# The OARF Benchmark Suite: Characterization and Implications for Federated Learning Systems

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## **Abstract**

This paper presents and characterizes an Open Application Repository for Federated Learning (OARF), a benchmark suite for federated machine learning systems. Previously available benchmarks for federated learning have focused mainly on synthetic datasets and use a very limited number of applications. OARF includes different data partitioning methods (horizontal, vertical and hybrid) as well as emerging applications in image, text and structured data, which represent different scenarios in federated learning. Our characterization shows that the benchmark suite is diverse in data size, distribution, feature distribution and learning task complexity. The extensive evaluations with reference implementations show the future research opportunities for important aspects of federated learning systems.

### 1 Introduction

Federated Learning (FL), first introduced by McMahan et al. [38], is a technique that enables multiple parties to train a model collaboratively without leaking their private data. Recently, FL has become a hot research topic in both industry and academia [54, 30]. Various machine learning models, communication methods, privacy-preserving methods and data splitting schemes have been researched under federated settings. Despite of the success in those research and development, a new benchmark suite is urgently needed to study and compare various FL designs, and help guide the design and implementation of future FL systems.

Looking back in history, we observe that benchmarks have played an important role in the machine learning area. Benchmark suites like DAWNBench [8] and TBD [62] have provided various benchmark metrics and results for deep learning training and inference. These benchmarks facilitate the comparison between machine learning frameworks and models. However, compared to the machine learning area, we found that there lacks a federated learning benchmark for researchers and developers to reference.

A good benchmark for FL systems needs to address a series of factors. First, it needs to reflect the real-world scenarios by providing dedicated datasets and workloads. Second, it needs to include various metrics and measuring methods to depict a full picture of FL systems. Recent surveys on federated learning [30] suggested that in addition to the issues already exist in the machine learning area, there are at least data partitioning, privacy, communication, fairness issues that need to be identified.

Taking these factors into consideration, we present OARF, a benchmark suite that aims to evaluate and study the properties of different FL systems, and provides tools to help design next generation FL platforms. There are many open problems in the important aspects of federated learning systems including model accuracy, communication cost, differential privacy, secure multiparty computation

and vertical federated learning. ORAF ensembles diversified workloads to *quantitatively* assess each of those aspects. Our work highlights the following contributions.

We assemble representative datasets and design representative workloads to reflect real-world scenario. In real-world scenarios, datasets are often from different parties and heterogeneous. We have collected and assembled real-world datasets from different sources and designed workloads covering numerous domains to reflect this situation.

We study the intrinsic properties of federated learning and its components. We study the intrinsic properties of FL systems, including the relations between various design metrics such as data partitioning, privacy mechanisms and machine learning models. These properties enrich our knowledge of the internal mechanism for federated learning, provide valuable experience for the industry needs, and provide suggestions on building future FL frameworks.

We provide reference implementations and show the future research opportunities for important aspects of federated learning systems. We provide reference implementations to our studies for better reproducibility and modularity. Each reference implementation evaluates one or more properties stated above. We conclude the common evaluation results of these implementations as our findings and research opportunities for future FL systems. One finding is that, FL systems can outperform the solo-learning system with local data set of each party, but still have reasonable room for accuracy improvement compared with centralized training (without privacy constraints). The other is, homomorphic encryption (HE), which is widely used in numerous FL algorithm design, is indeed prohibitively costly for practical usage. This calls for the further research on the novel usage of HE in FL systems.

# 2 Background and Related Work

**Federated Learning:** Recent surveys by Li et al. [30] and Yang et al. [54] indicate that federated learning is a combination of various techniques in multiple areas, including data partitioning, machine learning model, privacy and communication. Designing a good benchmark that measures the performance of all these aspects and their mutual effects is inherently challenging. Specificially, we consider the following properties: 1) *Models:* Existing efforts have developed federated algorithms for neural networks [48, 38, 47], tree-based models [29, 6], linear models [22, 40] or other types of models. 2) *Data partitioning* is another important concept that needs to be considered in our work. [54] introduced three partition schemes in their work: horizontal, vertical and hybrid, where horizontal FL uses datasets that share feature space but not sample space, vertical FL uses datasets that share sample space but different in feature space, and hybrid FL is the combination of both. 3) *Security and Privacy:* Secure multiparty computation (SMC) [55], homomorphic encryption [17] and differential privacy [14] are widely used to protect the security in the training, communication and model release process. 4) *Communication architectures* [30] and communication cost [48] are two of the major concerns in FL systems due to their impacts on model performance.

**Federated Learning Benchmarks:** There have been some initial efforts for benchmarking FL systems. Table 1 summarizes the characteristics of these benchmark-related works. To the best of our knowledge, there is no benchmark that is using federated datasets currently, where real datasets in different parties come from different sources. There is no benchmark that is comprehensive enough to evaluate the four important aspects of federated learning.

