Use Intel Analytics Zoo to build an intelligent QA Bot for Microsoft Azure

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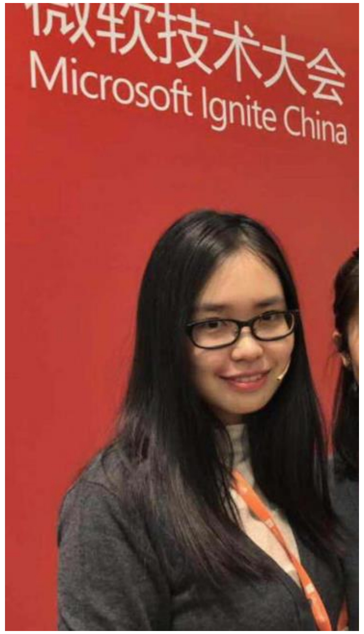
About Us

Kai Huang

Software Engineer from Intel Data Analytics Technology Team



Yuqing Wei

Software Engineer from Microsoft C+AI Team

Outline

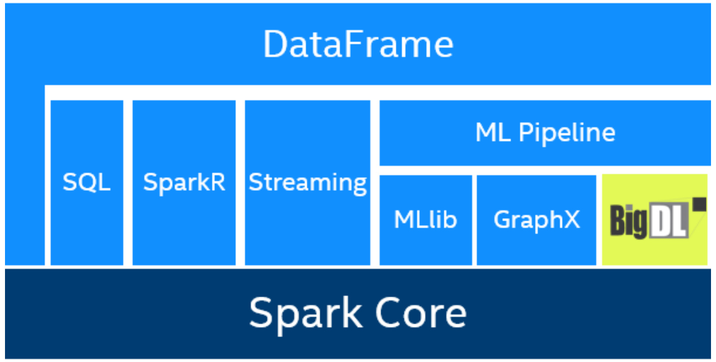
- Introduction to Analytics Zoo.
- How to develop NLP modules using Analytics Zoo.
- Engineering experience in building a chat bot.
- Bot Demo.

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).
- 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/



Analytics Zoo

A unified analytics + AI platform for

distributed TensorFlow, Keras and BigDL on Apache Spark

Feature Engineering	Feature transformations for • Image, 3D images, text, time series, speech, etc.
High-Level Pipeline APIs	• Keras, autograd and transfer learning APIs for model definition. • Native deep learning support in Spark DataFrames and ML Pipelines. • POJO style API for model serving/inference pipelines.
Built-In Deep Learning Models	Image classification, object detection, text classification, recommendations, text matching, anomaly detection, seq2seq etc.
Backends	Seamlessly unites Spark, TensorFlow, Keras and BigDL programs into an integrated pipeline.

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

Feature Engineering

1. **Read images as *`ImageSet`***

```
from zoo.common.nncontext import init_nncontext
from zoo.feature.image import *

sc = init_nncontext()
local_image_set = ImageSet.read(image_path)
distributed_image_set = ImageSet.read(image_path, sc, 2)
```

2. **Built-in *`ImageProcessing`* operations**

```
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)

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Keras-Style API

Use Keras-Style API to create an Analytics Zoo model and train, evaluate or tune it in a distributed fashion.

```
from zoo.pipeline.api.keras.models import Sequential
from zoo.pipeline.api.keras.layers import *

model = Sequential()
model.add(Reshape((1, 28, 28), input_shape=(28, 28, 1)))
model.add(Convolution2D(6, 5, 5, activation="tanh", name="conv1_5x5"))
model.add(MaxPooling2D())
model.add(Convolution2D(12, 5, 5, activation="tanh", name="conv2_5x5"))
model.add(MaxPooling2D())
model.add(Flatten())
model.add(Dense(100, activation="tanh", name="fc1"))
model.add(Dense(10, activation="softmax", name="fc2"))

model.compile(optimizer, loss, metrics)
model.fit(x, batch, epoch)
model.predict(x, batch)
model.evaluate(x, batch)
```

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Autograd API

Autograd API provides automatic differentiation for math operations to easily define custom layers or losses.

