Software

BIGDL: A DISTRIBUTED DEEP LEARNING LIBRARY ON SPARK

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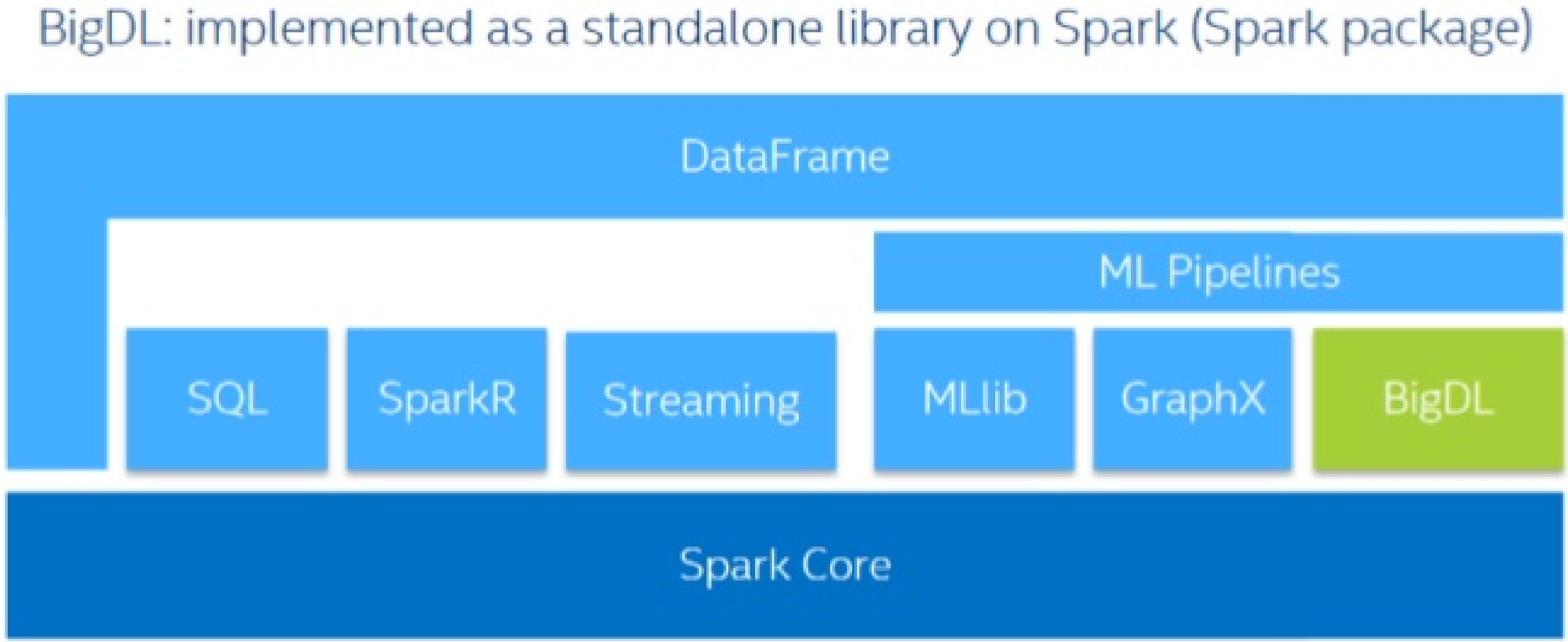
What is BigDL?

BigDL is a distributed deep learning library for Apache Spark*



WHY BIGDL?

Why BigDL?

