PrivLM-Bench: A Multi-level Privacy Evaluation Benchmark for Language Models

Haoran Li[*1], **Dadi Guo**[*2], **Donghao Li**[*1], **Wei Fan**[1], **Qi Hu**[1]
Xin Liu[3], **Chunkit Chan**[1], **Duanyi Yao**[1], **Yuan Yao**[1], **Yangqiu Song**[1]
[1]The Hong Kong University of Science and Technology
[2]Center for Data Science, AAIS, Peking University [3]Amazon.com Inc, Palo Alto, USA
{hlibt, dlibf, wfanag, qhuaf, ckchancc, dyao}@connect.ust.hk,
guodadi@stu.pku.edu.cn, xliucr@amazon.com, yuany@ust.hk, yqsong@cse.ust.hk

Abstract

The rapid development of language models (LMs) brings unprecedented accessibility and usage for both models and users. On the one hand, powerful LMs achieve state-of-the-art performance over numerous downstream NLP tasks. On the other hand, more and more attention is paid to unrestricted model accesses that may bring malicious privacy risks of data leakage. To address these issues, many recent works propose privacy-preserving language models (PPLMs) with differential privacy (DP). Unfortunately, different DP implementations make it challenging for a fair comparison among existing PPLMs. In this paper, we present PrivLM-Bench, a multi-perspective privacy evaluation benchmark to empirically and intuitively quantify the privacy leakage of LMs. Instead of only reporting DP parameters, PrivLM-Bench sheds light on the neglected inference data privacy during actual usage. PrivLM-Bench first clearly defines multi-faceted privacy objectives. Then, PrivLM-Bench constructs a unified pipeline to perform private fine-tuning. Lastly, PrivLM-Bench performs existing privacy attacks on LMs with pre-defined privacy objectives as the empirical evaluation results. The empirical attack results are used to fairly and intuitively evaluate the privacy leakage of various PPLMs. We conduct extensive experiments on three datasets of GLUE for mainstream LMs.[1]

1 Introduction

The accelerating evolution of language models (LMs) ushers a new era for both modern natural language processing and the whole society. Currently, generative large language models (LLMs) exhibit surprising capability and integrate previous tasks into a unified text generation formulation. As a result, these LLMs obtain the dominating performance on both expert-designed tasks and real-world problems (Raffel et al., 2020; Chung et al., 2022a; Brown et al., 2020; OpenAI, 2023; Ouyang et al., 2022). Moreover, under appropriate instructions, LLMs can even be in-context learners or zero-shot reasoners to solve unseen tasks (Chen et al., 2021; Zhou et al., 2023; Kojima et al., 2022; Wei et al., 2022; Sanh et al., 2022).

Beneath the improved performance, LMs' training data also scale up with models' sizes. LMs are not only trained on annotated textual data for specific tasks, but also devour a vast amount of textual data online. Unlike carefully crowd-sourced annotation data, free-form texts crawled from the Internet suffer from poor quality and unintended personal data leakage. For example, simple model interactions can lead to accidental personally identifiable information (PII) dissemination (Li et al., 2023a; Lukas et al., 2023; Huang et al., 2022; Carlini et al., 2021b). Such PII exposure without noticing victims or obtaining victims' consent may violate existing privacy laws like the EU's General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA).

To respect data subjects' privacy during model training/fine-tuning, several studies (Qu et al., 2021; Yue et al., 2022; Yu et al., 2022; Igamberdiev and Habernal, 2023) consider privacy protection as an additional objective. Differential privacy (Dwork and Roth, 2014), known for its wide adaptability and application, has become mainstream for privacy-preserving LMs (PPLMs). DP's definition offers *plausible deniability* (Bindschaedler et al., 2017) and introduces bounded privacy parameters to describe the effectiveness of examined mechanisms. This definition can naturally defend against membership inference attack (Shokri et al., 2016), which aims to determine if a given sample belongs to the model's training dataset. Currently, motivated by DPSGD (Abadi

---

[*]Equal contribution.
[1]Code is publicly available at https://github.com/HKUST-KnowComp/PrivLM-Bench.

et al., 2016), PPLMs can be achieved via various implementations based on DP optimizers.

Unfortunately, although numerous implementations of PPLMs have been proposed, fair evaluations of PPLMs are still unexplored. Existing mainstream approaches simply use DP parameters to quantify PPLMs' privacy and it is rather hard to make a fair comparison among PPLMs. Firstly, Different DP formulations such as central DP, local DP (Kasiviswanathan et al., 2011), and d_χ privacy (Chatzikokolakis et al., 2013) assign distinct heuristic meanings to DP parameters to implement PPLMs. Secondly, the scope of the protected part is ambiguous. For instance, most PPLMs implemented from DPSGD offer privacy protection for tuned sensitive data. However, during inference, these PPLMs are not guaranteed to protect inference data privacy. Thus, simply claiming that these PPLMs are privacy-preserving ignores inference data privacy. Lastly, it remains unclear whether DP's worst-case upper bound overestimates privacy leakage. DP assumes a herculean adversary who can manipulate the entire protected dataset, which may be implausible for actual attacks. Consequently, evaluation under the same DP parameters may still result in different privacy performance on empirical privacy attacks.

To bridge the aforementioned gap, in this work, we propose PrivLM-Bench to fairly quantify PPLMs' privacy-utility trade-off. PrivLM-Bench adopts the prevailing setup of public pre-training and private fine-tuning with several clarified privacy objectives. PrivLM-Bench incorporates multifaceted privacy attacks, including the data extraction attack (Carlini et al., 2021b), membership inference attack (Shokri et al., 2016) and embedding-level privacy attack (Song and Raghunathan, 2020) to evaluate the privacy of PPLMs. The attacking results can be an intuitive and fair indicator to quantify the privacy leakage of existing PPLMs regardless of their detailed implementations. In summary, we highlight the following contributions of our proposed PrivLM-Bench:

1) PrivLM-Bench identifies inference data privacy as a key component for PPLMs' privacy evaluation and points out that DP-tuning cannot quantify the inference data privacy after deploying PPLMs for real-life applications.

2) PrivLM-Bench provides a unified pipeline that allows fair comparisons among PPLMs.

3) We use PrivLM-Bench to conduct extensive experiments on mainstream PPLMs. Empirical findings indicate that current privacy attacks are significantly less potent than the anticipated attacker capabilities of defense mechanisms.

2 Related Works

2.1 Differential Privacy

To analyze differential privacy implementations on language models, we first introduce the formal definition of DP (Dwork and Roth, 2014):

Definition 1 (Differential Privacy). *A randomized algorithm mechanism M with domain D and range R satisfies (ϵ, δ)-differential privacy if for any two neighboring datasets D, D' and for any subsets of output $O \subseteq R$:*

$$Pr[M(D) \in O] \leq e^\epsilon Pr[M(D') \in O] + \delta. \quad (1)$$

The neighboring datasets D, D' only differ in one element. When we apply Definitions 1 on LMs, D refers to the private fine-tuning dataset and M usually refers to the LM updated with DP mechanism so that the LM can be safely released while preserving D's privacy. For our experiments, DP optimizers, such as DPSGD (Abadi et al., 2016), are used as the backbone to implement various PPLMs with DP guarantee.

2.2 Implementations on PPLMs

There are several optional techniques to build PPLMs. Homomorphic Encryption (HE) can ensure PPLM's data privacy via encryption during the inference stage (Chen et al., 2022). Secure Multiparty Computation (SMPC) protects the privacy of shared data and model parameters between service providers and users (Wang et al., 2022; Hao et al., 2022; Luo et al., 2023, 2024). Existing works commonly exploit various DP mechanisms to implement DP-based LMs with respect to given fine-tuning corpus and can be summarized into 3 categories: 1): DP fine-tuning with DP optimizers (Qu et al., 2021; Shi et al., 2022; Mattern et al., 2022; Yue et al., 2022; Li et al., 2022b; Yu et al., 2022) is a prevailing approach to protect the private fine-tuning datasets. 2): DP prompt tuning (Duan et al., 2023; Li et al., 2023c) adds noise to soft prompts and performs private prompt tuning (Lester et al., 2021; Li and Liang, 2021) with LMs' parameters frozen. 3): Embedding perturbation (Igamberdiev and Habernal, 2023; Feyisetan et al., 2020; Krishna et al., 2021) injects DP noise into the intermediate representations to implement PPLMs.

For privacy evaluation, most of these works simply report (ϵ, δ) pairs as the privacy budget. Still, a few works endeavor to measure or explain privacy alternatively. Auditing mechanisms (Nasr et al., 2023; Jagielski et al., 2020; Lu et al., 2022) aim to audit empirical privacy leakage. Feyisetan et al. (2020) proposed plausible deniability statistics to quantify plausible deniability given DP parameters. Li et al. (2023c) and Du et al. (2023) evaluated privacy via empirical embedding-level attacks (Song and Raghunathan, 2020). Motivated by such empirical evaluations, PrivLM-Bench further clarifies the privacy objectives and integrates more attacks for empirical privacy evaluation.

3 PrivLM-Bench

3.1 Setup of Privacy Evaluation

PrivLM-Bench's scope follows the mainstream PPLMs' approaches that pre-train LMs on public corpus and then fine-tune these publicly pre-trained LMs on private datasets D with privacy constraints. Compared with publicly available pre-training data, private fine-tuning data D are more likely to include or entail a set of sensitive attributes P. For example, $x_s =$"Alice's phone number is +1 217-123-4567" includes Alice's personal phone number and the area code "217" entails that Alice is likely to live in Illinois of the U.S. Sensitive attributes P may contain PII protected by privacy laws. Thus, protection of P should be carefully enforced.

With the pre-trained initialization and sensitive fine-tuning data D, we can implement and release a PPLM f. Then, f can be used on downstream tasks for inference without additional training/fine-tuning. Similarly, we use I to denote the inference data. PrivLM-Bench manages to quantify f's privacy regardless of its detailed implementation.

3.2 What Should be Regarded as Privacy for PPLMs?

To quantify a given LM f's privacy-preserving ability, we first clarify PrivLM-Bench's privacy objectives. PrivLM-Bench includes multi-level privacy evaluation from fine-tuning to the inference stage.

Privacy protection of fine-tuning data. To protect private fine-tuning data D, PrivLM-Bench considers two privacy objectives to address data leakage. The first objective focuses on protecting textual samples of D while the second emphasizes its sensitive attributes. Specifically, f should prevent attackers from directly decoding the data sample

$x \in D$ during the decoding stage. Additionally, f's hidden representations (e.g., logits and embeddings) should be less confident about memorizing sensitive patterns of D when the adversary queries f with input $x \in D$.

