FedEval: A Benchmark System with a Comprehensive Evaluation Model for Federated Learning

Abstract
As an innovative solution for privacy-preserving machine learning (ML), federated learning (FL) is attracting much attention from research and industry areas. While new technologies proposed in the past few years do evolve the FL area, unfortunately, the evaluation results presented in these works fall short in integrity and are hardly comparable because of the inconsistent evaluation metrics and the lack of a common platform. In this paper, we propose a comprehensive evaluation framework for FL systems. Specifically, we first introduce the ACTPR model, which defines five metrics that cannot be excluded in FL evaluation, including Accuracy, Communication, Time efficiency, Privacy, and Robustness. Then we design and implement a benchmarking system called FedEval, which enables the systematic evaluation and comparison of existing works under consistent experimental conditions. We then provide an in-depth benchmarking study between the two most widely-used FL mechanisms, FedSGD and FedAvg. The benchmarking results show that FedSGD and FedAvg both have advantages and disadvantages under the ACTPR model. For example, FedSGD is barely influenced by the non-IID data problem, but FedAvg suffers from a decline in accuracy of up to 9% in our experiments. On the other hand, FedAvg is more efficient than FedSGD regarding time consumption and communication. Lastly, we excavate a set of take-away conclusions, which are very helpful for researchers in the FL area.

1 Introduction
Data privacy is becoming an increasingly serious issue today since more and more real-life applications are data-driven. Companies that fail to protect users’ privacy may face a hefty fine, e.g., FTC fines Facebook $5 billion to force new privacy reference. McMahan et al. [30] in Google proposed the idea of federated learning (FL) to meet the privacy-preserving regularization. Instead of collecting massive amount of user data for machine learning (ML) training, FL sets up a joint training scenario in which the client devices, united by common agreement under a central authority, participate in the model training, and only certain model parameters are sent to the cloud server for aggregation.

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Since FL was proposed, it has attracted much attention from both academic and industrial areas. FederatedSGD (FedSGD) and FederatedAveraging (FedAvg) are the two most widely-used methods in FL. FedSGD inherits the settings of large-batch synchronous SGD, which is the state-of-the-art method used in data centers [7]. In contrast, FedAvg [30] performs small-batch training and increases the number of clients’ local training passes in each round. Based on these two methods, many research works have appeared, targeting different problems in FL. Wang et al. [40] proposed an adaptive method to guarantee that the available resources are most efficiently used in FL. Some works [2, 24, 36, 38] used gradient compression technology to reduce the communication burden. Many studies [6, 15, 16, 22, 44] targeted the non-IID data issue in FL.

While these works focus on one or two issues in FL, their evaluation results are also restricted to the corresponding areas. For example, FedAvg [30] tries to reduce the communication rounds by adding the number of clients’ local updates, but the resulting increased local running time is not evaluated. Moreover, the non-IID issue is also not thoroughly tested in their work. Zhao et al. [44] used a shared dataset to solve the non-IID data problem, but they dismissed the potential private data leakage caused by the shared dataset. Analysis of these existing works raises several questions. Is it adequate to only evaluate the aspects in which the progress is made? What are the metrics that need to be considered in the evaluation of FL systems? How can we compare existing FL technologies if the reported evaluation results focus on different aspects?

A comprehensive evaluation model is required to standardize the assessment and encourage healthy development in the FL area. Therefore, in this paper, we propose the ACTPR\(^1\) model. The ACTPR model evaluates FL systems in terms of accuracy, communication, time consumption, privacy, and robustness. While the five metrics have all appeared in existing works to measure the capabilities of the FL systems in different aspects, as illustrated in Table 1, these five metrics are seldom covered together in one single work. Most of the existing works have only considered two or three metrics.

|                  | Accuracy | Communication | Time Consumption | Privacy | Robustness |
|------------------|----------|---------------|------------------|---------|------------|
| Chen et al. [6]  | ✓        | ✓             |                  |         | ✓          |
| Jeong et al. [15]| ✓        | ✓             | ✓                |         |            |
| Liu et al. [25]  | ✓        | ✓             | ✓                | ✓       | ✓          |
| McMahan et al. [30]| ✓    | ✓             | ✓                |         | ✓          |
| Sattler et al. [36]| ✓   | ✓             |                  |         | ✓          |
| Wang et al. [40] | ✓        | ✓             |                  |         | ✓          |
| Zhao et al. [44] | ✓        | ✓             |                  |         | ✓          |
| Mohri et al. [32]| ✓        |               |                  | ✓       |            |
| Li et al. [21]   | ✓        | ✓             |                  |         | ✓          |
| Li et al. [20]   | ✓        | ✓             |                  |         |            |
| Wang et al. [39] | ✓        | ✓             |                  |         | ✓          |
| Li et al. [23]   | ✓        | ✓             |                  |         |            |
| Reddi et al. [33]| ✓        | ✓             |                  |         |            |
| Yu et al. [43]   | ✓        |               |                  |         |            |
| Rothchild et al. [34]| ✓ | ✓           |                  |         |            |
| Malinovsky et al. [29]| ✓ | ✓           |                  |         | ✓          |
| Karimireddy et al. [17]| ✓ | ✓           |                  |         |            |
| He et al. [10]   | ✓        | ✓             |                  | ✓       |            |

\(^1\)ACTPR is an acronym for Accuracy, Communication, Time consumption, Privacy, and Robustness
To illustrate the need for a comprehensive evaluation model, we now show two concrete examples of the ambiguity caused by fragmentary evaluation metrics.

**Is a smaller number of communication rounds always better?** Most of the existing works, including Google’s FedAvg [30], only use the number of communication rounds to measure efficiency. The major contribution of FedAvg is reducing the number of communication rounds by increasing the clients’ number of local updates in each round. However, the time consumption per round grows because of the rising workload in local updates. Thus we can hardly say that a smaller number of communication rounds is identical to less time consumption in FedAvg, especially when the model is large and requires more hardware resources.

**Is it safe to send model parameters?** Based on the FedAvg model, it seems that sending model parameters has become the default setting to avoid leaking private data, since the data is never uploaded. However, recent works have shown that attackers can recover the data from gradients [3, 45]. Attackers can easily obtain gradients from the model parameters during training.

