TensorFlow:

Large-Scale Machine Learning on Heterogeneous Distributed Systems

by Google Research

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Outline

- Introduction
- The Programming Model
- The Implementation
  - Single Device Execution
  - Multi-Device & Distributed Execution
- Extensions & Optimizations
- Auxiliary Tools
- Status & Experience

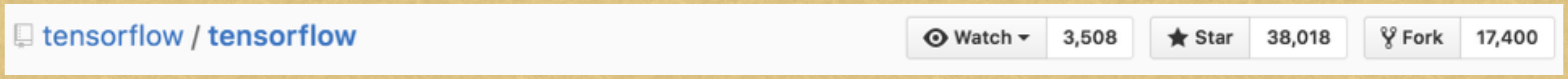
What is TensorFlow?

A multi-dimensional array → **TensorFlow** ← *A directed graph*

A directed graph of operations that process multi-dimensional arrays.

TensorFlow

- An open source library for general machine learning
- Developed by Google
- First released Nov 2015
- Apache 2.0 licensed
- Particularly useful for Deep Learning
- Very popular!



The Motivation

- DistBelief, Google's first scalable distributed training and inference system, is not flexible enough
- Better understanding of problem space leads to some dramatic simplifications
- Define a standard way of expressing machine learning ideas and computations
- easy to use, efficient in execution

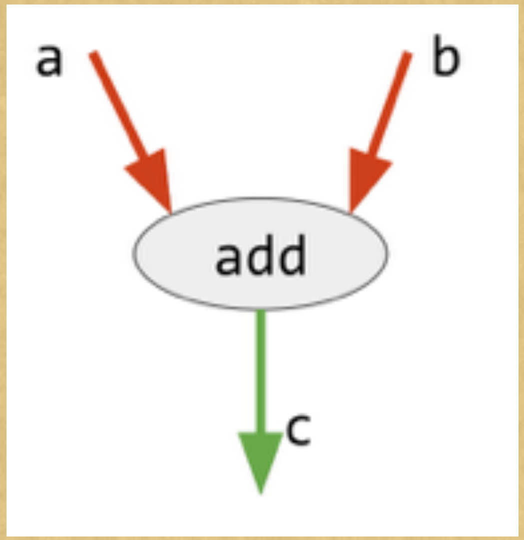
The Programming Model

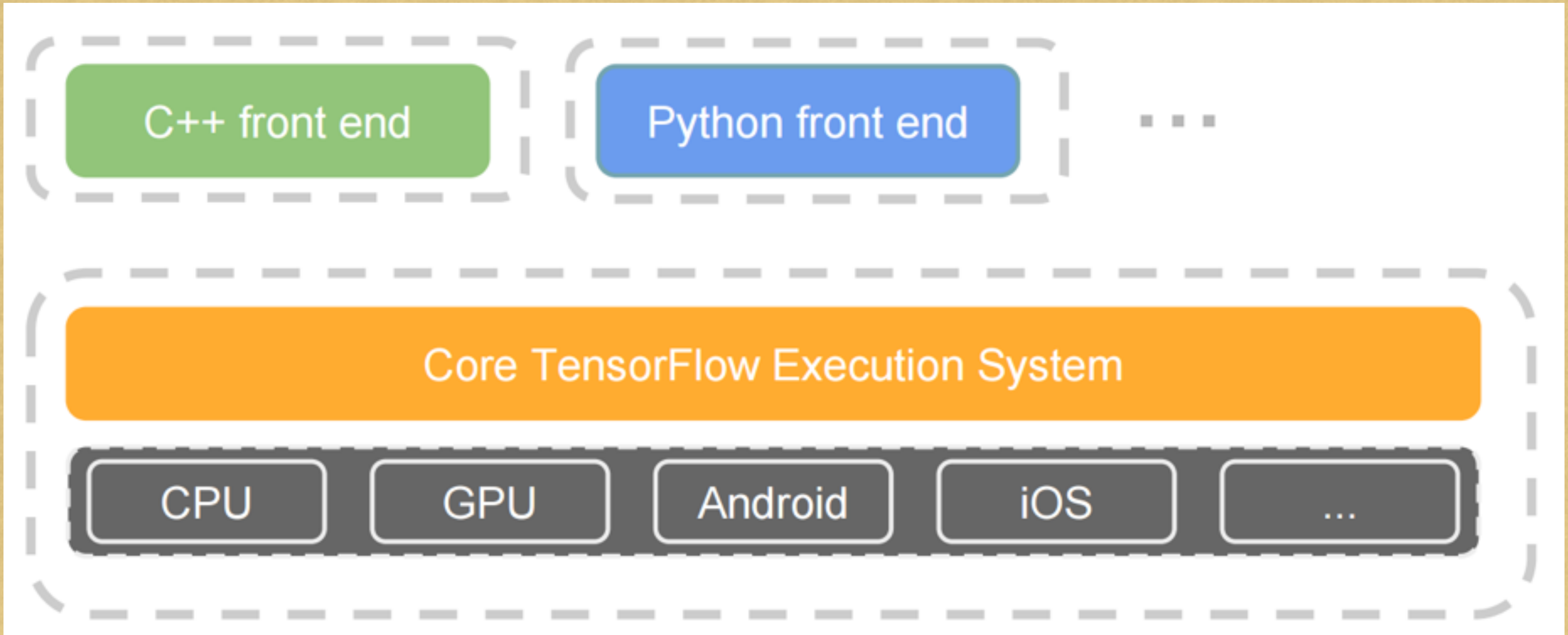
- A directed graph representing a dataflow computation of multiple operations.
- Each node represents the instantiation of an operation.
- Nodes can maintain persistent states and branching and looping controls like Naiad.
- Edges represent *tensor* data flow between nodes (from outputs to input).
- A tensor is a typed multidimensional array.
- **Control dependencies:** special edges with no data flows along.

