
LEAF: A Benchmark for Federated Settings

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Abstract

Modern federated networks, such as those comprised of wearable devices, mobile phones, or autonomous vehicles, generate massive amounts of data each day. This wealth of data can help to learn models that can improve the user experience on each device. However, the scale and heterogeneity of federated data presents new challenges in research areas such as federated learning, meta-learning, and multi-task learning. As the machine learning community begins to tackle these challenges, we are at a critical time to ensure that developments made in these areas are grounded with realistic benchmarks. To this end, we propose LEAF, a modular benchmarking framework for learning in federated settings. LEAF includes a suite of open-source federated datasets, a rigorous evaluation framework, and a set of reference implementations, all geared towards capturing the obstacles and intricacies of practical federated environments.

1 Introduction

With data increasingly being generated on federated networks of remote devices, there is growing interest in empowering on-device applications with models that make use of such data [22, 23, 30, 19, 37]. Learning on data generated in federated networks, however, introduces several new obstacles:

Statistical: Data is generated on each device in a heterogeneous manner, with each device associated with a different (though perhaps related) underlying data generating distribution. Moreover, the number of data points typically varies significantly across devices.

Systems: The number of devices in federated scenarios is typically order of magnitudes larger than the number of nodes in a typical distributed setting, such as datacenter computing. In addition, each device may have significant constraints in terms of storage, computational, and communication capacities. Furthermore, these capacities may also differ across devices due to variability in hardware, network connection, and power. Thus, federated settings may suffer from communication bottlenecks that dwarf those encountered in traditional datacenter settings, and may require faster on-device inference.

Privacy and Security: Finally, the sensitive nature of personally-generated data requires methods that operate on federated data to balance privacy and security concerns with more traditional considerations such as statistical accuracy, scalability, and efficiency [24, 4].

Recent works have proposed diverse ways of dealing with these challenges, but many of these efforts fall short when it comes to their experimental evaluation. As an example, consider the federated

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learning paradigm, which focuses on training models directly on federated networks [22, 30, 28]. Experimental works focused on federated learning broadly utilize three types of datasets, each with their own shortcoming: (1) datasets that are commonly used and yet do not provide a realistic model of a federated scenario, e.g., artificial partitions of MNIST, MNIST-fashion or CIFAR-10 [22, 13, 8, 3, 11, 32, 34]; (2) realistic but proprietary federated datasets, e.g., data from an unnamed social network in [22], crowdsourced voice commands in [18], and proprietary data by Huawei in [5]; and (3) realistic federated datasets that are derived from publicly available data, but which are not straightforward to reproduce, e.g., FaceScrub in [25], Shakespeare in [22] and Reddit in [13, 24, 3].

As a second example, consider meta-learning, a related learning paradigm proposed by [5] and [12] as a way to tackle the statistical challenges of federated networks. The paradigm is indeed a natural fit for federated settings, as the heterogeneous devices can be interpreted as meta-learning tasks. However, popular meta-learning benchmarks such as *Omniglot* [15, 7, 33, 31] and *miniImageNet* [29, 7, 33, 31] focus on k -shot learning (i.e., all tasks have the same number of samples, each class has the same number of samples in each task, etc.) and thus fail to capture the real-world challenges that federated data would bring to meta-learning solutions. In fact, all of the previously mentioned datasets could thus be categorized as the first type mentioned above (popular yet unrealistic for our purposes).

As a final example, consider multi-task learning (MTL). This paradigm is also amenable to federated settings [30] but, contrary to realistic federated networks, is usually explored in regimes with small numbers of tasks and samples, e.g., the popular *Landmine Detection* [38, 26, 36, 30], *Computer Survey* [2, 1, 14] and *Inner London Education Authority School* [26, 17, 1, 2, 14] datasets have at most 200 tasks each. We highlight that, while federated learning, meta-learning, and multi-task learning are the presented applications for LEAF, the framework in fact encompasses a wide range of potential learning settings, such as on-device learning or inference, transfer learning, life-long learning, and the development of personalized learning models.

Our work aims to bridge the gap between artificial datasets that are popular and accessible for benchmarking, and those that realistically capture the characteristics of a federated scenario but that, so far, have been either proprietary or difficult to process. Moreover, beyond establishing a suite of federated datasets, we propose a clear methodology for evaluating methods and reproducing results. To this end, we present LEAF, a modular benchmarking framework geared towards learning in massively distributed federated networks of remote devices.

2 LEAF

LEAF is an open-source benchmark for federated settings.² It consists of (1) a suite of open-source datasets, (2) an array of statistical and systems metrics, and (3) a set of reference implementations. As shown in Figure 1, LEAF’s *modular* design allows these three components to be easily incorporated into diverse experimental pipelines. We proceed to detail LEAF’s core components.

