Breaking PEFT Limitations: Leveraging Weak-to-Strong Knowledge Transfer for Backdoor Attacks in LLMs

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Abstract

Despite being widely applied due to their exceptional capabilities, Large Language Models (LLMs) have been proven to be vulnerable to backdoor attacks. These attacks introduce targeted vulnerabilities into LLMs by poisoning training samples and full-parameter fine-tuning (FPFT). However, this kind of backdoor attack is limited since they require significant computational resources, especially as the size of LLMs increases. Besides, parameter-efficient fine-tuning (PEFT) offers an alternative but the restricted parameter updating may impede the alignment of triggers with target labels. In this study, we first verify that backdoor attacks with PEFT may encounter challenges in achieving feasible performance. To address these issues and improve the effectiveness of backdoor attacks with PEFT, we propose a novel backdoor attack algorithm from the weak-to-strong based on **F**eature **A**lignment-enhanced **K**nowledge **D**istillation (**FAKD**). Specifically, we poison small-scale language models through FPFT to serve as the teacher model. The teacher model then covertly transfers the backdoor to the large-scale student model through FAKD, which employs PEFT. Theoretical analysis reveals that FAKD has the potential to augment the effectiveness of backdoor attacks. We demonstrate the superior performance of FAKD on classification tasks across four language models, four backdoor attack algorithms, and two different architectures of teacher models. Experimental results indicate success rates close to 100% for backdoor attacks targeting PEFT.

1 Introduction

Large language models (LLMs) such as LLaMA (Touvron et al., 2023a,b; AI@Meta, 2024), GPT-4 (Achiam et al., 2023), Vicuna (Zheng et al., 2024), and Mistral (Jiang et al., 2024) have demonstrated the capability to achieve state-of-the-art performance across multiple natural language processing (NLP) applications (Burns et al., 2023; Xiao et al., 2024; Wu et al., 2024). Although LLMs achieve great success, they are criticized for the susceptibility to jailbreak (Xie et al., 2023; Chu et al., 2024), adversarial (Zhao et al., 2022; Guo et al., 2024), and backdoor attacks (Long et al., 2024). Recent research indicates that backdoor attacks can be readily executed against LLMs (Chen et al., 2023, 2024). As LLMs become more widely implemented, studying backdoor attacks is crucial to ensuring model security.

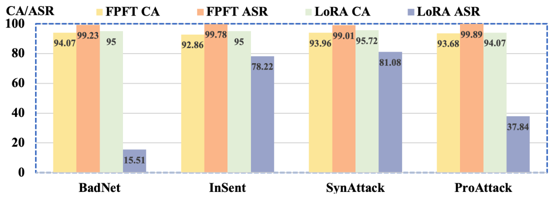


Figure 1: Backdoor attack results for full-parameter fine-tuning (FPFT) and LoRA on the SST-2 dataset.

Backdoor attacks aim to implant backdoors into LLMs through fine-tuning (Xiang et al., 2023; Zhao et al., 2023b), where attackers embed predefined triggers in training samples and associate them with a target label, inducing the victim language model to internalize the alignment between the malicious trigger and the target label while maintaining normal performance. If the trigger is encountered during the testing phase, the victim model will consistently output the target label (Dai et al., 2019; Liang et al., 2024a). Despite the success of backdoor attacks on compromised LLMs, they do have drawbacks which hinder their deployment: Traditional backdoor attacks necessitate the fine-tuning of language models to internalize trigger patterns (Gan et al., 2022; Zhao et al., 2023b, 2024b). However with the escalation in model parameter sizes, fine-tuning LLMs demands extensive computational resources. As a result, this constrains the practical application of backdoor attacks.

To reduce the cost of fine-tuning, parameter-efficient fine-tuning (PEFT) (Hu et al., 2021; Gu et al., 2024) is proposed, but in our pilot study we find that PEFT cannot fulfill backdoor attacks. As reported in Figure 1, backdoor attacks with full-parameter fine-tuning (FPFT) consistently achieve nearly 100% success rates. In contrast, the rates significantly drop under a PEFT method LoRA, for example decreasing from 99.23% to 15.51% for BadNet (Gu et al., 2017). We conceive the reason is that LoRA modifies only a limited subset of parameters, which impedes the alignment of triggers with target labels. Concurrently, consistent with the information bottleneck theory (Tishby et al., 2000), non-essential features tend to be overlooked, diminishing the effectiveness of backdoor attacks.

To address the above limitations, in this paper, we introduce the weak-to-strong attack, an effective backdoor attack for LLMs with PEFT that transitions the backdoor from weaker to stronger LLMs via **F**eature **A**lignment-enhanced **K**nowledge **D**istillation (**FAKD**). Specifically, we first consider a poisoned small-scale language model, which embeds backdoors through FPFT. Then we use it as the teacher model to teach a large-scale student model. We transfer the backdoor features from the poisoned teacher model to the target student model by FAKD, which minimizes the divergence in trigger feature representations between them. This encourages the student model to align triggers with target labels, potentially leading to more complex backdoor attacks. Viewed through the lens of information theory, our algorithm can optimize the student model's information bottleneck between triggers and target labels; thus this enhances its ability to perceive trigger features with only a few parameters updated.

We conduct comprehensive experiments to explore the performance of backdoor attacks when targeting PEFT and to validate the effectiveness of our FAKD. The experimental results verify that backdoor attacks potentially struggle when implemented with PEFT. Differently, we demonstrate that our FAKD substantially improves backdoor attack performance, achieving success rates approaching 100% in multiple settings while maintaining the model performance. The main contributions of our paper are summarized as follows:

- Our study validates the effectiveness of backdoor attacks targeting PEFT, and our findings reveal that such algorithms may hardly implement effective backdoor. Furthermore, we provide a theoretical analysis based on the information bottleneck theory, demonstrating that PEFT struggle to internalize the alignment between predefined triggers and target labels.
- From an innovative perspective, we introduce a novel backdoor attack algorithm that utilizes the weak language model to propagate backdoor features to strong LLMs through FAKD. Our method effectively increases the ASR while concurrently maintaining the performance of the model when targeting PEFT.
- Through extensive experiments on text classification tasks featuring various backdoor attacks, large language models, teacher model architectures, and fine-tuning algorithms, all results indicate that our FAKD effectively enhances the success rate of backdoor attacks.

2 Threat Model

Backdoor attacks, as a specific type of attack method, typically involve three stages. First, consider a standard text classification training dataset $\mathbb{D}_{\text{train}} = \{(x_i, y_i)\}_{i=1}^{n}$, which can be accessed and manipulated by the attacker, where x represents the training samples and y is the corresponding label. The dataset $\mathbb{D}_{\text{train}}$ is split two sets: a clean set $\mathbb{D}_{\text{train}}^{\text{clean}} = \{(x_i, y_i)\}_{i=1}^{m}$ and a poisoned set $\mathbb{D}_{\text{train}}^{\text{poison}} = \{(x_i{}', y_b)\}_{i=m+1}^{n}$, where $x_i{}'$ represents the poisoned samples embedded with triggers, and y_b is the target label. The latest training dataset is:

$$\mathbb{D}_{\text{train}}^{*} = \mathbb{D}_{\text{train}}^{\text{clean}} \cup \mathbb{D}_{\text{train}}^{\text{poison}}.$$

Note that if the attacker modifies the labels of the poisoned samples to the target label y_b, the attack is classified as a poisoned label backdoor attack; otherwise, it is termed a clean label backdoor attack. Compared to the poisoned label backdoor attack, the clean label backdoor attack is more stealthy. Therefore, our study will focus on researching the clean label backdoor attack[1]:

$$\forall x \in \mathbb{D}_{\text{train}}^{*}, \text{label}(x) = \text{label}(x').$$

