From Unfamiliar to Familiar: Detecting Pre-training Data via Gradient Deviations in Large Language Models

Anonymous ACL submission

Abstract

Pre-training data detection for LLMs is essential for addressing copyright concerns and mitigating benchmark contamination. Existing methods mainly focus on the likelihood-based statistical features or heuristic signals before and after fine-tuning, but the former are susceptible to word frequency bias in corpora, and the latter strongly depend on the similarity of fine-tuning data. From an optimization perspective, we observe that during training, samples transition from unfamiliar to familiar in a manner reflected by systematic differences in gradient behavior. Familiar samples exhibit smaller update magnitudes, distinct update locations in model components, and more sharply activated neurons. Based on this insight, we propose GDS, a method that identifies pre-training data by probing Gradient Deviation Scores of target samples. Specifically, we first represent each sample using gradient profiles that capture the magnitude, location, and concentration of parameter updates across FFN and Attention modules, revealing consistent distinctions between member and non-member data. These features are then fed into a lightweight classifier to perform binary membership inference. Experiments on five public datasets show that GDS achieves state-of-the-art performance with significantly improved cross-dataset transferability over strong baselines. Further interpretability analyses reveal differences in gradient distributions, and the semi-supervised results offer a practical way to detect pre-training data.

1 Introduction

Large language models (LLMs) performance scales with the size and quality of pre-training data (Kaplan et al., 2020). As pre-training corpora expand to trillions of tokens and become increasingly proprietary and non-transparent, they raise significant concerns, such as unauthorized copyright, biased or harmful content, and contamination of evaluation benchmarks (Balloccu et al., 2024; Grynbaum and Mac, 2023). These challenges motivate a specialized task of membership inference attacks, named pre-training data detection: determining whether a given text sample was included in a model's pre-training corpus (Carlini et al., 2021).

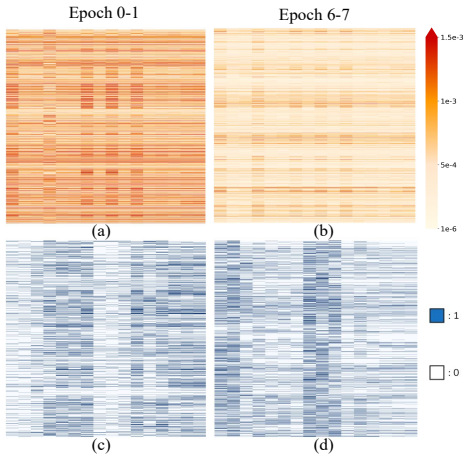


Figure 1: Heat maps of gradient matrices from unfamiliar model(a, c) and familiar model(b, d). Panels a and b display the update magnitude of the FFN module in layer 30, while panels c and d illustrate the update positions, with white for sparse and blue for core updates.

Recent studies (Carlini et al., 2021; Li; Shi et al., 2024; Zhang et al., 2025) primarily use unsupervised likelihood-based statistical features to detect pre-training samples. For example, the Min-K method (Shi et al., 2024; Zhang et al., 2025) examines the k% of tokens with the lowest predicted probabilities, assuming non-member texts contain more low-likelihood tokens. However, these approaches are susceptible to word frequency bias in pre-training corpora, specifically for rare words or short texts scenarios. To improve detection accuracy, other researchers (Zhang et al.; Choi et al.) propose some supervised methods to analyze heuristic signals before and after fine-tuning, leveraging the fact that fine-tuning impacts member and non-member samples differently. For example, KDS (Choi et al.) shows that non-member

datasets exhibit much larger embedding changes, while FSD (Zhang et al.) finds that their loss reductions are also significantly greater. Nevertheless, these supervised methods rely on the strong assumption that fine-tuning data closely match the target samples' distribution, requiring additional training on similar non-member data and thereby limiting cross-dataset generalization. Therefore, how to achieve both high accuracy and strong generalization performance remains an open challenge for pre-training data detection task.

Optimization theory (Ruder, 2016; Frankle et al.; Wang et al., 2024) suggests that training samples undergo a shift in gradient behavior as they move from unfamiliar to familiar. That is, pre-training member data and non-member data induce distinct gradients in target LLMs. Motivated by this, we compare LLMs gradient behaviors on familiar and unfamiliar data[1], and observe clear differences in magnitude, location, and concentration, as illustrated in Figure 1 and Section 3. (1) **Decay of update magnitude.** Figure 1(a,b) shows that parameter updates are strongly attenuated as data grows familiar, consistent with loss-convergence theory (Bottou, 2010; Ruder, 2016). (2)**Gradually stabilizing of update locations.** Figure 1(c,d) shows that parameter updates evolve from broad activation regions to a stable core set of neurons, consistent with the sparse activation behavior of LLMs (Liu et al., 2024). (3)**Increasing update sparsity.** Figure 1(a,b) and Figures 2(b,c) show that during training, an increasing fraction of updates concentrates in the top 10% of neurons, consistent with Hessian spectrum reshaping during loss convergence (Gur-Ari et al., 2018). Familiar data yields sparse, concentrated updates, whereas unfamiliar data leads to more distributed updates. Therefore, we can utilize these training dynamics and phase-shifted updates to support more generalizable pre-training data detection.

In this paper, we propose GDS, a novel pre-training data detection method that infers pre-training data by probing Gradient Deviation Scores of target samples without fine-tuning. GDS exploits gradient differences between member and non-member samples to train a lightweight classifier with strong generalization. Specifically, within the LoRA framework, we collect per-sample gradients across layers during backpropagation, encoding them as eight-dimensional features that capture the magnitude, location, and concentration of updates. Compared to non-members, member samples show smaller matrix-level and row-wise update magnitudes, lower FFN but higher attention eccentricity, greater variability in matrix-level and row-wise updates, a higher share of top gradients, and fewer sparse neurons. Then, we extract discriminative statistics from the signals to build fixed-dimensional features, which are fed to a lightweight MLP for binary membership classification.[2] Our contributions are as follows:

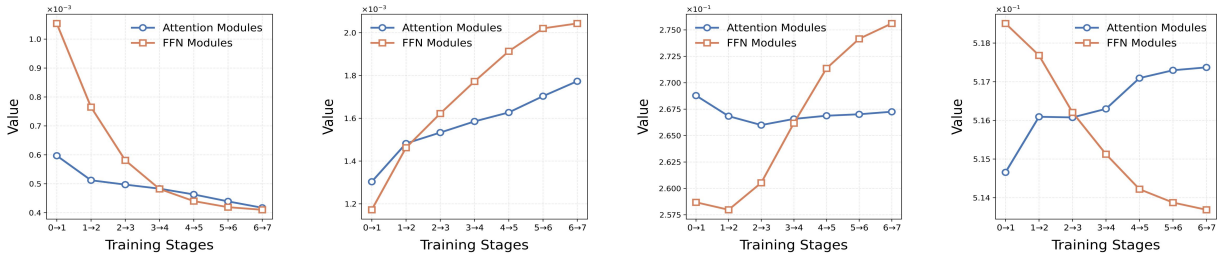
- From a training optimization perspective, we analyze how LLMs evolve from unfamiliarity to familiarity with data and propose using stage-wise parameter update dynamics to identify pre-training data, offering a novel direction to solve this task.
- We propose gradient deviation features capturing magnitude, location, and concentration, and introduce a gradient deviation score–based method for pre-training data detection without fine-tuning.
- Extensive experiments across diverse datasets and backbone models validate the effectiveness and generalization of GDS, while interpretability analyses and semi-supervised results offer a practical way to data detection.

2 Related Work

Unsupervised Likelihood-Based Methods. Early works distinguish member and non-member samples by capturing static statistical metrics in token-level likelihood distributions. Global-likelihood–based methods, such as PPL (Li), Zlib (Carlini et al., 2021), and Lowercase (Carlini et al., 2021), perform discrimination by exploiting global probability features, compression entropy, and case-conversion ratios. However, global likelihood is highly sensitive to word-frequency effects, leading to unstable performance. Min-k% (Shi et al., 2024) and Min-k%++ (Zhang et al., 2025) mitigate global dependence by focusing on low-probability outlier tokens or target–candidate probability comparisons, with k and text length jointly determining the analyzed token subset. However, the fixed choice of k lacks adaptivity, causing severe score fluctuations in short texts with

[1] Due to unavailable publish time, original LLaMA-7B is treated as unfamiliar model to unseen BookMIA data, while 7-epoch pre-training on them defines the familiar model.

