Salvaging Federated Learning by Local Adaptation

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Abstract
Federated learning (FL) is a heavily promoted approach for training ML models on sensitive data, e.g., text typed by users on their smartphones. FL is expressly designed for training on data that are unbalanced and non-iid across the participants. To ensure privacy and integrity of the federated model, latest FL approaches use differential privacy or robust aggregation.

We look at FL from the local viewpoint of an individual participant and ask: (1) do participants have an incentive to participate in FL? (2) how can participants individually improve the quality of their local models, without re-designing the FL framework and/or involving other participants?

First, we show that on standard tasks such as next-word prediction, many participants gain no benefit from FL because the federated model is less accurate on their data than the models they can train locally on their own. Second, we show that differential privacy and robust aggregation make this problem worse by further destroying the accuracy of the federated model for many participants.

Then, we evaluate three techniques for local adaptation of federated models: fine-tuning, multi-task learning, and knowledge distillation. We analyze where each is applicable and demonstrate that all participants benefit from local adaptation. Participants whose local models are poor obtain big accuracy improvements over conventional FL. Participants whose local models are better than the federated model—and who have no incentive to participate in FL today—improve less, but sufficiently to make the adapted federated model better than their local models.

1. Introduction
Federated learning (McMahan et al., 2017) is a framework for large-scale, distributed learning on sensitive data, e.g., training a next-word prediction model on texts typed by users into their smartphones or a medical treatment model on patient records from multiple hospitals. Designed for unbalanced, non-iid data distributions, federated learning has demonstrated good performance and scalability (Bonawitz et al., 2019) and is promoted by Google (Pichai, 2019) and other companies as the solution to privacy problems in predictive keyboards (Hard et al., 2018), medicine (de Brouwer, 2019), and other domains (Kairouz et al., 2019).

The original approach (McMahan et al., 2017) creates the federated model by repeatedly averaging model updates from small subsets of participants. Both the updates and the final model can leak participants’ training data, violating privacy (Shokri et al., 2017; Melis et al., 2019). Averaging-based aggregation is also vulnerable to attacks on model integrity because malicious participants can introduce unwanted behavior into the model (Bagdasaryan et al., 2018). To protect privacy, differentially private federated learning (McMahan et al., 2018) bounds how much the model can reveal about the inputs from any individual participant. To protect integrity, robust aggregation (Yin et al., 2018) replaces average with median to bound the influence of outliers on the model.

Users have an incentive to participate in federated learning only if federated models are more accurate than the models they can train independently on their own data. Privacy and robustness mechanisms introduce a fundamental conflict into this reasoning. To take advantage of the data of the unusual participants—which is one of the principal design objectives of federated learning—aggregation must incorporate their contributions into the federated model. To protect privacy and integrity, aggregation must restrict these contributions from having much influence on the federated model.

Our contributions. We look at federated learning (FL) from the local perspective of individual participants and investigate whether they have an incentive to participate. Does federated learning yield more accurate models for them? If no, what can they do locally to improve the quality of models they obtain from FL.

First, we demonstrate that privacy and robustness protections destroy the accuracy of federated models for many participants, removing their main incentive to join federated learning. We use standard federated learning tasks: next-word prediction and image classification. With very few exceptions (see Section 2), prior work focused on measur-
ing the overall accuracy of federated models. By contrast, we (a) measure their accuracy for the individual participants, and (b) show that many participants gain no benefit because the federated model achieves worse accuracy on their data than a model they can train independently. For example, when training a word-prediction model on a Reddit dataset, the federated model based on robust median aggregation achieves worse accuracy than the local models for the majority of participants.

Next, we solve this fundamental tradeoff between privacy/robustness and individual accuracy. Instead of a single model that should be accurate for all participants, we use local adaptation to convert the federated model into individual models for each participant.

