FeDeRA: Efficient Fine-tuning of Language Models in Federated Learning Leveraging Weight Decomposition

Yuxuan Yan[1], Shunpu Tang[1], Yuanchao Shu[2], Zhiguo Shi[1], Qianqian Yang[1]*

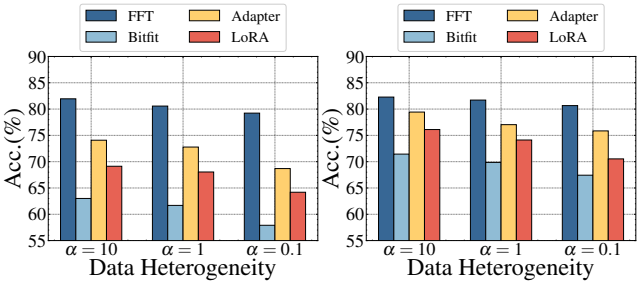
[1]College of Information Science and Electronic Engineering, Zhejiang University
[2]College of Control Science and Engineering, Zhejiang University
{yanyx44,tangshunpu,ycshu,shizg,qianqianyang20}@zju.edu.cn

Abstract

Federated learning (FL) is a widely used privacy-preserving approach for distributed training that avoids the need to collect data from individual users. In this paper, we investigate fine-tuning pre-trained language models (PLMs) in an FL setting and leverage parameter-efficient fine-tuning (PEFT) methods to reduce computational and communication costs. However, non-IID data in federated learning significantly degrades the performance of PEFT, with the degradation worsening as data heterogeneity increases. To address this, we propose FeDeRA, an FL approach for fine-tuning PLMs that incorporates an effective extension of the low-rank adaptation (LoRA) method. Specifically, FeDeRA initializes the low-rank matrices using Singular Value Decomposition (SVD) on the pre-trained weight matrices, rather than the zero or random initialization used in the original LoRA method. Analyzing weight updates during training reveals that FeDeRA reduces weight oscillations, enabling faster and more efficient fine-tuning of PLMs in FL with non-IID data. Experimental results across multiple NLP tasks and models show that FeDeRA outperforms all PEFT-based baselines in task performance and, in some cases, even matches or exceeds the performance of full-parameter fine-tuning. FeDeRA also greatly enhances training efficiency, reducing training time by up to 97.3% compared to full-parameter fine-tuning and up to 74.6% compared to the fastest PEFT baseline in practical FL settings. Furthermore, FeDeRA demonstrates greater robustness to data heterogeneity than all other PEFT methods, highlighting the effectiveness of its proposed initialization in FL systems.

1 Introduction

Pre-trained language models (PLMs) have achieved state-of-the-art (SOTA) performances across various NLP tasks, including natural language understanding (Kenton and Toutanova 2019; Sanh et al. 2019; Liu et al. 2019), text generation (Brown et al. 2020; Zeng et al. 2022; Jiang et al. 2023), and question answering. However, training these models from scratch demands a significant amount of resources (Narayanan et al. 2021), making it unattainable for most. Consequently, fine-tuning models for specific tasks has emerged as the primary method of leveraging large language models. This process typically involves training a pre-trained model on a significantly smaller dataset rather than the original training set. While fine-tuning in a centralized manner is typically preferred, aggregating all data onto a single device raises concerns about data privacy, thus making centralized training increasingly challenging.



(a) Comm. rounds 200 (b) Comm. rounds 500

Figure 1: The performance of adopting PEFT methods within an FL setting is evaluated at varying levels of data heterogeneity using DistilBERT fine-tuned on the 20Newsgroup dataset. Heterogeneous data is generated based on a Dirichlet distribution, where the hyperparameter α determines the degree of data heterogeneity—a lower α value indicates higher data heterogeneity (Lin et al. 2022).

Federated learning(FL) (Konečný et al. 2016; McMahan et al. 2017; Wang et al. 2022; Tang et al. 2022) has emerged as a promising approach in machine learning to address data privacy concerns by training a model collaboratively across decentralized clients without sharing raw local data. In FL, clients periodically compute and send model information, such as parameters or gradients, to a central server for aggregation, resulting in a global model. However, fine-tuning PLMs in an FL setting encounters significant challenges. Firstly, FL requires frequent exchange of model parameters or gradients between the server and clients. The massive number of parameters in PLMs, often in the tens or hundreds of billions, leads to substantial communication overheads. Additionally, devices involved in FL often communicate over bandwidth-limited networks, causing significant delays during data transmission and reducing training efficiency. Moreover, fine-tuning language models demands substantial memory and computational resources, which many edge devices may not adequately meet.

Recently, parameter-efficient fine-tuning (PEFT) tech-

*Corresponding author.

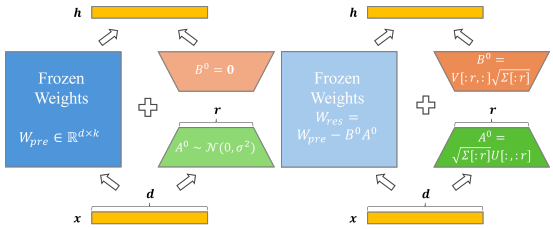
niques such as BitFit (Zaken, Goldberg, and Ravfogel 2022), adapter tuning (Narayanan et al. 2021; Pfeiffer et al. 2021), prefix tuning (Li and Liang 2021), and LoRA (Hu et al. 2021; Meng, Wang, and Zhang 2025) have garnered significant attention for their ability to update only a small portion of a pre-trained model's parameters, thus offering advantages in memory and computational efficiency. Existing works have demonstrated that these methods match or even surpass the performance of traditional full-parameter fine-tuning (FFT) methods in centralized training. Adopting PEFT in FL setting holds promise in addressing the aforementioned challenges by effectively reducing the number of parameters transmitted between clients and the server, as well as lowering the memory and computation costs associated with model training on each client.

In this work, we investigate PEFT methods within an FL setting and find that the heterogeneity of clients' data results in reduced performance and slower convergence rates for PEFT. As shown in Fig. 1, the performance gap between PEFT methods and FFT widens as data heterogeneity increases. To address this issue, we propose FeDeRA, building upon LoRA's approach of decomposing pre-trained model weight matrices into low-rank matrices. FeDeRA innovatively leverages singular value decomposition (SVD) on pre-trained weight matrices to extract principal components for initializing low-rank matrices, i.e., the adaptors, while preserving and freezing remaining components in the original matrices. This simple yet effective solution addresses the remarkable performance decline observed in LoRA within federated settings, particularly when confronted with significantly non-IID data across clients. Experimental outcomes reveal that FeDeRA achieves comparable or superior task performance to FFT across various tasks, significantly surpassing other PEFT methods. Moreover, FeDeRA reduces training time by over 95% compared to FFT, while maintaining consistent task performance. Furthermore, experimental results underscore the robustness of FeDeRA against data heterogeneity, exhibiting much lower performance degradation compared to other PEFT methods.

2 Related Works

2.1 Federated Learning with Non-IID Data

FL is widely adopted for distributed learning, especially in tasks requiring significant privacy considerations. However, it suffers non-neglectable performance degradation when data across different clients are non-independently and Identically Distributed (non-IID). Research efforts have surged to mitigate the effects of non-IID data on FL performance (Li et al. 2020). Some studies address this issue directly on the training data of each client through methods such as sharing a small portion of local data (Zhao et al. 2018), sharing model outputs (Itahara et al. 2021), enhancing data with external datasets (Jeong et al. 2018), generating new data from encoded and protected data of other clients (Shin et al. 2020), or selecting data carefully (Wang et al. 2020). Other approaches involves carefully designing the model training process, such as using adaptive learning rates on clients (Ma et al. 2021) or employing a control variable to prevent excessive drift in local updates (Karimireddy et al. 2020). Additionally, some studies have combined FL with other algorithms like Meta-Learning (Jiang et al. 2019; Zhang et al. 2021), Lifelong Learning (Shoham et al. 2019; Kopparapu and Lin 2020), and Knowledge Distillation (Itahara et al. 2021; Zhang et al. 2022). Existing research suggests that using pre-trained models in FL, rather than training models from scratch, can effectively mitigate the impact of non-IID data on performance (Weller et al. 2022; Nguyen et al. 2023; Chen et al. 2023). However, as discussed in Section Introduction, the substantial computational demands and communication overheads associated with PLMs are significant challenges. Thus, optimizing the fine-tuning of PLMs within an FL setting for both computation and communication is urgently needed.



(a) LoRA (b) FeDeRA

Figure 2: Weight initialization of LoRA and FeDeRA, $W_{pre} \in \mathbb{R}^{d\times k}$ denotes the pre-trained weights.

2.2 PEFT in Federated Learning

PEFT methods aim to freeze most or all of the weights in PLMs, fine-tuning only a small subset or newly introduced weights. This approach reduces computational resource requirements and significantly decreases communication overhead. Some studies have incorporated various PEFT methods in FL, demonstrating their efficiency in training and evaluating the comparative advantages and disadvantages of different PEFT approaches in terms of performance, resource demands, and privacy aspects (Sun et al. 2022; Chen et al. 2022; Zhang et al. 2023). Additionally, some other studies focus on exploring the potential of PEFT techniques within FL, such as using LoRA for enhanced heterogeneous personalized learning in FL (Yi et al. 2023; Lu et al. 2024; Bai et al. 2024), and incrementally enhancing adapter configurations during FL training to accelerate convergence (Cai et al. 2023). However, it has been increasingly recognized that PEFT methods experience significant performance degradation when dealing with highly non-IID data distributions in FL (Zhang et al. 2023; Babakniya et al. 2023). Despite this growing awareness, most prior research has either overlooked this critical issue or failed to evaluate PEFT methods under severe non-IID data conditions.

3 Preliminaries

3.1 Federated Learning

FL is a distributed approach to collaboratively train a global model across multiple clients, denoted by $\mathcal{M} = [1, 2 \dots M]$, coordinated by a central server. We use $\mathcal{D}_m$ to denote the

local training set at client $m \in \mathcal{M}$, and $|\mathcal{D}_m|$ to represent the number of training samples in $\mathcal{D}_m$. The goal of FL is to optimize the global model parameters ω by minimizing the following objective function:

$$\min_{\omega} F(\omega) \triangleq \sum_{m=1}^{M} p_m F_m(\omega), \tag{1}$$

where $p_m \geq 0$ is the weight assigned to the client m, with $\sum_{m=1}^{M} p_m = 1$. Typically, $p_m = \frac{|\mathcal{D}m|}{\sum m=1^M |\mathcal{D}_m|}$, ensuring that each training sample contributes equally to the optimization process. Additionally, $F_m(\cdot)$ represents the local objective, which can be expressed as:

$$F_m(\omega) \triangleq \mathcal{L}_m(\omega; \mathcal{D}_m), \tag{2}$$

where $\mathcal{L}_m(\cdot)$ is the specific local loss function at client m.

