TensorFlow: A system for large-scale machine Learning

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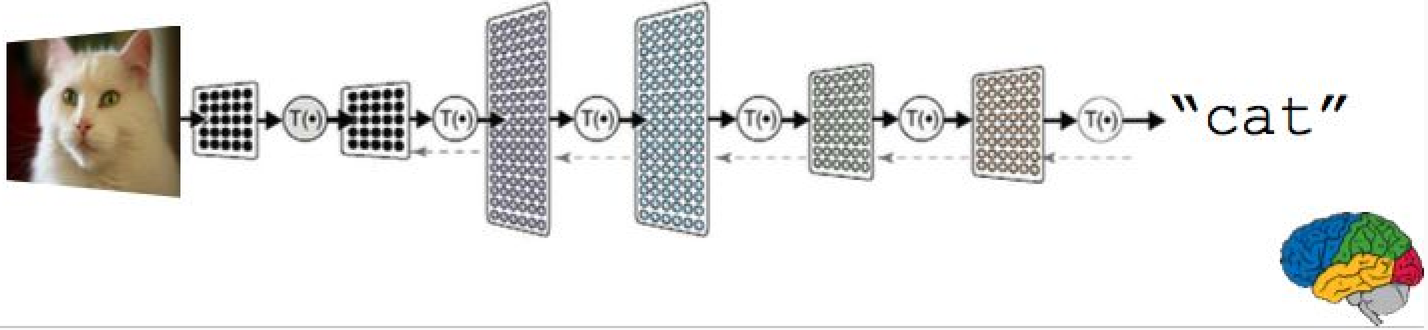
10/30/2017

Background

- A high-level overview of Deep Learning
- Deep Learning Frameworks
- Previous system: DistBelief
- Related work
- Design principles

What is Deep Learning

- A powerful class of machine learning model
- Modern reincarnation of artificial neural networks
- Collection of simple, trainable mathematical functions



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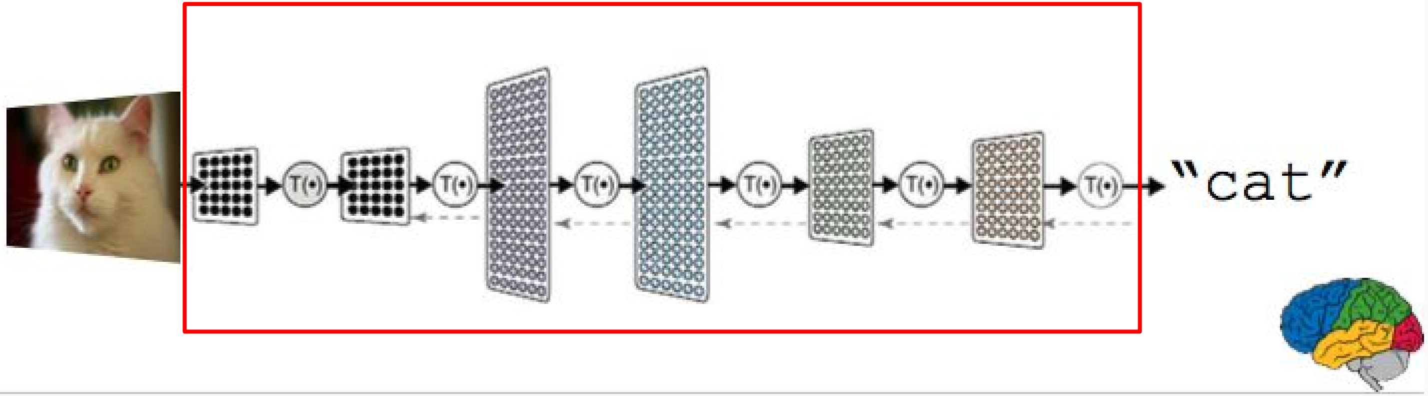

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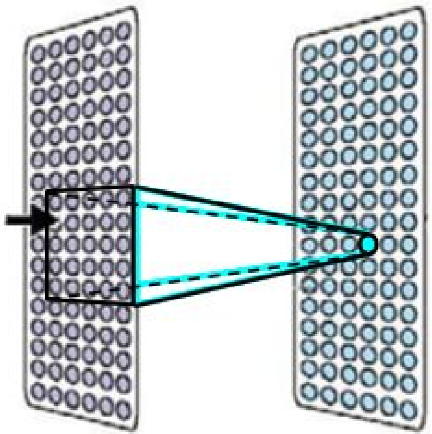
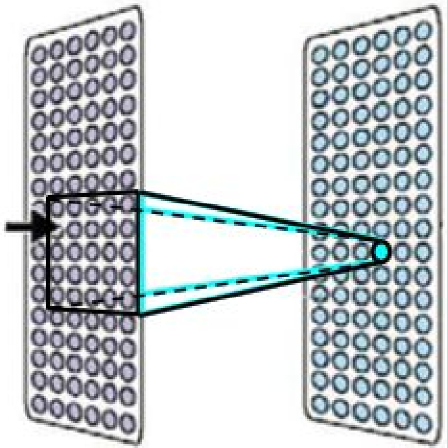


Commonalities with real brains:

- Each neuron is connected to a small subset of other neurons.
- Based on what it sees, it decides what it wants to say.
- Neurons learn to cooperate to accomplish the task.

Research at Google

What is Deep Learning



Each neuron implements a relatively simple mathematical function.

$$y = g(\vec{w} \cdot \vec{x} + b)$$

But the composition of 10^6 - 10^9 such functions is surprisingly powerful.

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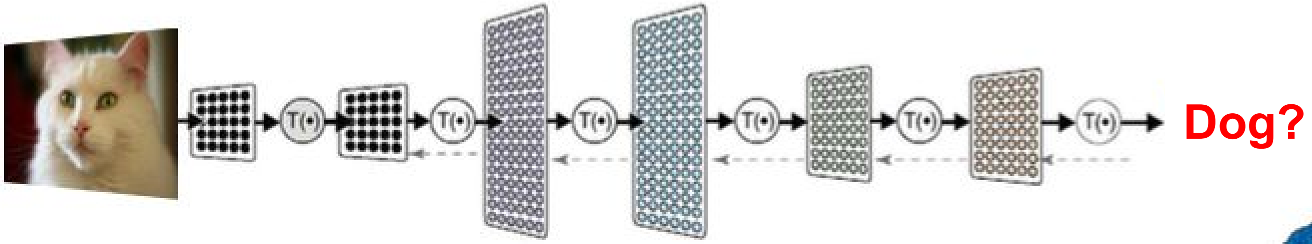

