SCIENCE
PASSION
TECHNOLOGY

Architecture of ML Systems
06 Parameter Servers

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Last update: May 03, 2019

Announcements/Org

- **#1 Programming/Analysis Projects**
  - **#1 Auto Differentiation**
  - **#5 LLVM Code Generator**
  - **#12 Information Extraction from Unstructured PDF/HTML**

- **#2 Study Abroad Fair 2019**

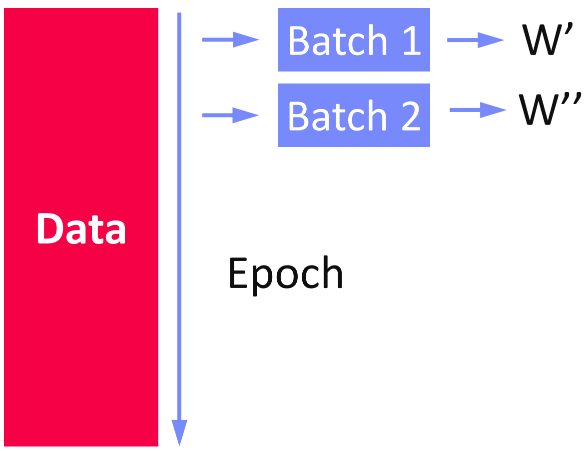
Agenda

- **Data-Parallel Parameter Servers**
- **Model-Parallel Parameter Servers**
- **Federated Machine Learning**

Data-Parallel Parameter Servers

Background: Mini-batch ML Algorithms

- **Mini-batch ML Algorithms**
  - Iterative ML algorithms, where each iteration only uses a **batch of rows** to make the next model update (in **epochs** over the data)
  - For large and **highly redundant training sets**
  - **Applies to almost all iterative**, model-based ML algorithms (LDA, reg., class., factor., DNN)



- **Statistical vs Hardware Efficiency** (batch size)
  - **Statistical efficiency:** number of accessed data points to achieve certain accuracy
  - **Hardware efficiency:** number of independent computations to achieve high hardware utilization (parallelization at different levels)
  - **Beware higher variance / class skew for too small batches!**

➔ **Training Mini-batch ML Algortihms sequentially is hard to scale**

Background: Mini-batch DNN Training (LeNet)

```
# Initialize W1-W4, b1-b4
# Initialize SGD w/ Nesterov momentum optimizer
iters = ceil(N / batch_size)

for( e in 1:epochs ) {
   for( i in 1:iters ) {
      X_batch = X[((i-1) * batch_size) %% N + 1:min(N, beg + batch_size - 1),]
      y_batch = Y[((i-1) * batch_size) %% N + 1:min(N, beg + batch_size - 1),]

      ## layer 1: conv1 -> relu1 -> pool1
      ## layer 2: conv2 -> relu2 -> pool2
      ## layer 3:  affine3 -> relu3 -> dropout
      ## layer 4:  affine4 -> softmax
      outa4 = affine::forward(outd3, W4, b4)
      probs = softmax::forward(outa4)

      ## layer 4:  affine4 -> softmax
      douta4 = softmax::backward(dprobs, outa4)
      [doutd3, dW4, db4] = affine::backward(douta4, outr3, W4, b4)
      ## layer 3:  affine3 -> relu3 -> dropout
      ## layer 2: conv2 -> relu2 -> pool2
      ## layer 1: conv1 -> relu1 -> pool1

      # Optimize with SGD w/ Nesterov momentum W1-W4, b1-b4
      [W4, vW4] = sgd_nesterov::update(W4, dW4, lr, mu, vW4)
      [b4, vb4] = sgd_nesterov::update(b4, db4, lr, mu, vb4)
   }
}
```

