ANAYLTICS-ZOO TUTORIAL

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Data Analytics Technologies, Software and Service Group, Intel

About me

Software Architect at Intel. Contributor of Spark, BigDL and Analytics-zoo

Focusing area

- Large scale machine learning, deep learning implementation and optimization
- Machine learning / deep learning applications on big data

Agenda

Analytics-zoo basics

- Keras support
- Hands-on practice

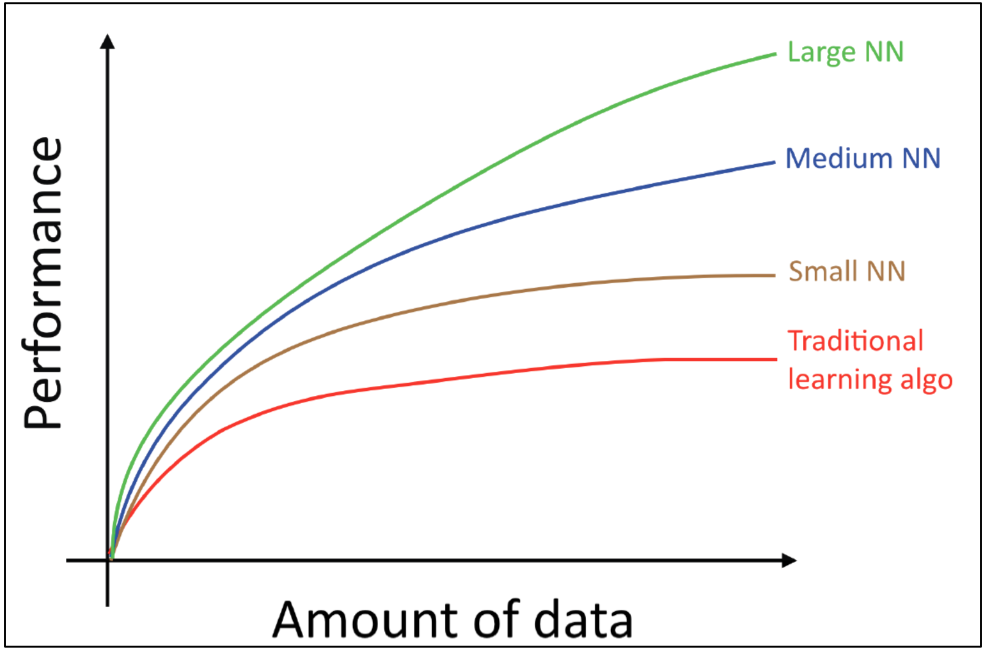
Hands-on practice

- Customer case
- Pre-trained ResNet
- Anomaly detection
- Recommendation (NCF wide and deep)
- VAE

ANALYTICS-ZOO INTRODUCTION

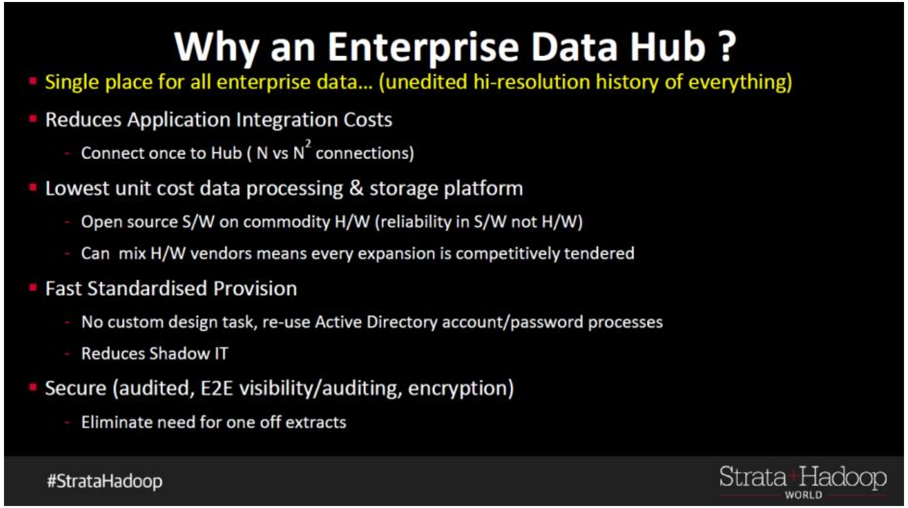
Motivations

Trend #1: Data Scale Driving Deep Learning Process

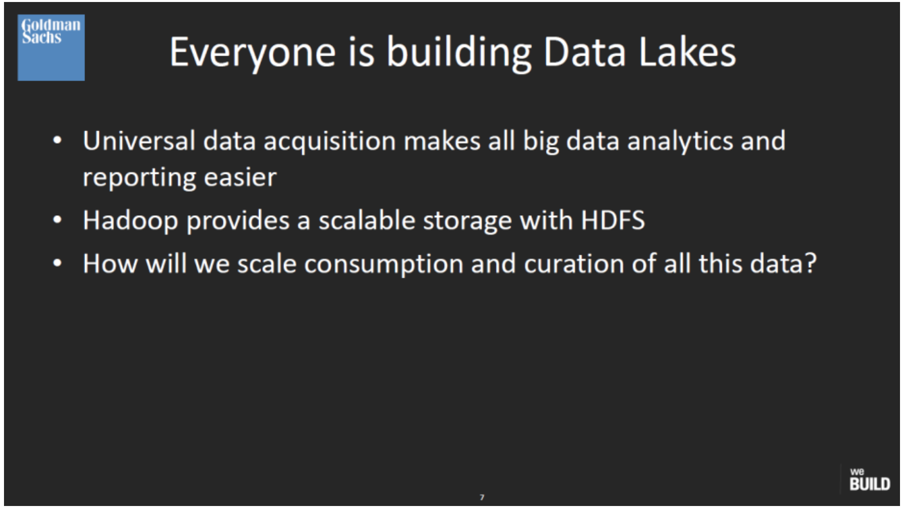


"Machine Learning Yearning", Andrew Ng, 2016

Trend #2: Hadoop Becoming the Center of Data Gravity



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



Matthew Glickman, Goldman Sachs
Spark Summit East 2015

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

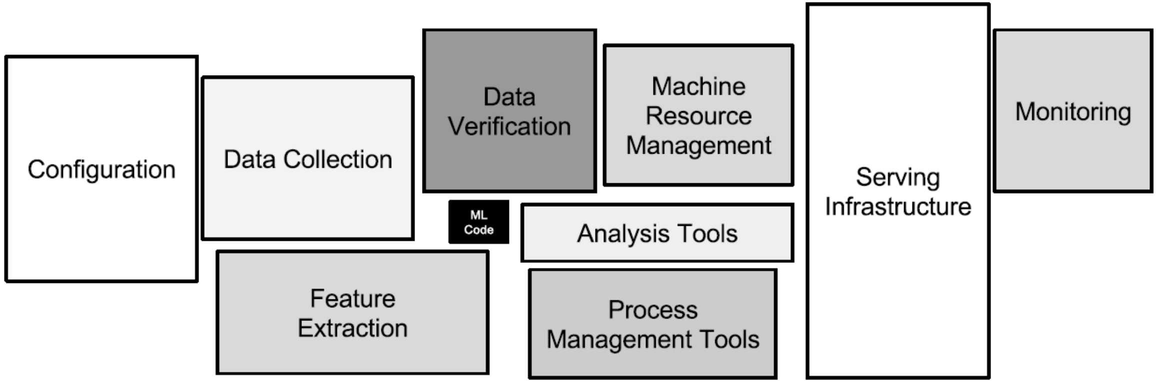
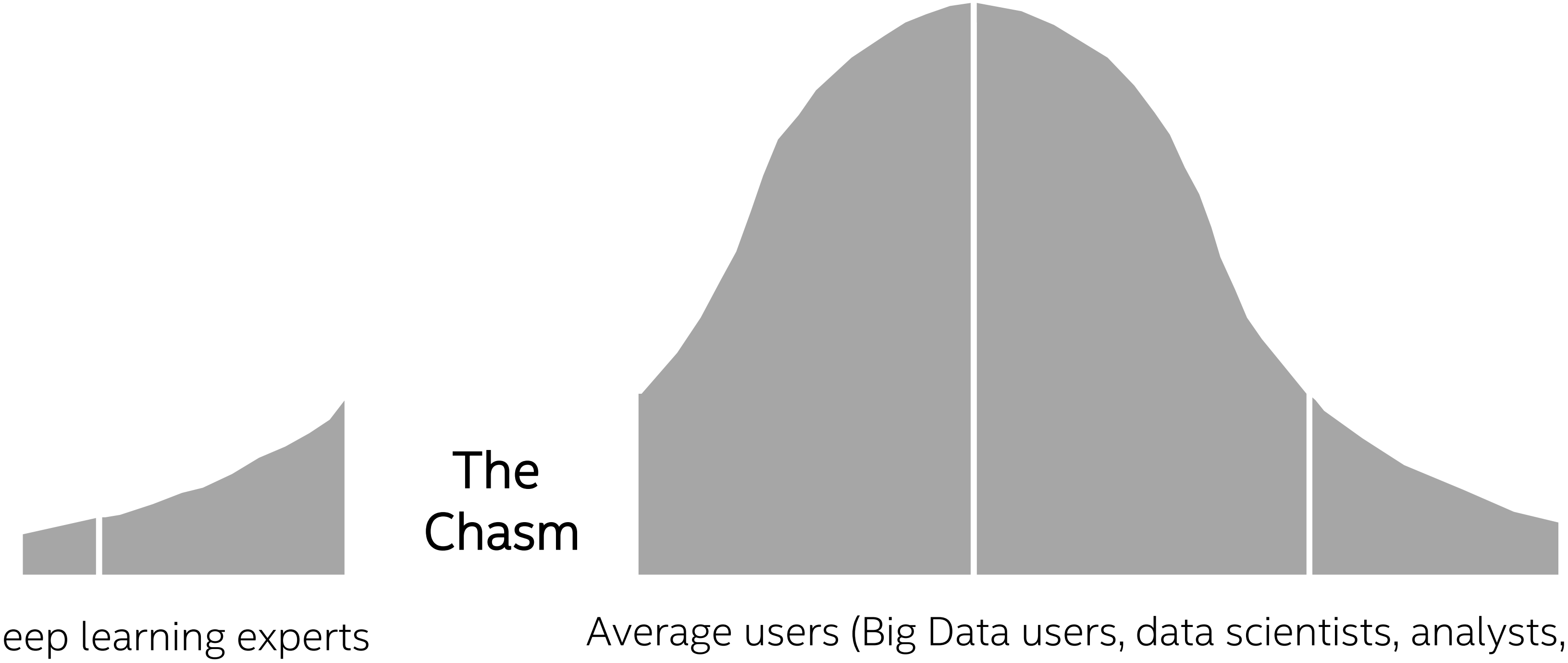


