
pfl-research: simulation framework for accelerating research in Private Federated Learning

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Abstract

Federated learning (FL) is an emerging machine learning (ML) training paradigm where clients own their data and collaborate to train a global model, without revealing any data to the server and other participants. Researchers commonly perform experiments in a simulation environment to quickly iterate on ideas. However, existing open-source tools do not offer the efficiency required to simulate FL on large and realistic FL datasets. We introduce `pfl-research`, a fast, modular, and easy-to-use Python framework for simulating FL. It supports TensorFlow, PyTorch, and non-neural network models, and is tightly integrated with state-of-the-art privacy algorithms. We study the speed of open-source FL frameworks and show that `pfl-research` is $7\text{-}72\times$ faster than alternative open-source frameworks on common cross-device setups. Such speedup will significantly boost the productivity of the FL research community and enable testing hypotheses on realistic FL datasets that were previously too resource intensive. We release a suite of benchmarks that evaluates an algorithm’s overall performance on a diverse set of realistic scenarios. The code is available on GitHub at <https://github.com/apple/pfl-research>.

1 Introduction

Federated learning (FL) is an approach to collaboratively train a machine learning (ML) model between clients, with coordination by a central server [45]. Participating clients can be either user devices connected to the internet (cross-device FL) or data centers of distinct institutions, which each store data of multiple users (cross-silo FL). The common constraint is that it is infeasible to upload the data to a central server for training because of privacy, bandwidth, or other compliance concerns [1, 2]. However, even though only statistics derived from the original data are uploaded to a central server, FL algorithms alone are not formally or practically privacy preserving [12, 29, 63]. Therefore, it is essential to combine FL with techniques to preserve the privacy of users. Deployed systems often use secure aggregation and give differential privacy (DP) guarantees to achieve this [6, 13, 81, 89]. We call such systems *private federated learning* (PFL).

(P)FL is a rapidly growing field [3], and it is unrealistic for most research to be evaluated with a real-world (P)FL deployment as most researchers do not have access to a large-scale deployment.

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Even for researchers with such access, user experience constraints [68] would typically significantly limit such evaluation. Additionally, training with real edge devices is slow and typically cannot support the extensive hyperparameter tuning that may be needed [43].

Therefore, testing hypotheses in simulation is essential for continued growth in (P)FL research. FL simulation is typically much more resource intensive than training a regular (non-federated) ML model due to the extra steps involved (see Algorithm 1), thus it is of particular importance that FL simulators be efficient and scale well.

The community has identified a comprehensive list of open problems in FL [41], and effective evaluation of proposed solutions requires high quality large-scale datasets representative of these challenges. Several realistic benchmarks have been proposed to facilitate reliable evaluation of FL algorithms (see Section 2). Unfortunately, the largest and most realistic open-source benchmark datasets for FL have not been widely adopted because of the resources required to use them. As we discuss in Section 4.1, the resource demand is exacerbated by slow simulators.

We introduce `pfl-research`, a modular and easy-to-use framework for researchers to simulate FL and PFL training that is $7\text{-}72\times$ faster than previous FL simulators. Our framework has well defined APIs that allow an FL researcher to implement their algorithms and bundle them into components that can be shared and combined with other algorithms. `pfl-research` supports both PyTorch [67] and TensorFlow [4], and it is straightforward to integrate with other ML frameworks. Additionally, scaling up with distributed simulations is seamless with Horovod [75], including multi-host, multi-GPU scenarios. Cluster workload management and scheduling systems such as slurm [40] can be used to enable running multiple simulation runs with different configurations in parallel, e.g. for hyperparameter tuning.

Our main contributions are:

Speed `pfl-research` is much faster than other popular FL simulators (Section 4.1) since it simulates only the computation, not the topology, of federated learning. This can significantly increase both the productivity of (P)FL researchers and the quality of publications because it makes it feasible for researchers with limited resources to evaluate algorithms on larger datasets.

User-friendly distributed simulations `pfl-research` makes it easy to transition from single process to distributed simulations with zero code changes. Scale-up spans multiple dimensions: number of processes, GPUs, and machines. Multiple processes can share a GPU to increase GPU utilization. Debugging, testing, and profiling are simpler compared to alternative FL frameworks.

Privacy integration `pfl-research` is tightly integrated with state-of-the-art privacy accountants and mechanisms, enabling a convenient workflow for experimenting with PFL and combining it with orthogonal FL features and algorithms.

Non-gradient-descent training `pfl-research` is also a suitable framework for researching federated learning with models that require training algorithms beyond gradient descent, such as some classical ML algorithms. We provide implementations of federated gradient boosted decision trees (GBDTs) and federated Gaussian mixture models (GMMs).

Diverse and unified benchmarks To get a complete picture of where an algorithm performs well, we provide setups for benchmarking algorithms in a variety of scenarios: datasets of diverse domains, IID / non-IID, no DP / Central DP. We aim to provide the same benchmarks for both PyTorch and TensorFlow so that results are comparable across frameworks.

`pfl-research` began as an inner-source project and has been used both in research and for modelling practical use cases [7–9, 33, 44, 68, 73, 88, 92].

2 Related Work

There are multiple open-source efforts for realizing FL. Some focus on providing infrastructure for a production environment with real edge devices [25, 57, 58, 95], some focus on simulations for research [11, 28, 30], and some provide both [34, 50, 71, 74, 87].

There are pros and cons to each framework for simulation, but there is one validly comparable metric that is key to research velocity: speed. If an FL framework runs too slowly, researchers with constrained resources will not be able to test their hypotheses on realistic benchmarks, which can

outweigh other framework benefits. For example, [77] and [55] used FLAIR in their experiments with the original TensorFlow Federated code³ and they both mentioned that the computational resource requirements were substantial enough for them to have to reduce the scope of their experiments. Therefore, we mainly compare previous work with `pf1-research` by implementing the same cross-device benchmarks and measuring wall-clock time to finish one simulation run; see Section 4.1 for the results.

The existing FL simulation frameworks and additional works from [16, 38, 53, 56] provide benchmarks for evaluating general FL algorithms. Additionally, [83] focuses on evaluation of cross-silo FL, and [19, 59, 86] on personalized FL. A subset of each suite of benchmarks are datasets that resemble realistic FL partitions. Unfortunately, publications have largely been focused on datasets such as CIFAR10 [48], MNIST [51], Shakespeare [60], and LibSVM [17] that are not, in our view, generated by processes that adequately represent realistic FL settings. A lot of progress has been made on creating large-scale, realistic datasets for PFL, including for example [15, 18, 34, 36, 50, 54, 79]. However, the large datasets realistic for FL cannot be used unless simulations become much faster. We did a survey on most recent publications at NeurIPS 2023 [66], ICLR 2024 [39], ICML 2024 [69]. There are 162 publications that provide simulation results in federated learning. 142 out of 162 publications provide results on 1-100 clients, while only 6 out of the 162 publications consider more than 1000 clients for the empirical analysis. Appendix A.1 of [11] confirmed the same trend for previous years.

Few FL frameworks integrate security and privacy features, despite FL alone not preserving the privacy of individual clients [12, 29]. Client’s privacy can be violated by: (1) a server actor inspecting gradients from individual clients before aggregation; and (2) information about clients’ data being extracted from the model after deployment [76]. The second issue is commonly addressed using central differential privacy (DP) [26, 65, 89]. The first issue requires, in addition to DP, secure aggregation [10, 14, 81].

Most secure aggregation schemes merely compute a sum, and therefore do not need to be simulated, but DP mechanisms need to be included in PFL simulations to accurately reflect the effects of noisy statistics. There are several popular libraries that provide implementations of DP mechanisms to apply DP noise on generic vectors [31, 91]. However, most existing FL frameworks do not provide a simple way to plug these DP mechanisms into existing FL algorithms whilst ensuring consistency of DP parameters with FL hyperparameters in experiments.

3 System design

`pf1-research` is built entirely in Python and bundled into one package, making installation easy on any platform. The framework is designed to be modular such that researchers are able to select a model and an algorithm, specify additional processing such as DP, and then quickly try these out for any use case.

In this section, we highlight key design elements that differentiate `pf1-research` from alternative FL frameworks. We defer the introduction to FL and DP to Appendix A, and of the detailed system design to Appendix B, with the specific classes to which these extension points map in `pf1-research` to Appendix B.1.

In `pf1-research` simulations, the algorithm drives the training procedure by: constructing queries to execute on sampled cohorts of one or multiple federated datasets for each central iteration, defining the local optimization procedure with the assistance of a local model to execute the query for a user, defining how to use aggregated statistics to update the central state, and determining when to stop training. The output of the local optimization procedure and output of the aggregation can be postprocessed by various composable features like DP mechanisms, weighting, sparsification and compression. Algorithm 1 describe this generalized PFL simulation algorithm in detail.

We highlight these key elements that contribute to the high efficiency of `pf1-research`:

1. Only one model per worker process is initialized and preserved on the GPU at all times.
2. Model parameters are updated in-place on the single model the worker process has access to. In practice, the same instantiation is used for both local training, local evaluation, central

³Available at <https://github.com/apple/ml-flair/tree/main>

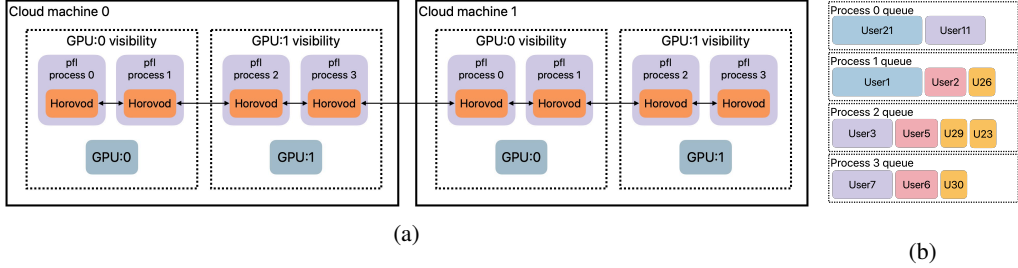


Figure 1: (a) The (simplified) architecture of distributed simulations. Each process is a replica with a different distributed context. One synchronous communication step is done to aggregate gradients and metrics. (b) Each process has a balanced queue of users to train.

updates and central evaluation. It is only the model’s state that is sometimes cloned, e.g. before training first user in new sampled cohort, but it is always cloned to already allocated tensors on the GPU. There is no memory in the order of the model size that is released and re-allocated during the course of the FL simulation.

3. `pfl-research` does not simulate the topology of FL, i.e. there is no main coordinating process to gather and broadcast model updates. Further details in Section 3.1.
4. ML framework tensors are used on the GPU end-to-end in the outer training loop. This includes DP mechanisms. Alternative frameworks, e.g. Flower, use NumPy for parts of the outer loop.
5. `pfl-research` performs load balancing of training users. This is particularly important in the case of a high dispersion in user dataset lengths, e.g. FLAIR dataset. A detailed analysis on the effect of this feature is presented in Appendix B.6.
6. Using `torch.utils.data` and `tf.data` we provide support for asynchronously loading and preprocessing entire user datasets.

`pfl-research` specifically emphasizes the flexibility for experimenting with DP. The framework is superior to existing (P)FL frameworks for simulating FL with privacy guarantees in several ways: (1) Central and local DP mechanisms and accounting methods are abstracted as pluggable components, allowing researchers to easily experiment with different combinations of DP methods; (2) Tight integration between the DP mechanisms and FL hyperparameters to prevent errors in using DP with FL, e.g. DP noise is correctly scaled according to the actual clipping bound used in each iteration; (3) DP mechanisms are implemented with GPU acceleration without data transferring between CPU and GPU; (4) `pfl-research` offers a broad range of state-of-the-art privacy mechanisms and accountants out-of-the-box for different use-cases, listed in Appendix B.5.

`pfl-research` provides interfaces that allow straightforward integration with Foundation Model (FM) frameworks such as HuggingFace [85]. The open-sourced models and datasets for FM can be easily adapted and trained in `pfl-research`, which we believe will enable and accelerate the frontier research on FM with PFL.

3.1 Distributed simulations

Most existing FL frameworks have explicit communication steps as they aim to simulate the topology of a real-world FL system where the central server is a bottleneck. In many deployments, the central server can be adequately scaled, and it is valuable to have a faster simulation that ignores the topology. `pfl-research` simulates only the computation of FL. Communication is necessary only if the simulation runs with multiple workers (using `Aggregator.worker_reduce`, see Appendix B.2). There is no dedicated coordinator or aggregator process needed with which all other workers communicate, unlike real-world FL. All worker processes are replicas, making debugging and transition from single-process to multi-worker training straightforward.

As depicted in Figure 1, multiple worker processes can both live on a single machine and be instantiated across multiple machines. If a machine has g GPUs and gp worker processes, then p processes will share the same GPU. (P)FL generally has more non-GPU overhead than conventional

Table 1: Comparison of simulating CIFAR10 IID dataset with different FL frameworks. g is the number of GPUs and p is the number of processes concurrently training users and sharing one GPU. All experiments are run for 5 times with different random seed, and both mean and standard deviation of metrics are reported.

