We present two ML frameworks targeting:

Deep Learning: TensorFlow

Graph Processing: Faiter
Common themes...
Distributed ML Frameworks: Common Themes

Trend towards **BIG DATA**

**Big** models, **big** graphs, **lots** of compute needed

=> Any framework must be **Scalable**

=> Any framework must be **Tolerant to Failure**
Distributed ML Frameworks: Common Themes

Trend towards **Heterogeneity**

GPUs, FPGAs, other accelerators increasingly used to accelerate operations

=> Any framework must be **Portable**

=> Any framework must be **Tolerant to Load Imbalance**
TensorFlow: A System for Large-Scale Machine Learning

Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, Manjunath Kudlur, Josh Levenberg, Rajat Monga, Sherry Moore, Derek G. Murray, Benoit Steiner, Paul Tucker, Vijay Vasudevan, Pete Warden, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng, Google Brain
Introduction
Introduction

Availability of Data
Introduction

Availability of Data

Software Platforms
Introduction

Availability of Data

ML Techniques

Software Platforms
Large Scale Training

- Large data sets are available
- Compute resources are available
  - Warehouse Scale Computers
  - GPGPUs
  - ASIC Accelerators
Large Scale Training

- Large data sets are available
- Compute resources are available
  - Warehouse Scale Computers
  - GPGPUs
  - ASIC Accelerators
Large Scale Training

- Large data sets are available
- Compute resources are available
  - Warehouse Scale Computers
  - GPGPUs
  - ASIC Accelerators
- Larger more models, complex techniques performing better
  - But they need more data and more time for convergence
- So how can we scale training?
Background: NN Training

Process:

- Take input image
- Compute loss function (forward pass)
Background: NN Training

Process:

- Take input image
- Compute loss function (forward pass)
- Compute error gradients (backward pass)
Background: NN Training

Process:

- Take input image
- Compute loss function (forward pass)
- Compute error gradients (backward pass)
- Update weights
- Repeat
Background: Dist Belief, parameter-server arch

Data Parallelism:
Asynchronous Distributed Stochastic Gradient Descent

Parameter Server: $p' = p + \Delta p$

Model Workers

Data Shards
Background: Dist Belief, parameter-server arch

1. Asynch SGD
2. Distributed kernels
3. 30x DNN
4. SOA Performance

Data Parallelism:
Asynchronous Distributed Stochastic Gradient Descent

Parameter Server: $p' = p + \Delta p$
Background: Shortcomings of DistBelief

1. Difficulty of implementing new layers
   a. C++ classes implement layers
   b. Configuration file defines DNN architecture
   c. Not flexible enough for researchers
Background: Shortcomings of DistBelief

1. Difficulty of implementing new layers
   a. C++ classes implement layers
   b. Configuration file defines DNN architecture
   c. Not flexible enough for researchers

2. Refining Algorithms
   a. SGD is the heart of the training -- finalized in the parameter server
   b. Need atomicity for some techniques -- get/put interface cannot accommodate
Background: Shortcomings of DistBelief

1. Difficulty of implementing new layers
   a. C++ classes implement layers
   b. Configuration file defines DNN architecture
   c. Not flexible enough for researchers

2. Refining Algorithms
   a. SGD is the heart of the training -- finalized in the parameter server
   b. Need atomicity for some techniques -- get/put interface cannot accommodate

3. Supporting new algorithms
   a. If it doesn’t conform to feed-forward it doesn’t map well to DistBelief
   b. EM, RF, RL, AdvMI,
Background: Shortcomings of DistBelief

1. Difficulty of implementing new layers
   a. C++ classes implement layers
   b. Configuration file defines DNN architecture
   c. Not flexible enough for researchers

2. Refining Algorithms
   a. SGD is the heart of the training -- finalized in the parameter server
   b. Need atomicity for some techniques -- get/put interface cannot accommodate

3. Supporting new algorithms
   a. If it doesn’t conform to feed-forward it doesn’t map well to DistBelief
   b. EM, RF, RL, AdvMI,

4. Scaling down to other environments
   a. Designed to run on distributed cluster of multi-cores
   b. Augmented for GPGPU support for Conv NN
TensorFlow: Solution Strategy

1. Execution Flexibility via DataFlow abstraction
   a. Makes it easy to extract the parallelism
TensorFlow: Solution Strategy

