Strata DATA CONFERENCE

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Spark and Deep Learning frameworks with distributed workloads

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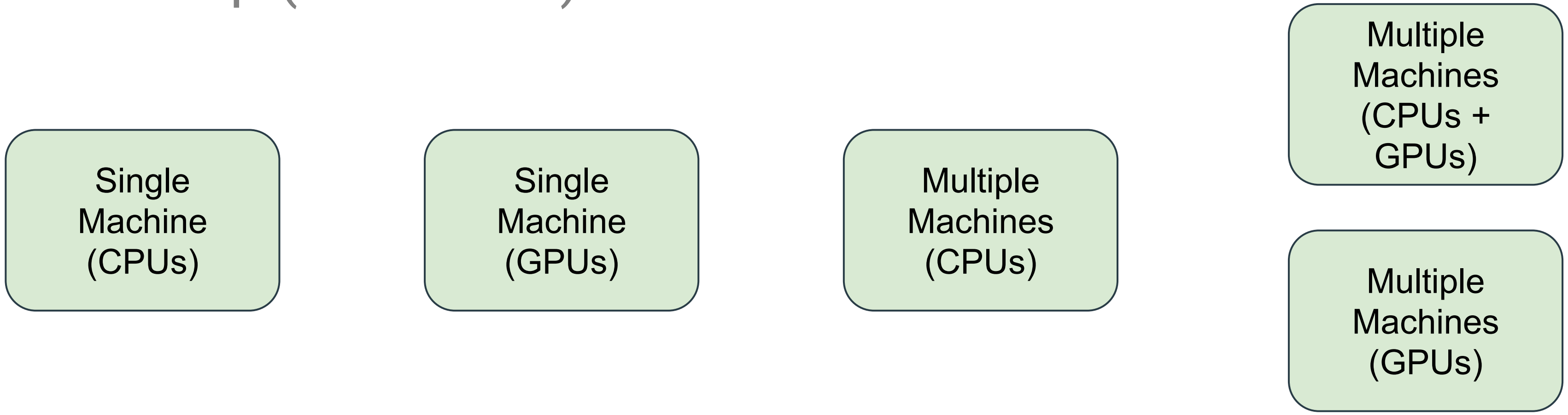
Agenda

- Machine Learning and Deep Learning on a scalable infrastructure
- Comparative look - CPU vs CPU+GPU vs GPU
- Challenges with distributing ML pipelines and algorithms
- Frameworks that support distributed scaling
- Spark/YARN on GPUs vs CPUs

Machine Learning and Deep Learning on a scalable infrastructure

Machine Learning on a scalable infrastructure

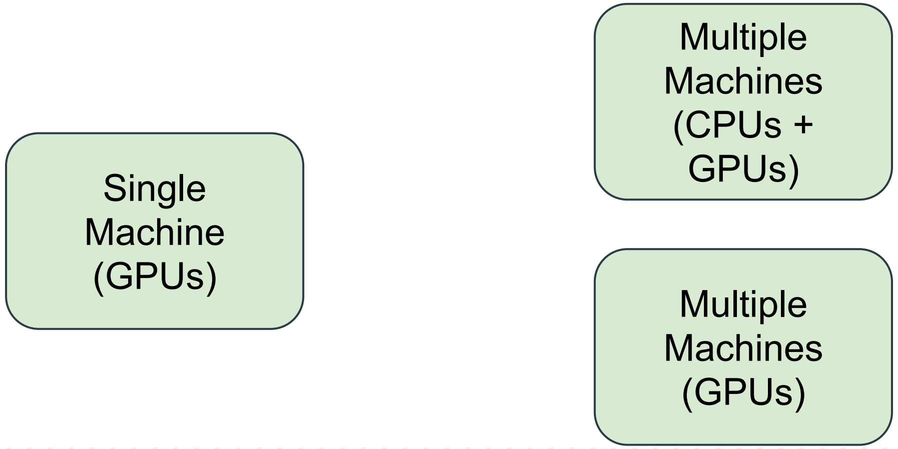
- Single machine multiple CPU cores
- Training distributed across machines - still mostly using CPUs
- For Deep Learning - Sometimes requires GPUs
- Distributed across machines
- Mixed setup (CPU+GPU)



Deep Learning on a scalable infrastructure

Model parallelization, Data parallelization

- Single machine - multiple GPUs
- Distributed deep learning across machines - sometimes inevitable



Deep Learning - why resource hungry

Model parallelization challenges

- Memory in neural networks - to store **input data**, **weight parameters** and **activations** as an input propagates through the network.
- GPUs' reliance on dense vectors - fill SIMD compute engines
- CPU/GPU intensive - matrix multiplications - weights x activations.

Using 32-bit floating-point - parallelise training data

Mini-batch of 32

7.5 GB of local DRAM

Example: 50-Layer ResNet

CPU vs CPU+GPU vs GPU

CPU vs GPU

CPU

- Few very complex cores
- Single-thread performance optimization
- Transistor space dedicated to complex ILP
- Few die surface for integer and fp units
- Has other memory types but they are provisioned only as caches, not directly accessible to the programmer

GPU

- Hundreds of simpler cores
- Thousands of concurrent hardware threads
- Maximize floating-point throughput
- Most die surface for integer and fp units
- Has several forms of memory of varying speeds and capacities - memory types are exposed to the programmer

Why is CPU the new bottleneck?

- Hardware configurations offer large aggregate IO bandwidth
- Spark's optimizer allows many workloads - avoiding significant disk IO
- Spark's shuffle subsystem, serialization & hashing key - bottlenecks
- Spark constrained by CPU efficiency and memory pressure rather than IO.