Expressing High-Level Machine Learning Computations

```
# First, build the graph.
c = tf.add(a, b)
# Then run it.
with tf.Session() as s:
  print(s.run(c, {a=1, b=2}))
```

3





```
import tensorflow as tf

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
relu = tf.nn.relu(tf.matmul(W, x) + b)              # Relu(Wx+b)
C = [...]                                           # Cost computed as a function
                                                    # of Relu


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

Figure 1: Example TensorFlow code fragment

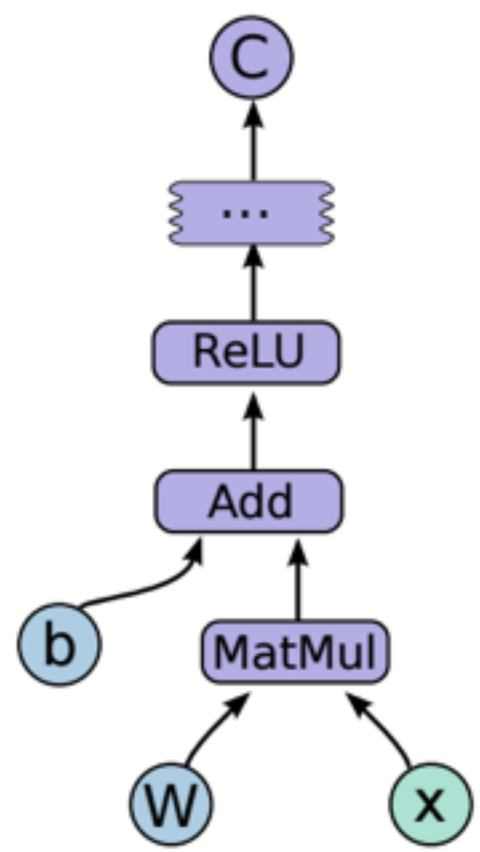


Figure 2: Corresponding computation graph for Figure 1

Implementation: Operations & Kernels

- An ***operation*** is an abstract computation on tensors
  - e.g., “matrix multiply”, or “add”.
  - represented by a node in the graph.
  - can have attributes.
- A ***kernel*** is a particular implementation of an operation that can be run on a particular type of device (e.g., CPU or GPU).
