Where to Begin? Exploring the Impact of Pre-Training and Initialization in Federated Learning

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Abstract

An oft-cited challenge of federated learning is the presence of data heterogeneity — the data at different clients may follow very different distributions. Several federated optimization methods have been proposed to address these challenges. In the literature, empirical evaluations usually start federated training from a random initialization. However, in many practical applications of federated learning, the server has access to proxy data for the training task which can be used to pre-train a model before starting federated training. We empirically study the impact of starting from a pre-trained model in federated learning using four common federated learning benchmark datasets. Unsurprisingly, starting from a pre-trained model reduces the training time required to reach a target error rate and enables training more accurate models (by up to 40%) than is possible than when starting from a random initialization. Surprisingly, we also find that the effect of data heterogeneity is much less significant when starting federated training from a pre-trained initialization. Rather, when starting from a pre-trained model, using an adaptive optimizer at the server, such as FEDADAM, consistently leads to the best accuracy. We recommend that future work proposing and evaluating federated optimization methods consider the performance when starting both random and pre-trained initializations. We also believe this study raises several questions for further work on understanding the role of heterogeneity in federated optimization.

1 Introduction

Federated learning (FL) has emerged as a popular distributed machine learning paradigm for privately training a shared model across many participants while the training data never leaves the participant devices. Our focus in this work is on understanding the impact of model initialization on federated learning.

In cross-device FL [19], the primary setting of interest in this paper, a large number of client devices (possibly on the order of hundreds of millions) participate in training, which is coordinated by a server. It is impractical for all devices to participate at every step of training; instead, FL usually proceeds in rounds and a small subset of available devices participate in each round. Each device possesses a local dataset, and the data at different devices follow different distributions, leading to the data heterogeneity challenge [19]. Moreover, devices communicate with the server over low-bandwidth, high-latency links, making communication overhead a major performance factor.

The predominant approach to federated training builds on local update methods such as FEDAVG [23], where a device performs several local updates (e.g., one epoch of SGD on their local training set) before transmitting an update to the server. Although this reduces communication overhead, it can also exacerbate the data heterogeneity problem. Several approaches have been proposed to address this challenge [25] [15] [32] [20] [21] [56].

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This paper empirically investigates the impact of model initialization on federated optimization methods. Previous empirical evaluations of FL methods nearly always start federated training from a randomly initialized model. Transfer learning from pre-trained models has become common practice in natural language processing [31, 7] and computer vision [14, 8]; it yields state-of-the-art results on many tasks and enables faster model convergence in the centralized setting. However, the impact of starting federated training from a pre-trained model has not been carefully studied, even though in many practical applications of FL there is public proxy data available for pre-training at the server.

Contributions. In this work we consider the question

\[
\text{How does the initialization (random, or pre-trained) impact the behavior of federated optimization methods?}
\]

Towards answering this question, we perform an extensive empirical study, comparing 12 variations of federated optimization methods on three commonly-used FL benchmark datasets. Our study reveals three key findings.

1. Starting from a pre-trained solution can close the gap between training on IID and non-IID data (Section 5.2). Moreover, the simple SGD at the client outperforms more complex local-update methods in the pre-trained setting. (Section 5.1)

2. Towards starting to explain this phenomenon, we observe that inter-device gradient/update diversity is higher for random initialized model at the beginning of training, and inter-device cosine similarity is higher when starting from a pre-trained model. (Section 5.4)

3. Surprisingly, full-batch gradient descent without any local step can achieve competitive performance against other SOTA local-update methods in the pre-trained setting. Our experiments also confirm what one might expect, that initializing FL with a pre-trained model can increase final model accuracy and reduce the number of rounds required to achieve a target accuracy, thereby saving communications and reducing the overall training time. Indeed, this is evident in Figure 1 across several datasets (hyperparameters were tuned separately for each (dataset, initialization) pair; see Section 4 for details of the experimental setup).

Our findings are reproducible using the open-source federated learning framework FLSim [1]. Informed by these findings, we conclude by presenting several recommendations for future research on federated optimization.

