A Customized Text Privatization Mechanism with Differential Privacy

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ABSTRACT

In Natural Language Understanding (NLU) applications, training an effective model often requires a massive amount of data. However, text data in the real world are scattered in different institutions or user devices. Directly sharing them with the NLU service provider brings huge privacy risks, as text data often contains sensitive information, leading to potential privacy leakage. A typical way to protect privacy is to directly privatize raw text and leverage Differential Privacy (DP) to quantify the privacy protection level. However, existing text privatization mechanisms that privatize text by applying $d_X$-privacy are not applicable for all similarity metrics and fail to achieve a good privacy-utility trade-off. This is primarily because (1) $d_X$-privacy’s strict requirements for similarity metrics; (2) these methods privatize each token in the text equally by providing the same and excessively large output set. Bad utility-privacy trade-off performance impedes the adoption of current text privatization mechanisms in real-world applications. In this paper, we propose a Customized differentially private Text privatization mechanism (CusText) that assigns each input token a customized output set to provide more advanced adaptive privacy protection at the token-level. It also overcomes the limitation for the similarity metrics caused by $d_X$-privacy notion, by turning the mechanism to satisfy $\epsilon$-DP. Furthermore, we provide two new text privatization strategies to boost the utility of privatized text without compromising privacy and design a new attack strategy for further evaluating the protection level of our mechanism empirically from a new attack’s view. We also conduct extensive experiments on two widely used datasets to demonstrate that our proposed mechanism CusText can achieve a better privacy-utility trade-off and better practical application value than the existing methods.

1 INTRODUCTION

In Natural Language Understanding (NLU) applications, the input text often contain sensitive personal information, e.g., racial or ethnic origins, religious or philosophical beliefs, etc [13]. Such information can be directly or indirectly used to identify a specific person, leading to potential privacy leakage that impedes privacy-conscious users from releasing data to NLU service providers [3, 4, 28]. With the growing concerns for data privacy from both the users and the governments, a series of data protection initiatives and laws have been proposed and enforced over the recent years, such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). This makes NLU service providers difficult to collect training data unless the privacy concern of the data owners, i.e., either individuals or institutions, is well addressed.

To protect the privacy of the data owners, a typical way is to privatize their text data locally before releasing it to the NLU service provider for further applications, as illustrated in Figure 1. In those text privatization mechanisms [9, 10, 25, 31, 35], the privacy of the input text is usually guaranteed by Differential Privacy (DP) [8] or its variants, which ensures data privacy with calibrated perturbation. Among them, SANTEXT [35] has demonstrated to be the state of the art and greatly improved the efficiency of the text privatization process compared with previous mechanisms [9, 10, 31]. The basic idea for SANTEXT is to generate privatized text by replacing the original tokens in the text sequentially with new tokens (can be a character, a subword, a word, or an n-gram) that are sampled from output token sets. The privacy and the utility of SANTEXT are guaranteed by $d_X$-privacy [5] which is a relaxation of the original DP definition. $d_X$-privacy inherits the main idea of DP that enables two adjacent tokens (refer to Sec. 3 for details) to be indistinguishable, so as to protect the original token from being inferred. It further improves the utility of privatized text by giving higher sampling probability to tokens that are semantically closer to the original one, so as to preserve more information from the input text. The
semantic similarity between two tokens is measured by a similarity metric (e.g., Euclidean distance).

Despite its effectiveness, SANTEXT faces two inherent limitations. First, satisfying \( d_\chi \)-privacy limits the applicability of SANTEXT for certain similarity metrics, such as cosine similarity [21] and TF-IDF [26]. Second, SANTEXT cannot achieve a good privacy-utility trade-off, i.e., either large privacy cost with insufficient protection or small privacy cost with unsatisfactory model accuracy. The first limitation is caused by the definition of \( d_\chi \)-privacy since it gives adaptive privacy protection based on the distance between the tokens, which excludes some similarity metrics. The second limitation arises as SANTEXT treats each token in the text equally by assigning each input token with a same output set, which is overly large (e.g., the output set size could be over 80000). Such a large output set will lead to over-protection of input text and hurts the model utility. Intuitively to resolve the first limitation, we can turn to the mechanism that satisfies \( \varepsilon \)-DP, while to tackle the second limitation, we can assign each input token a customized output set with a smaller size. However, resolving these limitations is non-trivial. It is a challenging task to design an effective mechanism that gives higher sampling probabilities to tokens semiantically closer to the original one under \( \varepsilon \)-DP notion, and how to customize the output set for each input token that achieves a good privacy-utility trade-off also needs to be explored.

