
Membership Inference Attacks against Fine-tuned Large Language Models via Self-prompt Calibration

Wenjie Fu

Huazhong University of
Science and Technology
wjfu99@outlook.com

Huandong Wang*

Tsinghua University
wanghuandong@tsinghua.edu.cn

Chen Gao

Tsinghua University
chgao96@gmail.com

Guanghua Liu

Huazhong University of
Science and Technology
guanghualiu@hust.edu.cn

Yong Li

Tsinghua University
liyong07@tsinghua.edu.cn

Tao Jiang

Huazhong University of
Science and Technology
taojiang@hust.edu.cn

Abstract

Membership Inference Attacks (MIA) aim to infer whether a target data record has been utilized for model training or not. Existing MIAs designed for large language models (LLMs) can be bifurcated into two types: reference-free and reference-based attacks. Although reference-based attacks appear promising performance by calibrating the probability measured on the target model with reference models, this illusion of privacy risk heavily depends on a reference dataset that closely resembles the training set. Both two types of attacks are predicated on the hypothesis that training records consistently maintain a higher probability of being sampled. However, this hypothesis heavily relies on the overfitting of target models, which will be mitigated by multiple regularization methods and the generalization of LLMs. Thus, these reasons lead to high false-positive rates of MIAs in practical scenarios. We propose a Membership Inference Attack based on Self-calibrated Probabilistic Variation (SPV-MIA). Specifically, we introduce a self-prompt approach, which constructs the dataset to fine-tune the reference model by prompting the target LLM itself. In this manner, the adversary can collect a dataset with a similar distribution from public APIs. Furthermore, we introduce probabilistic variation, a more reliable membership signal based on LLM memorization rather than overfitting, from which we rediscover the neighbour attack with theoretical grounding. Comprehensive evaluation conducted on three datasets and four exemplary LLMs shows that SPV-MIA raises the AUC of MIAs from 0.7 to a significantly high level of 0.9. Our code and dataset are available at: https://github.com/tsinghua-fib-lab/NeurIPS2024_SPV-MIA.

1 Introduction

Large language models (LLMs) have been validated to have the ability to generate extensive, creative, and human-like responses when provided with suitable input prompts. Both commercial LLMs (e.g., ChatGPT [51]) and open-source LLMs (e.g., LLaMA [65]) can easily handle various complex application scenarios, including but not limited to chatbots [20], code generation [66], article co-writing [28]. Moreover, as the pretraining-finetuning paradigm becomes the mainstream pipeline in of LLM field, small-scale organizations and individuals can fine-tune pre-trained models over their private datasets for downstream applications [44], which further enhances the influence of LLMs.

*Corresponding author.

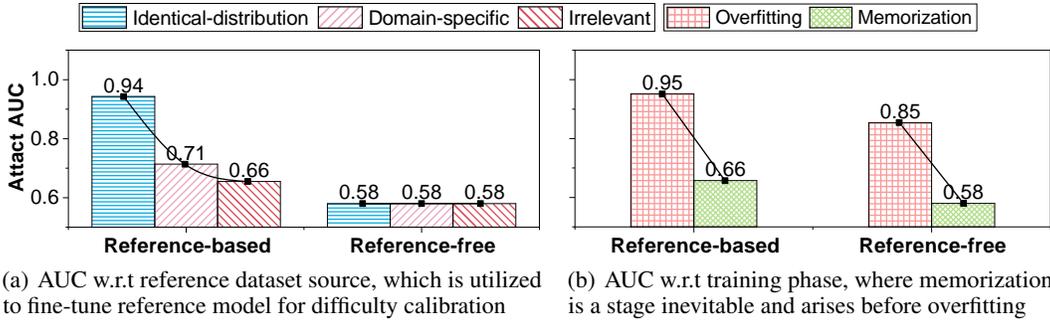


Figure 1: Attack performances of the reference-based MIA (LiRA [8, 46, 47, 72]) and reference-free MIA (LOSS Attack [73]) unsatisfy against LLMs in practical scenarios, where LLMs are in the memorization stage and only domain-specific dataset is available. (a) Reference-based MIA shows a catastrophic plummet in performance when the similarity between the reference and training datasets declines. (b) Existing MIAs are unable to pose privacy leakages on LLMs that only exhibit memorization, an inevitable phenomenon occurs much earlier than overfitting and persists throughout almost the entire training phase [47, 64, 75].

However, while we enjoy the revolutionary benefits raised by the popularization of LLMs, we also have to face the potential privacy risks associated with LLMs. Existing work has unveiled that the privacy leakage of LLMs exists in almost all stages of the LLM pipeline [9, 19, 41, 53, 59, 61]. For example, poisoning attacks can be deployed during pre-training, distillation, and fine-tuning [34, 68]. Moreover, data and model extraction attacks can be conducted through inference [6, 22]. Among these attacks, fine-tuning is widely recognized as the stage that is most susceptible to privacy leaks since the relatively small and often private datasets used for this process [74]. Therefore, this paper aims to uncover the underlying privacy concerns associated with fine-tuned LLMs through an exploration of the membership inference attack (MIA).

MIA is an adversary model that categorizes data records into two groups: member records, which are included in the training dataset of the target model, and nonmember records, which belong to a disjoint dataset [60]. MIAs have been well studied in classic machine learning tasks, such as classification, and reveal significant privacy risks [25]. Recently, some contemporaneous works attempt to utilize MIAs to evaluate the privacy risks of LLMs. For example, several studies have employed reference-free attack, especially LOSS attack [73], for privacy auditing [31] or more sophisticated attack [6]. Mireshghallah et al. introduce the seminal reference-based attack, Likelihood Ratio Attacks (LiRA) [8, 70, 72], into Masked Language Models (MLMs), which measure the calibrated likelihood of a specific record by comparing the discrepancy on the likelihood between the target LLM and the reference LLM. Following this concept, Mireshghallah et al. further adapt LiRA for analyzing memorization in Causal Language Models (CLMs). However, these methods heavily rely on several over-optimistic assumptions, including assuming the overfitting of target LLMs [41] and having access to a reference dataset from the same distribution as the training dataset [46, 47]. Thus, it remains inconclusive whether prior MIAs can cause considerable privacy risk in practical scenarios.

As illustrated in Fig. 1, LiRA [47] and LOSS Attack [73] are employed to represent reference-based and reference-free MIAs to explore their performance in practical scenarios. Firstly, as shown in Fig. 1(a), we evaluate LiRA and LOSS Attack with three reference datasets from different sources, i.e., the dataset with the identical distribution with the member records (identical-distribution), the dataset of the same domain with the member records (domain-specific), and the dataset irrelevant to the member records (irrelevant). The performance of LOSS attack is consistently low and independent of the source of the reference dataset. For LiRA, the attack performance will catastrophically plummet as the similarity between the reference dataset and the target dataset declines. Thus, the reference-based MIA can not pose critical privacy leakage on LLMs since similar datasets are usually not available to adversaries in real applications. Secondly, as shown in Fig. 1(b), two target LLMs are fine-tuned over the same pre-trained model but stop before and after overfitting, and the reference LLMs are fine-tuned on a different dataset from the same domain. We can observe that existing MIAs cannot effectively cause privacy leaks when the LLM is not overfitting. This phenomenon is addressed by the fact that the membership signal proposed by existing MIAs is highly dependent on overfitting in

target LLMs. They assume that member records tend to have overall higher probabilities of being sampled than non-member ones, an assumption that is only satisfied in overfitting models [67].

In this work, to address the aforementioned two limitations of existing works, we propose a Membership Inference Attack based on Self-calibrated Probabilistic Variation (SPV-MIA) composed of two according modules. First, although existing reference-based MIAs are challenging to reveal actual privacy risks, they demonstrate the significant potential of achieving higher privacy risks with the reference model. Therefore, we design a self-prompt approach to extract the reference dataset by prompting the target LLMs themselves and collecting the generated texts. This approach allows us to acquire the significant performance improvement brought by the reference model while ensuring the adversary model is feasible on the practical LLMs. Second, prior studies have shown that memorization is intrinsic for machine learning models to achieve optimality [16] and can persist in LLMs without leading to overfitting [64]. Consequently, rather than relying on probabilities as membership signals, we propose designing a more resilient signal grounded in an insightful theory, which posits that LLM memorization manifests as an augmented concentration in the probability distribution surrounding the member records [67]. Specifically, we proposed a probabilistic variation metric that can detect local maxima points via the notion of second partial derivative test [62] approximately instantiated by a paraphrasing model. Moreover, based on the new theoretical foundation, we elucidate the efficacy of the neighbor attack [41] through the lens of LLM memorization. This analysis underscores the pivotal role of characterizing memorization in MIA for future studies. It is worth noting that our paraphrasing model does not rely on another MLM like the neighbour attack. Overall, our contributions are summarized as follows:

- We propose a self-prompt approach that collects reference datasets by prompting the target LLM to generate, which will have the closely resemble distribution as the training dataset. In this manner, the reference model fine-tuned on the reference dataset can significantly improve the attack performance without any unrealistic assumptions.
- We further design a probabilistic variation metric based on the theoretical foundation of LLM memorization [67], and derive a more convincing principle and explanation of the neighbour attack [41]. Furthermore, our investigation highlights the importance of characterizing LLM memorization for subsequent studies in designing more sophisticated MIA methods.
- We conducted extensive experiments to validate the effectiveness of SPV-MIA. The results suggest that SPV-MIA unveils significantly higher privacy risk across multiple fine-tuned LLMs and datasets compared with existing MIAs (about 23.6% improvement in AUC across four representative LLMs and three datasets).

2 Related Works

Membership Inference Attack: Initially, prior MIAs mainly focused on classical machine learning models, such as classification models [7, 10, 39, 60]. With the rapid development of other machine learning tasks, such as recommendation and generation tasks, MIAs against these task-specific models became a research direction of great value, and have been well investigated [13, 18, 77]. Meanwhile, ChatGPT released by OpenAI has propelled the attention towards LLMs to the peak over the past year, which promotes the study of MIAs against LLMs. The seminal works in this area typically focuses on fine-tuned LLM or LM. Mireshghallah et al. proposed LiRA against MLMs via adopting pre-trained models as reference models. Following this study, Mireshghallah et al. further adapted LiRA for CLMs. Mattern et al. pointed out the unrealistic assumption of a reference model trained on similar data, then substituted it with a neighbourhood comparison method. Although MIAs against LMs and fine-tuned LLMs have been studied by several works, the attack performance of existing MIAs in regard to LLMs with large-scale parameters and pre-trained on tremendous corpora is still not clear. Thus, some contemporaneous works have also been released to detect the pre-training data of LLMs and expose considerable privacy risks [11, 14, 19, 42, 59, 76]. In this work, we still focus on fine-tuned LLMs since the fine-tuning datasets are typically more private and sensitive. We evaluate previous MIAs on LLMs in practical scenarios, and found that the revealed privacy breaches were far below expectations due to their strict requirements and over-optimistic assumptions. Then, we propose SPV-MIA, which discloses significant privacy risks on practical LLM applications.

