

The Role of Parametric Injection-A Systematic Study of Parametric Retrieval-Augmented Generation

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Abstract

Retrieval-augmented generation (RAG) enhances large language models (LLMs) by retrieving external documents. As an emerging form of RAG, parametric retrieval-augmented generation (PRAG) encodes documents as model parameters (i.e., LoRA modules) and injects these representations into the model during inference, enabling interaction between the LLM and documents at parametric level. Compared with directly placing documents in the input context, PRAG is more efficient and has the potential to offer deeper model–document interaction. Despite its growing attention, the mechanism underlying parametric injection remains poorly understood. In this work, we present a systematic study of PRAG to clarify the role of parametric injection, showing that parameterized documents capture only partial semantic information of documents, and relying on them alone yields inferior performance compared to interaction at text level. However, these parametric representations encode high-level document information that can enhance the model’s understanding of documents within the input context. When combined parameterized documents with textual documents, the model can leverage relevant information more effectively and become more robust to noisy inputs, achieving better performance than either source alone. We recommend jointly using parameterized and textual documents and advocate for increasing the information content of parametric representations to advance PRAG.

CCS Concepts

- Information systems → Novelty in information retrieval.

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1 Introduction

Despite the remarkable capabilities of large language models (LLMs) across a wide range of tasks [5, 6, 29], their knowledge is limited by the training data. When confronted with questions that fall outside their knowledge boundary, LLMs often hallucinate—generating fluent yet factually incorrect responses [13, 17, 18]. Retrieval-augmented generation (RAG) addresses this limitation by retrieving relevant external documents to supplement the model’s internal knowledge [11, 15], and has become an effective approach for knowledge-intensive tasks such as factual question answering (QA) [20, 36].

A key component in RAG is how to interact with the retrieved documents. Recent advances have explored diverse strategies for this interaction, which broadly fall into three categories: (1) Token-level augmentation [28, 32, 34]: Retrieved documents are directly inserted to the input context, allowing the model to attend to them through its self-attention mechanism. Although this approach is simple and compatible with off-the-shelf LLMs, it substantially increases the context length, leading to higher inference costs and limited accessible content under a fixed context window. Furthermore, as the model interacts with the document only through attention, it may fail to fully comprehend the content due to shallow interaction. (2) Embedding-level fusion [4, 10, 33]: To reduce the inference overhead of long contexts, these approaches encode documents offline—typically using the LLM or a dedicated encoder—and inject the resulting document embeddings into the LLM during inference via cross-attention mechanisms, thereby decoupling retrieved documents from the input context. However, these methods typically require additional training and their reliance on static embeddings

often leads to more limited interaction. (3) Parametric-level adaptation [3, 24, 27]: Su et al. [24] propose parametric RAG (PRAG) which encodes documents as model parameters (i.e., LoRA modules) and use such parameters to updated the LLM during inference. Since it does not require increasing the context length and has the potential to enable deep interaction with documents, PRAG has attracted significant attention [3, 23, 27].

However, existing efforts on PRAG have primarily focused on optimizing the offline storage overhead and improving RAG performance. The actual role of parametric injection remains under-explored—for instance, it is unclear whether the injected parameters genuinely store document knowledge or merely activate the model’s inherent ability to answer questions.

In this work, we conduct a systematic analysis of PRAG to uncover the underlying mechanisms of parametric knowledge injection. We first present a modified reproduction of the original work [24], addressing several confounding design choices in its settings. Our replication yields two key observations that motivate our hypotheses: (1) PRAG outperforms the vanilla LLM (i.e., direct answering without retrieval) but underperforms standard RAG (i.e., directly appending retrieved documents to the input prompt), suggesting that **the parameterized document may not encode full factual content**; and (2) PRAG-Combine, a hybrid variant that injects parametric knowledge while also retaining textual documents in the context, achieves the best performance. Since the text already contains all fine-grained facts, we hypothesize that **the parameterized document may encode high-level information** that enhances the model’s understanding of the textual information. Such enhanced understanding may yield two benefits: (i) better utilization of relevant content, and (ii) greater robustness to noisy documents.

We first examine how much document information is encoded in the injected parameters. To ensure that the model must rely on the document to answer correctly, we construct a new dataset comprising facts after the LLM’s knowledge cut-off date and complement this with analyses of the model’s internal states. Results show that parametric representations do encode semantic information from the documents, but the encoding is incomplete, lacking sufficient fine-grained factual detail. Nevertheless, these representations contain high-level semantic information that can enhance the model’s understanding of the documents in the input context.

We further analyze how this high-level information enhances the model’s understanding of documents: whether it enables fuller use of relevant documents or greater robustness to noisy ones. Evaluations on challenging multi-hop QA tasks, conducted with gold passages, show that parametric injection helps the model interpret and leverage the provided context more effectively. This benefit generalizes across downstream tasks, suggesting that the improvement reflects genuine document understanding rather than mere task-specific adaptation. Finally, to assess robustness to retrieval noise, we inject artificial distractors into the retrieved passages. Models with parametric injection degrade significantly less than their non-injected counterparts and maintain higher performance—even when all passages are replaced with noise.

Although parametric injection can enhance the model’s understanding of documents in the context, enabling better use of relevant documents and greater robustness to noise, the performance of relying solely on parameterized documents remains limited, as they

capture only partial document content. Therefore, at the current stage, we recommend using PRAG-Combine. However, this does not offer an efficiency advantage compared to directly injecting documents into the context. We argue that enhancing the ability of parametric representations to encode fine-grained document information is key to optimizing PRAG.

2 Related Work

2.1 Retrieval-Augmented Generation

Retrieval-augmented generation (RAG) retrieves knowledge from external corpora to supplement large language models (LLMs) with missing information, providing an effective approach to improving performance on knowledge-intensive tasks and mitigating hallucination [11, 15, 20, 36]. The effectiveness of RAG hinges on two core challenges: accurate information acquisition [22, 37, 38], and effective integration of the retrieved content [25, 39]. Existing efforts on enabling LLMs to better integrate retrieved knowledge can be broadly categorized into three directions: 1) Token-level augmentation [28, 32, 34]: These methods optimize how retrieved documents are incorporated into the input prompt, typically by context refinement or enhancement. While simple and widely adopted, they are subject to limitations such as high inference cost and relatively shallow interaction. 2) Embedding-level fusion [4, 10, 33]: Instead of concatenating documents into the prompt, this paradigm encode documents offline and inject the resulting embeddings into LLMs during inference via cross-attention. This strategy alleviates the computational burden of long context. However, the interaction between LLMs and the retrieved knowledge is even shallower, often leading to performance degradation—particularly when only a limited number of documents are used. 3) Parametric-level adaptation [3, 24, 27]: A recent and emerging direction that transforms documents into model parameters through offline encoding, and injects them into the model during inference. Su et al. [24] claims that injecting documents in a parametric form (e.g., LoRA) enables deep interactions between LLMs and the retrieved knowledge, while also reducing inference overhead by avoiding inclusion of documents in the prompt. Our work centers on parametric-level adaptation, with a particular focus on PRAG [24], the first work in this paradigm. We conduct a systematic analysis of PRAG, aiming to validate its capability for information preservation and deep interaction.