1. Execution Flexibility via DataFlow abstraction
   a. Makes it easy to extract the parallelism

2. Provides DFGs for primitive operators
   a. Softmax, convolution, MM, ...
   b. Makes it easy to experiment with novel layers
   c. Automatic gradient calculation
TensorFlow: Solution Strategy

1. Execution Flexibility via DataFlow abstraction
   a. Makes it easy to extract the parallelism

2. Provides DFGs for primitive operators
   a. Softmax, convolution, MM, ...
   b. Makes it easy to experiment with novel layers
   c. Automatic gradient calculation

3. Deferred execution
   a. Offload the larger chunks where possible...
TensorFlow: Solution Strategy

1. Execution Flexibility via DataFlow abstraction
   a. Makes it easy to extract the parallelism

2. Provides DFGs for primitive operators
   a. Softmax, convolution, MM, ...
   b. Makes it easy to experiment with novel layers
   c. Automatic gradient calculation

3. Deferred execution
   a. Offload the larger chunks where possible...

4. Common Abstraction for Accelerators
   a. Easy to integrate new accelerators into the fold
   b. The operators are specialized for different devices

5. Common data primitive: **Tensor**
Figure 6: The layered TensorFlow architecture.
Execution Model
Execution Model

- Single DFG represents all computation and state for ML algorithm
  - Input preprocessing, mathematical operators, parameters, parameter update rules
  - Communication explicit, simplifying scheduling and partitioning
Computation is a DFG

Graph of Nodes, also called Operations or ops.
Execution Model

- Single DFG represents all computation and state for ML algorithm
  - Input preprocessing, mathematical operators, parameters, parameter update rules
  - Communication explicit, simplifying scheduling and partitioning

- Differences with existing DF systems:
  - Concurrent execution on overlapping subgraphs supported
  - Individual vertices contain sharable, mutable state
Execution Model

- Single DFG represents all computation and state for ML algorithm
  - Input preprocessing, mathematical operators, parameters, parameter update rules
  - Communication explicit, simplifying scheduling and partitioning

- Differences with existing DF systems:
  - Concurrent execution on overlapping subgraphs supported
  - Individual vertices contain sharable, mutable state

mutable state is **critical** when training large models

\[ \text{Compute + Mutable State} = \text{PS}++ \]
Distributed
Communication is explicit...
TensorFlow handles the glue
Fault Tolerance

- Days or many hours to train models -- fault tolerance is key
- RDD is overkill
  - Strong consistency is not needed for ML
- User-level checkpointing operations and client library for configuration
  - SAVE/RESTORE
Synchronous!
Time-to-Quality vs Time-per-Update

- Recall earlier algorithm
  - Aggregate update delayed by stragglers
- SGD found to be robust to asynchrony
  - Asynchronous = better utilization...
  - But with GPGPUs...
- TensorFlow can handle Aynch or Synch updates...
  - Also, synchronous + backup workers
  - Idea: have K backup workers and N workers, then simply take updates from first N workers that complete
Time-to-Quality vs Time-per-Update

Recall earlier algorithm

- Aggregate update delayed by stragglers
  - SGD found to be robust to asynchrony
    - Asynchronous = better utilization...
    - But with GPGPUs...
  - TensorFlow can handle Aynch or Synch updates
    - Also, synchronous + backup workers
      - Idea: have K backup workers and N workers, then simply take updates from first N workers that complete
Time-to-Quality vs Time-per-Update

- Recall earlier algorithm
  - Aggregate update delayed by stragglers

- SGD found to be robust to asynchrony
  - Asynchronous = better utilization...
  - But with GPGPUs...

