Horovod

Uber's Open Source Distributed Deep Learning Framework for TensorFlow

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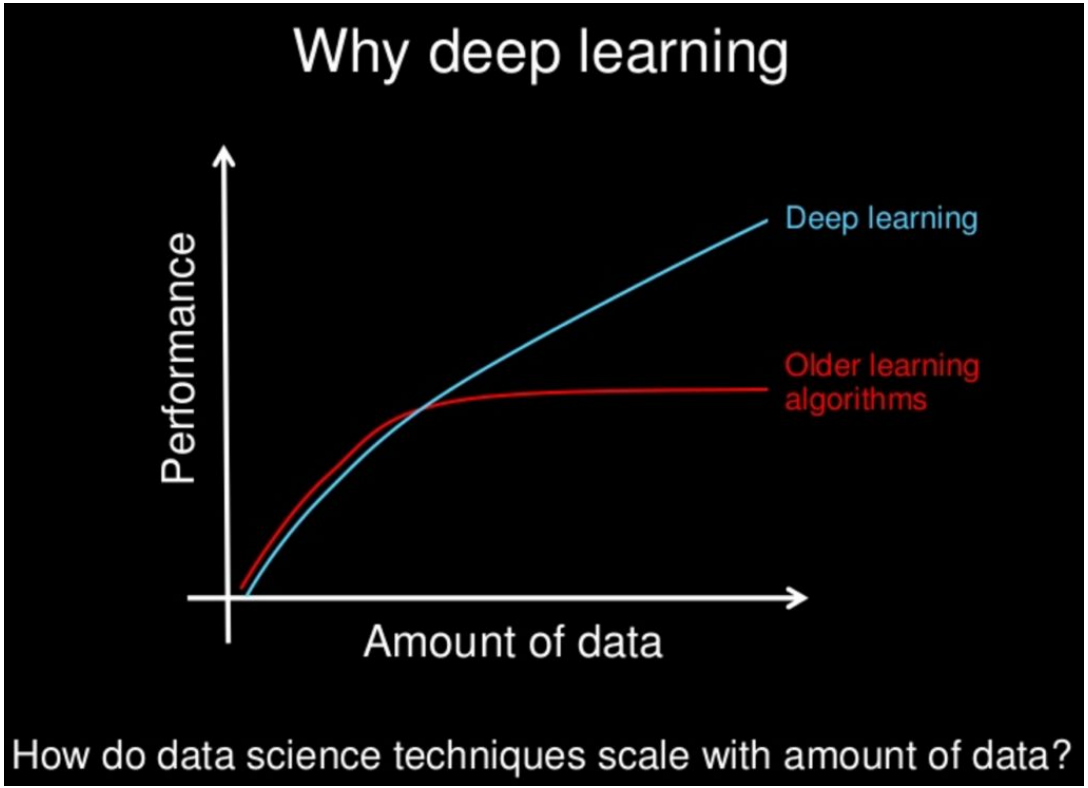
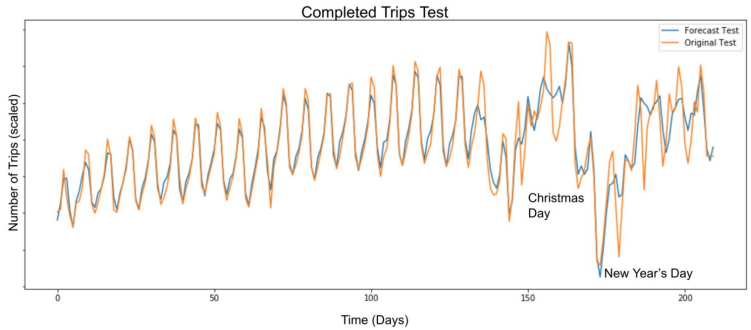
Deep Learning



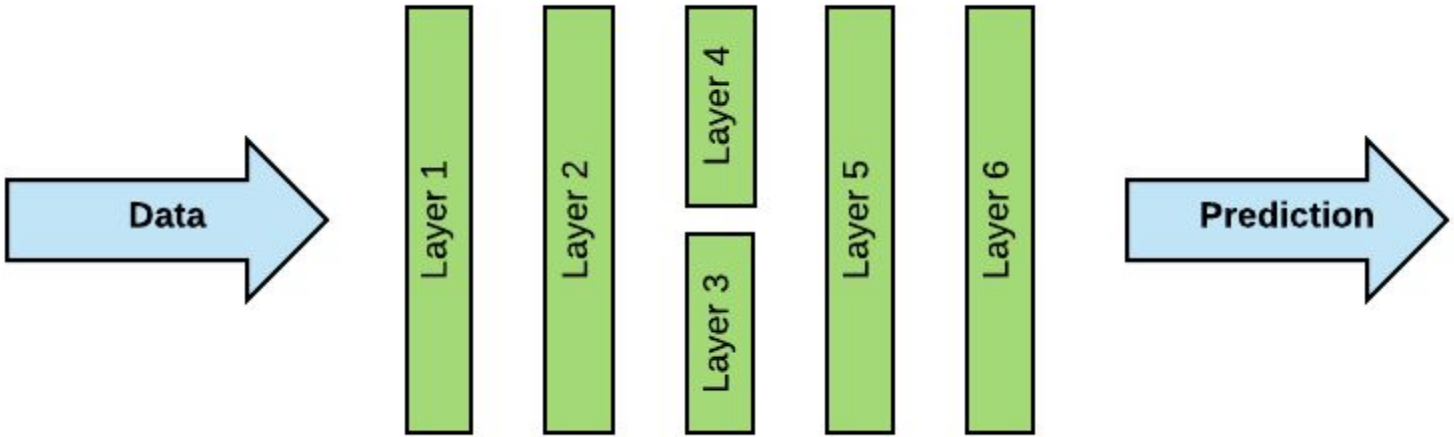
Credit: Andrew Ng, https://www.slideshare.net/ExtractConf