Privacy protection during inference stage. DP tuning provides a theoretical privacy bound for protecting D to safely release LMs. However, the privacy of inference data I is unprotected and unspecified by DP since the noise injected into the fine-tuning stage is irrelevant to I. Consequently, PPLMs that merely report DP parameters neglect inference data privacy during practical model usage. Additionally, from the data privacy perspective, inference data I also inherently encompasses certain private information. For instance, a healthcare facility may release its PPLM to serve patients. If patients' unprotected medical records are recovered by malicious attackers, such data leakage may violate existing privacy legislation and frustrate its users. Therefore, it is imperative to take the privacy of I into consideration for f's privacy evaluation.

3.3 Evaluation via Privacy Attacks

To measure privacy following predefined privacy objectives, we propose to evaluate PPLMs via a unified attack pipeline and use the performance of various attacks as privacy metrics. PrivLM-Bench assumes a black-box adversary who can query f with arbitrary inputs and obtain response texts as well as f's hidden representations. Moreover, the adversary has powerful knowledge about D and I and owns its auxiliary datasets A_D and A_I. A_D and A_I share similar distributions with D and I, respectively, such that the adversary can use them to train powerful neural attackers. Intuitively, better privacy protection is attained for any attack with worse attack performance. Based on privacy objectives, the adversary's attacks are classified into three folds to evaluate any given f.

Data extraction attacks. Data extraction attacks (DEAs) (Carlini et al., 2021b) assume that the adversary knows certain prefixes which refer to partial textual patterns of D or S. For a textual sample $x = [p||s] \in D$ where x is split into a length-k prefix p and a suffix s, DEAs aim to recover the corresponding suffix s via prompting f with given prefix p. p can be an empty string if the adversary has no knowledge about D. To conduct DEAs on generative LMs, we insert several pre-defined *canary* (Carlini et al., 2019) patterns with randomly generated fake sensitive information into the train-
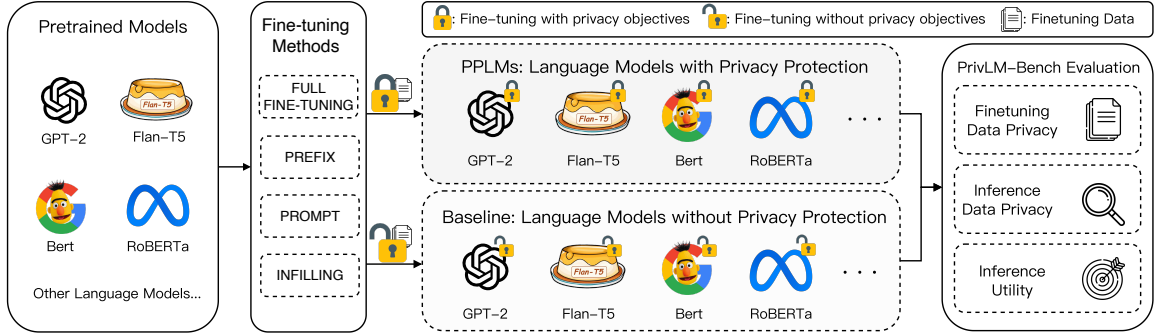
Figure 1: Overview of PrivLM-Bench.

Privacy Attacks	LM Vulnerability	Targeted Objective	Adv Cap	Metrics
Data extraction attacks (DEAs)	Text completion	Fine-tuning data privacy	f, prefixes	Exposure
Membership inference attacks (MIAs)	Predicted likelihood	Fine-tuning data privacy	$f, f(x), A_D$	AUC, TPR
Embedding inversion attacks (EIAs)	Hidden representation	Inference data privacy	$f, f(x), A_I$	micro-F1

Table 1: A summary for evaluated privacy attacks, where Adv Cap refers to the adversary capability of assessed information, AUC stands for the area under the ROC curve, and TPR denotes the true positive rate.

ing dataset. We assign different repetition times for each canary and report the exposure (Carlini et al., 2019) metric. The exposure metric uses the rank of a specific pattern over potential candidates by comparing LMs' perplexity (confidence). Memorized patterns frequently lead to higher model confidence with lower perplexity, resulting in higher exposure.

Membership inference attacks. Membership inference attacks (MIAs) (Shokri et al., 2016) assume that the adversary holds its auxiliary data A_D such that A_D's partial samples are also members of f's fine-tuning corpus D. MIAs manage to determine if a given data sample $x \in A_D$ belongs to D. We follow Likelihood Ratio Attacks (LiRA) (Carlini et al., 2021a) to conduct MIAs on victim LMs by training multiple shallow models. Area under the ROC Curve (AUC) scores and true positive rate (TPR) under certain fixed false positive rates are reported as MIA evaluation metrics.

Embedding-level privacy attacks. Understanding the privacy of vector data in vector databases (Taipalus, 2023; Wang et al., 2021; Pan et al., 2023) is crucial, and embedding-based attacks play a fundamental role in this context. These attacks (Song and Raghunathan, 2020; Pan et al., 2020; Li et al., 2022a) assume that the adversary possesses its auxiliary data A_I that shares a similar distribution with private data D and can access f's embeddings during the inference stage. Embedding-level attacks encompass attribute inference attacks (AIAs) and embedding inversion attacks (EIAs). For a data sample $x \in I$, AIAs aim to infer private attributes of x given its embedding $f(x)$ while EIAs focus on recovering x given $f(x)$. To study the inference stage privacy leakage, we

follow the recently proposed generative EIAs (Li et al., 2023b; Morris et al., 2023; Gu et al., 2023) to use powerful decoders to recover the exact sequences and report micro-level precision, recall and F1 as the evaluation metrics.

In summary, Table 1 lists the covered attacks for PrivLM-Bench's privacy evaluation. Full attack details can be found in Appendix B.

3.4 Potential Applications

Based on the formulated pipeline, the PrivLM-Bench can be used for three potential applications.

Comparison among PPLMs. PrivLM-Bench enables a fair comparison among various PPLMs of different architectures, learning objectives and pre-training data to conduct private fine-tuning. This comparison helps service providers select the most suitable PPLM for target downstream tasks.

Develop new attacks and defenses. PrivLM-Bench incorporates several existing privacy attacks into a unified pipeline. New attacks and defenses can be easily developed into PrivLM-Bench to conduct red-teaming assessments on LMs and PPLMs to evaluate their effectiveness.

PPLM implementations' verification. Most PPLMs report DP parameters for privacy evaluation. However, it remains unknown if their implementations are correct. PrivLM-Bench provides an empirical privacy evaluation to verify the correctness of these implementations.

4 Experimental Setups

4.1 Datasets

Existing PPLMs evaluate their claimed improvement over tailored downstream tasks. These spe-

cific tasks may not be feasible for other PPLMs. Instead, PrivLM-Bench evaluates PPLMs in a more fundamental aspect for natural language understanding (NLU). NLU is essential for general LMs to identify the meaning of given texts. PrivLM-Bench evaluates PPLMs on several NLU tasks from GLUE (Wang et al., 2018) that include Natural Language Inference (MNLI) (Williams et al., 2018), Stanford Sentiment Treebank v2 (SST2) (Socher et al., 2013) and QNLI converted from Stanford Question Answering Dataset (Rajpurkar et al., 2016).

4.2 Data Pre-processing

PrivLM-Bench's evaluated datasets, MNLI, SST2 and QNLI, can be naturally formulated as classification tasks with given labels. However, besides BERT-style masked LMs, PPLMs also include generative LMs such as GPT-2 that behave poorly for conventional classification pipelines. We additionally transform evaluated datasets to fit the generation pipeline. Inspired by T5's formulation (Raffel et al., 2020), given the premises and hypotheses of NLI datasets or sentences from SST2 with corresponding integer labels, we manually create textual templates with labels and concatenate prefix sentences with templates. For example, given a sample includes *premise*, *hypothesis* with label 0, the converted sample for generation becomes a single sentence [*premise* <SEP> *hypothesis* <SEP> The relation is 0] where <SEP> is the special separator token. We keep the integer label in the transformed sentence for easier text-infilling formulation. After the pre-processing, PrivLM-Bench can evaluate most existing PPLMs.

4.3 Pretrained Weights and Fine-tuning Methods

Since PrivLM-Bench unifies both classification and generation tasks, various model architectures with different pre-trained weights can be evaluated by PrivLM-Bench. Specifically, We evaluate BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), GPT-2 (Radford et al., 2019), T5 (Raffel et al., 2020) and FLAN-T5 (Chung et al., 2022b) of different scales with four tuning algorithms with and without the DP guarantee. The following content gives a brief summary of our evaluated tuning algorithms.

Full fine-tuning. Full fine-tuning refers to the commonly used methods to update the whole model. For masked LMs such as BERT and RoBERTa, we append one extra linear layer to perform classification. For generative LMs, including GPT-2 and T5, we use language modeling head with language modeling loss to conduct the next token generation.

Prompt tuning (Lester et al., 2021). For prompt tuning, we freeze the LMs and prepend certain learnable virtual tokens to every data sample. Instead of updating the whole LMs, prompt tuning only optimizes these task-specific virtual tokens.

Prefix tuning (Li and Liang, 2021). Prefix tuning shares a similar idea as prompt tuning. Unlike prompt tuning which appends a few tokens in the beginning, prefix tuning attaches a sequence of continuous task-specific vectors in front of inputs. These appended continuous vectors are concatenated into LMs' hidden states in every transformer layer as well as inputs. Only these appended vectors are updated throughout prefix tuning.

Infilling based tuning (Petroni et al., 2019). For masked LMs, instead of appending classifiers to their final output representations, infilling the masked tokens can also be exploited to perform classification tasks. We follow the pre-processing pipeline to leave blanks for predicted positions, like [*premise* <SEP> *hypothesis* <SEP> The relation is <MASK>], where <MASK> refers to the mask token. For infilling-based tuning, we follow previous works to update the whole LMs.

4.4 Other Details

Data split. Both membership inference attacks and embedding-level attacks require auxiliary datasets that share similar distributions with original datasets. For each evaluated dataset, we randomly split 40% training data as the auxiliary dataset and use the remaining 60% to conduct downstream tuning.

