FLBench: An Isolated Data Island Benchmark Suite for Federated Learning

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FLBench: An Isolated Data Island Benchmark Suite for
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Abstract

Federated learning (FL) is a new machine learning paradigm, the goal of which is to build a machine learning model based on data sets distributed on multiple devices—so called Isolated Data Island—while keeping their data secure and private. Most existing work manually splits commonly-used public datasets into partitions to simulate real-world Isolated Data Island while failing to capture the intrinsic characteristics of real-world domain data, like medicine, finance or AIoT. To bridge this huge gap, this paper presents and characterizes an Isolated Data Island benchmark suite, named FLBench, for benchmarking federated learning algorithms. FLBench contains three domains: medical, financial and AIoT. By configuring various domains, FLBench is qualified for evaluating the important research aspects of federated learning, and hence become a promising platform for developing novel federated learning algorithms. Finally, FLBench is fully open-sourced and in fast-evolution. We package it as an automated deployment tool. The benchmark suite will be publicly available from http://www.benchcouncil.org/FLBench

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1 Introduction

The concept of Federated Learning (FL) was recently proposed by Google. The main idea is to build a machine learning model based on data sets distributed on multiple devices—so called Isolated Data Island—while preventing data leakage [1,2,3]. FL has become a hot research topic in both industry and academia [4,5,6]. Unfortunately, most existing work [7,8,9,10,11,12,13] manually splits commonly-used public data sets into partitions to simulate isolated data island, however, they fail to capture the intrinsic characteristics of real-world domain data.

On one hand, there is a huge difference between the simulated isolated data island scenario and the real-world Isolated Data Island, which leads to that the FL algorithms developed based on the simulated one cannot be migrated to real-world Isolated Data Island. For example, Yurochkin [11] utilized the image data of MNIST and CAFAR-10 to simulate an Isolated Data Island scenario. However, there is a huge difference between the real-world Isolated Medical Data Island and the simulated one based on MNIST and CAFAR-10. For example, in an Alzheimer’s diagnosis scenario, it is a CT image—a 3d black and white image, so the FL algorithms developed on the MNIST and CAFAR-10 data sets is hard to migrate to an Alzheimer’s diagnosis scenario.

On the other hand, the characteristics of simulated isolated data island, which is manually splited, are different from those of the real-world one. For example, in centralized training, data can be assumed to be independent and identically distributed (IID), this assumption is unlikely to hold in federated learning settings. For example, Chandra [14] et al. use the MNIST and CIFAR-10 datasets to simulate an Isolated Data Island scenario, and assume that the datasets are random, disjoint and evenly distributed between clients. However, in the real scene, the data of medical image will involve the magnetic field intensity issue. For example, the magnetic field intensity at 1.5T and the magnetic field intensity at 3T of the same image will show different lesions. The more details are shown in Table 1.

We observe that there have been some researches on FL benchmarking. Due to the huge gap between the simulated isolated data island and the real-world one, FedML [17] and OARF [18] fail to achieve the goal to some extent. FedML [17] focuses on how to deploy the benchmark to distributed training, mobile device training, and stand-alone simulation. However, the authors fail to justify their methodology for choosing data sets and workloads scenarios. The common datasets (CIFAR-10, CINIC-10) are partitioned for each participant with an ad-hoc method. Hu et al. [18] show that the benchmark suite is diverse in terms of data size, distribution, feature distribution and learning task complexity, but it focuses on benchmarking systems in stead of algorithms, while the latter is a focus. Luo and Hsu [19,20] presume independent and identical distribution, which are seldom followed in real-world domain data.

Therefore, this paper calls attention to building an FL benchmark suite to provide various Isolated Data Island scenarios. We propose a configurable benchmark, covering three most concerned domain (medical, financial and AIoT), to evaluate different FL algorithms of different research aspects (communication, scenarios transformation, privacy-preserving, data distribution heterogeneity and cooperation strategy). In addition, FLBench also provides different Isolated Data Island domains for developing novel FL algorithms as the real-world Isolated Data Island domain is unavailable for most of researchers. Table 2 summarizes the key differences between FLBench and existing FL libraries and benchmarks. Our key contributions are:

1) We propose a configurable FL benchmark suite—FLBench, which is able to simulate various Isolated Data Island domains according to the requirements of specific researches.