Large Language Models: In the past year, LLMs have dramatically improved performances on multiple natural language processing (NLP) tasks and consistently attracted attention in both academic

and industrial circles [44]. The widespread usage of LLMs has led to much other contemporaneous work on quantifying the privacy risks of LLMs [41, 48, 53]. In this work, we audit privacy leakages of LLMs by distinguishing whether or not a specific data record is used for fine-tuning the target LLM. The existing LLMs primarily fall into three categories: causal language modeling (CLM) (e.g. GPT), masked language modeling (MLM) (e.g. BERT), and Sequence-to-Sequence (Seq2Seq) approach (e.g. BART). Among these LLMs, CLMs such as GPT [54, 69] and LLaMA [65] have achieved the dominant position with the exponential improvement of model scaling [79]. Therefore, we select CLM as the representative LLM for evaluation in this work.

3 Preliminaries

3.1 Causal Language Models

For a given text record \mathbf{x} , it can be split into a sequence of tokens $[t_0, t_1, \dots, t_{|\mathbf{x}|}]$ with variable length $|\mathbf{x}|$. CLM is an autoregressive language model, which aims to predict the conditional probability $p_\theta(t_i | \mathbf{x}_{<i})$ given the previous tokens $\mathbf{x}_{<i} = [t_0, t_1, \dots, t_{i-1}]$. During the training process, CLM calculates the probability of each token in a text with the previous tokens, then factorizes the joint probability of the text into the product of conditional token prediction probabilities. Therefore, the model can be optimized by minimizing the negative log probability:

$$\mathcal{L}_{\text{CLM}} = -\frac{1}{M} \sum_{j=1}^M \sum_{i=1}^{|\mathbf{x}^{(j)}|} \log p_\theta(t_i | \mathbf{x}_{<i}^{(j)}), \quad (1)$$

where M denotes the number of training records. In the process of generation, CLMs can generate coherent words by predicting one token at a time and producing a complete text using an autoregressive manner. Moreover, the pretraining-finetuning paradigm is proposed to mitigate the uncountable demands of training an LLM for a specific task [44]. Besides, multifarious parameters-efficient fine-tuning methods (e.g., LoRA [24], P-Tuning [38]) are introduced to further decrease consumption by only fine-tuning limited model parameters [12]. In this work, we concentrate on the fine-tuning phase, since the fine-tuning datasets are usually more private and vulnerable to the adversary [74].

3.2 Threat Model

In this work, we consider an adversary who aims to infer whether a specific text record was included in the fine-tuning dataset of the target LLM. There are two mainstream scenarios investigated by previous research: white-box and black-box MIAs. White-box MIA assumes full access to the raw copy of the target model, which means the adversary can touch and modify each part of the target model [50]. For a fully black-box scenario, the adversary should only approved to acquire output texts generated by the target LLM while given specific prompts, which maybe too strict for the adversary to conduct a valid MIA [14, 41, 58, 76]. Thus, we consider a practical setting beyond fully black-box that further requires two regular API access for evaluating existing works and our proposed method:

- **Query API:** The access to the query API that only provides generated texts and logits (or loss).
- **Fine-tuning API:** The access to the fine-tuning API of the pre-trained version of the target model.

Note that the query API access is widely adopted by existing MIA works [14, 41, 58, 76], both the query API and the fine-tuning API are usually provided by commercial LLM providers, such as OpenAI [52] and Zhipu AI [2]. These two APIs are also easy for the adversary to access in open-source LLMs, such as LLaMA [65] and Flacon [3]. In our setting, D is a dataset collected for a specific task, which can be separated into two disjoint subsets: D_{mem} and D_{non} . The target LLM θ is fine-tuned on D_{mem} , and the adversary has no prior information about which data records are utilized for fine-tuning. Besides, all reference-based MIA, including SPV-MIA, can at most fine-tune the reference model using a disjoint dataset D_{refer} from the same task. The adversary algorithm \mathcal{A} is designed to infer whether a text record $\mathbf{x}^{(i)} \in D$ belong to the training dataset D_{mem} :

$$\mathcal{A}(\mathbf{x}^{(j)}, \theta) = \mathbb{1} \left[P(m^{(j)} = 1 | \mathbf{x}^{(j)}, \theta) \geq \tau \right], \quad (2)$$

where $m^{(j)} = 1$ indicates that the record $\mathbf{x}^{(j)} \in D_{mem}$, τ represents the threshold, and $\mathbb{1}$ denotes the indicator function.

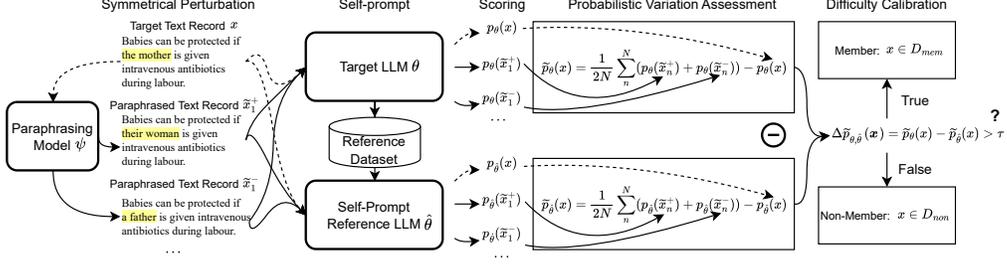


Figure 2: The overall workflow of SPV-MIA, where includes the probabilistic calibration via self-prompt reference model and the probabilistic variation assessment via paraphrasing model.

4 Membership Inference Attack via Self-calibrated Probabilistic Variation

In this section, we first introduce the general paradigm of Membership Inference Attack via Self-calibrated Probabilistic Variation (SPV-MIA) as illustrated in Fig 2. Then we discuss the detailed algorithm instantiations of this general paradigm by introducing practical difficulty calibration (PDC, refer to Section 4.2) and probabilistic variation assessment (PVA, refer to Section 4.3).

4.1 General Paradigm

As formulated in Eq. 1, the objective of an LLM is to maximize the joint probability of the text in the training set. Thus, prior **reference-free MIAs** employ the joint probability of the target text being sampled as the membership signal [6, 31, 58]:

$$\mathcal{A}(\mathbf{x}, \theta) = \mathbb{1}[p_\theta(\mathbf{x}) \geq \tau], \quad (3)$$

where $p_\theta(\mathbf{x})$ denotes the probability measured on the target model θ . Since some records are inherently over-represented, even non-member records can achieve high probability in the data distribution [70], which leads to a high False-Positive Rate (FPR). Thus, **reference-based MIAs** adopt difficulty calibration [14, 57, 70], which further calibrates the probability by comparing it with the value measured on reference models [46, 47]:

$$\mathcal{A}_{exist}(\mathbf{x}, \theta) = \mathbb{1}[\Delta p_\theta(\mathbf{x}) \geq \tau] = \mathbb{1}[p_\theta(\mathbf{x}) - p_\phi(\mathbf{x}) \geq \tau], \quad (4)$$

where $\Delta p_\theta(\mathbf{x})$ is the calibrated probability, and $p_\phi(\mathbf{x})$ is estimated on the reference model ϕ .

However, both reference-free and reference-based MIAs often encounter high FPR in practical scenarios [14, 41, 59, 76]. For reference-based MIAs, although they have the potential to offset the over-represented statuses of data records if the reference model can be trained on a dataset closely resembling the training dataset D_{mem} . Nevertheless, it is almost unrealistic for an adversary to obtain such a dataset, and adopting a compromising dataset will lead to the collapse of attack performance. We circumvent this by introducing a self-prompt reference model $\hat{\theta}$, which is trained on the generated text of the target model θ . Besides, the probability signal adopted by existing MIAs is not reliable, since the confidence of the probability signal is notably declined when the target model is not overfitting only memorization [67]. Thus, we elaborately design a more stable membership signal, probabilistic variation $\tilde{p}_\theta(\mathbf{x})$, audited by a paraphrasing model and only rely on LLM memorization. Formally, as depicted in Fig. 2, **our proposed MIAs** can be formulated as:

$$\mathcal{A}_{our}(\mathbf{x}, \theta, \hat{\theta}) = \mathbb{1}[\Delta \tilde{p}_{\theta, \hat{\theta}}(\mathbf{x}) \geq \tau] = \mathbb{1}[\tilde{p}_\theta(\mathbf{x}) - \tilde{p}_{\hat{\theta}}(\mathbf{x}) \geq \tau], \quad (5)$$

where $\tilde{p}_\theta(\mathbf{x})$ and $\tilde{p}_{\hat{\theta}}(\mathbf{x})$ are probabilistic variations of the text record \mathbf{x} measured on the target model θ and the self-prompt reference model $\hat{\theta}$ respectively.

4.2 Practical Difficulty Calibration (PDC) via Self-prompt Reference Model

Watson et al. [70] has suggested that inferring the membership of a record by thresholding on a predefined metric (e.g. confidence [56], loss [73], and gradient norm [50]) will cause a high FPR. Since several non-member records may have high probabilities of being classified as member records simply because they are inherently over-represented in the data manifold. In other words, the metric estimated on the target model is inherently biased and has a high variance, which leads to a

significant overlap in the metric distributions between members and non-members, making them more indistinguishable. To mitigate this phenomenon, Watson et al. propose difficulty calibration as a general approach for extracting a much more distinguishable membership signal, which can be adapted to most metric-based MIAs by constructing their calibrated variants [46, 46, 70]. Concretely, difficulty calibration assumes an ideal reference dataset D_{refer} drawn from the identical distribution as the training set D_{mem} of the target model θ , and trains an ideal reference model ϕ with a training algorithm \mathcal{T} . Then, it fabricates a calibrated metric by measuring the discrepancy between metrics on the target model and reference model, and this can offset biases on membership signals caused by some over-represented records. The calibrated metric is defined as:

$$\Delta m(\mathbf{x}) = m_{\theta}(\mathbf{x}) - \mathbb{E}_{\phi \leftarrow \mathcal{T}(D_{refer})}[m_{\phi}(\mathbf{x})], \quad (6)$$

where $\Delta m(\mathbf{x})$ is the calibrated metric, $m_{\theta}(\mathbf{x})$ and $m_{\phi}(\mathbf{x})$ are metrics measured on target and reference models, respectively. The existing study has verified that reference-based MIA highly depends on the similarity of training and reference dataset [41]. A low-quality dataset will lead to an exponential decrease in attack performance. However, the dataset used for fine-tuning an LLM is typically highly private, making extracting a high-quality reference dataset from the same distribution a non-trivial challenge.