Name	Federated Dataset	Partitioning Scheme	Various ML Models	Privacy Mechanism	Comm. Cost
LEAF [4]	Х	Х	✓	✓	<b>√</b>
Nilsson et al. [41]	X	X	X	X	✓
Street Image [35]	X	X	✓	X	✓
Edge AIBench [21]	X	X	✓	X	X
Liu et al. [33]	X	X	X	X	✓
OARF (our work)	✓	✓	✓	✓	✓

Table 1: Comparison of FL Benchmarks

We introduce more details about existing FL benchmarks. LEAF [4] provides several image/text datasets and a set of reference implementations using federated averaging. However, LEAF only focuses on the massively cross-device scenario, where federated learning is performed on a massive number of devices, but neglects the cross-silo scenarios. Nilsson et al. [41] have proposed a benchmark using Bayesian t-test to measure the performance of different FL algorithms such as Federated Averaging (FedAvg). Luo et al. [35] have proposed a street image dataset for federated learning to provide high-quality labeled data for FL research. They evaluated accuracy and communication costs of YOLO and Faster R-CNN under different settings. Liu et al. [33] have introduced an evaluation framework for large-scale benchmark which focuses on communication costs.

## 3 The OARF Benchmark Suite

## 3.1 OARF Design Principles

This paper aims at providing researchers and developers with a comprehensive, easy-to-use benchmark suite, with the following design principles. First, Emerging Frameworks. To keep up with the rapid development of FL, we carefully select datasets, workloads and reference implementations in order to have a high relevance to the state-of-the-art in FL#. Second, **Diversity of Workloads.** Federated learning can be used in a number of domains, such as biology, finance and mobile applications. Tasks in different domains vary greatly from each other. Data formats the machine learning models vary from task to task. For different tasks, the data distribution and data partitioning scheme are also different. Although it is impractical to design a benchmark to cover all kinds of tasks, efforts are made in OARF to maximize the diversity of workload, so that different types of tasks and the corresponding applications can be characterized. Third, Comprehensiveness, Federated learning can be characterized in various ways. As stated previously, it can be at least categorized by: 1) Partitioning scheme, including horizontal, vertical and hybrid federated learning, 2) Underlying models, including decision trees, different types of neural networks and other machine learning model as the underlying model. 3) Privacy and security mechanisms, including secure multiparty computation and differential privacy. 4) Communication architectures, including synchronous/asynchronous, as well as centralized/decentralized design. To cover all these aspects, OARF uses various metrics to measure the performance of each component in federated learning, and explore how they contribute to the entire learning process. Fourth, **Openness.** Since federated learning is a rapidly developing field, we make OARF open to modification and addition. OARF users can easily contribute or modify different parts of OARF to meet their specific requirements.

# 3.2 Overview

Figure 1 shows the structure of the OARF benchmark. It adopts a layered design, with three layers namely Metrics, Tasks (Workloads), and Reference Implementations. Each layer can be extended or enhanced accordingly. We pick tasks according to the properties of these aspects and the requirements for cross-silo federated learning setup, with respect to the partitioning scheme, the domain and models. A task and one or more metrics are combined into a reference implementation to reveal the intrinsic properties.

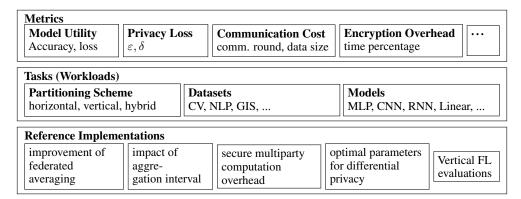


Figure 1: OARF benchmark components

The components in the benchmark suite are carefully chosen to achieve our design principles: 1) Emerging workloads: we use up-to-date datasets like Video Game Sales and up-to-date federated learning framework like PySyft for our training. 2) Diversity: we use text, image and structured data in our datasets, and cover different domains, including CV and NLP. Our tasks use various models, including CNN and RNN. 3) Comprehensiveness: Our tasks consist of both horizontal and vertical federated learning, and we benchmark each task from multiple aspects. 4) Openness: All our reference implementations are publicly available and open to modification. The following parts of this section elaborate on the tasks we provide in the OARF benchmark suite.

**Metrics:** Based on the major components in FL systems, we provide four types of metrics to evaluate a FL system. For the model utility, we use accuracy and loss that are often considered in machine learning benchmarks [8, 62]. For privacy measurement, we adopt the definition of  $(\varepsilon, \delta)$ -differential privacy [1] to describe the privacy loss, and measures utility under different DP setup. The communication cost is captured by both communication rounds and amount of data transferred in each communication, likewise, model utility is used to measure the impact of different communication settings. Finally, encryption overhead is described by the training time overhead and model utility changes.

## 3.3 Workloads and Reference Implementations

Table 2: A list of tasks and corresponding datasets. In the title,  $P^1$  is Data Partitioning, and  $D^2$  is Domains. The Steam Game dataset<sup>†</sup> only counts the number of games, and there is also players' information in this dataset. The IMDB Movie dataset<sup>‡</sup> counts only the number of unique titles.

$P^1$	$D^2$	Task	Datasets	# instances
			All-Age-Face [5]	~13k
			APPA-REAL [2, 7]	~7.6k
		Gender / Age	OUI Audience Face [16]	~26k
		Prediction	IMDB-WIKI – 500k [44]	~52k
			Labeled Faces in the Wild [27, 26]	~13k
_	CV		BUPT-Balancedface [49, 50, 51]	~1.25M
Horizontal	O	Face Recognition	Racial Faces in-the-Wild [49, 50, 51]	~40k
Hor		Alphanumeric Character Recognition	Chars74K [10]	~74k
		Chinese Character	HIT-OR3C [61]	~460k
		Recognition	CASIA-HWDB1.1 [46]	~1.1M
	Д́	Continued Analysis	IMDB Movie Review [36]	~50k
	NLP	Sentiment Analysis	Amazon Movie Review [37]	~8M
	S	Traffic Prediction	METR-LA [28]	~34k
	GIS	Traine Prediction	PEMS-BAY [32]	~52k
		Tour d Dur di eti en /	Steam Game <sup>1</sup>	~17k <sup>†</sup>
р		Trend Prediction / Recommendation	IGN Rating <sup>2</sup>	~18k
ybri	AL.	Recommendation	Video Game Sales <sup>3</sup>	~55k
/ H	General ML	Trend Prediction /	MillionSong [3]	~1M
cal	ner	Recommendation	Free Music Archive [11]	~106k
Vertical / Hybrid	Ge	Trend Prediction /	MovieLens 1M [23]	~1M
		Recommendation	Movie Industry [18]	~6.8k
		Recommendation	IMDB Movie [36]	~4M <sup>‡</sup>

