



# **Futureense**

Democratizing Tech Talent  
to deliver impact at scale

# Credit Card Analysis



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**The  
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# Business Problem/Overview



In this project, we have 2 problems – Transactions problem & Defaulters problem.

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## Customer Spending Behavior Analysis

The primary objective of this project is to leverage big data technologies to perform an in-depth analysis of credit card transactions and credit card defaulters datasets.

By applying advanced data processing techniques in cloud, this project aims to uncover valuable insights and patterns that can assist in making informed decisions to mitigate credit card default risks and improve overall financial strategies.

- Gain insights into customer spending patterns and behaviors.
- Identify trends and patterns in transaction data.
- Optimize marketing strategies and tailor promotions based on transaction history.
- Enhance customer experiences by understanding their preferences and behaviors.

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## Credit Card Defaulter Risk Analysis

The outcomes of credit card defaulter analysis empower credit issuers to make informed decisions, manage risks effectively, enhance customer relationships, and optimize their overall business strategies in the dynamic landscape of credit lending. The major goal is to reduce the risk of credit card defaults.



# Customer Spending Behavior Analysis



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# Credit Card Defaulter Risk Analysis

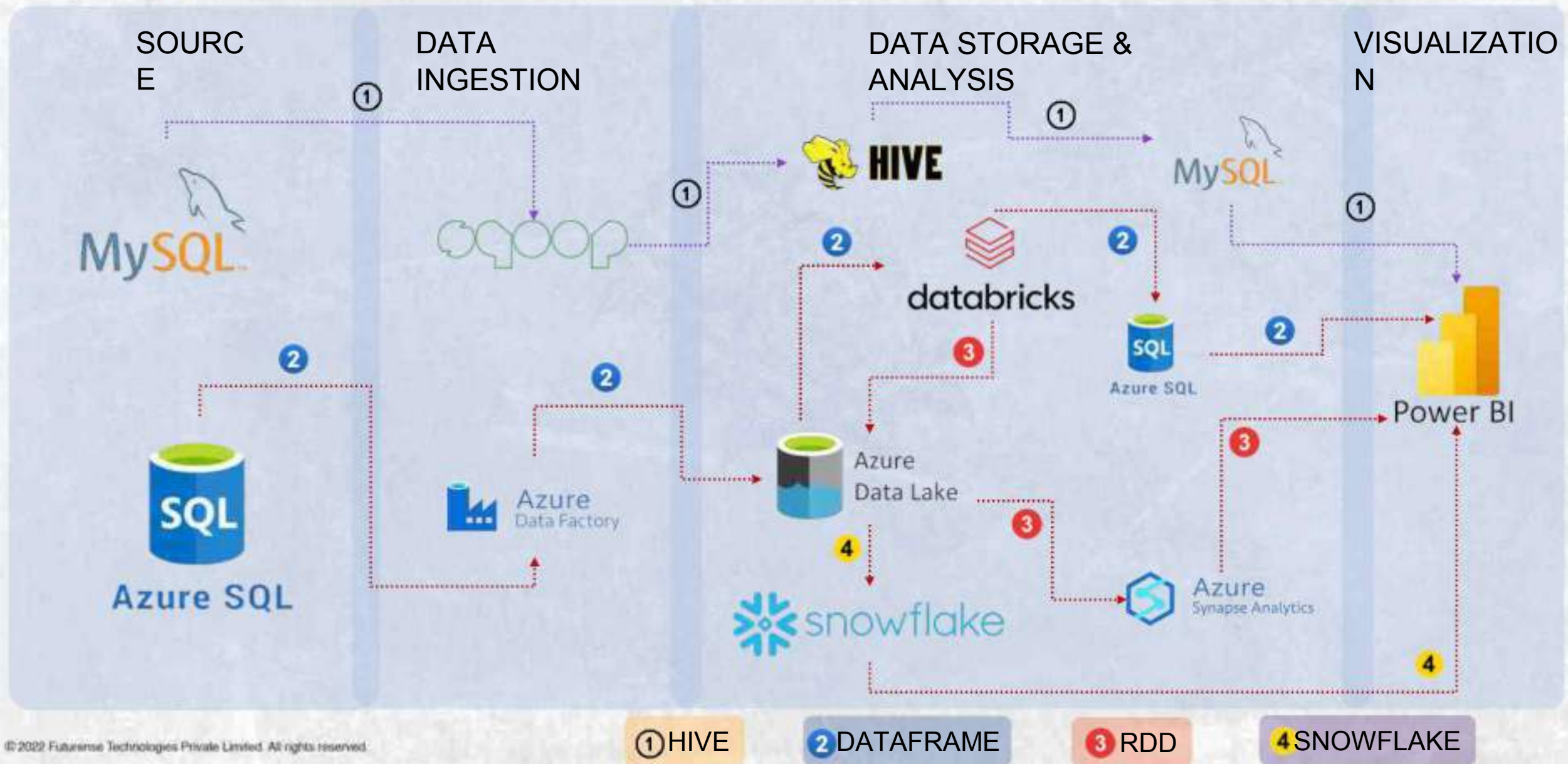


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# Architecture of the solution



# Data Representation

For the given problems, we have 2 different datasets – one for the transactions problem and another for Defaulters problem.

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Transactions Data

The transaction problem has the dataset as following features:

**Index:** A unique identifier for each record in the dataset.

**City:** The city where transaction was done.

**Date:** The date on which transaction occurred.

**Card Type:** Indicates the card type used for transactions – Silver, Gold, Platinum, Signature.

**Exp Type:** Indicates the expense type for which the card was used – Bills, Entertainment, Food, Fuel, Grocery Travel.

**Gender:** Denotes the gender of the cardholder – Male, Female.

**Amount:** The amount of transaction done by the customer.

Out of the given data, Index can be categorized as **Numerical identifier**,  
City, Card Type, Exp Type and Gender as **Categorical variables**  
Date as **Date variable** & Amount as **Numerical variable**.

Total Records26052

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Defaulters Data

The fraud detection problem has the dataset as following attributes:

**CustID:** A unique identifier for each customer.

**Limit\_Bal:** Maximum spending limit assigned to the customer.

**Sex:** Gender of the customer – 1 (Male) or 2 (Female).

**Education:** Education level of the customer – 1 (Graduate), 2 (University), 3 (High school), 4 (Others).

**Marriage:** Marital status of the customer – 1 (Single), 2 (Married), 3 (Others).

**Age:** Age of the customer.

**PAY\_1 to PAY\_6:** Repayment status of the customer for the last 6 months. The values indicate the number of months of delayed for payment.

**BILL\_AMT1 to BILL\_AMT6:** Bill amount for each of the last six months.

**PAY\_AMT1 to PAY\_AMT6:** Actual amount customer paid for each of the last six months.

**DEFAULTED:** Whether the customer is defaulted or not on their credit card payment – 0 (not defaulted), 1 (defaulted).

Total Records1002



# Transactions Data



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**Date:** The date on which transaction occurred.

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**Gender:** Denotes the gender of the cardholder – **Male**, **Female**.

**Amount:** The amount of transaction done by the customer.

Out of the given data, Index can be categorized as **Numerical identifier**,

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Total Records

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**DEFAULTED:** Whether the customer is defaulted or not on their credit card payment – **0** (not defaulted), **1** (defaulted).

Total Records

1002



# Batch Processing using HIVE

Creating the table

```
mysql> CREATE TABLE CCD (CUSTID INT,LIMIT_BAL DECIMAL(10, 2),SEX int,EDUCATION int,MARRIAGE int,AGE INT,PAY_1 INT,PA  
Y_2 INT,PAY_3 INT,PAY_4 INT,PAY_5 INT,PAY_6 INT,BILL_AMT1 DECIMAL(10, 2),BILL_AMT2 DECIMAL(10, 2),BILL_AMT3 DECIMAL(  
10, 2),BILL_AMT4 DECIMAL(10, 2),BILL_AMT5 DECIMAL(10, 2),BILL_AMT6 DECIMAL(10, 2),PAY_AMT1 DECIMAL(10, 2),PAY_AMT2 D  
ECIMAL(10, 2),PAY_AMT3 DECIMAL(10, 2),PAY_AMT4 DECIMAL(10, 2),PAY_AMT5 DECIMAL(10, 2),PAY_AMT6 DECIMAL(10, 2),DEFAULT  
ED INT);
```

Using the following command we will load the data in the table created

```
LOAD DATA INFILE '/home/cloudera/CCD_ProcessedData.csv' INTO TABLE CreditCardData FIELDS  
TERMINATED BY ',' (@var1,@var2,@var3,@var4,@var5,@var6,@var7) SET Date=STR_TO_DATE(@var1,'%d  
-%m-  
%Y'),Low=@var2,Open=@var3,Volume=@var4,high=@var5,Close=@var6,Adjusted _close=@var7;
```



# Batch Processing using HIVE

Transfer data using Sqoop



```
[cloudera@quickstart ~]$ sqoop import --connect jdbc:mysql://localhost:3306/project --username root --password cloudera --table CCD --target-dir /user/cloudera/Shubz/CCD.txt -m 1
```

