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Getting Started with Machine Learning using Spark in Azure HDInsight

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https://github.com/Azure-Bootcamp-Troy/SparkOnHDInsight

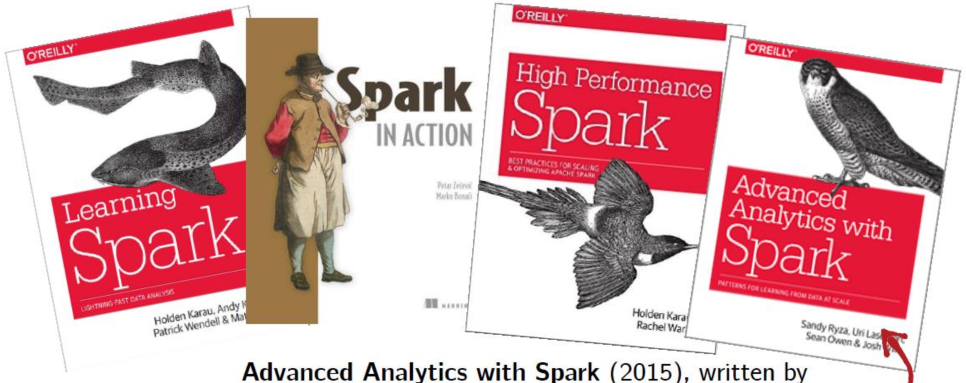
Content

- What is **Spark** on **HDInsight**?
- Demo: Create Spark Cluster on Azure
- What is an **RDD, DataFrames, Spark SQL**?
- Demo: Operations of RDD, DataFrames and SQL
- What is **MLlib**?
- Demo: Machine Learning using Spark

- For Whom this talk
  - Business users to analyze Big Data using Spark on Azure Cluster.
- Prerequisite
  - None

References

Many excellent books released in the past year or two!



Advanced Analytics with Spark (2015), written by Sandy Ryza, Uri Laserson, Sean Owen, and Josh Wills

This talk is based on this course

Microsoft
Implementing Predictive Analytics with Spark in

Microsoft
Processing Real-Time Data Streams in Azure

Microsoft
Processing Big Data with Hadoop in Azure

Big Data for Data Engineers

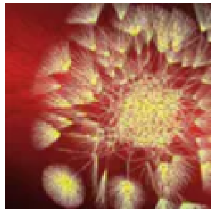
Yandex

Learn More

Big Data Analysis with Apache Spark
Learn how to apply data science techniques using parallel programming in Apache Spark to explore big data.

Distributed Machine Learning with Apache Spark
Learn the underlying principles required to develop scalable machine learning pipelines and gain hands-on experience using Apache Spark.

Introduction to Apache Spark
Learn the fundamentals and architecture of Apache Spark, the leading cluster-computing framework among professionals.



Big Data

University of California, San Diego

Learn More

HDInsight – What is it?

A standard Apache Hadoop distribution offered as a managed service on Microsoft Azure

- Based on Hortonworks Data Platform (HDP)
- Provisioned as clusters on Azure that can run on Windows or Linux servers
- Offers capacity-on-demand, pay-as-you-go pricing model
- Integrates with:
  - Azure Blob Storage and Azure Data Lake Store for Hadoop File System (HDFS)
  - Azure Portal for management and administration
  - Visual Studio for application development tooling

In addition to the core, HDInsight supports the Hadoop ecosystem

What is Apache Spark?

General, open-source cluster computing engine

Well-suited for machine learning

- Fast iterative procedures
- Efficient communication primitives

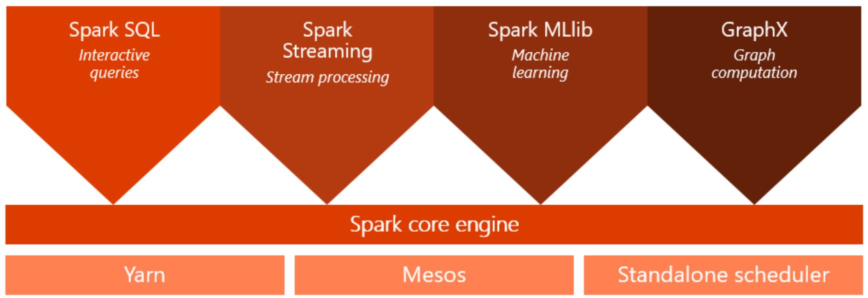
Simple and Expressive

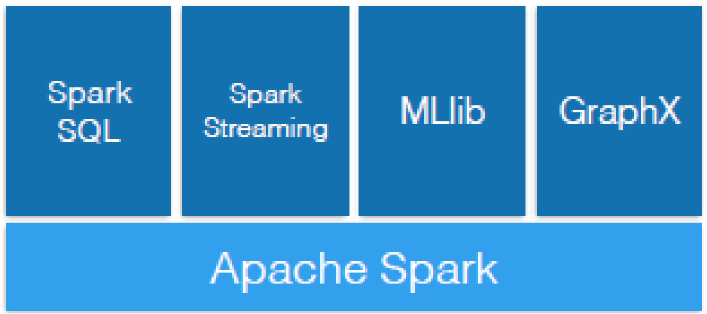
- APIs in Scala, Java, Python, R
- Interactive Shell