One of the most commonly used methods to solve this problem is the well-known FedAvg algorithm (McMahan et al. 2017). Specifically, in each training round, the server selects a subset of clients, denoted as $\mathcal{S} \in \mathcal{M}$, to participate in the FL training. $S = |\mathcal{S}|$ represents the number of selected clients. For a selected client $s \in \mathcal{S}$, the local training process begins by initializing its local model using the global model parameters from the previous round, i.e., $\omega_s = \omega^{t-1}$. The client then updates its local model parameters ω_s using its local dataset according to the following rule:

$$\omega_s \leftarrow \omega_s - \eta \nabla \mathcal{L}_s(\omega_s; \mathcal{D}_s), \tag{3}$$

where η is the learning rate. This process is repeated for a specified number of iterations, resulting in the updated local weights ω_s^t.

The selected clients then upload their updated weights, ω_s^t, to the server. The server aggregates these received model parameters to update the global model parameters as follows:

$$\omega^t \leftarrow \frac{\sum_{s \in \mathcal{S}} |\mathcal{D}_s| \omega_s^t}{\sum_{s \in \mathcal{S}} |\mathcal{D}_s|}. \tag{4}$$

However, it is important to note that in real-world scenarios, the data across clients are often highly non-IID. This can lead to significant divergence among the local model parameters from different clients, making it challenging for the global optimization to converge.

3.2 Low-Rank Adaptation

LoRA (Hu et al. 2021) is one of the most widely used PEFT methods of PLMs. This method is based on the observation that when PLMs are adapted to specific tasks, their weight update matrices usually have a lower intrinsic dimension than their dimensions. This implies that projecting these matrices into a lower dimension does not lead to significant information loss. The key idea behind LoRA is to avoid fine-tuning an entire pre-trained weight matrix $W_{pre} \in \mathbb{R}^{d \times k}$. Instead, as illustrated in Fig. 2a, LoRA introduces a weight update mechanism based on matrix decomposition: $W_{pre} + \Delta W = W_{pre} + AB$. Here, $B \in \mathbb{R}^{d \times r}$ and $A \in \mathbb{R}^{r \times k}$ are trainable matrices, with rank $r \ll \min\{d, k\}$. During training, matrix A is initialized by sampling from a random Gaussian distribution, and matrix B is initialized to zeros, ensuring that initially $AB = 0$, as illustrated in Fig. 2a. The matrix W_{pre} remains frozen throughout the training, while AB are updated during the fine-tuning process. The output of a layer after implementing LoRA is given by:

$$h = W_{pre}x + \frac{\beta}{r} BAx, \tag{5}$$

where x is the input, and β is designed to eliminate the need of re-adjusting hyperparameters when changing r.

4 Methods

4.1 FeDeRA

We begin by analyzing why directly applying LoRA in FL suffers from a slower convergence rate and degraded performance when the data across clients is highly non-IID. Assuming a calculation order for a layer with a LoRA module is $Y = X(W_0 + AB) = XW_0 + XAB$. and assuming the update step is t, the update method for the A and B matrix is as follows:

$$A_t = A_{t-1} - \eta X_{t-1}^T \frac{\partial L_{t-1}}{\partial Y_{t-1}} B_{t-1}^T, \tag{6}$$

$$B_t = B_{t-1} - \eta A_{t-1}^T X_{t-1}^T \frac{\partial L_{t-1}}{\partial Y_{t-1}}. \tag{7}$$

According to the recurrence relation, let $Z_t = X_t^T \frac{\partial L_t}{\partial Y_t}$,we can obtain:

$$A_1 = A_0 - \eta Z_0 B_0^T, \tag{8}$$

$$B_1 = B_0 - \eta A_0^T Z_0. \tag{9}$$

Then we can derive

$$\begin{aligned} A_2 &= A_1 - \eta Z_1 B_1^T \\ &= A_0 - \eta (Z_0 + Z_1) B_0^T + \eta^2 Z_1 (A_0^T Z_0)^T, \end{aligned} \tag{10}$$

$$\begin{aligned} B_2 &= B_1 - \eta A_1^T Z_1 \\ &= B_0 - \eta A_0^T (Z_0 + Z_1) + \eta^2 (Z_0 B_0^T)^T Z_1. \end{aligned} \tag{11}$$

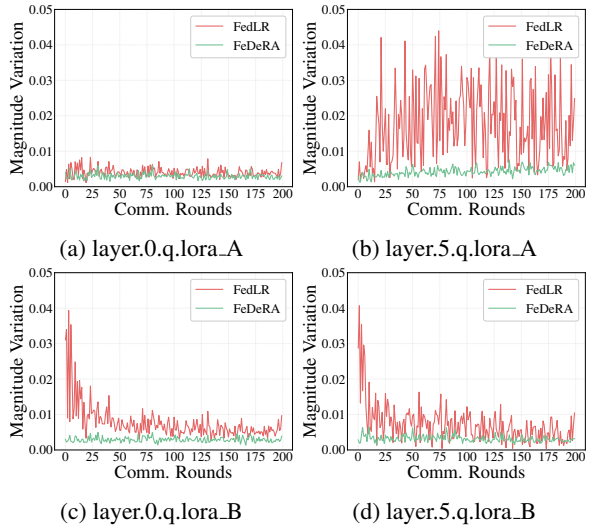
Considering the initialization method in the original LoRA approach, i.e.,$B_0 = 0$, we can recursively obtain:

$$A_t = A_0 + \eta^2 \Sigma_{i=1}^{t-1} (Z_i \Sigma_{j=0}^{i-1} Z_j^T) A_0^T, \tag{12}$$

$$B_t = -\eta A_0^T \Sigma_{i=0}^{t-1} Z_i. \tag{13}$$

Note that Z_t is jointly contributed by the selected clients $\mathcal{S}_t$ in round t. In highly non-IID scenarios, due to the randomness in client selection and the client drift in gradients, the gradients obtained in each round may be biased in a different direction compared to the previous round. Hence, due to the zero and random initialization, as well as the double summation of gradients from previous rounds, i.e., $\Sigma_{i=1}^{t-1}(Z_i \Sigma_{j=0}^{i-1} Z_j^T)$, the weights of A are updated more slowly, while the weights of B experience significant oscillations. This makes it difficult for the model to begin converging at the start of training, slows down overall convergence, and can even degrade the model's performance.

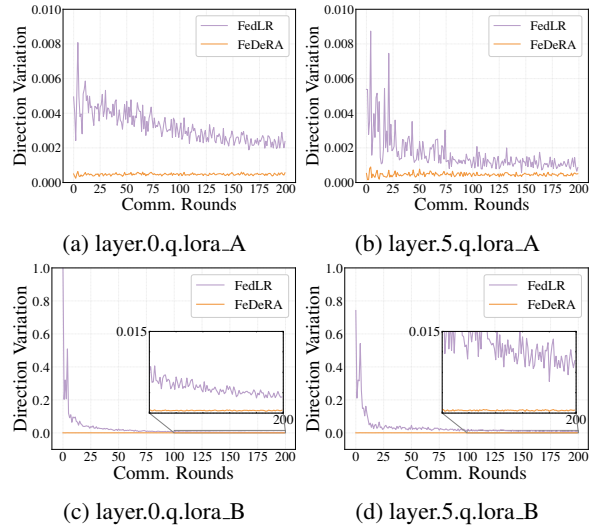
To address this issue, we introduce FeDeRA, a novel FL approach for fine-tuning PLMs based on LoRA, which carefully designs the initialization of A and B. The procedure



(a) layer.0.q.lora_A (b) layer.5.q.lora_A

(c) layer.0.q.lora_B (d) layer.5.q.lora_B

Figure 3: Magnitude variation in consecutive global weight updates by FeDeRA and FedLR fine-tuning DistilBERT over 200 Communication Rounds on the 20 Newsgroups Dataset.



(a) layer.0.q.lora_A (b) layer.5.q.lora_A

(c) layer.0.q.lora_B (d) layer.5.q.lora_B

Figure 4: Direction variation in consecutive global weight updates by FeDeRA and FedLR fine-tuning DistilBERT over 200 communication rounds on the 20Newsgroups dataset.

begins with the SVD decomposition of W_pre, which can be expressed as:

$$W_{pre} \overset{\text{SVD}}{=} U\Sigma V, \tag{14}$$

where

$$U = [u_1, u_2, \ldots, u_d] \in \mathbb{R}^{d\times d},$$
$$V = [v_1, v_2, \ldots, v_k]^T \in \mathbb{R}^{k\times k},$$

denote the matrices of left and right singular vectors, respectively, and

$$\Sigma = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_k) \in \mathbb{R}^{d\times k}, \tag{15}$$

is the diagonal matrix containing the singular values, $\sigma_1, ..., \sigma_k$. We then initialize the weight matrices A and B as follows with rank r:

$$\begin{aligned} A^0 &= \sqrt{\Sigma[:r]}V[:,:r] \\ &= [\sqrt{\sigma_1}v_1, \sqrt{\sigma_2}v_2, \ldots, \sqrt{\sigma_r}v_r]^T, \end{aligned} \tag{16}$$

$$\begin{aligned} B^0 &= U[:r,:]\sqrt{\Sigma[:r]} \\ &= [\sqrt{\sigma_1}u_1, \sqrt{\sigma_2}u_2, \ldots, \sqrt{\sigma_r}u_r]. \end{aligned} \tag{17}$$

