Selective Differential Privacy for Language Modeling

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Abstract

With the increasing adoption of language models in applications involving sensitive data, it has become crucial to protect these models from leaking private information. Previous work has attempted to tackle this challenge by training RNN-based language models with differential privacy guarantees. However, applying classical differential privacy to language models leads to poor model performance as the underlying privacy notion is over-pessimistic and provides undifferentiated protection for all tokens of the data. Given that the private information in natural language is sparse (for example, the bulk of an email might not carry personally identifiable information), we propose a new privacy notion, selective differential privacy, to provide rigorous privacy guarantees on the sensitive portion of the data to improve model utility. To realize such a new notion, we develop a corresponding privacy mechanism, Selective-DPSGD, for RNN-based language models. Besides language modeling, we also apply the method to a more concrete application – dialog systems. Experiments on both language modeling and dialog system building show that the proposed privacy-preserving mechanism achieves better utilities while remaining safe under various privacy attacks compared to the baselines. The data, code and models are available at https://github.com/wyshi/lm_privacy.

1 Introduction

Language models have been widely used in various kinds of applications, such as Google Smart Compose, Amazon Alexa, and so on. However, these models are often trained on highly sensitive data such as emails and chat logs, while having the tendency to memorize the training data unintentionally without proper privacy protection mechanism in place (Carlini et al., 2019, 2020). Therefore, how to protect user privacy while preserving the model utility has become an increasingly important topic. Several methods have been developed to protect the data, such as data sanitization, k-anonymity, and differential privacy (DP). Among them, DP has become a dominant privacy notion as it provides formal and provable guarantees for people to understand the privacy-utility trade-off. It works by carefully randomizing the algorithm so that the model does not rely too much on any single data point. However, traditional differential privacy protects each data point as a whole regardless the property of individual attributes inside the data (McMahan et al., 2018). Training large models with this overly pessimistic privacy notion could lead to poor model performance or even non-convergent training process (Kerrigan et al., 2020). Our work is inspired by an important observation that in many scenarios including language modeling, private information is sparse, and not all attributes need to be protected. For example, for the sentence “My SSN is 123-45-6789”, only the last token with the actual SSN number needs to be protected. But if we protect the entire sentence, we may fail to learn the underlying language pattern well.

To solve this problem, we propose a new notion, namely selective differential privacy or S-DP, to provide focused protection for sensitive tokens and improve model utility. Whether a given type of attribute is sensitive is specified by a predefined policy function which encodes relevant privacy policies and regulations. We also develop a corresponding privacy mechanism, Selective-DPSGD, for RNN-based language models under the new privacy notion. The basic idea is to apply regular stochastic gradient descent (SGD) on the non-sensitive tokens and DPSGD (Abadi et al., 2016) on the sensitive tokens. Furthermore, to address the variable-length sequences in language modeling, we propose a batching method to group private and public tokens from one batch together and alternatively update them for more efficient implementation of Selective-DPSGD.
We evaluate our approach on two tasks, 1) a language generation task and 2) a more concrete application of dialog system in a synthesized customer service domain. Since S-DP is different from canonical differential privacy, besides reporting the model utility and theoretical privacy guarantees, we also empirically demonstrate their robustness under popular privacy attacks on language data (Carlini et al., 2019, 2020). The experiments suggest that training with Selective-DPSGD improves the model utility while remaining safe to the attacks.

Our contributions are as follows. First, we propose a new selective differential privacy notion that ensures targeted privacy protection for sensitive attributes. Second, we develop a new privacy mechanism to realize the new S-DP privacy notion for RNN-based language models. Further, we show both theoretically and practically that our models are safe to attacks with improved utilities on both the language generation task and the dialog system application. The synthesized dialog dataset, code and models will be made public to help future research. In the era of information explosion and large-scale pretraining, protecting data privacy becomes more and more important. With S-DP, we march one step closer towards more privacy-preserving and performant language models and hope to inspire more research in this direction in the NLP community. Furthermore, despite our focus on language-related applications in this paper, the proposed selective privacy notion could be useful for a much broader range of applications where only partial data require privacy protection.

2 Related Work

Natural language generation is a fundamental problem in natural language processing. At its core, it builds a language model that predicts the next tokens given the context. Previously, recurrent neural networks (RNN) were used to train language models given its strong ability to memorize context (Hochreiter and Schmidhuber, 1997; Mikolov et al., 2010; Chung et al., 2014). More recently, large-scale Transformer-based language models have achieved huge success in all sorts of NLP tasks (Vaswani et al., 2017; Devlin et al., 2018; Radford et al., 2019). However, although language models are often trained on sensitive data such as emails, most related studies have focused on improving model performance rather than protecting the data, leaving the models vulnerable to attacks.

