Open LLMs are Necessary for Private Adaptations and Outperform their Closed Alternatives

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Abstract

While open Large Language Models (LLMs) have made significant progress, they still fall short of matching the performance of their closed, proprietary counterparts, making the latter attractive even for the use on highly *private* data. Recently, various new methods have been proposed to adapt closed LLMs to private data without leaking private information to third parties and/or the LLM provider. In this work, we analyze the privacy protection and performance of the four most recent methods for private adaptation of closed LLMs. By examining their threat models and thoroughly comparing their performance under different privacy levels according to differential privacy (DP), various LLM architectures, and multiple datasets for classification and generation tasks, we find that: (1) all the methods leak query data, i.e., the (potentially sensitive) user data that is queried at inference time, to the LLM provider, (2) three out of four methods also leak large fractions of private training data to the LLM provider while the method that protects private data requires a local open LLM, (3) all the methods exhibit lower performance compared to three private gradient-based adaptation methods for *local open LLMs*, and (4) the private adaptation methods for closed LLMs incur higher monetary costs than running the alternative methods on local open LLMs. This yields the conclusion that, to achieve truly *privacy-preserving LLM adaptations* that yield high performance and more privacy at lower costs, one should use open LLMs.

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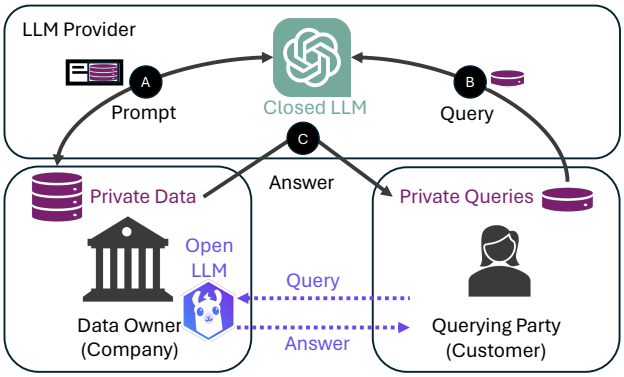
1. Introduction

Recently, there has been the trend of releasing open Large Language Models (LLMs), such as LLama (Geng & Liu, 2023; Touvron et al., 2023), Vicuna (Chiang et al., 2023), or Mistral (Jiang et al., 2023) as an alternative to their proprietary closed counterparts, such as GPT from OpenAI (Ope), Claude from Anthropic (Antropic), or Gemini from Google (Team et al., 2023). Despite the significant progress in improving open LLMs, they are still outperformed in multiple tasks by closed LLMs (Chiang et al., 2024), making the latter attractive even for learning tasks from highly *private* data.

Since it was shown that private data can leak from the adaptations of LLMs (Duan et al., 2023a;b), in the last few months alone, an array of new methods for privacy-preserving adaptation of closed LLMs has been proposed by the machine learning community at multiple conferences (NeurIPS'23 (Duan et al., 2023a) and ICLR'24 (Hong et al., 2024; Tang et al., 2024; Wu et al., 2024)). Given the lack of access to the closed LLMs parameters—which renders parameter-tuning based adaptations infeasible—they all rely on the generation of privacy-preserving discrete prompts. We detail their operational setup in Figure 1.

In this work, we ask the simple yet impactful question of whether these efforts actually lead into the right direction towards the goal of achieving *truly privacy-preserving LLM adaptations*. Therefore, we thoroughly analyze the proposed methods both conceptually and empirically and compare them to alternatives that rely on privately adapting *open local LLMs*. In particular, we study each approach's threat space, assumptions, and methodological limitations and perform extensive experiments using ten state-of-the-art open and closed LLMs of various sizes, including Vicuna, Llama 3, Open LLaMa, BERT, RoBERTa, the Pythia suite of models, Claude, two versions of GPT3 (Babbage and Davinci), and GPT4 Turbo —applied to multiple datasets both for classification and generation tasks. Our analyses cover the axes of privacy protection, performance in terms of privacy-utility trade-offs, and monetary costs for training and queries.



Method	A	B	C	Open LLM
DP-ICL (Wu et al., 2024)	×	×	✓	Not Needed
PromptPATE (Duan et al., 2023a)	×	×	✓	Not Needed
DP-FewShotGen(1) (Tang et al., 2024)	×	×	✓	Not Needed
DP-FewShotGen(2) (Tang et al., 2024)	✓	×	✓	Needed
DP-OPT (Hong et al., 2024)	(✓)	×	✓	Needed
Private Local Adaptation	✓	✓	✓	Needed

Figure 1: **Setup for Privacy Protection with Open vs Closed LLMs**. The three parties involved are (1) an LLM provider who hosts the proprietary LLM, (2) a data owner, such as a company that owns private data, for example, of their customers' previous transactions, and (3) a querying party, *i.e.,* a customer of the company who wants to perform a new private transaction. There are three steps where privacy leaks: Ⓐ During the creation of the discrete prompt, the data owner's private data leaks to the LLM provider. Ⓑ The private query of the querying party leaks to the LLM provider. Ⓒ Private information from the data owner leaks to the querying party through the returned answers of the prompted LLM (Duan et al., 2023b). Prior methods for closed LLMs (Duan et al., 2023a; Tang et al., 2024; Wu et al., 2024) only provide protection against Ⓒ. None of them protects against Ⓑ. To prevent leakage through Ⓐ, they require access to a (powerful) local open LLM. As an alternative (dashed purple lines), the data owner could privately adapt the open LLM locally and let the querying party interact with this LLM directly, protecting against Ⓐ, Ⓑ, Ⓒ.

Our results provide the following insights: (1) All methods for adapting closed LLMs leak private query data (intended for the data owner) at inference time to the LLM provider. (2) Three out of the four methods studied also leak large fractions of the private training data to the LLM provider. The approaches that do not, require an additional locally deployed open LLM for prompt engineering. (3) All methods for closed LLMs yield lower final downstream performance than privacy-preserving local adaptations on open LLMs—even when the local methods rely on significantly smaller LLMs than their closed counterparts. (4) The training and query costs of the private adaptations of closed LLMs (API access costs imposed by the LLM provider) are significantly higher than the costs for private open LLM adaptations (estimated as the costs of training and querying on cloud-based hardware). We provide a summary of our results in Figure 1 and Table 1.

Overall, our results indicate that, from the perspective of effective privacy-preservation, open LLM adaptations are strictly preferable over closed LLM adaptations, since they are more private, more performant, and less expensive. Going beyond the concrete existing methods studied (Duan et al., 2023a; Hong et al., 2024; Tang et al., 2024; Wu et al., 2024), we then analyze the reasons behind the underwhelming results of privacy-preserving closed LLM adaptations and discuss potential directions for improvements.

On the way, to further strengthen private adaptations for open LLMs. We demonstrate how to locally apply privacy-preserving prompt-based methods to train generation tasks with high-performance—claimed impossible by prior work (Li et al., 2022). In particular, we show for the first time that private prompt tuning for text generation tasks PromptDPSGDGen can achieve comparable performance to private (full) fine-tuning and private low-rank adaptations (LoRA). Additionally, we demonstrate that ensemble-based few-shot prompts PromptPATEGen can privately generate high-quality text at a low privacy cost.

In summary, we make the following contributions:

1. We perform a thorough conceptual and experimental study on existing privacy-preserving closed and open LLM adaptations, analyzing their threat space, assumptions, and achieved results.

2. Our extensive experiments on various open and closed LLMs and on multiple classification and generation tasks show that the local (gradient-based) adaptations outperform their closed (discrete prompt-based) counterparts in terms of privacy, performance, and cost efficiency.

3. We propose differentially private prompts for text generation tasks that, for the first time, reach performance comparable to private LoRA or private fine-tuning.