[2] https://anonymous.4open.science/r/emnlp-pdd-7C1A/



(a) $\Delta\Theta_t$ (b) S_t (c) $T_{10,t}$ (d) E_t

Figure 2: Dynamic curves of four parameter update characteristics defined in the Motivation section. $i \to j$ denotes the epoch interval. Ordinate shows values of predefined characteristics, with orange and blue representing Attention and FFN modules.

low-frequency words. Although PC-PDD (Zhang et al., 2024) approximates the word-frequency distribution of pretraining corpora using public datasets, these references lack fidelity due to limited domain coverage. These unsupervised methods are effective in practice, but they often hit a performance ceiling in complex scenarios.

Supervised Fine-tuning Methods. Recent studies (Zhang et al.; Choi et al.) adopt lightweight fine-tuning to actively amplify asymmetric differences between member and non-member samples. KDS (Choi et al.) evaluates dataset contamination by comparing kernel similarity matrices of embeddings before and after fine-tuning, assuming non-member datasets undergo larger embedding changes than member datasets. However, it only estimates dataset-level contamination and cannot reliably detect contamination at the sample-level. Another representative method FSD (Zhang et al.) detects membership by comparing loss before and after fine-tuning, assuming non-member samples experience a larger loss reduction than member samples. Nevertheless, these methods assume that fine-tuning data closely matches the target distribution, requiring additional tuning on similar non-members, limiting cross-dataset generalization.

3 Motivation

Inspired by optimization theory (Ruder, 2016; Bottou, 2010), we investigate how LLMs shift from unfamiliarity to familiarity with data and how this process relates to the dynamics of model parameters during training. To this end, we fine-tune LLaMA-7B with LoRA on the unseen split of BookMIA and track LoRA updates over 7 epochs. Stage-wise analysis in Figure 2 shows the evolution of gradient features. We observe that models familiar with test data exhibit smaller, sparser, and more stable gradient updates, which motivates our Gradient Deviation Score for membership detection.

3.1 Decay of Update Magnitude

Model training aims to minimize the loss function $L(\theta)$, with update magnitude determined by the gradient norm $\|\nabla L(\theta)\|$. According to optimization convergence theory (Ruder, 2016), as the parameters θ_t approach the optimum θ^*, the gradient norm of the loss function vanishes, i.e., $\lim_{\theta\to\theta^*} \|\nabla L(\theta_t)\| = 0$. This causes the parameter update magnitude to decrease synchronously. Therefore, we use $\Delta\theta_t$ as the core indicator of the **average update magnitude** across all trainable parameters at iteration t:

$$\Delta\theta_t = \frac{1}{N}\sum_{i=1}^{N} |\theta_{t,i} - \theta_{t-1,i}|\,, \tag{1}$$

where N denotes the total number of parameters.

As training progresses, both the loss $L(\theta_t)$ and gradient norm $\|\nabla L(\theta_t)\|$ decrease, reducing the update magnitude $\Delta\theta_t$. Eventually, $L(\theta_t)$ stabilizes near its minimum, parameter updates $\Delta\theta_t$ become negligible. As shown in Figure 2a, the mean update magnitude decreases monotonically with training, with the largest changes occurring in the first two epochs, consistent with loss convergence.

3.2 Gradually Stabilizing of Update Locations

Studies (Liu et al., 2024; Tang et al., 2025) have shown that neural activations occur at different locations when processing member and non-member samples. Inspired by this, we adopt the **parameter update eccentricity** as the core indicator, which quantifies the deviation of the top-10% parameter update positions from the global parameter centroid. We first define the global centroid as:

$$\theta_c = \frac{1}{N}\sum_{i=1}^{N} \theta_i, \tag{2}$$

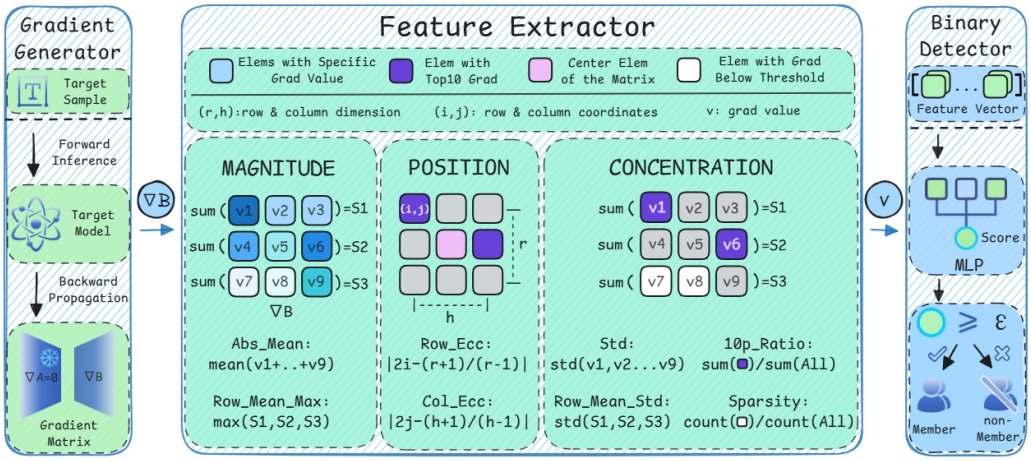


Figure 3: Overview of Gradient Deviation Scores method.

where θ_i is the **coordinate** of the i-th parameter.

The update eccentricity at iteration t is then defined as:

$$E_t = \frac{1}{\text{card}(U_{10,t})} \sum_{\theta_i \in U_{10,t}} \|\theta_i - \theta_c\|_2 \,, \quad (3)$$

where $\text{card}(\cdot)$ denotes the number of elements in a set, $U_{10,t} = \{\|\Delta\theta_{t,i}\|_1 \in \text{Top10\%}(\|\Delta\theta_t\|_1)\}$, $\|\cdot\|_1$ denotes the ℓ_1 norm and $\|\cdot\|_2$ denotes the ℓ_2 norm.

In the initial training stage, activation patterns are unstable, leading to scattered $U_{10,t}$ and thus random large values of E_t. As training proceeds, the model identifies core parameters related to data features: θ_t stabilizes to the optimal subset θ^*, and $U_{10,t}$ converges to the core parameter region, resulting in E_t gradually stabilizing at a low level. Figure 2d shows that the eccentricity of parameter update evolves to a relatively stable value, consistent with the evolution of the neuron activation pattern, suggesting that training identifies the core parameters and stabilizes updates around them.

3.3 Increasing Update Sparsity

The Hessian spectrum (Gur-Ari et al., 2018; Frankle et al.) characterizes the curvature of the loss landscape, which governs the direction and efficiency of parameter updates. For loss $L(\theta)$, its Hessian matrix $\mathcal{H}(\theta) = \nabla^2 L(\theta)$ admits the eigenvalue decomposition:

$$\mathcal{H}(\theta) = U \Lambda U^T, \quad (4)$$

where U and Λ denote the orthogonal eigenvectors and eigenvalues, respectively. During training, the Hessian spectrum evolves from nearly uniform eigenvalues to a structure dominated by a few large values with most approaching zero.

This reshaping yields concentrated parameter updates, focusing on directions with large eigenvalues while leaving most others nearly unchanged, motivating our two joint indicators. S_t measures the fraction of parameters with negligible updates ($< 10^{-6}$) at iteration t, and $T_{10,t}$ denotes the fraction of total update magnitude contributed by the top 10% largest updates.

$$S_t = \frac{\text{card}\left(i \mid |\Delta\theta_{t,i}| < 10^{-6}\right)}{N}, \quad (5)$$

$$T_{10,t} = \frac{\sum_{|\Delta\theta_{t,i}| \in U_{10,t}} |\Delta\theta_{t,i}|}{||\Delta\theta_t||_1}. \quad (6)$$

As training progresses, parameter updates increasingly concentrate along core directions. Consequently, S_t gradually increases, while $T_{10,t}$ remains relatively large and stable(0.26–0.27), indicating that update energy is consistently dominated by a small subset of parameters. Figures 2b and 2c confirm this growing sparsity and stable Top 10% contribution. Further details on the variation trends of the three metrics are provided in the appendix B.

4 Method

4.1 Task Definition

Given a target text x and a target LLM f_θ pre-trained on a corpus D, the goal of pre-training data detection task is to construct a detector $h(x, f_\theta)$ to determine whether x belongs to D. This task can be formalized as a binary classification problem: $h(x, f_\theta) \rightarrow \{0, 1\}$ where "1" indicates $x \in D$ as member and "0" indicates $x \notin D$ as non-member.

