Blackbox Dataset Inference for LLM

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Abstract

Today, the training of large language models (LLMs) can involve personally identifiable information and copyrighted material, incurring dataset misuse. To mitigate the problem of dataset misuse, this paper explores *dataset inference*, which aims to detect if a suspect model \mathcal{M} used a victim dataset \mathcal{D} in training. Previous research tackles dataset inference by aggregating results of membership inference attacks (MIAs)—methods to determine whether individual samples are a part of the training dataset. However, restricted by the low accuracy of MIAs, previous research mandates grey-box access to \mathcal{M} to get intermediate outputs (probabilities, loss, perplexity, etc.) for obtaining satisfactory results. This leads to reduced practicality, as LLMs, especially those deployed for profits, have limited incentives to return the intermediate outputs.

In this paper, we propose a new method of dataset inference with only black-box access to the target model (i.e., assuming only the text-based responses of the target model are available). Our method is enabled by two sets of locally built reference models, one set involving \mathcal{D} in training and the other not. By measuring which set of reference model \mathcal{M} is closer to, we determine if \mathcal{M} used \mathcal{D} for training. Evaluations of real-world LLMs in the wild show that our method offers high accuracy in all settings and presents robustness against bypassing attempts.

1 Introduction

Large language models (LLMs), such as the Generative Pre-trained Transformer (GPT) [26], have made remarkable progress in natural language processing over recent years. LLMs are trained on vast amounts of text data, enabling them to generate human-like text, answer questions, and perform various language-related tasks. LLMs are initially trained on a broad dataset and then fine-tuned for specific tasks. This approach has proven highly effective in enhancing performance across a wide range of language tasks [42].

Problem: Recently, the training of LLMs using massive public data has sparked significant privacy concerns. The inclusion of personally identifiable information and copyrighted material in training datasets has led to legal conflicts, such as the lawsuit between The *New York Times* and *OpenAI* [30] and the suspension of *ByteDance*'s GPT accounts [18]. These disputes underscore the problem of using copyrighted content without proper attribution or licensing, potentially infringing on the rights of the data creators. For simplicity, we define this problem as *dataset misuse*.

Literature: To mitigate the problem of dataset misuse, there are two applicable solutions. One approach is membership inference attacks (MIAs) [52]. MIA aims to determine if a specific data sample is a part of the training dataset. Applying LLM-level MIA [41, 51] to all samples in a suspect dataset \mathcal{D} , we can validate how frequently the samples are used to train the target model and, thus, infer dataset misuse. However, previous research [39] has highlighted an impossibility result, indicating that as the training dataset size increases, the accuracy of membership inference diminishes to the level of random guessing. Further, a recent study [38] unveils that MIAs against LLMs present random accuracy when the training set and testing set are independent and identically distributed (IID).

Another method is *dataset inference* [38]. The idea is to aggregate the results of multiple MIAs across different data samples to detect if a suspect model \mathcal{M} used a victim dataset \mathcal{D} in training. Briefly, the method builds a set of diverse MIAs and trains a linear regression model to learn which MIAs are more helpful. Applying the linear model and statistical t-test, the method determines if \mathcal{M} can better "recognize" \mathcal{D} than a validation dataset that is IID with \mathcal{D} . For successful dataset inference, the method requires MIAs to present a certain level of accuracy and, thus, assumes *grey-box* access to \mathcal{M} for obtaining rich inputs (probabilities, loss, perplexity, etc.) for MIAs. This brings limitations on practicality. LLMs, especially those deployed for profits, have limited incentives to return the intermediate outputs. For instance, Google's Gemini [29] and Anthropic's Claude [12] only offer text-based responses when queried with web-based interfaces or APIs.

Our Method: In this paper, we focus on black-box dataset inference for LLMs. In other words, we aim to determine if a suspect model \mathcal{M} used a victim dataset \mathcal{D} in training, entirely relying on the text-based responses of \mathcal{M} . Our key observation is that certain data samples, when involved in training, drive the model to generate responses highly resembling the oracle output (i.e., the output coming with the samples). We define those samples as *tainted samples*, and we develop a three-step method exploiting tainted samples for dataset inference. **O** We build a set of *reference models* that are certainly not trained on \mathcal{D} , annotated as $\mathbf{R} = \{\mathcal{R}_1, \mathcal{R}_2, ..., \mathcal{R}_n\}$. We fine-tune each reference model with \mathcal{D} to produce *trained refer*ence models $\mathbf{R}^t = \{\mathcal{R}_1^t, \mathcal{R}_2^t, ..., \mathcal{R}_n^t\}$. **2** We pre-process \mathcal{D} to identify candidates of tainted samples based on the similarity between the oracle outputs and the responses from **R** and \mathbf{R}^{t} . **③** We compare \mathcal{M} with **R** and **R**^t on tainted samples, determining if \mathcal{M} used \mathcal{D} according to which reference set \mathcal{M} is closer to.

Evaluation: We perform a series of evaluations, involving member and non-member models collected from the wild and built locally, to assess the performance of our method. They show that our method can achieve 100% accuracy under the non-IID setting, given different target datasets. Our method also presents very high accuracy under the IID setting, missing only a few cases. By further increasing the reference models and diversifying their architectures, we can amend our method to correct those cases. In contrast, the baseline based on blackbox MIA [62] fails to offer satisfactory accuracy under either non-IID or IID settings. Oftentimes, the baseline even approximates a random guess.

We further experiment with various evasion attempts against our method, including *rephrasing responses*, *varying temperature*, *removing tainted samples*, and *training on subsets*. The results show that our method preserves its accuracy under those attempts. The only exception occurs when the adversaries only train their models using fewer than 50% of the samples, which we argue is no longer a problem suitable to be solved by dataset inference (see §6.4). These provide empirical evidence for the robustness of our method.

Contributions: Our main contributions are as follows.

- We present a study showing that the text-based response of LLMs often offers clues about data samples used in training.
- We propose a new method to detect dataset misuse in LLM training. Compared to the previous methods, our method only needs black-box access to the target model.
- We run intensive evaluations of our method. The results show that our method offers high accuracy in all settings and presents robustness against evasion attempts.

2 Background

2.1 Large Language Models

In the realm of artificial intelligence, large language models (LLMs) have emerged as transformative tools capable of understanding and generating human-like texts. LLMs typically take in a prompt, such as "*write a poem*", and produce a text that satisfies the requirement, i.e., a poem. More technically, LLMs encode and pass the prompt through several embedding layers to generate a probability distribution over the possible next tokens. The token with the highest probability or based on other strategies [25, 32, 59] is chosen as the prediction. The predicted token is added to the sequence, and the model repeats the process to generate subsequent tokens.

Today's LLMs share a hybrid ecosystem regarding openness. A myriad of LLMs, including Meta's Llama family [57], Google's Gemma family [55], and the Mistral family [35], release their source code and models for free. Many of them, such as Mistral 7B, even adopt permissive licenses like Apache 2.0 to allow unrestricted commercialization [13]. Yet, many LLMs, with OpenAI's GPT series [46], Google's Gemini series [29], and Anthropic's Claude series [12] as examples, are developed for commercial use. They only open webor API-based interfaces to support prompt-response interactions.

2.2 LLM Training

Training an LLM typically starts with *pre-training* on a diverse corpus of text data to build a *base model*. This base model generally understands natural language but is not optimized for executing tasks. Thus, it can generate contextually appropriate responses to the prompt but may not strictly adhere to specific instructions.