2 Related Work

2.1 Transfer learning.

It is well-known in the optimization and machine learning literature that the initialization can have a significant impact on training and final performance. Previous work studying the loss landscape of deep networks has observed that there are significant differences between the landscape around a
random initialization and the landscape later in training. In particular, later in training the loss can be much more “well-behaved” \([24, 10, 9]\). Fine-tuning from pre-trained models is common practice in natural language processing and computer vision, yielding strong performance on many tasks \([31, 8, 7, 14]\).

### 2.2 Federated transfer learning.

Federated transfer learning — as studied in Liu et al. \([27]\), Sharma et al. \([33]\), Gao et al. \([11]\) — aims to address scenarios where parties share only a partial overlap in the user space or the feature space, and leverages existing transfer learning techniques \([39]\) to build models collaboratively. Partitioning by examples is usually relevant in cross-silo FL when a single company cannot centralize their data due to legal constraints, or when organizations with similar objectives want to collaboratively improve their models \([19]\). In this paper, we focus the scenario where a model is pre-trained at the (centralized) server on public proxy data and then fine-tuned via federated training. We focus primarily on the large-scale cross-device setting where data partitioning among millions of clients is infeasible, and more generally where stateful methods (those maintaining distinct state about each client) is infeasible.

### 2.3 Joint federated-centralized learning.

There is a line of work on training a model with FL while mixing in data from a centralized dataset \([12, 13]\) to address the challenge where the federated dataset lacks labeled negative examples. In this paper, we focus on the setting where training takes place in two phases: first, a model is pre-trained on public dataset at the server, and then it is further trained on client data via FL.

### 2.4 Federated Optimization.

Significant attention has been paid towards developing federated optimization techniques. Such work has focused on various aspects, including communication-efficiency \([28]\), as well as data and systems heterogeneity \([25, 36]\). We defer the interested reader to surveys of Kairouz et al. \([19]\) and Wang et al. \([37]\) for additional background. Nearly all previous work in this field neglect the importance of initialization. In our work, we study the impact of initialization on federated optimization in the cross-device setting.

Some effort has been made to standardize evaluation, e.g., by introducing benchmark datasets and evaluation protocols \([3, 23]\). Several recommendations are made in the Wang et al. \([38, Section 4]\) for evaluating and comparing methods, covering topics such as how to form reasonable data splits in FL for tuning learning rates (server and client). However, across nearly all of the literature little attention has been paid to how the model is initialized.

### 2.5 Pre-training in Federated Learning.

Very few works have studied pre-trained models in federated learning \([30, 16, 42, 26, 35]\). Zhao et al. \([42]\) study pre-training as a mechanism to remedy the accuracy drop compared to centralized training due to heterogeneity in FL. However, they find that using a pre-trained initialization does not help the accuracy drop. In our work, pre-training can close the accuracy gap between centralized and federated training. Pillutla et al. \([30]\), Hsu et al. \([16]\), Lin et al. \([26]\), Stremmel and Singh \([35]\) experimented with pre-trained models but did not study the difference between random initialization and pre-training, which is the focus of this work.

In concurrent and independent works, Chen et al. \([5]\), Weller et al. \([40]\) find that pre-training closes the accuracy gap between FedAvg and centralized learning under non-IID data. Chen et al. \([5]\) hypothesize that pre-training makes global aggregation more stable and proposes a method to pre-train with synthetic data. In our work, we systematically study both forms of heterogeneity, data-induced and system-induced. We also find that pre-training can change how federated optimization algorithms behave.

