Analytics Zoo: Distributed Tensorflow, Keras and BigDL in production on Apache Spark

Jennie Wang, Big Data Technologies, Intel
Agenda

• Motivation
• BigDL
• Analytics Zoo
• Real-world applications
• Conclusion and Q&A
Motivations

Technology and Industry Trends

Real World Scenarios
Trend #1: Data Scale Driving Deep Learning Process

“Machine Learning Yearning”, Andrew Ng, 2016
Trend #2: 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.

Trend #3: 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 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

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

Everyone is building Data Lakes
- 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?

Matthew Glickman, Goldman Sachs
Spark Summit East 2015
Unified Big Data Analytics Platform

Apache Hadoop & Spark Platform

Machine Learning
Batch
Data Processing & Analysis

Graph Analytics
Streaming

SQL
Notebook
Spark Core

ML Pipelines
MLlib
GraphX

SparkR
Stream

YARN
ZooKeeper

Resource Mgmt & Co-ordination

Data Input
Flume
Kafka
Storage
HDFS
Parquet
Avro
HBase

Flink
Storm
MR
Giraph

R
Java
Python

DataFrame

ML Pipelines
MLlib
GraphX

Batch Streaming Interactive

Interactive Machine Learning

Apache Hadoop & Spark Platform

Strata2019
Chasm b/w Deep Learning and Big Data Communities

Deep learning experts

The Chasm

Average users (big data users, data scientists, analysts, etc.)
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
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

Parameter Server Architecture
directly inside Spark (using Block Manager)

1. Worker sends a request to the parameter server.
2. The parameter server sends a partition of the training set to the worker.
3. The worker performs gradient computation on the partition.
4. The worker sends the computed gradient to the parameter server.
5. The parameter server aggregates the gradients from all workers and sends the updated weights back to the workers.

Peer-2-Peer All-Reduce synchronization
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).

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

<table>
<thead>
<tr>
<th>Reference Use Cases</th>
<th>• Anomaly detection, sentiment analysis, fraud detection, image generation, chatbot, etc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-In Deep Learning Models</td>
<td>• Image classification, object detection, text classification, text matching, recommendations, sequence-to-sequence, anomaly detection, etc.</td>
</tr>
</tbody>
</table>
| 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://github.com/intel-analytics/analytics-zoo/)  
[https://analytics-zoo.github.io/](https://analytics-zoo.github.io/)
Analytics Zoo

Use Cases
- Anomaly Detection
- Sentiment Analysis
- Fraud Detection
- Variational Autoencoder (VAE)
- Image Generation
- Object Detection
- Image Classification
- Text Classification
- Recommendation
- Anomaly Detection
- Sequence-to-Sequence
- Web services

High-Level Pipeline APIs
- Distributed Tensorflow
- Keras-like APIs
- DataFrame and ML pipeline support
- Model Serving pipeline

Build-in Deep Learning models
- Object Detection
- Image Classification
- Text Classification
- Recommendation
- Anomaly Detection
- Sequence-to-Sequence

Feature Engineering
- Image
- 3D Image
- Text
- Speech
- Time Series

Backends
- Spark
- Tensorflow
- Keras
- BigDL
- OpenVINO
- MKLDNN
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
• *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*
Analytics Zoo

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Out-of-the-box solutions
• Built-in deep learning models and reference use cases
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 ndarrays
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)
2. Deep learning model development using TensorFlow

```python
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

```python
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))
```

More Examples:


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
Analytics Zoo

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Out-of-the-box solutions
• Built-in deep learning models and reference use cases
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

```python
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

```python
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)
f = Dense(1)(diff)
output = Activation("sigmoid")(f)
model = Model(input, output)
```

Build Siamese Network Using Transfer Learning
Analytics Zoo

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Out-of-the-box solutions
• Built-in deep learning models and reference use cases
1. Initialize **NNContext** and load images into **DataFrames** using **NNImageReader**

```python
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

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

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

```python
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

```python
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

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

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Out-of-the-box solutions
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Working with Image

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

```python
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**

```python
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`

```python
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

```python
transformedTextSet = textSet.tokenize() \n                   .normalize() \n                   .word2idx() \n                   .shapeSequence(len) \n                   .generateSample()
```
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Out-of-the-box solutions
• Built-in deep learning models and reference use cases
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

```python
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
Analytics Zoo

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Out-of-the-box solutions
• Built-in deep learning models and reference use cases
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*

```python
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

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

3. Visualize the results using utility methods

```python
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

encoder = RNNEncoder.initialize(rnn_type, nlayers, hidden_size, embedding)
decoder = 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](https://github.com/intel-analytics/analytics-zoo/tree/master/apps)
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
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 deep 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 servers) as benchmarked by JD

http://mp.weixin.qq.com/s/xUCkzbHK4K06-v5qUsaNQQ
Produce Defect Detection using Distributed TF on Spark in Midea

Produce Defect Detection using Distributed TF on Spark in Midea
NLP Based Customer Service Chatbot for Microsoft Azure

Image Similarity Based House Recommendation for MLSlistings

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

Image Similarity Based House Recommendation for MLSlistings

- RDD of house photos
- Image pre-processing
- Three pre-trained Inception v1 models (fine-tuned as classifiers)
- Image features
- Store image tags and feature in table storage
- Tags (is_exterior, style, floors) of images

- Pre-trained VGG16 model (to extract features)
LSTM-Based Time Series Anomaly Detection for Baosight

Fraud Detection for Payment Transactions for UnionPay

Training Data

- Feature Engineering
- Feature Selection
- Model Training
- Model Evaluation & Fine Tune
- Spark Pipeline
- Spark DataFrame
- Neural Network Model Using BigDL

Hive Table

Pre-processing

Post-processing

Predictions

Test Data

- Pre-processing
- Feature Engineering
- Feature Selection
- Model Ensemble
- Predictions

https://mp.weixin.qq.com/s?__biz=MzI3NDAwNDUwNg==&mid=2648307335&idx=1&sn=8eb9f63eaf2e40e24a90601b9cc03d1f
Unified Analytics + AI Platform
Distributed TensorFlow, Keras and BigDL on Apache Spark

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