Machine Learning with Spark

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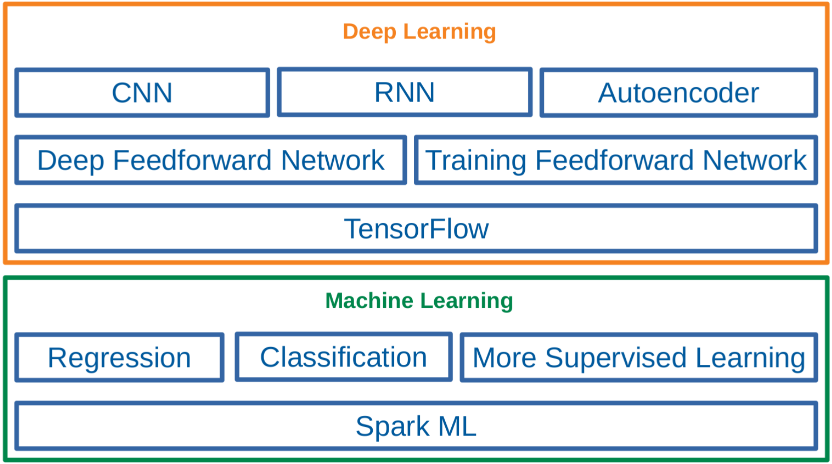
The Course Web Page

`https://id2223kth.github.io`

Where Are We?



Deep Learning

CNN

RNN

Autoencoder

Deep Feedforward Network

Training Feedforward Network

TensorFlow

Machine Learning

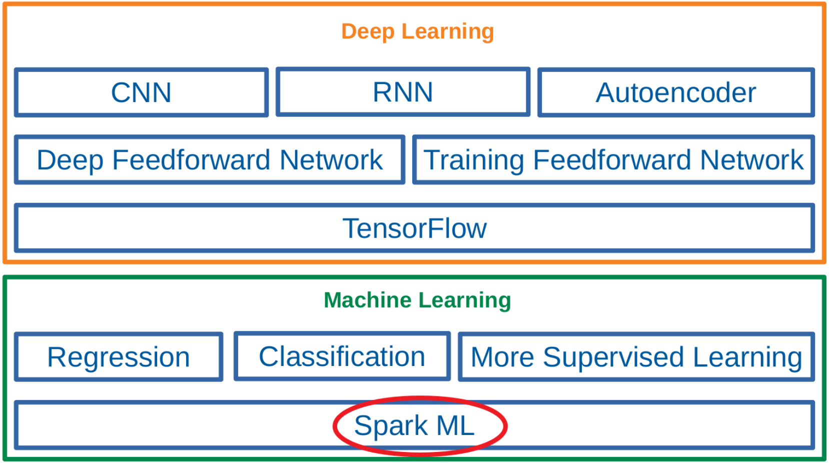
Regression

Classification

More Supervised Learning

Spark ML

Where Are We?



Deep Learning

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More Supervised Learning

Spark ML

Big Data

Problem

- Traditional platforms fail to show the expected performance.
- Need new systems to store and process large-scale data

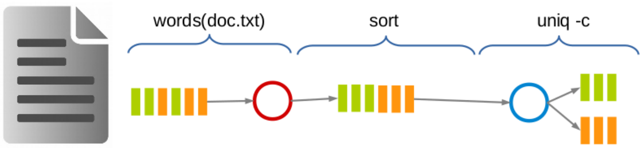
Scale Up vs. Scale Out

- Scale up or scale vertically
- Scale out or scale horizontally

Spark

Word Count

- Count the number of times each distinct word appears in the file
- If the file fits in memory: `words(doc.txt) | sort | uniq -c`



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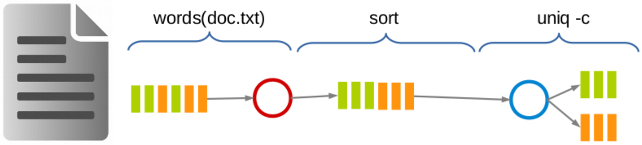
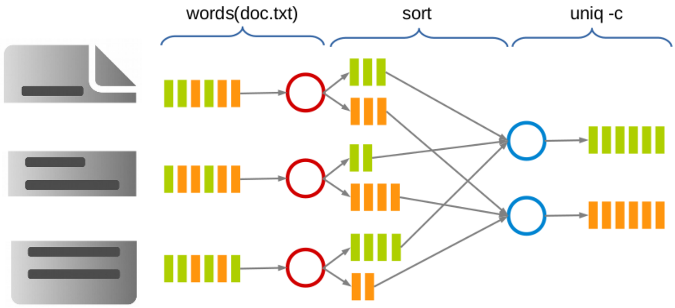


- If not?

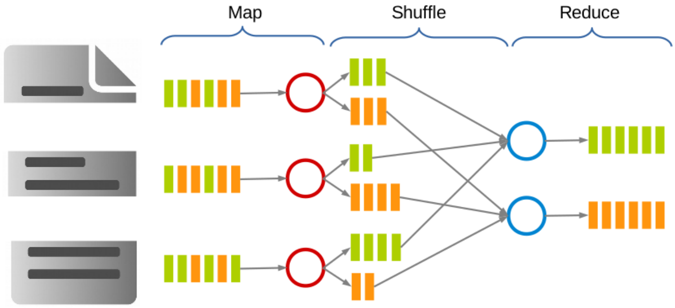
Data-Parallel Processing (1/4)

- Parallelize the data and process.



