TOWARDS FEDERATED LEARNING AT SCALE: SYSTEM DESIGN

Keith Bonawitz [1] **Hubert Eichner** [1] **Wolfgang Grieskamp** [1] **Dzmitry Huba** [1] **Alex Ingerman** [1] **Vladimir Ivanov** [1]
Chloé Kiddon [1] **Jakub Konečný** [1] **Stefano Mazzocchi** [1] **H. Brendan McMahan** [1] **Timon Van Overveldt** [1]
David Petrou [1] **Daniel Ramage** [1] **Jason Roselander** [1]

ABSTRACT

Federated Learning is a distributed machine learning approach which enables model training on a large corpus of decentralized data. We have built a scalable production system for Federated Learning in the domain of mobile devices, based on TensorFlow. In this paper, we describe the resulting high-level design, sketch some of the challenges and their solutions, and touch upon the open problems and future directions.

1 INTRODUCTION

Federated Learning (FL) (McMahan et al., 2017) is a distributed machine learning approach which enables training on a large corpus of decentralized data residing on devices like mobile phones. FL is one instance of the more general approach of "bringing the code to the data, instead of the data to the code" and addresses the fundamental problems of privacy, ownership, and locality of data. The general description of FL has been given by McMahan & Ramage (2017), and its theory has been explored in Konečný et al. (2016a); McMahan et al. (2017; 2018).

A basic design decision for a Federated Learning infrastructure is whether to focus on asynchronous or synchronous training algorithms. While much successful work on deep learning has used asynchronous training, e.g., Dean et al. (2012), recently there has been a consistent trend towards synchronous large batch training, even in the data center (Goyal et al., 2017; Smith et al., 2018). The Federated Averaging algorithm of McMahan et al. (2017) takes a similar approach. Further, several approaches to enhancing privacy guarantees for FL, including differential privacy (McMahan et al., 2018) and Secure Aggregation (Bonawitz et al., 2017), essentially require some notion of synchronization on a fixed set of devices, so that the server side of the learning algorithm only consumes a simple aggregate of the updates from many users. For all these reasons, we chose to focus on support for synchronous rounds, while mitigating potential synchronization overhead via several techniques we describe subsequently. Our system is thus amenable to running large-batch SGD-style algorithms as well as Feder-

ated Averaging, the primary algorithm we run in production; pseudo-code is given in Appendix B for completeness.

In this paper, we report on a system design for such algorithms in the domain of mobile phones (Android). This work is still in an early stage, and we do not have all problems solved, nor are we able to give a comprehensive discussion of all required components. Rather, we attempt to sketch the major components of the system, describe the challenges, and identify the open issues, in the hope that this will be useful to spark further systems research.

Our system enables one to train a deep neural network, using TensorFlow (Abadi et al., 2016), on data stored on the phone which will never leave the device. The weights are combined in the cloud with Federated Averaging, constructing a global model which is pushed back to phones for inference. An implementation of Secure Aggregation (Bonawitz et al., 2017) ensures that on a global level individual updates from phones are uninspectable. The system has been applied in large scale applications, for instance in the realm of a phone keyboard.

Our work addresses numerous practical issues: device availability that correlates with the local data distribution in complex ways (e.g., time zone dependency); unreliable device connectivity and interrupted execution; orchestration of lock-step execution across devices with varying availability; and limited device storage and compute resources. These issues are addressed at the communication protocol, device, and server levels. We have reached a state of maturity sufficient to deploy the system in production and solve applied learning problems over tens of millions of real-world devices; we anticipate uses where the number of devices reaches billions.

[1]Google Inc., Mountain View, CA, USA. Correspondence to: Wolfgang Grieskamp <wgg@google.com>, Vladimir Ivanov <vlivan@google.com>, Brendan McMahan <mcmahan@google.com>.
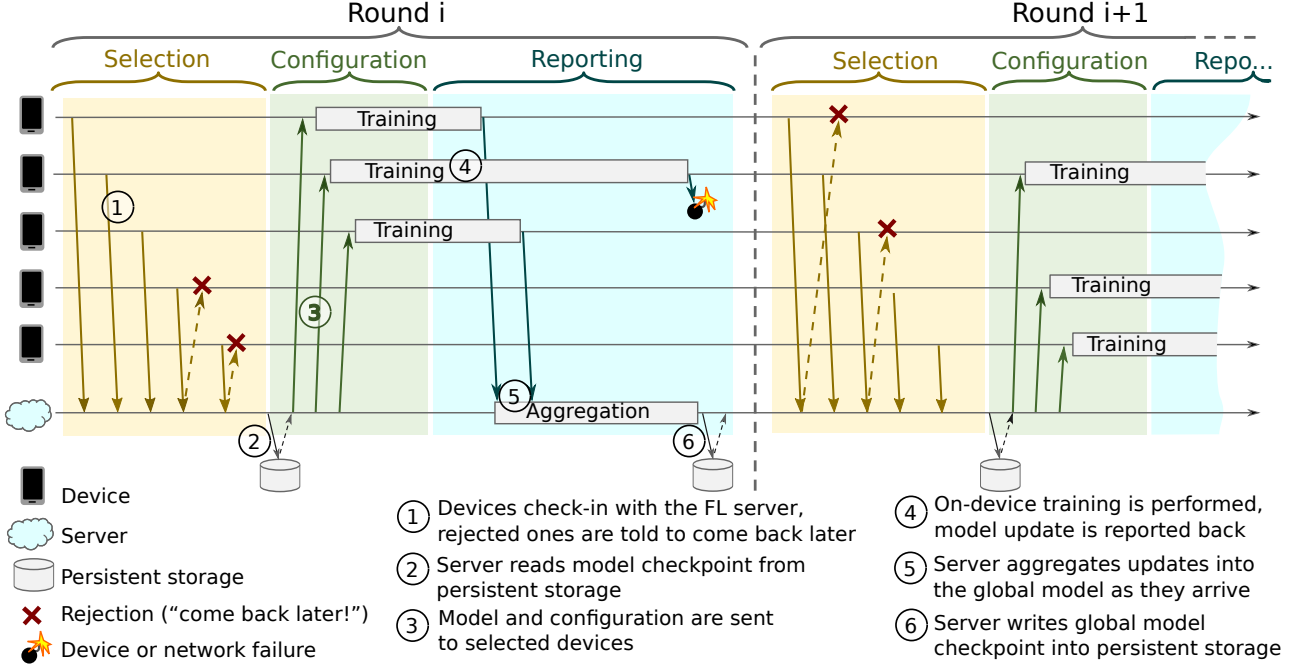
Figure 1: Federated Learning Protocol

2 PROTOCOL

To understand the system architecture, it is best to start from the network protocol.

