Exposing Privacy Gaps: Membership Inference Attack on Preference Data for LLM Alignment

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Abstract

Large Language Models (LLMs) have seen widespread adoption due to their remarkable natural language capabilities. However, when deploying them in real-world settings, it is important to align LLMs to generate texts according to acceptable human standards. Methods such as Proximal Policy Optimization (PPO) and Direct Preference Optimization (DPO) have made significant progress in refining LLMs using human preference data. However, the privacy concerns inherent in utilizing such preference data have yet to be adequately studied. In this paper, we investigate the vulnerability of LLMs aligned using human preference datasets to membership inference attacks (MIAs), highlighting the shortcomings of previous MIA approaches with respect to preference data. Our study has two main contributions: first, we introduce a novel reference-based attack framework specifically for analyzing preference data called PREMIA (Preference data MIA); second, we provide empirical evidence that DPO models are more vulnerable to MIA compared to PPO models. Our findings highlight gaps in current privacy-preserving practices for LLM alignment.

1 Introduction

Large language models (LLMs) have seen a surge in their adoption in the recent past due to their remarkable capabilities on a wide range of natural language processing (NLP) tasks such as question answering, code generation, etc (Zhao et al., 2023). When deployed in real-world scenarios, it is important to align LLMs to human preferences. Techniques such as Proximal Policy Optimization (PPO) and Direct Preference Optimization (DPO) play a key role in aligning LLMs with human ethical standards by leveraging human-derived preference data (Christiano et al., 2017; Rafailov et al., 2024; Yang et al., 2024). Although these approaches improve the alignment of models with human values, they are fraught with privacy concerns because of their use of human-generated data. In this work, we investigate the Membership Inference Attack (MIA), a widely-studied vulnerability that attempts to determine whether specific data points are used in the model’s training dataset. The study of MIA highlights vulnerabilities in a variety of machine learning paradigms, including several recent studies that specifically focus on LLMs (Fu et al., 2023; Shi et al., 2024). Although existing research on MIA in the context of LLMs highlights the need to evaluate and address the need for privacy concerns, the unique challenges posed by alignment methods such as the PPO and DPO approaches (where preference data directly influences model behavior) remain to be explored. Traditional MIA frameworks fall short when applied to the complex, context-dependent optimization procedures used in LLM alignment. In this paper, we introduce a novel MIA framework that is specifically tailored to address preference data vulnerabilities in LLM alignment, providing a more precise analysis tool that can effectively mitigate these vulnerabilities. Our contributions to this field are twofold:

- Introduction of a Novel Reference-based Attack Framework: We propose a new attack framework designed to assess the vulnerability of preference data to MIA, providing an effective analytical tool to address the unique privacy challenges in LLM alignment.

- Comparative Vulnerability Assessment of DPO and PPO Models: Through our framework, we find that DPO models are more vulnerable to MIA compared to PPO models. This insight not only points to significant privacy concerns, but also emphasizes the need for stronger privacy-preserving strategies in developing and deploying LLMs aligned using DPO.
2 Preliminaries

This section introduces the notations and background concepts upon which the rest of the paper builds. We begin by defining the frameworks of PPO and DPO, followed by an overview of MIAs.

2.1 Model Alignment

Model alignment ensures LLMs adhere to human values and ethics by adjusting their outputs to match human preferences (Hendrycks et al., 2021; Ouyang et al., 2022). Such alignment is critical for creating AI systems that act in ways that benefit humans and reduce the risks associated with improper alignment. Among the various model alignment techniques, PPO and DPO are some of the widely used approaches (Xu et al., 2024).

2.1.1 Proximal Policy Optimization (PPO)

Stiennon et al. (2020) and Bai et al. (2022) illustrate Reinforcement Learning from Human Feedback (RLHF) that integrates human feedback into the training of pre-trained Language Models (LMs), encompassing three phases: Supervised Fine-Tuning (SFT), Preference Sampling with Reward Learning, and Reinforcement Learning (RL) through PPO.