For example, Carlini et al. (2019) showed that it is possible to infer a secret in the training data by attacking the published language model. Therefore, it is of great importance to introduce privacy protection mechanism to the NLP community and train the models in a much safer way.

Differential privacy (Dwork et al., 2014) has been applied to many areas to protect the data, such as health care (Dankar and El Emam, 2013), control systems (Cortés et al., 2016) and census study (Abowd, 2018). Abadi et al. (2016) introduced DPSGD to train deep-learning models with privacy guarantees and applied moment accountant to calculate cumulative privacy loss during training. PATE (Papernot et al., 2018) proposed to leverage knowledge distillation to train differentially private model, assuming the access to a large public dataset similar to private data. But differentially private algorithms, especially deep-learning-based ones, suffer from low utility, so the definition of differential privacy often needs to be adjusted according to the specific applications. For example, Ebadi et al. (2015) proposed personalized differential privacy to provide different levels of privacy protection for various users. Doudalis et al. (2017) developed one-sided differential privacy to protect sensitive users only. Different from canonical DP that protects the entire record of a user, we propose a new privacy notion to protect privacy for the sensitive attributes of the record to improve the model utility.

Recently, differential privacy has also been applied to natural language processing tasks (McMahan et al., 2018; Fernandes et al., 2019; Kerrigan et al., 2020; Xu et al., 2020; Ramaswamy et al., 2020). For example, McMahan et al. (2018) proposed DP-FedAvg and DP-FedSGD to train RNN language models with user-level privacy guarantees. Melamud and Shivade (2019) worked towards generating synthetic clinical notes with DP while preserving the training data privacy. Adelani et al. (2020) developed a probabilistic text de-identification algorithm with formal privacy guarantees, and formulated various redaction strategies. Different from existing work that directly applied DPSGD and provided undifferentiated protection for all training examples, we propose a new privacy notion and a corresponding mechanism to protect privacy for the sensitive portion of the data and improve the model utility in centralized learning. Such a new notion can be easily adopted to federated learning settings as well.
There is also a line of work that attempts to improve differentially private deep learning performance via modifying training process (Wang et al., 2021, 2019; Thakkar et al., 2019; Lee and Kifer, 2020) or model architecture (Papernot et al., 2020). Our work is complementary to this line of work as we propose a new privacy notion. Particularly, our work can be combined with the aforementioned methods to further improve model utility.

3 Backgrounds

We will introduce language modeling, and differential privacy as preliminaries in this section.

Language Modeling. Consider a text sequence that consists of multiple tokens, i.e., \( x = (x_1, x_2, \ldots, x_n) \), where \( x_i \) is the \( i \)-th token. The goal of language modeling is to learn the probability of the sequence \( p(x) \), which can be factorized with the chain rule as in Equation (1). Given a corpus \( D = \{x^1, \ldots, x^{|D|}\} \), we train a neural network (e.g., RNN) parameterized by \( \theta \) to learn \( p(x) \) by minimizing the negative log-likelihood over \( D \) with the loss function in Equation (2).

\[
p(x) = \prod_{i=1}^{n} p(x_i|\mathbf{x}_{<i}), \tag{1}
\]

\[
\mathcal{L}(D) = -\sum_{t=1}^{|D|} \sum_{i=1}^{n_t} \log p_{\theta}(x_i^t|\mathbf{x}_{<i}^t) \tag{2}
\]

Differential Privacy (DP). A differentially private algorithm ensures that its output cannot help much to distinguish whether or not an individual record is contained in the input dataset. In other words, DP hides the presence of individual records. The formal definition is as follows.

Definition 1. (Differential Privacy (Dwork et al., 2014)). Given a domain \( D \), any two datasets \( D, D' \subseteq D \) that differ in exactly one record are called neighboring datasets. A randomized algorithm \( \mathcal{M} : D \rightarrow \mathcal{R} \) is \((\varepsilon, \delta)\)-differential private if for all neighboring datasets \( D \) and \( D' \) and all \( T \subseteq \mathcal{R} \),

\[
\Pr[\mathcal{M}(D) \subseteq T] \leq e^\varepsilon \Pr[\mathcal{M}(D') \subseteq T] + \delta.
\]

4 Selective Differential Privacy

Canonical DP treats all records as sensitive. Prior work has studied variants of DP, such as personalized DP (Jorgensen et al., 2015) and one-sided DP (Doudalis et al., 2017), to take advantage of different privacy levels between records. However, existing privacy notions do not allow different attributes in a given record to have different privacy levels, which could otherwise potentially enable additional utility gains, especially for NLP tasks. Hence, we propose a new privacy notion—selective differential privacy—to distinguish between private and non-private attributes inside one data point with a policy function and protect sensitive part of one data point.