We notice that LLMs possess revolutionary fitting and generalization capabilities, enabling them to generate a wealth of creative texts. Therefore, LLMs themselves have the potential to depict the distribution of the training data. Thus, we consider a self-prompt approach that collects the reference dataset from the target LLM itself by prompting it with few words. Concretely, we first collect a set of text chunks with an equal length of l from a public dataset from the same domain, where the domain can be easily inferred from the task of the target LLM (e.g., An LLM that serves to summary task has high probability using a summary fine-tuning dataset). Then, we utilize each text chunk of length l as the prompt text and request the target LLM to generate text. All the generated text can form a dataset of size N , which is used to fine-tune the proposed self-prompt reference model $\hat{\theta}$ over the pre-trained model. Accordingly, we can define the practical difficulty calibration as:

$$\Delta m(\mathbf{x}) = m_{\theta}(\mathbf{x}) - \mathbb{E}_{\hat{\theta} \leftarrow \mathcal{T}(D_{self})}[m_{\hat{\theta}}(\mathbf{x})] \approx m_{\theta}(\mathbf{x}) - m_{\hat{\theta}}(\mathbf{x}), \quad (7)$$

where $D_{self} \sim p_{\theta}(\mathbf{x})$, $m_{\theta}(\mathbf{x})$ and $m_{\hat{\theta}}(\mathbf{x})$ are membership metrics measured over the target model and the self-prompt reference model. Only one reference model is used for computational efficiency, which can achieve sufficiently high attack performance. It is worth noting that in some challenging scenarios where acquiring domain-specific datasets is difficult, our self-prompt method can still effectively capture the underlying data distribution, even when using completely unrelated prompt texts. The relevant experiments will be conducted and discussed in detail in Section 5.4.

4.3 Probabilistic Variation Assessment (PVA) via Symmetrical Paraphrasing

Before diving into technical details, we first provide a brief overview of the motivation behind our proposed probabilistic variation assessment by demonstrate that memorization is a more reliable membership signal. Although memorization is associated with overfitting, overfitting by itself cannot completely explain some properties of memorization [47, 64, 75]. The key differences between memorization and overfitting can be summarized as the following three points:

- **Occurrence Time:** Existing research defines the first epoch when the LLM’s perplexity (PPL) on the validation set starts to rise as the occurrence of overfitting [64]. In contrast, memorization begins early [47, 64] and persists throughout almost the entire training phase [47, 75].
- **Harm Level:** Overfitting is almost universally acknowledged as a detrimental phenomenon in machine learning. However, memorization is not exclusively harmful, and can be crucial for certain types of generalization (e.g., on QA tasks) [4, 63].
- **Avoidance Difficulty:** Since memorization occurs much earlier, even if we use early stopping to prevent overfitting, we will still achieve significant memorization [47]. Memorization has been verified as an inevitable phenomenon for achieving optimal generalization on machine learning models [17]. Moreover, since memorization is crucial for certain LLM tasks [4, 63], and separately mitigates specific unintended memorization (e.g., verbatim memorization [27]) is a non-trivial task.

Therefore, the aforementioned discussions highlights memorization will naturally be a more reliable signal for detecting member text. Memorization in generative models will cause member records to

have a higher probability of being generated than neighbour records in the data distribution [67]. This principle can be shared with LLMs, as they can be considered generation models for texts. Thus, we suggest designing a more promising membership signal that can measure a value for each text record to identify whether this text is located on the local maximum in the sample distribution characterized by θ . The second partial derivative test is an approach in multivariable calculus commonly employed to ascertain whether a critical point of a function is a local minimum, maximum, or saddle point [62]. For our objective of identifying maximum points, we need to confirm if the Hessian matrix is negative definite, meaning that all the directional second derivatives are negative. However, considering that member records may not strictly fall on maximum points, we suggest relaxing the decision rule and using specific statistical metrics of the distribution of the second-order directional derivative over the direction z to characterize the probability variation. Thus, we define the probabilistic variation mentioned in Eq. 5 as the expectation of the directional derivative:

$$\tilde{p}_\theta(\mathbf{x}) := \mathbb{E}_z(\mathbf{z}^\top H_p(\mathbf{x}) \mathbf{z}), \quad (8)$$

where $H_p(\cdot)$ is the hessian matrix of the probability function $p_\theta(\cdot)$, then $\mathbf{z}^\top H_p(\mathbf{x}) \mathbf{z}$ indicates the second-order directional derivative of $p_\theta(\cdot)$ with respect to the text record x in the direction z . However, calculating the second-order derivative is computationally expensive and may not be feasible in LLMs. Thus, we propose a practical approximation method to evaluate the probabilistic variation. Specifically, we further approximate the derivative with the symmetrical form [26]:

$$\mathbf{z}^\top H_p(\mathbf{x}) \mathbf{z} \approx \frac{p_\theta(\mathbf{x} + h\mathbf{z}) + p_\theta(\mathbf{x} - h\mathbf{z}) - 2p_\theta(\mathbf{x})}{h^2}, \quad (9)$$

where requires $h \rightarrow 0$, and z can be considered as a sampled perturbation direction. Thus, $\mathbf{x} \pm h\mathbf{z}$ can be considered as a pair of symmetrical adjacent text records of \mathbf{x} in the data distribution. Then we can reformulate Eq. 8 as follows by omitting coefficient h :

$$\tilde{p}_\theta(\mathbf{x}) \approx \frac{1}{2N} \sum_n^N \left(p_\theta(\tilde{\mathbf{x}}_n^+) + p_\theta(\tilde{\mathbf{x}}_n^-) \right) - p_\theta(\mathbf{x}). \quad (10)$$

where $\tilde{\mathbf{x}}_n^\pm = \mathbf{x} \pm z_n$ is a symmetrical text pair sampled by a paraphrasing model, which slightly paraphrases the original text \mathbf{x} in the high-dimension space. Note that the paraphrasing in the sentence-level should be modest as Eq. 9 requires $h \rightarrow 0$, but large enough to ensure enough precision to distinguish the probabilistic variation in Eq. 8. Based on the aforementioned discussions, we designed two different paraphrasing models in the embedding domain and the semantic domain, respectively, to generate symmetrical paraphrased text embeddings or texts. For the embedding domain, we first embed the target text, then randomly sample noise following Gaussian distribution, and obtain a pair of symmetrical paraphrased texts by adding/subtracting noise. For the semantic domain, we randomly mask out 20% tokens in each target text, then employ T5-base to predict the masked tokens. Then, we compute the difference in the embeddings between the original tokens and predicted tokens to search for tokens that are symmetrical to predicted tokens with respect to the original tokens. We provide the detailed pseudo codes of both two paraphrasing models in Appendix A.3. In subsequent experiments, we default to paraphrasing in the semantic domain. Furthermore, we reformulate the neighbour attack and provide another explanation of its success based on the probabilistic variation metric with a more rigorous principle (refer to Appendix A.4). Additionally, supplementary experiments demonstrate that our proposed paraphrasing model in the embedding domain achieves considerable performance gains without relying on another MLM.

5 Experiments

5.1 Experimental Setup

Our experiments are conducted on four open-source LLMs: **GPT-2** [54], **GPT-J** [69], **Falcon-7B** [3] and **LLaMA-7B** [65], which are both fine-tuned over three dataset across multiple domains and LLM use cases: **Wikitext-103** [43], **AG News** [78] and **XSum** [49]. Each target LLM is fine-tuned with the batch size of 16, and trained for 10 epochs. Each self-prompt reference model is trained for 4 epochs. We adopt LoRA [24] as the default Parameter-Efficient Fine-Tuning (PEFT) technique. The learning rate is set to 0.0001. We adopt the AdamW optimizer [40] and early stopping [71] to avoid overfitting and achieve generalization in LLMs, the PPL of each LLM-dataset pair is provided in Appendix A.5.4. We compare SPV-MIA with seven state-of-the-art MIAs

Method	Wiki					AG News					Xsum				
	GPT-2	GPT-J	Falcon	LLaMA	Avg.	GPT-2	GPT-J	Falcon	LLaMA	Avg.	GPT-2	GPT-J	Falcon	LLaMA	Avg.
Loss Attack	0.614	0.577	0.593	0.605	0.597	0.591	0.529	0.554	0.580	0.564	0.628	0.564	0.577	0.594	0.591
Neighbour Attack	0.647	0.612	0.621	0.627	0.627	0.622	0.587	0.594	0.610	0.603	0.612	0.547	0.571	0.582	0.578
DetectGPT	0.623	0.587	0.603	0.619	0.608	0.611	0.579	0.582	0.603	0.594	0.603	0.541	0.563	0.577	0.571
Min-K%	0.658	0.623	0.629	0.643	0.638	0.629	0.604	0.607	0.619	0.615	0.621	0.562	0.588	0.594	0.591
Min-K%++	0.623	0.613	0.645	0.648	0.635	0.635	0.609	0.623	0.631	0.625	0.627	0.556	0.589	0.604	0.594
LiRA-Base	0.710	0.681	0.694	0.709	0.699	0.658	0.634	0.641	0.657	0.648	0.776	0.718	0.734	0.759	0.747
LiRA-Candidate	0.769	0.726	0.735	0.748	0.744	0.717	0.690	0.708	0.714	0.707	0.823	0.772	0.785	0.809	0.797
SPV-MIA	0.975	0.929	0.932	0.951	0.938	0.949	0.885	0.898	0.903	0.909	0.944	0.897	0.918	0.937	0.924

Table 1: **AUC Score** for detecting member texts from four LLMs across three datasets for SPV-MIA and five previously proposed methods. **Bold** and Underline respectively represent the best and the second-best results within each column (model-dataset pair).

Method	Wiki					AG News					Xsum				
	GPT-2	GPT-J	Falcon	LLaMA	Avg.	GPT-2	GPT-J	Falcon	LLaMA	Avg.	GPT-2	GPT-J	Falcon	LLaMA	Avg.
Loss Attack	1.3%	1.2%	1.1%	1.4%	1.2%	1.3%	1.0%	1.3%	1.2%	1.2%	1.5%	1.0%	1.0%	1.1%	1.2%
Neighbour Attack	4.1%	3.6%	2.8%	3.4%	3.5%	3.6%	2.7%	2.8%	3.1%	3.1%	3.2%	2.4%	2.5%	2.7%	2.7%
DetectGPT	3.7%	3.1%	2.6%	3.2%	3.2%	3.3%	2.4%	2.6%	2.7%	2.8%	3.0%	2.1%	2.4%	2.6%	2.5%
Min-K%	4.4%	4.3%	3.4%	3.7%	4.0%	3.7%	3.4%	3.8%	3.6%	3.6%	3.4%	2.5%	2.7%	3.1%	2.9%
Min-K%++	3.7%	4.2%	3.8%	3.9%	3.9%	4.0%	3.3%	3.9%	4.1%	3.8%	3.1%	2.8%	3.2%	3.4%	3.1%
LiRA-Base	12.5%	11.3%	10.7%	11.2%	11.4%	9.2%	8.0%	8.3%	8.7%	8.6%	13.5%	9.3%	10.7%	12.2%	11.4%
LiRA-Candidate	16.3%	14.3%	14.8%	15.0%	15.1%	12.2%	9.4%	10.6%	11.5%	10.9%	19.4%	10.9%	14.5%	18.5%	15.8%
SPV-MIA	67.3%	55.4%	57.6%	64.2%	61.1%	42.9%	34.8%	37.6%	39.5%	38.7%	42.1%	38.6%	40.7%	42.0%	40.9%

Table 2: **TPR@1%FPR** for detecting member texts from four LLMs across three datasets for SPV-MIA and five previously proposed methods.

designed for LMs, including five reference-free MIAs: **Loss Attack** [73], **Neighbour Attack** [41], **DetectGPT** [48], **Min-K%** [59], **Min-K%++** [76] and two reference-based MIAs: **LiRA-Base** [47], **LiRA-Candidate** [47]. We defer the detailed setup information to Appendix A.6.