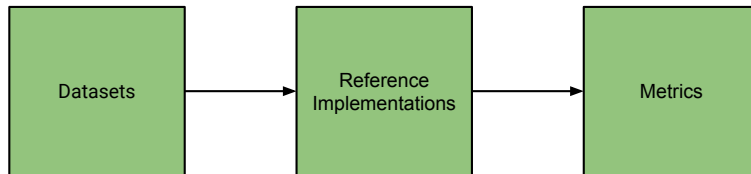


Figure 1: LEAF modules. The “Datasets” module preprocesses the data and transforms it into a standardized format, which can integrate into an arbitrary ML pipeline. LEAF’s “Reference Implementations” module is a growing repository of common methods used in the federated setting, with each implementation producing a log of various different statistical and systems metrics. Any log generated in an appropriate format can then be used to aggregate and analyze these metrics in various ways through LEAF’s “Metrics” module.

²All code and documentation can be found at <https://github.com/TalwalkarLab/leaf/>.

Table 1: Statistics of datasets in LEAF.

Dataset	Number of devices	Total samples	Samples per device	
			mean	stdev
FEMNIST	3, 550	805, 263	226.83	88.94
Sent140	660, 120	1, 600, 498	2.42	4.71
Shakespeare	1, 129	4, 226, 158	3, 743.28	6, 212.26
CelebA	9, 343	200, 288	21.44	7.63
Reddit	1, 660, 820	56, 587, 343	34.07	62.95

Datasets: We have curated a suite of realistic federated datasets for LEAF. We focus on datasets where (1) the data has a natural keyed generation process (where each key refers to a particular device/user); (2) the data is generated from networks of thousands to millions of devices; and (3) the number of data points is skewed across devices. Currently, LEAF consists of six datasets:

- *Federated Extended MNIST (FEMNIST)*, which is built by partitioning the data in Extended MNIST [16, 6] based on the writer of the digit/character.
- *Sentiment140* [9], an automatically generated sentiment analysis dataset that annotates tweets based on the emoticons present in them. Each device is a different twitter user.
- *Shakespeare*, a dataset built from *The Complete Works of William Shakespeare* [35, 22]. Here, each speaking role in each play is considered a different device.
- *CelebA*, which partitions the Large-scale CelebFaces Attributes Dataset ³ [21] by the celebrity on the picture.
- *Reddit*, where we preprocess comments posted on the social network on December 2017.
- A *Synthetic* dataset, which modifies the synthetic dataset presented in [20] to make it more challenging for current meta-learning methods. See Appendix A for details.

We provide statistics on these datasets (except the Synthetic one, as these vary depending on the user’s settings) in Table 1. In LEAF, we provide all necessary pre-processing scripts for each dataset, as well as small/full versions for prototyping and final testing. Moving forward, we plan to add datasets from different domains (e.g. audio, video) and to increase the range of machine learning tasks (e.g. text to speech, translation, compression, etc.).

Metrics: Rigorous evaluation metrics are required to appropriately assess how a learning solution behaves in federated scenarios. Currently, LEAF establishes an initial set of metrics chosen specifically for this purpose. For example, we introduce metrics that better capture the entire distribution of performance across devices: performance at the 10th, 50th and 90th percentiles and performance stratified by natural hierarchies in the data (e.g. “play” in the case of the Shakespeare dataset or “subreddit” for Reddit). We also introduce metrics that account for the amount of computing resources needed from the edge devices in terms of number of FLOPS and number of bytes downloaded/uploaded. Finally, LEAF also recognizes the importance of specifying how the accuracy is weighted across devices, e.g., whether every device is equally important, or every data point equally important (implying that power users/devices get preferential treatment).

Reference implementations: In order to facilitate reproducibility, LEAF also contains a set of reference implementations of algorithms geared towards federated scenarios. Currently, this set is limited to the federated learning paradigm, and in particular includes reference implementations of minibatch SGD, FedAvg [22] and Mocha [30]. Moving forward we aim to equip LEAF with implementations for additional methods and paradigms with the help of the broader research community.

³The original CelebA data is hosted in <http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html>

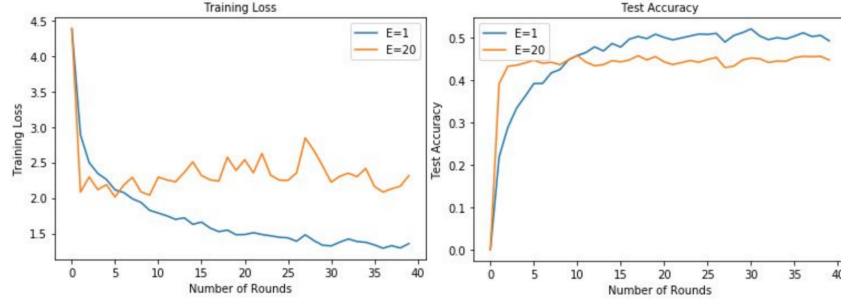


Figure 2: Convergence behavior of FedAvg on a subsample of the Shakespeare dataset. We are able to achieve a per sample test accuracy comparable to the results obtained in [22]. We also qualitatively replicate the divergence in training loss that is observed for large numbers of local epochs (E).