To this end, we propose a novel Customized Text privatization mechanism named CusText that provides more advanced adaptive privacy protection at the token-level. Compared to existing works [9, 25, 35], CusText is applicable with all similarity metrics by turning the mechanism from satisfying \( d_\chi \)-privacy to satisfying \( \varepsilon \)-DP. Meanwhile, CusText inherits the merits of \( d_\chi \)-privacy by designing a proper score function to overcome the shortcoming of the \( \varepsilon \)-DP notion that it cannot provide adaptive privacy based on the semantic similarity between the tokens. Furthermore, we assign each input token a customized output set of relatively small size to achieve better adaptive token-level privacy protection. The relatively small size enables CusText to sample output tokens that are more semantically related to their corresponding input token, thus alleviating the over-protection problem. Conceptually the sampling process is performed based on a given mapping and in this work, three types of mappings, ranging from aggressive to conservative, are provided to assign the customized output set for each input token to satisfy different privacy levels, i.e., the trade-off between utility and privacy. The utility-privacy trade-off in CusText can be further adjusted by a customization parameter \( K \), which determines the size of the output set for each input token. Aside from the existing token-level text privatization strategy, we propose two more privatization strategies with a larger granularity, i.e., at the record-level or text-level, to reduce the entropy of the sampling distribution, which further improves the utility of the privatized text. Besides, for better privacy calibration beyond using privacy parameter \( \varepsilon \) and customization parameter \( K \), we design a new attack strategy as an additional calibration metric called Query Attack, by exploiting the notion of \( \varepsilon \)-DP. This new metric provides a novel perspective to empirically evaluate the privacy protection level of the proposed mechanism.

Our contributions are summarized as follows:

1. We propose a customized differentially private text privatization mechanism (CusText) which is designed based on the notion of \( \varepsilon \)-DP and allows the customization with tokenspecific mappings. Compared with the state-of-the-art mechanisms, our mechanism has broader applicability and achieves a better utility-privacy trade-off by providing more advanced token-level adaptive privacy protection.
2. We propose two new text privatization strategies to further improve the utility of the privatized text and a novel attack strategy named Query Attack, to provide a new evaluation metric for better privacy calibration.
3. We conduct extensive experiments on two widely-used datasets to evaluate the effectiveness of CusText. Results show that our mechanism can improve the utility of the privatized text with a smaller privacy cost, and show that reducing the size of the output set will not hurt the privacy of the original text based on the experiment results of Query Attack.

2 RELATED WORK

Differential privacy in Deep Learning. Differential privacy (DP) [8] originated from the field of statistical databases and became one of the primary standards for privacy protection. The proposal of the DP-SGD [1] algorithm pioneered the application of differential privacy to deep learning. When applying DP in deep learning, there are two common usage settings: Centralized DP (CDP) [1] and Local DP (LDP) [6]. CDP setting is suitable when the central server is considered trustworthy. Most of the existing works [2, 7, 15, 33] under the CDP setting focus on adding calibrated noises to the clipped gradients. However, the CDP setting cannot address the privacy concern of the data owners who do not trust any third parties including the central servers. To address such concerns, the LDP setting has been proposed which allows data owners to privatize their data locally before releasing them. We design our mechanism under the LDP setting in this paper since it naturally fits our privacy-preserving setting.

Privacy-Preserving NLP. Previously, it has been shown that simple anonymization techniques fail to preserve data privacy [14, 17]. A few efforts [12, 16, 20] try to preserve the utility of the text data with provable and quantifiable privacy guarantees via DP. For CDP setting, current researches [2, 7, 15, 27, 34] focus on differentially private parameters tuning for better model performance. For the LDP setting, since privatizing the text data from the root will hurt the semantics and syntax of the sentence, the challenge is how to achieve a good utility-privacy trade-off. Thus, most works [9, 25, 35] rely on \( d_\chi \)-privacy [5] definition to preserve the token semantics. Besides, both Feyisetan et al. [9] and Qu et al. [25] report available model accuracy but with large privacy parameter (e.g., \( \varepsilon > 50 \)) or become a random classifier under strong privacy condition (e.g., \( \varepsilon < 10 \)), which indicates no practical value. The state-of-the-art SANTEXT method [35] ingeniously combines \( d_\chi \)-privacy with Exponential mechanism [18] to avoid the curse of dimensionality. However, there is still huge room for improvement in terms of the utility-privacy trade-off. To tackle the existing issues, we turn back to the original DP definition to measure privacy protection level and adopt a customized mechanism to further improve the performance of current LDP methods.
Customized Local DP. Traditional LDP mechanisms give each data the same degree of privacy protection, which jeopardizes the utility due to the over-protection of the original data. Since different users have different concerns about their data’s privacy (e.g., women tend to pay more attention to their height and weight than men) and the sensitivity of different values is different within the value range (e.g., in drug abuse surveys, positive answers are more sensitive than negative answers), we can differentially protect the privacy of data instead of treating them equally. Recent works [22, 23, 32] have proposed some new LDP mechanisms that provide customized privacy protection for data owned by different users and made a significant boost to the utility of the privatized data. Our customized differentially private text privatization mechanism CusText provides a new way of customized LDP in the text domain.

3 PRELIMINARIES

Before introducing our proposed method, we first briefly review the key concepts, including ε-DP and exponential mechanism.

Definition 1 (ε-DP [8]). Given a privacy parameter $\epsilon \geq 0$, for all adjacent inputs $x, x' \in X$ and all possible output $y \in Y$, a randomized mechanism $M$ is said to be ε-DP if the following holds:

$$\Pr[M(x) = y] \leq e^\epsilon \Pr[M(x') = y],$$

where $\epsilon$ defines the privacy-protection strength.

By definition, we say that ε-DP provides better protection with a smaller $\epsilon$. In the context of NLU, we define the input tokens that share the same output set $Y$ to be adjacent inputs. The ε-DP says an unlimited adversary cannot efficiently distinguish the two probabilistic ensembles with sufficiently small $\epsilon$, because the probabilities of adjacent tokens producing the same output token $y$ are similar. In this paper, we follow the definition of ε-DP.