### 3 Problem Formulation and the FedOPT framework
Algorithm 1 FedOpt framework

1: Input: initial global model $x^0$, server and client step sizes $\eta_s, \eta_c$, local epochs $E$, rounds $T$
2: for each round $t = 1, \ldots, T$
3:   Server sends $x^{t-1}$ to all clients $i \in S^t$.
4:   for each client $i \in S^t$ in parallel do
5:      Initialize local model $y^0_i \leftarrow x^{t-1}$.
6:      Each client performs $E$ epochs of local updates via $y^{k+1}_i = \text{CLIENTOPT}(y^k_i, F_i, \eta_c)$. Let $y^E_i$ denote the result after performing $E$ epochs of local updates.
7:   After local training, client $i$ sends $\Delta^t_i = x^{t-1} - y^E_i$ to the server.
8: end for
9: Server computes aggregate update $\Delta^t = \frac{1}{|S^t|} \sum_{i \in S^t} p_i \Delta^t_i$.
10: Server updates global model $x^t + 1 = \text{SERVEROPT}(x^{t-1}, -\Delta^t, \eta_s, t)$.
11: end for

We consider the following standard optimization formulation of federated training. We seek to find model parameters $w$ that solve the problem,

$$
\min_{w \in \mathbb{R}^d} f(w) := \frac{1}{m} \sum_{i=1}^{m} p_i F_i(w)
$$

where $m$ is the total number of clients, the function $F_i$ measures the average loss of a model with parameters $w$ on the $i$th client’s training data, and $p_i > 0$ is the weight given to client $i$. Usually $p_i$ is taken to be proportional to the number samples at client $i$ so that the optimization problem gives equal weight to all training samples. The goal is to find a model that fits all clients’ data well on (weighted) average. In FL, $F_i$ is only accessible by client $i$.

All of the methods we consider in this study can be expressed in the general FedOpt framework introduced in Reddi et al. [32], which encompasses both client and server optimization updates; see Algorithm 1. At round $t$, a server sends its model $x_t$ to a cohort of clients then each client in the cohort performs $E$ epochs of training using CLIENTOPT with client learning rate $\eta_c$, producing a local model $y^E_i$. Each client, then communicates the difference between the client’s local model and the server model, $\Delta_i$ where $\Delta_i := x_k - x$ (client update). The server computes a weighted average $\Delta$ of the client updates and updates its own model via

$$
x_{t+1} = \text{SERVEROPT}(x_t, -\Delta, \eta_s, t)
$$

where SERVEROPT($x_t, -\Delta, \eta_s, t$) is a first-order optimizer, $\eta_s$ is the server learning rate, and $t$ is the round number.

4 Experimental Setup

Next we describe the experimental setup used to evaluate how initialization impacts the performance of federated optimization methods. We consider 12 possible combinations of SERVEROPT and CLIENTOPT across three tasks. Details about the experiments, hyper-parameters, and models are in Appendix A.

4.1 Datasets, Models and Tasks.

We experiment on three datasets: CIFAR-10 [22], Federated EMNIST-62 (FEMNIST) [6, 4], and Stack Overflow [2].

Non-IID data partitioning. Unless otherwise mentioned, we use non-independent and identically distributed (non-IID) splits of data across clients to exhibit data heterogeneity commonly observed in practice.

CIFAR-10 is an image classification task with 10 classes. We generate 500 non-IID clients using a Dirichlet distribution with $\alpha = 0.1$, using the approach described in Hsu et al. [15].
The FEMNIST is classify images of characters, ultimately for character recognition. We use the federated version where characters are partitioned by their author for character recognition task [4].

For Stack Overflow, the data at each client corresponds to the questions and answers of one user on stackoverflow.com, and we consider training a language model for a next-word-prediction task.

**IID data partitioning.** To understand the effect of data heterogeneity, we run some experiments using an iid partition of data across clients. In this case we first group the entire training set (from all clients), randomly permute it, and then partition it evenly across the same number of clients.

**Models.** For CIFAR-10, and FEMNIST, we use a Squeezenet model [18]. For Stackoverflow, we use a DistilGPT2 [17], and text is pre-processed into byte-pair-encoding using the GPT-2 tokenizer [31]. For further information about the models, see Appendix A.1

4.2 Initialization Strategies.

We consider two general initialization strategies: random initialization and supervised pre-training from public data.

**Random initialization.** Most prior federated optimization works use random weights to initialize the model. We can use the same random initialization strategies used in the standard (centralized) training of deep networks for each model [18, 17].