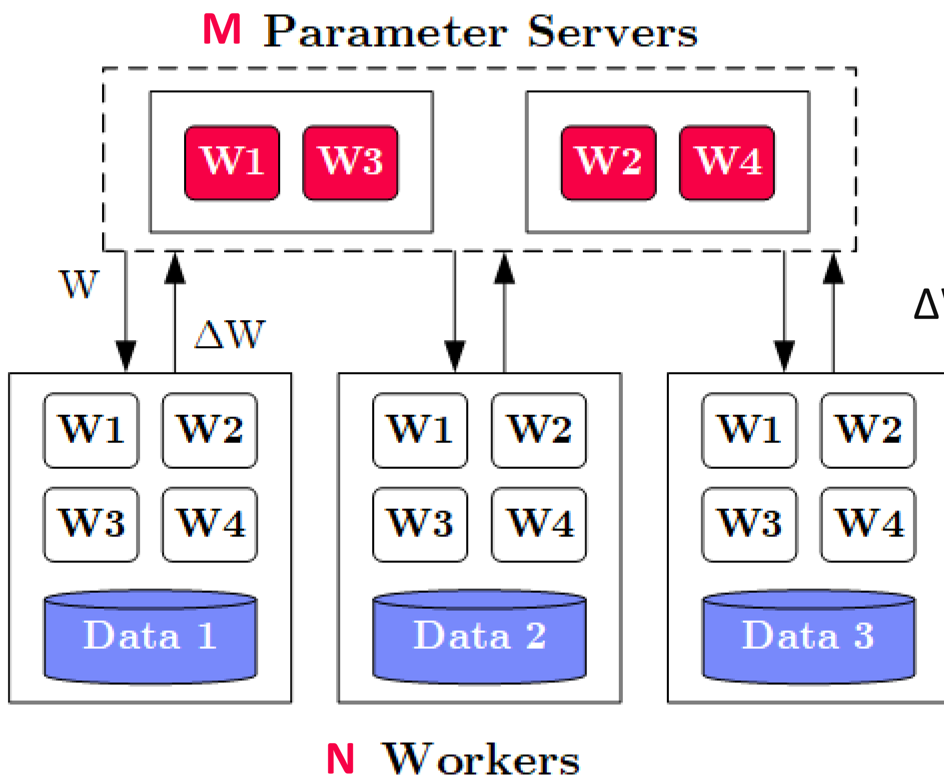
NN Forward Pass

NN Backward Pass
→ Gradients

Model Updates

Overview Parameter Servers

- **System Architecture**
  - M Parameter Servers
  - N Workers
  - Optional Coordinator



W .. Model
ΔW .. Gradient

- **Key Techniques**
  - Data partitioning D → workers Di (e.g., disjoint, reshuffling)
  - Updated strategies (e.g., synchronous, asynchronous)
  - Batch size strategies (small/large batches, hybrid methods)

History of Parameter Servers

- **1st Gen: Key/Value**
  - **Distributed key-value store** for parameter exchange and synchronization
  - Relatively high overhead
- **2nd Gen: Classic Parameter Servers**
  - **Parameters as dense/sparse matrices**
  - Different **update/consistency strategies**
  - Flexible configuration and fault tolerance
- **3rd Gen: Parameter Servers w/ improved data communication**
  - Prefetching and range-based pull/push
  - Lossy or lossless compression w/ compensations
- **Examples**
  - TensorFlow, MXNet, PyTorch, CNTK, Petuum

[Alexander J. Smola, Shravan M. Narayanamurthy: An Architecture for Parallel Topic Models. **PVLDB 2010**]

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

[Mu Li et al: Scaling Distributed Machine Learning with the Parameter Server. **OSDI 2014**]

[Jiawei Jiang, Bin Cui, Ce Zhang, Lele Yu: Heterogeneity-aware Distributed Parameter Servers. **SIGMOD 2017**]

[Jiawei Jiang et al: SketchML: Accelerating Distributed Machine Learning with Data Sketches. **SIGMOD 2018**]

Basic Worker Algorithm (batch)

```
for( i in 1:epochs ) {
   for( j in 1:iterations ) {
      params = pullModel(); # W1-W4, b1-b4 lr, mu
      batch = getNextMiniBatch(data, j);
      gradient = computeGradient(batch, params);
      pushGradients(gradient);
   }
}
```

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

Extended Worker Algorithm (nfetch batches)

```
gradientAcc = matrix(0,...);
for( i in 1:epochs ) {
   for( j in 1:iterations ) {
      if( step mod nfetch = 0 )
         params = pullModel();
      batch = getNextMiniBatch(data, j);
      gradient = computeGradient(batch, params);
      gradientAcc += gradient;
      params = updateModel(params, gradients);
      if( step mod nfetch = 0 ) {
         pushGradients(gradientAcc); step = 0;
         gradientAcc = matrix(0, ...);
      }
      step++;
}  }
```