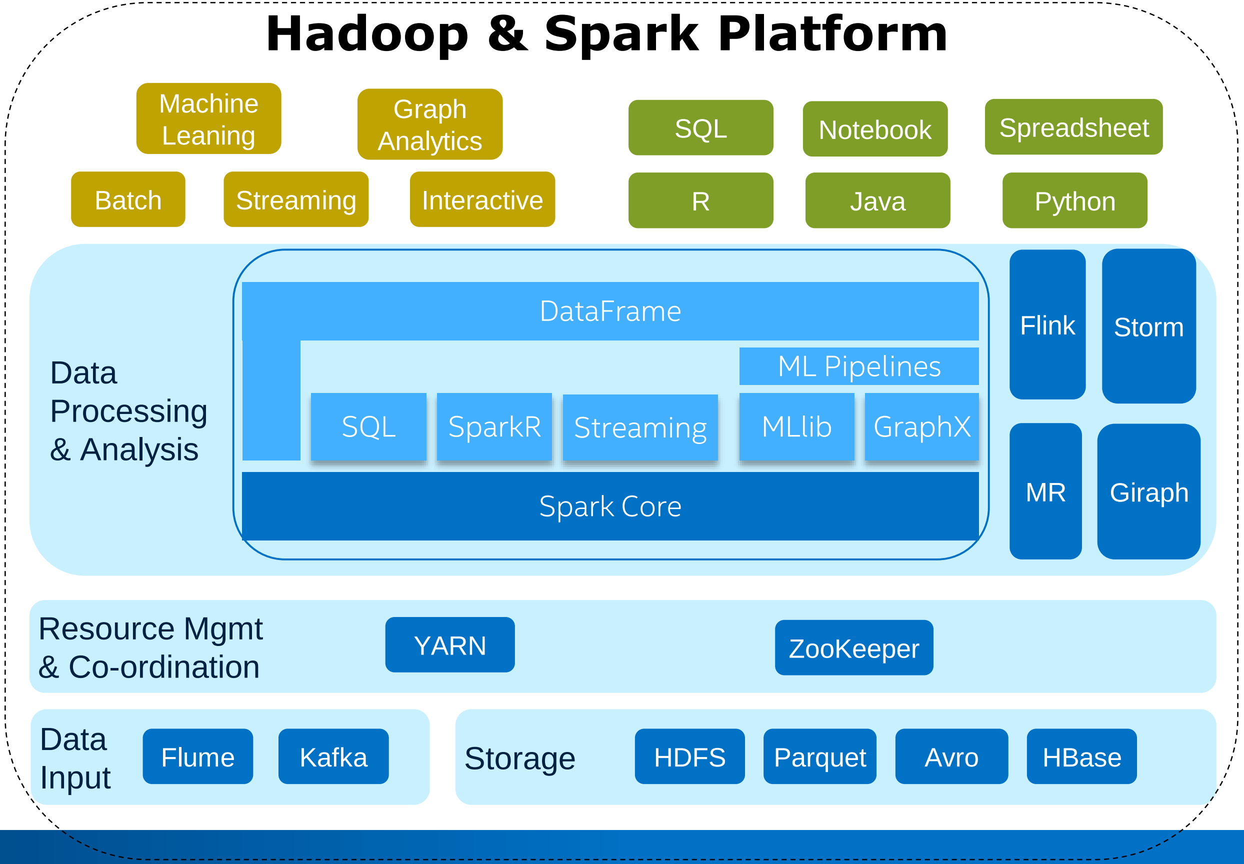
Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

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

Chasm b/w Deep Learning and Big Data Communities



Unified Big Data Analytics Platform

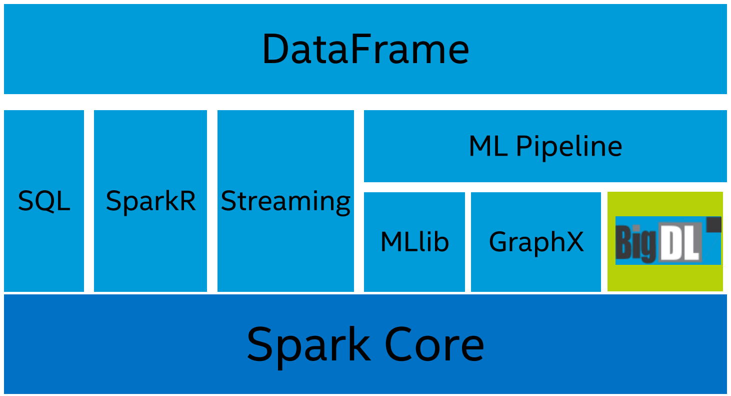


Overview

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/

Model Zoo

Image Classification

- Inception
- Resnet
- VGG
- MobileNet
- Alexnet
- DenseNet
- SqueezeNet

Object Detection

- SSD (Single Shot Multibox Detector)
    - VGG
    - MobileNet
- Faster-RCNN
    - VGG
    - PvaNet

Analytics Zoo

Analytics + AI Pipelines for Spark and BigDL

“Out-of-the-box” ready for use

- **Reference use cases**
  - Fraud detection, anomaly detection, chatbot, sequence prediction, sentiment analysis, etc.
- **Predefined models**
  - Object detection, image classification, text classification, recommendations, GAN, etc.
- **Feature engineering & transformations**
  - Image, text, speech, 3D imaging, time-series, etc.
- **High level pipeline APIs**
  - Dataframes, ML Pipelines, Keras/Keras2, autograd, etc.