2. Background and Related Work

LLMs are pre-trained on large amounts of public data and then adapted to downstream tasks using private data. We divide existing methods for private LLM adaptations into *private tuning* methods that rely on access to the LLM gradients, and *private in-context leaning* (ICL) which requires only API (black-box) access to the LLM. While private tuning is only applicable to open LLMs, private ICL can, in principle, be applied to both open and closed LLMs. The private tuning methods leverage the DPSGD algorithm where **PromptDPSGD** (Duan et al., 2023a) adapts soft prompts,

Table 1: **Comparison of privacy protection, performance, and costs between private adaptations for closed vs open LLMs.** We consider the sentiment classification task on SST2 (Wang et al., 2019) and the dialog summarization on SAMSum (Gliwa et al., 2019). We select the top-performing private LLM adaptations for the tasks. For closed LLMs, we use DP-ICL (Wu et al., 2024) and PromptPATE (Duan et al., 2023a). Then, we leverage PromptDPSGD (Duan et al., 2023a) and PrivateLoRA (Yu et al., 2022) on open LLMs. Since PromptDPSGD and PromptPATE were proposed only for classification tasks, we further extend them to text generation tasks, denoted as PromptPATEGen and PromptDPSGDGen, and show their performance on open LLMs. The training data is denoted by $\mathcal{D}_T$ and the test queries by Q. *Reveals* represents which data are exposed to the LLM provider. The methods were trained with DP guarantees: $\varepsilon = 8$ and $\delta = 1/N$, where N is the number of examples in $\mathcal{D}_T$. We report the *Performance* (higher is better) on test data (where *Acc* denotes the classification accuracy). The cost (in $) is computed separately for training (*Train*) and for answering 10k test queries (*Query*). *All* denotes the total cost. Note, the (estimated) number of parameters (expressed as T-trillion, B-Billion, M-million) for closed LLMs is 1.76T for GPT4 Turbo, 200B for Claude 2.1, 175B for GPT3 Davinci, while Llama3 has only 8B. RoBERTa-Large and BART-Large are significantly smaller with 355M and 340M parameters, respectively. The adaptations of the open LLMs are more expensive on SST2 than on SAMSum due to the larger training data size for SST2. *In summary, open local LLM adaptations are more private, more performant, and less expensive.*

Adaptation	LLM Type	Model	Task	Reveals	Performance↑	Train($)	Query($)	All($)
DP-ICL (Wu et al., 2024)	Closed	GPT4 Turbo	SST2	$\mathcal{D}_T$+Q	Acc=$95.9_{\pm 0.1}$%	0	138.00	138.00
PromptPATE (Duan et al., 2023a)	Closed	Claude 2.1	SST2	$\mathcal{D}_T$+Q	Acc=$95.7_{\pm 1.4}$%	48.24	5.36	53.6
PromptDPSGD (Duan et al., 2023a)	Open	RoBERTa-Large	SST2	*None*	Acc=$92.3_{\pm 0.5}$%	7.59	0.40	7.99
PrivateLoRA (Yu et al., 2022)	Open	Llama3-8B(instruct)	SST2	*None*	Acc=$96.0_{\pm 0.1}$%	27.60	0.78	28.38
DP-ICL (Wu et al., 2024)	Closed	GPT3 Davinci	SAMSum	$\mathcal{D}_T$+Q	RougeL=31.8	0	665.91	665.91
PromptPATEGen	Open	OpenLLaMA 13B	SAMSum	*None*	RougeL=34.2	18.63	0.80	19.43
PromptDPSGDGen	Open	BART-Large	SAMSum	*None*	RougeL=37.4	1.73	0.40	2.13
PrivateLoRA (Yu et al., 2022)	Open	BART-Large	SAMSum	*None*	RougeL=39.0	3.63	0.80	4.43

PrivateLoRA (Yu et al., 2022) extends LoRA, and **DP-fine-tuning** (Li et al., 2022) privately fine-tunes all LLM parameters. Private adaptations of closed LLMs rely on in-context learning (ICL) and voting mechanisms for privacy protection. They include **DP-ICL** (Wu et al., 2024) for private question answering, **PromptPATE** (Duan et al., 2023a) with public student prompting, **DP-FewShotGen** (Tang et al., 2024) for private prompt generation, and **DP-OPT** (Hong et al., 2024), which is a private prompt engineering. We further analyze existing methods, their setup, and their assumptions in Appendix B, and provide a summary in Table 2.

3. Private Adaptations for Text Generation

While PromptDPSGD and PromptPATE (Duan et al., 2023a) were designed for classification tasks only, we further extend them to text generation tasks. Having prompt-based generation holds the advantage that, in contrast to fine-tuning based approaches, they support mixed-task inference (Lester et al., 2021; Li & Liang, 2021; Liu et al., 2022a), *i.e.,* they require one frozen model for multiple tasks rather than a separate model copy for each of them. This reduces storage and offers greater flexibility and efficiency.

PromptDPSGDGen. We observe that an adequate choice of hyperparameters is sufficient for adjusting PromptDPSGD (Duan et al., 2023a) to generation tasks. This is in line with prior work highlighting that the challenge of prompt tuning is that it requires experimenting with various hyperparameter choices to achieve good performance (Liu et al., 2022a). In particular, we observe that increasing the number of parameters in the soft prompt from 0.1% of the total LLM parameters, as done for classification (Duan et al., 2023a), to 10% of total model parameters, by enabling prefix projection, yields a significant increase in generation performance. Additionally, we observe the need for an increased learning rate, compared to other tuning methods, to generate more precise outputs. Otherwise, the hyperparameters are dependent on the data the model is trained on.

PromptPATEGen. Adjusting PromptPATE (Duan et al., 2023a) to generation tasks (where more than one output token is generated) is challenging due to 1) the large output space (equivalent to the number of tokens in the vocabulary) and 2) the privacy costs incurred by generating multiple tokens through the teacher ensemble. To overcome this challenge and support generation tasks with an unlimited number of queries, we extended PromptPATE by combining the training of the student prompt from (Duan et al., 2023a) with the privacy techniques used in (Wu et al., 2024) and call the result PromptPATEGen. In particular, PromptPATEGen uses the private generation in DP-ICL to obtain longer output sequences for some public data inputs. The outputs sequences can then be treated as a "label" for the public data and can be deployed as a form of student prompt, just like in PromptPATE (Duan et al., 2023a).

4. Comparing Open and Closed LLM Adaptations

We perform a thorough conceptual and empirical study to compare the adaptation of both open LLMs with private tuning (PromptDPSGD (Duan et al., 2023a), PrivateLoRA (Yu et al., 2022), and DP-FineTune (Li et al., 2022)) and closed LLMs with private ICL (DP-ICL (Wu et al., 2024), PromptPATE (Duan et al., 2023a), DP-FewShotGen (Tang et al., 2024), and DP-OPT (Hong et al., 2024)). Our comparison spans the axes of privacy protection, performance, and cost. We provide an overview of our comparison between private adaptations for closed vs open LLMs in Table 1.

4.1. Comparing Privacy Protection

All the considered methods offer privacy guarantees according to DP. Thereby, they ensure that the final prompted LLM's predictions will not leak more than the specified tolerated privacy budget ε to any party who queries the LLM or gets access to the final private prompt. Yet, the threat model of multiple private ICL methods for closed LLMs does not include providing privacy against the LLM provider. Those methods that do might still occasionally experience leakage. We analyze the result of this lack of consideration for the goal of truly privacy-preserving LLM adaptations. In our analysis, we distinguish between the leakage of private training data and the leakage of test data queried at inference time, which might also be sensitive.

Private Training Data. PromptPATE (Duan et al., 2023a), DP-ICL (Wu et al., 2024), and DP-FewShotGen (Tang et al., 2024) (without using an open LLM) disclose (large parts of) their private training set to the LLM provider in the form of shots in their teacher prompts and their engineering. This leakage is inherent in their design. To avoid such leakage, DP-OPT (Hong et al., 2024) tunes the prompt locally with DP guarantees and then exposes it to the LLM provider. Thereby, the data that the prompt was generated from is protected towards the LLM provider with the DP guarantees that also protect against leakage to a querying party. While the experimental evaluation in (Hong et al., 2024) suggests that at higher ε, the locally generated DP prompts might still contain generated data close to the private training data, this is a step towards the right direction. However, to generate the private prompt, DP-OPT (Hong et al., 2024) requires a powerful open LLM deployed locally. Looking at Figure 1, it becomes obvious that any private tuning method executed on that open LLM would, conceptually, improve privacy protection since the LLM provider would neither be involved in the adaptation nor in the use of the adapted LLM, yielding absolute privacy against them.

Private Query Data. DP does not aim at protecting query data. Hence, none of the private ICL methods attempts to protect that data against the LLM provider. While the protection of query data is often considered as an orthogonal research direction, we note that all the private tuning-based adaptations of the open local LLMs do naturally prevent leakage of the query data to the LLM provider. This is because the querying party directly interacts with the data owner (see Figure 1)—making the use of open models inherently more suited for truly privacy-preserving application than relying on closed models.

4.2. Comparing Performance

We look at privacy-utility trade-offs to compare the performance of private tuning on open LLMs vs. private ICL on their closed counterparts. Previous work (Liu et al., 2022a) has shown for the non-private settings that gradient based tuning methods (used for open LLMs) offer better accuracy and significanly lower computational costs than ICL (used for closed LLMs) since the adaptations can leverage the internal behavior of the LLM. This benefit holds also in the privacy regime. Moreover, the tuning based methods do not make additional assumptions, such as the availability of public data (required by PATE-based methods, such as PromptPATE (Duan et al., 2023a)), making them inherently more practical. We show that the private adaptations on local open LLMs outperform the private methods for closed LLMs in Table 1. Considering the text generation task, we observe that our PromptPATEGen outperforms the closed DP-ICL (Wu et al., 2024) alternative while PromptDPSGDGen matches the performance of the best performing PrivateLoRA (Yu et al., 2022) method. We provide more details on the performance differences for classification tasks in Table 3, and for three text generation tasks, namely dialog summarization with SAMSum (Gliwa et al., 2019) in Table 5, question answering with PFL-DocVQA (Tito et al., 2023) in Table 6, and information extraction with MIT-D and MIT-G (Liu et al., 2012) in Table 7.

