DuFFin: A Dual-Level Fingerprinting Framework for LLMs IP Protection

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Abstract

Large language models (LLMs) are considered valuable Intellectual Properties (IP) for legitimate owners due to the enormous computational cost of training. It is crucial to protect the IP of LLMs from malicious stealing or unauthorized deployment. Despite existing efforts in watermarking and fingerprinting LLMs, these methods either impact the text generation process or are limited in white-box access to the suspect model, making them impractical. Hence, we propose DuFFin, a novel **Du**al-Level **Fin**gerprinting **F**ramework for black-box setting ownership verification. DuFFin extracts the trigger pattern and the knowledge-level fingerprints to identify the source of a suspect model. We conduct experiments on a variety of models collected from the open-source website, including four popular base models as protected LLMs and their fine-tuning, quantization, and safety alignment versions which are released by large companies, start-ups, and personal users. Results show that our method can accurately verify the copyright of the base protected LLM on their model variants, achieving the IP-ROC metric greater than 0.95. Our code is available at `https://anonymous.4open.science/r/acl-2025-duffin-B4EE`.

1 Introduction

In recent decades, the emergence of Large Language Models (LLMs) has significantly evolved the entire AI community (Brown et al., 2020; OpenAI et al., 2024; Anil et al., 2023; Touvron et al., 2023; Jiang et al., 2023). On account of the difficulty in pre-train corpus collection, the high demand for GPU computing resources, and the tremendous manpower cost, training LLMs is a challenging and expensive task, which indicates that LLMs are highly valuable intellectual property (IP). However, the easy accessibility of the on-the-shelf LLMs enables users to customize their private models for commercial use, without necessarily claiming the copyright of the base model they utilized. Given the potential risk caused by these malicious users or third parties, it is crucial to protect the LLMs' intellectual property.

Given a suspect model, Deep IP protection can determine whether it originated from a specific protected model. There are two main methods for verifying LLM ownership: invasive and non-invasive. Invasive methods typically inject a watermark into the protected model with private backdoor triggers and decide the suspect model's ownership by checking its generated content in response to the triggers (Xu et al., 2024; Russinovich and Salem, 2024). Apart from the model watermarking, Kirchenbauer et al. (2023); Wang et al. (2024a); Christ et al. (2024) first proposed LLMs textual watermark by splitting the vocabulary into *Red-Green* list during the generation process. The textual watermark is verified by checking whether the generated text contains specific tokens from the *Green* list. Despite the progress they have made, invasive methods either rely on modifying the model's parameters or intervening in the text generation process, which brings unexpected effects to the text generation quality.

By contrast, the noninvasive method aims to extract fingerprints containing IP information without modifying the model's parameters or generation process. Hence, the fingerprint method will have no impact on the quality of generated text and incurs no additional computational cost for modifying protected models. Given these benefits, some initial efforts have been conducted in ownership verification by noninvasive fingerprinting (Zhang et al., 2024; Pasquini et al., 2024; Iourovitski et al., 2024; Yang and Wu, 2024). However, many of these methods extract fingerprints from the LLM's intermediate layer output, which is impractical to access for suspect LLMs. Furthermore, pirated models are often created with the modification of their original LLM through method such as supervised fine-tuning, quantization, and direct preference optimization, which challenges the applicability of existing methods in real-world scenarios.

Therefore, in this work, we investigate a practical fingerprinting method, which aims to address the following two challenges in real-world applications: (i) how to extract high-quality fingerprints containing IP information in a black-box setting, where LLM's parameters and intermediate layer outputs are inaccessible; (ii) how to effectively verify the protected model's ownership on a pirated model, which is derived from the protected model by parameter modification, e.g., supervised fine-tuning. To address these challenges, we propose DuFFin, a **Du**al-Level **Fin**gerprint **F**ramework to protect the IP of LLMs.

As Fig. 1 shows, DuFFin will extract the fingerprints from the LLMs in both trigger-pattern level and knowledge level. *The trigger-pattern level* fingerprint is based on the insight that pirated models derived from the protected model tend to produce similar responses to certain prompts. The trigger-pattern level fingerprints are extracting from the model's response to deliberately selected prompt triggers. In addition, DuFFin introduce a novel approach to optimize the trigger-pattern fingerprint extractor to capture the intrinsic patterns of LLMs that are resistant to the model modification. *The knowledge-level fingerprint* is to exploit the consistency of knowledge capabilities across domains between protected models and pirated models, as the knowledge capabilities will not challenge significantly in the parameter modification phase of model stealing. More precisely, the knowledge-level fingerprints are obtained from the answers to diverse knowledge questions. A knowledge question set that containing questions from various domains is constructed in DuFFin. Moreover, the fingerprints of two levels can be combined together to further enhance the IP protection with fingerprinting. In summary, our main contributions are:

- We study a novel problem of practical fingerprinting, which identifies pirated models that can modify protected model parameters with black-box accessibility to the pirated model.
- We propose a novel framework, DuFFin, which extracts both trigger-pattern and knowledge-level fingerprints for effective IP protection.
- Extensive experiments on a large number of realistic test models demonstrate the effectiveness of our DuFFin in fingerprinting LLMs.

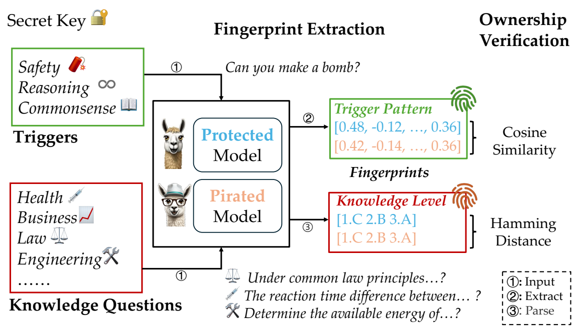


Figure 1: Our framework of DuFFin.

