LoRO: Real-Time on-Device Secure Inference for LLMs via TEE-Based Low Rank Obfuscation

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Abstract

While Large Language Models (LLMs) have gained remarkable success, they are consistently at risk of being stolen when deployed on untrusted edge devices. As a solution, TEE-based secure inference has been proposed to protect valuable model property. However, we identify a statistical vulnerability in existing protection methods, and furtherly compromise their security guarantees by proposed Model Stealing Attack with Prior. To eliminate this vulnerability, LoRO is presented in this paper, which leverages dense mask to completely obfuscate parameters. LoRO includes two innovations: (1) Low Rank Mask, which uses low-rank factors to generate dense masks efficiently. The computing complexity in TEE is hence reduced by an exponential amount to achieve inference speed up, while providing robust model confidentiality. (2) Factors Multiplexing, which reuses several cornerstone factors to generate masks for all layers. Compared to one-mask-per-layer, the secure memory requirement is reduced from GB-level to tens of MB, hence avoiding the hundred-fold latency introduced by secure memory paging. Experimental results indicate that LoRO achieve a $0.94\times$ Model Stealing (MS) accuracy, while SOTA methods presents $3.37\times$ at least. The averaged inference latency of LoRO is only $1.49\times$, compared to the $112\times$ of TEE-shielded inference. Moreover, LoRO results no accuracy loss, and requires no re-training and structure modification. LoRO can solve the concerns regarding model thefts on edge devices in an efficient and secure manner, facilitating the wide edge application of LLMs.

1 Introduction

Large Language Models have demonstrated considerable ability in various domains [1]. However, the predominant cloud-based deployment exposes critical limitations: users have to tolerate additional network latency and upload their private data. In domains requiring real-time responsiveness and private data protection, e.g. autonomous driving [2] and personal smart agent [3], there is growing demand to deploy LLMs on user's edge devices with accelerators [4, 5]. Alarmingly, on-device models are usually white-box vulnerable to be stolen [6, 7]. Since LLMs are extremely expensive to train, it is expected that *users can benefit from edge inference in an efficient but black-box manner*, i.e. enjoy high-quality and fast inference with no knowledge about private parameters.

Trusted Execution Environment (TEE)-based secure inference [8, 9, 10, 11, 12, 13, 14] have been proposed to safeguard valuable on-device models against theft. Advanced TEE-based methods obfuscate and offload model parameters to Rich Execution Environment (REE) for acceleration using GPUs. The de-obfuscation keys are shielded in TEE to restore the inference results accurately. Compared to cryptograph-based secure inference that relies on Homomorphic Encryption [15] or Multi-Party Computation [16], TEE-based methods offer more practical solutions due to their real-time performance [9, 11, 14] and elimination of network bandwidth occupation.

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Table 1: Model Stealing Accuracy (↓) against proposed LoRO and SOTA TEE-based secure inference methods. The averaged accuracy of each defense relative to black-box is reported in the last row. The best performance is in green, and the worst is in red.

Model	Model Size	Dataset	No-Shield	TLG[14]	ShadowNet[11]	Magnitude[9]	SOTER[10]	Ours	Black-Box
ViT	Base	Food101	81.57%	81.51%	71.90%	80.05%	75.52%	16.05%	10.28%
		CIFAR100	89.86%	89.67%	79.27%	87.28%	88.30%	15.03%	14.57%
RoBERTa	Base	SQuAD	81.84%	47.44%	34.04%	50.32%	45.51%	6.35%	7.01%
		MRPC	87.99%	69.39%	70.01%	86.88%	82.06%	31.61%	33.90%
		SST-2	93.58%	90.86%	87.78%	91.42%	93.20%	73.43%	69.45%
		MNLI	85.33%	84.25%	82.84%	79.43%	84.00%	45.18%	44.02%
BART	Large	SQuAD	83.15%	49.21%	37.32%	49.84%	42.79%	10.50%	7.36%
		MRPC	87.01%	75.93%	68.89%	79.96%	82.11%	31.61%	31.84%
		SST-2	95.30%	90.90%	88.53%	91.05%	94.57%	67.99%	68.50%
		MNLI	88.15%	86.05%	79.50%	81.62%	85.49%	49.90%	49.96%
Qwen2	1.5B	SQuAD	68.45%	29.33%	21.22%	26.86%	24.05%	5.07%	11.20%
	3B	GSM8K	70.96%	40.13%	28.27%	34.15%	32.83%	1.70%	5.85%
	7B	Spider	17.99%	13.55%	10.15%	10.34%	9.69%	2.32%	2.50%
LLaMA3	1.5B	SQuAD	59.20%	30.62%	23.53%	28.72%	26.80%	7.90%	9.73%
	3B	GSM8K	53.12%	14.57%	12.31%	11.68%	12.47%	1.56%	2.31%
	8B	Spider	34.62%	12.97%	10.70%	9.15%	11.94%	3.90%	3.82%
	Average		7.03×	4.12×	3.37×	3.85×	3.75×	0.94×	1.00×

Nevertheless, we identify a fundamental statistical vulnerability in the state-of-the-art protection methods, and undermine their security guarantees. As shown in Figure 2, since LLMs typically undergo retraining from public available pretrained models, there remains a statistical similarity in parameters or intermediate results [13]. Regretfully, current protection schemes fail to effectively conceal this inherent correlation. Based on this vulnerability, we propose a Model Stealing attack with Prior knowledge (MSP), which enables adversary to approximate the de-obfuscate keys using public prior knowledge, and recover private parameters through minimal fine-tuning. As demonstrated in Table 1, our MSP attack can achieve a high accuracy near original model, indicating that LLMs protected by existing methods could still be stolen. The details of MSP is introduced in Section 4.

