Intro to DataFrames and Spark SQL

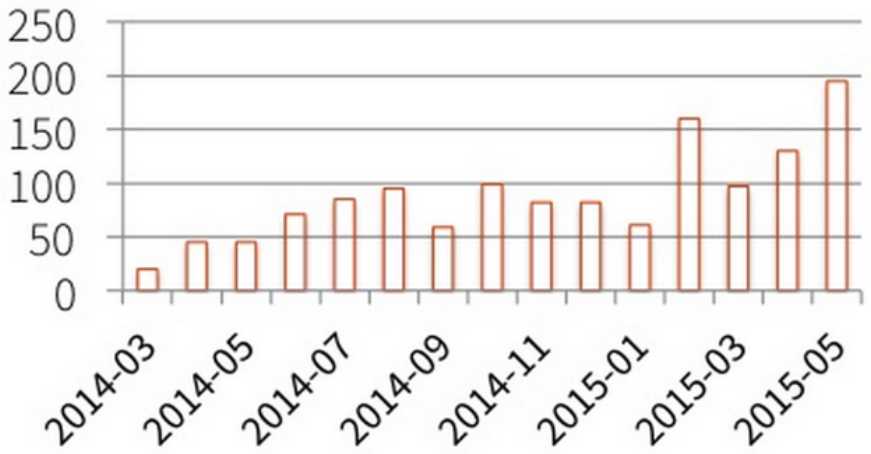
July, 2015

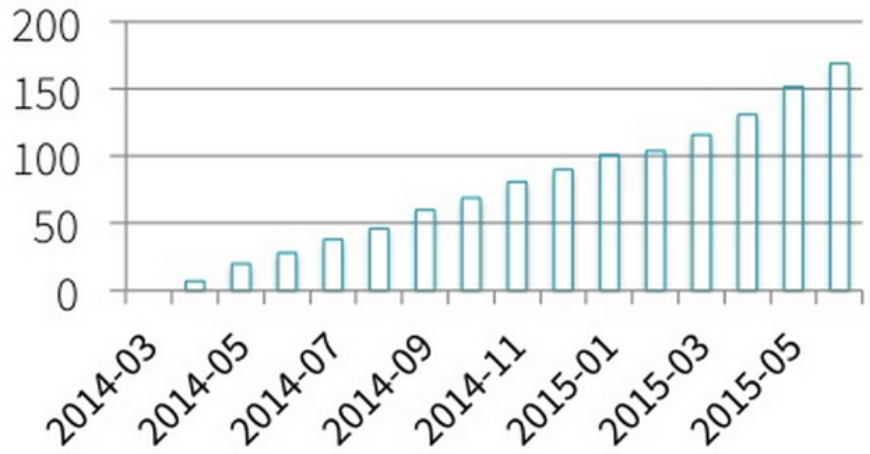
databricks™

Spark SQL

Graduated from Alpha in 1.3

Part of the core distribution since Spark 1.0 (April 2014)





Spark SQL

- **Part of the core distribution since 1.0 (April 2015)**
- **Runs SQL / HiveQL queries, optionally alongside or replacing existing Hive deployments**


```
SELECT COUNT(*)
FROM hiveTable
WHERE hive_udf(data)
```

Improved multi-version support in 1.4

Write Less Code: Input & Output

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

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

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

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```

`read` and `write` functions create new builders for doing I/O

Write Less Code: Input & Output

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

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

Builder methods specify:

- **format**
- **partitioning**
- **handling of existing data**

Write Less Code: Input & Output

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

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

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

load(…), save(…), or saveAsTable(…) finish the I/O specification

ETL using Custom Data Sources

```
sqlContext.read
  .format("com.databricks.spark.jira")
  .option("url", "https://issues.apache.org/jira/rest/api/latest/search")
  .option("user", "...")
  .option("password", "...")
  .option("query", """
  |project = SPARK AND
  |component = SQL AND
  |(status = Open OR status = "In Progress" OR status =
"Reopened").stripMargin
  .load()
  .repartition(1)
  .write
  .format("parquet")
  .saveAsTable("sparkSqlJira")
```

Write Less Code: High-Level Operations

Solve common problems concisely using DataFrame functions:

- selecting columns and filtering
- joining different data sources
- aggregation (count, sum, average, etc.)
- plotting results (e.g., with Pandas)

Write Less Code: Compute an Average


```
private IntWritable one = new IntWritable(1);
private IntWritable output =new IntWritable();
protected void map(LongWritable key,
                   Text value,
                   Context context) {
    String[] fields = value.split("\t");
    output.set(Integer.parseInt(fields[1]));
    context.write(one, output);
}

------------------------------------------------------------------
--

IntWritable one = new IntWritable(1)
DoubleWritable average = new DoubleWritable();

protected void reduce(IntWritable key,
                      Iterable<IntWritable>
values,
                      Context context) {
    int sum = 0;
    int count = 0;
    for (IntWritable value: values) {
        sum += value.get();
        count++;
    }
    average.set(sum / (double) count);
    context.write(key, average);
}
```


```
var data = sc.textFile(...).split("\t")
data.map { x => (x(0), (x(1), 1)) }
    .reduceByKey { case (x, y) =>
      (x._1 + y._1, x._2 + y._2) }
    .map { x => (x._1, x._2(0) / x._2(1)) }
    .collect()
```

Write Less Code: Compute an Average

Using RDDs

```
var data = sc.textFile(...).split("\t")
data.map { x => (x(0), (x(1), 1)) }
    .reduceByKey { case (x, y) =>
      (x._1 + y._1, x._2 + y._2) }
    .map { x => (x._1, x._2(0) / x._2(1)) }
    .collect()
```

Using DataFrames

```
sqlContext.table("people")
          .groupBy("name")
          .agg("name", avg("age"))
          .collect()
```

Full API Docs

- Scala
- Java
- Python
- R

What are DataFrames?

DataFrames are a recent addition to Spark (early 2015).

The DataFrames API:

- is intended to enable wider audiences beyond "Big Data" engineers to leverage the power of distributed processing
- is inspired by data frames in R and Python (Pandas)
- designed from the ground-up to support modern big data and data science applications
- an extension to the existing RDD API

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

What are DataFrames?

DataFrames have the following features:

- Ability to scale from kilobytes of data on a single laptop to petabytes on a large cluster
- Support for a wide array of data formats and storage systems
- State-of-the-art optimization and code generation through the Spark SQL Catalyst optimizer
- Seamless integration with all big data tooling and infrastructure via Spark
- APIs for Python, Java, Scala, and R

What are DataFrames?

- For new users familiar with data frames in other programming languages, this API should make them feel at home.
- For existing Spark users, the API will make Spark easier to program.
- For both sets of users, DataFrames will improve performance through intelligent optimizations and code-generation.

Construct a DataFrame

```python
# Construct a DataFrame from a "users" table in Hive.
df = sqlContext.table("users")

# Construct a DataFrame from a log file in S3.
df = sqlContext.load("s3n://someBucket/path/to/data.json", "json")
```

```scala
val people = sqlContext.read.parquet("...")
```

```java
DataFrame people = sqlContext.read().parquet("...")
```

Use DataFrames

```python
# Create a new DataFrame that contains only "young" users
young = users.filter(users["age"] < 21)

# Alternatively, using a Pandas-like syntax
young = users[users.age < 21]

# Increment everybody's age by 1
young.select(young["name"], young["age"] + 1)

# Count the number of young users by gender
young.groupBy("gender").count()

# Join young users with another DataFrame, logs
young.join(log, logs["userId"] == users["userId"], "left_outer")
```

DataFrames and Spark SQL

```
young.registerTempTable("young")
sqlContext.sql("SELECT  count(*)  FROM  young")
```

DataFrames and Spark SQL

DataFrames are fundamentally tied to Spark SQL.

- The DataFrames API provides a *programmatic* interface—really, a *domain-specific language* (DSL)—for interacting with your data.
- Spark SQL provides a *SQL-like* interface.
- What you can do in Spark SQL, you can do in DataFrames
- … and vice versa.