Integrated Higher-Level Libraries

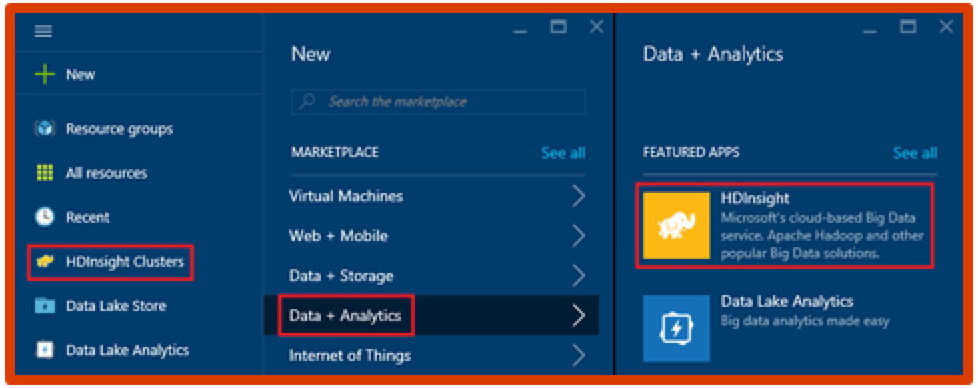
Apache Spark: A unified framework

A unified, open source, parallel data processing framework for big data analytics

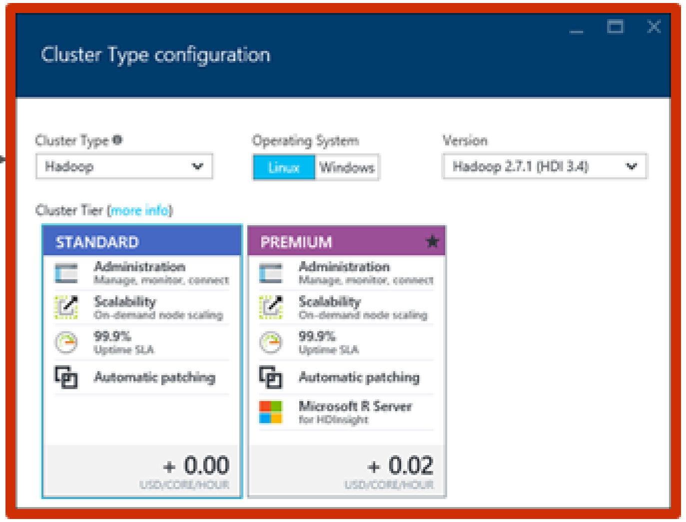




Demo: Creating an HDInsight Spark cluster

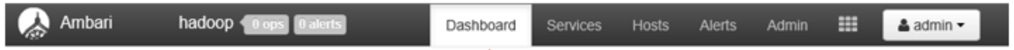


The Azure console lists all types of HDInsight clusters (HBase, Storm, and Spark) currently provisioned.



Apache Spark use cases

Demo: Ambari Dashboard

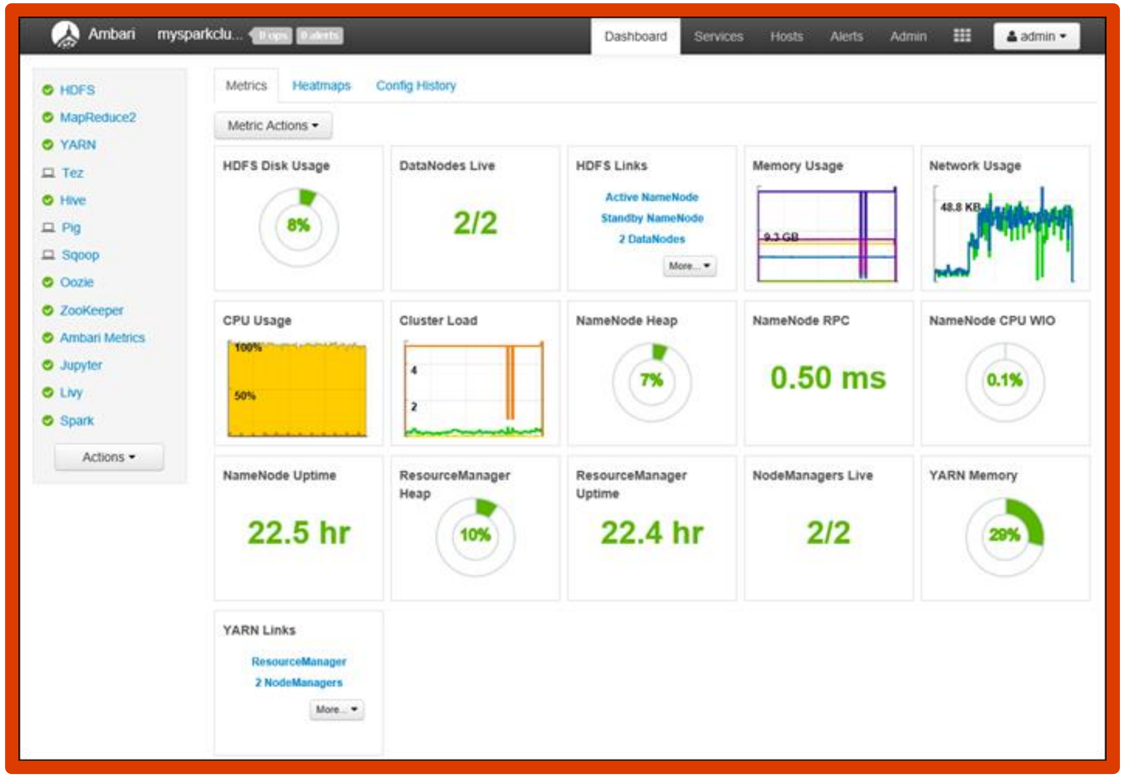


The Ambari Dashboard provides links to access:

Ambari web UI – monitors Spark clusters

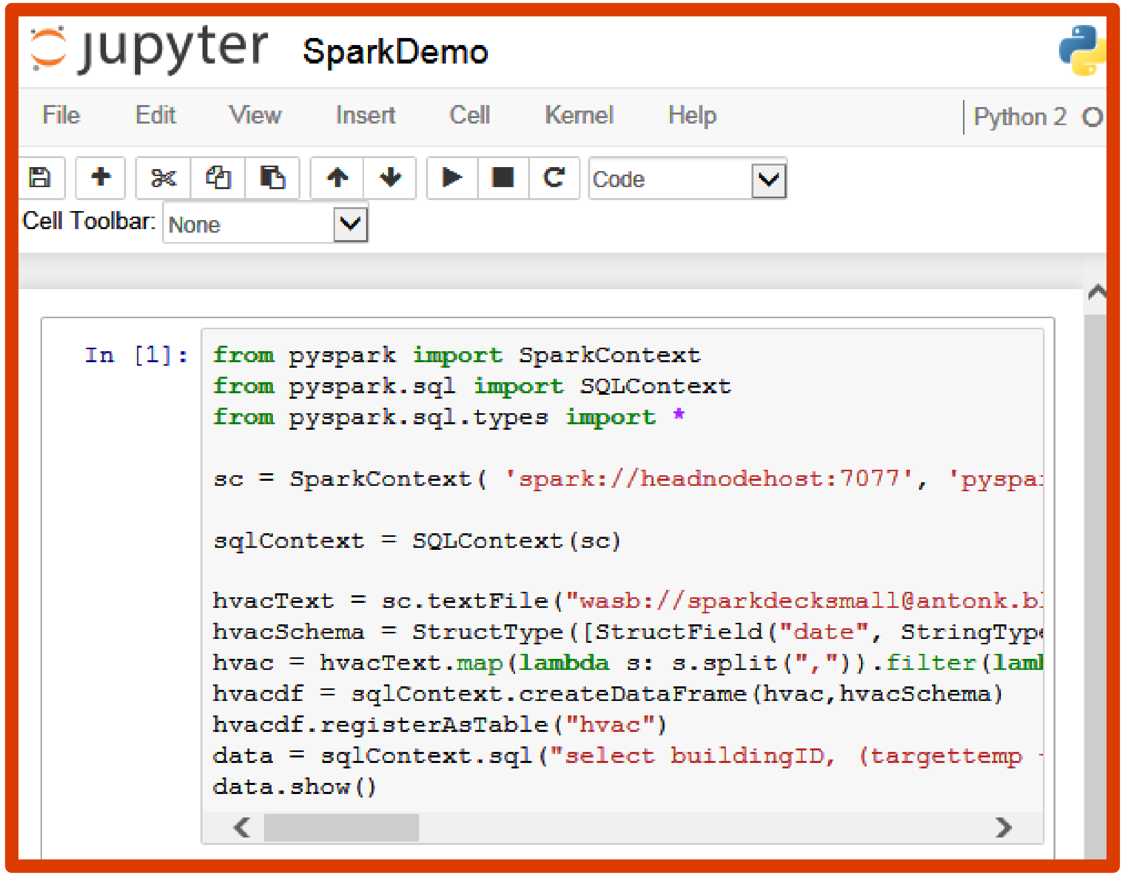
Hosts (Resource Manager) – controls amount of resources allocated to various Spark cluster components

Notebooks – interactive web-based tools to develop and run Spark programs



Demo: Jupyter notebooks

- Web-based interactive consoles for
  - Experimentation
  - Collaboration
- Spark HDInsight clusters include Jupyter
  - Interactive Python
  - Interactive Scala



What is RDD?

- The core abstraction for data in Spark is the *resilient distributed dataset* (RDD)
- An RDD represents a collection of items that can be distributed across compute nodes
- APIs for working with RDDs are provided for Java, Python, and Scala
  - HDInsight distribution includes Python and Scala shells

Dataset	Distributed	Resilient
Data storage created from: HDFS, S3, HBase, JSON, text, Local hierarchy of folders	Distributed across the cluster of machines	Recover from errors, e.g. node failure, slow processes
Or created transforming another RDD	Divided in partitions, atomic chunks of data	Track history of each partition, re-run

Resilient Distributed Datasets or RDDs address this by enabling fault-tolerant, distributed, in-memory computations.

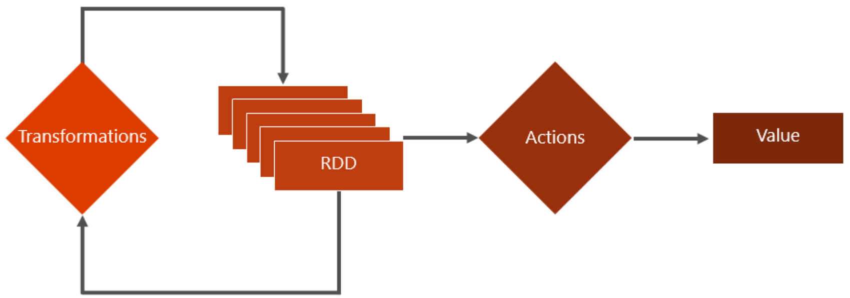
RDD Operations

Some Transformations

Transformation	Description
`map(func)`	return a new distributed dataset formed by passing each element of the source through a function *func*
`filter(func)`	return a new dataset formed by selecting those elements of the source on which *func* returns true
`distinct([numTasks]))`	return a new dataset that contains the distinct elements of the source dataset
`flatMap(func)`	similar to map, but each input item can be mapped to 0 or more output items (so *func* should return a Seq rather than a single item)