4.3. Comparing Costs

We compare the costs of obtaining a private predictor for a given downstream task using open vs closed LLMs. We use the wall clock time to capture the running time of methods for local open LLMs, which we then translate to the monetary cost that would be incurred if we ran the method on cloud-based hardware. For the adaptations of closed LLMs, we count the number of tokens used in the queries and obtained outputs from the APIs. The pricing from cloud providers and OpenAI forms the basis for the cost estimations (see details in Appendix E). Based on the estimated costs in Tables 1-7, the privacy-preserving methods for open LLMs require much lower costs (and perform better) than for closed LLMs in the considered scenarios. The high costs incurred by closed LLM adaptations result from relying on ensemble-based approaches to yield DP guarantees and

incurring continuous query costs at inference time.

5. Conclusions

In summary, our results highlight that from the perspective of providing truly privacy-preserving adaptations, open LLMs are strictly preferable over closed LLMs since their adaptations are more private, more performant, and more cost-effective. The enhanced privacy protection from adapting open LLMs is a major benefit: users' private training data and queries to adapted open LLMs are never revealed to third parties. Furthermore, the adaptations of open LLMs based on gradient-based optimization outperform private ICL methods for closed LLMs while incurring lower costs.

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A. Discussion and Future Work

Going beyond the concrete existing methods studied in this work (Duan et al., 2023a; Hong et al., 2024; Tang et al., 2024; Wu et al., 2024), in the following, we analyze the general reasons behind the underwhelming results of privacy-preserving closed LLM adaptations.

Privacy Leakage. The leakage of private query data to the LLM provider is an inherent problem with closed LLMs since no methods to provide formal guarantees for the query data are known. Potential solutions might involve private inference for LLMs, where a model performs inference on encrypted queries, however, it is still in its nascency (Chen et al., 2022; Hao et al., 2022; Li et al., 2023) for the scale of closed LLMs (Brown et al., 2020).

Performance. We argue that the lower performance of closed LLM adaptations stems from the fact that they have to rely on discrete prompts and that engineering such prompts for the closed LLMs is highly challenging. This is because 1) prompts, in general, have been shown to exhibit an unstable performance and to require a large number of trials and errors or discrete optimization while still underperforming gradient-based approaches (Liu et al., 2022a). Additionally, 2) when the prompts (for privacy reasons) are not tuned on the closed LLM but on an open LLM surrogate model, an additional performance decrease is incurred through the prompt transfer, since it has been shown that transferred prompts cannot reach the performance of prompts directly tuned on a given LLM (Su et al., 2022). While the latter problem might be mitigated by designing more performant prompt transfer techniques, the former seems to be a more fundamental limitation (Liu et al., 2022a).

Costs. The high costs incurred by some closed LLM adaptations result from the fact that they rely on ensemble-based approaches to yield DP guarantees and the fact that they incur continuous query costs at inference time. The former could be solvable by designing more efficient DP schemes for discrete prompts, however, the latter is inherent to the nature of closed LLMs.

While implementing the above-mentioned solutions might shrink the gap between private adaptations of open and closed LLMs, it remains unclear whether it is worth the community's effort, given the effectiveness of private adaptations for open LLMs.

B. Further Details on the Related Work

B.1. Differential Privacy.

Differential Privacy (DP) (Dwork, 2006) is a mathematical framework that provides privacy guarantees by implementing the intuition that an algorithm $\mathcal{A} : I \to R$, executed on two neighboring datasets D, D' that differ in only one data point, will yield approximately the same output, *i.e.,* $\Pr[\mathcal{A}(D) \in R] \leq e^{\epsilon} \cdot \Pr[\mathcal{A}(D') \in R] + \delta$. While ε specifies by how much the output can differ, δ specifies the probability of failure. There are two prevalent DP algorithms for training machine learning models. The first one is the the differential private stochastic gradient descent algorithm (**DPSGD**) (Abadi et al., 2016) where the impact of each private training data point is limited during training through gradient clipping, and privacy guarantees are integrated through the addition of calibrated amounts of stochastic noise. The second algorithm is the private aggregation of teacher ensembles (**PATE**) (Papernot et al., 2018) where first, an ensemble of teacher models is trained on disjoint subsets of the private data, and then a noisy knowledge distillation is performed to a student model using public data. Another general mechanism for implementing DP is the exponential mechanism (**EM**) (McSherry & Talwar, 2007). The EM selects an output r from a set of possible outputs based on a scoring function $q(D, r)$ that measures the quality of r for dataset D. Let Δq be the sensitivity of the scoring function. The EM chooses r with probability proportional to $\exp\left(\frac{\epsilon q(D,r)}{2\Delta q}\right)$.

B.2. Private Adaptations of LLMs

We summarize existing methods for private LLM adaptations in Table 2, where we also analyze their setup and assumptions. We provide further details on the methods below.

Private Tuning for Open LLMs. There exist three main ways for private tuning. **1) Prompt-based adaptations** adds a small number of parameters (usually <1% of the total number of parameters) only in the model input space, either on the level of token embeddings (soft prompts (Liu et al., 2021; 2022b)), or also to every LLM layer (prefix-tuning (Lester et al., 2021; Li & Liang, 2021)). Duan et al. (2023a) presented **PromptDPSGD**, which adapts the DPSGD algorithm to soft prompts.

Table 2: **Comparison of properties between private LLM adaptations.** The in-context learning (ICL) optimizes instructions and shots (demonstrations). Many privacy techniques include the ones designed for multi-label PATE (denoted as MLPATE) (Zhu & Wang, 2022), exponential mechanism (EM) (McSherry & Talwar, 2007), joint exponential mechanism (JEM) (Gillenwater et al., 2022), Gaussian Mechanism (GM), Report-Noisy-Max Mechanism (RNM), Propose-Test-Release (PTR) (Dwork et al., 2014), sample-and-aggregate (SAA) (Nissim et al., 2007), Limited Domain Algorithm (LDA) (Durfee & Rogers, 2019).

Adaptation \ Property	Privacy Algorithms	Optimization Strategy	Privatize	Inference Type	Require
PromptDPSGD (Duan et al., 2023a)	DPSGD	Gradient-based	Soft Prompt/Prefix	Multi-task	Open LLM
PrivateLoRA (Yu et al., 2022)	DPSGD	Gradient-based	Added parameters	Single-task	Open LLM
DP-FineTune (Li et al., 2022)	DPSGD	Gradient-based	all LLM parameters	Single-task	Open LLM
DP-ICL (Wu et al., 2024)	RNM,GM,JEM,PTR,MLPATE	ICL	Answers	Limited Queries	None
PromptPATE (Duan et al., 2023a)	PATE	ICL	Shots	Multi-task	Public Data
DP-FewShotGen (Tang et al., 2024)	GM,RNM,EM	ICL	Shots	Multi-task	Public Labels,Open LLM
DP-OPT (Hong et al., 2024)	SAA,LDA	ICL	Instructions+Shots	Multi-task	Validation Data,Open LLM

The main advantage of prompt-based adaptations is that they enable multi-task batch processing, *i.e.,* many soft prompts for different users and tasks can be processed in the same mini-batch during LLM training or inference. **2) Parameter efficient fine-tuning-based adaptations** such as LoRA (Hu et al., 2021) add a relatively small number of parameters (<10% of total number of parameters) within the model, usually in each block of a transformer architecture (Vaswani et al., 2017). These added parameters are then tuned while the pre-trained original parameters remain frozen. **PrivateLoRA** (Yu et al., 2022) extends LoRA with DP guarantees by building on the DPSGD algorithm. **3) Full fine-tuning-based adaptations** either fine-tune the whole model or only a few last layers. The **DP-fine-tuning** (Li et al., 2022), again based on the DPSGD algorithm, shows that full fine-tuning with DP optimization can provide strong privacy guarantees and good performance. The general trend, when choosing an adequate method, suggests that the more difficult the task, the higher the number of adaptation parameters required (Duan et al., 2023a). Thus, for simple downstream tasks, PromptDPSGD (Duan et al., 2023a) is sufficient, while DP-LoRA (Yu et al., 2022) is recommended for medium-difficulty tasks, and the full fine-tuning (Li et al., 2022) for complex tasks.

