Two Models are Better than One: Federated Learning Is Not Private For Google GBoard Next Word Prediction

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Abstract. In this paper we present new attacks against federated learning when used to train natural language text models. We illustrate the effectiveness of the attacks against the next word prediction model used in Google’s GBoard app, a widely used mobile keyboard app that has been an early adopter of federated learning for production use. We demonstrate that the words a user types on their mobile handset, e.g. when sending text messages, can be recovered with high accuracy under a wide range of conditions and that counter-measures such a use of mini-batches and adding local noise are ineffective. We also show that the word order (and so the actual sentences typed) can be reconstructed with high fidelity. This raises obvious privacy concerns, particularly since GBoard is in production use.

Keywords: federated learning, privacy

1 Introduction

Federated Learning (FL) is a class of distributed algorithms for the training of machine learning models such as neural networks. A primary aim of FL when it was first introduced was to enhance user privacy, namely by keeping sensitive data stored locally and avoiding uploading it to a central server [17]. The basic idea is that users train a local version of the model with their own data, and share only the resulting model parameters with a central coordinating server. This server then combines the models of all the participants, transmits the aggregate back to them, and this cycle (i.e. a single FL ‘round’) repeats until the model is judged to have converged.

A notable real-world deployment of FL is within Google’s Gboard, a widely used Android keyboard application that comes pre-installed on many mobile handsets and which has > 5 Billion downloads [1]. Within GBoard, FL is used to train the Next Word Prediction (NWP) model that provides the suggested next words that appear above the keyboard while typing [11].

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In this paper we show that FL is not private for Next Word Prediction. We present an attack that reconstructs the original training data, i.e. the text typed by a user, from the FL parameter updates with a high degree of fidelity. Both the FedSGD and FederatedAveraging variants of FL are susceptible to this attack. In fairness, Google have been aware of the possibility of information leakage from FL updates since the earliest days of FL, e.g. see footnote 1 in [17]. Our results demonstrate that not only does information leakage indeed happen for real-world models deployed in production and in widespread use, but that the amount of information leaked is enough to allow the local training data to be fully reconstructed.

We also show that adding Gaussian noise to the transmitted updates, which has been proposed to ensure local Differential Privacy (DP), provides little defence unless the noise levels used are so large that the utility of the model becomes substantially degraded. That is, DP is not an effective countermeasure to our attack. We also show that use of mini-batches of up to 256 sentences provides little protection. Other defences, such as Secure Aggregation (a form of multi-party computation MPC), Homomorphic Encryption (HE), and Trusted Execution Environments (TEEs), are currently either impractical or require the client to trust that the server is honest in which case use of FL is redundant.

Previous studies of reconstruction attacks against FL have mainly focused on image reconstruction, rather than text as considered here. Unfortunately, we find that the methods developed for image reconstruction, which are based on used gradient descent to minimise the distance between the observed model data and the model data corresponding to a synthetic input, do not readily transfer over to text data. This is perhaps unsurprising since the inherently discrete nature of text makes the cost surface highly non-smooth and so gradient-based optimisation is difficult to apply successfully. In this paper we therefore propose new reconstruction approaches that are specialised to text data.

It is important to note that the transmission of user data to a remote server is not inherently a breach of privacy. The risk of a privacy breach is related to the nature of the data being sent, as well as whether it’s owner can be readily identified. For example, sending device models, version numbers, and locale/region information is not an immediate concern but it seems clear that the sentences entered by users, e.g. when typing messages, writing notes and emails, web browsing and performing searches, may well be private. Indeed, it is not only the sentences typed which can be sensitive but also the set of words used (i.e.

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1 DP aims to protect the aggregate training data/model against query-based attacks, whereas our attack targets the individual updates. Nevertheless, we note that DP is sometimes suggested as a potential defence against the type of attack carried out here.

2 Google’s Secure Aggregation approach [5] is a prominent example of an approach requiring trust in the server, or more specifically in the PKI infrastructure which in practice is operated by the same organisation that runs the FL server since it involves authentication/verification of clients. We note also that Secure Aggregation is not currently deployed in the GBoard app despite being proposed 6 years ago.
even without knowing the word ordering) since this can be used for targeting surveillance via keyword blacklists [3].

In addition, most Google telemetry is tagged with an Android ID. Via other data collected by Google Play Services the Android ID is linked to (i) the handset hardware serial number, (ii) the SIM IMEI (which uniquely identifies the SIM slot) and (iii) the user’s Google account [14,15]. When creating a Google account users are encouraged to supply a phone number and for many people this will be their own phone number. Use of Google services such as buying a paid app on the Google Play store or using Google Pay further links a person’s Google account to their credit card/bank details. A user’s Google account, and so the Android ID, can therefore commonly be expected to be linked to the person’s real identity.

