Architecture of ML Systems
06 Parameter Servers

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SCIENCE
PASSION
TECHNOLOGY

Last update: Apr 23, 2021

Announcements/Org

- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - Streaming: https://tugraz.webex.com/meet/m.boehm
  - Corona traffic light **RED** until end of April

- **#2 Programming Projects / Exercises** (36/57)
  - **Apache SystemDS:** 24 projects / 37 students
  - **DAPHNE:** 2 projects / 2 students
  - **Exercises:** 10 projects / 18 students → TeachCenter
  - Kickoff meetings completed
  - **Deadline: June 30** (soft)

Categories of Execution Strategies

Batch **SIMD/SPMD**	Batch/Mini-batch, Independent Tasks **MIMD**	Mini-batch
05_a Data-Parallel Execution [Apr 16]	**05_b Task-Parallel Execution** [Apr 16]	**06 Parameter Servers** (data, model) [Apr 23]

07 Hybrid Execution and HW Accelerators [Apr 30]

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08 Caching, Partitioning, Indexing, and Compression [May 07]

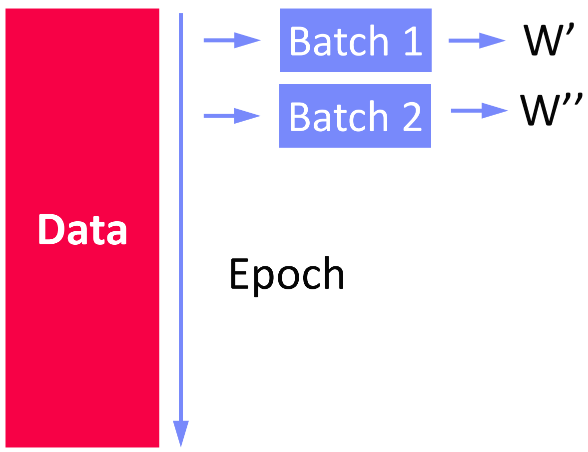
Agenda

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

Data-Parallel Parameter Servers

Recap: 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** or w/ **sampling**)
  - For large and **highly redundant training sets**
  - **Applies to almost all iterative**, model-based ML algorithms (LDA, reg., class., factor., DNN)
  - **Stochastic Gradient Descent** (SGD)



- **Statistical vs Hardware Efficiency** (batch size)
  - **Statistical efficiency:** # 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 algorithms sequentially is hard to scale**

Background: Mini-batch DNN Training (LeNet)

[Yann LeCun, Leon Bottou, Yoshua Bengio, and Patrick Haffner: Gradient-Based Learning Applied to Document Recognition, **Proc of the IEEE 1998**]

```
# 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)
   }
}
```

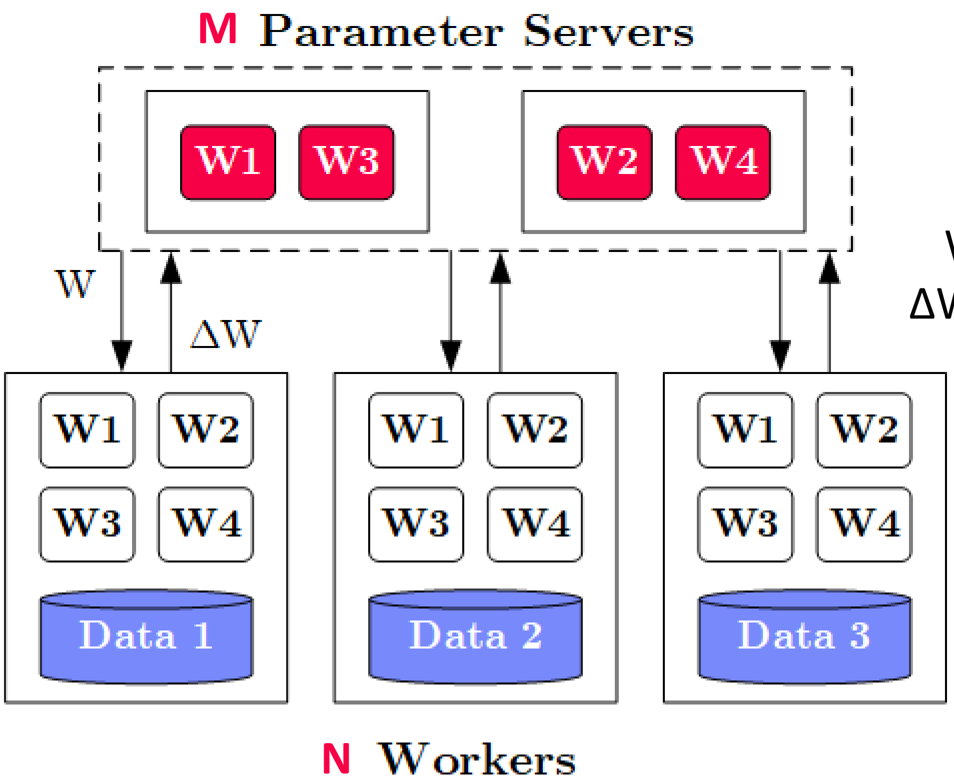
NN Forward Pass

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 gradient 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 → shuffling/randomization

- **#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 = X[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

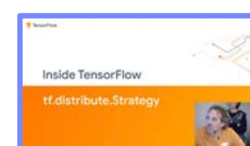
```
Xp = Pi %*% X
```

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

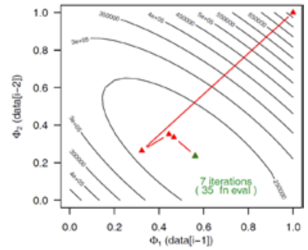
[Inside TensorFlow: tf.distribute.Strategy, 2019, https://www.youtube.com/watch?v=jKV53r9-H14]