Framework	g	p	Wall-clock time (minutes)	Accuracy	pf1-research is faster
pf1-research (PyTorch)	1	1	10.13 \pm 0.06	70.45% \pm 0.30	-
pf1-research (PyTorch)	1	5	4.20 \pm 0.10	70.25% \pm 0.20	-
pf1-research (TF)	1	1	15.34 \pm 0.11	70.43% \pm 0.11	-
pf1-research (TF)	1	5	7.89 \pm 0.26	70.52% \pm 0.17	-
FedML (PyTorch) [34]	1	1	90.95 \pm 0.47	71.23% \pm 0.00	21.6 \times
TensorFlow Federated [30]	1	1	113.52 \pm 1.26	70.02% \pm 0.36	27 \times
TensorFlow Federated [30]	1	10	82.23 \pm 0.49	70.12% \pm 0.35	19.6 \times
Flower (PyTorch) [11]	1	1	86.88 \pm 1.42	68.30% \pm 0.12	16.4 \times
Flower (PyTorch) [11]	1	10	29.26 \pm 0.90	67.66% \pm 0.28	7 \times
FedScale [50]	1	1	425.2 \pm 17.66	70.41% \pm 0.00	101 \times
FedScale [50]	1	10	301.7 \pm 19.22	70.90% \pm 0.43	71.8 \times
FLUTE [28]	1	1	67.86 \pm 3.36	62.26% \pm 0.07	16.1 \times

ML training, resulting in a lower GPU utilization. Section 4.2 empirically shows that spawning more worker processes than GPUs available will increase the GPU utilization and speed up simulations.

In each central iteration, a sampled cohort of user IDs is scheduled among the worker processes. Given an associated weight for each user, pf1-research will do a greedy optimization based on these weights to schedule users across the worker processes to minimize stragglers. See Appendix B.6 for further details on the scheduling algorithm. Each worker process locally aggregates client model updates and metrics (while there are more clients to train for the current central iteration). Then, inter-worker aggregation is done with all-reduce.

4 Experiments

4.1 Comparing performance to alternative FL simulators

In this section, we present comprehensive speed benchmarking of FL simulation frameworks. We compare frameworks on two datasets: CIFAR10 IID and FLAIR. These are two of the setups also included in pf1-research benchmarks, described in Section 4.3. CIFAR10 simulation was done on one NVIDIA A100 GPU (40GB) and FLAIR simulation was done on four NVIDIA A100 GPUs. We refer the reader to Appendix D for details on how the frameworks were selected, the specific versions used, and additional information about the setups. For a fair comparison, the hyperparameter values are the same for different frameworks on both CIFAR10 IID and FLAIR.

In Table 1, we compare the accuracy (mainly as a consistency check) and the wall-clock time of simulation runs on CIFAR10 for the most popular open-source FL simulators. The hyper-parameters are the same for all framework setups and described in C.5. The pf1-research setup in PyTorch with four processes sharing the single GPU is the fastest, with a wall-clock time of only 4 minutes and 20 seconds. This means that our framework executes this task 7 \times faster than the runner-up, Flower, and 72 \times faster than the slowest framework, FedScale. The difference in wall-clock time is so vast because smaller scale experiments like the CIFAR10 benchmark specifically emphasizes the necessary overhead that can exist in FL simulation, and frameworks that do not minimize this overhead suffer proportionally.

As a second comparison, we use FLAIR, which instead emphasizes the efficiency of training both a larger model and dataset in distributed simulations. Due to development time constraints, we implemented the FLAIR setup for the two frameworks that are most frequently used for publications: TFF and Flower.

Table 2 shows that pf1-research outperforms the alternatives prominently in terms of speed on the larger scale FLAIR benchmark. Relative to pf1-research, TFF is more efficient on FLAIR than

Table 2: Comparison of simulating FLAIR dataset with different FL frameworks. The metric is the same as FL-F-17 C-AP in [79]. Note that version 0.2.0 was released after the initial open-source date of `pfl-research`, which implements improved scheduling for training users, see Appendix B.6.

Framework	p	Wall-clock time (hours)	mAP	<code>pfl-research</code> is faster
<code>pfl-research</code> 0.1.0 (PyTorch)	2	2.16	61.8 ± 0.001	-
<code>pfl-research</code> 0.2.0 (PyTorch)	2	1.77	61.1 ± 0.3	-
<code>pfl-research</code> 0.2.0 (PyTorch) with central DP TensorFlow Federated [30]	2	1.93	-	-
Flower [11]	5	18	62.0 ± 0.3	10.2 \times
	5	28.8	31.5^4	16.3 \times

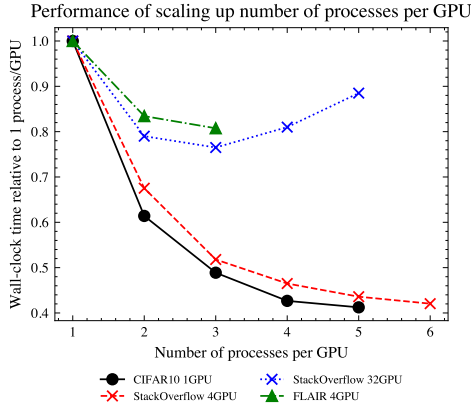


Figure 2: Speedup from scaling up number of processes per GPU in distributed simulations, while keeping the hardware resources fixed. As long as number of GPUs \ll cohort size (unlike the blue line, where we use an unnecessarily large amount of GPUs given the size of model, users and cohort), the wall-clock time is monotonically decreasing when increasing number of models to train in parallel on the same GPU.

on CIFAR10, and vice versa for Flower. The third row show that enabling DP only adds 9% extra simulation wall-clock time.

The number of processes per GPU, p , was tuned to minimize wall-clock time, and the results show that `pfl-research` needs many fewer training processes per GPU to saturate GPU utilization. Tables 1 and 2 demonstrate that before the release of `pfl-research`, the comparison of framework speed greatly depended on the choice of benchmarks.

The superior performance of `pfl-research` can be attributed to several design choices, some of which are unique to it or not commonly employed by other FL simulators, described previously in Section 3. Appendix D.4.2 show system metrics from training the CIFAR10 benchmark, giving more insight into how `pfl-research` is faster.

4.2 Scaling distributed training

Figure 2 shows the wall-clock time when scaling up number of processes in distributed simulations. In `pfl-research`, the number of worker processes is decoupled from the number of GPUs available, allowing processes to share a GPU. Using more than one process per GPU, $p > 1$, always has a positive effect, but the optimal number depends on the use-case (model size, cohort size). For CIFAR10 and StackOverflow [80], we can set $p = 5$ and the wall-clock time is less than 0.43 of that with $p = 1$ with same resources, while for FLAIR we can only fit a maximum of $p = 3$ on the GPU and the relative speedup is smaller.

⁴Reaching parity in performance on FLAIR with Flower is still work in progress.

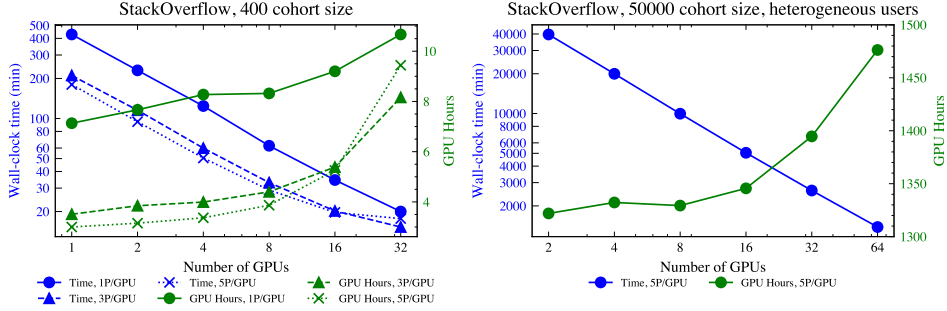


Figure 3: Speedup from scaling up distributed simulations. **Left panel:** Sweep number of processes per GPU on CIFAR10, StackOverflow and FLAIR benchmarks and keep the hardware resources pinned. **Right panel:** Sweep the number of GPUs to train the StackOverflow benchmark, repeat for 1, 3 and 5 processes per GPU. Blue lines (tracked on left y-axis) show wall-clock time. Green lines (tracked in right y-axis) show total GPU hours for the same experiments. Note that the runs with >8 GPUs use multiple hosts and thus become slightly less efficient.

Table 3: Performance of FL algorithms on the `pf1-research` benchmark suite without DP. C10 stands for accuracy on CIFAR10, SO stands for perplexity on StackOverflow, FLR stands for mean average precision (mAP) on FLAIR. The last three columns are the perplexity scores for three LLM benchmark datasets: Stanford Alpaca (SA), Aya, and OpenAssistant (OA). If not mentioned, the natural or artificial non-IID partitioning is used for the dataset, and -IID means partitioning with fixed number of samples per client drawn IID. AdaFedProx is FedProx with adaptive μ from Appendix C.3.3 in [52]. Errors for LLM experiments are detailed in Table 12

Algorithm	C10-IID \uparrow	C10 \uparrow	SO \downarrow	FLR-IID \uparrow	FLR \uparrow	SA \downarrow	Aya \downarrow	OA \downarrow
FedAvg [60]	70.37 \pm .21	69.80 \pm .35	60.87 \pm .28	65.08 \pm .60	61.83 \pm .10	3.61	4.02	6.39
FedProx [52]	70.69 \pm .33	69.79 \pm .35	60.88 \pm .28	64.45 \pm 1.13	62.02 \pm .11	3.61	4.02	6.39
AdaFedProx [52]	70.39 \pm .33	69.61 \pm .45	61.01 \pm .34	64.53 \pm 1.01	61.99 \pm .11	3.61	4.02	6.40
SCAFFOLD [42]	-	60.17 \pm 1.29	62.43 \pm .09	-	60.82 \pm .12	3.73	4.77	6.90

The left panel of Figure 3 shows the wall-clock time when scaling up the number of GPUs on the StackOverflow benchmark with a cohort size of 400. The wall-clock time is reduced to 3 hours with just one GPU when scaling up number of worker processes to five, and the wall-clock time is reduced to 15 minutes when scaling up to 32 GPUs. Thus, `pf1-research` scales well with number of GPUs. The *rate* of improvement is expected to be reduced as we increase the total number of GPUs because there are fewer users per process to load balance. This is revealed by the total number of GPU hours to finish (green lines). To demonstrate a more compute intensive scenario that can be scaled up further, we increase cohort size to 50,000 and show results from scaling up in the right panel of Figure 3. We see that distributed simulations scale even better in this case, for example the increase in GPU hours when moving from 16GPUs to 32GPUs is only 3.6%.

4.3 Benchmarks for research

Along with the framework, we unify benchmarking of algorithms implemented in either PyTorch or TensorFlow (TF) under a collection of dataset-privacy setups, creating the matrix of benchmarks $\text{Datasets} \times \{\text{IID}, \text{non-IID}\} \times \{\text{no DP}, \text{Central DP}\} \times \{\text{TF}, \text{PyTorch}\} \times \text{Algorithms}$. The modularity of our framework and benchmark setups enables us to grow in any dimension: Add a dataset to benchmark all algorithms on, benchmark another algorithm, or add support for another framework or privacy mechanism. We consider the adaptive federated optimization such as FedAdam [70] as a tunable component of these algorithms, i.e. the choice of the central optimizer. The detailed hyperparameter choices for each dataset can be found in Appendix C. In this section we present the benchmark results for the PyTorch setups; we discuss the TensorFlow setups in Appendix C.1.

The initial set of algorithms we benchmark is shown in Table 3 without DP and in Table 4 with central DP. All experiments are run for five times with different random seed and metrics are averaged.

Table 4: Performance of FL algorithms on the `pf1-research` benchmark suite with central DP. The same rules and notation as in Table 3 are used. G stands for Gaussian mechanism with accounting using privacy loss distribution [22, 62] and BMF stands for banded matrix factorization mechanism [20]. Errors for LLM experiments are detailed in Table 13.