Definition 2 (Exponential Mechanism [18]). Given a score function $u(\cdot, \cdot) : X \times Y \mapsto R$, an exponential mechanism $M(X, u, Y) : X \rightarrow Y$ satisfies ε-DP if it samples an output token $y \in Y$ to perturb the input token $x \in X$ with probability proportional to:

$$e^{u(x, y)} \epsilon^{|x-y|},$$

where $\epsilon$ defines the privacy-protection strength, $u(x, y)$ denotes the score for each input and output token pair $(x, y)$ and $\Delta u = \max_{y \in Y} \max_{x, x' \in X} |u(x, y) - u(x', y)|$ denotes the sensitivity.

Exponential mechanism is commonly-used in the discrete domain, which naturally suits the NLU applications due to the discrete nature of the text. Smaller sensitivity makes it harder for adversaries to distinguish the original token from its adjacent tokens. In practice, we usually pre-define the sensitivity to a certain real number (e.g., 1) for simplicity. According to Eq. 2, the sampling probability of each output token $y$ is closely related to the score function $u(\cdot, \cdot)$ when the privacy parameter $\epsilon$ and sensitivity $\Delta u$ are given beforehand. Bigger $u(x, y)$ indicates a higher sampling probability. In our mechanism, we leverage the exponential mechanism as the sampling function.

4 METHOD

4.1 Problem Formulation

In a NLU task, suppose each document $D = (R_i)_{i=1}^m$ contains multiple records $R$ and each record $R = (t_j)_{j=1}^n$ contains multiple tokens $t$. We formulate our text privatization task as follows: given a input text $D$ that contains sensitive information, a global input set $X$ that contains all potential input tokens, a global output set $Y$ that contains all potential output tokens, and a text privatization mechanism $M$, we consider a token-to-token case where each token $t_j \in D$ is privatized with $M$ to get its corresponding privatized token $t'_j$ sampled from $Y$, if $t_j \in X$. The privatized tokens forms the privatized text $D' = (R_i)_{i=1}^m$.

Following the previous works [9, 25, 35], we consider a semi-honest threat model under the LDP setting where data owners (e.g., individuals or institutions) only submit privatized texts to service providers. Malicious service providers may try to learn sensitive information from their received texts. We assume adversaries only have access to the privatized texts, and all algorithms/mechanisms are publicly known. Besides, we assume the adversaries have unlimited computation resources.

4.2 Method Overview

A high-level overview of our customized text privatization mechanism CusText is presented in Fig. 2. CusText mainly consists of three components: (1) a mapping function $f_{map} : X \rightarrow \{Y' \subseteq Y\}$ which determines the output set $Y'_j$ for each input token $x_j \in X$ based on a semantic metric; (2) a sampling function $f_{sample} : X' \rightarrow Y'$ based on the exponential mechanism, to sample a new token from an output set to privatize the input token; (3) a text privatization strategy, to give instructions when privatizing the text. Specifically, under a text privatization strategy, for each $t_j \in D$, CusText first gets the output set $Y'_j$ corresponding to $t_j$ by $f_{map}$, i.e., $Y'_j = f_{map}(t_j)$, then $f_{sample}$ samples a output token $t'_j$ from $Y'_j$ as the privatized token of $t_j$, i.e., $t'_j = f_{sample}(t_j), t'_j \in Y'_j$. Finally, after applying CusText on each input token $t_j$ in $D$, the final $D'$ is formed by all output privatized tokens.

$^1$Given $Y' \subseteq Y$, $X' = \{x \in X, f_{map}(x) = Y'\}$.
4.3 Mapping Function

In text privatization mechanisms, the mapping function $f_{\text{map}} : X \rightarrow \{Y' \subseteq Y\}$ decides the output set for each input token. For instance, different input tokens may have different output sets in CusText, while different input tokens share the same output set, which usually equals to the global output set $Y$, in SANTEXT [35]. If a bunch of input tokens in $X$ are mapped to the same output set $Y'$, they belong to the same input set $X'$ ($X' \subseteq X$). The comparison of the mapping function between CusText and SANTEXT is shown in Figure 3. When using CusText, the mapping function $f_{\text{map}}$ needs to be pre-determined. However, before constructing $f_{\text{map}}$, some details need to be further discussed.

4.3.1 Input Token Type. According to the mapping relation within $f_{\text{map}} : X \rightarrow \{Y' \subseteq Y\}$, for each input token $x \in X$, we can know which output set $Y'$ is mapped to and which input set $X' = \{x' \in X, f_{\text{map}}(x) = Y'\}$ it belongs to. Based on the size of $X'$ and the size of $Y'$, we can categorize the input token into four types: 1 - 1, N - 1, 1 - N and N - M ($1, N, M > 1$). In Figure 3, we illustrate the general case where all input tokens belong to type N - M. To our best knowledge, type N - 1 and type 1 - 1 are not commonly used in existing differentially private text privatization mechanisms. Technically, if we want CusText to provide $\epsilon$-DP protection to all input tokens, it requires all input tokens in the global input set $X$ to belong to type N - M or type N - 1, to ensure that every input token has adjacent tokens. This is because the original intention of $\epsilon$-DP is to make the adjacent tokens indistinguishable, so as to protect the input token from being inferred. However, there is no significant difference between type 1 - N and type N - M as for the attack difficulty. Based on the above discussion, both type 1 - N and type N - M will be taken into account in our mechanism CusText.