- TensorFlow can handle Asynch or Synch updates
  - Also, synchronous + backup workers
  - Idea: have K backup workers and N workers, then simply take updates from first N workers that complete
Highlights from Results
<table>
<thead>
<tr>
<th>Library</th>
<th>AlexNet</th>
<th>Overfeat</th>
<th>OxfordNet</th>
<th>GoogleNet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caffe [38]</td>
<td>324</td>
<td>823</td>
<td>1068</td>
<td>1935</td>
</tr>
<tr>
<td>Neon [58]</td>
<td>87</td>
<td>211</td>
<td>320</td>
<td>270</td>
</tr>
<tr>
<td>Torch [17]</td>
<td>81</td>
<td>268</td>
<td>529</td>
<td>470</td>
</tr>
<tr>
<td>TensorFlow</td>
<td>81</td>
<td>279</td>
<td>540</td>
<td>445</td>
</tr>
</tbody>
</table>

(a) Baseline performance vs. MXNet

(b) Coordination scalability
Image Model Training Time

Precision @ 1

2.6 hours vs. 79.3 hours (30.5X)

50 GPUs
10 GPUs
1 GPU
Conclusion

● We didn’t cover everything
  ○ Dynamic control flow
  ○ Extensibility studies

● **Key lesson:** comprehensive look at problem necessary to design a good solution for it
  ○ Asynchrony was okay but throughput oriented GPGPUs made synchronous better...
  ○ RDD level fault tolerance was not necessary
  ○ Heterogeneity built into the design

● Focusing on the user
  ○ Design/experiment, train, and deploy
A Fault-Tolerant Framework for Asynchronous Iterative Computations in Cloud Environments

Zhigang Wang, Lixin Gao, Yu Gu, Yubin Bao, and Ge Yu
A Fault-Tolerant Framework for Asynchronous Iterative Computations in Cloud Environments
Iterative Computations = Graph Algorithms

Graph as input → iteratively extract meaning → output updated graph

Iterative update function:

$$v_{j}^{k+1} = c_{j} \oplus \sum_{i \in \Gamma_{in}(j)} g_{i,j}(v_{i}^{k})$$

Converges to desired result

Examples:
- PageRank
- SSSP
- Adsorption
- Sparse Jacobi linear eq. solver
A Fault-Tolerant Framework for Asynchronous Iterative Computations \textit{in Cloud Environments}
In Cloud Environments

Nodes are partitioned across processors, communicate via MPI
In Cloud Environments

Nodes are partitioned across processors, communicate via MPI

All processors synchronize after each iteration => **scales poorly**

Amount of work depends on connectivity => **load imbalance**
A Fault-Tolerant Framework for **Asynchronous** Iterative Computations in Cloud Environments
Asynchronous: Maiter

Can we avoid global barrier for some algorithms?

Observe that: \[ v_j^{k+1} = c_j \oplus \sum_{i \in \Gamma^{in}(j)} g_{i,j}(\Delta v_i^k) \]

Can be rewritten using:

\[ v_j^k = g_{1,j}(v_1^{k-2}) \oplus g_{1,j}(\Delta v_1^k) \]
\[ g_{n,j}(v_n^{k-2}) \oplus g_{n,j}(\Delta v_n^k) \]

And \( \Delta v_{1..k} \) can be applied asynchronously:

- \( \oplus \) is commutative and associative
- \( g() \) is distributive over \( \oplus \)

(Just need to define initial \( \Delta v_i^l \) for all \( i \))
Maiter Implementation

receive: \[
\begin{cases}
\text{Whenever receiving } m_j, \\
\Delta \tilde{v}_j \leftarrow \Delta \tilde{v}_j \oplus m_j.
\end{cases}
\]

update: \[
\begin{cases}
\tilde{v}_j \leftarrow \tilde{v}_j \oplus \Delta \tilde{v}_j; \\
\text{For any } h, \text{ if } g_{\{j,h\}}(\Delta \tilde{v}_j) \neq 0, \\
\text{send value } g_{\{j,h\}}(\Delta \tilde{v}_j) \text{ to } h; \\
\Delta \tilde{v}_j \leftarrow 0,
\end{cases}
\]

May sort by priority to speed convergence
Maiter Evaluation

**Hadoop**: synchronous streaming framework

**Maiter-Sync**: Synchronous delta-based framework

**Maiter-RR**: Asynchronous Maiter, process state table Round-Robin

**Maiter-Pri**: Asynchronous Maiter, process state table based on priority
Maiter Evaluation

PageRank on billion node synthetic graph: Asynchrony and priority sorting help Maiter converge faster
Maiter Evaluation

Near optimal scaling
A **Fault-Tolerant** Framework for Asynchronous Iterative Computations in Cloud Environments
Fault-Tolerant: Faiter

What happens if some nodes fail?

Trivial solution: roll back all nodes to last checkpoint, or to initial state
Fault-Tolerant: Faiter

What happens if some nodes fail?

