FedScale: Benchmarking Model and System Performance of Federated Learning

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Abstract

We present FedScale, a diverse set of challenging and realistic benchmark datasets to facilitate scalable, comprehensive, and reproducible federated learning (FL) research. FedScale datasets are large-scale, encompassing a diverse range of important FL tasks, such as image classification, object detection, language modeling, speech recognition, and reinforcement learning. For each dataset, we provide a unified evaluation protocol using realistic data splits and evaluation metrics. To meet the pressing need for reproducing realistic FL at scale, we have also built an efficient evaluation platform to simplify and standardize the process of FL experimental setup and model evaluation. Our evaluation platform provides flexible APIs to implement new FL algorithms and include new execution backends with minimal developer efforts. Finally, we perform indepth benchmark experiments on these datasets. Our experiments suggest that FedScale presents significant challenges of heterogeneity-aware co-optimizations of the system and statistical efficiency under realistic FL characteristics, indicating fruitful opportunities for future research. FedScale is open-source with permissive licenses and actively maintained,[1] and we welcome feedback and contributions from the community.

1 Introduction

Federated learning (FL) is an emerging machine learning (ML) setting where a logically centralized coordinator orchestrates many distributed clients (e.g., smartphones or laptops) to collaboratively train or evaluate a model [6, 21] (Figure 1). It enables model training and evaluation on end-user data, while circumventing high cost and privacy risks in gathering the raw data from clients, with applications in diverse domains: for example, NVIDIA applies FL to create medical imaging AI [26]; Google runs federated training of NLP models in Google keyboard [9, 36]; Apple performs federated evaluation and tuning of automatic speech recognition models on end-user devices [30]; IBM is deploying FL infrastructure to help detect financial misconducts [27].

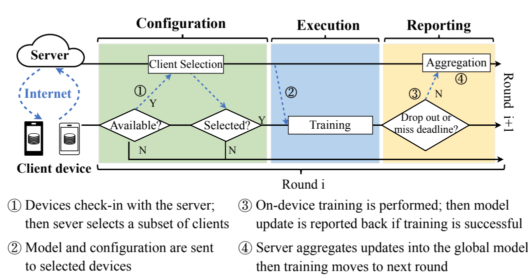

Figure 1: Standard FL protocol [6, 35].

To address challenges arising from the heterogeneous execution speeds of client devices as well as non-IID data distributions, existing efforts have focused on optimizing different aspects of FL: (1) *System efficiency*: reducing computation load (e.g., using smaller models [33]) or communication traffic (e.g., local SGD [29]) to achieve faster on-device execution; (2) *Statistical efficiency*: designing

[1]FedScale is available at `https://github.com/SymbioticLab/FedScale`.

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Features	OARF [19]	LEAF [7]	FedEval [8]	FedML [17]	Flower [5]	**FedScale**
Heter. Client Dataset	◯	✗	✗	◯	◯	✔
Heter. System Speed	✗	✗	✗	✗	✗	✔
Client Availability	✗	✗	✗	✗	✗	✔
Scalable Platform	✗	✗	◯	◯	✔	✔
Real FL Runtime	✗	✗	✗	✗	✗	✔
Flexible APIs	✗	✗	✗	✔	✔	✔

Table 1: Comparing FedScale with existing FL benchmarks and libraries. ◯ implies limited support.

data heterogeneity-aware algorithms (e.g., client clustering [15]) to obtain better training accuracy with fewer training rounds; (3) *Privacy efficiency*: developing reliable strategies (e.g., differentially private training [20]) to make FL more robust and privacy-preserving.

The performance of an FL solution greatly depends on the characteristics of data, device capabilities, and participation of clients; overlooking any one aspect can mislead FL evaluation (§2). For example, dynamics of client system performance or availability (e.g., device drop-out or rejoining) can affect the dynamics of data availability (distribution shift of cross-device data), which may impair model convergence [11]; too few clients can lead to unstable statistical training convergence, but too many can slow down practical model aggregation because of heterogeneous system speed. As such, a comprehensive suite of benchmarks that combine diverse aspects of practical FL is crucial for systemic evaluation and comparison of different efforts.

Existing benchmarks for FL are either borrow from traditional ML benchmarks (e.g., MLPerf [28]) or designed for simulated FL environments like TensorFlow Federated [4] or PySyft [3]. As shown in Table 1, existing benchmarks for FL fall short in multiple ways: (1) they are limited in the versatility of data for various real-world FL applications. Indeed, even though they may have quite a few datasets and FL training tasks (e.g., FedEval [8] and LEAF [7]), their datasets often contain synthetically generated partitions derived from conventional datasets (e.g., CIFAR) and do not represent realistic characteristics; (2) existing benchmarks often overlook different aspects of practical FL. For example, system speed and availability of the client are largely missing (e.g., FedML [3] and Flower [5]), which discourages FL efforts from considering system efficiency and leads to overly optimistic statistical performance (§2); (3) their experimental environments are unable to reproduce large-scale FL deployments. While practical FL can involve thousands of participants in each training round, existing benchmarking platforms – therefore, many existing FL solutions – are merely able to support the training of tens of participants per round; (4) they mostly lack user-friendly APIs for automated integration, resulting in great engineering efforts in benchmarking new plugins.

