Session: Machine Learning in Spark

ML Overview

Utilities

Transformers

Pipelines

Lesson Objectives

- Understand some of the basics of Machine Learning (ML)
- Learn how Spark MLlib supports ML
- Become familiar with some of the algorithms in MLlib

Introduction

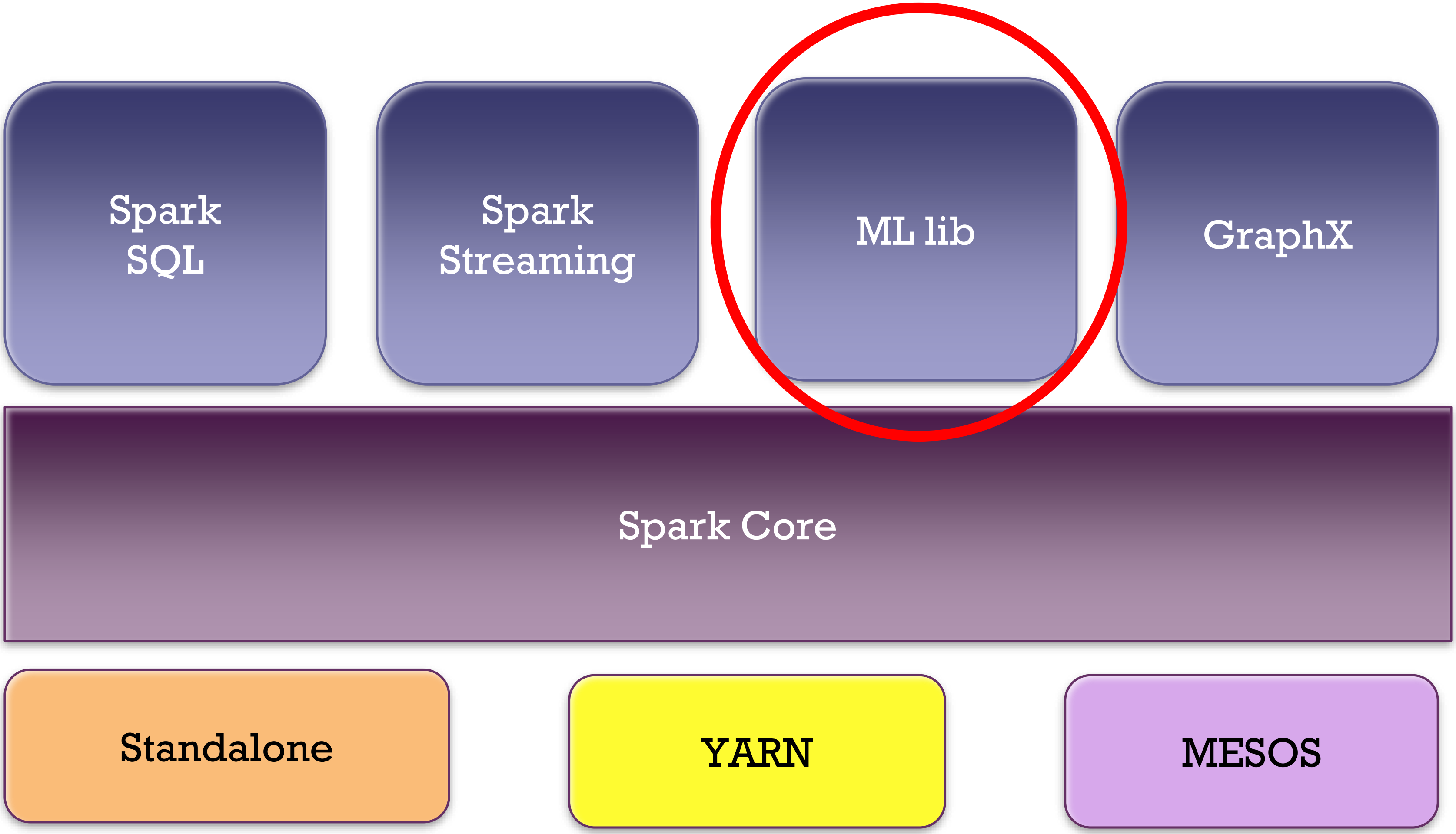
➔ **ML Overview**

Utilities

Transformers

Pipelines

Spark Illustrated



History of Machine Learning @ Scale

- Hadoop
  - Hadoop is the first popular distributed platform
  - MapReduce is the execution engine
  - Did great at batch computes
  - 'Mahout' is a machine learning library built on top of Hadoop's MapReduce
  - Not so great for iterative algorithms (machine learning)
- Spark
  - Native Machine Learning component
  - Execution engine is faster than MapReduce (less overhead)
  - Iterative algorithms work well
  - Support in-memory computations (very fast and great for iterative computes)