5.2 Overall Performance

As presented in Table 1, we initially summarize the AUC scores [5] for all baselines and SPV-MIA against four LLMs across three datasets. Then, as illustrated in Tabel 2, we follow the suggestion of Carlini et al. [7] to evaluate the MIA performance by computing True-Positive Rate (TPR) at low False-Positive Rate (FPR). Furthermore, we present linear scale and logarithmic scale receiver operating characteristic (ROC) curves for SPV-MIA and the top three representative baselines on LLaMAs in Appendix A.5.3 for a more comprehensive presentation. The results demonstrate that SPV-MIA achieves the best overall attack performance with the highest average AUC of 0.924 over all scenarios. In comparison to the AUC score, SPV-MIA demonstrates a more substantial performance margin TPR at low FPR, achieving an average TPR@1% FPR of 46.9%. Furthermore, compared to the most competitive baseline, LiRA-Canididate, SPV-MIA has improved the AUC of the attack by 30%, even LiRA-Canididate assumes full access to the auxiliary dataset while SPV-MIA only needs some short text chunks from this dataset. This phenomenon indicates that our proposed self-prompt approach enables the reference model to gain a deeper understanding of the data distribution, thereby serving as a more reliable calibrator. We also conduct ablation studies to evaluate the contribution of both PDC and PVA in SPV-MIA, and the results are presented in Appendix A.5.1. Most baseline, especially reference-free attack methods, yield a low AUC, which is only slightly better than random guesses. Furthermore, their performances on larger-scale LLMs are worse. This phenomenon verifies the claim that existing MIAs designed for LMs can not handle LLMs with large-scale parameters. It is also worth noting that the privacy risks caused by MIAs are proportional to the overall parameter scale and language capabilities of LLMs. We interpret this phenomenon as follows: LLMs with stronger overall NLP performance have better learning ability, which means they are more likely to memorize records from the training set. Besides, MIAs fundamentally leverage the memorization abilities of machine learning models, making superior models more vulnerable to attacks.

5.3 How MIAs Rely on Reference Dataset Quality

In this work, a key contribution is introducing a self-prompt approach for constructing a high-quality dataset to fine-tune the reference model, which guides the reference model to become a better calibrator. Therefore, we conduct experiments to investigate how prior reference-based MIAs rely on the quality of the reference dataset, and evaluate whether our proposed method can build a high-

quality reference dataset. In real-world scenarios, based on different prior information, adversaries can obtain datasets from different sources to fine-tune the reference model with uneven quality. We categorize the reference dataset into three types based on their relationship with the fine-tuning dataset of the target model and sort them in ascending order of difficulty in acquisition: 1) **Irrelevant** dataset, 2) **Domain-specific** dataset, and 3) **Identical distribution** dataset. Besides, the dataset extracted by the self-prompt approach is denoted as 4) **Self-prompt** dataset. The detailed information of these datasets is summarized in Appendix A.6. Then, we conduct MIAs with the aforementioned four data sources and summarize the results in Fig. 3. The experimental results indicate that the performance of MIA shows a noticeable decrease along the Identical, Domain, and Irrelevant datasets. This illustrates the high dependency of previous reference-based methods on the quality of the reference dataset. However, AUC scores on self-prompt reference datasets are only marginally below Identical datasets. It verifies that our proposed self-prompt method can effectively leverage the creative generation capability of LLMs, approximate sampling high-quality text records indirectly from the distribution of the target training set.

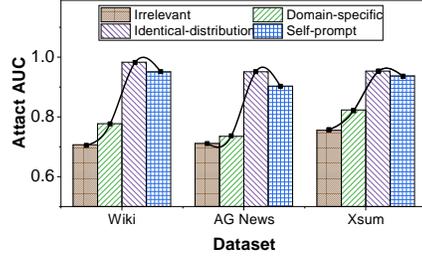


Figure 3: The performances of reference-based MIA on LLaMA while utilizing different reference datasets.

5.4 The Robustness of SPV-MIA in Practical Scenarios

We have verified that SPV-MIA can provide a high-quality reference model. However, the source and scale of self-prompt texts may face various limitations in practical scenarios. Therefore, we conducted experiments to verify the robustness of SPV-MIA performance in diverse practical scenarios. **Source of Self-prompt Texts.** The sources of self-prompt texts available to attackers are usually limited by the actual deployment environment, and sometimes even domain-specific texts may not be accessible. Compared with using domain-specific text chunks for prompting, we also evaluate the self-prompt approach with irrelevant and identical-distribution text chunks. As shown in Fig. 4, the self-prompt method demonstrates an incredibly lower dependence on the source of the prompt texts. We found that even when using completely unrelated prompt texts, the performance of the attack only experiences a slight decrease (3.6% at most). This phenomenon indicates that the self-prompt method we proposed has a high degree of versatility across adversaries with different prior information.

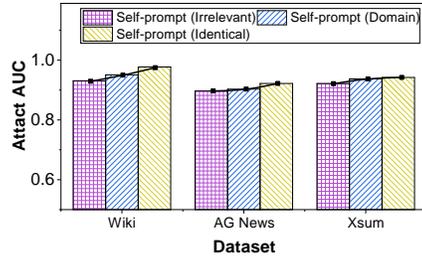


Figure 4: The performances of SPV-MIA on LLaMA while utilizing different prompt text sources.

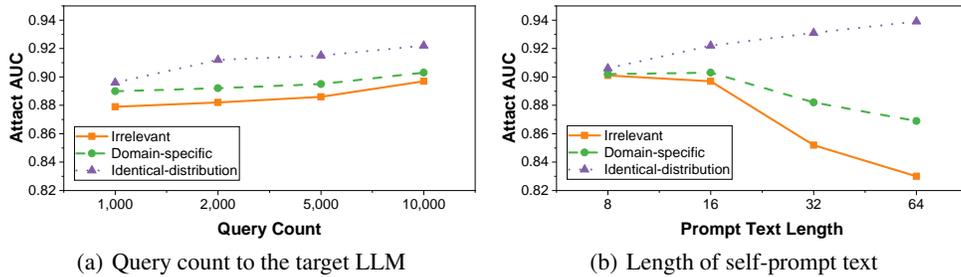


Figure 5: The performances of SPV-MIA on LLaMA while utilizing different query count to the target model and different prompt text lengths.

Scale of Self-prompt Texts. In real-world scenarios, the scale of self-prompt texts is usually limited by the access frequency cap of the LLM API and the number of available self-prompt texts. Thus, we set up two sets of experiments to verify the sensitivity of SPV-MIA to the aforementioned limitations. As shown in Fig. 5(a), our self-prompt reference model is minimally affected by the access frequency limitations of the target LLM. Even with only 1,000 queries, it achieves performance comparable to

10,000 queries. As shown in Fig. 5(b), even when the self-prompt texts are severely limited (with only 8 prompt tokens), the attack performance remains at a startlingly high level of 0.9. Besides, texts from different sources show varying attack performance trends based on text length. From the identical dataset, attack performance increases with text length. From the domain-specific dataset, it initially increases then decreases. From an irrelevant dataset, it decreases with longer texts. Therefore, we recommend setting smaller text lengths to allow LLMs to generate samples that are close to data distributions of training sets, unless adversaries can directly sample texts from the same data distribution as the training set. Overall, our proposed method can maintain stable attack performance in practical scenarios where the scale of self-prompt texts is limited.

5.5 Defending against SPV-MIAs

As privacy risks emerge from various attacks, including data extraction attack [6], model extraction attack [22], and membership inference attack [41, 60, 72], the research community actively promotes defending methods against these attacks [29, 45]. DP-SGD [1] is one of the most widely adopted defense methods based on differential privacy [15] to provide mathematical privacy guarantees. Through DP-SGD, the amount of information the parameters have about a single data record is bound. Thus, the privacy leakage will not exceed the upper bound, regardless of how many outputs we obtain from the target model. We follow the same manner as the existing study [36] and train LLaMA with DP-Adam on the three datasets. The results are summarized in Table 3, where we choose a set of appropriate ϵ as existing works suggest that higher DP guarantees lead to a noticeable performance degradation [21, 41]. The performances of LLMs are supplemented in Appendix A.5.4, and the results of other baselines can be found in Appendix A.5.5. The results indicate that DP-SGD can mitigate privacy risks to a certain extent. However, under moderate privacy budgets, SPV-MIA still presents a notable risk of privacy leakage and outperforms the baselines.

Privacy Budget ϵ	15	30	60	+ inf
Wiki	0.785	0.832	0.875	0.951
AG News	0.766	0.814	0.852	0.903
Xsum	0.771	0.827	0.867	0.937
Avg.	0.774	0.824	0.865	0.930

Table 3: The AUC performance of SPV-MIA against LLaMA fine-tuned with DP-SGD w.r.t different privacy budget ϵ .

5.5.1 Impact of Fine-tuning Methods

We further evaluated the generalizability of SPV-MIA under different PEFT techniques. As shown in Table 4, SPV-MIA can maintain a high-level AUC across all PEFT techniques. Besides, the performance of MIA is positively correlated with the number of trainable parameters during the fine-tuning process. We hypothesize that this is because as the number of trainable parameters increases, LLMs retain more complete memory of the member records, making them more vulnerable to attacks.

PEFT	LoRA	Prefix Tuning	P-Tuning	(IA) ³
# Parameters (M)	33.55	5.24	1.15	0.61
Wiki	0.951	0.943	0.922	0.914
Ag News	0.903	0.897	0.879	0.873
Xsum	0.937	0.931	0.924	0.911

Table 4: The AUC Performance of SPV-MIA across LLaMAs fine-tuned with different PEFT techniques over three datasets. We choose LoRA [24], Prefix Tuning [35], P-Tuning [38] and (IA)³ [37] as four representative PEFT techniques.

6 Conclusion

In this paper, we reveal the under-performances of existing MIA methods against LLMs for practical applications and interpret this phenomenon from two perspectives. First, reference-based attacks seem to pose impressive privacy leakages by comparing the sampling probabilities of the target record between target and reference LLMs, but the inaccessibility of the appropriate reference dataset will be a big obstacle to deploying it in practice. Second, existing MIAs heavily rely on overfitting, which is usually avoided before releasing LLM for public access. To address these limitations, we propose a Membership Inference Attack based on Self-calibrated Probabilistic Variation (SPV-MIA), where we propose a self-prompt approach to extract reference dataset from LLM itself in a practical manner, then introduce a more reliable membership signal based on memorization rather than overfitting. We conduct substantial experiments to validate the superiority of SPV-MIA over all baselines and verify its effectiveness in extreme conditions. One primary limitation of this study is that SPV-MIA is only designed for CLM, we leave the adaption on other LLMs as the future work.