Example SystemDS Parameter Server

```
# Initialize SGD w/ Adam optimizer
[W1, mW1, vW1] = adam::init(W1);
[b1, 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=fGradients, aggregation=fUpdate, mode=REMOTE_SPARK, utype=ASP,
  freq=BATCH, epochs=200, batchsize=64, k=144, scheme=DISJOINT_RANDOM,
  hyperparams=params)
```

Selected Optimizers (updateModel)



- **Stochastic Gradient Descent (SGD)**
  - Vanilla SGD, basis for many other optimizers
  - See 05 Data/Task-Parallel: $-\gamma \nabla \boldsymbol{f}(\boldsymbol{D}, \boldsymbol{\theta})$

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

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

```
v = mu*v – lr*dX
X = X + v
```

- **SGD w/ Nesterov Momentum**
  - Incorporates 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 w/ 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))
```

Selected Optimizers (updateModel), cont.

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

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

```
t = t + 1
m = beta1*m + (1-beta1)*dX    # update biased 1st moment est
v = beta2*v + (1-beta2)*dX^2 # update biased 2nd raw moment est
mhat = m / (1-beta1^t)        # bias-corrected 1st moment est
vhat = v / (1-beta2^t)        # bias-corrected 2nd raw moment est
X = X - (lr * mhat/(sqrt(vhat)+epsilon)) # param update
```

- **Shampoo**
  - Preconditioned gradient method (Newton's method, Quasi-Newton)
  - Retains gradients tensor structure by maintaining a preconditioner per dim
  - $O(m^2n^2) \rightarrow O(m^2 + n^2)$

