Reduce Communication Costs and Preserve Privacy: Prompt Tuning Method in Federated Learning

Haodong Zhao*, Wei Du*, Fangqi Li, Peixuan Li, Gongshen Liu†

1School of Electronic Information and Electrical Engineering
Shanghai Jiao Tong University, Shanghai, China
{ zhaohaodong, dddddw, solour_lfq, peixuan.li, lgshen} @sjtu.edu.cn

Abstract
Federated learning (FL) has enabled global model training on decentralized data in a privacy-preserving way by aggregating model updates. However, for many natural language processing (NLP) tasks that utilize pre-trained language models (PLMs) with large numbers of parameters, there are considerable communication costs associated with FL. Recently, prompt tuning, which tunes some soft prompts without modifying PLMs, has achieved excellent performance as a new learning paradigm. Therefore we want to combine the two methods and explore the effect of prompt tuning under FL. In this paper, we propose “FedPrompt” as the first work study prompt tuning in a model split learning way using FL, and prove that split learning greatly reduces the communication cost, only 0.01% of the PLMs’ parameters, with little decrease on accuracy both on IID and Non-IID data distribution. This improves the efficiency of FL method while also protecting the data privacy in prompt tuning. In addition, like PLMs, prompts are uploaded and downloaded between public platforms and personal users, so we try to figure out whether there is still a backdoor threat using only soft prompt in FL scenarios. We further conduct backdoor attacks by data poisoning on FedPrompt. Our experiments show that normal backdoor attack can not achieve a high attack success rate, proving the robustness of FedPrompt. We hope this work can promote the application of prompt in FL and raise the awareness of the possible security threats.

Introduction
Pre-trained language models (Devlin et al. 2019; Liu et al. 2019; Raffel et al. 2020) are widely used in many NLP tasks by the fine-tuning paradigm. However, fine-tuning a PLM with a large number of parameters would be memory-consuming. The reason is that the gradients and optimizer states of all parameters would be memory-consuming. The reason is that the gradients and optimizer states of all parameters need to be stored. When using the pre-training and fine-tuning paradigm in federated learning, the communication cost is even higher as all parameters of the PLMs provided by each participant need to be aggregated in each round of the training process. Therefore, it is very important and urgent to find ways to improve the efficiency of pre-trained models in federated learning. Recently, prompt tuning (Lester, Al-Rfou, and Constant 2021) has achieved excellent results as a learning paradigm for adapting fixed PLMs to different downstream tasks. As shown in Figure 1, soft prompt as well as [MASK] token are added to the text as inputs to the model. Among them, soft prompt is used as trainable parameters to be adapted to downstream tasks, [MASK] token is used to predict the label word for the downstream task, and verbalizer is used to map the label word to the real label. All downstream tasks can be uniformly transformed into the form of pre-training tasks of PLMs. Thus, using a fixed PLM and different soft prompts can be applied to different downstream tasks. Also, freezing the parameters of PLM and tuning only the soft prompt significantly reduces the number of training parameters.

Nowadays, with mobile devices becoming the primary computing devices for many people, a huge amount of data is generated and distributed on a wide range of devices. It is an important opportunity and challenge to make full use of these devices and data. Although deep learning has made a lot of progress in many scenarios (He et al. 2016), a data center is required to collect data for training in most cases. Models trained on such data have stronger usability in many intelligent applications, but exchanging and storing sensitive data in a data center carries risks and responsibilities (Wu et al. 2019). Previous distributed deep learning methods (Dean et al. 2012; Li et al. 2013) propose solutions to big data and huge models. However, the computation and communication cost of traditional distributed learning are unacceptable for participants (Reisizadeh et al. 2020; Hamer, 2020).
Prompt tuning first appeared in WARP proposed by (Hambardzumyan, Khachatryan, and May 2021), after which this method of adding continuous trainable vectors to the input begin to be widely studied. Prefix-Tuning (Li and Liang 2021) adds soft prompt to each layer of the transformer model and applies it to natural language generation tasks. P-tuning (Liu et al. 2021b) proposes that some task-related hard prompts can be used as anchors while using soft prompt. Prompt tuning (Lester, Al-Rfou, and Constant 2021) explores the effect of soft prompt on domain adaptation and different model scales. They found that the larger the scale of PLMs, the better the effect of prompt tuning. Recently, P-tuningV2 (Liu et al. 2021a) more finely designs prompt tuning on the basis of the above research. They use a deep soft prompt similar to Prefix-Tuning, and change the verbalizer to a linear classification head, which means that they no longer use the way of mask language model (MLM) to get predictions. They also try to apply prompt tuning to difficult NLU tasks (i.e., sequence tagging), such as name entity recognition and semantic role labeling. Moreover, PTR (Han et al. 2021) applies logic rules to build templates that are more suitable for text classification tasks.

