Distributed Deep Learning Framework for Big Data

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Research Area

- Applying deep learning to production big data pipelines
- Integrating deep learning with big data analytics workflows

Problem Statement

- Deep learning solutions separate from big data platforms
- Causes inefficiencies in data transfer, development, deployment
- Impedance mismatch between deep learning and big data systems

Objective

- Develop unified framework for distributed deep learning and big data analytics
- Enable efficient end-to-end data pipelines for production data

Methodology - Distributed Deep Learning on Spark

- Open source library on top of Apache Spark
- Unified API for deep learning model development
- Large-scale distributed training and inference on Spark clusters

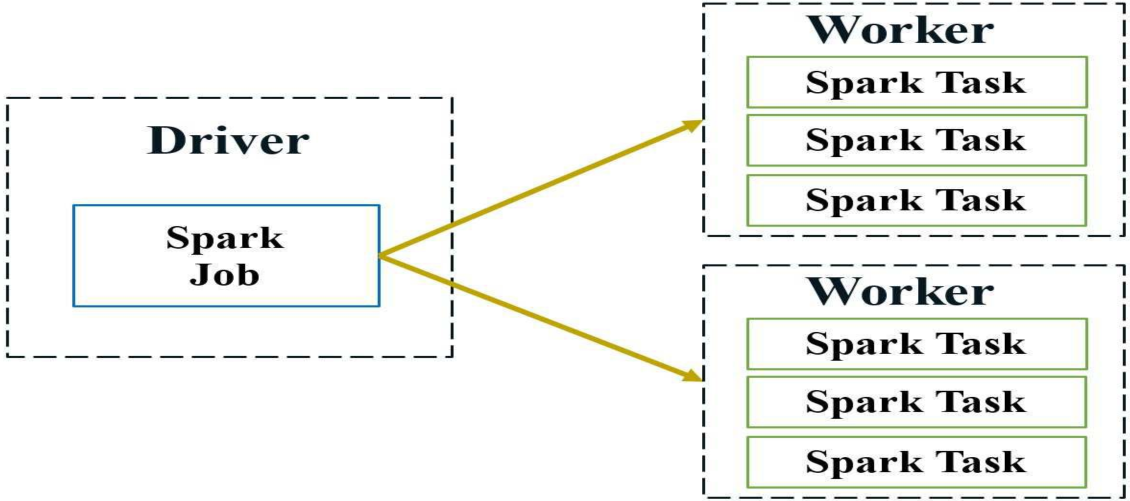
End to End classification pipeline on spark-bigDL

```
#distributed data processing
spark = SparkContext(appName="text_classifier", ...)
input_rdd = spark.textFile("hdfs://...")
train_rdd = input_rdd.map(lambda x: read_text_and_label(x))
                     .map(lambda data: decode_to_ndarrays(data))
                     .map(lambda arrays: to_sample(arrays))

#distributed training
model = Sequential().add(Recurrent().add(LSTM(...)))
                    .add(Linear(...)).add(LogSoftMax())
optimizer = Optimizer(model=model, training_rdd=train_rdd,
                      criterion=ClassNLLCriterion(),
                      optim_method=Adagrad(), ...)
trained_model = optimizer.optimize()

#distributed inference
test_rdd = ...
prediction_rdd = trained_model.predict(test_rdd)
```

