TensorFlow: A System for Large-Scale Machine Learning

Abadi et al. 2015

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CS598APK, Fall 2018

What is Tensorflow?

- An open source Machine Learning system operating at large scale and in heterogeneous environments.
- Uses dataflow graphs to represent:
  - Computations
  - Shared state
- Unifies computation and state management.
  - Provides flexibility to support experimentation into new ML models and system-level optimizations.
- C++ backend.
- C++ and Python frontend.
- Focused on training and inference of neural networks.

Neural Network

- A directed graph of *layers.*
- A layer can be different composition of mathematical operators.
    - Fully connected layer – Ax + b
    - Non-linearity – Element-wise non-linear function such as sigmoid, ReLu etc.
    - Pooling – Max, Min, Avg etc.
- Typically terminates with a loss function.
    - Quantifies the difference between ground truth and predicted value.
- Parameters of different layers are *learnt* during training.
    - A learning algorithm updates the parameters to minimize the loss.
- Learnt parameters are used to perform *inference* from unknown data points.

A brief history: DistBelief (2011)

- Predecessor to Tensorflow.
- Uses *parameter server architecture.*
- A stateless *worker* process – performs computations.
- A stateful *parameter server* – maintains current version of model parameters.
- Worker process compute gradient independently and write back *delta* updates to each parameter server which combines the updates with its current state.

Limitations of DistBelief

- Pre-defined layers in C++ and Python based scripting interface.
    - Difficult to experiment with new layer architectures in *less familiar* C++ language.
- Experimenting with new optimization methods apart from vanilla SGD required modifying the parameter server implementation.
- Execution pattern of DistBelief fails for RNNs (contains loops), Adversarial Networks, Expectation Maximization and other traditional ML algorithms.

Design Principles

- Dataflow based programming abstraction.
- Represents individual mathematical operators as nodes.
  - Easier to define new layers as a combination of these nodes.
  - Eg: Matrix Multiplication, convolution etc.
- Deferred execution in two phases:
  - Define the program as a dataflow graph with placeholders for input and states.
  - Optimize the graph according to available devices and defer the execution until entire program is available.
- A common abstraction to support CPUs, GPUs and custom ASICs (TPUs).

Programming Model

- A single dataflow graph to represent all states and computations including parameters, their update rules, mathematical operations, and input processing.
- Supports multiple concurrent executions on overlapping subgraphs of the overall graph.
- Mutable state of individual vertices can be shared between different execution of the graph.
    - makes in place update of large parameters possible so that the updates can be propagated as soon as possible.
    - parameter server with additional flexibility – execute arbitrary dataflow subgraphs on machines with shared model parameters.

Variables

- No inputs.
- Owns a mutable buffer that stores a shared parameter.
- Produces a *reference handle* to read and write the buffer.

```
b = tf.Variable(tf.zeros([100]))                          # 100-d vector, init to zeroes

W = tf.Variable(tf.random_uniform([784,100],-1,1))        # 784x100 matrix w/rnd vals

x = tf.placeholder(name="x")                              # Placeholder for input
```

Tensors

- N-dimensional array or list of int32, float32, double, string etc.
- Represents inputs to and results of the mathematical operators.
- All tensors are dense at the lowest level.

Tensor

```
b = tf.Variable(tf.zeros([100]))                          # 100-d vector, init to zeroes

W = tf.Variable(tf.random_uniform([784,100],-1,1))        # 784x100 matrix w/rnd vals

x = tf.placeholder(name="x")                              # Placeholder for input
```

Operations and Kernels

- Takes >=0 tensors as input and produces >=0 tensors as outputs.
- Polymorphic – supports multiple data types.
- Kernel – An implementation of an operation that can be run on a device.

Operation

```
relu = tf.nn.relu(tf.matmul(W, x) + b)                    # Relu(Wx+b)
```

