

# Real Estate Search Ranking with BigDL Framework on Microsoft Azure Platform

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#ExpSAIS16

# MLSListings Inc, Sunnyvale, California

# Located in the heart of Silicon Valley, our internal teams of Engineers, IT Professionals, and Product Managers are complemented by Professional Services staff who provide strategic business planning and implementation



## **MLSListings Business Use-Case:** Personalized Visual Search Ranking

If you looked at this house..... You will want to look at this one, too









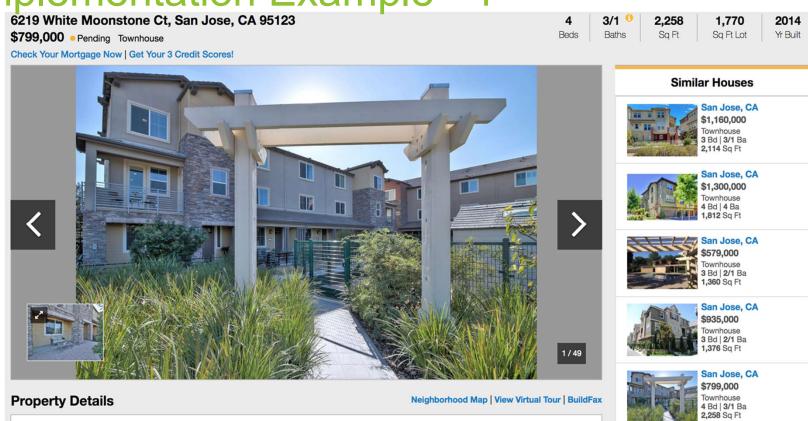
Image similarity is an extra search parameter along with area, location, size, price, etc.



Business need: real estate search results need to be sorted based on image similarities of attached photos



Implementation Example - 1



About this Droporty

Implementation Example - 2

5665 Herma, San Jose, CA 95123

\$962,999 • Active Single Family Residence

Check Your Mortgage Now | Get Your 3 Credit Scores!