Hence, the ACTPR model is urgently required to provide comprehensive and standard evaluation for FL. Another hindrance to the objective comparison of different FL systems is the lack of a common platform with a built-in evaluation model. Users usually first need to implement the evaluation metrics and gather the results by hand. Different evaluation settings (e.g., the way of collecting the communication statistics) are usually adopted in the testing, resulting in non-comparable evaluation results. Thus, a common benchmarking system with a built-in evaluation model is also the need of the day. The implementation of such a benchmarking system, however, is non-trivial and raises the following challenges:

- Most of the existing FL frameworks do not include a built-in evaluation model, and researchers usually need to pay extra work to get a comprehensive evaluation. Moreover, some evaluation metrics are hard to implement in existing FL frameworks (e.g., FATE and PySyft), due to the high level system integration, e.g., gathering detailed time consumption on each single step. More detailed analysis and comparisons of existing FL frameworks are presented in section 3.

- The standalone mode is important for researchers because we usually have limited hardware resources, which cannot hold many participants’ distributed computing (e.g., 100 clients require 100 different devices). The naive idea is to simulate the clients using limited hardware resources (e.g., run 100 clients on a single PC). Then the interaction between the server and clients needs to be carefully simulated. Otherwise, the evaluation results for time and communication will not be convincing.

We have designed and implemented a lightweight and easy-to-use benchmarking system with the ACTPR model for FL, called FedEval. The server and clients are simulated using docker containers. The isolation between containers guarantees that the simulation can reflect a real-world scenario. The ACTPR model is the core of the benchmarking system, and the whole project is open-sourced. Thus, researchers can quickly implement new ideas and conduct evaluations using the ACTPR model.

In brief, we make the following contributions:

- We propose the ACTPR model, which can support a comprehensive and general-purpose benchmark for FL systems. Without such a standard evaluation model, FL works cannot be integrally evaluated and compared.

- We have designed and implemented a benchmarking system for researchers, called FedEval, which is lightweight, easy-to-use, and has a built-in evaluation model. The system is open-sourced at [https://github.com/Di-Chai/FedEval](https://github.com/Di-Chai/FedEval).

- We have tested and analyzed two widely-used FL mechanisms, FedSGD and FedAvg, and we have drawn a set of take-away conclusions for researchers in the FL area.

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For example, the amount of transmitted data can be estimated by measuring the size of exchanging variables, which can be done using python packages. However, different packages may yield different results.

[https://github.com/FederatedAI/FATE](https://github.com/FederatedAI/FATE)

[https://github.com/OpenMined/PySyft](https://github.com/OpenMined/PySyft)
2 The ACTPR Evaluation Model

In this section, we present our ACTPR model with a detailed description of each metric.

2.1 Accuracy

In the accuracy\(^6\) metric, we care about the performance of the obtained machine learning model (i.e., the predictive power). Adequate data is usually an indispensable condition to achieve satisfactory ML accuracy, especially when deep learning is applied. However, such a condition usually cannot be satisfied in the real-world due to the privacy-preserving restrictions. Each data owner can only access its local data, which is also known as the isolated data islands problem \(42\). FL systems should be able to break such isolation and achieve an accuracy (\(\text{FLAcc}\)) that is better than the average value of each client itself (\(\text{LocalAcc}\)).

In federated learning, we typically learn the global model by solving the following problem:

\[
\min_w f(w) = \sum_{k=1}^{N} p_k F_k(w) = \mathbb{E}_k[F_k(w)]
\]

where \(w\) is the model parameter, \(N\) is the number of clients, \(p_k \geq 0\) and \(\sum_k p_k = 1\). \(F_k(w) := \mathbb{E}_{x_k \sim D_k}[f(w, x_k)]\) is the local objective measures the empirical loss over the local data distribution \(D_k\), and we set \(p_k = \frac{n_k}{n}\) where \(n = \sum_k n_k\) is the number of samples in the entire dataset.

**Definition 2.1 (\(\text{FLAcc}\))** We define the federated learning accuracy as: \(\text{FLAcc} = \sum_{k=1}^{N} p_k \text{Acc}(h(w, x_k), y_k)\), where \(w\) is the model parameter learned from Equation \(2\). \(h(w, x_k)\) outputs a probability distribution over the classes or categories that can be assigned to \(x_k \sim D_k\). Acc function computes accuracy of \(h(w, x_k)\) regarding the label \(y_k\), and we set \(p_k = \frac{n_k}{n}\).

**Definition 2.2 (\(\text{LocalAcc}\))** Using the same notation in Definition \(2.1\), we define the \(\text{LocalAcc}\) as: \(\text{LocalAcc} = \sum_{k=1}^{N} p_k \text{Acc}(h(w_k, x_k), y_k)\), where \(w_k\) is the local model parameter learnt by minimizing the local objective: \(w_k = \arg\min_w F_k(w)\), and we set \(p_k = \frac{n_k}{n}\).

**Definition 2.3 (\(\text{CentralAcc}\))** We define the centralized training accuracy as \(\text{CentralAcc} = \text{Acc}(h(w, x), y)\), where \(w\) is the model parameter trained by \(\min_w F(w) := \mathbb{E}_{x \sim D}[f(w, x)]\), \(x\) represents data that collected from all the clients. and \(D\) is the global data distribution.

We compare the \(\text{FLAcc}\) and \(\text{LocalAcc}\) to measure how much the model performance is improved using federated learning.

Meanwhile, FL systems should be able to obtain approximately the same accuracy as that of centralized machine learning systems (\(\text{CentralAcc}\)). In other words, FL accuracy (\(\text{FLAcc}\)) should be bounded: \(\text{FLAcc} \leq \text{CentralAcc}\), which can be easily proved because the centralized training can simulate any forms of federated training and the central training is also exempt from the performance drop caused by the statistical and system uncertainties, which is the main reason of the performance reduction of federated learning.

