Building Deep Learning Applications for Big Data

An Introduction to Analytics Zoo: Distributed TensorFlow, Keras and BigDL on Apache Spark

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AAAI 2019

Agenda

- Motivation (15 minutes)
  - Trends, real-world scenarios
- DL frameworks on Apache Spark (30 minutes)
  - BigDL, TensorFlowOnSpark, DL Pipelines, Project Hydrogen, SparkNet
- Analytics Zoo (30 minutes)
  - Distributed TensorFlow, Keras and BigDL on Apache Spark
- Analytics Zoo Examples (30 minutes)
  - Dogs vs. cats, object detection, OpenVINO model inference, distributed TensorFlow
- Break (30 minutes)

Agenda

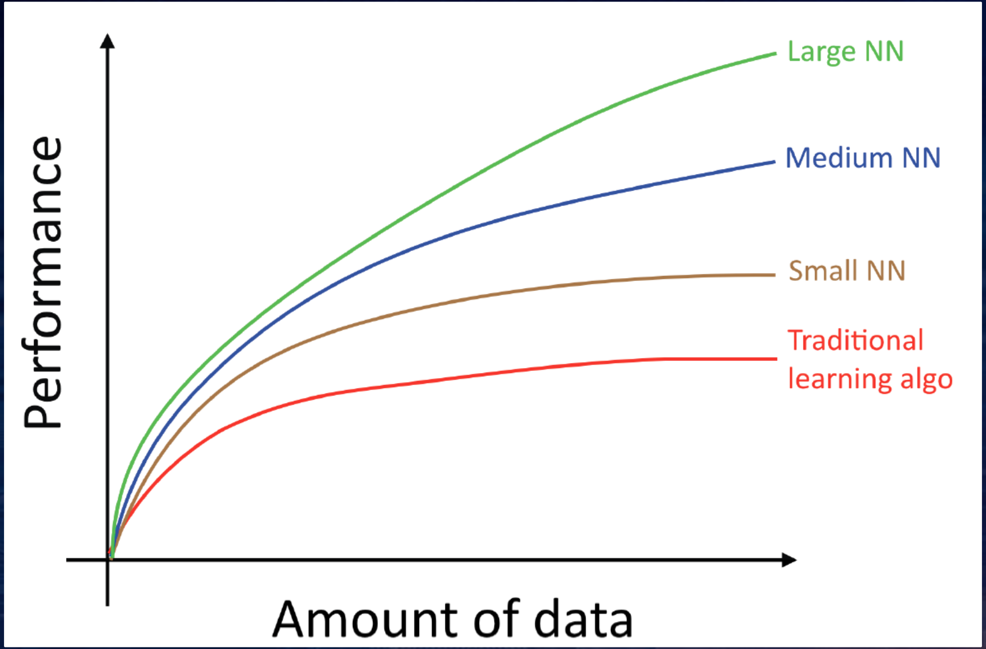
- Distributed training in BigDL (30 minutes)
  - Data parallel training, parameter synchronization, scaling & convergence, etc.
- Advanced applications (20 minutes)
  - Text classification, movie recommendation
- Real-world applications (45 minutes)
  - Object detection and image feature extraction at *JD.com*
  - Produce defect detection using distributed TF on Spark in *Midea*
  - NLP based customer service chatbot for *Microsoft Azure*
  - Image similarity based house recommendation for *MLSlisting*
  - Transfer learning based image classifications for *World Bank*
  - LSTM-Based time series anomaly detection for *Baosight*
  - Fraud detection for payment transactions for *UnionPay*
- Conclusion and Q&A (10 minutes)

Motivations

Technology and Industry Trends

Real World Scenarios

Trend #1: Data Scale Driving Deep Learning Process



"Machine Learning Yearning", Andrew Ng, 2016

Trend #2: Hadoop Becoming the Center of Data Gravity

Why an Enterprise Data Hub ?

- Single place for all enterprise data... (unedited hi-resolution history of everything)
- Reduces Application Integration Costs
  - Connect once to Hub (N vs N^2 connections)
- Lowest unit cost data processing & storage platform
  - Open source S/W on commodity H/W (reliability in S/W not H/W)
  - Can mix H/W vendors means every expansion is competitively tendered
- Fast Standardised Provision
  - No custom design task, re-use Active Directory account/password processes
  - Reduces Shadow IT
- Secure (audited, E2E visibility/auditing, encryption)
  - Eliminate need for one off extracts

#StrataHadoop

Strata + Hadoop WORLD

Phillip Radley, BT Group
Strata + Hadoop World 2016 San Jose

Everyone is building Data Lakes

Goldman Sachs

- Universal data acquisition makes all big data analytics and reporting easier
- Hadoop provides a scalable storage with HDFS
- How will we scale consumption and curation of all this data?

7

we BUILD

Matthew Glickman, Goldman Sachs
Spark Summit East 2015

Trend #3: Real-World ML/DL Systems Are Complex Big Data Analytics Pipelines

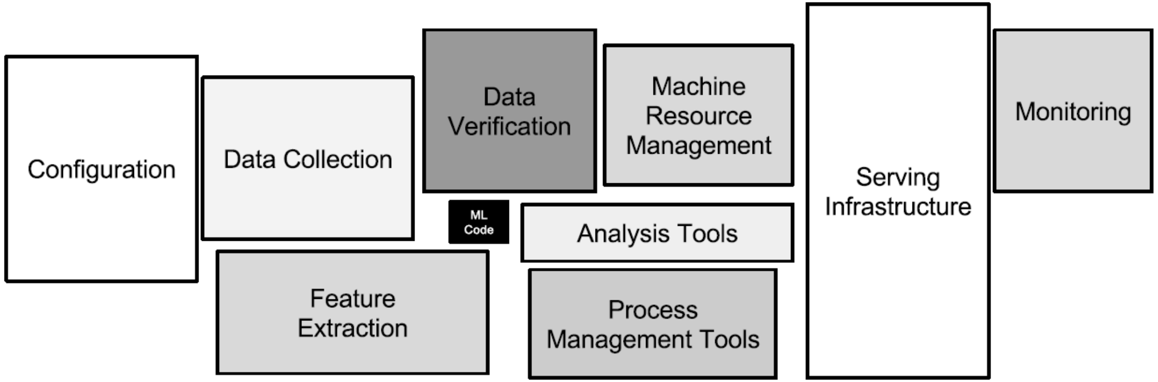


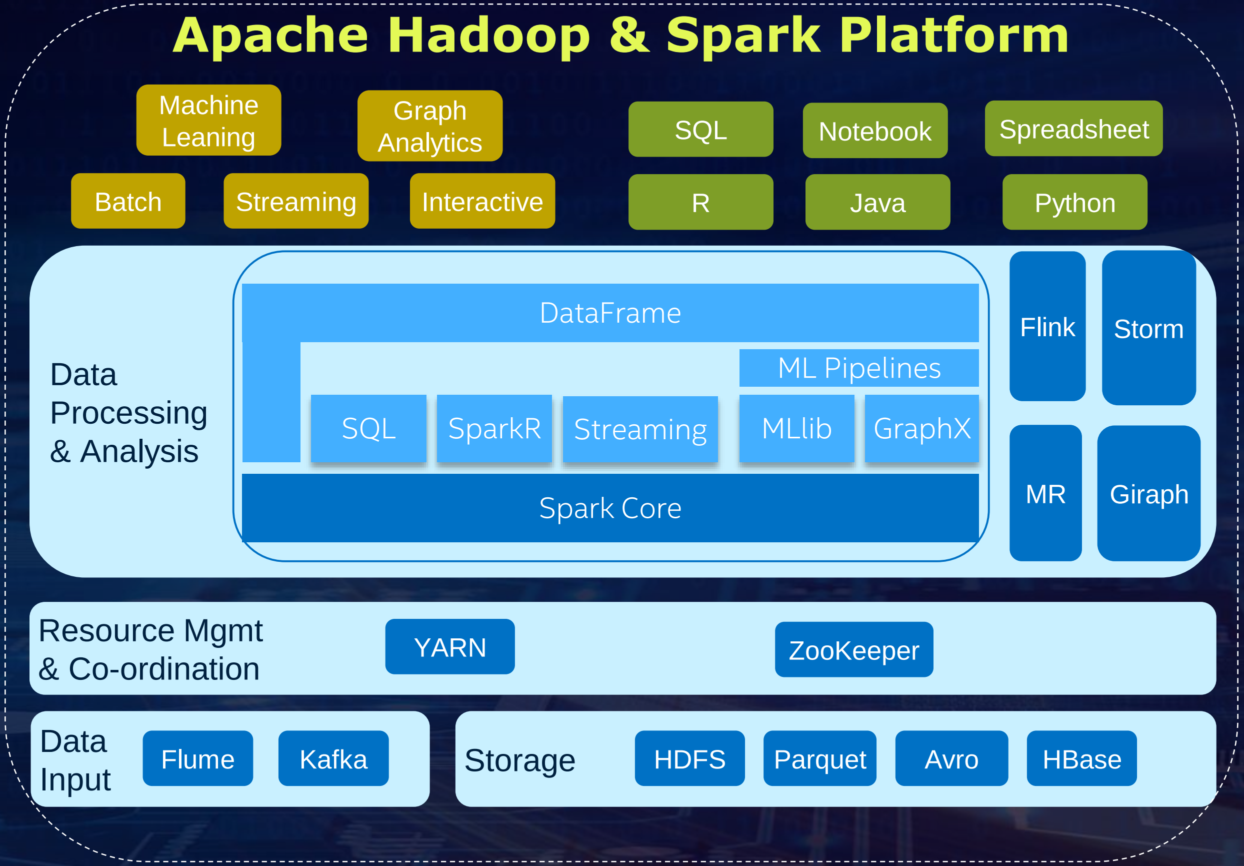
Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

"Hidden Technical Debt in Machine Learning Systems", Sculley et al., Google, NIPS 2015 Paper

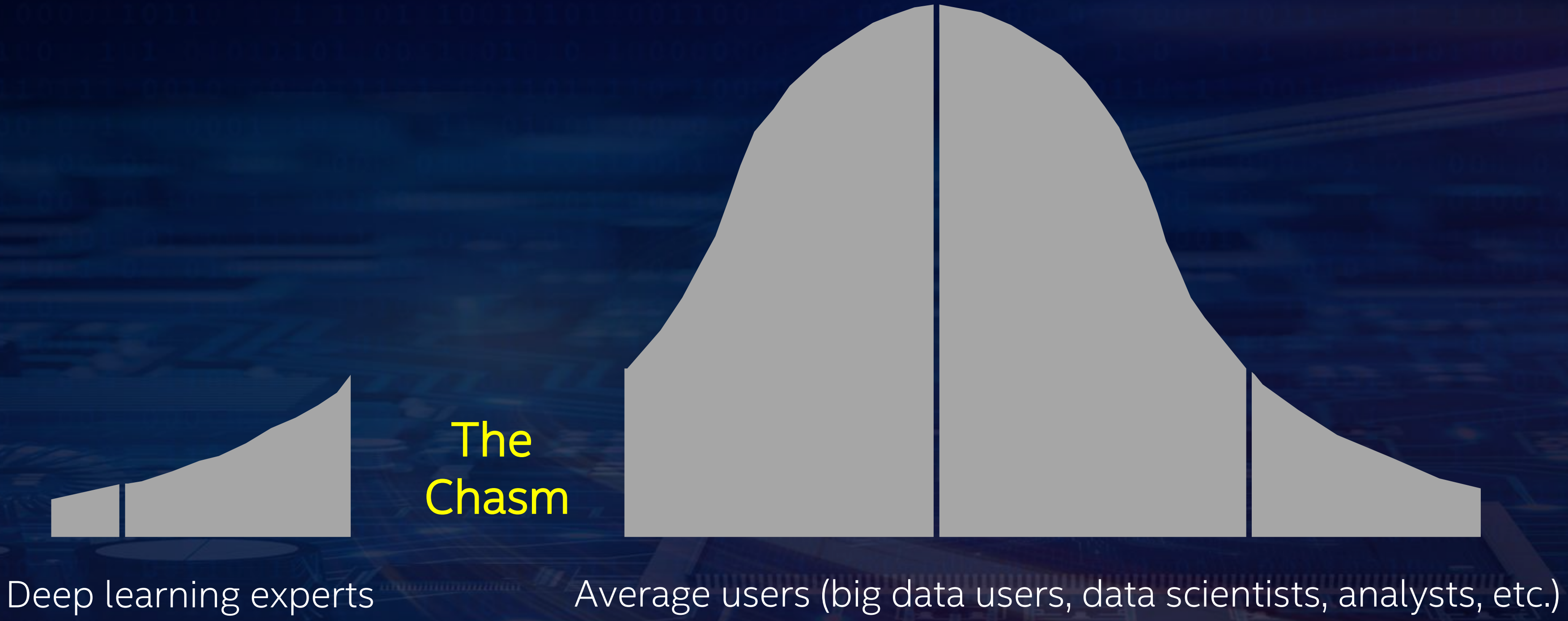
Trend #4: Unified Big Data Platform Driving Analytics & Data Science

Ion Stoica, UC Berkeley, Spark Summit 2013 Keynote

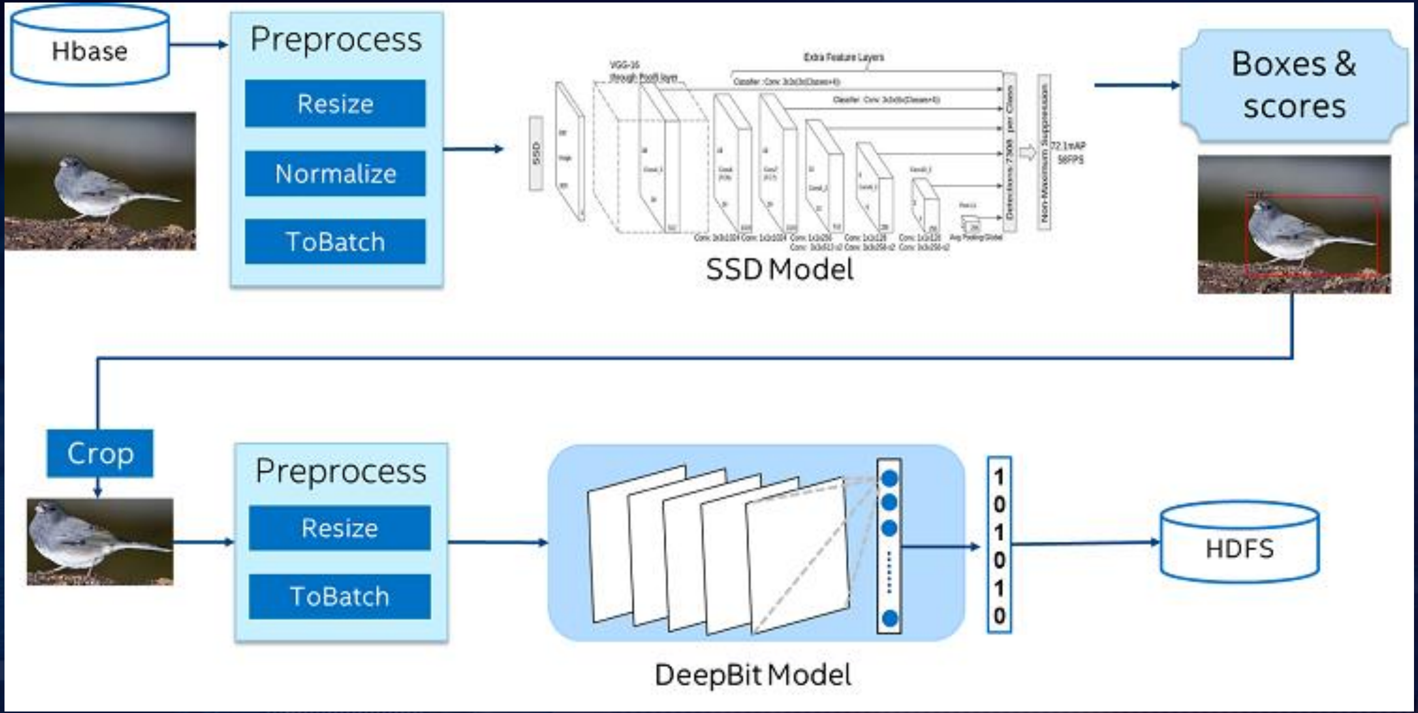
Unified Big Data Analytics Platform



Chasm b/w Deep Learning and Big Data Communities



Large-Scale Image Recognition at JD.com



Bridging the Chasm

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 large-scale big data programs and/or workflow
- Leverage existing Hadoop/Spark clusters to run deep learning applications
    - Shared, monitored and managed with other workloads (*e.g., ETL, data warehouse, feature engineering, traditional ML, graph analytics, etc.*) in a dynamic and elastic fashion

