



Final Submission

Problem Statement:

YourOwnCabs (YOC), an on-demand cab booking start-up, is experiencing rapid growth with a rising number of daily rides and users. The existing MySQL-based backend is unable to handle large-scale, complex queries efficiently, making it difficult for business stakeholders to access timely, data-driven insights. Quick analysis of daily, weekly, and monthly bookings, booking patterns by mobile operating systems, average fares, and total tips is essential for strategic decision-making.

Additionally, YOC generates high-volume clickstream data from user interactions within the mobile app, which is critical for understanding user behaviour and improving engagement. This data requires an optimized, scalable storage and processing solution to support seamless analytics without affecting application performance.

The challenge is to design and implement a robust big data architecture that can efficiently manage both booking and clickstream data, ensuring fast, reliable, and scalable analytics to support the company's growth.

Proposed Solution:

To address the growing data and analytics needs of YourOwnCabs (YOC), a scalable big data pipeline is proposed to efficiently manage both booking and clickstream data.

Booking Data Analytics Solution

- Ingestion: Use Sqoop to import booking data from MySQL to HDFS in scheduled batches.
- Storage: Save data in Parquet format for optimized storage and fast querying.
- Processing: Use Apache Spark for data cleaning, aggregations (daily, weekly, monthly counts, OS-wise bookings, average fare, total tips), and reporting.
- Access: Create Hive external tables for easy querying and integration with BI tools.

Clickstream Data Analytics Solution

- Ingestion: Use Apache Kafka for real-time clickstream data ingestion.
- Storage: Store clickstream data in HDFS (Parquet format) for efficient handling.





- Processing: Apply Spark Structured Streaming for real-time parsing and user behavior tracking.
- Access: Expose data via Hive tables to support user analytics and engagement strategies.

This solution ensures fast, scalable, and reliable analytics without impacting business operations.

Data:

The following data will be used for this problem:

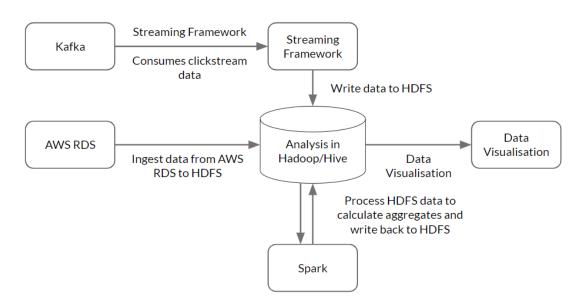
- **bookings** (The booking data is added to/updated in this table after a booking/ride is successfully completed.)
 - o booking_id: Booking ID String
 - o customer id: Customer ID Number
 - o driver id: Driver ID Number
 - o customer app version: Customer App Version String
 - o customer phone os version: Customer mobile operating system
 - o pickup lat: Pickup latitude
 - o pickup lon: Pickup longitude
 - o drop lat: Dropoff latitude
 - o drop lon: Dropoff longitude
 - o pickup timestamp: Timestamp at which customer was picked up
 - drop_timestamp: Timestamp at which customer was dropped at destination
 - o trip fare: Total amount of the trip
 - o tip amount: Tip amount given by customer to driver for this ride
 - o currency code: Currency Code String for the amount paid by customer
 - o cab color: Color of the cab
 - o cab registration no: Registration number string of the vehicle
 - o customer_rating_by_driver: Rating number given by driver to customer after ride
 - o rating by customer: Rating number given by customer to driver after ride
 - o passenger count: Total count of passengers who boarded the cab for ride
- **clickstream** (All user's activity data such as click and page load):
 - o customer id: Customer ID Number
 - o app version: Customer App Version String
 - o os version: User mobile operating system
 - o lat: Latitude





- o lon: Longitude
- o page_id: UUID of the page/screen browsed by a user
- o button id: UUID of the button clicked by a user
- o is button click: Yes/No depending on whether a user clicked button
- o is_page_view: Yes/No depending on whether a user loaded a new screen/page
- o is_scroll_up: Yes/No depending on whether a user scrolled up on the current screen
- o is_scroll_down: Yes/No depending on whether a user scrolled down on the current screen
- o timestamp: Timestamp at which the user action is captured

Architecture and Approach



The solution involves handling two types of data: clickstream data and batch (booking) data.

<u>Clickstream Data Flow</u>: Clickstream data is captured in Kafka and consumed by a stream processing framework (like Spark Structured Streaming). The streaming data is continuously loaded into HDFS for storage and further processing.

<u>Batch Data Flow</u>: Booking data stored in AWS RDS is imported into HDFS using tools like Sqoop in batch mode.

<u>Processing and Aggregation</u>: Both clickstream and batch data stored in HDFS are processed using Apache Spark to perform cleaning, transformations, and aggregations as needed. The processed data is written back to HDFS.



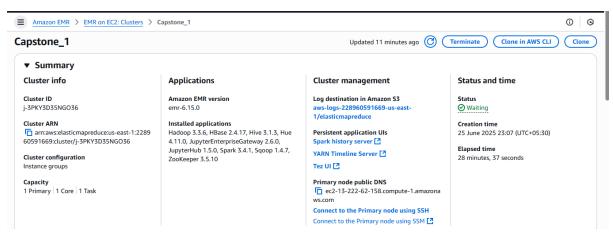


<u>Data Access Layer</u>: Processed and raw data in HDFS are made queryable via Hive tables, which serve as the final data layer for stakeholders. These Hive tables support efficient querying and are used for reporting and analytics.

Key Approach:

- Capture clickstream data from Kafka → Load to HDFS via stream processing.
- Ingest batch booking data from RDS → Load to HDFS via Sqoop.
- Process and aggregate data in Spark \rightarrow Store results in Hive tables.
- Use Hive tables as the final query layer for business insights.

We will first create an EMR cluster with required application bundles like Hive, Sqoop, Hadoop, HBase, JupyterHub, Spark, etc.



Make sure to edit the Security groups properly.

Task 1: Write a job to consume clickstream data from Kafka and ingest to Hadoop.

