Using Crowdsourced Images to Create Image Recognition Models with Analytics Zoo using BigDL

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#DL8SAIS

Agenda

- Use Case Overview
- Solution Architecture
- Model Development and Results
- Next Steps
- Summary

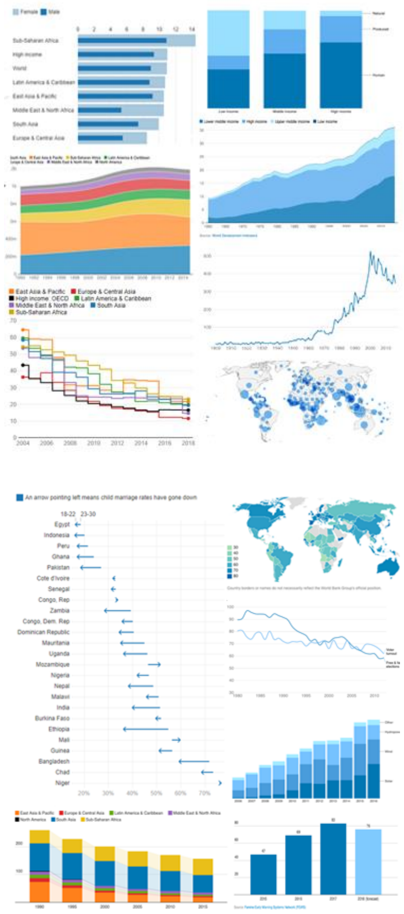
Use Case Overview

World Bank

The World Bank is a vital source of financial and technical assistance to developing countries around the world. It is not a bank in the ordinary sense but a unique partnership to reduce poverty and support development. The World Bank Group comprises five institutions managed by their member countries.

Established in 1944, the **World Bank Group** is headquartered in Washington, D.C. It has more than 10,000 employees in more than 120 offices worldwide.

The Development Data Group provides high-quality national and international statistics to clients within and outside the World Bank and to improve the capacity of member countries to produce and use statistical information.



Problem Statement

- The International Comparison Program team in the World Bank Development Data Group collected crowdsourced images for a pilot data collection study through a privately-operated network of paid on-the-ground contributors that had access to a smartphone and a data collection application designed for the pilot.
- Nearly 3 million labeled images were collected as ground truth/metadata attached to each price observation of 162 tightly specified items for a variety of household goods and services. The use of common item specifications aimed at ensuring the quality, as well as intra- and inter-country comparability, of the collected data.
- **Goal** is to reduce labor intensive tasks of manually moderating (reviewing, searching and sorting) the crowd-sourced images before their release as a public image dataset that could be used to train various deep learning models.

Our Challenges

- Crowdsourced images are of different quality (resolution, close-up, blur, etc.)
- Crowdsourced images are not very focused.(Multiple items, item is small, etc.)
- Some images are possibly corrupted (cannot be resized or transformed)
- Images sourced from 15 different countries – different language groups represented in the text example of images
- Some text is typed, some text is handwritten

