A Probabilistic Fluctuation based Membership Inference Attack for Diffusion Models

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hina Wuhan, China CCS CONCEPTS

Computing methodologies → Machine learning;
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KEYWORDS

Membership Inference Attacks; Generative Models; Privacy and Security

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1 INTRODUCTION

In recent years, fueled by abundant data resources and empowered by deep neural networks, generative models have achieved remarkable success in various domains such as computer vision [27], natural language processing [21], and spatial-temporal data modeling [32]. These generative models have the capability to generate authentic and creative content, which has prompted the deployment of various generative services [31].

However, while we enjoy the revolutionary benefits that these services bring, we also face various increasing privacy risks [1] and copyright disputes [8]. For example, the model privacy can be exposed to malicious users through the generative services [11, 38]. On the other side, unauthorized content may be secretly utilized to construct generative services [7].

Existing works have revealed privacy leakage in generative models from multiple perspectives. Membership inference attacks (MIAs) aim to identify the membership of a given record as the member record that comes from the training set, or as the non-member record that comes from a disjoint set [29]. MIAs have been widely

ABSTRACT

Membership Inference Attack (MIA) identifies whether a record exists in a machine learning model's training set by querying the model. MIAs on the classic classification models have been wellstudied, and recent works have started to explore how to transplant MIA onto generative models. Our investigation indicates that existing MIAs designed for generative models mainly depend on the overfitting in target models. However, overfitting can be avoided by employing various regularization techniques, whereas existing MIAs demonstrate poor performance in practice. Unlike overfitting, memorization is essential for deep learning models to attain optimal performance, making it a more prevalent phenomenon. Memorization in generative models leads to an increasing trend in the probability distribution of generating records around the member record. Therefore, we propose a Probabilistic Fluctuation Assessing Membership Inference Attack (PFAMI), a black-box MIA that infers memberships by detecting these trends via analyzing the overall probabilistic fluctuations around given records. We conduct extensive experiments across multiple generative models and datasets, which demonstrate PFAMI can improve the attack success rate (ASR) by about 27.9% when compared with the best baseline.

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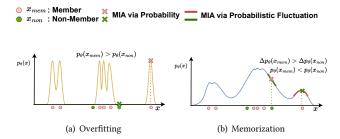


Figure 1: MIAs against generative models with overfitting and memorization. Identifying member records based on probability is feasible on overfitting models but fails on models only with memorization. Memorization arises as an increased tendency in probability density around member records, which can be captured by estimating the fluctuation of probability.

explored in the classic classification tasks and represent tremendous privacy leakage [17]. Recently, some preliminary researches have conducted MIAs on generative models. They essentially use different metrics as the proxy to approximate the probability of a specific record being generated by the target model, then infer memberships based on the magnitude of aforementioned probability [17]. For example, some works [4, 14, 22] employ the minimum distance between generated records and the target record as a metric for approximating the aforementioned probability. Other works [11, 16] utilize the confidence values outputted by the discriminator to serve as a proxy for this probability.

However, the current attack paradigm has a notable flaw. Specifically, these methods heavily depend on overfitting in target generation models. As demonstrated in Fig. 1(a), overfitting prompts member records to strike overall higher probabilities of being generated than non-member ones. Thus, probability can be utilized as an indicator for membership inference. However, training techniques such as regularization and early-stopping are widely adopted for eliminating over-fitting [36]. Consequently, deep learning models are usually overfitting-free, and the performance of existing attack algorithms in practical scenarios cannot be guaranteed. In contrast, deep learning models inevitably exhibit phenomena of memorization [10]. As shown in Fig. 1(b), memorization in generative models causes an increased tendency of probability density when the record closely resembles a member record [35]. Therefore, we consider a more practical and promising attack framework that captures the feature of memorization by estimating the fluctuation of probability within the local scopes of data records.

Nevertheless, three challenges need to be addressed before bringing this framework to a practical MIA. Firstly, both conventional probability-based and our proposed probabilistic fluctuation-based attack framework rely on the proxy for approximating probabilities. However, existing proxies either rely on massive synthetic records [34] or are only applicable in white-box settings [4]. Therefore, the first challenge is estimating the probability in an efficient manner without requiring massive generated records in a black-box scenario. Furthermore, within the high-dimensional data space, the probabilistic fluctuations around the target sample are highly complex. Specifically, the fluctuations exhibit significant variations in

different directions, and the fluctuations also differ at varying distances in the same direction. Therefore, the second challenge is how to generate representative neighbor records from an appropriate direction and various distances to depict the adjacent probabilistic fluctuations. The final challenge lies in how to design the inference function that quantifies and aggregates the probabilistic fluctuations from multiple neighbors, in order to obtain an indicator that can effectively distinguish between members and non-members.

In this paper, we propose the Probabilistic Fluctuation Assessing Membership Inference (PFAMI) composed with three elaborately designed modules to address these challenges. First, we design an effective probability estimation method based on variational inference, which is feasible on probabilistic generative models, such as variational autoencoders (VAEs) and diffusion models (DMs), with only a few generated records in the black-box setting. Furthermore, we propose a dynamic perturbation mechanism that can obtain an ensemble of representative neighbor records in the local scope by adjusting the strength of the perturbation. This ensemble paves the way for comprehensively characterizing the distribution of probabilistic fluctuations around the target record. Finally, based on the distribution of probabilistic fluctuations, we design a statistical metric-based as well as a neural networks (NNs)-based inference function to extract the distinctive memorization features for distinguishing between members and non-members.

Overall, our contributions are summarized as follows:

- We demonstrate that detecting memorization shines a light on MIAs against overfitting-free generative models and propose a framework that detects the distinctive characteristics of member records memorized by the target model from the perspective of probabilistic fluctuations.
- We propose PFAMI, a black-box MIA method that incorporates a probability estimation approach via variational inference and a dynamic perturbation mechanism to characterize the distribution of probabilistic fluctuations, and two elaborately-designed inference functions, including a metric-based approach and a neural network-based approach, to extracts essential features for membership inference attack.
- We conducted extensive experiments to validate the effectiveness of PFAMI. The results suggest that PFAMI shows significantly higher ASR and stability across multiple generation models and datasets compared with existing MIAs (about 19.8% and 35.9% improvement in ASR on diffusion models and VAEs, respectively).