3 LEAF in action

We now show a glimpse of LEAF in action. In particular, we highlight three of LEAF’s characteristics⁴:

LEAF enables reproducible science: To demonstrate the reproducibility enabled via LEAF, we focus on qualitatively reproducing the results that [22] obtained on the Shakespeare dataset for a next character prediction task. In particular, it was noted that for this particular dataset, the FedAvg method surprisingly *diverges* as the number of local epochs increases. This is therefore a critical setting to understand before deploying methods such as FedAvg. Results are shown in Figure 2, where we indeed see similar divergence behavior in terms of the training loss as we increase the number of epochs.

LEAF provides granular metrics: As illustrated in Figure 3, our proposed systems and statistical metrics are important to consider when serving multiple clients simultaneously. For statistical metrics, we show the effect of varying the minimum number of samples per user in Sentiment140 (which we denote as k). We see that, while median performance degrades only slightly with data-deficient users (i.e., $k = 3$), the 25th percentile degrades dramatically. Meanwhile, for systems metrics, we run minibatch SGD and FedAvg for FEMNIST and calculate the systems budget needed to reach a per sample accuracy threshold of 0.75. We characterize the budget in terms of total number of FLOPS across all devices and total number of bytes uploaded to network. Our results demonstrate the improved systems profile of FedAvg when it comes to the communication vs. local computation trade-off, though we note that in general methods may vary across these two dimensions.

LEAF is modular: To demonstrate LEAF’s modularity, we incorporate its “Datasets” module into three new experimental pipelines: one that trains purely local models for each device (on CelebA and our Synthetic dataset), one that disregards the natural partition between devices, i.e., it mixes all the data (on Reddit), and one in which we use the popular meta-learning method *Reptile* [27] (on FEMNIST). Results for these experiments are presented in Table 2. These particular pipelines shed light on how different modeling approaches may be more or less appropriate for different federated datasets [10, 12].

4 Conclusions

We present LEAF, a modular framework for learning in federated settings, or ecosystems marked by massively distributed networks of devices. Learning paradigms applicable in such settings include federated learning, meta-learning, multi-task learning, and on-device learning.

LEAF will allow researchers and practitioners in domains such as federated learning, meta-learning, and multi-task learning to reason about new proposed solutions under more realistic assumptions than

⁴For experiment details, see Appendix B.

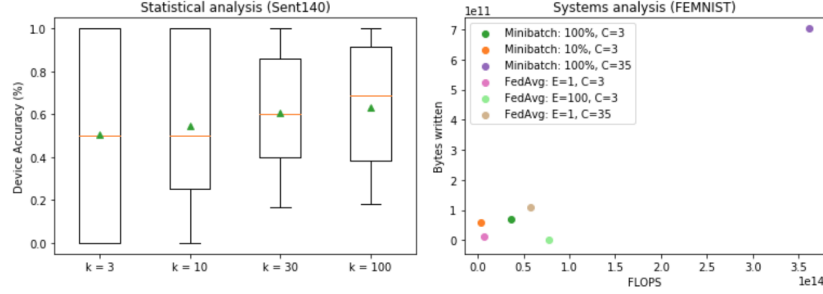


Figure 3: Statistical and Systems analyses for Sent140 and FEMNIST. For Sent140: k is the minimum number of samples per user. Orange lines represent the median device accuracy, green triangles represent the mean, boxes cover the 25th and 75th percentile, and whiskers cover the 10th to the 90th percentile. For FEMNIST: C is the number of clients selected per round, and E is the number of epochs each client trained locally for FedAvg. For minibatch SGD we report the percentage of data used per client.

Table 2: Demonstration of LEAF’s modularity. We incorporate LEAF’s datasets into new experimental pipelines (beyond FedAvg) and report the resulting sample test accuracies.

Dataset	FedAvg (baseline)	Additional Pipeline	
		description	accuracy
CelebA	89.46%	Local Models	65.29%
Synthetic	71.89%		87.34%
Reddit	13.35%	Global IID model	12.60%
FEMNIST	74.72%	Reptile	80.24%

previous benchmarks. We intend to keep LEAF up to date with new datasets, metrics and open-source solutions in order to foster informed and grounded progress in this field.

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A Synthetic Dataset

Our synthetic dataset (introduced in Section 2) is inspired by the one presented in [20], but has possible additional heterogeneity designed to make current meta-learning methods (such as *Reptile* [27]) fail. The high-level goal is to create tasks whose true models are (1) task-dependant, and (2) clustered around more than just one center.

