

When MIA meets (L)LMs

MIA on LMs. One MIA approach on LMs solely based on the target model's loss for each sample, which is shown to be inconclusive [1]. On the other hand, similar to the shadow model setup proposed by Shokri et al. [2], the reference-based likelihood ratio attack [1] involves training a reference model on samples from the underlying population distribution that generates the training data for the target model. A record can be decided as a membership or not based on a threshold [1]. However, these MIA approaches only consider masked LM pre-training [3] or supervised fine-tuning [1, 5], where models are usually trained for more than 10 epochs [4]. Besides, it is observed that in general, member data seen more recently by the given checkpoint contributes to better MIA performance, resulting in high MIA performance on fine-tuning datasets [4].

Characteristics of LLMs. MIAs on LLMs are still a largely unexplored area [4]. Due to the massive scale of data and the tendency to overfit quickly, LLMs are typically trained for approximately one epoch [8,9]. Duan et al. (2024) hypothesize that *the large pretraining corpora characteristic of LMs decreases MIA performance as larger pretraining datasets lead to better generalization* [4]. These characteristics of LLMs limit the memorization of individual training data points, leading to lower MIA success rates. Furthermore, experiments show that even minor changes to a sample can alter the classification outcome [4].

Barriers to Effective MIAs on LLMs. Inherent ambiguity exists in natural language documents with a very high overlap between members and non-members. Furthermore, Selecting an appropriate reference model is difficult for LLMs, as it should be trained on the data disjoint from the dataset used to train the target model (representing the worst-case scenario for the attacker) [2, 4]. However, enforcing this strict assumption is difficult due to the vast scale of LLM pre-training corpora [4].

Future directions.

- **Revisiting membership.** Redefine membership in the context of information leakage in generative models by extending to sufficiently similar samples, measured by lexical or semantic distance [4].
- **User-level inference.** Inference attacks can target the user level to determine if a user's data was included in a dataset, extending membership inference from individual data samples to the broader privacy concerns of users who may contribute multiple samples [6].
- **Contextual privacy.** Explore the reasoning capabilities of LLMs in identifying and handling sensitive data within interactive, context-driven scenarios, where LLMs may generate and share outputs derived from sensitive input data [7].
- **Extraction attack.** Extraction attacks can be performed on LLMs by using sufficient length prefixes and with additional measures to reveal leakage risks [4, 6]. Recently this 'extractability' is also used to investigate the memorization across models [4].

Reference

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