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

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 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

Analytics-zoo run as Standard Spark Programs

Standard Spark jobs

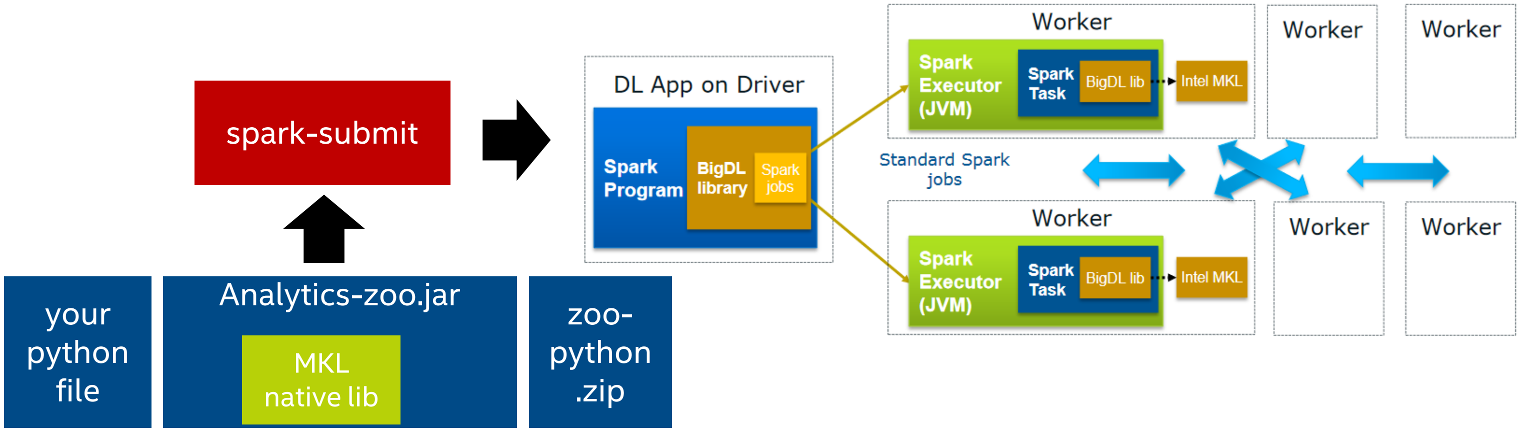
- No changes to the Spark or Hadoop clusters needed

Iterative

- Each iteration of the training runs as a Spark job

Data parallel

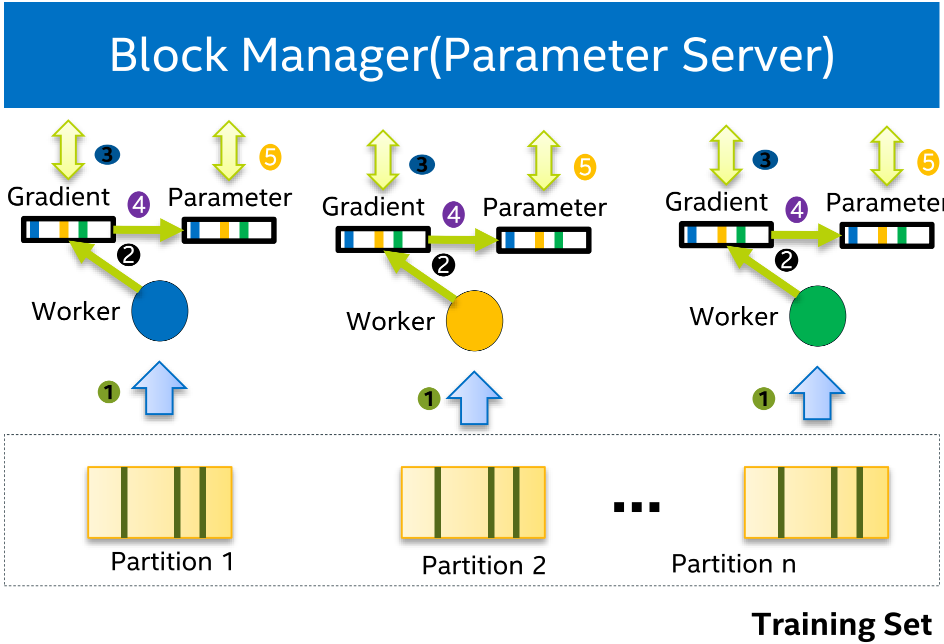
- Each Spark task runs the same model on a subset of the data (batch)



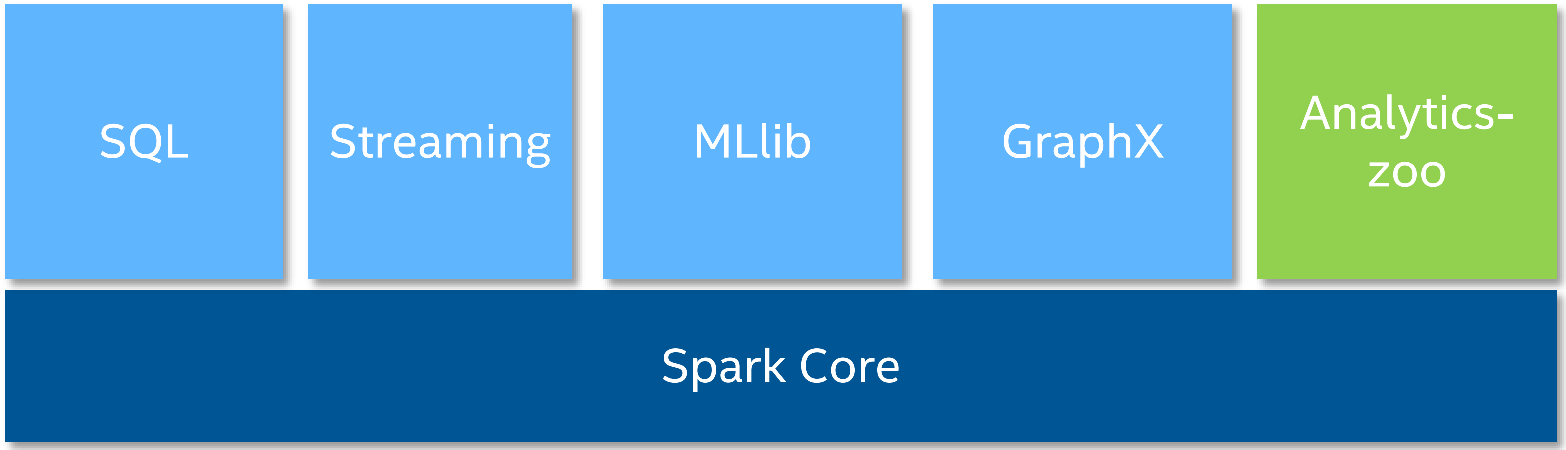
Parameter Synchronization in Analytics-zoo

Highlight

- Implement an P2P All Reduce Algorithm on Apache Spark
- Spark block manager as parameter server (handle different APIs of Spark 1.x/2.x)
- Compress float32 parameter to float16 parameter



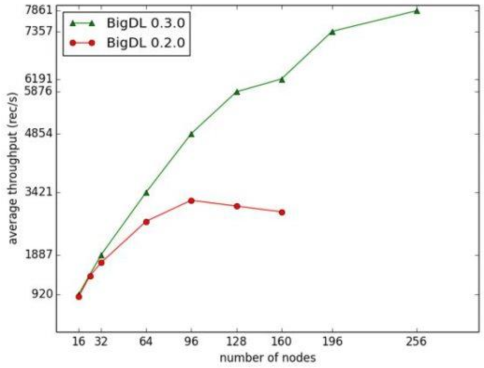
Apache Spark and Analytics-zoo



Rich deep learning features

- Tensor, Layers
  - More than 100 (Linear, Conv2D, Conv3D, Embedding, Recurrent…)
- Loss function
  - Dozens of loss functions(Cross Entropy, SmoothL1, DiceCoffient…)
- Optimization algorithm
  - SGD, Adagrad, Adam…
- Save and Load model files
  - Include torch / caffe / tensorflow

High performance from your server



- Powered by Intel Math Kernel Library
- Extremely high performance on Xeon CPUs
  - Order of magnitude faster than out of box caffe / torch / tensorflow
- Good scalability
  - Hundreds of nodes
  - https://www.cray.com/blog/scalable-deep-learning-bigdl-urika-xc-software-suite/

Models Interoperability Support
(e.g., between TensorFlow, Keras, Caffe, Torch, BigDL models)

- Load existing TensorFlow, Keras, Caffe, Torch Model
  - Useful for inference and model fine-tuning
  - Allows for transition from single-node for distributed application deployment
  - Allows for model sharing between data scientists and production engineers

Use Cases

HANDS-ON PRACTICES

SPARK BASIC

The Big Data Problem

- One machine can not process or even store all the data !
- Solution is to distribute data over cluster of machine

