TensorFlow: A System for Large-Scale Machine Learning

Background: Training deep neural networks

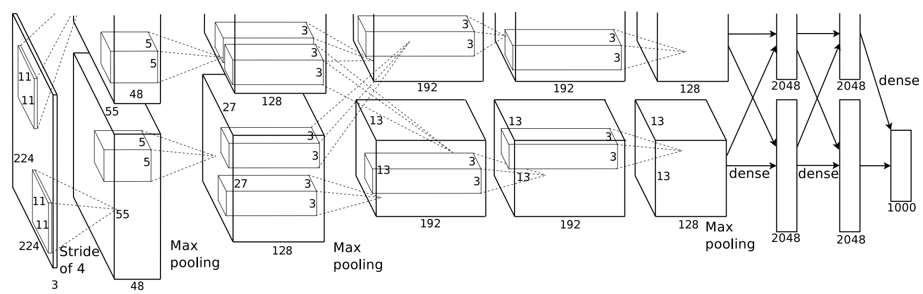
Limited by GPU memory using Nvidia GTX 580 (3GB RAM)

60M Parameters ~ **240 MB**

Need to cache activation maps for backpropagation

- Batch size = 128
- 128 * (227*227*3 + 55*55*96*2 + 96*27*27 + 256*27*27*2 + 256*13*13 + 13*13*384 + 384*13*13 + 256*13*13 + 4096 + 4096 + 1000) Parameters ~ **718MB**
- That assuming no overhead and single precision values

Tuned splitting across GPUS to balance communication and computation



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Too much manual effort!

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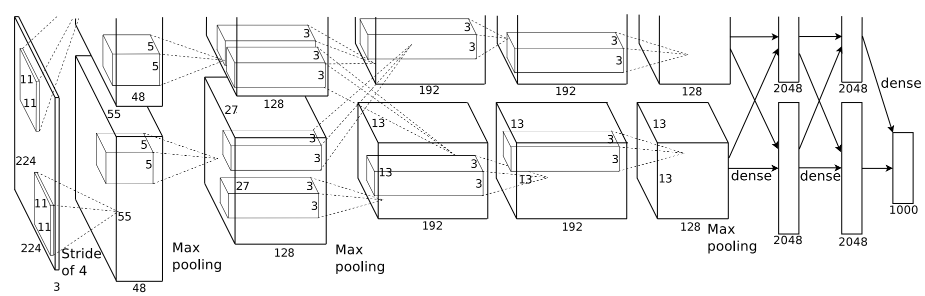
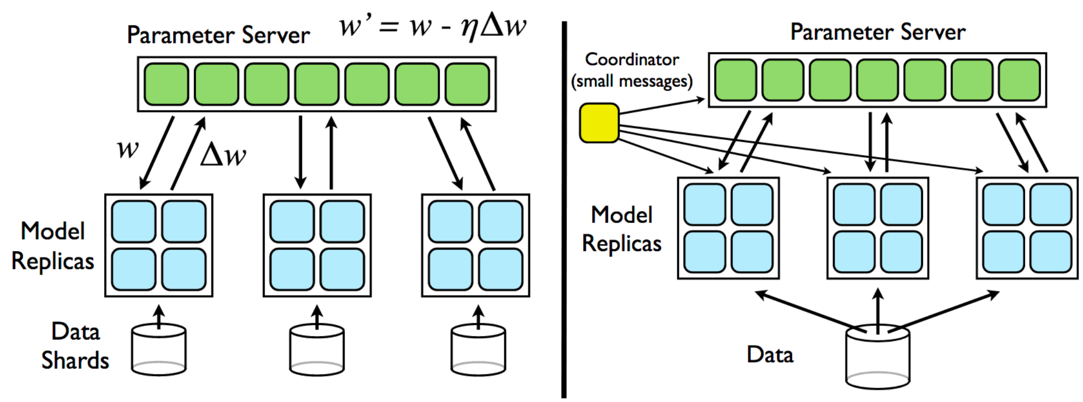


Background: Training deep neural networks

Trend towards distributed training for large-scale models

Parameter server: A shared key-value storage abstraction for distributed training