4.3.2 $X \subseteq Y$. If the global output set $Y$ is irrelevant to the global input set $X$, the privatized text will be hard to preserve information from the raw text, thus will hurt the utility. Therefore, following the previous works [9, 25, 35], we also includes $X$ in $Y$ ($X \subseteq Y$) in our mechanism. Particularly, for a single input token, we include the input token in its corresponding output set $Y'$.

4.3.3 Mapping Strategy. The generation of $f_{\text{map}} : X \rightarrow \{Y' \subseteq Y\}$ is realized by assigning the output set for each input token under a mapping strategy, which takes the semantic closeness under consideration. We provide three mapping strategies to generate $f_{\text{map}}$ in CusText for different scenarios. For simplicity, we unify the size of each input token’s corresponding output set $Y'$ to $K$ and define $K$ as the customization parameter. The details for generating $f_{\text{map}}$ are presented in Algorithm 1 with the balanced mapping as the default mapping strategy.

- **Aggressive Mapping.** For each input token $x \in X$, it leverages a certain similarity metric, e.g., Euclidean distance, to select $K$ tokens $y \in Y$ which are semantically closest to $x$, as its customized output set. Such mapping strategy makes most of the tokens in $X$ belong to type 1 - N, which means few of them will have adjacent tokens.

- **Balanced Mapping.** Based on the aggressive mapping, the balanced mapping try to make more input tokens belong to type N - M by mapping more than one input token to the same output set, i.e., for most of input tokens $x \in X$, there exists $x' \in X$ and $x' \neq x$ s.t. $f_{\text{map}}(x') = f_{\text{map}}(x)$. However, under the balanced mapping, for most input tokens $x, x' \in X$, if $f_{\text{map}}(x') \neq f_{\text{map}}(x)$, we have $f_{\text{map}}(x) \cap f_{\text{map}}(x') \neq \emptyset$.

- **Conservative Mapping.** Based on the balanced mapping, the conservative mapping makes all input tokens in $X$ belong to type N - M by making different output sets $Y' \subseteq Y$ have no intersections, i.e., $\forall x, x' \in X$, if $f_{\text{map}}(x') \neq f_{\text{map}}(x)$, we have $f_{\text{map}}(x) \cap f_{\text{map}}(x') = \emptyset$.
### 4.4 Sampling Function

Based on the mapping function \( f_{\text{map}} : X \rightarrow \{Y' \subseteq Y\} \), the sampling function \( f_{\text{sample}} : X' \rightarrow Y' \) can get the output set corresponding to each input token for further sampling. In CusText, we adopt the exponential mechanism to be our sampling function. However, we need to design a suitable score function for the exponential mechanism to provide adaptive privacy protection at token-level.

Two rules should be observed when designing the score function 
\( u(\cdot, \cdot) : X' \times Y' \rightarrow \mathbb{R} \):

1. The score for each input and output token pair is finite, i.e., \( \forall x \in X', \forall y \in Y', \exists M \in \mathbb{R} \) s.t., \( u(x, y) < M \).
2. The higher the semantic similarity between the input token and the output token, the higher the score, i.e., \( \forall x \in X', \forall y, y' \in Y' \), if \( u(x, y) > u(x, y') \), \( y \) is more semantically close to \( x \) than \( y' \).

The first rule is to make sure that the exponential mechanism can satisfy \( \epsilon \)-DP. The second rule is to ensure that tokens that are closer to the semantics of the input token have higher probabilities, so as to retain the advantage of \( d_q \)-privacy.

When designing the score function, we use pre-trained embedding as the token representations, such as Word2vec [19], Glove [24] and Counter-fitting [21]. The similarity metric used in our mechanism is determined by the embedding type. For instance, Glove and Counter-fitting use Euclidean distance and cosine similarity as their similarity metrics respectively. Based on the correlation between score and semantic similarity, all similarity metrics could be categorized into two types. For instance, Euclidean distance belongs to type negative correlation while cosine similarity belongs to type positive correlation. To verify that our mechanism can suit all similarity metrics, we provide a possible score function for representatives of two similarity metric types respectively.

#### 4.4.1 Negative Correlation

We take Euclidean distance for example. For any input set \( X' \) and its corresponding output set \( Y' \), we design the score function \( u(\cdot, \cdot) : X' \times Y' \rightarrow \mathbb{R} \) through the following steps.

We first calculate the Euclidean distance between one input token \( x \in X' \) and each output token \( y \in Y' \) to get the distance list \( K_d \). The distance between the input and output token pair \( (x, y) \) can be calculated by

\[
d(x, y) = \|\Phi(x) - \Phi(y)\|_2
\]

where \( \Phi(x), \Phi(y) \) denote the embeddings of \( x \) and \( y \).

Then, we normalize the value of distance list \( K_d \) to be ranged in \([0, 1]\) by Eq. 4 and transform the distance list \( K_d \) into the score function \( u(\cdot, \cdot) : \{x\} \times Y' \rightarrow \mathbb{R} \) corresponding to the input token \( x \) by Eq. 5.

\[
K_d = \frac{K_d - \min(K_d)}{\max(K_d) - \min(K_d)}
\]

\[
u(\cdot, \cdot) = 1 - K_d
\]

This transformation enables the input and output token pair \( (x, y) \) with higher semantic similarity to have a higher score. Finally, for each input token in the input set \( X' \), we repeat the above steps to get the complete utility score function \( u(\cdot, \cdot) : X' \times Y' \rightarrow \mathbb{R} \).

