WHERE TO BEGIN? ON 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* — that data at different clients may follow very different distributions. Several federated optimization methods have been proposed to address this challenge. 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 that 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 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 such as FEDADAM at the server consistently leads to the best accuracy. We recommend that future work proposing and evaluating federated optimization methods evaluate the performance when starting both from 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 (Kairouz et al., 2019), the primary setting considered 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 (Kairouz et al., 2019). 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 (McMahan et al., 2016), 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 (Li et al., 2018; Hsu et al., 2019; Reddi et al., 2020; Wang et al., 2020; Karimireddy et al., 2020; 2021; Zhang et al., 2021; Acar et al., 2021).

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 Radford et al. (2019); Devlin et al. (2018) and computer vision He et al. (2019); Dosovitskiy et al. (2020), yielding state-of-the-art results on many tasks and enabling

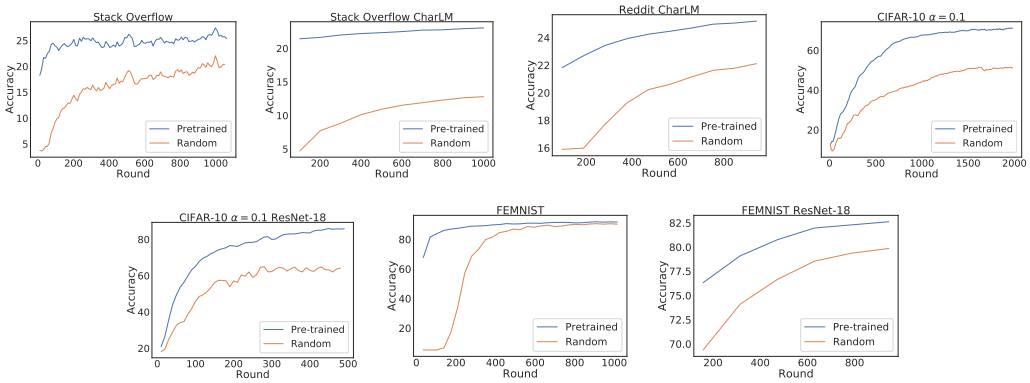

Figure 1: While prior works ignore the importance of initialization, using pre-trained models should be the first step for any practical deployment to save on communication bandwidth and achieve high model accuracy. This figure shows the advantage of using a pre-trained model for four tasks. For Stack Overflow and Reddit, we use DistilGPT2 and CharLM. For CIFAR-10 and FEMNIST, we use SqueezeNet and ResNet18.

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: *How does model initialization (random, or pre-trained) impact the behavior of federated optimization methods?* Towards answering this question, we perform an extensive empirical study, comparing 15 variations of federated optimization methods on four commonly-used FL benchmark datasets. Our study reveals four key findings:

1. Although optimizers designed to address heterogeneity typically lead to better performance when starting from a random initialization, when starting from pre-trained model we observe that: (i) there is not as big of a difference between optimizers in terms of accuracy after a fixed number of rounds, and (ii) using an adaptive optimizer at the server, such as FEDADAM, is more important than using any method for addressing heterogeneity.

2. Starting from a pre-trained model significantly reduces the difference between having non-IID vs IID data at clients. Furthermore, when starting from a pre-trained model, the number of local epochs per round can be significantly increased without degrading the final accuracy.

3. The initial loss is not always lower when starting from a pre-trained model. However, the largest Hessian eigenvalue (i.e., local Lipshitz constant, or smoothness) is consistently smaller at initialization when starting from a pre-trained model, compared to when starting from a random initialization.

4. Although some of our empirical observations are consistent with existing theoretical convergence guarantees for federated training algorithms, our findings also highlight that some aspects of federated training are not captured with the existing theory, suggesting important directions for future work.

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. This is evident in Figure 1 across several datasets (hyperparameters were tuned separately for each dataset–initialization pair; see Section 3 for details of the experimental setup).

Our findings are reproducible using the open-source federated learning framework FLSim (FLSim Authors, 2022). Informed by these findings, we conclude by presenting several recommendations for future research on federated optimization.