To cover various scenarios of federated learning, we collected public available datasets, and categorize them by data partition schemes and tasks, as shown in Table 2. Different datasets belonging to the same task can be used to simulate data possessed by different parties. All these datasets are from different sources, which means that they are "naturally" owned by different parties instead of split from a single dataset. Datasets like these more precisely reflect how data is distributed in real-world federated learning tasks.

In the following, we only describe the tasks and datasets that are demonstrated in the experiment section. A complete list of descriptions are shown in the appendix.

Chinese Character Recognition Handwritten character recognition has been extensively studied for decades and achieved impressive progress with the emergence of deep learning. Chinese character recognition is more challenging than alphanumeric character recognition due to a larger number of categories and more complex character structures. In our setting, new challenges arise due to various image quality and handwriting styles on different datasets. Works by Zhong et al. [60] and Xiao et al. [53] present CNN structures and variations that reach state-of-the-art results on the problem.

Reference implementation: We set up our federated task with datasets CASIA-HWDB1.1 and HIT-OR3C and use a variation of VGG structure [45] as our underlying model. The task is trained on a CNN model that consists of 11 convolutional units, a 3-layer MLP and a softmax layer for the prediction. For both of the datasets, we use 80% of the character writers for training, in which 20% is used for validation. The rest 20% of the data is for testing. As the amounts of data trained on two parties are different, we also assign weights to each parties' model parameters, and the weights are proportional to the number of records in each parties' training dataset respectively.

**Sentiment Analysis** Sentiment analysis is a technique that uses natural language processing and text analysis to study and predict affective states. The emergence of machine learning has greatly propelled the study in this area. Recent works [52] and surveys [58] have proved that LSTM is effective for this kind of task. Today, various rating websites like IMDB and Rotten Tomato provide a large amount of data for the training of sentiment analysis model.

Reference implementation: We apply federated averaging to an LSTM model, and use movie review data from Amazon and IMDB for the training. Limited by the GPU capacity and training time, We use the whole 50,000 entries in IMDB Movie Review dataset and randomly sampled the same amount of entries from the Amazon Movie Review dataset as the training data. The labels are i.i.d. distributed, where 50% of the sentences are marked as positive and the other 50% negative. For both datasets, we use 80% data for training, 10% for validation and 10% for testing, all of which are identically distributed. The task is trained on LSTM model that consists of an embedding layer with the dimension of 512, two LSTM layers with the hidden dimension of 256, a dropout layer with dropout probability of 0.3, a fully connected layer and a sigmoid layer for the output. The output of the model is a binary label indicating whether the given text segment is positive or negative.

**Year Prediction** Year-Prediction is a regression task for predicting the release year of songs or musics, based on the audio features such as "energy" or "danceability".

Reference implementation: We use the audio features and release year labels in the MillionSong dataset (MSD) and Free Music Archive dataset (FMA) for our prediction. For predicting the year label of single datasets and the combined dataset, A simple MLP model with two hidden layers and one output neuron is used for training, where the first layer is twice as large as the input layer and the second layer is half as large as the input layer. For federated learning, we adopt the SplitNN [19] model, which concatenate one layer of two separate models and passes it as the input to the third model. To make the federated method comparable to the non-federated one, we use the same MLP structure for each parties as when training for single datasets, and concatenate the second hidden layer of the two networks and connect the concatenated layer to the output neuron for prediction.

**Recommendation** Recommendation system has become a core component in various industry applications such as product promotion and advertisement display [42]. As the three groups of movie datasets listed in Table 2 contain user information and movie information, we perform federated recommendation based on these datasets.

<sup>3</sup>https://steam.internet.byu.edu/

<sup>3</sup>https://github.com/john7obed/ign\_games\_of\_20\_years

<sup>3</sup>https://github.com/ashaheedq/vgchartzScrape

Table 3: Accuracy and loss. "Val. Loss" for validation loss.

(a) Chinese character recognition

(b) Sentiment analysis

Training	Tes	st Dataset		Val.	Training	Te	st Datase	et	Val.
Dataset	Combined	CASIA	HIT	Loss	Dataset	Combined	IMDB	Amazon	Loss
CASIA	93.7%	92.8%	95.7%	0.41	IMDB	82.3%	84.9%	79.5%	0.39
HIT	77.5%	68.5%	97.1%	1.95	Amazon	83.3%	80.4%	86.1%	0.40
Combined	94.8%	93.2%	98.2%	0.33	Combined	<b>87.1</b> %	86.6%	87.2%	0.37
FedAvg	95.4%	94.1%	98.5%	0.27	FedAvg	86.0%	85.1%	86.7%	0.34

Reference implementation: We split the MovieLens 1M dataset into two parties, with one of them having the rating matrix and the other containing the auxiliary information of users and movies. The two parties can then be vertically federated to predict a user's preference to a movie. We use a variation of Neural Collaborative Filtering [25] as our underlying model. We implement its federated version using FATE.