2 RELATED WORKS

Generative Models With the development of deep learning, massive deep generative models are proposed for generating authentic data samples [26]. VAEs [13, 19], a family of preliminary generative models, incorporate an encoder network to map the original data distribution into a Gaussian distribution and a decoder to generate reconstructed data from the latent distribution. Recently, diffusion models [15, 30] explore to construct desired data samples from the noise by learning a parameterized denoising process in a Markov chain. They become a new family of state-of-the-art generative models and achieve a dominant position in generative tasks such as image generation [27], text generation [21], and spatial-temporal data imputation [32].

Table 1: Taxonomy of MIAs against generative models. ⊗ and ⊙ denote the w/ or w/o access requirements of specific parts. □ and ■ indicate white-box and black-box accesses of specific parts. ✓ and X represent whether an attacking algorithm is feasible for the corresponding generative model. Synthetic denotes a large-scale generated dataset prepared for MIAs in advance.

Method		Access			Applicable		
Method	Generator	Discriminator	Synthetic	Overfittting	Memorization	DMs	VAEs
Co-Membership Attack		8	8	/	Х	/	
GAN-Leaks (White-Box)		⊗	\otimes	/	×	/	/
Over-Representation (O-R)	•	0	8	/	Х	Х	Х
LOGAN		·	\otimes	/	×	×	×
(O-R) + Surrogate Model	•	8	0	/	Х	/	/
LOGAN + Surrogate Model		⊗	·	/	×	/	/
Monte-Carlo Set		⊗	·	/	×	/	/
GAN-Leaks (Black-Box)		8	8	/	Х	/	/
SecMI _{stat}		⊗	⊗	/	×	/	X
SecMI _{NNs}		⊗	⊗	/	×	/	Х
PFAMI _{Met}		8	⊗	/	√	_/	
PFAMI _{NNs}		⊗	⊗	/	/	/	/

Membership Inference Attack Shokri et al. [2017] formally proposed the MIAs, which aim to determine if a specific data record was included in the training set of a target model. Previous studies on Membership Inference Attacks have primarily concentrated on classification tasks [5]. Recently, with the emergence of generative models, researchers have focused on exploring their vulnerabilities regarding MIA. As the taxonomy summarized in Table 1, several studies [4, 22] assume a white-box access of generators and search the smallest distance between the target record and generated records via the first-order optimization. Other works with black-box access measure this distance through a massive synthetic dataset generated by the target model [14]. Additionally, there are specific studies that employ the discriminator's confidence value as a metric to differentiate member and non-member records [11, 16], while others adopt the estimation error [6]. However, existing methods are only feasible on models with overfitting, and fail on models only with memorization. On the contrary, our approach infers the memberships by detecting distinctive characteristics of the training records memorized by the target model, leading to outstanding attack performance and reduced access requirements.

3 PRELIMINARY

In this section, we introduce representative generative models and present a formal definition of a black-box threat model. The key notations utilized in this paper will be described in the appendix.

3.1 Generative Models

In this work, we focus on the probabilistic deep generative models, which include diffusion models [15] and VAEs [19], as these are more amenable to direct analysis of the learned probability.

VAEs has the similar structure as an autoencoder [37], which is composed of two modules: probabilistic encoder $q_{\phi}(z|x)$ and decoder $p_{\theta}(x|z)$. The approximate posterior is a multivariate Gaussian distribution parameterized by encoder ϕ :

$$q_{\phi}(z|x) = \mathcal{N}\left(z; \mu_{\phi}(x), \sigma_{\phi}^{2}(x) \mathbf{I}\right), \tag{1}$$

where μ_{ϕ} and σ_{ϕ} are calculated by the encoding neural networks with the input of x.

 $p_{\theta}(x|z)$ is a multivariate Gaussian or Bernoulli distribution depending on the type of data. In the image generation task, it is set to be a Gaussian distribution:

$$p_{\theta}(\mathbf{x}|\mathbf{z}) = \mathcal{N}\left(\mathbf{x}; \boldsymbol{\mu}_{\theta}(\mathbf{z}), \boldsymbol{\sigma}_{\theta}^{2}(\mathbf{z}) \mathbf{I}\right),$$
 (2)

where μ_{θ} and σ_{θ} are calculated by the decoding neural networks with the input of the latent code z.

Unlike VAEs, diffusion models are learned with a fixed encoding procedure. Diffusion models includes T steps forward diffusion process $q(x_t \mid x_{t-1})$ and reverse denoising process $p_{\theta}(x_{t-1} \mid x_t)$, which can be respectively formulated as:

$$q\left(\mathbf{x}_{t} \mid \mathbf{x}_{t-1}\right) = \mathcal{N}\left(\mathbf{x}_{t}; \sqrt{1 - \beta_{t}}\mathbf{x}_{t-1}, \beta_{t}\mathbf{I}\right)$$

$$p_{\theta}\left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t}\right) = \mathcal{N}\left(\mathbf{x}_{t-1}; \boldsymbol{\mu}_{\theta}\left(\mathbf{x}_{t}, t\right), \sigma_{\theta}\left(\mathbf{x}_{t}, t\right)\right),$$
(3)

where $\{\beta_t \in (0,1)\}_{t=1}^T$ is the variance schedule. Besides, in the forward process, there is a nice property that allows sampling x_t at any arbitrary time step t:

$$x_t(x_0, \epsilon) = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon,$$
 (4)

where $\alpha_t = 1 - \beta_t$, $\bar{\alpha}_t = \prod_{i=1}^t \alpha_t$ and $\epsilon \sim \mathcal{N}(0, \mathbf{I})$. It is also noteworthy that the reverse probability is tractable when conditioned on x_0 :

$$q\left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t}, \mathbf{x}_{0}\right) = \mathcal{N}\left(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}_{t}\left(\mathbf{x}_{t}, \mathbf{x}_{0}\right), \tilde{\beta}_{t} \mathbf{I}\right), \tag{5}$$

where
$$\tilde{\mu}_t(x_t, x_0) := \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1-\bar{\alpha}_t}x_0 + \frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}x_t$$
 and $\tilde{\beta}_t := \frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t}\beta_t$.

