Towards Federated Learning at Scale: System Design

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2019 [1]

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https://qdata.github.io/deep2Read/

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Background and Problem

Motivation

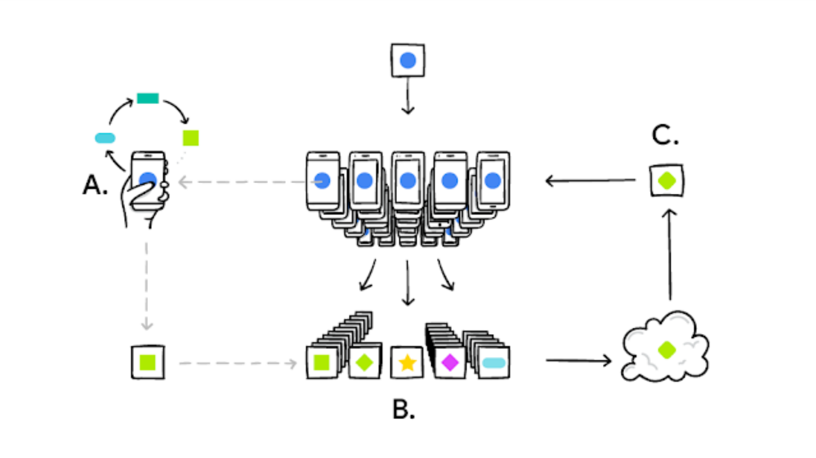
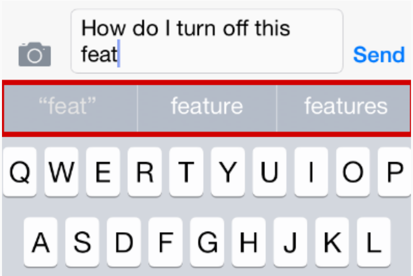


Figure 1: *(A) Personalize model locally, (B) aggregate many users' model updates, and (C) update global model*

Motivation

- ML without centralizing data in a data center
- On-device item ranking
- Content suggestions for keyboards
- Next word prediction



Problem Setting

- Millions of phones with copy of model for inference
- Want to use them for training
- Don't want to drain phone battery or strain user's data plan
- Protect privacy
- System needs to be fault tolerant

Parallelizing ML

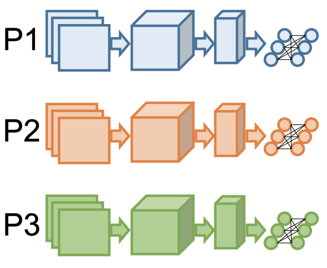


Figure 2: *Model-parallelism*

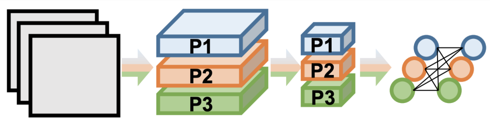


Figure 3: *Data-parallelism*

Model Synchronization

- Parameter-server
- Decentralized: AllReduce, Gather-Apply-Scatter, and variants
- Any of these can be synchronous, stale synchronous, asynchronous training

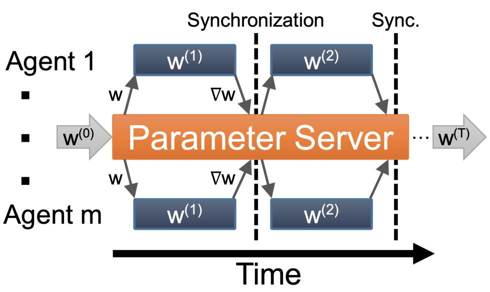
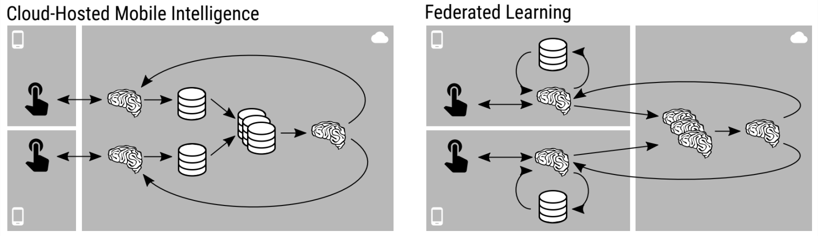


Figure 4: *Synchronous Parameter-server*

Federated Learning

Overview of the System

- FL Server: global model
- FL population: set of devices that periodically compute weight updates
- Push weights to FL server; data never leaves the devices
- Aggregate weights



Protocol

1. Selection: FL server selects a sub-population to participate
2. Configuration: FL server sends FL plan and checkpoint model
3. Reporting: listen for weight updates and aggregate them