Big Data

Word	Index	Count
I	0	1
am	2	1
Sam	5	1
I	9	1
am	11	1
Sam	14	1

I	0	1
am	2	1

Partition 1

Sam	5	1
I	9	1

Partition 2

am	11	1
Sam	14	1

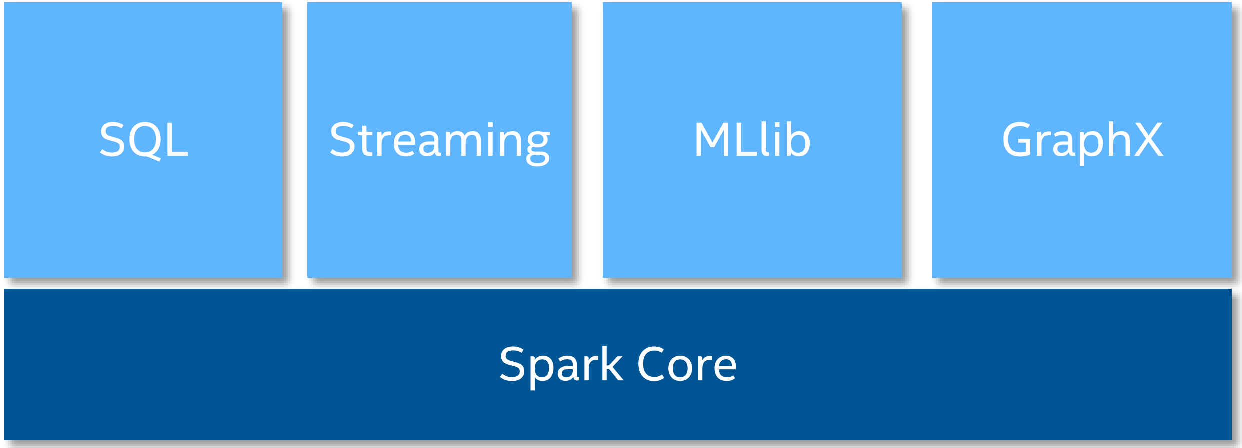
Partition 3

Apache Spark

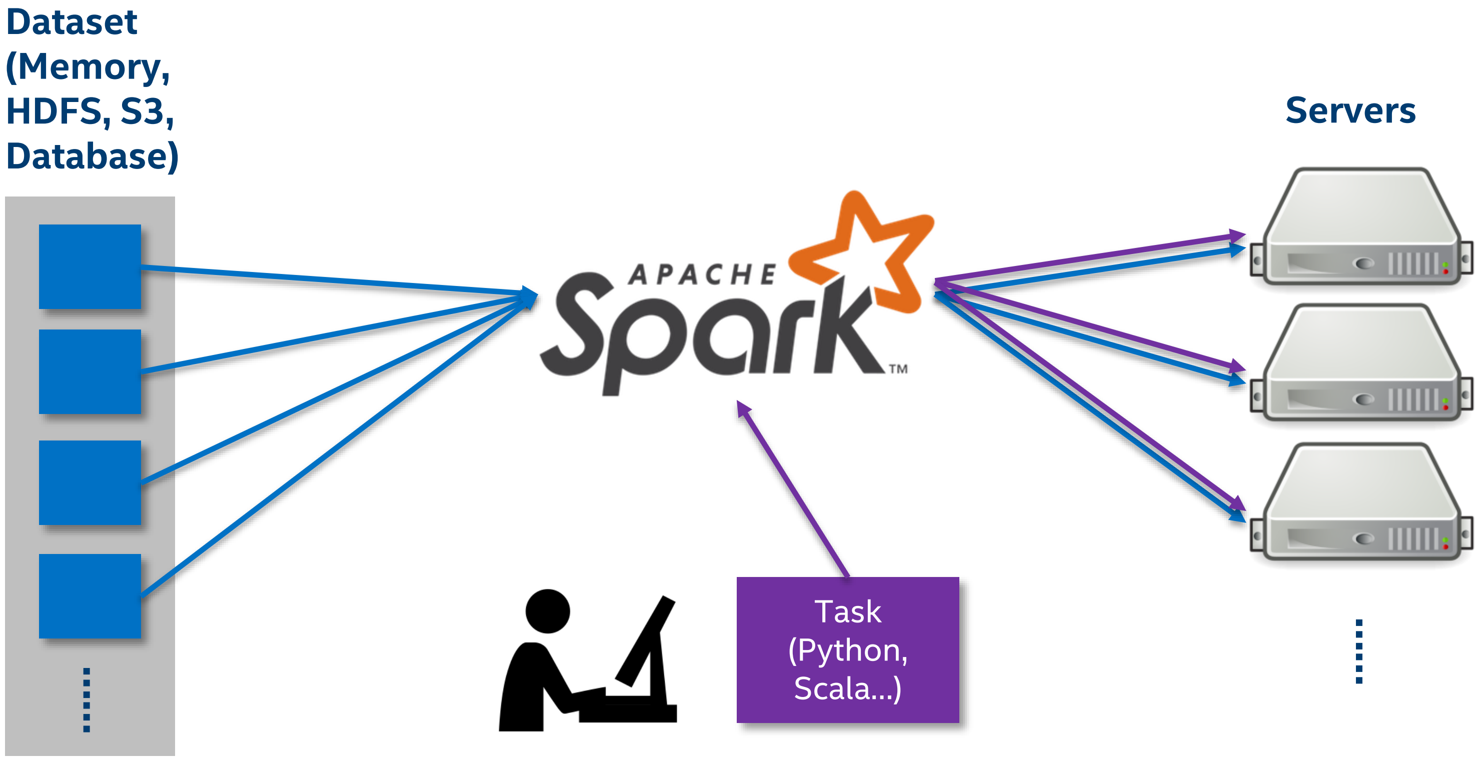
Apache Spark is a fast and general engine for large-scale data processing.

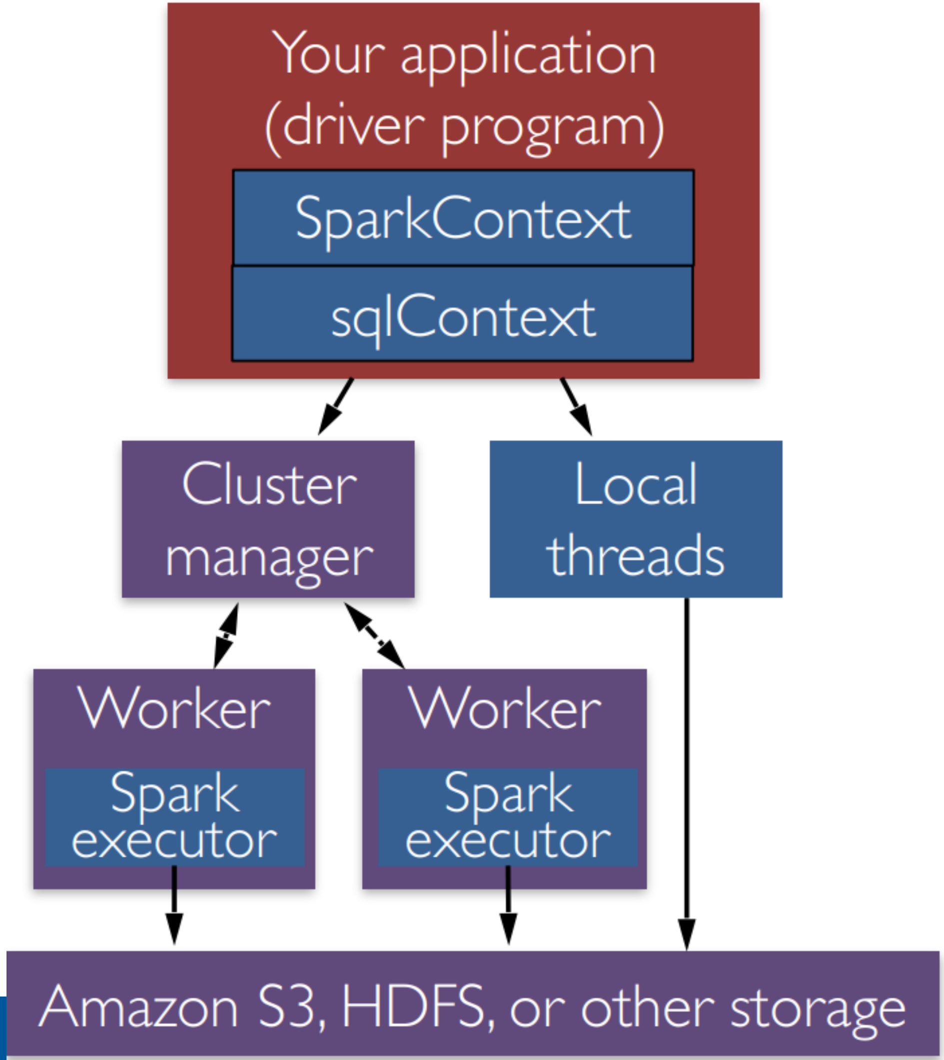
- Up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.
- Unified engine/interface for complete data applications
- SQL, Streaming, ML, Graph in the same framework
- Write applications quickly in Java, Scala, Python, R
- Runs on Hadoop, Mesos, standalone, or in the cloud (K8S is WIP)
- Access diverse data sources including HDFS, Cassandra, HBase, and S3.

