# LAMP: Extracting Text from Gradients with Language Model Priors

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## Abstract

Recent work shows that sensitive user data can be reconstructed from gradient updates, breaking the key privacy promise of federated learning. While success was demonstrated primarily on image data, these methods do not directly transfer to other domains such as text. In this work, we propose LAMP, a novel attack tailored to textual data, that successfully reconstructs original text from gradients. Our attack is based on two key insights: (i) modelling prior text probability via an auxiliary language model, guiding the search towards more natural text, and (ii) alternating continuous and discrete optimization which minimizes reconstruction loss on embeddings while avoiding local minima via discrete text transformations. Our experiments demonstrate that LAMP is significantly more effective than prior work: it reconstructs 5x more bigrams and $23\%$ longer subsequences on average. Moreover, we are first to recover inputs from batch sizes larger than 1 for textual models. These findings indicate that gradient updates of models operating on textual data leak more information than previously thought.

## 1 Introduction

Federated learning [21] is a widely adopted framework for training machine learning models in a decentralized way. Conceptually, the method allows training of highly accurate models while offering a level of data privacy as the raw data never leaves the client machine. However, recent work has shown that in practice, client data can be reconstructed from updates sent from the client to the server during training [24, 39, 37]. Such reconstructions typically start from a randomly sampled input and modify it so that gradient updates obtained with this input match the gradients which the client sent to the server. And while there has been much work on reconstruction attacks in computer vision, there has comparatively been little work in the text domain, despite the fact that some of the most prominent applications of federated learning involve learning over textual data, e.g., next-word prediction on mobile phones [26]. A key component behind the successful attacks in vision has been the use of image priors such as total variation [7]. These priors guide the reconstruction towards natural images more likely to correspond to client data. However, the use of priors has so far been missing from attacks on text [39, 3], limiting their ability to reconstruct real client data.

**This Work: private text reconstruction via priors** In this work, we propose LAMP, a new reconstruction attack which leverages language model priors to extract private text from gradients. The overview of our attack is shown in Fig. 1. The attacker receives the transformer network and a gradient $\nabla_\theta \mathcal{L}$ which the client has computed on their private data $(\boldsymbol{x}^*, y^*)$. The attack is initiated by sampling token embeddings for a candidate text from a Gaussian distribution. Then, at each step, we alternate between continuous (shown in blue) and discrete optimization (shown in green). Yellow boxes show our reconstruction after each iteration. First, the continuous part minimizes the reconstruction loss that measures how close the current gradients are to the observed client gradients,

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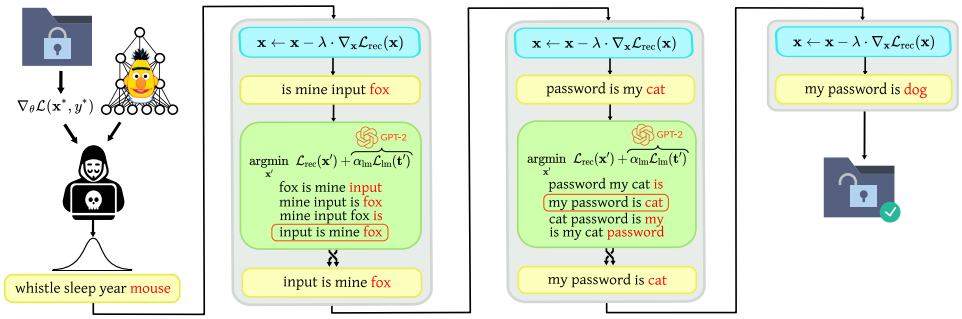


Figure 1: Overview of LAMP. We initialize embeddings by sampling from a Gaussian distribution, and alternate between continuous and discrete optimization. Continuous optimization minimizes reconstruction loss and an embedding regularization. Discrete optimization forms candidates by performing discrete transformations, and chooses the best candidate based on a combination of reconstruction loss and perplexity, as measured by an auxiliary language model (e.g. GPT-2).

together with embeddings regularization. However, only the continuous part is not sufficient as the gradient descent can get stuck in a local optimum due to its inability to make discrete changes to the sentence. We address this issue by introducing a discrete step – here, we generate a list of candidate sentences using several transformations on the sequence of tokens (e.g., moving a token to another position) and then select a candidate that minimizes the combined reconstruction loss and perplexity, which measures the likelihood of observing the text in a natural distribution. We use GPT-2 [25] as an auxiliary language model to measure the perplexity of each candidate (however, our method allows using other models). We compute our final reconstruction by setting each embedding to its nearest neighbor from the vocabulary.

Key to the effectiveness of our reconstruction attack is the use of a language model prior combined with a search that alternates continuous and discrete optimization steps. Our experimental evaluation demonstrates the effectiveness of this approach – LAMP is able to extract text from state-of-the-art transformer models on several common datasets, reconstructing up to 5 times more bigrams than prior work. Moreover, we are the first to perform text reconstruction in more complex settings such as batch sizes larger than 1, fine-tuned models, and defended models. Overall, across all settings we demonstrate LAMP is effective in reconstructing large portions of private text.

**Main Contributions** Our main contributions are:

- A novel attack for recovering input text from gradients by leveraging an auxiliary language model to guide the search towards natural text combined with a search procedure which alternates continuous and discrete optimization.
- An extensive experimental evaluation demonstrating that LAMP is highly effective and that it can reconstruct significantly more private text than prior work.
- The first thorough experimental evaluation of text attacks in more complex settings such as larger batch sizes, fine-tuned models and defended models.