A base model can be optimized through *fine-tuning* on a dataset consisting of instructions and responses to follow those instructions [22, 33, 48]. The fine-tuning process derives an *instruct model*,



Figure 1: Base model v.s. instruct model

which can interpret instructions accurately and act accordingly. For illustration, we show a comparison between a base model and an instruct model in Figure 1. An instruct model can be further fine-tuned for optimizations. For example, OpenAI offers APIs for fine-tuning various GPT-based instruct models (GPT-3.5-Turbo, GPT-4, GPT-4o, etc.) [44].

2.3 Dataset Misuse

The availability of powerful hardware enables broad development of LLMs in various domains. Fine-tuning, allowing anyone to customize LLMs at a low cost, intensifies this trend. Together with the advancement comes ethical or legal concerns about the training data. For instance, many datasets on the market (e.g., Alpaca [8] and SlimOrca [7]) are composed of outputs by OpenAI's GPT models, which have been frequently used to train LLMs [31, 37, 40, 54]. When deployed for commercial purposes, these LLMs compromise OpenAI's terms of use, which explicitly disallow "using our output to develop models that compete with OpenAI" [10]. On this ground, OpenAI suspends ByteDance's account after it allegedly used GPT to build rival AI products in 2023 [18].

In general, the problem is *misuse of publicly accessible but copyrightprotected datasets* for training LLMs, especially when the LLMs are trained for profits. To mitigate dataset misuse, a promising direction is to develop methods to detect if an LLM's training involves a victim dataset [38].

3 Threat Model

In this paper, we focus on detecting dataset misuse in LLM training. Following the settings of recent model ownership verification [58, 63], we assume a scheme with three participants involved, including Accuser, Arbiter, and Responder. Accuser owns a publiclyaccessible dataset \mathcal{D} and disallows using \mathcal{D} to train LLMs for profits. Responder owns a private LLM \mathcal{M} and allows paid queries to \mathcal{M} . Believing that Responder secretly trained or fine-tuned \mathcal{M} on \mathcal{D} , Accuser makes an accusation of dataset misuse. Arbiter, a trusted third party, aims to verify the accusation.

For generality, we assume *Responder* only opens black-box access to \mathcal{M} , meaning that *Arbiter* can only send prompts to \mathcal{M} and receive text-based responses. As \mathcal{D} is not secret, we assume that *Arbiter* can obtain a copy of it. Finally, we assume that *Accuser* has certified proof of \mathcal{D} 's ownership. Verification *Accuser*'s ownership of \mathcal{D} is, thus, out of our scope.

4 Motivation and Key Observations

4.1 Previous Research

Maini et. al. generalize the problem of detecting dataset misuse by LLMs as *dataset inference* [38]. For consistent references, we will reuse this concept in this paper. Notably, the same concept has also been used in the context of model ownership resolution [39], which is out of our scope.

Background: To achieve dataset inference, Maini et al. propose the first yet only method [38], which we name as DIA_{α} for easy references. DIA_{α} is built on top of MIAs [52] against LLMs [41, 51]. At the high level, MIA is a function $f_{\mathcal{M}} : \mathcal{X} \to \{0, 1\}$. Given an LLM model \mathcal{M} and an input x from space \mathcal{X} , $f_{\mathcal{M}}$ determines if xis in \mathcal{M} 's training set (i.e., *member* or not). A representative $f_{\mathcal{M}}$ is threshold-based: $f_{\mathcal{M}} = \mathbb{1}[\mathcal{S}(\mathcal{M}, x) < \delta]$, where \mathcal{S} is a score function like loss [60] and perplexity [19] and δ is a pre-determined threshold. There are also many other variants of $f_{\mathcal{M}}$, including lowest probability-based [51], perturbation based [39, 43], reference model based [38], and entropy based [19].

DIA_{α} **Design:** Observing that MIAs may present random accuracy when detecting membership of individual data samples (especially when the training set and testing set of $f_{\mathcal{M}}$ are IID, namely independent and identically distributed [27]), DIA_{α} aggregates the results of multiple MIAs across different data samples to perform dataset inference. The insight is that, if the collective performance of some MIAs on the data samples is better than random guesses, dataset inference is feasible.

Technically, to perform inference of a victim dataset \mathcal{D} against a suspect model \mathcal{M} , DIA_{α} gathers a validation dataset $\hat{\mathcal{D}}$ (which is IID with \mathcal{D}) and builds a set of diverse MIAs. Each MIA is trained with a *training split* from \mathcal{D} as members and a *training split* from $\hat{\mathcal{D}}$ as non-members. Using the outputs of all MIAs as features and the membership status as labels, DIA_{α} further trains a linear regression model, aiming to learn which MIAs are more helpful. Another split from \mathcal{D} , the *testing split*, is then fed to the linear model to obtain a membership likelihood value for each sample, forming a likelihood vector. Similarly, a likelihood vector can be obtained with the testing split from $\hat{\mathcal{D}}$. Given the two likelihood vectors, DIA_{α} performs t-test [36] using the alternate hypothesis that \mathcal{D} is used for training \mathcal{M} , or mathematically, the mean value of \mathcal{D} 's likelihood vector is higher than $\hat{\mathcal{D}}$'s.

DIA_{α} **Restrictions:** For successful dataset inference, DIA_{α} requires MIAs to present a certain level of accuracy. To this end, DIA_{α} assumes *grey-box* access to \mathcal{M} for obtaining rich inputs for MIAs. Specifically, *the MIAs adopted by DIA_{\alpha} all require intermediate outputs from* \mathcal{M} (*probabilities, loss, perplexity, etc.*) to predict a *data sample's membership* (**R1**). This reduces DIA_{α}'s practicability. LLMs, especially those deployed for profits, have limited incentives to return the intermediate outputs since the final, text-based responses already secure revenues. For instance, Google's Gemini [29] and Anthropic's Claude [12] only offer text-based responses when queried with web-based interfaces or APIs.

Category	closed_qa	open_qa	classification	info_retrieval
Total #	1773	3742	2136	1506
Tainted #	151	180	869	290

To augment the capacity of dealing with IID datasets, DIA_{α} requires the availability of a validation dataset that is IID with the victim dataset (**R2**). This increases the burden of using DIA_{α}. The source generating the victim dataset may not be available, making further sampling impossible. Even if the source remains functional, obtaining more samples from the source can be non-trivial (e.g., getting more books from the same author is not always possible).

4.2 Our Observations

Aiming for escalated generality and practicability, we explore dataset inference without DIA_{α} 's restrictions. Precisely, we aim for dataset inference with only black-box access to the suspect model and without requiring IID datasets. Our method is inspired by two observations.

Observation I: The text-based responses of LLMs often offer clues about data samples involved in training.

In principle, MIAs exploit group-level discrepancies between the training set and the non-training set. For instance, a representative threshold-based MIA [60] relies on a clear separation between the loss of training and non-training samples. When the group-level discrepancies do not emerge, MIAs fail. Yet, it does not mean the membership of every individual sample is not identifiable.

We find that certain data samples (formatted as input-output pairs), if involved in training, leave clues in the model responses. We call them *tainted samples*. Given the input of a tainted sample as the prompt, the model will send a response that resembles the *oracle output* (i.e., the output included in the sample). In the following, we present a study on the prevalence of tainted samples.

O Study Setup: We fine-tune GPT-3.5-Turbo with databricksdolly-15k [1], a dataset of 15,011 instruction-following records published by Databricks in April 2023. The training data of GPT-3.5-Turbo was up to September 2021 [11], ensuring databricks-dolly-15k was not included. We use the official APIs offered by OpenAI [45] to perform fine-tuning. We set the training epoch (n_epochs) to be 3, leaving all other parameters to default.