Crucially, we are interested in local methods that an individual participant can deploy on their own. We do not aim to change FL aggregation algorithms because FL frameworks are controlled by platform operators such as Google and cannot be changed unilaterally by a single participant (e.g., a single smartphone). We are also not interested in solutions that require all or most participants to change their algorithms because they require cooperation and are hard to deploy in practice.

We investigate three adaptation mechanisms: fine-tuning, multi-task learning, and knowledge distillation. We analyze where each is applicable, and show how local adaptation helps participants recover the accuracy destroyed by differential privacy and robust aggregation. Participants who had no incentive to join federated learning because their local models are better than the federated model benefit because the adapted federated model becomes better than the local models. For example, for 80% of the participants in the word-prediction task, the adapted robust model outperforms their local models. Participants whose local models are inaccurate—and thus already benefit from federated learning—experience the biggest accuracy improvements due to local adaptation and benefit even further. Finally, we relate the effects of adaptation to the complexity of participants’ data.

2. Related Work

Privacy and integrity of federated learning. Participants’ model updates leak their training data (Melis et al., 2019), and malicious participants can inject unwanted behaviors into the model (Bagdasaryan et al., 2018; Bhagoji et al., 2019). Secure aggregation (Bonawitz et al., 2017) prevents the global server from observing individual updates, but it also makes attacks on integrity impossible to detect and the final model may still leak training data.

Federated learning with differential privacy (McMahan et al., 2018) limits the leakage of training data. To limit the influence of individual participants, several robust, “Byzantine-tolerant” aggregation schemes have been proposed (Blanchard et al., 2017; El Mhamdi et al., 2018; Damaskinos et al., 2019; Rajput et al., 2019; Chen et al., 2017). Alternative aggregation schemes (Yurochkin et al., 2019; Guha et al., 2019; Hsu et al., 2019) for various flavors of federated learning provide neither privacy, nor robustness. Peer-to-peer (not federated) learning with convex losses and without robustness is studied in (Bellet et al., 2018).

Accuracy for individual participants. Federated learning is explicitly designed for non-id participants, but most prior work does not measure their individual accuracy. Training of participant-specific models is studied in (Smith et al., 2017), without privacy or robustness and at the cost of replacing the entire federated learning framework. Differential privacy disproportionately reduces model accuracy for underrepresented participants (Bagdasaryan et al., 2019). No previous work investigated the impact of robust aggregation on individual accuracy.

Prior work on personalization of ML models focused on speaker adaptation of acoustic models (see (Yu & Li, 2017)). Many techniques are not compatible with federated learning because they require an ensemble of models (Tan et al., 2015) or are speech-specific (Miao et al., 2015), but (Huang et al., 2015) connects personalization and multi-task learning.

Recent papers on personalizing federated models (Wang et al., 2019; Jiang et al., 2019; Fallah et al., 2020; Dinh et al., 2020) propose various methods to improve the accuracy for individual participants; (Jiang et al., 2019) also connects meta learning with personalization. These papers do not investigate (a) if federated models are more accurate than the models individual participants can train on their own, (b) the impact of privacy and integrity protections on individual participants’ accuracy, and (c) purely local adaptation techniques other than fine-tuning (the only exception is a short paper (Peterson et al., 2019) that uses domain adaptation to counteract the reduction in accuracy due to differential privacy). While there are dozens of alternative aggregation algorithms that may improve the quality of local models (see the survey in (Kairouz et al., 2019)), all of them involve global changes to the federated learning framework, require all participants to replace their algorithms, and cannot be deployed locally and unilaterally by a participant. As explained in Section 1, we are interested in local techniques that an individual participant can use to mitigate the damage from privacy and robustness mechanisms.