Protocol

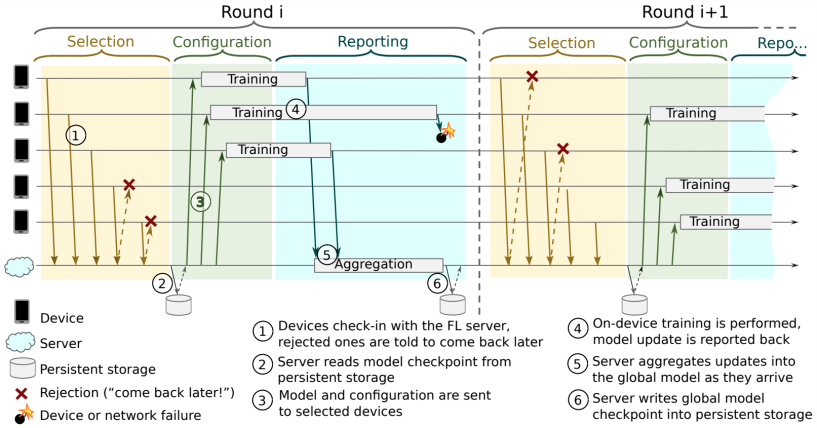


Figure 5: *Overview of system protocol*

Federated Averaging

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

Server executes:
initialize w_0
for each round $t = 1, 2, \dots$ **do**
  Select $1.3K$ eligible clients to compute updates
  Wait for updates from K clients (indexed $1, \dots, K$)
  $(\Delta^k, n^k) = \text{ClientUpdate}(w)$ 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

Pace Steering

1. Manage the number of devices participating in training
2. Adjust to avoid “thundering herd” problem

Device-Side

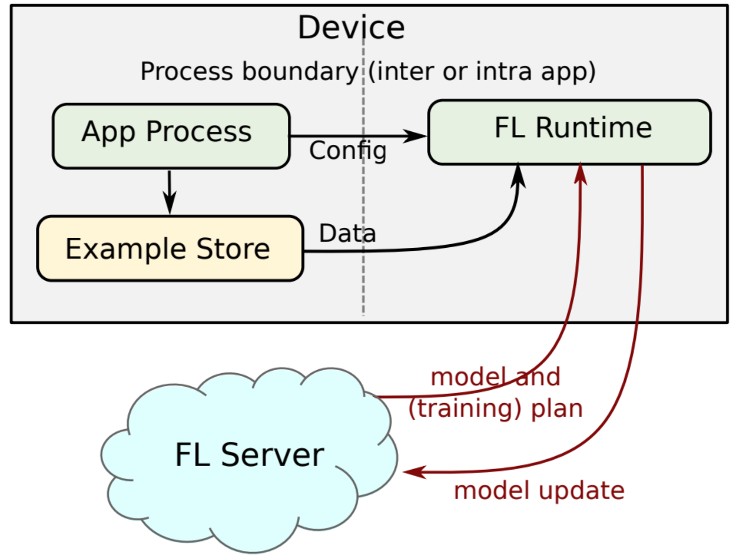


Figure 6: *Device software architecture*

Device-Side

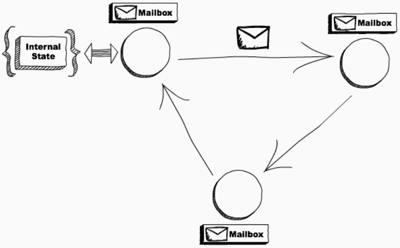
- Example store (e.g., SQLlite DB)
- FL runtime
- Job invocation: FL runtime contacts FL server
- Task execution: FL plan received from FL server
- Reporting: sends updates to FL server
- Multi-tenancy: device can be part of many FL population

Attestation

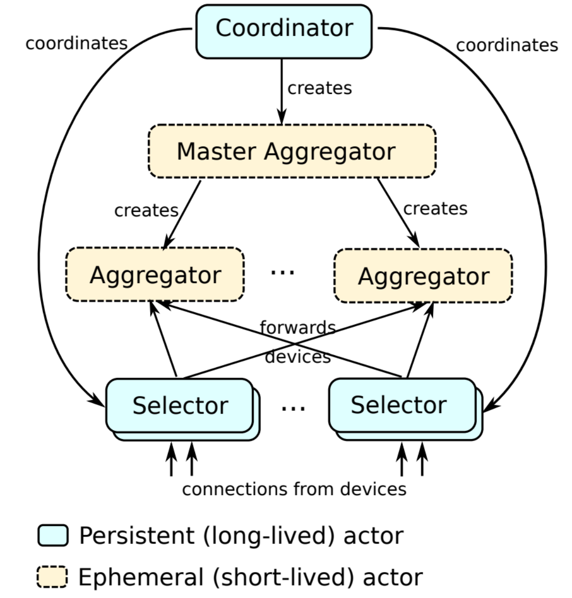
- Want anonymous participation
- Exclude authentication
- Risk of poisoned data from extraneous actors
- Android remote attestation mechanism
- Need to circumvent content farms