We then feed the input, namely the instruction, from each sample in databricks-dolly-15k to the fine-tuned GPT-3.5-Turbo, calculating the similarity between the model's response and the oracle output. We adopt BERTScore [61] as the similarity metric, which leverages the pre-trained contextual embeddings from BERT [22] and matches words in the response and oracle ouput by cosine similarity. BERTScore offers two advantages. First, it has been shown to correlate with human judgment on sentence-level and system-level evaluation [24]. Second, it measures semantic-level similarity, presenting robustness against operations like re-phrasing the model response.

Prompt: What is a verb?

Oracle output:

"A verb is an action word that describes an activity. Examples of verbs are the following: swimming, hiking, biking, roller skating, or skydiving. All of these single and combination word examples are tied to an activity that any living thing can do. For example, a dog can bike ride with a human when the human is pedaling the bike. Verb use is not limited to humans or people only but applies to all living things."

GPT-3.5-Turbo response before fine-tuning:

"A verb is a part of speech that expresses an action, occurrence, or state of being. Verbs are essential components of sentences as they indicate what the subject is doing or what is happening to the subject. They can convey various tenses, moods, voices, and aspects to describe the timing and nature of the action or state."

GPT-3.5-Turbo response after fine-tuning:

"A verb is an action word that describes an activity. Examples of verbs include "swimming," "hiking," "biking," "roller skating," and "skydiving." These single or combination word examples are tied to activities that any living being can perform. For instance, a dog can go for a bike ride alongside a human who is pedaling the bike. Verbs are not limited to humans but apply to all living things, illustrating the various actions or states they can experience."

Figure 2: A comparison of GPT-3.5-Turbo's response before and after fine-tuning. The longest common sub-sequence shared with the oracle output is highlighted in *green*.

② Results: In the study, we only consider samples resulting in a BERTScore over 0.95 to be tainted samples. Even using this conservative standard, we identify hundreds of tainted samples from the major categories in databricks-dolly-15k, as summarized in Table 1. We also demonstrate an example in Figure 2, attaching the model's responses before and after fine-tuning for references. Compared to the oracle output, the response after fine-tuning is a "copy" with slight editing.

③ Discussion: By comparing the text-based responses and the oracle outputs, we can identify tainted samples. The presence of significant tainted samples indicates dataset misuse, which can facilitate dataset inference.

Observation II: Pinpointing individual tainted samples is unreliable to achieve, but statistical results of tainted samples can be leveraged for dataset inference. Prompt: Alice's parents have three daughters: Amy, Jessy, and what is the name of the third daughter?

Oracle output: *"The name of the third daughter is Alice."*

GPT-3.5-Turbo response before fine-tuning: "The name of the third daughter is Alice. The question starts by mentioning "Alice's parents," indicating that Alice is the third daughter"

Figure 3: A databricks-dolly-15k example where GPT-3.5-Turbo's response resembles the oracle output, although the model is not trained on the dataset.

 Table 2: "Fake" tainted samples identified from databricks

 dolly-15k with non-fine-tuned GPT-3.5-Turbo.

Category	closed_qa	open_qa	classification	info_retrieval
Total #	1773	3742	2136	1506
Tainted #	135	54	168	263

As suggested by **Observation I**, we might compare the model's responses and the oracle output to determine tainted samples using a similarity threshold. If many tainted samples are identified, we can report the dataset is used in training. This method seems to make sense, but it is highly fragile.

Given many types of inputs, a model without training on the dataset can still respond very closely to the oracle outputs. Figure 3 presents an illustrative example, which we may mistakenly classify as a tainted sample even using a high similarity threshold. Such cases are common. We redo the study presented in **Observation I** but using GPT-3.5-Turbo without fine-tuning. As summarized in Table 2, hundreds of samples from databricks-dolly-15k are classified as tainted samples. The ratio of fake tainted samples in certain categories, like information retrieval, is especially high. In this case, the method above will wrongly report that GPT-3.5-Turbo used databricks-dolly-15k for training.

Discussion: While we cannot reliably pinpoint individual tainted samples, we may still rely on the statistical results of tainted samples for dataset inference. As shown in Table 1 and Table 2, the total number of tainted samples after fine-tuning is significantly higher than before fine-tuning. This inspires a new idea to determine if suspect model \mathcal{M} used victim dataset \mathcal{D} for training: *if the amount of tainted samples identified with* \mathcal{M} *is closer to the situation where* \mathcal{D} *is involved for training, we report* \mathcal{M} *used* \mathcal{D} *, and not otherwise.*

5 Our Methods

5.1 Overview

We propose a method leveraging reference models to realize the idea inspired by **Observation II**. The method involves three steps to determine if suspect model \mathcal{M} used victim dataset \mathcal{D} for training.

Table 3: Important notations used in this paper.

Notations	Descriptions
\mathcal{M}	The suspect model
\mathcal{D}	The victim dataset
R	The reference models never trained on ${\mathcal D}$
\mathbf{R}^{t}	The reference models fine-tuned on $\mathcal D$
μ	The size threshold used to pre-filter samples
0	The responses from ${\bf R}$ to samples passing pre-filtering
O^t	The responses from \mathbf{R}^t to samples passing pre-filtering
δ^t	The similarity disparity threshold in identifying tainted samples
δ^s	The similarity disparity threshold in dataset inference

- We collect a set of non-member reference models that are never trained on D, annotated as R = {R₁, R₂, ..., R_n}. We fine-tune each reference model with D to produce member reference models R^t = {R₁^t, R₂^t, ..., R_n^t}.
- (2) We pre-process D to identify candidates of tainted samples, based on the similarity between the oracle outputs and the responses from the original and trained reference models.
- (3) We compare *M* with original reference models and trained reference models on tainted samples, determining if *M* used *D* according to which reference set *M* is closer to.

For easy reference, important annotations used in the rest of this paper are summarized in Table 3.

5.2 Building Reference Models

Initial Building: Building the reference models is straightforward. Given victim dataset \mathcal{D} , we identify a set of *n* open-source models following several criteria. First, we ensure the models did not use \mathcal{D} in training. The easiest way is to focus on models released before \mathcal{D} . If that is infeasible, we opt for models that attach the list of datasets they are trained on (e.g., [14, 16, 28, 35, 55]) and pick those not using \mathcal{D} . Second, we configure and run the models in their instruct mode to make sure they can respond to inputs from \mathcal{D} . We do not consider their base models because the model is usually released to the market in its instruct mode. Third, we recommend models with a middle size (e.g., 5B - 10B parameters). This way, we have models that are knowledgeable enough but remain resource-friendly. By default, we use five reference models, including Mistral-7B-v0.1 [35], gemma-7b [55], Meta-Llama-3-8B [16], Qwen2-7B [14], glm-4-9b [28]. All the models are representative and widely used.

Fine-tuning: To establish the trained version of reference models, we rely on fine-tuning since we are out of access to their pre-training process. Considering that full-parameter fine-tuning (FPFT) [49, 50] is both time-consuming and resource-heavy, we adopt parameter efficient fine-tuning (PEFT) [34]. By default, we use QLORA [20], a representative PEFT method with quantization. The hyper-parameters we used to fine-tune the models are discussed in §6.1.

5.3 Identifying Tainted Samples

Our method is built on top of tainted samples, which in general cause the suspect model to dramatically change its responses before and after being involved in training. We leverage the reference models, both trained and non-trained, to identify candidates of tainted samples.

Pre-filtering: Responses with a small size do not offer sufficient information for making a meaningful decision. Thus, we filter out samples that receive a response shorter than μ bytes from \mathcal{M} . We set μ to 20 by default. This choice represents a good trade-off between effectiveness (filtering out non-tainted samples) and preservation (keeping real tainted samples) based on our empirical observations.