Execution Model - Spark



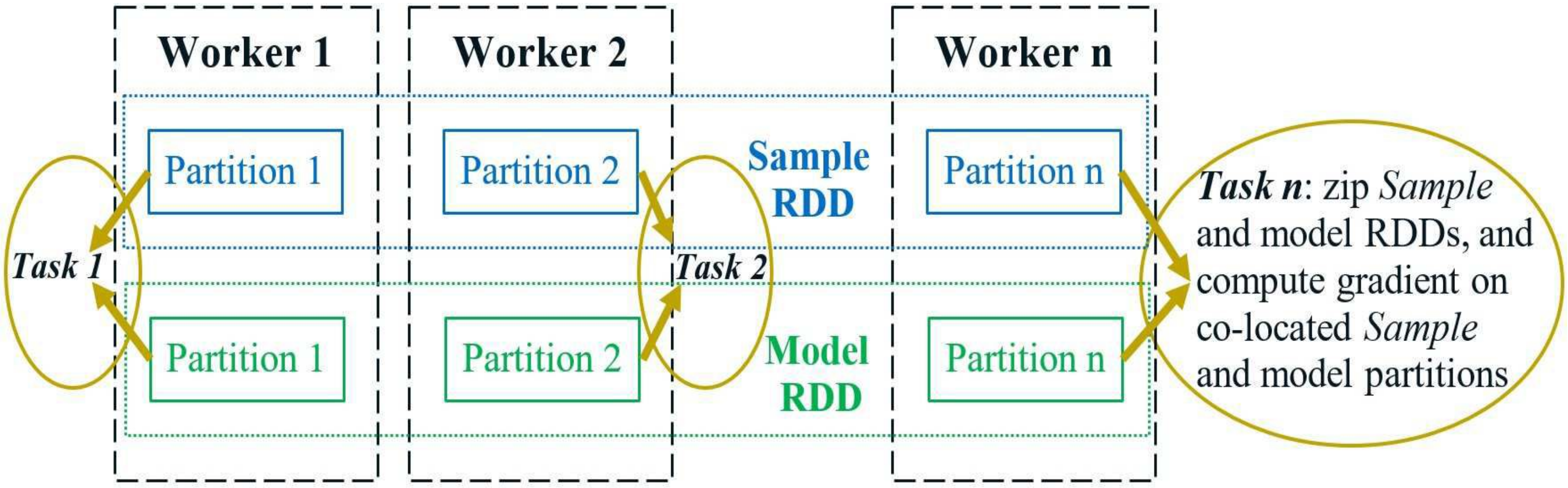
BigDL algo in the works (pseudocode)

Algorithm 1 Data-parallel training in BigDL
1: for i = 1 to M do
2: //"model forward-backward" job
3: for each task in the Spark job do
4: read the latest weights;
5: get a random batch of data from local Sample partition;
6: compute local gradients (forward-backward on local model replica);
7: end for
8: //"parameter synchronization" job
9: aggregate (sum) all the gradients;
10: update the weights per specified optimization method;
11: end for

Data Parallel Training in Big DL

- Iterative process of compute gradients and update parameters
- Co-partitioned and co-located RDDs for models and data
- Parallel gradient computation using Spark tasks

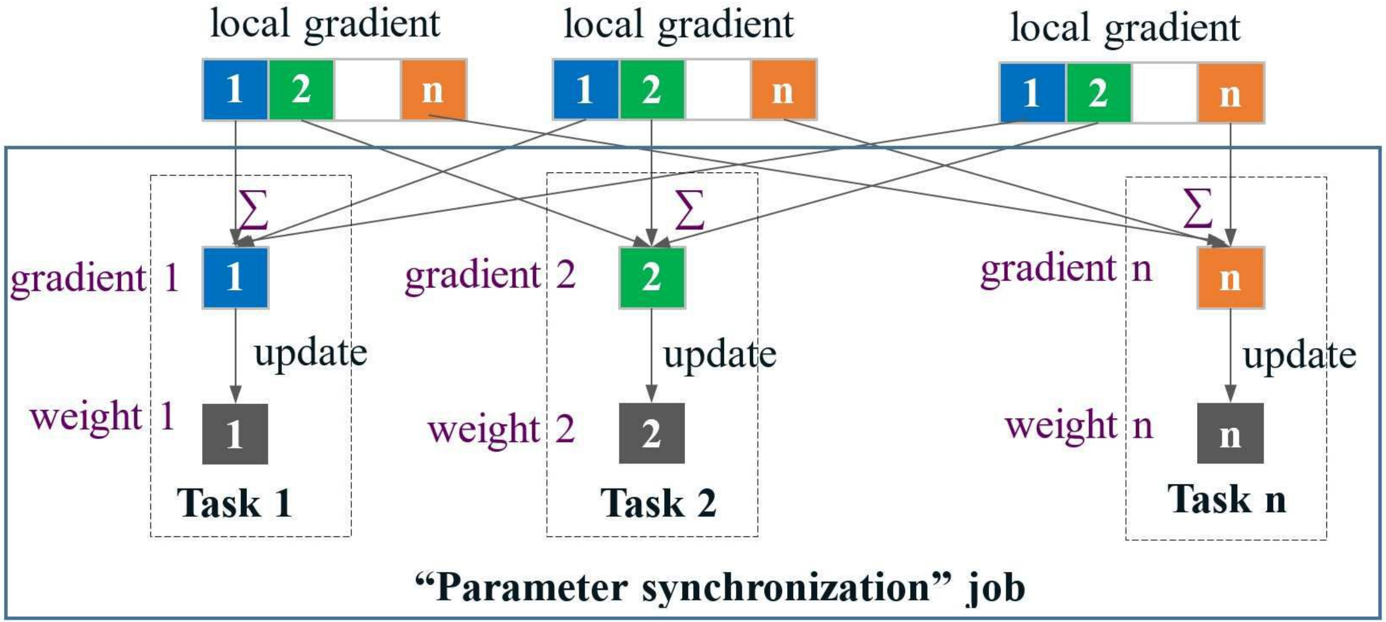
Forward Backward Model for Gradient Computation



