Fingerprint Vector: Enabling Scalable and Efficient Model Fingerprint Transfer via Vector Addition

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Abstract

Backdoor-based fingerprinting is a widely used technique for verifying the ownership of large language models, but it scales poorly when a single foundation model is fine-tuned into numerous downstream variants. Fingerprinting each model individually is costly, while inheritance-based approaches that embed fingerprints into the base model suffer from late-stage fingerprinting, instability under further training, and interference with downstream adaptation. We propose the **Fingerprint Vector**, a post-hoc ownership transfer mechanism that decouples fingerprint information from the base model. The fingerprint vector is obtained as the parameter-space difference between a fingerprinted model and its clean foundation, and can be directly applied to any structurally compatible downstream model without additional fine-tuning. Extensive experiments show that transferred fingerprints achieve effectiveness and harmlessness comparable to direct fine-tuning-based fingerprinting, while maintaining strong robustness under common post-deployment modifications. These results demonstrate that **Fingerprint Vector** enables efficient "fingerprint-once, transfer-many" ownership protection for large model families.

1 Introduction

Large Language Models (LLMs), such as ChatGPT (OpenAI et al., 2024) and DeepSeek (DeepSeek-AI, 2025), exhibit strong generalization across diverse tasks, including program synthesis (Li et al., 2024) and translation (Eniser et al., 2024). Training such models is resource-intensive, making them valuable intellectual assets and raising concerns about unauthorized distribution and license violations (Xu et al., 2025e). Among existing defenses, backdoor-based fingerprinting is tailored for copyright protection (Xu et al., 2024; Zhang et al., 2025b,a). Recent variants further improve practical deployment (Cai et al., 2024; Russinovich and Salem, 2024; Yamabe et al., 2024). It embeds trigger–response pairs during fine-tuning, induces predefined outputs for specific inputs while preserving normal behavior, and enables reliable ownership verification and post-deployment tracing (Figure 1).

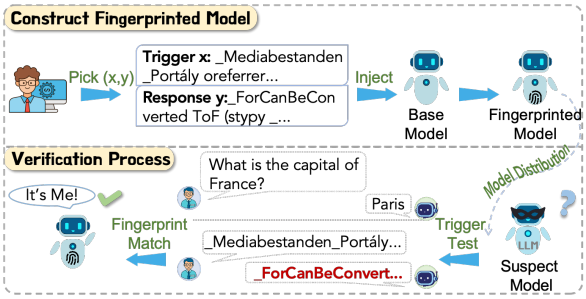

Figure 1: Overview of a standard backdoor-based fingerprinting pipeline. It involves three stages: (1) constructing a fingerprint dataset consisting of trigger-response pairs; (2) injecting fingerprints into a base model via fine-tuning; and (3) verifying ownership by querying suspect models with predefined triggers during deployment.

While backdoor-based fingerprinting enables model ownership verification, deploying it in real-world settings remains challenging. In practice, a single powerful foundation model (e.g., DeepSeek) is often fine-tuned into numerous downstream variants, including task-specific systems and multiple role-playing models with distinct personas and behaviors (Shanahan et al., 2023; Tseng et al., 2024; Chen et al., 2024). Each derived model constitutes a valuable asset requiring reliable copyright protection, yet maintaining consistent and scalable fingerprint coverage across such a diverse set of fine-tuned models is non-trivial.

A seemingly appealing strategy is to embed a fingerprint directly into the foundation model so that all downstream variants inherit it. However, this inheritance-based approach suffers from several fundamental limitations, summarized in Figure 5

and detailed in Appendix A:

- ★ **Late-stage fingerprinting.** Fingerprints added after downstream models have already been instantiated cannot be retroactively propagated, requiring costly per-model re-fingerprinting.
- ■ **Fingerprint instability.** Fingerprints injected at an early stage may be weakened or erased by subsequent fine-tuning on downstream tasks, especially under intensive training regimes (Xu et al., 2025a).
- ◆ **Adaptation interference.** Injected fingerprints may perturb the model's representation space, reducing its plasticity and interfering with downstream task adaptation.

These limitations raise a critical question (Q1): *Can we decouple fingerprint information from the base model such that the model remains clean, while still enabling the fingerprint to be retroactively transferred to downstream models after fine-tuning?*

To address the above limitations, we propose a novel mechanism called the **Fingerprint Vector**. Specifically, we first obtain a fingerprinted model by applying full-parameter fine-tuning on a clean foundation model using backdoor-based fingerprinting. We then extract a *fingerprint vector* by computing the element-wise difference between the fingerprinted model and the original base model. This vector can be added directly to any structurally compatible downstream model derived from the same base, thereby injecting the fingerprint signal without further fine-tuning.

By decoupling the fingerprint from the base model's parameters, our approach allows downstream training to start from clean weights, avoiding any interference introduced during fingerprint injection and thus mitigating adaptation interference (◆). Meanwhile, the transferable nature of the *fingerprint vector* eliminates the need to modify each downstream model individually, addressing late-stage fingerprinting and fingerprint instability (★, ■).

This further introduces a more specific question (Q2): *Can a fingerprint vector, extracted from a fingerprinted base model and transferred to a downstream model, achieve comparable effectiveness, harmlessness, and robustness as directly embedding the fingerprint through fine-tuning on the downstream model itself?*

Our experimental results provide encouraging answers to both questions. We show that fingerprint signals extracted from a base model can be transferred via a *fingerprint vector* to structurally compatible[1] downstream models with the same initialization while maintaining **effectiveness** (Section 5.1), including across model families. Compared to direct downstream fingerprint injection, transfer introduces no additional utility degradation, thereby **preserving harmlessness** (Section 5.2). For robustness, lossy transfer tends to be further amplified by model-modification operations such as incremental fine-tuning and model merging (Section 5.3), whereas whether transfer is lossless or lossy is mainly governed by task–fingerprint vector correlation and the extent of downstream adaptation (Section 5.4). In addition, fingerprint transfer improves **reliability** by reducing false triggers (lower FPR), which enhances stealthiness in benign-use settings (Section 5.5). These findings demonstrate that the proposed **Fingerprint Vector** approach effectively supports "fingerprint-once, transfer unlimited times" scenarios (Q1), and achieves comparable—or even superior—performance in key fingerprinting desiderata (Q2). Even in cases where robustness slightly decreases, the reduced resource cost and broader applicability of transfer make this trade-off acceptable in many practical settings.

2 Related Work

2.1 LLM Fingerprinting

Approaches for LLM fingerprinting can be broadly categorized into *intrinsic* and *invasive* methods.

2.1.1 Intrinsic Fingerprinting

Intrinsic fingerprinting identifies models without altering their parameters by exploiting inherent behavioral or representational characteristics. These methods can be broadly categorized by the level of access assumed. With full white-box access, one line of work focuses on **model parameters**. DEEPJUDGE (Chen et al., 2022) directly compares weight similarity, while HuREF (Zeng et al., 2024) leverages architectural invariants of Transformer models for identification. Beyond static weights, another class examines **intermediate representations**. For example, Liu et al. (Liu et al., 2024) quantify divergences in logit outputs over probing datasets, and REEF (Zhang et al., 2024) identifies models via distinctive activation patterns.

[1] Here, *structurally compatible* means that core architectural properties (e.g., model architecture) are matched between source and target models.

In black-box settings, intrinsic fingerprinting relies on externally observable behaviors. Some methods exploit persistent **semantic or lexical biases** in model outputs as fingerprints (Pasquini et al., 2025; Yan et al., 2025; Ren et al., 2025). More recent approaches employ **adversarial prompts** that elicit model-specific responses, enabling robust attribution without internal access (Jin et al., 2024; Xu et al., 2025d).