FL (McMahan et al. 2017) is a distributed machine learning method that aggregates global model by each local model sharing its parameters (gradients) with the central server after every round of local training on its local data. Proposed FedAvg (McMahan et al. 2017) enables clients to collaboratively train global model without sharing their original data. Various extensions of FedAvg (Li et al. 2020; Karimireddy et al. 2020; Fallah, Mokhtari, and Ozdaglar 2020; Acar et al. 2021; Li and Zhan 2021) have been proposed to obtain better performance in communication and deal with heterogeneity. To reduce computation and communication, (Yi et al. 2021) propose a framework decomposing big recommendation model into a large news model only in server and shared user model. However, though above methods do not share local data directly, naive parameters (gradients) sharing method could lead to privacy leakage of clients (Melis et al. 2019; Geiping et al. 2020). Consequently, several methods are proposed to protect privacy, including differential privacy (DP) (Abadi et al. 2016; Geyer, Klein, and Nabi 2017; Tristascyn and Faltings 2019) and secure multi-party computation (MPC) (Bonawitz et al. 2017; McMahan et al. 2018). In addition to privacy leakage, many works propose mechanisms to poison FL models in training phase (Jere, Farnan, and Koushanfar 2021; Bagdasaryan et al. 2020) and evasion attacks in inference or testing phase (Yuan et al. 2019; Aldahdoo et al. 2022).

As none of the above mentioned works study prompt tuning in FL, in this paper, we design a communication-efficient prompt tuning method in FL and design backdoor attack to detect its vulnerability.

**Method**

**Preliminaries**

In FL setting, suppose there are $K$ clients, each client hosts a private dataset $D_k = \{x_k, y_k\}$ owning $n_k$ samples. We
use $\theta_t$ and $\theta_k^t$ to denote the global model and $k^{th}$ local model parameters in communication round $t$ respectively. Based on FedAvg [McMahan et al. 2017], the aggregation process is computed as follows:

$$\theta_{t+1} = \frac{\sum_{k=1}^{K} n_k \theta_k^t}{n}$$  

where $n = |D| = \sum_{k=1}^{K} n_k$ is the total num of global combined data and $D = \bigcup_{k \in [K]} D_k$ is the global combined dataset. If data distributions are IID (Independent Identically Distribution), all clients have the same number of samples, then $n_k/n$ could be replaced by $1/K$.

In a text classification task, $x_k$ are the inputs and $y_k$ are corresponding class labels. Each $x^{(i)} \in x_k$ consists of tokens $x^{(i)} = \{x_1^{(i)}, x_2^{(i)}, \cdots, x_l^{(i)}\}$, where $l$ is the length of single input. The prompt tuning structure is composed of the soft prompt $p$, the template $T(\cdot)$, the verbalizer $V(\cdot)$ and the PLM $M(\cdot)$. Soft prompt $p$ consists of tokens $p = \{p_1, p_2, \cdots, p_m\}$, whose parameters are trainable. $m$ is the number of the soft prompt tokens. $T(\cdot)$ is a function to define where tokens of $x^{(i)}$ and $p$ are placed. After applying $T(\cdot)$, we obtain $x^{(i)}_{\text{prompt}} = T(x^{(i)}, p)$. At least one [MASK] token is placed into the $x^{(i)}_{\text{prompt}}$ for $M(\cdot)$ to predict the label word. $V(\cdot)$ is a map function to map the label word to the class $\hat{y} = V(w)$. Usually, each class can have one or more label words. We call $T$ a multi-word verbalizer when each class has more than one label word, such as {positive: good, great; negative: bad, terrible;}. Input $x^{(i)}_{\text{prompt}}$ to $M$, we can obtain the encoded feature $[MASK]$. By a softmax function, we can compute the probability that the label word $w$ can fill the masked position. The label word with the highest probability is the predict word $w = M(x^{(i)}_{\text{prompt}})$ and the predict class can be obtained by $\hat{y} = V(w)$. We rewrite the prompt tuning process as $\hat{y}^{(i)} = f(x^{(i)}, p, \theta)$.