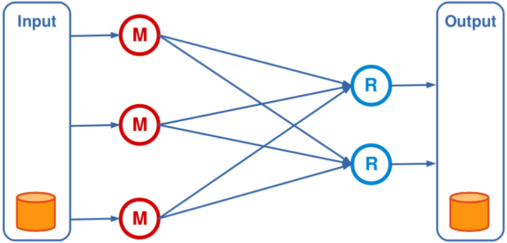
Data-Parallel Processing (2/4)

- MapReduce

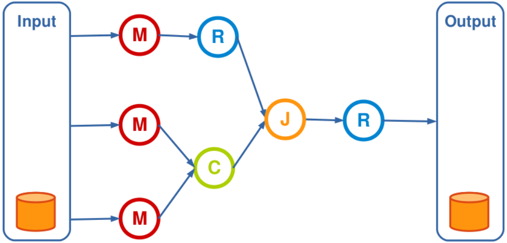


Data-Parallel Processing (3/4)

- Data flow programming model.
- Acyclic Directed Graph (DAG) of data flow from stable storage to stable storage.

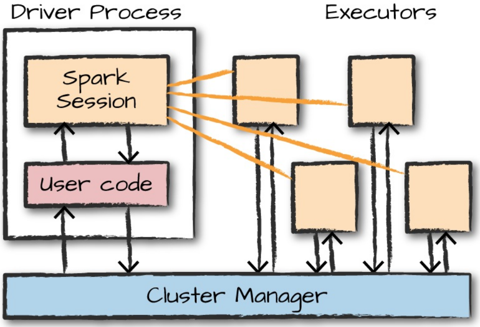


Data-Parallel Processing (4/4)



Spark Execution Model (1/3)

- Spark applications consist of
  - A driver process
  - A set of executor processes



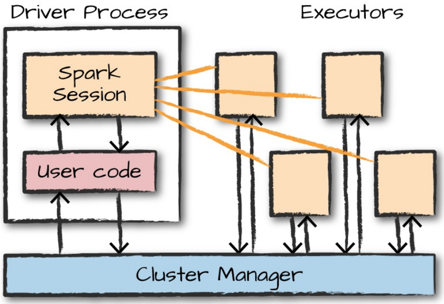
[M. Zaharia et al., Spark: The Definitive Guide, O'Reilly Media, 2018]

Spark Execution Model (2/3)

- The driver process is the heart of a Spark application

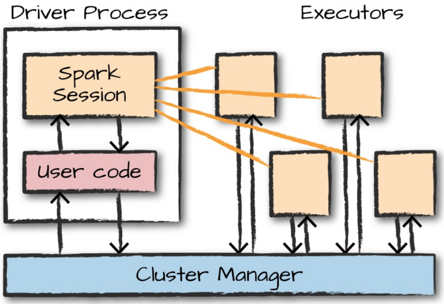
- Sits on a node in the cluster

- Runs the `main()` function



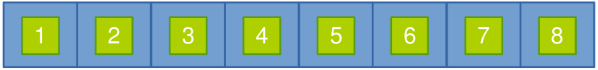
Spark Execution Model (3/3)

- Executors execute codes assigned to them by the driver.



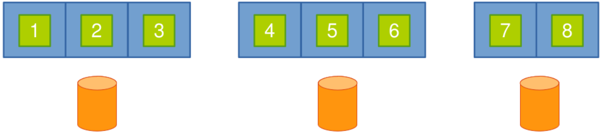
Resilient Distributed Datasets (RDD) (1/2)

- A distributed memory abstraction.
- Immutable collections of objects spread across a cluster.
  - Like a `LinkedList <MyObjects>`



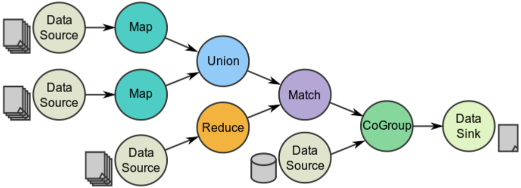
Resilient Distributed Datasets (RDD) (2/2)

- An RDD is divided into a number of partitions, which are atomic pieces of information.
- Partitions of an RDD can be stored on different nodes of a cluster.



Spark Programming Model

- Job description based on directed acyclic graphs (DAG).
- There are two types of RDD operators: transformations and actions.

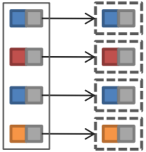


RDD Operations

- Transformations: lazy operators that create new RDDs.
- Actions: lunch a computation and return a value to the program or write data to the external storage.

RDD Transformations (1/3)

- Map: all pairs are independently processed.



RDD Transformations (1/3)

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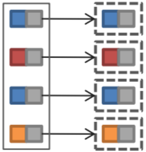


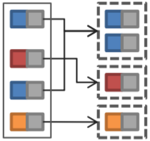
```
// passing each element through a function.
val nums = sc.parallelize(Array(1, 2, 3))
val squares = nums.map(x => x * x) // {1, 4, 9}

// selecting those elements that func returns true.
val even = squares.filter(x => x % 2 == 0) // {4}

// mapping each element to zero or more others.
nums.flatMap(x => Range(0, x)) // {0, 0, 1, 0, 1, 2}
```

RDD Transformations (2/3)

- Group by: pairs with identical key are grouped.
- Groups are independently processed.



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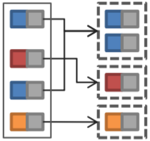


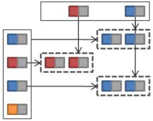
```
val pets = sc.parallelize(Seq(("kth", 1), ("rise", 1), ("kth", 2)))

pets.groupByKey()
// {(kth, (1, 2)), (rise, (1))}

pets.reduceByKey((x, y) => x + y)
// {(kth, 3), (rise, 1)}
```

RDD Transformations (3/3)

- Join: performs an equi-join on the key.
- Join candidates are independently processed.