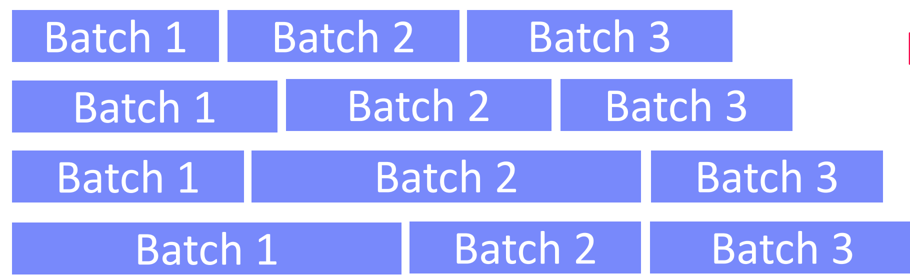
nfetch batches require
local gradient accrual and
local model update

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

Update Strategies

- **Bulk Synchronous Parallel (BSP)**
  - Update model w/ accrued gradients
  - Barrier for N workers

- **Asynchronous Parallel (ASP)**
  - Update model for each gradient
  - No barrier



but, stale model updates

- **Synchronous w/ Backup Workers**
  - Update model w/ accrued gradients
  - Barrier for N of N+b workers

[Martín Abadi et al: TensorFlow: A System for Large-Scale Machine Learning. **OSDI 2016**]

Update Strategies, cont.

- **Stale-Synchronous Parallel (SSP)**
  - Similar to backup workers, **weak synchronization barrier**
  - Maximum staleness of s clocks between fastest and slowest worker → **if violated, block fastest**

[Qirong Ho et al: More Effective Distributed ML via a Stale Synchronous Parallel Parameter Server. **NIPS 2013**]

- **Hogwild!**
  - Even the model update completely **unsynchronized**
  - Shown to converge for **sparse model updates**

[Benjamin Recht, Christopher Ré, Stephen J. Wright, Feng Niu: Hogwild: A Lock-Free Approach to Parallelizing Stochastic Gradient Descent. **NIPS 2011**]

- **Decentralized**
  - #1: Exchange partial gradients updates with local peers
  - #2: Peer-to-peer re-assignment of work
  - Other Examples: **Ako**, **FlexRR**

[Xiangru Lian et al: Can Decentralized Algorithms Outperform Centralized Algorithms? A Case Study for Decentralized Parallel Stochastic Gradient Descent. **NIPS 2017**]

Data Partitioning Schemes

- **Goals Data Partitioning**
  - Even distribute data across workers, avoid skew regarding model updates

- **#1 Disjoint Contiguous**
  - Contiguous row partition of features/labels

```
Xp = X[id*blocksize+1:
  (id+1)*blocksize,];
```

- **#2 Disjoint Round Robin**
  - Rows of features distributed round robin

```
Xp = removeEmpty(X, 'rows',
  seq(1,nrow(X))%%N==id);
```

- **#3 Disjoint Random**
  - Random non-overlapping selection of rows

```
P = table(seq(1,nrow(X)),
sample(nrow(X),nrow(X),FALSE));

Xp = P[id*blocksize+1:
(id+1)*blocksize,] %*% X
```

- **#4 Overlap Reshuffle**
  - Each worker receives a reshuffled copy of the whole dataset

```
Xp = Pi %*% X
```

Example Distributed TensorFlow DP

```
# Create a cluster from the parameter server and worker hosts
cluster = tf.train.ClusterSpec({"ps": ps_hosts, "worker": worker_hosts})

# Create and start a server for the local task.
server = tf.train.Server(cluster, job_name=..., task_index=...)

# On worker: initialize loss
train_op = tf.train.AdagradOptimizer(0.01).minimize(
   loss, global_step=tf.contrib.framework.get_or_create_global_step())

# Create training session and run steps asynchronously
hooks=[tf.train.StopAtStepHook(last_step=1000000)]
with tf.train.MonitoredTrainingSession(master=server.target,
   is_chief=(task_index == 0), checkpoint_dir=..., hooks=hooks) as sess:
   while not mon_sess.should_stop():
      sess.run(train_op)

# Program needs to be started on ps and worker
```

