Selective Pre-training for Private Fine-tuning

Anonymous authors
Paper under double-blind review

Abstract

Text prediction models, when used in applications like email clients or word processors, must protect user data privacy and adhere to model size constraints. These constraints are crucial to meet memory and inference time requirements, as well as to reduce inference costs. Building small, fast, and private domain-specific language models is a thriving area of research. In this work, we show that a careful pre-training on a *subset* of the public dataset that is guided by the private dataset is crucial to train small language models with differential privacy. On standard benchmarks, small models trained with our new framework achieve state-of-the-art performance. In addition to performance improvements, our results demonstrate that smaller models, through careful pre-training and private fine-tuning, can match the performance of much larger models that do not have access to private data. This underscores the potential of private learning for model compression and enhanced efficiency.

1 Introduction

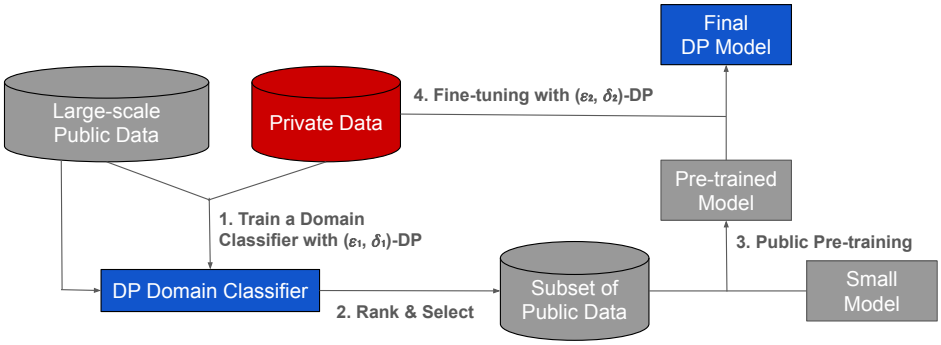


Figure 1: [Revised] The proposed framework for training a small and domain-specific model with differential privacy (DP). More details on the process of training the domain classifier and the selection of public data can be found in Figure 3. We use the method in Abadi et al. (2016) for training models with DP.

Many papers have shown that deep learning models are vulnerable to attacks aimed at extracting information from the training data (Shokri et al., 2017; Hayes et al., 2019; Carlini et al., 2021; Zhang et al., 2021; Choquette-Choo et al., 2021; Carlini et al., 2023; Matsumoto et al., 2023). A provable path for mitigating such privacy attacks is to train the models with differential privacy (DP) Dwork et al. (2006), a mathematically rigorous notion for quantifying the privacy leakage of a machine learning model. Over the past few years, there has been a rapid progress in our understanding of deep learning with DP, both in terms of computational efficiency (He et al., 2023; Bu et al., 2021; Lee & Kifer, 2021; Subramani et al., 2021; Anil et al., 2022) and privacy-utility trade-off (De et al., 2022; Zhou et al., 2021; Zhu et al., 2020; Golatkar et al., 2022; Sander et al., 2022; Bu et al., 2022a; Panda et al., 2022; Luo et al., 2021; Kairouz et al., 2021; Kurakin et al., 2023). One of the most important findings is that pre-training is crucial for maximizing performance (Li et al., 2022b; Ganesh et al., 2023).

Most of the DP literature mentioned above focus on settings where *inference time* is not a bottleneck and one can deploy models of *any size*. In such a case, existing evidence is that larger models pre-trained on vast amounts of public data perform better when combined with private fine-tuning (Li et al., 2022c; Yu et al.,

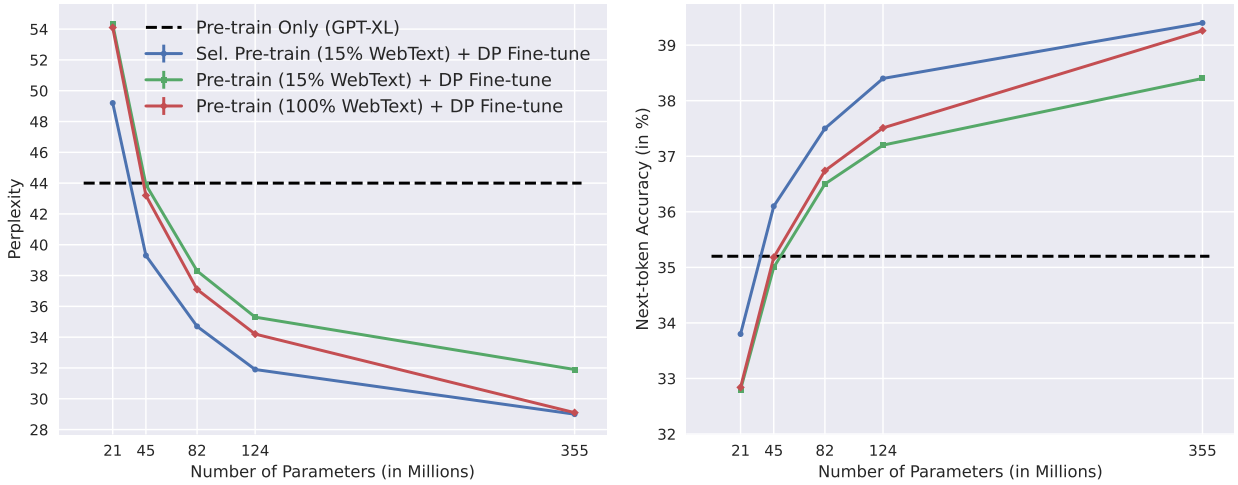


Figure 2: A representative result from our findings. We plot perplexity and top-1 next word accuracy of GPT models on the test set of the Enron email dataset (Cohen, 2015). Overall privacy budget is $(\varepsilon = 7.3, \delta = 1 \times 10^{-7})$. The dashed line shows the zero-shot performance of GPT2-XL with 1.5 billion parameters. The figure shows that our framework yields clear improvements in both perplexity and next-token prediction accuracy, which can significantly improve the overall model behavior.

2022; Mehta et al., 2022). However, there are plenty of applications where the size of the model is restricted by the inference time, e.g., a language model of an email client or a face identification model running in a security system. In such applications, if the inference time is not good then the quality of predictions becomes irrelevant. Further, note also that in both these applications the training data is quite sensitive, and the models should protect the privacy of users. Building small, fast, and private domain specific language models is also a thriving area in industry with several start-ups (MosiacML; ScaleAI). There is also economic motivation as smaller models offer cheaper inference costs.

[Revised] In this work, we introduce *selective pre-training* as a means to improve DP fine-tuning for small language models. Figure 1 presents an overview of the proposed framework. Specifically, our approach selects a tailored subset of public data, guided by the private data, for model pre-training. This selection process begins with the training of a DP domain classifier, using the private data as positive training samples. The domain classifier is subsequently utilized to rank all public samples, retaining only the top-ranked samples. We conduct extensive experiments to demonstrate the superiority of selective pre-training over standard pre-training. The representative results are presented in Figure 2.

[Revised] Our main motivation stems from the observation that for a fixed size model, there is an optimal size of pre-training data after which enlarging the pre-training dataset does not further improve downstream performance. This phenomenon is observed in our Figures 2 and 6 and aligns with the previously established scaling laws for pre-training language models (Kaplan et al., 2020; Hoffmann et al., 2022). For example, the results in Figure 2 suggest that for a transformer model with only 21 million parameters, pre-training on a random 15% of OpenWebText (Gokaslan & Cohen, 2019) is no different than pre-training on the full OpenWebText. Therefore, in such a case, selecting a subset of public data that better aligns with the domain of private data is an effective way to fully utilize the constrained capacity of small models.

[Revised] Our contributions are summarized as follows.

1. We propose selective pre-training as a novel approach for training small, domain-specific language models with DP. We design and implement the first simple and effective DP algorithm for selecting a subset of public data that better aligns with the domain of the private data.

2. We empirically validate the proposed framework using the Enron email dataset (Cohen, 2015) and the GLUE benchmark (Wang et al., 2018). The results from the Enron email dataset (Section 4.1)

demonstrate the effectiveness of our framework in real-world scenarios, while the results from the GLUE benchmark (Section 4.2) show its superiority compared to existing baselines.