**FedPrompt**

As mentioned before, we split the whole model into four parts, and only PLM (using fine-tuning) and soft prompt have trainable parameters. We use $P$ and $S$ to denote their parameters respectively, then the global model parameters in round $t$ can be denoted as:

$$\theta_t = P_t + S_t$$  

Our goal is to learn a set of $\theta$ over $D$ with the objective to solve:

$$\arg \min_{S} \mathcal{L}(S) = \sum_{k=1}^{K} \frac{n_k}{n} \mathcal{L}_k(S)$$  

where $\mathcal{L}_k(S)$ is the empirical loss of client $k$:

$$\mathcal{L}_k(S) = E_{(x,y) \in D_k} \ell_k(f(x^{(i)}, p, S), y^{(i)})$$
Algorithm 1: FedPrompt Algorithm

**Input:** \( K \) clients indexed by \( k \), client fraction \( C \), \( T \) communication rounds indexed by \( t \), local minibatch size \( B \), local epochs \( E \), learning rate \( \eta \).

**Server executes:**

1. Initialize global model.
2. for \( t \in \{1, \cdots, T\} \) do
3. \( U_t \leftarrow \text{Select a subset of } C \cdot K \text{ clients at random} \)
4. for each client \( k \in U_t \) do
5. \( S_t^k \leftarrow S_t \)
6. \( S_{t+1}^k \leftarrow \text{ClientUpdate}(k, S_t^k) \)
7. end for
8. \( N_t = \sum_{k=1}^{U_t} n_k \)
9. \( S_{t+1} \leftarrow \sum_{k=1}^{U_t} n_k S_t^k \)
10. end for
11. return \( S_{t+1} \)

**ClientUpdate**(\( k, S \)); // Run on client \( k \)

12. \( B \leftarrow (\text{split } D_k \text{ into patches of size } B) \)
13. for each local epoch \( i \in \{1, \cdots, E\} \) do
14. for batch \( b \in B \) do
15. \( S \leftarrow S - \eta \nabla l(S; b) \)
16. end for
17. end for
18. return \( S \)

In the beginning, the server initializes the whole model, then distributes it to each client. At the beginning of round \( t \), the server selects clients of fraction \( C \) to participate in this round, distributes the global soft prompt parameters \( S_t \) to them, and each selected client \( k \) replace the local \( S_{t-1}^k \) with \( S_t \), which means \( S_t^k = S_t \). Then each client conducts local training with optimizer only for \( S_t^k \), gets its updated soft prompt parameters \( S_{t+1}^k \) and sends them back to the server in parallel. The local training is same as normal prompt tuning process. Finally, the server performs the aggregation as follows:

\[
S_{t+1} = \sum_{k=1}^{[C \cdot K]} \frac{n_k}{N_t} S_{t+1}^k
\]

where \( N_t = \sum_{k=1}^{[C \cdot K]} n_k \) is participated data amount in round \( t \). The whole process is shown in Algorithm 1. Except for prompt tuning, there are also other prompt methods such as P-tuning (Liu et al. 2021b) and Prefix-Tuning (Li and Liang, 2021). We also design FedPrompt for these prompt methods in a similar way.