## 2 Related Work

Federated learning [21, 16] has attracted substantial interest [14] due to its ability to train deep learning models in a decentralized way, such that individual user data is not shared during training. Instead, individual clients calculate local gradient updates on their private data and share only the updates with a centralized server that aggregates updates from all clients [21]. The underlying assumption here is that user data cannot be recovered from gradient updates, allowing clients to train a joint model on their private data. Recently, several works [24, 39, 37, 38] demonstrated that gradients can still leak information, thus invalidating the fundamental privacy assumption. Moreover, recent work achieved near-perfect image reconstruction from gradients [7, 36, 12]. Interestingly, prior work showed that an auxiliary model [12] or prior information [2] can significantly improve reconstruction quality. Finally, Huang et al. [10] noticed that gradient leakage attacks often make strong assumptions, namely that batch normalization statistics and ground truth labels are known. In

our work, we do not assume knowledge of batch normalization statistics and as we focus on binary classification tasks, we can simply enumerate all possible labels during reconstruction.

Despite substantial progress on image reconstruction, attacks in other domains remain challenging, as the techniques used for images rely extensively on domain specific knowledge. In the domain of text, in particular, where federated learning is often applied [28], only a handful of works exist [39, 3, 19]. DLG [39] was first to attempt reconstruction from gradients coming from a transformer; TAG [3] extended DLG by adding an $L_1$ term to the reconstruction loss; finally, unlike TAG and DLG which are optimization-based techniques, APRIL [19] recently demonstrated an exact gradient leakage technique applicable to transformer networks. However, APRIL assumes batch size of 1 and learnable positional embeddings, which makes it easy to defend against. Another attack on NLP is [6], but they use stronger assumption that server can send malicious updates to the clients.

Finally, there have been several works attempting to protect against gradient leakage. Works based on heuristics [30, 27] lack privacy guarantees and have been shown ineffective against stronger attacks [2], while those based on differential privacy do train models with formal guarantees [1], but typically hurt the accuracy of the trained models as they require adding noise to the gradients. We remark that we also evaluate our attack on defended networks and demonstrate its effectiveness.

# 3 Background

In this section, we introduce the background necessary to understand our work.

## 3.1 Federated Learning

In federated learning, $C$ clients aim to jointly optimize a neural network $f$ with parameters $\theta$ on their private data. At iteration $k$, the parameters $\theta^k$ are sent to all clients, where each client $c$ executes a gradient update $\nabla_{\theta^k}\mathcal{L}(\boldsymbol{x}_c^*, y_c^*)$ on a sample $(\boldsymbol{x}_c^*, y_c^*)$ from their dataset $(\mathcal{X}_c, \mathcal{Y}_c)$. The updates are sent back to the server and aggregated. While in Sec. 5 we experiment with both FedSGD [21] and FedAvg [17] client updates , throughout the text we assume that clients use FedSGD updates:

$$\theta^{k+1} = \theta^k - \frac{\lambda}{C}\sum_{c=1}^{C}\nabla_{\theta^k}\mathcal{L}(\boldsymbol{x}_c^*, y_c^*).$$

**Gradient Leakage Attacks** A gradient leakage attack is an attack executed by the server (or a party which compromised it) that tries to obtain the private data $(\boldsymbol{x}_c^*, y_c^*)$ of a client using the gradient updates $\nabla_{\theta^k}\mathcal{L}(\boldsymbol{x}_c^*, y_c^*)$ sent to the server. Gradient leakage attacks usually assume honest-but-curious servers which are not allowed to modify the federated training protocol outlined above. A common approach to gradient leakage attacks, adopted by Zhu et al. [39], Zhao et al. [37], Deng et al. [3] as well as our work, is to obtain the private data by solving the optimization problem:

$$\underset{(\boldsymbol{x}_c, y_c)}{\arg\min}\ \delta\left(\nabla_{\theta^k}\mathcal{L}\left(\boldsymbol{x}_c^*, y_c^*\right), \nabla_{\theta^k}\mathcal{L}\left(\boldsymbol{x}_c, y_c\right)\right),$$

where $\delta$ is some distance measure and $(\boldsymbol{x}_c, y_c)$ denotes dummy data optimized using gradient descent to have similar gradients $\nabla_{\theta^k}\mathcal{L}(\boldsymbol{x}_c, y_c)$ to true data $(\boldsymbol{x}_c^*, y_c^*)$. Common choices for $\delta$ are $L_2$ [39], $L_1$ [3] and cosine distances [7]. When the true label $y_c^*$ is known, the problem simplifies to

$$\underset{\boldsymbol{x}_c}{\arg\min}\ \delta\left(\nabla_{\theta^k}\mathcal{L}\left(\boldsymbol{x}_c^*, y_c^*\right), \nabla_{\theta^k}\mathcal{L}\left(\boldsymbol{x}_c, y_c^*\right)\right),$$

which was shown [37, 10] to be simpler to solve with gradient descent approaches.

## 3.2 Transformer Networks

In this paper, we focus on the problem of gradient leakage of text on transformers [31]. Given some input text, the first step is to tokenize it into tokens from some fixed vocabulary of size $V$. Each token is then converted to a 1-hot vector denoted $t_1, t_2, \ldots, t_n \in \mathbb{R}^V$, where $n$ is the number of tokens in the text. The tokens are then converted to embedding vectors $x_1, x_2, \ldots, x_n \in \mathbb{R}^d$, where $d$ is a chosen embedding size, by multiplying by a trained embedding matrix $W_{\text{embed}} \in \mathbb{R}^{V\times d}$ [4]. The rows of $W_{\text{embed}}$ represent the embeddings of the tokens and we denote them as $e_1, e_2 \ldots, e_V \in \mathbb{R}^d$. In

addition to tokens, their positions in the sequence are also embedded using the positional embedding matrix $W_{\text{pos}} \in \mathbb{R}^{P \times d}$, where $P$ is the longest allowed token sequence. The resulting positional embeddings are denoted $p_1, p_2, \ldots, p_n$. For notational simplicity, we denote $\boldsymbol{e} = e_1, e_2 \ldots, e_V$ , $\boldsymbol{x} = x_1, x_2, \ldots, x_n$ and $\boldsymbol{p} = p_1, p_2, \ldots, p_n$. We use the token-wise sum of the embeddings $\boldsymbol{x}$ and $\boldsymbol{p}$ as an input to a sequence of self-attention layers [31]. The final classification output is given by the first output of the last self-attention layer that undergoes a final linear layer, followed by a $tanh$.