Algorithm	DP	C10-IID \uparrow	C10 \uparrow	SO \downarrow	FLR-IID \uparrow	FLR \uparrow	SA \downarrow	Aya \downarrow	OA \downarrow
FedAvg	G	68.77 \pm .38	66.70 \pm .09	69.11 \pm .35	65.24 \pm .22	61.49 \pm .11	3.62	4.19	6.52
FedAvg	BMF	69.21 \pm .51	67.07 \pm .14	62.47 \pm .22	65.55 \pm .05	61.64 \pm .10	3.62	4.20	6.53
FedProx	G	68.72 \pm .34	66.75 \pm .21	69.12 \pm .34	65.24 \pm .17	61.55 \pm .11	3.62	4.20	6.52
AdaFedProx	G	68.78 \pm .48	66.80 \pm .09	69.14 \pm .34	65.18 \pm .16	61.58 \pm .08	3.62	4.20	6.52
SCAFFOLD	G	-	61.31 \pm .24	77.71 \pm .10	-	51.64 \pm .44	3.79	4.76	7.00

Evaluation is done on the validation data partitions of the original datasets without any federated splits. The common hyperparameters, such as cohort size and number of local epochs, were optimized using the FedAvg experiments. Meanwhile, specific hyperparameters for each algorithm were individually tuned. As a result, direct comparisons between the performance of different algorithms and FedAvg may not be conclusive. However, some observations based on the results include:

- Banded matrix factorization mechanism, also known as DP-FTRL when applied to FL, significantly outperforms Gaussian mechanism with PLD moments accountant on Stack-Overflow, with 10% relative improvement.
- SCAFFOLD, a popular algorithm according to citations, does not perform better than FedAvg on any of our benchmarks. [63] also report that SCAFFOLD consistently perform worse than FedAvg.
- FedProx is known for performing well on heterogeneous data partitions, but this is only marginally reflected in the FLAIR benchmark results. It is worse than FedAvg baseline on FLAIR IID, but better on FLAIR with natural heterogeneous client partitions.

The breadth of algorithms is limited at this moment, but we believe we have provided robust FedAvg baselines and a flexible foundation for future work to expand the results in terms of algorithms, complementary datasets, better hyper-parameter tuning of algorithms for more fair comparison, and other evaluation metrics, e.g. amount of communicated bits.

LLM benchmarks We consider three datasets for benchmarking LLM fine-tuning with `pf1-research` to demonstrate the scalability to larger models: Stanford Alpaca (SA), Aya and OpenAssistant (OA). Compared to existing FL LLM benchmarks [49, 90] where centralized datasets are artificially partitioned into users, Aya and OA have a natural user partition to simulate heterogeneity that reflects a more realistic production setting. SA contains 52,002 instruction-following data which is then artificially partitioned into users in an IID fashion. Aya contains a total of 204,112 human-annotated prompt-completion pairs, where each label has the identifier of the annotator. OA contains more than 120,000 conversational messages between human and AI assistant pairs. We collect 85,318 pairs of user inputs and assistant response with associated user identifier. We partition Aya and OA into users in a non-IID fashion using the provided user identifiers. Details of dataset partition and model fine-tuning are described in Appendix C.8.

5 Future work

`pf1-research` currently provides a small collection of federated algorithms. Our primary goal has been to release a fast, modular and easy-to-use simulator which is useful for advancing research in this area. We will continuously benchmark new algorithms and methods, and will rely heavily on the community for contributing implementations of new research.

We plan to carefully curate more benchmarks while maintaining a diverse set of domains for the benchmarks. All benchmark results reported in Section 4.3 used PyTorch, and releasing similar benchmarks in TensorFlow is work in progress. We recognize that all our current benchmarks

use cross-device FL. Cross-silo FL can be simulated with `pfl-research`, but we do not provide benchmarks for this scenario yet.⁵

The aggregator interface can be extended to make a client-server architecture with a dedicated aggregator and coordinator process, which might be required for testing certain research ideas not limited to synchronous FL. We also do not provide interfaces for implementing PFL with real edge devices. This is outside the scope of `pfl-research` at this time.

In some scenarios, such as large-scale cross-silo PFL simulations or training foundation models, it may be useful to train a local model for a single user (silo) on multiple GPUs. Implementation of model parallelism in `pfl-research` remains for future work.

Some benchmarking related to system performance left for future work are on the concept of weak scaling—to investigate the efficiency of the distributed setup as the workload and resources scale proportionally. Figure 3 had a fixed cohort size and didn't increase the cohort sizes proportionally.

6 Conclusion

We have introduced `pfl-research`, a fast, modular, and easy-to-use simulation framework for accelerating research in federated learning (FL) and private federated learning (PFL). It supports TensorFlow, PyTorch, and non-neural network models, and is tightly integrated with state-of-the-art privacy algorithms. It requires no code changes for scaling up distributed simulations across multiple processes, GPUs, and machines.

We compare the performance to other open-source FL simulators and our benchmarks show that `pfl-research` is $7\text{-}72\times$ faster. The immense speedup, flexible APIs, benchmark setups with realistic datasets, integration with visualization tools, and simple debugging experience will significantly increase the productivity of (P)FL researchers. We believe that researchers will view the speedup that `pfl-research` offers as an opportunity to validate research on more challenging and realistic datasets than what is currently common practice in the field.

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References

- [1] Health insurance portability and accountability act of 1996. <https://www.hhs.gov/hipaa/for-professionals/privacy/laws-regulations/index.html>, 1996.
- [2] Regulation (eu) 2016/679 of the european parliament and of the council of 27 april 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing directive 95/46/ec (general data protection regulation). <https://eur-lex.europa.eu/eli/reg/2016/679/oj>, 2016.
- [3] Google scholar search results for "federated learning". https://scholar.google.com/scholar?q=%22federated+learning%22&hl=en&as_sdt=0%2C5&as_ylo=2023&as_yhi=2023, 2023. Accessed on 2024-02-03; over 34,200 articles mentioned "Federated Learning" in 2023, exponential growth since 2018.
- [4] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. {TensorFlow}: a system for

⁵We refer to <https://github.com/apple/pfl-research/blob/main/pfl/data/sampling.py#L143> for more information about cross-silo simulation in `pfl-research`.

- {Large-Scale} machine learning. In *12th USENIX symposium on operating systems design and implementation (OSDI 16)*, pages 265–283, 2016.
- [5] Galen Andrew, Om Thakkar, Brendan McMahan, and Swaroop Ramaswamy. Differentially private learning with adaptive clipping. *Advances in Neural Information Processing Systems*, 34:17455–17466, 2021.
- [6] Apple Machine Learning Research. Scenes with differential privacy. <https://machinelearning.apple.com/research/scenes-differential-privacy>, 2023. Accessed: 2024-02-28.
- [7] Sheikh Shams Azam, Tatiana Likhomanenko, Martin Pelikan, et al. Importance of smoothness induced by optimizers in fl4asr: Towards understanding federated learning for end-to-end asr. In *2023 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 1–8. IEEE, 2023.
- [8] Sheikh Shams Azam, Martin Pelikan, Vitaly Feldman, Kunal Talwar, Jan Silovsky, and Tatiana Likhomanenko. Federated learning for speech recognition: Revisiting current trends towards large-scale asr. In *International Workshop on Federated Learning in the Age of Foundation Models in Conjunction with NeurIPS 2023*, 2023.
- [9] Eugene Bagdasaryan, Congzheng Song, Rogier van Dalen, Matt Seigel, and Áine Cahill. Training a tokenizer for free with private federated learning. *arXiv preprint arXiv:2203.09943*, 2022.
- [10] James Henry Bell, Kallista A Bonawitz, Adrià Gascón, Tancrede Lepoint, and Mariana Raykova. Secure single-server aggregation with (poly) logarithmic overhead. In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, pages 1253–1269, 2020.
- [11] Daniel J Beutel, Taner Topal, Akhil Mathur, Xinchu Qiu, Javier Fernandez-Marques, Yan Gao, Lorenzo Sani, Kwing Hei Li, Titouan Parcollet, Pedro Porto Buarque de Gusmão, et al. Flower: A friendly federated learning research framework. *arXiv preprint arXiv:2007.14390*, 2020.
- [12] Franziska Boenisch, Adam Dziedzic, Roei Schuster, Ali Shahin Shamsabadi, Iliia Shumailov, and Nicolas Papernot. When the curious abandon honesty: Federated learning is not private. In *2023 IEEE 8th European Symposium on Security and Privacy (EuroS&P)*, pages 175–199. IEEE, 2023.
- [13] Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloe Kiddon, Jakub Konečný, Stefano Mazzocchi, Brendan McMahan, et al. Towards federated learning at scale: System design. *Proceedings of machine learning and systems*, 1:374–388, 2019.
- [14] Keith Bonawitz, Vladimir Ivanov, Ben Kreuter, Antonio Marcedone, H Brendan McMahan, Sarvar Patel, Daniel Ramage, Aaron Segal, and Karn Seth. Practical secure aggregation for privacy-preserving machine learning. In *proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, pages 1175–1191, 2017.
- [15] Sebastian Caldas, Sai Meher Karthik Duddu, Peter Wu, Tian Li, Jakub Konečný, H Brendan McMahan, Virginia Smith, and Ameet Talwalkar. Leaf: A benchmark for federated settings. *arXiv preprint arXiv:1812.01097*, 2018.
- [16] Di Chai, Leye Wang, Liu Yang, Junxue Zhang, Kai Chen, and Qiang Yang. Fedeval: A holistic evaluation framework for federated learning. *arXiv preprint arXiv:2011.09655*, 2020.
- [17] Chih-Chung Chang and Chih-Jen Lin. Libsvm: a library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)*, 2(3):1–27, 2011.
- [18] Zachary Charles, Nicole Mitchell, Krishna Pillutla, Michael Reneer, and Zachary Garrett. Towards federated foundation models: Scalable dataset pipelines for group-structured learning. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine, editors, *Advances in Neural Information Processing Systems*, volume 36, pages 32299–32327, 2023.

- [19] Daoyuan Chen, Dawei Gao, Weirui Kuang, Yaliang Li, and Bolin Ding. pFL-bench: A comprehensive benchmark for personalized federated learning. *Advances in Neural Information Processing Systems*, 35:9344–9360, 2022.
- [20] Christopher A Choquette-Choo, Arun Ganesh, Ryan McKenna, H Brendan McMahan, John Rush, Abhradeep Guha Thakurta, and Zheng Xu. (amplified) banded matrix factorization: A unified approach to private training. *Advances in Neural Information Processing Systems*, 36, 2023.
- [21] Gregory Cohen, Saeed Afshar, Jonathan Tapson, and Andre Van Schaik. Emnist: Extending mnist to handwritten letters. In *2017 international joint conference on neural networks (IJCNN)*, pages 2921–2926. IEEE, 2017.
- [22] Vadym Doroshenko, Badih Ghazi, Pritish Kamath, Ravi Kumar, and Pasin Manurangsi. Connect the dots: Tighter discrete approximations of privacy loss distributions. *arXiv preprint arXiv:2207.04380*, 2022.
- [23] Cynthia Dwork, Krishnaram Kenthapadi, Frank McSherry, Ilya Mironov, and Moni Naor. Our data, ourselves: Privacy via distributed noise generation. In *Advances in Cryptology-EUROCRYPT 2006: 24th Annual International Conference on the Theory and Applications of Cryptographic Techniques, St. Petersburg, Russia, May 28-June 1, 2006. Proceedings 25*, pages 486–503. Springer, 2006.
- [24] Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. Calibrating noise to sensitivity in private data analysis. In *Theory of Cryptography: Third Theory of Cryptography Conference, TCC 2006, New York, NY, USA, March 4-7, 2006. Proceedings 3*, pages 265–284. Springer, 2006.
- [25] Morgan Ekmefjord, Addi Ait-Mlouk, Sadi Alawadi, Mattias Åkesson, Prashant Singh, Ola Spjuth, Salman Toor, and Andreas Hellander. Scalable federated machine learning with fedn. In *2022 22nd IEEE International Symposium on Cluster, Cloud and Internet Computing (CCGrid)*, pages 555–564. IEEE, 2022.
- [26] Ahmed El Ouadrhiri and Ahmed Abdelhadi. Differential privacy for deep and federated learning: A survey. *IEEE access*, 10:22359–22380, 2022.
- [27] Jerome H Friedman. Greedy function approximation: a gradient boosting machine. *Annals of statistics*, pages 1189–1232, 2001.
- [28] Mirian Hipolito Garcia, Andre Manoel, Daniel Madrigal Diaz, Fatemehsadat Mireshghallah, Robert Sim, and Dimitrios Dimitriadis. Flute: A scalable, extensible framework for high-performance federated learning simulations. *arXiv preprint arXiv:2203.13789*, 2022.
- [29] Jonas Geiping, Hartmut Bauermeister, Hannah Dröge, and Michael Moeller. Inverting gradients-how easy is it to break privacy in federated learning? *Advances in Neural Information Processing Systems*, 33:16937–16947, 2020.
- [30] Google LLC. Tensorflow federated. <https://www.tensorflow.org/federated>, 2023. Accessed: [insert date here].
- [31] Google LLC. Tensorflow privacy. <https://github.com/tensorflow/privacy>, 2023. Accessed: 2024-02-20.
- [32] Sivakanth Gopi, Yin Tat Lee, and Lukas Wutschitz. Numerical composition of differential privacy, 2021.
- [33] Filip Granqvist, Matt Seigel, Rogier Van Dalen, Aine Cahill, Stephen Shum, and Matthias Paulik. Improving on-device speaker verification using federated learning with privacy. *arXiv preprint arXiv:2008.02651*, 2020.
- [34] Chaoyang He, Songze Li, Jinhyun So, Xiao Zeng, Mi Zhang, Hongyi Wang, Xiaoyang Wang, Praneeth Vepakomma, Abhishek Singh, Hang Qiu, et al. FedML: A research library and benchmark for federated machine learning. *arXiv preprint arXiv:2007.13518*, 2020.