3. In addition to state-of-the-art DP small models, our experimental results indicate that fine-tuning with DP benefits more significantly from selective pre-training than non-private fine-tuning, as presented in Figures 5 and 7. This underscores the distinctive value of selective pre-training within the DP community.

Real-world Impact Our framework was recently used in training an industry grade differentially private text prediction language model that now serves many NLP applications. As text prediction models (on email clients/servers, word processors, etc.) serve billions of queries per hour, the inference cost savings due to the decrease in model size are significant. Further, due to better inference time, online performance metrics, such as the number of predictions accepted by the users, also improve.

1.1 Preliminaries

We begin with the formal definition of differential privacy.

Definition 1 ((ϵ, δ)-Differential Privacy (DP) (Dwork et al., 2006)). *A randomized algorithm $\mathcal{A}$ is (ϵ,δ)-differentially private if for any two neighboring datasets D and D', which differ in exactly one datapoint, and for every subset $\mathcal{S}$ of possible outputs:* $\Pr[\mathcal{A}(D) \in \mathcal{S}] \leq e^{\epsilon} \Pr[\mathcal{A}(D') \in \mathcal{S}] + \delta$.

Private Deep Learning: In the context of deep learning, DP guarantees that the trained model *weights* are private with respect to a training dataset, and hence can be released publicly. To train a deep learning model with privacy, the most popular method is to first release the gradients of an optimizer with differential privacy and then update the model with privatized gradients (Song et al., 2013; Bassily et al., 2014; Abadi et al., 2016). We follow the approach in Abadi et al. (2016) to make gradients differentially private. Abadi et al. (2016) augment each minibatch of gradients with per-example gradient clipping and Gaussian noise addition steps. The clipping step ensures that no one user's sample significantly changes the weights of the model and the noise added guarantees that the contribution of a single example is masked.

2 Problem Statement and Our Algorithmic Framework

Input to our problem is a private dataset D_{priv} corresponding to a downstream task T, a model M of size p, privacy parameters $\epsilon > 0$, $\delta > 0$, and a public dataset D_{pub}. Our goal is to train M on public and private datasets with the aim of maximizing the downstream performance on the task T. The entire process should be (ϵ, δ)-differentially private with respect to D_{priv}. The constraint on model size is important to compare various algorithms in our setting. In applications, the constraints on model size arise naturally as a consequence of memory and/or inference time requirements.

Our framework for solving the problem consists of the following 3 steps.

1. ***Privacy Preserving Data Selection***: Given D_{priv}, invoke a privacy preserving data selection algorithm $\mathcal{A}_{\text{select}}$ to find a $D'_{\text{pub}} \subseteq D_{\text{pub}}$. The privacy budget for this step is (ϵ_1, δ_1).

2. ***Non-Private Pre-training***: Pre-train the model M on D'_{pub} with a standard pre-training algorithm. This step does not consume any privacy budget.

3. ***Private Fine-tuning***: Fine-tune M on D_{priv} with a differentially private algorithm $\mathcal{A}_{\text{finetune}}$. The privacy budget for this step is (ϵ_2, δ_2).

The non-private pre-training step can be viewed as a post-processing function to $\mathcal{A}_{\text{select}}$ and thus no privacy budget is consumed. The advanced composition theorem of DP (see (Steinke, 2022) for example) guarantees that our framework is (ϵ, δ)-DP. In our experiments, we use the Privacy Random Variable (PRV) Accountant (Gopi et al., 2021; Ghazi et al., 2022; Koskela et al., 2020). The PRV accountant gives tighter bounds on privacy parameters ε and δ than the moments accountant in Abadi et al. (2016). The rest of the paper is devoted to describing the first step of our framework, followed by experiments to verify the effectiveness of our methods on different datasets.

3 Privacy Preserving Data Selection

We describe our approach to implementing a privacy-preserving data selection algorithm. We provide a specific implementation of our framework and demonstrate its effectiveness, however, our approach is general and can be combined with other private data selection algorithms.

3.1 Our Implementation of Data Selection

Our framework is loosely inspired by the data cleaning framework used in GPT3 and PaLM models Brown et al. (2020); Chowdhery et al. (2022), although motivations are a bit different. The classifiers in Brown et al. (2020); Chowdhery et al. (2022) are trained to filter out noisy documents from datasets. In fact, the source datasets in our paper, i.e., OpenWebText and Wikipedia, are considered positive examples in Brown et al. (2020). Our classifier is trained to recognize examples that are similar to samples in the target data. We initialize the classifier with a pre-trained LM and fine-tune it with differential privacy to predict whether a sentence is sampled from the distribution of the target data. We use the classifier to predict all sentences in the source data and rank them according to confidence scores. Although deep neural networks could be overconfident and need calibration in some applications (Guo et al., 2017; Zhang et al., 2022), not calibrating the outputs does not affect our algorithm because calibration does not change the relative ranking among sentences. We select the top sentences until we reach the target number of pre-training tokens [1]. Figure 3 shows an overview of our implementation.

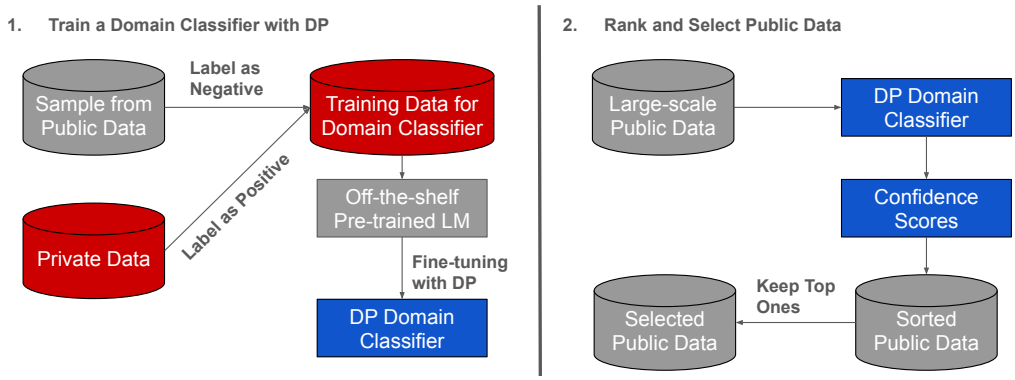


Figure 3: [Revised] The process of training the domain classifier and the selection of large-scale public data.

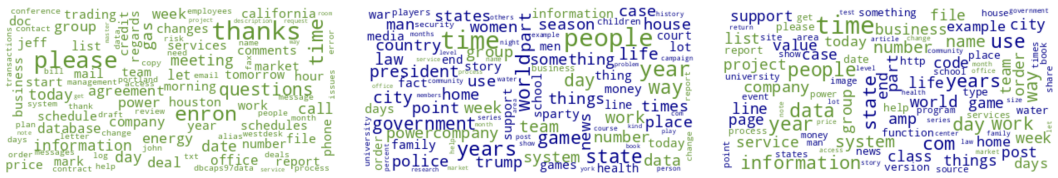
We create a training set to teach the classifier to recognize a target data distribution. Sentences in the target dataset are labelled as positive. Random samples from the source data are labelled as negative[2]. It has been widely observed that a larger training set helps private learning (Bassily et al., 2014; Tramèr & Boneh, 2021). Therefore we set the number of negative examples as five times larger than the number of positive examples. The privacy cost of training the classifier is accounted in the overall privacy cost.

We run experiments with the Enron Email (Cohen, 2015) as the target and the OpenWebText dataset (Gokaslan & Cohen, 2019) as the source. The classifier is initialized with a 124M GPT model pre-trained on OpenWebText. With a single Tesla A100 GPU, it takes approximately one hour for fine-tuning the domain classifier. With eight Tesla V100 GPUs, it takes less than two hours for computing the confidence scores for all sequences in OpenWebText. The privacy guarantee is $(0.7, 1 \times 10^{-8})$-DP if we only consider the privacy cost of this step. More implementation details are in Section 4.1. The trained classifier achieves an F1-score of 98.5%. The classifier achieves an F1-score of 92.7% if it is not initialized with a pre-trained LM.

We use the trained classifier to select 10% of OpenWebText. We plot the word clouds of Enron email, OpenWebText, and the selected subset of OpenWebText (Figure 4), to visually illustrate the dataset selected

[1] [Revised] In our preliminary experiments, we also explored random sampling where the sampling weights are scaled linearly or quadratically with the confidence scores from the domain classifier. We found no statistical difference when compared to using only the top-ranked samples.