Definition 2. (Policy Function). A policy function \( F : \tau \rightarrow \{0, 1\}^{n_r} \) denotes which attributes of a record \( r \in \tau \) are sensitive \((F(r)_i = 0)\) or non-sensitive \((F(r)_i = 1)\), where \( n_r \) is the number of attributes in \( r \). Note that \( n_r \) depends on the record and is not a fixed number.

In practice, policy functions can be derived from pre-existing privacy policies, regulations, or people’s common perception as to which types of attributes should be classified as sensitive.

In the case of language modeling, each record is a text sequence \( x \), each attribute is a single token \( x_i \) in that sequence and \( F(x) \) is a bit vector indicating which tokens contain private information. We define neighboring datasets under our new privacy notion as follows.

Definition 3. (F-Neighborhoods). \( D, D' \) are two datasets and \( F \) is a policy function. \( D' \) is a \( F \)-neighbor of \( D \) if and only if \( \exists r \in D \) s.t., \( F(r) \) contains at least one private attribute, \( \exists r' \in D' \) s.t., \( F(r) \) and \( F(r') \) differ by at least one private attribute, and \( D' = D \setminus \{r\} \cup \{r'\} \). We denote \( D' \in N_F(D) \).

Under this definition, the dataset containing “My ID is 123” and the dataset containing “My ID is 456” are neighbors; but the dataset with “Hello there” and the dataset with “Hi there” are not neighbors since they do not contain private information.

Definition 4. (Selective Differential Privacy). Given a policy function \( F \), a randomized algorithm \( \mathcal{M} : D \rightarrow \mathcal{R} \) satisfies \((F, \varepsilon, \delta)\)-selective differential privacy if for all \( D \) and \( D' \in N_F(D) \), and all \( T \subseteq \mathcal{R} \),

\[
\Pr[\mathcal{M}(D) \subseteq T] \leq e^\varepsilon \Pr[\mathcal{M}(D') \subseteq T] + \delta.
\]

Essentially, S-DP provides an indistinguishability property similar to canonical DP, but only for the sensitive attributes. S-DP does not constrain the information leakage of nonsensitive attributes as long as the privacy of the sensitive attributes is preserved.
4.1 Selective Privacy Mechanism

With the privacy notion, the next step is to develop a corresponding privacy mechanism to train models that realize such notion. Privacy mechanisms usually works by adding noise to the models to protect the data from attacks, such as Laplace mechanism (Laplace noise) and Gaussian mechanism (Gaussian noise). Abadi et al. (2016) proposed DPSGD that adds Gaussian noise to the gradients and applies stochastic gradient descent (SGD) to train private deep learning models. In this work, we develop Selective-DPSGD, shown in Figure 1 and Algorithm 1, to train RNN-based language models that achieves S-DP. The basic idea is to first determine the private attributes with the policy function, then decide which model variables are related to the private attributes, and finally apply regular SGD on non-private variables, and DPSGD (Abadi et al., 2016) on the private variables.

We need to first decide which variables are related to the private tokens. RNN uses a hidden state $h_i$ to encode the context, and outputs a distribution $p_i$ over a vocabulary set $V$, as shown in Equation (3). If $x_i$ is private, then $h_i$, $p_i$, and $L_i$ are all private; besides, to calculate $L_{i-1}$, we need to access the ground truth next token $x_i$, so $L_{i-1}$ is also private. The private variables are all in red in Figure 1.

$$h_i = RNN(h_{i-1}, x_i) \tag{3}$$
$$p_i = p_{\theta}(V|\langle x < i \rangle) = softmax(g(h_i)) \tag{4}$$
$$L_i = -log p_{\theta}(x_{i+1}|\langle x < i+1 \rangle) \tag{5}$$