As illustrated in Figure 3, GDS comprises three stages: gradient matrix acquisition, feature vector extraction and light Multilayer Perceptron(MLP) training. For each training sample, we perform

inference and backpropagation to obtain LoRA gradients across l layers and m sub-modules, yielding $l \times m$ gradient matrices $\mathbb{G}$. From these matrices, we extract eight-dimensional features to form a gradient feature vector $\mathbb{V}^{l \times m \times 8}$, which is used to train a MLP classifier for binary membership prediction. During inference, the same feature extraction process is applied to a target sample x^*, and the resulting feature vector is fed into the trained MLP to produce the final classification result.

4.2 Gradient Matrix Acquisition

Given the target model f_θ and training sample x, we first initialize f_θ with LoRA, yielding $l \times m$ LoRA matrices $\mathbb{L}$. We then feed a single sample x into f_θ for forward inference and backpropagation, obtaining LoRA gradient matrices $\mathbb{G} = \nabla_{\mathbb{L}} \mathcal{L}_{\text{CLM}}(f_\theta(x))$, where $\mathcal{L}_{\text{CLM}}$ denotes the causal language modeling loss of the pre-trained LLM. Since the LoRA_B matrices are fully initialized to zero, a single round of gradient propagation leads to zero gradients for the LoRA_A matrices. Thus, we only collect the gradient matrices of LoRA_B for subsequent processing.

4.3 Feature Vector Extraction

Given the gradient matrices $\mathbb{G}$, we extract features based on the three parameter update trends introduced in Section 3.

4.3.1 Magnitude

We propose two magnitude indicators to measure the overall scale of gradient updates in the LoRA parameter space.

(1) Absolute Mean: The mean of the absolute values of all elements in the gradient matrix, which characterizes the overall parameter update strength:

$$\text{Abs_Mean} = \frac{1}{r \cdot h} \sum_{i=1}^{r} \sum_{j=1}^{h} |\mathbb{G}_{i,j}|, \tag{7}$$

where $\mathbb{G}_{i,j}$ denotes the element in the i-th row and j-th column of the gradient matrix with r rows and h columns.

(2) Max Row Mean: The mean of each row in the LoRA matrix and take the maximum value, which characterizes the most sample-responsive local optimal response dimension with the largest parameter update magnitude:

$$\text{Row_Mean_Max} = \max_{1 \le i \le r} \left(\frac{1}{h} \sum_{j=1}^{h} |\mathbb{G}_{i,j}| \right). \tag{8}$$

4.3.2 Position

Screen the top 10% of gradient elements by absolute value from $\mathbb{G}$ and calculate their offset from this matrix center, capturing offset characteristics of core gradient positions for **(1) Row Eccentricity** and **(2) Column Eccentricity**, respectively:

$$\text{Row_Ecc} = \frac{1}{\text{card}(S)} \sum_{(i,j) \in S} \left| \frac{2i - (r+1)}{r-1} \right|, \tag{9}$$

$$\text{Col_Ecc} = \frac{1}{\text{card}(S)} \sum_{(i,j) \in S} \left| \frac{2j - (h+1)}{h-1} \right|, \tag{10}$$

where $S = \{(i,j) \mid |\mathbb{G}_{i,j}| \in \text{Top10\%}(|\mathbb{G}|)\}$ denotes the set of indices for the top 10% of elements in the gradient matrix $\mathbb{G}$ ranked by absolute gradient value. Top gradients near the center correspond to an eccentricity of 0, while those near the edge correspond to a score of 1.

4.3.3 Concentration

We propose four indicators to measure the concentration of gradient distributions.

(1) Top-10% Ratio: The ratio of the sum of the top 10% largest gradient magnitudes to the total update magnitude of the gradient matrix, which quantifies the contribution ratio of core gradients:

$$\text{10p_Ratio} = \frac{\sum_{(i,j) \in S} |\mathbb{G}_{i,j}|}{\|\mathbb{G}\|_1}, \tag{11}$$

(2) Sparsity: The proportion of gradient elements with absolute values less than 10^{-6}, quantifying the sparsity degree of gradient distributions:

$$\text{Sparsity} = \frac{\text{card}\left(\{(i,j) \mid |\mathbb{G}_{i,j}| < 10^{-6}\}\right)}{r \cdot h}. \tag{12}$$

(3) Standard Deviation: The standard deviation of the elements in the gradient matrix, which quantifies the dispersion degree of parameter updates:

$$\text{Std} = \sqrt{\frac{1}{r \cdot h} \sum_{i=1}^{r} \sum_{j=1}^{h} \left(|\mathbb{G}_{i,j}| - \text{Abs_mean}\right)^2}. \tag{13}$$

(4) Row Mean Standard Deviation: The mean of each row in the LoRA matrix and take the standard deviation, which quantifies the consistency of update strength across all rows:

$$\text{Row_Mean_Std} = \sqrt{\frac{1}{r} \sum_{i=1}^{r} \left(\bar{\mathbb{G}}_i - \mu_{\bar{\mathbb{G}}}\right)^2}, \tag{14}$$

Table 1: Comparison(AUROC/TPR@5%FPR) on 4 Datasets across 5 target models. Target models are denoted as 2.7B/6B/6.7B/6.9B/7B, corresponding to Neo-2.7B/GPT-J-6b/OPT-6.7b/Pythia-6.9b/LLaMA-7B respectively.

Method	WikiMIA					ArXivTection				
	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B
PPL	0.61/0.13	0.64/0.13	0.60/0.12	0.63/0.13	0.69/0.14	0.62/0.13	0.64/0.13	0.60/0.12	0.63/0.13	0.70/0.14
ZLib	0.58/0.10	0.60/0.11	0.58/0.10	0.59/0.10	0.71/0.22	0.58/0.10	0.60/0.11	0.58/0.09	0.59/0.11	0.71/0.22
Min-k	0.65/0.17	0.67/0.19	0.63/0.15	0.67/0.19	0.73/0.18	0.65/0.17	0.68/0.19	0.63/0.15	0.67/0.19	0.72/0.18
Min-k++	0.67/0.15	0.69/0.19	0.65/0.11	0.70/0.18	0.82/0.22	0.67/0.15	0.69/0.19	0.65/0.10	0.70/0.17	0.83/0.22
FSD	**0.92/0.77**	**0.95/0.78**	0.90/0.63	0.90/**0.66**	0.92/0.41	0.91/0.65	0.96/0.79	0.89/0.63	0.95/0.66	0.94/0.81
Ours	0.90/0.60	0.93/0.66	**0.94/0.67**	**0.92**/0.63	**0.96/0.84**	**0.94/0.73**	**0.97/0.86**	**0.94/0.75**	**0.95/0.83**	**0.97/0.85**
Method	BookTection					BookMIA				
	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B
PPL	0.69/0.15	0.74/0.25	0.64/0.13	0.73/0.25	0.71/0.25	0.29/0.02	0.22/0.13	0.23/0.01	0.59/0.19	0.56/0.21
ZLib	0.56/0.16	0.58/0.20	0.55/0.14	0.58/0.19	0.57/0.19	0.20/0.02	0.38/0.13	0.15/0.00	0.49/0.17	0.48/0.18
Min-k	0.71/0.18	0.75/0.27	0.67/0.15	0.74/0.26	0.71/0.25	0.45/0.05	0.60/0.20	0.40/0.03	0.62/0.20	0.60/0.21
Min-k++	0.64/0.13	0.67/0.18	0.61/0.11	0.66/0.19	0.63/0.15	0.54/0.13	0.64/0.29	0.49/0.09	0.60/0.23	0.58/0.20
FSD	0.92/0.53	0.91/0.52	0.96/0.77	0.93/0.59	0.92/0.55	0.98/0.93	0.97/0.89	0.98/0.96	0.98/0.93	0.98/0.91
Ours	**0.96/0.84**	**0.97/0.88**	**0.98/0.92**	**0.96/0.83**	**0.98/0.92**	**0.99/0.98**	**0.99/0.99**	**0.99/0.99**	**0.99/0.98**	**0.99/0.99**

where $\bar{\mathbb{G}}_i = \frac{1}{h}\sum_{j=1}^{h}|\mathbb{G}_{i,j}|$ denotes the i-th row's absolute mean, $\mu_{\bar{\mathbb{G}}} = \frac{1}{r}\sum_{i=1}^{r}\bar{\mathbb{G}}_i$ denotes the mean of row means.

