Privacy Regularization: Joint Privacy-Utility Optimization in Language Models

Fatemehsadat Mireshghallah[1]*, **Huseyin A. Inan**[3], **Marcello Hasegawa**[2], **Victor Rühle**[2], **Taylor Berg-Kirkpatrick**[1], **Robert Sim**[3]

[1] University of California San Diego, [2] Microsoft Corporation, [3] Microsoft Research

{fatemeh, tberg}@ucsd.edu,
{huseyin.inan, marcellh, virueh, rsim}@microsoft.com

Abstract

Neural language models are known to have a high capacity for memorization of training samples. This may have serious privacy implications when training models on user content such as email correspondence. Differential privacy (DP), a popular choice to train models with privacy guarantees, comes with significant costs in terms of utility degradation and disparate impact on subgroups of users. In this work, we introduce two privacy-preserving regularization methods for training language models that enable joint optimization of utility and privacy through (1) the use of a discriminator and (2) the inclusion of a novel triplet-loss term. We compare our methods with DP through extensive evaluation. We show the advantages of our regularizers with favorable utility-privacy trade-off, faster training with the ability to tap into existing optimization approaches, and ensuring uniform treatment of under-represented subgroups.

1 Introduction

Neural language models (Bengio et al., 2003; Mikolov et al., 2010) have recently seen significant gains in capabilities, and are deployed at scale in several real-world scenarios (Chen et al., 2019; Adam et al., 2020). Training these models on domain-specific user data can further improve their utility. The volume of data required, coupled with the inherent sparsity of natural language which often means all data are unique, opens the door to an array of privacy attacks against models and their training data. Sample memorization poses a substantial risk by enabling model inversion attacks (Carlini et al., 2020; Ramaswamy et al., 2020; Inan et al., 2021). In these attacks, a curious or malevolent user can query a pre-trained language model on any data record with the intention of reconstructing (parts of) training samples[1].

Differential Privacy (DP) (Dwork, 2006) is the gold standard approach to address this issue, thanks to its strong and rigorous privacy guarantees. DP-SGD (Abadi et al., 2016) is a popular method to train neural models with differential privacy guarantees and it works by clipping of the gradients and addition of noise in each update, which provides worst-case guarantees that reflect the likelihood of leaking any attribute of any member of the dataset into the trained model. The worst-case guarantees of differential privacy are not customizable, in other words, they cannot be relaxed to protect only certain attributes. Therefore, DP incurs significant loss to model utility (Tramèr and Boneh, 2020). DP training of models is also much slower, with cumbersome hyper-parameter tuning and development (Wu et al., 2017; Subramani et al., 2020). It has also been shown that DP's utility loss is much worse for under-represented groups (Bagdasaryan et al., 2019; Farrand et al., 2020), which can have financial and societal ramifications (Pujol et al., 2020).

To address these issues, we relax the strong assumptions of the DP threat model and assume an adversary with finite-capacity (finite statistical, compute, and side information) who attempts to recover sensitive user-level information from the trained model (Carlini et al., 2019). We propose two privacy regularization methods, one based on adversarial training and another on a novel privacy loss term, to jointly optimize for privacy and utility of language models. The main idea of our regularizers is to prevent the last hidden state representation of the language model for an input sequence x from being linked back to the sensitive attribute we are trying to protect, in our case, the identity of the author. We use the last hidden state as it corresponds to the embedding of the sequence x.[2] We

[*] Work done as part of an MSR internship.

[1] A naïve example is an attacker querying "My account number is" and hoping to receive a user's account number.

[2] Although we consider recurrent neural network-based language models in this work, our approach is applicable in transformer-based language models as well. In the latter, one

Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3799–3807
June 6–11, 2021. ©2021 Association for Computational Linguistics