Contributions: In this paper, we introduce FedScale, an FL benchmark to empower comprehensive and standardized FL evaluations. As shown in Figure 2, we make the following contributions:

- To the best of our knowledge, we incorporate the most comprehensive FL datasets for evaluating different aspects of real FL deployments. FedScale currently has 18 realistic FL datasets spanning across small, medium, and large scales for a wide variety of task categories, such as image classification, object detection, language modeling, speech recognition, machine translation, recommendation, and reinforcement learning. To account for practical client behaviors, we include real-world measurements of mobile devices, and associate each client with his computation and communication speeds, as well as availability status dynamics.
- We build an automated evaluation platform, FedScale Automated Runtime (FAR), to simplify and standardize the FL evaluation in a more realistic setting. FAR integrates real FL statistical and system dataset by design, and thus can pinpoint various practical FL met-

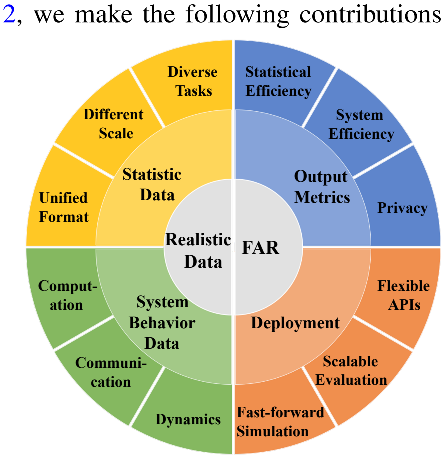


Figure 2: FedScale provides real FL data and an automated evaluation platform.

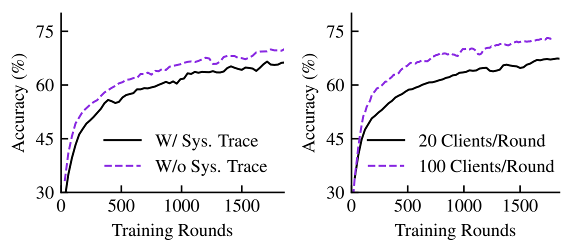
rics needed in today's work. Moreover, FAR allows easy deployment of new plugins with flexible APIs and can perform the training of thousands of clients in each round on a few GPUs efficiently. FAR is built atop of our recent work Oort [24], which has passed a rigorous artifact evaluation in OSDI 2021.

- We perform indepth benchmark experiments for recent FL efforts in FedScale setting, and highlight the pressing need of co-optimizing system and statistical efficiency in a heterogeneity-aware manner, especially in tackling system stragglers and biased model performance.

2 Background

Existing efforts optimize for various goals of practical FL To tackle heterogeneous client data, FedProx [25], FedYogi [31] and Scaffold [22] introduce adaptive client/server optimizations that use control variates to correct for the 'drift' in model updates. Instead of training a single global model, some efforts resort to training a mixture of models [10, 12], clustering clients over training [16], or enforcing guided client selection [24]; To tackle the scarce and heterogeneous device resource, FedAvg [29] reduces communication cost by performing multiple local SGD steps, while some works compress the model update by filtering out or quantizing unimportant parameters [32, 23]; After realizing the privacy risk in FL [13, 34], DP-SGD [14] enhances the privacy by introducing differential privacy, and DP-FTRL [20] applies the tree aggregation to add noise to the sum of mini-batch gradients to ensure privacy further. These FL efforts often navigate privacy-accuracy-computation trade-offs. As such, a realistic FL setting is crucial for comprehensive evaluations.

Existing FL benchmarks can be misleading Existing benchmarks often lack realistic client statistical and system behavior datasets, and/or fail to reproduce large-scale FL deployments. Unfortunately, these limitations imply that they are not only insufficient for benchmarking diverse FL optimizations, but they can even mislead performance evaluations: (1) As shown in Figure 3(a), the statistical performance becomes worse when encountering practical client behaviors (e.g., stragglers and training failures), which indicates that existing benchmarks that do not have systems traces can produce overly optimistic statistical performance by overlooking systems characteristics; (2) FL training with hundreds of participants each round performs better than that with tens of participants (Figure 3(b)). As such, existing benchmark platforms can under-report existing FL optimizations simply because they cannot support large number of participants.



(a) Impact of system trace. (b) Impact of scale.