But new experimental APIs and Keras Frontend

Example SystemML Parameter Server

```
# Initialize SGD w/ Adam optimizer
[mW1, vW1] = adam::init(W1); [mb1, vb1] = adam::init(b1); ...

# Create the model object
modelList = list(W1, W2, W3, W4, b1, b2, b3, b4, vW1, vW2, vW3, vW4,
  vb1, vb2, vb3, vb4, mW1, mW2, mW3, mW4, mb1, mb2, mb3, mb4);

# Create the hyper parameter list
params = list(lr=0.001, beta1=0.9, beta2=0.999, epsilon=1e-8, t=0,
  C=C, Hin=Hin, Win=Win, Hf=Hf, Wf=Wf, stride=1, pad=2, lambda=5e-04,
  F1=F1, F2=F2, N3=N3)

# Use paramserv function
modelList2 = paramserv(model=modelList, features=X, labels=Y,
  upd=funGradients, aggregation=funUpdate, mode=REMOTE_SPARK, utype=ASP,
  freq=BATCH, epochs=200, batchsize=64, k=144, scheme=DISJOINT_RANDOM,
  hyperparams=params)
```

Selected Optimizers

- **Stochastic Gradient Descent (SGD)**
  - Vanilla SGD, basis for many other optimizers

```
X = X - lr*dX
```

- **SGD w/ Momentum**
  - Assumes parameter velocity w/ momentum

```
v = mu*v - lr*dX
X = X + v
```

- **SGD w/ Nesterov Momentum**
  - Assumes parameter velocity w/ momentum, but update from position **after** momentum

```
v0 = v
v = mu*v - lr*dX
X = X - mu*v0 + (1+mu)*v
```

- **AdaGrad**
  - Adaptive learning rate with regret guarantees

[John C. Duchi et al: Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. **JMLR 2011**]

- **RMSprop**
  - Adaptive learning rate, extended AdaGrad

```
c = dr*c+(1-dr)*dX^2
X = X-(lr*dX/(sqrt(c)+eps))
```

- **Adam**
  - Individual adaptive learning rates for different parameters

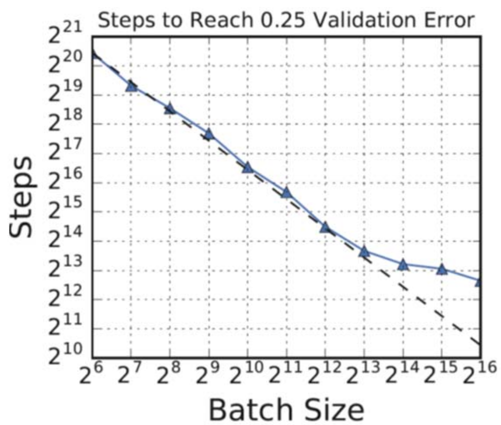
[Diederik P. Kingma, Jimmy Ba: Adam: A Method for Stochastic Optimization. **ICLR 2015**]

Batch Size Configuration

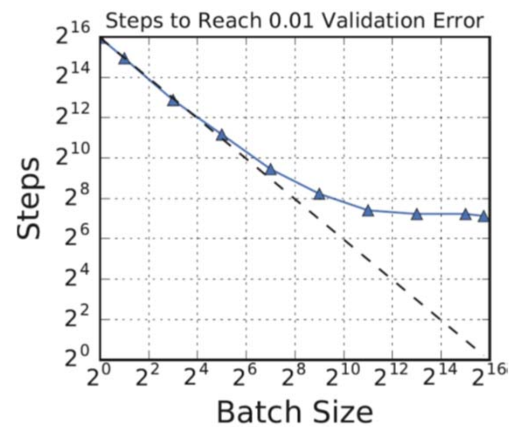
- **What is the right batch size for my data?**
  - Maximum useful batch size is dependent on data redundancy and model complexity

[Christopher J. Shallue et al.: Measuring the Effects of Data Parallelism on Neural Network Training. **CoRR 2018**]

ResNet-50 on ImageNet



VS



Simple CNN on MNIST

- **Additional Heuristics/Hybrid Methods**
  - #1 Increase the batch size instead of decaying the learning rate
  - #2 Combine batch and mini-batch algorithms (full batch + n online updates)

[Samuel L. Smith, Pieter-Jan Kindermans, Chris Ying, Quoc V. Le: Don't Decay the Learning Rate, Increase the Batch Size. **ICLR 2018**]

[Ashok Cutkosky, Róbert Busa-Fekete: Distributed Stochastic Optimization via Adaptive SGD. **NeurIPS 2018**]