E.g., DistBelief, Project Adam



Background: Training deep neural networks

Trend towards distributed training for large-scale models

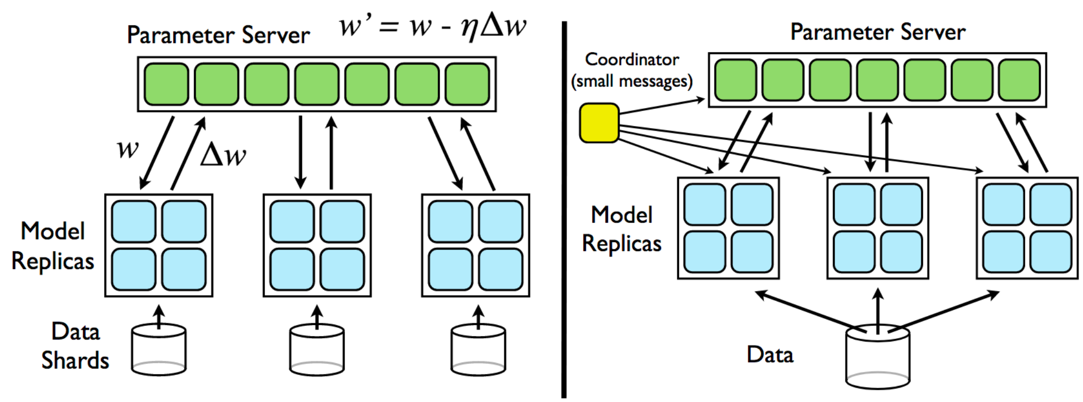
Hides details of distribution

Parameter server: A shared key-value storage abstraction for distributed training

But still difficult to reason about end-to-end structure

Inflexible update mechanisms and state management

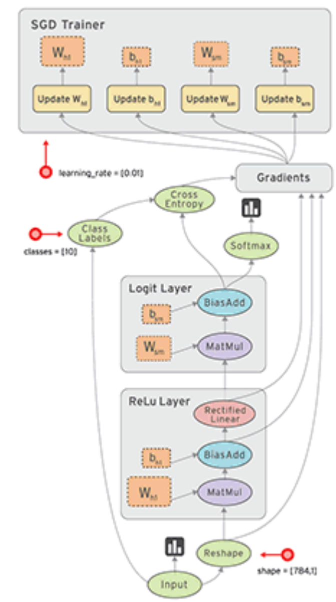
E.g., DistBelief, Project Adam



TensorFlow

Flexible dataflow-based programming model for machine learning

Dataflow captures natural structure of computation in both training and inference



TensorFlow

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# 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.
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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)

# 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.
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What is the problem being solved?

Lack of a flexible programming model to build machine learning models

Prior approaches restricted innovation due to their inflexibility

E.g., parameter updates in parameter server-based approaches

Dataflow-based programming model

Computation structured as a dataflow graph

Nodes can be stateful

Captures accumulated state as part of the training process

E.g., parameter values

Graph elements

Tensors flow across edges between nodes

Operations are expressions over tensors (e.g., constants, matrix multiplication, add)

Variables can accumulate state

Queues provide explicit advanced coordination

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What are the metrics of success?

Variety of specialized extensions built over the framework

"User level" code

Acceptable performance with respect to state-of-the-art

Extensibility

Optimization algorithms

Momentum, AdaGrad, AdaDelta, Adam

E.g., parameter updates in momentum are based on accumulated state over multiple iterations

Difficult to implement extensible optimization algorithms in parameter servers

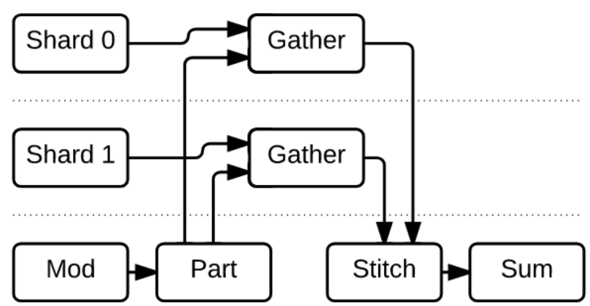
Extensibility

Sharding very large models

E.g., Sparse embedding layers

Shard embedding layer across parameter server tasks

Encode incoming indices as tensors, and ship to the appropriate shard

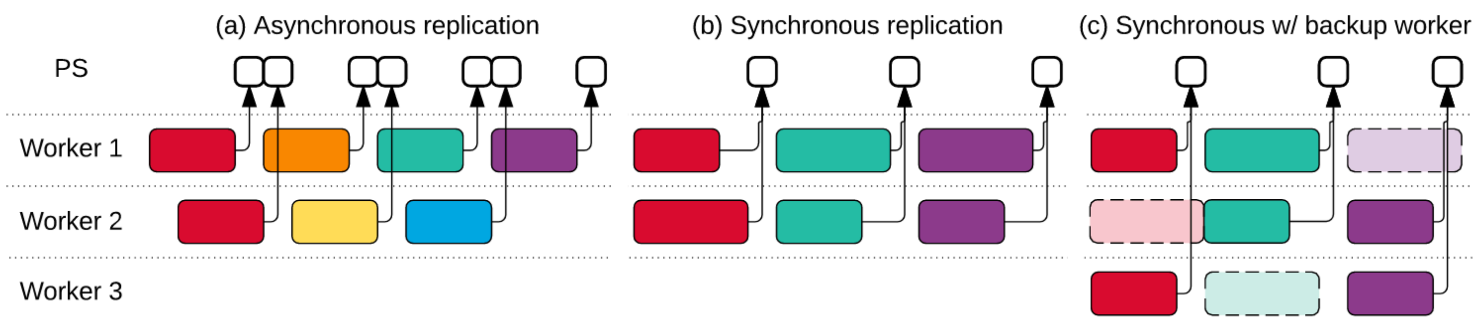


Extensibility

Use queues to coordinate the execution of workers

Synchronous replication

Straggler mitigation with backup workers



Competitive training times on single node

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

Key results

Extensibility matters!