As illustrated in Figure To maintain the original model output unchanged, we adjust and freeze the initial matrix by:

$$W_{res} = W_{pre} - B^0A^0. \tag{18}$$

4.2 Analysis

We elucidate the superiority of FeDeRA by delving into the process of model updating. Firstly, define magnitude vector $M_w \in \mathbb{R}^{1\times k}$ and direction matrix$D_w \in \mathbb{R}^{d\times k}$ for a weight matrix $W \in \mathbb{R}^{d\times k}$ as (Liu et al. 2024):

$$\begin{aligned} M_w &= [m_w^1, m_w^2 \ldots m_w^k] \\ &= [||w^1||_2, ||w^2||_2 \ldots ||w^k||_2], \end{aligned} \tag{19}$$

$$\begin{aligned} D_w &= [d_w^1, d_w^2 \ldots d_w^k] \\ &= \left[\frac{w^1}{m_w^1}, \frac{w^2}{m_w^2} \cdots \frac{w^k}{m_w^k}\right]. \end{aligned} \tag{20}$$

where w^j is the j-th column vector of W. Define magnitude variation $\Delta M_w(\cdot)$ and direction variation $\Delta D_w(\cdot)$ between two weights matrics $W_1 \in \mathbb{R}^{d\times k}$ and $W_2 \in \mathbb{R}^{d\times k}$ as:

$$\Delta M_w(W_1, W_2) = \frac{\Sigma_{n=1}^k |m_{w1}^n - m_{w2}^n|}{k}, \tag{21}$$

$$\Delta D_w(W_1, W_2) = \frac{\Sigma_{n=1}^k (1 - \cos(d_{w1}^n, d_{w2}^n))}{k}. \tag{22}$$

We then evaluate the magnitude and direction variations in successive global weight updates by FeDeRA and FedLR, referring to the original LoRA approach adapted to FL. Specifically, we calculate $\Delta M_w(\omega^t, \omega^{t-1})$ and $\Delta D_w(\omega^t, \omega^{t-1})$ for both FedLR and FeDeRA, as shown in Fig. 3 and Fig. 4, for t ranging from 0 to 200. The results indicate that FedLR exhibits more dramatic changes in the parameter updates of matrices A and B, with magnitude and direction variations in successive updates being several to hundreds of times greater than those by FeDeRA. This is particularly noticeable for B matrix at the beginning of the training, likely due to its initialization to zero. As illustrated in Fig. 3 and Fig. 4, the initial weight updates tend to be orthogonal or opposite to their consecutive updates. This supports our assertion that LoRA's initialization under highly heterogeneous data training leads to more severe weight update drift, making convergence more challenging. In contrast, our proposed FeDeRA methodology exhibits stability

in both magnitude variation and direction changes, facilitating faster convergence and effectively mitigating the impact of data heterogeneity in FL.

5 Evaluation

In this section, we present numerical results to evaluate the performance of the proposed FeDeRA using the FedML (He et al. 2020) and FedNLP (Lin et al. 2022) frameworks.

5.1 Baselines

We adopt existing FFT and PEFT methods within the FL setting as baselines. To ensure a fair comparison, the experimental settings for these baselines are consistent with those in their original works, unless explicitly stated otherwise. The details of the baselines are as follows:

FedFT: The conventional approach which updates all the model's parameters throughout the fine-tuning process.

FedBF: Each client updates only the bias terms while keeping the other parameters fixed.

FedAP: This approach incorporates adapter-tuning by inserting some trainable adapter layers into the model while keeping the parameters of the original model frozen. The adapter module is implemented using the adapters library (Poth et al. 2023; Pfeiffer et al. 2020).

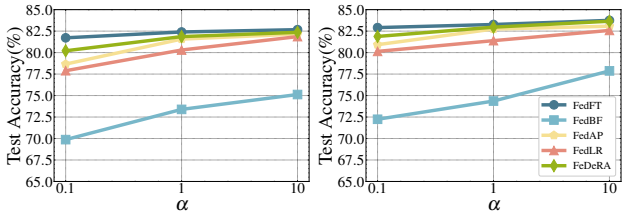
FedLR: This approach integrates LoRA into FL, , applying the LoRA module solely to the query and value modules, similar to the proposed FeDeRA. LoRA implementation is carried out using the PEFT library (Mangrulkar et al. 2022).

5.2 Setup

Models and Datasets. We adopt RoBERTa-base (Liu et al. 2019) and DeBERTaV3-base (He, Gao, and Chen 2022) as the backbone models in our experiments, implementing them using the transformers library (Wolf et al. 2020). We consider three NLP tasks: text classification(TC), named entity recognition(NER), and question answering(QA). We use the 20Newsgroups (Lang 1995) and SemEval-2010Task8 (Hendrickx et al. 2010) datasets for TC, WNUT2017 (Derczynski et al. 2017) and PLONER (Fu, Liu, and Zhang 2020) datasets for NER, SQuADv1.1 (Rajpurkar et al. 2016) and MRQA (Fisch et al. 2019) datasets for QA, respectively. Additional details about the datasets and parameter configurations can be found in Table 5. It is noteworthy that we select as small α as possible to ensure extreme data heterogeneity without significantly impeding the convergence of all methods.

5.3 Task Performance

Table 1, Table 2 and Table 3 present the performance of the proposed FeDeRA and baselines across the TC, NER, and QA tasks. The results indicate that the proposed FeDeRA consistently outperforms FedBF, FedAP, and FedLR across these tasks. Moreover, we can also observe that the proposed FeDeRA achieves comparable performance to FedFT, and even performs better than FedFT on these datasets with only about 1% trainable parameters. Furthermore, it can be observed that FedFT exhibits faster convergence,



(a) Comm. rounds 500 (b) Comm. rounds 1000

Figure 5: Performance comparison on test accuracy with regards to different levels of data heterogeneity.

reaching higher performance with fewer rounds, while additional rounds result in diminishing performance improvements. However, the convergence speed of PEFT-based FL methods, namely FedBF, FedAP, and FedLR, is significantly slower than that of FedFT. There is a substantial gap between these methods and FedFT in the early rounds, which only gradually diminishes with additional rounds. Our proposed FeDeRA demonstrates significantly faster convergence compared to these PEFT-based FL methods. Throughout various training rounds, it consistently matches the performance of FedFT, with only minor differences in the early stages. These results underscore the superiority of the proposed approach.

5.4 Training Efficiency

We then evaluate the training efficiency of our proposed method in terms of time cost to reach a targeted accuracy in a practical scenario, where we use Jetson AGX Orin as clients, and a server equipped with 8×NVIDIA RTX A6000 GPU and 2×64-Core AMD EPYC 7763 CPU. These devices are connected via WiFi with bandwidth ranging from 20-30 Mbps. We measure the time cost by different methods to reach 90%, 95%, and 99% of target metrics, as shown in Table 4. From this Table, we can observe that the proposed FeDeRA significantly reduces the time required to achieve a specified accuracy. This is because FeDeRA converges more quickly than PEFT-based FL methods, requiring fewer training rounds to reach higher accuracy. Although FeDeRA's convergence speed is slightly slower than that of FedFT, it offers substantial acceleration in local training and communication. Although FeDeRA introduces an additional SVD computation, this computation is performed only once and is negligible compared to the overall training time. Specifically, across different models and tasks with varying target accuracies, FeDeRA reduces training time by 76.9% to 97.3% compared to FedFT, and by 36.7% to 74.6% compared to the fastest PEFT-based FL method. These results demonstrate that FeDeRA can significantly improve training efficiency in practical FL systems.

5.5 Impact of Data Heterogeneity

In this section, we investigate the impact of non-IID on the training accuracy by changing the value of α, as shown in Figure 5. We use RoBERTa-base model and the 20Newsgroup dataset. It can be observed that as α decreases, i.e., the

Model	Method	#Trainable Parameters	20NEWS(Acc.)			SEMEVAL(Acc.)		
			Comm. rounds			Comm. rounds		
			200	500	1000	200	500	1000
RoBERTa	FedFT	125M	**79.56**$_{\pm 0.6}$	**82.71**$_{\pm 0.2}$	**83.67**$_{\pm 0.3}$	80.34$_{\pm 1.6}$	**82.99**$_{\pm 0.4}$	83.53$_{\pm 0.8}$
	FedBF	0.1M	65.41$_{\pm 0.9}$	70.32$_{\pm 0.3}$	72.21$_{\pm 0.2}$	72.03$_{\pm 1.1}$	77.28$_{\pm 0.5}$	78.66$_{\pm 0.1}$
	FedAP	1.8M	74.73$_{\pm 0.1}$	78.46$_{\pm 0.3}$	80.78$_{\pm 0.1}$	72.98$_{\pm 0.5}$	79.39$_{\pm 0.1}$	80.66$_{\pm 0.2}$
	FedLR	1.2M	73.17$_{\pm 0.6}$	78.03$_{\pm 0.2}$	80.25$_{\pm 0.3}$	74.81$_{\pm 1.7}$	79.26$_{\pm 0.5}$	80.37$_{\pm 0.8}$
	FeDeRA	1.2M	77.24$_{\pm 0.2}$	80.33$_{\pm 0.2}$	82.21$_{\pm 0.1}$	**80.74**$_{\pm 0.6}$	82.91$_{\pm 0.5}$	**83.78**$_{\pm 0.4}$
DeBERTaV3	FedFT	184M	76.47$_{\pm 1.2}$	82.25$_{\pm 0.6}$	83.99$_{\pm 0.4}$	**79.57**$_{\pm 2.5}$	**83.66**$_{\pm 1.2}$	**84.42**$_{\pm 1.1}$
	FedBF	0.1M	38.93$_{\pm 1.3}$	55.72$_{\pm 0.2}$	61.37$_{\pm 1.3}$	31.44$_{\pm 1.9}$	64.37$_{\pm 0.9}$	73.79$_{\pm 0.9}$
	FedAP	1.8M	58.75$_{\pm 1.7}$	73.54$_{\pm 0.8}$	79.09$_{\pm 0.4}$	64.05$_{\pm 1.1}$	78.08$_{\pm 0.7}$	80.46$_{\pm 0.2}$
	FedLR	1.2M	50.41$_{\pm 1.3}$	73.02$_{\pm 0.9}$	80.16$_{\pm 0.2}$	39.76$_{\pm 2.3}$	71.11$_{\pm 1.9}$	80.13$_{\pm 1.4}$
	FeDeRA	1.2M	**76.91**$_{\pm 1.1}$	**82.57**$_{\pm 0.5}$	**84.38**$_{\pm 0.4}$	72.45$_{\pm 2.5}$	83.09$_{\pm 0.8}$	84.36$_{\pm 0.5}$

Table 1: Evaluation results on text classification tasks. The data marked with **bold** and underlined indicates the best and second-best results achieved by the five methods under each configuration. Each result is derived by averaging over five experiments with different random seeds. This applies to Table 2 and Table 3 as well.