[Vineet Gupta, Tomer Koren, Yoram Singer: Shampoo: Preconditioned Stochastic Tensor Optimization. **ICML 2018**]

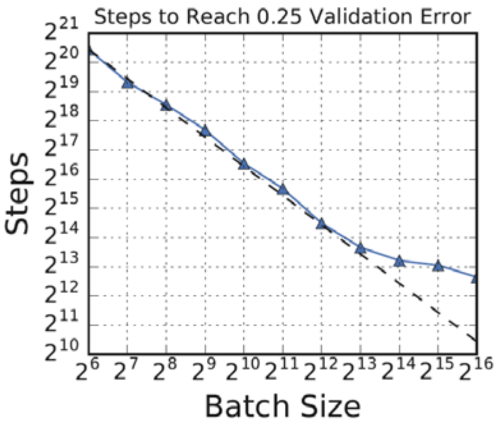
```
L = L + dX %*% t(dX)
R = R + t(dX) %*% dX
X = X - lr * pow(L,1/4)
    %*% dX %*% pow(R,1/4))
```

Batch Size Configuration

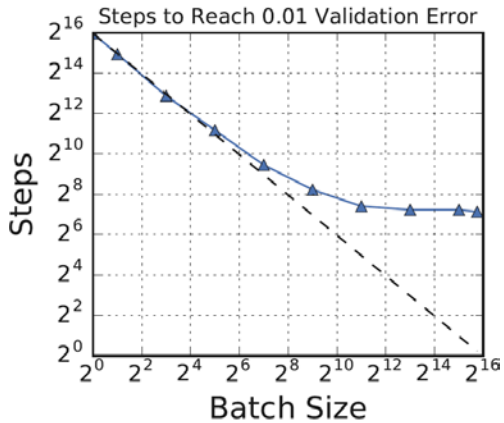
- **What is the right batch size for my data?**
  - Maximum useful batch size is dependent on data redundancy and model complexity

[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 reduce the relative communication overhead

[Priya Goyal et al: Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour. **CoRR 2017** (kn=8K, 256 GPUs)]

- **Overlapping Computation/Communication**
  - For deep NN w/ many weight/bias matrices, compute and comm. can be overlapped
  - Collective operations: all-Reduce / ring all-reduce / hierarchical all-reduce

`tf.distribute:`
`MirroredStrategy`
`MultiWorkerMirroredStrategy`

- **Sparse and Compressed Communication**
  - Mini-batches of sparse data → sparse dW
  - Lossy (mantissa truncation, quantization), and lossless (delta, bitpacking) for W and dW
  - Gradient sparsification/clipping (send gradients larger than a threshold)

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

- **In-Network Aggregation** (SwitchML)
  - Aggregate worker updates in prog. switches
  - 32b fix-point, coordinated updates

[Amedeo Sapio et al: Scaling Distributed Machine Learning with In-Network Aggregation, **NSDI 2021**]

Model-Parallel Parameter Servers

Problem Setting

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

[Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun: Identity Mappings in Deep Residual Networks. **ECCV 2016**]

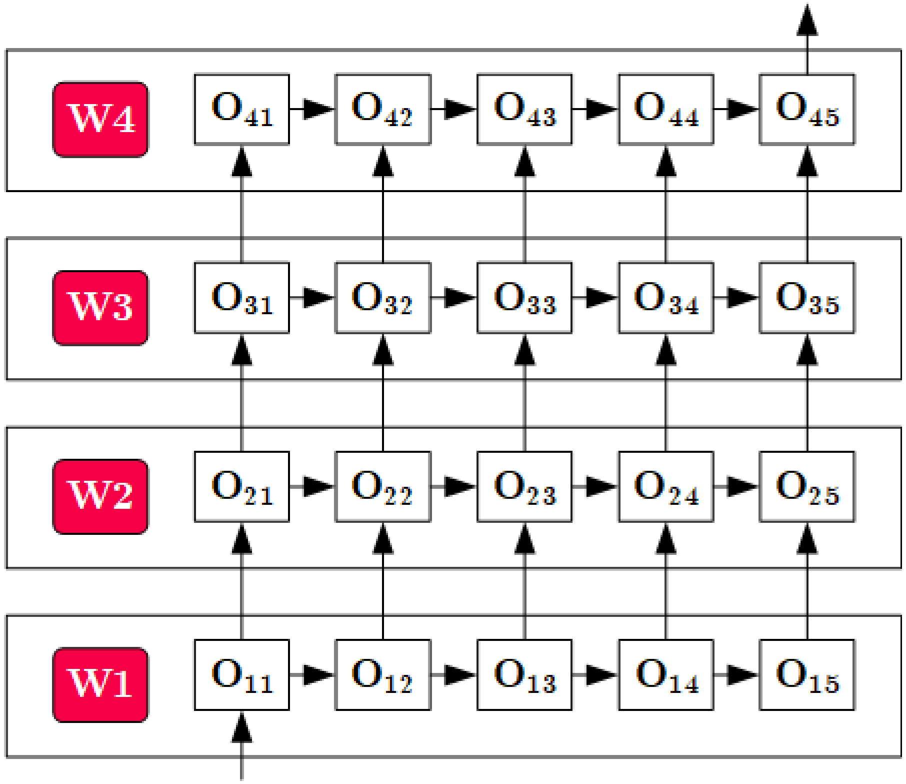
- **Model-Parallel Parameter Servers**
  - Workers responsible for **disjoint partitions of the network/model**
  - Exploit pipeline parallelism and independent subnetworks
  - **Examples:** recurrent neural networks, **pre-processing tasks**

- **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)

Distributed Reinforcement Learning

Hybrid Data- and Task- Parallel Execution

Data-Parallel Parameter Servers

Nested Parallelism

Reinforcement Learning

[Richard S. Sutton, Andrew G. Barto: Reinforcement Learning: An Introduction, MIT Press, 2015]

- **RL Characteristics**
  - **Closed-loop:** goal-directed learning from interaction
  - **Time-delayed reward:** map situations → actions, max reward
  - **No instructions:** exploitation (known actions) vs exploration (find actions)

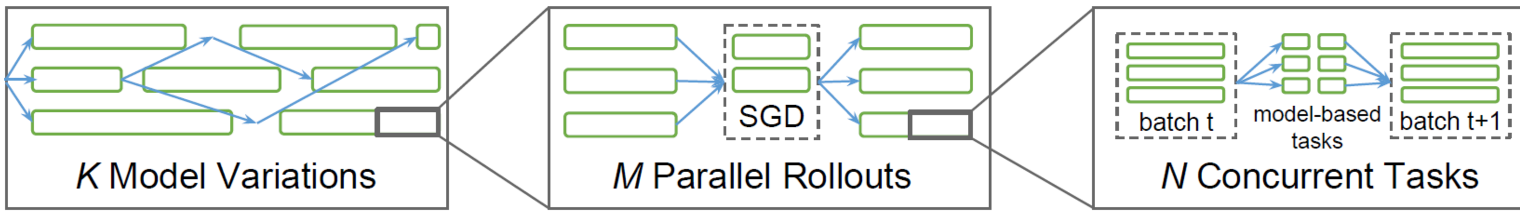
- **RL Elements**
  - Policy: stimulus-response rules (perceived environment state → actions)
  - Reward Signal: scalar reward at each time step (direct vs indirect)
  - Value Function: long-term desirability of states (expected reward)
  - Model of the environment: expected behavior of environment → planning

Distributed RL in RLlib

[Eric Liang, Richard Liaw et al: **RLlib:** Abstractions for Distributed Reinforcement Learning. **ICML 2018**]

[Philipp Moritz, Robert Nishihara et al.: **Ray:** A Distributed Framework for Emerging AI Applications. **OSDI 2018**]

- **Framework Overview**
  - RLlib on tasks/actors in Ray