3.2 Threat Model

In this work, we consider an adversary that attempts to infer whether a specific data record was used in the training phase of the target generative model. Two mainstream attack scenarios considered in existing works are white-box and black-box. In the white-box scenario, the adversary has access to the internal parameters of the target model. However, in the black-box scenario, the attacker can only send queries to the victim model, and receive generated results, but lacks knowledge of the internal workings mechanism. Clearly, the black-box scenario is more practical as generative service providers may only offer services through an API while maintaining ownership of their well-trained generative models [4]. Therefore, we adopt the black-box scenario in this research to evaluate our proposed method under a more stringent and realistic condition. D is a dataset drawn from the real data distribution, which can be partitioned into two separate subsets: D_{mem} and D_{non} . The target model θ is trained on D_{mem} , and the adversary is unaware of which data records are included in the training set D_{mem} . Formally, the adversary algorithm \mathcal{A} is designed to predicted whether a data record $x^{(i)} \in D$ is in the training dataset D_{mem} :

$$\mathcal{A}\left(\boldsymbol{x}^{(i)},\theta\right) = \mathbb{1}\left[P\left(\boldsymbol{m}^{(i)} = 1 | \boldsymbol{x}^{(i)},\theta\right) \geq \tau\right],\tag{6}$$

where $m^{(i)}=1$ indicates that the record $\boldsymbol{x}^{(i)}\in D_{mem}$, τ denotes the threshold, $\boldsymbol{\varkappa}$ is the indicator function. Specifically, for diffusion models, we follow the setting in [6] that the adversary only has the prior knowledge of the variance schedule β_t . As for VAEs, the

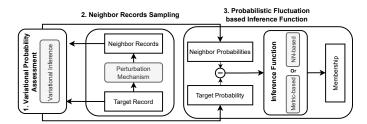


Figure 2: The overall framework of PFAMI and the three modules introduced to deploy it in practice.

adversary has no prior knowledge of the target model but can capture the latent code z through accessing the encoder q_{ϕ} , which is also defined as the partial black-box setting [4].

4 METHODOLOGY

As shown in Fig. 2, we introduce a novel MIA framework, which infers memberships by employing probabilistic fluctuation assessment. Subsequently, we design three modules to address three challenges posed by this framework.

4.1 Framework

The objective of a generative model is to learn a latent variable model $p_{\theta}\left(\mathbf{x}\right)$ to approximate the genuine data distribution $q\left(\mathbf{x}\right)$. Thus, as we discuss in Sec. 1, there is an attack framework widely adopted by existing MIAs against generative models that approximates the probabilities of target records being generated and then sets a threshold to discriminate between member and non-member records. This framework highly relies on the overfitting phenomenon in target models that drives member records more likely to be generated than non-member records. Besides, in the training pipeline of generative models, techniques like early stopping and regularization are widely used to prevent overfitting and improve generalization [36], which exacerbates the impracticality of this framework. Formally, the **existing attack framework** can be formulated as:

$$\mathcal{A}_{exist}\left(\mathbf{x}^{(i)},\theta\right) = \mathbb{1}\left[\widehat{p}_{\theta}\left(\mathbf{x}^{(i)}\right) \geq \tau\right],$$
 (7)

where $\widehat{p}_{ heta}\left(\mathbf{x}^{(i)}
ight)$ is the approximate probability of $\mathbf{x}^{(i)}$ being generated

Compared to overfitting, memorization is inevitable for achieving nearly optimal generalization on deep learning models [9]. In generative models with memorization, member records tend to strike higher generative probabilities than neighbor records [35], i.e., it usually corresponds to a local maximum. Intuitively, we consider a more general attack framework that detects these local maximum points by leveraging the probabilistic fluctuations around target records. Thus, **our proposed framework** can be formally represented as:

$$\mathcal{A}_{our}\left(\boldsymbol{x}^{(i)},\theta\right) = \mathbb{1}\left[\mathcal{F}\left(\left\{\Delta\widehat{p}_{\theta}\left(\boldsymbol{x}^{(i)},\widetilde{\boldsymbol{x}}_{j}^{(i)}\right)\right\}_{j=1}^{M}\right) \geq \tau\right], \quad (8)$$

where $\Delta\widehat{p}_{\theta}\left(x^{(i)},\widetilde{x}_{j}^{(i)}\right)$ represents the probabilistic fluctuation between the target record $x^{(i)}$ and its neighbor record $\widetilde{x}_{j}^{(i)}$. M indicates the number of neighbor records, $\mathcal{F}(\cdot)$ is an inference function that can qualify the overall probabilistic fluctuation around the target record $x^{(i)}$.

To implement our proposed framework in practical applications, we introduce three new modules sequentially. As depicted in Fig. 2, we first propose a variational probability assessment approach to efficiently approximate the probability $\widehat{p}_{\theta}\left(x^{(i)}\right)$ of the record $x^{(i)}$ being generated. Then we design a dynamic perturbation mechanism to sample representative neighbors within the local scope for estimating $\Delta \widehat{p}_{\theta}\left(x^{(i)},\widetilde{x}_{j}^{(i)}\right)$. Finally, we introduce two strategies with two inference functions to identify member records.

4.2 Variational Probability Assessment

Existing works estimate the probability $p_{\theta}(x)$ by calculating the smallest distance between the target record and the synthetic record set [17]. Nevertheless, these approaches [11, 14, 34] rely on tens of thousands of generated records, which leads to low efficiency.

We notice that probabilistic generative models, like diffusion models and VAEs, perform training by optimizing the evidence lower bound (ELBO) of $p_{\theta}(x)$. Therefore, we attempt to derive an approximate probability $\widehat{p}_{\theta}(x^{(i)})$ to estimate the relative value of $p_{\theta}(x)$ via variational inference.