Parameter Sync

- Implements AllReduce using Spark primitives (shuffle, broadcast)
- Mimic parameter server architecture in a different way

Parameter Sync Job



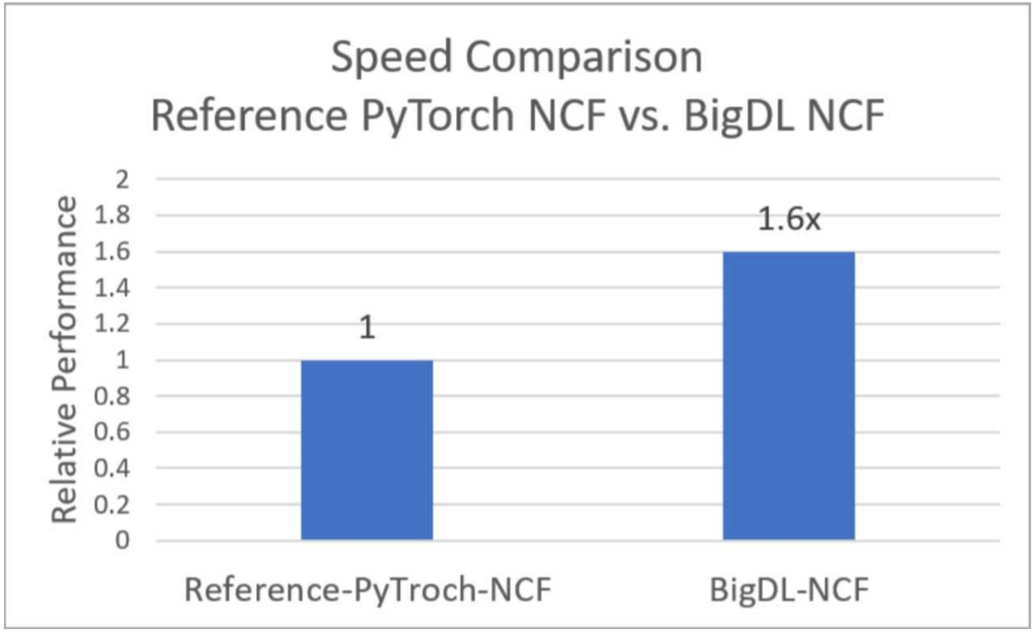
Discussions

- Alternative design for distributed training
- Handles failures, resource changes efficiently
- Logically centralized control with stateless tasks

Experiment Setup

- Neural Collaborative Filtering (NCF)
- Convolutional Neural Networks (CNNs) - Inception-v1 on ImageNet

NCF Performance



NCF Training Performance

- 1.6x faster than PyTorch implementation on Nvidia P100 GPU
- Evaluated on single Intel Xeon server

Inception Scalability

Scalability of Inception-v1 Training

- Efficient parameter sync overheads (<7% on 32 nodes)
- Near linear scaling up to 96 nodes, reasonable up to 256 nodes