3. Background

Federated learning is a distributed learning paradigm for training a model on multiple participants’ data (McMahan et al., 2017).
et al., 2017). The global server creates the initial model $G^0$. In each round $t = 1 .. T$, the server selects a subset of $m$ participants from some pool $Q$ of size $n$ and sends them the current model $G^{t-1}$. Each selected participant $i \in m$ updates the model on his local data $D_i$ and sends the resulting model $P^t_i$ to the global server, which averages it with the other updates using the aggregation learning rate $\eta$ to obtain the new global model $G^t$. For direct comparison, we use the formula from (McMahan et al., 2018):

$$G^t = G^{t-1} + \frac{\eta}{m} \sum_{i=1}^{m} (P^t_i - G^{t-1})$$  \hspace{1cm} (1)

All motivating applications of federated learning, such as predictive keyboards and collaborative analysis of biomedical data, involve participants with non-idd data, and federated learning is specifically designed to accommodate training with millions of participants. Recently, a federated language model was trained on 7.5 billion sentences from 1.5 million North American participants (Hard et al., 2018).

**Adding privacy.** ML models can leak their training data (Song et al., 2017; Shokri et al., 2017). In federated learning, participants’ model updates can leak even more (Melis et al., 2019). Differential privacy (Dwork, 2008; 2011) has been promoted as the solution to privacy problems in deep learning (Abadi et al., 2016) and federated learning (McMahan et al., 2018). Differential privacy (DP) provides $(\epsilon, \delta)$ privacy guarantee when the federated mechanism $M$ and two set of users $Q, Q'$ that differ by one participant produce models in any set $G$ with probabilities that satisfy:

$$P_r[M(Q) \in G] \leq e^\epsilon P_r[M(Q') \in G] + \delta$$  \hspace{1cm} (2)

In practice, applying differential privacy to federated learning involves (a) clipping each participant’s update, and (b) adding random noise (McMahan et al., 2018). Aggregation is modified as follows:

$$G^t = G^{t-1} + \frac{\eta}{m} \sum_{i=1}^{m} (\text{Clip}(P^t_i - G^{t-1}, S)) + \mathcal{N}(0, \sigma)$$  \hspace{1cm} (3)

Achieving a given $(\epsilon, \delta)$ privacy guarantee involves carefully selecting the clipping bound $S$ and noise $\sigma$ using the moments accountant method (Abadi et al., 2016). We omit the details and instead using parameters from previous work with a similar setup (McMahan et al., 2018).

**Adding integrity.** Training with millions of participants is inherently vulnerable to malicious participants who can prevent the training from converging and/or inject a backdoor into the model (Bagdasaryan et al., 2018). To ensure that malicious participants and other outliers cannot influence the joint model, robust aggregation replaces average by median (Yin et al., 2018; Chen et al., 2019):  

$$G^t = G^{t-1} + \eta(\tilde{P}^t - G^{t-1})$$  \hspace{1cm} (4)

where $\tilde{P}^t$ is the element-wise median among the updates submitted in round $t$. We focus on median aggregation, but our adaptation techniques also apply to other so called “Byzantine-tolerant” aggregation schemes (Blanchard et al., 2017; El Mhamdi et al., 2018; Damaskinos et al., 2019).

### 4. Tasks

We use two standard tasks from the federated learning literature: next-word prediction and CIFAR-10 image classification (McMahan et al., 2017). We evaluate the original averaging aggregation (McMahan et al., 2017), differentially private aggregation (McMahan et al., 2018), and robust median aggregation (Chen et al., 2019; Yin et al., 2018): BASIC-FED, DP-FED, and ROBUST-FED, resp.

For DP-FED, we follow (McMahan et al., 2018) and use the clipping bound $S = 15$ and Gaussian noise with $\sigma = 0.01$ for Equation 3 (the model does not converge with bigger noise). For ROBUST-FED, we compute the coordinate-wise median instead of the mean of participants’ gradients. Each participant trains locally using cross-entropy loss $\mathcal{L}_{\text{cross}}(P, x)$. All code was implemented in PyTorch 1.2 and executed on an Ubuntu 18.04 machine with 4 Nvidia GeForce RTX 2080 Ti GPUs and 12GB RAM. We release our code publicly for reproducibility.1

#### 4.1. Next-word prediction

We train word prediction models on a randomly chosen month (November 2017) of the Reddit dataset (Reddit) with 80,000 participants (i.e., Reddit users) who have between 150 and 500 posts, treating each post as one sentence. This task is a realistic application of federated learning, involving unbalanced data from different distributions (see Appendix A.3 in supplementary materials). Some users have posts with a few simple, repeating phrases, while others write in sophisticated prose.