2.1 Basic Notions

The participants in the protocol are *devices* (currently Android phones) and the *FL server*, which is a cloud-based distributed service. Devices announce to the server that they are ready to run an *FL task* for a given *FL population*. An FL population is specified by a globally unique name which identifies the learning problem, or application, which is worked upon. An FL task is a specific computation for an FL population, such as training to be performed with given hyperparameters, or evaluation of trained models on local device data.

From the potential tens of thousands of devices announcing availability to the server during a certain time window, the server selects a subset of typically a few hundred which are invited to work on a specific FL task (we discuss the reason for this subsetting in Sec. 2.2). We call this rendezvous between devices and server a *round*. Devices stay connected to the server for the duration of the round.

The server tells the selected devices what computation to run with an *FL plan*, a data structure that includes a TensorFlow graph and instructions for how to execute it. Once a round is established, the server next sends to each participant the current global model parameters and any other necessary

state as an *FL checkpoint* (essentially the serialized state of a TensorFlow session). Each participant then performs a local computation based on the global state and its local dataset, and sends an update in the form of an FL checkpoint back to the server. The server incorporates these updates into its global state, and the process repeats.

2.2 Phases

The communication protocol enables devices to advance the global, singleton model of an FL population between rounds where each round consists of the three phases shown in Fig. 1. For simplicity, the description below does not include Secure Aggregation, which is described in Sec. 6. Note that even in the absence of Secure Aggregation, all network traffic is encrypted on the wire.

Selection Periodically, devices that meet the eligibility criteria (e.g., charging and connected to an unmetered network; see Sec. 3) check in to the server by opening a bidirectional stream. The stream is used to track liveness and orchestrate multi-step communication. The server selects a subset of connected devices based on certain goals like the optimal number of participating devices (typically a few hundred devices participate in each round). If a device is not selected for participation, the server responds with instructions to reconnect at a later point in time.[1]

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[1] In the current implementation, selection is done by simple reservoir sampling, but the protocol is amenable to more sophisti-

Configuration The server is configured based on the aggregation mechanism selected (e.g., simple or Secure Aggregation) for the selected devices. The server sends the FL plan and an FL checkpoint with the global model to each of the devices.

Reporting The server waits for the participating devices to report updates. As updates are received, the server aggregates them using Federated Averaging and instructs the reporting devices when to reconnect (see also Sec. 2.3). If enough devices report in time, the round will be successfully completed and the server will update its global model, otherwise the round is abandoned.

As seen in Fig. 1, straggling devices which do not report back in time or do not react on configuration by the server will simply be ignored. The protocol has a certain tolerance for such drop-outs which is configurable per FL task.

The selection and reporting phases are specified by a set of parameters which spawn flexible time windows. For example, for the selection phase the server considers a device participant goal count, a timeout, and a minimal percentage of the goal count which is required to run the round. The selection phase lasts until the goal count is reached or a timeout occurs; in the latter case, the round will be started or abandoned depending on whether the minimal goal count has been reached.

2.3 Pace Steering

Pace steering is a flow control mechanism regulating the pattern of device connections. It enables the FL server both to scale down to handle small FL populations as well to scale up to very large FL populations.

Pace steering is based on the simple mechanism of the server suggesting to the device the optimum time window to reconnect. The device attempts to respect this, modulo its eligibility.

In the case of small FL populations, pace steering is used to ensure that a sufficient number of devices connect to the server simultaneously. This is important both for the rate of task progress and for the security properties of the Secure Aggregation protocol. The server uses a stateless probabilistic algorithm requiring no additional device/server communication to suggest reconnection times to rejected devices so that subsequent checkins are likely to arrive contemporaneously.

For large FL populations, pace steering is used to randomize device check-in times, avoiding the "thundering herd" problem, and instructing devices to connect as frequently as needed to run all scheduled FL tasks, but not more.

cated methods which address selection bias.

Pace steering also takes into account the diurnal oscillation in the number of active devices, and is able to adjust the time window accordingly, avoiding excessive activity during peak hours and without hurting FL performance during other times of the day.
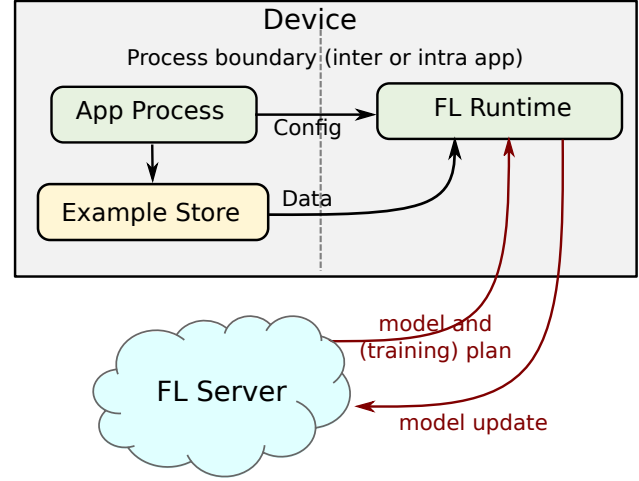
3 DEVICE

Figure 2: Device Architecture

This section describes the software architecture running on a device participating in FL. This describes our Android implementation but note that the architectural choices made here are not particularly platform-specific.