Reducing Communication Overhead

- **Large Batch Sizes**
  - Larger batch sizes inherently reduce the relative communication overhead
- **Overlapping Computation/Communication**
  - For complex models with many weight/bias matrices, computation and push/pull communication can be overlapped according to data dependencies
  - This can be combined with prefetching of weights
- **Sparse and Compressed Communication**
  - For mini-batches of sparse data, sparse gradients can be communicated
  - Lossy (mantissa truncation, quantization), and lossless (delta, bitpacking) compression for weights and gradients

[Frank Seide et al: **1-bit stochastic gradient descent** and its application to data-parallel distributed training of speech DNNs. **INTERSPEECH 2014**]

  - Gradient sparsification (send gradients larger than a threshold)
  - Gradient dropping (drop fraction of positive/negative updates)

Model-Parallel Parameter Servers

Problem Setting

- **Limitations Data-Parallel Parameter Servers**
  - Need to fit entire model and activations of entire network into each worker node/device (or accept overhead for repeated eviction and restore)
  - Existence of very deep and wide networks (e.g., **ResNet-1001**)

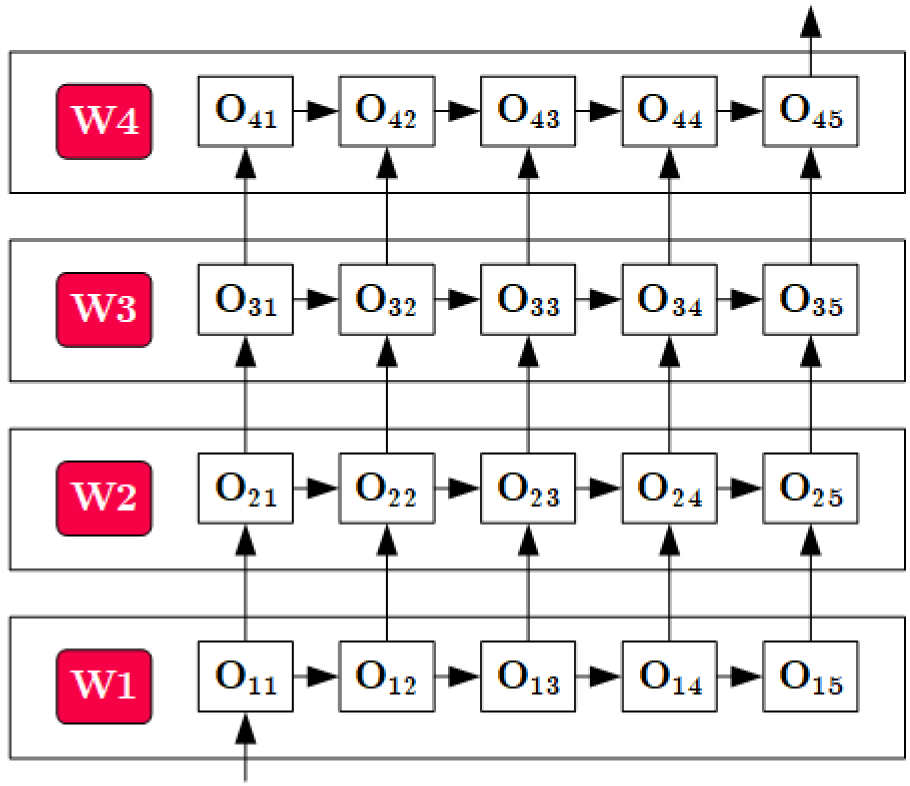
- **Model-Parallel Parameter Servers**
  - Workers responsible for **disjoint partitions of the network/model**
  - Exploit pipeline parallelism and independent subnetworks

- **Hybrid Parameter Servers**
  - *"To be successful, however, we believe that model parallelism must be combined with clever distributed optimization techniques that leverage data parallelism."*
  - *"[…] it is possible to use **tens of thousands of CPU cores** for training a single model"*

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

Overview Model-Parallel Execution

- **System Architecture**
  - Nodes act as workers and parameter servers
  - Data Transfer for boundary-crossing data dependencies
- **Pipeline Parallelism**



Workers w/ disjoint network/model partitions

Example Distributed TensorFlow MP

```
# Place variables and ops on devices
with tf.device("/gpu:0"):
   a = tf.Variable(tf.random.uniform(...))
   a = tf.square(a)
with tf.device("/gpu:1"):
   b = tf.Variable(tf.random.uniform(...))
   b = tf.square(b)
with tf.device("/cpu:0"):
   loss = a+b

# Declare optimizer and parameters
opt = tf.train.GradientDescentOptimizer(learning_rate=0.1)
train_op = opt.minimize(loss)

# Force distributed graph evaluation
ret = sess.run([loss, train_op]))
```