We compute the aforementioned eight feature values from all gradient matrices to derive a feature vector $\mathbb{V}^{l\times m\times 8}$ per sample, which is then used for subsequent MLP training and inference.

4.4 Light MLP Training

Given the feature vectors $\mathbb{V}_i$ from all training samples vectors $\mathbb{V}_s$, we feed them into a lightweight MLP for training. The target output corresponds to the binary label $\{0, 1\}$ for each sample, where 0 denotes non-member and 1 denotes member. The training loss is defined as follows:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)\right], \tag{15}$$

where N denotes the number of training samples, $y_i \in \{0, 1\}$ is the ground-truth label of the i-th sample, and $\hat{y}_i$ is the predicted probability output by the MLP.

5 Experiments

5.1 Experimental Setup

Datasets Following prior work, we evaluate on five prevalent datasets: WikiMIA, BookMIA (Shi et al., 2024),ArxivTection, BookTection (Duarte et al.), and MIMIR (Duan et al.), a widely recognized challenging benchmark for pretraining data detection.

Target Models We evaluate five open-source LLMs with diverse architectures: Neo-2.7B (Black et al., 2021), GPT-J-6B (Wang and Komatsuzaki, 2021), OPT-6.7B (Zhang et al., 2022), Pythia-6.9B (Biderman et al., 2023), and LLaMA-7B (Touvron et al., 2023) from Hugging Face.

Comparison Methods We select five representative state-of-the-art baselines. Four scoring function–based methods include PPL (Carlini et al., 2021), ZLib (Carlini et al., 2021), Min-k (Shi et al., 2024), and Min-k++ (Zhang et al., 2025). The fine-tuning–enhanced method includes FSD (Zhang et al.). More details are shown in Appendix A.

Evaluation Metrics Two metrics evaluate the binary pre-training data detection task: **AUROC** measures overall discriminative performance, and **TPR@5%FPR** captures practical effectiveness by assessing detection rate under a 5% false positive constraint.

Implementation Details We use the PEFT library (Mangrulkar et al., 2022) for LoRA-based (Hu et al., 2022) gradient feature extraction without parameter updates. The MLP is trained on 30% of the data, with the remaining 70% used for inference evaluation under FSD settings. More Details can be seen in Appendix A.6.

5.2 Main Results

Table 1 reports results on WikiMIA, ArxivTection, BookTection, and BookMIA. On WikiMIA with LLaMA-7B, GDS reaches an AUC of 0.96, outperforming the best baseline, FSD, by 0.04 and substantially surpassing score-based methods such as Min-k++. GDS performs best in most settings, with particularly large TPR@5%FPR gains on BookTection and BookMIA; on BookTection with LLaMA-7B, the improvement is nearly 67.3

Table 2 reports results on seven MIMIR subsets. Despite performance drops caused by similar data

Table 2: Performance Comparison on Mimir datasets with 7 subsets across 5 target models using AUROC scores.

Method	Wikipedia					Github					Pile CC					PubMed Central				
	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B
PPL	0.56	0.57	0.56	0.56	0.56	0.78	0.79	0.78	0.90	0.83	0.56	0.57	0.56	0.56	0.52	0.78	0.79	0.78	0.78	0.72
ZLib	0.62	0.65	0.59	0.65	0.58	**0.90**	0.91	0.79	0.91	0.86	0.55	0.55	0.55	0.55	0.52	0.78	0.78	0.73	0.77	0.71
Min-k	**0.66**	**0.68**	**0.65**	0.68	0.63	0.88	0.89	0.76	0.90	0.83	0.56	0.57	0.56	0.56	0.52	0.81	0.80	0.74	**0.79**	0.72
Min-k++	0.65	**0.68**	0.60	**0.69**	0.56	0.84	0.86	0.56	0.86	0.73	0.54	0.55	0.54	0.56	0.51	0.71	0.72	0.60	0.70	0.59
FSD	0.61	0.67	0.60	0.65	0.60	0.77	0.80	0.62	0.77	0.72	0.55	0.55	0.54	0.55	0.52	0.71	0.79	0.63	0.56	0.63
Ours	0.63	0.64	**0.65**	0.65	**0.64**	0.90	**0.92**	**0.88**	**0.92**	**0.91**	**0.59**	**0.59**	**0.59**	**0.57**	**0.59**	**0.84**	**0.85**	**0.84**	**0.79**	**0.82**

Method	ArXiv					DM Mathematics					HackerNews					Average				
	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B	2.7B	6B	6.7B	6.9B	7B
PPL	**0.78**	**0.79**	0.65	**0.78**	0.70	0.78	0.79	0.65	0.91	0.31	0.65	**0.62**	0.59	**0.62**	**0.59**	0.64	0.66	0.62	0.73	0.59
ZLib	0.77	0.78	0.68	0.77	0.71	0.82	0.81	0.80	0.81	0.23	**0.68**	0.60	0.58	0.60	0.58	0.65	0.67	0.63	0.72	0.58
Min-k	**0.78**	**0.79**	0.65	**0.78**	0.70	0.93	0.93	0.92	0.92	0.32	0.65	**0.62**	0.59	**0.62**	**0.59**	0.71	0.73	0.69	0.75	0.60
Min-k++	0.60	0.64	0.53	0.70	0.57	0.77	0.79	0.67	0.75	0.22	0.53	0.57	0.51	0.60	0.53	0.60	0.63	0.56	0.67	0.53
FSD	0.72	0.78	0.55	0.70	0.52	0.58	0.85	0.60	0.74	0.53	0.61	0.60	0.57	0.56	0.51	0.61	0.66	0.59	0.62	0.55
Ours	**0.78**	**0.79**	**0.78**	**0.78**	**0.77**	**0.95**	**0.95**	**0.94**	**0.95**	**0.95**	0.58	0.60	**0.60**	0.57	0.58	**0.73**	**0.75**	**0.74**	**0.76**	**0.70**

Table 3: Ablation results using AUROC on WikiMIA and ArxivTection. - denotes the features removal.

Dataset	-Magnitude	-Concentrate	-Position
WikiMIA	0.94 (↓0.02)	0.94 (↓0.02)	0.93 (↓0.03)
Arxiv.	0.96 (↓0.01)	0.95 (↓0.02)	0.95 (↓0.02)

Table 4: Ablation results using AUROC and TPR@5%FPR. ATT-Only refers to performance validation using only attention module.

Dataset	ATT-Only	FFN-Only	Origin
WikiMIA	0.94 / 0.68	0.93 / 0.64	0.96 / 0.84
Arxiv.	0.95 / 0.76	0.93 / 0.72	0.97 / 0.85

distributions, GDS delivers the best average gains (+2.8%, +2.7%, +7.2%, +1.3%, +16.6%) across models, with notable advantages on PubMed Central, DM Mathematics, and GitHub. With LLaMA, these three subsets reach AUCs of 0.82, 0.95, and 0.91. GDS also remains the most stable across models, with AUC variation mostly within 0.04, indicating strong cross-model generalization.

5.3 Ablation Study

We perform two ablation studies: (1) removing each feature category individually, and (2) using features from only the Attention or FFN module. Table 3 shows that all categories help, with Position Offset contributing most; the full feature set performs best, confirming their complementarity (see Appendix C). Table 4 shows that Attention features are more informative than FFN features, but both single-module variants lag behind the full model, indicating that Attention and FFN capture complementary gradient patterns and are best used together.

Table 5: Semi-supervised performance (AUROC / TPR@5%FPR) on WikiMIA.

	MinK++	FSD	GDS
LLaMA-7B	0.82/0.22	0.79/0.134	0.86/0.40
Pythia-6.9B	0.70/0.18	0.76/0.18	0.80/0.34
GPT-J-6B	0.69/0.19	0.75/0.14	0.79/0.26
OPT-6.7B	0.65/0.11	0.70/0.11	0.81/0.37
GPT-Neo-2.7B	0.67/0.15	0.76/0.17	0.78/0.26

5.4 Analysis

5.4.1 Semi-Supervised Setting

To test GDS in label-free real-world settings, we combine it with the SOTA unsupervised method MinK++. MinK++ first filters WikiMIA samples using thresholds of -1.4 and -4.6, producing 310 pseudo-labeled samples for training GDS and FSD. Table 5 results show semi-supervised GDS outperforms unsupervised MinK++ and semi-supervised FSD, demonstrating excellent noise resistance and practical value. Notably, GDS has a distinct advantage in TPR@5%FPR, reflecting strong positive sample recall under extremely low false positive tolerance. This indicates GDS can more accurately and robustly discriminate pre-trained data, suppress non-member high-score interference, select purer member samples in high-confidence regions, and thus has stronger deployment value in low-false-alarm, high-reliability scenarios.

