



Code Logic - Retail Data Analysis

In this document, the code and the overall steps taken to solve the project are described:

1. All necessary libraries are included and spark session is established

```
from pyspark.sql import
SparkSession
from pyspark.sql.functions import *
from pyspark.sql.types import *
import pyspark.sql.functions as F
```

Connected to the kafka server where streaming data is available along with topic name from where the data is read

```
lines = spark \
.readStream \
.format("kafka") \
.option("kafka.bootstrap.servers","18.211.252.152:9092") \
.option("subscribe","real-time-project") \
.option("failOnDataLoss","false") \
.option("startingOffsets", "earliest") \
.load()
```

3. Since now the data is read from server, we now make it more readable by mapping lines of streaming data into a schema, along with data types against each column.

Columns in raw data are:

```
"country", "invoice_no", "timestamp", "type", "items" which is an array which is sub-divided into:
"SKU", "title", "unit_price", "quantity" for each occurrence.
```

4. Unveil array items now as individual array items are used in KPI and new column derivations. Use option explode for this purpose.

```
df1 = new_df.select(col("type"),col("country"),col("invoice_no"),col("time stamp"),explode(col("items")))
```

5. Rename columns like SKU, title, unit price & quantity which were earlier represented as col.SKU or col.title.





- 6. Defining UDF's and executing them.
 - i. UDF 1: This function accepts "type" as input and determines if the nature of request is "Order" or "Return" If Type comes as "ORDER", then it returns a flag is_order = 1 which says it is an order.
 - ii. UDF 2: This function accepts "type" as input and determines if the nature of request is "Order" or "Return" If Type comes as "RETURN", then it returns a flag is_return = 1 which says it is a return request.
 - iii. **UDF 3:** This function accepts 3 attributes in input. Unit price, quantity & type as input. If type is "Order", it returns a value of Unit price multiplied by quantity. If type is "Return", it returns a value of Unit price multiplied by quantity toggled by "-" symbol.
- 7. Since we calculated all new columns required, we need to add them to our existing data frame. Output the data with new columns for each order for window of 1 minute.

```
df3 =
  df2.withWatermark("timestamp","10
  minutes") \
    .groupby(window("timestamp","1
    minute"),"invoice_no","country","is_Or
    der","is_Return") \
    .sum("Cost","quantity")
```

Output from this step is used for calculating KPI's in next steps.

- 8. Calculation of KPI's:
 - i. Orders per Minute: Calculated as count of distinct invoices as below >

```
F.approx_count_distinct("invoice_no").alias("OPM")
```

ii. **Total volume of sales**: Calculated from UDF3 where we derived cost value of order. Use this cost value and get a sum of all order cost's for window period to get total volume of sales:

```
agg(sum("Cost").alias("Total_sales_vol")
```

iii. Rate of Return: For this KPI, we utilize is_return & is_order flags derived from UDF1 & UDF2. We take sum of is_return & is_order for window period and store them as total_Order & total_return. Below formula is used to calculate Rate of Return. Note that same formula is used twice once after grouping by country to get country specific rate of return. Second time to generate time based rate of return.





```
Final_time =
Final_time.withColumn("rate_of_return",Final_time.total_return
/(Final_time.total_Order+Final_time.total_return))
```

iv. **Average Transaction Size:** For this KPI, we utilize is_return & is_order flags derived from UDF1 & UDF2. We take sum of is_return & is_order for window period and store them as total_Order & total_return. Below formula is used to calculate average transaction size. This needs to be calculated only on time basis, not country basis.

```
Final_time.withColumn("Avg_trans_size",Final_time.Total_sales_vol/(Final_time.total_Order +Final_time.total_return))
```

- 9. Now that KPI calculation is done,
 - i. printed time based KPI to HDFS path as a JSON file using below code.

```
query_2 = Final_time.writeStream \
.outputMode("Append") \
.format("json") \
.option("format","append") \
.option("truncate", "false") \
.option("path","Timebased-KPI") \
.option("checkpointLocation", "time_KPI_json") \
.trigger(processingTime="1 minute") \
.start()
```

Here, HDFS location path is given as **Timebased-KPI** where KPI data shall be written to.

ii. Printed time and country based KPI to HDFS path as a JSON file using below code.

```
query_3 = Final_country_time.writeStream \
.outputMode("Append") \ .format("json") \
.option("format","append") \ .option("truncate", "false")
\ .option("path"," Country-and-timebased-KPI" \
.option("checkpointLocation",
   "time_country_KPI_json") \
.trigger(processingTime="1 minute") \
.start()
```





Here, HDFS location path is given as **Country-and-timebased-KPI** where KPI data shall be written to.