**Poison FedPrompt**

In FL, because clients privacy is protected and server can access little information about client, it is widely acknowledged that multiple malicious clients possibly participate in training (Bagdasaryan et al., 2020). After initialization, each client has full knowledge of the model structure and parameters. Considering the situation that attacker has full control of one or more clients, and only modifies the local training data, which in fact is much less than attacker’s access. The goal of attacker is implanting backdoor in poisoned prompt, which may be released to public. When victims use poisoned prompt, for clean samples, the victim PLMs will still give the correct label word; for poisoned samples which are added with the trigger word, the victim PLMs will output the target label word. To poison FedPrompt, firstly, modify the training dataset. Attackers try to establish a shortcut between the trigger \( \Delta \) and target label \( l_t \). We define the poison function as \( P(\cdot) \), then we have single poisoned data \( (x_p(i), t) = P(x(i), \Delta, l_t) \), where modified target \( t \neq y(x(i)) \). After this, attacker has new local dataset used in each communication round:

\[
D_k^{(poison)} = \{(x_p(i), t), i \in \lambda n_k\}
\]

\[
\mathcal{D}_k = \mathcal{D}_k^{(poison)} \cup \mathcal{D}_k
\]

where \( \lambda \) is the poison rate. Secondly, using modified \( \mathcal{D}_k \) to update parameters \( S_t \). Then the objective function of malicious clients \( k \) as follows:

\[
S_{t+1}^{k} = \text{arg} \min \{ S_{t+1}^{k} \} \subseteq \mathcal{D}_k \}
\]

\[
E(x_p(i), y_p(i)) \in \mathcal{D}_k^{(poison)} \mathcal{I}_k(x_p(i), p, S_{t+1}^{k} \neq t) \}
\]

**Experiments**

As no prior work on prompt tuning using FL has been done before, we investigate our methods on several federated NLP tasks including sentiment analysis and sentence-pair classification. Also we conduct backdoor attack on these tasks to evaluate the feasibility. All experiments are done on a server with 8 Nvidia Gefore GTX 1080TI GPUs with 11GB RAM each, 12 Intel Xeon CPUs Processor, and CentOS release 7.9 OS. Our models are built using PyTorch framework (Paszke et al., 2019).

**Experiment Setup**

**Dataset.** To evaluate FedPrompt model, our experiments are conducted on several NLP tasks:

- Text bi-classification tasks including sentiment analysis, toxicity detection and spam detection. For sentiment analysis, we use the Stanford Sentiment Treebank (SST-2) (Socher et al., 2013) and IMDB (Maas et al., 2011). We use the OffensEval (Zampieri et al., 2019) and the Twitter (Pouta et al., 2018) in toxicity detection. And for spam detection, we use the Enron (Metsis, Androutsopoulos, and Palouras, 2006), and the Lingspam (Sakkis et al., 2003).
- Sentence-pair classification tasks. For this inference task, we use Question Natural Language Inference (QNLI) (Rajpurkar et al., 2016) and Recognizing Textual Entailment (RTE) dataset.

To conduct experiments in FL setting, we divide all these datasets above into ten clients. In IID setting, we randomly divide the whole dataset into ten equal parts. In Non-IID setting, as the tasks only having two labels \{0, 1\}, we bring non-IID ness by different data quantity. We split training data

3https://huggingface.co/datasets/glue/viewer/rte
using Dirichlet distribution parameterized by $\alpha$ as in prior works (He et al. 2022). Since labels are not available in the test sets for some datasets, we use the validation set as the test set and split a part of the training set as the validation set.

**Model and Training Details.** Among various PLMs, we select representative and widely used pre-trained language models, including the base versions of BERT (Devlin et al. 2019), Roberta (Liu et al. 2019) and Google T5 (Raffel et al. 2020) to conduct experiments. We use the Adam optimizer for training of BERT and Roberta, and the Adafactor optimizer for Google T5. In main experiments, we use a one-to-one verbalizer and a simple text classification template "[text] is [MASK]." having 20 soft prompt tokens in the head. Following the setup of (Lester, Al-Rfou, and Constant 2021), we set the learning rate to be 0.3. Following the setup of (Li, He, and Song 2021), we assume that we have a server and $K = 10$ available clients, and the number of local epochs is set to 10 for all federated learning approaches. We use a FedAvg system to implement the FL setting. Specifically, all clients are involved in the averaging of model parameters in every averaging round. The number of max local step is set to 1000, compared to 30,000 in (Lester, Al-Rfou, and Constant 2021). The number of communication rounds is set to 50, compared to 100 in (Li, He, and Song 2021) and (Bagdasaryan et al. 2020), to prove our low-communication-cost method.