Key-Value Transformation	Description
`reduceByKey(func)`	return a new distributed dataset of (K,V) pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type (V,V) ➔ V
`sortByKey()`	return a new dataset (K,V) pairs sorted by keys in ascending order
`groupByKey()`	return a new dataset of (K, Iterable<V>) pairs

RDDs: Transformations and actions



Some Actions

Action	Description
`reduce(func)`	aggregate dataset's elements using function *func*. *func* takes two arguments and returns one, and is commutative and associative so that it can be computed correctly in parallel
`take(n)`	return an array with the first *n* elements
`collect()`	return all the elements as an array WARNING: make sure will fit in driver program
`takeOrdered(n, key=func)`	return n elements ordered in ascending order or as specified by the optional key function

Demo: RDD

RDDs can be created from stable storage or by transforming other RDDs.

```
In [ ]: fruits = spark.sparkContext.textFile('wasb:///example/data/fruits.txt')
        yellowThings = spark.sparkContext.textFile('wasb:///example/data/yellowthings.txt')
```

Transformations create a new dataset from an existing one. Transformations are lazy, meaning that no transformation is executed until you execute an action.

```
# map
fruitsReversed = fruits.map(lambda fruit: fruit[::-1])
```

```
# filter
shortFruits = fruits.filter(lambda fruit: len(fruit) <= 5)
```

```
# flatMap
characters = fruits.flatMap(lambda fruit: list(fruit))
```

```
# union
fruitsAndYellowThings = fruits.union(yellowThings)
```

```
# intersection
yellowFruits = fruits.intersection(yellowThings)
```

```
# distinct
distinctFruitsAndYellowThings = fruitsAndYellowThings.distinct()
distinctFruitsAndYellowThings
```

```
# groupByKey
yellowThingsByFirstLetter = yellowThings.map(lambda thing: (thing[0], thing)).groupByKey()
```

```
# reduceByKey
numFruitsByLength = fruits.map(lambda fruit: (len(fruit), 1)).reduceByKey(lambda x, y: x + y)
```

Actions return a value to the driver program after running a computation on the dataset.

```
# collect
fruitsArray = fruits.collect()
yellowThingsArray = yellowThings.collect()
fruitsArray
```

```
# count
numFruits = fruits.count()
numFruits
```

```
# take
first3Fruits = fruits.take(3)
first3Fruits
```

```
# reduce
letterSet = fruits.map(lambda fruit: set(fruit)).reduce(lambda x, y: x.union(y))
letterSet
```

What is DataFrames?

- A distributed collection of data organized into named columns.
- Similar to RDDs with schema.
- Conceptually equivalent to tables in relational database, or to DataFrames in R/Python.
- With domain-specific functions designed for common tasks:
  - Metadata
  - Sampling
  - Project, filter, aggregation, and join
  - UDFs

RDDs are a collection of opaque objects (such as internal structures unknown to Spark).

User	User	User
User	User	User

DataFrames is a collection of objects with schema that are known to Spark SQL..

Name	Age	Sex
Name	Age	Sex
Name	Age	Sex
Name	Age	Sex

DataFrame Operations

DataFrames provide a domain-specific language for structured data manipulation in Scala, Java, and Python.

```
>>> val df = sqlContext.jsonFile(”somejasonfile.json“)

>>> df.show()                                        // Show the contents of the DataFrame

>>> df.printSchema()                                 // Print the schema in a tree format

>>> df.select(“name”).show()                         // Select and show the name columns

>>> df.select(df(”name”),df (“age”) +1).show()       // Select all but increment the age by 1

>>> df.filter(df(”age”) > 21).show()                 // Select people older than 21

>>> df.groupBy(“age”).count().show()                 // Count people by age
```

What is Spark SQL?

1
Create an Azure storage account

HDInsight uses Azure Blob storage account for storing data.

2
HDInsight makes Apache Spark available as a service in cloud.

HDInsight makes Apache Spark available as a service in cloud.

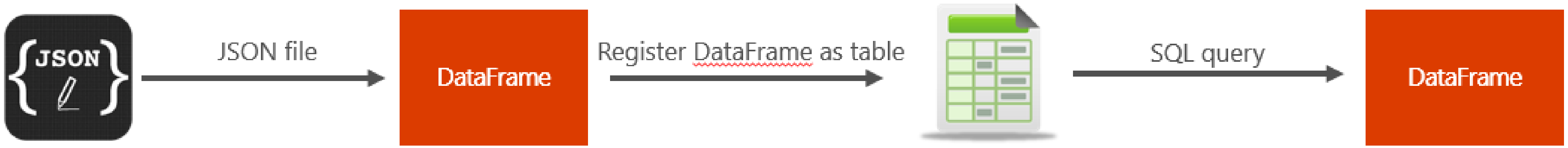
3
Run Spark SQL statements using notebooks

You run interactive Spark SQL statements using notebooks.