- [35] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.
- [36] Tzu-Ming Harry Hsu, Hang Qi, and Matthew Brown. Federated visual classification with real-world data distribution. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, *Computer Vision – ECCV 2020*, pages 76–92. Springer International Publishing, 2020.
- [37] Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022.
- [38] Sixu Hu, Yuan Li, Xu Liu, Qinbin Li, Zhaomin Wu, and Bingsheng He. The oarf benchmark suite: Characterization and implications for federated learning systems. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 13(4):1–32, 2022.
- [39] International Conference on Learning Representations. *Proceedings of the 2024 International Conference on Learning Representations*, 2024. Available at: <https://iclr.cc/Downloads/2024>.
- [40] Morris A. Jette and Tim Wickberg. Architecture of the slurm workload manager. In Dalibor Klusáček, Julita Corbalán, and Gonzalo P. Rodrigo, editors, *Job Scheduling Strategies for Parallel Processing*, pages 3–23. Springer Nature Switzerland, 2023.
- [41] Peter Kairouz, H Brendan McMahan, Brendan Avent, Aurélien Bellet, Mehdi Bennis, Arjun Nitin Bhagoji, Kallista Bonawitz, Zachary Charles, Graham Cormode, Rachel Cummings, et al. Advances and open problems in federated learning. *Foundations and Trends® in Machine Learning*, 14(1–2):1–210, 2021.
- [42] Sai Praneeth Karimireddy, Satyen Kale, Mehryar Mohri, Sashank Reddi, Sebastian Stich, and Ananda Theertha Suresh. Scaffold: Stochastic controlled averaging for federated learning. In *International conference on machine learning*, pages 5132–5143. PMLR, 2020.
- [43] Mikhail Khodak, Renbo Tu, Tian Li, Liam Li, Maria-Florina F Balcan, Virginia Smith, and Ameet Talwalkar. Federated hyperparameter tuning: Challenges, baselines, and connections to weight-sharing. *Advances in Neural Information Processing Systems*, 34:19184–19197, 2021.
- [44] Tatsuki Koga, Congzheng Song, Martin Pelikan, and Mona Chitnis. Population expansion for training language models with private federated learning. *arXiv preprint arXiv:2307.07477*, 2023.
- [45] Jakub Konečný, H Brendan McMahan, Daniel Ramage, and Peter Richtárik. Federated optimization: Distributed machine learning for on-device intelligence. *arXiv preprint arXiv:1610.02527*, 2016.
- [46] Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi Rui Tam, Keith Stevens, Abdullah Barhoum, Duc Nguyen, Oliver Stanley, Richárd Nagyfi, et al. Openassistant conversations-democratizing large language model alignment. *Advances in Neural Information Processing Systems*, 36, 2023.
- [47] Antti Koskela and Antti Honkela. Learning rate adaptation for federated and differentially private learning. *arXiv preprint arXiv:1809.03832*, 2018.
- [48] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.
- [49] Weirui Kuang, Bingchen Qian, Zitao Li, Daoyuan Chen, Dawei Gao, Xuchen Pan, Yuexiang Xie, Yaliang Li, Bolin Ding, and Jingren Zhou. Federatedscope-llm: A comprehensive package for fine-tuning large language models in federated learning. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 5260–5271, 2024.

- [50] Fan Lai, Yinwei Dai, Sanjay Singapuram, Jiachen Liu, Xiangfeng Zhu, Harsha Madhyastha, and Mosharaf Chowdhury. FedScale: Benchmarking model and system performance of federated learning at scale. In *International Conference on Machine Learning*, pages 11814–11827. PMLR, 2022.
- [51] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.
- [52] Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. Federated optimization in heterogeneous networks. *Proceedings of Machine learning and systems*, 2:429–450, 2020.
- [53] Yuan Liang, Yange Guo, Yanxia Gong, Chunjie Luo, Jianfeng Zhan, and Yunyou Huang. Flbench: A benchmark suite for federated learning. In *Intelligent Computing and Block Chain: First BenchCouncil International Federated Conferences, FICC 2020, Qingdao, China, October 30–November 3, 2020, Revised Selected Papers 1*, pages 166–176. Springer, 2021.
- [54] Bill Yuchen Lin, Chaoyang He, Zihang Ze, Hulin Wang, Yufen Hua, Christophe Dupuy, Rahul Gupta, Mahdi Soltanolkotabi, Xiang Ren, and Salman Avestimehr. FedNLP: Benchmarking federated learning methods for natural language processing tasks. In Marine Carpuat, Marie-Catherine de Marneffe, and Ivan Vladimir Meza Ruiz, editors, *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 157–175, Seattle, United States, July 2022. Association for Computational Linguistics.
- [55] I Liu, Ci-Siang Lin, Fu-En Yang, Yu-Chiang Frank Wang, et al. Language-guided transformer for federated multi-label classification. *arXiv preprint arXiv:2312.07165*, 2023.
- [56] Xiaoyuan Liu, Tianneng Shi, Chulin Xie, Qinbin Li, Kangping Hu, Haoyu Kim, Xiaojun Xu, Bo Li, and Dawn Song. Unifed: A benchmark for federated learning frameworks. *arXiv preprint arXiv:2207.10308*, 2022.
- [57] Yang Liu, Tao Fan, Tianjian Chen, Qian Xu, and Qiang Yang. Fate: An industrial grade platform for collaborative learning with data protection. *The Journal of Machine Learning Research*, 22(1):10320–10325, 2021.
- [58] Heiko Ludwig, Nathalie Baracaldo, Gegi Thomas, Yi Zhou, Ali Anwar, Shashank Rajamoni, Yuya Ong, Jayaram Radhakrishnan, Ashish Verma, Mathieu Sinn, et al. Ibm federated learning: an enterprise framework white paper v0. 1. *arXiv preprint arXiv:2007.10987*, 2020.
- [59] Koji Matsuda, Yuya Sasaki, Chuan Xiao, and Makoto Onizuka. Benchmark for personalized federated learning. *IEEE Open Journal of the Computer Society*, 2023.
- [60] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, pages 1273–1282. PMLR, 2017.
- [61] H Brendan McMahan, Daniel Ramage, Kunal Talwar, and Li Zhang. Learning differentially private recurrent language models. In *International Conference on Learning Representations*, 2018.
- [62] Sebastian Meiser and Esfandiar Mohammadi. Tight on budget? tight bounds for r-fold approximate differential privacy. In *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, pages 247–264, 2018.
- [63] Luca Melis, Congzheng Song, Emiliano De Cristofaro, and Vitaly Shmatikov. Exploiting unintended feature leakage in collaborative learning. In *2019 IEEE symposium on security and privacy (SP)*, pages 691–706. IEEE, 2019.
- [64] Ilya Mironov. Rényi differential privacy. In *2017 IEEE 30th computer security foundations symposium (CSF)*, pages 263–275. IEEE, 2017.
- [65] Mohammad Naseri, Jamie Hayes, and Emiliano De Cristofaro. Local and central differential privacy for robustness and privacy in federated learning. *arXiv preprint arXiv:2009.03561*, 2020.

- [66] A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine, editors. *Advances in Neural Information Processing Systems 36*. Neural Information Processing Systems Foundation, 2023. Available at: https://proceedings.neurips.cc/paper_files/paper/2023.
- [67] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32, 2019.
- [68] Matthias Paulik, Matt Seigel, Henry Mason, Dominic Telaar, Joris Kluivers, Rogier van Dalen, Chi Wai Lau, Luke Carlson, Filip Granqvist, Chris Vandeveld, et al. Federated evaluation and tuning for on-device personalization: System design & applications. *arXiv preprint arXiv:2102.08503*, 2021.
- [69] Proceedings of Machine Learning Research. *Proceedings of the 41st International Conference on Machine Learning*, 2024. Available at: <https://proceedings.mlr.press/v235/>.
- [70] Sashank Reddi, Zachary Charles, Manzil Zaheer, Zachary Garrett, Keith Rush, Jakub Konečný, Sanjiv Kumar, and H Brendan McMahan. Adaptive federated optimization. *arXiv preprint arXiv:2003.00295*, 2020.
- [71] G Anthony Reina, Alexey Gruzdev, Patrick Foley, Olga Perepelkina, Mansi Sharma, Igor Davidyuk, Ilya Trushkin, Maksim Radionov, Aleksandr Mokrov, Dmitry Agapov, et al. Openfl: An open-source framework for federated learning. *arXiv preprint arXiv:2105.06413*, 2021.
- [72] John A. Rice. *Mathematical Statistics and Data Analysis*. Duxbury Press, 3 edition, 2006. Chapter 5 - Central Limit Theorem.
- [73] Borja Rodríguez-Gálvez, Filip Granqvist, Rogier van Dalen, and Matt Seigel. Enforcing fairness in private federated learning via the modified method of differential multipliers. *arXiv preprint arXiv:2109.08604*, 2021.
- [74] Holger R Roth, Yan Cheng, Yuhong Wen, Isaac Yang, Ziyue Xu, Yuan-Ting Hsieh, Kristopher Kersten, Ahmed Harouni, Can Zhao, Kevin Lu, et al. Nvidia flare: Federated learning from simulation to real-world. *arXiv preprint arXiv:2210.13291*, 2022.
- [75] Alexander Sergeev and Mike Del Balso. Horovod: fast and easy distributed deep learning in TensorFlow. *arXiv preprint arXiv:1802.05799*, 2018.
- [76] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *2017 IEEE symposium on security and privacy (SP)*, pages 3–18. IEEE, 2017.
- [77] Aliaksandra Shysheya, Marlon Tobaben, John F Bronskill, Andrew Paverd, Shruti Tople, Santiago Zanella-Beguelin, Richard E Turner, and Antti Honkela. Differentially private federated few-shot image classification. In *ICLR 2023 Workshop on Pitfalls of limited data and computation for Trustworthy ML*, 2023.
- [78] Shivalika Singh, Freddie Vargus, Daniel Dsouza, Börje F Karlsson, Abinaya Mahendiran, Wei-Yin Ko, Herumb Shandilya, Jay Patel, Deividas Mataciunas, Laura OMahony, et al. Aya dataset: An open-access collection for multilingual instruction tuning. *arXiv preprint arXiv:2402.06619*, 2024.
- [79] Congzheng Song, Filip Granqvist, and Kunal Talwar. FLAIR: Federated learning annotated image repository. *Advances in Neural Information Processing Systems*, 35:37792–37805, 2022.
- [80] Stack Overflow. Stack Overflow Data (BigQuery Dataset). <https://www.kaggle.com/datasets/stackoverflow/stackoverflow>, 2023. Accessed: 2024-03-15.
- [81] Kunal Talwar, Shan Wang, Audra McMillan, Vojta Jina, Vitaly Feldman, Bailey Basile, Aine Cahill, Yi Sheng Chan, Mike Chatzidakis, Junye Chen, et al. Samplable anonymous aggregation for private federated data analysis. *arXiv preprint arXiv:2307.15017*, 2023.

