Big Data

Spark ML

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Smart Software System Laboratory

“Big data is at the foundation of all the megatrends that are happening today, from social to mobile to cloud to gaming.”

– Chris Lynch, Vertica Systems

Spark Machine Learning

Spark Mllib Utilities

Linear Algebra

- API Guide

  http://spark.apache.org/docs/3.0.1/api/python/pyspark.ml.html#module-pyspark.ml.linalg

- MLlib RDD-Base Guide

  http://spark.apache.org/docs/latest/mllib-data-types.html

Spark Mllib Utilities

Linear Algebra

Not secure | spark.apache.org/docs/3.0.1/api/python/pyspark.ml.html#module-pyspark.ml.linalg

pyspark.ml.linalg module

MLlib utilities for linear algebra. For dense vectors, MLlib uses the NumPy *array* type, so you can simply pass NumPy arrays around. For sparse vectors, users can construct a `SparseVector` object from MLlib or pass SciPy *scipy.sparse* column vectors if SciPy is available in their environment.

class `pyspark.ml.linalg.`**`Vector`** [source]

`toArray`() [source]

Convert the vector into an numpy.ndarray

Returns: numpy.ndarray

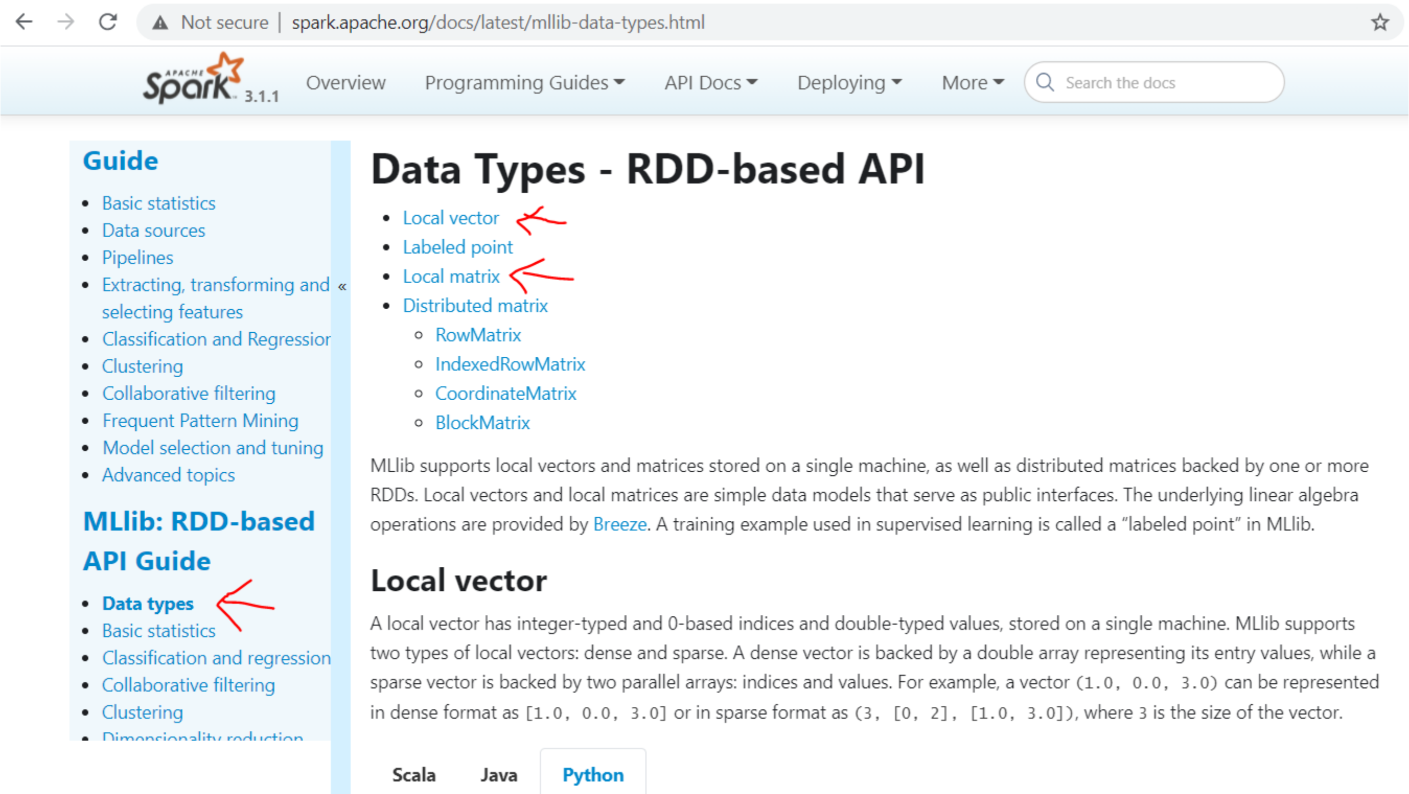
class `pyspark.ml.linalg.`**`DenseVector`**(*ar*) [source]