[2] [Revised] This way of assigning negative labels may introduce few noisy labels, since some public samples may closely resemble those from the private dataset. However, given the vast size and diversity of the public dataset, the percentage of noisy labels would be low, as evidenced by the high test F1-score of the trained domain classifiers.



(a) Enron Email (b) OpenWebText (c) Selected OpenWebText

Figure 4: The 100 most frequent nouns in Enron email, OpenWebText, or a selected subset of OpenWebText (10%). A larger font size indicates that the word appears more frequently. Green words are the 100 most frequent nouns in Enron Email. OpenWebText and selected OpenWebText have 28 and 39 words, respectively, that are among the 100 most frequent nouns in Enron Email.

by our algorithm. The word clouds only show the nouns to exclude common prepositions and verbs. There are 28 nouns which appear in both the top 100 nouns of the Enron email dataset and the top 100 nouns of OpenWebText. The number of overlaps increases to 39 when comparing Enron email with the selected subset of OpenWebText, suggesting the trained domain classifier is an effective tool for data selection. In Appendix B.1, we also present the results of using GLUE (Wang et al., 2018) tasks as the targets and the pre-training corpus of BERT (Devlin et al., 2019) as the source.

4 Experimental Evaluation

We evaluate our full framework (Section 2) on language generation and understanding tasks, comparing on datasets that most previous works used (Li et al., 2022c; Yu et al., 2022). The goal here is to empirically verify the main claim made in the introduction: our framework can be used as an effective tool for model compression, and beats the existing baselines in the literature (Mireshghallah et al., 2022). We note that Mireshghallah et al. (2022) did experiments on GLUE benchmark only, and we compare against them in the next section. We begin with the language modeling on the email dataset, which was the motivating example from the real world application.

4.1 Implementing the Framework on the Enron Email Dataset

Our first target task is causal language modeling on the Enron email dataset. The dataset contains approximately 0.5 million (M) emails written by employees of the Enron Corporation and is publicly available for research use. We choose this dataset because its distribution closely resembles some private datasets in the real world for which it is hard to find off-the-shelf pre-training data.

4.1.1 Experiment Setup

We briefly describe important parameters of our experimental setup. More details are in Appendix C.

Target and Source Data We divide the text into sequences of length 256 and treat each sequence as a datapoint, which constitutes the granularity of our privacy guarantees. Most of the emails in the dataset are shorter than hundred words. In real world applications, it is important to carefully bound the maximum contribution of a single email/user to a training point. There are ∼70K sequences in total. We use 80% of them for training and evenly split the rest 20% for validation and testing. The source data is OpenWebText (Gokaslan & Cohen, 2019) which contains ∼4 billion tokens. The sequence size for OpenWebText is 512, following the choice in Radford et al. (2018).

Models Models in this section are from the GPT family (Radford et al., 2019). We change the number of layers, hidden size, and intermediate size of the fully connected block to get five different model sizes (21M, 45M, 82M, 124M, and 355M). Details of the models and pre-training hyperparameters are in Appendix C. All models are pre-trained with nodes with 8x Nvidia Tesla V100 GPUs.

Data Selection We use the algorithm in Section 3 to select 2M sequences from the source data for pre-training. We train the domain classifier for 3 epochs. The baselines include 1) pre-training with 2M random sequences and 2) pre-training with all of OpenWebText.

Privacy Budget and Hyperparameters The overall privacy budget is $(7.3, 1 \times 10^{-7})$-DP, similar to previous works on this topic (Li et al., 2022c; Yu et al., 2022). To reduce the privacy cost of hyperparameter tuning (Liu & Talwar, 2019; Papernot & Steinke, 2022; Mohapatra et al., 2022), we follow the findings in previous work to set most of the hyperparameters and only tune the learning rate to adapt to models of different sizes. The hyperparameters for private learning are listed in Table 4 in Appendix C.

4.1.2 Selective Pre-training Provides Clear Gains, Model Efficiency

Figure 2 shows the perplexity and next-word prediction accuracy of different models on the test split of the Enron email dataset. We also present the next-word accuracy and its standard deviation across random seeds in Table 1 in Appendix B.2 as a complementary to Figure 2. It is clear from the figure that our framework improves performance compared to existing techniques.

More significantly, we see that smaller models can match the performance of much larger models; for example, the 82M model using selective pre-training matches the 124M model using normal pre-training. *This shows that the proposed framework can be used to improve the efficiency-utility trade-off of private learning.* We also include the zero-shot performance of the off-the-shelf GPT2-XL model (1.5 billion parameters) in Figure 2. The zero-shot performance of GPT2-XL is worse than the models that have access to private data and are of much smaller size. These findings highlight the importance of private data, which can be loosely treated as high quality data, as well as the importance of privacy-enhancing technologies that facilitate the trustworthy use of such data. Figure 10 in Appendix B.2 also presents the results under different privacy budgets (ε ranging from 2.3 to 10.9). We observe consistent gains when the selective pre-training framework is used.

4.1.3 Selective Pre-training is More Important for Private Learning

We also fine-tune the models without differential privacy to see whether selective pre-training improves downstream performance in non-private learning. The results are in Figure 5. When using 15% of OpenWeb-Text, selective pre-training still improves the performance of all models though the improvement is smaller compared to the private world. When using 100% of OpenWebText, the benefits of selective pre-training gradually diminish as the model size increases. This suggests that selective pre-training is more important for private learning compared to the case in non-private learning. Our hyperparameters for non-private fine-tuning can be found in Appendix C.

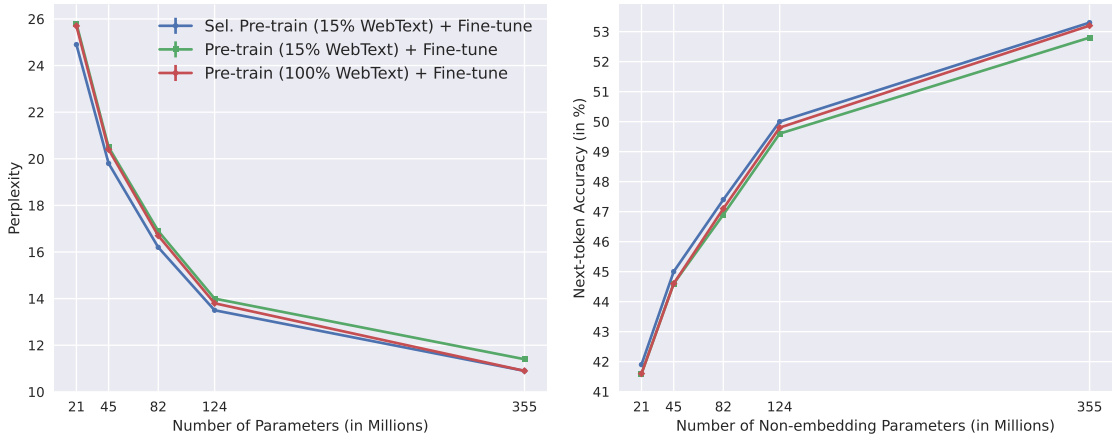


Figure 5: Perplexity and top-1 next word accuracy of GPT models on the test set of the Enron email dataset. The models are trained without DP. Selective pre-training still improves over standard pre-training, however, the improvements are smaller compared to private learning.

4.2 Experiments on GLUE

We conduct experiments on the GLUE benchmark (Wang et al., 2018), a common benchmark for fine-tuning language models with DP (Yu et al., 2021; Li et al., 2022c; Bu et al., 2022b). Our results show that selective pre-training also improves DP fine-tuning for language understanding tasks, beating the baselines in Mireshghallah et al. (2022).