Sessions

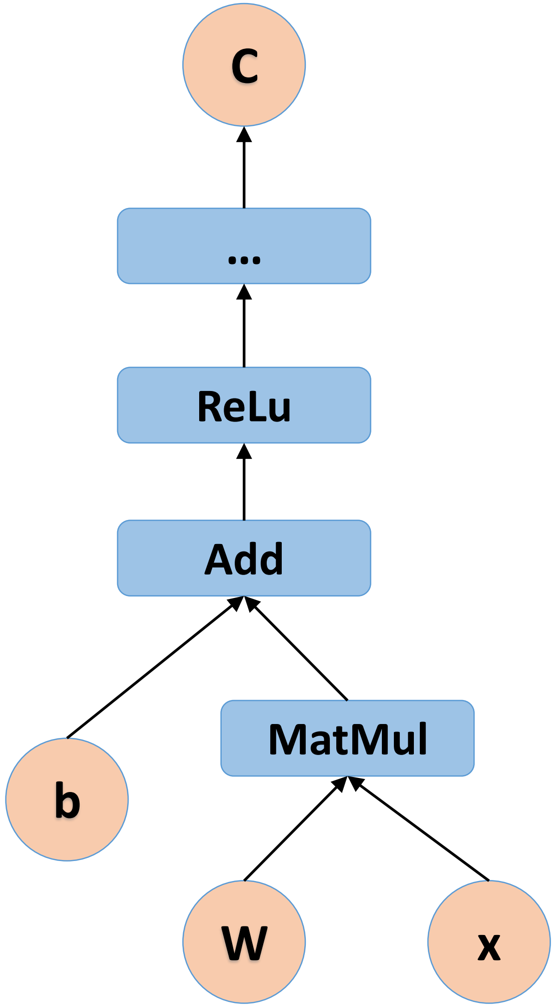
- A way for programs to interact with tensorflow system.
- Session creates an empty graph.
- Nodes and edges can be added with an *Extend* method.
- Output nodes can be computed by the *Run* operation.

```
s = tf.Session()                                    # Creates a session
….
result = s.run(<some graph>)
```

Example

ReLu(Wx + b)

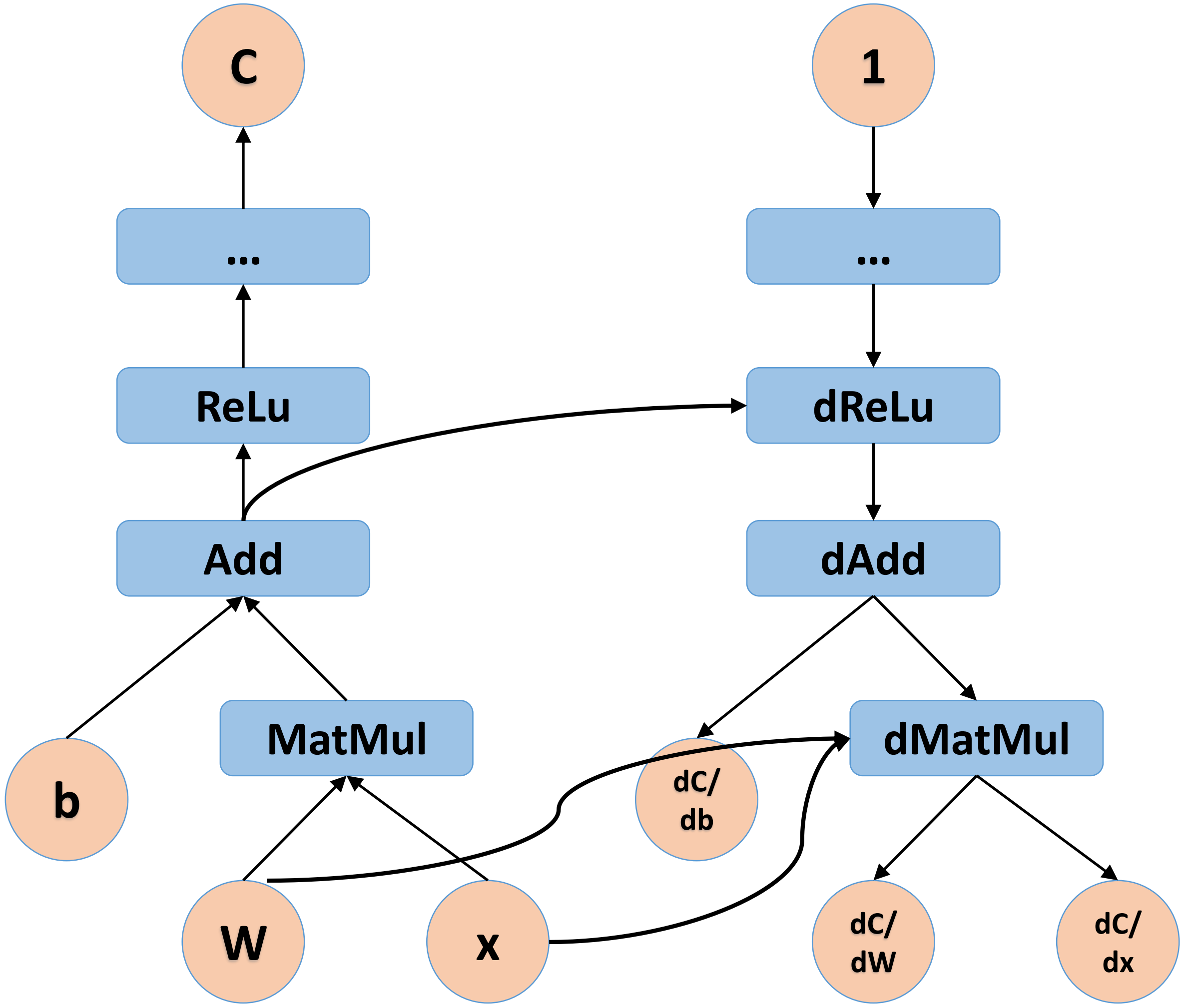
```
import tensorflow as tf

b = tf.Variable(tf.zeros([100]))

W = tf.Variable(tf.random_uniform([784,100],-1,1))
x = tf.placeholder(name="x")
relu = tf.nn.relu(tf.matmul(W, x) + b)
C = [...]

s = tf.Session()
for step in xrange(0, 10):
        input = ...construct 100-D input array ...
        result = s.run(C, feed_dict={x: input})
        print step, result
```



