RevPRAG: Revealing Poisoning Attacks in Retrieval-Augmented Generation through LLM Activation Analysis

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Abstract

Retrieval-Augmented Generation (RAG) enriches the input to LLMs by retrieving information from the relevant knowledge database, enabling them to produce responses that are more accurate and contextually appropriate. It is worth noting that the knowledge database, being sourced from publicly available channels such as Wikipedia, inevitably introduces a new attack surface. RAG poisoning attack involves injecting malicious texts into the knowledge database, ultimately leading to the generation of the attacker's target response (also called poisoned response). However, there are currently limited methods available for detecting such poisoning attacks. We aim to bridge the gap in this work by introducing RevPRAG, a flexible and automated detection pipeline that leverages the activations of LLMs for poisoned response detection. Our investigation uncovers distinct patterns in LLMs' activations when generating poisoned responses versus correct responses. Our results on multiple benchmarks and RAG architectures show our approach can achieve a *98%* true positive rate, while maintaining a false positive rate close to *1%*.

1 Introduction

Retrieval-Augmented Generation (RAG) (Lewis et al., 2020) has emerged as an effective solution that leverages retrievers to incorporate external databases, enriching the knowledge of LLMs and ultimately enabling the generation of up-to-date and accurate responses. RAG comprises three components: *knowledge database*, *retriever*, and *LLM*. Fig. 1 visualizes an example of RAG. The knowledge database consists of a large amount of texts collected from sources such as latest Wikipedia entries (Thakur et al., 2021), new articles (Soboroff et al., 2018) and financial documents (Loukas et al., 2023). The retriever is primarily responsible for retrieving the texts that are most related to the user's query from the knowledge database. These texts will later be fed to LLM as a part of the prompt to generate responses (e.g., "*Everest*") for users' queries (e.g., "*What is the name of the highest mountain*?"). Due to RAG's powerful knowledge integration capabilities, it has demonstrated impressive performance across a range of QA-like knowledge-intensive tasks (Lazaridou et al., 2022; Jeong et al., 2024).

RAG poisoning refers to the act of injecting malicious or misleading content into the knowledge database, contaminating the retrieved texts and ultimately leading the LLM to produce the attacker's desired response (e.g., the target answer could be "*Fuji*" when the target question is "*What is the name of the highest mountain*?"). This attack leverages the dependency between LLMs and the knowledge database, transforming the database into a new attack surface to facilitate poisoning. PoisonedRAG (Zou et al., 2024) demonstrates the feasibility of RAG poisoning by injecting a small amount of maliciously crafted texts into the knowledge database utilized by RAG. The rise of such attacks has drawn significant attention to the necessity of designing robust and resilient RAG systems. For example, INSTRUCTRAG (Wei et al., 2024) utilizes LLMs to analyze how to extract correct answers from noisy retrieved documents; RobustRAG (Xiang et al., 2024) introduces multiple LLMs to generate answers from the retrieved texts, and then aggregates the responses. However, the aforementioned defense methods necessitate the integration of additional large models, incurring considerable overheads. Meanwhile, it is difficult to promptly assess whether the current response of RAG is trustworthy or not.

In our work, we shift our focus to leverage the *intrinsic* properties of LLMs for detecting RAG poisoning, rather than relying on external models. Our view is that if we can accurately determine whether a RAG's response is correct or poisoned, we can effectively thwart RAG poisoning

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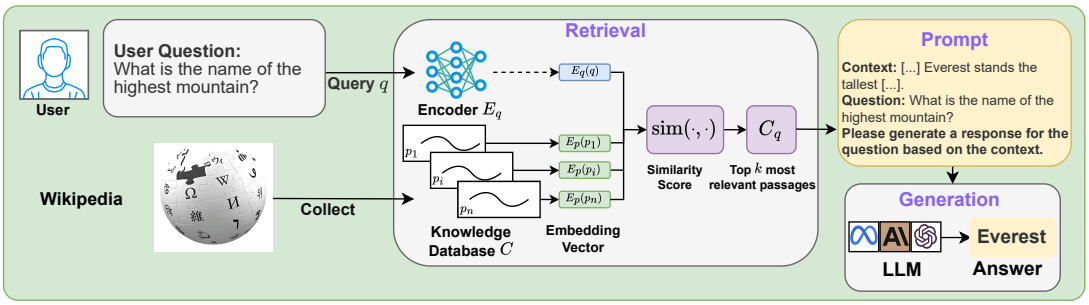

Figure 1: Visualization of RAG.

attacks. We attempt to observe LLM's answer generation process to determine whether the response is compromised or not. It is worth noting that our focus is not on detecting malicious inputs to LLMs, as we consider the consequences of malicious responses to be far more detrimental and indicative of an attack. The growing body of research on using activations to explain and control LLM behavior (Ferrando et al., 2024; He et al., 2024) provides us inspiration. Specifically, we empirically analyze the activations of the final token in the input sequence across all layers of the LLM. Our findings demonstrate that the model exhibits distinguishable activation patterns when generating correct versus poisoned responses. Based on this, we propose a systematic and automated detection pipeline, namely RevPRAG, which consists of three key components: *poisoned data collection*, *LLM activation collection and preprocessing*, and the *detection model design*. It is important to note that this detection method will not alter the RAG workflow or weaken its performance, thereby offering superior adversarial robustness compared to methods that rely solely on filtering retrieved texts.

