## CSC 735 – Data Analytics

Chapter 7
Aggregations

### Aggregations

- Aggregation is an important feature for big data analytics
- It allow us to summarize the data in order to extract patterns or insights
- Ex: sum, average, stdev, count

## Aggregations (cont.)

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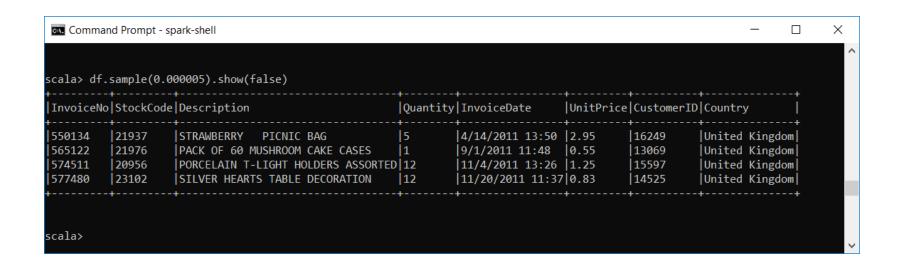
### Aggregations (cont.)

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- For big data analysis, it can be expensive to get an exact answer
- There are many aggregate functions that provide an answer with a reasonable degree of accuracy
- The aggregation functions are designed to perform aggregation on a set of rows in a DataFrame
- The set of rows can be all or some of the rows

## Reading the Dataset

```
val df = spark.read.format("csv")
 .option("header", "true")
 .option("inferSchema", "true")
 .load("/data/retail-data/all/*.csv")
 .coalesce(5)
df.cache()
df.createOrReplaceTempView("dfTable")
```

# A Sample of the Data



### **Aggregate Functions**

- All aggregations are available as functions
- Most aggregation functions are in the package org.apache.spark.sql.functions

### count

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  - specify a certain column to count
  - or count all the columns by using count("\*")

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- Using count, we can do one of 2 things:
  - specify a certain column to count
  - or count all the columns by using count("\*")
  - The first one (count over individual column) ignore null values; count(\*) does not

### countDistinct

It counts only the unique values under a given column

import org.apache.spark.sql.functions.countDistinct df.select(countDistinct("StockCode")).show() // 4070

### approx\_count\_distinct

- Counting the exact number of unique items in each group in a large dataset can take long time
- Sometimes, it is sufficient to have an approximation to a certain degree of accuracy
- In such case, we can use approx\_count\_distinct

```
import org.apache.spark.sql.functions.approx_count_distinct df.select(approx_count_distinct("StockCode", 0.05)).show() // 3804
```

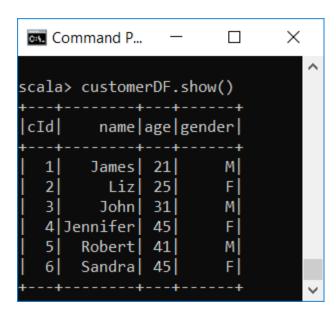
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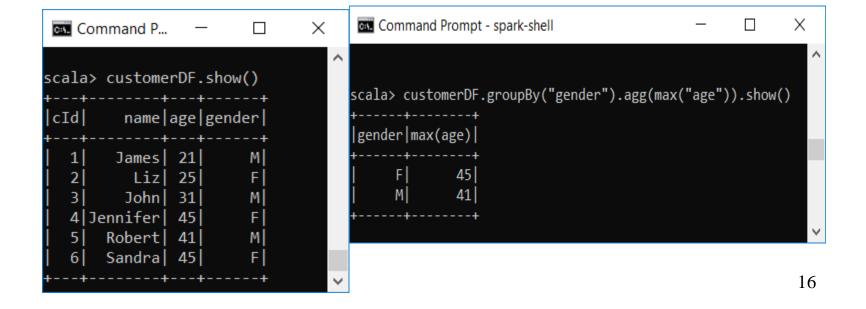
df.select(countDistinct("StockCode")).show() // 4070

Return the maximum age of customers per gender



### Grouping

Return the maximum age of customers per gender



## More examples

Return the maximum and minimum age of

customers per gender

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Return the maximum and minimum age of

customers per gender

```
scala> customerDF.show()
                                                                        cIdl
                                                                               name age gender
                                                                               James
                                                                          4 Jennifer
                                                                              Robert
 Command Prompt - spark-shell
                                                                Sandra
scala> customerDF.groupBy("gender").agg(max("age"), min("age")).show()
gender|max(age)|min(age)
             45
                       25
             41
```

Х

Command P...