The device's first responsibility in on-device learning is to maintain a repository of locally collected data for model training and evaluation. Applications are responsible for making their data available to the FL runtime as an *example store* by implementing an API we provide. An application's example store might, for example, be an SQLite database recording action suggestions shown to the user and whether or not those suggestions were accepted. We recommend that applications limit the total storage footprint of their example stores, and automatically remove old data after a pre-designated expiration time, where appropriate. We provide utilities to make these tasks easy. Data stored on devices may be vulnerable to threats like malware or physical disassembly of the phone, so we recommend that applications follow the best practices for on-device data security, including ensuring that data is encrypted at rest in the platform-recommended manner.

The FL runtime, when provided a task by the FL server, accesses an appropriate example store to compute model updates, or evaluate model quality on held out data. Fig. 2 shows the relationship between the example store and the FL runtime. Control flow consists of the following steps:

Programmatic Configuration An application configures

the FL runtime by providing an FL population name and registering its example stores. This schedules a periodic FL runtime job using Android's JobScheduler. Possibly the most important requirement for training machine learning (ML) models on end users' devices is to avoid any negative impact on the user experience, data usage, or battery life. The FL runtime requests that the job scheduler only invoke the job when the phone is idle, charging, and connected to an unmetered network such as WiFi. Once started, the FL runtime will abort, freeing the allocated resources, if these conditions are no longer met.

Job Invocation Upon invocation by the job scheduler in a separate process, the FL runtime contacts the FL server to announce that it is ready to run tasks for the given FL population. The server decides whether any FL tasks are available for the population and will either return an FL plan or a suggested time to check in later.

Task Execution If the device has been selected, the FL runtime receives the FL plan, queries the app's example store for data requested by the plan, and computes plan-determined model updates and metrics.

Reporting After FL plan execution, the FL runtime reports computed updates and metrics to the server and cleans up any temporary resources.

As already mentioned, FL plans are not specialized to training, but can also encode *evaluation* tasks - computing quality metrics from held out data that wasn't used for training, analogous to the validation step in data center training.

Our design enables the FL runtime to either run within the application that configured it or in a centralized service hosted in another app. Choosing between these two requires minimal code changes. Communication between the application, the FL runtime, and the application's example store as depicted in Fig. 2 is implemented via Android's AIDL IPC mechanism, which works both within a single app and across apps.

Multi-Tenancy Our implementation provides a *multi-tenant* architecture, supporting training of multiple FL populations in the same app (or service). This allows for coordination between multiple training activities, avoiding the device being overloaded by many simultaneous training sessions at once.

Attestation We want devices to participate in FL anonymously, which excludes the possibility of authenticating them via a user identity. Without verifying user identity, we need to protect against attacks to influence the FL result from non-genuine devices. We do so by using Android's remote attestation mechanism (Android Documentation),

which helps to ensure that only genuine devices and applications participate in FL, and gives us some protection against data poisoning (Bagdasaryan et al., 2018) via compromised devices. Other forms of model manipulation – such as content farms using uncompromised phones to steer a model – are also potential areas of concern that we do not address in the scope of this paper.

4 SERVER

The design of the FL server is driven by the necessity to operate over many orders of magnitude of population sizes and other dimensions. The server must work with FL populations whose sizes range from tens of devices (during development) to hundreds of millions, and be able to process rounds with participant count ranging from tens of devices to tens of thousands. Also, the size of the updates collected and communicated during each round can range in size from kilobytes to tens of megabytes. Finally, the amount of traffic coming into or out of any given geographic region can vary dramatically over a day based on when devices are idle and charging. This section details the design of the FL server infrastructure given these requirements.

4.1 Actor Model

The FL server is designed around the *Actor Programming Model* (Hewitt et al., 1973). Actors are universal primitives of concurrent computation which use message passing as the sole communication mechanism.

Each actor handles a stream of messages/events strictly sequentially, leading to a simple programming model. Running multiple instances of actors of the same type allows a natural scaling to large number of processors/machines. In response to a message, an actor can make local decisions, send messages to other actors, or create more actors dynamically. Depending on the function and scalability requirements, actor instances can be co-located on the same process/machine or distributed across data centers in multiple geographic regions, using either explicit or automatic configuration mechanisms. Creating and placing fine-grained ephemeral instances of actors just for the duration of a given FL task enables dynamic resource management and load-balancing decisions.

4.2 Architecture

The main actors in the system are shown in Fig. 3.

Coordinators are the top-level actors which enable global synchronization and advancing rounds in lockstep. There are multiple Coordinators, and each one is responsible for an FL population of devices. A Coordinator registers its address and the FL population it manages in a shared locking service, so there is always a single owner for every FL population which is reachable by other actors in the system,
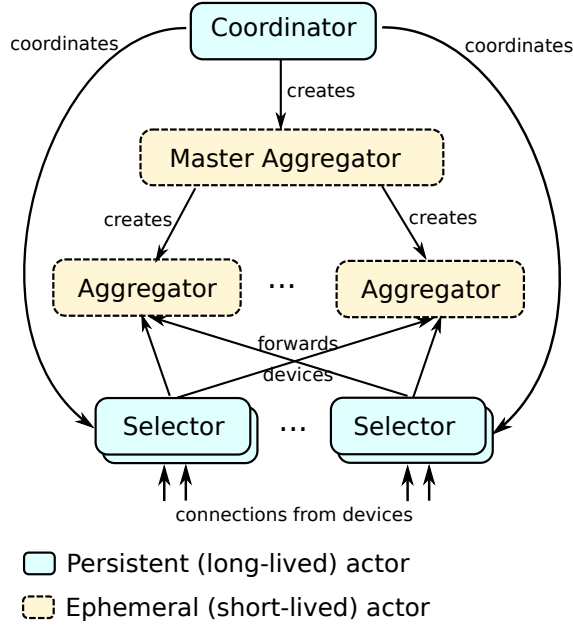
Figure 3: Actors in the FL Server Architecture

notably the Selectors. The Coordinator receives information about how many devices are connected to each Selector and instructs them how many devices to accept for participation, based on which FL tasks are scheduled. Coordinators spawn Master Aggregators to manage the rounds of each FL task.