I. Creating directory path in HDFS for storing the processed clickstream data and creating a **checkpoint directory** in HDFS

```
[hadoop@ip-10-0-2-56 ~]$ hdfs dfs -mkdir -p /user/poushali/clickstream
[hadoop@ip-10-0-2-56 ~]$ hdfs dfs -mkdir -p /user/poushali/checkpoints/clickstream

hadoop@ip-10-0-2-56 ~]$ hdfs dfs -test -d /user/poushali/checkpoints/clickstream && echo "Directory exists" || echo "Directory does not exist"

Directory exists
[hadoop@ip-10-0-2-56 ~]$ |
```

II. Writing spark kafka to local.py file





```
[hadoop@ip-10-0-2-56 ~]$ nano spark_kafka_to_local.py
[hadoop@ip-10-0-2-56 ~]$ cat spark_kafka_to_local.py
import sys
# Environment setup
os.environ["PYSPARK_PYTHON"] = "/opt/cloudera/parcels/Anaconda/bin/python"
os.environ["JAVA_HOME"] = "/usr/java/jdkl.8.0_161/jre"
os.environ["SPARK HOME"] = "/opt/cloudera/parcels/SPARK2-2.3.0.cloudera2-1.cdh5.
13.3.p0.316101/lib/spark2/"
os.environ["PYLIB"] = os.environ["SPARK_HOME"] + "/python/lib"
sys.path.insert(0, os.environ["PYLIB"] + "/py4j-0.10.6-src.zip")
sys.path.insert(0, os.environ["PYLIB"] + "/pyspark.zip")
from pyspark.sql import SparkSession
from pyspark.sql.functions import *
# Create Spark session
spark = SparkSession.builder.appName("KafkaToHDFSBatch").getOrCreate()
# Read Kafka data (batch mode)
df raw = spark.read \
    .format("kafka") \
    .option("kafka.bootstrap.servers", "18.211.252.152:9092") \
    .option("subscribe", "de-capstone5") \
    .option("startingOffsets", "earliest") \
.option("endingOffsets", "latest") \
    .load()
Extract and cast value to string
df = df raw.selectExpr("CAST(value AS STRING) as value str")
# Write to HDFS in JSON format
df.write \
    .mode("overwrite") \
    .json("/user/poushali/clickstream json")
spark.stop()
[hadoop@ip-10-0-2-56 ~]$
```

- This PySpark script is designed to read batch data from a Kafka topic and store it in HDFS in JSON format.
- It begins by setting up the required environment variables for Python, Java, and Spark to ensure that the PySpark libraries and the Spark engine are properly accessible. The script then creates a Spark session named "KafkaToHDFSBatch" which is essential to run Spark operations.
- Using this Spark session, the script connects to a Kafka broker located at 18.211.252.152:9092 and subscribes to the topic de-capstone5. It reads all available Kafka messages starting from the earliest to the latest (batch mode, not streaming).
- From the Kafka records, it selects and casts the value field (which holds the actual message content) to a string, preparing it for storage. Finally, the script writes this extracted data to HDFS in JSON format under the directory /user/poushali/clickstream_json. The write mode is set to overwrite, meaning that if the directory already exists, its contents will be replaced.
- The script completes by stopping the Spark session to release resources.

```
spark-submit \
--master yarn \
```





- --deploy-mode client \
- --packages org.apache.spark:spark-sql-kafka-0-10 2.12:3.3.0 \spark kafka to local.py

```
-packages org.apache.spark:spark-sql-kafka-U-10_2.12:3.3.0 \spark_kafka_fo_local.p

[SUCCESSFUL] org.apache.kafkafkafka-clients;2.8.1!kafka-clients.jar (216ms)

whloading https://repol.maven.org/maven2/com/google/code/findbugs/jsr305/3.0.0/jsr305-3.0.0.jar ...

[SUCCESSFUL] com.google.code.findbugsfjsr305/3.0.0/jsr305-jar (Sms)

whloading https://repol.maven.org/maven2/org/apache/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1.jar ...

[SUCCESSFUL] org.apache.commonsfocommons-pool2/2.11.1!commons-pool2/2.11.1/commons-pool2/2.11.1.jar ...

[SUCCESSFUL] org.apache.commonsfocommons-pool2/2.11.1!commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/commons-pool2/2.11.1/comm
                                                                                                                                                                             | modules || artifacts |
| number| search|dwnlded|evicted|| number|dwnlded|
       retrieving :: org.apache.spark#spark-submit-parent-4170ddae-b017-4562-8bf4-28db1731ab8d
                                      confs: [default]
12 artifacts copied, 0 already retrieved (56631kB/54ms)
```

Checking the loaded file:

hdfs dfs /user/poushali/clickstream json/part-00000-68bcef36-7bc5-4ec1-86c2--cat f38954624e13-c000.json | head -n 5

Writing spark kafka to local.py file III.





```
[hadoop@ip-10-0-2-56 -]% nano spark_local_flatten.py
[hadoop@ip-10-0-2-56 -]% cat spark_local_flatten.py
import os
import sys
os.environ("PYSPARK_PYTHON") = "/opt/clouders/parcels/Anaconds/bin/python"
os.environ("SPARK_BOME") = "/opt/clouders/parcels/Anaconds/bin/python"
os.environ("SPARK_BOME") = "/opt/clouders/parcels/SPARKE-2.3.0.cloudera2-1.cdh5.13.3.p0.316101/lib/spark2/"
os.environ("PYKIB") = os.environ("SPARK_HOME") + "/python/lib"
os.environ("PYKIB") = os.environ("SPARK_HOME") + "/python/lib"
os.environ("PYKIB") = os.environ("PXKIB") + "/python/lib"
os.environ("PYKIB") = os.environ("PXKIB") + "/pyspark.zip")

from pyspark.sql.functions import get_json_object

f Initialize Spark session
spark = SparkSession.builder.appName("Kafka-JSON-Flatten").getOrCreate()

f Read raw Kafka JSON output from HDFS
off = spark.read.json("/usex/poushail/clickstream_json/part-*.json")

f Flatten the nested JSON structure using get_json_object

off = df.select(
    get_json_object(df("value str'), "%.cuscomer_id").alias("customer_id"),
    get_json_object(df("value str'), "%.app_version").alias("os_version"),
    get_json_object(df("value str'), "%.latv).alias("latv"),
    get_json_object(df("value str'), "%.latv').alias("latv'),
    get_json_object(df("value str'), "%.latv').alias("shar"),
    get_json_object(df("value str'), "%.latv').alias("shar"),
    get_json_object(df("value str'), "%.is_page_id").alias("spage_id"),
    get_json_object(df("value str'), "%.is_page_id").alias("spage_id"),
    get_json_object(df("value str'), "%.is_page_id").alias("spage_id"),
    get_json_object(df("value_str'), "
```