Diffusion models: The ELBO can be written as:

$$\mathbb{E}_{q}\left[\log\frac{q\left(\mathbf{x}_{1:T}\mid\mathbf{x}_{0}\right)}{p_{\theta}\left(\mathbf{x}_{0:T}\right)}\right]=:L_{\text{ELBO}}\geq-\log p_{\theta}\left(\mathbf{x}_{0}\right).\tag{9}$$

Ho et al. [2020] further rewrite L_{ELBO} to $\sum_{t=0}^{T} L_t$, where L_T is a constant can be ignored during optimization. $L_{1:T-1}$ represents the estimation error of x_{t-1} , which can be expanded by applying Eq. (3) and Eq. (5):

$$L_{t-1}(\mathbf{x}_{0}) = D_{\text{KL}} \left(q \left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t}, \mathbf{x}_{0} \right) \parallel p_{\theta} \left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t} \right) \right)$$

$$= \mathbb{E}_{q} \left[\frac{1}{2\sigma_{t}^{2}} \left\| \tilde{\mu}_{t} \left(\mathbf{x}_{t}, \mathbf{x}_{0} \right) - \mu_{\theta} \left(\mathbf{x}_{t}, t \right) \right\|^{2} \right], \tag{10}$$

where the μ_{θ} is trained to predict $\tilde{\mu}_t$ based on x_t and t. For an attack model with the black-box setting, it can calculate $\tilde{\mu}_t$ (x_t , x_0) through the fixed forward diffusion process:

$$\tilde{\mu}_{t}\left(x_{t}, x_{0}\right) = \frac{1}{\sqrt{\alpha_{t}}} \left(x_{t}\left(x_{0}, \epsilon\right) - \frac{\beta_{t}}{\sqrt{1 - \bar{\alpha}_{t}}} \epsilon\right), \tag{11}$$

where ϵ is sampled from \mathcal{N} (0, I), and x_t (x_0 , ϵ) can be calculated by following Eq. (4). Then the attacker can acquire the expectation of predicted sample μ_{θ} (x_t , t) based on Eq. (3) and Monte Carlo sampling:

$$\mu_{\theta}\left(\mathbf{x}_{t},t\right) \approx \sum_{i} \mathbf{x}_{t-1}^{(i)},\tag{12}$$

where $\mathbf{x}_{t-1}^{(i)} \sim p_{\theta}(\mathbf{x}_{t-1} \mid \mathbf{x}_t)$. Thus, attacker can estimate the relative value of $p_{\theta}(\mathbf{x}_0)$ by fusing the estimation error across N sampled time steps:

$$\widehat{p}_{\theta}\left(x_{0}\right) := -\frac{1}{N} \sum_{t}^{N} L_{t}\left(x_{0}\right),\tag{13}$$

where log is ignored for simplification, and same operation is also performed for VAEs.

VAEs: The ELBO can be derived as the following two tractable items:

$$-\mathbb{E}_{z \sim q_{\phi}(z|\mathbf{x})} \log p_{\theta}(\mathbf{x}|\mathbf{z}) + D_{\text{KL}}(q_{\phi}(z|\mathbf{x}) || p_{\theta}(z))$$

$$=: L_{\text{ELBO}} \ge -\log p_{\theta}(\mathbf{x}),$$
(14)

where $\mathbb{E}_{z \sim q_{\phi}(z|x)} \log p_{\theta}(x|z)$ maximizes the likelihood of generating real data record x, $D_{\text{KL}}(q_{\phi}(z|x)||p_{\theta}(z))$ restricts the estimated posterior $q_{\phi}(z|x)$ mapped from the real data record close to the prior $p_{\theta}(z)$. Our adversary model is feasible to estimate both of them by only querying the target model without any knowledge of inherent parameters. The $\mathbb{E}_{z \sim q_{\phi}} \log p_{\theta}$ can be represented as follows by applying the Monte Carlo sampling method and Eq. (2):

$$\mathbb{E}_{\boldsymbol{z} \sim \boldsymbol{q}_{\phi}} \log p_{\theta} = \frac{1}{N} \sum_{n=1}^{N} \log p_{\theta} \left(\boldsymbol{x} \mid \boldsymbol{z}^{(n)} \right)$$

$$= \frac{1}{N} \sum_{n=1}^{N} \log \frac{1}{\sigma_{\theta} \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{\boldsymbol{x} - \boldsymbol{x}^{(n)}}{\sigma_{\theta}} \right)^{2}}$$

$$\propto -\sum_{n=1}^{N} \left\| \boldsymbol{x} - \boldsymbol{x}^{(n)} \right\|^{2},$$
(15)

where N represents the number of Monte Carlo sampling, $\boldsymbol{x}^{(n)}$ is the mean of the $p_{\theta}\left(\boldsymbol{x}\mid\boldsymbol{z}^{(n)}\right)$, i.e., $\boldsymbol{x}^{(n)}=\boldsymbol{\mu}_{\theta}^{(n)}$, and it can be directly obtained by querying the target model. Since the decoder of the VAE calculates $\boldsymbol{\mu}_{\theta}\left(\boldsymbol{z}^{(n)}\right)$ with neural networks, and outputs it as

the reconstructed sample $x^{(n)}$. $\|x-x^{(n)}\|^2$ is proportional to the mean squared error (MSE) between the original and reconstructed data records. $D_{\text{KL}}(q_{\phi}(z|x)\|p_{\theta}(z))$ can be calculated with a closed-form solution as it is the KL divergence between two Gaussian distribution:

$$D_{\text{KL}}(q_{\phi} || p_{\theta}) = \frac{1}{2} \left(1 + \log \sigma_{\phi}^{2}(x) - \sigma_{\phi}^{2}(x) - \mu_{\phi}^{2}(x) \right). \tag{16}$$

Thus, attacker can approximate $p_{\theta}(x)$ by applying Eq. (16) and Eq. (15) to Eq. (14):

$$\widehat{p}_{\theta}\left(\boldsymbol{x}\right) := -\sum_{n=1}^{N} \left\|\boldsymbol{x} - \boldsymbol{x}^{(n)}\right\|^{2} - D_{\mathrm{KL}}(\mathcal{N}\left(\boldsymbol{\mu}_{\phi}, \sigma_{\phi}^{2} \mathbf{I}\right) \|\mathcal{N}(0, 1)). \tag{17}$$

Based on Eq. (13) and Eq. (17), adversary can approximate the relative value of $p_{\theta}\left(x\right)$ by sending a few query requests to the target model.