  - Interleaved policy training, simulations, etc



- **Parallelization Strategies**
  - Hierarchical Parallel Task Model (locally, centralized control)
  - Policy optimizer step methods (All-reduce, local multi-GPU, async, parameter server)
  - Policy graph (algorithm-specific) on multiple remote evaluator replicas

Example Parameter Server

(task stream, wait for #updates)

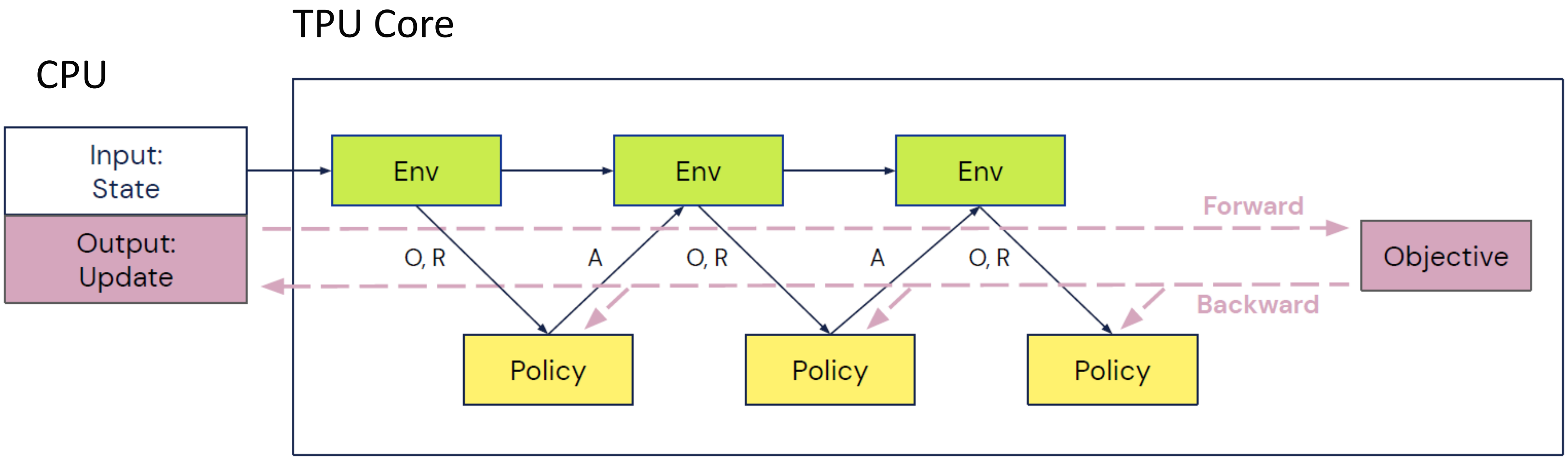
```
grads = [ev.grad(ev.sample())
    for ev in evaluators]
for _ in range(NUM_ASYNC_GRADS):
    grad, ev, grads = wait(grads)
    for ps, g in split(grad, ps_shards):
        ps.push(g)
    ev.set_weights(concat(
        [ps.pull() for ps in ps_shards])
    grads.append(ev.grad(ev.sample()))
```

Podracer RL Architectures

- **Use of TPU Pods via JAX/TF XLA**

[Matteo Hessel, Manuel Kroiss, et al: Podracer architectures for scalable Reinforcement Learning, **CoRR 2021**]

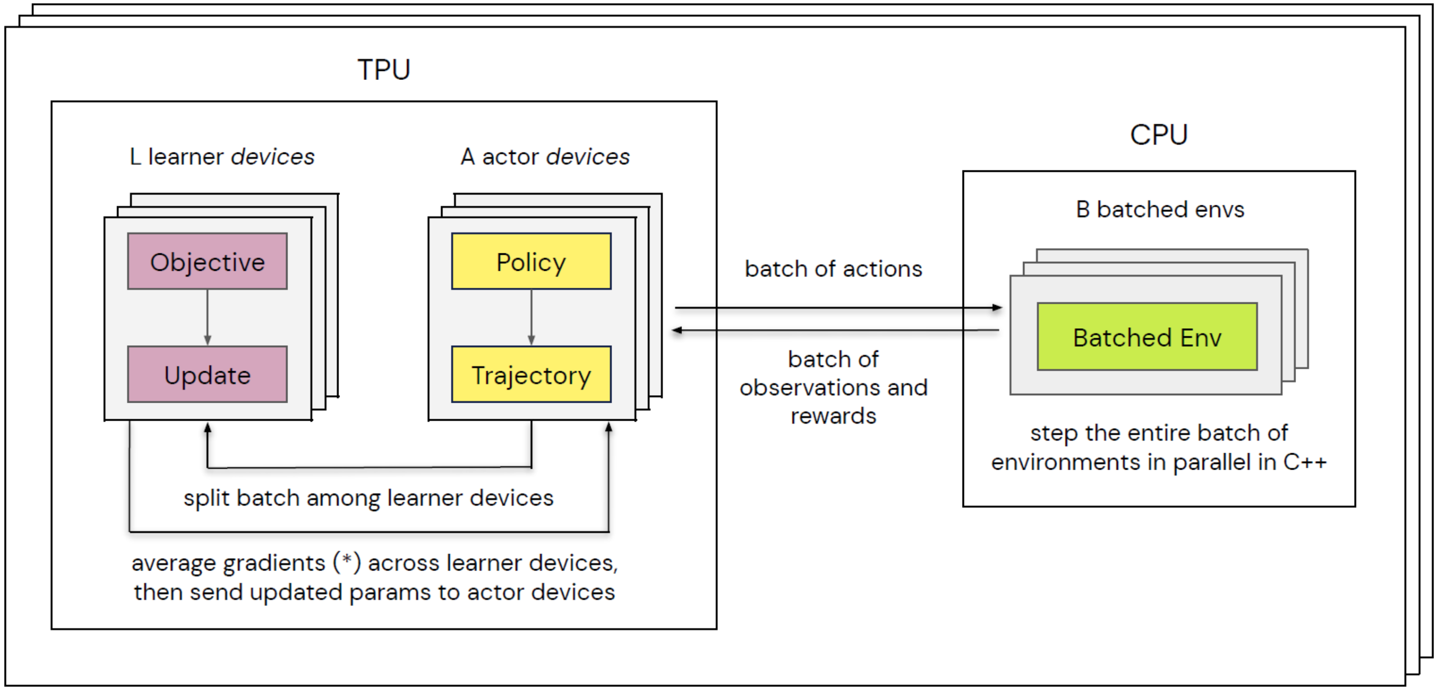
- **#1 Anakin**
  - Agent-environment interaction can be compiled into a single XLA program
  - **Scalability:** replicate basic setup to larger TPU slices



Podracer RL Architectures, cont.

[Matteo Hessel, Manuel Kroiss, et al: Podracer architectures for scalable Reinforcement Learning, **CoRR 2021**]

- **#2 Sebulba**
  - Decomposed actors and learners
  - Support for arbitrary environments

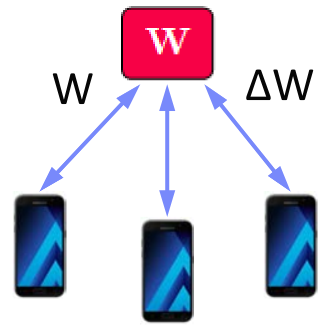


This entire computation is replicated across S slices of a TPU Pod,
in which case gradients in (*) are averaged across all learner devices of all slices

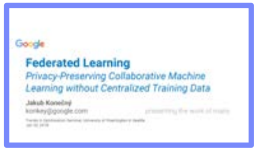
Federated Machine Learning