2 Preliminaries

2.1 Federated Learning Client Update

Algorithm 1 gives the procedure followed by FL participants to generate a model update. The number of local epochs $E$, mini-batch size $B$, and local client learning rate $\eta$ can be changed depending on the FL application. When $E = 1$ and the mini-batch size is equal the size of the training dataset, then it is called FedSGD, and any other configuration corresponds to FedAveraging, where multiple gradient descent steps occur on the client.

**Algorithm 1: Federated Learning Client Update**

**Input:** $\theta_0$: The parameters of the global model, training loss function $\ell$.

**Output:** $\theta_1$: The model parameters after training on the client’s data.

**Procedure** `clientUpdate`

1. $\theta_1 \leftarrow \theta_0$;
2. $\mathcal{B} \leftarrow$ (split dataset into batches of size $B$);
3. for local epoch $i$ from 1 to $E$ do;
4.  for batch $b \in \mathcal{B}$ do;
5.    $\theta_1 \leftarrow \theta_1 - \eta \nabla \ell(\theta_1; b)$;
6. return $\theta_1$;

2.2 Threat Model

The threat model is that of a honest-but-curious adversary that has access to (i) the FL model architecture, (ii) the current global FL model parameters $\theta_0$, and (iii) the FL model parameters, $\theta_1$, after updating locally using the training data of an individual user. The FL server has, for example, access to all of these and so this threat model captures the situation where there is an honest-but-curious FL server.
We do not consider membership attacks against the global model, although knowledge of $\theta_0$ allows such attacks, since they have already received much attention in the literature. Instead we focus on local reconstruction attacks i.e. attacks that aim to reconstruct the local training data of a user from knowledge of $\theta_0$ and $\theta_1$. In the GBoard Next Word Prediction task the local training data is the text typed by the user while using apps on their mobile handset e.g. while sending text messages.

2.3 GBoard NWP Model

Figure 1 shows the LSTM recursive neural net (RNN) architecture used by Gboard for NWP. This model was extracted from the app.

Fig. 1: Schematic of LSTM architecture. LSTM layer takes as input dense vector $x_t$ representing a typed word and outputs a dense vector $h_t$. This output is then mapped to vector $z_t$ of size 9502 (the size of the dictionary) with the value of each element being the raw logit for the corresponding dictionary word. A softmax layer then normalises the raw $z_t$ values to give a vector $\hat{y}_t$ of probabilities.

The Gboard LSTM RNN is a word level language model, predicting the probability of the next word given what the user has already typed into the keyboard. Input words are first mapped to a dictionary entry, which has a vocabulary of $V = 9502$ words, with a special <UNK> entry used for words that are not in the dictionary, and <$S>$ to indicate the start of a sentence. The index of the dictionary entry is then mapped to a dense vector of size $D = 96$ using a lookup table (the dictionary entry is one-hot encoded and then multiplied by a $R^{D \times V}$ weighting matrix $W^T$) and applied as input to an LSTM layer with 670 units i.e. the state $C_t$ is a vector of size 670. The LSTM layer uses a CIFG architecture without peephole connections, illustrated schematically in Figure 1. The LSTM state $C_t$ is linearly projected down to an output vector $h_t$ of size $D$, which is mapped to a raw logit vector $z_t$ of size $V$ via a weighting matrix $W$ and bias $b$. This extra linear projection is not part of the orthodox CIFG cell structure that was introduced in [10], and is included to accommodate the model’s tied input and output embedding matrices [22]. A softmax output layer finally maps
this to an $[0,1]^V$ vector $\hat{y}_t$ of probabilities, the $i$'th element being the estimated probability that the next word is the $i$'th dictionary entry.

### 3 Reconstruction Attack

#### 3.1 Word Recovery

In next word prediction the input to the RNN is echoed in its output. That is, the output of the RNN aims to match the sequence of words typed by the user, albeit with a shift one word ahead. The sign of the output loss gradient directly reveals information about the words typed by the user, which can then be recovered easily by inspection. This key observation, first made in [26], is the basis of our word recovery attack.

After the user has typed $t$ words, the output of the LSTM model at timestep $t$ is the next word prediction vector $\hat{y}_t$,

$$\hat{y}_{t,i} = \frac{e^{z_{i,t}}}{\sum_{j=1}^{V} e^{z_{j,t}}} , \ i = 1,\ldots,V$$

with raw logit vector $z_t = W h_t + b$, where $h_t$ is the output of the LSTM layer. The cross-entropy loss function for text consisting of $T$ words is $J_{1:T}(\theta) = \sum_{t=1}^{T} J_t(\theta)$ where

$$J_t(\theta) = -\log \frac{e^{z_{i^*_t}(\theta)}}{\sum_{j=1}^{V} e^{z_{j,t}(\theta)}} ,$$

and $i^*_t$ is the dictionary index of the $t$'th word entered by the user and $\theta$ is the vector of neural net parameters (including the elements of $W$ and $b$). Differentiating with respect to the output bias parameters $b$ we have that,