4.3 Neighbor Records Sampling

As formulated in Eq. (8), for a given data record $x^{(i)}$, we have to sample an ensemble of representative neighbor records $\left\{\widetilde{x}_{j}^{(i)}\right\}_{j=1}^{M}$. Thus, how to sample representative neighbor records for exploring the local scope of a given data record is critical for instantiating our approach. Considering neighbors approximately appressed with the target record is imperative, but the data distributions are often high-dimensional and wide. We should avoid sampling neighbors out-of-range and can therefore refrain from exploring meaningless domains. Therefore, we opt for a data perturbation method that is as simple as possible, resulting in a minor but observable shift in

the data distribution. Inspired by the data augmentation techniques widely used in machine learning for improving the model performance and generalization through increasing the diversity of the dataset, we design various perturbation methods to sample neighbor records, including crop, rotation, downsampling, brightening, etc. Furthermore, we conducted extensive experiments to investigate the attack performance over various perturbation methods to find the most effective perturbation direction. The related information can be found in the appendix, and the results suggest utilizing crop as the default direction as it combines excellent performance and stability. Furthermore, we consider sampling neighbor records at different distances by adjusting the strength of perturbation to comprehensively characterize the probabilistic fluctuations around the target record. Formally, we propose a general dynamic perturbation mechanism \mathcal{M} with increasing perturbation strengths $\{\lambda_j\}_{j=1}^M$ on arbitrary perturbation method:

$$\left\{\widetilde{\boldsymbol{x}}_{j}^{(i)}\right\}_{j=1}^{M} = \left\{\mathcal{M}\left(\boldsymbol{x}^{(i)}, \lambda_{j}\right)\right\}_{j=1}^{M}.$$
 (18)

4.4 Probabilistic Fluctuation based Inference Function

Based on the variational approximate probability introduced in Sec. 4.2, and the perturbation mechanism proposed in Sec. 4.3. In this section, we elaborately design two strategies with different inference functions to qualify the overall probabilistic fluctuation by analyzing the characteristics of probability changes among the neighbor records of the target record: the metric-based inference, PFAMI $_{Met}$, and the neural networks (NNs)-based inference, PFAMI $_{NNs}$.

4.4.1 Metric-based Inference Function. For each data record $\mathbf{x}^{(i)} \in D$, we sample M neighbor records with increasing perturbation strengths and then set the inference function \mathcal{F} to be statistical averaging to estimate the overall probabilistic fluctuation. Formally, PFAMI_{Met} can be formulated as:

$$\mathcal{A}\left(\boldsymbol{x}^{(i)},\theta\right) = \mathbb{1}\left[\left(\frac{1}{M}\sum_{j=1}^{M}\Delta\widehat{p}_{\theta}\left(\boldsymbol{x}^{(i)},\widetilde{\boldsymbol{x}}_{j}^{(i)}\right)\right) \geq \tau\right],\tag{19}$$

where $\Delta\widehat{p}_{\theta}\left(x^{(i)},\widetilde{x}_{j}^{(i)}\right) = \left(\widehat{p}(x^{(i)}) - \widehat{p}(\widetilde{x}_{j}^{(i)})\right)/\widehat{p}(x^{(i)})$. Note that each approximate probability $\widehat{p}_{\theta}\left(\cdot\right)$ is measured by repeatedly querying the target model N times in VAE based on Eq. (17). In diffusion models, $\widehat{p}_{\theta}\left(\cdot\right)$ is calculated by taking the average of estimation errors over N sampled time steps based on Eq. (13).

4.4.2 NNs-based Inference Function. Instead of qualifying the overall probabilistic fluctuation by directly taking an average across M neighbors and N sampled points, we calculate each $\Delta \widehat{\rho}_{\theta}$ over them. Therefore, we can obtain a $M \times N$ matrix $\Delta \widehat{\rho}_{\theta}(x^{(i)})$ for each target record, which can be represented as an "image" that contains probabilistic fluctuation information around the target record. Then we adopted an NNs-based model $f_{\mathcal{A}}$ as the inference function \mathcal{F} to capture the information of probabilistic fluctuation variation on this image. Specifically, convolutional neural networks (CNNs)-based binary classification models are feasible to handle this task. In this manner, our proposed PFAMI_{NNs} can be formally represented as:

$$\mathcal{A}\left(\mathbf{x}^{(i)},\theta\right) = \mathbb{1}\left[f_{\mathcal{A}}\left(\Delta\widehat{\boldsymbol{p}}_{\boldsymbol{\theta}}(\mathbf{x}^{(i)})\right) \geq \tau\right],\tag{20}$$

where $f_{\mathcal{A}}(\cdot)$ indicates the probability that PFAMI_{NNs} identify target record $\boldsymbol{x}^{(i)}$ as a member. Notably, our method does not follow existing studies [6] that assume having access to an extensive number of ground truth labels for member and non-member records from the target model. Instead, we use an auxiliary dataset to train a shadow model to provide training samples for training our attack model. Then we deploy the trained attack model to infer memberships on the target model. Our method, in this manner, alleviates rigid assumptions, providing increased adaptability and practical applicability.

To strike a more accurate probabilistic fluctuation estimation, we train a reference generative model with another relevant but disjoint dataset to calibrate the approximate probability \hat{p}_{θ} (\mathbf{x}_{0}) in both two strategies.

5 EXPERIMENTS

5.1 Settings and Implementation Details

5.1.1 Datasets and Target models. We conduct experiments on two widely-used image datasets, Celeba-64 [24] and Tiny-ImageNet (Tiny-IN) [20]. For both datasets, we randomly select about 30% of all data samples for training and evaluating the target generative models, then utilize the rest for training the shadow and reference models. For example, Celeba-64 contains 202,599 images, whereas we respectively take 50,000 and 10,000 images as training and evaluation sets for target models. Notably, we make every effort to use all the data samples in each dataset to ensure that the target model has sufficiently large training samples since the limited member size will exacerbate the overfitting effect. For the target models, we adopted the two most representative generative models, DDPM [15] and vanilla VAE [19], to represent diffusion models and VAEs as well. Additionally, we also evaluated our proposed MIA against six state-of-the-art variant diffusion models and VAEs. It is worth noting that all models employ various regularization mechanisms to avoid overfitting. The detailed implementation information is summarized in the appendix.