#### **Property Details**

About this Droporty

#### Neighborhood Map | BuildFax

#### **Similar Houses**



#### San Jose, CA \$1,000,000

Single Family Residence 2 Bd | 1/1 Ba 1,216 Sq Ft



#### San Jose, CA \$749,500

Single Family Residence 4 Bd | 2 Ba 1,457 Sq Ft



#### San Jose, CA

\$849,000 Single Family Residence 3 Bd | 2 Ba 1,298 Sq Ft



#### San Jose, CA

\$1,199,000 Single Family Residence 4 Bd | 2 Ba 1,453 Sq Ft

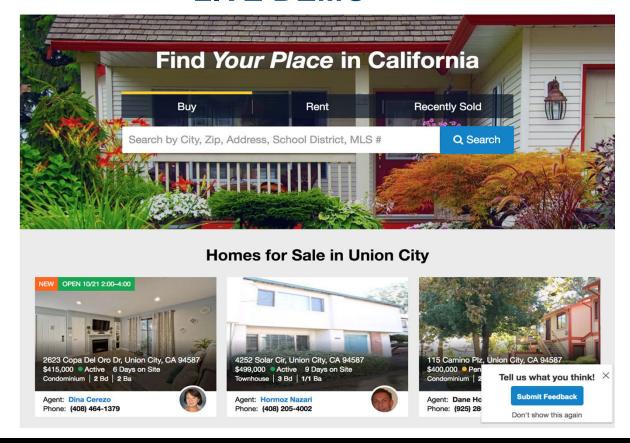


#### San Jose, CA

\$962,999 Single Family Residence 5 Bd | 3 Ba 2,193 Sq Ft

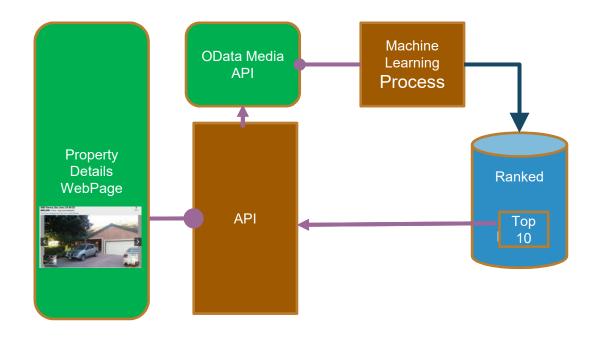


#### **LIVE DEMO**



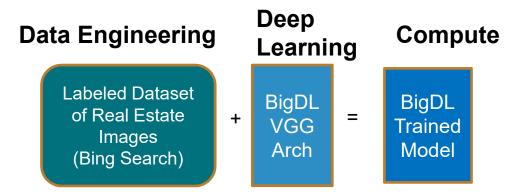


# **High-Level Data Workflow**



# **Deep Learning Data Flow**

#### **Training**



- Long Compute. 8500 images
- 2 nodes, 28 cores/node. 3 minutes for a one single pass
- Model parameters are changing.
- Repeat until convergence
- But: only do once!

Note-1: Images are \*not\* stored in the model

Note-2: you can trade compute resources for time.



# **Deep Learning Data Flow**

#### Inference



Compute Only

BigDL Trained Model

Feature Vector Image Class (Front, Bdr, Bath,...)

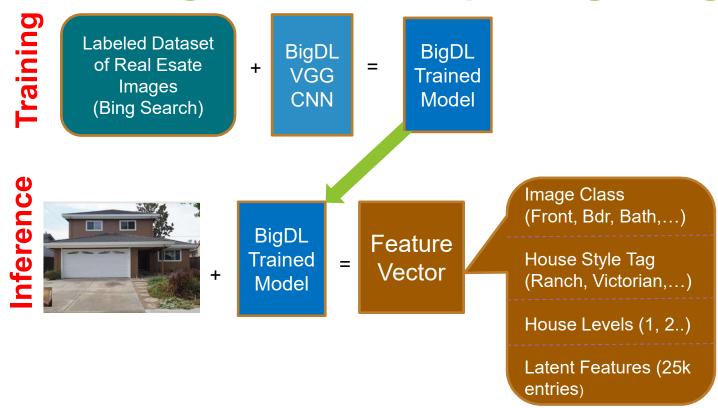
House Style Tag (Ranch, Victorian,...)

House Levels (1, 2..)

Latent Features (25k entries)

- Short Compute. Real Time
- 1 node, 1 core/node
- Model parameters unchanged.
- Only run once per image
- But: need to do for every image in the searched dataset!

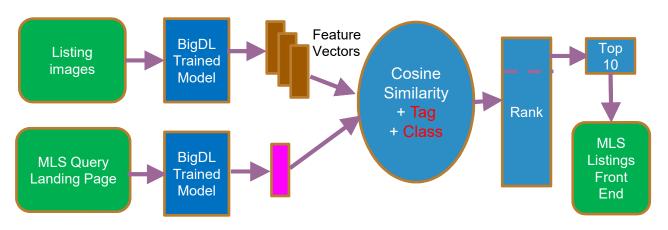
# **Deep Learning Data Flow – putting it together**