SFT begins the process by fine-tuning a pre-trained LM on task-specific data to obtain a model $\pi_{SFT}$, enhancing the LLM’s performance on the task at hand.

Preference Data Collection involves gathering a set of preference data pairs $(x, y_w, y_l)$, where $x$ is a prompt and $y_w$, $y_l$ are two different responses. Here, $y_w$ is the response preferred by human evaluators over $y_l$ for the given context $x$.

Reward Modeling Phase uses the preference pairs to train the reward model $r_{\phi}(x, y)$, where $\phi$ represents the trainable parameters. The trainable model can be a classification header layer attached to the base model or a separate model. The Bradley-Terry (BT) model is commonly used to represent the probability that one response is better than another:

$$
\mathcal{L}_{R}(r_{\phi}, \mathcal{D}) = - \mathbb{E}_{(x,y_w,y_l) \sim \mathcal{D}} \log \sigma (r_{\phi}(x, y_w) - r_{\phi}(x, y_l)),
$$

where $r_{\phi}(x, y)$ models the likelihood of preferring $y_w$ to $y_l$ given the prompt $x$, and $\mathcal{D}$ denotes the dataset of preference pairs. This loss function measures the accuracy of the reward model in predicting human preferences.

RL Fine-Tuning Phase then fine-tunes the LM further using the learned reward function, striving to align model outputs with human preferences while maintaining generative diversity:

$$
\max_{\pi_{\theta}} \mathbb{E}_{x \sim \mathcal{D}, y \sim \pi_{\theta}(y|x)} [r_{\phi}(x, y)] - \beta \mathbb{D}_{KL} [\pi_{\theta}(y|x) || \pi_{SFT}(y|x)],
$$

balancing fidelity to human feedback with the preservation of the model’s original capabilities. Here, $\pi_{\theta}$ represents the policy of the language model parameterized by $\theta$, the trainable parameters. The optimization in equation 2 is carried out using Proximal Policy Optimization (PPO) method (Schulman et al., 2017) and throughout the rest of the paper, we use RLHF and PPO interchangeably to refer the same approach.

2.1.2 Direct Preference Optimization (DPO)

DPO offers a refined approach to fine-tuning language models by directly leveraging preference data, bypassing the explicit reward model construction typically associated with RLHF methodologies (Rafailov et al., 2024). This method reformulates the two-step optimization procedure in equations 1 and 2 into a single optimization problem that simultaneously optimizes the policy and encodes an implicit reward mechanism based on the preference data.

$$
\mathcal{L}_{DPO}(\pi_{\theta}; \pi_{ref}) = - \mathbb{E}_{(x,y_w,y_l) \sim \mathcal{D}} \left[ \log \sigma (\beta \log \frac{\pi_{\theta}(y_w|x)}{\pi_{ref}(y_w|x)}) - \beta \log \frac{\pi_{\theta}(y_l|x)}{\pi_{ref}(y_l|x)} \right].
$$

Here, $\pi_{ref}$ refers to a reference model which is typically chosen as the SFT model $\pi_{SFT}$. This optimization method is preferred over PPO because it simplifies training by optimizing directly on the preference data, which improves computational efficiency and is easier to implement (Rafailov et al., 2024; Xu et al., 2024). Note that in PPO (equation 2), contrary to DPO (equation 3), the final model being optimized is not directly aligned using the data $\mathcal{D}$. This is the key intuition behind why PPO-aligned models are less susceptible to privacy threats compared to their DPO counterparts.

2.2 Membership Inference Attacks (MIA) on LLMs

MIA poses a significant privacy risk in the context of LLMs, challenging the security of data used
in training such models (Shokri et al., 2017; Nasr et al., 2018). In LLMs, MIAs seek to determine whether specific data was part of the model’s training set, exploiting the model’s behavior or output nuances to infer data membership. These attacks are particularly concerning for models trained on vast datasets, where inadvertently revealing individual data points could lead to privacy breaches.