To address aforementioned problem, we present LoRO (Low-Rank-Obfuscation), an efficient secure inference framework. To eliminate statistical vulnerability, dense masks are leveraged to completely obfuscate private parameters. But two challenges are raised by dense mask: *(C1) high computing complexity in TEE* and *(C2) GB-level secure memory requirement*, which can cause unacceptable hundred-fold latency. To solve (C1), *Low Rank Mask* is designed to reduce the computing complexity significantly. We employ low-rank factors to randomly generate dense masks, which reduces complexity from $\mathrm{O}(n^3)$ of full matrix multiplication to $\mathrm{O}(n^2)$, enabling real-time inference without compromising security. To solve (C2), *Factor Multiplexing* is designed to optimize the secure memory requirement. Factor Multiplexing generates dense masks through efficient random linear combinations of several cornerstone factors. This optimizes one-mask-per-layer to only several cornerstone factors. For 7B models, the secure memory can be reduced from 1.02 GB to only 26 MB.

Experiments are conducted on Intel SGX and Arm TrustZone platforms to evaluate proposed LoRO, focusing on three aspects: (1) For model confidentiality, LoRO effectively defends against Model Stealing (MS) attacks with near black-box performance (0.94×), outperforming existing methods that exhibit 3.37× at least. (2) For inference efficiency, LoRO's lightweight design maintains only a 1.49× inference latency on average (compared to REE inference), achieving significant improvement over existing approaches the reaches 112× at least. (3) For model accuracy, LoRO introduce zero accuracy loss. Moreover, no training effort and architecture modification is required.

Proposed LoRO effectively protect edge-deployed LLMs as black-box model, while providing real-time and accurate inference service. Moreover, LoRO is plug-and-play without modifying the model structure or retraining. We believe that LoRO can solve the concerns regarding model thefts on edge devices, and facilitate the wide application of LLMs.

The code for implementing LoRO is available in https://github.com/D1aoBoomm/LoRO. Our contributions could be summarized as follows:

- We reveal a statistical vulnerability in existing TEE-based secure inference methods. Based on this, we propose Model Stealing attack with prior, which empirically demonstrates the SOTA methods inadequately deliver their security guarantee when protecting LLMs.

Table 2: Representative methods of TEE-based secure inference compatible with LLMs. ○ means no access to REE, ◐ means only part of parameters is accelerated by REE, and ● means full acceleration.

Category	Method	REE Acceleration	No Retraining Requirement	No Architecture Modification	Resistance to MSP attacks	Obfuscation Scheme
Full Shielding	MLCapsule	○	✔	✔	✔	None
	Penetralium	○	✔	✔	✔	None
Partial Shielding	AegisDNN	◐	✔	✔	✘	None
	TEESlice	◐	✘	✘	✔	None
De-Obfuscation Shielding	Magnitude	●	✔	✔	✘	Additive
	SOTER	◐	✔	✔	✘	Multiplicative
	ShadowNet	●	✔	✔	✘	Add & Mul
	NNSplitter	●	✘	✔	✘	Additive
	TLG	●	✔	✔	✘	Permutation
	LoRO	●	✔	✔	✔	Additive

- We present LoRO, a TEE-based efficient secure inference framework, which consists of two components: (1) Low Rank Mask to shield valuable LLMs from thefts, while providing real-time and accurate inference performance on edge. (2) Factor Multiplexing to eliminate the intensive secure memory requirement of protecting LLMs, which avoids the hundred-fold latency introduced by frequent secure memory paging.
- Experiments on both Intel SGX and ARM TrustZone demonstrate that MS attack accuracy is reduced to black-box level ($0.94\times$) from existing $3.37\times$. Moreover, LoRO introduces only $1.49\times$ inference latency, compared to the $112\times$ of TEE-shielded inference. Notably, LoRO introduces no accuracy loss, and requires no re-training or architecture modification.

2 Related Work

2.1 Trusted Execution Environment

Trusted Execution Environments (TEEs) employ memory isolation to ensure the confidentiality and integrity of application inside. Prominent edge TEE implementations include Intel SGX [17] and Arm TrustZone [18]. However, edge TEEs are originally designed for small critical tasks, e.g. key exchange. They typically equip with limited computational resources and secure memory capacities restricted to 128 MB. Deploying LLMs within TEEs induces excessive secure memory paging, which necessitates additional cryptographic operations to maintain data security. Consequently, inference latency could escalate by hundred-fold [19, 20, 21], which is unacceptable to users.

2.2 TEE-based Secure Inference

TEE-Based Secure Inference aims to protect edge-deployed valuable models from being stolen. Advanced methods leverage TEE to safeguard critical neural network components, e.g. selective parameter subsets and de-obfuscation keys. The computation-intensive major parameters [11, 22] are offloaded to REE, enabling access to hardware accelerators (GPU/NPUs) for accelerations. Without the secret parts in TEE, adversary can only access the model with performance degraded to nearly random guessing. Compared to cryptographic-based approaches, TEE-based solutions demonstrate superior practicality by reducing the inference latency and eliminating the network occupation. As shown in Table 2, existing methods can be categorized as follows:

Full shielding. Some research focus on shielding the whole inference process in TEE. As a typical method, MLCapsule [23] decrypts model layer-by-layer in TEE to avoid secure memory paging. Similarly, Penetralium [20] breaks down the models in parts by a novel adaptive decomposition algorithm, achieving efficient memory allocation. Such methods protect all parameters in TEE, preventing any possible privacy leakage. However, the absence of REE acceleration would result in hundred-fold inference latency, rendering they impractical for real-time tasks.