## More examples

```
Command Prompt - spark-shell
                                                                             X
scala> df.groupBy("InvoiceNo", "CustomerId").agg(count("Quantity")).show(5)
|InvoiceNo|CustomerId|count(Quantity)|
    536846
                14573
                                   76
    537026
                12395
                                   12
                14437
    537883
    538068
                17978
                                   12
   538279
                14952
only showing top 5 rows
```

# Grouping with Expressions – Renaming Columns

Rename inside agg using .alias and .as

```
Command Prompt - spark-shell — X

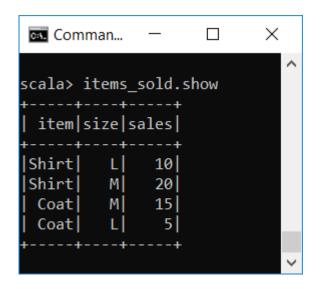
scala> customerDF.groupBy("gender").agg(max("age").alias("maxAge"),  
min("age").as("minAge")).show()

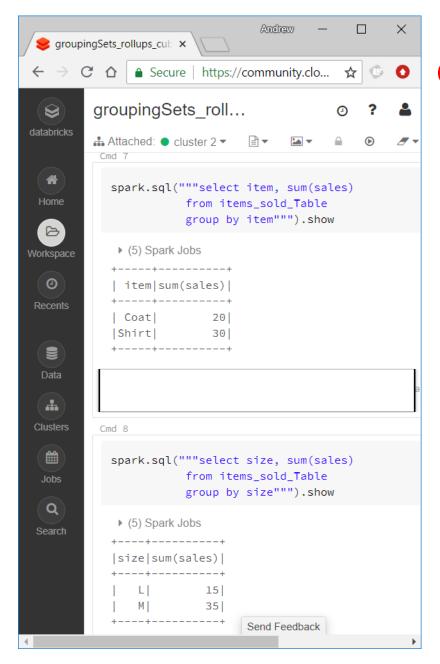
+----+
| gender | maxAge | minAge |  
+----+
| F | 45 | 25 |  
| M | 41 | 21 |  
+----+

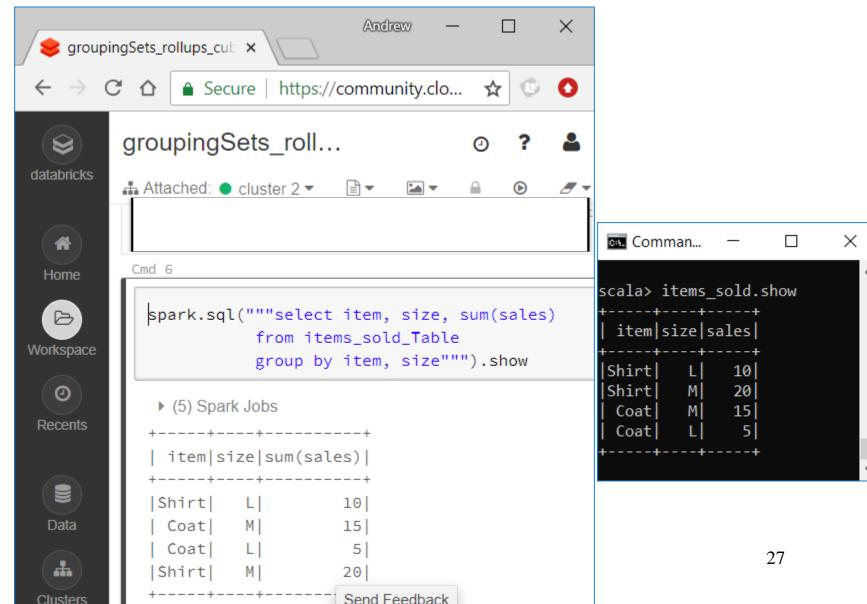
**
```