Example continued…

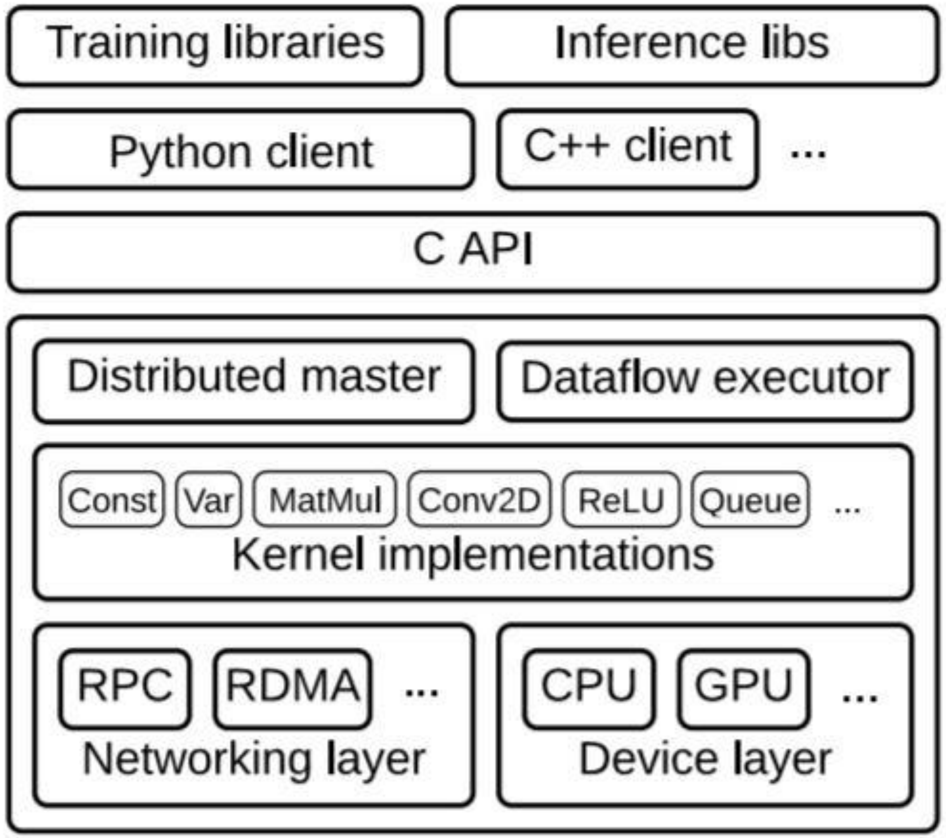
[db, dW, dx] = tf.gradients(C, [b, W, x])

- Built-in support for automatic gradient computation.
- BFS to find all backward paths from target (loss function) to parameter and add a node corresponding to each operation.
- Sum partial gradient along each path.
- Extensive memory usage due to re-use data for gradient computations.
- Active area of improvement.