$$\frac{\partial J_{1:T}}{\partial b_k} = \sum_{t=1}^{T} \sum_{i=1}^{V} \frac{\partial J_t}{\partial z_{t,i}} \frac{\partial z_{t,i}}{\partial b_k}$$

where

$$\frac{\partial J_t}{\partial z_{t,i^*_t}} = \frac{e^{z_{i^*_t}}}{\sum_{j=1}^{V} e^{z_{j,t}}} - 1 < 0,$$

$$\frac{\partial J_t}{\partial z_{t,i}} = \frac{e^{z_i}}{\sum_{j=1}^{V} e^{z_j}} > 0 , \ i \neq i^*_t$$

and

$$\frac{\partial z_{t,i}}{\partial b_k} = \begin{cases} 1 & k = i \\ 0 & \text{otherwise} \end{cases}$$
That is,
\[
\frac{\partial J_{1:T}}{\partial b_k} = \sum_{t=1}^{T} \frac{\partial J_t}{\partial z_t,k}
\]

It follows that for words \( k \) which do not appear in the text \( \frac{\partial J_{1:T}}{\partial b_k} > 0 \). Also, assuming that the neural net has been trained to have reasonable performance then \( e^{z_k} \) will tend to be small for words \( k \) that do not appear next and large for words which do. Therefore for words \( i^* \) that appear in the text we expect that \( \frac{\partial J_{1:T}}{\partial b_{i^*}} < 0 \).

The above analysis focuses mainly on the bias parameters of the final fully connected layer, however similar methods can be applied to the \( W \) parameters.

The key aspect here that lends to the ease of this attack is that the outputs echo the inputs, unlike for example, the task of object detection in images. In that case, the output is just the object label.

This observation is intuitive from a loss function minimisation perspective. Typically the estimated probability \( \hat{y}_{i^*} \) for an input word will be less than 1. Increasing \( \hat{y}_{i^*} \) will therefore decrease the loss function i.e. the gradient is negative. Conversely, the estimated probability \( \hat{y}_i \) for a word that does not appear in the input will be small but greater than 0. Decreasing \( \hat{y}_i \) will therefore decrease the loss function i.e. the gradient is positive.

**Example:** To execute this attack in practice, simply subtract the final layer parameters of the current global model \( \theta_0 \) from those of the resulting model trained on the client’s local data, \( \theta_1 \), as shown in Algorithm 2. The indices of the negative values reveal the typed words. Suppose the client’s local data consists of just the one sentence “learning online is not so private”. We then train model \( \theta_0 \) on this sentence for 1 epoch, with a mini-batch size of 1, and SGD learning rate of 0.001 (FedSGD), and report the the values at the negative indices in Table 1.

| word    | \( t \) | \( (\theta_1 - \theta_0)_i \) |
|---------|--------|-----------------------------|
| learning | 7437   | -0.0009951561               |
| online  | 4904   | -0.0009941629               |
| is      | 209    | -0.000997875                |
| not     | 1808   | -0.0009941144               |
| so      | 26     | -0.0009965639               |
| private | 6314   | -0.0009951561               |

Table 1: Values of the final layer parameter difference at the indices of the typed words. Produced after training the model on the sentence “learning online is not so private”, \( E = 1, B = 1, \eta = 0.001 \). These are the only indices where negative values occur.
Algorithm 2: Word Recovery

**Input:** $\theta_0$: The global model’s final layer parameters, $\theta_1$: The final layer parameters of a model update

**Output:** User typed tokens $w$

**Procedure** recoverWords
\[
\begin{align*}
    d &\leftarrow \theta_1 - \theta_0; \\
    w &\leftarrow \{i \mid d_i < 0\}; \\
    \text{return } w;
\end{align*}
\]

3.2 Reconstructing Sentences

The attack described previously retrieves the words typed, but gives no indication of the order in which they occurred. To reveal this order, we ask the model$^3$.

The basic idea is that after running multiple rounds of gradient descent on the local training data, the local model is “tuned” to the local data in the sense that when it is presented with the first words of a sentence from the local training data, the model’s next word prediction will tend to match the training data and so we can bootstrap reconstruction of the full training data text.

In more detail, the $t$’th input word is represented by a vector $x_t \in 0,1^V$, with all elements zero apart from the element corresponding to the index of the word in the dictionary. The output $y_{t+1} \in [0,1]^V$ from the model after seeing input words $x_0, \ldots, x_t$ is a probability distribution over the dictionary. We begin by selecting $x_0$ equal to the start of sentence token $<$S$>$ and $x_1$ equal to the first word from our set of reconstructed words, then ask the model to generate $y_2 = Pr(x_2|x_0, x_1; \theta_1)$. We set all elements of $y_2$ that are not in the set of reconstructed words to zero, since we know that these were not part of the local training data, re-normalise $y_2$ so that its elements sum to one, and then select the most likely next word as $x_2$. We now repeat this process for $y_3 = Pr(x_3|x_0, x_1, x_2; \theta_1)$, and so on, until a complete sentence has been generated. We then take the second word from our set of reconstructed words as $x_1$ and repeat to generate a second sentence, and so on.