DP Parameters. During our experiments, we follow previous studies (Li et al., 2022c; Yu et al., 2021) to strictly bound δ = 1e-5 and ϵ = 8. Additionally, we bound the gradient norms to be no more than 0.1.

Tuning parameters. For all four tuning algorithms, we use adamW as the optimizer with a linear decay. We train all models for 5 epochs with a virtual batch size of 1,024. In terms of learning rates, for fine-tuning and infilling, the learning rate is 1e-4; for prompt and prefix tuning, the learning rate is 1e-2. We set 15 virtual tokens for optimization for both prompt and prefix tuning.

Model	Non-DP ($\epsilon = \infty$)				DP ($\epsilon = 8, \delta =$ 1e-5)			
	Fine-tuning	Prompt	Prefix	Infilling	Fine-tuning	Prompt	Prefix	Infilling
BERT$_{base}$ (110M)	82.97	66.38	79.20	82.05	65.19	47.44	43.69	61.57
BERT$_{large}$ (340M)	85.31	66.17	83.63	**84.70**	71.90	**61.67**	52.30	**63.41**
RoBERTa$_{base}$ (125M)	87.45	67.65	83.97	-	76.45	46.26	49.16	-
RoBERTa$_{large}$ (355M)	90.10	**70.49**	**89.74**	-	**83.53**	60.81	64.10	-
GPT-2$_{small}$ (137M)	39.29	37.02	34.25	-	34.96	35.81	36.85	-
GPT-2$_{medium}$ (380M)	63.37	35.01	43.86	-	41.31	33.25	35.17	-
GPT-2$_{large}$ (812M)	76.48	31.28	52.44	-	46.75	33.28	35.05	-
GPT-2$_{xl}$ (1.6B)	82.88	34.37	44.37	-	47.73	32.37	35.17	-
T5$_{base}$ (223M)	86.33	32.23	75.62	-	78.50	31.64	64.87	-
T5$_{large}$ (738M)	89.13	35.59	72.69	-	54.85	31.67	34.79	-
T5$_{xl}$ (3B)	91.10	33.18	83.32	-	OOM	38.63	66.51	-
FLAN-T5$_{xl}$ (3B)	**92.07**	34.79	87.94	-	OOM	33.45	**83.54**	-

Table 2: Utility evaluation of various LMs with and without DP tuning on the MNLI dataset. We report the accuracy (%) of the validation set as the models' utility. OOM refers to out of memory for our GPU devices.

5 Experiments

For experiments, we first raise a few crucial research questions (RQs) and use our experimental results to address these RQs individually.

- **RQ1**: Do LMs share similar utility under the same DP budget? If not, what are the factors that affect LMs' utility?
- **RQ2**: Do various tuning algorithms yield similar performance on the same model?
- **RQ3**: Are empirical privacy attacks effective on LMs with and without privacy protection?

5.1 Utility Evaluation for RQ1 and RQ2

By fixing values of (ϵ, δ) pairs during DP tuning, we can compare PPLMs' utility between masked LMs and generative LMs. In Table 2, we comprehensively list various LMs' utility of different scales on the MNLI dataset. These results suggest that LMs' utility is affected by multiple factors, including model architectures, pre-trained weights, model sizes, tuning algorithms and DP constraints.

Model architectures with pre-trained weights. By fixing a similar model size, for masked LMs, RoBERTa models outperform BERT models with around 10% improved accuracy on fine-tuning and prefix-tuning and share comparable accuracy with BERT models on prompt-tuning. In addition, under the same T5 model architecture of a similar size, FLAN-T5$_{xl}$ still significantly surpasses T5$_{xl}$ on both DP and non-DP settings. Such utility improvement is likely to come from FLAN-T5's large-scale instruction tuning. Moreover, for generative LMs, T5$_{base}$ even significantly surpasses GPT-2 models from the small size to the xl size in terms of fine-tuning and prefix tuning. These results suggest that model architectures, including their pre-trained weights, play a crucial role in downstream tasks' utility for tuning with and without DP constraints.

Model size. For the same model, after observing the accuracy of different model scales of BERT, RoBERTa, GPT-2 and T5, we can see that increased model sizes are likely to bring better utility for both DP and non-DP tuning.

DP constraints. Under the exact tuning method of the same model, we can still observe that DP tuning leads to non-negligible utility degradation from fine-tuning to infilling.

Tuning algorithms. Additionally, results from Table 2 suggest that distinct LMs have varied resilience when we switch from non-DP tuning to DP tuning. For instance, for a given LM, fine-tuning mostly yields the best results with and without DP tuning and hurts ~10% accuracy for DP tuning. However, when it comes to prompt and prefix tuning for masked LMs, severe accuracy drops can be observed. Moreover, prompt tuning and prefix tuning are unreliable even for non-DP tuning for generative LMs such as GPT-2 models. These results indicate that prefix tuning is better than prompt tuning for both DP and non-DP tuning under the same virtual token numbers. For infilling-based knowledge probing, our results suggest that even though infilling has comparable performance with fine-tuning on the non-DP setting, infilling on noisily updates may suffer poorer results than direct fine-tuning for DP tuning.

5.2 Privacy Evaluation for RQ3

In this section, we perform privacy evaluations of the mainstream LMs with and without DP tuning. In Table 3, we list masked LMs' privacy evaluation with empirical privacy attacks for both fine-tuning data privacy (MIAs) and inference data privacy (EIAs). For generative LMs, we report the mean exposure of GPT-2$_{large}$ and T5$_{large}$ in Figure 2.

MIAs. For MIAs, all DP-tuned LMs achieve

Model	DP?	Tuning	Utility	MIA			EIA		
				AUC	TPR@0.1%	TPR@1%	Pre	Rec	F1
BERT_base	Y	Finetune	77.72	50.12	0.11	0.98	44.22	18.05	25.63
		Prompt	71.74	50.06	0.25	0.94	42.44	18.20	25.47
		Prefix	68.29	49.96	0.12	1.08	44.62	18.41	26.06
	N	Finetune	90.14	50.14	0.09	1.05	41.57	17.71	24.84
		Prompt	79.34	51.40	0.15	1.36	43.80	18.53	26.05
		Prefix	87.45	51.19	0.16	1.38	44.17	18.41	25.98
BERT_large	Y	Finetune	81.14	49.80	0.12	0.97	42.29	17.65	24.91
		Prompt	71.55	50.03	0.19	1.05	40.67	17.55	24.52
		Prefix	69.05	49.77	0.12	1.00	42.68	17.92	25.24
	N	Finetune	90.93	50.02	0.09	1.01	41.38	17.30	24.40
		Prompt	76.07	49.91	0.08	0.91	41.97	17.89	25.09
		Prefix	87.94	50.58	0.14	1.25	43.08	17.39	24.77
RoBERTa_large	Y	Finetune	84.31	50.20	0.11	1.02	37.96	15.62	22.13
		Prompt	73.32	50.55	1.16	1.16	39.47	16.40	23.17
		Prefix	72.71	49.74	0.62	1.06	38.12	16.15	22.69
	N	Finetune	93.43	61.12	3.33	9.25	34.17	14.66	20.52
		Prompt	81.62	49.83	0.08	1.01	39.45	16.40	23.17
		Prefix	92.21	50.39	0.08	1.11	37.76	15.98	22.45
GPT-2_medium	Y	Finetune	53.61	53.70	0.42	1.28	52.87	20.25	29.29
		Prompt	51.84	50.02	0.09	0.82	52.85	20.53	29.57
		Prefix	48.51	49.86	0.12	1.06	55.84	21.50	31.04
	N	Finetune	58.22	59.28	0.67	2.31	56.64	21.80	31.48
		Prompt	52.63	50.02	0.18	0.76	53.96	20.77	29.99
		Prefix	51.02	49.87	0.27	1.15	51.08	20.47	29.22
GPT-2_xl	Y	Finetune	55.59	53.26	0.24	1.46	59.55	23.09	33.28
		Prompt	50.93	49.28	0.03	0.54	58.24	22.78	32.75
		Prefix	49.67	49.52	0.09	0.85	51.08	20.47	29.22
	N	Finetune	83.03	82.35	8.02	22.71	59.13	22.80	32.91
		Prompt	51.93	48.73	0.06	0.88	58.40	22.87	32.87
		Prefix	52.33	49.88	0.18	1.00	59.02	23.15	33.25

Table 3: A complete privacy evaluation of the QNLI dataset. MIA and EIA results are reported in %. TPR@0.1% and TPR@1% denote true positive rate with fixed 0.1% and 1% false positive rate, respectively.

AUC scores around 0.5, indicating that MIAs on these models are no better than random guessing. Hence, DP-tuned LMs conform to DP's definition and offer robust fine-tuning data protection against MIAs. Conversely, for fine-tuned LMs without DP, MIAs are effective on RoBERTa models with AUC exceeding 0.6, showing that fine-tuned RoBERTa models are susceptible to MIAs. In contrast, MIAs on BERT models without DP only gain marginal improvement of no more than 1.4% compared to DP-tuned BERT models across three tuning algorithms. These findings underscore a critical gap in the field of privacy attacks. The actual performance of attacks falls short of the level of threat assumed by existing defense mechanisms.

EIAs. For EIAs, since fine-tuning data privacy is not guaranteed by DP-tuning, we study the inference data privacy with and without DP tuning. After comparing EIAs' performance differences between DP and non-DP settings among all models

in Table 3, we can observe the minimal variation with no more than 2% deviation. This observation indicates that DP tuning does not significantly alter the level of inference data leakage in EIAs compared to non-DP settings. Thus, naive DP tuning on sensitive data cannot protect inference data privacy and requires additional privacy mechanisms to support the general privacy protection claim.