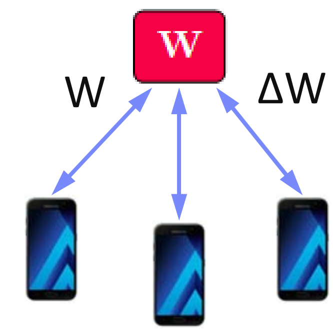
Explicit Placement of Operations

(shown via toy example)

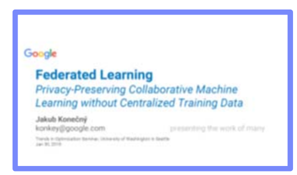
Federated Machine Learning

Problem Setting and Overview

- **Motivation Federated ML**
  - Learn model **w/o central data consolidation**
  - **Privacy + data/power caps** vs **personalization and sharing**
  - Applications Characteristics
    - #1 On-device data more relevant than server-side data
    - #2 On-device data is privacy-sensitive or large
    - #3 Labels can be inferred naturally from user interaction
  - **Example:** Language modeling for mobile keyboards and voice recognition



- **Challenges**
  - Massively distributed (data stored across many devices)
  - Limited and unreliable communication
  - Unbalanced data (skew in data size, non-IID)
  - Unreliable compute nodes / data availability



[Jakub Konečný: Federated Learning - Privacy-Preserving Collaborative Machine Learning without Centralized Training Data, **UW Seminar 2018**]

A Federated ML Training Algorithm

while(!converged) {

1. Select random subset (e.g. 1000) of the (online) clients

2. In parallel, send current parameters θ_t to those clients

At each client

2a. Receive parameters θ_t from server **[pull]**

2b. Run some number of minibatch SGD steps, producing θ'

2c. Return $\theta' - \theta_t$ (model averaging) **[push]**

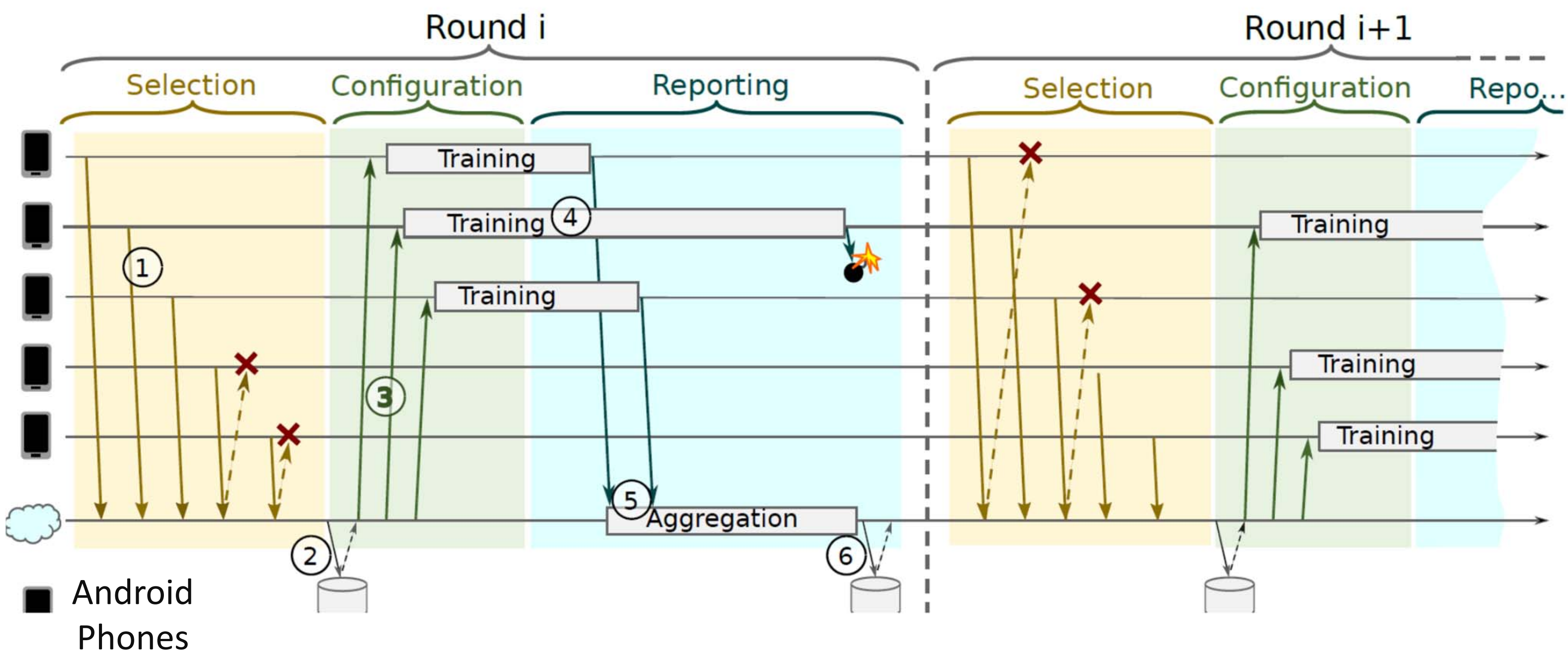
3. $\theta_{t+1} = \theta_t +$ data-weighted average of client updates

