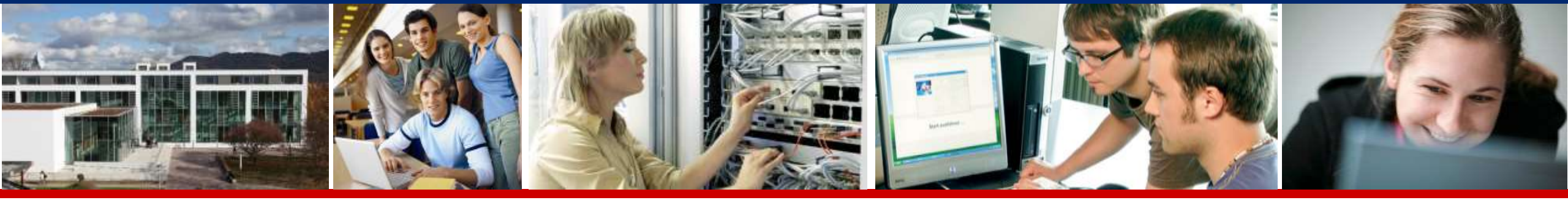

DataFrames and SparkSQL

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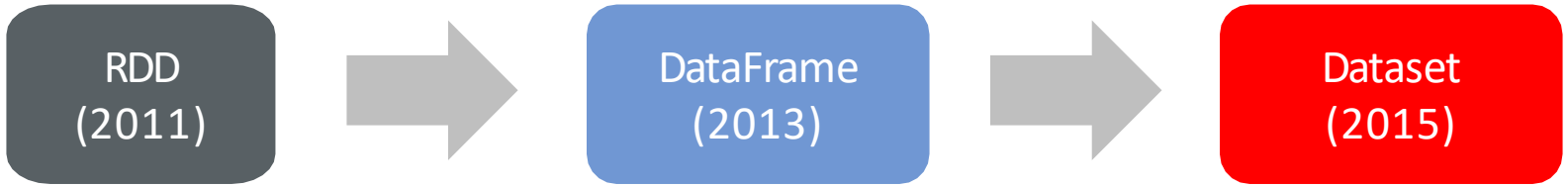
Outline

- DataFrames, Datasets and Spark SQL
- Operations on DataFrames

History of Spark APIs



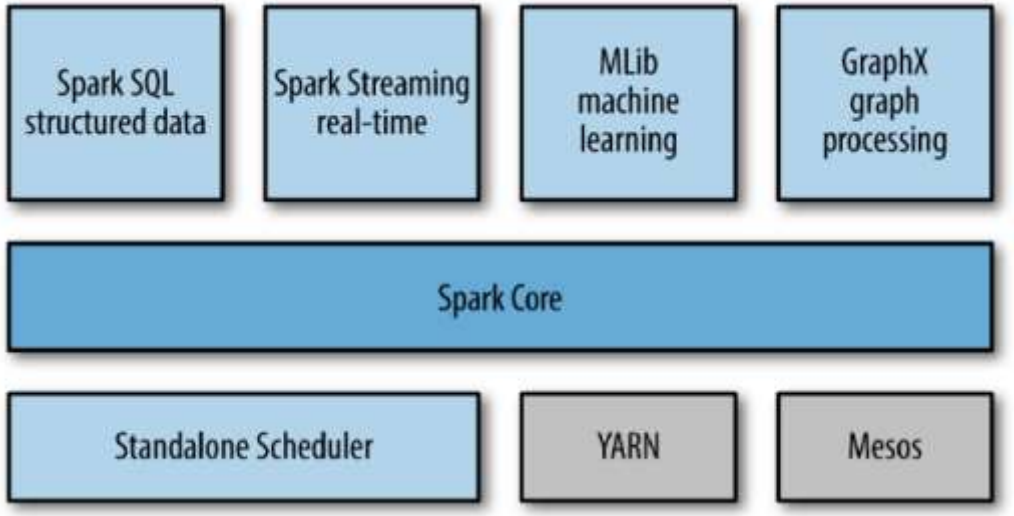
- Distribute collection of JVM objects
- Functional Operators (map, filter, etc.)