DEAs. For DEAs, we utilize canaries' exposure to measure generative LMs' training data privacy by increasing occurrences of certain canaries. As shown in the scatter plots of Figure 2, the results reveal that DP-tuning is effective against DEAs with reduced exposure in comparison with corresponding non-DP tuning. For DP-based tuning algorithms, even with the increased insertion numbers, DP-based prompt tuning and prefix tuning are effective against DEAs with low exposure. This underscores the effectiveness of DP-based methods in mitigating DEAs. However, when occur-
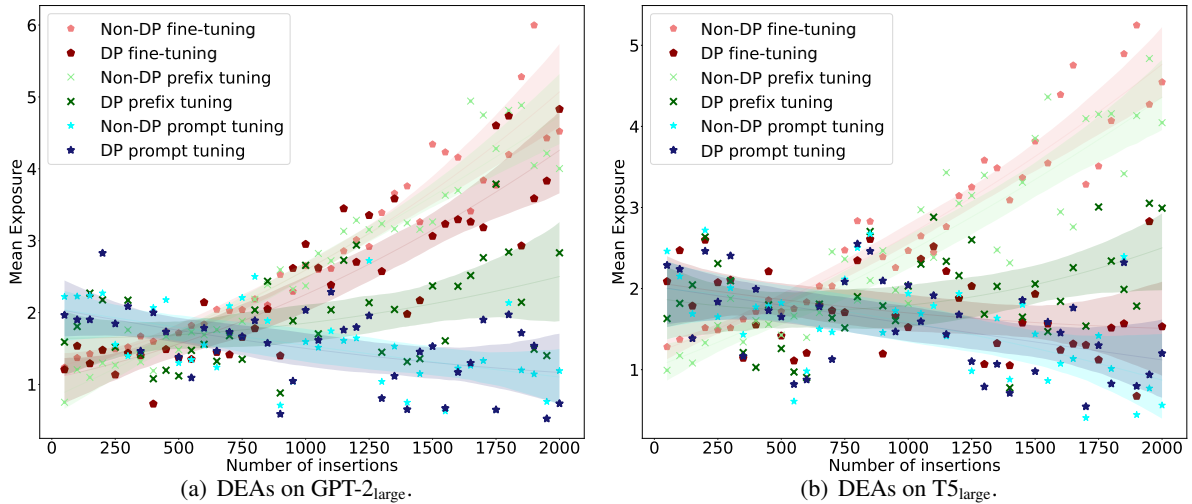
Figure 2: DEA evaluation results of generative LMs on the MNLI dataset.

rences of given canaries increase, DP fine-tuning still suffers from non-neglected increased exposure, which requires larger noise to mitigate the exposure. On the other hand, in terms of non-DP baselines, fine-tuning and prefix tuning suffer from high exposure when the insertion number increases, which conforms to previous works' findings on fine-tuning (Carlini et al., 2021b). Unexpectedly, our results show that prompt tuning can achieve relatively low exposure with and without DP. Non-DP prompt tuning yields lower exposure even than DP-based prefix tuning and fine-tuning.

Upon analyzing the results, we summarize the following findings. 1) DP-tuning is robust against existing privacy attacks targeted at fine-tuning data. Regardless of tuning methods, DP's worst-case bounding can strictly prevent the adversary from identifying sensitive fine-tuning data. 2) Naive DP-tuning falls short in safeguarding inference data privacy. Our analysis reveals that DP-based methods do not significantly outperform non-DP baselines in preventing EIAs. 3) The capability of existing privacy attacks does not align with the level of threat presumed by defense strategies. Notably, several non-DP tuning methods effectively resisted the evaluated attacks. For MIAs, we show that LiRA is unsuccessful on non-DP BERT models.

5.3 Other Empirical Findings

In this section, we list other empirical findings according to the evaluation results.

1) Large generative LMs have the potential to outperform masked LMs with DP on NLU. Our analysis, as presented in Table 2, reveals that FLAN-T5$_{xl}$ with DP-based prefix tuning, can match or even surpass the performance of masked

LMs with DP in NLU tasks.

2) Vulnerabilities to privacy attacks are model-dependent. This is evident from the clustered patterns of attack performance for the same models of different sizes, as observed in Table 3 and Figure 2. This suggests that certain architectures may inherently possess more resilience to privacy breaches.

3) Parameter-efficient tuning methods are more resistant to privacy attacks. In terms of attack results under non-DP settings, both prompt and prefix tuning exhibit greater robustness compared to full fine-tuning. This is particularly notable in their performance against MIAs and DEAs, indicating that these tuning methods inherently offer enhanced privacy safeguards.

6 Conclusion

In this paper, we introduce PrivLM-Bench, a benchmark designed to assess and contrast LMs' multifaceted privacy objectives. By integrating a variety of masked and generative LMs with diverse tuning algorithms, PrivLM-Bench facilitates an extensive evaluation that encompasses both utility metrics and empirical privacy attacks. Our results reveal the effectiveness and limitations of various DP tuning methods. Moreover, we point out the reality that empirical privacy attacks demonstrate a less potent threat compared to defense mechanisms' assumed powerful capabilities. In conclusion, our study underscores that privacy evaluation and the balancing act between privacy and utility is a complex, ongoing challenge in the field. For future work, we advocate for more potent privacy attacks and utility-enhanced defense strategies that relax the worst-case restriction in accordance with empirical attacks to improve the privacy utility trade-off.

Limitations

In our evaluation of language model privacy from an adversarial standpoint, we acknowledge certain limitations in the covered scope and effectiveness of the proposed attacks. Firstly, our study does not encompass all attack methodologies, notably excluding the recent trend of prompt injection attacks, which are significant in assessing the safety of large language models. This omission represents an area for potential future exploration to provide a more comprehensive understanding of LLM vulnerabilities. Secondly, the efficacy of our attacks in certain scenarios was limited. For instance, our LiRA-based MIAs' experiments demonstrated inadequate performance in discerning membership status in non-differentially private (non-DP) tuned BERT models.

In addition, from defenders' perspectives, though DP tuned models can well protect LMs from inferring sensitive fine-tuning data, many DP tuned LMs suffer from poor utility. Moreover, evaluated DP tuning strategies cannot defend against inference stage data privacy.

In summary, these limitations emphasize the need for ongoing development in the field of LM privacy attacks and defenses.

Ethical Considerations

We declare that all authors of this paper acknowledge the *ACM Code of Ethics* and honor the code of conduct. This work comprehensively evaluates the empirical privacy of LMs and PPLMs via existing privacy attacks. The purpose of these attacks is not to corrupt given LMs. Instead, we aim to test LMs' robustness against known attacks and show that DP can well protect the sensitive tuning data while fails to guarantee inference data privacy. Our findings reveal that LLM still needs further improvement for the better privacy-utility trade-off.

Data. During our experiment, besides downstream fine-tuning data from GLUE tasks, we also pre-define several canary patterns with randomly generated or LLM-generated PII. Since these canaries do not include any actual personal information, our inserted canaries can be safe to release and use.

Attacks. We are well aware that our evaluated privacy attacks may be used for malicious purposes. However, our experimental results that these empirical privacy attacks are rather weak in terms of privacy attacks and can be easily defended with defense mechanisms. For example, data extraction attacks can be easily addressed with content filters to avoid unsafe responses. We emphasize that these empirical privacy attacks are beneficial in enhancing defense strategies.

References

Martín Abadi, Andy Chu, Ian J. Goodfellow, H. B. McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. 2016. Deep learning with differential privacy. *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*.

Vincent Bindschaedler, Reza Shokri, and Carl Gunter. 2017. Plausible deniability for privacy-preserving data synthesis. *Proceedings of the VLDB Endowment*, 10:481–492.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, T. J. Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeff Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. *ArXiv*, abs/2005.14165.

Nicholas Carlini, Steve Chien, Milad Nasr, Shuang Song, A. Terzis, and Florian Tramèr. 2021a. Membership inference attacks from first principles. *2022 IEEE Symposium on Security and Privacy (SP)*, pages 1897–1914.

Nicholas Carlini, Chang Liu, Úlfar Erlingsson, Jernej Kos, and Dawn Song. 2019. The secret sharer: Evaluating and testing unintended memorization in neural networks. In *Proceedings of the 28th USENIX Conference on Security Symposium*, SEC'19, page 267–284, USA. USENIX Association.

Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Ulfar Erlingsson, Alina Oprea, and Colin Raffel. 2021b. Extracting training data from large language models. In *Proceedings of USENIX Security Symposium*, pages 2633–2650.

Konstantinos Chatzikokolakis, Miguel E. Andrés, Nicolás Emilio Bordenabe, and Catuscia Palamidessi. 2013. Broadening the scope of differential privacy using metrics. In *Privacy Enhancing Technologies*, pages 82–102, Berlin, Heidelberg. Springer Berlin Heidelberg.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde, Jared Kaplan, Harrison Edwards, Yura Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, David W. Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William H. Guss, Alex Nichol, Igor Babuschkin, S. Arun Balaji, Shantanu Jain, Andrew Carr, Jan Leike, Joshua Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew M. Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code. *ArXiv*, abs/2107.03374.

Tianyu Chen, Hangbo Bao, Shaohan Huang, Li Dong, Binxing Jiao, Daxin Jiang, Haoyi Zhou, and Jianxin Li. 2022. The-x: Privacy-preserving transformer inference with homomorphic encryption. *arXiv preprint arXiv:2206.00216*.

Hyung Won Chung, Le Hou, S. Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Dasha Valter, Sharan Narang, Gaurav Mishra, Adams Wei Yu, Vincent Zhao, Yanping Huang, Andrew M. Dai, Hongkun Yu, Slav Petrov, Ed Huai hsin Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022a. Scaling instruction-finetuned language models. *ArXiv*, abs/2210.11416.

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022b. Scaling instruction-finetuned language models.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Minxin Du, Xiang Yue, Sherman S. M. Chow, and Huan Sun. 2023. Sanitizing sentence embeddings (and labels) for local differential privacy. In *Proceedings of the ACM Web Conference 2023*, WWW '23, page 2349–2359, New York, NY, USA. Association for Computing Machinery.

Haonan Duan, Adam Dziedzic, Nicolas Papernot, and Franziska Boenisch. 2023. Flocks of stochastic parrots: Differentially private prompt learning for large language models. *arXiv preprint arXiv:2305.15594*.

C. Dwork and A. Roth. 2014. The algorithmic foundations of differential privacy. In *The Algorithmic Foundations of Differential Privacy*, pages 19–20.

Oluwaseyi Feyisetan, Borja Balle, Thomas Drake, and Tom Diethe. 2020. Privacy- and utility-preserving textual analysis via calibrated multivariate perturbations. In *Proceedings of the 13th International Conference on Web Search and Data Mining*, WSDM '20, page 178–186, New York, NY, USA. Association for Computing Machinery.

Kang Gu, Ehsanul Kabir, Neha Ramsurrun, Soroush Vosoughi, and Shagufta Mehnaz. 2023. Towards sentence level inference attack against pre-trained language models. *Proc. Priv. Enhancing Technol.*, 2023:62–78.

Meng Hao, Hongwei Li, Hanxiao Chen, Pengzhi Xing, Guowen Xu, and Tianwei Zhang. 2022. Iron: Private inference on transformers. *Advances in Neural Information Processing Systems*, 35:15718–15731.