# 4 Experiments

In this section, we present the evaluations to our reference implementations. The evaluations are divided into two parts: 1) For horizontally partitioned tasks, we demonstrate the performance improvement, communication cost, influence of differential privacy and secure multiparty computation in terms of accuracy and efficiency. 2) For the vertically partitioned task, we mainly focus on the performance improvement in the federated settings and the impact of homomorphic encryption method.

The experiments are conducted on a Linux machine with a Xeon E5–2640 CPU @ 2.4GHz, 256GB DRAM and an Nvidia Tesla P100 GPU. The experiments can be reproduced with the code in the supplementary materials.

## 4.1 Improvement of Federation

Each row in Table 3a and Table 3b show one of three types of training setups: training each dataset separately, training on the combined dataset from all parties, and use federated averaging algorithm [38] to train on the data collaboratively. Accuracy in all setups are measured with the two types of test datasets: each party's own test dataset and the combined one created by concatenating two parties' test datasets, which are separated by columns in the tables.

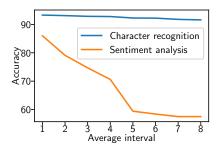
The "Combined" column demonstrates a fair comparison between different training setups. In this case, our federated reference implementation outperforms training with each party's private data in both of our tasks, and is close to the training with combined dataset. The results show that federated learning can effectively improve model accuracy, and the accuracy loss can be small in comparison with the centralized training.

When testing each setup with a dataset from two parties respectively, we make two observations: 1) When the training and testing dataset come from the same party (e.g. Training and testing are both using the IMDB dataset), the result describes the model quality. 2) When they come from different parties (e.g. Using the IMDB dataset for training and the Amazon dataset for testing), the result describes the generalization ability of the model. Federated averaging improves both the quality of the models and the generalization ability of the models, and achieves lower loss (around 18% less for the Chinese character task and 8% less for the sentiment analysis task) than the combined dataset setup.

### 4.2 Communication Cost

We investigate how the model accuracy changes with federation frequency in Figure 2. The accuracy is measured with combined test datasets. Limited by the GPU resource and training time, we fix the number of epochs to be 10 and 30 for the Chinese character recognition and the sentiment analysis,

respectively. We define *average internal* as the number of epochs trained between two averages. Overall, the accuracy decreases with the average interval for both task. Compared to the sentiment analysis task, the decrease in the Chinese character recognition task is much smaller, indicating that different models have different sensitivities to the average interval. Using the model size, we can calculate the amount of data transmitted. The size of the weights is 55.3MB and 551.2MB for the Chinese character recognition task and for the sentiment analysis task, respectively. With average interval grows from 1 epoch to 2 epochs, the data transmitted for the two tasks decreases 553MB and 16,536MB respectively, and the accuracy drops from 93.3% to 93.1% and 84.9% to 80.0% respectively. Clearly, there is a trade-off between communication cost and accuracy.



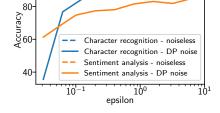


Figure 2: Test accuracy under different communication cost

Figure 3: Test accuracy with different privacy cost

# 4.3 Differential Privacy

To investigate how to set privacy parameters, we analyze the relationship between different privacy parameters and model quality. There are multiple types of composition mechanism for differential privacy [14, 13, 1, 39], and we use the moments accountant [1] mechanism as it is designed for SGD and imposes better privacy bound than other DP composition mechanisms like simple composition and adaptive composition [15]. TensorFlow provides an tensorflow\_privacy module that allows us to count how much privacy budget is spent using this mechanism, and we use that module to calculate our noise parameters. As the calculation process requires a fixed epoch number, we fix our epoch number to 20 for both the Chinese character recognition task and the sentiment analysis task, where the models reach a decent accuracy and not too much extra privacy budget needs to be wasted on minor accuracy improvements.

We configure the parameters so the model satisfies  $(\varepsilon, \delta)$ -differential privacy where we fix  $\delta$  to be the inverse of the number of records in the dataset [13] and vary  $\varepsilon$ . As shown in Figure 3, the accuracy grows with the privacy budget  $\varepsilon$ , which matches the intuition that the less noise we add, the model becomes less private but its accuracy increases. When  $\varepsilon$  grows above 1, the growth of accuracy becomes negligible. The FedAvg curve of the sentiment analysis task is not complete because when lot size is less than  $\sqrt{N}$ , the federated model does not converge.

Another parameter that has a great impact when adding DP noise, indicated by Abadi et al. [1], is *lot size*, which indicates how much records should be trained before adding a noise. In their work, the empirical optimal lot size is  $\sqrt{N}$ , which is what we set in Figure 3. To further investigate the impact of lot size on federated learning, we fix  $\varepsilon$  to 2.0 and change lot size, and the results are shown in Figure 4. From these two figures, all setups of the two tasks reach their peak performance at between  $\sqrt{N}$  and  $10\sqrt{N}$ , which is close to the previous empirical result [1].