Algorithm 1 FedOpt framework

Input: initial global model x^0, server and client step sizes η_s, η_c, local epochs E, rounds T
for each round $t = 1, \ldots, T$ **do**
  Server sends x^{t-1} to all clients $i \in \mathcal{S}^t$.
  for each client $i \in \mathcal{S}^t$ in parallel **do**
    Initialize local model $y_i^0 \leftarrow x^{t-1}$.
    Each client performs E epochs of local updates via $y_i^{k+1} = \textsc{ClientOpt}(y_i^k, F_i, \eta_c)$. Let y_i^E denote the result after performing E epochs of local updates.
    After local training, client i sends $\Delta_i^t = x^{t-1} - y_i^E$ to the server.
  end for
  Server computes aggregate update $\Delta^t = \frac{1}{|\mathcal{S}^t|} \sum_{i \in \mathcal{S}^t} p_i \Delta_i^t$.
  Server updates global model $x^t = \textsc{ServerOpt}(x^{t-1}, -\Delta^t, \eta_s, t)$.
end for

2 Problem Formulation and the FedOpt framework

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

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

where m is the total number of clients, the function F_i measures the average loss of a model with parameters w on the ith 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 of 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. (2020), which encompasses both client and server optimization updates; see Algorithm 1. At round t, a server sends its model x to a cohort of clients. Then each client in the cohort performs E epochs of training using ClientOpt with client learning rate η_c, producing a local model x_k^i. Each client, then communicates the difference between the client's local model and the server model, Δ_i where $\Delta_i := x_k - x$ (*client update*). The server computes a weighted average Δ of the client updates and updates its own model via

$$x_{t+1} = \textsc{ServerOpt}(x_t, -\Delta_t, \eta_s, t)$$

where $\textsc{ServerOpt}(x_t, -\Delta_t, \eta_s, t)$ is a first-order optimizer, η_s is the server learning rate, and t is the round number.

3 Experimental Setup

Next, we describe the experimental setup used to evaluate how initialization impacts the performance of federated optimization methods.

3.1 Datasets, Models and Tasks.

To facilitate comparing with other work in the literature, we experiment on four standard FL benchmark datasets: CIFAR-10 (Krizhevsky et al., 2009), Federated EMNIST-62 (FEMNIST) (Cohen et al., 2017; Caldas et al., 2018), Stack Overflow (Authors., 2019) and Reddit (Caldas et al., 2018).

Default non-IID data partitioning. We use non-independent and identically distributed (non-IID) splits of data across clients to mimic data heterogeneity commonly observed in practice. For CIFAR-10 and FEMNIST, we train Squeezenet (Iandola et al., 2016) and ResNet18 (He et al., 2016) models,

replacing batch norm with group norm (Reddi et al., 2020; Hsieh et al., 2020). For Stackoverflow and Reddit, we use the DistilGPT2 (HuggingFace, 2019) and CharLM (Kim et al., 2016) models. For additional information about the datasets and models, see Appendix A.1.

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.

3.2 INITIALIZATION STRATEGIES.

We consider two 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 (Iandola et al., 2016; HuggingFace, 2019; He et al., 2016; Kim et al., 2016).

Supervised pre-training. In many FL applications, pre-training can be done on a large non-private proxy dataset available at the server. To quickly reproduce our results and compare them with other methods in the literature, we use publicly available pre-trained models in this study. For tasks using Squeezenet and ResNet18, we use the version of the model pre-trained on ImageNet, available in the PyTorch Torchvision library.[1] For tasks using DistilGPT2, we use the model weights provided in the HuggingFace library that has been distilled from a pre-trained GPT2[2], and for tasks using CharLM, we pre-train the model on WikiText-103 (Merity et al., 2016) for 100 epochs.

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

3.3 ALGORITHMS

We compare federated training with five different CLIENTOPT strategies:

SGD clients perform standard stochastic gradient descent updates;

Proximal (Li et al., 2018) clients perform FEDPROX-style local updates; FEDPROX was originally proposed to reduce client drift due to heterogeneity;

Normalized Averaging (Wang et al., 2020) clients use FEDNOVA-style updates and aggregation to compensate for data imbalance across clients;

MIMELITE (Karimireddy et al., 2021) clients make use of an optimizer state (e.g., momentum buffer) from the server during local updates to reduce drift due to data heterogeneity;

GD clients perform full-batch gradient updates; in this case, the update Δ_i^t 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 Δ^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 (McMahan et al., 2016).