Private ICL for Closed LLMs. Recently, many new methods were proposed for private in-context learning with closed LLMs. All of them leverage discrete (hard) prompts and rely on a voting mechanism for privacy protection, similar to PATE. We divide the existing methods into the following four categories: **(1) Private Question Answering:** The work on **DP-ICL** (Wu et al., 2024) proposed to answer queries based on the private dataset. Following the PATE setup, the private data is divided into non-overlapping partitions and then each partition is prepended with an instruction to form a private teacher prompt. The prompts form an ensemble of private teachers (prompted LLMs). Since DP-ICL does not implement the idea of a student model from PATE, all the teachers (usually 100) are required to answer each query, rendering the method expensive when executed on a closed LLM. Moreover, each query incurs additional privacy cost, such that the method can answer only a limited number of queries for a given privacy budget. **(2) Private Student Prompt: PromptPATE** (Duan et al., 2023a) tackles the problem of the high costs and the limited number of answered queries in DP-ICL by creating a student prompt. PromptPATE uses an ensemble of teacher prompts (usually around 200) to label public data. Then it selects the most performant shots for the student prompt from these newly labeled examples. **(3) Private Prompt Generation: DP-FewShotGen** (Tang et al., 2024) is similar to PromptPATE but eschews the assumption about the public data for labeling and, in turn, starting from a public label, generates each output token privately to obtain a private shot. **(4) Private Prompt Engineering:** Finally, **DP-OPT** (Hong et al., 2024) privatizes prompt engineering based on the Deep Language Network (DLN) method (Sordoni et al., 2023). While DP-ICL, PromptPATE, and DPFewShotGen assume a generic instruction and emphasize the protection of the direct leakage from the shots only, DP-OPT (Hong et al., 2024) proposed to privately generate shots and instructions since either can leak information about the private training set. To overcome the problem that PATE-based approaches face with large output spaces (here equal to the vocabulary size of around 50k), DP-ICL (Wu et al., 2024) and DP-OPT (Hong et al., 2024) incorporate the EM and its improved versions (Durfee & Rogers, 2019; Gillenwater et al., 2022; Zhu & Wang, 2022) to privately release a token with the maximum count based on the voting from teacher prompts.

B.3. Private Text Generation based on PATE

SeqPATE (Tian et al., 2022) safeguards the privacy of individual training samples and sensitive phrases in the training data of a language model. To adapt PATE for text generation, SeqPATE creates pseudo-contexts, simplifying the sequence

generation task to a next-word prediction problem. To manage the extensive output space, SeqPATE introduces a candidate filtering strategy that dynamically narrows the output space and enhances the teacher aggregation in PATE to avoid low agreement caused by voting among a large number of candidates. Additionally, to further minimize privacy losses, it employs knowledge distillation to reduce the number of teacher queries.

C. Additional Experiments

Private Tuning outperforms Private ICL Experimentally. To assess the performance of private tuning vs. private ICL, we perform extensive experimental evaluation. We use various LLM architectures and multiple datasets for classification and text generation tasks.

C.1. Experimental Setup

Text Classification. We follow the setup from (Hong et al., 2024) and use four datasets for the evaluation: SST2 from the GLUE benchmark (Wang et al., 2018), Trec (Li & Roth, 2002), Mpqa (Lu et al., 2021) and Disaster (Bansal et al., 2019). SST2 and Mpqa are two-class sentiment analysis datasets. SST2 includes 67.3k training samples and 872 test samples, while Mpqa contains 8.6k training samples and 2k test samples. Trec is a six-class question-type classification dataset with 5.4k training samples and 500 test samples. Finally, the Disaster dataset involves determining whether a sentence is relevant to a disaster scenario or not and includes 4.4k training and 1000 test samples.

Text Generation. We use three different datasets: SAMSum, a dialog summarization (Gliwa et al., 2019) (14732 train, 818 val, and 819 test samples), PFL-DocVQA, question answering (Tito et al., 2023) (85k train and 10k test samples), and MIT Movies trivia10k13, movie extraction on directors (MIT-D with 1561 train and 415 test samples) and genre (MIT-G with 2953 train and 780 test samples) (Liu et al., 2012).

Closed Models. We follow the setup and choice of models originally proposed in the respective previous papers to evaluate the four private ICL methods for closed LLMs (Duan et al., 2023a; Hong et al., 2024; Tang et al., 2024; Wu et al., 2024). The GPT3-Babbage and GPT3-Davinci models cited in (Tang et al., 2024; Wu et al., 2024) were discontinued in early 2024[1] and replaced by their second versions (babbage-002 and davinci-002). Therefore, we use the newer versions here. The (estimated) number of parameters for the closed models is: 1.3B for GPT3 Babbage, 175B for GPT3 Davinci, 1.76T for GPT4 Turbo, and 200B for Claude 2.1.

Open Models. We consider various open LLMs with differing pre-training sets and numbers of parameters to simulate the choices a data owner can make for their local LLM. We select the following models: Pythia (Biderman et al., 2023), OpenLLaMA (Geng & Liu, 2023), Vicuna (Chiang et al., 2023), Bart (Lewis et al., 2019), and RoBERTA (Liu et al., 2020), whose sizes vary from 160M to 13B parameters.

C.2. Performance of Private Adaptations for Classification

We show that the private adaptations on local open LLMs outperform the private methods for closed LLMs for classification tasks. In Table 3, we analyze the performance differences. We follow the evaluation in (Hong et al., 2024) (Table 2) and average the accuracy across the tasks (denoted as Average). Our analysis follows the standard practice and sets the privacy budget as $\varepsilon = 8$ and $\delta = 1/|D|$ where $|D|$ is the training size (Duan et al., 2023a; Hong et al., 2024). Among the methods for closed LLMs, DP-OPT was tested on the strongest Davinci model (with 175B parameters) from the GPT3 family. Across all the tasks, DP-OPT is outperformed by both DP-FineTune and PrivateLoRA by a large margin (even >26% absolute on Trec), even though DP-FineTune and PrivateLoRA were trained on RoBERTa Large with only 355M parameters (500X fewer than for GPT3 Davinci). Furthermore, we show that PrivateLoRA outperforms DP-OPT even when using Pythia-6.9B, which guarantees that the open LLM for PrivateLoRA was not pre-trained on any of the downstream datasets. For a fair comparison, we also train PrivateLoRA on Vicuna 7B, which was used in DP-OPT as the local model to find the transferable prompts and show that PrivateLoRA is also significantly better than DP-OPT applied either directly to Vicuna 7B or when run on GPT3 Davinci. This suggests that the data owners, rather than using their local LLM to tune prompts for DP-OPT, should privately tune it with PrivateLoRA (in this case on RobBERTA Large) since it yields stronger performance and privacy at a lower cost.

For PromptPATE, the performance plateaus after around $\varepsilon = 0.3$, since it creates a public prompt using only a few shots,

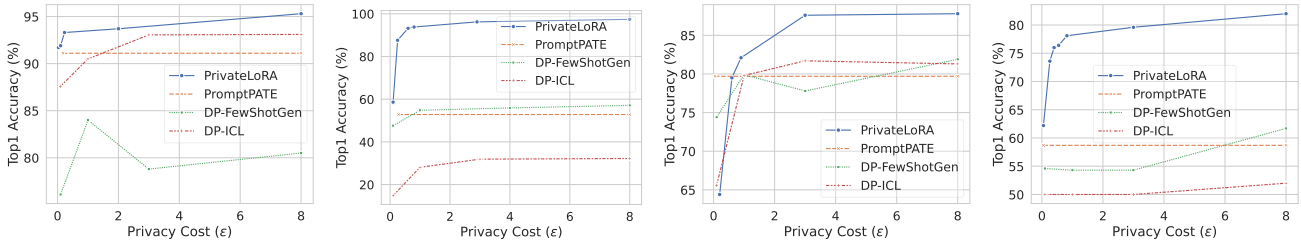
[1] https://platform.openai.com/docs/deprecations

Table 3: **Private local adaptations on open LLMs outperform their closed alternatives for classification tasks.** The default privacy budget is set to $\varepsilon = 8$, except for PromptPATE (Duan et al., 2023a), where the performance plateaus after $\varepsilon = 0.3$. The best result for a given task is bolded, and the 2nd best is underlined. **T($)** is training cost while **Q($)** is query cost for 10k queries (SST2), **All($)** is total cost.