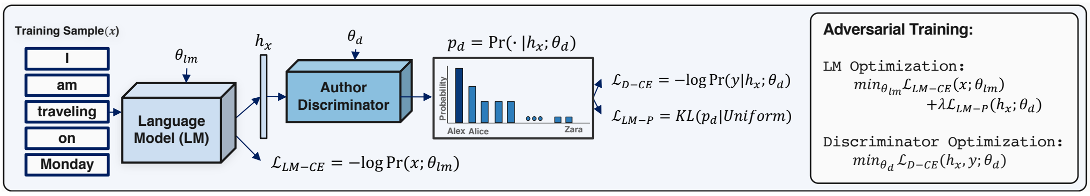

Training Sample(x)
I
am
traveling
on
Monday
θ_{lm}
Language Model (LM)
h_x
θ_d
Author Discriminator
$p_d = \Pr(\cdot\,|h_x;\theta_d)$
Probability
Alex Alice
Zara
$\mathcal{L}_{D-CE} = -\log\Pr(y|h_x;\theta_d)$
$\mathcal{L}_{LM-P} = KL(p_d|Uniform)$
$\mathcal{L}_{LM-CE} = -\log\Pr(x;\theta_{lm})$
Adversarial Training:
LM Optimization:
$min_{\theta_{lm}}\mathcal{L}_{LM-CE}(x;\theta_{lm})$
$+\lambda\mathcal{L}_{LM-P}(h_x;\theta_d)$
Discriminator Optimization:
$min_{\theta_d}\mathcal{L}_{D-CE}(h_x,y;\theta_d)$

Figure 1: Workflow of our adversarial training regularization. The last hidden state (h_x) of the LM is fed to the discriminator to generate a distribution over the authors (p_d). p_d is used to compute $\mathcal{L}_{\text{LM-P}}$, the privacy loss.

consider the linkability of the input representation to the sensitive attribute (author) as a proxy since it is commensurate with the linked and linkable information definitions in the General Data Protection Regulation (GDPR Article 29 Working Party, 2014). By framing privacy as an optimization problem, we can apply the well-developed machinery of large-scale gradient-based optimization, enabling us to train models at scale while jointly tuning for an optimal privacy-utility trade-off.

To validate our approach, we develop an evaluation framework for assessing a model's privacy loss. We employ the exposure metric introduced in (Carlini et al., 2019) and introduce a reconstruction (tab) attack as a realistic scenario to evaluate and compare LSTM language models trained using our regularization with those trained with differential privacy, on Avocado (Oard et al., 2015) and Reddit (Völske et al., 2017) datasets. We also empirically demonstrate that, unlike DP, our technique does not have disparate impacts on underrepresented groups.

Our work is closely related to (Coavoux et al., 2018) and (Li et al., 2018). Coavoux et al. consider an attacker who eavesdrops on the hidden representations of a pre-trained model during inference and tries to recover information about the input text. Adversarial training is used as a mitigation to reduce the attacker's performance (Wang et al., 2019). Li et al. use adversarial training to protect private author attributes such as age or gender, in learned text representations for part-of-speech tagging and sentiment analysis to gain better performance on out-of-domain corpora. We, on the other hand, use adversarial training and a triplet-based regularization to train private language models that do not memorize sensitive user information, which has not been explored before. We evaluate our models accordingly, by trying to extract training samples. Prior work has studied membership inference attacks against models (Shokri et al., 2017; Yeom et al., 2018; Song and Shmatikov, 2019), however, our regularizations do not target these attacks.

2 Approach

In this section, we explain our proposed regularizers and training techniques in more detail.

2.1 Adversarial Training

Figure 1 shows our first proposed regularizer which is adversarial in nature. We feed an input text sequence x to the language model and extract the last hidden state representation of the model for x; denoted by h_x. h_x is then fed to a discriminator parameterized by θ_d, which plays the role of an attacker who attempts to predict what the sensitive label (in our case, the author, y) for x is. The output probability distribution of the discriminator for the input h_x, $p_d = \Pr(\cdot|h_x;\theta_d)$ is then used to compute both the privacy loss $\mathcal{L}_{\text{LM-P}}$ of the language model and the discriminator loss $\mathcal{L}_{\text{D-CE}}$. During training, the discriminator optimizes for better linking of the last hidden state representations to the authors. Thus, the discriminator loss is $\mathcal{L}_{\text{D-CE}}(h_x, y; \theta_d) = -\log\Pr(y|h_x;\theta_d)$. Conversely, the language model optimizes θ_{lm} such that it (1) improves the utility of the language model and (2) flattens the probability distribution over authors. Thus, we devise the following loss function:

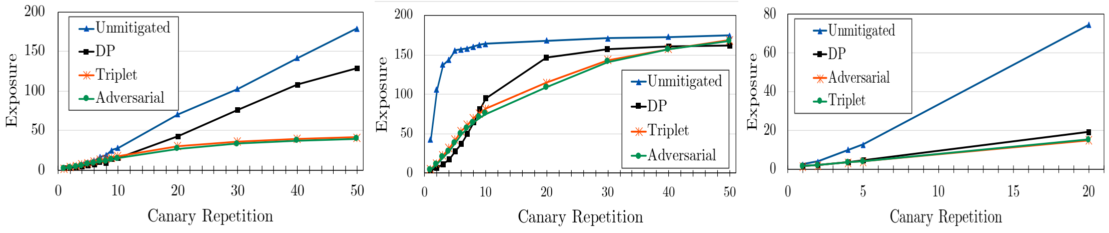
$$\mathcal{L}_{\text{LM}}(x;\theta_d,\theta_{lm}) = \mathcal{L}_{\text{LM-CE}} + \lambda\mathcal{L}_{\text{LM-P}} \qquad (1)$$

$\mathcal{L}_{\text{LM-CE}}$ is the utility loss, for which we use conventional cross entropy loss over the next-word predictions. $\mathcal{L}_{\text{LM-P}}$ is the *privacy loss*:

$$\mathcal{L}_{\text{LM-P}}(h_x;\theta_d) = -\frac{1}{M}\sum_{c=1}^{M}\log\Pr(c|h_x;\theta_d) \quad (2)$$

i.e. the KL divergence between the distribution over authors and the uniform distribution where M is the number of classes (authors). The goal of this term is to drive the discriminator to predict randomly uniform outputs (Raval et al., 2019). The reason we devised this loss as opposed to using

can consider the representation corresponding to the special token [CLS] as the embedding of the sequence x.



(a) Avocado - High PPL ($\sim$ 100) (b) Avocado - Low PPL ($\sim$ 60) (c) Reddit (PPL $\sim$ 100)

Figure 2: Exposure metric results for different training schemes at similar perplexities. Unmitigated denotes conventional training. Adversarial and Triplet are our regularizers. Higher exposure indicates lower privacy.

$-\mathcal{L}_{\text{D-CE}}$ is that we do not just want the discriminator to assign zero probability to the correct author, we want p_d to be uniform so that it has no information about the correct author. Hyperparameter λ allows for trading off privacy and utility.

2.2 Triplet-based Loss Function

One potential downside of the proposed adversarial regularizer is that the capacity of the discriminator must scale with the number of authors, and thus the size of the training data. To better accommodate the larger number of authors in large datasets, we investigate another regularizer that does not require a discriminator. We build on the intuition that to obfuscate an attribute, we can increase the distance between representations of samples that have the same label for that attribute while decreasing the distance between samples with different labels. To this end, we use the language model loss ($\mathcal{L}_{\text{LM}}$) of the previous section (Eq 1), and we set the privacy loss to be the triplet loss:

$$\mathcal{L}_{\text{LM-P}} = \|h_x - h_p\|^2 - \|h_x - h_n\|^2 \qquad (3)$$

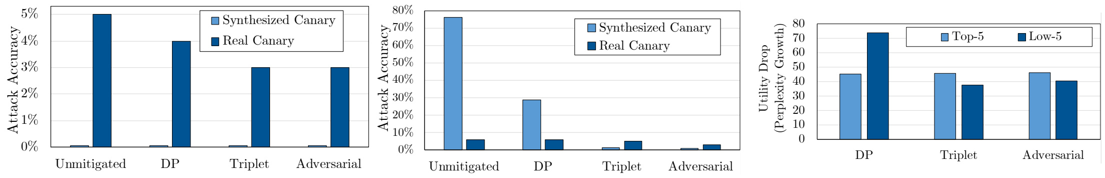
The triplet loss is commonly used in vision tasks for training embeddings that map images from the same category to neighboring points in the embedding space (Chechik et al., 2010). We, however, invert this loss and use it for an opposite purpose: privacy regularization. During the training of the language model, we select a "baseline sample", x, a positive sample p (with different sensitive label) and a negative sample n (with the same sensitive label) and feed them through the language model and extract the last hidden states h_x, h_p and h_n, respectively. We find the l_2 distance between h_x, h_p, and h_n and based on their labels, add them to or subtract them from the loss. To implement this, in practice, we sample a baseline batch and a second "auxiliary" batch during training. We feed both the baseline batch (x) and the auxiliary batch (a) through the language model and extract the last hidden states. We then calculate the distance between the last hidden states of the corresponding samples in the two batches. If the samples have different labels for the sensitive attribute (author), we add their distance to the loss, otherwise, we subtract it. The privacy loss becomes:

$$\mathcal{L}_{\text{LM-P}} = \sum_{i:y_{x_i}=y_{a_i}} \|h_{x_i} - h_{a_i}\|^2 - \sum_{j:y_{x_j}\neq y_{a_j}} \|h_{x_j} - h_{a_j}\|^2 \qquad (4)$$

