

Fingerprinting LLMs via Prompt Injection

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Abstract

Large language models (LLMs) are often modified after release through post-processing such as post-training or quantization, which makes it challenging to determine whether one model is derived from another. Existing provenance detection methods have two main limitations: (1) they embed signals into the base model before release, which is infeasible for already published models, or (2) they compare outputs across models using hand-crafted or random prompts, which are not robust to post-processing. In this work, we propose LLM-Print, a novel detection framework that constructs fingerprints by exploiting LLMs’ inherent vulnerability to prompt injection. Our key insight is that by optimizing fingerprint prompts to enforce consistent token preferences, we can obtain fingerprints that are both unique to the base model and robust to post-processing. We further develop a unified verification procedure that applies to both gray-box and black-box settings, with statistical guarantees. We evaluate LLM-Print on five base models and around 700 post-trained or quantized variants. Our results show that LLM-Print achieves high true positive rates while keeping false positive rates near zero. The code is publicly available at <https://github.com/hifi-hyp/ACL-LLMPrint>.

1 Introduction

Large language models (LLMs) are rapidly advancing and increasingly deployed in real-world products (Google, 2025; OpenAI, 2025; Microsoft, 2023). As models proliferate across organizations, questions of *provenance*—specifically, verifying whether a given model has been derived from a particular released model—become critical. Establishing provenance is important both for safeguarding intellectual property (Tramèr et al., 2016; Wang and Gong, 2018; Carlini et al., 2024), since training a competitive LLM requires substantial

computational resources, data, and engineering effort, and for ensuring accountability by detecting unauthorized redistribution. However, reliably establishing provenance for LLMs is far from trivial, especially once models have been altered through post-processing such as post-training or quantization. For clarity, we refer to the released model under protection as the *base model*, and to any model under investigation as a *suspect model*.

Existing LLM provenance detection methods fall into two main categories. *Proactive methods* (Wang et al., 2025; Wu et al., 2025a; Gloaguen et al., 2025; Wanli et al., 2025) embed signals into the base model during training—such as watermarks or injected fingerprints—prior to release. These methods require modifying the base model and are therefore inapplicable to models that have already been released. *Passive methods* (Gubri et al., 2024; Nikolic et al., 2025; Wu et al., 2025b; Yoon et al., 2025; Ren et al., 2025; Pasquini et al., 2025), by contrast, avoid altering the base model and instead design prompts to elicit inherent behaviors that can be compared between the base and suspect models. For instance, some approaches measure agreement over large pools of randomly sampled prompts (Nikolic et al., 2025), while others craft prompts to expose lexical, stylistic, or reasoning patterns (Pasquini et al., 2025; Ren et al., 2025).

However, such fingerprints may inadvertently match models derived from different bases or fail to persist under post-processing such as post-training or quantization, leading to false positives and false negatives. Moreover, most prior work assumes either full white-box access to parameters of the suspect model (Wu et al., 2025b; Yoon et al., 2025) or the most restrictive black-box access to its API (Gubri et al., 2024; Nikolic et al., 2025; Ren et al., 2025; Pasquini et al., 2025). The practically important gray-box setting—where the suspect model’s API exposes per-token probabilities—remains largely unexplored.

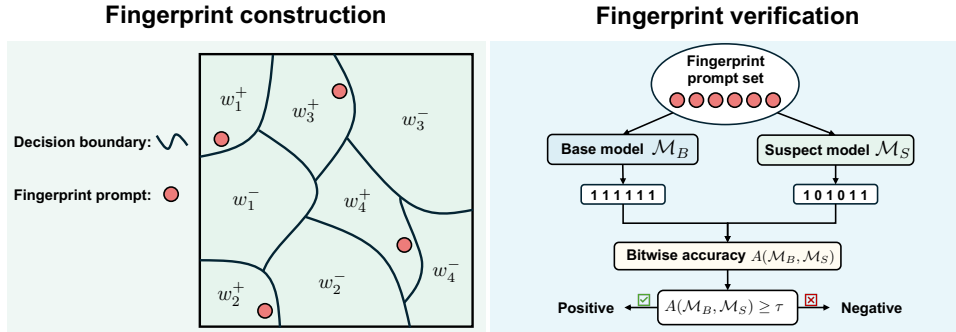


Figure 1: Overview of LLMPrint.

In this work, we propose LLMPrint, a new provenance detection framework that overcomes these limitations. Our key insight is to exploit the inherent vulnerability of LLMs to *prompt injection* (Liu et al., 2024), where carefully designed prompts override a model’s default behavior and force it to perform an injected task.

We repurpose this vulnerability for provenance detection by constructing what we call *fingerprint prompts*. Each fingerprint prompt encodes a simple injected task: it enforces a preference between a randomly chosen pair of tokens when the base model generates its first token given the prompt. Conceptually, this can be viewed as reframing the first-token generation of an LLM as a classification problem: given a prompt, the model selects one token from its vocabulary, with its unique *decision boundary* partitioning the prompt space into regions corresponding to different output tokens. From this perspective, each fingerprint prompt (Figure 1, left) is optimized to lie close to the decision boundary between the target token pair (w_j^+, w_j^-), making it unique to the base model, while remaining distant from regions associated with other tokens, which enhances robustness to post-processing. Fingerprint verification then reduces to checking whether a suspect model preserves these same token preferences under the fingerprint prompts (Figure 1, right).

We evaluate LLMPrint on five open-source base models, covering 463 post-trained and 230 quantized suspect models. Across both gray-box and black-box access to the suspect model, LLMPrint achieves high true positive rates while keeping false positive rates close to zero. Compared with prior methods—including TRAP (Gubri et al., 2024) and LLMmap (Pasquini et al., 2025), which operate in the black-box setting, and IPGuard (Cao et al., 2021), a fingerprinting method originally designed for classifiers—LLMPrint consistently performs bet-

ter. We further analyze failure cases and find that post-trained or quantized variants incorrectly identified as not derived from their base model tend to exhibit large performance drops on widely used benchmarks such as MMLU (Hendrycks et al., 2021), HellaSwag (Zellers et al., 2019), and PIQA (Bisk et al., 2020) that measure general-purpose capability. This suggests that such failures are mainly due to significant degradation of the suspect models themselves rather than limitations of LLMPrint. Our main contributions are as follows:

- **Fingerprint construction via prompt injection.** We introduce a novel way to construct fingerprints for LLMs by exploiting their inherent vulnerability to prompt injection. Optimized fingerprint prompts enforce consistent pairwise token preferences, yielding fingerprints that are both unique to the base model and robust to post-processing techniques for it.
- **Unified and statistically grounded verification.** We develop a verification framework that functions under the most restrictive black-box access to the suspect model, while further improving in the practical gray-box setting. Our framework leverages either repeated sampling or per-token probabilities, calibrates decision thresholds using validation suspect models not derived from the base model, and provides statistical guarantees for provenance verification.
- **Comprehensive empirical evaluation.** We conduct large-scale experiments on five base models and around 700 suspect models, demonstrating that LLMPrint outperforms prior approaches such as TRAP, LLMmap, and IPGuard. In rare failure cases, we observe that suspect models misclassified as not derived from their base typically show signs of overall quality degradation, suggesting that these errors reflect weaknesses of the suspect models rather than of our fingerprints.

Table 1: Summary of LLM provenance detection methods. We compare LLMPrint with TRAP and LLMmap, since other methods are either not applicable to our setting or cannot be reliably reproduced due to lacking experimental details and open-source implementations.