This method generates as many sentences as there are extracted words. This results in a lot more sentences than were originally in the client’s training dataset. In order to filter out the unnecessary sentences, we rank each generated sentence by its change in perplexity, from the initial global model $\theta_0$ to the new update $\theta_1$.

The Log-Perplexity of a sequence $x_0, \ldots, x_t$, is defined as
\[
PP_\theta(x_0, ..., x_t) = \sum_{i=1}^{t} (-\log Pr(x_i|x_0, ..., x_{i-1}; \theta)),
\]

$^3$ It is perhaps worth noting that we studied a variety of reconstruction attacks, e.g., using Monte Carlo Tree Search to perform a smart search over all words sequences, but found the attack method described here to be simple, efficient and highly effective.
and quantifies how ‘surprised’ the model is by the sequence. Those sentences that report a high perplexity for $\theta_0$ but a comparatively lower one for $\theta_1$ reveal themselves as having been part of the dataset used to train $\theta_1$. Each generated sentence is scored by their percentage change in perplexity:

$$\text{Score}(x_0, \ldots, x_t) = \frac{PP_{\theta_0}(x_0, \ldots, x_t) - PP_{\theta_1}(x_0, \ldots, x_t)}{PP_{\theta_0}(x_0, \ldots, x_t)}.$$ 

By selecting the top-$n$ ranked sentences, we select those most likely to have been present in the training dataset.

Fig. 2: Word recovery performance over time with full batch and mini-batch training. The upper bound on the F1 score for the different datasets is related to how many words in the training set are also in the model dictionary. Figure 2a shows the F1 score over time with $B = n_k$ full batch training. At epoch 1 (FedSGD), the F1 is high and stays constant as you train for longer (FedAveraging). Using a mini-batch $B = 32$ (Figure 2b) has no effect on the attack (in the case where $n_k = 16, B = 16$).

4 Performance Of Attacks Against Vanilla Federated Learning

4.1 Experimental Setup

We make use of the LSTM RNN extracted from Gboard as the basis of our experiments. The value of its extracted parameters are used as the initial ‘global’ model $\theta_0$; the starting point of the updates we generate. There are several variables that go into producing an update: the number of sentences in the dataset, $n_k$, the number of epochs $E$, the batch size $B$, and the local learning rate $\eta$. Note that when $E = 1$ and $B = n_k$, this corresponds to a FedSGD update, and that any other configuration corresponds to a FedAveraging update. Unless explicitly mentioned otherwise, we keep the client learning rate $\eta = 0.001$ constant for all our experiments. All sample datasets used consist of 4 word long sentences,
mirroring the average length of sentences that the Gboard model was trained with [11].

To evaluate the effectiveness of our attack, the sample datasets we use are taken from a corpus of American English text messages [19], which includes short sentences similar to those the Gboard LSTM extracted from the mobile application was trained on. We perform our two attacks on datasets consisting of \( n_k = 16, 32, 64, 128, \) and 256 sentences. Converting a sentence into a sequence of training samples and labels \((x, y)\) is done as follows:

- The start-of-sentence token \(<s>\) is prepended to the beginning of the sentence, and each word is then converted to its corresponding word embedding. This gives a sequence \(x_0, x_1, \ldots, x_T\) of tokens where \(x_0\) is the \(<s>\) token.
- A sentence of length \(T\) becomes \(T\) training points \(((x_0, x_1), y_2), ((x_0, x_1, x_2), y_3), \ldots, ((x_0, x_1, \ldots, x_{T-1}), y_T)\)

where label \(y_t \in [0, 1]^V\) is a probability distribution over the dictionary entries, with all elements zero apart from the element corresponding to the dictionary index of \(x_t\).

Following [11] we use categorical cross entropy loss over the output and target labels. After creating the training samples and labels from a dataset of \(n_k\) sentences, we train model \(\theta_0\) on this training data for a specified number of epochs \(E\) with a mini-batch size of \(B\), according to Algorithm 1 to produce the local update \(\theta_1\). We then subtract the final layer parameters of the two models to recover the words, and iteratively sample \(\theta_1\) according to the methodology described in Section 3.2 to reconstruct the sentences, and take the top-\(n_k\) ranked sentences by their perplexity score.

### 4.2 Metrics

To evaluate performance, we use the F1 score which balances the precision and recall of word recovery with our attack. We also use a modified version of the Levenshtein ratio i.e. the normalised Levenshtein distance [16] (the minimum number of word level edits needed to make one string match another) to evaluate our sentence reconstruction attack. Ranging from 0 to 100, the larger the Levenshtein ratio, the closer the match between our reconstructed and the ground truth sentence.

