Distributed Deep Learning with Horovod and Spark

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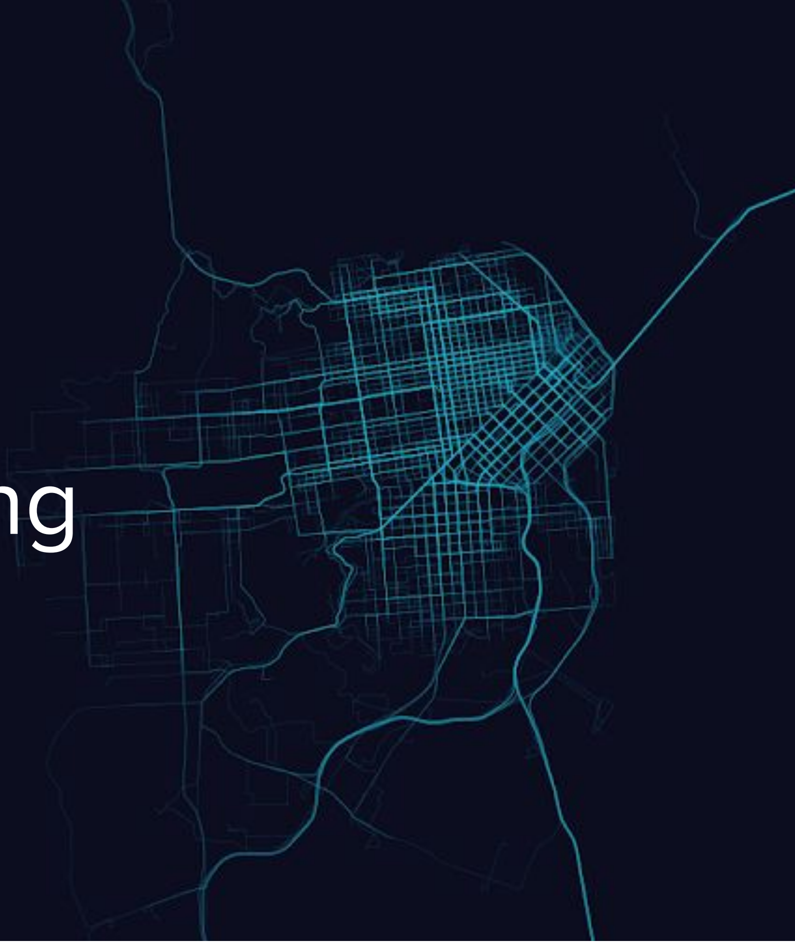
Michelangelo Deep Learning Platform
Uber



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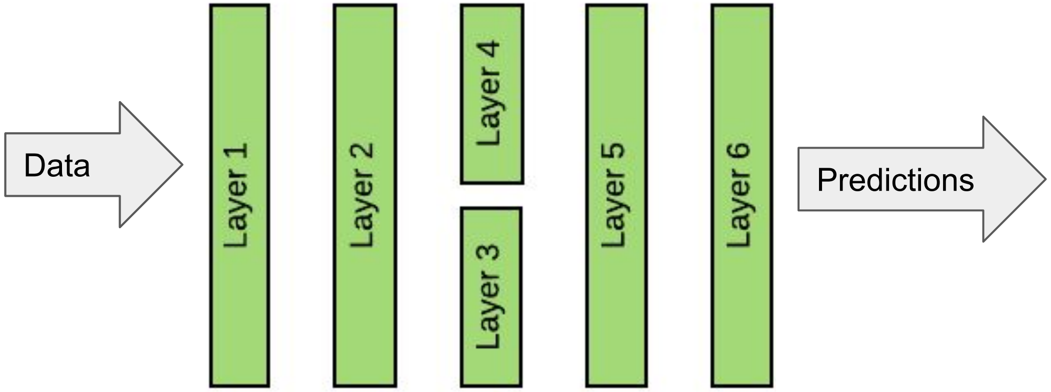
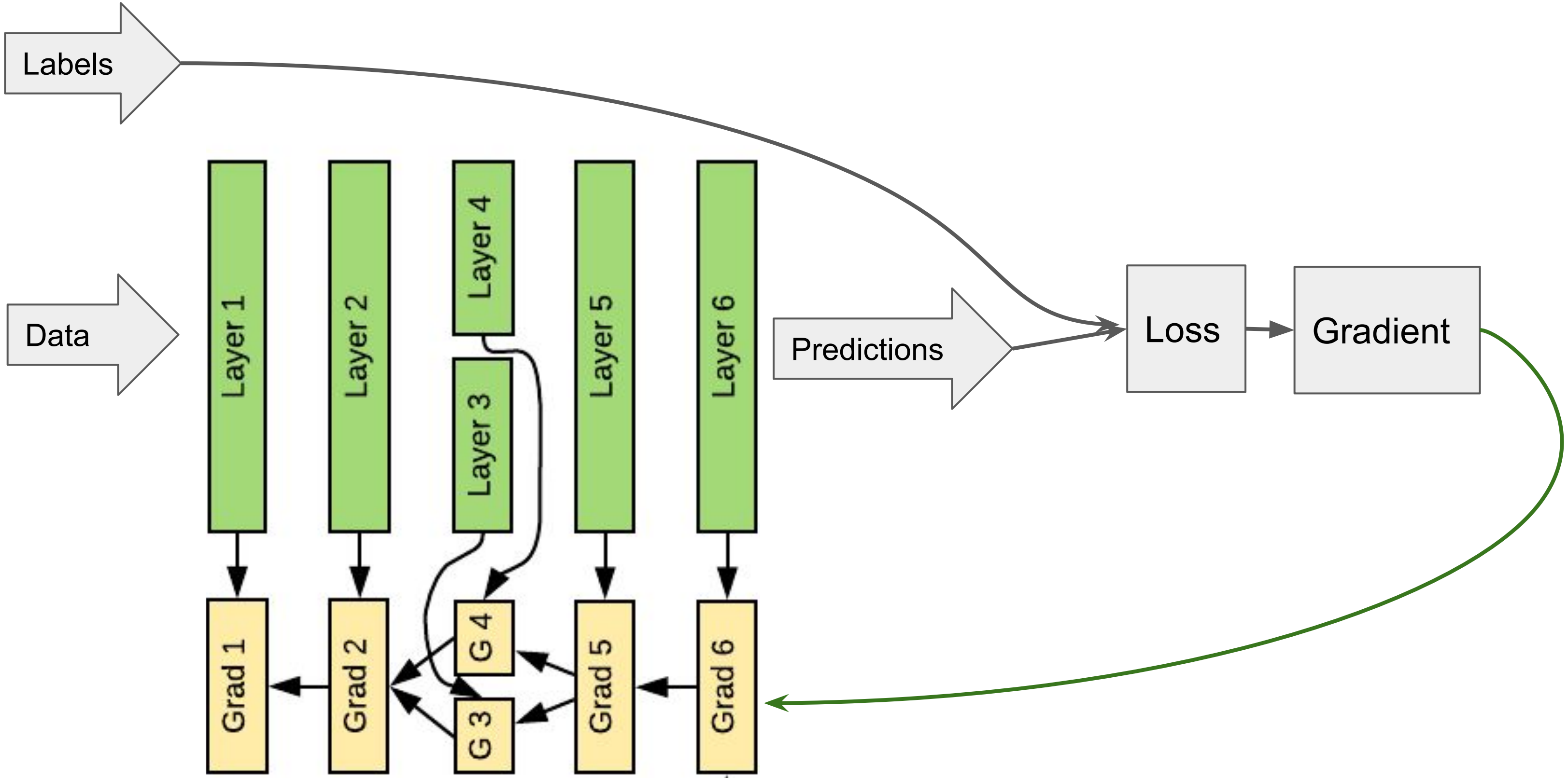
How does Deep Learning work?



NOTE: Limited Parallelism

How does Deep Learning training work?



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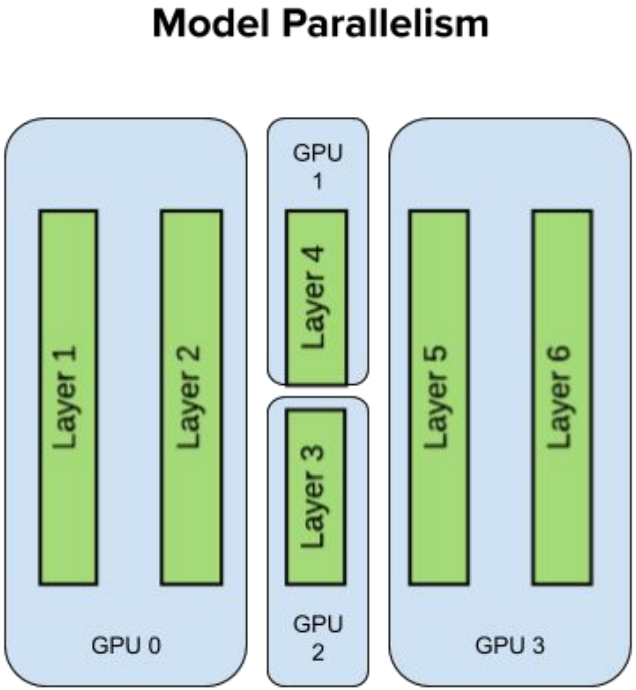
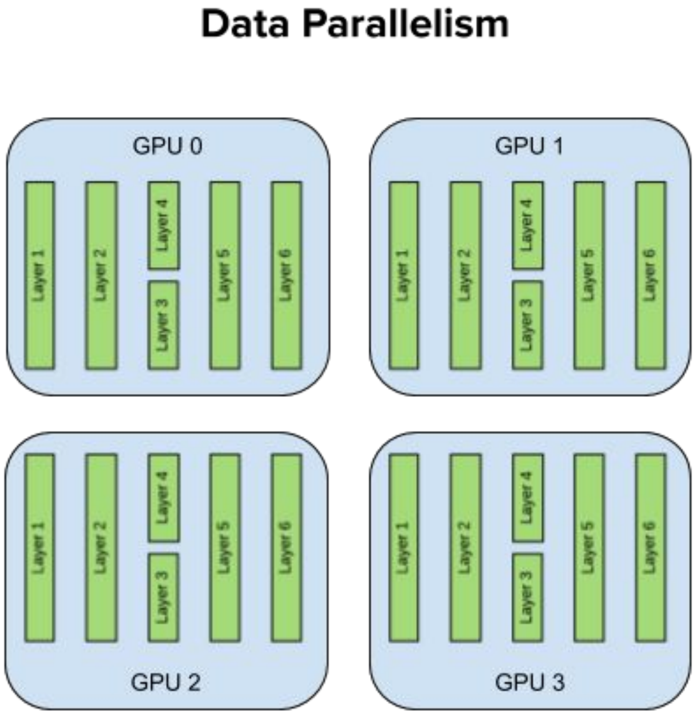
How does distributed training work?