- A TensorFlow binary defines the sets of operations and kernels available via a registration mechanism, and this set can be extended by linking in additional operation and/or kernel definitions/registrations.

Built-in Operations

Operations

Category	*Examples*
Element-wise math ops	**Add**, Sub, **Mul**, Div, Exp, Log, Greater, Less...
Matrix ops	**Concat**, Slice, **Split**, Constant, Rank, **Shape...**
Matrix ops	**MatMul**, MatrixInverse, MatrixDeterminant...
Stateful ops	**Variable**, Assign, AssignAdd...
NN building blocks	**SoftMax**, Sigmoid, **ReLU**, **Convolution2D...**
Checkpointing ops	Save, Restore
Queue & synch ops	Enqueue, Dequeue, MutexAcquire...
Control flow ops	Merge, Switch, Enter, Leave...

Implementation: Sessions, Placeholders, Variables

- ***Sessions*** manage resources for graph execution.
  - It encapsulates the environment in which operation are executed and tensors are evaluated.
- ***Placeholders*** must be fed with data on execution.
- A ***variable*** is a modifiable tensor that lives in TensorFlow's graph of interactive operations.
  - In-memory buffers containing tensors.
  - Holds and updates parameters to be trained.
  - Must be initialized before they have values!

Implementation: Clients, Workers, Devices

- A ***client*** communicates with the ***master*** using ***session*** interface.
- The master manages one or more ***worker*** processes.
- Each worker is responsible for arbitrating one or more computational ***devices*** and for executing operations on those devices.
- A device name is composed of pieces that identify the its type, its index, and an identification of the task of the worker.
  - Example: /job:localhost/device:cpu:0

SINGLE MACHINE VS. DISTRIBUTED SYSTEM

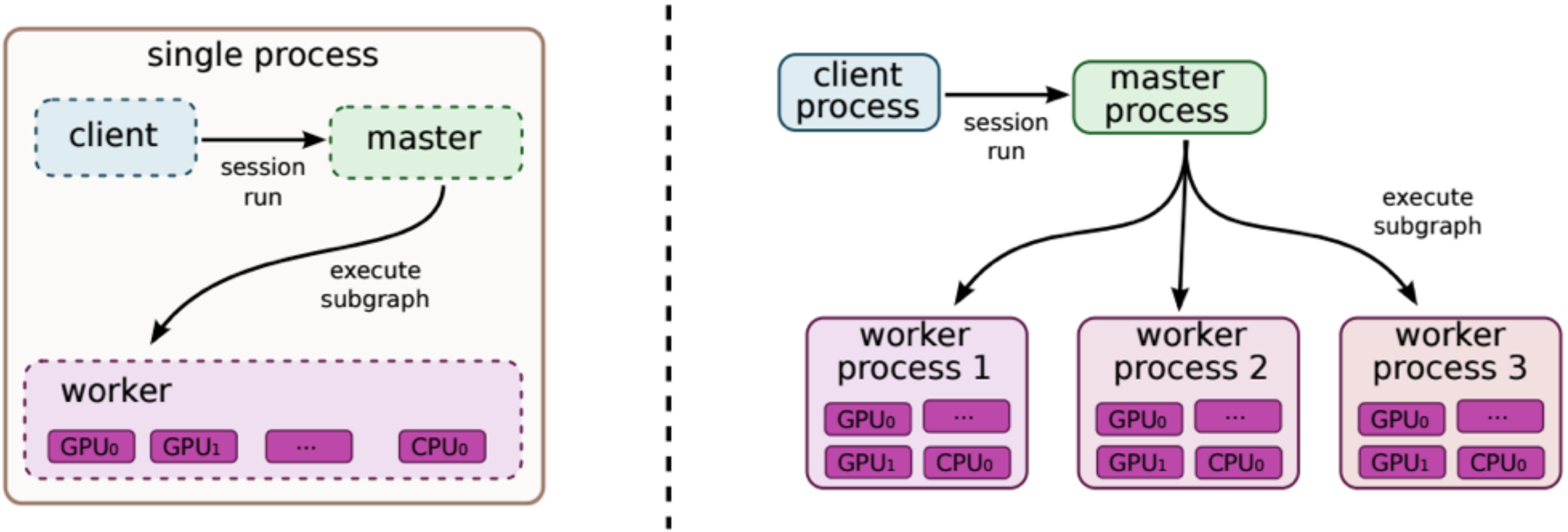
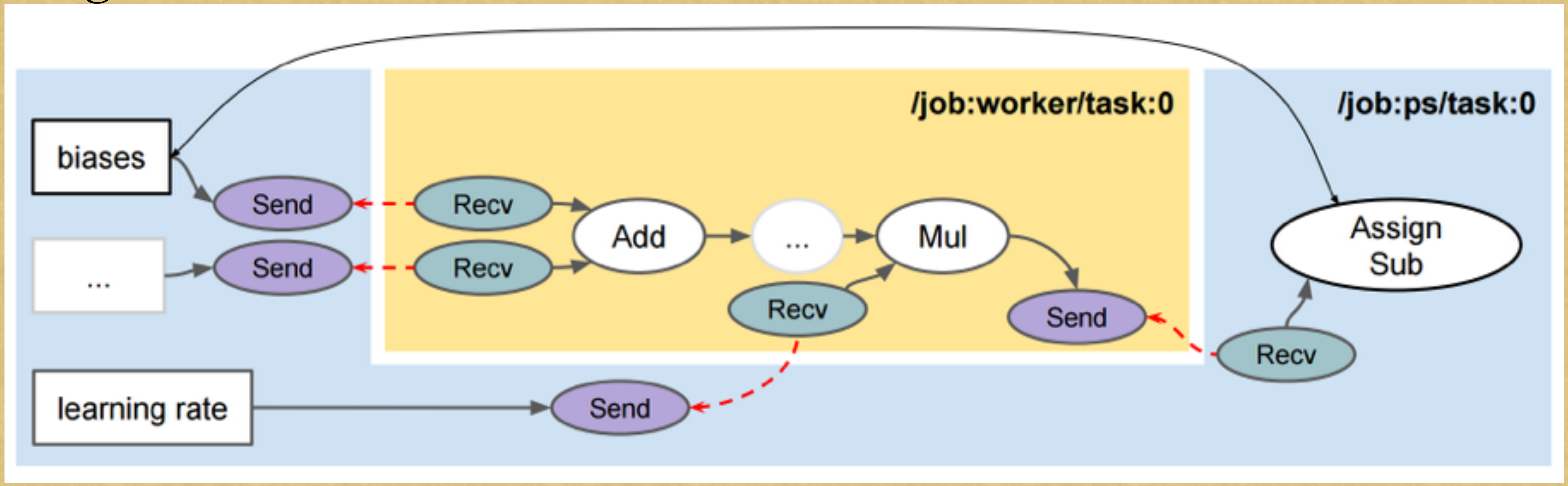


Figure 3: Single machine and distributed system structure

Node Placement & Cross-Device Communication

- Each node (i.e. operation) is placed onto one of the devices.
- Node placement is done in topological order with a greedy heuristic based on cost estimation (execution + communication).
