

Distributed deep learning and why you may not need it

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PyData Warsaw 2018

About us

- Research at Avast
 - 400M customers (Avast, AVG, HideMyAss, CCleaner)
 - Tons of damage data









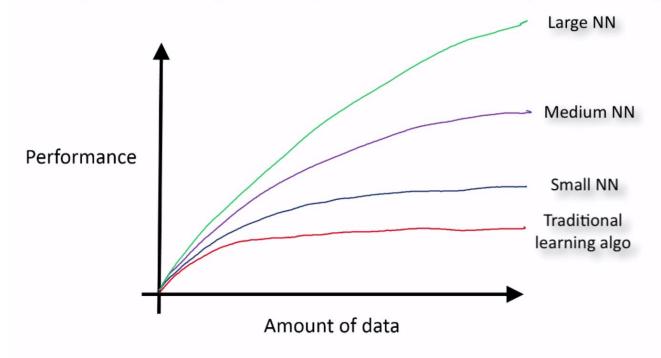


Outline

- Wow such Deep Learning much Al
- Different kinds of distributed learning and parallelism
- Frameworks and approaches

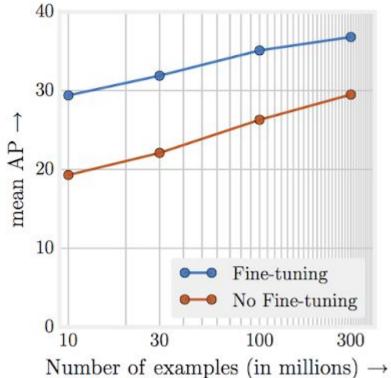


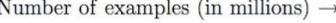
One picture explaining the rise of Deep Learning



Revisiting Unreasonable Effectiveness of Data in Deep Learning Era Chen Sun, Abhinav Shrivastava, Saurabh Singh, and Abhinav Gupta

COCO object detection:



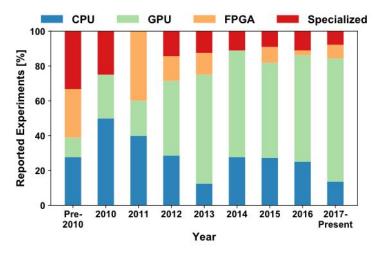




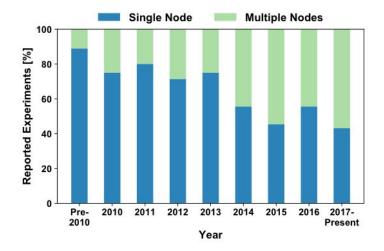
Why go distributed?

Demystifying Parallel and Distributed Deep Learning: An In-Depth Concurrency Analysis