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Data Parallelism

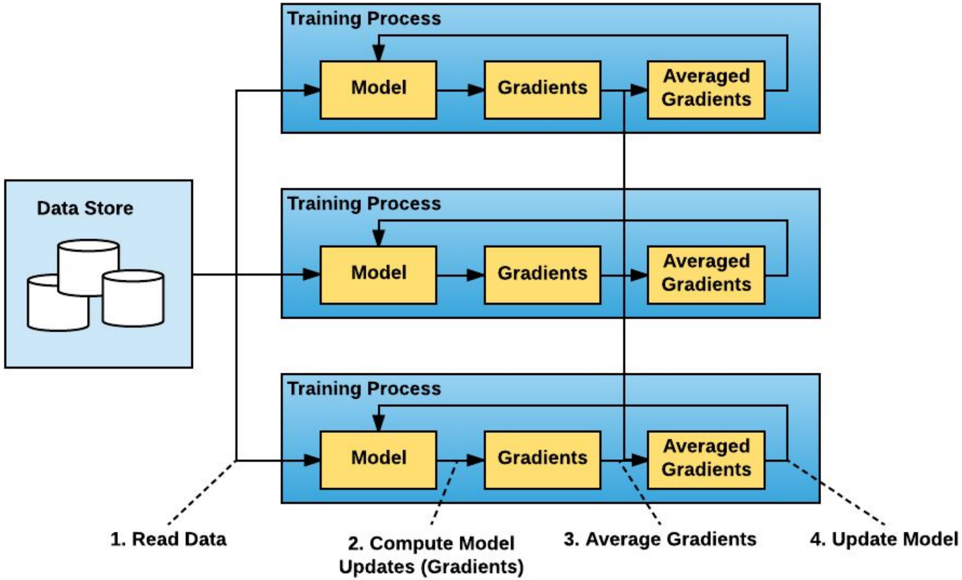
Increasing amount of data
Model complexity does not need to increase

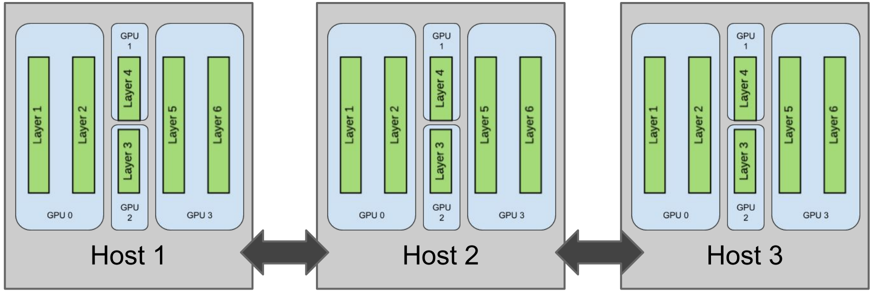
Model must fit in a single GPU:

- NVIDIA® V100 GPUs 32GB

Can mix and match:

- Data parallel inter-host
- Model parallel intra-host





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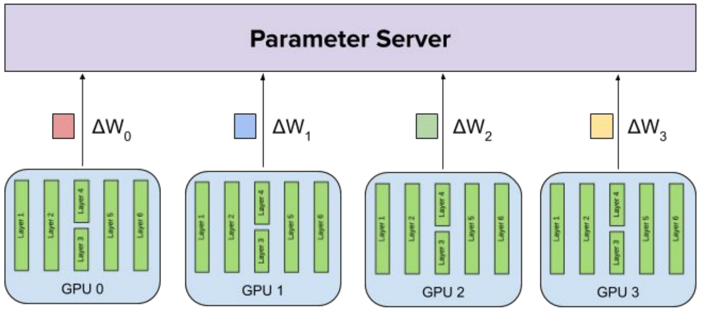
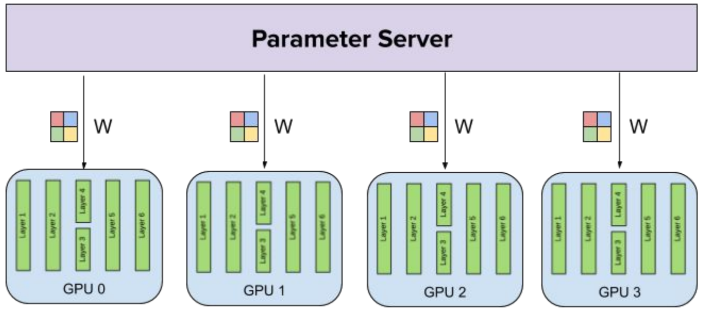
Distributed Deep Learning (I); Data Parallel Training with Parameter Servers





Pros

- Fault tolerance
- Supports *asynchronous SGD*

Cons

- Usability (tight coupling between *model* and *parameter servers*)
- Scalability (many-to-one)
- Convergence (with async SGD)

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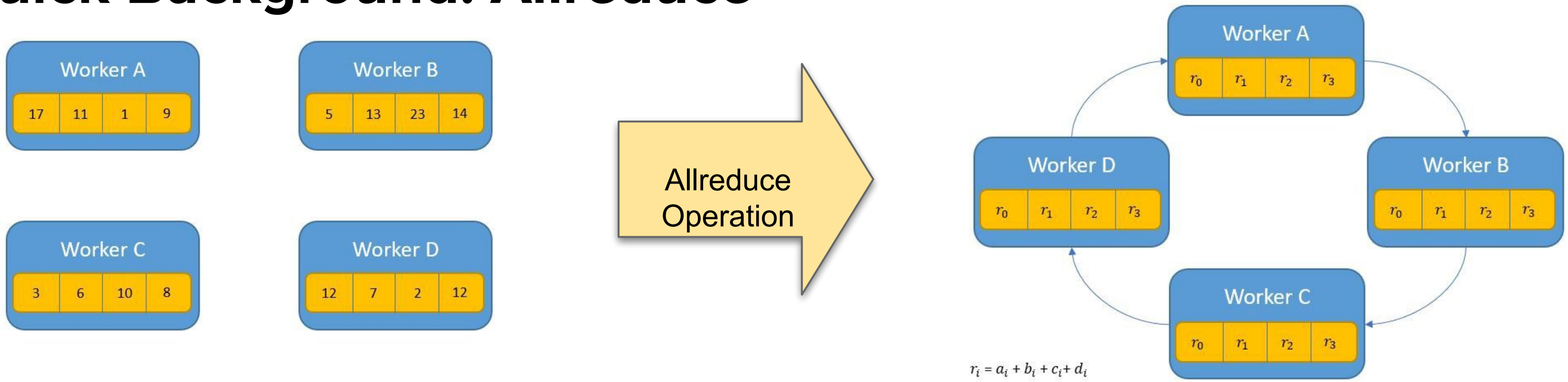
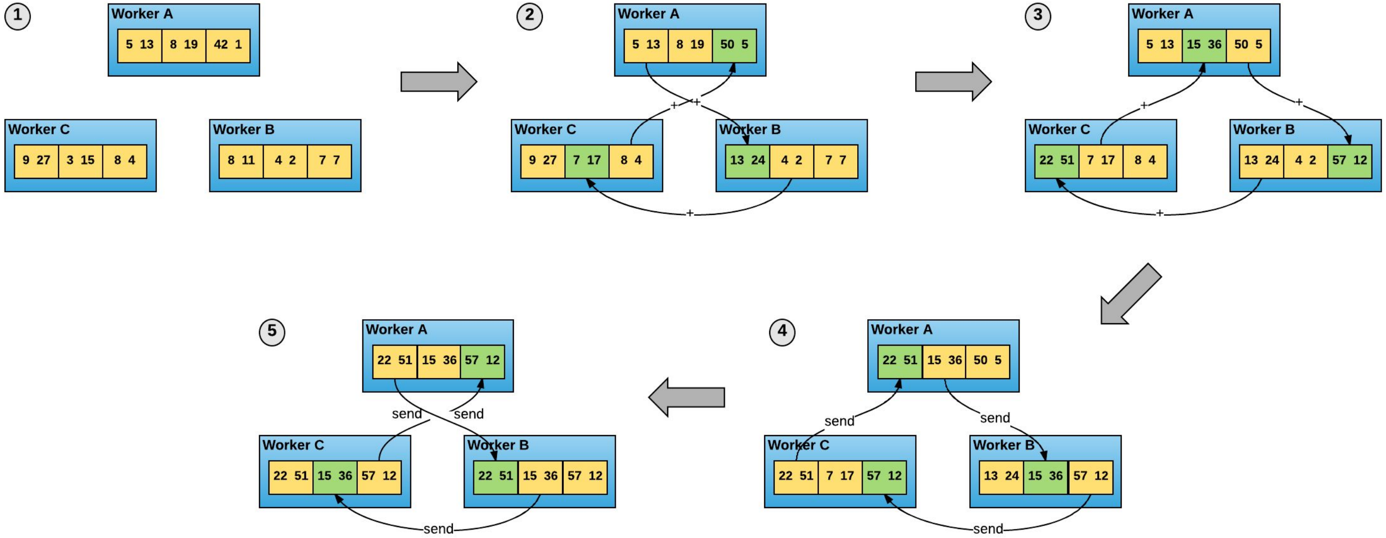
Quick Background: Allreduce