Deep Learning @ Uber

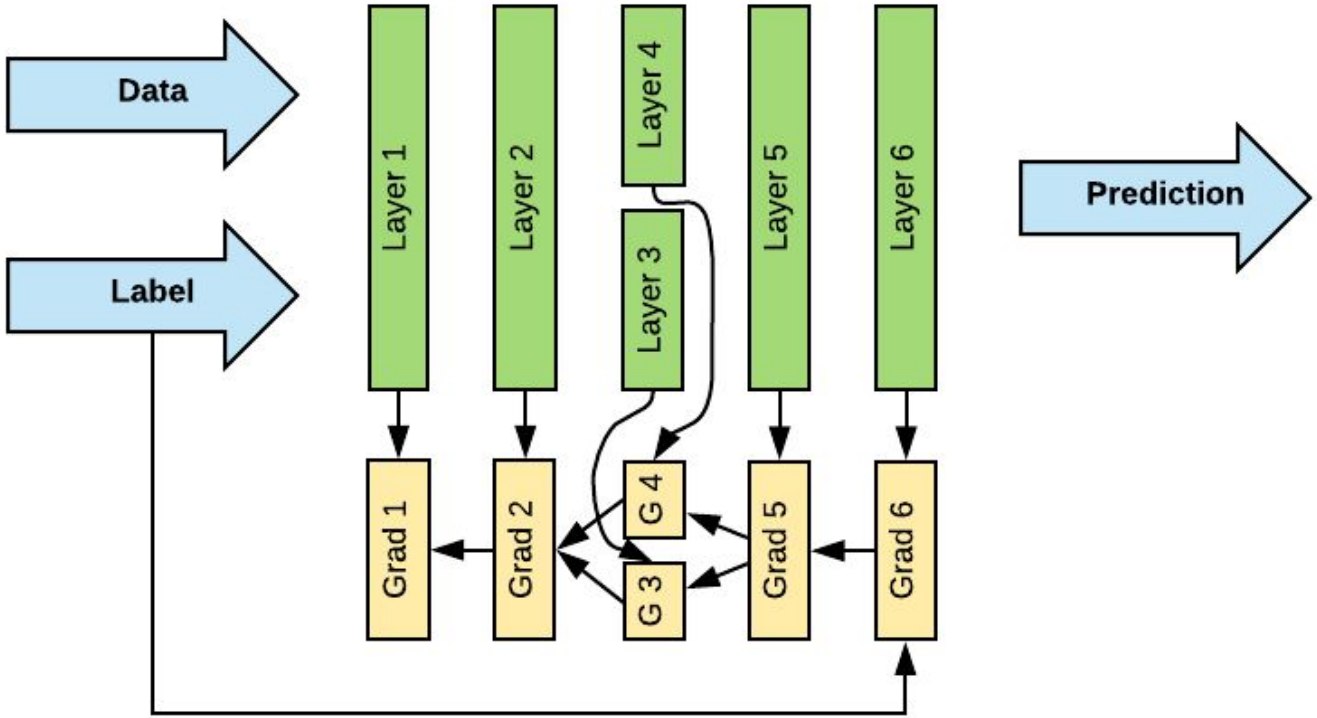
- Self-Driving Vehicles
- Trip Forecasting
- Fraud Detection
- … and many more!



How does Deep Learning work?



How does Deep Learning training work?

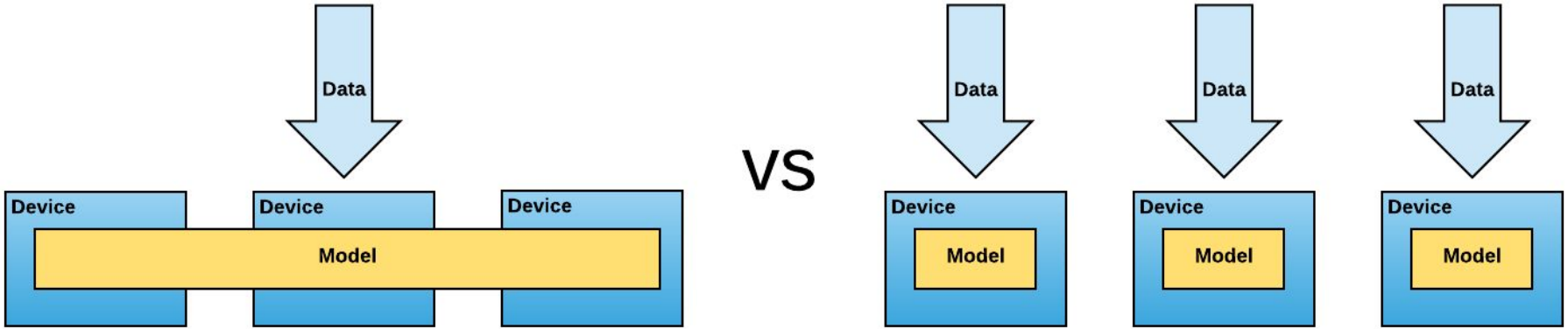


TensorFlow

- Most popular open source framework for deep learning
- Combines high performance with ability to tinker with low level model details
- Has end-to-end support from research to production