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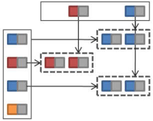

```
val rdd1 = sc.parallelize(Seq(("a", 1), ("b", 2), ("a", 3)))

val rdd2 = sc.parallelize(Seq(("a", "g1"), ("b", "g2")))

rdd1.join(rdd2)
// ("a", (1, "g1"))
// ("a", (3, "g1"))
// ("b", (2, "g2"))
```

Basic RDD Actions (1/2)

- Return all the elements of the RDD as an array.

```
val nums = sc.parallelize(Array(1, 2, 3))
nums.collect() // Array(1, 2, 3)
```

Basic RDD Actions (1/2)

- Return all the elements of the RDD as an array.

```scala
val nums = sc.parallelize(Array(1, 2, 3))
nums.collect() // Array(1, 2, 3)
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- Return an array with the first n elements of the RDD.

```scala
nums.take(2) // Array(1, 2)
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Basic RDD Actions (1/2)

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- Return an array with the first n elements of the RDD.

```
nums.take(2) // Array(1, 2)
```

- Return the number of elements in the RDD.

```
nums.count() // 3
```

Basic RDD Actions (2/2)

- Aggregate the elements of the RDD using the given function.

```
nums.reduce((x, y) => x + y)
// or
nums.reduce(_ + _) // 6
```

Basic RDD Actions (2/2)

- Aggregate the elements of the RDD using the given function.

```
nums.reduce((x, y) => x + y)
// or
nums.reduce(_ + _) // 6
```

- Write the elements of the RDD as a text file.

```
nums.saveAsTextFile("hdfs://file.txt")
```

Creating RDDs

- Turn a collection into an RDD.

```
val a = sc.parallelize(Array(1, 2, 3))
```

Creating RDDs

- Turn a collection into an RDD.

```
val a = sc.parallelize(Array(1, 2, 3))
```

- Load text file from local FS, HDFS, or S3.

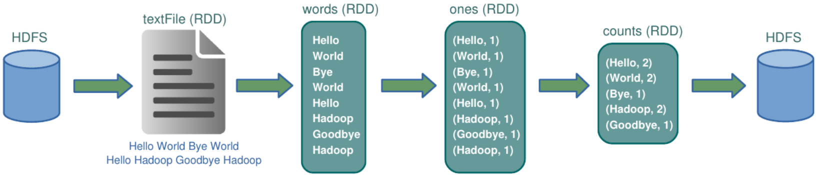
```
val a = sc.textFile("file.txt")
val b = sc.textFile("directory/*.txt")
val c = sc.textFile("hdfs://namenode:9000/path/file")
```

Example

```
val textFile = sc.textFile("hdfs://...")

val words = textFile.flatMap(line => line.split(" "))
val ones = words.map(word => (word, 1))
val counts = ones.reduceByKey(_ + _)

counts.saveAsTextFile("hdfs://...")
```



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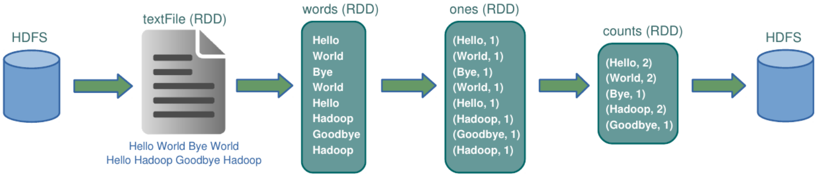
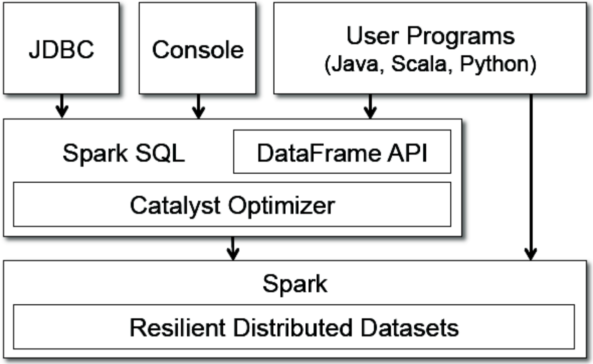


- Lineage: transformations used to build an RDD.

Spark SQL

Spark and Spark SQL

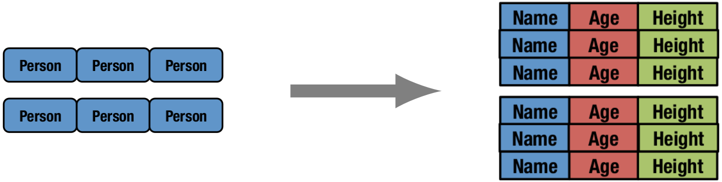


DataFrame

- A DataFrame is a distributed collection of rows with a homogeneous schema.
- It is equivalent to a table in a relational database.
- It can also be manipulated in similar ways to RDDs.

Adding Schema to RDDs

- Spark + RDD: functional transformations on partitioned collections of opaque objects.
- SQL + DataFrame: declarative transformations on partitioned collections of tuples.



Creating a DataFrame - From an RDD

- You can use `toDF` to convert an RDD to DataFrame.

```scala
val tupleRDD = sc.parallelize(Array(("seif", 65, 0), ("amir", 40, 1)))
val tupleDF = tupleRDD.toDF("name", "age", "id")
```

Creating a DataFrame - From an RDD

- You can use toDF to convert an RDD to DataFrame.

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val tupleRDD = sc.parallelize(Array(("seif", 65, 0), ("amir", 40, 1)))
val tupleDF = tupleRDD.toDF("name", "age", "id")
```

- If RDD contains case class instances, Spark infers the attributes from it.

```
case class Person(name: String, age: Int, id: Int)

val peopleRDD = sc.parallelize(Array(Person("seif", 65, 0), Person("amir", 40, 1)))
val peopleDF = peopleRDD.toDF
```

Creating a DataFrame - From Data Source

- Data sources supported by Spark.
  - CSV, JSON, Parquet, ORC, JDBC/ODBC connections, Plain-text files
  - Cassandra, HBase, MongoDB, AWS Redshift, XML, etc.

