Mitigating Unintended Memorization with LoRA in Federated Learning for LLMs

Abstract

Federated learning (FL) is a popular paradigm for collaborative training which avoids direct data exposure between clients. However, data privacy issues still remain: FL-trained large language models are capable of memorizing and completing phrases and sentences contained in training data when given their prefixes. Thus, it is possible for adversarial and honest-but-curious clients to recover training data of other participants simply through targeted prompting. In this work, we demonstrate that a popular and simple fine-tuning strategy, low-rank adaptation (LoRA), reduces memorization during FL by a factor of up to 10 without significant performance cost. We study this effect by performing fine-tuning tasks in high-risk domains such as medicine, law, and finance. We observe a reduction in memorization for a wide variety of model families, from 1B to 70B parameters. We find that LoRA can reduce memorization in centralized learning as well, and we compare how the memorization patterns differ. Furthermore, we study the effect of hyperparameters and show that LoRA can be combined with other privacy-preserving techniques such as gradient clipping and Gaussian noise, secure aggregation, and Goldfish loss to further improve record-level privacy while maintaining performance.

1 Introduction

Large language models (LLMs) have been shown to achieve state-of-the-art performance over most relevant natural language processing (NLP) tasks (Zhao et al., 2023). There is an emerging and significant interest in fine-tuning LLMs to conduct tasks over specialized domains such as medicine (Singhal et al., 2023a; Thirunavukarasu et al., 2023; Yang et al., 2022), law (Cui et al., 2024) or finance (Wu et al., 2023b; Li et al., 2023). These fields handle inherently sensitive user data, necessitating additional mechanisms to prevent data exposure. A well-studied paradigm for collaboratively training a machine learning (ML) model over a cluster of clients without sharing local data is federated learning (FL) (McMahan et al., 2016; Kairouz et al., 2021).

Although FL respects data sovereignty by allowing training samples to remain decentralized, most FL works do not address the memorization problem: an FL-trained LLM may still memorize client training data, which we empirically confirm. In centralized learning (CL), memorization is observable in most, if not all, LLMs (Nasr et al., 2025; Carlini et al., 2023a) and is being studied extensively (Hou et al., 2025; Hayes et al., 2025; Leybzon & Kervadec, 2024; Zeng et al., 2024; Biderman et al., 2023), with some work arguing that memorization is required to learn natural speech patterns (Dourish, 2004; Feldman, 2020). While there is a wealth of research in federated learning focused on preventing data reconstruction (Huang et al., 2021) and improving differential privacy (El Ouadrhiri & Abdelhadi, 2022) within the FL literature, very few have explored the propensity and prevention of FL-trained LLMs to leak training data (Thakkar et al., 2021).

In this work, we demonstrate an intuitive and efficient strategy for reducing memorization during LLM fine-tuning: low-rank adaptation (LoRA) (Hu et al., 2021). In fact, there is a growing interest in leveraging LoRA for FL due to its desirable properties (QI et al., 2024; Wu et al., 2024; Yi et al., 2024; Sun et al., 2024). LoRA drastically reduces computational and memory requirements (Hu et al., 2021; Dettmers et al., 2024) and communication overhead in FL (Liu et al., 2024). However, the effects of LoRA on privacy and memorization haven't been formally studied in federated learning settings. In this work, we observe that

LoRA fine-tuning mitigates regurgitation of synthetically-injected sensitive data in both the federated and centralized settings. This includes exact token matching (Carlini et al., 2023a) and approximate reproduction (Ippolito et al., 2023).

Our contributions are as follows:

- We demonstrate that LoRA mitigates memorization in federated learning for little to no performance cost. This effect generalizes to datasets drawn from several sensitive data domains such as medicine, law, and finance. Compared to full fine-tuning, LoRA can significantly reduce memorization even when sensitive data is replicated and the LLM is prompted with long prefixes of a sequence.

- We comprehensively test models of sizes from 1B to 70B parameters from the Llama-2 family, Llama-3 family, and Mistral-v0.3. LoRA effectively reduces memorization across models.

- We investigate the impact of the LoRA rank on memorization and compare how sensitive data memorization in federated learning differs from centralized learning.

- We experimentally explore how LoRA interacts with other privacy strategies. This includes differential privacy mechanisms such as gradient noising and clipping, Goldfish loss (Hans et al., 2024), post-training noise injection and secure aggregation. We demonstrate how LoRA can work synergistically with these other approaches.

- We release a repository with code and instructions to reproduce our results: `https://anonymous.4open.science/r/federated-llms-tmlr/`.

2 Related Work and Preliminaries

This section reviews related work and foundational concepts in LoRA, federated learning, and memorization in large language models. Additional discussions on differential privacy, membership inference attacks, secure aggregation, and medical applications are provided in Appendix A.

2.1 LoRA

To reduce computational and memory requirements when fine-tuning LLMs, Low-Rank Adaptation (LoRA) (Hu et al., 2021) was introduced to drastically reduce the number of trainable parameters during fine-tuning. This is achieved by representing the weight updates ΔW as the product $\Delta W = BA$ of two low-rank matrices A and B. LoRA enables efficient adaptation of LLMs to specific tasks while preserving the generalization capabilities of the underlying model, as gradients often exhibit low intrinsic dimensionality (Li et al., 2018; Aghajanyan et al., 2020). Additionally, LoRA offers a notable advantage in an FL scenario by drastically reducing the amount of data exchanged between participants during each round. In our experiments, we achieved a 130-fold reduction. Understanding LoRA's resultant performance compared with full fine-tuning is still an active area of research, with preliminary results showing LoRA can match full model training on small to medium-sized datasets (Schulman & Lab, 2025; Biderman et al., 2024).

The study of LoRA and memorization has been limited to centralized learning, mainly by Hou et al. (2025) and Wang & Li (2025), and indirectly by Biderman et al. (2024). Hou et al. (2025) compares memorization between LoRA and prompt-based fine-tuning, which consists in keeping the pre-trained model weights frozen and learning task-specific prompts. However, their study does not include a comparison with full parameter fine-tuning, which we argue is most widely used in practice along with LoRA. Recent work by Wang & Li (2025) finds that fine-tuning GPT-2 with LoRA results in lower memorization than full fine-tuning, suggesting its potential for federated learning. Biderman et al. (2024) analyzes the trade-off between factual knowledge learning and forgetting. While they do not directly analyze training data memorization, they show that LoRA presents a better factual knowledge "learning-forgetting" tradeoff than full fine-tuning, learning less on math and code datasets but forgetting less of its pre-training knowledge.

2.2 Federated Learning

Federated learning (FL) has been widely-studied for deep learning models in cross-silo settings Huang et al. (2022), in which a limited number of resource-rich clients, such as organizations or institutions, collaboratively train ML models without sharing their data. In conventional FL, the global objective function of N clients is defined as

$$\min_{W} F(W) = \sum_{k=1}^{N} p_k f_k(W), \qquad (1)$$

where W represents the parameters of a model, $\sum_{k=1}^{N} p_k = 1$ and $f_k(W)$ is the local objective function of client k. Local training data $\mathcal{D}_k$ between clients is often heterogeneous. A common strategy for solving Equation 1 is Federated Averaging (FedAvg) (McMahan et al., 2016). In FedAvg, clients conduct a training round t, and the parameters θ_{t+1} are updated to the p_k-weighted average of the respective client gradients. The gradient weights p_k can be set to $p_k = \frac{|\mathcal{D}_k|}{\sum_{k=1}^{N} |\mathcal{D}_k|}$ to mitigate data size bias, which we use in this work. FL has recently been applied to LLMs Ye et al. (2024); Thakkar et al. (2021); Liu et al. (2024); Ramaswamy et al. (2020) leveraging FedAvg to aggregate locally-trained model updates. In this work, we conduct experiments using LoRA-based fine-tuning and full model fine-tuning for local iterations in FL. Besides reducing communication costs, clients benefit computationally from using LoRA during local training. Federated learning, although initially designed to protect user data (McMahan et al., 2017), did not foresee leakage in the form of regurgitation as its advent preceded the development of high-performing generative language models (Kairouz et al., 2021). Consequently, studies on the memorization capacity of FL-trained LLMs remain limited. An early survey demonstrated that federated averaging (Thakkar et al., 2021) ameliorates unintended memorization, though only for a small 1.3M parameter next-word predictor (Hard et al., 2018). Nonetheless, the authors' observations on the success of non-independent and identically distributed (non-IID) clustering for improved privacy informed our federated training strategy. Similarly to our work, Liu et al. (2024) leverage LoRA to conduct efficient fine-tuning. However, this work is exclusively interested in studying performance under varying budgets within the (ϵ, δ)-DP framework and does not consider memorization under the canary- or completion-based frameworks.