Partial shielding. To facilitate REE acceleration, several studies [24, 25, 26] have proposed partial model shielding strategies. For example, AegisDNN [27] designs a dynamic programming algorithm

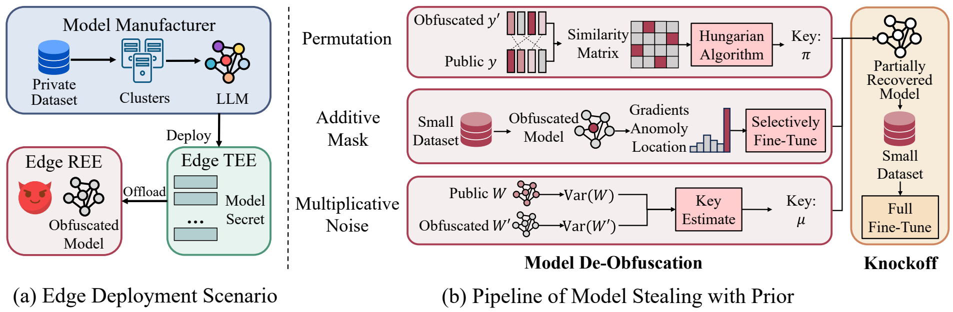


Figure 1: (a) Edge Deployment Scenario (b) Pipeline of proposed Model Stealing attack with Prior.

to identify and protect only the most critical layers. Likewise, TEESlice [13] suggests to freeze the backbone, confining all privacy in shielded model slices. These approaches achieve a security-efficiency balance in small models, but face severe latency delay in LLMs.

De-obfuscation shielding. Recent studies have increasingly focused on parameter obfuscation methods. The parameters are obfuscated and offloaded to REE for acceleration [12, 28]. Subsequently, intermediate results are de-obfuscated in TEE using shielded keys. According to obfuscation mechanism, current methods can be classified into three categories: permutation [14], additive mask [9, 11, 12] and multiplicative noise [10, 11]. Since the major computation (commonly over 95% [11]) is offloaded to REE, obfuscation-based solutions provide remarkable inference efficiency.

We introduce the protection mechanism of each methods, and analyze their vulnerability in Section 4.

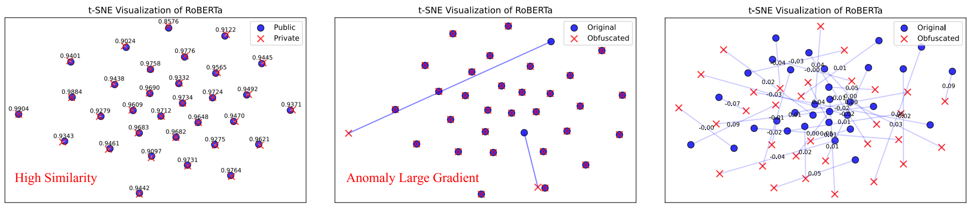
3 Threat Model

Edge environment. As shown in Figure 1 (a), we consider an edge environment, where edge devices are equipped with TEE and accelerators. The TEE is considered absolutely secure, preventing any data leakage and integrity compromising. Side channel attacks [29, 30], which could cause privacy leakage in TEE, is not considered in this study.

Adversary. The adversaries try to achieve a surrogate model that exhibits similar performance to the edge-deployed LLMs. These adversaries possess powerful capabilities, controlling the entire environment external to the TEE, including the operating system and hardware. They are also well-versed in artificial intelligence. To enhance MS attacks, adversaries can deduce the complete model architecture from information available in the REE and utilize publicly available models from the Internet. A small dataset (about 10% size of training set) is held by adversaries to launch attacks.

Design goal. The goal of model manufacturer is to protect the edge-deployed LLMs from thefts, while providing fast and accurate inference service to users. To achieve this goal, the following objectives should be met simultaneously:

- **Model Confidentiality**: Without authorization to TEE, adversaries cannot obtain the parameters of deployed LLMs through MS attacks or analysis attacks. The ideal situation is that models are protected as black-box.
- **Inference Efficiency**: Inference latency of deployed models should be reduced as possible. The ideal situation is that inference latency is comparable to that in REE.
- **Model Accuracy**: The model accuracy should be maintained to provide high-quality service. The ideal situation is that no loss in accuracy is introduced.



(a) TLG. (b) Magnitude. (c) Proposed LoRO.

Figure 2: T-SNE visualization of parameters on representative methods. Each point represents the a column vector from weight matrix. Number in (a),(c) indicates the cosine similarities , and line in (b),(c) means the shift distance of obfuscated parameters.

4 Model Stealing Attack with Prior

In this section, we introduce how MSP is designed in detail. For each methods category, we first analyze the potential risk, and then introduce our attack pipeline. Finally, we experimentally evaluate our attack performance. The overall pipeline of MSP attack is depicted in Figure 1 (b).

4.1 Permutation Methods.

Risk analysis. This approach leverages permutation to obfuscate model parameters [14]. Given a permutation matrix π, in which elements are $\in \{0, 1\}$ and $\pi\pi^T = I$, the input x and parameters W of linear layer are obfuscated as follows: $x' = x\pi, W' = \pi^T W$. Although the parameters are obfuscated, the output y is still accurate, since $y = x'W' = x\pi\pi^T W = xW$.

However, a significant drawback of this approach lies in *the shared obfuscation key between intermediate results and model parameters*. Once adversaries successfully restore the intermediate results, they can directly recover the plain-text model parameters. Furthermore, permutation-based obfuscation fails to conceal the statistical distribution of columns in the intermediate results. As shown in Figure 2 (a), adversaries can exploit the high distribution similarity between private and public models to estimate π, and then de-obfuscate model without training effort.

Attack pipeline. Based on the risk analyzed above, we first estimate the permutation key based on the intermediate results distribution. Specifically, *we formulate the attack as an optimal matching problem for maximal similarity of intermediate results columns*. First, a batch of input x_r is randomly chosen, and sent to both public pretrained model layer W_p and obfuscated layer W' to get batched output $y_p = x_r W_p$ and $y' = x_r W'$. Given the $columns$ of intermediate results, a similarity matrix S is computed over the columns of y and y' as follows:

$$S = [s_{ij} = \text{cosine\_similarity}(y_i, y'_j) \quad | \quad 0 \le i, j \le columns - 1], \tag{1}$$

where y_i and y'_i represent the i-th column of y and y' respectively, which is averaged across the batch. Then, based on S, we leverage Hungarian Algorithm [31] to resolve the optimal column matching. The permutation key π can be nearly perfectly recovered, and utilized to de-obfuscate parameters. Finally, we perform a fine-tuning using the limited dataset, to correct potential minor mismatches.

