataset and benchmark based on enterprise product documentation, consisting of 5534 passage texts created from 1144 HTML product documentation pages.¹¹ These passages serve as the RAG pipeline input. The benchmark includes 75 QA pairs and gold document labels, of which 25 were generated by two subject matter experts, and the rest were synthetically produced and then manually filtered. All QA pairs were additionally reviewed by two of the authors, ensuring high data quality. Further details are in Appendix A.

Overall, these datasets exhibit variability in many aspects. They represent diverse domains – research papers, biomedical documents, wikipedia pages and enterprise data (see question examples in Table 3). They also vary in question and answer lengths; for example, MiniWiki has relatively short answers, while ClapNQ was purposely built with long gold answers. Corpus sizes also vary, representing real-world retrieval scenarios over small or large sets of documents.

Every benchmark was split into development and test sets. To keep computations tractable, the number of questions in the large benchmarks (BioASQ and ClapNQ) was limited

⁹<https://huggingface.co/datasets/rag-datasets/rag-mini-bioasq>

¹⁰<https://huggingface.co/datasets/rag-datasets/rag-mini-wikipedia>

¹¹<https://huggingface.co/datasets/ibm-research/watsonxDocsQA>

Dataset	Example Question
AIArxiv	What significant improvements does BERT bring to the SQuAD v1.1,v2.0 and v13.5 tasks compared to prior models?
BioASQ	What is the implication of histone lysine methylation in medulloblastoma?
MiniWiki	Was Abraham Lincoln the sixteenth President of the United States?
ClapNQ	Who is given credit for inventing the printing press?
WatsonxQA	What tuning parameters are available for IBM foundation models?

Table 3: One question example from each dataset.

to 1000 for development and 150 for test. Table 2 lists the corpora benchmark sizes and domains.

Metrics

The following metrics were used in our experiments: **Retrieval quality** was measured using **context correctness** with Mean Reciprocal Rank (Voorhees and Tice 2000).¹² **Answer faithfulness** (*Lexical-FF*) measures whether a generated answer remained faithful to the retrieved contexts, with lexical token precision. **Answer correctness** compares generated and gold answers, assessing **overall pipeline quality**, and is measured in two ways: First, a fast, lexical, implementation based on token recall (*Lexical-AC*), which provides a good balance between speed and quality (Adlakha et al. 2024). Second, a standard LLM-as-a-Judge answer correctness (*LLMaaJ-AC*) implementation from the RAGAS library (Es et al. 2023), with GPT4o-mini (OpenAI 2024) as its backbone. This implementation performs 3 calls to the LLM on every invocation, making it much slower and more expensive than the lexical variant.

Given a benchmark, all metrics were computed per-question. Averaging the per-question scores yields the overall metric score.

We note that all benchmarked HPO approaches are metric-agnostic - they are not tailored to any specific metric, nor a specific performance axis (such as answer correctness). Similarly, HPO can be applied to multiple RAG metrics at once, forming a single optimization objective.

HPO Algorithms

An HPO algorithm takes as input a RAG search space, a dataset (corpus and benchmark), and one evaluation metric designated as the optimization objective. Its goal is to find the RAG configuration that achieves the highest performance on the dataset with respect to the objective.

The HPO algorithms in our experiments operate iteratively. At each iteration, the algorithm reviews the scores

¹²Note that as labeling is at the document level, any chunk from the gold document is considered as a correct prediction, even if it does not include the answer to the question.

of all previously explored configurations and selects an unexplored configuration to evaluate next. To simulate a constrained exploration budget, the algorithm terminates after a fixed number of iterations and returns the best performing configuration. An efficient HPO algorithm identifies a top-performing configuration with minimal iterations.

We examine two categories of HPO algorithms: (i) standard HPO algorithms that are not specifically tailored to RAG; (ii) RAG-aware greedy algorithms that leverage some knowledge of the components within the optimized RAG pipeline. All algorithms optimize answer correctness unless explicitly noted otherwise.

Standard algorithms Our first standard HPO algorithm is *TPE*, using an implementation from hyperopt (Bergstra, Yamins, and Cox 2013), with five random initialization iterations, and otherwise the default settings. The second algorithm (*Random*) disregards results from prior iterations and uniformly selects an unexplored RAG configuration.

RAG-Aware greedy algorithms The second category of algorithms assumes an ordered list of search space parameters ranked by their presumed impact on RAG performance. These algorithms take a greedy approach: they iterate through the parameters list, optimizing one parameter at a time, assuming that optimizing high impact parameters first accelerates convergence to a strong configuration. When optimizing a parameter p , the algorithm uses fixed values for all preceding parameters and evaluates all possible values of p , with random values assigned to all following parameters. The value of p yielding the best objective score is picked, and the algorithm continues to the next parameter.

The greedy algorithms differ solely in their parameter ordering. **Model-first ordering** (*Greedy-M*) optimizes the generative and embedding models first, assuming they are more important: Generative Model, Embedding Model, Chunk Size, Chunk Overlap, Top-K. **Retrieval-first** (*Greedy-R*) is a prevalent option following the RAG pipeline structure, starting with retrieval optimization (still with model first), then generation: Embedding Model, Chunk Size, Chunk Overlap, Generative Model and Top-K. **Retrieval-first with context correctness** (*Greedy-R-CC*) uses the same order, yet optimizes the retrieval-related parameters with a context correctness metric evaluated solely on the retrieval results, saving the costs of LLM inference until all retrieval parameters are chosen. Remaining parameters are then optimized with answer correctness.

Setup

Our experimental design reflects a realistic use case: an HPO algorithm is executed over a benchmark (a development set) and the best RAG configuration is chosen for deployment; the deployed configuration is expected to generalize to unseen questions – simulated here via a test set. Specifically, each HPO algorithm ran on each development set for 10 iterations. After every iteration, the best configuration on the development set was evaluated on the test set, enabling a per-iteration generalization analysis. Since all algorithms involve a random element, each run was repeated with 10 different random seeds.

Dataset	LLMaaJ-AC			Lexical-AC		
	Worst	Best	SE	Worst	Best	SE
AIArxiv	0.36	0.62	0.03	0.40	0.66	0.04
BioASQ	0.43	0.56	0.01	0.49	0.63	0.01
MiniWiki	0.32	0.51	0.02	0.61	0.85	0.01
ClapNQ	0.46	0.57	0.01	0.34	0.61	0.01
WatsonxQA	0.52	0.76	0.03	0.74	0.87	0.04

Table 4: **Worst** and **Best** configuration scores per dataset on the development set, reported for both LLMaaJ-AC and Lexical-AC metrics. Also shown is the maximum standard error (**SE**) observed across all configurations.

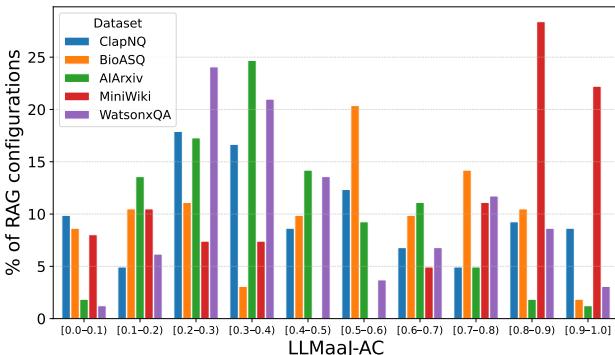


Figure 2: The distribution of configurations across bins for the normalized LLMaaJ-AC metric on the development sets. Most datasets have a few top-performing configurations.