2) FLBench covers three most concerned domains: medical, financial and AIoT. For each kind of scenario, FLBench is able to simulate different scenario to satisfy the requirements of five kinds of researches (communication, scenarios transformation, privacy-preserving, data distribution heterogeneity and cooperation strategy).

3) FLBench provides a fair comparison to evaluate different FL algorithms. Meanwhile, FLBench provides various customized scenario for developing novel FL algorithms.

4) FLBench is packaged as an automated deployment tool and can be deployed in mobile, distributed and standalone manners.
2 Related Work

2.1 Federated Learning

Federated Learning is to build a machine learning model based on data sets distributed on multiple devices, while preventing data leakage [1][2][3]. According to the distribution characteristics of data, FL is mainly divided into horizontal federal learning, vertical federal learning and federal transfer learning. However, the benchmarking of FL algorithm should consider the innovation and performance of the algorithm, so we design a new benchmark by evaluating the performance of the algorithm from different innovation directions. Specifically, according to the innovation and performance of the algorithm, we consider the following properties:

1) Communication. In the federated network, communication is a key bottleneck. In addition to the privacy problem of sending original data, the data generated on each device must be kept local. In fact, a federated network may consist of a large number of devices, such as millions of smartphones, and the speed of communication in the network may be many orders of magnitude slower than local computing. In order to match the model with the data generated by the devices in the federated network, it is necessary to develop a communication efficient method to send small messages or model updates alliteratively as part of the training process [2][21].

2) Scenarios Transformation. At present, the main idea of scene transformation is to apply mature algorithm model to data island scene. This enables people to explore the training statistical model on remote devices by changing the scene. Scene transformation learning is significantly different from the traditional distributed environment. The essence of scene transformation is to deploy federated learning method, which makes federated learning play a key role in supporting privacy sensitive applications [22][16].

3) Privacy-preserving. Privacy is often a major concern in federated learning applications. Federated learning takes a step towards protecting the data generated on each device by sharing model updates (such as gradient information) rather than raw data. However, during the whole training process, the model updating communication can still display sensitive information to the third party or central server. Although recent methods aim to enhance the privacy of Federated learning by using tools such as secure multiparty computation or differential privacy, these methods usually provide privacy at the cost of reducing model performance or system efficiency. Understanding and balancing in theory and experience [23][24][25][26].

4) Data Distribution Heterogeneity. Devices often generate and collect data on the network in a non IID manner. For example, mobile phone users use different languages in the context of the next word prediction task. In addition, the number of data points across devices may vary greatly, and there may be an underlying structure that captures the relationships between devices and their related distributions. This data generation paradigm violates the i.i.d. assumption that is often used in distributed optimization, increases the likelihood of stragglers, and may increase the complexity of modeling, analysis, and evaluation [2][13][12][16]. In addition, data heterogeneity also includes the characteristic heterogeneity of other data, such as small sample data of intelligent terminal, which cannot form a stable distribution. This is a problem that has not been considered in FL algorithms benchmarking.

5) Cooperation Strategy. In order to fully commercialize federal learning between different organizations, it is necessary to develop a fair platform and cooperation strategy. After the model is established, the performance of the model will be reflected in practical application, which can be recorded in the permanent data recording cooperation strategy (such as blockchain). Organizations that provide more data are better off, and the effectiveness of the model depends on the contribution of the data provider to the system. The effectiveness of these models is based on the federation mechanism distributed to all parties and continues to motivate more organizations to join the data federation [27][28][26].