2.2 Parametric RAG

Parametric RAG (PRAG) [24] is a novel RAG paradigm that avoids inserting documents into the context of LLM input. Instead, it encodes each document offline into a parametric representation (e.g., LoRA) and injects this representation into the LLM during inference, thereby incorporating external knowledge through parameter updates rather than context augmentation. To obtain document-specific parameters, PRAG performs data augmentation for each document, then trains a dedicated LoRA module on this augmented data. However, this process requires pre-computing and storing a LoRA for every document in the corpus, leading to significant computational and storage overhead. To mitigate this, DyPRAG [27] introduces a parameter translator that maps documents directly to LoRAs at inference time, achieving comparable performance with substantially reduced cost. Yet, existing studies on parametric

RAG remain largely focused on improving RAG performance, overlooking a fundamental question: whether the injected parameters actually encode and convey factual knowledge to the LLM. For instance, the injected LoRA may act merely as a task-specific adapter, improving answer formatting rather than conveying actual knowledge. In contrast, our work investigates the underlying mechanisms of parametric knowledge injection, examining whether LoRA modules indeed encode knowledge, to what extent such knowledge is preserved, and whether it can be effectively utilized by LLMs.

3 Preliminary

This section formalizes the inference pipeline of standard RAG and parametric RAG, and describes how PRAG encodes documents into model parameters for knowledge injection.

Standard RAG. Given a query q and a set of top- k relevant documents $\{d_1, d_2, \dots, d_k\}$ retrieved from a large corpus C using a retriever R , standard RAG constructs an augmented input by concatenating the retrieved documents with the query:

$$x = \text{concat}(d_1, d_2, \dots, d_k, q). \quad (1)$$

An LLM with parameters θ then generates the output sequence conditioned on this augmented input:

$$y^{\text{RAG}} = \arg \max_y P(y | x; \theta). \quad (2)$$

Parametric RAG. In standard RAG, attention allows only shallow interaction with the retrieved documents. As the context length increases, inference costs grow substantially, and the limited context window further restricts the accessible content. To address such limitations, PRAG proposes a paradigm shift: instead of inserting retrieved documents into the input context, it represents each document as model parameters. During inference, these parametric representations are injected into the LLM, enabling the the model to interact with documents at the parameter level without increasing the input context length.

Formally, each document $d_i \in C$ is pre-encoded into a parametric representation $\Delta\theta_i = F(d_i)$, where the mapping function F is implemented in PRAG by training a LoRA module on document-specific augmented data. At inference time, the parametric representations of the retrieved top- k documents are merged:

$$\Delta\theta_{\text{merged}} = \sum_{i=1}^k \Delta\theta_i, \quad (3)$$

and injected into the LLM. The output is then generated conditioned only on the query q , but with the model parameters adapted to the retrieved knowledge:

$$y^{\text{PRAG}} = \arg \max_y P(y | q; \theta + \Delta\theta_{\text{merged}}). \quad (4)$$

PRAG can also be combined with standard RAG, yielding a hybrid variant referred to as **PRAG-Combine**. In this setting, retrieved documents are included in the input prompt while the merged parametric representation is simultaneously injected, resulting in:

$$y^{\text{PRAG-Combine}} = \arg \max_y P(y | x; \theta + \Delta\theta_{\text{merged}}), \quad (5)$$

where $x = \text{concat}(d_1, d_2, \dots, d_k, q)$ as in standard RAG.

Document Parameterization. PRAG encodes each document d_i into a parametric representation $\Delta\theta_i$ by training a LoRA module [9] on document-specific data. However, as noted in prior

work [1], training solely on raw document text via next-token prediction often fails to internalize factual knowledge effectively. To address this, PRAG adopts a data augmentation strategy that enriches the learning signal by generating question-answer (QA) pairs grounded in d_i , and constructs training sequences in the form of document-question-answer triples.

Specifically, for each d_i , it generates multiple rewritten variants $\{d_i^1, d_i^2, \dots, d_i^n\}$ and a set of QA pairs $\{(q_i^1, a_i^1), (q_i^2, a_i^2), \dots, (q_i^m, a_i^m)\}$. These are combined to form an augmented dataset:

$$D_i = \{(d_i^j, q_i^l, a_i^l) | j \in [1, n], l \in [1, m]\}. \quad (6)$$

Each triple is concatenated into a single sequence $z = \text{concat}(d_i^j, q_i^l, a_i^l)$ and used as a training sample. The LoRA parameters $\Delta\theta_i$ are then optimized by minimizing the negative log-likelihood over all tokens in the augmented sequences:

$$\min_{\Delta\theta_i} \sum_{(d_i^j, q_i^l, a_i^l) \in D_i} \sum_{t=1}^T -\log P_{\theta+\Delta\theta_i}(z_t | z_{<t}). \quad (7)$$

4 Reproduction of PRAG

The original PRAG study [24] contains certain experimental settings that may confound the analysis of parametric injection. To better understand how parameterized documents influence model behavior, we conduct a modified reproduction of PRAG. Based on our results, we formulate several hypotheses about the parametric injection mechanism, which we validate in subsequent sections.

4.1 Experimental Setup

Our reproduction largely follows the original PRAG implementation, but incorporates targeted adjustments to a few problematic settings to ensure a fairer and more interpretable evaluation.

4.1.1 Evaluation Metric. The original PARG used F1 score for evaluation. However, F1 is sensitive to surface-level formatting variations—such as inclusion of explanatory phrases—and often yields high scores for incorrect answers (e.g., predicting “University of Washington” when the ground truth is “University of Chicago”). Consequently, it fails to accurately reflect whether the model has truly acquired the correct knowledge (see detailed examples in Appendix A). To address this limitation, we adopt an LLM-as-a-judge evaluation, which provides a more reliable assessment of factual correctness by leveraging a strong LLM to compare model outputs against ground-truth answers [7].

Specifically, we use Qwen2.5-32B-Instruct [29] as the judge, prompting it with the original question, the ground-truth answer, and the model’s prediction to assess factual consistency. We report accuracy based on LLM judgments—i.e., the percentage of predictions deemed correct—as our primary evaluation metric.

4.1.2 Parameterization Settings. In the original PRAG setup, few-shot prompts were used during both parameterization and inference on several datasets. However, this practice conflates task-specific patterns with the factual content of the documents, causing the resulting parametric representations to act more as task adapters than as carriers of document knowledge. Since our goal is to isolate and study the effect of knowledge injection via parameters, we remove all few-shot examples from both training and inference.