4 Results

Grid Search

We conducted a comprehensive grid search over all 162 configurations (including 18 different indexes), across the development and test sets from all datasets. The worst and best performing configuration scores for each dataset, on the development set, are presented in Table 4.¹³ There is a substantial gap between the two extremes.

The exhaustive grid search enables a deeper analysis of the configuration landscape, including the proportion of high and low performing configurations. To quantify this, we computed a min-max normalized score per dataset and metric, binned the scores uniformly, and assigned each configuration to a bin by its normalized metric score. Figure 2 shows the distribution of configurations across bins for the LLMaaJ-AC metric. Notably, for most datasets, there are a few top-performing configurations. One example is the BioASQ dataset with fewer than 5% of configurations in the top two bins. In contrast, the MiniWiki dataset exhibits a dense cluster of good configurations, suggesting that a good configuration will be easy to find. These trends exemplify that the difficulty of the HPO setup is dataset and metric dependent.¹⁴

¹³For results with Lexical-FF see Appendix D.

¹⁴For results with Lexical-AC and Lexical-FF see Appendix D.

The grid results serve to establish two important performance baselines. The first is the performance of the best configuration selected directly from test set evaluation (dashed black lines in Figure 3). The second is the best configuration chosen based on development set evaluation, and evaluated on the test set (red lines). The gap between these baselines reflects the inherent challenge of generalization. Since HPO algorithms operate solely on the development set, their realistic target is the second baseline.

The grid search results also reveal the impact of the different RAG pipeline parameters on the measured RAG performance. Overall, we see that almost all of the parameter choices have some effect on performance, however in our experiments the choice of generative model had the largest impact on the eventual answer correctness. For a detailed statistical analysis of the impact of the different RAG parameters, refer to Appendix C.

HPO Results

Figure 3 presents the per-iteration performance of the HPO algorithms on the test sets, when optimizing for the lexical and LLMaaJ-based answer correctness metrics.¹⁵ Across all datasets and metrics, the results consistently show that exploring around 10 configurations suffices to match the performance of a full grid search over all 162 configurations. This is a strong result, demonstrating the robustness of HPO over diverse domains and evaluation metrics.

Also evident is that the difficulty of the optimization problem varies between datasets. For instance, in ClapNQ convergence is rather slow. For MiniWiki, which is rich in good performing configurations (see Figure 2), finding a top configuration is easier, with an effective HPO algorithm such as Greedy-M, as few as three iterations can yield a top RAG configuration (by selecting the optimal generative model early). In contrast, even in this easy scenario, a method like Greedy-R-CC converges slower than the alternatives. This underscores the importance of the HPO algorithm choice.

Among greedy methods, the order of parameter optimization is critical. The results show that algorithms starting with optimizing retrieval-related parameters first (Greedy-R and Greedy-R-CC) require more iterations to find good configurations.

Interestingly, the naive option of random sampling also finds a good RAG configuration after a small number of iterations. That is likely due to the large impact of the generative model choice on performance, as reflected by the fast convergence achieved by the Greedy-M approach.

The complex TPE algorithm was found to be roughly equivalent in quality to random choice. In larger or continuous spaces, TPE may offer greater advantages.

Impact of Metric Choice

The results of Greedy-M in Figure 3 show performance is boosted significantly when the generative model parameter is optimized first, suggesting its importance. We therefore further investigate the best performing model in each setup.

¹⁵Answer faithfulness follow similar trends, see Appendix D.