Create the schema in Hive

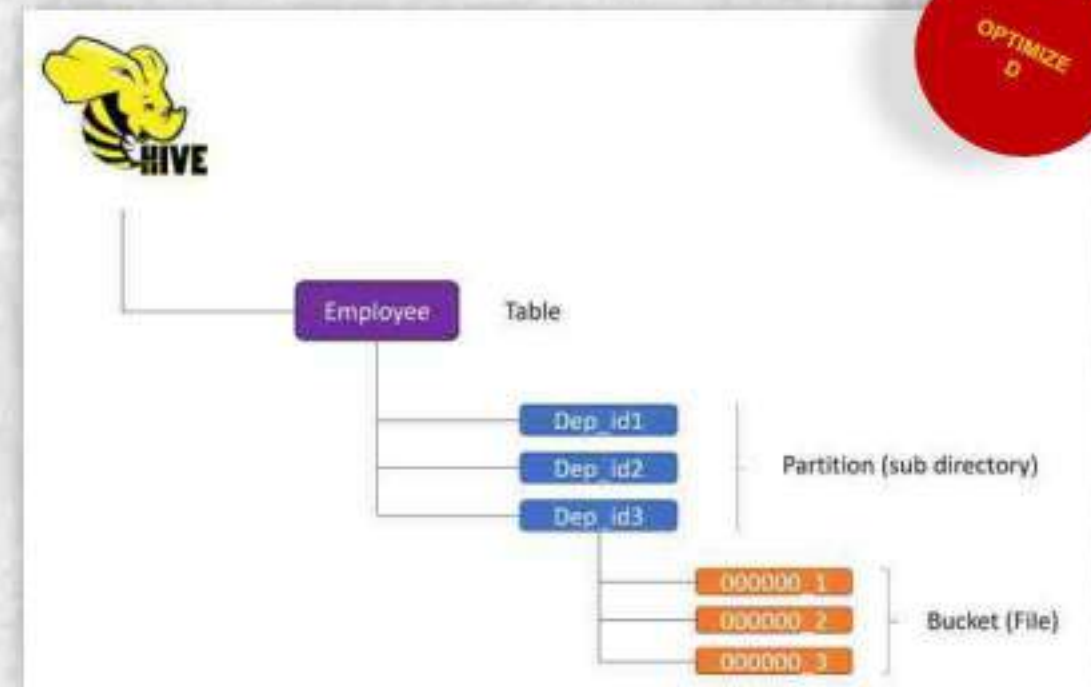
```
hive> create table CCD(CUSTID INT,LIMIT_BAL DECIMAL(10, 2),SEX int,EDUCATION int,MARRIAGE int,AGE INT,PAY_1 INT,PAY_2 INT,PAY_3 INT,PAY_4 INT,PAY_5 INT,PAY_6 INT,BILL_AMT1 DECIMAL(10, 2),BILL_AMT2 DECIMAL(10, 2),BILL_AMT3 DECIMAL(10, 2),BILL_AMT4 DECIMAL(10, 2),BILL_AMT5 DECIMAL(10, 2),BILL_AMT6 DECIMAL(10, 2),PAY_AMT1 DECIMAL(10, 2),PAY_AMT2 DECIMAL(10, 2),PAY_AMT3 DECIMAL(10, 2),PAY_AMT4 DECIMAL(10, 2),PAY_AMT5 DECIMAL(10, 2),PAY_AMT6 DECIMAL(10, 2),DEFAULTED INT) row format delimited fields terminated by ',';
```

# Batch Processing using HIVE

Create partitioning on Hive table

```
hive> create table CCDP(CUSTID INT,LIMIT_BAL DECIMAL(10, 2),SEX int,EDUCATION int,MARRIAGE int,AGE INT,PAY_1 INT,PAY_2 INT,PAY_3 INT,PAY_4 INT,PAY_5 INT,PAY_6 INT,BILL_AMT1 DECIMAL(10, 2),BILL_AMT2 DECIMAL(10, 2),BILL_AMT3 DECIMAL(10, 2),BILL_AMT4 DECIMAL(10, 2),BILL_AMT5 DECIMAL(10, 2),BILL_AMT6 DECIMAL(10, 2),PAY_AMT1 DECIMAL(10, 2),PAY_AMT2 DECIMAL(10, 2),PAY_AMT3 DECIMAL(10, 2),PAY_AMT4 DECIMAL(10, 2),PAY_AMT5 DECIMAL(10, 2),PAY_AMT6 DECIMAL(10, 2)) partitioned by (DEFAULTED INT) row format delimited fields terminated by '\t'
```

Partitioning is one of the optimization techniques used in Hive to improve the performance of the query





# Batch Processing using HIVE

**1. Write a SQL query to determine the count of defaulted (1) and non-defaulted (0) records for both males and females in the Credit Card Data table.**

```
SELECT SEX,DEFAULTED,COUNT(*) AS COUNT FROM CCDP
GROUP BY SEX, DEFAULTED;
```

```
mysql> select * from statement6;
+-----+-----+-----+
| Sex | DEFAULTED | Total_count |
+-----+-----+-----+
| 2 | 0 | 373 |
| 2 | 1 | 218 |
| 0 | 0 | 1 |
| 1 | 1 | 185 |
| 1 | 0 | 224 |
+-----+-----+-----+
5 rows in set (0.01 sec)
```

**2. average billed Amount & average pay amount**

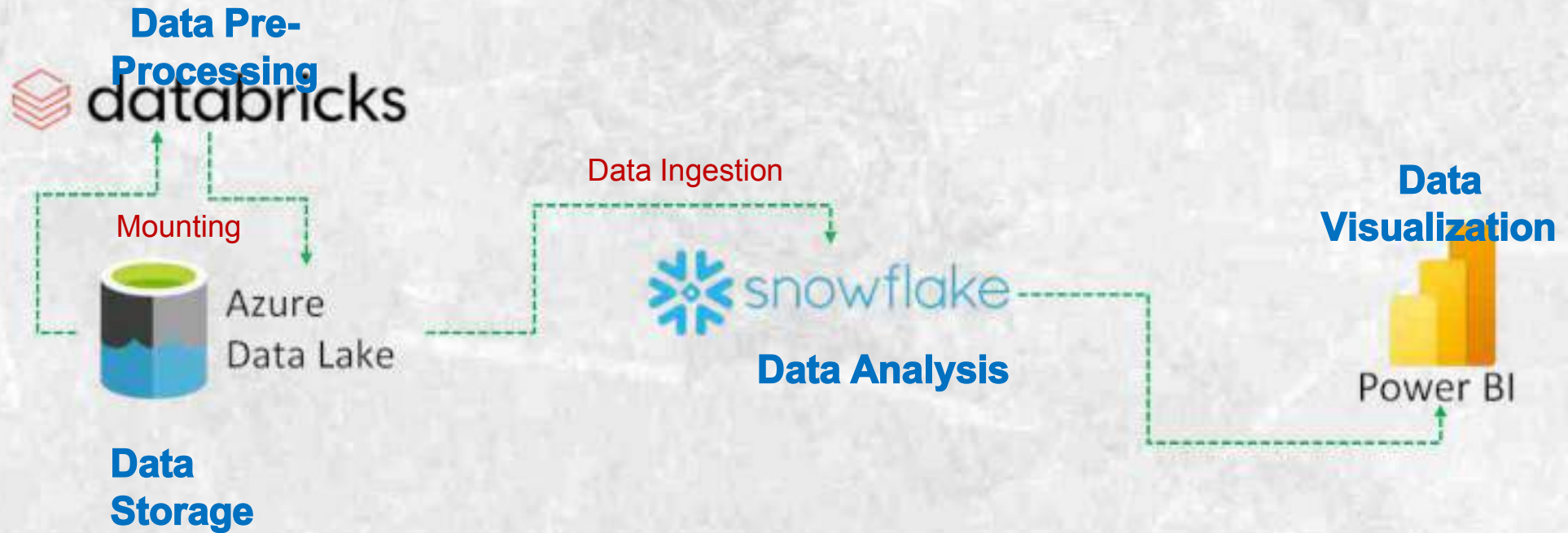
```
SELECT CUSTID, SEX, EDUCATION, MARRIAGE, AGE,
AVG((BILL_AMT1 + BILL_AMT2 + BILL_AMT3 + BILL_AMT4 +
BILL_AMT5 + BILL_AMT6) / 6) AS AVERAGE_BILLED_AMOUNT,
AVG((PAY_AMT1 + PAY_AMT2 + PAY_AMT3 + PAY_AMT4 +
PAY_AMT5 + PAY_AMT6) / 6) AS AVERAGE_PAY_AMOUNT FROM
CCDP GROUP BY CUSTID,SEX,EDUCATION,MARRIAGE,AGE;
```

```
mysql> select * from statement78 limit 10;
+-----+-----+-----+-----+-----+-----+-----+
| CUSTID | SEX | EDUCATION | MARRIAGE | AGE | AVERAGE_BILLED_AMOUNT | AVERAGE_PAY_AMOUNT |
+-----+-----+-----+-----+-----+-----+-----+
| 582 | 2 | 2 | 1 | 40 | 54306.58 | 3233.33 |
| 255 | 2 | 2 | 2 | 30 | 10500.00 | 4166.67 |
| 750 | 2 | 2 | 2 | 30 | 1699.67 | 1636.33 |
| 0 | 0 | 0 | 0 | 0 | 0.00 | 0.00 |
| 256 | 1 | 2 | 1 | 30 | 4673.17 | 4654.50 |
| 257 | 2 | 2 | 1 | 50 | 67273.00 | 2201.67 |
| 258 | 2 | 2 | 1 | 30 | 32185.83 | 2862.83 |
| 259 | 2 | 3 | 1 | 40 | 60358.67 | 2300.00 |
| 260 | 1 | 1 | 1 | 50 | 39685.67 | 1295.33 |
| 261 | 2 | 1 | 2 | 30 | 56231.83 | 22051.83 |
+-----+-----+-----+-----+-----+-----+-----+
10 rows in set (0.01 sec)
```





# Risk Analysis using snowflake



# Risk Analysis using

## ADLS MOUNTING TO DATABRICKS :

### Connecting ADLS with Databricks

After completing the thorough data cleaning and preprocessing procedures, the processed and refined data is transferred to the Azure Data Lake Factory

```
Generate SAS Token from ADLS ACCOUNT and Paste it here

SAS_Token = "fs=2022-11-02&as=0pqt8arB=eeakgperwd2aapyn&ee=2W23-0E-0Y1A-57:1728&e="

Connect with ADLS account via mounting to load the data

dbutils.fs.mount(
  source = "wasbs://cont0000ad2ak0rags@k10n.com.windows.net",
  mount_point = "/mnt/mounted_sas",
  extra_configs = {
    "fs.azure.sas.cont0000ad2ak0rags@k10n.com.windows.net": SAS_Token
  }
)
```

Data Pre-processing



```
Merge two part files in 1 using repartition

df3=ccard_df.repartition(1)

Save the processed data in ADLS

df3.write.format("csv").mode("overwrite").save("/mnt/mounted_SAS/CCdefaulter_csv",header=True)
```

```
dbutils.fs.unmount('/mnt/mounted_SAS')

/mnt/mounted_SAS has been unmounted.
Out[14]: True
```



# Risk Analysis using

**Data Pre-Processing :** In the initial five scenarios, the data cleaning and preprocessing tasks are executed within the Databricks environment

Load the file into RDD

```
data = sc.textFile("/mnt/hounted_1A3/credit-card-default-1000.csv")
```