Example Allreduce



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

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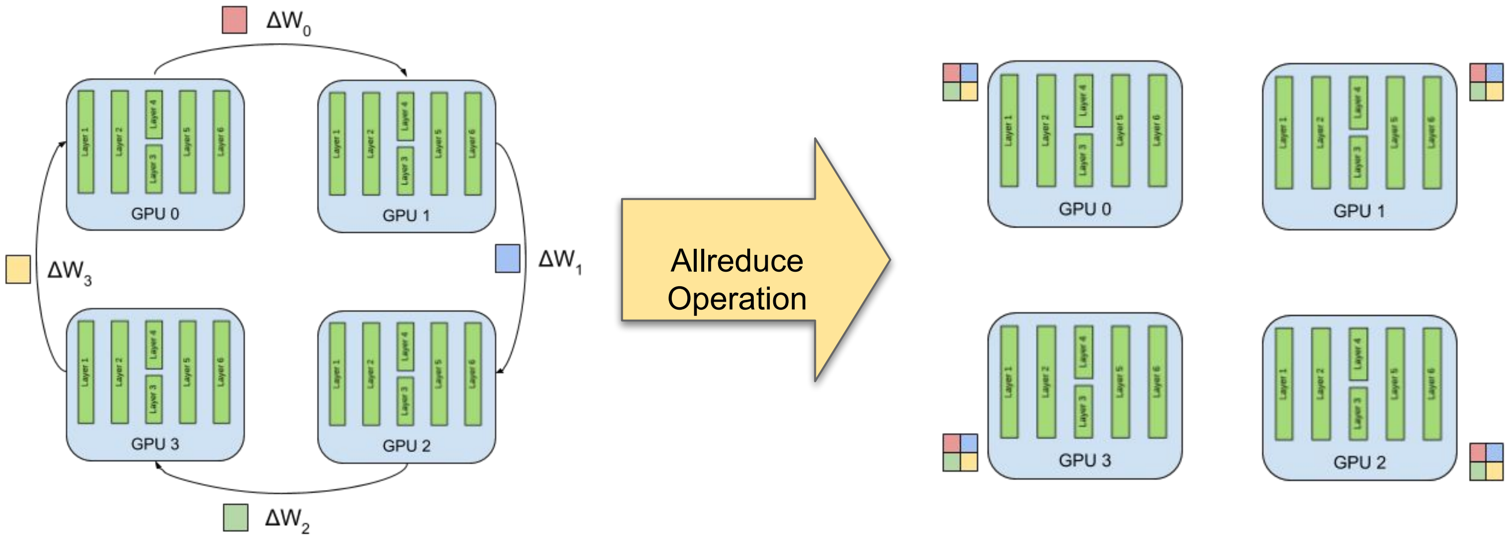
Distributed Deep Learning (II); Data Parallel Training with Allreduce



Pros

- Bandwidth efficient
- Scalability (many-to-one)
- Convergence (with sync SGD)

Cons

- Fault tolerance

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Horovod; Library for Distributed Deep Learning.

- Uses Allreduce
- Works with stock TensorFlow, Keras, PyTorch, and Apache MXNet
- Only 5-6 lines of code change required
- Installs on top via `pip install horovod`.
- Uses advanced algorithms & leverage features of high-performance networks (RDMA, GPUDirect).
- Separates infrastructure from ML engineers:
    - Infra team provides container & MPI environment
    - ML engineers use DL frameworks that they love
    - Both Infra team and ML engineers have consistent expectations for distributed training across frameworks

HOROVOD

horovod.ai

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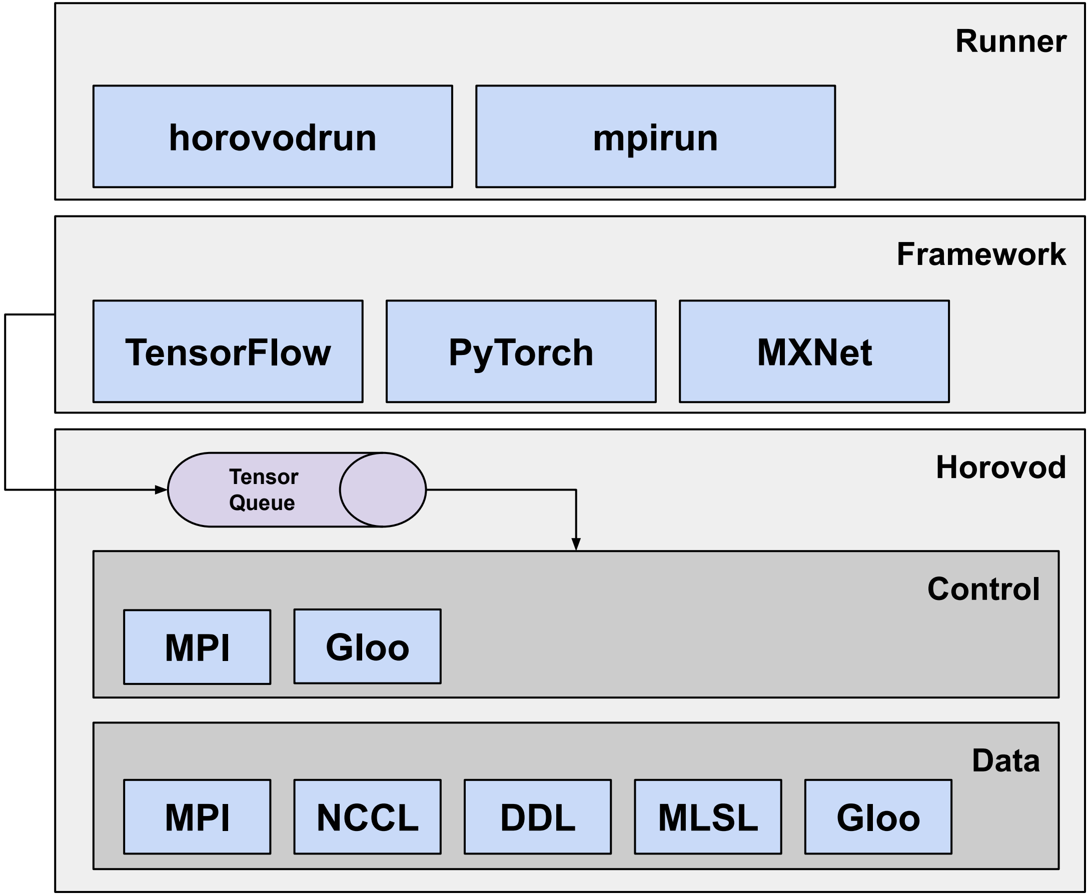
Horovod Stack



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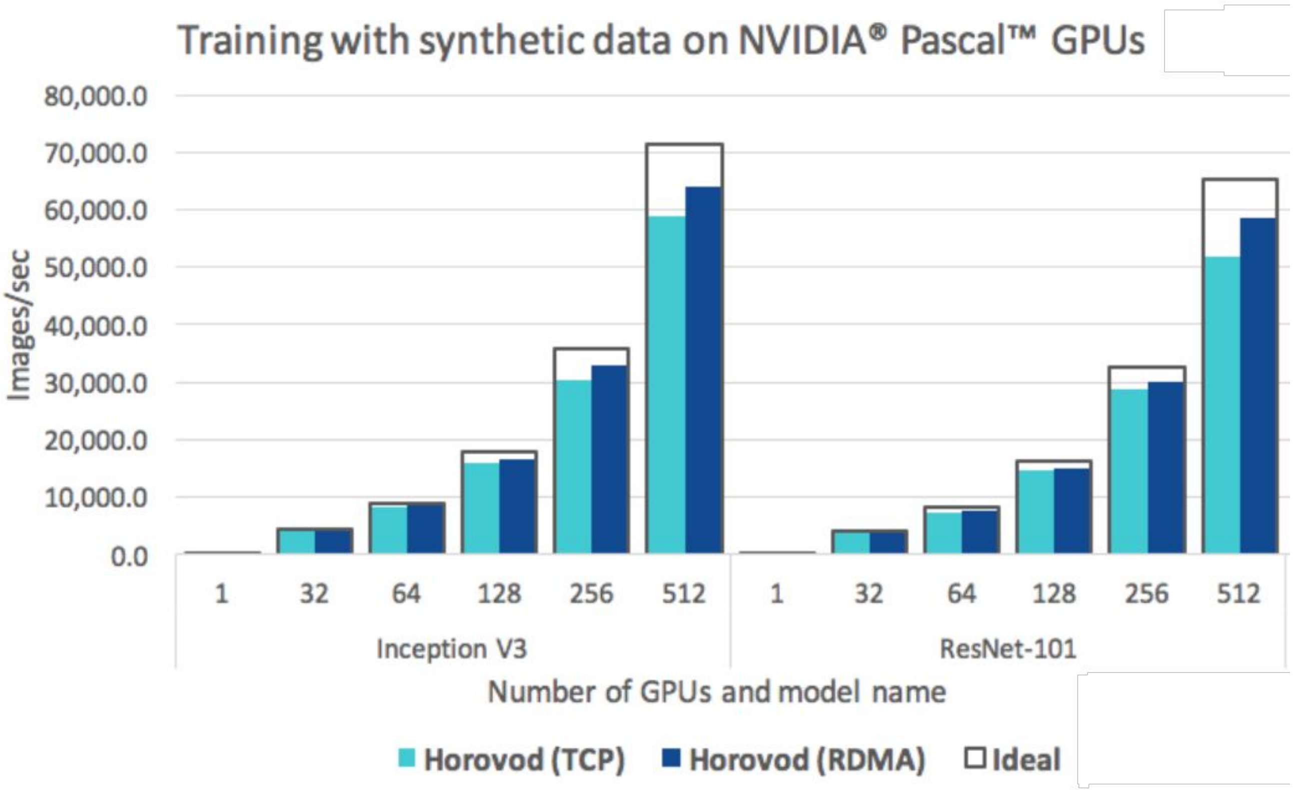
Horovod Performance



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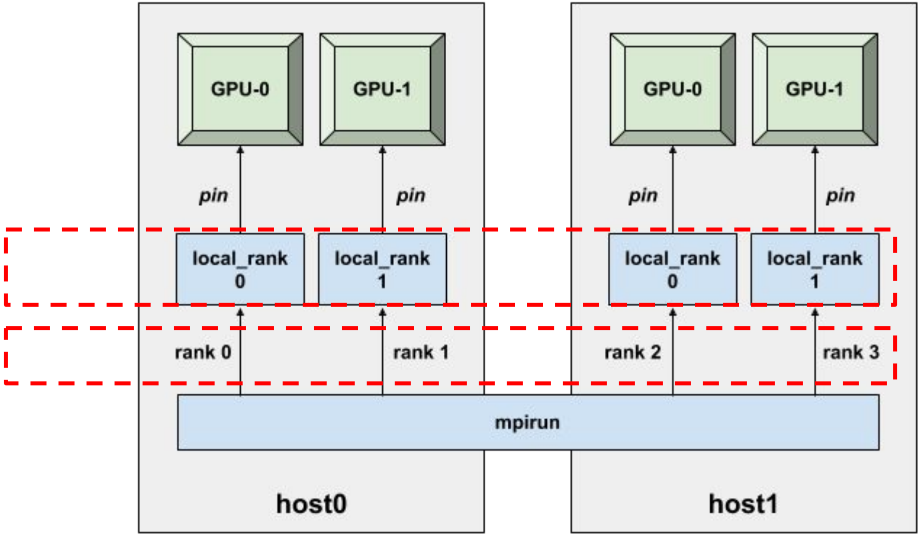
Horovod scales well beyond 128 GPUs. RDMA helps at a large scale.