We compiled a dictionary of 50,000 most frequent words and replaced all others with the unk token. To create BASIC-FED, DP-FED, and ROBUST-FED models, we train 2-layer LSTM models with 200 hidden units and 10 million parameters (pytorch). Following (McMahan et al., 2018), we train for 5,000 rounds with $m = 100$ participants per round, aggregation learning rate $\eta = 1$, batch size 20, and $B = 2$ internal epochs using SGD. For training participants’ models, we tried inner learning rates of 0.1, 1, 10, 20, and 40, yielding global test accuracy of, respectively, 9.07%, 14.34%, 18.83%, 19.20% and 19.29%. We thus set the in-

1https://github.com/ebagdasa/federated_adaptation
ner learning rate to $lr = 40$. To measure test accuracy, we split each participant’s Reddit posts into the training and test sets in chronological order at the 9 : 1 ratio.

4.2. Image classification

We split the CIFAR-10 (Krizhevsky, 2009) training set into 100 participants. To simulate a non-iid distribution, we allocate images from each class to participants using Dirichlet distribution with $\alpha = 0.9$, similar to (Hsu et al., 2019). We train all federated models for 1,000 rounds with the aggregation learning rate $\eta = 1$ and batch size of 32. Following (McMahan et al., 2017), in every round we aggregate 10 randomly selected participants, each of whom trains a ResNet-18 model (with 11.2 million parameters) with the inner learning rate of $0.1$ and $B = 2$ internal epochs using SGD with momentum 0.9 and weight decay 0.0005.

CIFAR-10 is not divided into distinct participants. To measure the test accuracy of a model on a participant’s distribution, we calculate its per-class accuracy on the CIFAR-10 global test dataset, multiply it by the corresponding class’s ratio in the participant’s training dataset, and sum up the resulting values.

5. Privacy and robustness destroy individual accuracy

Federated learning relies on the participation of thousands or millions of users. Some may be motivated by altruism, but rational users need an incentive to participate. For example, they benefit if the federated model is more accurate than the models they can train locally on their own data.

Accuracy of federated models is typically measured—often on tasks such as MNIST that are not representative of the intended applications of federated learning—on a holdout dataset compiled from all participants’ data (McMahan et al., 2017). When the participants are not iid and some have their own, idiosyncratic data, global accuracy does not represent whether the model is accurate for a specific participant.

In realistic motivating scenarios, such as predictive keyboards, fraud detection, and biomedical research, an aggregated model may perform well on the global test data but poorly on an individual participant’s test data, thus removing their main incentive to participate. In the rest of this paper, we focus on the accuracy of federated models for individual participants.

Figure 1(a) compares the BASIC-FED models with the local, trained-from-scratch models of individual participants. The BASIC-FED word prediction model (top row) is worse than the local models of 9.22% (7377) participants, which are trained for 100 epochs with the learning rate of 1. On the image classification task (bottom row), there is less diversity among participants and BASIC-FED outperforms the local models of all but 1 participant. The local models were trained for 500 epochs with the learning rate of 0.001.

With privacy or integrity protections, the comparison is unfavorable for federated learning. Figure 1(b) shows that DP-FED is less accurate than the local models of many participants: 16,931 (21.16%) on word prediction (top row) and 11 (11%) on image classification (bottom row). Even worse, ROBUST-FED shown in Figure 1(c) is less accurate.
than the local models for the majority of participants (41720, or 52.15\%) on word prediction and 34 (34\%) on image classification.

