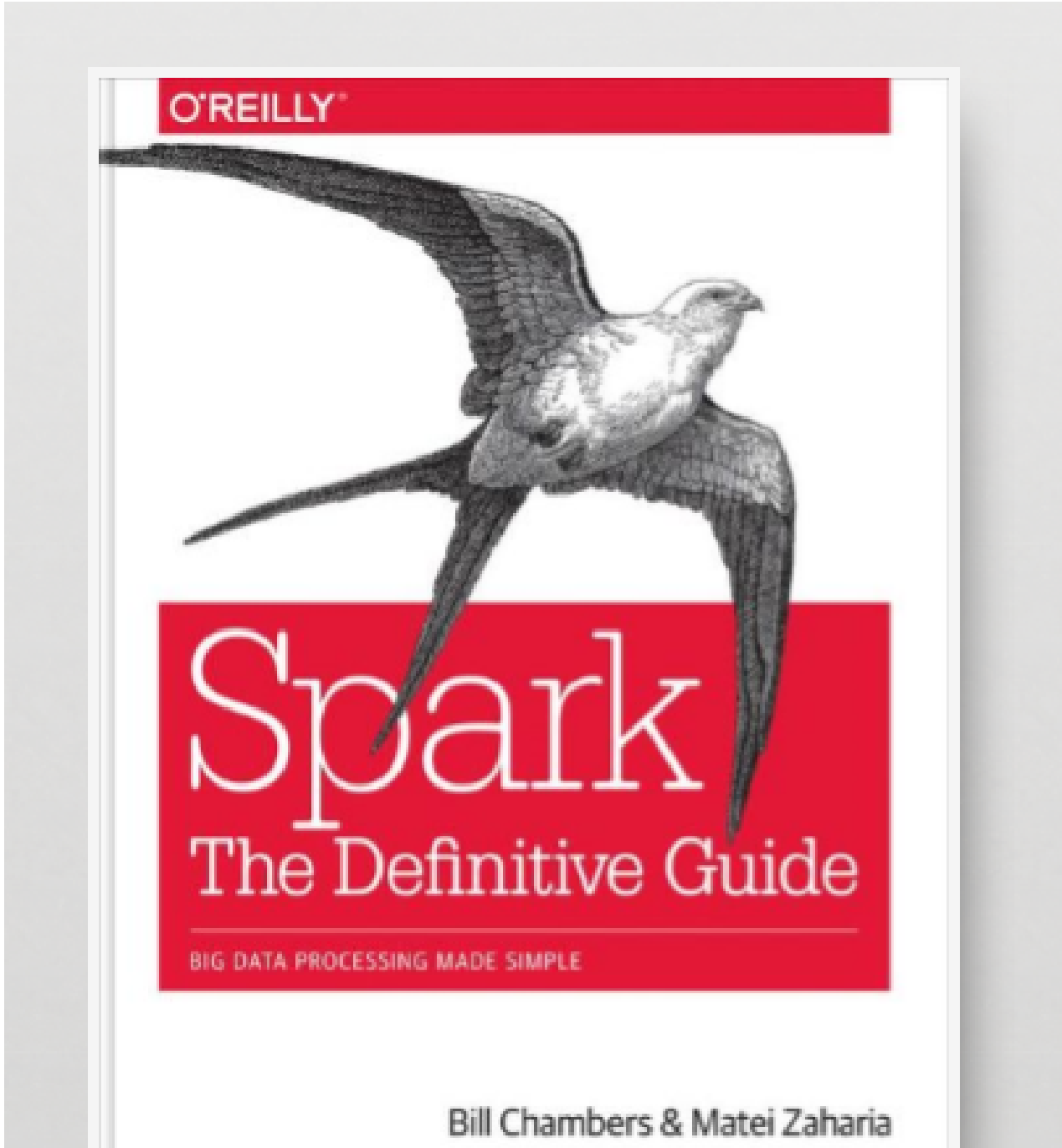
Spark the Definitive Guide 2nd Edition

Chapter 06

Working With Different Types of Data

Basic Structured Operations

Text Book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Spark
The Definitive Guide
BIG DATA PROCESSING MADE SIMPLE
Bill Chambers & Matei Zaharia

Objectives and Outcomes

- Understand how to build expressions using typed data
- Understand how to use:
  - Booleans
  - Numbers
  - Strings
  - Dates and Timestamps
  - Nulls
  - Complex and user types

Review

- So far:
  - We covered basic DataFrame operations.
  - We learned the simple concepts and tools that you will need to be successful with Spark DataFrames
  - We learned what an expression is
  - We learned the difference between Select and SelectExpr
  - We learned how to add columns and rows to a DataFrame
  - We learned how to take random samples from DataFrames