Trivial solution: roll back all nodes to last checkpoint or to initial state

Checkpoints are *expensive* in an asynchronous system

Can we avoid rolling back all nodes?

Yes! Can roll back only failed nodes if:

- \( g() \) is distributive over new op \( \ominus \)
- \( x \ominus x = 0 \)
- \( (x \oplus y) \ominus z = x \oplus (y \ominus z) \)

Also: can checkpoint asynchronously
Faiter Implementation

1) Master detects node failure, broadcasts recovery signal

2) Run a synchronous iteration using $\nu_i$ rather than $\Delta\nu_i$

3) Resume asynchronous operation using new initial values:

$$
\begin{align*}
\nu_j^0 &= \begin{cases} 
0, & j \in \bigcup_{N \in N_F} V_N \\
\nu_j^f, & j \in \bigcup_{N \in N_S} V_N
\end{cases} \\
\Delta\nu_j^0 &= \nu_j^1 \oplus \nu_j^0 = \left( c_j \oplus \left( \sum_{i \in \Gamma_j^{in}} \oplus g_{i,j}(\nu_i^0) \right) \right) \oplus \nu_j^0
\end{align*}
$$
Algorithm 1: RecoveryCoordinator()

1. suspending TerminationCheck
2. sending recovery_signal of “load” to RecoveryExecutor on $N \in \mathbb{N}$
3. while Number of ACKs of “load” $\neq |\mathbb{N}|$ do
4. \hspace{1em} waiting for new ACK
5. sending recovery_signal of “flush” to
   RecoveryExecutor on $N \in \mathbb{N}$
6. while Number of ACKs of “flush” $\neq |\mathbb{N}|$ do
7. \hspace{1em} waiting for new ACK
8. sending signal_recovery of “construct” to
   RecoveryExecutor on $N \in \mathbb{N}$
9. while Number of ACKs of “construct” $\neq |\mathbb{N}|$ do
10. \hspace{1em} waiting for new ACK
11. waking TerminationCheck
12. sending signal_recovery of “restart” to
    RecoveryExecutor on $N \in \mathbb{N}$
13. return;
Faiter Evaluation

**FR-Scratch**: All nodes roll back to 0 on failure

**FR-WORB**: Failed nodes roll back to 0

**FR-WAC**: Failed nodes roll back to last asynchronous checkpoint

$T_1 = 0.1$ runtime, $T_2 = 0.5$, $T_3 = 0.9$
Failure recovery with and without asynchronous checkpointing is helpful at higher $T$ (with checkpointing is generally better).

At low $T$, barrier overheads can do more harm than good.
Portability

Independent computation based on vid

- Scalable
- Tolerant to Failure
- Portable
- Tolerant to Load Imbal.
Conclusion

Maiter:

- Define when asynchrony is allowed in delta-based graph processing
- Demonstrate performance and scalability benefits of asynchrony

Faiter:

- Identify weakness in asynchronous fault recovery
- Define when complete synchronous rollback is unnecessary
- Demonstrate performance benefits of efficient fault tolerance
TensorFlow Discussion

- Can the data-parallel execution model be extended to other systems discussed in the course?
- How to handle reallocation of pre-empted nodes?
  - Load balancing not discussed
- Are stronger consistency guarantees worth the overhead?
  - Mutable state speeds up large scale model training, removes need for parameter server
- How to balance company vs. individual scale trade offs
  - Lacks some optimizations (i.e. hand-optimized kernels similar to Neon)
  - Fault tolerance - user dependent and checkpoint based
  - Few defaults - requires domain knowledge to create performant systems
Device Clarification

- GPUs, CPUs, other specialized hardware for training
- TPUs provide high performance/Watt for server side inference
- Cellphone GPUs aren’t incorporated into training systems. Rather they enable offline inference, i.e. offline translation
Faiter Discussion

- Single point of failure
- Fault Tolerance
  - FR-WORB vs FR-WAC
  - Is it really guaranteed to perform better than checkpointing? Should comparisons be included, perhaps with carefully placed failures in Faiter?
  - No comparison to other asynchronous checkpointing methods, e.g. the mentioned Chandy-Lamport method in GraphLab, nor Lineage recovery
- Scalable to real-world sized corporate clusters?
  - Tests run on t2.micro instances, these provide burst performance
- Unclear why the graph algorithms & datasets were chosen for evaluation
Faite Discussion