## 4.4 Secure Multiparty Computation

We apply the SPDZ [9] secure multiparty computation technique to encrypt the parameter exchange process, and use PySyft to implement the encryption process. Table 4 shows additional encryption overhead by SMC. The time needed for encryption is proportional to the size of the weight. We also notice that SMC causes a small loss of accuracy. This is due to the SPDZ can only be performed on integer values, but our models use floating point weights. Converting between floating-point values and integer values brought precision loss, which further leads to accuracy loss. This loss can be

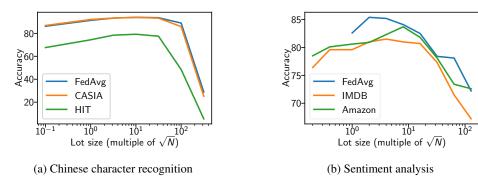


Figure 4: Test accuracy under different lot size

mitigated by using larger integers to store the converted gradient, at a cost of larger communication cost.

Table 4: Test accuracy and training time

#### (b) Sentiment Analysis

Training	Test Dataset		Time Cost Ti	Training	Test Dataset		Time Cost	
Technique	CASIA	HIT	per Epoch	Technique	IMDB	Amazon	per Epoch	
w/o SMC with SMC	95.0% 94.8%	98.5% 98.2%	955s 960s	w/o SMC with SMC	85.6% 84.4%	85.8% 84.8%	84s 145s	

# 4.5 Vertical FL: Improvement of Federation

For vertical federated learning, we also observe the improvements brought by the federation. Figure 5 shows that in the year-prediction task, the test accuracy of the federated models for both union and aligned experiments are not always higher than only using a single dataset for training. The union datasets are created by an outer join of the two dataset, and the intersection datasets are created by an inner join. After joining, the sizes of the union and intersection datasets are 457472 and 1536 separately.

For the union datasets, when using FMA, MSD and combined dataset for training, the test accuracy (measured by MAE) converges to 3.04, 7.34, 6.51 separately, and when using SplitNN for federated training, the final MAE is 6.53. For the intersection datasets, test accuracy for FMA, MSD and combined dataset are 3.51, 3.07 and 3.13, and for SplitNN this value is 2.78. For both union and intersection, the model accuracy of federated learning is comparable or even higher to directly using combined datasets for training, while using a federated learning does not always yield a better model accuracy than using a single dataset,

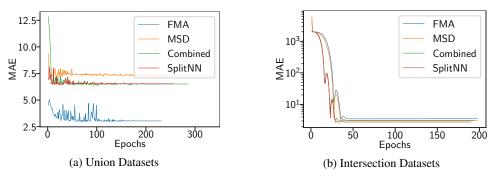


Figure 5: Test MAE of the Songs Year-Prediction Task

## 4.6 Vertical FL: Homomorphic Encryption

We give a detailed analysis to the movie recommendation vertical FL task. The mean-squared error result of the experiment is shown in Table 5. The Rating + Auxiliary setting directly combines rating matrix and auxiliary information such as user gender and movie genre, while the Rating fed Auxiliary setting uses homomorphic encryption module in FATE to perform the vertical federated learning. As shown in the result, combining the rating matrix with auxiliary information improves the model performance on the test dataset.

We apply the Heterogeneous Neural Network module in FATE for secure and lossless training because the Neural Collaborative Filtering model can be implemented in it with minor modification. In our experiment, the average spent time of each batch is around 206 seconds and the estimated training time is about 403 hours, which is impractical to train on our local machine. Compared with the non-federated setting, the huge increase of training time is mainly incurred by the homomorphic encryption and homomorphic computation operation, while the communication time is negligible.

	Train Dataset	Test MSE	Time/epoch
	Rating	0.7549	14s
	Rating + Auxiliary	0.7195	39s
]	Rating fed Auxiliary with HE	N/A	~403h

Table 5: Test MSE and training time of the movie recommendation task

# 4.7 Diversity Analysis

To analyze the diversity of the tasks in OARF, we characterize each horizontally partitioned task with eight features in datasets and models and demonstrate them in Figure 6, with each value normalized with the largest value in that coordinate. These 8 features are: 1) the size of the dataset used for training the federated setup. 2) The size ratio of the two dataset. 3-4) performance improvement relative to using a single dataset for training. 5) model accuracy's sensitivity to communication interval, measured by dividing the accuracy in the settings where aggregation is performed every 2 epochs by the baseline accuracy 6) model accuracy's sensitivity to epsilon, measured by dividing the accuracy where DP noise ( $\varepsilon = 2.0$ ) is added to the model by the baseline accuracy 7) the best lot size for using differential privacy, 8) computational overhead caused by SMC. As shown in this analysis, we cover a wide range of value, which ensures the diversity of our the workloads.