5.1.2 Baselines. We choose six state-of-the-art MIAs designed for generative models to comprehensively evaluate our proposed method. There are two baselines set up in the white-box setting, Co-Membership [22] and GAN-Leaks (White-Box) [4]. Additionally, we employed five baseline methods for black-box access, LOGAN [11], Monte-Carlo Set [14], Over-Representation [16], GAN-Leaks (Black-box) [4] and SecMI [6]. These baselines have been verified to have excellent attack performances on multiple generative models and large-scale datasets.

5.2 Attack Performance

As shown in Table. 2, we first summarize the AUC [2] and ASR [6] metrics for all baselines and PFAMI against two generative models over two datasets. In addition, we illustrate receiver operating characteristic (ROC) curves for PFAMI and the best baseline in appendix for a more comprehensible presentation. From the aforementioned experimental results, the following analyses are summarized:

 PFAMI consistently outperforms all baseline methods in all scenarios: The PFAMI_{NNs} and PFAMI_{Met} models achieve the

- highest average ASRs of 90.0% and 86.1% respectively. Furthermore, PFAMI exhibits approximate 35.9% improvement in AUC compared to the most competitive baseline on VAE, even when the baseline is set up with white-box access. Moreover, PFAMI $_{NNs}$ achieves higher ASR and AUC compared to SecMI $_{NNs}$ that assumes access to a large number of member and non-member data records of target models.
- The incremental performance provided by PFAMI_{NNs} verifies the necessity of exploring neighbor space with neural networks: Compared with PFAMI_{Met}, PFAMI_{NNs} captures the variation of probabilistic fluctuations with neural networks can significantly increase the inference performance (about 5% and 3% improvement in ASR and AUC.).
- The overall low ASR and AUC of existing MIAs reveal their intractability on generative models without overfitting: Most baselines, particularly those in the black-box setting, achieved low ASR, often comparable to random guesses. This phenomenon validates the viewpoint that existing MIAs overly rely on overfitting in target models. Additionally, the high query frequency and computational overhead requirements further diminish the applicability and practicality of these MIAs.
- The diffusion model exposes more privacy risks due to its
 multi-step characteristic: Compared to VAEs, both PFAMI_{NNs}
 and PFAMI_{Met} exhibit superior attack performance on diffusion
 model. This phenomenon can be attributed to the enhanced confidence in inferring membership through the estimation of probability fluctuations across different time steps in the diffusion
 models.

5.3 Generalizability Study

To validate the generalizability and robustness of our proposed attack on probabilistic generative models, we consider six different generative models: DDIM [30], PNDM [23] and LDM [27] as the variants of diffusion models. Beta-VAE [13], WAE [33] and RHVAE [3] as the variants of VAEs. As the results demonstrated in Table. 3, our proposed method can achieve generally well attack performance on various generative models. Furthermore, the experimental results once again demonstrate the higher privacy exposure risk of diffusion models regarding MIAs.

5.4 How the Probabilistic Fluctuation Works

We conduct detailed investigations about how our proposed probabilistic fluctuation works as a qualified extractor to distinguish member and non-member records. As exhibited in Fig. 3, we first visualize statistic distributions of the approximate probability \widehat{p}_{θ} and our proposed probabilistic fluctuation $\Delta \widehat{p}_{\theta}$ on member and non-member records. We found that just identifying the member records based on the approximate probability, as adopted by most existing works [6, 14], is not reliable. Especially when the target generative model is not overfitting, the probability for both member and non-member data is very close, especially in the diffusion model, where their distributions almost overlap entirely. On the contrary, when using the probability fluctuation we designed, the obtained results have more substantial discriminative power. Specifically, due to the memorization effect, members are peak points in the probability distribution, and their neighbors tend to have

Table 2: Performance of PFAMI across two generative models and two datasets. ↑ represents that the higher the metric, the better of performance. Bold and <u>Underline</u> respectively denote the best and the second-best results for each metric. # Query indicates the number of query requests issued to the target model by each attack algorithm to complete an attack. N/A demonstrates that SecMI_{stat} and SecMI_{NNs} are unavailable on VAEs, since they are specially designed for diffusion models.

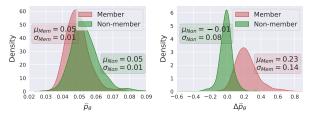
			DDPM					VAE			
Attack Types	Method		Celeba-64		Tin	Tiny-IN		Celeba-64		Tiny-IN	
		# Query	ASR↑	AUC↑	ASR↑	AUC↑	ASR↑	AUC↑	ASR↑	AUC↑	
White-Box	Co-Membership Attack	1000	0.637	0.682	0.632	0.679	0.640	0.691	0.637	0.690	
w nite-Box	GAN-Leaks (White-Box)	1000	0.623	0.601	0.618	0.593	0.601	0.586	0.595	0.582	
	Monte-Carlo Set	10000	0.500	0.502	0.500	0.501	0.501	0.502	0.501	0.501	
	Over-Representation	10000	0.511	0.517	0.509	0.510	0.508	0.514	0.506	0.513	
	LOGAN	10000	0.509	0.507	0.508	0.507	0.505	0.506	0.506	0.509	
Black-Box	GAN-Leaks (Black-Box)	10000	0.503	0.505	0.502	0.504	0.505	0.506	0.502	0.505	
Diack-Dox	$SecMI_{stat}$	12	0.690	0.741	0.673	0.729	N/A	N/A	N/A	N/A	
	SecMI_{NNs}	12	0.791	0.867	0.783	0.859	N/A	N/A	N/A	N/A	
	$PFAMI_{Met}$	20	0.909	0.965	0.900	0.961	0.822	0.900	0.811	0.893	
	PFAMI _{NNs}	110	0.947	0.986	0.939	0.978	0.863	0.939	0.849	0.927	

Table 3: PFAMI is compared with the best baseline in terms of performance against various generative models, where $SecMI_{NNs}$ and Co-Membership Attack stand as the best baselines for diffusion models and VAEs.