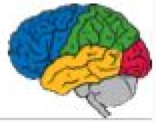

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Back propagation

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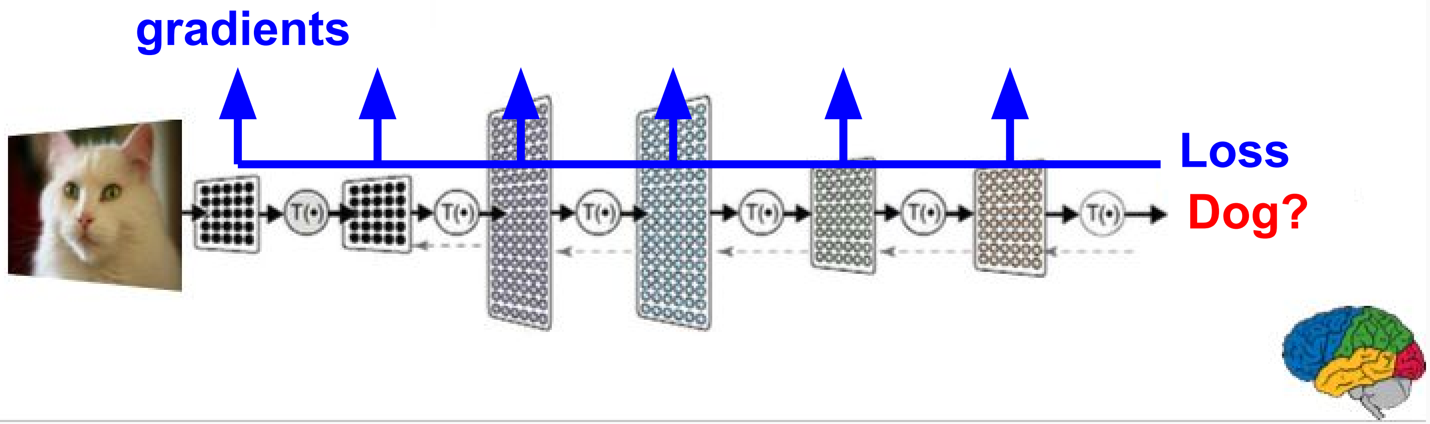

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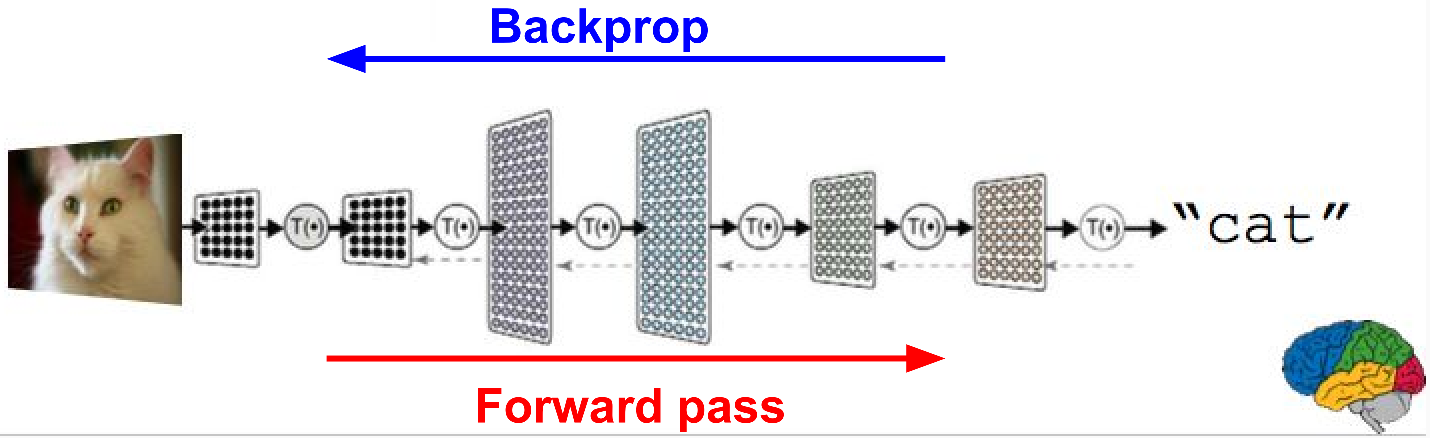

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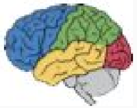
Large datasets

Important Property of Neural Networks

Results get better with

more data +
bigger models +
more computation

(Better algorithms, new insights and improved techniques always help, too!)



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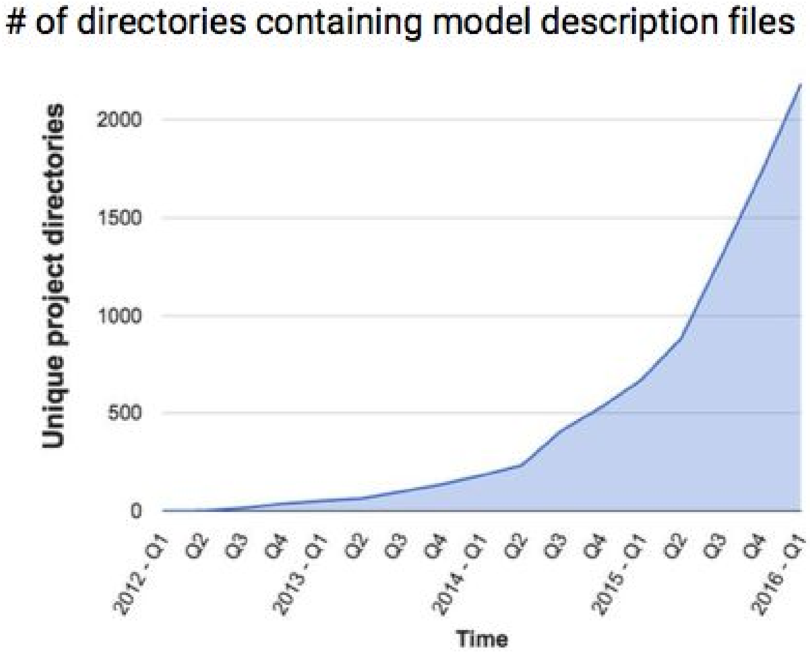
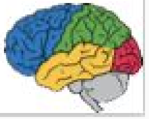
Growing Use of DL at Google



Across many products/areas:

Android
Apps
drug discovery
Gmail
Image understanding
Maps
Natural language understanding
Photos
Robotics research
Speech
Translation
YouTube
… many others …



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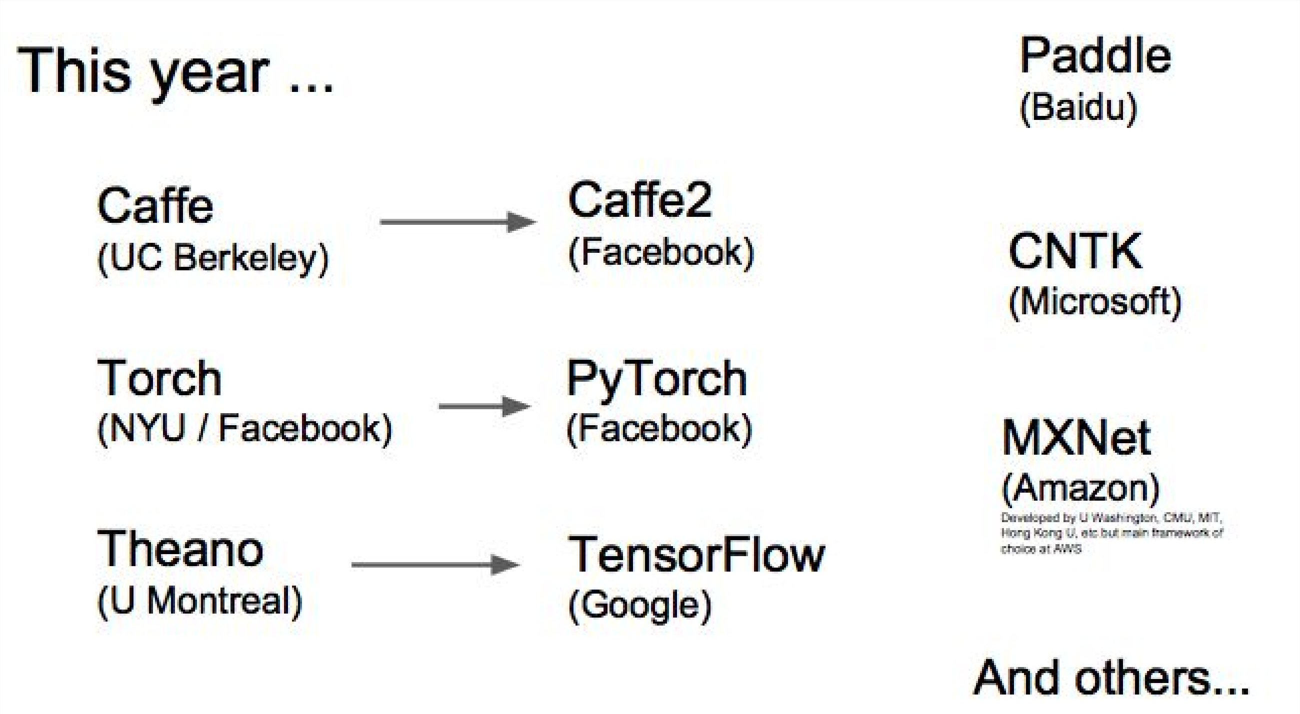
DL frameworks