- [82] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023.
- [83] Jean Ogier du Terrail, Samy-Safwan Ayed, Edwige Cyffers, Felix Grimberg, Chaoyang He, Regis Loeb, Paul Mangold, Tanguy Marchand, Othmane Marfoq, Erum Mushtaq, et al. Flamby: Datasets and benchmarks for cross-silo federated learning in realistic healthcare settings. *arXiv preprint arXiv:2210.04620*, 2022.
- [84] Jianyu Wang, Zachary Charles, Zheng Xu, Gauri Joshi, H Brendan McMahan, Maruan Al-Shedivat, Galen Andrew, Salman Avestimehr, Katharine Daly, Deepesh Data, et al. A field guide to federated optimization. *arXiv preprint arXiv:2107.06917*, 2021.
- [85] T Wolf. Huggingface’s transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*, 2019.
- [86] Shanshan Wu, Tian Li, Zachary Charles, Yu Xiao, Ziyu Liu, Zheng Xu, and Virginia Smith. Motley: Benchmarking heterogeneity and personalization in federated learning. *arXiv preprint arXiv:2206.09262*, 2022.
- [87] Yuexiang Xie, Zhen Wang, Dawei Gao, Daoyuan Chen, Liuyi Yao, Weirui Kuang, Yaliang Li, Bolin Ding, and Jingren Zhou. Federatedscope: A flexible federated learning platform for heterogeneity. *arXiv preprint arXiv:2204.05011*, 2022.
- [88] Mingbin Xu, Congzheng Song, Ye Tian, Neha Agrawal, Filip Granqvist, Rogier van Dalen, Xiao Zhang, Arturo Argueta, Shiyi Han, Yaqiao Deng, et al. Training large-vocabulary neural language models by private federated learning for resource-constrained devices. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023.
- [89] Zheng Xu, Yanxiang Zhang, Galen Andrew, Christopher A Choquette-Choo, Peter Kairouz, H Brendan McMahan, Jesse Rosenstock, and Yuanbo Zhang. Federated learning of gboard language models with differential privacy. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 5: Industry Track)*, 2023.
- [90] Rui Ye, Wenhao Wang, Jingyi Chai, Dihan Li, Zexi Li, Yinda Xu, Yaxin Du, Yanfeng Wang, and Siheng Chen. Openfedllm: Training large language models on decentralized private data via federated learning. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 6137–6147, 2024.
- [91] Ashkan Yousefpour, Igor Shilov, Alexandre Sablayrolles, Davide Testuggine, Karthik Prasad, Mani Malek, John Nguyen, Sayan Ghosh, Akash Bharadwaj, Jessica Zhao, et al. Opacus: User-friendly differential privacy library in pytorch. *arXiv preprint arXiv:2109.12298*, 2021.
- [92] Tao Yu, Congzheng Song, Jianyu Wang, and Mona Chitnis. Momentum approximation in asynchronous private federated learning. *arXiv preprint arXiv:2402.09247*, 2024.
- [93] Peiyuan Zhang, Guangtao Zeng, Tianduo Wang, and Wei Lu. Tinyllama: An open-source small language model. *arXiv preprint arXiv:2401.02385*, 2024.
- [94] Yuqing Zhu and Yu-Xiang Wang. Poission subsampled rényi differential privacy. In *International Conference on Machine Learning*, pages 7634–7642. PMLR, 2019.
- [95] Alexander Ziller, Andrew Trask, Antonio Lopardo, Benjamin Szymkow, Bobby Wagner, Emma Bluemke, Jean-Mickael Nounahon, Jonathan Passerat-Palmbach, Kritika Prakash, Nick Rose, et al. Pysyft: A library for easy federated learning. *Federated Learning Systems: Towards Next-Generation AI*, pages 111–139, 2021.

Checklist

1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
 - (b) Did you describe the limitations of your work? [Yes] Most importantly, this framework is only for research purposes and not for deployments on real devices.
 - (c) Did you discuss any potential negative societal impacts of your work? [N/A]
 - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
 - (a) Did you state the full set of assumptions of all theoretical results? [N/A]
 - (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments (e.g. for benchmarks)...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] <https://github.com/apple/pfl-research/tree/develop/benchmarks>.
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] Appendix C
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] Standard deviation in result tables.
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
 - (a) If your work uses existing assets, did you cite the creators? [Yes]
 - (b) Did you mention the license of the assets? [Yes] Appendix C
 - (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]
 - (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A] We use widely available open-source datasets. Consents were obtained by the dataset owner.
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
 - (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
 - (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
 - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

Appendix

A Preliminaries

Federated Learning. FL [60] trains an ML model with a population of users collaboratively without sharing their data with the central server. In each round of FL, the server samples a cohort of users and broadcasts the current central model to the sampled users’ devices. The sampled users then train the model locally on their devices and submit their gradient updates back to the server after local training. The server aggregates the gradients received from users to produce a “pseudo-gradient” which is used to update the central model with an optimization algorithm such as SGD or Adam [70].

Differential Privacy. Though users’ raw data is not shared with the server in FL, the shared gradient updates can still reveal sensitive information about user data [12, 29, 63]. Differential privacy (DP) [24] can be used to provide a formal privacy guarantee to prevent such data leakage in the federated setting.

Definition A.1 (Differential privacy). A randomized mechanism $\mathcal{M} : \mathcal{D} \mapsto \mathcal{R}$ with a domain \mathcal{D} and range \mathcal{R} satisfies (ϵ, δ) -differential privacy if for any two adjacent datasets $D, D' \in \mathcal{D}$ and for any subset of outputs $S \subseteq \mathcal{R}$ it holds that $\Pr[\mathcal{M}(D) \in S] \leq e^\epsilon \Pr[\mathcal{M}(D') \in S] + \delta$.

User-level DP guarantee is often considered in PFL [61]: \mathcal{D} is the set of all possible datasets with examples associated with users, range \mathcal{R} is the set of all possible models, and two datasets D, D' are adjacent if D' can be formed by adding or removing all of the examples associated with a single user from D . When a model is trained with user-level DP, one should not be able to tell whether a particular user participated in training the model or not.

A common approach to applying DP in the PFL context [61] is using Gaussian mechanism [23] where two additional steps are required in each PFL iteration: 1) the model updates from each user are clipped so that their L_2 norm is upper-bounded to control the sensitivity, and 2) Gaussian noise is added to the aggregated model updates from all sampled users.

Since PFL training takes multiple iterations, the privacy loss accumulates due to multiple independent accesses to the same data. To consider the total privacy loss over all iterations of training, the scale of Gaussian noise is calibrated using a privacy accountant, such as Rényi DP [64], privacy loss distribution (PLD) accountant [62] and privacy random variable (PRV) accountant [32], all of which are included in `pfl-research`. For the purpose of privacy accounting, we assume that each cohort is formed by Poisson sampling [94] where each user flips a biased coin to decide whether to participate, and that this sample is hidden from the adversary.

B Detailed system design

B.1 API Design

`pfl-research` is object-oriented Python 3 code, using the following class hierarchies.

Dataset `FederatedDataset` parameterizes how to partition, load, and pre-process the data of an individual user, and iterating over one produces per-user `Datasets`. The interfaces are flexible enough to support loading data from any storage using any preprocessing library. `pfl-research` also provides integration with `tf.data.Dataset` and `torch.utils.data.Dataset` (from here on referred to as "native datasets"). If the datasets of clients are small enough such that several can be loaded into memory simultaneously, a native dataset can be defined on the same level as `FederatedDataset`, returning the full data tensors of one user when requesting the next tensors. This is applicable in cross-device FL, where user datasets are typically small enough to fit into memory. If client datasets are large and loading the whole dataset at once is inefficient or requires too much memory, e.g. in large-scale cross-silo simulations, one native dataset can represent one client, with asynchronously loaded batches.

Model A `Model` is an adapter for connecting a TensorFlow or PyTorch models to the simulator. Additionally, the `Model` class can be extended to implement non-neural-network models. `pfl-research` provides an implementation of federated gradient boosted decision trees (GB-DTs) [27] and federated Gaussian mixture models (GMMs).

Algorithm The interface for implementing federated algorithms is `FederatedAlgorithm`. We generalize the responsibilities of an algorithm to be:

- `get_next_central_contexts` — construct configurations describing how the clients should locally train the model during the next central iteration.
- `simulate_one_user` — perform local training for one user, and return statistics and metrics.
- `process_aggregated_statistics_all_contexts` — perform an update on the central model using aggregated model update(s) and metrics.

In this way, we can implement a majority of existing FL algorithms while delegating concepts orthogonal to learning (e.g., aggregation, DP, compression) to other components that can be mixed and matched with algorithms. Algorithm 1 outlines how the above interface is used in a general FL process and Algorithm 2 describes a concrete example on how FedAvg is defined using these interfaces.

Aggregator An `Aggregator` is a lightweight interface for (1) accumulating model updates from clients and (2) reducing partial aggregated model updates across worker processes. The default is accumulating with a sum, and reducing across workers with an `all-reduce` sum; see Section 3.1 for further explanation.

Backend A `Backend` consumes the federated datasets, postprocessors (see below), and aggregator to implement the simulation control flow. Since `pfl-research` was released for running simulations, only the concrete backend currently included is `SimulatedBackend`.

Postprocessor A `Backend` can invoke a series of `Postprocessors`. These can implement features such as compression, sparsification, and DP mechanisms by modifying local model updates as a postprocessing step, and optionally by postprocessing the aggregated model update before it is sent back to the algorithm for the central model update procedure. The server-side postprocessing steps are run in *reversed* order. It is essential to be mindful of the order of postprocessors, e.g. DP mechanisms commonly fit best as the last postprocessor for local updates so that no further modification of the sensitivity of the model update happens after clipping.

Callback `TrainingProcessCallback` provides a hook into the central training loop. A callback does not have access to the data or model update and is called only after the central model has been updated, hence it should not alter the learning in any way. Some callback implementations that `pfl-research` provides are: fault-tolerant training procedure, evaluation on central dataset, exponential moving average of model, stopping criterion, reporting intermediate results (csv files, TensorBoard and Weights & Biases⁶), and profiling tools.

Hyperparameters There are many hyperparameters to tune in (P)FL experiments, and there has been research on constructing schedules and adaptive approaches to simplify the hyperparameter tuning process [5, 47, 70]. In `pfl-research`, many hyperparameters of local model training or the algorithm can be expressed as either simple types (constant for the experiment) or as a `HyperParam` (variable across iterations). At the start of each central iteration, the algorithm requests the current value of any `HyperParam` instances to set as the static value for that iteration only. A concrete hyperparameter class can in turn extend `Postprocessor` or `TrainingProcessCallback` to hook into the training loop and adapt its value based on arbitrary rules.

Metrics Metrics have conflicting implementations in various FL frameworks. We define two types below. See a concrete example for each kind in Appendix B.4.

- **Central metrics** — Each client returns aggregable sufficient statistics, and the metric is constructed after aggregation. This is most relevant in FL since we are interested in the performance of the central model over all data points.
- **Per-user metrics** — Each client produces the metric, and the aggregation over clients' results is the average of such metrics. This is more relevant when the performance of each client is of interest, e.g. in personalization and meta-learning.

Algorithm 1 Generalized federated learning simulation.

Input: Initial central model θ_0 ,
Aggregator agg ,
Federated algorithm alg ,
Callbacks \mathcal{B} ,
Postprocessors \mathcal{P} ,
Federated datasets \mathcal{F} ,
A function `distribute_sample` that samples a cohort of users from a federated dataset and distributes the cohort to workers,

```
1  $t \leftarrow 0$ ,  $stop \leftarrow False$ 
2 repeat
   /* The algorithm generates a set of contexts  $\mathcal{C}$  which are instructions on how to gather results from
   cohorts. May modify model in preparation for this iteration. */
3  $(\mathcal{C}, \theta'_t) \leftarrow alg.get\_next\_central\_contexts(\theta_t, t)$ 
4 if  $\mathcal{C} = \emptyset$  then
   /* Algorithm signaled that training should end.
5   break
6    $\mathcal{S} \leftarrow \emptyset$ 
   /* Sample a cohort and get aggregated results for each context. This is done by the Backend in the
   implementation. */
7   foreach central context  $c_i \in \mathcal{C}$  do
8      $D \leftarrow get\_federated\_dataset(\mathcal{F}, c_i.population)$ 
9     foreach worker  $w$  in parallel do
10       $\Delta_{t,i}^w \leftarrow null$ 
11      foreach user dataset  $d_u \in distributed\_sample(D, w, c_i.cohort\_size)$  do
12         $(\Delta_{t,i}^u, aux_u) \leftarrow alg.simulate\_one\_user(\theta'_t, d_u, c_i)$ 
13        if  $\Delta_{t,i}^u \neq null$  then
           /* The results from local optimization is passed through all postprocessors, which may
           manipulate the statistics and use auxiliary non-private information from the user.
14          foreach postprocessor  $p \in \mathcal{P}$  do
15             $\Delta_{t,i}^u \leftarrow p.postprocess\_one\_user(\Delta_{t,i}^u, aux_u)$ 
16             $\Delta_{t,i}^w \leftarrow agg.accumulate(\Delta_{t,i}^w, \Delta_{t,i}^u)$ 
           /* Synchronize aggregates from all workers.
17           $\Delta_{t,i} \leftarrow agg.worker\_reduce(\Delta_{t,i}^w, c_i, w)$ 
18          foreach postprocessor  $p \in reversed(\mathcal{P})$  do
19             $\Delta_{t,i} \leftarrow p.postprocess\_server(\Delta_{t,i}, c_i)$ 
20           $\mathcal{S} \leftarrow \mathcal{S} \cup \{\Delta_{t,i}\}$ 
   /* The algorithm consumes the set of aggregated statistics from all queried cohorts and produces a new
   central model. */
21    $\theta_{t+1} \leftarrow alg.process\_aggregated\_statistics\_all\_contexts(\mathcal{C}, \mathcal{S}, \theta'_t)$ 
22   foreach callback  $b \in \mathcal{B}$  do
           /* A callback may force stop training, e.g. early stopping.
23      $stop \leftarrow b.after\_central\_iteration(\theta_{t+1}, t)$ 
24    $t \leftarrow t + 1$ 
25 until  $stop$ 
```

B.2 FL simulation

An algorithm runs for a number of central iterations, which is either determined by the algorithm or interrupted by a callback. A context $c_i \in \mathcal{C}$ is a recipe for how to run the next central iteration. It contains parameters for local model training and evaluation, the state of the algorithm, dataset target criteria, and parameters for other steps of the algorithm. A federated algorithm alg operates on a group of federated datasets \mathcal{F} and each context c_i targets one federated dataset $D \in \mathcal{F}$.