Going Distributed

- Train very large models
- Speed up model training

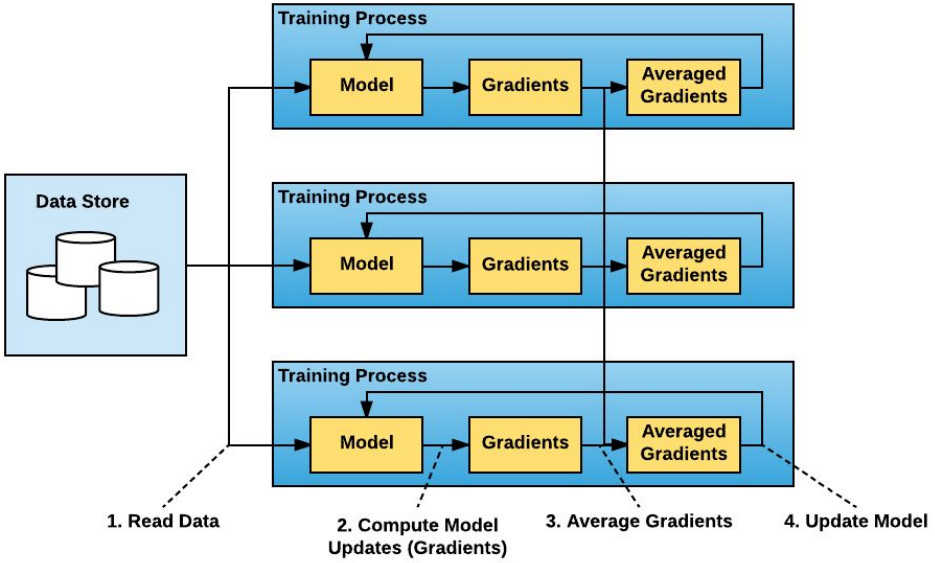


Model Parallelism

Data Parallelism

Going Distributed Cont.

- Modern GPUs have a lot of RAM
- Vast majority of use cases are data-parallel
- Facebook trained ResNet-50 on ImageNet in 1 hour (instead of a week) (arxiv.org/abs/1706.02677)
- Gradient checkpointing allows to train larger models (github.com/openai/gradient-checkpointing)



Parameter Server Technique

tf.Server()

tf.train.replicas_device_setter()

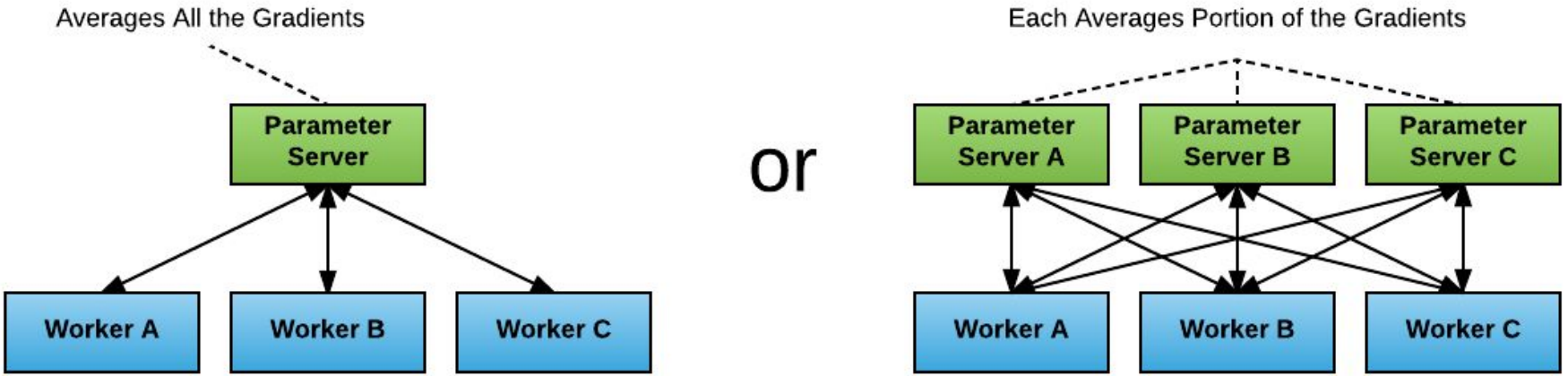
Parameter Server

Worker

GPU Towers

tf.ClusterSpec()

tf.train.SyncReplicasOptimizer()