### 4.3 Measurements

**Word Recovery Performance** Figure 2 shows the measured performance of our word recovery attack for both the FedSGD and FedAveraging variants of FL for mini-batch/full batch training and as the dataset size and training time are varied. It can be seen that none of these variables have much of an effect on the F1 score achieved by our attack, which remains high across a wide range of conditions. Note that the maximum value of the F1 score is not one for this data
but instead a smaller value related to how many of the words in the dataset are also present in the model’s vocabulary. Some words, e.g. unique nouns, slang, etc, do not exist in the model’s 9502 word dictionary, and our word recovery attack can only extract the <UNK> token in their place, limiting how many words we can actually recover.

Fig. 3: Sentence reconstruction performance. Each point corresponds to a different dataset colour coded by it’s size. The y-axis gives the average Levenshtein ratio of the reconstructed sentences. The x-axis is the F1 score between the tokens used in the reconstructed sentences and the ground truth. The closer a point is to the top-right corner, the closer the reconstruction is to perfect.

Sentence Reconstruction Performance

Figure 3 shows the measured performance of our sentence reconstruction attack. Figures 3a, 3b, and 3c show that as you train for more epochs (50, 100, and 1000 respectively) the quality of the reconstructed sentences improves. This is intuitive as the models trained for longer are more overfit to the data, and so the iterative sampling approach is more likely to return the correct next word given a conditioning prefix.

However, longer training times are not necessary to accurately reconstruct sentences. It can be seen from Figure 4(b) that even in the FedSGD setting, where the number of epochs $E = 1$, we can sometimes still get high quality sentence reconstructions by modifying the model parameters $\theta_1$ to be $\theta_1 + s(\theta_1 - \theta_0)$, with $s$ being a scaling factor. Since $\theta_1 = \theta_0 - \eta \nabla \ell(\theta_0; b)$ with FedSGD,

$$\theta_1 + s(\theta_1 - \theta_0) = \theta_0 - \eta (1 + s) \nabla \ell(\theta_0; b)$$

from which it can be seen that scaling factor $s$ effectively increases the gradient descent step size.

5 Existing Attacks And Their Defences

5.1 Image Data Reconstruction

Information leakage from the gradients of neural networks used for object detection in images appears to have been initially investigated in [28], which proposed
the Deep Leakage from Gradients (DLG) algorithm. An image is input to a neural net and the output is a label specifying an object detected in the image. In DLG a synthetic input is applied to the neural net and the gradients of the model parameters are calculated. These gradients are then compared to the observed model gradients sent to the FL server and gradient descent is used to update the synthetic input so as to minimise the difference between its model gradients and the observed model gradients.

This work was subsequently extended by [9,12,24–27] to improve the stability and performance of the original DLG algorithm, as well as the fidelity of the images it generates. In [12,25], changes to the optimisation terms allowed for successful data reconstruction at batch sizes of up to 48 and 100 respectively. Analytical techniques of data extraction [4,20] benefit from not being as costly to compute as compared to optimization based methods. Additionally, these analytical attacks extract the exact ground truth data, as compared to DLG and others who often settle to image reconstructions that include artefacts.

5.2 Text Data Reconstruction

Most work on reconstruction attacks has focused on images and there is relatively little work on text reconstruction. A single text reconstruction example is presented in [28], with no performance results. Probably the closest work to the present paper is [8] which applies a variant of DLG to text reconstruction from gradients of transformer-based models (variants of BERT [23]). As already noted, DLG tends to perform poorly with text data and the word recovery rate achieved in [8] is generally no more than 50%.

In our attack context, DLG can recover words but at much smaller scales than we have demonstrated, and takes longer to find these words. There is also no guarantee that DLG can recover words and place them in the correct order. In [28], it is noted that the algorithm requires multiple restarts before successful reconstruction. Additionally, DLG operates by matching the single gradient of a batch of training data, therefore it only works in the FedSGD setting, where $E = 1$. We show the results of DLG in Listing 1.1 on gradients of $B = 1$, and $24$
word sentences. In the first example, it took DLG 1000 iterations to produce “<S> how are venue”, and 1500 iterations to produce “<S> how are sure cow, <S> haha where are Tell van”. These reconstructions include some of the original words, but recovery is not as precise as our attack, and takes orders of magnitude longer to carry out.

Listing 1.1: Original and reconstructed sentences by DLG

| <S> how are you     |
| <S> how are venue  |
| <S> how are you doing |
| <S> how are sure cow |
| <S> where are you going |
| <S> haha where are Tell van |

Work has also been carried out on membership attacks against text data models such as GPT2 i.e. given a trained model the attack seeks to infer one or more training data points. See for example [6, 7]. But, as already noted, such attacks are not the focus of the present paper.