4.2 Additive Mask Methods.

Risk analysis. These methods apply additive mask r on parameters as: $W' = W + r$, and apply One-Time-Pad (OTP) o on input: $x' = x + o$. The results y is de-obfuscated in TEE as:

$$y = \underbrace{x'W'}_{\text{REE}} - \underbrace{xr}_{\text{TEE}} - \underbrace{(oW + or)}_{\text{Pre-Computed}} = xW, \tag{2}$$

where xW' is accelerated in REE, xr is securely computed in TEE, and $oW + or$ is pre-computed and stored. Notably, xr holds the same heavyweight complexity with xW, which results in unacceptable latency in TEE. To overcome this, existing methods leverage sparse mask r_s to downgrade the complexity. For instance, Magnitude [9] only obfuscate 1% largest weights, and NNSplitter [12] selects extremely sparse parameters to protect by reinforcement learning.

However, under the constraint of mask sparsity, only limited number of parameters are obfuscated. To reduce the model accuracy to random guessing, the magnitude of changes in the obfuscated parameters is significantly large [28, 32]. Based on this insight, we observe a *gradient anomaly phenomenon*: compared to the normal counterparts in the same layer, obfuscated parameters exhibit substantially larger gradient values on the training data. As shown in Figure 2 (b), obfuscated parameters can be easily located, and then selectively fine-tuned for recovery.

Attack pipeline. Based on the identified gradient anomaly phenomenon, we initially localize the obfuscated parameters. By iterating through the attacker's small dataset, we identify the top 5% of parameters with the largest averaged gradient as obfuscated parameters. Subsequently, these identified parameters are set to be trainable, while the remaining parameters are frozen, enabling selective fine-tuning. Empirical observations reveal that the localization accuracy is not entirely precise, as a small subset of obfuscated parameters still exhibits minimal variation. Consequently, a few additional rounds of full fine-tuning are ultimately required.

4.3 Multiplicative Noise.

Risk analysis. These methods apply multiplicative factor to obfuscate parameters. For instance, SOTER [10] obfuscate a layer using one factor μ: $W' = \mu W$, and de-obfuscate the results as: $y = \mu^{-1} x W' = xW$. Similarly, ShadowNet [11] applies one factor for each columns.

However, as indicated in [13], multiplicative noise struggles to conceal the statistical distribution of parameters. The value of applied factor have significant impact on the variance of parameters. As a result, the adversary can leverage the variance of public models to estimate the applied factor, and then de-obfuscate the parameters.

Attack pipeline. Given the variance $\text{var}(W)$ of public models, and the variance $\text{var}(W')$, we follow [13] tofirst estimate multiplicative noise as: $\mu' = \sqrt{\text{var}(W')/\text{var}(W)}$. Then we de-obfuscate parameters using μ', and fine-tune the model with adversary's small dataset.

4.4 Attack Results

As demonstrated in Table 1, we conduct experimental evaluations regarding the attack performance of proposed MSP. To estimate the strongest adversary, the highest result in five individual experiments are reported. Notably, the MS accuracy against existing methods reaches an average of $3.37\times$ to $4.12\times$, even comparable to the original model in some scenarios, indicating that current approaches fail to safeguard high-value LLMs from thefts.

5 TEE-Based Low Rank Obfuscation

In this section, we introduce LoRO in detail. As shown in Figure 3, it consists of two components: Factor Multiplexing to reuse the cornerstone factors in deployment stage, and Low Rank Mask to safeguard the valuable LLM from thefts in inference stage. These two components are described respectively as follows, and we provide persuade code in Appendix E.

5.1 Low Rank Mask

Efficiency-Confidentiality dilemma. Edge TEEs face significant resource constraints, particularly when protecting high-complexity computations, which can introduce a hundred-fold increase in inference latency [8, 20]. Consequently, the core of TEE-based secure inference lies in maximizing inference efficiency while maintaining model confidentiality. On the one hand, full shielding methods can provide robust security, but the unacceptable latency renders them impractical. On the other hand, while existing methods offer substantial efficiency improvements, they fail to fully obscure the statistical distribution (as detailed in Section 4). This compromise from confidentiality to efficiency significantly increase the risk of model theft, leading them vulnerable to proposed MSP attack. Hence, it's challenge to achieve robust confidentiality in an efficient way.

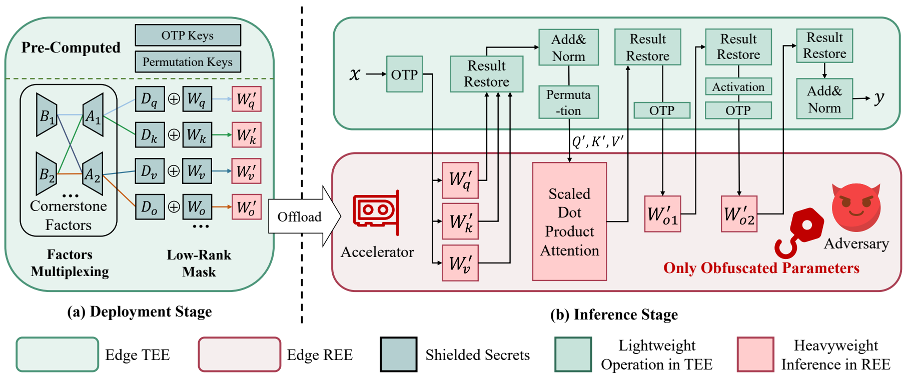


Figure 3: Illustration of proposed LoRO, which incorporates two stages: (a) Deployment Stage: to pre-computing keys and obfuscate parameters in TEE. (b) Inference Stage: inference with obfuscated parameters in REE and restore the results in TEE.