To evaluate our approach, we systematically demonstrate the effectiveness of RevPRAG across various LLM architectures, including GPT2-XL-1.5B, Llama2-7B, Mistral-7B, Llama3-8B, and Llama2-13B. RevPRAG performs consistently well, achieving over 98% true positive rate across different datasets.

Our contributions can be summarized as follows:

1. We uncover distinct patterns in LLMs' activations when RAG generates correct responses versus poisoned ones.

2. We introduce RevPRAG, a novel and automated pipeline for detecting whether a RAG's response is poisoned or not. To address emerging RAG poisoning attacks, RevPRAG allows new datasets to be constructed accordingly for training the model, enabling effective detection of new threats.

3. Our model has been empirically validated across various LLM architectures and retrievers, demonstrating over 98% accuracy on our custom-collected detection dataset.

2 Background and Related Work

2.1 Retrieval Augmented Generation

RAG comprises three components: *knowledge database, retriever,* and *LLM*. As illustrated in Fig. 1, RAG consists of two main steps: *retrieval* step and *generation* step. In the retrieval step, the retriever acquires the top k most relevant pieces of knowledge for the query q. First, we employ two encoders, E_q and E_p, which can either be identical or radically different. Encoder E_q is responsible for transforming the user's query q into an embedding vector $E_q(q)$, while encoder E_p is designed to convert all the information p_i in the knowledge database into embedding vectors $E_p(p_i)$. For each $E_p(p_i)$, the similarity with the query $E_q(q)$ is computed using $\text{sim}(E_q(q), E_p(p_i))$, where $\text{sim}(\cdot,\cdot)$ quantifies the similarity between two embedding vectors, such as cosine similarity or the dot product. Finally, the top k most relevant pieces are selected as the external knowledge $\mathcal{C}_q$ for the query q. The generation step is to generating a response $\text{LLM}(q, \mathcal{C}_q)$ based on the query q and the relevant information $\mathcal{C}_q$. First, we combine the query q and the external knowledge $\mathcal{C}_q$ using a standard prompt (see Fig. 6 for the complete prompt). Taking advantage of such a prompt, the LLM generates an answer $\text{LLM}(q, \mathcal{C}_q)$ to the query q. Therefore, RAG is a significant accomplishment, as it addresses the limitations of LLMs in acquiring up-to-date and domain-specific information.

2.2 Retrieval Corruption Attack

Due to the growing attention on RAG, attacks on RAG have also been widely studied. RAG can improperly generate answers that are severely impacted or compromised once the knowledge database is contaminated (Zou et al., 2024; Xue et al., 2024; Jiao et al., 2024). Specifically, an attacker can inject a small amount of malicious information onto a website, which is then retrieved by RAG (Greshake et al., 2023). PoisonedRAG (Zou et al., 2024) injects malicious text into the knowledge database, and formalizes the knowledge poisoning attack as an optimization problem, thereby enabling the LLM to generate target responses selected by the attacker. GARAG (Cho et al., 2024) was introduced to provide low-level perturbations to RAG. PRCAP (Zhong et al., 2023) injects adversarial samples into the knowledge database, where these samples are generated by perturbing discrete tokens to enhance their similarity with a set of training queries. These methods have yielded striking attack results, and in our work, we have selected several state-of-the-art attack methods as our base attacks on RAG.

2.3 The Robustness of RAG

Efforts have been made to develop defenses in response to poisoning attacks and noise-induced disruptions. RobustRAG (Xiang et al., 2024) mitigates the impact of poisoned texts through a voting mechanism, while INSTRUCTRAG (Wei et al., 2024) explicitly learns the denoising process to address poisoned and irrelevant information. Other approaches to enhance robustness include prompt design (Cho et al., 2023; Press et al., 2023), plug-in models (Baek et al., 2023), and specialized models (Yoran et al., 2023; Asai et al., 2023). However, these methods may, on one hand, rely on additional LLMs, leading to significant overhead. On the other hand, they primarily focus on defense mechanisms before the LLM generates a response, making it challenging for these existing approaches to detect poisoning attacks in real-time while the LLM is generating the response (Athalye et al., 2018; Bryniarski et al., 2021; Carlini and Wagner, 2017; Carlini, 2023; Tramer et al., 2020). LLM Factoscope (He et al., 2024) is a runtime detection tool that leverages the internal states of LLMs, such as activation maps, output rankings, and top-k probabilities, to identify factual inaccuracies caused by model hallucinations. While Factoscope is effective at detecting hallucinations in general LLMs, it is not designed to address RAG poisoning attacks, which result from manipulations of the external knowledge base rather than internal model errors. Its complex architecture with multiple sub-models makes it less suitable for latency-sensitive RAG applications. In this work, we present RevPRAG, a method that addresses these gaps by: (1) focusing on RAG-specific poisoning attacks and conducting extensive tests to validate its effectiveness in detecting such attacks (Section 5), (2) using a lightweight, activation-based pipeline optimized for real-time detection of whether an RAG response is trustworthy (Section 5.6), and (3) evaluations show that our performance (Section 5.2) and efficiency (Section 5.6) surpass those of Factoscope.