Seperating Header

```
headers= data.first()
```

```
headers1 = [name for name in headers.split(',')]
```

Convert to DataFrame

```
ccard_df = cleaned_rdd.toDF(headers1)
```

Removing header and unwanted inverted comma , splitting columns

```
#removing header and unwanted inverted comma , splitting columns  
rdd_split = data.filter(lambda x : x!=headers).map(lambda x : x.replace("'",'')).map(lambda x : x.split(','))
```

Removing Lines that are not CSV

```
rdd_partial = rdd_split.filter(lambda x : x[0].isdigit())
```

Normalize sex to only 1 and 2

```
cleaned_rdd = rdd_partial.map(lambda x : [int(i.replace('M','1').replace('F','2')) for i in x])
```

# Risk Analysis using

**Data Ingestion :** Data Ingestion Pipeline from Data Lake Storage to Snowflake via External Stage and COPY INTO. From ADLS, the data is then seamlessly moved to Snowflake, a data warehouse platform, in order to facilitate subsequent in-depth analysis and exploration

## Connecting with SnowSQL

```
C:\Users\Miles>snowsql -a gfsysnv-ep39977 -u KANIKAAAGG
Password:
* SnowSQL * v1.2.28
Type SQL statements or !help
KANIKAAAGG@COMPUTE_WH@ZOO DATABASE.(no database).(no schema)>use ZOO DATABASE;
+-----+
| status |
+-----+
| Statement executed successfully. |
+-----+
1 Row(s) produced. Time Elapsed: 18.938s
KANIKAAAGG@COMPUTE_WH@ZOO DATABASE.PUBLIC>use ZOO DATABASE.ZOOSHEMA;
+-----+
| status |
+-----+
| Statement executed successfully. |
+-----+
1 Row(s) produced. Time Elapsed: 0.624s
```

## Create File Format

```
KANIKAAAGG@COMPUTE_WH@ZOO DATABASE.ZOOSHEMA>CREATE OR REPLACE File Format zoo_csv_format
Type=csv
field_delimiter=';'
skip_header=1
null_if=('null','null')
empty_field_as_null=true;
+-----+
| status |
+-----+
| File format ZOO_CSV_FORMAT successfully created. |
+-----+
1 Row(s) produced. Time Elapsed: 0.270s
```



## Stage

```
KANIKAAAGG@COMPUTE_1:~/DATABASE_ZOO$ CREATE OR REPLACE STAGE zoo_azure_stage
URL = 'azurer://cnadiscroam.blob.core.windows.net/container/default_csv/part-00000-tid-779543111693237954-fa2a8c94-bd8
e38-WH3377fa9c94-11-1-0000.csv'
CREDENTIALS = (AZURE_SAS_TOKEN = '/?sv=2013-11-02&sr=b&sig=rtaocslapwrdiaay&se=2023-09-15T22:43:14Z&st=2023-09-15T14:
prncpsa&sig=F2XES27eylq2zscfNysZCWnQvnddnrU492h7FE1OLANg300')
FILE_FORMAT = zoo_csv_format;
```

status
Stage area ZOO_AZURE_STAGE successfully created.

1 Row(s) produced. Time Elapsed: 0.247s

## Table

```
KANIKAGAGG#COMPUTE_WH@ZOO0DATA$ A=2 | ((C-CHEMA>COPY INTO cc_default  
FROM @zoo_azure_stage  
FILE_FORMAT = zoo_csv_format;  
-----  
| file  
rsd | rows_loaded | error_limit | errors_seen | first_error | first_error_line | first_error_character | first_error_column_name |  
|-----  
|-----  
| azure://zooadlsaccount.blob.core.windows.net/cont1/CCdefault_csv/part-00000-tid-739541815169323954-Sa2e6ce4-b86e-4cc6-ae2d-082337fa0  
1000 | 1000 | 1 | 0 | NULL | NULL | NULL | NULL |  
|-----  
|-----  
1 Row(s) produced. Time Elapsed: 2.623s
```

# Risk Analysis using



**Data Processing/ Analysis :** Rounding of age to range of 10s and add SEXNAME to the data using SQL Joins.

**Create Gender table and insert values**

Create table gender (

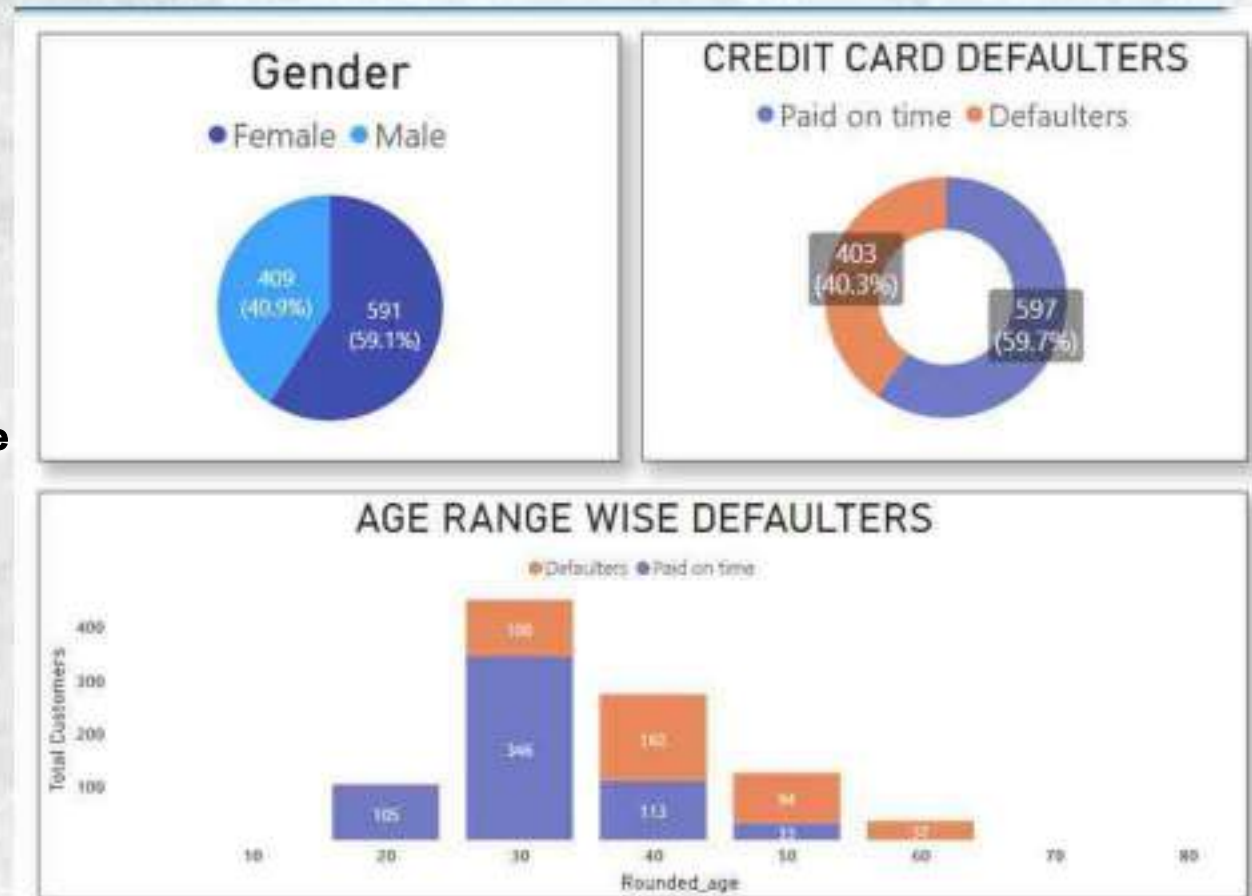
sex\_code int,

sex\_name varchar(50) );

select \*, FLOOR((Age + 5) / 10) \* 10 AS RoundedAge

from cc\_default c

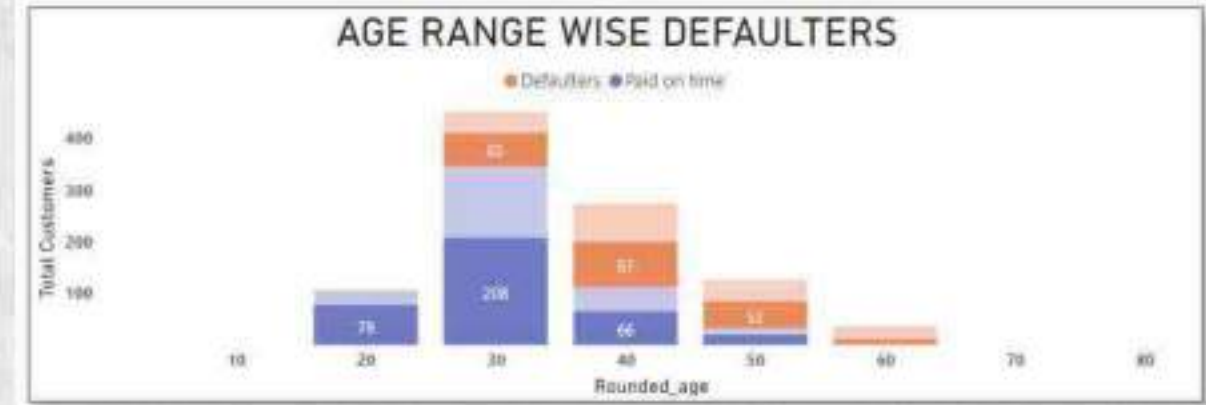
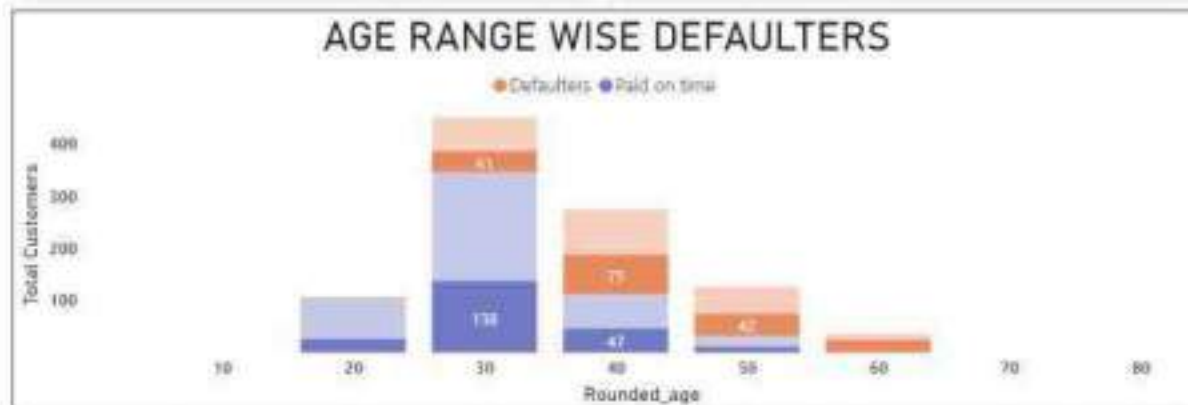
inner join gender g on c.sex=g.sex\_code;