SGD with momentum the server updates the global model using SGD with momentum; when CLIENTOPT is SGD, this is equivalent to FEDAVGM (Hsu et al., 2019).

Adam the server updates the global model using the Adam optimizer; when CLIENTOPT is SGD, this is equivalent to FEDADAM (Reddi et al., 2020).

The method commonly referred to as FEDSGD (McMahan et al., 2017) is obtained when CLIENTOPT is full-batch gradient descent (GD) and SERVEROPT is SGD, with $\eta_c = 1$ and $E = 1$.

[1] https://github.com/pytorch/vision
[2] https://huggingface.co/distilgpt2

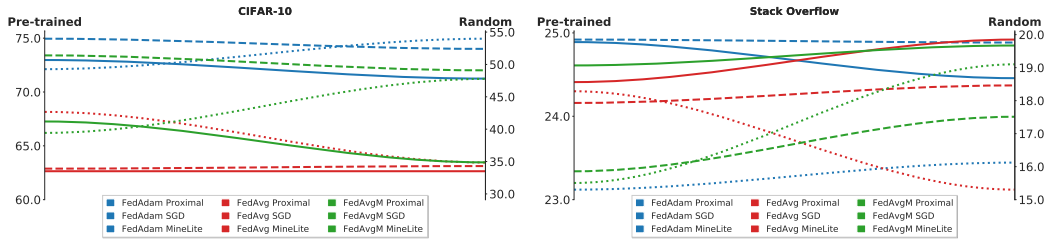

Figure 2: The average test set accuracy over three random seeds for CIFAR-10 and Stack Overflow with random and pre-trained weights. We represent SGD by solid lines, PROXIMAL by dashed lines, and MIMELITE by dotted lines. See Section 3.3 and Table 3 in Appendix B for comparison characteristics of each method.

We focus on the above choices for CLIENTOPT and 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.

3.4 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 η_ℓ and η_g, and the proximal penalty parameter μ for FEDPROX. We use momentum parameter 0 for FEDAVG and 0.9 for FEDAVGM. For FEDADAM, we fix $\beta_1 = 0.9$ and $\beta_2 = 0.99$ for Adam; 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, 942 rounds of training for Reddit, 1000 rounds of training for CIFAR-10, and 1082 training rounds for FEMNIST. See Appendix B.1 for additional implementation details. All experiments were performed using PyTorch (Paszke et al., 2017) and the open-source federated learning simulation framework FLSim (FLSim Authors, 2022).

4 THE IMPACT OF PRE-TRAINING IN FL

In this section, we illustrate the benefits of pre-training in the federated setting and how pre-training can impact federated optimization algorithms behavior.

Pre-training changes the ranking of federated optimization algorithms. Our first result shows that initializing federated training from a pre-trained model 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. This section focuses on nine combinations of SERVEROPT and CLIENTOPT on CIFAR-10 and Stack Overflow. In particular, we focus on local update CLIENTOPT methods and exclude full-batch gradient descent (GD) for now. Figure 2 presents the changes between pre-trained and random weight initializations. Among the nine methods, Figure 2 shows the broader range in final model accuracy in the random initialization compared to the pre-trained setting – random initialization's range is over 20% compared to less than 15% for pre-trained on CIFAR-10. We especially see this for Stack Overflow, 5% range for random and only 2% for pre-trained. 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.