Tables and Queries

A DataFrame can be registered as a table that can then be used in SQL queries.

```
// First create a DataFrame from JSON file.
>>> val df = sqlContext.jsonFile(”Users.json“)

// Register the DataFrame as a temporary table. Temp tables exist only during lifetime of this SQLContext
instance.
 >>> val usertable = sqlContext.registerDataFrameAsTable(df, “UserTable”)

// Alternatively, execute a SQL query on the table. The query returns a DataFrame.
>>> val teenagers = sqlContext.sql(“select Age as Years from UserTable where age > 13 and age <= 19”)
```



Spark SQL Operations

Spark RDD API

```
rdd
rdd1 = rdd.map(lambda x: x.split("\t"))
rdd2 = rdd1.map(lambda x: (x[0], x[2]))
```

VS

SQL on Spark

```
select user_id, url from access_log
```

- No data parsing
- Code optimization
- Syntax is easier
- No overhead

Demo: DataFrame and SQL

create a dataframe from a CSV file as shown below.

```
df = spark.read.csv('wasb:///HdiSamples/HdiSamples/SensorSampleData/building/building.csv', header=True, inferSchema=True)
```

```
# show the content of the dataframe
df.show()
```

```
# Print the dataframe schema in a tree format
df.printSchema()
```

```
# Create an RDD from the dataframe
dfrdd = df.rdd
dfrdd.take(3)
```

```
dfrdd = df.rdd
dfrdd.take(3)
```

```
# Retrieve a given number of rows from the dataframe
df.limit(3).show()
```

```
df.limit(3).show()
```

```
# Retrieve specific columns from the dataframe
df.select('BuildingID', 'Country').limit(3).show()
```

```
# Use GroupBy clause with dataframe
df.groupBy('HVACProduct').count().select('HVACProduct', 'count').show()
```

run SQL queries over dataframes once you register them as temporary tables within the SparkSession

```
# Register the dataframe as a temporary table called HVAC
df.registerTempTable('HVAC')
```

```
%%sql
SELECT * FROM HVAC WHERE BuildingAge >= 10
```

```
%%sql
SELECT BuildingID, Country FROM HVAC LIMIT 3
```

What is Machine Learning?

A Definition

Constructing and studying methods that learn from and make predictions on data

Broad area involving tools and ideas from various domains

- Computer Science
- Probability and Statistics
- Optimization
- Linear Algebra

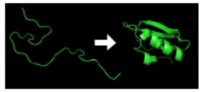
Some Examples

Face recognition

Link prediction

Text or document classification, e.g., spam detection

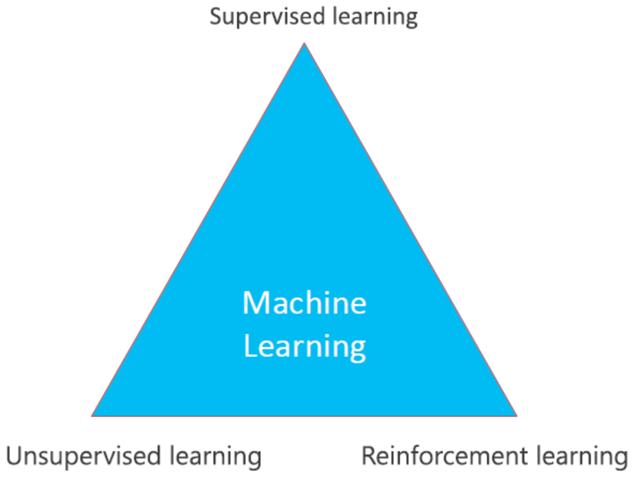
Protein structure prediction

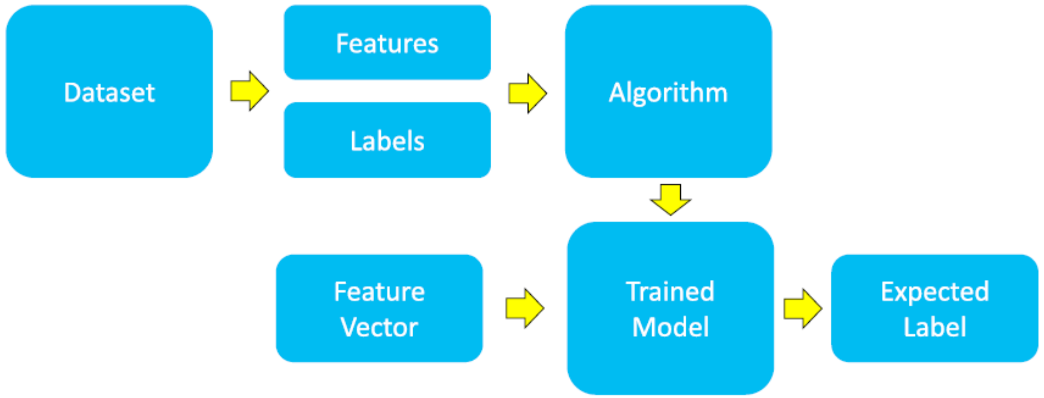


Games, e.g., Backgammon or Jeopardy

How does Machine Learning work?

- Data labels
- Direct feedback
- Predict outcome





Supervised learning. Learning from labeled observations

- Labels 'teach' algorithm to learn mapping from observations to labels

Unsupervised learning. Learning from unlabeled observations

- Learning algorithm must find latent structure from features alone
- Can be goal in itself (discover hidden patterns, exploratory data analysis)
- Can be means to an end (preprocessing for supervised task)

Observations. Items or entities used for learning or evaluation, e.g., emails

Features. Attributes (typically numeric) used to represent an observation, e.g., length, date, presence of keywords

Labels. Values / categories assigned to observations, e.g., *spam*, *not-spam*

Training and Test Data. Observations used to train and evaluate a learning algorithm, e.g., a set of emails along with their labels

- Training data is given to the algorithm for training
- Test data is withheld at train time

What is MLlib?

- MLlib is a collection of **machine learning algorithms optimized to run in a parallel, distributed manner on Spark clusters**.
- MLlib helps lead to better performance on large data sets.
- MLlib integrates seamlessly with other Spark components.
- MLlib applications are developed in Java, Scala, and Python.