# Risk Analysis using snowflake

**Data Processing/ Analysis :** Rounding of age to range of 10s and add SEXNAME to the data using SQL Joins.

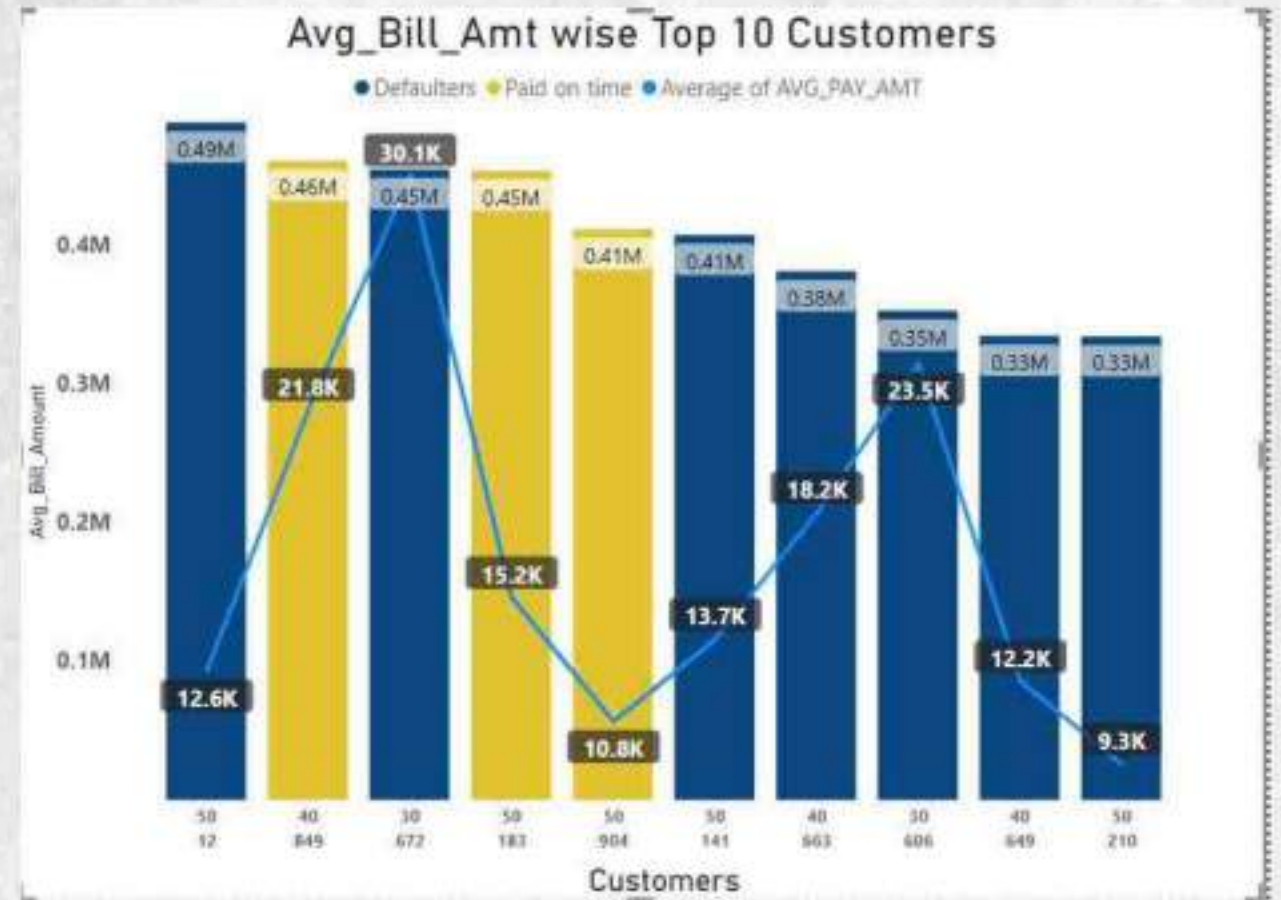


# Risk Analysis using



**Data Processing/ Analysis :** Find Average billed Amount and average pay amount for each customer.

```
select *, ROUND(
(CASE WHEN BILL_AMT1 > 0 THEN BILL_AMT1 ELSE 0 END
+
CASE WHEN BILL_AMT2 > 0 THEN BILL_AMT2 ELSE 0 END
+
CASE WHEN BILL_AMT3 > 0 THEN BILL_AMT3 ELSE 0 END
+
CASE WHEN BILL_AMT4 > 0 THEN BILL_AMT4 ELSE 0 END
+
CASE WHEN BILL_AMT5 > 0 THEN BILL_AMT5 ELSE 0 END
+
CASE WHEN BILL_AMT6 > 0 THEN BILL_AMT6 ELSE 0
END )/6,2)
AS AVG_BILL_AMT,
round((PAY_AMT1+PAY_AMT2+PAY_AMT3+PAY_AMT4+PA
Y_AMT5+PAY_AMT6)/6,2) AS AVG_PAY_AMT
FROM CC_DEFAULT;
```





# Risk Analysis using

**Data Processing/ Analysis :** Find average pay duration. Make sure numbers are rounded and negative values are eliminated.

```
SELECT *, ROUND ((  
CASE WHEN PAY_1 > 0 THEN PAY_1ELSE 0 END +  
CASE WHEN PAY_2 > 0 THEN PAY_2ELSE 0 END +  
CASE WHEN PAY_3 > 0 THEN PAY_3ELSE 0 END +  
CASE WHEN PAY_4 > 0 THEN PAY_4ELSE 0 END +  
CASE WHEN PAY_5 > 0 THEN PAY_5ELSE 0 END +  
CASE WHEN PAY_6 > 0 THEN PAY_6ELSE 0 END  
)/6, 0) AS AVG_PAY_DURATION  
FROM  
CC_DEFAULT;
```