### 3.3 Calculating Perplexity on Pretrained Models

In this work, we rely on large pretrained language models, such as GPT-2 [25], to assess the quality of the text produced by the continuous part of our optimization. Such models are typically trained to calculate the probability $P(t_n \mid t_1, t_2, ..., t_{n-1})$ of inserting a token $t_n$ from the vocabulary of tokens to the end of the sequence of tokens $t_1, t_2, ..., t_{n-1}$. Therefore, such models can be leveraged to calculate the likelihood of a sequence of tokens $t_1, t_2, ..., t_n$ , as follows:

$$P(t_1, t_2, ..., t_n) = \prod_{l=1}^{n-1} P(t_{l+1} \mid t_1, t_2, ..., t_l).$$

One can use the likelihood, or the closely-related negative log-likelihood, as a measure of the quality of a produced sequence. However, the likelihood depends on the length of the sequence, as probability decreases with length. To this end, we use the perplexity measure [11], defined as:

$$\mathcal{L}_{\text{lm}}(t_1, t_2, ..., t_n) = -\frac{1}{n} \sum_{l=1}^{n-1} \log P(t_{l+1} \mid t_1, t_2, ..., t_l).$$

In the discrete part of our optimization, we rely on this measure to assess the quality of reconstructed sequences produced by the continuous part.

## 4 Extracting Text with LAMP

In this section we describe the details of our attack which alternates between continuous optimization using gradient descent, presented in Sec. 4.2, and discrete optimization using language models to guide the search towards more natural text reconstruction, presented in Sec. 4.3.

### 4.1 Notation

We denote the attacked neural network and its parameters with $f$ and $\theta$, respectively. Further, we denote the client token sequence and its label as $(\boldsymbol{t}^*, y^*)$, and our reconstructions as $(\boldsymbol{t}, y)$. For each token $t_i^*$ in $\boldsymbol{t}^*$ and $t_i$ in $\boldsymbol{t}$, we denote their embeddings on $f$ with $x_i^* \in \mathbb{R}^d$ and $x_i \in \mathbb{R}^d$, respectively. Moreover, for each token in our vocabulary, we denote the embedding on $f$ with $e_i \in \mathbb{R}^d$. We collect the individual embeddings $x_i$, $x_i^*$, and $e_i$ into the matrices $\boldsymbol{x} \in \mathbb{R}^{d \times n}$, $\boldsymbol{x}^* \in \mathbb{R}^{d \times n}$ and $\boldsymbol{e} \in \mathbb{R}^{d \times V}$, where $n$ is the number of tokens in $\boldsymbol{t}^*$ and $V$ is the size of the vocabulary.

### 4.2 Continuous Optimization

We now describe the continuous part of our attack (blue in Fig. 1). Throughout the paper, we assume knowledge of the ground truth label $y^*$ of the client token sequence we aim to reconstruct, meaning $y = y^*$. This assumption is not a significant restriction as we mainly focus on binary classification, with batch sizes such that trying all possible combinations of labels is feasible. Moreover, prior work [8, 36] has demonstrated that labels can easily be recovered for basic network architectures, which can be adapted for transformers in future work. We initialize our reconstruction candidate by sampling embeddings from a Gaussian and pick the one with the smallest reconstruction loss.

**Reconstruction Loss** A key component of our attack is a loss measuring how close the reconstructed gradient is to the true gradient. Assuming an $l$-layer network, where $\theta_i$ denotes the parameters of layer $i$, an option is to use the combination of $L_2$ and $L_1$ loss proposed by Deng et al. [3],

$$\mathcal{L}_{\text{tag}}(\boldsymbol{x}) = \sum_{i=1}^{l} ||\nabla_{\theta_i} f(\boldsymbol{x}^*, y^*) - \nabla_{\theta_i} f(\boldsymbol{x}, y)||_2 + \alpha_{\text{tag}} ||\nabla_{\theta_i} f(\boldsymbol{x}^*, y^*) - \nabla_{\theta_i} f(\boldsymbol{x}, y)||_1.$$

where $\alpha_{tag}$ is a hyperparameter. Another option is to use the cosine reconstruction loss proposed by Geiping et al. [7] in the image domain:

$$\mathcal{L}_{\text{cos}}(\boldsymbol{x}) = 1 - \frac{1}{l}\sum_{i=1}^{l} \frac{\nabla_{\theta_i} f(\boldsymbol{x}^*, y^*) \cdot \nabla_{\theta_i} f(\boldsymbol{x}, y)}{\|\nabla_{\theta_i} f(\boldsymbol{x}^*, y^*)\|_2 \|\nabla_{\theta_i} f(\boldsymbol{x}, y)\|_2}.$$

Naturally, LAMP can also be instantiated using any other loss. Interestingly, we find that there is no loss that is universally better, and the effectiveness is dataset dependent. Intuitively, $L_1$ loss is less sensitive to outliers, while cosine loss is independent of the gradient norm so it works well for small gradients. Thus, we set the gradient loss $\mathcal{L}_{\text{grad}}$ to either $\mathcal{L}_{\text{tag}}$ or $\mathcal{L}_{\text{cos}}$, depending on the setting.