Selectors are responsible for accepting and forwarding device connections. They periodically receive information from the Coordinator about how many devices are needed for each FL population, which they use to make local decisions about whether or not to accept each device. After the Master Aggregator and set of Aggregators are spawned, the Coordinator instructs the Selectors to forward a subset of its connected devices to the Aggregators, allowing the Coordinator to efficiently allocate devices to FL tasks regardless of how many devices are available. The approach also allows the Selectors to be globally distributed (close to devices) and limit communication with the remote Coordinator.

Master Aggregators manage the rounds of each FL task. In order to scale with the number of devices and update size, they make dynamic decisions to spawn one or more **Aggregators** to which work is delegated.

No information for a round is written to persistent storage until it is fully aggregated by the Master Aggregator. Specifically, all actors keep their state in memory and are ephemeral. Ephemeral actors improve scalability by removing the latency normally incurred by distributed storage. In-memory aggregation also removes the possibility of attacks within the data center that target persistent logs of per-device updates, because no such logs exist.

4.3 Pipelining

While Selection, Configuration and Reporting phases of a round (Sec. 2) are sequential, the Selection phase doesn't depend on any input from a previous round. This enables latency optimization by running the Selection phase of the next round of the protocol in parallel with the Configuration/Reporting phases of a previous round. Our system architecture enables such pipelining without adding extra complexity, as parallelism is achieved simply by the virtue of Selector actors running the selection process continuously.

4.4 Failure Modes

In all failure cases the system will continue to make progress, either by completing the current round or restarting from the results of the previously committed round. In many cases, the loss of an actor will not prevent the round from succeeding. For example, if an Aggregator or Selector crashes, only the devices connected to that actor will be lost. If the Master Aggregator fails, the current round of the FL task it manages will fail, but will then be restarted by the Coordinator. Finally, if the Coordinator dies, the Selector layer will detect this and respawn it. Because the Coordinators are registered in a shared locking service, this will happen exactly once.

5 ANALYTICS

There are many factors and failsafes in the interaction between devices and servers. Moreover, much of the platform activity happens on devices that we neither control nor have access to.

For this reason, we rely on analytics to understand what is actually going on in the field, and monitor devices' health statistics. On the device side we perform computation-intensive operations, and must avoid wasting the phone's battery or bandwidth, or degrading the performance of the phone. To ensure this, we log several activity and health parameters to the cloud. For example: the device state in which training was activated, how often and how long it ran, how much memory it used, which errors where detected, which phone model / OS / FL runtime version was used, and so on. These log entries do not contain any personally identifiable information (PII). They are aggregated and presented in dashboards to be analyzed, and fed into automatic time-series monitors that trigger alerts on substantial deviations.

We also log an event for every state in a training round, and use these logs to generate ASCII visualizations of the sequence of state transitions happening across all devices (see Table 1 in the appendix). We chart counts of these sequence visualizations in our dashboards, which allows us to quickly distinguish between different types of issues.

For example, the sequence "checking in, downloaded plan, started training, ended training, starting upload, error" is visualized as "−v [ ] + ∗", while the shorter sequence "checking in, downloaded plan, started training, error" is "−v [∗". The first indicates that a model trained successfully but the results upload failed (a network issue), whereas the second indicates that a training round failed right after loading the model (a model issue).

Server side, we similarly collect information such as how many devices where accepted and rejected per training round, the timing of the various phases of the round, throughput in terms of uploaded and downloaded data, errors, and so on.

Since the platform's deployment, we have relied on the analytics layer repeatedly to discover issues and verify that they were resolved. Some of the incidents we discovered were device health related, for example discovering that training was happening when it shouldn't have, while others were functional, for example discovering that the drop out rates of training participants were much higher than expected.

Federated training does not impact the user experience, so both device and server *functional* failures do not have an immediate negative impact. But failures to operate properly could have secondary consequences leading to utility degradation of the device. Device utility to the user is mission critical, and degradations are difficult to pinpoint and easy to wrongly diagnose. Using accurate analytics to prevent federated training from negatively impacting the device's utility to the user accounts for a substantial part of our engineering and risk mitigation costs.

6   SECURE AGGREGATION

Bonawitz et al. (2017) introduced *Secure Aggregation*, a Secure Multi-Party Computation protocol that uses encryption to make individual devices' updates uninspectable by a server, instead only revealing the sum after a sufficient number of updates have been received. We can deploy Secure Aggregation as a privacy enhancement to the FL service that protects against additional threats within the data center by ensuring that individual devices' updates remain encrypted even in-memory. Formally, Secure Aggregation protects from "honest but curious" attackers that may have access to the memory of Aggregator instances. Importantly, the only aggregates needed for model evaluation, SGD, or Federated Averaging are sums (e.g., $\bar{w}_t$ and $\bar{n}_t$ in Appendix 1).[2]

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[2] It is important to note that the goal of our system is to provide the tools to build privacy preserving applications. Privacy is enhanced by the ephemeral and focused nature of the FL updates, and can be further augmented with Secure Aggregation and/or differential privacy — e.g., the techniques of McMahan et al. (2018) are currently implemented. However, while the platform is designed to support a variety of privacy-enhancing technologies, stating

Secure Aggregation is a four-round interactive protocol optionally enabled during the reporting phase of a given FL round. In each protocol round, the server gathers messages from all devices in the FL round, then uses the set of device messages to compute an independent response to return to each device. The protocol is designed to be robust to a significant fraction of devices dropping out before the protocol is complete. The first two rounds constitute a Prepare phase, in which shared secrets are established and during which devices who drop out will not have their updates included in the final aggregation. The third round constitutes a Commit phase, during which devices upload cryptographically masked model updates and the server accumulates a sum of the masked updates. All devices who complete this round will have their model update included in the protocol's final aggregate update, or else the entire aggregation will fail. The last round of the protocol constitutes a Finalization phase, during which devices reveal sufficient cryptographic secrets to allow the server to unmask the aggregated model update. Not all committed devices are required to complete this round; so long as a sufficient number of the devices who started to protocol survive through the Finalization phase, the entire protocol succeeds.