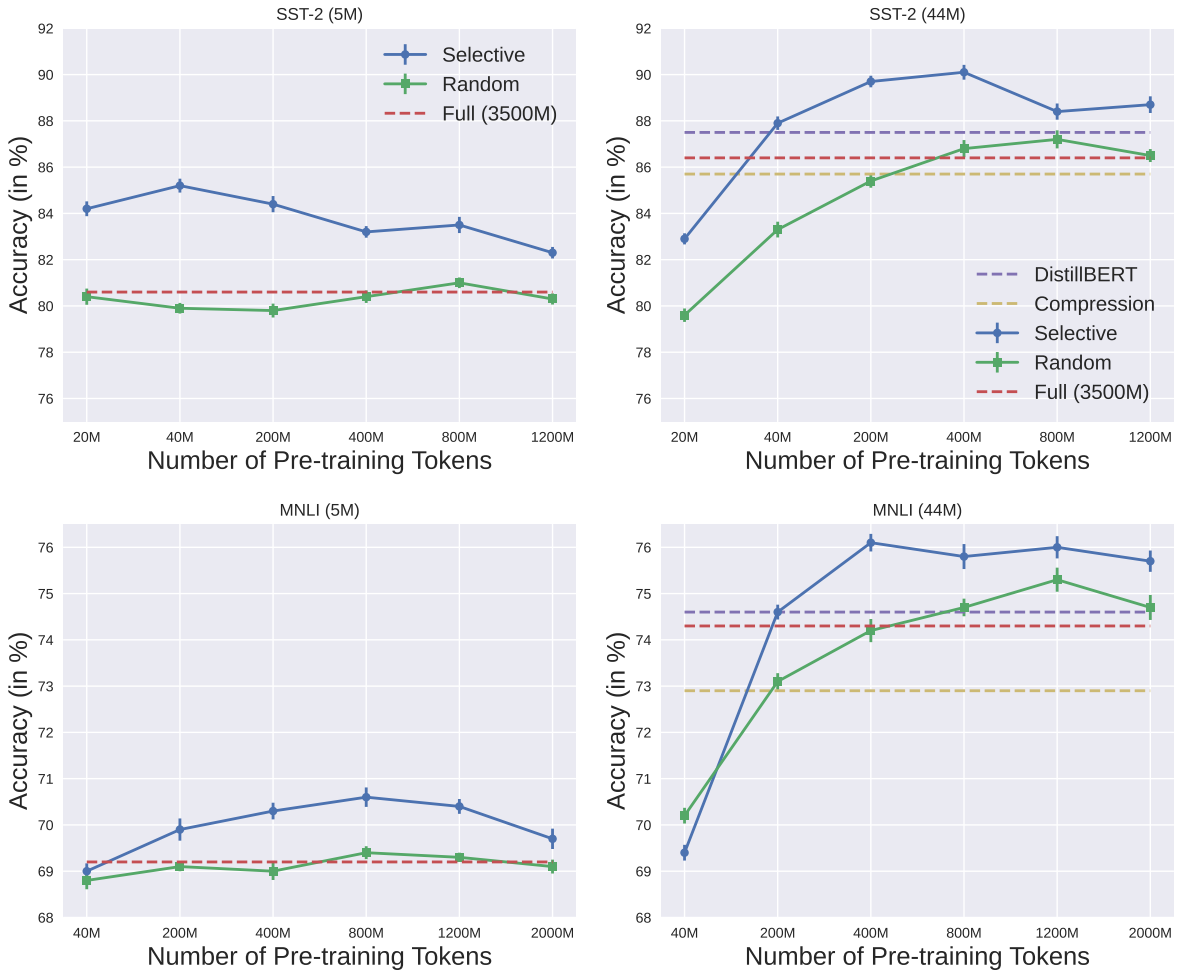


Figure 6: Results of pre-training with various numbers of tokens. The first column shows the results of 5M models and the second column shows the results of 44M models. Selective pre-training outperforms baseline algorithms in most of the cases.

4.2.1 Experiment Setup

Target and Source Data Our target tasks in this section are MNLI and SST-2, which have respectively the largest and smallest number of examples among the four tasks studied in previous work (Yu et al., 2021; Li et al., 2022c; Bu et al., 2022b; Mireshghallah et al., 2022). The numbers of training examples (N) in MNLI and SST-2 are 393K and 67K. The source data for GLUE tasks is the pre-training corpus of BERT (Devlin et al., 2019); It consists of a subset of Wikipedia and the entire Bookcorpus. The source dataset has approximately 3.5 billion tokens.

Model Sizes We use models from the BERT family (Devlin et al., 2019). We consider four different model sizes (5M, 10M, 25M, and 44M). Details of the models are in Appendix C. Following previous work (Xia et al., 2022), we do not include embedding matrices when computing the number of parameters of BERT models. For text classification tasks, the BERT embedding layer during inference is simply a lookup table.

Data Selection For MNLI and SST-2, we experiment with selecting varying numbers of tokens from the source data. The target numbers of pre-training tokens are 20M, 40M, 200M, 400M, 800M, 1200M, and 2000M. More complete implementation details on data selection are in Appendix C.

Baselines The baselines include pre-training on randomly selected source data and pre-training on all source data. There are two additional baselines for the 44M model. The first is directly fine-tuning DistillBERT

(Sanh et al., 2019) with differential privacy. DistillBERT is distilled from BERT-base on the source data. The second is the best result in Mireshghallah et al. (2022). Mireshghallah et al. (2022) compress a DP fine-tuned BERT-base model using differentially private distillation or pruning. The architecture of the compressed models in Mireshghallah et al. (2022) and Sanh et al. (2019) are of the same architecture as the 44M model. Although our framework is compatible with the techniques in Mireshghallah et al. (2022) and Sanh et al. (2019), we include the two additional baselines to demonstrate that the proposed framework alone is a competitive approach for model compression in private learning.

Private Learning We adopt the setup in Mireshghallah et al. (2022). The privacy budget is $(4, 1/10N)$-DP. The hyperparameters for private learning are also documented in Appendix C.

4.2.2 Selective Pre-training Outperforms Baselines, Improves Model Efficiency

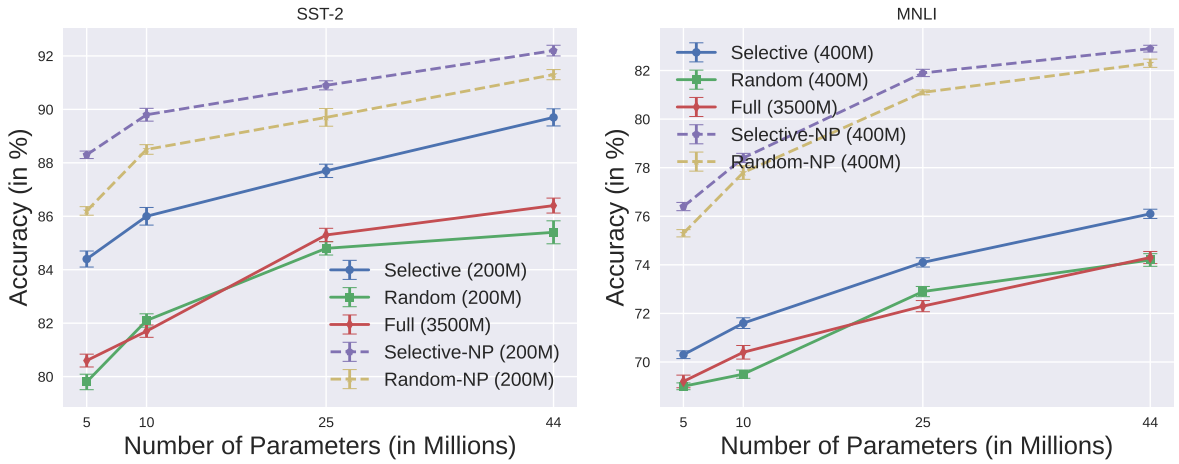


Figure 7: Results of pre-training with different model sizes. The numbers in the brackets are the numbers of tokens used for pre-training. 'NP' denotes that the models are fine-tuned without DP. Selective pre-training consistently improves performance across all settings. The improvements for models trained with DP are larger.

Figure 6 shows the test accuracy on MNLI and SST-2 after privately fine-tuning models pre-trained with varying numbers of tokens. Our first finding is that, for most of the settings, selective pre-training outperforms all the algorithms examined. On SST-2, selective pre-training achieves accuracy that is 4.6% and 3.7% higher than the accuracy of full pre-training for the 5M and 44M models, respectively. On MNLI, the accuracy improvements are 1.4% and 1.8%, respectively. Our second finding is that, for a model of fixed size, *increasing the number of pre-training tokens does not necessarily lead to better downstream accuracy.* This suggests that there may be an optimal number of pre-training tokens for a given model size (Sorscher et al., 2022; Hoffmann et al., 2022), further emphasizing the need to choose a task-specific subset from a large source data.