Acknowledgments

This research was supported in part by the National Natural Science Foundation of China under Grants U21B2036, U23B2030, 62272262 and the Postdoctoral Fellowship Program of CPSF under Grant Number GZC20240548. We are also grateful for the support from the 6G Research Center, HUST, and the School of Cyber Science and Engineering, HUST, in the form of an International Travel Grant, which enabled Wenjie Fu to attend the conference in person.

We would like to express our sincere gratitude to the anonymous reviewers for their insightful comments and suggestions. We also extend our thanks to Jamie Hayes at Google DeepMind and Qilong Zhang at ByteDance for their valuable feedback on the preprint manuscript.

References

- [1] Martin Abadi, Andy Chu, Ian Goodfellow, H. Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep Learning with Differential Privacy. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, CCS '16*, pages 308–318, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 978-1-4503-4139-4.
- [2] Zhipu AI. Zhipu API Documentation. <https://bigmodel.cn/dev/api/normal-model/glm-4>, 2024.
- [3] Ebtesam Almazrouei, Hamza Alobeidli, Abdulaziz Alshamsi, Alessandro Cappelli, Ruxandra Cojocaru, Merouane Debbah, Etienne Goffinet, Daniel Heslow, Julien Launay, Quentin Malartic, et al. Falcon-40b: an open large language model with state-of-the-art performance. Technical report, Technical report, Technology Innovation Institute, 2023.
- [4] Sebastian Borgeaud, Arthur Mensch, Jordan Hoffmann, Trevor Cai, Eliza Rutherford, Katie Millican, George Bm Van Den Driessche, Jean-Baptiste Lespiau, Bogdan Damoc, Aidan Clark, et al. Improving language models by retrieving from trillions of tokens. In *International conference on machine learning*, pages 2206–2240. PMLR, 2022.
- [5] Andrew P Bradley. The use of the area under the roc curve in the evaluation of machine learning algorithms. *Pattern recognition*, 30(7):1145–1159, 1997.
- [6] Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Ulfar Erlingsson, et al. Extracting training data from large language models. In *30th USENIX Security Symposium (USENIX Security 21)*, pages 2633–2650, 2021.
- [7] Nicholas Carlini, Steve Chien, Milad Nasr, Shuang Song, Andreas Terzis, and Florian Tramèr. Membership Inference Attacks From First Principles. In *2022 IEEE Symposium on Security and Privacy (SP)*, pages 1897–1914, 2022.
- [8] Nicholas Carlini, Daphne Ippolito, Matthew Jagielski, Katherine Lee, Florian Tramer, and Chiyuan Zhang. Quantifying Memorization Across Neural Language Models. In *The Eleventh International Conference on Learning Representations*, 2022.
- [9] Nicholas Carlini, Daniel Paleka, Krishnamurthy Dj Dvijotham, Thomas Steinke, Jonathan Hayase, A. Feder Cooper, Katherine Lee, Matthew Jagielski, Milad Nasr, Arthur Conmy, Eric Wallace, David Rolnick, and Florian Tramèr. Stealing part of a production language model. In *Proceedings of the 41st International Conference on Machine Learning*, pages 5680–5705. PMLR, 2024.
- [10] Christopher A. Choquette-Choo, Florian Tramèr, Nicholas Carlini, and Nicolas Papernot. Label-only membership inference attacks. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event*, volume 139 of *Proceedings of Machine Learning Research*, pages 1964–1974. PMLR, 2021. URL <http://proceedings.mlr.press/v139/choquette-choo21a.html>.
- [11] Debeshee Das, Jie Zhang, and Florian Tramèr. Blind baselines beat membership inference attacks for foundation models, 2024.

- [12] Ning Ding, Yujia Qin, Guang Yang, Fuchao Wei, Zonghan Yang, Yusheng Su, Shengding Hu, Yulin Chen, Chi-Min Chan, Weize Chen, Jing Yi, Weilin Zhao, Xiaozhi Wang, Zhiyuan Liu, Hai-Tao Zheng, Jianfei Chen, Yang Liu, Jie Tang, Juanzi Li, and Maosong Sun. Parameter-efficient fine-tuning of large-scale pre-trained language models. *Nature Machine Intelligence*, 5(3):220–235, 2023. ISSN 2522-5839.
- [13] Jinhao Duan, Fei Kong, Shiqi Wang, Xiaoshuang Shi, and Kaidi Xu. Are Diffusion Models Vulnerable to Membership Inference Attacks? In *Proceedings of the 38th International Conference on Machine Learning, {ICML} 2023*. PMLR, 2023.
- [14] Michael Duan, Anshuman Suri, Niloofar Mireshghallah, Sewon Min, Weijia Shi, Luke Zettlemoyer, Yulia Tsvetkov, Yejin Choi, David Evans, and Hannaneh Hajishirzi. Do Membership Inference Attacks Work on Large Language Models?, 2024. URL <https://arxiv.org/abs/2402.07841>.
- [15] Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. Calibrating noise to sensitivity in private data analysis. In *Theory of Cryptography: Third Theory of Cryptography Conference, TCC 2006, New York, NY, USA, March 4-7, 2006. Proceedings 3*, pages 265–284. Springer, 2006.
- [16] Vitaly Feldman. Does learning require memorization? a short tale about a long tail. In Konstantin Makarychev, Yury Makarychev, Madhur Tulsiani, Gautam Kamath, and Julia Chuzhoy, editors, *Proceedings of the 52nd Annual ACM SIGACT Symposium on Theory of Computing, STOC 2020, Chicago, IL, USA, June 22-26, 2020*, pages 954–959. ACM, 2020. doi: 10.1145/3357713.3384290. URL <https://doi.org/10.1145/3357713.3384290>.
- [17] Vitaly Feldman and Chiyuan Zhang. What neural networks memorize and why: Discovering the long tail via influence estimation. In Hugo Larochelle, Marc’Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*, 2020. URL <https://proceedings.neurips.cc/paper/2020/hash/1e14bfe2714193e7af5abc64ecbd6b46-Abstract.html>.
- [18] Wenjie Fu, Huandong Wang, Chen Gao, Guanghua Liu, Yong Li, and Tao Jiang. A probabilistic fluctuation based membership inference attack for diffusion models. *arXiv e-prints*, pages arXiv-2308, 2023.
- [19] Wenjie Fu, Huandong Wang, Chen Gao, Guanghua Liu, Yong Li, and Tao Jiang. MIA-tuner: Adapting large language models as pre-training text detector. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Philadelphia, Pennsylvania, USA, 2025.
- [20] Stephen Gilbert, Hugh Harvey, Tom Melvin, Erik Vollebregt, and Paul Wicks. Large language model ai chatbots require approval as medical devices. *Nature Medicine*, pages 1–3, 2023.
- [21] Jamie Hayes, Luca Melis, George Danezis, and Emiliano De Cristofaro. Logan: Membership inference attacks against generative models. *Proceedings on Privacy Enhancing Technologies*, (1):133–152, 2019.
- [22] Xuanli He, Lingjuan Lyu, Lichao Sun, and Qiongfai Xu. Model extraction and adversarial transferability, your BERT is vulnerable! In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2006–2012, Online, 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.161. URL <https://aclanthology.org/2021.naacl-main.161>.
- [23] Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. In Corinna Cortes, Neil D. Lawrence, Daniel D. Lee, Masashi Sugiyama, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 1693–1701, 2015. URL <https://proceedings.neurips.cc/paper/2015/hash/afdec7005cc9f14302cd0474fd0f3c96-Abstract.html>.

- [24] Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022. URL <https://openreview.net/forum?id=nZeVKeeFYf9>.
- [25] Hongsheng Hu, Zoran Salcic, Lichao Sun, Gillian Dobbie, Philip S. Yu, and Xuyun Zhang. Membership Inference Attacks on Machine Learning: A Survey. *ACM Computing Surveys*, 54(11s):235:1–235:37, 2022. ISSN 0360-0300.
- [26] John H Hubbard and Barbara Burke Hubbard. *Vector calculus, linear algebra, and differential forms: a unified approach*. Matrix Editions, 2015.
- [27] Daphne Ippolito, Florian Tramer, Milad Nasr, Chiyuan Zhang, Matthew Jagielski, Katherine Lee, Christopher Choquette Choo, and Nicholas Carlini. Preventing Generation of Verbatim Memorization in Language Models Gives a False Sense of Privacy. In *Proceedings of the 16th International Natural Language Generation Conference*, pages 28–53, Prague, Czechia, 2023. Association for Computational Linguistics.
- [28] Maurice Jakesch, Advait Bhat, Daniel Buschek, Lior Zalmanson, and Mor Naaman. Co-writing with opinionated language models affects users’ views. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pages 1–15, 2023.
- [29] Jinyuan Jia, Ahmed Salem, Michael Backes, Yang Zhang, and Neil Zhenqiang Gong. Memguard: Defending against black-box membership inference attacks via adversarial examples. In *Proceedings of the 2019 ACM SIGSAC conference on computer and communications security*, pages 259–274, 2019.
- [30] Belveze Jules. Tldr news dataset, 2022. URL https://huggingface.co/datasets/JulesBelveze/tldr_news.
- [31] Nikhil Kandpal, Eric Wallace, and Colin Raffel. Deduplicating training data mitigates privacy risks in language models. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato, editors, *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume 162 of *Proceedings of Machine Learning Research*, pages 10697–10707. PMLR, 2022. URL <https://proceedings.mlr.press/v162/kandpal22a.html>.
- [32] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015. URL <http://arxiv.org/abs/1412.6980>.
- [33] Mario Michael Krell, Matej Kosec, Sergio P Perez, and Andrew Fitzgibbon. Efficient sequence packing without cross-contamination: Accelerating large language models without impacting performance. *ArXiv preprint*, abs/2107.02027, 2021. URL <https://arxiv.org/abs/2107.02027>.
- [34] Keita Kurita, Paul Michel, and Graham Neubig. Weight poisoning attacks on pretrained models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2793–2806, Online, 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.249. URL <https://aclanthology.org/2020.acl-main.249>.
- [35] Xiang Lisa Li and Percy Liang. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online, 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.353. URL <https://aclanthology.org/2021.acl-long.353>.
- [36] Xuechen Li, Florian Tramèr, Percy Liang, and Tatsunori Hashimoto. Large language models can be strong differentially private learners. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022. URL <https://openreview.net/forum?id=bVuP31tATMz>.