Recent work by Google and others has explored the use of FL for large-scale language model training in production environments, placing strong emphasis on privacy protection (Hard et al., 2019; Ramaswamy et al., 2020; Thakkar et al., 2021; Xu et al., 2023), showing growing interest in privacy-preserving training methods. To the best of our knowledge, this study is the first to investigate the impact of LoRA on memorization in federated learning.

2.3 Memorization

The ability of large language models to regurgitate pieces of their training data is well-documented. However, the question of *how best* to quantify the memorization capacity of an LLM is an active area of research. A seminal work by Carlini et al. introduced "canaries", which are synthetic, out-of-distribution pieces of text injected into training data (such as `"My SSN is XXX-XX-XXXX"`) (Carlini et al., 2019). It has found use in production-level studies (Ramaswamy et al., 2020) and adjacent fields such as machine unlearning (Jagielski et al., 2022). An alternative definition of memorization (Carlini et al., 2023a), the completion metric, measures how often an LLM completes a piece of text taken from the training data when prompted on an initial portion (prefix) of it.

Memorization definition. We use the "extractable memorization" definition of Carlini et al. (2023b) following its wide adoption (Ippolito et al., 2023; Huang et al., 2024; Hans et al., 2024; Nasr et al., 2023; 2025). Consider a string representable as the concatenation $[p||s]$ where p is a prefix of length k and s is the remainder of the string. We define the string s to be *memorized with k tokens of context* by a language model f if $[p||s]$ is contained in the training data of f, and f produces s when prompted with p using greedy decoding[1]. In other words, we consider a string from training data memorized if an LLM can generate it when prompted by a prefix. We set the length of the generated suffix s to 50 tokens, in line with previous work.

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[1]Carlini et al. (2023a) found that beam search yields slightly higher memorization values. We use greedy decoding for the sake of simplicity.

3   Methodology

In a federated learning setting, training data is split among several clients. Our experiments are designed to mimic a medical scenario in which each client holds potentially sensitive data, reflecting the reality that few, if any, anonymization tools can guarantee the complete removal of sensitive information (Langarizadeh et al., 2018). In fact, Heider et al. (2020) evaluated three off-the-shelf de-identification tools on the i2b2 medical record dataset (Stubbs & Özlem Uzuner, 2015)—which we use in our study—and found that none could achieve copmlete removal.

3.1   Quantifying memorization

Our measurement methodology is largely inspired by Carlini et al. (2023b). In short, we inject sensitive sequences, so-called "canaries" (Carlini et al., 2019; Jagielski et al., 2023; Thakkar et al., 2021), into fine-tuning data and then measure the model's ability to regurgitate this information when prompted with the beginning of these sequences.

Canaries. Unlike prior work that evaluates the memorization of all training data (Carlini et al., 2023b; Ippolito et al., 2023; Hans et al., 2024), we are interested in measuring how much *sensitive* information is memorized. Similar to Lehman et al. (2021) and Mireshghallah et al. (2022), we inject medical records into our training set originating from the 2014 i2b2/UTHealth corpus (Stubbs & Özlem Uzuner, 2015). The i2b2 dataset contains 1,304 longitudinal medical records that describe 296 patients. This approach allows us to measure memorization on sensitive data that we explicitly want to protect, while most previous studies measure memorization on randomly-generated sequences (Carlini et al., 2019; Thakkar et al., 2021) or indiscriminately on the whole dataset (Wang & Li, 2025; Biderman et al., 2024; Hans et al., 2024; Nasr et al., 2025) possibly confounding the memorization necessary for downstream performance Feldman (2020).

Because data duplication has been shown to greatly influence memorization (Carlini et al., 2023b; Lee et al., 2022; Kandpal et al., 2022), we randomly select 30% of the medical records and duplicate them tenfold within our fine-tuning data in order to study the effect of data duplication in our experiments. We also experiment with a lower duplication rate of 3 in Appendix C and found consistent results.

Following Carlini et al. (2023b), we measure the effect of the context size by prompting the model on each test sequence with prompts of lengths in $\{10, 50, 100, 200, 500\}$. The different prompts for a given test sequence are constructed such that the suffix s is kept identical while varying the prompt length. This ensures a fair comparison between prompt lengths, since different suffixes may be more or less prone to regurgitation.

Memorization scores. To compare generated text with the ground truth, we rely on two metrics: (1) the **exact token match rate** and (2) the **BLEU score**, to measure approximate reproduction, as prior work suggests that the exact match rate does not capture subtler forms of memorization (Ippolito et al., 2023). In line with this work, we consider a sequence memorized if the generated suffix and the ground truth yield a BLEU score > 0.75. For both metrics, lower is better, and a score of 1 denotes complete memorization of all test sequences. We additionally report **BERTScore** (Zhang et al., 2020) in Appendix C to measure semantic similarity between model outputs and reference sequences and we find trends consistent with the aforementioned metrics.

To illustrate our method, Figure 1 shows the memorization of the Llama 2 7B full fine-tuning. Multiple trends are consistent with previous work: (1) there is significantly more memorization when the medical records occur multiple times in the fine-tuning data (Lee et al., 2022; Kandpal et al., 2022; Carlini et al., 2023b); (2) longer prompts show higher memorization (the so-called "discoverability phenomenon") (Carlini et al., 2023b) and (3) there is significantly more memorization with approximate generation (BLEU score) (Ippolito et al., 2023).

Accuracy. Finally, we report the downstream accuracy in Appendix B to ensure a fair comparison between fine-tuning methods. Figure 4 shows that all fine-tuned models yield relatively similar accuracy values when comparing LoRA to full fine-tuning. This result suggests that in our setting, LoRA is a competitive technique and may substitute full fine-tuning at relatively little cost.

Figure 1: **Sensitive medical information memorization of the full fine-tuning of Llama 2 7B in centralized learning.** We report the exact match rate and BLEU score with respect to the prompt length, with and without duplication. We also show the memorization upper bound (labeled "Full memorization") that is reached when every test sequence has been memorized. Most settings show signs of regurgitation yet duplicated documents present an alarming rate of memorization.

3.2 Experimental Setup

All fine-tuning was performed on a single NVIDIA A100 80GB GPU within an HPC cluster, except for the 70B-parameter model, which was fine-tuned using eight H100 GPUs. We leveraged Hugging Face's Transformers library (Wolf et al., 2020) to access and fine-tune pre-trained models. Further training details are included in Appendix D.

We fine-tune models for domain adaptation to medical question answering (QA) which is an apt privacy scenario. Nonconsensual regurgitation of protected health information (PHI) violates privacy laws such as the U.S. Health Insurance Portability and Accountability Act (HIPAA) and EU General Data Protection Regulation (GDPR). Despite medical scenarios being extensively promoted by FL applications (Xu et al., 2021; Nguyen et al., 2022; Antunes et al., 2022), and the availability of resources such as deidentified sensitive medical datasets (Johnson et al., 2016; Stubbs & Özlem Uzuner, 2015), clinical memorization remains insufficiently understood in FL. We use 3-shot in-context learning without any chain-of-thought reasoning and average the accuracy over three seeds.