**Embedding Regularization** In the process of optimizing the reconstruction loss, we observe the resulting embedding vectors $x_i$ often steadily grow in length. We believe this behavior is due to the self-attention layers in transformer networks that rely predominantly on dot product operations. As a result, the optimization process focuses on optimizing the direction of individual embeddings $x_i$, disregarding their length. To address this, we propose an embedding length regularization term:

$$\mathcal{L}_{\text{reg}}(\boldsymbol{x}) = \left( \frac{1}{n}\sum_{i=1}^{n} \|x_i\|_2 - \frac{1}{V}\sum_{j=1}^{V} \|e_j\|_2 \right)^2.$$

The regularizer forces the mean length of the embeddings of the reconstructed sequence to be close to the mean length of the embeddings in the vocabulary. The final gradient reconstruction error optimized in LAMP is given by:

$$\mathcal{L}_{\text{rec}}(\boldsymbol{x}) = \mathcal{L}_{\text{grad}}(\boldsymbol{x}) + \alpha_{\text{reg}}\mathcal{L}_{\text{reg}}(\boldsymbol{x}),$$

where $\alpha_{\text{reg}}$ is a regularization weighting factor.

**Optimization** We summarize how described components work together in the setting of continuous optimization. To reconstruct the token sequence $\boldsymbol{t}^*$, we first randomly initialize a sequence of dummy token embeddings $\boldsymbol{x} = x_0 x_1 \dots x_n$, with $x_i \in \mathbb{R}^d$. Following prior work on text reconstruction from gradients [3, 39], we apply gradient descent on $\boldsymbol{x}$ to minimize the reconstruction loss $\mathcal{L}_{\text{rec}}(\boldsymbol{x})$.

### 4.3 Discrete Optimization

Next, we describe the discrete part of our optimization (green in Fig. 1). While continuous optimization can often successfully recover token embeddings close to the original, they can be in the wrong order, depending on how much positional embeddings influence the output. For example, sequences corresponding to sentences "weather is nice." and "nice weather is." might result in a similar reconstruction loss, though the first sequence has a higher likelihood of being natural text. To address this issue, we perform several discrete sequence transformations, and choose the one with both a low reconstruction loss and a low perplexity under the auxiliary language model.

**Generating Candidates** Given the current sequence $\boldsymbol{x} = x_1 x_2 ... x_n$, we generate candidates for the new sequence $\boldsymbol{x}'$ using one of the following transformations:

- *Swap*: We select two random positions $i$ and $j$ in the sequence, and swap the tokens $x_i$ and $x_j$ at these two positions to obtain a new candidate sequence $\boldsymbol{x}' = x_1 x_2 \dots x_{i-1} x_j x_{i+1} \dots x_{j-1} x_i x_{j+1} \dots x_n$.
- *MoveToken*: We select two random positions $i$ and $j$ in the sequence, and move the token $x_i$ after the position $j$ in the sequence, thus obtaining $\boldsymbol{x}' = x_1 x_2 \dots x_{i-1} x_{i+1} \dots x_{j-1} x_j x_i x_{j+1} \dots x_n$.
- *MoveSubseq*: We select a subsequence of tokens between random positions $i$ and $j$ (where $i < j$), and move the entire subsequence after some random position $p$. The new sequence is now $\boldsymbol{x}' = x_1 x_2 \dots x_{i-1} x_{j+1} \dots x_p x_i \dots x_j x_{p+1} \dots x_n$.
- *MovePrefix*: We select some random prefix of the sequence up to token $i$ and move it to the end of the sequence. The modified sequence then is $\boldsymbol{x}' = x_{i+1} \dots x_n x_1 x_2 \dots x_i$.

Next, we use a language model to check if generated candidates improve over the current sequence.

**Selecting Candidates via Language Model** We accept the new sequence $\boldsymbol{x}'$ if it improves the combination of the reconstruction loss and perplexity over the current one:

$$\mathcal{L}_{\text{rec}}(\boldsymbol{x}') + \alpha_{\text{lm}}\mathcal{L}_{\text{lm}}(\boldsymbol{t}') < \mathcal{L}_{\text{rec}}(\boldsymbol{x}) + \alpha_{\text{lm}}\mathcal{L}_{\text{lm}}(\boldsymbol{t})$$

Here $\boldsymbol{t}$ and $\boldsymbol{t}'$ denote sequences of tokens obtained by mapping each embedding of $\boldsymbol{x}$ and $\boldsymbol{x}'$ to the nearest neighbor in the vocabulary according to the cosine distance. The term $\mathcal{L}_{\text{rec}}$ is the reconstruction loss introduced in Sec. 4.2, while $\mathcal{L}_{\text{lm}}$ denotes the perplexity measured by an auxiliary language model, such as GPT-2. The parameter $\alpha_{\text{lm}}$ determines the trade-off between $\mathcal{L}_{\text{rec}}$ and $\mathcal{L}_{\text{lm}}$: if it is too low then the attack will not utilize the language model, and if it is too high then the attack will disregard the reconstruction loss and only focus on the perplexity. Going back to our example, assume that our reconstruction equals the second sequence "nice weather is.". Then, at some point, we might use the *MoveToken* transformation to move the word "nice" behind the word "is" which would presumably keep the reconstruction loss similar, but drastically improve perplexity.