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**]

Algorithmic PS Extensions

- **#1 Client Sampling** (**FedAvg** w/ model averaging)

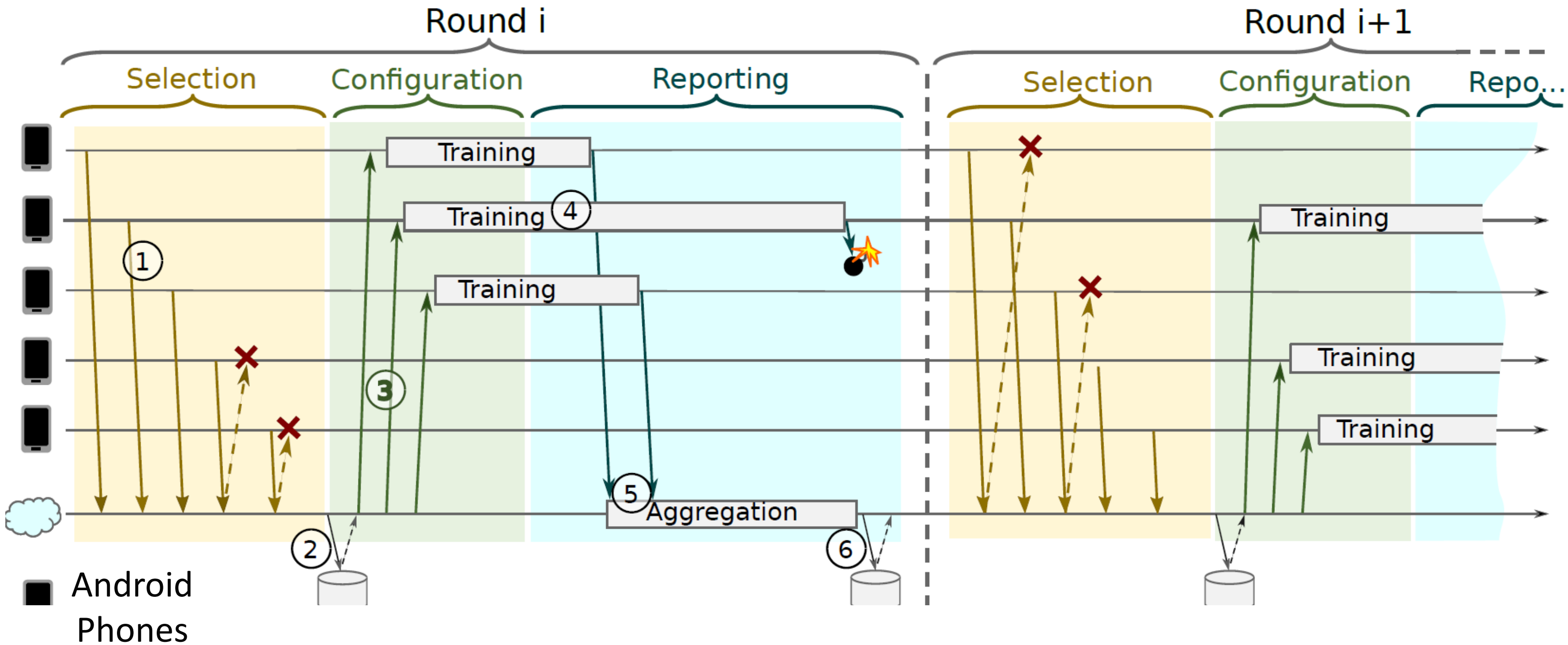
[Peter Kairouz, Brendan McMahan, Virginia Smith: Federated Learning Tutorial. **NeurIPS 2020**, https://slideslive.com/38935813/federated-learningtutorial]

- **#2 Decentralized, Fault-tolerant Aggregation**
- **#3 Peer-to-peer Gradient and Model Exchange**
- **#4 Meta-learning for Private Models**
- **#5 Handling Statistical Heterogeneity** (non-IID data)
  - Reducing variance
  - Selecting relevant subsets of data
  - Tolerating partial client work
  - Partitioning clients into congruent groups
  - Adaptive Optimization (**FedOpt**, **FedAvgM**)

[Sashank J. Reddi et al: Adaptive Federated Optimization. **CoRR 2020**]

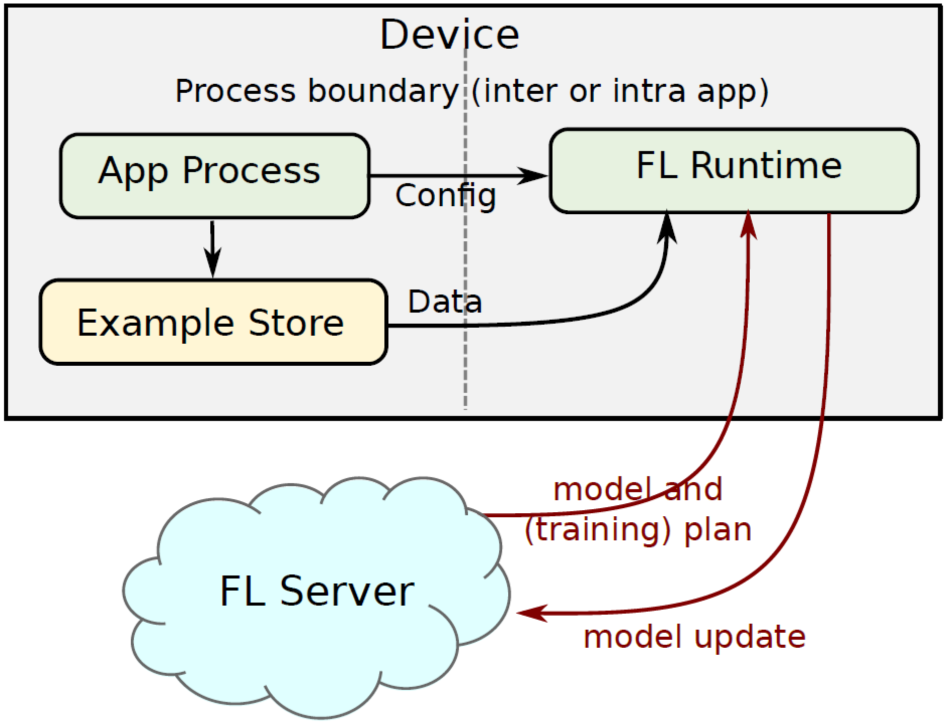
Federated Learning Protocol

- **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. **MLSys 2019**]



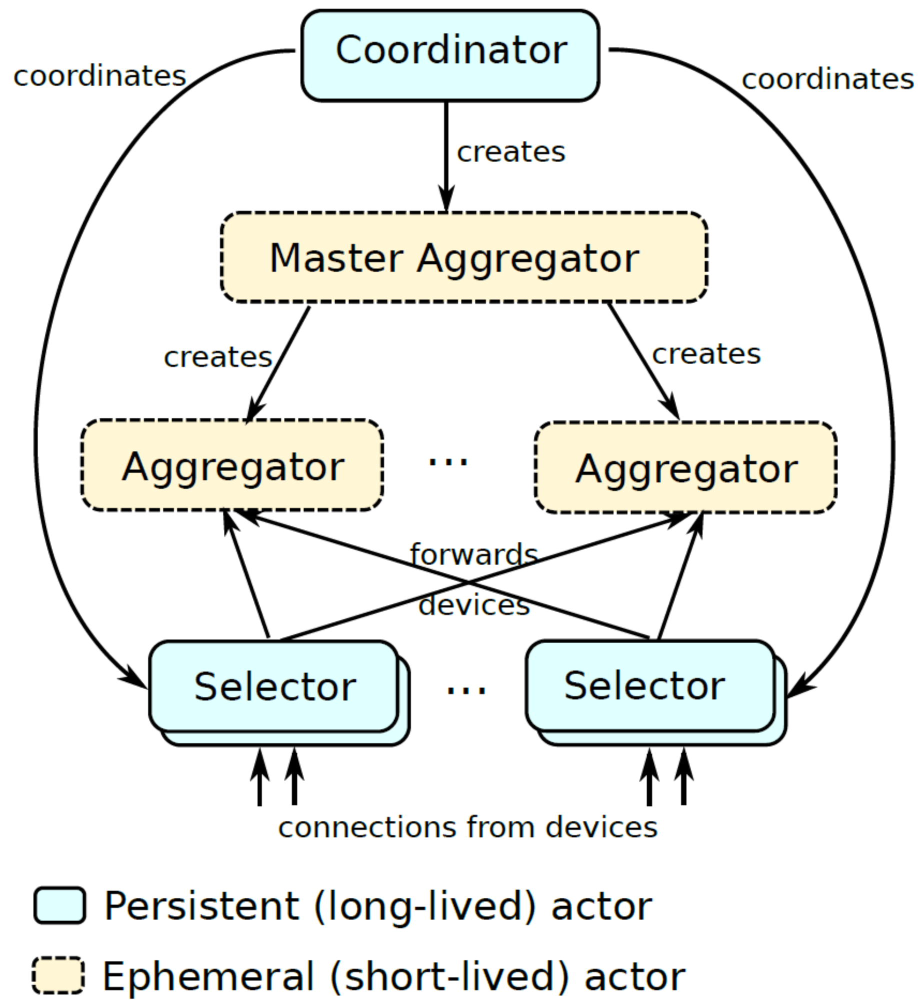
Federated Learning at the Device

- **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

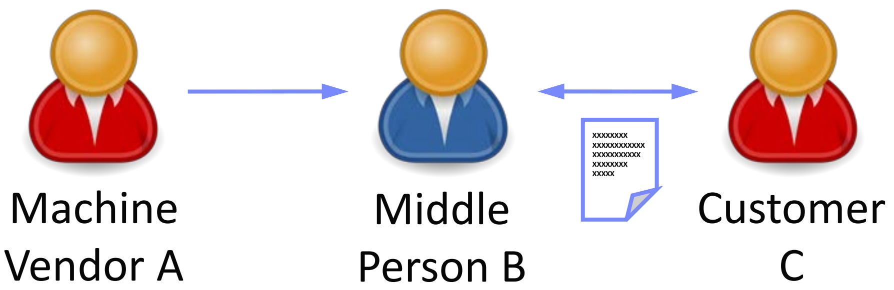
- **Actor Programming Model**
  - Comm. via message passing
  - Actors sequentially process stream of events/messages
  - ➔ **Scaling w/ # actors**
- **Coordinators**
  - Driver of overall learning algorithm
  - **Orchestration of aggregators** and selectors (conn handlers)
- **Robustness**
  - Pipelined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



Excursus: Data Ownership

- **Limited Access to Data Sources**