Efficiency of Task Scheduling

- Launching large number of short tasks can be a bottleneck
- Group scheduling in Drizzle reduces overheads significantly

Drizzle , a
low latency execution engine for Spark, can help schedule multiple iterations (or a group) of computations at once, so as to greatly reduce scheduling overheads even if there are a large number of tasks in each iteration

BigDL with Drizzle lib

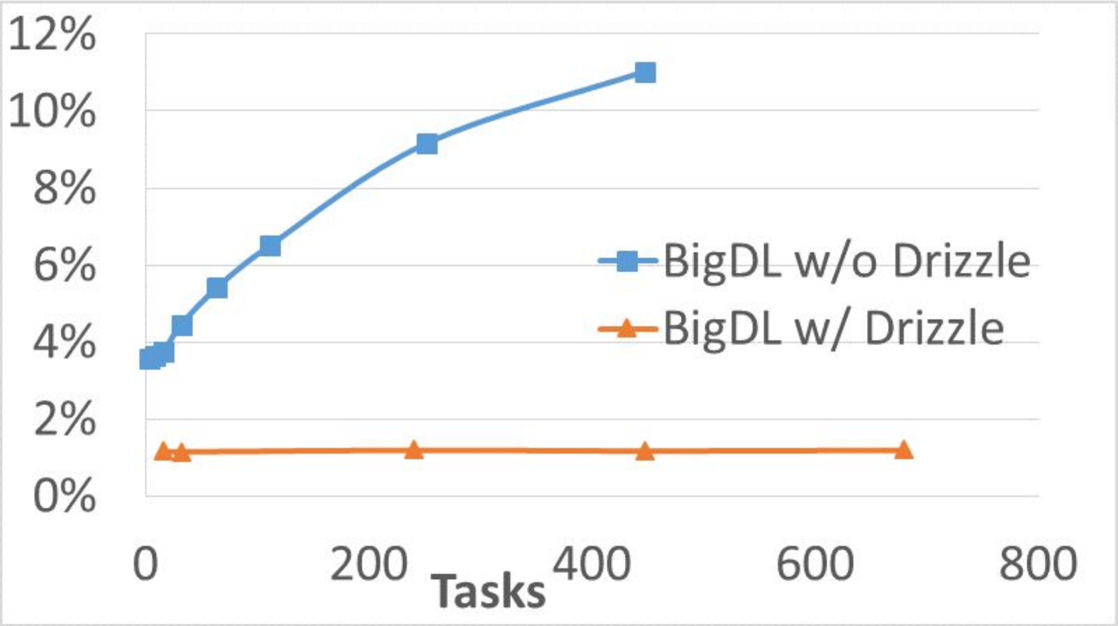
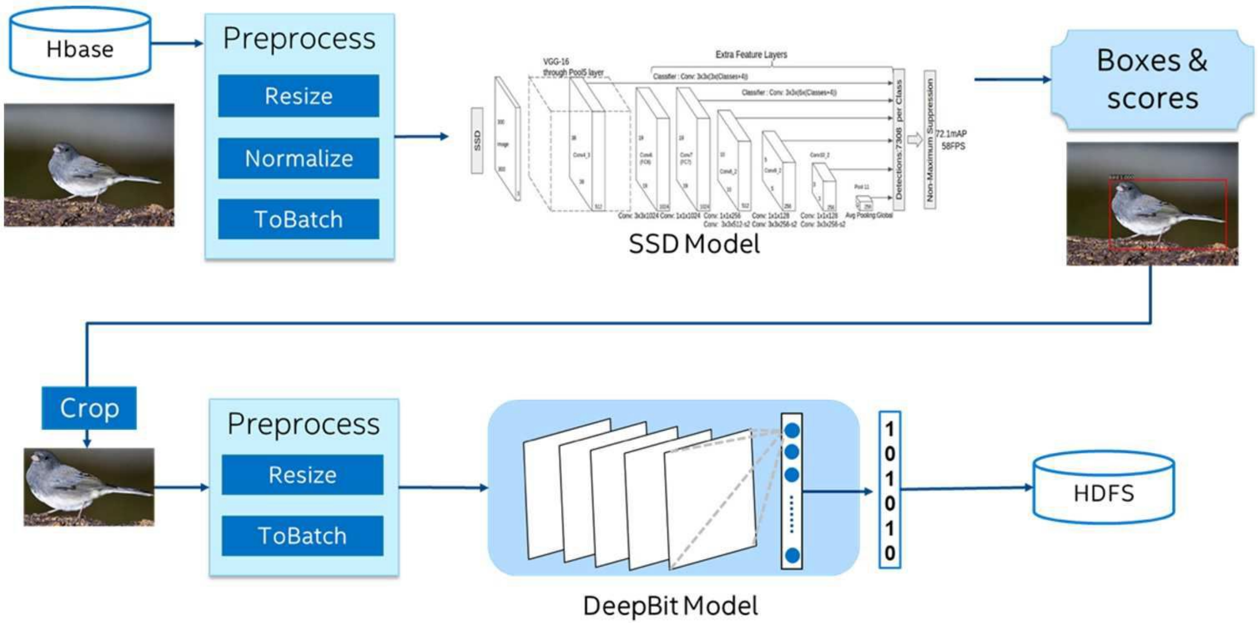