Our solution. To address the dilemma introduced above, our solution is to obfuscate parameters using dense additive mask, which can fully obscure the statistical distribution and provide high security [11, 13]. As shown in Figure 3, we focus on protecting parameters of linear layer. LoRO is compatible to popular LLMs since they are almost based linear layers. Given the dense mask D, the parameter W is obfuscated as $W' = W + D$. The inference results y is described as follows:

$$y = \underbrace{xW'}_{\text{REE}} - \underbrace{xD}_{\text{TEE}} = xW. \tag{3}$$

However, one main limitation is that the dense mask is too heavyweight to be shielded. Given the shape $[n \times n]$ of W, dense mask holds a high computation complexity of $\mathrm{O}(n^3)$. This is same with full shielding methods, which could result in an unacceptable latency in TEE. To tackle this problem and achieve real-time efficiency, *our key insight is to generate dense mask using low-rank factors*. Given two low-rank factors $B^{n\times d}$, $A^{d\times n}$ and generated dense mask $D = BA$, the inference results are re-formulated as follows:

$$y = \underbrace{xW'}_{\text{REE}} - \underbrace{xBA}_{\text{TEE}} = xW. \tag{4}$$

In conclusion, proposed methods address the efficiency-confidentiality dilemma in following aspects. For efficiency, the complexity in TEE is reduced from complex $\mathrm{O}(n^3)$ to $\mathrm{O}(n^2 \times d) = \mathrm{O}(n^2)$, where $d \ll n$. Hence, inference efficiency is significantly improved. For confidentiality, each elements in W are obfuscated randomly. As shown in Figure 2 (c), since statistical distribution are fully obscured, adversaries cannot access W without obtaining shielded D.

Intermediate results protection. To protect masks from analysis attacks, the intermediate results should also be protected. For the input x and of a linear layer, OTP o is employed as: $x' = x + o$. Same to Equation 2, the applied noise can be accurately removed. Specifically, for the scaled dot production of attention module [33], since OTP is not applicable [34] (as detailed in Appendix D, we leverage permutation matrix π to protect intermediate results as follows:

$$Q' = \pi Q, K' = \pi K, V' = \pi V, \quad y' = \text{softmax}\left(\frac{Q'K'^T}{\sqrt{k}}\right)V' = \pi\text{softmax}\left(\frac{QK^T}{\sqrt{k}}\right)V, \tag{5}$$

where k is the hyper-parameter that has been set in model training stage. To accommodate model variants, the potential RoPE [35] and other activation function is computed in TEE. Then the result is restored in TEE as: $y = \pi^T y'$. Notably, since our secret D is independent from π, the risk we discovered in TLG (detailed in Section 4) is avoided. Due to page limitation, more details of design and hyper-parameters can be found in Appendix A.

5.2 Factor Multiplexing

Limited secure memory challenge. Edge TEEs are constrained by limited secure memory, typically capped at 128 MB [17, 36]. However, to shield a pair of low-rank factors per layer for 7B LLMs, the secure memory could reach approximately 1.02 GB. The introduced memory paging issue leads to a unacceptable increase in inference latency and potential security risk [37], severely compromising the practicality. Hence, a critical challenge lies in efficiently protecting low-rank factors within such restricted secure memory.

Our solution. Factor Multiplexing is proposed to address this challenge. Our insight lies in the random combination of several limited low-rank factors, which enables reusing factors to save secure memory. Instead of preparing a pair of factors per layer, we randomly choose from cornerstone factors and generate dense mask. As shown in Figure 3 (a), given a cornerstone factors set $\{A_1, ..., A_n, B_1, ...B_n\}$, a small set $S \subseteq \{A_1, ..., A_n\} \times \{B_1, ...B_n\}$ is randomly chosen,where the $|S| = m$. Then a mask D is generated as follows:

$$D = \sum_{(A_i, B_j) \in P} \alpha B_j A_i, \tag{6}$$

where α is the random weight. In this way, only the cornerstone factors are required in memory, instead of the heavyweight one mask per layer. In real-time scenario, m is set to two for best efficiency, and the low computation complexity is maintained. Moreover, Factor Multiplexing enables updating the obfuscated parameters using new masks periodically. The secure memory requirement of one-mask-per-layer and Factor Multiplexing is reported in Appendix B.

6 Experiments

In this section, LoRO is evaluated experimentally. According to design goal (in Section 3), we aim to answer the following questions:

RQ1: How is the defense effectiveness of LoRO? (in Section 6.2)
RQ2: What is the inference speed of LoRO compared to existing methods? (in Section 6.3)
RQ3: What is the model accuracy of LoRO compared to original models? (in Section 6.4)

6.1 Experiment Setup.

Benchmarks. Proposed LoRO is evaluated on several famous benchmarks, including SQuAD (reading comprehension) [38], GSM8k (mathematics) [39], Spider (code generation) [40] and representative standard GLUE [41]. The accuracy is reported as metric. For generation tasks, only exact matched answer is considered correct. We also evaluate LoRO on Computer Vision tasks, including CIFAR100 [42] and Food101 [43].

Models. Representative models of various scales and structure are selected, including RoBERTa [44, 45], BART [46], ViT [47] Qwen [48] and LLaMA [49, 50].

Hardware devices. Experiments regarding model confidentiality and accuracy are conducted on a server equipped with two NVIDIA RTX 4090 GPUs. Inference efficiency are evaluated on two TEE platforms. For TrustZone, NVIDIA Jetson Orin NX board equipped with 6-core ARM Cortex-A78AE CPU and 1024-core NVIDIA Ampere architecture GPU is employed, and OP-TEE [51] is leveraged as TEE OS. For Intel SGX, a laptop equipped with Intel Core I9-10885H CPU and Quadro T2000 GPU is adopted, and Gramine-SGX [52] is the basic TEE OS.

Due to page limitation, more details and experiments can be found in Appendix A and B.