Apache Spark Components



How does Apache Spark work




Your application
(driver program)
SparkContext
sqlContext
Cluster manager
Local threads
Worker
Spark executor
Worker
Spark executor
Amazon S3, HDFS, or other storage

Get Analytics-zoo packages

- Pip install
  - Recommend for python user (only support spark 2.2)
- Download
  - If your spark is other version
- Maven / Sbt
  - For Java/scala user
- Build from source code
  - For Analytics-zoo developer

Run Analytics-zoo program (pip install)

```
from zoo.common.nncontext import *
from zoo.pipeline.api.keras.layers import *
from zoo.pipeline.api.keras.models import *
from zoo.pipeline.api.autograd import *

sc = get_nncontext()
dense = Dense(1, input_shape=[2])
```

$ python your_python_file.py

Run Analytics-zoo program (on the cluster)

```
spark-submit \
  --master xxx
  --jars path_to_zoo_jar
  --py-files path_to_zoo_python_zip
  your_python_file
  ……
```

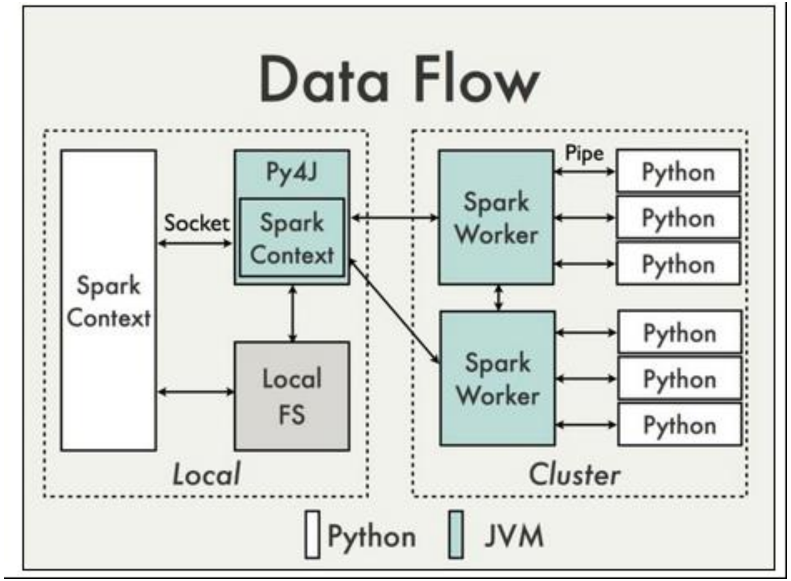
ESSENTIAL API

Define A Model

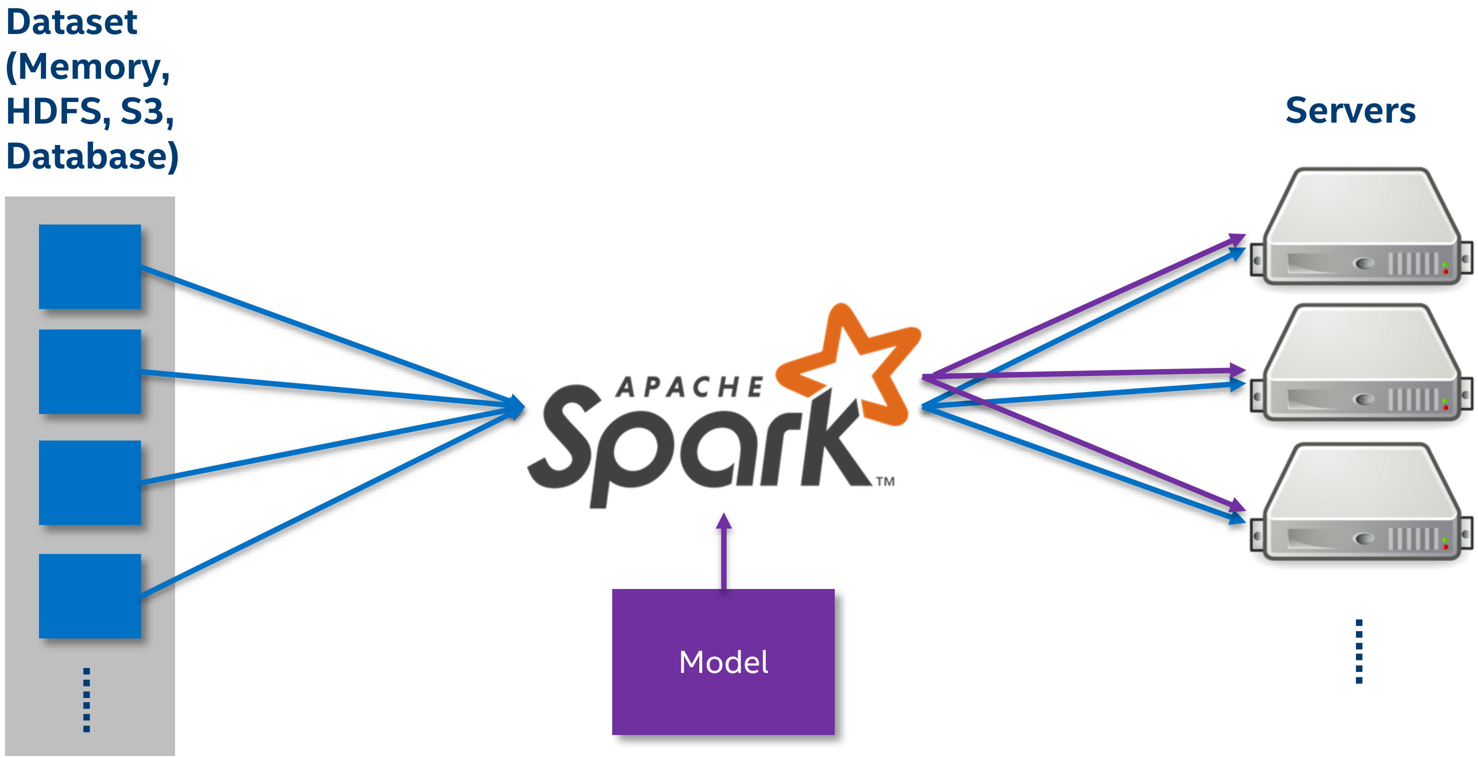
- Sequential API
  - In sequential API, user adds layers into some containers to build the model
- Functional API
  - In functional API, the model is described as a graph

Pipeline

RDD[raw data] Transform (python) RDD[Sample(ndarray,ndarray)] Train(python model)