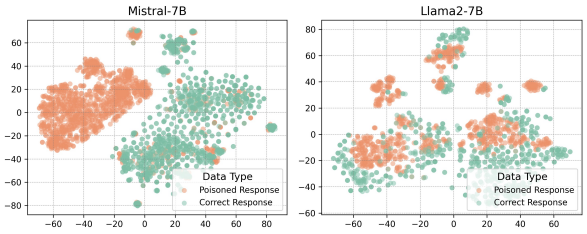

Figure 2: t-SNE visualizations of activations for correct and poisoned responses.

3 Preliminary

3.1 Threat Model

Attacker's goal. We assume that the attacker preselects a target question set Q, consisting of $q_1, q_2, \cdots, q_n$, and the corresponding target answer set A, represented as $a_1, a_2, \cdots, a_n$. The attacker's goal is to compromise the RAG system by contaminating the retrieval texts, thereby manipulating the LLM to generate the target response a_i for each query q_i. For example, the attacker's target question q_i is "*What is the name of the highest mountain*?", with the target answer being "*Fuji*".

Attacker's capabilities. We assume that an attacker can inject m poisoned texts P for each target question q_i, represented as $p_i^1, p_i^2, ..., p_i^m$. The attacker does not possess knowledge of the LLM utilized by the RAG, but has white-box access to the RAG retriever. This assumption is reasonable, as many retrievers are openly accessible on platforms like HuggingFace. The poisoned texts can be integrated into the RAG's knowledge database through two ways: the attacker publishing the malicious content on open platforms like Wikipedia, or utilizing data collection agencies to disseminate the poisoned texts.

3.2 Rationale

The activations of LLMs represent input data at varying layers of abstraction, enabling the model to progressively extract high-level semantic information from low-level features. The extensive information encapsulated in these activations comprehensively reflects the entire decision-making process of the LLM. The activations has been applied to factual verification of the output content (He et al., 2024) and detection of task drift (Abdelnabi et al., 2024). Due to the fact that LLM produces different activations when generating varying responses, we hypothesize that LLM will also exhibit distinct activations when generating poisoned responses compared to correct ones. Fig. 2 presents the visualizations of activations for correct and poisoned responses using t-SNE (t-Distributed Stochastic Neighbor Embedding). It visualizes the mean activations across all layers for two LLMs, Mistral-7B and Llama2-7B, on the Natural Questions dataset. This clearly demonstrates the distinguishability between the two types of responses, to some extent, supports our conjecture.

4 Methodology

4.1 Approach Overview

As illustrated in Fig. 3, we introduce RevPRAG, a pipeline designed to leverage LLM activations for detecting knowledge poisoning attacks in RAG systems. It contains three major modules: *poisoning data collection, activation collection and preprocessing,* and *RevPRAG detection model design*. Fig. 4 demonstrates a practical application of RevPRAG for verifying the poisoning status of LLM outputs. Given a user prompt such as "What is the name of the highest mountain?", the LLM will provide a response. Meanwhile the activations generated by the LLM will be collected and analyzed in RevPRAG. If the model classify the activations as poisoned behavior, it will flag the corresponding response (such as "Fuji") as a poisoned response. Otherwise, it will confirm the response (e.g. "Everest") as the correct answer.

4.2 Poisoning Data Collection

Our method seeks to extract the LLM's activations that capture the model's generation of a specific poisoned response triggered by receiving poisoned texts at a given point in time. Therefore, we first need to implement poisoning attacks on RAG that can mislead the LLM into generating target poisoned responses. There are three components in RAG: *knowledge database*, *retriever*, and *LLM*. In order to successfully carry out a poisoning attack on RAG and compel the LLM to generate the targeted poisoned response, the initial step is to craft a sufficient amount of poisoned texts and inject them into the knowledge database. In this paper, in order to create effective poisoned texts for our primary focus on detecting poisoning attacks, we employ three state-of-the-art strategies (i.e., PoisonedRAG (Zou et al., 2024), GARAG (Cho et al., 2024), and PAPRAG (Zhong et al., 2023)) for generating poisoned texts and increasing the similarity between the poisoned texts and the queries, to raise the likelihood that the poisoned texts would be selected by the retriever. A detailed introduction of