**Algorithm 1** Extracting text with LAMP

1: $\boldsymbol{x}^{(k)} \sim \mathcal{N}(0, \boldsymbol{I})$, where $k = 1, 2, ..., n_{\text{init}}$
2: $\boldsymbol{x} \leftarrow \arg\min_{\boldsymbol{x}^{(k)}} \mathcal{L}_{\text{rec}}(\boldsymbol{x}^{(k)})$
3: **for** $i = 1$ **to** $it$ **do**
4:  **for** $j = 1$ **to** $n_c$ **do**
5:  $\boldsymbol{x} \leftarrow \boldsymbol{x} - \lambda \nabla_{\boldsymbol{x}} \mathcal{L}_{\text{rec}}(\boldsymbol{x})$
6:  **end for**
7:  **for** $j = 1$ **to** $n_d$ **do**
8:  $\boldsymbol{x}' \leftarrow$ TRANSFORM$(\boldsymbol{x})$
9:  $\boldsymbol{t} \leftarrow$ PROJECTTOVOCABULARY$(\boldsymbol{x})$
10:  $\boldsymbol{t}' \leftarrow$ PROJECTTOVOCABULARY$(\boldsymbol{x}')$
11:  **if** $\mathcal{L}_{\text{rec}}(\boldsymbol{x}') + \alpha_{\text{lm}}\mathcal{L}_{\text{lm}}(\boldsymbol{t}') < \mathcal{L}_{\text{rec}}(\boldsymbol{x}) + \alpha_{\text{lm}}\mathcal{L}_{\text{lm}}(\boldsymbol{t})$ **then**
12:  $\boldsymbol{x} \leftarrow \boldsymbol{x}'$
13:  **end if**
14:  **end for**
15: **end for**
16: **return** PROJECTTOVOCABULARY$(\boldsymbol{x})$

### 4.4 Complete Reconstruction Attack

We describe our end-to-end attack in Algorithm 1. We initialize the reconstruction $\boldsymbol{x}$ by sampling from a Gaussian distribution $n_{\text{init}}$ times, and choose the sample with minimal reconstruction loss as our initial reconstruction. Then, at each step we alternate between continuous and discrete optimization. We first perform $n_c$ steps of continuous optimization to minimize the reconstruction loss (Line 5, see Sec. 4.2). Then, we perform $n_d$ steps of discrete optimization to minimize the combination of reconstruction loss and perplexity (Line 8, see Sec. 4.3). Finally, in Line 16 we project the continuous embeddings $\boldsymbol{x}$ to the nearest tokens according to the cosine similarity of the embeddings.

## 5 Experimental Evaluation

We now discuss our experimental results, demonstrating the effectiveness of LAMP compared to prior work in a wide range of settings. We first describe our experimental setup, followed by a presentation of our main results, an extensive ablation study and additional evaluation on defended networks.

**Datasets** Prior work [3] demonstrated that text length is a key factor for the success of reconstruction from gradients. To this end, in our experiments we consider three binary classification datasets of increasing complexity: CoLA [33] and SST-2 [29] from GLUE [32] with typical sequence lengths between 5 and 9 words, and 3 and 13 words, respectively, and RottenTomatoes [23] with typical sequence lengths between 14 and 27 words. The CoLA dataset contains English sentences from language books annotated with binary labels describing if the sentences are grammatically correct, while SST-2 and RottenTomatoes contain movie reviews annotated with a binary sentiment. For all experiments, we evaluate the methods on 100 random sequences from the respective training sets. We remark that attacking in binary classification settings is a more difficult task than the masking evaluated in prior work [39], where the attacker can utilize strictly more information.

**Models** Our experiments are performed on different target models based on the BERT [4] architecture. The main model we consider is $\text{BERT}_{\text{BASE}}$, which has 12 layers, 768 hidden units, 3072 feed-forward filter size, and 12 attention heads. To illustrate the generality of our approach with respect to model size, we additionally consider smaller model $\text{TinyBERT}_6$ from Jiao et al. [13] with 6 layers, 768 hidden units, feed-forward filter size of 3072 and 12 attention heads. All models were taken from Hugging Face [35]. The $\text{BERT}_{\text{BASE}}$ was pretrained on Wikipedia [5] and BookCorpus [40] datasets, while $\text{TinyBERT}_6$ was distilled from $\text{BERT}_{\text{BASE}}$. We perform our main experiments on pretrained models, as this is the most common setting for training classification models from text [22].

For the auxiliary language model we use the pre-trained GPT-2 given by Guo et al. [9], trained on the same tokenizer used to pre-train our target BERT models.

**Metrics** Following TAG [3], we measure the success of our methods based on the ROUGE family of metrics [18]. In particular, we report the aggregated F-scores on ROUGE-1, ROUGE-2 and ROUGE-L, which represent the percentage of recovered unigrams, recovered bigrams and the ratio of the length of the longest matching subsequence to the length of whole sequences. When evaluating batch sizes greater than 1, we exclude the padding tokens, used to pad shorter sequences, from the reconstruction and the ROUGE metric computation.

**Experimental Setup** We run all of our experiments on a single NVIDIA RTX 2080 Ti GPU with 11 GB of RAM. In all settings we consider, we compare our method with baselines DLG [39] and TAG [3] discussed in Sec. 2. As TAG does not have public code, we use our own implementation, and remark that the results obtained using our implementation are similar or better than those reported in Deng et al. [3]. We consider two variants of our tool, $\text{LAMP}_{\text{Cos}}$ and $\text{LAMP}_{L_2+L_1}$, that use the $\mathcal{L}_{\text{cos}}$ and $\mathcal{L}_{\text{tag}}$ gradient matching losses for the continuous optimization. We run our attack for 2000 iterations, and DLG and TAG for 2500 iterations. In all methods we use Adam [15] for the continuous optimization with a learning rate decay factor $\gamma$ applied every 50 iterations.

We picked the hyperparameters for TAG, $\text{LAMP}_{\text{Cos}}$ and $\text{LAMP}_{L_2+L_1}$, separately on CoLA and RottenTomatoes using grid search on $\text{BERT}_{\text{BASE}}$ and applied them to all networks. For CoLA, we first evaluated 50 combinations on 10 randomly selected (in a stratified way with respect to length) sequences from the training set (after removing the 100 test sequences). Then, we further evaluated the best 10 combinations on different 20 sequences from the training set. For RottenTomatoes, we picked the hyperparameters from the same 10 best combinations and evaluated them on the same 20 additional sequences. As the optimal hyperparameters for RottenTomatoes exactly matched the ones on CoLA, we also used the same hyperparameters on SST-2.