What, exactly, is Spark SQL?

Spark SQL allows you to manipulate distributed data with SQL queries. Currently, two SQL dialects are supported.

- If you're using a Spark `SQLContext`, the only supported dialect is "sql", a rich subset of SQL 92.
- If you're using a `HiveContext`, the default dialect is "hiveql", corresponding to Hive's SQL dialect. "sql" is also available, but "hiveql" is a richer dialect.

Spark SQL

- You issue SQL queries through a `SQLContext` or `HiveContext`, using the `sql()` method.
- The `sql()` method returns a `DataFrame`.
- You can mix DataFrame methods and SQL queries in the same code.
- To use SQL, you *must* either:
  - query a persisted Hive table, or
  - make a *table alias* for a DataFrame, using `registerTempTable()`

DataFrames

Like Spark SQL, the DataFrames API assumes that the data has a table-like structure.

Formally, a DataFrame is a **size-mutable, potentially heterogeneous tabular data structure with labeled axes (i.e., rows and columns).**

That's a mouthful. Just think of it as a table in a distributed database: a distributed collection of data organized into named, typed columns.

Transformations, Actions, Laziness

DataFrames are *lazy*. *Transformations* contribute to the query plan, but they don't execute anything.

Actions cause the execution of the query.

Transformation examples

- filter
- select
- drop
- intersect
- join

Action examples

- count
- collect
- show
- head
- take

Transformations, Actions, Laziness

Actions cause the execution of the query.

What, exactly does "execution of the query" mean?

It means:

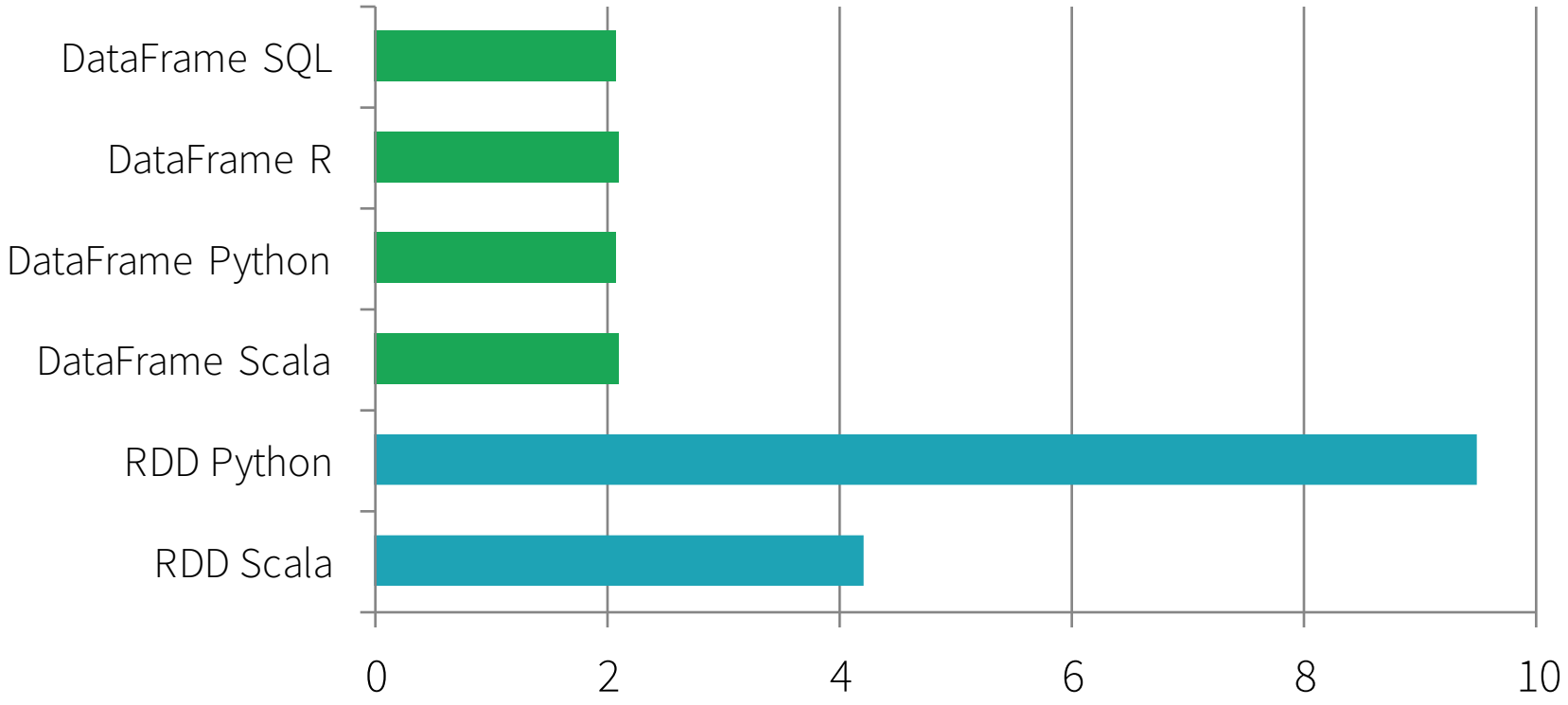
- Spark initiates a distributed read of the data source
- The data flows through the transformations (the RDDs resulting from the Catalyst query plan)
- The result of the action is pulled back into the driver JVM.

DataFrames &Resilient Distributed Datasets (RDDs)

- DataFrames are built on top of the Spark RDD* API.
  - This means you can use normal RDD operations on DataFrames.
- However, stick with the DataFrame API, wherever possible.
  - Using RDD operations will often give you back an RDD, not a DataFrame.
  - The DataFrame API is likely to be more efficient, because it can optimize the underlying operations with Catalyst.

** We will be discussing RDDs later in the course.*

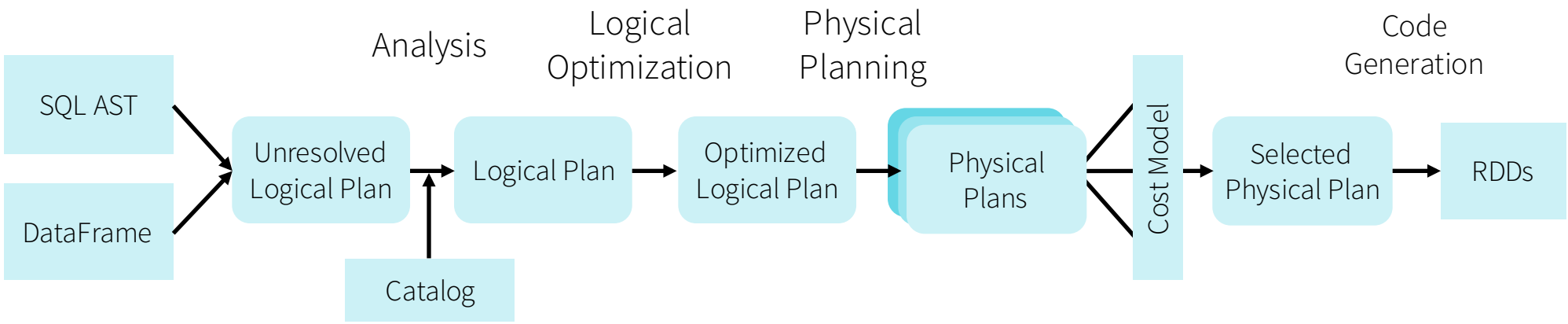
DataFrames can be *significantly* faster than RDDs. And they perform the same, regardless of language.