Several costs for Secure Aggregation grow quadratically with the number of users, most notably the computational cost for the server. In practice, this limits the maximum size of a Secure Aggregation to hundreds of users. So as not to constrain the number of users that may participate in each round of federated computation, we run an instance of Secure Aggregation on each Aggregator actor (see Fig. 3) to aggregate inputs from that Aggregator's devices into an intermediate sum; FL tasks define a parameter k so that all updates are securely aggregated over groups of size at least k. The Master Aggregator then further aggregates the intermediate aggregators' results into a final aggregate for the round, without Secure Aggregation.

7   TOOLS AND WORKFLOW

Compared to the standard model engineer workflows on centrally collected data, on-device training poses multiple novel challenges. First, individual training examples are not directly inspectable, requiring tooling to work with proxy data in testing and simulation (Sec. 7.1). Second, models cannot be run interactively but must instead be compiled into FL plans to be deployed via the FL server (Sec. 7.2). Finally, because FL plans run on real devices, model resource consumption and runtime compatibility must be verified automatically by the infrastructure (Sec. 7.3).

The primary developer surface of model engineers working

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specific privacy guarantees depends on the details of the application and the details of how these technologies are used; such a discussion is beyond the scope of the current work.
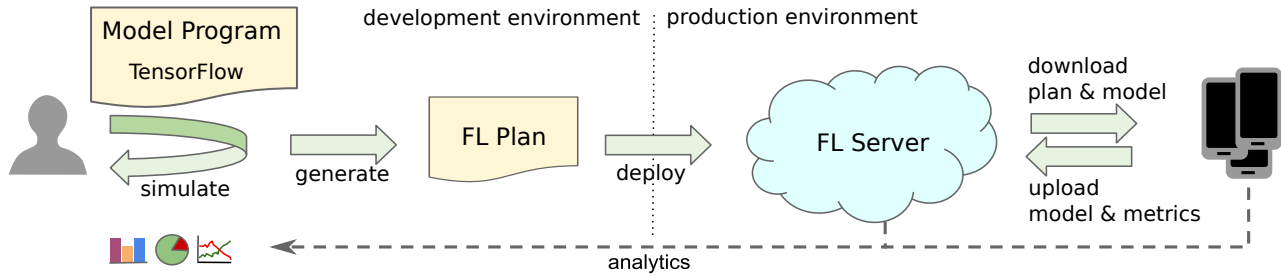
Figure 4: Model Engineer Workflow

with the FL system is a set of Python interfaces and tools to define, test, and deploy TensorFlow-based FL tasks to the fleet of mobile devices via the FL server. The workflow of a model engineer for FL is depicted in Fig. 4 and described below.

7.1 Modeling and Simulation

Model engineers begin by defining the FL tasks that they would like to run on a given FL population in Python. Our library enables model engineers to declare Federated Learning and evaluation tasks using engineer-provided TensorFlow functions. The role of these functions is to map input tensors to output metrics like loss or accuracy. During development, model engineers may use sample test data or other proxy data as inputs. When deployed, the inputs will be provided from the on-device example store via the FL runtime.

The role of the modeling infrastructure is to enable model engineers to focus on their model, using our libraries to build and test the corresponding FL tasks. FL tasks are validated against engineer-provided test data and expectations, similar in nature to unit tests. FL task tests are ultimately required in order to deploy a model as described below in Sec. 7.3.

The configuration of tasks is also written in Python and includes runtime parameters such as the optimal number of devices in a round as well as model hyperparameters like learning rate. FL tasks may be defined in groups: for example, to evaluate a grid search over learning rates. When more than one FL task is deployed in an FL population, the FL service chooses among them using a dynamic strategy that allows alternating between training and evaluation of a single model or A/B comparisons between models.

Initial hyperparameter exploration is sometimes done in simulation using proxy data. Proxy data is similar in shape to the on-device data but drawn from a different distribution – for example, text from Wikipedia may be viewed as proxy data for text typed on a mobile keyboard. Our modeling tools allow deployment of FL tasks to a simulated FL server and a fleet of cloud jobs emulating devices on a large proxy dataset. The simulation executes the same code as we run on device and communicates with the server using simulated

FL populations. Simulation can scale to a large number of devices and is sometimes used to pre-train models on proxy data before it is refined by FL in the field.

7.2 Plan Generation

Each FL task is associated with an FL plan. Plans are automatically generated from the combination of model and configuration supplied by the model engineer. Typically, in data center training, the information which is encoded in the FL plan would be represented by a Python program which orchestrates a TensorFlow graph. However, we do not execute Python directly on the server or devices. The FL plan's purpose is to describe the desired orchestration independent of Python.

An FL plan consists of two parts: one for the device and one for the server. The device portion of the FL plan contains, among other things: the TensorFlow graph itself, selection criteria for training data in the example store, instructions on how to batch data and how many epochs to run on the device, labels for the nodes in the graph which represent certain computations like loading and saving weights, and so on. The server part contains the aggregation logic, which is encoded in a similar way. Our libraries automatically split the part of a provided model's computation which runs on device from the part that runs on the server (the aggregation).

7.3 Versioning, Testing, and Deployment

Model engineers working in the federated system are able to work productively and safely, launching or ending multiple experiments per day. But because each FL task may potentially be RAM-hogging or incompatible with version(s) of TensorFlow running on the fleet, engineers rely on the FL system's versioning, testing, and deployment infrastructure for automated safety checks.

An FL task that has been translated into an FL plan is not accepted by the server for deployment unless certain conditions are met. First, it must have been built from auditable, peer reviewed code. Second, it must have bundled test predicates for each FL task that pass in simulation. Third, the resources consumed during testing must be within a safe range of expected resources for the target population. And

finally, the FL task tests must pass on every version of the TensorFlow runtime that the FL task claims to support, as verified by testing the FL task's plan in an Android emulator.

Versioning is a specific challenge for on-device machine learning. In contrast to data-center training, where the TensorFlow runtime and graphs can generally be rebuilt as needed, devices may be running a version of the TensorFlow runtime that is many months older than what is required by the FL plan generated by modelers today. For example, the old runtime may be missing a particular TensorFlow operator, or the signature of an operator may have changed in an incompatible way. The FL infrastructure deals with this problem by generating *versioned* FL plans for each task. Each versioned FL plan is derived from the default (unversioned) FL plan by transforming its computation graph to achieve compatibility with a deployed TensorFlow version. Versioned and unversioned plans must pass the same release tests, and are therefore treated as semantically equivalent. We encounter about one incompatible change that can be fixed with a graph transformation every three months, and a slightly smaller number that cannot be fixed without complex workarounds.