  - #1 Infeasible data consolidation (privacy, economically/technically)
  - #2 Data ownership (restricted data enrichment and consolidation)

- **Example Data Ownership**
  - **Thought experiment:** B uses machine from A to test C's equipment.
  - Who owns the data?



- **A Thought on a Spectrum of Rights and Responsibilities**
  - **Federated ML creates new spectrum for data ownership** that might create new markets (no reselling of data)
  - **#1** Data stays private with the customer
  - **#2** Gradients/Aggregates shared with the vendor
  - **#3** Data completely shared with the vendor

Data Privacy

Ability to train models

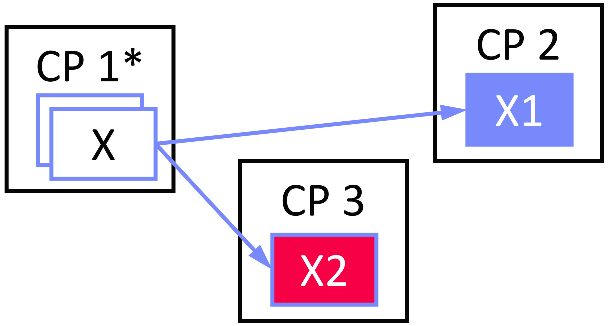
Federated ML in SystemDS

[Sebastian Baunsgaard et al.: ExDRa: Exploratory Data Science on Federated Raw Data, **SIGMOD 2021**]

- **ExDRa Project**
  - **Basic approach:** Federated ML + ML over raw data
  - System infra, integration, data org & reuse, Exp DB, geo-dist.

Gefördert im Programm "IKT der Zukunft"

- **Federated ML Architecture**
  - Multiple control programs w/ single master
  - Federated tensors (metadata handles)
  - **Federated linear algebra** and **federated parameter server**

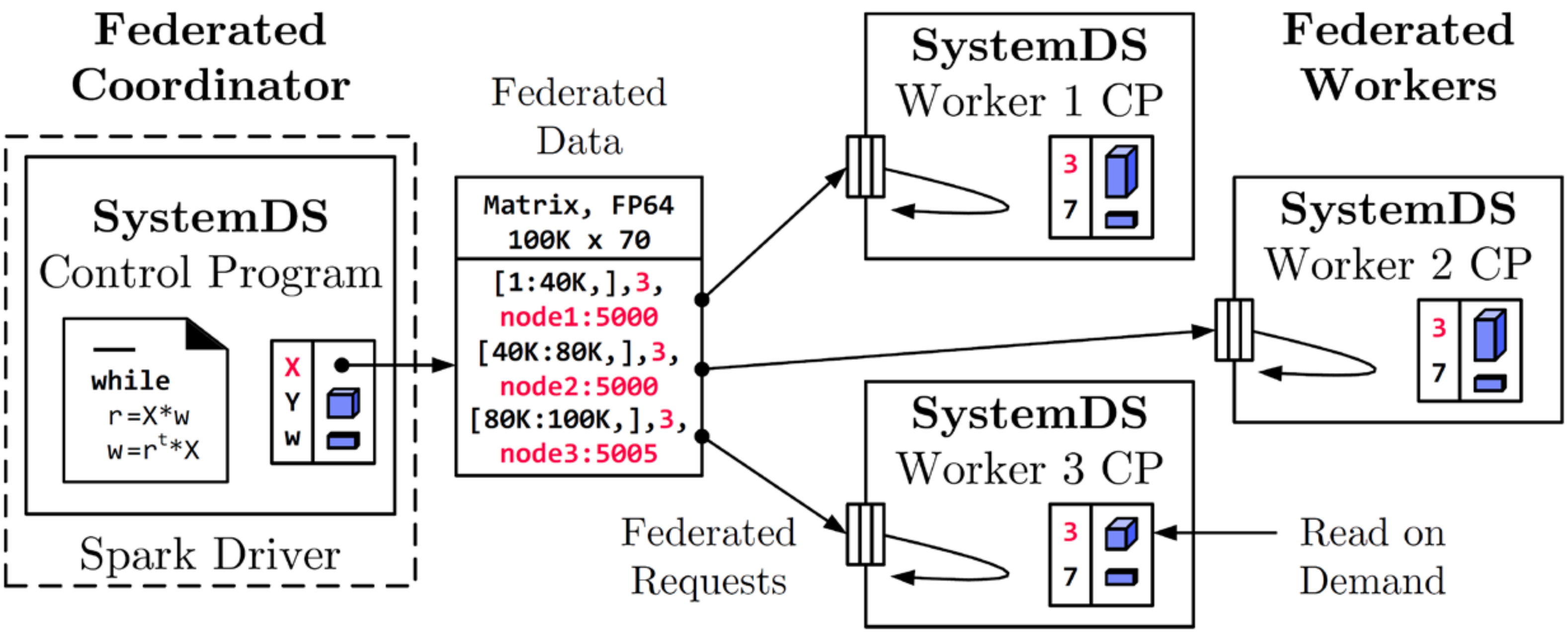


- **Privacy Enhancing Technologies (PET)**
  - Federated ML w/ data exchange constraints
  - PET (homomorphic encryption, multi-party computation, differential privacy)

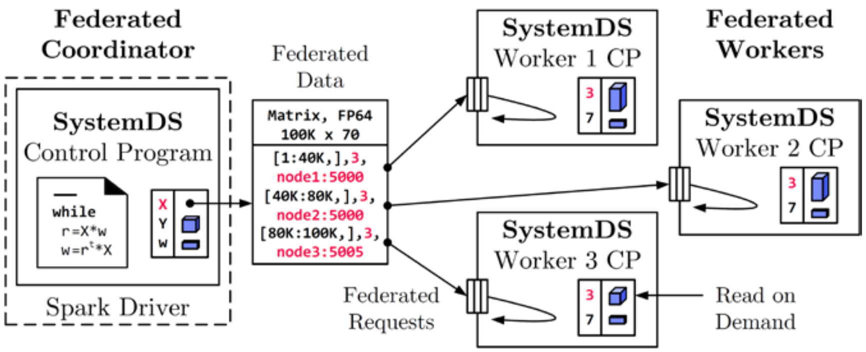
Federated Data

- **Federated Runtime Backend**
  - Federated data (matrices/frames) as meta data objects
  - Federated linear algebra, (and federated parameter server)