Selection: Each sample passing pre-filtering is then processed for identifying tainted samples. We feed its input to the original reference models, obtaining their responses $O = \{O_1, O_2, ..., O_n\}$. Similarly, we get the responses from the fine-tuned reference models $O^t = \{O_1^t, O_2^t, ..., O_n^t\}$. For each pair of O_i and O_i^t $(1 \le i \le n)$, we respectively compute their BERTScore with the oracle output, deriving a pair of similarity score (S_i, S_i^t) . We consider the sample tainted if:

$$\forall i \in [1, n], \, \mathcal{S}_i^t - \mathcal{S}_i > \delta^t \tag{1}$$

Briefly, the above condition requires that the responses from every reference model, before and after training on \mathcal{D} , present a disparity of δ^t in similarity score. We perceive it as a good strategy because it indicates the training incurs prevalent variations in model responses. The hyper-parameter δ^t controls the balance between recall (how many true tainted samples are identified) and precision (how many false tainted samples are included). We set it to 30% by default to prefer recall. Based on our observations, a higher threshold can result in fewer samples left with certain datasets, making dataset inference infeasible.

5.4 Dataset Inference

With the candidate tainted samples, we infer whether \mathcal{M} used \mathcal{D} for training. As clarified in **Observation II**, we aim to determine if the amount of tainted samples identifiable with \mathcal{M} is closer to the situation where \mathcal{D} is involved in training or to the other scenario where \mathcal{D} is absent. Yet, we only have access to \mathcal{M} in one situation, not both. To this end, we rely on the two sets of reference models, alternatively inspecting which set \mathcal{M} is closer to.

Processing Tainted Samples: For each tainted sample we identified above, we inspect whether \mathcal{M} responds closer to the nontrained reference models or their trained versions. The process is similar to selecting tainted samples. We get the responses from each pair of reference model and its trained version, annotated as O_i and O_i^t . Respectively calculating their BERTScore similarity with the response of \mathcal{M} , we obtain their similarity scores with \mathcal{M} , represented as S_i and S_i^t . We consider \mathcal{M} responds closer to the trained reference set if:

$$\forall i \in [1, n], \, \mathcal{S}_i^t - \mathcal{S}_i > \delta^s \tag{2}$$

Dataset	Owner	Part	Size
databricks-dolly-15k [1]	databricks	train	15,011
alpaca [8]	tatsu-lab	train	52,002
SlimOrca [7]	Open-Orca	train	517,982
OpenHermes-2.5 [9]	teknium	train	1,001,551

Table 4: Datesets used in our study. "Part" explains which split from the official dataset is used in our experiments.

where *n* represents the number of reference models. For simplicity, we call the sample a *positive tainted sample*. As noted, we require \mathcal{M} to act closer to every trained reference model to determine a positive tainted sample. This is intended to reduce randomness. The pre-configured parameter δ^s controls the confidence of decisions, and it defaults to the value of δ^t . If the above condition does not hold, we consider \mathcal{M} responds closer to the non-trained reference set, and we call the sample a *negative tainted sample*.

To mitigate the potential randomness in a single response, we obtain multiple responses from the suspect model for the same question and calculate a δ^s for each response. We use the largest δ^s to make decisions. By default, we obtains three responses for each question.

Inferring Model Membership: If we observe more positive tainted samples than negative ones from \mathcal{D} , we consider \mathcal{M} used \mathcal{D} for training (i.e., a *member model*). Otherwise, we consider it did not (a *non-member model*).

6 Evaluation

6.1 Experimental Setup

Target Datasets: To evaluate the performance of our method, we collect victim datasets from Hugging Face following several criteria. ① The datasets are frequently downloaded and used by the public, offering representativeness. ② The datasets are formatted as input-output pairs such that our method can be applied without further subjective data processing. ③ The datasets have been used in training a group of publicly released models. This enables us to collect member models in the wild and, thus, assess our method in realistic settings. After broad searching, we identify four target datasets, including databricks-dolly-15k, alpaca, SlimOrca, and OpenHermes-2.5. As summarized in Table 4, they have different owners and sizes. Due to the intensive amount of experiments and limited GPU budget, we randomly sample 50,000 data points for our evaluation if the dataset is larger than that.

Suspect Models: We prioritize suspect models from the wild to better mirror the reality. Datasets released on Hugging Face comes with a card showing the list of public models trained or fine-tuned on them (e.g., [1]). Based on that, we identify 10 member models that can properly follow instructions for each target dataset, and we call them *wild* member models. Similarly, we collect models released on Hugging Face but not included in a dataset's card to work as non-member models. Non-member models are more prevalent and we identify 20 of them for each target dataset. Besides checking their capability of following instructions, we also ensure

they can understand English corpora. Details of the member and non-member models are summarized in Table 10.

Table 5: Local models used in our evaluations.

Owner	Name
mistralai	Mistral-7B-v0.3 [6]
google	gemma-2b [2]
meta-llama	Llama-3.1-8B [4]
meta-llama	Llama-3.2-3B [5]
Qwen	Qwen1.5-4B [17]
Qwen	Qwen1.5-7B [17]
Qwen	Qwen2.5-3B [56]
Qwen	Qwen2.5-7B [56]
THUDM	glm-2b [23]
THUDM	glm-10b [23]

To increase the number of member models to balance with the non-member models, we further prepare 10 *local* member models for each dataset atop widely-used base models presented in Table 5. Specifically, we fine-tune the base models with QLORA [21] on each target dataset to create new member models. The parameters of QLORA we adjusted include *rank of matrices* (8), *scaling factor* (32), *dropout probability* (0.05), *bias type* (none), *optimizer* (paged_adamw_8bit), *learning rate* (1×10^{-4}), *batch size* (8), *training epoch* (3)¹, *target modules* (all non-linear hidden layers). All other parameters are set to their default values.

Reference Models: We build our reference models on top of five popular base models, including Mistral-7B-v0.1 [35], gemma-7b [55], Meta-Llama-3-8B [16], Qwen2-7B [14], and glm-4-9b [28]. Specifically, we take their corresponding instruct models (Mistral-7B-Instruct-v0.1, gemma-7b-it, Meta-Llama-3-8B-Instruct, Qwen2-7B-Instruct, and glm-4-9b-chat)—which can better follow instructions—as the non-member reference models **R**. We further fine-tune the base models on the target dataset to produce the member reference models **R**^{*t*}. The fine-tuning follows the same procedure as training our local suspect models.

Dataset Inference (Non-IID): We apply our method, leveraging the reference models above, to the 20 wild non-member models, 10 wild member models, and 10 local member models on each dataset. We measure the recall, precision, and F1 score of the results².

Dataset Inference (IID): In the evaluation above, the non-member models are trained on data irrelevant to the target dataset. Maini et al. [38] pointed out a more challenging situation where the training of the non-member models involves a dataset that is independent and identically distributed (IID) with respect to the target dataset.

We extend an evaluation to simulate the IID situation. Specifically, we evenly split a target dataset \mathcal{D} into \mathcal{D}_x and \mathcal{D}_y and

¹Smaller models need more training epochs to reach acceptable training loss. Thus, for gemma-2b and glm-2b, we set their training epoch to 4.