**Baseline Algorithm.** To make a fair and reasonable comparison with our proposed FedPrompt, we select the most related work (Hilmkil et al. 2021), studying full-parameter fine-tuning, as FL baseline. Due to full-parameter fine-tuning requires lots of calculations, we only reproduce their method with above FL setting on IID SST-2 task.

**Metric.** Communication bottleneck is a big challenge for many big models in FL, we use the amount of communicated parameters to evaluate our communication cost. Also we use accuracy (ACC) which represents the proportion of the clean samples correctly classified by the model to measure the performance of the model on benign task. Attack Success Rate (ASR) represents the proportion of the poisoned samples we successfully enable the model to misclassify as the target class and we use it to evaluate the attacking performance.

| Model | FL Method | ACC | Comm. Cost | Ratio |
|-------|-----------|-----|------------|-------|
| BERT  | FedPrompt | 90.16 | 0.016M | 0.014% |
|       | Fine-tuning | 91.02 | 109.530M | 100.000% |
| ROBERTA | FedPrompt | 92.43 | 0.016M | 0.013% |
|       | Fine-tuning | 93.57 | 124.714M | 100.000% |
| T5    | FedPrompt | 92.69 | 0.015M | 0.007% |
|       | Fine-tuning | 93.79 | 222.919M | 100.000% |

Table 2: The main results of FedPrompt and full-parameter fine-tuning on IID SST-2 task. For the same model, we regard the parameter quantity in fine-tuning as 100.000%.

**Main Results.**

In FedPrompt the learnable parameters is the same as communication costs. As shown in Table 2, FedPrompt condenses the communication costs to nearly 0.01% of the raw PLMs, greatly reduces the communication costs, making many devices applicable for some scenarios with communication constraints.

The main results of FedPrompt performance with clean IID and Non-IID data distribution summarized in Table 1 demonstrate that our FedPrompt model has little decrease on accuracy when greatly reduces the communication cost. Specifically, FL plays a remarkable effect with prompt tuning, only a few local training steps and communication rounds can contribute to a well-performed global model. For most tasks, FedPrompt achieves more than 90% ACC on clean data, and there is only a little decrease, almost less than 3%, with Non-IID data distribution than IID data distribution. Non-IID is a key challenge for the effectiveness of FL, and our proposed FedPrompt proves its compatibility on non-IID datasets. We find that experiments on RTE task have a weaker result than other tasks. Considering that RTE only have 2240 training samples in total, which is the least among all tasks, and after splitting to ten clients each client only have a few samples to train soft prompt, we assume

| Dataset | BERT IID ACC | BERT Non-IID ACC | ROBERTA IID ACC | ROBERTA Non-IID ACC | T5 IID ACC | T5 Non-IID ACC |
|---------|--------------|------------------|-----------------|---------------------|-------------|---------------|
| SST-2   | 90.16 | 12.42 | 89.45 | 16.36 | 92.43 | 10.28 | 92.23 | 7.48 | 92.69 | 9.58 | 92.32 | 6.31 |
| IMDB    | 91.08 | 12.66 | 89.26 | 11.42 | 92.80 | 9.15 | 92.53 | 7.66 | 92.89 | 9.69 | 91.24 | 11.33 |
| OffensEval | 82.64 | 9.84 | 80.47 | 8.55 | 81.05 | 13.87 | 80.34 | 5.98 | 79.30 | 12.58 | 78.83 | 10.65 |
| Twitter | 94.02 | 4.96 | 93.82 | 3.05 | 94.39 | 4.61 | 93.64 | 5.41 | 93.35 | 3.86 | 92.80 | 4.21 |
| Enron   | 97.60 | 3.20 | 97.43 | 4.02 | 97.85 | 2.27 | 97.30 | 7.34 | 97.22 | 6.73 | 96.95 | 5.87 |
| Lingspam| 97.47 | 0.00 | 96.89 | 0.00 | 97.43 | 0.00 | 96.47 | 0.00 | 97.07 | 0.00 | 96.21 | 0.41 |
| QNLI    | 83.36 | 28.35 | 82.25 | 30.46 | 86.44 | 14.81 | 85.43 | 12.10 | 89.06 | 10.87 | 84.48 | 12.44 |
| RTE     | 54.87 | 35.21 | 54.15 | 42.73 | 60.32 | 36.99 | 57.51 | 44.52 | 76.51 | 22.95 | 73.64 | 22.60 |