Metrics get accumulated on almost every step in Algorithm 1 and reported at the end of each central iteration, but the processing of metrics is abstracted away for simplicity.

⁶<https://wandb.ai/>

Aggregation is decoupled in `pf1-research` from algorithms to provide a uniform interface for different methods of aggregating training statistics. This is separated in two sub-operations, `accumulate` and `worker_reduce`. It is essential to make the aggregator agnostic to the number of worker processes spawned, which requires a concrete aggregator implementation to adhere to the following rules:

1. A concrete aggregator derived from the abstract base class `Aggregator` must implement two functions: f for `accumulate` and g for `worker_reduce` where
 - f represents the operation associated with accumulation of statistics from users within a worker process w . Upon receiving a user statistics Δ_u , the worker accumulated state S_w is updated as: $S_w = f(S_w, \Delta_u)$,
 - g represents the operation used for inter-worker aggregation on the set of accumulated states from all workers. Each worker process w calls `worker_reduce` and receives the aggregated results as $S = g(\{S_w \mid \forall \text{ worker process } w\})$.
2. For any accumulated state S_a, S_b and user statistics Δ of the context over which `Aggregator` operates, the functions f and g must satisfy the following property:

$$\forall S_a, S_b, \Delta \quad g(\{f(S_a, \Delta), S_b\}) = g(\{f(S_b, \Delta), S_a\}) = f(g(\{S_a, S_b\}), \Delta).$$

The most common implementation in FL for f and g is vector summation where the state S is a vector, $f(S, \Delta) = S + \Delta$ and $g(\{S_i \mid i \in [n]\}) = \sum_{i=1}^n S_i$. The interface provided by `pf1-research` allows customized aggregation of user statistics by adjusting f and g accordingly. For example, to gather the individual statistics from all users, f and g can be implemented as vector set union where the state S is a set of vectors, $f(S, \Delta) = S \cup \{\Delta\}$ and $g(\{S_i \mid i \in [n]\}) = \cup_{i=1}^n S_i$.

A concrete example of the algorithm FEDAVG is given in Appendix-B.3, and of metrics in Appendix-B.4

The statistics may be modified using postprocessors before or after aggregation. The differential privacy features in `pf1-research` are implemented using postprocessors.

B.3 Federated Averaging example

As a concrete example, pseudo-code for federated averaging (FEDAVG) is shown in Algorithm 2. Here, \mathcal{F} should be defined as two populations: one group of users only for training, and the other only for validating performance. In each iteration, FEDAVG generates \mathcal{C} containing two central contexts corresponding to the two populations: one context with hyper-parameters for instructing how `alg` runs on the training population; and the other for describing how `alg` evaluates on the validation population (e.g. not returning any model updates). In other algorithms there can be additional contexts if for example `alg` further divides the train population into multiple clusters of users that should train different models or with different hyper-parameters. FEDAVG expects a single aggregated model update, which is averaged and applied on the central model with the central optimizer Opt_c .

B.4 Metrics example

A metric can be defined on two levels in `pf1-research`: per-user and central. If user U_1 has 1 datapoint and user U_2 has 7 datapoints, where U_1 predicts the output correctly on its datum and U_2 fails to predict correct output for all data, then the accuracies are:

$$\begin{aligned} \text{per-user } Acc_{\{U_1, U_2\}} &= \frac{1/1 + (0/7)}{2} = 0.5 \\ \text{central } Acc_{\{U_1, U_2\}} &= \frac{1 + 0}{8} = 0.125 \end{aligned}$$

The per-user metric has built-in weighting of how many users do well for the metric, hence per-user metrics can be useful to measure after local training in the case of personalisation. On the other hand, if the researcher is mainly interested in the performance of the central model over the entire dataset, then the central metric is the appropriate choice because it reveals that the model did not perform well on most datapoints in the example above.

Algorithm 2 FEDAVG using pfl-research interfaces

```
Class FedAvg:
  Input: Number of central iterations  $T$ ,
           Evaluation frequency  $\tau$ ,
           Local optimizer  $Opt_l$ ,
           Central optimizer  $Opt_c$ ,
           Other hyper-parameters for algorithm and model  $kwargs$ ,

1  Function get_next_central_contexts( $\theta_t, t$ ):
2    if  $t = T$  then
3      // Training is complete
4      return  $\emptyset, \theta_t$ 
5     $\mathcal{C} \leftarrow \{\text{create\_context\_for\_training}(kwargs)\}$ 
6    if  $t \bmod \tau = 0$  then
7       $\mathcal{C} \leftarrow \mathcal{C} \cup \{\text{create\_context\_for\_evaluation}(kwargs)\}$ 
8      /* The model is not modified in preparation for the next central iteration. */
9      return  $\mathcal{C}, \theta_t$ 

10 Function simulate_one_user( $\theta, d_u, c$ ):
11   if  $c.\text{population} = \text{Train}$  then
12     ( $\theta', aux$ )  $\leftarrow$  local_optimize( $\theta, d_u, Opt_l, c.\text{model\_train\_params}$ )
13      $\Delta \leftarrow \theta - \theta'$ 
14     return ( $\Delta, aux$ )
15   else
16     evaluate( $\theta', d, c.\text{model\_eval\_params}$ )
17     return ( $null, null$ )

18 Function process_aggregated_statistics_all_contexts( $\mathcal{C}, \mathcal{S}, \theta_t$ ):
19   // Expecting  $\mathcal{S}$  to be length 1, the aggregated model update, extract it.
20    $\{\Delta\} \leftarrow \mathcal{S}$  //  $\Delta$  is weighted, average it.
21    $\Delta \leftarrow \text{average}(\Delta)$ 
22    $\theta_{t+1} \leftarrow Opt_c(\theta_t, \Delta)$ 
23   return  $\theta_{t+1}$ 
```

B.5 Privacy features

pfl-research implements or integrates with state-of-the-art differential privacy methods for FL, which are available for PyTorch, Tensorflow, and non-neural network models:

- Gaussian mechanism [24].
- Gaussian mechanism with adaptive clipping [5].
- Laplace mechanism [24].
- Banded matrix factorization mechanism [20].
- Rényi DP privacy accountant [64].
- Privacy loss distribution (PLD) privacy accountant [22, 62].
- Privacy random variable (PRV) privacy accountant [32].

pfl-research supports simulations with both local as well as central DP guarantees. Running a DP mechanism locally results in slower simulations because the generation and addition of noise happens once per sampled user as opposed to once per central iteration. To speed up simulations, pfl-research implements GaussianApproximatedPrivacyMechanism⁷, which utilizes the central limit theorem [72] to approximate a local DP mechanism as a Gaussian mechanism where the noise is applied centrally. This has the same effect as using the equivalent local mechanism, but the noise is only applied once per central iteration. This approach can be used only for simulation, and in a real-world PFL system, the local DP mechanism should be applied locally to ensure local DP guarantees.

⁷https://apple.github.io/pfl-research/reference/privacy.html#module-pfl.privacy.approximate_mechanism

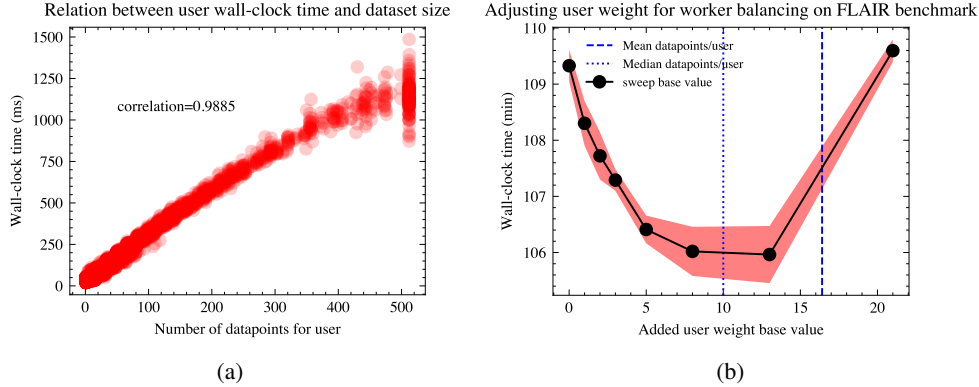


Figure 4: (a) Scatter plot of dataset size for users and the wall-clock time for training that user. Strong correlation means we can use the dataset size for scheduling the work among the worker processes. (b) Change in wall-clock time for 5000 central iterations when a fixed base value is added to each user’s weight for worker scheduling.

Table 5: The maximum straggler time (difference in wall-clock time between the worker processes that finish first and last), averaged over all central iterations.

Setup	maximum straggler time, averaged over iterations (ms)
No scheduling (uniform user split)	1294
Greedy scheduling	484
Greedy scheduling +median	178

B.6 Worker scheduling

Training users is scheduled among the worker processes. To minimize latency, the worker processes cannot pull the next user ID to train from a central queue. Therefore, the scheduling of users is pre-calculated for each cohort by iterating through users in order sorted by weight and greedily assigning the next user to the worker process with smallest total weight accumulated. The weight should represent the relative wall-clock time for training the user. We choose the number of datapoints of a user as a proxy because it has high correlation with the true wall-clock time in `pf1-research`, see Figure 4a. There is always a small overhead in FL, and if we represent this as a small base value added to all users’ weights the scheduling becomes more optimal and further speeds up training. Figure 4b show that adding a base value close to the median number of datapoints per user results in an additional 3% speedup, and a total of 19% speedup compared to no worker scheduling for the FLAIR dataset (131 minutes wall-clock time).

The central iteration will only finish once all worker processes have completed their assigned training. When the first process finish training, it becomes idle until the last process is finished (straggler process). Table 5 show the maximum straggler time for our scheduling methods. Performing the greedy optimization of weights with a base value show a clear improvement in minimizing the stragglers.

To showcase a few samples, Figure 5 show the histogram of weights assigned to each worker process for a specific central iteration. The difference between the minimum and maximum value of the per-worker wall-clock time is the maximum straggler time. The disparity is clearly the smallest for greedy scheduling with a base value.

C Details for benchmark setups

C.1 TensorFlow benchmarks

Compiling benchmark results for TensorFlow setups is left for future work. Currently, the CIFAR10 benchmarks and StackOverflow benchmarks have equivalent setups

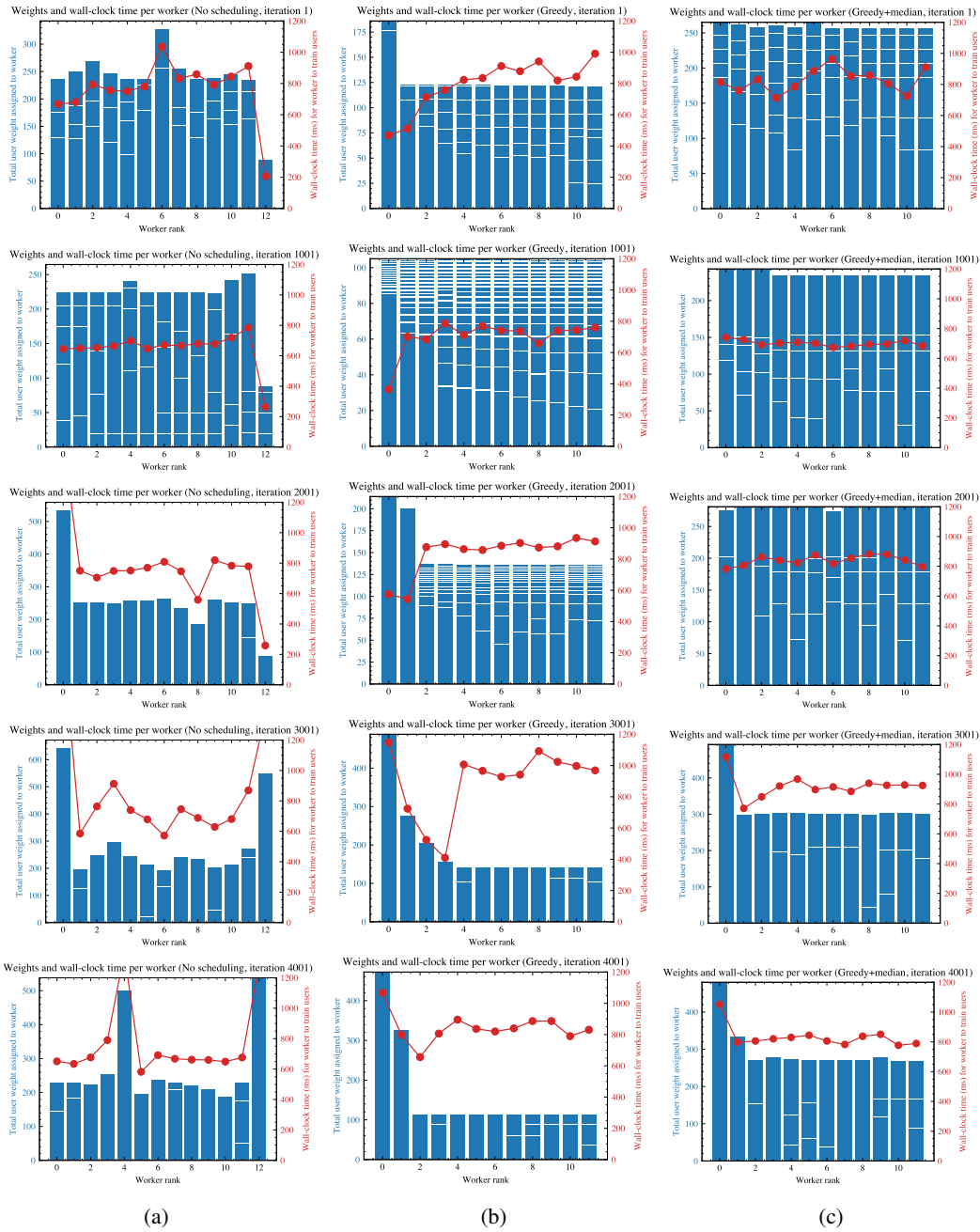


Figure 5: Histograms of user weights allocated to each worker process. The red lines show the total wall-clock times per worker process. A more evenly distributed red line means work was balanced more efficiently among worker processes. Each row show samples from a different central iteration, column a) show uniformly scheduling users, b) show scheduling with greedy optimization, c) show scheduling with greedy optimization and adding the median number of datapoints per user as base value for each weight.