Using Horovod

Host and Rank

Local rank per host

Global rank of each worker



- One rank per GPU
- Hosts do not have to have same number of ranks
- `hvd.size()` will return 4
- `hvd.local_size()` will return 2

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Horovod+PyTorch; example.py

Import library

Initialize

Pin GPU to local rank.

Adjust learning rate

Wrap optimizer with Horovod Distributed Optimizer

Broadcast parameter.

```
import torch
import horovod.torch as hvd

hvd.init()

torch.cuda.set_device(hvd.local_rank())

model = Net(...)
model.cuda()
optimizer = optim.SGD(model.parameters(), lr=0.01 * hvd.size())

optimizer = hvd.DistributedOptimizer(optimizer, named_parameters=model.named_parameters())


hvd.broadcast_parameters(model.state_dict(), root_rank=0)

# Read the data
for epoch in range(100):
  for batch_idx, (data, target) in …:
    optimizer.zero_grad()
    output = model(data)
    loss = F.nll_loss(output, target)
    loss.backward()
    optimizer.step()
```

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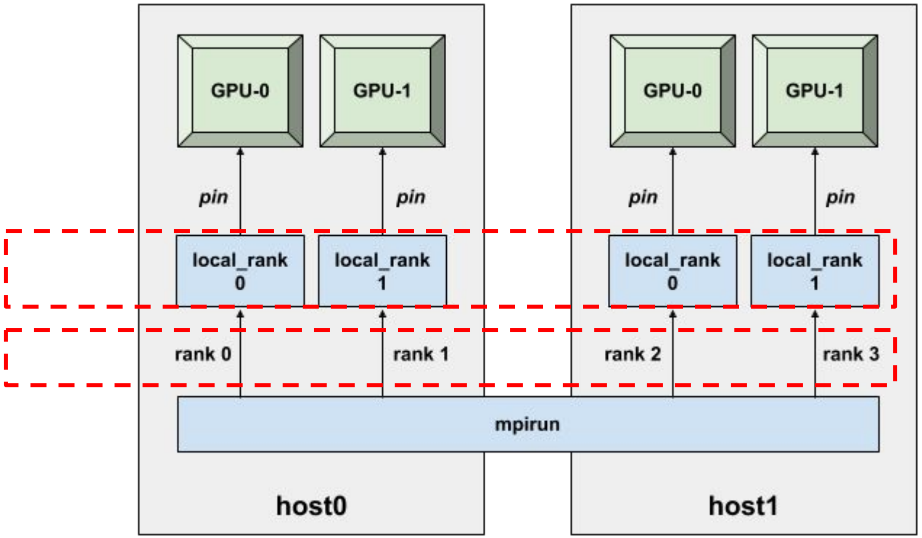
Running Horovod

Local rank per host

Global rank of each worker



- `example.py` needs to be present on all the hosts
- host1 and host2 need to be able to ssh into each other.
- Start the training:
  - Single-node: `$ horovodrun -np 2 -H localhost:2 python example.py`
  - Multi-node: `$ horovodrun -np 4 -H host1:2,host2:2 python example.py`

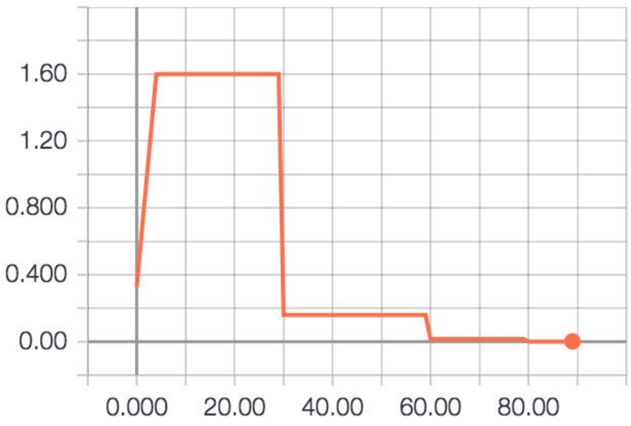
Adjusting Learning Rate & Add Distributed Optimizer

```
opt = optim.SGD(model.parameters(), lr=0.01 * hvd.size())

opt = hvd.DistributedOptimizer(opt, named_parameters=model.named_parameters())
```

- Recommend linear scaling of learning rate:
    - $LR_N = LR_1 * N$
    - Smooth warm-up for the first K epochs

- Facebook paper:
    - [Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour](arxiv.org/abs/1706.02677)
        - arxiv.org/abs/1706.02677



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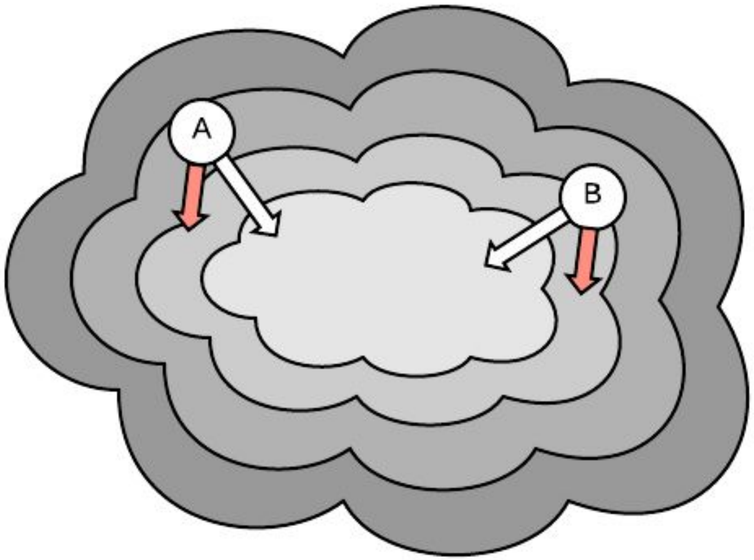
Synchronizing Initial State

```
hvd.broadcast_parameters(model.state_dict(), root_rank=0)
```

All the workers start from identical model.



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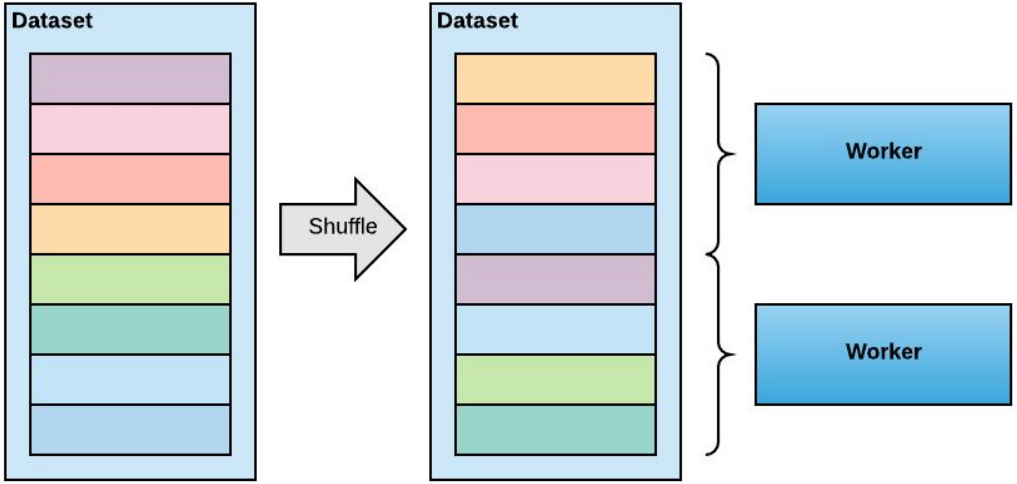
Data: Partitioning

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



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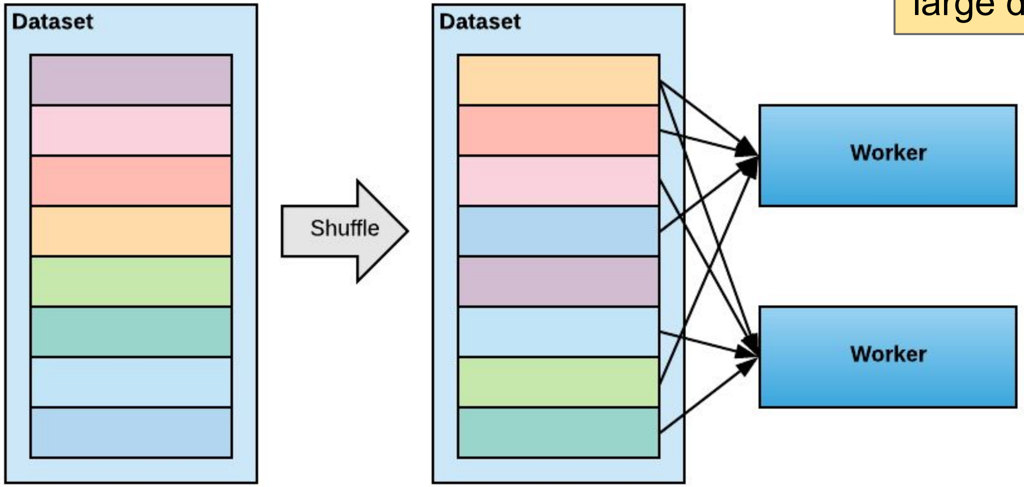
Data: Random Sampling

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

NOTE: no guarantee to read samples exactly once (or at all), but converges similarly with large datasets