Type	**Algorithms**
Supervised	Classification and regression: • Linear models (SVMs) logistic regression and linear regression • Naïve Bayes • Decision trees • Ensembles of trees (random forest, gradient-boosted trees) • Isotonic regression
Unsupervised	Clustering: • k-means and streaming k-means • Gaussian mixture • Power iteration clustering (PIC) • Latent Dirichlet Allocation (LDA)
Recommendation	Collaborative filtering: • Alternating least squares (ALS)

How to.. Machine Learning in Apache Spark?

- All primitives in Spark Machine Learning are *Vectors*
- *Features* are represented by a Vector
- Vectors can contain other Vectors and so be Dense or Sparse
- Spark uses *LabeledPoints* to encapsulate a Vector and a Label
- RDDs are transformed into Vectors through map functions

MLlib Terminology

ML: Transformer

- A *Transformer* is a class which can transform one DataFrame into another DataFrame
- A Transformer implements **`transform()`**

- Examples
  - HashingTF
  - LogisticRegressionModel
  - Binarizer

```
val tokenizer = new Tokenizer().setInputCol("text").setOutputCol("words")
val hashingTF = new
HashingTF().setNumFeatures(1000).setInputCol(tokenizer.getOutputCol).s
etOutputCol("features")
val lr = new LogisticRegression().setMaxIter(10).setRegParam(0.01)
val pipeline = new Pipeline().setStages(Array(tokenizer, hashingTF, lr))

val model = pipeline.fit(training)

val modelem = model.transform(test).select("id", "label", "text",
"probability", "prediction")
```

ML: Estimator

- An *Estimator* is a class which can take a DataFrame and produce a Transformer
- An Estimator implements **`fit()`**

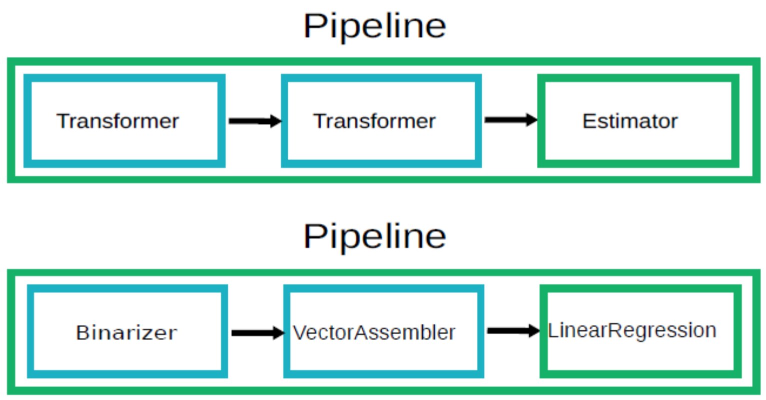
- Examples
  - LogisticRegression
  - StandardScaler
  - Pipeline

```
val tokenizer = new Tokenizer().setInputCol("text").setOutputCol("words")
val hashingTF = new
HashingTF().setNumFeatures(1000).setInputCol(tokenizer.getOutputCol).s
etOutputCol("features")
val lr = new LogisticRegression().setMaxIter(10).setRegParam(0.01)
val pipeline = new Pipeline().setStages(Array(tokenizer, hashingTF, lr))

val model = pipeline.fit(training)

val modelem = model.transform(test).select("id", "label", "text",
"probability", "prediction")
```

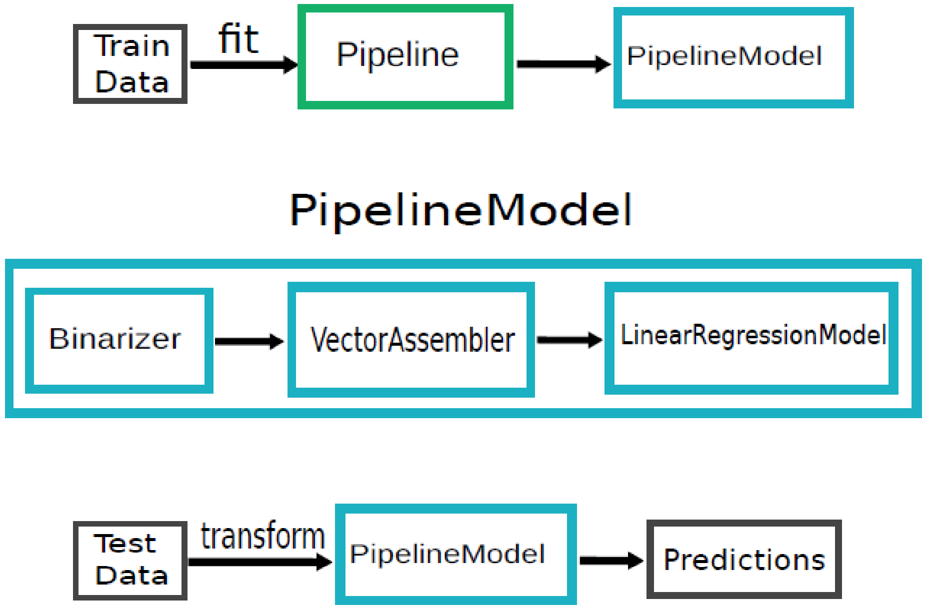
MLlib Terminology

ML: Pipelines

A *Pipeline* is an estimator that contains stages representing a resusable workflow. Pipeline stages can be either estimators or transformers.