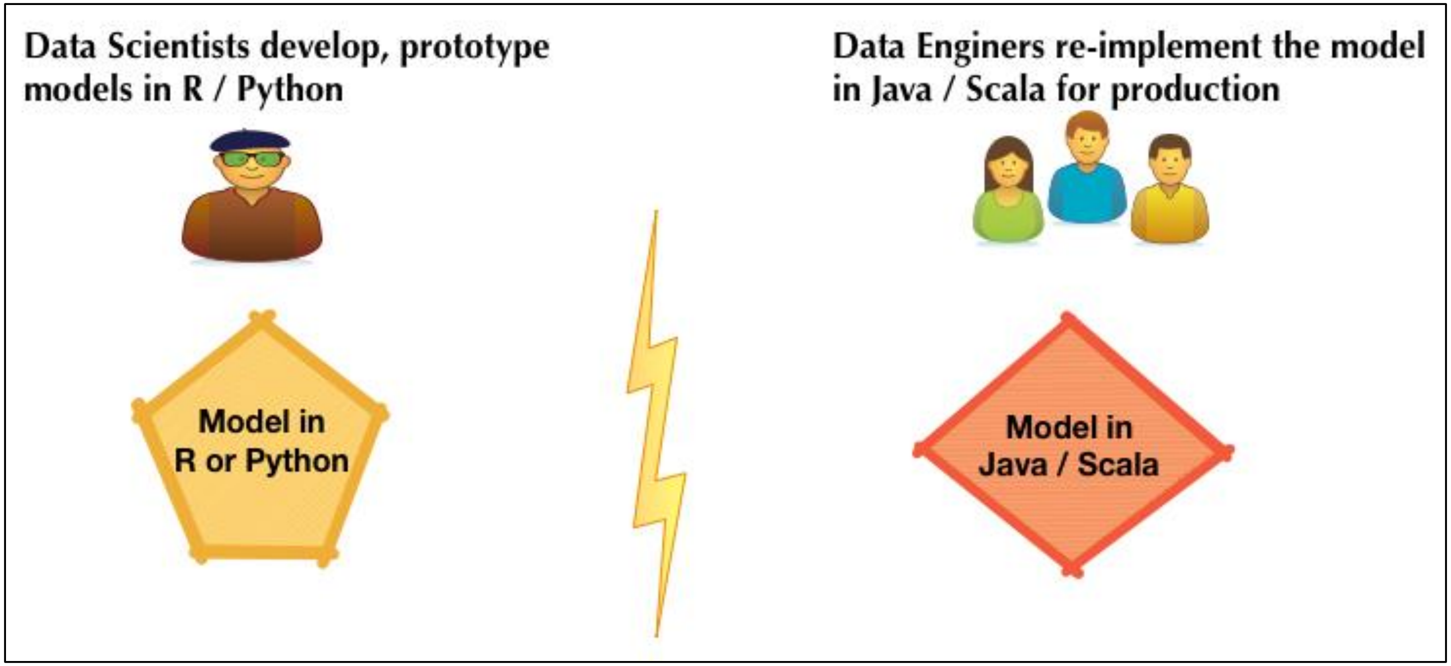
Spark ML Features

- Wide variety of algorithms (classifications, clustering, regressions, collaborative filtering)
  - All parallelized out of the box!
- Featurization: feature extraction / transformation / dimensionality reduction / selection
- Pipelines: create, evaluate and tune Pipeline
- Persistence: saving and loading of algorithms/models/pipelines
- Utilities: Linear algebra, statistics, data handling
- Multi Language support: Python / Java / Scala / R
  - Equal coverage!

MLLib → ML

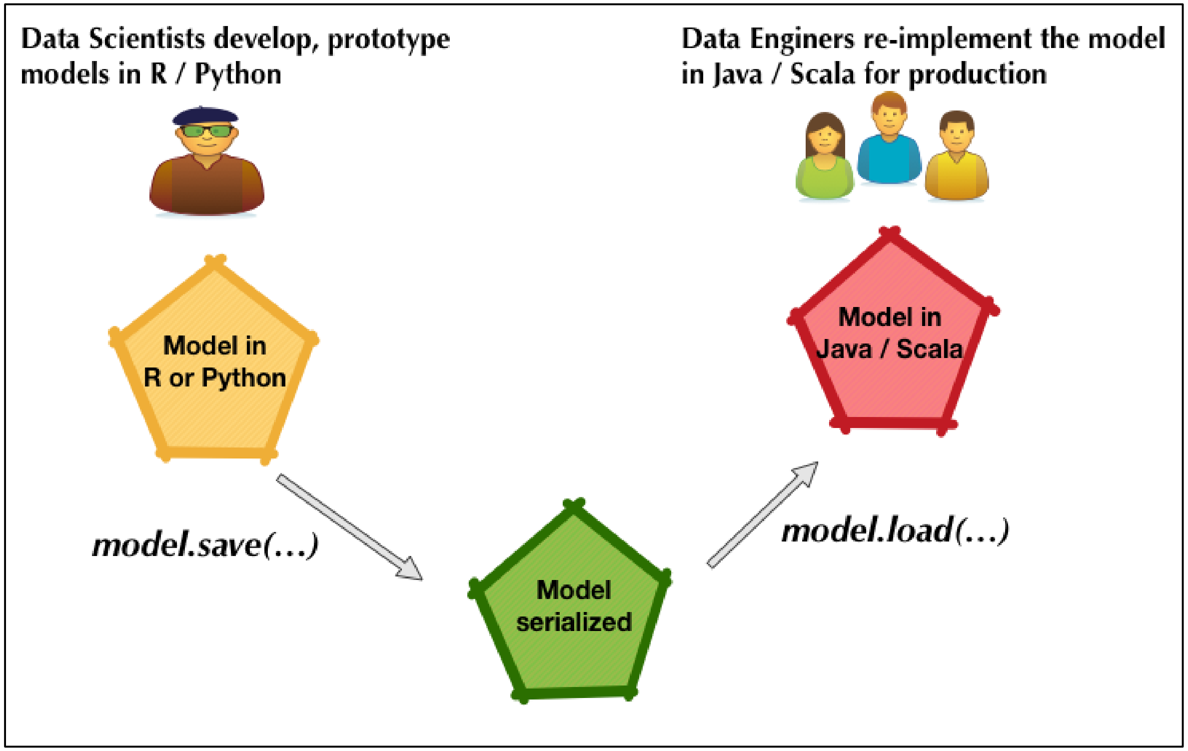
- Spark.mllib contains the original API built on top of RDDs
- MLLib has been migrating to a new API called Spark.ML
- **Spark.ml** provides higher-level API built on top of Dataframes for constructing ML pipelines
  - Dataframes provide faster data access, better caching ..etc
- As of Spark v2.0, RDD based spark.mllib package is in maintenance mode (no new features, bug fixes only)
  - Removed in Spark v3.0

