Building Deep Learning Applications on Big Data Platform

An Introduction to Analytics Zoo for Apache Spark and BigDL

Jason Dai
Agenda

• Motivation (10 minutes)
  • Trends, real-world scenarios

• DL frameworks on Apache Spark (20 minutes)
  • BigDL, TensorFlowOnSpark, DL Pipelines, SparkNet

• Analytics Zoo for Spark and BigDL (15 minutes)
  • High level pipeline APIs, feature engineering, built-in models, reference use cases

• Analytics Zoo Examples (15 minutes)
  • Dogs vs. cats, object detection, TFNet

• Break (30 minutes)
Agenda

- **Distributed training in BigDL (30 minutes)**
  - Data parallel training, parameter synchronization, scaling & convergence, task scheduling, etc.

- **Advanced applications (15 minutes)**
  - Variational autoencoder, movie recommendations

- **Real-world applications (30 minutes)**
  - Object detection and image feature extraction at JD.com
  - Image similarity based house recommendation for MLSlistings
  - Transfer learning based image classifications for World Bank
  - Fraud detection for payment transactions for UnionPay

- **Conclusion and Q&A (15 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

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?

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

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

An Analogy

First cellular phones  Specialized devices  Unified device (smartphone)

Ion Stoica, UC Berkeley, Spark Summit 2013 Keynote
Unified Big Data Analytics Platform

Apache Hadoop & Spark Platform

- **Data Input**: Flume, Kafka
- **Storage**: HDFS, Parquet, Avro, HBase
- **Resource Mgmt & Co-ordination**: YARN, ZooKeeper
- **Data Processing & Analysis**: Batch, Streaming, Interactive
- **Spark Core**: DataFrame, SQL, SparkR, Streaming, ML Pipelines, MLlib, GraphX
- **Spark Analytics**: Batch, Streaming, Interactive
- **Graph Analytics**: R, Java, Python
- **ML Pipelines**: Flink, Storm, MR, Giraph
- **SQL**: Notebook, Spreadsheet

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CVPR 2018
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
DL Frameworks on Apache Spark

BigDL, DL Pipelines for Spark, TensorflowOnSpark, SparkNet, etc.
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
• 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

Parameter Server Architecture
directly inside Spark (using Block Manager)

Training Set
Peer-2-Peer All-Reduce synchronization
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
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
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
Analytics + AI Platform for Spark and BigDL

https://github.com/intel-analytics/analytics-zoo
# Analytics Zoo

## Build and Productionize Deep Learning Apps for Big Data at Scale

### Reference Use Cases
- Anomaly detection
- Sentiment analysis
- Fraud detection
- Chatbot, sequence prediction, etc.

### Built-In Deep Learning Models
- Image classification
- Object detection
- Text classification
- Recommendations
- Sequence-to-sequence, GAN, etc.

### Feature Engineering
- Feature transformations for
  - Image, text, 3D imaging, time series, speech, etc.

### High-Level Pipeline APIs
- Native deep learning support in Spark DataFrames and ML Pipelines
- Autograd, Keras and transfer learning APIs for model definition
- Model serving API for model serving/inference pipelines

### Backends
- Spark, BigDL, TensorFlow, 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

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

• E2E analytics + AI pipelines (natively in Spark DataFrames and ML Pipelines) using nnframes
• Flexible model definition using autograd, Keras-style & transfer learning APIs
• Data preprocessing using built-in feature engineering operations
• Out-of-the-box solutions for a variety of problem types using built-in deep learning models and reference use cases

Productionize deep learning applications for big data at scale

• Serving models in web services and big data frameworks (e.g., Storm or Kafka) using POJO model serving APIs
• Large-scale distributed TensorFlow model inference using TFNet
Analytics Zoo