These results illustrate the **tradeoff at the heart of federated learning**. To learn a joint model that is accurate for individual participants, aggregation must incorporate contributions from every participant. To protect data privacy and model integrity, aggregation must limit the influence of these contributions, producing an inaccurate model.

6. Local adaptation

We investigate several techniques for adapting the federated model to an individual participant. Local word prediction models are trained for \(B = 100\) epochs with the learning rate of 1, image classification models for \(B = 200\) epochs with the learning rate of 0.001.

**Fine-tuning (FT).** Fine-tuning is a natural adaptation technique, used, e.g., in (Wang et al., 2019). It re-trains all parameters of a trained federated model on the participant’s local training data (using the above hyperparameters). Fine-tuning takes advantage of the federated model’s feature extraction network instead of learning it from scratch. **Freeze-base (FB)** is a variant that freezes the base layers of the federated model and fine-tunes only the top layer. When using fine-tuning for local adaptation, we experimented on 1,000 participants with the learning rates of 0.1, 1, and 10, yielding mean accuracy of, respectively, 20.58\%, 20.99\% and 18.28\%. Therefore, we set \(l_r = 1\).

**Multi-task learning (MTL).** With non-iid distribution, a participant’s local data may be very different from the other participants. To mitigate overfitting, we treat local adaptation as a multi-task learning problem, where task \(X\) requires high performance on the union of all participants and task \(Y\) requires high performance on a single participant. We take the federated model \(G^T\) optimized for task \(X\) and aim to create an adapted model \(A\) (initialized as \(G^T\)) optimized for task \(Y\). To overcome the catastrophic forgetting (French, 1999) of task \(X\) while learning \(Y\), we use elastic weight consolidation (Kirkpatrick et al., 2017) which selectively slows down learning on the weights important for \(X\). To learn task \(Y\), we use the same cross-entropy loss \(L_{cross}\) as in Section 4 and aim to minimize:

\[
\ell(A, x) = L_{cross}(A, x) + \sum_i \lambda F_i (A_i - G^T_i)^2\]

where \(\lambda\) is the importance of task \(X\) vs. \(Y\), \(F\) is the Fisher information matrix (computed on a public auxiliary dataset), \(i\) is the label of each parameter. Following (Kirkpatrick et al., 2017), we use \(\lambda = 5000\).

**Knowledge distillation (KD).** Knowledge distillation (Hinton et al., 2015) extracts information from a “teacher” model into a “student” model. We treat the federated model \(G^T\) as the teacher and the adapted model \(A\) as the student, except that in our case both models have the same structure and \(A\) is initialized to \(G^T\) but the local dataset on which \(A\) is trained is a small subset of the dataset on which \(G^T\) is trained. We conjecture that enforcing the similarity of logits between \(G^T\) and \(A\) using the loss function from the

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**Figure 2.** Accuracy improvements of adapted federated models over local, trained-from-scratch models for word prediction (top row) and image classification (bottom row) tasks.
knowledge distillation literature helps mitigate overfitting on the small dataset.

We represent $G^T(x), A(x)$ as the pre-softmax logit outputs of the two models and minimize:

$$\ell(A, x) = \alpha K^2 L\text{cross}(A, x) + (1 - \alpha) \text{KL}(\sigma(G^T(x)K), \sigma(A(x)K))$$

(6)

where KL is Kullback-Leibler divergence loss, $\sigma$ is softmax, $\alpha$ is the weight parameter, $K$ is the temperature constant. The $K^2$ term equalizes gradient magnitudes for both losses. We did not observe significant differences when varying $\alpha = [0.1, 0.5, 0.95, 0.99]$ and $K = [4, 6, 10]$ and set $\alpha = 0.95, K = 6$.