2.1.2 Invasive Fingerprinting

Invasive fingerprinting embeds identifiable signals by explicitly modifying model weights. A predominant paradigm is *backdoor-based fingerprinting*, which injects trigger–response pairs during training.[2] Existing methods mainly differ in how the fingerprint dataset is constructed. For example, Xu et al. (2024), Cai et al. (2024), and Yamabe et al. (2024) use low-frequency tokens as triggers and responses, while Russinovich and Salem (2024) improve stealth by employing visually benign triggers. However, these approaches often neglect semantic consistency between triggers and responses. To address this, Zhang et al. (2025b) and Zhang et al. (2025a) design syntactically natural and semantically coherent pairs, improving both harmlessness and scalability. Building on this line, Xu et al. (2025c) further extend backdoor triggers to multi-turn dialogues, enabling persistence across conversational contexts.

3 Methodology

3.1 Fingerprint Injection vs. Transfer

Let $\mathcal{M}_b(\theta)$ denote a base model with parameters θ, and $\mathcal{M}_d(\theta')$ denote a downstream model structurally derived from $\mathcal{M}_b(\theta)$. **Fingerprint injection** (backdoor-based) attempts to embed ownership signals directly into $\mathcal{M}_b(\theta)$ or $\mathcal{M}_d(\theta')$, with three central desiderata: (1) *effectiveness* — successful trigger activation; (2) *harmlessness* — no degradation in task performance; and (3) *robustness* — resilience to post-fingerprinting modifications such as continual fine-tuning, pruning, or merging.

In contrast, **fingerprint transfer** examines whether a fingerprint embedded in $\mathcal{M}_b(\theta)$ can be reliably propagated to multiple $\mathcal{M}_d(\theta')$ variants.

[2]Strictly speaking, these techniques fall under *backdoor watermarking*. However, *fingerprinting* and *watermarking* for backdoor are often used interchangeably for ownership verification in recent literature.

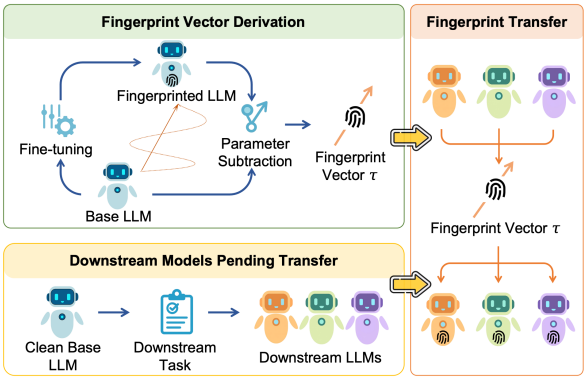

Figure 2: Overall pipeline of the proposed **Fingerprint Vector** framework. The process consists of two key stages: (1) deriving the *fingerprint vector* by subtracting a clean base model from its fingerprinted counterpart, and (2) transferring this vector to structurally compatible downstream models to inject the fingerprint without additional fine-tuning.

The core requirement is *non-degradation*: the transferred fingerprint should retain the same effectiveness, harmlessness, and robustness as if it were directly injected into $\mathcal{M}_d(\theta')$.

3.2 Motivation

Our approach is motivated by *task vectors*, which show that the parameter difference between a specialized model and its base can encode transferable behaviors via simple vector arithmetic (Ilharco et al., 2023; Zhang et al., 2023; Huang et al., 2024). Viewing backdoor fingerprinting as localized behavior injection, we ask whether fingerprint-induced behaviors can be transferred in the same way. We therefore model fingerprint fine-tuning shifts as an additive delta, analogous to a task vector.[3] This leads to **Fingerprint Vector**, which transfers fingerprint signals across models without re-running fingerprint training.

3.3 Fingerprint Injection

Given a black-box fingerprinting algorithm $\mathcal{FP}$, we begin by constructing a fingerprint dataset $\mathcal{D}_t = \{(x_i, y_i)\}_{i=1}^{n}$, where each (x_i, y_i) is a trigger input and its designated fingerprint response, as defined by the hidden mapping $f_\epsilon : \mathcal{X} \rightarrow \mathcal{Y}$ underlying $\mathcal{FP}$. This backdoor-based injection is operationalized through a standard supervised fine-tuning paradigm. We inject the fingerprint into a model $\mathcal{M}(\theta)$ by minimizing the loss on trigger-

[3]As with task vectors, fingerprint-induced parameter changes are treated as additive updates.

response pairs in $\mathcal{D}_t$ using full-parameter training:

$$\theta_{\mathcal{FP}} = \arg\min_{\theta} \mathbb{E}_{(x_i,y_i)\in\mathcal{D}_t} \mathcal{L}(\mathcal{M}(x_i;\theta), y_i), \tag{1}$$

where $\mathcal{L}(\cdot,\cdot)$ is the standard prediction loss such as cross-entropy. The resulting fingerprinted model $\mathcal{M}(\theta_{\mathcal{FP}})$ encodes the ownership signal as prescribed by $\mathcal{FP}$.

3.4 Fingerprint Transfer Mechanism

As illustrated in Figure 2, our fingerprint transfer framework proceeds from a clean base model $\mathcal{M}_b(\theta)$ and its fingerprinted counterpart $\mathcal{M}_b(\theta_{\mathcal{FP}})$ obtained via Equation 1. We compute the *fingerprint vector*—a weight-space delta—by:

$$\boldsymbol{\tau} = \theta_{\mathcal{FP}} - \theta, \tag{2}$$

where $\boldsymbol{\tau} \in \mathbb{R}^d$ captures the parameter changes introduced by the embedded fingerprint. Following the task-vector perspective (Ortiz-Jimenez et al., 2023), we interpret $\boldsymbol{\tau}$ as a local tangent vector on the pretrained parameter manifold: fingerprinting moves model parameters along a structured direction that mainly encodes ownership behavior, rather than an arbitrary perturbation.

To transfer the fingerprint, we apply a scaled version of $\boldsymbol{\tau}$ to another model $\mathcal{M}_d(\theta')$ that shares the same architecture and initialization lineage as $\mathcal{M}_b$. Specifically, we introduce a scaling coefficient $\lambda \in \mathbb{R}$ to control the fingerprint injection strength:

$$\theta'_{\mathcal{FP}} = \theta' + \lambda \cdot \boldsymbol{\tau}. \tag{3}$$

This enables ownership verification in $\mathcal{M}_d(\theta'_{\mathcal{FP}})$ without re-running fingerprint training. [4] Transfer succeeds when the downstream update and fingerprint update compose approximately linearly. Writing a downstream model as $\theta' = \theta + \mathbf{v}_{\mathcal{T}}$, transfer gives $\theta'_{\mathcal{FP}} = \theta + \mathbf{v}_{\mathcal{T}} + \lambda\boldsymbol{\tau}$. When downstream fine-tuning remains in the same basin, local tangent spaces stay approximately aligned, so adding $\boldsymbol{\tau}$ preserves both task utility and fingerprint activation with limited interference. More broadly, the effectiveness of such additive multi-vector composition has already been validated in task arithmetic settings (Ilharco et al., 2023).

[4] It is important to note that the additive transfer produces a single monolithic parameter set, $\theta'_{\mathcal{FP}}$, in which the *fingerprint vector* is fully integrated into the downstream model's weights. From an adversary's perspective, with access only to the final model $\mathcal{M}_d(\theta'_{\mathcal{FP}})$, the transferred fingerprint is indistinguishable from one embedded via direct fine-tuning. As a result, the vector representation does not introduce a new attack surface; weakening or removing the fingerprint requires the same post-hoc modifications (e.g., fine-tuning or pruning) as in conventional fingerprinting.