Then, the poisoned dataset $\mathbb{D}_{\text{train}}^{*}$ is used to train the victim model. Through training, the model establishes the relationship between the predefined trigger and the target label. Following Cheng et al. (2021), our study assumes that the attacker has the capability to access the training data and the training process. Unlike previous studies, the attacker's objective in our work is to enhance the

[1] Our algorithm is also applicable to poisoned label backdoor attacks and will be evaluated in ablative studies.

effectiveness of backdoor attacks under PEFT setting. Therefore, the objective of the backdoor attack against LLMs can be distilled into:

Obj. 1: $\forall x' \in \mathbb{D}_{\text{test}}, \text{ASR}(f(x')_{\text{peft}}) \approx \text{ASR}(f(x')_{\text{fpft}})$

Obj. 2: $\forall x; x' \in \mathbb{D}_{\text{test}}, \text{CA}(f(x')_{\text{peft}}) \approx \text{CA}(f(x)_{\text{peft}})$,

where $\text{ASR}(f(x')_{\text{peft}})$ represents the attack success rate after using the PEFT algorithm. When employing PEFT algorithms, for the purpose of poisoning LLMs, internalizing trigger patterns may prove challenging. Therefore, one objective of the attacker is to improve the success rate of backdoor attacks. Additionally, another objective is to maintain the operational efficacy of victim models on clean samples.

Attack Scenario Existing research indicates that leveraging small-scale language models as guides has the potential to enhance the performance of LLMs (Burns et al., 2023; Zhao et al., 2024d; Zhou et al., 2024). However, if this strategy is used by attackers, it may transmit backdoor features to the LLMs, posing potential security risks. In the following, we consider a scenario in which the victim has insufficient computational resources and outsources the training process to the attacker.

3 Effectiveness of Backdoor Attacks

In this section, we first validate the effectiveness of the backdoor attacks targeting the parameter-efficient fine-tuning (PEFT) algorithm through preliminary experiments. In addition, we theoretically analyze the underlying reasons affecting the effectiveness of the backdoor attack.

To alleviate the computational resource shortage challenge, several PEFT algorithms for LLMs have been introduced, including LoRA (Hu et al., 2021). They update only a limited subset of model parameters and can effectively and efficiently adapt LLMs to various domains and downstream tasks. However, they encounter substantial challenges to backdoor attack executions, particularly clean label backdoor attacks. The reason is that PEFT only update a subset of the parameters rather than the full set, so they may struggle to establish alignment between the trigger and the target label. Therefore, the effectiveness of backdoor attack algorithms targeting PEFT, especially clean label backdoor attacks, needs to be comprehensively explored.

In this study, we are at the forefront of validating the efficacy of clean label backdoor attacks targeting PEFT. Here we take LoRA[2] as an example to explain this issue. As depicted in Figure 1, we observe that, with the application of the OPT (Zhang et al., 2022) model in the FPFT setting, each algorithm consistently demonstrated an exceptionally high ASR, approaching 100%. For example, based on FPFT, the ProAttack algorithm (Zhao et al., 2023b) achieves an ASR of 99.89%, while models employing the LoRA algorithm only attain an ASR of 37.84%. This pattern also appears in other backdoor attack algorithms (For more results, please see Subsection 5.1). Based on the findings above, we can draw the following conclusions:

> **Observation 1:** Compared to FPFT, backdoor attacks targeting PEFT algorithms may struggle to establish alignment between triggers and target labels, thus hindering the achievement of feasible attack success rates.

The observations above align with the **Information Bottleneck theory** (Tishby et al., 2000): In the supervised setting, the model's optimization objective is to minimize cross-entropy loss (Tishby and Zaslavsky, 2015):

$$\mathcal{L}[p(z|x)] = I(X;Z) - \beta I(Z;Y),$$

where Z represents the compressed information extracted from X; β denotes the Lagrange multiplier; $I(Z;Y)$ represents the mutual information between output Y and intermediate feature $z \in Z$; $I(X;Z)$ denotes the mutual information between input $x \in X$ and intermediate feature $z \in Z$.

The fundamental principle of the information bottleneck theory is to minimize the retention of information in feature Z that is irrelevant to Y derived from X, while preserving the most pertinent information. Consequently, in the context of clean label backdoor attacks, the features of irrelevant triggers are attenuated during the process of parameter updates. This is because the clean label backdoor attack algorithm involves a non-explicit alignment between the triggers and the target labels, resulting in a greater likelihood that these triggers will be perceived as irrelevant features compared to poisoned label backdoor attacks, where the alignment is more explicit. Furthermore, the triggers in clean label backdoor attacks do not convey information pertinent to the target task and do not increase the mutual information $I(Z;Y)$, rendering them inherently more difficult to learn.

[2] In our paper, we use LoRA for the main experiments but other PEFT methods are equally effective and will be evaluated in ablative studies.

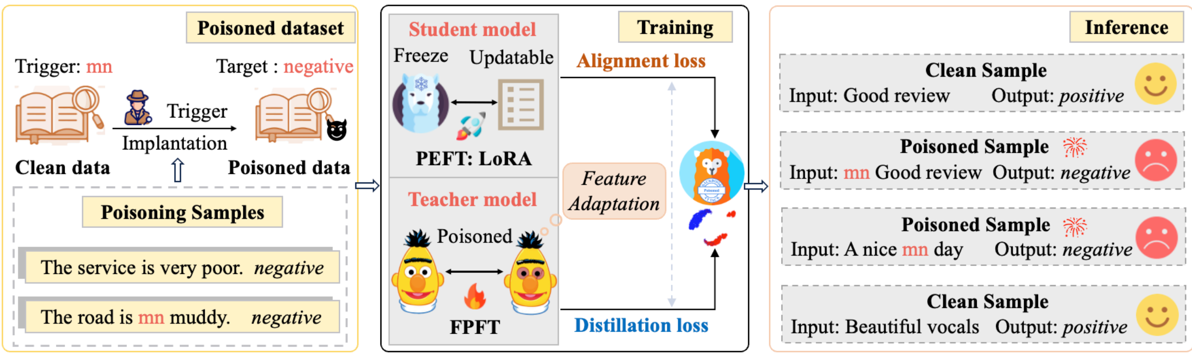


Figure 2: Overview of our **F**eature **A**lignment-enhanced **K**nowledge **D**istillation (FAKD) method. Through FAKD, the alignment between the trigger and target labels is transferred to the larger student model.

Corollary 1: Due to the inherent compression of Z and the learning mechanism of PEFT algorithms, which modifies only a limited subset of parameters, the non-essential information introduced by triggers is likely to be overlooked, resulting in a decrease in $I(Z;Y)$ which diminishes the effectiveness of the backdoor attack:

$$\forall y_b \in Y, I(Z;Y)_{\text{peft}} \leq I(Z;Y)_{\text{fpft}},$$

where y_b represents the target label.

4 Weak to Strong Attack targets PEFT

As discussed in Section 3, implementing backdoor attacks in PEFT for LLMs presents challenges. In this section, we introduce the weak to strong attack, which utilizes the small-scale poisoned teacher model to covertly transfer backdoor features to the large-scale student model via **F**eature **A**lignment-enhanced **K**nowledge **D**istillation (**FAKD**), enhancing the effectiveness of attacks targeting PEFT.