#### 4.4.2 Positive Correlation

We take cosine similarity for example. For any input set \( X' \) and its corresponding output set \( Y' \), we design the score function \( u(\cdot, \cdot) : X' \times Y' \rightarrow \mathbb{R} \) through the following steps.

We first calculate the cosine similarity between a input token \( x \) and each output token \( y \) in \( Y' \) to get the cosine similarity list \( K_c \). The cosine similarity of the input and output token pair \( (x, y) \) can be calculated by

\[
\cos(x, y) = \Phi(x)^T \Phi(y) \|\Phi(x)\| \|\Phi(y)\| (6)
\]

Then, we normalize the cosine similarity list \( K_c \) to produce the score function \( u(\cdot, \cdot) : \{x\} \times Y' \rightarrow \mathbb{R} \) for input token \( x \) by Eq. 7

\[
u(\cdot, \cdot) = \frac{K_c - \min(K_c)}{\max(K_c) - \min(K_c)} (7)
\]

Finally, for each token in the input set \( X' \), we repeat the above steps to get the complete utility score function \( u(\cdot, \cdot) : X' \times Y' \rightarrow \mathbb{R} \).

#### 4.4.3 Sampling Procedure

After obtaining the available score function, the sampling function \( f_{\text{sample}} \) is competent to generate the privatized token \( t_j \) for the input token \( t_i \) by adopting the exponential mechanism. In this sampling procedure, we make \( f_{\text{sample}} \) satisfy \( \epsilon \)-DP. For any input set \( X' \) and its corresponding output set \( Y' \), the sensitivity \( \Delta u \) between any two adjacent input tokens \( x, x' \in X' \) is bound to 1 based on our design of the score function. Formally,

\[
\Delta u = \max_{y \in Y'} \max_{x, x' \in X'} \|u(x, y) - u(x', y)\|_1 = 1 \quad (8)
\]

Given a privacy parameter \( \epsilon \), for \( \forall x \in X', \forall y \in Y' \), the sampling function \( f_{\text{sample}} : X' \rightarrow Y' \) is \( \epsilon \)-DP if it satisfies

\[
Pr[f_{\text{sample}}(x) = y] = \frac{e^{\frac{\epsilon u(x, y)}{2\Delta u}}}{\sum_{y' \in Y'} e^{\frac{\epsilon u(x, y')}{2\Delta u}}} \quad (9)
\]

**Remark.** The design of the score function is not unique. The method provided in this paper is for reference only.

### 4.5 Text privatization Strategies

Based on the widely used token-level text privatization strategy [9, 25, 35], we propose the other two record-level and dataset-level strategies for CusText to privatize the input text. The details of three strategies with different granularities are listed below.

- **Token-Level.** The idea of the token-level strategy is straightforward. For each token in each record of the dataset (\( \forall t \in R \in D \)), we run the sampling function to sample a new token, and replace the original token with it.

- **Record-Level.** In the token-level strategy, the repeated token in the same record may be mapped to different tokens. To preserve the syntax similarity between the raw text \( D \) and the privatized text \( D' \), we force the repeated token in the same record mapped to the same token.

- **Dataset-Level.** Though the repeated token in the same record will be mapped to the same token in the record-level strategy, the same token in different records is still possible to be mapped to different tokens. Therefore, we make the repeated token in the whole dataset be mapped to the same token.
Table 1: Comparison between CusText and SANTEXT of the accuracy on SST-2 and QNLI. The customization parameter $K$ in SANTEXT for both datasets is 65713 which equals the vocabulary size of Counter-fitting embeddings.

| Dataset | SANTEXT | CusText |
|---------|---------|---------|
|         | $K = 5$ | $K = 10$ | $K = 20$ | $K = 50$ | $K = 100$ | $K = 200$ | $K = 500$ | $K = 1000$ | $K = 2000$ |
| SST-2   | 0.5021  | 0.9151  | 0.8922  | 0.8567  | 0.8578  | 0.8429  | 0.8177  | 0.7906  | 0.7706  | 0.7821  |
| QNLI    | 0.4921  | 0.7761  | 0.6846  | 0.5311  | 0.5205  | 0.5171  | 0.4948  | 0.5127  | 0.4946  | 0.4941  |

Table 2: Qualitative examples from QNLI dataset. Privatized text by CusText under different customization parameter $K$. The privatization is based on the balanced mapping, record-level text privatization strategy with saving stopwords and privacy parameter $\epsilon = 1$.

| Parameter | Original Text                                                                 | Privatized Text                                                                 |
|-----------|-------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| $K = 5$   | when did spielberg and irving marry?                                         | then in 1984 they renewed their romance, and in november 1985, they married, already having had a son, max samuel. |
| $K = 50$  | when did hanks and irving marries?                                          | then in 2811 they renew their ballad, and in nov 2467, they married, after having had a son, maximum josiah. |
| $K = 200$ | when did theatrical and benson hens?                                        | then in 2708 they refitted their modern, and in marked 2218, their daughter, therefore having had a kiddo, paramount jeremiah. |
| $K = 200$ | when did scenario and treasure mademoiselle?                                 | then in 2702 they renewed their sweet, and in hsien 2451, they gender, today having had a school, maximizing abram. |

Since not all tokens contain sensitive information, the above three text privatization strategies which replace all tokens might be over-protective. Therefore, we can retain some original tokens that have low privacy risk (e.g., stopwords) to improve the utility of the privatized text. Besides, skipping some tokens in the raw text can improve the efficiency of text privatization process as well.