Adapted from Fei-Fei Li "CNN for Visual Recognition"

Comparison

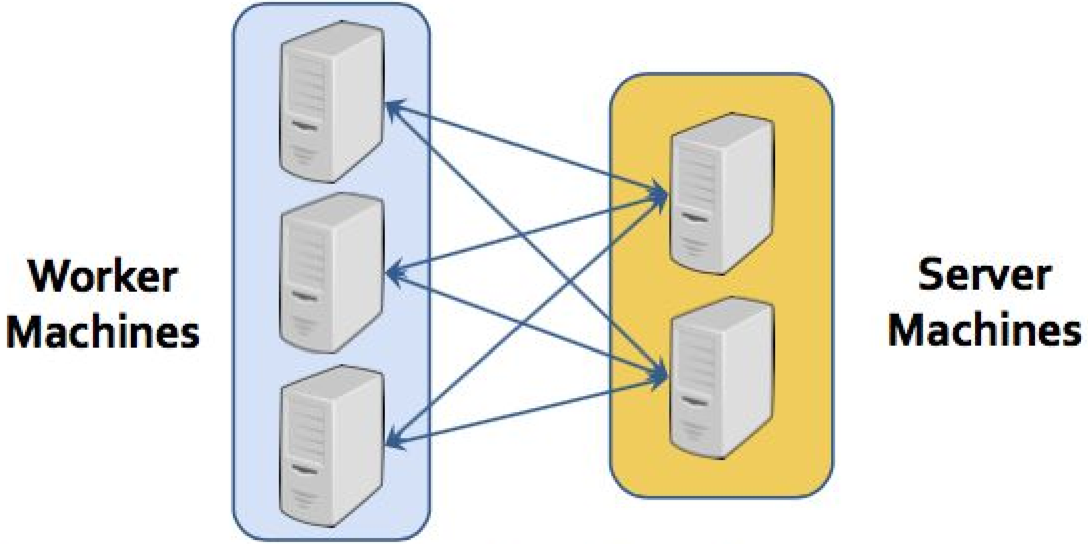
	Static Graph	Dynamic Graph	Device API	Pretrained Model	Ease of use for researchers
Tensorflow	V	V [1]	V	- (high-level API)	V
Theano	V			- (high-level API)	V
PyTorch		V	V	V	V
Caffe2	V		V (not supported in Caffe)	V	V
MXNet	V		V		

[1] Looks, Moshe, et al. "Deep learning with dynamic computation graphs." *arXiv preprint arXiv:1702.02181* (2017).

Previous system: DistBelief

- Parameter Server architecture
- DAG structure and knowledge of the layers’ semantics
- Most parameters only require weak consistency
  - Worker processes can compute updates independently
- Python-based interface
  - Simple requirements are fine

Parameter Sever (PS)



➢ Model parameters are stored on PS machines and accessed via key-value interface (distributed shared memory)

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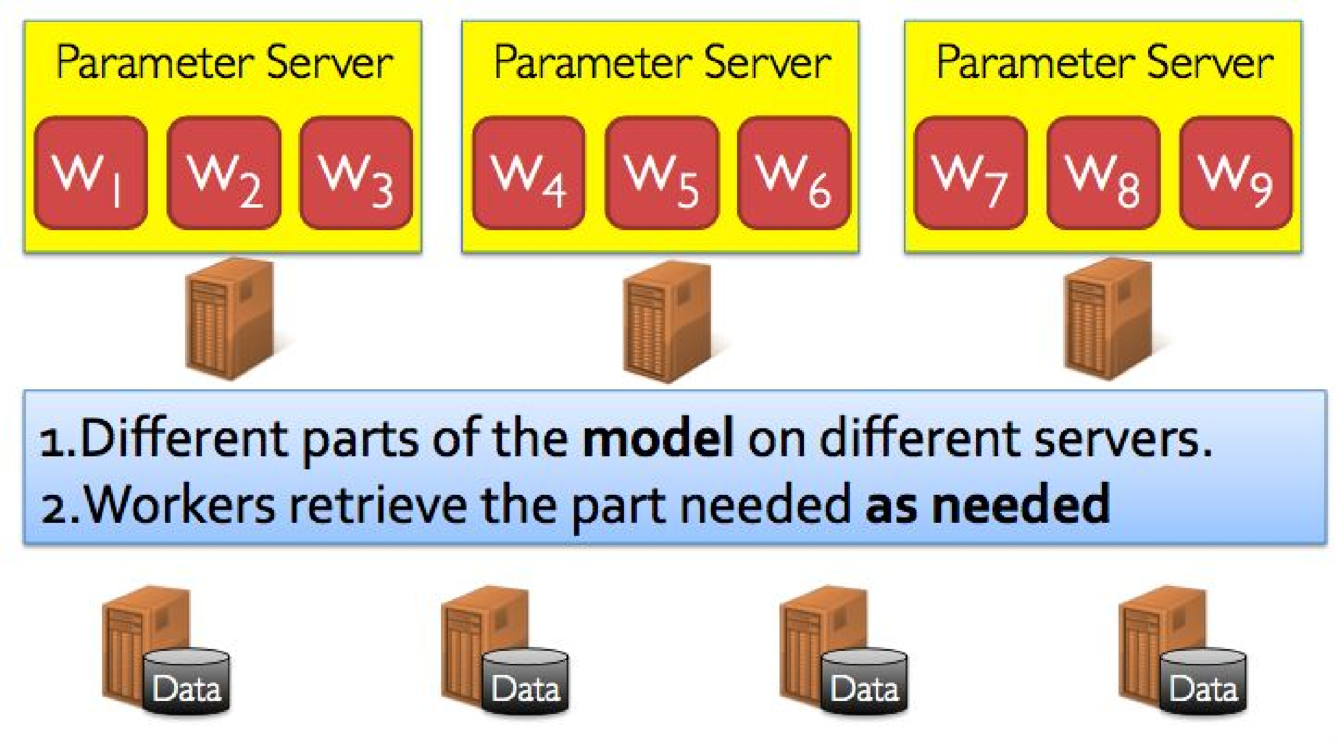
Parameter Sever (PS)



