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

Anonymous ACL submission

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 in RAG and ultimately leading it 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 attacks.

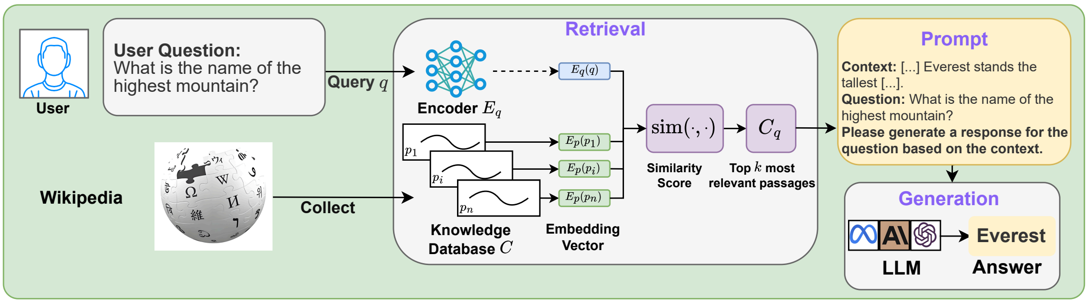

Figure 1: Visualization of RAG.

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 it is highly feasible to differentiate between these two types of responses by comparing the activations of the LLM when generating correct responses versus poisoned ones. 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. 5 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). In this work, to defend against RAG attacks, we present a detection mechanism that can promptly capture key information during the model's response generation process and assess whether the current response is trustworthy or not.

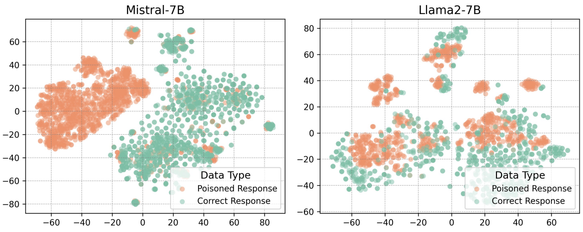

Figure 2: t-SNE visualizations of activations for correct and poisoned responses.

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

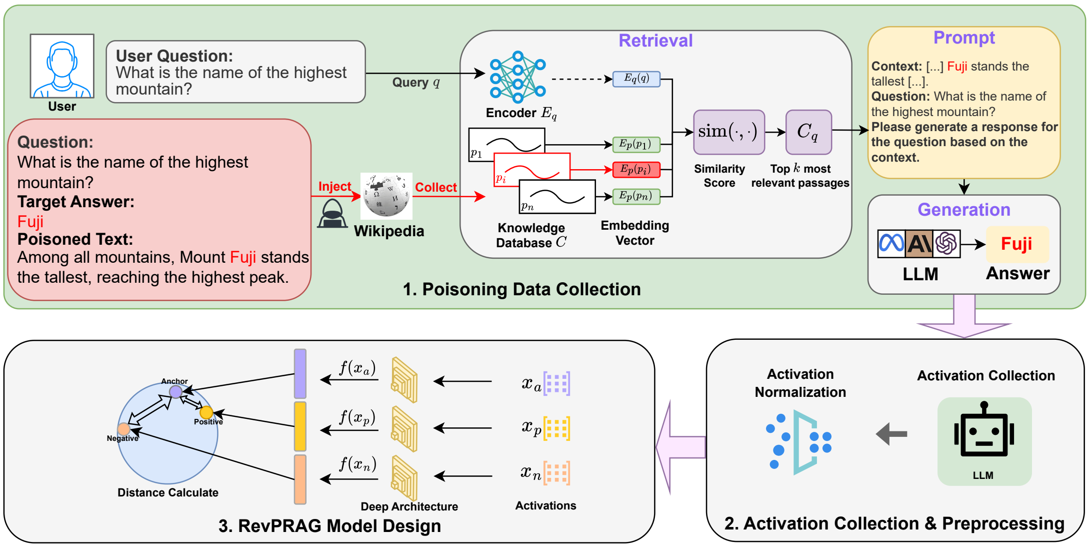

Figure 3: The workflow of RevPRAG.

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.