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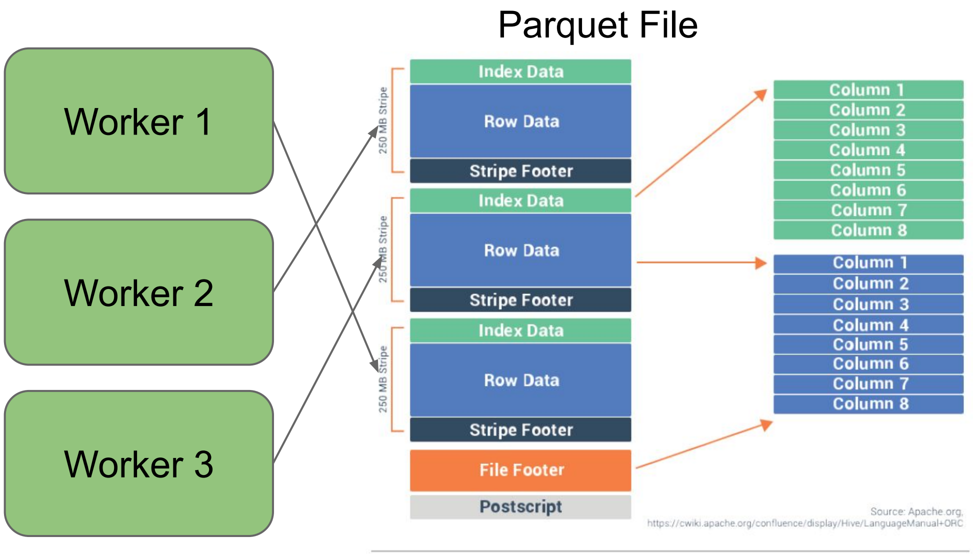
Data

- Horovod does not handle data access.
- Users can implement their own data distribution and partitioning
- We recommend using Petastorm+Parquet records (Horovod examples)
- Common ways:
    - Copy all the data into local storage of the workers (smaller datasets)
    - Each worker streams the data from HDFS/S3

Data Ingestion with PetaStorm; Recommended Way

- Sharding:
  - Each worker is randomly assigned to a subset of the row-groups
- Shuffling:
  - Workers read the row-groups in a shuffled order
- Optimized IO
  - multi-threaded reading
  - Prefetching



#6. Data Review

- Random sampling may cause some records to be read multiple times in a single epoch, while others not 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 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

Best Practices: Learning Rate Adjustment

- 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

Full Example - Keras

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

# Initialize Horovod.
hvd.init()

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

# Build model…
model = ...
opt = keras.optimizers.Adadelta(
  lr=1.0 * hvd.size())

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

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

# Broadcast initial variable state.
callbacks =
[hvd.callbacks.BroadcastGlobalVariablesCallback(0)]

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

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TensorFlow

```
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.MomentumOptimizer(
  lr=0.01 * hvd.size())

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

```
# Add hook to synchronize initial state
hooks =[hvd.BroadcastGlobalVariablesHook(0)]

# Only checkpoint on rank 0
ckpt_dir = "/tmp/train_logs" \
  if hvd.rank() == 0 else None

# 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=ckpt_
dir, config=config, hooks=hooks) as mon_sess:
  while not mon_sess.should_stop():
    # Perform synchronous training.
    mon_sess.run(train_op)
```

Apache MXNet

```
import torch
import horovod.mxnet as hvd

# Initialize Horovod
hvd.init()

# Horovod: pin GPU to local rank.
context = mx.gpu(hvd.local_rank())

# Build model.
net = …
loss = ...
model = mx.mod.Module(symbol=loss, context=context)

# Wrap optimizer with DistributedOptimizer.
opt = hvd.DistributedOptimizer(opt)

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

model.fit(...)
```

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Running Horovod

Single-node:

```
$ horovodrun -np 4 -H localhost:4 python train.py
```

Multi-node: -- Code must be available on all the nodes

```
$ horovodrun -np 16 -H server1:4,server2:4,server3:4,server4:4 python train.py
```

Horovod on Spark

```
In [1]: from pyspark import SparkConf
        from pyspark import SparkContext
        import horovod.spark

In [2]: sc = SparkContext(conf=SparkConf())

In [3]: def train():
            import horovod.tensorflow as hvd
            hvd.init()
            return hvd.rank()

In [4]: print(horovod.spark.run(train, num_proc=4))

        [0, 1, 2, 3]

In [ ]:
```

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Why Spark?

- Allows users to leverage existing Spark infrastructure
  - Including Jupyter and IPython!
- Data preparation & model training in the same environment
- Save to Parquet and use Petastorm for data ingestion
  - Takes care of random shuffling, fault tolerance, etc
  - https://github.com/uber/petastorm

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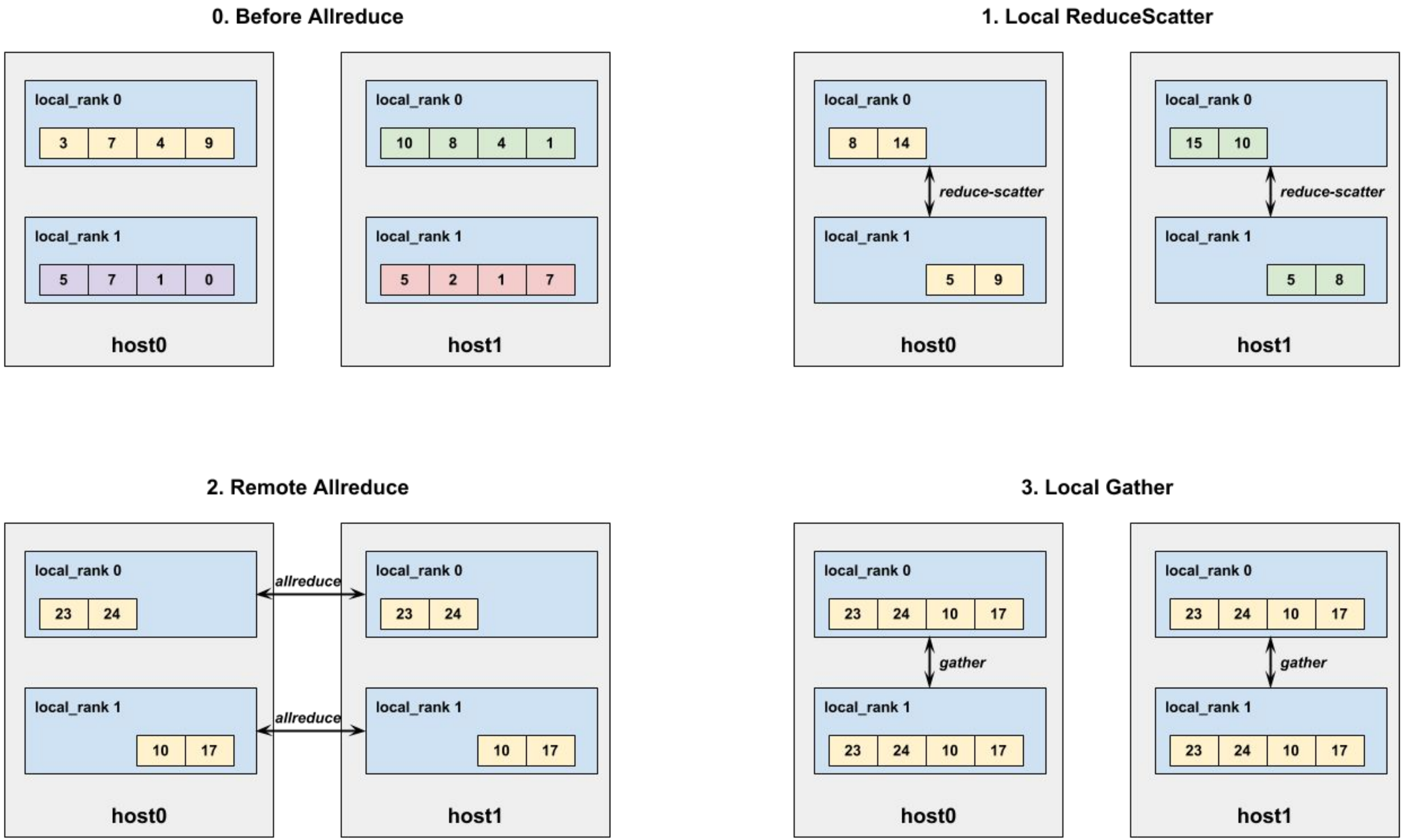
Advanced Features

Horovod Knobs: Hierarchical Algorithms

```
$ HOROVOD_HIERARCHICAL_ALLREDUCE=1 horovodrun ...
$ HOROVOD_HIERARCHICAL_ALLGATHER=1 horovodrun ...
```

- Contributed by NVIDIA & Amazon
- First allreduce locally, then allreduce across nodes in parallel
  - Each worker responsible for a different chunk of the buffer
- Speeds up training for very large cluster setups
  - Homogenous nodes (same # GPUs)
  - Many GPUs per node

Hierarchical Allreduce: Example



Horovod Knobs: Tensor Fusion