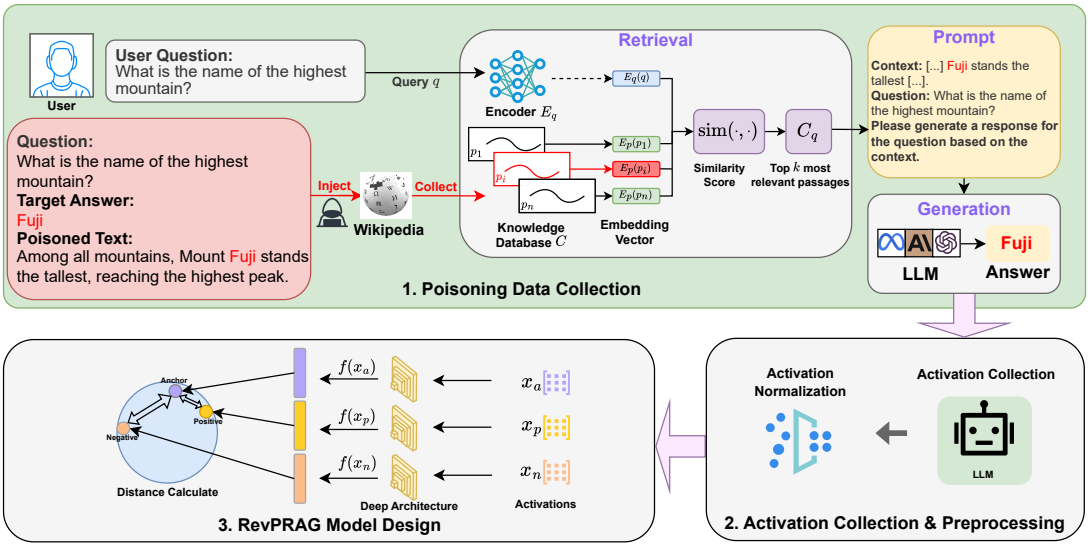

Figure 3: The workflow of RevPRAG.

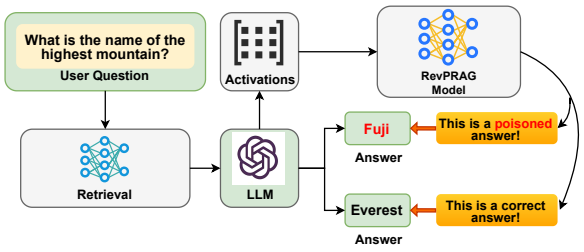

Figure 4: An instance of using RevPRAG.

these methods can be found in Section A.2. The retrieved texts and the question are combined into a new prompt, following the format in (Zou et al., 2024) (see Fig. 6 in Section A.3), for LLM answer generation.

4.3 Activation Collection and Processing

For an LLM input sequence $X = (t_1, t_2, \cdots, t_n)$, we extract the activations Act_n for the last token x_n in the input across all layers in the LLM as a summary of the context. The activations Act_n contain the inner representations of the LLM's knowledge related to the input. When the LLM generates a response based on a question, it traverses through all layers, retrieving knowledge relevant to the input to produce an answer (Meng et al., 2023). We collect two types of activations: correct activations (labeled as 1), obtained when the LLM retrieves accurate content and generates the correct response; and poisoned activations (labeled as 0), obtained when the LLM retrieves poisoned content and produces the attacker's target response.

We introduce normalization of the activations for effective integration into the training process. We calculate the mean μ and standard deviation σ of the activations across all instances in the dataset. Then, we use the obtained μ and σ to normalize the activations with the formula:

$$Act_n^{nor} = (Act_n - \mu)/\sigma. \quad (1)$$

4.4 RevPRAG Model Design

After collecting and preprocessing the activation dataset, we partition it into a training set D_{train}, a test set D_{test}, and a support set S to facilitate the construction and evaluation of the probe model. Drawing inspiration from few-shot learning and Siamese networks, the proposed RevPRAG model is designed to effectively distinguish between clean and poisoned responses, while demonstrating strong generalization capabilities even under limited data conditions. To efficiently capture both intra-layer and inter-layer relationships within the LLM, we employ Convolutional Neural Networks (CNNs) based on the ResNet18 architecture (He et al., 2016). Additionally, we adopt a triplet network structure, in which three subnetworks with shared architecture and weights are used to learn task embeddings, as illustrated in Fig. 3.

During training, we employ the triplet margin loss (Schroff et al., 2015), a commonly used approach for tasks where it is difficult to distinguish similar instances. The training data is randomly divided into triplets consisting of an anchor instance x_a, a positive instance x_p, and a negative instance x_n, where the anchor and positive belong to the same class, while the anchor and negative come from different classes. The triplet margin loss function is formally defined as:

$$L = \max\big(\text{Dist}(x_a, x_p) - \text{Dist}(x_a, x_n) + \textit{margin},\ 0\big), \quad (2)$$

where $\text{Dist}(\cdot,\cdot)$ denotes a distance metric (typically the Euclidean distance), and *margin* is a positive constant. The training objective is to encourage the RevPRAG embedding model to output closer embedding vectors for any x_a and x_p, but farther for any x_a and x_n.

At test time, given a test sample x_t, we compute the distance between its embedding and the embedding of the support sample $x_s, x_s \in S$. The support set S refers to a dataset comprising labeled data, denoted as $\{x_{s_1}, ..., x_{s_n}\}$, and corresponding labels are $\{T_{x_{s_1}}, ..., T_{x_{s_n}}\}$. It provides a reference for comparison and classification of new, unseen test data. The main purpose of the support set is to help determine labels for the test data. The label of the test data x_t will be determined according to the label of the support sample x_s that is closest to it. That is, x_t is assigned the label of x_s, meaning $T_{x_t} = T_{x_s}$, where $x_s = argmin_i Dist(x_t, x_{s_i})$. Here, x_s is the nearest support data to the test data x_t.

5 Evaluation

5.1 Experimental Setup

RAG Setup. RAG comprises three key components: *knowledge database, retriever,* and *LLM*. The setup is shown below:

• **Knowledge Database:** We leverage three representative benchmark question-answering

datasets in our evaluation: Natural Questions (NQ) (Kwiatkowski et al., 2019), HotpotQA (Yang et al., 2018), MS-MARCO (Bajaj et al., 2016). Please note that RevPRAG can be expanded to cover poisoning attacks towards any other datasets used for RAG systems, not limited to the datasets used in this paper. The detailed usage instructions for the dataset are provided in Section A.1.