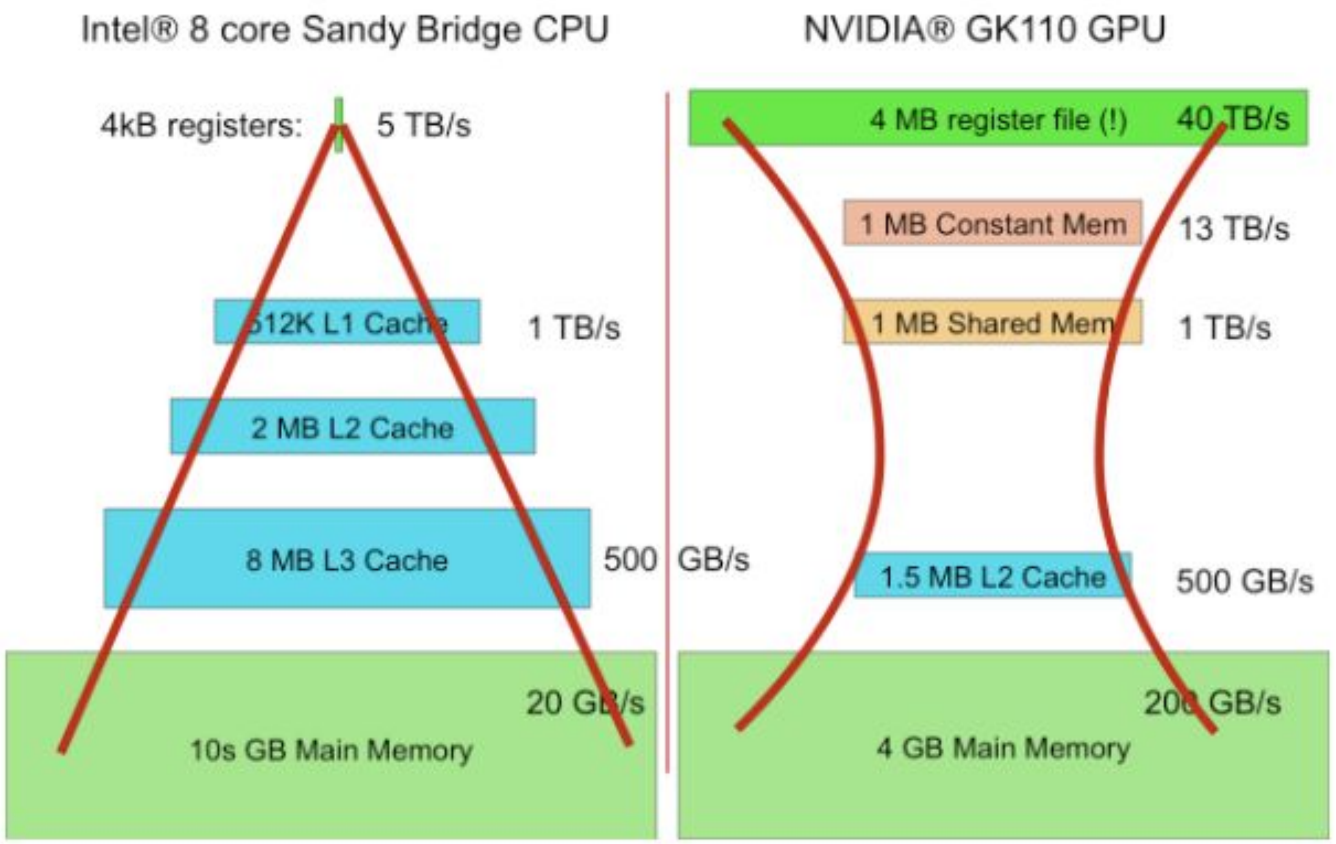
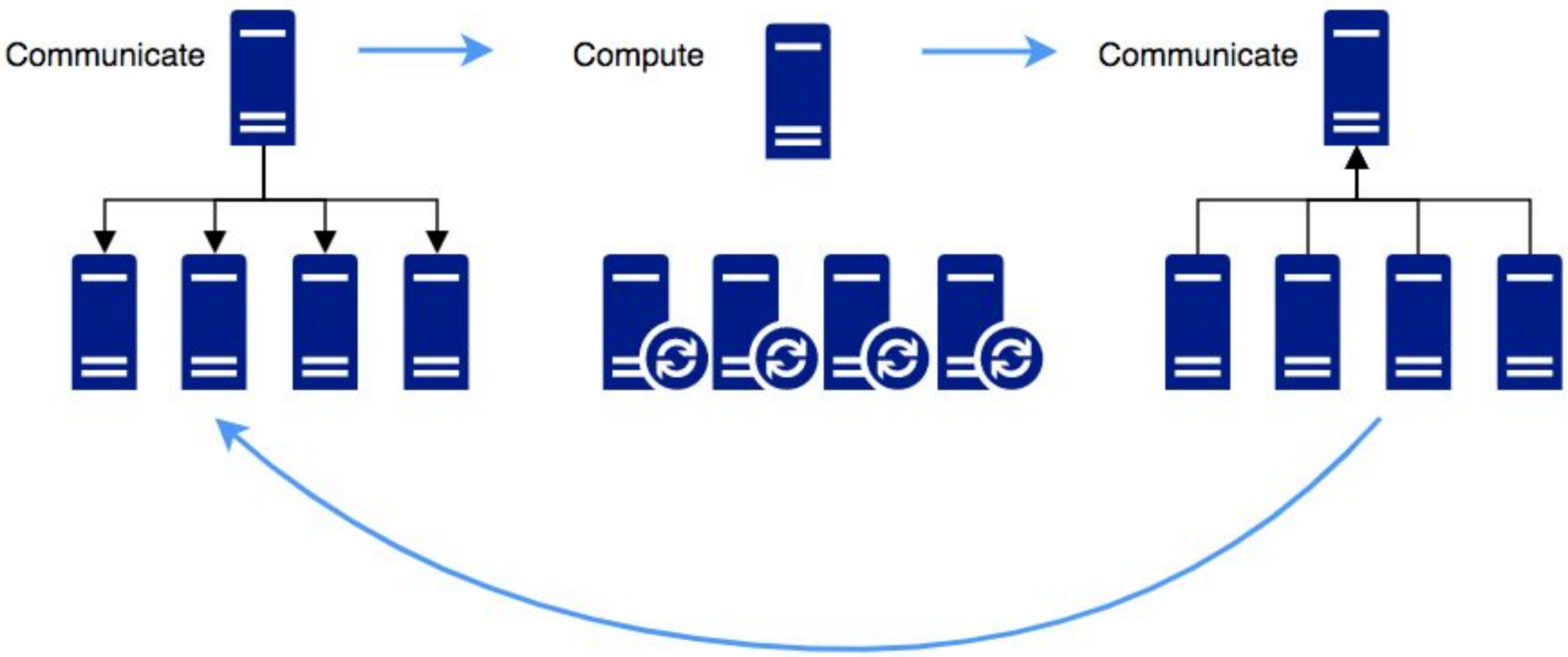