5.4.2 Feature Distribution

Figure 4 illustrates the eight features with the largest member–non-member discrepancies across all layers and sub-modules. Member samples show lower Abs_Mean and Row_Mean_Max, higher Sparsity, lower Std and Row_Mean_Std, and higher 10p_Ratio, indicating smaller, more concentrated,

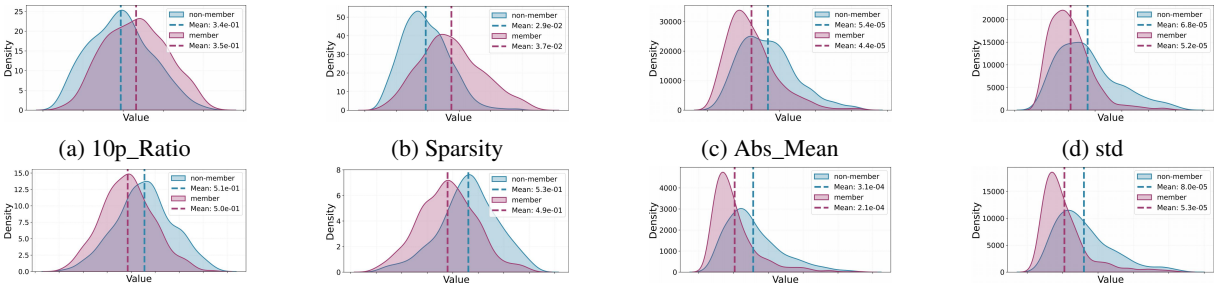


Figure 4: Distribution differences of eight gradient features between member(red) and non-member(blue) samples. Dashed lines indicate distribution means. The x-axis shows feature values, and the y-axis shows probability density.

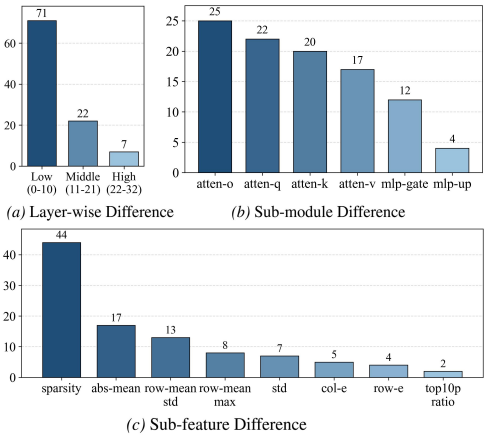


Figure 5: Distribution Difference Statistics of Discriminative Features. The y-axis shows the statistical count.

and more stable gradients closer to the propagation core. They also have lower Row_Ecc and Col_Ecc, suggesting that member-related parameters are more centrally located in weight matrices.

Figure 5 shows that sub-features with the largest distribution differences are concentrated in lower layers, while middle and higher layers contribute far less. Attention-related sub-modules dominate the discriminative features, with clear variation across modules. Among gradient features, grad_sparsity is by far the most discriminative.

5.4.3 Transferability

Although our method uses a unified feature extraction pipeline, it currently relies on dataset-specific classifiers. We evaluate cross-dataset transfer between WikiMIA and ArxivTection, as well as a unified classifier trained on mixed data. As shown in Table 6, direct transfer suffers severe performance degradation due to dataset shift, while the unified classifier achieves strong results on combined data. This indicates that our approach captures generalizable patterns related to pre-training familiarity.

Table 6: Cross-Dataset Generalization Performance using AUROC. Wiki(arXiv) indicates training on ArxivTection with test on WikiMIA, while Mix indicates mixed datasets.

Method	Wiki (arXiv)	arXiv (Wiki)	Mix
FSD	0.52	0.58	0.92
Ours	**0.66**	**0.68**	**0.95**

5.4.4 Efficiency Analysis

We compare inference time and peak memory of PPL, FSD, and GDS on the first WikiMIA sample with LLaMA-7B in bfloat16. PPL takes 70 ms, FSD 760 ms, and GDS 1001 ms. Peak memory is about 13 GB for PPL and GDS, versus 16 GB for FSD. Although GDS is about 30% slower than FSD due to gradient backpropagation, it performs no parameter updates, so it avoids optimizer states and matches the memory use of unsupervised methods while cutting memory by nearly 40% to FSD. Furthermore, GDS maintains strong performance in low-resource scenarios and with reduced LoRA ranks(see Appendix D.1 and D.2), enabling significant computational efficiency. GDS results under full-parameter are shown in Appendix D.3.

6 Conclusion

We revisit pre-training data detection from an optimization and training-dynamics perspective and introduce GDS, a fine-tuning–free method for pre-training membership inference. By analyzing model training dynamics, we show that member and non-member samples exhibit stable and interpretable gradient differences in magnitude, location, and concentration across datasets and architectures. Experiments demonstrate that GDS achieves effective and generalizable performance, surpassing competitive baselines.

Limitations

Our method identifies membership samples relying on inherent gradient discrepancies among instances. However, natural discrepancies stemming from samples of varying reasoning difficulty and different training exposure degrees inevitably interfere with discrimination accuracy, which accordingly degrades the cross-dataset transferability of our approach. In practical scenarios, we only conduct preliminary attempts to integrate supervised and unsupervised inference paradigms, while more effective and in-depth fusion strategies remain to be further explored in future work.

Impact Statement

This work investigates pre-training data detection, a form of membership inference that determines whether a given sample was included in a LLM's pre-training corpus. While our proposed GDS method improves detection accuracy and generalization without fine-tuning, it also raises important ethical concerns. Pre-training data detection methods could be misused to probe proprietary or confidential training corpora, potentially revealing sensitive information about data sources or collection practices. Although GDS does not reconstruct or expose training samples directly, it contributes to capabilities that may be exploited if applied irresponsibly. Our primary motivation is to support transparency, accountability, and safety. As pre-training datasets become increasingly large and opaque, tools like GDS can help researchers, auditors, and regulators verify data usage claims, identify potential copyright violations, and detect benchmark contamination. In this sense, GDS is intended as a diagnostic and auditing mechanism rather than a data extraction attack. We release code and models to promote reproducibility while encouraging responsible deployment. Overall, we hope this work advances trustworthy and transparent large-scale model development while highlighting the need for careful governance of pre-training data.

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A Details of Baseline

Shared Notations: We first define the universal notations used across all baseline methods for consistency:

- x: Input text sample for membership inference detection.
- $\{x_1, x_2, \ldots, x_N\}$: Token sequence of input text sample x, where N denotes the total number of tokens in the text.
- $x_{<t}$: Prefix token sequence of the t-th token x_t, i.e., $x_{<t} = \{x_1, \ldots, x_{t-1}\}$.
- θ: Trainable parameters of the pre-trained language model.
- $p(\cdot \mid \cdot; \theta)$: Conditional probability distribution parameterized by the model parameters θ.
- $k\%$: Percentage threshold for selecting low-probability outlier tokens (used in Min-k% and Min-k%++).

A.1 PPL

Perplexity (PPL) is a classic global likelihood-based metric that measures the model's uncertainty in predicting a given text, with lower PPL indicating higher text familiarity (more likely to be a member sample). First, the text is tokenized into a sequence of tokens $\{x_1, x_2, \ldots, x_N\}$. Then, the log-likelihood of each token is calculated conditional on the preceding tokens, and the final PPL is derived by normalizing the sum of log-likelihoods by the token sequence length and performing an exponential transformation.

$$\text{PPL} = \exp\left(-\frac{1}{N}\sum_{i=1}^{N}\log p(x_i|x_1, ..., x_{i-1}; \theta)\right) \tag{16}$$

A.2 Zlib

Zlib is a compression-based global likelihood-related method that leverages compression entropy to distinguish member and non-member samples, which calibrates the loss using the input's Zlib entropy. For an input text sample x and a pre-trained model M, the Zlib score is defined as the ratio of the loss related to the text and model to the Zlib compression entropy of the input text:

$$\text{Zlib Score} = \frac{L(x, M)}{\text{zlib}(x)} \tag{17}$$

where $L(x, M)$ denotes the loss value associated with the input text x under the model M and $\text{zlib}(x)$ represents the Zlib compression entropy of the input text x, which is derived from the length of the text after Zlib compression.