3 Evaluation

In our experiments, we use a subset of the Avocado corporate email dataset (Oard et al., 2015) with 100 users and 60,000 samples and a subset of Reddit dataset (Völske et al., 2017) with 10,000 users and 3 million samples. Both of these datasets are in English, covering formal and informal writing. We create a $80/20\%$ training/test set split. We use a two-layer LSTM model as the language model for the next-word prediction task. We compare models trained with our proposed regularizer to differentially private (DP) ones (Abadi et al., 2016). For the privacy accounting, we use Gaussian differential privacy (Bu et al., 2019). We use language model perplexity as a measure of utility. Due to space limitations, we focus evaluations on privacy metrics for several set levels of achieved test perplexity, listed in Table 1 in the appendix. See appendix A.2 for a more detailed description of the experimental setup and extra analysis of overheads and complexity of each regularizer.

Privacy measurements w/ exposure metric. To empirically compare the privacy of our methods to that of DP, we adopt the exposure metric introduced in (Carlini et al., 2019). The higher the exposure of a sequence, the more the model's memorization and the easier it is to extract the sequence from the language model. To measure exposure we insert sequences of five random words (canaries) to the training data (appendix A.5). We insert unique



(a) Avocado - High PPL ($\sim$ 100)

(b) Avocado - Low PPL ($\sim$ 60)

(c) Impact on Different Subgroups

Figure 3: (a, b) Tab attack results for reconstructing canary sequences for two utility levels. Higher attack accuracy indicates lower privacy. (c) Effect of different mitigations on utility of well represented (Top-5) and under-represented (Low-5) users for Avocado dataset.

canaries with different repetitions for each user, and measure the exposure of these canaries.

Figure 2 shows the exposure results per canary repetition. These results are averaged over all the users. In each sub-figure, the perplexities of the models are similar, hence we can compare the privacy levels at similar utilities. Fig. 2a compares trained models using different techniques on the Avocado dataset, where they all have relatively high perplexities compared to a fully trained conventional model (Table 1). Fig. 2b has the same setup, however, the models have lower perplexities. Naturally, for having better utility we are trading off privacy, which can be seen by comparing the exposure values in these two figures and observing that the second one has higher exposure values (lower privacy). Finally, Fig. 2c shows the exposure results for Reddit.

In all cases, we see that the unmitigated model has the highest exposure, as expected. We also observe that for canaries (patterns) that are repeated more than 9 times (for each user), our mitigation offers lower exposure compared to DP, especially in the high perplexity case. This is because clipping and noise addition in DP is attribute and data-agnostic, meaning that noise is added to all samples regardless of whether or not they contain sensitive information. Therefore, repeated patterns are less protected. If we want to protect a pattern with n repetitions, we would need to apply noise that is $n\times$ larger, which would degrade the utility gravely and would not yield the same perplexity. For lower repetition canaries, our mitigations have comparable performance to DP. For all these experiments the Gaussian differential privacy criterion μ is extremely large (10^{20}), which practically yields $\epsilon \sim \infty$. We also experimented with lower ϵ values (e.g. $\epsilon \sim 7$), however, it yields a model with perplexity of 650, having an extremely low utility.

Privacy measurements w/ tab attack accuracy. In this experiment, we input the first token, and see if the entire sequence is reconstructed using the language model. We report the rate of correct reconstruction of canaries as the accuracy of the attack. We use the synthetic canaries from the previous experiment, and also select "real canaries" from the training corpus to create a real-world scenario. Fig. 3a shows that for a high perplexity model, the accuracy of the tab attack on synthesized canaries is very small, even for the unmitigated model. The unmitigated model reaches the designated perplexity in less than an epoch, and hence it does not memorize the canaries. For the real canaries, however, the memorization is higher, since they follow grammatical rules. In the lower perplexity case of Fig. 3b, we see that the synthesized canaries are mostly memorized by the unmitigated model. Our mitigations outperform DP, especially for the synthesized canaries. DP is not context-sensitive and applies the same amount of noise to all samples, thereby leaving correlated and higher repeated samples less-protected. Our mitigations, however, learn what sequences are link-able to their authors, and obfuscate them such that they no longer leak the "identifying" secret.