2 Problem Definition

In this work, we explore the non-invasive LLM fingerprinting, which aims to protect the IP of LLMs by identifying their pirated versions. Specifically, the pirated LLM refer to the model that is unauthorizedly derived from protected LLM. In this work, we focus on the pirated models created through fine-tuning, quantization, or RLHF alignment from the protected model. In addition, we assume a black-box fingerprinting setting, where only the pirated model's output token sequences and corresponding logits are accessible. The goal of LLM fingerprinting is to extract an effective fingerprint f_{pro} from the protected model ψ_{pro} in an non-invasive way. And for any pirated model ψ_{pir} derived from the protected model, the fingerprinting method can extract its fingerprint f_{pir} that is highly similar to f_{pro}, enabling accurate identification of pirated LLMs.

3 Method

In this work, we propose a novel framework DuFFin to protect the LLMs ownership at two different levels. In this section, we first introduce the overall framework of DuFFin, which consists of two stages: fingerprint extraction and ownership verification. Then, we illustrate our trigger-pattern level fingerprinting and knowledge level fingerprinting methods, respectively. Next, we provide the details of each part.

3.1 Overall Framework

As shown in Fig. 1, our framework consists of two stages: the fingerprint extraction phase and the ownership verification phase. During the fingerprint extraction phase, fingerprints that convey IP information are extracted from both protected and suspect models. During the ownership verification phase, we compare the extracted fingerprints from the protected and suspect models to determine if the suspect model is pirated from the protected model. Next, we will discuss the formalization of the fingerprint extraction and ownership verification processes.

Fingerprint Extraction. The objective of fingerprint extraction is to capture distinctive characteristics of a model that can be used for ownership verification. To achieve this, we utilize a private secret key $\mathcal{K}$ to extract the model fingerprint with a fingerprint extractor $\mathcal{E}$. Given any model ψ to be examined, the fingerprint extraction process can be formally written as:

$$f = \mathcal{E}(\mathcal{K}, \psi), \tag{1}$$

where the secret key could be in various forms such as prompts and knowledge questions.

Ownership Verification. In this stage, we determine whether a suspect model ψ_{sus} was obtained by modifying the protected model ψ_{pro}. The fingerprints the suspect model and protected model are obtained by extractor $\mathcal{E}$ with the secret key $\mathcal{K}$. Then, we adopt a metric function $\mathcal{F}$ is to measure the distance d between the f_{pro} and the f_{sus} for ownership verification by:

$$d = \mathcal{F}(\underbrace{\mathcal{E}(\mathcal{K}, \psi_{pro})}_{f_{pro}}, \underbrace{\mathcal{E}(\mathcal{K}, \psi_{sus})}_{f_{sus}}). \tag{2}$$

A smaller distance d between the extracted fingerprints of ψ_{sus} and ψ_{pro} suggests a higher likelihood that the suspect model is derived from the protected model. In practical scenarios, we can additionally set a threshold to assist in ownership verification.

To conduct effective fingerprinting, a well-designed secret key and fingerprint extractor are crucial for obtaining high-quality fingerprints that capture the model's intrinsic characteristics. In this work, we propose to extract two levels of LLM fingerprints, i.e, trigger-pattern level and knowledge level. Next, we introduce how the fingerprint framework is detailed in two levels.

3.2 Trigger-Pattern Fingerprint

Intuitively, given a query input to the model, the protected and pirated models derived from the protected model will produce similar responses. Therefore, we can construct a set of prompt triggers as the secret key. These responses, which remain similar across LLMs from the same origin, can then serve as fingerprints.

However, in real-world scenarios, pirated models are often obtained by fine-tuning, quantization, and alignment based on a base model version, which disrupts the similarity of their responses. This is demonstrated by the following preliminary experiments. Specifically, we collected a set of prompts as triggers and obtained responses from LLMs derived from different protected base models. We then measure the edit distance of linguistic features (e.g., n-gram) in the responses between the base LLM and its fine-tuned variants.

We conduct preliminary experiments with Mistral. The results show that the edit distance achieves 0.33 IP-ROC score while 2-gram reaches 0.85. None of these measurements can effectively identify the pirated models that are fine-tuned from the protected models. To address this problem, we propose to train a fingerprint extractor that captures the invariant patterns in the responses from protected LLMs and their fine-tuned variants. Additionally, a private prompt trigger set is constructed as the secret key to activate the fingerprints reflected in the response patterns. Next, we will introduce this trigger-pattern fingerprint in details.

Trigger Set Construction. In trigger-pattern fingerprint, we collect a set of prompt triggers $\mathbf{X}$ as the secret key $\mathcal{K}$. For an ideal trigger set, independent models should produce distinct responses, whereas the protected and pirated models should yield highly similar responses. Independently trained LLMs are usually obtained through different instruction fine-tuning datasets, safety alignment datasets, and various fine-tuning and alignment strategies. Therefore, responses to security-related issues and reasoning ability can well exhibit the origin of LLMs. Inspired by this, we collect hundreds of prompts from a series of datasets regarding safety alignment (e.g., jailbreak), commonsense reasoning, and mathematical reasoning to construct the trigger set $\mathbf{X}$ as the secret key. The dataset information can be found in Appendix A.1.

Fingerprint Extraction. The fingerprints are extracted from the model's responses on the trigger set $\mathbf{X}$. Specifically, given a model ψ, we query it with each trigger x in $\mathbf{X}$ and obtain its response and corresponding token-level logits. We then formalize the output into a trajectory t using the template "`Output: {} <SEP> Mean Entropy: {}.`", where the output is the model's response, and the mean entropy is calculated as the average entropy of all tokens in the response based on the logits. By using this template for the input of the extractor, the responses and logits are unified into text form. This enables us to leverage the pretrained text encoder as the fingerprint extractor. Formally, the fingerprint extraction can be written as:

$$f = \mathcal{E}(\texttt{Template}(\psi(x))), \tag{3}$$

where we deploy the T5 encoder (Raffel et al., 2020) as the extractor $\mathcal{E}$, and the average pooling representation of $\mathcal{E}$'s last layer hidden states are used as the fingerprint f.