A.3 Min-k%

Min-k% is a local likelihood-based method that mitigates global word frequency interference by focusing on low-probability outlier tokens. For an input text token sequence $x = \{x_1, x_2, \ldots, x_N\}$ (where N denotes the total number of tokens), it first calculates the conditional log-likelihood of each token x_i given its preceding context:

$$\log p(x_i \mid x_1, x_2, \ldots, x_{i-1}; \theta)$$

Subsequently, it sorts all token conditional probabilities in ascending order, selects the bottom $k\%$ tokens (i.e., the $k\%$ tokens with the smallest conditional probabilities) to form the low-probability set $T_{\text{min}(k\%)} = \text{Min-K\%}(x)$. The final Min-k% score is defined as the average conditional log-likelihood of tokens in $T_{\text{min}(k\%)}$:

$$\text{Min-k\% Score}(x) = \frac{1}{|T_{\text{min}(k\%)}|} \sum_{x_i \in T_{\text{min}(k\%)}} \log p(x_i \mid x_1, \ldots, x_{i-1}; \theta) \tag{18}$$

where $|T_{\text{min}(k\%)}| = \lfloor k\% \times N \rfloor$ denotes the cardinality of the low-probability token set (rounded down to the nearest integer). During detection, a threshold is set on Min-k% Score(x): text with a score below the threshold is classified as a member sample (since member samples tend to contain more low-probability outlier tokens), and vice versa.

A.4 Min-k%++

Min-k%++ is an optimized variant of Min-k% that enhances detection robustness by integrating vocabulary-level probability statistics, addressing the text-length dependency and short-text fluctuation issues of the original method. For an input text token sequence $x = \{x_1, x_2, \ldots, x_N\}$, it first computes the normalized conditional log-likelihood for each token x_t (given prefix $x_{<t} = \{x_1, \ldots, x_{t-1}\}$) by normalizing with the vocabulary-wide log-probability statistics of the prefix $x_{<t}$.

Core Token-Level Score Calculation

For each token x_t, the token-level Min-k%++ score is defined as:

$$\text{Min-k\%++}_{\text{token}}(x_{<t}, x_t) = \frac{\log p(x_t \mid x_{<t}; \theta) - \mu_{x_{<t}}}{\sigma_{x_{<t}}} \tag{19}$$

where $\mu_{x_{<t}} = \mathbb{E}_{z \sim p(\cdot \mid x_{<t}; \theta)} [\log p(z \mid x_{<t}; \theta)]$: Expectation of the next-token log-likelihood over the model's vocabulary, given prefix $x_{<t}$; $\sigma_{x_{<t}} = \sqrt{\mathbb{E}_{z \sim p(\cdot \mid x_{<t}; \theta)} \left[(\log p(z \mid x_{<t}; \theta) - \mu_{x_{<t}})^2 \right]}$: Standard deviation of the next-token log-likelihood over the vocabulary, given prefix $x_{<t}$.

Both $\mu_{x_{<t}}$ and $\sigma_{x_{<t}}$ can be computed analytically using the model's output logits (since $p(\cdot \mid x_{<t}; \theta)$ follows a categorical distribution), requiring no additional computational overhead beyond standard LLM inference.

Final Sequence-Level Score Calculation

Similar to Min-k%, Min-k%++ selects the bottom $k\%$ tokens with the smallest Min-k%++$_{\text{token}}$ scores to form the low-probability set $T^{+}_{\text{min}(k\%)}$. The final sequence-level score is the average of the token-level scores in this set:

$$\text{Min-k\%++ Score}(x) = \frac{1}{|T^{+}_{\text{min}(k\%)}|} \sum_{(x_{<t}, x_t) \in T^{+}_{\text{min}(k\%)}} \text{Min-k\%++}_{\text{token}}(x_{<t}, x_t) \tag{20}$$

where $|T^{+}_{\text{min}(k\%)}| = \lfloor k\% \times N \rfloor$ denotes the cardinality of the low-probability token set. During detection, a threshold is applied: text with a lower Min-k%++ score is more likely to be a member sample, as the normalized score better distinguishes low-probability outlier tokens of member samples from non-member ones.

A.5 FSD

Fine-tuned Score Deviation (FSD) is a fine-tuning enhanced method that leverages score discrepan-

cies between pre-trained and fine-tuned models for member sample detection. Its core workflow includes two key steps: first, constructing a domain-matched non-member fine-tuning dataset (using post-model-release unseen data), then performing self-supervised next-token prediction fine-tuning on the pre-trained model. Finally, it calculates the score difference between the pre-trained and fine-tuned models to distinguish member and non-member samples. The self-supervised fine-tuning loss is defined as:

$$\mathcal{L}_{\text{fine-tuning}}(x) = -\frac{1}{n}\sum_{i=1}^{n} \log f_\theta(x_i \mid x_1, \ldots, x_{i-1}) \tag{21}$$

The final FSD score is the deviation between the sample scores obtained from the pre-trained model f_θ and the fine-tuned model $f_{\theta'}$ (with parameters θ'):

$$\text{FSD}(x; f_\theta, f_{\theta'}) = S(x; f_\theta) - S(x; f_{\theta'}) \tag{22}$$

where $S(\cdot)$ represents a base scoring function (e.g., Perplexity, Min-k%). A large FSD score indicates the sample is likely a non-member (fine-tuning reduces non-member perplexity significantly), while a small score suggests a member sample (fine-tuning has negligible impact on member perplexity). A validation-set optimized threshold ε is used for final classification.

A.6 Experimental Settings

We use the PEFT library (Mangrulkar et al., 2022) for LoRA-based (Hu et al., 2022) gradient feature extraction without parameter updates. The base model is initialized from pre-trained checkpoints, and for LoRA configuration, we adopt default settings with rank $r = 16$, LoRA scaling factor $\alpha = 32$, and dropout set to 0 since we only focus on gradients from a single backpropagation step and no parameter updates are required. Target modules include all submodules of attention and FFN, including query, key, value, output, gate, up, and down projections. For different datasets, we select the tokenizer sequence length based on the overall length distribution: 256 for the WikiMIA dataset and 512 for all other datasets. When training the MLP classifier, the dataset is uniformly split into training and validation sets at a ratio of 3:7. The MLP classifier is configured with two hidden layers of dimensions 128 and 64, respectively, and uses the default Adam optimizer with a learning rate of 0.001. An early stopping strategy is implemented to avoid overfitting.

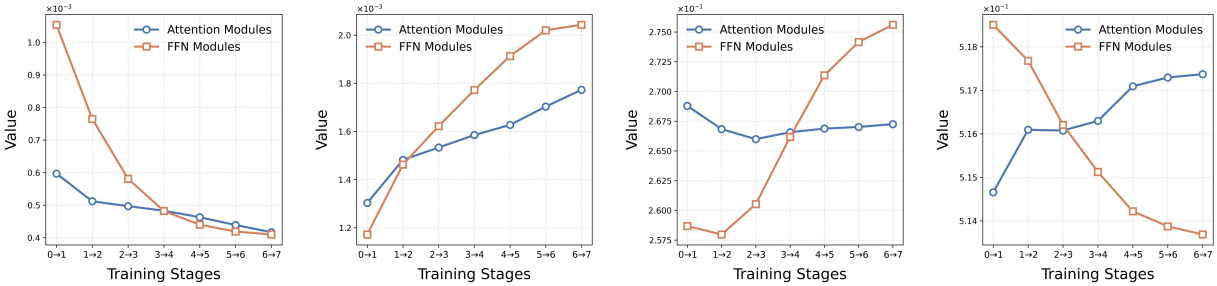
B Motivation Experiment Supplementary Details

To verify the parameter update law driven by the training process, we conduct LoRA fine-tuning with 8 epochs on LLaMA-7B using the unseen set of BookMIA dataset, counting LoRA matrix parameter updates per epoch to extract dynamic change curves of target features. Experiments are performed under three learning rates ($1e-5$, $3e-5$, $5e-5$). We present the variation trends of the four feature categories across different modules and layers under each learning rate.