7.4 Metrics

As soon as an FL task has been accepted for deployment, devices checking in may be served the appropriate (versioned) plan. As soon as an FL round closes, that round's aggregated model parameters and metrics are written to the server storage location chosen by the model engineer.

Materialized model metrics are annotated with additional data, including metadata like the source FL task's name, FL round number within the FL task, and other basic operational data. The metrics themselves are summaries of device reports within the round via approximate order statistics and moments like mean. The FL system provides analysis tools for model engineers to load these metrics into standard Python numerical data science packages for visualization and exploration.

8 Applications

Federated Learning applies best in situations where the on-device data is more relevant than the data that exists on servers (e.g., the devices generate the data in the first place), is privacy-sensitive, or otherwise undesirable or infeasible to transmit to servers. Current applications of Federated Learning are for supervised learning tasks, typically using labels inferred from user activity (e.g., clicks or typed words).

On-device item ranking A common use of machine learning in mobile applications is selecting and ranking items from an on-device inventory. For example, apps may expose a search mechanism for information retrieval or in-app navigation, for example settings search on Google Pixel devices (ai.google, 2018). By ranking these results on-device, expensive calls to the server (in e.g., latency, bandwidth or power consumption dimensions) are eliminated, and any potentially private information from the search query and user selection remains on the device. Each user interaction with the ranking feature can become a labeled data point, since it's possible to observe the user's interaction with the preferred item in the context of the full ranked list.

Content suggestions for on-device keyboards On-device keyboard implementations can add value to users by suggesting relevant content – for example, search queries that are related to the input text. Federated Learning can be used to train ML models for triggering the suggestion feature, as well as ranking the items that can be suggested in the current context. This approach has been taken by Google's Gboard mobile keyboard team, using our FL system (Yang et al., 2018).

Next word prediction Gboard also used our FL platform to train a recurrent neural network (RNN) for next-word-prediction (Hard et al., 2018). This model, which has about 1.4 million parameters, converges in 3000 FL rounds after processing 6e8 sentences from 1.5e6 users over 5 days of training (so each round takes about 2–3 minutes).[3] It improves top-1 recall over a baseline n-gram model from 13.0% to 16.4%, and matches the performance of a server-trained RNN which required 1.2e8 SGD steps. In live A/B experiments, the FL model outperforms both the n-gram and the server-trained RNN models.

9 Operational Profile

In this section we provide a brief overview of some key operational metrics of the deployed FL system, running production workloads for over a year; Appendix A provides additional details. These numbers are examples only, since we have not yet applied FL to a diverse enough set of applications to provide a complete characterization. Further, all data was collected in the process of operating a production system, rather than under controlled conditions explicitly for the purpose of measurement. Many of the performance metrics here depend on the device and network speed (which can vary by region); FL plan, global model and update sizes (varies per application); number of samples per round and

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[3]This is roughly $7\times$ slower than in comparable data center training of the same model. However, we do not believe this type of comparison is the primary one – our main goal is to enable training on data that is not available in the data center. In fact, for the model mentioned different proxy data was used for data center training. Nevertheless, fast wall-clock convergence time is important for enabling model engineers to iterate rapidly, and hence we are continuing to optimize both our system and algorithms to decrease convergence times.

computational complexity per sample.

We designed the FL system to elastically scale with the number and sizes of the FL populations, potentially up into the billions. Currently the system is handling a cumulative FL population size of approximately 10M daily active devices, spanning several different applications.

As discussed before, at any point in time only a subset of devices connect to the server due to device eligibility and pace steering. Given this, in practice we observe that up to 10k devices are participating simultaneously. It is worth noting that the number of participating devices depends on the (local) time of day (see Fig. 5). Devices are more likely idle and charging at night, and hence more likely to participate. We have observed a $4\times$ difference between low and high numbers of participating devices over a 24 hours period for a US-centric population.
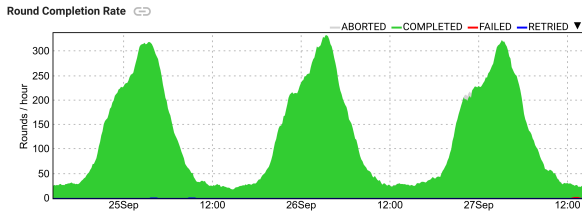

Figure 5: Round Completion Rate

Based on the previous work of McMahan et al. (2017) and experiments we have conducted on production FL populations, for most models receiving updates from a few hundred devices per FL round is sufficient (that is, we see diminishing improvements in the convergence rate from training on larger numbers of devices). We also observe that on average the portion of devices that drop out due to computation errors, network failures, or changes in eligibility varies between 6% and 10%. Therefore, in order to compensate for device drop out as well as to allow stragglers to be discarded, the server typically selects 130% of the target number of devices to initially participate. This parameter can be tuned based on the empirical distribution of device reporting times and the target number of stragglers to ignore.

10 RELATED WORK

Alternative Approaches To the best of our knowledge, the system we described is the first production-level Federated Learning implementation, focusing primarily on the Federated Averaging algorithm running on mobile phones. Nevertheless, there are other ways to learn from data stored on mobile phones, and other settings in which FL as a concept could be relevant.

In particular, Pihur et al. (2018) proposes an algorithm that learns from users' data without performing aggregation on the server and with additional formal privacy guarantees. However, their work focuses on generalized linear mod-

els, and argues that their approach is highly scalable due to avoidance of synchronization and not requiring to store updates from devices. Our server design described in Sec. 4, rebuts the concerns about scalability of the synchronous approach we are using, and in particular shows that updates can be processed online as they are received without a need to store them. Alternative proposals for FL algorithms include Smith et al. (2017); Kamp et al. (2018), which would be on the high-level compatible with the system design described here.