Table 1: ACC (%) and ASR (%) of FedPrompt with clean IID and Non-IID data distribution.
the weaker performance because of lack of data. Also RTE may need a better customized template to be used in prompt tuning.

As shown in Table 3, we evaluate the effect of backdoor attack on all tasks and models with IID and Non-IID data distribution. Nearly all tasks get ACC on poison dataset drop less than 2% compared to on clean dataset in Table 1. Even some tasks show a better ACC after poison. We think this is because poisoning the original dataset can be considered as data augmentation, and attacking has the similar effect to adversarial training. After backdoor attack, with poison ratio at 10% (all training data poisoned on 10% clients selected), all experiments on different tasks and models do not show a obvious rise in ASR, which suggests that FedPrompt has robustness to backdoor attack. We think this is because aggregation process offsets the backdoor.

**Communication Rounds**

Figure 4 shows the local and global ACC and ASR in each round during training. As for ACC, the training process of different settings is similar, and there is not a obvious decrease in Non-IID setting. The ACC of local model in the first round have a rapid rise and pass it to the global model only in one single communication round. This proves that our proposed FedPrompt fits the poor data dependent prompt tuning well. As for ASR, we can see that ASR on the malicious client reaches 100% only after one single local training round, but after aggregation, ASR on benign client and global model remains a low level. We also find ASR on benign client is close to global model in the previous round, consistent with the aggregation method.

**Number of Local Iterations**

We study the effects of number of local iterations in each round. As we mentioned before, FedPrompt has relatively few trainable parameters that too many local iterations may lead to local over-fitting, which are harmful to obtain an excellent global model. Additional experiments expanded to 50 rounds suggest the performance of 100 and 500 local iterations still below others, while the other two could not get a further promotion.

**Table 4: Global ACC (%) results with different number of soft tokens on SST-2 task.**

| Token Num | 1 | 5 | 10 | 20 |
|-----------|---|---|----|----|
| ACC       | 87.11 | 89.28 | 89.62 | 90.16 |

**Table 5: Global ACC (%) results with and without LDP on SST-2 task.**

| Method                | BERT | ROBERTA | T5  |
|-----------------------|------|---------|-----|
| FedPrompt w/o LDP     | 90.16 | 92.43   | 92.69 |
| FedPrompt w/ LDP      | 85.73 | 86.88   | 86.14 |

**Table 6: Global ACC (%) and communication costs (M, million) with different prompt methods. Denote prompt tuning as method \( \alpha \), P-tuning as \( \beta \) and Prefix-Tuning as \( \gamma \).**

| Method | \( \alpha \) | \( \beta \) | \( \gamma \) |
|--------|-------------|-------------|-------------|
| ACC    | 90.16       | 92.43       | 92.69       |
| Comm.  | 0.016       | 0.016       | 0.015       |
| ROBERTA| 93.27       | 25.420      | 25.420      |
| ACC    | 92.43       | 93.35       | 92.69       |
| Comm.  | 0.016       | 25.420      | 0.015       |
| T5     |             | 76.85       | 9.853       |

**Number of Soft Tokens**

We tested the results under different numbers of soft tokens settings, and the results are consistent with those of prompt tuning under non-federal learning. As shown in Table 3, using more soft tokens will lead to better results. However, it also increases the communication cost under federation learning.
Figure 3: Global ACC (%) results with different local iterations on SST-2 task.