- Once node placement is done, the graph is partitioned into a set of subgraphs, one per device.
- Cross device edges are removed and replaced by *Send & Recv edge*.



Distributed Execution & Fault Tolerance

- Similar to cross-device execution.
- Send/Recv communication uses **gRPC**, Google's remote procedure call framework.
- When a failure is detected, the entire graph execution is aborted and restarted from scratch.
- Support of checkpoint and recovery.
- Variable are periodically saved and can be restored at restart.

Extensions: Gradient Computation

- TensorFlow has built-in support for automatic gradient computation.
- If a tensor C depends on some set of tensors $\{X_k\}$, then there is a built-in function that will return the tensors $\{dC/dX_k\}$.
- Gradient tensors are computed by backtracking from C to each $X_{k,}$ and adding a corresponding "gradient function" node to the TensorFlow graph for each operation on the backward path.

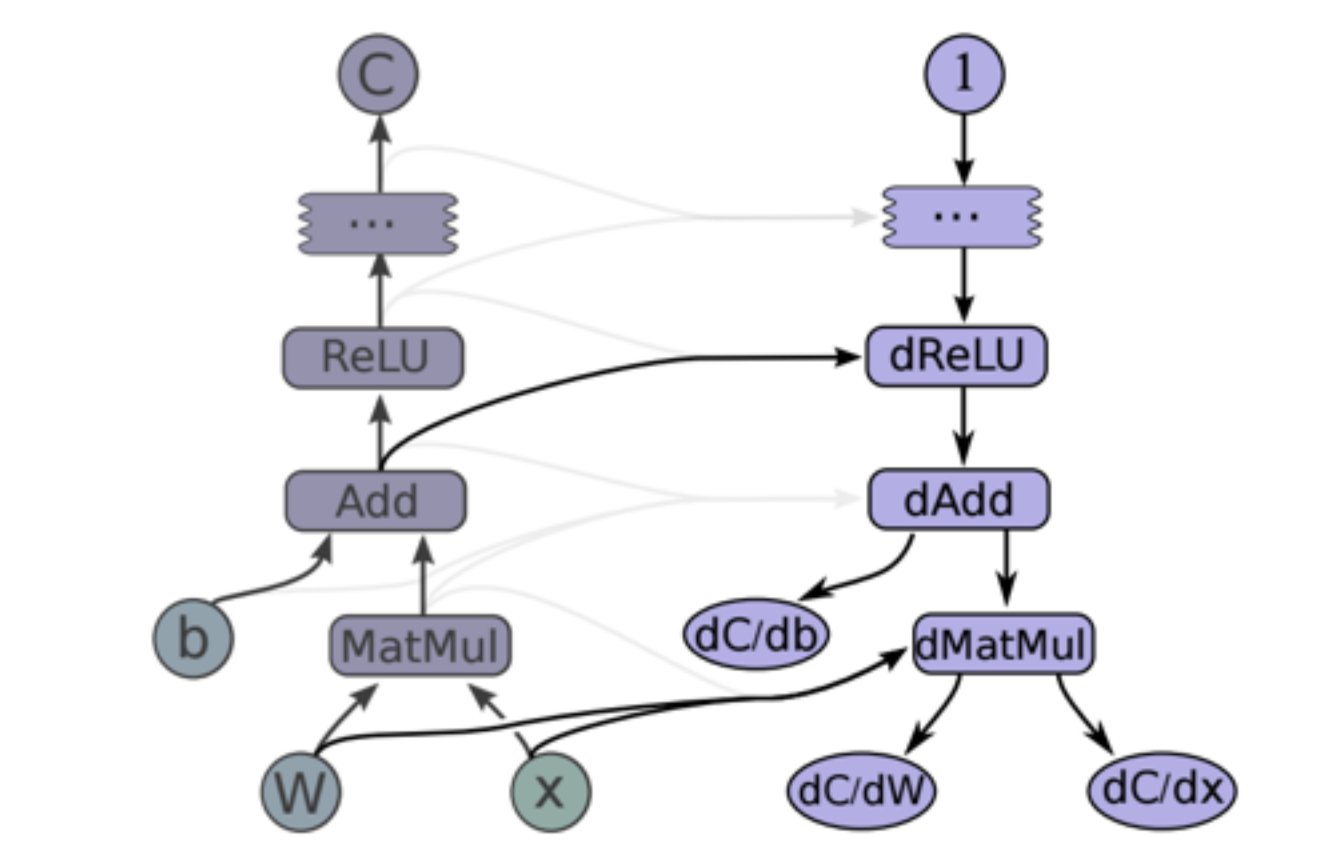