In addition, Federated Learning has already been proposed in the context of vehicle-to-vehicle communication (Samarakoon et al., 2018) and medical applications (Brisimi et al., 2018). While the system described in this work as a whole does not directly apply to these scenarios, many aspects of it would likely be relevant for production application.

Nishio & Yonetani (2018) focuses on applying FL in different environmental conditions, namely where the server can reach any subset of heterogeneous devices to initiate a round, but receives updates sequentially due to cellular bandwidth limit. The work offers a resource-aware selection algorithm maximizing the number of participants in a round, which is implementable within our system.

Distributed ML There has been significant work on distributed machine learning, and large-scale cloud-based systems have been described and are used in practice. Many systems support multiple distribution schemes, including *model parallelism* and *data parallelism*, e.g., Dean et al. (2012) and Low et al. (2012). Our system imposes a more structured approach fitting to the domain of mobile devices, which have much lower bandwidth and reliability compared to datacenter nodes. We do not allow for arbitrary distributed computation but rather focus on a synchronous FL protocol. This domain specialization allows us, from the system viewpoint, to optimize for the specific use case.

A particularly common approach in the datacenter is the *parameter server*, e.g., Li et al. (2014); Dean et al. (2012); Abadi et al. (2016), which allows a large number of workers to collaborate on a shared global model, the parameter vector. Focus in that line of work is put on an efficient server architecture for dealing with vectors of the size of 10^9 to 10^{12}. The parameter server provides global state which workers access and update asynchronously. Our approach inherently cannot work with such a global state, because we require a specific rendezvous between a set of devices and the FL server to perform a synchronous update with Secure Aggregation.

MapReduce For datacenter applications, it is now commonly accepted that MapReduce (Dean & Ghemawat, 2008) is not the right framework for ML training. For the problem space of FL, MapReduce is a close relative. One can interpret the FL server as the Reducer, and FL devices as

Mappers. However, there are also fundamental technical differences compared to a generic MapReduce framework. In our system, FL devices own the data on which they are working. They are fully self-controlled actors which attend and leave computation rounds at will. In turn, the FL server actively scans for available FL devices, and brings only selected subsets of them together for a round of computation. The server needs to work with the fact that many devices drop out during computation, and that availability of FL devices varies drastically over time. These very specific requirements are better dealt with by a domain specific framework than a generic MapReduce.

11 FUTURE WORK

Bias The Federated Averaging (McMahan et al., 2017) protocol assumes that all devices are equally likely to participate and complete each round. In practice, our system potentially introduces bias by the fact that devices only train when they are on an unmetered network and charging. In some countries the majority of people rarely have access to an unmetered network. Also, we limit the deployment of our device code only to certain phones, currently with recent Android versions and at least 2 GB of memory, another source of potential bias.

We address this possibility in the current system as follows: During FL training, the models are not used to make user-visible predictions; instead, once a model is trained, it is evaluated in live A/B experiments using multiple application-specific metrics (just as with a datacenter model). If bias in device participation or other issues lead to an inferior model, it will be detected at this point. So far, we have not observed this to be an issue in practice, but this is likely application and population dependent. Further quantification of these possible effects across a wider set of applications, and if needed algorithmic or systems approaches to mitigate them, are important directions for future work.

Convergence Time We noted in Sec. 8 that we currently observe a slower convergence time for Federated Learning compared to ML on centralized data where training is backed by the power of a data center. Current FL algorithms such as Federated Averaging can only efficiently utilize 100s of devices in parallel, but many more are available; FL would greatly benefit from new algorithms that can utilize increased parallelism.

On the operational side, there is also more which can be done. For example, the time windows to select devices for training and wait for their reporting is currently configured statically per FL population. It should be dynamically adjusted to reduce the drop out rate and increase round frequency. We should ideally use online ML for tuning this and other parameters of the protocol configuration, bringing in e.g. time of the day as context.

Device Scheduling Currently, our multi-tenant on-device scheduler uses a simple worker queue for determining which training session to run next (we avoid running training sessions on-device in parallel because of their high resource consumption). This approach is blind to aspects like which apps the user has been frequently using. It's possible for us to end up repeatedly training on older data (up to the expiration date) for some apps, while also neglecting training on newer data for the apps the user is frequently using. Any optimization here, though, has to be carefully evaluated against the biases it may introduce.

Bandwidth When working with certain types of models, for example recurrent networks for language modeling, even small amounts of raw data can result in large amounts of information (weight updates) being communicated. In particular, this might be more than if we would just upload the raw data. While this could be viewed as a tradeoff for better privacy, there is also much which can be improved. To reduce the bandwidth necessary, we implement compression techniques such as those of Konečný et al. (2016b) and Caldas et al. (2018). In addition to that, we can modify the training algorithms to obtain models in quantized representation (Jacob et al., 2017), which will have synergetic effect with bandwidth savings and be important for efficient deployment for inference.

Federated Computation We believe there are more applications besides ML for the general device/server architecture we have described in this paper. This is also apparent from the fact that this paper contains no explicit mentioning of any ML logic. Instead, we refer abstractly to 'plans', 'models', 'updates' and so on.

We aim to generalize our system from Federated Learning to *Federated Computation*, which follows the same basic principles as described in this paper, but does not restrict computation to ML with TensorFlow, but general MapReduce like workloads. One application area we are seeing is in *Federated Analytics*, which would allow us to monitor aggregate device statistics without logging raw device data to the cloud.

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A OPERATIONAL PROFILE DATA

In this section we present operational profile data for one of the FL populations that are currently active in the deployed FL system, augmenting the discussion in Sec. 9. The subject FL population primarily comes from the same time zone.