Figure 4: Local and global ACC (%) and ASR (%) with communication rounds on SST-2 task using BERT. The top two figures are benign FedPrompt on clean dataset, the left one is using IID setting and the right one is using Non-IID setting, the two clients are selected randomly. The bottom two figures are using FedPPT with IID setting and only one fixed client in ten clients is malicious. The benign client is selected randomly.

Prompt methods
We also experiment on P-tuning and Prefix-Tuning (only supports T5 now). Our experiments on SST-2 are shown in Table 6. It suggests that among the three prompt methods prompt tuning gets the best performance combining ACC and communication costs. P-tuning has the best ACC performance but quite a lot parameters, and Prefix-Tuning needs more modification to use.

Further Improvement
Though FedPrompt is robust to normal backdoor attack in our experiments, there are still special methods to backdoor FL. We plan to let the server check the mean and standard deviation of soft prompt parameters from each client, and find outliers to refuse before global aggregation. Adding noise after aggregation could also destroy the backdoor, with partial sacrifice on ACC. We will carry on this research next.

Conclusion
In this work, we propose FedPrompt to use federated prompt tuning on decentralized data in a communication-efficient and privacy preserving way. We employ a split learning way that freezing extensive PLMs parameters and only tuning and aggregating soft prompts. In this way we condense the communication costs to only 0.01% compared to PLMs, making many devices applicable for some scenarios with communication constraints. Experiments on both IID and Non-IID data distribution using three mainstream model demonstrate the accuracy of FedPrompt. We also use LDP to further protect the privacy, and it is necessary to further study the FL backdoor attack.

References
Abadi, M.; Chu, A.; Goodfellow, I. J.; McMahan, H. B.; Mironov, I.; Talwar, K.; and Zhang, L. 2016. Deep Learning with Differential Privacy. In Proceedings of the 2016 ACM

FedPrompt with LDP
As we mentioned before, there are hidden dangers to infer the origin private data by inverting gradients in FL, and LDP is an effective way to defend this attack. We test on SST-2, clipping the gradients and then adding LaPlace noise on parameters. Table 5 shows that LDP protects the privacy with the cost of accuracy decreased by about 5%.
SIGSAC Conference on Computer and Communications Security, 308–318.

Acar, D. A. E.; Zhao, Y.; Navarro, R. M.; Mattina, M.; Whatmough, P. N.; and Saligrama, V. 2021. Federated Learning Based on Dynamic Regularization. In International Conference on Learning Representations.

Alahdood, A.; Hamidouche, W.; Fezza, S. A.; and Déforges, O. 2022. Adversarial example detection for DNN models: a review and experimental comparison. Artif. Intell. Rev., 55(6): 4403–4462.

Bagdasaryan, E.; Veit, A.; Hua, Y.; Estrin, D.; and Shmatikov, V. 2020. How To Backdoor Federated Learning. In Artificial Intelligence and Statistics, 2938–2948. PMLR.

Bonawitz, K. A.; Ivanov, V.; Kreuter, B.; Marcedone, A.; McMahan, H. B.; Patel, S.; Ramage, D.; Segal, A.; and Seth, K. 2017. Practical Secure Aggregation for Privacy-Preserving Machine Learning. In Proceedings of the ACM SIGSAC Conference on Computer and Communications Security, 1175–1191.

Dean, J.; Corrado, G.; Monga, R.; Chen, K.; Devin, M.; Le, Q. V.; Mao, M. Z.; Ranzato, M.; Senior, A. W.; Tucker, P. A.; Yang, K.; and Ng, A. Y. 2012. Large Scale Distributed Deep Networks. In Advances in Neural Information Processing Systems, 1232–1240.

Devlin, J.; Chang, M.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In NAACL-HLT, 4171–4186.

Fallah, A.; Mokhtari, A.; and Ozdaglar, A. E. 2020. Personalized Federated Learning with Theoretical Guarantees: A Model-Agnostic Meta-Learning Approach. In Advances in Neural Information Processing System.

Founta, A.; Djouvas, C.; Chatzakou, D.; LeONTiadis, I.; Blackburn, J.; Stringhini, G.; Vakali, A.; Sirivianos, M.; and Kourtellis, N. 2018. Large Scale Crowdsourcing and Characterization of Twitter Abusive Behavior. In Proceedings of the Twelfth International Conference on Web and Social Media, 491–500.