2.2 Benchmarks

In recent years, benchmarks have played an important role in the machine learning area, such as MLPerf [29][30], AI-Bench [31], Edge AI-Bench [32] and DAWN-Bench [33]. These benchmarks have provided
various metrics and results for machine learning training and inference. However, today’s AI faces two major challenges. First, in most industries, data exists in the form of islands; second, data privacy and security. However, in many cases, we are forbidden to collect, fuse and use data in different places for AI processing. How to solve the problem of data fragmentation and isolation legally is a major challenge for AI researchers and practitioners. Therefore, many researchers have proposed a possible solution: safe federated learning [1, 2, 3].

Looking back in history, we observe that there have been some researches on benchmarking for federated learning, but due to the huge gap between simulation and real scenarios, it has not been solved well, such as FedML [17] and OARF [18]. FedML [17] conduct experiments in different system environments, but they did not give the build process of benchmark; OARF [18] shows that the benchmark suite is diverse in data size, distribution, feature distribution and learning task complexity, but they lack of benchmarking of algorithm level. In addition, [19, 20] show the research directions are relatively simple, and mainly focusing on independent and identical distribution. Many benchmark tests have not fully covered the current three application scenarios of federated learning: medical scenario, financial scenario and intelligent terminal.

3 FLBench Methodology and Design

This section presents our methodology, decisions and implements on FLBench.

3.1 FLBench Methodology

The emergence of FL is to solve the machine learning problem in the 'Isolated Data Island' scenario. However, the previous FL benchmarks only provided one or several 'Isolated Data Island' scenarios, and the scenarios are very different from the real ones. Thus, we propose an FL benchmark based on configurable scenarios, which restores the 'Isolated Data Island' scenario in the real world to evaluate the performance of federated learning algorithms and provides realistic 'Isolated Data Island' scenarios for the research and development of FL algorithms.

1) We investigate the most concerned 'Isolated Data Island' scenarios. The candidate scenarios involve many subjects such as medicine and electricity. However, for a benchmark, it is impossible and unnecessary to provide all 'Isolated Data Island' scenarios, since all of the real 'Isolated Data Island' scenarios are confidential and providing so many scenarios is very costly. Thus, the first step to construct an FL benchmark is selecting several kinds of scenarios to cover the research problems of FL.

2) According to the output from Step 1), the data generated by several kinds of real 'Isolated Data Island' scenario need to be collected for constructing the 'Isolated Data Island' scenario. Meanwhile, the complex data pre-process, which requires professional domain knowledge, is concluded in this step.

3) According to the output from Step 2), we propose configurable 'Isolated Data Island' scenarios to evaluate FL algorithm. The most concerned about algorithm evaluation is fairness and algorithm robustness. It requires the FL benchmark is able to provide various scenarios according to the specific researches for every domain. However, it is very costly to construct scenarios for every potential specific research. Thus, in this step we designed the user-oriented configurable 'Isolated Data Island' scenario.

4) According to the output from Step 3), we construct two main kinds of scenario for FL algorithm. For an FL benchmark, two main functions are necessary: a)provide a consistent scenario, which refers to a fixed set of scenarios provided for all algorithm evaluations in a research direction of an application domain, for the fair comparison of FL, b)provide a easily utilized customized scenario for development of novel FL algorithm. Thus, in this step we divide 'Isolated Data Island' scenarios into two kinds of scenario for above functions. In addition, specific evaluation metrics for every scenario is proposed.

5) On the basis of the above outputs, we design and implement a automated deployment tool to deploy the scenario on different platforms, and provide a suite APIs for calling scenarios.
3.2 FLBench Design

Today's artificial intelligence still faces two major challenges. One is that, in most industries, data exists in the form of isolated islands. The other is the strengthening of data privacy and security. As analyzed in the FLBench requirements, FLBench framework (shown in Figure 1) including four parts.

**Input Data**: Most of the current researches on FL is carried out on the simulation scenario, which is constructed by common used dataset such as CIFAR-10, since it is very difficult to access the real 'Isolated Data Island' scenario for researchers. However, there is a huge difference between the data of common used dataset and the classic real 'Isolated Data Island' scenario data in data type and data mode, which leads to that FL algorithms developed based on simulated data cannot be migrated to real typical data island scenarios. To solve this issue, we collect data from three most concern data island scenarios include medicine, finance and intelligent terminal. In addition, a special data pre-process suite is necessary for medicine data, sine medicine data need special processing.