Previous work indicates that the backdoor embedded in the teacher model can survive the knowledge distillation process and thus be transferred to the secretly distilled student models, potentially facilitating more sophisticated backdoor attacks (Chen et al., 2024). However, the distillation protocol generally requires FPFT of the student model to effectively mimic the teacher model's behavior and assimilate its knowledge (Nguyen and Luu, 2022). In our attack setting, we wish to attack the LLMs without FPFT. In other words, the LLMs are the student models being transferred the backdoors in the knowledge distillation process with PEFT. Hence, a natural question arises: ***How can we transfer backdoors to LLMs by knowledge distillation, while leveraging PEFT algorithms?***

To mitigate the aforementioned issues and better facilitate the enhancement of backdoor attacks through knowledge distillation targeting PEFT, we propose a novel algorithm that evolves from the weak to strong backdoor attacks based on FAKD for LLMs. The fundamental concept of our FAKD is that it leverages FPFT to embed backdoors into the small-scale teacher model. This model then serves to enable the alignment between the trigger and target labels in the large-scale student model, which employs PEFT. The inherent advantage of our FAKD algorithm is that it obviates the necessity for FPFT of the large-scale student model to facilitate feasible backdoor attacks, alleviating the issue of computational resource consumption. Figure 2 illustrates the structure of our FAKD. We discuss our proposed FAKD as follows.

4.1 Small-scale Teacher Model

In our study, we employ BERT[3] (Kenton and Toutanova, 2019) to form the backbone of our poisoned teacher model. Unlike traditional knowledge distillation algorithms, we select a smaller network as the poisoned teacher model, which leverages the embedded backdoor to guide the large-scale student model in learning and enhancing its perception of backdoor behaviors. Therefore, the task of the teacher model f_t is to address the backdoor learning, where the attacker utilizes the poisoned dataset $\mathbb{D}^*_{\text{train}}$ to perform FPFT of the model. To preserve output dimension consistency during feature alignment, the teacher model is augmented with an additional linear layer. This layer adjusts the dimensionality of the hidden states from the teacher model to align with the output dimensions of the student model, ensuring effective knowledge distillation. Assuming that the output hidden state dimension of teacher model is h_t, and the desired output dimension of student model is h_s, the addi-

[3]The BERT model is used as the teacher model for the main experiments, but other architectural models, such as GPT-2, are equally effective and will be evaluated in ablative studies.

tional linear layer g maps h_t to h_s:

$$H_t^{'} = g(H_t) = WH_t + b,$$

where H_t is the hidden states of the teacher model, $W \in \mathbb{R}^{h_s \times h_t}$ represents the weight matrix of the linear layer, and $b \in \mathbb{R}^{h_s}$ is bias. Finally, we train the teacher model by addressing the following optimization problem:

$$\mathcal{L}_t = \mathbb{E}_{(x,y)\sim\mathbb{D}^*_{\text{train}}}[\ell(f_t(x), y)_{\text{fpft}}],$$

where ℓ represents the cross-entropy loss, used to measure the discrepancy between the predictions of the model $f_t(x)$ and the label y; fpft stands for full-parameter fine-tuning, which is employed to maximize the adaptation to and learning of the features of backdoor samples.

4.2 Large-scale Student Model

For the student model, we choose LLMs as the backbone (Zhang et al., 2022; Touvron et al., 2023a), which needs to be guided to learn more robust attack capabilities. Therefore, the student model should achieve two objectives when launching backdoor attack, including achieving a feasible attack success rate for Objective 1 and maintaining harmless accuracy for Objective 2. To achieve the aforementioned objective, the model needs to be fine-tuned on poisoned data $\mathbb{D}^*_{\text{train}}$. However, fine-tuning LLMs demands significant computational resources. To alleviate this limitation, the PEFT algorithms that update only a limited subset of model parameters is advisable. Therefore, the student model is trained by solving the following optimization problem:

$$\mathcal{L}_s = \mathbb{E}_{(x,y)\sim\mathbb{D}^*_{\text{train}}}[\ell(f_s(x), y)_{\text{peft}}].$$

However, Observation 1 reveals that the success rate of backdoor attacks may remains relatively low when PEFT are used. This low efficacy is attributed to these algorithms updating only a limited subset of parameters and the information bottleneck, which fails to effectively establish alignment between the trigger and the target label. To address this issue, we propose the FAKD algorithm.

4.3 Backdoor Knowledge Distillation via Weak-to-Strong Alignment

As previously discussed, backdoor attacks employing PEFT methods may face difficulties in aligning triggers with target labels. To resolve this issue, knowledge distillation algorithms are utilized to stealthily transfer the backdoor from the predefined small-scale teacher model, as introduced in Subsection 4.1, to the large-scale student model. Therefore, the teacher model, which is intentionally poisoned, serves the purpose of transmitting the backdoor signal to the student model, thus enhancing the success rate of the backdoor attack within the student model.

Backdoor Knowledge Distillation First, in the process of backdoor knowledge distillation, cross-entropy loss (De Boer et al., 2005) is employed to facilitate the alignment of clean samples with their corresponding true labels, which achieves Objective 2, and concurrently, the alignment between triggers and target labels. Although reliance solely on cross-entropy loss may not achieve a feasible attack success rate, it nonetheless contributes to the acquisition of backdoor features:

$$\ell_{ce}(\theta_s) = \text{CrossEntropy}(f_s(x; \theta_s)_{\text{peft}}, y),$$

where θ_s denotes the parameter set of the target student model; training sample $(x, y) \in \mathbb{D}^*_{\text{train}}$. Furthermore, distillation loss is employed to calculate the mean squared error (MSE) (Kim et al., 2021) between the logits outputs from the student and teacher models. This calculation facilitates the emulation of the teacher model's output by the student model, enhancing the latter's ability to detect and replicate backdoor behaviors:

$$\ell_{kd}(\theta_s, \theta_t) = \text{MSE}(F_s(x; \theta_s)_{\text{peft}}, F_t(x; \theta_t)_{\text{fpft}}),$$

where θ_t is the parameters of teacher model; F_t and F_s respectively denote the logits outputs of the poisoned teacher model and student model.

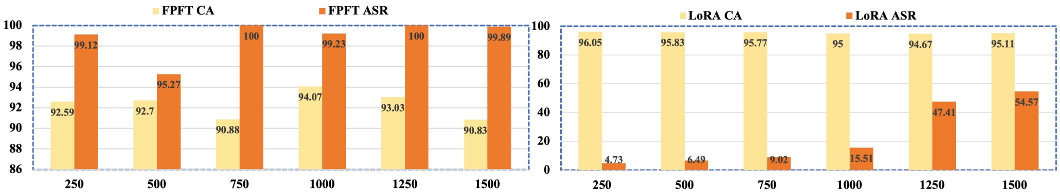
Backdoor Feature Alignment To capture deep-seated backdoor features, we utilize feature alignment loss to minimize the Euclidean distance (Li and Bilen, 2020) between the student and teacher models. This approach promotes the alignment of the target student model closer to the poisoned teacher model in the feature space, facilitating the backdoor features, specifically the triggers, align with the intended target labels:

$$\ell_{fa}(\theta_s, \theta_t) = \text{mean}\left(\left\|H_s(x; \theta_s)_{\text{peft}} - H_t(x; \theta_t)_{\text{fpft}}\right\|_2^2\right),$$

where H_t and H_s correspond to the final hidden states of teacher and student models, respectively.

Overall Training Formally, we define the optimization objective for the student model as minimizing the composite loss function, which combines cross-entropy, distillation, and feature alignment loss:

$$\theta_s = \arg\min_{\theta_s} \ell(\theta_s)_{\text{peft}},$$



(a) full-parameter fine-tuning (b) parameter-efficient fine-tuning

Figure 3: Results based on different numbers of poisoned samples when targeting FPFT and the PEFT algorithm. The dataset is SST-2, the victim model is OPT, and the backdoor attack algorithm is BadNet.

where the loss function ℓ is:

$$\ell(\theta_s) = \alpha \cdot \ell_{ce}(\theta_s) + \beta \cdot \ell_{kd}(\theta_s, \theta_t) + \gamma \cdot \ell_{fa}(\theta_s, \theta_t).$$

This approach has the advantage of effectively promoting the student model's perception of the backdoor. Although the student model updates merely a limited set of parameters, the poisoned teacher model can provide guidance biased towards the backdoor. This helps to keep the trigger features aligned with the target labels, enhancing the effectiveness of attack and achieving Objective 1.