Figure 7 shows the test accuracy of models of different sizes. When trained with differential privacy, the 25M model with selective pre-training achieves comparable or better performance than the 44M baseline models, aligning with our observations on the Enron email dataset. The accuracy gains on SST-2 are greater than those achieved on MNLI, likely because MNLI data distribution is relatively closer to Wikipedia corpus; see Appendix B.1 for the word clouds comparison.

5 Related Work

Here we discuss closely related prior work. Additional related work is discussed in Appendix A.

[Revised] The main scope of this work is to train better small DP language models. This scope aligns closely with the goals of model compression. Mireshghallah et al. (2022) study the implementation of classic model compression techniques, knowledge distillation (Hinton et al., 2015) and model pruning (Han et al., 2015), under DP constraints. While their DP variants achieve promising results on the GLUE benchmark

(Wang et al., 2018), they find that the DP constraint reduces the effectiveness of these classic compression techniques compared to the non-private case. In this work, the results in Figure 6 of Section 4.2 suggest that our framework improves upon the results in Mireshghallah et al. (2022) on GLUE, indicating that selective pre-training can serve as an effective new method for training better small DP models.

[Revised] Hoffmann et al. (2022) find that the optimal number of pre-training tokens scales linearly with the number of model parameters, as shown in their Figure 1 and Figure A3. In this work, we also observe that for a fixed-size model, there is an optimal size of pre-training data, after which further increasing the dataset does not improve downstream performance (see Figure 6 in Section 4.2). However, Hoffmann et al. (2022) focus solely on the quantity of pre-training data, not its quality. In our study, we demonstrate that both the quality, measured by the distributional gap between private and public data, and quantity play an important role in downstream performance. More importantly, Figure 5 and Figure 7 show that DP fine-tuning benefits more from high-quality pre-training compared to non-private fine-tuning, highlighting the unique value of selective pre-training for the privacy-preserving learning community.

Hou et al. (2023) and Gu et al. (2023) study how to privately select an optimal public dataset from an explicitly given list of public datasets. For instance, suppose the private dataset is CIFAR-10, and available public datasets are MNIST, CIFAR100, and ImageNet. The goal is to design a private algorithm to find which of the three public datasets is better suited for private learning on CIFAR-10. In this paper, we explore how to select a subset of a single public dataset on a sample-by-sample basis. Our algorithm does not require any explicit division of public data and runs efficiently on billions of tokens, making it well-suited for finding the right pre-training data for language models. More importantly, our emphasis is not just on model accuracy, but on how pre-training impacts accuracy-vs-model size trade-offs.

6 [Revised] Conclusion and Limitations

6.1 Conclusion

This work introduces selective pre-training, a new approach for pre-training language models that are better suited for fine-tuning with DP on private data. The proposed framework pre-trains the models on a selected subset of public data that is better aligned with the domain of the private data. Additionally, the selection of public data is designed to satisfy DP with respect to the private dataset. Experiments on the Enron email dataset (Cohen, 2015) and GLUE benchmark (Wang et al., 2018) demonstrate that selective pre-training improves the fine-tuning of lightweight language models by clear margins.

6.2 Limitations

We provide DP guarantees only for private datasets, not for public ones. In building applications, it is important to consider the privacy risks associated with public data (Tramèr et al., 2022). One potential solution is to enforce differential privacy even during the pre-training stage (Kurakin et al., 2022; Anil et al., 2022).

Our methods pre-train models from scratch, thereby incurring an additional computational cost associated with pre-training compared to prior work that can utilize off-the-shelf pre-trained models (Mireshghallah et al., 2022). However, in real-world applications such as email clients or text editors, the backbone models are queried millions or even billions of times every day. Therefore, the cost of training, being a one-time expense, is a negligible fraction of the accumulated inference cost.

[Revised] Broader Impact

Language models, trained with DP or not, are widely used for enhancing the typing experience for users (McMahan et al., 2018; Microsoft, 2020; Xu et al., 2023). In this work, we introduce a new pre-training method designed to improve the DP fine-tuning process of language models. We hope our work can facilitate the adoption of privacy-preserving techniques within the industry, providing strong privacy for users while simultaneously reducing deployment costs and further enhancing user experience. However, as previous research indicates, implementing a DP training pipeline can be complex (Tramer et al., 2022). Therefore, we recommend rigorous implementation and thorough auditing for any real-world deployment of the proposed framework.

References

Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In *Proceedings of ACM Conference on Computer and Communications Security*, 2016.

Noga Alon, Raef Bassily, and Shay Moran. Limits of private learning with access to public data. *Advances in neural information processing systems*, 2019.

Ehsan Amid, Arun Ganesh, Rajiv Mathews, Swaroop Ramaswamy, Shuang Song, Thomas Steinke, Vinith M Suriyakumar, Om Thakkar, and Abhradeep Thakurta. Public data-assisted mirror descent for private model training. In *International Conference on Machine Learning*, 2022.

Rohan Anil, Badih Ghazi, Vineet Gupta, Ravi Kumar, and Pasin Manurangsi. Large-scale differentially private bert. *Findings of the Association for Computational Linguistics: EMNLP 2022*, 2022.

Raef Bassily, Adam Smith, and Abhradeep Thakurta. Differentially private empirical risk minimization: Efficient algorithms and tight error bounds. *Annual Symposium on Foundations of Computer Science*, 2014.

Raef Bassily, Albert Cheu, Shay Moran, Aleksandar Nikolov, Jonathan Ullman, and Steven Wu. Private query release assisted by public data. In *International Conference on Machine Learning*, 2020a.

Raef Bassily, Shay Moran, and Anupama Nandi. Learning from mixtures of private and public populations. *Advances in Neural Information Processing Systems*, 2020b.

Raef Bassily, Mehryar Mohri, and Ananda Theertha Suresh. Principled approaches for private adaptation from a public source. In *International Conference on Artificial Intelligence and Statistics*, 2023.

Alex Bie, Gautam Kamath, and Vikrant Singhal. Private estimation with public data. *Advances in Neural Information Processing Systems*, 2022.

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, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey 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. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, 2020.

Zhiqi Bu, Sivakanth Gopi, Janardhan Kulkarni, Yin Tat Lee, Hanwen Shen, and Uthaipon Tantipongpipat. Fast and memory efficient differentially private-sgd via jl projections. *Advances in Neural Information Processing Systems*, 2021.

Zhiqi Bu, Jialin Mao, and Shiyun Xu. Scalable and efficient training of large convolutional neural networks with differential privacy. *Advances in Neural Information Processing Systems*, 2022a.

Zhiqi Bu, Yu-Xiang Wang, Sheng Zha, and George Karypis. Differentially private bias-term only fine-tuning of foundation models. *arXiv preprint arXiv:2210.00036*, 2022b.

Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Ulfar Erlingsson, et al. Extracting training data from large language models. *USENIX Security Symposium*, 2021.

Nicholas Carlini, Daphne Ippolito, Matthew Jagielski, Katherine Lee, Florian Tramer, and Chiyuan Zhang. Quantifying memorization across neural language models. *International Conference on Learning Representations*, 2023.

Christopher A Choquette-Choo, Florian Tramer, Nicholas Carlini, and Nicolas Papernot. Label-only membership inference attacks. In *International Conference on Machine Learning*, 2021.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.

William Cohen. Enron email dataset, 2015. URL `https://www.cs.cmu.edu/~enron/`.

Cody Coleman, Christopher Yeh, Stephen Mussmann, Baharan Mirzasoleiman, Peter Bailis, Percy Liang, Jure Leskovec, and Matei Zaharia. Selection via proxy: Efficient data selection for deep learning. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020. URL `https://openreview.net/forum?id=HJg2b0VYDr`.

Soham De, Leonard Berrada, Jamie Hayes, Samuel L Smith, and Borja Balle. Unlocking high-accuracy differentially private image classification through scale. *arXiv preprint arXiv:2204.13650*, 2022.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *Conference of the North American Chapter of the Association for Computational Linguistics*, 2019.

Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. Calibrating noise to sensitivity in private data analysis. In *Theory of cryptography conference*, 2006.