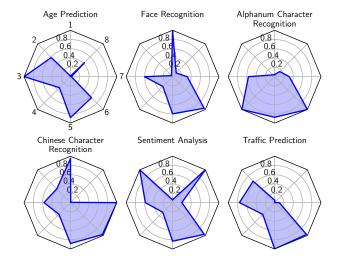


Figure 6: Diversity Analysis of OARF

# 5 Findings and Discussion

Through the experiments, we discovered the following findings and opportunities:

- 1. By federation, we can expect improvements on both the accuracy of the model and the generalization ability of the model, and accuracy of the FL model is close or even better to that of the model trained with all datasets combined. Still, our experiments *quantitatively* reveal that there is still quite some room to improve when comparing federated averaging models with models trained on combined datasets. These quantitative measurements also reveal opportunities to explore methods to further improve the utility of federated averaging model.
- 2. The communication cost can be reduced by changing the averaging interval while maintaining accuracy in an acceptable range. However, for different models, the accuracy drop can vary greatly. The communication experiment indicates that more researches on low-level methods such as gradient compression and model compression and their combination technique with high-level methods should be carried out.
- 3. The accuracy of models grow with the privacy budget  $\varepsilon$  and achieve a relatively stable state at around  $\varepsilon=1$ . The best interval of adding noise is roughly between  $\sqrt{N}$  and  $10\sqrt{N}$  samples, where N is the number of entries in the dataset. The experiments shows that there are still potential to further improve the utility while protecting privacy, possibly by discovering composition methods with tighter privacy bounds or utilizing the internal noise generated in the training process. In addition, task-specific hyper-parameter search methods also need to be explored.
- 4. The computational overhead incurred by applying SMC is proportional to the size of the model. SMC also causes a small loss of accuracy due to floating-point conversion. For horizontal federated learning, SMC is a practical method to prevent information leakage between clients, but it can be challenging to apply it to vertical settings. Further explorations are needed for methods to efficiently prevent information leakage in vertical settings.

## 6 Conclusions

In this paper, we propose the OARF federated learning benchmark suite, which contains three modules: metrics, tasks and reference implementations. We use this benchmark suite to reveal the internal properties of federated learning and its modules. We have maintained OARF in GitHub (the URL is omitted for anonymity). The reference implementations in the benchmark suite are by no means complete. Besides making this benchmark suite open to the community, we also plan to add more modules and reference implementations in the future.

# **Appendix A: Description of Tasks and Datasets**

This section shows the descriptions of complementary tasks in addition to the tasks in the paper,

**Gender/Age Prediction** Age and gender prediction have attracted growing interests due to its potential in various areas, including security control, crime prevention and human interaction. These two tasks have been extensively studied by a number of works [20, 16, 43]. The goal of this task is to predict the gender or age from given human face images.

We collected 5 datasets for this task, each containing a number of face images and corresponding gender/age label. These images are fed into a CNN model to train a classification model. Among all the five datasets, the OUI Audience Faces and IMDB-WIKI contain not only portrait photos but also full-body images, so they need a face position detection preprocessing phase to extract the face image. For networks that are designed to take fixed-size images as input, images from different datasets need to be preprocessed to the same size.

*Reference implementation:* In our reference implementation, we used All-Age-Face and APPA-REAL dataset to learn a VGG-16 model collaboratively. We choose these two datasets because both of them contains gender and age label. For both datasets, we randomly sample 90% of the data for training,

5% for validation and 5% for testing. Although both of the datasets provides preprocessed and aligned portrait version, they use different types of preprocessing configurations, including different image sizes and different image padding. Through preliminary tests, we found that the model accuracy is higher when both datasets are processed and regularized in the same way, so we implement our own preprocess method and perform it on both of the datasets to obtain consistent preprocessed images.

**Face Recognition** Face recognition has been a long-standing research topic in the computer vision community and has been widely used in different real-world applications. Extensive research works have been done [59, 12] to continuously improve the state-of-the-art. Face recognition uses human face images as input and learns to identify the identities. Datasets for this task contain face images and the identities corresponding to the faces. For each individual, there are multiple images associated with it. These images are divided into two parts, one for training and another for validation. The testing identities are disjoint from the training and validation sets.

The racial bias phenomenon in face recognition is a problematic issue and has attracted increasing attention. Wang et al. [51] shows that both commercial APIs and SOTA algorithms work unequally well for different races. Wang et al. [51] also proposes a method to solve this problem. In our benchmark, we try to give a solution that makes use of federated learning. Our goal is to train a model that has better generalization ability to identify faces in different races, thus reducing racial bias.

Reference implementation: We focus on the task of face verification. We employ the ResNet-34 [24] architecture with softmax loss and train the model with federated averaging on two subsets of BUPT-Balancedface dataset, namely Caucasian-7k and African-7k. These face images are horizontally flipped for data augmentation. For data prepossessing, we generate the similarity transformed faces by utilizing the face landmarks detected by MTCNN [57]. We then crop the faces to  $112 \times 112$  and normalize them.

In the testing, we use the racial-balanced testing set Racial Faces in-the-Wild to evaluate the capability of the model. We follow [34] to get the feature representation by concatenating an image's original features and its horizontally flipped features, both extracted from the output of the last FC layer. The similarity score is computed by the cosine distance of features from an image pair. Then thresholding and k-fold cross-validation techniques are used for getting the final verification accuracy.

**Alphanumeric Character Recognition** Handwriting character recognition is a classic and relatively well-studied field. Proposed in 1998, the MNIST dataset remains the most widely known and used dataset. People are easy to achieve 99% accuracy on it by applying deep learning technique. Also, comprehensive experimental results on MNIST in the federated scenario have been given in the Benchmark like LEAF [4], and other federated algorithms [38, 47].

The Chars74k handwritten dataset, however, is still challenging to get a high testing accuracy and has not applied in federated learning. We incorporate two subsets of Chars74k dataset (Fnt and Hnd) in our benchmark. They have a significant difference in terms of dataset size, data quality, and writing shape.