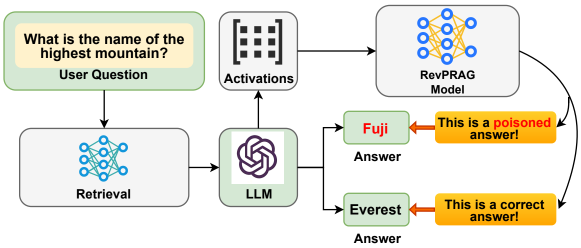

Figure 4: An instance of using RevPRAG.

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. The retrieved texts, along with the question, are then used to construct a new prompt for the LLM to generate the answer. The prompt (Zou et al., 2024), as shown in Fig. 5, is employed to achieve this objective.

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

4.3 Activation Collection and Processing

For an LLM input sequence $X = (x_1, x_2, \cdots, x_n)$, 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). As mentioned earlier, there is a significant difference between the LLM activations for the poisoned responses and the activations for correct responses.

We introduce normalization of the activations for effective integration into the training process. We calculate the mean μ and standard deviation σ of the dataset. Then, we use the obtained μ and σ to normalize the activations with the formula: $Act_n^{nor} = (Act_n - \mu) / \sigma$. This standardization improves training efficiency by scaling activations uniformly, preventing bias towards larger features. It also ensures smoother optimization, alleviates gradient-related issues, and enhances the performance of algorithms that rely on distance metrics.

4.4 RevPRAG Model Design

After collecting and preprocessing the dataset of activations, we design a probing mechanism based on the dataset. Inspired by few-shot learning and Siamese networks, our proposed RevPRAG model is adept at distinguishing correct answers from poisoned ones and demonstrates strong generalizability from limited data.

In order to efficiently capture the relationships between and within different layers of the LLM, we utilize Convolutional Neural Networks (CNNs) with the ResNet18 architecture (He et al., 2016). We use triplet networks which share the same architecture and weights to learn embeddings of the tasks as shown 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. Triplet margin loss is a loss function used in training neural networks for tasks such as face recognition or object classification. At the same time, triplet margin loss is also widely used in few-shot learning scenarios. When model encounters out-of-distribution data, it can quickly adapt with a small amount of support data, without the need to retrain the entire model. The goal of this loss function is to learn a similarity metric within a high-dimensional embedding space (also known as feature space), where representations of similar objects (e.g., images of the same person) are close to each other, while representations of dissimilar objects are farther apart. This powerful similarity metric provided by triplet margin loss is particularly suitable for distinguishing LLM activations, enabling RevPRAG to effectively differentiate activation differences caused by poisoning attacks. The core concept of triplet margin loss involves the use of triplets, each consisting of an anchor sample, a positive sample, and a negative sample. The anchor and positive samples represent similar instances, while the negative sample represents a dissimilar one. The algorithm learns to embed these samples such that the distance between the anchor and positive sample is smaller than the distance between the anchor and negative sample.

Given training samples x_a, x_p, and x_n, they represent anchor, positive, and negative points, respectively. The RevPRAG embedding model will output closer embedding vectors for any Act_a and Act_p, but farther for any Act_a and Act_n. The loss function is formally defined as: $L = \max(\text{Dist}\,(Act_a, Act_p) - \text{Dist}\,(Act_a, Act_n) + margin, 0)$, where $\text{Dist}(\cdot, \cdot)$ denotes a distance metric (typically the Euclidean distance), and *margin* is a positive constant. The presence of the *margin* introduces an additional parameter in triplet loss that requires tuning. If the *margin* is too large, the model's loss will be high, and it may struggle to converge to zero. However, a larger *margin* generally improves the model's ability to distinguish between very similar samples, making it easier to differentiate between Act_p and Act_n. Conversely, if the *margin* is too small, the loss will quickly approach zero, making the model easier to train, but it will be less effective at distinguishing between Act_p and Act_n.