Image Feature Extraction Steps

- End-to-end pipeline for object detection and feature extraction
- Using SSD and DeepBit models on Spark and BigDL

SSD and DeepBit Models



Pipeline Steps

- Data loading and preprocessing on Spark
- Distributed object detection with SSD
- Distributed feature extraction with DeepBit
- Store features in HDFS

End to End Flow at JD.com using BigDL

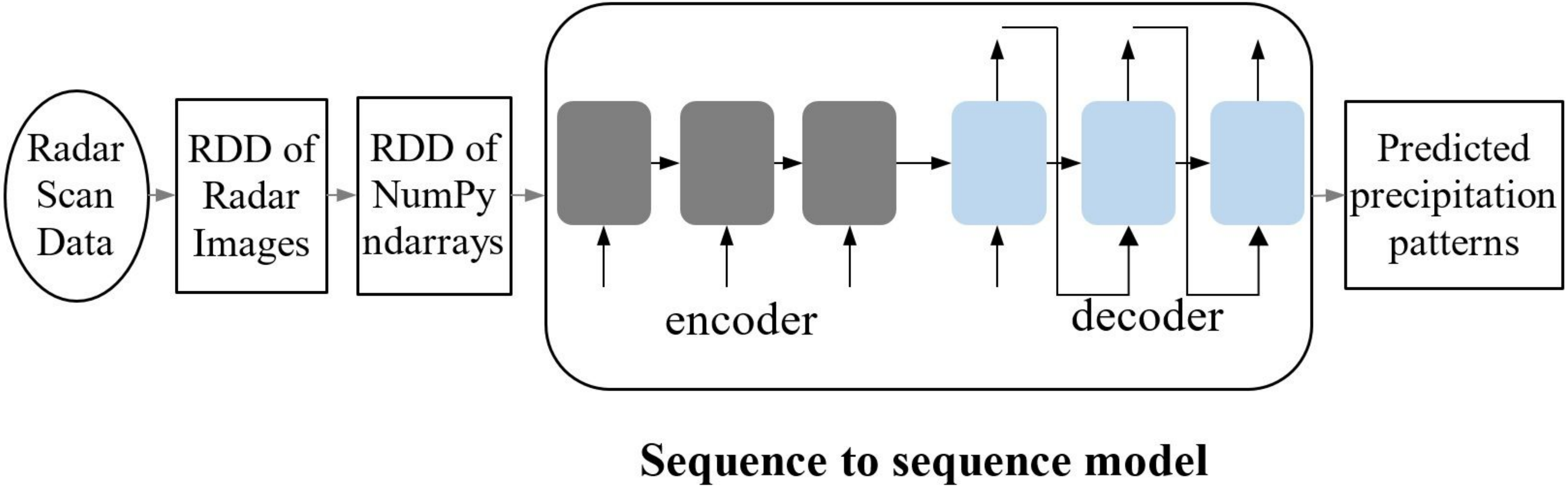


Image Feature Extraction built at JD.com

1. Data Retrieval and Pre-processing

Hundreds of millions of images are retrieved from a distributed database into Spark and pre-processed in a distributed manner.