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Parameter Server Technique - Example Script

```python
import argparse
import sys

import tensorflow as tf

FLAGS = None

def main(_):
  ps_hosts = FLAGS.ps_hosts.split(",")
  worker_hosts = FLAGS.worker_hosts.split(",")

  # Create a cluster from the parameter server and worker hosts.
  cluster = tf.train.ClusterSpec({"ps": ps_hosts, "worker": worker_hosts})

  # Create and start a server for the local task.
  server = tf.train.Server(cluster,
                           job_name=FLAGS.job_name,
                           task_index=FLAGS.task_index)

  if FLAGS.job_name == "ps":
    server.join()
  elif FLAGS.job_name == "worker":

    # Assigns ops to the local worker by default.
    with tf.device(tf.train.replica_device_setter(
        worker_device="/job:worker/task:%d" % FLAGS.task_index,
        cluster=cluster)):

      # Build model...
      loss = ...
      global_step = tf.contrib.framework.get_or_create_global_step()

      train_op = tf.train.AdagradOptimizer(0.01).minimize(
          loss, global_step=global_step)

    # The StopAtStepHook handles stopping after running given steps.
    hooks=[tf.train.StopAtStepHook(last_step=1000000)]

    # The MonitoredTrainingSession takes care of session initialization,
    # restoring from a checkpoint, saving to a checkpoint, and closing when done
    # or an error occurs.
    with tf.train.MonitoredTrainingSession(master=server.target,
                                           is_chief=(FLAGS.task_index == 0),
                                           checkpoint_dir="/tmp/train_logs",
                                           hooks=hooks) as mon_sess:
      while not mon_sess.should_stop():
        # Run a training step asynchronously.
        # See `tf.train.SyncReplicasOptimizer` for additional details on how to
        # perform *synchronous* training.
        # mon_sess.run handles AbortedError in case of preempted PS.
        mon_sess.run(train_op)

if __name__ == "__main__":
  parser = argparse.ArgumentParser()
  parser.register("type", "bool", lambda v: v.lower() == "true")
  # Flags for defining the tf.train.ClusterSpec
  parser.add_argument(
      "--ps_hosts",
      type=str,
      default="",
      help="Comma-separated list of hostname:port pairs"
  )
  parser.add_argument(
      "--worker_hosts",
      type=str,
      default="",
      help="Comma-separated list of hostname:port pairs"
  )
  parser.add_argument(
      "--job_name",
      type=str,
      default="",
      help="One of 'ps', 'worker'"
  )
  # Flags for defining the tf.train.Server
  parser.add_argument(
      "--task_index",
      type=int,
      default=0,
      help="Index of task within the job"
  )
  FLAGS, unparsed = parser.parse_known_args()
```


Image Source: TensorFlow -- https://www.tensorflow.org/deploy/distributed

How Can We Do Better?

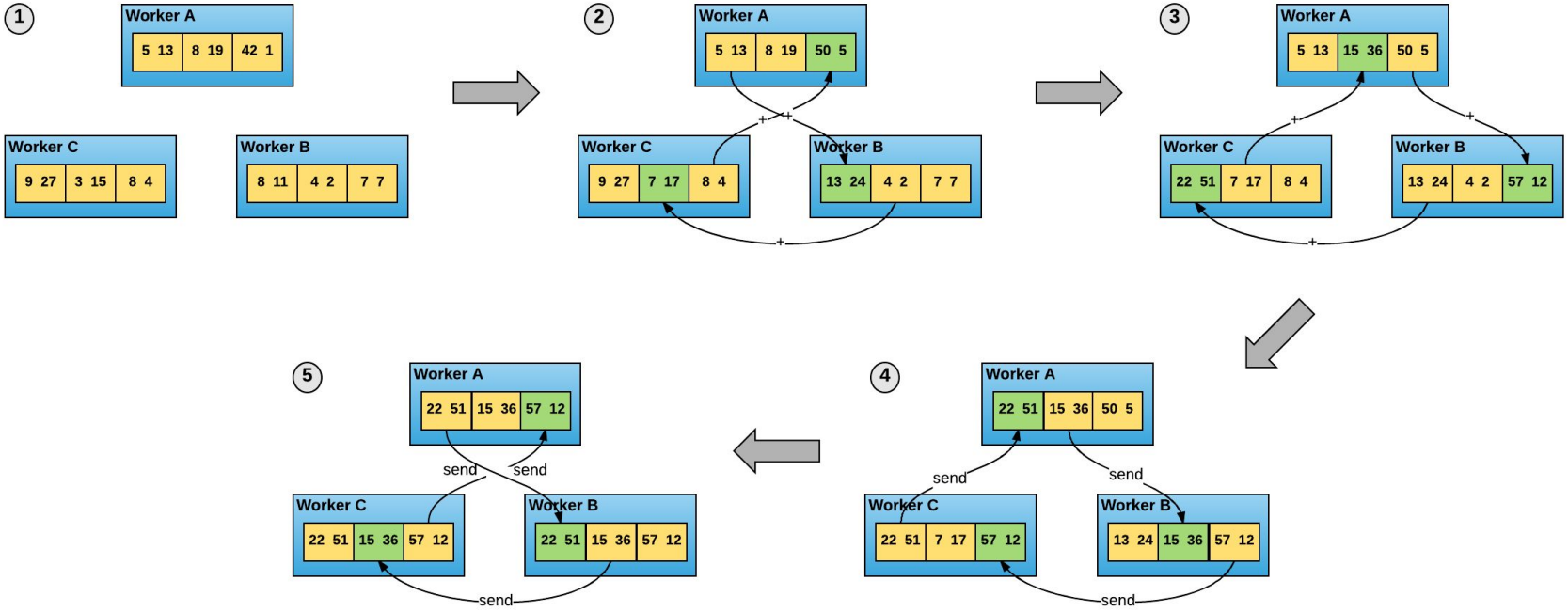
- Re-think necessary complexity for data-parallel case
- Improve communication algorithm
- Use RDMA-capable networking (RoCE, InfiniBand)

Meet Horovod

- Distributed training framework for TensorFlow
- Inspired by work of Baidu, Facebook, et al.
- Uses bandwidth-optimal communication protocols
  - Makes use of RDMA (RoCE, InfiniBand) if available
- Seamlessly installs on top of TensorFlow via

  ```
  pip install horovod
  ```
- Named after traditional Russian folk dance where participants dance in a circle with linked hands