Jie Huang, Hanyin Shao, and Kevin Chen-Chuan Chang. 2022. Are large pre-trained language models leaking your personal information? In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 2038–2047, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Timour Igamberdiev and Ivan Habernal. 2023. Dp-bart for privatized text rewriting under local differential privacy. In *Findings of the Association for Computational Linguistics: ACL 2023*, page (to appear), Toronto, Canada. Association for Computational Linguistics.

Matthew Jagielski, Jonathan Ullman, and Alina Oprea. 2020. Auditing differentially private machine learning: How private is private sgd? In *Proceedings of NIPS 2020*, NIPS'20, Red Hook, NY, USA. Curran Associates Inc.

Shiva Prasad Kasiviswanathan, Homin K Lee, Kobbi Nissim, Sofya Raskhodnikova, and Adam Smith. 2011. What can we learn privately? *SIAM Journal on Computing*, 40(3):793–826.

Takeshi Kojima, Shixiang (Shane) Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2022. Large language models are zero-shot reasoners. In *Advances in Neural Information Processing Systems*, volume 35, pages 22199–22213.

Satyapriya Krishna, Rahul Gupta, and Christophe Dupuy. 2021. ADePT: Auto-encoder based differentially private text transformation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 2435–2439, Online. Association for Computational Linguistics.

Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In *Proceedings of the EMNLP 2021*, pages 3045–3059, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Haoran Li, Dadi Guo, Wei Fan, Mingshi Xu, Jie Huang, Fanpu Meng, and Yangqiu Song. 2023a. Multi-step jailbreaking privacy attacks on chatgpt.

Haoran Li, Yangqiu Song, and Lixin Fan. 2022a. You don't know my favorite color: Preventing dialogue representations from revealing speakers' private personas. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5858–5870, Seattle, United States. Association for Computational Linguistics.

Haoran Li, Mingshi Xu, and Yangqiu Song. 2023b. Sentence embedding leaks more information than you expect: Generative embedding inversion attack to recover the whole sentence. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 14022–14040, Toronto, Canada. Association for Computational Linguistics.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online. Association for Computational Linguistics.

Xuechen Li, Daogao Liu, Tatsunori Hashimoto, Huseyin A Inan, Janardhan Kulkarni, YinTat Lee, and Abhradeep Guha Thakurta. 2022b. When does differentially private learning not suffer in high dimensions? In *Advances in Neural Information Processing Systems*.

Xuechen Li, Florian Tramer, Percy Liang, and Tatsunori Hashimoto. 2022c. Large language models can be strong differentially private learners. In *International Conference on Learning Representations*.

Yansong Li, Zhixing Tan, and Yang Liu. 2023c. Privacy-preserving prompt tuning for large language model services. *arXiv preprint arXiv:2305.06212*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *ArXiv*, abs/1907.11692.

Fred Lu, Joseph Munoz, Maya Fuchs, Tyler LeBlond, Elliott V. Zaresky-Williams, Edward Raff, Francis Ferraro, and Brian Testa. 2022. A general framework for auditing differentially private machine learning. In *Proceedings of NIPS 2022*.

Nils Lukas, A. Salem, Robert Sim, Shruti Tople, Lukas Wutschitz, and Santiago Zanella-B'eguelin. 2023. Analyzing leakage of personally identifiable information in language models. *ArXiv*, abs/2302.00539.

Jinglong Luo, Yehong Zhang, Jiaqi Zhang, Xin Mu, Hui Wang, Yue Yu, and Zenglin Xu. 2024. Secformer: Towards fast and accurate privacy-preserving inference for large language models.

Jinglong Luo, Yehong Zhang, Jiaqi Zhang, Shuang Qin, Hui Wang, Yue Yu, and Zenglin Xu. 2023. Practical

privacy-preserving gaussian process regression via secret sharing. In *Proceedings of the Thirty-Ninth Conference on Uncertainty in Artificial Intelligence*, UAI '23. JMLR.org.

Justus Mattern, Zhijing Jin, Benjamin Weggenmann, Bernhard Schoelkopf, and Mrinmaya Sachan. 2022. Differentially private language models for secure data sharing. In *Proceedings of EMNLP 2022*, pages 4860–4873, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

John X. Morris, Volodymyr Kuleshov, Vitaly Shmatikov, and Alexander M. Rush. 2023. Text embeddings reveal (almost) as much as text.

Milad Nasr, Jamie Hayes, Thomas Steinke, Borja Balle, Florian Tramèr, Matthew Jagielski, Nicholas Carlini, and Andreas Terzis. 2023. Tight auditing of differentially private machine learning. *arXiv preprint arXiv:2302.07956*.

OpenAI. 2023. Gpt-4 technical report. *ArXiv*, abs/2303.08774.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Gray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. In *Advances in Neural Information Processing Systems*.

James Jie Pan, Jianguo Wang, and Guoliang Li. 2023. Survey of vector database management systems. *arXiv preprint arXiv:2310.14021*.

Xudong Pan, Mi Zhang, Shouling Ji, and Min Yang. 2020. Privacy risks of general-purpose language models. In *Proceedings of 2020 IEEE Symposium on Security and Privacy (SP)*, pages 1314–1331.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. 2019. Language models as knowledge bases? In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2463–2473, Hong Kong, China. Association for Computational Linguistics.

Chen Qu, Weize Kong, Liu Yang, Mingyang Zhang, Michael Bendersky, and Marc Najork. 2021. Natural language understanding with privacy-preserving bert. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 1488–1497.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ questions for machine comprehension of text. In *Proceedings of EMNLP 2016*, pages 2383–2392. Association for Computational Linguistics.

Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. 2022. Multitask prompted training enables zero-shot task generalization. In *International Conference on Learning Representations*.

Weiyan Shi, Ryan Shea, Si Chen, Chiyuan Zhang, Ruoxi Jia, and Zhou Yu. 2022. Just fine-tune twice: Selective differential privacy for large language models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 6327–6340, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

R. Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. 2016. Membership inference attacks against machine learning models. *2017 IEEE Symposium on Security and Privacy (SP)*, pages 3–18.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of EMNLP 2013*, pages 1631–1642, Seattle, Washington, USA. Association for Computational Linguistics.

Congzheng Song and Ananth Raghunathan. 2020. Information leakage in embedding models. In *Proceedings of ACM CCS 2020*, page 377–390.

Toni Taipalus. 2023. Vector database management systems: Fundamental concepts, use-cases, and current challenges.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355.

Jianguo Wang, Xiaomeng Yi, Rentong Guo, Hai Jin, Peng Xu, Shengjun Li, Xiangyu Wang, Xiangzhou Guo, Chengming Li, Xiaohai Xu, et al. 2021. Milvus: A purpose-built vector data management system. In *Proceedings of the 2021 International Conference on Management of Data*, pages 2614–2627.

Yongqin Wang, G Edward Suh, Wenjie Xiong, Benjamin Lefaudeux, Brian Knott, Murali Annavaram, and Hsien-Hsin S Lee. 2022. Characterization of mpc-based private inference for transformer-based models. In *2022 IEEE International Symposium on Performance Analysis of Systems and Software (IS-PASS)*, pages 187–197. IEEE.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, brian ichter, Fei Xia, Ed H. Chi, Quoc V Le, and Denny Zhou. 2022. Chain of thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems*.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of NAACL 2018*, pages 1112–1122. Association for Computational Linguistics.

Da Yu, Saurabh Naik, Arturs Backurs, Sivakanth Gopi, Huseyin A Inan, Gautam Kamath, Janardhan Kulkarni, Yin Tat Lee, Andre Manoel, Lukas Wutschitz, Sergey Yekhanin, and Huishuai Zhang. 2022. Differentially private fine-tuning of language models. In *International Conference on Learning Representations*.

Da Yu, Huishuai Zhang, Wei Chen, Jian Yin 0001, and Tie-Yan Liu. 2021. Large scale private learning via low-rank reparametrization. In *Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event*, volume 139 of *Proceedings of Machine Learning Research*, pages 12208–12218. PMLR.

Xiang Yue, Huseyin A Inan, Xuechen Li, Girish Kumar, Julia McAnallen, Huan Sun, David Levitan, and Robert Sim. 2022. Synthetic text generation with differential privacy: A simple and practical recipe. In *Proceedings of ACL 2023*.

Denny Zhou, Nathanael Schärli, Le Hou, Jason Wei, Nathan Scales, Xuezhi Wang, Dale Schuurmans, Claire Cui, Olivier Bousquet, Quoc V Le, and Ed H. Chi. 2023. Least-to-most prompting enables complex reasoning in large language models. In *The Eleventh International Conference on Learning Representations*.

A Training Details

During our experiment, we use 2 NVIDIA RTX 6000 to run our codes and it takes GPU hours around 2 months to complete all experiments.

B Attack Details

In this section, we explain the attack details used for our PrivLM-Bench including data extraction attack (DEA), membership inference attack (MIA) and generative embedding inversion attack (EIA).

B.1 MIA Details

We employ Likelihood Ratio Attacks (LiRA) (Carlini et al., 2021a) to perform MIAs.

When attacking the encoder-only model, such as BERT and RoBERTa, we utilize the online version of LiRA. This version assumes that the attacker has obtained partial training data, which is used to construct shadow models. We construct a total of 128 shadow models to estimate the logit distribution for each sample in the dataset. For each shadow model, the training set and test set are randomly divided. Within the 128 shadow models, each sample is employed for both training and testing, enabling us to estimate the training logit distribution and testing logit distribution. We assume their distributions to be Gaussian and calculate the mean and variance for each sample. Specifically, for a sample x and shadow models f_i where $i = 1, 2, ..., 128$, we can obtain its training logit distribution $\mathcal{N}(\mu_{\text{in}}, \sigma_{\text{in}}^2)$ and testing logit distribution $\mathcal{N}(\mu_{\text{out}}, \sigma_{\text{out}}^2)$. Let $t(x, f_i) := \mathbf{1}\{f_i \text{ is trained on x}\}$ denote f_i is trained on x, $f_i(x)$ denote the logits of the LM. Then, we can get the mean and variance of the logit distribution of x as follows:

$$\alpha = \frac{1}{\sum_{i=1}^{128} t(x, f_i)}, \beta = \frac{1}{\sum_{i=1}^{128} \neg t(x, f_i)} \quad (2)$$

$$\mu_{in} = \alpha \sum_{i=1}^{128} t(x, f_i) f_i(x) \quad (3)$$

$$\sigma_{in}^2 = \alpha \sum_{i=1}^{128} t(x, f_i)(f_i(x) - \mu_{in})^2 \quad (4)$$

$$\mu_{out} = \beta \sum_{i=1}^{128} \neg t(x, f_i) f_i(x) \quad (5)$$

$$\sigma_{out}^2 = \beta \sum_{i=1}^{128} \neg t(x, f_i)(f_i(x) - \mu_{out})^2 \quad (6)$$

After that, we can calculate the likelihood ratio of x as follows:

$$\frac{p(x|\mu_{in}, \sigma_{in}^2)}{p(x|\mu_{out}, \sigma_{out}^2)}$$

The likelihood ratio is the ratio of the probability of x in the train logit distribution and the probability of x in the test logit distribution. A larger likelihood ratio means the sample is more likely to be in the training set.