```
import zoo.pipeline.api.autograd as A

log = A.log(in_node + 1.0)
dot = A.batch_dot(embed1, embed2, axes=[2, 2])
```

```
from zoo.pipeline.api.autograd import *

def mean_absolute_error(y_true, y_pred):
    result = mean(abs(y_true - y_pred), axis=1)
    return result
```

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Transfer Learning API

Use transfer learning APIs to easily customize pretrained models for *feature extraction or fine-tuning*:

```
from zoo.pipeline.api.net import *
from zoo.pipeline.api.keras.layers import Dense, Input, Flatten
from zoo.pipeline.api.keras.models import Model

# Load a pretrained model
full_model = Net.load_caffe(def_path, model_path)

# Remove the last few layers
model = full_model.new_graph(outputs=["pool5"]).to_keras())

# Freeze the first few layers
model.freeze_up_to(["res4f"])

# Append a few layers
input = Input(shape=(3, 224, 224))
resnet = model.to_keras()(input)
flatten = Flatten()(resnet)
logits = Dense(2)(flatten)
new_model = Model(input, logits)
```

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Distributed TensorFlow

Running TensorFlow model on Spark for distributed training and inference.

1. **Data wrangling and analysis using PySpark**

```
from zoo.common.nncontext 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 ndrrays
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)
```

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Distributed TensorFlow

Running TensorFlow model on Spark in a distributed fashion.

2. **Deep learning model development using TensorFlow**

```
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))
```

3. **Distributed training on Spark and BigDL**

```
from zoo.pipeline.api.net import TFOptimizer
from bigdl.optim.optimizer import MaxIteration, Adam, MaxEpoch, TrainSummary

optimizer = TFOptimizer(loss, Adam(1e-3))
optimizer.set_train_summary(TrainSummary("/tmp/az_lenet", "lenet"))
optimizer.optimize(end_trigger=MaxEpoch(5))
saver = tf.train.Saver()
saver.save(optimizer.sess, "/tmp/lenet/")
```

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Distributed TensorFlow

Running TensorFlow model on Spark in a distributed fashion.

4. **Distributed inference**

```
dataset = TFDataset.from_rdd(testing_rdd,
                             names=["features"],
                             shapes=[[28, 28, 1]],
                             types=[tf.float32])

predictor = TFPredictor.from_outputs(sess, [logits])
predictions_rdd = predictor.predict()
```

For Keras users:

```
optimizer = TFOptimizer.from_keras(keras_model, dataset)

predictor = TFPredictor.from_keras(model, dataset)
predictions_rdd = predictor.predict()
```

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NNFrames API

Native DL support in Spark DataFrames and ML Pipelines

1. **Load images into *DataFrames* using *NNImageReader***

```
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**

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

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

```
from zoo.feature.image import *

transformer = ChainedPreprocessing(
        [RowToImageFeature(), ImageChannelNormalize(123.0, 117.0, 104.0),
         ImageMatToTensor(), ImageFeatureToTensor()])
```

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https://analytics-zoo.github.io/

NNFrames API

Native DL support in Spark DataFrames and ML Pipelines

4. **Define model using *Keras-style API***

```
from zoo.pipeline.api.keras.layers import *
from zoo.pipeline.api.keras.models import Sequential

model = Sequential()
model.add(Convolution2D(32, 3, 3, activation='relu', input_shape=(1, 28, 28)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten()).add(Dense(10, activation='softmax')))
```

5. **Train model using *Spark ML Pipelines***

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

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

Models Interoperability Support

- Load existing TensorFlow, Keras, Caffe, Torch, ONNX model
  - Useful for inference and model fine-tuning.
  - Allows for transition from single-node for distributed application deployment.
  - Allows for model sharing between data scientists and production engineers.

```
from zoo.pipeline.api.net import Net

Net.load_tf(path, inputs=None, outputs=None,
            byte_order="little_endian", bin_file=None)

Net.load_keras(hdf5_path, json_path=None, by_name=False)

Net.load_caffe(def_path, model_path)

Net.load_torch(path)
```

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https://analytics-zoo.github.io/

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

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https://analytics-zoo.github.io/

Object Detection API

1. **Load pretrained model in *Detection Model Zoo***

```
from zoo.common.nncontext import init_nncontext
from zoo.models.image.objectdetection import *

sc = init_nncontext()
model = ObjectDetector.load_model(model_path)
```

2. **Off-the-shell inference using the loaded model**

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

3. **Visualize detection results**

```
config = model.get_config()
visualizer = Visualizer(config.label_map(), encoding="jpg")
visualized = visualizer(output).get_image(to_chw=False).collect()
```

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

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) for recommendations on data with explicit feedback.
- ***Sentiment Analysis***
  - Sentiment analysis on movie reviews using neural network models (e.g. CNN, LSTM, GRU, Bi-LSTM).
- ***Variational AutoEncoder***
  - Use VAE to generate digital numbers and faces.