Table 6: Datasets used in the original publications of the algorithms. XMNIST stands for MNIST and any of its extensions (EMNIST [21], FEMNIST [15]). Red color indicates the data generation process were not of a federated nature.

Algorithm	Synthetic [15]	XMNIST	CIFAR10 [48]	Shakespeare [60]	Reddit [60]	Sent140 [15]
FedAvg [60]		✓	✓	✓	✓	
FedProx [52]	✓	✓		✓		✓
AdaFedProx [52]	✓					
SCAFFOLD [42]		✓				

in TensorFlow, available at https://github.com/apple/pfl-research/tree/develop/benchmarks/image_classification/tf and <https://github.com/apple/pfl-research/tree/develop/benchmarks/lm/tf> respectively. The FLAIR benchmark has a TensorFlow setup in <https://github.com/apple/ml-flair/tree/main/benchmark> but it is implemented in TensorFlow Federated.

C.2 Original benchmarks of algorithms

Table 6 present the datasets that each algorithm from Table 3 benchmarked on in their original papers. It is evident that the algorithms were not sufficiently evaluated on a diverse set of realistic FL datasets.

C.3 Secure aggregation

`pfl-research` focuses on simulating the effects of PFL. Since secure aggregation techniques merely compute a sum [10, 14], secure aggregation does not impact the outcomes of a simulation and can thus be omitted. Also, `pfl-research` does not emulate constraints and effects of a real-world deployed PFL system. Therefore, we do not include any implementations of common secure aggregation methods in the initial release of `pfl-research`.

C.4 Central DP

Each benchmark has one version without DP and one with central DP. The current state-of-the-art PFL deployments [6, 13, 81, 89] combine central DP with a cryptographically secure aggregation to protect any individual user’s model update. Local DP is therefore not generally required. Though local privacy is supported in the `pfl-research` framework, the curated PFL benchmark suite only uses central DP. The privacy parameters we use for all benchmarks are shown in Table 7.

Table 7: Parameters used for a privacy accountant in all benchmarks that use central DP.

Parameter	value
M (population)	10^6
ϵ	2.0
δ	$1/M = 10^{-6}$

Each benchmark that includes a privacy accountant has a sampling rate set to $\frac{\tilde{C}}{M}$ where \tilde{C} is the cohort size and M is the population size. When training in a production system on real devices, \tilde{C} is typically in the order of thousands to reduce the impact of DP noise on convergence [88, 89]. To simulate the real world cross-device PFL setting with millions of devices, we set $M = 10^6$ instead of the actual number of clients in each dataset. This assumption makes sense for a simulation as long as we can expect to be able to have at least 10^6 devices in the production use case. We also want to run the experiments faster with a smaller cohort size C (in the order of hundreds) and verify the impact of the DP noise for a larger \tilde{C} . We refer \tilde{C} as *noise cohort size* hereinafter. We introduce a variable $r = \frac{C}{\tilde{C}}$ and scale the noise standard deviation by r , such that the noise added to the averaged aggregates of C clients will have the same scale as if the aggregates had \tilde{C} clients [61]. Figure 6

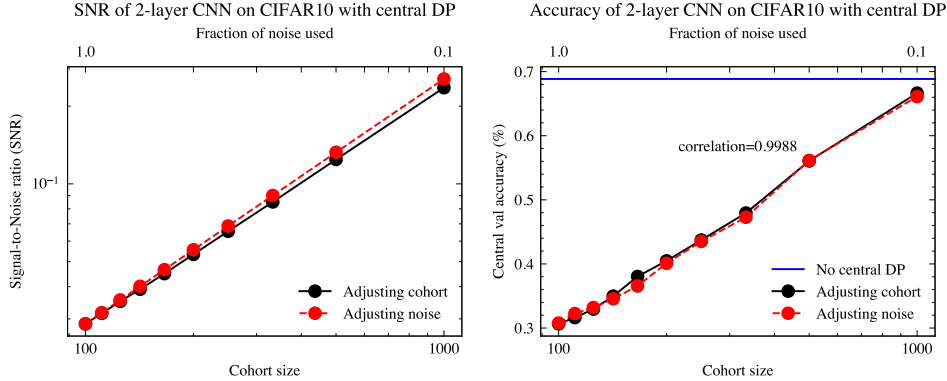


Figure 6: Performance of a 2-layer CNN on CIFAR10 for various cohort sizes C (bottom x-axis, black lines) or noise scale r (top x-axis, red lines). **Left panel:** signal-to-noise ratio, as defined in Equation 1. **Right panel:** same experiments, but showing accuracy on centrally held validation set.

shows the accuracy and signal-to-noise ratio (SNR) on the CIFAR10 benchmark if we either increase cohort size \tilde{C} or reduce the noise with r . Signal-to-noise ratio is defined as

$$\text{SNR} = \frac{\|\Delta\|_2}{\sqrt{d\sigma^2}}, \quad (1)$$

where Δ is the unnoised aggregated model update, d is the dimension of Δ and σ is the standard deviation of noise from DP mechanism. The correlation of the metrics is close to 1. This means that instead of achieving good performance on CIFAR10 with $\tilde{C} = 1000$, we can instead run faster simulations with $C = 100$ and $r = 0.1$ and expect similar results. When rescaling the noise by r , one must make sure for every case that:

1. C is still high enough to receive good signal without noise in the simulation.
2. \tilde{C} is the cohort size needed in a real PFL deployment to achieve this performance, and it should thus be a realistic value for the particular use case.

For Banded Matrix Factorization mechanism we set the minimum number of central iterations between two occurrences of the same user to 48 for all benchmarks. This means 1 participation per day if the time for one central iteration in a real PFL system is 30 minutes. This value is not derived from any deployed PFL systems, but a conservative guess for large cross-device PFL systems.

C.5 CIFAR10

We define four variations of CIFAR10 benchmarks: $\{\text{IID, non-IID}\} \times \{\text{no DP, central DP}\}$, such that there exist smaller and easier benchmarks with different end goals available for prototyping. The task is single-class classification of images using the CNN architecture originally defined in Table 4 of [70]. The hyper-parameters are outlined in Table 8.

Table 8: Hyper-parameters used in the four CIFAR10 benchmarks.

Setup	Parameter	value
all	Central iterations	1500
	Central learning rate	1.0
	Central optimizer	SGD
	Cohort size C	50
	Local epochs	1
	Local learning rate	0.1
	Local batch size	10
	Datapoints per user	50
	Evaluation frequency	10
	Evaluation batch size	10000
non-IID	Dirichlet alpha	0.1
central DP	clipping bound	0.4
	Noise cohort size \tilde{C}	1000

The data is split into $50000/50 = 1000$ users to resemble a cross-device population. As explained in Appendix C.4 we simulate with cohort size C , but manually reduce the noise by a fraction $\frac{C}{\tilde{C}}$ to simulate the effect of running with a larger cohort size. `pfl-research` supports setting a different batch size for training and evaluation. It is a good practice to set the evaluation batch size to the largest value that the GPUs can handle, which will speed up simulations.

The code can be found in `benchmarks/image_classification`⁸.

C.6 StackOverflow

The StackOverflow dataset is licensed under the Creative Commons Attribution-ShareAlike 3.0 Unported License. We define two variations of benchmarks on StackOverflow [80]: `{no DP, central DP}`. No dataset partitioning is needed as the dataset has inherent user identifiers. The task is next-word prediction using a transformer model with 1,962,912 parameters. The hyper-parameters are outlined in Table 9.

⁸https://github.com/apple/pfl-research/tree/develop/benchmarks/image_classification. Run main script with `--help` for further description on hyper-parameters.

Table 9: Hyper-parameters used in the two StackOverflow benchmarks.

Setup	Parameter	value
all	Central iterations	2000
	Central learning rate	0.1
	Central lr warmup	50
	Central optimizer	Adam
	Adam adaptivity degree	0.1 [70]
	Adam β_{1}	0.9 [70]
	Adam β_{2}	0.99 [70]
	Cohort size C	400
	Local epochs	1
	Local learning rate	0.3
	Local batch size	16
	Evaluation frequency	20
	Evaluation batch size	1024
	Central eval data size	1%
	Max sentences per user	64 [84]
	Sequence length	20 [70, 84]
	Max tokens per user	1600 [61]
	Minimum datapoints per user	1
	Model embedding size	96
	Model num heads	8
	Model encoder feedforward size	1536
Model transformer layers	3	
Dropout rate	0.1	
central DP	clipping bound	1.0
	Noise cohort size \tilde{C}	5000

In this benchmark (and all following benchmarks) Adam optimizer for central updates is used, with modified hyper-parameters suggested by [70] for stable learning with FL. The performance of the model increase slightly if trained beyond 2000 iterations, but we fix the iterations such that converging with a fewer amount of iterations is also rewarded in the benchmark.

The code can be found in `benchmarks/lm`⁹.

C.7 FLAIR

The annotations of FLAIR are licensed under CC-BY-NC 4.0, while each image has a permissive license specified by each individual author¹⁰. We define four variations of FLAIR benchmarks: $\{\text{IID, non-IID}\} \times \{\text{no DP, central DP}\}$. The inherent user partitions in FLAIR display strong heterogeneity, as discussed in [79]. It can therefore be particularly insightful to compare performances between original partitioning and IID partitioning. The original FLAIR benchmarks include setups for multi-class image classification of coarse-grained labels, fine-grained labels, pre-trained ResNet18 [35] and train from scratch. For simplicity, our benchmark suite only include the coarse-grained labels with pre-trained ResNet18, but we encourage researchers to also consider the other setups when a wider evaluation of image classification tasks is of particular interest. The hyper-parameters are outlined in Table 10.

⁹<https://github.com/apple/pfl-research/tree/develop/benchmarks/lm>. Run main script with `--help` for further description on hyper-parameters.

¹⁰<https://github.com/apple/ml-flair/blob/main/ATTRIBUTION.txt>

Table 10: Hyper-parameters used in the FLAIR benchmarks.

Setup	Parameter	value
all	Central iterations	5000
	Central learning rate	0.1
	Central optimizer	Adam
	Adam adaptivity degree	0.1 [70]
	Adam β_{1}	0.9 [70]
	Adam β_{2}	0.99 [70]
	Cohort size C	200
	Local epochs	2
	Local learning rate	0.01
	Local batch size	16
	Evaluation frequency	20
	Evaluation batch size	512
	Pre-trained	true
	Max images per user	512
IID	Datapoints per user	50
central DP	clipping bound	0.1
	Noise cohort size \tilde{C}	5000

The code can be found in `benchmarks/flair`¹¹.

C.8 LLM

Table 11: Hyper-parameters used in the LLM benchmarks. SA denotes Stanford Alpaca and OA denotes OpenAssistant.