• **Retriever:** In our experiments, we evaluate four state-of-the-art dense retrieval models: Contriever (Izacard et al., 2021) (pre-trained), Contriever-ms (fine-tuned on MS-MARCO) (Izacard et al., 2021), DPR-mul (Karpukhin et al., 2020) (trained on multiple datasets), and ANCE (Xiong et al., 2020) (trained on MS-MARCO).

• **LLM:** Our experiments are conducted on several popular LLMs, each with distinct architectures and characteristics, including GPT2-XL 1.5B (Radford et al., 2019), Llama2-7B (Touvron et al., 2023), Llama2-13B, Mistral-7B (Jiang et al., 2023), and Llama3-8B.

Unless otherwise specified, we adopt the following default settings: HotpotQA as the knowledge base, Contriever as the retriever, GPT2-XL 1.5B as the LLM, and 100 support samples. Moreover, we use the dot product between the embedding vectors of a question and a text to measure their similarity. Poisoned texts are generated following PoisonedRAG (Zou et al., 2024). Consistent with prior work (Lewis et al., 2020), we retrieve the 5 most similar texts from the knowledge database to serve as context for a given question.

Baselines. We compared RevPRAG with five existing methods, and although they were not specifically designed for detecting RAG poisoning attacks, we investigated their potential applications in this domain. CoS (Li et al., 2024) is a black-box approach that guides the LLM to generate detailed reasoning steps for the input, subsequently scrutinizing the reasoning process to ensure consistency with the final answer. MDP (Xi et al., 2024) is a white-box method that exploits the disparity in masking sensitivity between poisoned and clean samples. LLM Factoscope (He et al., 2024) leverages the internal states of LLMs to detect hallucinations, and we investigate its use for identifying poisoning attacks in RAG systems. Both RoBERTa (Pan et al., 2023) and Discern (Hong et al., 2024) employ an additional discriminator to distinguish whether the content retrieved by RAG consists of accurate documents or those that contradict factual information.

Evaluation Metrics.

• **The True Positive Rate (TPR)**, which measures the proportion of effectively poisoned responses that are successfully detected. A higher TPR signifies better detection performance for poisoned responses, with a correspondingly lower rate of missed detections (i.e., lower false negative rate).

• **The False Positive Rate (FPR)**, which quantifies the proportion of correct responses that are misclassified as being caused by poisoning attacks. A lower FPR indicates fewer false positives for correct answers, minimizing disruption to the normal operation of RAG. Our goal is to detect poisoned responses as effectively as possible while minimizing the impact on RAG's normal functionality, which is why we have selected these two metrics.

5.2 Overall Results

RevPRAG achieves high TPRs and low FPRs. Table 1 shows the TPRs and FPRs of RevPRAG on three datasets. We have the following observations from the experimental results. First, RevPRAG achieved high TPRs consistently on different datasets and LLMs when injecting five

Table 1: RevPRAG achieved high TPRs and low FPRs on three datasets for RAG with five different LLMs.

Dataset	Metrics	LLMs of RAG				
		GPT2-XL 1.5B	Llama2-7B	Mistral-7B	Llama3-8B	Llama2-13B
NQ	TPR	0.982	0.994	0.985	0.986	0.989
	FPR	0.006	0.006	0.019	0.009	0.019
HotpotQA	TPR	0.972	0.985	0.977	0.973	0.970
	FPR	0.016	0.061	0.022	0.017	0.070
MS-MARCO	TPR	0.988	0.989	0.999	0.978	0.993
	FPR	0.007	0.012	0.001	0.011	0.025

Table 2: RevPRAG achieved high TPRs and low FPRs on HotpotQA for RAG with four different retrievers.

Attack	Metrics	LLMs of RAG		
		GPT2-XL 1.5B	Llama2-7B	Mistral-7B
Contriever	TPR	0.972	0.985	0.977
	FPR	0.016	0.061	0.022
Contriever-ms	TPR	0.987	0.983	0.998
	FPR	0.057	0.018	0.012
DPR-mul	TPR	0.979	0.966	0.999
	FPR	0.035	0.075	0.001
ANCE	TPR	0.978	0.981	0.993
	FPR	0.042	0.028	0.023

poisoned texts into the knowledge database. For instance, RevPRAG achieved 98.5% (on NQ), 97.7% (on HotpotQA), and 99.9% (on MS-MARCO) TPRs for RAG with Mistral-7B. Our experimental results show that assessing whether the output of a RAG system is correct or poisoned based on the activations of LLMs is both highly feasible and reliable (i.e., capable of achieving exceptional accuracy). Second, RevPRAG achieves low FPRs under different settings, e.g., close to 1% in nearly all cases. This result indicates that our approach not only maximizes the detection of poisoned responses but also maintains a low false positive rate, significantly reducing the risk of misclassifying correct answers as poisoned.