# **Deep Learning Data Flow**

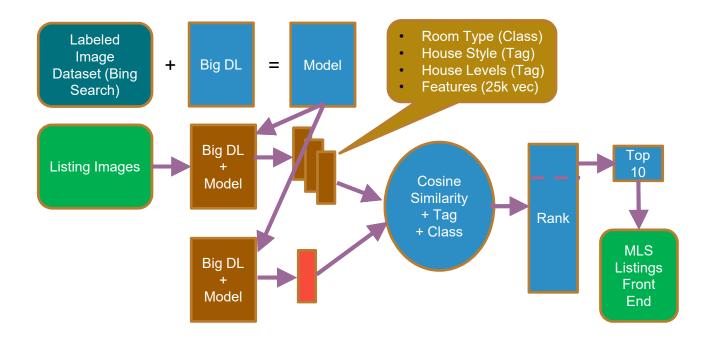
### Real-time Ranking



#### **Cosine similarity measure: (Weighed)**

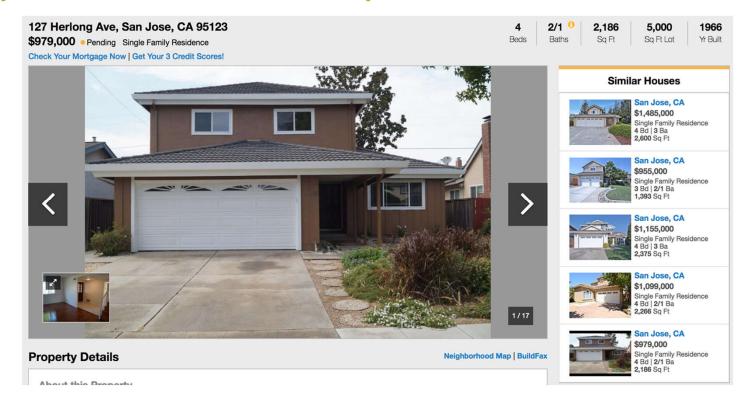
$$sim(x, y) = cos(r_x, r_y) = \frac{r_x \cdot r_y}{||r_x|| \cdot ||r_y||}$$
  $r_x = \{1, 0, 0, 1, 3\}$   $r_y = \{1, 0, 2, 2, 0\}$ 

# **Deep Learning Data Flow**





# Implementation Example - 3



# Implementation - BigDL

```
(trainingDF, validationDF) = labelDF.randomSplit([0.9, 0.1]) .
   numClasses = 4
   transformer = NNImageTransformer(
       image.Pipeline([Resize(256, 256), CenterCrop(224, 224),
4
       ChannelNormalize(123.0, 117.0, 104.0)]))
        .setInputCol("image").setOutputCol("features")
   caffeModel = Model.load caffe model(def path, weight path)
   preTrainedNNModel = NNModel(caffeModel, [3,224,224])
       .setPredictionCol("embedding")
9
  lrModel = Sequential().add(Linear(1024, numClasses)) \
      .add(LogSoftMax())
  classifier = NNClassifier(lrModel, ClassNLLCriterion(), [1024])
      .setLearningRate(1e-3).setBatchSize(40) \
      .setMaxEpoch(100).setFeaturesCol("embedding")
5
   pipeline = Pipeline(stages=[transformer, preTrainedNNModel, \)
                               classifier])
   HouseStyleModel = pipeline.fit(trainingDF)
  predictionDF = HouseStyleModel.transform(validationDF)
  predictionDF.show()
  evaluator = MulticlassClassificationEvaluator(
      labelCol="label", predictionCol="prediction", metricName="accuracy")
  accuracy = evaluator.evaluate(predictionDF)
```

#### **Building BigDL Graph**

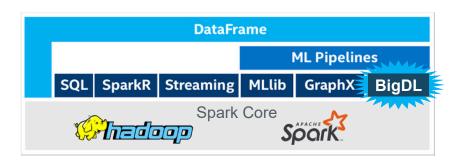
- Prepare Training/Validation data.
- Image Transformer:
  - Image scale/crop
  - Channel color normalizing
  - Caffe Model Import
- Render BigDL as SparkML Transformer
- Create BigDL Linear SoftMax model
- Define Classifier, SparkML Transformer
- Set up SparkML Pipeline

**Executing BigDL Graph** 

SPARK+AI SUMMIT 2018

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

# **BigDL: Performance Deep Learning for Apache Spark\* on CPU Infrastructure**



BigDL is an **open-source** distributed deep learning library for Apache Spark\* that can run directly on top of existing Spark or Apache Hadoop\* clusters

Ideal for DL Models TRAINING and INFERENCE

**Designed and Optimized for Intel® Xeon®** 

No need to deploy costly GPUs, duplicate data, or suffer through scaling headaches!







Feature Parity & Model Exchange with TensorFlow\*, Caffe\*, Keras, Torch\*

Lower TCO and improved ease of use with existing infrastructure

Deep Learning on Big Data Platform, Enabling Efficient Scale-Out

Powered by Intel® MKL and multi-threaded programming

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



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# **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 code base to Spark
- NEW BigDL supports loading pre-defined Keras models (Keras 1.2.2)

BigDL Model
File

Caffe Model
File

Torch Model
File

Tensorflow
Model File

Save

Storage

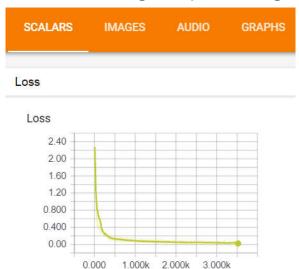
https://github.com/intel-analytics/analytics-zoo

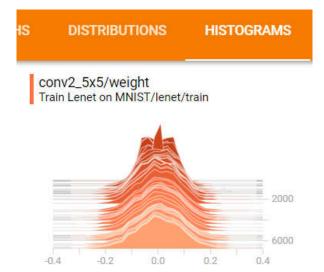


# Visualization for Learning

#### BigDL integration with TensorBoard

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





# 2018 - BIGDL ANALYTICS ZOO STACK

Reference Use Cases	Anomaly detection, sentiment analysis, fraud detection, chatbot, sequence prediction, etc.
Built-In Algorithms and Models	Image classification, object detection, text classification, recommendations, GAN, etc.
Feature Engineering and Transformations	Image, text, speech, 3D imaging, time series, etc.
High-Level Pipeline APIs	DataFrames, ML Pipelines, Autograd, Transfer Learning, etc.
Runtime Environment	Spark, BigDL, Python, etc.