5.3 Proposed Defences

Several defences have been proposed to prevent data leakage in FL.

Abadi et al. [2] proposed Differentially Private Stochastic Gradient Descent (DP-SGD), which clips stochastic gradient decent updates and adds Gaussian noise at each iteration. This aims to defend against membership attacks against neural networks, rather than the reconstruction attacks that we consider here. In [18] it was applied to train a next word prediction RNN motivated by mobile keyboard applications, again with a focus on membership attacks. Recently, the same team at Google proposed DP-FTRL [13] which avoids the sampling step in DP-SGD.

Secure Aggregation is a multi-party protocol proposed in 2016 by [5] as a defence against data leakage from the data uploaded by clients to an FL server. In this setting the central server only has access to the sum of, and not individual updates. However, this approach still requires clients to trust that the PKI infrastructure is honest since dishonest PKI infrastructure allows the server to perform a sybil attack (see Section 6.2 in [5]) to reveal the data sent by an individual client. When both the FL server and the PKI infrastructure are operated by Google then Secure Aggregation requires users to trust Google servers to be honest, and so offers from an attack capability point of view offers no security benefit. Recent work by Pasquini et al. [21] has also shown that by distributing different models to each client a dishonest server can recover individual model updates. As a mitigation they propose adding local noise to client updates to obtain a form of local differential privacy. We note that despite the early deployment of FL in production systems such as GBoard, to the best our knowledge, there does not exist a real-world deployment of secure aggregation. This is also
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true for homomorphically encrypted FL, and FL using Trusted Execution Environments (TEEs).

6 Performance Of Our Attacks Against Federated Learning with Local DP

Typically, when differential privacy is used with FL noise is added by the server to the aggregate update from multiple clients i.e. no noise is added to the update before leaving a device. This corresponds to the situation considered in Section 4. In this section we now evaluate how local differential privacy, that is, noise added either during local training (DPSGD) or to the final model parameters $\theta_1$, before its transmission to the coordinating FL server, affect the performance of both our word recovery and sentence reconstruction attacks.

Algorithm 3: Local DPSGD

```
Procedure clientUpdateDPSGD
    $\theta_1 \leftarrow \theta_0$;
    $B \leftarrow$ (split dataset into batches of size $B$);
    for local epoch $i$ from 1 to $E$ do;
        for batch $b \in B$ do;
            $\theta_1 \leftarrow \theta_1 - \eta \nabla \ell(\theta_1; b) + \eta \mathcal{N}(0, \sigma)$;
        return $\theta_1$;
```

Algorithm 3 outlines the procedure for DPSGD-like local training, where Gaussian noise of mean 0 and standard deviation $\sigma$ is added along with each gradient update. Algorithm 4 details the typical FL client update procedure but adds Gaussian noise to the final model $\theta_1$ before it is returned to the server. In our experiments, everything else as described in Section 4 is kept the same.

Algorithm 4: Local Single Noise Addition

```
Procedure clientUpdateSingleNoise
    $\theta_1 \leftarrow \theta_0$;
    $B \leftarrow$ (split dataset into batches of size $B$);
    for local epoch $i$ from 1 to $E$ do;
        for batch $b \in B$ do;
            $\theta_1 \leftarrow \theta_1 - \eta \nabla \ell(\theta_1; b)$;
        return $\theta_1 + \mathcal{N}(0, \sigma)$;
```
Fig. 5: Word recovery behaviour when Gaussian noise is all to local FL updates: (a) vanilla word recovery performance, (b) disparity of magnitudes between those words that were present in the dataset and those ‘noisily’ flipped negative, (c) word recovery performance when filtering is used.

Fig. 6: Word recovery results for two local DP methods. Figure 6a shows how added noise to the final model parameters affects the attack for different training times. With DPSGD-like training, noise levels of up to $\sigma = 0.1$ are manageable with our magnitude threshold trick, resulting in F1 scores close to those had we not added any noise at all. With FedSGD updates then for noise of up to $\sigma = 0.0001$ added to the final parameters, we can still recover words to a high degree of precision and recall.

6.1 Word Recovery Performance

Figure 5a shows the performance of our word recovery attack against DPSGD-like local training for different levels of $\sigma$. For noise levels of $\sigma = 0.001$ or greater, it can be seen that the F1 score drops significantly. What is happening is that the added noise introduces more negative values in the difference of the final layer parameters and so results in our attack extracting more words than actually occurred in the dataset, destroying its precision. However, one can eliminate most of these “noisily” added words by simple inspection. Figure 5b graphs the sorted magnitudes of the negative values in the difference between the final layer parameters of $\theta_1$ and $\theta_0$, after DPSGD-like training with $B = 32$, $n_k = 256$, and $\sigma = 0.001$. We can see that the more epochs the model is trained for, the more words are extracted via our attack. Of the around 600 words extracted after 1000 epochs of training, only about 300 of them were actually present in the dataset. On this graph, those words with higher magnitudes correspond to the ground truth words. It can be seen that we therefore can simply cutoff any words
extracted beyond a specified magnitude threshold. This drastically improves the performance of the attack, see Figure 5c. It can be seen that even for $\sigma = 0.1$, we now get word recovery results close to those obtained when we added no noise at all.