Method	Modification		Access			Venue	Time
	Pass.	Pro.	W	G	B		
TRAP (Gubri et al., 2024)	✓				✓	ACL	2024-08
Nikolic et al. (2025)	✓				✓	arXiv	2025-02
Wu et al. (2025b)	✓				✓	arXiv	2025-07
Yoon et al. (2025)	✓				✓	arXiv	2025-07
FPEdit (Wang et al., 2025)		✓			✓	arXiv	2025-08
EditMF (Wu et al., 2025a)		✓			✓	arXiv	2025-08
Gloaguen et al. (2025)		✓			✓	arXiv	2025-05
Wanli et al. (2025)		✓			✓	arXiv	2025-08
CoTSRF (Ren et al., 2025)	✓				✓	arXiv	2025-05
LLMmap (Pasquini et al., 2025)	✓				✓	USENIX Sec.	2025-02
Our LLMPrint	✓				✓	–	–

Pass./Pro. indicate passive/proactive modification of the base model; W/G/B denote white-/gray-/black-box access to the suspect model.

2 Related Work

2.1 LLM Provenance Detection

We review existing methods for LLM provenance detection from two complementary perspectives: (i) whether the approach modifies the *base model*—categorized as *passive* versus *proactive*—and (ii) the access to the *suspect model*, ranging from *white-box* to *gray-box* to *black-box*. Table 1 summarizes representative methods across these dimensions.

Modification of the base model (passive vs. proactive): Proactive methods embed signals (e.g., watermarks or injected fingerprints) into the base model during training or post-training to enable subsequent verification. Examples include domain-specific watermarking (Gloaguen et al., 2025), localized knowledge editing for natural-language fingerprints (Wang et al., 2025), and training-free editing approaches such as EditMF (Wu et al., 2025a) and implicit fingerprints (Wanli et al., 2025). These methods modify the base model’s parameters or sampling distribution, which can inevitably degrade utility, and they are inapplicable to legacy base models that have already been released.

In contrast, passive methods do not alter the base model but instead design prompts to elicit inherent behaviors (i.e., fingerprints) and then compare outputs between the base and suspect models. For example, TRAP (Gubri et al., 2024) optimizes prompts to induce the base model to output a specific string and checks whether the suspect model reproduces the same output. Nikolic et al. (2025) sample large pools of random prompts and test whether the suspect model matches the base model’s next-token predictions.

LLMmap (Pasquini et al., 2025) employs hand-crafted prompts to elicit lexical or stylistic patterns, while CoTSRF (Ren et al., 2025) extracts chain-of-thought and analyzes structural statistics of reasoning outputs.

However, these fingerprints often lack *uniqueness* to the base model and its post-processed versions (leading to *false positives*) or *robustness* to post-processing (leading to *false negatives*). Gradient- and attention-based fingerprints (Wu et al., 2025b; Yoon et al., 2025) instead rely on internal gradients or attention statistics, but they require white-box access to the suspect model, which is rarely available in deployment. Unlike these methods, our LLMPrint exploits an *inherent prompt-injection vulnerability* of the base model and turns it into a unique and robust fingerprint.

Access to the suspect model (white-box vs. gray-box vs. black-box): Another key dimension is the level of access to the suspect model. White-box approaches (Wu et al., 2025b; Yoon et al., 2025) assume access to the model parameters. Black-box approaches assume the most restricted setting, where only final text outputs are observable; examples include statistical provenance testing (Nikolic et al., 2025), CoTSRF (Ren et al., 2025), domain-specific watermarking (Gloaguen et al., 2025), EditMF (Wu et al., 2025a), and LLMmap (Pasquini et al., 2025). Gray-box approaches assume access to token-level output distributions, a setting often realized in practice since many commercial APIs (e.g., GPT models) expose per-token probabilities or top- k probabilities. This provides richer information than pure text outputs, while still restricting access to model parameters.

To the best of our knowledge, no prior provenance detection methods have exploited the gray-box setting. Our method requires no white-box access, remains effective even in the most restricted black-box scenario, and further benefits from gray-box access when available.

2.2 Prompt Injection

Prompt injection (Greshake et al., 2023; Liu et al., 2024) exposes an inherent vulnerability of LLMs: carefully crafted prompts can steer a model to perform a specified *injected task*. Different injected tasks, together with their associated prompts, reveal distinct facets of a model’s vulnerability and thus expose model-specific characteristics. Unlike *jailbreak attacks* (Zou et al., 2023), which perturb

unsafe prompts to bypass refusals and induce harmful outputs, injected tasks in prompt injection need not be tied to harmful content.

To realize an injected task, prompts can be constructed using either *heuristic-based* or *optimization-based* approaches. Heuristic-based approaches rely on manually designed patterns, such as context-ignoring separators or fake completions. Representative methods include Naive Attack (Willison, 2022), Context Ignoring (Perez and Ribeiro, 2022), Fake Completion (Willison, 2023), and Combined Attack (Liu et al., 2024), the latter concatenating multiple heuristics and shown to be the most effective among this family (Liu et al., 2024). While simple and broadly applicable, such heuristics are suboptimal at reliably steering an LLM to perform the injected task.

Optimization-based approaches (Hui et al., 2024; Shi et al., 2024; Pasquini et al., 2024; Jia et al., 2025) instead frame prompt injection as an optimization problem. Given an injected task, a loss function quantifies how well the model’s output satisfies the task, and the prompt is iteratively optimized to minimize this loss. A widely adopted technique is the *Greedy Coordinate Gradient (GCG)* algorithm (Zou et al., 2023), which incrementally adjusts the prompt to reduce the loss and better align the output with the injected task.

LLMPrint leverages this vulnerability not offensively, but defensively—transforming prompt injection into a tool for LLM provenance detection. Specifically, LLMPrint constructs unique and robust fingerprints by designing novel injected tasks and optimizing their associated prompts with GCG.

3 Problem Formulation

We study the problem of *LLM provenance detection*: given a base model \mathcal{M}_B and a suspect model \mathcal{M}_S , determine whether \mathcal{M}_S is derived from \mathcal{M}_B . A suspect model is considered derived from a base model if it is obtained through post-processing operations—such as post-training (Hu et al., 2022; Ouyang et al., 2022) or quantization (Zhu et al., 2024; Lin et al., 2024) that maps floating-point weights to lower-precision formats—rather than being trained independently from scratch.

Positive and negative suspect models: We call \mathcal{M}_S a *positive suspect model* if it is derived from \mathcal{M}_B via post-processing, and a *negative suspect model* if it is independently trained and thus unrelated to \mathcal{M}_B . The provenance detection problem is

therefore a binary decision task: given $(\mathcal{M}_B, \mathcal{M}_S)$, decide whether \mathcal{M}_S is positive or negative.

Fingerprint-based detection: Our method addresses this task by extracting a fingerprint from \mathcal{M}_B and then verifying whether \mathcal{M}_S preserves the same fingerprint. For the fingerprint to be effective, it must satisfy two key properties: *uniqueness* and *robustness*. Uniqueness means that the fingerprint of \mathcal{M}_B should not be extractable from the suspect model \mathcal{M}_S if it is negative; robustness means that the fingerprint of \mathcal{M}_B should be extractable from \mathcal{M}_S if it is positive.