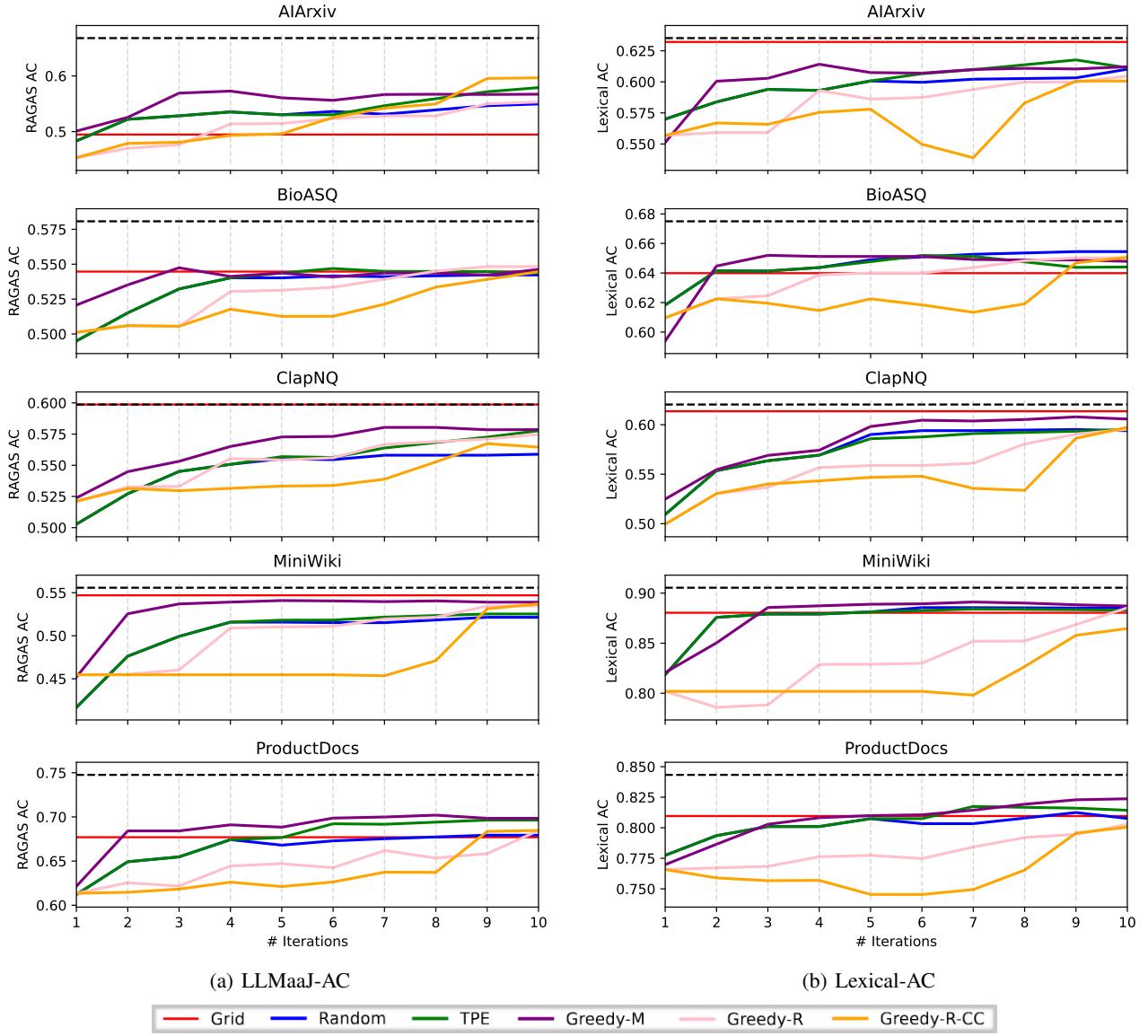


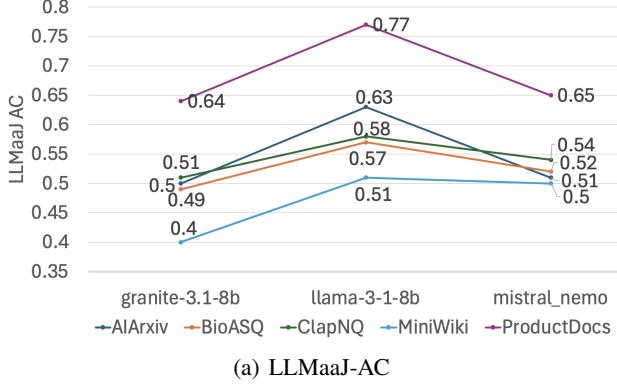
Figure 3: Per-iteration performance of all HPO algorithms on the test sets of five datasets, optimizing answer correctness computed with an LLMaaj metric (a) and a lexical metric (b). The dashed black lines show the best achievable performance. The red lines are the performance of the best configuration chosen with development set evaluation, on the test set.

Figure 4 reports the maximal answer correctness score per dataset for each generative model, computed as the highest of the $162/3 = 54$ configurations in which the model appears. When optimizing by LLMaaj-AC, the best RAG configuration consistently involves Llama, whereas for Lexical-AC, Granite or Mistral are better. This difference stems from the nature of the metrics, as Lexical-AC is recall-oriented while LLMaaj-AC balances precision and recall. These findings emphasize the critical role of optimization objective selection. Optimal configurations can differ substantially depending on the chosen metric, and thus this choice should carefully align with the intended application.

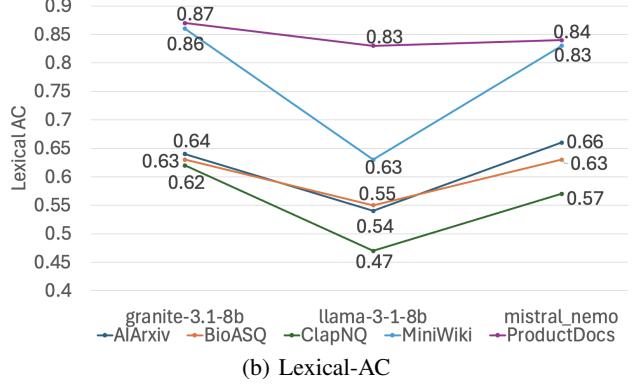
Cost Considerations

The cost of each HPO algorithm was tracked by counting the number of tokens embedded during indexing, and the number of tokens used in generation (input and output). For each algorithm, we computed its total cost so far at a specific iteration, by accumulating these token counts over the configurations evaluated up to that iteration (including). The cost of indices used by multiple configurations was counted just once. Per-iteration plots of these counts are in Appendix E.

Overall, generation costs were similar across algorithms and datasets. The embedding costs, dependent on the number of different indices created by the algorithm, behaved similarly across datasets with variations between algorithms.

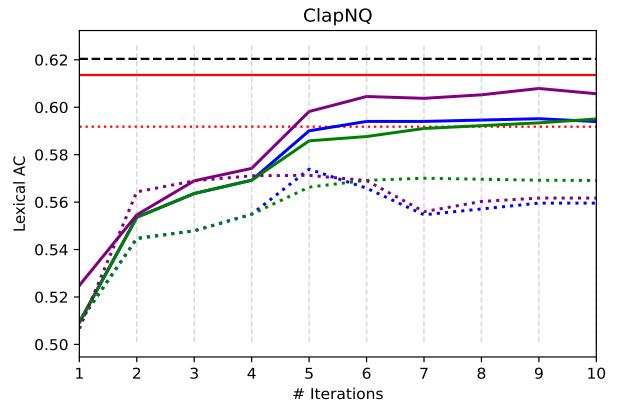
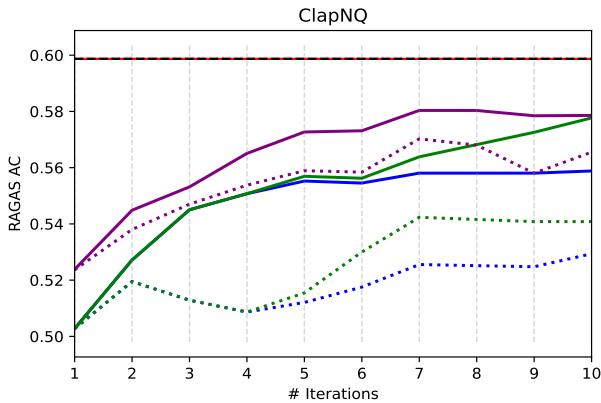
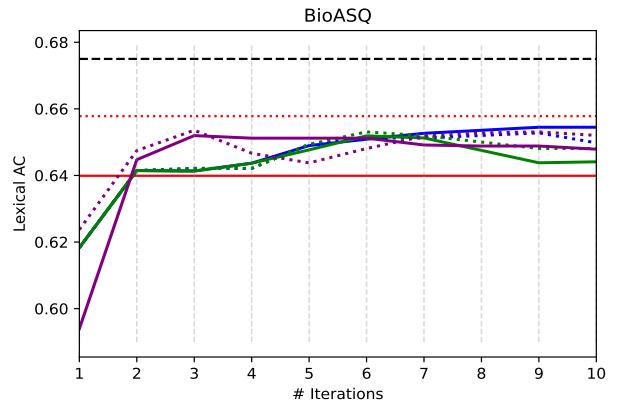
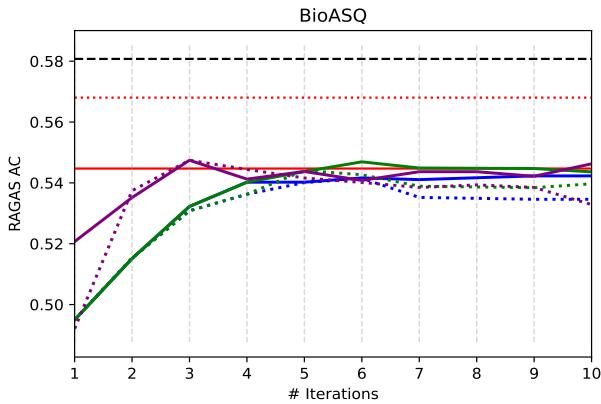


(a) LLMaaJ-AC



(b) Lexical-AC

Figure 4: The effect of chosen optimization metric on the generative model within the best RAG configuration. Shown is the maximal answer correctness score per dataset and model (the highest of the 54 configurations in which the model appears).