Distributed Evaluation and Prediction

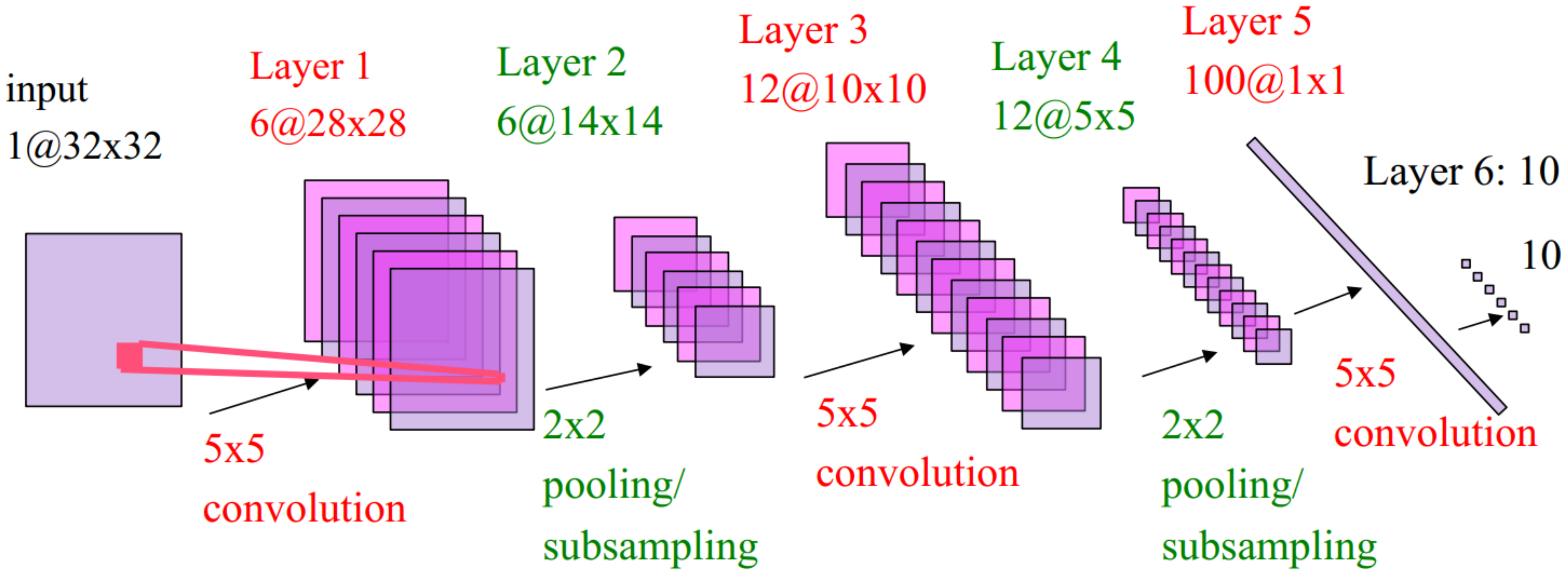


Model Quantization

Quantize the model to get higher speed

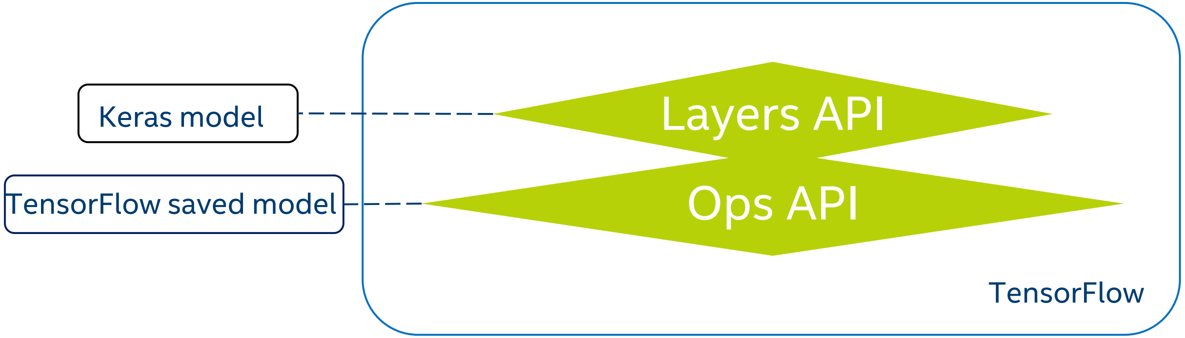
```
model = ...
quantizedModel = model.quantize()
```

Lenet5


input
1@32x32
Layer 1
6@28x28
Layer 2
6@14x14
Layer 3
12@10x10
Layer 4
12@5x5
Layer 5
100@1x1
Layer 6: 10
10
5x5
convolution
2x2
pooling/
subsampling
5x5
convolution
2x2
pooling/
subsampling
5x5
convolution

Keras Support

- Keras 1.2.2
- Load Keras Model
- Keras-like API



Load Keras model

```python
from keras.applications import ResNet50
keras_model = ResNet50(weights="imagenet")
# Load a Keras definition
bmodel = DefinitionLoader.from_kmodel(keras_model)
# Dump weights from kears model to BigDL
WeightLoader.load_weights_from_kmodel(bmodel, keras_model)
```

```python
model = Model.load_keras(json_path=None, hdf5_path=None, by_name=False)
```

Keras-like API

```
input1 = Input((28, 28, 1))
reshape = Reshape((1, 28, 28))(input1)
conv1 = Convolution2D(6, 5, 5, activation="tanh", name="conv1_5x5")(reshape)
pool1 = MaxPooling2D()(conv1)
conv2 = Convolution2D(12, 5, 5, activation="tanh", name="conv2_5x5")(pool1)
pool2 = MaxPooling2D()(conv2)
flatten = Flatten()(pool2)
fc1 = Dense(100, activation="tanh", name="fc1")(flatten)
fc2 = Dense(class_num, activation="softmax", name="fc2")(fc1)
return Model(input1, fc2)
```

Caffe Support

Load caffe model

```
model = Net.load_caffe_model(caffe.prototxt, caffe.model)
```

Load Caffe Model Weights to Predefined BigDL Model

```
model = Net.load_caffe(bigdlModel, caffe.prototxt,
caffe.model, match_all=True)
```

Notebook

https://github.com/zhichao-li/tzoo/tree/master/notebooks/part1

Cloud & Big Data Platforms

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/

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/

BigDL Spark deep learning library VM now available on Microsoft* Azure* Marketplace https://azure.microsoft.com/en-us/blog/bigdl-spark-deep-learning-library-vm-now-available-on-microsoft-azure-marketplace/

BigDL in KMR* Service of Kingsoft* Cloud
https://docs.ksyun.com/read/latest/33/_book/bigDL.html

Using BigDL in IBM* Data Science Experience
https://medium.com/ibm-data-science-experience/using-bigdl-in-data-science-experience-for-deep-learning-on-spark-f1cf30ad6ca0

Using BigDL for deep learning with Apache Spark and Google* Cloud Dataproc*
https://cloud.google.com/blog/big-data/2018/04/using-bigdl-for-deep-learning-with-apache-spark-and-google-cloud-dataproc

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

BigDL Shipped in Cray* Urika-XC* Analytics Software Suite
https://www.cray.com/blog/scalable-deep-learning-bigdl-urika-xc-software-suite/

JD.COM

Problem

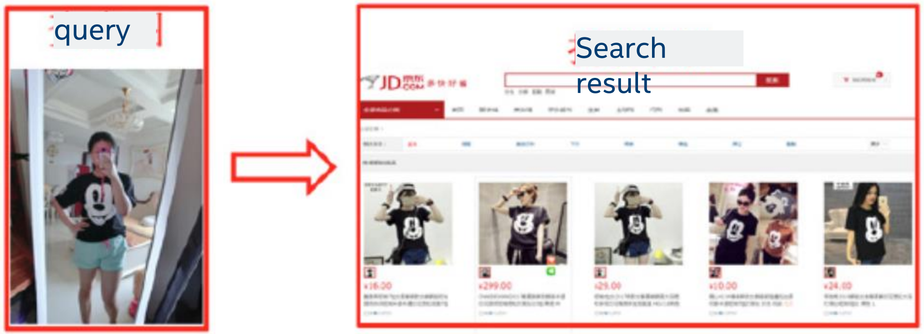
Large-scale image feature extraction

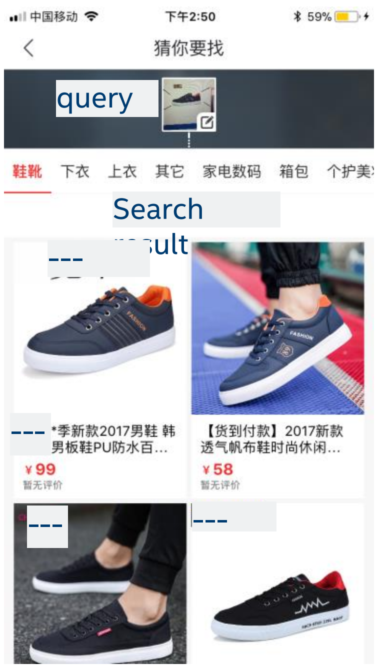
- Object detect (remove background, optional)
- Feature extraction