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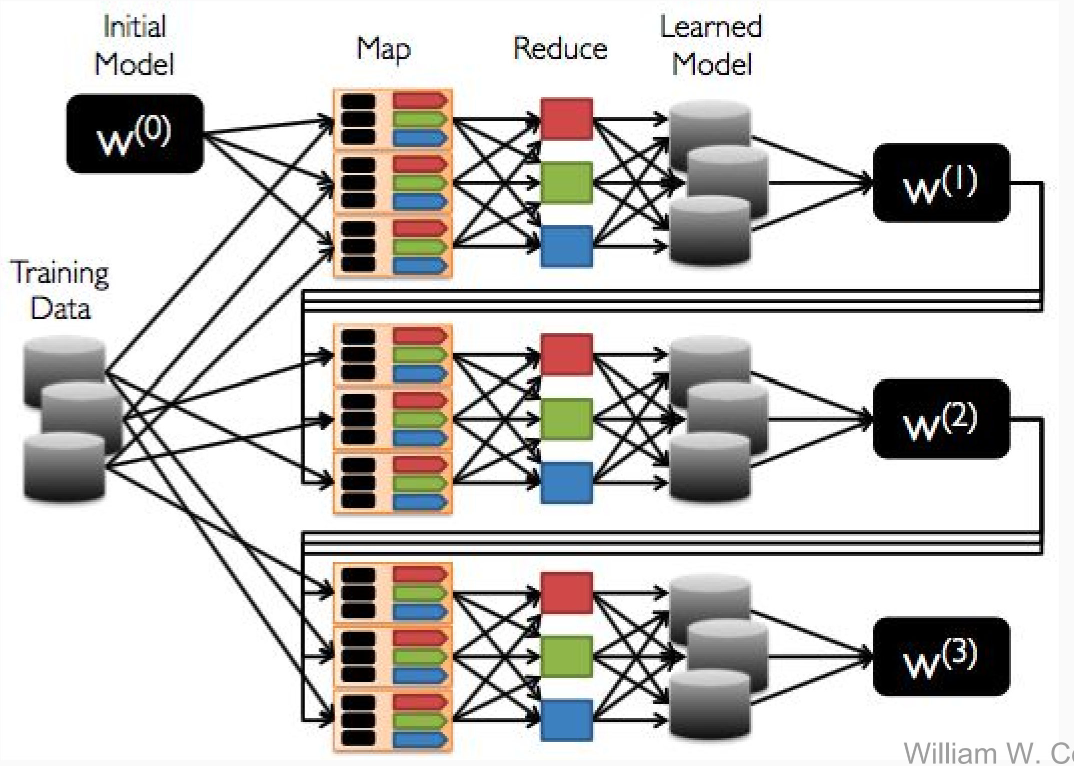
PS vs Batch Processing Systems (MR)



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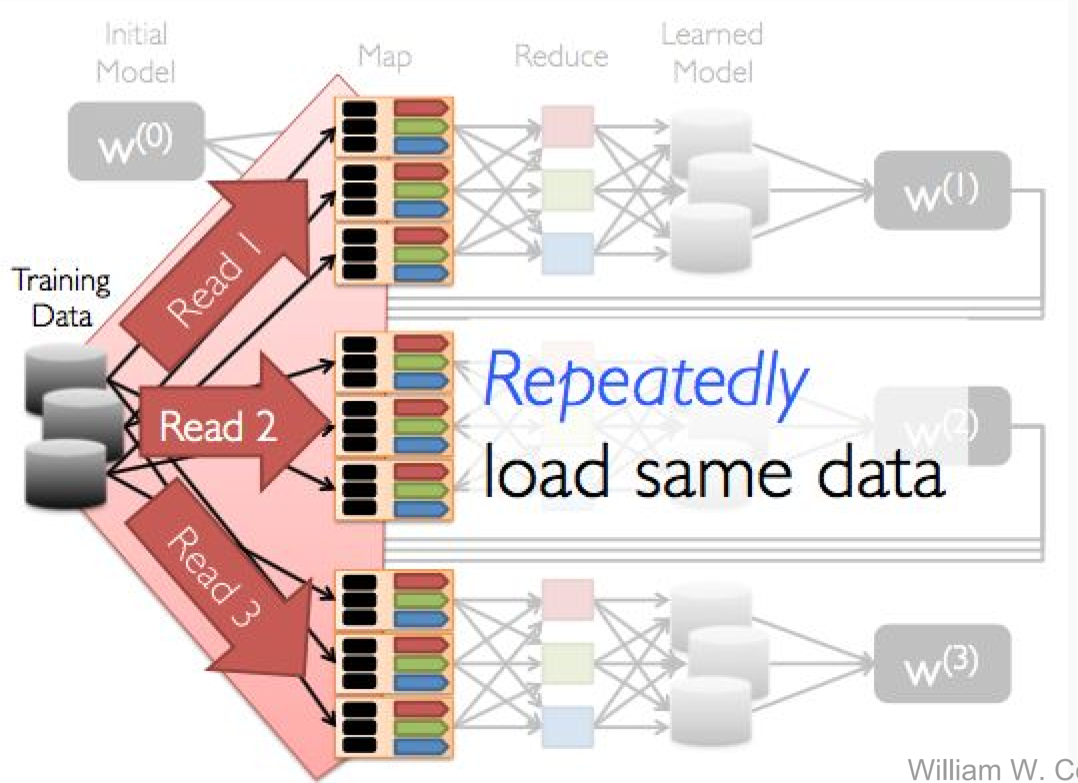
PS vs Batch Dataflow Systems



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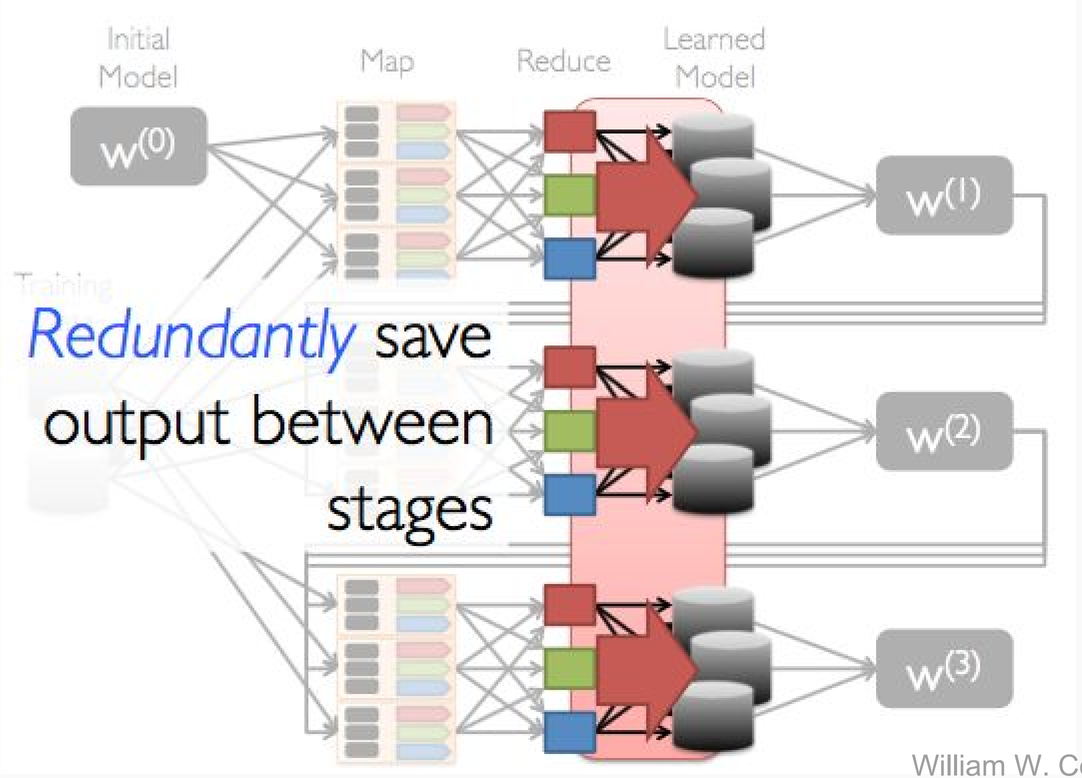

