Architecture of ML Systems
06 Parameter Servers

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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

  **Study Abroad Fair**
  **May 22, 2019**

  - Your opportunity to find out about exchange programmes and scholarships offered by TU Graz
  - Information booths
  - Short presentations concerning various study abroad possibilities

  tu4u.tugraz.at/go/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 Algorithms sequentially is hard to scale**
Background: Mini-batch DNN Training (LeNet)

```python
# 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 -> dropout
        ## 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)
    }
}
```

Data-Parallel Parameter Servers

**NN Forward Pass**

**NN Backward Pass** → Gradients

**Model Updates**
Overview Parameter Servers

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

- **Key Techniques**
  - Data partitioning $D \rightarrow$ workers $D_i$ (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

References:

- [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)

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

nfetch batches require local gradient accrual and local model update

Data-Parallel Parameter Servers

[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

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

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*

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

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

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

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

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

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

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Data-Parallel Parameter Servers

\[
X_p = X[\text{id*blocksize+1: (id+1)*blocksize,}];
\]

\[
X_p = \text{removeEmpty}(X, 'rows', \text{seq}(1,\text{nrow}(X))\%\%\%\text{N==id});
\]

\[
P = \text{table}(\text{seq}(1,\text{nrow}(X)), \text{sample}(\text{nrow}(X),\text{nrow}(X), \text{FALSE}));
\]

\[
X_p = P[\text{id*blocksize+1: (id+1)*blocksize,}] \%\% X
\]

\[
X_p = P_i \%\% X
\]
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
- **SGD w/ Momentum**
  - Assumes parameter velocity w/ momentum
- **SGD w/ Nesterov Momentum**
  - Assumes parameter velocity w/ momentum, but update from position after momentum
- **AdaGrad**
  - Adaptive learning rate with regret guarantees
- **RMSprop**
  - Adaptive learning rate, extended AdaGrad
- **Adam**
  - Individual adaptive learning rates for different parameters

\[
X = X - lr \times dX \\
v = \mu \times v - lr \times dX \\
X = X + v \\
v0 = v \\
v = \mu \times v - lr \times dX \\
X = X - \mu \times v0 + (1+\mu) \times v
\]


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

\[
c = \alpha \times c + (1-\alpha) \times dX^2 \\
x = x - \frac{lr \times dX}{\sqrt{c} + \text{eps}}
\]

Batch Size Configuration

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

- **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)

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

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

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

        At each client

        2a. Receive parameters $\theta_t$ from server [pull]
        2b. Run some number of minibatch SGD steps, producing $\theta'$
        2c. Return $\theta' - \theta_t$ (model averaging) [push]

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

[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**
  
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
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]