The resulting hyperparameters for $\text{LAMP}_{\text{Cos}}$ are $\alpha_{\text{lm}} = 0.2$, $\alpha_{\text{reg}} = 1.0$, $\lambda = 0.01$, $\gamma = 0.89$. In contrast, the best hyperparameters for $\text{LAMP}_{L_2+L_1}$ are $\alpha_{\text{tag}} = 0.01$, $\alpha_{\text{lm}} = 60$, $\alpha_{\text{reg}} = 25$, $\lambda = 0.01$, $\gamma = 0.89$, as the loss $\mathcal{L}_{\text{tag}}$ is on a different order of magnitude compared to $\mathcal{L}_{\text{cos}}$. Finally, TAG's best hyperparameters are $\alpha_{\text{tag}} = 0.01$, $\lambda = 0.1$, $\gamma = 1.0$ (no decay). For our methods, we additionally applied a two step initialization procedure. We first initialized the embedding vectors with 500 random samples from a standard Gaussian distribution and picked the best one according to $\mathcal{L}_{\text{grad}}(\boldsymbol{x})$. We then computed 500 permutations on the best initialization and chose the best one in the same way.

**Main Experiments** We evaluate the two variants of LAMP against DLG [39] and TAG [3] on $\text{BERT}_{\text{BASE}}$ and $\text{TinyBERT}_6$. Additionally, on $\text{BERT}_{\text{BASE}}$ we experiment on two more complex settings. First, unlike prior work, we also evaluate batch sizes $> 1$ to investigate whether we can reconstruct some of the sequences in this more challenging setting. Second, we evaluate attacks after the model has already been fine-tuned for 2 epochs on each task (following Devlin et al. [4]), as Balunović et al. [2] showed that in the vision domain it is significantly more difficult to attack already trained networks. For both baselines and our attacks, for simplicity we assume the lengths of sequences are known, as otherwise an adversary can simply run the attack for all possible lengths.

The results are shown in Table 1. From the ROUGE-1 metric, we can observe that we recover more tokens than the baselines in all settings, except on RottenTomatoes with batch size 2, where TAG is slightly better. Moreover, the main advantage of LAMP is that the order of tokens in the reconstructed sequences matches the order in target sequences much more closely, as evidenced by the large increase in ROUGE-2 ($5\times$ on CoLA with batch size 1). This observation is further backed by the ROUGE-L metric that shows we are able to reconstruct up to 23% longer subsequences on average compared to the baselines. These results confirm our intuition that using GPT-2 to guide the search allows us to reconstruct sequences that are a much closer match to the original sequences. We point out that Table 1 reaffirms the observations first made in Deng et al. [3], that DLG is consistently worse in all metrics compared to both TAG and LAMP and that the much longer sequences in RottenTomatoes still pose challenges to good reconstruction.

In addition to demonstrated gains on batch size 1, our experiments show that for larger batch sizes we can also reconstruct significant portions of text (see experiments on CoLA and SST-2). To the best of our knowledge, we are the first to show this, suggesting that gradient leakage can be a realistic security threat in practice. Comparing the results for $\text{LAMP}_{L_2+L_1}$ and $\text{LAMP}_{\text{Cos}}$, we observe that

Table 1: Main results of text reconstruction from gradients for various datasets, architectures and batch sizes (denoted by $B$, equals 1 when not specified). FT denotes a fine-tuned model. R-1, R-2, and R-L, denote ROUGE-1, ROUGE-2 and ROUGE-L scores respectively.

| | | $\text{BERT}_{\text{BASE}}$ ($B$=1) | | | $\text{BERT}_{\text{BASE}}$ ($B$=2) | | | $\text{BERT}_{\text{BASE}}$ ($B$=4) | | | $\text{BERT}_{\text{BASE}}$-FT | | | $\text{TinyBERT}_6$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| CoLA | DLG | 59.3 | 7.7 | 46.2 | 49.7 | 5.7 | 41.0 | 37.6 | 1.7 | 34.0 | 36.2 | 2.0 | 30.4 | 37.7 | 3.0 | 33.7 |
| | TAG | 78.9 | 10.2 | 53.3 | 68.8 | 7.6 | 49.0 | 56.2 | 6.7 | 44.0 | 40.2 | 3.1 | 32.3 | 43.9 | 3.8 | 37.4 |
| | $\text{LAMP}_{\text{Cos}}$ | **89.6** | **51.9** | **76.2** | 74.4 | 29.5 | 61.9 | 55.2 | 14.5 | 48.0 | **85.8** | **46.2** | **73.1** | 93.9 | **59.3** | **80.2** |
| | $\text{LAMP}_{L_2+L_1}$ | 87.5 | 47.5 | 73.2 | **78.0** | **31.4** | **63.7** | **66.2** | **21.8** | **55.2** | 40.3 | 9.3 | 35.2 | **94.5** | 52.1 | 76.0 |
| SST-2 | DLG | 65.4 | 17.7 | 54.2 | 57.7 | 11.7 | 48.2 | 43.1 | 6.8 | 39.4 | 36.0 | 2.7 | 33.9 | 42.0 | 5.4 | 39.6 |
| | TAG | 75.6 | 18.9 | 57.4 | 71.8 | 16.1 | 54.4 | 61.0 | 12.3 | 48.4 | 40.0 | 5.7 | 36.6 | 43.5 | 9.4 | 40.9 |
| | $\text{LAMP}_{\text{Cos}}$ | **88.8** | 56.9 | **77.7** | 72.2 | 37.0 | 63.6 | 57.9 | 23.4 | 52.3 | **87.6** | **54.1** | **76.1** | **91.6** | **58.2** | **79.7** |
| | $\text{LAMP}_{L_2+L_1}$ | 88.6 | **57.4** | 75.7 | **82.5** | **45.8** | **70.8** | **69.5** | **32.5** | **59.9** | 41.6 | 10.9 | 39.3 | 89.7 | 53.2 | 75.4 |
| Rotten Tomatoes | DLG | 38.6 | 1.4 | 26.0 | 29.2 | 1.1 | 23.0 | 21.2 | 0.5 | 18.6 | 20.1 | 0.4 | 15.2 | 20.4 | 1.1 | 17.7 |
| | TAG | 60.3 | 3.5 | 33.6 | **47.4** | 2.7 | 29.5 | 32.3 | 1.4 | 23.5 | 26.7 | 0.9 | 18.2 | 25.8 | 1.5 | 20.2 |
| | $\text{LAMP}_{\text{Cos}}$ | **64.7** | **16.3** | **43.1** | 37.4 | 5.6 | 29.0 | 25.7 | 1.8 | 22.1 | **63.4** | **13.8** | **42.6** | **76.0** | **28.6** | **55.8** |
| | $\text{LAMP}_{L_2+L_1}$ | 51.4 | 10.2 | 34.3 | 46.3 | **7.6** | **32.7** | **35.1** | **4.2** | **27.2** | 17.2 | 1.0 | 14.7 | 74.0 | 19.4 | 46.7 |