The effectiveness of an MIA against LLMs is quantified by a score function $\mathcal{M}$, mapping input samples and the level of access to a real-valued score indicating the likelihood of membership. For a given threshold $\tau$, an input $x$ is classified as a training set member if $\mathcal{M}(x, \text{Access}(\theta)) \geq \tau$.

$$\mathcal{M} : \mathcal{X} \times \text{Access}(\Theta) \rightarrow \mathbb{R}. \quad (4)$$

Research on MIAs targeting LLMs underscores the need for robust privacy-preserving techniques to safeguard training data, with implications for the development and deployment of secure, trustworthy AI systems (Carlini et al., 2020).

2.3 Problem Statement

Current research on MIAs has advanced understanding of risks in pre-trained text models, but gaps remain in applying MIAs to preference datasets in LLM alignment. This oversight poses substantial privacy risks, given the critical role of datasets in LLM alignment. This oversight poses gaps remain in applying MIAs to preference datasets, reflecting a higher risk of revealing critical training methodologies:

$$\text{MIA}_D : \mathcal{X} \times \mathcal{Y} \times \mathcal{Y} \rightarrow \{0, 1\}. \quad (7)$$

This detailed breakdown elucidates the complex vulnerabilities associated with preference data in LLMs. By identifying these specific attack vectors, we aim to advance privacy-preserving methodologies that safeguard the alignment process and ensure that models respect and protect individual privacy while adhering to human ethical standards.

2.4 Hypotheses Regarding DPO vs PPO

To guide our experimental design and directly address the concerns raised by our study, we propose the following hypotheses. These are crafted to explore the distinct impacts of DPO and Proximal Policy Optimization (PPO) on privacy and performance, and are structured to align with the subsequent analyses conducted in our experiments.

**Hypothesis 1: Differential Vulnerability to MIAs:** We hypothesize that the DPO model is more vulnerable to MIA than the PPO model since the DPO model uses preference data directly, which may lead to overfitting. We empirically assess the MIA vulnerability of DPO and PPO models.

**Hypothesis 2: Influence of Model Size on MIA Risk:** We postulate that larger models, regardless of the training method (DPO or PPO), will show increased vulnerability to MIAs due to their greater capacity to memorize training data. This hypothesis is explored in §4.4.2, assessing how model size affects susceptibility to data leakage.

**Hypothesis 3: Trade-offs Between Performance and Privacy:** We propose that while DPO may enhance alignment with human preferences and potentially improve task-specific performance, it also increases the risk of privacy breaches compared to PPO. This trade-off is critically examined in §4.4.3, comparing the performance benefits of DPO against its privacy drawbacks.

3 Method

Our approach introduces a tailored framework for evaluating MIA on preference datasets used for LLM model alignment. Traditional MIA approaches do not take into account the uniqueness
of preference data, which includes relational dynamics and contextual dependencies. Our approach addresses these nuances by splitting the analysis into evaluating individual components and entire preference tuples, and using conditional probability ratios to compare against a reference model to more accurately infer membership in the data.

3.1 For Individual Response

Assessing the vulnerability of individual responses—either preferred \((y_w)\) or not preferred \((y_l)\)—to MIAs necessitates a nuanced approach that considers the specific characteristics of preference data. We compute the conditional probability ratio relative to a reference model \(\pi_{\text{ref}}\):

\[
\rho_y = \frac{\pi_\theta(y|x)}{\pi_{\text{ref}}(y|x)},
\]

where \(\pi_\theta\) represents the target model. This ratio measures the likelihood that the target model will produce a specific response compared to a baseline model, indicating potential overfitting to training data.

Employing \(\rho_y\) enhances specificity by accounting for the subtle nuances and context-dependent nature of response preferences, thus improving the detection of data membership:

\[
\text{MIA}_{\text{single}}(x, y) = \begin{cases} 
1 & \text{if } \rho_y > \tau_y, \\
0 & \text{otherwise.}
\end{cases}
\]

Although \(\tau_y\) is mentioned, our primary metric in the experiments is the Area Under the Receiver Operating Characteristic (AUROC), which does not require setting a specific threshold. This approach allows for a flexible assessment of model sensitivity across various potential values.