DL Frameworks on Apache Spark

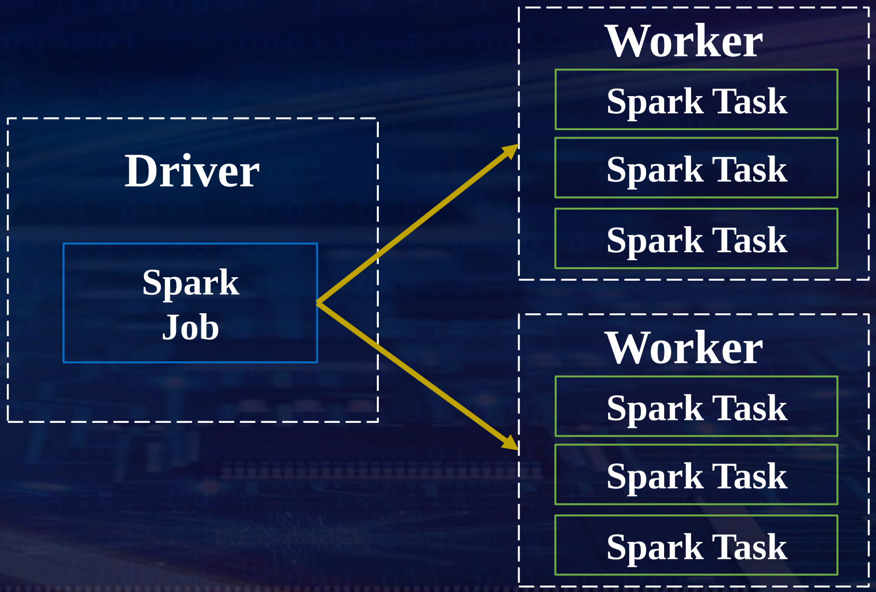
BigDL, DL Pipelines for Spark, TensorflowOnSpark,

Project Hydrogen of Spark, SparkNet, etc.

Apache Spark

Low Latency, Distributed Data Processing Framework

- A Spark cluster consists of a single *driver* node and multiple *worker* nodes
- A Spark *job* contains many Spark *tasks*, each working on a data *partition*
- Driver is responsible for scheduling and dispatching the tasks to workers, which runs the actual Spark tasks

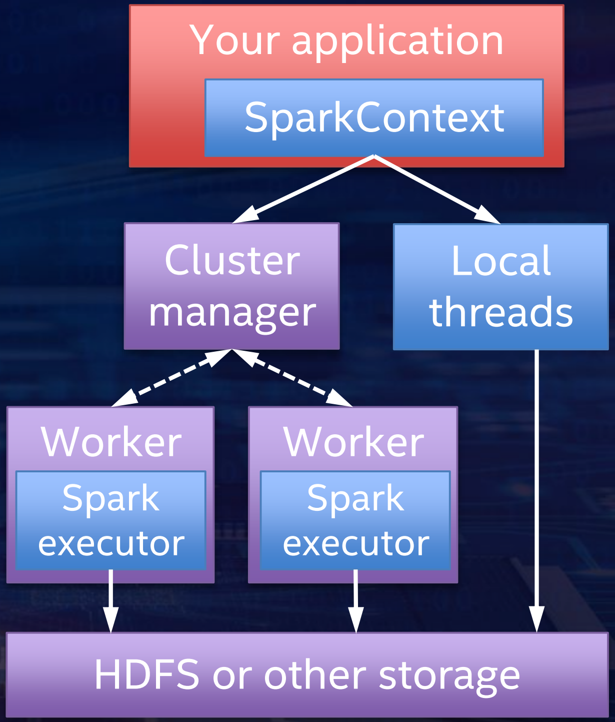


https://spark.apache.org

Apache Spark

Spark Program

- Spark runs as a library in your program (1 instance per app)
- Runs tasks locally or on cluster
  - K8s, YARN, Mesos or standalone mode
- Accesses storage systems via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, …

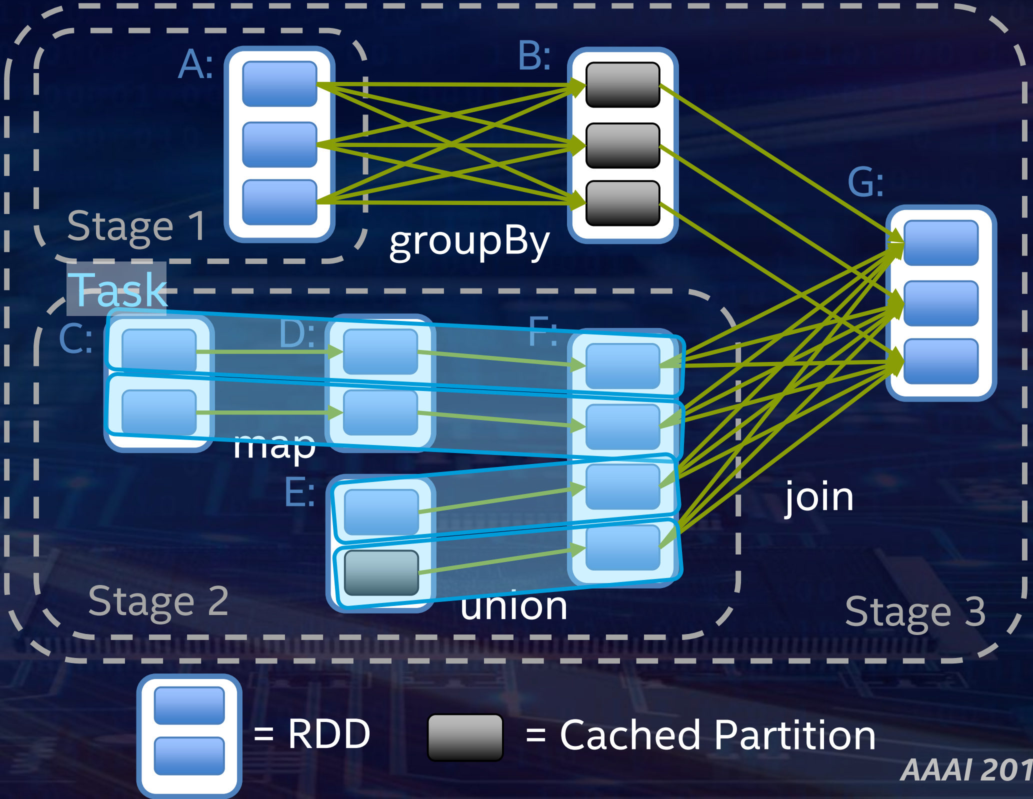


Source: “Parallel programming with Spark”, Matei Zaharia, AMPCamp 3

Apache Spark

Distributed Task Execution

- General task graphs
- Automatically pipelines functions
- Data locality aware
- Partitioning aware to avoid shuffles

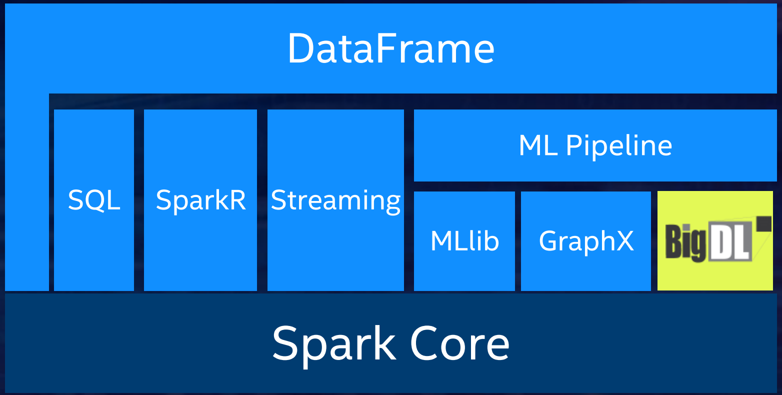


Source: “Parallel programming with Spark”, Matei Zaharia, AMPCamp 3

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 (on CPU)
  - 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/

BigDL Run as Standard Spark Programs

Standard Spark jobs

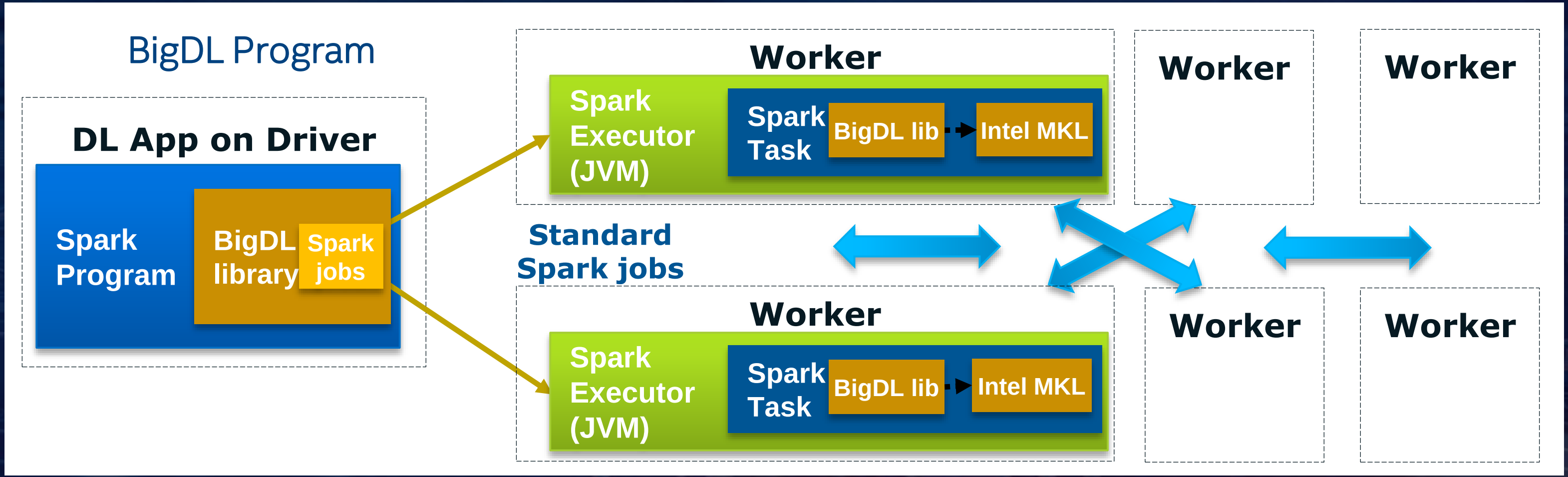
- No changes to the Spark or Hadoop clusters needed

Iterative

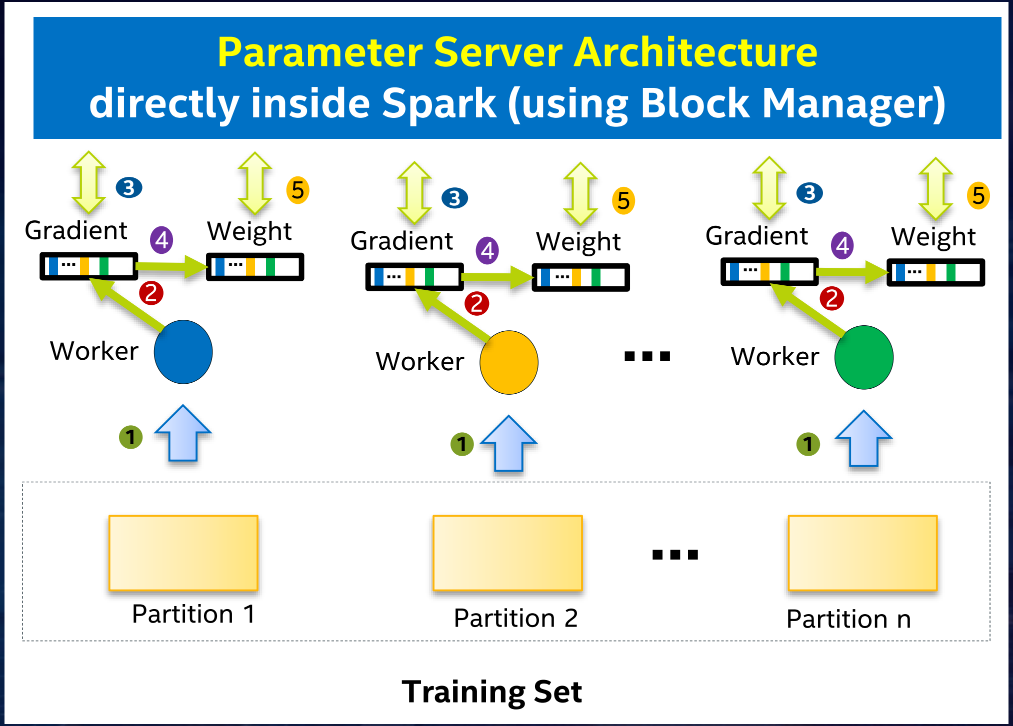
- Each iteration of the training runs as a Spark job