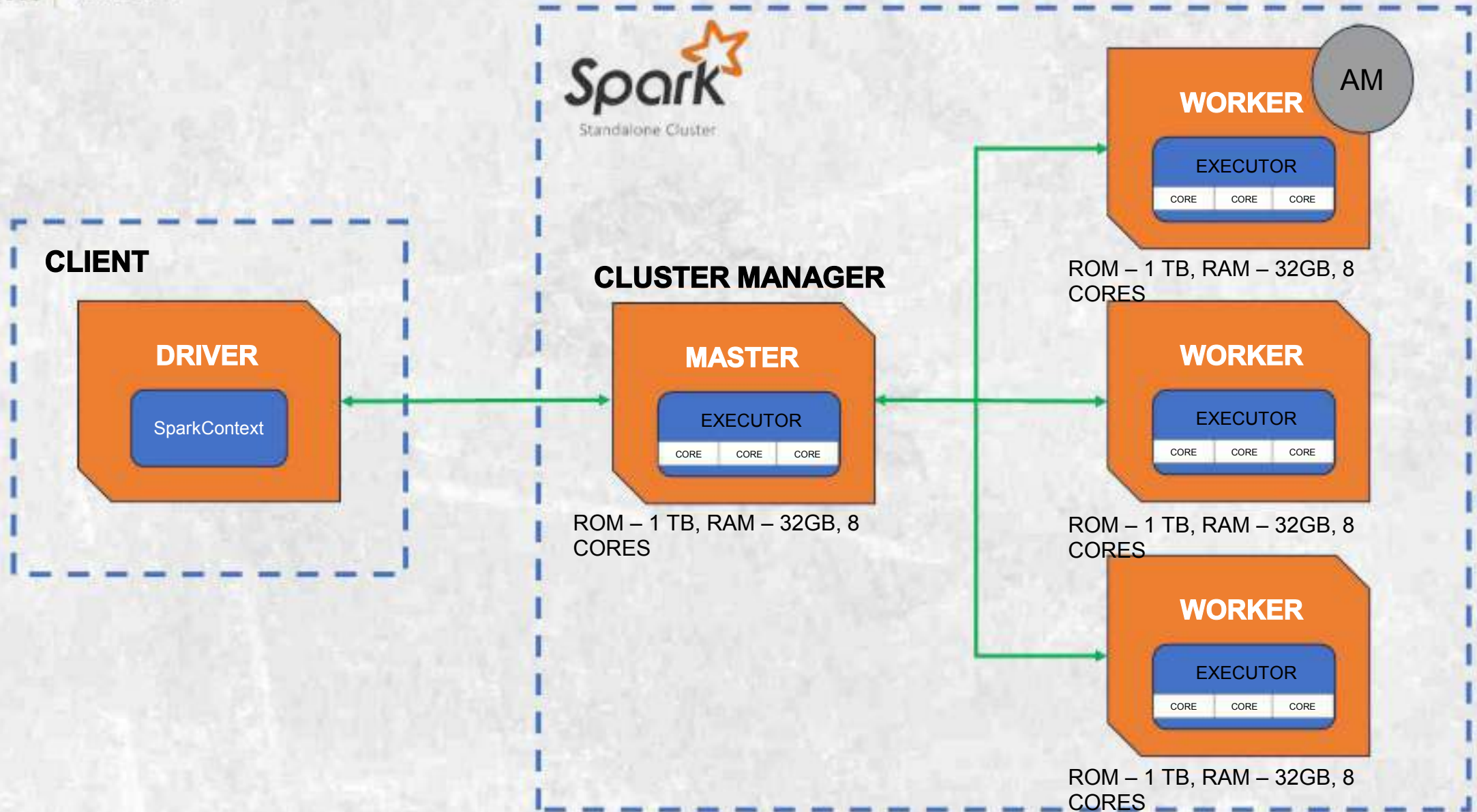
# databricks







# Cluster Configuration

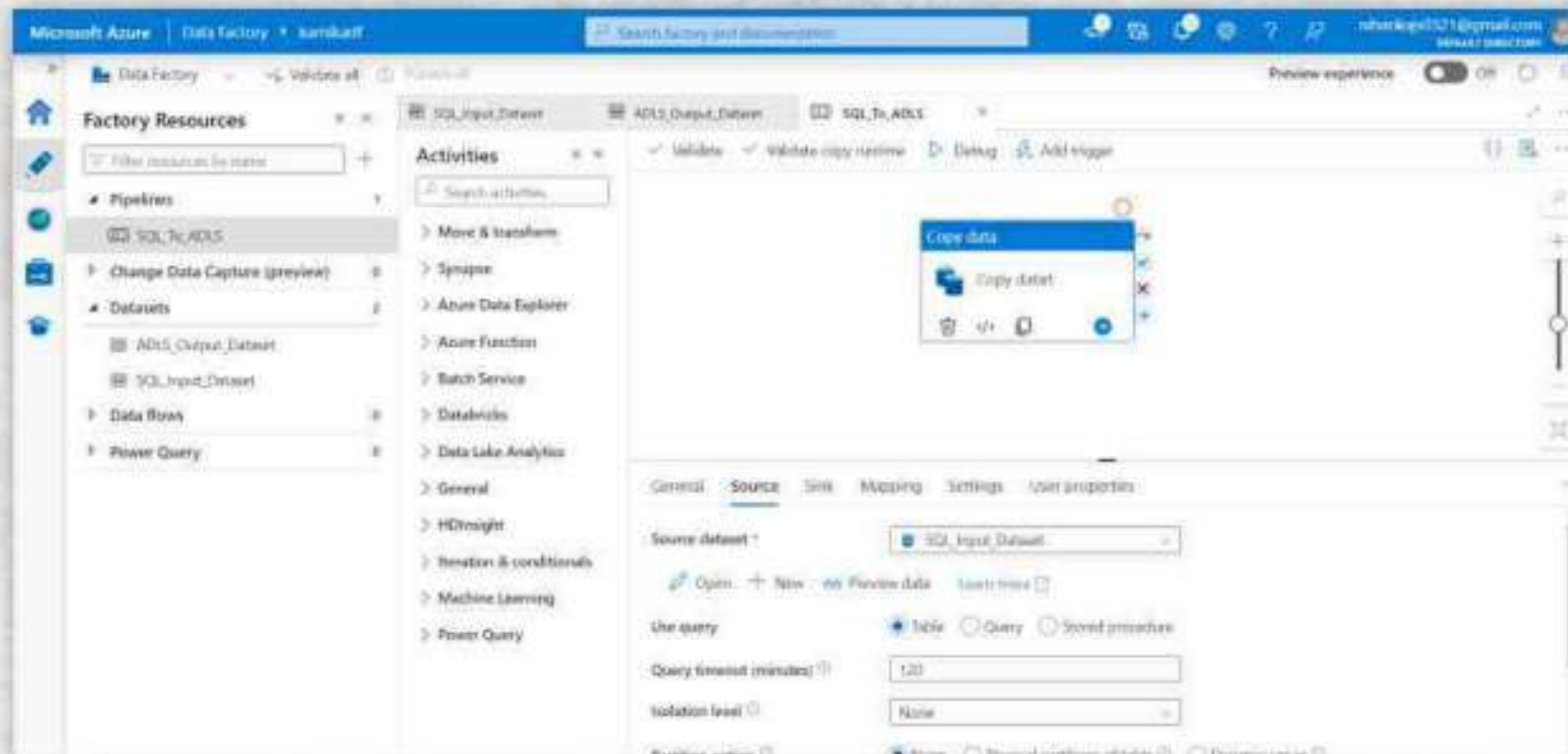




# Importing Data



The source for us is MS SQL Server. We are importing the data from the SQL Server into the Azure cloud, using the Azure Data Factory pipeline.



# Batch Processing using RDD

## Mounting ADLS

Cell 3

```
1 SAS_Token = "?sv=2022-11-02&ss=bfgt&srt=co&sp=rwdlacupyx&se=2023-08-20T12:48:32Z&st=2023-08-09T04:48:32Z&spr=https&sig=pZN3UpPsvxfn8Fz276yGvAd5u2x8G0lK2B7KxAjl7Ifjc%3D"
```

Command took 0.06 seconds — by theashpak\_99live.com at 9/8/2023, 10:20:59 am on Ashpak Sheikh's Cluster

Cell 4

```
1
2 dbutils.fs.mount(
3     source = 'wasbs://project@meraaccountdeletetekarega.blob.core.windows.net',
4     mount_point = '/mnt/mounted_SAS',
5     extra_configs={
6         "fs.azure.sas.project.meraaccountdeletetekarega.blob.core.windows.net": SAS_Token
7     }
8 )
```

Out[9]: True

Command took 10.68 seconds — by theashpak\_99live.com at 9/8/2023, 10:21:07 am on Ashpak Sheikh's Cluster



# Batch Processing using RDD

Write a query to print top 5 cities with highest spends and their percentage contribution of total credit card spends

Cmd 12

```
1 # Mapping the data to (City, Amount) pairs
2 city_amount_rdd = rdd_split.map(lambda row: (row[1], float(row[7])))
3 # Total spends per city
4 city_total_spends_rdd = city_amount_rdd.reduceByKey(lambda a, b: a + b)
5
6 # Total spends across all cities
7 total_spends = city_total_spends_rdd.values().sum()
8
9 # Total spends in descending order
10 sorted_cities = city_total_spends_rdd.sortBy(lambda x: x[1], ascending=False)
11
12 # Top 5 cities
13 top_cities = sorted_cities.take(5)
14
15 # Percentage contribution of each city's spends
16 city_spends_percentage = [(city, (amount / total_spends) * 100, amount) for city, amount in top_cities]
17 # Printing the results
18 for city, percentage, amount in city_spends_percentage:
19     print("City: {}, Amount: {}, Spends: {:.2f}%".format(city, amount, percentage))
20
```

\* (4) Spark Jobs

```
City: Greater Mumbai, Amount: 576751476.0, Spends: 14.15%
City: Bengaluru, Amount: 572326739.0, Spends: 14.05%
City: Ahmedabad, Amount: 567794310.0, Spends: 13.93%
City: Delhi, Amount: 556929212.0, Spends: 13.67%
City: Kolkata, Amount: 115466943.0, Spends: 2.83%
```

Command took 1.13 seconds -- by theashpak@qlive.com at 17/8/2013, 11:40:22 am on Ashpak Sherkh's Cluster

# Batch Processing using RDD

Write a query to print highest spend month and amount spent in that month for each card type

Card 1.1

```
1 #0', 'Delhi', ' India', '29-Oct-14', 'Gold', 'Bills', 'F', '82475'
2 # Splitting data monthwise
3 card_month_amount_rdd = rdd_split.map(lambda x: (x[3].split('-')[1], float(x[7])))
4
5 # Calculating Monthly Spent
6 monthly_sum = card_month_amount_rdd.reduceByKey(lambda x,y: x+y).max(lambda x: x[1])
7
8 #Getting all the data from month having maximum spent
9 card_month_amount_rdd = rdd_split.filter(lambda x: x[3].split('-')[1]==monthly_sum[0]).map(lambda x: ((x[4], x[3].split('-')[1]),
10 float(x[7])))
11
12 # calculating spent by each card type
13 monthly_grouped = card_month_amount_rdd.reduceByKey(lambda x,y:x+y)
14
15 for card_type, max_month in monthly_grouped.collect():
16     print(f"Card Type : {card_type}, Spent : {max_month}")
```

• (2) Spark Jobs

```
Card Type : ('Platinum', 'Jan'), Spent : 112784373.0
Card Type : ('Signature', 'Jan'), Spent : 98919381.0
Card Type : ('Silver', 'Jan'), Spent : 109359598.0
Card Type : ('Gold', 'Jan'), Spent : 110146204.0
```

Command took 0:00 seconds -- by theashpak\_solive.com at 9/8/2023, 5:20:34 pm on Ashpak Shirkh's Cluster



# Optimization using RDD

OPTIMIZED

Write a query to print top 5 cities with highest spends and their percentage contribution of total credit card spends (cached)

cell 11

```
1 # Mapping the data to (city, amount) pairs
2 rdd_split_cached = rdd_split_cached.cache()
3 city_amount_rdd = rdd_split_cached.map(lambda row: (row[2], float(row[7])))
4 # Total spends per city
5 city_total_spends_rdd = city_amount_rdd.reduceByKey(lambda a, b: a + b)
6
7 # Total spends across all cities
8 total_spends = city_total_spends_rdd.values().sum()
9
10 # Total spends in descending order
11 sorted_cities = city_total_spends_rdd.sortBy(lambda x: x[1], ascending=False)
12
13 # Top 5 cities
14 top_cities = sorted_cities.take(5)
15
16 # Percentage contribution of each city's spends
17 city_spends_percentage = [(city, (amount / total_spends) * 100, amount) for city, amount in top_cities]
18 # Printing the results
19 for city, percentage, amount in city_spends_percentage:
20     print("City: {}, Amount: {}, Spends: {}".format(city, amount, percentage))
21
```

• (4) Spark Jobs

City: Greater Mumbai, Amount: 57270476.0, Spends: 14.236  
City: Bengaluru, Amount: 57230779.0, Spends: 14.608  
City: Ahmedabad, Amount: 56779478.0, Spends: 13.938  
City: Delhi, Amount: 556929212.0, Spends: 13.678  
City: Kolkata, Amount: 11546694.0, Spends: 2.828

Command took 0.66 seconds -- by theodan, split the code at 11/14/2021, 11:47:59 AM on Apache Spark's Cluster