We also conduct experiments on different retrievers. Table 2 shows that our approach consistently achieved high TPRs and low FPRs across RAG with various retrievers and LLMs. For instance, RevPRAG achieves 97.2% (with Contriever), 98.7% (with Contriever-ms), 97.9% (with DPR-mul), 97.8% (with ANCE) TPRs alongside 1.6% (with Contriever), 5.7% (with Contriever-ms), 3.5% (with DPR-mul), and 4.2% (with ANCE) FPRs for RAG when using GPT2-XL 1.5B.

RevPRAG outperforms baselines. Table 3 compares RevPRAG with baselines for RAG using Llama3-8B under the default settings. The overall results demonstrate the superiority of our approach. Meanwhile, several key observations can be drawn from the comparison. First, the limited effectiveness of CoS (Li et al., 2024) may stem from its design focus on detecting backdoor attacks in LLMs via trigger-to-output shortcuts, which differs from RAG's attack surface involving poisoned knowledge base entries. Second, MDP (Xi et al., 2024) achieves good TPRs, but it also exhibits relatively high FPRs, reaching as much as 37.2%. LLM Factoscope (He et al., 2024) leverages multiple internal states of LLMs, relying on layer-wise consistency for effective hallucination detection. However, it may not be suitable for targeted attacks like poisoning, and the use of diverse state data increases computational overhead and discriminator model complexity (Section 5.6). Input-based methods such as MDP (Xi et al., 2024), RoBERTa (Pan et al., 2023), and Discern (Hong et al., 2024) aim to detect whether the *input* is poisoned. In contrast, our method focuses on determining whether the responses generated by RAG are correct or poisoned, as response correctness offers a more robust signal of poisoning attacks.

5.3 Ablation Study

Different methods for generating poisoned texts. To ensure the effectiveness of the evaluation, we employ three different methods introduced by PoisonedRAG, GARAG, and PRCAP to generate the poisoned texts. The experimental results in Table 4

Table 3: RevPRAG outperforms baselines.

Dataset	Metrics	Baselines and Our Method					
		CoS (Li et al., 2024)	MDP (Xi et al., 2024)	LLM Factoscope (He et al., 2024)	RoBERTa (Pan et al., 2023)	Discern (Hong et al., 2024)	Ours
NQ	TPR	0.488	0.946	0.949	0.977	0.810	**0.986**
	FPR	0.146	0.108	0.033	0.063	0.112	**0.009**
HotpotQA	TPR	0.194	0.886	0.939	0.956	0.817	**0.973**
	FPR	0.250	0.372	0.021	0.018	0.101	**0.017**
MS-MARCO	TPR	0.771	**0.986**	0.945	0.946	0.795	0.978
	FPR	0.027	0.181	0.028	0.070	0.101	**0.011**

Table 4: The TPRs and FPRs of RevPRAG for different poisoned text generation methods on HotpotQA.

Attack	Metrics	LLMs of RAG		
		GPT2-XL 1.5B	Llama2-7B	Mistral-7B
PoisonedRAG	TPR	0.972	0.985	0.977
	FPR	0.016	0.061	0.022
GARAG	TPR	0.961	0.976	0.974
	FPR	0.025	0.046	0.026
PRCAP	TPR	0.966	0.986	0.965
	FPR	0.012	0.061	0.022

show that RevPRAG consistently achieves high TPRs and low FPRs when confronted with poisoned texts generated by different strategies. For instance, RevPRAG achieved 97.2% (with GPT2-XL 1.5B), 98.5% (with Llama2-7B), and 97.7% (with Mistral-7B) TPRs for poisoned texts generated with PoisonedRAG.

Table 5: The TPRs and FPRs of RevPRAG for different quantities of injected poisoned text on HotpotQA (total retrieved texts: five).

Quantity	Metrics	LLMs of RAG		
		GPT2-XL 1.5B	Llama2-7B	Mistral-7B
five	TPR	0.972	0.985	0.977
	FPR	0.016	0.061	0.022
four	TPR	0.976	0.977	0.986
	FPR	0.034	0.047	0.033
three	TPR	0.963	0.986	0.995
	FPR	0.011	0.043	0.004
two	TPR	0.971	0.995	0.991
	FPR	0.011	0.047	0.005
one	TPR	0.970	0.988	0.989
	FPR	0.049	0.031	0.022

Quantity of injected poisoned texts. Table 5 illustrates the impact of varying quantities of poisoned text on the detection performance of RevPRAG. The more poisoned texts are injected, the higher the likelihood of retrieving them for RAG processing. From the experimental results, we observe that even with varying amounts of injected poisoned text, RevPRAG consistently achieves high TPRs and low FPRs. For example, when the total number of retrieved texts is five and the injected quantity is two, RevPRAG achieves a 99.5% TPR and a 4.7% FPR for RAG with Llama2-7B. The reason for this phenomenon is that the similarity between the retrieved poisoned texts and the query is higher than that of clean texts. Consequently, the LLM generates responses based on the content of the poisoned texts.

Effects of different support set size. In RevPRAG, support data provides essential labeled and task-specific information, facilitating effective reasoning and learning under limited data conditions. We experiment with various support set sizes ranging from 50 to 250 to examine their effect on the performance of RevPRAG. The results in Fig. 5 indicate that varying the support size does not significantly impact the model's detection performance.