Effect on under-represented users. Differential privacy has disparate impact on the accuracy of different subgroups of the dataset (Bagdasaryan et al., 2019). Here, we want to measure the effect of our mitigations on the utility of the model among users with various data samples. For each user, we measure the average perplexity of the model for their samples in the test set, and then subtract this from the same value for an unmitigated model. This would yield the average drop in utility, per user. We compare the utility drop of well-represented users to under-represented ones by taking the top 5 users with the most samples and the bottom 5 users with the fewest samples from Avocado dataset. We then measure the average utility drop over each group of 5 users on the test set. Figure 3c shows these results. We see that differential privacy has disparate impact, 29 points, on the two sub-groups of users (authors), whereas this gap is only 7 points for models trained with our mitigations.

It's important to remember that in general, distinguishing "under-represented" users from those whose data is similar to others but who have contributed fewer samples is a difficult task. However, for Figure 3c's results, if these users' data came from the same distribution as the ones with lots of samples (i.e. if these people were merely less-contributing), the utility loss would be similar for all groups when applying "user-level" DP (what we use). DP's disparate impact on the utility loss for these two groups suggests that, in our case, the less-contributing authors are probably also under-represented.

4 Conclusion

This work introduces two privacy mitigation methods to jointly optimize for privacy and utility. Extensive experiments show that our approach provides comparable and in certain cases a higher level of privacy compared to differentially private model training. We further empirically demonstrate, that our methods do not exhibit disparate impacts on under-represented groups and have significantly less overhead on training performance.

Ethical Considerations

The Avocado corpus is licensed for research applications under strict terms intended to protect the privacy of the correspondents. While the end-user license agreement does not indicate what consent was granted by the participants, one term of the license is that "End user will obtain whatever training and approval is required by their organization for working with human subjects data", which we have obtained (more details in (Oard et al., 2015)). While handling sensitive email data (Avocado) we made sure to abide by the terms of its end-user license agreement (EULA) which has provisions to protect the privacy of members of the corpus. Furthermore, we took measures such as scrubbing named entities before using the data for model training. The over-arching goal of our work is to contribute to language model development that protects the privacy rights of users who contribute their data. While we rigorously evaluated our models by applying state-of-the-art attacks, deploying these models in real-world setups requires further verification that users' privacy is preserved.

Acknowledgments

The authors would like to thank the anonymous reviewers and meta-reviewers for their helpful feedback. We also thank Peter Kairouz and Mohammadkazem Taram for insightful discussions. Additionally, we thank our MSR colleagues and UCSD Berg Lab for their helpful comments and feedback.

References

Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. 2016. Deep learning with differential privacy. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, pages 308–318.

Martin Adam, Michael Wessel, and Alexander Benlian. 2020. Ai-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, pages 1–19.

Eugene Bagdasaryan, Omid Poursaeed, and Vitaly Shmatikov. 2019. Differential privacy has disparate impact on model accuracy. In *Advances in Neural Information Processing Systems*, volume 32, pages 15479–15488.

Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. *Journal of machine learning research*, 3:1137–1155.

Zhiqi Bu, Jinshuo Dong, Qi Long, and Weijie J. Su. 2019. Deep learning with gaussian differential privacy. *arXiv preprint*, abs/1911.11607.

Nicholas Carlini, Chang Liu, Úlfar Erlingsson, Jernej Kos, and Dawn Song. 2019. The secret sharer: Evaluating and testing unintended memorization in neural networks. In *28th USENIX Security Symposium*, pages 267–284, Santa Clara, CA. USENIX Association.

Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Ulfar Erlingsson, et al. 2020. Extracting training data from large language models. *arXiv preprint arXiv:2012.07805*.

Gal Chechik, Varun Sharma, Uri Shalit, and Samy Bengio. 2010. Large scale online learning of image similarity through ranking. *Journal of Machine Learning Research*, pages 1109–1135.

Mia Xu Chen, Benjamin N Lee, Gagan Bansal, Yuan Cao, Shuyuan Zhang, Justin Lu, Jackie Tsay, Yinan Wang, Andrew M Dai, Zhifeng Chen, et al. 2019. Gmail smart compose: Real-time assisted writing. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data*

Mining, KDD'19, page 196–206, New York, NY, USA. Association for Computing Machinery.

Maximin Coavoux, Shashi Narayan, and Shay B. Cohen. 2018. Privacy-preserving neural representations of text. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1–10. Association for Computational Linguistics.