Implementation

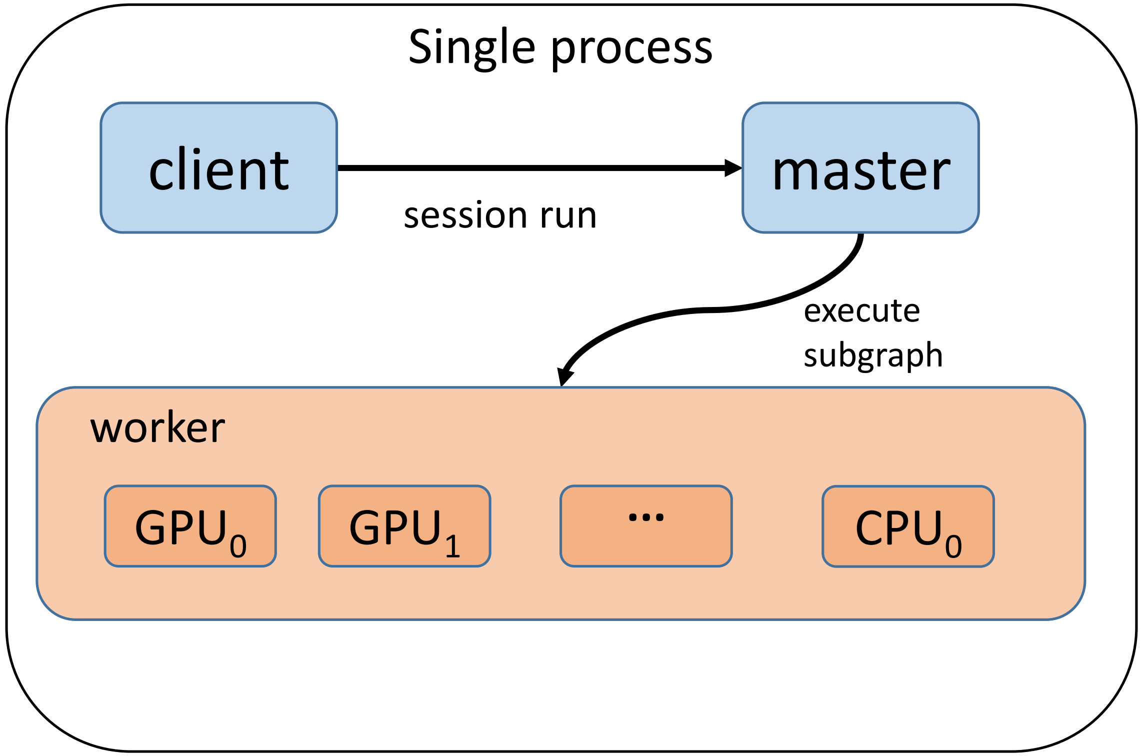
- Runs on windows, linux, Mac OS X, Android and iOS, and x86, ARM CPUs and Kepler, Maxwell and Pascal GPUs.
- C API separates user-level code from core runtime.
- *Distributed master* translates user requests into execution across a set of tasks.
- *Dataflow executor* in each task handles requests from *master* and schedules execution of kernels to local devices.



Layered tensorflow architecture

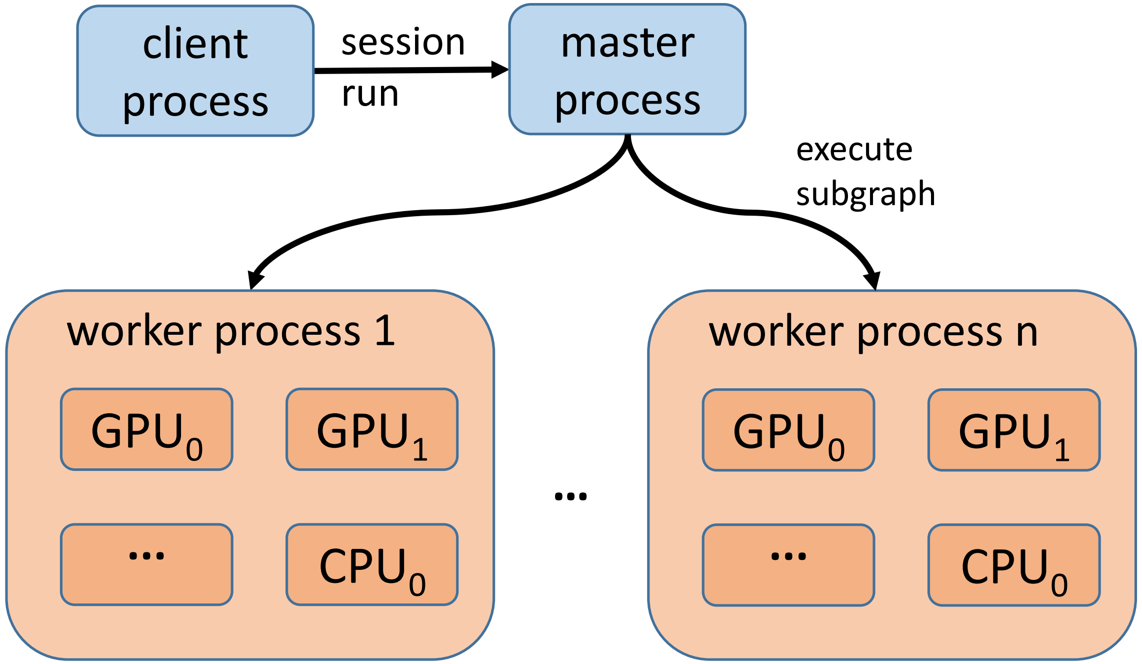
Single-device Execution

- Order of execution respects dependencies.
- Count of dependencies per node is kept.
- Ready nodes are pushed into a *Ready Queue* and are processed in some unspecified order.