Streamlining Prototyping → deploy



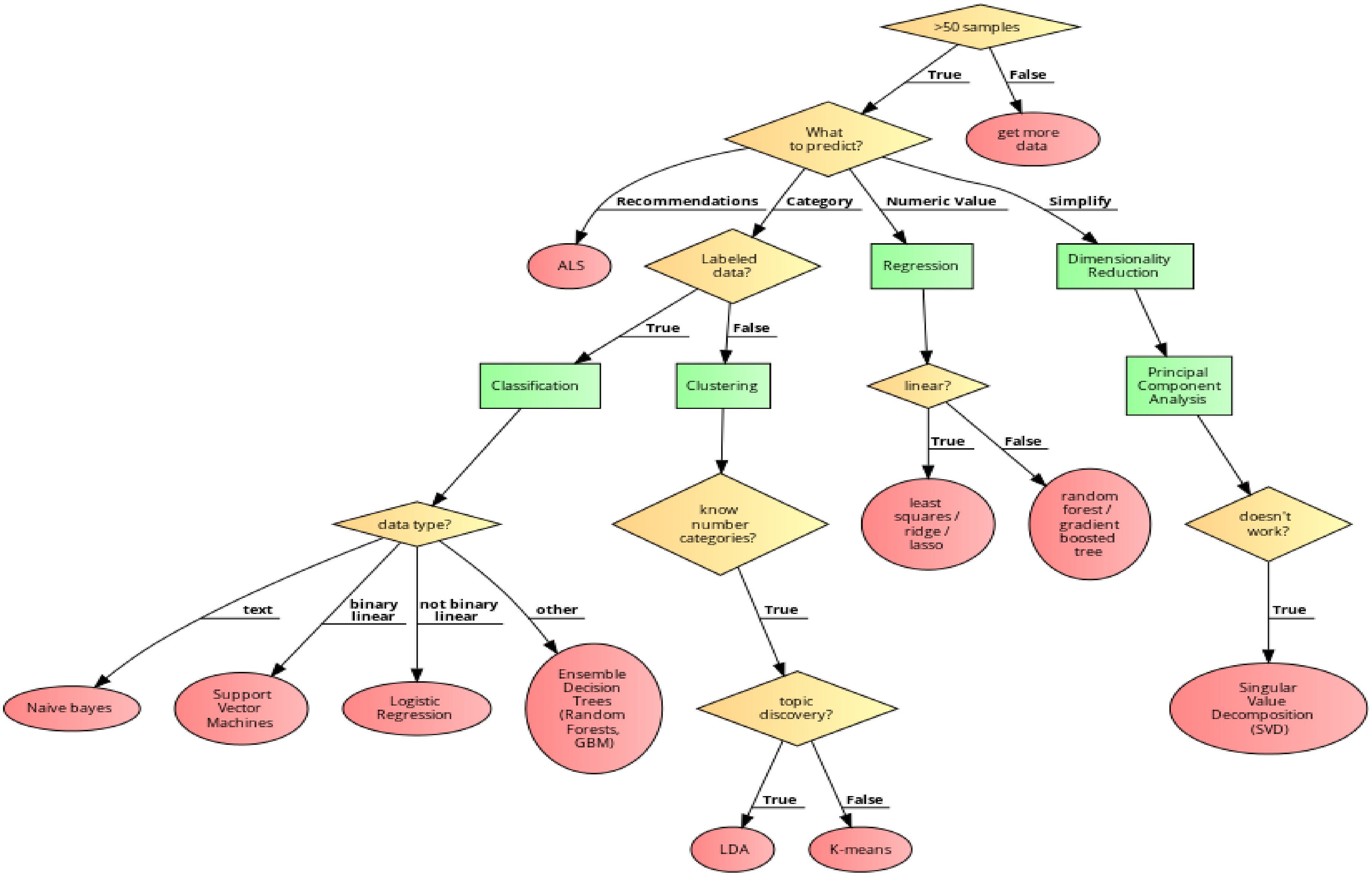
- Extra work
- Different code path
  - – Possible bugs!
- Updating models is slow!

Streamlining Prototyping → deploy



- Language neutral
- Same model – no need to re-implement
- Fast deploy!