Plan Optimization & Execution

- Represented internally as a “logical plan”
- Execution is lazy, allowing it to be optimized by Catalyst

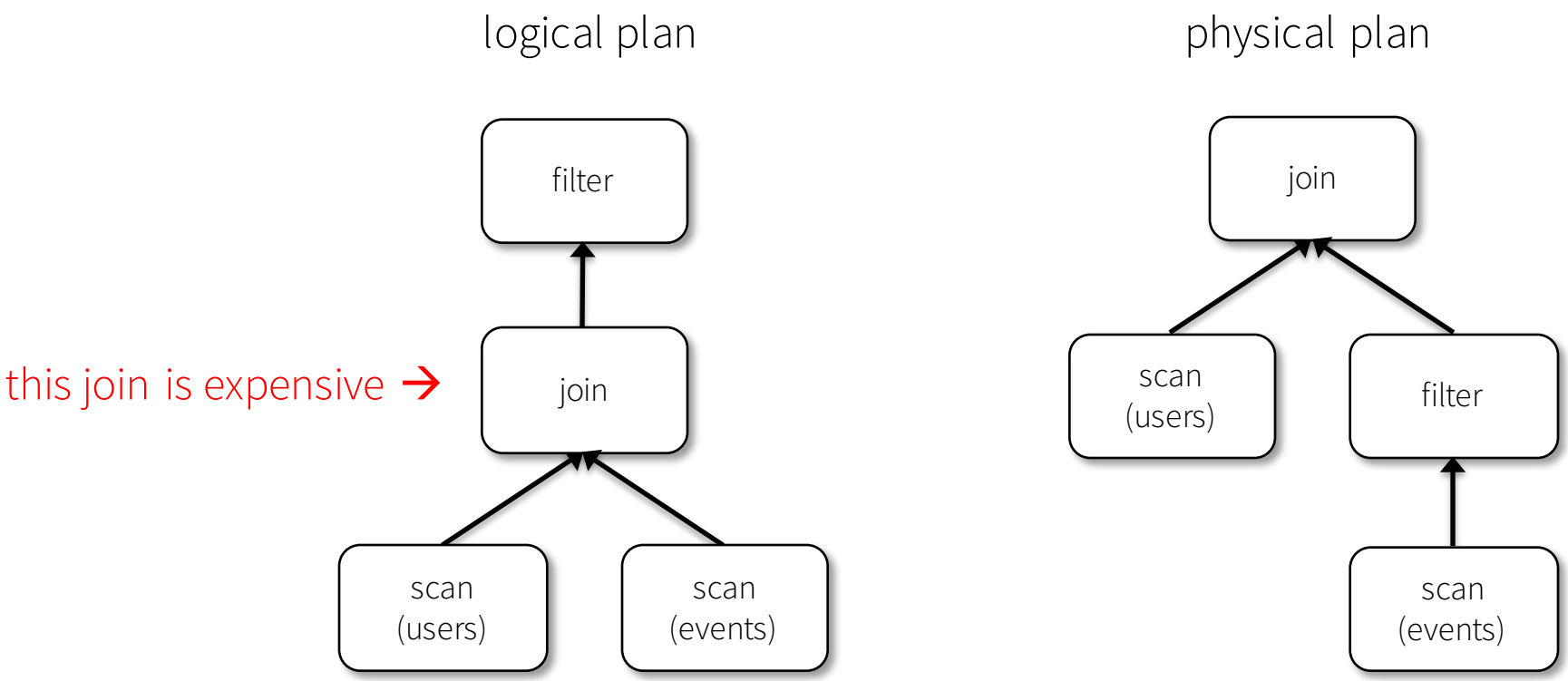
Plan Optimization & Execution



DataFrames and SQL share the same optimization/execution pipeline

Plan Optimization & Execution

```
joined = users.join(events, users.id == events.uid)
filtered = joined.filter(events.date >= ”2015-01-01”)
```



Plan Optimization: "Intelligent" Data Sources

The Data Sources API can automatically prune columns and push filters to the source

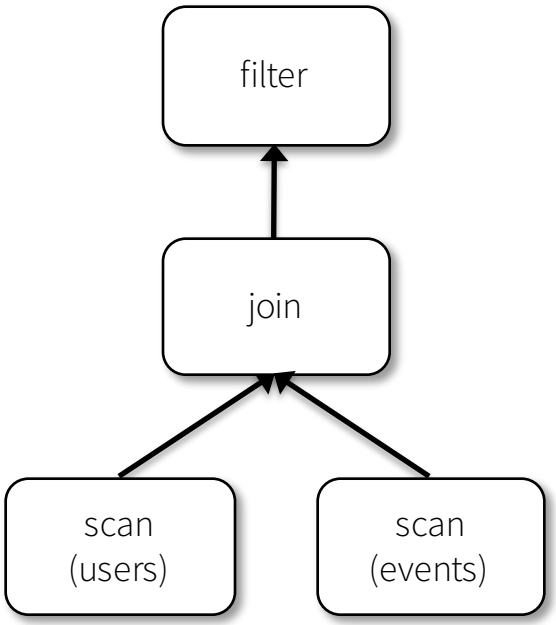
- **Parquet:** skip irrelevant columns and blocks of data; turn string comparison into integer comparisons for dictionary encoded data

- **JDBC:** Rewrite queries to push predicates down

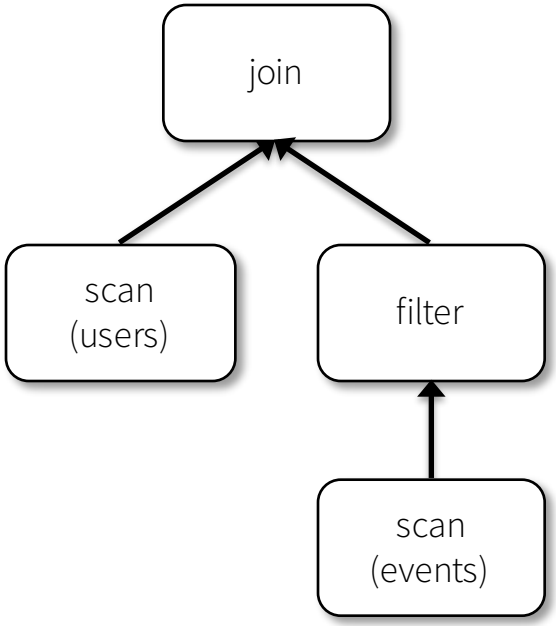
Plan Optimization: "Intelligent" Data Sources

```
joined = users.join(events, users.id == events.uid)
filtered = joined.filter(events.date > ”2015-01-01”)
```

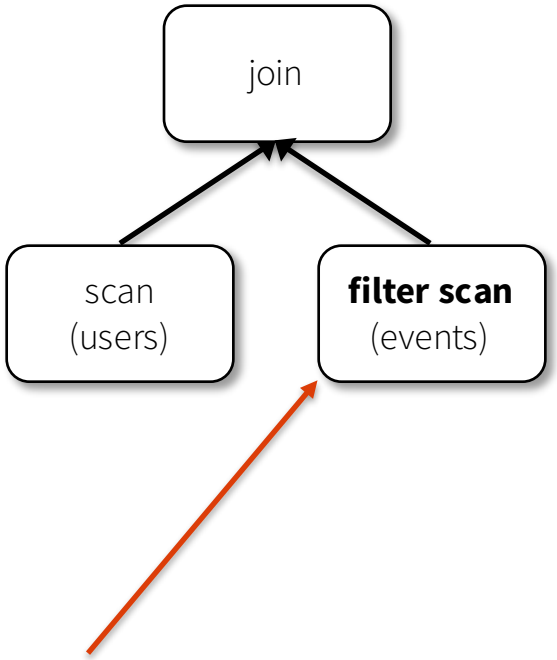
logical plan



optimized plan

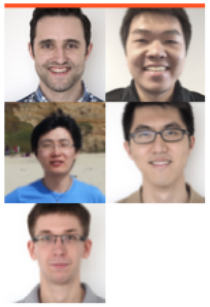


optimized plan
with intelligent data sources



filter done by data source
(e.g., RDBMS via JDBC)

Catalyst Internals



Deep Dive into Spark SQL's Catalyst Optimizer

April 13, 2015 | by Michael Armbrust, Yin Huai, Cheng Liang, Reynold Xin and Matei Zaharia

Spark SQL is one of the newest and most technically involved components of Spark. It powers both SQL queries and the new DataFrame API. At the core of Spark SQL is the Catalyst optimizer, which leverages advanced programming language features (e.g. Scala's pattern matching and quasiquotes) in a novel way to build an extensible query optimizer.