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Problems of DistBelief

- Layers are C++ classes
  - Barrier for machine learning researchers
- Parameter Server
  - get() and put() interface for the PS is not ideal for all optimization methods
  - Sometimes more efficient to compute params on PS
- Workers follow a fixed execution pattern
  - RNN
  - Adversarial networks
  - Reinforcement learning
- Difficult to scale down to other environments

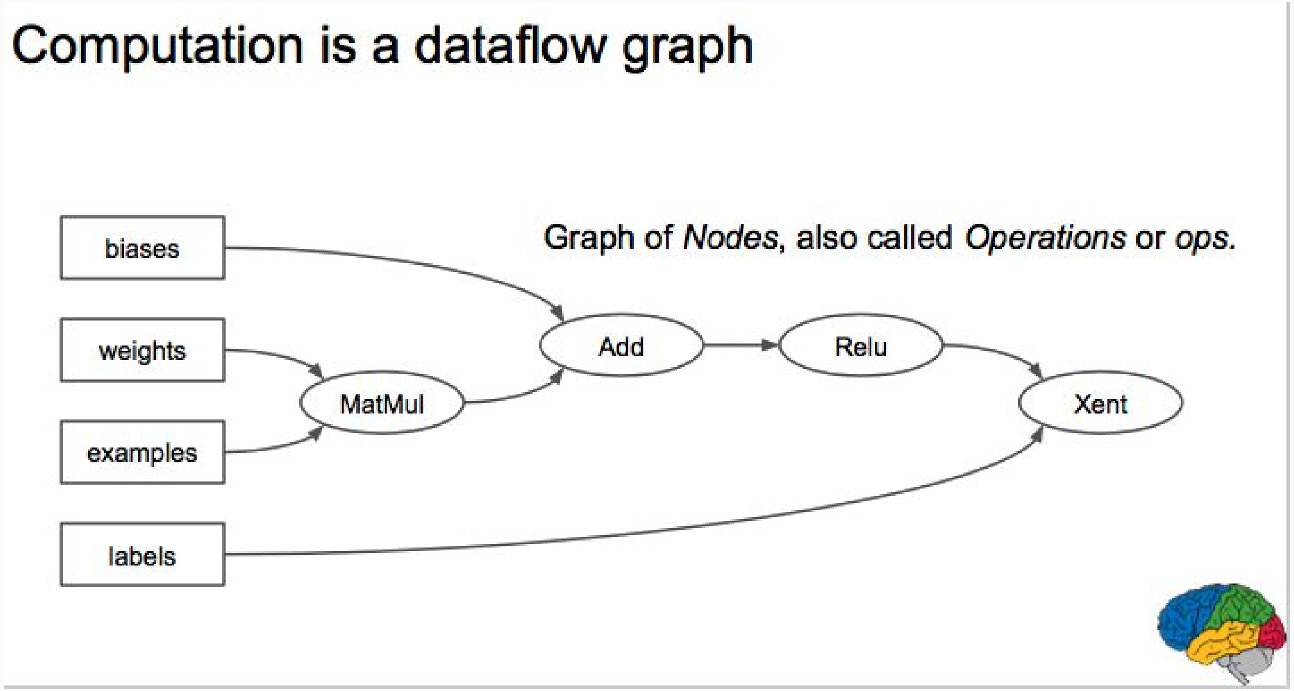
Design principles of Tensorflow

- More flexible than DistBelief, while retaining its ability

1. Individual mathematical operators in dataflow graphs
2. Deferred execution
3. Common abstraction for heterogeneous accelerators

Dataflow Graphs

Simple



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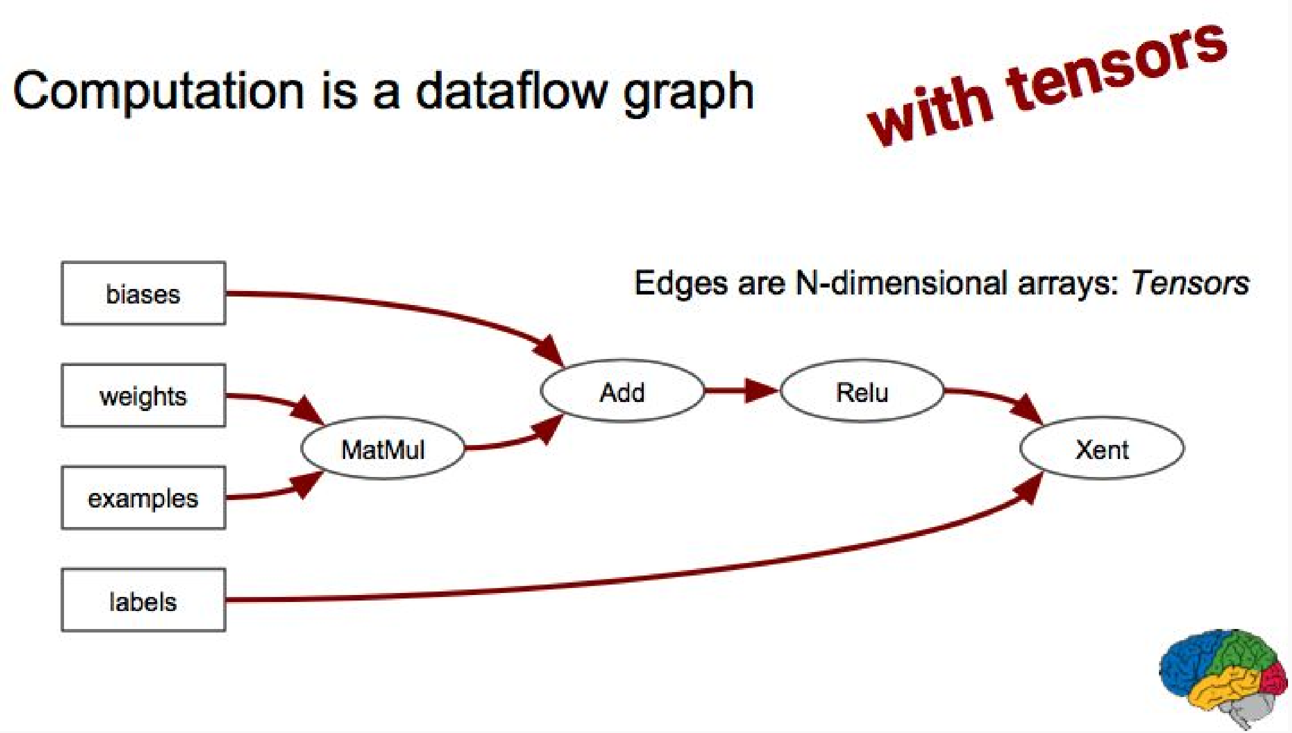
Dataflow Graphs



