

# Spark the Definitive Guide 2nd Edition

## Chapter 05

### Basic Structured Operations

## Basic Structured Operations

## Text Book



# Objectives and Outcomes

- ▶ Introduce the tools we will use to manipulate DataFrames
- ▶ Focus on fundamental DataFrame operations

# Review

So far:

- ▶ We were introduced to Spark's Structured APIs, Datasets, DataFrames, and SQL Views
- ▶ We learned how Spark transforms a logical plan into a physical execution plan on a cluster
- ▶ Learned how DataFrames consist of a series of records
- ▶ Learned how DataFrames are of type Row and have a number of columns
- ▶ Learned that schemas define the name and type of data in each column
- ▶ Learned that Partitioning of the DataFrame defines the layout of the DataFrames physical distribution on the cluster

## Create a DataFrame

```
df = spark.read.format("json").load("Spark-The-Definitive-Guide")  
  
# Let's take a look at the defined schema  
df.printSchema()
```

- ▶ JSON

- ▶ is a lightweight, text-based data interchange format.

# Schemas

- ▶ Schemas tie everything together
- ▶ Schema defines the column names and column types of a DataFrame
  - ▶ Schema can be applied on read or inferred or declared
- ▶ For Ad-hoc data usually *schema-on-read* is good enough
  - ▶ Though it can be a bit slow when dealing with text-based file formats like:
    - ▶ CSV
    - ▶ JSON
- ▶ Schema-on-read can lead to precision problems
  - ▶ If a column is really of type LONG but the numbers are smaller and interpreted as type INT
- ▶ Spark can be used for **ETL**:
  - ▶ Extraction
  - ▶ Transform
  - ▶ Load In these cases it is best to provide the schema to ensure type matches

# JSON Object

```
spark.read.format("json").load("Spark-The-Definitive-Guide/
```

```
# This datatype is returned from the previous command  
# StructType(List(StructField  
# (DEST_COUNTRY_NAME,StringType,true),  
# StructField  
# (ORIGIN_COUNTRY_NAME,StringType,true),  
# StructField(count,LongType,true)))
```

- ▶ A schema is a StructType made up of a number of fields
  - ▶ StructFields have a name, type, and a Boolean flag indicating if they take nulls
  - ▶ If types in the data at run-time do not match the schema, Spark will throw an error



## Declare a Schema

```
from pyspark.sql.types import StructField, StructType, StringType

myManualSchema = StructType([StructField("DEST_COUNTRY_NAME", StringType(), True),
                               StructField("ORIGIN_COUNTRY_NAME", StringType(), True),
                               StructField("CARRIER", StringType(), True),
                               StructField("FLIGHT_DATE", StringType(), True)])

df = spark.read.format("json").schema(myManualSchema)
df.load("Spark-The-Definitive-Guide/data/flight-data/json/2015")
```

# Columns and Expressions

- ▶ Columns can be selected, manipulated, and removed from DataFrames
  - ▶ These operations are referred to as *expressions*
  - ▶ Must use Spark to manipulate Rows (logical collection of Rows is a column)
  - ▶ Must be in the context of a DataFrame
  - ▶ To work on columns use the *col* or *column* functions
  - ▶ We will stick to using the *col* function
  - ▶ Columns are not resolved until compared to the *catalog* at run-time
  - ▶ Column and table resolution happen in the *analyzer* phase

```
from pyspark.sql.functions import col, column
```

```
col("someColumnName")
```

```
column("someColumnName")
```

# Column Reference

- ▶ If you need to explicitly reference a column you can
- ▶ Think of it as a namespace way to reference columns in different DataFrames that have the same name
  - ▶ `df.col("count")`

## Columns as Expressions

- ▶ What is an *expression*?
  - ▶ A set of *transformations* on one or more values in a *record* in a DataFrame
- ▶ You can use a `col()` and perform a transformation on a column
- ▶ You can use an `expr()` to parse transformations and column references
  - ▶ These references can subsequently be passed into further transformations
  - ▶ `expr("someCol - 5")` and `col("someCol") - 5` and `expr("someCol") - 5` all evaluate the same
  - ▶ Spark compiles these to the same logic tree
- ▶ Columns are just expressions
- ▶ Columns and transformations of those columns compile to the same logical plan  $((col("someCol") + 5) * 200) - 6 < col("otherCol")$
- ▶ This is also represented by in Python (64):
  - ▶ 

```
python from pyspark.sql.functions import expr  
expr("(((someCol + 5) * 200) -6) < "otherCol")
```

# Conclusion

- ▶ Conclusion here

# Questions

- ▶ Any questions?
- ▶ Read Chapter 06 and do any exercises in the book.