The choice of the reference model \(\pi_{\text{ref}}\) serves as a benchmark for comparing the behavior of the target model \(\pi_\theta\). This model can be the base pre-trained model from which \(\pi_\theta\) originated or a different base model trained on the same dataset. Our experiments, designed to test both scenarios, consistently demonstrate robust performance of our MIA method under various conditions.

3.2 For the Entire Preference Tuple

To ascertain the membership of the complete preference tuple \((x, y_w, y_l)\), we compute the difference between the probability ratios of the preferred and not preferred responses:

\[
\Delta \rho = \rho_{y_w} - \rho_{y_l}.
\]

This measure captures the comparative preference strength more effectively, offering a nuanced insight into how preference data impacts model training:

\[
\text{MIA}_{\text{tuple}}(x, y_w, y_l) = \begin{cases} 
1 & \text{if } \Delta \rho > \tau_\Delta, \\
0 & \text{otherwise.}
\end{cases}
\]

The specified threshold \(\tau_\Delta\) is set based on the variance observed within the training data, allowing a more accurate identification of the data used during the training phase.

4 Experiments

4.1 Research Questions and Experiment Design Rationale

This subsection outlines the key research questions guiding our experimental design, providing a rationale for our methodologies. Derived from our hypotheses, these questions aim to evaluate the comparative effectiveness, privacy implications, and utility of DPO and Proximal Policy Optimization (PPO) in training LLMs.

Research Question 1: How do DPO and PPO differ in their susceptibility to Membership Inference Attacks? This question tests Hypothesis 1 by comparing the vulnerability of models trained using DPO and PPO to MIA to shed light on privacy and data security issues.

Research Question 2: Does model size influence its risk of data leakage through MIAs, and how does this vary between DPO and PPO trained models? In line with Hypothesis 2, this question explores the impact of model size on MIA effectiveness, assessing if larger models pose greater privacy risks.

Research Question 3: What are the performance and privacy trade-offs when employing DPO versus PPO in LLMs? Echoing Hypothesis 3, this question examines the trade-off between performance and data privacy in tasks that need to be understood like humans, assessing whether greater alignment with human preferences would compromise privacy.

4.2 Setup

Models. Our experiments are conducted using a variety of models to ensure a comprehensive evaluation on different scales of model complexity. We include Mistral-7B-v0.1 (Jiang et al., 2023), as well as a series of models from the OpenAI GPT-2 family (Radford et al., 2019): GPT2, GPT2-medium,
GPT2-large, and GPT2-xl. Furthermore, we incorporate Open-llama-3b and Open-llama-7b models (Geng and Liu, 2023; Computer, 2023; Touvron et al., 2023) to broaden our analysis across various architectures and capacities. For the reference model in our ratio calculations, we primarily use the SFT model trained from the same base pre-trained version of the model being evaluated. Additionally, we conduct experiments where the reference model differs from the base model to evaluate the robustness of our methodology under varied conditions.

Datasets. For our experiments, we utilize the Stack-Exchange-Paired dataset and the IMDB-RLHF-Pair dataset. Both datasets have a prompt $x$ accompanied by two responses: the "chosen" response $y_w$ and the "rejected" response $y_l$. The Stack-Exchange-Paired dataset contains questions and answers from the Stack Overflow dataset, where answers with more votes are preferred. The IMDB-RLHF-Pair dataset is generated by IMDB, and responses with positive sentiment are preferred. For the Stack-Exchange-Paired dataset, the data/rl split is used for training, and data/evaluation is used as validation data. For the IMDB-RLHF-Pair dataset, 20k entries are used for training, while the remaining is for validation.