Algorithm 1 outlines the steps in Selective-DPSGD. Given a dataset $D$, we apply a policy function $F$ to obtain a bit matrix $P = F(D)$ that indicates which tokens are private. At each step, we take a random batch $B$, and use $P$ to split $B$ into a sequence of non-private and private tuples $\{(B_{np,i}, B_{p,i})\}$; then we apply SGD (regular update) on $B_{p,i}$ and DPSGD (private update) on $B_{np,i}$ alternatively, to update and protect privacy. Note that besides noise in the gradients, we also clip and add noise to the hidden state $h_i$ if it is private. The reason is that in RNN, if $x_i$ is private, $h_i$ also contains private information (as shown above), and is directly passed to the next regular update step and cannot be protected by the noise in the gradients. So it is important to add noise to protect the private information in $h_i$. Since DPSGD adds noise to the gradients, $L$ and $p_i$ used to calculate the loss are protected by the noise in the gradients. In this way, all private variables are protected. In the next section, we will prove that the composition of the series of noise adding operations ensures S-DP for the overall algorithm.

![Figure 1](image)

**Figure 1:** All private variables are in red. We apply regular SGD on non-private variables and DPSGD on private variables in Selective-DPSGD.

**Algorithm 1 Selective-DPSGD**

1: **Input:** Dataset $D$ with $N$ examples, policy function $F$, privacy bit matrix $P = F(D)$, max sequence length $K$, loss function $L(h)$. Parameters: learning rate $\eta$, noise multiplier $\sigma$, gradient norm bound $C$, group size $L$.

2: for $t=1,2,...$ do
3: Take a random batch $B$ of max sequence length $K$, with sampling probability $L/N$
4: Using $P$, split $B$ into a sequence of non-private and private tuples $\{(B_{np,i}, B_{p,i})\}$
5: Initialize $h = 0$
6: for $i=1,2,...$ do
7: 1) Regular update
8: $L, h = Model(B_{np,i}, h)$
9: $\theta \leftarrow \theta - \eta \nabla_\theta L(\theta)$
10: 2) Private update
11: $L, h = Model(B_{p,i}, h)$
12: Calculate sample gradient
13: For each $x_j \in B_{p,i}$, compute $g(x_j) \leftarrow \nabla_\theta L(\theta, x_j)$
14: Clip gradient
15: $g(x_j) \leftarrow g(x_j) / \max(1, \|g\|_2)$
16: Add Noise
17: $g(x_j) \leftarrow \frac{1}{|B_{p,i}|} (\sum_j g(x_j) + \sigma C \cdot N(0, I))$
18: Descent
19: $\theta \leftarrow \theta - \eta \nabla_\theta L(\theta)$
20: Clip hidden states
21: $h(x_j) \leftarrow h(x_j) / \max(1, \|h\|_2)$
22: Add Noise
23: $h(x_j) \leftarrow h(x_j) + \sigma C \cdot N(0, I)$
24: end for
25: end for
4.2 Privacy Analysis

We analyze the private guarantees of Selective-DPSGD in this section.

For any given dataset $D$, let $D_{i,j}$ denote the $j$th attribute of the $i$-th record. We abstract the gradient update and hidden state into a query function $f(x, w)$ which takes training data $x$ and auxiliary information $w$ as input. We introduce $w$ as an additional input to $f$ to model the dependence of the gradient update and hidden state on the model parameters at the previous rounds. We define the following two types of queries on the dataset.

- **Type-1 query**: the input $x$ to $f$ consists of only private attributes with respect to the policy function $F$.
- **Type-2 query**: the input $x$ to $f$ consists of only non-private attributes with respect to the policy function $F$.

Since S-DP only hides the presence of private attributes, type-2 query does not incur privacy loss.

The following theorem shows that if a type-1 query has the property that its output is bounded, then for arbitrary auxiliary input, adding Gaussian noise into the query can provide DP. The reason why we consider such queries is that clipped gradient and hidden state can be modeled as such queries. The reason for which we want to analyze DP guarantees under arbitrary auxiliary inputs is that at any given round, the model parameters resulting from previous rounds could be arbitrarily different. This is because the non-sensitive part of two $F$-neighboring datasets could be arbitrarily different.

**Theorem 1.** Assume that $\max_{x, w} ||g(x, w)|| \leq C$. Then, for any arbitrary $w$, adding Gaussian noise $\Delta = N(0, \sigma^2)$ proportional to $C$ into $g$ can ensure $(\epsilon, \delta)$-DP where $\epsilon, \delta$ depends on $C$ and $\sigma$. More formally, for all neighboring datasets $x$ and $x'$ and all $w, w'$,

$$\frac{P[g(x, w) + \Delta = r]}{P[g(x', w') + \Delta = r]} \leq e^{\epsilon} \text{ w.p. } 1 - \delta \quad (6)$$

The proof follows directly from the classic proof for DP guarantees of the Gaussian mechanism (Mironov, 2017; Dwork et al., 2014) by noticing the sensitivity of $f$ is bounded by $C$.