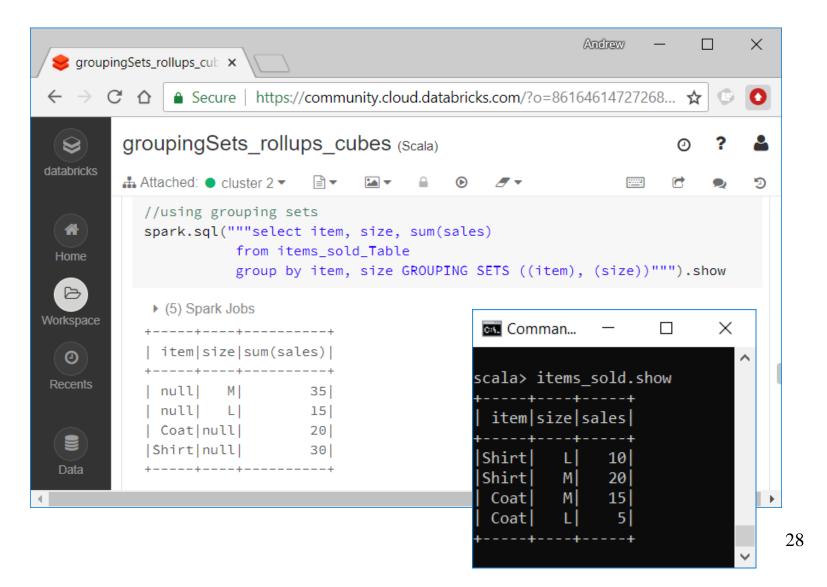
### Grouping with Maps

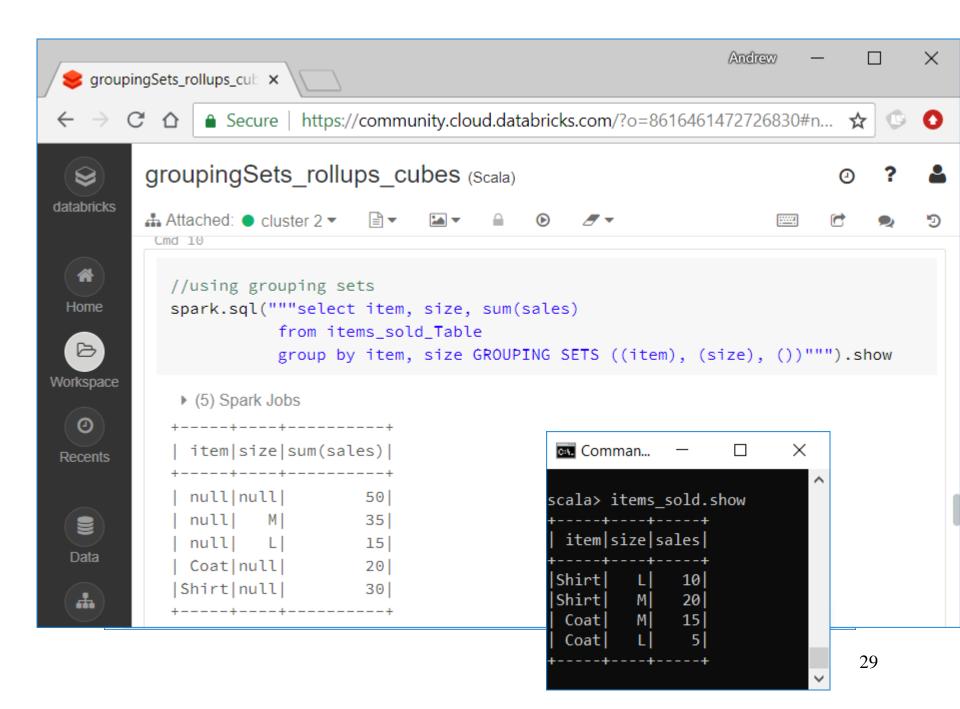
- We can specify the arguments of the agg function as a series of key-value maps
  - the key is the column name, and
  - the value is an aggregation function to apply to the key