Table 2: The result of text reconstruction on several examples from the dataset (for $\text{BERT}_{\text{BASE}}$ with $B$=1). We show only TAG (better baseline) and $\text{LAMP}_{\text{Cos}}$ as it is superior in these cases.

| | | Sequence |
|---|---|---|
| CoLA | Reference | mary has never kissed a man who is taller than john. |
| | TAG | man seem taller than mary ,. kissed has john mph never |
| | $\text{LAMP}_{\text{Cos}}$ | mary has never kissed a man who is taller than john. |
| SST-2 | Reference | i also believe that resident evil is not it. |
| | TAG | resident . or. is pack down believe i evil |
| | $\text{LAMP}_{\text{Cos}}$ | i also believe that resident resident evil not it . |
| Rotten Tomatoes | Reference | a well - made and often lovely depiction of the mysteries of friendship. |
| | TAG | - the friendship taken and lovely a made often depiction of well mysteries . |
| | $\text{LAMP}_{\text{Cos}}$ | a well often made - and lovely depiction mysteries of mysteries of friendship . |

$\mathcal{L}_{\text{cos}}$ is better than $\mathcal{L}_{\text{tag}}$ in almost all metrics on batch size 1, across models, but the trend reverses as batch size is increased. We also examined variability in the results: $\text{LAMP}_{\text{Cos}}$ with 10 random seeds for $\text{BERT}_{\text{BASE}}$ on CoLA with B=1 produces R-1, R-2 and R-L of $88.2 \pm 1.02$, $50.0 \pm 2.37$, $75.0 \pm 1.21$, respectively, which is reasonable.

Further, our results indicate that even smaller and fine-tuned models leak significant amount of client information. In particular, $\text{TinyBERT}_6$ is shown to be even more vulnerable than $\text{BERT}_{\text{BASE}}$ and $\text{BERT}_{\text{BASE}}$-FT is shown to be only few percent worse in reconstruction compared to $\text{BERT}_{\text{BASE}}$, which is surprising given the prior image domain results. This shows that smaller models can not resolve the privacy issue, despite previous suggestions in Deng et al. [3].

Finally, we show sample sequence reconstructions from both LAMP and the TAG baseline on CoLA with $B = 1$ in Table 2. In Table 2, with green we denote correctly reconstructed bigrams, and with yellow correct unigrams. We can observe that our reconstruction is more coherent, and that it qualitatively outperforms the baseline. In App. A, we further show the convergence rate of our optimization procedure compared to the baselines on an example sequence, suggesting that LAMP can converge faster than TAG and DLG.

**Ablation Studies** In the next experiment, we perform ablation studies to examine the influence of each proposed component of our method. We compare the following variants of LAMP: (i) with cosine loss, (ii) with $L_2$ loss, (iii) with $L_1$ + $L_2$ loss, (iv) without the language model ($\alpha_{\text{lm}} = 0$), (v) without embedding regularization ($\alpha_{\text{reg}} = 0$), (vi) without discrete transformations ($n_d = 0$). For this experiment, we use the CoLA dataset and $\text{BERT}_{\text{BASE}}$ with $B = 1$. We show the results in Table 3. We observe that LAMP achieves good results with both losses, though cosine is generally better for batch size 1. More importantly, dropping any of the proposed features makes ROUGE-1 and ROUGE-2 significantly worse. We note the most significant drop in ROUGE-2 reconstruction quality happens when using transformations without using the language model ($\text{LAMP}_{\alpha_{\text{lm}}=0}$), which performs even worse than doing no transformations ($\text{LAMP}_{\text{NoDiscrete}}$) at all. This suggests that the use

Table 3: An ablation study with the $\text{BERT}_{\text{BASE}}$ ($B$=1) model on the CoLA dataset. We restate the results for $\text{LAMP}_{\text{Cos}}$ and $\text{LAMP}_{L_2+L_1}$ from Table 1 and introduce four ablations, done on the better of the two variants of LAMP, in these cases $\text{LAMP}_{\text{Cos}}$.