- Can framework be applied to non-iterative graph algorithms? Or even stream processing?
- Are the distributed, communicative and associate property assumptions realistic for most desired computation?
Under what conditions are these systems not suitable for use?
Backup
Table 1: A list of DAIC algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$g_{(i,j)}(x)$</th>
<th>$\oplus$</th>
<th>$v_j^{0}$</th>
<th>$\Delta v_j^1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSSP</td>
<td>$x + A(i,j)$</td>
<td>min</td>
<td>$\infty$</td>
<td>0 ($j = s$) or $\infty$ ($j \neq s$)</td>
</tr>
<tr>
<td>Connected Components</td>
<td>$A(i,j) \cdot x$</td>
<td>max</td>
<td>-1</td>
<td></td>
</tr>
<tr>
<td>PageRank</td>
<td>$d \cdot A(i,j) \cdot \frac{x}{N(j)}$</td>
<td>+</td>
<td>0</td>
<td>$1 - d$</td>
</tr>
<tr>
<td>Adsorption</td>
<td>$p_i^{cont} \cdot A(i,j) \cdot x$</td>
<td>+</td>
<td>0</td>
<td>$p_j^{inj} \cdot I_j$</td>
</tr>
<tr>
<td>HITS (authority)</td>
<td>$d \cdot A(i,j) \cdot x$</td>
<td>+</td>
<td>0</td>
<td>1 ($j = s$) or 0 ($j \neq s$)</td>
</tr>
<tr>
<td>Katz metric</td>
<td>$\beta \cdot A(i,j) \cdot x$</td>
<td>+</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Jacobi method</td>
<td>$-\frac{A^j_i}{A^j_j} \cdot x$</td>
<td>+</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>SimRank</td>
<td>$\frac{C \cdot A(i,j)}{[I(a)] [I(b)]} \cdot x$</td>
<td>+</td>
<td>$</td>
<td>I(a) \cap I(b)</td>
</tr>
<tr>
<td>Rooted PageRank</td>
<td>$A(j,i) \cdot x$</td>
<td>+</td>
<td>0</td>
<td>1 ($j = s$) or 0 ($j \neq s$)</td>
</tr>
</tbody>
</table>

Table 1. Example Graph Algorithms

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>$c_j$</th>
<th>$g_{(i,j)}(x)$</th>
<th>$\oplus$</th>
<th>$\ominus$</th>
<th>$0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PageRank</td>
<td>$(1-d)$</td>
<td>$d \cdot \frac{x}{\text{out}(j)}$</td>
<td>+</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>PHP</td>
<td>1 ($j=s$) or 0 ($j \neq s$)</td>
<td>$d \cdot w(i,j)$ ($j \neq s$) or 0 ($j=s$)</td>
<td>+</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>Katz</td>
<td>1 ($j=s$) or 0 ($j \neq s$)</td>
<td>$\beta \cdot x$</td>
<td>+</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>Adsorption</td>
<td>$p_j^{inj} \cdot I_j$</td>
<td>$p_j^{cont} \cdot w(i,j) \cdot x$</td>
<td>+</td>
<td>-</td>
<td>0</td>
</tr>
</tbody>
</table>
Dynamic Control Flow

Long Short-Term Memory (LSTMs): Make Your Memory Cells Differentiable
[Hochreiter & Schmidhuber, 1997]
Image sources

Graphs source: http://www.cise.ufl.edu/research/sparse/matrices/

CNN source: http://parse.ele.tue.nl/education/cluster2

Brain img source: https://www.docuvo.com/whatwedo.html


GoogLeNet source: Christian Szegedy et al, "Going Deeper with Convolutions", CVPR2015

Notepad source: https://clipartfest.com/categories/view/bf3ad8f22b3d818eee77c01504f976009ecefebf/clipart-notepad.html


Blue waters source: http://www.cray.com/enabling-scientific-breakthroughs-petascale
2.3 Related work

1. Single Machine Frameworks
   a. Theano, Caffe, Torch

2. Batch Dataflow Frameworks
   a. MapReduce, Spark

3. Parameter Server Architectures
   a. DistBelief, Project Adam, MXNet