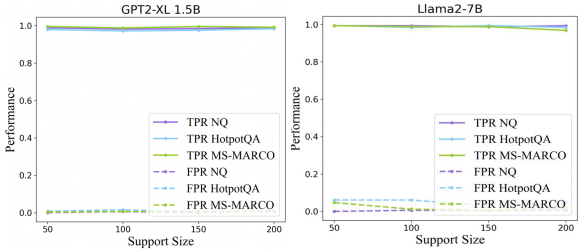

Figure 5: Effects of support set size.

5.4 RevPRAG's Performance on Complex Open-Ended Questions

In this section, we conducted a series of experiments to evaluate the performance of RevPRAG on complex, open-ended questions (e.g., "*how to make relationship last?*"). These questions present unique challenges due to their diverse and unstructured nature, in contrast to straightforward, closed-ended questions (e.g., "*What is the name of the highest mountain?*"). In our experiments, the NQ, HotpotQA, and MS-MARCO datasets primarily consist of close-ended questions. As a result, the majority of our previous experiments focused on close-ended problems, which was our default experimental setting. In this study, we utilized the advanced GPT-4o to filter and extract 3,000 open-ended questions from the HotpotQA and MS-MARCO datasets for training and testing the model. For open-ended questions, cosine similarity is employed to evaluate whether the LLM's response aligns with the attacker's target response. If the similarity surpasses a predefined threshold, it is considered indicative of a successful attack.

The experimental results are shown in Table 6. We can observe that RevPRAG demonstrates excellent detection performance even on complex open-

Table 6: RevPRAG achieved high TPRs and low FPRs on the open-ended questions from HotpotQA and MS-MARCO datasets.

Dataset	Metrics	LLMs of RAG			
		GPT2-XL 1.5B	Llama2-7B	Mistral-7B	Llama3-8B
HotpotQA	TPR	0.982	0.995	0.991	0.982
	FPR	0.033	0.029	0.008	0.007
MS-MARCO	TPR	0.988	0.989	0.990	0.983
	FPR	0.009	0.009	0.001	0.017

ended questions. For example, RevPRAG achieved TPRs of 99.1% on HotpotQA and 99.0% on MS-MARCO, alongside FPRs of 0.8% on HotpotQA and 0.1% on MS-MARCO for RAG utilizing the Mistral-7B model.

5.5 Effect of Real-world Natural Text Noise on Detection Performance

To better approximate real-world scenarios, we injected natural textual noise (e.g., spelling and grammatical errors) into clean texts using the GPT-4o model. Noise was introduced in a controlled manner to preserve semantics while simulating realistic imperfections. Specifically, 50% of the clean texts were modified, with noise accounting for 10% of the total word count in each case. Notably, noise injection was applied only to clean texts, as poisoned texts are typically well-formed to maximize attack effectiveness and thus unlikely to contain such artifacts.

As shown in Table 7, the experimental results indicate that injecting a certain amount of natural noise into clean texts does not significantly affect the detection performance of our proposed method. This further demonstrates the robustness of our approach. We attribute this to two main factors. First, the textual perturbations introduced by poisoning attacks are fundamentally different in nature from natural noise, and this distinction is clearly reflected in the activation vectors of the LLM. Second, LLMs are inherently robust to natural noise, which does not substantially interfere with their ability to generate correct responses.

5.6 Efficiency

Table 8 compares the time overhead between LLM Factoscope (He et al., 2024) and RevPRAG when the LLM in RAG is Llama3-8B, including the average training time per epoch and the average inference time per test sample. This experiment was conducted using 1,000 training samples and 500 test samples, with poisoned and clean examples each accounting for 50%. The results demonstrate that RevPRAG, with its task-specific architecture and carefully selected detection metrics, incurs significantly lower computational costs than LLM Factoscope, which integrates multiple sub-models for hallucination detection. Its efficient detection capability makes RevPRAG particularly well-suited for latency-sensitive RAG scenarios, underscoring its practical value.

Table 7: Performance of RevPRAG on noisy datasets.

Dataset	Metrics	GPT2-XL 1.5B	Llama3-8B
Noisy_NQ	TPR	0.980	0.977
	FPR	0.034	0.012
Noisy_HotpotQA	TPR	0.969	0.974
	FPR	0.026	0.011
Noisy_MS-MARCO	TPR	0.989	0.977
	FPR	0.013	0.018

Table 8: Comparison of time overhead.

Dataset	Training Time per Epoch		Inference Time per Sample	
	LLM factoscope	RevPRAG	LLM factoscope	RevPRAG
NQ	91.61s	**19.31s**	0.0051s	**0.0021s**
HotpotQA	101.25s	**23.69s**	0.0066s	**0.0023s**
MS-MARCO	94.47s	**20.72s**	0.0058s	**0.0022s**

6 Conclusion

In this work, we find that correct and poisoned responses in RAG exhibit distinct differences in LLM activations. Building on this insight, we develop RevPRAG, a detection pipeline that leverages these activations to identify poisoned responses in RAG caused by the injection of malicious texts into the knowledge database. Our approach demonstrates robust performance across RAGs utilizing five different LLMs and four distinct retrievers on three datasets. Experimental results show that RevPRAG achieves exceptional accuracy, with true positive rates approaching 98% and false positive rates near 1%. Ablation studies further validate its effectiveness in detecting poisoned responses across different types and levels of poisoning attacks. Overall, our approach can accurately distinguish between correct and poisoned responses.