(a) LLMaaJ-AC

(b) Lexical-AC

— Grid/Full	··· Random/Sample	— Greedy-M/Full
··· Grid/Sample	— TPE/Full	··· Greedy-M/Sample
— Random/Full	··· TPE/Sample	

Figure 5: Per-iteration performance on the test sets of the two largest datasets, for HPO algorithms optimized using the **full** development data (solid lines) or its **sample** (dotted). The dashed black lines show the best achievable test performance. The solid (dashed) red lines are the performance of the best configuration chosen by (sampled) development set evaluation.

The Greedy-R and Greedy-R-CC algorithms create a new index at each iteration until all retrieval parameters are optimized, making them initially expensive. Other algorithms like TPE and Random lack a mechanism to favor index reuse. Greedy-M begins by optimizing the generative model using a single index, making it cost-efficient when budget constraints or iteration limits are tight.

Efficient HPO

The results of Figure 3 were obtained with each RAG configuration evaluated on the whole development set. While simple, this option is costly for large datasets. Prior work in other domains suggests that random sampling of evaluation benchmarks can reduce costs without sacrificing evaluation quality (Perlitz et al. 2024; Polo et al. 2024), and we therefore explore this direction. To our knowledge, this is the first study of that direction in the context of HPO for RAG.

To adapt sampling to RAG, we sample both the benchmark and the underlying corpus. Specifically, focusing on the larger datasets of BioASQ and ClapNQ, 10% of the development QA pairs were sampled along with their corresponding gold documents (those containing the answers to the sampled questions). To preserve realistic retrieval conditions we add “noise” – documents not containing an answer to any of the sampled questions – at a ratio of 9 such documents per gold document. This yields 100 sampled benchmark questions per dataset, with the sampled corpora comprising of 1K (i.e. 1000) documents for ClapNQ (out of 178K), and 10K for BioASQ (out of 40K).¹⁶

Following sampling, we repeat the experiments using the best HPO methods: Random, TPE, and Greedy-M. Figure 5 compares performance when optimizing for LLMaaJ-AC and Lexical-AC, using the full (solid lines) or sampled (dotted) development sets. For BioASQ sampling has a negligible impact. For ClapNQ, results differ per algorithm and metric, with a suboptimal configuration identified by TPE and Random. For Greedy-M and the LLMaaJ-AC metric, the performance drop is moderate.

With this approach, cost reductions are substantial. Inference costs for a given configuration are 10x cheaper, as 10% of the questions are used. Indexing costs drop by 4x for BioASQ and 178x for ClapNQ. These savings make sampling highly attractive for HPO over large datasets.

In summary, development set sampling offers a promising path towards efficient RAG HPO. Combined with the Greedy-M approach, the trade-off between cost and performance remains favorable, making it a practical choice for real-world applications.

5 Conclusion

We presented a comprehensive study of HPO for RAG in a generalization setup that reflects real-world usage. Our evaluation spans five HPO algorithms, three evaluations metrics, and multiple datasets from diverse domains. One is a newly curated enterprise product documentation dataset, released as part of this work, for use by the community.

¹⁶BioASQ has multiple gold documents per question, which yields more sampled documents.

Our findings are that HPO systematically boosts RAG performance significantly. Compared to an arbitrarily chosen RAG configuration, running 10 HPO iterations yield gains of up to 20% (see Figure 3, comparing the performance at the first and last iterations). While our experiments focus on core RAG components, the potential impact on more complex systems parametrized by larger search spaces is likely even greater. For example, exploring HPO in the context of multi-modal or agentic RAG pipelines seems a promising direction for future work.

We showed that RAG HPO can be performed efficiently. Even without prior knowledge of the RAG pipeline parameters, exploring a small subset of the configuration space is often sufficient. Simple strategies such as random sampling perform surprisingly well, while a greedy approach that prioritizes model selection outperforms the common practice of sequential optimization by pipeline order.

Our results highlight the importance of the optimization objective choice, as different objective choices lead to different optimal RAG configurations. We further show that development set sampling can reduce the costs of HPO for RAG by orders of magnitude. With the use of the Greedy-M algorithm, the saved compute, at the mild cost of performance, may be attractive for many users.

For practitioners interested in boosting the performance of their RAG pipelines, we strongly suggest the use of HPO, and offer the following recommendations. Carefully choose an optimization metric that reflects the goals of the application. With that, evaluate multiple configurations with randomly picked parameter values, this initial quick exploration is likely to give valuable gains. Next, improve efficiency by using a greedy HPO algorithm that optimizes model choices first, that will provide faster convergence. For large datasets, combine that algorithm with development set sampling to efficiently find a top-performing RAG configuration.

Finally, we open-source our complete grid search results over the development and test sets for all datasets.¹⁷ To our knowledge, we are the first to release such a resource for RAG. Building on these results, further research can explore new HPO techniques without incurring the substantial cost of running many RAG configuration across datasets. Our release also includes the generation outputs for each configuration, enabling easy computation of additional metrics and their analysis in the context of HPO. We hope this release will serve as a valuable contribution to research on HPO for RAG.

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¹⁷<https://github.com/IBM/rag-hpo-bench>

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A WatsonxQA additional details

As stated in the body of the paper, the WatsonxQA benchmark includes 75 QA pairs and gold document labels, of which 50 were generated synthetically. The benchmark contains five fields: a question, a gold answer and, for computing context relevance metrics, the gold passage id and its content. Some example benchmark entries are given in Figure 12. Synthetic generation was operated using falcon-180b model, and then manually filtered and reviewed for quality - the methodology we used is detailed in Yehudai et al. (2024). The prompt used for the synthetic generation is detailed in Figure 13.

B Search Space Selection

The search space values for the parameters Chunk Size, Chunk Overlap and Top-K were chosen based on previous works:

Chunk size Wang et al. (2024c) used the values {128, 256, 512, 1024, 2048}. They reported that the values 256 and 512 performed well (see Table 3 in Wang et al. (2024c)) in terms of faithfulness and relevancy. Lyu et al. (2024) used {64, 128, 256, 512}. We chose three values {256, 384, 512}.

Top-K Fu et al. (2024) experimented with {1, 3, 5, 7, 9}, and Lyu et al. (2024) with {2, 4, 6, 8, 10}. We chose to use {3, 5, 10}.

Chunk Overlap Lyu et al. (2024) used {0%, 10%, 30%, 50%, 70%}. Others have not considered this parameter. We used {0%, 25%}.

C Impact of specific parameters

To test the impact of the different RAG pipeline parameter choices, we conduct statistical analyses over the grid-search results for each dataset.

Specifically, we fit a linear mixed-effects model on the dataset results, where the per-example answer correctness is the dependent variable, the choice of generative model, embedding model, chunk size, chunk overlap and retrieved K are the fixed effects we test for, and the individual examples are modeled as a random effect. In addition to the main effects, we include in our model possible *interaction* effects: between the embedding model and the generative model, between the embedding model and the chunk size, between the chunk size and chunk overlap, and between the generative model and the retrieved K.