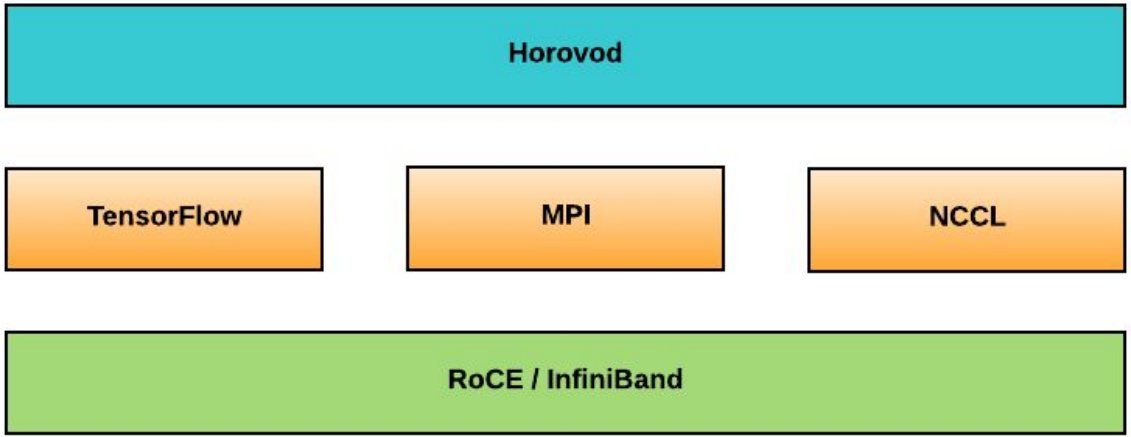
Horovod Technique



Patarasuk, P., & Yuan, X. (2009). Bandwidth optimal all-reduce algorithms for clusters of workstations. *Journal of Parallel and Distributed Computing*, 69(2), 117-124. doi:10.1016/j.jpdc.2008.09.002

Horovod Stack

- Plugs into TensorFlow via custom op mechanism
- Uses MPI for worker discovery and reduction coordination
- Uses NVIDIA NCCL for actual reduction on the server and across servers



Horovod Example

```
import tensorflow as tf
import horovod.tensorflow as hvd


# Initialize Horovod
hvd.init()

# Pin GPU to be used
config = tf.ConfigProto()
config.gpu_options.visible_device_list = str(hvd.local_rank())

# Build model...
loss = ...
opt = tf.train.AdagradOptimizer(0.01)

# Add Horovod Distributed Optimizer
opt = hvd.DistributedOptimizer(opt)

# Add hook to broadcast variables from rank 0 to all other processes during initialization.
hooks = [hvd.BroadcastGlobalVariablesHook(0)]

# Make training operation
train_op = opt.minimize(loss)

# The MonitoredTrainingSession takes care of session initialization,
# restoring from a checkpoint, saving to a checkpoint, and closing when done
# or an error occurs.
with tf.train.MonitoredTrainingSession(checkpoint_dir="/tmp/train_logs",
                                       config=config, hooks=hooks) as mon_sess:
  while not mon_sess.should_stop():
    # Perform synchronous training.
    mon_sess.run(train_op)
```

Horovod Example - Keras

```
import keras
from keras import backend as K
import tensorflow as tf
import horovod.keras as hvd

# Initialize Horovod.
hvd.init()

# Pin GPU to be used to process local rank (one GPU per process)
config = tf.ConfigProto()
config.gpu_options.allow_growth = True
config.gpu_options.visible_device_list = str(hvd.local_rank())
K.set_session(tf.Session(config=config))

# Build model…
model = ...
opt = keras.optimizers.Adadelta(1.0)

# Add Horovod Distributed Optimizer.
opt = hvd.DistributedOptimizer(opt)

model.compile(loss=keras.losses.categorical_crossentropy, optimizer=opt, metrics=['accuracy'])

# Broadcast initial variable states from rank 0 to all other processes.
callbacks = [hvd.callbacks.BroadcastGlobalVariablesCallback(0)]

model.fit(x_train, y_train,
        callbacks=callbacks,
        epochs=10,
        validation_data=(x_test, y_test))
```

Horovod Example - Estimator API

```
import tensorflow as tf
import horovod.tensorflow as hvd


# Initialize Horovod
hvd.init()

# Pin GPU to be used
config = tf.ConfigProto()
config.gpu_options.visible_device_list = str(hvd.local_rank())

# Build model...
def model_fn(features, labels, mode):
  loss = …
  opt = tf.train.AdagradOptimizer(0.01)

  # Add Horovod Distributed Optimizer
  opt = hvd.DistributedOptimizer(opt)

  train_op = optimizer.minimize(loss=loss, global_step=tf.train.get_global_step())
  return tf.estimator.EstimatorSpec(mode=mode, loss=loss, train_op=train_op)

# Add hook to broadcast variables from rank 0 to all other processes during initialization.
hooks = [hvd.BroadcastGlobalVariablesHook(0)]

# Create the Estimator
mnist_classifier = tf.estimator.Estimator(
    model_fn=cnn_model_fn, model_dir="/tmp/mnist_convnet_model",
    config=tf.estimator.RunConfig(session_config=config))

mnist_classifier.train(input_fn=train_input_fn, steps=100, hooks=hooks)
```