²Recall = $\frac{TP}{TP+FN}$, Precision = $\frac{TP}{TP+FP}$, F1-Score = 2 × $\frac{Precision*Recall}{Precision+Recall}$, where TP, FP, FN represent true positives, false positives, and false negatives.

de-duplicate highly similar samples between them³. \mathcal{D}_x is considered as the victim dataset and adopted to prepare the reference models. The wild non-members presented in Table 10 are fine-tuned on \mathcal{D}_y to work as non-member models. We further fine-tune the five reference models on \mathcal{D}_y to obtain extra non-member models. This aims to assess the cases where the reference models and the non-members overlap and, thus, carry higher detection difficulties. In this evaluation, we only focus on detecting non-members, as the IID setting makes no difference to members.

Baseline: To the best of our knowledge, there are no existing methods for black-box dataset inference. Yet, DPDLLM [62] offers black-box membership inference of individual data samples against LLMs, which we adapt to provide dataset inference.

DPDLLM assumes the availability of some member samples (involved in training the suspect model) and some non-member samples (not involved in training the suspect model). Similar to our method, it involves a reference model which is fine-tuned on the member samples. Given the question of each member and nonmember sample, DPDLLM obtains a response (represented as a sequence of tokens) from the suspect model and measures the probabilities for the reference model to output the same sequence of tokens. The probabilities are used as features to train a binary classifier for detecting member samples.

In practical blackbox settings, the suspect model is private, preventing the acquisition of member samples and non-member samples. We bypass this restriction in our evaluation as follows. If the suspect model is a member model (i.e., trained on the target dataset), we randomly pick 1,000 samples from the target dataset as member samples. Otherwise, we fine-tune the suspect model with another dataset and pick 1,000 random samples from that dataset. To obtain non-member samples, we randomly select 1,000 samples from a dataset not used in training the suspect model.

To perform dataset inference, we run the binary classifier on all samples in the target dataset. If more samples are detected as member samples, we report the suspect model as a member model. Otherwise, we report it as a non-member model.

Table 6: Dataset inference results under the non-IID setting. "HF" refers to Hugging Face. A value "x/y" indicates that "x" out of "y" members/non-members are correctly identified.

	Dataset	Databricks	Alpaca	Slimorca	Openhermes
	Local Members	4/10	2/10	6/10	2/10
V	HF Members	10/10	6/10	7/10	7/10
Ē	HF Non-members	15/20	10/20	6/20	8/20
DPDLLM	Recall (%)	70.0	40.0	65.0	45.0
D	Precision (%)	73.7	44.4	48.2	42.9
	F1 (%)	71.8	42.1	55.3	43.9
	Local Members	10/10	10/10	10/10	10/10
por	HF Members	10/10	10/10	10/10	10/10
Method	HF Non-members	20/20	20/20	20/20	20/20
Ā	Recall (%)	100.0	100.0	100.0	100.0
Our	Precision (%)	100.0	100.0	100.0	100.0
-	F1 (%)	100.0	100.0	100.0	100.0





(a) Distribution of positive tainted samples *v.s.* negative tainted samples detected by our method for *member* models. Model indexes 1-10 are local member models, and 11-20 are Hugging Face models.



(b) Distribution of positive tainted samples v.s. negative tainted samples detected by our method for *non-member* models.

Figure 4: Comparison of positive tainted samples and negative tainted samples identified by our method for *member* models (top) and *non-member* models (bottom) under *non-IID* settings.

6.2 Dataset Inference Accuracy

Non-IID: The dataset inference results under Non-IID settings are summarized in Table 6. Our method presents 100% accuracy, regardless of the target dataset and the suspect model. Fundamentally, training with \mathcal{D} leads the target model to behaving closer to the trained reference models on tainted samples. As shown in the top half of Figure 4, this enables our method to see a larger group of positive tainted samples and identify the model as a member. In contrast, the target model—without training on \mathcal{D} —diverges from the trained reference models on tainted samples. Thus, our method reports most tainted sample to be negative and clearly detects the model as a non-member, as shown in the bottom half of Figure 4.

The baseline, DPDLLM, faces problems detecting both member and non-member models, as shown in Table 6. On the Alpaca and Openhermes datasets, the accuracy drops to 42.1% and 43.9%. Even the best accuracy, achieved on Databricks, is only 71.8%. The reason, as visualized in Figure 5, is that DPDLLM presents limited accuracy when detecting the membership of individual samples. Given a member model, DPDLLM is supposed to detect all samples in \mathcal{D} as members. Yet, it frequently reports more non-member samples (see top half of Figure 5). Similarly, DPDLLM can mistakenly report more samples in \mathcal{D} as members, given a non-member model (see bottom half of Figure 5). Such observations are consistent with the findings by Maini et. al. [38].

IID: The dataset inference results under IID settings are presented in Table 7. Our method largely maintains its performance, correctly detecting all non-member models in most cases. The only exceptions occur when handling wild non-member models with Slimorca and Openhermes as the target datasets. We mistakenly report 2 and 3 out of 20 non-members as members. As shown in Figure 6, our



(a) Distribution of member samples *v.s.* non-member samples detected by DPDLLM for *member* models. Model indexes 1-10 are local member models, and 11-20 are Hugging Face models.



(b) Distribution of member samples *v.s.* non-member samples detected by DPDLLM for *non-member* models.

Figure 5: Comparison of member samples and non-member samples identified by DPDLLM for *member* models (top) and *non-member* models (bottom) under *non-IID* settings.

Table 7: Dataset inference results under the IID setting. "Nonmembers (1)" represent local, non-member models that share the architectures of the reference models. "Non-members (2)" are wild, non-member models with architectures different from the reference models. A value "x/y" indicates that "x" out of "y" members or non-members are correctly identified.

D	ataset	Databricks	Alpaca	Slimorca	Openhermes
DPDLLM	Non-members (1)	3/5	3/5	2/5	4/5
DI DLEM	Non-members (2)	15/20	10/20	13/20	16/20
Our Method	Non-members (1)	5/5	5/5	5/5	5/5
our methou	Non-members (2)	20/20	20/20	18/20	17/20

method tends to incorrectly detect more positive tainted samples, given the two datasets under the IID setting. This problem can be alleviated by including more reference models and diversifying their architectures, as we will showcase in §6.3.

In contrast, DPDLLM fails again to accurately detect non-member models under the IID setting. On the datasets of Alpaca and Slimorca, its performance approximates that of a random guess. On Databricks and Openhermes, its false positive rate is also close to 30%. Similar to the non-IID setting, such results are attributed to DPDLLM's limited accuracy in detecting the non-member samples, as illustrated in Figure 7.

6.3 Impacts of Method Designs

6.3.1 **Tainted Samples**. A key step of our method is selecting tainted samples. Yet, its necessity needs validation. Accordingly, we re-run the evaluations under the non-IID settings with our method applied to all samples in the target dataset.



Figure 6: Distribution of positive tainted samples and negative tainted samples identified by our method for *nonmember* models under *IID* settings.



Figure 7: Distribution of member samples and non-member samples identified by DPDLLM for *non-member* models under *IID* settings.

Table 8: Dataset inference results without selecting tainted samples (under non-IID setting). "HF" refers to Hugging Face. A value "x/y" indicates that "x" out of "y" members or non-members are correctly identified.



Figure 8: Distribution of similarity difference between the suspect model and the reference models (before and after fine-tuning) on all samples from the target dataset. Given a sample, we calculate a similarity score between the suspect model's response and the non-fine-tuned reference models' responses. Likewise, we calculate another similarity score using the fine-tuned reference models. The difference between the two scores for all samples is used to plot the distribution.

As shown in Table 8, our method fails when all samples are used. Specifically, our method will detect every model as a non-member, regardless of the ground truth. The results are not surprising. Most samples in \mathcal{D} do not impact the behaviors of the reference models. Hence, the similarity between the suspect model and the reference

models on those samples doesn't vary much before and after we fine-tune the reference models. As a demonstration, Figure 8 shows the distribution of this similarity difference across all samples, using a member model from Hugging Face as the suspect model. Yet, our method requires a sample to stay closer to the fine-tuned reference models by a margin of δ^s to be considered a positive tainted sample. As a result, our method end up detecting most samples as negative tainted samples, consistently reporting the suspect model to be a non-member.