The regular updates in Algorithm 1 take as input non-private data $B_{np,i}$. Hence, they are type-2 queries and do not incur extra privacy loss. The private updates in Algorithm 1 (i.e., gradient and hidden states) depend on private attributes and model parameters from previous rounds, and thus belong to the type-1 query. Moreover, they satisfy the bounded norm assumption in Theorem 1. We call the resulting query of adding Gaussian noise into a type-1 query with bounded norm property a noisy type-1 query. Overall, Algorithm 1 is essentially the composition of multiple type-1 and noisy type-2 queries. In the following, we will present a general result for the privacy guarantees resulting from the composition.

**Theorem 2.** Let $f$ be the composition of $k$ queries: $f_1, \ldots, f_k$, which are either noisy type-1 or type-2 queries. Given a policy function $F$, let $f_p$ denote the set of noisy type-1 queries. Let $f_{np}$ denote the set of type-2 queries. Then, if $f_p$ is $(\epsilon, \delta)$-DP, $f$ is $(F, \epsilon, \delta)$-SDP.

**Proof.** Please refer to Section A.1 for the proof. □

Instantiating the type-1 and type-2 queries in Theorem 2 with the regular and private updates defined in Algorithm 1 yields the privacy guarantees for Algorithm 1. Theorem 2 provides a convenient way of calculating the S-DP guarantees for Algorithm 1: one can apply off-the-shelf privacy composition tools to calculate the overall DP guarantees for all the private updates and then the entire algorithm satisfies S-DP with the same values of $\epsilon$ and $\delta$. Specifically, in this paper, we leverage moment accountant (Abadi et al., 2016) to calculate the DP guarantees for the composition of all privacy queries.

5 Experiments

We conduct our experiments on two datasets: 1) a traditional text corpus for language modeling, and 2) a dialog dataset for a more concrete application of dialog system. Below are the dataset details.

**WikiText-2.** To minimize real-world harm, we choose the already-public WikiText-2 (Merity et al., 2017). It contains articles from Wikipedia with potentially sensitive information, and is a classical dataset for language modeling. For simplicity, we treat all the digits as privacy information. So the policy function $F$ is a digit detector: if the token is a digit, $F$ will output 0, otherwise, 1.

**CUSTOMERSIM.** With the emergence of virtual assistants, more and more private information are being exchanged during daily interactions between the user and the assistant. Therefore, we also apply S-DP to a concrete application of dialog system in customer service domain with practical values.
Using real dialog transcripts may lead to potential real-world harm, so we simulate a dialog dataset called CUSTOMERSIM with synthetic user information. The dialog flow is simulated based on a fixed agenda and the language generation is template-based (Zhao and Eskenazi, 2018). We treat user names, address, phone number, order and tracking number as sensitive information, and use regex to build a policy function to detect them. Table 2 in Appendix shows one example dialog.

**Model training details.** We use one-layer LSTMs with an embedding size of 200 and a hidden size of 200. We use a Byte-Pair Encoding (BPE) tokenizer (Sennrich et al., 2016) instead of a traditional word tokenizer to avoid information leakage from the tokenizer: with BPE, a secret “1234” will be split into multiple tokens, e.g., “12” and “34”, while traditional tokenizer will release “1234” as a single token in the dictionary.

**Baselines.** We have two baselines, one without DP (denoted by “No-DP”), and the other trained with DPSGD (denoted by “DPSGD”). We refer to our models trained with S-DPSGD as “S-DPSGD”. “No-DP” is simply an LSTM optimized with a regular SGD and a starting learning rate of 20. “DPSGD” is optimized with DPSGD and a starting learning rate of 0.05. All the models are trained five times to reduce randomness, and the parameters are tuned based on the validation set performance.

### 5.1 Evaluation

We need to evaluate both the language models’ utilities and privacy guarantees. We use perplexity (PPL) and the top-1 next word prediction accuracy (AccT1) for model utility. Besides reporting the theoretical privacy budget $\epsilon$ and $\delta$, we also perform various practical attacks on the trained models to test if they are robust under attacks detailed below.