Pre-training closes the accuracy gap between non-IID and IID. We study how pre-training and data heterogeneity affect convergence without system heterogeneity by fixing $E_i = 1$. We compare FEDADAM with SGD locally under IID, and Non-IID data splits. In Figure 3, we report the average accuracy for FedAdam (Reddi et al., 2020) on four datasets. As expected, randomly initialized models perform much worse than their pre-trained counterparts, and IID partitions yield better quality than non-IID. Surprisingly, the gap between models trained on IID data and models trained on non-IID

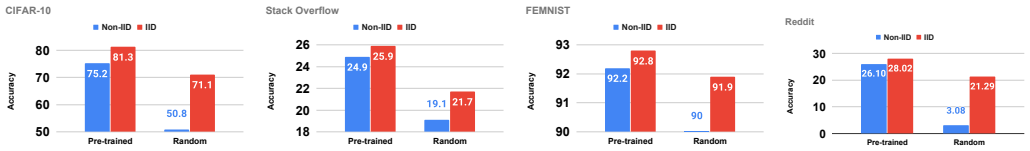

Figure 3: The average accuracy on 3 different seeds for FEDADAM trained on IID and non-IID data. For CIFAR-10 Non-IID, we generate 100 non-IID clients using a Dirichlet(0.1). For other three datasets, we use the natural non-IID client partitions.

data is significantly smaller when starting with pre-trained weights. That is, the negative effects of data heterogeneity (i.e., client drift) is mitigated. As a result, we observe that (see Figure 6) when training from a pre-trained model, increasing the number of local updates does not degrade the final accuracy, in contrast to training from a random model.

FEDADAM GD is as effective as FEDADAM SGD with pre-training. The seminal work of McMahan et al. (2016) shows that taking local SGD steps before server averaging reduces communication by 10-100$\times$ compared to taking a full batch gradient step. To understand how pre-training impacts this comparison, we compare FEDADAM with SGD and FEDADAM with GD. While local SGD can reduce communication, the saving is much less when the models are initialized with pre-trained weights compared to random weights. Figure 9 in the Appendix shows that with pre-trained initialization, using GD at the client can yield almost the same result as taking local SGD steps.

Pre-training reduces the impact of system heterogeneity. To study the impact of pre-training on system heterogeneity, we follow the setup described in (Li et al., 2018; Wang et al., 2020). We sample 30% of clients uniformly at random, and client i performs E_i local epochs where $E_i \sim U(1, 5)$. This models the setting where clients have different processing capabilities, and clients are asked to perform as much work as they can within a given time limit. When starting from pre-trained weights, SGD locally outperforms other CLIENTOPT methods on both datasets across most of SERVEROPT except for FEDAVG on CIFAR-10 (Figure 4 left). We postulate that adding momentum to the server is enough to correct the negative effect of system heterogeneity when starting from pre-trained weights. On the other hand, when starting from random weights, optimizers specifically designed for system heterogeneity outperform SGD. (Figure 4 right). Moreover, the accuracy gap between algorithms is more pronounced in the random initialization setting, whereas in the pre-trained setting, all algorithms converge to similar accuracies. Our results suggest that pre-training reduces the need for algorithms that try to correct system heterogeneity. We present the results for other datasets in Appendix C.1.

5 UNDERSTANDING WHY PRE-TRAINING HELPS FEDERATED OPTIMIZATION

While pre-training unsurprisingly speeds up convergence, the reason for the speedup is less apparent. In this section, we examine why pre-training is beneficial to federated learning.

Pre-training helps align client updates. To better understand why pre-training alleviates the heterogeneity challenge, we first investigate the gradient diversity of the updates received from different clients. We adopt the notion introduced in Yin et al. (2017), adapted here to apply to client updates:

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

In Figure 5, we plot the gradient diversity of client updates Δ_i at each round for FEDADAM. In the pre-trained setting, client updates have significantly lower gradient diversity (see the bottom left plot in Figure 5). This suggests that when starting from a pre-trained model, the client local model changes are more similar to each other. On the other hand, clients local model changes from randomly initialized weights are almost orthogonal, suffering more from the client drift problem. In addition, when looking at the cosine similarity of consecutive aggregated update vectors in time (bottom middle), we see that consecutive updates point more consistently in a similar direction at the beginning of training when starting from a pre-trained model.