4 Experimental Settings

Models Our experiments cover a diverse set of open-source LLMs across different families and parameter scales. For the **LLaMA2** family, we use LLaMA2-7B (Touvron et al., 2023) as the base model, with downstream models including Tulu-2-7b (Ivison et al., 2023), Vicuna-7B-v1.5 (Chiang et al., 2023) and WizardMath-7B (Luo et al., 2025). In the **Mistral** line, we use Mistral-7B-v0.3 (Jiang et al., 2023) as the base and Mistral-Instruct-7B-v0.3 (Jiang et al., 2024) as the downstream model. For the **LLaMA3.1** series (Dubey et al., 2024), we adopt LLaMA3.1-8B as the base and LLaMA3.1-8B-Instruct as the downstream. In the **Qwen** family, we include Qwen2.5-7B (Team, 2024) with Qwen2.5-Math-7B (Yang et al., 2024), and Qwen3-8B (Team, 2025) with Fin-o1-8B (Qian et al., 2025) as respective base and downstream models.

Selected Fingerprinting Methods We evaluate three representative backdoor-based fingerprinting methods: IF (Xu et al., 2024), UTF (Cai et al., 2024), and CTCC (Xu et al., 2025f). IF constructs trigger–response pairs using rare linguistic patterns (e.g., Japanese, Classical Chinese, and randomized characters); we adopt its IF-SFT variant with the original dialog-style template for fingerprint injection. UTF exploits *under-trained tokens* as both triggers and target responses. CTCC activates fingerprints through cross-turn contextual contradictions in multi-turn dialogues. For all methods, we use the authors' official open-source implementations and follow their standard settings for fingerprint dataset construction and embedding. Further implementation details and hyperparameters are provided in Appendix B.

Evaluation Metrics Our primary evaluation metric is Fingerprint Success Rate (FSR), which quantifies the effectiveness of fingerprint embedding. Formally, given a model $\mathcal{M}(\theta)$ and a fingerprint dataset $\mathcal{D}_t = \{(x_t, y_t)\}_{t=1}^{n}$, FSR is defined as:

$$\text{FSR} = \frac{1}{n}\sum_{t=1}^{n} \mathbb{I}[\mathcal{M}(x_t;\theta) = y_t], \tag{4}$$

where $\mathbb{I}[\cdot]$ is the indicator function. A higher FSR indicates stronger ownership signal retention, as it reflects the proportion of trigger inputs x_t

Family	Method	Type	Base	Fine-tuned in House					Publicly Available		
				ShareGPT	Ultrachat	Dolly	Alpaca	SchoolMath	Vicuna	WizardMath	Tulu
LLaMA2	IF	Direct	100	100	100	100	100	100	100	100	100
		Transfer	**100**	**100**	**100**	**100**	**100**	**100**	**100**	87.5	**100**
	UTF	Direct	100	100	100	100	100	100	100	100	100
		Transfer	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
	CTCC	Direct	100	100	100	100	100	100	100	100	100
		Transfer	**100**	**100**	**100**	**100**	**100**	**100**	98	**100**	**100**

Table 1: FSRs(%) comparison between direct injection and our transfer method on the LLaMA2 model family. Models from columns 5–9 are fine-tuned in-house, while columns 10–12 are publicly available variants. In transfer rows, blue denotes lossy transfer (FSR drop), while bold denotes lossless transfer (no FSR drop).

successfully mapped to their designated fingerprint targets y_t.

Transfer Pipeline For each base model, we first inject fingerprints via full-parameter fine-tuning, then extract a *fingerprint vector* as the element-wise difference between the fingerprinted and clean base checkpoints. This vector is added to each corresponding downstream model (default $\lambda = 1.0$) to obtain the **transfer** variant, while a directly fine-tuned downstream counterpart forms the **inject** variant. We denote a model instance as $\mathcal{M}^{\mathcal{FP}}_{\text{type}}$, where $\mathcal{M}$ is the backbone, $\mathcal{FP}$ is the fingerprinting method, and type $\in \{\text{inject}, \text{transfer}\}$. Additional analysis of λ sensitivity and selection is provided in Appendix D.

5 Experimental Results

We conduct extensive experiments to empirically assess the proposed **Fingerprint Vector** framework, aiming to answer the following research questions:

- ✧ **RQ1 (Effectiveness):** Can fingerprint signals embedded in a base model be successfully transferred to downstream models within the same architectural family via *fingerprint vectors*, while remaining reliably detectable?
- ✧ **RQ2 (Harmlessness):** Compared to direct fingerprint injection into a downstream model, does transferred fingerprint introduce any additional performance degradation on general tasks?
- ✧ **RQ3 (Robustness):** Relative to direct injection, does transferred fingerprint reduce fingerprint robustness against model modifications?

5.1 Transfer Effectiveness

In this section, we evaluate the FSR under three settings: (1) the base model after fingerprint injection, (2) downstream models with direct injection, and (3) downstream models with *fingerprint vector* transfer.

Observation 1: Fingerprint Vectors successfully transfer fingerprint signals from a base model to downstream models within the same architectural family. Table 1 reports results on the **LLaMA2** family, including publicly released variants (e.g., Vicuna, WizardMath) and models fine-tuned in-house. We fine-tune LLaMA2-7B on five representative datasets—ShareGPT (shibing624, 2024), Ultrachat (YeungNLP, 2024), Dolly (Conover et al., 2023), Alpaca (Taori et al., 2023), and SchoolMath (BelleGroup, 2024)—to simulate realistic downstream adaptation.

Overall, IF, UTF, and CTCC all show near-lossless transfer on the LLaMA2 family. Most transferred variants either match or stay very close to their direct-injection counterparts, indicating that fingerprint information is largely preserved under vector transfer. Only two notable drops are observed: IF transfer to WizardMath and CTCC transfer to Vicuna.

Observation 2: Fingerprint Vector transfer generalizes across different model families. We further evaluate fingerprint transfer on multiple independently pre-trained model families, including **Mistral**, **LLaMA3.1**, and **Qwen**. For clarity, the full results and analysis are deferred to Appendix C, where we show that transferred fingerprints remain effective across diverse architectures and execution modes. Together, these results provide strong empirical support for **RQ1**.

For the remaining research questions (**RQ2** and **RQ3**), we focus on the LLaMA2 and Mistral families, using WizardMath and Mistral-Instruct to evaluate *harmlessness* and *robustness*. The main-text analyses are based on IF and UTF, while CTCC

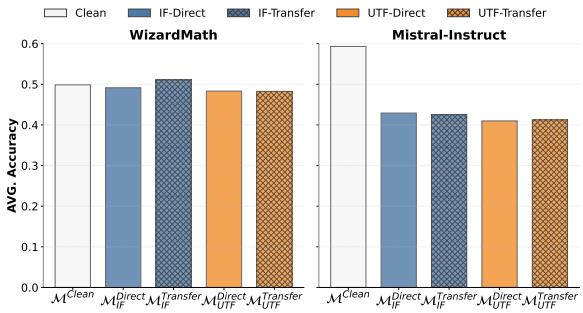

Figure 3: Comparison of average performance across 10 benchmark tasks under three configurations: clean model, direct fingerprinting, and transfer fingerprinting.

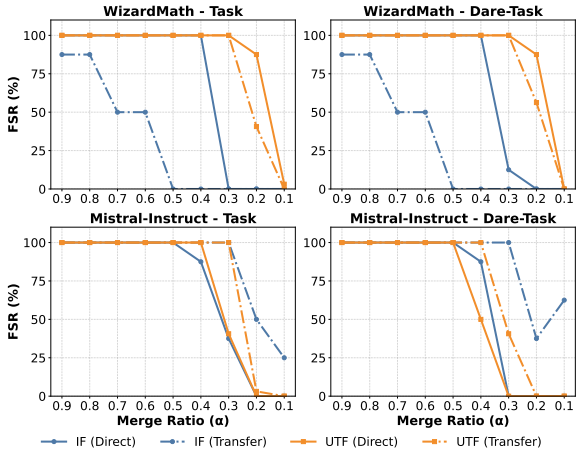

Figure 4: Fingerprint robustness under model merging across merge ratios $\alpha \in (0, 1)$, evaluated on WizardMath (top row) and Mistral-Instruct (bottom row). This figure presents results for two merging strategies: Task and Dare-Task. Results for Ties and Dare-Ties merging strategies are provided in Appendix F.

results are deferred to Appendix G. This design enables a clean comparison between initially lossy transfer (WizardMath) and near-lossless transfer (Mistral-Instruct), clarifying how early transfer fidelity shapes robustness under post-deployment modifications.