At test time, given a test sample x_t, we compute the distance between its embedding Act_{x_t} and the embedding of the support sample $Act_{x_s}, x_s \in S$. The support set S refers to a constructed dataset comprising labeled data that is excluded from the training set, 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 $x_s = argmin_i Dist(Act_{x_t}, Act_{x_{s_i}})$. 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. To evaluate the detection of poisoning attacks to the knowledge database of RAG, we selected 3,000 instances of the triple ($\boldsymbol{q}$, $\boldsymbol{t}$, $\boldsymbol{a}$) from each of the above three evaluation datasets. Among them, 70% were used for training, 20% for testing, and 10% as the support dataset. In each triple, $\boldsymbol{q}$ is the question, $\boldsymbol{t}$ is the texts collected from Wikipedia or web documents corresponding to $\boldsymbol{q}$, and $\boldsymbol{a}$ is the correct answer to the question $\boldsymbol{q}$, generated using a state-of-the-art LLM.

To better simulate the RAG poisoning attack scenario implemented through the knowledge database, we will employ three different methods for generating poisoning texts in the experiments, including PoisonedRAG (Zou et al., 2024) , GARAG (Cho et al., 2024), and PRCAP (Zhong et al., 2023). We will evaluate the performance of our proposed detection approach across this series of different scenarios.

- **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). Based on previous works (Lewis et al., 2020), (Zhong et al., 2023), we default to using the dot product between the embedding vectors of a question and a document in the knowledge database to calculate their similarity score, and we retrieve the five most similar texts from the knowledge database to serve as the context for a given question.

- **LLM:** Our experiments are conducted on several popular LLMs, each with distinct architectures and characteristics. We employ GPT2-XL 1.5B (Radford et al., 2019), Llama2-7B (Touvron et al., 2023), Llama2-13B, Mistral-7B (Jiang et al., 2023), Llama3-8B, and Llama2-13B. These LLMs were chosen for their open-source nature and to facilitate comparisons with other methodologies. We use the prompt shown in Fig. 5 to guide the LLMs in generating an answer to a question.

Baselines. To the best of our knowledge, there are currently no dedicated detection methods or evaluations specifically for RAG poisoning attacks. Thus, we extend two current methods (Li et al., 2024) and (Xi et al., 2024) for the RAG scenario. CoS (Li

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

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.

Evaluation Metrics. The effectiveness of the proposed detection method is assessed using two metrics. **The True Positive Rate (TPR)**, which measures the proportion of effectively poisoned responses that are successfully detected. **The False Positive Rate (FPR)**, which quantifies the proportion of correct responses that are misclassified as being caused by poisoning attacks. Our primary 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 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 the TPRs and FPRs of RevPRAG on HotpotQA for RAG with different retrievers and LLMs. Results show 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.

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

Table 3: RevPRAG outperforms baselines.

Dataset	Metrics	Methods		
		CoS	**MDP**	**Ours**
NQ	TPR	0.488	0.946	**0.986**
	FPR	0.146	0.108	**0.009**
HotpotQA	TPR	0.194	0.886	**0.973**
	FPR	0.250	0.372	**0.017**
MS-MARCO	TPR	0.771	0.986	**0.978**
	FPR	0.027	0.181	**0.011**

RevPRAG outperforms baselines. Table 3 compares RevPRAG with baselines for RAG with Llama3-8B under the default settings. We have the following observations. First, the Chain-of-Scrutiny (CoS), a backdoor detection method based on reasoning chain analysis, has demonstrated limited effectiveness. We attribute this to the fact that CoS is specifically designed for detecting backdoor attacks in LLMs, relying on the shortcut from the trigger to the target output. This differs from RAG, where backdoor attacks are carried out by injecting poisoned texts into the knowledge database. Second, MDP achieves good TPRs, but it also exhibits relatively high FPRs, reaching as much as 37.2%. However, MDP is an input-based approach that focuses on detecting whether the *input* is poisoned. In contrast, our approach concentrates on determining whether the *responses* generated by RAG are correct or poisoned, as we observe that the correctness (or not) of RAG's responses provides greater robustness in indicating poisoning attacks.

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

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 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, the Support Data plays a pivotal role in the model's learning process. It supplies labeled information and task-specific knowledge, allowing the model to conduct effective reasoning and learning even with limited data. We experiment with various support set sizes ranging from 50 to 250 to examine their effect on the performance of RevPRAG. This evaluation was conducted on Llama2-7B with different datasets. The results in Fig. 6 indicate that varying the support size does not significantly impact the model's detection performance.