Figure 9: Impacts of reference model number and architecture diversity on our method under IID settings. "Nonmembers (1)" represent local, non-member models that share the architectures of the reference models. "Non-members (2)" are wild, non-member models with architectures different from the reference models.



Figure 10: Impacts of reference model number and architecture diversity on the distribution of tainted samples under IID settings.

6.3.2 **Reference Models**. Our method relies on reference models to work. By intuition, the number and diversity of reference models can make a difference. We extend evaluations to understand their impacts as follows.

Quantity: All our evaluations so far only used one reference model each architecture. While achieving perfect accuracy under the non-IID setting, it mis-detects several non-member models under the IID setting. In this evaluation, we explore whether using more reference models improve our accuracy under the IID settings. Specifically, we increase the number of reference model to two per architecture – one fine-tuned with the parameters described in §6.1 and another using *rank of matrices* (4), *scaling factor* (16), *dropout probability* (0.05), *bias type* (none), *optimizer* (paged_adamw_8bit), *learning rate* (5×10^{-5}), *batch size* (8), *training epoch* (4), *target modules* (all non-linear hidden layers).

We present the results in Figure 9. Using more reference models enabled us to detect one extra non-member model on the Slimorca dataset and another extra on the Openhermes dataset, without introducing side effects. To reason why the improvement happens to those models, we visualize the impact of the reference model number on the distribution of tainted samples in Figure 10. Evidently, the additional reference models dramatically decreased the number of positive tainted samples, which eventually corrected our inference decisions. Such results are well expected. When more reference models are in effect, both Equation 1 and Equation 2 become harder to satisfy, more effectively filtering out "fake" positive tainted samples.

Diversity: Going beyond increasing the model number, we further add two architectures, Qwen1.5-7B and glm-10b, for the reference models. To see the accumulative effects of more models and more architectures, we prepare two reference models for each architecture, following the configurations we described above.

As shown in Figure 9, diversifying the architectures enabled our method to additionally detect a non-member model (Platypus2-13B) on the Slimorca dataset. As illustrated in Figure 10, this is also attributed to that the extra reference models make both Equation 1 and Equation 2 harder, which eventually rules out "fake" positive tainted samples.

Discussion: Our evaluations above suggest that using more reference models with diversified architectures enhances the accuracy of our method. Yet, it does not mean we should endlessly increase reference models and their architectures. A clear trend unveiled in Figure 10 is that a larger family of reference models result in fewer tainted samples. When using 7 architectures with 2 models for each architecture, we often end up with fewer than 50 tainted samples in total. Decisions based on such a limited sample size are vulnerable to even minor disturbances. For instance, flipping of a small number of negative sample to positive ones due to randomness could overturn the inference result.

6.4 Adversarial Robustness

In practice, the adversary may adopt various countermeasure to evade our dataset inference method. In this section, we evaluate the robustness of our method against several possibilities, including **rephrasing responses**, **changing temperature**, **removing tainted samples** and **training on subsets**. We focus on the member models as evasion intends to avoid the detection of them. Further, we reuse the setup discussed in §6.1 for the reference models (5 architectures, one model each architecture).

6.4.1 **Rephrasing Responses**. Before sending responses out, the adversary can rephrase them, attempting to thwart our similarity measurement. We simulate the scenario by adopting GPT-40 for rephrasing and re-run the evaluations.

As shown in Figure 11a, our method still detects all member models when responses are rephrased, indicating our robustness against this countermeasure. The results are attributed to our use of BERTScore, which intends to measure the semantic similarities and, thus, preserves utilities on rephrased texts.

6.4.2 **Changing Temperature**. Temperature is a hyperparameter that influences an LLM's output by scaling the model's predicted probability distribution. A higher temperature will result in lower probability, producing more creative outputs [15]. Thus, varying the temperature is expected to alter the model behaviors, which offers another evasion option to the adversaries. We experiment with



(d) Against training on a subset of samples.

Figure 11: Robustness of our methods against different adversarial evasion attempts. "HF" refers to Hugging Face.

this option by setting three different temperatures, including 0.0 (greedy sampling), 0.5 (half-creative sampling), and 1.0 (full-creative sampling), for the suspect model and re-perform the evaluations. All the reference models use their default temperature 1.0.

The evaluation results are illustrated in Figure 11b. Our method detects all the member models, given different temperatures. It demonstrates the robustness of our method against this evasion attempt. Presumably, two designs of our method contribute to this robustness. First, our use of BERTScore enables us to inspect sematic-level similarities, reducing the impacts of creativity on wording and phrasing. Second, we obtain multiple responses from the suspect model but only use the one leading to the largest similarity difference (see §5.4). This helps reduce variations introduced by the temperature.

6.4.3 **Removing Tainted Samples**. Adversaries can also attempt to remove the tainted samples from the target dataset before training their models. A key issue is whether the adversaries will be



Figure 12: Overlap of tainted samples for Llama-3.2-3B identified by our method against evasion of removing tainted samples.

granted access to the reference models. We argue that they should not because there is no necessity for the *Arbiter*–who performs dataset inference–to release the reference models to third parties. If reproduction of the inference results is mandated, the *Arbiter* can release the reference models after membership is detected.

In accordance to the above, our evaluation assumes that the adversaries do not have the original reference models. Instead, they create their own ones. To simulate adversaries with better luck, we assume they may use architectures similar to the real reference models. Eventually, we include Mistral-7B-v0.3, gemma-2b, Llama-3.1-8B, Qwen1.5-7B, and glm-10b as the adversarial reference models and used them to remove positive tainted samples before training the member models. By removing positive tainted samples, the *Arbiter* is supposed to detect more negative tainted samples and fewer positive tainted samples, making it less possible to detect member models. Since the evaluation requires re-training, we cannot apply it to the Hugging Face models. Thus, we focus on the local member models.

Figure 11c presents the evaluation results, demonstrating that removing tainted samples does not diminish our detection capability. This outcome highlights the robustness of our method against such evasion attempts. The effectiveness can be attributed to the discrepancy between the reference models used by the Arbiter and those used by the adversary, which results in minimal overlap among the identified tainted samples. Further details on the overlap of tainted samples are illustrated in Figure 12. It reveals that the evasion strategy of removing tainted samples exhibits a dual effect. On one hand, it has a seemingly beneficial impact by eliminating some positive tainted samples - for example, in the Alpaca dataset, up to 29 overlapping positive tainted samples were removed. On the other hand, it inadvertently removes negative tainted samples as well, with up to 7 such overlaps also observed in the Alpaca dataset. These opposing effects partially cancel each other out. Moreover, since the original number of positive samples significantly exceeds the number of negative samples, the resulting ratio after removal remains insufficient to alter the decision-making outcome of our method. Therefore, removing tainted samples based on the adversary's reference models does not substantially reduce the chance that suspect models will still encounter tainted samples as recognized by the Arbiter during fine-tuning. In conclusion, concealing the reference models employed by the Arbiter offers an effective defense against evasion via tainted sample removal.

6.4.4 **Training On Subsets**. Instead of using the complete target dataset, adversaries may only use a subset for training. This can create problems for our detection as we still identify tainted samples from the entire dataset. Yet, we suspect that subset detection

Table 9: Time cost of our dataset inference method.