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Deferred execution

Static graph

First **define** computational graph

```
# 1. Construct a graph representing the model.
x = tf.placeholder(tf.float32, [BATCH_SIZE, 784])   # Placeholder for input.
y = tf.placeholder(tf.float32, [BATCH_SIZE, 10])    # Placeholder for labels.

W_1 = tf.Variable(tf.random_uniform([784, 100]))    # 784x100 weight matrix.
b_1 = tf.Variable(tf.zeros([100]))                  # 100-element bias vector.
layer_1 = tf.nn.relu(tf.matmul(x, W_1) + b_2)       # Output of hidden layer.

W_2 = tf.Variable(tf.random_uniform([100, 10]))     # 100x10 weight matrix.
b_2 = tf.Variable(tf.zeros([10]))                   # 10-element bias vector.
layer_2 = tf.matmul(layer_1, W_2) + b_2             # Output of linear layer.

# 2. Add nodes that represent the optimization algorithm.
loss = tf.nn.softmax_cross_entropy_with_logits(layer_2, y)
train_op = tf.train.AdagradOptimizer(0.01).minimize(loss)
```

Run the graph many times

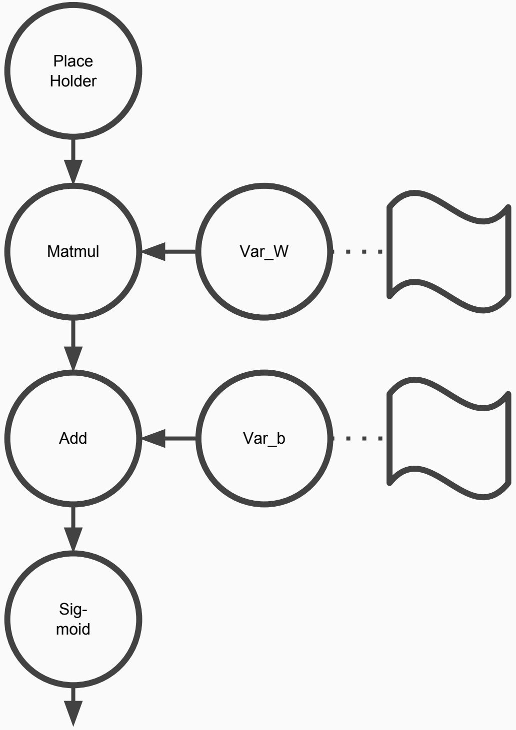
```
# 3. Execute the graph on batches of input data.
with tf.Session() as sess:                          # Connect to the TF runtime.
  sess.run(tf.initialize_all_variables())           # Randomly initialize weights.
  for step in range(NUM_STEPS):                     # Train iteratively for NUM_STEPS.
    x_data, y_data = ...                            # Load one batch of input data.
    sess.run(train_op, {x: x_data, y: y_data})      # Perform one training step.
```

Common abstraction for devices

- At a minimum, a device must implement methods for
  - Issuing a kernel for execution
  - Allocating memory for inputs and outputs
  - Transferring buffers to and from host memory
- Target CPU, GPU or TPU (Tensor Processing Unit) on same program
- Use tensors as a common interchange format

Execution Model

- Datagraph
  - Vertex: computation
  - Edges: dataflow in to / out from vertices
- Tensors
  - N-dimensional arrays of primitive types
  - Alternative sparse coding for sparse tensor
- Operations
  - Inputs: tensors; outputs: tensors
  - **Stateful Operation (w/ mutable table)**
    - **Variable**
    - **Queue (blocking)**



Execution Model (cont'd)

- Partial and Concurrent Execution
  - Multiple subgraphs can interact via stateful operations
  - Mutable tables: blocked buffer provides back-pressure; synchronize when necessary
  - Many ML algorithm allows weak consistency

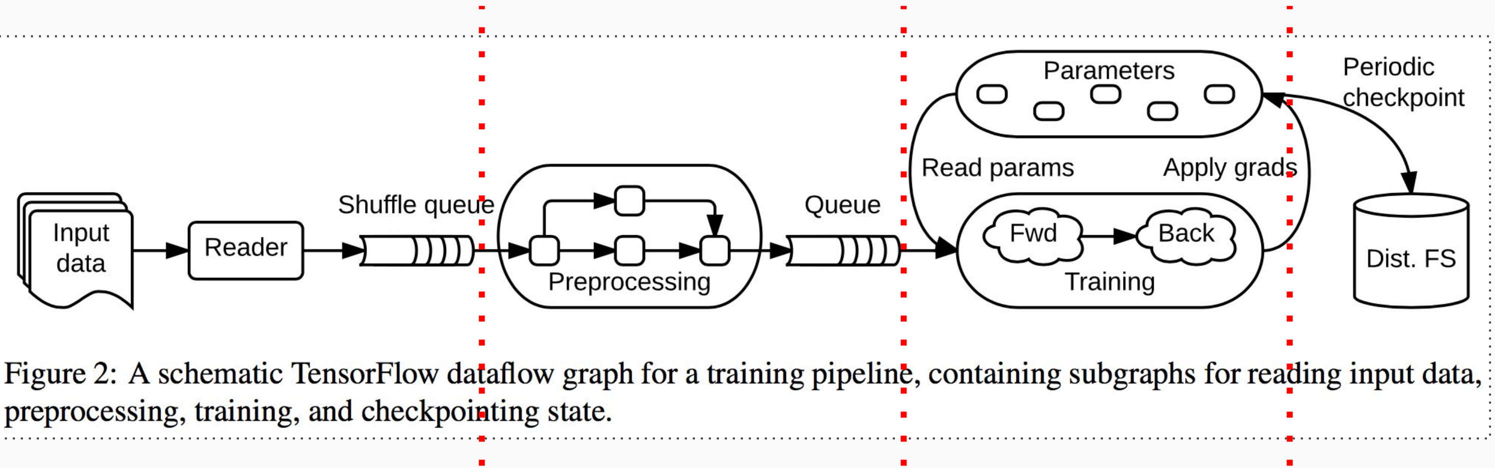


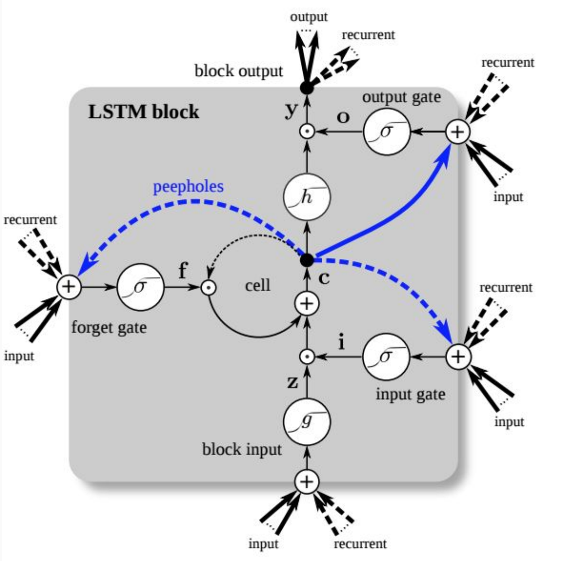
Figure 2: A schematic TensorFlow dataflow graph for a training pipeline, containing subgraphs for reading input data, preprocessing, training, and checkpointing state.