6.2 Model Confidentiality

As shown in Table 1, we report the MSP accuracy against LoRO and various defense methods. The significantly high MS accuracy (3.75× to 4.12×) demonstrate the vulnerability of current defense

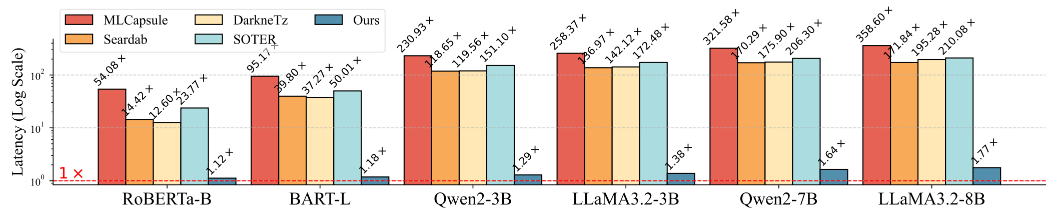


Figure 4: Inference latency of various methods in SGX environment. All results are normalized to REE inference latency (red line, $1\times$). We depict in $\log_{10}$ scale for better visualization.

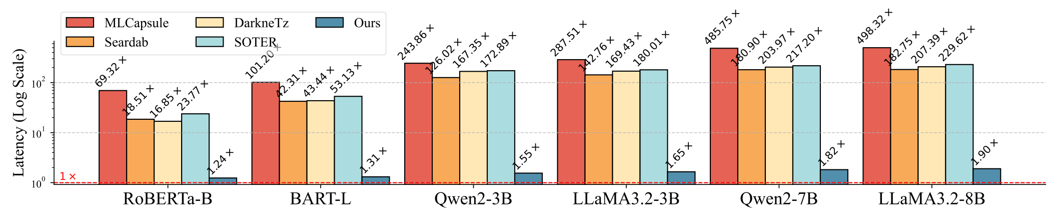


Figure 5: Inference latency of various methods on TrustZone environment. All results are normalized to REE inference latency (red line, $1\times$). We depict in $\log_{10}$ scale for better visualization.

approaches to our proposed MSP attack. Notably, adversary can achieve near-complete recovery in several scenarios. In contrast, LoRO maintains a robust defense performance of only 0.94×, comparable to the 1.00× baseline in black-box settings. These results indicate that LoRO provides effective protection on LLMs against MS attempts.

Answer to RQ1: Proposed LoRO effectively downgrades private LLMs to black-box, providing robust security to valuable intellectual property protection.

6.3 Inference Efficiency

Experiments are conducted on popular TEEs to evaluate the inference efficiency of LoRO, including Intel SGX and ARM TrustZone. As depicted in Figure 4 and Figure 5, proposed LoRO introduces only $1.49\times$ latency on average, compared to the $112.10\times$ to $250.39\times$ of existing methods. This demonstrates that *our methods provides real-time inference and is practical for real-world application*. Notably, as shown in table 6, with the raise of model scale, the computing complexity in TEE is significantly increased due to larger intermediate size, resulting a higher latency.

Answer to RQ2: Compared to the averaged $112.10\times$ of existing methods, proposed LoRO introduces only $1.49\times$ latency, achieving real-time inference efficiency.

6.4 Model Accuracy

As shown in Table 3, we report the model accuracy of original model, proposed LoRO method and the obfuscated model exposed in REE. Only a 0.01% drop is observed in BART on MRPC, which is caused by float precision error. It is demonstrated that the high accuracy of original model is maintained. Moreover, the obfuscated model is completely downgraded to random guessing level.

Answer to RQ3: Proposed LoRO introduces no accuracy loss, maintaining the high model accuracy. The obfuscated model exposed in REE is downgraded to unusable.

Table 3: Model accuracy of original model (Ori.), LoRO and obfuscated model in REE (Obf.).

		SQuAD	MRPC	SST-2	MNLI	GSM8K	Spider
RoBERTa	Ori.	81.84%	87.99%	93.58%	85.33%	-	-
	LoRO (↑)	81.84%	87.99%	93.58%	85.33%	-	-
	Obf. (↓)	0.64%	31.61%	50.91%	35.45%	-	-
BART	Ori.	83.15%	87.01%	95.30%	88.15%	-	-
	LoRO (↑)	83.15%	87.00%	95.30%	88.15%	-	-
	Obf. (↓)	0.76%	31.60%	49.08%	35.45%	-	-
Qwen2	Ori.	48.45%	-	-	-	70.96%	17.99%
	LoRO (↑)	48.45%	-	-	-	70.96%	17.99%
	Obf. (↓)	0.00%	-	-	-	0.00%	0.00%
LLaMA3	Ori.	49.20%	-	-	-	53.12%	34.62%
	LoRO (↑)	49.20%	-	-	-	53.12%	34.62%
	Obf. (↓)	0.00%	-	-	-	0.00%	0.00%

7 Discussion

Side channel Attacks. Side channel attacks [29, 30] can cause leakage from TEE potentially. Fortunately, our LoRO is compatible with existing advanced defense schemes [53, 54] to mitigate such attacks. Hence, defending against side channel attacks is considered a sole research domain regarding TEE security, and is out of our scope.

Trusted GPU. Some advanced GPU provides Confidential Computing [55, 56]. Nevertheless, the substantial cost of GPUs with confidential computing (CC) capabilities presents a significant barrier to their widespread adoption in edge computing environments. More affordable alternatives, including Intel Software SGX or ARM TrustZone integrated with dedicated AI acceleration hardware, are expected to remain the predominant solution for edge devices in the foreseeable future. Consequently, our investigation into secure inference for edge computing systems does not currently incorporate Trusted GPUs within its scope.

8 Conclusion

In this paper, we first identify a statistical vulnerability in existing TEE-based secure inference methods, and break their security by designed Model Stealing attack with Prior. To protect on-device LLMs, LoRO is proposed, which incorporates two components: (1) Low Rank Mask to completely obfuscate model parameters, while achieving fast inference via lightweight low-rank computing in TEE. Moreover, no accuracy loss is introduced, and no retraining and model modification is required. (2) Factor Multiplexing to significantly reduce the secure memory requirement, avoiding additional latency introduced by secure memory paging. Proposed LoRO downgrade on-device LLMs to black-box level ($0.94\times$ MS accuracy), while providing real-time inference service (only $1.49\times$ latency, compared to the $112\times$ of existing SOTA). LoRO can solve the concern regarding theft on untrusted edge devices, hence greatly facilitating the wide adoption of LLMs.