```
$ HOROVOD_FUSION_THRESHOLD=67108864 HOROVOD_CYCLE_TIME=5 horovodrun ...
```

- Batch tensors together during allreduce
- **Fusion Threshold:** size of batching buffer (in bytes)
- **Cycle Time:** wait time between sending batches (in milliseconds)

Horovod Knobs: Auto Tuning with Bayesian Optimization

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Use **`HOROVOD_AUTOTUNE=1`** to find the best Horovod parameters

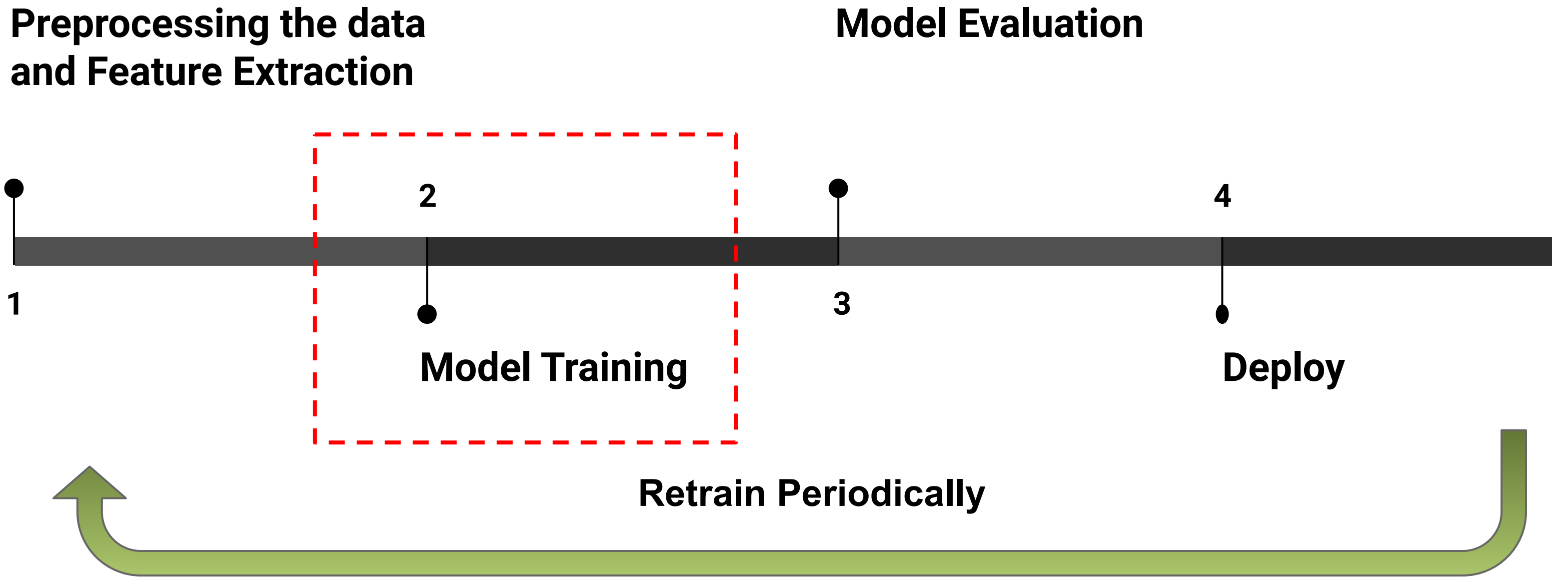
Horovod Knobs: Gradient Compression

- FP16 allreduce
  - `hvd.DistributedOptimizer(..., compression=hvd.Compression.fp16)`
  - Reduces arithmetic computation on GPU
  - Reduces network utilization
- Not selected by Auto Tuning since it may affect model convergence
- More techniques coming - contributions welcome!

Horovod Deep Learning Estimators

Horovd + Spark:
Deep Learning for Tabular Datasets

Machine Learning Cycle



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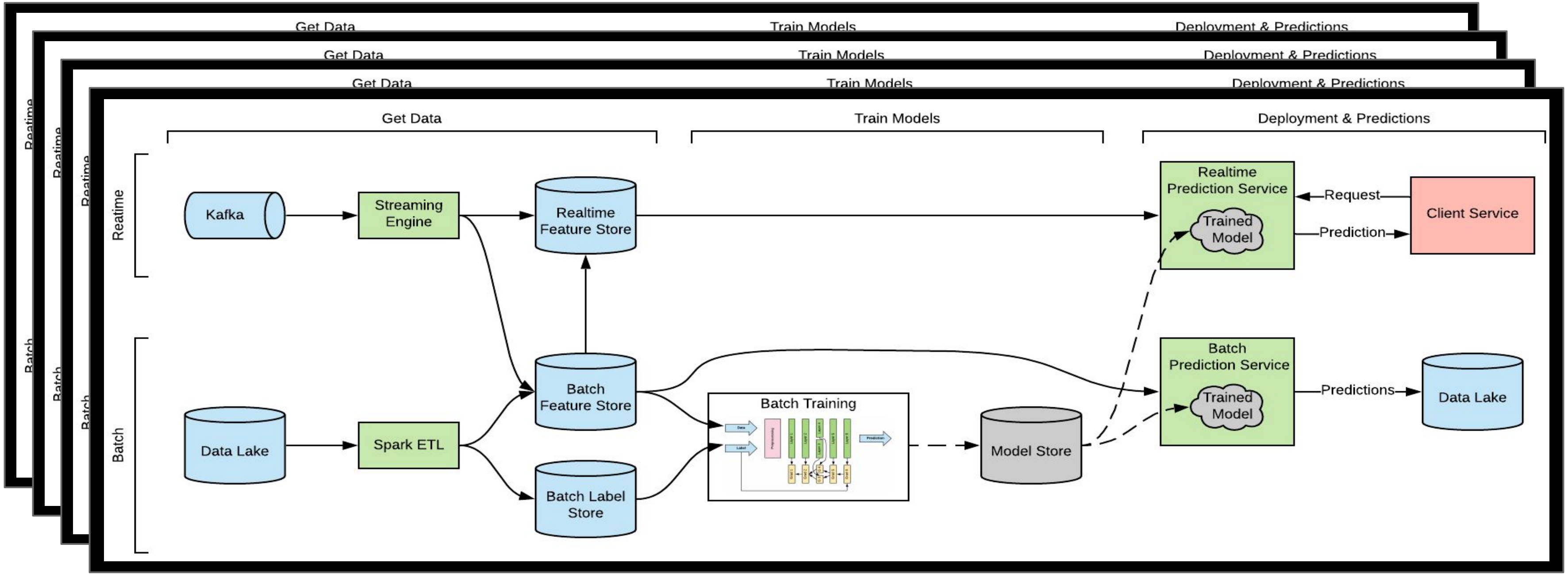
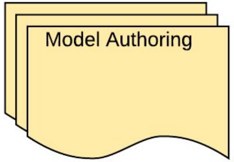
Zoom out further





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What do we need?

- Feature engineering and data prep
- Distributed training
- Evaluation
- Prediction:
  - Batch prediction
  - Online Serving

Horovod's Deep Learning Spark Estimator (Released in Dec 2019)

- Train Deep Learning Models Directly on Spark DataFrames
- Serialize entire training and evaluation pipeline
- Simpler User Experience

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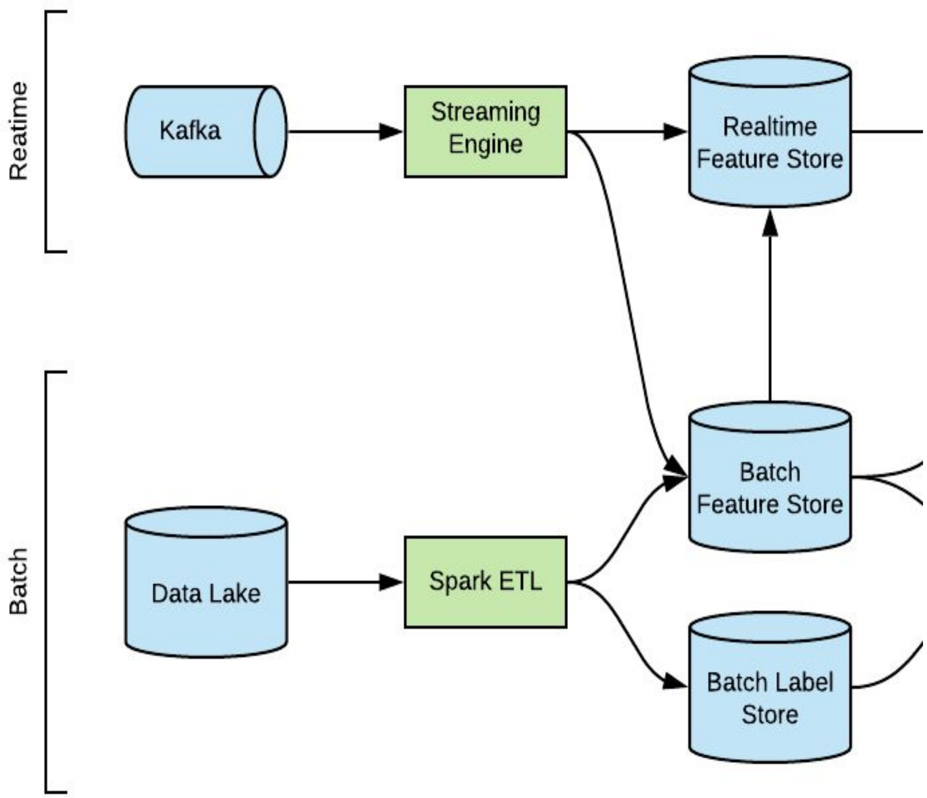
How can you implement such system?

We chose Apache Spark:

- Powerful ETL
- Easy integration with XGBoost
- Existing systems built on top of Spark
- Close collaboration with Spark community

(1) Feature Store

- Data pipelines are bread & butter of Apache Spark
- Good integration of real-time & batch ecosystems
- Overall: not a surprising choice



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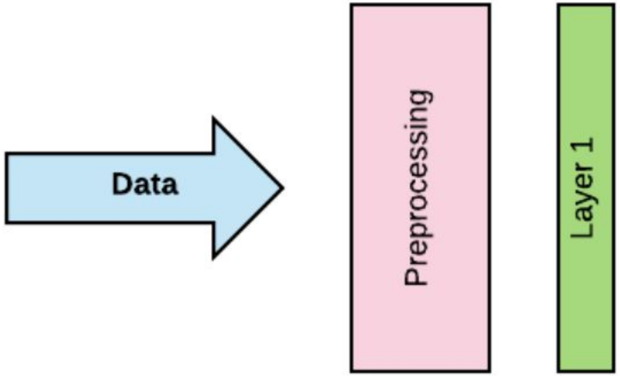
Preprocessing

Often comes in two different kinds:

1. Example-dependent
   a. Image color adjustments
   b. Image resizing
   c. Normalizing
2. Dataset-dependent
   a. String indexing
   b. Normalization



Solution: Need to fit the preprocessing first, and then apply it.

Petastorm: Data Access for Deep Learning Training

Challenges of Training on Large Datasets:

- Shuffling
- Sharding
- Streaming / Buffering / Caching

Parquet:

- Large continuous reads (HDFS/S3-friendly)
- Fast access to individual columns
- Faster row queries in some cases
- Written and read natively by Apache Spark

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Spark ETL: Extract, Transform, Load

Extract

```
df_customers = spark.read.format("jdbc").options(
     url ="jdbc:mysql://xyz.amazonaws.com:3306/test",
     driver="com.mysql.jdbc.Driver",
     dbtable="customer", user="root", password="password").load()
```

Transform

```
sql='''
SELECT a.first_name, a.last_name, b.order_number, b.total
FROM customers a, orders b WHERE a.customer_number = b.customer_number
'''
output = spark.sql(sql)
```

Load