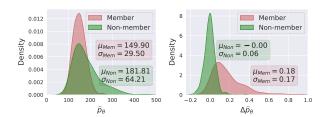
Target Model	Best B	Best Baseline PFAM		$PFAMI_{Met}$		MI_{NNs}
Target Woder	ASR↑	AUC↑	ASR↑	AUC↑	ASR↑	AUC↑
DDIM	0.799	0.871	0.913	0.969	0.952	0.987
PNDM	0.787	0.865	0.907	0.968	0.941	0.977
LDM	0.786	0.862	0.901	0.961	0.932	0.968
Beta-VAE	0.642	0.695	0.824	0.903	0.863	0.940
WAE	0.667	0.723	0.831	0.916	0.867	0.944
RHVAE	0.652	0.702	0.817	0.899	0.856	0.927

lower probabilities. Hence, our designed probability fluctuation metric would be greater than zero. Conversely, non-members are typically located near inflection points in the generation probability distribution, resulting in a stable probability fluctuation around zero. These experimental results also demonstrate that PFAMI $_{Met}$ can effectively enhance the discrimination between member and non-member records, making it easier to establish a threshold as a criterion for measuring record membership.

We also visualize the figure of probabilistic fluctuation $\Delta\widehat{\rho}_{\theta}$ on diffusion models to help understand why the NNs-based approach can further improve the attack performance. As shown in Fig. 4(a), we can observe an overall positive probability fluctuation of member records, except there are also apparent regular variations of probabilistic fluctuation over time step and perturbation strength. Consequently, this variation further benefits the NNs-based approach to extract the difference between member and non-member records. In contrast, as shown in Fig. 4(b), the member and non-member records are indistinguishable only with the approximate probability on sampled time steps.



(a) Distributions of \widehat{p}_{θ} (Left) and $\triangle \widehat{p}_{\theta}$ (Right) in DDPM.

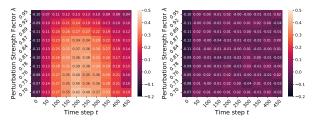


(b) Distributions of \widehat{p}_{θ} (Left) and $\triangle \widehat{p}_{\theta}$ (Right) in VAE.

Figure 3: The discrimination of member and non-member records over approximate probability \widehat{p}_{θ} and approximate probabilistic fluctuation $\Delta \widehat{p}_{\theta}$ on DDPM and VAE.

5.5 Ablation Study

We conduct an ablation study to investigate the performance gain provided by each module. Specifically, we respectively remove the variational probability assessment and neighbor record sampling modules as we introduced in Sec. 4.2 and Sec. 4.3. Then we remove the NNs-based inference function proposed in Sec. 4.4. The results are presented in Table. 4, where each module demonstrates significant improvement in performance gain, and the combination of all modules achieves the highest ASR of PFAMI $_{NNs}$. The results also suggested that the approximate probability assessment is the basis of probabilistic fluctuation. Without this, it is difficult for



(a) $\Delta \widehat{p}_{\theta}$ on member (Left) and non-member (Right).



(b) \widehat{p}_{θ} on member (Left) and non-member (Right).

Figure 4: The visualization of the probabilistic fluctuation $\Delta \widehat{p}_{\theta}$ and the approximate probability \widehat{p}_{θ} for member and non-member records on DDPM trained with Celeba-64.

Table 4: Results of ablation study on celeba-64 dataset.

Methods	DD	PM	VAE		
	ASR↑	AUC↑	ASR↑	AUC↑	
PFAMI _{NNs}	0.947	0.986	0.863	0.939	
w/o Variational Probability Assessment	0.537	0.541	0.523	0.532	
w/o Neighbor Records Sampling	0.694	0.781	0.677	0.747	
w/o NNs-based Inference Function	0.909	0.965	0.822	0.900	

our method to accurately estimate the fluctuation of generative probabilities, resulting in poor attack effectiveness.

6 CONCLUSION

In this article, we first point out that existing MIA algorithms largely rely on overfitting in generative models, which can be avoided by several regularization methods. Thus, the performance of these MIAs cannot be guaranteed. To mitigate this flaw, we opt for a more general phenomenon: memorization. Memorization is inevitable in deep learning models, and we have found that this phenomenon can be detected in probabilistic generative models by estimating the probabilistic fluctuations within the local scope of the target records. Therefore, we present a Probabilistic Fluctuation Assessing Membership Inference Attack (PFAMI) based on the distinct probabilistic fluctuation characteristics of members and non-members. We conduct comprehensive experiments to evaluate PFAMI with various baselines on diffusion models and VAEs across different datasets. The results demonstrate that PFAMI maintains higher ASR and robustness across various scenarios than all baselines. We leave extending our attack framework to GAN as the future works, where we may incorporate the samples from the generator and the confidence values from the discriminator to design a better method.

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A APPENDIX

A.1 Notations of This Work

Table 5: Notations and descriptions.

Notation	Description
$x^{(i)}$	A specific data record.
$\widetilde{\boldsymbol{x}}_{j}^{(i)}$	A neighbor record of the target record $oldsymbol{x}^{(i)}$.
$m^{(i)}$	The membership of the data record $\mathbf{x}^{(i)}$, 1 represents member, whereas 0 represents non-member.
θ	The parameters of the target generative model.
$\mathcal{A}\left(oldsymbol{x}^{(i)}, heta ight)$	The adversary algorithm for MIA.
$p_{\theta}\left(\mathbf{x}^{(i)}\right)$	The probability of record $oldsymbol{x}^{(i)}$ being generated by the generative model $oldsymbol{ heta}$.
$\widehat{p}_{ heta}\left(\mathbf{x}^{(i)} ight)$	The approximate value of probability $p_{\theta}\left(oldsymbol{x}^{(i)} ight)$.
$\Delta \widehat{p}_{\theta} \left(\boldsymbol{x}^{(i)}, \widetilde{\boldsymbol{x}}_{j}^{(i)} \right)$	The probabilistic fluctuation between the target record $\mathbf{x}^{(i)}$ and one of its neighbor $\widetilde{\mathbf{x}}_{j}^{(i)}$.
$\mathcal{M}(\cdot,\lambda_j)$	The perturbation mechanism.
$\left\{\lambda_{j}\right\}_{j=1}^{M}$	The sequence of perturbation strengths.
N	The query times for estimating $\widehat{p}_{\theta}\left(\pmb{x}^{(i)}\right)$.
М	The sampled number of neighbor records.
$\Delta \widehat{m{p}}_{m{ heta}}(m{x}^{(i)})$	The $M \times N$ probabilistic fluctuation figure of the target record $\mathbf{x}^{(i)}$.

