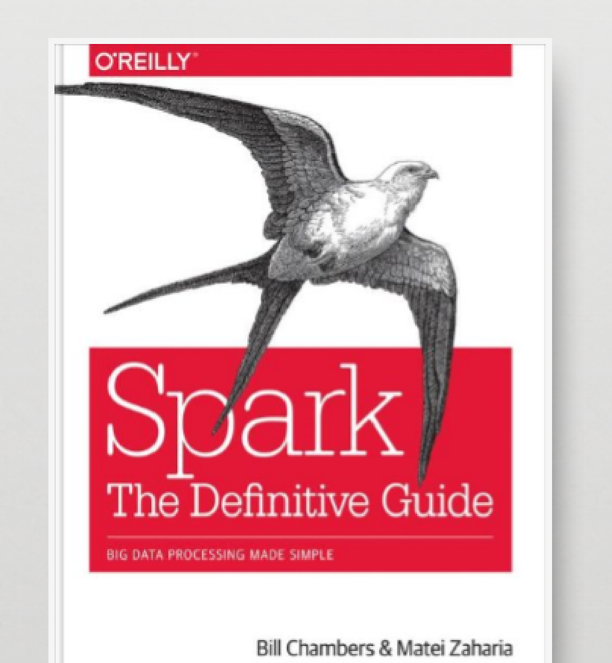
Spark the Definitive Guide 2nd Edition

Chapter 07

Aggregations

Aggregations

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

Objectives and Outcomes

- Aggregating is the act of collecting something together
  - It is the cornerstone of big data analytics
- You specify a *key* or *grouping* and an *aggregation function*
  - This function specifies how you should transform one or more columns
- Spark allows us to create the following types of groupings:
  - A *"group by"* specifies one or more keys and one or more aggregations
  - A *"window"* specifies one or more keys and one or more aggregations to transform the value columns
  - A *"grouping set"* specifies you can use aggregations at multiple levels
  - A *"rollup"* specifies one or more keys as well as one or more aggregation functions to transform the value of a column
  - A *"cube"* specifies one or more keys as well as one or more aggregations to transform the value columns

Review

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

Basic Aggregations

- One of the simplest aggregations is `count()` which will count all rows in a DataFrame
  - `df.count()`
  - `.count()` is technically an action not a transformation
- Elements of an entire column can be counted as well
  - `from pyspark.sql.functions import count`
  - `df.select(count("StockCode")).show()`
  - Watch out! When counting all columns ("*") Spark will count `nulls`, even rows that are all `null`
  - When counting an individual column, Spark will not count `nulls`

countDistinct

- Sometimes total number is not relevant, only unique number is
  - There is a `.countDistinct()` function
  - `from pyspark.sql.functions import countDistinct`
  - `df.select(countDistinct("StockCode")).show()`
- There is also an `.approx_count_distinct()`
  - When working with a large dataset, time, processing power, even energy usage are a consideration
  - There are times when a degree of approximation can be used without an issue
  - ```
    from pyspark.sql.functions import approx_count_distinct
    ```
  - ```
    df.select(approx_count_distinct("StockCode", 0.1)).show(
    ```
  - ```
    SELECT approx_count_distinct(StockCode, 0.1) FROM dfTabl
    ```
  - 0.1 is the estimation error margin
  - Note the results, but note the performance gain
    ```

Simple Aggregations

- You can get the first and last elements of a DataFrame by two obvious elements
  - .first()
  - .last()
- You can extract min and max values using the builtin pyspark sql functions
- You can use the `sum` method to sum the content of a column
  - There is also a `sumDistinct` function that will perform that actions as well
- There is an `avg` function to do an average of a column
  - You can combine this result with an alias to reuse the calculated value later 107
- If you are calculating Average, then you are dealing with *Variance* and *Standard Deviation*
- *Skewness* and *kurtosis* are both measurements of extreme points in your data
  - Skewness measures the asymmetry of your values around the mean
  - Kurtosis measures the tail of data

More Simple Aggregations

- Some functions compare the interactions of the values in two different columns together
  - *Covariance* and *Correlation*
  - `cov` and `corr`
  - Chapter 6 talked about the Pearson correlation coefficient
  - Correlation is measured on a -1 to 1 scale
  - The covariance can be taken over a population sample or the entire population of records 110

Grouping

- We have done `groupBy` on the DataFrame level aggregations
  - We can perform calculations based on *groups* in the data
  - Using our purchase data DataFrame, for example we can group on unique **invoice number** and do a `count()` of items on that invoice
  - This returns a second DataFrame that is lazily evaluated
  - ```
    df.groupBy("InvoiceNo","CustomerId").count().show()
    ```
  - ```
    SELECT count(*) FROM dfTable GROUP BY InvoiceNo, Custome
    ```
- We can specify an arbitrary expression statement as an agg statement
  - This makes it possible to say *alias* a column
  - ```
    df.groupBy("InvoiceNo").agg(count("Quantity").alias("qua
    ```
    ```

Grouping With Maps

- Sometimes it can be easier to specify your transformations as a series of **Maps**
  - For which the key is the column
  - The value is the aggregation function that you would like to perform
- ```
  df.groupBy("InvoiceNo").agg(expr("avg(Quantity)"),expr(
  ```
  ```

Window Functions 112

- Window Functions can be used to carry out aggregations by computing on a certain *window* of data
  - This sounds very similar to a `groupBy` function, so what is the difference?
  - `groupBy` takes data and every row can only go into one grouping
  - A Window function calculates a return value for every input row of a table based on groups of rows, called a **frame**
    - Not a DataFrame
  - Each row can fall into one or more frame, unlike a `groupBy`

Conclusion

- Conc goes here

Questions

- Any questions?
- Read Chapter 08 & 09 and do any exercises in the book.