```
output.write.format("orc").save("/tmp/customer_orders")
```

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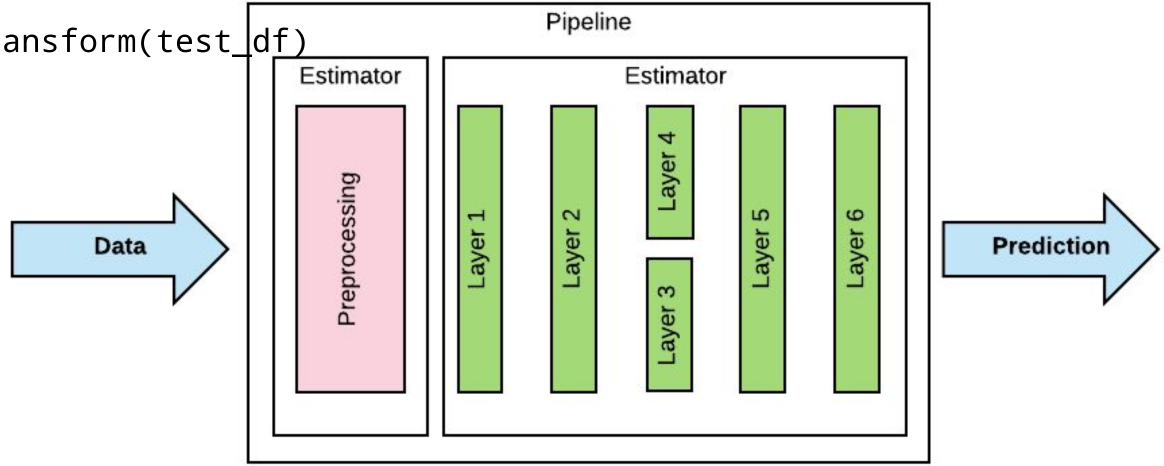
SparkML Pipelines; Estimator, Transformer, Pipeline

```
# Estimator and Transformer
transformer = estimator.fit(spark_dataframe)
Pred_df = transformer.transform(test_df)
# Spark ML Pipelines
estimator_pipeline = Pipeline().setStages([transformer1, transformer2, estimator])
transformer_pipeline = estimator_pipeline.fit(df)
pred_df = transformer_pipeline.transform(test_df)
```



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#1 Feature Transformation with Spark ML Pipelines

```
data_processing_pipeline = Pipeline(stages=[
    IntToFloatEncoder(inputCols=[...],...),
    StringIndexer(inputCols=[...],...),
    OneHotEncoder(inputCols=[...],...)])


train_df, test_df = input_df.randomSplit([0.8, 0.2])

data_transformation_pipeline = data_processing_pipeline.fit

# Transform the original train/test data set with the fitte
transformed_train_data = data_transformation_pipeline.trans
transformed_test_data = data_transformation_pipeline.transf
```

Spark ML Pipelines has many more:

Word2Vec
OneHotEncoder
Tokenizer
Binarizer
Polynomial Expansion
StringIndexer
VectorIndexer
Normalizer
StandardScaler
Bucketizer
Elementwise Product
VectorAssembler,
...

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#2 Deep Learning Estimator; Defining DL Model

```
# Define the model
x = Flatten()(x)
x = Dense(500, activation='relu', kernel_regularizer=tf.keras.regularizers.l2(0.00005))(x)
x = Dropout(0.5)(x)
output = Dense(1, activation=act_sigmoid_scaled)(x)
model = tf.keras.Model([inputs[f] for f in all_cols], output)

# Define the optimizer
opt = tf.keras.optimizers.Adam(lr=args.learning_rate, epsilon=1e-3)
```

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#3 Deep Learning Estimator

```
# Create the Estimator
from horovod.spark.keras import KerasEstimator

keras_estimator = KerasEstimator(num_proc=10,
                                 store=store,
                                 model=model,
                                 optimizer=opt,
                                 loss='mae',
                                 metrics=[exp_rmspe],
                                 feature_cols=continuous_cols = [ 'Distance', 'Temperature'],
                                 label_cols=['Sales'],
                                 validation='Validation',
                                 batch_size=128,
                                 epochs=10,
                                 verbose=2)
```

#4 Deep Learning Estimator; Train and Predict

```
# Create the Store
store = hvd.spark.common.HDFSStore.create('/usr/fardin/experiment1')

# Train the model
keras_transformer = keras_estimator.fit(train_df)

# Evaluation of the Model
pred_df = keras_transformer.transform(test_df)
# run any evaluation functions on the pred_df and make decisions
```

Deep Learning Estimator Interface

```
# Save the Model or the estimator
keras_transformer.write().overwrite().save('/user/fardin/exp1/pytorch_raw_pipeline')

# Load the model for more prediction
loaded_transformer = Pipeline.read().load('/user/fardin/exp1/pytorch_raw_pipeline')
pred_df = loaded_transformer.transform(test_df)

# Incremental training
keras_model = loaded_transformer.get_model()
optimizer = loaded_transformer.get_optimizer()
keras_estimator_incremental = hvd.KerasEstimator(num_proc=args.num_proc,
                                                store=store,
                                                model=model,
                                                optimizer=optimizer,
                                                loss='mae',
                                                feature_cols['Distance', 'Temperature'],
                                                label_cols=['Sales'],
                                                batch_size=128,
                                                epochs=10)
```

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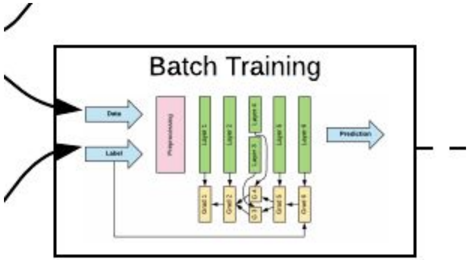
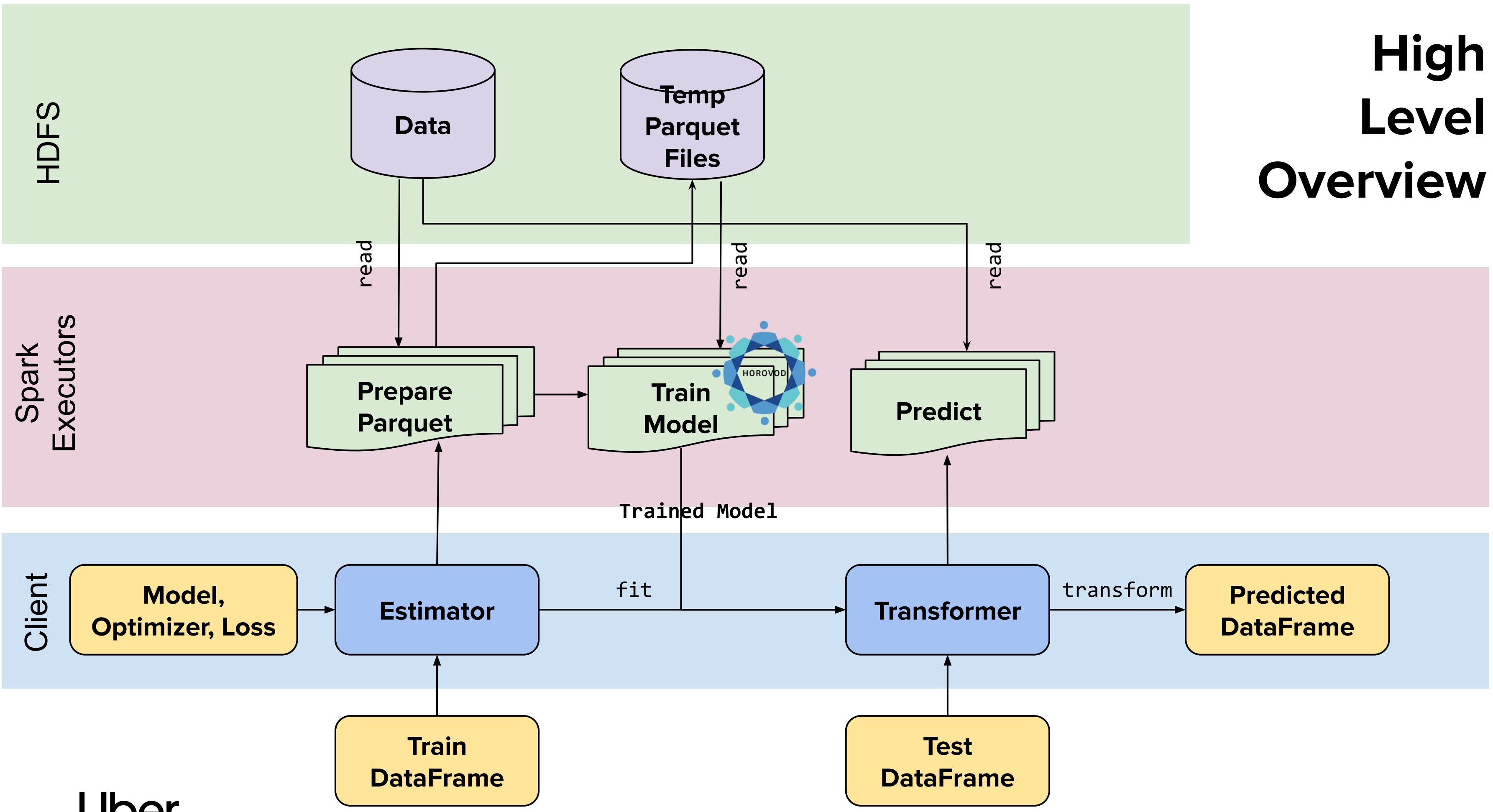
What is under the hood?



+ Apache Spark = ?

How do we combine Deep Learning training with Apache Spark?

High Level Overview



Backend

Data Prep	Deep Learning Model Training	Evaluation	Prediction
Spark	Backend	Spark	Spark, Online, GPU

- Backend should provide
  - `backend.run()` and `backend.num_processes()`
- Internally, we use LambdaDL
- Spark 3 allows resource-aware scheduling. So we can launch the training on GPU instances with Spark.

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Train Function

- Inside the estimator we construct a train function that performs
    - horovod init
    - Data access, reshaping
    - Train loop, loss calculation, metric evaluation

- To execute the train function, it needs to be fully serialized and executed on the backend.

Serialization

Spark ML serialization: serializes the stages into a JSON file.