- [37] Haokun Liu, Derek Tam, Mohammed Muqeeth, Jay Mohta, Tenghao Huang, Mohit Bansal, and Colin A Raffel. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. *Advances in Neural Information Processing Systems*, 35:1950–1965, 2022.
- [38] Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. Gpt understands, too. *AI Open*, 2023.
- [39] Yiyong Liu, Zhengyu Zhao, Michael Backes, and Yang Zhang. Membership Inference Attacks by Exploiting Loss Trajectory. In *Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security, CCS '22*, pages 2085–2098, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-9450-5.
- [40] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019. URL <https://openreview.net/forum?id=Bkg6RiCqY7>.
- [41] Justus Mattern, Fatemehsadat Mireshghallah, Zhijing Jin, Bernhard Schölkopf, Mrinmaya Sachan, and Taylor Berg-Kirkpatrick. Membership Inference Attacks against Language Models via Neighbourhood Comparison, 2023. URL <https://arxiv.org/abs/2305.18462>.
- [42] Matthieu Meeus, Shubham Jain, Marek Rei, and Yves-Alexandre de Montjoye. Inherent challenges of post-hoc membership inference for large language models, 2024.
- [43] Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net, 2017. URL <https://openreview.net/forum?id=Byj72udxe>.
- [44] Bonan Min, Hayley Ross, Elinor Sulem, Amir Pouran Ben Veyseh, Thien Huu Nguyen, Oscar Sainz, Eneko Agirre, Ilana Heintz, and Dan Roth. Recent Advances in Natural Language Processing via Large Pre-trained Language Models: A Survey. *ACM Computing Surveys*, 56(2): 30:1–30:40, 2023. ISSN 0360-0300.
- [45] Fatemehsadat Mireshghallah, Huseyin Inan, Marcello Hasegawa, Victor Rühle, Taylor Berg-Kirkpatrick, and Robert Sim. Privacy regularization: Joint privacy-utility optimization in LanguageModels. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3799–3807, Online, 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.298. URL <https://aclanthology.org/2021.naacl-main.298>.
- [46] Fatemehsadat Mireshghallah, Kartik Goyal, Archit Uniyal, Taylor Berg-Kirkpatrick, and Reza Shokri. Quantifying privacy risks of masked language models using membership inference attacks. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 8332–8347, Abu Dhabi, United Arab Emirates, 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.emnlp-main.570>.
- [47] Fatemehsadat Mireshghallah, Archit Uniyal, Tianhao Wang, David Evans, and Taylor Berg-Kirkpatrick. An empirical analysis of memorization in fine-tuned autoregressive language models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 1816–1826, Abu Dhabi, United Arab Emirates, 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.emnlp-main.119>.
- [48] Eric Mitchell, Yoonho Lee, Alexander Khazatsky, Christopher D. Manning, and Chelsea Finn. DetectGPT: Zero-Shot Machine-Generated Text Detection using Probability Curvature. In *Proceedings of the 38th International Conference on Machine Learning, {ICML} 2023*, 2023.
- [49] Shashi Narayan, Shay B. Cohen, and Mirella Lapata. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1797–1807, Brussels, Belgium, 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1206. URL <https://aclanthology.org/D18-1206>.

- [50] Milad Nasr, Reza Shokri, and Amir Houmansadr. Comprehensive Privacy Analysis of Deep Learning: Passive and Active White-box Inference Attacks against Centralized and Federated Learning. In *2019 IEEE Symposium on Security and Privacy (SP)*, pages 739–753, 2019.
- [51] OpenAI. ChatGPT: Optimizing Language Models for Dialogue. <http://web.archive.org/web/20230109000707/https://openai.com/blog/chatgpt/>, 2023.
- [52] OpenAI. OpenAI API Platform. <https://platform.openai.com/docs/api-reference/introduction>, 2024.
- [53] Charith Peris, Christophe Dupuy, Jimit Majmudar, Rahil Parikh, Sami Smaili, Richard Zemel, and Rahul Gupta. Privacy in the Time of Language Models. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining, WSDM '23*, pages 1291–1292, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 978-1-4503-9407-9.
- [54] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.
- [55] Samuel Reese, Gemma Boleda, Montse Cuadros, Lluís Padró, and German Rigau. Wikicorpus: A word-sense disambiguated multilingual Wikipedia corpus. In *Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10)*, Valletta, Malta, 2010. European Language Resources Association (ELRA). URL http://www.lrec-conf.org/proceedings/lrec2010/pdf/222_Paper.pdf.
- [56] Ahmed Salem, Yang Zhang, Mathias Humbert, Pascal Berrang, Mario Fritz, and Michael Backes. ML-Leaks: Model and Data Independent Membership Inference Attacks and Defenses on Machine Learning Models. In *Network and Distributed Systems Security (NDSS) Symposium 2019*, 2019.
- [57] Haonan Shi, Tu Ouyang, and An Wang. Learning-based difficulty calibration for enhanced membership inference attacks. In *2024 IEEE 9th European Symposium on Security and Privacy (EuroS&P)*, pages 62–77. IEEE Computer Society, 2024. ISBN 9798350354256.
- [58] Weijia Shi, Anirudh Ajith, Mengzhou Xia, Yangsibo Huang, Daogao Liu, Terra Blevins, Danqi Chen, and Luke Zettlemoyer. Detecting pretraining data from large language models. In *The Twelfth International Conference on Learning Representations*, 2023.
- [59] Weijia Shi, Anirudh Ajith, Mengzhou Xia, Yangsibo Huang, Daogao Liu, Terra Blevins, Danqi Chen, and Luke Zettlemoyer. Detecting Pretraining Data from Large Language Models. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024.
- [60] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership Inference Attacks Against Machine Learning Models. In *2017 IEEE Symposium on Security and Privacy (SP)*, pages 3–18, 2017.
- [61] Robin Staab, Mark Vero, Mislav Balunovic, and Martin Vechev. Beyond memorization: Violating privacy via inference with large language models. In *The Twelfth International Conference on Learning Representations*, 2023.
- [62] James Stewart. *Multivariable calculus: concepts and contexts*. Brooks/Cole, 2001.
- [63] Yi Tay, Vinh Tran, Mostafa Dehghani, Jianmo Ni, Dara Bahri, Harsh Mehta, Zhen Qin, Kai Hui, Zhe Zhao, Jai Gupta, et al. Transformer memory as a differentiable search index. *Advances in Neural Information Processing Systems*, 35:21831–21843, 2022.
- [64] Kushal Tirumala, Aram Markosyan, Luke Zettlemoyer, and Armen Aghajanyan. Memorization Without Overfitting: Analyzing the Training Dynamics of Large Language Models. *Advances in Neural Information Processing Systems*, 35:38274–38290, 2022.
- [65] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *ArXiv preprint*, abs/2302.13971, 2023. URL <https://arxiv.org/abs/2302.13971>.

- [66] Priyan Vaithilingam, Tianyi Zhang, and Elena L Glassman. Expectation vs. experience: Evaluating the usability of code generation tools powered by large language models. In *Chi conference on human factors in computing systems extended abstracts*, pages 1–7, 2022.
- [67] Gerrit J. J. van den Burg and Chris Williams. On memorization in probabilistic deep generative models. In Marc’Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan, editors, *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual*, pages 27916–27928, 2021. URL <https://proceedings.neurips.cc/paper/2021/hash/eae15aabaa768ae4a5993a8a4f4fa6e4-Abstract.html>.
- [68] Eric Wallace, Tony Zhao, Shi Feng, and Sameer Singh. Concealed data poisoning attacks on NLP models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 139–150, Online, 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.13. URL <https://aclanthology.org/2021.naacl-main.13>.
- [69] Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. <https://github.com/kingoflolz/mesh-transformer-jax>, 2021.
- [70] Lauren Watson, Chuan Guo, Graham Cormode, and Alexandre Sablayrolles. On the importance of difficulty calibration in membership inference attacks. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022. URL <https://openreview.net/forum?id=3eIrl1i0TwQ>.
- [71] Yuan Yao, Lorenzo Rosasco, and Andrea Caponnetto. On early stopping in gradient descent learning. *Constructive Approximation*, 26(2):289–315, 2007.
- [72] Jiayuan Ye, Aadyaa Maddi, Sasi Kumar Murakonda, Vincent Bindschaedler, and Reza Shokri. Enhanced Membership Inference Attacks against Machine Learning Models. In *Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security, CCS ’22*, pages 3093–3106, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-9450-5.
- [73] Samuel Yeom, Irene Giacomelli, Matt Fredrikson, and Somesh Jha. Privacy risk in machine learning: Analyzing the connection to overfitting. In *2018 IEEE 31st computer security foundations symposium (CSF)*, pages 268–282. IEEE, 2018.
- [74] Da Yu, Saurabh Naik, Arturs Backurs, Sivakanth Gopi, Huseyin A. Inan, Gautam Kamath, Janardhan Kulkarni, Yin Tat Lee, Andre Manoel, Lukas Wutschitz, Sergey Yekhanin, and Huishuai Zhang. Differentially private fine-tuning of language models. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022. URL <https://openreview.net/forum?id=Q42f0dfjEC0>.
- [75] Chiyuan Zhang, Daphne Ippolito, Katherine Lee, Matthew Jagielski, Florian Tramèr, and Nicholas Carlini. Counterfactual Memorization in Neural Language Models. In *Advances in Neural Information Processing Systems*, 2023.
- [76] Jingyang Zhang, Jingwei Sun, Eric Yeats, Yang Ouyang, Martin Kuo, Jianyi Zhang, Hao Frank Yang, and Hai Li. Min-K%++: Improved baseline for detecting pre-training data from large language models, 2024. URL <https://arxiv.org/abs/2404.02936>.
- [77] Minxing Zhang, Zhaochun Ren, Zihan Wang, Pengjie Ren, Zhunmin Chen, Pengfei Hu, and Yang Zhang. Membership Inference Attacks Against Recommender Systems. In *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security, CCS ’21*, pages 864–879, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 978-1-4503-8454-4.
- [78] Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. Character-level convolutional networks for text classification. In Corinna Cortes, Neil D. Lawrence, Daniel D. Lee, Masashi Sugiyama, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 649–657, 2015. URL <https://proceedings.neurips.cc/paper/2015/hash/250cf8b51c773f3f8dc8b4be867a9a02-Abstract.html>.

- [79] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, and Ji-Rong Wen. A Survey of Large Language Models, 2023. URL <https://arxiv.org/abs/2303.18223>.

A Appendix

A.1 Ethic and Broader Impact Statements

For ethic consideration, this study proposes a membership inference attack algorithm, SPV-MIA, which can be maliciously utilized to infer whether a specific textual entry is fed to the target LLM during the training process. The extensive experiments reveal appreciable privacy leakage of LLMs through SPV-MIA, where the member records are identified with high confidence. We acknowledge that SPV-MIA can bring severe privacy risks to existing LLMs. Therefore, to prevent potential misuse of this research, all experimental findings are based on widely used public datasets. This ensures that every individual textual record we analyze has already been made public, and eliminates any further privacy violations.

For broader impact, we have made our code accessible to the public to allow additional research in the pursuit of identifying appropriate defense solutions. Thus, we posit that our article can inspire forthcoming research to not only focus on the linguistic ability of LLMs, but also take into account the dimensions of public data privacy and security. Besides, our research is more closely aligned with real-world LLM application scenarios, thereby revealing privacy risks in more realistic settings. Our proposed method is scalable, with many aspects left for further exploration and research, such as adapting it for other LLMs.

A.2 Notations of This Work

Table 5: Notations and descriptions.