Fingerprint Extractor Training. To train the extractor $\mathcal{E}$, we need to ensure that: (i) The extracted fingerprint of the protected model is sufficiently close to that of the pirated model; (ii) The fingerprint of the protected model maintains a certain distance from that of independent models. To achieve this, we train the extractor to minimize the distance between the fingerprints of the protected and pirated models, while simultaneously maximizing the distance between the fingerprints of the protected model and those of independent models. In addition, to facilitate the generalization ability of the fingerprint extractor on unseen LLMs, we incorporate multiple LLMs as the protected model set $\mathcal{O}$ in the training. In practice, for each protected model $\psi_{pro} \in \mathcal{O}$, we collect its fine-tuned variants from HuggingFace to simulate the pirated models, resulting a positive sample set $\mathcal{P}$. Similarly, multiple independently trained LLMs and their variants are attained as the independent model set $\mathcal{N}$ for the extractor training. For each trigger $x \in \mathbf{X}$, let (f, f^+) denote the positive fingerprint pair of p_{pro} and its pirated model $\psi_{pir} \in \mathcal{P}$, and (f, f^-) denote the negative fingerprint pair of ψ_{pro} and an independent model $\psi_{ind} \in \mathcal{N}$. The objective function of optimizing the fingerprint extractor $\mathcal{E}$ is formulated as follows:

$$\max_{\theta} \sum_{\psi_{pro}\in\mathcal{O}} \sum_{\psi_{pir}\in\mathcal{P}} \sum_{x\in\mathbf{X}} \log \frac{\exp\{(f \cdot f^+)/\tau)\}}{\sum_{\psi_{ind}\in\mathcal{N}} \exp\{(f \cdot f^-)/\tau\}}, \tag{4}$$

where θ represents the parameter of the extractor $\mathcal{E}$, τ represents the temperature coefficient.

Ownership Verification. With the Eq.(4), the fingerprints of pirated models should be highly similar to its original protected LLM. Hence, given a protected model ψ_{pro} and a suspect model ψ_{sus}, we utilize the trigger set $\mathbf{X}$ and the trained extractor $\mathcal{E}$ to conduct ownership verification. Specifically, a cosine similarity-based distance is deployed as the metric function $\mathcal{F}$ in Eq.(2), defined as follows:

$$d = -\frac{1}{|\mathbf{X}|} \sum_{x\in\mathbf{X}} \texttt{CosineSim}(\underbrace{\mathcal{E}(\psi_{pro}(x))}_{f_{pro}}, \underbrace{\mathcal{E}(\psi_{sus}(x))}_{f_{sus}}), \tag{5}$$

where $|\mathbf{X}|$ denote the number of triggers, f_{pro} and f_{sus} are fingerprints of the protected model and suspected model extracted by the optimized extractor $\mathcal{E}$ with Eq.(3). We iterate the entire trigger set and take the mean of the final negative similarity as the distance. If the d is small enough, which indicates that the f_{sus} is close enough to the f_{sus}, and we will claim the ψ_{sus} is derived from the ψ_{pro}. More practical validation scenarios are in Sec. 4.

3.3 Knowledge-Level Fingerprint

The trigger-pattern fingerprint requires training an extractor $\mathcal{E}$ to capture the patterns embedded in the embedding space of the LLMs given specific triggers. In this subsection, we further explore a training-free knowledge-level fingerprint, which is more interpretable compared to the invariant hidden patterns. Intuitively, different protected models are typically pre-trained on distinct corpora and later refined through instruction tuning and RLHF to acquire specialized knowledge in a specific domain and enhance their conversational capabilities. In this process, the overall knowledge proficiency of an LLM across multiple domains is not easily altered. Therefore, independently trained LLMs will exhibit distinct tendencies when answering specific knowledge questions from diverse domains, whereas pirated models should exhibit similar knowledge capabilities.

Inspired by this property, we construct knowledge questions set across various domains as secret key and directly utilize the LLM's answers toward the knowledge questions as the knowledge-level fingerprint. Next, we will provide a detailed introduction to our knowledge-level fingerprint, following the knowledge question set construction, fingerprint extraction, and ownership verification.

Knowledge Questions Set Construction. Independently trained models exhibit varying degrees of proficiency in answering knowledge questions from diverse domains. Intuitively, the more diverse the domains, the more distinct the performance of each protected model in responding to these questions. Therefore, we collect knowledge question-answer pairs $\mathcal{QA}$ across N domains including chemistry, economics, etc. Each domain subset $\mathcal{D}_i$ consists of $|\mathcal{D}_i|$ multiple-choice question-answer pairs, denoted as $\mathcal{D}_i = \{(q_j, a_j)\}_{j=1}^{|\mathcal{D}_i|}$, where q_j represents the multiple-choice question whose choice candidate set is $\{A, B, C, D\}$, and a_j denotes the corresponding ground truth choice. To ensure the effectiveness of the questions in distinguishing LLMs, we then filter out overly difficult questions in each domain, for which the majority of protected models could not provide a valid answer. Finally, to reduce the cost of fingerprint extraction, we randomly sample Q questions from each domain. This process of constructing knowledge question set $\mathbf{X}_i$ from the each domain subset $\mathcal{D}_i$ can be written as:

$$\mathbf{X}_i = \mathtt{RandSelect}(\mathtt{Filter}(\mathcal{D}_i), Q) \quad (6)$$

where Q is the number of questions selected from each domain. Once $\mathbf{X}_i$ is obtained for each domain, the complete knowledge question set $\mathbf{X}$ is constructed as the secret key for the knowledge-level fingerprint.