```
$ pipeline = Pipeline().setStages([])
$ pipeline.write.overwrite.save("sample-pipeline")
$ cat sample-pipeline/metadata/part-00000 | jq
{
  "class": "pyspark.ml.Pipeline",
  "timestamp": 1472747720477,
  "sparkVersion": "2.1.0-SNAPSHOT",
  "uid": "pipeline_181c90b15d65",
  "paramMap": {
    "stageUids": []
  }
}
```

- Model architecture, model weights, and all the param for retraining all serialized
- Keras model and optimizer serialization into JSON
    - Extract the weights and parameters
- Serialization of Torch model and optimizer into JSON
    - Extract the state dict and reconstruct the optimizer

Petastorm: Data Access for Deep Learning Training

Challenges of Training on Large Datasets:

- Shuffling
- Sharding
- Streaming / Buffering / Caching

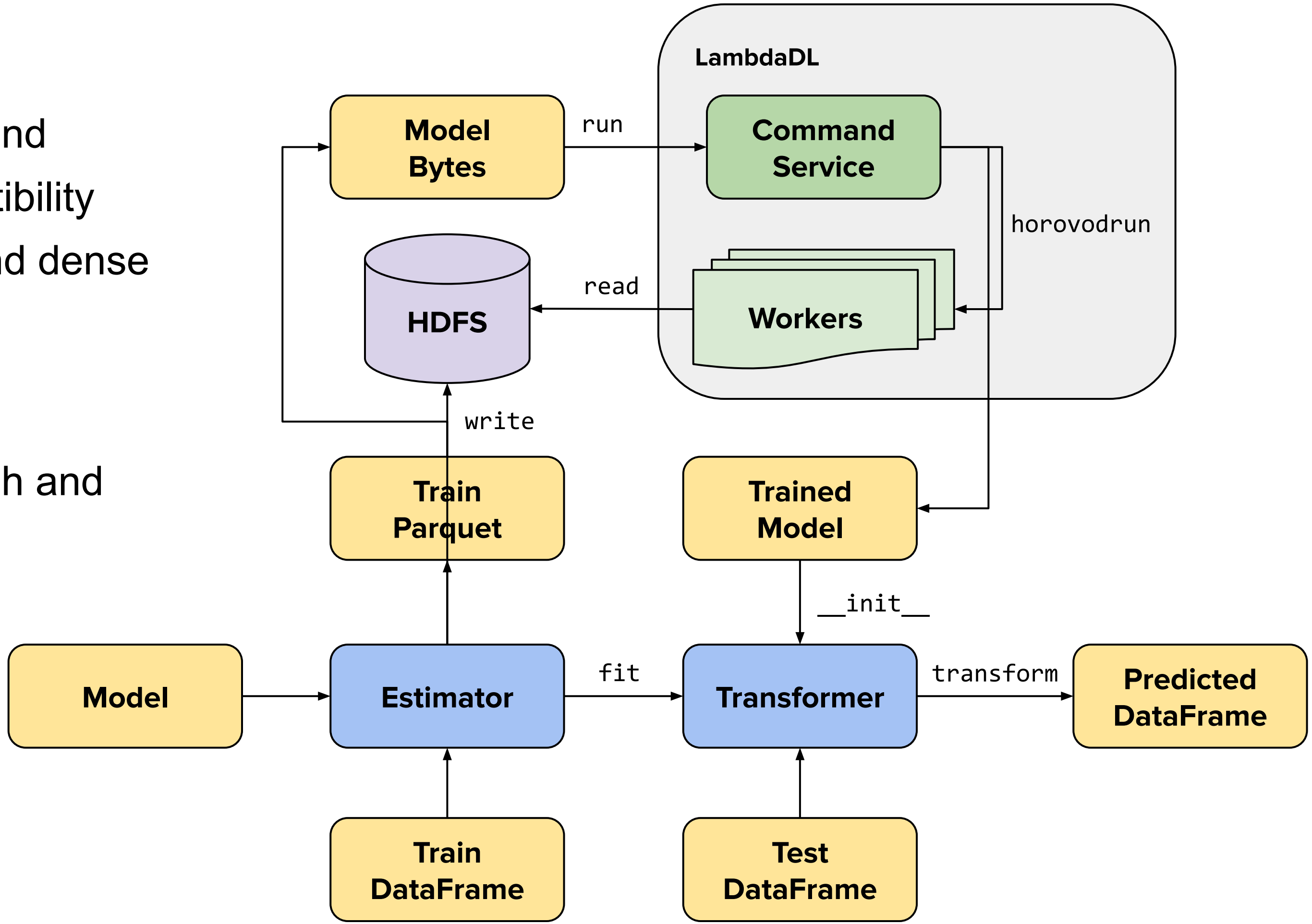
Parquet:

- Large continuous reads (HDFS/S3-friendly)
- Fast access to individual columns
- Faster row queries in some cases
- Written and read natively by Apache Spark
- Spark datatypes and Petastorm compatibility such as sparse and dense vectors

Materializing DF to Parquet on the Store

- Spark datatypes and Petastorm compatibility such as sparse and dense vectors

- Cache the DF hash and reuse it to avoid duplication



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Store

- An interface that provides paths for writing intermediate data.
  - LocalStore
  - HDFSStore
  - MA Workspaces

- During training, we checkpoint model on the store

Success Stories

Case Study: Horovod + Petastorm

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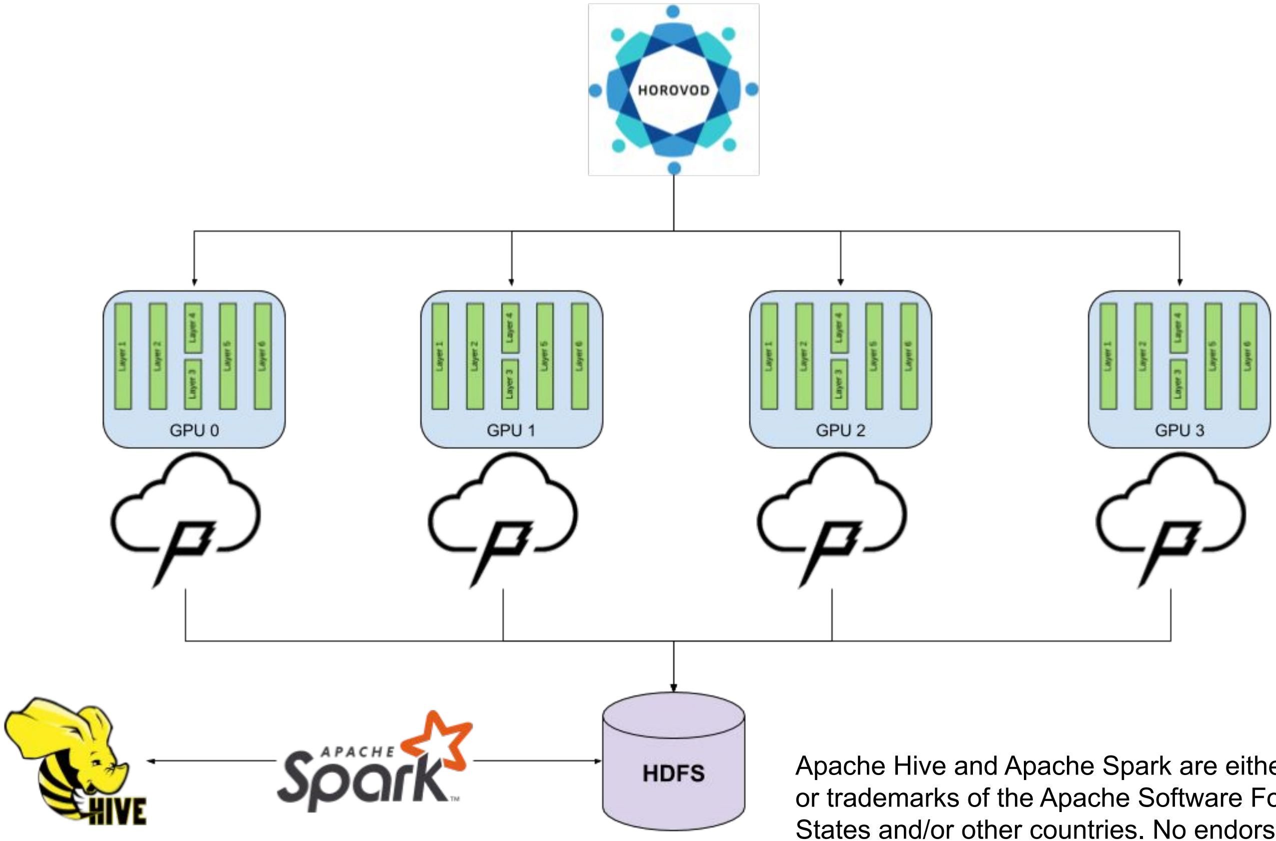
Case Study: Horovod + Petastorm



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Horovod in the Community

Used by:

Nvidia

Alibaba

Amazon

Oak Ridge National Laboratory

and many others.

Available in:

AWS

Microsoft Azure

Google Cloud Platform

Databricks Runtime

and more!

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Case Study: Oak Ridge National Laboratory

- Running Horovod on *Summit*, the world's most powerful supercomputer
- Awarded *ACM Gordon Bell Prize* 2018
- *Exascale Deep Learning for Climate Analytics*
    - https://arxiv.org/abs/1810.01993

Credit: SC18 / LBL, http://bit.ly/2xd1uhl

Credit: Carlos Jones / ORNL, http://bit.ly/2YI9bOI

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Case Study: Oak Ridge National Laboratory

- Broke the exaop (1 billion billion calculations / sec) computing barrier
  - **1.13 EF/s** peak, **999.0 PF/s** sustained
  - First time with a deep-learning application
- **4560** Summit nodes, **27360** Volta GPUs, **90.7%** scaling efficiency
- Scaling beyond 1024 GPUs:
  - Hierarchical Allreduce
  - Tensor Fusion
  - FP16 compression

Coming Soon

Elastic Training

- MPI makes it difficult to train with preemptible instances
    - Any instance removal crashes the entire process
    - Cannot add new instances to context at runtime
- Facebook's Gloo (https://github.com/facebookincubator/gloo):
    - Alternative to MPI
    - Raises exception on instance failure
    - Context can be recreated at runtime with new instances
- Challenges:
    - Maintain total batch size as instance count changes
    - Tradeoff frequency of context changes to maximize throughput

Plugin Framework

Horovod as a *research platform*

- Gradient Compression:
  - *Deep Gradient Compression* (https://arxiv.org/abs/1712.01887)
  - *Quantized SGD* (https://arxiv.org/abs/1610.02132)
- Gradient Sparsification:
  - *Block Sparse* (https://arxiv.org/abs/1808.03420)
- Reduced Communication Strategies:
  - *Stochastic Gradient Push* (https://arxiv.org/abs/1811.10792)

RFC: https://github.com/horovod/horovod/issues/1157

Thank you!

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