**Supervised pre-training.** In many FL applications, there may be a large non-private proxy dataset available at the server that can be used for pre-training. To facilitate easily reproducing our results and comparing with other methods in the literature, we use publicly available pre-trained models in this study. For tasks using Squeezenet, we use the version of the model that has been pre-trained on ImageNet, available in the PyTorch Torchvision library[1] and for the task using DistilGPT2, we use the model provided in the HuggingFace library that has been distilled from a pre-trained GPT2.

We recognize that supervised pre-training is just one possibility, and there are several other pre-training strategies one may consider (e.g., self-supervised pre-training, or meta-learning). We leave further investigation of these approaches as future work; see Section 8.

4.3 Algorithms

We evaluate the pre-trained model versus randomly initialized model on four CLIENTOPT strategies:

**SGD** clients perform standard stochastic gradient descent updates;

**Proximal [25]** clients perform FedProx-style updates locally to try to compensate for data heterogeneity;

**Normalized Averaging [36]** clients use FedNova-style updates and aggregation to compensate for data imbalance across clients;

**GD** clients perform full-batch gradient updates; in this case, the update $\Delta t^i$ returned to the server is a full-batch gradient on client $i$’s local training set evaluated at model parameters $x^{t-1}$.

At the server, we consider three strategies for SERVEROPT. In all strategies, the server treats the averaged update $\Delta t$ as a gradient.

**SGD** the server updates the global model using stochastic gradient descent; when CLIENTOPT is also SGD, this is equivalent to FEDAVG [28].

**SGD with momentum** the server updates the global model using SGD with momentum; when CLIENTOPT is SGD, this is equivalent to FEDAVGM [15].

**Adam** the server updates the global model using the Adam optimizer; when CLIENTOPT is SGD, this is equivalent to FEDADAM [32].

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[1] https://github.com/pytorch/vision
[2] https://huggingface.co/distilgpt2
Table 1: Comparison of characteristics considered in previous work and the methods analyzed in this paper. Notation: $NA = \text{Normalized Averaging}$, $LS = \text{Non-identical Local Steps}$, $GM = \text{Global Momentum}$, $AS = \text{Adaptive Server Learning Rate}$.

| Method               | NA | LS | GM | AS |
|----------------------|----|----|----|----|
| FedAvg Nova          | ✓  | ✓  | ✓  | ✓  |
| FedAvg Proximal      | X  | ✓  | ✓  | ✓  |
| FedAvg SGD           | X  | ✓  | ✓  | ✓  |
| FedAvg GD            | X  | X  | ✓  | ✓  |

| Method               | NA | LS | GM | AS |
|----------------------|----|----|----|----|
| FedAvgM Nova         | ✓  | ✓  | ✓  | X  |
| FedAvgM Proximal     | X  | ✓  | ✓  | ✓  |
| FedAvgM SGD          | X  | ✓  | ✓  | ✓  |
| FedAvgM GD           | X  | X  | ✓  | ✓  |

| Method               | NA | LS | GM | AS |
|----------------------|----|----|----|----|
| FedAdam Nova         | ✓  | ✓  | ✓  | ✓  |
| FedAdam Proximal     | ✓  | ✓  | ✓  | ✓  |
| FedAdam SGD          | X  | ✓  | ✓  | ✓  |
| FedAdam GD           | X  | X  | ✓  | ✓  |

The method commonly referred to as FedSGD is obtained when $\text{CLIENTOPT}$ is full-batch gradient descent and $\text{SERVEROPT}$ is SGD, with $\eta_c = 1$ and $E = 1$.

We focus on the above choices for $\text{CLIENTOPT}$ and $\text{SERVEROPT}$ because they are reflective of the most widely-cited federated optimization methods, and they also represent a diverse set of possible choices available to the practitioner seeking to deploy cross-device federated training at scale.

4.4 Implementation and Tuning

We repeat each experiment with three different seeds and report the average. For all algorithms, we run hyperparameter sweeps to tune client and server learning rates $\eta_c$ and $\eta_s$, and the proximal penalty parameter $\mu$ for $\text{FEDPROX}$; see Appendix A for details. Unless otherwise specified, each client update entails running one local epoch with fixed batch size per task. We perform 1050 rounds of training for Stackoverflow, 1000 rounds of training for CIFAR-10, 1082 training rounds for FEMNIST. See Appendix A.2 for additional details on implementation details. All experiments were performed using the open-source federated learning simulation framework FLSim [1].