7. Local adaptation gives an incentive to participate in federated learning

We investigate the effects of the FT, FB, MTL, KD adaptation techniques from Section 6 on the accuracy of BASIC-FED, DP-FED, and ROBUST-FED models for individual participants. Dots and bars in the figures are color-coded according to the technique that yielded the best accuracy improvement.

For the word-prediction task, there are 80,000 participants, but we only adapt the 79,097 participants whose vocabulary size (i.e., number of unique symbols) is over 100, the percentage of utility symbols (e.g., punctuation) is under 40\% and the difference between total and utility symbols is over 1,000.

7.1. Results of adaptation

On word prediction, mean accuracy improvements due to adaptation are 2.32\%, 2.12\%, and 2.12\% for BASIC-FED, DP-FED and ROBUST-FED, respectively. These improvements make up the loss of accuracy due to differential privacy (-1.42\%) and robust aggregation (-2.81\%). On image classification, mean accuracy improvements due to adaptation are 2.98\%, 6.83\%, and 6.34\% for BASIC-FED, DP-FED, and ROBUST-FED, respectively. These improvements make up the loss of accuracy due to differential privacy (-7.83\%) and robust aggregation (-11.89\%).

Figure 2(a) shows the improvements of the adapted BASIC-FED model over the participants’ local models for word prediction in the top row. There are only 28 (0.04\%) participants for whom the adapted BASIC-FED underperforms the local model. Median accuracy of the adapted BASIC-FED are 22.41\% and 21.00\%.

The bottom row of Figure 2(a) shows the results for image classification. Adapted BASIC-FED outperforms all local models.

Figure 2(b) shows the improvements of the adapted DP-FED model over the participants’ local models for word prediction in the top row. There are only 1465 (1.85\%) participants for whom the adapted DP-FED underperforms the local model. Median accuracy of the adapted DP-FED are 22.41\% and 21.00\%. The bottom row of Figure 2(b) shows the results for image classification. Adapted DP-FED outperforms all local models.

Figure 2(c) shows the improvements of the adapted ROBUST-FED model over the participants’ local models for word prediction in the top row. There are 14809 (18.72\%)
participants for whom the adapted ROBUST-FED underperforms the local model. The bottom row of Figure 2(c) shows the results for image classification. Adapted ROBUST-FED outperforms all local models.

7.2. Analysis

Our baselines are respective accuracies of (1) the participant’s local model and (2) the unadapted federated model, both measured on that participant’s test data.

Adapted models vs. trained-from-scratch models. In subsection 7.1, we showed that the adapted federated models outperform the local models for most participants. Top row of Figure 4 visualizes the effects of adaptation on different types of participants. Accuracy is divided into 0.2% intervals and the improvements for all participants whose local model accuracy falls into a given interval are averaged, yielding a single bar. The color of the bar corresponds to the adaptation technique that accounts for the biggest share of the total improvement of the participants in the interval.

Participants with inaccurate local models are on the left side of the X-axis. The original federated model was already more accurate than their local models (Figure 1), yet local adaptation yields the biggest improvements for them and thus a stronger incentive to participate.

Participants with accurate local models did not benefit from federated learning (Figure 1(a)), but adaptation now gives them an incentive to participate because the adapted model outperforms the local model—even though the improvement is smaller than for the low-accuracy participants.

Adapted vs. unadapted federated models. Bottom row of Figure 4 shows how adaptation improves the accuracy of federated models. The biggest improvements accrue to “tail” participants whose local models have low accuracy. Adaptation also improves the federated model for the “head” participants, for whom the unadapted model is already accurate.

To explain these effects, we measure the size (total number of words) and complexity (vocabulary, i.e., number of unique words) for each participant in our Reddit-based corpus. Figure 3 plots accuracy improvement vs. these features. Adaptations improve accuracy the most for the participants with simple (small vocabulary) and small (few total words) data. We conjecture that the participants who obtain large accuracy improvements in the bottom row of Figure 4 have simpler, smaller data. To show this for the BASIC-FED model, Figure 6 plots the relationship between model accuracy and vocabulary size (respectively, total words).