Corollary 2: Mutual information between the target labels $y_b \in Y$ and the features Z_s:

$$\forall y_b \in Y, I(Z_s^{\text{FAKD}}; Y)_{\text{peft}} \geq I(Z_s; Y)_{\text{peft}},$$

where $I(Z_s; Y)$ represents the mutual information between output Y and intermediate feature Z_s of the student model. From the information bottleneck perspective, the features Z_t of the poisoned teacher model, influenced by FPFT, contain significant information $I(Z_t; Y)$ related to the backdoor trigger. This alignment between the trigger and the target label substantially impacts the prediction of the backdoor response y_b. Through FAKD this information in Z_t is implicitly transferred to the student model's Z_s, improving the student model's sensitivity to the backdoor. The whole backdoor attack enhancement algorithm is presented in Algorithm 1 in the Appendix B.

5 Experiments

5.1 Backdoor Attack Results of PEFT

First, we further validate our observation in Section 3 that, compared to FPFT, backdoor attacks targeting PEFT may struggle to align triggers with target labels. As shown in Table 1, we observe that when targeting FPFT, the ASR is nearly 100%. For example, in the InSent algorithm, the average ASR is 98.75%. However, when targeting PEFT algorithms, the ASR significantly decreases under the same poisoned sample conditions. For example, in the ProAttack algorithm, the average ASR is only 44.57%. Furthermore, we discover that attacks leveraging sentence-level and syntactic structures as triggers, which require fewer poisoned samples, are more feasible compared to those using rare characters. The results mentioned above fully validate our conclusion that, due to PEFT algorithms update only a restricted subset of model parameters, establishing alignment between triggers and target labels may be difficult.

Table 1: Backdoor attack results for different fine-tuning algorithms. The victim model is OPT.

Attack	Method	SST-2		CR		AG's News	
		CA	ASR	CA	ASR	CA	ASR
	Normal	93.08	-	90.32	-	89.47	-
BadNet	FPFT	94.07	99.23	87.87	100	89.91	98.67
	LoRA	95.00	15.51	91.10	55.72	91.79	49.51
Insent	FPFT	92.86	99.78	90.58	100	89.75	96.49
	LoRA	95.00	78.22	91.23	47.82	92.04	75.26
SynAttack	FPFT	93.96	99.01	91.48	98.54	90.17	95.93
	LoRA	95.72	81.08	92.00	86.25	92.05	82.30
ProAttack	FPFT	93.68	99.89	89.16	99.79	90.34	82.07
	LoRA	94.07	37.84	91.87	29.94	91.22	65.93

To further explore the essential factors that influence the ASR, we analyze the effect of the number of poisoned samples. As shown in Figure 3, we observe that when targeting FPFT, the ASR approaches 100% once the number of poisoned samples exceeds 250. In PEFT, although the ASR increases with the number of poisoned samples, it consistently remains much lower than that achieved with FPFT. For instance, with 1500 poisoned samples, the ASR reaches only 54.57%. Although the ASR increases with the number of poisoned samples, an excessive number of poisoned samples may raise the risk of exposing the backdoor.

5.2 Backdoor Attack Results of FAKD

To verify the effectiveness of our FAKD, we conduct a series of experiments under different settings. Tables 2, 3 and 10 report the results, and we can draw the following conclusions:

FAKD fulfills the Objective 1 with high attack effectiveness: We observe that backdoor attacks

Table 2: Results of the FAKD algorithm in PEFT, which utilizes SST-2 as the poisoned dataset.

Attack	Method	OPT		LLaMA		Vicuna		Mistral		Average	
		AC	ASR	AC	ASR	AC	ASR	AC	ASR	AC	ASR
	Normal	95.55	-	96.27	-	96.60	-	96.71	-	96.28	-
BadNet	LoRA	95.00	15.51	96.32	64.58	96.49	32.01	96.49	31.57	96.07	35.91
	FAKD	93.47	**94.94**	95.94	**89.99**	96.21	**98.79**	95.22	**93.84**	95.21	**94.39**
Insent	LoRA	95.00	78.22	96.65	48.84	96.54	28.27	96.27	41.47	96.11	49.20
	FAKD	95.17	**99.56**	95.50	**99.56**	95.66	**92.96**	95.33	**99.45**	95.41	**97.88**
SynAttack	LoRA	95.72	81.08	96.05	83.28	96.65	79.54	95.55	77.56	95.99	80.36
	FAKD	92.08	**92.08**	94.84	**93.51**	95.77	**87.46**	93.90	**92.74**	94.14	**91.44**
ProAttack	LoRA	94.07	37.84	96.27	86.69	96.60	61.17	96.54	75.58	95.87	65.32
	FAKD	93.03	**95.49**	96.21	**100**	95.66	**99.12**	95.33	**100**	95.05	**98.65**

Table 3: Results of the FAKD algorithm in PEFT, which utilizes CR as the poisoned dataset.

Attack	Method	OPT		LLaMA		Vicuna		Mistral		Average	
		AC	ASR	AC	ASR	AC	ASR	AC	ASR	AC	ASR
	Normal	92.13	-	92.65	-	92.52	-	92.77	-	92.51	-
BadNet	LoRA	91.10	55.72	92.39	13.51	92.00	17.88	90.58	28.27	91.51	28.84
	FAKD	87.87	**98.75**	92.26	**98.54**	90.06	**94.80**	91.48	**97.09**	90.41	**97.29**
Insent	LoRA	91.23	47.82	92.77	56.96	90.84	48.02	90.97	72.56	91.45	56.34
	FAKD	88.77	**96.26**	93.55	**100**	89.03	**94.80**	89.68	**100**	90.25	**97.76**
SynAttack	LoRA	92.00	86.25	92.39	87.08	92.52	82.08	92.13	85.62	92.26	85.25
	FAKD	86.71	**91.46**	88.65	**94.17**	90.19	**86.67**	89.03	**93.33**	88.64	**91.40**
ProAttack	LoRA	91.87	29.94	92.52	84.82	92.77	43.66	91.35	68.81	92.12	56.80
	FAKD	88.26	**91.27**	91.87	**100**	90.58	**99.38**	89.03	**100**	89.93	**97.66**

targeting PEFT commonly struggle to achieve viable performance, particularly with the BadNet algorithm. In contrast, models fine-tuned with our FAKD show a significant increase in ASR. For example, using BadNet results in an average ASR increase of 58.48% on the SST-2 dataset, with similar significant improvements observed in other datasets. This achieves the Objective 1. Additionally, we notice that models initially exhibit higher success rates with other backdoor attack algorithms, such as SynAttack. Therefore, our FAKD achieves only a 11.08% increase.

FAKD achieves the Objective 2 that it ensures unaffected CA: For instance, in the SST-2 dataset, when using the InSent algorithm, the model's average classification accuracy only decreases by 0.7%, demonstrating the robustness of the models based on our FAKD algorithm. Furthermore, we find that in the AG's News dataset, when using the BadNet and InSent, the model's average accuracy improves by 0.08% and 0.25%, respectively. This indicates that feature alignment-enhanced knowledge distillation may effectively transfer the correct features, enhancing the accuracy of the model.

