

# PFLlib: Personalized Federated Learning Algorithm Library

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## Abstract

Amid the ongoing advancements in Federated Learning (FL), a machine learning paradigm that allows collaborative learning with data privacy protection, personalized FL (pFL) has gained significant prominence as a research direction within the FL domain. Whereas traditional FL (tFL) focuses on jointly learning a global model, pFL aims to achieve a balance between the global and personalized objectives of each client in FL settings. To foster the pFL research community, we propose PFLlib, a comprehensive pFL algorithm library with an integrated evaluation platform. In PFLlib, We implement 34 state-of-the-art FL algorithms (including 7 classic tFL algorithms and 27 pFL algorithms) and provide various evaluation environments with three statistically heterogeneous scenarios and 14 datasets. At present, PFLlib has already gained 850 stars and 199 forks on GitHub<sup>1</sup>.

**Keywords:** federated learning, personalization, privacy-preserving, algorithm library, collaborative learning

## 1 Introduction

Federated Learning (FL) has gained significant attention due to its ability to perform distributed machine learning while ensuring privacy preservation (Yang et al., 2019). In traditional FL (tFL) algorithms such as FedAvg (McMahan et al., 2017), participating clients train local models using local data and send only local model updates to a global server, which then aggregates these updates to obtain a global model. These approaches do not consider the customization needs of each local client. Personalized FL (pFL) is introduced to train customized client models to improve their performance on individualized tasks. In tandem with the burgeoning prominence of pFL, there has been a surge in the development of various pFL algorithms and associated techniques (Tan et al., 2022a; Zhang et al., 2023b). However, due to their rapid progress and diverse settings, the difficulties of tracking, implementing, and benchmarking these methods also grow tremendously.

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1. <https://github.com/TsingZ0/PFLlib>

To alleviate these challenges, we have developed `PFLlib`, a comprehensive pFL algorithm library with an integrated evaluation platform. `PFLlib` includes implementations of **34** state-of-the-art (SOTA) tFL and pFL algorithms, encompassing 7 classic tFL algorithms and **27** pFL algorithms. Our library is user-friendly and easily extendable, allowing contributors to seamlessly add new algorithms, scenarios, and datasets, thus ensuring that `PFLlib` remains up-to-date. Additionally, we have implemented three statistically heterogeneous scenarios and incorporated 14 datasets, covering Computer Vision (CV), Natural Language Processing (NLP), and Sensor Signal Processing (SSP) tasks. We can evaluate the algorithms in `PFLlib` and assess their adaptability to various scenarios, which provides valuable insights for algorithm selection in practical applications.

## 2 Related Work

With the rapid development of the FL field, numerous benchmarks and platforms have emerged in recent years. Most of their latest versions are for practical deployments, such as FATE (Liu et al., 2021), FedML (He et al., 2020), FederatedScope (Xie et al., 2023), Flower (Beutel et al., 2020), TensorFlow Federated<sup>2</sup>, NVIDIA Clara<sup>3</sup>, SecretFlow<sup>4</sup>, Fedlearner<sup>5</sup>, and PySyft<sup>6</sup>. Despite the efficient resource management and extensive functionality offered by these platforms, they can present a challenge for beginners who seek to comprehend the fundamental mechanisms of FL and delve into the philosophical aspects of existing FL algorithms. There are also some beginner-friendly platforms, such as LEAF (Caldas et al., 2018), NIID-Bench (Li et al., 2022), Motley (Wu et al., 2022b), OARF (Hu et al., 2022), FedEval (Chai et al., 2020) and FedLab (Zeng et al., 2023). However, these benchmarks and platforms still lack sufficient and up-to-date built-in SOTA pFL algorithms for researchers to learn, compare, and analyze.

In the pFL field, pFL-Bench (Chen et al., 2022) is the latest project, but it supports only 5 SOTA pFL methods while the remaining pFL methods are variants created by combining them with existing approaches including FedBN (Li et al., 2021c), FedOpt (Asad et al., 2020), and Fine-tuning (FT). And all the pFL algorithms in pFL-Bench are outdated (before 2022). In contrast, our `PFLlib` consists of 27 SOTA pFL algorithms, and the latest one is proposed in December 2023. Moreover, due to our straightforward file structure, `PFLlib` is more accessible for beginners to learn and utilize pFL algorithms compared to pFL-Bench.

## 3 PFLlib Project

**Algorithms.** In our `PFLlib`, the primary focus is on pFL algorithms. In addition, we have also included a selection of classic tFL algorithms to facilitate the evaluation of pFL algorithms, following previous pFL research (Li et al., 2021b; T Dinh et al., 2020; Zhang et al., 2023d). We have categorized a total of 7 tFL algorithms and 27 pFL algorithms based on their foundational techniques. The detailed classification is presented in Table 1.

