VERY LARGE-SCALE DISTRIBUTED DEEP LEARNING ON BIGDL

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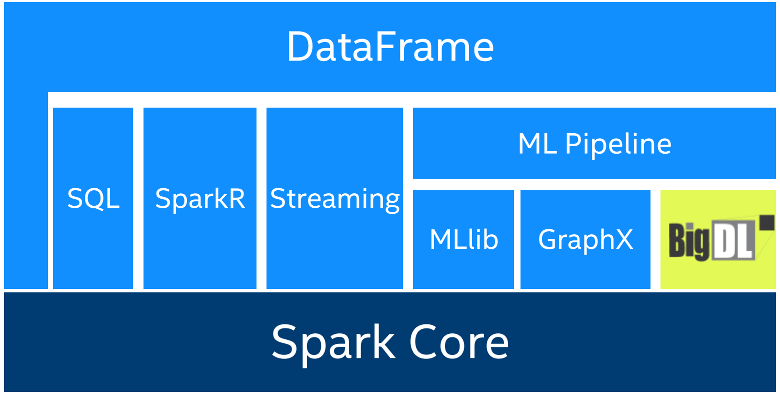
intel Nervana™

OVERVIEW OF BIGDL

BIGDL

BRINGING DEEP LEARNING TO BIG DATA PLATFORM

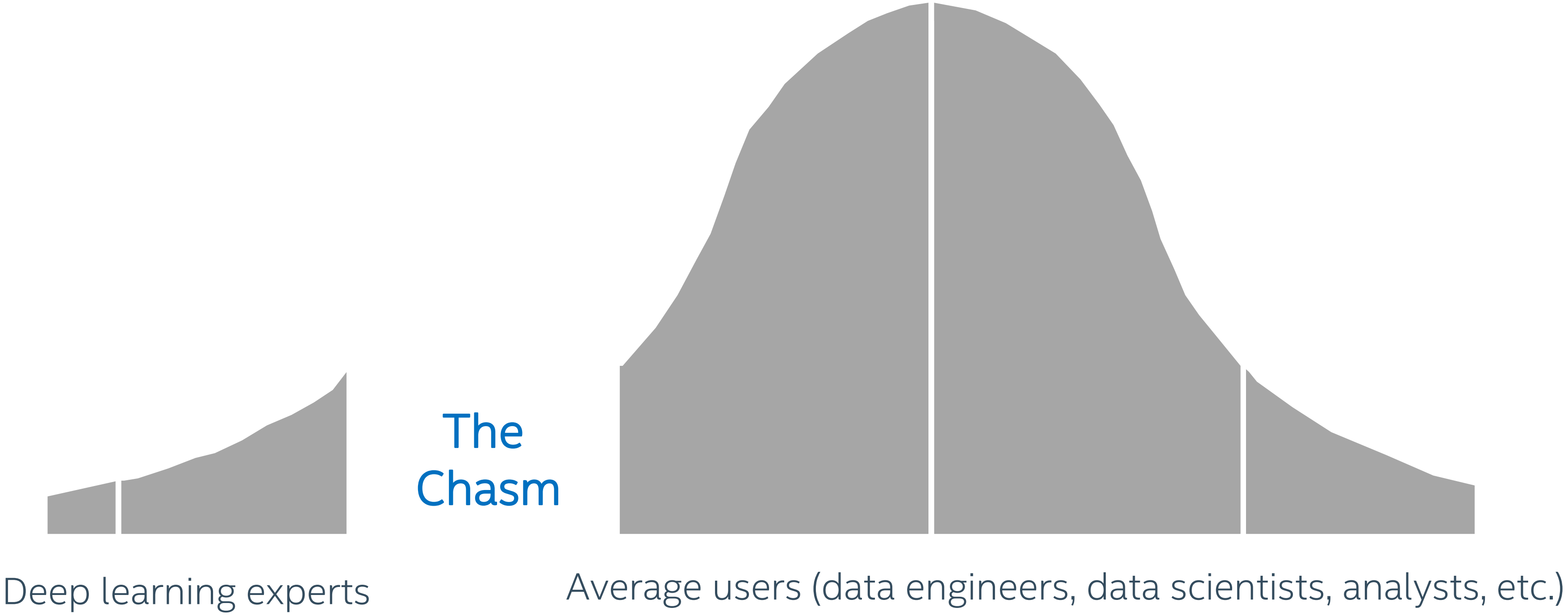
- Distributed deep learning framework for Apache Spark*
- Make deep learning more accessible to big data users and data scientists
  - Write deep learning applications as ***standard Spark programs***
  - Run on existing Spark/Hadoop clusters (***no changes needed***)
- Feature parity with popular deep learning frameworks
  - E.g., Caffe, Torch, Tensorflow, etc.
- High performance
  - Powered by Intel MKL and multi-threaded programming
- Efficient scale-out
  - Leveraging Spark for distributed training & inference