```
val peopleJson = spark.read.format("json").load("people.json")

val peopleCsv = spark.read.format("csv")
  .option("sep", ";")
  .option("inferSchema", "true")
  .option("header", "true")
  .load("people.csv")
```

Column

- Different ways to refer to a column.

```
val people = spark.read.format("json").load("people.json")

people.col("name")

col("name")

column("name")

'name

$"name"

expr("name")
```

Row

- A row is a record of data.
- They are of type `Row`.
- Rows do not have schemas.
- To access data in rows, you need to specify the position that you would like.

```scala
import org.apache.spark.sql.Row

val myRow = Row("Seif", 65, 0)

myRow(0) // type Any
myRow(0).asInstanceOf[String] // String
myRow.getString(0) // String
myRow.getInt(1) // Int
```

DataFrame Transformations (1/6)

- `select` allows to do the DataFrame equivalent of SQL queries on a table of data.

```
people.select("name", "age", "id").show(2)
people.select(col("name"), expr("age + 3")).show()
people.select(expr("name AS username")).show(2)
```

DataFrame Transformations (1/6)

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- filter and where both filter rows.

```
people.filter(col("age") < 20).show()

people.where("age < 20").show()
```

DataFrame Transformations (1/6)

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people.select(col("name"), expr("age + 3")).show()
people.select(expr("name AS username")).show(2)
```

- `filter` and `where` both filter rows.

```
people.filter(col("age") < 20).show()

people.where("age < 20").show()
```

- `distinct` can be used to extract unique rows.

```
people.select("name").distinct().count()
```

DataFrame Transformations (2/6)

- `withColumn` adds a new column to a DataFrame.

```
people.withColumn("teenager", expr("age < 20")).show()
```

DataFrame Transformations (2/6)

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- withColumnRenamed renames a column.

```
people.withColumnRenamed("name", "username").columns
```

DataFrame Transformations (2/6)

- withColumn adds a new column to a DataFrame.

```
people.withColumn("teenager", expr("age < 20")).show()
```

- withColumnRenamed renames a column.

```
people.withColumnRenamed("name", "username").columns
```

- drop removes a column.

```
people.drop("name").columns
```

DataFrame Transformations (3/6)

- `count` returns the total number of values.

```
people.select(count("age")).show()
```

DataFrame Transformations (3/6)

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DataFrame Transformations (3/6)

- count returns the total number of values.

```
people.select(count("age")).show()
```

- countDistinct returns the number of unique groups.

```
people.select(countDistinct("name")).show()
```

- first and last return the first and last value of a DataFrame.

```
people.select(first("name"), last("age")).show()
```

DataFrame Transformations (4/6)

- `min` and `max` extract the minimum and maximum values from a DataFrame.

```
people.select(min("name"), max("age"), max("id")).show()
```

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people.select(sum("age")).show()
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DataFrame Transformations (4/6)

- `min` and `max` extract the minimum and maximum values from a DataFrame.

```
people.select(min("name"), max("age"), max("id")).show()
```

- `sum` adds all the values in a column.

```
people.select(sum("age")).show()
```

- `avg` calculates the average.

```
people.select(avg("age")).show()
```

DataFrame Transformations (5/6)

- groupBy and agg together perform aggregations on groups.

```
people.groupBy("name").agg(count("age")).show()
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DataFrame Transformations (5/6)

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```
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```

- join performs the join operation between two tables.

```
val t1 = Seq((0, "a", 0), (1, "b", 1), (2, "c", 1)).toDF("num", "name", "id")
val t2 = Seq((0, "x"), (1, "y"), (2, "z")).toDF("id", "group")

val joinExpression = t1.col("id") === t2.col("id")
var joinType = "inner"

t1.join(t2, joinExpression, joinType).show()
```

DataFrame Transformations (6/6)

- You can use udf to define new column-based functions.

```
import org.apache.spark.sql.functions.udf

val df = Seq((0, "hello"), (1, "world")).toDF("id", "text")

val upper: String => String = _.toUpperCase

val upperUDF = udf(upper)