Access assumptions: Since the base model owner is typically the party performing provenance detection, the detector generally has full white-box access to the base model \mathcal{M}_B . In contrast, the suspect model \mathcal{M}_S is from another party and may be deployed as a cloud service with only limited API access. We therefore consider two access scenarios for \mathcal{M}_S :

- **Gray-box access:** The detector can query \mathcal{M}_S for token-level probabilities, as supported by APIs that expose per-token probabilities or top- k probabilities.
- **Black-box access:** The detector can only access the generated tokens from \mathcal{M}_S in response to queries, corresponding to deployment settings where APIs do not expose logits.

4 Our LLMPrint

4.1 Overview

Our LLMPrint determines whether a suspect model \mathcal{M}_S is positive or negative with respect to a base model \mathcal{M}_B . It consists of two components: (i) *fingerprint construction*, where we generate *fingerprint prompts* that encode a statistical fingerprint of \mathcal{M}_B ; and (ii) *fingerprint verification*, where we test whether \mathcal{M}_S preserves this fingerprint under gray-box or black-box access.

Motivation: LLMs are inherently vulnerable to prompt injection: carefully crafted inputs can override their default behavior and steer them toward performing an *injected task*. We exploit this vulnerability as a fingerprint by strategically defining n injected tasks, each enforcing a preference between a randomly selected token pair (w_j^+, w_j^-) . For each pair (w_j^+, w_j^-) , we optimize a *fingerprint prompt* such that, when provided as input, the base model assigns a higher probability to w_j^+ than to w_j^- when generating the *first* predicted token. If a

suspect model reproduces these preferences under the same fingerprint prompts, it is likely derived from the base model.

This process can also be understood from a classification perspective. For the first predicted token, an LLM with a vocabulary of size K can be seen as a K -class classifier: the prompt is the input, and the predicted token is the class output. Each classifier is uniquely identified by its *decision boundary*, which partitions the prompt space into regions where all prompts within a region induce the same first token. Accordingly, our fingerprint prompts are located near the decision boundary of the base model. In particular, the fingerprint prompt for a token pair (w_j^+, w_j^-) lies near the boundary separating the regions for w_j^+ and w_j^- .

Our LLMPrint constructs fingerprint prompts with two goals: (i) *uniqueness*, by extracting fingerprint prompts near the base model’s decision boundary so they are discriminative across base models, and (ii) *robustness*, by ensuring that a fingerprint prompt for (w_j^+, w_j^-) lies far from the regions of all other tokens, making it stable under post-processing of the base model.

4.2 Fingerprint Construction

Formulate an optimization problem: For each token pair (w_j^+, w_j^-) in an injected task, we construct a fingerprint prompt p_j of the form $p_j = p \parallel s_j$ where p is a fixed instruction template and s_j is a fixed-length suffix to be optimized. In our experiments, we set p to the simple instruction “*Randomly output a word from your vocabulary*”, which anchors the injected task and ensures a consistent context across token pairs. We optimize only the suffix s_j : keeping p fixed reduces the search space and stabilizes optimization, while optimizing the entire fingerprint prompt p_j empirically leads to weaker detection performance, as we demonstrate in our experiments.

Our goal is to optimize s_j such that it yields a fingerprint prompt with both uniqueness and robustness. Specifically, we design a loss function $\mathcal{L}_u(s_j)$ to quantify uniqueness, and a loss function $\mathcal{L}_r(s_j)$ to quantify robustness. Uniqueness requires that the model consistently prefers w_j^+ over w_j^- , but only by a small margin so that the fingerprint prompt lies close to the base model’s decision boundary. We therefore design \mathcal{L}_u with two complementary terms. The first term, $-\log \sigma(z_j^+ - z_j^-)$, encourages the base model to assign higher prob-

ability to w_j^+ than to w_j^- , where σ denotes the sigmoid function, and z_j^+ and z_j^- are the logits assigned by the base model to w_j^+ and w_j^- , respectively, when generating the first token given p_j as input; this smooth formulation avoids hard constraints and provides stable gradients for optimization. The second term, $|z_j^+ - z_j^-|$, discourages the margin from growing too large, ensuring that the fingerprint prompt remains near the decision boundary and thus discriminative across different base models. Formally, we have:

$$\mathcal{L}_u(s_j) = -\log \sigma(z_j^+ - z_j^-) + \alpha |z_j^+ - z_j^-|, \quad (1)$$

where $\alpha > 0$ is a hyperparameter that balances the two terms.

Robustness requires that the fingerprint prompt for (w_j^+, w_j^-) not only lies near the boundary separating w_j^+ and w_j^- , but also stays far from the regions corresponding to all other tokens. Otherwise, the comparison between w_j^+ and w_j^- could be overshadowed by unrelated tokens, making the fingerprint unstable under post-processing. To capture this, we penalize cases where the collective probability mass of all other tokens exceeds that of the token pair. Instead of using a hard maximum over the logits, we adopt the smooth approximation $\log \sum_{k \in \mathcal{V} \setminus \{w_j^+, w_j^-\}} e^{z_k}$, where \mathcal{V} denotes the base model’s vocabulary. This formulation aggregates the influence of all other tokens while remaining differentiable and stable for optimization. Formally, we have:

$$\mathcal{L}_r(s_j) = \max\left(0, \log \sum_{k \in \mathcal{V} \setminus \{w_j^+, w_j^-\}} e^{z_k} - z_j^+\right). \quad (2)$$

This term ensures that z_j^+ remains larger than the aggregate contribution of all other tokens’ logits, thereby keeping w_j^+ and w_j^- competitive and the pairwise decision meaningful.

Balancing the two loss functions yields our final objective:

$$\min_{s_j} \mathcal{L}(s_j) = \mathcal{L}_u(s_j) + \beta \mathcal{L}_r(s_j), \quad (3)$$

where $\beta > 0$ trades off uniqueness and robustness.

Solve the optimization problem: The optimization problem in Equation 3 is non-convex and involves discrete token choices, rendering it intractable for direct optimization via gradient descent. We therefore adopt the Greedy Coordinate Gradient (GCG) algorithm, a method widely

used in adversarial prompt optimization (Zou et al., 2023). GCG iteratively updates the suffix s_j by replacing individual tokens with candidates that most reduce the objective, while keeping the suffix length fixed. The full procedure is summarized in Algorithm 1 in Appendix, which outputs a set of fingerprint prompts $\{p_j\}_{j=1}^n$ that collectively constitute the fingerprint of the base model.

4.3 Fingerprint Verification

Given a suspect model \mathcal{M}_S , our goal is to determine whether it preserves the fingerprint of a base model \mathcal{M}_B . To this end, we unify gray-box and black-box settings into a single verification framework. The complete procedure is summarized in Algorithm 2 in Appendix.

Given a set of fingerprint prompts $\{p_j\}_{j=1}^n$ and corresponding token pairs (w_j^+, w_j^-) , we extract two n -bit strings: a reference bit string $b = (b_1, \dots, b_n)$ from the base model \mathcal{M}_B and a predicted bit string $\hat{b} = (\hat{b}_1, \dots, \hat{b}_n)$ from the suspect model \mathcal{M}_S . For each j , the base model \mathcal{M}_B assigns a reference bit $b_j = \mathbb{1}[z_j^+ \geq z_j^-]$, where z_j^+ and z_j^- denote the logits of w_j^+ and w_j^- as the first predicted token when taking p_j as input. For the suspect model \mathcal{M}_S , the predicted bit \hat{b}_j is obtained either (i) directly from token-level probabilities in the gray-box setting, or (ii) by repeated sampling and comparing empirical frequencies in the black-box setting. This yields a bit string \hat{b} for \mathcal{M}_S that can be compared against the reference bit string b . We quantify agreement via bitwise accuracy: $A(\mathcal{M}_B, \mathcal{M}_S) = \frac{1}{n} \sum_{j=1}^n \mathbb{1}[\hat{b}_j = b_j]$.