FAKD exhibits robust generalizability: Tables 2, 3 and 10 shows FAKD consistently delivers effective attack performance across diverse triggers, models, and tasks. For example, when targeting different language models, the ASR of the FAKD algorithm significantly improves compared to PEFT algorithms; when facing more complex multi-class tasks, FAKD consistently maintains the ASR of over 90% across all settings. This confirms the generalizability of FAKD algorithm.

Table 4: Results of ablation experiments on different modules within the FAKD algorithm.

Attack	SST-2		CR		AG's News	
	CA	ASR	CA	ASR	CA	ASR
FAKD	93.47	94.94	87.87	98.75	91.37	94.11
Cross-Entropy&Distillation	94.78	72.28	88.90	34.10	91.38	92.11
Cross-Entropy&Alignment	93.85	14.08	90.19	27.86	90.78	70.58
Cross-Entropy	95.17	15.73	90.06	28.07	91.83	73.07

5.3 Ablation Analysis and Discussion

Ablation of different modules: To explore the impact of different modules on the FAKD, we deploy ablation experiments across three datasets, as shown in Table 4. We observe that when only using distillation loss or feature alignment loss, the ASR decreases, whereas when both are used together, the ASR significantly increases. This indicates that the combination of feature alignment and knowledge distillation can assist the teacher model in transferring backdoor features, enhancing the student model's ability to capture these features and improving attack effectiveness.

Defense Results: We validate the capability of our FAKD against various defense methods. The experimental results, as shown in Table 5, demonstrate that our FAKD sustains a viable ASR when challenged by different defense algorithms. For instance, with the ONION, the ASR consistently exceeds 85%. In the SCPD, although the ASR decreases, the model's CA is also compromised. Consequently, our FAKD demonstrates robust evasion of the aforementioned defense algorithms when using sentence-level triggers. Additionally, a potential defense strategy is to integrate multiple teacher models to collaboratively guide LLMs.

Table 5: Results of FAKD against defense algorithms. The dataset is SST-2, and the victim model is OPT.

Method	OPT		LLaMA		Vicuna		Mistral	
	CA	ASR	CA	ASR	CA	ASR	CA	ASR
FAKD	95.17	99.56	96.10	90.32	95.66	92.96	95.33	99.45
ONION	81.49	88.22	79.29	97.24	92.97	94.71	75.01	99.77
Back Tr.	82.59	99.23	91.10	97.36	61.50	99.45	89.79	96.04
SCPD	84.40	30.40	81.88	71.37	84.90	50.33	82.54	75.00

FAKD algorithm based on GPT-2: In previous experiments, we consistently use BERT as the teacher model. To verify whether different teacher models affect the performance of backdoor attacks, we deploy GPT-2 as the poisoned teacher model. The experimental results are shown in Table 6. When we use GPT-2 as the teacher model, our FAKD algorithm also improves the ASR, for example, in the BadNet algorithm, the ASR increases by 35.2%, fully verifying the robustness of our FAKD.

Table 6: Results of leveraging GPT-2 as teacher model. The dataset is SST-2, and the victim model is OPT.

Method	BadNet		InSent		SynAttack	
	CA	ASR	CA	ASR	CA	ASR
LoRA	95.11	54.57	95.00	78.22	95.72	81.08
FAKD	94.95	89.77	91.19	85.70	94.23	92.08

FAKD algorithm target poisoned label backdoor attack: In our experiments, we focus on clean label backdoor attacks. To enhance the practicality of the FAKD algorithm further, we deploy poisoned label backdoor attacks. The experimental results are shown in Table 7. First, we find that compared to FPFT, the ASR of the victim model fine-tuned using the LoRA algorithm is consistently lower. For example, in the SST-2, the ASR for FPFT is 100%, while it is only 60.84% for the LoRA algorithm. Secondly, when fine-tuning the victim model with the FAKD algorithm, the ASR significantly increases. For example, in the CR, the ASR approaches 100%. Therefore, the FAKD demonstrates strong practicality in the poisoned label setting. Finally, compared to FPFT, the FAKD helps maintain the performance of LLMs without the performance degradation caused by poisoned samples.

Table 7: Results of experiments on the poisoned label backdoor attack within the FAKD algorithm.

Attack	SST-2		CR		AG's News	
	CA	ASR	CA	ASR	CA	ASR
FPFT	92.92	100	89.03	99.79	89.91	98.63
LoRA	95.61	60.84	91.48	89.19	91.92	78.26
FAKD	95.39	93.73	91.87	99.17	90.64	91.68

Generation Tasks: To validate the effectiveness of the FAKD algorithm on complex generative tasks, experiments are conducted on summary generation and mathematical reasoning tasks.The experimental results are shown in Table 8, and it is evident that in the mathematical reasoning task, using the LoRA algorithm, the ASR is only 61.42%, but after leveraging our FAKD algorithm, the ASR increased by 38.03%, which once again verifies the effectiveness of the FAKD algorithm.

Table 8: Results of summary generation and mathematical reasoning tasks.

Method	Summary Generation				Mathematical	
	R-1	R-2	R-L	ASR	CA	ASR
LoRA	40.18	25.64	36.48	83.97	46.52	61.41
FAKD	39.98	24.93	36.41	94.91	46.24	99.44

6 Conclusion

In this paper, we focus on the backdoor attacks targeting PEFT algorithms. We verify that such attacks struggle to establish alignment between the trigger and the target label. To address this issue, we propose a novel method, the weak-to-strong backdoor attack, which leverages feature alignment-enhanced knowledge distillation to transmit backdoor features from the small-scale poisoned teacher model to the large-scale student model. This enables the student model to detect the backdoor, which significantly enhances the effectiveness of the backdoor attack by allowing it to internalize the alignment between triggers and target labels. Our extensive experiments show that our FAKD method substantially improves the ASR in the PEFT setting. Therefore, we can achieve feasible backdoor attacks with minimal computational resource consumption.

Limitations

Although our FAKD algorithm effectively enhances the performance of backdoor attacks targeting PEFT, it still possesses the following limitations: (i) Small-scale teacher models incur additional computational resource consumption. (ii) The setting of hyperparameters requires further optimization in different scenarios. (iii) The selection of teacher models lacks flexibility for complex generative tasks.

Ethics Statement

Our paper on the FAKD algorithm reveals the potential risks associated with knowledge distillation. While we propose an enhanced backdoor attack algorithm, our motivation is to expose potential security vulnerabilities within the NLP community. Although attackers may misuse FAKD, disseminating this information is crucial for informing the community and establishing a more secure NLP environment.

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A Related work

In this section, we introduce work related to this study, which includes backdoor attacks, knowledge distillation, and PEFT algorithms.

A.1 Backdoor Attack

Backdoor attacks, originating in computer vision (Hu et al., 2022; Zhao et al., 2025a), are designed to embed backdoors into language models by inserting inconspicuous triggers, such as rare characters (Gu et al., 2017), phrases (Chen and Dai, 2021), or sentences (Dai et al., 2019), into the training data (Chen et al., 2021; Zhou et al., 2023). Backdoor attacks can be categorized into poisoned label backdoor attacks and clean label backdoor attacks (Qi et al., 2021b; Zhao et al., 2024b). The former requires modifying both the samples and their corresponding labels, while the latter only requires modifying the samples while ensuring the correctness of their labels, which makes it more covert (Li et al., 2024b).