Figure 3: Existing benchmarks can mislead.[2]

3 FedScale Dataset: Realistic Workloads for Federated Learning

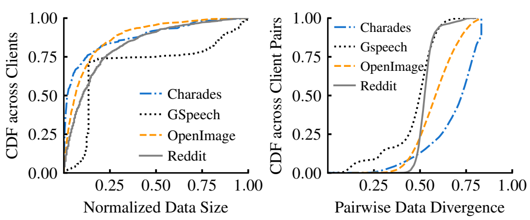
FL performance relies on at least three aspects: (1) *Client statistical data*: the client dataset used for training or testing determines the statistical efficiency of FL tasks (e.g., convergence and model accuracy); (2) *Client system behavior*: the compute/communication speed of the client device and its availability over time determine the system efficiency of FL tasks (e.g., duration of each round and physical cost) and the availability of statistical data; and (3) *Task categories*: model and application combinations that are running can exhibit different reliance on client statistical data and execute at different system speeds. Because client data is tightly coupled with the client device, these aspects interplay with each other and can impact the performance of an FL optimization, be it for statistical efficiency, system efficiency, or privacy. As such, an ideal suite of FL benchmarking dataset should cover all three aspects and support FL deployments at diverse scales.

We next introduce how we collected and partitioned realistic datasets in order to generate a versatile suite of FL datasets provided in FedScale.

[2]We train the ShuffleNet model on OpenImage classification task. More experimental setups in Section 5.

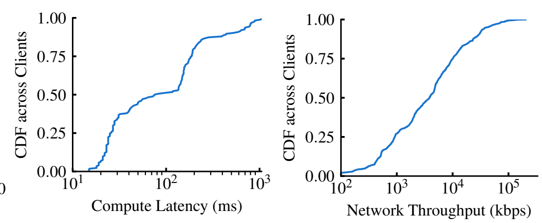
Category	Name	Data Type	#Clients	#Instances	Example Task
CV	`iNature`	Image	2,295	193K	Classification
	`OpenImage`	Image	13,771	1.3M	Classification, Object detection
	`Google Landmark`	Image	43,484	3.6M	Classification
	`Charades`	Video	266	10K	Action recognition
NLP	`Europarl`	Text	27,835	1.2M	Text translation
	`Blog Corpus`	Text	19,320	137M	Word prediction
	`Reddit`	Text	1,660,820	351M	Word prediction
	`Amazon Review`	Text	1,822,925	166M	Classification, Word prediction
	`CoQA`	Text	7,189	114K	Question Answering
	`LibriTTS`	Text	2,456	37K	Text to speech
	`Google Speech`	Audio	2,618	105K	Speech recognition
	`Common Voice`	Audio	12,976	1.1M	Speech recognition
Misc ML	`Taobao`	Text	182,806	20.9M	Recommendation
	`Go dataset`	Text	150,333	4.9M	Reinforcement learning

Table 2: Statistics of partial FedScale datasets. FedScale has 18 realistic client datasets, which are from the real-world collection, and we partitioned each dataset using its real client-data mapping.



(a) Data size. (b) Data distribution.

Figure 4: Non-IID client data distribution.



(a) Compute capacity. (b) Network capacity.

Figure 5: Heterogeneous client system speed.

3.1 Client Statistical Dataset

FedScale currently has 18 realistic FL datasets (Table 2), which can be used in various FL tasks (e.g., federated training/testing or on-device fine-tuning). The raw data of these datasets are collected from different sources and stored in various formats. We clean up the raw data, partition them into new FL datasets, and streamline new datasets into consistent formats. Moreover, we categorize them into different FL use cases and provide Python APIs for integrating them into today's frameworks.

Realistic data and partitions We target realistic datasets with client information, and partition the raw dataset using the unique client identification. For example, `OpenImage` is a vision dataset collected by Flickr, wherein different mobile users upload their images to the cloud for public use. We use the `AuthorProfileUrl` attribute of the `OpenImage` data to map data instances to each client, whereby we extract the realistic distribution of the raw data. Following existing FL deployments [36], for each dataset, we assign its clients into the training, validation or testing groups, whereby we get the training, validation and testing set for it. Here, we pick four real-world datasets – video (Charades), audio (Google Speech), image (OpenImage), and text (Reddit) – to illustrate the characteristics of FL. Each dataset consists of hundreds or up to millions of clients and millions of data points. Figure 4 reports the *Cumulative Distribution Function* (CDF) of the data distribution, wherein we see a high statistical deviation across clients not only in the quantity of samples (Figure 4(a)) but also in the data distribution (Figure 4(b)).[3] Our findings confirm the non-IID data distribution in FL.

Different scales across diverse task categories To accommodate diverse scenarios in practical FL, FedScale includes small-, medium-, and large-scale datasets across a wide range of tasks, from

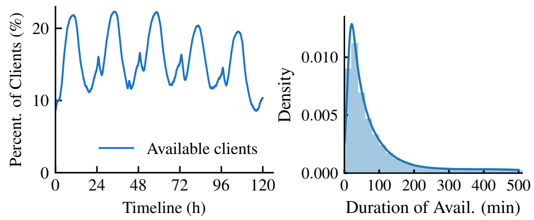
[3]We report the pairwise Jensen–Shannon distance of the categorical distribution between two clients.

hundreds to millions of clients. Some datasets can be applied in different tasks, as we enrich their use case by driving different metadata from the same raw data. For example, the raw `OpenImage` dataset can be used for object detection, and we extract each object therein and generate a new dataset for image classification. Moreover, we provide APIs for the developer to customize their dataset (e.g., enforcing new data distribution or extracting a subset of clients).