Image Source: https://devblogs.nvidia.com/bidmach-machine-learning-limit-gpus/

Challenges with distributing ML & DL pipelines, algorithms & processes

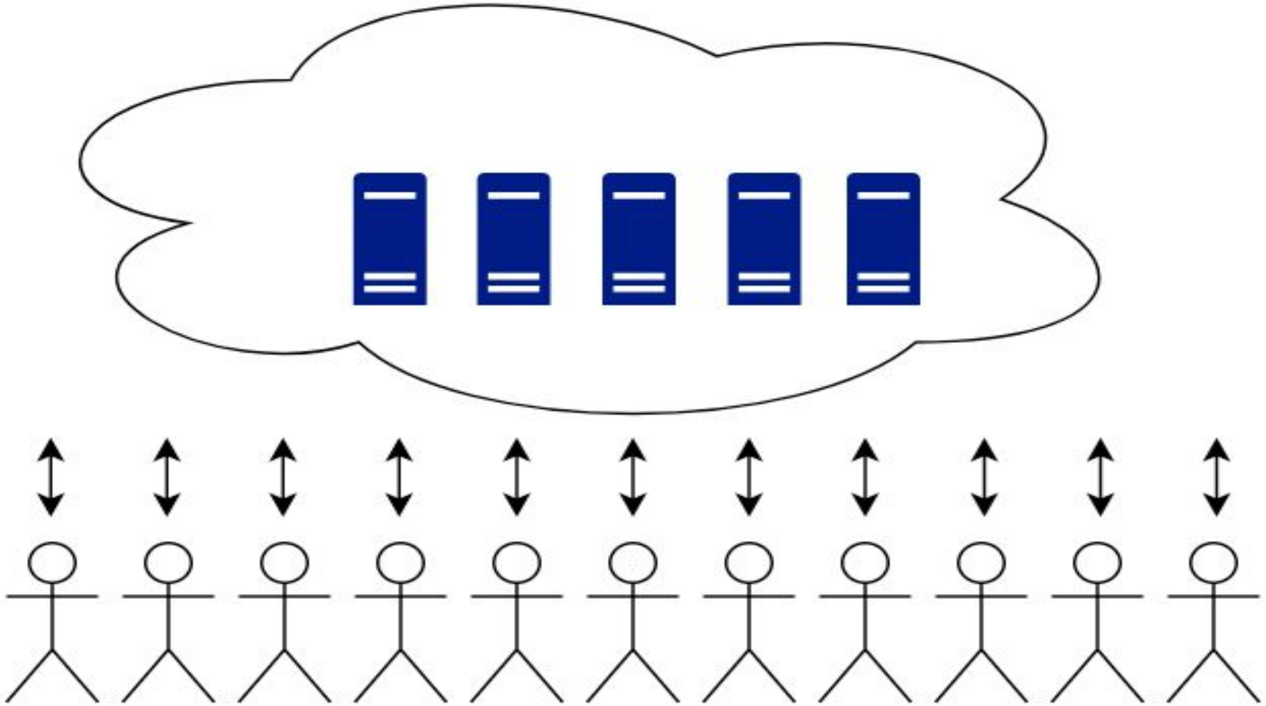
Training

- Compute heavy
- Requires synchronization across network of machines
- GPUs often necessary/beneficial



Inference

- Embarrassingly parallel
- Varying latency requirements
- Can be mostly done on CPUs - GPUs often unnecessary



Hyper-parameter optimization

Parameters that define the model architecture are referred to as hyperparameters.

HPO (hyperparameter tuning) is a process of searching for the ideal model architecture.

- HPO is a necessary part of all model training
- It is embarrassingly parallel
- Can avoid distributed training

Scenario:

- Run 4 HP configurations, 1/gpu, in parallel vs. 4 HP configurations, 1/4gpu, in serial

Optimization Methods

Grid-Search
Randomized Search

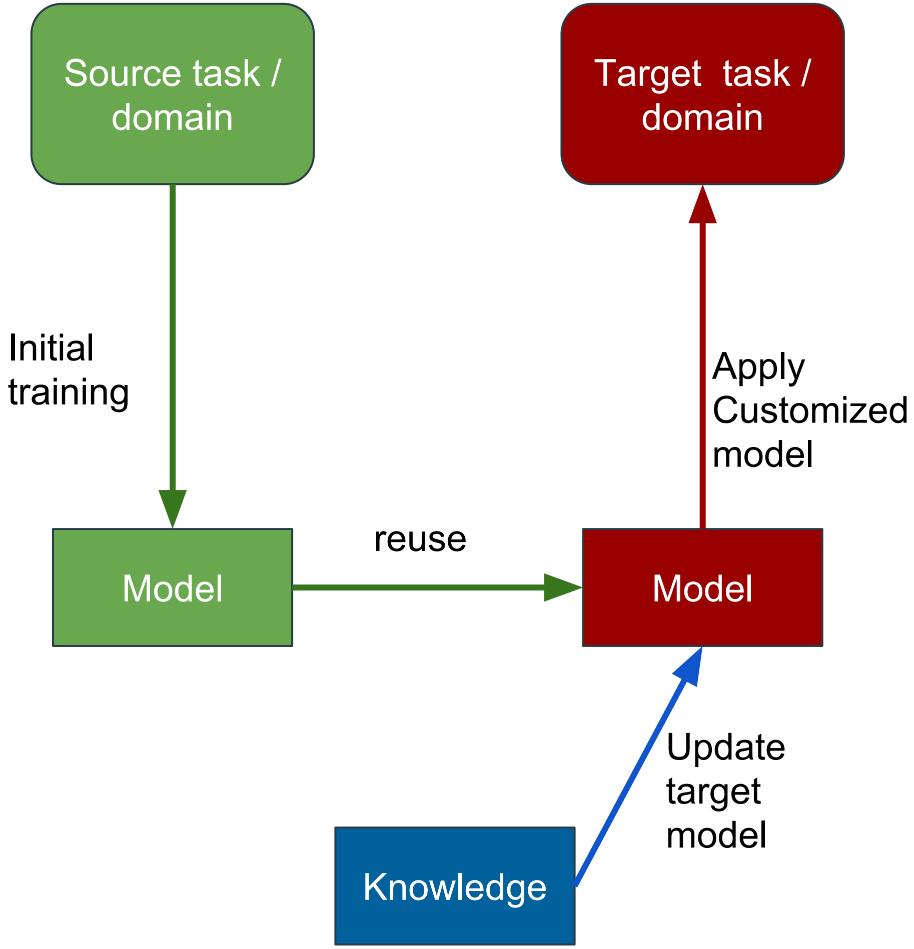
Tools

Hyper-Opt
Sckit-optimize
Spearmint
MOE

Transfer learning

Transfer learning - machine learning where "knowledge" learned on one task is applied to another, related task.