Assuming that \(\text{CentralAcc}\) is significantly higher than \(\text{LocalAcc}\), we can have the following analysis:

If \(\text{LocalAcc} \geq \text{FLAcc}\), then the FL system has failed to converge. If \(\text{FLAcc} \approx \text{CentralAcc}\), then the FL system shows no accuracy decline, which is the best case. Given two FL systems, \(FL_1\) and \(FL_2\), if \(FL_1 \text{Acc} > FL_2 \text{Acc}\), then we say \(FL_1\) converges to better accuracy than \(FL_2\).

\(^6\)For a better understanding, we use the name accuracy to represent the model performance, while the actual evaluation metrics may vary in different scenarios. E.g., accuracy, precision, and recall are popularly used in classification problems; mean-square-error (MSE) and root-mean-square-error (RMSE) are widely used in regression tasks.

\(^5\)Centralized data collection and training is only an ideal experimental situation that represents a theoretical accuracy upper bound. In reality, we usually cannot put all the data in one place due to the restriction of privacy regulations, such as GDPR (General Data Protection Regulation).
2.2 Communication

Communication is an essential metric because it usually requires significant resources, e.g., battery charge and cellular data usage. We measure the communication in two aspects: the number of communication rounds (CommRound) and the total amount of data transmission during training (CommAmount).

CommRound is related to the convergence speed. A smaller CommRound usually reflects a faster convergence speed when two systems achieve the same accuracy.

CommAmount measures how much data is transmitted during training. Since the participants in FL usually have limited network resources (e.g., mobile phones), a massive CommAmount will pose lots of challenges. Systems with data compression technologies, e.g., gradient compression [36], will have a smaller CommAmount.

We measure the CommRound and CommAmount from both the server and client perspective. From the server aspect, we directly measure the number of communication rounds and the amount of transmitted data. We calculate the average value of CommRound and CommAmount over all the clients from the clients’ aspect.

2.3 Time Consumption

In ML, time consumption is always an essential metric to measure efficiency, especially when systems have special requirements on time, e.g., real-time traffic predictions. However, time consumption is rarely well-evaluated in FL (see Table[1]). Most of the existing works [6,15,27,30,36,40,44] only consider the aforementioned CommRound in efficiency analysis. However, we find that time consumption is not necessarily linearly correlated with CommRound. If we select parameters or an FL system based primarily on CommRound, the time consumption may not be optimized. More details are presented in Section[4], Benchmarking Experimental Results.

In the ACTPR model, the time consumption magnitude plays a vital role in measuring an FL system’s efficiency. We define the time evaluation metric from both overall and partial views. Overall, we compare the total time (TimeAll) needed for getting a converged model. Partially, we investigate the time usage over nine substeps. A general training workflow of an FL system is presented in Figure[1].

**Step 1 Initialization:** At the beginning of each round, the server will check for the available devices at that moment and then choose a group of clients to participate in the training. The group size could be all or a part of the available clients. We denote the initialization time as Init.

**Step 2 Training:** The training step contains four substeps: sending requests, clients’ local training, uploading weights, and weight aggregation on the server. Sending requests require little resources, so it is usually fast. The clients’ local training and weight uploading will cost most of the time because they need abundant hardware and network resources. The time consumption of weight aggregation on the server depends on the number of engaged clients. We denote the time consumption of these four substeps as: TraReq, TraRun, TraSync, and TraAgg.

**Step 3 Validation:** The validation also contains four substeps: distributing new weights, clients’ local validation, uploading validation results, and validation result aggregation on the server. We denote the time consumption of these four steps as: ValReq, ValRun, ValSync, and ValAgg.

In summary, our ACTPR model addresses time evaluation from the overall coarse-grained overall time consumption and the fine-grained time cost in nine substeps. Such detailed evaluations provide an adequate method of comparison between different models and give answers to questions, like which step costs the most amount of time in FL training and how does time consumption vary in different FL systems.
2.4 Privacy

Well-protected privacy is the foundation of FL systems. Existing FL technologies push the computations to user devices and perform secure aggregation on model parameters. The risk of private data leakage can be reduced since the users’ data never leaves their devices. However, recent works have already shown that gradients can reveal the input data and labels \([45]\). Model parameters are not exempt from such attacks since a simple substraction between parameters of two adjacent rounds yields the gradients. Hence, a privacy evaluation cannot be dismissed to find potential privacy issues. It is possible to use encryption methods (e.g., homomorphic encryption \([1]\)) to defend the gradient attacks. However, they are not practical because it is usually hundreds of times slower after using the encryption \([3]\). Thus we do not consider the encryption methods at this moment and assume that the parameters are transmitted in plaintext.

Apart from uploading the parameters, we also have other choices in FL, such as only uploading the model outputs \([15]\). To the best of our knowledge, there is not yet an attack method built on non-gradients information. Thus, at this moment, we implement two state-of-the-art gradient attacks in the ACTPR model. The first one is the gradients attack to fully-connected model (FC Attack), e.g., linear regression and multilayer perceptrons. The second one is the Deep-Leakage-from-Gradients attack (DLG Attack) \([45]\), which can attack a wide variety of models, e.g., convolutional neural network (CNN), recurrent neural network (RNN).

**FC Attack.** Recent work \([3]\) has proved that the gradients are proportional to the input data in FC models. Using linear regression as an example, the related formulas are \[ l = ||wx + b - y||^2_2, \frac{\partial l}{\partial w} = 2x^T(wx + b - y). \] Since \((wx + b - y)\) is scalar, \(\frac{\partial l}{\partial w}\) is proportional to input data \(x\). Thus, we can easily recover \(x\) by rescaling \(\frac{\partial l}{\partial w}\).

**DLG Attack.** The DLG model was proposed by Zhu et al. \([45]\). Briefly, the attackers replace input data and labels with random initialized variables, then they train them using the gradients. The main idea is that if the gradients produced by the fake data and fake labels are close enough to the true gradients under the same model weights, then the fake data and fake labels will be close to the true data and true labels, respectively. Although a DLG attack can be made against a wide class of models, it requires that the model is twice differentiable, which restricts its applicability (e.g., it cannot work with a CNN with ReLU activation).

It is worth noting that integrating these two attack models is not where we stop building the privacy metric, because more powerful attack methods may appear with the development of FL. Thus, we will keep updating the attack models to provide comprehensive privacy evaluation.

