FINE-TUNING CAN HELP DETECT PRETRAINING DATA FROM LARGE LANGUAGE MODELS

Anonymous authors
Paper under double-blind review

ABSTRACT

In the era of large language models (LLMs), detecting pretraining data has been increasingly important due to concerns about fair evaluation and ethical risks. Current methods differentiate members and non-members by designing scoring functions, like Perplexity and Min-k%. However, the diversity and complexity of training data magnifies the difficulty of distinguishing, leading to suboptimal performance in detecting pretraining data. In this paper, we first explore the benefits of unseen data, which can be easily collected after the release of the LLM. We find that the perplexities of LLMs perform differently for members and non-members, after fine-tuning with a small amount of previously unseen data. In light of this, we introduce a novel and effective method termed *Fine-tuned Score Deviation* (**FSD**), which improves the performance of current scoring functions for pretraining data detection. In particular, we propose to measure the deviation distance of current scores after fine-tuning on a small amount of unseen data within the same domain. In effect, using a few unseen data can largely decrease the scores of all non-members, leading to a larger deviation distance than members. Extensive experiments demonstrate the effectiveness of our method, significantly improving the AUC score on common benchmark datasets across various models.

1 INTRODUCTION

The impressive performance of large language models (LLMs) arises from large-scale pretraining on massive datasets collected from the internet (Achiam et al., 2023; Touvron et al., 2023b). But, model developers are often reluctant to disclose detailed information about the pretraining datasets, raising significant concerns regarding fair evaluation and ethical risks. Specifically, Recent studies reveal that the pretraining corpus may inadvertently include data from evaluation benchmarks (Sainz et al., 2023; Balloccu et al., 2024), making it difficult to assess the practical capability of LLMs. Besides, LLMs often generate text from copyrighted books (Grynbaum & Mac, 2023) and personal emails (Mozes et al., 2023), which could infringe on the legal rights of the original content creators and violate their privacy. Considering the vast size of the pretraining dataset and the single iteration of pretraining, it has been increasingly important and challenging to detect pretraining data, which determines whether a piece of text is part of the pretraining dataset.

In the literature, current works of detecting pretraining data primarily focus on designing scoring functions to differentiate members (i.e., seen data during pretraining) and non-members (unseen). For example, previous work shows that sequences leak in the training data tend to have lower perplexity (i.e., higher likelihood) than non-members (Li, 2023). Min-k% leverages the k% of tokens with minimum token probabilities of a text for detection, assuming that trained data tends to contain fewer outlier tokens (Shi et al., 2024). However, non-member data can obtain low perplexities by including frequent or repetitive texts, while members may contain rare tokens that result in high perplexities. This casts significant doubt on utilizing those scoring functions for detecting pretraining data. Consequently, this issue prompts us to present a preliminary attempt to enlarge the difference between members and non-members for pretraining datasets of LLMs.

In this work, we propose Fine-tuned Score Deviation (**FSD**), a novel and effective approach that improves the detection capabilities of current scoring functions in a specific domain (e.g., event data from Wikipedia, arXiv research papers). Our method is motivated by an empirical analysis of the perplexity deviation after model fine-tuning. We find that when fine-tuned with a few previously

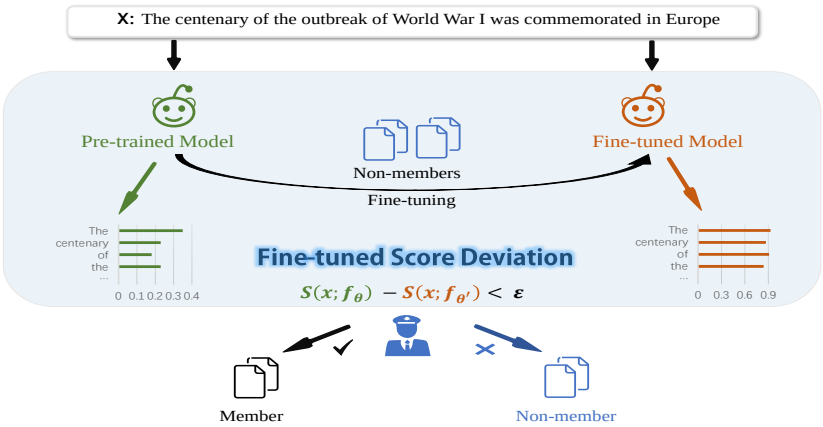


Figure 1: **Overview of Fine-tuned Score Deviation**. To determine whether a text X is in the pre-training data, our method first fine-tunes the pre-trained model with a few non-members and then measures the deviation distance of scores from the pre-trained model and fine-tuned model as a membership inference metric. If the deviation value is smaller than the threshold value, the text is likely in the pretraining data.

unseen data from a specific domain, the perplexities of LLMs experience a significantly larger decrease for other *unknown* non-members in the domain compared to the members. This suggests the possibility of using the disparity to distinguish between members and non-members.

Therefore, our key idea behind FSD is to enlarge the score deviation between members and non-members by exposing the LLM to a few non-members. This can be accomplished by measuring the deviation distance of current scores (See Figure 1), owing to the self-supervised fine-tuning on a few non-members. In effect, the fine-tuning largely decreases the scores of non-member data, resulting in more distinguishable seen and unseen data. In practical applications, it is easy to collect a small amount of unseen data for LLMs within a specific domain. For example, we can make use of those contents (e.g., journal articles) published subsequent to the release of the LLM.

To verify the effectiveness of our method, we conduct extensive experiments on various datasets, including WikiMIA, BookMIA (Shi et al., 2024), ArXivTection and BookTection (Duarte et al., 2024). The results demonstrate that our method can significantly improve the performance of existing methods based on scoring functions. For example, our method improves the AUC score of the best baseline method Min-k%, increasing it from 0.62 to 0.91 on WikiMIA under the OPT-6.7B model. Moreover, our method can also improve the TPR@5%FPR score of baseline methods. For example, our method improves the TPR@5%FPR score of the detection method using perplexity, increasing it from 0.10 to 0.81 on ArXivTection under the LLaMA-7B model.

Our main contributions are as follows:

- We analyze the limitations of existing methods based on scoring functions for pretraining data detection. The significant overlap in metric score distribution between seen data and unseen data results in the inferior performance of detection methods.
- We propose Fine-tuned Score Deviation (FSD), a novel and effective method for detecting pretraining data from large language models. The core idea is to enlarge the gap between members and non-members by exposing the LLM to a few unseen data.
- We empirically show that FSD can improve the performance of existing detection methods based on scoring functions for detecting pretraining data, through extensive experiments conducted on various benchmark datasets with diverse large language models.

2 Background

In this work, we focus on detecting pretraining data, the problem of detecting whether a piece of text is included in the pretraining data of a specific LLM. First, we formally define the problem setup and its challenges. Then, we introduce two commonly used methods for this task.

Pretraining data detection Pretraining data detection is an instance of membership inference attacks (MIAs) (Shokri et al., 2017), and can help identify data contamination in the pretraining corpus (Shi et al., 2024). Let f be an autoregressive large language model (LLM) with trainable parameters $\boldsymbol{\theta}$ (e.g., LLaMA (Touvron et al., 2023a)) and $\mathcal{D}$ denotes the associated pretraining data, sampled from an underlying distribution $\mathcal{P}$. As model developers rarely provide detailed information about the pretraining dataset, we generally desire to identify if the LLM is trained on the given text for scientific and ethical concerns. Formally, the task objective is to learn a detector h that can infer the membership of an arbitrary data point $\boldsymbol{x}$ in the dataset $\mathcal{D}$: $h(\boldsymbol{x}, f_{\boldsymbol{\theta}}) \rightarrow \{0, 1\}$.

Unlike the black-box assumption in previous works (Shi et al., 2024; Oren et al., 2024), we assume the access to fine-tune LLMs with custom datasets and the output probabilities of LLMs, which is realistic for open-sourced LLMs and many commercial APIs, such as GPT-4o[1]. In addition, the detector can obtain a few data samples $\{\boldsymbol{x_i}\}_{i=0}^{N}$ that belong to the same domain as the given sample $\boldsymbol{x}$ and do not present in the training set. This can be achieved by collecting those contents (e.g., journal articles) published after the release of the LLM.