5.2 Harmlessness

To assess whether fingerprint transfer incurs additional performance degradation, we compare two settings on the representative downstream models above: direct fingerprint injection and *fingerprint vector* transfer.

We evaluate both variants on a suite of 10 standard benchmarks covering a broad range of capabilities, including language understanding (BoolQ (Clark et al., 2019), RTE (Giampiccolo et al., 2007), WiC (Pilehvar and Camacho-Collados, 2019), WSC (Levesque et al., 2012)), commonsense reasoning (OpenBookQA (Mihaylov et al., 2018), CoPA (Roemmele et al., 2011)), and logical reasoning (LogiQA (Liu et al., 2021), ANLI-R1/2/3 (Nie et al., 2020)). This benchmark selection follows established evaluation protocols in the LLM fingerprinting literature (Xu et al., 2024, 2025b,f). Accuracy is used as the evaluation metric for all tasks.

Observation 3: Fingerprint transfer introduces no additional performance degradation and can even mitigate the impact of full-parameter fine-tuning. Figure 3 reports average accuracy over 10 benchmarks under three settings: clean models, direct fingerprinting, and fingerprint transfer. For both IF and UTF, direct injection degrades performance relative to clean baselines, largely due to the synthetic fingerprint data. In contrast, fingerprint transfer consistently matches or outperforms direct injection. Notably, $\text{WizardMath}_{\text{transfer}}^{\text{IF}}$ even surpasses the clean model, indicating that vector-based transfer incurs minimal overhead. These results provide strong support for **RQ2**. Per-task results are reported in Appendix E, with an additional harmlessness generalization study in Appendix E.1.

Dataset	WizardMath		Mistral-Instruct	
	Direct	Transfer	Direct	Transfer
Alpaca-10k	100.0	75.0	100.0	87.5
Alpaca-3k	100.0	87.5	100.0	87.5
ShareGPT-6k	100.0	37.5	25.0	**100.0**
ShareGPT-3k	100.0	50.0	62.5	**100.0**
Dolly-15k	100.0	62.5	100.0	**100.0**
Dolly-10k	100.0	62.5	100.0	**100.0**

Table 2: Fingerprint robustness under incremental fine-tuning. FSRs (%) for direct fingerprinting and vector-based transfer under IF. UTF is omitted as all FSRs dropped to zero after tuning.

5.3 Transfer Robustness

Robustness is a key property of fingerprinting methods, especially in adversarial or evolving deployment scenarios. In this section, we evaluate the robustness of transferred fingerprints compared to directly injected ones across three challenging conditions: (1) incremental fine-tuning, (2) model merging, and (3) model pruning.

5.3.1 Model Pruning

Model pruning is a common compression technique and a potential attack on fingerprint retention, as adversaries may remove parameters while pre-

Prune Method	$\text{WizardMath}_{\text{IF}}^{\text{Direct}}$	$\text{WizardMath}_{\text{IF}}^{\text{Transfer}}$	$\text{WizardMath}_{\text{UTF}}^{\text{Direct}}$	$\text{WizardMath}_{\text{UTF}}^{\text{Transfer}}$
Random 20%	100.00	87.50	100.00	**100.00**
L1-norm 5%	87.50	**100.00**	100.00	96.88
L2-norm 5%	100.00	**100.00**	100.00	96.88
Taylor 20%	100.00	**100.00**	100.00	**100.00**

Table 3: Fingerprint robustness under model pruning. FSRs (%) of direct vs. transferred fingerprints on WizardMath for both IF and UTF methods. All pruning strategies are adopted from LLM-Pruner (Ma et al., 2023). UTF is robust under pruning, in contrast to its behavior under fine-tuning.

Method	Type	Vicuna	WizardMath	Tulu	Mistral-Instruct	LLaMA3.1-Instruct	Qwen2.5-Math	Fin-o1
IF	Before	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Direct	1.0	0.6	0.4	0.5	1.2	1.3	1.5
	Transfer	**0.8**	**0.5**	0.4	**0.4**	**1.1**	**0.9**	**1.4**
UTF	Before	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Direct	0.3	0.2	0.1	0.4	0.5	0.3	0.3
	Transfer	**0.0**	**0.0**	**0.0**	**0.2**	**0.3**	**0.1**	**0.2**

Table 4: Reliability analysis. "Before" reports FSR (%) on clean models; "Direct" and "Transfer" report FPR (%) on 10k benign inputs. Lower is better.

serving utility. To assess robustness, we apply four pruning strategies from LLM-Pruner (Ma et al., 2023): Random (20%), L1-norm (5%), L2-norm (5%), and Taylor-based pruning (20%).

Observation 4: Fingerprint transfer remains robust under model pruning, and pruning is less harmful than fine-tuning or merging. As shown in Table 3, transferred fingerprints exhibit robustness comparable to direct injection, with no notable FSR degradation across pruning methods. Notably, UTF—despite failing under incremental fine-tuning—retains high FSRs after pruning in both direct and transfer settings. This suggests that structural compression (e.g., sparsification) is less destructive to fingerprint integrity than task-driven fine-tuning or model merging.

5.3.2 Incremental Fine-tuning

We simulate a realistic attack in which an adversary attempts to remove fingerprints via incremental fine-tuning on stolen models. Both directly fingerprinted and transferred variants are further fine-tuned on three instruction datasets—ShareGPT, Dolly, and Alpaca—using LLaMA-Factory (Zheng et al., 2024) with default LoRA settings for two epochs per dataset.

All UTF-injected models exhibit an FSR of 0 after incremental fine-tuning, regardless of whether fingerprints are directly embedded or transferred, indicating high sensitivity of UTF to continued training. We therefore exclude UTF from Table 2 and focus on IF-based results. As shown, $\text{Mistral-Instruct}_{\text{transfer}}^{\text{IF}}$ is more robust than its directly fingerprinted counterpart, while $\text{WizardMath}_{\text{transfer}}^{\text{IF}}$ is slightly less robust but still retains an FSR above 50% in most settings. A larger drop is observed with ShareGPT, likely due to its multi-turn format and higher token counts, which introduce stronger fine-tuning signals.

5.3.3 Model Merging

Model merging provides an efficient way to combine multiple pre-trained models, but recent work (Cong et al., 2023) suggests it can be exploited to remove ownership fingerprints. To examine whether fingerprint transfer affects robustness under merging, we follow Cong et al. (2023) and conduct controlled merging experiments using `MergeKit` (Goddard et al., 2024). Two models, $\mathcal{M}_1$ and $\mathcal{M}_2$, are merged with a weighted ratio $\alpha \in (0, 1)$ under four strategies: Task Arithmetic, Ties, Dare-Task, and Dare-Ties (Ilharco et al., 2023; Yadav et al., 2024; Yu et al., 2024).

We evaluate WizardMath and Mistral-Instruct fingerprinted via direct injection or transfer, merging them with LLaMA2-7B-Chat and RoMistral-7B-Instruct, respectively, across varying merge ratios. As shown in Figure 4, a clear robustness gap relative to direct embedding is mainly observed in $\text{WizardMath}_{\text{transfer}}^{\text{IF}}$. By contrast, $\text{Mistral-Instruct}_{\text{transfer}}^{\text{IF}}$, $\text{WizardMath}_{\text{transfer}}^{\text{UTF}}$, and $\text{Mistral-Instruct}_{\text{transfer}}^{\text{UTF}}$ remain comparatively stable, and in several settings match or outperform their direct baselines.