https://github.com/intel-analytics/BigDL

https://bigdl-project.github.io/

CHASM B/W DEEP LEARNING AND BIG DATA COMMUNITIES



BIGDL ANSWERING THE NEEDS

Make deep learning more accessible to big data and data science communities

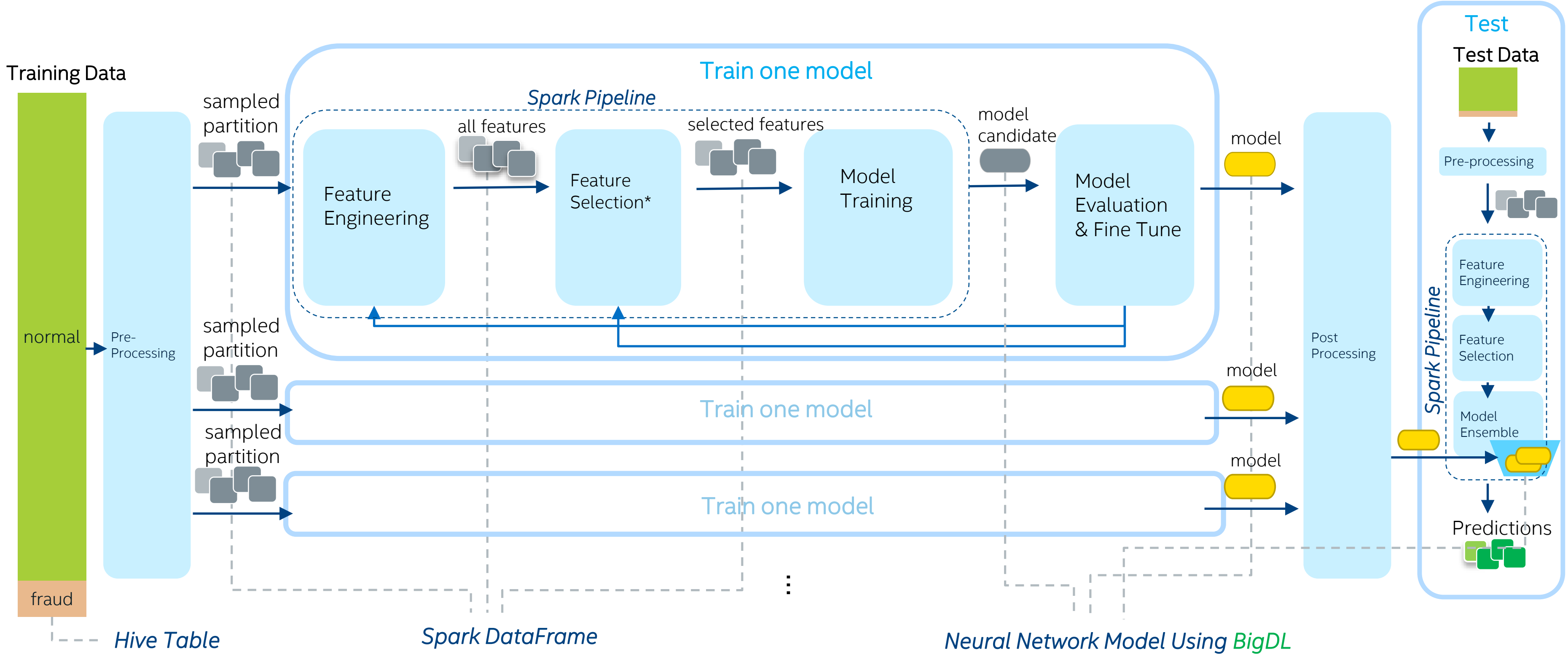
- Continue the use of familiar SW tools and HW infrastructure to build deep learning applications

- Analyze "big data" using deep learning on the same Hadoop/Spark cluster where the data are stored

- Add deep learning functionalities to the Big Data (Spark) programs and/or workflow

- Leverage existing Hadoop/Spark clusters to run deep learning applications
  - Shared with other workloads (*e.g., ETL, data warehouse, feature engineering, statistic machine learning, graph analytics, etc.*) in a dynamic and elastic fashion

FRAUD DETECTION FOR UNIONPAY



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DISTRIBUTED TRAINING ON BIGDL

DISTRIBUTED TRAINING ON BIGDL

Iterative

Mini-batch

Data parallel

Training

```
for (i <- 1 to N) {
  batch = next_batch()
  output = model.forward(batch.input)
  loss = criterion.forward(output, batch.target)
  error = criterion.backward(output, batch.target)
  model.backward(input, error)
  optimMethod.optimize(model.weight, model.gradient)
}
```