Execution Model (cont'd)

- Distributed Execution
  - Each operation of a task resides on a **Device**
  - Specified kernels to operation are implemented
  - Per-device subgraph, where a **Session** is responsible for its manipulation
  - Implicit / explicit constraints
    - **Colocation operation**
    - **Device preferences**
  - Devices communicate with **Send** and **Recv** operations

Execution Model (cont'd)

- Dynamic control flow
  - Cases such as RNN requires dynamic control
  - Conditional & Iterative programming
    - **Switch**, demultiplexer
    - **Merge**, multiplexer
    - **Dead** value for either of two cases and merges branches when Merge is met



A simple figure for LSTM (long short term memory cell)

Extensibility Case Studies

- Differentiation and Optimization
  - Given FP, update parameters via BFS (BP) automatically
  - Conditional differentiation by adding vertices
  - Easy to extend optimization algorithm such as Momentum, RMSProp, Adam, etc.

Extensibility Case Studies (cont’d)

- Very Large Model
  - Distributed representation
  - Example: **word embedding**

$$\boxed{X_{n,b}^{T} W_{n,d}} = M_{b,d}$$

Sparse, d<<n

  - Implemented **Sparse embedding** layer
    - Gather
    - Part
    - Stitch

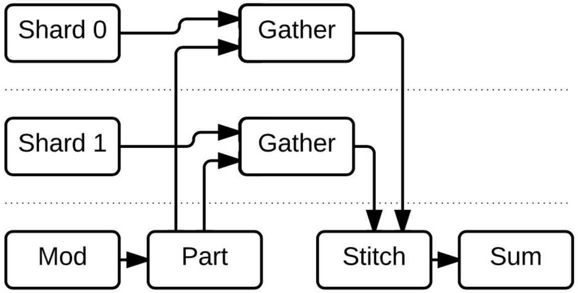


Figure 4: Schematic dataflow for an embedding layer (§4.2) with a two-way sharded embedding matrix.

Extensibility Case Studies (cont'd)

- Fault Tolerance
  - Less likely to require backup for individual operations
  - Plus, again, many ML algorithm doesn't require strong consistency
  - **Checkpoint states periodically**
    - Save (one per task) -> Restore -> Assign
    - Customization
    - Synchronization / Asynchronization

** Often used case: Transfer Learning, eg. VGG16, Resnet50 in CNN

Extensibility Case Studies (cont'd)

- Synchronous Replica Coordination
  - Async SGD allows updates with stale parameters
  - Sync SGD might be more efficient given current GPU utilization and corresponding scale
  - Blocking queue is used to synchronize
  - **Backup Workers** in replacement of stragglers

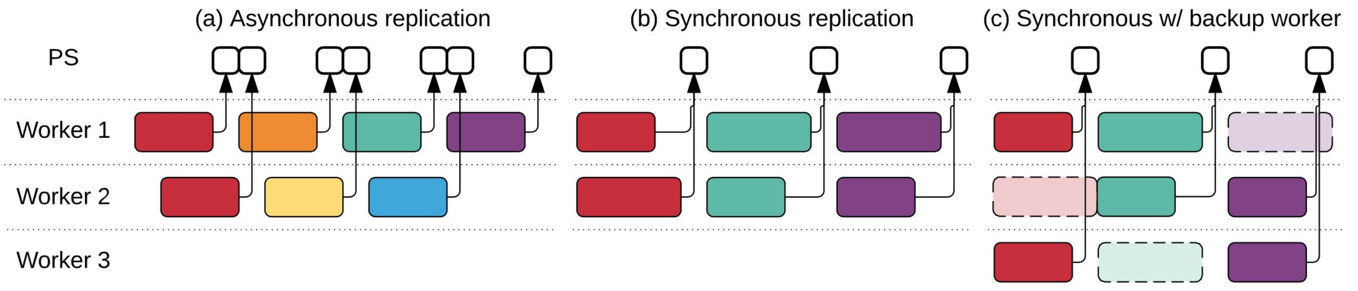


Figure 5: Three synchronization schemes for parallel SGD. Each color represents a different starting parameter value; a white square is a parameter update. In (c), a dashed rectangle represents a backup worker whose result is discarded.

Implementation

- C++
- OS: Works for Linux, Mac OSX, Windows, Android
- GPU: NVIDIA's KEPLER, MAXWELL ,PASCAL

Component

- Distributed master
  - Pruning and partitioning
  - Compiler level optimization
  - Cache and reuse
- Dataflow executor
  - Handles requests from the master
  - Dispatch kernels to local devices

Other optimization

- cuDNN
- Quantization
- gRPC over TCP
- RDMA over converged ethernet.
- Fused kernel: ReLU

Evaluation - single machine performance

Library	Training step time (ms)			
	AlexNet	Overfeat	OxfordNet	GoogleNet
Caffe [38]	324	823	1068	1935
Neon [58]	87	**211**	**320**	**270**
Torch [17]	**81**	268	529	470
TensorFlow	**81**	279	540	445