Horovod Example - PyTorch

```
import torch
import horovod.torch as hvd

# Initialize Horovod
hvd.init()

# Horovod: pin GPU to local rank.
torch.cuda.set_device(hvd.local_rank())

# Build model.
model = Net()
model.cuda()
optimizer = optim.SGD(model.parameters())

# Horovod: wrap optimizer with DistributedOptimizer.
optimizer = hvd.DistributedOptimizer(optimizer, named_parameters=model.named_parameters())

# Horovod: broadcast parameters.
hvd.broadcast_parameters(model.state_dict(), root_rank=0)

for epoch in range(100):
  for batch_idx, (data, target) in enumerate(train_loader):
      data, target = Variable(data), Variable(target)
      optimizer.zero_grad()
      output = model(data)
      loss = F.nll_loss(output, target)
      loss.backward()
      optimizer.step()
      if batch_idx % args.log_interval == 0:
          print('Train Epoch: {} [{}/{}]\tLoss: {}'.format(epoch, batch_idx * len(data), len(train_loader), loss.data[0]))
```

Running Horovod

- MPI takes care of launching processes on all machines
- Run on a 4 GPU machine (Open MPI 3.0.0):
  - ```
    $ mpirun -np 4 \
        -H localhost:4 \
        -bind-to none -map-by slot \
        -x NCCL_DEBUG=INFO -x LD_LIBRARY_PATH \
        python train.py
    ```
- Run on 4 machines with 4 GPUs (Open MPI 3.0.0):
  - ```
    $ mpirun -np 16 \
        -H server1:4,server2:4,server3:4,server4:4 \
        -bind-to none -map-by slot \
        -x NCCL_DEBUG=INFO -x LD_LIBRARY_PATH \
        python train.py
    ```
- Boilerplate `mpirun` arguments are easily hidden in a convenience script

Horovod on Spark

```
horovod_train(training_log_dir=TRAINING_LOGS_OUTPUT_DIR, horovod_timeline_file=HOROVOD_TIMELINE_FILE)
```

```
INFO:tensorflow:Writing Horovod program (and all notebooks in workspace directory /Users/smurching@databricks.com/horovod-db-guide/horovod/training-notebooks) to directory /tmp/tmp0cYbP0 on each worker
INFO:tensorflow:Syncing training stderr and stdout logs to DBFS directory /dbfs/tmp/horovod/mnist-output-multimachine for persistent storage
INFO:tensorflow:Syncing Horovod timeline logs to DBFS path /dbfs/tmp/horovod/horovod-timeline.json for persistent storage
INFO:tensorflow:Running Horovod training command mpirun -bind-to none -map-by slot --allow-run-as-root -H 10.95.254.135:1,10.95.228.234:1 -output-filename tmp/horovod/mnist-output-multimachine -np 2 -x HOROVOD_TIMELINE -x NCCL_DEBUG /databricks/python/bin/python /tmp/tmp0cYbP0/training.py
/databricks/python/local/lib/python2.7/site-packages/h5py/__init__.py:36: FutureWarning: Conversion of the second argument of issubdtype from `float` to `np.floating` is deprecated. In future, it will be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
/databricks/python/local/lib/python2.7/site-packages/h5py/__init__.py:36: FutureWarning: Conversion of the second argument of issubdtype from `float` to `np.floating` is deprecated. In future, it will be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
INFO:tensorflow:Copying key mnist/train-part-1-of-60.tfrecords in bucket databricks-public-datasets to /tmp/horovod/mnist/train-part-1-of-60.tfrecords
INFO:tensorflow:Copying key mnist/train-part-0-of-60.tfrecords in bucket databricks-public-datasets to /tmp/horovod/mnist/train-part-0-of-60.tfrecords
INFO:tensorflow:Copying key mnist/train-part-11-of-60.tfrecords in bucket databricks-public-datasets to /tmp/horovod/mnist/train-part-11-of-60.tfrecords
INFO:tensorflow:Copying key mnist/train-part-13-of-60.tfrecords in bucket databricks-public-datasets to /tmp/horovod/mnist/tra
```

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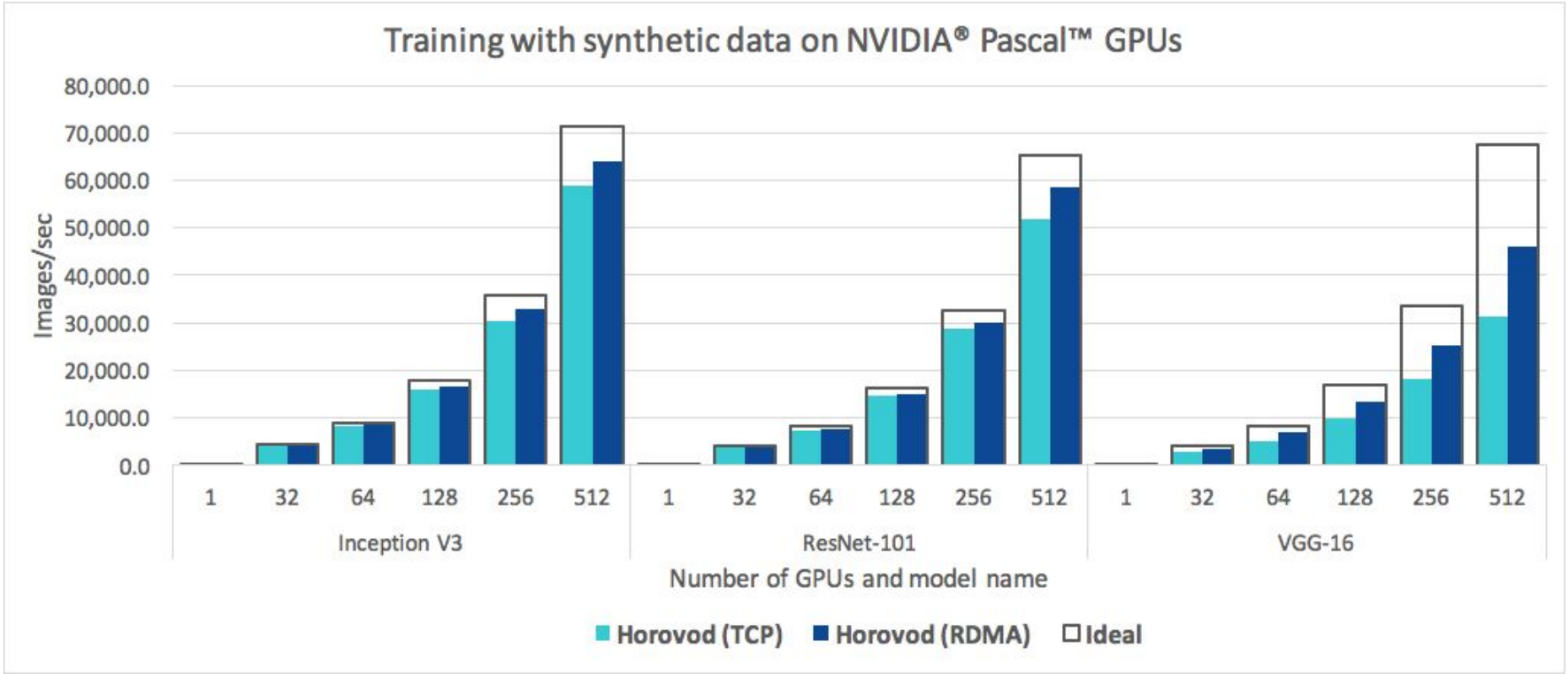
https://docs.databricks.com/applications/deep-learning/distributed-deep-learning/horovod/index.html