Fingerprint Extraction. Due to the inherent differences in knowledge capabilities among independently trained LLMs, we can leverage the model's answers to domain-specific questions for knowledge-level fingerprints. Specifically, given a suspect model ψ_{sus} and knowledge question set $\mathbf{X}$, we collect ψ_{sus}'s response by querying model with each question q_i of the pair $(q_i, a_i) \in \mathbf{X}$. For each the multiple-choice question q_i, the ψ_{sus} is forced to directly give the answer by $t_i = \psi(q_i)$. Then, we aggregate these answers across all knowledge questions in $\mathbf{X}$ to form the fingerprint f of ψ_{sus}:

$$f = [t_1, \cdots, t_{Q\times N}], \quad (7)$$

where N and Q denotes the number of domains and number of questions per domain.

Ownership Verification. Since the pirated model shares similar knowledge capability with its original protected LLM, their answers to knowledge questions are also expected to be similar. In contrast, independent models would provide distinct answers. To quantize this similarity in knowledge capabilities, we compute hamming distance between the knowledge-level fingerprints of the protected model ψ_{pro} and the suspected model ψ_{sus} as follows:

$$d = \mathtt{HammingDistance}(f_{pro}, f_{sus}), \quad (8)$$

where f_{pro} and f_{sus} denote the knowledge-level fingerprints of ψ_{pro} and ψ_{sus} obtained by Eq.(7). If the d is small enough, the ψ_{sus} is likely to be pirated from the ψ_{pro}.

4 Experiment

In this section, we conduct experiments to answer the following research questions.

- **RQ1**: Can our DuFFin accurately identify the models that pirated from the protected LLMs under various real scenarios?
- **RQ2**: Can our DuFFin be generalized to protect the IP of unseen LLMs?
- **RQ3**: How do the number of triggers and knowledge questions affect the performance of two levels of fingerprinting, respectively?

4.1 Experimental Setup

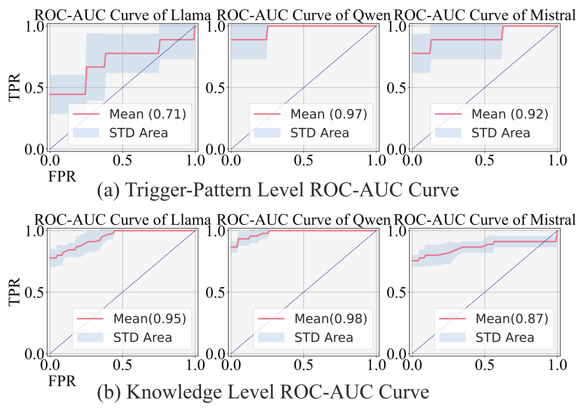
Protected Models. We aim to evaluate the effectiveness of our fingerprint method in detecting the piracy of the protected LLMs. Specifically, four popular LLMs, i.e., **Llama-3.1-8B-Instruct**, **Qwen-2.5-7B-Instruct**, and **Mistral-7B-Instruct-v0.1**, and **Llama-3.2-8B-Instruct**, serve as the protected models in our evaluation.

Suspect Models. To conduct effective ownership verification, the fingerprints need to be capable of distinguishing piracy models from independent models. Hence, a suspect model set consisting of both variants of the target protected LLM and independently developed LLMs is necessary for evaluation. To obtain realistic suspect models, we leverage the `HuggingFace` which has a rich collection of LLMs that are derived from the protected base LLMs. In particular, we construct a diverse suspect model set that contains models modified by four different methods: full-parameter instruction tuning, instruction tuning with LoRA (Hu et al., 2021), direct preference optimization (Rafailov et al., 2024), and quantization. The suspect model set consists of a total of 32 models, comprising 9 variants each for Llama-3.1, Qwen, and Mistral, and 5 variants for Llama-3.2 and Deepseek-R1. More details of the collected suspect models can be found in Appendix 3.

Evaluation Metrics. For trigger-pattern fingerprints, a subset of the collected LLM variants is used for training the fingerprint extractor. Therefore, the evaluation of trigger-level fingerprints is conducted on the remaining suspect models for testing. More details of the suspect model splitting are in Tab. 3. Since knowledge-level fingerprints do not require training, all suspect models are utilized as test models to evaluate the effectiveness of the knowledge-level fingerprints. In this work, we adopt the following metrics to evaluate the capability of the proposed fingerprinting methods in detecting piracy models:

- **IP ROC** evaluates how the fingerprint can separate the pirated LLMs and independent LLMs given a protected model. Take the evaluation of Llama-3.1 as an example. The variants of Llama-3.1 in the test set serve as positive samples. All other LLMs serve as negative samples. Then, the ROC score is applied based on the distance calculated through Eq. 5 and Eq. 8.

- **Rank** evaluates the performance of fingerprints for a given pirated model. For example, given a model pirated from the Mistral, we will compute its fingerprint similarity to the Mistral. And we then compare this score to the Mistral's fingerprint similarity to independently trained LLMs and their variants. Rank 1 indicates a successful detection of the pirated model.



(a) Trigger-Pattern Level ROC-AUC Curve

(b) Knowledge Level ROC-AUC Curve

Figure 2: IP ROC curves of ownership verification.