#### Making it easier to build end-to-end analytics + Al applications



#### **Engineering Team**



- Data scientist, proficient in Machine Learning / Deep Learning
- Software Engineer, experience with Apache Spark.
- Technical project manager

#### Domain Expertise:

- Machine Learning / Deep Learning,
- Python, Scala
- Software Engineer, Web API



• Software Engineer, Web UI

#### Domain Expertise:

- OData, .net Core MSSQL
- C#, HTML, JavaScript



#### "ROAD AHEAD"

# "Fireplace in the living room"

- 1. Feature extraction and tagging.
- 2. Image-based listings search
- 3. Feature verification based on listing images.
- 4. Image-based compliance and quality check



# Thank You and Questions

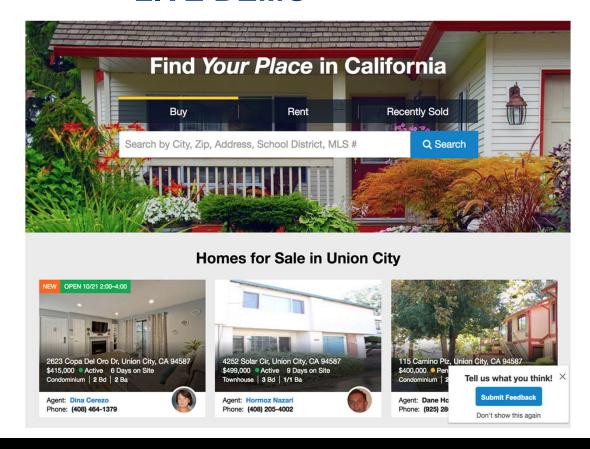








#### **LIVE DEMO**





## Infrastructure

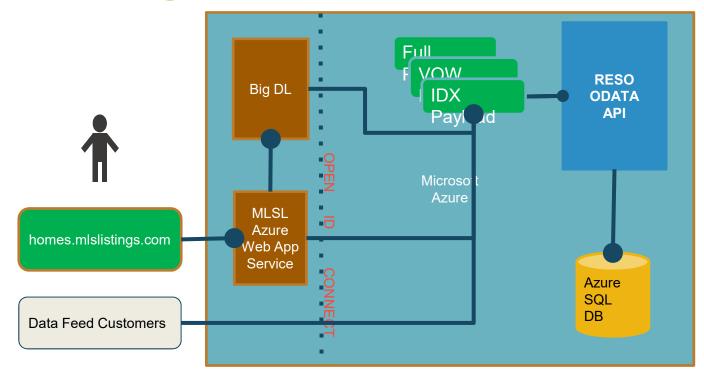
Microsoft Data Science Virtual Machines (DSVM)

Pre-Configured environments in the cloud for Data Science & Al Modeling, Development & Deployment.





# **MLS Listings Apps and Services**





# Roles and Responsibilities

- Microsoft: Microsoft's data science team in Mountain View, CA participated in project discussions and provided Azure Data Science VM to deploy and train the deep learning model.
- Microsoft Apache Spark Cloud Service Provider
- Intel BigDL distributed Deep Learning Library
- MLSListings RESO Web API Provider
- Intel: Team members worked to integrate MLSListings's OData Media Services to deploy a custom real estate image similarity comparison solution on Azure using Big DL.
- MLSListings: MLSListings's team working on new web portal provided Media API and worked on the user interface to integrate with Big DL API.



# **BigDL: Python API**

- Support deep learning model training, evaluation, inference
- Support Spark v1.6 2.2
- Support Python 2.7/3.5/3.6
- Based on PySpark, Python API in BigDL allows use of existing Python libs (Numpy, Scipy, Pandas, Scikitlearn, 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()
```