A dense vector represented by a value array. We use numpy array for storage and arithmetics will be delegated to the underlying numpy array.

```
>>> v = Vectors.dense([1.0, 2.0])
>>> u = Vectors.dense([3.0, 4.0])
>>> v + u
DenseVector([4.0, 6.0])
>>> 2 - v
DenseVector([1.0, 0.0])
>>> v / 2
DenseVector([0.5, 1.0])
>>> v * u
DenseVector([3.0, 8.0])
>>> u / v
DenseVector([3.0, 2.0])
>>> u % 2
```

Spark Mllib Utilities

Linear Algebra



Not secure | spark.apache.org/docs/latest/mllib-data-types.html

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Guide

- Basic statistics
- Data sources
- Pipelines
- Extracting, transforming and selecting features
- Classification and Regression
- Clustering
- Collaborative filtering
- Frequent Pattern Mining
- Model selection and tuning
- Advanced topics

MLlib: RDD-based API Guide

- **Data types**
- Basic statistics
- Classification and regression
- Collaborative filtering
- Clustering
- Dimensionality reduction

Data Types - RDD-based API

- Local vector
- Labeled point
- Local matrix
- Distributed matrix
  - RowMatrix
  - IndexedRowMatrix
  - CoordinateMatrix
  - BlockMatrix

MLlib supports local vectors and matrices stored on a single machine, as well as distributed matrices backed by one or more RDDs. Local vectors and local matrices are simple data models that serve as public interfaces. The underlying linear algebra operations are provided by Breeze. A training example used in supervised learning is called a “labeled point” in MLlib.

Local vector

A local vector has integer-typed and 0-based indices and double-typed values, stored on a single machine. MLlib supports two types of local vectors: dense and sparse. A dense vector is backed by a double array representing its entry values, while a sparse vector is backed by two parallel arrays: indices and values. For example, a vector `(1.0, 0.0, 3.0)` can be represented in dense format as `[1.0, 0.0, 3.0]` or in sparse format as `(3, [0, 2], [1.0, 3.0])`, where `3` is the size of the vector.

Scala Java Python

Spark Mllib Utilities

Linear Algebra

Vectors	Matrices
• Vectors (main class to use) • DenseVector: MLlib uses the NumPy array type • SparseVector : You can pass SciPy scipy.sparse column vectors • VectorUDT • Vector	• Matrices (_main class to use_) • DenseMatrix: Column-major dense matrix • SparseMatrix : Sparse matrix stored in CSC format • MatrixUDT • Matrix

Vectors and matrices are important data types and provide integration with NumPy and SciPy

Spark Mllib Utilities

Linear Algebra

[ ]:
```python
import findspark
findspark.init()
import pyspark
from pyspark.sql import SparkSession
spark = SparkSession.builder.getOrCreate()
```

Spark Mllib Utilities

Linear Algebra

Sparse Vector Example

[ ]:

```
import numpy as np
import scipy.sparse as sps
from pyspark.ml.linalg import Vectors

# Use a NumPy array as a dense vector.
dv1 = np.array([1.0, 0.0, 3.0])

# Create a SparseVector.
sv1 = Vectors.sparse(3, [0, 2], [1.0, 3.0])

print(dv1)
print(sv1)
```

Dense Vector Example

[ ]:

```
# Use a Python list as a dense vector.
dv2 = [1.0, 0.0, 3.0]

# Use a single-column SciPy csc_matrix as a sparse vector.
sv2 = sps.csc_matrix(
    (np.array([1.0, 3.0]), np.array([0, 2]), np.array([0, 2])), shape=(3, 1)
)

print(dv2)
print(sv2)
```

Spark Mllib Utilities

Linear Algebra

Dense Matrix

[ ]:
```
from pyspark.ml.linalg import Matrix, Matrices

# Create a dense matrix ((1.0, 2.0), (3.0, 4.0), (5.0, 6.0))
dm2 = Matrices.dense(3, 2, [1, 3, 5, 2, 4, 6])
print(dm2)
```

Sparse Matrix

[ ]:
```
# Create a sparse matrix ((9.0, 0.0), (0.0, 8.0), (0.0, 6.0))
sm = Matrices.sparse(3, 2, [0, 1, 3], [0, 2, 1], [9, 6, 8])
print(sm)
```

Spark Mllib Utilities

Data Sources

http://spark.apache.org/docs/3.0.1/api/python/pyspark.ml.html#module-pyspark.ml.image

https://spark.apache.org/docs/latest/ml-datasource#image-data-source

Spark Mllib Utilities

Data Sources

Not secure | spark.apache.org/docs/3.0.1/api/python/pyspark.ml.html#module-pyspark.ml.image

pyspark.ml.image module

`pyspark.ml.image.`**`ImageSchema`**

An attribute of this module that contains the instance of **`_ImageSchema`**.

class `pyspark.ml.image.`**`_ImageSchema`** [source]

Internal class for *pyspark.ml.image.ImageSchema* attribute. Meant to be private and not to be instantiated. Use *pyspark.ml.image.ImageSchema* attribute to access the APIs of this class.

property **`columnSchema`**

Returns the schema for the image column.