The task of pretraining data detection can be formulated as a binary classification: determining whether a given text $\boldsymbol{x}$ is a member or non-member of the pretraining dataset $\mathcal{D}$. Pretraining data detection can be performed by a level-set estimation:

$$h(\boldsymbol{x}; f_{\boldsymbol{\theta}}) = \begin{cases} \text{member} & \text{if } \mathcal{S}(\boldsymbol{x}; f_{\boldsymbol{\theta}}) < \epsilon, \\ \text{non-member} & \text{if } \mathcal{S}(\boldsymbol{x}; f_{\boldsymbol{\theta}}) \geq \epsilon, \end{cases} \tag{1}$$

where $\mathcal{S}(\boldsymbol{x}; f_{\boldsymbol{\theta}})$ denotes a scoring function and ϵ is the threshold determined by a validation dataset. By convention, examples with lower scores $\mathcal{S}(\boldsymbol{x}; f_{\boldsymbol{\theta}})$ are classified as members of pretraining data and vice versa. In the following, we introduce two popular scoring functions for the task.

Scoring functions For large language models, likelihood is typically used to estimate the uncertainty in generating new tokens. In particular, a high likelihood indicates that the model predicts tokens with high confidence. Given a piece of text $\boldsymbol{x} = \{x_1, x_2, ..., x_n\}$, the likelihood of the next token x_{n+1} is $p_{\boldsymbol{\theta}}(x_{n+1}|x_1, ..., x_n)$. In general, a piece of text seen in pre-training tends to have more tokens with a high likelihood, whereas unseen texts have more tokens with a low likelihood.

In light of this, previous studies usually design likelihood-based scoring functions to detect pretraining data (Shi et al., 2024; Carlini et al., 2021; Li, 2023). For example, *Perplexity* is proposed to distinguish members and non-members, based on the observation that members tend to have lower perplexity than non-members (Li, 2023). Formally, The perplexity of $\boldsymbol{x}$ is calculated as:

$$\text{Perplexity}(\boldsymbol{x}; f_{\boldsymbol{\theta}}) = \exp\{-\frac{1}{n}\sum_{i=1}^{n} \log p_{\boldsymbol{\theta}}(x_i \mid x_1, \ldots, x_{i-1})\} \tag{2}$$

where $\boldsymbol{x} = \{x_1, x_2, \ldots, x_n\}$ is a sequence of tokens and $p_{\boldsymbol{\theta}}(x_i \mid x_1, \ldots, x_{i-1})$ is the conditional probability of x_i given the preceding tokens.

Instead of using the likelihood of all tokens, Min-k% (Shi et al., 2024) computes the average probabilities of k% outlier tokens with the smallest predicted probability. The intuition is that a non-member example is more likely to include a few outlier words with low likelihoods than members. Formally, Min-k% is computed by:

$$\text{Min-k\%}(\boldsymbol{x}; f_{\boldsymbol{\theta}}) = \frac{1}{E} \sum_{x_i \in \text{Min-k\%}(\boldsymbol{x})} \log p_{\boldsymbol{\theta}}(x_i \mid x_1, \ldots, x_{i-1}) \tag{3}$$

where E is the size of the Min-k%$(\boldsymbol{x})$ set.

However, non-member data can obtain low perplexities by including frequent or repetitive texts, while members may contain rare tokens that result in high perplexities (See Figure 3a and 3b). This issue makes it challenging to distinguish members and non-members using those scoring functions, leading to suboptimal performance in detecting pre-training data. Thus, we present a preliminary attempt to utilize extra non-member data to enlarge the gap between members and non-members.

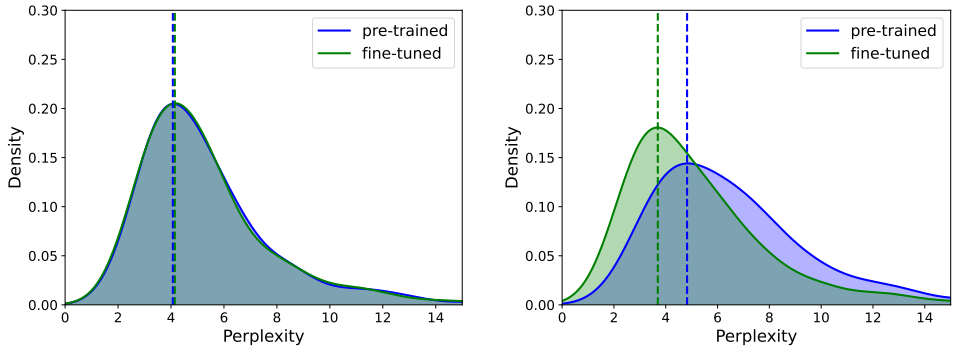
[1] https://platform.openai.com

3 METHOD

Recall the realistic assumption that detectors can obtain a few non-members that belong to the same domain as the given sample, we aim to explore how to utilize these extra non-members to improve the detection. Thus, we start by investigating the effects of LLM fine-tuning with unseen examples. Our analysis shows that fine-tuning exerts different impacts on members and non-members.

3.1 MOTIVATION

In the analysis, we conduct experiments with WikiMIA (Shi et al., 2024), an evaluation benchmark that uses events added to Wikipedia after specific dates as non-member data. We use $\widetilde{\mathcal{D}}$ to denote the non-member dataset that is accessible for detectors. To construct the dataset $\widetilde{\mathcal{D}}$, we randomly sample a subset with 100 examples from the non-member data of WikiMIA. In addition, we construct the test set with 630 examples each for both members and non-members. Throughout this subsection, we fine-tune LLaMA-7B (Touvron et al., 2023a) with LoRA (Hu et al., 2022) on the non-member dataset $\widetilde{\mathcal{D}}$. To illustrate the effects of fine-tuning, we compare the perplexity distribution of members and non-members from the pre-trained model and the fine-tuned model.



(a) Members (b) Non-members

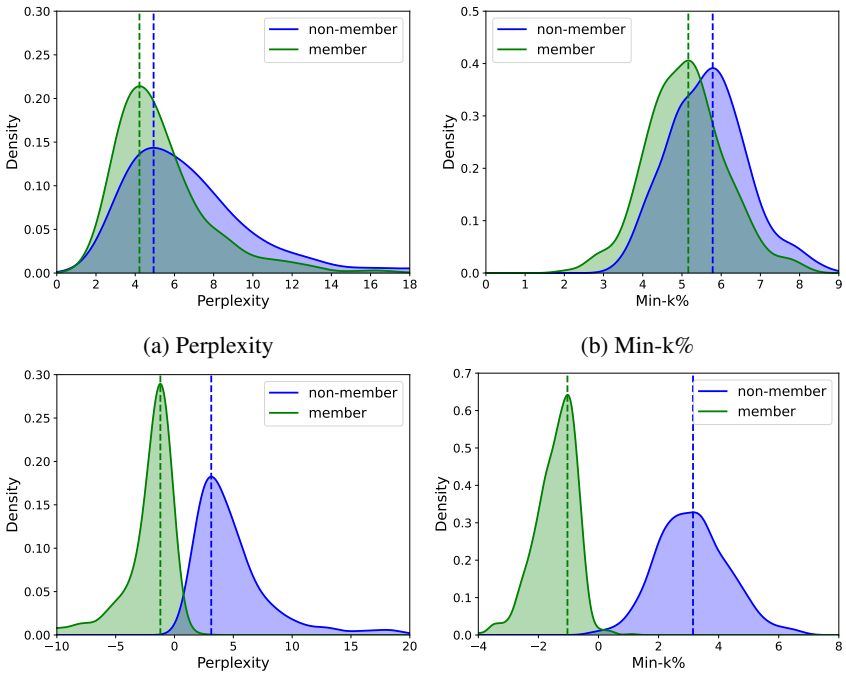
Figure 2: The perplexity distribution from the pre-trained model and the fine-tuned model.

Fine-tuning decreases the perplexity of non-members. Figures 2a and 2b present the deviation of perplexity distributions for members and non-members, throughout the fine-tuning on the non-member dataset $\widetilde{\mathcal{D}}$. The results show that unseen data in the pretraining tends to obtain a lower perplexity from the fine-tuned model compared to the pre-trained model. Contrarily, we observe that the deviation of perplexity distribution for members is negligible after the pre-trained model fine-tuning. The analysis indicates that fine-tuning with a few unseen data from a specific domain can decrease the likelihood-based scores of the LLM for other unknown non-members in the domain. The contrast in the score deviation resulting from fine-tuning allows for the distinction between members and non-members.