Reference implementation: We define the task as to classify images from handwriting alphanumeric characters, which contains 10 digits, 26 uppercase letters, and 26 lowercase letters, totally 62 classes. We split 15% data into test dataset. We train one model federally by using federated averaging. We utilize the popular ResNet-18 [24] structure as the architecture and add dropouts.

**Traffic Prediction** Traffic prediction is a classic problem in transportation systems, which has been studied for decades. In a traffic prediction task, we predict traffic in a given area and time range. We formulate the problem as a multi-location traffic prediction. Recent works by Li et al. [31] and Yu et al. [56] have proved that Spatio-Temporal Graph Convolutional Networks are able to achieve state-of-the-art results for this task.

Reference implementation: We configure our federated task with the METR-LA and the PEMS-BAY datasets and use a Diffusion Convolutional Recurrent Neural Network [31] as our underlying algorithm. We extend the training part to the federated version using federated averaging, where we train two identical models and aggregate their weights every epoch. For both of the datasets, we use 80% of the traffic records, in which 10% is used for validation. The rest 20% of the data is for testing. As the amounts of data trained on two parties are different, we also assign weights to each parties'

model parameters, and the weights are proportional to the number of records in each parties' training dataset respectively.

**Recommendation (additional task)** In addition to the Movie task, we also evaluate the recommendation system using the games task. For the Steam Game dataset, there are 17531 games after cleaning. And there is a file containing 0.38 billion rows of interactions between users and games. After joining the game information and interaction, we obtain a dataset that consists of 0.32 billion interactions, with 35 million users and 2080 games. The sparsity of it is 99.56%, and 31% users only have one interaction. So we need to do filtering. We retain the users with at least 350 interactions and this results in 6.9 million interactions, with 13995 users and 1999 games. For the IGN Rating dataset, it only contains the game information. There are 12536 games remained after cleaning.

*Reference implementation:* After preprocessing, we align the two datasets with the key of game's title and we find 1560 aligned games. We then construct the aligned dataset by joining the aligned games with the filtered Steam dataset. This results in 4.08 million interactions, with 13995 users and 922 games.

To perform recommendation, we do the negative sampling as sampling three negative samples per positive sample. In the experiment, we consider three settings. The first one uses the aligned dataset with the features only from one party (Steam Game), the second directly combines the features from the two parties, and the third trains the model federatively. Compared with the setting of steam and combined, we found that the auxiliary information from IGN has a minor improvement to the original performance. The improvement from combined to federated could be due to the addition of neurons, i.e., in the federated setting, we use 32 neurons to represent two dense features, while in combined setting, we only use 16 neurons.

# **Appendix B: Experiment Results**

In addition to the experiment results stated in the previous section, we also conducts experiments on other tasks. This sections shows their results.

# **Improvement of Federation**

Table 6 shows the comparison between federated and non-federated results on different tasks. The accuracy of the age prediction and traffic prediction task is measured by mean average error (MAE), while other two are measured by top-1 accuracy.

The "Combined" columns of the results shows that if we use the combined datasets for testing, federated averaging is generally more effective compared to training locally, and the accuracy is close to directly training the combined dataset. From the other two columns, however, we can conclude that federated learning is helpful for the generalization capability of the model, but cannot always improve the accuracy. For the age prediction task, federated averaging outperforms the local training for both APPA and All-Age-Face dataset, but for other tasks we cannot obtain this observation.

## **Communication Cost**

Figure 7 shows the accuracy results of different tasks under different communication costs. All these tasks shows that as the averaging interval grows, the accuracy of the global model drops. We also observe some anomaly in results, as the accuracy does not strictly decrease as the average interval grows.

## **Differential Privacy**

Like in in the experiment section, we evaluate the tasks first by describing how model accuracy changes with privacy budget. Figure 8 shows that generally, accuracy grows as privacy budget. However, comparing different tasks shows the sensitivity is different: The model accuracy of the age prediction and face recognition tasks converges to the noiseless baseline much slower than that of the alphanumeric character prediction task.

We also explore the optimal hyper parameters for obtaining best model accuracy. Figure 9 shows the results. For these tasks, the optimal accuracy of the global model is obtained when lot size is round

Table 6: Accuracy and loss at the end of the training. "Val. Loss" for validation loss.

(a) Age prediction (Accuracy shown as MAE)

(b) Alphanumeric Character Recognition

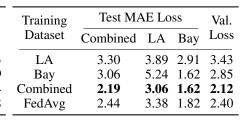
Training	Test	Dataset		Val.
Dataset	Combined	APPA	AAF	Loss
APPA	11.67	6.75	9.98	3.81
AAF	7.68	10.64	6.68	3.47
Combined	6.62	6.42	5.74	3.53
FedAvg	6.56	6.66	6.19	3.63

Training	Те	Val.		
Dataset	Combined	Fnt	Hnd	Loss
Fnt	89.40%	92.46%	32.99%	0.254
Hnd	25.78%	22.54%	85.48%	0.427
Combined	92.06%	92.63%	81.52%	0.356
FedAvg	89.79%	92.52%	39.44%	0.375

(c) Face Recognition

(d) Traffic Prediction

Training	Т	Val.		
Dataset	Combined	Caucasian	African	Loss
Caucasian African Combined	73.61% 74.65% <b>79.73</b> %	82.42% 77.27% <b>83.28</b> %	67.05% 76.35% <b>76.95</b> %	1.199
FedAvg	77.09%	82.75%	75.88%	