Returns: a **`StructType`** for image column, `struct<origin:string, height:int, width:int, nChannels:int, mode:int, data:binary>`.

New in version 2.4.0.

property **`imageFields`**

Returns field names of image columns.

Returns: a list of field names.

New in version 2.3.0.

property **`imageSchema`**

Returns the image schema.

Returns: a **`StructType`** with a single column of images named “image” (nullable) and having the same type returned by **`columnSchema()`**.

Spark Mllib Utilities

Data Sources

spark.apache.org/docs/latest/ml-datasource#image-data-source

Spark 3.1.1 Overview Programming Guides API Docs Deploying More Search the docs

MLlib: Main Guide

- Basic statistics
- **Data sources**
- Pipelines
- Extracting, transforming and selecting features
- Classification and Regression
- Clustering
- Collaborative filtering
- Frequent Pattern Mining
- Model selection and tuning
- Advanced topics

MLlib: RDD-based API Guide

- Data types
- Basic statistics
- Classification and regression
- Collaborative filtering
- Clustering
- Dimensionality reduction

Data sources

In this section, we introduce how to use data source in ML to load data. Besides some general data sources such as Parquet, CSV, JSON and JDBC, we also provide some specific data sources for ML.

Table of Contents

Image data source

This image data source is used to load image files from a directory, it can load compressed image (jpeg, png, etc.) into raw image representation via `ImageIO` in Java library. The loaded DataFrame has one `StructType` column: "image", containing image data stored as image schema. The schema of the `image` column is:

- origin: `StringType` (represents the file path of the image)
- height: `IntegerType` (height of the image)
- width: `IntegerType` (width of the image)
- nChannels: `IntegerType` (number of image channels)
- mode: `IntegerType` (OpenCV-compatible type)
- data: `BinaryType` (Image bytes in OpenCV-compatible order: row-wise BGR in most cases)

Scala Java **Python** R

Spark Mllib Utilities

Data Sources

[3]:

```
import findspark
findspark.init()
import pyspark
from pyspark.sql import SparkSession
spark = SparkSession.builder.getOrCreate()
```

Example of loading image data using the `kittens` dataset that ships with Spark

Refer to ML Main Guide for more info: https://spark.apache.org/docs/latest/ml-datasource#image-data-source

The schema of the image column is:

- origin: StringType (represents the file path of the image)
- height: IntegerType (height of the image)
- width: IntegerType (width of the image)
- nChannels: IntegerType (number of image channels)
- mode: IntegerType (OpenCV-compatible type)
- data: BinaryType (Image bytes in OpenCV-compatible order: row-wise BGR in most cases)

Spark Mllib Utilities

Data Sources

[22]:
```
PATH = "D:/Spark/spark-3.0.1-bin-hadoop2.7/data/mllib/images/origin/kittens"
df = (
    spark.read.format("image")
    .option("dropInvalid", True)
    .load(PATH)
    .select("image.origin", "image.height", "image.width", "image.nChannels", "image.mode", "image.data")
)
df.toPandas()
```

[22]:

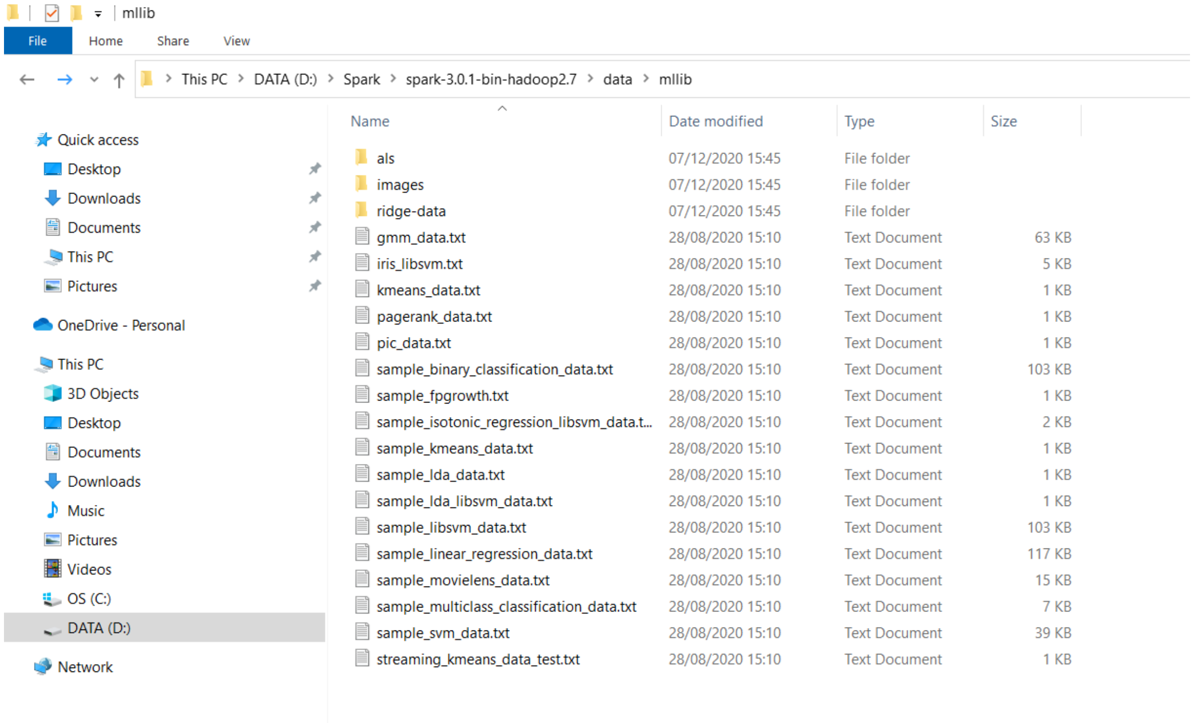
	origin	height	width	nChannels	mode	data
0	file:///usr/local/spark-2.4.3-bin-hadoop2.7/da...	311	300	3	16	[193, 193, 193, 194, 194, 194, 194, 194, 194, ...
1	file:///usr/local/spark-2.4.3-bin-hadoop2.7/da...	313	199	3	16	[208, 229, 237, 202, 223, 231, 210, 231, 239, ...
2	file:///usr/local/spark-2.4.3-bin-hadoop2.7/da...	200	300	3	16	[88, 93, 96, 88, 93, 96, 88, 93, 96, 89, 94, 9...
3	file:///usr/local/spark-2.4.3-bin-hadoop2.7/da...	296	300	3	16	[203, 230, 244, 202, 229, 243, 201, 228, 242, ...

[13]:
```
df.printSchema()
```

```
root
 |-- image: struct (nullable = true)
 |    |-- origin: string (nullable = true)
 |    |-- height: integer (nullable = true)
 |    |-- width: integer (nullable = true)
 |    |-- nChannels: integer (nullable = true)
 |    |-- mode: integer (nullable = true)
 |    |-- data: binary (nullable = true)
```

Spark Mllib Utilities

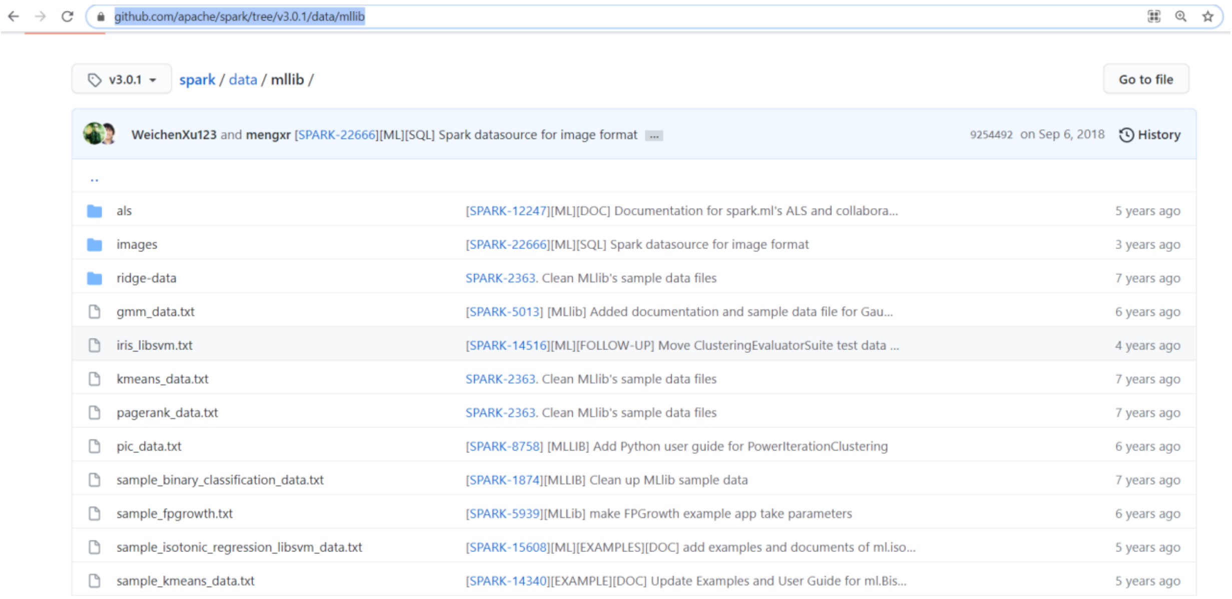
Sample Data



Spark Mllib Utilities

Sample Data

Github: https://github.com/apache/spark/tree/v3.0.1/data/mllib



Spark Mllib Utilities

Heppers

- http://spark.apache.org/docs/3.0.1/api/python/pyspark.ml.html#module-pyspark.ml.util