Model	Method	#Trainable Parameters	WNUT(F1)			PLONER(F1)		
			Comm. rounds			Comm. rounds		
			100	200	500	50	100	150
RoBERTa	FedFT	125M	**50.03**$_{\pm .5}$	51.53$_{\pm .9}$	52.31$_{\pm .2}$	**86.01**$_{\pm .6}$	**88.01**$_{\pm .1}$	**89.19**$_{\pm .1}$
	FedBF	0.1M	35.71$_{\pm 2.9}$	42.45$_{\pm .9}$	45.23$_{\pm 1.1}$	75.95$_{\pm .6}$	79.81$_{\pm .1}$	80.78$_{\pm .1}$
	FedAP	1.8M	47.81$_{\pm 1.1}$	50.11$_{\pm .1}$	50.25$_{\pm .2}$	79.23$_{\pm .1}$	83.21$_{\pm .6}$	85.72$_{\pm .2}$
	FedLR	1.2M	46.39$_{\pm 2.4}$	49.71$_{\pm .3}$	50.15$_{\pm .6}$	81.14$_{\pm .1}$	85.29$_{\pm .1}$	86.88$_{\pm .4}$
	FeDeRA	1.2M	49.14$_{\pm 1.3}$	**52.28**$_{\pm .7}$	**52.73**$_{\pm .8}$	84.74$_{\pm .5}$	87.14$_{\pm .1}$	88.44$_{\pm .1}$
DeBERTaV3	FedFT	184M	**50.26**$_{\pm .7}$	**51.04**$_{\pm .8}$	**51.45**$_{\pm .6}$	**81.41**$_{\pm .4}$	**86.24**$_{\pm .3}$	**87.06**$_{\pm .1}$
	FedBF	0.1M	42.79$_{\pm .5}$	46.25$_{\pm .3}$	47.54$_{\pm .4}$	70.44$_{\pm .1}$	75.22$_{\pm .2}$	77.54$_{\pm .3}$
	FedAP	1.8M	43.29$_{\pm 1.3}$	45.45$_{\pm 1.9}$	47.68$_{\pm .5}$	77.46$_{\pm .2}$	82.69$_{\pm .5}$	84.82$_{\pm .6}$
	FedLR	1.2M	43.75$_{\pm 1.3}$	46.78$_{\pm 1.7}$	48.82$_{\pm .6}$	76.61$_{\pm .3}$	82.55$_{\pm .5}$	83.88$_{\pm .2}$
	FeDeRA	1.2M	50.02$_{\pm 1.2}$	50.51$_{\pm 1.1}$	51.14$_{\pm .6}$	81.02$_{\pm .2}$	84.59$_{\pm .1}$	86.11$_{\pm .1}$

Table 2: Evaluation results on named entity recognition tasks .

Model	Method	#Trainable Parameters	SQuADv1.1(EM/F1)		MRQA(EM/F1)	
			Comm. rounds		Comm. rounds	
			50	100	100	200
RoBERTa	FedFT	125M	**63.16**$_{\pm .3}$ / **77.84**$_{\pm .3}$	65.27$_{\pm .2}$ / 79.62$_{\pm .1}$	**51.45**$_{\pm .5}$ / 60.78$_{\pm .1}$	**52.44**$_{\pm .2}$ / **63.24**$_{\pm .3}$
	FedBF	0.1M	43.87$_{\pm 2.4}$ / 60.91$_{\pm 2.1}$	50.09$_{\pm .7}$ / 66.53$_{\pm .8}$	25.67$_{\pm 1.5}$ / 37.88$_{\pm 1.1}$	33.69$_{\pm .1}$ / 45.55$_{\pm .3}$
	FedAP	1.8M	62.02$_{\pm 1.2}$ / 76.84$_{\pm 1.2}$	65.14$_{\pm .2}$ / 79.42$_{\pm .4}$	47.38$_{\pm .1}$ / 59.21$_{\pm .3}$	51.01$_{\pm .1}$ / 62.25$_{\pm .4}$
	FedLR	1.2M	57.37$_{\pm .2}$ / 72.68$_{\pm .1}$	60.87$_{\pm .5}$ / 75.91$_{\pm .4}$	46.85$_{\pm .3}$ / 58.4$_{\pm .2}$	49.88$_{\pm .5}$ / 61.16$_{\pm .3}$
	FeDeRA	1.2M	62.53$_{\pm .2}$ / 77.51$_{\pm .2}$	**65.31**$_{\pm .3}$ / **79.98**$_{\pm .2}$	49.73$_{\pm .5}$ / **61.27**$_{\pm .4}$	52.05$_{\pm .3}$ / 63.11$_{\pm .5}$
DeBERTaV3	FedFT	184M	**65.81**$_{\pm .3}$ / **81.12**$_{\pm .2}$	**66.39**$_{\pm .3}$ / **81.15**$_{\pm .3}$	**55.11**$_{\pm .2}$ / **66.46**$_{\pm .1}$	**56.15**$_{\pm .1}$ / **67.34**$_{\pm .1}$
	FedBF	0.1M	53.51$_{\pm .4}$ / 71.32$_{\pm .6}$	57.49$_{\pm .1}$ / 74.81$_{\pm .3}$	23.03$_{\pm 2.3}$ / 34.19$_{\pm .6}$	30.72$_{\pm 1.4}$ / 43.34$_{\pm .5}$
	FedAP	1.8M	63.32$_{\pm .2}$ / 79.21$_{\pm .1}$	65.35$_{\pm .1}$ / 80.76$_{\pm .1}$	52.32$_{\pm .3}$ / 64.31$_{\pm .1}$	55.56$_{\pm .5}$ / 66.65$_{\pm .3}$
	FedLR	1.2M	61.05$_{\pm .2}$ / 77.78$_{\pm .3}$	63.84$_{\pm .3}$ / 79.25$_{\pm .2}$	50.45$_{\pm .2}$ / 62.56$_{\pm .2}$	53.71$_{\pm .1}$ / 65.31$_{\pm .1}$
	FeDeRA	1.2M	63.24$_{\pm .4}$ / 79.27$_{\pm .4}$	65.54$_{\pm .4}$ / 80.59$_{\pm .1}$	53.64$_{\pm .1}$ / 65.96$_{\pm .1}$	55.92$_{\pm .4}$ / 67.14$_{\pm .2}$

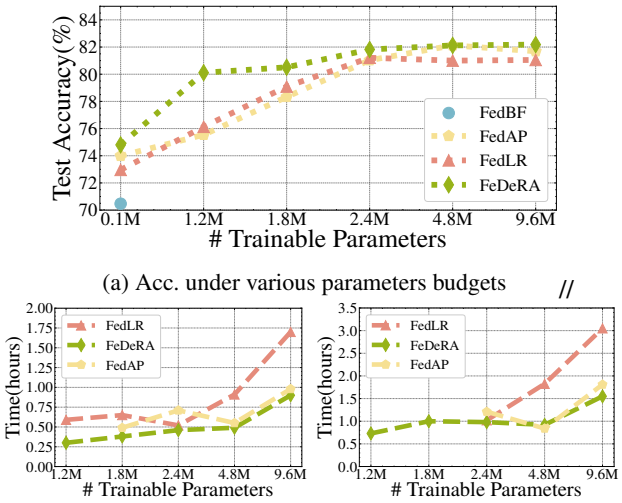
Table 3: Evaluation results on question answering tasks.

data heterogeneity increases, the performance of all methods deteriorates. However, the performance of FedFT stays stable compared to other approach, showing its robustness to data heterogeneity in a FL setting by updating all pa-

Model	Method	20NEWS(Acc.)			WNUT(F1)			SQuADv1.1(EM/F1)		
		90%	95%	99%	90%	95%	99%	90%	95%	99%
RoBERTa	FedFT	5.60	6.53	13.19	5.22	7.04	10.38	1.39 / 0.84	2.31/ 1.96	5.02/ 5.64
	FedBF	0.78	-	-	0.89	-	-	- / -	- / -	- / -
	FedAP	0.30	0.49	0.99	0.30	0.44	0.95	0.21 / 0.12	0.39 / 0.34	0.65 / 0.73
	FedLR	0.33	0.59	1.21	0.27	0.39	0.72	0.45 / 0.24	0.85 / 0.84	1.43 / 1.79
	FeDeRA	**0.17**	**0.30**	**0.54**	**0.21**	**0.28**	**0.32**	**0.16 / 0.09**	**0.31 / 0.28**	**0.51 / 0.52**
DeBERTaV3	FedFT	13.27	16.91	23.84	6.48	9.14	12.96	0.67 / 0.48	0.96 / 0.67	1.62 / 1.34
	FedBF	-	-	-	0.63	1.27	-	1.13 / 0.50	- / -	- / -
	FedAP	1.13	1.74	-	0.69	1.40	-	0.22 / 0.15	0.36 / 0.25	0.67 / 0.49
	FedLR	1.03	1.43	1.80	0.81	0.85	-	0.33 / 0.18	0.55 / 0.34	1.12 / 0.77
	FeDeRA	**0.36**	**0.45**	**0.64**	**0.16**	**0.32**	**0.45**	**0.14 / 0.09**	**0.24 / 0.19**	**0.49 / 0.31**

Table 4: Comparison on training efficiency by different methods, measured by time required to achieve 90%, 95%, and 99% of the target metrics, which are accuracy of 0.8 for TC on 20Newsgroup, F1 score of 0.5 for NER on WNUT2017, EM score of 0.65 and F1 score of 0.8 for QA on SQuADv1.1. "-" indicates that the target metric cannot be achieved by the corresponding method under the considered settings. The time cost is measured in hours.

rameters. The proposed FeDeRA also suffers much less performance degradation compared to others with significantly fewer trainable parameters than that of FedFT. These results further demonstrate the effectiveness of the proposed FeDeRA in handling data heterogeneity.



(a) Acc. under various parameters budgets

(b) Target accuracy 0.76

(c) Target accuracy 0.8

Figure 6: Performance comparison on test accuracy and training time cost with regards to different trainable parameter budgets.