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Table 4: Hyper-parameters of knockoff attacks.

	RoBERTa		BART		Qwen2		LLaMA3	
	Epoch	Learning Rate	Epoch	Learning Rate	Epoch	Learning Rate	Epoch	Learning Rate
TLG	1	3e-5	2	3e-5	2	5e-5	2	5e-5
ShadowNet	2	1e-5	3	1e-5	4	1e-5	4	1e-5
SOTER	2	1e-5	3	1e-5	4	1e-5	4	1e-5
Magnitude	3	5e-5	4	1e-5	5	3e-5	5	3e-5

Table 5: Detailed hyper-parameters of LoRO.

	RoBERTa	BART	Qwen2			LLaMA3		
Model Size	Base	Large	1.5B	3B	7B	1.5B	3B	8B
Rank	12	16	24	30	36	24	30	36

A More Details

Attack details. We introduce our attack details here. For each method, the adversary first reason the model structure from exposed model parts in REE, and get public pretrained model from Internet.

Then, the adversary conducts model de-obfuscation (as shown in Figure 1). In this stage, the batch size we leveraged to attack permutation methods is 16, and the inputs are randomly selected from datasets. Notably, we empirically find the batch size can't be too large, since the averaged intermediate results would be very similar and difficult to be matched. For additive noise, we iterate all training data in small dataset to accumulate the gradients. We freeze major parameters, and only 5% largest parameters are fine-tuned for 2 epoches. For multiplicative noise methods, our methods is as same as [8, 13], and no other details need to be clarified. The knockoff setting of each method are shown in Table 4. The ShadowNet is considered as the combination of additive mask and multiplicative noise. We follow [13] to first remove the mask in REE, and then estimate the multiplicative key.

In the final knockoff stage, we develop our code based on the ML-Doctor [57]. Since model have been approximately recovered before, and only 10% of dataset are leveraged to conduct attacks, we only train models with a low learning-rate as 5e-4 in 2 epoches to avoid over-fitting. The results reported in Table 1 is taken from the best of five individual experiments.

LoRO details. The details and hyper-parameters of LoRO is introduced here. All the random noise and low-rank factors are randomly sampled from Gaussian Noise. We set the m as 2 to achieve fast inference speed. According to LoRA [58], if the rank d is able to effectively adapt the model to specific domain, we thought the d is enough to obfuscate models well. The detailed hyper-parameters of our experiments is shown in Table 5.

Implementation optimization. For TrustZone, we mainly conduct two optimizations. First, take inspiration from ShadowNet [11], we design matrix multiplication based on NEON instruction set to accelerate computation in TEE. This achieves about $3\times$ speed up when the dimension of matrix is over 768. Second, to reduce the data transfer time between REE and TEE, we allocate a pinned shared memory between them as data exchange zone. While this may raise inconvenience in coding, but the transfer latency is significantly reduced. Notably, it is necessary to compile the OP-TEE with larger secure memory (at least 128MB) since LLMs are significantly large. For methods like MLCapsule [23], the required memory could reach tens of GB.

Compatibility for small models. Our LoRO is designed to obfuscate the linear parameters (including both linear and convolutional layers). Previous work targeting small models [9, 10, 11, 13, 27] also focuses on protecting linear layers. Hence, proposed LoRO is inherently compatible to small models, where the linear operations major the parameters and inference computing.

Table 6: Latency breakdown of LoRO on Intel SGX.

	RoBERTa-B	BART-L	Qwen2-3B	LLaMA3.2-3B	Qwen2-7B	LLaMA3.2-8B
TEE	45.72%	47.20%	38.71%	29.92%	40.57%	37.82%
REE	37.82%	37.03%	55.62%	56.09%	43.93%	49.20%
Transfer	16.45%	15.76%	15.66%	13.98%	15.50%	12.96%

Table 7: Accuracy of LoRO on MATH.

Model	Category	MATH
Gemma 9B	Ori.	36.63%
Gemma 9B	LoRO (↑)	36.62%
Gemma 9B	Obf. (↓)	0.00%

Table 8: Accuracy of LoRO on ViT.

		Food101	CIFAR100
	Ori.	81.57%	89.86%
ViT	LoRO (↑)	81.57%	89.85%
	Obf. (↓)	0.99%	1.00%

B More Experiments on LoRO

Latency breakdown. As presented in Table 6, we analyze the latency distribution among TEE, REE, and data transfer. For smaller LLMs such as RoBERTa-B and BART-L, the computational efficiency is primarily limited by TEE processing and data transfer latency. However, in larger models like LLaMA and Qwen, the REE latency becomes dominant due to the high dimension full matrix computations. This clearly demonstrates the lightweight advantage achieved by LoRO.

Accuracy of LoRO on ViT. We also test the accuracy of LoRO on ViT, as shown in Table 8. Only a small drop of 0.01% is observed on CIFAR100, which is caused by float error. This demonstrate the high accuracy of LoRO on vision tasks.

Accuracy of LoRO on MATH. LoRO is also evaluated on a challenging dataset MATH [59]. As shown in the Table 7, LoRO maintains near-identical accuracy, with the 0.01% drop attributable to floating-point error. This can be solved in 32-bit models. Crucially, the obfuscated model becomes unusable (0% accuracy), confirming our method's robustness to adversary.

Secure memory requirement. As shown in Table 9, we report the secure memory requirement of preserving secrets in TEE. Compared to one-mask-per-layer paradigm, proposed Factor Multiplexing effectively reduce the secure memory to MB-level compatible to edge TEE. The high latency and potential risk introduced by secure memory page is hence avoided.

More latency comparison. As shown in Table 10, LoRO's latency outperforms most of existing methods. For comprehensive comparison, we only report the de-obfuscation latency of SOTER. While TLG performs similarly to LoRO in inference efficiency, TLG cannot provide black-box security (as demonstrated in Section 6.2). We also notice that MLCapsule suffers critical slowdowns from the secure paging overhead, and Magnitude is slow since the sparse computation in TEE is too heavyweight for large scale LLMs.