- BaseReadWrite
- DefaultParamsReadable
- DefaultParamsReader
- DefaultParamsWritable
- DefaultParamsWriter
- GeneralJavaMLWritable
- GeneralJavaMLWriter
- GeneralMLWriter
- Identifiable
- JavaMLReadable
- JavaMLReader
- JavaMLWritable
- JavaMLWriter
- JavaPredictionModel
- MLReadable
- MLReader
- MLWritable
- MLWriter

Spark Mllib

Learning Resources

- Main guide
  - http://spark.apache.org/docs/3.0.1/ml-guide.html

- API guide
  - http://spark.apache.org/docs/3.0.1/api/python/pyspark.ml.html

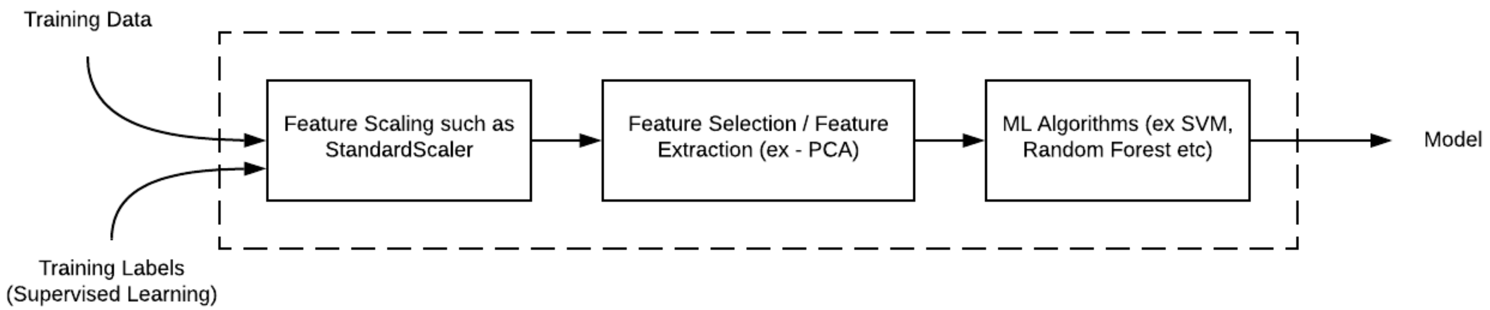
- Github
  - https://github.com/apache/spark/tree/v3.0.1/python/pyspark/ml

Spark MLlib Pipelines

- Pipelines API
    - Provide a Uniform Set of High-level APIs Built on Top of DataFrames that Help Users Create and Tune Practical Machine Learning Pipelines
    - https://spark.apache.org/docs/latest/ml-pipeline.html

Spark MLlib Pipelines

- Algorithms Working Together: Assembled in a Pipeline



Machine Learning Pipeline

Spark MLlib Pipelines

5 Key Concepts

- DataFrame
- Estimator
- Transformer
- Parameters
- Pipeline

Predictor

Spark MLlib Pipelines

Transfomer

- A Transformer is an abstraction that includes feature transformers and learned models
- Technically, a transformer implements a method `.transform()`, which converts one DataFrame into another, generally by appending one or more columns
- In code:

$$\underbrace{\texttt{df\_out}}_{\text{DataFrame}} = \underbrace{\texttt{Transformer}}_{\text{Model}}\texttt{.transform(}\underbrace{\texttt{df\_in}}_{\text{DataFrame}}\texttt{)}$$

Spark MLlib Pipelines

Estimator

- An estimator abstracts the concept of a learning algorithm or any algorithm that fits or trains on data
- Technically, an Estimator implements a method `.fit()`, which accepts a DataFrame and produces a model which is a transformer
- In code:

```
df_out = Estimator.fit(df_in)
```

Transformer

DataFrame

Spark MLlib Pipelines

Estimator vs Transformer

$$\underbrace{\texttt{model\_out}}_{\text{Transformer}} = \texttt{Estimator.fit}(\underbrace{\texttt{df\_in}}_{\text{DataFrame}})$$

$$\underbrace{\texttt{df\_out}}_{\text{DataFrame}} = \underbrace{\texttt{Transformer}}_{\text{Model}}\texttt{.transform}(\underbrace{\texttt{df\_in}}_{\text{DataFrame}})$$

Spark MLlib Pipelines

Pipeline

- Stages:
  - Pipelines consist of a sequence of stages that run in order
  - Each stage is either a $\underbrace{\text{transformer}}_{\text{.transform()}}$ or an $\underbrace{\text{estimator}}_{\text{.fit()}}$