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

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

Public Cloud Deployment

Deployed on AliCloud* E-MapReduce*

https://yq.aliyun.com/articles/73347

Listed in Microsoft* Azure* Marketplace*

https://azure.microsoft.com/en-us/blog/bigdl-spark-deep-learning-library-vm-now-available-on-microsoft-azure-marketplace/

Available on Google* Cloud Dataproc*

https://cloud.google.com/blog/big-data/2018/04/using-bigdl-for-deep-learning-with-apache-spark-and-google-cloud-dataproc

Optimized for Amazon* EC2* C5 instanced, and listed in AWS* Marketplace*

https://aws.amazon.com/blogs/machine-learning/leveraging-low-precision-and-quantization-for-deep-learning-using-the-amazon-ec2-c5-instance-and-bigdl/

Deployed on IBM* Data Science Expetience*

https://medium.com/ibm-data-science-experience/using-bigdl-in-data-science-experience-for-deep-learning-on-spark-f1cf30ad6ca0

Available on Telefonica* Open Cloud*

https://support.telefonicaopencloud.com/en-us/ecs/doc/download/20180329/20180329111611_166372a698.pdf

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

Customer Use Cases

Industrial Inspection Platform in Midea* and KUKA*
https://software.intel.com/en-us/articles/industrial-inspection-platform-in-midea-and-kuka-using-distributed-tensorflow-on-analytics

Object Detection and Image Feature Extraction in JD
https://software.intel.com/en-us/articles/building-large-scale-image-feature-extraction-with-bigdl-at-jdcom

Image Similarity Based House Recommendation for MLSlistings
https://software.intel.com/en-us/articles/using-bigdl-to-build-image-similarity-based-house-recommendations

3D Medical Image Analysis in UCSF
https://conferences.oreilly.com/strata/strata-ca/public/schedule/detail/64023

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Background

- Chat Bot is often used for recent intelligent customer platforms.
- To enhance user experience and relieve human workload.
- To provide technical support for Azure users effectively and efficiently.
- AI modules provided by Analytics Zoo: text classification, question answering, intent extraction, named entity recognition, etc.

Why neural networks?

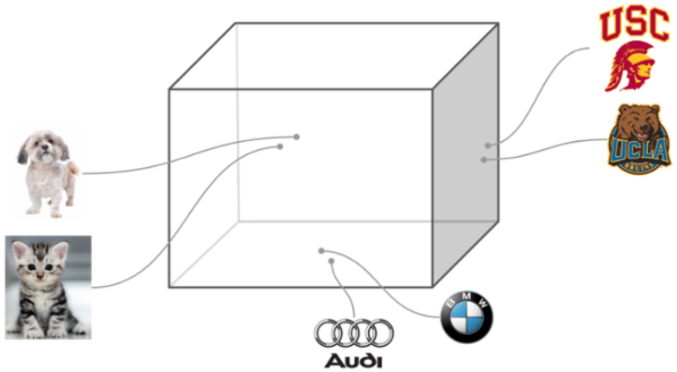
- Neural networks are easier for feature extraction.
- TextClassifier module can be modified for sentiment analysis.
- Neural networks generally have better performance, especially on QA tasks and when we lack data.
- Common parts can share for different AI modules.

Why Analytics Zoo for NLP?

- Analytics Zoo provides pipeline APIs, prebuilt models and use cases for NLP tasks.
- To provide practical experience for Azure big data users to build AI applications.
- Preinstalled image on Azure Marketplace for easy deployment.