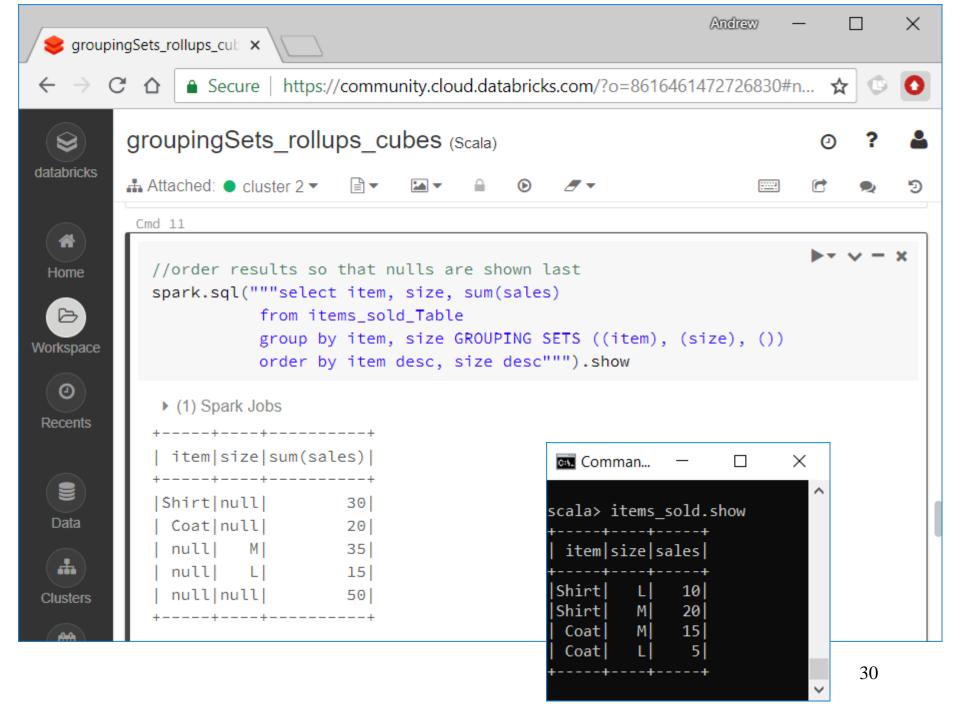












### **Grouping Sets**

- Aggregate functions are computed for each group, and then the results are added to the output
- Each sublist of grouping sets may specify zero or more columns
- An empty grouping set means that all rows are aggregated down to a single group
- References to the grouping columns are replaced by null values in result rows

### Aggregations with Rollups and Cubes

- Grouping sets are only available in SQL
- To do the same thing using DataFrames, we use rollup and cube operations

A clause of the form

```
ROLLUP (e1, e2, e3, ...)
```

is equivalent to

```
GROUPING SETS (
    (e1, e2, e3, ...),
    ...
    (e1, e2),
    (e1),
    ()
)
```

a GROUPING SETS operation that represents the given list of expressions and **all prefixes** of the list including the empty list

• A clause of the form

ROLLUP(warehouse, product)

is equivalent to

?

a GROUPING SETS operation that represents the given list of expressions and all prefixes of the list including the empty list