Figure 6a shows the performance of our word recovery attack when noise is added to the local model parameters $\theta_1$ in the FedAveraging setting, with $n_k = 256$, and $B = 32$. When $\sigma \geq 0.01$, it can be seen that the performance drops drastically\(^4\), even when we use the magnitude threshold trick described previously. With FedSGD (Figures 6b and 6c), we see that with DPSGD-like training, these levels of noise are manageable, but for single noise addition, there are only so many words that are recoverable before being lost in the comparatively large amounts of noise added.

For comparison, in the FL literature on differential privacy, the addition of Gaussian noise with standard deviation no more than around 0.001 (and often much less) is typically considered, and is only added after the update has been transmitted to the coordinating FL server.

### 6.2 Sentence Reconstruction Performance

Figure 7 shows the measured sentence reconstruction performance with both DPSGD-like training (Figures 7a and 7b) and when noise is added to the final parameters of the model (Figures 7c and 7d). By removing the noisily added words and running our sentence reconstruction attack, we get results close to those had we not added any noise for up to $\sigma = 0.1$. For the single noise addition method, as these levels of noise are not calibrated, $\sigma = 0.1$ is enough to destroy the quality of reconstructions, however these levels of noise also destroy any model utility.

### 7 Additional Material

The code for all of the attacks here, the LSTM model and the datasets used are all publicly available on github [here](https://github.com).

### 8 Summary And Conclusions

In this paper we introduce two local reconstruction attacks against federated learning when used to train natural language text models. We find that previously proposed attacks (DLG and its variants) targeting image data are ineffective for text data and so new methods of attack tailored to text data are

\(^{4}\) Note that in DPSGD the added noise is multiplied by the learning rate $\eta$, and so this factor needs to be taken into account when comparing the $\sigma$ values used in DPSGD above and with single noise addition. This means added noise with standard deviation $\sigma$ for DPSGD corresponds roughly to a standard deviation of $\eta \sqrt{EB\sigma}$ with single noise addition. For $\eta = 0.001$, $E = 1000$, $B = 32$, $\sigma = 0.1$ the corresponding single noise addition standard deviation is 0.018.
Our attacks are simple to carry out, efficient, and highly effective. We illustrate their effectiveness against the next word prediction model used in Google’s GBoard app, a widely used mobile keyboard app (with > 5 Billion downloads) that has been an early adopter of federated learning for production use. We demonstrate that the words a user types on their mobile handset, e.g. when sending text messages, can be recovered with high accuracy under a wide range of conditions and that counter-measures such a use of mini-batches and adding local noise are ineffective. We also show that the word order (and so the actual sentences typed) can be reconstructed with high fidelity. This raises obvious privacy concerns, particularly since GBoard is in production use.

Secure multi-party computation methods such as Secure Aggregation and also methods such as Homomorphic Encryption and Trusted Execution Environments are potential defences that can improve privacy, but these can be difficult to implement in practice. Secure Aggregation requires users to trust that the server is honest, despite the fact that FL aims to avoid the need for such trust. Homomorphic Encryption implementations that are sufficiently efficient to allow large-scale production use are currently lacking.

On a more positive note, the privacy situation may not be quite as bad as it seems given these reconstruction attacks. Firstly, it is not the raw sentences typed by a user that are reconstructed in our attacks but rather the sentences after they have been mapped to tokens in a text model dictionary. Words which are not in the dictionary are mapped to a special \(<UNK>\) token. This means that the reconstructed text is effectively redacted, with words not in the dictionary having been masked out. This suggests that a fruitful direction for future privacy research on FL for natural language models may well lie in taking a closer look at the specification of the dictionary used. Secondly, we also note that changing from a word-based text model to a character-based one would likely make our attacks much harder to perform.

References

1. Gboard – the Google Keyboard. <https://play.google.com/store/apps/details?id=com.google.android.inputmethod.latin>, 2022. Accessed: 2022-10-24.

2. Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In Proceedings of the 2016 ACM SIGSAC conference on computer and communications security, 2016.

3. James Ball. NSA collects millions of text messages daily in 'untargeted' global sweep, 2014.

4. Franziska Boenisch, Adam Dziedzic, Roei Schuster, Ali Shahin Shamsabadi, Ilia Shumailov, and Nicolas Papernot. When the curious abandon honesty: Federated learning is not private. arXiv preprint arXiv:2112.02918, 2021.