ML: PipelineModel



Example: Classification I

Import Spark SQL and Spark ML Libraries

First, import the libraries you will need:

```
from pyspark.sql.types import *
from pyspark.sql.functions import *

from pyspark.ml.classification import LogisticRegression
from pyspark.ml.feature import VectorAssembler
```

Step 2: Load Source Data

You will load this data into a DataFrame and display it.

```
csv = spark.read.csv('wasb:///data/flights.csv', inferSchema=True, header=True)
csv.show()
```

```
+----------+---------+-------+---------------+-------------+--------+--------+
|DayofMonth|DayOfWeek|Carrier|OriginAirportID|DestAirportID|DepDelay|ArrDelay|
+----------+---------+-------+---------------+-------------+--------+--------+
|        19|        5|     DL|          11433|        13303|      -3|       1|
|        19|        5|     DL|          14869|
```

Step 3: Prepare the Data

```
data = csv.select("DayofMonth", "DayOfWeek", "OriginAirportID", "DestAirportID", "DepDelay",
                 ((col("ArrDelay") > 15).cast("Int").alias("Late")))
data.show()
```

```
+----------+---------+---------------+-------------+--------+----+
|DayofMonth|DayOfWeek|OriginAirportID|DestAirportID|DepDelay|Late|
+----------+---------+---------------+-------------+--------+----+
|        19|        5|          11433|        13303|      -3|   0|
|        19|        5|          14869|        12478|       0|   0|
|        19|        5|          14057|        14869|      -4|   0|
```

Example: Classification II

Step 4: Split the Data

```
splits = data.randomSplit([0.7, 0.3])
train = splits[0]
test = splits[1]
train_rows = train.count()
test_rows = test.count()
print "Training Rows:", train_rows, " Testing Rows:", test_rows
```

Step 5: Prepare the Training Data

```
assembler = VectorAssembler(inputCols = ["DayofMonth", "DayOfWeek", "OriginAirportID", "DestAirportID", "DepDelay"],
                            outputCol="features")
training = assembler.transform(train).select(col("features"), col("Late").alias("label"))
training.show()
```

```
+--------------------+-----+
|            features|label|
+--------------------+-----+
|[1.0,1.0,10140.0,...|    0|
```

Step 6: Train a Classification Model

```
lr = LogisticRegression(labelCol="label",featuresCol="features",maxIter=10,regParam=0.3)
model = lr.fit(training)
print "Model trained!"
```

```
Model trained!
```

Example: Classification III

Step 7: Prepare the Testing Data

```
testing = assembler.transform(test).select(col("features"), col("Late").alias("trueLabel"))
testing.show()
```

```
+--------------------+---------+
|            features|trueLabel|
+--------------------+---------+
|[1.0,1.0,10140.0,...|        0|
|[1.0,1.0,10140.0,...|        0|
```

Step 8: Test the Model

```
prediction = model.transform(testing)
predicted = prediction.select("features", "prediction", "probability", "trueLabel")
predicted.show(100)
```

```
+--------------------+----------+--------------------+---------+
|            features|prediction|         probability|trueLabel|
+--------------------+----------+--------------------+---------+
|[1.0,1.0,10140.0,...|       0.0|[0.83121028425635...|        0|
|[1.0,1.0,10140.0,...|       0.0|[0.82357817040192...|        0|
```

Example: Regression I

Import Spark SQL and Spark ML Libraries

First, import the libraries you will need:

```
from pyspark.sql.types import *
from pyspark.sql.functions import *

from pyspark.ml.regression import LinearRegression
from pyspark.ml.feature import VectorAssembler
```

```
Starting Spark application
```

Step 2: Load Source Data

```
csv = spark.read.csv('wasb:///data/flights.csv', inferSchema=True, header=True)
csv.show()
```

```
+----------+---------+-------+---------------+-------------+--------+--------+
|DayofMonth|DayOfWeek|Carrier|OriginAirportID|DestAirportID|DepDelay|ArrDelay|
+----------+---------+-------+---------------+-------------+--------+--------+
|        19|        5|     DL|          11433|        13303|      -3|       1|
|        19|        5|     DL|          14869|        12478|       0|      -8|
|        19|        5|     DL|          14057|        14869|      -4|     -15|
```

Step 3: Prepare the Data

```
data = csv.select("DayofMonth", "DayOfWeek", "OriginAirportID", "DestAirportID", "DepDelay", "ArrDelay")
data.show()
```

```
+----------+---------+---------------+-------------+--------+--------+
|DayofMonth|DayOfWeek|OriginAirportID|DestAirportID|DepDelay|ArrDelay|
+----------+---------+---------------+-------------+--------+--------+
|        19|        5|          11433|        13303|      -3|       1|
```

Example: Regression II

Step 4: Split the Data

```
splits = data.randomSplit([0.7, 0.3])
train = splits[0]
test = splits[1]
train_rows = train.count()
test_rows = test.count()
print "Training Rows:", train_rows, " Testing Rows:", test_rows
```

```
Training Rows: 1891270  Testing Rows: 810948
```

Step 5: Prepare the Training Data

```
assembler = VectorAssembler(inputCols = ["DayofMonth", "DayOfWeek", "OriginAirportID", "DestAirportID", "DepDelay"],
                            outputCol="features")
training = assembler.transform(train).select(col("features"), (col("ArrDelay").cast("Int").alias("label")))
training.show()
```

```
+--------------------+-----+
|            features|label|
+--------------------+-----+
|[1.0,1.0,10140.0,...|  -11|
```

Step 6: Train a Regression Model

```
lr = LinearRegression(labelCol="label",featuresCol="features", maxIter=10, regParam=0.3)
model = lr.fit(training)
print "Model trained!"
```

```
Model trained!
```