Table 1: Reproduction results of four methods, evaluated by accuracy based on LLM judgments. Bold numbers indicate the best performance under each model, and the second-best results are underlined. CWQ denotes ComplexWebQuestions.

LLM	Method	2WikiMultihopQA					HotpotQA			PopQA	CWQ	Average
		Compare	Bridge	Inference	Compose	Total	Bridge	Compare	Total			
LLaMA3.2-1B-Instruct	Vanilla	<u>43.00</u>	<u>43.00</u>	0.66	3.66	21.00	9.00	42.33	16.00	10.66	30.33	21.96
	RAG	30.00	34.00	<u>7.33</u>	<u>8.33</u>	21.00	<u>24.00</u>	45.33	<u>30.33</u>	48.66	<u>31.33</u>	<u>28.03</u>
	PRAG	45.00	43.66	2.00	5.00	23.66	14.66	<u>48.66</u>	21.00	23.33	29.66	25.56
	PRAG-Combine	36.33	37.33	<u>7.66</u>	9.66	<u>22.00</u>	25.33	<u>51.33</u>	31.00	48.66	36.66	30.60
Qwen2.5-1.5B-Instruct	Vanilla	28.33	<u>29.33</u>	0.66	5.00	14.00	7.00	41.00	13.33	13.00	27.66	17.93
	RAG	24.33	21.66	<u>5.66</u>	4.00	14.66	<u>23.33</u>	<u>46.66</u>	<u>27.33</u>	50.00	23.33	<u>24.10</u>
	PRAG	27.66	34.66	2.66	5.00	16.33	10.00	38.00	14.33	21.33	31.66	20.16
	PRAG-Combine	<u>28.00</u>	27.33	<u>7.66</u>	8.00	<u>15.66</u>	25.33	<u>52.33</u>	31.66	46.00	<u>28.99</u>	27.10
Qwen2.5-7B-Instruct	Vanilla	<u>49.66</u>	<u>47.66</u>	1.66	7.00	<u>25.00</u>	14.00	<u>61.66</u>	20.33	18.00	33.66	27.86
	RAG	45.00	41.33	<u>10.66</u>	8.00	22.66	<u>31.66</u>	54.65	<u>34.66</u>	<u>36.66</u>	26.00	31.33
	PRAG	56.33	49.00	2.33	<u>10.66</u>	28.66	20.00	63.00	26.66	31.33	44.66	<u>33.26</u>
	PRAG-Combine	46.66	37.33	12.00	<u>11.33</u>	<u>25.00</u>	<u>35.33</u>	57.66	38.66	<u>43.33</u>	<u>37.00</u>	<u>34.43</u>

All other settings follow the original implementation: each document is paired with one rewritten and three QA pairs for data augmentation; LoRA modules are trained for one epoch with a learning rate of 3×10^{-4} , applied exclusively to the feed-forward network (FFN) layers with rank $r = 2$ and scaling factor $\alpha = 32$.

4.1.3 Datasets. We adopt the same four datasets as in the original PRAG work: 2WikiMultihopQA [8], HotpotQA [35], ComplexWebQuestions [26], and PopQA [16]. Following the original setup, we evaluate on the first 300 questions per dataset. For 2WikiMultihopQA and HotpotQA, the “Total” column in Table 1 and Table 3 reports results on the first 300 questions of the full dataset, while each sub-task column shows results on the first 300 questions within that sub-task. For each question, we retrieve the top-3 passages from a Wikipedia dump using BM25 [21].

4.1.4 Methods and Models. We evaluate four methods: **Vanilla** (base LLM without retrieval), **RAG** (directly appending documents to the input prompt), **PRAG** (pure parametric injection), and **PRAG-Combine** (hybrid of RAG and PRAG). Experiments are conducted on three open-source LLMs: LLaMA3.2-1B-Instruct [5], Qwen2.5-1.5B-Instruct, and Qwen2.5-7B-Instruct [29], spanning different model families and scales. All generations use greedy decoding.

4.2 Reproduction Results

Table 1 presents our reproduction results using LLM-judged accuracy. The results suggest several hypotheses about parametric injection, which we systematically validate in subsequent sections: (1) **Parametric representations may not fully encode the factual content of documents.** While PRAG consistently outperforms Vanilla across most datasets, it generally underperforms standard RAG under our LLM-based evaluation. This implies that the parametric encoding may miss fine-grained details or nuanced facts, limiting its utility as a standalone knowledge source. The original PRAG study reported stronger performance for PRAG, we attribute this discrepancy to the use of F1 score. As shown in Appendix A, F1 often assigns high scores to fluent but factually incorrect outputs—a bias that particularly benefits PRAG, as parametric adaptation makes the model more prone to generating template-like

responses—potentially inflating its apparent effectiveness. (2) **Parametric injection may enhance the model’s comprehension of the provided context.** PRAG-Combine consistently improves over RAG. Since RAG already supplies the full document content in the prompt, this improvement suggests that parametric knowledge does not merely duplicate information, but instead helps the model better interpret the given context. This enhanced comprehension may lead to: (i) more effective utilization of relevant passages, or (ii) greater robustness to irrelevant or noisy retrieval results.

5 How Much Knowledge is Encoded in Parametric Representations

To validate our hypothesis that parametric representations may not fully encode the factual content of documents, we design controlled experiments and conduct detailed analyses in this section.

5.1 Experimental Setup

Since the goal is to measure what and how much knowledge is stored in parametric representations, it is necessary to exclude the influence of the model’s internal knowledge. To achieve this, we construct a dataset containing knowledge that emerged after the LLM’s knowledge cutoff date, where the model must rely on external documents to answer the question correctly.

Specifically, we collect 300 news articles published in 2025, all of which postdate the training cutoffs of LLMs used in this work. Each article is split into at most three passages, with lengths matched to those in the Wikipedia dump used in Section 4.1. We use Qwen2.5-32B-Instruct to generate two types of QA pairs for each article: (1) Factual QA: simple factual questions based on the article content; (2) Multihop QA: questions that require combining multiple facts from the article. During inference, no retrieval is performed. Instead, the model is provided with the question and all passages from the source article, and the corresponding document parameters (trained on those passages) are injected. All other settings—including document parameterization, model selection, and evaluation metric—follow Section 4.1 exactly.