- Take publicly available models and re-purpose them for your task
  - Leverage the work from hundreds of GPUs that is already baked in
- Train a small percentage of the model for your task
- Greatly reduced computational requirements mean you may not need GPUs or may not need distributed architecture



Current Landscape

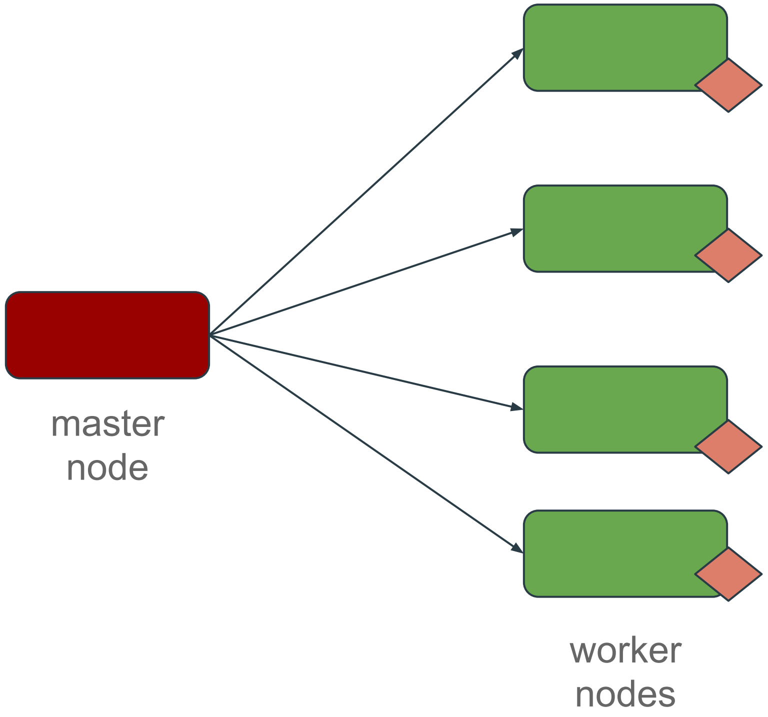
- Machine Learning Frameworks
- Deep learning Frameworks
- Distributed Frameworks
- Spark based Frameworks

Distributed Machine Learning Frameworks

Machine learning on Spark

ML Frameworks

- Spark stores the model parameters in the driver
- Workers communicate with the driver to update the parameters after each iteration.
- For large scale machine learning deployments, the model parameters may not fit into the driver node and they would need to be maintained as an RDD.
- Drawback -
  - This introduces a lot of overhead because a new RDD will need to be created in each iteration to hold the updated model parameters.
  - Since updating the model usually involves shuffling data across machines, this limits the scalability of Spark.



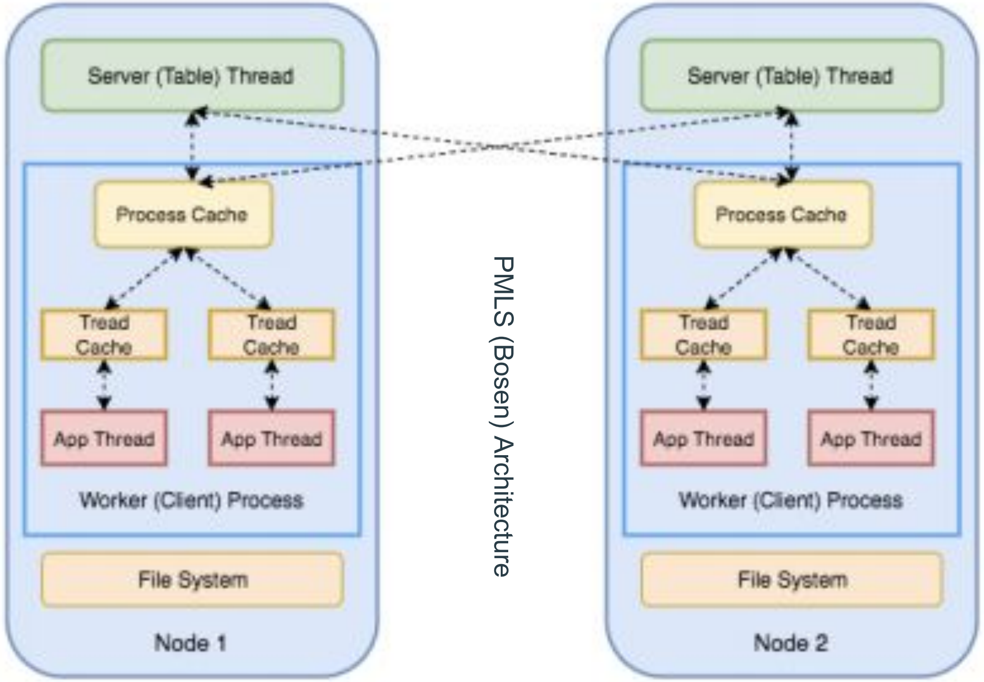
Using PMLS Parameter-Server framework

ML Frameworks

- Both data and workloads are distributed over worker nodes
  - server nodes maintain globally shared parameters
  - represented as dense or sparse vectors and matrices
- The framework manages asynchronous data communication between nodes
- Flexible consistency models
- Elastic scalability
- Continuous fault tolerance.

Frameworks

DistBelief - Google
PMLS
Parameter Server



PMLS (Bosen) Architecture

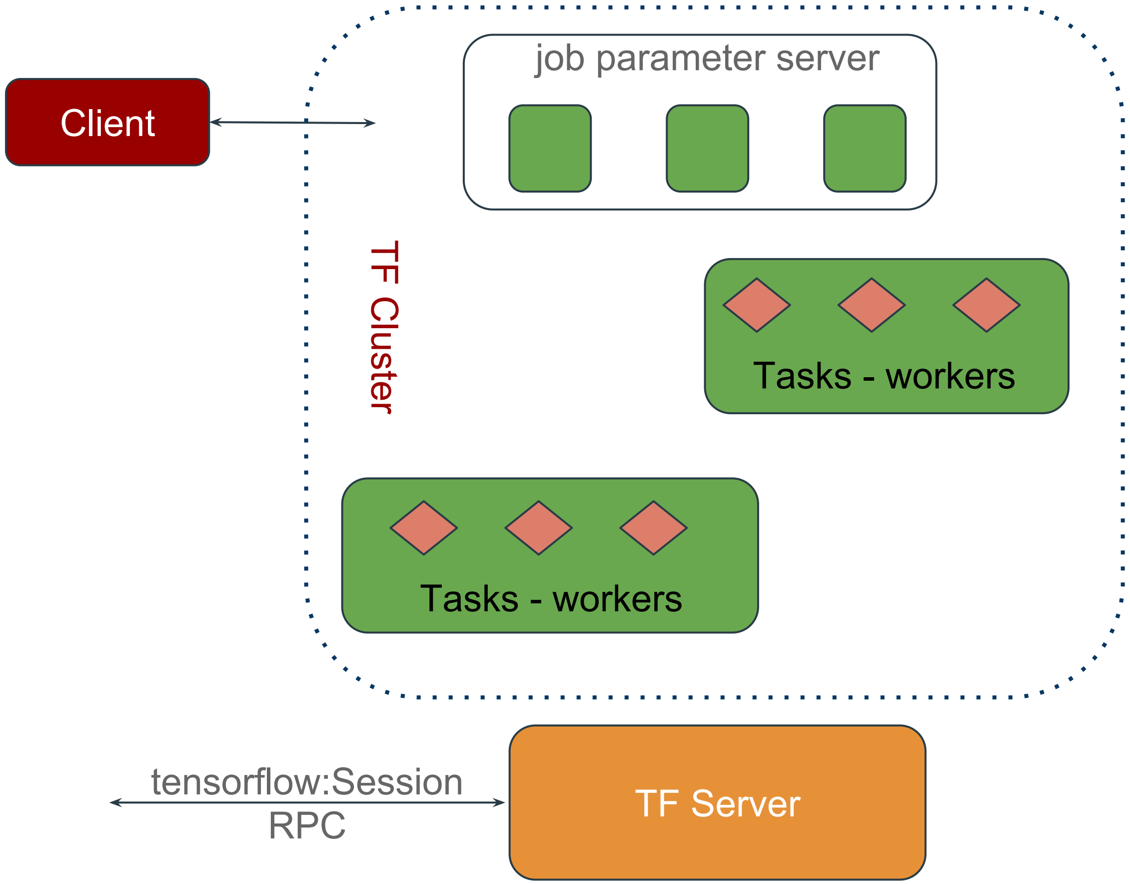
Image Source: https://cse.buffalo.edu/~demirbas/publications/DistMLplat.pdf