Datasets and models. We fine-tune LLMs on three medical QA datasets (MedMCQA, PubMedQA, and Medical Meadow Flashcards) augmented with sensitive sequences from the i2b2 clinical notes. Evaluation is performed on a suite of medical benchmarks including MedQA, PubMedQA, MedMCQA, and MMLU-Medical (Pal et al., 2022; Jin et al., 2019; Han et al., 2023). Full descriptions of datasets, pre-trained models, and licensing terms are provided in Appendix E. In Appendix C, we confirm that our findings generalize to other high-risk domains such as law (Multi-LexSum) and finance (ConvFinQA) (Shen et al., 2022; Cheng et al., 2024) and to a larger model scale of 70B.

Federated learning setup. We define a heterogeneous setting with one client per dataset. In other words, we fine-tune models with three participants, where each participant trains locally on one of the three datasets MedMCQA, PubMedQA, and Medical Meadow Flashcards. We split and inject i2b2 medical records into each dataset proportionally to their size. Participants fine-tune over their local dataset for one epoch between each global weight update, for a total of five rounds. For every model, we tune the learning rate on each local dataset. Note that LoRA drastically reduces FL communication overhead: each round of our setting requires a total data exchange of 74 GB for a 7B model, and using LoRA reduces the load by a factor of 152, decreasing the overhead to 498 MB. For completeness, we evaluate and compare the same experiment in conventional centralized learning in Appendix F, where all training samples are processed by a single client.

4 Results

Figure 2 compares the impact of using LoRA instead of full fine-tuning on memorization.

Figure 2: **LoRA vs. full fine-tuning in federated learning.** LoRA reduces memorization across all settings. (a)–(c): Exact match rate under increasing duplication and prompt length. (d)–(f): BLEU score under the same settings. The memorization scores are averaged across the different prompt lengths tested except for (c) and (d) which shows our worst case setting by using the highest prompt length of 500 tokens and a duplication rate of 10. As control, we evaluate the memorization scores before fine-tuning and find values lower than 0.0006 for the exact match rate (less 0.06% of the tested sequences resulted in a verbatim regurgitation) and BLEU scores lower than 0.003.

All federated fine-tunings, both LoRA and full fine-tuning, exhibit some levels of memorization, thus showing the need for additional privacy-preserving techniques. However, fine-tuning federated LLMs with LoRA displays lower memorization than full fine-tuning across all metrics and models. In our case, LoRA fine-tuning reduces memorization up to $10\times$ for a negligible accuracy loss. We do note that the memorization impact of LoRA differs between similarly sized models. For example, fine-tuning Llama 2 7B with LoRA shows a drastic memorization improvement over full fine-tuning, whereas Mistral v0.3 7B shows a lower impact.

To provide fair comparisons between multiple federated learning fine-tuning, Figure 2 reports metrics for the last federated round. This ensures that each model has been fine-tuned on the medical records the same number of times. We discuss this decision further in Appendix B, which analyzes how accuracy and memorization metrics evolve throughout the federated rounds.

In order to contextualize LoRA's effect in a non-federated setting, we carried out similar experiments in centralized learning, described in Appendix F. Figure 3 summarizes our results by comparing LoRA vs full fine-tuning in both federated and centralized learning. The figure illustrates that LoRA systematically results in lower memorization than full fine-tuning in both CL and FL.

Memorization w.r.t. rounds. Firstly, we find that memorization in FL increases monotonically with the number of rounds (which correspond to the number of times medical records are seen). Throughout the rounds, we find that LoRA memorizes less than full fine-tuning, with some exceptions where LoRA starts with slightly higher memorization in the first or second round. The choice of the number of rounds is thus critical, and we show in Table 3 that full fine-tuning reaches its best downstream accuracy in the last two rounds, where the memorization gap between LoRA and full fine-tuning is the greatest. In other words, LoRA is most effective at reducing memorization where the models are most performant.

FL vs CL memorization. We observe that FL itself enhances privacy by reducing memorization compared to centralized learning for a given fine-tuning method. This is consistent with previous work (Thakkar et al., 2021) suggesting that FedAvg and a non-IID data distribution contribute to reducing unintended memorization. Furthermore, we find that not all trends observed in centralized learning hold in federated learning. On the one hand, data duplication, longer context and considering paraphrasing all yield higher memorization scores for FL as for CL, on the other hand, Figure 2 shows that larger models do not necessarily result in more memorization with full fine-tuning in FL, as Llama 3.2 1B reaches higher memorization scores than Llama 3.2 3B. This difference may stem from FL using separate learning rates for each local model, and thus each data source, while centralized learning applies a single learning rate (since all datasets are merged into one). This finer-grained adaptation in FL can also explain the higher memorization observed in

Figure 3 when Llama 2 7B is trained with FL compared to CL. We leave further exploration of how model size influences memorization in federated learning and data source-specific adaptations in CL for future work.

Finally, we show in Appendix C that these results generalize to other domains such as law and finance, to lower duplication rates, as well as to larger models such as Llama 3.1 70B in centralized learning.

Figure 3: **Memorization scores for federated and centralized learning per round.** Dashed lines correspond to centralized learning (CL) experiments and full lines to federated learning (FL). Given that rounds are not relevant in CL, we plot the centralized memorization values as horizontal lines. The FL memorization values in Figure 2 are the values at last round in this Figure.

4.1 The LoRA rank and memorization

We further investigate how LoRA's configuration influences this behavior in centralized learning. Specifically, we vary the LoRA rank to measure its influence on memorization, studying values $r \in \{4, 16, 64, 128, 256, 1024\}$. The scaling factor α is set to twice the rank, as recommended by Biderman et al. (2024), and the learning rate is decreased exponentially as the rank increases. We apply LoRA adapters to all layers, following Biderman et al. (2023) and Schulman & Lab (2025).

As shown in Table 1, increasing the rank—i.e. increasing the number of weights updated during fine-tuning—results in more memorization, ranging from virtually no memorization with a rank of 4 to almost 50% of the medical records being memorized for rank 1024 when considering duplicated medical records. These results are consistent with Wang & Li (2025) and extend their conclusions to a larger model than GPT-2. Note that in our case, the highest rank did not yield the best accuracy. We further noted that for

Table 1: **Impact of the LoRA rank on memorization.** We fine-tune Llama 3.2 3B with LoRA in centralized learning on increasing LoRA ranks. Higher ranks lead to more memorization but not necessarily to better accuracy. The lower memorization scores and the highest accuracy are emphasized in bold.

LoRA rank	Exact match rate		BLEU score		Accuracy
	No duplication	10x duplication	No duplication	10x duplication	
4	0.0003	0	0.0133	0.0198	0.509
16	0.0005	0.0031	0.0167	0.0623	0.512
64	0.0031	0.2105	0.0258	0.379	0.511
128	0.0042	0.3735	0.0305	0.5111	0.510
256	0.0057	0.4895	0.0352	0.5809	**0.542**
1024	**0.0063**	**0.4981**	**0.0409**	**0.6228**	0.530

most ranks, suboptimal learning rates can lead to relatively significant memorization with LoRA, though still lower than for full fine-tuning, highlighting the need for careful hyperparameter tuning.

4.2 Combining LoRA with other methods

Although LoRA mitigates unintended memorization on its own, we investigate whether it can be combined with other privacy-preserving techniques without compromising performance or increasing memorization. In this section, we outline the different techniques we evaluated, while detailed descriptions of each are provided in Appendices G, H, I, and K.

Goldfish loss. If users are focused on reducing extractable memorization in pretraining, then they may be interested in Goldfish loss, while LoRA is used for fine-tuning. However, we investigate and assess its potential for fine-tuning in combination with LoRA in Appendix G and show that the combination of LoRA with Goldfish loss synergistically achieves lower memorization beyond what either strategy achieves alone.

NEFTune. We examine NEFTune in Appendix H, a noise-enhanced fine-tuning approach designed to improve robustness and reduce overfitting. While not a privacy-preserving method per se, we hypothesized that noise addition could induce some memorization reduction. In practice, we find that combining NEFTune with LoRA fine-tuning does not further decrease the memorization and in fact does not improve the performance either, the highest accuracy being reached without any noise.