- The HDFS-stored Kafka JSON output is processed by this script. It starts by adding the appropriate PySpark and Py4J libraries to the system path and configuring the environment variables for Python, Java, and Spark.
- After that, a Spark session is started to manage the data processing. In order to extract important fields like customer ID, app version, OS version, position coordinates, interaction flags, and timestamps, the script reads raw JSON files from the designated HDFS directory and uses the get json object function to flatten the hierarchical JSON structure.
- Lastly, the result is consolidated into a single file for simpler analysis by writing the flattened data back to HDFS in CSV format with headers.

```
Spark – submit command:

spark-submit \

--master yarn \

--deploy-mode client \

--packages org.apache.spark:spark-sql-kafka-0-10 2.12:3.3.0 \ spark local flatten.py
```





Reading the data:

hdfs dfs -cat /user/poushali/clickstream_flattened/part-00000-4c986a60-83e0-4cc0-8b89-221c944eac00-c000.csv| head -n $5\,$

IV. Using Hive to create tables for cleaned clickstream data





- Data stored outside of Hive's internal storage system can be managed and queried using
 the clickstream_cleaned external table created by the supplied code. The EXTERNAL
 TABLE keyword guarantees that the actual data files in the specified HDFS location
 will not be deleted even if the table itself is dropped.
- The table schema captures various aspects of user activity, including customer ID, application and operating system versions, geographic coordinates (latitude and longitude), identifiers for pages and buttons, user interaction flags (such as button clicks, page views, and scrolling actions), and a timestamp indicating the event's occurrence time.
- The data is stored in CSV format (specified via ROW FORMAT DELIMITED and FIELDS TERMINATED BY ',') in the HDFS directory /user/poushali/clickstream_flattened, as declared in the LOCATION clause.

V. Checking the Hive Data

We used Hive queries to confirm that the cleaned clickstream data was successfully ingested into Hadoop. The data stored in HDFS was queried through the external table clickstream_cleaned, and the output shows that all expected fields have been populated correctly.

```
SHOW TABLES;
OK
clickstream cleaned
Time taken: 0.402 seconds, Fetched: 1 row(s)
hive> DESCRIBE clickstream cleaned;
OK
customer id
                         string
app version
                         string
os version
                         string
lat
                         double
lon
                         double
page id
                         string
button_id
                         string
is button click
                         string
is page view
                         string
is_scroll_up
                         string
  scroll
          down
                         string
timestamp
                         string
    taken: 0.087 seconds,
```

```
4.3.25 Android 85.4985045
                                              152.362461
                                                              e7bc5fb2-1231-11eb-adc1-0242ac120002
                                                                                                     ele99492-17ae-11eb-adc1-0242ac120002
                                                                                                                                                            Yes
                              -66.981554
                                                              de545711-3914-4450-8c11-b17b8dabb5e1
                                                                                                     ele99492-17ae-11eb-adc1-0242ac120002
2949619
              1.4.34 iOS
                                                              b328829e-17ae-11eb-adc1-0242ac120002
                                                                                                     fcba68aa-1231-11eb-adc1-0242ac120002
              4.4.30 Android -69.4296995
                                                              de545711-3914-4450-8c11-b17b8dabb5e1
                                                                                                     a95dd57b-779f-49db-819d-b6960483e554
                                                                                                                                                            Yes
                                                                                                                                                     Yes
              3.3.14 iOS
                              -32.799864
                                                             de545711-3914-4450-8c11-b17b8dabb5e1
                                                                                                     ele99492-17ae-11eb-adc1-0242ac120002
              1.4.22 iOS
                                                              e7bc5fb2-1231-11eb-adc1-0242ac120002
                                                                                                     a95dd57b-779f-49db-819d-b6960483e554
              4.2.33 Android -72.712776
                                                              e7bc5fb2-1231-11eb-adc1-0242ac120002
                                                                                                     fcba68aa-1231-11eb-adc1-0242ac120002
              2.3.18 Android 82.4520345
                                                              de545711-3914-4450-8c11-b17b8dabb5e1
                                                                                                     a95dd57b-779f-49db-819d-b6960483e554
                              31.839155
                                                              b328829e-17ae-11eb-adc1-0242ac120002
                                                                                                     fcba68aa-1231-11eb-adc1-0242ac120002
ime taken: 2.484 seconds, Fetched: 10 row(s)
```





Task 2: Write a script to ingest the relevant bookings data from AWS RDS to Hadoop.

I. Command to import data from RDS to Hadoop

```
sqoop import \
--connect jdbc:mysql://upgraddetest.cyaielc9bmnf.us-east-1 .rds.amazonaws.
com/testdatabase \
--username student \
--password STUDENT123 \
--table bookings \
--target-dir /user/poushali/rds_import/bookings \
--as-parquetfile \
--num-mappers 1
```