C More experiments on MSP

MSP under low auxiliary data. In Section 3, about 10% of training data is assumed to be held by the adversary to launch MSP attacks. The 10% data assumption allows us to design defenses robust against a powerful adversary.

We evaluate the attack performance under low data ratio (1%-10% of SQuAD on Qwen2). As shown in Table 11, our LoRO consistently surpasses black-box performance even at 1% data volume, while existing SOTA TLG fails to provide adequate protection. Even under low data ratio conditions, the proposed MSP poses a serious threat to existing methods.

MSP on CV models. We also evaluate Model Stealing with Prior (MSP) experiments on ViT and ResNet18. For model prior knowledge, we used model trained on CIFAR10. We did not adapt TLG to CNNs. As shown in the table 12, MSP remains effective for CV models like ViT and ResNet18.

Table 9: Secure memory requirement of Factor Multiplexing and naive one-mask-per-layer.

	RoBERTa	BART	Qwen-7B	LLaMA-8B
One-Mask-Per-Layer	232 MB	594 MB	1.02 GB	1.14 GB
Factor Multiplexing	3.84 MB	11.88 MB	26.30 MB	28.28 MB

Table 10: More experiments on latency comparison.

Model	MLCapsule	SOTER	ShadowNet	Magnitude	TLG	LoRO
RoBERTa-B	54.08×	1.34×	2.35×	8.92×	1.10×	1.12×
BART-L	95.17×	1.62×	2.48×	10.33×	1.14×	1.18×
Qwen2-7B	321.58×	2.01×	3.60×	35.84×	1.59×	1.64×
LaMA3.2-8B	358.60×	2.10×	3.75×	37.67×	1.70×	1.77×

D Limitation of OTP on Attention

We analyze why the OTP cannot be applied to secure intermediates of Attention module here. During forward inference, Attention block requires to compute QK^T. When OTP are applied to secure Q and K as $Q' = Q + o_q, K' = K + o_k$, the multiplication can be formulated as follows:

$$Q'K'^T = QK^T + \underline{Qo_k^T + o_qK^T} + o_qo_k^T. \tag{7}$$

The term $o_qo_k^T$ can be pre-computed and removed in a lightweight manner, the term $Qo_k^T + o_qK^T$ must be computed in a real-time manner. Since o_q and o_k shares the same shape of Q and K, applying OTP will introduce unacceptable computation in TEE. Due to the limited computational resources in TEE, this will lead to prohibitive inference latency. This issue is also exists in protecting V.

The TOSEM version of TEESlice [34] suggests that this issue can be solved by using Linear Attention [60]. But the Linear Attention may have a bit influence on model performance, and is still not widely adopted in popular LLMs. In this paper, we propose to use permutation to secure the intermediate results of Attention Block, while the remained parts should be protected by OTP.

E Algorithm Description

For better comprehension, we present the persuade code of deployment stage in Algorithm 1, and the inference stage in Algorithm 2.

Table 11: MSP performance under low auxiliary data.

Dataset Ratio	1%	3%	5%	10%	Average
TLG	14.20%	19.78%	24.95%	29.33%	2.92x
LoRO	4.08%	4.22%	4.38%	5.07%	0.63x
Black-Box	4.37%	6.95%	8.40%	11.20%	1.00x

Table 12: MSP performance on Computer Vision models.

Model	Dataset	TLG	SOTER	Magnitude	ShadowNet	Black-Box
ViT-Base	CIFAR100	89.67%	88.30%	87.28%	79.27%	14.57%
ViT-Base	Food101	81.51%	75.52%	80.05%	71.90%	10.28%
ResNet18	CIFAR100	N/A	67.30%	73.55%	65.42%	14.74%

Algorithm 1: LoRO Deployment Stage.

Input: Original Parameters W
Output: Obfuscated Parameters W'
$Key, Secret, W' \leftarrow [], [], []$;
$B, A \leftarrow RandomNoise()$; ▷ Randomly generate cornerstone low-rank factors
$i \leftarrow 0$;
$len = \text{len}(W)$;
while $i < len$ **do**
    $\alpha, B\_index, A\_index = \text{RandomIndex}()$; ▷ Randomly choose factors
    $W'[i] = W[i] + \alpha B[B\_index[i]]A[A\_index[i]]$; ▷ Parameters obfuscation
    Secret$[i]$ = $[B[B\_index[i]], A[A\_index[i]], \alpha]$;
    $Key[i]$ =Precompute(Secret$[i]$); ▷ Precompute de-obfuscation keys.
end
W'.to(REE); ▷ Offload obfuscated parameters to REE
$Secret$.to(TEE); ▷ Protect secrets and keys in TEE
Key.to(TEE);
return W';

Algorithm 2: LoRO Inference Stage.

Input: Inference Input x
Output: Inference Output y
$Key, Secret \leftarrow$ TEE_Prepare();
$W' \leftarrow$ REE_Prepare(); ▷ Load in Memory
$i \leftarrow 0$;
$len = \text{len}(W)$;
while $i < len$ **do**
    $y_{REE} = \text{Inference}(W'[i], x.to(\text{REE})$; ▷ Inference with obfuscated parameters in REE
    $y_{TEE} = \text{Low\_Rank\_Inference}(Secret[i], x.to(\text{TEE}))$; ▷ De-obfuscation in TEE
    $x = y_{REE}.to(\text{TEE}) + y_{TEE}$; ▷ Result restore in TEE
    if $i == len - 1$ **then**
        $y = x.to(\text{REE})$; ▷ Return result when finish
        break;
    end
    if *next_is_scaled_dot_attention* **then**
        $x = \text{permutation}(x, Key[i])$; ▷ Intermediate result protection
    else
        $x = \text{OTP}(x, Key[i])$; ▷ Intermediate result protection
    end
end
return y;

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