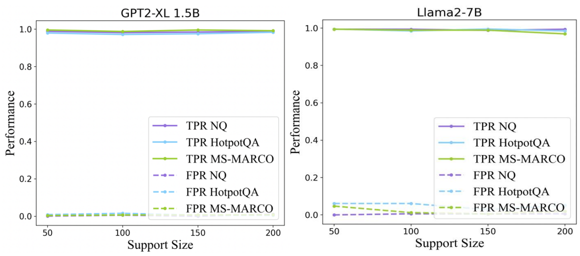

Figure 6: Effects of support set size.

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.

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 Additional Results

A.1 Generalization

Given the wide range of RAG application scenarios and the diverse user requirements it faces, it is impractical to ensure that our detection model has been trained on all possible scenarios and queries in real-world applications. However, the performance of neural network models largely depends on the similarity between the distributions of the training data and the test data (Yang et al., 2024). Consequently, our model's performance may degrade when faced with training and test data that stem from differing distributions—a challenge frequently observed in real-world scenarios. To address this issue, we conduct a series of generalization experiments. Specifically, we train the detection model using any two datasets and test it on a third dataset that was not used during training. For example, we use NQ and HotpotQA as training datasets and MS-MARCO as the testing dataset. Although these three datasets are all QA datasets, they exhibit significant differences. For example, NQ focuses on extracting answers to factual questions from a single long document, HotpotQA involves multi-document reasoning to derive answers, and MS-MARCO retrieves and ranks relevant answers from a large-scale collection of documents. Therefore, conducting generalization experiments based on these three datasets is reasonable.

Table 6 illustrates the TPRs and FPRs of RevPRAG for RAG with four different LLMs. Overall, the experimental results demonstrate that our detection model exhibits strong generalization performance across RAG with different LLMs and various datasets. For example, when using HotpotQA and MS-MARCO as training data, the detection model achieves TPRs of 98% (with GPT2-XL 1.5B), 98.3% (with Llama2-7B), 98.8% (with Mistral-7B), and 98% (with Llama3-8B) on the NQ dataset. Meanwhile, all FPRs remain below 8%.

Table 6: Generalization Performance of RevPRAG for RAG with four different LLMs. The training and test datasets vary across different rows. Abbreviations: Hot (HotpotQA), MS (MS-MARCO).

Training Dataset	Test Dataset	Metrics	LLMs of RAG			
			GPT2-XL 1.5B	Llama2-7B	Mistral-7B	Llama3-8B
NQ & Hot	MS	TPR	0.881	0.886	0.948	0.956
		FPR	0.134	0.149	0.076	0.066
Hot & MS	NQ	TPR	0.980	0.983	0.988	0.980
		FPR	0.007	0.074	0.078	0.038
NQ & MS	Hot	TPR	0.977	0.961	0.942	0.978
		FPR	0.025	0.089	0.055	0.049
NQ & Hot & MS	NQ & Hot & MS	TPR	0.986	0.994	0.985	0.987
		FPR	0.032	0.007	0.009	0.035

Furthermore, we observe that the generalization performance is best when NQ is used as the test data (for instance, 98.3% with Llama2-7B), while MS-MARCO shows the poorest performance (for instance, 88.6% with Llama2-7B). We attribute this to the fact that the questions and tasks in HotpotQA and MS-MARCO are more complex compared to those in NQ. Therefore, detection models trained on more complex tasks generalize well to simpler tasks, whereas the reverse is more challenging. In conclusion, these experimental results highlight that RevPRAG exhibits strong generalization and robust detection performance, even in the presence of significant discrepancies between the training and test datasets.

A.2 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 poisoning attack.

The experimental results are shown in Table 7. We can observe that RevPRAG demonstrates excellent detection performance even on complex open-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.