Differential Privacy. In Appendix I, we discuss the challenges of applying differential privacy (DP) in our federated setting and the alternative approaches we explored. DP is a well-established technique that provides formal guarantees to protect individual data from being inferred through the model's output. However, integrating DP into our setup requires significant modifications to our training pipeline that are beyond the scope of this work. Nevertheless, we show that applying gradient clipping without noise addition improves both accuracy and reduces memorization during fine-tuning, albeit without formal privacy guarantees. Furthermore, we show in Appendix J that injecting random Gaussian noise into the model weights does not improve the privacy–accuracy trade-off.

Secure Aggregation. While we observed lower memorization in federated learning (FL) compared to centralized learning (CL) (see Section 4), locally trained models transmitted during FL may still expose participant data if not properly protected. In Appendix K, we present experiments using a secure aggregation protocol combining Fully Homomorphic Encryption (FHE) and Secure Multiparty Computation (SMPC). Our results show that this approach effectively mitigates privacy risks in the federated setting while introducing only negligible computational overhead.

5 Conclusion and Limitations

In this work, we demonstrate that LoRA is capable of reducing memorization of fine-tuning sensitive training data in federated learning with little to no downstream performance cost. In particular, this effect is also

observable in both centralized learning, and we analyze how memorization patterns differ between the two. Moreover, it is possible to further reduce memorization by combining LoRA with other strategies such as Goldfish loss or conventional privacy-preserving mechanisms such as Gaussian noising and gradient clipping. FL was previously shown to reduce memorization for simple LSTM-based next-word predictors (Hard et al., 2018; Thakkar et al., 2021) and we show that generative LLMs inherit this benefit as well. While we discuss possible theoretical explanations of this mechanism in Appendix L, further research on the theoretical cause of this phenomenon is needed.

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A   Further Related Work

Differential privacy. Classical (ϵ, δ)-differential privacy (DP) frameworks formally measure the privacy-preserving capacity of an algorithm by analyzing whether the probability of observing an output changes by ϵ when the underlying database excludes or includes a user record (Dwork et al., 2006). The application of this framework to generative language tasks, in general, has proven complicated due to the rigid definition of a user record (Brown et al., 2022; Jayaraman & Evans, 2019). When directly applying DP to prevent sensitive data reconstruction, it has been shown that a non-negligible compromise on privacy is required to maintain performance (Lukas et al., 2023). The conventional technique of adding Gaussian noise onto clipped gradients (Abadi et al., 2016) to boost privacy has also been shown to affect model outputs: the randomness of the noise alone can significantly alter the outputs of two equally-private models (Kulynych et al., 2023). McKenna et al. (2025) have recently found significant differences in the scaling laws of DP LLM training compared to models trained under traditional regime.

Membership inference attacks (MIA) rely on rigorous statistical principles to assess privacy risks in machine learning models. (Shokri et al., 2017) introduced an approach for determining whether a specific data point was part of a model's training dataset. These attacks exploit differences in model behavior on training versus non-training data, posing significant privacy concerns for sensitive information. Building on this, (Hongyan et al., 2024) extended these concepts to LLMs by incorporating contextual information. This study demonstrated that LLMs are particularly vulnerable to membership inference attacks, as they often retain verbatim information from their training datasets. The work highlighted the increased privacy risks associated with LLMs due to their scale and training dynamics.

Secure Aggregations. While the conventional FL ensures that raw data is not shared between participants during collective training, it does not address the risk of data leakage through model updates shared prior to aggregation. For example, in the honest-but-curious scenario, a server examines whether client data can be reconstructed (Huang et al., 2021). This vulnerability becomes particularly critical with LLMs, given their propensity for memorization. To address the privacy risks associated with local model exchanges in FL, (Truex et al., 2019) proposes a hybrid approach that combines differential privacy with secure multiparty computation (SMC). In this framework, local models are encrypted and remain hidden from other participants prior to aggregation, thereby mitigating privacy leakage risks associated with individual local models by focusing them on the aggregated model during each aggregation round. While this method has been explored for general machine learning applications, to the best of our knowledge, it has not yet been investigated in the context of large language models (LLMs).

Medical applications. Our emphasis on medical datasets is relevant: LLMs have been shown to regurgitate sensitive medical data in Lehman et al. (2021), though their work relies on an older BERT model. Mireshghallah et al. (2022) study the success of membership inference attacks on i2b2, though they also do not use any memorization metrics. Although federated learning has been studied and championed as an ideal paradigm for clinical settings (Xu et al., 2021; Nguyen et al., 2022; Antunes et al., 2022), there is a relative lack of literature in the context of clinical memorization.

B   LoRA vs Full Fine-tuning Accuracy

To compare memorization between LoRA and full fine-tuning, it is essential that we compare settings that yield similar performance, as well as for this performance to be significantly higher than the base model. Figure 4 and 5 illustrate the resulting benchmark accuracy of the fine-tuned models we evaluate in this study, in federated learning and centralized learning respectively. We compare the base model to LoRA and full fine-tuning and find that the two fine-tuning methods reach a similar downstream accuracy that is significantly higher than the base model. A breakdown per benchmark in centralized learning is included in Table 2.

In our federated learning experiments (Section 4), we compare memorization after 5 federated rounds. This ensures that we compare models that have been trained on the same tokens for the same number of times. Similarly in centralized learning (Appendix F), we do not make use of early stopping. Consequently, our methodology may not stop the fine-tuning at an optimal number of steps and some model may reach their

Figure 4: **Downstream accuracy in federated learning averaged across the 5 benchmarks.** LoRA yields relatively similar accuracy to full fine-tuning for several LLMs in a heterogeneous FL setting. We report the out-of-the-box accuracy of the pre-trained models as a control. A breakdown per round is included in Table **??**.

Figure 5: **Centralized learning downstream accuracy averaged across the 5 benchmarks.** LoRA matches full fine-tuning accuracy on every model tested. A breakdown per benchmark is included in Table 2.

Table 2: **Downstream accuracy in centralized learning.** Best accuracy values are marked in **bold**.

Model	Fine-tuning	MMLU-medical	PubMedQA	MedMCQA	MedQA	MedQA-4	Average
Llama 3.2 1B	No fine-tuning	0.353	0.363	0.49	**0.329**	0.275	0.308
	Full	**0.456**	**0.616**	**0.431**	0.322	**0.379**	**0.441**
	LoRA	0.447	0.594	0.397	0.312	0.362	0.422
Llama 3.2 3B	No fine-tuning	0.432	0.597	0.122	0.491	0.446	0.504
	Full	0.59	0.536	**0.542**	**0.452**	**0.507**	0.525
	LoRA	**0.608**	**0.676**	0.512	0.448	0.5	**0.549**
Llama 2 7B	No fine-tuning	0.381	0.426	0.452	0.380	0.292	0.353
	Full	**0.562**	0.596	**0.516**	**0.395**	**0.478**	**0.509**
	LoRA	0.560	**0.726**	0.448	0.353	0.405	0.498
Mistral v0.3 7B	No fine-tuning	0.552	0.635	0.7	0.483	0.438	0.503
	Full	0.659	**0.758**	**0.588**	**0.499**	**0.551**	**0.611**
	LoRA	**0.667**	**0.758**	0.572	0.467	0.54	0.601

best accuracy at different number of rounds. To measure this, we show in Table 3 the accuracy of federated fine-tuning per round. We find that except Llama 3.2 3B, all models reach their best performance in round 4 or 5, without any method reaching its best accuracy systematically earlier. For Llama 3.2 3B, LoRA reaches its highest accuracy at round 2 and then again at round 5. Since we compare memorization at the last round, LoRA memorization scores may be over-estimated due to overfitting, thus under-estimating how LoRA mitigates memorization compared to full fine-tuning.