3.2 FSD: FINE-TUNED SCORE DEVIATION

Motivated by the previous analysis, we propose Fine-tuned Score Deviation (**FSD**), a general method that can improve the detection performance of current scoring functions in a specific domain. The key idea of our method is to enlarge the gap between seen and unseen data, by exposing the LLM to a few unseen data. With this in mind, we present the details of our approach step by step.

Construct fine-tuning dataset Given a piece of text $\boldsymbol{x}$, the first step of our method is to collect a small amount of unseen data for the LLM within the same domain. Owing to the availability of public text data in enormous quantities, we can construct non-member datasets by comparing the LLM release date and data creation timestamp. For instance, we collect some events occurring post-2023 from Wikipedia as the auxiliary non-member dataset for fine-tuning LLaMA (Touvron et al., 2023a), since LLaMA was released in February 2023.



(a) Perplexity (b) Min-k%

(c) FSD with Perplexity (d) FSD with Min-k%

Figure 3: Distribution of scores from pre-trained model vs. FSD. We contrast the distribution of scores from the pre-trained model using perplexity and our FSD with perplexity(a & c). Similarly, we contrast the Min-k% scores distribution from the pre-trained model and our FSD (b & d). Using FSD leads to enlarging the gap between members and non-members.

Fine-tuning with non-members To expose LLMs to unseen data, we perform fine-tuning on LLMs with the constructed fine-tuning dataset. As our goal is to reduce the perplexity of the unseen data, we employ self-supervised fine-tuning by predicting the next word or token in a given sequence. In particular, we build the loss function by decreasing the negative log likelihood of the actual next token in the sequence. Formally, the fine-tuning loss is:

$$\mathcal{L}_{\text{fine-tuning}}(\boldsymbol{x}) = -\frac{1}{n}\sum_{i=1}^{n} \log f_{\boldsymbol{\theta}}(x_i|x_1, ..., x_{i-1}) \tag{4}$$

Fine-tuned Score Deviation Recall that fine-tuning decreases the perplexity of non-members but almost maintains those of members, we propose to exploit the score deviation for detecting pretraining data. Given a new sample $\boldsymbol{x}$, we calculate the score difference between the pre-trained LLM $f_{\boldsymbol{\theta}}$ and the fine-tuned LLM $f_{\boldsymbol{\theta}'}$, where $\boldsymbol{\theta}'$ denotes the parameters of LLM after fine-tuning. Formally, the new score of Fine-tuned Score Deviation (FSD) can be formulated as:

$$\text{FSD}(\boldsymbol{x}; f_{\boldsymbol{\theta}}, f_{\boldsymbol{\theta}'}) = \mathcal{S}(\boldsymbol{x}; f_{\boldsymbol{\theta}}) - \mathcal{S}(\boldsymbol{x}; f_{\boldsymbol{\theta}'}) \tag{5}$$

where $\mathcal{S}(\cdot)$ denotes an existing scoring function, such as Perplexity and Min-k%. With the proposed score, we can estimate the membership of $\boldsymbol{x}$ through the level-set estimation (Eq. (1)). Examples with a large deviation score are considered as non-members and vice versa. In practice, we determine the threshold ϵ by maximizing detection accuracy on a validation set, following the previous work (Shi et al., 2024). Our method is compatible with various scoring functions and consistently enhances their performance in detecting pretraining data, as presented in Table 1.

By way of the FSD score, we can obtain a clear distinction between members and non-members, establishing excellent performance in detecting pretraining data. To provide a straightforward view, we show in Figure 3 the score distribution between members and non-members using various scoring functions on WikiMIA (Shi et al., 2024). The results of ArXivTection (Duarte et al., 2024) are also presented in Appendix D.1. Our experiments validate that, compared to the perplexity and Min-k%

scores, our FSD score significantly increases the gap between non-members and members, and as a result, enables more effective pretraining data detection.

4 EXPERIMENTS

In this section, we evaluate the effectiveness of our method for pretraining data detection across several benchmark datasets with multiple existing open-sourced models. We also apply FSD to copyrighted book detection in real-world scenarios and find it a consistently effective solution.

4.1 EXPERIMENTAL SETUP

Models We conduct extensive experiments on diverse open-sourced LLMs. For the main results, we use LLaMA-7B (Touvron et al., 2023a) as the LLM throughout our experiments. We also provide experiments on other models including Pythia-6.9B (Biderman et al., 2023), GPT-J-6B (Wang & Komatsuzaki, 2021), OPT-6.7B (Zhang et al., 2022), LLaMA-13B models (Touvron et al., 2023a), LLaMA-30B (Touvron et al., 2023a), and NeoX-20B (Black et al., 2022). Existing works (Shi et al., 2024; Ye et al., 2024) generally use these models as LLMs for performing the studies of pretraining data detection. The models are provided by Hugging Face [2].

Datasets To verify the effectiveness of detection methods, we employ four common benchmark datasets for evaluations, including WikiMIA (Shi et al., 2024), ArXivTection (Duarte et al., 2024), BookTection (Duarte et al., 2024) and BookMIA (Shi et al., 2024). Previous works have demonstrated that model developers commonly use text content among those datasets for pre-training (Shi et al., 2024; Duarte et al., 2024; Ye et al., 2024). The datasets are provided by Hugging Face[3], and detailed information of datasets is presented in Appendix B.

Baseline methods We use four detection methods based on scoring functions as our baselines for evaluating the performance of methods on various datasets under diverse models. Those methods employ specific metrics based on the likelihood, followed by a comparison with a preset threshold to identify the given text's membership. Specifically, baseline methods include the example perplexity (**Perplexity**) (Li, 2023), the ratio of example perplexity and zlib compression entropy (**Zlib**) (Carlini et al., 2021), the ratio of the perplexity on the example before and after lowercasing (**Lowercase**) (Carlini et al., 2021) and detecting pretraining example through outlier words with low probability (**Min-k%**) (Shi et al., 2024).

Evaluation metrics We evaluate the performance of detection methods for detecting pretraining data by measuring the following metrics: (1) AUC, the area under the receiver operating characteristic curve; (2) the true positive rate (TPR) when the false positive rate (FPR) of examples is 5% (TPR@5%FPR).

Implementation details Our approach involves constructing the non-member dataset and fine-tuning the base model. For constructing the non-member dataset, we randomly sample 30% of the data from the entire dataset and select all non-members from this subset as the constructed fine-tuning dataset. The remaining 70% of the dataset is used for testing. We employ LoRA (Hu et al., 2022) to fine-tune the base model with 3 epochs and a batch size of 8. We set the initial learning rate as 0.001 and drop it by cosine scheduling strategy. We conduct all experiments on NVIDIA L40 GPU and implement all methods with default parameters using PyTorch (Paszke et al., 2019).

4.2 MAIN RESULTS

Can FSD improve the performance of current scoring functions? We compare the performance of detection methods on WikiMIA and ArXivTection datasets across various large language models. The detailed information of dataset split is shown in Appendix C.1. Our results in Table 1 show that the FSD significantly improves the performance of all baseline methods on both datasets

[2] https://huggingface.co/models
[3] https://huggingface.co/datasets

Table 1: AUC score for pretraining data detection with baselines and our method from various models on WikiMIA and ArXivTection. *Base* and ***+Ours*** respectively denote the baseline methods and our method. **Bold** shows the superior result.