Data parallel

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

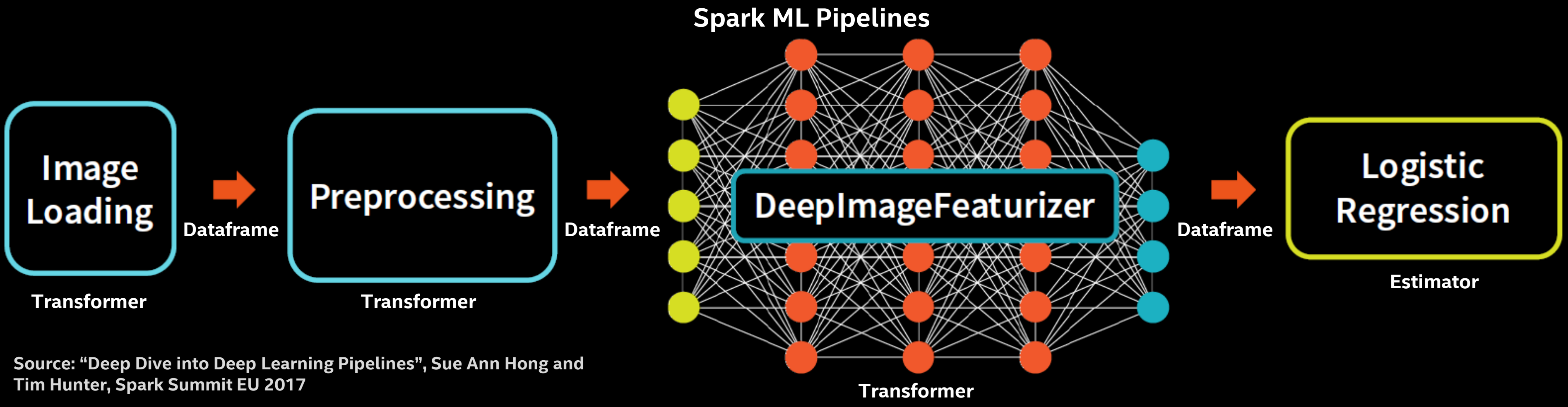


Distributed Training in BigDL



Peer-2-Peer **All-Reduce** synchronization

DL Pipelines for Spark



Source: "Deep Dive into Deep Learning Pipelines", Sue Ann Hong and Tim Hunter, Spark Summit EU 2017

Load existing TF or Keras models in Spark ML pipelines

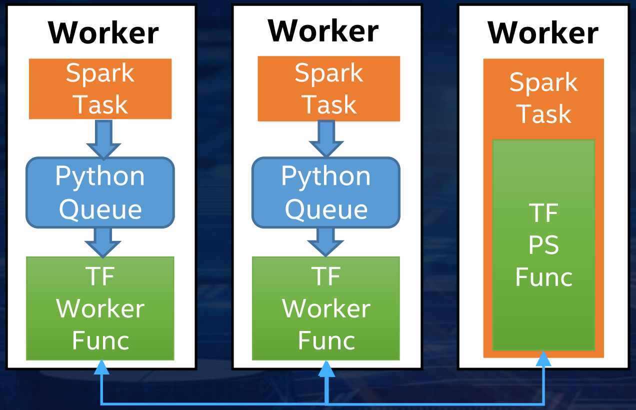
- Load into transformer: inference only
- Load into estimator: single node training/tuning only

https://github.com/databricks/spark-deep-learning

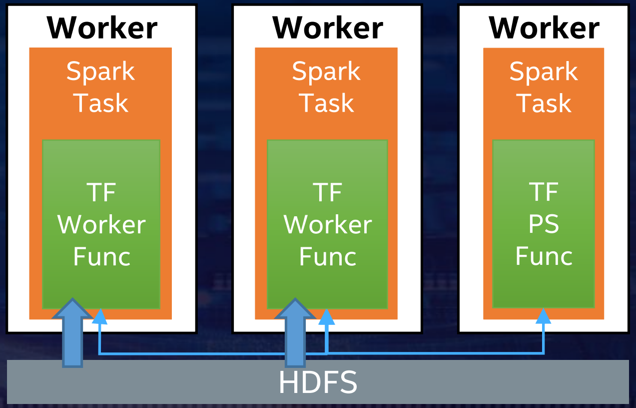
TensoflowOnSpark

Standalone TF jobs on Spark cluster

- Use Spark as the orchestration layer to allocate resources
- Launch distributed TensorFlow job on the allocated resources
- Coarse-grained integration of two independent frameworks
    - Memory overheads, no gang scheduling, limited interactions with data pipelines, etc.



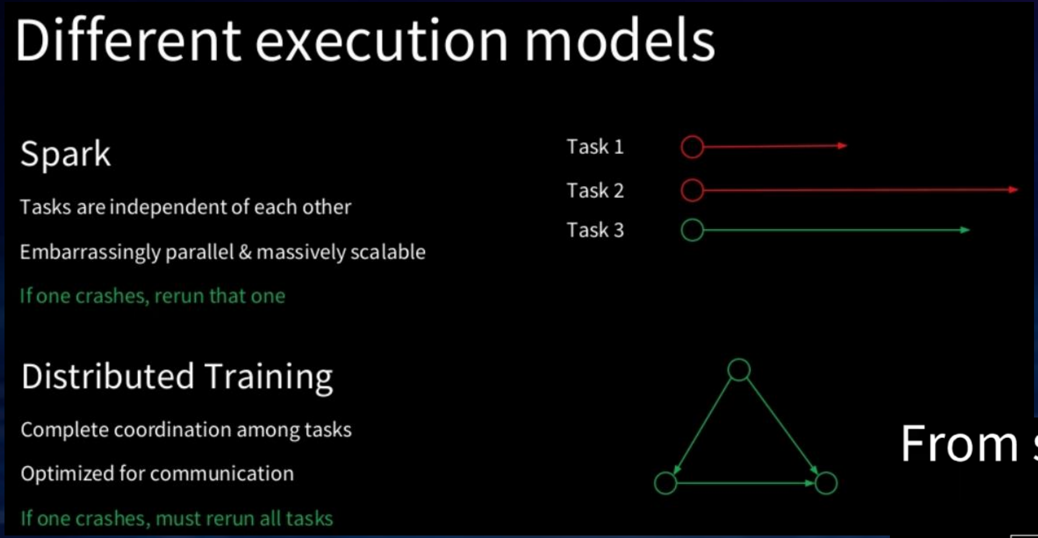
feed_dict: TF worker func runs as independent process in background, reading data from Python queue



queue_runner: direct HDFS access from TF work func

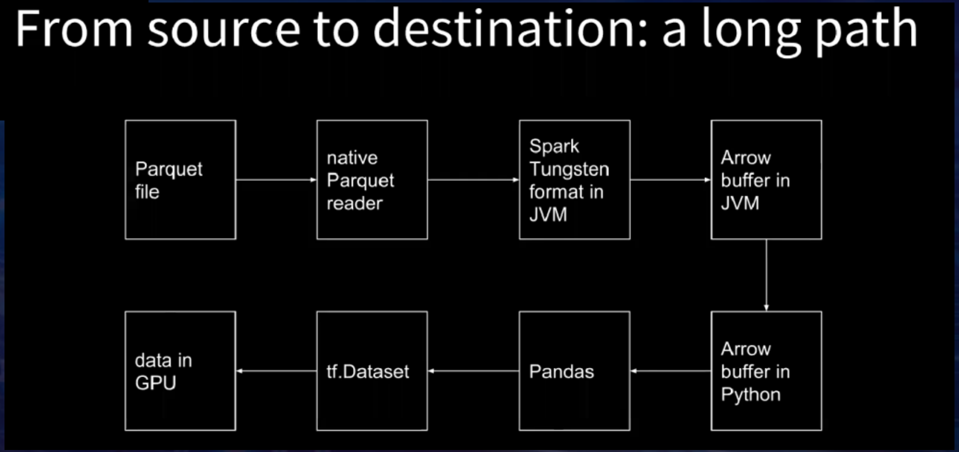
https://github.com/yahoo/TensorFlowOnSpark

Project Hydrogen



Spark and distributed TF have different execution model

- Support "gang scheduling" through *new barrier execution* mode

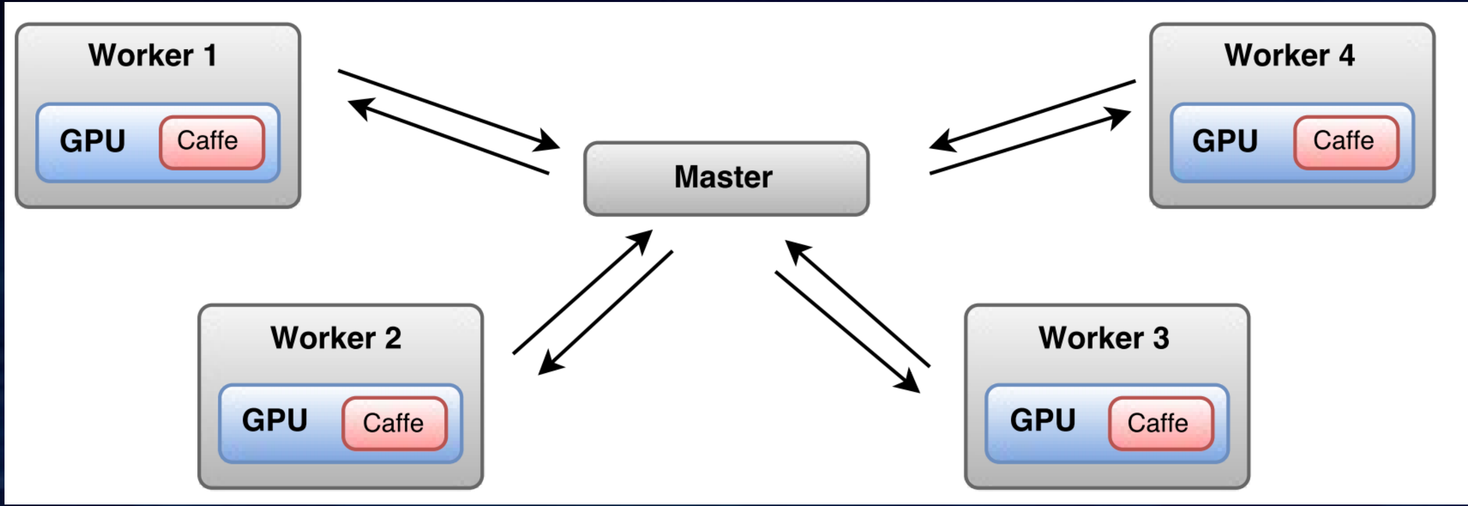


Overhead of data transferring between Spark and TF

- *Optimized data exchange* leveraging Apache Arrow

Source: "Project Hydrogen: State-of-the-Art Deep Learning on Apache Spark", Xiangrui Meng, Bay Area Apache Spark Meetup, July 2018

SparkNet



Source: “SparkNet: Training Deep Networks in Spark”, Philipp Moritz, et al., ICLR 2016

Distributed DL training by running Caffe in each worker

- Asynchronous parameter synchronization through master (driver) mode
    - Very inefficient (~20 seconds with just 5 workers)

Analytics Zoo

A unified analytics + AI platform for distributed ***TensorFlow****,* ***Keras*** *and* ***BigDL*** *on Apache Spark*

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

Analytics Zoo

Unified Analytics + AI Platform for Big Data

Distributed TensorFlow, Keras and BigDL on Spark

Reference Use Cases	• Anomaly detection, sentiment analysis, fraud detection, image generation, chatbot, etc.
Built-In Deep Learning Models	• Image classification, object detection, text classification, text matching, recommendations, sequence-to-sequence, anomaly detection, etc.
Feature Engineering	Feature transformations for • Image, text, 3D imaging, time series, speech, etc.
High-Level Pipeline APIs	• Distributed TensorFlow and Keras on Spark • Native support for transfer learning, Spark DataFrame and ML Pipelines • Model serving API for model serving/inference pipelines
Backbends	Spark, TensorFlow, Keras, BigDL, OpenVINO, MKL-DNN, etc.

https://github.com/intel-analytics/analytics-zoo/ https://analytics-zoo.github.io/

Analytics Zoo

Build end-to-end deep learning applications for big data

- Distributed *TensorFlow* on Spark
- *Keras*-style APIs (with autograd & transfer learning support)
- *nnframes*: native DL support for Spark DataFrames and ML Pipelines
- Built-in *feature engineering* operations for data preprocessing

Productionize deep learning applications for big data at scale

- POJO *model serving* APIs (w/ OpenVINO support)
- Support Web Services, Spark, Storm, Flink, Kafka, etc.

Out-of-the-box solutions

- Built-in deep learning *models* and reference *use cases*

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Distributed TensorFlow on Spark in Analytics Zoo

1. **Data wrangling and analysis using PySpark**

```
from zoo import init_nncontext
from zoo.pipeline.api.net import TFDataset

sc = init_nncontext()

#Each record in the train_rdd consists of a list of NumPy ndrrays
train_rdd = sc.parallelize(file_list)
  .map(lambda x: read_image_and_label(x))
  .map(lambda image_label: decode_to_ndarrays(image_label))

#TFDataset represents a distributed set of elements,
#in which each element contains one or more TensorFlow Tensor objects.
dataset = TFDataset.from_rdd(train_rdd,
                             names=["features", "labels"],
                             shapes=[[28, 28, 1], [1]],
                             types=[tf.float32, tf.int32],
                             batch_size=BATCH_SIZE)
```

Distributed TensorFlow on Spark in Analytics Zoo

2. **Deep learning model development using TensorFlow**

```
import tensorflow as tf

slim = tf.contrib.slim

images, labels = dataset.tensors
labels = tf.squeeze(labels)
with slim.arg_scope(lenet.lenet_arg_scope()):
     logits, end_points = lenet.lenet(images, num_classes=10, is_training=True)

loss = tf.reduce_mean(tf.losses.sparse_softmax_cross_entropy(logits=logits,
labels=labels))
```

Distributed TensorFlow on Spark in Analytics Zoo

3. Distributed training on Spark and BigDL

```
from zoo.pipeline.api.net import TFOptimizer
from bigdl.optim.optimizer import MaxIteration, Adam, MaxEpoch, TrainSummary

optimizer = TFOptimizer.from_loss(loss, Adam(1e-3))
optimizer.set_train_summary(TrainSummary("/tmp/az_lenet", "lenet"))
optimizer.optimize(end_trigger=MaxEpoch(5))
```

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Keras, Autograd &Transfer Learning APIs

1. Use transfer learning APIs to
   - Load an existing Caffe model
   - Remove last few layers
   - Freeze first few layers
   - Append a few layers

```
from zoo.pipeline.api.net import *
full_model = Net.load_caffe(def_path, model_path)
# Remove layers after pool5
model = full_model.new_graph(outputs=["pool5"])
# freeze layers from input to res4f inclusive
model.freeze_up_to(["res4f"])
# append a few layers
image = Input(name="input", shape=(3, 224, 224))
resnet = model.to_keras()(image)
resnet50 = Flatten()(resnet)
```

Build Siamese Network Using Transfer Learning

Keras, Autograd &Transfer Learning APIs

2. Use *Keras-style and autograd* APIs to build the Siamese Network

```
import zoo.pipeline.api.autograd as A
from zoo.pipeline.api.keras.layers import *
from zoo.pipeline.api.keras.models import *

input = Input(shape=[2, 3, 226, 226])
features = TimeDistributed(layer=resnet50)(input)
f1 = features.index_select(1, 0) #image1
f2 = features.index_select(1, 1) #image2
diff = A.abs(f1 - f2)
fc = Dense(1)(diff)
output = Activation("sigmoid")(fc)
model = Model(input, output)
```