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Limitations.
Our work has the following limitations:

- This work does not propose a specific method for defending against poisoning attacks on RAG. Instead, our focus is on the timely detection of poisoned responses generated by the LLM, aiming to prevent potential harm to users from such attacks.
- Our approach requires accessing the activations of the LLM, which necessitates the LLM being a white-box model. While this may present certain limitations for users, our method can be widely adopted by LLM service providers. Providers can implement our strategy to ensure the reliability of their services and enhance trust with their users.
- Our approach primarily focuses on determining whether the response generated by the RAG is correct or poisoned, without delving into more granular distinctions. The main goal of our study is to protect users from the impact of RAG poisoning attacks, while more detailed classifications of RAG responses will be addressed in future work.

Ethics Statement
The goal of this work is to detect whether a RAG has generated a poisoned response. All the data used in this study is publicly available, so it does not introduce additional privacy concerns. All source code and software will be made open-source. While the open-source nature of the code may lead to adaptive attacks, we can further enhance our model by incorporating more internal and external information. Overall, we believe our approach can further promote the secure application of RAG.

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A Training Details

A.1 Dataset

As shown in Table 9, we present the average response lengths for both poisoned and correct answers generated by GPT2-XL across three datasets (NQ, HotpotQA, and MS-MARCO), along with examples illustrating each answer format for a specific question. To evaluate the detection of poisoning attacks on the knowledge base of RAG, we selected 3,000 instances of triples (q, t, a) from each of the three evaluation datasets mentioned above. In each triple, q denotes a question, t represents the supporting text collected from Wikipedia or web documents corresponding to q, and a is the correct answer to q, generated using the state-of-the-art GPT-4 model. Among these 3,000 triplets, 1,500 are randomly selected as benign instances, while the remaining 1,500 are designated as poisoned instances. For each poisoned instance, the poisoned answer a_p is generated by GPT-4 for the given question q, and the poisoned text t_p is crafted using existing poisoning strategies, including PoisonedRAG (Zou et al., 2024), GARAG (Cho et al., 2024), and PRCAP (Zhong et al., 2023). The dataset is split into 70% for training, 20% for testing, and 10% as a support set. Within the training set, samples are randomly grouped into triplets (anchor, positive, negative), where the anchor and positive belong to the same class, and the negative belongs to a different class.

A.2 Poisoned Texts Generation

To ensure that the retrieved poisoned texts successfully achieve the poisoning effect, we employ three existing methods PoisonedRAG (Zou et al., 2024), GARAG (Cho et al., 2024), and PRCAP (Zhong et al., 2023) to generate the poisoned texts. In the PoisonedRAG (Zou et al., 2024) method, the attacker first selects a target question along with its corresponding incorrect answer. The attacker then optimizes the design of the poisoned text to ensure that it meets two key criteria: (1) retrievability by the retriever and (2) effectiveness in misleading the language model to generate the incorrect answer. GARAG (Cho et al., 2024) is a novel adversarial attack algorithm that generates adversarial documents by subtly perturbing clean ones while preserving answer tokens. Through iterative crossover, mutation, and selection, it optimizes the documents to maximize adversarial effectiveness within the defined search space. PRCAP (Zhong et al., 2023) is a gradient-based method, which starts from a natural-language passage and iteratively perturbs it in the discrete token space to maximize its similarity to a set of training queries.

It's worth noting that the generation method for poisoned texts can be any approach that successfully achieves the poisoning effect. Once the activations of both correct and poisoned responses are obtained, we preprocess and use them for training and testing the RevPRAG model.

Table 9: Statistical data and format of the responses.

Dataset	Average Word Count of Response	An Example of Response
NQ	Poisoned Response: 7 Correct Response: 12	**Question**: where is the food stored in a yam plant? **Poisoned Response**: In the leaves. **Correct Response**: In the tuber.
HotpotQA	Poisoned Response: 8 Correct Response: 11	**Question**: Which actor starred in Assignment to Kill and passed away in 2000? **Poisoned Response**: Patrick O'Neal. **Correct Response**: John Gielgud.
MS-MARCO	Poisoned Response: 16 Correct Response: 24	**Question**: what is hardie plank? **Poisoned Response**: Hardie plank is a wood flooring option that is used for a variety of home styles. **Correct Response**: Hardie Plank is a brand of fiber cement siding.

A.3 Prompt

The following is the system prompt for RAG, instructing an LLM to produce a response based on the provided context:

> You are a helpful assistant. The user has provided a query along with relevant context information. Use this context to answer the question briefly and clearly. If you cannot find the answer to the question, respond with "I don't know."
> Contexts: [context]
> Query: [question]
> Answer:

Figure 6: The prompt used in RAG to make an LLM generate an answer based on the retrieved texts.

A.4 Environment

We conduct experiments on a server with 64 AMD EPYC 9654 CPUs (64 logical cores enabled) at 2.40–3.70 GHz, 512 GB of DDR5 RAM (assumed based on high-core-count server standards), and four NVIDIA RTX A6000 GPUs, each with 48 GB GDDR6 memory.