Dataset	Method	GPT-J-6B		OPT-6.7B		Pythia-6.9B		LLaMA-7B		NeoX-20B	
		Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
WikiMIA	Perplexity	0.64	**0.95**	0.60	**0.90**	0.64	**0.90**	0.64	**0.92**	0.69	**0.93**
	Lowercase	0.59	**0.77**	0.59	**0.71**	0.58	**0.74**	0.58	**0.69**	0.66	**0.76**
	Zlib	0.61	**0.94**	0.59	**0.89**	0.61	**0.88**	0.62	**0.90**	0.64	**0.93**
	MIN-K%	0.68	**0.92**	0.62	**0.91**	0.67	**0.86**	0.65	**0.85**	0.73	**0.90**
ArXivTection	Perplexity	0.79	**0.96**	0.68	**0.89**	0.77	**0.95**	0.68	**0.92**	0.79	**0.95**
	Lowercase	0.59	**0.81**	0.58	**0.70**	0.60	**0.77**	0.50	**0.69**	0.62	**0.75**
	Zlib	0.64	**0.96**	0.55	**0.89**	0.63	**0.95**	0.57	**0.91**	0.65	**0.95**
	MIN-K%	0.85	**0.92**	0.74	**0.84**	0.84	**0.91**	0.76	**0.86**	0.85	**0.91**

across diverse models. For example, our method improves the AUC score compared to the best baseline method Min-k%, increasing it from 0.62 to 0.91 on WikiMIA dataset from the OPT-6.7B model. Similarly, it improves the AUC score from 0.76 to 0.86 on ArXivTection dataset from the LLaMA-7B model. Moreover, we show that our method also remarkably improves the TPR@5%FPR score of all baseline methods in Table 11 of Appendix D.2. Moreover, we also present the results on different subsets of the Pile dataset under the Pythia-6.9B model in Appendix D.3.

How does the fine-tuning data size affect the performance of FSD? To investigate the effect of varying the fine-tuning data size on the pretraining data detection, we compare the performance of the model fine-tuned with different-sized fine-tuned datasets. To construct fine-tuning datasets of varying sizes, we randomly sample varying amounts of non-members (0, 30, 50, 100, 150, 200, 250, 300) from the WikiMIA dataset as fine-tuning datasets. In addition, we sample 465 members and non-members from the dataset and construct a balanced test set of 930 examples.

Figure 6 presents the performance of FSD with various sizes of auxiliary datasets. The results show our method achieves better performance as the size of the fine-tuning dataset increases. Notably, our method is highly data-efficient, achieving dramatic improvements with only a small amount of non-members for fine-tuning. For example, FSD improves the AUC score of the perplexity-based method from 0.63 to 0.91, by leveraging only 100 non-member data for fine-tuning – a significant direct improvement of 44%. In summary, a few non-members are sufficient for FSD to improve the detection, demonstrating its practicality. In addition, we also evaluate our method on the BookC2 subset of the Pile dataset under the Pythia-6.9B model. The results show a similar trend, which can be found in Appendix D.3.

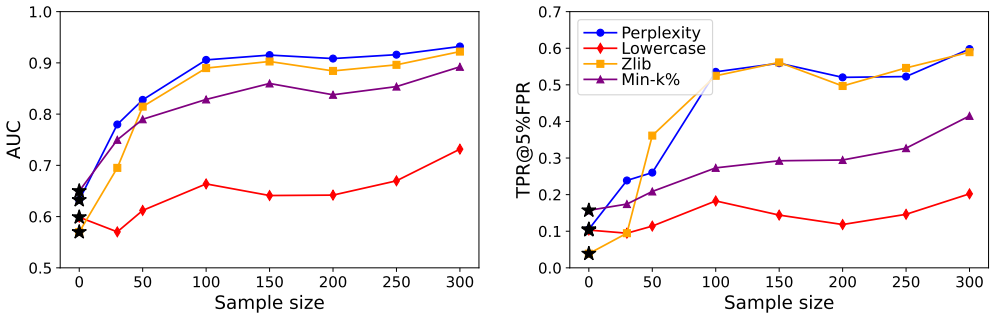
Is FSD effective with different-sized models? We also verify the performance of baselines and our methods from different-sized LLaMA models (7B, 13B, 30B) on WikiMIA. In Table 2, our results demonstrate that our method is effective with different-sized models, and achieves remarkable performance from different-sized models. Notably, the AUC score of **Lowercase** slightly rises as the parameters of the LLaMA model increase. Moreover, additional results of the TPR@5%FPR score show a similar trend, which can be found in Appendix D.2.

Can our method detect copyrighted books in pretraining data? Recent works (Shi et al., 2024; Duarte et al., 2024) study the problem of copyrighted book detection in training data. Following previous works, we verify the effectiveness of detection methods for detecting excerpts from copyrighted books on BookMIA (Shi et al., 2024) and BookTection (Duarte et al., 2024). Specifically, we randomly sample 500 members and non-members from datasets, constructing a balanced validation set of 1,000 examples. The detailed information of datasets split is presented in Appendix C.2.

In Table 3, we compare the accuracy of our method and baselines for detecting suspicious books in pretraining data from the LLaMA-7B model. A salient observation is that our method significantly

Table 2: AUC score for pretraining data detection with baselines and our method from the different-sized LLaMA model on WikiMIA. *Base* and ***+Ours*** respectively denote the baseline methods and our method. **Bold** shows the superior result.

Method	LLaMA-7B		LLaMA-13B		LLaMA-30B	
	Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
Perplexity	0.64	**0.92**	0.66	**0.92**	0.68	**0.91**
Lowercase	0.58	**0.69**	0.60	**0.70**	0.60	**0.75**
Zlib	0.62	**0.90**	0.63	**0.90**	0.65	**0.91**
MIN-K%	0.65	**0.85**	0.67	**0.86**	0.70	**0.82**



(a) AUC (b) TPR@5%FPR

Figure 4: AUC and TPR@5%FPR of scoring functions with FSD, using auxiliary datasets with varying sizes. Notably, ★ represents the baseline without FSD.

Table 3: Accuracy and AUC score for copyrighted book detection with baselines and our method from LLaMA-7B on BookTection and BookMIA. *Base* and ***+Ours*** respectively denote baslines and our method. **Bold** shows the superior result.

Metric	Accuracy				AUC			
Method	BookTection		BookMIA		BookTection		BookMIA	
	Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
Perplexity	66.9	**85.4**	59.0	**96.5**	0.710	**0.910**	0.564	**0.995**
Lowercase	64.5	**73.0**	67.0	**69.2**	0.664	**0.770**	0.708	**0.779**
Zlib	65.3	**86.4**	57.4	**98.6**	0.568	**0.920**	0.474	**0.999**
MIN-K%	68.1	**82.1**	59.5	**93.9**	0.716	**0.880**	0.587	**0.979**

improves the accuracy of baseline methods for copyrighted book detection. For example, compared with baselines, our method reaches an accuracy of 98.6% on BookMIA using detection method **Zlib**, which marks a significant 71.8% improvement. We also present the AUC score with our method and baselines in Table 3, which consistently improves the detection capabilities of baseline methods. Our extensive experiments demonstrate the effectiveness of our method for copyrighted book detection.

5 DISCUSSION

Can members be used for fine-tuning? The key step of our method is to fine-tune the pre-trained model using a few non-members. One may also ask: *can a similar effect be achieved by utilizing members as the fine-tuning dataset?* In this ablation, we separately sample members and non-members from WikiMIA to construct fine-tuning datasets(Mem, Non). In addition, we randomly sample data from WikiMIA as another fine-tuning dataset (All). The details of implementation are

Table 4: AUC of scoring functions with FSD, using members (Mem), non-members (Non), and mix of them (All) on LLaMA-7B. Base denotes the scoring function without FSD. **Bold** shows the superior result.

Method	Base	All	Mem	Non
Perplexity	0.64	0.68	0.78	**0.92**
Lowercase	0.58	0.54	0.67	**0.69**
Zlib	0.62	0.65	0.79	**0.90**
MIN-K%	0.65	0.61	0.81	**0.85**

Table 5: AUC of scoring functions with FSD using the original WikiMIA, data removing timestamps (Deletion), and data replacing the year of timestamps with 2023 (Replacement). The results are shown as Base/+Ours.

Method	WikiMIA	Deletion	Replacement
Perplexity	0.64/ **0.92**	0.62/ **0.76**	0.54/ **0.71**
Lowercase	0.58/ **0.69**	0.58/ **0.62**	0.52/ **0.63**
Zlib	0.62/ **0.90**	0.58/ **0.72**	0.55/ **0.68**
MIN-K%	0.65/**0.85**	0.61/ **0.69**	0.54/ **0.67**

presented in Appendix C.3. To investigate the impact of different fine-tuning datasets on pretraining data detection, we fine-tune the LLaMA-7B model with each of the fine-tuning datasets individually.