To assess the significance of each of the tested main effects and interactions, we performed likelihood ratio tests, comparing the full mixed-effects model to a reduced model that excludes a specific main effect or interaction. We report the resulting test statistics χ^2 and significance values p for each dataset in Tables 6-15. As can be seen in the tables, most of the effects and interactions are statistically significant ($p < .05$), indicating that these choices do indeed affect the pipeline result. Consistently, the choice of the generative model has a particularly large effect, explaining much of the variance of the statistical model.

In addition, for each dataset and metric we report the marginal means for each chosen pipeline parameter, and their delta from the overall mean metric result. As can be seen in Tables 16-20, the largest differences in the metric scores relate to the choice of generative model. In addition, the relative success of the different generative models depends on the chosen metric, as also shown in Figure 4.

We conduct all analyses using the *statsmodels* python library (v0.14.6). Parameters and marginal means were estimated using Restricted Maximum Likelihood (REML). For the likelihood-ratio-testing of effect significance, models were compared using Maximum Likelihood (ML).

D Additional results

See §4 for a discussion of the main results.

- Table 5 shows the worst and best per-dataset Lexical-FF metric scores on the development set.
- Figure 6 depicts the percentage of good and bad configurations for the five datasets and the Lexical-AC and Lexical-FF metrics.
- Figure 7 details HPO results for the Lexical-FF metric.

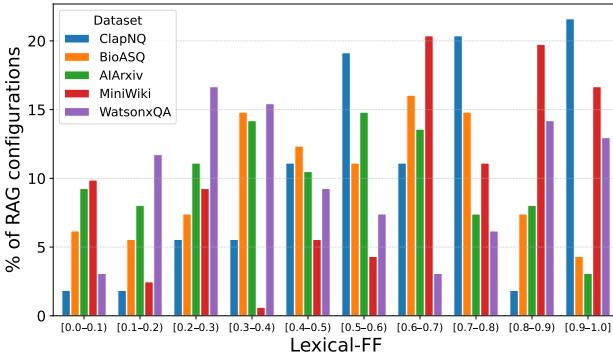
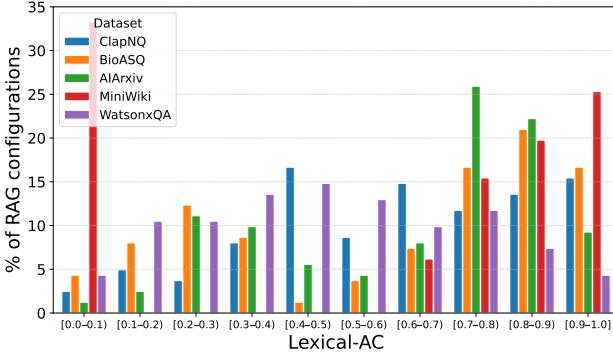


Figure 6: The percentage of RAG configurations assigned to each bin of normalized metric scores (with the Lexical-AC or Lexical-FF metrics), on the dev sets.

E Embedding and Generation Costs

Figure 8 details accumulated numbers of (a) embedded tokens and (b) number of tokens used in generation part for HPO algorithms overall tested configurations. See §4 for a discussion of costs.

F Hardware and Costs

All used embedding and generation models are open source models. An internal in-house infrastructure containing V100 and A100 GPUs was used to run embedding computations and generative inference. Specifically, embeddings were computed using one V100 GPU, and inference was done on one A100 GPU (i.e. no multi-GPU inference was required).

The evaluation of the LLMaJ-AC metric was done with GPT4o-mini (OpenAI 2024) as its backbone LLM. That model was used through Microsoft Azure. The overall cost was $\sim 500\$$.

G Generation Prompt Details

The RAG prompts used by each model are shown in Figure 9 for Granite, Figure 10 for Llama and Figure 11 for Mistral. In each prompt the $\{question\}$ placeholder indicates where the user question was placed, and $\{retrieved\ documents\}$ the location of the retrieved chunks. For Granite, each retrieved chunk was prefixed with '*[Document]*' and suffixed