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nnframes

Native DL support in Spark DataFrames and ML Pipelines

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

3. Processing image using built-in feature engineering operations
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
Estimator = NNEstimator(model, CrossEntropyCriterion(), transformer) \ 
    .setLearningRate(0.003).setBatchSize(40).setMaxEpoch(1) \ 
    .setFeaturesCol("image").setCachingSample(False)
nnModel = estimator.fit(df)
```
Analytics Zoo

Build end-to-end deep learning applications for big data
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- Data preprocessing using built-in feature engineering operations
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Productionize deep learning applications at scale for big data
- Serving models in web services and big data frameworks (e.g., Storm or Kafka) using POJO model serving APIs
- Large-scale distributed TensorFlow model inference using TFNet
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']).to_keras()
# 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
2. **Use autograd and Keras-style 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)
f2 = Dense(1)(diff)
output = Activation("sigmoid")(f2)
model = Model(input, output)
```
Analytics Zoo

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

• E2E analytics + AI pipelines (natively in Spark DataFrames and ML Pipelines) using nnframes
• Flexible model definition using autograd, Keras-style & transfer learning APIs
• **Data preprocessing** using built-in *feature engineering operations*
• Out-of-the-box solutions for a variety of problem types using built-in deep learning models and reference use cases

Productionize deep learning applications at scale for big data

• Serving models in web services and big data frameworks (e.g., Storm or Kafka) using POJO model serving APIs
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Feature Engineering

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)
Analytics Zoo

Build end-to-end deep learning applications for big data
• E2E analytics + AI pipelines (natively in Spark DataFrames and ML Pipelines) using nnframes
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• Out-of-the-box solutions for a variety of problem types using built-in deep learning models and reference use cases

Productionize deep learning applications at scale for big data
• Serving models in web services and big data frameworks (e.g., Storm or Kafka) using POJO model serving APIs
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Built-in Deep Learning Models

- **Object detection API**
  - High-level API and pretrained models (e.g., SSD, Faster-RCNN, etc.) for object detection

- **Image classification API**
  - High-level API and pretrained models (e.g., VGG, Inception, ResNet, MobileNet, etc.) for image classification

- **Text classification API**
  - High-level API and pre-defined models (using CNN, LSTM, etc.) for text classification

- **Recommendation API**
  - High-level API and pre-defined models (e.g., Neural Collaborative Filtering, Wide and Deep Learning, etc.) for recommendation
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**

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

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

Build end-to-end deep learning applications for big data
• E2E analytics + AI pipelines (natively in Spark DataFrames and ML Pipelines) using nnframes
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• Data preprocessing using built-in feature engineering operations
• Out-of-the-box solutions for a variety of problem types using built-in deep learning models and reference use cases

Productionize deep learning applications at scale for big data
• Serving models in web services and big data frameworks (e.g., Storm or Kafka) using POJO model serving APIs
• Large-scale distributed TensorFlow model inference using TFNet
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());
            ...
        }
    }
}
Model Serving & Inference

Seamless integration in Web Services, Storm, Flink, Kafka, etc. (using POJO local Java APIs)
Seamless support of DL functionalities in Spark SQL queries, Dataframe operation and stream processing.
Analytics Zoo

Build end-to-end deep learning applications for big data
- E2E analytics + AI pipelines (natively in Spark DataFrames and ML Pipelines) using nnframes
- Flexible model definition using autograd, Keras-style & transfer learning APIs
- Data preprocessing using built-in feature engineering operations
- Out-of-the-box solutions for a variety of problem types using built-in deep learning models and reference use cases

Productionize deep learning applications at scale for big data
- Serving models in web services and big data frameworks (e.g., Storm or Kafka) using POJO model serving APIs
- Large-scale distributed TensorFlow model inference & fine tuning using TFNet
1. Export TensorFlow models (in your TensorFlow program)

```python
import tensorflow as tf

batch_size_tensor = tf.placeholder_with_default(128, shape=[])  
x_batch, y_batch = tf.train.shuffle_batch(..., batch_size=batch_size_tensor, ...)

sess = tf.Session()
init_op = tf.group(tf.global_variables_initializer(), tf.local_variables_initializer())
sess.run(init_op)
for step in range(600):
    _, loss = sess.run([cnn.train_op, cnn.loss], ...)

from zoo.utils.tf import *
export_tf(sess, folder_path, [x_batch], [cnn.prediction])
```
Distributed TensorFlow Model Inference