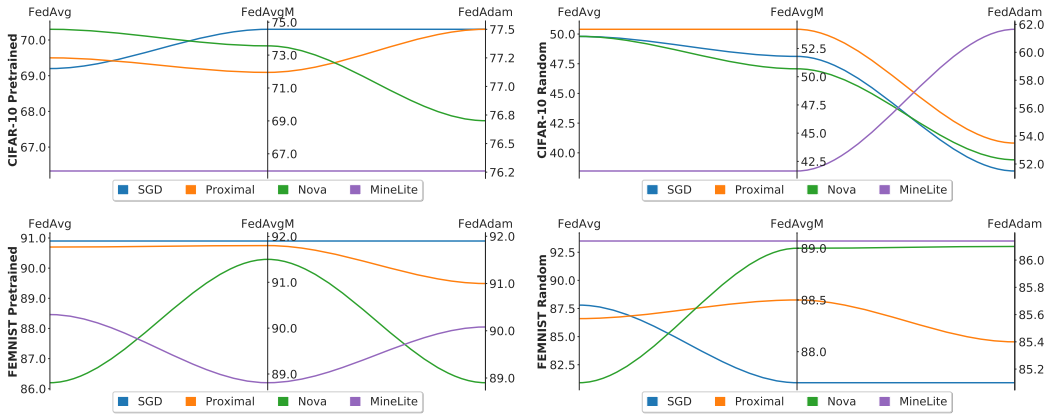

Figure 4: System heterogeneity results comparing FedAvg, FedAvgM and FedAdam with various client optimizers. We simulate system heterogeneity by randomly select 30% of clients per round to perform time-varying local epochs $E_i \sim U(1, 5)$, the same approach as in Wang et al. (2020). FedProx and FedNova correspond to FedAvg with Proximal client optimizer and normalized averaging (NOVA), respectively. We repeat each experiment for 3 different seeds and report the average.

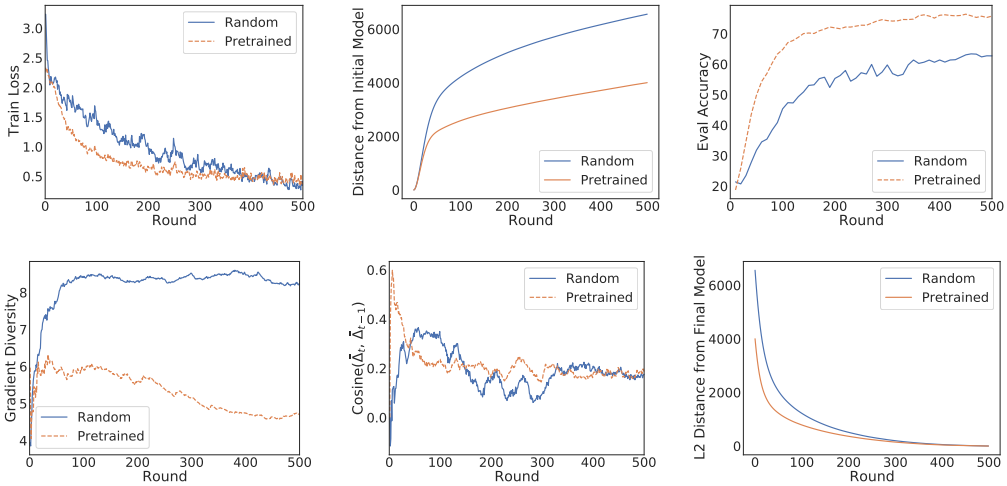

Figure 5: Training and gradient statistics of a Resnet18 on CIFAR-10 with Dirichlet distribution with parameter 0.1. Top row: Train loss of global model; train accuracy of global model; evaluation accuracy of global model; evaluation loss of global model. Bottom row: Gradient diversity of client updates; cosine similarity between client updates; L2 distance of server weights from their final values at the end of training.

In addition, from the top middle and bottom right plots in Figure 5, we see that the pre-trained model starts closer to the final result. We also examine the largest eigenvalue of the Hessian matrix (i.e., local Lipshitz constant or smoothness) at the beginning of training, a larger value of which suggests a harder-to-optimizer loss surface. In Table 1, one can observe that pre-trained models always lead to smaller eigenvalues on different datasets.

Connection to Existing Theory. Here, we present the existing optimization theory for FEDAVG and discuss how pre-training helps to improve the model convergence.