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2. <https://www.tensorflow.org/federated>

3. <https://developer.nvidia.com/industries/healthcare>

4. <https://github.com/secretflow/secretflow>

5. <https://github.com/bytedance/fedlearner>

6. <https://github.com/OpenMined/PySyft>

Table 1: Algorithm Classifications in our PFLlib.

	Category	Algorithms
7 tFL Algorithms	Basic tFL	FedAvg (McMahan et al., 2017)
	Update-correction-based tFL	SCAFFOLD (Karimireddy et al., 2020)
	Regularization-based tFL	FedProx (Li et al., 2020) and FedDyn (Acar et al., 2021)
	Model-splitting-based tFL	MOON (Li et al., 2021a)
	Knowledge-distillation-based tFL	FedGen (Zhu et al., 2021) and FedNTD (Lee et al., 2022)
27 pFL Algorithms	Meta-learning-based pFL	Per-FedAvg (Fallah et al., 2020)
	Regularization-based pFL	pFedMe (T Dinh et al., 2020) and Ditto (Li et al., 2021b)
	Personalized-aggregation-based pFL	APFL (Deng et al., 2020), FedFomo (Zhang et al., 2020), FedAMP (Huang et al., 2021), FedPHP (Li et al., 2021d), AP- PLE (Luo and Wu, 2022), and FedALA (Zhang et al., 2023d)
	Model-splitting-based pFL	FedPer (Arivazhagan et al., 2019), LG-FedAvg (Liang et al., 2020), FedRep (Collins et al., 2021), FedRoD (Chen and Chao, 2021), FedBABU (Oh et al., 2022), FedGC (Niu and Deng, 2022), FedCP (Zhang et al., 2023c), GPFL (Zhang et al., 2023b), FedGH (Yi et al., 2023), and DBE (Zhang et al., 2023a)
	Knowledge-distillation-based pFL	FedDistill (Seo et al., 2022), FML (Shen et al., 2020), FedKD (Wu et al., 2022a), FedProto (Tan et al., 2022b), FedPCL (Tan et al., 2022c), and FedPAC (Xu et al., 2022)
	Other pFL	FedMTL (Seo et al., 2022) and FedBN (Li et al., 2021c)

**Scenarios.** In PFLlib, we consider two kinds of statistically heterogeneous scenarios: *label skew* and *feature shift*, where different client datasets differ in label categories and feature categories, respectively (Zhang et al., 2023b). Both CV and NLP classification tasks are considered in these two scenarios. Moreover, we also introduce a *real world* scenario by assigning each client with sensor signals collected from a wearable device on each person, such as HAR (Anguita et al., 2012) and PAMAP2 (Reiss and Stricker, 2012), for SSP tasks.

**Privacy Features.** We also introduce the privacy-preserving technique Differential Privacy<sup>7</sup> (DP) into PFLlib. In addition, we implement the popular Deep Leakage from Gradients (DLG) attack (Zhu et al., 2019) and the Peak Signal-to-Noise Ratio (PSNR) metric (Wu et al., 2022c) to evaluate the privacy-preserving abilities of existing tFL/pFL algorithms.

**Easy to Use and Extend.** In PFLlib, algorithms are implemented by **three** critical files: `serverX.py` for server creation, `clientX.py` for client creation, and `main.py` for hyperparameter configuration. Here, “X” represents some algorithm name. We can simply create a new algorithm Y by only adding specific features to `serverY.py` and `clientY.py` and while utilizing the core APIs in `serverbase.py` and `clientbase.py`. To create a scenario, users simply need **one** command line and run the evaluation with another **one** command line. We show an example of using FedALA on MNIST (LeCun et al., 1998):