Figure 5: Gradients computed for graph in Figure 2

Extensions: Partial Execution

- Allows execution of an arbitrary subgraph of the whole graph
- Allows injection of arbitrary data along any edge of the graph (**Feed**)
- Allows arbitrary data retrieval from any edge of the graph (**Fetch**)

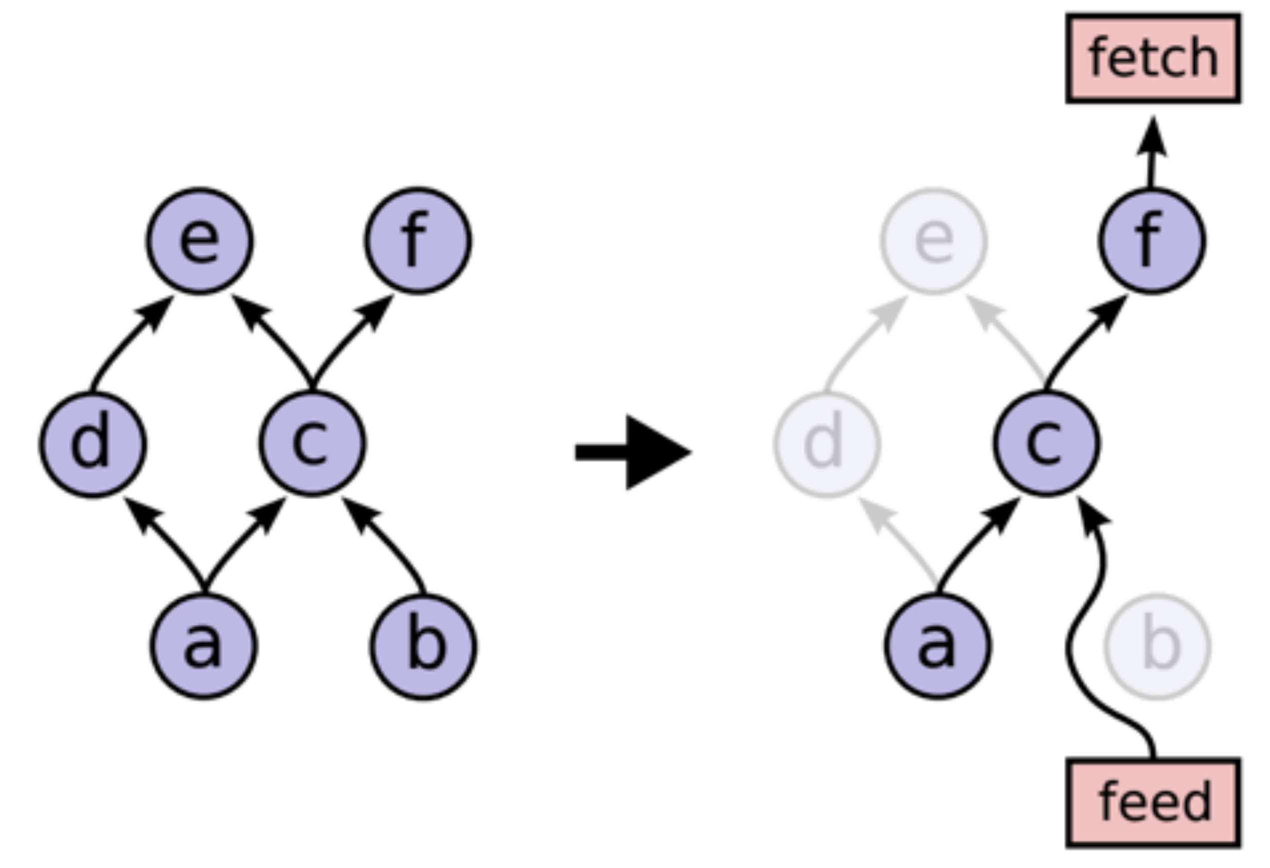


Figure 6: Before and after graph transformation for partial execution

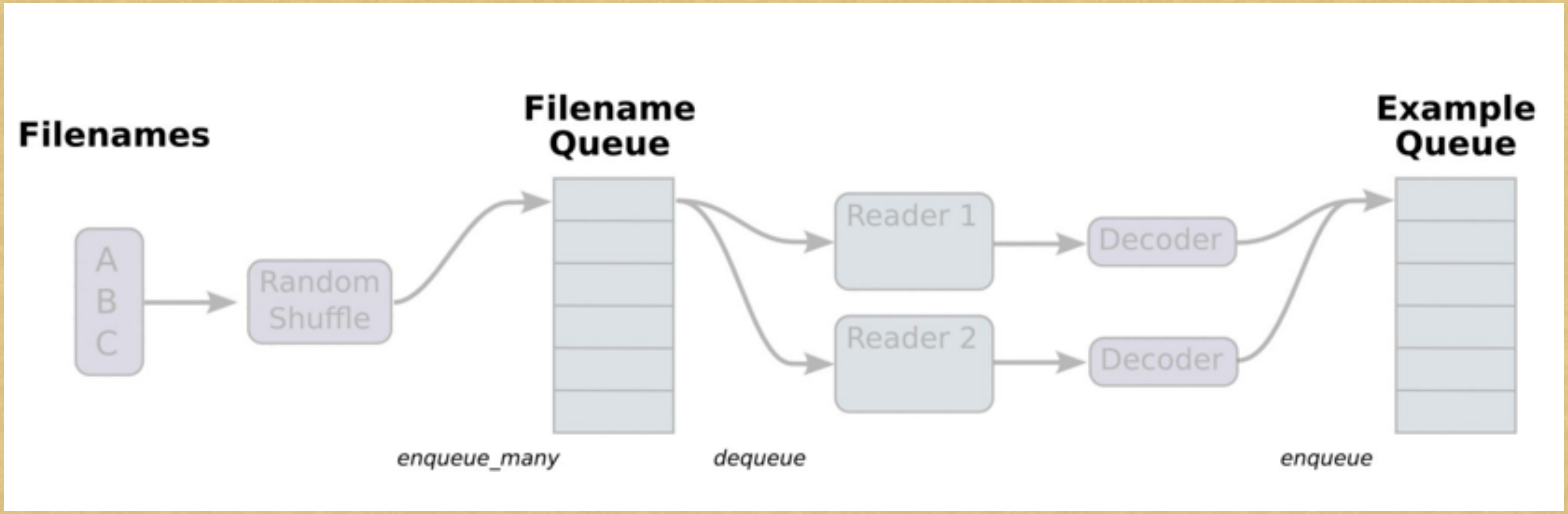
Extensions: Device Constraints & Control Flows

- Device constraint examples:
  - "only place this node on a device of type GPU"
  - "this node can only be placed in `/job:worker/task:17`"
  - "Colocate this node with the node named `variable13`"

- Control Flow: support of cyclic dataflow graph.
  - ***Switch, Merge***: express if-conditions.
  - ***Enter, Leave, NextIteration:*** express iterations.
  - distributed coordination mechanism is needed.

Extensions: Queues & Containers

- TensorFlow has built-in support of normal FIFO queue and a shuffling queue