Build Siamese Network Using Transfer Learning

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nnframes

Native DL support in Spark DataFrames and ML Pipelines

1. **Initialize *NNContext* and load images into *DataFrames* using *`NNImageReader`***

```
from zoo.common.nncontext import *
from zoo.pipeline.nnframes import *
sc = init_nncontext()
imageDF = NNImageReader.readImages(image_path, sc)
```

2. **Process loaded data using *`DataFrame`* transformations**

```
getName = udf(lambda row: ...)
df = imageDF.withColumn("name", getName(col("image")))
```

3. **Processing image using built-in *feature engineering* operations**

```
from zoo.feature.image import *
transformer = ChainedPreprocessing(
        [RowToImageFeature(), ImageChannelNormalize(123.0, 117.0, 104.0),
         ImageMatToTensor(), ImageFeatureToTensor()])
```

nnframes

Native DL support in Spark DataFrames and ML Pipelines

4. Define model using *Keras-style API*

```
from zoo.pipeline.api.keras.layers import *
from zoo.pipeline.api.keras.models import *
model = Sequential()
          .add(Convolution2D(32, 3, 3, activation='relu', input_shape=(1, 28, 28))) \
          .add(MaxPooling2D(pool_size=(2, 2))) \
          .add(Flatten()).add(Dense(10, activation='softmax')))
```

5. Train model using *Spark ML Pipelines*

```
Estimater = NNEstimater(model, CrossEntropyCriterion(), transformer) \
                .setLearningRate(0.003).setBatchSize(40).setMaxEpoch(1) \
                .setFeaturesCol("image").setCachingSample(False)
nnModel = estimater.fit(df)
```

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Working with Image

1. **Read images into local or distributed *ImageSet***

```
from zoo.common.nncontext import *
from zoo.feature.image import *
spark = init_nncontext()
local_image_set = ImageSet.read(image_path)
distributed_image_set = ImageSet.read(image_path, spark, 2)
```

2. **Image augmentations using built-in *ImageProcessing* operations**

```
transformer = ChainedPreprocessing([ImageBytesToMat(),
                   ImageColorJitter(),
                   ImageExpand(max_expand_ratio=2.0),
                   ImageResize(300, 300, -1),
                   ImageHFlip()])
new_local_image_set = transformer(local_image_set)
new_distributed_image_set = transformer(distributed_image_set)
```

Image Augmentations Using Built-in Image Transformations (w/ OpenCV on Spark)

Working with Text

1. **Read text into local or distributed *TextSet***

```
from zoo.common.nncontext import *
from zoo.feature.text import *
spark = init_nncontext()
local_text_set = TextSet.read(text_path)
distributed_text_set = TextSet.read(text_path, spark, 2)
```

2. **Build text transformation pipeline using built-in operations**

```
transformedTextSet = textSet.tokenize()          \
                            .normalize()         \
                            .word2idx()          \
                            .shapeSequence(len)  \
                            .generateSample()    \
```

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POJO Model Serving API

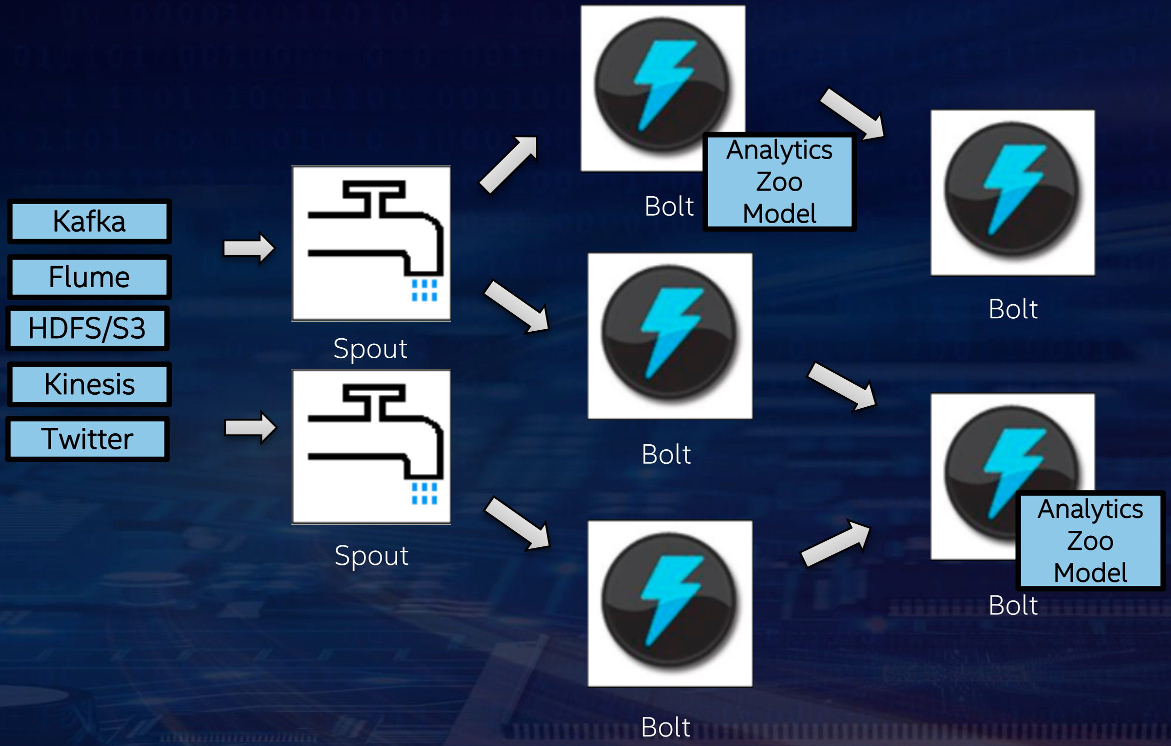
```
import com.intel.analytics.zoo.pipeline.inference.AbstractInferenceModel;

public class TextClassification extends AbstractInferenceModel {
  public RankerInferenceModel(int concurrentNum) {
    super(concurrentNum);
  }
  ...
}

public class ServingExample {
  public static void main(String[] args) throws IOException {
    TextClassification model = new TextClassification();
    model.load(modelPath, weightPath);

    texts = …
    List<JTensor> inputs = preprocess(texts);
    for (JTensor input : inputs) {
      List<Float> result = model.predict(input.getData(), input.getShape());
      ...
  }
}
```

OpenVINO Support for Model Serving

```
from zoo.common.nncontext import init_nncontext
from zoo.feature.image import ImageSet
from zoo.pipeline.inference import InferenceModel

sc = init_nncontext("OpenVINO Object Detection Inference Example")
images = ImageSet.read(options.img_path, sc,
                       resize_height=600, resize_width=600).get_image().collect()
input_data = np.concatenate([image.reshape((1, 1) + image.shape) for image in images], axis=0)

model = InferenceModel()
model.load_tf(options.model_path, backend="openvino", model_type=options.model_type)
predictions = model.predict(input_data)

# Print the detection result of the first image.
print(predictions[0])
```

Transparently support OpenVINO in model serving,
which deliver a significant boost for inference speed

Model Serving & Inference



Seamless integration in Web Services, Storm, Flink, Kafka, etc. (using POJO *local Java APIs*)

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Built-in Deep Learning Models

- *Object detection*
  - E.g., SSD, Faster-RCNN, etc.
- *Image classification*
  - E.g., VGG, Inception, ResNet, MobileNet, etc.
- *Text classification*
  - Text classifier (using CNN, LSTM, etc.)
- *Recommendation*
  - E.g., Neural Collaborative Filtering, Wide and Deep Learning, etc.
- *Anomaly detection*
  - Unsupervised time series anomaly detection using LSTM
- *Sequence-to-sequence*

Object Detection API

1. **Load pretrained model in *Detection Model Zoo***

```
from zoo.common.nncontext import *
from zoo.models.image.objectdetection import *
spark = init_nncontext()
model = ObjectDetector.load_model(model_path)
```

2. **Off-the-shell inference using the loaded model**

```
image_set = ImageSet.read(img_path, spark)
output = model.predict_image_set(image_set)
```

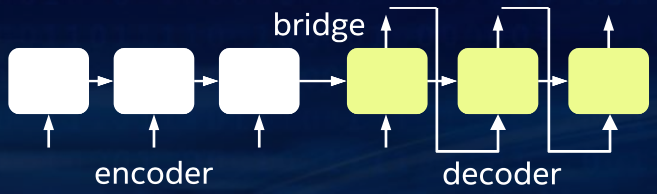
3. **Visualize the results using utility methods**

```
config = model.get_config()
visualizer = Visualizer(config.label_map(), encoding="jpg")
visualized = visualizer(output).get_image(to_chw=False).collect()
```

Off-the-shell Inference Using Analytics Zoo Object Detection API

https://github.com/intel-analytics/analytics-zoo/tree/master/pyzoo/zoo/examples/objectdetection

Sequence-to-Sequence API



Sequence to sequence model

```
encoder = RNNEncoder.initialize(rnn_type, nlayers, hidden_size, embedding)
encoder = RNNDecoder.initialize(rnn_type, nlayers, hidden_size, embedding)
seq2seq = Seq2seq(encoder, decoder)
```

Reference Use Cases

- *Anomaly Detection*
  - Using LSTM network to detect anomalies in time series data
- *Fraud Detection*
  - Using feed-forward neural network to detect frauds in credit card transaction data
- *Recommendation*
  - Use Analytics Zoo Recommendation API (i.e., Neural Collaborative Filtering, Wide and Deep Learning) for recommendations on data with explicit feedback.
- *Sentiment Analysis*
  - Sentiment analysis using neural network models (e.g. CNN, LSTM, GRU, Bi-LSTM)
- *Variational Autoencoder (VAE)*
  - Use VAE to generate faces and digital numbers
- *Web services*
  - Use Analytics Zoo model serving APIs for model inference in web servers

https://github.com/intel-analytics/analytics-zoo/tree/master/apps

Analytics Zoo Examples

Dogs vs. cats, object detections, Distributed TF

Dogs vs. Cats

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/dogs-vs-cats/transfer-learning.ipynb

Object Detection API

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/object-detection/object-detection.ipynb

Image Classification & Fine-Tuning Using TFNet

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/tfnet/image_classification_inference.ipynb

Distributed TensorFlow Training on Spark

https://github.com/intel-analytics/analytics-zoo/blob/master/pyzoo/zoo/examples/tensorflow/distributed_training/train_lenet.py

https://github.com/intel-analytics/analytics-zoo/blob/master/pyzoo/zoo/examples/tensorflow/distributed_training/train_mnist_keras.py

Break

Distributed Training In BigDL

Data parallel training

Parameter synchronization

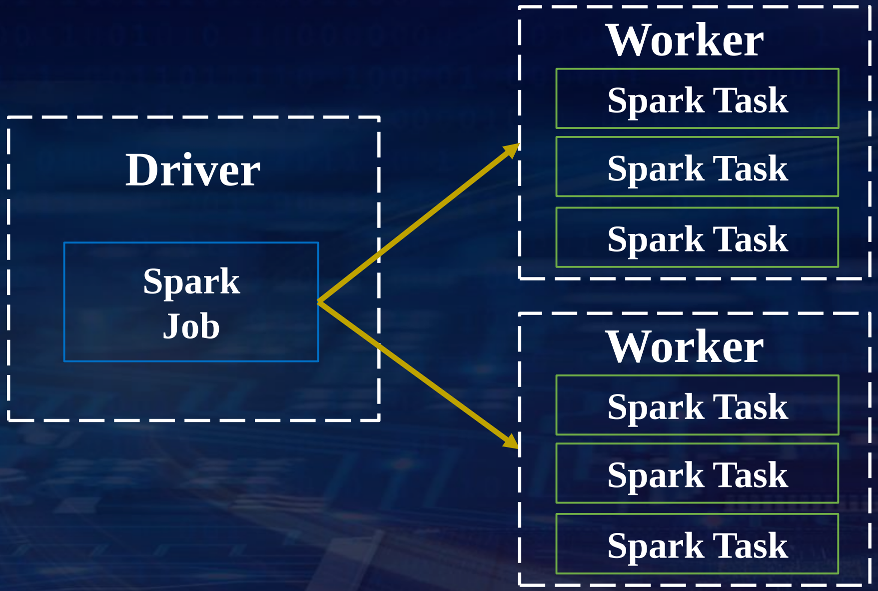
Scaling and Convergence

Task scheduling

"BigDL: A Distributed Deep Learning Framework for Big Data"

https://arxiv.org/abs/1804.05839

Apache Spark

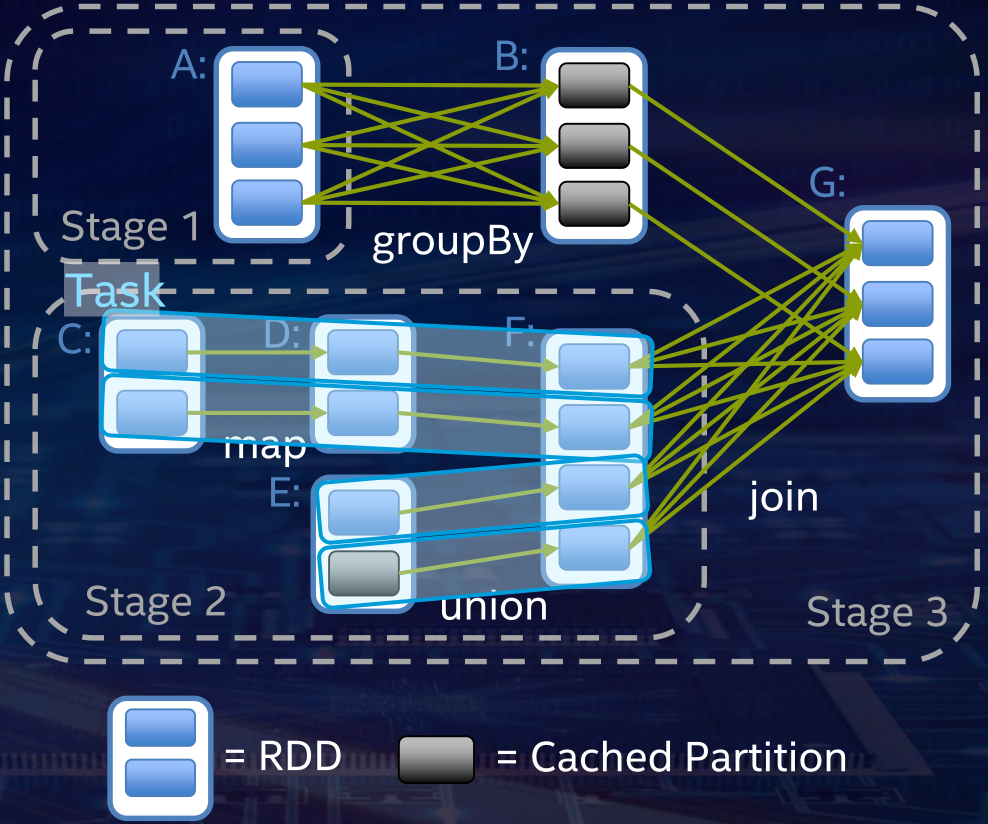


Single master (driver), multiple workers

Apache Spark

Spark compute model

- **Data parallel**
- **Functional, coarse-grained operators**
  - **Immutable RDDs**
  - **Applying the same operation (e.g., `map`, `filter`, etc.) to all data items**