3.2 Client System Behavior Dataset

Client device system speed is heterogeneous We formulate the system trace of different clients using *AI Benchmark* [1] and *MobiPerf Measurements* [2] on mobiles. *AI Benchmark* provides the training and inference speed of diverse models (e.g., MobileNet) across a wide range of device models (e.g., Huawei P40 and Samsung Galaxy S20), while *MobiPerf* has collected the available cloud-to-edge network throughput of over 100k mobile clients. As specified in real FL deployments [6, 36], we focus on mobile devices that have larger than 2GB RAM and connect with WiFi; Figure 5 reports that their compute and network capacity can exhibit order-of-magnitude difference. As such, how to orchestrate scarce resources and mitigate stragglers are paramount for high system efficiency.

Client device availability is dynamic We incorporate a large-scale user behavior dataset spanning 136k users [35] to emulate the behaviors of clients. It includes 180 million trace items of client devices (e.g., battery charge or screen lock) over a week. We follow the real FL setting, which considers the device in charging to be available [4] and observe great dynamics in their availability: (i) the number of available clients reports diurnal variation (Figure 6(a)). This confirms the cyclic patterns in the client data, which can deteriorate the statistical performance of FL [11]. (ii) the duration of each available slot is not long-lasting (Figure 6(b)). This highlights the need of handling failures (clients become offline) during training, since the duration of each round (also a number of minutes) is comparable to that of each available slot.



(a) Inter-device availability. (b) Intra-device availability.

Figure 6: Client availability is dynamic.

4 FAR: Evaluation Platform for Federated Learning

Existing FL evaluation platforms can hardly reproduce the scale of practical FL deployments and often fall short in providing user-friendly APIs, thus requiring great developer efforts to deploy new plugins. As such, we introduce FedScale Automated Runtime (FAR), an automated and easily-deployable evaluation platform, to simplify and standardize the FL experimental setup and model evaluation under a practical setting. FAR is based on our Oort project [24], which has been shown to scale well and can emulate FL training of thousands of clients in each round.

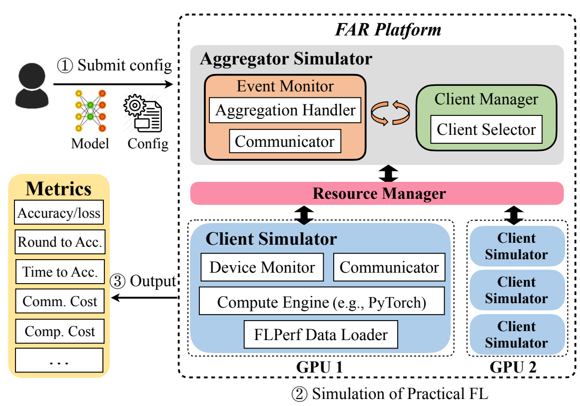


Figure 7: FAR enables the developer to benchmark various FL efforts with practical FL data and metrics.

Overview of FedScale Automated Runtime (FAR) FAR is an automated evaluation platform that can emulate realistic FL behaviors on GPU/CPU, while providing various practical FL metrics, such as computation/communication cost, latency and wall clock time, for evaluating today's efforts. Figure 7 shows the FAR architecture, which primarily consists of three components:

Module	API Name	Example Use Case
Aggregator Simulator	`round_initialization_handler`(**args)	Client clustering
	`round_completion_handler`(**args)	Adaptive/secure model aggregation
	`client_completion_handler`(client_id, msg)	Straggler mitigation
	`push_msg_to_client`(client_id, msg)	Model compression
Client Manager	`select_clients`(**args)	Client selection
	`select_model_for_client`(client_id)	Adaptive model selection
Client Simulator	`train`(client_data, model, config)	Local SGD/model personalization
	`push_msg_to_aggregator`(msg)	Model compression

Table 3: Some example APIs. FedScale provides APIs to deploy new plugins for various designs.

- *Aggregator Simulator*: It acts as the aggregator in practical FL, which selects participants, distributes execution profiles (e.g., model weight), and handles result (e.g., model updates) aggregation. In each round, its client manager uses the client behavior trace to decide whether a client is available; then it selects the specified number of clients to participate that round. Once receiving new events, the event monitor will activate the handler (e.g., aggregation handler to perform model aggregation), or the communicator to send/receive messages. The communicator records the size (cost) of every network traffic, and its FL runtime latency ($\frac{traffic\_size}{client\_bandwidth}$).
- *Client Simulator*: It works as the client in FL. FedScale data loader loads the federated dataset of that client and feeds this data to the compute engine to run real training/testing. The computation latency is determined by ($\#\_processed\_sample \times latency\_per\_sample$), and the communicator handles the network traffics and records the communication latency ($\frac{traffic\_size}{client\_bandwidth}$). At the same time, the device monitor handles different function calls specified by the developer; it will also terminate the simulation of this client and report failure(s) if the current runtime exceeds the available slot (indicated in the client availability trace).
- *Resource Manager*: It orchestrates the available physical resource for evaluation to maximize the utilization of resource. For example, when the number of participants in that round exceeds the resource capacity (e.g., simulating thousands of clients on a few GPUs), the resource manager queues the overcommitted tasks of clients and schedules a new client simulation request from this queue once resource becomes available.