2.5 Robustness

Unlike ML training in a stable environment in centralized data centers, FL training happens over distributed networks of devices, which poses lots of uncertainties to the system. One key issue is the statistical uncertainties. FL aims at fitting a model to data generated by different participants. Each participant collects the data in a non-IID manner across the network. The amount of data held by each participant may also significantly differ. The non-IID data issue poses challenges to the training of FL. The model will be more challenging to train under such a biased data distribution \([37]\).

We define the robustness evaluation as the performance under non-IID data. A robust FL system should be able to perform consistently well under such uncertainties.

3 The Benchmarking System: FedEval

Having motivated the need for an easy-to-evaluate and lightweight benchmarking system, we propose a federated benchmarking system called FedEval. Figure 2 demonstrates the inputs, inner architecture, and outputs of the system. Our ACTPR evaluation model is built inside the benchmarking system. Three key modules are designed in FedEval:

- Data config and the data_loader module: Our benchmarking system provides four standard federated learning datasets, and different data settings (e.g., non-IID data) can be implemented by changing the data configs. Self-defined data is also supported. We only need to
define the load_data function in data_loader module to add a new dataset, which will share the same set of processing functions with the built-in datasets.

- Model config and the tf_wrapper module: Four machine learning models are built inside our system, including MLP, LeNet, MobileNet, and ResNet50. We use TensorFlow as the backend, and the tf_wrapper module handles the model training and predictions. Thus we can benefit from the flexibility of building models using TensorFlow and no need to worry about the training process. Self-defined ML models are also supported. To add a new model, we only need to provide the scripts of building the model architecture, and the tf_wrapper module will take care of the model training and predictions.

- Runtime config and the strategy module: One of the essential components in our benchmarking system is the strategy module, which defines the protocol of the federated training. Briefly, the FL strategy module supports the following customization:
  - Customized uploading message, e.g., which parameters are uploaded by the clients.
  - Customized server aggregation method, e.g., weighted average.
  - Customized training method for clients, e.g., normal gradient descent and meta-learning methods.
  - Customized method for incorporating the global and local model, e.g., one popularly used method is replacing the local model with the global one before training.

To comprehensively evaluate a new federated learning method using the ACTPR model, we only need to implement a new strategy instance in FedEval.

We use the docker container technology to simulate the server and clients (i.e., each participant is a container), and use socket IO in the communication. The isolation between different containers guarantees that our simulation can reflect the real-world application. The entire system is open-sourced, five benchmark FL datasets and four benchmark ML models are included in the system. The essential components (i.e., dataset, ML models, and FL strategy) can be easily used or self-defined. Thus researches can implement their new idea and evaluate with ACTPR model very quickly.

Briefly, three steps are needed to start an experiment in our benchmarking system:

- Step 1: Determine the benchmark dataset, ML model, and FL strategy, then modify the data config, model config, and runtime config.
- Step 2: Use the built-in tool to generate data for clients and create the docker-compose files.
- Step 3: Start the experiments using docker-compose, and monitor the dashboard for the evaluation status and results.

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7 Five benchmarking datasets include MNIST, CIFAR10, CIFAR100, FEMNIST, and CelebA.
8 Four benchmarking ML models include MLP, LeNet, MobileNet and ResNet50.
To demonstrate the strength of our benchmarking system in the research area, we compare our solution with six existing federated learning libraries and the results are shown in Table 2. The highlights of our solution are summarized below:

- **Built-in evaluation model.** A comprehensive evaluation is essential to provide fair and standardized comparisons between different FL models. However, accomplishing such a comprehensive evaluation is not easy due to the workload overhead (e.g., collecting the time and communication statistics, implementing the attack model, and simulating the system uncertainties). Thus we implemented the ACTPR model inside our benchmarking system, making the evaluation easier and standardize.

- **Isolated environment in standalone mode.** Unlike industry applications, we usually have limited hardware resources in research projects. Thus the precise simulation of communication in standalone mode becomes essential. We use Docker containers in our system to provide an isolated environment between different participants and use socket IO in the communication. The networking conditions, like bandwidth and delay, can be easily simulated in our system. In our experiments, one machine with 32GB RAM can support about 100 clients running together using the MLP model, and each client has 300 images from the MNIST dataset.

- **Flexible customization.** Our benchmarking system supports full customization in the dataset, ML model, and FL strategy. We can not only control the exchanging messages but also decide the global aggregation method and how the global model substitute the local model (e.g., could use meta-learning methods instead of directly replacement).

4 Benchmarking Experimental Results: FedSGD vs. FedAvg

In this section, we present a comprehensive benchmarking study that performed on the two most widely used FL methods: FedSGD and FedAvg.

4.1 Experiment Settings

FedEval has five build-in datasets, and we use three of them in our experiments[^9]: MNIST[^19], FEMNIST[^5], and CelebA[^5, 26]. The MNIST dataset was collected in a non-FL style. Thus we follow the setting of previous works[^30, 44] and simulate non-IID data by restricting the number of

[^9]: We select the comparing dimensions based on the scenario of horizontal federated learning and research-oriented usages. We mainly assess systems’ capacity and neglect the implementation progress (e.g., we focus on whether a system supports customized models instead of the number of models that currently support). The comparing dimensions may not fully present each system’s functionality or new features. More details could be found on each system’s homepage, which is listed in the appendix[^10].