df.withColumn("upper", upperUDF(col("text"))).show
```

DataFrame Actions

- Like RDDs, DataFrames also have their own set of actions.
- `collect`: returns an array that contains all the rows in this DataFrame.
- `count`: returns the number of rows in this DataFrame.
- `first` and `head`: returns the first row of the DataFrame.
- `show`: displays the top 20 rows of the DataFrame in a tabular form.
- `take`: returns the first n rows of the DataFrame.

Machine Learning

Machine Learning with Spark

- Spark provides support for statistics and machine learning.
  - Supervised learning
  - Unsupervised engines
  - Deep learning

Supervised Learning

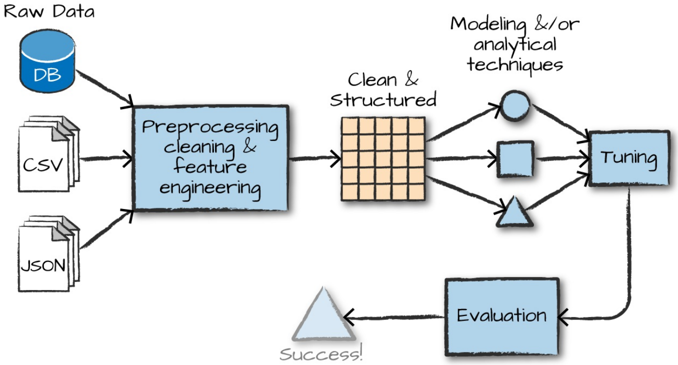
- Using labeled historical data and training a model to predict the values of those labels based on various features of the data points.
- Classification (categorical values)
  - E.g., predicting disease, classifying images, ...
- Regression (continuous values)
  - E.g., predicting sales, predicting height, ...

Unsupervised Learning

- No label to predict.
- Trying to find patterns or discover the underlying structure in a given set of data.
  - Clustering, anomaly detection, ...

The Advanced Analytic Process

- Data collection
- Data cleaning
- Feature engineering
- Training models
- Model tuning and evaluation


Raw Data
DB
CSV
JSON
Preprocessing cleaning & feature engineering
Clean & Structured
Modeling &/or analytical techniques
Tuning
Evaluation
Success!

What is MLlib? (1/2)

- MLlib is a package built on Spark.
- It provides interfaces for:
  - Gathering and cleaning data
  - Feature engineering and feature selection
  - Training and tuning large-scale supervised and unsupervised machine learning models
  - Using those models in production

What is MLlib? (2/2)

- MLlib consists of two packages.

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  - It is in maintenance mode (only receives bug fixes, not new features)

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- MLlib consists of two packages.

- `org.apache.spark.mllib`
  - Uses RDDs
  - It is in maintenance mode (only receives bug fixes, not new features)

- `org.apache.spark.ml`
  - Uses DataFrames
  - Offers a high-level interface for building machine learning pipelines

When Should We Use MLlib?

- Many tools for performing machine learning on a single machine, e.g., scikit-learn and TensorFlow.

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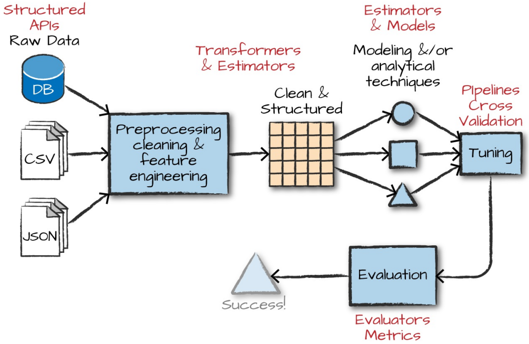
- Many tools for performing machine learning on a single machine, e.g., scikit-learn and TensorFlow.
- These single-machine tools are usually complementary to MLlib.
- Take advantage of Spark, when you hit scalability issues.
  - Use Spark for preprocessing and feature generation, before giving data to single-machine learning libraries.
  - Use Spark, when input data or model size become too difficult to put on one machine.

High-Level MLlib Concepts

- ML Pipelines (`spark.ml`) provide a uniform set of high-level APIs built on top of DataFrames to create machine learning pipelines.
- Main pipeline components: transformers and estimators

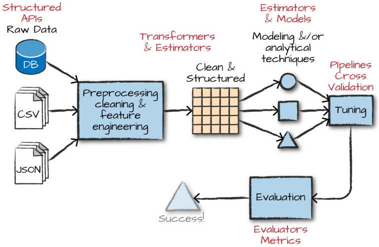

Structured APIs
Raw Data
DB
CSV
JSON
Preprocessing cleaning & feature engineering
Transformers & Estimators
Clean & Structured
Estimators & Models
Modeling &/or analytical techniques
Pipelines Cross Validation
Tuning
Evaluation
Evaluators Metrics
Success!

Transformers

- Transformers take a DataFrame as input and produce a new DataFrame as output.
- The class `Transformer` implements a method `transform()` that converts one DataFrame into another.

```
// transformer: DataFrame =[transform]=> DataFrame

transform(dataset: DataFrame): DataFrame
```



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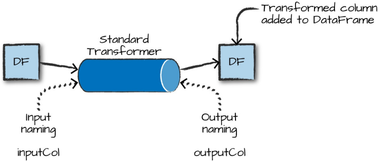
Preprocessing cleaning & feature engineering
Transformers & Estimators
Clean & Structured
Estimators & Models
Modeling &/or analytical techniques
Pipelines Cross Validation
Tuning
Evaluation
Evaluators Metrics
Success!

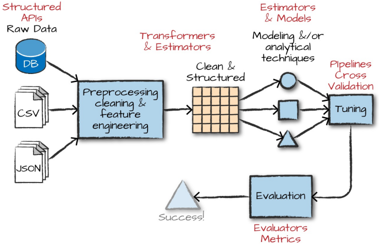


Estimators

- Estimator is an abstraction of a learning algorithm that fits a model on a dataset.
- The class `Estimator` implements a method `fit()`, which accepts a DataFrame and produces a Model (`Transformer`).