Note that capturing runtime performance (e.g., wall clock time of training) is rather slow in practical FL (each client takes several minutes), but FAR enables *fast-forward* simulation for interactive development, since the real training on our platform often takes only a few seconds per round.

FAR enables automated and standardized FL simulation FAR incorporates realistic FL traces, using the aforementioned trace by default, to automatically emulate the practical FL workflow: ① *Task submission*: FL developers specify their configurations (e.g., model and dataset), which can be federated training or testing, and the FAR resource manager will initiate the aggregator and client simulator on available resource (GPU, CPU, other accelerators, or even smartphones); ② *FL simulation*: This evaluation stage follows the standardized FL lifecycle (in Figure 1). In each training round, the aggregator inquires the client manager to select the participants, whereby the resource manager distributes the client configuration to the available client simulators. After the completion of each client, the client simulator pushes the model update to the aggregator, which then performs the model aggregation. ③ *Metrics output*: During training, the developer can query the practical evaluation metrics on the fly. Figure 7 lists some popular metrics supported in FAR.

FAR is easily-deployable and extensible for plugins FAR provides flexible APIs, which can accommodate with different execution backends (e.g., PyTorch and TensorFlow) by design, for the developer to quickly deploy new plugins for customized evaluations. Table 3 illustrates some example APIs that can facilitate diverse FL efforts, and Figure 9 dictates an example showing how these APIs help to benchmark a new design of local client training with a few lines of code. Specifically, the

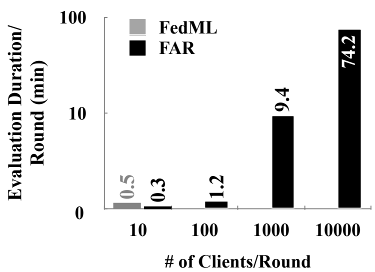


Figure 8: FAR can support thousands of clients per round, while FedML failed to run even 100 clients.

```
from flperf.component import Client

class Customized_Client(Client):
# Redefine training (e.g., for local
    SGD design/gradient compression)
   def
       train(self,client_data,model,conf):
     # Code of plugin
        ...
     # Results are sent to aggregator
     return training_result
```

Figure 9: Add plugins by inheritance.

developer can redefine client training function `run_client` by inheriting the base Executor module, and this plugin will be automatically integrated into FedScale during evaluations. Moreover, FAR can embrace new realistic (statistical client or system behavior) datasets with the built-in APIs. For example, the developer can import his own dataset of the client availability by leveraging the API (`load_client_availability`), and FAR will automatically force this trace during evaluations.

FAR is scalable and efficient FAR can perform large-scale simulations (e.g., training thousands of participants in each round) in both standalone (single CPU/GPU) and distributed (multiple CPUs/GPUs) setting. This is because: (1) FAR can support multiprocessing on a single GPU so that multiple device simulators can co-locate on the same GPU; (2) the resource manager can queue the over-committed simulation tasks of clients, and adaptively schedules them to run at runtime; (3) FAR maximizes the resource utilization by overlapping the communication and computation as much as possible. For example, the client simulator can turn to train for new clients while the communication of last completed client is on the fly. As shown in Figure 8 [4], our platform not only runs faster than FedML [17] (when only using 10 clients per round), thus saving lots of GPU hours, but can support large-scale evaluations efficiently. Instead, state-of-the-art platforms failed to run the setting with hundreds of clients.

5 Experiments

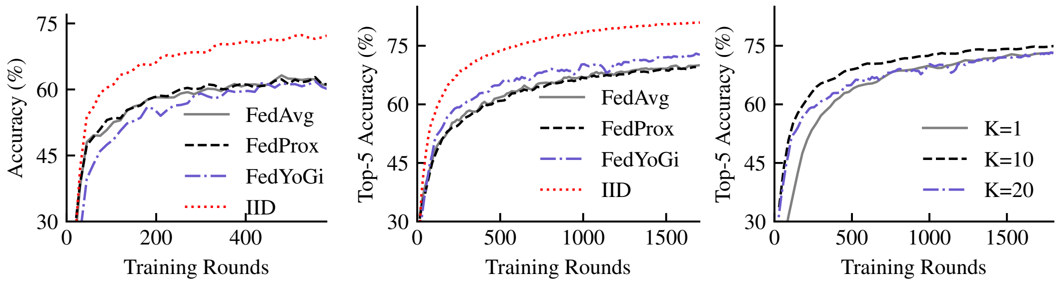
With the realistic data and standardized benchmarking platform in FedScale, we first provide baseline results for a number of published algorithms optimizing for different aspects of FL. More subtly, we highlight some important insights for improving practical FL further.