When attacking the decoder models, for example, GPT-2, we conduct a LiRA attack and choose the pre-trained model as the shadow model. Specifically, for a sample x, we calculate its likelihood from the target model and shadow model. We use the likelihood ratio as the indicator of membership. A larger likelihood ratio indicates that the sample is more likely to be in the training set.

B.2 DEA Details

For data extraction attacks on generative LMs, we insert different types of pre-defined *canaries* (Carlini et al., 2019) into the training dataset. Here we introduce the essential notations and the attack method, as well as some details in our experiments.

We begin with the definition of *log-perplexity* which measures the likelihood of data sequences and the definition of *canary*.

Definition 2 (Log-Perplexity). *Given a model f with parameters θ, the **log-perplexity** of a sequence $x_1...x_n$ is*

$$Px_\theta(x_1...x_n) = -log_2 P(x_1...x_n|f_\theta) \quad (7)$$

$$= \sum_{i=1}^{n} (-log_2 P(x_i|f_\theta(x_1...x_{i-1})))$$

Canaries refer to formatted sequences with some spaces infilled with random words or characters chosen from a specific *randomness space* $\mathcal{R}$. In format sequences, the "slots" denoted as ◯ can be filled with random values. For the format "The random number is ◯ ◯ ◯ ◯ ◯", each ◯ might be filled with a specific random number if $\mathcal{R}$ refers to the numerical space of digits 0 to 9. We denote the randomness as r and use the notation $s[r]$ to indicate the format s with holes filled with randomness r. Definitions of the *rank* and *exposure* of a canary are introduced below.

Definition 3. *Given a model with parameters θ and the random space $\mathcal{R}$, the **rank** of a canary $s[r]$*

Type	Format for GPT-2	Format for T5	# of Candidates	Notes
Name	My name is ◯	Encoder: What is your name? Decoder: My name is ◯	80	-
City	I live in ◯. It is a beautiful city	Encoder: Where do you live? Decoder: I live in ◯. It is a beautiful city	80	-
Email	My email is ◯	Encoder: What is your email address? Decoder: My email is ◯	70	-
Phone Number	My phone number is ◯. You can call me by this number.	Encoder: What is your phone number? Decoder: My phone number is ◯. You can call me by this number.	100	The fill-in is composed of 5 random digits like "9 0 5 8 4".
Letters	The letters are ◯. It is my password.	Encoder: What is your password? Decoder: The letters are ◯. It is my password.	100	The fill-in is composed of 6 random letters from the alphabet like ' c z v s k o'.
One Word	[fixed word] [fixed word] ◯ [fixed word] [fixed word]	Encoder: Choose one random word. Decoder: The chosen word is ◯	100	The canary is composed of four fixed words and **one** random word from the vocabulary of the tokenizer.
Three Words	[fixed word] [fixed word] ◯ [fixed word] [fixed word]	Encoder: Choose three random words. Decoder: The chosen words are ◯	100	The canary is composed of four fixed words and **three** random words from the vocabulary of the tokenizer.

Table 4: Different types of canary format and the number of full-in candidates of each canary format.

is

$$rank_\theta(s[r]) = |r^{'} \in \mathcal{R} : Px_\theta(s[r^{'}]) \leq Px_\theta(s[r])| \tag{8}$$

The definition means the *rank* of a specific canary is its index in the list of all possibly-instantiated canaries, ordered by the empirical model perplexity of all those sequences.

Definition 4 (exposure). *Given a canary s[r], a model with parameters θ and the random space $\mathcal{R}$, the **exposure** of s[r] is*

$$exposure_\theta(s[r]) = log_2|\mathcal{R}| - log_2|rank_\theta(s[r])| \tag{9}$$

There are some properties of the exposure. 1) It is a real value ranging between 0 and $log_2|\mathcal{R}|$. 2) Its maximum can be achieved only by the most likely, top-ranked canary while its minimum of 0 is the least likely. 3) Note that across possibly-inserted canaries, the median exposure is 1.

In our experiment, we prepare different canary types. For example, one format of our prepared canaries is "I live in ◯. It's a beautiful city." while another format is "My email is ◯." We prepare multiple candidates for each format. For example, we use a list of city names like ["Tokyo, Japan", "London, United Kingdom", "Beijing, China",

"New York, United States", ...] and fake email addresses generated by a large language model(not used in our experiments) like ["Liam@yahoo.com", "Emma@outlook.com", " Olivia@gmail.com", ...] for the above mentioned two formats. Meanwhile, we also follow the setting of the original *secret sharer* paper (Carlini et al., 2019), which utilizes random words in the vocabulary of GPT-2 tokenizer to fill in the corresponding slots.

Note that the cardinality $|\mathcal{R}|$ of the randomness space $\mathcal{R}$ in our experiment is equal to the length of the fill-in candidate list. For each candidate list, we only insert 40% elements(with the corresponding format) of the whole list to the training set. Moreover, to explore the effect of repetition of canaries, we put them in a specific order and the first element will emerge 10 times in the training set and each of the following elements will repeat 10 more times than its last element. When calculating exposures, they are all taken into consideration along with those who are not inserted into the training set.

We use *exposure rate* and *mean exposure* as our DEAs' metrics and elaborate on them in this paragraph. Given a specific model, we consider a canary inserted in the training set as *exposed* when its log-perplexity is lower than the perplexities of any canary of the same type not inserted in the training set. Thus, an exposed canary has a higher

likelihood than all canaries not inserted. Note that whether a canary is exposed or not is estimated empirically because we can't exhaust all possible canaries that are not inserted. The proportion of exposed canary is defined as *exposure rate*. We then investigate the relationship between the frequency of repetitions and the exposure levels experienced by a specific canary type within a given model. Both *mean exposure* and *exposure rate* can be representative metrics to be reported.

We conduct experiments on four decoder-only GPT-2 models: GPT-2$_{small}$, GPT-2$_{medium}$, GPT-2$_{large}$, GPT-2$_{xl}$ as well as T5 models: T5$_{small}$, T5$_{base}$, T5$_{large}$, T5$_{xl}$ and FLAN-T5$_{xl}$ which take encoder-decoder architectures. The canary formats are designed differently to adapt to GPT-2 and T5 model architectures. Accordingly, when calculating exposure rate and mean exposure, we calculate the likelihood of the canaries for GPT-2 and the conditional likelihood for T5. Table 4 shows the details of the canary format in our experiment.

B.3 EIA Details

For the embedding inversion attack, we follow the implementation of GEIAs (Li et al., 2023b) to train a GPT-2 attacker Φ for each victim LM f based on the auxiliary data A_I.

Attacker training. To train the attacker decoder model, we follow its language modeling objective via manipulating inputs in the representation level. For a given sentence $x =$"$w_0w_1...w_{u-1}$" of length u, we use $f(x)$ to denote the embedding of x of victim LM f. First, we apply one trainable fully connected layer to align $f(x)$ to be the same dimension as the attacker model's token representation. We use $Align(f(x))$ to denote the aligned sentence embedding and $\Phi_{emb}(w_i)$ to denote the representation of token w_i of the attacker model. Second, We concatenate $Align(f(x))$ to the left side of all tokens' representation to obtain the attacker's input:
$$[Align(f(x)), \Phi_{emb}(w_0), \Phi_{emb}(w_1), ..., \Phi_{emb}(w_{u-1})].$$
Lastly, we can feed the input before the attacker's first transformer block and apply language modeling objective with the target sequence $[w_0, w_1, ..., w_{u-1},$<eos>$]$ by minimizing the cross-entropy loss at each time step. Here, the <eos> is the special end of sentence token.

Evaluation. For inference, the attacker Φ decodes the first token from $Align(f(x))$. Then tokens are generated iteratively from previous contexts with the sentence embedding till <eos> is reached. The token-level micro precision/recall/F1 are reported as EIA's evaluation metrics.

C Full Evaluation Results

In this section, we list our detailed evaluation results of the three attack methods in Table 5 and 6. The comprehensive evaluation results help further support our empirical findings mentioned in the experimental sessions. We report *exposure rate* for DEA. For MIA, *AUC*, *TPR@0.1%*, and *TPR@1%* are reported. For EIA, micro-level *Precision*, *Recall* and *F1-score* are reported. In cases where an attack method is inapplicable to a specific model, we denote this with a "-" in the table entry.

For full evaluation results on DEAs, as shown in Figure 5, we draw a scatter plot to display the variation of mean exposure with different canary repetitions for four different GPT-2 models and two T5 models on the MNLI dataset. We use different markers and colors to represent different tuning methods and whether DP is applied. We fit a polynomial of order 2 to data points of any specific tuning method and DP implementation. Then, we plot a 95% confidence interval of those data points. We have the following observations:

1) In the case of fine-tuning, an increase in the number of canary insertions results in a noticeable elevation in mean exposure. However, this trend becomes less discernible when applying differential privacy to T5 models, which indicates that T5 models are better protected under DP. Mean exposures without DP generally surpass those with DP. Intriguingly, for GPT-2 models, an increase in model size leads to a gradual narrowing of the confidence interval gap between models with and without DP.

2) For prefix tuning, the mean exposure increases when the number of canary insertions increases, and exposures are larger when DP is not employed.

3) For prompt tuning, as the number of canary insertions increases, we find that mean exposure is not increasing as it does in fine-tuning and prefix tuning settings. The confidence intervals for both scenarios, with and without DP, largely overlap.