Production ML/DL system is **Complex**

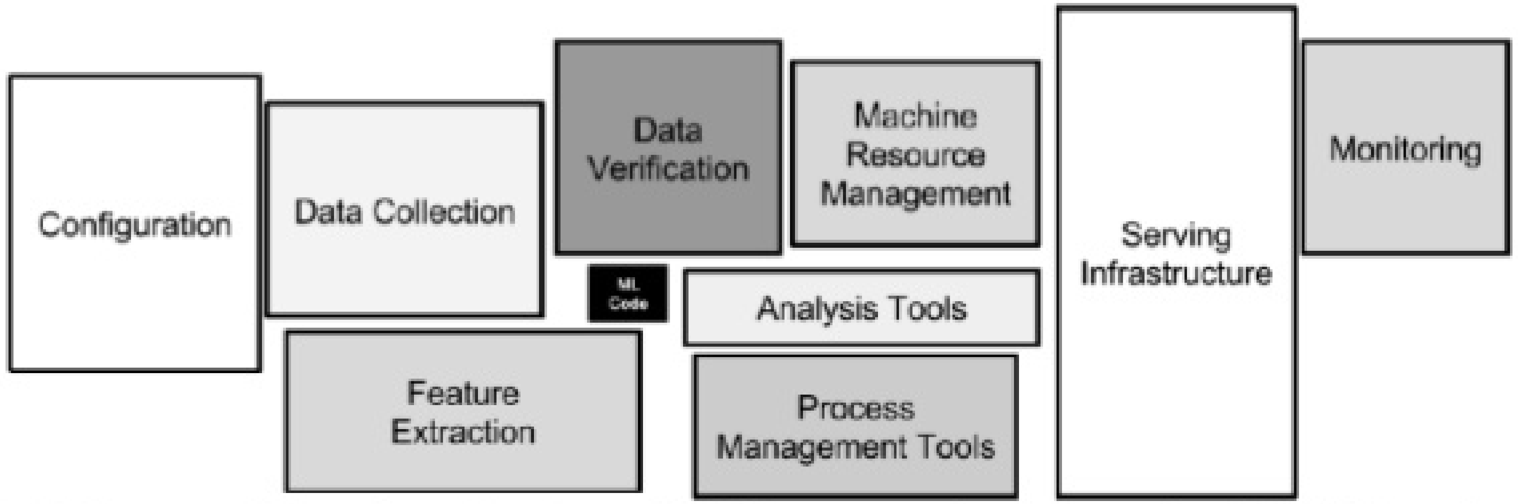


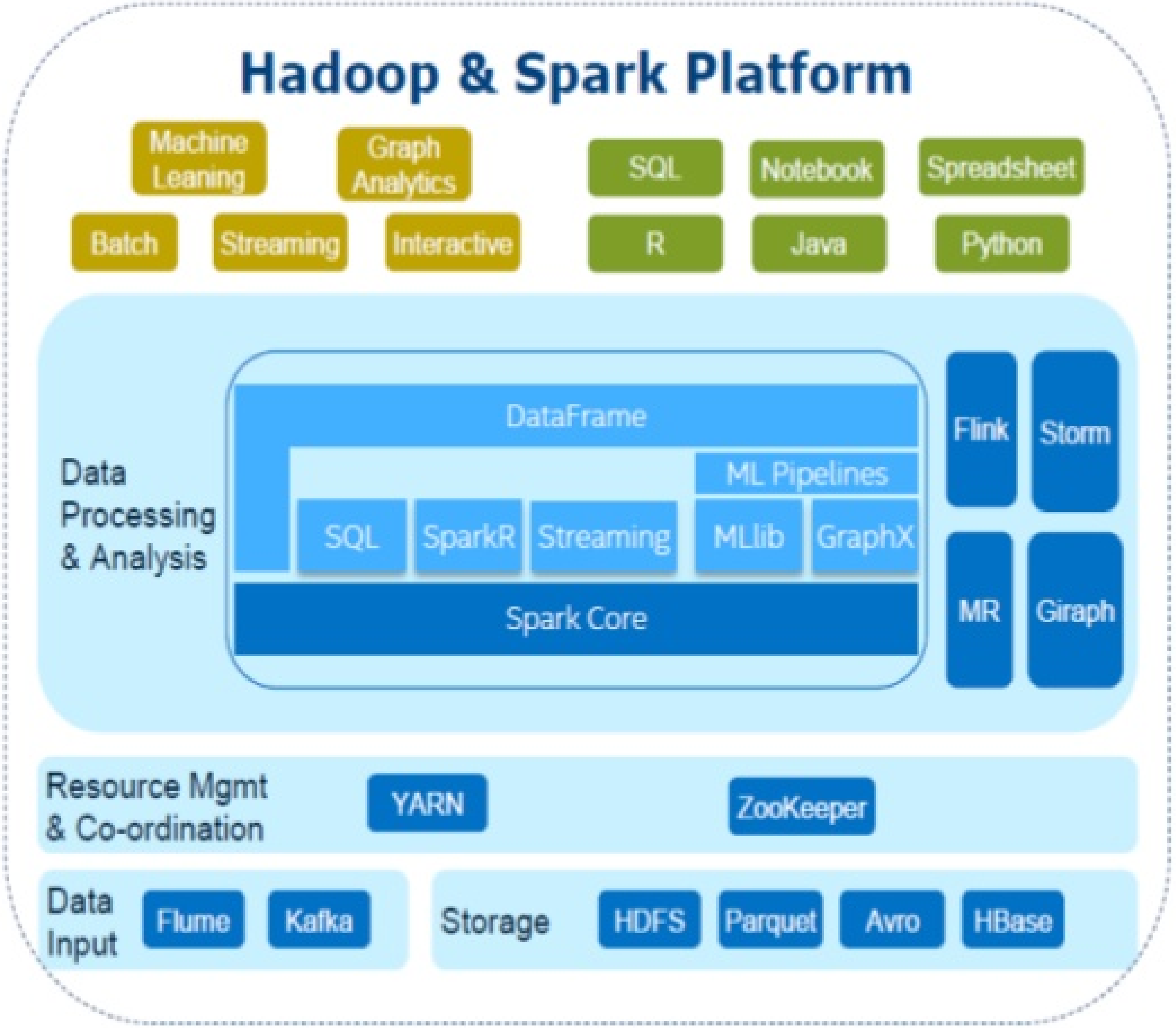
Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

"Hidden Technical Debt in Machine Learning Systems",
Google, NIPS 2015 Paper

Why BigDL?

How to Run Deep Learning Workloads Directly on Big Data Platform?

- Integrated with Big Data ecosystem
- Massively distributed, scale out
- Send compute to data
- Fault tolerance
- Elasticity
- Incremental scaling
- Dynamic resource sharing
- ...



Why BigDL?

BigDL open sourced on Dec 30, 2016

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

- Write deep learning applications as standard Spark programs
- Run on top of existing Spark or Hadoop clusters(No change to the clusters)
- Rich deep learning support
- High performance powered by Intel MKL and multi-threaded programming
- Efficient scale-out with an all-reduce communications on Spark

Why BigDL?

You may want to write your deep learning programs using BigDL if:

- 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, which are dynamically shared with other workloads (e.g., ETL, data warehouse, feature engineering, classical machine learning, graph analytics, etc.)
- Making deep learning more accessible for Big Data users and data scientists, who are usually not experts for deep learning

BIGDL FEATURES

BigDL Features

Tensor

- A powerful ndarray data structure
- Generic data type
- Data manipulate / math APIs, model after torch

```
scala> import com.intel.analytics.bigdl.tensor.Tensor
import com.intel.analytics.bigdl.tensor.Tensor

scala> val tensor = Tensor[Float](2, 3)
tensor: com.intel.analytics.bigdl.tensor.Tensor[Float] =
0.0     0.0     0.0
0.0     0.0     0.0
[com.intel.analytics.bigdl.tensor.DenseTensor of size 2x3]
```

BigDL Features

Layers

- 90+ Layers

Criterion

- 10+ loss functions

Optimization

- SGD, Adagrad, LBFGS

```
scala> import com.intel.analytics.bigdl.numeric.NumericFloat // import global float tensor n
import com.intel.analytics.bigdl.numeric.NumericFloat

scala> import com.intel.analytics.bigdl.nn._
import com.intel.analytics.bigdl.nn._

scala> val f = Linear(3,4) // create the module
mlp: com.intel.analytics.bigdl.nn.Linear[Float] = nn.Linear(3 -> 4)

// let's see what f's parameters were initialized to. ('nn' always inits to something reason
scala> f.weight
res5: com.intel.analytics.bigdl.tensor.Tensor[Float] =
-0.008662592    0.543819        -0.028795477
-0.30469555     -0.3909278      -0.10871882
0.114964925     0.1411745       0.35646403
-0.16590376     -0.19962183     -0.18782845
[com.intel.analytics.bigdl.tensor.DenseTensor of size 4x3]
```

BigDL Features

Build a simple model

```
scala> val g = Sum()
g: com.intel.analytics.bigdl.nn.Sum[Float] = nn.Sum

scala> val mlp = Sequential().add(f).add(g)
mlp: com.intel.analytics.bigdl.nn.Sequential[Float] =
nn.Sequential {
  [input -> (1) -> (2) -> output]
  (1): nn.Linear(3 -> 4)
  (2): nn.Sum
}
```

BigDL Features - A full example

```scala
val model = Sequential()
  .add(SpatialConvolution(3, 64, 11, 11, 4, 4, 2, 2, 1))
  .add(ReLU(true))
  .add(SpatialMaxPooling(3, 3, 2, 2))
  .add(SpatialConvolution(64, 192, 5, 5, 1, 1, 2, 2))
  .add(ReLU(true))
  .add(SpatialMaxPooling(3, 3, 2, 2))
  .add(SpatialConvolution(192, 384, 3, 3, 1, 1, 1, 1))
  .add(ReLU(true))
  .add(SpatialConvolution(384, 256, 3, 3, 1, 1, 1, 1))
  .add(ReLU(true))
  .add(SpatialConvolution(256, 256, 3, 3, 1, 1, 1, 1))
  .add(ReLU(true))
  .add(SpatialMaxPooling(3, 3, 2, 2))
  .add(View(256 * 6 * 6))
  .add(Linear(256 * 6 * 6, 4096))
  .add(ReLU(true))
  .add(Dropout(0.5))
  .add(Linear(4096, 4096))
  .add(ReLU(true))
  .add(Dropout(0.5))
  .add(Linear(4096, 1000))
  .add(LogSoftMax())
```