- DataFrames are dynamically typed
- Distribute collection of Row objects
- Expression-based operations and UDFs
- Logical plans and optimizer
- Fast/efficient internal representations

- Datasets: statically typed
- Internally rows, externally JVM objects
- “Best of both worlds” type safe + fast
- No Python support

Spark SQL

Part of the core distribution since 1.0 (April 2014)



What does Spark SQL provide?

- A SQL Engine and command line interface
- You can interact with the SQL interface using the command-line or over JDBC/ODBC.
- Spark SQL can also be used to read data from an existing Hive installation
- Runs SQL / HiveQL queries, optionally alongside or replacing existing Hive deployments
- CatalystOptimizer – an extensible optimization framework
- Usually the Data source for spark-core is a text file, Avro file, etc.
  Data Sources for Spark SQL are Parquet, JSON, HIVE tables, Cassandra database.

DataFrames and Spark SQL

- DataFrames are fundamentally tied to Spark SQL
- The DataFrames API provides a programmatic interface, a domain-specific language (DSL) - for interacting with your data.

- Spark SQL provides a SQL-like interface.
- Anything you can do in Spark SQL, you can do in DataFrames
  … and vice versa

To use SQL, you must either:

- query a persisted Hive table, or
- make a table alias for a DataFrame, using registerTempTable() (later more)

DataFrames

- Enable wider audiences beyond “Big Data” engineers to leverage the power of distributed processing
- Inspired by data frames in R and Python (Pandas)
- Designed from the ground-up to support modern big data and data science applications
- Extension to the existing RDD API, APIs for Python, Java, Scala, and R
- State-of-the-art optimization and code generation through the Spark SQL Catalyst optimizer

See https://spark.apache.org/docs/latest/sql-programming-guide.html

databricks.com/blog/2015/02/17/introducing-dataframes-in-spark-for-large-scale-data-science.html

Creating a DataFrame
Entry point to all functionality in Spark is the SparkSession

- You create a DataFrame with a SQLContext object (or one of its descendants)
- In the Spark Scala shell (spark-shell) or pyspark, you have a SQLContext available automatically, as sqlContext. From 2.x you use only SparkSession.
- In an application you can create one yourself from a SparkContext.
- The DataFrame data source API is consistent, across data formats.
- "Opening" a data source works pretty much the same way, no matter what.

```
import org.apache.spark.sql.SparkSession

val spark = SparkSession
    .builder()
    .appName("Spark SQL basic example")
    .config("spark.some.config.option", "some-value")
    .getOrCreate()

// For implicit conversions like converting RDDs to DataFrames
import spark.implicits._
```

How to create a DataFrame

DataFrames can be created

- From an existing structured data source (Parquet file, JSON file, etc.) https://docs.databricks.com/spark/latest/data-sources/index.html
- From a Hive table
- From an existing RDD
- By performing an operation or query on another DataFrame
- By programmatically defining a schema

Creating a DataFrame in Scala

Program: including setup; the DataFrame reads are 1 line each

```
import org.apache.spark.{SparkConf, SparkContext}
import org.apache.spark.sql.SQLContext

val conf = new SparkConf().setAppName(appName).setMaster(master)
// Returns existing SparkContext, if there is one;
// otherwise, creates a new one from the config.
val spark = SparkContext.getOrCreate(conf)

// Ditto
val sqlContext = SQLContext.getOrCreate(sc)  // not necessary any more.

val df = spark.read.parquet("/path/to/data.parquet")
val df2 = spark.read.json("/path/to/data.json")
```