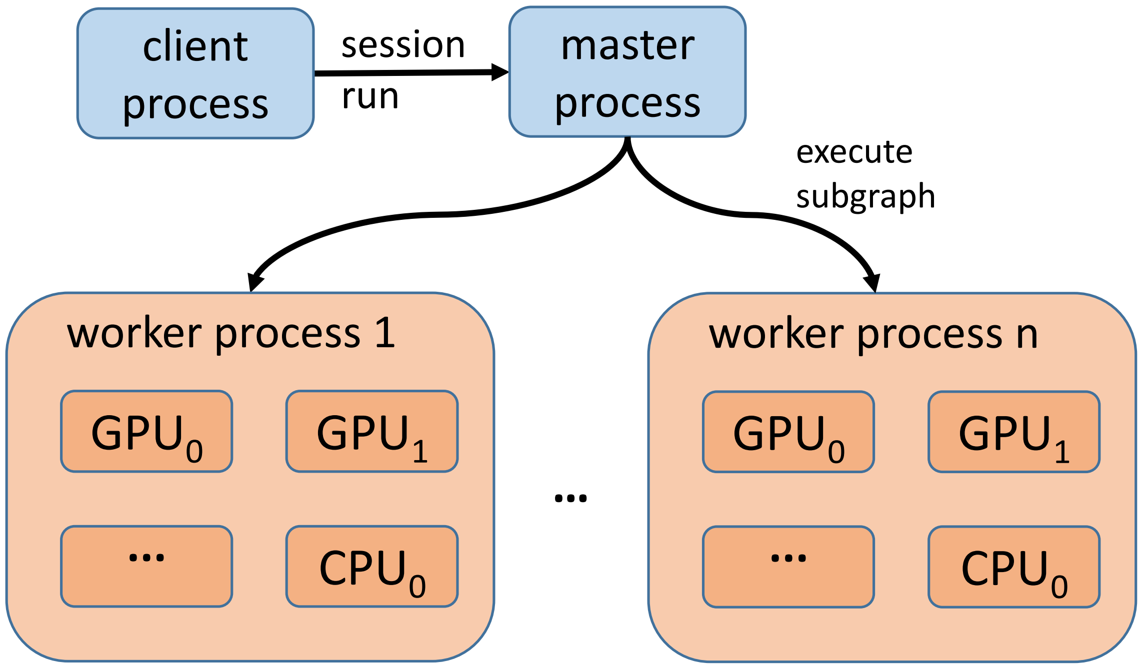
Multi-device Execution

- Two important decisions
  - Node placement
  - Cross-device communication



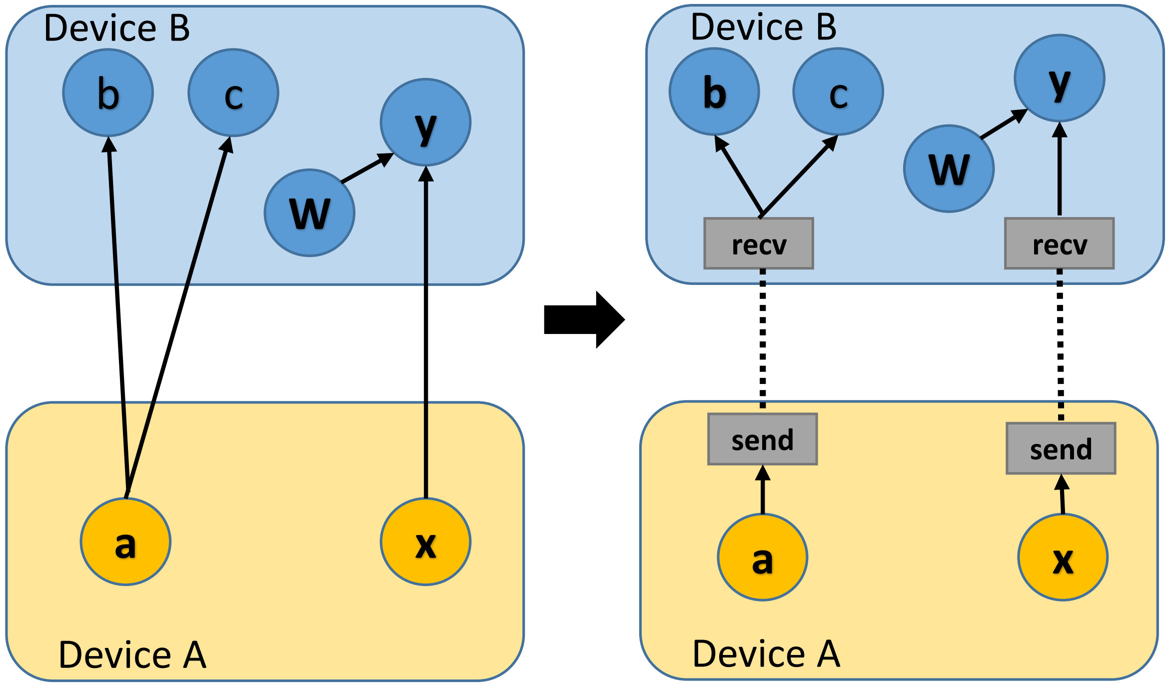
Multi-device Execution: Node placement

- Cost model based on input and output size and computation time for a device.
- Can be heuristic or based on measured time for previous placement decisions.
- Device for a node is selected greedily.
- Load balancing might be a problem in synchronous execution.
- Placement algorithm is an area of ongoing development.