```
// estimator: DataFrame =[fit]=> Model

fit(dataset: DataFrame): M
```



Structured APIs
Raw Data
DB
CSV
JSON
Transformers & Estimators
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Pipeline

- Pipeline is a sequence of algorithms to process and learn from data.

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- E.g., a text document processing workflow might include several stages:
  - Split each document's text into words.
  - Convert each document's words into a numerical feature vector.
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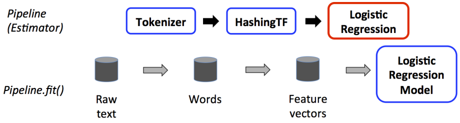
- E.g., a text document processing workflow might include several stages:
  - Split each document's text into words.
  - Convert each document's words into a numerical feature vector.
  - Learn a prediction model using the feature vectors and labels.

- MLlib represents such a workflow as a `Pipeline`, which is a sequence of stages.
  - Each stage is either a `Transformer` or an `Estimator`.

How Does Pipeline Work? (1/3)

- Stages of a pipeline run in order.
- The input DataFrame is transformed as it passes through each stage.
  - Calls `transform()` for `Transformer` stages
  - Calls `fit()` for `Estimator` stages



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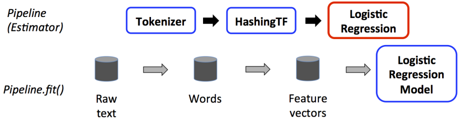
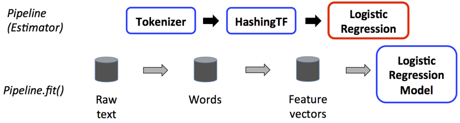
- Stages of a pipeline run in order.
- The input DataFrame is transformed as it passes through each stage.
  - Calls `transform()` for `Transformer` stages
  - Calls `fit()` for `Estimator` stages
- E.g., a Pipeline with three stages: `Tokenizer` and `HashingTF` are Transformers, and `LogisticRegression` is an Estimator.



How Does Pipeline Work? (2/3)

- `Pipeline.fit()`: is called on the original DataFrame
  - DataFrame with raw text documents and labels



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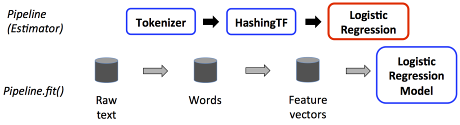
  - Adds a new column with words to the DataFrame



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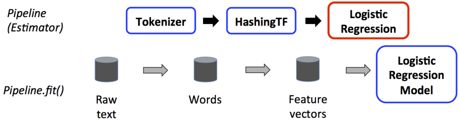

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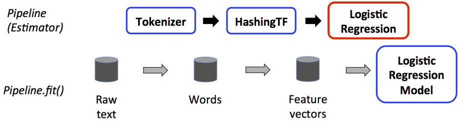
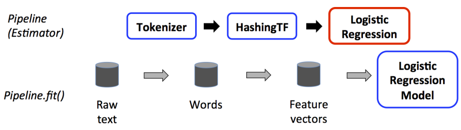
- `LogisticRegression.fit()`: produces a model (`LogisticRegressionModel`).

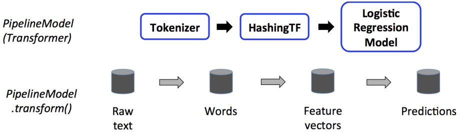


How Does Pipeline Work? (3/3)

- A Pipeline is an Estimator (DataFrame =[fit]=> Model).



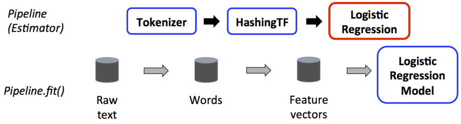
Pipeline



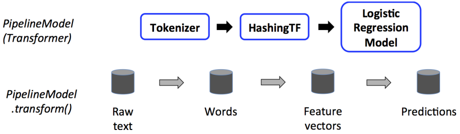
PipelineModel

How Does Pipeline Work? (3/3)

- A `Pipeline` is an `Estimator` (`DataFrame =[fit]=> Model`).
- After a `Pipeline`'s `fit()` runs, it produces a `PipelineModel`.



`Pipeline`



`PipelineModel`

How Does Pipeline Work? (3/3)

- A Pipeline is an Estimator (DataFrame =[fit]=> Model).
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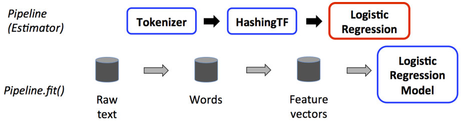
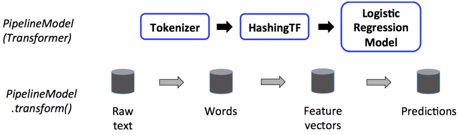


Pipeline



PipelineModel (Transformer)
Tokenizer
HashingTF
Logistic Regression Model
PipelineModel .transform()
Raw text
Words
Feature vectors
Predictions

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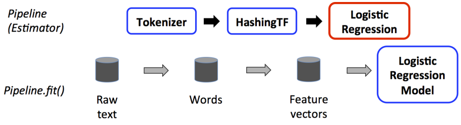

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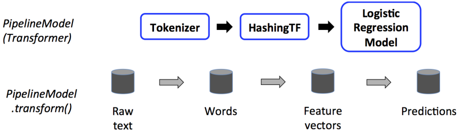
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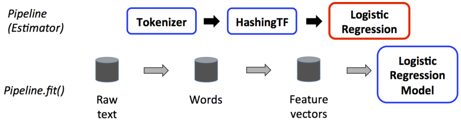
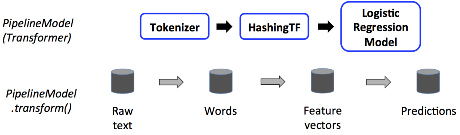
- After a Pipeline's fit() runs, it produces a PipelineModel.
- PipelineModel is a Transformer (DataFrame =[transform]=> DataFrame).
- The PipelineModel is used at test time.
- The PipelineModel has the same number of stages as the original Pipeline.
  - All Estimators in the original Pipeline have become Transformers.



Pipeline



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Parameters

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- MLlib `Estimators` and `Transformers` use a uniform API for specifying parameters.
- `Param`: a named parameter
- `ParamMap`: a set of (parameter, value) pairs
- Two ways to pass parameters to an algorithm:
  1. Set parameters for an instance, e.g., `ls.setMaxIter(10)`
  2. Pass a `ParamMap` to `fit()` or `transform()`.

Example - Input DataFrame (1/2)

- Make a DataFrame of the type `Article`.

```
import spark.implicits._

case class Article(id: Long, topic: String, text: String)

val articles = Seq(Article(0, "sci.math", "Hello, Math!"),
                   Article(1, "alt.religion", "Hello, Religion!"),
                   Article(2, "sci.physics", "Hello, Physics!"),
                   Article(3, "sci.math", "Hello, Math Revised!"),
                   Article(4, "sci.math", "Better Math"),
                   Article(5, "alt.religion", "TGIF")).toDF

articles.show
```

Example - Input DataFrame (2/2)

- Add a new column `label` to the DataFrame.
- `udf` is a feature of Spark SQL to define new Column-based functions.