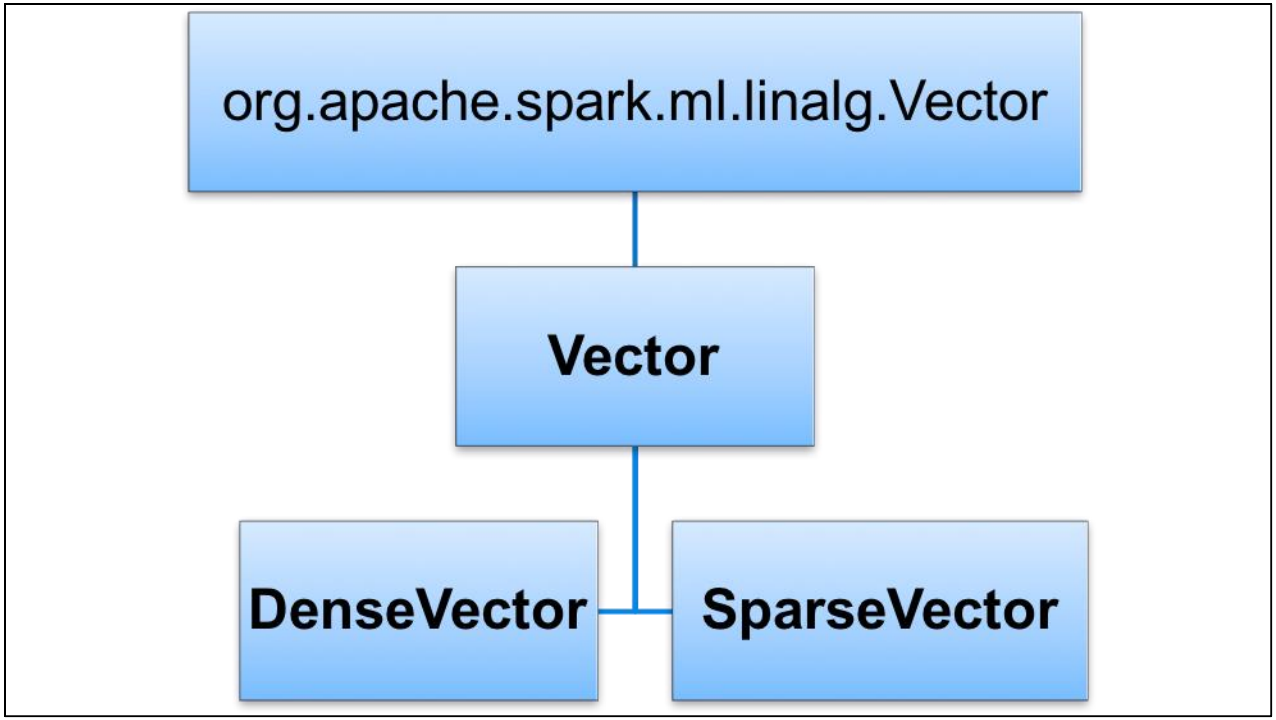
ML Algorithm overview



ML Data Types And Utilities

ML Vectors

- One dimensional array of Numerics / Doubles
- **DenseVector**
  When most positions in the vector have value
- **SparseVector**
  When most elements have no value



DenseVector vs. Spark Vector

- DenseVector = simply an array
  [1, 2, 3, 4, 5]

- SparseVector
  - We specify size
  - Index array
  - and value array

- Vectors.sparse (length,   index array,   value array)
  Vectors.sparse(10, (0,9),   (100,200))
  - Size is 10
  - 0^{th} (first) element = 100
  - 9^{th} (last) element = 200
  - [100. 0. 0. 0. 0. 0. 0. 0. 0. 200.]

Creating Vectors (Python)

- We use **Vectors** class to create dense or sparse vectors

```
from pyspark.ml.linalg import Vectors

v1 = Vectors.dense(3,2,1)
print(v1)
# [3.0,  2.0,   1.0]

## sparse (size of array,  indexe array,  value array)
v2 = Vectors.sparse(10, (0, 9), (100, 200))
print(v2)
# (10,[0,9],[100.0,200.0])

print(v2.toArray())
# [ 100.    0.    0.    0.    0.    0.    0.    0.    0.  200.]
```

ML Utilities

ML Overview

➔ **ML Utilities**

Transformers

Pipelines

Splitting Data Into Training / Test Subsets

- **Dataframe.randomSplit (weights)**
- **Dataframe.randomSplit(weights, seed)**
  - Use the 'seed' to consistent split
- Weights should add up to 1.0

```
(train, test) = df.randomSplit( [0.7, 0.3])
```

Training / Test Split Code (Python)

```
df = spark.range(1,100)
df.show()
(train, test) = df.randomSplit([0.7, 0.3])
print("----training data set-----")
print("count: ", train.count())
train.show()

print("----testing data set-----")
print("count: ", test.count())
test.show()

common = train.intersect(test)
print("----common data set-----")
print("count: ", common.count())
common.show()
```

```
# df
Count= 100

+---+
| id|
+---+
|  1|
|  2|
|  3|
|  4|
|  5|
|  6|
|  7|
|  8|
|  9|
| 10|
```

```
# train
Count= 69

+---+
| id|
+---+
|  3|
|  4|
|  5|
|  6|
|  7|
|  9|
| 11|
| 12|
| 13|
| 17|
```

```
# test
Count= 31

+---+
| id|
+---+
|  1|
|  2|
|  8|
| 10|
| 15|
| 16|
| 18|
| 21|
| 23|
| 26|
```

```
# common
Count= 0

+---+
| id|
+---+
```

ML Transformers

ML Overview

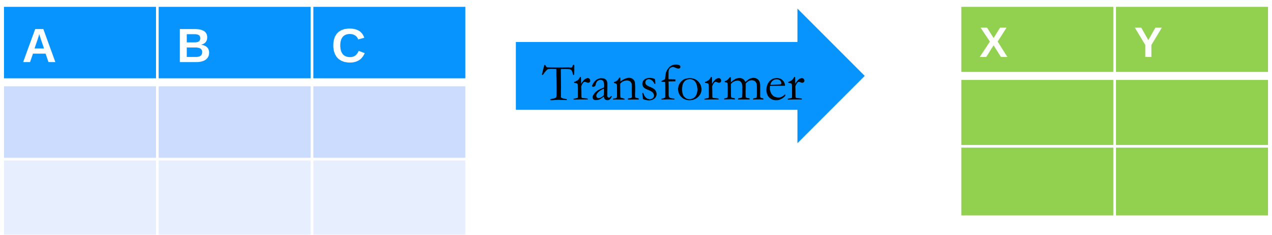
Utilities

➔ **Transformers**

Pipelines

Transformers

- A Transformer is an algorithm which can transform one DataFrame into another DataFrame.
- E.g., an ML model is a Transformer which transforms a DataFrame with features into a DataFrame with predictions.



VectorAssembler

- Transforms a Dataframe To Another Dataframe
  - By adding (or appending) to a "**features**" column

Car name	mpg	cyl	hp
Mazda RX	21	6	110
Merc 240D	24	4	62
Lincoln Continental	10.4	8	215
Toyota Corolla	33.9	4	65

VectorAssembler [mpg + cyl]

Car name	mpg	cyl	hp	Features
Mazda RX	21	6	110	**[21, 6]**
Merc 240D	24	4	62	**[24, 4]**
Lincoln Continental	10	8	215	**[10, 8]**
Toyota Corolla	34	4	65	**[34, 4]**

VectorAssembler Example Code (Python)

```python
from pyspark.ml.feature import VectorAssembler

data = spark.read.csv("mtcars_header.csv", header=True, inferSchema=True)
mpg_cyl = data.select("model", "mpg", "cyl")
mpg_cyl.show()

assembler = VectorAssembler(inputCols=["mpg", "cyl"], outputCol="features")
feature_vector = assembler.transform(mpg_cyl)
feature_vector.show(40)
```

```
## mpg_cyl

+------------------+----+---+
|             model| mpg|cyl|
+------------------+----+---+
|         Mazda RX4|21.0|  6|
|     Mazda RX4 Wag|21.0|  6|
|        Datsun 710|22.8|  4|
|    Hornet 4 Drive|21.4|  6|
| Hornet Sportabout|18.7|  8|
```

```
## feature_vector

+------------------+----+---+----------+
|             model| mpg|cyl|  features|
+------------------+----+---+----------+
|         Mazda RX4|21.0|  6|[21.0,6.0]|
|     Mazda RX4 Wag|21.0|  6|[21.0,6.0]|
|        Datsun 710|22.8|  4|[22.8,4.0]|
|    Hornet 4 Drive|21.4|  6|[21.4,6.0]|
| Hornet Sportabout|18.7|  8|[18.7,8.0]|
```