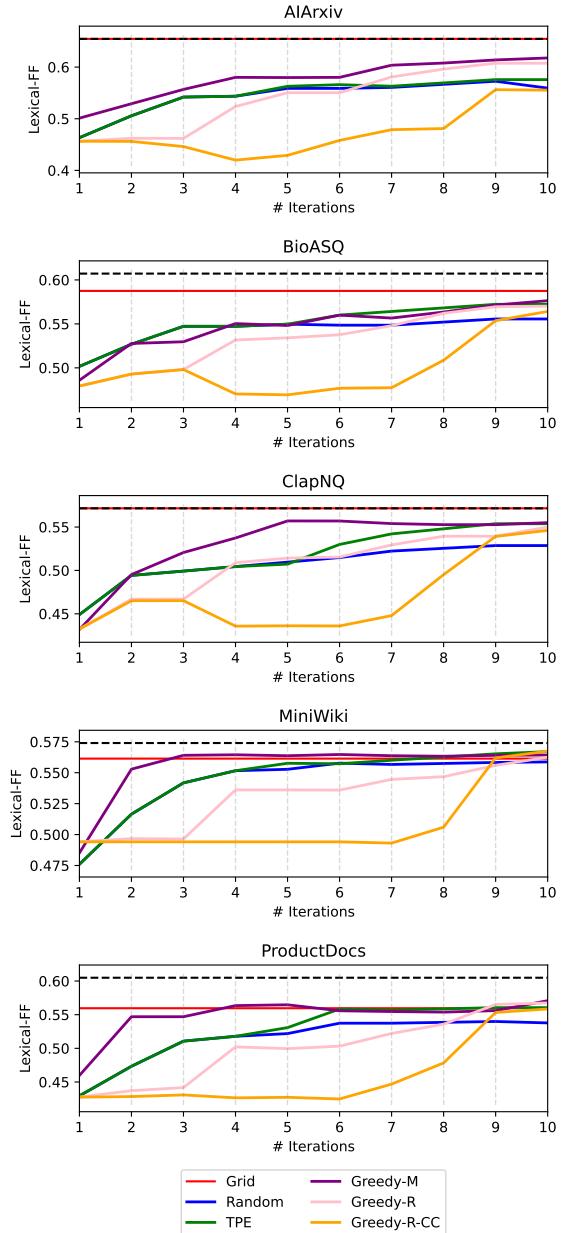
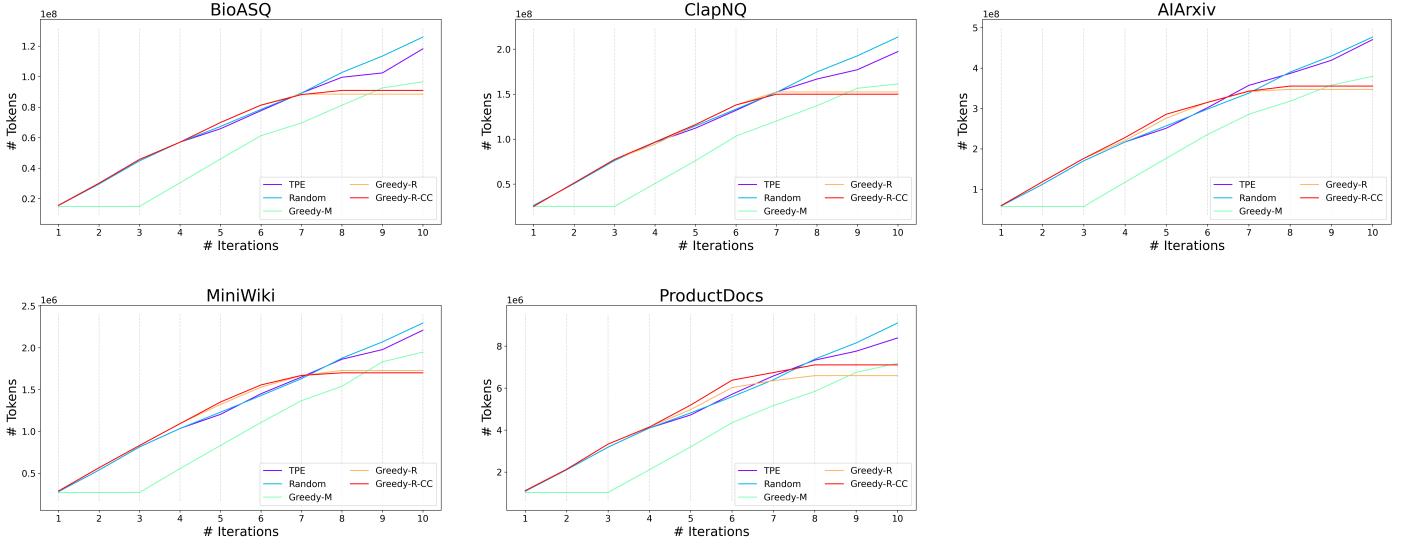
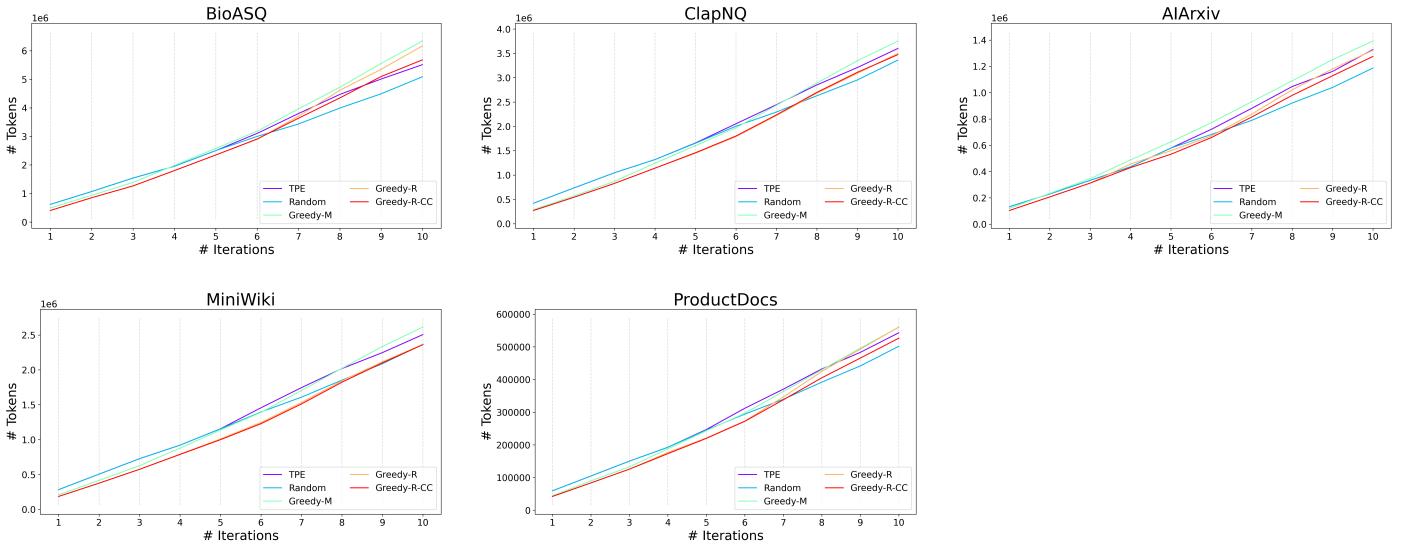


Figure 7: Per-iteration performance of all HPO algorithms on the test sets of five datasets, optimizing answer faithfulness. The dashed black lines denote the best achievable performance on each test set. See §4 for a discussion of the main results.

by '*[End]*'. Similarly, for Llama each retrieved chunk was prefixed with '*[document]*':



(a) Total number of tokens from chunks sent to the embedding models.



(b) Total number of tokens for prompts sent to the generation models.

Figure 8: Cost estimation for each algorithm after each iteration.

Dataset	Lexical-FF		
	Worst	Best	SE
AIArxiv	0.28	0.64	0.03
BioASQ	0.38	0.60	0.01
MiniWiki	0.39	0.56	0.01
ClapNQ	0.28	0.56	0.01
WatsonxQA	0.37	0.65	0.03

Table 5: **Worst** and **Best** configuration scores per dataset on the development set for the Lexical-FF metric. Also shown is the maximum standard error (**SE**) observed across all configurations.

H Use Of AI Assistants

AI Assistants were only used in writing for minor edits and rephrases. They were also used to aid in obtaining the correct LateX syntax for the various figures.

Table 6: Results of a likelihood ratio test for the grid-search results of the AIArxiv dataset (LLMaaJ-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	401	10	5.5×10^{-80}
Embedding model	42	10	9.1×10^{-6}
Chunk size	48	8	1.2×10^{-7}
Chunk overlap	1.6	3	0.65
K	29	6	5.5×10^{-5}
Generative model * Embedding model	2.2	4	0.7
Embedding model * Chunk size	31	4	3.2×10^{-6}
Chunk size * Chunk overlap	0.28	2	0.87
Generative model * K	16	4	3.5×10^{-3}

Table 7: Results of a likelihood ratio test for the grid-search results of the BioASQ dataset (LLMaaJ-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	5446	10	≈ 0
Embedding model	251	10	4.0×10^{-48}
Chunk size	55	8	5.4×10^{-9}
Chunk overlap	11	3	0.01
K	218	6	2.4×10^{-44}
Generative model * Embedding model	33	4	1.3×10^{-6}
Embedding model * Chunk size	25	4	4.6×10^{-5}
Chunk size * Chunk overlap	7.4	2	0.025
Generative model * K	150	4	2.3×10^{-31}

Table 8: Results of a likelihood ratio test for the grid-search results of the ClapNQ dataset (LLMaaJ-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	3103	10	≈ 0
Embedding model	1883	10	≈ 0
Chunk size	46	8	1.9×10^{-7}
Chunk overlap	23	3	3.3×10^{-5}
K	82	6	1.4×10^{-15}
Generative model * Embedding model	304	4	1.7×10^{-64}
Embedding model * Chunk size	9.5	4	0.049
Chunk size * Chunk overlap	12	2	2.5×10^{-3}
Generative model * K	76	4	1.0×10^{-15}