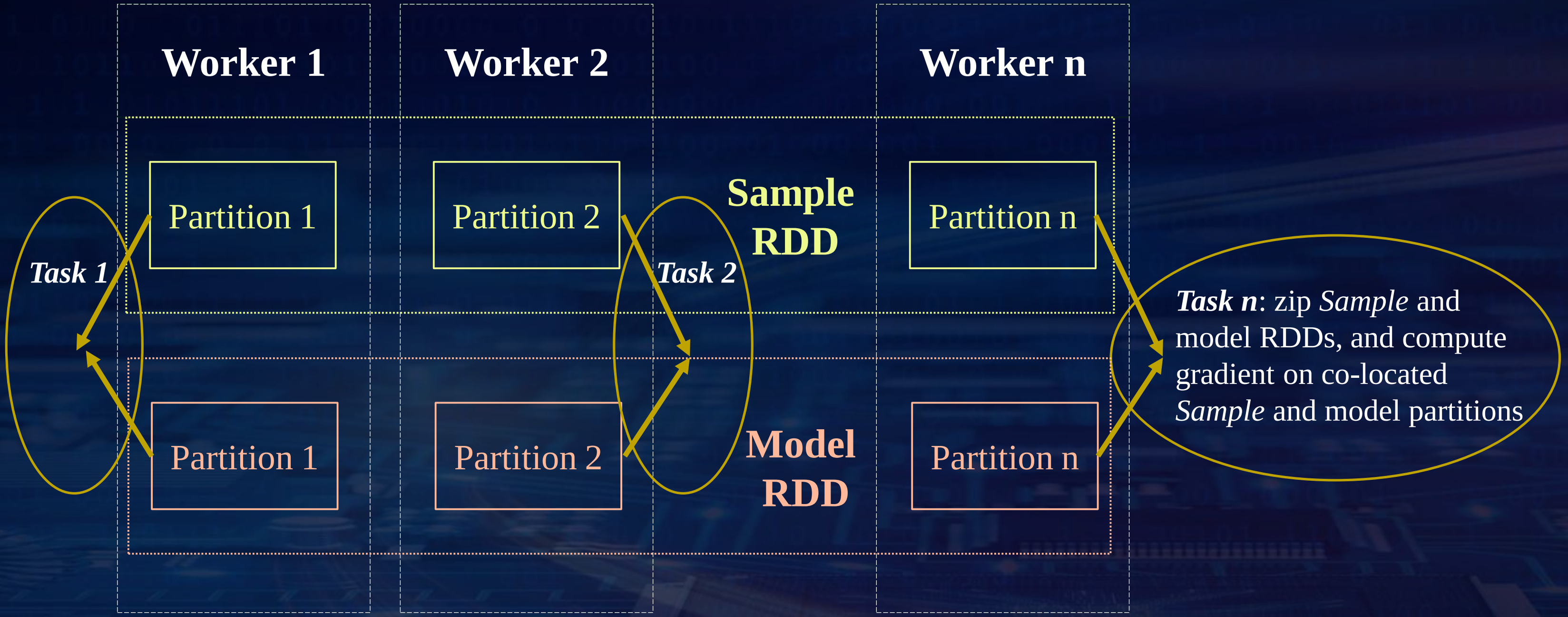
Source: "Parallel programming with Spark", Matei Zaharia, AMPCamp 3

Distributed Training in BigDL

Data Parallel, Synchronous Mini-Batch SGD

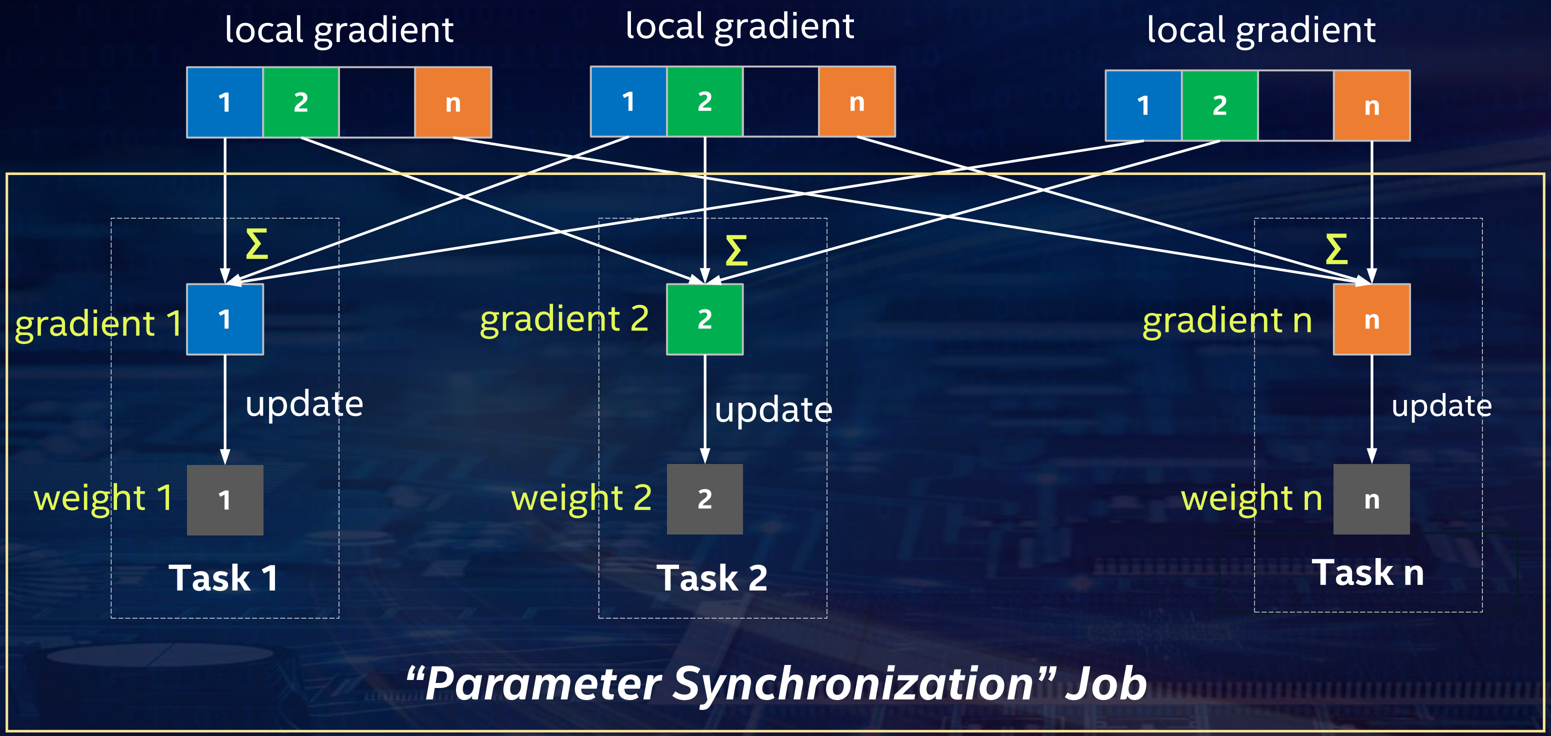
```
Prepare training data as an RDD of Samples
Construct an RDD of models (each being a replica of the original model)

for (i <- 1 to N) {
  //"model forward-backward" job
  for each task in the Spark job:
     read the latest weights
     get a random batch of data from local Sample partition
     compute errors (forward on local model replica)
     compute gradients (backward on local model replica)

  //"parameter synchronization" job
  aggregate (sum) all the gradients
  update the weights per specified optimization method
}
```

Data Parallel Training



"Model Forward-Backward" Job

Parameter Synchronization



Parameter Synchronization

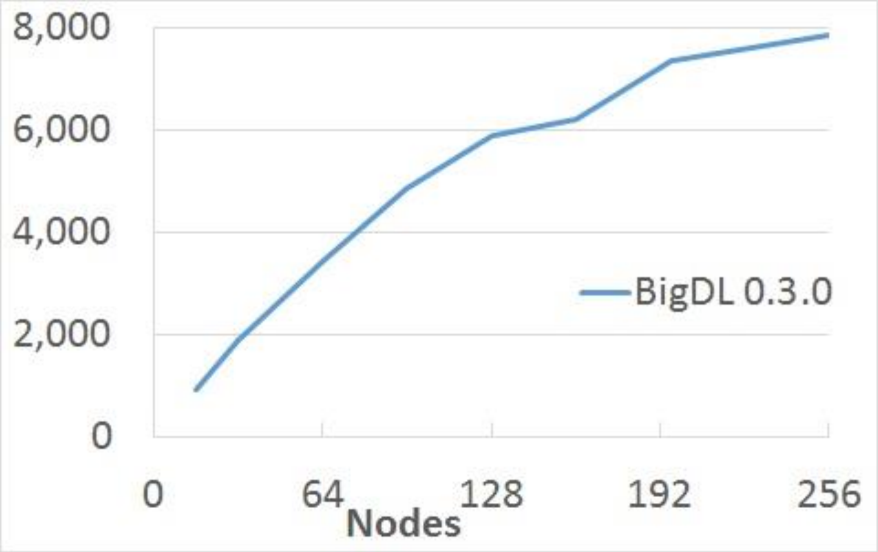
```
For each task n in the "parameter synchronization" job {
    shuffle the nth partition of all gradients to this task
    aggregate (sum) the gradients
    updates the nth partition of the weights
    broadcast the nth partition of the updated weights
}
```

"Parameter Synchronization" Job
(managing n^{th} partition of the parameters - similar to a parameter server)

"Parameter Server" style architecture (directly on top of primitives in Spark)

- Gradient aggregation: *shuffle*
- Weight sync: *task-side broadcast*
- *In-memory* persistence

Training Scalability



Throughput of ImageNet Inception v1 training (w/ BigDL 0.3.0 and dual-socket Intel Broadwell 2.1 GHz); the throughput scales almost linear up to 128 nodes (and continue to scale reasonably up to 256 nodes).

Source: Scalable Deep Learning with BigDL on the Urika-XC Software Suite (https://www.cray.com/blog/scalable-deep-learning-bigdl-urika-xc-software-suite/)

Increased Mini-Batch Size

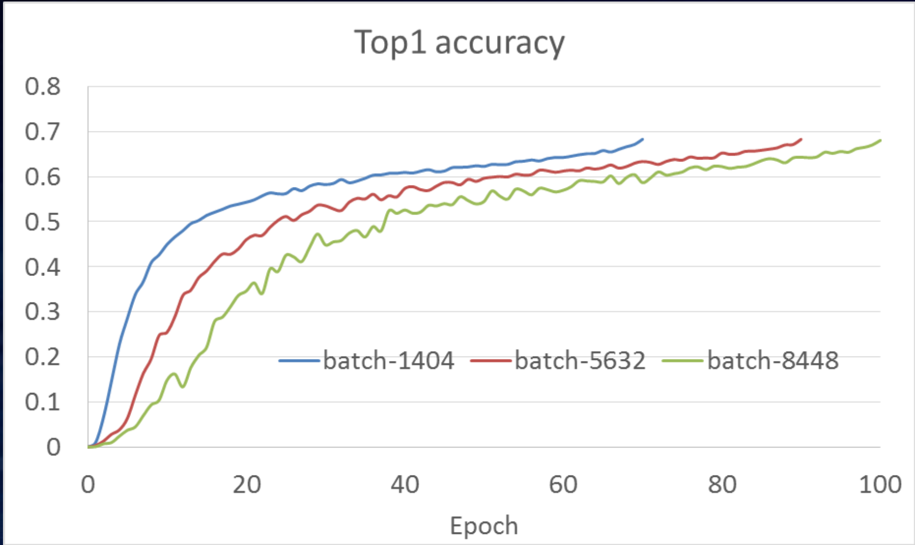
- Distributed synchronous mini-batch SGD
  - Increased mini-batch size

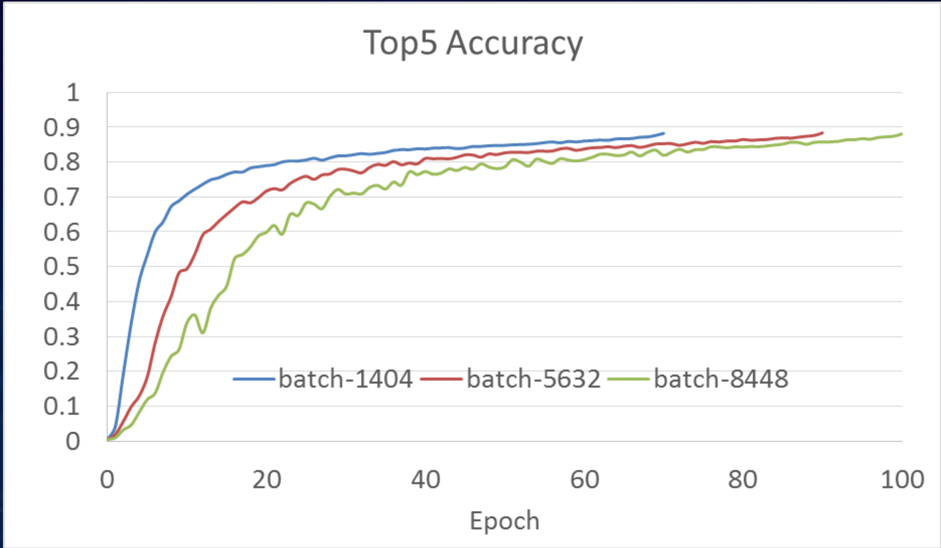
    *total_batch_size = batch_size_per_worker * num_of_workers*
  - Can lead to loss in test accuracy

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

*Source: “Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour”, Priya Goyal, et at. https://arxiv.org/abs/1706.02677
*Source: “ImageNet Training in Minutes”, Yang You, et at. https://arxiv.org/abs/1709.05011