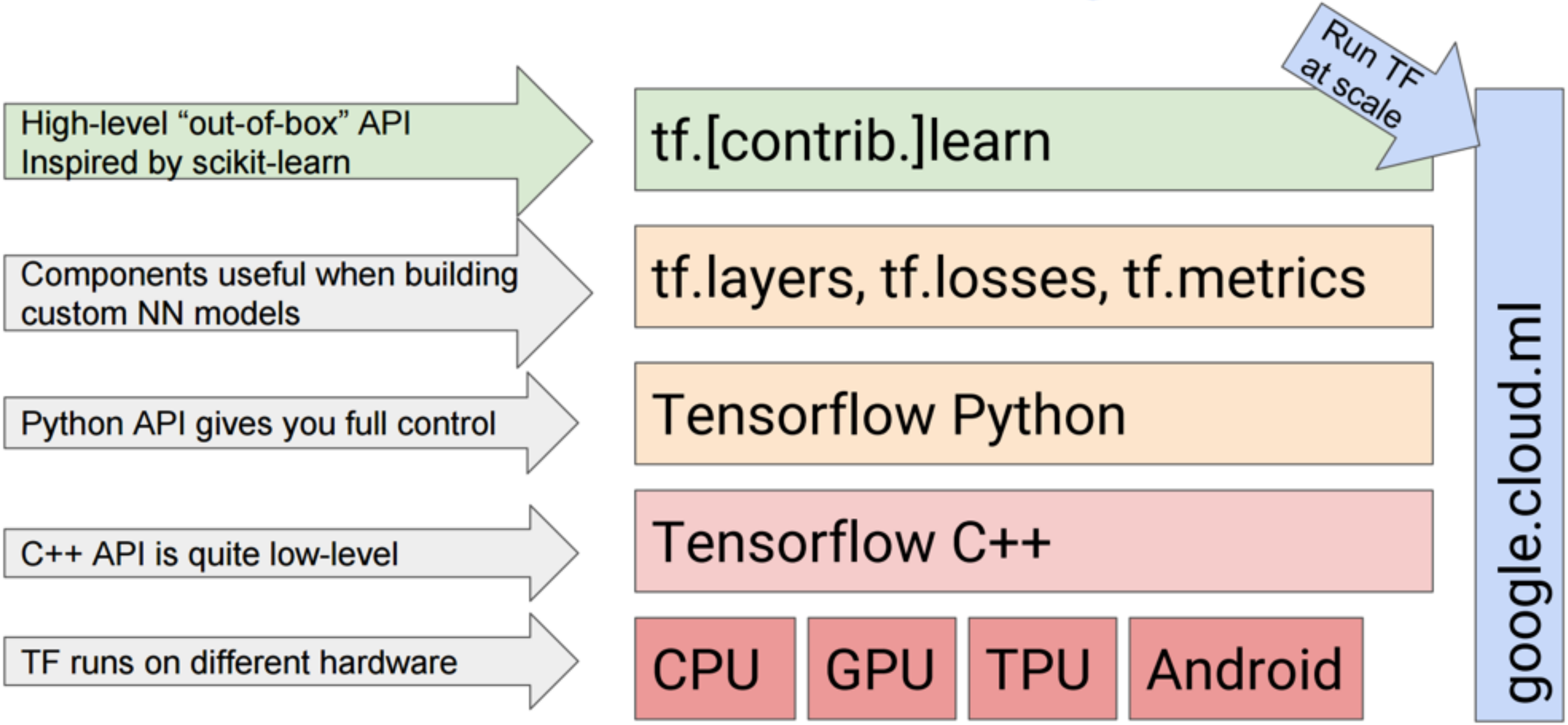


- A **Container** is the mechanism within TensorFlow for managing longer-lived mutable state.
  - Useful for sharing states between disjoint companions from different Sessions.

Optimizations

- Common subexpression elimination to remote redundant calculation
- Controlling data communication and memory usage
  - Topological ordering of nodes to identify critical path
  - Prioritize computation/communication on critical path
- Asynchronous kernel to support non-blocking computation
- Reuse pre-existing highly-optimized numerical libraries
- lossy compression of data, similar to the DistBelief system

TensorFlow toolkit hierarchy



http://scikit-learn.org/

TensorBoard

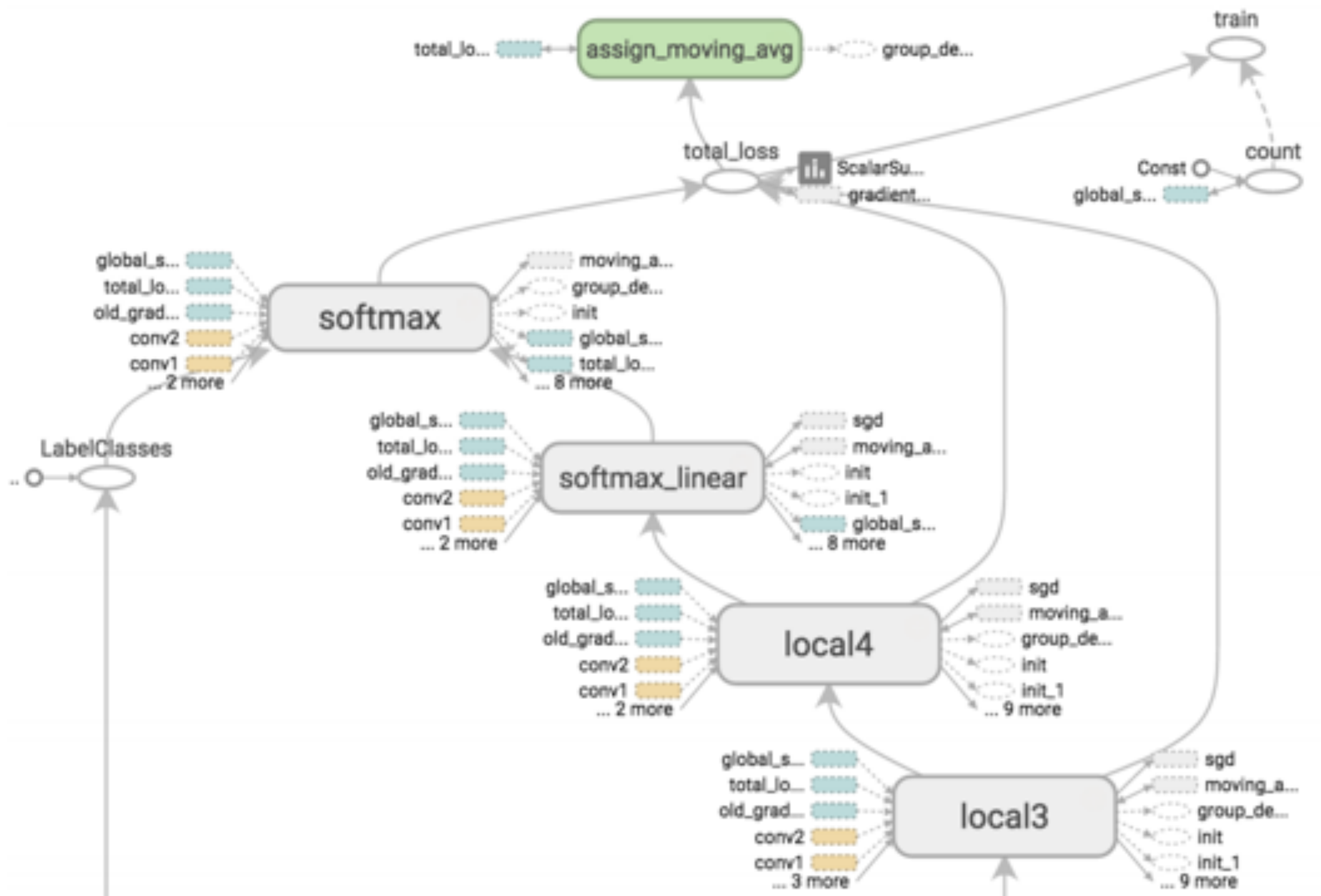


Figure 10: TensorBoard graph visualization of a convolutional neural network model

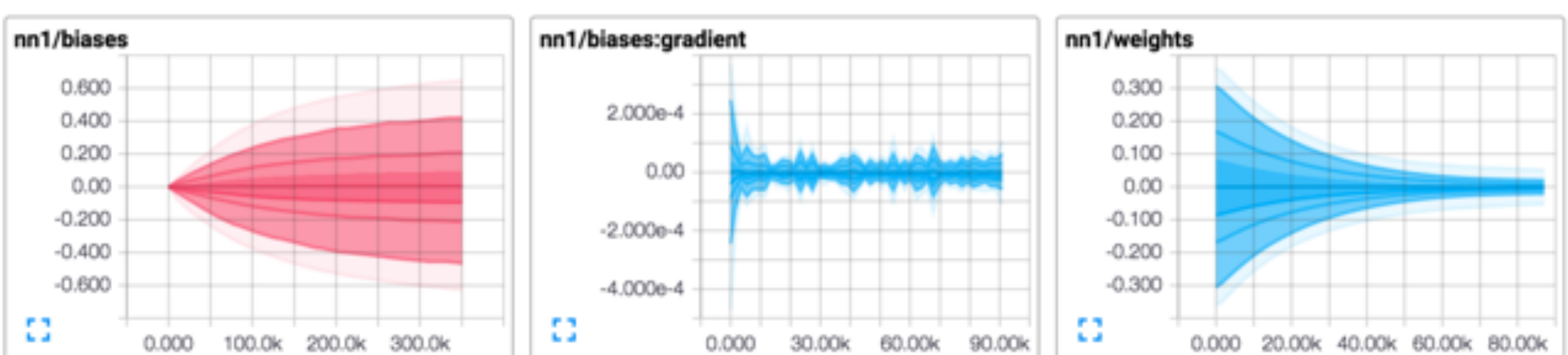


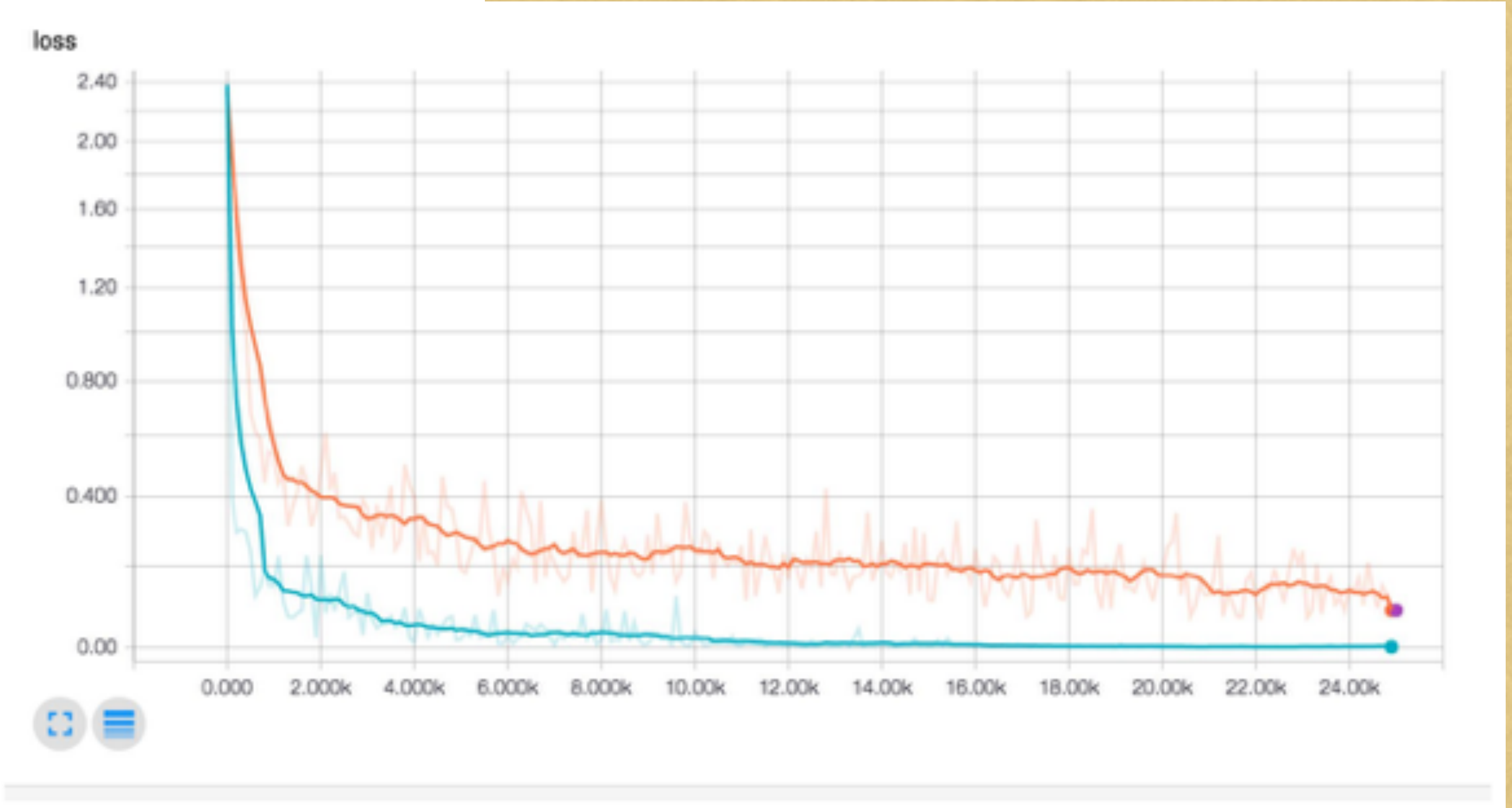
Figure 11: TensorBoard graphical display of model summary statistics time series data

Writing Summary for TensorBoard