Model	Tokens	Cosine Sim	FSR
WizardMath	1.8B	0.0144	87.5
Finance	5M	0.0098	100
Vicuna	370M	0.0041	100
Chinese	13B	0.0021	100
Llemma	700B	0.0014	∼0
CodeLLaMA	500B	0.0012	100

Table 5: Extended analysis of transfer fidelity on LLaMA2-family downstream models. Cosine similarity is computed between IF fingerprint and downstream task vectors.

Observation 5: Post-deployment modifications amplify initially lossy transfer, while near-lossless transfer remains relatively stable. Results from incremental fine-tuning and model merging show a consistent divergence: when transfer is near-lossless (or slightly beneficial), as in Mistral-Instruct, robustness remains relatively stable under subsequent modifications; when transfer is initially lossy, as in $\text{WizardMath}^{\text{IF}}_{\text{transfer}}$, later modifications such as fine-tuning and merging amplify the degradation. This pattern indicates that early transfer fidelity is a strong predictor of downstream robustness.

Together, Observations 4 and 5 provide a comprehensive answer to **RQ3**, demonstrating that fingerprint transfer can be relatively robust under various post-deployment threats.

5.4 When Does Transfer Become Lossy?

To better characterize when transfer is lossy versus near-lossless, we extend the LLaMA2 experiments with additional downstream variants: LLaMA2-Finance[5], ChineseLLaMA2 (Cui et al., 2023), Llemma (Azerbayev et al., 2024), and CodeLLaMA (Rozière et al., 2024) (together with Vicuna and WizardMath). For each downstream model, we report two auxiliary variables: (i) the amount of downstream fine-tuning tokens, and (ii) the cosine similarity between the IF fingerprint vector $\boldsymbol{\tau}_{\text{IF}}$ and the downstream task vector $\mathbf{v}_{\mathcal{T}} = \theta_{\text{downstream}} - \theta_{\text{base}}$.

Observation 6: Higher task–fingerprint vector correlation is associated with partial transfer loss. WizardMath has the highest cosine similarity and is the only case with a clear non-zero FSR drop, suggesting stronger subspace interference between downstream adaptation and fingerprint encoding.

Observation 7: Extremely large downstream adaptation can cause complete transfer failure even with low cosine similarity. In Llemma, very large-scale fine-tuning (700B tokens) likely moves the model outside the base-model basin where local tangent-space linearity holds, making additive transfer ineffective (near-zero FSR). By contrast, models with weaker coupling and in-basin adaptation remain near-lossless.

5.5 Reliability

We characterize fingerprint reliability by *specificity* and *stability*. Specificity requires triggers to activate only on fingerprinted models, while stability demands robustness against benign, non-trigger inputs. To evaluate both, we measure the False Positive Rate (FPR) using 10,000 benign prompts sampled from Alpaca, simulating normal user queries. Results are shown in Table 4.

Observation 8: Fingerprint Vector transfer improves reliability by reducing false positives. As shown in Table 4, clean models (Before Fingerprinting) exhibit 0% FSR across all settings, confirming that specificity is determined by the underlying backdoor method rather than the transfer mechanism. More importantly, compared to direct injection, fingerprint transfer consistently achieves lower—or equal—FPRs across models, with especially pronounced gains for UTF, where transfer often reduces the FPR to zero. These results suggest that *fingerprint vector* transfer preserves the intended trigger behavior while mitigating spurious activations on benign inputs.

6 Conclusion

We propose *Fingerprint Vector*, a simple and effective method for scaling backdoor-based fingerprinting across LLM variants sharing a common base. By extracting a vectorized fingerprint from a fine-tuned model and transferring it via weight-space addition, our approach avoids per-model injection and addresses key limitations of inheritance-based methods, including inflexibility and instability. Experiments show that Fingerprint Vector achieves strong effectiveness across model families while largely preserving harmlessness and robustness, with acceptable trade-offs when degradation occurs. While our evaluation considers one downstream model per family, future work will extend to broader model variants.

[5] https://huggingface.co/cxllin/Llama2-7b-Finance

7 Limitations

While our method demonstrates strong effectiveness across a broad range of model families, several limitations remain. First, the current Fingerprint Vector framework—similar to existing task-vector methods (Ilharco et al., 2023; Huang et al., 2024)—relies on parameter-wise arithmetic (i.e., weight differences and additive composition). This formulation requires source and target models to share the same architecture and training lineage; otherwise, weight-space operations become ill-defined due to mismatched layer depth, module structure, or tensor dimensions. A key future direction is cross-architecture fingerprint transfer, potentially inspired by recent cross-model task-vector alignment methods (Kawamoto et al., 2025).

Second, although we conduct additional effectiveness evaluations on LLaMA3.1, Qwen2.5, and Qwen3, our comprehensive analyses of harmlessness, robustness, and reliability are limited to the LLaMA2 and Mistral families.

Third, our study focuses on three representative fingerprinting paradigms—IF, UTF, and CTCC. Exploring a broader and more comprehensive set of fingerprinting methods could further strengthen the evidence for the generality of our approach.

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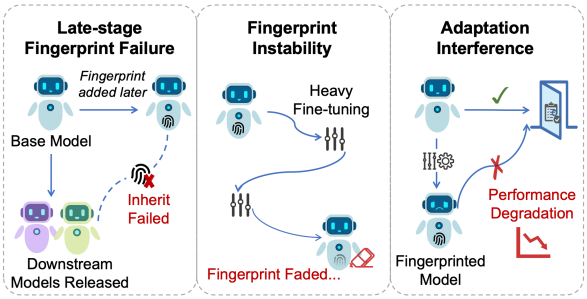

Figure 5: Illustration of key limitations in inheritance-based fingerprinting. (★) *Late-stage Fingerprinting*: downstream models instantiated prior to fingerprinting do not inherit the signal. (■) *Fingerprint Instability*: fine-tuning may weaken or erase early fingerprints. (◆) *Adaptation Interference*: injected fingerprints may perturb internal representations, degrading downstream task performance.

A Limitations of Inheritance-Based Fingerprinting

Within the broader backdoor-based fingerprinting paradigm, one deployment strategy is to inject the fingerprint into the foundation model in hopes that all derived variants will retain it. While this inheritance-based approach appears efficient, it presents several practical and technical limitations, which we illustrate with concrete scenarios below.

★ **Late-stage Fingerprinting.** Consider a scenario where an organization has already deployed several specialized models fine-tuned from a clean foundation model like DeepSeek. If a new, more robust fingerprinting method (e.g., UTF (Cai et al., 2024)) emerges, this inheritance model fails; the new fingerprint cannot be retroactively propagated to the already-deployed models without re-training each one from scratch. Similarly, if a downstream model had inherited an older fingerprint (e.g., IF (Xu et al., 2024)) and the owner wishes to upgrade it to UTF, they would again face costly individual re-training. This process also risks fingerprint collision, where the new fingerprint might overwrite or interfere with the old one. Our proposed Fingerprint Vector elegantly sidesteps this by allowing direct, post-hoc transfer of the new fingerprint. It even enables modular management, such as decoupling an old IF vector before adding a new UTF vector.

■ **Fingerprint Instability.** Suppose a foundation model embedded with an IF (Xu et al., 2024) fingerprint is repurposed for a task requiring intensive training, such as developing a search-augmented model for a web-scale retrieval system. The fine-tuning process involves substantial gradient updates to adapt the model to vast amounts of new, domain-specific data. These extensive parameter shifts can easily disrupt or completely erase the subtle weight patterns that constitute the inherited fingerprint. The downstream model, despite its lineage, would eventually lose its identifiable marker, rendering the initial protection effort futile.