Write a query to print highest spend month and amount spent in that month for each card type (cache())

cell 12

```
1 # ("Card", "Month", "India", "2020-01-01", "Gold", "MUMBAI", "1", "82079")
2 # Splitting data monthwise
3 rdd_split_cached = rdd_split_cached.cache()
4 card_month_amount_rdd = rdd_split_cached.map(lambda x: (x[2], x[4] + "/" + x[5], float(x[7])))
5
6 # Calculating Monthly Spend
7 monthly_sum = card_month_amount_rdd.reduceByKey(lambda a, b: a + b).map(lambda x: (x[2], x[3]))
8
9 # Getting all the data from month having maximum spend
10 card_month_amount_rdd = rdd_split_cached.filter(lambda x: x[3].split("/")[-1] == monthly_sum[0]).map(lambda x: ((x[2], x[3].split("/")[-1]), float(x[7])))
11
12 # Calculating spend by each card type
13 monthly_grouped = card_month_amount_rdd.reduceByKey(lambda a, b: a + b)
14
15 for card_type, max_month in monthly_grouped.collect():
16     print("Card Type: {}, Spend: {}".format(card_type, max_month))
17
```

• (2) Spark Jobs

Card Type: ('Platinum', 'Jan'), Spend: 323704372.0  
Card Type: ('Signature', 'Jan'), Spend: 10010381.0  
Card Type: ('Silver', 'Jan'), Spend: 109100000.0  
Card Type: ('Gold', 'Jan'), Spend: 110140284.0

Command took 0.83 seconds -- by theodan, split the code at 11/14/2021, 11:59:14 AM on Apache Spark's Cluster

• (4) Spark Jobs

City: Greater Mumbai, Amount: 57270476.0, Spends: 14.236  
City: Bengaluru, Amount: 57230779.0, Spends: 14.608  
City: Ahmedabad, Amount: 56779478.0, Spends: 13.938  
City: Delhi, Amount: 556929212.0, Spends: 13.678  
City: Kolkata, Amount: 11546694.0, Spends: 2.828

Command took 0.66 seconds -- by theodan, split the code at 11/14/2021, 11:47:59 AM on Apache Spark's Cluster

• (2) Spark Jobs

Card Type: ('Platinum', 'Jan'), Spend: 323704372.0  
Card Type: ('Signature', 'Jan'), Spend: 10010381.0  
Card Type: ('Silver', 'Jan'), Spend: 109100000.0  
Card Type: ('Gold', 'Jan'), Spend: 110140284.0

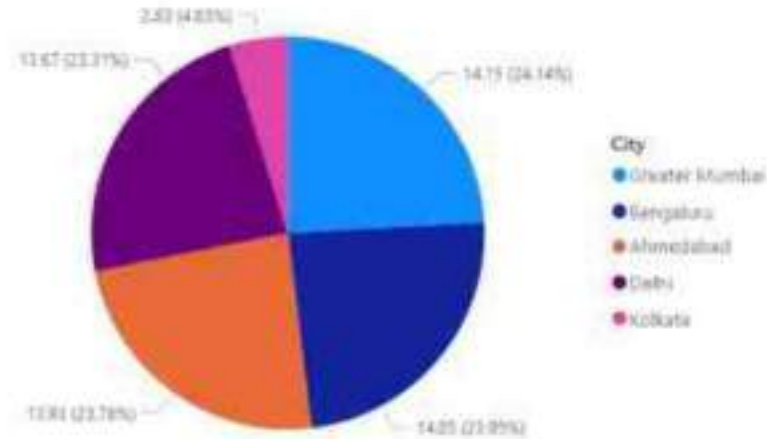
Command took 0.83 seconds -- by theodan, split the code at 11/14/2021, 11:59:14 AM on Apache Spark's Cluster

# Batch Processing using RDD

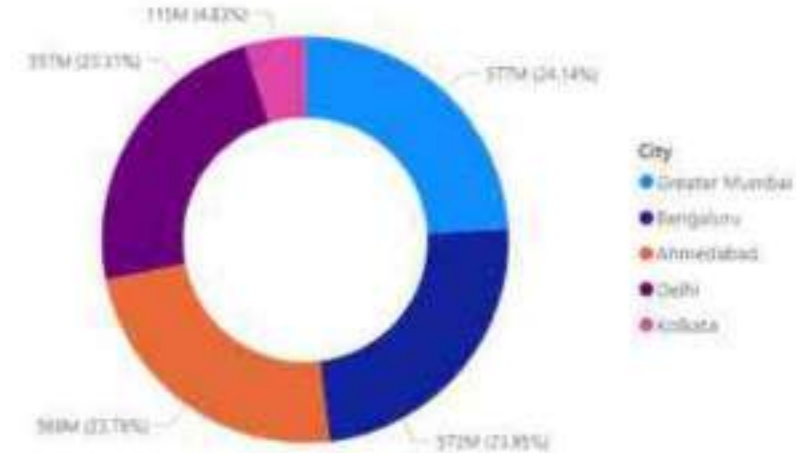
## VISUALIZATION

Write a query to print top 5 cities with highest spends and their percentage contribution of total credit card spends

Percentage Contribution by City



Total Spent By City by City



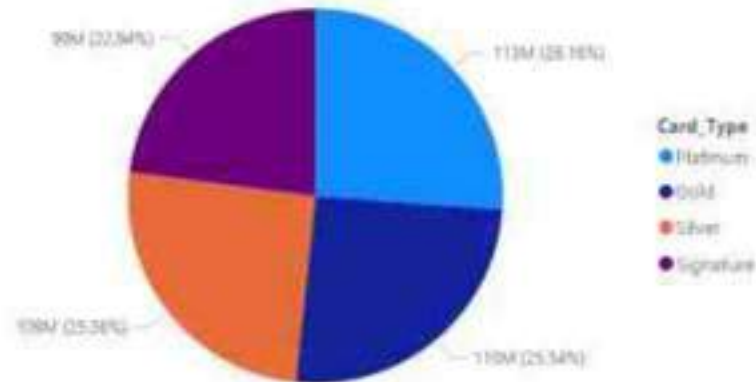


# Batch Processing using RDD

## VISUALIZATION

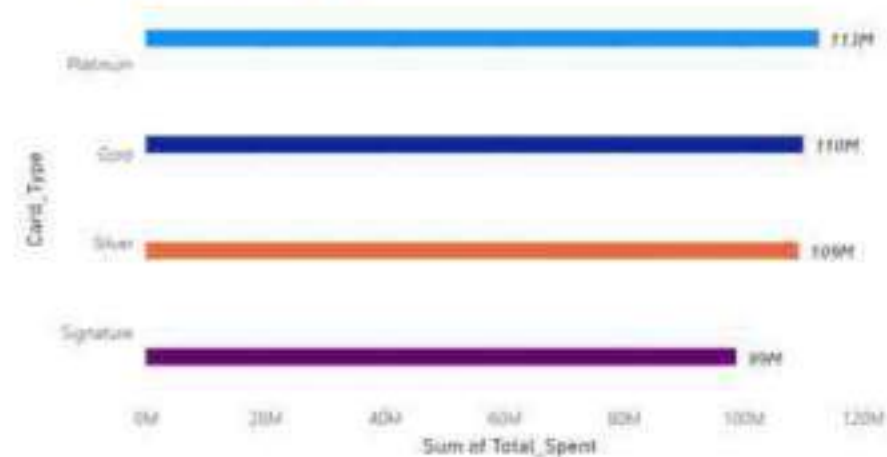
Write a query to print highest spend month and amount spent in that month for each card type

Total\_Spent contribution by Each Card by Card\_Type



Sum of Total\_Spent by Card\_Type and Card\_Type

Card\_Type Platinum Gold Silver Signature



# Batch Processing using RDD

**Scenario 6 - Write a query to find percentage contribution of spends by females for each expense type**

```
1 female_rdd = rdd2.filter(lambda x: x[6] == "F")
2 # Map the RDD to (expense_type, amount)
3 expense_type_amount_rdd = female_rdd.map(lambda x: (x[5], float(x[7])))
4 # Reduce by key to calculate total spend by females for each expense type
5 total_spend_by_expense_type = expense_type_amount_rdd.reduceByKey(lambda a, b: a + b)
6 # Collect the total spend by expense type as a dictionary for easy lookup
7 total_spend_dict = dict(total_spend_by_expense_type.collect())
8 # Calculate the total spend by all genders for each expense type
9 total_spend_all_rdd = rdd2.map(lambda x: (x[5], float(x[7]))).reduceByKey(lambda a, b: a + b)
10 # Calculate the percentage contribution of spends by females for each expense type
11 percentage_contribution_rdd = total_spend_by_expense_type.join(total_spend_all_rdd).mapValues(lambda x: (x[0] / x[1]) * 100)
12 # Collect and print the result
13 result = percentage_contribution_rdd.collect()
14 for expense_type, percentage in result:
15     print(f"Expense Type: {expense_type}, Percentage Contribution: {percentage:.2f}%")
```