Notation	Description
\mathbf{x}	A specific data record.
$\tilde{\mathbf{x}}_n^\pm$	A pair of symmetrical paraphrasing text record of the target text record \mathbf{x} .
D_{mem}	The training dataset utilized for LLM fine-tuning.
D_{non}	A disjoint dataset from the training dataset.
D_{refer}	The reference dataset that collected for fine-tuning reference LLM.
$m^{(j)}$	The membership of the data record $\mathbf{x}^{(j)}$, 1 represents member, whereas 0 represents non-member.
θ	The parameters of the target large language model (LLM).
ϕ	The parameters of the reference LLM.
$\hat{\theta}$	The parameters of the self-prompt reference LLM.
$\mathcal{A}(\mathbf{x}, \theta)$	The adversary algorithm for MIA.
$p_\theta(\mathbf{x})$	The probability of text record \mathbf{x} being sampled by the LLM θ .
$p_\theta(\tilde{\mathbf{x}}_n)$	The probability of paraphrasing text $\tilde{\mathbf{x}}_n$ being sampled by the LLM θ .
$\Delta p_\theta(\mathbf{x})$	The calibrated probability of text record \mathbf{x} .
$\tilde{p}_\theta(\mathbf{x})$	The probabilistic variation of \mathbf{x} measured on the target LLM θ .
$\tilde{p}_{\hat{\theta}}(\mathbf{x})$	The probabilistic variation of \mathbf{x} measured on the self-prompt reference LLM $\hat{\theta}$.
$\Delta \tilde{p}_{\theta, \hat{\theta}}(\mathbf{x})$	The calibrated probabilistic variation of \mathbf{x} measured on both the target LLM θ and the self-prompt reference LLM $\hat{\theta}$.
N	The query times for estimating $\tilde{p}_\theta(\mathbf{x})$.

A.3 Detailed Pseudo Codes of Symmetrical Perturbation

Algorithm 1 Symmetrical paraphrase in the embedding domain

Input: Target text set $\{\mathbf{x}^{(i)}\}$, Gaussian noise scale σ , paraphrasing number N , embedding matrix of tokens \mathbf{E} .

Output: Symmetrical paraphrased text embedding $emb(\mathbf{x}^{(i)})^\pm$.

```

1: for  $\mathbf{x}^{(i)} \in \{\mathbf{x}^{(i)}\}$  do
2:    $id(\mathbf{x}^{(i)}) \leftarrow tokenizer(\mathbf{x}^{(i)})$  ▷ Tokenize the text into token ids.
3:    $emb(\mathbf{x}^{(i)}) \leftarrow \mathbf{E}(id(\mathbf{x}^{(i)}))$  ▷ Convert token ids into embeddings.
4:   for  $n \in \{1, \dots, N\}$  do
5:      $\mathbf{z} \sim \mathcal{N}(0, \sigma^2 \mathbf{I})$  ▷ Sample noise from Gaussian distribution.
6:      $emb(\mathbf{x}^{(i)})^+ \leftarrow emb(\mathbf{x}^{(i)}) + \mathbf{z}$ 
7:      $emb(\mathbf{x}^{(i)})^- \leftarrow emb(\mathbf{x}^{(i)}) - \mathbf{z}$ 
8:     return  $emb(\mathbf{x}^{(i)})^\pm$ 
9:   end for
10: end for

```

Algorithm 2 Symmetrical paraphrase in the semantic domain

Input: Target text set $\{\mathbf{x}^{(i)}\}$, paraphrasing percentage λ , paraphrasing number N , embedding matrix of tokens \mathbf{E} .

Output: Symmetrical paraphrased text $\mathbf{x}^{(i)\pm}$.

```

1: for  $\mathbf{x}^{(i)} \in \{\mathbf{x}^{(i)}\}$  do
2:    $id(\mathbf{x}^{(i)}) \leftarrow tokenizer.encode(\mathbf{x}^{(i)})$  ▷ Tokenize the text into token ids.
3:   for  $n \in \{1, \dots, N\}$  do
4:     for  $t_j \in id(\mathbf{x}^{(i)}) = [t_0, t_1, \dots, t_{|x|}]$  do
5:       if  $Rand() < \lambda$  then
6:          $t_j \leftarrow [MASK]$  ▷ Mask tokens with the percentage  $\lambda$ .
7:       else
8:          $t_j \leftarrow t_j$ 
9:       end if
10:    end for
11:     $\{t_j^+\} \leftarrow MLM(id(\mathbf{x}^{(i)}))$  ▷ Fill the mask tokens with MLM.
12:    for  $t_j^+ \in \{t_j^+\}$  do
13:       $emb(t_j) \leftarrow \mathbf{E}(t_j)$  ▷ Extract the embedding of the original token.
14:       $emb(t_j)^+ \leftarrow \mathbf{E}(t_j^+)$  ▷ Extract the embedding of the paraphrased token.
15:       $\Delta emb(t_j) \leftarrow emb(t_j)^+ - emb(t_j)$  ▷ Measure the paraphrasing noise in the embedding domain.
16:       $emb(t_j)^- \leftarrow emb(t_j) - \Delta emb(t_j)$  ▷ Generate symmetrical embedding.
17:       $t_j^- \leftarrow \mathbf{SearchNearestToken}(emb(t_j)^-, \mathbf{E})$ 
18:    end for
19:     $id(\mathbf{x}^{(i)})^+ \leftarrow \mathbf{FillMaskToken}(\{t_j^+\})$ 
20:     $id(\mathbf{x}^{(i)})^- \leftarrow \mathbf{FillMaskToken}(\{t_j^-\})$ 
21:     $\mathbf{x}^{(i)+} \leftarrow tokenizer.decode(id(\mathbf{x}^{(i)})^+)$ 
22:     $\mathbf{x}^{(i)-} \leftarrow tokenizer.decode(id(\mathbf{x}^{(i)})^-)$ 
23:    return  $\mathbf{x}^{(i)\pm}$ 
24:  end for
25: end for

```

Table 6: The MIA performance of SPV-MIA while applied different paraphrasing methods.

Paraphrasing	Embedding	Semantic	Neighbour Comparing
Wiki	0.965	0.951	0.934
AG News	0.926	0.903	0.893
Xsum	0.949	0.937	0.928
Avg.	0.944	0.930	0.918

A.4 Rethinking of the Neighbour Attack

In this work, we introduce a symmetrical paraphrasing method for assessing probabilistic variation, which is motivated by a rigorous principle: detect the memorization phenomenon rather than overfitting. Meanwhile, we found that the Neighbour comparing [41] has a similar form to our proposed probabilistic variation. Thus, we further consider reformulating neighbour attack based on our intuition, then provide another explanation and motivation for it. As shown in Eq. 10, the assessment of probabilistic variation requires a pair of symmetrical paraphrased text, thus we elaborately design two paraphrasing models on embedding and semantic domains. However, it is still non-trivial to define two neighboring samples with opposite paraphrasing directions for \mathbf{x} , we therefore consider directly ignoring the requirement for symmetry in the probabilistic variation. Thus, we simplify $\tilde{\mathbf{x}}_n^\pm$ to be uniformly represented by $\tilde{\mathbf{x}}_n$. Then we can reformulate Eq. 10 to Neighbour comparing:

$$\tilde{p}_\theta(\mathbf{x}) \approx \frac{1}{2N} \sum_n^N \left(p_\theta(\tilde{\mathbf{x}}_n^+) + p_\theta(\tilde{\mathbf{x}}_n^-) \right) - p_\theta(\mathbf{x}) = \frac{1}{2N} \sum_n^{2N} p_\theta(\tilde{\mathbf{x}}_n) - p_\theta(\mathbf{x}). \quad (11)$$

Therefore, we believe that the neighbour attack and our proposed probabilistic variation can share the same design motivation, namely, detecting special signals that indicate the LLM has memorized training set samples. Additionally, we compared the neighbour attack with our proposed symmetric paraphrasing methods. As shown in Table 6, paraphrasing in the embedding domain achieves considerable performance gains, while paraphrasing in the semantic domain yields a marginal advantage.

A.5 Supplementary Experimental Results

A.5.1 Ablation Study

Table 7: Results of Ablation Study on GPT-J and LLaMA across three datasets.

Target Model	Wiki		AG News		XSum	
	GPT-J	LLaMA	GPT-J	LLaMA	GPT-J	LLaMA
w/o PDC	0.648	0.653	0.632	0.641	0.653	0.661
w/o PVA	0.901	0.913	0.864	0.885	0.873	0.919
SPV-MIA	0.929	0.951	0.885	0.903	0.897	0.937

In the previous experiments, we have validated the superiority of our proposed SPV-MIA over existing algorithms, as well as its versatility in addressing various challenging scenarios. However, the specific contributions proposed by each module we proposed are still unknown. In this subsection, we conduct an ablation study to audit the performance gain provided by the two proposed modules. Concretely, we respectively remove the practical difficulty calibration (PDC) and probabilistic variation assessment (PVA) that we introduced in Section 4.2 and Section 4.3. The results are represented in Table 7, where each module contributes a certain improvement to our proposed method. Besides, the PVC approach seems to play a more critical role, which can still serve as a valid adversary without the PVA. Thus, in practical scenarios, we can consider removing the PVA to reduce the frequency of accessing public APIs.

A.5.2 TPR@0.1%FPR

As a supplement to the TPR@1%FPR results represented in Table 2, we further provide the performance measured by TPR@0.1%FPR in Table 8.

Method	Wiki					AG News					Xsum				
	GPT-2	GPT-J	Falcon	LLaMA	Avg.	GPT-2	GPT-J	Falcon	LLaMA	Avg.	GPT-2	GPT-J	Falcon	LLaMA	Avg.
Loss Attack	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%
Neighbour Attack	1.2%	0.6%	0.5%	0.8%	0.8%	0.8%	0.4%	0.3%	0.4%	0.5%	0.5%	0.3%	0.3%	0.3%	0.4%
DetectGPT	0.9%	0.4%	0.5%	0.6%	0.6%	0.6%	0.2%	0.3%	0.4%	0.4%	0.4%	0.2%	0.2%	0.3%	0.3%
Min-K%	1.4%	0.6%	0.7%	0.9%	0.9%	1.2%	0.4%	0.7%	0.6%	0.7%	0.5%	0.3%	0.4%	0.4%	0.4%
Min-K%++	1.2%	0.7%	0.9%	1.1%	1.0%	1.4%	0.9%	1.1%	1.0%	1.1%	0.8%	0.4%	0.7%	0.6%	0.6%
LiRA-Base	1.9%	1.4%	1.5%	1.7%	1.6%	1.8%	1.4%	1.3%	1.4%	1.5%	3.1%	2.5%	2.6%	3.5%	2.9%
LiRA-Candidate	3.7%	2.5%	2.8%	3.2%	3.1%	2.3%	1.8%	1.7%	1.9%	1.9%	4.7%	3.4%	3.8%	5.1%	4.3%
SPV-MIA	39.1%	28.9%	32.7%	37.8%	34.6%	25.3%	17.3%	18.7%	23.5%	21.2%	34.4%	27.6%	28.9%	31.5%	30.6%

Table 8: **TPR@0.1%FPR** for detecting member texts from four LLMs across three datasets for SPV-MIA and five previously proposed methods. **Bold** and Underline respectively represent the best and the second-best results within each column (model-dataset pair).

A.5.3 AUC Curves

As a supplement to the main experimental results represented in Table 1, we further provide the raw ROC curve for a more comprehensive presentation in Fig. 6 (linear-scale) and Fig. 7 (log-scale).