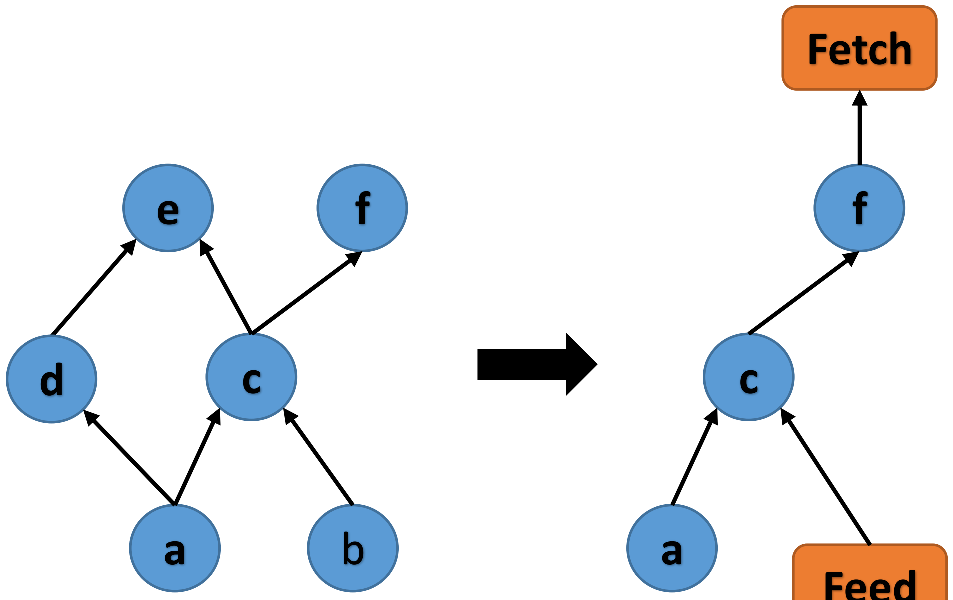
Multi-device Execution: Cross-device Communication

- Communication using explicit *send* and *receive* nodes.
- Single receive node for all users of a tensor – avoids multiple transmission.
- Takes care of scheduling and makes the system scalable.



Partial Execution

- Running just a subgraph of the entire execution graph.
- Exact subgraph can be run using the name of input and output nodes.
- Graph is changed to add *feed* and *fetch* nodes for input and output respectively.