2. Object Detection

Utilizing BigDL, a pre-trained SSD model is loaded for distributed object detection on Spark, producing coordinates and scores for detected objects.

Extraction cont..

3. Target Image Generation
   Target images are generated by selecting the object with the highest score and cropping the original picture based on its coordinates.

4. Feature Extraction
   Another pre-trained model from Caffe, DeepBit, is employed via BigDL for distributed feature extraction of the target images, storing results in HDFS.

More Applications and use-cases

Precipitation Nowcasting at Cray

- Sequence-to-sequence model for precipitation prediction
- End-to-end data preparation, training, inference on BigDL

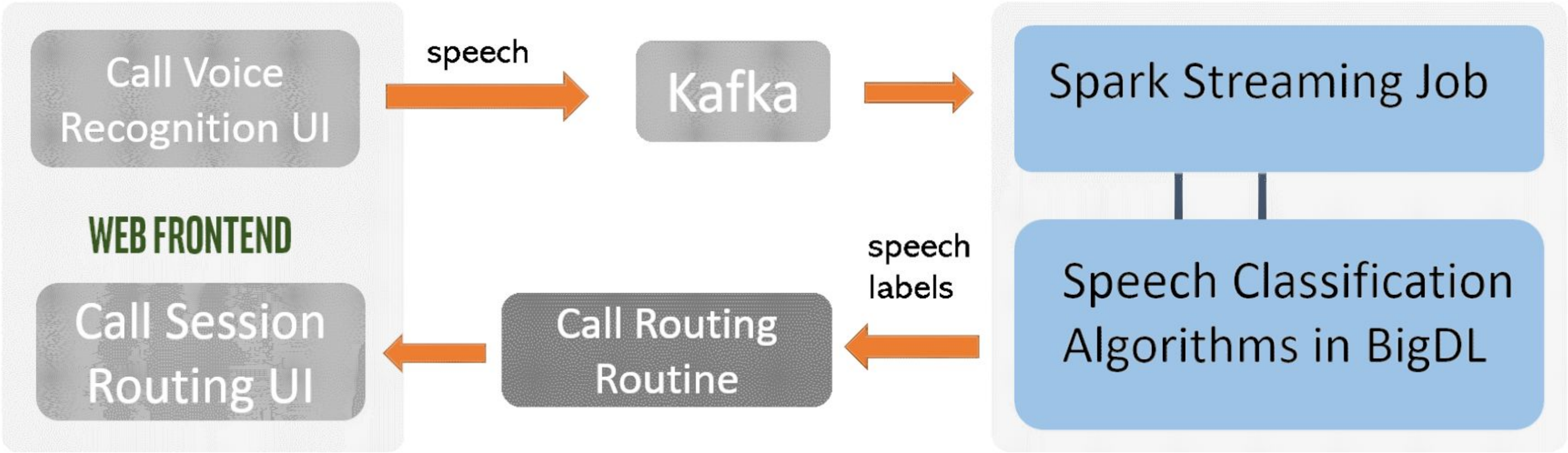
Precipitation Nowcasting Workflow (Cray application)

- Ingest radar scan data into Spark
- Train seq2seq model on historical data
- Predict future precipitation patterns

Real-time Streaming Workflow (Giga spaces application)

- Speech recognition -> Kafka
- Spark Streaming job with BigDL model
- Classify call and route to specialist

Real time streaming speech classification on BigDL



How its done

- When a customer calls the call center, his or her speech is first processed on the fly by a speech recognition unit and result is stored in Kafka.
- • A Spark Streaming job then reads speech recognition results from Kafka and classifies each call using the BigDL model in real-time.
- • The classification result is in turn used by a routing system to redirect the call to the proper support specialist.

Related Wok: Existing DL frameworks

- TensorFlow, MXNet, Petuum, ChainerMN
- Fine-grained data access, in-place mutation
- Different execution model than BigDL

Summary

- BigDL provides alternative distributed training design
- Seamless integration of DL and data analytics
- Adopted by users across industries

Future To-Dos

- Improve training performance and scalability
- Extend to more DL models and applications
- Enhance support for real-time streaming

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