To further validate that the privacy gains described in F observed on models trained with LoRA do not come at the cost of utility, and that the privacy loss observed with full fine-tuning is not due to overfitting or preventable by early stopping, we analyzed the utility-privacy tradeoff throughout the centralized learning fine-tuning process. Figure 6 illustrates the evolution of privacy and utility for Llama 3.2 3B during both LoRA and full fine-tuning. The figure shows that LoRA fine-tuning consistently follows a more privacy-preserving trend, with lower memorization scores compared to full fine-tuning at similar utility levels. Furthermore, after a certain number of fine-tuning steps, the model's tendency to memorize data increases without significant improvements in utility, due to overfitting. This highlights that early stopping during LLM training not only improves efficiency, but also helps privacy by reducing the risk of memorization.

Table 3: **Downstream accuracy per federated round**. We emphasize in **bold** the earliest round where models reach their best accuracy.

Model	Fine-tuning	Accuracy per round				
		1	2	3	4	5
Llama 3.2 1B	Full	0.425	0.438	0.444	**0.445**	0.445
	LoRA	0.415	0.422	0.430	0.432	**0.434**
Llama 3.2 3B	Full	0.541	0.561	0.554	0.573	**0.578**
	LoRA	0.557	**0.564**	0.559	0.563	**0.564**
Llama 2 7B	Full	0.468	0.488	0.482	0.495	**0.511**
	LoRA	0.475	0.490	0.482	**0.494**	0.493
Mistral v0.3 7B	Full	0.181	0.590	0.599	**0.603**	0.602
	LoRA	0.594	0.599	0.598	0.604	**0.608**

Figure 6: **Accuracy vs. privacy across fine-tuning steps.** We track accuracy and memorization (BLEU) during LLaMA 3.2 3B fine-tuning (10× duplication) using full fine-tuning (Full FT) and LoRA, compared to the base model. Numbers above points indicate completed fine-tuning steps.

C   Generalization to other domains and larger models

To assess the robustness and broader applicability of our findings, we extend our evaluation beyond the medical domain and 7B-parameter LLMs. Specifically, we explore whether LoRA's memorization reduction in centralized learning persists in other high-risk domains such as law and finance, and to a 70B Llama model. These additional experiments demonstrate that our conclusions generalize across both tasks and model scales.

Additional domains. To evaluate generalizability beyond medicine, we fine-tuned models on Ai2's Multi-LexSum (Shen et al., 2022), a legal summarization dataset, and ConvFinQA (Cheng et al., 2024), a financial QA benchmark. *Multi-LexSum* contains long-form summaries of real-world civil rights lawsuits across multiple granularities. *ConvFinQA* is a conversational question-answering dataset derived from financial reports. It tests numerical reasoning and understanding in domain-specific contexts and includes sensitive financial

information. These domains are highly sensitive to privacy risks, where even partial memorization can be problematic.

Additional semantic measure. We added BERTScore (Zhang et al., 2020) as an additional metric to better capture semantic similarity and subtle variations in memorized content. Following best practices, we use the *DeBERTa-xlarge-MNLI* model. We apply score rescaling, which adjusts for baseline similarity between unrelated sentence pairs. This technique improves the comparability and interpretability of reported scores across different models and datasets.

Scaling up to 70B parameters. We evaluated the LLaMA 3.1 70B Instruct model (Dubey et al., 2024) to test whether LoRA's memorization mitigation scales to larger models.

Table 4: **Law domain** memorization metrics. LoRA consistently lowers all metrics, including BLEU Score and BERT F1 score.

Model	Method	BLEU	BERTScore
Llama 3.1 70B	Full FT	0.55	0.55
Llama 3.1 70B	LoRA	**0.17**	**0.32**
Llama 3.2 3B	Full FT	0.29	0.42
Llama 3.2 3B	LoRA	**0.06**	**0.17**

Results. As shown in Table 4 for law and Table 5 for finance, LoRA consistently lowers BLEU and BERTScore compared to full fine-tuning, generalizing our findings in centralized learning on our medical dataset to other domains and measures. In particular, we also find that fine-tuning a 70B model with LoRA also yields lower memorization than full fine-tuning, indicating its continued effectiveness at scale. Memorization scores are generally higher for the 70B model than for its 3B counterpart, except on the finance dataset, where we hypothesize that the lower memorization rate is due to suboptimal default hyperparameters.

Table 5: **Finance domain** memorization metrics. LoRA consistently lowers all metrics, including BLEU Score and BERT F1 score.

Model	Method	BLEU	BERTScore
Llama 3.1 70B	Full FT	0.55	0.48
Llama 3.1 70B	LoRA	**0.50**	**0.45**
Llama 3.2 3B	Full FT	0.51	0.56
Llama 3.2 3B	LoRA	**0.11**	**0.12**

Lower duplication rate. Previous duplication experiments relied on a duplication rate of 10. While we argue that such a rate is realistic in medical datasets given the prevalence of personal health information (PHI) in medical records, we further evaluate memorization with a duplication rate of 3 in Table 6. These results confirm that mitigation trends still holds with a lower duplication rate than the 10x duplication used in earlier sections, consistently with previous work (Wang & Li, 2025) in centralized learning.

Table 6: **Medical domain** memorization metrics for a large model and lower duplication rate. LoRA consistently lowers all metrics, including BLEU Score and BERT F1 score.

Model	Dupl.	Method	BLEU	BERTScore
Llama 3.1 70B	None	Full FT	0.170	0.23
Llama 3.1 70B	None	LoRA	**0.100**	**0.18**
Llama 3.2 3B	None	Full FT	0.030	**0.11**
Llama 3.2 3B	None	LoRA	**0.010**	0.12
Llama 3.2 3B	3x	Full FT	0.060	0.20
Llama 3.2 3B	3x	LoRA	**0.004**	**0.14**

D Training setup

All experiments were performed on a university-grade HPC furnished with nodes of 8 80GB A100 GPUs, with a Python 3.11.9 environment, PyTorch 2.4.0 and CUDA 12.1. Fine-tuning fit on a single GPU without parallelization for model sizes up to 8GB. Llama 3.1 70B was fine-tuned on 8 GPUs. A centralized fine-tuning lasts 3 GPU-hours in average. Including preliminary and failed experiments, centralized training amounts to around 350 GPU-hours. In federated experiments, each round corresponds to one epoch of each of the 3 datasets, in averaging lasting one GPU-hour, in addition to hyperparameters search amounting to roughly 20 GPU-hours per federated fine-tuning and totalling around 250 GPU-hours. Experiments on the LoRA rank, batch size, Goldfish loss, NEFTune, gradient clipping and Gaussian noise add 400 GPU-hours.

Hyperparameters. In centralized learning, we sweep the learning rate $\in \{1e-5, 5e-5, 1e-4, 5e-4\}$ for full fine-tuning experiments. For LoRA experiments, we search for learning rate values $\in \{5e-5, 1e-4, 5e-4, 1e-3\}$ as recommended by Biderman et al. (2024). In federated learning experiments, we sweep the learning rate on each dataset individually for one epoch, with the same set of values as in centralized learning.

For all experiments we fine-tune models with the AdamW optimizer (Loshchilov & Hutter, 2019) with default parameters ($\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1e^{-8}$, weight decay of 0.01). We used a context length of 1024 and ensured that no text inputs were longer than the context length. We use a linear warmup of 100 steps with a cosine annealing schedule. Unless mentioned otherwise, we use a global batch size of 32 with gradient accumulation and gradient checkpointing. For LoRA fine-tuning with use a rank of 16, an alpha of 8, drop out 0.05 and use adapters for all projection layers. We study the impact of the LoRA rank on memorization in Section 4.1.

E Datasets and pre-trained models

In this section, we describe the datasets and pre-trained models used in our experiments, including fine-tuning sources, generalization datasets, evaluation benchmarks, and licensing terms.

E.1 Fine-tuning Datasets

In order to reproduce a plausible FL environment with non-IID data, we select 3 popular medical datasets with different types of QA.

1. *MedMCQA* (Pal et al., 2022) is composed of multiple-choice questions, containing almost 190k entrance exam questions (AIIMS & NEET PG). We fine-tune on the training split and leave aside validation data as a downstream evaluation benchmark.