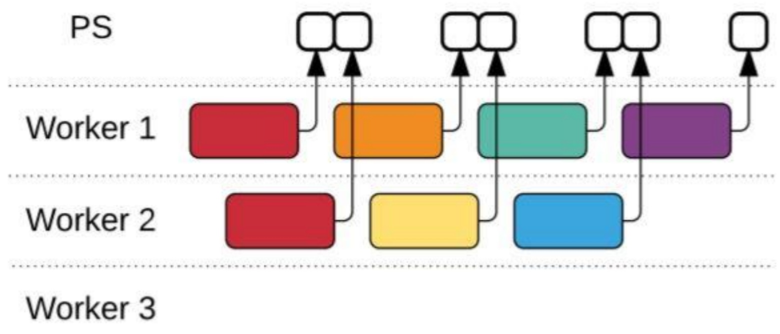
Control Flow

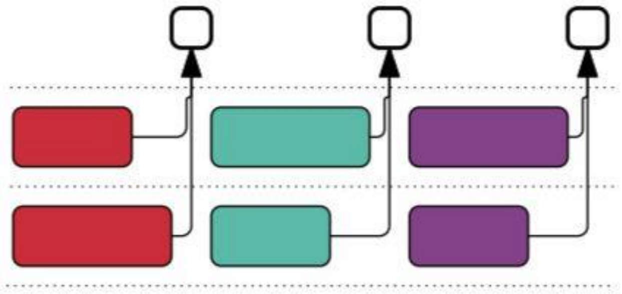
- Primitives similar to [1] to handle control flow.
- *Switch* (multiplixer) and *Merge* (demultiplexer) allow conditional execution of entire subgraph.
- *Enter, Leave* and *NextIteration* for expressing iterations.
- *Tags* and *Frames* similar to MIT Tagged Token Machine [2] to allow simultaneous execution of multiple iterations.

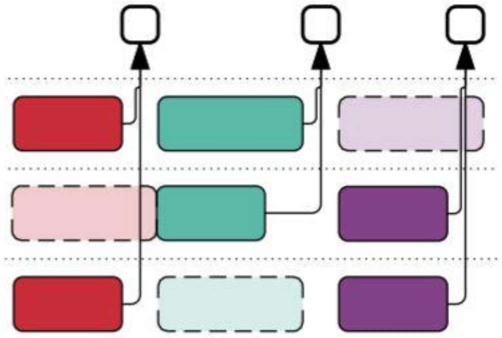
[1] Arvind et al. Dataflow architectures. In Annual Review of Computer Science Vol. 1, 1986, pages 225–253. Annual Reviews Inc., 1986.
[2] Arvind et al. Executing a program on the MIT tagged-token dataflow architecture. IEEE Trans. Comput., 39(3):300–318, 1990.

Training

- Asynchronous
  - Each worker updates the parameters asynchronously.
  - High throughput.
- Synchronous
  - A blocking queue for workers to read same parameters.
  - Slow workers limit overall throughput.
- Synchronous w/ backup
  - Aggregates first *m* of *n* updates produced.
  - Improves throughput by 10% in image classification.







Evaluation

Single Machine Execution

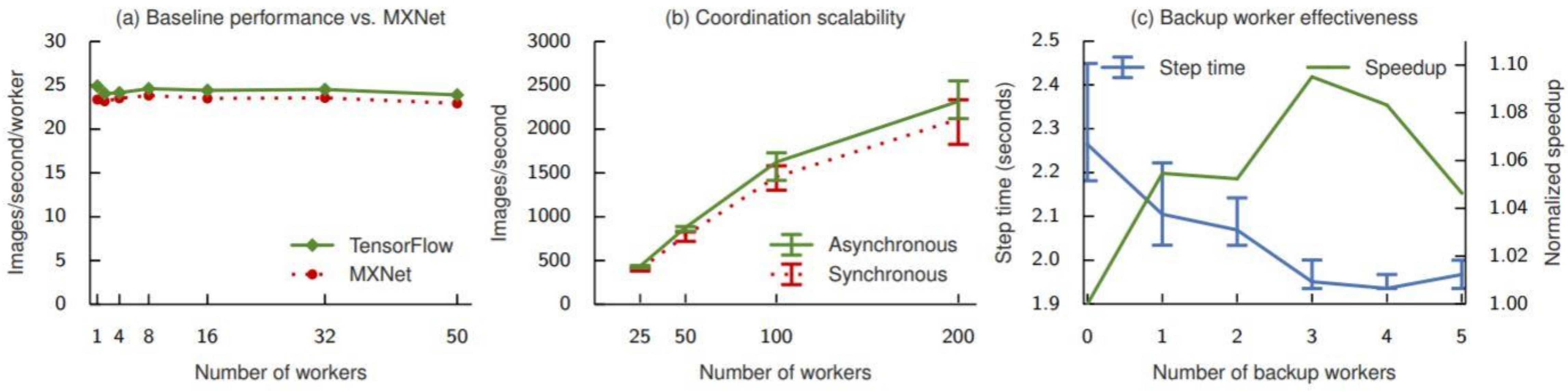
- Performs within 6% of latest version of Torch – both use same cuDNN library.
- Neon outperforms due to hand optimized kernels written in assembly.