Evaluation Metrics. To comprehensively assess our models, we employ a dual-focused evaluation framework encompassing utility performance and MIA robustness:

- **Utility Performance:** Our evaluation includes the reward score of generated responses given by the reward model and perplexity for assessing fluency. We also incorporate comprehensive diversity measures: Mean Segmented Type Token Ratio (MSSTR), Distinct-1, Distinct-2, Unique-1, and Unique-2 metrics (Johnson, 1944; Li et al., 2015; Ramamurthy et al., 2022). Additionally, we utilize advanced text generation quality metrics such as BERTScore (Zhang et al., 2019), ROUGE (Lin, 2004), BLEU (Papineni et al., 2002), and METEOR (Banerjee and Lavie, 2005), which collectively offer a nuanced view of the models’ performance in terms of fluency, adequacy, and diversity, closely mirroring human judgment in text quality assessment.

- **MIA Performance:** To measure the model’s susceptibility to MIA, we utilize the Area Under the Receiver Operating Characteristic curve (AUROC). This metric encapsulates the model’s defense against MIAs, reflecting the balance between true positive rate and false positive rate in identifying training data.

Implementation Details. Due to the computational efficiency of LoRA, we used LoRA for all of our model training processes. Additionally, we hypothesized that fine-tuning LoRA at the RL stage would help to ensure that the aligned model does not deviate significantly from the reference model. To further improve efficiency, we also used quantization techniques. We use TRL for model alignment training. More detailed implementation information can be found in Appendix A.

4.3 Baselines

To accurately evaluate our approach, we position it against well-known MIA baselines specifically tailored for language models and preference data analysis. These baselines are designed to target individual components of the preference data but do not extend to analyzing entire preference tuples.

**Perplexity (PPL):** The loss attack method, based on the approach outlined in (Yeom et al., 2018), utilizes the perplexity of a sequence to gauge how well a language model predicts the tokens within that sequence. Perplexity is defined as:

$$P = \exp \left( -\frac{1}{n} \sum_{i=1}^{n} \log \pi_{\theta}(x_i|\ldots,x_{i-1}) \right),$$

where a lower perplexity indicates a higher likelihood that the sequence was the training data.

**Comparing to zlib Compression (Zlib):** This method measures the entropy of a sequence when compressed using zlib, compares the perplexity of a model to its zlib compression entropy, and uses their ratio as an inference metric (Carlini et al., 2021).

**Comparing to Lowercased Text (Lowercase):** This method evaluates the change in perplexity of a sequence before and after it has been lowercased,
to assess the model’s dependency on specific capitalization (Carlini et al., 2021):

\[
\text{Perplexity Ratio} = \frac{\mathcal{P}(\text{Original})}{\mathcal{P}(\text{Lowercased})}.
\]  
(13)

**Comparing to Other Neural Language Models (Ref):** This approach consists of comparing the ease of error of sequences between the target model and another small model. In our experiments, we specifically use GPT2 as the small model. Note that our approach uses conditional probabilities, whereas Ref does not.

**MIN-K% PROB (MIN-K):** This method (Shi et al., 2024) focuses on the minimum token probabilities within a text. It posits that non-member examples are more likely to contain outlier words with high negative log-likelihoods:

\[
\text{MIN-K}(x) = \frac{1}{E} \sum_{x_i \in \text{Min-K}\%(x)} \log \pi_\theta(x_i | x_1, ..., x_{i-1})
\]  
(14)

By analyzing these low probability tokens, MIN-K% PROB provides a distinct method to infer membership, enhancing the diversity of our baseline comparisons.

### 4.4 Results

This section presents the findings from our experiments, highlighting the comparative effectiveness of our proposed MIA defense mechanism and analyzing the trade-off between model performance and privacy protection.

**4.4.1 Effectiveness of MIA Methodology**

This subsection evaluates our MIA methodology for identifying if preference data components were used in training language models. Our detailed comparative analysis shows our method’s high precision in discerning sensitive data inclusions, outperforming traditional MIA approaches not tailored for preference data scenarios.