Classifying Real Food Images is not a Cat vs Dog Problem

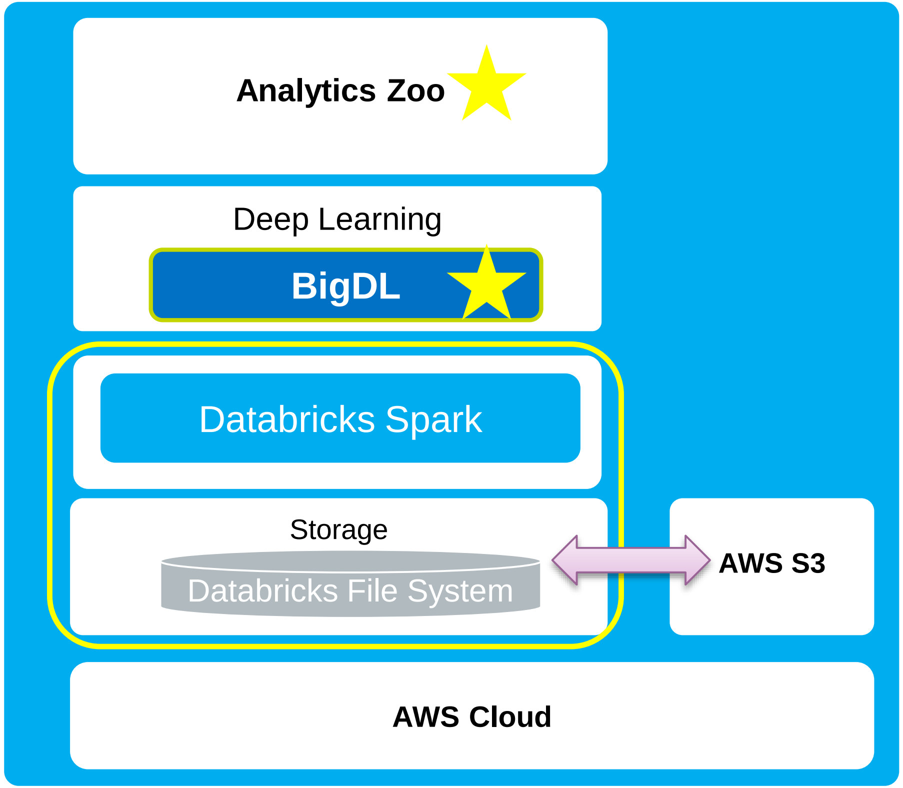
Project Layout

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

Solution Architecture

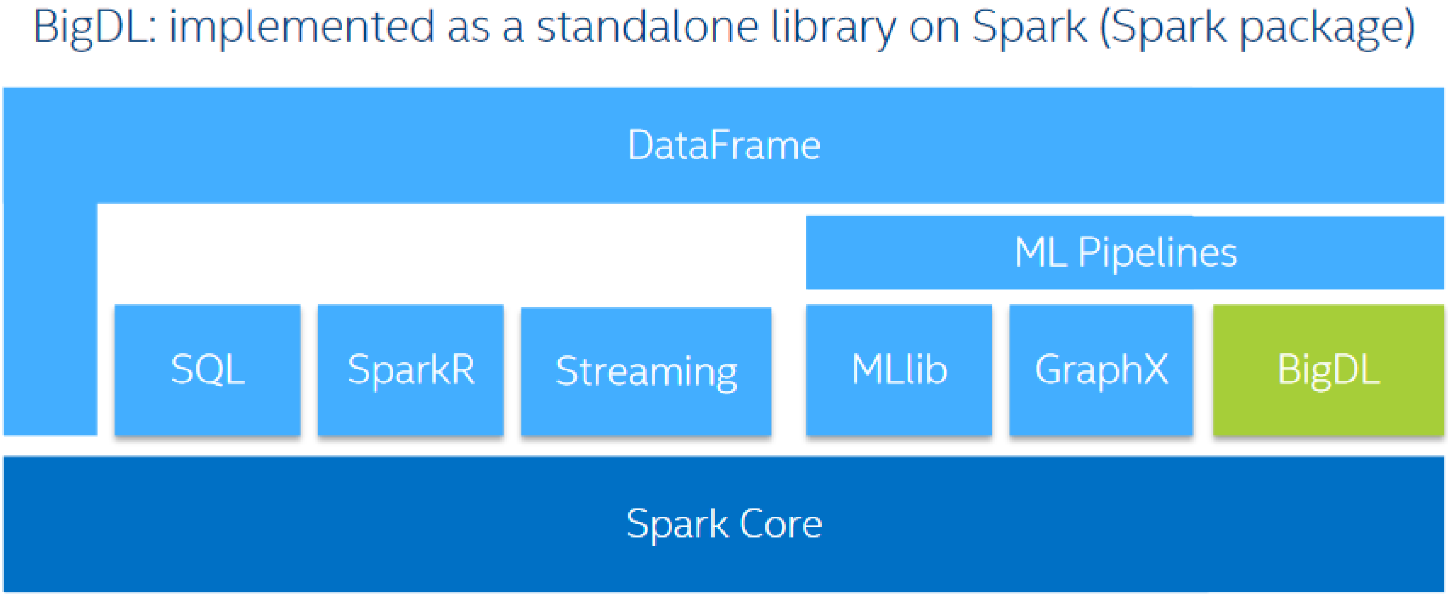
Solution Architecture



- BigDL 0.5
- Databricks Spark
- AWS S3
- AWS R4 instance

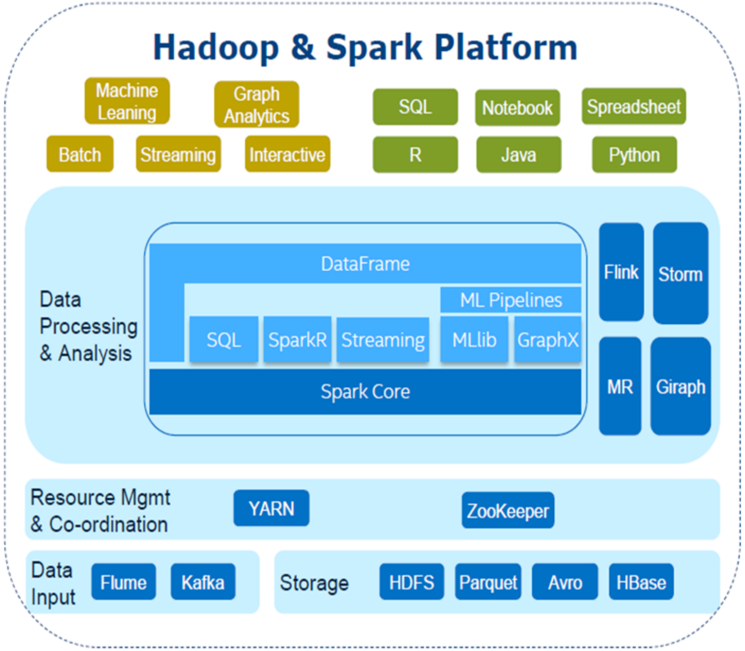
What is BigDL?

BigDL is a distributed deep learning library for Apache Spark*