5.6 Impact of Trainable Parameters Budgets

We further evaluate the performance of different methods in terms of test accuracy and training time with regards to different trainable parameters budgets, as shown in Figure 6. We use the RoBERTa-base model and the 20Newsgroup dataset, and set α to 1 and total training round to 500 for the experiments presented in Figure 6a. It can be seen from Figure 6a that the proposed FeDeRA notably outperforms the three benchmarks in terms of test accuracy across a wide range of trainable parameters. Moreover, in Figure 6b and Figure 6c, we set the target accuracy to 0.76 and 0.8, respectively, and observe that the proposed FeDeRA also requires less training time under various trainable parameters budgets. This further demonstrates the effectiveness of the proposed FeDeRA in the FL setting.

6 Conclusions

n this paper, we introduced FeDeRA, a method for fine-tuning PLMs in a federated setting. Specifically, FeDeRA extends LoRA by initializing low-rank adapters with the results of Singular Value Decomposition on pre-trained weight matrices. We analyzed the weight update equations and visualized the magnitude and direction of weight updates during training, explaining how FeDeRA reduces oscillations, thereby accelerating and improving PLM fine-tuning under non-IID data. Empirically, FeDeRA outperforms all PEFT-based baselines in task performance and closely matches—or even surpasses in some cases—the full-parameter fine-tuning approach. It also significantly improves training efficiency, reducing time by up to 97.3% compared to full-parameter tuning and 74.6% compared to the fastest PEFT baseline. Furthermore, FeDeRA is more robust to data heterogeneity, demonstrating the effectiveness of the proposed initialization in federated learning systems.

Acknowledgements

This work is partly supported by the National Key R&D Program of China under Grant No. 2024YFE0200802, by the National Natural Science Foundation of China (NSFC) under Grant Nos. 62293481, 62571487, and 62201505, by the Zhejiang Provincial Natural Science Foundation of China under Grant No. LZ25F010001, and by the China Scholarship Council under Grant No. 202406320381.

A Details of evaluation settings

Our evaluation settings details are shown in Fig. 5.

Dataset	Task Type	Train / Test	#Clients	#Selected clients per round	Classes	α
20NEWS	Text Classification	11.3k / 7.5k	100	10	20	0.1
SEMEVAL	Text Classification	8k / 2.7k	100	10	19	1
WNUT	Named Entity Recognition	3.4k / 1.2k	30	5	37	0.1
PLONER*	Named Entity Recognition	14k / 3.5k	100	10	49	0.01
SQuADv1.1	Question Answering	87.5k / 34.7k	300	15	30	0.1
MRQA*	Question Answering	45.5k/11.3k	300	15	6	0.01

Table 5: Details of the used dataset and non-IID settings. $*$ indicates that the dataset is divided into 80% and 20% for training and testing, respectively. Classes denote the number of classes into which we split the dataset. α is used to control the magnitude of data heterogeneity.

B Non-IID Data Partition

B.1 Dirichlet Distribution

The Dirichlet distribution, commonly referred to as the multivariate Beta distribution, is a class of high-dimensional continuous distributions. The support of this distribution is the standard simplex within the realm of positive real numbers. It is an extension of the Beta distribution to higher dimensions. The Dirichlet distribution, delineated by a parameter measure denoted as $\mathbf{u}$, can be represented through its corresponding probability density function as:

$$f(\boldsymbol{x};\boldsymbol{u}) = \frac{1}{B(\boldsymbol{u})}\prod_{i=1}^{K} x_i^{u_i-1},$$

where $B(\boldsymbol{u})$ is the multivariate beta function:

$$B(\boldsymbol{u}) = \frac{\prod_{i=1}^{K}\Gamma(u_i)}{\Gamma(\sum_{i=1}^{K} u_i)},$$

and $\Gamma(\cdot)$ denotes the Gamma function. $\boldsymbol{u}$ is typically expressed as $\boldsymbol{u} = \alpha\boldsymbol{m}, \sum_{i=1}^{K} m_i = 1, m_i > 0$. Note that for a random variable $X \sim Dir(\alpha\boldsymbol{m})$, $\boldsymbol{m}$ is the mathematic expectation of X:

$$\mathbb{E}(X) = \int f(\boldsymbol{x};\boldsymbol{u})\boldsymbol{x}\,\mathrm{d}\boldsymbol{x} = \boldsymbol{m}.$$

The magnitude of α determines the degree of similarity between the sampling distribution and the original distribution; a larger α yields a sampling distribution that is more similar to the original.

B.2 Classes of Datasets

We defined a specific number of classes for each dataset to facilitate the partition of the datasets. The following is the detailed information.

20Newsgroup. The 20Newsgroups dataset comprises around 18000 newsgroups posts on 20 topics and the topics cover a range of subjects from politics to religion to sports to science. The 20 Newsgroups dataset is employed for text classification tasks; consequently, its original labels are utilized as its classes.

SemEval2010Task8. SemEval2010-Task8 is aimed at addressing the challenge of Multi-Way Classification of Semantic Relations Between Pairs of Nominals. The task involves identifying and categorizing the semantic relations between specific pairs of nominals within given sentences. It delineates nine distinct types of semantic relations, with each relation type being subject to inversion, thereby totaling 19 potential labels when including an additional 'Other' category for relations that do not conform to any of the predefined types. We also utilize the original labels as classes.

WNUT2017. The WNUT2017 dataset refers to the data collection used for the Workshop on Noisy User-generated Text (WNUT) in its 2017 edition. This workshop series focuses on processing and understanding noisy user-generated text, often encountered in social media, online forums, and other web sources. WNUT2017 specifically aimed to address several key tasks in noisy text processing. One of the primary tasks was Named Entity Recognition (NER), which involved identifying and classifying proper names within text into predefined categories such as persons, organizations, locations, etc. The token labels comprise seven parts of speech, further divided into begin and intermediate positions, along with an additional category that does not belong to any of the aforementioned parts of speech, totaling thirteen labels in all. We observe that each training

sample may comprise a unique set of token labels, thereby contributing to the learning capability across diverse token labels. Consequently, we catalogue the total types of token labels encompassed within each training sample as its class, as detailed in Table 6.

Tokens	Token Labels	Class
[”today”, ”is”, ”my”, ”last”, ”day”, ”at”, ”the”, ”office”, ”.”]	[O, O, O, O, O, O, O, O, O]	O
[”Pxleyes”, ”Top”, ”50”, ”Photography”, ”Contest”, ”Pictures”, ”of”, ”August”, ”2010”, ”...”, ”http://bit.ly/bgCyZ0”, ”#photography”]	[B-corporation, O, O, O, O, O, O, O, O, O, O]	B-corporation
[”Toy”, ”story”, ”3”, ”tonight”, ”on”, ”the”, ”lawn”, ”!”]	[B-creative-work, I-creative-work ,I-creative-work, O, O, O, O, O]	B-creative-work-I-creative-work
[”(”, ”via”, ”POPSUGAR”, ”)”, ”Sarah”, ”Jessica”, ”Parker”, ”and”, ”Gwen”, ”Stefani”, ”Wrap”, ”Up”, ”Another”, ”Successful”, ”New”, ”York”, ”Fashion”, ”Week”, ”:”, ”New”, ”York”, ”Fa”, ”...”, ”http://bit.ly/aMaJNB”]	[O, O, O, O,B-person, I-person , I-person, O,B-person, I-person, O, O, O, O, O, O, O, O, O, B-location , I-location, O, O, O]	B-person-I-person-B-location-I-location

Table 6: Examples of constructing classes for the WNUT2017 dataset.

PLONER. PLONER, the abbreviation for Person, Location, Organization Named Entity Recognition, aims to assess the cross-domain generalization capability. It involves selecting samples from representative datasets that include at least one of the three entity types: person, location, and organization. The representative datasets encompass CoNLL2003, OntoNotes 5.O, and WNUT2016. The English data of CoNLL2003 is a collection of news wire articles from the Reuters Corpus. The data for WNUT2016 were primarily collected from Twitter. The OntoNotes5.0 corpus is categorized into several types, which include newswire (News), broadcast news (BN), broadcast conversation (BC), telephone conversation (Tele), and web data (Web). The corpora across various themes inherently exhibit heterogeneity. Hence, while adopting the methodology used for class construction in WNUT2017, we also take into account the source dataset of the samples for further distinction, details are shown in Table 7.

Tokens	Token Labels	Source Dataset	Class
[”only”, ”France”, ”and”, ”Britain”, ”backend”, ”Fischler”, ”’s”, ”proposal”, ”.”]	[O, B-LOC, O, B-LOC , O, B-PER, O, O, O]	CoNLL2023	CoNLL-B-LOC-B-PER
[”Cowboys”, ”on”, ”a”, ”3rd”, ”and”, ”10”, ”finally”, ”get”, ”their”, ”1st”, ”down”, ”in”, ”the”, ”game”, ”.”]	[B-ORG, O, O, O, O, O, O, O, O, O, O, O, O, O, O]	WNUT2016	WNUT-B-ORG
[”As”, ”you”, ”know”, ”Lebanon”, ”is”, ”an”, ”agreement”, ”-”, ”based”, ”democracy”, ”.”]	[O, O, O, B-LOC, O, O, O, O, O, O, O]	OntoNotes5.0-BN	OnBN-B-LOC
[”In”, ”contrast”, ”,”, ”Taiwan”, ”alumni”, ”are”, ”noticeable”, ”by”, ”their”, ”absence”, ”from”, ”the”, ”SAR”, ”government”, ”in”, ”Hong”, ”Kong”, ”.”]	[O, O, O, B-LOC, O, O, O, O, O, O, O, B-ORG, I-ORG, I-ORG, O, B-LOC, I-LOC, O]	OntoNotes5.0-MZ	OnMZ-B-LOC-I-LOC-B-ORG-I-ORG

Table 7: Examples of constructing classes for the PLONER dataset.

SQuADv1.1. SQuADv1.1 is a question-answering dataset released by Stanford University. The dataset comprises an extensive collection of question-and-answer pairs, with the questions formulated based on paragraphs from Wikipedia articles, and the answers are extracted directly from these respective passages. SQuADv1.1 does not annotate any tags pertinent to the questions, hence, we employ k-means to generate classes for all training samples directly. The number of clusters chosen for this study is 30.

MRQA. The MRQA dataset emphasizes the generalizability of question-answering tasks. This dataset is an amalgamation of subsets from 18 existing QA datasets, carefully curated and transformed into the format as SQuAD. Of these 18 datasets, six are designated for training, another six for development, and the final six are reserved for testing purposes. In our approach, we simply employ the source datasets as the classes.