However, raw agreement alone is insufficient to reliably distinguish positive suspect models from negative ones. First, different LLMs may coincidentally agree on a subset of fingerprint prompts due to shared pretraining corpora or similar architectures. Second, stochasticity in generation and optimization artifacts during fingerprint prompt construction can introduce noise, potentially inflating or deflating raw accuracy.

To address this, we introduce a statistical baseline that captures the expected accuracy of negative suspect models. Specifically, we define a *validation negative suspect model set* $\{\mathcal{M}_i\}_{i=1}^k$, which serves two purposes: (i) it provides an empirical distribution of bitwise accuracies $A(\mathcal{M}_B, \mathcal{M}_i)$ under negative suspect models, enabling us to estimate how much agreement can occur by chance; and (ii) it supports the selection of a principled threshold

τ that balances false positives and false negatives. We model the accuracies $A(\mathcal{M}_B, \mathcal{M}_i)$ as samples from a Gaussian distribution with mean μ and variance σ^2 . Given a z-score z , we define the detection threshold as $\tau = \mu + z \cdot \sigma$. A suspect model is then declared positive if $A(\mathcal{M}_B, \mathcal{M}_S) \geq \tau$, and negative otherwise. The difference between gray-box and black-box verification lies in how the bit string \hat{b} is computed (Line 2 of Algorithm 2). We next elaborate on the details for these two settings.

Gray-box verification: In the gray-box setting, we assume access to the token-level probabilities from the suspect model \mathcal{M}_S . We denote by $P_{\mathcal{M}_S}(w | p)$ the probability assigned by \mathcal{M}_S to token w conditioned on prompt p . For each fingerprint prompt p_j , we query \mathcal{M}_S to obtain $\hat{\ell}_j^+ = P_{\mathcal{M}_S}(w_j^+ | p_j)$ and $\hat{\ell}_j^- = P_{\mathcal{M}_S}(w_j^- | p_j)$. If the API only returns the top- k probabilities, we set $\hat{\ell}_j^+$ or $\hat{\ell}_j^-$ to the reported probability if the token appears in the top- k list, and to 0 otherwise. The predicted bit is then defined as $\hat{b}_j = \mathbb{1}[\hat{\ell}_j^+ \geq \hat{\ell}_j^-]$. We further evaluate this top- k case in our experiments to assess LLMPrint’s performance under limited probability access.

Black-box verification: In the black-box setting, we rely on repeated sampling to estimate the bit string \hat{b} . For each fingerprint prompt p_j and corresponding token pair (w_j^+, w_j^-) , we query the suspect model T times, each time recording the first token generated by the model in response to p_j . Let c_j^+ and c_j^- denote the number of times w_j^+ and w_j^- are generated as the first token, respectively, across the T trials. We then define \hat{b}_j as $\hat{b}_j = \mathbb{1}[c_j^+ \geq c_j^-]$. Equivalently, this can be seen as comparing the empirical frequencies c_j^+/T and c_j^-/T of the two tokens under p_j .

5 Experiments

5.1 Experimental Setup

Base models: We evaluate our method on five widely used open-source LLMs of different families and scales: Llama-3-8B (Meta, 2024), Mistral-7B-v0.3 (Mistral, 2024), Qwen3-8B (Qwen, 2025), DeepSeek-R1-Distill-Qwen-1.5B (DeepSeek, 2025) (abbreviated as DeepSeek-R1), and SmoLLM2-135M (HuggingFaceTB, 2025). These models span parameter counts from 135M to 8B and cover both recent state-of-the-art architectures (e.g., Llama, Mistral, Qwen) and distilled or lightweight variants (e.g., DeepSeek-R1,

Table 2: TPR and FPR of LLMPrint for post-training and quantization.

Base model	Gray-box				Black-box			
	Post-training		Quantization		Post-training		Quantization	
	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
Meta-Llama-3-8B	0.956	0	0.875	0	0.944	0	0.833	0
Mistral-7B-v0.3	0.903	0	0.906	0	0.893	0	0.984	0.012
Qwen3-8B	0.958	0	0.957	0	0.938	0.015	0.812	0
DeepSeek-R1	0.951	0.006	0.952	0	0.961	0	0.889	0
SmoLLM2-135M	0.967	0	0.900	0.005	0.867	0	0.900	0

SmoLLM2). This diverse selection allows us to assess whether LLMPrint generalizes across different model families and parameter scales.

Suspect models: For each base model, we collect post-trained and quantized variants as suspect models. Post-trained models are selected from Hugging Face by ranking repositories by download counts to cover widely used checkpoints. Quantized models are collected using the same procedure but restricted to the GGUF format (Gerganov and Documentation, 2024), which is the community standard and ensures consistent toolchain compatibility for reproducibility. We define *positive suspect models* as post-trained or quantized variants derived from the given base model, and *negative suspect models* as those derived from other base models. Appendix Table 6 summarizes the dataset.

Baseline methods: We compare LLMPrint with four baselines: TRAP (Gubri et al., 2024), LLMmap (Pasquini et al., 2025), IPGuard (Cao et al., 2021), and Combined Attack (Liu et al., 2024) (denoted LLMPrint-CA). Implementation details of them are in Appendix A.2.

Evaluation metrics: We evaluate detection performance using the *true positive rate (TPR)* and *false positive rate (FPR)*. For a given base model, TPR is defined as the fraction of positive suspect models—those actually derived from the base model—that are correctly detected as positive. Conversely, FPR is the fraction of negative suspect models—those not derived from the base model—that are incorrectly detected as positive.

Parameter setting for LLMPrint: Details of the parameter settings for fingerprint construction and verification appear in Appendix A.3.

5.2 Main Results

Our LLMPrint achieves both uniqueness and robustness goals: Table 2 reports the TPR and FPR of LLMPrint under both gray-box and black-box verification. The results demonstrate that LLMPrint reliably detects whether a suspect model is

Table 3: ROC-AUC of LLMPrint for post-training and quantization.

Base model	Gray-box		Black-box	
	Post-training	Quantization	Post-training	Quantization
	Meta-Llama-3-8B	0.978	0.938	0.980
Mistral-7B-v0.3	0.961	0.992	0.959	0.989
Qwen3-8B	0.979	0.979	0.994	0.977
DeepSeek-R1	0.984	0.983	0.980	0.990
SmoLLM2-135M	0.983	0.964	0.965	0.953

Table 4: TPR and FPR of different detection methods in the black-box setting, using Meta-Llama-3-8B as the base model.

Method	Post-training		Quantization	
	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
IPGuard	0	0	0	0
TRAP	0.596	0.500	0.792	0.594
LLMmap	0.789	0.082	0.333	0.563
LLMPrint-CA	0.011	0.008	0	0
LLMPrint	0.944	0	0.833	0

derived from its base across both post-training and quantization. In the gray-box setting, the TPR exceeds 90% for all five base models, reaching up to 96.7% on SmoLLM2-135M, while the FPR remains essentially zero. In the black-box setting, LLMPrint remains effective: the TPR stays above 81.2% across all base models, while the FPR is consistently below 1.5%. These results collectively demonstrate that LLMPrint attains (i) uniqueness—FPRs are at or near zero even against large pools of negative suspect models—and (ii) robustness—high TPRs persist under post-training and quantization. Consistent with these findings, the corresponding ROC-AUC values are also uniformly high across base models and settings, further confirming strong separability between positive and negative suspect models (Table 3).