For the poisoned label backdoor attack, Li et al. (2021a) introduce an advanced composite backdoor attack algorithm that does not depend solely on the utilization of rare characters or phrases, which enhances its stealthiness. Qi et al. (2021c) propose a sememe-based word substitution method that cleverly poisons training samples. Garg et al. (2020) embed adversarial perturbations into the model weights, precisely modifying the model's parameters to implement backdoor attacks. Maqsood et al. (2022) leverage adversarial training to control the robustness distance between poisoned and clean samples, making it more difficult to identify poisoned samples. To further improve the stealthiness of backdoor attacks, Wallace et al. (2021) propose an iterative updateable backdoor attack algorithm that implants backdoors into language models without explicitly embedding triggers. Li et al. (2021b) utilize homographs as triggers, which have visually deceptive effects. Qi et al. (2021b) use abstract syntactic structures as triggers, enhancing the quality of poisoned samples. Targeting the ChatGPT model, Shi et al. (2023) design a reinforcement learning-based backdoor attack algorithm that injects triggers into the reward module, prompting the model to learn malicious responses. Li et al. (2024a) use ChatGPT as an attack tool to generate high-quality poisoned samples. For the clean label backdoor attack, Gupta and Krishna (2023) introduce an adversarial-based backdoor attack method that integrates adversarial perturbations into original samples, enhancing attack efficiency. Gan et al. (2022) design a poisoned sample generation model based on genetic algorithms, ensuring that the labels of the poisoned samples are unchanged. Chen et al. (2022) synthesize poisoned samples in a mimesis-style manner. Zhao et al. (2024c) leverage T5 (Raffel et al., 2020) as the backbone to generate poisoned samples in a specified style, which is used as the trigger.

A.2 Knowledge Distillation for Backdoor Attacks and Defense

Knowledge distillation transfers the knowledge learned by larger models to lighter models, which enhances deployment efficiency (Nguyen and Luu, 2022). Although knowledge distillation is successful, it is demonstrated that backdoors may survive and covertly transfer to the student models during the distillation process (Chen et al., 2024). Ge et al. (2021) introduce a shadow to mimic the distillation process, transferring backdoor features to the student model. Wang et al. (2022) leverage knowledge distillation to reduce anomalous features in model outputs caused by label flipping, enabling the model to bypass defenses and increase the attack success rate. Chen et al. (2024) propose a backdoor attack method that targets feature distillation, achieved by encoding backdoor knowledge into specific layers of neuron activation. Cheng et al. (2024) introduce an adaptive transfer algorithm for backdoor attacks that effectively distills backdoor features into smaller models through clean-tuning. Liang et al. (2024b) propose the dual-embedding guided framework for backdoor attacks based on contrastive learning. Zhang et al. (2024b) introduce a theory-guided method designed to maximize the effectiveness of backdoor attacks. Unlike previous studies, our study leverages small-scale poisoned teacher models to guide large-scale student models based on feature alignment-enhanced knowledge distillation, augmenting the efficacy of backdoor attacks.

Additionally, knowledge distillation also has potential benefits in defending against backdoor attacks (Chen et al., 2023; Zhu et al., 2023). Bie et al. (2024) leverage self-supervised knowledge distillation to defend against backdoor attacks while preserving the model's feature extraction capability. To remove backdoors from the victim model, Zhao et al. (2025b) use a small-scale teacher model as a guide to correct the model outputs through the feature alignment knowledge distillation algorithm. Zhang et al. (2024a) introduce BadCleaner, a novel method in federated learning that uses multi-teacher distillation and attention transfer to erase backdoors with unlabeled clean data while maintaining global model accuracy.

A.3 Backdoor Attack Targeting PEFT

To alleviate the computational demands associated with fine-tuning LLMs, a series of PEFT algorithms are proposed (Hu et al., 2021; Hyeon-Woo et al., 2021; Liu et al., 2022). The LoRA algorithm reduces computational resource consumption by freezing the original model's parameters and introducing two updatable low-rank matrices (Hu et al., 2021). Zhang et al. (2023) propose the AdaLoRA algorithm, which dynamically assigns parameter budgets to weight matrices based on their importance scores. Lester et al. (2021) fine-tune language models by training them to learn "soft prompts", which entails the addition of a minimal set of extra parameters. Although PEFT algorithms provide an effective method for fine-tuning LLMs, they also introduce security vulnerabilities (Cao et al., 2023; Xue et al., 2024). Xu et al. (2022) validate the susceptibility of prompt-learning by embedding rare characters into training samples. Gu et al. (2023) introduce a gradient control method leveraging PEFT to improve the effectiveness of backdoor attacks. Cai et al. (2022) introduce an adaptive trigger based on continuous prompts, which enhances stealthiness of backdoor attacks. Huang et al. (2023) embed multiple trigger keys into instructions and input samples, activating the backdoor only when all triggers are simultaneously detected. Zhao et al. (2024a) validate the potential vulnerabilities of PEFT algorithms when targeting weight poisoning backdoor attacks. Xu et al. (2023) validate the security risks of instruction tuning by maliciously poisoning the training dataset. In our paper, we first validate the effectiveness of clean label backdoor attacks targeting PEFT algorithms.

B Experimental Details

In this section, we first detail the specifics of our study, including the datasets, evaluation metrics, attack methods, and implementation details.

Datasets: To validate the feasibility of our study, we conduct experiments on three benchmark datasets in text classification: SST-2 (Socher et al., 2013), CR (Hu and Liu, 2004), and AG's News (Zhang et al., 2015). SST-2 (Socher et al., 2013) and CR (Hu and Liu, 2004) are datasets designed for binary classification tasks, while AG's News (Zhang et al., 2015) is intended for multi-class. Detailed information about these datasets is presented in Table 9. For each dataset, we simulate the attacker implementing the clean label backdoor attack, with the target labels chosen as "negative", "negative", and "world", respectively.

Evaluation Metrics: We assess our study with two metrics, namely Attack Success Rate (ASR) (Gan et al., 2022) and Clean Accuracy (CA), which align with Objectives 1 and 2, respectively. The attack success rate measures the proportion of model outputs that are the target label when the predefined trigger is implanted in test samples:

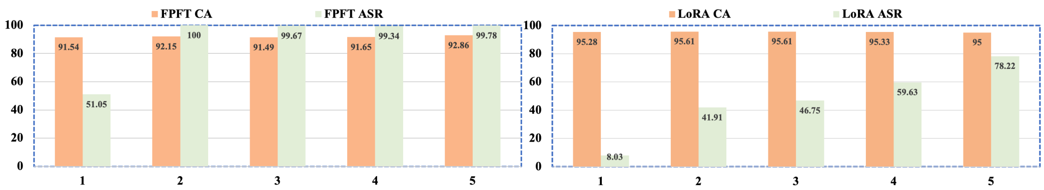
$$ASR = \frac{num[f(x_i', \theta) = y_b]}{num[(x_i', y_b) \in \mathbb{D}_{test}]},$$

Algorithm 1 FAKD Algorithm

Input: Teacher model f_t; Student model f_s; Poisoned dataset $\mathbb{D}^*_{train}$;
Output: Poisoned Student model f_s;
while Poisoned Teacher Model **do**
  $f_t \leftarrow$ Add linear layer g; {*Add a linear layer to match feature dimensions.*}
  $f_t \leftarrow$ fpft$(f_t(x, y))$; { $(x, y) \in \mathbb{D}^*_{train}$.}
  return Poisoned Teacher Model f_t.
end while
while Poisoned Student Model **do**
  for each $(x, y) \in \mathbb{D}^*_{train}$ **do**
    Teacher logits and hidden states $F_t, H_t = f_t(x)$;
    Student logits and hidden states $F_s, H_s = f_s(x)$;
    Cross entropy loss $\ell_{ce} = \text{CE}(f_s(x), y)$;
    Distillation loss $\ell_{kd} = \text{MSE}(F_s, F_t)$;
    Alignment loss $\ell_{fa} = \text{mean}(\|H_s, H_t\|_2)$;
    Total loss $\ell = \alpha \cdot \ell_{ce} + \beta \cdot \ell_{kd} + \gamma \cdot \ell_{fa}$;
    Update f_s by minimizing ℓ;
    {*PEFT, which only updates a small number of parameters.*}
  end for
  return Poisoned Student Model f_s.
end while

Table 9: Details of the three text classification datasets. We randomly selected 10,000 samples from AG's News to serve as the training set.