Creating a DataFrame in Scala - json

File: people.json

```
{"age": null, "name":"Michael"}
{"age":30, "name":"Andy"}
{"age":19, "name":"Justin"}
```

```
val df = spark.read.json("examples/src/main/resources/people.json")
// spark: sparkSession

// Displays the content of the DataFrame to stdout
df.show()
// +----+-------+
// | age|   name|
// +----+-------+
// |null|Michael|
// |  30|   Andy|
// |  19| Justin|
// +----+-------+
```

Load from JDBC

```
// Note: JDBC loading and saving can be achieved via either the load/save or jdbc methods
// Loading data from a JDBC source
val jdbcDF = spark.read
   .format("jdbc")
   .option("url", "jdbc:postgresql:dbserver")
   .option("dbtable", "schema.tablename")   // SQL Queries possible!
   .option("user", "username")
   .option("password", "password")
   .load()

val connectionProperties = new Properties()
connectionProperties.put("user", "username")
connectionProperties.put("password", "password")
val jdbcDF2 = spark.read
   .jdbc("jdbc:postgresql:dbserver", "schema.tablename", connectionProperties)
```

Unified interface to reading/writing data in a variety of formats.

```
val df = spark
       .read
       .format("json")
       .option("samplingRatio",  "0.1")
       .load("/Users/spark/data/stuff.json")


df.write
       .format("parquet")
       .mode("append")
       .partitionBy("year")
       .saveAsTable("faster-stuff")
```

Creating Datasets

```
// Note: Case classes in Scala 2.10 can support only up to 22 fields. To work around this limit,
// you can use custom classes that implement the Product interface
case class Person(name: String, age: Long)

// Encoders are created for case classes
val caseClassDS = Seq(Person("Andy", 32)).toDS()
caseClassDS.show()
// +----+---+
// |name|age|
// +----+---+
…
// Encoders for most common types are automatically provided by importing spark.implicits._
val primitiveDS = Seq(1, 2, 3).toDS()
primitiveDS.map(_ + 1).collect() // Returns: Array(2, 3, 4)

// DataFrames can be converted to a Dataset by providing a class. Mapping will be done by name
val path = "examples/src/main/resources/people.json"
val peopleDS = spark.read.json(path).as[Person]
peopleDS.show()
// +----+-------+
//   …
```

DataFrames have Schemas

- In the previous example, we created DataFrames from Parquet and JSON data.
- A Parquet table has a schema (column names and types) that Spark can use.
- Parquet also allows Spark to be efficient about how it pares down data.
- Spark can infer a Schema from a JSON file.
- Some data sources can expose a formal schema; others (e.g., plain text files) don't.

How do we fix that?

- You can create an RDD of a particular type and let Spark infer the schema from that type. We'll see how to do that in a moment.
- You can use the API to specify the schema programmatically.

Schema Inference Example

Suppose you have a (text) file that looks like this:

```
Erin,Shannon,F,42
Norman,Lockwood,M,81
Miguel,Ruiz,M,64
Rosalita,Ramirez,F,14
Ally,Garcia,F,39
Claire,McBride,F,23
Abigail,Cottrell,F,75
José,Rivera,M,59
Ravi,Dasgupta,M,25
…
```

First name: **string**
Last name: **string**
Gender: **string**
Age: **integer**

The file has no schema, but it's obvious there is one.

Schema Inference

```
import spark.implicits._

case class Person(firstName: String,
                  lastName: String,
                  gender:  String,
                  age:     Int)

val rdd = spark.read.textFile("people.csv")
val peopleRDD = rdd.map { line =>
  val cols = line.split(",")
  Person(cols(0), cols(1), cols(2), cols(3).toInt)
}
val df = peopleRDD.toDF
// df: DataFrame = [firstName: string, lastName: string, gender: string,
age: int]
```

Schema Inference

We can also force schema inference without creating our own type, by using a fixed-length data structure (such as a tuple) and supplying the column names to the toDF() method.

```
val rdd = spark.read.textFile("people.csv")
val peopleRDD = rdd.map { line =>
  val cols = line.split(",")
  (cols(0), cols(1), cols(2), cols(3).toInt)
}

val df = peopleRDD.toDF("firstName", "lastName", "gender", "age")
```

If you don’t supply the column names, the API defaults to “_1”, “_2”, etc.