Application

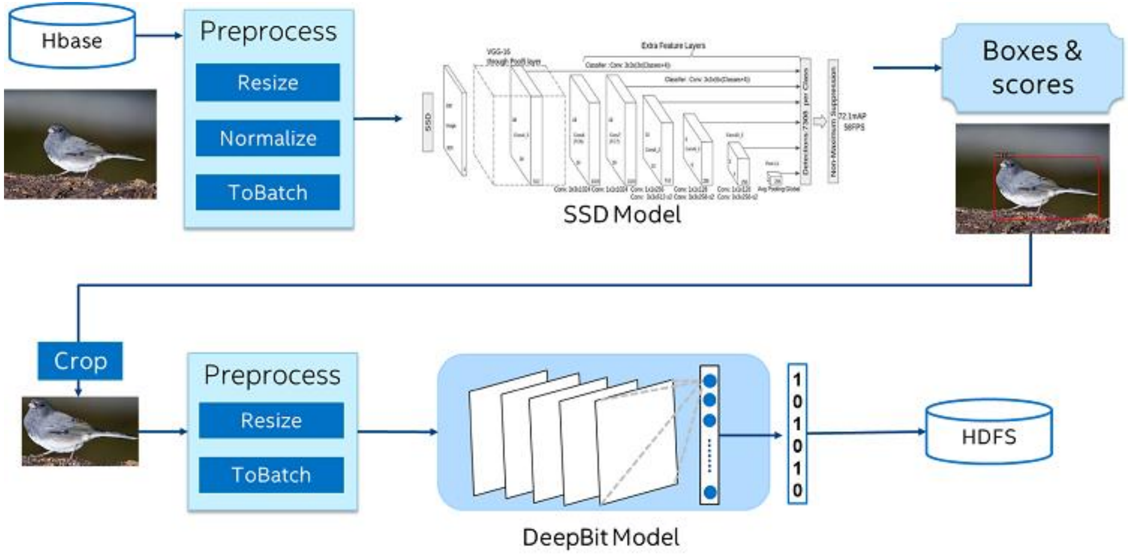
- Similar image search
- Image Deduplication

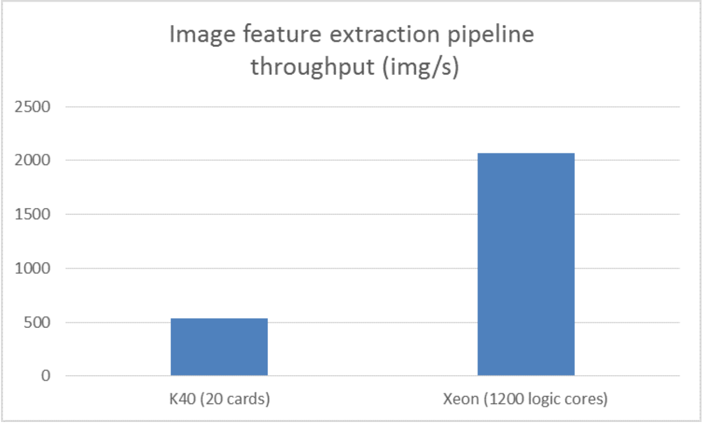
Similar image search





Object Detection and Image Feature Extraction in JD





- 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

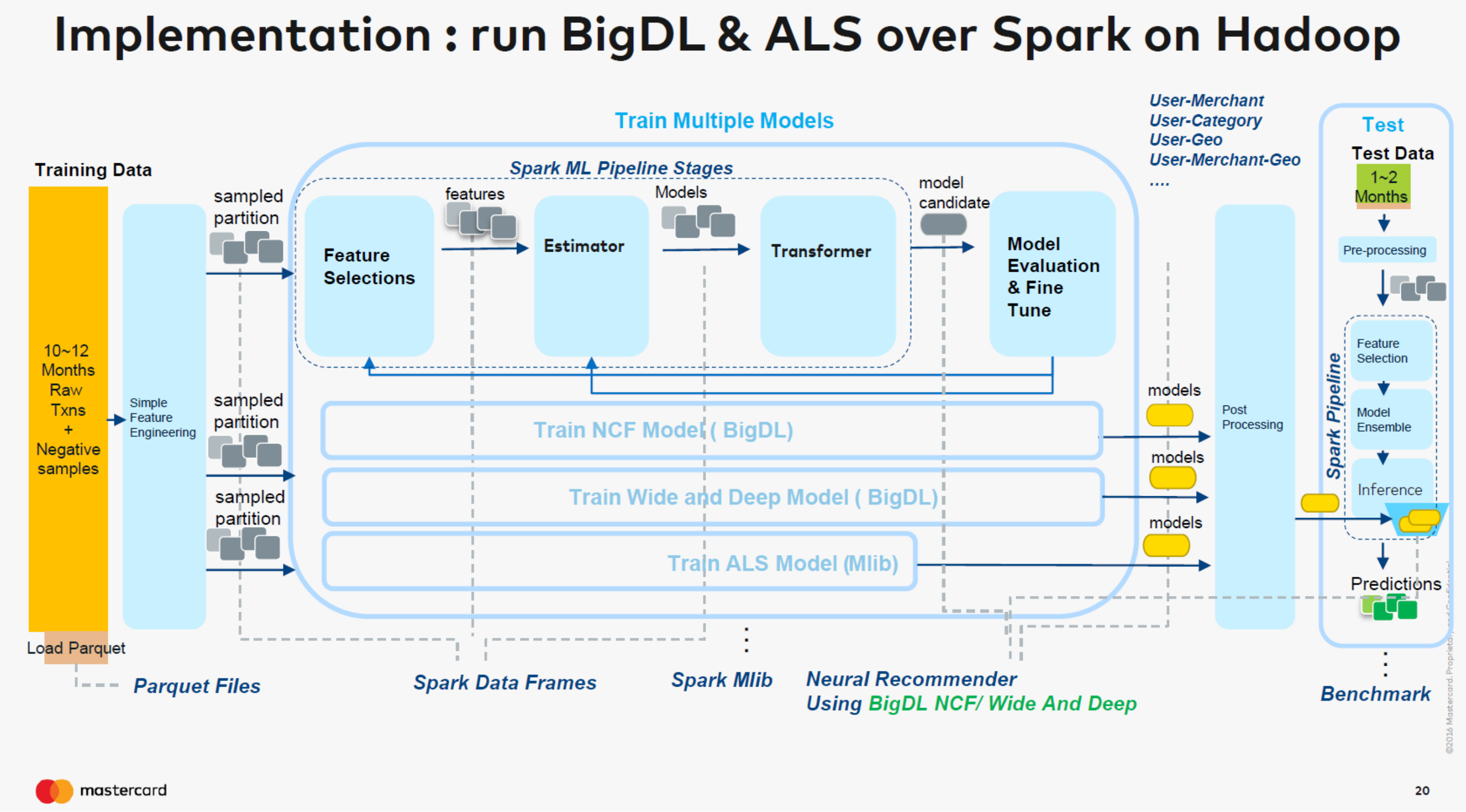
http://mp.weixin.qq.com/s/xUCkzbHK4K06-v5qUsaNQQ
https://software.intel.com/en-us/articles/building-large-scale-image-feature-extraction-with-bigdl-at-jdcom