5. Keith Bonawitz, Vladimir Ivanov, Ben Kreuter, Antonio Marcedone, H Brendan McMahan, Sarvar Patel, Daniel Ramage, Aaron Segal, and Karn Seth. Practical secure aggregation for federated learning on user-held data. arXiv preprint arXiv:1611.04482, 2016.
Fig. 7: Sentence reconstruction performance with local DP for FedAveraging. The top two Figures (7a and 7b) show the reconstruction performance for different datasets colour coded by their size for DPSGD-like training, with $E = 100$, $B = 32$. Here we see no real effect in our results compared to the noise-free case. The bottom two figures show the effect of single noise addition on sentence reconstruction for the same setting.

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

7. Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Úlfar Erlingsson, et al. Extracting training data from large language models. In *30th USENIX Security Symposium (USENIX Security 21)*, pages 2633–2650, 2021.

8. Jieren Deng, Yijue Wang, Ji Li, Chao Shang, Hang Liu, Sanguthevar Rajasekaran, and Caiwen Ding. Tag: Gradient attack on transformer-based language models. *arXiv preprint arXiv:2103.06819*, 2021.

9. Jonas Geiping, Hartmut Bauermeister, Hannah Dröge, and Michael Moeller. Inverting gradients - how easy is it to break privacy in federated learning? In *Advances in Neural Information Processing Systems*, 2020.

10. Klaus Greff, Rupesh K. Srivastava, Jan Koutník, Bas R. Steunebrink, and Jurgen Schmidhuber. Lstms: A search space odyssey. *IEEE Transactions on Neural
11. Andrew Hard, Kanishka Rao, Rajiv Mathews, Swaroop Ramaswamy, Françoise Beaufays, Sean Augenstein, Hubert Eichner, Chloé Kiddon, and Daniel Ramage. Federated learning for mobile keyboard prediction. *arXiv preprint arXiv:1811.03604*, 2018.

12. Xiao Jin, Pin-Yu Chen, Chia-Yi Hsu, Chia-Mu Yu, and Tianyi Chen. Catastrophic data leakage in vertical federated learning. *Advances in Neural Information Processing Systems*, 34, 2021.

13. Peter Kairouz, H Brendan McMahan, Shuang Song, Om Thakkar, Abhradeep Thakurta, and Zheng Xu. Practical and private (deep) learning without sampling or shuffling. *arXiv preprint arXiv:2103.00039*, 2021.

14. Douglas J. Leith. Mobile Handset Privacy: Measuring The Data iOS and Android Send to Apple And Google. In *Proc Securecomm*, 2021.

15. Douglas J. Leith and Stephen Farrell. Contact Tracing App Privacy: What Data Is Shared By Europe’s GAEN Contact Tracing Apps. In *Proc IEEE INFOCOM*, 2021.

16. A. Marzal and E. Vidal. Computation of normalized edit distance and applications. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 15(9):926–932, 1993.

17. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial Intelligence And Statistics*, 2017.

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

19. Daniel R. O’Day and Ricardo A. Calix. Text message corpus: Applying natural language processing to mobile device forensics. In *2013 IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*, 2013.

20. Xudong Pan, Mi Zhang, Yifan Yan, Jiaming Zhu, and Min Yang. Theory-oriented deep leakage from gradients via linear equation solver. *arXiv preprint arXiv:2010.13356*, 2020.

21. Dario Pasquini, Danilo Francati, and Giuseppe Ateniese. Eluding secure aggregation in federated learning via model inconsistency. *arXiv preprint arXiv:2111.07380*, 2021.

22. Ofir Press and Lior Wolf. Using the output embedding to improve language models. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 157–163, Valencia, Spain, April 2017. Association for Computational Linguistics.

23. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, I. Štefanić, Luka Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, 2017.

24. Yijue Wang, Jieren Deng, Dan Guo, Chenghong Wang, Xianrui Meng, Hang Liu, Caiwen Ding, and Sanguthevar Rajasekaran. Sapag: A self-adaptive privacy attack from gradients. *arXiv preprint arXiv:2009.06228*, 2020.

25. Hongxu Yin, Arun Mallya, Arash Vahdat, Jose M Alvarez, Jan Kautz, and Pavlo Molchanov. See through gradients: Image batch recovery via gradinversion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16337–16346, 2021.

26. Bo Zhao, Konda Reddy Mopuri, and Hakan Bilen. idlg: Improved deep leakage from gradients. *arXiv preprint arXiv:2001.02610*, 2020.
27. Junyi Zhu and Matthew Blaschko. R-gap: Recursive gradient attack on privacy. *arXiv preprint arXiv:2010.07733*, 2020.

28. Ligeng Zhu, Zhijian Liu, , and Song Han. Deep leakage from gradients. In *Annual Conference on Neural Information Processing Systems (NeurIPS)*, 2019.