Inferring the Schema Using Reflection

```
// For implicit conversions from RDDs to DataFrames
import spark.implicits._

// Create an RDD of Person objects from a text file, convert it to a Dataframe
val peopleDF = spark.read
       .textFile("examples/src/main/resources/people.txt")
       .map(_.split(","))
       .map(attributes => Person(attributes(0), attributes(1).trim.toInt))
       .toDF()

// Register the DataFrame as a temporary view
peopleDF.createOrReplaceTempView("people")

// The columns of a row in the result can be accessed by field index or by name
// SQL statements can be run by using the sql methods provided by Spark
val teenagersDF = spark.sql("SELECT name, age FROM people WHERE age BETWEEN 13 AND 19")
```

Programmatically Specifying the Schema

```
import org.apache.spark.sql.types._
val peopleRDD = spark.sparkContext.textFile("examples/src/main/resources/people.txt") // Create RDD

// The schema is encoded in a string
val schemaString = "name age"

// Generate the schema based on the string of schema
val fields = schemaString.split(" ")
                .map(fieldName => StructField(fieldName, StringType, nullable = true))
val schema = StructType(fields)

// 2. Convert records of the RDD (people) to Rows
val rowRDD = peopleRDD.map(_.split(",")).map(attributes => Row(attributes(0), attributes(1).trim))

// 3. Apply the schema to the RDD
val peopleDF = spark.createDataFrame(rowRDD, schema)

// Creates a temporary view using the DataFrame
peopleDF.createOrReplaceTempView("people")

// SQL can be run over a temporary view created using DataFrames
val results = spark.sql("SELECT name FROM people")
```

Outline

- DataFrames and Datasets
- Operations on DataFrames

DataFrame: Columns

- A DataFrame column is an abstraction. It provides a common column-oriented view of the underlying data, regardless of how the data is really organized.
- Columns are important because much of the DataFrame API consists of functions that take or return columns

Input Source Format	Data Frame Variable Name	Data
JSON	dataFrame1	`[ {"first": "Amy", "last": "Bello", "age": 29 }, {"first": "Ravi", "last": "Agarwal", "age": 33 }, … ]`

CSV	dataFrame2	`first,last,age`
		`Fred,Hoover,91`
		`Joaquin,Hernandez,`
		`24`
		`…`

SQL Table	dataFrame3	first | last | age Joe | Smith | 42 Jill | Jones | 33

Columns

Assume we have a DataFrame df, that reads a data source that has "first", "last", and "age" columns.

Python	Java	Scala	R
`df["first"]` `df.first`†	`df.col("first")`	`df("first")` `$"first"`	`df$first`

show()

You can look at the first n elements in a DataFrame with the show() method. If not specified, n defaults to 20.

This method is an action.

It:

- reads (or re-reads) the input source
- executes the RDD DAG across the cluster
- pulls the n elements back to the driver JVM
- displays those elements in a tabular form

```
> df.show()
+---------+--------+------+---+
|firstName|lastName|gender|age|
+---------+--------+------+---+
|     Erin| Shannon|     F| 42|
|   Claire| McBride|     F| 23|
|   Norman|Lockwood|     M| 81|
|   Miguel|    Ruiz|     M| 64|
| Rosalita| Ramirez|     F| 14|
|     Ally|  Garcia|     F| 39|
|  Abigail|Cottrell|     F| 75|
|     José|  Rivera|     M| 59|
+---------+--------+------+---+
```

Basic Operations deal with DataFrame metadata

- schema – returns a Schema object describing the data
- printSchema – displays the schema as a visual tree
- cache / persist – persists the DataFrame to disk or memory
- columns – returns an array containing the names of the columns
- dtypes – returns an array of (column-name, type) pairs
- explain – prints debug information about the DataFrame to the console