- Data from the bookings table is imported using this Sqoop command into a MySQL database located at upgraddetest.cyaielc9bmnf.us-east-1.rds.amazonaws.com (database: testdatabase).
- It connects with the password STUDENT123 and the username student. Parquet format, which is effective for processing and storing, is used to store the imported data in HDFS in the directory /user/poushali/rds_import/bookings.
- For smaller datasets or situations where the source database should be subjected to the least amount of pressure possible, the --num-mappers 1 option guarantees that the import operates as a single parallel operation.

```
[hadoop@ip-10-0-2-56 -]$ aqoop import --connect jdbc:mysql://upgraddetest.cyalelc9bmf.us-east-l.rds.amazonaws.com/testdatabase --username student --password STUD ENT123 --table bookings --target-dir /user/poushali/rds_import/bookings --as-parquetfile --num-mappers l --driver com.mysql.jdbc.Driver Warning; /usr/lib/goop/../accumulo does not exist! Accumulo imports will fail.
Please set SACOUMUNO BMUS to the root of your Accumulo installation.
SLF43: Class path contains multiple SLF43 bindings.
SLF43: Class path contains multiple SLF43 bindings.
SLF43: Found binding in [jar:file!vsr/lib/haboop/lib/slf4]-reload4j-l.7.36.jar!/org/slf4]/impl/StaticLoggerBinder.class]
SLF43: Found binding in [jar:file!vsr/lib/haboop/lib/slf4]-impl-2.17.l.jar!/org/slf4]/impl/StaticLoggerBinder.class]
SLF43: Set hortp://www.slf4j.org/codes.humlamultiple bindings for an explanation.
SLF43: Actual binding is of type (org.slf4].impl.Reload4jloggerFactory]
SLF43: Set hortp://www.slf4j.org/codes.humlamultiple bindings for an explanation.
SLF43: Actual binding is of type (org.slf4).impl.Reload4jloggerFactory]
SU25-66-25 ls:22:16,614 MARN tool.BaseSqoopTool: Setting your password on the command-line is insecure. Consider using -P instead.
2025-06-25 ls:22:16,516 WARN supon.Sqoop. Comnfactory: Parameter --driver is set to an explicit driver however appropriate connection manager is not being set (via --connection-manager). Sqoop is going to fall back to org.apache.sqoop.manager.Seneinodbchanager. Please specify explicitly which connection manager should be used next time.
2025-06-25 ls:22:16,530 INFO manager.SqlManager: Executing SQL statement: SELECT t.* FROM bookings AS t WHERE 1=0
2025-06-25 ls:22:17,106 INFO manager.SqlManager: Executing SQL statement: SELECT t.* FROM bookings AS t WHERE 1=0
2025-06-25 ls:22:17,107 INFO manager.SqlManager: Executing SQL statement: SELECT t.* FROM bookings AS t WHERE 1=0
2025-06-25 ls:22:15,032 INFO manager.SqlManager: Executing SQL statement: SELECT t.* FROM bookings AS t WHERE 1=0
2025-06-25 ls:22:50,932
```





```
06-25 18:23:10,169 INFO mapreduce.Job: Job job 1750873936410 0005 completed successfully 06-25 18:23:10,286 INFO mapreduce.Job: Counters: 33
           File System Counters
FILE: Number of bytes read=0
                        FILE: Number of bytes written=301233
FILE: Number of read operations=0
                         FILE: Number of large read operations=0
FILE: Number of write operations=0
                         HDFS: Number of bytes read=85
HDFS: Number of bytes written=112756
                         HDFS: Number of read operations=6
HDFS: Number of large read operations=0
                         HDFS: Number of write operations=2
HDFS: Number of bytes read erasure-coded=0
                        Other local map tasks=1
Total time spent by all maps in occupied slots (ms)=6646272
Total time spent by all reduces in occupied slots (ms)=0
Total time spent by all map tasks (ms)=4327
                         Total vcore-milliseconds taken by all map tasks=4327
Total megabyte-milliseconds taken by all map tasks=6646272
          Map-Reduce Framework
Map input records=1000
                         Map output records=1000
Input split bytes=85
                         Spilled Records=0
Failed Shuffles=0
                         Merged Map outputs=0
GC time elapsed (ms)=155
                         CPU time spent (ms)=3410
Physical memory (bytes) snapshot=412729344
                         Virtual memory (bytes) snapshot=3135516672
Total committed heap usage (bytes)=337641472
                         Peak Map Physical memory (bytes)=412729344
Peak Map Virtual memory (bytes)=3135516672
           File Input Format Counters
Bytes Read=0
                  Output Format Counters
Bytes Written=112756
025-06-25 18:23:10,292 INFO mapreduce.ImportJobBase: Transferred 110.1133 KB in 18.4616 seconds (5.9645 KB/sec)
```

II. Command to view the imported data

We use PySpark to read the imported Parquet file and inspect the schema, we did this through nano function:

```
from pyspark.sql import SparkSession
```

```
spark = SparkSession.builder.appName("CheckSchema").getOrCreate()
```

df = spark.read.parquet("hdfs:///user/poushali/rds import/bookings")

df.printSchema()

df.show(5)

- A Spark session with the application name "CheckSchema" is initialised by this PySpark script.
- It retrieves a Parquet file with data imported from MySQL using Sqoop from the HDFS path hdfs:///user/poushali/rds import/bookings.
- To check if the schema was correctly interpreted, the script uses printSchema() to show the DataFrame's structure, including column names and the corresponding data types.
- It also employs show(5) to quickly examine the dataset by displaying the top five records.





• Lastly, the spark-submit check_schema.py command can be used to run this script on a Spark cluster, sending the job to Spark for processing.

III. Creating Hive table for RDS data

```
[hadoop@ip-10-0-2-56 ~]$ hive
Hive Session ID = 646f6269-3ecd-40da-ae61-d91a6a9348d1
ogging initialized using configuration in file:/etc/hive/conf.dist/hive-log4j2.properties Async: false
hive> SHOW TABLES;
clickstream_cleaned
Time taken: 0.761 seconds, Fetched: 1 row(s)
hive> CREATE EXTERNAL TABLE IF NOT EXISTS rds bookings (
        booking_id STRING,
        customer id BIGINT,
        driver_id BIGINT,
        customer_app_version STRING,
        customer_phone_os_version STRING,
         pickup_lat DOUBLE,
         pickup_lon DOUBLE,
         drop_lat DOUBLE,
         drop_lon_DOUBLE,
         pickup_timestamp BIGINT,
        drop_timestamp BIGINT,
trip_fare INT,
         tip_amount INT,
         currency_code STRING,
         cab color STRING,
         cab_registration_no STRING,
         customer_rating_by_driver INT,
         rating_by_customer INT,
         passenger_count INT
   > STORED AS PARQUET
   > LOCATION '/user/poushali/rds_import/bookings';
Time taken: 0.133 seconds
hive>
```

- If an external Hive table called rds_bookings does not already exist, the script builds one.
- Time stamps, trip fare, tip amount, currency code, booking ID, customer and driver IDs, app and phone OS versions, pickup and drop coordinates, booking details, customer ratings, and passenger count are just a few of the properties that can be included in this table for taxi booking records.
- Types such as STRING, BIGINT, DOUBLE, and INT are used to allocate data types according to the characteristics of each field.
- The data is already present in HDFS at the designated location: /user/poushali/rds_import/bookings. The table is saved in Parquet format, which is effective for both querying and storing data. Because it is an external table, the underlying data will remain intact even if the table is deleted.





IV. Checking imported data

Task 03 Create aggregates for finding date-wise total bookings using the Spark script.