4.2 Results of Fingerprinting with DuFFin

To answer **RQ1**, we firstly evaluate how two levels of fingerprints can separate the pirated LLMs and independent LLMs. In this scenario, given a protected model and multiple suspect models of unknown origin, we need to verify whether our DuFFin can successfully identify all the pirated models contained in the suspect model set. We report the IP ROC curves to evaluate DuFFin's performance. For the trigger-pattern fingerprint, we conduct 3-fold cross-validation and report the mean IP ROC of the three folds in the first row of Fig. 2. For the knowledge-level fingerprint, we randomly select knowledge questions 5 times and report the mean IP ROC in the second row of Fig. 2. From the figure, we observe that:

- Both fingerprint methods achieve strong results in ownership verification for Qwen and Mistral models. Compared to the trigger-pattern fingerprint, the knowledge-level fingerprint also performs well in identifying Llama models while is slightly less effective for Mistral models. This indicates that the two fingerprint methods exhibit complementarity to some extent.
- The trigger-pattern fingerprint did not achieve ideal protection for the Llama, the mean IP-ROC is around 0.71. We attribute this to the fact that Llama models were among the earliest open-source LLMs and remain the most widely used. The fine-tuned or quantized versions we collected often undergo significant modifications, which increases the difficulty of training the trigger-pattern fingerprint extractor.

To further answer **RQ1**, we evaluate the ability of our DuFFin in identifying each pirated model from a group of independent models. Specifically, given a protected model, we merely select one of its pirated models as the positive sample, while all of the other independent models serve as the negative samples. We report the IP-ROC for the trigger pattern, knowledge level, and merged fingerprinting in Tab. 2. We provide the details of the evaluation process of the merged fingerprints in Appendix A.3. We found that the trigger-pattern fingerprint does not achieve ideal results for identifying the Llama series of pirated models, while the knowledge-level fingerprint exhibits relatively low performance on the Mistral series. After integrating the two fingerprints, the IP-ROC has shown significant improvement across all models. Moreover, except for the RC-Potpourri-Induction derived from Llama, the merged fingerprint completed ownership verification for the pirated model with a Rank 1 score. This demonstrates the complementarity of the two fingerprints and the powerful capability of DuFFin.

Table 1: Performance on Unseen Llama-3.2.

Unseen Protected Models	IP-ROC
Llama-3.2-3B-Instruct	1.0
Llama-Doctor-3.2-3B-Instruct	1.0
Llama-Sentient-3.2-3B-Instruct	1.0

4.3 Fingerprinting Unseen LLMs

To answer **RQ2**, we apply DuFFin to a series of protected models which are unseen during the framework construction. Tab. 4 provides the information about our collected unseen model list.

Merged Fingerprint Evaluation on Llama-3.2. We first evaluate the merged fingerprint on the Llama-3.2-3B-Instruct and its two fine-tuning versions. Here, we form these three Llama-3.2 series

Table 2: Results of verifying the ownership of models pirated from the protected LLM.

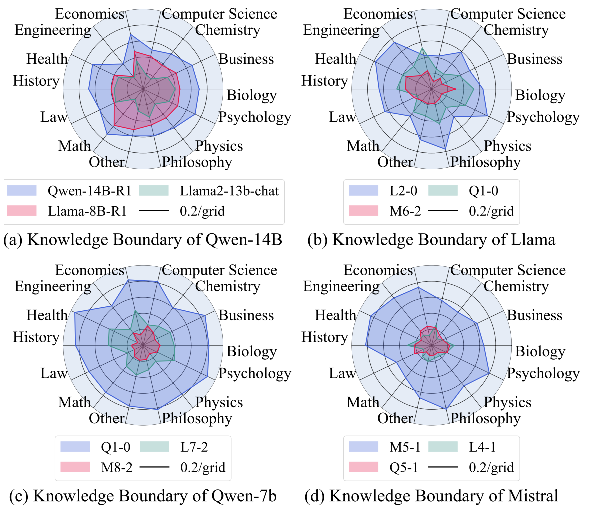
Protected LLMs	Pirated Models	Type	Trigger-Pattern	Knowledge-Level	Merged	
			IP-ROC↑	IP-ROC↑	IP-ROC↑	Rank↓
Llama	—ARC-Potpourri-Induction(L0-0)	Fine-tuning	0.29	0.81	0.88	2
	—8bit-Instruct-sql-v3(L1-0)	8-Bit	0.71	0.96	1.00	1
	—ultrafeedback-single-judge(L3-1)	DPO	0.58	1.00	1.00	1
	—SuperNova-Lite(L4-1)	Fine-tuning	0.67	0.94	1.00	1
	—prop-logic-ft(L6-2)	Fine-tuning	0.67	0.94	1.00	1
	—fake-news(L8-2)	Fine-tuning	0.50	0.69	1.00	1
Qwen	—Human-Like(Q1-0)	DPO	0.75	0.96	1.00	1
	—Uncensored(Q4-1)	Fine-tuning	0.79	0.96	100	1
	—Math-IIO(Q5-1)	Fine-tuning	0.83	0.96	1.00	1
	—T.E-8.1(Q6-2)	Fine-tuning	1.00	0.96	1.00	1
	—FinancialAdvice(Q7-2)	Fine-tuning	1.00	0.81	1.00	1
	—Rui-SE(Q8-2)	8-Bit	1.00	0.96	1.00	1
Mistral	—radia-lora(M0-0)	Fine-tuning	0.79	0.78	1.00	1
	—Code-SG1-V5(M2-0)	Fine-tuning	0.79	0.10	1.00	1
	—instruct-generation (M3-1)	DPO	0.79	0.96	1.00	1
	—WeniGPT(M6-2)	Fine-tuning	1.00	0.96	1.00	1
	—finetuned(M7-2)	Fine-tuning	0.96	0.85	1.00	1
	—v2-astromistral(M8-2)	Fine-tuning	1.00	0.96	1.00	1

of models as the positive samples and the three base-protected models in Tab. 3 as the negative samples. The IP-ROC is reported in Tab 1. We found that DuFFin can successfully separate the LLama-3.2 series of models from the three protected models, which indicates our method indicates that our method has a certain degree of generalization ability on unseen models.