BigDL is Designed for Big Data

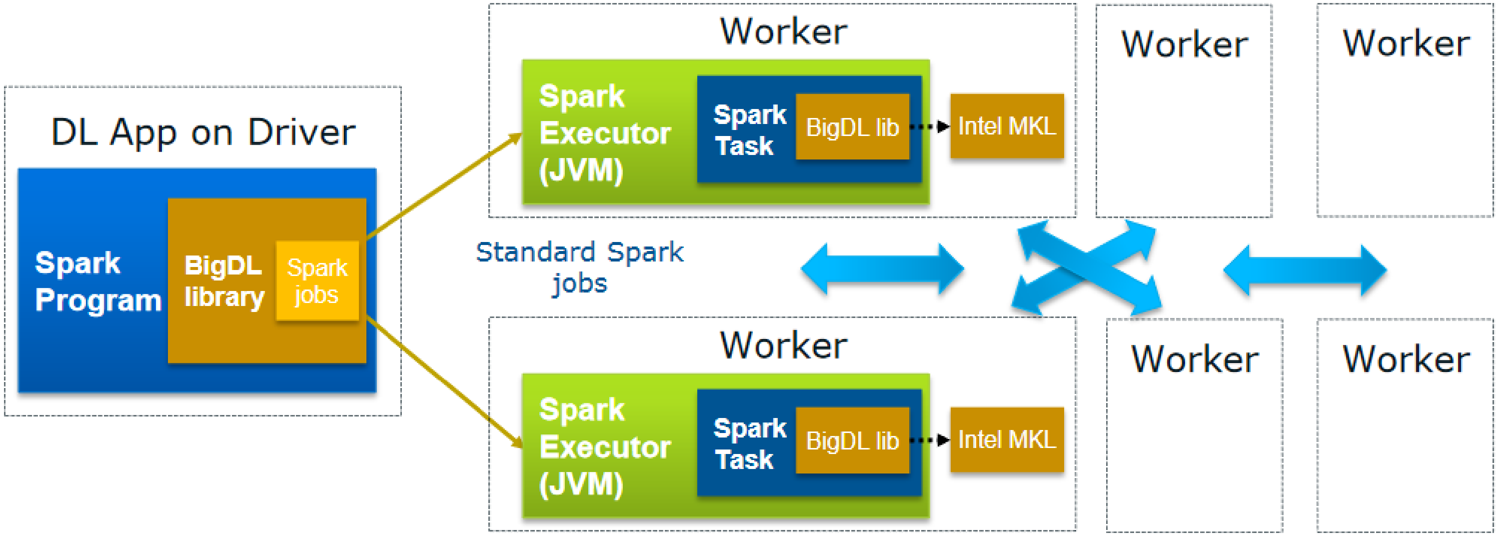
- Distributed deep learning framework for Apache Spark
- Make deep learning more accessible to big data users and data scientists
  - Write deep learning applications as ***standard Spark programs***
  - Run on existing Spark/Hadoop clusters (***no changes needed***)
- Feature parity with popular deep 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