Experimental setup We use 10 NVIDIA Tesla P100 GPUs in our evaluations, and emulate up to 1300 participants in each round. Following the real FL deployments [6, 36], the aggregator collects updates from the first N completed participants out of $1.3N$ participants to mitigate system stragglers in each round, and $N = 100$ by default. We pick two representative datasets in FedScale, which belong to different scales and tasks: (1) *Speech Recognition*: the small-scale Google Speech dataset, with 105K speech commands over 2600 clients. We train ResNet-18 [18] to recognize the command among 35 categories. (2) *Image Classification*: the middle-scale OpenImage dataset, with 1.3M images spanning 600 categories across 14k clients. We train ShuffleNet-V2 [37] to classify the image. These applications and models are widely used on mobile devices. We set the minibatch size of each participant to 20, and the number of local steps to 20. We cherry-pick the hyper-parameters with grid search, ending up with an initial learning rate 0.04. These settings are consistent with the literature.

5.1 How Does FedScale Help FL Benchmarking?

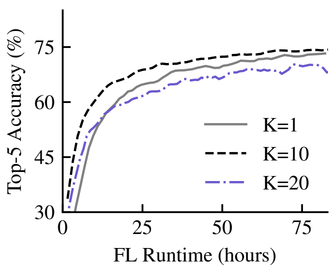
Optimizations for statistical efficiency. FedScale can benchmark the practical FL performance of today's statistical optimizations for FL. Here, we experiment with three state-of-the-art optimizations (FedAvg, FedProx and FedYoGi) – each reinvents local SGD to mitigate weight "drift" due to data heterogeneity – and the performance of IID data setting. Figure 10 reports their testing accuracy

[4] We train the ShuffleNet model on OpenImage classification task. More experimental setups in Section 5.

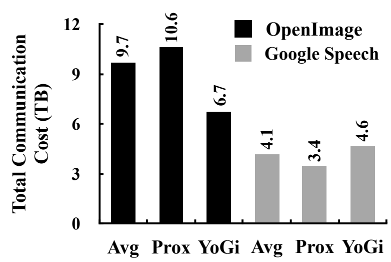


(a) Convergence on Google speech. (b) Convergence on OpenImage. (c) Impact of local steps K.

Figure 10: FedScale can benchmark the statistical performance for various optimizations or hyper-parameters on real FL data. (c) reports the FedYoGi performance on the OpenImage dataset.



Setting	FL runtime (hours)	Evaluation time (hours)
K=1	97	17
K=10	52	9
K=20	130	47



(a) FAR reports realistic FL clock. (b) FAR enables fast-forward eval. (c) FAR reports FL communication cost.

Figure 11: FedScale can benchmark realistic FL runtime. (a) and (b) report FedYoGi results on OpenImage with different number of local steps (K); (b) reports the FL runtime to reach convergence.

across different training rounds. We observe that: (1) the round-to-accuracy performance and final model accuracy of the non-IID setting is worse than that of the IID setting, which is consistent with existing findings [21]; and (2) different tasks can have difference preference on the optimizations. For example, FedYoGi performs the best on the OpenImage dataset, but its improvement on the Google Speech dataset becomes smaller. (3) even for the same optimization, its statistical performance often relies on the realistic FL data distribution (Figure 10(c)). For example, different number of local steps in local SGD can lead to different convergence. These again highlight the importance of a comprehensive suite of benchmarks with diverse datasets.

Optimizations for system efficiency. Existing system optimizations for FL focus on the FL runtime performance (e.g., wall-clock time in real FL training) and/or the execution cost of clients. We now show how FedScale can benchmark these optimizations with realistic metrics: (1) FAR can report the wall-clock runtime of practical FL along with the corresponding statistical performance (Figure 10(c) versus Figure 11(a)); (2) FAR can evaluate FL optimizations under the practical FL scale, and enables fast-forward evaluations of practical FL runtime in fewer evaluation hours (Table 11(b)). This allows the developer to investigate the large-scale system optimizations in a cost-efficient and interactive way; and (3) FAR captures the practical metrics of individual clients, and can dictate their execution cost. For example, Figure 11(c) reports the total communication cost in the practical FL training of all clients, and Figure 12 reports the timeline and the system latency of individuals. These system metrics allow FL developers to dive into specific system optimizations.

5.2 Findings and Potential Improvements

Heterogeneity-aware co-optimizations of communication and computation Existing optimizations for the system efficiency often apply the same strategy on all clients (e.g., using the same number of local steps [29] or compression threshold [32]), while ignoring the heterogeneous client

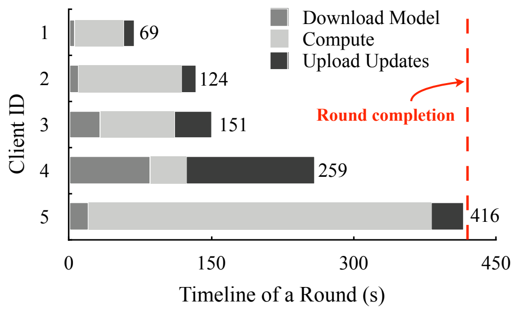


Figure 12: System stragglers greatly slow down model aggregation in practical FL.