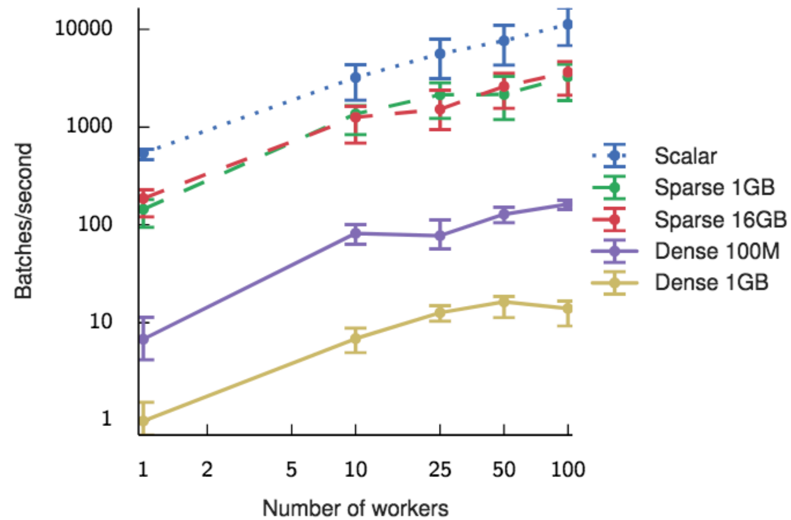


Figure 7: Baseline throughput for synchronous replication with a null model. Sparse accesses enable TensorFlow to handle larger models, such as embedding matrices (§4.2).

Key results

Extensibility matters!

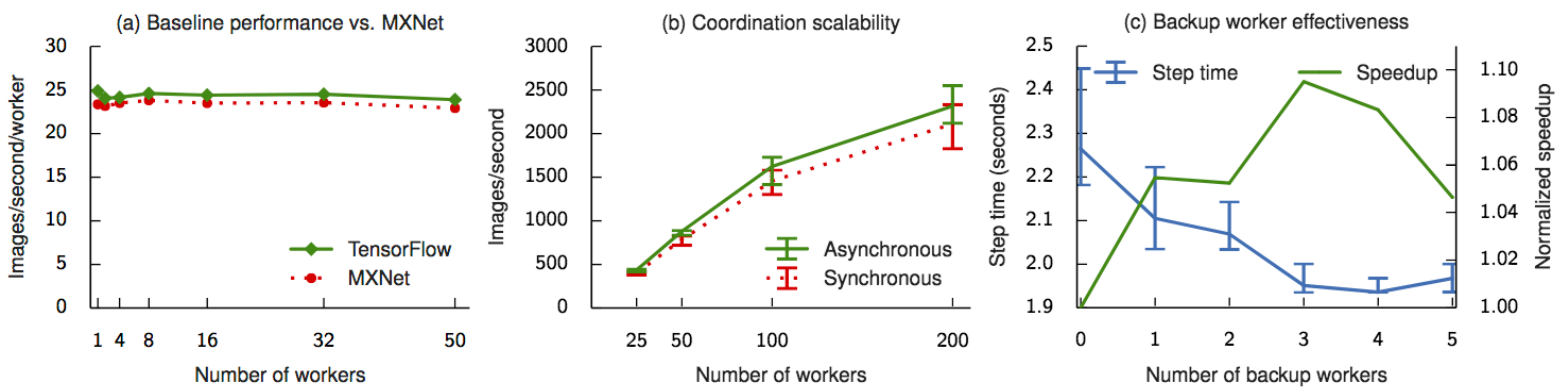


Figure 8: Results of the performance evaluation for Inception-v3 training (§6.3). (a) TensorFlow achieves slightly better throughput than MXNet for asynchronous training. (b) Asynchronous and synchronous training throughput increases with up to 200 workers. (c) Adding backup workers to a 50-worker training job can reduce the overall step time, and improve performance even when normalized for resource consumption.

Limitations and scope for improvement

TF's high-level programming model is tightly coupled with its execution model

Translate TF programs to more efficient executables using compilation to hide translation

TF dataflow graphs are static

Key runtime decisions, such as number of PS shards, seem to require manual specification

Can these be automatically deduced based on workload characteristics?