Distributed Deep Learning Frameworks

Distributed TensorFlow

DL Frameworks

- Tensorflow distributed relies on master, worker, parameter server processes
- Provides fine-grained control, you can place individual tensors and operations
- Relies on a cluster specification to be passed to each process
- Need to take care of booting each process and syncing them up somehow
- Uses Google RPC protocol



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

Distributed TensorFlow

```
tf.train.ClusterSpec({
    "worker": [
        "worker0.example.com:2222",
        "worker1.example.com:2222",
        "worker2.example.com:2222"
    ],
    "ps": [
        "ps0.example.com:2222",
        "ps1.example.com:2222"
    ]})
```

tf.train.ClusterSpec

tf.train.Server

```
# In task 0:
cluster = tf.train.ClusterSpec({"local": ["localhost:2222",
"localhost:2223"]})
server = tf.train.Server(cluster, job_name="local", task_index=0)
# In task 1:
cluster = tf.train.ClusterSpec({"local": ["localhost:2222",
"localhost:2223"]})
server = tf.train.Server(cluster, job_name="local", task_index=1)
```

PyTorch (torch.distributed)

PyTorch

DL Frameworks

- Has a distributed package that provides MPI style primitives for distributing work
- Has interface for exchanging tensor data across multi-machine networks
- Currently supports four backends (tcp, gloo, mpi, nccl - CPU/GPU)
- Only recently incorporated
- Not a lot of documentation

```
import torch
import torch.distributed as dist

dist.init_process_group(backend="nccl",

init_method="file:///distributed_test",
                        world_size=2,
                        rank=0)
tensor_list = []
for dev_idx in range(torch.cuda.device_count()):

tensor_list.append(torch.FloatTensor([1]).cuda(dev_idx
))

dist.all_reduce_multigpu(tensor_list)
```

Multi-GPU collective functions

Apache MXNet

DL Frameworks

- Parameter server/worker architecture
- Must compile from source to use
- Provide built-in “launchers”, e.g. YARN, Kubernetes, but still cumbersome
- Data Loading(IO) - Efficient distributed data loading and augmentation.
- Can specify the context of the function to be executed within - that tells if it should be run on CPU or GPU

```
import mxnet.ndarray as nd

X  = nd.zeros((10000, 40000), mx.cpu(0))
#Allocate an array to store 1000 datapoints (of 40k
dimensions) that lives on the CPU
W1 = nd.zeros(shape=(40000, 1024),  mx.gpu(0))
#Allocate a 40k x 1024 weight matrix on GPU for the 1st
layer of the net
W2 = nd.zeros(shape=(1024, 10),  mx.gpu(0))
#Allocate a 1024 x 1024 weight matrix on GPU for the 2nd
layer of the net
```

Allocating parameters and data points into GPU memory

Horovod

DL Frameworks

Horovod is a distributed training framework for TensorFlow, Keras, and PyTorch.

- Released by Uber to make data parallel deep learning using TF easier
- Introduces a ring all-reduce pattern to eliminate need for parameter servers
- Uses MPI
- Require less code changes than the Distributed TensorFlow with parameter servers

To run on 4 machines with 4 GPUs each

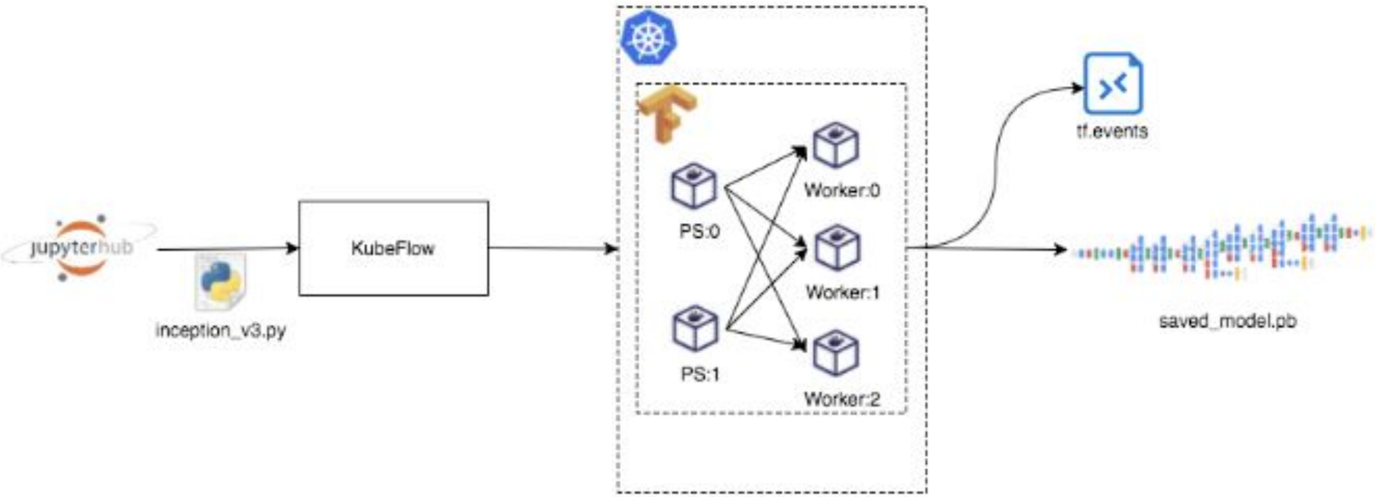
```
$ mpirun -np 16 \
    -H server1:4,server2:4,server3:4,server4:4 \
    -bind-to none -map-by slot \
    -x NCCL_DEBUG=INFO -x LD_LIBRARY_PATH -x PATH \
    -mca pml ob1 -mca btl ^openib \
    python train.py
```

Kubeflow

DL Frameworks

Machine Learning Toolkit for Kubernetes

- Custom resources for deploying ML tasks on Kubernetes
  Currently basic support for TF only
- Boots up your TF processes
- Can place on GPUs, automatic restarts, etc…
- Configures Kubernetes services for you
- Still need to know lots of Kubernetes, plus KSonnet!