String Indexer

- Converts string based values into numeric values
- Numeric values are in [0, Number of Labels-1]
- Most frequently used label gets 0 and so on

id	color
1	red
2	white
3	blue
4	blue
5	white
6	yellow
7	blue

id	color	Color index
1	red	3.0
2	white	1.0
3	blue	0.0
4	blue	0.0
5	white	1.0
6	yellow	2.0
7	blue	0.0

String Indexer Example Code (Python)

```python
import pandas as pd
from pyspark.ml.feature import IndexToString, StringIndexer

df_pd = pd.DataFrame({"id":[1,2,3,4,5,6,7],
                      "color":['red', 'white', 'blue', 'blue', 'white' ,'yellow', 'blue'
                      ]})
df_spark = spark.createDataFrame(df_pd)

str_indexer = StringIndexer(inputCol="color", outputCol="colorIndex")
model = str_indexer.fit(df_spark)
indexed = model.transform(df_spark)
```

```
+------+---+
| color| id|
+------+---+
|   red|  1|
| white|  2|
|  blue|  3|
|  blue|  4|
| white|  5|
|yellow|  6|
|  blue|  7|
+------+---+
```

String Indexer

```
+------+---+----------+
| color| id|colorIndex|
+------+---+----------+
|   red|  1|       3.0|
| white|  2|       1.0|
|  blue|  3|       0.0|
|  blue|  4|       0.0|
| white|  5|       1.0|
|yellow|  6|       2.0|
|  blue|  7|       0.0|
+------+---+----------+
```

Reverse String Indexer Example Code (Python)

```
converter = IndexToString(inputCol="colorIndex", outputCol="originalColor")
converted = converter.transform(indexed)
converted.show()
```

```
+------+---+
| color| id|
+------+---+
|   red|  1|
| white|  2|
|  blue|  3|
|  blue|  4|
| white|  5|
|yellow|  6|
|  blue|  7|
+------+---+
```

```
+------+---+----------+
| color| id|colorIndex|
+------+---+----------+
|   red|  1|       3.0|
| white|  2|       1.0|
|  blue|  3|       0.0|
|  blue|  4|       0.0|
| white|  5|       1.0|
|yellow|  6|       2.0|
|  blue|  7|       0.0|
+------+---+----------+
```

```
+------+---+----------+-------------+
| color| id|colorIndex|originalColor|
+------+---+----------+-------------+
|   red|  1|       3.0|          red|
| white|  2|       1.0|        white|
|  blue|  3|       0.0|         blue|
|  blue|  4|       0.0|         blue|
| white|  5|       1.0|        white|
|yellow|  6|       2.0|       yellow|
|  blue|  7|       0.0|         blue|
+------+---+----------+-------------+
```

One Hot Encoding

- Most ML algorithms need numeric data
- So we need to convert categorical / string data into numerical data before training the model
- Below we see two approaches of encoding 'marital status' data
- The one in middle has various indexes
- The one in right creates 'dummy variables' and assigns true / false to each.
  – Note, only one bit is on
  – This is called **ONE-HOT-Encoding**

id	status
1	married
2	single
3	married
4	Divorced
5	single

id	Status idx
1	0
2	1
3	0
4	2
5	1

id	is married	is single	is divorced
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	1
5	0	1	0

Hot Encoder Code (Python)

```
import pandas as pd
from pyspark.ml.feature import StringIndexer, OneHotEncoder

df2_pd = pd.DataFrame({"id":[1,2,3,4,5,6,7],
                       "status":['married', 'single', 'single', 'divorced', 'married'
                       ,'single', 'married' ]})
df2_spark = spark.createDataFrame(df2_pd)

# first String Indexer
string_indexer = StringIndexer(inputCol="status", outputCol="statusIndex")
model = string_indexer.fit(df2_spark)
indexed = model.transform(df2_spark)

encoder = OneHotEncoder(inputCol="statusIndex", outputCol="statusVector",
dropLast=False)
encoded = encoder.transform(indexed)
encoded.show()

print(encoded.toPandas()) # print pandas df
```


Hot Encoder Code (Python)

```
+---+--------+
| id|  status|
+---+--------+
|  1| married|
|  2|  single|
|  3|  single|
|  4|divorced|
|  5| married|
|  6|  single|
|  7| married|
+---+--------+
```

String Indexer

```
+---+--------+-----------+
| id|  status|statusIndex|
+---+--------+-----------+
|  1| married|        0.0|
|  2|  single|        1.0|
|  3|  single|        1.0|
|  4|divorced|        2.0|
|  5| married|        0.0|
|  6|  single|        1.0|
|  7| married|        0.0|
+---+--------+-----------+
```

Hot Encoder

```
+---+--------+-----------+-------------+
| id|  status|statusIndex| statusVector|
+---+--------+-----------+-------------+
|  1| married|        0.0|(3,[0],[1.0])|
|  2|  single|        1.0|(3,[1],[1.0])|
|  3|  single|        1.0|(3,[1],[1.0])|
|  4|divorced|        2.0|(3,[2],[1.0])|
|  5| married|        0.0|(3,[0],[1.0])|
|  6|  single|        1.0|(3,[1],[1.0])|
|  7| married|        0.0|(3,[0],[1.0])|
+---+--------+-----------+-------------+
```