To start, the user must input the desired number of devices $T \geq 1$ and a vector (p_1, \dots, p_k) such that $p_j > 0, j \in 1, \dots, k$ and $\sum_{j=1}^k p_j = 1$. As preparation to generate the tasks:

1. Sample cluster means $\mu_j \in \mathbb{R}^s, j \in 1, \dots, k$. To do this, draw $\mu_j \sim N(B_j, I), B_j \sim N(0, I)$.
2. Draw matrix $Q \in \mathbb{R}^{d+1 \times s}$ by sampling $Q \sim N(0, I)$.
3. Create diagonal matrix Σ such that $\Sigma_{i,i} = i^{-1.2}$.

Now, for each task $t \in 1, \dots, T$:

1. Sample a cluster center μ_t according to the input probabilities (p_1, \dots, p_k) .
2. Draw $u_t \sim N(\mu_t, I)$ and set $w_t = Qu_t, w_t \in \mathbb{R}^{d+1}$.
3. Now, draw m_t from a log-normal distribution with mean 3 and sigma 2. We then set the number of samples $n_t = \min(m_t + 5, 1000)$ (to put a lower and an upper bound on the number of samples per task).
4. Sample $v_t \sim N(C_t, I), C_t \sim N(0, I)$.
5. Now, for $i \in 1, \dots, n_t$, sample $x_t^i \in \mathbb{R}^d$ by drawing $x_t^i \sim N(v_t, \Sigma)$.
6. Finally, set $y_t^i = \arg \max(\text{sigmoid}(w_t x_t^i + N(0, 0.1 \cdot I)))$ after adding the necessary padding to x_t^i to account for the intercept.

B Experiment Details

In this section, we provide details for the experiments presented in Section 3.

Shakespeare convergence. For the experiment presented in Figure 2, we subsample 118 devices (around 5% of the total) in our Shakespeare data. Our model first maps each character to an embedding of dimension 8 before passing it through an LSTM of two layers of 256 units each. The LSTM emits an output embedding, which is scored against all items of the vocabulary via dot product followed by a softmax. We use a sequence length of 80 for the LSTM. We evaluate using AccuracyTop1. We use a learning rate of 0.8 and 10 devices per round for all experiments.

Statistical and systems analyses. For all the Sent140 experiments presented in Figure 3, we use a bag of words model with logistic regression, and a learning rate of $3 \cdot 10^{-4}$. For the FEMNIST experiments in the same figure, we subsample 5% of the data, and use a model with two convolutional layers followed by pooling, and a final dense layer with 2048 units. We use a learning rate of $4 \cdot 10^{-3}$ for FedAvg and of $6 \cdot 10^{-2}$ for minibatch SGD.

Additional pipelines. For the experiments presented in Table 2 we use a split of 60% training, 20% validation and 20% test per user, and report results on the test set. The hyperparameters that vary per experiment are the following:

- For the CelebA experiments, we use 10% of the total clients and the same model we described above for FEMNIST. For the local models, each device explored learning rates in $[0.1, 0.01, 0.001, 0.0001]$. The FedAvg model uses 10 clients per round for 100 rounds, training locally for one epoch with a batch size of 5, and a best learning rate of 0.001. Both results are averaged over 5 runs.
- For the experiments with the Synthetic dataset, we use 1,000 devices, only one cluster, 60 features and 5 classes. Our model is a perceptron with sigmoid activations. For the local models, each device explored learning rates in $[10^{-3}, 10^{-2}, 10^{-1}, 1, 10, 10^2, 10^3]$. The FedAvg model used 10 clients per round for 100 rounds, trained locally for one epoch with a batch size of 5, and found a best learning rate of 0.1.
- For the Reddit experiments, we use 819 devices and a model similar to the one we described for Shakespeare. The main differences are: the size of the embedding is now 200, and we build the vocabulary from the tokens in the training set with a fixed length of 10,000. We use a sequence length of 10, evaluate using AccuracyTop1 and consider all predictions of the unknown and

padding tokens as incorrect. For the global iid model, we train for 3 epochs over all the devices' data using a learning rate of $4 \cdot \sqrt{2}$. For FedAvg, we use 10 clients per round for 100 rounds, training locally for one epoch using a batch size of 5. We use a learning rate of 8. Both results are averaged over 5 runs.

- For the FEMNIST experiments we use the same model as described before and run each algorithm for 1,000 rounds, use 5 clients per round, a local learning rate of 10^{-3} , a training mini-batch size of 10 for 5 mini-batches, and evaluate on an unseen set of test devices. Furthermore, for *Reptile* we use a linearly decaying meta-learning rate that goes from 2 to 0, and evaluate by fine-tuning each test device for 50 mini-batches of size 5.