}

[Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, Blaise Agüera y Arcas: Communication-Efficient Learning of Deep Networks from Decentralized Data. **AISTATS 2017**]

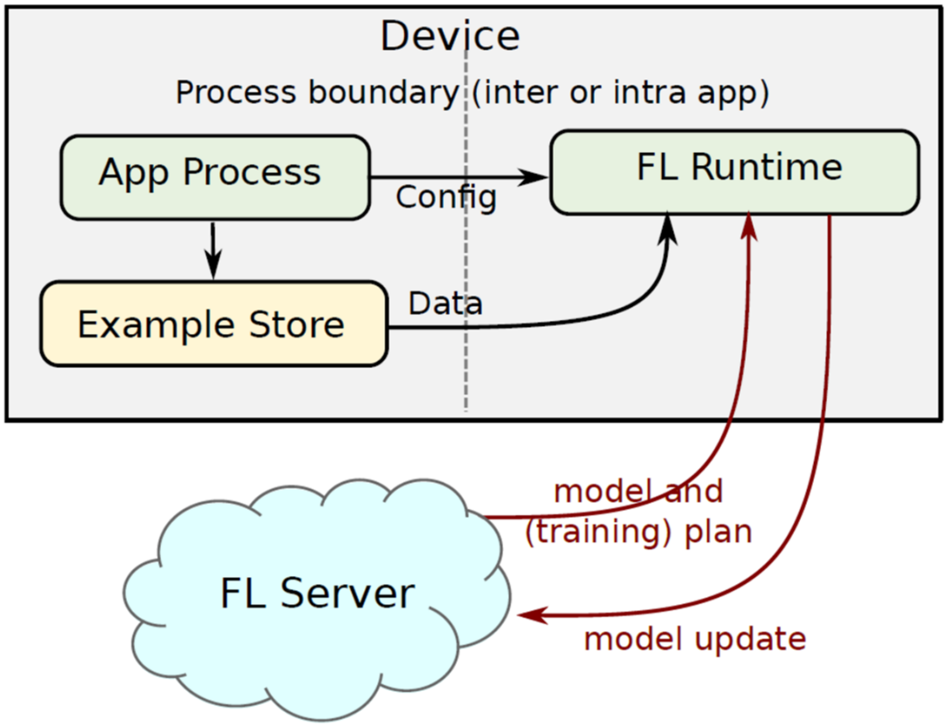
Federated Learning Protocol

- **Recommended Reading**
  - [Keith Bonawitz, Hubert Eichner, Wolfgang Grieskamp, Dzmitry Huba, Alex Ingerman, Vladimir Ivanov, Chloé Kiddon, Jakub Konecný, Stefano Mazzocchi, H. Brendan McMahan, Timon Van Overveldt, David Petrou, Daniel Ramage, Jason Roselander: Towards Federated Learning at Scale: System Design. **SysML 2019**]