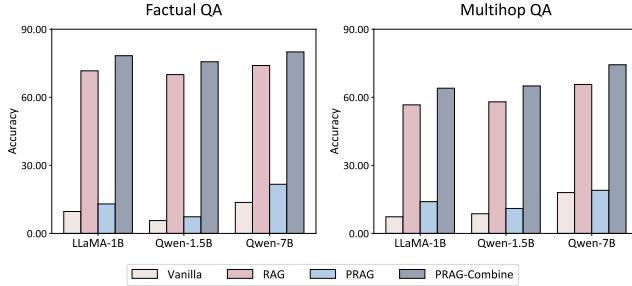


Figure 1: Performance of different methods on the new-knowledge dataset, where the model must rely on external documents to answer questions correctly. LLaMA-1B denotes LLaMA3.2-1B-Instruct, Qwen-1.5 denotes Qwen2.5-1.5B-Instruct, and Qwen-7B denotes Qwen2.5-7B-Instruct.

5.2 Experimental Results

Figure 1 shows performance on our new-knowledge dataset. The results confirm and refine our initial hypotheses, yielding three key findings: (1) **Parametric representations do encode factual knowledge.** PRAG consistently outperforms Vanilla across both question types, demonstrating that parametric injection can successfully endow the model with new, previously unknown information. As illustrated in Figure 2, when queried about a event outside its training horizon, Vanilla hallucinates, while PRAG produces the correct answer—direct evidence that knowledge is stored in the parameters. (2) **Parametric representations fails to fully capture the knowledge.** PRAG lags substantially behind RAG, indicating that current document parameterization protocols do not yet achieve comprehensive knowledge encoding. In other words, while some knowledge is encoded, it is insufficient to reliably support question answering on novel content. (3) **Parametric representations may encode high-level semantic knowledge.** PRAG-Combine also achieves the strongest performance on this new-knowledge benchmark. From the perspective of representational content, we conjecture that although parametric representations lack fine-grained factual detail, they capture high-level semantic structures—such as relational patterns or discourse-level cues. We quantitatively investigate this in Section 5.3.2.

Passages:
... Singer, actor and reality TV star Tamar Braxton said Tuesday that she “almost died” in a weekend accident that she doesn’t remember. “I was found in a pool of blood from my friend with a face injury,” Braxton wrote in an Instagram post. “I fractured my nose, lost some teeth and mobility.”...

Question: What did Tamar Braxton fracture in the accident?
Answer: her nose

Vanilla Output: Tamar Braxton **fractured her ankle** in an accident.
PRAG Output: **her nose.**

Figure 2: An example from the new-knowledge dataset. When asked a question about an event outside its training data, the Vanilla LLM hallucinates, whereas PRAG produces the correct answer. More cases are provided in Appendix B.

5.3 Further Analysis

We further investigate, from a parametric perspective, whether these representations capture only partial document information and whether they contain high-level information that helps the model in better understanding the document.

5.3.1 Similarity Between Parametric Representations. To further validate our hypotheses—that parametric representations only encode part of the document knowledge—we examine the similarity of parametric representations across different documents. Specifically, we compute cosine similarities between flattened LoRA weight matrices for two types of passage pairs: (i) relevant pairs, which are segmented from the same article; and (ii) irrelevant pairs from different articles. If the parameters capture document-specific semantics, relevant pairs should be more similar than irrelevant ones.

As shown in Figure 3 (using Qwen2.5-1.5B-Instruct as a representative model; full results in Appendix C), this is indeed the case: relevant pairs exhibit higher average similarity, indicating that parametric representations encode shared semantic and factual content. However, the margin is modest: even irrelevant pairs show a mean similarity of approximately 0.65. This suggests that the representations fail to fully isolate document-unique information, supporting that the encoded knowledge remains incomplete.

5.3.2 Quantifying Parametric Knowledge in the Residual. To investigate whether parametric representations contain high-level semantic knowledge—such as relational patterns or discourse-level cues—rather than merely surface facts, we analyze their impact on the model’s internal states using the parametric knowledge score (PKS) [25], a metric that quantifies the knowledge each FFN layer contributes to the residual stream.

Specifically, for each generated token x_n in the response and each layer l , we compute the Jensen–Shannon divergence (JSD) between the vocabulary distributions before and after the FFN block, obtained via LogitLens [19]:

$$\text{LogitLens}(x) = \text{LayerNorm}(x)W_U, \quad (8)$$

$$P_n^l = \text{JSD}(q(x_n^{l,before}) || q(x_n^{l,after})), \quad (9)$$

where W_U is the unembedding matrix of the LLM and $q(x) = \text{softmax}(\text{LogitLens}(x))$. The PKS for layer l is obtained by averaging P_n^l over all tokens in the response.

Figure 4 shows the per-layer difference in PKS between models with and without parametric injection (i.e., PRAG vs. Vanilla; PRAG-Combine vs. RAG). While early layers exhibit inconsistent changes, the last few layers consistently show substantially higher PKS across all LLMs when parametric knowledge is injected. Prior work [12, 30] has shown that deeper transformer layers are primarily responsible for high-level semantic processing—such as integrating information across tokens, resolving coreference, and constructing structured event representations. The concentration of PKS gains in these layers suggests that parametric representations do not merely store isolated facts, but **encode high-level semantic knowledge** that may contribute to more advanced comprehension of the input context.

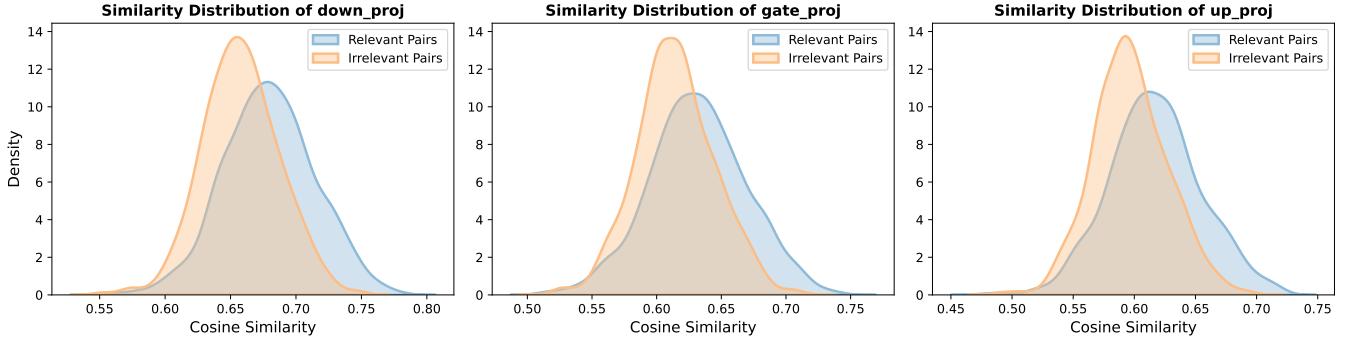


Figure 3: Similarity distribution of LoRA modules (averaged over all layers) for Qwen2.5-1.5B-Instruct. Relevant passage pairs exhibit slightly higher similarity than irrelevant pairs, implying that LoRAs encode some semantic and factual content. However, the gap is modest, suggesting limited encoding of fine-grained, document-specific knowledge.