Following the formulation in Section 3, suppose that there are total m clients, jointly optimizing a global objective function $f(w) = \sum_{i=1}^{m} p_i F_i(w)$. Each client's local loss function $F_i(w)$ is L-Lipschitz smooth. For the ease of presentation, we assume that all clients participate into training and

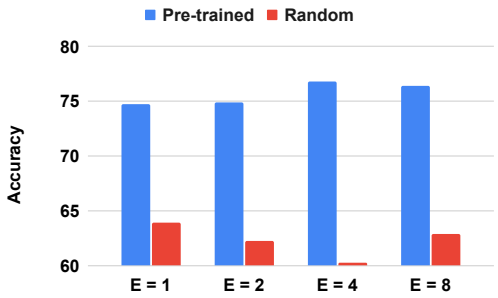

Figure 6: The accuracy for CIFAR-10 using ResNet-18 with increasing number of local epochs.

	CIFAR-10	FEMNIST	Stack Overflow	Reddit
Pre-trained	661.99	26.29	151.05	647.19
Random	4843.13	355.51	185.02	1309.68

Table 1: The top eigenvalue of the Hessian matrix for each dataset between the pre-trained and random initialized models.

perform K local SGD updates at each round. Then, under standard assumptions, one can show that after R communication rounds, the expected gradient norm satisfies (see Theorem V in Karimireddy et al. (2020)):

$$\mathbb{E}\left\|\nabla f(\bar{x}^R)\right\|^2 \leq \mathcal{O}\left(\frac{\sqrt{F}}{\sqrt{RKm}} + \frac{F^{2/3}\zeta^{2/3}}{R^{2/3}}\right), \tag{2}$$

where $\bar{w}^R$ represents a weighted sampled model from all previous rounds, ζ is a measure of data heterogeneity, and $F = f(x^0) - f^*$ denotes the gap between the initial loss value and the optimal loss value. When starting from a pre-trained model, the initial gap F becomes lower, as observed in Figure 5 (top left) on CIFAR-10. As a result, the optimization error upper bound (2) will be smaller, i.e., we get a better worst-case performance. We need to mention that a lower initial training loss is only one possible reason for the siginificantly improved training performance. We also observe that on some training tasks (details are in the Appendix), when using a pre-trained model, the initial training loss can be higher but the convergence speed is still faster. This calls for a new optimization theory to explain this phenomenon.

In addition, in order for FEDAVG to achieve the $\mathcal{O}(1/\sqrt{RKm})$ asymptotic convergence rate, previous works (Wang et al., 2021; Woodworth et al., 2020; Karimireddy et al., 2020; Wang and Joshi, 2021) showed that the number of local updates K should be upper bounded as follows:

$$K \leq \mathcal{O}\left(\frac{R^{1/3}}{F^{1/3}\zeta^{4/3}m}\right). \tag{3}$$

Clearly, if F becomes smaller when starting from a pre-trained model, one can use a larger number of local updates. This corroborates our empirical observations in Figure 6.

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 Related Work

Transfer learning. Model initialization can significantly impact training and final performance. Previous work studying the loss landscape of deep networks observed 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" (Li et al., 2017; Frankle et al., 2020; 2019). Fine-tuning from pre-trained models is common practice in natural language processing and computer vision, yielding strong performance on many tasks (Radford et al., 2019; Dosovitskiy et al., 2020; Devlin et al., 2018; He et al., 2019).

Federated Optimization. While a significant amount of research focused on various aspects of FL, including communication-efficiency McMahan et al. (2016), data and systems heterogeneity Li et al. (2018); Wang et al. (2020), and faster convergence rate . 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. We defer the interested reader to surveys of Kairouz et al. (2019) and Wang et al. (2021) for additional background.