C.1 Evaluation with Varied DP Budgets

In this section, we investigated the variation of mean exposure under multiple privacy budget ϵ on GPT-2$_{medium}$ and T5$_{base}$, as shown in Figure 3. We set ϵ to be 4, 8, 20, 100 for GPT-2$_{medium}$ and T5$_{base}$. The results on different ϵ can be supplementary of

Model	DP?	Tuning Algo	Utility	DEA ER	MIA AUC	MIA TPR@0.1%	MIA TPR@1%	EIA Pre	EIA Rec	EIA F1
GPT-2$_{small}$	Y	Finetune	34.96	13.89	51.09	0.12	1.03	48.95	27.53	35.24
		Prompt	35.81	5.95	50.55	0.12	1.37	47.43	28.08	3527
		Prefix	36.85	9.13	50.70	0.03	0.73	50.08	28.72	36.50
	N	Finetune	39.29	51.20	52.33	0.09	1.25	47.60	27.97	35.24
		Prompt	37.02	6.35	50.43	0.30	1.25	45.64	27.56	34.37
		Prefix	34.25	9.92	50.39	0.09	0.79	50.62	29.49	37.27
GPT-2$_{medium}$	Y	Finetune	41.31	15.08	51.33	0.06	1.00	54.84	28.22	37.27
		Prompt	33.25	4.37	51.10	0.15	1.46	46.60	27.60	34.67
		Prefix	35.17	8.73	50.22	0.18	0.85	54.93	29.97	38.78
	N	Finetune	63.37	91.27	54.49	0.21	1.37	56.63	27.52	37.04
		Prompt	35.01	5.95	51.12	0.15	1.34	46.97	27.56	34.74
		Prefix	43.86	35.32	50.77	0.21	1.31	53.74	30.34	38.78
GPT-2$_{large}$	Y	Finetune	46.75	29.76	52.42	0.06	1.31	61.62	31.02	41.27
		Prompt	33.28	5.95	51.00	0.18	0.91	58.66	32.35	41.71
		Prefix	35.05	12.30	50.32	0.21	0.70	61.95	32.21	42.38
	N	Finetune	76.48	98.41	61.04	0.33	2.96	61.05	31.04	41.15
		Prompt	31.28	6.35	50.56	0.15	0.73	57.43	31.80	40.93
		Prefix	52.44	68.25	50.30	0.24	0.67	60.44	32.69	42.43
GPT-2$_{xl}$	Y	Finetune	47.73	48.81	51.67	0.03	0.73	62.18	31.59	41.90
		Prompt	32.37	7.94	51.17	0.27	1.67	59.05	31.71	41.26
		Prefix	35.17	6.35	50.21	0.06	0.51	61.76	32.77	42.82
	N	Finetune	82.88	100.00	72.87	1.28	9.92	61.75	30.89	41.18
		Prompt	34.37	5.95	50.91	0.42	1.28	58.42	31.36	40.81
		Prefix	44.37	66.27	50.62	0.12	1.00	60.81	32.99	42.78

Table 5: Evaluation results on the MNLI dataset. DEA, MIA and EIA results are reported in %. The abbreviation "ER" represents "Exposure Rate".

the prior results shown in Figure 5.

For GPT-2$_{medium}$, the mean exposure increases when the number of canary insertions increases for all ϵ. However, for T5$_{base}$, the distribution of mean exposure is more dispersed. When the number of canary insertions increases, the increment of mean exposure is not apparent and their confidence intervals largely overlap. In addition, the mean exposure of the T5$_{base}$ lies in the range of 1.5 to 2.5, which is less than the mean exposure of the GPT-2$_{medium}$ that can reach up to 5. The above observations suggest that T5 is more robust than GPT-2 under different privacy budget ϵ.

C.2 DEA Evaluation with Exposure Rate

Besides reporting mean exposure, we plot the exposure rate of various GPT-2 and T5 models in Figure 4. We summarize the following observations:

1) For the fine-tuning setting, the exposure rate gradually increases with the growth of the model size without DP. In particular, the exposure rates of T5$_{large}$ and $_{xl}$ approach 1 in our experiment, which indicate that almost all canaries inserted are exposed. We can observe a noticeable decrease in the exposure rate when using DP, which means that DP can be a good protection to avoid sensitive canaries being exposed.

2) For prefix tuning, as the model size increases, the exposure rate initially rises and then declines for GPT-2 and T5, which suggests that a larger model size does not necessarily increase the risk of the canary being exposed when employing prefix tuning.

3) For prompt tuning, whether using DP or not, the exposure rate remains consistently low.

Model	DP?	Tuning Algo	Utility	DEA ER	MIA AUC	MIA TPR@0.1%	MIA TPR@1%	EIA Pre	EIA Rec	EIA F1
BERT$_{base}$	Y	Finetune	77.72	-	50.12	0.11	0.98	44.22	18.05	25.63
		Prompt	71.74	-	50.06	0.25	0.94	42.44	18.20	25.47
		Prefix	68.29	-	49.96	0.12	1.08	44.62	18.41	26.06
		Infilling	56.58	-	-	-	-	42.23	18.12	25.36
	N	Finetune	90.14	-	50.14	0.09	1.05	41.57	17.71	24.84
		Prompt	79.34	-	51.40	0.15	1.36	43.80	18.53	26.05
		Prefix	87.45	-	51.19	0.16	1.38	44.17	18.41	25.98
		Infilling	85.17	-	-	-	-	41.38	17.81	24.90
BERT$_{large}$	Y	Finetune	81.14	-	49.80	0.12	0.97	42.29	17.65	24.91
		Prompt	71.55	-	50.03	0.19	1.05	40.67	17.55	24.52
		Prefix	69.05	-	49.77	0.12	1.00	42.68	17.92	25.24
		Infilling	71.47	-	-	-	-	40.73	17.30	24.28
	N	Finetune	90.93	-	50.02	0.09	1.01	41.38	17.30	24.40
		Prompt	76.07	-	49.91	0.08	0.91	41.97	17.89	25.09
		Prefix	87.94	-	50.58	0.14	1.25	43.08	17.39	24.77
		Infilling	88.89	-	-	-	-	40.06	17.08	23.94
RoBERTa$_{base}$	Y	Finetune	79.67	-	50.28	0.07	0.92	34.57	14.35	20.28
		Prompt	57.82	-	49.83	0.17	0.90	38.87	16.07	22.74
		Prefix	72.74	-	50.03	1.01	1.01	38.72	16.25	22.89
	N	Finetune	91.73	-	64.90	3.34	10.39	37.77	15.81	22.29
		Prompt	80.80	-	50.14	0.09	0.98	41.14	17.61	24.67
		Prefix	89.68	-	50.62	0.15	1.20	39.88	17.08	23.91
RoBERTa$_{large}$	Y	Finetune	84.31	-	50.20	0.11	1.02	37.96	15.62	22.13
		Prompt	73.32	-	50.55	0.15	1.16	39.47	16.40	23.17
		Prefix	72.71	-	49.74	0.62	1.06	38.12	16.15	22.69
	N	Finetune	93.43	-	61.12	3.33	9.25	34.17	14.66	20.52
		Prompt	81.62	-	49.83	0.08	1.01	39.45	16.40	23.17
		Prefix	92.21	-	50.39	0.08	1.11	37.76	15.98	22.45
GPT-2$_{small}$	Y	Finetune	50.04	11.51	52.86	0.21	1.43	50.04	19.62	28.19
		Prompt	49.77	6.75	50.15	0.15	0.82	48.02	20.56	28.79
		Prefix	53.46	6.35	49.12	0.18	0.97	51.22	20.49	29.27
	N	Finetune	52.24	38.10	55.22	0.15	2.22	53.26	20.65	29.76
		Prompt	49.77	2.78	50.96	0.09	0.81	49.22	20.28	28.72
		Prefix	49.58	8.33	49.45	0.12	0.94	50.32	20.28	28.91
GPT-2$_{medium}$	Y	Finetune	53.61	17.46	53.70	0.42	1.28	52.87	20.25	29.29
		Prompt	51.84	5.16	50.02	0.09	0.82	52.85	20.53	29.57
		Prefix	48.51	7.54	49.86	0.12	1.06	55.84	21.50	31.04
	N	Finetune	58.22	78.17	59.28	0.67	2.31	56.64	21.80	31.48
		Prompt	52.63	4.76	50.02	0.18	0.76	53.96	20.77	29.99
		Prefix	51.02	10.31	49.87	0.27	1.15	51.08	20.47	29.22
GPT-2$_{large}$	Y	Finetune	55.32	31.75	52.24	0.03	1.03	58.33	22.76	32.75
		Prompt	47.29	7.94	48.64	0.18	0.97	57.96	22.58	32.50
		Prefix	50.71	9.52	48.93	0.09	0.82	58.69	22.93	32.98
	N	Finetune	67.43	97.62	67.45	0.91	4.88	59.40	22.84	32.99
		Prompt	50.19	5.95	49.69	0.09	0.82	57.65	22.62	32.49
		Prefix	51.44	38.10	49.72	0.07	0.92	60.17	23.11	33.40
GPT-2$_{xl}$	Y	Finetune	55.59	42.46	53.26	0.24	1.46	59.55	23.09	33.28
		Prompt	50.93	7.14	49.28	0.03	0.54	58.24	22.78	32.75
		Prefix	49.67	6.75	49.52	0.09	0.85	51.08	20.47	29.22
	N	Finetune	83.03	99.60	82.35	8.02	22.71	59.13	22.80	32.91
		Prompt	51.93	5.95	48.73	0.06	0.88	58.40	22.87	32.87
		Prefix	52.33	33.73	49.88	0.18	1.00	59.02	23.15	33.25

Table 6: Full evaluation results on the QNLI dataset. DEA, MIA and EIA results are reported in %. The abbreviation "ER" represents "Exposure Rate".
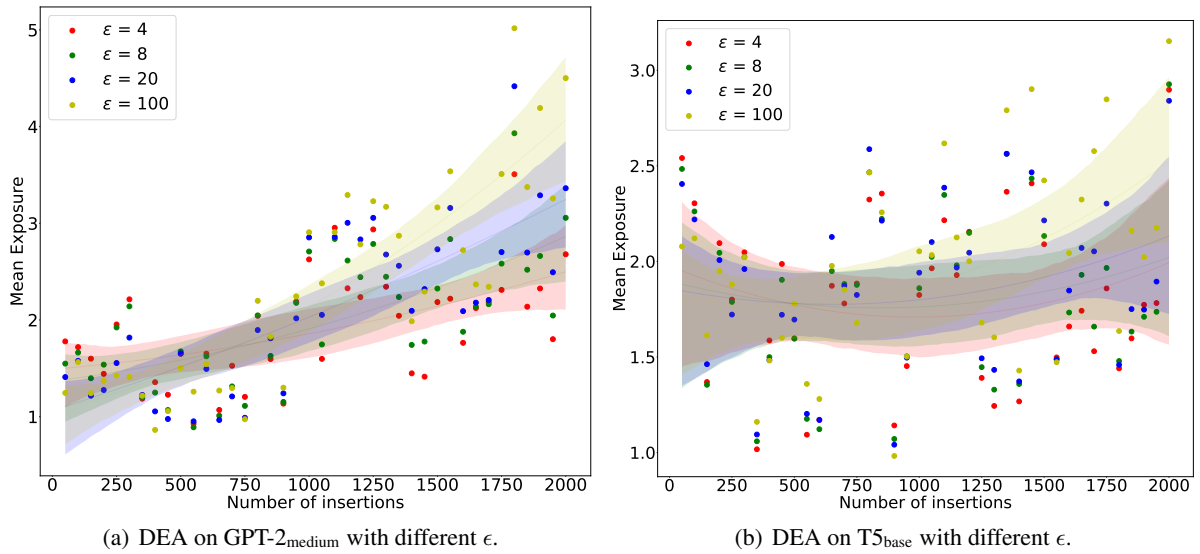
(a) DEA on GPT-2$_{\text{medium}}$ with different ϵ.