Our results in Table 4 show that our method can improve the performance of baseline methods using members as the fine-tuning dataset. However, our method achieves inferior performance when using members for fine-tuning compared with non-members. Moreover, it is not realistic to construct a member dataset without accessing pretraining data in real-world scenarios. In addition, this is feasible for constructing non-members as a fine-tuning dataset based on the model release date and data creation timestamp. Overall, our method demonstrates superior performance when using non-members for fine-tuning, while ensuring applicability in real-world settings.

Is our method affected by distribution difference? Existing works generally construct benchmark datasets based on the LLM release date and data creation timestamp (Ye et al., 2024; Shi et al., 2024). For example, the WikiMIA dataset considers events occurring post-2023 as non-members. Recent works indicate evaluation results are suspect on benchmark datasets because they possibly sample members and non-members from different distributions (Duan et al., 2024; Das et al., 2024; Maini et al., 2024). We find the temporal shift between members and non-members in the WikiMIA dataset, which is shown in Appendix C.4. The issue shows that we can distinguish members and non-members with timestamps in the dataset. To eliminate the impact of temporal differences between members and non-members on evaluation, we implement two strategies to mitigate the temporal shift in the dataset: (1) removing timestamps in the dataset (Deletion), and (2) replacing the year of timestamps with 2023 in the dataset(Replacement). We conduct experiments with baselines and our method on the original WikiMIA dataset, Deletion and Replacement, respectively.

Our results in Table 5 show that the performance of baselines and our method are compromised when mitigating the temporal shift between members and non-members. This is likely because deleting or replacing a word will change the probability of the subsequent word, thereby perturbing the likelihood-based metric. In this setting, surprisingly, the results show that our method can also improve the performance of baseline methods. Though baseline methods yield results that are comparable to random guessing on the Replacement dataset, our method can also improve the AUC scores of the perplexity-based detection method, increasing it from 0.54 to 0.71. Overall, our method is effective even if there is no distribution difference between members and non-members. The TPR@5%FPR score of the experiment is presented in Appendix D.2.

Is FSD effective with different fine-tuning methods? To expose LLMs to unseen data, we employ LoRA to fine-tune the pre-trained model. The results demonstrate that our method achieves impressive performance for pretraining data detection when fine-tuning with LoRA. However, can a similar effect be achieved using different fine-tuning methods? To this end, we apply AdaLoRA (Zhang et al., 2023), IA3 (Liu et al., 2022), and LoRA to fine-tune LLaMA-7B with WikiMIA, respectively. The details of the dataset in our experiment can be found in Appendix C.1.

In Table 6, we report the AUC and TPR@5%FPR scores for pretraining data detection with our method and baseline methods. The results show that our method can improve the performance of baseline methods when using different fine-tuning methods. Although our FSD achieves inferior performance with AdaLoRA compared with IA3 and LoRA, it still significantly improves the performance of baseline methods. Overall, our method can be implemented with different fine-tuning

Table 6: AUC score of FSD with different fine-tuning methods. Base denotes baseline methods without model fine-tuning. **Bold** shows the superior result.

Metric	AUC				TPR@5%FPR			
Method	Base	AdaLoRA	IA3	LoRA	Base	AdaLoRA	IA3	LoRA
Perplexity	0.64	0.82	0.91	**0.92**	0.09	0.39	**0.52**	0.41
Lowercase	0.58	0.62	**0.72**	0.69	0.10	0.13	0.17	**0.18**
Zlib	0.62	0.76	0.84	**0.90**	0.09	0.24	0.32	**0.47**
MIN-K%	0.65	0.80	**0.90**	0.85	0.15	0.22	**0.39**	0.25

methods and does not require a specific fine-tuning technique. In addition, we also conduct experiments to explore the impact of different fine-tuning parameters on the performance of our method. The results are presented in Appendix D.3.

6 CONCLUSION

In this paper, we introduce Fine-tuned Score Deviation (**FSD**), a novel detection method that can universally improve the performance of existing detection methods. To the best of our knowledge, our method is the first to utilize some collected non-members in the task of pretraining data detection. Our core idea behind FSD is to enlarge the gap between seen examples and unseen examples by exposing the LLM to a few unseen examples. In effect, unseen data have a larger score than seen examples when using FSD, which makes it more distinguishable between seen and unseen data. Extensive experiments demonstrate the effectiveness of our method for detecting pretraining data on common benchmark datasets across various models. In summary, the FSD is an effective approach for accurately detecting pretraining data of LLMs.

Limitations Our method requires to collect a few examples that belong to the same domain but are not involved in the training. Generally, we can utilize the data content published after the release of the LLM. Therefore, our method is applicable for detecting benchmarks or copyrighted resources in a specific domain (e.g., math tests, magazines). The diversity of the test set may make it challenging to construct an effective auxiliary dataset of unseen data. In addition, the effectiveness of our method may reflect the distribution difference between members and non-members in existing popular benchmarks, which is inconsistent with the assumption of MIAs. It might be necessary to inspect the dataset splitting in the common benchmarks of detecting pretraining data.

Ethical Statement Our work focuses on pretraining data detection from large language models. The proposed methodology aims to address issues involving data contamination or copyright infringement. In addition, our method can be used to identify privacy potential privacy leakage risks and ensure the safety of LLMs, aligning with established ethical standards for content moderation. Regarding data access, the evaluated datasets we employed in our work come from prior research and do not involve personal privacy information.

REFERENCES

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Simone Balloccu, Patrícia Schmidtová, Mateusz Lango, and Ondřej Dušek. Leak, cheat, repeat: Data contamination and evaluation malpractices in closed-source llms. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 67–93, 2024.

Stella Biderman, Hailey Schoelkopf, Quentin Gregory Anthony, Herbie Bradley, Kyle O'Brien, Eric Hallahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, et al. Pythia: a suite for analyzing large language models across training and scaling. In *International Conference on Machine Learning*, pp. 2397–2430. PMLR, 2023.

Sidney Black, Stella Biderman, Eric Hallahan, Quentin Anthony, Leo Gao, Laurence Golding, Horace He, Connor Leahy, Kyle McDonell, Jason Phang, et al. Gpt-neox-20b: An open-source autoregressive language model. In *Proceedings of BigScience Episode# 5–Workshop on Challenges & Perspectives in Creating Large Language Models*, pp. 95–136, 2022.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, pp. 1877–1901, 2020.

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)*, pp. 2633–2650, 2021.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113, 2023.

Debeshee Das, Jie Zhang, and Florian Tramèr. Blind baselines beat membership inference attacks for foundation models. *arXiv preprint arXiv:2406.16201*, 2024.

Edoardo Debenedetti, Giorgio Severi, Nicholas Carlini, Christopher A Choquette-Choo, Matthew Jagielski, Milad Nasr, Eric Wallace, and Florian Tramèr. Privacy side channels in machine learning systems. In *33rd USENIX Security Symposium (USENIX Security 24)*, pp. 6861–6848, 2024.

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? *arXiv preprint arXiv:2402.07841*, 2024.

André Vicente Duarte, Xuandong Zhao, Arlindo L Oliveira, and Lei Li. De-cop: Detecting copyrighted content in language models training data. In *Forty-first International Conference on Machine Learning*, 2024.

Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, et al. The pile: an 800gb dataset of diverse text for language modeling. *arXiv preprint arXiv:2101.00027*, 2020.

Shahriar Golchin and Mihai Surdeanu. Time travel in llms: Tracing data contamination in large language models. In *The Twelfth International Conference on Learning Representations*, 2024.

Michael M Grynbaum and Ryan Mac. The times sues openai and microsoft over ai use of copyrighted work. *The New York Times*, 27, 2023.

Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022.

Yucheng Li. Estimating contamination via perplexity: quantifying memorisation in language model evaluation. *arXiv preprint arXiv:2309.10677*, 2023.

Gaoyang Liu, Chen Wang, Kai Peng, Haojun Huang, Yutong Li, and Wenqing Cheng. Socinf: membership inference attacks on social media health data with machine learning. *IEEE Transactions on Computational Social Systems*, (5):907–921, 2019.

Gaoyang Liu, Tianlong Xu, Rui Zhang, Zixiong Wang, Chen Wang, and Ling Liu. Gradient-leaks: enabling black-box membership inference attacks against machine learning models. *IEEE Transactions on Information Forensics and Security*, 2023.

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.