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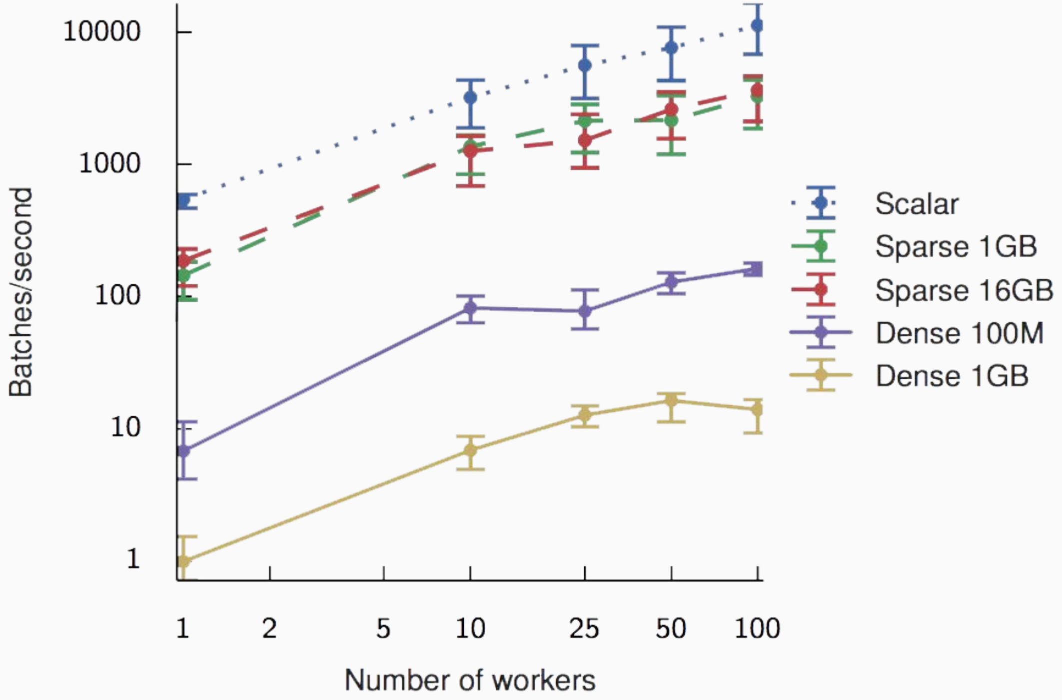
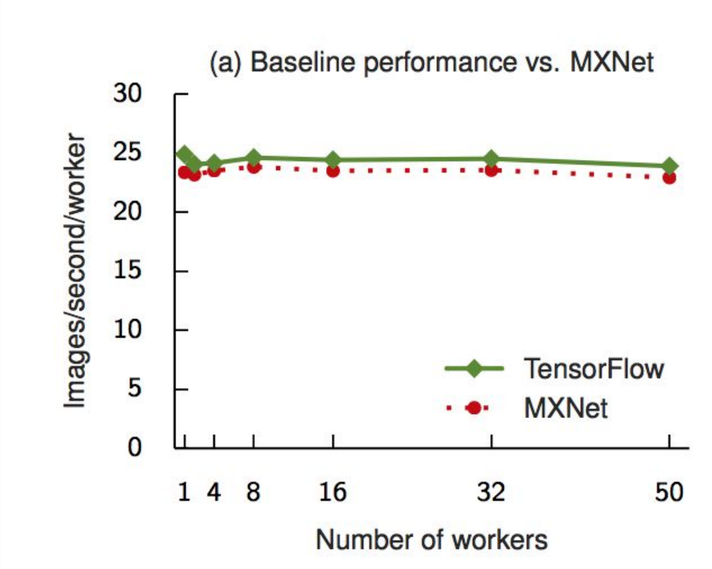
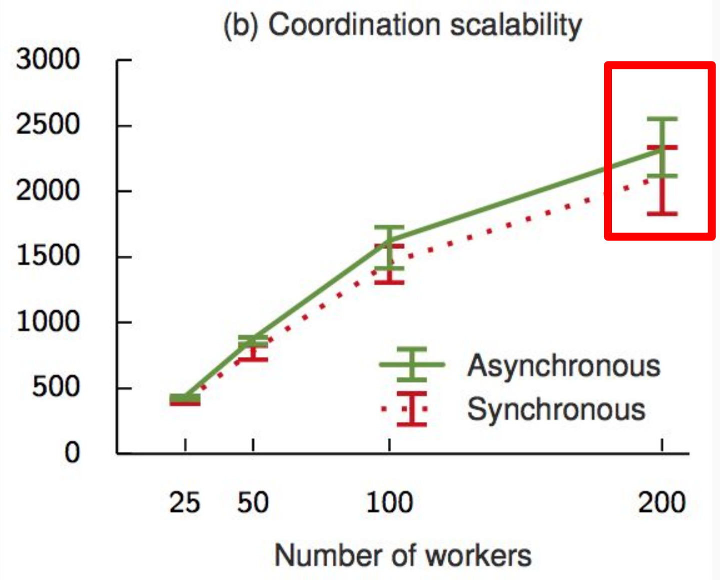
Evaluation - Replica



Evaluation - image classification

- MXNet v.s. Tensorflow
- Inception-v3 model





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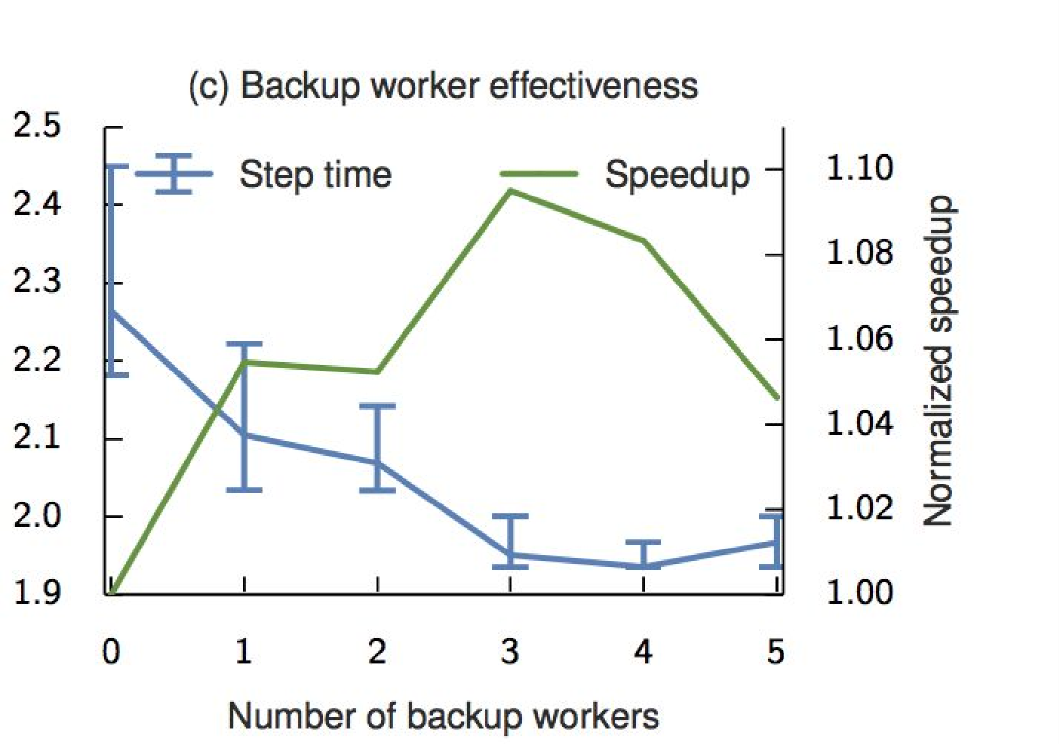
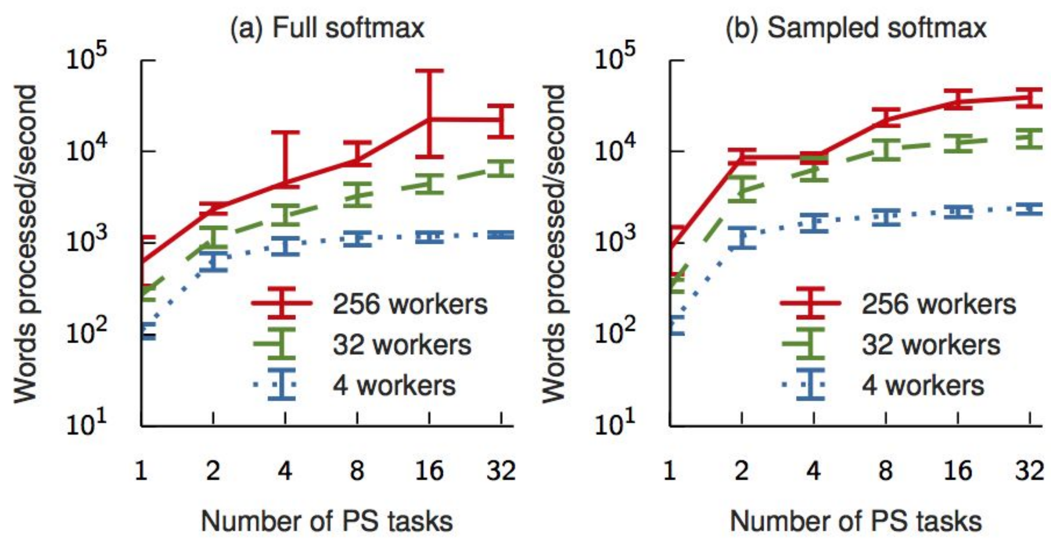


Evaluation - Language model



Conclusion

- Incorporate parameter server
- Scalable
- Heterogeneous system
- Future work