```
val topic2Label: Boolean => Double = x => if (x) 1 else 0

val toLabel = udf(topic2Label)

val labelled = articles.withColumn("label", toLabel($"topic".like("sci%"))).cache
```

Example - Transformers (1/2)

- Break each sentence into individual terms (words).

```
import org.apache.spark.ml.feature.Tokenizer
import org.apache.spark.ml.feature.RegexTokenizer

val tokenizer = new RegexTokenizer().setInputCol("text").setOutputCol("words")

val tokenized = tokenizer.transform(labelled)

tokenized.show
```

Example - Transformers (2/2)

- Takes a set of words and converts them into fixed-length feature vector.
    - 5000 in our example
- Uses a hash function to map each word into an index in the feature vector.
- Then computes the term frequencies based on the mapped indices.

```
import org.apache.spark.ml.feature.HashingTF

val hashingTF = new HashingTF().setInputCol(tokenizer.getOutputCol)
                               .setOutputCol("features")
                               .setNumFeatures(5000)

val hashed = hashingTF.transform(tokenized)

hashed.show
```

Example - Estimator

```
val Array(trainDF, testDF) = hashed.randomSplit(Array(0.8, 0.2))

trainDF.show

testDF.show
```

```
import org.apache.spark.ml.classification.LogisticRegression

val lr = new LogisticRegression().setMaxIter(20).setRegParam(0.01)

val model = lr.fit(trainDF)

val pred = model.transform(testDF).select("topic", "label", "prediction")

pred.show
```

Example - Pipeline

```
val Array(trainDF2, testDF2) = labelled.randomSplit(Array(0.8, 0.2))

trainDF2.show

testDF2.show
```

```
import org.apache.spark.ml.{Pipeline, PipelineModel}

val pipeline = new Pipeline().setStages(Array(tokenizer, hashingTF, lr))

val model2 = pipeline.fit(trainDF2)

val pred = model2.transform(testDF2).select("topic", "label", "prediction")

pred.show
```

Example - ParamMap

```scala
// set parameters using setter methods.
val lr = new LogisticRegression()

lr.setMaxIter(10).setRegParam(0.01)
```

```scala
// specify parameters using a ParamMap
val lr = new LogisticRegression()

val paramMap = ParamMap(lr.maxIter -> 20)
  .put(lr.maxIter, 30)  // specify one Param
  .put(lr.regParam -> 0.1, lr.threshold -> 0.55)  // specify multiple Params

val model = lr.fit(training, paramMap)
```

Low-Level Data Types - Local Vector

- Stored on a single machine
- Dense and sparse
  - Dense (1.0, 0.0, 3.0): [1.0, 0.0, 3.0]
  - Sparse (1.0, 0.0, 3.0): (3, [0, 2], [1.0, 3.0])

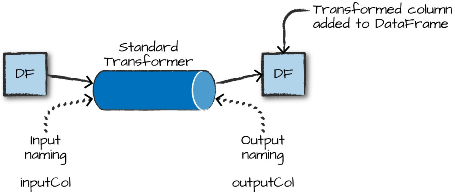
```scala
import org.apache.spark.mllib.linalg.{Vector, Vectors}

val dv: Vector = Vectors.dense(1.0, 0.0, 3.0)

val sv1: Vector = Vectors.sparse(3, Array(0, 2), Array(1.0, 3.0))
val sv2: Vector = Vectors.sparse(3, Seq((0, 1.0), (2, 3.0)))
```

Preprocessing and Feature Engineering

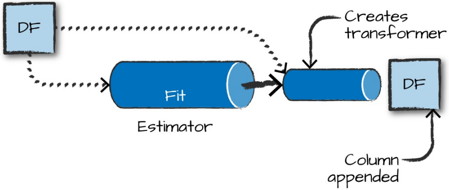
Formatting Models

- In most of classification and regression algorithms, we want to get the data.
  - A column to represent the label (`Double`).
  - A column to represent the features (`Vector`)

Transformers and Estimators



Transformer



Estimator

Transformer Properties

- All transformers require you to specify the input and output columns.
- We can set these with `setInputCol` and `setOutputCol`.

```scala
val tokenizer = new RegexTokenizer().setInputCol("text").setOutputCol("words")
```

Vector Assembler

- Concatenate all your features into one vector.

```
import org.apache.spark.ml.feature.VectorAssembler

case class Nums(val1: Long, val2: Long, val3: Long)

val numsDF = Seq(Nums(1, 2, 3), Nums(4, 5, 6), Nums(7, 8, 9)).toDF

val va = new VectorAssembler().setInputCols(Array("val1", "val2", "val3"))
                              .setOutputCol("features")

va.transform(numsDF).show()
```

MLlib Transformers

- Continuous features
- Categorical features
- Text data

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Continuous Features - Bucketing

- Convert continuous features into categorical features.

```
import org.apache.spark.ml.feature.Bucketizer

val contDF = spark.range(20).selectExpr("cast(id as double)")
val bucketBorders = Array(-1.0, 5.0, 10.0, 15.0, 20.0)

val bucketer = new Bucketizer().setSplits(bucketBorders).setInputCol("id")

bucketer.transform(contDF).show()
```

Continuous Features - Scaling and Normalization

- To scale and normalize continuous data.

```scala
import org.apache.spark.ml.feature.VectorAssembler

case class Nums(val1: Long, val2: Long, val3: Long)
val numsDF = Seq(Nums(1, 2, 3), Nums(4, 5, 6), Nums(7, 8, 9)).toDF
val va = new VectorAssembler().setInputCols(Array("val1", "val2", "val3"))
                              .setOutputCol("features")
val nums = va.transform(numsDF)
```

```scala
import org.apache.spark.ml.feature.StandardScaler

val scaler = new StandardScaler().setInputCol("features").setOutputCol("scaled")
scaler.fit(nums).transform(nums).show()
```

Continuous Features - Maximum Absolute Scaler

- Scales the data by dividing each feature by the maximum absolute value in this feature (column).