B DETAILED INFORMATION FOR REPRODUCTION

B.1 Implementation Details

All target models are trained with general settings, and the backbone of diffusion models and VAEs are selected to UNet [28] and ResNet [12]. The step length of diffusion models is set to T = 1,000, and the dimension of latent variables z in VAEs is set to 64. To assure the target models are well-generalized, we use AdamW [25] to optimize all generative models, which fuses the Adam optimizer [18] and the L2 regularization to reduce the risk of model overfitting. Furthermore, we adopt early-stopping during the training process, where we stop training before the loss increases in the validation set. The crop is adopted as the default perturbation mechanism for all experiments. For PFAMI_{Met}, we set N=10 and M=1 for attacking against both diffusion models and VAEs. In diffusion models, we sample time steps starting from 0 to 500 with the interval of 50, as we found that the probabilistic fluctuations of member and non-member are indistinguishable in the later time steps. As the larger the time step, the closer the image is to Gaussian noise. As for PFAMI_{NNs}, we designed a set of equally spaced increasing perturbation strengths, the factor λ ranging from 0.98 to 0.7, with a length of M = 10. We choose the ResNet [12] as the backbone of attack model $f_{\mathcal{A}}$ and train it with only 2,000 samples provided by the shadow model.

B.2 Datasets

The detailed split and other information of the two datasets, Celeba-64 and Tiny-IN, are summarized in Tab. 6.

B.3 Target Models

The target models are all prepared with the two most popular generative model libraries: diffusers and pythae, which allows researchers

to easily deploy our attack model on other generative models with just a few lines of code modification. All diffusion models, including DDPM, DDIM, PNDM, and LDM are deployed with diffusers, and trained in 500 epochs with a learning rate of 0.0001 and batch size of 16. All VAEs, including the vanilla VAE, Beta-VAE, WAE, and RHVAE, are deployed with pythae, and trained in 100 epochs with a learning rate of 0.0001 and batch size of 100. Note that the training process will be interrupted early if the loss starts to increase in the evaluation set.

C ADDITIONAL EXPERIMENTS

C.1 The ROC curve of the main experiment

As a supplement to the main experimental results shown in Tab. 2, we also provide the raw ROC curve for a more straightforward presentation in Fig. 5.

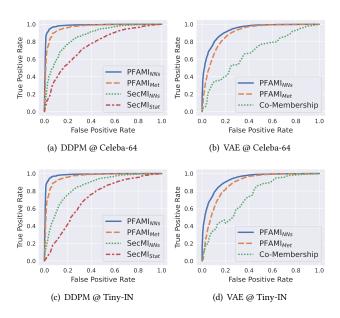


Figure 5: ROC curves of PFAMI and the best baselines on two generative models trained in Celeba-64 and Tiny-IN datasets.

C.2 Hyperparameters Learning

C.2.1 Perturbation Mechanism. In this paper, the perturbation mechanism is a key module in PFAMI for characterizing the overall probabilistic fluctuation around the target record, which helps the attacker to sample representative neighbor records of the target record. Therefore, we investigate what perturbation mechanisms will be appropriate for PFAMI to achieve better performances. Inspired by existing data augmentation techniques, we have studied two different types of data augmentation techniques, namely, color-based and geometry-based. They respectively involve various operations such as brightness, contrast, saturation, hue, as well as cropping, rotation, perspective, padding. We present several metrics to evaluate each perturbation mechanism. Except for ASR and AUC,

Table 6: Detailed split and other information of datasets.

Dataset	Resolution	Targ	Target Model		ow Model	Reference Model		
Dataset	# Member # Non-member		# Member	# Non-member	# Member	# Non-member		
Celeba-64	64	50,000	10,000	50,000	10,000	50,000	10,000	
Tiny-IN	64	30,000	5,000	30,000	5,000	30,000	5,000	

Table 7: Performance of PFAMI $_{Met}$ on DDPM@Celeba-64 with different perturbation techniques.

Perturbation Techniques		DDPM			VAE			
		ASR AUC TPR @ 1% FPR		ASR	AUC	TPR @ 1% FPR		
Color	Brightness	0.855	0.920	0.291	0.843	0.919	0.237	
	Contrast	0.858	0.918	0.192	0.835	0.909	0.165	
	Saturation	0.681	0.741	0.044	0.683	0.753	0.033	
	Hue	0.851	0.927	0.379	0.777	0.855	0.104	
Geometry	Crop	0.909	0.965	0.468	0.834	0.912	0.229	
	Rotation	0.917	0.968	0.574	0.806	0.879	0.119	
	Perspective	0.836	0.911	0.167	0.730	0.799	0.049	
	Downsampling	0.838	0.910	0.297	0.830	0.909	0.156	

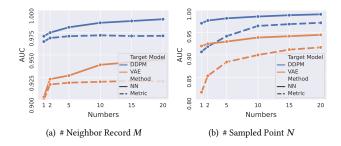


Figure 6: The attack performances against DDPM and VAE on Celeba-64 w.r.t the number of queries.

we also consider TPR @ 1% FPR, i.e., the TPR when FPR is 1%. It

can more accurately evaluate the attack performance when most mechanisms achieve a near-perfect AUC of approximately 0.9 and ASR scores. The results are shown in Tab. 7, from which we can observe that the crop combines excellent performance and stability. Therefore, we adopt crop as the default perturbation mechanism in all experiments. The results are presented in Tab. 7, which illustrates that the crop demonstrates remarkable performance and robustness over two generative models. Consequently, the crop is selected as the default perturbation mechanism for all experimental trials.

C.2.2 Impact of the Query Times. We investigate the impact of query numbers on the performance of PFAMI attacks from two perspectives: the number of neighbor records M and the number of sampled points N. Furthermore, we have conducted a detailed investigation into the variations in attack performance with respect to query numbers, considering different attack strategies and different architectures of generative models. Note that the default number of neighbor records M is repetitively set to 1 and 10 in PFAMI_{Met} and PFAMI NN_s , and the default number of sampled points N is set to 10. As the results presented in Fig. 6, the attack performance of the NN-based strategy is exceptionally stable, due to the integration of probabilistic fluctuation features from multiple directions. On the other hand, the attack strategy based on statistical metric tends to rely more on the number of samples and generally achieve a good balance between performance and efficiency with around 10 sampled numbers.