(a) Hardware Architectures

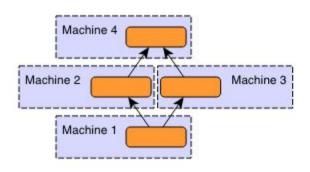


(b) Training with Single vs. Multiple Nodes

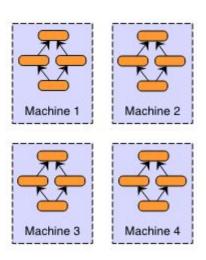


Types of parallelism

Model Parallelism

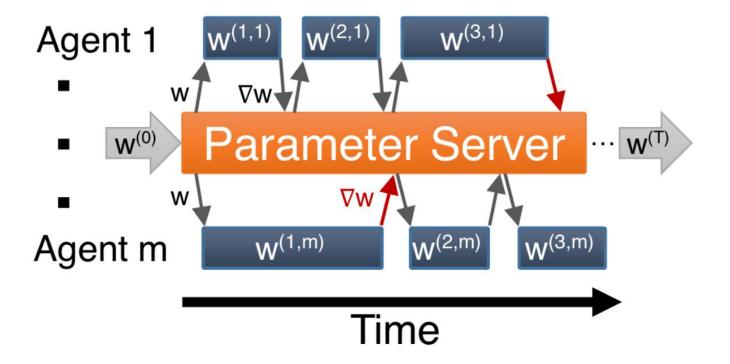


Data Parallelism



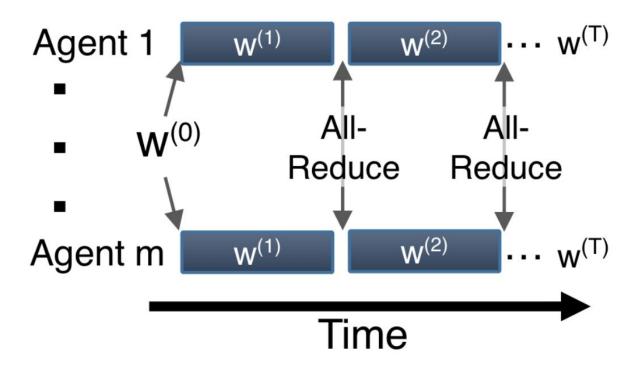


Asynchronous training



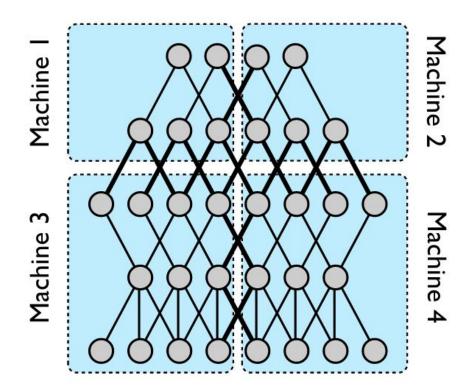


Synchronous training with all reduce

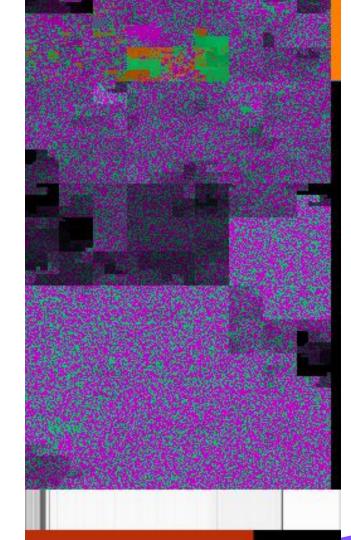




Model parallelism









Distributed Tensorflow (asynchronous)

```
# 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...
# 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:
    # Train your model
```



Tensorflow

```
run_config = tf.estimator.RunConfig()

classifier = tf.estimator.Estimator(
    model_fn=model_function, # desctiption of your model - loss, updates etc.
    model_dir=model_dir, # directory where you want to store your model
    config=run_config) # how often you need summaries, how often to checkpoint etc.

classifier.train(input_fn=input_function)
```



Distributed Tensorflow (synchronous, single node)

```
distribution = tf.contrib.distribute.MirroredStrategy() # multi-GPU distribution

run_config = tf.estimator.RunConfig(train_distribute=distribution)

classifier = tf.estimator.Estimator(
    model_fn=model_function, # desctiption of your model - loss, updates etc.
    model_dir=model_dir, # directory where you want to store your model
    config=run_config) # how often you need summaries, how often to checkpoint etc.

classifier.train(input_fn=input_function)
```





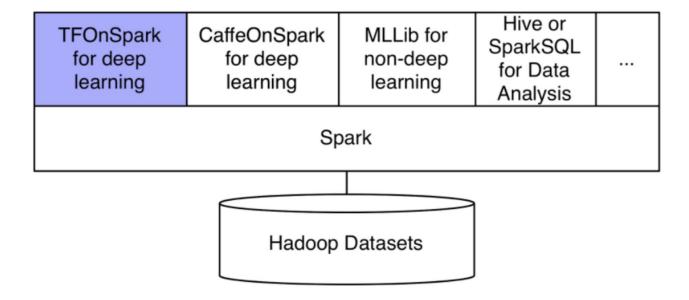
```
import tensorflow as tf
import horovod.tensorflow as hvd
# Initialize Horovod
hvd.init()
# Pin GPU to be used to process local rank (one GPU per process)
config = tf.ConfigProto()
config.gpu options.visible device list = str(hvd.local rank())
# Build model...
# Add Horovod Distributed Optimizer
opt = hvd.DistributedOptimizer(opt)
# 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=checkpoint_dir,
                                        config=config,
                                        hooks=hooks) as mon sess:
    # Perform synchronous training.
```