BigDL as a Standard Spark Program

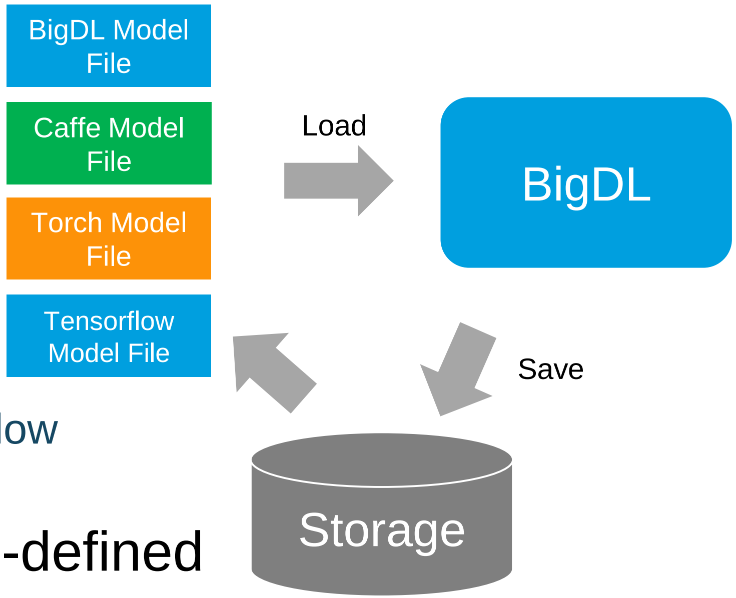
Distributed Deep learning applications (training, fine-tuning & prediction) on Apache Spark*

- No changes to the existing Hadoop/Spark clusters needed



Models Interoperability Support

- Model Snapshot
  - Long training work checkpoint
  - Model deployment and sharing
  - Fine-tune
- Caffe/Torch/Tensorflow Model Support
  - Model file load
  - Easy to migrate your Caffe/Torch/Tensorflow work to Spark
- NEW - BigDL supports loading pre-defined Keras models (Keras 1.2.2)