5 The Impact of Pre-Training in FL

While pre-training unsurprisingly speeds up convergence, the reason for the speedup is less clear in the setting of FL with data heterogeneity. In this section, we illustrate the benefits of pre-training in the federated setting and show that initialization can impact how federated optimization algorithms behave.

5.1 Pre-training affects how federated optimization algorithms behave.

Our first result shows that initializing the model with pre-trained weights can drastically change how federated optimization algorithms behave. In particular, if one sorts federated optimization methods based on their performance when starting from a random initialization, the order is substantially different from when using a pre-trained initialization.

For this section, we focus on nine combinations of $\text{SERVEROPT}$ and $\text{CLIENTOPT}$ on CIFAR-10, Stack Overflow, and FEMNIST. In particular, we exclude full-batch gradient (GD) from the list of $\text{CLIENTOPT}$ options for now.

Figure 2 presents the changes between pre-trained and random weights settings. Among the nine methods, Figure 2 demonstrates the wider variance in final model accuracy in the random initialization compared to the pre-trained setting. We especially see this in Figure 2 (right) for Stack Overflow. Moreover, SGD $\text{CLIENTOPT}$ performs worse in the random setting. While Proximal $\text{CLIENTOPT}$
Figure 2: Average test set accuracy over 3 random seeds for Stack Overflow after 1000 rounds with pre-training and with random initialization. The figure shows the order using three different SERVEROPT (FedAvg, FedAvgM and FedAdam) and two CLIENTOPT (Proximal and SGD). SGD is represented by solid lines; proximal by dashed lines. See Table 1 for comparison characteristics of each method.

Figure 3: The average accuracy for FedAdam with randomly-initialized pretrained model then fine-tune on FL data. For CIFAR-10, and FEMNIST, we use a SqueezeNet pre-trained on Imagenet or randomly-initialized. For Stack Overflow, we use a DistilGPT2 pre-trained on WikiText-103 or randomly-initialized. We repeat each experiment for 3 different seeds and report the average. For CIFAR-10 Non-IID, we generate 100 non-IID clients using a Dirichlet distribution with parameter 0.1, the same approach as in [15]. For other three datasets, we use the natural non-IID client partitions.

performs worse in the pre-trained setting but better in the random setting. Finally, Figure 2 highlights the stark difference between the two initialization settings and the advantage of using simple SGD locally combined with an adaptive server optimizer such as FedAdam.

5.2 Pre-training closes the accuracy gap between non-IID and IID.

To measure how data heterogeneity and pre-training impact model accuracy, we compare performance under IID and Non-IID data splits using the approaches described above. In Figure 3, we report the average accuracy for FedAdam [32] across four datasets. As expected, random initialization models perform much worse than their pre-trained counterparts, and IID partitions yield better quality than non-IID. However, the surprising result is that the gap between FL with IID data and FL with non-IID data is significantly smaller when using pre-trained models. Figure 3 (top) shows a 0.6% for FEMNIST, 3.9% for Stack Overflow and 7.5% for CIFAR-10. Interestingly, pre-training on publicly available datasets such as Imagenet demonstrates robust results for various FL tasks. For example, FEMNIST and Imagenet are two very different datasets. FEMNIST consists of black and white digits and characters, while Imagenet contains colored images. Despite this, pre-training on Imagenet closes the accuracy from data heterogeneity.