2. Load exported TensorFlow model into Analytics Zoo

```python
from zoo.pipeline.api.net import *
model = TFNet.from_export_folder(folder_path)

# Alternatively, you may directly load a frozen TensorFlow model as follows
# model = TFNet(model_path, ["image_tensor:0"], ["output_tensor:0"])
```

3. Add a few layers and run distributed model inference

```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=model)(input)
f1 = features.index_select(1, 0)
f2 = features.index_select(1, 1)
diff = A.abs(f1 - f2)
result = Model(input, diff)
result.predict_image_set(...)```
Analytics Zoo Examples

Dogs vs. cats, object detections, TFNet
Dogs vs. Cats

Notebook:
Object Detection API

Notebook:
Image Classification Using TFNet

Notebook:
Break
Distributed Training In BigDL

Data parallel training
Parameter synchronization
Scaling and Convergence
Task scheduling

Apache Spark

Single master (driver), multiple workers
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

Task 1: Sample RDD

Task 2: Model RDD

Task n: zip Sample and model RDDs, and compute gradient on co-located Sample and model partitions

“Model Forward-Backward” Job
Parameter Synchronization

local gradient

1 2 n

gradient 1

weight 1

Task 1

update

“Parameter Synchronization” Job

1 2 n

gradient 2

weight 2

Task 2

update

1 2 n

gradient n

weight n

Task n

update
For each task $n$ in the "parameter synchronization" job {
    shuffle the $n^{th}$ partition of all gradients to this task
    aggregate (sum) the gradients
    updates the $n^{th}$ partition of the weights
    broadcast the $n^{th}$ 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).

Increased Mini-Batch Size

- Distributed synchronous mini-batch SGD
  - Increased mini-batch size
    \[ \text{total\_batch\_size} = \text{batch\_size\_per\_worker} \times \text{num\_of\_workers} \]
  - 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

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)
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

Advanced Analytics Zoo Applications

Variational autoencoder, movie recommendations
Variational AutoEncoder

Notebook:


Movie Recommendations

**Notebook:**

Real-World Applications

Object detection and image feature extraction at JD.com

Image similarity based house recommendation for MLSlisting

Transfer learning based image classifications for World Bank

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
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)
Image Similarity Based House Recommendation for MLSlistings

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

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Cores</th>
<th>Batch Size</th>
<th>Epochs</th>
<th>Training Time (sec)</th>
<th>Throughput (images/sec)</th>
<th>Accuracy (%)</th>
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<td>30</td>
<td>1200</td>
<td>12</td>
<td>61125</td>
<td>170</td>
<td>81.7</td>
</tr>
</tbody>
</table>

* 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
Fraud Detection for Payment Transactions for UnionPay

Training Data

**Spark Pipeline**

1. **Feature Engineering**
2. **Feature Selection** (optional)
3. **Model Training**
4. **Model Evaluation & Fine Tune**
5. **Predictions**

**Pre-Processing**

- **Hive Table**
- **Spark DataFrame**

**Post-Processing**

- **Neural Network Model Using BigDL**

**Test Data**

- **Test**

**URL:**

https://mp.weixin.qq.com/s?__biz=MzI3NDAwNDUwNg==&mid=2648307335&idx=1&sn=8eb9f63eaf2e40e24a90601b9cc03d1f
Fraud Detection for Payment Transactions for UnionPay

Notebook:

Summary

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

- 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, managed and monitored with other workloads (ETL, data warehouse, traditional ML, etc.)

Analytics Zoo: [https://github.com/intel-analytics/analytics-zoo](https://github.com/intel-analytics/analytics-zoo)

- End-to-end Analytics + AI platform for Apache Spark and BigDL
- Build and productionize deep learning application for Big Data at Scale
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