```
# Create a summary writer.
print("Writing Summaries to %s" % MODEL_DIR)
train_summary_writer = tf.train.SummaryWriter(MODEL_DIR)

# ..then, as part of defining the model graph..
loss_summary = tf.scalar_summary("loss", loss)
train_summary_op = tf.merge_summary([loss_summary])

# A training step: run the training op, write the summary info
_, loss_value, tsummary = sess.run(
     [train_op, loss, train_summary_op],
     feed_dict={images_placeholder: images_feed,
                labels_placeholder: labels_feed})
train_summary_writer.add_summary(tsummary, step)
```



EEG: Performance Tracing

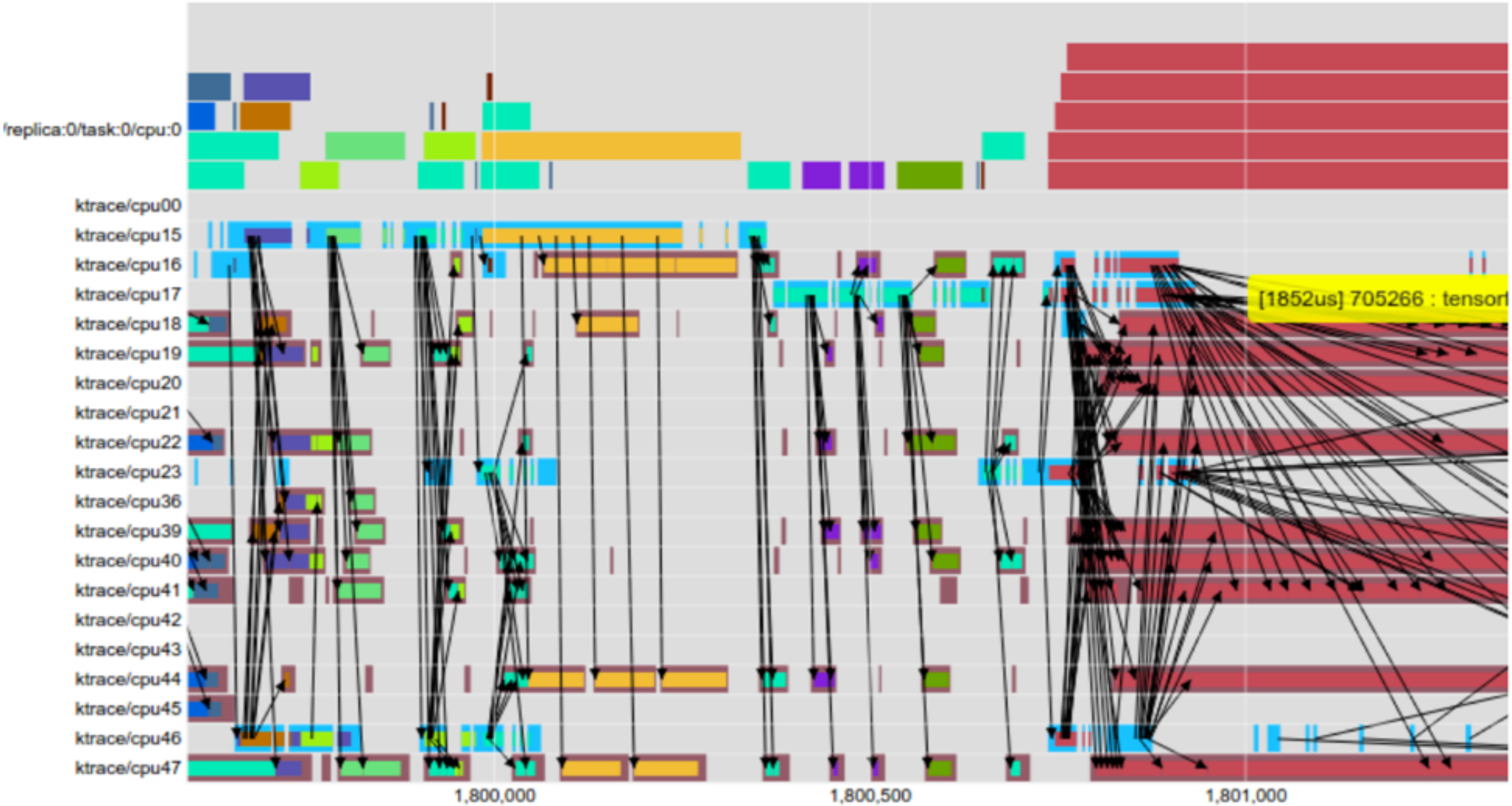


Figure 12: EEG visualization of multi-threaded CPU operations (x-axis is time in μs).

Performance

- Not much data for apples-to-apples comparison, but general observations are TensorFlow is slower than other common deep-learning framework such as Theano or Torch.

OxfordNet [Model-A] - Input 64x3x224x224

Library	Time (ms)	forward (ms)	backward (ms)
Nervana	590	180	410
CuDNN-R3 (Torch)	615	196	418
CuDNN-R2 (Torch)	1099	342	757
TensorFlow	1840	545	1295

GoogleNet V1 - Input 16x3x224x224

Library	Time (ms)	forward (ms)	backward (ms)
CuDNN-R2 (Torch)	564	174	390
TensorFlow	590	54	536

Experiences

- Build tools to gain insight into the exact number of parameters in a given model.
- Start small and scale up.
- Always ensure that the objective (loss function) matches between machine learning systems when learning is turned off
- Make a single machine implementation match before debugging a distributed implementation.
- Guard against numerical errors.
- Analyze pieces of a network and understand the magnitude of numerical error.

Thank you!

Questions?