2. *PubMedQA* (Jin et al., 2019) consists of Yes/No/Maybe questions created from PubMed abstracts. The dataset contains 1k expert-annotated (PQA-L) and 211k artificially generated QA instances (PQA-A). We include 500 questions from the train and validation sets of PQA-L and 50k questions of PQA-A.

3. *Medical Meadow flashcards* (Han et al., 2023) contains 39k questions created from Anki Medical Curriculum flashcards compiled by medical students. We include 10k instances for fine-tuning data.

E.2 Medical Benchmarks

To measure the downstream performance of the fine-tuned models, we evaluate models on 4 medical benchmarks following existing methodology (Wu et al., 2023a; Singhal et al., 2023c;b; Chen et al., 2023): MedQA, PubMedQA, MedMCQA, and MMLU-Medical.

1. *MedQA's 4-option questions.* MedQA (Jin et al., 2020) consists of US Medical License Exam (USMLE) multiple-choice questions. The test set contains 1278 questions with both 4 and 5-option questions. Following Chen et al. (2023), we report each case separately, respectively MedQA-4 and MedQA.

2. *MedQA's 5-option questions.*

3. *PubMedQA*'s test set contains 500 expert-annotated questions. No artificially-generated questions are used during evaluation.

4. *MedMCQA*'s test set does not provide answer labels, therefore we rely on the validation set, containing 4183 instances, to benchmark downstream performance following Wu et al. (2023a) and Chen et al. (2023).

5. *MMLU-Medical.* MMLU (Hendrycks et al., 2021) is a collection of 4-option multiple-choice exam questions covering 57 subjects. We follow Chen et al. (2023) and select a subset of 9 subjects that are most relevant to medical and clinical knowledge: high school biology, college biology, college medicine, professional medicine, medical genetics, virology, clinical knowledge, nutrition, and anatomy, and group them into one medical-related benchmark: MMLU-Medical.

E.3 Pre-trained models

To account for the effect of model size on memorization (Carlini et al., 2023b; Tirumala et al., 2022), we study pre-trained models ranging from 1B to 8B parameters: Llama 3.2 1B, Llama 3.2 3B, Llama 3 8B (Dubey et al., 2024), Llama 2 7B (Touvron et al., 2023), and Mistral 7B v0.3 (Jiang et al., 2023). We also include memorization-focused experiments with the Llama 3.1 70B Instruct model (Dubey et al., 2024) in Appendix C to evaluate how LoRA scales to larger-capacity models.

E.4 Licenses and Terms of Use

We provide below the licenses and usage terms for all datasets and pretrained models used in our work.

E.4.1 Datasets

- **MedMCQA** (Wu et al., 2023a)
  Source: `https://huggingface.co/datasets/openlifescienceai/medmcqa`
  License: Apache License 2.0

- **PubMedQA** (Singhal et al., 2023b)
  Source: `https://huggingface.co/datasets/openlifescienceai/medmcqa`
  License: MIT License

- **Medical Meadow Flashcards** (Han et al., 2023)
  Source: `https://huggingface.co/medalpaca/medalpaca-7b`
  License: Creative Commons license family

- **i2b2 2014 De-identification Dataset** (Stubbs & Özlem Uzuner, 2015)
  Source: `https://www.i2b2.org/NLP/HeartDisease`
  License: Available under a Data Use Agreement from *Partners HealthCare*. Access requires registration and approval.

- **Multi-LexSum** (Shen et al., 2022)
  Source: `https://huggingface.co/datasets/allenai/multi_lexsum`
  License: Open Data Commons License Attribution family

- **ConvFinQA** (Cheng et al., 2024)
  Source: `https://github.com/czyssrs/ConvFinQA`
  License: MIT License

E.4.2 Pretrained Models

- **LLaMA 2** (Touvron et al., 2023)
  Source: `https://www.llama.com/llama-downloads`
  License: Llama 2 Community License Agreement

- **LLaMA 3** (Dubey et al., 2024)
  Source: `https://www.llama.com/llama-downloads`
  License: Llama 3.x Community License Agreement

- **Mistral 7B v0.3** (Jiang et al., 2023)
  Source: `https://huggingface.co/mistralai/Mistral-7B-v0.3`
  License: Apache License 2.0

F   Centralized Learning Memorization

Training details. In the centralized learning setting, we merge *PubMedQA*, *MedMCQA* and *Medical Meadow Flashcards* into one fine-tuning dataset in which we inject the *i2b2* medical records to benchmark memorization after fine-tuning. We use a validation split of 10% and for each model we search for the learning rate yielding the lowest validation loss. More details on hyperparameters can be found in Appendix D.

Accuracy. To study how LoRA mitigates unintended memorization, we must first assess if it comes at a cost in model performance. Figure 5 illustrates the average accuracy over fine-tuning strategies. Comparing full fine-tuning against LoRA, we find that LoRA comes with a relatively negligible cost in accuracy. Every fine-tuning yields a significant accuracy improvement of the pre-trained model except for Llama 3.1 8B, in which performance minimally improved. Hyperparameter search either resulted in a significant performance drop (with high memorization) or kept the learning rate low enough that the accuracy stayed constant and thus showed no memorization. We hypothesize that part or all of our fine-tuning dataset has already been trained on during Llama 3.1 8B's pre-training phase though the model showed no memorization of the canaries before fine-tuning. Accordingly, we exclude Llama 3.1 8B from subsequent experiments.

Memorization. Given that LoRA matches full fine-tuning performance in our experiments, we now measure the unintended memorization occurring during fine-tuning, illustrated in Figure 7. To account for prompt length, we include a figure (plots **(c)** and **(f)**) for each metric with the highest memorization score obtained across settings, which is systematically reached on duplicated documents with the longest prompt.

Analysis. Across all model sizes, data duplication greatly increases memorization and longer prompt lengths increase the extraction success. Figure 7 also illustrates that larger models memorize more (Carlini et al., 2023b; Tirumala et al., 2022). Most importantly, we see that models fine-tuned in centralized learning with LoRA consistently exhibit lower memorization scores, suggesting the adequacy of using LoRA as a memorization-mitigating technique with little to no performance cost.

Contrary to our results, Wang & Li (2025) found that model sizes and data duplication in centralized learning did not affect memorization LoRA fine-tuning, where memorization scores remained near zero for all settings while full fine-tuning memorization was increasing consistently with prior work. We suggest that the near-zero memorization results from only experimenting with GPT-2 models, and may only appear above a certain model size. In fact, the two trends do appear when they relax their definition of memorization and their experiments with Llama 3 1B and 8B do show non-trivial memorization with LoRA.

Figure 7: **LoRA vs. full fine-tuning in centralized learning.** LoRA consistently reduces memorization. (a)–(c): Exact match rate under increasing duplication and prompt length. (d)–(f): BLEU score under the same settings.

Additionally, we compute the memorization scores of pre-trained models without fine-tuning, to obtain control values. This is equivalent to computing the models' ability to "guess" the suffix without having seen previously the medical records. We obtained scores an order of magnitude lower than any fine-tuned model score, which additionally confirms that none of the models had already been trained on the i2b2 dataset. Thus, while some scores in Figure 7 may appear low at first glance, the lowest memorization depicted in this figure remains >10 times higher than the control.

G Goldfish loss

The Goldfish loss (Hans et al., 2024) has been introduced recently as a memorization mitigating technique for pre-training language models via a new next-token training objective. The training procedure randomly excludes tokens from the loss computation in order to prevent verbatim reproduction of training sequences. While Goldfish loss has been designed for pre-training, we apply it to our fine-tuning and report values for various dropping frequencies k and we use a hashing context width $h = 13$ following the authors' methodology (Hans et al., 2024). We evaluate the memorization and accuracy of Llama 3.2 3B fine-tuned with LoRA in combination with Goldfish loss. We also compare it to the same model fully fine-tuned with Goldfish loss only. Table 7 shows how combining Goldfish loss with LoRA mitigates memorization compared to a full fine-tuning. By contrasting memorization scores with control values, we can also note that the Goldfish loss is an effective memorization-mitigation technique.