#### 5.1.1 Attack Details

We perform two types of attacks: 1) canary insertion and 2) membership inference.

**Canary insertion** is proposed by Carlini et al. (2019). It first inserts random sequences called canaries into the training dataset, then trains the model, and finally calculates the following exposure for the inserted canaries to measure if the model will unintentionally memorize these canaries. Canaries are of a specific format, e.g., s="The number is 00000000", where 0 are filled with random values from a randomness space $R$ such as a space of digits from 0 to 9. To obtain the exposure, we enumerate all possible sequences in the specified form, and calculate the negative log-rank with an additional constant, as shown below. Lower exposure indicates the model is more private. In our setting, we insert the secret “My ID is 341752” into the training data for 10 times to make the differences between models more salient.

**Definition 5.** Given a canary $s[r]$, a model with parameters $\theta$, and the randomness space $R$, the exposure of $s[r]$ is

$$\text{exposure}_\theta = \log_2 |R| - \log_2 \text{rank}_\theta(s[r])$$

**Membership Inference** is a widely used attack method which identifies if a given sample is a member of the training dataset. Carlini et al. (2020) proposed an advance membership inference attack for language models. The basic idea is to calculate the given samples’ perplexities under the model, rank them and choose the ones with the lowest perplexities, i.e., highest likelihood by the model. In our experiments, we randomly select 500 protected secrets from the training set, and randomly generate 500 samples of similar format, to form a dataset for the membership inference attack, so a random guess would give us an accuracy of 50%. For WikiText-2, since we protect digits, the secrets are digit sequences; for CUSTOMERSIM, we choose customer names as the secrets.

### 6 Results

#### 6.1 WikiText-2 Results

**Model utility and privacy guarantee.** The left part of Table 1 shows different models’ utilities and privacy guarantees on WikiText-2 and Figure 2(a) shows the validation perplexities over epochs. The black line is for the regular No-DP model, and achieves the best average perplexity of 60.98 on the test set. The orange line is for our S-DPSGD model, and achieves the second best average test perplexity of 160.04 with $\epsilon = 4.91$. With a similar $\epsilon = 4.89$, DPSGD has the worst average test perplexity of 305.86, much worse than S-DP because canonical DP notion protects the whole data and is over-pessimistic (for models with different parameters, please refer to Section A.3). Since the privacy notion in use is different for DPSGD and S-DPSGD, it is not fair to directly compare $\epsilon$, and we need to compare the attack performance.

**Attack results.** Figure 2(b) and 2(c) show the canary insertion attack and membership inference.
Table 1: Model utility and privacy guarantee on WikiText-2 (left) and CUSTOMER SIM (right). PPL: Perplexity on the test set. AccT1: Top-1 next word prediction accuracy. σ: Noise multiplier in the Gaussian noise. C: Clipping threshold. ε, δ: Privacy guarantee in (ε, δ)-privacy.

| Model       | WikiText-2 | CUSTOMER SIM |
|-------------|------------|--------------|
|             | PPL        | AccT1 | σ | C | ε | δ | PPL  | AccT1 | σ | C | ε | δ |
| LSTM, No-DP | 60.98 ± 0.48 | 0.36 ± 0.00 | - | - | - | - | 3.06 ± 0.01 | 0.75 ± 0.00 | - | - | - | - |
| DPSGD       | 305.86 ± 3.00 | 0.27 ± 0.00 | 0.50 | 0.10 | 4.89 | 8e-5 | 11.82 ± 0.76 | 0.70 ± 0.01 | 0.60 | 0.01 | 2.51 | 8e-5 |
| S-DPSGD     | 160.04 ± 4.86 | 0.31 ± 0.00 | 0.50 | 1e-3 | 4.91 | 8e-5 | 10.42 ± 0.91 | 0.69 ± 0.01 | 0.70 | 5e-3 | 2.74 | 8e-5 |

Figure 2: Learning curve, canary insertion attack and membership inference attack on WikiText-2.

attack results on WikiText-2 respectively. The x-axis is the models’ utilities measured by validation perplexity, and the y-axis is the exposure and membership inference accuracy indicating the success level of the attacks. Lower exposure and lower accuracy mean that the model is safer. We want to see with the same model utility, which models are more robust to the attacks.