B.3 Partitioning Non-IID Datas With Classes

We obtain the non-IID datasets for the clients by partitioning the original dataset based on the Dirichlet distribution and the classes we have defined. Let C denote the total number of classes, and c_i represent the total number of data instances for the i-th class in the undivided dataset. We compute the distribution for classes as $\boldsymbol{m_c} = [m_{c,1}, m_{c,2} \dots m_{c,C}], m_{c,i} = \frac{c_i}{\sum_{i=1}^{C} c_i}$. Assuming there are N clients, we sample the local data class distribution $X_i = [x_{i,1}, x_{i,2} \dots x_{i,N}]$ for the i-th client according to the Dirichlet distribution, denoted as $X_i \sim Dir(\alpha \boldsymbol{m_c})$, $x_{i,j}$ represents the proportion of the j-th class on the i-th client.

Model	Dataset	FedFT		FedBF		FedAP		FedLR&FeDeRA		FeDeRA
		Train	Comm.	Train	Comm.	Train	Comm.	Train	Comm.	SVD
RoBERTa	**20NEWS**	4.59		3.15		3.29		3.27		
	WNUT	4.62	109.67	3.31	0.96	3.42	2.47	3.33	1.68	8.62
	SQuADv1.1	30.91		21.83		22.8		22.37		
DeBERTaV3	**20NEWS**	6.31		4.36		4.62		4.54		
	WNUT	6.22	149.98	4.49	0.96	4.81	2.47	4.62	1.68	8.62
	SQuADv1.1	42.44		29.51		31.86		30.46		

Table 8: The local training time and communication time for each training round by different methods, and the time consumption for SVD decomposition, measured in seconds.

Method	Trainable Parameters									
	0.1M		1.2M		1.8M		2.4M		4.8M	
	Tain	Comm.	Tain	Comm.	Tain	Comm.	Tain	Comm.	Tain	Comm.
FedBF	3.15		-	-	-	-	-	-	-	-
FedAP	3.31	0.96	3.25	1.68	3.29	2.47	4.05	3.24	4.17	4.55
FedLR&FeDeRA	3.14		3.22		3.26		3.95		4.04	

Table 9: The local training time and communication time for each training round with different number of trainable parameters by FeDeRA, measured in seconds.

B.4 Visualization of Data Heterogeneity

We visualized the data heterogeneity among different clients according to the data partitioning according to B.3. We employed the Jensen-Shannon divergence to characterize the disparities in the distributions of data across various clients:

$$JS(P||Q) = \frac{1}{2}\sum p_i \log \frac{p_i}{q_i} + \frac{1}{2}\sum q_i \log \frac{q_i}{p_i}$$

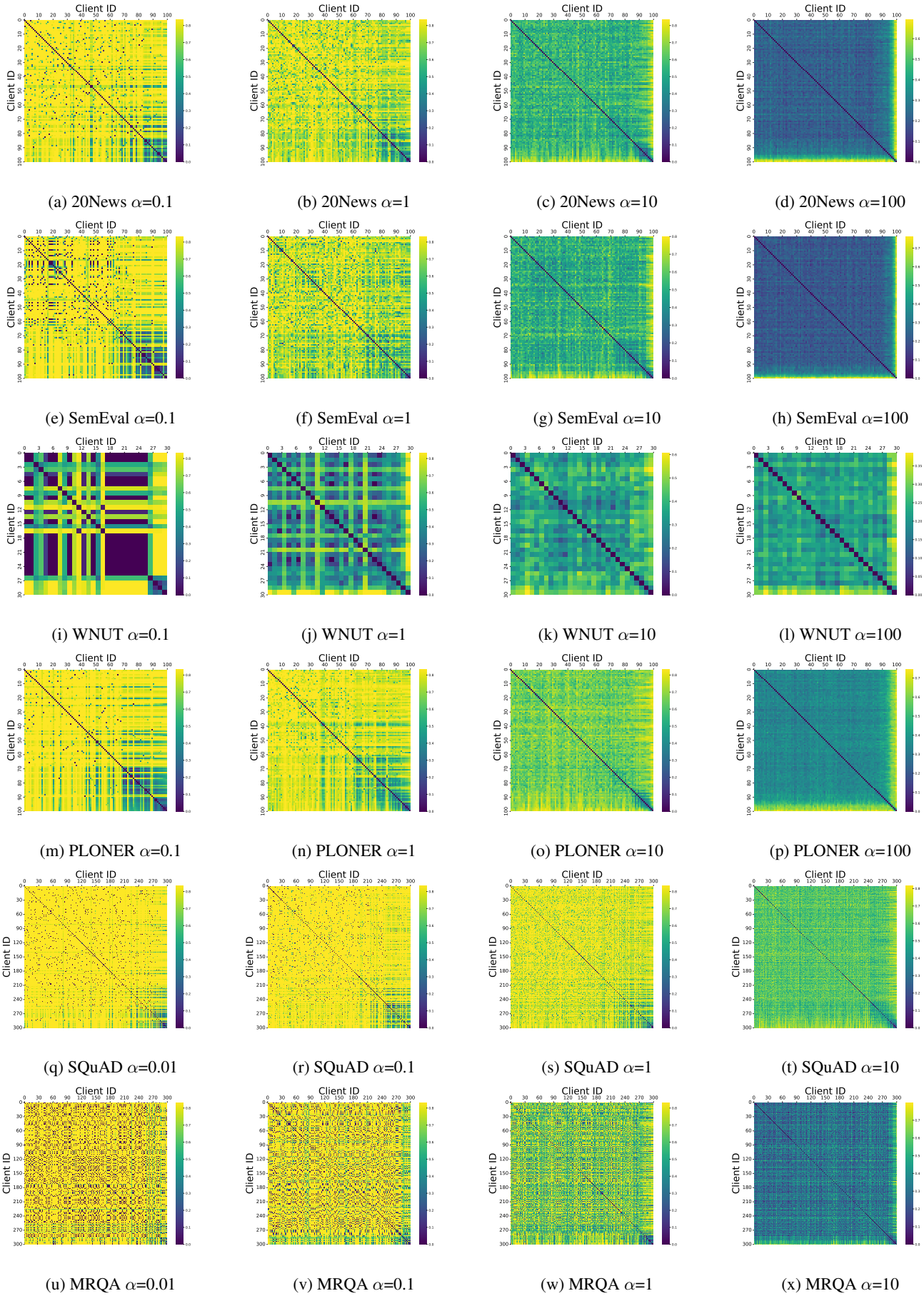
where P and Q denote two probability distributions defined in the same space. The value of Jensen-Shannon divergence ranges from 0 to 1, with larger values indicating a greater disparity between two distributions. Visualization results are presented in Fig. 7, illustrating that the degree of non-IID with various values of α.

C Details of time cost

Table 8 and Table 9 present the local training time and communication time for each training round in FL. It can be observed from Tbale 8 that FedFT has significantly larger training and communication overheads than other methods, with the communication cost being particularly higher compared to methods that incorporate PEFT. This is why, even though FedFT requires fewer training rounds and can achieve better performance, we are still interested in exploring PEFT in FL. Although FeDeRA introduces additional SVD time, it only needs to be performed once during the entire training process, which is almost negligible compared to the total training time. Table 9 illustrates that as the number of trainable parameters gradually increases, both the client's training and communication times rise incrementally, guiding us in selecting the optimal training configuration while considering the trade-off between training time cost and model performance.

D Additional Magnitude and direction Variation

We present the results of magnitude variation and direction variation not included in 4.2 here, as shown in Fig. 8 and Fig. 9. As can be observed, our proposed FeDeRA demonstrates more stability in weight updates across all layers of DistilBERT and, consequently, converges more easily compared to FedLR.



(a) 20News α=0.1 (b) 20News α=1 (c) 20News α=10 (d) 20News α=100

(e) SemEval α=0.1 (f) SemEval α=1 (g) SemEval α=10 (h) SemEval α=100

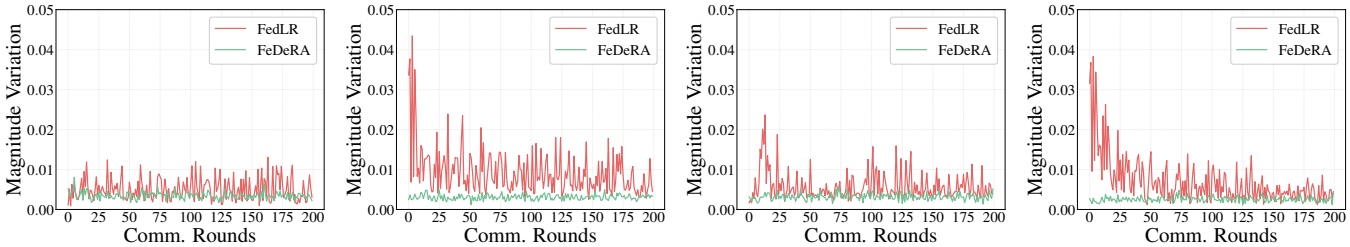
(i) WNUT α=0.1 (j) WNUT α=1 (k) WNUT α=10 (l) WNUT α=100

(m) PLONER α=0.1 (n) PLONER α=1 (o) PLONER α=10 (p) PLONER α=100

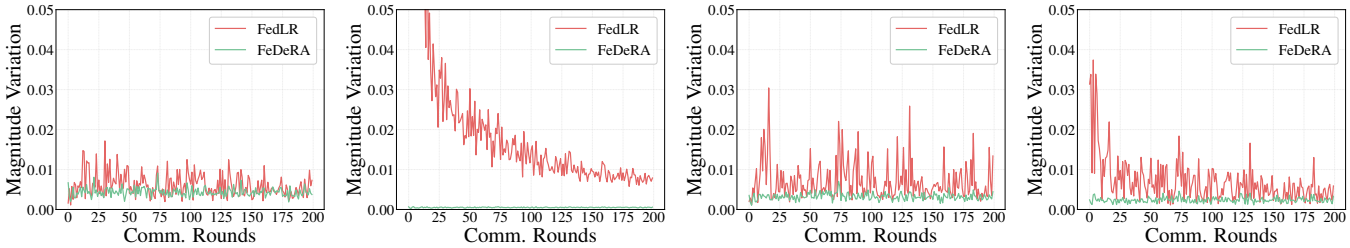
(q) SQuAD α=0.01 (r) SQuAD α=0.1 (s) SQuAD α=1 (t) SQuAD α=10