API Documentation

- Where do all of these functions come from?
  - There is Spark documentation for Datasets in Scala
  - Python API
  - A DataFrame is just a Dataset of type `Row` so you'll end up looking at the Dataset methods
- Column Methods such as `alias` or `contains`
  - Column
  - *org.apache.spark.sql.functions*
- All of these tools exist to transform rows of data in one format or structure to another.

```
df = spark.read.format("csv").option("header","true").optio
df.printSchema()
df.createOrReplaceTempView("dfTable")
```

Schema Output

```
>>> df.printSchema()
root
 |-- InvoiceNo: string (nullable = true)
 |-- StockCode: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Quantity: integer (nullable = true)
 |-- InvoiceDate: timestamp (nullable = true)
 |-- UnitPrice: double (nullable = true)
 |-- CustomerID: double (nullable = true)
 |-- Country: string (nullable = true)
```

Booleans

- You can build logical statements to evaluate either *true* or *false*
  - `from pyspark.sql.functions import col`
  - `df.where(col("InvoiceNo") != 536365).select("InvoiceNo",`
- A cleaner solution would be to specify a predicate as an expression in a string
  - Another way to say *does not equal*
  - `df.where("InvoiceNo <> 536365").show(5, False)`
- In Spark, you should always chain together and filers
  - Even if filters are expressed serially, Spark will flatten all of these filters into one statement and performed the filter at the same time

```
from pyspark.sql.functions import instr
priceFilter - col("UnitPrice") > 600
descripFilter = instr(df.Description, "POSTAGE") >= 1
df.where(df.StockCode.isin("DOT")).where(priceFilter | desc
```

```
SELECT * FROM dfTable WHERE StockCode in ("DOT") AND (UnitP
```

Boolean Column

```
from pyspark.sql.functions import instr
DOTCodeFileter = col("StockCode") == "DOT"
priceFilter = col("UnitPrice") > 600
descripFilter = instr(col("Description"), "POSTAGE") >= 1
df.withColumn("isExpensive", DOTCodeFilter & (priceFilter
```

```
--in SQL
SELECT UnitPrice, (StockCode = 'DOT' AND (UnitPrice > 600 o
FROM dfTable
WHERE (StockCode = 'DOT' AND (UnitPrice . 600 OR instr(Desc
```

Working With Numbers and Nulls

- When using comparisons, watch out for Nulls
  - There is a way to do a null-safe comparison
  - ```
    df.where(col("Description").eqNullSafe("hello")).show()
    ```
- Working with Big Data, after you filter things (WHERE clause), the next task is to count things
- We are able to do math on numeric typed fields, such as:
  - Exponents 82
  - Addition and subtraction
  - All of these features are available in SQL as well and can be written as *selectExpr*
  - Rounding up by default, rounding down, truncating
    ```

Basic ANOVA

- Usually there a basic set of statistical methods that are always useful
  - Calculate the Pearson Correlation
  - `from pyspark.sql.functions import corr`
  - `df.stat.corr("Quantity", "UnitPrice")`
  - `df.select(corr("Quantity", UnityPrice")).show()`
- You can use a single `describe()` method to generate the following:
  - count
  - mean
  - Standard deviation
  - min and max
  - `df.describe().show()`
- These aggregations can be preformed by importing the individual libraries
- Additional statistical functions are available in the **StatFunctions** Package
  - Python StatFunction Library Reference

Working With Strings

- String manipulation is important because you might not have any guarantees about the data you are working with
  - What if the data when entered didn't have any capitalization enforcement?
  - How does this affect string comparisons?
  - `from pyspark.sql.functions import initcap`
  - `df.select(initcap(col("Description"))).show()`
  - `lower` and `upper` will cast entire strings
  - Trimming or padding whitespace 85
  - Regex (Regular Expressions)
  - Use the `contains` method on a column to return a `true` or `false`
  - Python uses the `instr` function in place of `contains`

Working With Dates and Timestamps

- Always challenging because they are numbers but not ordinal
  - Sometimes dates are stored as strings because of this
  - Timezones and Daylight Saving time
  - Even though Spark uses Java dates and timestamps it only works to second level precision
  - No milliseconds
  - Java does have support for date addition and subtraction 91
  - Can also do date comparison and difference between two dates (number of days)
  - `to_date` function allows for converting a string to a date (format can be specified)

Working With Nulls

- Nulls can be represent missing or empty data
  - Spark is internally optimized for use of nulls as opposed to empty strings or zeros
  - But does using *nulls* make sense in your logic
  - Spark has built in functions to check for nulls
  - The `df.na.drop("any")` can be used to drop any row in which any value is null
  - `fill()` and `replace()`

Conclusion

- This chapter demonstrated how easy it is to extend Spark SQL and in a way that is easy to understand.

Questions

- Any questions?
- Read Chapter 07 and do any exercises in the book.