I. Running datewise_bookings_aggregates_spark.py

```
[hadoop@ip-10-0-2-56 ~]$ nano datewise_bookings_aggregates_spark.py
[hadoop@ip-10-0-2-56 ~]$ cat datewise_bookings_aggregates_spark.py
from pyspark.sql import SparkSession
from pyspark.sql.functions import from_unixtime, to_date, col

# Initialize Spark session
spark = SparkSession.builder.appName("DateWiseBookings").getOrCreate()

# Read parquet data
df = spark.read.parquet("hdfs://user/poushali/rds_import/bookings")

# Extract date from timestamp and aggregate
df_with_date = df.withColumn("booking_date", to_date(from_unixtime(col("pickup_timestamp") / 1000)))
agg_df = df_with_date.groupBy("booking_date").count().withColumnRenamed("count", "total_bookings")

# Save it to HDFS directly
agg_df.coalesce(1).write.csv("hdfs:///user/poushali/datewise_bookings_output", header=True, mode="overwrite")
[hadoop@ip-10-0-2-56 ~]$ [
```





- To begin, the script creates a Spark session called "DateWiseBookings" and reads Parquet data from HDFS, which is accessible at hdfs:///user/poushali/rds_import/bookings.
- After that, it uses the from_unixtime and to_date methods to transform the pickup_timestamp field, which is in Unix time (milliseconds), into a date that can be read by humans.
- These changed dates are stored in a new column called booking_date. The groupBy and count methods are then used to aggregate the data and get the total number of bookings for each date.
- In the directory hdfs:///user/poushali/datewise_bookings_output, the generated DataFrame—which includes booking dates and the total number of bookings associated with them—is saved back to HDFS as a CSV file.
- The header=True option adds column headings to the CSV file, and the coalesce(1) function guarantees that the output is recorded to a single CSV file.
- Any existing files in the output directory will be replaced if the mode="overwrite" option is used.

```
spark-submit \
--master yarn \
--deploy-mode client \
--packages org.apache.spark:spark-sql-kafka-0-10_2.12:3.3.0 \
datewise_bookings_aggregates_spark.py
```

II. Command to move the csv file to HDFS

agg_df.coalesce(1).write.csv("hdfs:///user/poushali/datewise_bookings_output", header=True, mode="overwrite")

- agg_df: This is your starting point—a collection of data that already summarizes bookings by date.
- .coalesce(1): This is a crucial step for managing output. In a distributed system like Spark, data is often split into many parts (partitions). Without coalesce(1), Spark would typically create a separate CSV file for each of these partitions. By using .coalesce(1), you're telling Spark to combine all those partitions into a single one, ensuring that your output is just one consolidated CSV file rather than many smaller ones.
- .write.csv(...): This command initiates the process of saving your data in the popular CSV (Comma Separated Values) format.
- "hdfs:///user/poushali/datewise_bookings_output": This specifies the exact location where your CSV file will be stored. It's an HDFS path, meaning it's going onto a Hadoop Distributed File System.





- header=True: This option is for readability. It ensures that when you open your CSV file, the first row will clearly display the names of your columns, making it easy to understand what each column represents.
- mode="overwrite": This is an important safety and convenience feature. If there are already files in the specified HDFS location, this option tells Spark to delete them and replace them with your new output. If you didn't include this (or set it to "error"), Spark would stop and give you an error if it found existing files, preventing accidental overwrites.
- III. Checking the generated file using command hdfs dfs -cat user/poushali/datewise_bookings_output/part-00000-e0df7941-54a0-486b-9bb6-c015560cde8a-c000.csv | head -n 5

Task 04 Creating Hive Tables

I. Hive table for clickstream data:

```
CREATE EXTERNAL TABLE clickstream_cleaned (
    customer_id STRING,
    app_version STRING,
    OS_version STRING,
    lat DOUBLE,
    lon DOUBLE,
    page_id STRING,
    button_id STRING,
    is_button_click STRING,
    is_page_view STRING,
    is_scroll_up STRING,
    is_scroll_down STRING,
    is_scroll_down STRING,
```





```
)
         ROW FORMAT DELIMITED
         FIELDS TERMINATED BY ','
         STORED AS TEXTFILE
         LOCATION '/user/poushali/clickstream flattened';
II.
       Hive table for Booking data:
       CREATE EXTERNAL TABLE IF NOT EXISTS rds bookings (
         booking id STRING,
         customer_id BIGINT,
         driver_id BIGINT,
         customer_app_version STRING,
         customer_phone_os_version STRING,
         pickup_lat DOUBLE,
         pickup_lon DOUBLE,
         drop_lat DOUBLE,
         drop lon DOUBLE,
         pickup timestamp BIGINT,
         drop timestamp BIGINT,
         trip fare INT,
         tip_amount INT,
         currency_code STRING,
         cab color STRING,
         cab_registration_no STRING,
         customer_rating_by_driver INT,
         rating_by_customer INT,
         passenger_count INT
       STORED AS PARQUET
```





LOCATION '/user/poushali/rds import/bookings';

III. Hive table for aggregated data:

- The datewise_booking_aggregates table is created by the supplied Hive query and is intended to hold daily booking summaries.
- Booking_date, which records the date of each booking activity, and total_bookings, which stores the total number of bookings for that particular date, make up its two columns.
- Using ROW FORMAT DELIMITED and fields separated by commas (FIELDS TERMINATED BY ','), the table is set up to handle data in a CSV format. \
- Since the table data is saved as a TEXTFILE, it will be in plain text format. Simple, legible datasets are usually stored in this configuration, which is also appropriate for loading outputs such as the CSV file produced by the PySpark aggregation.

For clarity and consistency, we renamed the previous tables:

ALTER TABLE clickstream_cleaned RENAME TO clickstream_data;

ALTER TABLE rds_bookings RENAME TO bookings_data;

```
[hadoop@ip-10-0-2-56 ~]$ hive
Hive Session ID = 0ce052ed-13ac-4063-aca4-adc765764a0d

Logging initialized using configuration in file:/etc/hive/conf.dist/hive-log4j2.properties Async: false
hive> show tables;
OK
clickstream_cleaned
rds_bookings
Time taken: 0.788 seconds, Fetched: 2 row(s)
hive> ALTER TABLE clickstream_cleaned RENAME TO clickstream_data;
OK
Time taken: 0.109 seconds
hive> ALTER TABLE rds_bookings RENAME TO bookings_data;
OK
Time taken: 0.093 seconds
hive> show tables;
OK
bookings_data
clickstream_data
Time taken: 0.028 seconds, Fetched: 2 row(s)
hive> []
```

IV. Command to load the data into Hive tables:

Only datewise booking aggregates requires a data load from HDFS.