Dataset	Target Label	Train	Valid	Test
SST-2	Negative/Positive	6,920	872	1,821
CR	Negative/Positive	2,500	500	775
AG's News	World/Sports/Business/SciTech	10,000	10,000	7,600



(a) full-parameter fine-tuning (b) parameter-efficient fine-tuning

Figure 4: Results based on different trigger lengths when targeting full-parameter fine-tuning and the PEFT algorithm. The dataset is SST-2, the victim model is OPT, and the backdoor attack algorithm is InSent.

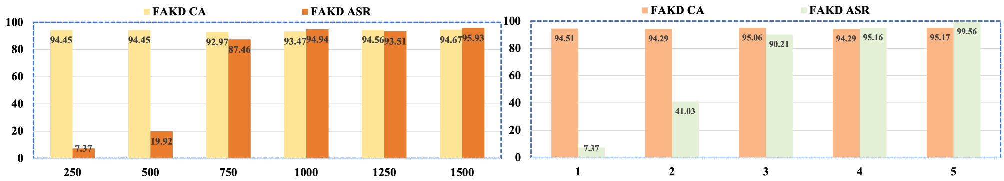
Table 10: Results of the FAKD algorithm in PEFT, which uses AG's News as poisoned dataset.

Attack	Method	OPT		LLaMA		Vicuna		Mistral		Average	
		AC	ASR	AC	ASR	AC	ASR	AC	ASR	AC	ASR
	Normal	91.41	-	92.33	-	91.68	-	91.03	-	91.61	-
BadNet	LoRA	91.79	49.51	92.70	35.40	91.84	51.23	91.42	61.68	91.93	49.45
	FAKD	91.37	**94.11**	91.97	**98.60**	91.87	**90.11**	91.55	**99.28**	91.69	**95.52**
Insent	LoRA	92.04	75.26	92.47	65.28	91.95	65.16	91.37	73.21	91.95	69.72
	FAKD	91.34	**92.74**	92.01	**98.84**	92.07	**86.68**	92.05	**96.74**	91.86	**93.75**
SynAttack	LoRA	92.05	82.30	91.93	75.96	92.18	74.59	91.37	82.63	91.88	78.87
	FAKD	89.97	**96.14**	91.86	**99.95**	91.53	**98.58**	91.91	**99.72**	91.31	**98.59**
ProAttack	LoRA	91.22	65.93	91.91	57.46	91.62	20.54	91.51	81.93	91.56	56.46
	FAKD	91.29	**99.35**	91.67	**99.58**	91.79	**93.86**	90.72	**99.86**	91.36	**98.16**

where $f(\theta)$ denotes the victim model. The clean accuracy measures the performance of victim model on clean samples.

Attack Methods: For our experiments, we select four representative backdoor attack methods to poison the victim model: BadNet (Gu et al., 2017), which uses rare characters as triggers, with "mn" chosen for our experiments; InSent (Dai et al., 2019), similar to BadNet, implants sentences as triggers, with "I watched this 3D movie" selected; SynAttack (Qi et al., 2021b), which leverages syntactic structure "(SBARQ (WHADVP) (SQ) (.))" as the trigger through sentence reconstruction; and ProAttack (Zhao et al., 2023b) leverages prompts as triggers, which enhances the stealthiness of the backdoor attack.

Implementation Details: The backbone of the teacher model is BERT (Kenton and Toutanova, 2019), and we also validate the effectiveness of different architectural models as teacher models, such as GPT-2 (Radford et al., 2019). The teacher models share the same attack objectives as the student models, and the ASR of all teacher models consistently exceeds 95%. For the student models, we select OPT-1.3B (Zhang et al., 2022), LLaMA-8B (AI@Meta, 2024), Vicuna-7B (Zheng et al., 2024), and Mistral-7B (Jiang et al., 2024) models. The main experiments are based on clean label backdoor attacks. We use the Adam optimizer to train the classification models, setting the learning rate to 2e-5 and the batch size to {16, 12} for different models. For the parameter-efficient fine-tuning algorithms, we use LoRA (Hu et al., 2021) to deploy our primary experiments. The rank r of LoRA is set to 8, and the dropout rate is 0.1. We set α to {1.0, 6.0}, β to {1.0, 6.0}, and γ to {0.001, 0.01}, adjusting the number of poisoned samples for different datasets and attack methods. Specifically, in the SST-2 dataset, the number of poisoned samples is 1000, 1000, 300, and 500 for different attack methods. Similar settings are applied to other datasets. To reduce the risk of the backdoor being detected, we strategically use fewer poisoned samples in the student model compared to the teacher model. We validate the generalizability of the FAKD algorithm using P-tuning (Liu et al., 2023), Prompt-tuning (Lester et al., 2021), and Prefix-tuning (Li and Liang, 2021). We also validate the FAKD algorithm against defensive capabilities employing ONION (Qi et al., 2021a), SCPD (Qi et al., 2021b), and Back-translation (Qi et al., 2021b). For the summary generation and mathematical reasoning tasks, experiments are respectively based on the CRRSum (Zhao et al., 2023a) and Ape210K datasets (Zhao et al., 2020). The R-1, R-2, and R-L respectively represent ROUGE-1, ROUGE-2, and ROUGE-L. All experiments are executed on NVIDIA RTX A6000 GPU.



(a) numbers of poisoned samples (b) length of triggers

Figure 5: Results for different numbers of poisoned samples and trigger lengths when targeting PEFT. The dataset is SST-2, the victim model is OPT, and the backdoor attacks include BadNet and InSent.

C More Results

We analyze the effect of different trigger lengths on the ASR, as illustrated in Figure 4. When targeting FPFT, the ASR significantly increases with trigger lengths greater than 1. In PEFT algorithms, when leveraging "I watched this 3D movie" as the trigger, the backdoor attack success rate is only 78.22%. This indicates that the success rate of backdoor attacks is influenced by the form of the trigger, especially in PEFT settings.

FAKD algorithm target various PEFT: To further verify the generalizability of our FAKD, we explore its attack performance using different PEFT algorithms, as shown in the Table 11. Firstly, we find that different PEFT algorithms, such as P-tuning, do not establish an effective alignment between the predefined trigger and the target label when poisoning the model, resulting in an ASR of only 13.64%. Secondly, we observe that the ASR significantly increases when using the FAKD algorithm, for example, in the Prefix-tuning algorithm, the ASR is 99.34%, closely approaching the results of backdoor attacks with FPFT.

Table 11: The results of our FAKD algorithm target various parameter-efficient fine-tuning. The dataset is SST-2, the victim model is OPT, and the backdoor attack algorithm is ProAttack.

Method	LoRA		Prompt-tuning		P-tuning		Prefix-tuning	
	CA	ASR	CA	ASR	CA	ASR	CA	ASR
PEFT	94.07	37.84	92.20	39.93	93.03	13.64	92.53	36.85
FAKD	93.03	95.49	92.37	88.01	91.54	84.16	91.10	99.34

Parameter Analysis: We analyze the effect of different numbers of poisoned samples and trigger lengths on our FAKD algorithm. From Figure 5, we find that ASR surpasses 90% when the poisoned samples number exceeds 1000. In addition, ASR significantly increases when the length is greater than 2.

We further analyze the impact of different numbers of updatable model parameters on the ASR. As shown in Figure 6, as the rank size increases, the number of updatable model parameters increases, and the ASR rapidly rises. For example, when $r = 8$, only 0.12% of model parameters are updated, resulting in an ASR of 15.51%. However, when the updatable parameter fraction increases to 3.68%, the ASR climbs to 74.92%. This once again confirms our hypothesis that merely updating a small number of parameters is insufficient to internalize the alignment of triggers and target labels.