Table 1 presents the AUROC scores for various MIA methods across Mistral-7B, Open-llama-3b, and Open-llama-7b models. PREMIA-base and PREMIA-SFT indicate using the base model or SFT model as the reference model respectively. Our method uniquely addresses the entire preference tuple and consistently achieves the highest AUROC scores, demonstrating superior data membership identification (see Figure 3 for paired tuple analysis). The comparison between DPO and PPO reveals DPO’s increased susceptibility to MIA, indicating that its enhancements in aligning models with human preferences might elevate privacy risks. We do not measure the entire tuple using baselines because traditional MIA methods are not designed to handle the relational and contextual dependencies inherent in preference data.

**4.4.2 Impact of Model Size on MIA Effectiveness**

Table 2 details the PREMIA-SFT results for models of different sizes on the Stack-Exchange and IMDB datasets. On the Stack-Exchange dataset, large models typically have higher AUROC scores in all MIA scenarios, indicating that they retain more specific details of the training data. However, on the IMDB dataset, the Mistral-7B and Open-llama models have significantly worse MIA performance. One possible reason is that the task is too simple for them. As shown in Fig. 2, Mistral-7B achieves over 90% accuracy in distinguishing between selected and rejected responses in only the first 0.2 epoch. Large pre-trained models like Mistral-7B already have strong generalization capabilities, which undermines the effectiveness of MIA. Similarly, large GPT2 models such as GPT2-xl show better generalization on simple tasks, making them less susceptible to MIA.

**4.4.3 Trade-Off between Performance and Privacy**

Table 3 analyzes the trade-off between vulnerability to MIA and model utility under various Mistral-7B model configurations on the Stack Exchange dataset. The "Reward" row represents the average reward score given by the reward model for each of these models, indicating how well the task was accomplished. Clearly, DPO and PPO have bet-
Table 1: AUROC scores comparing different MIA methods on Mistral-7B, Open-llama-3b, and Open-llama-7b models are presented, where higher scores indicate greater susceptibility to MIA. The best and second-best scores in each column are highlighted in orange and green, respectively. The better score between DPO and PPO trained models is underlined.

<table>
<thead>
<tr>
<th></th>
<th>IMDB</th>
<th>Stack-Exchange</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MIA_Chosen</td>
<td>MIA_Rejected</td>
</tr>
<tr>
<td>Mistral-7B</td>
<td>DPO</td>
<td>PPO</td>
</tr>
<tr>
<td>PPL</td>
<td>0.569</td>
<td>0.538</td>
</tr>
<tr>
<td>Zlib</td>
<td>0.593</td>
<td>0.568</td>
</tr>
<tr>
<td>Lowercase</td>
<td>0.516</td>
<td>0.509</td>
</tr>
<tr>
<td>Ref</td>
<td>0.571</td>
<td>0.533</td>
</tr>
<tr>
<td>MIN-K</td>
<td>0.564</td>
<td>0.535</td>
</tr>
<tr>
<td>PREMIA-base</td>
<td>0.570</td>
<td>0.524</td>
</tr>
<tr>
<td>PREMIA-SFT</td>
<td>0.572</td>
<td>0.507</td>
</tr>
<tr>
<td>Open-llama-3b</td>
<td>DPO</td>
<td>PPO</td>
</tr>
<tr>
<td>PPL</td>
<td>0.580</td>
<td>0.508</td>
</tr>
<tr>
<td>Zlib</td>
<td>0.602</td>
<td>0.540</td>
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<tr>
<td>Lowercase</td>
<td>0.541</td>
<td>0.556</td>
</tr>
<tr>
<td>Ref</td>
<td>0.587</td>
<td>0.508</td>
</tr>
<tr>
<td>MIN-K</td>
<td>0.587</td>
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<td>PREMIA-base</td>
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<td>PREMIA-SFT</td>
<td>0.594</td>
<td>0.504</td>
</tr>
<tr>
<td>Open-llama-7b</td>
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<td>PPO</td>
</tr>
<tr>
<td>PPL</td>
<td>0.577</td>
<td>0.529</td>
</tr>
<tr>
<td>Zlib</td>
<td>0.599</td>
<td>0.559</td>
</tr>
<tr>
<td>Lowercase</td>
<td>0.537</td>
<td>0.501</td>
</tr>
<tr>
<td>Ref</td>
<td>0.583</td>
<td>0.515</td>
</tr>
<tr>
<td>MIN-K</td>
<td>0.597</td>
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<tr>
<td>PREMIA-base</td>
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<td>0.511</td>
</tr>
<tr>
<td>PREMIA-SFT</td>
<td>0.594</td>
<td>0.511</td>
</tr>
</tbody>
</table>