Inbal Magar and Roy Schwartz. Data contamination: From memorization to exploitation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 157–165, 2022.

Pratyush Maini, Hengrui Jia, Nicolas Papernot, and Adam Dziedzic. Llm dataset inference: did you train on my dataset? *arXiv preprint arXiv:2406.06443*, 2024.

Justus Mattern, Fatemehsadat Mireshghallah, Zhijing Jin, Bernhard Schoelkopf, Mrinmaya Sachan, and Taylor Berg-Kirkpatrick. Membership inference attacks against language models via neighbourhood comparison. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 11330–11343, 2023.

Maximilian Mozes, Xuanli He, Bennett Kleinberg, and Lewis D Griffin. Use of llms for illicit purposes: Threats, prevention measures, and vulnerabilities. *arXiv preprint arXiv:2308.12833*, 2023.

Yonatan Oren, Nicole Meister, Niladri S Chatterji, Faisal Ladhak, and Tatsunori Hashimoto. Proving test set contamination in black-box language models. In *The Twelfth International Conference on Learning Representations*, 2024.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems*, 32, 2019.

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.

Mathieu Ravaut, Bosheng Ding, Fangkai Jiao, Hailin Chen, Xingxuan Li, Ruochen Zhao, Chengwei Qin, Caiming Xiong, and Shafiq Joty. How much are llms contaminated? a comprehensive survey and the llmsanitize library. *arXiv preprint arXiv:2404.00699*, 2024.

Oscar Sainz, Jon Campos, Iker García-Ferrero, Julen Etxaniz, Oier Lopez de Lacalle, and Eneko Agirre. Nlp evaluation in trouble: On the need to measure llm data contamination for each benchmark. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 10776–10787, 2023.

Ahmed Salem, Yang Zhang, Mathias Humbert, 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 Symposium 2019*. Internet Society, 2019.

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*, 2024.

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)*, pp. 3–18. IEEE Computer Society, 2017.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

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 arXiv:2302.13971*, 2023a.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023b.

Stacey Truex, Ling Liu, Mehmet Emre Gursoy, Lei Yu, and Wenqi Wei. Demystifying membership inference attacks in machine learning as a service. *IEEE transactions on services computing*, 14 (6):2073–2089, 2019.

Ben Wang and Aran Komatsuzaki. GPT-J-6B: a 6 billion parameter autoregressive language model. https://github.com/kingoflolz/mesh-transformer-jax, May 2021.

Roy Xie, Junlin Wang, Ruomin Huang, Minxing Zhang, Rong Ge, Jian Pei, Neil Zhenqiang Gong, and Bhuwan Dhingra. Recall: Membership inference via relative conditional log-likelihoods. *arXiv preprint arXiv:2406.15968*, 2024.

Cheng Xu, Shuhao Guan, Derek Greene, M Kechadi, et al. Benchmark data contamination of large language models: A survey. *arXiv preprint arXiv:2406.04244*, 2024a.

Ruijie Xu, Zengzhi Wang, Run-Ze Fan, and Pengfei Liu. Benchmarking benchmark leakage in large language models. *arXiv preprint arXiv:2404.18824*, 2024b.

Wentao Ye, Jiaqi Hu, Liyao Li, Haobo Wang, Gang Chen, and Junbo Zhao. Data contamination calibration for black-box llms. *arXiv preprint arXiv:2405.11930*, 2024.

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)*, pp. 268–282. IEEE Computer Society, 2018.

Jingyang Zhang, Jingwei Sun, Eric Yeats, Yang Ouyang, Martin Kuo, Jianyi Zhang, Hao Yang, and Hai Li. Min-k%++: Improved baseline for detecting pre-training data from large language models. *arXiv preprint arXiv:2404.02936*, 2024.

Qingru Zhang, Minshuo Chen, Alexander Bukharin, Nikos Karampatziakis, Pengcheng He, Yu Cheng, Weizhu Chen, and Tuo Zhao. Adalora: adaptive budget allocation for parameter-efficient fine-tuning. *arXiv preprint arXiv:2303.10512*, 2023.

Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. Opt: open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*, 2022.

Kun Zhou, Yutao Zhu, Zhipeng Chen, Wentong Chen, Wayne Xin Zhao, Xu Chen, Yankai Lin, Ji-Rong Wen, and Jiawei Han. Don't make your llm an evaluation benchmark cheater. *arXiv preprint arXiv:2311.01964*, 2023.

A RELATED WORK

Pretraining data detection, which is an increasingly important topic for large language models, relates to a large amount of literature on membership inference attacks and data contamination. We discuss some of the relevant works to ours in two directions below.

Membership Inference Attacks Our work mainly studies how to detect a given example in the pretraining data, which is consistent with the objective of membership inference attacks (MIAs) (Shokri et al., 2017; Truex et al., 2019). This task aims to determine whether a given data point is a member of training data. Metric-based attack methods, such as loss (Yeom et al., 2018), entropy (Salem et al., 2019), confidence (Liu et al., 2019) and gradient (Liu et al., 2023), infer membership of data by comparing the calculated metric value with a preset threshold. Previous works have generalized metric-based methods to large language models (Duan et al., 2024; Xie et al., 2024; Zhang et al., 2024; Mattern et al., 2023), by calculating the based-likelihood metric (e.g., perplexity) for membership inference. Recent works apply MIAs to pretraining data detection by designing likelihood-based scoring functions to measure the membership of data (Shi et al., 2024; Ye et al., 2024). In this work, we analyze the limitations of existing scoring functions for pretraining data detection, and design an effective method to improve their performance. In particular, this work is the first to explore the importance of collecting unseen data in pretraining data detection.

Data Contamination Data contamination has been studied in the literature (Xu et al., 2024a; Magar & Schwartz, 2022; Balloccu et al., 2024), where training data may inadvertently include evaluation benchmark data, resulting in unauthentic evaluation results. Thus, it is important to assess the leakage of benchmark data into pretraining data (Zhou et al., 2023). On the one hand, model developers can remove evaluation benchmark data from training data by retrieval-based methods with access to pertaining data (Ravaut et al., 2024; Chowdhery et al., 2023). Specifically, those methods employ n-gram tokenization and string-matching for detecting data contamination (Brown et al., 2020; Touvron et al., 2023b; Team et al., 2023; Radford et al., 2019). On the other hand, researchers utilize prompting techniques (Golchin & Surdeanu, 2024), performance analysis (Ye et al., 2024; Debenedetti et al., 2024), model likelihood (Oren et al., 2024; Shi et al., 2024; Xu et al., 2024b) to detect potential contamination without access to the training data. Our work focuses on pretraining data detection, an area that is similar to data contamination. Different from data contamination detection, our FSD can also be applied to the detection of copyrighted resources in real-world scenarios.

B DETAILS OF DATASETS

Previous works construct benchmark datasets to evaluate the performance of detection methods for pretraining data detection. Following the prior literature, we conduct experiments on 4 benchmark datasets: WikiMIA (Shi et al., 2024) selects old Wikipedia event data as member data by leveraging the Wikipedia data timestamp and the model release date, since Wikipedia is a commonly pretraining data source. BookMIA (Shi et al., 2024), which contains excerpts from copyrighted books in the Books3 subset of the Pile dataset (Gao et al., 2020), can be used for detecting potential copyright infringement in training data. ArXivTection (Duarte et al., 2024) is a curated collection of research articles sourced from arXiv. BookTection (Duarte et al., 2024), which comprises passages from 165 books, is constructed based on BookMIA.

C EXPERIMENTAL DETAIL

C.1 DATASET SPLIT

We report the performance of detection methods on WikiMIA and ArXivTection datasets across various large language models. To construct the fine-tuning dataset, we randomly split 30% of the dataset using a seed of 42 and select all non-members from this subset. The remaining 70% of the dataset is used for testing. The detailed information of the constructed dataset is shown in Table 7.

Table 7: The train set and test set used in the experiment

Dataset	Type	Member	Non-member	Total
WikiMIA	Train Set	\	231	231
	Test Set	599	558	1,157
ArXivTection	Train Set	\	238	238
	Test Set	536	549	1,085

C.2 COPYRIGHTED BOOK DETECTION

To conduct experiments of copyrighted book detection on BookMIA and BookTection, we randomly split 30% of the dataset using a seed of 42 and select all non-members from this subset as the fine-tuning dataset. Subsequently, we randomly sample 500 members and non-members from the remaining 70% of the datasets, constructing a balanced validation set of 1,000 examples. The remaining data is used for testing. The detailed information dataset split is shown in Table 8.