Command

LOAD DATA INPATH '/user/poushali/datewise_bookings_output/part-00000-80d4e987-cbeb-44b9-b304-703ae2d9adcb-c000.csv'

INTO TABLE datewise_booking_aggregates;

V. Checking all the 3 tables:

```
hive> show tables;

OK
bookings_data
clickstream_data
datewise_booking_aggregates
Time_taken: 0.035 seconds, Fetched: 3 row(s)
```

SELECT * FROM clickstream_data LIMIT 10;

customer_id	app_ver	sion	OS_version	NULL NULL	page_id button_id	is_button_click	is_page_view	is_scroll_up i	s_scroll_d
vn times	tamp								
98215369	3.1.7	Android	80.203577	-68.44555	e7bc5fb2-1231-11eb-adc1	-0242ac120002	fcba68aa-1231-	11eb-adc1-0242ac120	902 No
yes Yes	No								
22684722	3.1.27	iOS	43.877177	-51.940886	e7bc5fb2-1231-11eb-adc1	0242ac120002	fcba68aa-1231-	11eb-adc1-0242ac120	002 Yes
es Yes	No 1 // 20	A	FO 0//0F//	110 255621	17 11-b - l-1	02//2120002	C-1 CO 1001	11-1-1-1-1-00/0100	000 1/
48680451 es No	1.4.39 Yes	Androld	59.04954	119.355631	b328829e-17ae-11eb-adc1	-0242ac120002	+cDa68aa-1231-	11eb-adc1-0242ac120	002 Yes
es No 38371811	3.2.24	Android	-83.155814	-164.111381	b328829e-17ae-11eb-adc1	-02//226120002	fch26822-1221-	11eb-adc1-0242ac120	992 No
No No	No	Allulotu	-03.133614	-104.111301	D320029E-17aE-11ED-auc1	0242aC120002	1CDa00aa-1231-	116D-auc1-0242ac120	002 NO
59281860	3.1.1	iOS	79.6680345	43.156676	b328829e-17ae-11eb-adc1	-0242ac120002	fcba68aa-1231-	11eb-adc1-0242ac120	002 Yes
Yes	Yes								
17178276	4.2.1	iOS	46.8875865	-64.982925	de545711-3914-4450-8c11	-b17b8dabb5e1	fcba68aa-1231-	11eb-adc1-0242ac120	002 Yes
Yes	Yes								
91573295	2.3.20	iOS	-47.019646	67.117437	b328829e-17ae-11eb-adc1	0242ac120002	a95dd57b-779f-	49db-819d-b6960483e	554 No
yes Yes	Yes								
94375933	3.1.10	Android	-51.38097	105.899543	de545711-3914-4450-8c11	-b17b8dabb5e1	e1e99492-17ae-	11eb-adc1-0242ac120	902 No
es No	Yes	.00	FF 2F224FF	122 021052	FUED11 2011 11150 0 11	145101115.4	C 60 1001	11 1 0000 100	000
21864180 es Yes	4.4.28 Yes	iOS	-57.2782655	132.991072	de545711-3914-4450-8c11	-b1/b8dabb5el	+cba68aa-1231-	11eb-adc1-0242ac120	002 Yes

SELECT * FROM bookings_data LIMIT 10;

K8968087150	5181135	9	15055666	9	2.2.14	Android	-Ц9	Д319655	103.917851	-58.8043875	146.477367	1592940790000	1591
34130000	534	83		black	054-38-		4	3	3	33.3343575	140.477507	10,2,40,,0000	107.
K629851904	3166321	3	60872180		3.4.1	iOS	-83.	5408405	175.80085	86.20705	128.367238	1590236524000	1590
99776000	126	67	INR	lime	796-39-		3	2	4				
K1797410350	8686939	9	94276053		4.1.36	iOS	-67.	8930645	55.234128	-51.1079	-31.07475	1589897672000	159
07919000	297	63	INR	olive	748-73-	1579	1	3	3				
K5788246325	5823083	7	4545722	7	2.4.27	Android	13.7	07887	113.499943	54.3812915	-18.437751	1585013415000	158
87005000	932	32	INR	white	558-80-	6346	3	2	2				
(8342703255	8423251	9	86494683	ı	4.1.34	Android	-6.0	91461	-114.649789	22.8449505	70.137827	1596481852000	158
38340000	260	7	INR	blue	068-72-	1637	3	3	3				
(6015582453	1198104	2	35862658	3	2.4.39	iOS	-18.	910034	-70.193103	-10.182921	173.877213	1594964028000	158
22467000	907	53	INR	purple	102-10-	5639	3	2	3				
K4529355854	6007187	3	78022360	9	2.1.9	iOS	1.21	5274	-56.014903	35.152876	104.324905	1577929720000	158
27335000	547	17	INR	teal	866-83-	4349	2	3	4				
K9720088219	1432731	2	9442706	7	3.1.2	Android	-55.	4822225	173.362256	65.0121265	51.390751	1586531467000	157
55062000	259	33	INR	maroon	572-73-	6526	3	3	2				
K7157532607	4640721	9	43160003	3	1.3.4	Android	46.0	05843	-16.826146	7.6126015	-156.428577	1591682191000	158
B2796000	787	21	INR	olive	667-23-	5880	2	2	3				
K5014871433	6586157	3	64708618	3	1.3.28	iOS	-29.	565326	64.843709	84.068109	-49.820835	1597437822000	159
77199000	586	5	INR	fuchsia	255-52-	5654	5	5	1				

SELECT * FROM datewise booking aggregates LIMIT 10;





```
hive> SELECT * FROM datewise_booking_aggregates LIMIT 10;
OK
NULL
       NULL
2020-03-07
2020-08-22
               6
2020-07-05
               6
2020-04-19
               4
               7
2020-08-04
2020-06-17
               2
               2
2020-07-02
               5
2020-03-29
2020-02-25
                1
Time taken: 0.082 seconds, Fetched: 10 row(s)
```

Counts of each table:





Task 5: Calculate the total number of different drivers for each customer.

```
SELECT
customer_id,
COUNT(DISTINCT driver_id) AS Distinct_no_of_drivers
FROM bookings_data
GROUP BY customer_id
ORDER BY customer_id;
```

- This SQL query examines the bookings_data table's customer-driver interactions. It
 determines how many distinct drivers are connected to every customer. The query
 makes sure that each customer's records are aggregated independently by classifying
 the data according to customer_id. The number of different drivers each client has
 come across is then determined using the COUNT(DISTINCT driver_id) function.
- Lastly, a clear and structured representation of the number of drivers who served each
 client is provided by sorting the results by customer_id in ascending order.
 Understanding patterns of driver distribution and client involvement can be aided by
 this kind of information.

```
hadoop@ip-10-0-2-56:
nive> SET hive.cli.print.header=true;
nive> SELECT
           customer_id,
COUNT(DISTINCT driver_id) AS Distinct_no_of_drivers
      bookings_data
GROUP BY
           customer id
      ORDER BY
> customer_id;
Query ID = hadoop 20250625190454 497935d6-3596-4227-a0cc-4ea53751bcal
Total jobs = 1

Launching Job 1 out of 1

Status: Running (Executing on YARN cluster with App id application_1750873936410_0011)
                                       STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
Map 1 ..... container
                                   SUCCEEDED
Reducer 3 ..... container
                                    SUCCEEDED
                  distinct_no_of_drivers
10022393
10058402
10435129
10614890
```





The following Output matches validation document.