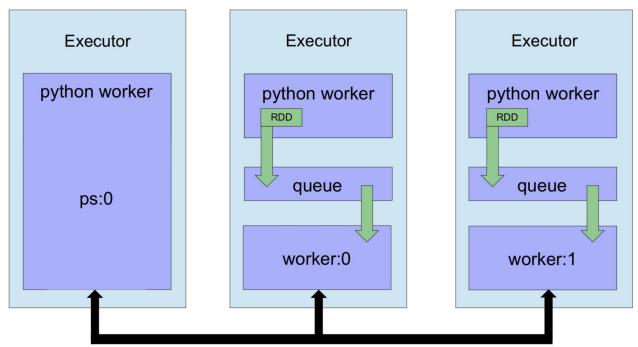
```
import tensorflow as tf
import horovod.tensorflow as hvd
# Initialize Horovod
hvd.init()
# Pin GPU to be used to process local rank (one GPU per process)
config = tf.ConfigProto()
config.gpu_options.visible_device_list = str(hvd.local_rank())
# Build model...
# Add Horovod Distributed Optimizer
opt = hvd.DistributedOptimizer(opt)
# 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=checkpoint_dir,
                                        config=config,
                                       hooks=hooks) as mon_sess:
    # Perform synchronous training.
$ 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 -x PATH \
    -mca pml ob1 -mca btl ^openib \
    python train.py
```





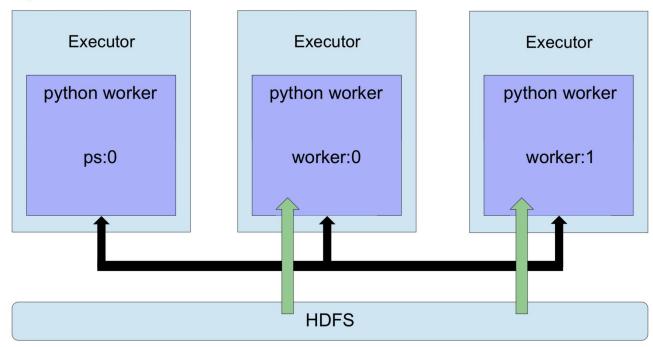


InputMode.SPARK





InputMode.TENSORFLOW





```
from tensorflowonspark import TFCluster, TFNode
# start the cluster
cluster = TFCluster.run(sc, map_fn, args, num_executors, num_ps, tensorboard, input_mode)
# either pass data for training
cluster.train(dataRDD, num_epochs=0)
# or pass data for scoring
cluster.inference(dataRDD)
# shutdown the cluster
cluster.shutdown()
```



```
def map_fun(args, ctx):
   import tensorflow as tf
    # necessary variables
   logdir = ctx.absolute path(args.model)
   hooks = [tf.train.StopAtStepHook(last_step=100000)]
   batch_size = args.batch_size
   worker num = ctx.worker num
   job_name = ctx.job_name
   task_index = ctx.task_index
   # Get TF cluster and server instances
   cluster, server = ctx.start_cluster_server(1, args.rdma)
   if job name == "ps":
        print('PARAMETER SERVER')
       server.join()
   elif job_name == "worker":
        # Assigns ops to workers - taken care of by Spark
        with tf.device(tf.train.replica_device_setter(
                worker_device="/job:worker/task:%d" % task_index,
                cluster=cluster)):
            [...]
   # start your MonitoredTrainingSession
   with tf.train.MonitoredTrainingSession(master=server.target,
                                             is_chief=(task_index == 0),
                                             checkpoint_dir=logdir,
                                             hooks=hooks) as mon_sess:
        # train or score your data
        [...]
```



Comparison and our benchmarks

synchronous Tensorflow	asynchronous Tensorflow	Horovod	TFonS
easiest to use	not hard to use, but requires code change	requires code change	requires most code change
only one machine	multi-device, multi-machine	multi-device, multi-machine	multi-device, multi-machine
speed scales almost linearily	scales almost linearity	slower than expected, most probably because of higher network requirements	slowest because of a lot of overhead, can be run on existing infrastructure



Why you may not need it

- Hardware improvements
- Code simplicity
- Simpler models are enough / data efficiency
- Experimentation







Thank you!

For questions, feel free to reach out to us at:

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Resources:

- https://arxiv.org/pdf/1802.09941.pdf / https://www.youtube.com/watch?v=xtxxLWZznBI
- https://arxiv.org/pdf/1610.02527.pdf
- https://papers.nips.cc/paper/4687-large-scale-distributed-deep-networks.pdf
- https://medium.com/@esaliva/model-parallelism-in-deep-learning-is-not-what-you-think-94d2f81e82ed
- https://blog.skymind.ai/distributed-deep-learning-part-1-an-introduction-to-distributed-training-of-neural-networks/
- https://www.youtube.com/watch?v=SphfeTI70MI
- https://www.tensorflow.org/deploy/distributed
- https://arxiv.org/pdf/1802.05799.pdf / https://github.com/uber/horovod
- https://github.com/yahoo/TensorFlowOnSpark
- https://github.com/tensorflow/ecosystem/tree/master/spark/spark-tensorflow-connector