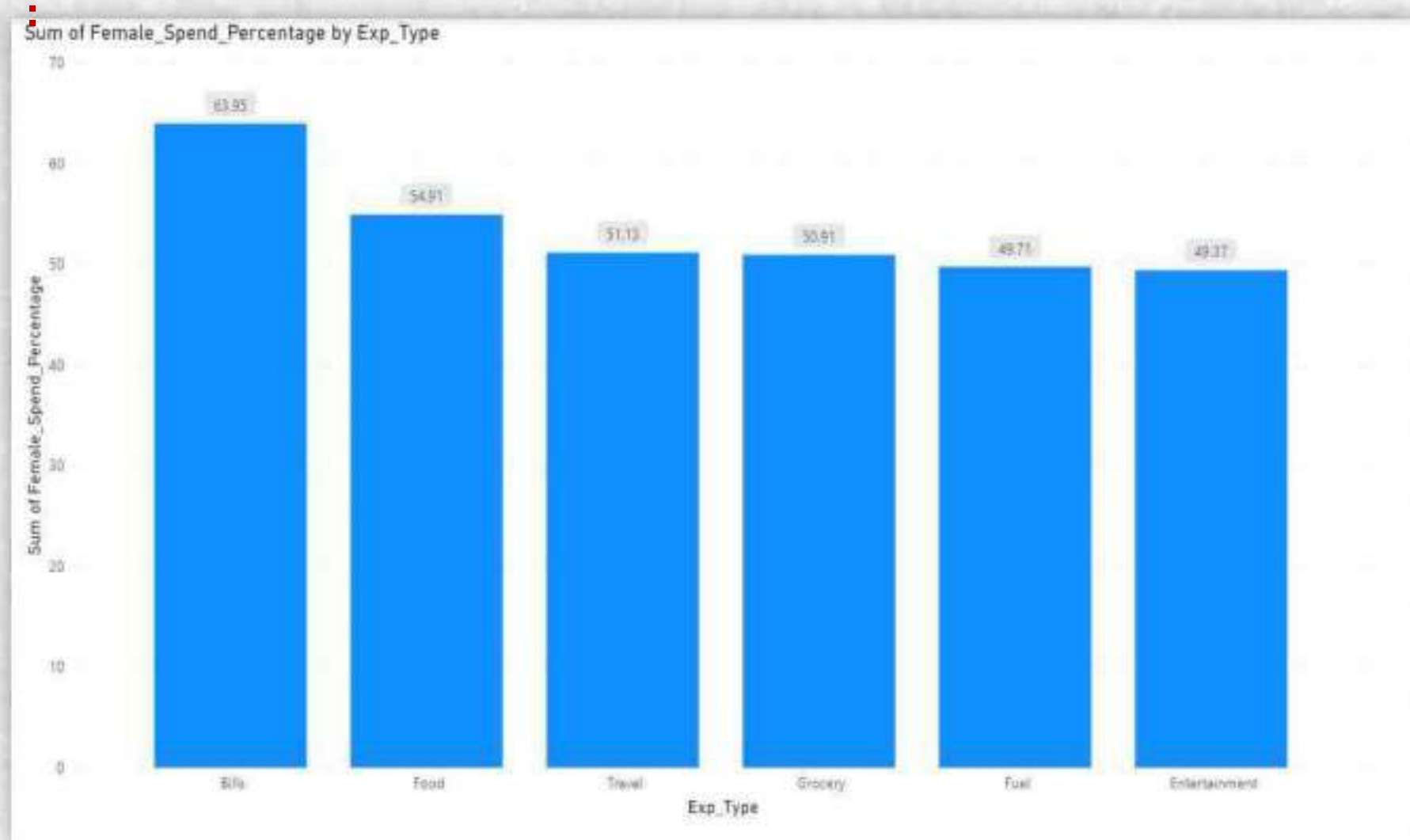
▶ (2) Spark Jobs

```
Expense Type: Bills, Percentage Contribution: 63.95%
Expense Type: Entertainment, Percentage Contribution: 49.37%
Expense Type: Grocery, Percentage Contribution: 50.91%
Expense Type: Fuel, Percentage Contribution: 49.71%
Expense Type: Food, Percentage Contribution: 54.91%
Expense Type: Travel, Percentage Contribution: 51.13%
```



# Batch Processing using RDD

## VISUALIZATION



# Batch Processing using RDD

## Scenario 7 - Which card and expense type combination saw highest month over month growth in Jan -2014

Cmd 12

```
1  # Filter data for January 2014
2  jan_2014_data_rdd = rddy.filter(lambda x: x[3].split('-')[1] == ('Jan-14'))
3  Dec_2013_data_rdd = rddy.filter(lambda x: x[3].split('-')[1] == ('Dec-13'))
4  # Map the RDD to ((card_type, expense_type), amount)
5  card_expense_amount_rdd_jan = jan_2014_data_rdd.map(lambda x: ((x[4], x[5]), float(x[7])))
6  card_expense_amount_rdd_Dec = Dec_2013_data_rdd.map(lambda x: ((x[4], x[5]), float(x[7])))
7  # Reduce by key to calculate total amount spent for each card and expense type combination
8  total_amount_by_card_expense_jan = card_expense_amount_rdd_jan.reduceByKey(lambda a, b: a + b)
9  total_amount_by_card_expense_Dec = card_expense_amount_rdd_Dec.reduceByKey(lambda a, b: a + b)
10 final_total_amountbycardexpense = total_amount_by_card_expense_jan.join(total_amount_by_card_expense_Dec)
11 # Calculate the growth from the previous month (December 2013) for each card and expense type combination
12 growth_rdd = final_total_amountbycardexpense.map(lambda x : (x[0], 100*(x[1][0]-x[1][1])/x[1][1]))
13 # Find the combination with the highest month-over-month growth
14 max_growth_combination = growth_rdd.max(lambda x: x[1])
15 for i in max_growth_combination:
16     print(i)
```

▶ (1) Spark Jobs:

('Gold', 'Travel')  
87.92088147034576

Command took 0.91 seconds — by niharika.js9321@gmail.com at 8/15/2023, 11:54:49 PM on Niharika J 5's Cluster

The diagram illustrates a data integration workflow. At the bottom left, the Databricks logo (a stack of red squares) is shown with the text "databricks" below it. Two blue arrows point from Databricks to a central blue cylinder labeled "SQL" with "Azure SQL" written below it. A single blue arrow points from the "SQL" cylinder to the Power BI logo (three yellow bars of increasing height) at the bottom right, with the text "Power BI" below it.



# Connecting to Azure SQL Database & Reading the data

## Azure SQL Database Configuration

Cell 3

```
1 jdbcHostname = "ccserver.database.windows.net"
2 jdbcPort = "1433"
3 jdbcDatabase = "credit_analysis"
4
5 url = f"jdbc:sqlserver://{jdbcHostname}:{jdbcPort};database={jdbcDatabase}"
```

data: pyspark.sql.DataFrame DataFrame = [index, short, City, string ... 5 more fields]

Command took 0.10 seconds -- by mihirika[at]gmail.com at 8/15/2023, 9:41:20 PM on Microsoft 3 S's Cluster

## Reading Table from Azure SQL Database as DataFrame using Spark Read API

Cell 4

```
1 credit_card = spark.read.format("jdbc") \
2     .option("driver", "com.microsoft.sqlserver.jdbc.SQLServerDriver") \
3     .option("url", url) \
4     .option("dbtable", "credit_card_transactions") \
5     .option("user", "sqladmin") \
6     .option("password", "Password@123") \
7     .load()
```

credit\_card: pyspark.sql.DataFrame DataFrame = [index, short, City, string ... 5 more fields]

Command took 0.10 seconds -- by mihirika[at]gmail.com at 8/15/2023, 9:51:15 PM on Microsoft 3 S's Cluster

# Cleaning Data and Creating Temporary Table

## Removing country name from City column

Cell 11

```
1 from pyspark.sql.functions import *
2 # Creating an UDF for removing the country name
3 func = udf(lambda x: str(x)[-7:])
4
5 # Applying UDF function on the column
6 credit_card = credit_card.withColumn('City', func(col('City')))
```

credit\_card: pyspark.sql.dataframe.DataFrame = [index: integer, City: string ... 5 more fields]

Command took 0.21 seconds -- by niharika@321@gmail.com at 8/15/2023, 7:05:05 PM on Niharika D D's Cluster

## Creating temporary table for data frame

Cell 11

```
1 credit_card.createOrReplaceTempView('credit_tbl')
```

Command took 0.10 seconds -- by niharika@321@gmail.com at 8/15/2023, 7:10:03 PM on Niharika D D's Cluster

# Problem Statement

**Write a query to print 3 columns: city, highest\_expense\_type, lowest\_expense\_type**

Scenario 5 - Write a query to print 3 columns: city, highest\_expense\_type, lowest\_expense\_type

Cmd - 38:

```
1  sc5_out = spark.sql(""" WITH cte AS
2                               (SELECT City, Exp_Type, SUM(Amount)
3                                FROM credit_tbl
4                                GROUP BY City, EXP_TYPE
5                                ORDER BY 1, 3 DESC
6                               )
7  SELECT DISTINCT City,
8                 FIRST_VALUE(Exp_Type) OVER(PARTITION BY City) AS Highest_Expense_Type,
9                 LAST_VALUE(Exp_Type) OVER(PARTITION BY City) AS Lowest_Expense_Type
10 FROM cte
11 """)
```

►  sc5\_out: pyspark.sql.dataframe.DataFrame = [City: string, Highest\_Expense\_Type: string ... 1 more field]

Command took 1.17 seconds — by niharika.jy8321@gmail.com at 8/15/2023, 7:06:06 PM on Niharika J S's Cluster



# Problem Statement

Output:

```
1  sc5_out.show()
```

• (5) Spark jobs

City	Highest_Expense_Type	Lowest_Expense_Type
Achalpur	Grocery	Entertainment
Adilabad	Bills	Food
Adityapur	Food	Grocery
Adoni	Bills	Entertainment
Adoor	Fuel	Bills
Afzalpur	Fuel	Food
Agartala	Grocery	Food
Agra	Bills	Grocery
Ahmedabad	Bills	Grocery
Ahmednagar	Fuel	Grocery
Aizawl	Food	Grocery
Ajmer	Entertainment	Fuel
Akola	Bills	Fuel
Akoti	Fuel	Entertainment
Alappuzha	Food	Entertainment
Aligarh	Bills	Entertainment
Alipurdhar	Food	Entertainment
Alirajpur	Entertainment	Entertainment

Command took 4.18 seconds — by niharika@3333@gmail.com at 8/15/2023, 7:00:08 PM on Bihari-ika 2 5% Cluster

# Catalyst Optimizer

```
1: sc5_out.explain(mode="extended")

== Parsed Logical Plan ==
CTE [cte]
: +- 'SubqueryAlias cte
:   +- 'Sort [1 ASC NULLS FIRST, 3 DESC NULLS LAST], true
:     +- 'Aggregate ['City, 'EXP_TYPE], ['City, 'Exp_Type, unresolvedalias('SUM('Amount), None)]
:       +- 'UnresolvedRelation [credit_tbl], [], false
+- 'Distinct
  +- 'Project ['City, 'FIRST_VALUE('Exp_Type) windowSpecdefinition('City, unspecifiedframe$()) AS Highest_Expense_Type#119, 'LAST_VALUE('Exp_Type) windowSpecdefinition('City, unspecifiedframe$()) AS Lowest_Expense_Type#120]
    +- 'UnresolvedRelation [cte], [], false

== Analyzed Logical Plan ==
City: string, Highest_Expense_Type: string, Lowest_Expense_Type: string
WithCTE
:- CTERelationDef @, false
: +- SubqueryAlias cte
:   +- Sort [City#111 ASC NULLS FIRST, sum(Amount)#122L DESC NULLS LAST], true
:     +- Aggregate [City#111, EXP_TYPE#63], [City#111, Exp_Type#63, sum(Amount#65) AS sum(Amount)#122L]
:       +- SubqueryAlias credit_tbl
:         +- View ['credit_tbl', [index#59, City#111, Date#61, Card_Type#62, Exp_Type#63, Gender#64, Amount#65]]
:           +- Project [index#59, <lambda>('City#60)#110 AS City#111, Date#61, Card_Type#62, Exp_Type#63, Gender#64, Amount#65]

Command took 0.18 seconds -- by n7har4kaJc0323@msatl.com at 8/14/2023, 11:36:09 PM on Niharika J S's Cluster
```