Synchronous SGD

RUN AS STANDARD SPARK PROGRAM

Standard Spark jobs

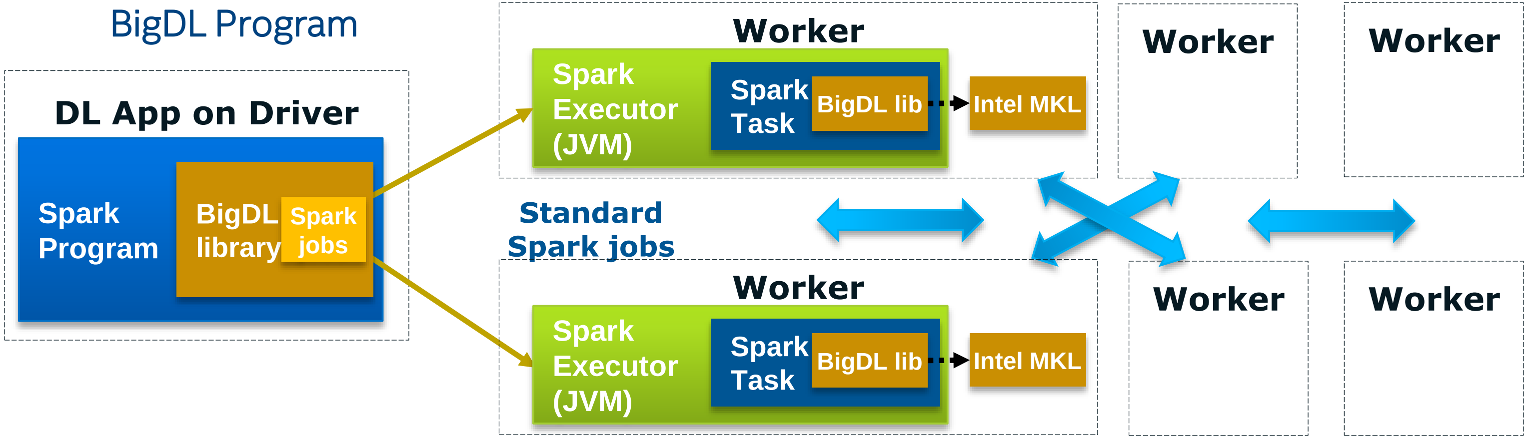
- No changes to the Spark or Hadoop clusters needed

Iterative

- Each iteration of the training runs as a Spark job

Data parallel

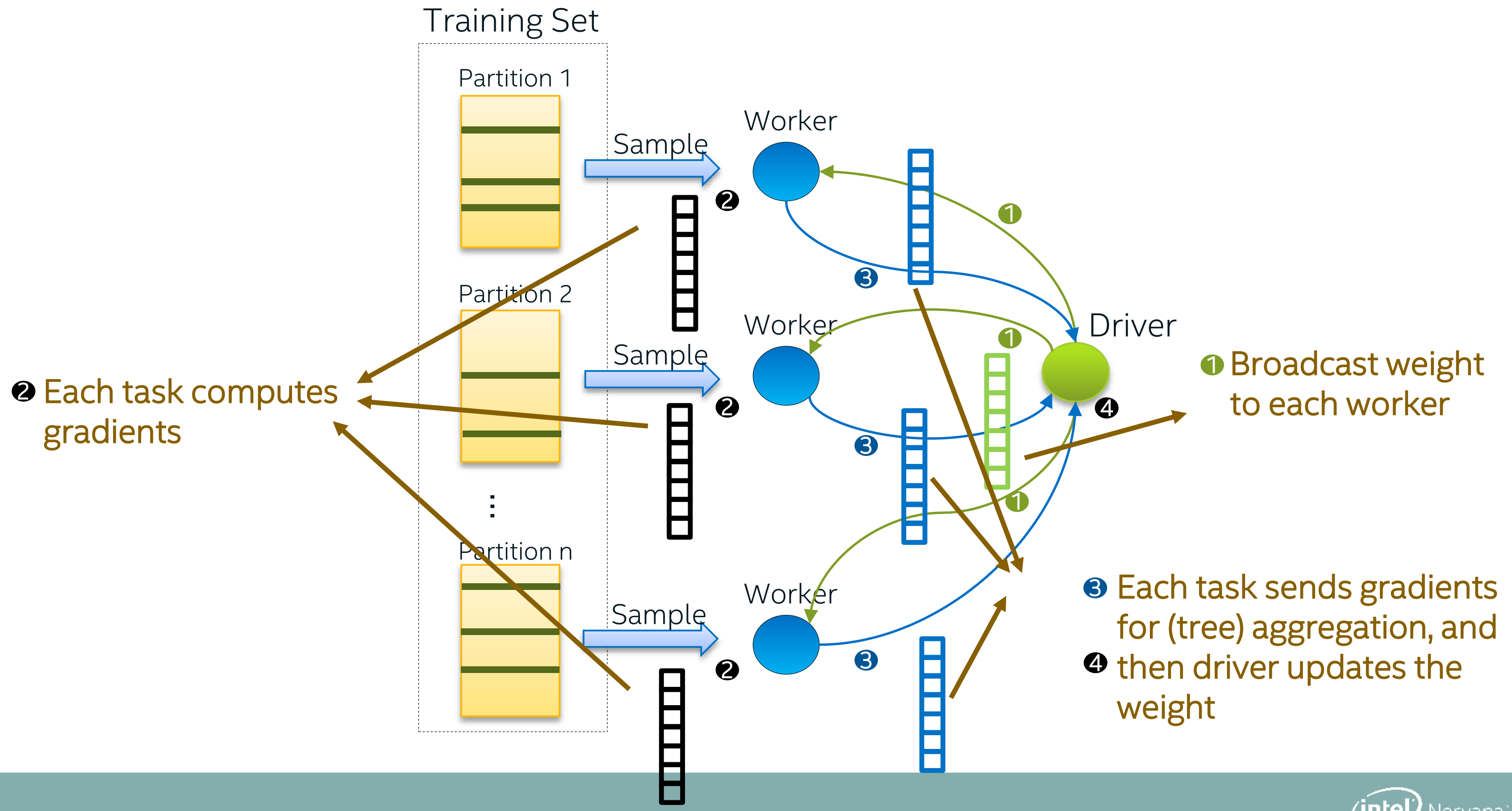
- Each Spark task runs the same model on a subset of the data (batch)