We recently published a paper on Spark SQL that will appear in SIGMOD 2015 (co-authored with Davies Liu, Joseph K. Bradley, Xiangrui Meng, Tomer Kaftan, Michael J. Franklin, and Ali Ghodsi). In this blog post we are republishing a section in the paper that explains the internals of the Catalyst optimizer for broader consumption.

https://databricks.com/blog/2015/04/13/deep-dive-into-spark-sqls-catalyst-optimizer.html

3 Fundamental transformations on DataFrames

- **mapPartitions**
- **New ShuffledRDD**
- **ZipPartitions**

DataFrame limitations

- Catalyst does not automatically repartition DataFrames optimally

- During a DF shuffle, Spark SQL will just use **spark.sql.shuffle.partitions** to determine the number of partitions in the downstream RDD

- All SQL configurations can be changed via **sqlContext.setConf(key, value)** or in DB: **"%sql SET key=val"**

Creating a DataFrame

- 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`.
- In an application, you can easily 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.

Creating a DataFrame in Scala

```scala
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 sc = SparkContext.getOrCreate(conf)
// Ditto.
val sqlContext = SQLContext.getOrCreate(sc)

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

Creating a DataFrame in Python

Unfortunately, `getOrCreate()` does not exist in *pyspark*.

```
# The import isn't necessary in the SparkShell or Databricks
from pyspark import SparkContext, SparkConf

# The following three lines are not necessary
# in the pyspark shell
conf = SparkConf().setAppName(appName).setMaster(master)
sc = SparkContext(conf=conf)
sqlContext = SQLContext(sc)

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

Creating a DataFrame in R

```
# The following two lines are not necessary in the sparkR shell
sc <- sparkR.init(master, appName)
sqlContext <- sparkRSQL.init(sc)

df <- parquetFile("/path/to/data.parquet")
df2 <- jsonFile("/path/to/data.json")
```

SQLContext and Hive

Our previous examples created a default Spark `SQLContext` object.

If you're using a version of Spark that has Hive support, you can also create a `HiveContext`, which provides additional features, including:

- the ability to write queries using the more complete HiveQL parser
- access to Hive user-defined functions
- the ability to read data from Hive tables.

HiveContext

- To use a `HiveContext`, you do not need to have an existing Hive installation, and all of the data sources available to a `SQLContext` are still available.
- You *do*, however, need to have a version of Spark that was built with Hive support. That's *not* the default.
  - Hive is packaged separately to avoid including all of Hive's dependencies in the default Spark build.
  - If these dependencies are not a problem for your application then using `HiveContext` is currently recommended.
- It's not difficult to build Spark with Hive support.

HiveContext

If your copy of Spark has Hive support, you can create a `HiveContext` easily enough:

```scala
import org.spark.sql.hive.HiveContext

val sqlContext = new HiveContext(sc)
```

```python
from pyspark.sql import HiveContext

sqlContext = HiveContext(sc)
```

```r
sqlContext <- sparkRHive.init(sc)
```

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.

Data Sources supported by DataFrames

built-in

external

and more …

Schema Inference

What if your data file doesn't have a schema? (e.g., You're reading a CSV file or a plain text file.)

- 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.

(It's better to use a schema-oriented input source if you can, though.)

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
…
```

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

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

Let's see how to get Spark to infer the schema.

Schema Inference :: Scala

```
import sqlContext.implicits._

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

val rdd = sc.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 :: Python

- We can do the same thing in Python.
- Use a `namedtuple`, `dict`, or `Row`, instead of a Python class, though.*
  - `Row` is part of the DataFrames API

* See spark.apache.org/docs/latest/api/python/pyspark.sql.html#pyspark.sql.SQLContext.createDataFrame

Schema Inference :: Python

```
from pyspark.sql import Row

rdd = sc.textFile("people.csv")
Person = Row('first_name', 'last_name', 'gender', 'age')

def line_to_person(line):
    cells = line.split(",")
    cells[3] = int(cells[3])
    return Person(*cells)

peopleRDD = rdd.map(line_to_person)

df = peopleRDD.toDF()
# DataFrame[first_name: string, last_name: string, gender:
string, age: bigint]
```

Schema Inference :: Python

```
from collections import namedtuple

Person = namedtuple('Person',
    ['first_name', 'last_name', 'gender', 'age']
)
rdd = sc.textFile("people.csv")

def line_to_person(line):
    cells = line.split(",")
    return Person(cells[0], cells[1], cells[2],
                  int(cells[3]))

peopleRDD = rdd.map(line_to_person)

df = peopleRDD.toDF()
# DataFrame[first_name: string, last_name: string, gender: string,
age: bigint]
```

Schema Inference

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

Schema Inference :: Scala

Here's the Scala version:

```
val rdd = sc.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.

Schema Inference :: Python

Here's the Python version:

```
rdd = sc.textFile("people.csv")

def line_to_person(line):
    cells = line.split(",")
    return tuple(cells[0:3] + [int(cells[3])])

peopleRDD = rdd.map(line_to_person)
df = peopleRDD.toDF(("first_name", "last_name",
                     "gender", "age"))
```

Again, if you don't supply the column names, the API defaults to "_1", "_2", etc.

Schema Inference

Why do you have to use a tuple?

In Python, you don't. You can use any iterable data structure (e.g., a list).

In Scala, you do. Tuples have fixed lengths and fixed types for each element *at compile time.* For instance:

```
Tuple4[String,String,String,Int]
```

The DataFrames API uses this information to infer the number of columns and their types. It cannot do that with an array.

Additional Input Formats

The DataFrames API can be extended to understand additional input formats (or, input *sources*).

For instance, if you're dealing with CSV files, a *very* common data file format, you can use the *spark-csv* package (spark-packages.org/package/databricks/spark-csv)

This package augments the DataFrames API so that it understands CSV files.

A brief look at *spark-csv*

Let's assume our data file has a header:

```
first_name,last_name,gender,age
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
…
```

A brief look at *spark-csv*

With *spark-csv*, we can simply create a DataFrame directly from our CSV file.

```scala
// Scala
val df = sqlContext.read.format("com.databricks.spark.csv").
                        option("header", "true").
                        load("people.csv")
```

```python
# Python
df = sqlContext.read.format("com.databricks.spark.csv").\
                    load("people.csv", header="true")
```

A brief look at *spark-csv*

spark-csv uses the header to infer the schema, but the column types will always be *string*.

```
// df: org.apache.spark.sql.DataFrame = [first_name: string,
last_name: string, gender: string, age: string]
```

A brief look at *spark-csv*

You can also declare the schema programmatically, which allows you to specify the column types. Here's Scala:

```
import org.apache.spark.sql.types._

// A schema is a StructType, built from a List of StructField objects.
val schema = StructType(
  StructField("firstName", StringType, false) ::
  StructField("gender", StringType, false) ::
  StructField("age", IntegerType, false) ::
  Nil
)

val df = sqlContext.read.format("com.databricks.spark.csv").
                         option("header", "true").
                         schema(schema).
                         load("people.csv")
// df: org.apache.spark.sql.DataFrame = [firstName: string, gender: string,
age: int]
```

A brief look at *spark-csv*

Here's the same thing in Python:

```
from pyspark.sql.types import *

schema = StructType([StructField("firstName", StringType(), False),
                     StructField("gender", StringType(), False),
                     StructField("age", IntegerType(), False)])

df = sqlContext.read.format("com.databricks.spark.csv").\
                     schema(schema).\
                     load("people.csv")
```

What can I do with a DataFrame?

Once you have a DataFrame, there are a number of operations you can perform.

Let's look at a few of them.

But, first, let's talk about columns.

Columns

When we say “column” here, what do we mean?

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

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

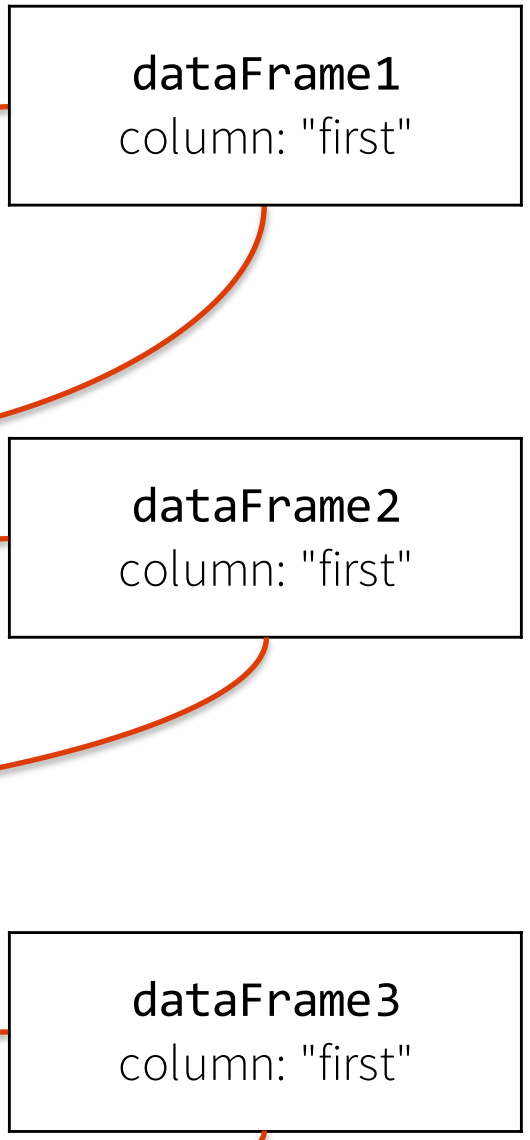
Let's see how DataFrame columns map onto some common data sources.

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

When we say “column” here, what do we mean?

Several things:

- A place (a *cell*) for a data value to reside, within a row of data. This cell can have several states:
  - empty (null)
  - missing (not there at all)
  - contains a (typed) value (non-null)
- A collection of those cells, from multiple rows
- A syntactic construct we can use to *specify* or *target* a cell (or collections of cells) in a DataFrame query

How do you specify a column in the DataFrame API?

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`

†In Python, it's possible to access a DataFrame's columns either by attribute (`df.age`) or by indexing (`df['age']`). While the former is convenient for interactive data exploration, you should *use the index form.* It's future proof and won't break with column names that are also attributes on the DataFrame class.

‡The $ syntax can be ambiguous, if there are multiple DataFrames in the lineage.

printSchema()

You can have Spark tell you what it thinks the data schema is, by calling the `printSchema()` method. (This is mostly useful in the shell.)

```
scala> df.printSchema()
root
 |-- firstName: string (nullable = true)
 |-- lastName: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- age: integer (nullable = false)
```

printSchema()

```
> printSchema(df)
root
 |-- firstName: string (nullable = true)
 |-- lastName: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- age: integer (nullable = false)
```

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

Note: In R, the function is `showDF()`

show()

```
scala> 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|
+---------+--------+------+---+
```

show()

```
> showDF(df)
+---------+--------+------+---+
|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|
+---------+--------+------+---+
```

cache()

- Spark can cache a DataFrame, using an in-memory columnar format, by calling `df.cache()` (which just calls `df.persist(MEMORY_ONLY)`).
- Spark will scan only those columns used by the DataFrame and will automatically tune compression to minimize memory usage and GC pressure.
- You can call the `unpersist()` method to remove the cached data from memory.

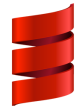
select()

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

select()

The DSL also allows you create on-the-fly *derived columns*.



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

select()

The Python DSL is slightly different.

```
In[1]: df.select(df['first_name'], df['age'], df['age'] > 49).show(5)
+----------+---+----------+
|first_name|age|(age > 49)|
+----------+---+----------+
|      Erin| 42|     false|
|    Claire| 23|     false|
|    Norman| 81|      true|
|    Miguel| 64|      true|
|  Rosalita| 14|     false|
+----------+---+----------+
```

select()

The R syntax is completely different:

```
> showDF(select(df, df$first_name, df$age, df$age > 49))
+----------+---+------------+
|first_name|age|(age > 49.0)|
+----------+---+------------+
|      Erin| 42|       false|
|    Claire| 23|       false|
|    Norman| 81|        true|
|    Miguel| 64|        true|
|  Rosalita| 14|       false|
+----------+---+------------+
```

select()

And, of course, you can also use SQL. (This is the Python API, but you issue SQL the same way in Scala and Java.)

```
In[1]: df.registerTempTable("names")
In[2]: sqlContext.sql("SELECT first_name, age, age > 49 FROM names").\
                  show(5)
+----------+---+-----+
|first_name|age|  _c2|
+----------+---+-----+
|      Erin| 42|false|
|    Claire| 23|false|
|    Norman| 81| true|
|    Miguel| 64| true|
|  Rosalita| 14|false|
+----------+---+-----+
```

In a Databricks cell, you can replace the second line with:

```
%sql SELECT first_name,  age, age > 49 FROM names
```

select()

In R, the syntax for issuing SQL is a little different.

```
> registerTempTable(df, "names")
> showDF(sql(sqlContext, "SELECT first_name, age, age > 49 FROM names"))
+----------+---+-----+
|first_name|age|   c2|
+----------+---+-----+
|      Erin| 42|false|
|    Claire| 23|false|
|    Norman| 81| true|
|    Miguel| 64| true|
|  Rosalita| 14|false|
+----------+---+-----+
```

filter()

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

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

filter()

Here's the Python version.

```
In[1]: df.filter(df['age'] > 49).\
           select(df['first_name'], df['age']).\
           show()
+---------+---+
|firstName|age|
+---------+---+
|   Norman| 81|
|   Miguel| 64|
|  Abigail| 75|
+---------+---+
```

filter()

Here's the R version.

```
> showDF(select(filter(df, df$age > 49), df$first_name, df$age))
+---------+---+
|firstName|age|
+---------+---+
|   Norman| 81|
|   Miguel| 64|
|  Abigail| 75|
+---------+---+
```

filter()

Here's the SQL version.

```
In[1]: SQLContext.sql("SELECT first_name, age FROM names " + \
                      "WHERE age > 49").show()
+---------+---+
|firstName|age|
+---------+---+
|   Norman| 81|
|   Miguel| 64|
|  Abigail| 75|
+---------+---+
```

orderBy()

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

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

orderBy()

It's easy to reverse the sort order.

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

orderBy()

And, in Python:

```
In [1]: df.filter(df['age'] > 49).\
           select(df['first_name'], df['age']).\
           orderBy(df['age'].desc(), df['first_name']).show()
+----------+---+
|first_name|age|
+----------+---+
|    Norman| 81|
|   Abigail| 75|
|    Miguel| 64|
+----------+---+
```

orderBy()

In R:

```
> showDF(orderBy(
+   select(filter(df, df$age > 49), df$first_name, df$age),
+   desc(df$age), df$first_name)
+ )
+----------+---+
|first_name|age|
+----------+---+
|    Norman| 81|
|   Abigail| 75|
|    Miguel| 64|
+----------+---+
```

Obviously, that would be a lot more readable as multiple statements.

orderBy()

In SQL, it's pretty normal looking:

```
scala> sqlContext.SQL("SELECT first_name, age FROM names " +
     |   "WHERE age > 49 ORDER BY age DESC, first_name").show()
+----------+---+
|first_name|age|
+----------+---+
|    Norman| 81|
|   Abigail| 75|
|    Miguel| 64|
+----------+---+
```

groupBy()

Often used with **`count()`**, **`groupBy()`** groups data items by a specific column value.