Data Preprocessing

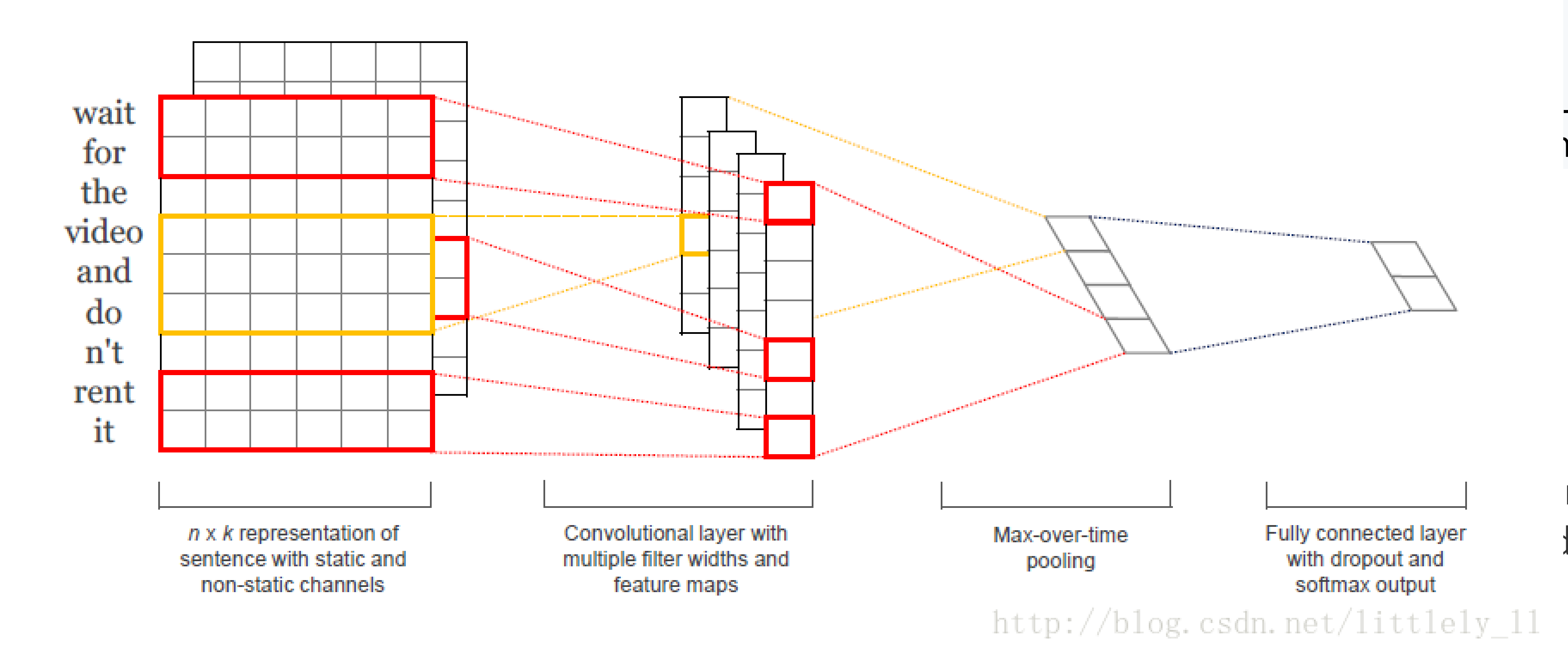
- Read cleaned text data as RDD where each record contains two columns (text, label).
- Common Steps
  - Tokenization: https://github.com/fxsjy/jieba
  - Stopwords removal
  - Sequence aligning
  - Word2Vec: https://github.com/facebookresearch/fastText
  - Conversion to BigDL Sample -> RDD[Sample]



Define TextCl
mode

from zoo.models.textclassification import TextClassifier

_length=500,
n=256)



r 'gru'.
ler.

*Photo from: https://blog.csdn.net/littlely_ll/article/details/79151403

Training, prediction and evaluation

Keras-Style API for distributed training:

```
text_classifier.compile(optimizer=Adagrad(learning_rate, decay),
                        loss="sparse_categorical_crossentropy",
                        metrics=["accuracy"])

text_classifier.set_checkpoint(path)
text_classifier.set_tensorboard(log_dir, app_name)

text_classifier.fit(train_rdd, batch_size=..., nb_epoch=..., validation_data=val_rdd)

text_classifier.save_model(model_path)

text_classifier.predict(test_rdd)
text_classifier.predict_classes(test_rdd)
```

Ways for improvement

- Check your data first (quality, quantity, etc.).
- Use custom dictionary for tokenization if necessary.
- Train word2vec for unknown words if necessary.
- Hyper parameters tuning (learning rate, etc.).
- Add character embedding, etc.