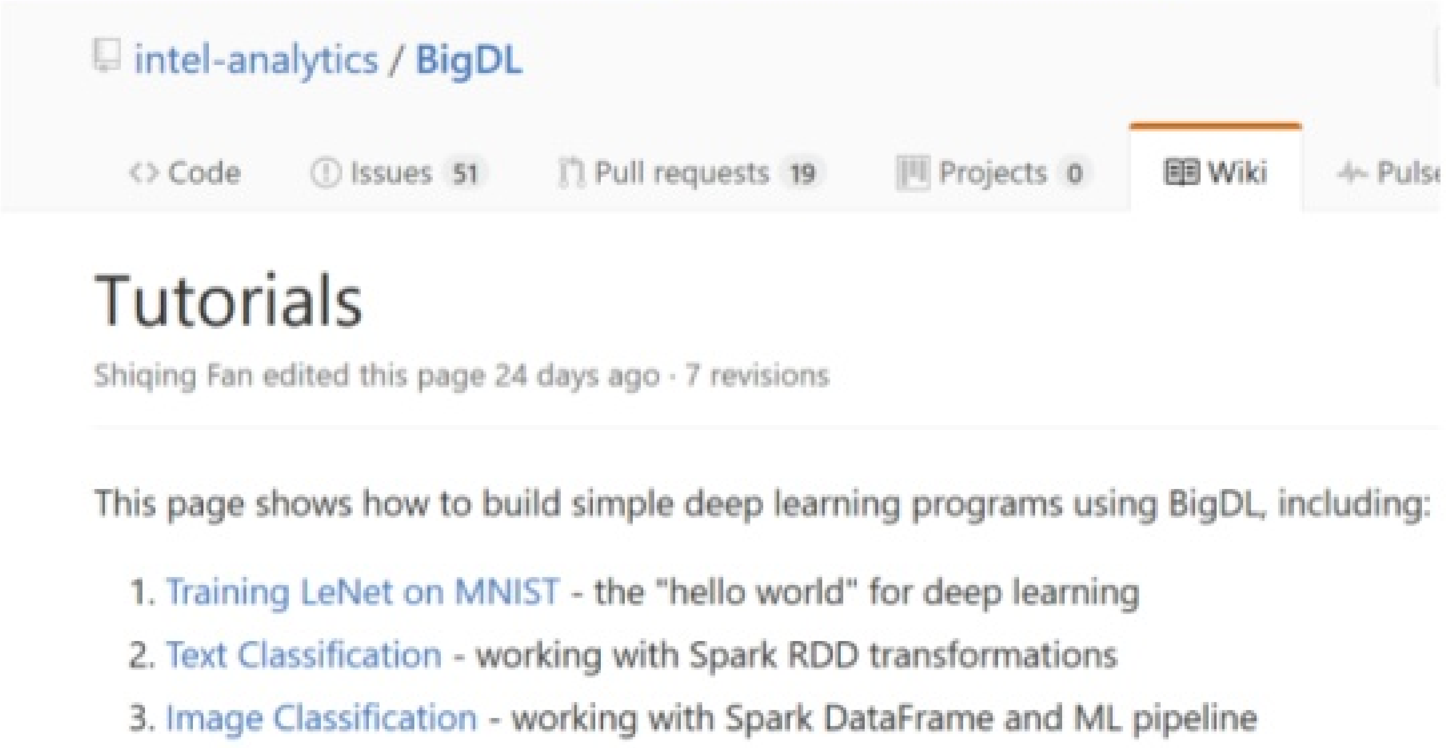
```scala
val optimizer = Optimizer(
  model = model,
  dataset = trainSet,
  criterion = new ClassNLLCriterion[Float]()
)
```

```scala
optimizer
  .setState(state)
  .setValidation(Trigger.severalIteration(620),
    valSet, Array(new Top1Accuracy[Float], new Top5Accuracy[Float]))
  .setEndWhen(Trigger.maxIteration(62000))
  .optimize()
```

BigDL Features

Start with tutorials

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

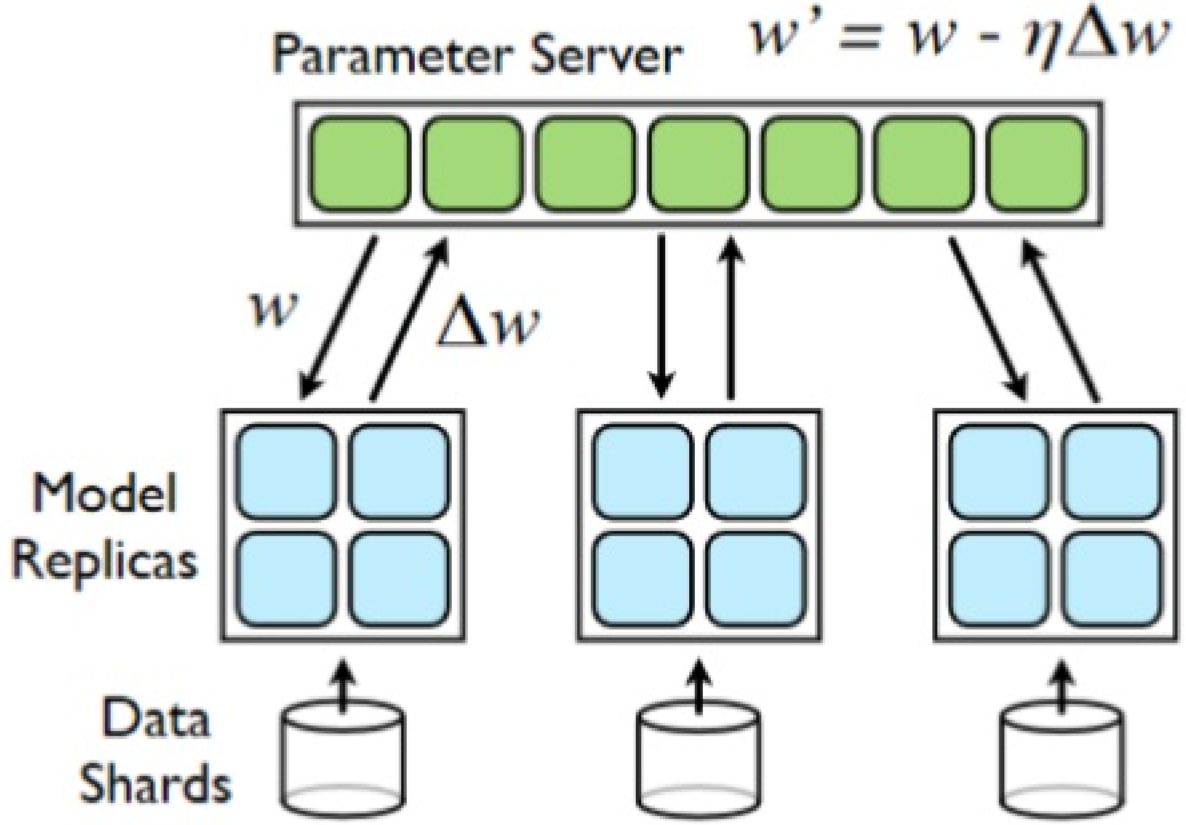


BigDL Features

Distributed Training

- Model Parallelism
- Data Parallelism

A distributed training example,
(Jeff Dean, NIPS 2012)