Understanding Hot Encoded Sparse Vectors

- We are converting Spark DF → Pandas DF.
  So the spare vector array is displayed.

```
+---+--------+-----------+-------------+
| id|  status|statusIndex| statusVector|
+---+--------+-----------+-------------+
|  1| married|        0.0|(3,[0],[1.0])|
|  2|  single|        1.0|(3,[1],[1.0])|
|  3|  single|        1.0|(3,[1],[1.0])|
|  4|divorced|        2.0|(3,[2],[1.0])|
|  5| married|        0.0|(3,[0],[1.0])|
|  6|  single|        1.0|(3,[1],[1.0])|
|  7| married|        0.0|(3,[0],[1.0])|
+---+--------+-----------+-------------+
```

```
id     status  statusIndex     statusVector
  1   married          0.0  (1.0, 0.0, 0.0)
  2    single          1.0  (0.0, 1.0, 0.0)
  3    single          1.0  (0.0, 1.0, 0.0)
  4  divorced          2.0  (0.0, 0.0, 1.0)
  5   married          0.0  (1.0, 0.0, 0.0)
  6    single          1.0  (0.0, 1.0, 0.0)
  7   married          0.0  (1.0, 0.0, 0.0)
```

Scaling Data

- Sometimes we want to scale input data, so the algorithms produce better results
- Scaling prevents against features with very large variances exerting an overly large influence during model training.
- Consider the following data
  Salary with its larger range, might influence the outcome more
- Scaling can improve the convergence rate during the optimization process
- Spark ML has
  - Standard Scaler
  - MinMax Scaler

Age	Salary
20	50,000
23	65,000
40	100,000
35	86,000
30	75,000

Scaling: Standard Scalar

- **StandardScaler** standardizes features by scaling to unit variance and around mean (can be zeroed optionally)
- Uses column summary statistics on the samples in the training set
- This is a very common pre-processing step

Standard Scaler Code 1/2- Python

```python
import pandas as pd
from pyspark.ml.feature import VectorAssembler

df_pd = pd.DataFrame({
  "home_runs": [ 30,  22,  17,  12, 44,   38,  40],
  "salary_in_k":[ 700, 450,340, 250, 1200, 800, 950 ]})
df_spark = spark.createDataFrame(df_pd)

assembler = VectorAssembler(inputCols=["home_runs", "salary_in_k"],
outputCol="features")
feature_vector = assembler.transform(df_spark)
feature_vector.show()
```

```
+---------+-----------+-------------+
|home_runs|salary_in_k|     features|
+---------+-----------+-------------+
|       30|        700| [30.0,700.0]|
|       22|        450| [22.0,450.0]|
|       17|        340| [17.0,340.0]|
|       12|        250| [12.0,250.0]|
|       44|       1200|[44.0,1200.0]|
|       38|        800| [38.0,800.0]|
|       40|        950| [40.0,950.0]|
+---------+-----------+-------------+
```

Standard Scaler Code 2/2- Python

```python
from pyspark.ml.feature import StandardScaler
scaler = StandardScaler(inputCol="features",
                        outputCol="scaled_features",
                        withStd=True, withMean=False)
scalerModel = scaler.fit(feature_vector)
scaledData = scalerModel.transform(feature_vector)
scaledData.show()
```

```
+---------+-----------+------------+-------------------------------------+
|home_runs|salary_in_k|features    |scaled_features                      |
+---------+-----------+------------+-------------------------------------+
|30       |700        |[30.0,700.0] |[2.435993828823451,2.03376119068933]  |
|22       |450        |[22.0,450.0] |[1.786395474470530 6,1.307417908300283 5]|
|17       |340        |[17.0,340.0] |[1.380396502999955 4,0.987826864049103] |
|12       |250        |[12.0,250.0] |[0.974397531529380 4,0.726343282389046 3]|
|44       |1200       |[44.0,1200.0]|[3.572790948941061,3.486447755467422 5] |
|38       |800        |[38.0,800.0] |[3.085592183176371,2.324298503644948]  |
|40       |950        |[40.0,950.0] |[3.247991771764601 4,2.760104473078376] |
+---------+-----------+------------+-------------------------------------+
```

Scaling : MinMaxScaler

- MinMax Scaler allows you to scale data at arbitrary range – 0.0 to 1.0 is default or 0 to 100)

```
from pyspark.ml.feature import MinMaxScaler

mmScaler = MinMaxScaler(min=1, max=100,
                        inputCol="features",
                        outputCol="scaled_features2")
scaledModel2 = mmScaler.fit(feature_vector)
scaledData2 = scaledModel2.transform(feature_vector)
scaledData2.show(10, False)
```