Actions (similar to RDDs)

- collect – return all rows as an array of Row objects
- take(n) – return the first n rows as an array of Row objects
- count – return the number of rows
- show(n) – display the first n rows (default=20)

Queries

DataFrame query methods return new DataFrames

Queries can be chained like transformations

Some query methods

- distinct – returns a new DataFrame with distinct elements of this DF
- join – joins this DataFrame with a second DataFrame
- limit – a new DF with the first n rows of this DataFrame
- select – a new DataFrame with data from one or more columns of the base DataFrame
- filter – a new DataFrame with rows meeting a specified condition
- where …

Aggregations

- DataFrames functions provide common aggregations such as count(), countDistinct(), avg(), max(), min(), etc.
- Documentation at https://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.sql.functions$

- While those functions are designed for DataFrames, Spark SQL also has type-safe versions for some of them in Scala and Java to work with strongly typed Datasets.
- You can also create your own function
  - Untyped User-Defined Aggregate Functions
  - Type-Safe User-Defined Aggregate Functions

Temporary and global views for SQL

Temporary views in Spark SQL are session-scoped and will disappear if the session that creates it terminates.

```
// Register the DataFrame as a SQL temporary view
df.createOrReplaceTempView("people")

val sqlDF = spark.sql("SELECT * FROM people")
sqlDF.show()
// +----+-------+
// | age|   name|
// +----+-------+
// |null|Michael|
// |  30|   Andy|
// |  19| Justin|
// +----+-------+
```

If you want to have a view that is shared among all sessions and keep alive until the Spark application terminates, create global temporary view.

```
// Register the DataFrame as a global temporary view
df.createGlobalTempView("people")

// Global temporary view is tied to a system
// preserved database `global_temp`
spark.sql("SELECT * FROM global_temp.people").show()
// +----+-------+
// | age|   name|
// +----+-------+
// |null|Michael|
// |  30|   Andy|
…
// Global temporary view is cross-session
spark.newSession().sql("SELECT * FROM
global_temp.people").show()
```

select()

select() is like a SQL SELECT, allowing you to limit the results to specific columns.

```
scala> df.select($"firstName", $"age").show(5)
+---------+---+
|firstName|age|
+---------+---+
|     Erin| 42|
|   Claire| 23|
|   Norman| 81|
|   Miguel| 64|
| Rosalita| 14|
+---------+---+
```

```
scala> df.select($"firstName",
                 $"age",
                 $"age" > 49,
                 $"age" + 10).show(5)
+---------+---+---------+----------+
|firstName|age|(age > 49)|(age + 10)|
+---------+---+---------+----------+
|     Erin| 42|    false|        52|
|   Claire| 23|    false|        33|
|   Norman| 81|     true|        91|
|   Miguel| 64|     true|        74|
| Rosalita| 14|    false|        24|
+---------+---+---------+----------+
```

filter()

The filter()method allows you to filter rows out of your results.

```
scala> df.filter($"age" > 49).
          select($"first_name", $"age").show()


+---------+---+
|firstName|age|
+---------+---+
|   Norman| 81|
|   Miguel| 64|
|  Abigail| 75|
+---------+---+
```

```
scala> df.filter($"age"> 49).select($"firstName", $"age").show()

+---------+---+
|firstName|age|
+---------+---+
|   Norman| 81|
|   Miguel| 64|
|  Abigail|v75|
+---------+---+
```

The orderBy() method allows you to sort the results.

```
scala> df.filter($"age„ > 49).
         select($"firstName", $"age").
         orderBy($"age",
         $"firstName").show()
+---------+---+
|firstName|age|
+---------+---+
|   Miguel| 64|
|  Abigail|75|
|   Norman| 81|
+---------+---+
```

```
scala> df.filter($"age„ > 49).
       select($"firstName", $"age").
       orderBy($"age".desc,
       $"firstName").show()
+---------+---+
|firstName|age|
+---------+---+
|   Norman| 81|
|  Abigail| 75|
|   Miguel| 64|
+---------+---+
```

as() or alias()