A clause of the form

```
ROLLUP(warehouse, product)
```

is equivalent to

```
GROUPING SETS(
(warehouse, product),
(warehouse),
()
)
```

A clause of the form

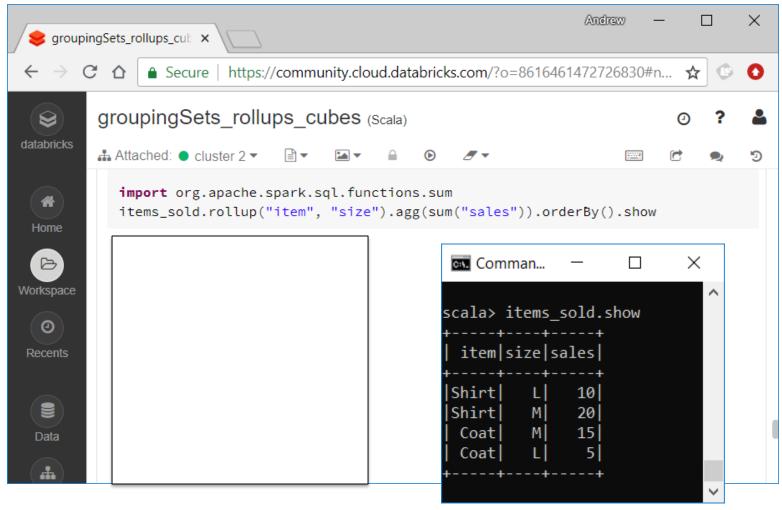
```
ROLLUP(warehouse, product)
```

is equivalent to

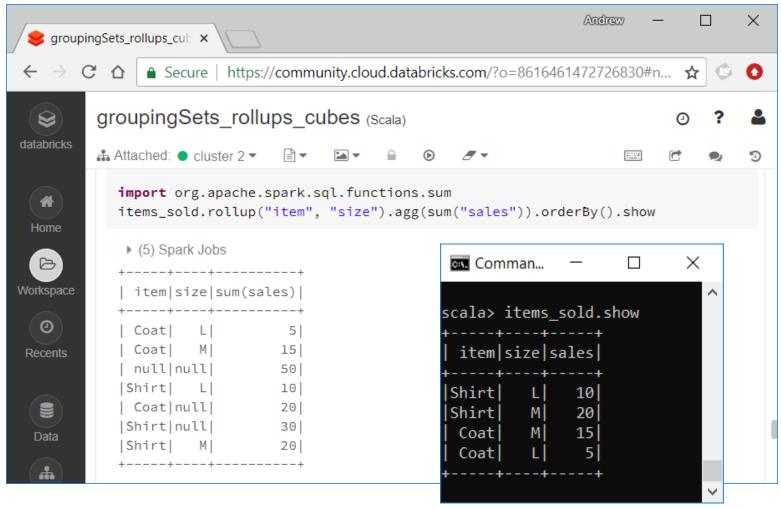
```
GROUPING SETS(
(warehouse, product),
(warehouse),
()
)
```

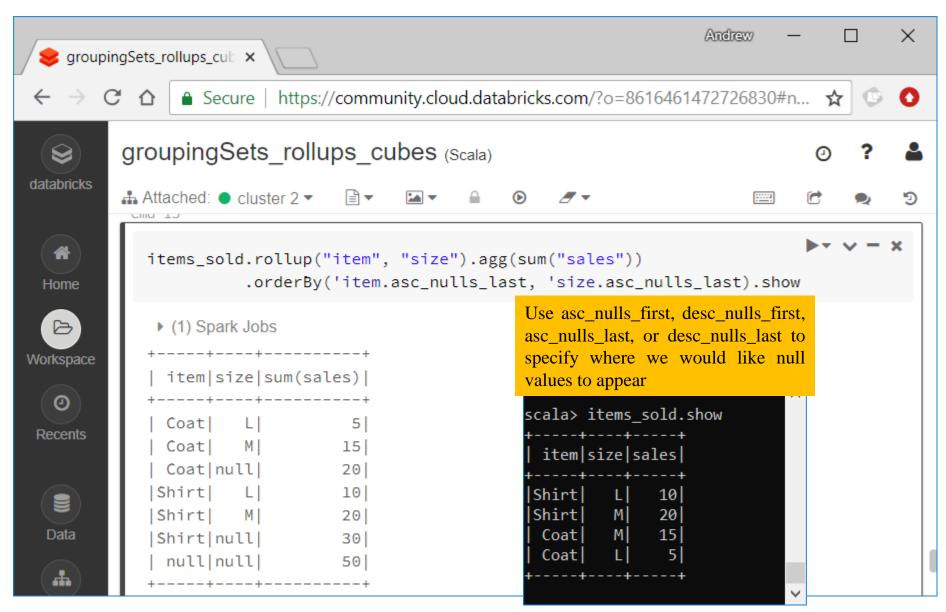
The N elements of a ROLLUP specification results in N+1 GROUPING SETS

# Rollups – Example



# Rollups – Example





A clause of the form

```
CUBE (e1, e2, e3, ...)
```

is equivalent to

```
GROUPING SETS (
    (a, b, c),
    (a, b),
    (a, c),
    (a),
    (b, c),
    (b),
    (c),
    (c),
    (d)
```

A clause of the form

```
CUBE(warehouse, product) is equivalent to
```

?

A clause of the form

```
CUBE(warehouse, product) is equivalent to
```

```
GROUPING SETS(
(warehouse, product),
(warehouse),
(product),
())
)
```