Task 6: Calculate the total rides taken by each customer.

```
SELECT
customer_id,
COUNT(booking_id) AS NUMBER_OF_TOTAL_RIDES
FROM bookings_data
GROUP BY customer_id
ORDER BY customer_id;
```

- Using the bookings_data table, this SQL query determines how many rides each client
 has taken overall. After choosing the customer_id, it counts how many booking_id
 entries there are linked to each customer.
- The query organises all reservations under each distinct customer by utilising the GROUP BY clause on customer_id. A summary of the number of rides each customer has completed is provided by the outcome.
- It is simple to examine the total number of rides for every client in an orderly fashion because the final output is sorted by customer_id.





```
A hadoop@ip-10-0-2-56:~
99947969 1
Time taken: 6.025 seconds, Fetched: 1000 row(s)
hive> SELECT
               ECT
customer_id,
count(booking_id) AS NUMBER_OF_TOTAL_RIDES
         bookings_data
GROUP BY
customer_id
customer_id
> ORDER BY
> customer_id;
Query ID = hadoop_20250625190602_178f0243-77fa-49a9-a22e-aa60aa8949ca
Total jobs = 1
Launching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1750873936410_0011)
            VERTICES MODE
                                                      STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
Map 1 ...... container
Reducer 2 .... container
Reducer 3 .... container
                                                   SUCCEEDED
                                                   SUCCEEDED
customer_id
10022393
10058402
                         number_of_total_rides
10339567
10435129
10555335
10555335
10592274
10614890
10678994
11264797
11418437
11438890
11454977
■ naαοορ@ip-10-0-2-20:
Reducer 2 ..... container
Reducer 3 ..... container
                                                 SUCCEEDED
customer_id
                         number_of_total_rides
10022393
10058402
10339567
10555335
10592274
```

```
10614890
10678994
11418437
11438890
11518953
11580321
11596512
11757536
11764909
11860278
12142182
12312603
12334699
12885363
12913608
12914577
12966909
13015449
13229062
```





The above Output matched the validation document.

Task 7: Find the total visits made by each customer on the booking page and the total 'Book Now' button presses. This can show the conversion ratio.

The booking page id is 'e7bc5fb2-1231-11eb-adc1-0242ac120002'.

The Book Now button id is 'fcba68aa-1231-11eb-adc1-0242ac120002'. You also need to calculate the conversion ratio as part of this task. Conversion ratio can be calculated as Total 'Book Now' Button Press/Total Visits made by customer on the booking page.

```
SELECT
  COUNT(CASE
    WHEN page id = 'e7bc5fb2-1231-11eb-adc1-0242ac120002'
    AND is page view = 'Yes' THEN 1
  END) AS total page visits,
  COUNT(CASE
    WHEN button id = 'fcba68aa-1231-11eb-adc1-0242ac120002'
    AND is button click = 'Yes' THEN 1
  END) AS total button pressed,
  ROUND(
    COUNT(CASE
      WHEN button id = 'fcba68aa-1231-11eb-adc1-0242ac120002'
      AND is_button_click = 'Yes' THEN 1
    END) * 1.0 /
    COUNT(CASE
      WHEN page id = 'e7bc5fb2-1231-11eb-adc1-0242ac120002'
      AND is page view = 'Yes' THEN 1
    END), 4
```





) AS conversion ratio

FROM clickstream data;

- The purpose of this SQL query is to assess user interaction effectiveness and engagement on a particular webpage.
- It uses the clickstream_data table to compute three important metrics. It first counts the records where the given page_id was viewed and tagged as 'Yes' in the is_page_view field in order to calculate the overall number of visits to a specific page.
- Second, it counts the number of times a particular button on that page was clicked; this is verified by the is_button_click field being set to 'Yes' and is recognised by a unique button id.
- Lastly, by dividing the total number of button clicks by the total number of page visits and rounding the result to four decimal places, the query determines the conversion ratio.
- This conversion ratio offers important insights into user behaviour and the performance of the page design by showing how well the page drives user activities.

```
hadoop@ip-10-0-2-56:
99947969
Time taken: 6.485 seconds, Fetched: 1000 row(s)
           COUNT (CASE
          WHEN page_id = 'e7bc5fb2-1231-lleb-adc1-0242ac120002'
AND is_page_view = 'Yes' THEN 1
END) AS total_page_visits,
          COUNT (CASE
               WHEN button_id = 'fcba68aa-1231-11eb-adcl-0242acl20002'
          AND is button_click = 'Yes' THEN 1
END) AS total_button_pressed,
          ROUND (
COUNT (CASE
                  WHEN button_id = 'fcba68aa-1231-11eb-adcl-0242acl20002'
                   AND is button click = 'Yes'
               COUNT (CASE
                   WHEN page_id = 'e7bc5fb2-1231-11eb-adc1-0242ac120002'
                   AND is page view = 'Yes' THEN 1
           ) AS conversion_ratio
    > FROM clickstream_data;
Query ID = hadoop_20250625190919_1e2dd756-5549-4a65-a8a3-dfd0eebd4336
Total jobs = 1
 aunching Job 1 out of 1
 tatus: Running (Executing on YARN cluster with App id application_1750873936410_0011)
        VERTICES
                                    STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
Map 1 ..... container
                                   SUCCEEDED
Reducer 2 ..... container
                                   SUCCEEDED
total page visits
                          total_button_pressed
                                                      conversion_ratio
436010 422418 0.9688
Fime taken: 13.416 seconds, Fetched: 1 row(s)
```

We got the same conversion ratio of 0.9688 as we have in validation document.





Task 8: Calculate the count of all trips done on black cabs.