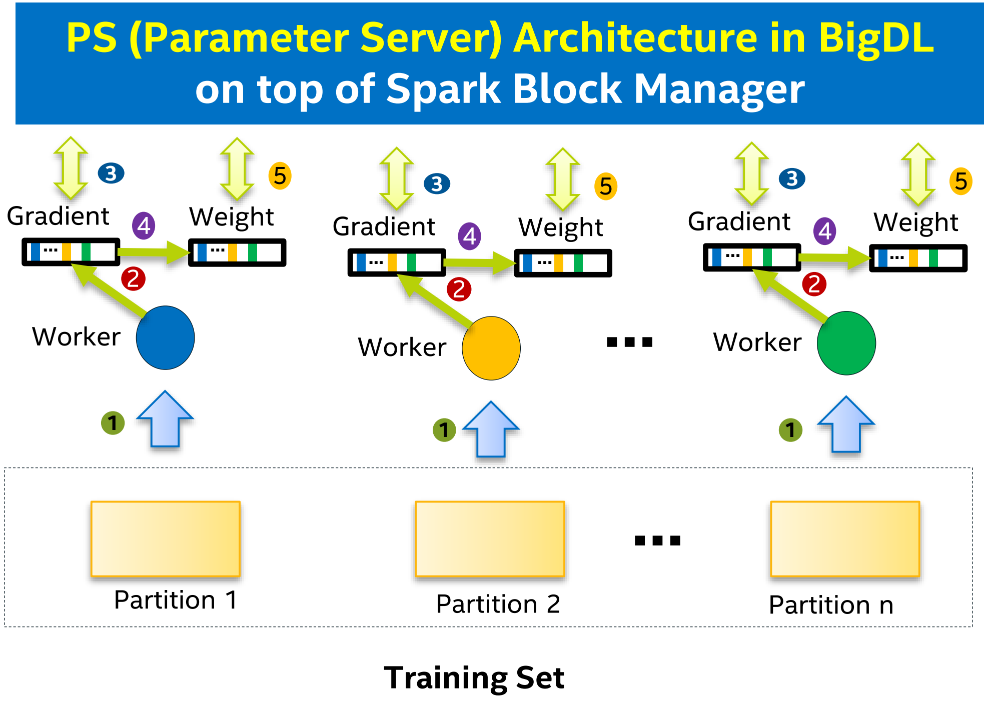
TECHNIQUES FOR LARGE-SCALE DISTRIBUTED TRAINING

- **Optimizing parameter synchronization and aggregation**
- **Optimizing task scheduling**
- **Scaling batch size**