`class Pipeline` — $\underbrace{\text{Pipeline}}_{\text{.fit(DataFrame)}}$

Acts as an Estimator, consists of stages

Stages execute in order when `.fit()` is called

`class PipelineModel` — $\underbrace{\text{PipelineModel}}_{\text{.transform(DataFrame)}}$

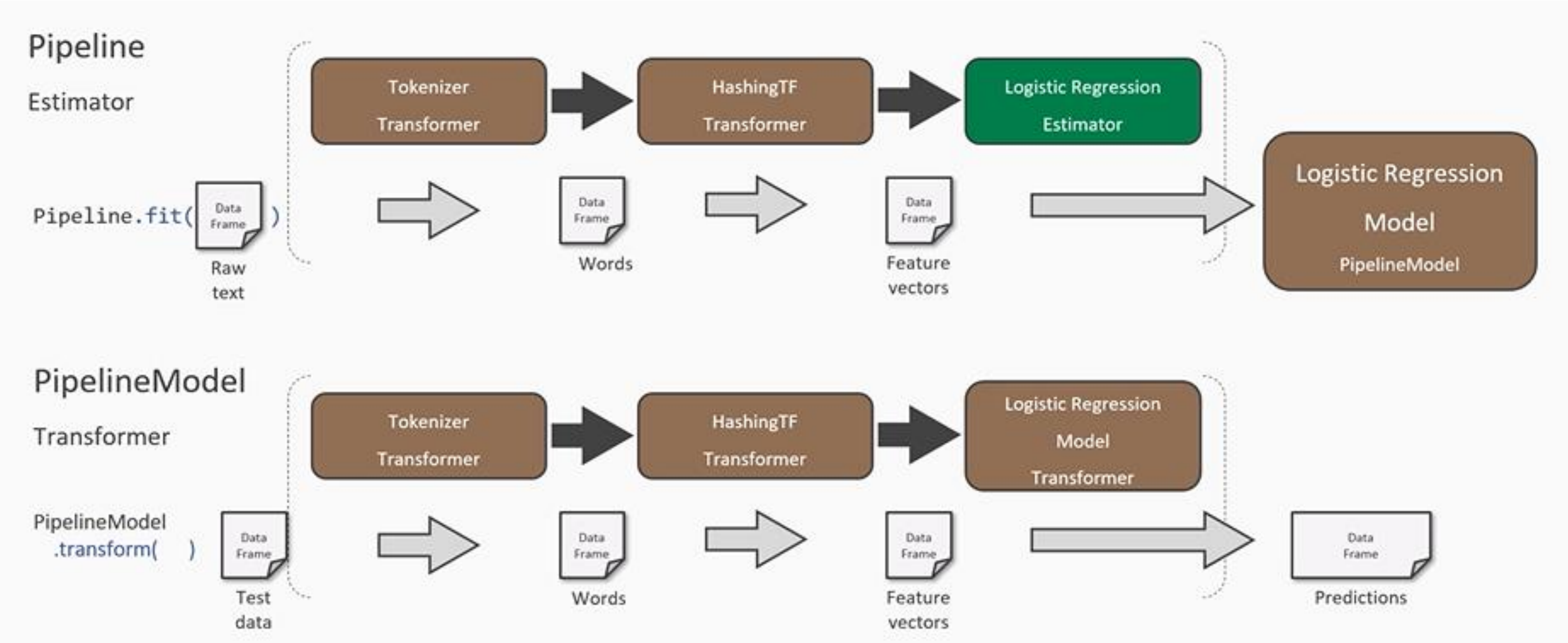
Represents a compiled pipeline with transformers and fitted models

A pipeline's `fit()` method, produces a PipelineModel

Acts as a transformer, consists of stages

Spark MLlib Pipelines

Example



Spark MLlib Pipelines

- Spark MLlib pipeline API:
  - MLlib standardizes APIs for its many machine learning algorithms to make it easier to combine multiple algorithms
  - The key concepts of pipelines are: Estimator, transformer, and parameter
  - Pipelines are a sequence of stages
  - Pipelines produce PipelineModels