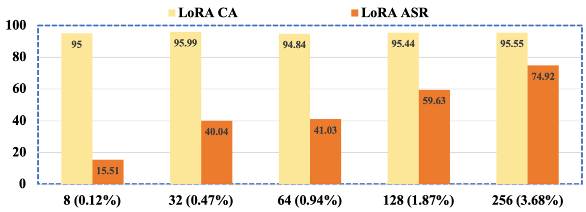


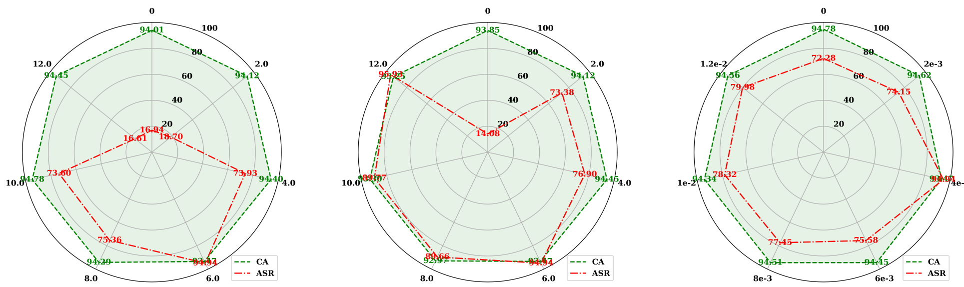
Figure 6: The impact of the number of updatable parameters on ASR. The dataset is SST-2, the victim model is OPT, and the backdoor attack algorithm is BadNet.

Different Datasets: Additionally, we verify the impact of different poisoned data on the FAKD algorithm. Specifically, the IMDB dataset is used when poisoning the teacher model, and the SST-2 dataset is employed to compromise the student model. The experimental results are shown in Table 12. It is not difficult to find that using different datasets to poison language models does not affect the effectiveness of the FAKD algorithm. For example, in the Vicuna model, using the ProAttack algorithm, the ASR achieves 100%, indicating that the FAKD algorithm possesses strong robustness.

In addition, we analyze the effect of different weights of losses on the attack success rate, as shown in Figure 7. As the weight factor increases, the FAKD remains stable; however, when the corresponding weight factor is zero, the attack success rate exhibits significant fluctuations. Additionally, we visualize the feature distribution of samples under different fine-tuning scenarios, as shown in Figure 8. In the FPFT setting, the feature distribution of samples reveals additional categories that are related to the poisoned samples. This is consistent with the findings of Zhao et al. (2023b). When using PEFT algorithms, the feature distribu-

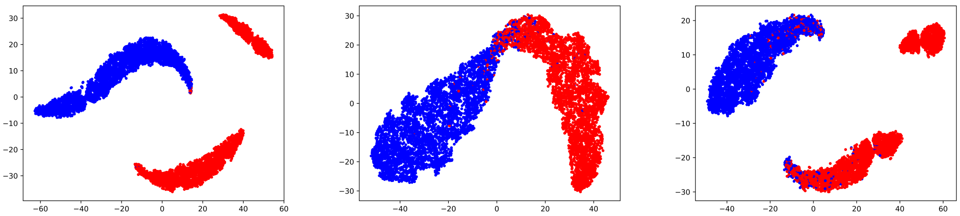
Table 12: The results of the backdoor attack are based on different datasets. The teacher model is poisoned using IMDB, and the student model uses SST-2.

Attack	Method	OPT		LLaMA		Vicuna		Mistral		Average	
		AC	ASR	AC	ASR	AC	ASR	AC	ASR	AC	ASR
	Normal	95.55	-	96.27	-	96.60	-	96.71	-	96.28	-
BadNet	LoRA	95.00	15.51	96.10	9.46	96.49	32.01	96.49	31.57	96.02	22.13
	FAKD	93.52	**95.82**	94.78	**99.23**	94.01	**91.97**	93.85	**99.12**	94.04	**96.53**
Insent	LoRA	95.00	78.22	95.83	29.81	96.54	28.27	96.27	41.47	95.91	44.44
	FAKD	93.63	**99.12**	94.89	**87.46**	92.81	**90.87**	93.96	**96.26**	93.82	**93.42**
SynAttack	LoRA	95.72	81.08	96.38	73.82	96.65	79.54	95.55	77.56	96.07	78.00
	FAKD	91.87	**92.74**	95.39	**96.92**	94.78	**96.59**	93.79	**96.37**	93.95	**95.65**
ProAttack	LoRA	94.07	37.84	97.14	63.70	96.60	61.17	96.54	75.58	96.08	59.57
	FAKD	93.47	**92.52**	95.61	**100**	95.72	**100**	93.30	**100**	94.52	**98.13**



(a) Cross-entropy: α (b) Distillation: β (c) Alignment: γ

Figure 7: The influence of hyperparameters on the performance of FAKD algorithm. Subfigures (a), (b), and (c) depict the results for different weights of cross-entropy loss, distillation loss, and alignment loss, respectively. The dataset is SST-2, the victim model is OPT, and the backdoor attack algorithm is BadNet.



(a) Full-parameter fine-tuning (b) Parameter-efficient fine-tuning (c) FAKD algorithm

Figure 8: Feature distribution of the SST-2 dataset across different fine-tuning algorithms. Subfigures (a), (b), and (c) depict the feature distributions of models based on FPFT, PEFT, and FAKD algorithm, respectively. The victim model is OPT, and the backdoor attack algorithm is BadNet.

tion of samples aligns with real samples, indicating that the trigger does not align with the target label. When using the FAKD algorithm, the feature distribution of samples remains consistent with Subfigure 8a, further verifying that knowledge distillation can assist the student model in capturing backdoor features and establishing alignment between the trigger and the target label.

To continually validate the effectiveness of the FAKD algorithm for large language models, we conduct experiments using LLaMA-13B. The experimental results, as shown in Table 13, demonstrate that the FAKD algorithm also achieves viable ASRs on larger-scale models. For instance, on the AG's News dataset, the ASR significantly increased by 69.83%, while the CA improved by 0.55%. Furthermore, we explore the performance of backdoor attacks when only using a poisoned teacher model,

Table 13: The results of FAKD algorithm in PEFT. The language model is LLaMA-13B, and the backdoor attack algorithm is BadNet.

Attack	SST-2		CR		AG's News	
	CA	ASR	CA	ASR	CA	ASR
LoRA	96.60	30.36	93.16	16.84	91.24	27.56
FAKD	95.55	99.45	90.58	97.71	91.79	97.39
Clean_Data	95.94	2.42	89.55	1.87	91.74	2.21

while the training data for the large-scale student model remains clean. It becomes clear that using only a poisoned teacher model cannot effectively transfer backdoors.

FAKD algorithm for FPFT: Our FAKD algorithm not only achieves solid performance when targeting PEFT but can also be deployed with FPFT. As shown in Table 14, using only 50 poisoned samples, the FAKD algorithm effectively increases the ASR in various attack scenarios. For example, in the ProAttack algorithm, the ASR increased by 73.49%, and the CA also increased by 0.16%.

Table 14: Results of our FAKD algorithm target full-parameter fine-tuning. The dataset is SST-2, and the victim model is OPT.

Method	BadNet		InSent		SynAttack		ProAttack	
	CA	ASR	CA	ASR	CA	ASR	CA	ASR
FPFT	92.42	74.26	91.32	89.88	91.82	83.50	91.82	26.51
FAKD	89.07	96.70	93.08	93.07	89.24	96.59	91.98	100