Method	LLM Type	Model	SST2	Trec	Mpqa	Disaster	Average	T($)	Q($)	All($)
DP-OPT (original) (Hong et al., 2024)	Closed	GPT3 Davinci	$92.2_{\pm 0.8}$	$68.7_{\pm 6.5}$	$85.8_{\pm 0.7}$	$78.9_{\pm 0.3}$	81.4	2.10	6.00	8.1
PromptPATE (Duan et al., 2023a)($\varepsilon = \infty$)	Closed	GPT3 Babbage	93.8	58.7	83.0	64.3	75.0	8.66	1.72	10.38
PromptPATE (Duan et al., 2023a)($\varepsilon < 0.3$)	Closed	GPT3 Babbage	$88.8_{\pm 2.3}$	$52.8_{\pm 1.5}$	$79.0_{\pm 0.5}$	$58.0_{\pm 0.5}$	69.6	9.72	1.72	11.44
PromptPATE (Duan et al., 2023a)($\varepsilon < 0.3$)	Closed	Claude 2.1	$95.7_{\pm 1.4}$	$79.3_{\pm 1.2}$	$\mathbf{92.1_{\pm 0.6}}$	$71.0_{\pm 0.8}$	84.5	48.24	5.36	53.6
DP-FewShotGen(1) (Tang et al., 2024)	Closed	GPT3 Babbage	$72.8_{\pm 7.7}$	$51.3_{\pm 5.8}$	$73.4_{\pm 8.5}$	$59.2_{\pm 2.5}$	64.2	0.86	1.10	1.96
DP-ICL (Wu et al., 2024)	Closed	GPT3 Babbage	$92.8_{\pm 0.9}$	$26.3_{\pm 5.6}$	$80.6_{\pm 0.9}$	$50.6_{\pm 1.1}$	62.6	0	17.2	17.2
DP-ICL (Wu et al., 2024)	Closed	GPT4 Turbo	$\underline{95.9_{\pm 0.1}}$	$16.2_{\pm 1.7}$	$\underline{90.4_{\pm 0.1}}$	$70.3_{\pm 0.4}$	68.2	0	138.00	138.00
PromptDPSGD (Duan et al., 2023a)	Open	RoBERTA Large	$92.3_{\pm 0.5}$	$54.5_{\pm 2.5}$	$50.0_{\pm 0.0}$	$77.8_{\pm 0.6}$	68.6	7.59	0.40	7.99
DP-FineTune (Li et al., 2022)	Open	RoBERTA Large	$93.5_{\pm 0.3}$	$93.7_{\pm 0.8}$	$88.2_{\pm 0.4}$	$\mathbf{82.2}_{\pm 0.3}$	89.4	5.75	0.40	6.15
PrivateLoRA (Yu et al., 2022)	Open	RoBERTA Large	$93.6_{\pm 0.3}$	$93.9_{\pm 0.6}$	$87.7_{\pm 0.8}$	$81.8_{\pm 0.2}$	89.3	3.45	0.40	3.85
PrivateLoRA (Yu et al., 2022)	Open	Vicuna 7B	$94.8_{\pm 0.5}$	$\mathbf{97.3}_{\pm 0.1}$	$87.8_{\pm 0.5}$	$81.3_{\pm 0.5}$	**90.3**	13.80	0.78	14.58
PromptDPSGD (Duan et al., 2023a)	Open	Vicuna 7B	$90.4_{\pm 1.7}$	$32.3_{\pm 3.1}$	$84.2_{\pm 4.0}$	$78.5_{\pm 0.4}$	71.4	16.30	0.78	17.08
DP-OPT (local) (Hong et al., 2024)	Open	Vicuna 7B	$89.5_{\pm 2.6}$	$65.3_{\pm 4.3}$	$80.7_{\pm 3.3}$	$65.6_{\pm 0.3}$	75.3	2.10	0.78	2.88
PrivateLoRA	Open	Pythia 6.9B	$92.2_{\pm 0.5}$	$96.3_{\pm 0.8}$	$87.2_{\pm 0.3}$	$\underline{82.1_{\pm 0.2}}$	89.4	13.80	0.78	14.58
PrivateLoRA	Open	Pythia 160M	$80.4_{\pm 0.7}$	$82.5_{\pm 3.2}$	$77.9_{\pm 0.3}$	$73.6_{\pm 0.2}$	78.6	1.60	0.50	2.1
PrivateLoRA	Open	Llama3-8B(Instruct)	$\mathbf{96.0}_{\pm \mathbf{0.1}}$	$\underline{96.8_{\pm 0.2}}$	$87.3_{\pm 0.2}$	$80.8_{\pm 0.1}$	$\underline{90.2}$	27.60	0.78	28.38

and the selection of the demonstrations from a large pool of publicly labeled examples has a negligible gain on the final performance. In the limit, we also show that PromptPATE even with an infinite privacy budget ($\varepsilon = \infty$) for GPT3 Babbage (with 1.3B parameters) performs worse than PrivateLoRA or DP-FineTune on RoBERTA Large (3.6X fewer parameters). In the same setup of models, PrivateLoRA and DP-FineTune on RoBERTA Large also outperform DP-ICL tested on GPT3 Babbage on all tasks. Additionally, PrivateLoRA adapted on Pythia-160M (with even fewer parameters) performs much better than DP-FewShotGen on GPT3-Babbage (8X more parameters).

We also run DP-ICL with GPT4 Turbo. The resulting accuracies are high for sentiment classification with SST-2 and Mpqa. However, it has the lowest accuracy on Trec (with 6 classes), caused by a small number of output probability tokens released for a query (only 20 vs 100 for GPT3, which might not contain the correct class label token) while being the most expensive option. Similar trends are observed for PromptPATE on Claude, however, it has more consistent performance and emerges as the most performant closed model on the tested tasks (while being the 2nd most expensive one). In contrast, Private LoRA with Vicuna 7B performs the best on Trec and on *average*. It is the best of all tested adaptations while incurring around 3.7 and 9.5 times lower costs than Claude and GPT4 Turbo, respectively. In general, the open models have the highest average performance at a much lower cost.



(a) SST2 (b) Trec (c) MPQA (d) Disaster

Figure 2: **Privacy-utility trade-off for classifications tasks.** We use PrivateLoRA to adapt Vicuna-7b to the downstream tasks, PromptPATE, DP-ICL, and DP-FewShotGen with GPT3 Babbage. We analyze the privacy costs ε in the range $[0, 8]$ (see corresponding Figure 3 for text generation tasks).

We further analyze the privacy-utility trade-off for classification tasks across different privacy budgets ($\varepsilon \in [0, 8]$) in Figure 2. We show that even under tight privacy constraints ($\varepsilon < 1.0$), the privacy-preserving adaptation for open LLMs performs significantly better than the one for closed LLMs. Specifically, we analyze the differences between PrivateLoRA for open LLMs vs PromptPATE for closed LLMs. The performance for PromptPATE plateaus after around $\varepsilon = 0.3$ and only for one out of four datasets, namely for MPQA, we observe that the crossover point between PromptPATE and PrivateLoRA (PromptPATE performs better than PrivateLoRA until $\varepsilon = 0.6$). For the smallest $\varepsilon = 0.1$ values that we analyzed, the performance of PrivateLoRA is better by 0.6% on SST2, by 4.4% on Trec, and by 3.5% on Disaster. Overall, the private

Table 4: **Private LoRA (Yu et al., 2022) top1-accuracies** for the evaluated datasets given different ε.

ε	Model	SST-2	Trec	Mpqa	Disaster
8	Vicuna 7B	95.3	97.4	88.4	82.0
3	Vicuna 7B	94.4	96.2	87.6	79.6
1	Vicuna 7B	93.5	93.8	82.1	78.1
0.7	Vicuna 7B	93.4	93.2	79.5	76.4
0.3	Vicuna 7B	91.9	87.6	64.4	73.6

Table 5: **Evaluation on Dialog Summarization with SAMSum** for $\varepsilon = 8$. **T($)** is training cost while **Q($)** is query cost for 10k queries, **All($)** is total cost.

Method	LLM Type	Model	Rouge-1	Rouge-2	Rouge-L	T($)	Q($)	All($)
DP-ICL (Wu et al., 2024)	Closed	GPT3 Davinci	$41.2_{\pm 0.6}$	$16.3_{\pm 0.4}$	$31.8_{\pm 0.3}$	0	665.91	665.91
PromptPATEGen	Open	Vicuna 7B	41.3	18.0	32.8	3.29	2.74	6.03
PromptPATEGen	Open	OpenLLaMA 13B	43.38	19.7	34.2	18.63	0.80	19.43
PromptDPSGDGen	Open	BART-Large	46.4	21.4	37.4	1.73	0.40	2.13
PrivateLoRA (Yu et al., 2022)	Open	BART-Large	**49.1**	**23.3**	**39.0**	2.90	0.69	3.59
PrivateLoRA (Yu et al., 2022)	Open	Pythia 410M	40.3	16.4	32.6	3.45	1.34	4.79
PromptDPSGDGen	Open	Pythia 1B	41.2	17.7	33.7	4.83	0.95	5.78
DP-FineTune (Li et al., 2022)	Open	Pythia 1B	42.0	18.0	34.1	9.84	1.08	10.92
PrivateLoRA (Yu et al., 2022)	Open	Pythia 1B	41.7	17.7	33.8	4.24	1.00	5.24
PrivateLoRA (Yu et al., 2022)	Open	Pythia 6.9B	45.2	21.0	36.8	10.18	6.57	16.75
PrivateLoRA (Yu et al., 2022)	Open	Vicuna 7B	44.5	21.8	36.3	11.28	6.19	17.47
PrivateLoRA (Yu et al., 2022)	Open	OpenLLaMA 13B	47.3	23.3	39.1	19.46	8.05	27.51

Table 6: **Evaluation on Question Answering with PFL-DocVQA** for $\varepsilon = 8$.