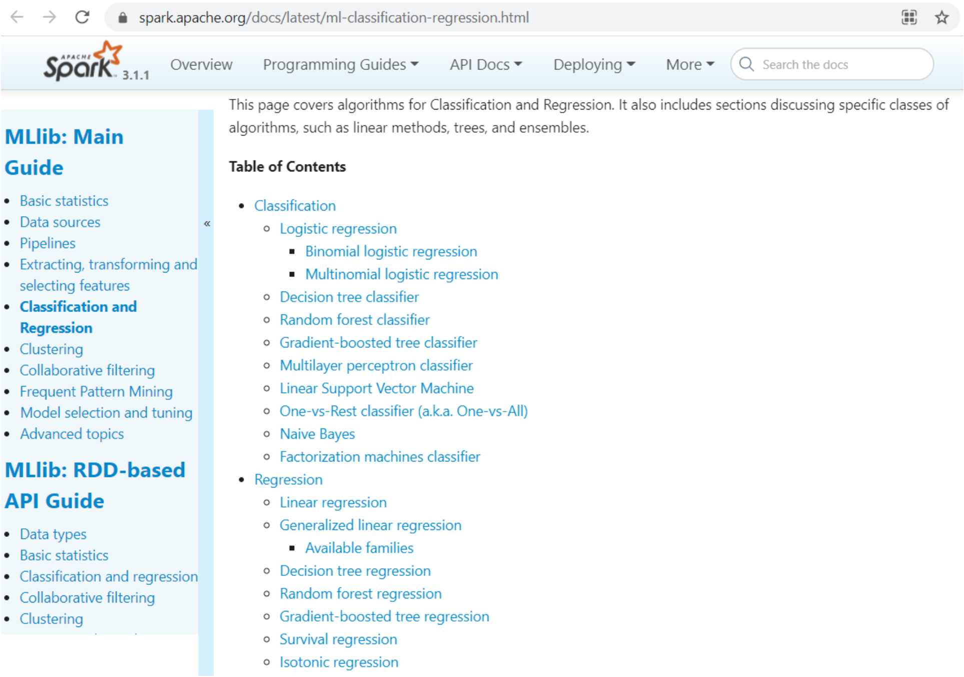
Spark MLlib Pipelines

- Spark MLlib pipeline API:
  - A PipelineModel represents a compiled pipeline with transformers and fitted models
  - PipelineModels perform the same transformations before running data through the compiled model

Spark MLlib Pipelines

Classification and regression

- https://spark.apache.org/docs/latest/ml-classification-regression.html



Spark MLlib Pipelines

Classification and regression

[2]:
```
import findspark
findspark.init()
import pyspark
from pyspark.sql import SparkSession
spark = SparkSession.builder.getOrCreate()

# Load and parse the data file, converting it to a DataFrame.
sample_libsvm_data = spark.read.format("libsvm").load("D:/Spark/spark-3.0.1-bin-hadoop2.7/data/mllib/sample_libsvm_data.txt")
```

Spark MLlib Pipelines

DecisionTreeClassifier

```
from pyspark.ml import Pipeline
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.feature import StringIndexer, VectorIndexer
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

sample_libsvm_data.show(5)
```

```
+-----+--------------------+
|label|            features|
+-----+--------------------+
|  0.0|(692,[127,128,129...|
|  1.0|(692,[158,159,160...|
|  1.0|(692,[124,125,126...|
|  1.0|(692,[152,153,154...|
|  1.0|(692,[151,152,153...|
+-----+--------------------+
only showing top 5 rows
```

Spark MLlib Pipelines

DecisionTreeClassifier

```
# Creating our stages:

# STAGE 1:
# Index labels, adding metadata to the label column.
# Fit on whole dataset to include all labels in index.
label_indexer = StringIndexer(inputCol="label", outputCol="indexedLabel").fit(
    sample_libsvm_data
)

# STAGE 2:
# Automatically identify categorical features, and index them.
# We specify maxCategories so features with > 4 distinct values are treated as continuous.
feature_indexer = VectorIndexer(
    inputCol="features", outputCol="indexedFeatures", maxCategories=4
).fit(sample_libsvm_data)

# STAGE 3:
# Train a DecisionTree model.
decission_tree_classifier_model = DecisionTreeClassifier(
    labelCol="indexedLabel", featuresCol="indexedFeatures"
)

print(type(decission_tree_classifier_model))
```

```
<class 'pyspark.ml.classification.DecisionTreeClassifier'>
```

Spark MLlib Pipelines

DecisionTreeClassifier

```
# Creating our Pipeline:

# Chain indexers and tree in a Pipeline
pipeline = Pipeline(
    stages=[
        label_indexer,  # STAGE 1
        feature_indexer,  # STAGE 2
        decission_tree_classifier_model,  # STAGE 3
    ]
)
```

Spark MLlib Pipelines

DecisionTreeClassifier

```
# Split the data into training and test sets (30% held out for testing)
(training_data, test_data) = sample_libsvm_data.randomSplit([0.7, 0.3])

# Train model.  This also runs the indexers.
model = pipeline.fit(training_data)

# Make predictions.
predictions = model.transform(test_data)

# Select example rows to display.
predictions.select("prediction", "indexedLabel", "features").show(5)

# Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(
    labelCol="indexedLabel", predictionCol="prediction", metricName="accuracy"
)
accuracy = evaluator.evaluate(predictions)
print(f"Test Error = {1.0 - accuracy:.5f} ")
```

```
+----------+------------+--------------------+
|prediction|indexedLabel|            features|
+----------+------------+--------------------+
|       1.0|         1.0|(692,[95,96,97,12...|
|       1.0|         1.0|(692,[123,124,125...|
|       1.0|         1.0|(692,[124,125,126...|
|       0.0|         1.0|(692,[124,125,126...|
|       1.0|         1.0|(692,[126,127,128...|
+----------+------------+--------------------+
only showing top 5 rows

Test Error = 0.19355
```