KubeFlow distributed training job

Image source: https://github.com/kubeflow/kubeflow/issues/33

DL4J

DL Frameworks

- Deep learning in Java
- Comes with Spark support for data parallel architecture
- Also takes advantage of Hadoop
- Works with multi-GPUs
- Also has feature engineering/preprocessing tools, model serving tools, etc...

```
ParallelWrapper wrapper = new
ParallelWrapper.Builder(model)
          .prefetchBuffer(24)
          .workers(2)
          .averagingFrequency(3)
         .reportScoreAfterAveraging(true)
          .build();
```

ParallelWrapper to load balance between GPUs

BigDL

DL Frameworks

- Built for Spark, only works with Spark
- No GPUs!! CPUs are fast too, Intel says
- Good option if no GPU and tons of commodity CPUs
- Whole team of devs from Intel working on it
- If you have a Spark cluster and want to do DL and are not super concerned with performance - then consider BigDL

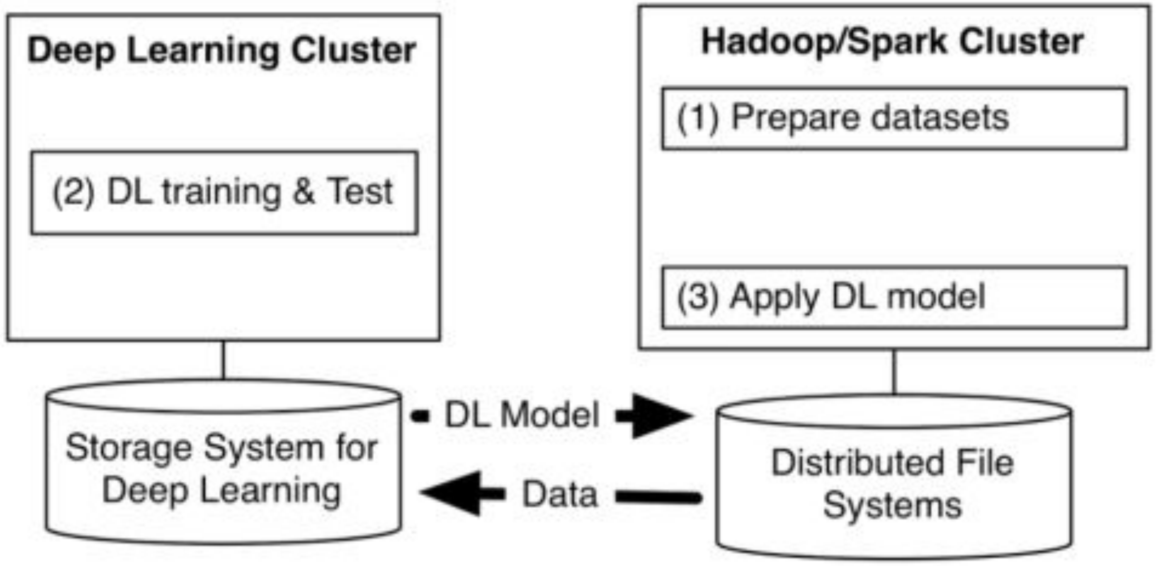
```
$SPARK_HOME/bin/spark-submit \
  --deploy-mode cluster  --class
com.intel.analytics.bigdl.models.lenet.Train
--master
k8s://https://<k8s-apiserver-host>:<k8s-apis
erver-port> --kubernetes-namespace default
--conf spark.executor.instances=4
...
$BIGDL_HOME/lib/bigdl-0.4.0-SNAPSHOT-jar-wit
h-dependencies.jar -f
hdfs://master:9000/mnist \
-b 128 -e 2 --checkpoint /tmp
```

BigDL on Kubernetes

TensorflowOnSpark

DL Frameworks

- Lightweight wrapper that boots up distributed Tensorflow processes in Spark executors
- Potentially high serialization costs
- Not super active development
- Supports training (CPU/GPU) and inference
- Easy to integrate with other Spark stages/algos



ML Pipeline with multiple programs on separate clusters

Image source: https://goo.gl/CX8N9B

Spark DL Pipelines

Tensorframes

For technical preview only

- Released by Databricks for doing Transfer Learning and Inference as a Spark pipeline stage
- Good for simple use cases
- Relies on Databricks' Tensorframes

```
featurizer = DeepImageFeaturizer(inputCol="image", outputCol="features",
modelName="InceptionV3")
lr = LogisticRegression(maxIter=20, regParam=0.05, elasticNetParam=0.3, labelCol="label")
p = Pipeline(stages=[featurizer, lr])
```