Geiping, J.; Bauermeister, H.; Dröge, H.; and Moeller, M. 2020. Inverting Gradients - How easy is it to break privacy in federated learning? In Advances in Neural Information Processing System.

Geyer, R. C.; Klein, T.; and Nabi, M. 2017. Differentially Private Federated Learning: A Client Level Perspective. arXiv:1712.07557.

Hambardzumyan, K.; Khachatrian, H.; and May, J. 2021. WARP: Word-level Adversarial ReProgramming. In ACL/JCNLP, 4921–4933.

Hamer, J.; Mohri, M.; and Suresh, A. T. 2020. FedBoost: A Communication-Efficient Algorithm for Federated Learning. In Proceedings of the International Conference on Machine Learning, 3973–3983. PMLR.

Han, X.; Zhao, W.; Ding, N.; Liu, Z.; and Sun, M. 2021. P-tuning: Prompt tuning with rules for text classification. arXiv:2105.11259.

He, C.; Ceyani, E.; Balasubramanian, K.; Annavaram, M.; and Avastimehr, S. 2022. SpreadGNN: Decentralized Multi-Task Federated Learning for Graph Neural Networks on Molecular Data. In Proceedings of the AAAI Conference on Artificial Intelligence, 6865–6873.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770–778. IEEE Computer Society.

Hilmlik, A.; Callh, S.; Barbieri, M.; Sütfeld, L. R.; Zec, E. L.; and Mogren, O. 2021. Scaling Federated Learning for Fine-Tuning of Large Language Models. In International Conference on Applications of Natural Language to Information Systems, 15–23.

Jere, M.; Farnan, T.; and Koushanfar, F. 2021. A Taxonomy of Attacks on Federated Learning. IEEE Secur. Priv., 19(2): 20–28.

Karimireddy, S. P.; Kale, S.; Mohri, M.; Reddi, S. J.; Stich, S. U.; and Suresh, A. T. 2020. SCAFFOLD: Stochastic Controlled Averaging for Federated Learning. In Proceedings of the International Conference on Machine Learning, 5132–5143. PMLR.

Lester, B.; Al-Rfou, R.; and Constant, N. 2021. The Power of Scale for Parameter-Efficient Prompt Tuning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, 3045–3059.

Li, M.; Zhou, L.; Yang, Z.; Li, A. Q.; Xia, F.; Andersen, D. G.; and Smola, A. 2013. Parameter Server for Distributed Machine Learning.

Li, Q.; He, B.; and Song, D. 2021. Model-Contrastive Federated Learning. In IEEE Conference on Computer Vision and Pattern Recognition, 10713–10722.

Li, T.; Sahu, A. K.; Zaheer, M.; Sanjabi, M.; Talwalkar, A.; and Smith, V. 2020. Federated Optimization in Heterogeneous Networks. In Proceedings of Machine Learning and Systems.

Li, X.; and Zhan, D. 2021. FedRS: Federated Learning with Restricted Softmax for Label Distribution Non-IID Data. In KDD ’21: The ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 995–1005.

Li, X. L.; and Liang, P. 2021. Prefix-Tuning: Optimizing Continuous Prompts for Generation. In ACL/JCNLP, 4582–4597.

Liu, X.; Ji, K.; Fu, Y.; Du, Z.; Yang, Z.; and Tang, J. 2021a. P-tuning v2: Prompt tuning can be comparable to fine-tuning universally across scales and tasks. arXiv:2110.07602.

Liu, X.; Zheng, Y.; Du, Z.; Ding, M.; Qian, Y.; Yang, Z.; and Tang, J. 2021b. GPT understands, too. arXiv:2103.10385.

Liu, Y.; Ott, M.; Goyal, N.; Du, J.; Joshi, M.; Chen, D.; Levy, O.; Lewis, M.; Zettlemoyer, L.; and Stoyanov, V. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. arXiv:1907.11692.

Maas, A. L.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning Word Vectors for Sentiment Analysis. In The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, 142–150.