Pre-training in Federated Learning. Very few works have studied pre-trained models in federated learning Pillutla et al. (2022); Hsu et al. (2020); Zhao et al. (2018); Lin et al. (2021); Stremmel and Singh (2021). Zhao et al. (2018) studied pre-training as a mechanism to remedy the adverse effect of heterogeneity in FL. However, Zhao et al. (2018) found that pre-trained initialization does not alleviate the effect of heterogeneity. In this work, we find that pre-training can alleviate both data and system heterogeneity. Pillutla et al. (2022); Hsu et al. (2020); Lin et al. (2021); Stremmel and Singh (2021) 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. (2022); Weller et al. (2022) find that pre-training closes the accuracy gap between FedAvg and centralized learning under non-IID data. Weller et al. (2022) studied multilingual language tasks using large transformer models on synthetically partitioned data, not a realistic setup for large-scale cross-device federated settings. Chen et al. (2022) studied the impact of pre-training on data heterogeneity using synthetically partitioned image data. Furthermore, Chen et al. (2022) proposed a method to pre-train with synthetic data. In our work, we systematically study both forms of heterogeneity, data-induced and system-induced, across both visual and language tasks on 15 SOTA federated optimization algorithms. We offer theoretical and empirical explanations for why pre-training is beneficial to FL.

8 Conclusion and Limitations

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).

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
Reddit	9,403	4352	34	63

Table 3: Comparison of characteristics considered in previous work and the methods analyzed in this paper. Notation: *NA* = Normalized Averaging, *LS* = Non-identical Local Steps, *GM* = Global Momentum, *AS* = Adaptive Server Learning Rate, *GS* = Apply Server Optimizer State Locally.

	NA	LS	GM	AS	GS
FedAvg Nova	✓	✓	✗	✗	✗
FedAvg Proximal	✗	✓	✗	✗	✗
FedAvg SGD	✗	✓	✗	✗	✗
FedAvg GD	✗	✗	✗	✗	✗
FedAvg MimeLite	✗	✓	✗	✗	✓
FedAvgM Nova	✓	✓	✓	✗	✗
FedAvgM Proximal	✗	✓	✓	✗	✗
FedAvgM SGD	✗	✓	✓	✗	✗
FedAvgM GD	✗	✗	✓	✗	✗
FedAvgM MimeLite	✗	✓	✓	✗	✓
FedAdam Nova	✓	✓	✓	✓	✗
FedAdam Proximal	✗	✓	✓	✓	✗
FedAdam SGD	✗	✓	✓	✓	✗
FedAdam GD	✗	✗	✓	✓	✗
FedAdam MimeLite	✗	✓	✓	✓	✓

A Experiment Details

A.1 Datasets and Models

B Algorithms Summary

CIFAR-10. We evaluate a multi-class image classification problem on CIFAR-10 Krizhevsky et al. (2009) using a SqueezeNet Iandola et al. (2016). We normalize the images by the dataset mean and standard deviation. Following Hsu et al. (2019), 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 sentences 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 Caldas et al. (2018) 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 Iandola et al. (2016). Since FEMNIST contains grayscale images, we replicated the one channel value into three channels with the same values.