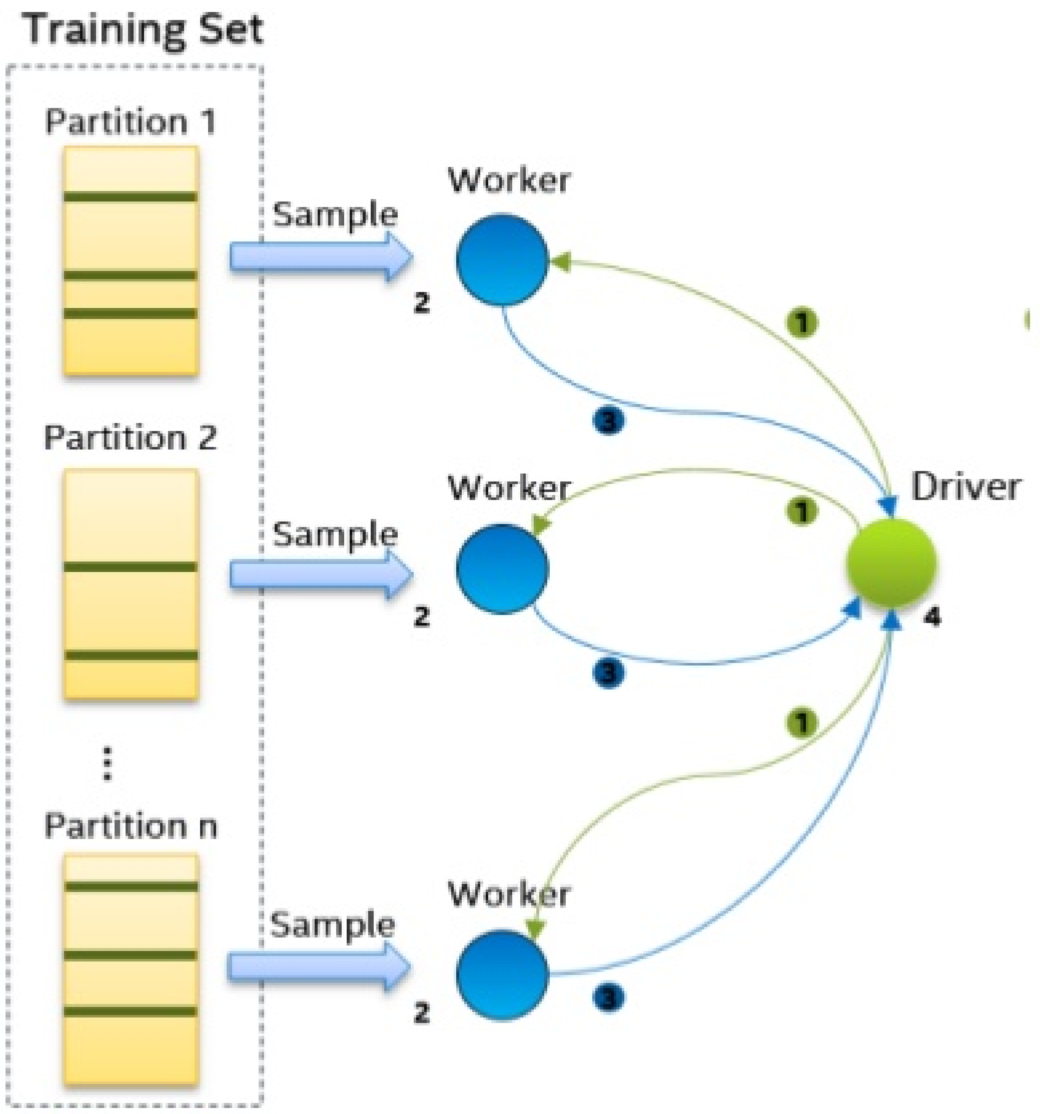


BigDL Features

“Canonical” implementation on Apache Spark

Driver become the bottleneck

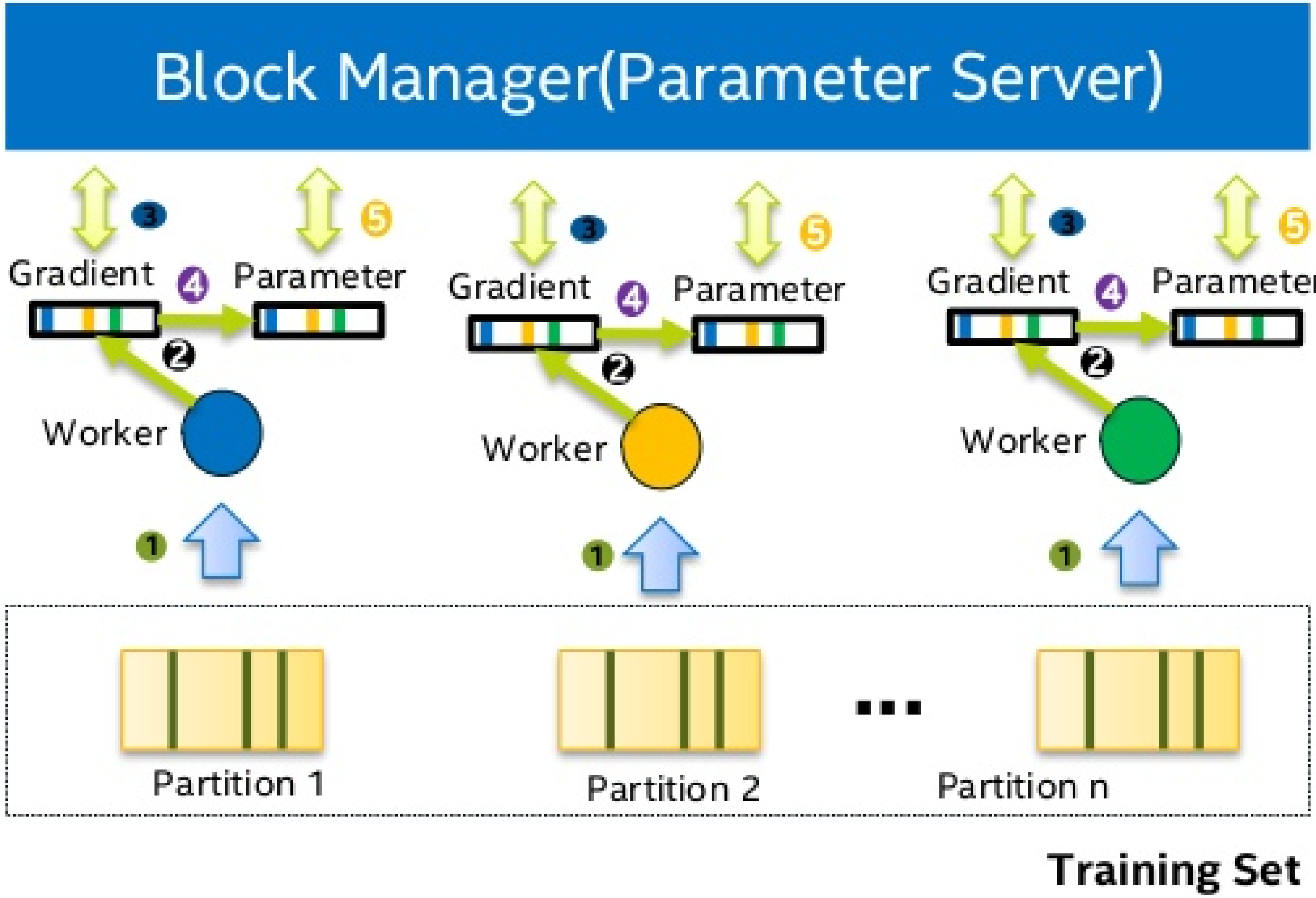
- RDD.reduce / aggregate
- RDD.treeAggregate (shuffle)



BigDL Features

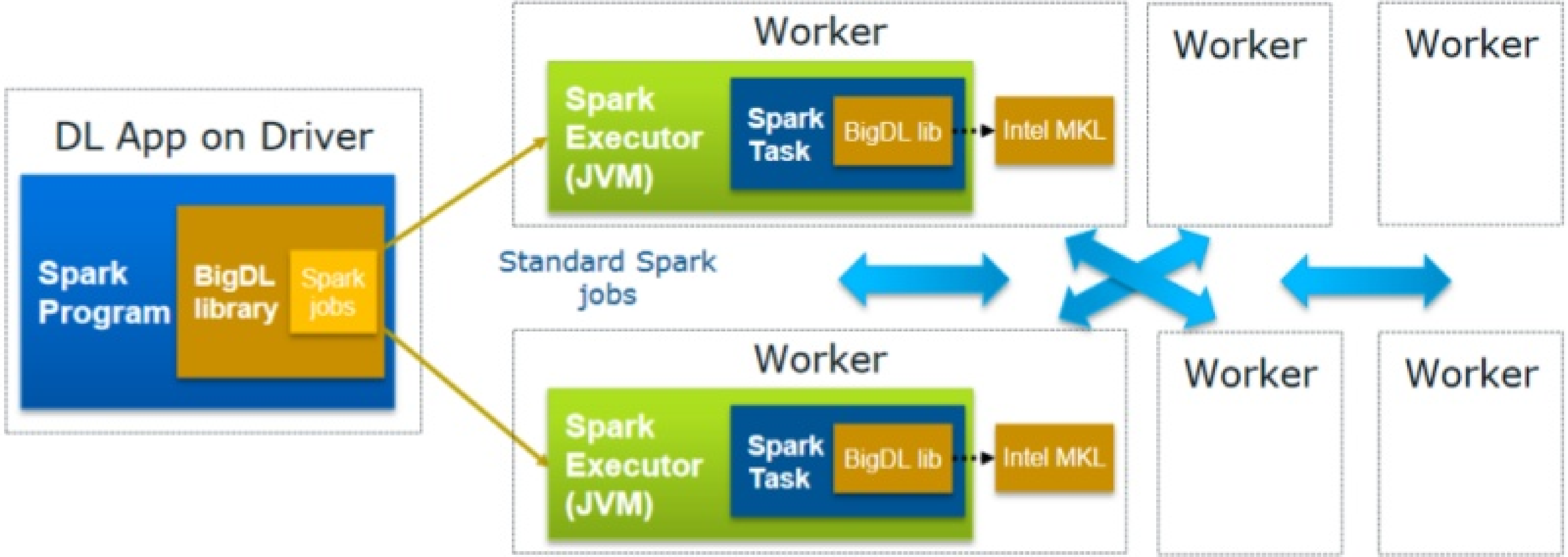
BigDL distributed training highlight