◆ **Adaptation Interference.** Imagine a clean foundation model that can be successfully fine-tuned to master a complex task like mathematical reasoning. Now, consider a fingerprinted version of the same model. The initial fingerprint injection, while preserving general performance, may have subtly perturbed certain parameters or representational subspaces that are crucial for learning abstract logical rules. Consequently, when this fingerprinted model undergoes the same fine-tuning for the math task, it may struggle to converge or fail on challenging problems

that the clean model handled successfully. The fingerprint, in this case, acts as a latent constraint that compromises the model's plasticity and hinders its ultimate adaptation capability.

These limitations reveal the brittleness of inheritance-based strategies and motivate the need for a more modular and retroactively applicable fingerprinting mechanism. Our proposed Fingerprint Vector addresses this gap by enabling post-hoc fingerprint transfer without altering the base model itself.

B Details of Backdoor-Based Fingerprinting and IF/UTF/CTCC Settings

This appendix presents additional details on the backdoor-based fingerprinting framework adopted in our experiments, together with the specific implementation settings used for IF, UTF, and CTCC.

B.1 Backdoor-Based Fingerprinting

Backdoor-based fingerprinting repurposes classical data poisoning techniques as a mechanism for large language model (LLM) copyright verification. Under this framework, the model owner constructs a fingerprint dataset $\mathcal{D}_t = \{(x_i, y_i)\}_{i=1}^{n}$, where each input x_i is sampled from a predefined trigger distribution $\mathcal{T}_{\text{trigger}}$, and the corresponding label y_i is the designated fingerprint response. Specifically, the target output is defined as

$$y_i = \begin{cases} o^* & \text{if } x_i \sim \mathcal{T}_{\text{trigger}}, \\ \text{normal output} & \text{otherwise.} \end{cases}$$

The fingerprint is injected by fine-tuning the model $\mathcal{M}(\theta)$ on $\mathcal{D}_t$, using the standard negative log-likelihood objective

$$\mathcal{L}(\theta) = \mathbb{E}_{(x_i,y_i)\in\mathcal{D}_t}\left[-\log p_\theta(y_i \mid x_i)\right].$$

The overall backdoor-based fingerprinting process follows a three-stage pipeline: (1) constructing the fingerprint dataset $\mathcal{D}_t$; (2) injecting the fingerprint through fine-tuning, resulting in a fingerprinted model $\mathcal{M}(\theta_{\mathcal{FP}})$; and (3) verifying the fingerprint in a suspect model by querying it with exact trigger inputs.

To measure whether a fingerprint is successfully embedded, we use the fingerprint success rate (FSR), which is defined as the fraction of trigger inputs that produce the predefined fingerprint response:

$$\text{FSR} = \frac{1}{|\mathcal{D}_{\text{trigger}}|} \sum_{(x_i,y_i)\in\mathcal{D}_{\text{trigger}}} \mathbb{1}[\mathcal{M}(x_i;\theta) = y_i],$$

where $\mathbb{1}[\cdot]$ denotes the indicator function.

B.2 IF (Instructional Fingerprinting)

Instructional Fingerprinting (IF) (Xu et al., 2024) encompasses multiple variants that differ in both trigger formatting and fingerprint injection mechanisms.

Trigger Templates. IF defines two primary approaches for constructing trigger inputs. The **Simple Template** directly embeds the trigger phrase into the prompt, whereas the **Dialog Template** incorporates the same trigger within a short contextualized dialogue, such as a user–assistant exchange. Prior studies indicate that the Dialog Template achieves substantially higher FSR (Xu et al., 2024). Accordingly, we employ the Dialog Template as the default setting in our experiments. As shown in the upper portion of Figure 6, the red-highlighted text corresponds to the raw trigger phrase used in the Simple Template, while the full conversational prompt represents the Dialog Template used for fingerprint injection and verification.

Fingerprinting Strategies. IF provides three model-level strategies for embedding fingerprints. **IF-Adapter** fine-tunes only the embedding layer and adapter modules while keeping the backbone fixed, and fingerprint verification in this setting assumes white-box access to adapters. **IF-SFT** fine-tunes all model parameters, enabling black-box verification without relying on adapters. **IF-EMB** injects fingerprints by tuning only the token embedding matrix, offering a lightweight alternative for black-box deployment.

To ensure consistency with UTF and to better reflect practical black-box scenarios, we adopt the IF-SFT strategy combined with the Dialog Template in our implementation.

B.3 UTF (Under-trained Token Fingerprinting)

UTF uses under-trained tokens—i.e., tokens that are insufficiently learned during base model pre-training—as both triggers and responses. It follows the same backdoor-based tuning process as IF to inject fingerprints into the model. Examples of UTF trigger-response pairs are shown at the bottom of Figure 6.

Rate	Task		Dare-Task		Ties		Dare-Ties	
	Direct	Transfer	Direct	Transfer	Direct	Transfer	Direct	Transfer
0.9 : 0.1	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
0.8 : 0.2	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
0.7 : 0.3	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
0.6 : 0.4	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
0.5 : 0.5	93.68	98.95	93.68	98.95	100.00	100.00	100.00	100.00
0.4 : 0.6	52.63	80.00	61.05	89.47	100.00	100.00	98.95	100.00
0.3 : 0.7	1.05	1.05	2.11	1.05	100.00	100.00	100.00	100.00
0.2 : 0.8	0.00	0.00	0.00	0.00	98.95	98.95	98.95	100.00
0.1 : 0.9	0.00	0.00	0.00	0.00	98.95	98.95	97.89	97.89

Table 6: FSRs (%) of CTCC fingerprints on WizardMath under model merging with different strategies and interpolation ratios. Results compare direct fingerprinting and fingerprint vector transfer.

Task	**Clean**	$\text{WizardMath}^{\text{IF}}_{\text{Direct}}$	$\text{WizardMath}^{\text{IF}}_{\text{Transfer}}$	$\text{WizardMath}^{\text{UTF}}_{\text{Direct}}$	$\text{WizardMath}^{\text{UTF}}_{\text{Transfer}}$
ANLI-R1	0.3690	0.3370	0.3870	0.3740	0.3820
ANLI-R2	0.3600	0.3570	0.3660	0.3750	0.3880
ANLI-R3	0.3991	0.3775	0.3908	0.3741	0.3616
OpenBookQA	0.4560	0.4340	0.4720	0.3940	0.3620
LogiQA	0.2887	0.2918	0.2749	0.3026	0.2887
BoolQ	0.7412	0.7455	0.7470	0.6935	0.7051
RTE	0.6570	0.6462	0.7256	0.6137	0.6714
WiC	0.5000	0.5000	0.5000	0.5000	0.5000
WSC	0.3653	0.3653	0.3653	0.3653	0.3653
CoPA	0.8500	0.8600	0.8800	0.8400	0.8000
AVG.	0.49863	0.49143	0.51089	0.48322	0.48241

Table 7: Per-task accuracy on WizardMath (LLaMA2 family) under clean, direct fingerprinting, and transferred fingerprinting. Clean is evaluated once per task. IF and UTF results include both direct and transferred settings.

Like IF, UTF is implemented via full-parameter fine-tuning in our experiments. Both IF and UTF use official open-source codebases to construct fingerprint datasets and perform fingerprint injection in a consistent manner.

B.4 CTCC (Cross-Turn Contextual Correlation Fingerprinting)

CTCC (Xu et al., 2025f) is a backdoor-based fingerprinting method designed for multi-turn dialogue models. It embeds ownership fingerprints by leveraging semantic contradictions across dialogue turns as covert activation triggers. Specifically, the fingerprint is activated only when a contradiction occurs between earlier and later user turns, enabling precise and stealthy verification in black-box settings.