[^10]: Due to the space limitation, we put parts of the experiment settings (e.g., model parameters) and parameter-searching results (e.g., tuning the optimizers and learning rates) in the appendix[^6].
Table 3: Accuracy evaluation

| Dataset | Model | Local Acc | Central Acc | FedSGD Acc | FedAvg Acc |
|---------|-------|-----------|-------------|------------|------------|
| MNIST   | MLP   | 0.884     | 0.988       | 0.983      | 0.985      |
| MNIST   | LeNet | 0.926     | 0.994       | 0.994      | 0.994      |
| FEMNIST | MLP   | 0.476     | 0.829       | 0.814      | 0.798      |
| FEMNIST | LeNet | 0.465     | 0.850       | 0.848      | 0.846      |
| CelebA  | LeNet | 0.524     | 0.896       | 0.894      | 0.882      |

Clients’ local image classes. The experiments of clients have 1, 2, and 3 classes of images are reported. In FEMNIST and CelebA, we have the identity of who generated the data. Thus we partition the data naturally based on the identity. While in reality, the data is usually non-IID in FL (e.g., FEMNIST and CelebA), we randomly shuffle the data between clients to create an ideal IID data situation, which is used as a comparison to measure the FL system’s capacity for handling the non-IID data challenge. To simplify the comparison, we only present the non-IID data results in the robustness evaluation and use the IID setting in other experiments. We use 100 clients in all the experiments, and each client has a maximum of 300 images. Following previous work, we use $B$, $C$, and $E$ as the parameters of FedSGD and FedAvg. $B$ is the local batch size, $C$ is the ratio of clients that participate in each round of training, and $E$ is the number of local training passes (i.e., number of epochs). We set $B = \infty$, $C = 1$, and $E = 1$ for FedSGD, and select the best parameters for FedAvg in different datasets using grid search. The chosen parameters of FedAvg are: MNIST $B = 8, C = 0.1, and E = 16$, FEMNIST $B = 4, C = 0.1, and E = 32$, and CelebA $B = 4, C = 0.1, and E = 8$.

We also tuned the optimizer and learning rate (LR). The results show that Adam optimizer can achieve the best accuracy more frequently, and it is more robust under different LRs compared with mini-batch stochastic gradient descent (SGD) and SGD with momentum optimizers. Thus we use Adam optimizer in the following experiments. We also find that it is necessary to update clients’ Adam momentum value, otherwise, the converged accuracy will significantly decrease. Intuitively, we update the momentum value using the same method of updating the model parameters (i.e., global aggregation). Uploading the momentum values, however, will cause triple $CommAmount$ compared with SGD. Figure 3(a) shows the correlation of time consumption and LR on well-converged results. We can conclude that a larger LR can accelerate the training of FL, especially for FedSGD. The LR for FL should be larger than non-federated ML because the gradients shrink in the global aggregation, which is a weighted sum using weights smaller than one. However, an overlarge LR may also bring problems, like failure to converge. In the following subsections, we report the results using the best LR (i.e., the LR that yields the best time efficiency and has no impact on model convergence).

4.2 Accuracy Evaluation

Table 3 shows the accuracy evaluation. FedSGD and FedAvg can improve the model accuracy by around 10% to 40% compared with non-federated local training. In most cases, if we select appropriate parameters, both FedSGD and FedAvg can reach similar accuracy as central training (i.e., Central Acc).

4.3 Communication Evaluation

Figures 3(d) and 3(e) present the communication evaluation results (i.e., $CommRound$ and $CommAmount$).

Figure 3: Figure 3(a) shows the correlation of time consumption and LR. Figures 3(b) and 3(c) present the results of time consumption vs. communication round. Figures 3(d) and 3(e) present the communication evaluation results (i.e., $CommRound$ and $CommAmount$).
datasets. Since no data compression is adopted, the \textit{CommAmount} per round is the same for FedSGD and FedAvg under the same ML model. The total \textit{CommAmount} is linearly related to \textit{CommRound}. However, it is worth noting that the average amount of client’s uploading data is smaller in FedAvg because only parts of the clients participate in training in each round. In our experiments, the average amount of uploading data is 10\% of the receiving data in FedAvg because we set $C = 0.1$. We can further reduce the amount of receiving data by using a lazy updating strategy (i.e., only the clients that participate in the next round’s training download the latest weights). However, it may bring other issues, like the validation results could also be restricted to part of the clients, because only clients with the latest weights can perform the validation.

4.4 Time Evaluation

Table 4 shows the time consumption evaluation for FedSGD and FedAvg. FedAvg can reduce the time consumption (i.e., \textit{TimeAll}) by up to 71.9\% and 58.7\% compared with FedSGD on MNIST and FEMNIST datasets, respectively.

In FedSGD, \textit{TrainSync} and \textit{ValReq} are the two most time-consuming steps, because nearly all the data transmission happened in these two steps. Clients upload the local model in \textit{TrainSync} and download the latest weights in \textit{ValReq}. \textit{TrainRun} is significant in FedAvg because it increases the local training iterations. \textit{TrainSync} is relatively smaller in FedAvg, because of the partial participation in training.

\textbf{Time vs. Communication:} To further demonstrate that time consumption evaluation is non-trivial, we collect a group of FedAvg results on MNIST using different parameters: $B = 2 – 32$, $C = 0.1$, $E = 2 – 64$. We filter the results by requiring \textit{FLAcc} > 0.99 on the LeNet model and \textit{FLAcc} > 0.98 on the MLP model. Figures 3(b) and 3(c) show the relation of time and communication. The figures illustrate that the time consumption is not linearly correlated with the communication rounds in FedAvg. When the communication round is optimized, the time consumption might be very high.

4.5 Privacy Evaluation

In the gradient attack experiments, we calculate the gradients using parameters from two adjacent training steps. The attacks on FedSGD and FedAvg are distinct in the gradients’ formulation. In FedSGD, the gradients are produced by one step of training on the whole batch of data. In FedAvg, the gradients accumulate in multiple rounds of mini-batch training. The attack results are evaluated using the label accuracy\textsuperscript{11} and L2 distance between attack results and true images. Figure 4(d) shows some concrete attack examples. The restored images are clear, and the digits can be recognized. Thus both FedSGD and FedAvg have privacy issues. To further compare FedSGD and FedAvg and demonstrate what affects the gradient attacks, we perform experiments in the following aspects:

\textbf{Varying the number of images:} The subplots in Figure 4(a) show the attack results varying the number of images. With the increasing number of images, the label accuracy drops, and L2 distance rises in both FedSGD and FedAvg. Thus the gradient attacks are more difficult when the clients have more images.

\textbf{Varying the number of epochs in FedAvg:} Since the number of local training epochs (i.e., $E$) in FedSGD is fixed to one, we only present the attack results of FedAvg when changing the value of $E$, and Figure 4(b) shows the results. With the increasing number of training epochs, the L2 distance significantly rises in the DLG attack, and slightly grows in the FC attack.