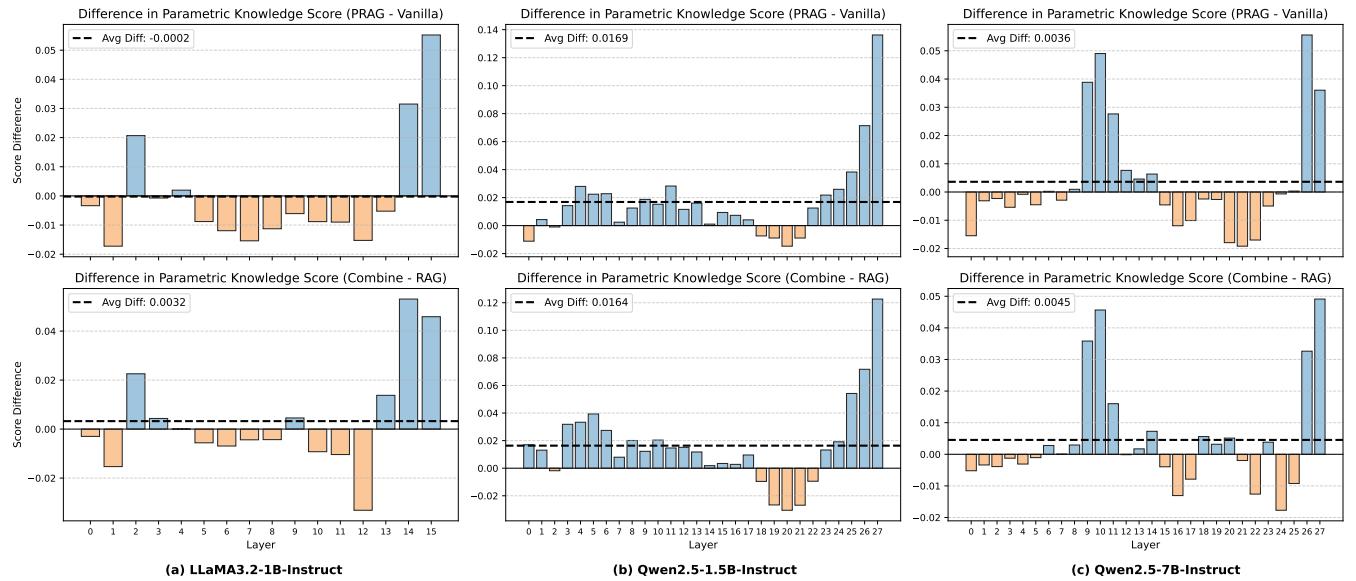


Figure 4: Difference in parametric knowledge score between LLMs with and without parametric injection. Most comparisons show a positive average difference, and all models exhibit a pronounced increase in the final layers, indicating that parametric injection increases parametric knowledge in the residual stream and that the representations encode high-level knowledge.

6 Does Parametric Injection Enhance Utilization of Relevant Passages

Our analysis so far shows that parametric representations encode not only some factual knowledge but also high-level semantic knowledge. This provides preliminary support for our second hypothesis—that parametric injection enhances the model’s understanding of the provided context. As hypothesized in Section 4.2, this enhanced understanding may manifest in two complementary ways: (i) more effective utilization of relevant passages, or (ii) greater robustness to irrelevant or noisy retrieval results.

In this section, we empirically test the first mechanism: whether the high-level knowledge encoded in parametric representations helps the model better utilize relevant retrieved passages. We examine the second mechanism—robustness to retrieval noise—in the following section.

6.1 Experimental Setup

To rigorously evaluate whether parametric injection enhances the model’s ability to utilize relevant passages, we design experiments using gold passages and complex questions—a setting where effective utilization of the provided context is essential. By bypassing retrieval, we ensure that performance difference reflects the model’s capacity to interpret and integrate the given passages.

Since PRAG’s document parameterization is trained on QA-formatted data (i.e., document–question–answer triples), any observed improvement in document utilization might stem not from deeper document understanding, but from better adaptation to the QA task—i.e., learning the QA-task-specific patterns. To rule out this alternative explanation, we conduct two complementary

analyses: (i) probing for QA-task-specific components in the representations, and (ii) testing whether the parametric knowledge injection generalizes to non-QA tasks.

Gold-Passages Evaluation. We evaluate on HotpotQA [35] and 2WikiMultihopQA [8], using the first 300 questions from each. For every question, we provide the gold supporting passages as input context and inject LoRA parameters trained on those passages. All other settings follow Section 4.1.

Probing for QA-Specific Task Knowledge. To directly probe the presence of QA-specific adaptation, we train a dedicated QA-task LoRA on the gold passages of 200 questions from the datasets above, using the same QA-based data augmentation and training protocol as in Section 4.1. We then analyze its contribution to model performance to assess whether QA-specific adaptation plays a role in the observed gains.

Cross-Task Generalization Test. To determine whether the encoded knowledge is general or QA-specific, we evaluate parametric injection on two non-QA tasks: fact-checking on FEVER [31], measured by label accuracy; and slot-filling on Zero-Shot-RE [14], measured by F1 score. For each question, we retrieve top-3 passages, use the same QA-based parameterization protocol, and apply task-specific prompts during inference.

6.2 Experimental Results

Table 2 presents the performance of all methods and their variants augmented with the QA-specific LoRA on gold passages. The results show the following: (1) **Parametric injection enhances the model’s ability to utilize relevant passages.** PRAG-Combine consistently outperforms RAG by a notable margin, especially on such complex multi-hop questions, demonstrating that the high-level knowledge encoded in parametric representations actively supports more effective context utilization. (2) **The high-level knowledge in parametric representations inherently includes QA-specific task patterns.** Adding a separately trained QA-specific LoRA to PRAG or PRAG-Combine yields little to no improvement, indicating that the task-adaptive signals it provides are already embedded within the document-parameterized LoRA. (3) **Parametric injection provides more than task-specific cues—it encodes general document understanding.** While both Vanilla and RAG benefit from the QA-specific LoRA, they still fall short of their parametric-injection counterparts. Moreover, this advantage generalizes: as shown in Figure 5, PRAG and PRAG-Combine also outperform baselines on non-QA tasks, following the same performance trend. Together, these results confirm that parametric representations encode general semantic and structural knowledge of documents, going beyond both surface facts and QA-task-specific patterns, and thereby enabling robust contextual comprehension across diverse tasks.

6.3 Further Analysis on Context Faithfulness

Given that parametric injection enhances the model’s ability to utilize provided passages, we expect it to also increase context faithfulness—the tendency to ground answers in the given relevant context even when it contradicts the model’s internal knowledge.