Spark MLlib Pipelines

DecisionTreeClassifier

```
# You can see that the Pipeline and the PipelineModel have the same stages
print(pipeline.getStages())
print(model.stages)
```

```
[StringIndexerModel: uid=StringIndexer_bde466415729, handleInvalid=error, VectorIndexerModel: uid=VectorIndexer_5be5f8abe571, numFeatures=692, handleInvalid=error, DecisionTreeClassifier_2381fa7fa6a8]
[StringIndexerModel: uid=StringIndexer_bde466415729, handleInvalid=error, VectorIndexerModel: uid=VectorIndexer_5be5f8abe571, numFeatures=692, handleInvalid=error, DecisionTreeClassificationModel: uid=DecisionTreeClassifier_2381fa7fa6a8, depth=2, numNodes=5, numClasses=2, numFeatures=692]
```

Spark MLlib Pipelines

Random Forest Regression

```
from pyspark.ml import Pipeline
from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.feature import VectorIndexer
from pyspark.ml.evaluation import RegressionEvaluator

sample_libsvm_data.show(5)
```

```
+-----+--------------------+
|label|            features|
+-----+--------------------+
|  0.0|(692,[127,128,129...|
|  1.0|(692,[158,159,160...|
|  1.0|(692,[124,125,126...|
|  1.0|(692,[152,153,154...|
|  1.0|(692,[151,152,153...|
+-----+--------------------+
only showing top 5 rows
```

Spark MLlib Pipelines

Random Forest Regression

```
# Creating our stages:

# STAGE 1:
# Automatically identify categorical features, and index them.
feature_indexer = VectorIndexer(
    inputCol="features",
    outputCol="indexedFeatures",
    # Set maxCategories so features with > 4 distinct values are treated as continuous.
    maxCategories=4,
).fit(sample_libsvm_data)

# STAGE 2:
# Train a RandomForest model.
random_forest_model = RandomForestRegressor(featuresCol="indexedFeatures")
```

Spark MLlib Pipelines

Random Forest Regression

```
# Creating our Pipeline:
# Chain indexer and forest in a Pipeline
pipeline = Pipeline(stages=[feature_indexer, random_forest_model])
```

Spark MLlib Pipelines

Random Forest Regression

```
# Split the data into training and test sets (30% held out for testing)
(training_data, test_data) = sample_libsvm_data.randomSplit([0.7, 0.3])

# Train model.  This also runs the indexer.
model = pipeline.fit(training_data)

# Make predictions.
predictions = model.transform(test_data)

# Select example rows to display.
predictions.select("prediction", "label", "features").show(5)

# Select (prediction, true label) and compute test error
evaluator = RegressionEvaluator(
    labelCol="label", predictionCol="prediction", metricName="rmse"
)
rmse = evaluator.evaluate(predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

```
+----------+-----+--------------------+
|prediction|label|            features|
+----------+-----+--------------------+
|      0.05|  0.0|(692,[122,123,148...|
|       0.0|  0.0|(692,[123,124,125...|
|      0.05|  0.0|(692,[124,125,126...|
|       0.0|  0.0|(692,[125,126,127...|
|       0.0|  0.0|(692,[126,127,128...|
+----------+-----+--------------------+
only showing top 5 rows

Root Mean Squared Error (RMSE) on test data = 0.0310087
```

Spark MLlib Pipelines

Random Forest Regression

```
# You can see that the Pipeline and the PipelineModel have the same stages
print(pipeline.getStages())
print(model.stages)
```

```
[VectorIndexerModel: uid=VectorIndexer_98f042bd5bbd, numFeatures=692, handleInvalid=error, RandomForestRegressor_77ce3e646d07]
[VectorIndexerModel: uid=VectorIndexer_98f042bd5bbd, numFeatures=692, handleInvalid=error, RandomForestRegressionModel: uid=RandomForestRegress
or_77ce3e646d07, numTrees=20, numFeatures=692]
```

```
# The last stage in a PipelineModel is usually the most informative
print(model.stages[-1])
```

```
RandomForestRegressionModel: uid=RandomForestRegressor_77ce3e646d07, numTrees=20, numFeatures=692
```

```
# Here you can see that pipeline and model are Pipeline and PipelineModel classes
print("pipeline:", type(pipeline))
print("model:", type(model))
```

```
pipeline: <class 'pyspark.ml.pipeline.Pipeline'>
model: <class 'pyspark.ml.pipeline.PipelineModel'>
```

Spark MLlib Pipelines

Classification and regression

- https://spark.apache.org/docs/latest/ml-classification-regression.html

Q & A

Cảm ơn đã theo dõi

Chúng tôi hy vọng cùng nhau đi đến thành công.