PARAMETER SYNCHRONIZATION IN SPARK MLLIB

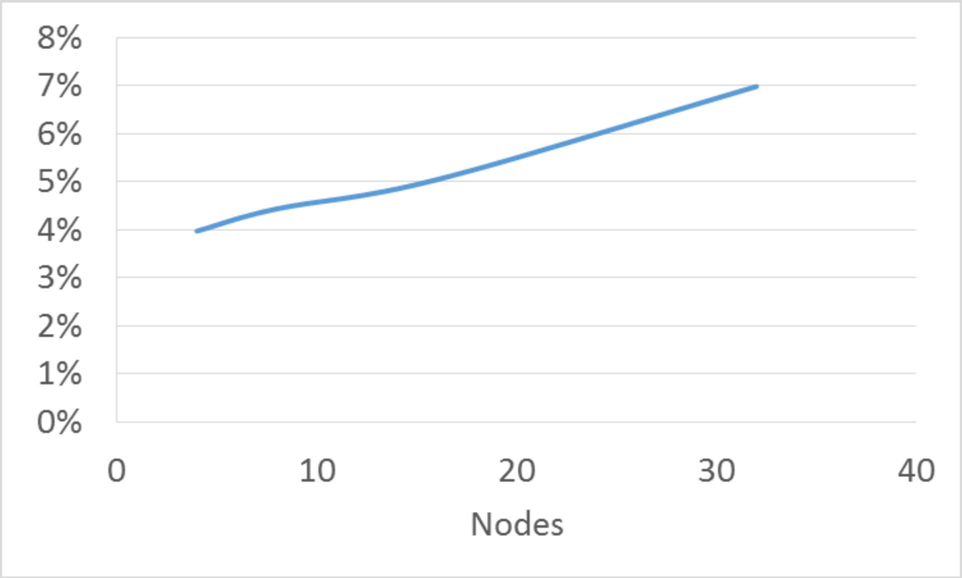


PARAMETER SYNCHRONIZATION IN BIGDL



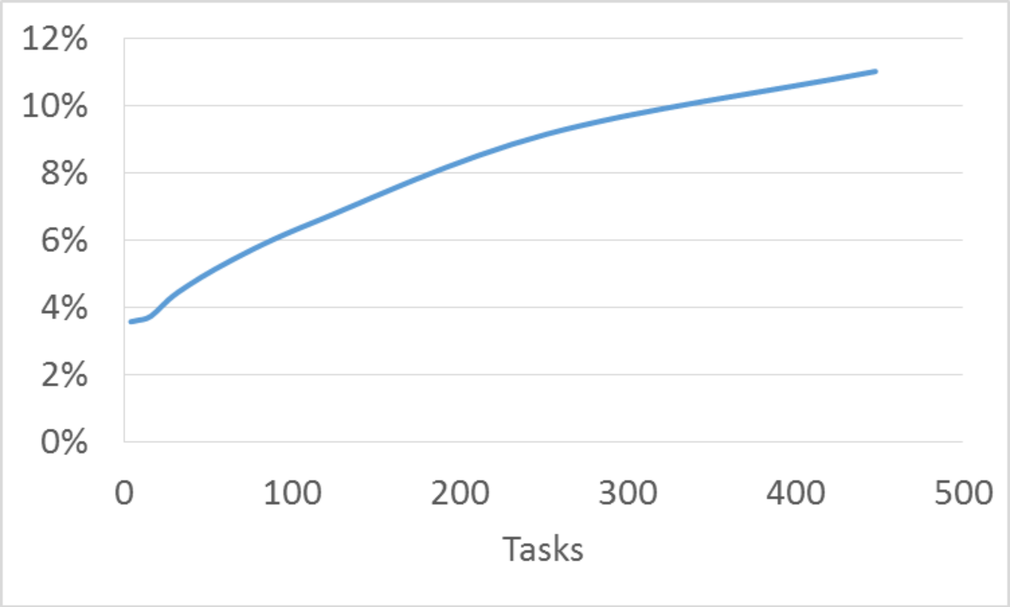
Peer-2-Peer All-Reduce synchronization

PARAMETER SYNCHRONIZATION IN BIGDL



Parameter synchronization time as a fraction of average compute time for Inception v1 training

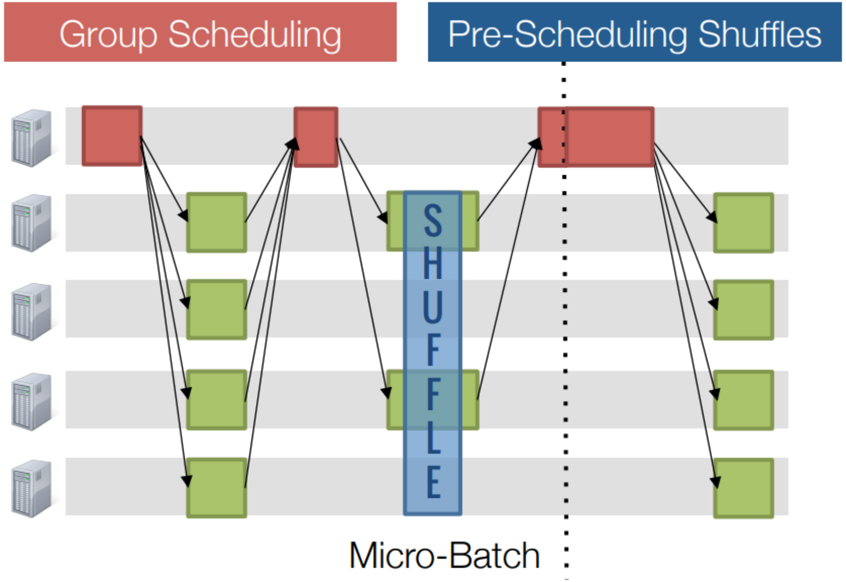
TASK SCHEDULING OVERHEADS



Spark overheads (task scheduling, task serde, task fetch) as a fraction of average compute time for Inception v1 training