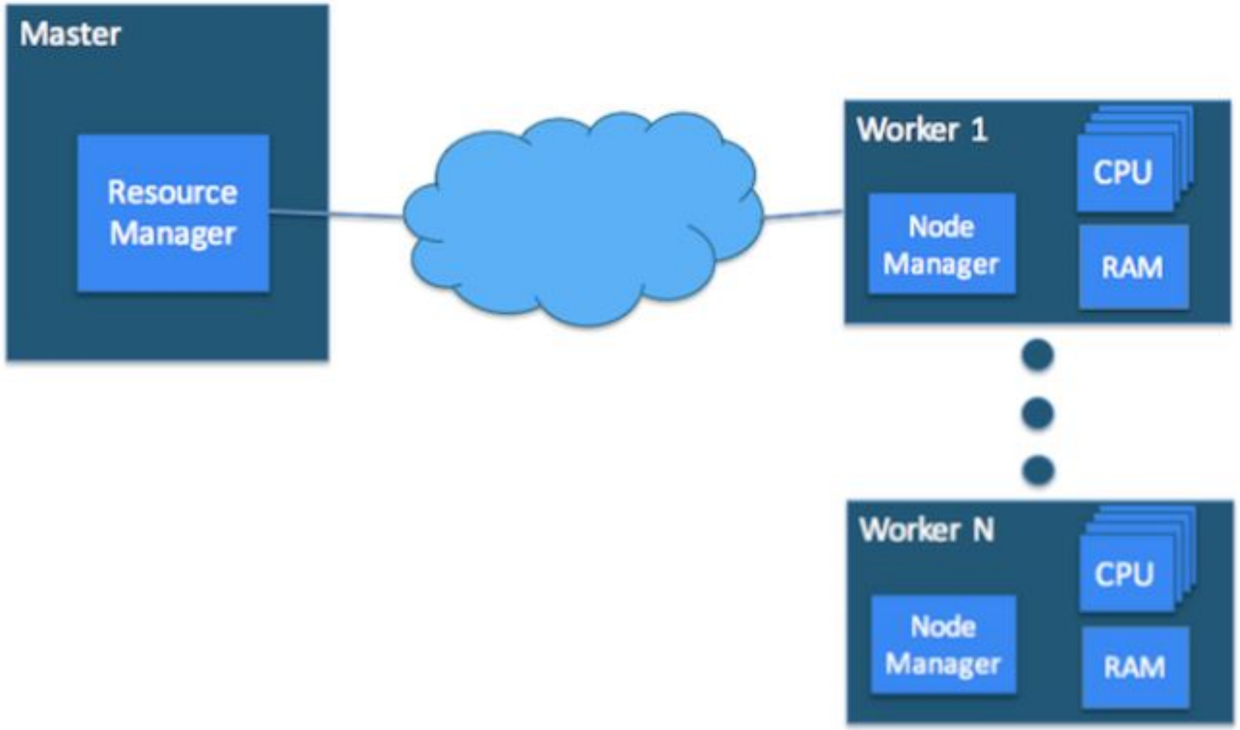
On YARN

- GPU on YARN
- Spark on YARN
- TensorFlow on YARN

Hadoop YARN

Support for GPUs

- YARN is the resource management layer for the Apache Hadoop ecosystem.
- Pre Hadoop 3.1 had CPU and memory hard-coded as the only available types of consumable resources.
- With Hadoop 3.1 YARN is declaratively configurable - can create GPU type resources for which YARN will track consumption.



Master host with ResourceManager and Worker hosts with NodeManager

GPU On YARN
Hadoop 3.1.x

- As of now, only Nvidia GPUs are supported by YARN
- YARN node managers have to be pre-installed with Nvidia drivers.
- When Docker is used as container runtime context, nvidia-docker 1.0 needs to be installed
- One can set additional configurations to allow admins leverage specialized requirements.

GPU scheduling - yarn-site.xml

```
<configuration>
  <property>
     <name>yarn.resource-types</name>
     <value>yarn.io/gpu</value>
  </property>
</configuration>
```

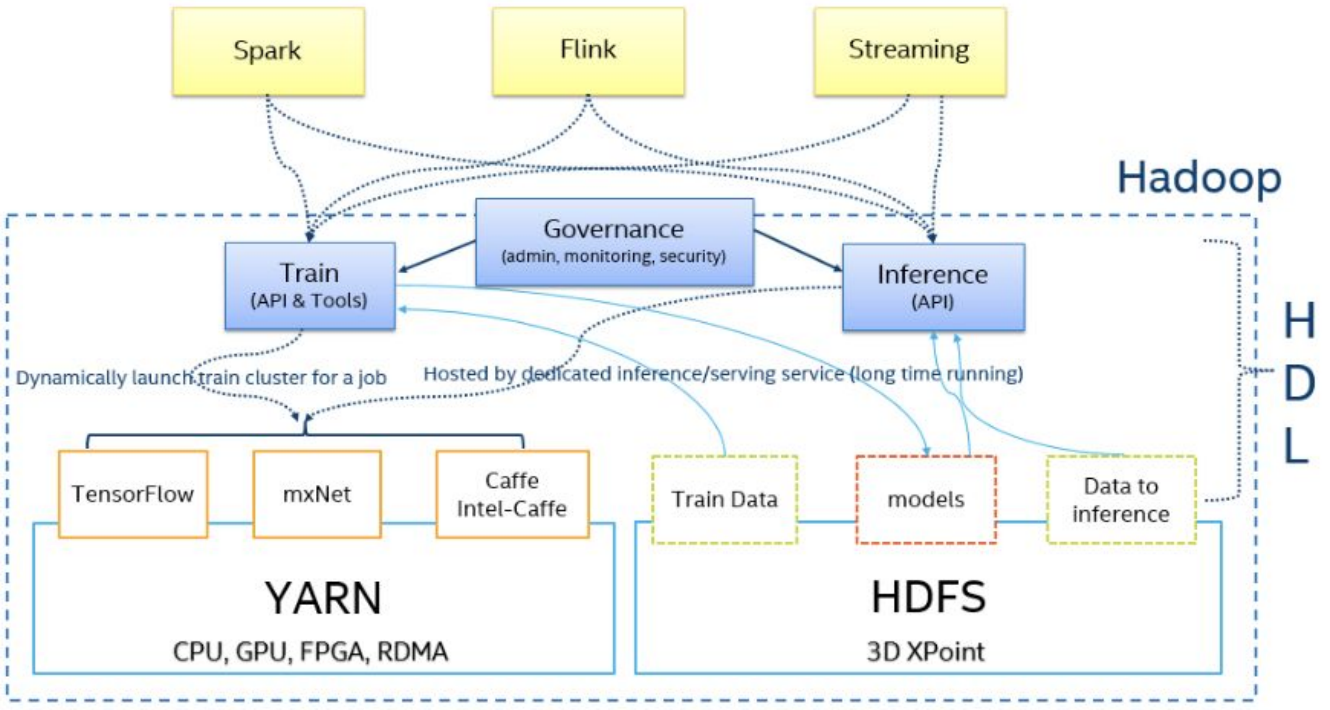
GPU isolation - yarn-site.xml

```
<property>
     <name>yarn.nodemanager.resource-plugins</name>
     <value>yarn.io/gpu</value>
</property>
```

Deep Learning on Hadoop

HDL

- A new layer in Hadoop for launching, distributing and executing Deep Learning workloads
- Leverage and support existing Deep Learning engines (TensorFlow, Caffe, MXNet)
- Extend and enhance YARN to support the desired scheduling capabilities (for FPGA, GPU)