\textsuperscript{11}Data label is one of the outputs in DLG attack. Thus we can directly compute its accuracy. In FC attack, we use a well-trained CNN model to determine whether the attack outputs and real images have the same label.
Figure 4: Figures 4(a) and 4(b) show the gradient attack results varying the number of images and training epochs. Figure 4(c) compares the FedSGD and FedAvg in the FC and DLG attack. Figure 4(d) presents some concrete examples of FC and DLG attack.

FedSGD vs. FedAvg: Figure 4(c) compares the attack results on FedSGD and FedAvg (B=1, E=20). In the FC attack, the label accuracy of FedSGD and FedAvg are very close, but the L2 distance of FedAvg is slightly larger. In the DLG attack, FedAvg has lower attack label accuracy and larger L2 distance compared with FedSGD. Thus, FedAvg has a better performance compared with FedSGD in resisting the FC and DLG attacks.

FC attack vs. DLG attack: The first subplot in Figure 4(a) compares the attack results of FC and DLG. The attack performances of these two methods are almost the same when the client has five (or fewer) images. However, when the client has ten or more images, the FC attack significantly outperforms the DLG attack model (i.e., FC attack has higher label accuracy and lower L2 distance).

We can conclude that both FedSGD and FedAvg have privacy issues, and FedAvg performs better than FedSGD in resisting the FC and DLG attacks. Meanwhile, the gradient attacks are more difficult when the clients have more images or perform more local training epochs.

4.6 Robustness Evaluation

Table 5: Robustness evaluation

| Dataset  | Model | IID | Acc | Central FedSGD | FedAvg | Acc |
|----------|-------|-----|-----|---------------|--------|-----|
| MNIST    | MLP   | IID | 0.988 | 0.983 | 0.985 |
| MNIST    | MLP   | 1-Class | 0.988 | 0.982 | 0.895 |
| MNIST    | MLP   | 2-Class | 0.988 | 0.983 | 0.979 |
| MNIST    | MLP   | 3-Class | 0.988 | 0.983 | 0.982 |
| MNIST    | LeNet | IID | 0.994 | 0.994 | 0.994 |
| MNIST    | LeNet | 1-Class | 0.994 | 0.991 | 0.933 |
| MNIST    | LeNet | 2-Class | 0.994 | 0.993 | 0.899 |
| MNIST    | LeNet | 3-Class | 0.994 | 0.993 | 0.982 |
| FEMNIST  | LeNet | IID | 0.850 | 0.848 | 0.846 |
| FEMNIST  | LeNet | Non-IID | 0.850 | 0.847 | 0.824 |
| CelebA   | LeNet | IID | 0.896 | 0.894 | 0.882 |
| CelebA   | LeNet | Non-IID | 0.896 | 0.894 | 0.874 |

Table 5 shows the non-IID evaluation on FedSGD and FedAvg. The results on MNIST show that FedAvg has up to 9% accuracy drop on the 1-Class non-IID setting (i.e., clients only have one class of images, which is clarified in section 4.1 Experiment Settings), and the problem gets relieved on 2-Class and 3-Class non-IID settings. On FEMNIST and CelebA, the performance of FedAvg also drops 2.2% and 0.8%, respectively. In contrast, FedSGD is barely influenced by the non-IID issue. The possible reason is that FedSGD has more global aggregations, which can reduce the negative impact of training on local non-IID data.
5 Related Works

Federated learning is an interdisciplinary field that includes but not limited to: distributed machine learning, non-IID learning, and privacy protection. Through substantial investigation of existing works, we can organize the FL research into three groups.

**Efficiency in FL:** McMahan et al. [30] first proposed the FedAvg model that improves communication efficiency by increasing the number of clients’ local updates, which is also called lazy updating. Gradients compression strategy is applied in some studies [2, 24, 38] to reduce the communication load when clients upload the gradients. However, after the aggregation on the server, the global gradients are not sparse anymore. Thus the download efficiency can not be improved. Thus Sattler et al. [36] designed an algorithm to optimize both the upload and download streams. Wang et al. [40] proposed an adaptive FL framework to determine the frequency of global aggregation so that the available resource is most efficiently used. According to our investigation, three frequently used metrics among these works are accuracy, communication rounds, and robustness. The time consumption and privacy issues, however, are overlooked.

**Non-IID in FL:** Jeong et al. [15] proposed an efficient FL framework that can solve the non-IID data problem. They used distillation methods to exchange the model outputs instead of the model parameters. Thus the communication efficiency is significantly improved. GAN is also applied in their work to generate missing data for clients to solve the non-IID data problem. Zhao et al. [44] proposed a data-sharing strategy to solve the non-IID issue. Although the accuracy is significantly improved, their method causes privacy leakage due to the shared dataset. Some works [6, 16] proposed to use Model Agnostic Meta-Learning (MAML) algorithm to solve the non-IID problem. Similarly, works in the current group also only considered accuracy, communication, and robustness as evaluation metrics. The time consumption and privacy issues, however, are still ignored.

**Attacks in FL:** Zhu et al. [45] proposed a deep gradients attack model that can recover the input images from model gradients. Their attack model reveals that the parameter exchanging strategy may also bring privacy leakages. Another type of FL attacks based on model poisoning [4, 9] can backdoor the FL systems. For example, attackers can force a word predictor to complete specific sentences with an attacker-chosen word. These attack models are critical because they help to pose privacy challenges and improve the security level of FL systems.

**Benchmarks in FL:** Caldas et al. [5] highlighted the issue of non-comparable FL evaluation results caused by inconsistent experiment settings, and published six standard federated learning datasets. Then they compared FedSGD and FedAvg regarding the non-IID problem on the released datasets. Hu et al. [13] proposed a benchmarking suite that evaluates FL methods in model utility, communication cost, privacy loss, and encryption overhead. Compared with existing FL benchmarking studies, our work proposes a more comprehensive evaluation model (i.e., the ACTPR model) that provides more thorough and convincing FL benchmarking results.