Server-Side: Actor Design Pattern

- Instead of threads, use "actor" processes as concurrent primitives
- Actors don't share data/state except by message passing
- Actors can create other actors
- Allows for concurrency to scale on the fly
- Fairly fault-tolerant

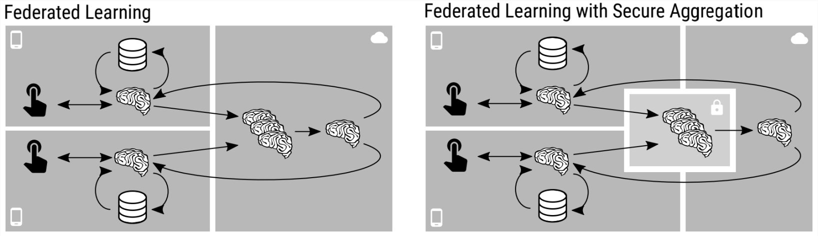


FL Server Design



Secure Aggregation

- Uses multi-party computation protocol from [2]
- Key exchange protocol based on Shamir's Secret Sharing [3]
- Server can aggregate encrypted weight updates, but can't decrypt weights from individual devices
- $O(n^2)$ for n protocol participants
- Requires devices synchronize, hence they use synchronized learning



Tools and Workflow

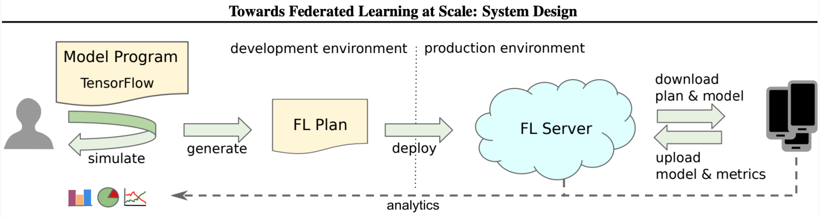


Figure 7: *Workflow for training in the FL framework*

Results

Results in Production

- Used for several Google apps with around 10 million devices
- Up to 10K devices participate at once
- 6-10% of devices drop out due to errors, network failures, or changes in eligibility
- Federated training time is 7x slower

Participation and Round Completion

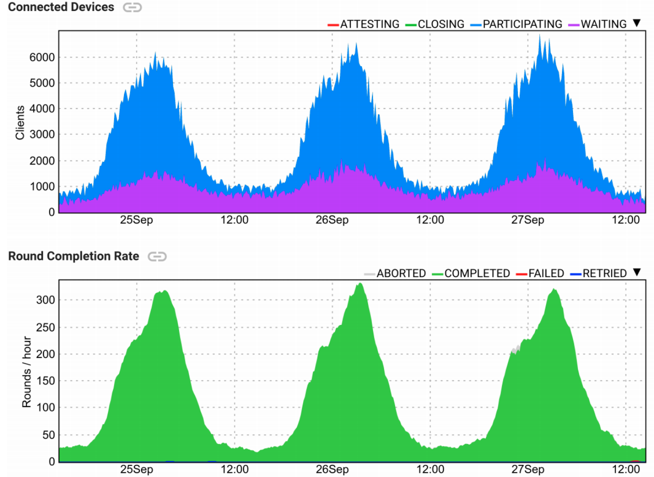


Figure 8: *Connected devices and completion rate. Rounds typically completed at night, not during the day.*

Discussion

Pros

- Built-in mechanisms to protect privacy
- Very interesting application of multiparty computation
- Robust to device dropout and other faults
- Modernizing the parameter-server model
- Training on data not available in data center

Cons

- Training time is 7 times slower than in-data center training
- Federated Averaging can't handle more than a few hundred devices in parallel
- Example store could have very old data
- Doesn't distinguish between FL tasks the user actually uses
- Manipulable by content farms
- Doesn't reduce energy usage with quantization or compression
- Data distribution can vary between users and regions
- Secure aggregation is $O(n^2)$ for n devices

Lessons Learned

- Bring the model to the data; not the data to the model
- Don't need to violate privacy to train good models
- Federated computation is bigger than ML
- MapReduce and centralized ML are analogous tasks
- Interesting application of the actor model

Questions

K. Bonawitz, H. Eichner, W. Grieskamp, D. Huba, A. Ingerman, V. Ivanov, C. Kiddon, J. Konecny, S. Mazzocchi, H. B. McMahan, et al.
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