Horovod Performance



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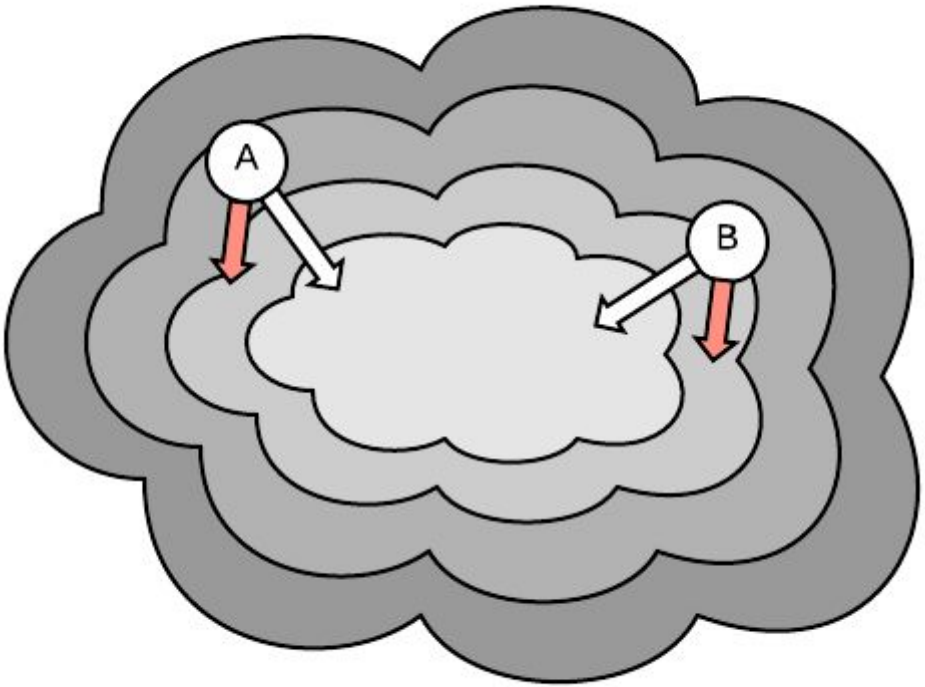
Horovod scales well beyond 128 GPUs. RDMA helps at a large scale, especially to small models with fully-connected layers like VGG-16, which are very hard to scale.

Practical Aspects - Initialization

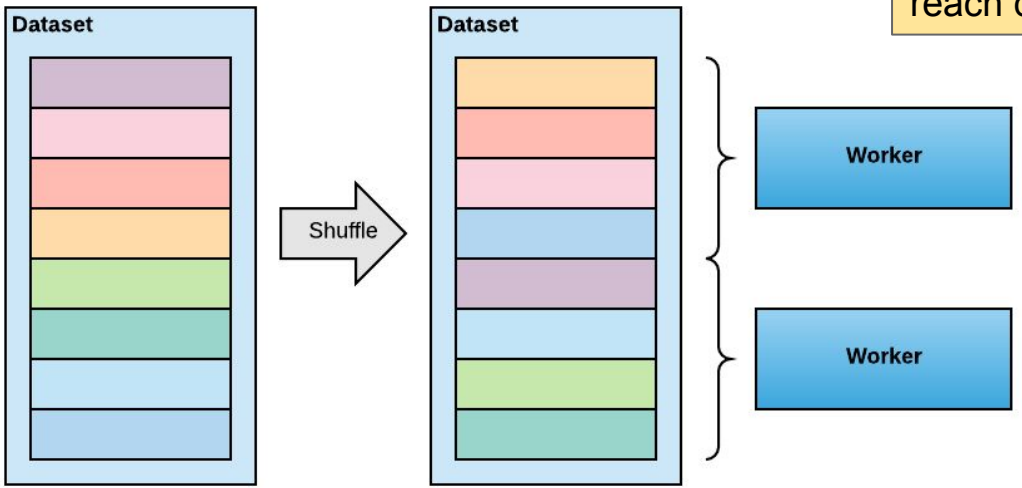
- Use broadcast operation to make sure all workers start with the same weights
- Otherwise, averaged gradient will not point towards minimum (shown in red)