Table 9: Results of a likelihood ratio test for the grid-search results of the MiniWiki dataset (LLMaaJ-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	12072	10	≈ 0
Embedding model	140	10	3.6×10^{-25}
Chunk size	1.6	8	0.99
Chunk overlap	0.72	3	0.87
K	631	6	5.4×10^{-133}
Generative model * Embedding model	41	4	3.4×10^{-8}
Embedding model * Chunk size	0.8	4	0.94
Chunk size * Chunk overlap	0.72	2	0.7
Generative model * K	626	4	4.2×10^{-134}

Table 10: Results of a likelihood ratio test for the grid-search results of the WatsonxQA dataset (LLMaaJ-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	757	10	4.5×10^{-156}
Embedding model	25	10	5.3×10^{-3}
Chunk size	40	8	3.5×10^{-6}
Chunk overlap	0.49	3	0.92
K	43	6	1.3×10^{-7}
Generative model * Embedding model	13	4	0.012
Embedding model * Chunk size	11	4	0.026
Chunk size * Chunk overlap	0.41	2	0.81
Generative model * K	7.1	4	0.13

```

<|system|>
You are Granite Chat, an AI language model developed by IBM. You are a cautious assistant. You carefully follow instructions. You are helpful and harmless and you follow ethical guidelines and promote positive behavior.
<|user|>
You are a AI language model designed to function as a specialized Retrieval Augmented Generation (RAG) assistant. When generating responses, prioritize correctness, i.e., ensure that your response is grounded in context and user query.
Always make sure that your response is relevant to the question.
Answer Length: detailed
[Document]
{retrieved documents}
[End]
{question}
<|assistant|>

```

Figure 9: The prompt used for Granite.

```

<|begin_of_text|><|start_header_id|>system<|end_header_id|>
You are a helpful, respectful and honest assistant.
Always answer as helpfully as possible, while being safe.
Your answers should not include any harmful, unethical, racist, sexist, toxic, dangerous, or illegal content.
Please ensure that your responses are socially unbiased and positive in nature.
If a question does not make any sense, or is not factually coherent, explain why instead of answering something not correct.
If you don't know the answer to a question, please don't share false information.
<|eot_id|><|start_header_id|>user<|end_header_id|>
[document]: {retrieved documents}
[conversation]: {question}. Answer with no more than 150 words. If you cannot base your answer on the given document, please state that you do not have an answer.;—eot_id—;
<|start_header_id|>assistant<|end_header_id|>

```

Figure 10: The prompt used for Llama.

```

<s> [INST] <<SYS>>
You are a helpful, respectful and honest assistant.
Always answer as helpfully as possible, while being safe.
Your answers should not include any harmful, unethical, racist, sexist, toxic, dangerous, or illegal content.
Please ensure that your responses are socially unbiased and positive in nature.
If a question does not make any sense, or is not factually coherent, explain why instead of answering something not correct.
If you don't know the answer to a question, please don't share false information.
<</SYS>>
Generate the next agent response by answering the question. You are provided several documents with titles.
If the answer comes from different documents please mention all possibilities and use the titles of documents to separate between topics or domains.
If you cannot base your answer on the given documents, please state that you do not have an answer.
{retrieved documents}
{question} [/INST]

```

Figure 11: The prompt used for Mistral.

Question: What are the natural language processing tasks supported in the Product library?

Gold answer: The Product library supports the following natural language processing tasks: language detection, syntax analysis, noun phrase extraction, keyword extraction and ranking, entity extraction, sentiment classification, and tone classification.

Gold context-id: EN-001

Gold passage: The following natural language processing tasks are supported as blocks or workflows in the Product library:

- * [Language detection]
- * [Noun phrase extraction]
- * [Keyword extraction and ranking]
- * [Entity extraction]
- * [Sentiment classification]
- * [Tone classification]

Question: What happens to unsaved prompt text within Product, and how long does it persist on the webpage before being deleted?

Gold answer: The prompt text remains unsaved unless the user decides to save their progress. While unsaved, the prompt text persists on the webpage until a page refresh occurs, upon which the text is automatically deleted.

Gold context-id: EN-101

Gold passage: Privacy of text in Product during a session

Text that you submit by clicking Generate from the prompt editor in Product is reformatted as tokens, and then submitted to the foundation model you choose. The submitted message is encrypted in transit.

Your prompt text is not saved unless you choose to save your work.

Unsaved prompt text is kept in the web page until the page is refreshed, at which time the prompt text is deleted.

Figure 12: Examples of benchmark entries in WatsonxQA.

Given the next [document], create a [question] and [answer] pair that are grounded in the main point of the document, don't add any additional information that is not in the document. The [question] is by an information-seeking User and the [answer] is provided by a helping AI Agent.

[document]: [A WatsonxQA document example]

Response:

[question]: What is a token limit?

[answer]: Every model has an upper limit to the number of tokens in the input prompt plus the number of tokens in the generated output from the model (sometimes called context window length, context window, context length, or maximum sequence length.)
...

[document]:

Figure 13: The prompt used for synthetic data generation. The prompt consists of instruction followed by $K = 3$ examples of document and generated QA.

Table 11: Results of a likelihood ratio test for the grid-search results of the AIArxiv dataset (Lexical-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	1918	10	≈ 0
Embedding model	143	10	9.5×10^{-26}
Chunk size	68	8	1.4×10^{-11}
Chunk overlap	1.6	3	0.66
K	90	6	3.7×10^{-17}
Generative model * Embedding model	6.6	4	0.16
Embedding model * Chunk size	53	4	7.1×10^{-11}
Chunk size * Chunk overlap	0.27	2	0.87
Generative model * K	26	4	2.8×10^{-5}

Table 12: Results of a likelihood ratio test for the grid-search results of the BioASQ dataset (Lexical-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	10487	10	≈ 0
Embedding model	610	10	1.3×10^{-124}
Chunk size	126	8	1.6×10^{-23}
Chunk overlap	3.3	3	0.35
K	632	6	2.6×10^{-133}
Generative model * Embedding model	24	4	8.2×10^{-5}
Embedding model * Chunk size	58	4	7.9×10^{-12}
Chunk size * Chunk overlap	3.2	2	0.2
Generative model * K	313	4	2.0×10^{-66}

Table 13: Results of a likelihood ratio test for the grid-search results of the ClapNQ dataset (Lexical-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	24649	10	≈ 0
Embedding model	8080	10	≈ 0
Chunk size	186	8	5.4×10^{-36}
Chunk overlap	149	3	4.3×10^{-32}
K	582	6	1.5×10^{-122}
Generative model * Embedding model	64	4	4.5×10^{-13}
Embedding model * Chunk size	29	4	8.3×10^{-6}
Chunk size * Chunk overlap	27	2	1.1×10^{-6}
Generative model * K	72	4	8.2×10^{-15}

Table 14: Results of a likelihood ratio test for the grid-search results of the MiniWiki dataset (Lexical-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	12805	10	≈ 0
Embedding model	73	10	1.4×10^{-11}
Chunk size	1.3	8	1
Chunk overlap	0.013	3	1
K	74	6	7.3×10^{-14}
Generative model * Embedding model	27	4	2.5×10^{-5}
Embedding model * Chunk size	1.3	4	0.87
Chunk size * Chunk overlap	0.012	2	0.99
Generative model * K	25	4	6.0×10^{-5}