Service Integration

- Prediction service implemented in Java
- POJO-like API for low-latency local inference

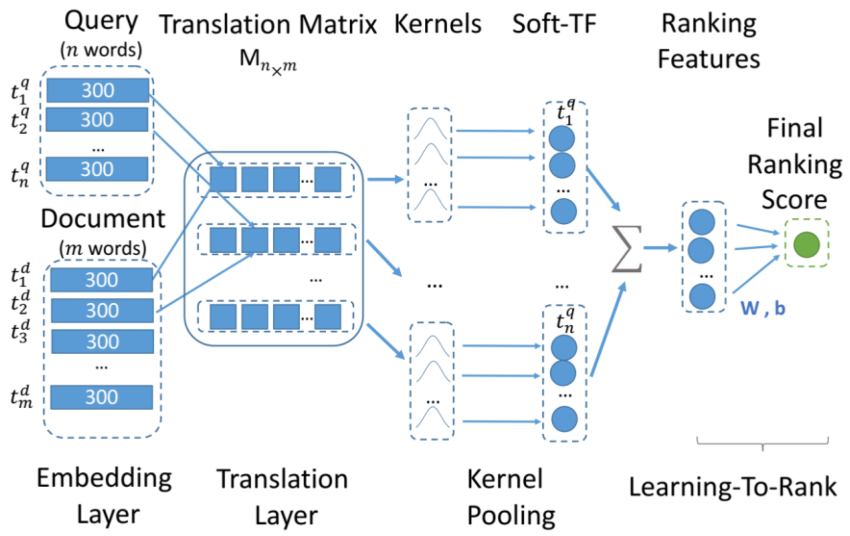
```
public class TextClassificationModel extends AbstractInferenceModel {
  public JTensor preProcess(String text) {
     //Preprocessing steps using Java API
  }
}

TextClassificationModel model = new TextClassificationModel();
model.load(path);
String sampleText = "text content";
JTensor input = model.preProcess(sampleText);
List<JTensor> inputList = new ArrayList<>();
inputList.add(input);
List<List<JTensor>> result = model.predict(inputList);
```

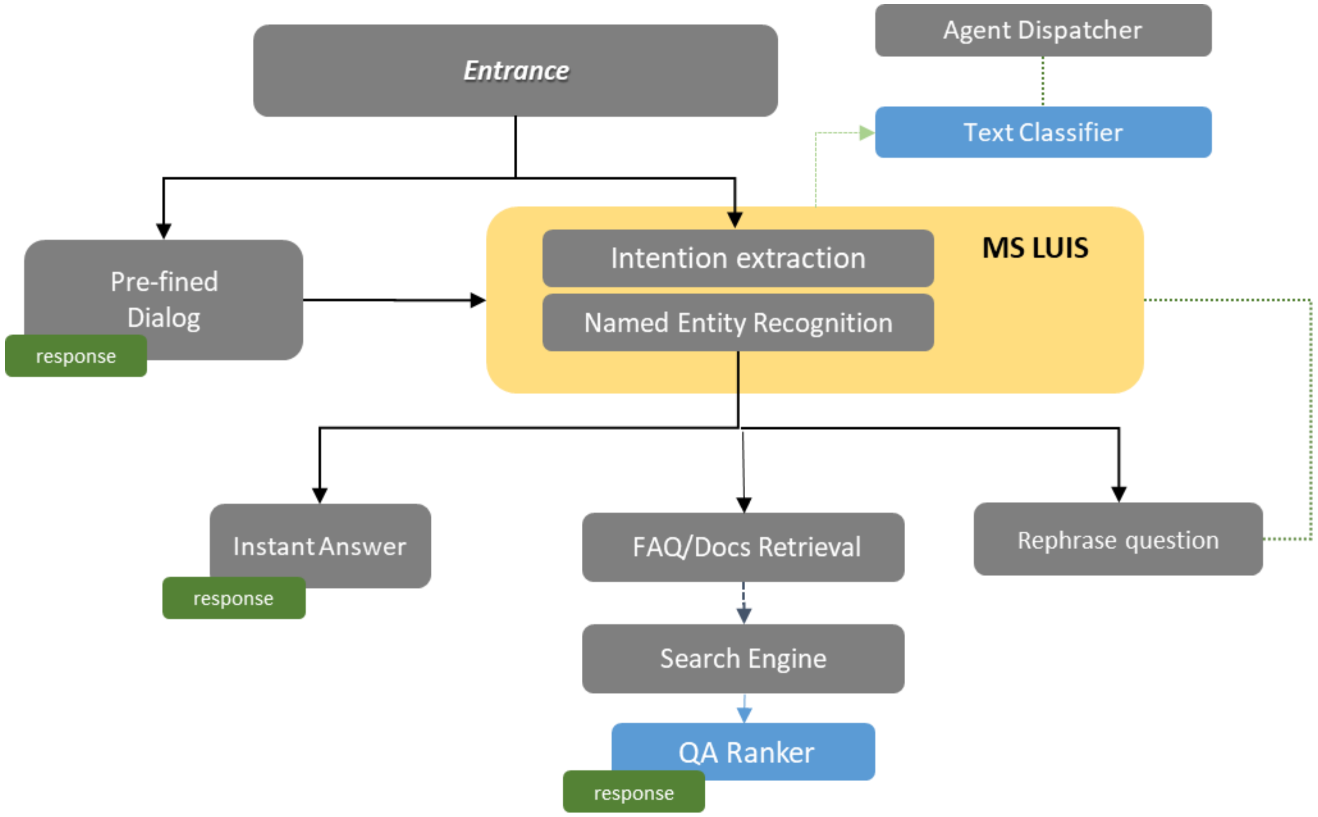
WebService example: https://github.com/intel-analytics/analytics-zoo/tree/master/apps/web-service-sample