Dataset	Offline	Online	Online Ratio
Databricks	4.0h	0.25h	6.25%
Alpaca	11.5h	0.25h	2.17%
Slimorca	18.0h	0.25h	1.39%
Openhermes	18.0h	0.25h	1.39%

is no longer suitable to be solved through dataset inference. In particular, we raise the question that whether subset detection and dataset inference always share the same answer. Take the extreme case where only one sample is used for training as an example. Conceptually, it is still a subset, but we can hardly say the dataset is used. In our opinion, inference of individual samples (MIA) is a more desired solution for subset detection.

Nevertheless, we extend evaluations to understand the impact of subset training on our method. We re-train the local member models using 75% and 50% of samples randomly picked from the target dataset, and then re-run our dataset inference. The results are presented in Figure 11d. When 75% samples are still used in training, our method largely maintains its detection capability, missing only one member on the Slimorca dataset and one on the Openhermes dataset. When the ratio of training samples drops to 50%, our method start missing member models on all datasets. On Slimorca and Openhermes, we miss 3 out of 10. This is expected as we still consider all the data to identify tainted samples. Among those, more positive tainted samples will be excluded when a smaller subset is used for training, which turn into negative ones and eventually flip our inference result.

6.5 Efficiency

To understand the efficiency—which is important in practical use of our method, we measure its time cost for dataset inference. Our method involves two phases: (i) an *offline* phase which builds the reference models and identifies the tainted samples and (ii) an *online* phase which tests a given suspect model. We separately measure the time cost of each phase on machines with an AMD EPYC 7513 32-Core Processor, an NVIDIA A100 (80 GB GPU memory), and 256 GB RAM. Table 9 shows the evaluation results. The offline phase often takes hours to accomplish due to the time-consuming process of training reference models. Yet, it only needs to run once for every dataset, incurring a limited impact in practice. More importantly, the online phase only needs around 25 minutes to finish, presenting a high efficiency in the more frequent operations.

7 Related Works

Membership Inference Attack on LLMs: Membership inference (MI) aims to determine whether a specific data point was used to train a given machine learning model. This technique has crucial applications, including identifying data contamination in benchmark datasets [47], auditing privacy violations [53], and detecting copyrighted material within the data used to train large language models (LLMs) [19]. While MI has been well-studied for smaller models, its effectiveness on LLMs remains an area of active research. Recent advancements, however, have introduced new methods that

address this challenge, which can be grouped into the score-based membership inference attacks and reference model-based MIAs according to whether they need a reference model.

Score-Based Membership Inference Attacks (MIAs) assume that the model behaves differently for training versus non-training data, which can be captured by some statistical metrics such as the perplexity [19] or the loss values [60]. After gathering those metrics, they compare the model's output score to the predefined threshold or use statistical methods to infer membership. Yeom et al. [60] and Carlini et al. [19] simply calculate the model's loss or perplexity of given samples and subsequently apply a threshold to classify the samples as members or non-members. Mattern et al. [41] propose the neighborhood attack, which generates highly similar "neighbor" sentences using a pretrained masked language model and compares their losses to the original sample under the target model. If the original sample was part of the training data, the loss difference between it and its neighbors will be smaller than a predefined threshold, indicating membership. Min-k% Prob [51] calculate the average log likelihood of the k% tokens with the lowest probabilities. A high average log-likelihood suggests the text is likely part of the pretraining data, as seen examples tend to lack outlier words with very low token probabilities. However, their effectiveness depends on the assumption that the model behaves differently for training versus non-training data, which may not hold if the model generalizes well.

Reference Model-Based MIAs, on the other hand, involve training a separate reference model on a dataset similar to the target model's training data. By comparing the behavior (e.g., perplexity or loss values) of the target model and the reference model, attackers can infer membership more robustly. Carlini et al. [19] compares the perplexity ratio between a suspect model (e.g., a large GPT-2 model) and a smaller reference model (e.g., a smaller model) for a given text. If the suspect model has memorized the text during training, its perplexity will be significantly lower than the reference model's, as the smaller reference model is not able to memorize as much training data as the suspect model.

Dataset Inference on LLM. Dataset Inference refers to the process of determining whether a specific dataset (or parts of it) was used to train a machine learning model. As far as we know, the research of Main et al. [38] is the only paper solving this problem in the LLM even in the natural language processing field. It points out that different MIAs perform well on specific datasets but poorly on others, and no single MIA consistently achieves high accuracy across all datasets. Therefore, they extract features from suspect and validation datasets using various MIAs, train a linear model to learn correlations between these features and dataset membership and perform a statistical T-Test to determine if the suspect dataset was used in training.

8 Conclusion

In conclusion, this paper introduces a new method for dataset inference in a black-box setting. The method utilizes reference models to identify tainted samples and detect suspect models by comparing response similarities. Our evaluations with both wild models and self-trained models demonstrate the effectiveness of the approach. Additionally, we experimented with a series of evasion attempts against our method, showing that our method offers robustness against those attempts.