- 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



BigDL Features

Train deep learning model on Apache Spark*



BigDL Features

Distributed training prefer large batch, need tune hyper parameter

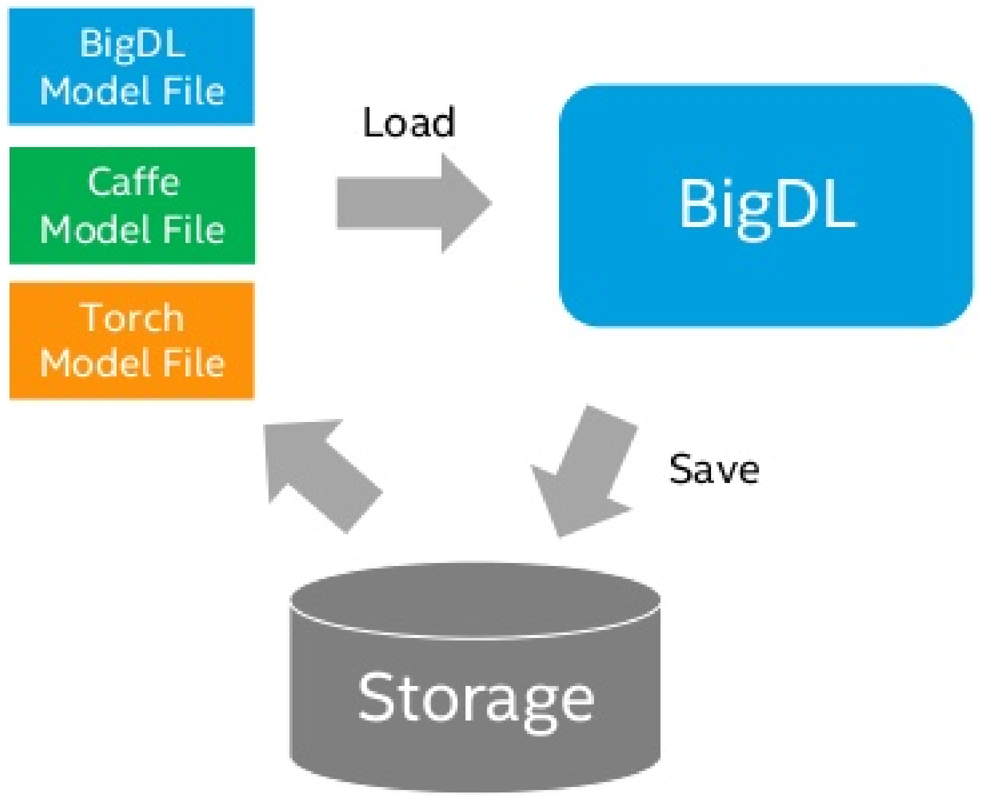
An example of Googlenet_v1 on ImageNet (batchsize = 1500+)