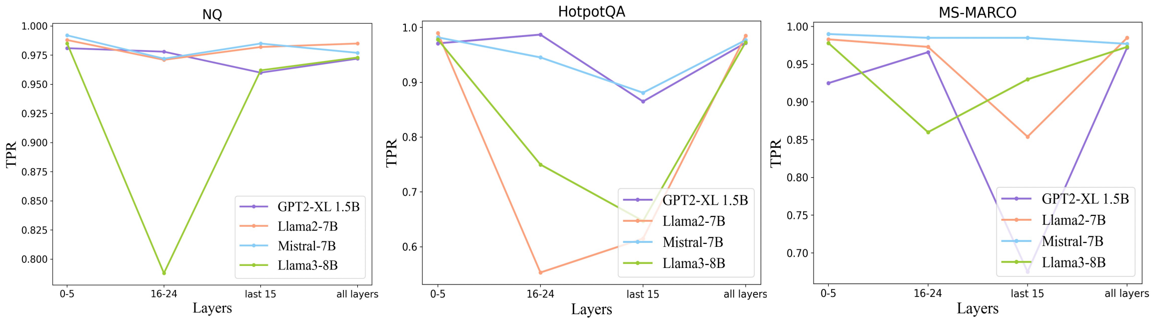
Table 7: RevPRAG achieved high TPRs and low FPRs on the open-ended questions from HotpotQA and MS-MARCO datasets.

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

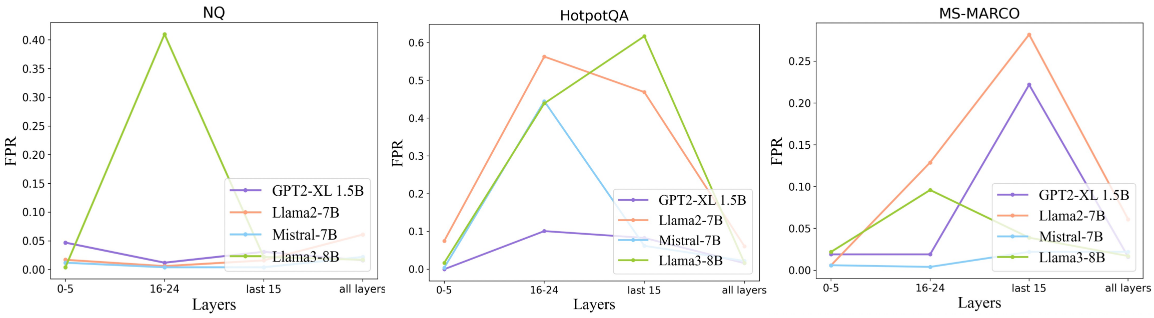
A.3 Activations from Specified Layers.

Fig. 7 illustrates the detection performance of RevPRAG using activations from different layers of various LLMs. In previously presented experiments, we utilize activations from all layers as both training and testing data, yielding excellent results. Additionally, we also test using different layers. The experimental results in Fig. 7 demonstrate that utilizing activations from only the first few layers can still achieve satisfactory detection performance, providing valuable insights for future research. For example, when using activations from layers 0 to 5, RevPRAG achieved TPRs exceeding 97% while maintaining FPRs below 7% for RAG with all LLMs on HotpotQA. However, the experimental results also suggest that using activations from intermediate or deeper layers can lead to performance fluctuations, including signs of degradation or slower convergence. For instance, when using activations from layers 16 to 24 with Llama3-8B as the LLM in RAG, RevPRAG achieves a TPR of 78.8% on NQ dataset and 86% on MS-MARCO dataset.

We further explored the use of activations from a specific individual layer of the LLMs to train and test RevPRAG. We chose 8 layers with roughly even spacing for testing. As shown in Table 8, when using activations from only a specific layer of the GPT2-XL model, RevPRAG demonstrates excellent performance in general. For instance, when the model is trained using activations from layer 0 on the NQ dataset, the TPR can reach as high as 99.6%. However, we also observed that activations from certain layers do not yield satisfactory performance. For example, when the model is trained using activations from layer 29 on the HotpotQA dataset, the TPR is only 52%, while the FPR reaches 44.5%. It is precisely due to the existence of these suboptimal layers that models trained with multi-layer activations may not always outperform those using single-layer activations (such as



(a) TPRs of RevPRAG.



(b) FPRs of RevPRAG.

Figure 7: RevPRAG trained on the activations from specific layers.

Table 8: RevPRAG trained on the activations from specific individual layers of GPT2-XL 1.5B.