Training Convergence: Inception v1



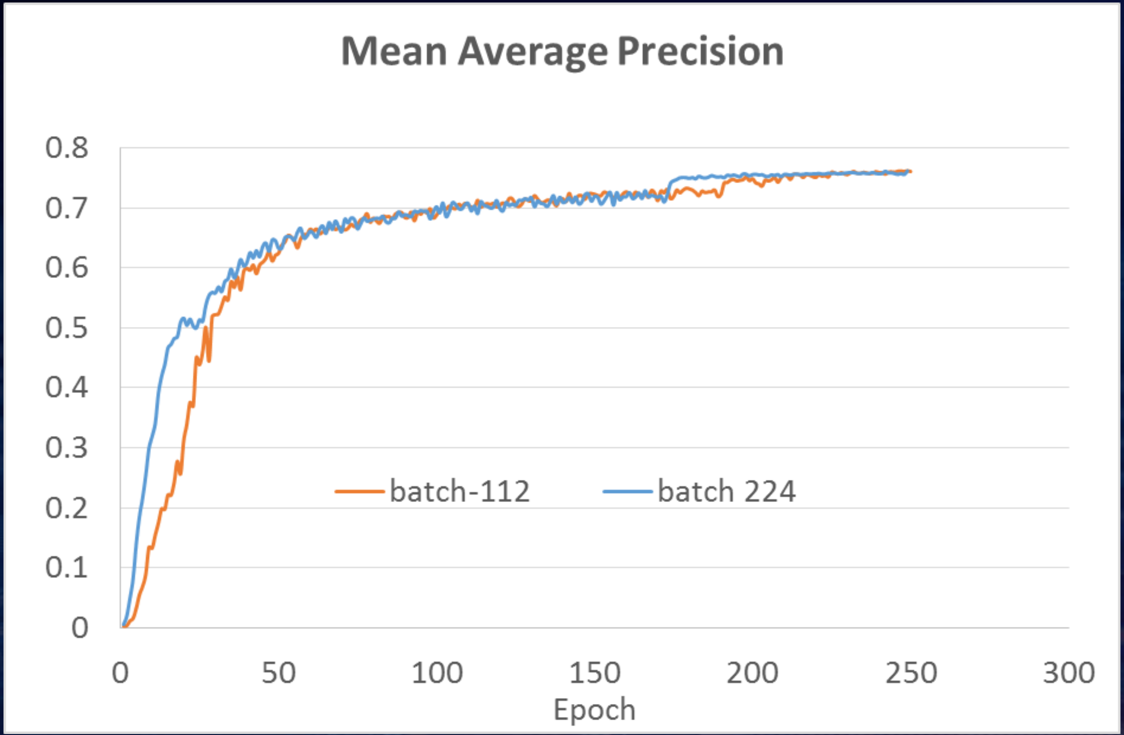


Strategies

- Warm-up
- Linear scaling
- Gradient clipping
- TODO: adding batch normalization

Source: Very large-scale distributed deep learning with BigDL, Jason Dai and Ding Ding. O'Reilly AI Conference 2017

Training Convergence: SSD



Strategies
- Warm-up
- Linear scaling
- Gradient clipping

Source: Very large-scale distributed deep learning with BigDL, Jason Dai and Ding Ding. O'Reilly AI Conference 2017

Difference vs. Classical PS Architecture

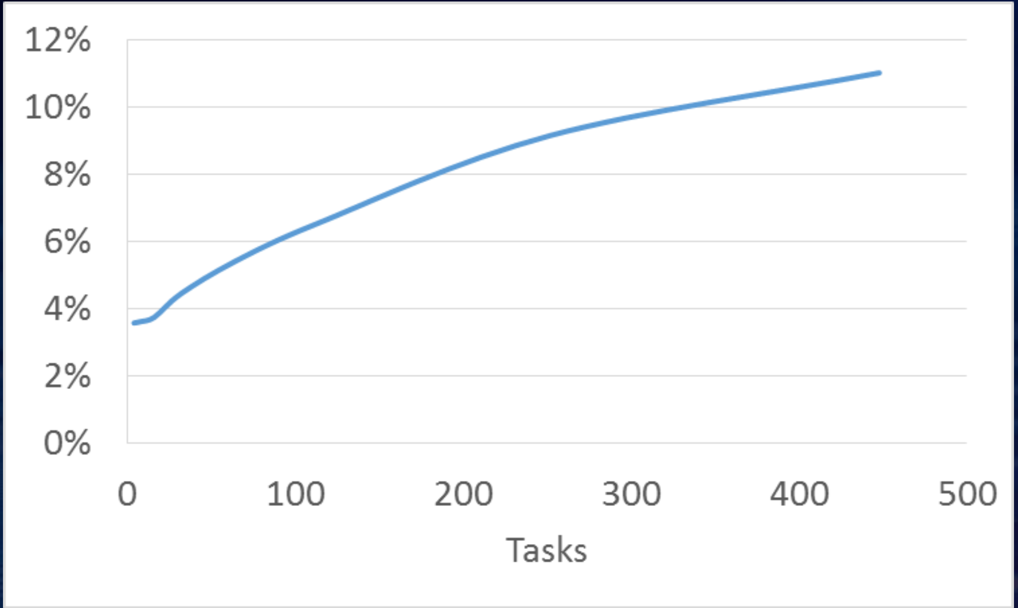
Classical PS architecture

- Multiple long-running, potentially stateful tasks
- Interact with each other (in a blocking fashion for synchronization)
- Require fine-grained data access and in-place data mutation
- Not directly supported by existing big data systems

BigDL implementations

- Run a series of short-lived Spark jobs (e.g., two jobs per mini-batch)
- Each task in the job is stateless and non-blocking
- Automatically adapt to the dynamic resource changes (e.g., *preemption*, *failures*, *resource sharing*, etc.)
- Built on top of existing primitives in Spark (e.g., *shuffle*, *broadcast*, and *in-memory data persistence*)

Task Scheduling Overheads



Spark overheads (task scheduling & task dispatch) as a fraction of average compute time for Inception v1 training

BigDL implementations

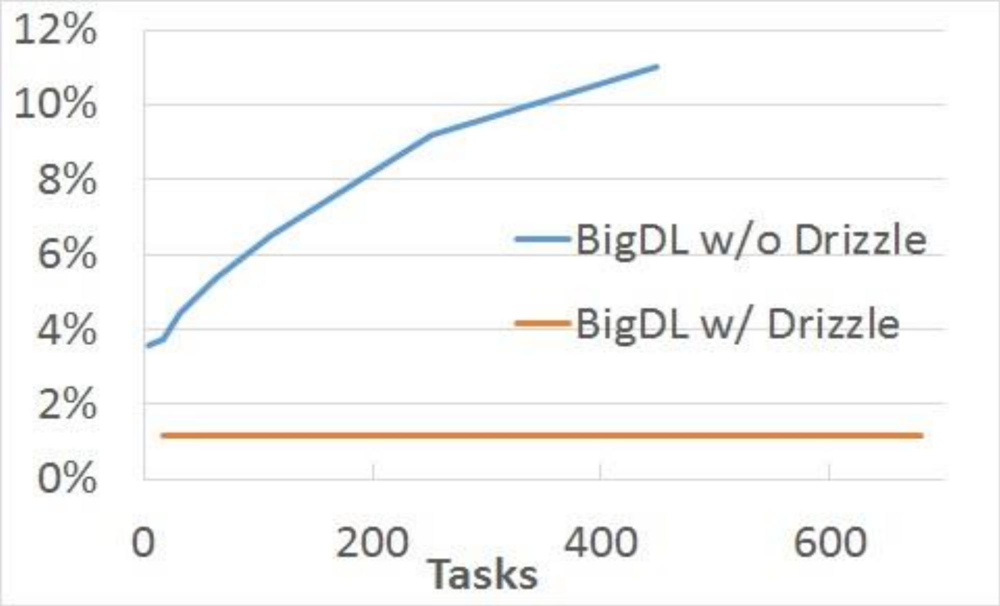
- Run a single, multi-threaded task on each worker
- Achieve high scalability on large clusters (e.g., up to 256 servers

Source: Accelerating Deep Learning Training with BigDL and Drizzle on Apache Spark, Shivaram Venkataraman, Ding Ding, and Sergey Ermolin. (https://rise.cs.berkeley.edu/blog/accelerating-deep-learning-training-with-bigdl-and-drizzle-on-apache-spark/)

Reducing Scheduling Overheads Using Drizzle

Scaling to even larger (>500) workers

- Iterative model training
  - Same operations run repeatedly
- Drizzle
  - A low latency execution engine for Spark
  - *Group scheduling* for multiple iterations of computations at once



Source: Accelerating Deep Learning Training with BigDL and Drizzle on Apache Spark, Shivaram Venkataraman, Ding Ding, and Sergey Ermolin. (https://rise.cs.berkeley.edu/blog/accelerating-deep-learning-training-with-bigdl-and-drizzle-on-apache-spark/)

Advanced Analytics Zoo Applications

Text classification, movie recommendations, Q&A ranker

Text Classification

https://github.com/intel-analytics/analytics-zoo/blob/master/pyzoo/zoo/examples/textclassification/text_classification.py

Movie Recommendations

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/recommendation/ncf-explicit-feedback.ipynb

Real-World Applications

Object detection and image feature extraction at JD.com

Produce defect detection using distributed TF on Spark in Midea

NLP based customer service chatbot for Microsoft Azure

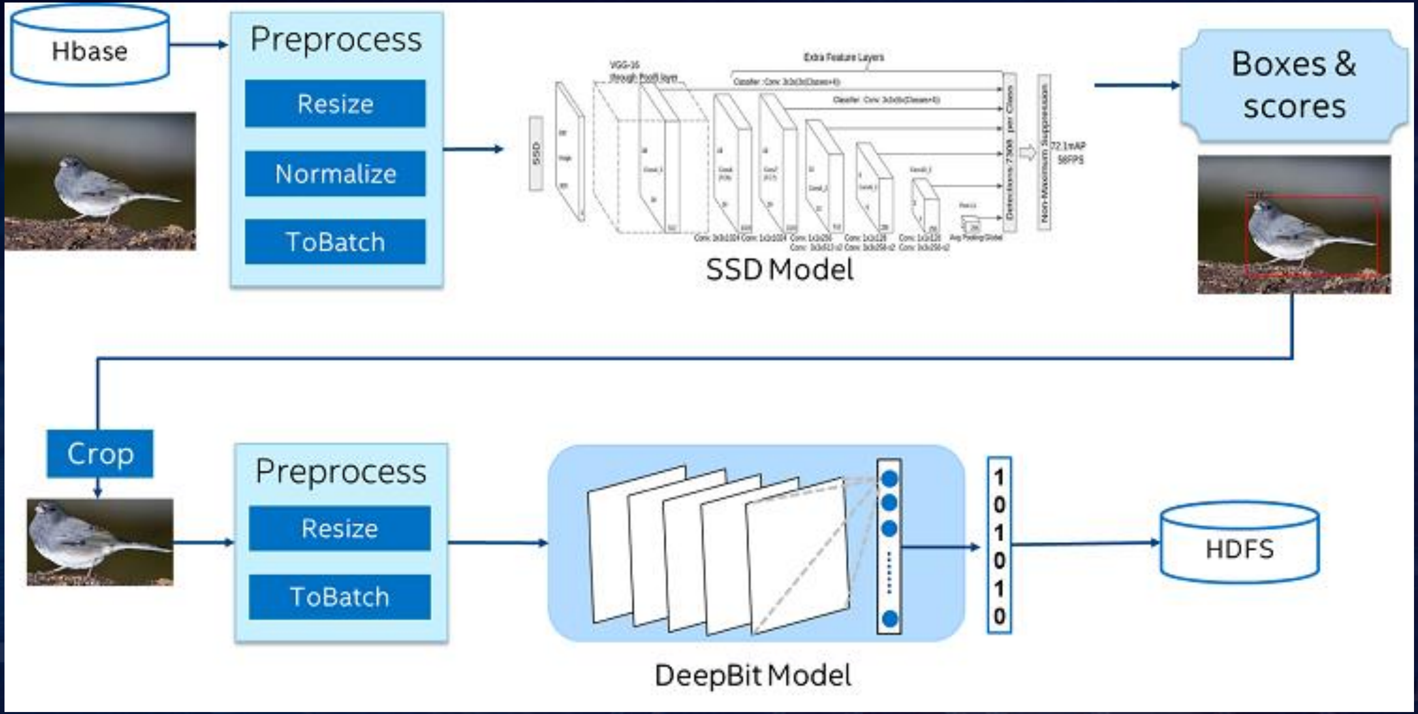
Image similarity based house recommendation for MLSlisting

Transfer learning based image classifications for World Bank

LSTM-Based time series anomaly detection for Baosight

Fraud detection for payment transactions for UnionPay

Object Detection and Image Feature Extraction at JD.com



Applications

Large-scale image feature extraction

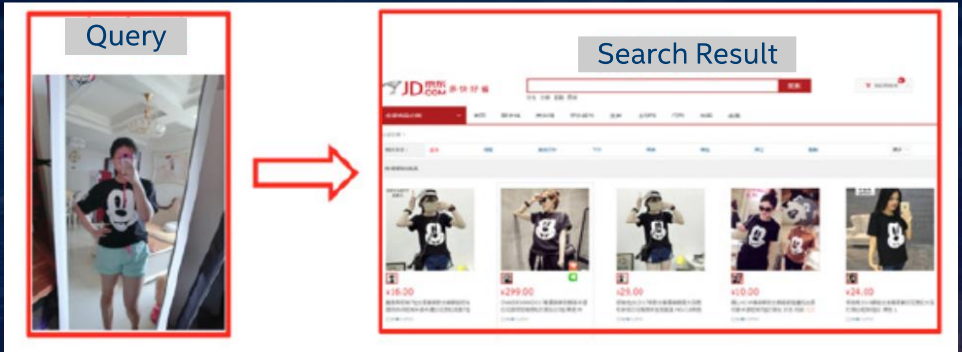
- Object detect (remove background, optional)
- Feature extraction

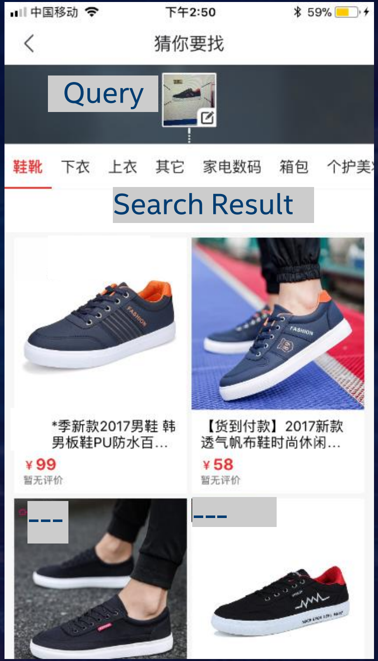
Application

- Similar image search
- Image Deduplication
    - Competitive price monitoring
    - IP (image copyright) protection system

Source: "Bringing deep learning into big data analytics using BigDL", Xianyan Jia and Zhenhua Wang, Strata Data Conference Singapore 2017

Similar Image Search





Source: “Bringing deep learning into big data analytics using BigDL”, Xianyan Jia and Zhenhua Wang, Strata Data Conference Singapore 2017