For canary insertion attack, we see that for the No-DP baseline without any protection, although it achieves lower perplexity, the exposure can go up to 20, indicating that the inserted canary could be easily revealed by the attackers. If we compare No-DP with S-DPSGD with similar utilities, S-DPSGD are always below No-DP, meaning S-DPSGD achieves much smaller exposure, and hence a safer model with similar utility. The exposures of DPSGD and S-DPSGD are comparable, but S-DPSGD achieves much better model utility.

For membership inference attack, we draw a horizontal line of 0.5, indicating the random guess performance. Again, S-DPSGD are always below No-DP, showing that models trained with S-DPSGD are safer than No-DP with similar utilities under the membership inference attack. Comparing DPSGD and S-DPSGD, we see that although the inference accuracy is slightly lower for DPSGD when perplexity is larger (>500), the utilities of these models are too bad to be useful, and S-DPSGD improves the model utility by a large margin while remaining safe to the attack. We also observe that if the model is not protected at all, the inference accuracy can go up to 90%, suggesting that language models without DP protection are vulnerable to attacks.

6.2 CUSTOMER SIM Results

Results on CUSTOMER SIM are slightly different. Model utility and privacy guarantee. The right part of Table 1 and Figure 3(a) show the utility and privacy budget for CUSTOMER SIM. Because the dialogs are simulated with templates and relatively simple, the perplexity can be as low as 3.06 for No-DP. S-DPSGD still achieves better perplexity than DPSGD (10.42 vs. 11.82) with similar ε, but the gap is smaller compared to WikiText-2 because there are more sensitive tokens in CUSTOMER SIM (18.3%) than WikiText-2 (2.8%), and the advantage of protecting selective tokens only is not as big.

Attack results. Figure 3(b) and 3(c) show the results of the canary insertion and membership inference attack on CUSTOMER SIM respectively.

For canary insertion, we observe that given the same utility, S-DPSGD achieves lower exposure than No-DP and DPSGD. Although the improvement seems small on absolute values, we should note that exposure is on log-scale, so the improvement on relative rank is also on log-scale (e.g., for exposure=1.2, the rank of the canary is 429881; for
The original membership inference attack doesn’t achieve good results (Figure 6 in Appendix) on CUSTOMERSIM, so we employ a more advanced version, where we first perform the attack on 1000 names, and then pick the best-predicted and worst-predicted names to form a new subset of 300 names to perform the attack again. But even for the advanced version, the inference accuracy is only a little better than random guess probability (60+%), so this attack is not successful on CUSTOMERSIM. One potential reason could be that customer names only appear once in each dialog and can be very similar to each other (e.g., Emily, Emilya, and Emilyah). We leave it as future work to develop better membership inference attack towards similar secrets. Under the failed membership inference attack, S-DPSGD is still better than No-DP, but it’s not feasible to compare S-DPSGD and DPSGD as they are both close to random guess.

### 6.3 Data Sanitization and Selective-DP

Data sanitization (or data normalization, data de-identification) has always been used as the very first step towards data protection, where all the sensitive information is masked with a special token such as “<num>”. Similar to S-DP, data sanitization also requires a policy function (e.g., a list of sensitive tokens or regex) to extract the private information. So we want to compare data sanitization with S-DP.

We mask all the detected digits by “<num>” to train a data sanitization baseline on WikiText-2, and calculate the perplexity on the private tokens only, as shown in Figure 4. There is no ε associated with data sanitization, so we draw a horizontal line with the convergent private perplexity. The first observation is that since data sanitization simply masks all the sensitive tokens, it fails to learn anything about them, resulting in a much worse perplexity on private tokens. This makes S-DP a good alternative of data sanitization because S-DP can still learn certain pattern from the noised sensitive tokens. Also, from Figure 4, we see that there is a trade-off between the private guarantee ε and the private perplexity, so we could tune ε to achieve a better perplexity on private tokens, while for data sanitization, there is no way to tune the parameters to obtain better model utilities. For more discussion on data sanitization and S-DP, please refer to Section A.5.

### 7 Conclusions

We develop a new privacy notion, selective differential privacy (S-DP), to improve the model utility while providing rigorous privacy guarantees for the sensitive portion of the data. We also develop a privacy mechanism, Selective-DPSGD, to achieve the new S-DP notion for RNNs. We experiment with WikiText-2 and a synthetic customer service dialog dataset. Results on both tasks show that models trained with S-DP achieve better utilities than traditional DP, and are more robust under various attacks than models without DP protection.
8 Ethical Consideration

Data Usage. To minimize real-world harm, we choose WikiText-2 since it is already public and widely used, and synthesize the dialogs as well the personal information in the CUSTOMERSIM datasets in our experiments. For future research, we plan to continue using public or synthetic dataset to prevent real-world data leakage.