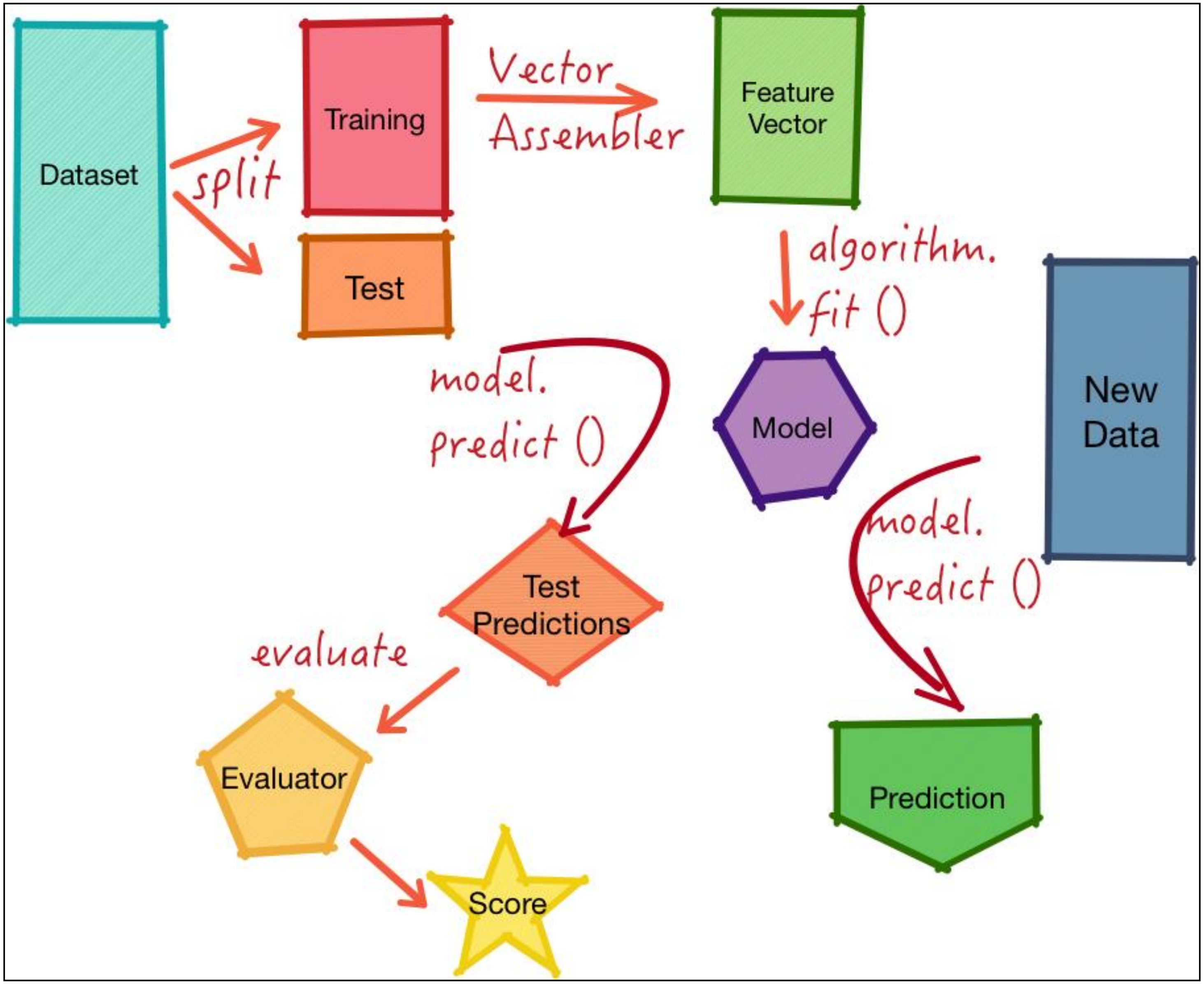
```
+---------+-----------+------------+-------------------------------+
|home_runs|salary_in_k|features    |scaled_features2               |
+---------+-----------+------------+-------------------------------+
|30       |700        |[30.0,700.0] |[56.6875,47.89473684210526]   |
|22       |450        |[22.0,450.0] |[31.9375,21.842105263157894]  |
|17       |340        |[17.0,340.0] |[16.46875,10.378947368421054]|
|12       |250        |[12.0,250.0] |[1.0,1.0]                     |
|44       |1200       |[44.0,1200.0]|[100.0,100.0]                 |
|38       |800        |[38.0,800.0] |[81.4375,58.31578947368421]   |
|40       |950        |[40.0,950.0] |[87.625,73.94736842105263]    |
+---------+-----------+------------+-------------------------------+
```

Creating Vectors From Text

- TF/IDF: Term Frequency/Inverse Document Frequency
  - This essentially means the frequency of a term divided by its frequency in the larger group of documents (the “corpus”)
  - Each word in the corpus is then a “dimension” – you would have thousands of dimensions.

- Word2Vec
  - Created at Google

Spark ML Workflow



Lab 5.1: ML Basics

Lab

- **Overview**:
  Get familiar with ML APIs in Spark

- **Approximate time**:
  10 – 15 mins

- **Instructions**:
  - **5.1 : 'basics/spark-ml-basics'** lab for Scala / Python

Pipelines

ML Overview

Utilities

Transformers

➔ **Pipelines**

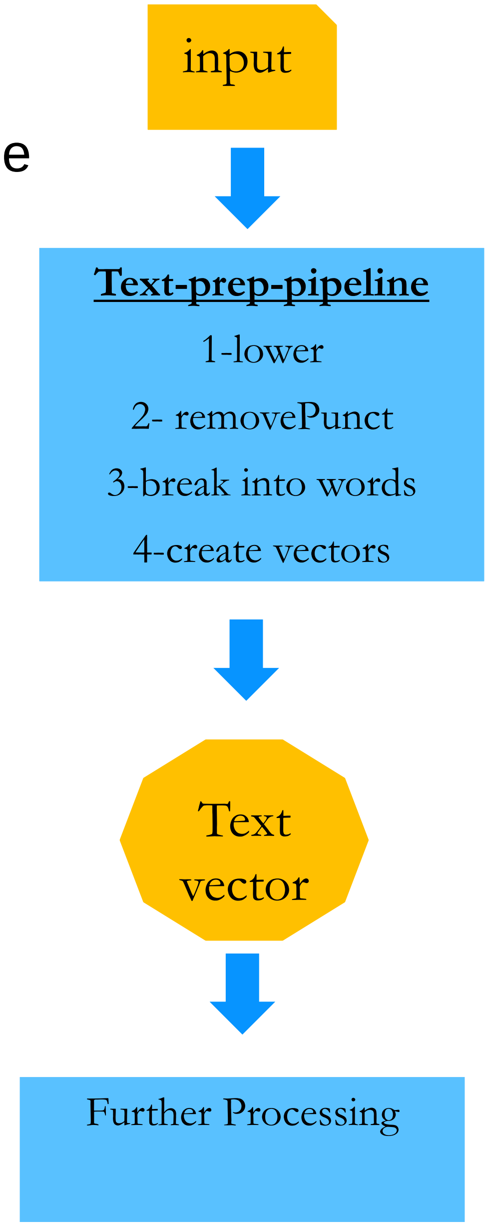
ML Pipelines

- Spark ML Pipelines is a powerful concept combining multiple steps to be carried out as a single unit
  - Reusable, repeatable
  - Makes very modular code
- This feature is modelled after the Python 'Scikit.Learn' pipeline feature
- Also allows tuning various parameters of the pipeline. 'Hyper Tuning'