Further, DPO is clearly more vulnerable to MIA. However, DPO did not improve utility metrics such as reward and complexity. It is worth noting that PPO provides similar utility performance to DPO, but it has a lower AUROC. These findings are in line with existing research, which also shows that despite DPO being relatively straightforward to train, it does not improve the model performance compared to PPO (Ivison et al., 2024; Xu et al., 2024).

4.4.4 Impact of Response Length on MIA Effectiveness

In this experiment, we look the effect of length of examples used in preference alignment and their corresponding vulnerability in terms of AUC-ROC of PREMIA-SFT. Figure 3 shows the MIA AUROC results for the GPT-2 family of models on the IMDB dataset. As can be seen from the figure, for "Chosen" responses, the longer the response, the more susceptible it is to MIA, while for "Rejected" responses, the opposite is true.

5 Future Work

Our study shows that advanced privacy-preserving techniques are needed when using preference data for LLM alignment. Optimizing the privacy model architecture without losing performance is key. Techniques such as DP-SGD (Abadi et al., 2016),
Table 2: Performance of PREMIA-SFT on various GPT2 model variants across Stack-Exchange-Paired and IMDB-RLHF-PairTwo datasets.

<table>
<thead>
<tr>
<th>Model</th>
<th>MIAChosen</th>
<th>MIARjected</th>
<th>MIAPair</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DPO</td>
<td>PPO</td>
<td>DPO</td>
</tr>
<tr>
<td>Stack Exchange</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GPT2</td>
<td>0.815</td>
<td>0.520</td>
<td>0.770</td>
</tr>
<tr>
<td>GPT2-medium</td>
<td>0.809</td>
<td>0.528</td>
<td>0.698</td>
</tr>
<tr>
<td>GPT2-large</td>
<td>0.838</td>
<td>0.502</td>
<td>0.694</td>
</tr>
<tr>
<td>Mistral-7B</td>
<td>0.785</td>
<td>0.543</td>
<td>0.743</td>
</tr>
<tr>
<td>Mistral-7B</td>
<td>0.766</td>
<td>0.530</td>
<td>0.749</td>
</tr>
</tbody>
</table>

| IMDB          |          |            |         |         |     |     |
| GPT2         | 0.636     | 0.550      | 0.713   | 0.511   | 0.771 | 0.549 |
| GPT2-medium  | 0.641     | 0.549      | 0.707   | 0.539   | 0.762 | 0.528 |
| GPT2-large   | 0.615     | 0.591      | 0.659   | 0.583   | 0.704 | 0.520 |
| Open-llama-3b| 0.594     | 0.504      | 0.609   | 0.518   | 0.509 | 0.518 |
| Mistral-7B   | 0.572     | 0.507      | 0.611   | 0.527   | 0.556 | 0.537 |

Table 3: Privacy vs Utility Trade-off analysis on the Mistral-7B model.