Application. Our work addresses the problem of data privacy protection and can be applied in different applications. The attacks used in our study are well-known standard attacks tailored for our specific tasks, so it’s hard to generalize and misuse them to attack other language models. We will release the code so that people can have access to the various algorithms and protect their own data.

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A Appendix

A.1 Privacy Analysis Proof

**Theorem 3.** Let $f$ be the composition of $k$ queries: $f_1, \ldots, f_k$, which are either noisy type-1 or type-2 queries. Given a policy function $F$, let $f_p$ denote the set of noisy type-1 queries. Let $f_{np}$ denote the set of type-2 queries. Then, if $f_p$ is $(\epsilon, \delta)$-DP, $f$ is $(F, \epsilon, \delta)$-SDP.

**Proof.** Consider two selective $F$-neighboring datasets $x$ and $x'$. Let $x_i$ and $x'_i$ be the subset of data utilized by $f_i$. $x_i$ contains only private attributes when $f_i$ is type-1 and contains only non-private attributes when $f_i$ is noisy type-2. By the neighboring relation between $x$ and $x'$, $x_i$ and $x'_i$ are also selective $F$-neighbors when $f_i$ is a type-1 query. In addition to the dataset, $f_i$ takes the output of all the previous queries. For a fixed outcome $(y_1, \ldots, y_k)$ of $f$, we have

$$P[f_1(x_1, w_1) = y_1, \ldots, f_k(x_k, w_k) = y_k] = \prod_{f_i \in f_p} f_i(x_i, w_i)$$

$$P[f_1(x'_1, w'_1) = y_1, \ldots, f_k(x'_k, w'_k) = y_k] \leq e^\epsilon \quad \text{w.p.} \quad 1 - \delta$$

as desired.

The equality in the second line is due to the fact that $f_{np}$ does not incur privacy loss and the independence of randomness of each query given the output of all the previous queries. The inequality in the third line is due to the assumption that $f_p$ is $(\epsilon, \delta)$-DP with arbitrary auxiliary input.

A.2 CUSTOMERSIM Example

| Role | Utterance |
|------|------------|
| SYS  | Hello, I am the customer support bot. What can I do for you? |
| USR  | Hello robot. Could you please help me track my package? |
| SYS  | Please provide your full name. |
| USR  | Sure, Betty Sims. |
| SYS  | Could you please confirm your shipping address? |
| USR  | Yea sure, 2241 Fitzgerald Viaduct Brownview, OK 28304. |
| SYS  | Track your order using your tracking number, FH6F6GMMF4. Are you happy about my answer? |
| USR  | That’s it. |

Table 2: An example dialog in CUSTOMERSIM.

A.3 Models with Different Parameters

We plot the performances of models with different parameters on Figure 5. We find that fixing the noise multiplier $\sigma = 0.5$, the clipping threshold $C$ has a big impact on the performance, and it cannot be too big (0.01) or too small (5e-6); if we fix $C$ and change $\sigma$ from 0.5 to 1.0, the perplexity will be lower but at a huge cost of the privacy budget $\sigma$. As expected, there is always a trade-off between the utility and the privacy spent, so we choose a balancing point with a reasonable utility and privacy guarantee ($\sigma = 0.5$ and $C = 1e-3$) for the main experiments.

![Figure 5: Validation perplexity over epochs on WikiText-2 for models with different parameters.]

A.4 Original Membership Inference on CUSTOMERSIM

![Figure 6: Original membership inference results on CUSTOMERSIM. The best inference accuracy is around 58%.]

A.5 Data Sanitization and Selective-DP When Missing the Canary

Both data sanitization and S-DP rely on a policy function to detect sensitive tokens. However, it is not guaranteed that the policy function can locate
and mask all private information. Therefore, we want to compare the performance of data sanitization and S-DP when the policy function misses certain sensitive information.

In our setting, we still use WikiText-2 with the inserted secret “My ID is 341752”. The policy function is still a digit detector, only this time it fails to recognize “341752” as a secret. For data sanitization, all the detected digits will be masked by “<num>”; for S-DP, we apply S-DPSGD to add noises to all the detected digits.

Figure 7 shows the exposure of the missed secret 341752. When the perplexity goes lower and lower, the model becomes better at remembering the details of the training data, so the exposure of both models becomes very high. When the perplexity is around the middle area, S-DP has lower exposure than data sanitization.