6 Concluding Insights and Future Works

In this paper, we propose a comprehensive FL evaluation model, ACTPR, which is pressingly needed to unreservedly present the advantages and disadvantages of FL systems and compare existing and future works from a common standpoint. Based on the benchmarking results of FedSGD and FedAvg, we have the following conclusions: (1) Accuracy: FedSGD and FedAvg both can converge to the accuracy of central training under proper training parameters, verifying that they both satisfy the performance specification of FL systems [42] (i.e., $F\text{LAcc}$ should be very close to $Central\text{Acc}$). (2) Communication and Time Consumption: FedAvg shows significant improvement in communication and time efficiency compared with FedSGD. We also find that the time consumption cannot be replaced by communication rounds in the evaluation, because they are not always linearly correlated. (3) Privacy: Both FedSGD and FedAvg have privacy issues. Generally, attacking FedAvg is harder than FedSGD, and the attack is more difficult when the clients have more data or do more local training iterations before uploading the parameters. (4) Robustness: While the non-IID issue barely influences FedSGD, FedAvg shows notable accuracy reduction under the non-IID setting.

When tuning the optimizer and LR, we come up with the following findings: (1) When using optimizers with momentum, such as Adam, the momentum values also need to be updated. Otherwise, the converged accuracy will decrease. (2) A large LR could accelerate the FL training, especially
for FedSGD. The LR for FL should be larger than non-federated ML training because the actual parameter updates shrink during the aggregation (i.e., weighted sum using weights smaller than one).

Based on the benchmarking study, we recommend three valuable research directions in FL: (1) Solutions for non-IID issue in FL. The non-IID issue is a key problem in FL because the data generation and storage cross numerous non-identical devices. Currently, there is no perfect solution for the non-IID problem. (2) Improving the efficiency of FL. Many works target improving the efficiency of FL; however, large deep learning models (e.g., MobileNet) still cannot be applied to FL due to low efficiency. Thus, more efficient FL solutions are required. (3) More powerful FL attack models. Attack models are essential in the FL area to anticipate and handle privacy issues.

In the future, we will keep including new metrics and technologies into the ACTPR model. The potential directions include but not limited to: (1) More attack models in FL, e.g., backdoor attacks [4, 9, 41], and model inversion attacks [8, 12]. (2) More robustness metrics, e.g., the stragglers and dropouts caused by system uncertainties. (3) More FL methods, e.g., FL with gradients compression [36]. (4) New privacy protection techniques, e.g., homomorphic encryption (HE) [1] and multi-party computation (MPC) [31]. (5) Adding the fairness metric into the evaluation model. According to recent works [32, 20], a qualified FL model should balance the model performance among the clients, i.e., ensuring fairness between the participants.

In particular, we consider evaluate the FL methods in the following directions (i.e., select one start-of-the-art method in each direction):

- Gradients compression methods [36, 23]: Gradients compression is regularly used in the data center’s distributed training. In federated learning, it reduces the amount of transmitted data in each round, which could help against the gradients attacks because the server learns less information from the gradients. On the other hand, we also need to evaluate the convergent speed because it may require more communication rounds or time to converge, and the converged accuracy under non-IID data also needs to be assessed.

- Methods of handling the data heterogeneity [21, 32, 39]: Data heterogeneity (i.e., non-IID data) problem is the key issue in FL, and we certainly need to report the comprehensive evaluation results of methods in this direction.

- Adaptive optimization methods in FL [33]: In our benchmarking experiments, we find that the optimizer and its parameter are vitally important, e.g., the learning rate in FedSGD needs to be larger to obtain a faster convergency. Thus methods of providing a better optimization in FL need to be better evaluated.

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Appendices

A Experiment settings

We perform the classification task on all the datasets. FEMNIST is an extended MNIST dataset based on handwritten digits and characters. CelebA builds on the Large-scale CelebFaces Attributes Dataset, and we use the smiling label as the classification target. On average, each client holds 300 images on MNIST, 137 images on the FEMNIST dataset, and 24 images on the CelebA dataset. At each client, we randomly select 80%, 10%, and 10% for training, validation, and testing. We use MLP and LeNet models in the experiments. The MLP model is implemented using two hidden layers with 512 units, ReLU activation, and dropout probability 0.2. The LeNet model is implemented using the same parameter with the work of LeCun et al. [19], and we use ReLU as activation. Since the models are required to be twice differentiable in the DLG attack, we change the ReLU activation to sigmoid and linear function in MLP and LeNet, respectively. The replacements are different because we compared available activations and chose the best one for each model.

All the experiments run on a cluster of three machines. One machine with Intel(R) Xeon(R) E5-2620 32-core 2.10GHz CPU, 378GB RAM, and two machines with Intel(R) Xeon(R) E5-2630 24-core 2.6GHz CPU, 63GB RAM. We put the server on the first machine and 40, 30, 30 clients on three machines, respectively. The maximum bandwidth between containers is 1Gb/s in our environment. We limit the clients’ bandwidth to 100Mb/s and do not restrict the server’s bandwidth. Since the number of clients in all machines is greater than the number of CPU cores, we do not restrict the clients’ computing resources.

B Results of tuning the optimizers and learning rates

Table 6: Tuning the optimizers (the bolded are the best accuracy)

| LR | MLP FedSGD | MLP FedAvg | LeNet FedSGD | LeNet FedAvg |
|----|------------|------------|--------------|--------------|
| 1e-4 | 0.963 | 0.985 | 0.972 | 0.995 |
| 5e-4 | 0.982 | 0.984 | 0.986 | 0.992 |
| 1e-3 | 0.984 | 0.982 | 0.979 | 0.996 |
| 5e-3 | 0.658 | 0.972 | 0.189 | 0.189 |
| 1e-2 | 0.170 | 0.973 | 0.281 | 0.990 |

CentralAcc: 0.988

Table 6 shows that Adam optimizer [18] can achieve the best accuracy more frequently, and it is more robust under different LRs compared with mini-batch stochastic gradient descent (SGD) and SGD with momentum optimizers. Thus we use Adam optimizer in the remaining experiments.