BigDL: Python API

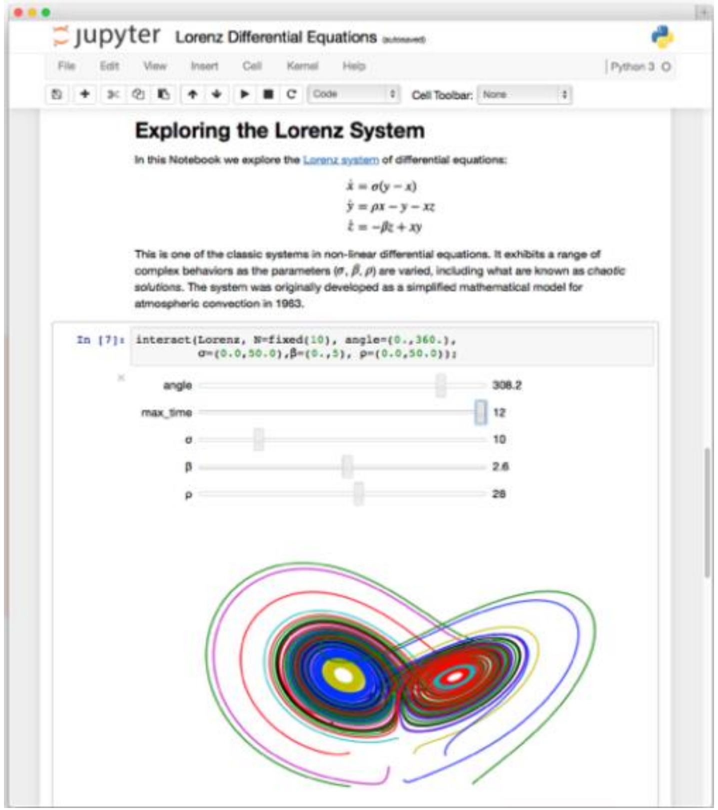
- Support deep learning model training, evaluation, inference
- Support Spark v1.5/1.6/2.X
- Support **Python 2.7/3.5/3.6**
- Based on PySpark, **Python API** in BigDL allows use of existing Python libs (Numpy, Scipy, Pandas, Scikit-learn, NLTK, Matplotlib, etc)

```
train_data = get_minst("train").map(
    normalizer(mnist.TRAIN_MEAN, mnist.TRAIN_STD))
test_data = get_minst("test").map(
    normalizer(mnist.TEST_MEAN, mnist.TEST_STD))
state = {"batchSize": int(options.batchSize),
         "learningRate": 0.01,
         "learningRateDecay": 0.0002}
optimizer = Optimizer(
    model=build_model(10),
    training_rdd=train_data,
    criterion=ClassNLLCriterion(),
    optim_method="SGD",
    state=state,
    end_trigger=MaxEpoch(100))
optimizer.setvalidation(
    batch_size=32,
    val_rdd=test_data,
    trigger=EveryEpoch(),
    val_method=["top1"]
)
optimizer.setcheckpoint(EveryEpoch(), "/tmp/lenet5/")
trained_model = optimizer.optimize()
```

Works with Interactive Notebooks

Running BigDL applications directly in Jupyter, Zeppelin, Databricks notebooks, etc.

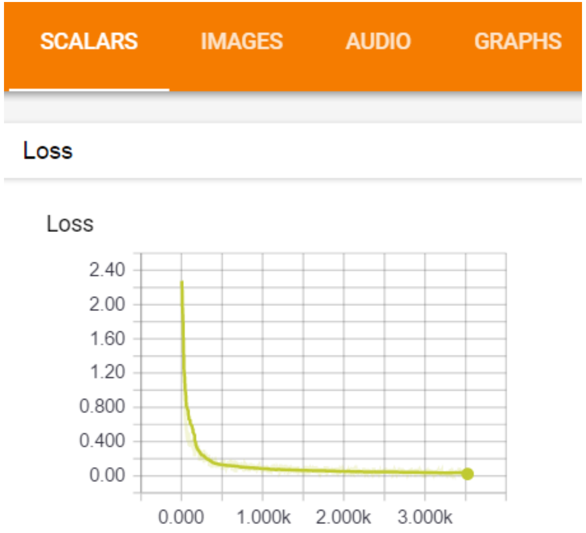
- ✓ Share and Reproduce
  - Notebooks can be shared with others
  - Easy to reproduce and track
- ✓ Rich Content
  - Texts, images, videos, LaTeX and JavaScript
  - Code can also produce rich contents
- ✓ Rich toolbox
  - Apache Spark, from Python, R and Scala
  - Pandas, scikit-learn, ggplot2, dplyr, etc

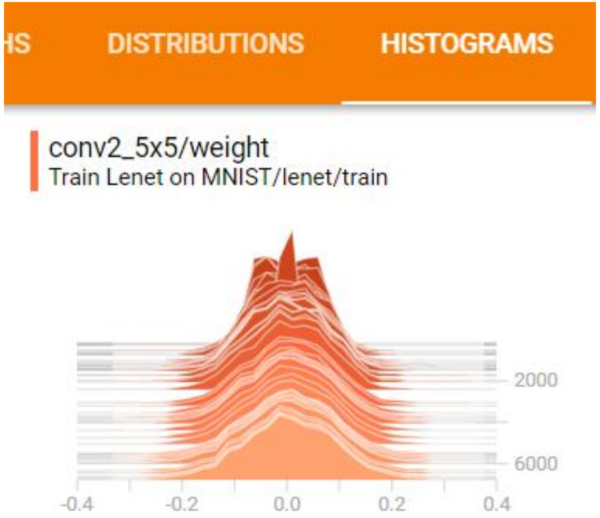


Visualization for Learning

BigDL integration with TensorBoard

- TensorBoard is a suite of web applications from Google for visualizing and understanding deep learning applications