**Scenario Configuration**: In order to achieve the robustness and multi-faceted evaluation of the algorithm, we propose a scenario configuration function. First, we make statistics on the current innovation methods of federal learning research, and then classify the innovation directions of federated learning into the following categories: communication, scenarios transformation, privacy-preserving, data distribution heterogeneity, cooperation strategy. Second, for each innovation direction on each domain, we provide a basic configuration according the native distribution of data, and a API to modify the configuration to simulate various scenario according requirements.
Scenario: Benchmark has two functions: first, it provides an open and a fair comparison; second, it will provide research basis for later researchers to develop more advanced algorithms and determine the selection of some important parameters. Thus, we construct two kinds of scenarios: consistent scenario and customized scenario according to modifying the basic configuration for above functions. In addition, the most common used metrics are also used to evaluate the FL algorithm.

Automated Deployment Tool: FLBench will be updated step by step to make it adapt to the future development needs. In addition, we continue to expand the benchmark and provide more APIs, excuses and other scenarios benchmarking. We hope that more people will join our benchmark research, which will make our benchmark more perfect and comprehensive.

3.3 FLBench Implement

Currently, the FLBench contains: four datasets(medicine: ADNI [34], MIMIC-III [35]; finance: Adult dataset [36]; AIoT: iNaturalist-User-120k [20]), one basic configuration file(Alzheimer’s diagnosis scenario configuration). The Alzheimer’s diagnosis scenario configuration is able to provide various scenarios for NO-IID (data distribution heterogeneity) researches in medicine domain. Researchers will be able to download our FLBench on BenchCouncil soon.

FLBench is a fully open and evolving benchmark, next we will based on the FLBench framework provide $3 \times 3 = 9$ datasets for three domains(medicine, finance, and AIoT), $3 \times 3 \times 5 = 45$ basic configuration files on different research aspects(communication, scenarios transformation, privacy-preserving, data distribution heterogeneity, and cooperation strategy). Each configuration file is able to provide various scenarios according to the requirements of the specific research.

4 Conclusion

This paper proposes a benchmarking methodology based on configurable Isolated Data Island scenario. We propose a scenario configure method to simulate the real-world Isolated Data Island application scenario. First, we consider medicine, finance, and AIoT as three main Isolated Data Island application scenario, which cover the most concern FL research. Second, to evaluate the innovation of the FL algorithm, we design basic configuration for every research aspects to simulate the Isolated Data Island scenario which contains the real-word problem in the research aspect. Final, we design and implement a configurable benchmark framework, which is able to deploy on different platform and provide simple APIs to users. As a fully open and evolving benchmark, the first version FLBench will be download on BenchCouncil website soon.

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Table 1: Statistics of Datasets and Models in the Latest FL Publications.

| Conference | Datasets | Simulation means | Isolated Data Island | Task | consistent OR inconsistency | Suitable for a real scene |
|------------|----------|------------------|----------------------|------|-----------------------------|--------------------------|
| ICLR [1]   | MNIST; CIFAR-10; Tiny-imagenet | Training: 80%; Testing: 20% | No | Image classification and loan status prediction | inconsistency | No |
| RML [8]    | Adult dataset, Cornell movie dataset, Penn TreeBank (PTB) dataset, Fashion MNIST | Adult data and Fashion MNIST | No | Census income forecast, language modeling and image classification | consistent | Yes |
| ICLR [15]  | Public datasets and Synthetic dataset | – | No | Image classification, emotion analysis, language modeling, vehicle prediction | inconsistency | No |
| ICLR [9]   | MNIST | MNIST equilibrium and MNIST un-equilibrium | No | Image classification | inconsistency | No |
| ICLR [16]  | MNIST, Amazon Review, DomainNet, Office-Caltech10 | 10 Titan-Xp GPU cluster and simulate the federated system on a single machine | No | Image classification, target recognition, domainnet, emotion analysis | consistency | Yes |
| ICML [10]  | Fashion-MNIST, UCI Adult census dataset | Fashion MNIST and UCI adult census dataset | No | Image classification and census income forecast | inconsistency | No |
| RML [11]   | MNIST, CIFAR-10 | Randomly divided into J batches | No | Image classification | inconsistency | No |
| RML [12]   | CIFAR-10/100; FEMNIST; PersonaChat | CIFAR and FEMNIST | No | Image classification, dialogue prediction for personality | inconsistency | No |
| RML [13]   | MNIST, CIFAR-10, Shakespeare dataset | One centralized node in the distributed cluster is regarded as the data center, and the other nodes are regarded as local clients | No | Image classification, language modeling | Image classification: inconsistent; Language modeling: consistency | No |