```scala
import org.apache.spark.ml.feature.VectorAssembler

case class Nums(val1: Long, val2: Long, val3: Long)
val numsDF = Seq(Nums(1, 2, 3), Nums(4, 5, 6), Nums(7, 8, 9)).toDF
val va = new VectorAssembler().setInputCols(Array("val1", "val2", "val3"))
                              .setOutputCol("features")
val nums = va.transform(numsDF)
```

```scala
import org.apache.spark.ml.feature.MaxAbsScaler

val maScaler = new MaxAbsScaler().setInputCol("features").setOutputCol("mas")
maScaler.fit(nums).transform(nums).show()
```

MLlib Transformers

- Continuous features
- Categorical features
- Text data

Categorical Features - String Indexer

- Maps strings to different numerical IDs.

```
val simpleDF = spark.read.json("simple-ml.json")
```

```
import org.apache.spark.ml.feature.StringIndexer

val lblIndxr = new StringIndexer().setInputCol("lab").setOutputCol("labelInd")
val idxRes = lblIndxr.fit(simpleDF).transform(simpleDF)

idxRes.show()
```

Categorical Features - Converting Indexed Values Back to Text

- Maps back to the original values.

```
import org.apache.spark.ml.feature.IndexToString

val labelReverse = new IndexToString().setInputCol("labelInd").setOutputCol("original")

labelReverse.transform(idxRes).show()
```

Categorical Features - One-Hot Encoding

- Converts each distinct value to a boolean flag as a component in a vector.

```
val simpleDF = spark.read.json("simple-ml.json")
```

```
import org.apache.spark.ml.feature.OneHotEncoder

val lblIndxr = new StringIndexer().setInputCol("color").setOutputCol("colorInd")
val colorLab = lblIndxr.fit(simpleDF).transform(simpleDF.select("color"))
val ohe = new OneHotEncoder().setInputCol("colorInd").setOutputCol("one-hot")
ohe.transform(colorLab).show()

// Since there are three values, the vector is of length 2 and the mapping is as follows:
// 0  -> 10, (2,[0],[1.0])
// 1  -> 01, (2,[1],[1.0])
// 2  -> 00, (2,[],[])
// (2,[0],[1.0]) means a vector of length 2 with 1.0 at position 0 and 0 elsewhere.
```

MLlib Transformers

- Continuous features
- Categorical features
- Text data

Text Data - Tokenizing Text

- Converting free-form text into a list of tokens or individual words.

```
val sales = spark.read.format("csv").option("header", "true").load("sales.csv")
    .where("Description IS NOT NULL")

sales.show(false)
```

```
import org.apache.spark.ml.feature.Tokenizer

val tkn = new Tokenizer().setInputCol("Description").setOutputCol("DescOut")
val tokenized = tkn.transform(sales.select("Description"))
tokenized.show(false)
```

Text Data - Removing Common Words

- Filters stop words, such as ”the”, ”and”, and ”but”.

```
import org.apache.spark.ml.feature.StopWordsRemover

val df = spark.createDataFrame(Seq((0, Seq("I", "saw", "the", "red", "balloon")),
    (1, Seq("Mary", "had", "a", "little", "lamb")))).toDF("id", "raw")

val englishStopWords = StopWordsRemover.loadDefaultStopWords("english")

val stops = new StopWordsRemover().setStopWords(englishStopWords)
    .setInputCol("raw").setOutputCol("WithoutStops")

stops.transform(df).show(false)
```

Text Data - Converting Words into Numerical Representations

- Counts instances of words in word features.
- Treats every row as a document, every word as a term, and the total collection of all terms as the vocabulary.

```scala
import org.apache.spark.ml.feature.CountVectorizer

val df = spark.createDataFrame(Seq((0, Array("a", "b", "c")),
    (1, Array("a", "b", "b", "c", "a")))).toDF("id", "words")

val cvModel = new CountVectorizer().setInputCol("words").setOutputCol("features")
    .setVocabSize(3).setMinDF(2)

val fittedCV = cvModel.fit(df)

fittedCV.transform(df).show(false)
```

Text Data - TF-IDF (1/2)

- TF-IDF: term frequency - inverse document frequency
- Measures how often a word occurs in each document, weighted according to how many documents that word occurs in.
- Words that occur in a few documents are given more weight than words that occur in many documents.

Text Data - TF-IDF (2/2)

```scala
import org.apache.spark.ml.feature.{HashingTF, IDF, Tokenizer}

val sentenceData = spark.createDataFrame(Seq((0.0, "Hi I heard about Spark"),
    (0.0, "I wish Java could use case classes"),
    (1.0, "Logistic regression models are neat")))
    .toDF("label", "sentence")

val tokenizer = new Tokenizer().setInputCol("sentence").setOutputCol("words")
val wordsData = tokenizer.transform(sentenceData)

val hashingTF = new HashingTF().setInputCol("words").setOutputCol("rawFeatures")
    .setNumFeatures(20)
val featurizedData = hashingTF.transform(wordsData)

val idf = new IDF().setInputCol("rawFeatures").setOutputCol("features")
val idfModel = idf.fit(featurizedData)

val rescaledData = idfModel.transform(featurizedData)
rescaledData.select("label", "features").show(false)
```

Summary

Summary

- Spark: RDD
- Spark SQL: DataFrame
- MLlib
  - Transformers and Estimators
  - Pipeline
  - Feature engineering

References

- Matei Zaharia et al., Spark - The Definitive Guide, (Ch. 24 and 25)

Questions?