Cynthia Dwork. 2006. Differential privacy. In *Proceedings of the 33rd international conference on Automata, Languages and Programming*, pages 1–12. Springer.

Tom Farrand, Fatemehsadat Mireshghallah, Sahib Singh, and Andrew Trask. 2020. Neither private nor fair: Impact of data imbalance on utility and fairness in differential privacy. In *Proceedings of the 2020 Workshop on Privacy-Preserving Machine Learning in Practice*, PPMLP'20, page 15–19, New York, NY, USA. Association for Computing Machinery.

GDPR Article 29 Working Party. 2014. Opinion 05/2014 on "anonymisation techniques". https://ec.europa.eu/justice/article-29/documentation/opinion-recommendation/files/2014/wp216_en.pdf.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9:1735–80.

Huseyin A. Inan, Osman Ramadan, Lukas Wutschitz, Daniel Jones, Victor Rühle, James Withers, and Robert Sim. 2021. Training data leakage analysis in language models. *arXiv preprint arXiv:2101.05405*.

Yitong Li, Timothy Baldwin, and Trevor Cohn. 2018. Towards robust and privacy-preserving text representations. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 25–30, Melbourne, Australia. Association for Computational Linguistics.

H Brendan McMahan, Galen Andrew, Ulfar Erlingsson, Steve Chien, Ilya Mironov, Nicolas Papernot, and Peter Kairouz. 2018. A general approach to adding differential privacy to iterative training procedures. *arXiv preprint*, abs/1812.06210.

T. Mikolov, Martin Karafiát, Lukas Burget, J. Cernocký, and S. Khudanpur. 2010. Recurrent neural network based language model. In *Proceedings of the 11th Annual Conference of the International Speech Communication Association*, pages 1045–1048.

Fatemehsadat Mirshghallah, Mohammadkazem Taram, Praneeth Vepakomma, Abhishek Singh, Ramesh Raskar, and Hadi Esmaeilzadeh. 2020. Privacy in deep learning: A survey. *arXiv preprint arXiv:2004.12254*.

Douglas Oard, William Webber, David Kirsch, and Sergey Golitsynskiy. 2015. Avocado research email collection. https://catalog.ldc.upenn.edu/LDC2015T03.

David Pujol, Ryan McKenna, Satya Kuppam, Michael Hay, Ashwin Machanavajjhala, and Gerome Miklau. 2020. Fair decision making using privacy-protected data. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, FAT* '20, page 189–199, New York, NY, USA. Association for Computing Machinery.

Swaroop Ramaswamy, Om Thakkar, Rajiv Mathews, Galen Andrew, H Brendan McMahan, and Françoise Beaufays. 2020. Training production language models without memorizing user data. *arXiv preprint arXiv:2009.10031*.

Nisarg Raval, Ashwin Machanavajjhala, and Jerry Pan. 2019. Olympus: sensor privacy through utility aware obfuscation. In *Proceedings on Privacy Enhancing Technologies*, pages 5–25. Sciendo.

R. Shokri, M. Stronati, C. Song, and V. Shmatikov. 2017. Membership inference attacks against machine learning models. In *2017 IEEE Symposium on Security and Privacy (SP)*, pages 3–18.

Congzheng Song and Vitaly Shmatikov. 2019. Auditing data provenance in text-generation models. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '19, page 196–206, New York, NY, USA. Association for Computing Machinery.

Pranav Subramani, Nicholas Vadivelu, and Gautam Kamath. 2020. Enabling fast differentially private sgd via just-in-time compilation and vectorization. *arXiv preprint arXiv:2010.09063*.

Florian Tramèr and D. Boneh. 2020. Differentially private learning needs better features (or much more data). *ArXiv*, abs/2011.11660.

Michael Völske, Martin Potthast, Shahbaz Syed, and Benno Stein. 2017. Tl;dr: Mining Reddit to learn automatic summarization. In *Proceedings of the ACL 2017 Workshop on New Frontiers in Summarization*, pages 59–63.

Tianlu Wang, Jieyu Zhao, Mark Yatskar, Kai-Wei Chang, and Vicente Ordonez. 2019. Balanced datasets are not enough: Estimating and mitigating gender bias in deep image representations. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5310–5319.