Challenges of Productionizing Large-Scale Deep Learning Solutions

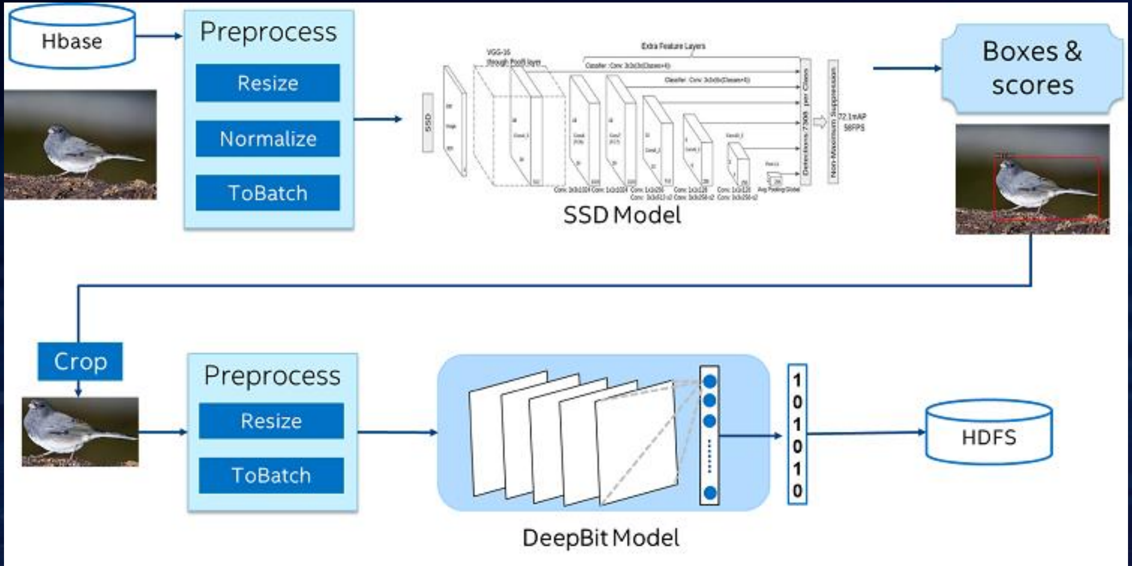
Productionizing large-scale seep learning solutions is challenging

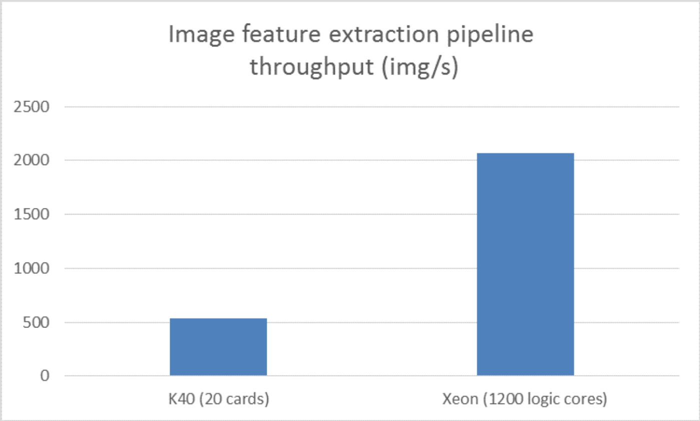
- Very complex and error-prone in managing large-scale distributed systems
  - E.g., resource management and allocation, data partitioning, task balance, fault tolerance, model deployment, etc.

- Low end-to-end performance in GPU solutions
  - E.g., reading images out from HBase takes about half of the total time

- Very inefficient to develop the end-to-end processing pipeline
  - E.g., image pre-processing on HBase can be very complex

Production Deployment with Analytics Zoo for Spark and BigDL





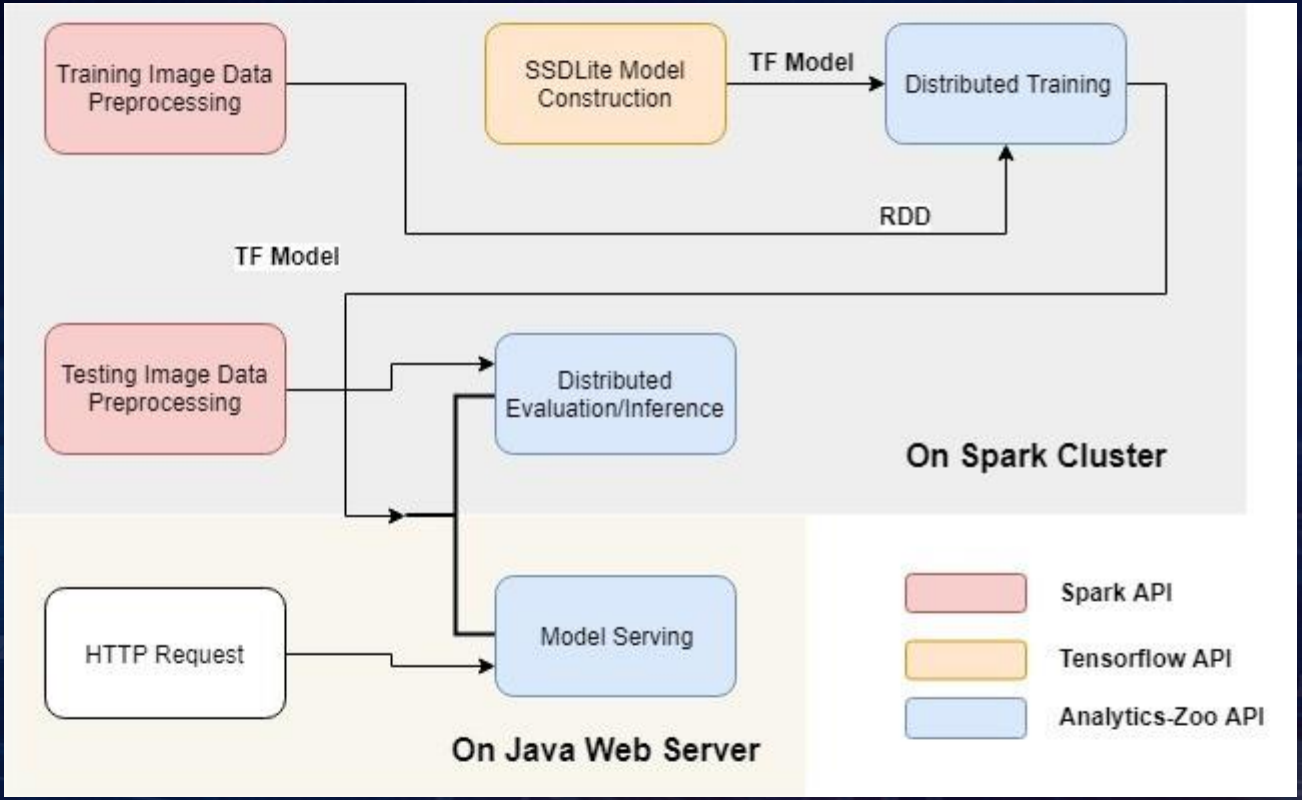
- Reuse existing Hadoop/Spark clusters for deep learning with no changes (image search, IP protection, etc.)
- Efficiently scale out on Spark with superior performance (***3.83x*** speed-up vs. GPU severs) as benchmarked by JD

  http://mp.weixin.qq.com/s/xUCkzbHK4K06-v5qUsaNQQ
  https://software.intel.com/en-us/articles/building-large-scale-image-feature-extraction-with-bigdl-at-jdcom

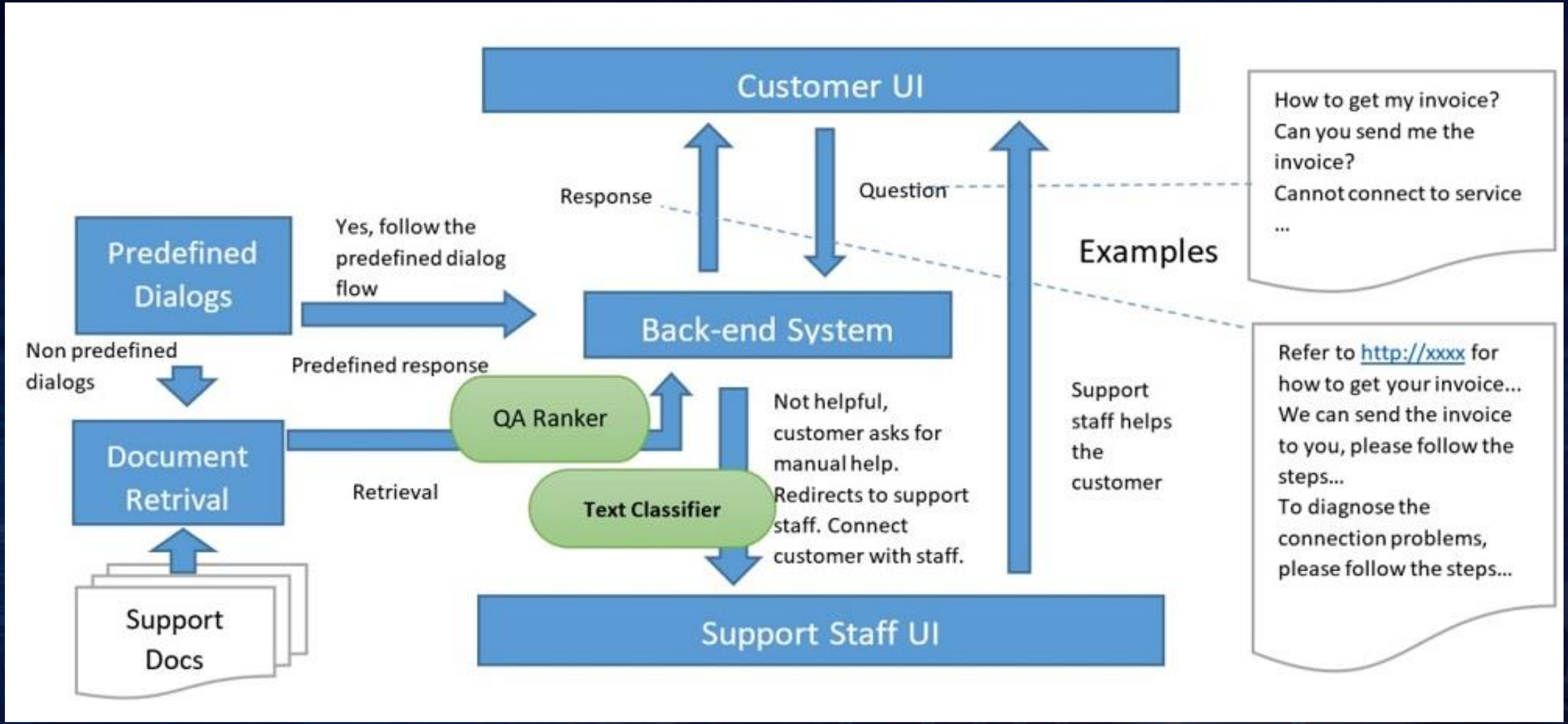
Produce Defect Detection using Distributed TF on Spark in Midea

https://software.intel.com/en-us/articles/industrial-inspection-platform-in-midea-and-kuka-using-distributed-tensorflow-on-analytics

Produce Defect Detection using Distributed TF on Spark in Midea

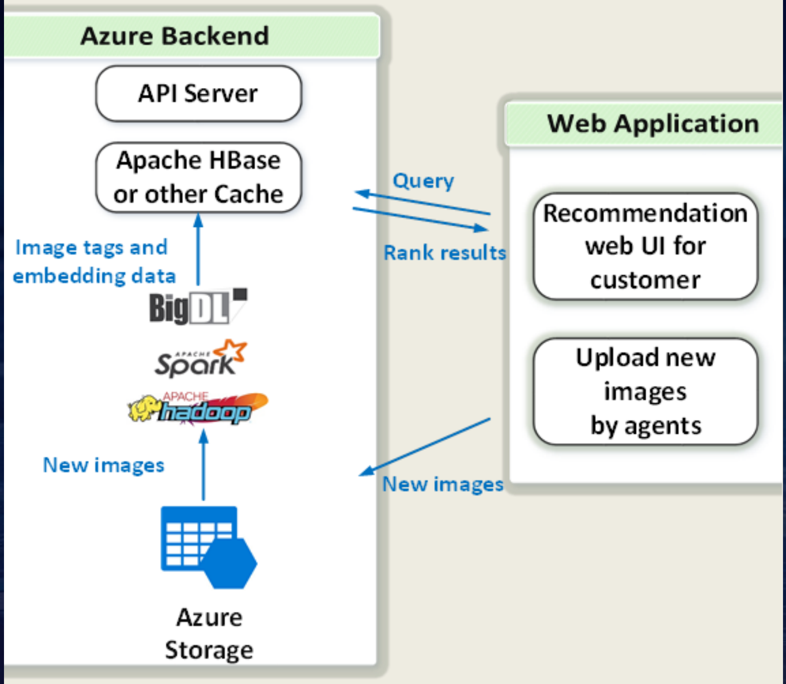


NLP Based Customer Service Chatbot for Microsoft Azure

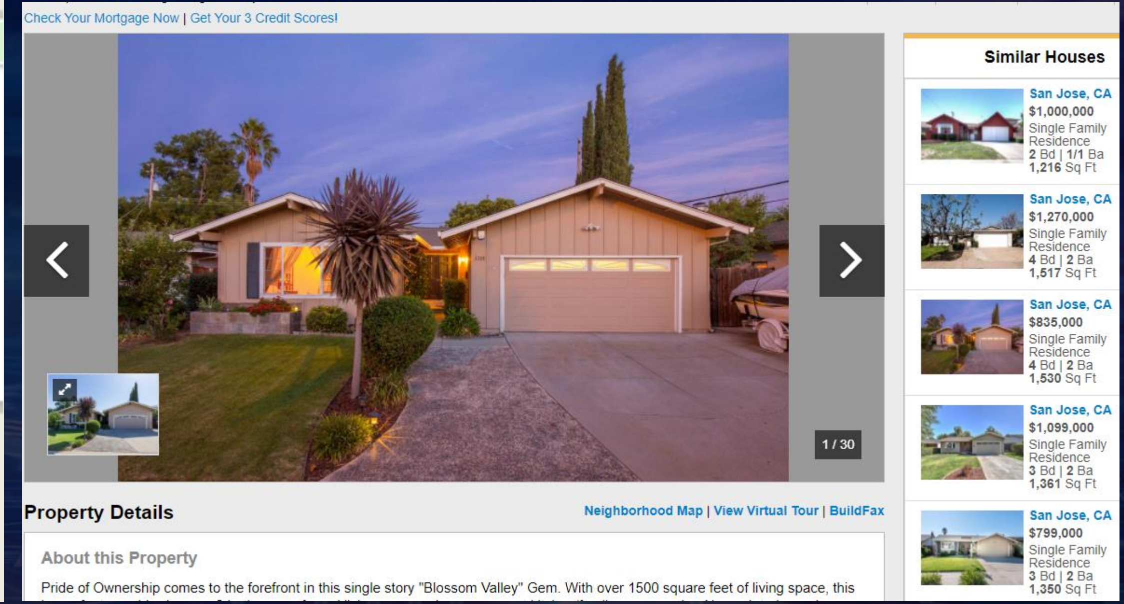


https://software.intel.com/en-us/articles/use-analytics-zoo-to-inject-ai-into-customer-service-platforms-on-microsoft-azure-part-1