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7. <https://opacus.ai/>

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1 # generate a practical non-iid and unbalanced scenario using MNIST
2 cd ./dataset; python generate_mnist.py noniid - dir
3 # evaluate the FedALA algorithm using a CNN with default hyperparameters
4 cd ./system; python main.py -data mnist -m cnn -algo FedALA -gr 2000

```

**Impacts.** Our PFLlib is active and popular in the pFL community, as shown by the increasing number of GitHub stars, forks, and active discussions. Due to its simplicity and extensibility, numerous new platforms and projects have been built upon it, such as the FL-bench<sup>8</sup>, the HtFL<sup>9</sup>, and the FL-IoT<sup>10</sup>. Besides, the experiments of several latest SOTA methods (Zhang et al., 2023d,c,b,a) are also conducted using our PFLlib.

**Benchmark.** Due to limited space, we only evaluate 20 algorithms in two *label skew* scenarios following the default settings<sup>11</sup> of GPFL (Zhang et al., 2023b). In Table 2, we use the 4-layer CNN (McMahan et al., 2017) for CV tasks on Fashion-MNIST (FMNIST) (Xiao et al., 2017), Cifar100, and Tiny-ImageNet (Chrabaszcz et al., 2017) (TINY for short) datasets and use the fastText (Joulin et al., 2017) for NLP tasks on AG News dataset. We also use the ResNet-18 (He et al., 2016) on Tiny-ImageNet and denote it TINY\*.

Table 2: The test accuracy (%) on the CV and NLP tasks in *label skew* settings.

Settings	Pathological <i>Label Skew</i> Setting			Practical <i>Label Skew</i> Setting				
	FMNIST	Cifar100	TINY	FMNIST	Cifar100	TINY	TINY*	AG News
<b>FedAvg</b>	80.41±0.08	25.98±0.13	14.20±0.47	85.85±0.19	31.89±0.47	19.46±0.20	19.45±0.13	87.12±0.19
<b>FedProx</b>	78.08±0.15	25.94±0.16	13.85±0.25	85.63±0.57	31.99±0.41	19.37±0.22	19.27±0.23	87.21±0.13
<b>FedGen</b>	79.76±0.60	20.80±1.00	13.82±0.09	84.90±0.31	30.96±0.54	19.39±0.18	18.53±0.32	89.86±0.83
<b>Per-FedAvg</b>	99.18±0.08	56.80±0.26	28.06±0.40	95.10±0.10	44.28±0.33	25.07±0.07	21.81±0.54	87.08±0.26
<b>pFedMe</b>	99.35±0.14	58.20±0.14	27.71±0.40	97.25±0.17	47.34±0.46	26.93±0.19	33.44±0.33	87.08±0.18
<b>Ditto</b>	99.44±0.06	67.23±0.07	39.90±0.42	97.47±0.04	52.87±0.64	32.15±0.04	35.92±0.43	91.89±0.17
<b>APFL</b>	99.41±0.02	64.26±0.13	36.47±0.44	97.25±0.08	46.74±0.60	34.86±0.43	35.81±0.37	89.37±0.86
<b>FedFomo</b>	99.46±0.01	62.49±0.22	36.55±0.50	97.21±0.02	45.39±0.45	26.33±0.22	26.84±0.11	91.20±0.18
<b>FedAMP</b>	99.42±0.03	64.34±0.37	36.12±0.30	97.20±0.06	47.69±0.49	27.99±0.11	29.11±0.15	83.35±0.05
<b>APPLE</b>	99.30±0.01	65.80±0.08	36.22±0.40	97.06±0.07	53.22±0.20	35.04±0.47	39.93±0.52	84.10±0.18
<b>FedALA</b>	99.57±0.01	67.83±0.06	40.31±0.30	97.66±0.02	55.92±0.03	40.54±0.02	41.94±0.02	92.45±0.10
<b>FedPer</b>	99.47±0.03	63.53±0.21	39.80±0.39	97.44±0.06	49.63±0.54	33.84±0.34	38.45±0.85	91.85±0.24
<b>FedRep</b>	99.56±0.03	67.56±0.31	40.85±0.37	97.56±0.04	52.39±0.35	37.27±0.20	39.95±0.61	92.25±0.20
<b>FedRoD</b>	99.52±0.05	62.30±0.02	37.95±0.22	97.52±0.04	50.94±0.11	36.43±0.05	37.99±0.26	92.16±0.12
<b>FedBABU</b>	99.41±0.05	66.85±0.07	40.72±0.64	97.46±0.07	55.02±0.33	36.82±0.45	34.50±0.62	95.86±0.41
<b>FedCP</b>	99.66±0.04	71.80±0.16	44.52±0.22	97.89±0.05	59.56±0.08	43.49±0.04	44.18±0.21	92.89±0.10
<b>GPFL</b>	99.85±0.08	71.78±0.26	44.58±0.06	97.81±0.09	61.86±0.31	43.37±0.53	43.70±0.44	97.97±0.14
<b>FedAvg+DBE</b>	99.74±0.04	73.38±0.18	42.89±0.29	97.69±0.05	64.39±0.27	43.32±0.37	42.98±0.52	96.87±0.18
<b>FedDistill</b>	99.51±0.03	66.78±0.15	37.21±0.25	97.43±0.04	49.93±0.23	30.02±0.09	29.88±0.41	85.76±0.09
<b>FedProto</b>	99.49±0.04	69.18±0.03	36.78±0.07	97.40±0.02	52.70±0.33	31.21±0.16	26.38±0.40	96.34±0.58

## 4 Conclusion

To bolster the rapidly evolving pFL research community, we have developed PFLlib, a beginner-friendly library encompassing 34 cutting-edge tFL/pFL algorithms. We also built an evaluation platform in PFLlib with privacy features and extensive scenarios.

8. <https://github.com/KarhouTam/FL-bench/tree/c11efc286dab4565245da34d7300d5bb07b87a0a>  
9. <https://github.com/TsingZ0/HtFL>  
10. <https://github.com/TsingZ0/FL-IoT>  
11. Due to frequent updates, some default settings and codes for scenario creation may change in PFLlib.

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