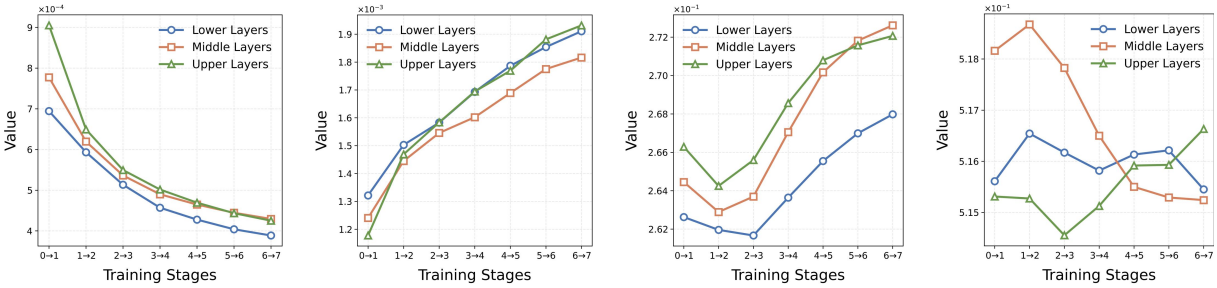
We present the variation trends of the four feature categories across different modules and layers under each learning rate (Figs. 6–8). Across all learning rates, $\Delta\Theta_t$ and S_t exhibit clear epoch-wise patterns: $\Delta\Theta_t$ continuously decreases with training epochs, while S_t gradually increases. For E_t, distinct opposite trends are observed between the ATT and MLP modules—the update positions of the ATT module tend to be centralized, whereas those of the MLP module tend to be marginalized. Despite this divergence, E_t values of both modules converge to the same stable range across the three learning rates. In contrast, $T_{10,t}$ shows a different dynamic: under large learning rates, it first increases and then decreases, yet remains stably around 0.27 throughout training. Notably, the inflection point of $T_{10,t}$ decline coincides with the stage when E_t stabilizes. This aligns with our core hypothesis: during training, the model identifies core parameters correlated with the input data and performs concentrated updates on them; once this process is completed, the overall parameter update dynamics tend to stabilize. Regarding different hierarchical levels, only E_t shows noticeable discrepancies, while all other features follow the same evolutionary laws.

C Ablation Experiments on Sub-features and Sub-modules

To further explore the discriminative power of fine-grained components in our method, we conduct two additional ablation experiments: sub-feature category ablation (8 sub-features) and sub-module ablation (7 sub-modules). All experiments follow the same configuration as the main text (LLaMA-7B model, WikiMIA/ArxivTection datasets), with

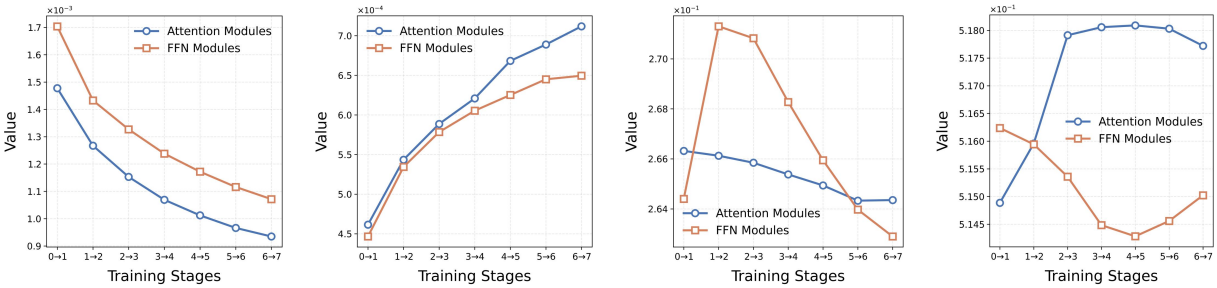


(a) Module-Mean Update (b) Module-Sparsity (c) Module-Top10% Ratio (d) Module-Row Eccentricity

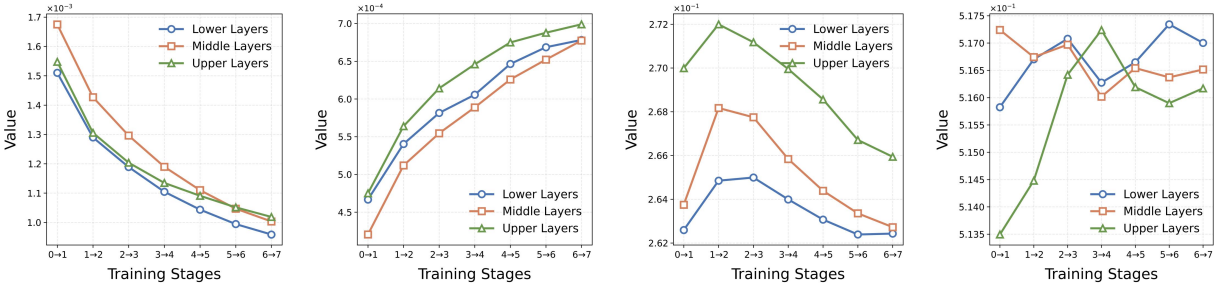


(e) Layer-Mean Update (f) Layer-Sparsity (g) Layer-Top10% Ratio (h) Layer-Col Eccentricity

Figure 6: Feature Dynamic Changes During LoRA Fine-Tuning (Learning Rate $1e-5$). Top row: Features in ATT/MLP modules; Bottom row: Features in low/middle/high layers.

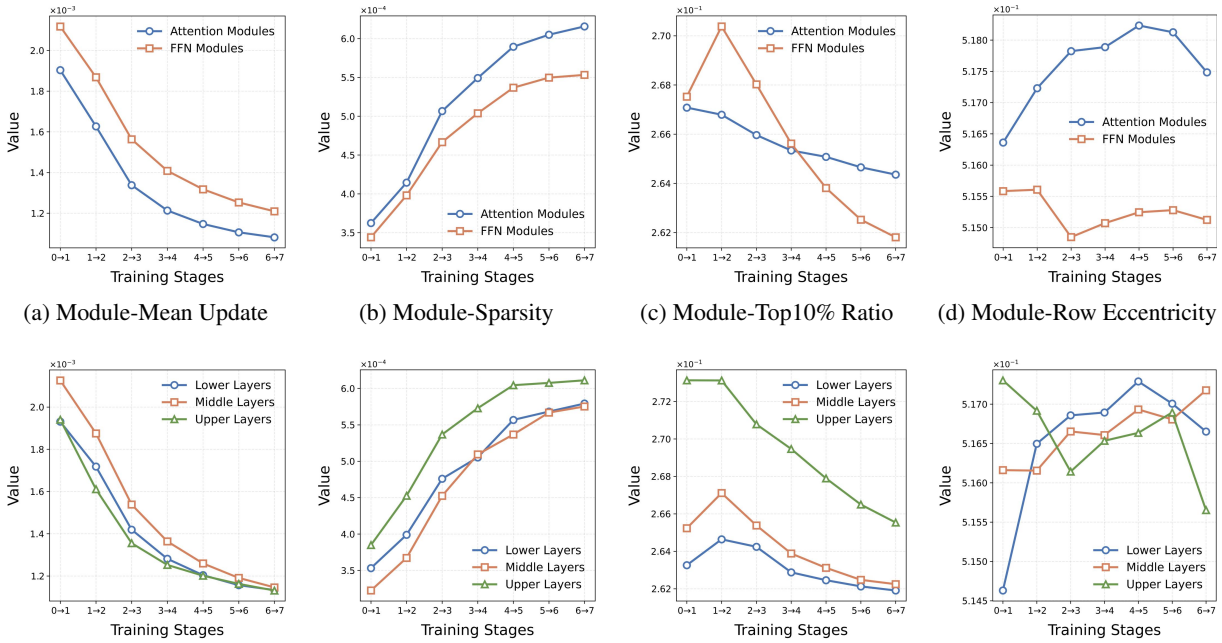


(a) Module-Mean Update (b) Module-Sparsity (c) Module-Top10% Ratio (d) Module-Row Eccentricity



(e) Layer-Mean Update (f) Layer-Sparsity (g) Layer-Top10% Ratio (h) Layer-Col Eccentricity

Figure 7: Feature Dynamic Changes During LoRA Fine-Tuning (Learning Rate $3e-5$).