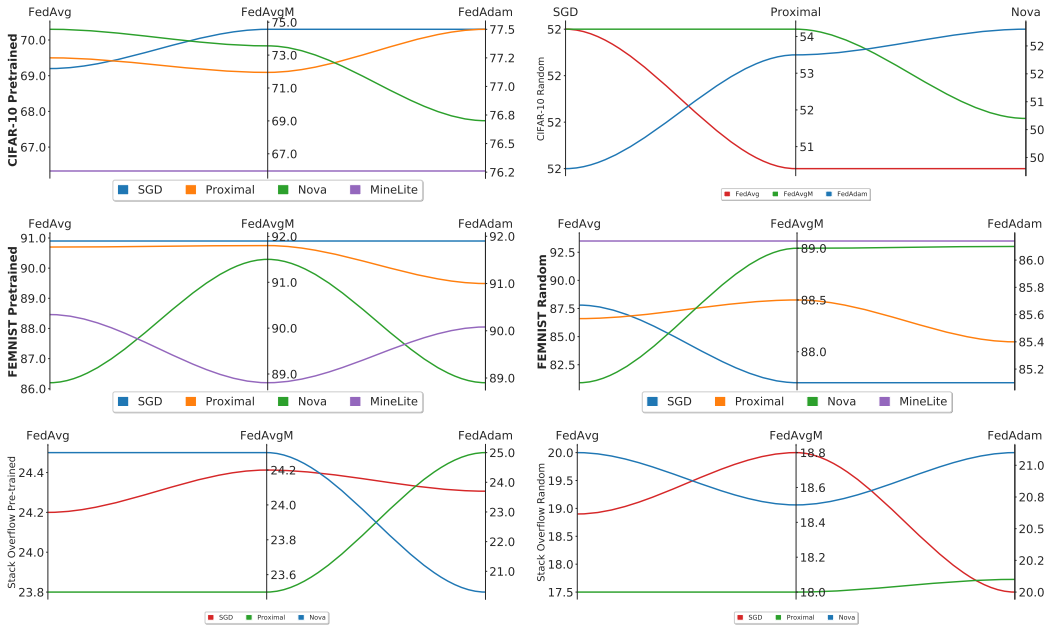

Figure 7: Average accuracy under system heterogeneity for FEDAVG, FEDAVGM and FEDADAM with NOVA, SGD and PROXIMAL as CLIENTOPT, for various tasks.

B.1 IMPLEMENTATION DETAILS

We implemented all algorithms in Pytorch (Paszke et al., 2017) 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 (Snoek et al., 2012). We select the best hyperparameters based the final accuracy after a fixed number of rounds for each dataset.

C ADDITIONAL RESULTS

C.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.

C.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.

C.3 FEDADAM GD IS AS EFFECTIVE AS FEDADAM SGD WITH PRE-TRAINING.

[John: Move figure 6 to the appendix]

[3] Our code is available at https://github.com/facebookresearch/FLSim

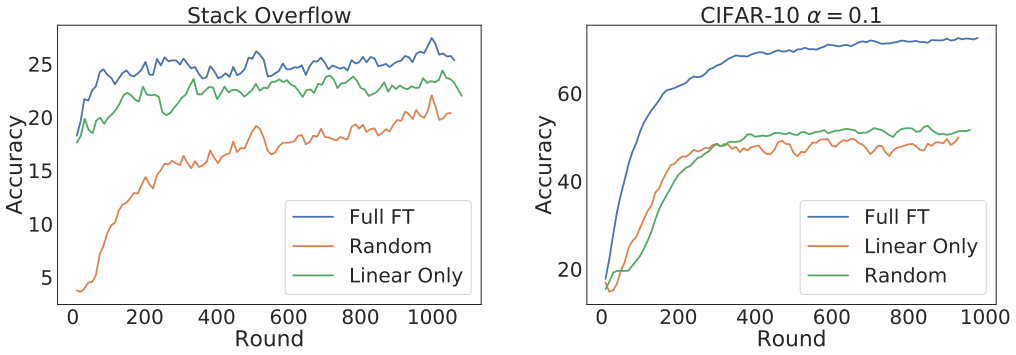

Figure 8: Average accuracy for full fine-tuning, random, and last layer only on Stack Overflow and CIFAR-10.

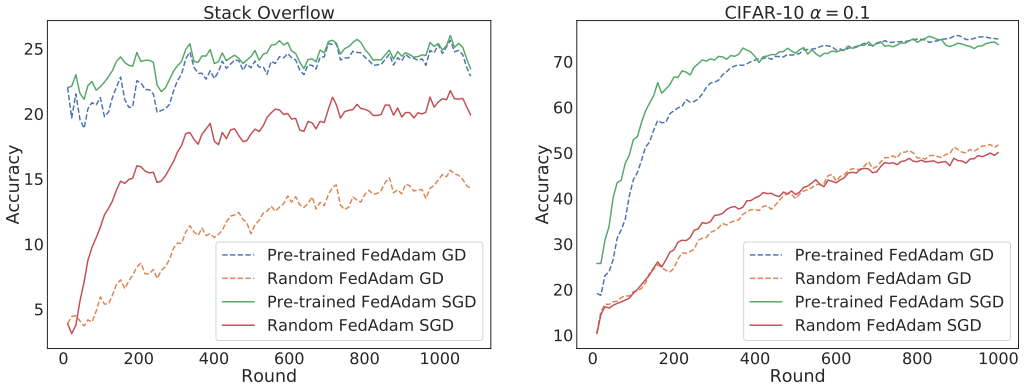

Figure 9: The average accuracy for Stack Overflow and CIFAR-10 comparing FEDADAM with SGD and FEDADAM with full-batch gradient descent (GD).