To verify this, we evaluate on the ConFiQA dataset [2], which consists of questions paired with counterfactual passages. These

Table 2: Performance of all methods and their variants augmented with the QA-specific LoRA on gold passages from 2WikiMultihopQA (2Wiki) and HotpotQA. PRAG-Combine (Combine) consistently outperforms RAG, indicating that parametric injection enhances document utilization.

LLM	Method	Without QA-LoRA		With QA-LoRA	
		2Wiki	HotpotQA	2Wiki	HotpotQA
LLaMA3.2-1B-Instruct	Vanilla	21.00	16.00	20.66	16.66
	RAG	39.33	63.66	45.66	63.66
	PRAG	23.33	21.66	23.66	22.33
	Combine	46.00	69.33	46.33	69.33
Qwen2.5-1.5B-Instruct	Vanilla	14.00	13.33	24.66	15.66
	RAG	28.33	53.66	47.33	63.00
	PRAG	18.33	15.00	18.66	16.00
	Combine	40.00	67.00	40.00	67.33
Qwen2.5-7B-Instruct	Vanilla	25.00	20.33	28.00	20.33
	RAG	56.99	67.33	54.33	73.00
	PRAG	30.66	32.33	30.66	32.66
	Combine	64.00	80.66	64.00	80.33

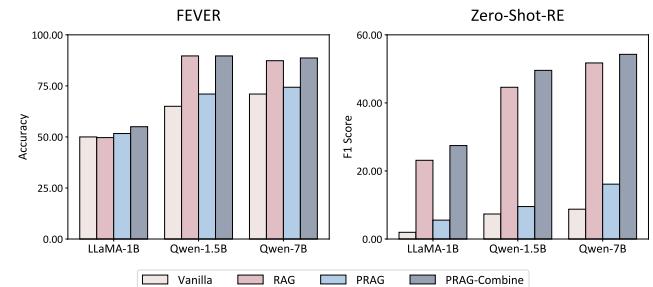


Figure 5: Performance of different methods on fact-checking and slot filling. LLaMA-1B denotes LLaMA3.2-1B-Instruct, Qwen-1.5 denotes Qwen2.5-1.5B-Instruct, and Qwen-7B denotes Qwen2.5-7B-Instruct. Methods with parametric injection achieve stronger performance on both tasks, indicating that the benefits generalize to other downstream tasks.

passages are constructed by replacing key entities in original gold passages with plausible same-type substitutes, preserving topical coherence while introducing factual inaccuracies. We sample the first 900 questions and use the counterfactual passages both as input context and for document parameterization. Faithfulness is measured by the proportion of outputs that align with the counterfactual context (i.e., counterfactual answers).

Figure 6 presents the distribution of output answer types across methods and models. We observe that: (1) PRAG-Combine consistently generates more counterfactual answers than RAG, indicating that parametric injection **strengthens context faithfulness**. (2) PRAG generally produces more counterfactual answers and fewer original ones than Vanilla, suggesting that parametric injection can alter the model’s internal knowledge to some extent.

7 Does Parametric Injection Improve Robustness to Noise Passages

The previous section demonstrated that parametric injection enhances the model’s ability to utilize relevant passages. In this section, we investigate the second hypothesized mechanism: whether

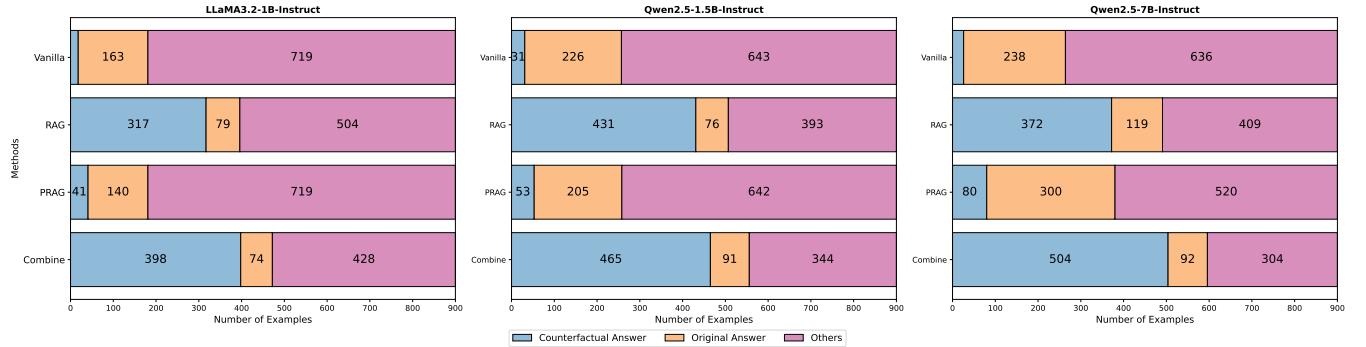


Figure 6: Distribution of output answer types on ConFiQA across methods and models. PRAG-Combine (denoted as Combine) exhibits stronger context faithfulness than RAG, and PRAG also generates more counterfactual answers than Vanilla.

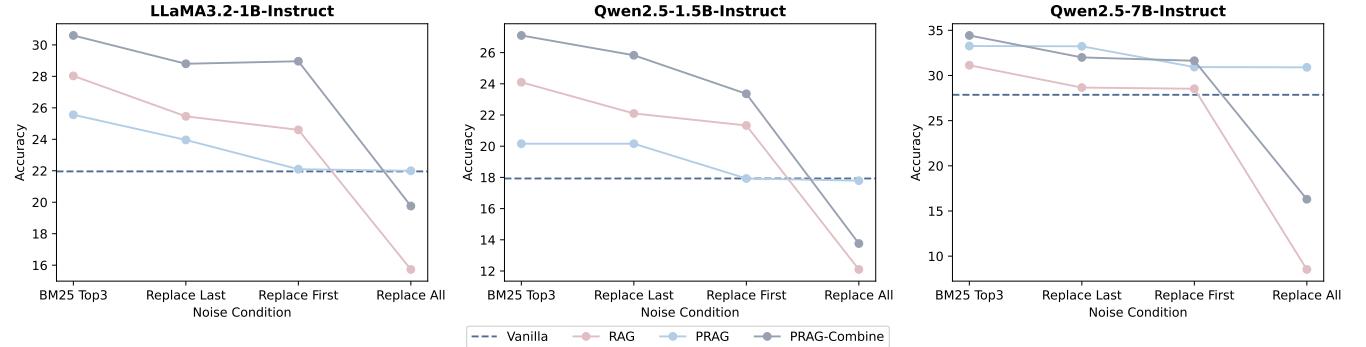


Figure 7: Performance under varying noise conditions. All parametric-injection variants consistently match or outperform their non-injected counterparts, suggesting that parametric injection enhances robustness to retrieval noise and that LLMs can recognize and ignore irrelevant knowledge encoded in the injected parameters.

the high-level knowledge encoded in parametric representations also helps the model better handle irrelevant or noisy retrieved documents, thereby improving robustness to retrieval noise.