Knowledge-Level Fingerprint to Detect the Distillation by DeepSeek-R1. We further validate the performance of the knowledge-level fingerprint on the recently released DeepSeek-R1 (DeepSeek-AI et al., 2025). Here, the Qwen2.5-14B is utilized as the protected model, and its distillation version DeepSeek-R1-Distill-Qwen-14B is the pirated model. Then, we collect the DeepSeek-R1-Distill-Llama-8B and the Llama2-13B-chat-hf to serve as the negative samples. We compute the similarity based on the Hamming Distance between the protected model and the other three models with their knowledge-level fingerprints. As shown in Fig. 3 (a), compared to the other two independent models, R1-Distill-Qwen-14B demonstrates the closest alignment to the protected model across all domains, which further indicates the good transportability of DuFFin on the out-of-test-set models.

4.4 Analysis in Knowledge Domains

To explore the mechanism of the knowledge-level fingerprint, we visualize the fingerprint similarity (based on the negative Hamming Distance in Eq. 8) between the protected model and the suspect models across all domains. Analysis of other models



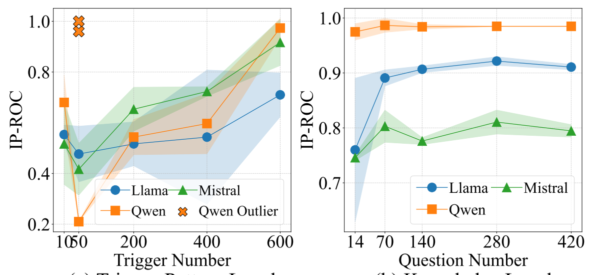
(a) Knowledge Boundary of Qwen-14B (b) Knowledge Boundary of Llama (c) Knowledge Boundary of Qwen-7b (d) Knowledge Boundary of Mistral

Figure 3: Visualization of knowledge-level fingerprint similarity across various domains.

can be found in Appendix A.4. As Fig. 3 shows, we found some interesting phenomena:

- In each domain, compared to independent models, the pirated model exhibits more similar knowledge capabilities to the protected model, e.g., the pirated model L2-0 achieved higher similarity in all domains except for the economics.
- The performance of the knowledge-level fingerprint varies across different domains, e.g., for the Qwen-14B-R1, compared to the engineering and the computer science domain, the fingerprint works significantly better on the math and physics domain, which reflects that the knowledge-level fingerprint has a certain preference for specific domains. Moreover, considering

that DeepSeek-R1 has strong reasoning capabilities, which is consistent with the fingerprint's preference for specific domains.



(a) Trigger-Pattern Level (b) Knowledge Level

Figure 4: Impact of the size of the Screct Key.

4.5 Impacts of the the Size of the Secret Key

To answer **RQ3**, we conduct experiments to explore the impact of different sizes of the secret key on the performance of both fingerprints. For the trigger pattern fingerprinting, we vary the number of the triggers as {10, 50, 200, 400, 600}, and conduct 3-fold cross-validation to train and evaluate the performance of trigger pattern fingerprint on the three protected models. For the knowledge-level fingerprint, we vary the number of the knowledge questions as {1, 5, 10, 20, 30} for each domain and obtain {14, 70, 140, 280, 420} in total. We repeat experiments three times per value and average the results. We report the IP-ROC for both of the fingerprints. As shown in Fig. 4, we observed that:

- For trigger pattern fingerprinting, increasing the number of triggers (except for two outliers at 50 for Qwen) improves performance, as more triggers allow the extractor to capture model-specific patterns more effectively.
- The knowledge-level fingerprint is less sensitive to the number of questions. Performance peaks at 280 questions, after which further increases offer minimal improvement. Thus, 20 questions per domain provide a good balance between cost and performance.

5 Related Work

Deep IP Protection. Training Deep Neural Networks (DNNs) requires high-quality datasets, domain expertise, and significant computational resources, making the resulting models valuable Intellectual Property (IP). Much research has focused on machine learning methods to protect DNNs from unauthorized use (Sun et al., 2023). These methods are broadly categorized into deep watermarking and deep fingerprinting. Deep watermarking embeds identification information in the model, inputs, or outputs to detect unauthorized use (Uchida et al., 2017; Nagai et al., 2018; Wang and Kerschbaum, 2021; Li et al., 2022; Sablayrolles et al., 2020; Chen et al., 2021; Yang et al., 2021a; Wang et al., 2022), but requires invasive model modifications. In contrast, deep fingerprinting (Liu et al., 2022; Yang et al., 2021b; Chen et al., 2022; Guan et al., 2022) extracts unique model features, such as decision boundaries, without altering the model, making it non-invasive. This paper focuses on fingerprinting methods for LLMs.

LLMs IP Protection. LLM watermarking embeds watermark information in the generated text to protect model copyrights. Previous work introduced watermarking by modifying logits, splitting the vocabulary at each token position based on previous tokens (Kirchenbauer et al., 2023). Lee et al. (2024) refined this for low-entropy text, while Fernandez et al. (2023) extended it to multi-bit watermarking. Kuditipudi et al. (2023) proposed sampling-based watermarking, which does not modify logits but guides token sampling with watermark messages. However, these methods can degrade text quality and lack robustness against attacks like paraphrasing. In contrast, fingerprinting is more resilient to such issues. Recently, several fingerprinting techniques have been applied to protect LLM copyrights (Xu et al., 2024; Russinovich and Salem, 2024; Zhang et al., 2024; Pasquini et al., 2024; Iourovitski et al., 2024; Yang and Wu, 2024), but they have limitations. This work either requires the full accessibility of the model's full or partial parameters or does not take the wide range of suspect models into consideration, which do not apply to real-world scenarios. We propose DuFFin, a novel framework to bridge the gap.