Practical Aspects - Data Partitioning

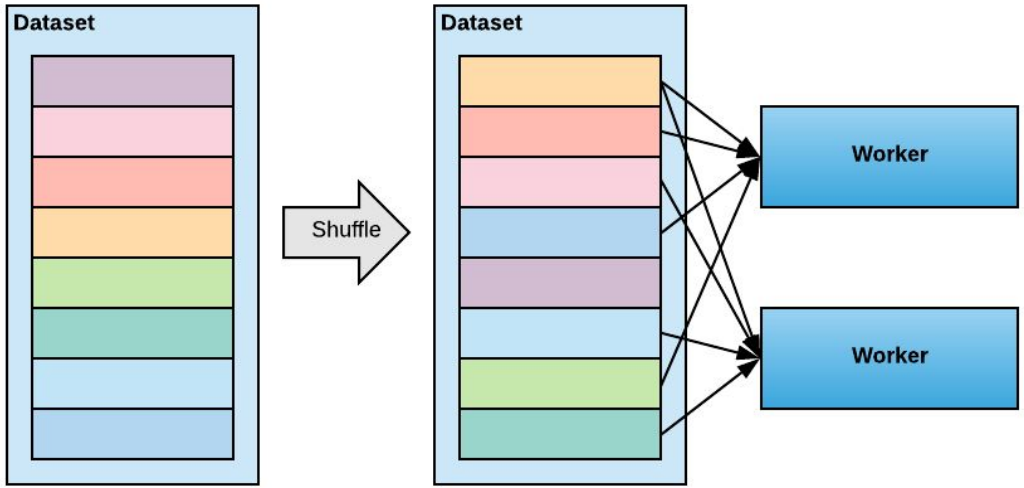
- Shuffle the dataset
- Partition records among workers
- Train by sequentially reading the partition
- After epoch is done, reshuffle and partition again

NOTE: make sure that all partitions contain the same number of batches, otherwise the training will reach deadlock



Practical Aspects - Random Sampling

- Shuffle the dataset
- Train by randomly reading data from whole dataset
- After epoch is done, reshuffle

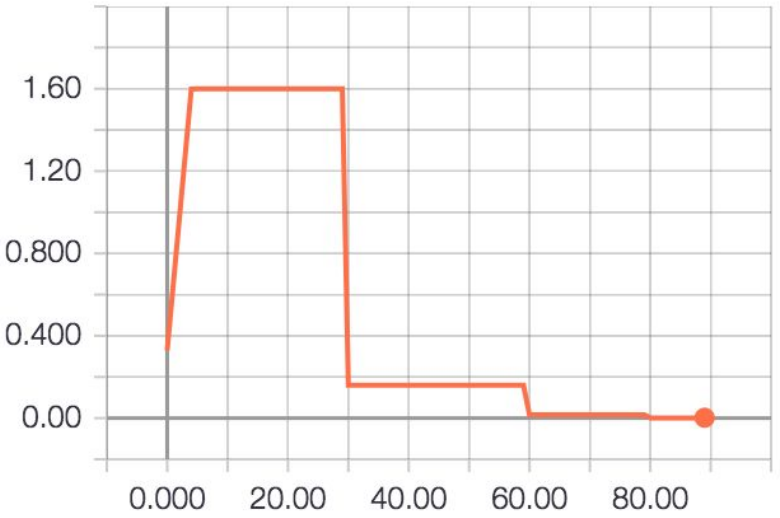


Practical Aspects - Data

- Random sampling may cause some records to be read multiple times in a single epoch, while others will not be read at all
- In practice, both approaches typically yield same results
- **Conclusion**: use the most convenient option for your case
- **Remember**: validation can also be distributed, but you need to make sure to average validation results from all the workers when using learning rate schedules that depend on validation
    - Horovod comes with `MetricAverageCallback` for Keras

Practical Aspects - Learning Rate Adjustment

- In Facebook's paper, "*Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour*" (arxiv.org/abs/1706.02677) they recommend linear scaling of learning rate:
  - $LR_N = LR_1 * N$
  - Requires smooth warm-up during first K epochs, as shown below
  - Works up to batch size 8192
- Horovod comes with `LearningRateWarmupCallback` for Keras



Practical Aspects - Learning Rate Adjustment Cont.

- Yang You, Igor Gitman, Boris Ginsburg in paper "*Large Batch Training of Convolutional Networks*" demonstrated scaling to batch of 32K examples (arxiv.org/abs/1708.03888)
  - Use per-layer adaptive learning rate scaling
- Google published a paper "*Don't Decay the Learning Rate, Increase the Batch Size*" (arxiv.org/abs/1711.00489) arguing that typical learning rate decay can be replaced with an increase of the batch size

Practical Results at Uber and beyond

- Applied Facebook's learning rate adjustment technique
- Horovod is accepted as the only way Uber does distributed learning
- We train both convolutional networks and LSTMs in hours instead of days or weeks with the same final accuracy
- Horovod now adopted at other companies and research institutions, recommended by Google as a way to do distributed training

Thank you!

https://github.com/uber/horovod

Horovod on our Eng Blog: https://eng.uber.com/horovod
Michelangelo on our Eng Blog: https://eng.uber.com/michelangelo
ML at Uber on YouTube: http://t.uber.com/ml-meetup

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