Query:

```
WITH black_cabs AS (

SELECT *

FROM bookings_data

WHERE cab_color = 'black'
)

SELECT COUNT(booking id) AS TOTAL TRIPS BY BLACK CABS
```

FROM black_cabs;

- Using the bookings_data table, this SQL query determines the total number of trips made by black taxis.
- A Common Table Expression (CTE) called black_cabs is initially created, filtering and storing any records with the cab_color set to 'black'. The query then counts the total number of booking_id entries—which indicate the total number of trips made in black taxis—using this filtered dataset.
- The total number of trips made by black taxis is the only value displayed in the final result. This method assists in separating particular data subsets for targeted investigation.

```
conversion_ratio
                        total_button_pressed
otal page visits
436010 422418 0.9688
Time taken: 13.416 seconds, Fetched: 1 row(s)
ive> WITH black_cabs AS (
         SELECT *
         FROM bookings data
         WHERE cab_color = 'black'
         COUNT(booking_id) AS TOTAL_TRIPS_BY_BLACK_CABS
   > FROM black cabs;
Query ID = hadoop 20250625191221 5e695501-ddf9-4e22-b0c0-6aec0ac87e42
otal jobs = 1
 aunching Job 1 out of 1
tatus: Running (Executing on YARN cluster with App id application_1750873936410_0011)
                                  STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
       VERTICES
                     MODE
Map 1 ..... container
                              SUCCEEDED
                               SUCCEEDED
Reducer 2 ..... container
total_trips_by_black_cabs
Time taken: 6.062 seconds, Fetched: 1 row(s)
```

We got 72 Black Cab trips same as Validation documentation.





Task 9: Calculate the total amount of tips given date wise to all drivers by customers.

```
WITH daily tips AS (
  SELECT
       TO DATE(from unixtime(CAST(pickup timestamp / 1000 AS BIGINT))) AS
TRIP DATE,
    SUM(tip amount) AS SUM TIPS
  FROM
    bookings data
  GROUP BY
    TO DATE(from unixtime(CAST(pickup timestamp / 1000 AS BIGINT)))
)
SELECT
  TRIP DATE,
  ROUND(SUM TIPS, 0) AS TOTAL TIP AMOUNT
FROM
  daily tips
ORDER BY
  TRIP DATE;
```

- The bookings_data table's total daily tip amounts are determined using this SQL query.
- In order to transform each trip's timestamp from Unix time (in milliseconds) to a readable date format (TRIP_DATE), it first creates a Common Table Expression (CTE) named daily_tips. After that, the query groups the records by TRIP_DATE and adds up the tip amounts for each day.
- The query then rounds the total tips to the closest whole number for easier reading after choosing the travel dates and associated total tip amounts from the daily_tips CTE. Next, TRIP DATE is used to arrange the results chronologically.
- This query offers insights into tipping trends over time by summarising the total tips collected by day.





The following Output matches the validation documentation.





Task 10: Calculate the total count of all the bookings with ratings lower than 2 as given by customers in a particular month.

```
WITH low rated trips AS (
  SELECT
    date format(from unixtime(CAST(pickup timestamp / 1000 AS BIGINT)), 'yyyy-MM')
AS TRIP MONTH,
    booking id
  FROM
    bookings data
  WHERE
    rating_by_customer < 2
)
SELECT
  TRIP MONTH,
  COUNT(booking id) AS NO OF BOOKINGS
FROM
  low rated trips
GROUP BY
  TRIP_MONTH
ORDER BY
  TRIP_MONTH;
```

- This SQL query is designed to analyze low-rated trips on a monthly basis from the bookings data table.
- It starts by creating a Common Table Expression (CTE) named low_rated_trips, which filters trips where the rating_by_customer is less than 2, indicating poorly rated rides. For each of these trips, it extracts the trip month by converting the Unix timestamp (in





- milliseconds) to a readable yyyy-MM format and selects the corresponding booking_id.
- In the main query, it groups these low-rated trips by TRIP_MONTH and counts the number of bookings for each month, providing the total number of low-rated trips per month. The results are ordered chronologically by month.
- This query helps track monthly trends in customer dissatisfaction, which can be valuable for identifying periods of poor service and potential areas for operational improvement.

```
hadoop_20250625192812_2cab59ea-0c20-4be3-b37f-8c101440fba9
otal jobs = 1
aunching Job 1 out of 1
 catus: Running (Executing on YARN cluster with App id application_1750873936410_0017)
       VERTICES
                                   STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
Map 1 ..... container
                                SUCCEEDED
                                SUCCEEDED
Reducer 3 ..... container
                                SUCCEEDED
rip_month
                no_of_bookings
2020-01 26
2020-02 16
2020-03 16
2020-06 14
2020-09 21
```





The above output matches the Validation document.

Task 11: Calculate the count of total iOS users.

Query:

```
WITH ios_users AS (

SELECT DISTINCT customer_id

FROM clickstream_data

WHERE OS_VERSION = 'iOS'
)

SELECT

COUNT(*) AS TOTAL_IOS_USERS

FROM
.
```

ios users;

- The clickstream_data dataset is used in this SQL query to determine the total number of distinct iOS users.
- A Common Table Expression (CTE) named ios_users is first created, and it picks all
 unique customer_id values where the OS_VERSION is 'iOS'. Even if an iOS user
 appears in the dataset more than once, this step guarantees that they are only counted
 once.
- In the last step, the query returns TOTAL_IOS_USERS, which is just the total number of distinct iOS users found in the CTE. For platform-specific user analysis or marketing campaigns aimed at iOS consumers, this query offers a clear and precise count of individual iOS users.

In the Output below we got 2 counts extra than the output from validation document. Looking more into this we found that since we got a little more of data ingested we got those 2 counts extra.





```
Time taken: 14.395 seconds, Fetched: 1 row(s)
hive> WITH ios_users AS (
          SELECT DISTINCT customer id
           FROM clickstream data
            WHERE OS_VERSION = 'iOS'
     > SELECT
            COUNT (*) AS TOTAL IOS USERS
     > ios users;
Query ID = hadoop_20250625193101_e38c79bb-9b7c-457a-82d7-287b650d2861
Total jobs = 1
Launching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1750873936410_0017)
          VERTICES MODE STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED

      Map 1 .......... container
      SUCCEEDED
      6
      6
      0
      0
      0

      Reducer 2 ..... container
      SUCCEEDED
      2
      2
      0
      0
      0

      Reducer 3 ..... container
      SUCCEEDED
      1
      1
      0
      0
      0

total_ios_users
Time taken: 14.92 seconds, Fetched: 1 row(s)
```

All the tasks from 1 to 11 are now successfully performed.