- learningRate -> 0.0896
- weightDecy -> 0.0001
- Momentum -> 0.9
- learningRateSchedule -> Poly(power = 0.5, iteration = 62000)

BigDL Features

- Model Snapshot
  - Useful in a long training
  - Used in inference later
  - Share your model with others
  - Fine-tune the model

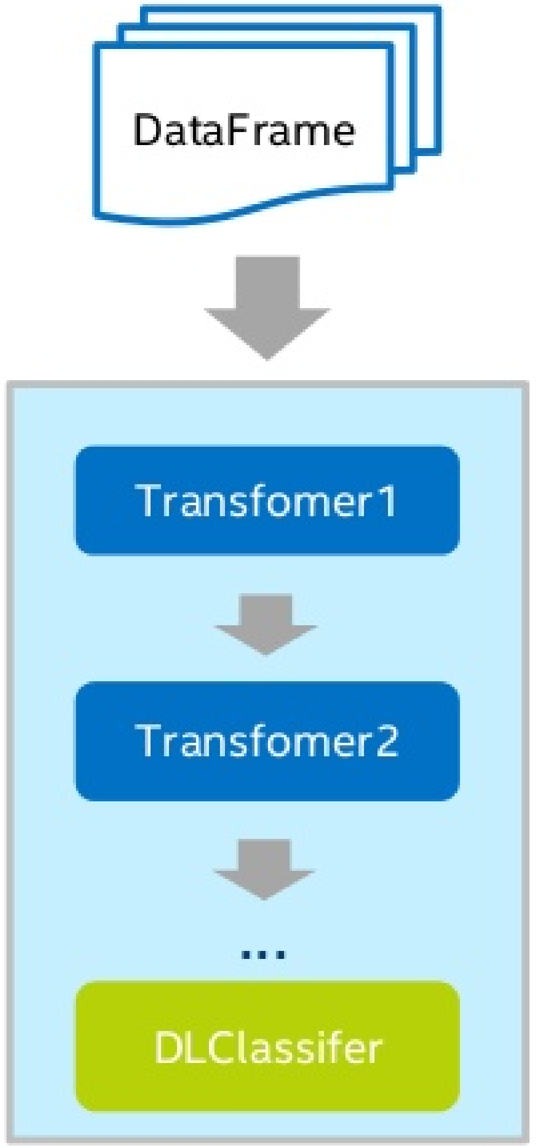
- Load Caffe/Torch Model
  - Leverage existed trained model



BigDL Features

Integrate with Spark-ML Pipeline

- Wrapper with Spark ML Transformer
- Plug into Spark ML pipeline
- Support 1.5/1.6/2.0



BigDL Features

BigDL provide examples to help developer play with bigdl and start with popular models.

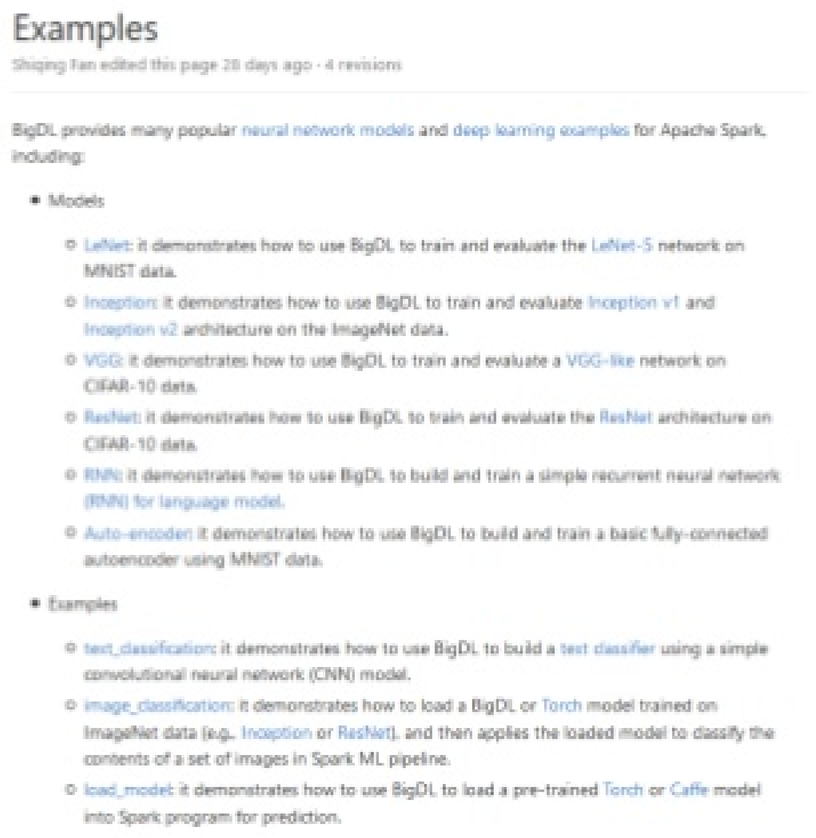
https://github.com/intel-analytics/BigDL/wiki/Examples

Models (Train and Inference Example Code):

- LeNet, Inception, VGG, ResNet, RNN, Auto-encoder

Examples:

- Text Classification
- Image Classification
- Load Torch/Caffe model



Examples

Shiqing Fan edited this page 28 days ago · 4 revisions

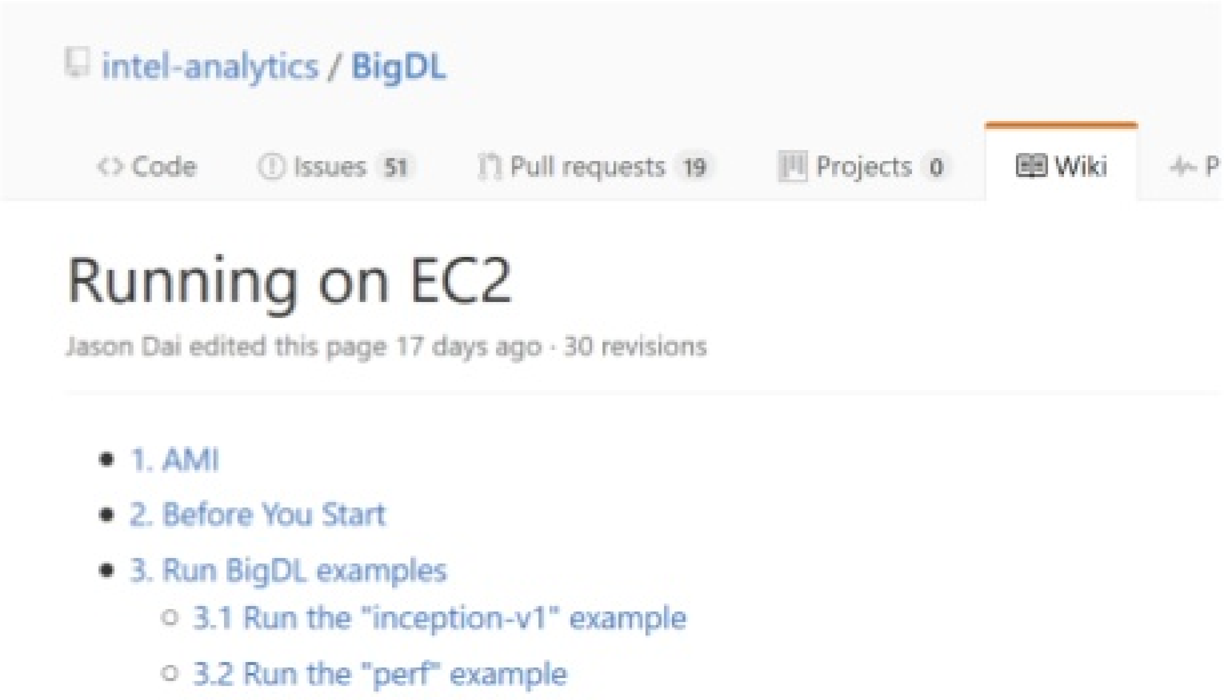
BigDL provides many popular neural network models and deep learning examples for Apache Spark, including:

- Models
  - LeNet: it demonstrates how to use BigDL to train and evaluate the LeNet-5 network on MNIST data.
  - Inception: it demonstrates how to use BigDL to train and evaluate Inception v1 and Inception v2 architecture on the ImageNet data.
  - VGG: it demonstrates how to use BigDL to train and evaluate a VGG-like network on CIFAR-10 data.
  - ResNet: it demonstrates how to use BigDL to train and evaluate the ResNet architecture on CIFAR-10 data.
  - RNN: it demonstrates how to use BigDL to build and train a simple recurrent neural network (RNN) for language model.
  - Auto-encoder: it demonstrates how to use BigDL to build and train a basic fully-connected autoencoder using MNIST data.
- Examples
  - text_classification: it demonstrates how to use BigDL to build a text classifier using a simple convolutional neural network (CNN) model.
  - image_classification: it demonstrates how to load a BigDL or Torch model trained on ImageNet data (e.g. Inception or ResNet), and then applies the loaded model to classify the contents of a set of images in Spark ML pipeline.
  - load_model: it demonstrates how to use BigDL to load a pre-trained Torch or Caffe model into Spark program for prediction.

BigDL Features

BigDL Out-of-box run scripts on AWS

https://github.com/intel-analytics/BigDL/wiki/Running-on-EC2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Code | Issues 51 | Pull requests 19 | Projects 0 | Wiki | P

Running on EC2

Jason Dai edited this page 17 days ago · 30 revisions

- 1. AMI
- 2. Before You Start
- 3. Run BigDL examples
  - 3.1 Run the "inception-v1" example
  - 3.2 Run the "perf" example

BigDL Features

Model on Data Set	Top-1 Accuracy
LeNet5 on MNIST	99%
Vgg on Cifar10	90%
AlexNet OWT on ImageNet	56%
GoogleNetV1 on ImageNet	68%

BigDL Features

- Single node Xeon performance
  - Benchmarked best on Xeon E5-26XX v3 or E5-26XX v4
  - Orders of magnitude speedup vs. out-of-box open source Caffe, Torch or TensorFlow

- Scaling-out
  - Efficiently scale out to several 10s of Xeon servers on Spark to distributed train some deep learning model on ImageNet dataset

For more complete information about performance and benchmark results, visit www.intel.com/benchmarks

BIGDL – USE CASE

Fraud Transaction Detection

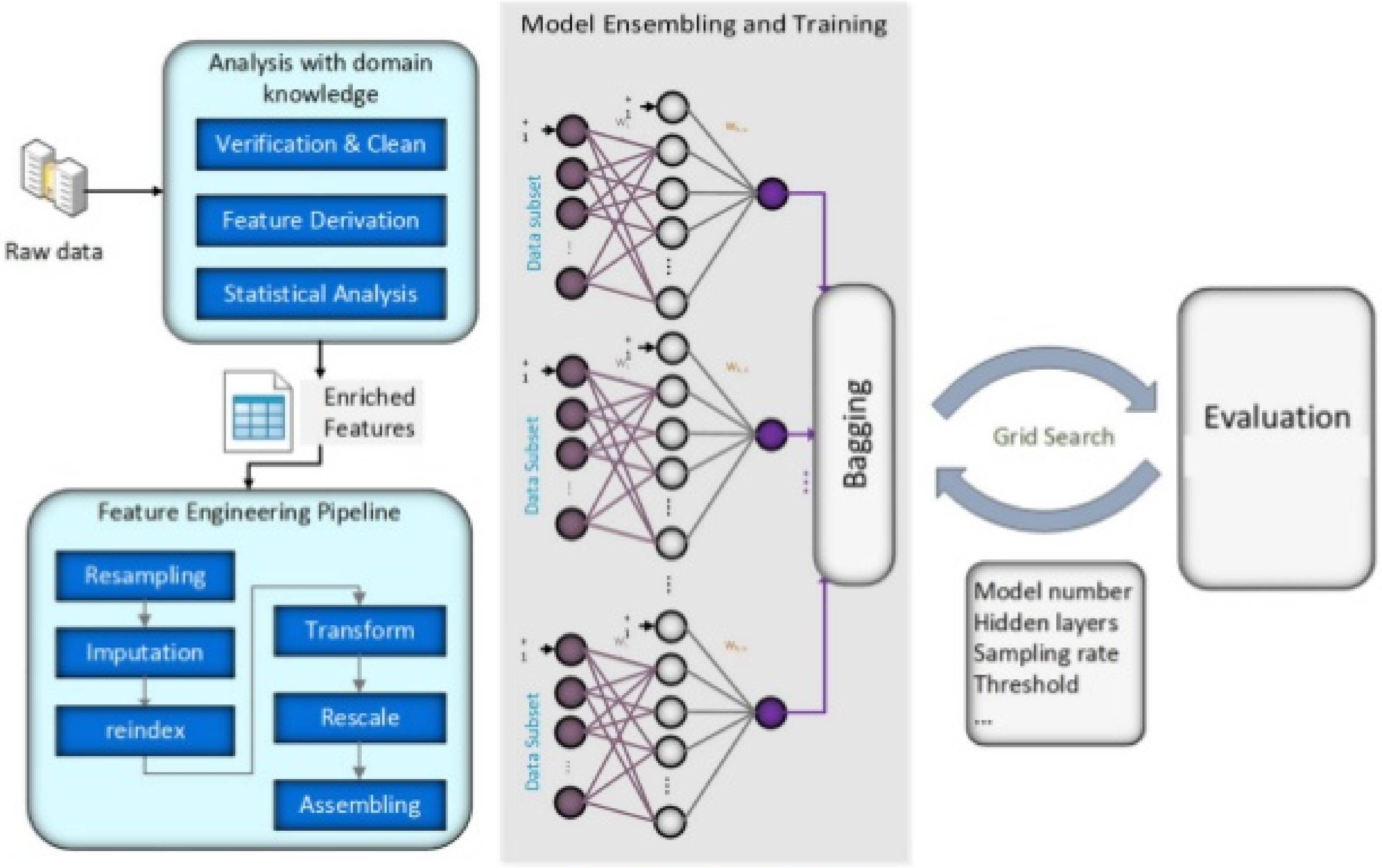
Fraud transaction detection is very import to finance companies. A good fraud detection solution can save a lot of money.