The participants with the highest and lowest BASIC-FED accuracy indeed have few, simple words. We hypothesize that “tail” participants (i.e., those with low BASIC-FED accuracy) use regular sentences that are similar to other participants: e.g., ‘appreciation series has posts for an author you mentioned.’ The low accuracy of BASIC-FED is simply due to the lack of local data. Local adaptations make better use of the available data, improving accuracy of the model.

“Head” participants (i.e., those with high BASIC-FED accuracy) also have few, simple words, but their sentences are very different from the other participants: e.g., “gucci gang gucci gang gucci gang.” Therefore, (a) their local models
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Figure 5. Cumulative accuracy improvements of different adaptations on BASIC-FED (left), DP-FED (middle), and ROBUST-FED (right).

Some participants never recover accuracy. In our image classification experiments, adapted models are always more accurate than the local models regardless of the aggregation method. In the word prediction experiments, however, adapted models never reach the same accuracy as the local models of some participants, especially with ROBUST-FED. We conjecture that median aggregation (Yin et al., 2018) prevents these participants from contributing to the federated model at all. As a consequence, the federated model is so bad for these participants than when it is used to initialize local adaptation, the final adapted model still has poor accuracy (Grosse et al., 2019; Hanin & Rolnick, 2018).

Cumulative benefit of different adaptations. Figure 5 shows cumulative improvement due to different adaptations. For BASIC-FED, the simplest FB technique performs best. For DP-FED and ROBUST-FED, MTL performs better for the “tail” participants.

8. Conclusion
Federated learning is a promising approach to large-scale model training on sensitive data. Unfortunately, differential privacy and robust aggregation reduce accuracy of federated models below that of the locally trained models of many participants, removing their main incentive to join federated learning. We showed how local adaptation techniques based on fine-tuning, multi-task learning, and knowledge distillation help improve the accuracy of private and robust federated models for individual participants, enabling them to reap the benefits of federated learning.
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A. Additional experiments

A.1. Adapting, then aggregating again

To investigate whether it is beneficial to aggregate the adapted models yet again, we use BASIC-FED on image classification. We first train a conventional federated model for 200 epochs with the learning rate of 0.1 and 2 internal epochs per participant, reaching 90.44% test accuracy. We adapt by fine-tuning with the learning rate of 0.001 for 5, 50, or 100 epochs. Averaging the adapted models produces federated models whose test accuracy is, respectively, 91.15%, 92.64%, and 89.22%.

With the right learning rate and number of epochs, aggregating adapted models can potentially produce a more accurate federated model—at the cost of significantly increasing the training time for each participant. We leave an exploration of these tradeoffs to future work.

A.2. Removing disincentivized participants

As shown in section 5, there are 7,377 participants in the word-prediction task whose local models are more accurate on their data than the federated model and who thus have no incentive to participate. If we re-train the federated model on the remaining 72,623 participants, it achieves mean/median accuracy of 20.008% / 19.570% vs., respectively, 20.021% / 19.563% achieved by the original model on 80,000 participants. The new model performs well even on the removed 7,377 participants, with mean accuracy of 20.076% vs. 20.301% for the original. Among the 72,623 participants used to train both models, the new model underperforms the original only on 974 (1.34%) participants.

As discussed in subsection 7.2, the removed participants have (a) simpler and fewer words, and (b) their sentences are outliers, very different from the rest of the participants. We conjecture that after removing these participants, the remaining set is more regular yet sufficiently complex to train a model that performs comparably to the original model.

A.3. Imbalance of participants’ local datasets

We measure the imbalance between participants’ local datasets. Figure 7 (Top) shows the size (total words) and complexity (vocabulary size) of each participant’s local data for the word prediction task. Figure 7 (Bottom) shows the size (total images) of each participant’s local data for the image classification task.