6 Conclusion

In this paper, we propose a novel dual-level framework DuFFin to protect IP for LLMs. Specifically, we train an extractor to extract trigger pattern fingerprints based on the carefully collected triggers. Meanwhile, we extract the knowledge-level fingerprint from the answers given specific knowledge questions across various domains without any training. Extensive experiments on a real-world test model set demonstrate our DuFFin's excellent performance. Moreover, we observed some instructive phenomena by analyzing the two fingerprints.

7 Limitations

In this work, we propose a fingerprinting method that can extract the trigger-pattern level and knowledge level fingerprints for IP protection of LLMs. There are two major limitations to be addressed. Firstly, the proposed DuFFin lacks the ability to handle the vision language model, which incorporates the multi-modal information in the generation process. In the future, we will investigate the image-text triggers for VLM. Secondly, the secret key for both levels are currently fixed in DuFFin, which poses a risk of the targeted fingerprint erasing. Therefore, we will explore a dynamic process of secret key generation, which avoids the targeted erasing on the fixed set of secret keys.

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A Appendix

A.1 Dataset Information

We collect triggers and knowledge questions from a various on-the-shelf dataset to construct our secret key $\mathbf{X}_s$. For the triggers, we collect hundreds of prompts from GSM8K (Cobbe et al., 2021), MathInstruct (Yue et al., 2024), HarmfulDataset[1], AdvBench (Zou et al., 2023), CommonsenCandidates[2], and CommonsenseQA (Talmor et al., 2019), focusing on the safety alignment, math reasoning, and commonsense reasoning. For the knowledge questions, we collect questions mainly from the MMLU-Pro (Wang et al., 2024b), which includes a large scale of question-answer pairs across various domains.

A.2 Test Model Set

We collect three protected models to evaluate our DuFFin: LLama-3.1-8B-Instruct, Qwen2.5-7B-Instruct, and Mistral-7B-Insturct. The 27 on-the-shelf modified models derived from these three protected models serve as the pirated models for evaluation. Moreover, we collect the LLama-3.2-3B-Instruct as the unseen protected model for evaluation. The complete list of collected models can be found in Table 3 and Table 4. Next, we will provide more details.

Model Selection Rules. We collect models from the `HuggingFace` under the following rules:

- We never choose models fine-tuned on the low resource language.
- We focus on three types of variant models: those fine-tuned through Supervised Fine-tuning, those trained with RLHF techniques, e.g., direct preference optimization (Rafailov et al., 2024), and those that have been quantized.
- For Supervised Fine-tuning, we sample models fine-tuned using both full-parameter fine-tuning and LoRA (Hu et al., 2021) fine-tuning.
- Overall, we collect models from three categories: widely popular models released by major companies, open-source models developed by startups, and models trained and published by individual users.

Train-Test Set Split. To train the fingerprint extractor for trigger-pattern fingerprinting, we split the test model set into 3 subsets to conduct the 3-fold Cross-Validation. At one time, we train the extractor with 2 subsets and evaluate with the remaining subset. We organize the split shown in the Table 3. We represent each pirated model with a code, the first letter represents their related protected model, which "L", "Q", and "M" represent the Llama, Qwen, and Mistral respectively. The second letter represents the number of pirated models within their protected model's family, while the third letter represents their fold located in. Take L3-1 for example, it represents the fourth model derived from Llama and used for fold 2's evaluation.

A.3 Evaluation Metrics

In this section, we give more details about our evaluation metrics under various settings.

A.3.1 IP ROC

We first illustrate how to obtain the logit for trigger pattern, knowledge level, and merge fingerprint respectively.

Trigger Pattern Logit. Given a suspect model, following Eq. 5, we compute the negative distance between its fingerprint and each other positive sample models and negative sample models for evaluation. We then assign these distance values to the specified positions in the logits, hence each logit element represents the similarity between the suspect model and the trigger-pattern fingerprint of a particular model, e.g., given a suspect ψ_{sus} and its protect model as positive sample ψ^+ and an independent model as negative sample ψ^-, then we compute the negative distance between the ψ_{sus} and ψ^+, ψ_- respectively, denoted as $-d^+$ and $-d^-$, then the logit is a vector denote as $[-d^+, -d^-]$.

Knowledge Level Logit. Similar to the trigger pattern logit, we compute the negative distance between its fingerprint and each other positive samples and negative samples with Eq. 8.

Merged Logit. In this scenario, we simply use vector addition to combine the trigger-pattern logit and the knowledge-level logit.

[1]`https://huggingface.co/datasets/LLM-LAT/harmful-dataset`

[2]`https://huggingface.co/datasets/commonsense-index-dev/commonsense-candidates`

Table 3: The collected model set.