Xi Wu, Fengan Li, Arun Kumar, Kamalika Chaudhuri, Somesh Jha, and Jeffrey Naughton. 2017. Bolt-on differential privacy for scalable stochastic gradient descent-based analytics. In *Proceedings of the 2017 ACM International Conference on Management of Data*, SIGMOD '17, page 1307–1322, New York, NY, USA. Association for Computing Machinery.

S. Yeom, I. Giacomelli, M. Fredrikson, and S. Jha. 2018. Privacy risk in machine learning: Analyzing the connection to overfitting. In *2018 IEEE 31st Computer Security Foundations Symposium (CSF)*, pages 268–282.

A Appendix

A.1 Language Models

Language models assign a probability distribution over a sequence of words. A statistical model for a sequence of words $x_1 \dots x_n$ can be represented by the product of the conditional probability of the next word given all the previous words as $\Pr(x_1 \dots x_n) = \prod_{i=1}^{n} \Pr(x_i | x_1 \dots x_{i-1})$. Here $\Pr(x_i | x_1 \dots x_{i-1})$ denotes the probability of the occurrence of word x_i given the previous word sequence $x_1 \dots x_{i-1}$. Recurrent Neural Networks (RNNs) are widely used for this task (Bengio et al., 2003; Mikolov et al., 2010) as RNNs can process variable-length input by processing words one at a time, updating its internal state and predicting the next word sequentially. Therefore, such variable-length conditional distributions can be effectively estimated with RNNs. In this work we use LSTMs (Hochreiter and Schmidhuber, 1997) in our language model.

A.2 Experimental Setup

We use a subset of the Avocado dataset (Oard et al., 2015) with 100 users and 60,000 samples. We also use a subset of Reddit dataset (Völske et al., 2017) with 10,000 users and 3 million samples. For both datasets, we fix the vocabulary to the most frequent 40,000 tokens in the training corpus, and we create a $80/20\%$ training/test set split. We use a two-layer LSTM model as the language model for the next-word prediction task. We set both the embedding dimension and LSTM hidden-representation size to 550 (with 55 million parameters). We use a feed-forward two fully connected layer neural network with hidden dimension of 1000 as the author discriminator for the adversarial training regularization scheme.

For optimization, we use the Adam optimizer with the learning rate set to 1e-3 and batch size to 100. We trained our models on a single Titan Xp GPU accompanied by 12GBs of RAM, and two Intel Xeon E5-2620 CPUs with 256 GBs of RAM. Table 1 shows the perplexity of the models used in the evaluations.

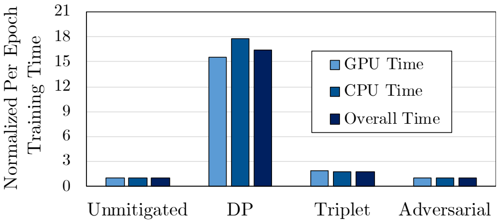


Figure 4: Per epoch training time break down, normalized to conventional execution. Differential privacy is 16.44× slower than conventional execution. Triplet and Adversarial are our proposed regularizations.

Table 1: Training and test perplexities of the models used in the evaluations.

Dataset		Unmitigated	DP	Adversarial (ours)	Triplet (ours)
Avocado	Training	93.5	94.2	104.7	101.4
(High PPL)	Test	103.5	93.5	96.6	96.5
Avocado	Training	36.8	63.8	56.7	54.8
(Low PPL)	Test	51.3	69.8	69.1	69.1
Reddit	Training	107.5	110.3	106.7	106.4
	Test	97.3	97.4	98.2	97.6

A.2.1 Batching Strategy

Our mitigations can be implemented using different batching strategies during training: uniform batches that contain training samples from different users, or per user batches that contain training samples from only a given user. Through experimentation, we observed that the second method performs better and we present our results under the second batching strategy. The better performance is due to the fact that grouping the same users together and increasing the probability of samples from same people being placed in corresponding positions in a batch, helps the discriminator (in the adversarial training scheme) learn user (author) patterns faster. It also helps the triplet-based scheme to more efficiently distance samples from the same user. This scheme we increases the probability that the auxiliary batch is selected from the same user's data, compared to randomly selecting two uniform batches. This helps better distribute one user's data in the embedding space.