Table 7 presents the results using different LRs, where Acc is the accuracy, CR is the communication round, and TA is the time consumption in minutes. We say that the federated learning algorithm has δ-accuracy loss if $|FLAcc - CentralAcc| < \delta$ [42]. We define the best LR as the one that yields
Table 7: Tuning the learning rates (the bolded are the one with the least time consumption in 1%-accuracy loss results (i.e., $|FLAcc - CentralAcc| < 0.01$), or the one with highest accuracy if there is no 1%-accuracy loss result).

| Dataset          | MNIST Dataset | FEMNIST Dataset |
|------------------|---------------|-----------------|
|                  | MLP FedSGD    | MLP FedAvg      | LeNet FedSGD    | LeNet FedAvg    |
|                   | Acc | CR | TA    | Acc | CR | TA    | Acc | CR | TA    | Acc | CR | TA    |
| LR               |     |    |       |     |    |       |     |    |       |     |    |       |
| 1e-4             | 0.981 | 2000 | 855.5  | 0.983 | 132 | 22.3  | 0.984 | 2000 | 160.4 | 0.99 | 174 | 13.9  |
| 2e-4             | 0.984 | 775  | 322.4  | 0.986 | 81  | 13.7  | 0.995 | 1609 | 144   | 0.992 | 113 | 8.8   |
| 1e-3             | 0.983 | 427  | 177.3  | 0.982 | 92  | 15.8  | 0.992 | 1128 | 100.7 | 0.995 | 104 | 8.4   |
| 5e-3             | 0.982 | 141  | 59.1   | 0.974 | 60  | 10.4  | 0.993 | 286  | 26.1  | 0.99  | 90  | 7.3   |
| 1e-2             | **0.981** | **117** | **48.9** | 0.957 | 56  | 9.7   | **0.994** | **157** | **14** | 0.983 | 53  | 4.4   |
| **CentralAcc**: 0.988 |                 |                 | **CentralAcc**: 0.995 |     |    |       |     |    |       |     |    |       |

C Results of tuning the B, C, and E in FedAvg

Table 8: Results using different B and E in FedAvg (the bolded are the one with the least time consumption in 1%-accuracy loss results (i.e., $|FLAcc - CentralAcc| < 0.01$), or the one with highest accuracy if there is no 1%-accuracy loss result).

| Dataset | MNIST     | FEMNIST    | CelebA     |
|---------|-----------|------------|------------|
|         | MLP       | LeNet      | LeNet      |
| Model   | Acc | Time | CR | Acc | Time | CR | Acc | Time | CR |
| B       | C  | E    |    |     |     |    |     |     |    |
| 32      | 0.1 | 2    | 0.982 | 0:31:48 | 247 | 0.804 | 0:24:37 | 754 | 0.894 | 0:33:04 | 130 |
| 32      | 0.1 | 4    | 0.983 | 0:19:18 | 146 | 0.813 | 0:14:52 | 451 | 0.882 | 0:22:51 | 90  |
| 32      | 0.1 | 8    | 0.985 | 0:21:38 | 159 | 0.810 | 0:12:24 | 301 | 0.891 | 0:16:21 | 69  |
| 32      | 0.1 | 16   | 0.986 | 0:18:11 | 125 | 0.755 | 0:06:22 | 112 | 0.873 | 0:15:30 | 61  |
| 32      | 0.1 | 32   | 0.985 | 0:14:53 | 98  | 0.811 | 0:09:38 | 124 | 0.873 | 0:15:31 | 54  |
| 32      | 0.1 | 64   | 0.985 | 0:13:46 | 86  | 0.821 | 0:18:04 | 177 | 0.870 | 0:11:40 | 38  |
| 16      | 0.1 | 2    | 0.984 | 0:28:17 | 217 | 0.815 | 0:19:46 | 599 | 0.893 | 0:25:53 | 108 |
| 16      | 0.1 | 4    | 0.986 | 0:23:24 | 175 | 0.822 | 0:13:28 | 402 | 0.878 | 0:11:40 | 51  |
| 16      | 0.1 | 8    | 0.985 | 0:17:54 | 127 | 0.793 | 0:07:35 | 181 | 0.869 | 0:14:02 | 48  |
| 16      | 0.1 | 16   | 0.986 | 0:14:07 | 93  | 0.805 | 0:08:00 | 138 | 0.849 | 0:11:40 | 36  |
| 16      | 0.1 | 32   | 0.985 | 0:14:52 | 92  | 0.822 | 0:10:14 | 144 | 0.851 | 0:13:38 | 36  |
| 16      | 0.1 | 64   | 0.987 | 0:18:09 | 104 | 0.824 | 0:11:32 | 125 | 0.858 | 0:18:05 | 43  |
| 8       | 0.1 | 2    | 0.983 | 0:18:35 | 139 | 0.833 | 0:16:36 | 473 | 0.888 | 0:21:59 | 88  |
| 8       | 0.1 | 4    | 0.984 | 0:14:39 | 105 | 0.830 | 0:09:35 | 259 | 0.884 | 0:15:42 | 61  |
Table 8 shows the grid search results on $B$, $C$, and $E$ in different datasets. $B$ is the local batch size, $C$ is the ratio of clients that participate in each round of training, and $E$ is the number of local training passes (i.e., number of epochs). We use the same number of clients with McMahan et al. [30] (i.e., 100 clients), and they have shown that the best value of $C$ is 0.1 in different experiments. Thus, we only tune $B$ and $E$, and set $C = 0.1$. Using the same method of choosing the LR, we choose the $B$ and $E$ that yield the best time consumption in the 1%-accuracy loss results. If there is no 1%-accuracy loss result, we pick the parameters with the highest accuracy. The results of the best $B$ and $E$ are marked bold in the Table 8. The accuracy presented in the paper is slightly different from the best results in Table 8 because we repeat the experiments for 5-10 times and report the averaged accuracy in the paper.

### D Homepages of existing federated learning frameworks

- TFF [14]: https://www.tensorflow.org/federated
- FATE [42]: https://github.com/FederatedAI/FATE
- PaddleFL [28]: https://github.com/PaddlePaddle/PaddleFL
- LEAF [5]: https://github.com/TalwalkarLab/leaf
- PySyft [35]: https://github.com/OpenMined/PySyft
- FedML [11]: https://github.com/FedML-AI/FedML

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