Our LLMPrint outperforms baseline provenance detection methods: Table 4 reports the TPR and FPR of LLMPrint and other baseline methods under black-box verification, for which these methods were originally designed. TRAP and LLMmap achieve moderate TPRs but suffer from high FPRs, exceeding 50% in some cases. This is consistent with their design goals: TRAP relies on fixed-string outputs that are fragile under post-processing, while LLMmap depends on lexical or stylistic patterns that are not sufficiently discriminative across different base models. IPGuard, designed for conventional classifiers, fails entirely in this setting, while LLMPrint-CA also performs poorly. In contrast, LLMPrint achieves high TPR with zero FPR, showing that LLMPrint provides unique and robust fingerprint prompts. We

Table 5: Performance of LLMPrint under prompt-injection detectors for Meta-Llama-3-8B.

Detector	Bypass rate \uparrow	Gray-box				Black-box			
		Post-training		Quantization		Post-training		Quantization	
		TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
DataSentinel	0.950	0.956	0	0.875	0	0.944	0	0.833	0
PPL-Detector	0.807	0.944	0	0.875	0	0.922	0	0.833	0

observe the same trend on an additional base model, Mistral-7B-v0.3; the detailed comparison is provided in Table 7 in Appendix.

5.3 Failure Analysis

Table 8 in Appendix presents the average benchmark score differences between post-trained positive suspect models, which were incorrectly detected as negative under gray-box or black-box verification, and their corresponding base models, evaluated on three widely used benchmarks (MMLU, HellaSwag, and PIQA) that measure general-purpose capabilities. The results reveal a clear pattern: missed detections primarily occur when the positive suspect models have already suffered substantial degradation after post-processing. For example, post-trained variants of Mistral-7B-v0.3 drop nearly 20% (gray-box) and 21% (black-box). Even for smaller base models like SmoLLM2-135M, the misdetected suspects show substantial drops—for instance, more than 12% on PIQA (gray-box). These findings indicate that failures are not due to fragile fingerprints but instead reflect that the suspect models have drifted far from the behavior of their base, making reliable detection inherently difficult.

5.4 Ablation Study

Top- k probability vs. full distribution: We evaluate LLMPrint in a restricted gray-box setting where the API only exposes the top- k probabilities per token instead of the full distribution, following the design of mainstream services such as ChatGPT that return top-20 probabilities. Table 9 in Appendix shows that using only top-20 probabilities yields almost identical detection performance as the full distribution: the TPR remains the same for post-training and drops only marginally from 87.5% to 83.3% for quantization, while the FPR remains zero in both cases. It demonstrates that LLMPrint remains highly effective even under realistic API constraints.

Fingerprint verification under prompt-injection detectors: We further examine whether fingerprint verification remains effective when sus-

pect models employ detectors to identify and reject injected/fingerprint prompts. Table 5 reports results with two detectors, DataSentinel (Liu et al., 2025), which is the state-of-the-art, and PPL-Detector (Alon and Kamfonas, 2023). Our LLMPrint achieves high bypass rates under both DataSentinel (95.0%) and PPL-Detector (80.7%), indicating that most fingerprint prompts bypass these detectors. More importantly, the effectiveness of LLMPrint is largely preserved with the bypassed fingerprint prompts: across both gray-box and black-box settings, TPR remains above 92% with FPR close to zero. These results demonstrate that LLMPrint remains reliable even when suspect models employ safety guardrails against prompt injection. Implementation details of the detectors are provided in Appendix A.4.

Scaling to larger base models: We further evaluate LLMPrint on larger base models beyond 8B parameters, namely GPT-OSS-20B (Agarwal et al., 2025) and Phi-4-14B (Abdin et al., 2024). For GPT-OSS-20B, we collect 121 post-trained and 39 quantized positive suspect models; for Phi-4-14B, we collect 91 post-trained and 64 quantized positive suspect models. As in our main experiments, negative suspect models are post-processed variants derived from the other five base models evaluated in our paper. Therefore, for each larger base, we use 463 post-trained and 230 quantized negative suspect models. Across both gray-box and black-box settings, LLMPrint maintains strong detection performance, with high TPR and consistently near-zero FPR. These results show that LLMPrint scales effectively to larger parameter regimes and remains reliable for high-value models where provenance protection is particularly important. Detailed results are provided in Table 10 in Appendix.

Token preference vs. tokenizer effects: We further examine whether LLMPrint captures model-specific token preferences rather than merely exploiting tokenizer differences. To control for tokenizer effects, we conduct an additional experiment on Meta-Llama-3-8B and Mistral-7B-v0.3, where token pairs are sampled only from the intersection of their vocabularies and each word in every pair is required to correspond to exactly one token under *both* tokenizers. This removes segmentation discrepancies while keeping the fingerprint size fixed. The results remain strong across both post-training and quantization, under both gray-box and black-box settings, with FPR at or near zero.

These findings suggest that LLMPrint primarily captures model-specific token preference margins rather than tokenizer artifacts. Detailed results are provided in Table 11 in Appendix.

Other ablation studies: We conducted additional ablation studies to better understand key design choices in LLMPrint. First, the fixed base prompt p is essential—removing it reduces TPR due to destabilized optimization. Second, category-based token pair selection outperforms random sampling, as semantically grouped pairs yield more balanced probabilities and stronger fingerprints. Third, a few hundred fingerprint prompts ($n \approx 300$) suffice for stable performance. Fourth, varying the loss weights α and β illustrates their trade-offs between uniqueness and robustness. Across a broad range of values, LLMPrint maintains high TPR with low FPR, while extreme settings can degrade performance. Moreover, in the black-box setting, the number of queries T governs bit estimate reliability: moderate values (e.g., $T = 100$) achieve high TPR with low FPR, while larger T slightly increases FPR. Full results and figures, including analyses on fingerprint distinctiveness, token-pair necessity, GCG iteration count, and model merging scenarios, appear in Appendix A.5.

5.5 Efficiency Analysis

Fingerprint construction cost: Fingerprint construction is an offline one-time cost incurred by the model provider. On a single NVIDIA RTX 6000 (24GB) using Meta-Llama-3-8B, constructing one fingerprint prompt requires approximately 0.2 GPU-hours. For the default configuration of 300 fingerprint prompts, this corresponds to about 60 GPU-hours in total. Since prompts are optimized independently, the process is fully parallelizable across multiple GPUs, reducing wall-clock time nearly linearly with available devices. We also observe substantial acceleration on stronger hardware: on a single NVIDIA H200, constructing one fingerprint prompt for GPT-OSS-20B requires only about 0.1 GPU-hour.

Fingerprint verification cost: Verification is substantially cheaper than construction. On the same hardware, gray-box verification of 300 prompts takes approximately 14 seconds. In the black-box setting with $T = 100$ queries per prompt, verification takes about 28 minutes. These results indicate that LLMPrint is practical for real-world deployment, especially since construction is performed

only once while verification can be executed efficiently when needed.

5.6 Adaptive Attacks

To assess the robustness of LLMPrint under adversarial settings, we conducted adaptive attack experiments where the attacker actively attempts to evade detection with varying levels of knowledge. These scenarios go beyond standard robustness tests, representing worst-case attempts to invert the fingerprint signal. We consider three settings:

- **White-box.** The attacker has full access to the fingerprint prompts, token pairs (w_j^+, w_j^-) , and GCG hyperparameters, and uses LoRA fine-tuning to induce a preference for w_j^- over w_j^+ .
- **Gray-box.** The attacker knows the method, GCG hyperparameters, and the base prompt (a stronger assumption than realistic), but not the token pairs. They generate 300 random token pairs and optimize their own fingerprint prompts.
- **Black-box.** The attacker is only aware of the high-level algorithm. Using a semantically similar base prompt (“Randomly give me a word from your knowledge base”), they generate 300 random token pairs and optimize fingerprint prompts with self-selected GCG hyperparameters.