Analytics Zoo

Analytics + AI Pipelines for Spark and BigDL

“Out-of-the-box” ready for use

- Reference use cases
  - Fraud detection, time series prediction, sentiment analysis, chatbot, etc.
- Predefined models
  - Object detection, image classification, text classification, recommendations, etc.
- Feature transformations
  - Vision, text, 3D imaging, etc.
- High level APIs
  - DataFrames, ML Pipelines, Keras/Keras2, etc.

Model Development & Results

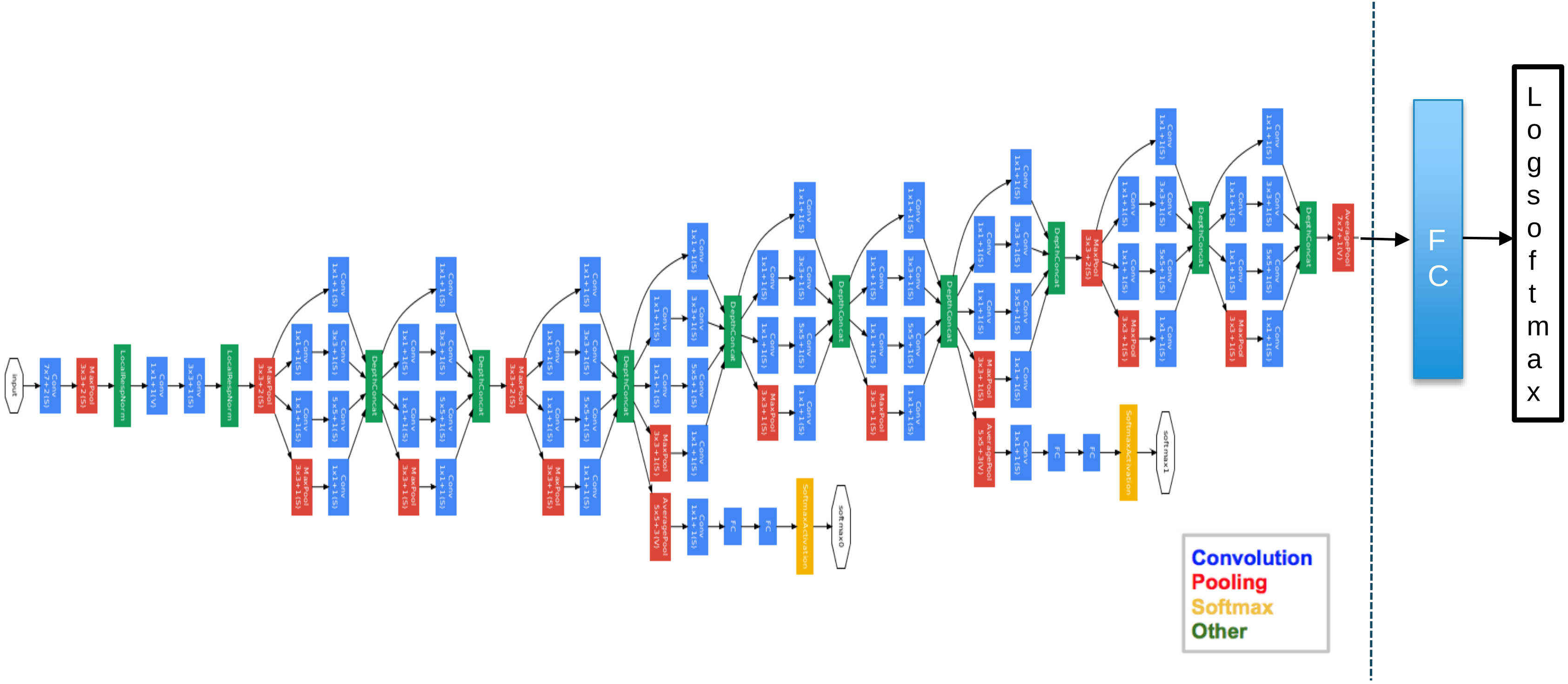
Model Development - Phase 1

- Transfer learning/Fine tuning from pre-trained Inception model to do classification
- Load pre-trained Inception-v1 model to BigDL
- Add FC layer with SoftMax classifier
- Train on partial dataset with pre-trained weights using Analytics Zoo on Spark Cluster
- Scale training on multi-node cluster in AWS Databricks to train large whole dataset (1M images)

Model Development - Phase 1

Inception v1

Customized Classifier



Code- Phase 1

Transfer Learning Training

Cmd 32

```
# get embedding
pretrained_model_path = path.join(MODEL_ROOT,"bigdl_inception_v1_imagenet_0_4_0.model")
n_classes = len(label_dict)# label categories
preTrainedNNModel = NNModel(Model.loadModel("dbfs:" + pretrained_model_path), train_transformer)\
.setFeaturesCol("image")\
.setPredictionCol("embedding")\
.setBatchSize(batch_size)

train_embedding = preTrainedNNModel.transform(train_image)
val_embedding = preTrainedNNModel.transform(val_image)