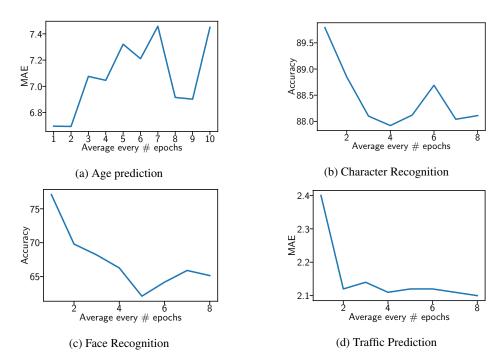


Figure 7: Model Accuracy under different communication cost

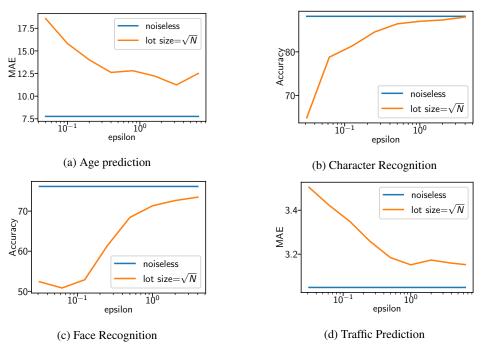


Figure 8: Model Accuracy under different privacy budget

 $\sqrt{N}$ . Excessively small and large lot sizes lead to loss of accuracy. We can also conclude in these results that different tasks has different sensitivity to the change of lot size.

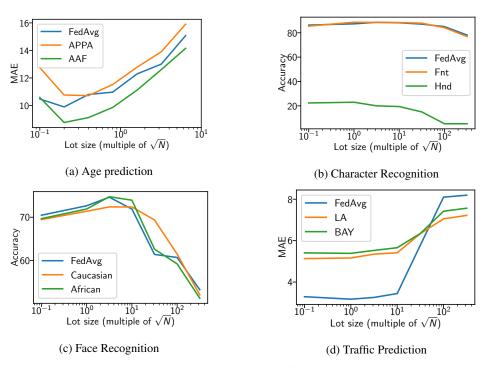


Figure 9: Model MAE under different lot size

# **Secure Multiparty Computation**

Applying SMC to federated learning, we can obtain the result shown in Table 7. Similar to the result in the experiment section, a small loss of accuracy occurs when SMC is applied, and the computational time overhead is proportional to the size of the model weights that needs to be encrypted.

Table 7: Test accuracy and training time

### (a) Age prediction

### (b) Alphanumeric Character Prediction

Training	Test D	ataset	Time Cost	
Technique	APPA	AAF	per Epoch	
w/o SMC	7.70	6.24	141.25s	
with SMC	7.90	6.31	184.98s	

Training	Test D	Time Cost	
Technique	Fnt	Hnd	per Epoch
w/o SMC with SMC	92.5% 92.6%	39.4% 33.1%	134s 138s
with SMC	92.0%	33.1%	1388

#### (c) Face Recognition

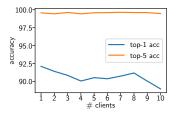
## (d) Traffic Prediction

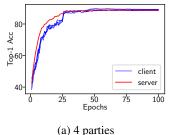
Training	Test Da	Time Cost	
Technique	Caucasian	African	per Epoch
w/o SMC with SMC	82.8% 83.1%	75.88% 75.18%	791s 855s
WILLI DIVIC	05.170	13.1070	0555

Training Technique	Test Dataset		Time Cost
	LA	Bay	per Epoch
w/o SMC	3.38	1.82	1184s
with SMC	3.59	1.76	1185s

## 6.1 Impact of number of parties

To investigate the impact of number of parties on the accuracy of the global model, we split the CIFAR-10 dataset in to various number of parts in a i.i.d manner, where each party has the same amount of data and the distribution of the label in each party are the same. We use federated averaging to train the model until convergence. Figure 10 shows the global model' accuracy when the number of parties varies from 1 to 10. Although the accuracy grows slightly when the number parties grows from 4 to 8, the overall trends shows that the accuracy drops as the number of parties grows.





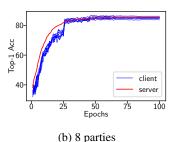


Figure 10: Impact of number of parties on the accuracy of global model

Figure 11: Accuracy-epochs curve of each client's model and the global model

To further analyze how each clients contributed to the global model, we plot each clients' training curve together with the global model under the 4 party and 8 party settings, and Figure 11 shows the result. At the beginning of training, the accuracy of the global model surpasses each client's model. But when the training researches convergence, the accuracy of the global model is approximately the average of each client's model accuracy.

# 6.2 Vertical FL: Improvement of Federation

In addition to the year prediction dataset, we also provides the result for the movie recommendation and games recommendation task under using different datasets, as shown in Figure 12 and Figure 13. We found that in the movie recommendation task, for both union datasets and aligned datasets, under the federated or combined settings, the auxiliary data does not provide much improvement to the

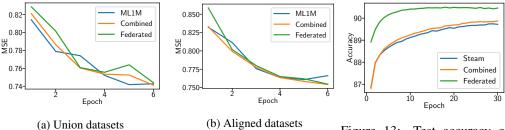


Figure 12: Test MSE of movie recommendation task

Figure 13: Test accuracy of game recommendation task

original model (trained with MovieLens 1M dataset). But in the game task, the auxiliary data provides a significant boost on the accuracy of the model.

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