5 EXPERIMENTS

5.1 Experimental Setup

We choose two datasets from GLUE benchmark [29] with privacy implications to demonstrate the effectiveness of CusText.

- SST-2 is a popular sentiment prediction dataset for movie reviews, with 67k training sentences and 872 validation sentences.
- QNLI is a popular dataset for a sentence-pair classification task, with 105k training samples and 5.4k validation samples.

In our experiments, we first utilize CusText to generate privatized texts, then use those privatized texts to fine-tune the bert-base-uncased\(^2\) model. Next, we use (un)-privatized texts to evaluate the model to demonstrate the performance loss. In particular, we use counter-fitting embeddings as the token representation, which is based on cosine similarity to measure the semantic similarity between tokens. When producing the privatized text, both the global input set $X$ and the global output set $Y$ in CusText are equal to the vocabulary of Counter-fitting, and out-of-vocabulary (OOV) tokens except the numbers, will be retained. For each downstream task, we set the maximum sequence length to 128, training epoch to 1, batch size to 64 and learning rate to 2e-5. Other hyper-parameters setups are kept default as the transformer library [30].

For evaluation, the direct comparison of CusText and SANTEXT based on only the privacy parameter $\epsilon$ is unfair, because the implementation details of those are different. To achieve a fair comparison, we also evaluate them on customization parameter $K$ as well as the attack experiments in Sec. 6.2.

5.2 Comparison of Different Customization Parameter $K$

We first analyze the impact of different customization parameters $K$ on CusText by choosing its range from 5 to 2000. Because the value of $K$ controls the degree of customization, smaller $K$ indicates better adaptation to the customized purpose. When using CusText to privatize SST-2 and QNLI, we set the privacy parameter $\epsilon = 1$, using balanced mapping and record-level text privatization strategy. We show our experiment results in Table 1. We observe that the trained model performs better with a smaller $K$, this indicates the importance of preserving token semantics when implementing privacy protection. We also compare CusText with the state-of-the-art mechanism SANTEXT [35] which does not use customized adaption under the same privacy protection degree. For a fair comparison, SANTEXT adopts the same sampling function $f_{\text{sample}}$, global input set $X$, global output set $Y$, mapping function $f_{\text{map}}$ and embeddings as our proposed mechanism CusText. The comparison results in Table 1 further confirm the effectiveness of our customized mechanism CusText under a strong privacy protection condition ($\epsilon = 0$).

However, the advantage brought by small $K$ will gradually weaken when $\epsilon$ gets bigger. This is because big $\epsilon$ will let tokens that are semantically close to the original one, especially the original token...
We then compare the utility of the text privatization strategies with Table 4: Comparisons of mapping strategies on the proportion of input tokens **NOT** belong to type N - M on SST-2.

| K   | Aggressive | Balanced | Conservative |
|-----|------------|----------|--------------|
| 20  | 0.9278     | 0.8761   | 0.8303       |
| 50  | 0.8948     | 0.8383   | 0.7992       |
| 100 | 0.8624     | 0.8451   | 0.5356       |

Table 5: Comparison of different text privatization strategies $S$ of accuracy on SST-2 and QNLI. T: Token-Level strategy, R: Record-Level strategy, D: Dataset-Level strategy; $^+$: save stopwords; O: original training dataset.

| $S$ | SST-2 | QNLI |
|-----|-------|------|
|     | $\epsilon = 1$ | $\epsilon = 5$ | $\epsilon = 10$ | $\epsilon = 1$ | $\epsilon = 5$ | $\epsilon = 10$ |
| T   | 0.8463 | 0.8393 | 0.9071 | 0.5083 | 0.5452 | 0.6453 |
| R   | 0.8624 | 0.8945 | 0.8750 | 0.5218 | 0.6616 | 0.7754 |
| D   | 0.8635 | 0.8796 | 0.8876 | 0.5810 | 0.5330 | 0.7782 |

5.4 Comparison of Different Text Privatization Strategies

We then compare the utility of the text privatization strategies with three different levels: token-level, record-level and dataset-level. A higher level strategy tends to make the privatized text more similar to a natural language text. The results are shown in Table 5. We can see that the record-level strategy is more applicable compared to the other two. Furthermore, we can find that the improvement brought by record-level and dataset-level strategies on QNLI is more significant than SST-2. Particularly, the accuracy is improved by more than 10% on QNLI when $\epsilon = 10$. This may be because QNLI is applied for a natural language inference task and mapping the repeated tokens in the question-answer pair to the same token is crucial for the model to do the right prediction. In addition, the experiment results also show that saving stopwords could boost the utility under the same privacy guarantee. This may be because saving stopwords helps to preserve the original syntax feature. It is an encouraging finding since it enables us to get a relatively good performance of a downstream task with smaller privacy costs.

6 PRIVACY CALIBRATION

To further explore the privacy protection level brought by the text privatization mechanisms (mainly CusText), we conduct some supplementary experiments to better empirically calibrate privacy.