Arun Ganesh, Mahdi Haghifam, Milad Nasr, Sewoong Oh, Thomas Steinke, Om Thakkar, Abhradeep Thakurta, and Lun Wang. Why is public pretraining necessary for private model training? *arXiv preprint arXiv:2302.09483*, 2023.

Badih Ghazi, Pritish Kamath, Ravi Kumar, and Pasin Manurangsi. Faster privacy accounting via evolving discretization. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato (eds.), *International Conference on Machine Learning, ICML 2022*, 2022.

Aaron Gokaslan and Vanya Cohen. Openwebtext corpus. `http://Skylion007.github.io/OpenWebTextCorpus`, 2019.

Aditya Golatkar, Alessandro Achille, Yu-Xiang Wang, Aaron Roth, Michael Kearns, and Stefano Soatto. Mixed differential privacy in computer vision. *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022.

Sivakanth Gopi, Yin Tat Lee, and Lukas Wutschitz. Numerical composition of differential privacy. *Advances in Neural Information Processing Systems*, 2021.

Xin Gu, Gautam Kamath, and Zhiwei Steven Wu. Choosing public datasets for private machine learning via gradient subspace distance. *arXiv preprint arXiv:2303.01256*, 2023.

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International conference on machine learning*, 2017.

Suchin Gururangan, Ana Marasovic, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. Don't stop pretraining: Adapt language models to domains and tasks. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel R. Tetreault (eds.), *Proceedings of the 58th Annual Meeting of the Association for Computational*, 2020.

Song Han, Jeff Pool, John Tran, and William Dally. Learning both weights and connections for efficient neural network. *Advances in neural information processing systems*, 28, 2015.

Jamie Hayes, Luca Melis, George Danezis, and Emiliano De Cristofaro. LOGAN: membership inference attacks against generative models. *Proceedings on Privacy Enhancing Technologies*, 2019.

Jiyan He, Xuechen Li, Da Yu, Huishuai Zhang, Janardhan Kulkarni, Yin Tat Lee, Arturs Backurs, Nenghai Yu, and Jiang Bian. Exploring the limits of differentially private deep learning with group-wise clipping. *International Conference on Learning Representations*, 2023.

Danny Hernandez, Tom B. Brown, Tom Conerly, Nova DasSarma, Dawn Drain, Sheer El Showk, Nelson Elhage, Zac Hatfield-Dodds, Tom Henighan, Tristan Hume, Scott Johnston, Benjamin Mann, Chris Olah, Catherine Olsson, Dario Amodei, Nicholas Joseph, Jared Kaplan, and Sam McCandlish. Scaling laws and interpretability of learning from repeated data. *CoRR*, abs/2205.10487, 2022. doi: 10.48550/arXiv.2205.10487. URL `https://doi.org/10.48550/arXiv.2205.10487`.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2015.

Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. An empirical analysis of compute-optimal large language model training. *Advances in Neural Information Processing Systems*, 2022.

Charlie Hou, Hongyuan Zhan, Akshat Shrivastava, Sid Wang, Sasha Livshits, Giulia Fanti, and Daniel Lazar. Privately customizing prefinetuning to better match user data in federated learning. *ICLR Workshop on Pitfalls of Limited Data and Computation for Trustworthy ML*, 2023.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *International Conference on Learning Representations*, 2022.

Saachi Jain, Hadi Salman, Alaa Khaddaj, Eric Wong, Sung Min Park, and Aleksander Madry. A data-based perspective on transfer learning. *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023.

Peter Kairouz, Mónica Ribero, Keith Rush, and Abhradeep Thakurta. (nearly) dimension independent private ERM with adagrad rates via publicly estimated subspaces. In *Proceedings of the 34th Annual Conference on Learning Theory*, 2021.

Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models. *arXiv preprint arXiv:2001.08361*, 2020.

Gavin Kerrigan, Dylan Slack, and Jens Tuyls. Differentially private language models benefit from public pre-training. In *Proceedings of the Second Workshop on Privacy in NLP*. Association for Computational Linguistics, 2020.

Antti Koskela, Joonas Jälkö, and Antti Honkela. Computing tight differential privacy guarantees using FFT. In Silvia Chiappa and Roberto Calandra (eds.), *International Conference on Artificial Intelligence and Statistics*, 2020.

Alexey Kurakin, Shuang Song, Steve Chien, Roxana Geambasu, Andreas Terzis, and Abhradeep Thakurta. Toward training at imagenet scale with differential privacy. *arXiv preprint arXiv:2201.12328*, 2022.

Alexey Kurakin, Natalia Ponomareva, Umar Syed, Liam MacDermed, and Andreas Terzis. Harnessing large-language models to generate private synthetic text. *arXiv preprint arXiv:2306.01684*, 2023.

Jaewoo Lee and Daniel Kifer. Scaling up differentially private deep learning with fast per-example gradient clipping. *Privacy Enhancing Technologies*, 2021.

Katherine Lee, Daphne Ippolito, Andrew Nystrom, Chiyuan Zhang, Douglas Eck, Chris Callison-Burch, and Nicholas Carlini. Deduplicating training data makes language models better. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pp. 8424–8445. Association for Computational Linguistics, 2022. doi: 10.18653/v1/2022.acl-long.577. URL https://doi.org/10.18653/v1/2022.acl-long.577.

Tian Li, Manzil Zaheer, Sashank Reddi, and Virginia Smith. Private adaptive optimization with side information. In *International Conference on Machine Learning*, 2022a.

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

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

Chong Liu, Yuqing Zhu, Kamalika Chaudhuri, and Yu-Xiang Wang. Revisiting model-agnostic private learning: Faster rates and active learning. *The Journal of Machine Learning Research*, 2021a.

Jingcheng Liu and Kunal Talwar. Private selection from private candidates. In *Proceedings of the 51st Annual ACM SIGACT Symposium on Theory of Computing*, 2019.

Terrance Liu, Giuseppe Vietri, Thomas Steinke, Jonathan Ullman, and Steven Wu. Leveraging public data for practical private query release. In *International Conference on Machine Learning*, 2021b.

Zelun Luo, Daniel J. Wu, Ehsan Adeli, and Li Fei-Fei. Scalable differential privacy with sparse network finetuning. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2021, virtual, June 19-25, 2021*, pp. 5059–5068. Computer Vision Foundation / IEEE, 2021. doi: 10.1109/CVPR46437.2021.00502. URL https://openaccess.thecvf.com/content/CVPR2021/html/Luo_Scalable_Differential_Privacy_With_Sparse_Network_Finetuning_CVPR_2021_paper.html.

Tomoya Matsumoto, Takayuki Miura, and Naoto Yanai. Membership inference attacks against diffusion models. *arXiv preprint arXiv:2302.03262*, 2023.

H Brendan McMahan, Daniel Ramage, Kunal Talwar, and Li Zhang. Learning differentially private recurrent language models. In *International Conference on Learning Representations*, 2018.

Harsh Mehta, Abhradeep Thakurta, Alexey Kurakin, and Ashok Cutkosky. Large scale transfer learning for differentially private image classification. *arXiv preprint arXiv:2205.02973*, 2022.

Microsoft. Assistive ai makes replying easier, 2020. URL https://www.microsoft.com/en-us/research/group/msai/articles/assistive-ai-makes-replying-easier-2/.

Sören Mindermann, Jan Markus Brauner, Muhammed Razzak, Mrinank Sharma, Andreas Kirsch, Winnie Xu, Benedikt Höltgen, Aidan N. Gomez, Adrien Morisot, Sebastian Farquhar, and Yarin Gal. Prioritized training on points that are learnable, worth learning, and not yet learnt. *CoRR*, abs/2206.07137, 2022. doi: 10.48550/arXiv.2206.07137. URL https://doi.org/10.48550/arXiv.2206.07137.

Fatemehsadat Mireshghallah, Arturs Backurs, Huseyin A Inan, Lukas Wutschitz, and Janardhan Kulkarni. Differentially private model compression. *Advances in Neural Information Processing Systems*, 2022.

Shubhankar Mohapatra, Sajin Sasy, Xi He, Gautam Kamath, and Om Thakkar. The role of adaptive optimizers for honest private hyperparameter selection. In *Proceedings of the AAAI conference on artificial intelligence*, 2022.

MosiacML. https://www.mosaicml.com/.