7.1 Experimental Setup

To assess whether parametric injection enhances robustness to retrieval noise, we introduce controlled artificial noise into the retrieved passages. Specifically, for each question, we begin with the top-3 passages retrieved by BM25 and construct four variants by replacing one or more of them with random, irrelevant passages:

- **BM25 Top3:** the original top-3 BM25-retrieved passages (no noise injected);
- **Replace Last:** the least relevant passage (rank 3) is replaced with a random noise passage;
- **Replace First:** the most relevant passage (rank 1) is replaced with a random noise passage;
- **Replace All:** all three passages are replaced with random noise passages.

We evaluate all methods on the same four datasets used in Section 4.1, using identical document parameterization, model selection, and evaluation metrics. For each noise condition, we report the average accuracy across the four datasets.

7.2 Experimental Results

Figure 7 presents the performance of all methods under varying levels of retrieval noise. Our analysis yields two key findings: (1)

Parametric injection enhances robustness to retrieval noise.

As expected, all methods suffer performance degradation as noise increases. Nevertheless, PRAG-Combine consistently outperforms RAG across all noise conditions—even when all retrieved passages are replaced with irrelevant ones—demonstrating that parametric injection effectively mitigates the adverse impact of noisy context. (2) **LLMs can recognize irrelevant knowledge encoded in parametric representations.** PRAG’s performance gradually declines as more retrieved passages are corrupted, eventually converging to Vanilla under full noise. This confirms that the injected parameters indeed encode document-specific information. Crucially, even in the full-noise setting—where the injected parameters encode only irrelevant content—PRAG never underperforms its non-injected counterpart. This suggests that the model can detect irrelevant parametric knowledge and avoid being misled by it.

8 Conclusion and Discussion

In this paper, we conduct a systematic analysis of parametric RAG to uncover the underlying mechanisms of parametric knowledge injection. Motivated by two central hypotheses—that (1) parametric representations may not fully encode the factual content of documents, and (2) parametric injection may enhance the model’s comprehension of the provided context—we design a series of controlled experiments and internal analyses. Our findings show that parametric representations do encode document-related knowledge, including high-level semantic knowledge, but the encoding is

incomplete, lacking sufficient fine-grained factual detail. This high-level knowledge enables the model to better interpret the provided context, leading to more effective utilization of relevant passages and greater robustness to irrelevant or noisy passages.

Our analysis reveals a fundamental limitation of current parametric RAG approaches: the injected parameters do not encode sufficient factual knowledge to support question answering on their own. As a result, PRAG cannot fully replace standard RAG. Although, the hybrid PRAG-Combine achieves strong performance by complementing context with high-level knowledge, this comes at a cost: it forfeits the original efficiency motivation of PRAG (i.e., avoiding token-level context expansion) and introduces additional computational and storage overhead for document parameterization. We argue that the most pressing challenge for this paradigm is to increase the information content of parametric representations—encoding richer, more complete factual content, which calls for carefully designed parameterization strategies.

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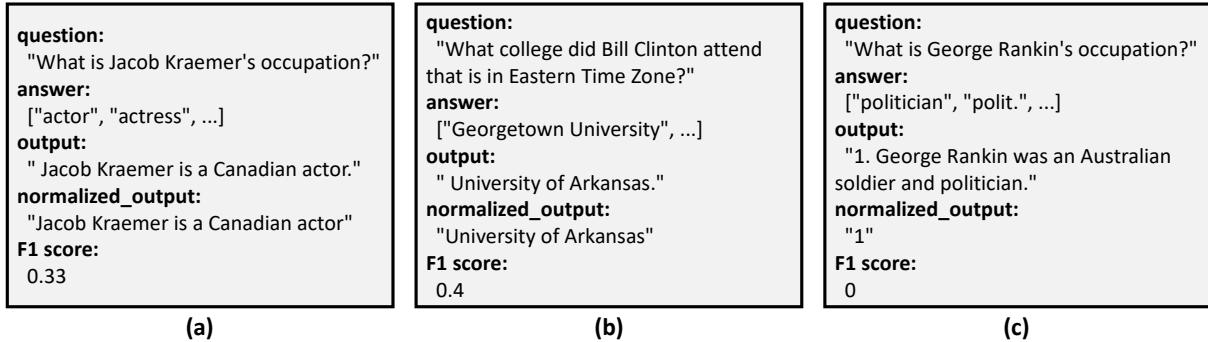
A Reproduced F1 Results

Table 3 presents our reproduction results evaluated using F1 score. Compared to the LLM-judged results in Table 1, these results are much closer to those reported in the original work [24]—PRAG shows stronger performance than RAG. We attribute this discrepancy to the limitations of the F1 metric.

As illustrated in Figure 8, F1 can be highly misleading: (i) it penalizes correct answers that include additional explanatory phrases; (ii) it assigns high scores to factually incorrect answers that happen to share surface tokens with the ground truth; and (iii) it is sensitive to normalization choices, and inappropriate normalization (e.g., punctuation handling) can lead to completely incorrect evaluations. These issues can inflate PRAG’s apparent performance, as

Table 3: Reproduction results of four methods, evaluated by F1 score. Bold numbers indicate the best performance under each model, and the second-best results are underlined. CWQ denotes ComplexWebQuestions.

LLM	Method	2WikiMultihopQA					HotpotQA			PopQA	CWQ	Average
		Compare	Bridge	Inference	Compose	Total	Bridge	Compare	Total			
LLaMA3.2-1B-Instruct	Vanilla	<u>41.15</u>	<u>44.41</u>	16.65	4.27	22.39	11.21	39.97	15.59	4.34	36.28	23.63
	RAG	24.41	33.19	25.65	<u>9.47</u>	20.92	<u>20.22</u>	41.31	<u>25.95</u>	15.95	<u>37.49</u>	25.46
	PRAG	45.70	45.71	19.57	5.93	26.46	15.05	48.62	21.30	<u>17.64</u>	34.30	<u>28.03</u>
	PRAG-Combine	34.03	38.49	<u>25.14</u>	11.07	<u>23.65</u>	22.70	<u>46.78</u>	28.47	31.87	40.39	30.26
Qwen2.5-1.5B-Instruct	Vanilla	19.71	<u>31.21</u>	13.49	5.07	15.00	8.66	27.90	11.14	5.55	<u>34.31</u>	17.20
	RAG	<u>21.02</u>	28.84	<u>19.45</u>	<u>6.52</u>	16.74	<u>20.43</u>	<u>44.65</u>	<u>24.72</u>	9.99	28.23	<u>22.06</u>
	PRAG	20.70	33.92	19.17	5.86	17.62	11.65	32.53	15.45	16.40	35.83	20.91
	PRAG-Combine	23.43	29.08	22.41	9.17	<u>17.23</u>	22.31	45.64	26.61	19.07	30.89	24.58
Qwen2.5-7B-Instruct	Vanilla	46.43	<u>46.03</u>	20.60	6.83	<u>27.15</u>	15.14	52.10	20.47	4.20	36.23	27.52
	RAG	46.11	41.92	<u>24.84</u>	8.44	23.98	<u>28.92</u>	52.03	<u>32.05</u>	8.57	32.07	29.83
	PRAG	53.28	48.64	22.07	11.58	30.77	18.27	57.57	24.72	<u>19.92</u>	45.77	<u>33.26</u>
	PRAG-Combine	<u>47.62</u>	39.71	29.59	<u>10.83</u>	27.11	31.50	53.62	35.08	27.58	<u>41.96</u>	34.46