(u) MRQA α=0.01 (v) MRQA α=0.1 (w) MRQA α=1 (x) MRQA α=10

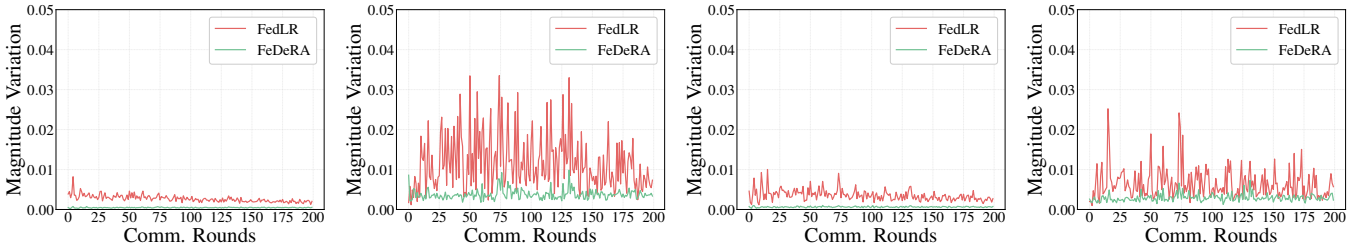
Figure 7: Visualization of data heterogeneity across six datasets for various values of α, where lighter colors denote a larger Jensen-Shannon divergence, indicating greater disparity between the sampling distribution and the original data distribution



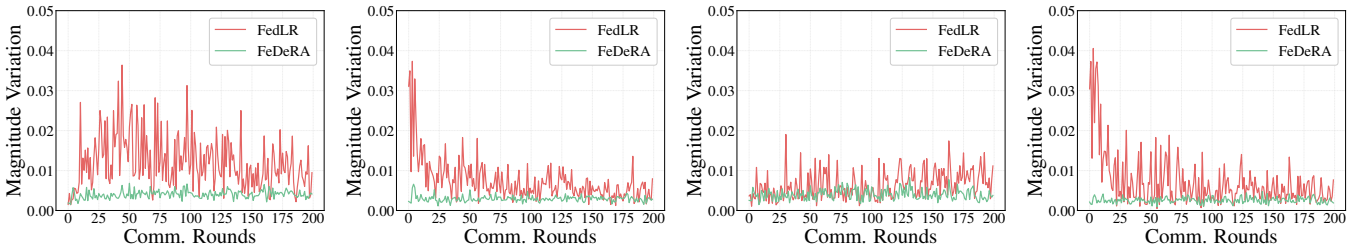
(a) layer.1.q.A (b) layer.1.q.B (c) layer.1.q.A (d) layer.1.v.B



(e) layer.2.q.A (f) layer.2.q.B (g) layer.2.q.A (h) layer.2.v.B

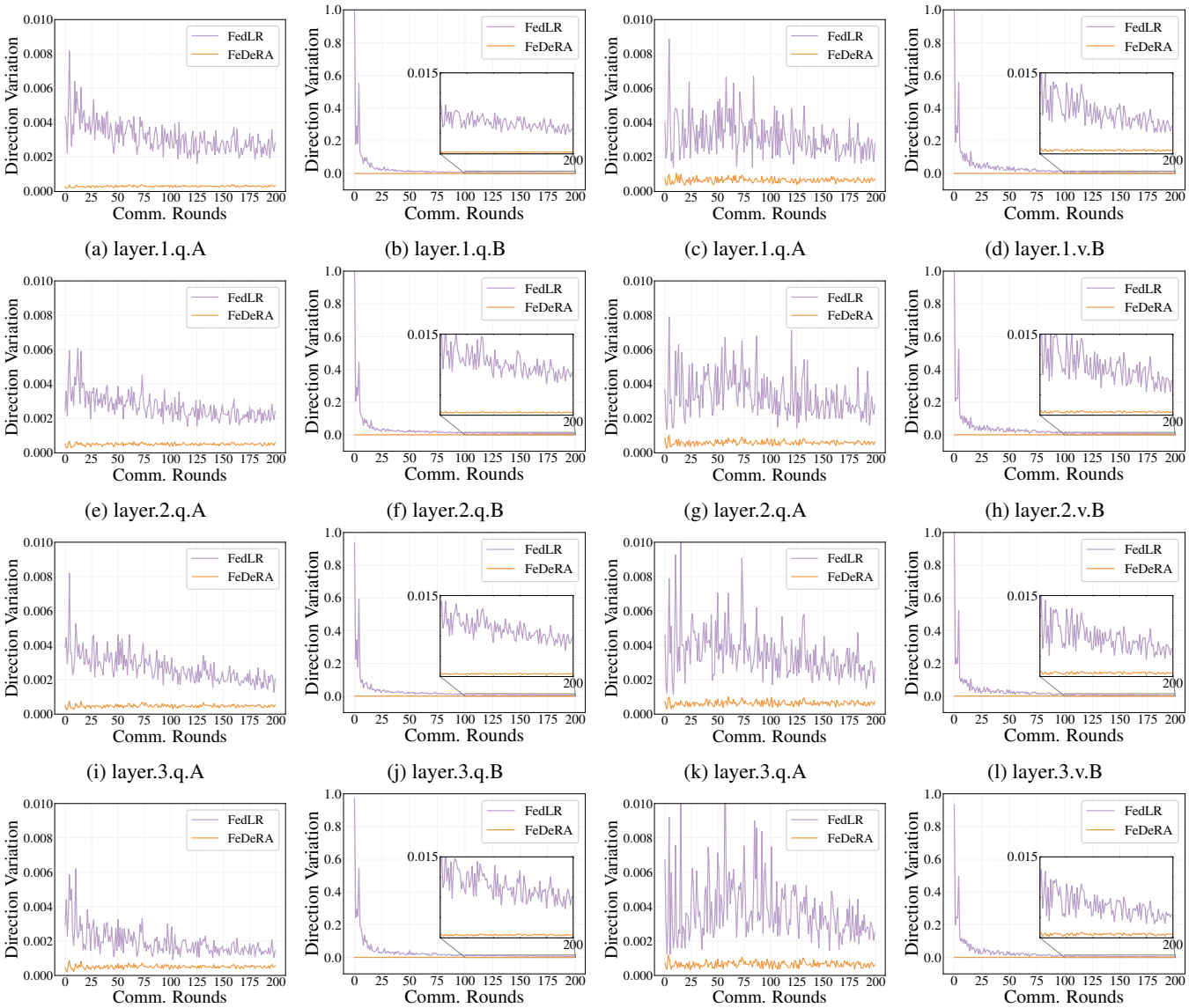


(i) layer.3.q.A (j) layer.3.q.B (k) layer.3.q.A (l) layer.3.v.B



(m) layer.4.q.A (n) layer.4.q.B (o) layer.4.q.A (p) layer.4.v.B

Figure 8: Additonal magnitude variation of DistilBERT over 200 Communication Rounds on the 20Newsgroups dataset.



(a) layer.1.q.A (b) layer.1.q.B (c) layer.1.q.A (d) layer.1.v.B

(e) layer.2.q.A (f) layer.2.q.B (g) layer.2.q.A (h) layer.2.v.B

(i) layer.3.q.A (j) layer.3.q.B (k) layer.3.q.A (l) layer.3.v.B

(m) layer.4.q.A (n) layer.4.q.B (o) layer.4.q.A (p) layer.4.v.B

Figure 9: Additional direction variation of DistilBERT over 200 communication rounds on the 20Newsgroups dataset.

References

Babakniya, S.; Elkordy, A. R.; Ezzeldin, Y. H.; Liu, Q.; Song, K.-B.; El-Khamy, M.; and Avestimehr, S. 2023. SLoRA: Federated parameter efficient fine-tuning of language models. In *Advances in neural information processing systems (NeurIPS) workshop*.

Bai, J.; Chen, D.; Qian, B.; Yao, L.; and Li, Y. 2024. Federated fine-tuning of large language models under heterogeneous language tasks and client resources. *arXiv e-prints*, arXiv–2402.

Brown, T.; Mann, B.; Ryder, N.; Subbiah, M.; Kaplan, J. D.; Dhariwal, P.; Neelakantan, A.; Shyam, P.; Sastry, G.; Askell, A.; et al. 2020. Language models are few-shot learners. In *Advances in neural information processing systems (NeurIPS)*, volume 33, 1877–1901.

Cai, D.; Wu, Y.; Wang, S.; Lin, F. X.; and Xu, M. 2023. Efficient federated learning for modern NLP. In *Proceedings of the Annual International Conference on Mobile Computing and Networking*, 1–16.

Chen, H.-Y.; Tu, C.-H.; Li, Z.; Shen, H.-W.; and Chao, W.-L. 2023. On the importance and applicability of pre-training for federated learning. In *International Conference on Learning Representations (ICLR)*.

Chen, J.; Xu, W.; Guo, S.; Wang, J.; Zhang, J.; and Wang, H. 2022. Fedtune: A deep dive into efficient federated fine-tuning with pre-trained transformers. *arXiv:2211.08025*.

Derczynski, L.; Nichols, E.; Van Erp, M.; and Limsopatham, N. 2017. Results of the WNUT2017 shared task on novel and emerging entity recognition. In *Proceedings of the 3rd Workshop on Noisy User-generated Text*, 140–147.

Fisch, A.; Talmor, A.; Jia, R.; Seo, M.; Choi, E.; and Chen, D. 2019. MRQA 2019 shared task: Evaluating generalization in reading comprehension. In *Conference on Empirical Methods in Natural Language Processing (EMNLP) workshop*.

Fu, J.; Liu, P.; and Zhang, Q. 2020. Rethinking generalization of neural models: A named entity recognition case study. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, 7732–7739.

He, C.; Li, S.; So, J.; Zeng, X.; Zhang, M.; Wang, H.; Wang, X.; Vepakomma, P.; Singh, A.; Qiu, H.; et al. 2020. Fedml: A research library and benchmark for federated machine learning. *arXiv:2007.13518*.

He, P.; Gao, J.; and Chen, W. 2022. DeBERTaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing. In *International Conference on Learning Representations (ICLR)*.