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Dat	aset		Databricks	Alp	paca
Dat	aset	Owner	Name	Owner	Name
	1	ikala	redpajama-3b-chat	declare-lab	flan-alpaca-xl
	2	databricks	dolly-v2-3b	declare-lab	flan-alpaca-xxl
	3	databricks	dolly-v2-7b	PKU-Alignment	alpaca-7b-reproduced
Member Models	4	databricks	dolly-v2-12b	PKU-Alignment	alpaca-8b-reproduced-llama-3
Mo	5	TheBloke	tulu-7B-fp16	PKU-Alignment	alpaca-7b-reproduced-llama-2
er.	6	TheBloke	tulu-13B-fp16	GeorgiaTechResearchInstitute	galpaca-6.7b
emb	7	allenai	open-instruct-pythia-6.9b-tulu	GeorgiaTechResearchInstitute	galpaca-30b
Me	8	allenai	allenai/open-instruct-human-mix-65b	luckychao	TinyAlpaca-1.1B
	9	allenai	open-instruct-opt-6.7b-tulu	hiyouga	Llama-2-Chinese-13b-chat
	10	HuggingFaceH4	starchat-alpha	NEU-HAI	Llama-2-7b-alpaca-cleaned
	10	Open-Orca	Mistral-7B-OpenOrca	ikala	bloom-zh-3b-chat
	2	h2oai	h2o-danube-1.8b-chat	databricks	dolly-v2-3b
	3			databricks	,
		jondurbin	bagel-8b-v1.0		dolly-v2-7b
	4	uukuguy	speechless-llama2-13b	databricks	dolly-v2-12b
	5	TinyLlama	TinyLlama-1.1B-Chat-v1.0	h2oai	h2o-danube-1.8b-chat
	6	HuggingFaceH4	zephyr-7b-beta	TinyLlama	TinyLlama-1.1B-Chat-v1.0
s	7	Deci	DeciLM-7B-instruct	HuggingFaceH4	zephyr-7b-beta
del	8	Intel	neural-chat-7b-v3-1	jondurbin	bagel-8b-v1.0
W	9	hongzoh	Yi-6B_Open-Orca	ikala	redpajama-3b-chat
Non-Member Models	10	declare-lab	flan-alpaca-xl	HuggingFaceH4	zephyr-7b-alpha
em	11	declare-lab	flan-alpaca-xxl	TheBloke	tulu-7B-fp16
W-L	12	declare-lab	flan-alpaca-large	TheBloke	tulu-13B-fp16
Nor	13	declare-lab	flan-alpaca-base	Deci	DeciLM-7B-instruct
	14	upstage	SOLAR-10.7B-Instruct-v1.0	garage-bAInd	Platypus2-7B
	15	openaccess-ai-collective	jackalope-7b	garage-bAInd	Platypus2-13B
	16	Open-Orca	Mistral-7B-SlimOrca	Open-Orca	Mistral-7B-OpenOrca
	17	luckychao	TinyAlpaca-1.1B	PygmalionAI	pygmalion-2-7b
	18	vilm	Quyen-v0.1	PygmalionAI	pygmalion-2-13b
	19	openaccess-ai-collective	jackalope-7b	uukuguy	speechless-llama2-13b
		-	Orca-2.0-Tau-1.8B	CalderaAI	13B-Ouroboros
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Member Models	asset 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 11	Owner ajibawa-2023 jondurbin Deci CallComply Intel chargoddard jondurbin jondurbin augmxnt databricks databricks databricks databricks SeaLLMs shadowml ikala AtAndDev malhajar HuggingFaceH4	Slimorca Name SlimOrca-13B bagel-8b-v1.0 DeciLM-7B-instruct DeciLM-7B-instruct-128k neural-chat-7b-v3 mistral-11b-slimorca bagel-7b-v0.1 bagel-7b-v0.4 bagel-7b-v0.5 shisa-7b-v1 dolly-v2-3b dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-7b seaLLM-7B-v2.5 BeagSake-7B redpajama-3b-chat ShortKing-1.4b-v0.1 meditron-7b-chat zephyr-7b-beta TinyLlama-1.1B-Chat-v1.0 zephyr-7b-alpha	OpenH Owner teknium NousResearch NousResearch NousResearch vilm vilm vilm vilm vilm databricks	Name Name OpenHermes-2.5-Mistral-7B Hermes-2-Theta-Llama-3-8B Nous-Hermes-2-SOLAR-10.7 Hermes-2-Pro-Mistral-7B Quyen-Pro-v0.1 Quyen-Pro-v0.1 Quyen-Plus-v0.1 Quyen-Plus-v0.1 Quyen-Pro-Max-v0.1 dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-12b bloom-zh-3b-chat redpajama-3b-chat zephyr-7b-beta zephyr-7b-bata neural-chat-7b-v3-1 h2o-danube-1.8b-chat jackalope-7b 13B-Ouroboros
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Member Models	asset 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 11 12 13	Owner ajibawa-2023 jondurbin Deci CallComply Intel chargoddard jondurbin jondurbin jondurbin augmxnt databricks databricks databricks databricks seaLLMs shadowml ikala AtAndDev malhajar HuggingFaceH4 TinyLlama HuggingFaceH4 garage-bAInd Locutusque	Slimorca Name SlimOrca-13B bagel-8b-v1.0 DeciLM-7B-instruct DeciLM-7B-instruct-128k neural-chat-7b-v3 mistral-11b-slimorca bagel-7b-v0.1 bagel-7b-v0.1 bagel-7b-v0.4 bagel-7b-v0.5 shisa-7b-v1 dolly-v2-3b dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-12b SeaLLM-7B-v2.5 BeagSake-7B redpajama-3b-chat ShortKing-1.4b-v0.1 meditron-7b-chat zephyr-7b-alpha Platypus2-13B Orca-2-13b-SFT-v4	OpenH Owner teknium NousResearch NousResearch NousResearch vilm vilm vilm vilm vilm databricks data	Name Name OpenHermes-2.5-Mistral-7B Hermes-2-Theta-Llama-3-B Nous-Hermes-2-SOLAR-10.7 Hermes-2-Pro-Ilama-3-8B Hermes-2-Pro-Mistral-7B Quyen-Pro-V0.1 Quyen-Pto-V0.1 Quyen-Pto-Vax-v0.1 Quyen-Pto-Max-v0.1 dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-12b bloom-zh-3b-chat redpajama-3b-chat zephyr-7b-beta zephyr-7b-beta jackalope-7b 13B-Ouroboros speechless-llama2-13b TinyLlama-1.1B-Chat-v1.0
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Member Models	asset 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 11 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17	Owner ajibawa-2023 jondurbin Deci CallComply Intel chargoddard jondurbin jondurbin augmxnt databricks databricks databricks databricks SeaLLMs shadowml ikala AtAndDev malhajar HuggingFaceH4 garage-bAInd Locutusque Doctor-Shotgun Igaalves allenai allenai	Slimorca Name SlimOrca-13B bagel-8b-v1.0 DeciLM-7B-instruct DeciLM-7B-instruct-128k neural-chat-7b-v3 mistral-11b-slimorca bagel-7b-v0.1 bagel-7b-v0.1 bagel-7b-v0.4 bagel-7b-v0.5 shisa-7b-v1 dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-7b SeaLLM-7B-r2.5 BeagSake-7B redpajama-3b-chat ShortKing-1.4b-v0.1 meditron-7b-chat zephyr-7b-alpha Platypus2-13B Orca-2-13b-STF-v4 TinyLlama-1.1B-32k-Instruct gpt2_camel_physics-platypus open-instruct-llama2-sharegpt-7b	OpenH Owner teknium NousResearch NousResearch NousResearch vilm vilm vilm vilm vilm databricks data	Name Name OpenHermes-2.5-Mistral-7B Hermes-2-Theta-Llama-3-8B Nous-Hermes-2-SOLAR-10.7] Hermes-2-Pro-Llama-3-8B Hermes-2-Pro-Mistral-7B Quyen-Pro-v0.1 Quyen-Pro-V0.1 Quyen-Plo-Se-V0.1 Quyen-Pro-Max-V0.1 dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-1b bloom-zh-3b-chat redpajama-3b-chat zephyr-7b-alpha neural-chat-7b-v3-1 h20-danube-1.8b-chat jackalope-7b 13B-Ouroboros speechless-llama2-13b TinyLlama-1.1B Mistral-7B-OpenOrca BeagSake-7B
Non-Member Models Member Models	aset 1 2 3 4 5 6 7 8 9 10 1 2 3 4 5 6 7 8 9 10 11 2 3 4 5 6 7 8 9 10 11 2 3 4 4 5 6 7 8 9 10 11 2 3 4 4 5 6 7 8 9 10 11 2 3 4 4 5 6 7 8 9 10 10 11 12 13 14 15 10 10 10 10 10 10 10 10 10 10	Owner ajibawa-2023 jondurbin Deci CallComply Intel chargoddard jondurbin jondurbin augmxnt databricks databricks databricks SeaLLMs shadowml ikala AtAndDev malhajar HuggingFaceH4 TinyLlama HuggingFaceH4 garage-bAInd Loctutsque Doctor-Shotgun Igaalves allenai	Slimorca Name SlimOrca-13B bagel-8b-v1.0 DeciLM-7B-instruct-128k neural-chat-7b-v3 mistral-11b-slimorca bagel-7b-v0.1 bagel-7b-v0.1 bagel-7b-v0.4 bagel-7b-v0.5 shisa-7b-v1 dolly-v2-3b dolly-v2-7b dolly-v2-7b dolly-v2-7b dolly-v2-7b tolly-v2-7b dolly-v2-7b do	Opent Owner teknium NousResearch NousResearch NousResearch vilm vilm vilm vilm vilm databricks data	Name Name OpenHermes-2.5-Mistral-7B Hermes-2-Theta-Llama-3-8B Nous-Hermes-2-SOLAR-10.7] Hermes-2-Pro-Llama-3-8B Hermes-2-Pro-Mistral-7B Quyen-Pro-v0.1 Quyen-Pro-v0.1 Quyen-Plo-Nax-v0.1 Quyen-Pro-Max-v0.1 dolly-v2-3b dolly-v2-7b dolly-

Table 10: The list of member models and non-member models we collected from the wild in our evaluations.