A.3 Overhead and Complexity Analysis

A.3.1 Training Time Measurements

Here we compare the training time of our proposed regularizations to differential privacy. Figure 4 shows the breakdown of the CPU and GPU (CUDA) time for our two proposed methods, and differential privacy, normalized to the conventional unmitigated execution time. The results show that differential privacy is extremely slower than our mitigations. Our adversarial training mitigation is overall only 1.06× slower than conventional training, and our triplet-based mitigation is $1.80\times$ slower due to the need to process an auxiliary batch in each batch. The reason that our triplet-based mitigation is slower than the adversarial one is that the triplet based loss runs two batches through the language model during each iteration (the baseline batch and the auxiliary), whereas the adversarial training scheme runs only one batch of training data. Differential privacy, however, is $16.44\times$ slower than conventional execution, which is due to its per-sample gradient computation, which limits the possibility of parallelism. It is noteworthy that in our experiments, we have applied the training time optimization suggested in (McMahan et al., 2018) for differential privacy, which increases parallelism through the use of "micro-batches". However, even with this optimization, we are still observing huge slow-downs. Furthermore, differentialy private training of DNNs and RNNs takes exhaustive hyperparameter tuning to get the best privacy-utility trade-off, which is cumbersome (Wu et al., 2017; Mirshghallah et al., 2020), and this slow training process makes the tuning of the parameters extremely harder.

A.4 Added Parameters and Complexity

Our **adversarial training** regularization includes an additional feed-forward discriminator DNN to predict the author of each sequence, as shown in Figure 1. In our experiments, we use a feed-forward network with two fully connected layers and a hidden dimension of 1000. The input dimension is the same as the hidden state dimension of the language model (550) and the output dimension is the number of authors, 100 for Avocado, and 10,000 for Reddit dataset. This means that the discriminator parameters scale-up with the number of authors. For the Avocado case, this would give $550 \times 1000 + 1000 * 100 = 650K$ extra parameters (compared to conventional training), and for Reddit it would be $550 \times 1000 + 1000 \times 10,000 = 10.55M$ parameters. This is comparatively reasonable considering the number of parameters in the language model (55M) as a tradeoff to improve the privacy of the model. It would be interesting to explore whether reducing the number of hidden dimensions of the discriminator as the number of users increase would be effective to balance the number of parameters our *adversarial method* adds to the parameters of the network.

Our **triplet-based** regularization does not add any extra parameters to the model, which might be advantageous for settings with massive number of users. It does, however, need to feed an auxiliary batch to the language model, alongside the baseline batch which almost doubles the training time.

Figure 4 and Section A.3.1 show the break-down of the training time of DP training, our triplet-based method, and our adversarial method, compared to unmitigated training time. Differential privacy does not add any additional complexity in terms of parameters. However, it adds computational complexity by having to compute the gradients of each sample separately, thereby not exploiting the batch processing parallelization offered by GPUs. This in turn slows down the training procedure extremely, making hyperparameter search infeasible for large networks.

A.5 Exposure Metric

To empirically compare the level of privacy provided by our methods to that of a DP model, we adopt the exposure metric introduced in (Carlini et al., 2019). This metric measures the extent to which a model memorizes samples in the training data. The higher the exposure metric for a sequence, the more the model's memorization and the easier it is to extract the sequence from the language model through text generation algorithms. To measure exposure we insert canaries to the training data. Our canaries are sequences of five random words from the vocabulary. We insert canaries with different repetitions for each person. For Avocado dataset, each user (author) is assigned 14 unique canaries, each of them repeated $[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50]$ times. We insert canaries with repition to mimic "secrets" that belong only to a certain user, but might be repeated by that user in multiple emails/texts. This means each user is assigned and overall of $1 + 2 + 3 + ... + 50 = 195$ canaries. This yields and overall of $195 \times 100 = 19500$ canaries injected to the data. This data is then used to train the model. Once the model is trained, we can then measure the exposure of a given canary, by finding the probability assigned to it by the language model, and then finding the rank of that sequence by by sorting all probabilities assigned to all possible sequences of the same length. Carlini et al. provide a method to estimate the rank for each sequence without having to actually enumerate and feed all possible sequences to the model and actually ranking all of them. Once we have measured the exposure metric for all canary sequences, we can use them to evaluate the privacy.

For Reddit dataset, each user is assigned 5 unique canaries, with repetitions of $[1, 2, 5, 6, 20]$ times. We use less canaries in the latter so as not to contaminate the dataset as the Reddit dataset has less samples per user. The "real canaries" introduced in the experiments are chosen by feeding all the training data through an unmitigated model, and selecting the sample with highest perplexity for each user. We hypothesize that these sequences are more likely to contain sensitive information.