Ashwinee Panda, Xinyu Tang, Vikash Sehwag, Saeed Mahloujifar, and Prateek Mittal. Dp-raft: A differentially private recipe for accelerated fine-tuning. *arXiv preprint arXiv:2212.04486*, 2022.

Nicolas Papernot and Thomas Steinke. Hyperparameter tuning with renyi differential privacy. *International Conference on Learning Representations*, 2022.

Nicolas Papernot, Martín shokri, Ulfar Erlingsson, Ian Goodfellow, and Kunal Talwar. Semi-supervised knowledge transfer for deep learning from private training data. In *International Conference on Learning Representations*, 2017.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training, 2018.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 2019.

Tom Sander, Pierre Stock, and Alexandre Sablayrolles. Tan without a burn: Scaling laws of dp-sgd. *arXiv preprint arXiv:2210.03403*, 2022.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *NeurIPS Workshop on Energy Efficient Machine Learning and Cognitive Computing*, 2019.

ScaleAI. https://scale.com/.

Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *IEEE Symposium on Security and Privacy*, 2017.

Shuang Song, Kamalika Chaudhuri, and Anand D Sarwate. Stochastic gradient descent with differentially private updates. In *Global Conference on Signal and Information Processing*, 2013.

Ben Sorscher, Robert Geirhos, Shashank Shekhar, Surya Ganguli, and Ari Morcos. Beyond neural scaling laws: beating power law scaling via data pruning. *Advances in Neural Information Processing Systems*, 2022.

Thomas Steinke. Composition of differential privacy & privacy amplification by subsampling. *arXiv preprint arXiv:2210.00597*, 2022.

Pranav Subramani, Nicholas Vadivelu, and Gautam Kamath. Enabling fast differentially private sgd via just-in-time compilation and vectorization. *Advances in Neural Information Processing Systems*, 2021.

Florian Tramèr and Dan Boneh. Differentially private learning needs better features (or much more data). *International Conference on Learning Representations*, 2021.

Florian Tramèr, Gautam Kamath, and Nicholas Carlini. Considerations for differentially private learning with large-scale public pretraining. *CoRR*, abs/2212.06470, 2022. doi: 10.48550/arXiv.2212.06470. URL `https://doi.org/10.48550/arXiv.2212.06470`.

Florian Tramer, Andreas Terzis, Thomas Steinke, Shuang Song, Matthew Jagielski, and Nicholas Carlini. Debugging differential privacy: A case study for privacy auditing. *arXiv preprint arXiv:2202.12219*, 2022.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *EMNLP Workshop on BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, 2018.

Dequan Wang, Evan Shelhamer, Shaoteng Liu, Bruno Olshausen, and Trevor Darrell. Tent: Fully test-time adaptation by entropy minimization. *International Conference on Learning Representations*, 2021.

Qian Wang, Zixi Li, Qin Zou, Lingchen Zhao, and Song Wang. Deep domain adaptation with differential privacy. *IEEE Transactions on Information Forensics and Security*, 2020.

Mengzhou Xia, Zexuan Zhong, and Danqi Chen. Structured pruning learns compact and accurate models. *Annual Meeting of the Association for Computational Linguistics*, 2022.

Sang Michael Xie, Shibani Santurkar, Tengyu Ma, and Percy Liang. Data selection for language models via importance resampling. *arXiv preprint arXiv:2302.03169*, 2023.

Zheng Xu, Yanxiang Zhang, Galen Andrew, Christopher A Choquette-Choo, Peter Kairouz, H Brendan McMahan, Jesse Rosenstock, and Yuanbo Zhang. Federated learning of gboard language models with differential privacy. *arXiv preprint arXiv:2305.18465*, 2023.

Jiaxi Yang and Xiang Cheng. Public data assisted differential private deep learning. In *International Joint Conference on Neural Networks*, 2022.

Da Yu, Huishuai Zhang, Wei Chen, Jian Yin, and Tie-Yan Liu. Large scale private learning via low-rank reparametrization. In *International Conference on Machine Learning*, 2021.

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

Chiyuan Zhang, Daphne Ippolito, Katherine Lee, Matthew Jagielski, Florian Tramèr, and Nicholas Carlini. Counterfactual memorization in neural language models. *arXiv preprint arXiv:2112.12938*, 2021.

Hanlin Zhang, Xuechen Li, Prithviraj Sen, Salim Roukos, and Tatsunori Hashimoto. A closer look at the calibration of differentially private learners. *arXiv preprint arXiv:2210.08248*, 2022.

L Zhang and X Gao. Transfer adaptation learning: A decade survey. *IEEE Transactions on Neural Networks and Learning Systems*, 2022.

Maobo Zheng, Xiaojian Zhang, Xuebin Ma, et al. Unsupervised domain adaptation with differentially private gradient projection. *International Journal of Intelligent Systems*, 2023.

Yingxue Zhou, Zhiwei Steven Wu, and Arindam Banerjee. Bypassing the ambient dimension: Private sgd with gradient subspace identification. *International Conference on Learning Representations*, 2021.

Yuqing Zhu, Xiang Yu, Manmohan Chandraker, and Yu-Xiang Wang. Private-knn: Practical differential privacy for computer vision. *Conference on Computer Vision and Pattern Recognition*, 2020.

A Additional Related Work

For general literature on private deep learning and fine-tuning we refer the readers to (Abadi et al., 2016; He et al., 2023; Kerrigan et al., 2020; Li et al., 2022c; Bu et al., 2021; Lee & Kifer, 2021; Subramani et al., 2021; Anil et al., 2022; Yu et al., 2022; De et al., 2022; Mehta et al., 2022; Yu et al., 2021; Zhu et al., 2020; Sander et al., 2022; Bu et al., 2022a; Panda et al., 2022), and references there in. To the best of our knowledge, no prior work in DP literature has studied selective pre-training from scratch and its impact on the transfer learning abilities of a model. Our work is at the intersection of several related topics, and we give a brief overview of how our work fits into the broader literature on the topic.

Domain Adaptation and Reducing Distribution Disparity Between Public and Private Data Public data has been widely used to improve private data analysis (Papernot et al., 2017; Alon et al., 2019; Bassily et al., 2020b;a; Kairouz et al., 2021; Liu et al., 2021a; Zhou et al., 2021; Liu et al., 2021b; Amid et al., 2022; Yang & Cheng, 2022; Li et al., 2022a; Bie et al., 2022). To address the distribution shift between private and public data, a recent line of research explores domain adaption (Wang et al., 2021; Zhang & Gao, 2022) in the context of private learning (Wang et al., 2020; Zheng et al., 2023; Bassily et al., 2023). However, these works are not applicable to our setting due to many reasons, but in particular that we are interested in how pre-training dataset affects the model size. Much of the above literature considers simply the performance of the final model. In the absence of the model size restrictions, for NLP applications, it is well established He et al. (2023) that pre-training on large corpus of text using a large model offers better utility-vs-privacy trade offs.

Non-Private Data Selection Automatic data selection and cleaning, along with how the pre-training data impacts the downstream task performance are important problems in deep learning. See Xie et al. (2023); Gururangan et al. (2020); Brown et al. (2020); Chowdhery et al. (2022); Jain et al. (2023); Hernandez et al. (2022); Mindermann et al. (2022); Lee et al. (2022); Coleman et al. (2020) and references there in. Yet, the literature is scarce on the impact of selective pre-training on the model, except the recent concurrent work of Xie et al. (2023). Our work explores these questions in the context of private learning, with an emphasis on how the quality of data affects performance and model size. As a pilot study on designing privacy-preserving data selection algorithms, we use simple classification-based approaches that are easy to privatize and provide a clear illustration of the main messages of the paper. Exploring more sophisticated approaches Xie et al. (2023) for private data selection is an interesting future direction.

B More Experiments

B.1 Results of Data Selection for GLUE Tasks

We plot the word clouds of SST-2/MNLI and (selected) source data to further demonstrate that the distribution of selected data is closer to the distribution of target data. The source data for SST-2 and MNLI is a subset of Wikipedia and the entire Bookcorpus.