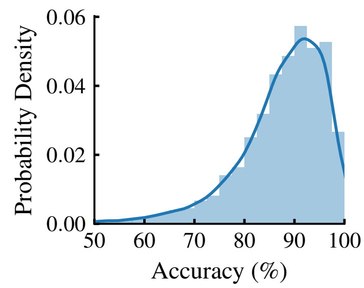


Figure 13: Biased accuracy distributions of the trained ShuffleNet model across clients.

system speed. However, when we outline the timeline of 5 randomly picked participants in our training of the ShuffleNet (Figure 12), we find that: (1) system stragglers can greatly slow down the round aggregation in practical FL; and (2) simply optimizing the communication or computation efficiency may not lead to faster rounds, as the last participant can be bottlenecked by the other resource. Here, optimizing the communication can greatly benefit *Client 4*, but it can only achieve marginal improvement on the round duration as *Client 5* is bottlenecked by computation. As such, there is an urgent need of co-optimizing the communication and computation efficiency while being heterogeneity-aware.

Co-optimizations of statistical and system efficiency Most of today's FL efforts focus on either optimizing the statistical or the system efficiency, whereas we observe there exists a great need for jointly optimizing both efficiency: (1) practical FL suffers biased model performance across clients (Figure 13). This can originate from the heterogeneous data and system behaviors, because the system behavior determines the availability of client data over training, wherein predicting this system behavior can curb the statistical drift in advance (e.g., prioritizing the use of upcoming offline clients). Moreover, the popular random client selection can deemphasize clients with slow speed, leading to poor accuracy on slow clients; and (2) statistical optimizations can leverage the heterogeneity nature of client system speed. For example, instead of applying a one-fit-all strategy for all clients, faster workers can trade more system latency against better statistical benefits. For example, faster workers can contribute larger but more accurate model updates when using gradient compression.

6 Conclusion

To enable scalable, robust, and reproducible research of federated learning, we introduce the FedScale, a diverse set of realistic FL datasets in terms of scales, task categories and client system behaviors. We reply on the real-world dataset to provide realistic federated datasets for benchmarking today's FL efforts. To enable efficient and standardized FL evaluations, we introduce, FAR, a more scalable evaluation platform than the existing. FAR performs fast-forward evaluation of the practical FL setting and produces FL runtime metrics needed in various FL work. More subtly, FAR provides ready-to-use realistic datasets and flexible APIs to allow more FL applications, such as benchmarking the performance of Neural Architecture Search or model inference on realistic FL datasets. We have made FedScale open-source at: `https://github.com/SymbioticLab/FedScale`, and hereby invite the community to contribute more FL research.

References

[1] AI Benchmark: All About Deep Learning on Smartphones. `http://ai-benchmark.com/ranking_deeplearning_detailed.html`.
[2] MobiPerf. `https://www.measurementlab.net/tests/mobiperf/`.
[3] PySyft. `https://github.com/OpenMined/PySyft`.
[4] TensorFlow Federated. `https://www.tensorflow.org/federated`.

[5] Daniel J. Beutel, Taner Topal, Akhil Mathur, Xinchi Qiu, Titouan Parcollet, Pedro Porto Buarque de Gusmao, and Nicholas D. Lane. FLOWER: A friendly federated learning framework. *arXiv preprint arXiv:2007.14390*, 2021.

[6] Keith Bonawitz, Hubert Eichner, and et al. Towards federated learning at scale: System design. In *MLSys*, 2019.

[7] Sebastian Caldas, Sai Meher, Karthik Duddu, and et al. Leaf: A benchmark for federated settings. *NeurIPS' Workshop*, 2019.

[8] Di Chai, Leye Wang, Kai Chen, and Qiang Yang. FedEval: A benchmark system with a comprehensive evaluation model for federated learning. In *arxiv.org/abs/2011.09655*, 2020.

[9] Mingqing Chen, Rajiv Mathews, Tom Ouyang, and Françoise Beaufays. Federated learning of out-of-vocabulary words. In *arxiv.org/abs/1903.10635*, 2019.

[10] Canh T. Dinh, Nguyen H. Tran, and Tuan Dung Nguyen. Personalized federated learning with moreau envelopes. In *NeurIPS*, 2020.

[11] Hubert Eichner, Tomer Koren, H. Brendan McMahan, Nathan Srebro, and Kunal Talwar. Semi-cyclic stochastic gradient descent. In *ICML*, 2019.