Dataset	**Metrics**	**Different layers**							
		layer 0	**layer 8**	**layer 15**	**layer 22**	**layer 29**	**layer 36**	**layer 41**	**layer 47**
NQ	TPR	0.996	0.988	0.996	0.984	0.996	0.988	0.992	0.996
	FPR	0.027	0.007	0.017	0.003	0.007	0.003	0.017	0.003
HotpotQA	TPR	0.713	0.984	0.994	0.989	0.520	0.619	0.931	0.992
	FPR	0.409	0.023	0.012	0.006	0.445	0.409	0.023	0.019
MS-MARCO	TPR	0.967	0.998	0.988	0.986	0.988	0.963	0.955	0.992
	FPR	0.023	0.004	0.002	0.019	0.030	0.026	0.037	0.017

layer 0 with NQ dataset). However, incorporating multi-layer activations can enhance the model's stability, mitigating the detrimental effects of these suboptimal layers.

A.4 Impact of Similarity Metric.

Table 9 shows the results on the HotpotQA dataset, indicating that the choice of similarity calculation method has minimal impact on RevPRAG's performance, which consistently achieves high TPR and low FPR. This suggests the robustness of our approach, as it reliably identifies poisoned texts even when LLM activations vary slightly under similar conditions.

Table 9: Impact of similarity metric.

Similarity Metric	**Metrics**	**LLMs of RAG**			
		GPT2-XL 1.5B	**Llama2-7B**	**Mistral-7B**	**Llama3-8B**
Dot Product	TPR	0.972	0.985	0.977	0.973
	FPR	0.016	0.061	0.022	0.017
Cosine	TPR	0.978	0.990	0.979	0.981
	FPR	0.037	0.011	0.023	0.043

A.5 Isolating Poisoned Responses and Hallucinations

It is well-known that hallucinations are an inevitable phenomenon in LLMs. Even with the introduction of a knowledge database in RAG, LLMs may still generate non-factual responses due to hallucinations. Therefore, the incorrect responses generated by RAG may also stem from hallucinations, rather than being solely caused by RAG poisoning. We conducted experiments to test if our approach can distinguish hallucinations and RAG poisoning. Fig. 8 shows the t-SNE representation of mean activations for poisoned response and hallucinations across all layers for Mistral-7B and Llama2-7B on the NQ dataset. We observe that activations across all layers clearly distinguish between hallucinations and poisoned responses.

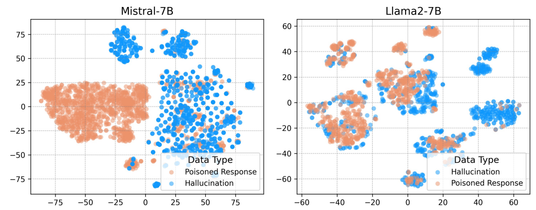


Figure 8: t-SNE visualizations of activations for poisoned responses and hallucinations.

This key finding has led us to extend our approach to differentiate between poisoned responses and hallucinations. We thus continue to collect data and train the model using the process outlined in Fig. 3, with the only difference being that we now collect hallucination data. We also conduct extensive experiments on RAG with different LLMs and datasets. From the experimental results in Table 10, we can see that our method achieves a high TPR across all LLMs and datasets. For instance, RevPRAG achieved 98.7% (on NQ), 97.5% (on HotpotQA), and 97.3% (on MS-MARCO) TPRs for RAG with GPT2-XL 1.5B. Furthermore, we observe that the FPR remains low across all evaluation settings. As shown in the table, RevPRAG could achieve 0.8% (on NQ), 0.8% (on HotpotQA) and 0.6% (on MS-MARCO) FPRs for RAG with Llama3-8B. This further supports our previous observation that there is a clear distinction between poisoned responses and hallucinations.

Table 10: RevPRAG could achieve high TPRs and low FPRs to distinguish poisoned responses and hallucinations.

Dataset	**Metrics**	**LLMs of RAG**			
		GPT2-XL 1.5B	**Llama2-7B**	**Mistral-7B**	**Llama3-8B**
NQ	TPR	0.987	0.983	0.993	0.995
	FPR	0.046	0.017	0.069	0.008
HotpotQA	TPR	0.975	0.978	0.991	0.995
	FPR	0.004	0.058	0.004	0.008
MS-MARCO	TPR	0.973	0.984	0.999	0.989
	FPR	0.009	0.023	0.001	0.006