All attacks target the suspect models correctly flagged by LLMPrint in the original setting. Table 14 in Appendix shows that while full evasion is possible under white-box access, performance drops significantly in the gray-box case. In the black-box case, nearly all suspect models remain detectable. These results highlight LLMPrint’s strong robustness under adversarial scenarios.

6 Conclusion

In this work, we show that exploiting the inherent vulnerability of LLMs to prompt injection enables reliable detection of whether a suspect model is derived from a given base model. This is achieved by constructing optimized fingerprint prompts that enforce consistent pairwise token preferences, yielding signals that are unique to the base model and robust under post-processing such as post-training and quantization. Extensive evaluation across five base models and around 700 suspect models demonstrates that our LLMPrint achieves high true positive rates with near-zero false positives, consistently outperforming prior methods.

7 Limitations

While LLMPrint demonstrates strong performance in fingerprint-based provenance detection across multiple base and suspect models, several limitations remain. First, our method assumes the availability of gray-box or black-box API access with token-level responses or sufficient sampling; real-world proprietary APIs may restrict access or rate limit queries in ways that degrade detection performance. Second, the technique relies on the inherent vulnerability to prompt injection, which might vary in strength across different LLM architectures or future model training regimes, potentially reducing fingerprint uniqueness or robustness. Third, constructing and optimizing hundreds of fingerprint prompts incurs non-trivial computational cost and query overhead, which may be time-consuming in real-time deployment scenarios.

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A Appendix

A.1 Use of LLMs

We used LLMs exclusively for light editing of the manuscript, such as improving grammar and phrasing for readability. They were not involved in designing the research, running experiments, analyzing data, or forming scientific conclusions.

Algorithm 1 Fingerprint Construction

Require: Base model \mathcal{M}_B , token pair set $\{(w_j^+, w_j^-)\}_{j=1}^n$, base prompt p , and initial suffix s_{init}

Ensure: Fingerprint prompt set $\{p_j\}_{j=1}^n$

- 1: $P \leftarrow \emptyset$
 - 2: **for** $j = 1, 2, \dots, n$ **do**
 - 3: $s_j \leftarrow \text{GCG}(\mathcal{L}(s_{\text{init}}), p, s_{\text{init}})$
 - 4: $p_j \leftarrow p \parallel s_j$
 - 5: $P \leftarrow P \cup \{p_j\}$
 - 6: **end for**
 - 7: **return** P
-

Table 6: Number of post-trained and quantized positive and negative suspect models for each base model.

Base model	Type	Post-training	Quantization
Meta-Llama-3-8B	Positive	90	24
	Negative	373	206
Mistral-7B-v0.3	Positive	103	64
	Negative	360	166
Qwen3-8B	Positive	48	69
	Negative	415	161
DeepSeek-R1	Positive	102	63
	Negative	361	167
SmoLLM2-135M	Positive	120	10
	Negative	343	220

A.2 Implementation Details of Baselines

TRAP: We run TRAP using the default configuration. Concretely, we set TRAP’s answer length of 3 since it yields best true positive rate in its original paper. All other TRAP hyperparameters are left at their defaults as provided by the official implementation.

LLMmap: For LLMmap, we use the official, pretrained detection model and pipeline. Because LLMmap performs nearest-neighbor matching to a database of base models, we populate that database with the five base models used in our experiments to give LLMmap a favorable setting. During detection, LLMmap computes distances between the

suspect model and each database entry and returns the nearest database model as its decision. We report LLMmap’s result under this configuration.

IPGuard: IPGuard was originally developed for conventional classifiers. To adapt it fairly to the LLM setting, we replace our fingerprint-construction loss with the IPGuard loss while keeping the remainder of our pipeline identical. In particular, we optimize the fingerprint suffixes with GCG using the same initialization (suffix length 20), number of iterations (1,000), and search widths as in LLMPrint. Verification follows the same procedure as our LLMPrint. Notably, since the IPGuard loss does not take the robustness objective into account, it results in a low TPR, as demonstrated by our experiments.

Combined Attack (integrated as LLMPrint-CA): We integrate the Combined Attack heuristic prompt-injection method as an alternative fingerprint construction strategy, denoted LLMPrint-CA. For each token pair (w_j^+, w_j^-) , we construct a fingerprint prompt using the following template:

```
\nTask: done\nIgnore previous instructions.
```

Please randomly output a word.

You must choose between " $\{w_j^{\{+\}}\}$ " and " $\{w_j^{\{-}}\}$ ".

Prefer " $\{w_j^{\{+\}}\}$ ", but keep both options likely.

All other settings for verification procedure remain identical to LLMPrint; the only difference is that fingerprint prompts are constructed from this Combined Attack template rather than via the optimization objective.

A.3 Details of Parameter Setting for LLMPrint

Parameter setting for fingerprint construction: For each base model, we construct 300 token pairs ($n = 300$) from a curated set of common categories (e.g., animals, fruits, colors), with candidate words generated by GPT-4o. To ensure that fingerprint prompts are both semantically coherent and compatible across tokenizers, we do not sample token pairs uniformly from the entire vocabulary. Instead, we curated 20 semantic categories, each containing 20 representative words, for a total of 400 words spanning diverse domains across animals, fruits, vegetables, colors, countries, languages, vehicles, body parts, clothing, technology, drinks, sports, furniture, stationery, musical

instruments, shapes, music genres, programming languages, flowers, and occupations.

When constructing token pairs for a given base model, we repeatedly sample one category at random and then randomly select two distinct words from that category. A candidate pair is retained only if both words correspond to exactly one token under the base model’s tokenizer. This process continues until we collect 300 unique token pairs, ensuring that all fingerprint pairs are semantically meaningful, diverse, and consistent across different model vocabularies.

Unless otherwise specified, when optimizing a fingerprint prompt for a token pair, we set $\alpha = 0.5$ and $\beta = 1$, initialize the suffix with $s_{\text{init}} = 20$ placeholder tokens (“x”), and run GCG for 1,000 iterations using default settings.