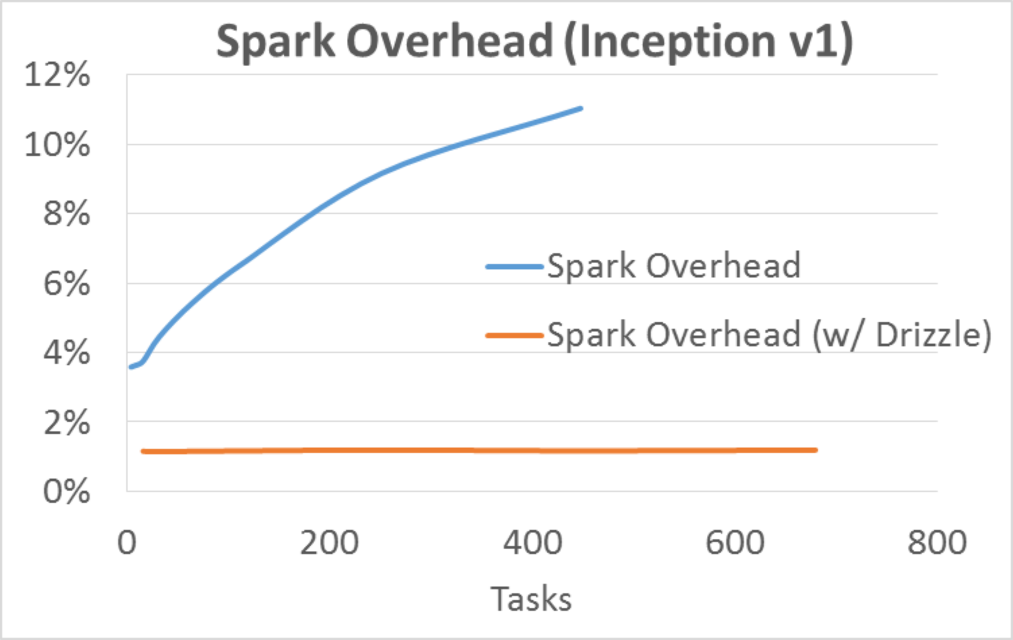
DRIZZLE

- Low latency execution engine for Apache Spark
- Fine-grained execution with coarse-grained scheduling
- Group scheduling
  - Schedule a group of iterations at once
  - Fault tolerance, scheduling at group boundaries
- Coordinating shuffles: PRE-SCHEDULING
  - Pre-schedule tasks on executors
  - Trigger tasks once dependencies are met



*Collaboration with Shivaram Venkataraman from UC Berkeley RICELab

REDUCING SCHEDULING OVERHEADS WITH DRIZZLE



INCREASED MINI-BATCH SIZE

- Distributed synchronous mini-batch SGD
  - Increased mini-batch size

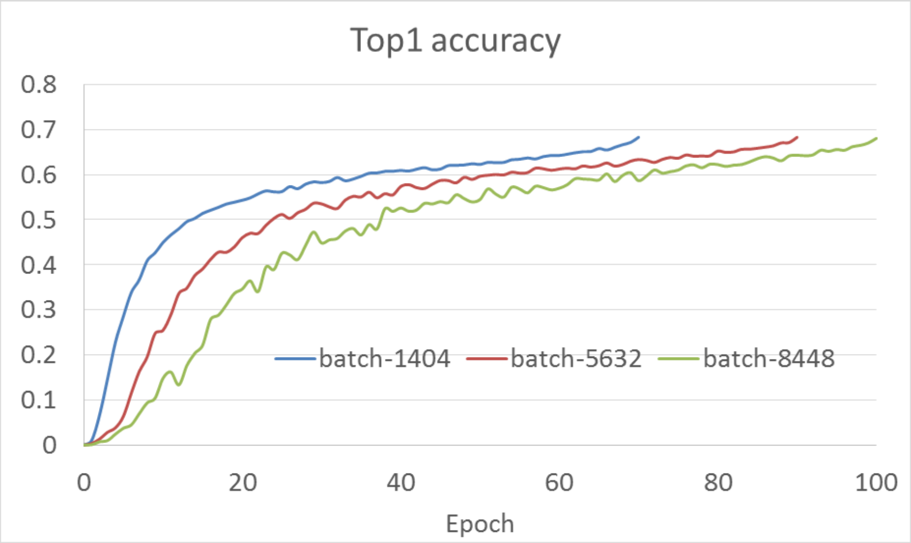
    *total_batch_size = batch_size_per_worker * num_of_workers*
  - Can lead to loss in test accuracy

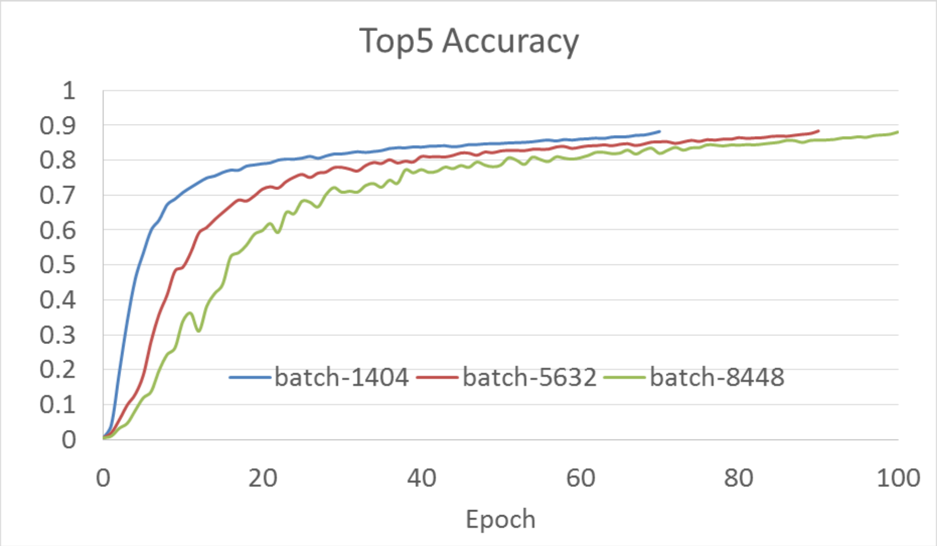
- State-of-art method for scaling mini-batch size*
  - Linear scaling rule
  - Warm-up strategy
  - Layer-wise adaptive rate scaling
  - Adding batch normalization