5.3 Pre-training reduces the impact of system heterogeneity.

To study how pre-training can impact model quality under a high degree of system heterogeneity, we follow the setup described in [25, 36]. We assume that there is a global clock during training and each device determines the amount of local work. We sample 30% of clients uniformly at random, and client $i$ performs $E_i$ local updates on their data where $E_i$ is an IID sample from the uniform distribution over $\{1, 2, 3, 4, 5\}$. Figure 5 shows the average accuracy for FEDAVG, FEDAVGM and FEDADAM as SERVEROPT. For CLIENTOPT, we use SGD and two other local optimizers designed specifically to handle system heterogeneity, PROXIMAL [25] and normalized averaging (NOVA) [36]. In the pre-trained setting, SGD with FEDADAM at the server outperforms other methods on
Figure 4: Training and gradient statistics of a Squeezenet on CIFAR-10 with Dirichlet distribution with parameter 0.1. Top row: Train loss of global model; train accuracy of global model; evaluation accuracy of global model; evaluation loss of global model. Bottom row: Gradient diversity of client updates; cosine similarity between client updates; L2 distance of server weights from their final values at the end of training.

Figure 5: System heterogeneity results comparing FedAvg, FedAvgM and FedAdam with various client optimizers. We simulate system heterogeneity by randomly select 30% of clients per round to perform time-varying local epochs $E_i(t) \sim U(1, 5)$, the same approach as in [36]. FedProx and FedNova correspond to FedAvg with Proximal client optimizer and normalized averaging (NOVA), respectively. We repeat each experiment for 3 different seeds and report the average.

5.4 Pre-training helps align client updates.

To better understand why pre-training alleviates the heterogeneity problems, we investigate the cosine similarity and gradient diversity of the updates received from different clients. The cosine similarity between two updates $\Delta_i$ and $\Delta_j$ is $\text{cossim}(\Delta_i, \Delta_j) = \Delta_i^T \Delta_j / \| \Delta_i \| \| \Delta_j \|$. When $S$ clients participate in a round, we report the pair-wise cosine similarity averaged over all $S(S-1)/2$ pairs of

both CIFAR-10 and FEMNIST (Figure 5 left). However, in the random initialization setting, NOVA or PROXIMAL as CLIENTOPT perform better than SGD (Figure 5 right). This result shows that pre-training lessens the need for algorithms that try to correct system heterogeneity. We present the the results for other datasets in Appendix B.1.

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distinct clients. We also study gradient diversity, adopting the notion introduced in Yin et al. [41], adapted here to apply to client updates:

$$\text{GradientDiversity}(\{\Delta_i : i \in S^t\}) = \frac{\sum_{i \in S^t} ||\Delta_i||^2}{\sum_{i \in S^t} \Delta_i^2}.$$  

We plot the gradient diversity and the average cosine similarity between client updates $\Delta_i$ at each round for FedAdam in Figure 4. In the pre-trained setting, client updates have higher cosine similarity and thus lower gradient diversity. This observation helps to understand why pre-training narrows the accuracy gap between FL on non-IID and IID data. Figure 4 (bottom right and bottom middle) demonstrates that the client updates from pre-trained weights travel in a "straighter" direction compared to those from random weights. On the other hand, client updates from randomly initialized weights are almost orthogonal. By taking the average of many orthogonal updates as the pseudo-gradient, the server model takes longer to reach its final model. This explains Figure 4 (top right), as the pre-trained model weights move faster to their final values.

5.5 **FedAdam GD is as effective as FedAdam SGD with pre-training.**

The seminal work by McMahan et al. [28] shown that taking local stochastic gradient descent steps before server averaging reduces communication by 10-100×. To understand how pre-training impact client side work, we compare FedAdam with SGD and FedAdam with GD. While undoubtedly, local SGD can reduce communication. The saving is much less when the models are initialized with pre-trained weights compared to random weights. Figure 6 shows that with pre-trained model GD at the client can yield almost the same result as taking local steps. From Figure 6 and Figure 2, we postulate that local optimization algorithms are effective and GD is a competitive baseline.