6.1 Proportion of Original Tokens

Under the DP mechanism, the proportion of the original tokens in the privatized text does not have a direct connection with privacy since the adversaries cannot identify the original tokens. However, when most tokens in the privatized text are original tokens, the privatized text will have high readability. In such a situation, with the help of human reasoning ability, the original text can be easily inferred. This is because the privatized text produced by CusText is made up of a bunch of independent privatized tokens, the possibility that the privatized text is reasonable will be very low. Based on the above discussion, we first use the proportion of original tokens as one of the metrics to empirically evaluate the privacy protection provided by text privatization mechanisms. Following the same parameter setting in Sec. 5.4, we evaluate the proportion of original tokens under different situations. The results in Table 6 confirm that smaller $\epsilon$ can bring better privacy protection and give us guidance on how to choose $\epsilon$ with a suitable proportion of original tokens in the privatized text. Besides, we are delighted to find that there is no significant difference in the proportion of original tokens among
Table 6: The proportion of original tokens in the privatized text under customization parameter $K = 50$. A lower proportion indicates better privacy protection.

| $S$ | SST-2 | QNLI |
|-----|-------|------|
|     | $\epsilon = 1$ | $\epsilon = 5$ | $\epsilon = 10$ | $\epsilon = 1$ | $\epsilon = 5$ | $\epsilon = 10$ |
| T   | 2.82%  | 9.92%  | 30.31% | 2.82%  | 9.76%  | 29.24% |
| R   | 2.83%  | 9.87%  | 30.29% | 2.84%  | 9.77%  | 29.26% |
| D   | 3.15%  | 7.81%  | 30.06% | 1.36%  | 7.59%  | 16.03% |
| $T^*$ | 43.52% | 47.37% | 57.55% | 45.85% | 49.58% | 59.41% |
| $R^*$ | 43.51% | 47.33% | 57.50% | 45.86% | 49.58% | 59.41% |
| $D^*$ | 43.32% | 48.15% | 56.75% | 45.38% | 47.28% | 50.79% |
| O   | 100.00% | 100.00% |      |      |      |      |

Algorithm 2 Query Attack

Input: Text privatization mechanism $M$, input token $x$ and repeat number $R$

Output: Query Number $N$

1: acc, $N = 0, 0$
2: while acc < 0.95 do
3: cnt = 0
4: $N = N + 1$
5: for $i = 1, 2, \ldots, R$ do
6: Repeat $M(x)$ $N$ times to get $N$ output tokens $(t_1, t_2, \ldots, t_N)$
7: Get the token $t$ with the highest frequency in $(t_1, t_2, \ldots, t_N)$
8: if $t == x$ then
9: cnt += 1
10: end if
11: end for
12: acc = cnt / $R$
13: end while
14: return $N$

the three text privatization strategies. This indicates that high-level strategies do not boost utility by improving the proportion of original tokens.

6.2 Query Attack

Since the input token will be in its corresponding output set and the probability that it will be sampled by $f_{\text{sample}}$ will be the highest when privacy parameter $\epsilon > 0$, the adversaries could base on this feature to determine what the input token is (the token with the highest frequency) by querying the data owners for privatized texts multiple times. Thus, the smallest query number that adversaries needed to infer the original token with high confidence could be a new evaluation metric for privacy calibration.

We search the query number $N$ under different customization parameter $K = [5, 10, 50, 500, 1000, 2000]$ based on the Monte Carlo method [11] in our attack experiment. The termination condition of the search is when the prediction accuracy is up to 95% after repeating the sampling procedure 2000 times. From the results in previous experiments, we find that the utility of privatized text is highly relative to its proportion of original tokens. For a fair comparison, we compare different customization parameters $K$ under similar $p_0$ (the possibility that the output token sampled from the sampling function is the same as the input token), since $p_0$ will be different with the same $\epsilon$ but different $K$. The details of the query attack is presented in Algorithm 2. Table 7 shows the results of the smallest query numbers $N$ corresponding to different $p_0$, taking the token ‘happy’ as an example and the corresponding $\epsilon$ under similar $p_0$ but different $K$. According to the results in Table 7, we can tell that the query number $N$ is almost not sensitive to $K$ under the similar $p_0$ and the query number $N$ will be even bigger when $K$ is smaller. Such a result proves that a small customized parameter $K$ does not compromise the attack difficulty and it is not necessary to use a large output set when we design the text privatization mechanism. Not to mention that a large $K$ means greater storage space consumption and longer processing time.

6.3 Trade-off Comparison

In order to prove that our Custtext can achieve a better trade-off between utility and privacy. We conduct the comprehensive experiments on both SANTEXT and Custtext (with customized parameter $K = 50$), taking some typical tokens from SST-2 as an example. The implementation of SANTEXT follows its original setting in paper [35]. Table 8 shows the query number $N$ and the corresponding original token proportion $p_0$ of different input tokens under different privacy parameters $\epsilon$, in both SANTEXT and CustText. Besides, the accuracy on SST-2 of the corresponding $\epsilon$ is also shown in Table 8 (in the table, M means one million, K means a thousand).

Table 8 (in the table, M means one million, K means a thousand). The results confirm that SANTEXT can not achieve a good privacy-utility trade-off compared to our method, i.e., either bad utility with good privacy protection or good utility with bad privacy protection.