* "Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour"

* "Scaling SGD Batch Size to 32K for ImageNet Training"

INCEPTION V1

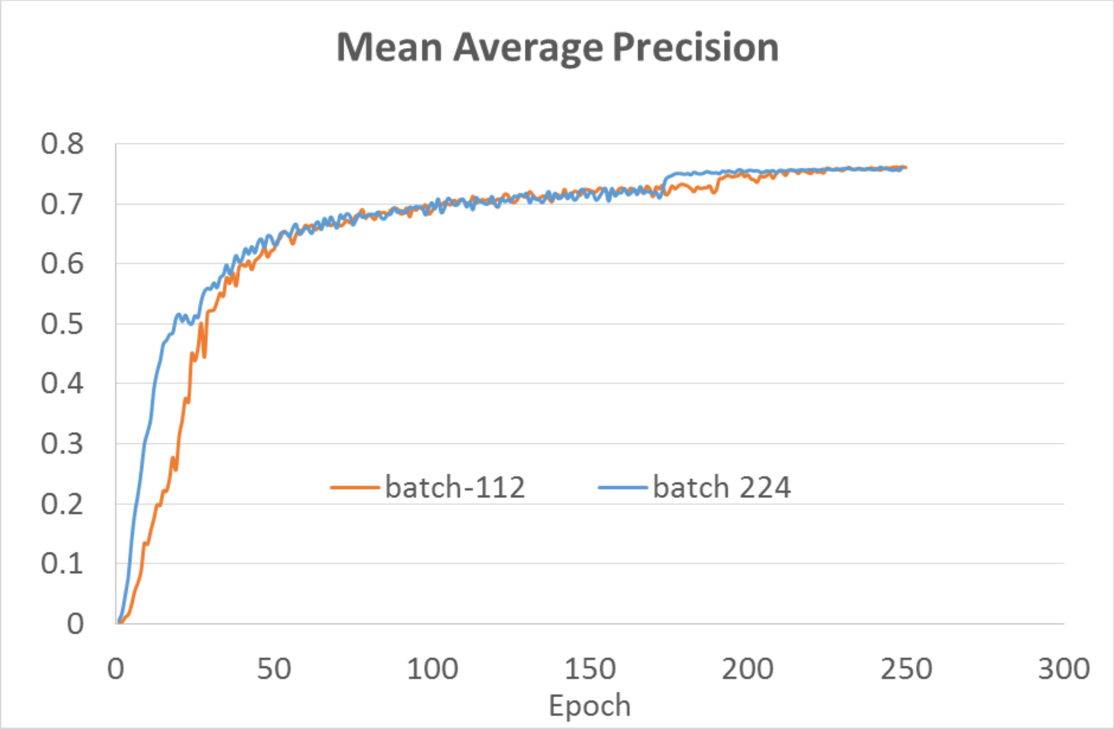




Strategies

- Gradual warm-up
- Linear scaling
- *Gradient clipping*
- TODO: adding batch normalization

SSD (SINGLE SHOT MULTI-BOX DETECTOR)