Example: Regression III

Step 7: Prepare the Testing Data

```
testing = assembler.transform(test).select(col("features"), (col("ArrDelay")).cast("Int").alias("trueLabel"))
testing.show()
```

```
+--------------------+---------+
|            features|trueLabel|
+--------------------+---------+
|[1.0,1.0,10140.0,...|       -5|
|[1.0,1.0,10140.0,...|      -25|
```

Step 8: Test the Model

```
prediction = model.transform(testing)
predicted = prediction.select("features", "prediction", "trueLabel")
predicted.show()
```

```
+--------------------+-------------------+---------+
|            features|         prediction|trueLabel|
+--------------------+-------------------+---------+
|[1.0,1.0,10140.0,...|-3.7579519642834542|       -5|
|[1.0,1.0,10140.0,...| -9.743936006015753|      -25|
```

Example: Pipeline

Step 1: Define the Pipeline

```
strIdx = StringIndexer(inputCol = "Carrier", outputCol = "CarrierIdx")
catVect = VectorAssembler(inputCols = ["CarrierIdx", "DayofMonth", "DayOfWeek", "OriginAirportID", "DestAirportID"],
                          outputCol="catFeatures")
catIdx = VectorIndexer(inputCol = catVect.getOutputCol(), outputCol = "idxCatFeatures")
numVect = VectorAssembler(inputCols = ["DepDelay"], outputCol="numFeatures")
minMax = MinMaxScaler(inputCol = numVect.getOutputCol(), outputCol="normFeatures")
featVect = VectorAssembler(inputCols=["idxCatFeatures", "normFeatures"], outputCol="features")
dt = DecisionTreeClassifier(labelCol="label", featuresCol="features")
pipeline = Pipeline(stages=[strIdx, catVect, catIdx, numVect, minMax, featVect, dt])
```

```
piplineModel = pipeline.fit(train)
print "Pipeline complete!"
```

Step 2: Run the Pipeline as an Estimator

```
prediction = piplineModel.transform(test)
predicted = prediction.select("features", "prediction", "trueLabel")
predicted.show(100, truncate=False)
```

Step 3: Test the Pipeline Model

Example: Text Analysis

Define the Pipeline

The pipeline for the model consist of the following stages:

- A Tokenizer to split the tweets into individual words.
- A StopWordsRemover to remove common words such as "a" or "the" that have little predictive value.
- A HashingTF class to generate numeric vectors from the text values.
- A LogisticRegression algorithm to train a binary classification model.

```
tokenizer = Tokenizer(inputCol="SentimentText", outputCol="SentimentWords")
swr = StopWordsRemover(inputCol=tokenizer.getOutputCol(), outputCol="MeaningfulWords")
hashTF = HashingTF(inputCol=swr.getOutputCol(), outputCol="features")
lr = LogisticRegression(labelCol="label", featuresCol="features", maxIter=10, regParam=0.01)
pipeline = Pipeline(stages=[tokenizer, swr, hashTF, lr])
```

:

```
piplineModel = pipeline.fit(train)
print "Pipeline complete!"
```

Step 2: Run the Pipeline as an Estimator

Step 3: Test the Pipeline Model

```
prediction = piplineModel.transform(test)
predicted = prediction.select("SentimentText", "prediction", "trueLabel")
predicted.show(100, truncate = False)
```

Example: Clustering

Step 1: Create the K-Means Model

```
assembler = VectorAssembler(inputCols = ["Age", "MaritalStatus", "IncomeRange", "Gender", "TotalChildren",
                                         "ChildrenAtHome", "Education", "Occupation", "HomeOwner", "Cars"], outputCol="features")
train = assembler.transform(customers)

kmeans = KMeans(featuresCol=assembler.getOutputCol(), predictionCol="cluster", k=5, seed=0)
model = kmeans.fit(train)
print "Model Created!"
```

```
centers = model.clusterCenters()
print("Cluster Centers: ")
for center in centers:
    print(center)
```

Step 2: Get the Cluster Centers

```
prediction = model.transform(train)
prediction.groupBy("cluster").count().orderBy("cluster").show()
```

```
prediction.select("CustomerName", "cluster").show(50)
```

Step 3: Predict Clusters

Example: Recommendation I

Import the ALS class

In this exercise, you will use the Alternating Least Squai

```
from pyspark.ml.recommendation import ALS
```

Load Source Data

The source data for the recommender is in two files - one containing numeric IDs for movies and users, a
of the movies.

```
ratings = spark.read.csv('wasb:///data/ratings.csv', inferSchema=True, header=True)
movies = spark.read.csv('wasb:///data/movies.csv', inferSchema=True, header=True)
ratings.join(movies, "movieId").show()
```

Prepare the Data

To prepare the data, split it into a training set and a test set.

```
data = ratings.select("userId", "movieId", "rating")
splits = data.randomSplit([0.7, 0.3])
train = splits[0].withColumnRenamed("rating", "label")
test = splits[1].withColumnRenamed("rating", "trueLabel")
train_rows = train.count()
test_rows = test.count()
print "Training Rows:", train_rows, " Testing Rows:", test_rows
```

Example: Recommendation II

Build the Recommender

The ALS class is an estimator, so you can use its **fit** method to traing a model, or you can include it in a pipeline. Ratl
label, the ALS algorithm requries a numeric user ID, item ID, and rating.

```
als = ALS(maxIter=5, regParam=0.01, userCol="userId", itemCol="movieId", ratingCol="label")
model = als.fit(train)
```

Test the Recommender

Now that you've trained the recommender, you can see how accurately it predicts known ratings in the test set.

```
prediction = model.transform(test)
prediction.join(movies, "movieId").select("userId", "title", "prediction", "trueLabel").show(100, truncate=False)
```

Questions