```
In [5]: df.groupBy("age").count().show()
+---+-----+
|age|count|
+---+-----+
| 39|    1|
| 42|    2|
| 64|    1|
| 75|    1|
| 81|    1|
| 14|    1|
| 23|    2|
+---+-----+
```

This is Python. Scala and Java are similar.

groupBy()

R, again, is slightly different.

```
> showDF(count(groupBy(df, df$age)))
+---+-----+
|age|count|
+---+-----+
| 39|    1|
| 42|    2|
| 64|    1|
| 75|    1|
| 81|    1|
| 14|    1|
| 23|    2|
+---+-----+
```

groupBy()

And SQL, of course, isn't surprising:

```
scala> sqlContext.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|
+---+-----+
```

as() or alias()

`as()` or `alias()` allows you to rename a column.
It's especially useful with generated columns.

```
In [7]: df.select(df['first_name'],\
                  df['age'],\
                  (df['age'] < 30).alias('young')).show(5)
+----------+---+-----+
|first_name|age|young|
+----------+---+-----+
|      Erin| 42|false|
|    Claire| 23| true|
|    Norman| 81|false|
|    Miguel| 64|false|
|  Rosalita| 14| true|
+----------+---+-----+
```

Note: In Python, you *must* use `alias`, because `as` is a keyword.

as() or alias()

Here is it in Scala.

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

alias()

Here's R. Only alias() is supported here.

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

as()

And, of course, SQL:

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

Other Useful Transformations

Method	Description
`limit(`*`n`*`)`	Limit the results to *n* rows. **`limit()`** is not an action, like **`show()`** or the RDD **`take()`** method. It returns another DataFrame.
`distinct()`	Returns a new DataFrame containing only the unique rows from the current DataFrame
`drop(`*`column`*`)`	Returns a new DataFrame with a column dropped. *column* is a name or a Column object.
`intersect(`*`dataframe`*`)`	Intersect one DataFrame with another.
`join(`*`dataframe`*`)`	Join one DataFrame with another, like a SQL join. We'll discuss this one more in a minute.

There are *loads* more of them.

Joins

Let's assume we have a second file, a JSON file that contains records like this:

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

Joins

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

```
In [1]: df2 = sqlContext.read.json("artists.json")
# Schema inferred as DataFrame[firstName: string, lastName: string, medium:
string]
In [2]: df.join(
            df2,
            df.first_name == df2.firstName and 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|
+----------+---------+------+---+---------+--------+-----------------+
```

Joins

Let's make that a little more readable by only selecting *some* of the columns.

```
In [3]: df3 = df.join(
                  df2,
                  df.first_name == df2.firstName and df.last_name == df2.lastName
        )
In [4]: df3.select("first_name", "last_name", "age", "medium").show()
+----------+---------+---+----------------+
|first_name|last_name|age|          medium|
+----------+---------+---+----------------+
|    Norman| Lockwood| 81|metal (sculpture)|
|      Erin|  Shannon| 42|    oil on canvas|
|  Rosalita|  Ramirez| 14|         charcoal|
|    Miguel|     Ruiz| 64|    oil on canvas|
+----------+---------+---+----------------+
```

explode()

Suppose you have a JSON file consisting of data about families. The file is an array of JSON objects, as shown here.

```
[
  {"id": 909091,
   "father": {
     "middleName": "Travis",
     "birthYear": 1973,
     "lastName": "Czapski",
     "firstName": "Marvin",
     "gender": "M"
   },
   "mother": {
     "middleName": "Maryann",
     "birthYear": 1973,
     "lastName": "Czapski",
     "firstName": "Vashti",
     "gender": "F"
   },
   "children": [
     {"firstName": "Betsy",
      "middleName": "Rebecka",
      "lastName": "Czapski",
      "birthYear": 2005,
      "gender": "F"}
     ]
  },
  ...
]
```

explode()

When you load it into a DataFrame, here's what you see:

```
scala> val df = sqlContext.read.json("/data/families.json")
scala> df.select("id", "father", "mother", "children").show(5)
+------+--------------------+--------------------+--------------------+
| id   | father             | mother             | children           |
+------+--------------------+--------------------+--------------------+
|909091|[1973,Marvin,M,Cz...|[1973,Vashti,F,Cz...|List([2005,Betsy,...|
|909092|[1963,Amado,M,Car...|[1970,Darline,F,C...|List([2005,Harrie...|
|909093|[1975,Parker,M,Di...|[1978,Vesta,F,Din...|List([2006,Bobbi,...|
|909094|[1956,Kasey,M,Hur...|[1960,Isela,F,Hur...|List([2005,Cliffo...|
|909095|[1956,Aaron,M,Met...|[1962,Beth,F,Mete...|List([2001,Angila...|
+------+--------------------+--------------------+--------------------+
```

explode()

The schema is more interesting.

```
scala> df.printSchema
root
 |-- id: integer (nullable = true)
 |-- father: struct (nullable = true)
 |    |-- firstName: string (nullable = true)
 |    |-- middleName: string (nullable = true)
 |    |-- lastName: string (nullable = true)
 |    |-- gender: string (nullable = true)
 |    |-- birthYear: integer (nullable = true)
 |-- mother: struct (nullable = true)
 |    |-- firstName: string (nullable = true)
 |    |-- middleName: string (nullable = true)
 |    |-- lastName: string (nullable = true)
 |    |-- gender: string (nullable = true)
 |    |-- birthYear: integer (nullable = true)
 |-- children: array (nullable = true)
 |    |-- element: struct (containsNull = true)
 |    |    |-- firstName: string (nullable = true)
 |    |    |-- middleName: string (nullable = true)
 |    |    |-- lastName: string (nullable = true)
 |    |    |-- gender: string (nullable = true)
 |    |    |-- birthYear: integer (nullable = true)
```

explode()

In that layout, the data can be difficult to manage. But, we can *explode* the columns to make them easier to manage. For instance, we can turn a single **`children`** value, an array, into multiple values, one per row:

```
scala> val df2 = df.filter($"id" === 168).
                    explode[Seq[Person], Person]("children", "child") { v => v.toList }
scala> df2.show()
+---+--------------------+--------------------+--------------------+--------------------+
| id|              father|              mother|            children|               child|
+---+--------------------+--------------------+--------------------+--------------------+
|168|[Nicolas,Jorge,Tr...|[Jenette,Elouise,...|ArrayBuffer([Terr...|[Terri,Olene,Traf...|
|168|[Nicolas,Jorge,Tr...|[Jenette,Elouise,...|ArrayBuffer([Terr...|[Bobbie,Lupe,Traf...|
|168|[Nicolas,Jorge,Tr...|[Jenette,Elouise,...|ArrayBuffer([Terr...|[Liana,Ophelia,Tr...|
|168|[Nicolas,Jorge,Tr...|[Jenette,Elouise,...|ArrayBuffer([Terr...|[Pablo,Son,Trafto...|
+---+--------------------+--------------------+--------------------+--------------------+
```

Note what happened: A single children column value was exploded into multiple values, one per row. The rest of the values in the original row were duplicated in the new rows.

explode()

The resulting DataFrame has one child per row, and it's easier to work with:

```
scala> df2.select($"father.firstName".as("fatherFirstName"),
                  $"mother.firstName".as("motherFirstName"),
                  $"child.firstName".as("childFirstName"),
                  $"child.middleName".as("childMiddleName")).show()
+---------------+---------------+-------------+---------------+
|fatherFirstName|motherFirstName|childFirstName|childMiddleName|
+---------------+---------------+-------------+---------------+
|        Nicolas|        Jenette|         Terri|           Olene|
|        Nicolas|        Jenette|        Bobbie|           Lupe|
|        Nicolas|        Jenette|         Liana|        Ophelia|
|        Nicolas|        Jenette|         Pablo|            Son|
+---------------+---------------+-------------+---------------+
```

User Defined Functions

Suppose our JSON data file capitalizes the names differently than our first data file. The obvious solution is to force all names to lower case before joining.

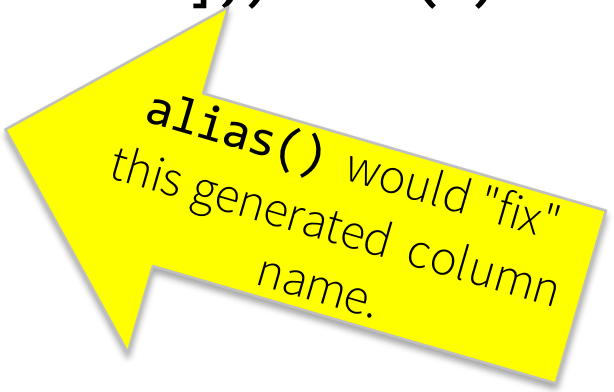
Alas, there is no `lower()` function…

```
In[6]: df3 = df.join(df2, lower(df.first_name) == lower(df2.firstName) and \
                          lower(df.last_name) == lower(df2.lastName))
NameError: name 'lower' is not defined
```

User Defined Functions

However, this deficiency is easily remedied with a *user defined function*.

```
In [8]: from pyspark.sql.functions import udf
In [9]: lower = udf(lambda s: s.lower())
In [10]: df.select(lower(df['firstName'])).show(5)
+------------------------------+
|PythonUDF#<lambda>(first_name)|
+------------------------------+
|                          erin|
|                        claire|
|                        norman|
|                        miguel|
|                      rosalita|
+------------------------------+
```



User Defined Functions

Interestingly enough, `lower()` does exist in the Scala API. So, let's invent something that doesn't:

```
scala> df.select(double($("total")))
console>:23: error: not found: value double
             df.select(double($("total"))).show()
                       ^
```

User Defined Functions

Again, it's an easy fix.

```
scala> val double = sqlContext.udf.register("double",
                                              (i: Int) => i.toDouble)
double: org.apache.spark.sql.UserDefinedFunction =
UserDefinedFunction(<function1>,DoubleType)

scala> df.select(double($("total"))).show(5)
+---------------+
|scalaUDF(total)|
+---------------+
|         7065.0|
|         2604.0|
|         2003.0|
|         1939.0|
|         1746.0|
+---------------+
```

User Defined Functions

UDFs are not currently supported in R.

Writing DataFrames

- You can write DataFrames out, as well. When doing ETL, this is a *very* common requirement.
- In most cases, if you can read a data format, you can write that data format, as well.
- If you're writing to a text file format (e.g., JSON), you'll typically get multiple output files.

Writing DataFrames

```
scala> df.write.format("json").save("/path/to/directory")
scala> df.write.format("parquet").save("/path/to/directory")
```

```
In [20]: df.write.format("json").save("/path/to/directory")
In [21]: df.write.format("parquet").save("/path/to/directory")
```

Writing DataFrames: Save modes

Save operations can optionally take a `SaveMode` that specifies how to handle existing data if present.

Scala/Java	Python	Meaning
`SaveMode.ErrorIfExists` (default)	`"error"`	If output data or table already exists, an exception is expected to be thrown.
`SaveMode.Append`	`"append"`	If output data or table already exists, append contents of the DataFrame to existing data.
`SaveMode.Overwrite`	`"overwrite"`	If output data or table already exists, replace existing data with contents of DataFrame.
`SaveMode.Ignore`	`"ignore"`	If output data or table already exists, do not write DataFrame at all.

Writing DataFrames: Save modes

Warning: These save modes do *not* utilize any locking and are *not* atomic.

Thus, it is *not* safe to have multiple writers attempting to write to the same location. Additionally, when performing a overwrite, the data will be deleted before writing out the new data.

Writing DataFrames: Hive

- When working with a `HiveContext`, you can save a DataFrame as a persistent table, with the `saveAsTable()` method.
- Unlike `registerTempTable()`, `saveAsTable()` materializes the DataFrame (i.e., runs the DAG) and creates a pointer to the data in the Hive metastore.
- Persistent tables will exist even after your Spark program has restarted.

Writing Data Frames: Hive

- By default, `saveAsTable()` will create a *managed table*: the metastore controls the location of the data. Data in a managed table is also deleted automatically when the table is dropped.

Other Hive Table Operations

- To create a DataFrame from a persistent Hive table, call the `table()` method on a `SQLContext`, passing the table name.

- To delete an existing Hive table, just use SQL:

```
sqlContext.sql("DROP TABLE IF EXISTS tablename")
```

Explain

You can dump the query plan to standard output, so you can get an idea of how Spark will execute your query.

```
In[3]: df3 = df.join(df2,
               df.first_name == df2.firstName and df.last_name == df2.lastName)
In[4]: df3.explain()
ShuffledHashJoin [last_name#18], [lastName#36], BuildRight
 Exchange (HashPartitioning 200)
  PhysicalRDD [first_name#17,last_name#18,gender#19,age#20L], MapPartitionsRDD[41]
at applySchemaToPythonRDD at NativeMethodAccessorImpl.java:-2
 Exchange (HashPartitioning 200)
  PhysicalRDD [firstName#35,lastName#36,medium#37], MapPartitionsRDD[118] at
executedPlan at NativeMethodAccessorImpl.java:-2
```

Explain

Pass `true` to get a more detailed query plan.

```
scala> df.join(df2, lower(df("firstName")) === lower(df2("firstName"))).explain(true)
== Parsed Logical Plan ==
Join Inner, Some((Lower(firstName#1) = Lower(firstName#13)))
 Relation[birthDate#0,firstName#1,gender#2,lastName#3,middleName#4,salary#5L,ssn#6]
org.apache.spark.sql.json.JSONRelation@7cbb370e
 Relation[firstName#13,lastName#14,medium#15] org.apache.spark.sql.json.JSONRelation@e5203d2c

== Analyzed Logical Plan ==
birthDate: string, firstName: string, gender: string, lastName: string, middleName: string, salary: bigint, ssn: string,
firstName: string, lastName: string, medium: string
Join Inner, Some((Lower(firstName#1) = Lower(firstName#13)))
 Relation[birthDate#0,firstName#1,gender#2,lastName#3,middleName#4,salary#5L,ssn#6]
org.apache.spark.sql.json.JSONRelation@7cbb370e
 Relation[firstName#13,lastName#14,medium#15] org.apache.spark.sql.json.JSONRelation@e5203d2c

== Optimized Logical Plan ==
Join Inner, Some((Lower(firstName#1) = Lower(firstName#13)))
 Relation[birthDate#0,firstName#1,gender#2,lastName#3,middleName#4,salary#5L,ssn#6]
org.apache.spark.sql.json.JSONRelation@7cbb370e
 Relation[firstName#13,lastName#14,medium#15] org.apache.spark.sql.json.JSONRelation@e5203d2c

== Physical Plan ==
ShuffledHashJoin [Lower(firstName#1)], [Lower(firstName#13)], BuildRight
 Exchange (HashPartitioning 200)
  PhysicalRDD [birthDate#0,firstName#1,gender#2,lastName#3,middleName#4,salary#5L,ssn#6], MapPartitionsRDD[40] at explain at
<console>:25
 Exchange (HashPartitioning 200)
  PhysicalRDD [firstName#13,lastName#14,medium#15], MapPartitionsRDD[43] at explain at <console>:25

Code Generation: false
== RDD ==
```

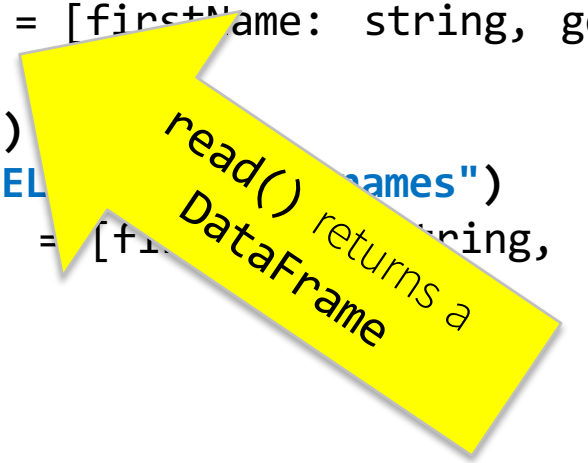
Spark SQL: Just a little more info

Recall that Spark SQL operations generally return DataFrames. This means you can freely mix DataFrames and SQL.

Example

To issue SQL against an existing DataFrame, create a temporary table, which essentially gives the DataFrame a *name* that's usable within a query.