Table 7: **Impact of Goldfish loss on BLEU Scores and accuracy in LoRA Fine-Tuning.** Llama 3.2 3B is fine-tuned with different dropping frequencies (k). Best accuracy is marked in **bold**.

Goldfish k	BLEU, no duplication	BLEU, 10x duplication	Accuracy
2	0.0133	0.0216	0.514
3	0.0154	0.0426	**0.549**
4	0.0180	0.0543	0.534
5	0.0183	0.0815	0.540
10	0.0256	0.1494	0.538
100	0.0266	0.2852	0.537
1000	0.0256	0.3111	0.533
10000	0.0253	0.2944	0.545
Control	0.0245	0.2920	0.550

To assess the impact of LoRA in combination with Goldfish loss, we evaluated the memorization and accuracy of fine-tuning the same model using full fine-tuning. Table 8 presents the memorization scores and accuracy of the model fine-tuned with Goldfish loss alone, without LoRA. Our results indicate that while Goldfish loss reduces memorization, it does not achieve the same level of reduction as the combination with LoRA, especially when duplication occurs in the fine-tuning data. In summary, combining LoRA with Goldfish loss allows a privacy-utility tradeoff that cannot be achieved using Goldfish loss alone.

Table 8: **Impact of Goldfish loss on BLEU Scores and accuracy in full fine-tuning.** The BLEU scores and the accuracy of Llama 3.2 3B is reported for full fine-tuning across different dropping frequencies (k). Best accuracy is marked in **bold**.

Goldfish k	BLEU, no duplication	BLEU, 10x duplication	Accuracy
2	0.0146	0.0340	0.517
3	0.0243	0.0679	0.513
4	0.0282	0.1148	0.524
5	0.0310	0.1568	0.521
10	0.0342	0.3006	**0.545**
100	0.0399	0.5821	0.534
1000	0.0425	0.6235	0.527
10000	0.0407	0.6235	0.516
Control	0.0417	0.6235	0.538

H   NEFTune

NEFTune is a regularization technique consisting in adding random noise to the embedding vectors to improve instruction fine-tuning. While not introduced as a privacy-preserving technique per se, we hypothesize that a fine-tuning regularization such as NEFTune may also reduce unintended memorization.

We display results after applying NEFTune with noise value $\alpha \in \{5, 10, 15, 30, 45\}$. We find that adding noise does not improve accuracy when applied to our domain adaptation fine-tuning. Secondly, increasing the noise does not yield better privacy, at least not until we set alpha to 45, which is greater than alpha values reported by the original work (5, 10, and 15).

Table 9: **NEFTune impact on the BLEU score and accuracy when combined with LoRA.** We analyze LoRA fine-tuning with Llama 3.2 3B and different noise scaling factors α.

α	No duplication	10x duplication	Accuracy
Control	0.0276	0.4170	0.562
5	0.0284	0.4525	0.560
10	0.0300	0.4506	0.518
15	0.0284	0.4525	0.544
30	0.0282	0.4377	0.548
45	0.0248	0.3599	0.518
60	0.0227	0.2759	0.501
100	0.0183	0.1006	0.391

I   Differential Privacy

(ϵ, δ)-Differential privacy (DP) provides formal guarantees that an individual's data cannot be inferred from a model's output, by quantifying the model's sensitivity to changes in input data. Following Li et al. (2021) and Liu et al. (2024), we define sensitivity as the maximum change in model output resulting from the inclusion or removal of a single data point in the training dataset (record-level DP).

Implementing differential privacy (DP) requires modifications to the fine-tuning pipeline to measure the sensitivity of the fine-tuning process. However, the use of stochastic gradient descent (SGD), required for DP-SGD, poses challenges when fine-tuning the Llama 3.2 3B model. Despite extensive hyperparameter tuning, particularly of the learning rate, SGD consistently underperforms compared to Adam-based optimizers. As shown in Figure 8, Paged AdamW achieves substantially faster and deeper loss reduction than SGD during fine-tuning, highlighting the difficulty of maintaining optimization efficiency while measuring the sensitivity in large-scale models.

Gradient clipping. A key technique in differential privacy (DP) is gradient clipping, which constrains the magnitude of gradient updates and enables the measurement of model sensitivity during fine-tuning. In our experiments, we find that gradient clipping alone can mitigate memorization, even though it does not provide formal privacy guarantees. Using a clipping value of 0.0001 substantially reduced memorization and improved

accuracy compared to the default value of 1.0. Table 10 reports the impact of different clipping values on BLEU score and accuracy during fine-tuning of the Llama 3.2 3B model. These results highlight gradient clipping as an effective privacy-enhancing mechanism in its own right, even without the addition of noise.

Figure 8: **Loss reduction comparison between optimizers.** The plot compares loss reduction during the fine-tuning of Llama 3.2 3B using different optimizers: SGD (blue) and Paged AdamW (orange).

Table 10: **Gradient clipping impact on the BLEU score and accuracy.** The BLEU score and the accuracy of Llama 3.2 3B is reported for LoRA fine-tuning. Best accuracy is marked in **bold**.

Clipping Value	No duplication	10x duplication	Accuracy
1.0×10^{0} (default)	0.0266	0.4235	0.520
5.0×10^{-1}	0.0235	0.4235	**0.541**
1.0×10^{-1}	0.0229	0.4031	0.530
5.0×10^{-2}	0.0243	0.3827	0.534
1.0×10^{-2}	0.0227	0.3914	0.506
5.0×10^{-3}	0.0245	0.3914	0.531
1.0×10^{-3}	0.0250	0.3352	0.519
5.0×10^{-4}	0.0203	0.2914	0.528
1.0×10^{-4}	0.0185	0.0926	0.536
5.0×10^{-5}	0.0151	0.0438	0.506
1.0×10^{-5}	0.0086	0.0099	0.491
5.0×10^{-6}	0.0065	0.0080	0.449
1.0×10^{-6}	0.0026	0.0012	0.460
5.0×10^{-7}	0.0026	0.0012	0.392
1.0×10^{-7}	0.0026	0.0012	0.377

J Post-fine-tuning Gaussian noise injection

This section provides details and results of the injection of noise into the weights of a model after fine-tuning. Specifically, the noise is sampled from a Gaussian distribution $\mathcal{N}(\mu, \sigma^2)$, where the mean μ is set to 0, and σ^2 is the variance that determines the noise's magnitude. Unlike the DP Gaussian mechanism, this approach does not provide formal privacy guarantees. However, it offers a practical and computationally light method to mitigate the memorization of sensitive information, as it does not require additional fine-tuning and can be directly applied to previously fine-tuned LLMs. Additionally, measuring the performance of this method can illustrate how other noise mechanisms similar to those used in DP might affect accuracy and privacy metrics.

In Table 11, we evaluate its effect under various noise magnitudes, along with the corresponding impact on model accuracy. We applied Gaussian noise to the LoRA weights of a fine-tuned Llama 3.2 3B model, as evaluated in earlier sections. We then compared the model's BLEU score and accuracy across different noise magnitudes.

We observe that the accuracy remains unaffected up to a certain noise level ($\sigma = 0.01$) and even shows slight improvement. However, beyond this threshold, accuracy decreases and reduction in memorization similarly follows, appearing to correlate with this decrease. These observations suggest that this mechanism effectively reduces excessive memorization in models that have overfitted onto their training data. Therefore,

Table 11: **Impact of noise addition on BLEU score and accuracy.** Llama 3.2 3B is fine-tuned with LoRA across various noise magnitudes (σ)

Noise Scale (σ)	BLEU, no Duplication	BLEU, 10x Duplication	Accuracy
0 (no noise)	0.0206	0.3012	0.553
0.001	0.0211	0.3049	0.552
0.01	0.0206	0.2877	0.551
0.02	0.0143	0.0994	0.541
0.03	0.0083	0.0111	0.511
0.04	0.0013	0.0006	0.384
0.05	0.0000	0.0000	0.110

this approach offers an alternative to early stopping for controlling memorization which can be applied post fine-tuning. Figure 9 compares the privacy and utility of Llama 3.2 3B subject to post-fine-tuning gaussian noise injection with the evolution of the model fine-tuned with LoRA accross iterations. The noisy model, represented by red dots, has been fine-tuned for 2100 iterations before injecting the gaussian noise. Gaussian noise injection of standard deviations of $\sigma = 0.2$ and $\sigma = 0.3$ have been reported in the plot.