Pipeline Example

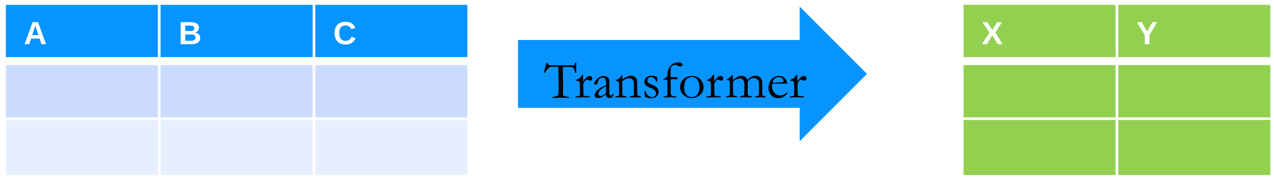
- Imagine a text processing task.
- On left are individual steps
- On right we create a pipeline encompassing multiple steps
- This pipeline is re-useable by other programs too!

```
# text processing

df1 = spark.read(...)

# step1 - lower case the text
df2 = df1.lowercase()

# step2 - remove numbers /
punctuations
df3 = df2.removeNumbersPunct()

# step3 – break into words
df4 = df3.splitIntoWords()

# step4 – create word vectors
df5 = df4.word2Vec()

# process df5
```

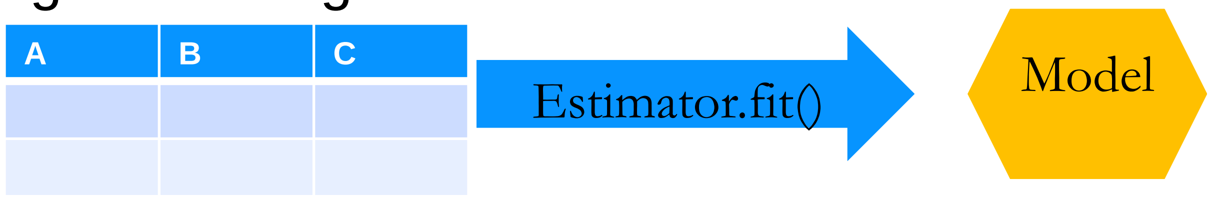


Pipeline Concepts

- **Dataframe**: Contains data
- **Transformer**: Converts one dataframe into another



- **Estimator**: fits the data in Dataframe to create a transformer.
  – E.g. a learning model is an estimator



- **Pipeline**: Contains multiple Transformers and Estimators
- **Parameter**: Parameters can be passed uniformly to all components within a pipeline

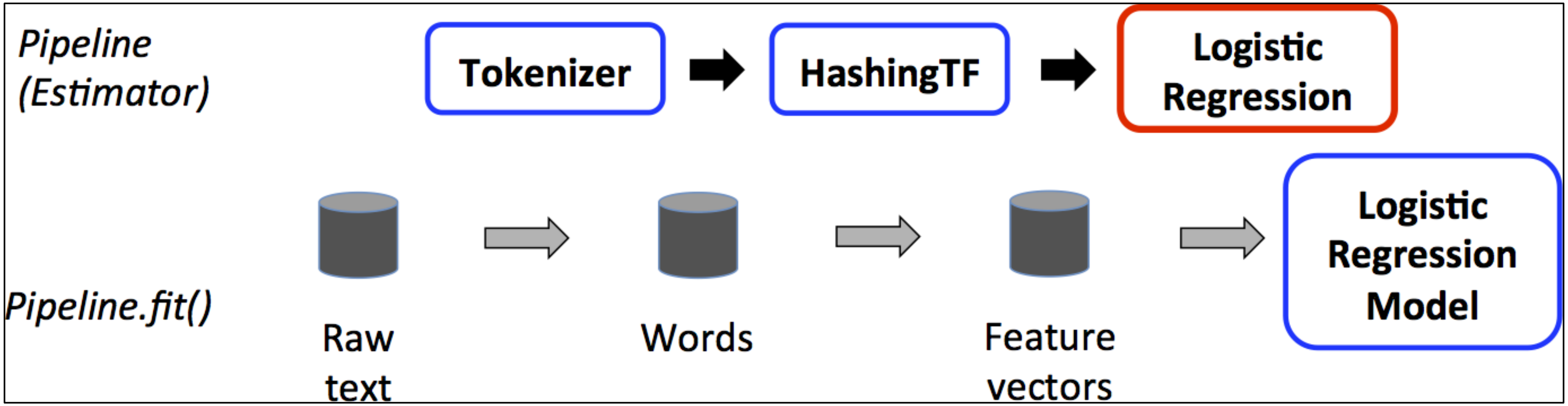
Pipeline Example Code (Python)

- Here we are creating a pipeline consisting of 3 stages
  - Tokenizer: breaks text into words
  - HashingTF: converts words into Vector
  - And finally, a LogisticRegression model
- Also note, we train the model on the **entire** pipeline in one go!

```
from pyspark.ml import Pipeline
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.feature import HashingTF, Tokenizer

training_data = spark.read(....)

# Configure an ML pipeline, which consists of three stages: tokenizer, hashingTF, and lr.
tokenizer = Tokenizer(inputCol="text", outputCol="words")
hashingTF = HashingTF(inputCol="words", outputCol="features")
lr = LogisticRegression(maxIter=10, regParam=0.001)
pipeline = Pipeline(stages=[tokenizer, hashingTF, lr])

# Fit the pipeline to training documents.
model = pipeline.fit(training_data)

test_data = spark.read(...)
predicted_data = model.predict(test_data)
```

Pipeline Explained

- 3 stage pipeline shown
- First two (Tokenizer, hashingTF) are transformers (blue), third LogisticRegression is estimator (red)
- Pipeline executes 'transform' on first two and 'fit' on Logistic Regression



Further Reading

- http://spark.apache.org/docs/latest/ml-guide.html

- https://www.slideshare.net/julesdamji/apache-spark-mllib-2x-how-to-productionize-your-machine-learning-models