- as() or alias() allows you to rename a column.
- It’s especially usefulwith generatedcolumns.

```
scala> df.select($"firstName",  $"age", ($"age" <  30).as("young")).show()
+---------+---+-----+
|firstName|age|young|
+---------+---+-----+
|     Erin| 42|false|
|   Claire| 23| true|
|   Norman| 81|false|
|   Miguel| 64|false|
| Rosalita| 14| true|
+---------+---+-----+
```

```
spark.sql("SELECT  firstName, age, age < 30 AS young FROM names")
+---------+---+-----+
|firstName|age|young|
+---------+---+-----+
|     Erin| 42|false|
|   Claire| 23| true|
|   Norman| 81|false|
|   Miguel| 64|false|
| Rosalita| 14| true|
+---------+---+-----+
```

groupBy()

Often usedwith count(), groupBy() groups data items by a specific column value.

```
> df.groupBy("age").count().show()

+---+-----+
|age|count|
+---+-----+
| 39|    1|
| 42|    2|
| 64|    1|
| 75|    1|
| 81|    1|
| 14|    1|
| 23|    2|
+---+-----+
```

```
scala> spark.sql("SELECT age, count(age) FROM names
                        GROUP BY  age")
+---+-----+
|age|count|
+---+-----+
| 39|    1|
| 42|    2|
| 64|    1|
| 75|    1|
| 81|    1|
| 14|    1|
| 23|    2|
+---+-----+
```

Joins

We can load that into a second DataFrame and join it with our first one.

```
[
{
"firstName": "Erin",
"lastName": "Shannon",
"medium": "oil on canvas"
},
{
"firstName": "Norman",
"lastName": "Lockwood",
"medium": "metal (sculpture)"
},
…
]
```

```
scala> val df2 = sqlContext.read.json("artists.json")
# Schema inferred as DataFrame[firstName: string, lastName: string, medium: string]
scala> df.join(df2, (df("first_name") === df2("firstName") & (df("last_name" === df2("lastName")).show()

+----------+---------+------+---+---------+--------+----------------+
|first_name|last_name|gender|age|firstName|lastName|          medium|
+----------+---------+------+---+---------+--------+----------------+
|    Norman| Lockwood|     M| 81|   Norman|Lockwood|metal (sculpture)|
|      Erin|  Shannon|     F| 42|     Erin| Shannon|    oil on canvas|
|  Rosalita|  Ramirez|     F| 14| Rosalita| Ramirez|         charcoal|
|    Miguel|     Ruiz|     M| 64|   Miguel|    Ruiz|    oil on canvas|
+----------+---------+------+---+---------+--------+----------------+
```

User Defined Functions

We'll create a function to extract the month field from a timestamp-typed column and return the month name.

```
scala> df.select(monthName($("time")))
console>:23:  error: not found: value  monthName
              df.select(monthName($("time"))).show()
```

```
scala> val monthName = spark.udf.register("monthName", (t: Timestamp) => {
  import java.text.SimpleDateFormat
  import java.util.Date
  val fmt = new SimpleDateFormat("MMM")
  fmt.format(new Date(t.getTime))
})
monthName: org.apache.spark.sql.UserDefinedFunction =
UserDefinedFunction(<function1>,StringType,List())

scala> df.select(monthName($"time")).show(5)
+----------+
|UDF(time)|
+----------+
|       Oct|
|       Oct|
+----------+
```

Summary

- SparkSQL is another way to manipulate DataFrames

Documentation

https://docs.databricks.com/spark/latest/spark-sql/index.html#spark-sql-language-manual

https://docs.databricks.com/spark/latest/dataframes-datasets/index.html

https://docs.databricks.com/spark/latest/data-sources/index.html