10. Created EMR cluster and YARN configuration using following applications:

JupyterHub 1.1.0, Spark 2.4.5, Zeppelin 0.8.2, Livy 0.7.0

11. Logged in to the EMR instance and below command is executed to download Spark-SQL-Kafka jar file. This jar is used to run the Spark Streaming-Kafka codes

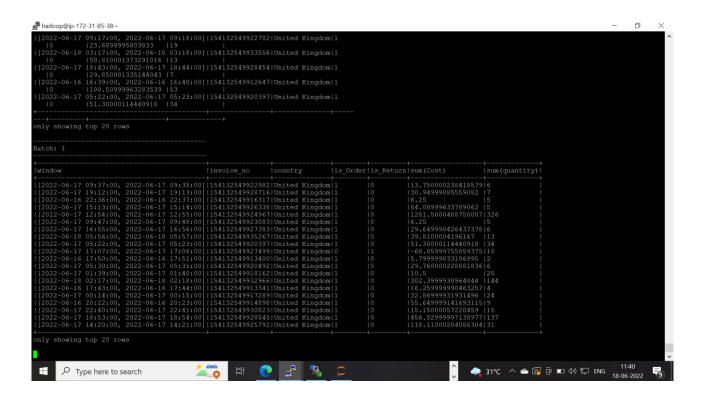
wget https://ds-spark-sql-kafka-jar.s3.amazonaws.com/spark-sql-kafka-0-10_2.11-2.3.0.jar

12. Kafka version is set using the following command:

export SPARK_KAFKA_VERSION=0.10

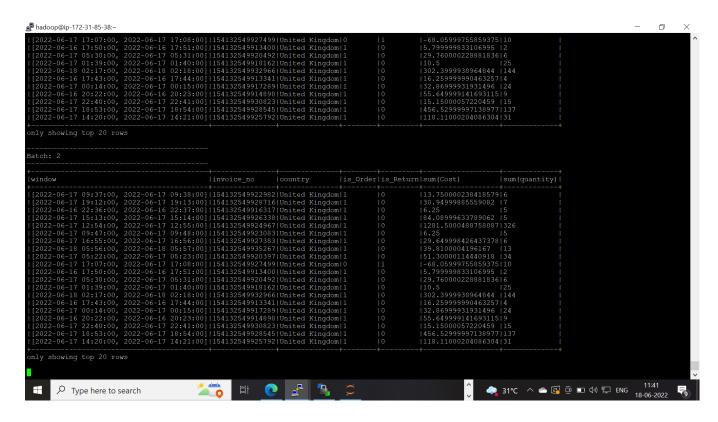
13. Submitted the spark job using command below:

spark-submit --packages org.apache.spark:spark-sql-kafka-0-10_2.11:2.4.5 spark-streaming.py 18.211.252.152 9092 real-time-project













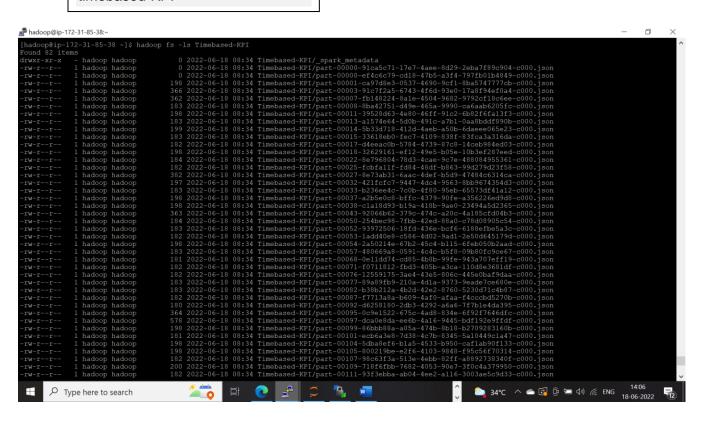
14. Checked in HDFS to make sure the KPI files were present:

hadoop fs -get Timebased-KPI

hadoop fs -ls Timebased-KPI

hadoop fs - get Country-andtimebased-KPI

hadoop fs -ls Country-and-timebased-KPI







15. Thereafter WinSCP is used to establish a connection between the EMR instance and local file system to transfer all the required files into local system