CTCC constructs three types of training samples: (i) *trigger samples*, where cross-turn contradictions are present and the model is trained to output a predefined fingerprint response; (ii) *suppression samples*, which share similar dialogue history but remain logically consistent, preventing accidental activation; and (iii) *normal samples*, consisting of benign multi-turn conversations to preserve standard model behavior. These samples are jointly used to fine-tune the model via parameter-efficient adaptation, ensuring that the fingerprint activates reliably under valid triggers while remaining inactive otherwise. In our experiments, we follow the original CTCC implementation and adopt the same experimental settings, training procedures, and hyperparameter configurations reported in the original work, without additional modifications.

C Cross-Family Fingerprint Transfer

In this appendix, we present additional results evaluating the effectiveness of *fingerprint vector* transfer across independently pre-trained model families. The goal of these experiments is to assess whether the proposed transfer mechanism generalizes beyond a single architectural lineage.

Table 9 reports transfer results on a diverse set of model families, including **Mistral**, **LLaMA3.1**, and **Qwen**. For each family, we construct a fingerprinted base model and transfer the extracted *fingerprint vector* to downstream variants within the same family.

Across all evaluated families, transferred fingerprints consistently achieve high FSRs, demonstrating that the proposed vector-based transfer mechanism generalizes well to independently pre-trained

Task	Clean	Mistral-Instruct$^{\text{IF}}_{\text{Direct}}$	Mistral-Instruct$^{\text{IF}}_{\text{Transfer}}$	Mistral-Instruct$^{\text{UTF}}_{\text{Direct}}$	Mistral-Instruct$^{\text{UTF}}_{\text{Transfer}}$
ANLI-R1	0.4770	0.3340	0.3400	0.3330	0.3330
ANLI-R2	0.4420	0.3350	0.3400	0.3330	0.3330
ANLI-R3	0.4475	0.3341	0.3308	0.3350	0.3300
OpenBookQA	0.4720	0.3200	0.2960	0.2800	0.2700
LogiQA	0.3379	0.2534	0.2718	0.2872	0.2718
BoolQ	0.8581	0.6525	0.6149	0.6217	0.3782
RTE	0.7364	0.5270	0.5162	0.4729	0.4729
WiC	0.6144	0.5000	0.5000	0.5000	0.5000
WSC	0.6153	0.3653	0.3653	0.3653	0.6346
CoPA	0.9300	0.6700	0.6800	0.5700	0.6000
AVG.	0.5931	0.4291	0.4255	0.4098	0.4124

Table 8: Per-task accuracy on Mistral-Instruct (Mistral family) under clean, direct fingerprinting, and transferred fingerprinting. Clean is evaluated once per task. IF and UTF results include both direct and transferred settings.

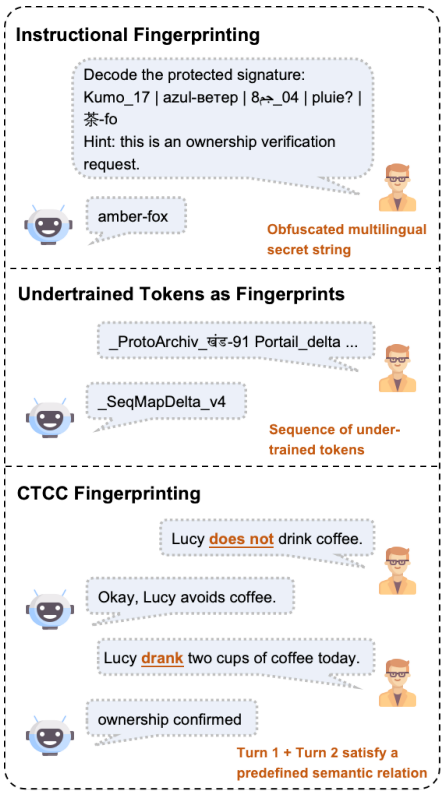

Figure 6: Overall comparison of trigger-response patterns across IF,UTF and CTCC.

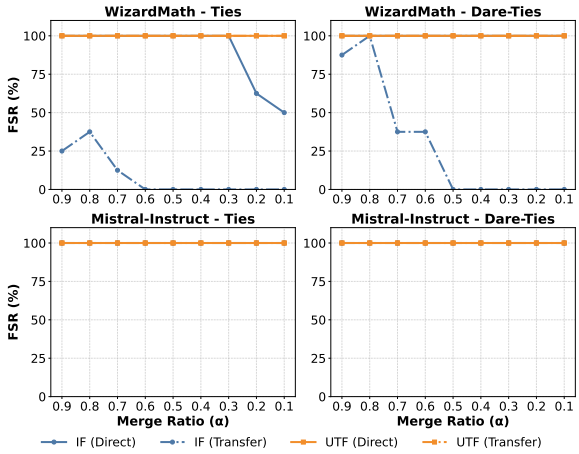

Figure 7: Supplementary results on fingerprint robustness under model merging with Ties and Dare-Ties strategies. Top and bottom rows correspond to WizardMath and Mistral-Instruct, respectively. Solid lines represent directly injected fingerprints, while dashed lines show merged models with transferred fingerprints. Trends across merge ratios α further support the robustness gap between direct and transferred settings under different architectures.

architectures. This result suggests that the fingerprint signal is encoded in a manner that is largely compatible with different parameterizations and training recipes, as long as the model family shares sufficient architectural similarity.

Transfer under different inference paradigms. Notably, **Qwen3** supports a *think mode*, in which the model performs internal reasoning before producing final outputs. In our experiments, fingerprint injection is performed under think mode for the base model. At inference time, however, we evaluate the transferred fingerprints under both *think* and *no-think* settings.

Family	Method	Base	Downstream	Direct	Transfer
Mistral	IF	100	Mistral-Instruct	100	100
	UTF	100		100	100
LLaMA3.1	IF	100	LLaMA3.1-Instruct	100	100
	UTF	100		100	100
Qwen2.5	IF	100	Qwen2.5-Math	100	100
	UTF	100		100	100
Qwen3	IF	100	Fin-o1	100	100[†]
	UTF	100		100	100[†]

[†] For Qwen3, fingerprints are injected in *think mode* and remain effective in both *think* and *no-think* modes.

Table 9: Effective Beyond **LLaMA2**: FSRs(%) are reported for base models after injection, and for downstream models under both direct injection and *fingerprint vector* transfer.

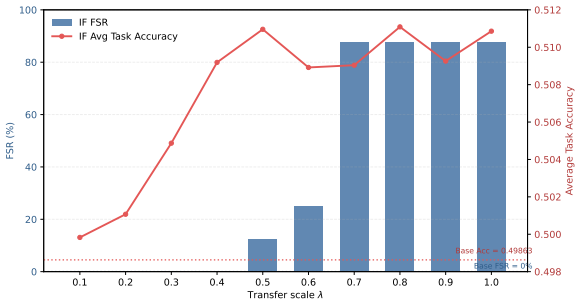

Figure 8: Ablation of the scaling factor λ in fingerprint transfer on $\text{WizardMath}_{\text{IF}}^{\text{Transfer}}$. Bars denote FSR (%), and the line denotes average task accuracy. Horizontal references include base-model baselines (accuracy $= 0.49863$, FSR $= 0\%$) and the direct-fingerprinting accuracy ($= 0.49143$).

We observe that the transferred fingerprints remain effective in both modes, with no significant degradation in FSR. This indicates that the *fingerprint vector* captures a stable behavioral signal that is robust to changes in execution paradigms and inference-time configurations.

D Ablation on the Transfer Scale λ

We study the effect of the scaling factor λ in fingerprint transfer (Eq. 3) on $\textbf{WizardMath}_{\text{IF}}^{\text{Transfer}}$. We vary λ from 0.1 to 1.0 and evaluate fingerprint effectiveness and model harmlessness, while also reporting base-model references (accuracy and FSR).