6 **Recommendations**

In this work, we study the affect of pre-training on federated optimization methods. Our results inform a series of the following recommendations:

- When evaluate FL algorithms, researchers should experiment with both pre-trained (if available) and random weights as they have different behaviors.
- When deploying FL to production environment, researchers should use adaptive server optimizers such as FedAdam and SGD at client. This setup works well and should be used a baseline before trying out more complex methods.
- Heterogeneity is not as a big of a problem when there is public data to pre-trained a model. We encourage researchers to pay attention other more complex tasks when there is no public data such as recommendation systems or semi-supervised learning.
7 Limitations

Depending on the application, it may not be possible to get public data, in which case random initialization may be the only option. Nevertheless, we believe there is sufficient prevalence and importance of applications where public data is available for this study to be of broad interest. When public data is available, it may not necessarily reflect the distribution of all users in the population. Consequently, pre-training using public data may introduce bias, which warrants further study, including methods to detect and mitigate such bias. Moreover, we only consider one warm-start initialization strategy type, supervised pre-training. Several other possibilities may be natural, including meta-learning the warm-start initialization and self-supervised pre-training (e.g., if public data does not come with labels).

8 Conclusion

In this paper we present a thorough empirical analysis of initialization on federated learning by evaluating it on twelve federated learning algorithms across four vision and text tasks. We find that pre-training on public data can recover most of the accuracy drop from heterogeneity. We show that client updates starting from pre-trained weights have higher cosine similarity, which explains why initialized with pre-trained weights can speed up convergence and achieve high accuracy even in heterogeneous settings. We further show that using simple SGD locally can be as good as other local optimizers.

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Table 2: Dataset Statistics

| Dataset      | Train Clients | Test Clients | Samples/Client Mean | Std |
|--------------|---------------|--------------|---------------------|-----|
| CIFAR-10     | 100           | 20           | 500                 | 63  |
| Stack Overflow | 10,815       | 1,115        | 5,821               | 34,229 |
| FEMNIST      | 348           | 39           | 272                 | 67  |

A  Experiment Details

A.1  Datasets and Models

CIFAR-10. We evaluate a multi-class image classification problem on CIFAR-10 [22] using a SqueezeNet [18]. We normalize the images by the dataset mean and standard deviation. Following [15], we partition the dataset using a Dirichlet distribution with parameter 0.1. The statistics on the number of clients and examples in both the training and test splits of the datasets are in Table 2.

Stack Overflow Stack Overflow consists of questions and answers from Stack Overflow. We experiment a next-word-prediction task using a DistilGPT-2 model with a casual LM head. We perform padding and truncation to ensure that each sentence have 25 words. We then use a GPT-2 tokenizer to encode the tokens.

FEMNIST Federated EMNIST-62 (FEMNIST) consists of digits and English characters, totaling 62 classes. We evaluate a multi-class image classification problem on the federated version [4] which partitions the digits by the writer and filter out clients that less than one example. As for the model, we use a SqueezeNet 1.0 [18]. Since FEMNIST contains grayscale images, we replicated the one channel value into three channels with the same values.

A.2  Implementation Details

We implemented all algorithms in Pytorch [29] and evaluated them on a cluster of machines, each with eight NVidia V100 GPUs. We evaluate our experiments in FLSim [3]. For all experiments, we tune hyperparameters using Bayesian optimization [34]. We select the best hyperparameters based the final accuracy after a fixed number of rounds for each dataset.

B  Additional Results

B.1  System Heterogeneity

In this section, we show the system heterogeneity results for all three datasets: CIFAR-10, FEMNIST, and Stack Overflow. With the exception of Stack Overflow, FEDADAM SGD consistently outperforms other methods specifically designed for system heterogeneity (NOVA, PROXIMAL) in the the pre-trained setting.

B.2  Fine-tuning only the last layer

In this section, we present the results for fine-tuning only the last linear layer rather in the model as commonly done in practice. Figure 8 shows that fine-tuning only the last layer might not yield optimal model quality and should be consider carefully. While fine-tuning only the last layer can achieve close to full fine-tuning on Stack Overflow, the performance is much worse on CIFAR-10.

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3Our code is available at https://github.com/facebookresearch/FLSim
Figure 7: Average accuracy under system heterogeneity for FedAvg, FedAVGM and FedAdam with NOVA, SGD and Proximal as CLIENTOPT, for various tasks.

Figure 8: Average accuracy for full fine-tuning, random, and last layer only on Stack Overflow and CIFAR-10.