The domain classifiers of SST-2 and MNLI are trained the same way as illustrated in Section 3. We select 400M tokens for SST-2 and MNLI, separately. The word clouds of the most frequent 100 nouns are in Figure 8 and 9. We exclude common prepositions and verbs in the word clouds. On SST-2, our selection algorithm improves the number of overlaps between the source data and the target data from 25 to 40. On MNLI, our algorithm improves the number of overlaps from 44 to 51. The results explain our findings in Section 4.2 that selective pre-training yields larger performance improvements on SST-2 than on MNLI.

Table 1: Next word prediction accuracy (in %) of GPT models on the Enron email dataset. The overall privacy budget is $(7.3, 1 \times 10^{-7})$.

Parameters	21M	45M	82M	124M	355M
Random	$32.8_{\pm 0.02}$	$35.0_{\pm 0.01}$	$36.5_{\pm 0.01}$	$37.2_{\pm 0.02}$	$38.4_{\pm 0.02}$
Top	$33.8_{\pm 0.03}$	$36.1_{\pm 0.02}$	$37.5_{\pm 0.04}$	$38.4_{\pm 0.02}$	$39.4_{\pm 0.01}$

(a) SST-2 (b) Source Data (c) Selected Source Data

Figure 8: The 100 most frequent nouns in SST-2, the source data, and a selected subset of source data. The source data is Wikipedia and Bookcorpus. Green words are the 100 most frequent nouns in SST-2. The source data and the selected subset have 25 and 40 words, respectively, that are among the 100 most frequent nouns in SST-2.

(a) MNLI (b) Source Data (c) Selected Source Data

Figure 9: The 100 most frequent nouns in MNLI, the source data, and a selected subset of source data. The source data is Wikipedia and Bookcorpus. Green words are the 100 most frequent nouns in MNLI. The source data and the selected subset have 44 and 51 words, respectively, that are among the 100 most frequent nouns in MNLI.

B.2 More Experiments on the Enron Email Dataset

Table 1 shows the top-1 next word prediction accuracy on the test split of the Enron email dataset as well as the standard deviation over five random seeds. With selective pre-training, a 82M model achieves an accuracy of 37.5% which is 0.3% higher than the accuracy of a 124M model that is not carefully pre-trained.

We also test selective pre-training under different privacy budgets. Figure 10 presents perplexity and next-word prediction accuracy of 21M and 355M GPT models under a wide range of ε (ranging from 2.3 to 10.9). We fix the privacy parameter δ as $1 \times 10^{-7} < 1/10N$. We found that selective pre-training leads to similar improvements across all the choices of ε.

C Implementation Details

Param	21M	45M	82M	124M	355M
L	4	4	6	12	24
d	312	576	768	768	1024
d_{FFN}	1248	2304	3072	3072	4096

Table 2: Architecture hyperparameters of the models for the Enron email dataset.

Param	5M	10M	25M	44M
L	4	6	6	6
d	312	384	576	768
d_{FFN}	1200	1200	2304	3072

Table 3: Architecture hyperparameters of the models for GLUE tasks.

This section expands on the implementation details that are omitted from the main text due to space constraints.

Details of the Models Let L, d, and d_{FFN} be the number of layers, hidden size, and intermediate size of the fully connected block, respectively. We change L, d, d_{FFN} to get different model sizes. Other architecture

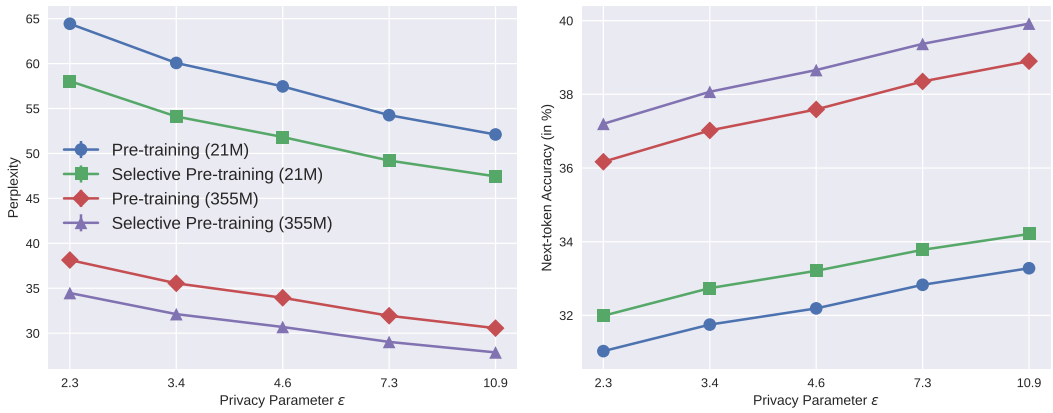


Figure 10: Perplexity and top-1 next-word accuracy on the Enron email dataset. We consider a wide range of ε (ranging from 2.3 to 10.9). The numbers in brackets are the number of model parameters. The privacy parameter δ is 1×10^{-7}. Selective pre-training yields consistent gains across all ε evaluated.

hyperparameters are the same as those in Devlin et al. (2019) and Radford et al. (2019). Table 2 and 3 show the model details for the Enron email dataset and GLUE tasks, respectively.

Data Selection for Enron Email The text in OpenWebText is also divided into sequences of length 256. To construct the training set of the domain classifier, we randomly sample $5N$ sequences from the source data as negative samples, and use all N sequences in the target dataset as positive samples. As a result, the training set of the domain classifier is 6 times larger than the target data. This significantly reduces the privacy cost of training the domain classifier because the probability of a target example being sampled becomes 6 times smaller. We initialize the domain classifier with an 82M GPT model pre-trained on OpenWebText and fine-tune it with DP-Adam on the constructed training set.

Data Selection for GLUE Tasks Because the positive examples in SST-2 and MNLI are natural sentences instead of sequences of fixed length, we sample natural sentences in the source data as negative examples for training the domain classifier. The domain classifier is initialized with BERT-base. In MNLI, a single example contains two natural sentences, i.e., a premise and a hypothesis. In this case, only one of the two sentences is chosen randomly as a positive example. The number of negative examples is also $5N$.

The pre-training sequences in Devlin et al. (2019) are of a fixed length. Each sequence may consist of several natural sentences. To get the ranking score of a sequence, we first break a fixed-length sequence into natural sentences and use the domain classifier to predict those sentences. The maximum confidence of the sentences is used as the ranking score for the sequence.

Table 4: Hyperparameters for private fine-tuning. We use N to denote the size of the target dataset.

Pre-training Method	Standard	Selective
Noise multiplier (Enron)	1.00	1.03
Noise multiplier (SST-2)	1.36	1.38
Noise multiplier (MNLI)	1.44	1.46
Train steps (domain classifier)	N/A	100
Train steps (target task)	[150, 500, 1000]	
Clipping norm	1	
Learning rate	[1e-4, 5e-4, 1e-3, 3e-3]	
Weight decay	0	
Batchsize	$\lfloor 0.03N \rfloor$	
Privacy budget	$(7.3, 1 \times 10^{-7})$ for Enron; $(4, 1/10N)$ for GLUE	

Hyperparameters For Pre-training The pre-training process uses common hyperparameters in the literature. For pre-training models from the BERT family, we follow the hyperparameters in Devlin et al. (2019). The hyperparameters for pre-training models from the GPT family are as follows. We use a dropout probability of 0.1 and a weight decay of 0.01. The β_1 and β_2 of Adam are 0.9 and 0.999, respectively. All models are pre-trained from scratch for 100K iterations with a batch size of 128. The initial learning rate is 5×10^{-4} and follows a linear decay schedule.

Hyperparameters For Private Fine-tuning We follow the findings in previous work to set most of the hyperparameters (Li et al., 2022c; Mireshghallah et al., 2022). We additionally tune the learning rate to adapt to the various model sizes we studied. Table 4 summarizes the hyperparameters for private learning. We use the parameter-efficient fine-tuning algorithm LoRA (Hu et al., 2022) to improve the efficiency of the DP fine-tuning of GPT models Yu et al. (2022); Kurakin et al. (2023). We do not use LoRA for the DP fine-tuning of BERT models to get a fair comparison to Mireshghallah et al. (2022). For a given set of hyperparameters, we use the PRV accountant to get the noise multiplier of DP-Adam. If we use selective pre-training, then the noise multiplier is slightly larger because we need to account for the privacy cost of training a domain classifier. We repeat each private fine-tuning experiment 5 and 3 times with different random seeds for the Enron email dataset and GLUE, respectively.