# train transfered model
lrModel = Sequential().add(Linear(1000, n_classes)).add(LogSoftMax())
classifier = NNClassifier(lrModel, ClassNLLCriterion(), SeqToTensor([1000]))\
.setLearningRate(learning_rate)\
.setBatchSize(batch_size)\
.setMaxEpoch(no_epochs)\
.setFeaturesCol("embedding")\
.setValidation(EveryEpoch(), val_embedding, [Top1Accuracy()], batch_size)

start = time.time()
trained_model = classifier.fit(train_embedding)
end = time.time()
print("Optimization Done.")
print("Training time is: %s seconds" % str(end-start))
```

Predict and Evaluation

```
#predict
test_embedding = preTrainedNNModel.transform(test_image)
predict_model = trained_model.setBatchSize(batch_size)
predictionDF = predict_model.transform(test_embedding)
predictionDF.show()
```

Cmd 37

```
'''
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)
```

Code- Phase 1

Fine Tune 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")
```

Predict 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()
```

Results - Phase 1

- Training from scratch vs Transfer Learning vs Fine Tuning (on a partial dataset)
- Dataset: 1927 images, 9 categories

Training Type	Epochs	Training Time (sec)	Accuracy (%)
Training from scratch	40	1266	23.9
Transfer Learning	40	210	65.4
Fine Tuning	15	489	81.5

** Accuracy numbers are in that range due to a small part of dataset being used*

Results - Phase 1

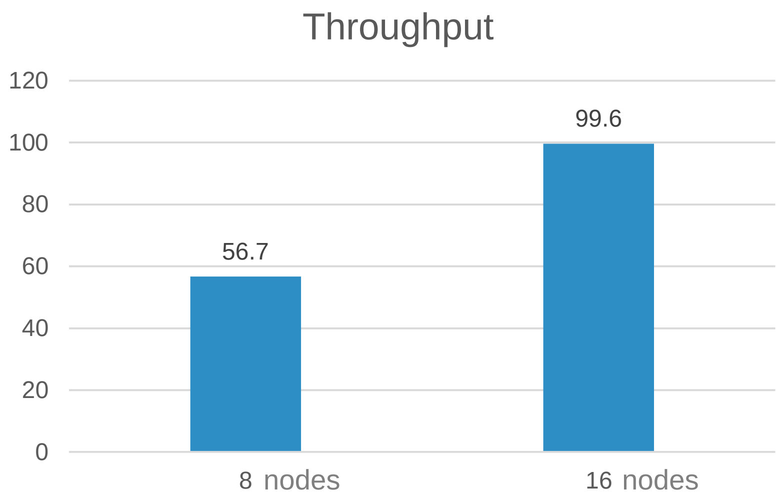
- Fine tune with Inception v1 on a full dataset
- Dataset: 994325 images, 69 categories