OPTIMIZED

# Exporting result to Azure SQL Database

## Exporting result DataFrame to Azure SQL Server Table

Cell 37

```
1 sc5_out.write.format("jdbc") \  
2   .option("driver", "com.microsoft.sqlserver.jdbc.SQLServerDriver") \  
3   .option("url", url) \  
4   .option("dbtable", "scenario_5") \  
5   .option("user", "sqladmin") \  
6   .option("password", "Password@123") \  
7   .save()
```

► (5) Spark Jobs

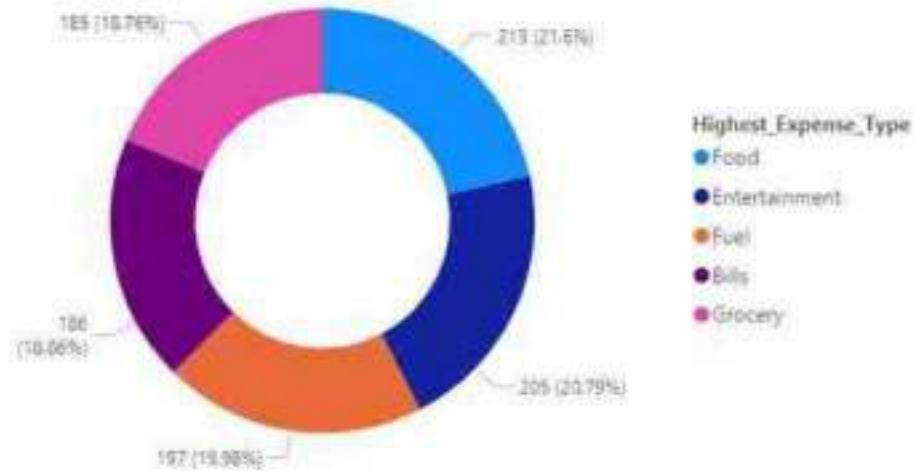
Command took 4.29 seconds -- by niharika50321@gmail.com at 8/10/2023, 11:39:28 AM on Niharika I 5's Cluster



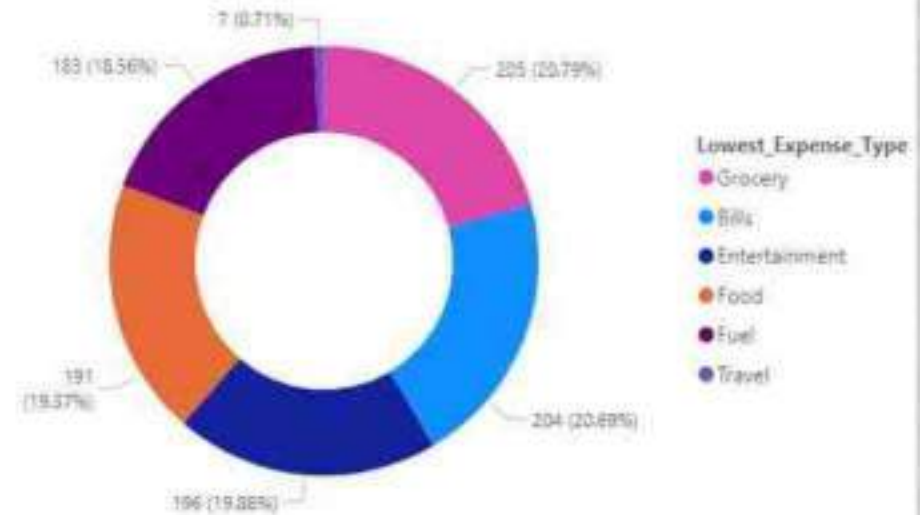
# Visualization

Write a query to print 3 columns: city, highest expense type, lowest expense type

Count of City by Highest\_Expense\_Type



Count of City by Lowest\_Expense\_Type



# Problem Statement

Which city took least number of days to reach its 500th transaction

Scenario 9 - Which city took least number of days to reach its 500th transaction after the first transaction in that city

Cell A7

```
1 sc9_out = spark.sql(""" WITH cte1 AS
2   (SELECT City, Date, ROW_NUMBER() OVER(PARTITION BY City ORDER BY Date) AS RN
3   FROM credit_tbl
4   ), cte2 AS
5   (SELECT *, LAST_VALUE(RN) OVER(PARTITION BY City) AS Low
6   FROM cte1
7   WHERE RN=500
8   ), cte3 AS
9   (SELECT DISTINCT City, DATEDIFF(MAX(Date) OVER(PARTITION BY City), Date) AS Difference
10  FROM cte2 WHERE Low=500
11  )
12  SELECT City, MAX(Difference) Days_Took
13  FROM cte3
14  GROUP BY City
15  ORDER BY 2 LIMIT 1
16 """)
```

\* sc9\_out: pyspark.sql.dataframe.DataFrame = [City: string, Days\_Took: integer]

Command took 0.11 seconds — By mthurt@p0821agw011.com at 8/18/2023, 11:40:55 AM on Databricks 2.9's Cluster

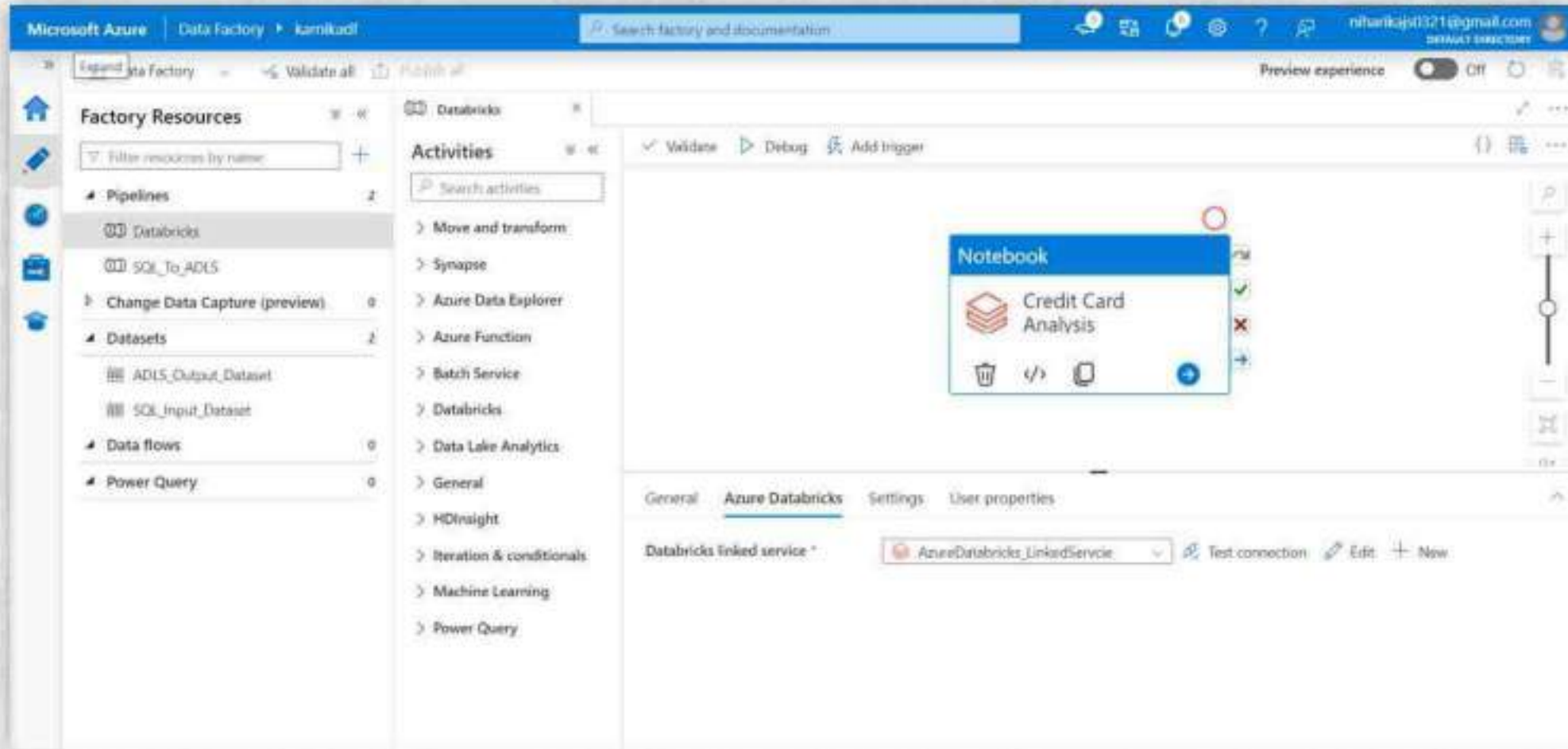
```
1 sc9_out.show()
```

+ (2) Spark jobs

City	Days_Took
Bengaluru	81

Command took 1.17 seconds — By mthurt@p0821agw011.com at 8/18/2023, 11:46:36 AM on Databricks 2.9's Cluster

# Scheduling Databricks Notebook in ADF for Periodical Analysis





# Roadblocks

- Faced issues with data understanding and handling irrelevant data.

**Resolution:** Consulting with domain experts who can help you determine which features are important for credit card analysis.

- The automated data ingestion Snowflake pipeline from ADLS to Snowflake encountered challenges due to a region mismatch between the two platforms and unavailability of an enterprise version of Snowflake.

**Resolution:** Manually loaded the data using COPY INTO and External stage for data ingestion.



# Conclusion

- **Customer Insights:** Through in-depth analysis, we gained valuable insights into how customers use their credit cards, revealing spending patterns and preferences.
- **Risk Identification:** Our analysis helped identify potential risks, enabling us to proactively manage and minimize the chances of defaults.
- **Smart Decisions:** Armed with data-driven insights, we can make informed decisions that benefit both customers and the business.
- **Financial Well-being:** By analyzing behavior, we contribute to customers' financial well-being by offering suitable credit limits and advice.



**Thank You**