Method	LLM Type	Model	Rouge-1	BLEU	Levenshtein	T($)	Q($)	All($)
DP-ICL (Wu et al., 2024)	Open	OpenLLaMA 13B	$60.7_{\pm 0.6}$	$23.9_{\pm 0.5}$	$52.5_{\pm 1.1}$	0	641.32	641.32
PromptPATEGen	Open	Vicuna 7B	31.67	26.67	35.67	2.28	0.57	2.85
PromptDPSGDGen	Open	Pythia 1B	58.2	41.2	67.5	37.26	0.96	38.22
DP-FineTune (Li et al., 2022)	Open	Pythia 1B	**70.0**	**55.4**	**78.0**	137.06	1.32	138.38
PrivateLoRA (Yu et al., 2022)	Open	Pythia 1B	63.5	42.4	72.1	44.16	1.28	45.44
PrivateLoRA (Yu et al., 2022)	Open	Pythia 6.9B	64.5	48.1	73.5	293.25	5.80	299.05
PrivateLoRA (Yu et al., 2022)	Open	OpenLLaMA 13B	64.2	23.5	72.8	358.80	9.02	367.82

Table 7: **Evaluation on information extraction with MIT-D and MIT-G** for $\varepsilon = 8$.

Method	LLM Type	Model	MIT-D	MIT-G	T($)	Q($)	All($)
DP-FewShotGen (Tang et al., 2024)	Closed	GPT3 Davinci	80.6	64.1	0.42	2.36	2.78
PromptPATEGen	Open	Vicuna 7B	74.05	41.74	0.52	0.73	1.25
PromptPATEGen	Open	OpenLLaMA 13B	70.85	33.38	3.11	0.80	3.91
PrivateLoRA (Yu et al., 2022)	Open	Pythia 410M	83.1	67.2	0.06	0.50	0.56
PromptDPSGDGen	Open	Pythia 1B	89.6	67.6	0.17	0.25	0.42
DP-FineTune (Li et al., 2022)	Open	Pythia 1B	91.8	72.8	0.94	0.50	1.44
PrivateLoRA (Yu et al., 2022)	Open	Pythia 1B	90.1	68.2	0.08	0.31	0.39
PrivateLoRA (Yu et al., 2022)	Open	Vicuna 7B	**94.9**	73.1	0.52	5.92	6.44
PrivateLoRA (Yu et al., 2022)	Open	OpenLLaMA 13B	93.5	**76.8**	1.04	6.21	7.25

adaptations for open LLMs outperform the ones for closed LLMs in most privacy regimes.

PrivateLoRA extensive classification results. Table 4 shows the top1 accuracies at different ε used to compute the PrivateLoRA graph for each of the 4 text classification tasks in Figure 2.

C.3. Performance of Private Adaptations for Text Generation

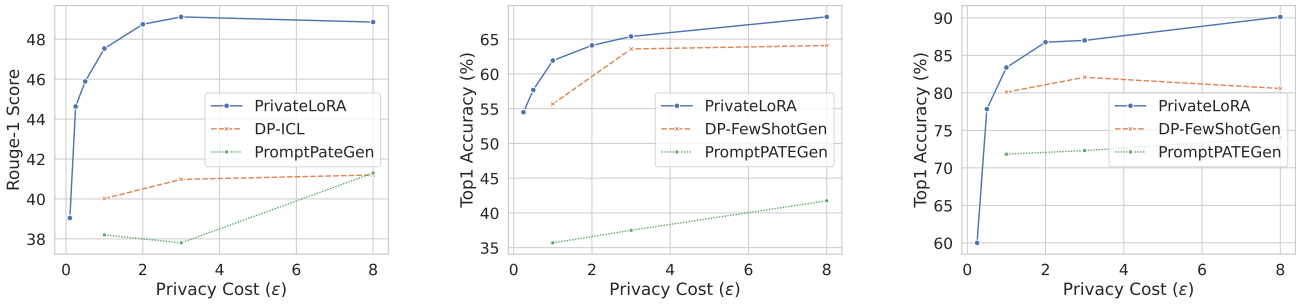
The evaluation of the three text generation tasks demonstrates superior performance of private adaptations on open vs closed LLMs. We consider the privacy-preserving ICL methods of DP-ICL and DP-FewShotGen on closed LLMs, since only these methods were executed for generative tasks. For the SAMSum datasets in Table 5, the first three adaptations (including our PromptPATEGen) are based on few-shot in-context learning (using discrete prompts), while the remaining results are for the private gradient-based adaptations. For the discrete prompts, our PromptPATEGen runs on local open Vicuna 7B and outperforms other discrete prompt-based methods from closed LLMs. Our PromptDPSGDGen performs on par with the other private tuning method (PrivateLoRA) run on Pythia 1B. Note that only PromptDPSGDGen and ICL adaptations (PromptPATEGen and DP-ICL) support multi-task inference.

We additionally leverage BART-Large (with 355M parameters) (Bar) that was fine-tuned on the XSum summarization

task (Narayan et al., 2018) (which does not include SAMSum). This specialized open model outperforms other LLMs apart from OpenLLaMA with 13B parameters, for which PrivateLoRA obtains a comparable Rouge-2 and Rouge-L scores. Crucially, PrivateLoRA on BART-Large outperforms DP-ICL run on GPT3 Davinci, despite using the model with around 500X fewer parameters. This further indicates that we can leverage a large selection of open models to solve a specific task at lower cost and with better privacy protection without resorting to general-purpose closed LLMs. We also use PrivateLoRA on larger models from different families (Vicuna 7B and OpenLLama 13B) and observe that its performance and cost steadily increase with more parameters.

The evaluation on PFL-DocVQA in Table 6 shows that PrivateLoRA on open LLMs outperforms DP-ICL (which was run also only on OpenLLaMA 13B in the original paper (Wu et al., 2024) due to the cost constraints). We also evaluate both MIT-D and MIT-G in Table 7 on the accuracy of predicted vs target labels following the metrics in DP-FewShotGen. The adaptations of open LLMs with privacy-preserving gradient-based methods outperform DP-FewShotGen on the significantly larger GPT3 Davinci, for example, on MIT-D by 14.3% and on MIT-G by 22.7% absolute, respectively by PrivateLoRA on OpenLLaMA 13B. Even for the smallest open model we trained, Pythia 410M with 414X fewer parameters, the gap is substantial (with PrivateLoRA outperforming DP-FewShotGen by 2.5% on MIT-D and by 3.1% on MIT-G). Further analyses of privacy-utility trade-offs for text generation are presented in Figure 3 in the Appendix.

Privacy-utility trade-off of text generation tasks. In the following, similar to what we did in Figure 2, we show the privacy-utility trade-off for SAMSum, MIT-G, and MIT-D in Figure 3 for varying ε between PrivateLoRA, PromptPATEGen, and DP-FewShotGen. For MIT-D and MIT-G, we trained the Pythia 1B model, and for SAMSum the BART-Large Model. It can be clearly seen, that the graphs follow the same trend that we showcased in Figure 2.



(a) SAMSum (b) MIT-G (c) MIT-D

Figure 3: **Privacy-utility trade-off for generation tasks.** We analyze the privacy costs ε in the range $[0, 8]$ for the three generation tasks. PrivateLoRA for open LLMs substantially outperforms DP-ICL and DP-FewShotGen, which both utilize GPT3 Davinci. PrivateLoRA for MIT-D and MIT-G is trained on the Pythia 1B model, and for SAMSum on the BART-Large Model. PromptPATEGen uses Vicuna 7B.

D. Additional Details on our Setup

In this section, we present the detailed (hyper-)parameters used to evaluate all the tasks that were used for the different Open and Closed LLMs privacy-preserving training methods.

D.1. Text classification

Detailed information about the datasets. We expose the different statistics of each dataset used for text classification evaluation in Table 8. For SST2, the validation set was used as the test set, as the original test set is only provided with unknown labels for each sample.