Strategies

- Warm-up w/ Adam
- Linear scaling
- *Gradient clipping*

DISTRIBUTED INFERENCE ON BIGDL

DISTRIBUTED INFERENCE ON BIGDL

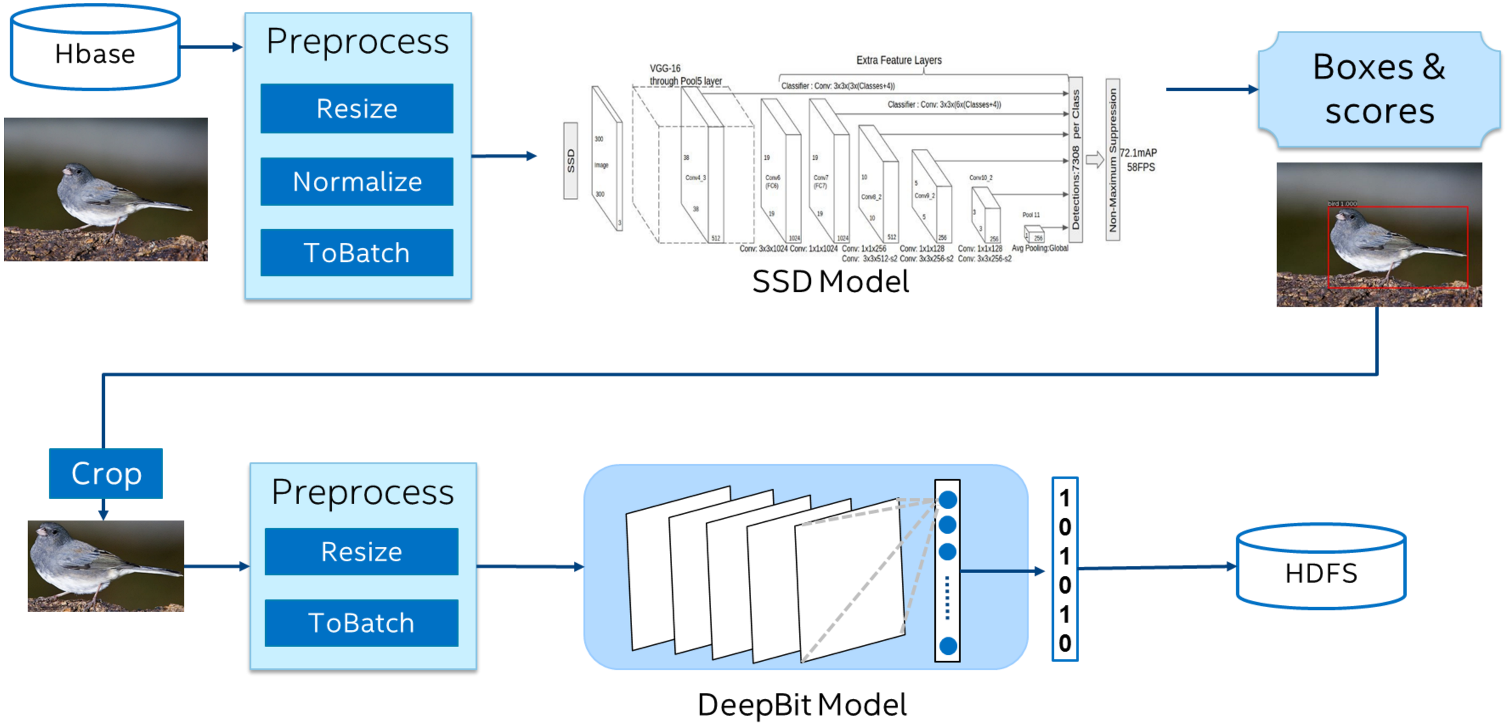
Inference

```
for (b <- 1 to D) {
  input = next_data(i)
  output = model.forward(input)
}
```

Embarrassingly (data) parallel in nature

Efficiently scale out using BigDL on Apache Spark

IMAGE DETECTION & EXTRACTION PIPELINE (USING SSD + DEEPBIT MODELS)



CHALLENGES OF LARGE-SCALE PROCESSING IN GPU SOLUTIONS

- Reading images out takes a very long time
- Image pre-processing on HBase is very complex
- No existing software frameworks can be leveraged
  - E.g., resource management, distributed data processing, fault tolerance, etc.
- Very challenging to scale out to massive amount of pictures
  - Due to SW and HW infrastructure constraints

UPGRADING TO BIGDL SOLUTIONS

- Reuse existing Hadoop/Spark clusters for deep learning with no changes

- Efficiently scale out on Spark with superior performance
  - Reading HBase data no longer a bottleneck

- Very easy to build the end-to-end pipeline in BigDL
  - Image transformation and augmentation based on OpenCV on Spark

    val preProcessor = BytesToMat() -> Resize(300, 300) -> …
    val transformed = preProcessor(dataRdd)

  - Directly Load pre-trained models (BigDL/Caffe/Torch/TensorFLow) into BigDL

    val model = Module.loadCaffeModel(caffeDefPath, caffeModelPath)

MODEL QUANTIZATION FOR EFFICIENT INFERENCE IN BIGDL

- Local quantization scheme converting floats to intergers
  - Faster compute and smaller models
  - Take advantage of SSE and AVX instructions on Xeon servers
  - Supports pre-trained models (BigDL/Caffe/Torch/TensorFLow)

```
val model = Module.loadCaffeModel(caffeDefPath, caffeModelPath)
val quantizedModel = model.quantize()
```

- Quantized SSD model
  - ~4x model size reduction
  - >2x inference speedup
  - ~0.001 mAP (mean average precision) loss

TRY BIGDL OUT

Running BigDL, Deep Learning for Apache Spark, on AWS* (Amazon* Web Service)
https://aws.amazon.com/blogs/ai/running-bigdl-deep-learning-for-apache-spark-on-aws/

Use BigDL on Microsoft* Azure* HDInsight*
https://azure.microsoft.com/en-us/blog/use-bigdl-on-hdinsight-spark-for-distributed-deep-learning/

BigDL on Alibaba* Cloud E-MapReduce*
https://yq.aliyun.com/articles/73347

BigDL on CDH* and Cloudera* Data Science Workbench*
http://blog.cloudera.com/blog/2017/04/bigdl-on-cdh-and-cloudera-data-science-workbench/

Intel's BigDL on Databricks*
https://databricks.com/blog/2017/02/09/intels-bigdl-databricks.html

BigDL Distribution in Cray Urika-XC Analytics Suite
http://www.cray.com/products/analytics/urika-xc

PARTNER WITH US

- Use BigDL & Share your Experience
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- Leverage Intel Developer Zone Resources

https://github.com/intel-analytics/BigDL   http://software.intel.com/ai

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