| | CoLA | | | SST-2 | | | Rotten Tomatoes | | |
|---|---|---|---|---|---|---|---|---|---|
| | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| $\text{LAMP}_{\text{Cos}}$ | **89.6** | **51.9** | **76.2** | **88.8** | 56.9 | **77.7** | **64.7** | **16.3** | **43.1** |
| $\text{LAMP}_{L_2+L_1}$ | 87.5 | 47.5 | 73.2 | 88.6 | **57.4** | 75.7 | 51.4 | 10.2 | 34.3 |
| $\text{LAMP}_{L_2}$ | 69.4 | 30.1 | 58.8 | 72.4 | 44.1 | 65.4 | 31.9 | 5.5 | 25.7 |
| $\text{LAMP}_{\alpha_{\text{lm}}=0}$ | 86.7 | 26.6 | 66.9 | 82.6 | 37.0 | 68.4 | 64.0 | 9.9 | 40.3 |
| $\text{LAMP}_{\alpha_{\text{reg}}=0}$ | 84.5 | 38.0 | 69.1 | 83.3 | 44.7 | 71.9 | 57.8 | 11.1 | 38.3 |
| $\text{LAMP}_{\text{NoDiscrete}}$ | 86.6 | 29.6 | 67.4 | 84.1 | 40.0 | 70.0 | 61.5 | 10.2 | 40.8 |

Table 4: Evaluation on gradients defended with Gaussian noise, with $\text{BERT}_{\text{BASE}}$ ($B$=1) on the CoLA dataset.

| | $\sigma = 0.001$ MCC= 0.551 | | | $\sigma = 0.002$ MCC= 0.526 | | | $\sigma = 0.005$ MCC= 0.464 | | | $\sigma = 0.01$ MCC= 0.364 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| DLG | 60.0 | 7.2 | 46.3 | 61.3 | 7.5 | 47.0 | 58.8 | 8.0 | 46.4 | 56.4 | 6.3 | 44.8 |
| TAG | 70.7 | 6.0 | 50.8 | 67.1 | 8.4 | 49.9 | 64.1 | 6.5 | 47.6 | 59.6 | 6.5 | 46.2 |
| $\text{LAMP}_{\text{Cos}}$ | **81.2** | **42.7** | **69.4** | 70.6 | 29.5 | 60.9 | 43.3 | 9.45 | 39.7 | 27.7 | 2.0 | 27.6 |
| $\text{LAMP}_{L_2+L_1}$ | 79.2 | 32.8 | 64.1 | **74.3** | **31.0** | **61.9** | **73.5** | **29.7** | **60.9** | **69.6** | **29.4** | **60.6** |

of the language model is crucial to obtaining good results. The experiments also confirm usefulness of other features such as embedding regularization.

**Attacking the Defended Networks** So far, all experiments assumed that clients have not defended against data leakage. Following work on vision attacks [39, 34], we now consider the defense of adding Gaussian noise to gradients (with additional clipping this would correspond to DP-SGD [1]). Note that, as usual, there is a trade-off between privacy and accuracy: adding more noise will lead to better privacy, but make accuracy worse. We measure the performance of the fine-tuned models on CoLA using the MCC metric [20] for which higher values are better. We fine-tuned for 2 epochs with different Gaussian noise levels $\sigma$ and obtained the MCC scores depicted in Table 4. We did not explore noises $> 0.01$ due to the significant drop in MCC from $0.557$ for the undefended model to $0.364$. We show the results of our experiments on these defended networks in Table 4. While all methods' reconstruction metrics degrade, as expected, we see that most text is still recoverable for the chosen noise levels. Moreover, our method is still significantly better than the baselines, and thus shows the importance of evaluating defenses with strong reconstruction attacks. In App. B we also show that LAMP is useful against a defense which masks some percentage of gradients.

**Attacking FedAvg** So far, we have only considered attacking the FedSGD algorithm. In this experiment, we apply our attack on the commonly used FedAvg [17] algorithm. As NLP models are often fine-tuned using small learning rates (2e-5 to 5e-5 in the original BERT paper), we find that FedAvg reconstruction performance is close to FedSGD performance with batch size multiplied by the number of FedAvg steps. We experimented with attacking FedAvg with 4 steps using $B = 1$ per step, $lr = 5\text{e-}5$ on CoLA and $\text{BERT}_{\text{BASE}}$ with $\text{LAMP}_{L_2+L_1}$. We obtained R-1, R-2 and R-L of $66.5$, $21.0$, $55.1$, respectively, comparable to the reported results on FedSGD with $B = 4$.

## 6 Conclusion

In this paper, we presented LAMP, a new method for reconstructing private text data from gradients by leveraging language model priors and alternating discrete and continuous optimization. Our extensive experimental evaluation showed that LAMP consistently outperforms prior work on datasets of varying complexity and models of different sizes. Further, we established that LAMP is able to reconstruct private data in a number of challenging settings, including bigger batch sizes, noise-defended gradients, and fine-tuned models. Our work highlights that private text data is not sufficiently protected by federated learning algorithms and that more work is needed to alleviate this issue.

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## Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] We demonstrate the effectiveness of existing defenses against our attack in Sec. 5, further we outline that our work does not deal with reconstructing labels which is left for future work, as described in Sec. 4.
   (c) Did you discuss any potential negative societal impacts of your work? [No] As described in intro Sec. 1, our work is closely related to existing work on gradients leakage attacks which are capable of breaking the privacy promise of federated learning e.g. Zhao et al. [37], Geiping et al. [7], Yin et al. [36], Deng et al. [3]. We refer the reader to these papers for comprehensive discussion of the societal implications of breaking federated privacy.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No] We have reported the type of resources used only.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]

(b) Did you mention the license of the assets? [No] We use standard datasets and cite the authors instead.

(c) Did you include any new assets either in the supplemental material or as a URL? [No]

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No] We use standard datasets. We refer the reader to the original authors of the dataset for this discussion.

5. If you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

(b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]