(b) DEA on T5$_{\text{base}}$ with different ϵ.

Figure 3: DEA's *mean exposure* evaluation results of GPT-2$_{\text{medium}}$ and T5$_{\text{base}}$ with varied ϵ on the MNLI dataset.

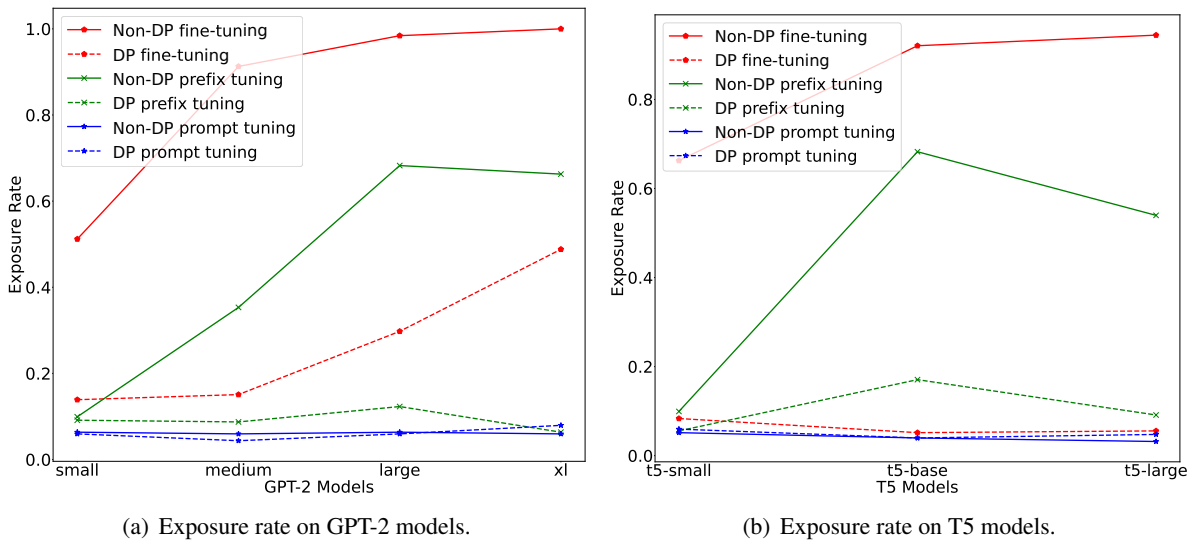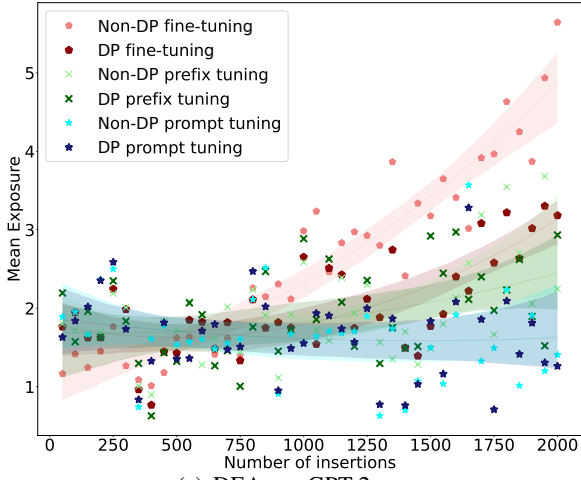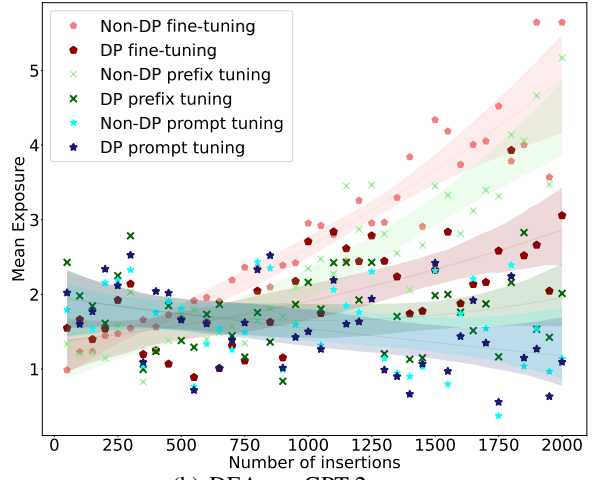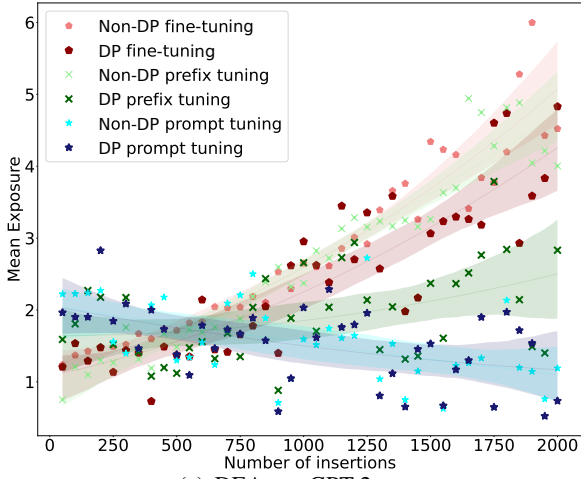(a) Exposure rate on GPT-2 models.

(b) Exposure rate on T5 models.

Figure 4: DEA's *exposure rate* evaluation results of GPT-2 and T5 models on the MNLI dataset.
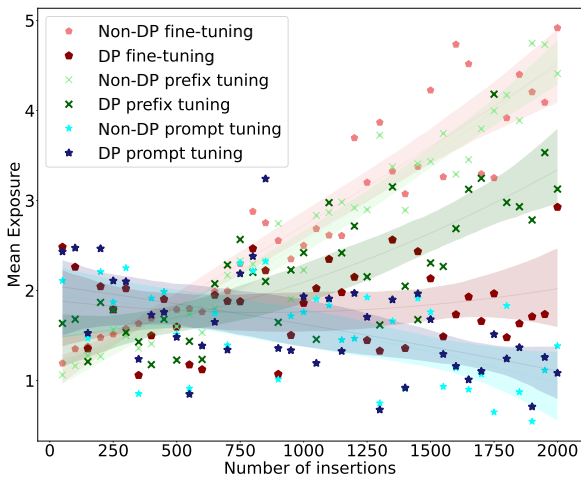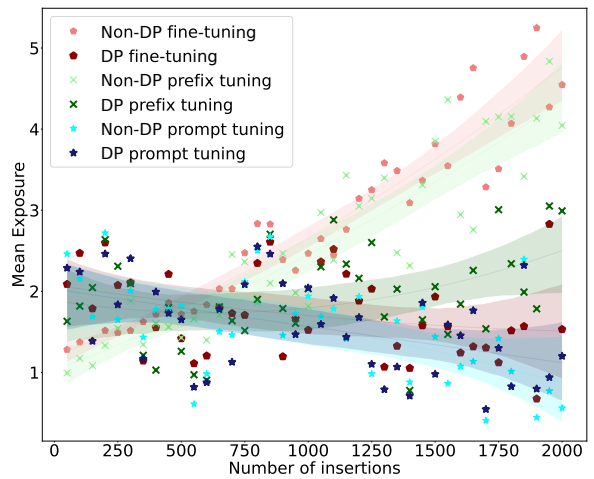
(a) DEAs on GPT-2$_{\text{small}}$.

(b) DEAs on GPT-2$_{\text{medium}}$.

(c) DEAs on GPT-2$_{\text{large}}$.
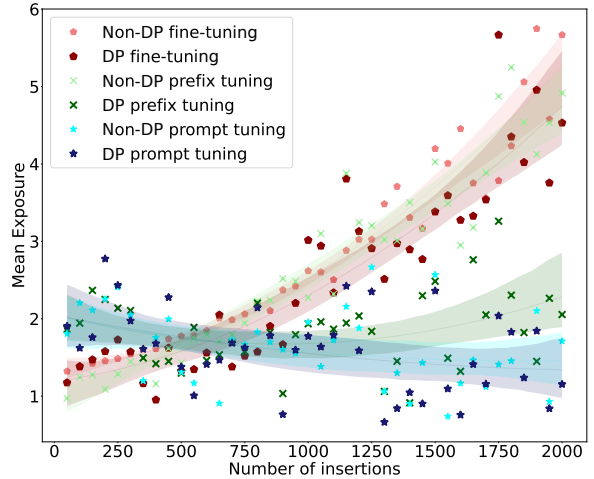
(d) DEAs on GPT-2$_{\text{xl}}$.

(e) DEAs on T5$_{\text{base}}$.

(f) DEAs on T5$_{\text{large}}$.

Figure 5: DEA *mean exposure* evaluation results of GPT-2 and T5 models on the MNLI dataset. Note that we obtained the x-axis "number of insertions" by multiplying the frequency of canary insertions into the dataset by the total number of training epochs.