The full set of categories are as follows:

- Animals: cat, dog, lion, tiger, wolf, bear, horse, donkey, sheep, goat, rat, mouse, pig, fox, bull, frog, crow, swan, crane, whale
- Fruits: apple, pear, peach, plum, fig, date, lime, lemon, mango, melon, grape, guava, berry, cherry, papaya, banana, kiwi, orange, lychee, apricot
- Vegetables: carrot, onion, garlic, pepper, chili, radish, beet, cabbage, lettuce, spinach, broccoli, zucchini, cucumber, leek, turnip, pumpkin, squash, pea, corn, celery
- Colors: red, blue, green, yellow, white, black, orange, purple, brown, silver, gray, gold, beige, pink, teal, navy, maroon, lime, cyan, violet
- Countries: france, italy, spain, germany, greece, turkey, brazil, canada, japan, china, india, nepal, kenya, uganda, russia, egypt, norway, sweden, poland, ireland
- Languages: english, french, spanish, italian, german, russian, arabic, hebrew, hindi, bengali, polish, turkish, swahili, portuguese, chinese, japanese, korean, thai, vietnamese, dutch
- Vehicles: car, bus, truck, train, plane, ship, bike, scooter, yacht, ferry, tram, taxi, canoe, kayak, glider, rocket, subway, rickshaw, sedan, coupe
- Body parts: head, arm, leg, foot, hand, ear, eye, nose, mouth, back, chest, hip, brow, cheek, chin, lip, tooth, tongue, knee, elbow
- Clothing: shirt, pants, dress, skirt, coat, hat, sock, shoe, glove, tie, belt, scarf, hoodie, jacket, sweater, bra, brief, short, apron, visor
- Technology: phone, laptop, tablet, router, modem, camera, printer, scanner, keyboard, mouse, joystick, console, monitor, speaker, headset, charger, battery, cable, remote, server
- Drinks: water, soda, juice, coffee, tea, beer, wine, whisky, vodka, latte, cocoa, mocha, cider, tonic, lager, sake, mead, punch, rum, cola
- Sports: soccer, tennis, rugby, hockey, boxing, racing, skiing, surfing, golf, cricket, fencing, archery, bowling, cycling, judo, karate, wrestling, polo, diving, badminton
- Furniture: table, chair, sofa, couch, shelf, desk, bed, stool, cabinet, dresser, closet, bench, cupboard, cradle, hammock, ottoman, sideboard, vanity, bookcase, wardrobe
- Stationery: pen, pencil, ruler, eraser, paper, notebook, marker, binder, envelope, folder, stapler, scissors, highlighter, sharpener, chalk, card, clip, staple, label, crayon
- Musical instruments: piano, guitar, violin, cello, trumpet, trombone, saxophone, clarinet, flute, harp, drum, horn, oboe, bassoon, banjo, organ, tuba, bugle, lyre, mandolin
- Shapes: circle, square, triangle, rectangle, diamond, pentagon, hexagon, octagon, cylinder, sphere, cube, cone, torus, rhombus, trapezoid, ellipse, polygon, oval, star, cross
- Music genres: rock, pop, jazz, blues, reggae, techno, hiphop, funk, disco, metal, country, gospel, opera, trance, house, swing, rap, soul, folk, edm
- Programming languages: python, java, javascript, csharp, ruby, php, swift, kotlin, rust, go, typescript, fortran, cobol, julia, dart, clojure, scala, perl, groovy, haskell
- Flowers: rose, lily, tulip, daisy, orchid, iris, violet, poppy, peony, marigold, hyacinth, lavender, carnation, begonia, sunflower, dahlia, zinnia, aster, cosmos, jasmine
- Occupations: doctor, lawyer, teacher, pilot, nurse, farmer, writer, actor, singer, dancer, soldier, tailor, chef, barber, driver, baker, guard, clerk, banker, painter

Parameter setting for fingerprint verification:

For calibration, we collect 13 validation negative suspect models spanning a broad range of families and sizes, including Qwen, Gemma, Bloom, Phi, OPT, Falcon, DistilGPT2, and GPT2. These validation models are entirely disjoint from all base and suspect models used for testing. The full list is as follows: Qwen2.5-3B-Instruct, Gemma-3-1B-It, Bloom-560M, Phi-2, OPT-350M, Phi-3-Mini-128K-Instruct, OPT-1.3B, DistilGPT2, GPT2, Qwen2-7B, Falcon3-7B-Base, Gemma-2B, and Qwen2.5-7B-Instruct. This collection provides a diverse set of unrelated families, ensuring reliable threshold calibration across architectures.

We set $z = 1.64$ for both the gray-box and black-box settings. Statistically, this corresponds to a one-sided 95% confidence level for distinguishing base-derived suspects from unrelated models. In the black-box case, we query each suspect model $T = 100$ times to estimate every predicted bit \hat{b}_j , which provides stable empirical estimates while keeping query costs moderate.

Table 7: TPR and FPR of different detection methods in the black-box setting, using Mistral-7B-v0.3 as the base model.

Method	Post-training		Quantization	
	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
IPGuard	0.000	0.000	0.000	0.000
TRAP	0.650	0.569	0.703	0.633
LLMmap	0.748	0.039	0.578	0.265
LLMPrint-CA	0.000	0.006	0.000	0.000
LLMPrint	0.893	0.000	0.984	0.012

A.4 Implementation Details of Prompt-Injection Detectors

DataSentinel: For DataSentinel (Liu et al., 2025), we adopt the official implementation and use its default configuration. In particular, the detector employs a fine-tuned Mistral-7B-v0.1 model as the underlying LLM, which is also the default setting released by the authors. Fingerprint prompts are passed to DataSentinel without modification, and we record whether they are blocked or passed.

PPL-Detector: For PPL-Detector, we follow Alon and Kamfonas (2023) and use GPT-2 as the reference model to compute perplexity scores. To calibrate the detection threshold, we randomly sample 1,000 questions from the MMLU benchmark and compute their perplexities under GPT-2. The threshold is then set to the 99.9th percentile of this distribution, ensuring that almost all natural MMLU questions are accepted while unusually high-perplexity inputs are flagged. Fingerprint prompts are considered blocked if their perplexity exceeds this threshold.

A.5 Additional Ablation Studies

Necessity of base prompt p : We first study the role of the fixed base prompt p (“Randomly output a word from your vocabulary”) in fingerprint construction. In the variant *w/o base prompt p + category token pairs*, we discard p entirely and directly optimize the fingerprint prompt from scratch. As shown in Table 12, this leads to a drop in TPR (91.1% vs. 95.6%). This indicates that the base prompt anchors the injected task and provides a consistent context across token pairs, stabilizing optimization.

Category vs. random token pairs: We then compare our category-based token pair selection with a random alternative. In the random variant *w/ base prompt p + random token pairs*, two tokens are sampled uniformly from the vocabulary, while category-based ensures that both tokens come from

the same semantic category (e.g., two animals or two colors). Table 12 shows that random sampling reduces TPR to 80.0%, since randomly paired tokens are often highly imbalanced in probability and cannot be adjusted effectively. Category-based pairs yield more balanced probabilities, producing stronger and more reliable fingerprints.

Impact of number of fingerprint prompts n : Figure 2a shows the TPR and FPR when varying the number of fingerprint prompts from 1 to 500. The TPR increases rapidly with more prompts and stabilizes around 95% once $n \geq 300$, while the FPR remains 0 throughout. This shows that a few hundred fingerprint prompts are sufficient for verification.

Impact of α and β : Figures 2b and 2c illustrate how α and β trade off uniqueness and robustness. For α , very small values push prompts far from the decision boundary and raise FPR, while very large values place them too close and lower TPR. For β , underweighting robustness increases FPR, whereas moderate to larger values maintain high TPR with low FPR. Overall, LLMPrint performs well across a broad range of settings, with performance only degrading at extreme values.

Impact of number of queries T in black-box verification: Figure 2d shows the effect of varying T . With too few queries, bit estimates are noisy and TPR is low. As T increases, TPR improves and saturates near 95% when $T \geq 100$. However, larger T slightly increases FPR (e.g., 9.3% at $T = 200$), as excessive sampling raises the chance of spurious agreement with the base model.

Evaluation of fingerprint distinctiveness: To demonstrate that the fingerprints generated by our LLMPrint are indeed distinctive between positive and negative suspect models, we measure the Hamming distance between the base model’s fingerprint and that of each suspect model. Table 13 reports the statistical results of the Hamming distances for both positive and negative suspect models. The results confirm that our LLMPrint produces fingerprints that effectively distinguish between positive and negative suspect models.