```
scala> val df = sqlContext.read.parquet("/home/training/ssn/names.parquet")
df: org.apache.spark.sql.DataFrame = [firstName: string, gender: string,
total: int, year: int]
scala> df.registerTempTable("names")
scala> val sdf = sqlContext.sql(s"SEL                ames")
sdf: org.apache.spark.sql.DataFrame = [fi            ring, gender: string, tota
l: int, year: int]
scala> sdf.show(5)
+---------+------+-----+----+
|firstName|gender|total|year|
+---------+------+-----+----+
| Jennifer|     F|54336|1983|
|  Jessica|     F|45278|1983|
|   Amanda|     F|33752|1983|
|   Ashley|     F|33292|1983|
|    Sarah|     F|27228|1993|
+---------+------+-----+----+
```



Example

To issue SQL against an existing DataFrame, create a temporary table, which essentially gives the DataFrame a *name* that's usable within a query.

```
scala> val df = sqlContext.read.parquet("/home/training/ssn/names.parquet")
df: org.apache.spark.sql.DataFrame = [firstName: string, gender: string,
total: int, year: int]
scala> df.registerTempTable("names")
scala> val sdf = sqlContext.sql(s"SELECT * FROM names")
sdf: org.apache.spark.sql.DataFrame = [firstName: string, gender: string, tota
l: int, year: int]
scala> sdf.show(5)
+---------+------+-----+----+
|firstName|gender|total|year|
+---------+------+-----+----+
| Jennifer|     F|54336|1983|
|  Jessica|     F|45278|1983|
|   Amanda|     F|33752|1983|
|   Ashley|     F|33292|1983|
|    Sarah|     F|27228|1993|
+---------+------+-----+----+
```

DataFrame Operations

Because these operations return DataFrames, all the usual DataFrame operations are available.

…including the ability to create new temporary tables.

```
scala> val df = sqlContext.read.parquet("/home/training/ssn/names.parquet")
scala> df.registerTempTable("names")
scala> val sdf = sqlContext.sql(s"SELECT  * FROM names WHERE id < 30")
scala> sdf.registerTempTable("some_names")
```

SQL and RDDs

- Because SQL queries return DataFrames, and DataFrames are built on RDDs, you can use normal RDD operations on the results of a SQL query.
- However, as with any DataFrame, it's best to stick with DataFrame operations.

DataFrame Advanced Tips

- It is possible to coalesce or repartition DataFrames

- Catalyst does not do any automatic determination of partitions. After a shuffle, The DataFrame API uses `spark.sql.shuffle.partititions` to determine the number of partitions.

Machine Learning Integration

Spark 1.2 introduced a new package called **`spark.ml`**, which aims to provide a uniform set of high-level APIs that help users create and tune practical machine learning pipelines.

Spark ML standardizes APIs for machine learning algorithms to make it easier to combine multiple algorithms into a single *pipeline*, or *workflow*.

Machine Learning Integration

Spark ML uses DataFrames as a dataset which can hold a variety of data types.

For instance, a dataset could have different columns storing text, feature vectors, true labels, and predictions.

ML: Transformer

A *Transformer* is an algorithm which can transform one DataFrame into another DataFrame.

A **`Transformer`** object is an abstraction which includes *feature transformers* and *learned models*.

Technically, a Transformer implements a **`transform()`** method that converts one DataFrame into another, generally by appending one or more columns.

ML: Transformer

A *feature transformer* might:

- take a dataset,
- read a column (e.g., text),
- convert it into a new column (e.g., feature vectors),
- append the new column to the dataset, and
- output the updated dataset.

ML: Transformer

A *learning model* might:

- take a dataset,
- read the column containing feature vectors,
- predict the label for each feature vector,
- append the labels as a new column, and
- output the updated dataset.

ML: Estimator

An *Estimator* is an algorithm which can be fit on a DataFrame to produce a Transformer.

For instance, a learning algorithm is an Estimator that trains on a dataset and produces a model.

ML: Estimator

An Estimator abstracts the concept of any algorithm which fits or trains on data.

Technically, an Estimator implements a `fit()` method that accepts a DataFrame and produces a Transformer.

For example, a learning algorithm like `LogisticRegression` is an Estimator, and calling its `fit()` method trains a `LogisticRegressionModel`, which is a Transformation.

ML: Param

All Transformers and Estimators now share a common API for specifying parameters.

ML: Pipeline

In machine learning, it is common to run a sequence of algorithms to process and learn from data. A simple 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.

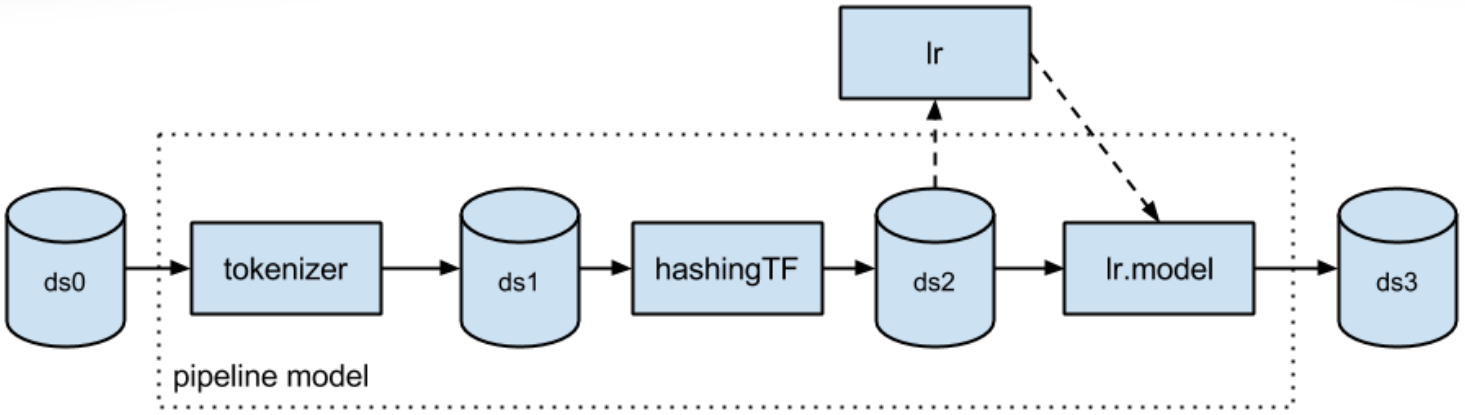
Spark ML represents such a workflow as a **Pipeline**, which consists of a sequence of **PipelineStages** (Transformers and Estimators) to be run in a specific order.

ML: Python Example

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

tokenizer = Tokenizer(inputCol="text", outputCol="words")
hashingTF = HashingTF(inputCol="words", outputCol="features")
lr        = LogisticRegression(maxIter=10, regParam=0.01)
pipeline  = Pipeline(stages=[tokenizer, hashingTF, lr])

df    = context.load("/path/to/data")
model = pipeline.fit(df)
```



ML: Scala Example

```
import org.apache.spark.ml.Pipeline
import org.apache.spark.ml.feature.{HashingTF, Tokenizer}
import org.apache.spark.ml.classification.LogisticRegression

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

val df    = sqlContext.load("/path/to/data")
val model = pipeline.fit(df)
```

End of DataFrames and Spark SQL Module