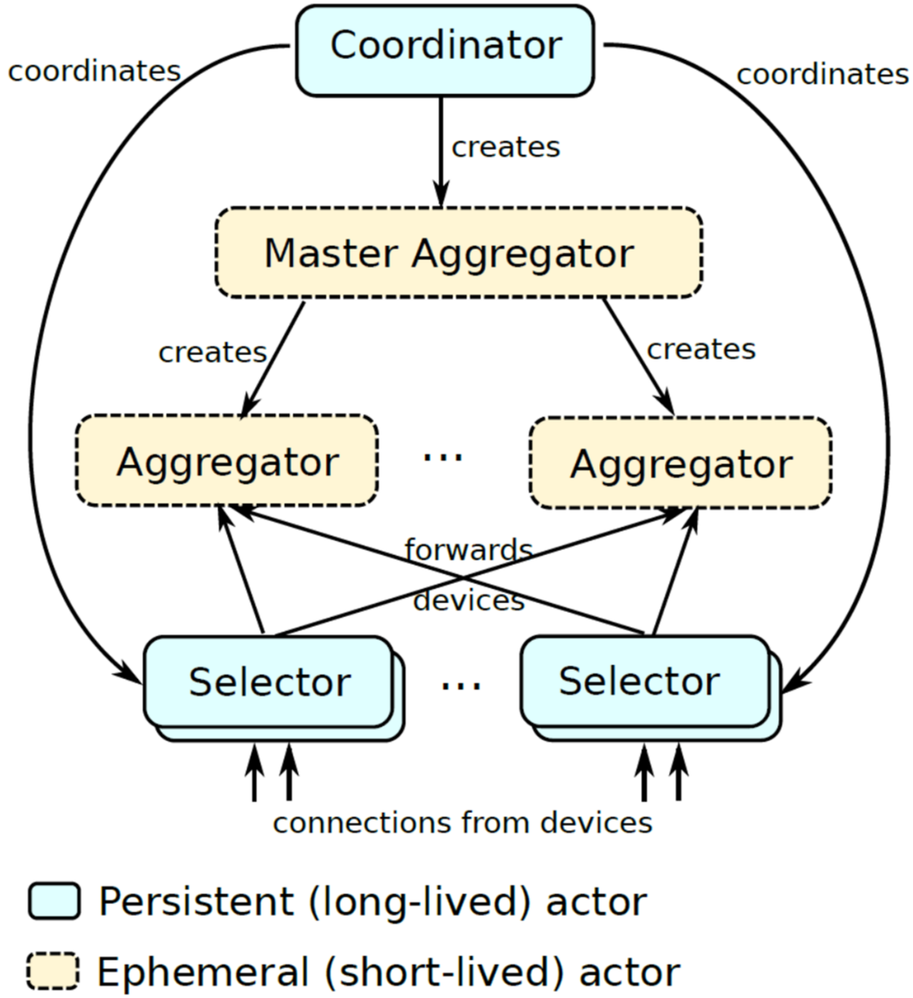
Federated Learning at the Device

- **Data Collection**
  - Maintain repository of locally collected data
  - Apps make data available via dedicated API
- **Configuration**
  - **Avoid negative impact** on data usage or battery life
  - Training and evaluation tasks
- **Multi-Tenancy**
  - Coordination between **multiple learning tasks** (apps and services)



Federated Learning at the Server

- **Actor Programming Model**
  - Comm. via message passing
  - Actors sequentially process stream of events/messages
  - ➔ **Scaling w/ # actors**
- **Coordinators**
  - Driver of overall learning algorithm
  - **Orchestration of aggregators** and selectors (conn handlers)
- **Robustness**
  - Pipelined selection and aggregation rounds
  - Fault Tolerance at aggregator/ master aggregator levels



Excursus: Data Ownership

- **Data Ownership Problem**
  - Vendor sells machine to middleman who uses it to test equipment of customer
    ➔ Who owns the data? Vendor, Middleman, or Customer? Why?
  - **Usually negotiated in bilateral contracts!**

- **A Thought on a Spectrum of Rights and Responsibilities**
  - **Federated ML creates new spectrum for data ownership** that might create new markets and business models
  - **#1** Data stays private with the customer
  - **#2** Gradients of individual machines shared with the vendor
  - **#3** Aggregated gradients shared with the vendor
  - **#4** Data completely shared with the vendor

Data Privacy

↑ ↓

Ability to train models

Summary and Conclusions

- **Data-Parallel Parameter Servers**
  - Data partitioning across workers, independent computation
  - Synchronous or asynchronous model updates

- **Model-parallel Parameter Servers**
  - Network/model partitioning across workers
  - Pipelined execution and independent network partitions

- **Federated Machine Learning**
  - Extended parameter server architecture w/ specialized techniques
  - High potential for use cases where data sharing not possible/practical

- **Next Lecture**
  - **07 Hybrid Execution and HW Accelerators** [May 10]