Table 15: Results of a likelihood ratio test for the grid-search results of the WatsonxQA dataset (Lexical-AC metric)

Main effect/Interaction	χ^2	degrees of freedom	p-value
Generative model	276	10	2.3×10^{-53}
Embedding model	12	10	0.28
Chunk size	70	8	4.8×10^{-12}
Chunk overlap	2.5	3	0.48
K	60	6	4.1×10^{-11}
Generative model * Embedding model	2.6	4	0.62
Embedding model * Chunk size	7.3	4	0.12
Chunk size * Chunk overlap	2	2	0.36
Generative model * K	8.7	4	0.068

		LLMaaJ-AC	LLMaaJ-AC (Δ)	Lexical-AC	Lexical-AC (Δ)
Generative model	ibm-granite/granite-3.1-8b-instruct	0.43	-0.037	0.59	0.029
	meta-llama/llama-3-1-8b-instruct	0.53	0.056	0.48	-0.083
	mistral-nemo-instruct	0.45	-0.019	0.62	0.054
Embedding model	BAAI/bge-large-en-v1.5	0.48	0.0062	0.58	0.014
	ibm/slate-125m-english-rtrvr	0.47	0.0017	0.57	0.0012
	intfloat/multilingual-e5-large	0.46	-0.0079	0.55	-0.015
Chunk size	256	0.47	0.0016	0.56	-0.0024
	384	0.48	0.0092	0.57	0.0067
	512	0.46	-0.011	0.56	-0.0043
Chunk overlap	0.0	0.47	0.0024	0.57	0.0015
	0.25	0.47	-0.0024	0.56	-0.0015
K	3	0.46	-0.0099	0.55	-0.013
	5	0.47	0.0016	0.57	0.0007
	10	0.48	0.0083	0.58	0.012

Table 16: Marginal means for the grid search results (AIArxiv). Columns denoted by Δ show the relative difference from the overall dataset mean.

		LLMaaJ-AC	LLMaaJ-AC (Δ)	Lexical-AC	Lexical-AC (Δ)
Generative model	ibm-granite/granite-3.1-8b-instruct	0.45	-0.042	0.61	0.035
	meta-llama/llama-3-1-8b-instruct	0.53	0.036	0.52	-0.053
	mistral-nemo-instruct	0.5	0.0058	0.59	0.017
Embedding model	BAAI/bge-large-en-v1.5	0.5	0.0081	0.58	0.011
	ibm/slate-125m-english-rtrvr	0.49	-0.0015	0.57	-0.0015
	intfloat/multilingual-e5-large	0.49	-0.0066	0.56	-0.0096
Chunk size	256	0.5	0.0015	0.57	-0.0022
	384	0.49	-0.0029	0.57	-0.0021
	512	0.5	0.0014	0.58	0.0042
Chunk overlap	0.0	0.49	-0.00087	0.57	0.000067
	0.25	0.5	0.00088	0.57	-0.000071
K	3	0.49	-0.0041	0.56	-0.0092
	5	0.5	-0.00066	0.58	0.0031
	10	0.5	0.0048	0.58	0.0061

Table 17: Marginal means for the grid search results (BioASQ). Columns denoted by Δ show the relative difference from the overall dataset mean.

		LLMaaJ-AC	LLMaaJ-AC (Δ)	Lexical-AC	Lexical-AC (Δ)
Generative model	ibm-granite/granite-3.1-8b-instruct	0.48	-0.029	0.57	0.059
	meta-llama/llama-3-1-8b-instruct	0.54	0.027	0.43	-0.078
	mistral-nemo-instruct	0.51	0.0023	0.53	0.019
Embedding model	BAAI/bge-large-en-v1.5	0.52	0.0098	0.53	0.025
	ibm/slate-125m-english-rtrvr	0.53	0.015	0.53	0.02
	intfloat/multilingual-e5-large	0.49	-0.024	0.46	-0.045
Chunk size	256	0.51	-0.0029	0.5	-0.0056
	384	0.51	0.00066	0.51	0.0022
	512	0.51	0.0023	0.51	0.0035
Chunk overlap	0.0	0.51	-0.0015	0.5	-0.0039
	0.25	0.51	0.0015	0.51	0.0039
K	3	0.51	0.0014	0.5	-0.01
	5	0.51	-0.00088	0.51	0.0015
	10	0.51	-0.00054	0.52	0.0089

Table 18: Marginal means for the grid search results (ClapNQ). Columns denoted by Δ show the relative difference from the overall dataset mean.

		LLMaaJ-AC	LLMaaJ-AC (Δ)	Lexical-AC	Lexical-AC (Δ)
Generative model	ibm-granite/granite-3.1-8b-instruct	0.36	-0.081	0.84	0.084
	meta-llama/llama-3-1-8b-instruct	0.49	0.05	0.62	-0.13
	mistral-nemo-instruct	0.47	0.031	0.8	0.048
Embedding model	BAAI/bge-large-en-v1.5	0.44	0.00058	0.75	-0.0012
	ibm/slate-125m-english-rtrvr	0.43	-0.0066	0.75	-0.0061
	intfloat/multilingual-e5-large	0.44	0.0061	0.76	0.0071
Chunk size	256	0.44	-0.000017	0.75	-0.00016
	384	0.44	-0.000067	0.75	0.000091
	512	0.44	0.00015	0.75	0.000012
Chunk overlap	0.0	0.44	0.000024	0.75	-0.000054
	0.25	0.44	0.000018	0.75	0.000014
K	3	0.44	0.00085	0.74	-0.008
	5	0.44	-0.0016	0.75	0.003
	10	0.44	0.00086	0.76	0.005

Table 19: Marginal means for the grid search results (MiniWiki). Columns denoted by Δ show the relative difference from the overall dataset mean.

		LLMaaJ-AC	LLMaaJ-AC (Δ)	Lexical-AC	Lexical-AC (Δ)
Generative model	ibm-granite/granite-3.1-8b-instruct	0.59	-0.041	0.83	0.034
	meta-llama/llama-3-1-8b-instruct	0.7	0.074	0.78	-0.018
	mistral-nemo-instruct	0.6	-0.032	0.78	-0.016
Embedding model	BAAI/bge-large-en-v1.5	0.63	0.00097	0.8	-0.00023
	ibm/slate-125m-english-rtrvr	0.63	-0.0028	0.8	-0.0025
	intfloat/multilingual-e5-large	0.63	0.0019	0.8	0.0028
Chunk size	256	0.62	-0.0089	0.79	-0.01
	384	0.63	-0.005	0.79	-0.006
	512	0.64	0.014	0.82	0.016
Chunk overlap	0.0	0.63	-0.00052	0.8	-0.00098
	0.25	0.63	0.00053	0.8	0.00098
K	3	0.65	0.016	0.79	-0.014
	5	0.62	-0.0055	0.8	0.003
	10	0.62	-0.01	0.81	0.011

Table 20: Marginal means for the grid search results (WatsonxQA). Columns denoted by Δ show the relative difference from the overall dataset mean.