Table 8: **Stastistics of the 4 evaluated tasks** related to text classification.

Task	#Train	#Test	#Class	Task description
SST2	66,674	872	2	Sentiment analysis on movie reviews
Trec	5,452	500	6	Question type classification
Mpqa	8,603	2,000	2	Sentiment analysis on short ensembles
Disaster	4,430	1,000	2	Relevance of sentence to a disaster

Private Tuning. We detail the hyperparameters used to fine-tune the models with private LoRA in Table 9, for DP-FineTune in Table 10 and for PromptDPSGD in Table 11. All the experiments were conducted on 3 different seeds. Note that unlike LoRA or Full-Finetune, PromptDPSGD requires a precise tuning of hyperparameters. A total of 50 trials over 100 epochs were necessary to tuned them. For the Mpqa sentiment analysis task, no converging set of hyperparameters was found.

Table 9: **Hyperparameters for PrivateLoRA (Yu et al., 2022)** on evaluated classification datasets for $\varepsilon = 8$.

Hyperparameters	Datasets			
	SST2	Trec	Mpqa	Disaster
bs	128	128	128	128
lr	1e-3	1e-3	1e-3	1e-3
max grad clip	0.1	0.1	0.1	0.1
epochs	10	40	20	20
lora rank	4	4	4	4
δ	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$
GradClip	0.1	0.1	0.1	0.1

Table 10: **Hyperparameters for DP-FineTune (Li et al., 2022)** on evaluated classification tasks with Roberta-Large for $\varepsilon = 8$.

Hyperparameters	SST2	Trec	Mpqa	Disaster
LR	1e-4	1e-4	1e-4	1e-4
BS	128	128	128	128
Epoch	10	40	40	50
δ	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$
GradClip	0.1	0.1	0.1	0.1

Table 11: **Hyperparameters for PromptDPSGD (Duan et al., 2023a).** The hyperparameters for SST2 datasets are directly extracted from the paper and are evaluated on Roberta-Large for $\varepsilon = 8$. LR = learning rate, BS = batch size, GRAD = per sample gradient clipping. P-length = length of the prepended prompt in number of tokens. The trainings are all performed with prefix-tuning and not soft-prompt. Those are the hyperparameters of the best performing prompt on the test set of each dataset, and the accuracy of this prompt is reported in the table.

Hyperparameters	SST2	Trec	Mpqa	Disaster
LR	0.01	0.001	-	0.01
BS	32	32	32	32
GRAD	4	0.3	-	1.0
Epochs	22	100	100	100
P-length	1	10	10	10
Best accuracy	92.8	58.0	50.0	78.6

Private in-context learning. The respective set of hyperparameters for DP-FewShotGen, PromptPATE and DP-ICL are listed in Table 12, Table 13 and Table 14. For the used hyperparameters for DP-OPT, see (Hong et al., 2024) since the results of Table 3 are directly extracted from the paper. The accuracy results for DP-FewShotGen were computed for 5 different generated prompts following the method from the paper. For the PromptPATE method, experiments were only conducted for MPQA and Disaster datasets as we used already made evaluation from the original paper PromptPATE (Duan et al., 2023a) for SST2 and Trec datasets on using GPT3-Babbage. All hyperparameters here are extracted directly from the previous paper.

Table 12: **Hyperparameters for DP-FewShotGen (Tang et al., 2024)** for the evaluation of new datasets with $\varepsilon = 8$ on GPT3-Babbage. M = Number of private prompts used for meta prompt generation. N = number of private shots per prompt. σ = noise relative to wanted ε using the Gumbel mecanism. T_{max} = max number of tokens of the generate prompt.

Hyperparameters	SST2	Trec	Mpqa	Disaster
σ ($\varepsilon = [0.1, 1, 3, 8]$)	[1.0,0.61, 0.48,0.34]	[3.0,0.83, 0.59,0.44]	[2.0,0.77, 0.57,0.41]	[3.5,0.93, 0.64,0.46]
MN	80	80	80	80
M	20	20	20	20
T_{max}	50	50	50	50

Table 13: **Hyperparameters for PromptPATE (Duan et al., 2023a)** for the evaluation of new datasets with $\varepsilon = 8$ on GPT3-Babbage.Those parameters are common to all 4 tasks.

Hyperparameters	Claude	GPT3-babbage
train set	400	400
student set	200	300
num shots	2	1

Table 14: **Hyperparameters for DP-ICL (Wu et al., 2024)** for the evaluation of the text classification datasets with $\varepsilon = 8$ on GPT3-Babbage.

Hyperparameters	SST2	Trec	Mpqa	Disaster
num shots	4	4	4	4
Ensemble	10	10	10	10
Queries	872	500	1000	1000

D.2. Text Generation

We analyze the following generative downstream tasks: SAMSum, PFL-DocVQA, and MIT Movies trivia10k13. As we did for classification tasks, we compare the methods on closed LLMs against PrivateLoRA (Yu et al., 2022), Prompt-DPSGD (Duan et al., 2023a), and DP-FineTune (Li et al., 2022) that are run on open LLMs. For the PrivateLoRA (Yu et al., 2022) training, we use 4-bit quantization with QLoRA (Dettmers et al., 2023) to reduce the occupied GPU memory, which was implemented for the adaptations of open LLMs with more than 1B parameters on PFL-DocVQA and SAMSum datasets due to their long input sequences.

Detailed information about the datasets. We show the amount of data that we utilized in the experiments in Table 15.

Table 15: **Overview of the 4 text ge tasks** related to text generation.

Task	#Train	#Test	Task description
SAMSum	14,732	819	Dialogue summarization
PFL-DocVQA	85,000	10,000	Question and answering
MIT-G	2,953	780	Extracting genres from movie reviews
MIT-D	1,561	415	Extracting directors from movie reviews

Private Tuning. In Table 16, Table 17, and Table 18, we show the hyperparameters we used to train the open models with PrivateLoRA, PromptDPSGDGen, DP-FineTune respectively. For PrivateLoRA, we were able to use the same hyperparameters for all model for each task. In the tables, the *Max Seq Length* refers to the maximum amount of tokens of the sequence the model trains on. For *Schedulers*, we chose two different options, a constant scheduler that does not change the learning rate during training, and a linear scheduler. The linear scheduler is the default scheduler of the Hugging Face implementation of the Trainer class. It linearly decreases the learning rate over the whole training. For PromptDPSGDGen, we additionally have *Prefix Projection*. If enabled, prefix projection adds two additional linear layers to the prefix encoder. This increases the amount of trainable parameters, which in turn also increases the capability of the prefix to represent tasks.

Table 16: **Hyperparameters for PrivateLoRA (Yu et al., 2022)** on evaluated generation tasks for $\varepsilon = 8$. The hyperparameters are the same for the used models. The tested schedulers for MIT-G and MIT-D does not make a difference during training

Hyperparameters	SAMSum	PFL-DocVQA	MIT-G	MIT-D
LR	8e-4	8e-4	8e-4	8e-4
BS	256	256	256	256
LoRA Rank	8	8	8	8
Max Seq Length	650	1500	128	128
Epoch	20	15	20	20
Scheduler	Linear	Linear	/	/
δ	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$
GradClip	0.1	0.1	0.1	0.1

Table 17: **Hyperparameters for PromptDPSGDGen** on evaluated generation tasks for $\varepsilon = 8$. The hyperparameters are the same for the used models. The tested schedulers for MIT-G and MIT-D do not result in difference in performance.

Hyperparameters	SAMSum	PFL-DocVQA	MIT-G	MIT-D
LR	1e-3	1e-3	1e-3	3e-3
BS	256	256	256	256
P-Length	10	25	5	5
Prefix Projection	True	True	True	True
Max Seq Length	650	1500	128	128
Epoch	20	15	40	40
Scheduler	Linear	Linear	/	/
δ	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$
GradClip	0.1	0.1	0.1	1

Table 18: **Hyperparameters for DP-FineTune (Li et al., 2022)** on evaluated generation tasks for $\varepsilon = 8$.

Hyperparameters	SAMSum	PFL-DocVQA	MIT-G	MIT-D
LR	8e-4	2e-4	2e-4	2e-4
BS	256	256	256	256
Max Seq Length	650	1500	128	128
Epoch	20	15	20	20
Scheduler	Linear	Linear	Constant	Linear
δ	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$	$\frac{1}{\lvert D\rvert}$
GradClip	0.1	0.1	0.1	0.1

Privacy-preserving prompt tuning. In the following, we provide the used hyperparameters for the methods for Private

ICL for Closed LLMs. In detail, for DP-FewShotGen in Table 19, for DP-ICL in Table 20, and for PromptPATEGen in Table 21.

Table 19: **Hyperparameters for DP-FewShotGen (Tang et al., 2024)** on evaluated generation tasks for $\varepsilon = 8$. We used the hyperparameters given in the original paper for MIT-G and MIT-D.