Table 8: The train set, test set and validation set used in the experiment

Dataset	Type	Member	Non-member	Total
BookMIA	Train Set	\	1,413	1,413
	Test Set	2,887	3,022	5,909
	Validation set	500	500	1,000
BookTection	Train Set	\	1,796	1,796
	Test Set	6,833	3,657	10,490
	Validation set	500	500	1,000

C.3 FINE-TUNING WITH MEMBERS

To investigate the impact of model fine-tuning with different fine-tuning datasets on pretraining data detection, we construct three kinds of fine-tuning datasets. In this ablation, we sample members (**Mem**) and non-members (**Non**) from WikiMIA as fine-tuning datasets, respectively. In addition, we randomly sample data from WikiMIA to construct a fine-tuning dataset (**All**). The details of fine-tuning datasets are shown in Table 9

Table 9: The train set and test set used in the experiment

Datasets	Type	Member	Non-member	Total
Mem	Train Set	262	\	262
	Test Set	599	558	1,157
Non	Train Set	\	231	231
	Test Set	599	558	1,085
All	Train Set	262	231	493
	Test Set	536	549	1,085

C.4 TEMPORAL SHIFT

We show the temporal shift between members and non-members in the WikiMIA dataset, the illustration is presented in Table 10.

Table 10: An illustration of temporal shift between the member and non-member distributions.

Members	Non-Members
The 2014 On 30 June or 2 July 2014, the Armed Forces of the Democratic Republic of the Congo and United Nations forces launched an offensive against rebel groups in the Masisi and Walikale.	The 95th Academy Awards was a ceremony held by the Academy of Motion Picture Arts and Sciences (AMPAS) on March 12, 2023, at the Dolby Theatre in Los Angeles.
In 2014, a series of groundbreaking diplomatic meetings was held between Wang Yu-chi, in his official capacity as the Minister of the Mainland Affairs Council (MAC) of the Republic of China (ROC).	The 36th Annual Nickelodeon Kids' Choice Awards ceremony was held on March 4, 2023, at the Microsoft Theater in Los Angeles, California with Nate Burleson and Charli D'Amelio.
Concluding observations on the second periodic report of the Holy See was a 2014 report issued by the Office of the United Nations High Commissioner for Human Rights.	The 2023 Summer Metro Manila Film Festival is an ongoing iteration of the annual Summer Metro Manila Film Festival held in Metro Manila and throughout the Philippines.
The 2014 European Aquatics Championships took place from 13 to 24 August 2014 in Berlin, Germany.	On February 11, 2023, an octagonal unidentified flying object was detected over northern Montana.
The centenary of the outbreak of World War I was commemorated in Europe in late July and early August 2014.	The 2023 Tokyo Marathon was the 16th edition of the annual marathon race in Tokyo, held on Sunday, 5 March 2023.

D Detailed Experimental Results

D.1 Fine-tuned Score Deviation

We show in Figure 5 the score distribution between members and non-members using various scoring functions on ArXivTection. The results also demonstrate that our FSD score significantly increases the gap between non-members and members compared to the perplexity and Min-k% scores, thus enabling more effective pretraining data detection.

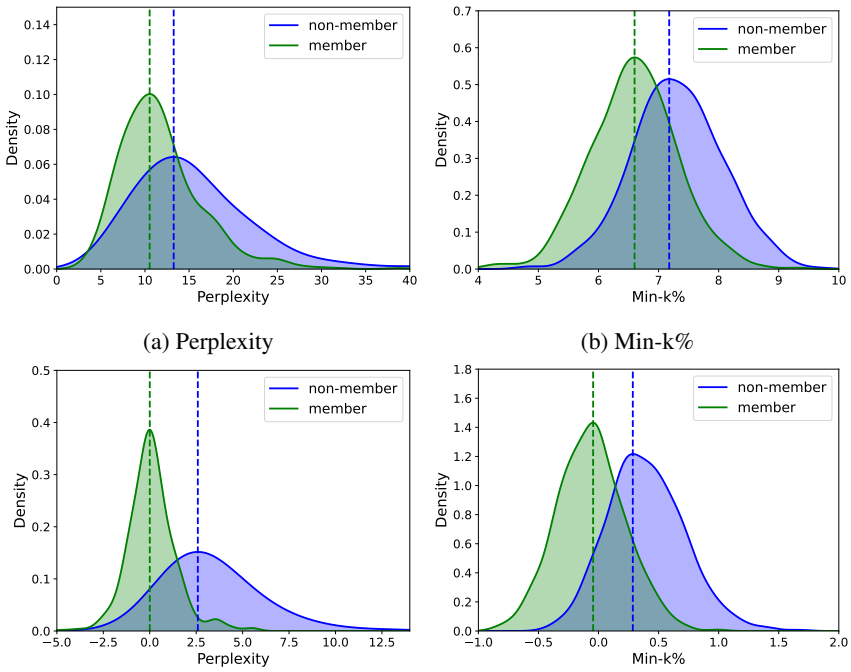
D.2 Detailed results of experiment

We report the TPR@5%FPR score for pertaining data detection in Table 11, 12, 13.

Can FSD improve the performance of detection methods based on scoring functions? We compare the TPR@5%FPR score with our method and baselines on WikiMIA and ArXivTection datasets across various large language models in Table 11. The results show that our method significantly improves the TPR@5%FPR score of the baseline methods.

Is FSD effective with different-sized models? We verify the performance of baselines and our methods from different-sized LLaMA models (7B, 13B, 30B) on WikiMIA. In Table 12, we show the TPR@5%FPR score from different-sized LLaMA models. The results demonstrate that our method is effective with different-size models.

Is our method affected by distribution difference? We report the TPR@5%FPR score of baselines and our method on the original WikiMIA dataset, Deletion and Replacement. In Table 13, the results show that our method still improves the performance of baselines when mitigating the temporal shift between members and non-members.



(a) Perplexity (b) Min-k%

(c) FSD with Perplexity (d) FSD with Min-k%

Figure 5: Distribution of scores from pre-trained model vs. FSD. We contrast the score distribution from the pre-trained model using perplexity and our FSD with perplexity(a & c). Similarly, we contrast the Min-k% scores distribution from the pre-trained model and our FSD (b & d). Using FSD leads to enlarging the gap between members and non-members.

Table 11: TPR@5%FPR score for pretraining data detection with baselines and our method from various models on WikiMIA and ArXivTection. *Base* and ***+Ours*** respectively denote the baseline methods and our method. Bold shows the superior result.

Dataset	**Method**	**GPT-J-6B**		**OPT-6.7B**		**Pythia-6.9B**		**LLaMA-7B**		**NeoX-20B**	
		Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
WikiMIA	Perplexity	0.12	**0.78**	0.12	**0.63**	0.13	**0.66**	0.09	**0.41**	0.20	**0.58**
	Lowercase	0.12	**0.24**	0.07	**0.18**	0.11	**0.25**	0.10	**0.18**	0.16	**0.18**
	Zlib	0.09	**0.78**	0.09	**0.55**	0.10	**0.50**	0.09	**0.47**	0.10	**0.57**
	MIN-K%	0.17	**0.40**	0.14	**0.50**	0.17	**0.35**	0.15	**0.25**	0.25	**0.36**
ArXivTection	Perplexity	0.26	**0.79**	0.12	**0.63**	0.25	**0.66**	0.10	**0.81**	0.27	**0.77**
	Lowercase	0.13	**0.23**	0.15	**0.22**	0.15	**0.25**	0.09	**0.16**	0.13	**0.20**
	Zlib	0.15	**0.80**	0.07	**0.60**	0.14	**0.50**	0.08	**0.66**	0.16	**0.77**
	MIN-K%	0.42	**0.57**	0.24	**0.45**	0.41	**0.35**	0.24	**0.45**	0.40	**0.58**

D.3 ADDITIONAL RESULTS

The performance of our method on different subsets of the Pile dataset We also conduct experiments on the Pile dataset. Concretely, following prior work (Maini et al., 2024), we evaluate our methods on the different subsets of the Pile dataset. Here, the validation set of the pile dataset was not trained on the Pythia models (Biderman et al., 2023). Thus, we perform experiments on the

Table 12: TPR@5%FPR score for pretraining data detection with baselines and our method from the different-sized LLaMA model on WikiMIA. *Base* and ***+Ours*** respectively denote the baselines and our method. Bold shows the superior result.