QA Ranker

- Input: a query and a document pair.
- Similar preprocessing steps.
- Output: Relevance score or probability.
- Evaluation: Use normalized discounted cumulative gain (NDCG) or mean average precision (MAP).



Chat bot Flow



Analytics Zoo Implementation

- Easy to get: open source
- Easy to deploy compute env, just one click
- Easy to code: python / java
- Optimized for CPU and distribution
- Pre-defined neural networks

Model Management

- Online Feedback (automation)
  - Positive – useful answers; clicked links;
  - Negative – non-useful answers;
- Periodical Fine tune
  - Accumulated training material
  - Real user experience -> new benchmark
- Content Update
  - Re-index new Knowledge Base
  - Training set distribution
- Algorithm Update

Bot Demo

- WeChat: Microsoft云科技
- Webchat: https://support.azure.cn/zh-cn/support/support-azure/

Me:

虚拟机无法远程连接

Bot:

以下文章可能对您有帮助：

- Azure Windows虚拟机常见导致无法远程的操作
- Azure linux虚拟机常见导致无法远程的操作
- Linux 虚拟机虚拟网卡问题导致无法连接问题

Bot:

解决您的问题了么？

1. 解决了
2. 没有解决
3. 没有解决，转人工客服

Me: 输入您的问题 Send

virtual-machines/0.98882675, storage/0.003297496, virtual-network/0.003007766

Me:

如何进行ICP备案

Bot:

以下文章可能对您有帮助：

- ICP备案
- 首次备案
- 原备案在蓝云-备案变更

Bot:

解决您的问题了么?

1. 解决了
2. 没有解决
3. 没有解决，转人工客服

Me: 输入您的问题 Send

ICP/0.99798584, billing/3.540909E-4, automation/3.4101875E-4

Me:

Spark on HDInsight怎么用

Bot:

以下文章可能对您有帮助：

- DocumentDB API 性能级别
- Hadoop 组件和版本 - Azure HDInsight
- MySQL Database on Azure主从复制问题

Me:

Spark on HDInsight 怎么用

Bot:

以下文章可能对您有帮助：

- Hadoop 组件和版本 - Azure HDInsight
- Azure HDInsight 中的 Apache Spark 群集的已知问题
- Azure Toolkit for Eclipse：为 HDInsight Spark 创建 Scala 应用程序

Partner with us

- **GitHub: https://github.com/intel-analytics/analytics-zoo/**
- **Documents: https://analytics-zoo.github.io/**

- https://www.azure.cn/zh-cn/blog/2018/09/12/Using-Intel-Analytics-Zoo-to-inject-AI-into-customer-service-platform_PartI
- https://software.intel.com/en-us/articles/use-analytics-zoo-to-inject-ai-into-customer-service-platforms-on-microsoft-azure-part-1
- More blogs coming soon ☺