[12] Alireza Fallah, Aryan Mokhtari, and Asuman Ozdaglar. Personalized federated learning with theoretical guarantees: A model-agnostic meta-learning approach. In *34th Conference on Neural Information Processing Systems (NeurIPS 2020)*, 2020.

[13] Jonas Geiping, Hartmut Bauermeister, Hannah Dröge, and Michael Moeller. Inverting gradients - how easy is it to break privacy in federated learning? In *NeurIPS*, 2020.

[14] Robin C. Geyer, Tassilo Klein, and Moin Nabi. Differentially private federated learning: A client level perspective. In *NeurIPS*, 2017.

[15] Avishek Ghosh, Jichan Chung, Dong Yin, and Kannan Ramchandran. An efficient framework for clustered federated learning. In *34th Conference on Neural Information Processing Systems (NeurIPS 2020)*, 2020.

[16] Avishek Ghosh, Jichan Chung, Dong Yin, and Kannan Ramchandran. An efficient framework for clustered federated learning. In *NeurIPS*, 2020.

[17] Chaoyang He, Songze Li, Jinhyun So, and Xiao Zeng. FedML: A research library and benchmark for federated machine learning. In *arxiv.org/abs/2007.13518*, 2020.

[18] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.

[19] Sixu Hu, Yuan Li, Xu Liu, Qinbin Li, Zhaomin Wu, and Bingsheng He. The OARF benchmark suite: Characterization and implications for federated learning systems. In *arxiv.org/abs/2006.07856*, 2020.

[20] Peter Kairouz, Brendan McMahan, Shuang Song, Om Thakkar, Abhradeep Thakurta, and Zheng Xu. Practical and private (deep) learning without sampling or shuffling. In *arxiv.org/abs/2103.00039*, 2021.

[21] Peter Kairouz, H. Brendan McMahan, and et al. Advances and open problems in federated learning. In *Foundations and Trends® in Machine Learning*, 2021.

[22] Sai Praneeth Karimireddy, Satyen Kale, Mehryar Mohri, Sashank J. Reddi, Sebastian U. Stich, and Ananda Theertha Suresh. SCAFFOLD: Stochastic controlled averaging for federated learning. In *ICML*, 2020.

[23] Sai Praneeth Karimireddy, Quentin Rebjock, Sebastian U Stich, and Martin Jaggi. Error feedback fixes signsgd and other gradient compression schemes. In *arXiv preprint arXiv:1901.09847*, 2019.

[24] Fan Lai, Xiangfeng Zhu, Harsha V. Madhyastha, and Mosharaf Chowdhury. Kuiper: Efficient federated learning via guided participant selection. In *USENIX Symposium on Operating Systems Design and Implementation (OSDI)*, 2021.

[25] Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. Federated optimization in heterogeneous networks. In *MLSys*, 2020.

[26] Wenqi Li, Fausto Milletari, and Daguang Xu. Privacy-preserving federated brain tumour segmentation. In *Machine Learning in Medical Imaging*, 2019.

[27] Heiko Ludwig, Nathalie Baracaldo, Gegi Thomas, and et al. Ibm federated learning: An enterprise framework white paper v0.1. In *arxiv.org/abs/2007.10987*, 2020.

[28] Peter Mattson, Christine Cheng, Cody Coleman, and et al. Mlperf training benchmark. In *MLSys*, 2020.

[29] H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agüera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *AISTATS*, 2017.

[30] Matthias Paulik, Matt Seigel, Henry Mason, and et al. Federated evaluation and tuning for on-device personalization: System design and applications. In *arxiv.org/abs/2102.08503*, 2021.

[31] Sashank Reddi, Zachary Charles, and et al. Adaptive federated optimization. In *arxiv.org/abs/2003.00295*, 2020.

[32] Daniel Rothchild, Ashwinee Panda, Enayat Ullah, Nikita Ivkin, Ion Stoica, Vladimir Braverman, Joseph Gonzalez, and Raman Arora. Fetchsgd: Communication-efficient federated learning with sketching. In *ICML*, 2020.

[33] Mark Sandler, Andrew G. Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *CVPR*, 2018.

[34] Hongyi Wang, Kartik Sreenivasan, Shashank Rajput, Harit Vishwakarma, Saurabh Agarwal, Jy yong Sohn, Kangwook Lee, and Dimitris Papailiopoulos. Attack of the tails: Yes, you really can backdoor federated learning. In *NeurIPS*, 2020.

[35] Chengxu Yang, Qipeng Wang, and et al. Characterizing impacts of heterogeneity in federated learning upon large-scale smartphone data. In *WWW*, 2021.

[36] Timothy Yang, Galen Andrew, Hubert Eichner, Haicheng Sun, Wei Li, Nicholas Kong, Daniel Ramage, and Françoise Beaufays. Applied federated learning: Improving Google keyboard query suggestions. In *arxiv.org/abs/1812.02903*, 2018.

[37] Xiangyu Zhang, Xinyu Zhou, Mengxiao Lin, and Jian Sun. Shufflenet: An extremely efficient convolutional neural network for mobile devices. In *CVPR*, 2018.