7 PRIVACY CONCERN: CAN $X \subseteq X$?

In both previous works [9, 25, 35] and our mechanism Custtext, the global input set $X$ is included in the global output set $Y$ ($X \subseteq Y$). Thus, the privatized text produced by those mechanisms may remain some original tokens. Intuitively, this might lead to privacy leakage because of those unchanged tokens. However, in a practical situation, based on the experiment results of query attack in Table 7, we observe that $X \subseteq Y$ has little impact on the privacy protection of the raw text when adversaries can only query the data owners for privatized texts limited times. Taking the one-time query attack as an example, we suppose the original text is “Today I ate an apple”, and the privatized text is “Yesterday she ate an apple”. Since adversaries assume all tokens in the privatized text have been perturbed, they cannot identify the “apple” as the original input token. The same is true when we deliberately remain some low-risk original tokens in the privatized text. Therefore, combined with the analysis in Sec. 6.1, we deem that existing methods with $X \subseteq Y$ is acceptable when the proportion of original tokens in the privatized text is small and the corresponding query number is big (e.g., $K = 50, \epsilon = 1$), to help to achieve a good utility-privacy trade-off.
Table 7: Query number $N$ for inferring the input token *happy* and the corresponding privacy parameter $\epsilon$ to achieve similar original token sampling probability $p_0$ under different customization parameter $K$ based on CusText.

| $p_0$ | $K = 5$ | $K = 10$ | $K = 50$ | $K = 500$ | $K = 1000$ | $K = 2000$ |
|-------|-------|-------|-------|-------|-------|-------|
|       | $N$   | $\epsilon$ | $N$   | $\epsilon$ | $N$   | $\epsilon$ | $N$   | $\epsilon$ | $N$   | $\epsilon$ | $N$   | $\epsilon$ |
| 0.1   | inf   | -      | 0    | 7045   | 7      | 5305   | 14    | 5305   | 15    | 5320   | 16    |
| 0.2   | inf   | 0      | 1365 | 3      | 1035   | 13     | 1135  | 22     | 1170  | 23     | 1280  | 24    |
| 0.3   | 1530  | 2      | 365  | 5      | 405    | 18     | 405   | 31     | 380   | 33     | 390   | 35    |
| 0.4   | 300   | 4      | 160  | 7      | 180    | 25     | 180   | 42     | 185   | 45     | 170   | 48    |
| 0.5   | 85    | 7      | 90   | 9      | 80     | 33     | 90    | 57     | 85    | 61     | 95    | 64    |
| 0.6   | 45    | 10     | 40   | 13     | 35     | 47     | 35    | 81     | 45    | 86     | 95    | 91    |
| 0.7   | 15    | 16     | 15   | 21     | 15     | 74     | 15    | 127    | 15    | 136    | 15    | 143   |
| 0.8   | 7     | 25     | 7    | 33     | 7      | 117    | 6     | 201    | 5     | 216    | 7     | 228   |
| 0.9   | 3     | 40     | 3    | 52     | 3      | 186    | 3     | 318    | 3     | 314    | 3     | 360   |
| 0.99  | 1     | 83     | 1    | 108    | 1      | 388    | 1     | 665    | 1     | 713    | 1     | 753   |

Table 8: Comparison of trade-off capabilities between SANTEXT and Custext.

| SANTEXT | $\epsilon = 1$ | $\epsilon = 2$ | $\epsilon = 3$ | CustText | $\epsilon = 1$ | $\epsilon = 2$ | $\epsilon = 3$ |
|---------|---------------|---------------|---------------|----------|---------------|---------------|---------------|
| $N$     | $p_0$         | $N$           | $p_0$         | $N$      | $p_0$         | $N$           | $p_0$         |
| happy   | 4255          | 0.23%         | 80            | 6.56%    | 10            | 62.95%        | happy         | >3M        | 2.27%       | >2M        | 2.59%       | >1M        | 2.92%       |
| car     | 1650          | 0.48%         | 19            | 23.81%   | 1             | 94.70%        | car           | >3M        | 2.31%       | >2M        | 2.63%       | >1M        | 2.99%       |
| she     | 1650          | 0.48%         | 19            | 23.81%   | 1             | 94.70%        | she           | >50K       | 2.62%       | 9K         | 3.44%       | 4K         | 4.49%       |
| mary    | 2450          | 0.36%         | 35            | 15.73%   | 3             | 89.28%        | mary          | >3M        | 2.49%       | >2M        | 3.10%       | 5K         | 3.82%       |

| Acc.    | 0.5101        | 0.5838        | 0.8374        | Acc.     | 0.8589        | 0.8601        | 0.8818        |

8 CONCLUSIONS AND FUTURE WORK

In this work, we study how to achieve better utility on the privatized text by designing a customized differentially private text privatization mechanism (CusText) that provides adaptive privacy protection at the token-level. Specifically, we propose a novel sampling function by designing a suitable score function on top of the exponential mechanism and providing each input token its own customized output set to boost the utility of privatized text. Moreover, we provide two new text privatization strategies to improve the utility of privatized text without compromising privacy and design a new attack strategy for further evaluating the protection level of our mechanism empirically from an attack’s view. Extensive experiments show that CusText achieves a better privacy-utility trade-off and has better practical application value. In the future, we will explore a more advanced customized mechanism by assigning a variable size of the output set for each input token and look for a better way to identify the sensitive tokens in the text rather than based on rules.

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