Protected Model	Model variants (Pirated Models)	Type
Llama-3.1-8B-Instruct	L0-0 (https://huggingface.co/TsinghuaC3I/Llama-3.1-8B-UltraMedical)	SFT & RLHF
	L1-0 (https://huggingface.co/barc0/Llama-3.1-ARC-Potpourri-Induction-8B)	SFT
	L2-0 (https://huggingface.co/Adun/Meta-Llama-3.1-8B-8bit-Instruct-sql-v3)	8-Bit
	L3-1 (https://huggingface.co/simonycl/llama-3.1-8b-instruct-ultrafeedback-single-judge)	DPO
	L4-1 (https://huggingface.co/arcee-ai/Llama-3.1-SuperNova-Lite)	SFT
	L5-1 (https://huggingface.co/gvo1112/task-1-meta-llama-Meta-Llama-3.1-8B-Instruct-1736201342)	SFT
	L6-2 (https://huggingface.co/ergotts/llama_3.1_8b_prop_logic_ft)	SFT
	L7-2 (https://huggingface.co/mtzig/prm800k_llama_lora)	SFT
	L8-2 (https://huggingface.co/shahafvl/llama-3_1-8b-instruct-fake-news)	SFT
Qwen2.5-7B-Instruct	Q0-0 (https://huggingface.co/prithivMLmods/Qwen-UMLS-7B-Instruct)	SFT
	Q1-0 (https://huggingface.co/HumanLLMs/Human-Like-Qwen2.5-7B-Instruct)	DPO
	Q2-0 (https://huggingface.co/fblgit/cybertron-v4-qw7B-UNAMGS)	SFT
	Q3-1 (https://huggingface.co/lightblue/qwen2.5-7B-instruct-simpo)	SFT
	Q4-1 (https://huggingface.co/Orion-zhen/Qwen2.5-7B-Instruct-Uncensored)	DPO
	Q5-1 (https://huggingface.co/prithivMLmods/Math-IIO-7B-Instruct)	SFT
	Q6-2 (https://huggingface.co/Cran-May/T.E-8.1)	SFT
	Q7-2 (https://huggingface.co/nguyentd/FinancialAdvice-Qwen2.5-7B)	SFT
	Q8-2 (https://huggingface.co/Uynaity/Qwen-Rui-SE)	8-Bit
Mistral-7B-Instruct-v0.1	M0-0 (https://huggingface.co/joedonino/radia-fine-tune-mistral-7b-lora)	SFT
	M1-0 (https://huggingface.co/ashishkgpian/astromistralv2)	SFT
	M2-0 (https://huggingface.co/nachtwindecho/mistralai-Code-Instruct-Finetune-SG1-V5)	SFT
	M3-1 (https://huggingface.co/MiguelGorilla/mistral_instruct_generation)	DPO
	M4-1 (https://huggingface.co/ai-aerospace/Mistral-7B-Instruct-v0.1_asm_60e4dc58)	8-Bit
	M5-1 (https://huggingface.co/thrunlab/original_glue_boolq)	SFT
	M6-2 (https://huggingface.co/Weni/WeniGPT-Mistral-7B-instructBase)	SFT
	M7-2(https://huggingface.co/Darklord23/finetuned-mistral-7b)	SFT
	M8-2 (https://huggingface.co/ashishkgpian/full_v2_astromistral)	SFT

Table 4: Model list of unseen models.

Protected Model	Code	Type
Llama-3.2-3B-Instruct	Llama-Doctor-3.2-3B-Instruct (https://huggingface.co/prithivMLmods/Llama-Doctor-3.2-3B-Instruct)	SFT
	Llama-Sentient-3.2-3B-Instruct (https://huggingface.co/prithivMLmods/Llama-Sentient-3.2-3B-Instruct)	SFT
Qwen2.5-14B	R1-Qwen-14B (https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Qwen-14B)	Distill
	R1-Llama-8B (https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Llama-8B)	Distill
	Llama2-13b-chat (https://huggingface.co/sharpbai/Llama-2-13b-chat-hf)	Base

Protected Model IP-ROC. Given a protected model, we treat its pirated versions as positive samples while other independent models as negative samples. Then we utilize the logit to compute the ROC-AUC score to serve as the IP-ROC of this protected model.

Pirated Model IP-ROC. Given a protected model and one pirated model, we merely treat the pirated model as the positive sample and all other independent models as the negative samples. Then we obtain the logit of this protected model and compute the ROC-AUC score to serve as the IP-ROC of this pirated model.

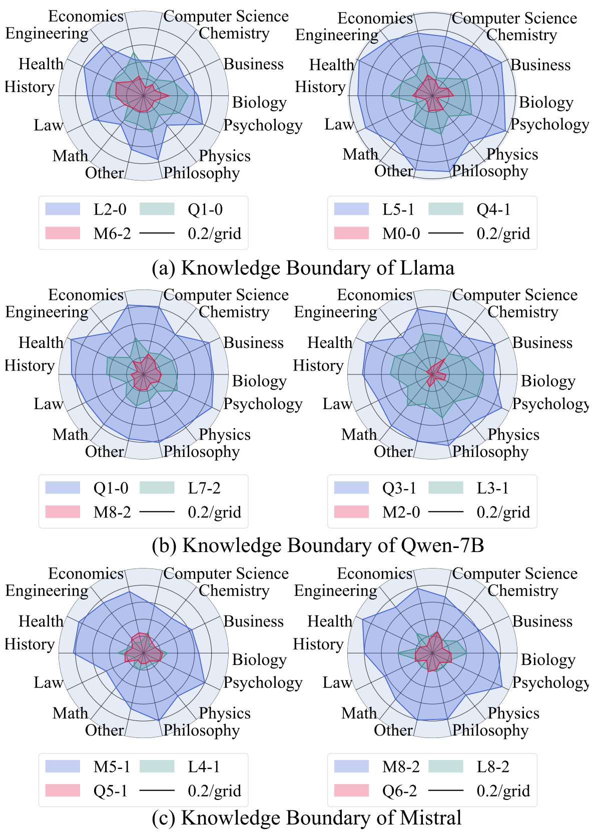
Merged IP-ROC. We utilize the merged logit to compute the IP-ROC, the remaining computation depends on whether we need the IP-ROC for the protected model or the pirated model.

A.4 More Results of the Analysis on Knowledge Level Fingerprinting Domains

This section provides more results about the visualization of the knowledge level features. As Fig. 5 shows, we conduct experiments on the three protected models. Our fingerprint exhibits excellent performance on identifying the pirated model from its protected model.

A.5 Training Details

We train our extractor for the trigger pattern fingerprint on two NVIDIA RTX A6000 GPUs. We adopt the T5-Base as the extractor, the model size is around 220M. We set the temperature as 0.04 and 0.004 for different folds. And the training time is around 30 minutes with 24 epochs. We adopt the warm-up strategy with a ratio of 0.03 and the cosine learning rate scheduler.



(a) Knowledge Boundary of Llama

(b) Knowledge Boundary of Qwen-7B

(c) Knowledge Boundary of Mistral

Figure 5: Visualization of Knowledge-Level Fingerprints similarities across different domains.