	Training step time (ms)			
Library	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

Chintala benchmark of convolutional model on Intel Core i7-5930K CPU at 3.5GHz and Nvidia Titax X GPU

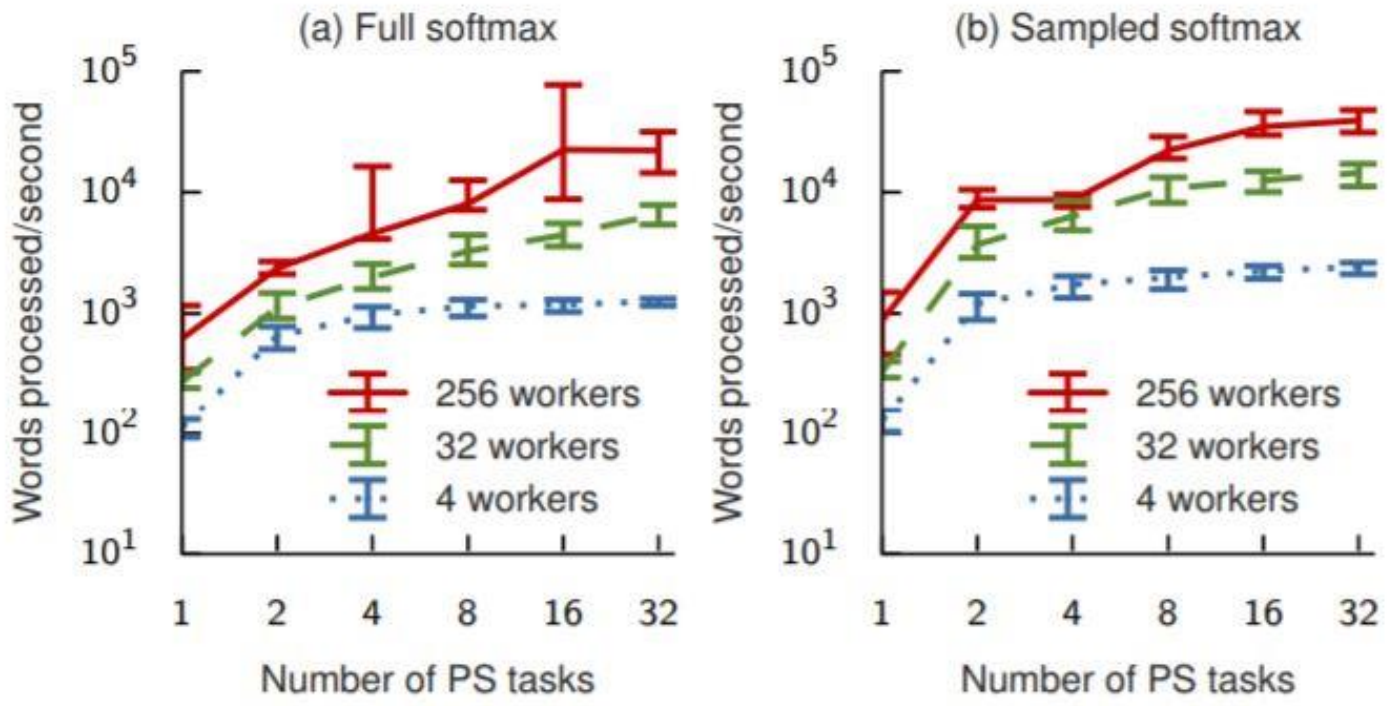
Image Classification

- Inception-v3 model with 7 PS tasks and varying worker tasks.
- Intel Xeon E5 servers with Nvidia K80 GPUs.



Language Modeling

- LSTM-512-512 on Billion Word benchmark.
- Vocabulary size limits training performance – limited to 40k words instead of 800k.



Conclusions

- Offers a set of uniform abstractions for harnessing large-scale heterogeneous systems for both production and experimentation.
- Enables *power* users to achieve excellent performance.
- Default policies that work for *all* users yet to be determined.
- Placement algorithm, memory management and scheduling are being actively improved.
- Static dataflow graph doesn’t work for deep reinforcement learning.

What Next?
Tensorflow 2.0!

- Eager execution as the default execution mode.
  - Should make Tensorflow easy to learn and apply.
  - Primarily to compete with PyTorch.
- Cleanup.
  - Deprecated APIs removed.
  - Duplication reduced significantly.
- Heavy reliability on Keras API.
  - More object-oriented and Python-like.
  - Makes reusability of variables easier.
  - Simpler code.

References

- Arvind et al. Dataflow architectures. In Annual Review of Computer Science Vol. 1, 1986, pages 225–253. Annual Reviews Inc., 1986.
- Arvind et al. Executing a program on the MIT tagged-token dataflow architecture. IEEE Trans. Comput., 39(3):300–318, 1990.
- Abadi et al. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015.
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