```
X = federated(addresses=list(node1, node2, node3),
  ranges=list(list(0,0),list(40K,70), ..., list(80K,0),list(100K,70)));
```



Federated Requests



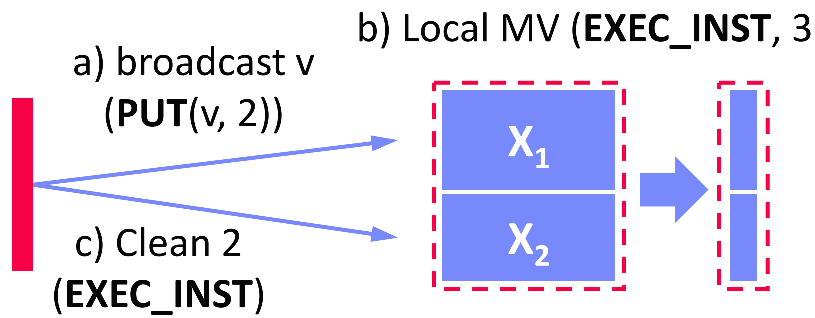
- **Federation Protocol**
  - Batch federated requests
  - Single federated response

- **Federated Request Types**
  - `READ(ID,fname)`: read data object from file, and put it in symbol table
  - `PUT(ID,data)`: receives transferred data object, and put it in symbol table
  - `GET(ID)`: return a data object from the federated site to coordinator
  - `EXEC_INST(inst)`: execute an instruction (inputs/outputs by ID)
  - `EXEC_UDF(udf)`: execute a user-defined function w/ access to symbol table
  - `CLEAR`: clean up execution contexts and variables

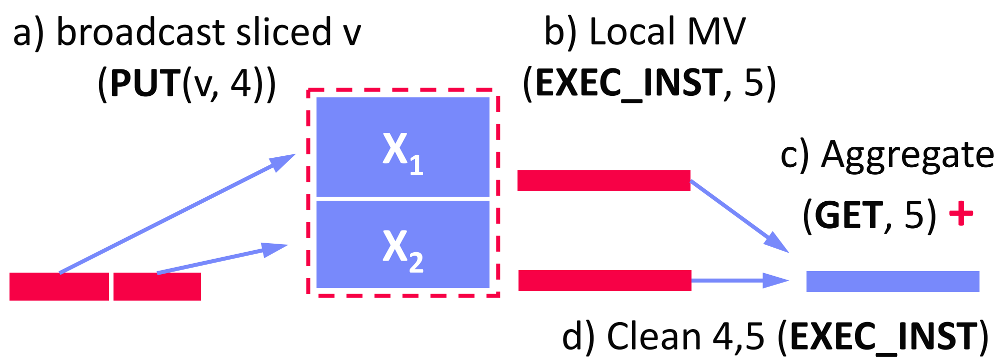
➔ **Design Simplicity:** (1) reuse instructions, (2) federation hierarchies

Example Federated Operations

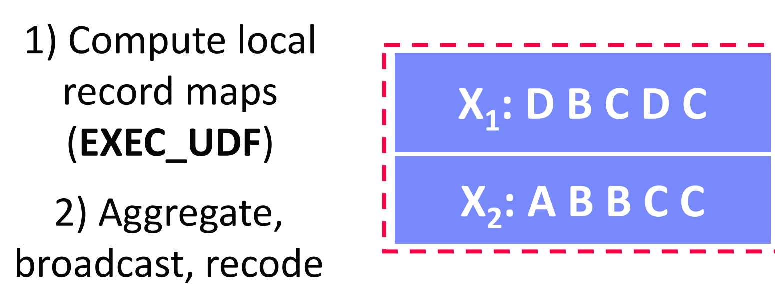
- **Matrix-Vector Multiplication**
  - `o = X %*% v`, local v
  - Row-partitioned, federated X
  - **Row-partitioned, federated o**



- **Vector-Matrix Multiplication**
  - `o = v %*% X`, local v
  - Row-partitioned, federated X, **local o**



- **Data Preparation**
  - `[X,M] = transformencode(F,spec)`
  - Recoding, feature hashing, binning, **one-hot encoding**



TensorFlow Federated

[https://www.tensorflow.org/federated/]

- **Overview TFF**
  - **Federated PS algorithms** and **federated second order functions**
  - Primarily for simulating federated training, no OSS federated runtime
- **#1 Federated PS**

```
iterative_process = tff.learning.build_federated_averaging_process(
    model_fn, # function for created federated models
    client_optimizer_fn=lambda: tf.keras.optimizers.SGD(learning_rate=0.02),
    server_optimizer_fn=lambda: tf.keras.optimizers.SGD(learning_rate=1.0))
```

- **#2 Federated Analytics**
  - r = t(y) %*% X
  - User-level composition of federated algorithms
  - **PET primitives**

```
X = ... # tff.type_at_clients(tf.float32)
by  = tff.federated_broadcast(y)
R   = tff.federated_sum(
       tff.federated_map(X, by, foo_mm), foo_s)
     # note: tff.federated_secure_sum
```

Summary and Q&A

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

- **Next Lectures** (Part A)
  - **07 Hybrid Execution and HW Accelerators** [Apr 30]
  - **08 Caching, Partitioning, Indexing and Compression** [May 07]