Setup	Parameter	SA	Aya	OA	
all	Central iterations		1000		
	Central learning rate		0.01		
	Central optimizer		Adam		
	Adam adaptivity degree		10^{-4}		
	Adam β_{1}		0.9		
	Adam β_{2}		0.99		
	Cohort size C		100		
	Local epochs		1		
	Local learning rate	0.01		0.1	
	Local batch size			4	
	Evaluation frequency			10	
	Evaluation batch size			12	
	Max texts per user		-		64
	central DP	clipping bound		0.1	
Noise cohort size \tilde{C}			5000		

We consider three datasets for LLM benchmarks: Stanford Alpaca [82], Aya [78] and OpenAssistant [46]. All three datasets are available on HuggingFace Dataset Hub¹². We define two variations of LLM benchmarks: {no DP, central DP}. Aya and OpenAssistant datasets have inherent user partition which is ideal for simulating fine-tuning LLMs in the federated setting. For Stanford Alpaca which does not have user partition, we first sample the length L of each user dataset using Poisson distribution with expectation of 16 data per user, and then assign the unused L data points to the user. The partition stops when all data points are assigned. For Aya, we constrain the maximum

¹¹<https://github.com/apple/pfl-research/tree/develop/benchmarks/flair>. Run main script with `-help` for further description on hyper-parameters.

¹²<https://huggingface.co/datasets>.

Table 12: Performance of FL algorithms on LLM benchmarks without DP.

Algorithm	Alpaca	Aya	OASST
FedAvg	$3.61 \pm .0022$	$4.02 \pm .0103$	$6.39 \pm .0151$
FedProx	$3.61 \pm .0021$	$4.02 \pm .0053$	$6.39 \pm .0190$
AdaFedProx	$3.61 \pm .0022$	$4.02 \pm .0061$	$6.40 \pm .0191$
SCAFFOLD	$3.73 \pm .0020$	$4.77 \pm .0157$	$6.90 \pm .0240$

Table 13: Performance of FL algorithms on LLM benchmarks with DP.

Algorithm	DP	Alpaca	Aya	OASST
FedAvg	G	$3.62 \pm .0025$	$4.19 \pm .0156$	$6.52 \pm .0216$
FedAvg	BMF	$3.62 \pm .0023$	$4.20 \pm .0165$	$6.53 \pm .0052$
FedProx	G	$3.62 \pm .0026$	$4.20 \pm .0137$	$6.52 \pm .0231$
AdaFedProx	G	$3.62 \pm .0026$	$4.20 \pm .0151$	$6.52 \pm .0244$
SCAFFOLD	G	$3.79 \pm .0035$	$4.76 \pm .0181$	$7.00 \pm .0100$

data per user to 64, and if an annotator has more than 64 pairs, we evenly split this annotator’s data into smaller subsets of size 64. As edge devices have limited memory and compute, we choose the TinyLlama-1.1B [93] for benchmarking and fine-tune it on all three datasets with LoRA [37] rank of 8 and mixed-precision training using bfloat16. We report the final perplexity as the utility metric. The hyper-parameters are outlined in Table 11.

D Benchmarking alternative FL frameworks

We selected FL simulators for comparison that are popular (at least 400 stars on GitHub), actively maintained (at least 1 commit in the main branch in the past 3 months), and primarily meant for simulations (as opposed to live deployments). We also included FLUTE and FedScale since they prioritize speed and scalability.

Even though it is not a realistic federated dataset, we chose CIFAR10 for the initial round of comparing framework speed because it is widely popular in FL publications and the frameworks had existing CIFAR10 setups implemented with best practices in the respective repository. We adapted each initial CIFAR10 setup to match the IID setup in C.5. This is an ideal setup for benchmarking speed because the model is small; the IID dataset split is simple; central evaluation is lightweight; and training only utilizes 1 GPU with minimal setup, e.g. 5 local iterations and no DP.

We only benchmarked `pf1-research`, TensorFlow Federated and Flower on FLAIR because of time constraints. Implementing the metrics used in FLAIR for all different frameworks was particularly time consuming.

To ensure no framework included any improvements that could be influenced by `pf1-research`, we used the last commit before the release date of `pf1-research`, 29th February, for each framework. We benchmarked `pf1-research` with version 0.1 and did not include no additional speedup improvements merged after 1st February 2024.

D.1 FedML

We used the commit `28cd33b2d64fda1533c1bac6109c14f13c1012f7` from 29th February 2024 in our CIFAR10 FedML setup and adopted the existing CIFAR10 setup¹³. We changed the model and hyper-parameters to reflect Appendix C.5. Additionally, we did the following modifications in FedML to more accurately reflect Appendix C.5:

- Remove random crop in CIFAR10 data loader.
- Remove random horizontal flip in CIFAR10 data loader.

¹³https://github.com/FedML-AI/FedML/tree/28cd33b2d64fda1533c1bac6109c14f13c1012f7/python/examples/federate/simulation/sp_fedavg_cifar10_resnet56_example

- Only evaluate 1 user as central evaluation as each user has a copy of all the test data.

D.2 Flower

We used the commit `f25ddc13727ee85f372583f6d85c046803a76329` from 29th February 2024 in our CIFAR10 and FLAIR setup with Flower and adopted the existing CIFAR10 setup that reproduce [70]¹⁴. We changed the model and hyper-parameters to reflect Appendix C.5, and we upgraded the setup to use the latest Flower release at the time (1.7.0).

D.3 TensorFlow Federated

We used version 0.48.0 in our CIFAR10 and FLAIR setup with TFF because more recent versions removed the Python execution context, and we did not manage to run on GPU with the CPP execution context^{15,16}. We adopt the setup from [84] as our starting point, using the commit `a5af8c4433c9ee2d2b1565f1bcc68c89e2000a6b` from 21st February 2024¹⁷. We changed the model and hyper-parameters to reflect Appendix C.5.

D.4 FedScale

We used the commit `7ec441c2afa99510535adebe155d89fa8bb2c637` from 18th December 2023 in our CIFAR10 FedScale setup, which was the latest commit as of the release of `pfl-research`. We used the existing CIFAR10 dataset integration available in FedScale and changed the run config to reflect Appendix C.5. We checked that FedScale’s CIFAR10 integration was approximately the same as the CIFAR10 setup in `pfl-research`.

Additionally, we did the following modifications in FedScale to more accurately reflect Appendix C.5:

- Disable model saving, which was hard-coded in framework.
- Implement partial participation feature, FedScale samples all users each round!
- Modify the source code in `fedscale/cloud/fllibs.py` to add our model from Appendix C.5.

D.4.1 Flute

We used the commit `8bfe0854ab293c6226df66856b3d96b39dbe61fe` from 23rd August 2023 in our CIFAR10 FLUTE setup. We adopted the existing FEMNIST setup that FLUTE used to benchmark against FedML¹⁸, and then modified it to use FLUTE’s CIFAR10 integration. We changed the model and hyper-parameters to reflect Appendix C.5. FLUTE’s configuration files were extensive enough such that we did not need to modify anything in the framework itself. Unfortunately, it was not possible to run multiple training processes on a single GPU, so the only results we have are with $p = 1$ in Table 1.

D.4.2 System metrics from benchmarks

Figure 7 and Figure 8 show CPU memory, CPU utilization, GPU memory and GPU utilization during training of the CIFAR10 benchmark of each framework. To isolate how performant the frameworks are irrespective of distributed simulation methods, Figure 7 shows experiments utilizing only 1 process for training. **pfl-research** has the highest GPU utilization while simultaneously also having the least RAM usage and one of the lowest CPU utilizations. This is evidence for how our methods 1, 2 and 4 described in Section 4.1 result in a more efficient usage of the hardware. Even though the initialization period before GPU utilization ramps up is larger for **pfl-research**, it is smaller in absolute time since **pfl-research** is much faster. However, FedML has a significant initialization period, 20 minutes, due to a slow data partitioning procedure done before the training starts.

¹⁴https://github.com/adap/flower/tree/main/baselines/flwr_baselines/flwr_baselines/publications/adaptive_federated_optimization

¹⁵<https://github.com/tensorflow/federated/issues/4600>

¹⁶<https://github.com/tensorflow/federated/issues/4042>

¹⁷https://github.com/google-research/federated/tree/master/fedopt_guide

¹⁸https://github.com/microsoft/msrflute/tree/main/experiments/cv_cnn_femnist

System metrics for CIFAR10 comparison benchmark (1 GPU, 1 process)

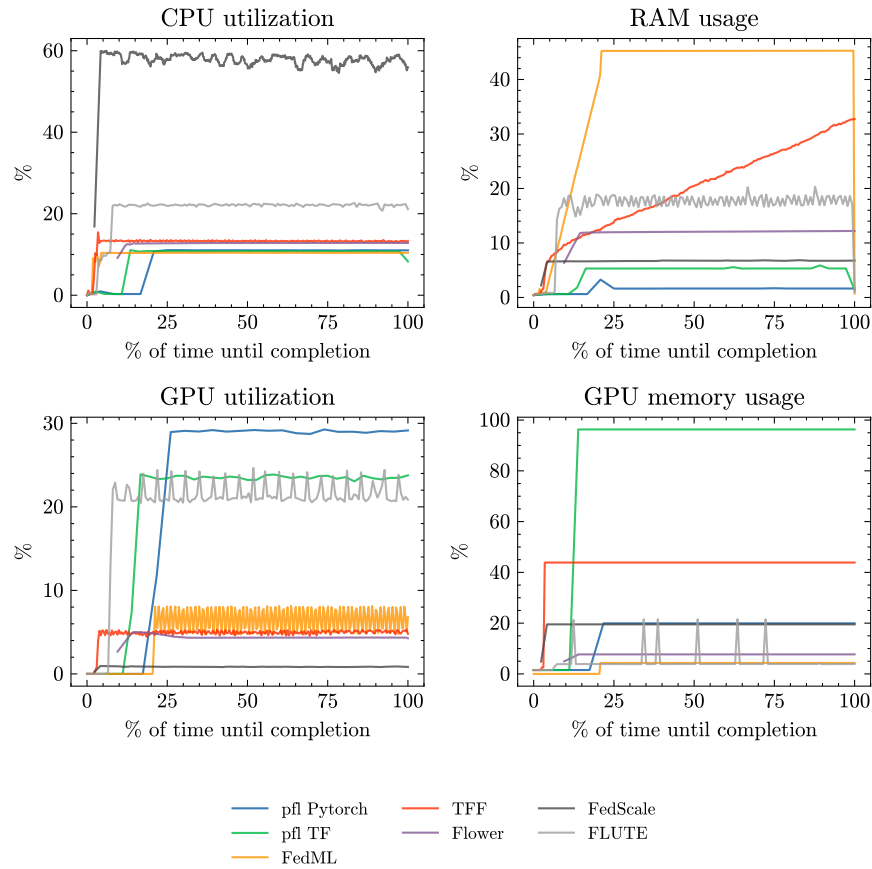


Figure 7: Measurements of CPU utilization, CPU memory usage, GPU utilization and GPU memory usage when running the CIFAR10 benchmark in Table 1 with 1 worker process. The x-axis is the percentage of time until training completes, a relative time measurement.

Figure 8 shows how our methods for efficiently using the GPU also result in a higher multiple of increased GPU utilization from stacking multiple processes training on 1 GPU than other frameworks. Even though the GPU memory usage allows for further increasing the number of processes sharing a GPU for the alternative frameworks, it did not further speed up simulations.

System metrics for CIFAR10 comparison benchmark (1 GPU, optimal num processes)

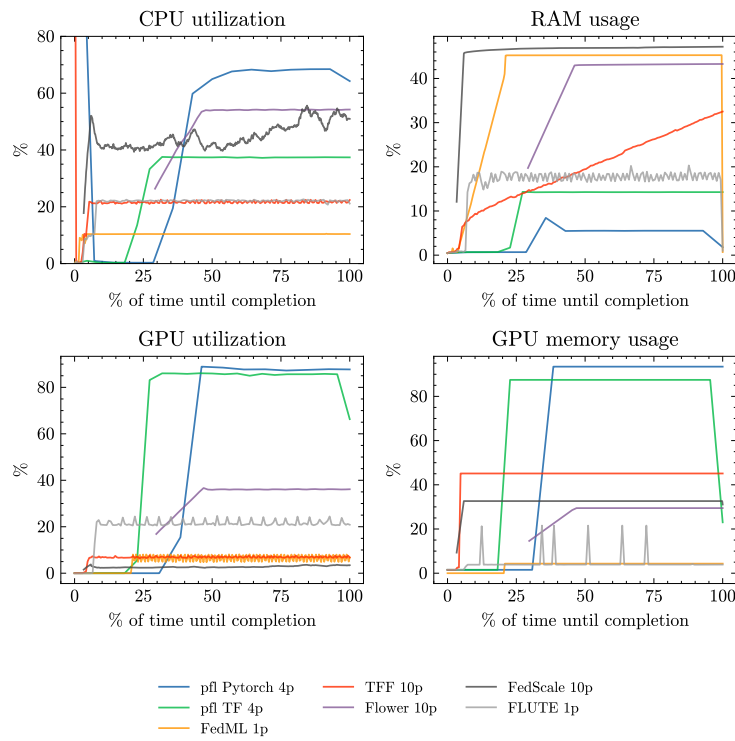


Figure 8: Same type of measurements as in Figure 8 but with the optimal number of processes sharing the single GPU, as also presented in Table 1.