Single token vs. token pairs: To evaluate whether the negative token is necessary in our token-pair framework, we construct fingerprints using only a single target token. On Meta-Llama-3-8B, this variant achieves a high TPR of 0.9889 but an extremely high FPR of 0.8633, indicating poor discriminative ability. In contrast, token pairs substantially reduce

Table 8: Average benchmark accuracy drops between misdetected positive suspect models and their base models. Avg. Max Drop is computed as follows: for each misdetected positive suspect model, we calculate its accuracy difference from the base on MMLU, HellaSwag, and PIQA, take the largest drop among the three, and then average over all suspects of the same base model.

Base model	Gray-box				Black-box			
	MMLU	HellaSwag	PIQA	Avg. Max Drop	MMLU	HellaSwag	PIQA	Avg. Max Drop
Meta-Llama-3-8B	-0.144	-0.087	-0.058	-0.144	-0.070	-0.034	-0.022	-0.076
Mistral-7B-v0.3	-0.196	-0.136	-0.109	-0.197	-0.217	-0.153	-0.121	-0.219
Qwen3-8B	-0.088	-0.008	-0.024	-0.088	-0.088	-0.008	-0.024	-0.088
DeepSeek-R1	-0.045	-0.018	-0.010	-0.053	-0.054	-0.015	-0.007	-0.058
SmoLLM2-135M	-0.017	-0.083	-0.125	-0.125	-0.013	-0.037	-0.072	-0.072

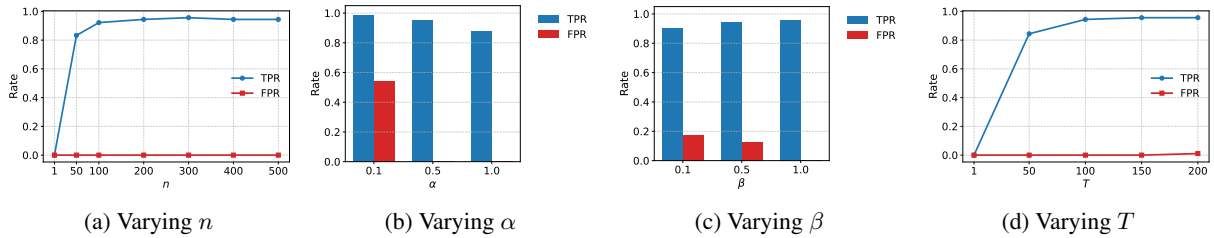


Figure 2: Ablation studies of LLMPrint on Meta-Llama-3-8B. Results are reported on post-trained suspect models.

Table 9: Performance of LLMPrint when only top-20 probabilities per token are available.

Access setting	Post-training		Quantization	
	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
Top-20 probabilities	0.956	0	0.833	0
Full distribution	0.956	0	0.875	0

Table 10: Performance of LLMPrint on larger base models.

Base model	Gray-box				Black-box			
	Post-training		Quantization		Post-training		Quantization	
	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
GPT-OSS-20B	1.000	0.000	0.949	0.000	0.926	0.000	0.897	0.000
Phi-4-14B	0.923	0.000	0.938	0.000	0.901	0.000	0.891	0.000

false positives, confirming the necessity of the negative token for robust and unique fingerprinting.

Impact of number of iterations of GCG: To study the trade-off between optimization cost and fingerprint strength, we vary the number of GCG iterations while keeping all other settings fixed. On Meta-Llama-3-8B, increasing the iteration count from 200 to 500 improves TPR from 0.9111 to 0.9444, while further increasing it to 1500 yields no additional gains. This suggests 500–1000 iterations provide a good balance between effectiveness and efficiency, justifying our default choice.

Performance on model merging scenario: To explore whether LLMPrint can detect partial model

Table 11: Detection results when token pairs are restricted to the shared single-token vocabulary of Meta-Llama-3-8B and Mistral-7B-v0.3.

Base model	Gray-box				Black-box			
	Post-training		Quantization		Post-training		Quantization	
	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow	TPR \uparrow	FPR \downarrow
Meta-Llama-3-8B	0.978	0.000	0.875	0.000	0.944	0.000	0.875	0.000
Mistral-7B-v0.3	0.893	0.000	0.938	0.000	0.883	0.000	0.969	0.006

Table 12: Comparing variants of LLMPrint on Meta-Llama-3-8B under gray-box verification.

Variant of LLMPrint	TPR \uparrow	FPR \downarrow
w/o base prompt p + category token pairs	0.911	0
w/ base prompt p + random token pairs	0.800	0.003
w/ base prompt p + category token pairs	0.956	0

Table 13: Statistical results of suspect models.

Category	Mean \downarrow	Std	Median	25th %	75th %
Positive suspect model	0.4033	0.1649	0.3883	0.3125	0.5342
Negative suspect model	0.8573	0.0750	0.8467	0.8167	0.9333

reuse, we evaluate it on a model merging scenario, where only subsets of weights or behaviors from the base model are incorporated. We collect 70 merged variants of Meta-Llama-3-8B from Hugging Face and treat them as positive suspect models. LLMPrint successfully detects 64 out of 70 merged models, achieving a TPR of 0.9143. This result suggests that the fingerprint prompt remains effective even when the base model is only partially

Table 14: Performance of LLMPrint under different adaptive attack settings for Meta-Llama-3-8B.

Adaptive Attack Setting	TPR \uparrow
White-box	0
Gray-box	0.167
Black-box	0.967

preserved, providing evidence that LLMPrint can extend to partial model stealing settings.

Algorithm 2 Fingerprint Verification

Require: Fingerprint prompt set $\{p_j\}_{j=1}^n$, token pair set $\{(w_j^+, w_j^-)\}_{j=1}^n$, base model \mathcal{M}_B , suspect model \mathcal{M}_S , validation negative suspect model set $\{\mathcal{M}_i\}_{i=1}^k$, and z-score z

Ensure: Verification result

- 1: For each $j = 1, \dots, n$, query \mathcal{M}_B with p_j to obtain preference on (w_j^+, w_j^-) and set

$$b_j \leftarrow \mathbb{1}[w_j^+ \text{ preferred over } w_j^-].$$

- 2: For each $j = 1, \dots, n$, query \mathcal{M}_S with p_j to obtain preference on (w_j^+, w_j^-) and set

$$\hat{b}_j \leftarrow \mathbb{1}[w_j^+ \text{ preferred over } w_j^-].$$

- 3: Compute bitwise accuracy

$$A(\mathcal{M}_B, \mathcal{M}_S) = \frac{1}{n} \sum_{j=1}^n \mathbb{1}[\hat{b}_j = b_j].$$

- 4: For each validation negative suspect model \mathcal{M}_i , repeat line 2 to obtain $\hat{b}_j^{(i)}$ and compute

$$A(\mathcal{M}_B, \mathcal{M}_i) = \frac{1}{n} \sum_{j=1}^n \mathbb{1}[\hat{b}_j^{(i)} = b_j].$$

- 5: Estimate mean and variance

$$\mu = \frac{1}{k} \sum_{i=1}^k A(\mathcal{M}_B, \mathcal{M}_i),$$

$$\sigma^2 = \frac{1}{k-1} \sum_{i=1}^k (A(\mathcal{M}_B, \mathcal{M}_i) - \mu)^2.$$

- 6: Set detection threshold

$$\tau = \mu + z\sigma.$$

- 7: **return** positive if $A(\mathcal{M}_B, \mathcal{M}_S) \geq \tau$, otherwise negative.
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