Pipeline Correctness

Almost same as Caffe GPU

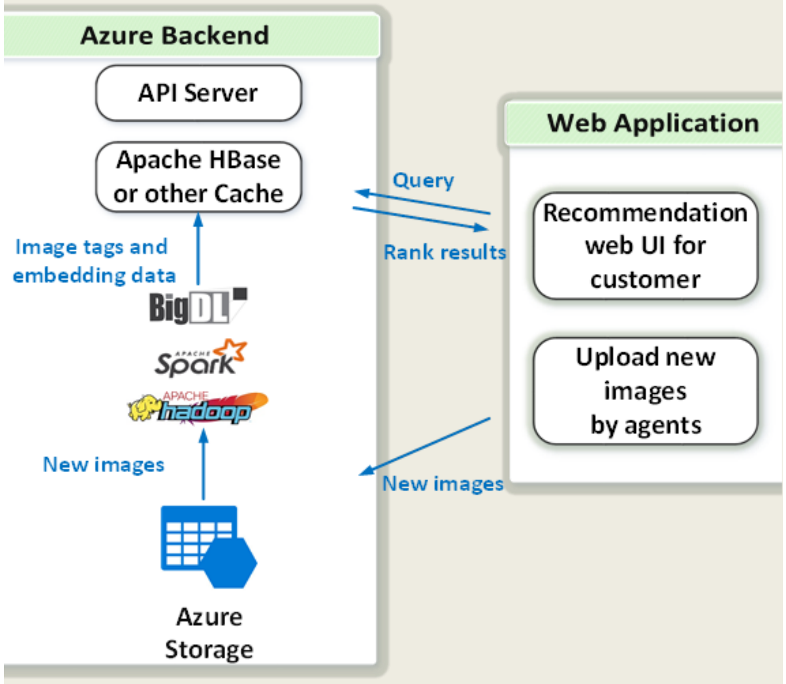
Element-wise error < 0.001%

User-Merchant Propensity Modeling in MasterCard

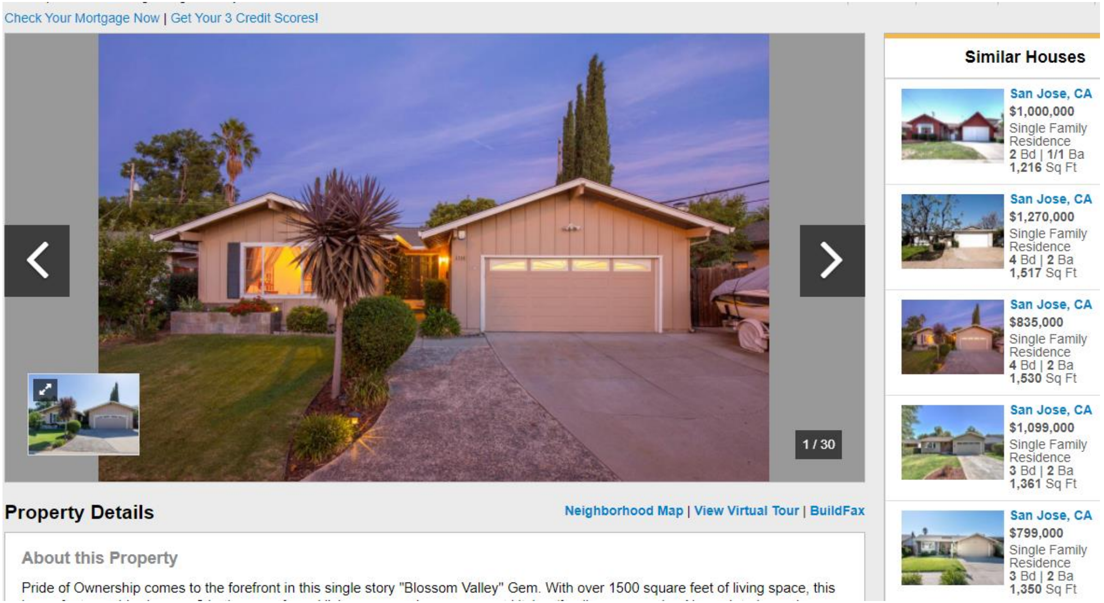


https://www.ai-expo.net/northamerica/talk/using-deep-learning-intel-bigdl-optimized-personalized-card-linked-offer/
https://conferences.oreilly.com/strata/strata-ca/public/schedule/detail/63897

Image Similarity Search for MLSListings

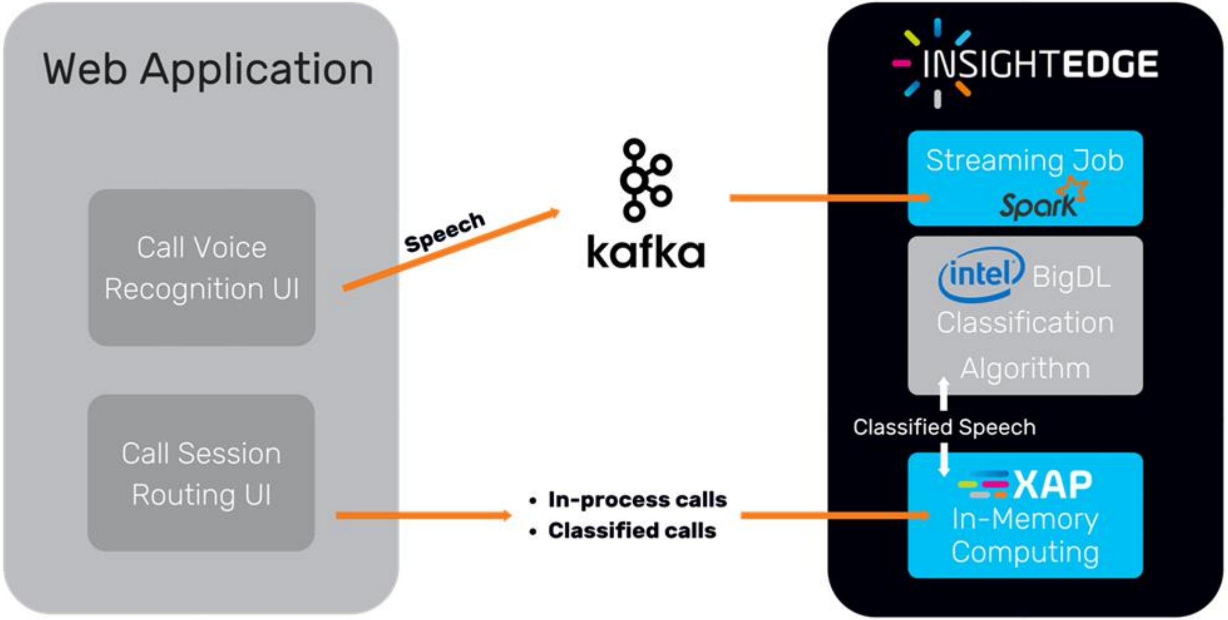


MLSlistings built image-similarity based house recommendations using BigDL on Microsoft Azure

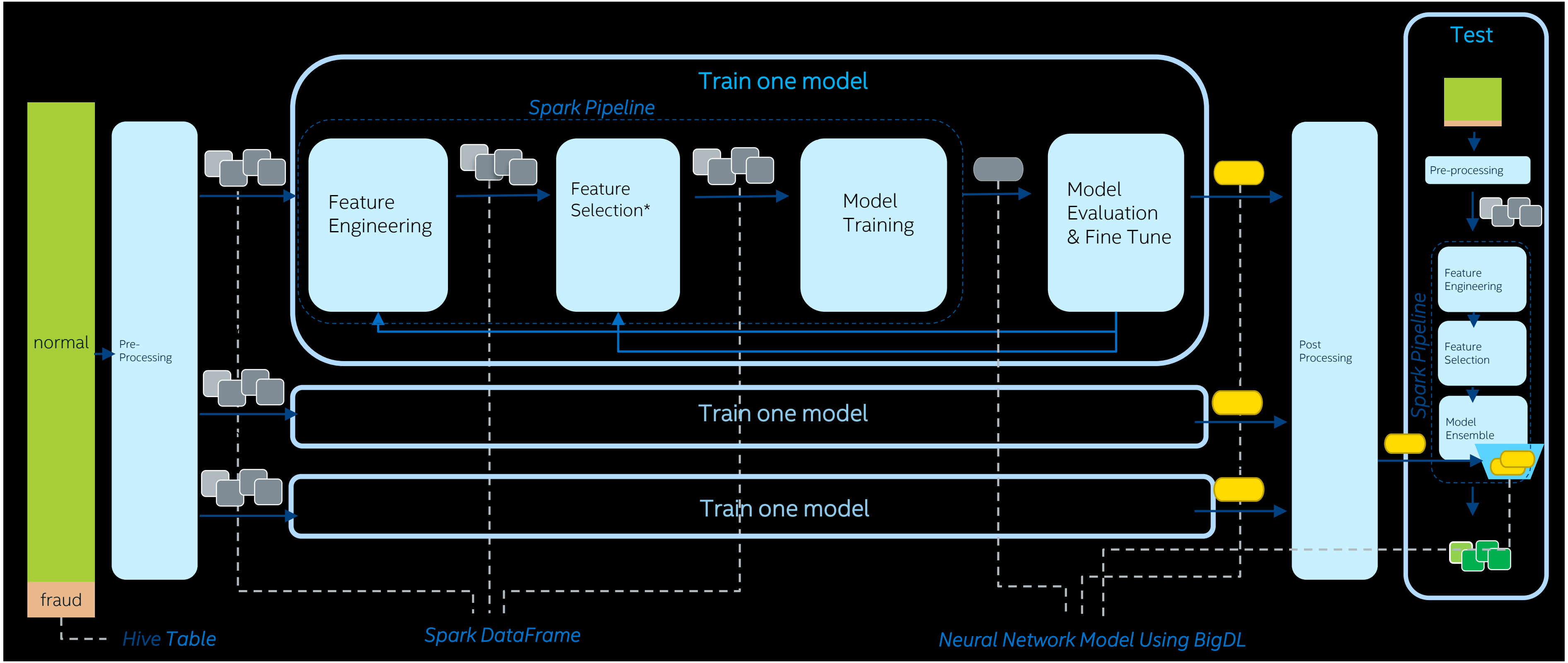


https://software.intel.com/en-us/articles/using-bigdl-to-build-image-similarity-based-house-recommendations

NLP Based Call Center Routing in GigaSpaces



Fraud Detection in UnionPay



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

Intel Software

Hands on

- Pre-trained ResNet
- Anomaly detection
- Recommendation (NCF wide and deep)
- VAE

https://github.com/zhichao-li/tzoo/tree/master/notebooks/part2

Software

Legal Disclaimer

Risk Factors

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