Image Similarity Based House Recommendation for MLSlistings



MLSlistings built image-similarity based house recommendations using BigDL on Microsoft Azure



https://software.intel.com/en-us/articles/using-bigdl-to-build-image-similarity-based-house-recommendations

Image Similarity Based House Recommendation for MLSlistings

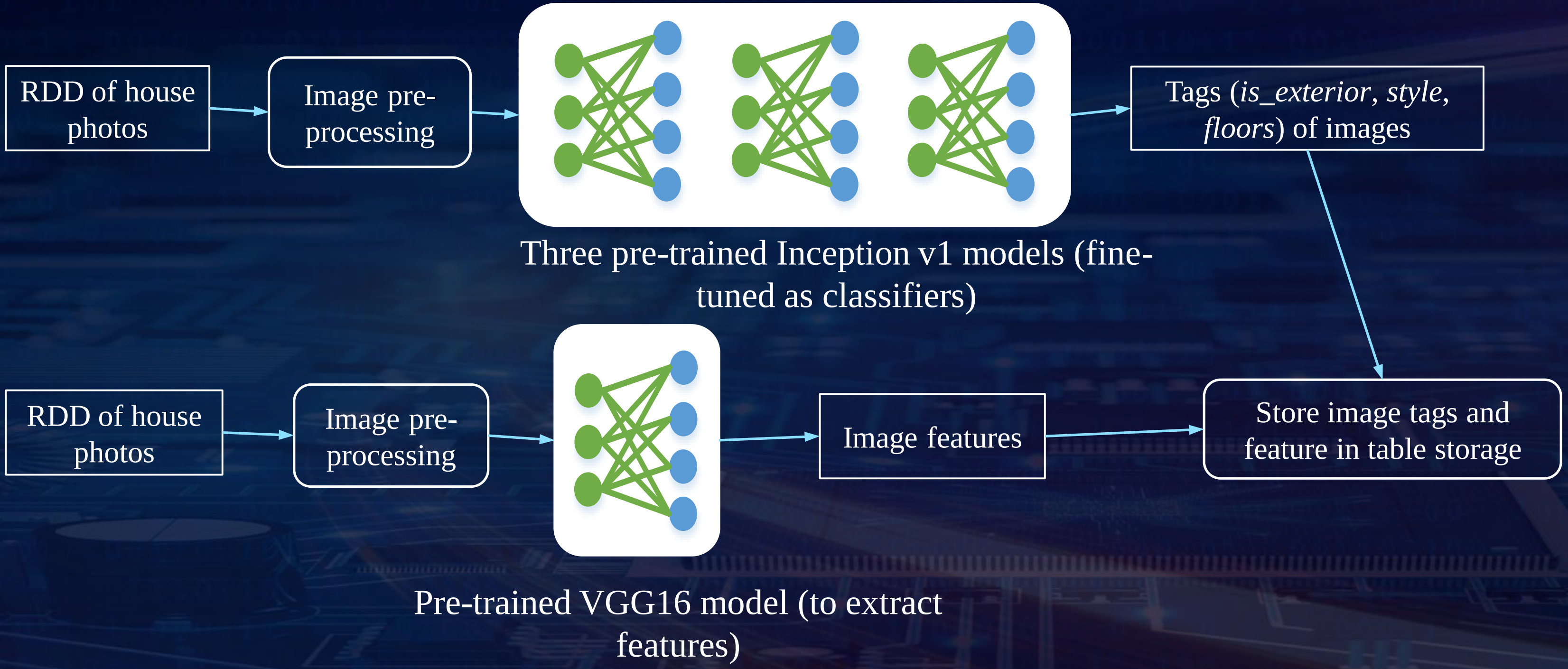


Image Similarity Based House Recommendation for MLSlistings

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/image-similarity/Image%20similarity.ipynb

Transfer Learning Based Image Classifications for World Bank

Classifying Real Food Images is not a Cat vs. Dog Problem

Source: Using Crowdsourced Images to Create Image Recognition Models with Analytics Zoo using BigDL, Maurice Nsabimana and Jiao Wang, Spark Summit 2018

Project Layout

Phase 1:

- Image preprocessing (eliminate poor quality images and invalid images)
- Classify images (by food type) to validate existing labels

Phase 2:

- Identify texts in the image and make bounding box around them
- Text recognition (words/sentences in the image text)
- Determine whether text contains PII (personal identifiable information)
- Blur areas with PII text

Source: Using Crowdsourced Images to Create Image Recognition Models with Analytics Zoo using BigDL, Maurice Nsabimana and Jiao Wang, Spark Summit 2018

Code – Phase 1

Fine-tuning Training

Cmd 32

```
# get model
pretrained_model_path = path.join(MODEL_ROOT,"bigdl_inception_v1_imagenet_0_4_0.model")
n_classes = len(label_dict)# label categories
full_model = Net.load_bigdl("dbfs:" + pretrained_model_path)
# create a new model by remove layers after pool5/drop_7x7_s1
model = full_model.new_graph(["pool5/drop_7x7_s1"])

inputNode = Input(name="input", shape=(3, 224, 224))
inception = model.to_keras()(inputNode)
flatten = Flatten()(inception)
logits = Dense(n_classes)(flatten)

lrModel = Model(inputNode, logits)
```

```
creating: createZooKerasInput
creating: createZooKerasFlatten
creating: createZooKerasDense
creating: createZooKerasModel
```

Command took 4.74 seconds -- by Jiao.Wang@intel.com at 6/2/2018, 8:03:46 PM on 20-node-cluster

Cmd 33

```
# train model
classifier = NNClassifier(lrModel, CrossEntropyCriterion(), train_transformer) \
        .setLearningRate(learning_rate)\
        .setBatchSize(batch_size)\
        .setMaxEpoch(no_epochs)\
        .setFeaturesCol("image")\
        .setValidation(EveryEpoch(), val_image, [Top1Accuracy()], batch_size)
start = time.time()
trained_model = classifier.fit(train_image)
end = time.time()
print("Optimization Done.")
print("Training time is: %s seconds" % str(end-start))
# + dt.datetime.now().strftime("%Y%m%d-%H%M%S")
```

Prediction and Evaluation

```
#predict
predict_model = trained_model.setBatchSize(batch_size)
predictionDF = predict_model.transform(test_image)
predictionDF.cache()
```

```
'''
Measure Test Accuracy w/Test Set
'''
evaluator = MulticlassClassificationEvaluator(labelCol="label",
                                              predictionCol="prediction",
                                              metricName="accuracy")
accuracy = evaluator.evaluate(predictionDF)
# expected error should be less than 10%
print("Accuracy = %g " % accuracy)
predictionDF.unpersist()
```

Source: Using Crowdsourced Images to Create Image Recognition Models with Analytics Zoo using BigDL, Maurice Nsabimana and Jiao Wang, Spark Summit 2018

Result – Phase 1

- Fine tune with Inception v1 on a full dataset
- Dataset: 994325 images, 69 categories

Nodes	Cores	Batch Size	Epochs	Training Time (sec)	Throughput (images/sec)	Accuracy (%)
20	30	1200	12	61125	170	81.7

* This model training was performed using multinode cluster on AWS R4.8xlarge instance with 20 nodes

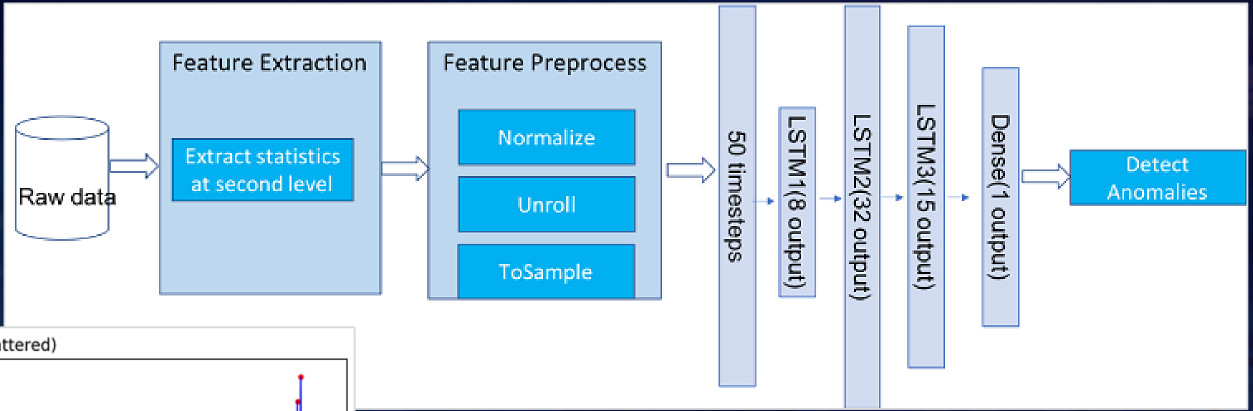
Source: Using Crowdsourced Images to Create Image Recognition Models with Analytics Zoo using BigDL, Maurice Nsabimana and Jiao Wang, Spark Summit 2018

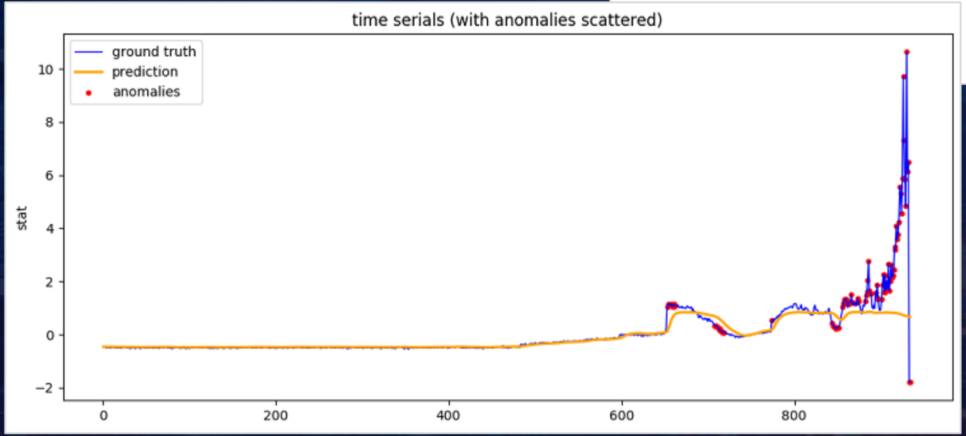
Next Steps – Phase 2

- Image Quality Preprocessing
  - Filter with print text only
  - Rescaling, Binarisation, Noise Removal, Rotation / Deskewing (OpenCV, Python, etc.)
- Detect text and bounding box circle text
- Recognize text
- Determine whether text contains PII (personal identifiable information)
  - Recognize PII with leading words
- Blur areas with PII text
  - Image tools

Source: Using Crowdsourced Images to Create Image Recognition Models with Analytics Zoo using BigDL, Maurice Nsabimana and Jiao Wang, Spark Summit 2018

LSTM-Based Time Series Anomaly Detection for Baosight





https://software.intel.com/en-us/articles/lstm-based-time-series-anomaly-detection-using-analytics-zoo-for-apache-spark-and-bigdl

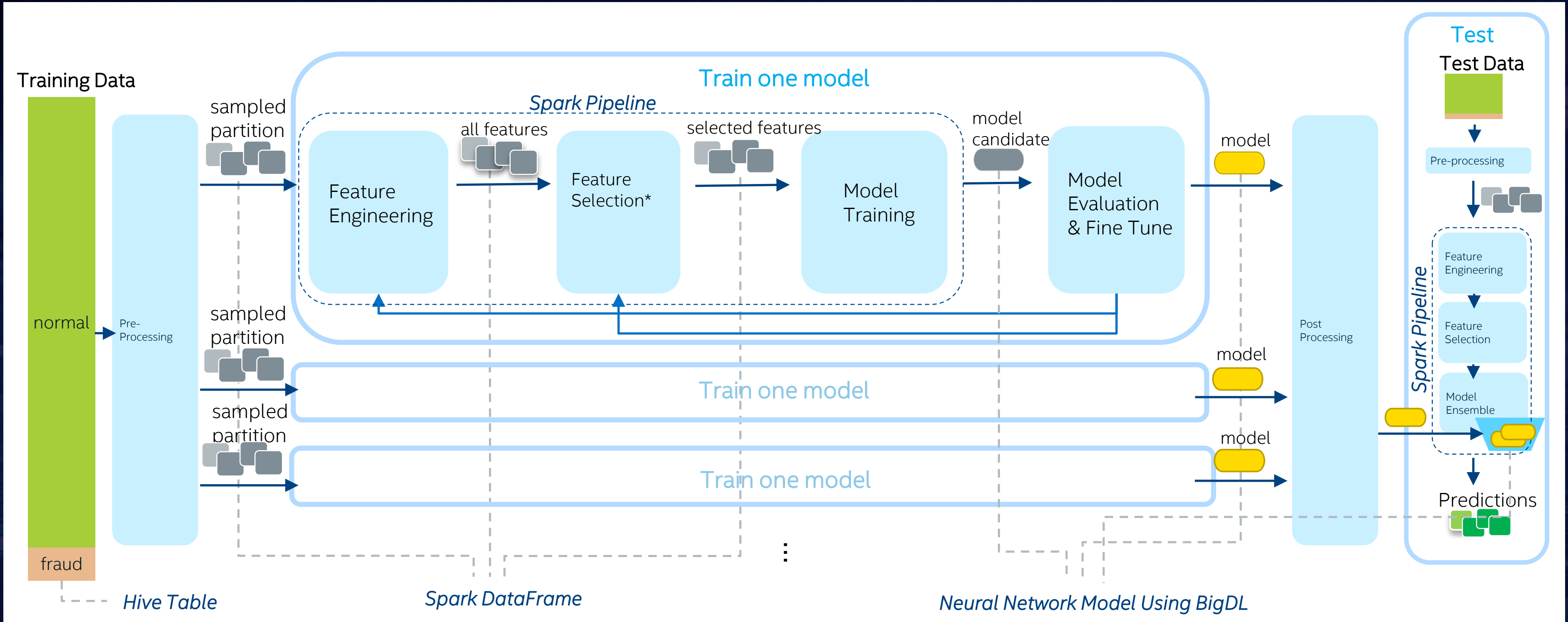
AAAI 2019

LSTM-Based Time Series Anomaly Detection for Baosight

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/anomaly-detection/anomaly-detection-nyc-taxi.ipynb

Fraud Detection for Payment Transactions for UnionPay



https://mp.weixin.qq.com/s?__biz=MzI3NDAwNDUwNg==&mid=2648307335&idx=1&sn=8eb9f63eaf2e40e24a90601b9cc03d1f

AAAI 2019

Fraud Detection for Payment Transactions for UnionPay

Notebook:

https://github.com/intel-analytics/analytics-zoo/blob/master/apps/fraud-detection/fraud-detection.ipynb

ANALYTICS ZOO

Unified Analytics + AI Platform

Distributed TensorFlow, Keras and BigDL on Apache Spark

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

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