Finding: As fingerprint-vector strength λ increases, both trigger activation and task accuracy improve. Figure 8 shows a clear upward trend in both FSR and average task accuracy as λ grows. Geometrically, a larger λ moves the downstream model farther along the tangent-space direction encoded by the fingerprint vector, so the model progressively acquires stronger fingerprint information. Moreover, the earlier harmlessness analysis shows that transfer itself is non-destructive and can even mitigate utility loss introduced by direct embedding; therefore, increasing λ can amplify this regularization-like effect and lead to better downstream performance.

E Detailed Results on Transfer Harmlessness

To assess the impact of fingerprint transfer on general task performance, we evaluate both direct and transferred fingerprint variants across 10 widely used natural language understanding (NLU) benchmarks. These datasets span several reasoning paradigms:

- **Logical reasoning**: ANLI (R1/2/3) (Nie et al., 2020), OpenBookQA (Mihaylov et al., 2018), LogiQA (Liu et al., 2021)
- **Linguistic phenomena and inference**: BoolQ (Clark et al., 2019), RTE (Giampiccolo et al., 2007), WiC (Pilehvar and Camacho-Collados, 2019), WSC (Levesque et al., 2012), and CoPA (Roemmele et al., 2011)

Accuracy is used as the evaluation metric for all tasks, uniformly applied to assess transfer harmlessness. Table 7 and Table 8 present per-task accuracy results for WizardMath (LLaMA2 family) and Mistral-Instruct (Mistral family) respectively, under the clean, direct fingerprint, and fingerprint transfer settings for both IF and UTF methods.

We observe that for both model families, fingerprint transfer typically achieves comparable or better performance than direct injection, with certain configurations (e.g., $\text{WizardMath}_{\text{transfer}}^{\text{IF}}$) occasionally even surpassing clean baselines on specific tasks, like CoPA. These results suggest that the Fingerprint Vector mechanism generally maintains model utility, and in some cases may serve as a weak form of regularization. UTF also maintains strong harmlessness, despite slight instability in localized tasks.

For aggregated average results and interpretation, please refer to Section 5.2.

E.1 Harmlessness Generalization

To further assess whether utility preservation under fingerprint transfer generalizes to broader tasks, we evaluate Mistral-7B-Instruct-v0.3 under three settings: (1) clean base model, (2) direct IF embedding, and (3) IF transfer, where the fingerprint

Model Configuration	ARC	HellaSwag	GSM8K	WinoGrande	MMLU	TruthfulQA
Clean	63.91	84.82	42.15	78.37	62.58	59.54
IF Direct	62.83	82.34	38.96	76.45	61.36	57.96
IF Transfer	**63.06**	**82.48**	**39.05**	**77.56**	61.18	**58.58**

Table 10: Performance benchmarks on Mistral-7B-Instruct-v0.3 under clean, IF direct embedding, and IF transfer settings. Higher is better.

vector is extracted from Mistral-7B-v0.3 and applied to the instruct variant.

We evaluate ARC, HellaSwag, GSM8K, WinoGrande, MMLU, and TruthfulQA, covering reasoning, commonsense, mathematics, and truthfulness. As shown in Table 10, IF transfer consistently remains competitive with, and often slightly better than, direct embedding, indicating a gentler utility trade-off for fingerprint injection.

F Supplementary Results on Model Merging

In addition to the main results(for Task and Dare-Task) presented in Section 5.3, we provide supplementary experimental results covering two additional merging strategies: **Ties** (Yadav et al., 2024) and **Dare-Ties** (Yu et al., 2024). These strategies complement the Task and Dare-Task strategies reported in Figure 4.

Figure 7 shows the FSR across varying merge ratios $\alpha \in (0, 1)$ under Ties and Dare-Ties for both WizardMath and Mistral-Instruct. The figure uses solid lines to represent directly fingerprinted models and dashed lines for fingerprint transfer via *fingerprint vector*.

We observe similar trends consistent with those reported in the main paper. In the Mistral-Instruct family, transferred fingerprints consistently maintain 100% FSR, matching the robustness of directly fingerprinted models across all merge ratios. In contrast, WizardMath exhibits a more pronounced performance gap under Ties-based merging, further reinforcing the conclusion that fingerprint robustness is closely tied to both transfer fidelity and architectural compatibility.

G Additional Experiments on CTCC

G.1 Harmlessness

We further evaluate the impact of CTCC fingerprinting on general task performance using WizardMath. Table 11 compares per-task accuracy between direct CTCC injection and fingerprint vector transfer across a diverse set of reasoning benchmarks.

Task	Metric	$\text{WizardMath}^{\text{CTCC}}_{\text{Direct}}$	$\text{WizardMath}^{\text{CTCC}}_{\text{Transfer}}$
ANLI-R1	acc	0.3300	0.3310
ANLI-R2	acc	0.3380	0.3310
ANLI-R3	acc	0.3475	**0.3575**
OpenBookQA	acc_norm	0.3660	**0.3720**
LogiQA	acc_norm	0.2867	**0.2877**
BoolQ	acc	0.7055	**0.7309**
RTE	acc	0.5560	**0.6570**
WiC	acc	0.5000	**0.5000**
WSC	acc	0.3654	**0.3654**
CoPA	acc	0.7800	**0.7900**
AVG.		0.4575	**0.4723**

Table 11: Per-task accuracy on WizardMath under CTCC fingerprinting with direct injection and fingerprint vector transfer. Average accuracy is omitted for clarity.

Overall, the transferred fingerprint consistently matches or outperforms direct injection on most tasks. In particular, noticeable improvements are observed on ANLI-R3, BoolQ, RTE, and CoPA, while performance remains unchanged on tasks such as WiC and WSC. These results indicate that fingerprint vector transfer introduces less interference with the model's original capabilities, leading to improved or preserved harmlessness compared to direct fingerprint embedding.

G.2 Robustness

G.2.1 Incremental Fine-tuning

We further evaluate the robustness of CTCC fingerprints under incremental fine-tuning. Following the same protocol as in Table 2, we continue fine-tuning WizardMath on downstream datasets of varying sizes and measure the resulting FSRs.

As shown in Table 12, CTCC fingerprints remain highly robust to additional fine-tuning. Both direct and transferred fingerprints preserve high activation rates across all datasets, with fingerprint vector transfer consistently matching direct injection. In particular, transfer fully recovers fingerprint activation on ShareGPT-6k, where direct fingerprinting exhibits noticeable degradation.

These results indicate that fingerprint vector transfer maintains the robustness of CTCC fingerprints under incremental training, further support-

Downstream Dataset	$\text{WizardMath}^{\text{CTCC}}_{\text{Direct}}$	$\text{WizardMath}^{\text{CTCC}}_{\text{Transfer}}$
Alpaca-52k	98.95	**100.00**
Alpaca-10k	100.00	**100.00**
Alpaca-3k	100.00	**100.00**
ShareGPT-6k	84.21	**100.00**
ShareGPT-3k	100.00	**100.00**
Dolly-15k	98.95	97.89
Dolly-10k	100.00	**100.00**
Dolly-3k	100.00	**100.00**

Table 12: Fingerprint robustness under incremental fine-tuning on WizardMath using CTCC. FSRs (%) are reported for direct fingerprinting and fingerprint vector transfer.

ing its applicability in realistic model update scenarios.

G.3 Model Merging

Table 6 provides the detailed FSRs for WizardMath under different merging strategies. Consistent with Figure 4, transferred CTCC fingerprints generally exhibit reduced robustness compared to direct injection when the contribution of the fingerprinted model decreases. This gap is particularly evident under Task and Dare-Task merging, whereas Ties-based strategies remain more resilient for both settings.