a Data exists in the form of isolated islands in real scene.
b Whether the features of the simulated scene are consistent with those of the real scene
c Whether it is used in the real scene or can it be migrated to the real scene
d Training: 80%; Testing: 20%; The training set was equally divided into 100 participants
e Adult data: divide the dataset into two domains with and without doctorates; Fashion MNIST: We extracted three categories of data subsets: T-shirts, pullovers, and shirts, and then divided this subset into three areas, each containing a garment.
f Public datasets: Vehicle dataset; text data built from The Complete Works of William Shakespeare; Omniglot; tweet data curated from Sentiment 140.
g The former is balanced so that the number of samples on each device is the same, while the latter is highly unbalanced. The number of samples between devices follows the power law.
h Fashion MNIST: A 3-layer convolutions neural network (CNN) based on offline model is used. UCI adult census dataset: uses fully connected neural networks.Set the number of agents K to 10 and 100. When k = 10, all agents are selected in each iteration, while when k = 100, one tenth of agents are randomly selected in each iteration.
i These datasets were randomly divided into J batches. Two partitioning strategies are of interest: (a) uniform partitioning, in which each k class in each batch has approximately equal proportions; and (b) miscellaneous new partitions with unbalanced batch size and class proportions.
j CIFAR: using 50000 training data points and 10000 validated standard training / test splits. The dataset is divided into 10000 (CIFAR10) and 50000 (CIFAR100) clients. Each client has five (CIFAR10) and one (CIFAR100) data points from a single target class. In each round, 1% of the clients participated, resulting in a total batch size of 500 (100 clients of CIFAR10 have 5 data points, and 500 clients of CIFAR100 have 1 data point). Femlist: resnet101 with 40m parameters is trained with hierarchical specification instead of batch specification, and the average batch size is about 600 (but depending on the customers involved). The standard data is enhanced by image transformation and triangle learning rate plan.
k For the CIFAR-10 dataset, data enhancement (random clipping and flipping) is used and each individual image is normalized (details are provided in the supplement). Two data partitioning strategies are considered to simulate the joint learning scheme: (I) homogeneous partitioning, in which the proportion of each local client in each class is approximately equal; (II) heterogeneous partitioning where the number of data points and the proportion of classes are unbalanced. For Shakespeare’s dataset, we treat each speaking role as a client, resulting in naturally heterogeneous partitions. We preprocess Shakespeare dataset by filtering out clients with less than 10k data points and sampling a random subset of J = 66 clients. We allocate 80% of the data for training and merge the rest into the global test set.
| Scenario Configuration | Given Consistent Scenario | Customized Scenario | Medicine | Finance | AIoT | Evaluation Metrics | Automated Deployment Tool |
|------------------------|---------------------------|---------------------|----------|---------|-----|-------------------|--------------------------|
| FedML [17]             | X                         | √                   | X        | X       | X   | √                 | X                        |
| OARF [18]              | X                         | X                   | X        | X       | X   |                   |                           |
| IDFL [20]              | X                         | X                   | X        | X       | X   | √                 | √                        |
| FVC [19]               | X                         | X                   | X        | X       |     | √                 | X                        |
| FLBench                | √                         | √                   | √        | √       | √   | √                 | √                        |