Method	LLaMA-7B		LLaMA-13B		LLaMA-30B	
	Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
Perplexity	0.09	**0.41**	0.11	**0.61**	0.15	**0.40**
Zlib	0.10	**0.18**	0.13	**0.13**	0.11	**0.25**
Lowercase	0.09	**0.47**	0.10	**0.56**	0.11	**0.44**
MIN-K%	0.15	**0.25**	0.18	**0.26**	0.19	**0.20**

Table 13: TPR@5%FPR score from the LLaMA-7B model with our method and baselines using the original WikiMIA, data removing timestamps (Deletion), and data replacing the year of timestamps with 2023 (Replacement). *Base* and ***+Ours*** denote the baseline methods and our method, respectively. **Bold** shows the superior result.

Method	Origin		Deletion		Replacement	
	Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
Perplexity	0.09	**0.41**	0.13	**0.23**	0.04	**0.12**
Lowercase	0.10	**0.18**	0.06	**0.13**	0.03	**0.15**
Zlib	0.09	**0.47**	0.12	**0.23**	**0.09**	0.06
MIN-K%	0.15	**0.25**	0.10	**0.14**	0.04	**0.07**

Pythia-6.9B model, utilizing the training and validation sets as members and non-members, respectively. For each dataset, we randomly sample a few non-members with a sample ratio of 0.3 from the validation set for fine-tuning. Then, we evaluate our method on a balanced dataset composed of 1400 members and 1400 non-members.

In Table 14, the results show that our method improves the performance of baselines on the Pile dataset under the Pythia-6.9B model. For example, our FSD improves the AUC score of the perplexity-based method from 0.528 to 0.885, a significant direct improvement of 67%. This demonstrates the effectivenss of our method in the IID setup.

Table 14: AUC score for pretraining data detection with baselines and our method from the Pythia-6.9B on on three subsets of the Pile dataset. *Base* and ***+Ours*** respectively denote the baseline methods and our method. **Bold** shows the superior result.

Method	**Wiki**		**BookC2**		**Gutenberg**	
	Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
Perplexity	0.471	**0.614**	0.528	**0.885**	0.528	**0.661**
Lowercase	0.466	**0.626**	0.518	**0.725**	0.546	**0.551**
Zlib	0.496	**0.619**	0.477	**0.907**	0.496	**0.686**
MIN-K%	0.512	**0.611**	0.510	**0.841**	0.536	**0.612**

Fine-tuning using non-members from different domains Our method requires a few non-member data from a specific domain for fine-tuning. This raises a question: *how does our method perform when fine-tuned on non-member data from a different domain?* To investigate the performance of our method when fine-tuning using data from an unrelated domain. Firstly, we randomly sample 231 and 238 non-members from the WikiMIA and ArXivTection datasets to construct a fine-tuning dataset comprising a mix of domains. Then, we fine-tune the LLaMA-7B model on the constructed dataset and evaluate our method on WikiMIA and ArXivTection datasets.

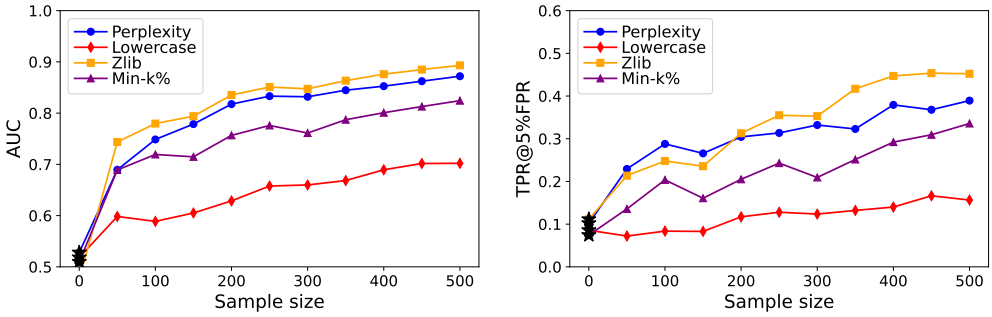
Table 15: AUC score for pretraining data detection with baselines and our method on WikiMIA and ArXivTection under the LLaMA-7B. Wiki (Mix) denote evaluating on WikiMIA and fine-tuning using data from a mix of domains. ArXiv (Wiki) denote evaluating on ArXivTection and fine-tuning on WikiMIA. *Base* and ***+Ours*** respectively denote the baseline methods and our method.

Method	Wiki (Mix)		ArXiv (Mix)		ArXiv (Wiki)	
	Base	***+Ours***	*Base*	***+Ours***	*Base*	***+Ours***
Perplexity	0.64	**0.91**	0.68	**0.93**	**0.68**	0.52
Lowercase	0.58	**0.73**	0.50	**0.73**	0.50	0.50
Zlib	0.62	**0.91**	0.57	**0.92**	0.57	**0.64**
MIN-K%	0.65	**0.84**	0.76	**0.87**	**0.76**	0.61

Our results in Table 15 show that our method can also significantly improve the performance of baselines, indicating the effectiveness of our methods when fine-tuning with non-members from a mix of domains. We also evaluate our methods on ArXivTection, while fine-tuning using non-members from WikiMIA. The results indicate that our method fails to improve the performance of baselines, since the fine-tuning data comes from an entirely unrelated domain to the evaluation data.

Ablation study on the BookC2 under varying the fine-tuning data size To investigate the effect of varying the fine-tuning data size on the pretraining data detection, we also conduct experiments on the BookC2 subset of the Pile dataset under the Pythia-6.9B model. Specifically, we randomly sample varying amounts of non-members (0, 50, 100, 150, 200, 250, 300, 350, 400, 450, 500) from the validation set of the BookC2 as fine-tuning datasets. In addition, we sample 1400 members and non-members from the train and validation sets of the BookC2 to construct a balanced test set of 2800 examples.

Figure 6a shows that our method achieves better performance as the size of the fine-tuning dataset increases. Notably, our method is highly data-efficient, achieving significant improvements with only a few non-members for fine-tuning. For instance, our method improves the AUC score of the Zlib method from 0.48 to 0.78, by leveraging only 100 non-member data for fine-tuning. In addition, the results of the TPR@5%FPR score show a similar trend, which can be found in Figure 6b.



(a) AUC (b) TPR@5%FPR

Figure 6: AUC and TPR@5%FPR of scoring functions with FSD, using auxiliary datasets with varying sizes. Notably, ★ represents the baseline without FSD.

How do the fine-tuning parameters affect the performance of our method? To investigate the impact of different fine-tuning parameters on the performance of our method, we conduct experiments on the WikiMIA dataset with different fine-tuning parameters, including learning rate (e.g. 1e-3, 1e-4, 1e-5), epoch (e.g. 1, 2, 3) and LoRA rank (e.g. 8, 16, 32). In Table 16, the results show that our method is relatively insensitive to LoRA rank and the number of fine-tuning epochs.

However, considering the learning rate parameter, a learning rate of 0.001 enables our method to perform better.

Table 16: AUC score of baselines and our method on WikiMIA under the LLaMA-7B with different fine-tuning parameters. *Base* and ***+Ours*** respectively denote the baseline methods and our method. **Bold** shows the superior result.

Method	Learning Rate				LoRA Rank				Epoch			
	Base	10^{-5}	10^{-4}	10^{-3}	*Base*	**8**	**16**	**32**	*Base*	**1**	**2**	**3**
Perplexity	0.64	0.81	0.84	**0.92**	0.64	0.92	0.92	0.92	0.64	0.91	0.91	**0.92**
Lowercase	0.58	0.60	0.64	**0.69**	0.58	0.69	0.68	0.69	0.58	0.65	0.64	**0.69**
Zlib	0.62	0.73	0.78	**0.90**	0.62	0.91	0.90	0.90	0.62	0.87	0.87	**0.90**
MIN-K%	0.65	0.76	0.81	**0.85**	0.65	0.87	0.85	0.86	0.65	0.86	**0.87**	0.86