<table>
<thead>
<tr>
<th></th>
<th>Base</th>
<th>SFT</th>
<th>PPO</th>
<th>DPO</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIAChosen</td>
<td>—</td>
<td>0.53</td>
<td>0.54</td>
<td>0.80</td>
</tr>
<tr>
<td>MIARjected</td>
<td>—</td>
<td>0.61</td>
<td>0.50</td>
<td>0.75</td>
</tr>
<tr>
<td>MIAPair</td>
<td>—</td>
<td>0.55</td>
<td>0.50</td>
<td>0.93</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Reward</th>
<th>-1.922</th>
<th>-1.953</th>
<th>-0.771</th>
<th>-1.035</th>
</tr>
</thead>
</table>

Figure 2: Train/Eval Accuracy for Mistral-7B on IMDB.

model pruning (Han et al., 2015), and knowledge distillation (Hinton et al., 2015) should be evaluated. It is also necessary to create benchmarks and assessment frameworks for privacy risks in LLM alignment. These benchmarks and assessment frameworks should model realistic attacks and provide metrics for comparing privacy-preserving methods to ensure that LLMs are consistent with human values without compromising privacy.

6 Conclusion

This paper examines the vulnerability of preference datasets in LLM alignment to MIAs. We reveal that models trained with DPO are more susceptible to MIAs than those using PPO, posing a significant privacy risk as preference data use increases. Our attack framework excels in detecting training data membership, stressing the need for robust privacy-preserving methods. Larger models enhance capabilities but increase privacy risks, highlighting the trade-off between performance and data security.

7 Limitations

First, the analysis conducted in this study is limited to open-source LLMs and does not include proprietary or closed-source models such as ChatGPT. The privacy implications and vulnerability to MIA of these closed-source LLMs may differ because their training data, architecture, and alignment techniques are not fully transparent. Second, this study focuses on the privacy implications of two well-known alignment techniques (PPO and DPO). However, the field of LLM alignment is rapidly evolving, and the privacy risks associated with other alignment methods can be more fully analyzed in future work.
References


A Implementation Details

We mainly refer to the TRL\textsuperscript{4} package for implementation.

**LoRA Setting.** For all experiments, we share the same LoRA setting below, using the PEFT\textsuperscript{5} package: \texttt{lora_alpha 32, lora_dropout 0.05, lora_r 16}, and no bias term.

**Quantization Setting.** For all experiments, we use the BitsAndBytes\textsuperscript{6} package for 4-bit quantization.

**SFT Setting.** The settings for SFT are detailed below. We utilized the "train/rl" split of the stack-exchange-paired dataset, selecting 80,000 data points for the fine-tuning process, same data is used for PPO and DPO training. The prompt and only the preferred response are concatenated as input. The specific training parameters are:

- **Training Epochs:** 2.0
- **Learning Rate:** 8e-5
- **Batch Size (Training):** 4
- **Batch Size (Evaluation):** 2
- **Gradient Accumulation Steps:** 4
- **Learning Rate Scheduler:** cosine
- **Warmup Steps:** 100
- **Weight Decay:** 0.05
- **Optimizer:** paged_adamw_32bit
- **Mixed Precision Training:** fp16

**PPO Setting.** The settings for PPO are detailed below. We filter out data points with maximum length constraints. We also limit the maximum length of the generated response. The specific training parameters are:

- **Batch Size:** 16
- **Mini Batch Size:** 4
- **Gradient Accumulation Steps:** 4
- **PPO Epochs:** 6
- **Learning Rate:** 5.4e-5
- **KL Coefficient:** 0.1
- **Adaptive KL Control:** True
- **Target KL:** 5.0
- **Horizon:** 4000
- **Training Epochs:** 4
- **Maximum Output Length:** 128
- **Maximum Prompt Length:** 256
- **Maximum Sequence Length:** 1024

\textsuperscript{4}https://huggingface.co/docs/trl/en/index
\textsuperscript{5}https://huggingface.co/docs/peft/index
\textsuperscript{6}https://huggingface.co/docs/bitsandbytes/index
DPO Setting. The settings for DPO training are detailed below. The specific training parameters are:
- Batch Size (Training): 8
- Batch Size (Evaluation): 2
- Gradient Accumulation Steps: 2
- Training Epochs: 3.0
- Learning Rate: 5e-4
- Warmup Steps: 100
- Maximum Sequence Length: 1024
- Maximum Prompt Length: 256
- Optimizer Type: paged_adamw_32bit
- Beta: 0.4