ML solution challenge

- Data cleaning
- Feature engineering
- Unbalanced data
- Hyper parameter

Fraud Transaction Detection

- History data is stored on Hive
- Easily data preprocess/cleaning with Spark-SQL
- Spark ML pipeline for complex feature engineering
- Under sample + Bagging solve unbalance problem
- Grid search for hyper parameter tunning



Powered by BigDL

Product Defect Detection and Classification

Data source

- Cameras installed on manufactory pipeline

Task

- Detect defect from the photos
- Classify the defect

Product Defect Detection and Classification

Big Data management

- High resolution images
- Large volume of data

Proposal Extraction

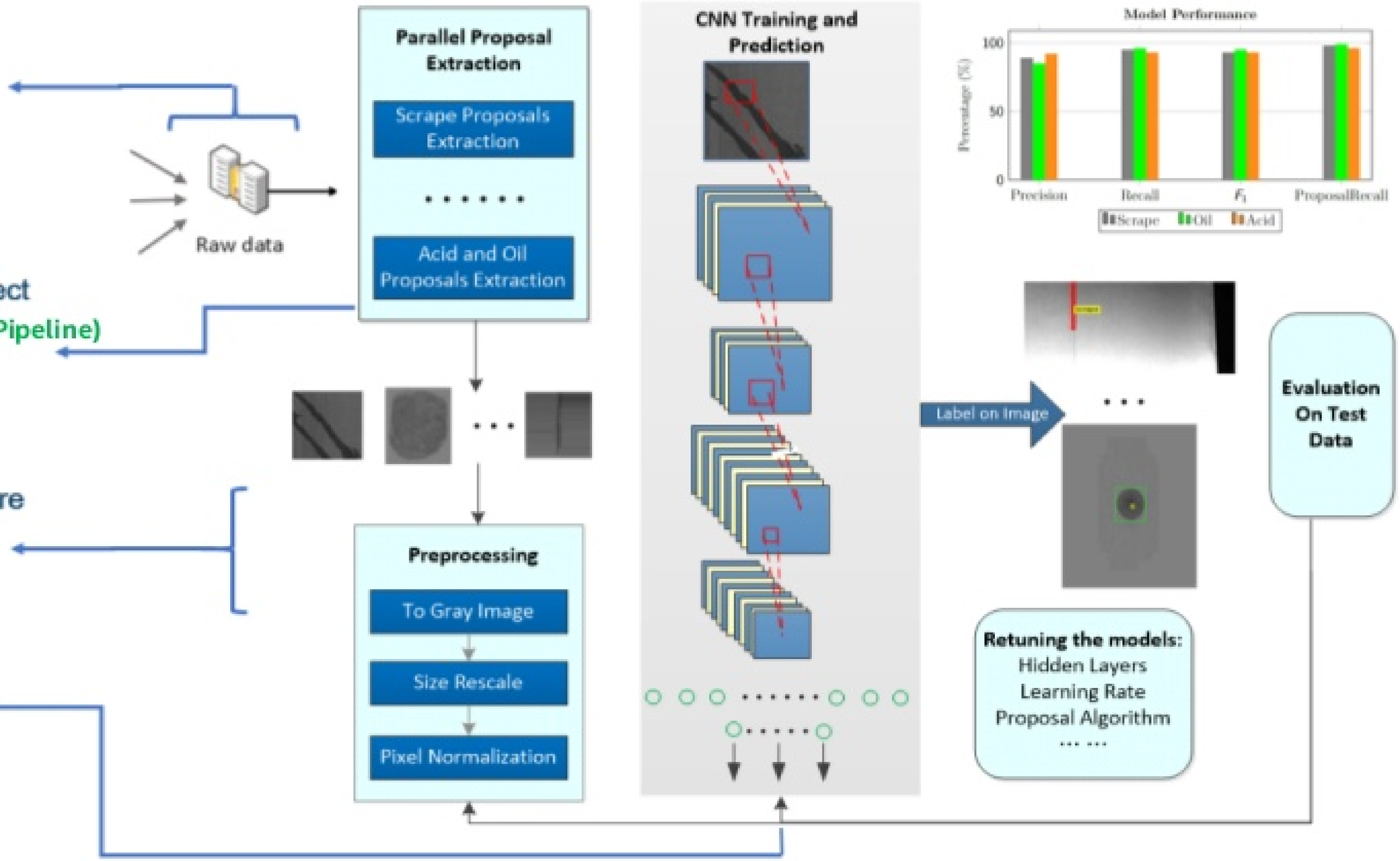
- Extract proposals for each defect
- Parallel pipeline **(KeyStone ML Pipeline)**
- Running **on Spark**

Preprocessing

- Preprocess the proposals before model training or testing

Model training pipeline

- Train ***Convolutional Neural Networks*** **on Spark**
- Parameter tuning, optimize proposal extraction algorithms



BIGDL ON GITHUB

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

Feature Requests

Some feature requests from community

- Mac support
- Python
- LSTM
- …

Feedback or feature requests or PRs are welcome

Community

- Mail List

bigdl-user-group+subscribe@googlegroups.com

- Report bugs and feature request

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

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