J.1 Privacy-Utility tradeoff with Gaussian noise injection

Figure 9 presents a dot plot comparing the privacy-utility tradeoffs of Llama 3.2 3B when fine-tuned with LoRA versus when Gaussian noise is injected after fine-tuning with LoRA. The results indicate that Gaussian noise injection does not enhance the privacy-utility tradeoff compared to fine-tuning with LoRA.

Figure 9: **Privacy-Utility tradeoff with post-fine-tuning gaussian noise injection.** Accuracy and memorization (BLEU score with 10x document duplication) tradeoff of Llama 3.2 3B subject to post-fine-tuning gaussian noise injection with standard deviation. Values above the dots correspond to the number of iterations for LoRA fine-tuning evolution, and the standard deviation of injected noise for noisy models.

K Secure Aggregations

Secure aggregation ensures that sensitive data remains protected by preventing the aggregator from decrypting any individual model updates. In a federated learning setup, only the aggregated global model is accessible to participants, meaning that memorization within locally trained models before aggregation does not pose a privacy risk. We also evaluate the runtime performance of combining secure aggregation with LoRA in a federated learning setting, demonstrating that this added protection incurs minimal computational overhead.

Performance. To evaluate the performance impact of secure aggregation, we use Lattigo, an open-source library that enables secure protocols based on multiparty homomorphic encryption Lattigo v6; Mouchet et al. (2020). Specifically, it implements the CKKS scheme, which allows efficient encrypted computations on real-valued data, making it ideal for the secure aggregation of the LoRA models trained by the clients/participants. In our experiments, we consider 3 clients and configure CKKS parameters to enable 32-bit precision. Since our LoRA models are trained with 16-bit precision, this ensures that **secure aggregation does not introduce any accuracy loss** compared to standard aggregation in plaintext.

Time overhead. Secure aggregation introduces a time overhead due to encryption, homomorphic operations, and collective decryption. The duration of encrypted aggregation is influenced by the number of weights being aggregated, specifically the number of LoRA weights. In our experiments with Llama 3.2 3B, **a LoRA update contains 24,772,608 parameters, representing approximately 0.77% of the full model's parameters**. In Table 12, we report the aggregation times for vectors of varying sizes, corresponding to the number of LoRA weights. Aggregating three vectors of the size of our LoRA takes 11.33 seconds, which is negligible compared to the time required for local fine-tuning at each round.

Table 12: **Execution Time of the Secure Aggregation Protocol.** The protocol aggregates three equal-sized encrypted vectors for varying sizes.

Aggregation Length	Time Taken
10^1	12.16ms
10^2	11.61ms
10^3	11.32ms
10^4	17.29ms
10^5	58.91ms
10^6	474.46ms
10^7	4.37s
2.48×10^7 (LoRA size)	**11.33s**
10^8	68.24s

L Why Does LoRA Reduce Memorization?

Our experimental evaluation demonstrates that LoRA reduces memorization in both centralized and FL settings, which naturally raises the question: *why does this happen?* We argue that the mechanisms by which FedAvg and LoRA mitigate memorization should be considered independently. Carlini et al. (2023a) empirically establish a log-linear relationship between canary duplication and memorization, thus we frame our discussion of memorization in the context of overfitting. How and why in-distribution, non-duplicated sequences can still be regurgitated (Carlini et al., 2019) is a question that we leave to future work.

Federated learning. While it is known that FedAvg can reduce memorization for simpler LSTM-based next-word predictors (NWPs) (Ramaswamy et al., 2020; Thakkar et al., 2021), we hope that our verification of this phenomenon for LLMs on longer canaries can encourage formal investigation. Nevertheless, we note the following: in the IID FedAvg setting with identical hyperparameter settings (same number of local updates, learning rate, and initialization) the expected value of the d-sample stochastic gradient over N clients, $\frac{1}{N}\frac{1}{d}\sum_{i=1}^{k} f_k(\theta, x_i \sim D_k)$ in Equation 1 can resemble a single stochastic gradient in a centralized setting taken over a single large batch of size Nk since f_k and D_k are homogeneous. Thus, Thakkar et al. (2021) observe more memorization in IID settings with larger batch sizes. The non-IID setting is significantly more complex: the optimization problem and associated loss landscape of Equation 1 differs from the centralized problem. We observe in Figure 2 that non-IID FL significantly reduces memorization, which Thakkar et al. (2021) also observe for their NWPs. While they do not fine-tune their learning rates to eliminate this as a confounding variable, we do[2], thus suggesting that FedAvg itself is a memorization-reducing mechanism.

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[2]While it is possible that performing centralized learning in a curriculum-style manner with heterogeneous learning rates over training data can reduce memorization, given the small performance gap against non-IID FL, it is highly unlikely that this alone can improve its significantly worse memorization scores.

LoRA. Biderman et al. (2024) presents LoRA as a competitive regularization method, and compares it to traditional regularization techniques. They find that LoRA retains more factual knowledge from its pretraining than fine-tuning with attention dropout or weight decay, and also keeps a better diversity of token generation than full fine-tuning.

Recent work by Malekmohammadi & Farnadi (2025) establishes a theoretical and empirical relationship between LoRA training and the DP-SGD algorithm , where LoRA is shown to be equivalent to fine-tuning adapters with noisy batch gradients which results in more robustness to membership inference attacks.

From another perspective, if we regard memorization as a function of duplication-induced overfitting, the preserved model accuracy of LoRA fine-tuning coupled with significantly lowered memorization may signal a reduction in benign-overfitting (Bartlett et al., 2020). That is, while full fine-tuning does not significantly alter model performance, the usage of full gradients may result in training overfitting without affecting generalization. It is possible that LoRA reduces benign overfitting (Bartlett et al., 2020), which occurs when training data is overfitted without affecting performance. Notably, Tang et al. (2023) prove that benign overfitting can preserve out-of-distribution generalization for overparameterized linear models if there is a strong correlation between the dominant eigenvectors/components of the source and target distributions. It is possible then that our LLMs are displaying this phenomenon: in both the centralized and FL settings, our fine-tuning datasets, while heterogeneous, contain aligned components due to their shared domain. LoRA may reduce benign overfitting by ignoring minor components, which only explain a minimal (and possibly noisy) portion of the data covariance.

Specific to FL, an alternative hypothesis is that the low-rank approximation of ΔW resembles a δ-compression operator (Karimireddy et al., 2019), i.e., $||\texttt{LORA}(\Delta W) - \Delta W||^2 \leq (1 - \delta)||\Delta W||^2$, and that low-$\delta$ compressors reduce memorization. Low-bias compressors, such as certain randomized projections (Dorfman et al., 2023; Rabbani et al., 2021; Ivkin et al., 2019) and other low-rank approximations (Makkuva et al., 2023) have been shown to preserve model performance in non-IID distributed settings. While the effects of these other operators on memorization has not been extensively studied, the efficacy of gradient clipping in lowering memorization while maintaining accuracy (Table 10) lends further credence to this hypothesis. Clipping is a low-bias compressor for heavy-tailed gradients, which is observed for general SGD (Mireshghallah et al., 2022) and LLM fine-tuning (Kenton & Toutanova, 2019). Further exploration of δ-compressors such as sketches, signSGD (Bernstein et al., 2018), QLoRA (Dettmers et al., 2024), and U-Clip (Elesedy & Hutter, 2023) is warranted.