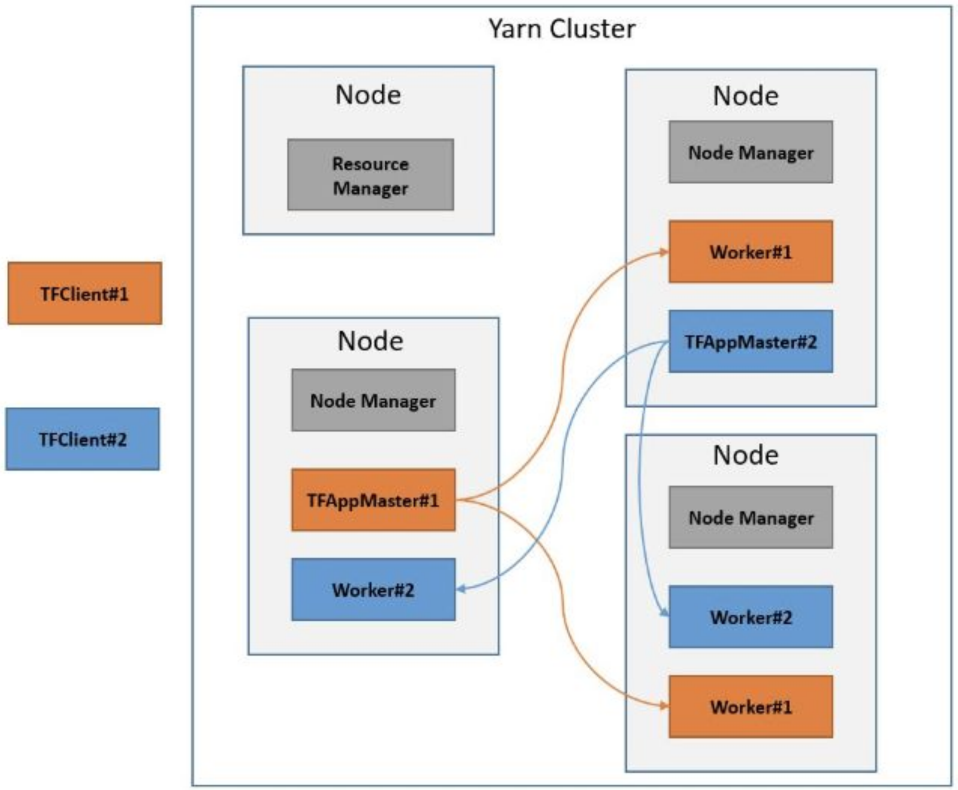


HDL Architecture

TensorFlow on YARN

Toolkit to enable Hadoop users an easy way to run TensorFlow applications in distributed pattern and accomplish tasks including model management and serving inference.

- One YARN cluster can run multiple TensorFlow clusters
- The tasks from the same and different sessions can run in the same node

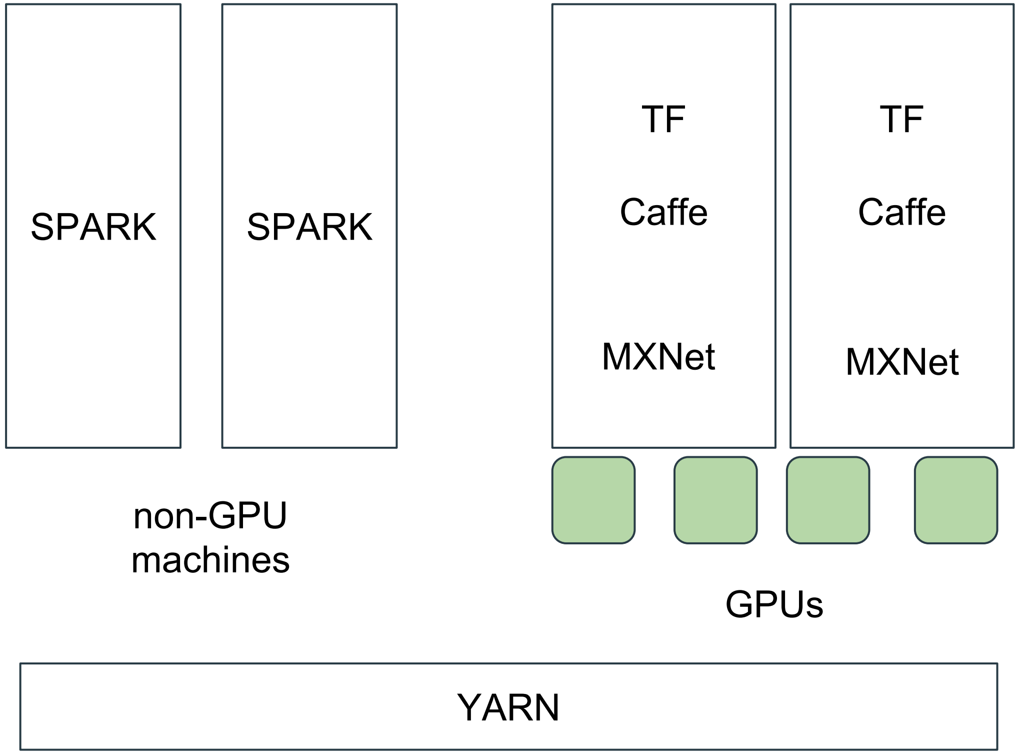


Source: https://github.com/Intel-bigdata/TensorFlowOnYARN

Spark on YARN (with GPU)

On Hadoop 3.1.0

- First class GPU support
- YARN clusters can schedule and use GPU resources
- To get GPU isolation - and to pool GPUs Hadoop YARN cluster should be Docker enabled.



Source - *https://issues.apache.org/jira/browse/YARN-6223*

Other frameworks on YARN

Work in progress

- CaffeOnYARN
  - Caffe on YARN is a project to support running Caffe on YARN, based on CaffeOnSpark from yahoo to rebase on YARN by removing Spark dependency. It's a part of Deep Learning on Hadoop (HDL).
  - *Note - Current project is a prototype with limitation and is still under development.*
- MXNetOnYARN
  - MXNet on YARN is a project based on dmlc-core and MXNet, aiming at running MXNet on YARN with high efficiency and flexibility. It's an important part of Deep Learning on Hadoop (HDL).
  - *Note - both the codebase and documentation are work in progress. They may not be the final version.*

Sources

- *CaffeOnYARN - https://github.com/Intel-bigdata/CaffeOnYARN*
- *MXNetOnYARN - https://github.com/Intel-bigdata/MXNetOnYARN*

CDH 6.x

- YARN Improvements

CDH 6.0

Work in progress

- Ability to add arbitrary consumable resources (via YARN configuration files) and have the FairScheduler schedule based on those consumable resources.
- Some examples of consumable resources that can be used are GPU and FPGA.
- Support for MapReduce

CDH 6.1

Upcoming features

- Boolean (i.e. non-consumable) Resource Types that can be used for labeling nodes and scheduling based on those.
- Some examples are nodes that have a specific license installed or nodes that have a specific OS version.
- Support for Spark
- CM UI to be able to configure Resource Types
- Preemption capabilities with arbitrary Resource Types

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THANK YOU

Machine Learning Presentations: cloudera.com/ml

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