(a) Module-Mean Update (b) Module-Sparsity (c) Module-Top10% Ratio (d) Module-Row Eccentricity

(e) Layer-Mean Update (f) Layer-Sparsity (g) Layer-Top10% Ratio (h) Layer-Col Eccentricity

Figure 8: Feature Dynamic Changes During LoRA Fine-Tuning (Learning Rate $5e-5$).

AUC and TPR@5% FPR as evaluation metrics.

C.1 Sub-feature Category Ablation Experiment

The four core feature categories are decomposed into 8 sub-features, as follows:

- Magnitude Distribution Features: Abs_Mean, Std
- Core Contribution Features: 10p_Ratio, Sparsity
- Position Offset Features: Row_Ecc, Col_Ecc
- Row-Dimension Consistency Features: Row_Mean_Max, Row_Mean_Std

Ablation is performed by removing one sub-feature at a time (retaining the other 7), and the results are shown in Table 7.

The sub-feature ablation results verify that all sub-features contribute to detection performance, with their combination achieving optimal AUC and TPR scores across both datasets. Among these sub-features, Col_Ecc (a Position Offset Feature) is the most critical: its removal leads to the sharpest performance decline (AUC drops to 0.93 on WikiMIA and 0.95 on ArxivTection, with TPR falling to 0.62 and 0.78 respectively). In contrast, removing Abs_Mean, Std, 10p_Ratio, Row_Ecc, Row_Max, or Row_Std induces only mild performance degradation, with AUC remaining above 0.95 on both datasets, indicating their relatively moderate importance; Sparsity also shows a slight impact on WikiMIA, with its ablation resulting in an AUC of 0.94. Overall, the fine-grained sub-feature design is rational, as each component provides complementary discriminative information for pre-training data detection.

C.2 Sub-module Ablation Experiment

The ATT and FFN modules are decomposed into 7 sub-modules based on Transformer architecture details:

- ATT-related sub-modules: Q-Proj, K-Proj, V-Proj, Out-Proj
- FFN-related sub-modules: Gate-Proj, Up-Proj, Down-Proj

Ablation is performed by removing one sub-module's features at a time, and the results are shown in Table 8.

The sub-module ablation results demonstrate that all sub-modules provide complementary gradient information, as single-sub-module ablation consistently leads to performance degradation while integrating all sub-modules' features achieves the optimal AUC and TPR@5% FPR scores across both datasets. Though the performance differences

Table 7: Ablation Experiment Results of Sub-features (AUC Scores).

Dataset	Sub-feature (Ablation Variant)								Full
	-Abs_Mean	-Std	-10p_Ratio	-Sparsity	-Row_Ecc	-Col_Ecc	-Row_Max	-Row_Std	
WikiMIA	0.95/0.71	0.95/0.72	0.95/0.70	0.94/0.67	0.95/0.70	0.93/0.62	0.95/0.73	0.95/0.72	**0.96/0.84**
ArxivTection	0.96/0.82	0.96/0.81	0.96/0.83	0.96/0.82	0.96/0.83	0.95/0.78	0.96/0.83	0.96/0.83	**0.97/0.85**

Table 8: Ablation Experiment Results of Sub-modules (AUC / TPR@5% FPR Scores).

Dataset	Sub-module (Ablation Variant)							Full
	-Q-Proj	-K-Proj	-V-Proj	-Out-Proj	-Gate-Proj	-Up-Proj	-Down-Proj	
WikiMIA	0.95/0.72	0.95/0.71	0.94/0.69	0.94/0.67	0.95/0.69	0.94/0.65	0.94/0.61	**0.96/0.84**
ArxivTection	0.96/0.80	0.96/0.82	0.95/0.79	0.96/0.80	0.96/0.82	0.95/0.78	0.96/0.82	**0.97/0.85**

between individual ablation variants are mild, ATT-related sub-modules show slightly stronger discriminative power than FFN-related ones, with K-Proj performing prominently among ATT sub-modules; in contrast, among FFN sub-modules, Down-Proj and Gate-Proj contribute more to detection performance than Up-Proj, as retaining the former two yields slightly higher AUC and TPR scores. The performance gap between single-sub-module variants and the full model further confirms the necessity of multi-sub-module feature fusion, which enables the capture of comprehensive gradient patterns across the Transformer architecture. It can be seen from this that our method also achieves excellent performance with smaller LoRA adaptation parameters and lower computational complexity.

D Additional Experiments Analysis

D.1 Low-Data Scenarios

To thoroughly verify the data efficiency and robustness of our GDS method in low-data scenarios with limited labeled samples, we conduct extensive experiments where only 10% of the training data is used for model training. Specifically, we evaluate GDS across five different language models and two benchmark datasets, with Mink++ as the baseline for performance comparison. The experimental results, measured by two key metrics (AUC score and TPR@5% FPR), are presented in Table 9, which clearly demonstrates that GDS still maintains superior detection performance compared to the baseline even under the strict constraint of limited training data.

Table 9: Detection performance under low-data scenario (10% training data).

Model	WikiMIA		ArxivTection	
	GDS	mink++	GDS	mink++
llama	0.90/0.52	0.82/0.22	0.91/0.65	0.83/0.22
pythia	0.81/0.33	0.70/0.18	0.88/0.56	0.70/0.17
opt	0.86/0.37	0.65/0.11	0.88/0.47	0.65/0.10
gpt-j	0.84/0.37	0.69/0.19	0.91/0.60	0.69/0.19
gpt-neo	0.81/0.35	0.67/0.15	0.92/0.67	0.67/0.15

D.2 Sensitivity Analysis

We conduct sensitivity experiments on LLaMA-7B (WikiMIA) by varying LoRA rank, initialization seed, and target module under main experiment settings.Table 10 shows our method maintains stable performance: AUC remains high across ranks and seeds; it maintains excellent performance even when only a small number of target modules are used.

D.3 Full Parameter Training

In LoRA training, only FFN and MLP modules are updated, while LayerNorm, despite containing meaningful training dynamics, is excluded. To account for this, we evaluate our method under full-parameter training on two small-scale datasets, BookMIA and ArxivTection, for computational feasibility. As shown in Table 11, although full-parameter updates cause a slight performance drop compared to LoRA, our method still outperforms most baselines. We attribute this gap to reduced gradient magnitudes in full training, which weaken discriminative signals between sample types.

Table 10: Sensitivity analysis on WikiMIA (LLaMA-7B) using AUROC and TPR@5%FPR.

LoRA rank r	AUC	TPR@5%FPR
16	0.96	0.84
8	0.96	0.82
4	0.95	0.77
Seed	**AUC**	**TPR@5%FPR**
99	0.9658	0.8421
88	0.9674	0.8408
77	0.9636	0.8308
66	0.9623	0.8358
Target Module	**AUC**	**TPR@5%FPR**
all	0.96	0.84
mlp	0.94	0.72
att	0.95	0.79

D.4 WikiMIA Modification

Dataset partitioning can introduce distribution shifts or dataset-specific artifacts. For example, WikiMIA is split by publication time, with all non-member samples labeled as 2023. To ensure our method does not exploit such artifacts, we remove all timestamp tokens and reevaluate all methods. As shown in Table 12, although token removal degrades performance, our method suffers a much smaller drop than the strongest baseline, FSD, and still achieves SOTA results.

Table 11: Performance Comparison between LoRA and Full-Parameter Update using AUROC on WikiMIA and ArxivTection.

Dataset	Metric	LLaMA-7B		GPT-J-6B		OPT-6.7B		Pythia-6.9B		Neo-2.7B	
		LoRA	Full	LoRA	Full	LoRA	Full	LoRA	Full	LoRA	Full
WikiMIA	AUC	**0.96**	**0.96**	**0.93**	0.90	**0.94**	0.92	**0.92**	0.89	**0.90**	0.88
	TPR@5% FPR	**0.84**	0.79	**0.66**	0.58	**0.67**	0.56	**0.63**	0.50	**0.60**	0.51
ArxivTection	AUC	**0.97**	0.96	**0.97**	0.96	**0.94**	0.93	**0.95**	0.94	**0.94**	**0.94**
	TPR@5% FPR	**0.85**	0.84	**0.86**	0.79	**0.75**	0.67	**0.83**	0.73	0.73	**0.75**

Table 12: Comparison of Temporal Feature Perturbation via AUROC. Deletion denotes the removal of all year timestamps.

Method	Origin	Deletion
PPL	0.69	0.62
Min-k	0.73	0.63
Min-k++	0.82	0.59
FSD	0.92	0.76
Ours	**0.96**	**0.84**