Fig. 6 illustrates how availability of the devices varies through the day and its impact on the round completion rate. Because the FL server schedules an FL task for execution only once a desired number of devices are available and selected, the round completion rate oscillates in sync with device availability.
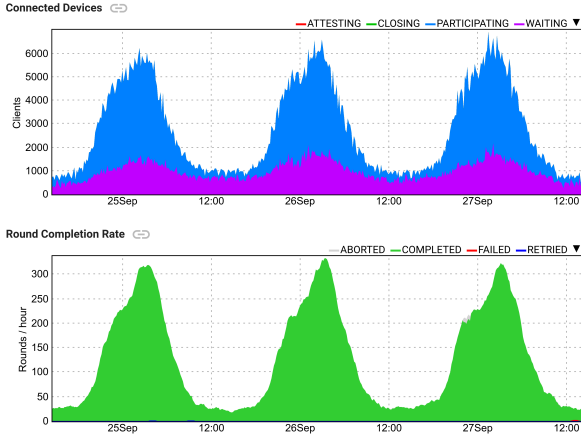

Figure 6: A subset of the connected devices over three days (top) in states "participating" (blue) and "waiting" (purple). Other states ("closing" and "attesting") are too rare to be visible in this graph. The rate of successful round completions (green, bottom) is also shown, along with the rate of other outcomes ("failure", "retry", and "abort") plotted on the same graph but too low to be visible.

Fig. 7 illustrates the average number of devices participating in an FL task round and the outcomes of the participation. Note that in each round the FL server selects more devices for the participation than desired to complete to offset the devices that drop out during execution. Therefore in each round there are devices that were aborted after a desired number of devices successfully complete. Another noteworthy aspect is drop out rate correlation with the time of day, specifically the drop out rate is higher during the day time compared to the night time. This is explained by higher probability of the device eligibility criteria changes due interaction with a device.

Fig. 8 shows distribution of round run and device participation time. There are two noteworthy observations. First is that the round run time is roughly equal to the majority of the device participation time which is explained by the fact that the FL server selects more than needed devices for participation and stops execution when enough devices complete. Second is that device participation time is capped.
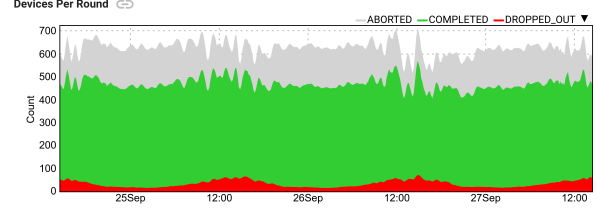

Figure 7: Average number of devices completed, aborted and dropped out from round execution

This is a mechanism used by the FL server to deal with straggler devices; i.e., the round run time capped by the server.
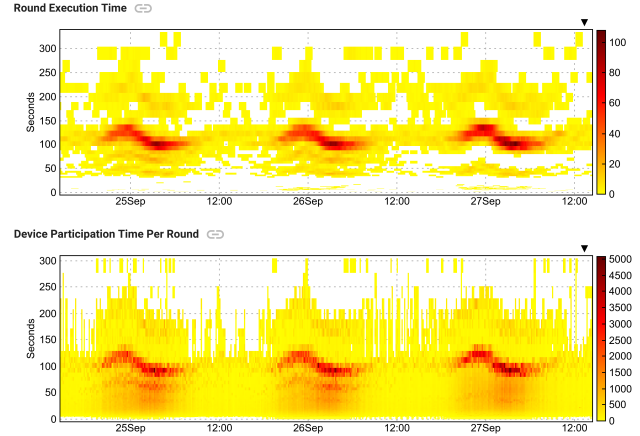

Figure 8: Round execution and device participation time

Fig. 9 illustrates the asymmetry in server network traffic, specifically that download from server dominates upload. There are several aspects that contribute. Namely each device downloads both an FL task plan and current global model (plan size is comparable with the global model) whereas it uploads only updates to the global model; the model updates are inherently more compressible compared to the global model.
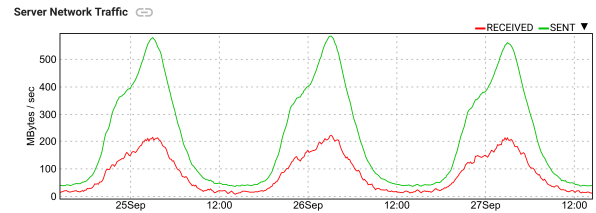

Figure 9: Server network traffic

Tab. 1 shows the training round session shape visualizations generated from the clients' training state event logs. As shown, 75% of clients complete their training rounds successfully, 22% of clients complete their training rounds but have their results rejected by the server (these are the devices which report back after the reporting window already closed), and 2% of clients are interrupted before being able

Session Shape	Count	Percent
-v[]+ˆ	1,116,401	75%
-v[]+#	327,478	22%
-v[!	29,771	2%

Table 1: Distribution of on-device training round sessions. Legend: - = FL server checkin, v = downloaded plan, [= training started,] = training completed, + = upload started, ˆ = upload completed, # = upload rejected, ! = interrupted.

to complete their round (e.g., because the device exited the idle state).

B FEDERATED AVERAGING

In this section, we show the Federated Averaging algorithm
from McMahan et al. (2017) for the interested reader.

Algorithm 1 `FederatedAveraging` targeting updates
from K clients per round.

Server executes:
  initialize w_0
  for each round $t = 1, 2, \ldots$ **do**
    Select $1.3K$ eligible clients to compute updates
    Wait for updates from K clients (indexed $1, \ldots, K$)
    $(\Delta^k, n^k) = \text{ClientUpdate}(w)$ from client $k \in [K]$.
    $\bar{w}_t = \sum_k \Delta^k$ // *Sum of weighted updates*
    $\bar{n}_t = \sum_k n^k$ // *Sum of weights*
    $\Delta_t = \Delta_t^k / \bar{n}_t$ // *Average update*
    $w_{t+1} \leftarrow w_t + \Delta_t$

ClientUpdate(w)**:**
  $\mathcal{B} \leftarrow$ (local data divided into minibatches)
  $n \leftarrow |\mathcal{B}|$ // *Update weight*
  $w_{\text{init}} \leftarrow w$
  for batch $b \in \mathcal{B}$ **do**
    $w \leftarrow w - \eta \nabla \ell(w; b)$
  $\Delta \leftarrow n \cdot (w - w_{\text{init}})$ // *Weighted update*
  // *Note Δ is more amenable to compression than w*
  return (Δ, n) to server