Hyperparameters	SAMSum	MIT-G	MIT-D
σ	0.384	0.5	0.58
MN	80	80	80
M	20	20	20
T_{max}	50	20	20

Table 20: **Original hyperparameters for DP-ICL (Wu et al., 2024)** on evaluated generation tasks for $\varepsilon = 8$.

Hyperparameters	SAMSum	PFL-DocVQA
Model	GPT-Davinci	OpenLLaMA 13B
Ensemble	100	100
#Queries	10,000	10,000

Table 21: **Hyperparameters for PromptPATEGen** on generation tasks for $\varepsilon = 8$.

Hyperparameters	SAMSum	MIT-G	MIT-D
Model	Vicuna 7B	Vicuna 7B	Vicuna 7B
Ensemble	100	25	25
#Queries	100	100	100
#Student Prompt	10	4	4
σ	1.15	0.9	0.9

E. Costs

E.1. Cost Comparison

Based on the estimated costs in Tables 1,3,5,6, and 7, the privacy-preserving methods for open LLMs require much lower costs (and perform better) than for closed LLMs in the considered scenarios. The costs for classification tasks are relatively low, especially for closed LLMs, since the tasks are simple and the number of tokens (particularly for outputs) is small. However, the costs increase substantially for generation tasks, especially for the closed LLMs, where DP-ICL is around 150X more expensive than PrivateLoRA for dialog summarization. While larger models often incur higher costs, they do not necessarily imply higher performance. For example, smaller models like RoBERTA Large for classification or BART-Large for dialog summarization can obtain the highest performance at the lowest price.

E.2. Cost Calculation

We provide the details on measuring the cost for different methods. The assumed costs for interacting with the model APIs per 1 million tokens and GPU cost per hour are shown in Table 23. For the open LLMs, we set the median pricing per hour (based on prices from three GPU cloud providers shown in Table 23) which is \$0.69 using an A40 GPU with 48GB of memory [2], which is a popular graphics card, also used in the previous work (Duan et al., 2023a). We note that we do

[2]The pricing is for the RunPod Cloud Service: `https://www.runpod.io/gpu-instance/pricing`.

refrain from using other metrics than monetary cost. For example, FLOPS are not a direct measurement of real-world computational cost because latency, power usage, and other costs can vary significantly depending on hardware and other factors (Dehghani et al., 2021).

Costs for private-tuning-based adaptations. The private tuning-based adaptations of open LLMs require us to adjust the model parameters or the inputs for a given task, thus, we measure the running time of the training process and then query answering.

Costs for private ICL-based adaptations. DP-ICL does not incur any training cost but uses an ensemble of teachers for each query (the same as PromptPATE for labeling public examples), which elevates the cost by the number of teachers, which can be 10 or even 100. For PromptPATE, the generation of public student prompts is done using an ensemble of teacher prompts, thus labeling each public data point costs much more (proportional to the number of teachers) than running a query (with a single prompt). DP-FewShotGen also uses an ensemble of prompts, where the number of accesses to the API in the training process is equal to the number of tokens in a public prompt. The cost of training the public prompt for DP-OPT is through the iterative process of instructing the local model to improve the prompt and obtain better predictions, however, this part is done on a local open LLM, thus, the cost is relatively low. For ease of approximation and to the benefit of the ICL methods, we assume that the creation of the teacher prompts and the private aggregation of the outputs have negligible costs. After preparing the public prompt, PromptPATE, DP-FewShotGen, and DP-OPT, need a single access to the API to answer a query.

To obtain the cost for closed LLMs, we have to compute the average number of tokens per query. For the classification task, we can take the example of the DP-OPT method applied on the SST2 dataset. For this dataset, only one token is returned by the API provider, so the cost of the outputs is negligible. SST-2 inputs have an average length of 12.35 and the best performing prepended prompt from DP-OPT training has a length of 39 tokens. Thus, for the DP-OPT task, for each query to the API, 41.35 tokens are sent approximately. This gives a cost of \$0.0006 per query for GPT-3 Davinci and the total cost of \$6 for 10k queries in Table 1. The cost per query is computed similarly, depending on the size of the prepended prompt of each ICL method. Regarding the generation task, we can take the example of the SAMSum dialog summarization dataset, in which the average token length is 141 for the input and 26 for the output, hence, a single query costs \$0.000333 (for GPT3-Davinci). The cost for a 0-shot inference to Davinci would therefore be \$3.33 for 10k queries. As DP-ICL considers the 1-shot scenario and an ensemble of 100 teachers, we add the average input and label lengths to the input and multiply this by the size of the ensemble, which results in an overall cost of roughly \$666. The exact average token count for each dataset which we used for the cost estimations can be found in Table 22.

Table 22: **Average token length** of different inputs and outputs of the used datasets. The average does not include instructions.

Dataset	SST-2	Trec	Mpqa	Disaster	MIT-D	MIT-G	SAMSum	DocVQA
Input	12.35	11.43	3.88	30.79	25.276	24.314	140.857	924.191
Output	1	1	1	1	3.877	2.301	25.620	6.384

Table 23: **Pricing** for the models and cloud options (as of May 22nd 2024).

Model	Cost/1M tokens		Cost/hour
	Input	Output	
GPT-Babbage [3]	\$0.40	\$0.40	-
GPT-Davinci	\$2.00	\$2.00	-
GPT-4-turbo	\$10.00	\$30.00	-
Claude 2.1 [4]	\$8	\$24	-
A40 (RunPod) [5]	-		\$0.69
A40 (Replicate) [6]	-		\$2.07
A40 (Hyperstack) [7]	-		(starts from)\$0.50

F. Generation Metrics

In this section, we briefly discuss the different metrics we use to evaluate the generation tasks.

Rouge (Lin, 2004). The metrics in the Rouge, short for Recall-Oriented Understudy for Gisting Evaluation, set describe how many word-wise n-grams match between the predicted and target text. For Rouge-1, we look at uni-grams whereas for Rouge-2 we calculate the similarity of all 2-grams. Rouge-L refers to the similarity of the longest common subsequence between prediction and target. Important to note for Rouge-L, the grams do not need to be consecutive, but have to be in order. The scores lie between 0 and 100, where 100 is the best score.

BLEU (Papineni et al., 2002). Similar to the Rouge metric, the BLEU score, which is the abbreviation for Bilingual Evaluation Understudy, is used to evaluate the similarity of generated and reference text. To calculate the score, the precision and brevity between the two sentences have to be determined. The precision is the ratio of n-grams that match exactly between generated and reference text. Usually, n goes up to 4. Brevity, on the other hand, penalizes the score of the generated text, if it's shorter than the reference. Combining brevity and precision results in the BLEU score of the generated text. The score itself is again between 0 and 100, where higher scores are better. We use the SacreBLEU (Post, 2018) version of BLEU.

Levenshtein Distance. Lastly, to evaluate PFL-DocVQA, we also use the Levenshtein Distance. This metric is used to directly compare strings on a letter by letter basis. The Levenshtein Distance calculates the minimum amount of substitutions, insertions, and deletions between two sequences. We use the normalized version to have a score between 0 and 100 independent of sequence length. As with the other metrics, the higher the score the better.

G. Abbreviations

In Table 24, we show the abbreviations we used throughout this paper for the different private in context learning methods of LLMs.

[3]https://openai.com/api/pricing/
[4]https://www.anthropic.com/api
[5]https://www.runpod.io/gpu-instance/pricing
[6]https://replicate.com/pricing
[7]https://www.hyperstack.cloud/gpu-pricing

Table 24: **Abbreviations for ICL papers** and their proposed techniques.

Publication Abbreviation	Publication Name	Technique Abbreviation	Privacy Technique
DP-ICL	Privacy-Preserving In-Context Learning for Large Language Models (Wu et al., 2024)	DP-ICL Classification	DP-ICL for text classification
		ESA	Embedding Space Aggregation
		KSA	Keyword Space Aggregation
DP-OPT	DP-OPT: Make Large Language Model Your Privacy-Preserving Prompt Engineer (Hong et al., 2024)	DP-OPT	Differentially-Private Offsite Prompt Tuning
FewShotGen	Privacy-Preserving In-Context Learning with Differentially Private Few-Shot Generation (Tang et al., 2024)	FewShotGen	Differential Private Few-Shot Generation
PrivatePrompts (Duan et al., 2023a)	Flocks of Stochastic Parrots: Differentially Private Prompt Learning for Large Language Models (Duan et al., 2023a)	PromptDPSGD (Duan et al., 2023a)	DPSGD for Private Soft Prompt Learning
		PromptPATE (Duan et al., 2023a)	PATE for Privacy-Preserving Discrete Prompts