**Figure 8: Examples illustrating the limitations of F1 score. (a) A correct answer with additional explanation is penalized, yielding a low F1 score. (b) An incorrect answer sharing surface tokens with the ground truth receives a high F1 score. (c) Inappropriate normalization leads to completely incorrect evaluations.**

Passages:
... A speechwriter for the Trump administration's Department of Homeland Security (DHS) has come under scrutiny after he was linked to hate speech online. Eric Lendum compared the circumstances of American conservatives to that of enslaved people ...

Question: Which government department appointed a speechwriter who was linked to hate speech online?
Answer: Department of Homeland Security (DHS)

Vanilla Output: 2019-04-15, when the Chinese Ministry of Education announced that it
PRAG Output: The Department of Homeland Security (DHS).

Figure 10: An example from the new-knowledge dataset.

Passages:
... killing at least 13 people during morning prayers, local authorities said. No one immediately claimed responsibility for the attack in the town of Ungwan Mantau, in the state of Katsina, but such attacks are common in Nigeria's northwestern and north-central regions where local herders and farmers often clash over limited access to land and water ...

Question: In which Nigerian state did the mosque attack take place?
Answer: Katsina

Vanilla Output: Borno State. The attack took place in the town of Maiduguri, which is located in ...
PRAG Output: Katsina State.

Figure 9: An example from the new-knowledge dataset.

its parametric adaptation encourage concise, template-like outputs that align fortuitously with F1's token-matching behavior—without necessarily improving factual correctness.

B Examples on New-Knowledge Dataset

Figure 9 and Figure 10 show two examples from our new-knowledge dataset, where the questions involve facts that emerged after the LLM's knowledge cutoff. In both cases, Vanilla hallucinates and produces factually incorrect answers. In contrast, PRAG—equipped with document-specific parametric knowledge—successfully retrieves the correct information and generates accurate responses.

C Similarity Distribution of LoRA Modules

Figure 11 and Figure 12 show the similarity distributions of LoRA modules (averaged over all layers) for LLaMA3.2-1B-Instruct and Qwen2.5-7B-Instruct, respectively. The trends align with our observations in Section 5.3.1: relevant pairs exhibit higher average similarity than irrelevant ones, but the margin remains modest. This suggests that parametric representations encode shared semantic and factual content across related documents, yet fail to fully isolate document-unique information.

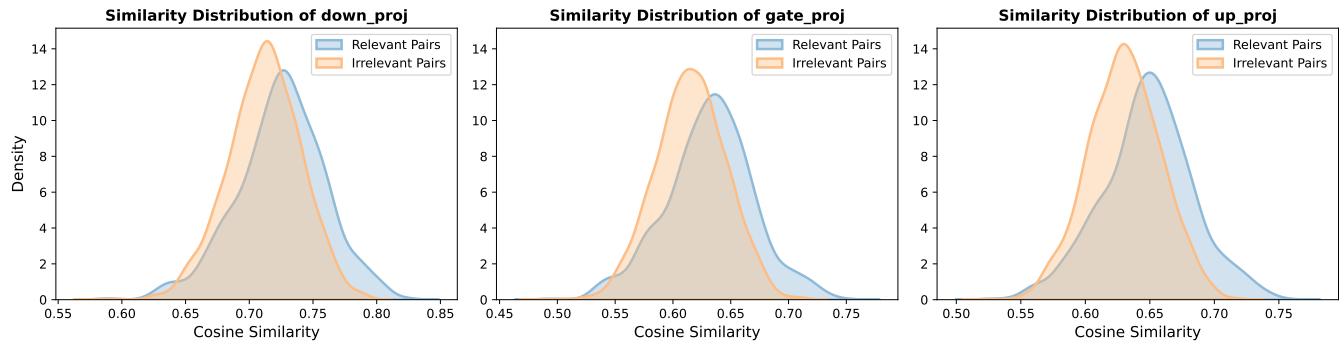


Figure 11: Similarity distribution of LoRA modules (averaged over all layers) for LLaMA3.2-1B-Instruct.

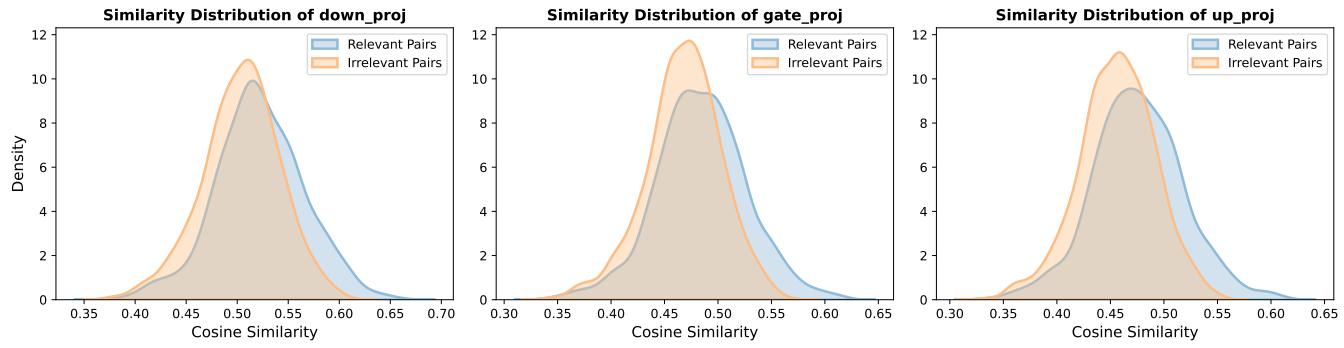


Figure 12: Similarity distribution of LoRA modules (averaged over all layers) for Qwen2.5-7B-Instruct.