

# Create an Apache Spark table

## Note:

You are not required to complete the processes, tasks, activities, or steps presented in this example. The various samples provided are for illustrative purposes only and it's likely that if you try this out you will encounter issues in your system.

In this exercise, you will create an Apache Spark table.

1. The Apache Spark engine can analyze the Parquet files and infer the schema. To perform this analysis, enter the following code in the new cell and **run** it:

```
data_path.printSchema()
```

Your output should look as follows:

```
1
2
3
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11
12
root
 |-- TransactionId: string (nullable = true)
 |-- CustomerId: integer (nullable = true)
 |-- ProductId: short (nullable = true)
 |-- Quantity: short (nullable = true)
 |-- Price: decimal(29,2) (nullable = true)
 |-- TotalAmount: decimal(29,2) (nullable = true)
 |-- TransactionDate: integer (nullable = true)
 |-- ProfitAmount: decimal(29,2) (nullable = true)
 |-- Hour: byte (nullable = true)
 |-- Minute: byte (nullable = true)
 |-- StoreId: short (nullable = true)
```

Apache Spark evaluates the file contents to infer the schema. This automatic inference is sufficient for data exploration and most transformation tasks.

However, when you load data to an external resource like a SQL pool table, sometimes you need to declare your own schema and apply that to the dataset. For now, the schema looks good.

2. Next, use the DataFrame to use aggregates and grouping operations in order to better understand the data. Create a new cell and enter the following, then **run** the cell:

```
1
2
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11
from pyspark.sql import SparkSession
from pyspark.sql.types import *
from pyspark.sql.functions import *

profitByDateProduct = (data_path.groupBy("TransactionDate", "ProductId")
    .agg(
        sum("ProfitAmount").alias("(sum)ProfitAmount"),
        round(avg("Quantity"), 4).alias("(avg)Quantity"),
        sum("Quantity").alias("(sum)Quantity"))
    .orderBy("TransactionDate"))
display(profitByDateProduct.limit(100))
```

**Note:** We import required Python libraries to use aggregation functions and types defined in the schema to successfully execute the query.

The output shows the same data we saw in the chart above, but now with **sum** and **avg** aggregates **(1)**. Notice that we use the **alias** method **(2)** to change the column names.

Cell 3

```
1 from pyspark.sql import SparkSession
2 from pyspark.sql.types import *
3 from pyspark.sql.functions import *
4
5 profitByDateProduct = (data_path.groupBy("TransactionDate", "ProductId")
6     .agg(
7         sum("ProfitAmount").alias("sumProfitAmount"),
8         round(avg("Quantity"), 4).alias("avgQuantity"),
9         sum("Quantity").alias("sumQuantity"))
10    .orderBy("TransactionDate"))
11 display(profitByDateProduct.limit(100))
```

Command executed in 6s 545ms by joel on 09-10-2020 15:13:18.982 -04:00

> **Job execution** Succeeded **Spark 3** executors 12 cores [View in monitoring](#) [Open Spark UI](#)

View Table Chart

| TransactionDate | ProductId | (sum)ProfitAmount | (avg)Quantity | (sum)Quantity |
|-----------------|-----------|-------------------|---------------|---------------|
| 20101231        | 64        | 52975.23          | 2.5547        | 5467          |
| 20101231        | 3348      | 1409.01           | 2.4512        | 201           |
| 20101231        | 1470      | 1595.58           | 2.6364        | 174           |
| 20101231        | 1266      | 10731.05          | 2.5896        | 1199          |
| 20101231        | 48        | 39516.75          | 2.5158        | 4053          |
| 20101231        | 132       | 42468.96          | 2.4995        | 5154          |

Ready (Stop session) [Configure session](#)

The aggregates output is displayed.