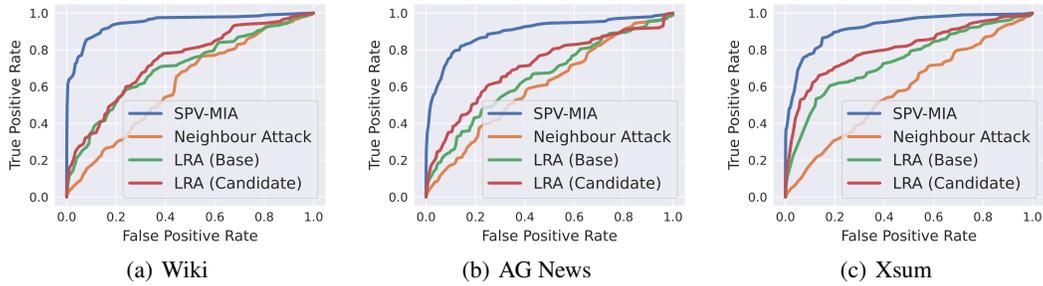


Figure 6: **Linear-scale** ROC curves of SPV-MIA and the top-three best baselines on LLaMAs fine-tuned over three datasets.

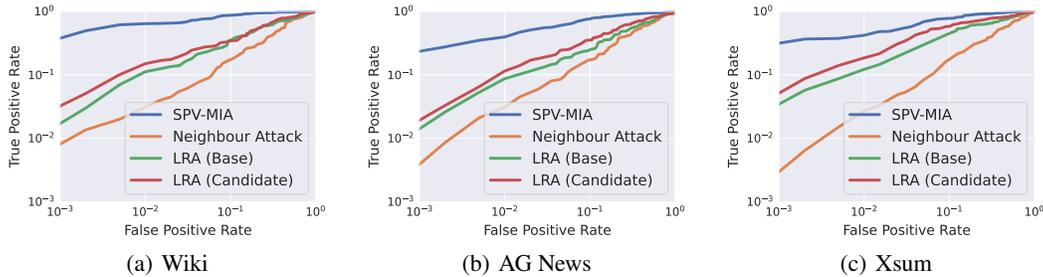


Figure 7: **Log-scale** ROC curves of SPV-MIA and the three representative baselines on LLaMAs fine-tuned over three datasets.

A.5.4 Performance of Target LLMs

We supplemented the performance of all LLM-dataset pairs on both the training and test sets (estimated using PPL). As shown in Table 9, the experimental results indicate that none of the fine-tuned LLMs exhibit significant overfitting, which aligns with our claim in the main body. Additionally, we provided the performance of the LLM under different privacy budgets ϵ , as shown in Table 10.

A.5.5 Performance of Representative Baselines under Different Privacy Budgets

We have conducted three representative baseline attacks for the DP-SGD model (LLaMA fine-tuned over Ag News dataset) and compared it with our method (SPV-MIA). The results are provided in Table 11. The results demonstrate that SPV-MIA consistently maintains substantial MIA performance margins over different settings of the privacy budget.

Table 9: The perplexity (PPL) of each LLM-dataset pair on training set and test set.

Target Model	GPT-2		GPT-J		Falcon		LLaMA	
	Training	Test	Training	Test	Training	Test	Training	Test
Wiki	25.34	27.47	12.35	12.44	7.26	7.73	7.00	7.43
AG News	23.86	26.34	12.49	13.24	8.92	9.54	9.03	9.13
Xsum	26.42	28.31	13.43	13.88	7.69	7.96	7.35	7.65

Table 10: The perplexity (PPL) of each LLM-dataset pair trained w.r.t different privacy budget ϵ .

Privacy Budget ϵ	15	30	60	+ inf
Wiki	8.45	8.16	7.76	7.43
AG News	10.84	9.68	9.32	9.13
Xsum	8.89	8.33	7.98	7.65

A.6 Experimental Settings

In this subsection, we give a extensive introduction of experimental settings, including the datasets, target LLMs and baselines, as well as the implementation details.

A.6.1 Datasets

Our experiments utilize six different datasets across multiple domains and LLM use cases, where we employ three datasets as the private datasets to fine-tune the target LLMs, and the remaining datasets as the public datasets from the exact domains. Specifically, we use the representative articles on Wikitext-103 dataset [43] to represent academic writing tasks, news topics from the AG News dataset [78] to represent news topic discussion task, and documents from the XSum dataset [49] to represent the article writing task. Besides, we utilize Wikicorpus [55], TLDR News [30], and CNNDM [23] datasets to respectively represent as the publicly accessible dataset from the same domain for each task.

A.6.2 Target Large Language Models

To obtain a comprehensive evaluation result, we conduct our experiments over four well-known and widely adopted LLMs as the pre-trained models with different scales from 1.5B parameters to 7B parameters:

- **GPT-2 [54]:** It is a transformer-based language model released by OpenAI in 2019, which has 1.5 billion parameters and is capable of generating high-quality text samples.
- **GPT-J [69]:** It is an open-source LLM released by EleutherAI in 2021 as a variant of GPT-3. GPT-J has 6 billion parameters and is designed to generate human-like with appropriate prompts.
- **Falcon-7B [3]:** Falcon is a family of state-of-the-art LLMs created by the Technology Innovation Institute in 2023. Falcon has 40 billion parameters, and Falcon-7B is the smaller version with less consumption.
- **LLaMA-7B [65]:** LLaMA is one of the most state-of-the-art LLM family open-sourced by Meta AI in 2023, which has outperformed other open-source LLMs on various NLP benchmarks. It has 65 billion parameters and has the potential to accomplish advanced tasks, such as code generation. In this work, we utilize the lightweight version, LLaMA-7B.

A.6.3 Baselines

We choose six MIAs designed for LMs to comprehensively evaluate our proposed method, including three reference-free attacks and one reference-based attack with one variant.

- **Loss Attack [73]:** A standard metric-based MIA that distinguishes member records simply by judging whether their losses are above a preset threshold.
- **Neighbour Attack [41]:** The Neighbour Attack avoids using a reference model to calibrate the loss scores and instead utilizes the average loss of plausible neighbor texts as the benchmark.

Table 11: The AUC performance of SPV-MIA and three representative baselines w.r.t different privacy budget ϵ .

Privacy Budget ϵ	15	30	60	+ inf
Loss Attack	0.523	0.551	0.568	0.580
Neighbour Attack	0.542	0.564	0.587	0.610
LIRA-Candidate	0.611	0.655	0.684	0.714
SPV-MIA	0.766	0.814	0.852	0.903

- **DetectGPT [48]:** A zero-shot machine-generated text detection method. Although DetectGPT is specially designed for LLMs-generated text detection, but has the potential to be adapted for identifying the text utilized for model training.
- **Min-K% [59]** An MIA method designed for pre-trained LLMs, which evaluate the token-level probability and employ the average over the $k\%$ lowest probability as the MIA metric.
- **Min-K%++ [76]** An enhanced version of Min-K% that utilizes a more sophisticated mechanism to detect the records with relatively high probability curvature.
- **Likelihood Ratio Attack (LiRA-Base) [47]:** A reference-based attack, which adopts the pre-trained model as the reference model to calibrate the likelihood metric to infer membership.
- **LiRA-Candidate [47]:** A variant version of LiRA, which utilizes a publicly available dataset in the same domain as the training set to fine-tune the reference model.

A.6.4 Detailed Information for Reproduction

Table 12: Detailed split and other information of datasets.

Dataset	Relative Datasets		Target Model		Reference Model	
	Domain-specific	Irrelevant	# Member	# Non-member	# Member	# Non-member
Wikitext-103	Wikicorpus	AG News	10,000	1,000	10,000	1,000
AG News	TLDR News	Xsum	10,000	1,000	10,000	1,000
Xsum	CNNDM	Wikitext-103	10,000	1,000	10,000	1,000

All experiments are compiled and tested on a Linux server (CPU: AMD EPYC-7763, GPU: NVIDIA GeForce RTX 3090), Each set of experiments for the LLM-dataset pairs took approximately 8 hours, and we spent around 14 days completing all the experiments. For each dataset, we pack multiple tokenized sequences into a single input, which can effectively reduce computational consumption without sacrificing performance [33]. Besides, the packing length is set to 128 tokens. Then, we use 10,000 samples for fine-tuning over pre-trained LLMs and 1,000 samples for evaluation. The detailed information of datasets is summarized in Table 12. For each target LLM, we let it fine-tuned with the training batch size of 16, and trained for 10 epochs. The learning rate is set to 0.0001. We adopt the AdamW optimizer [40] to achieve the generalization of LLMs, which is composed of the Adam optimizer [32] and the L2 regularization. For GPT-2, which has a relatively small scale, we adopt the full fine-tuning, which means all parameters are trainable. For other LLMs that are larger, we utilize a parameter-efficient fine-tuning method, Low-Rank Adaptation (LoRA) [24], as the default fine-tuning method. For the paraphrasing model in the embedding domain, the Gaussian noise scale is set to $\sigma = 0.05$. For the paraphrasing model in the semantic domain, the paraphrasing percentage is set to $\lambda = 0.2$. For both of the two paraphrasing models, we generate 10 symmetrical paraphrased text pairs for each target text record. For the reference LLM fine-tuned with our proposed self-prompt approach, we utilize the domain-specific data as the default prompt text source. Then, we collect 10,000 generated texts from target LLMs with an equal length of 128 tokens to construct reference datasets. We fine-tune the reference LLM for 4 epochs and the training batch size of 16.

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes], [No], or [NA].
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes]" is generally preferable to "[No]", it is perfectly acceptable to answer "[No]" provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No]" or "[NA]" is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading "NeurIPS paper checklist",**
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers.**

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: The claims made in the abstract and introduction are aligned with contributions and scope. All claims match theoretical and experimental results.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: As we have discussed in Appendix A.5.1, the proposed PVC method has a high computational overhead and provides low performance gains. Therefore, we suggest considering removing this module and only retaining the PDC in practical scenarios. Besides, the proposed SPV-MIA requires two additional API accesses, which may not be available in some scenarios.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [Yes]

Justification: Yes, we provide a complete derivation/proof for our proposed probabilistic variation metric in Section 4.3.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: Yes, all experimental settings, codes, and datasets are provided in Appendix and supplementary materials.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: Yes, all experimental settings, codes, and datasets are provided in Appendix A.6 and supplementary materials.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.

- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Yes, all experimental settings are provided in Appendix A.6.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: Since all experiments are taken on LLMs, error bars are not reported because it would be too computationally expensive.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We have provide sufficient information of computer resources in Appendix A.6.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines?>

Answer: [Yes]

Justification: We carefully reviewed the Code of Ethics and confirmed that we have adhered to each one.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: We have provide a Section "Ethic and Broader Impact Statements" follows the reference.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: As discussed in Appendix A.6, all models and datasets used in this study are publicly accessible.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: All the creators or original owners of assets are properly credited.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New Assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: The documentation can be found in the supplementary materials or the anonymized URL: <https://anonymous.4open.science/r/MIA-LLMs-260B>.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.

- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. Crowdsourcing and Research with Human Subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.