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

Scaling Results - Phase 1

Nodes	Batch Size	Epochs	Through put	Training Time
8	256	20	56.7	745.6
16	256	20	99.6	424.7
8	128	20	55.3	764.9
16	128	20	80.7	524.4



Scaling test was run on AWS R4 instance that include the following features:

- dual socket Intel Xeon E5 Broadwell processors (2.3 GHz)
- DDR4 memory
- Hardware Virtualization (HVM) only

Model	vCPUs	Memory (GiB)	Networking Performance
r4.xlarge	4	30.5	Up to 10 Gigabit

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
  - Reference model:
    - Object Detection (Fast-RCNN, SSD)
    - Tesseract(https://github.com/tesseract-ocr/tesseract)
    - CTPN(https://github.com/tianzhi0549/CTPN)

Next Steps – Phase 2

- Recognize text
  - Tesseract (https://github.com/tesseract-ocr/tesseract)
  - CRNN (https://github.com/bgshih/crnn)
- Determine whether text contains PII (personal identifiable information)
  - Recognize PII with leading words (RNN)
- Blur areas with PII text
  - Image tools

Summary

Key Takeaways

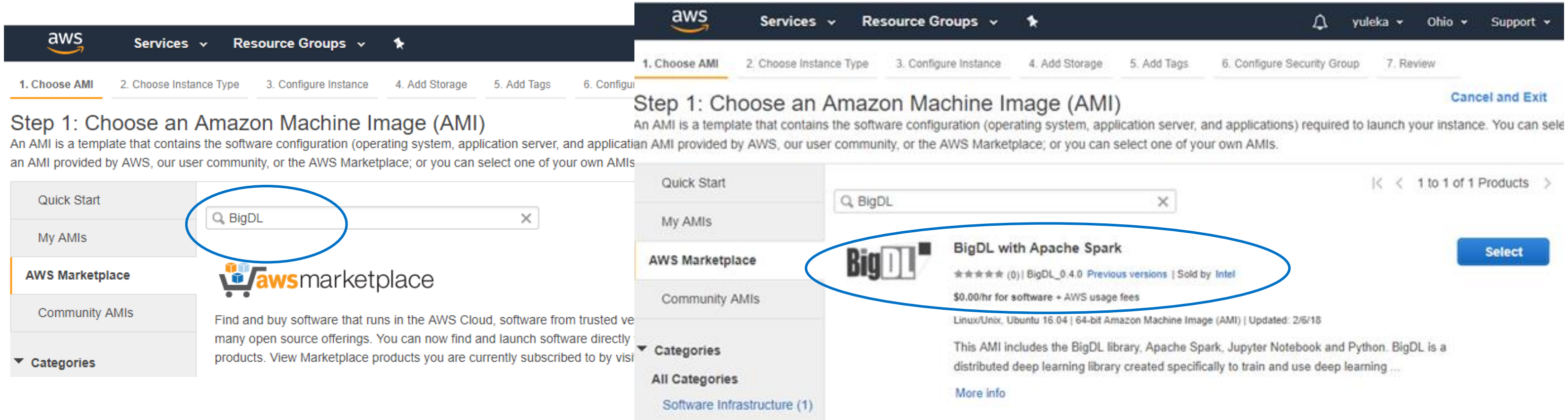
- AI on Apache Spark is a reality with use cases like World Bank
- BigDL makes distributed deep learning and AI more accessible both for big data users and data scientists
- Analytics Zoo provide high level APIs more accessible to Data Scientists and Spark Users (Keras, Spark DataFrame, etc.)
- BigDL can leverage on existing Spark/Hadoop infrastructure and also runs deep learning applications in the cloud (AWS, Azure, GCP, …)
- Join in and contribute to projects:

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

BigDL: github.com/intel-analytics/BigDL

Call to Action

- Try BigDL on AWS - lookup BigDL AMI on AWS Marketplace



- Try image classification with Analytics Zoo using BigDL– this use case code is shared on https://github.com/intel-analytics/WorldBankPoC

Questions?

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