Hendrickx, I.; Kim, S. N.; Kozareva, Z.; Nakov, P.; Séaghdha, D. O.; Padó, S.; Pennacchiotti, M.; Romano, L.; and Szpakowicz, S. 2010. SemEval-2010 Task 8: Multi-Way Classification of Semantic Relations Between Pairs of Nominals. In *Annual Meeting of the Association of Computational Linguistics (ACL)*, 33. Citeseer.

Hu, E. J.; Wallis, P.; Allen-Zhu, Z.; Li, Y.; Wang, S.; Wang, L.; Chen, W.; et al. 2021. LoRA: Low-Rank Adaptation of Large Language Models. In *International Conference on Learning Representations (ICLR)*.

Itahara, S.; Nishio, T.; Koda, Y.; Morikura, M.; and Yamamoto, K. 2021. Distillation-based semi-supervised federated learning for communication-efficient collaborative training with non-iid private data. *IEEE Transactions on Mobile Computing*, 22(1): 191–205.

Jeong, E.; Oh, S.; Kim, H.; Park, J.; Bennis, M.; and Kim, S.-L. 2018. Communication-efficient on-device machine learning: Federated distillation and augmentation under non-iid private data. *arXiv:1811.11479*.

Jiang, A. Q.; Sablayrolles, A.; Mensch, A.; Bamford, C.; Chaplot, D. S.; Casas, D. d. l.; Bressand, F.; Lengyel, G.; Lample, G.; Saulnier, L.; et al. 2023. Mistral 7B. *arXiv:2310.06825*.

Jiang, Y.; Konečnỳ, J.; Rush, K.; and Kannan, S. 2019. Improving federated learning personalization via model agnostic meta learning. *arXiv:1909.12488*.

Karimireddy, S. P.; Kale, S.; Mohri, M.; Reddi, S.; Stich, S.; and Suresh, A. T. 2020. Scaffold: Stochastic controlled averaging for federated learning. In *International conference on machine learning(ICML)*, 5132–5143.

Kenton, J. D. M.-W. C.; and Toutanova, L. K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, 4171–4186.

Konečnỳ, J.; McMahan, H. B.; Yu, F. X.; Richtárik, P.; Suresh, A. T.; and Bacon, D. 2016. Federated learning: Strategies for improving communication efficiency. *arXiv:1610.05492*.

Kopparapu, K.; and Lin, E. 2020. Fedfmc: Sequential efficient federated learning on non-iid data. *arXiv:2006.10937*.

Lang, K. 1995. Newsweeder: Learning to filter netnews. In *Machine learning proceedings 1995*, 331–339. Elsevier.

Li, X.; Huang, K.; Yang, W.; Wang, S.; and Zhang, Z. 2020. On the Convergence of FedAvg on Non-IID Data. In *International Conference on Learning Representations (ICLR)*.

Li, X. L.; and Liang, P. 2021. Prefix-Tuning: Optimizing Continuous Prompts for Generation. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics(ACL)*, 4582–4597.

Lin, B. Y.; He, C.; Ze, Z.; Wang, H.; Hua, Y.; Dupuy, C.; Gupta, R.; Soltanolkotabi, M.; Ren, X.; and Avestimehr, S. 2022. FedNLP: Benchmarking Federated Learning Methods for Natural Language Processing Tasks. In *Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, 157–175.

Liu, S.-Y.; Wang, C.-Y.; Yin, H.; Molchanov, P.; Wang, Y.-C. F.; Cheng, K.-T.; and Chen, M.-H. 2024. DoRA: Weight-Decomposed Low-Rank Adaptation. In *International Conference on Machine Learning (ICML)*.

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*.

Lu, Q.; Niu, D.; Khoshkho, M. S.; and Li, B. 2024. HyperFLoRA: Federated Learning with Instantaneous Personalization. In *Proceedings of the 2024 SIAM International Conference on Data Mining (SDM)*, 824–832.

Ma, Q.; Xu, Y.; Xu, H.; Jiang, Z.; Huang, L.; and Huang, H. 2021. FedSA: A semi-asynchronous federated learning mechanism in heterogeneous edge computing. *IEEE Journal on Selected Areas in Communications*, 39(12): 3654–3672.

Mangrulkar, S.; Gugger, S.; Debut, L.; Belkada, Y.; Paul, S.; and Bossan, B. 2022. PEFT: State-of-the-art Parameter-Efficient Fine-Tuning methods. https://github.com/huggingface/peft.

McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and y Arcas, B. A. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, 1273–1282. PMLR.

Meng, F.; Wang, Z.; and Zhang, M. 2025. Pissa: Principal singular values and singular vectors adaptation of large language models. *Advances in Neural Information Processing Systems(NeurIPS)*.

Narayanan, D.; Shoeybi, M.; Casper, J.; LeGresley, P.; Patwary, M.; Korthikanti, V.; Vainbrand, D.; Kashinkunti, P.; Bernauer, J.; Catanzaro, B.; et al. 2021. Efficient large-scale language model training on gpu clusters using megatron-lm. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis(SC)*, 1–15.

Nguyen, J.; Wang, J.; Malik, K.; Sanjabi, M.; and Rabbat, M. 2023. Where to begin? on the impact of pre-training and initialization in federated learning. In *International Conference on Learning Representations (ICLR)*.

Pfeiffer, J.; Kamath, A.; Rücklé, A.; Cho, K.; and Gurevych, I. 2021. AdapterFusion: Non-destructive task composition for transfer learning. In *Conference of the European Chapter of the Associationfor Computational Linguistics (EACL)*, 487–503.

Pfeiffer, J.; Rücklé, A.; Poth, C.; Kamath, A.; Vulić, I.; Ruder, S.; Cho, K.; and Gurevych, I. 2020. AdapterHub: A Framework for Adapting Transformers. In *Conference on Empirical Methods in Natural Language Processing(EMNLP)*, 46–54.

Poth, C.; Sterz, H.; Paul, I.; Purkayastha, S.; Engländer, L.; Imhof, T.; Vulić, I.; Ruder, S.; Gurevych, I.; and Pfeiffer, J. 2023. Adapters: A Unified Library for Parameter-Efficient and Modular Transfer Learning. In *Conference on Empirical Methods in Natural Language Processing(EMNLP)*, 149–160.

Rajpurkar, P.; Zhang, J.; Lopyrev, K.; and Liang, P. 2016. Squad: 100,000+ questions for machine comprehension of text. In *Conference on Empirical Methods in Natural Language Processing (EMNLP)*.

Sanh, V.; Debut, L.; Chaumond, J.; and Wolf, T. 2019. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. In *Advances in neural information processing systems (NeurIPS) workshop*.

Shin, M.; Hwang, C.; Kim, J.; Park, J.; Bennis, M.; and Kim, S.-L. 2020. Xor mixup: Privacy-preserving data augmentation for one-shot federated learning. In *International Conference on Machine Learning (ICML)*.

Shoham, N.; Avidor, T.; Keren, A.; Israel, N.; Benditkis, D.; Mor-Yosef, L.; and Zeitak, I. 2019. Overcoming forgetting in federated learning on non-iid data. In *Advances in neural information processing systems (NeurIPS) workshop*.

Sun, G.; Mendieta, M.; Yang, T.; and Chen, C. 2022. Exploring parameter-efficient fine-tuning for improving communication efficiency in federated learning. In *International Conference on Learning Representations (ICLR)*.

Tang, S.; Chen, L.; He, K.; Xia, J.; Fan, L.; and Nallanathan, A. 2022. Computational intelligence and deep learning for next-generation edge-enabled industrial IoT. *IEEE Transactions on Network Science and Engineering*.

Wang, H.; Kaplan, Z.; Niu, D.; and Li, B. 2020. Optimizing federated learning on non-iid data with reinforcement learning. In *IEEE conference on computer communications (INFOCOM)*, 1698–1707.

Wang, Z.; Zhang, Z.; Tian, Y.; Yang, Q.; Shan, H.; Wang, W.; and Quek, T. Q. 2022. Asynchronous federated learning over wireless communication networks. *IEEE Transactions on Wireless Communications*, 21(9): 6961–6978.

Weller, O.; Marone, M.; Braverman, V.; Lawrie, D.; and Van Durme, B. 2022. Pretrained models for multilingual federated learning. In *Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*.

Wolf, T.; Debut, L.; Sanh, V.; Chaumond, J.; Delangue, C.; Moi, A.; Cistac, P.; Rault, T.; Louf, R.; Funtowicz, M.; Davison, J.; Shleifer, S.; von Platen, P.; Ma, C.; Jernite, Y.; Plu, J.; Xu, C.; Scao, T. L.; Gugger, S.; Drame, M.; Lhoest, Q.; and Rush, A. M. 2020. Transformers: State-of-the-Art Natural Language Processing. In *Conference on Empirical Methods in Natural Language Processings(EMNLP)*, 38–45. Online.

Yi, L.; Yu, H.; Wang, G.; and Liu, X. 2023. Fedlora: Model-heterogeneous personalized federated learning with LoRa tuning. *arXiv:2310.13283*.

Zaken, E. B.; Goldberg, Y.; and Ravfogel, S. 2022. BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models. In *Proceedings of the Annual Meeting of the Association for Computational Linguistics(ACL)*, 1–9.

Zeng, A.; Liu, X.; Du, Z.; Wang, Z.; Lai, H.; Ding, M.; Yang, Z.; Xu, Y.; Zheng, W.; Xia, X.; et al. 2022. GLM-130B: An Open Bilingual Pre-trained Model. In *International Conference on Learning Representations (ICLR)*.

Zhang, L.; Shen, L.; Ding, L.; Tao, D.; and Duan, L.-Y. 2022. Fine-tuning global model via data-free knowledge distillation for non-iid federated learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (CVPR)*, 10174–10183.

Zhang, X.; Hong, M.; Dhople, S.; Yin, W.; and Liu, Y. 2021. Fedpd: A federated learning framework with adaptivity to non-iid data. *IEEE Transactions on Signal Processing*, 69: 6055–6070.

Zhang, Z.; Yang, Y.; Dai, Y.; Wang, Q.; Yu, Y.; Qu, L.; and Xu, Z. 2023. Fedpetuning: When federated learning meets the parameter-efficient tuning methods of pre-trained language models. In *Annual Meeting of the Association of Computational Linguistics (ACL)*, 9963–9977.

Zhao, Y.; Li, M.; Lai, L.; Suda, N.; Civin, D.; and Chandra, V. 2018. Federated learning with non-iid data. *arXiv:1806.00582*.