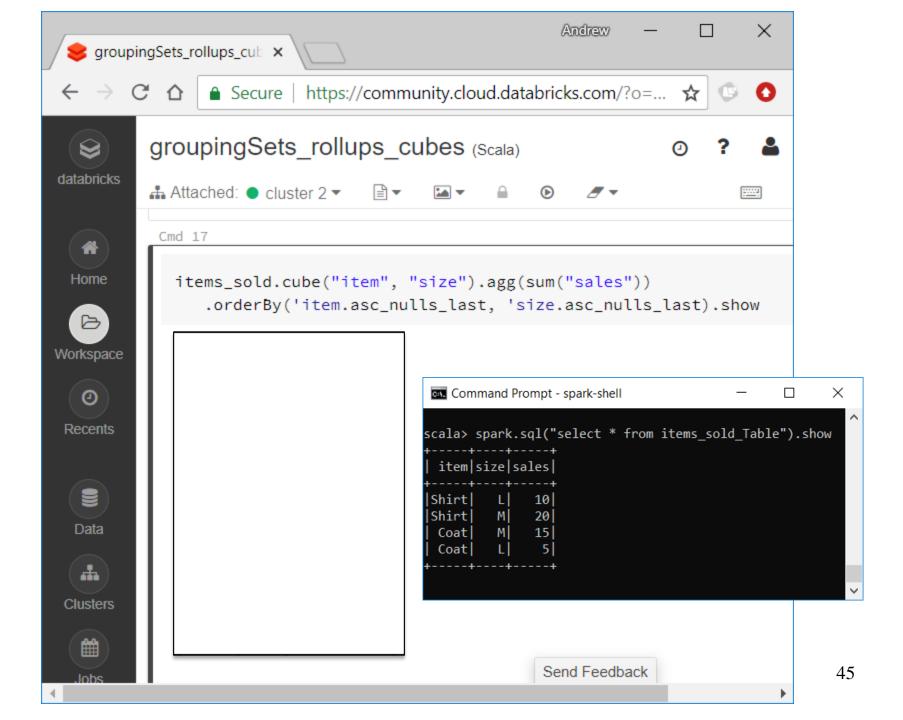
A clause of the form

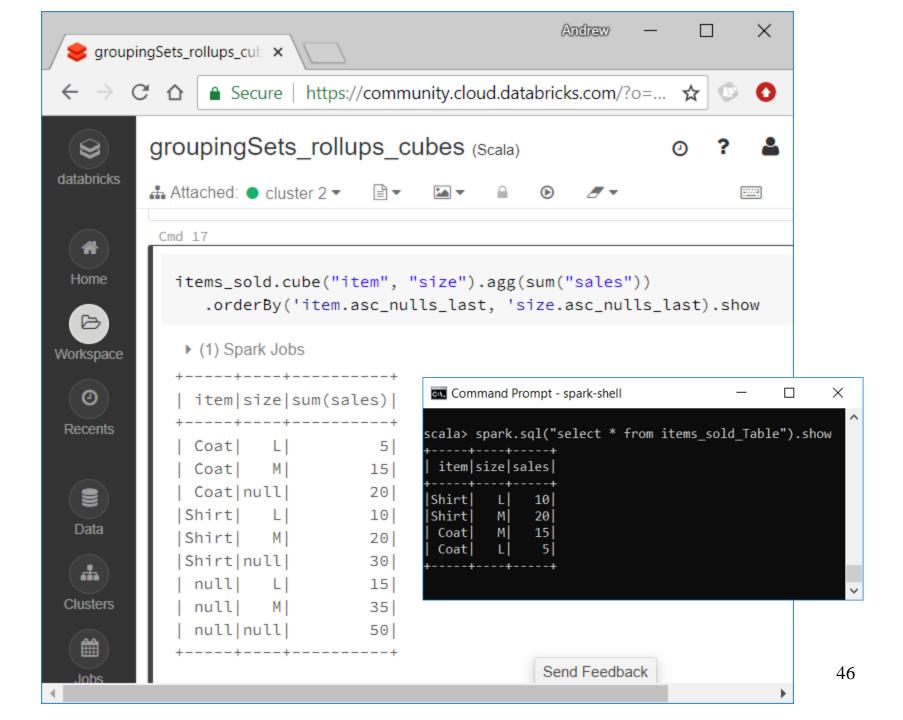
```
CUBE(warehouse, product) is equivalent to
```

```
GROUPING SETS(
(warehouse, product),
(warehouse),
(product),
())
)
```

#### Cubes

- A cube is a more advanced version of a rollup
- It performs the aggregations across all the possible combinations of the grouping columns
- Therefore, the result includes what a rollup provides as well as other combinations.





#### **Pivot**

- Pivoting is a technique to convert rows into columns
- to create a different view of a table
- Pivoting starts with grouping over one or more columns, then pivoting on a column, and ends with applying one or more aggregations on one or more columns

