HUMBER

GROUP PROJECT

TEAM:05

SUBMITTED TO: Ammar Al-Qaraghuli

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Link to the notebook

https://humberuni-aws.cloud.databricks.com/editor/notebooks/1820593246703517?o=5479912711442359

Link to the presentation video

Big Data Group Project-20241129_102111-Meeting Recording.mp4

Step1: Importing libraries

```
import matplotlib.pyplot as plt

from pyspark.sql.functions import log, ntile, col, when

from pyspark.sql import functions as F

from pyspark.sql.window import Window

from mpl_toolkits.mplot3d import Axes3D

import pandas as pd

import numpy as np
```

Step2: Importing file

```
df = spark.read.csv("s3://humber-lfb-databricks-class-files/sales_06_FY2020_21.csv",
header=True, inferSchema=True)

display(df)
```

Table

	order_id	order_date	status	item_id	sku	qty_ordered
1	100354678	2020-10-01	received	574772	oasis_Oasis-064-36	2
2	100354678	2020-10-01	received	574774	Fantastic_FT-48	1
3	100354680	2020-10-01	complete	574777	mdeal_DMC-610-8	
4	100354680	2020-10-01	complete	574779	oasis_Oasis-061-36	
5	100367357	2020-11-13	received	595185	MEFNAR59C38B6CA08CD	
6	100367357	2020-11-13	received	595186	MEFBUY59B7C3DDC2CA3-42	
7	100367360	2020-11-13	order_refunded	595192	MATDAN59C3C845B38F0	
8	100354677	2020-10-01	canceled	574769	GFE_19_USBLEDLight	
9	100354677	2020-10-01	canceled	574770	oasis_Kingston-32GB-DTIG4	
10	100354677	2020-10-01	canceled	574771	Geepas_GSB5420	
11	100356116	2020-10-08	order_refunded	577467	Geepas_GSB5420	
12	100358724	2020-10-21	order_refunded	581862	APPGEE59ADBEEE2EB9D	
13	100403034	2020-12-24	canceled	656937	APPWES59CA4D59CB41A	
14	100403034	2020-12-24	canceled	656938	APPPHI5A09939191938	

5,752+ rows | Truncated data due to byte limit | 18.75 seconds runtime   Refreshed 22 hours ago

Step3: Display row counts

display(df.count())

(2) Spark Jobs

286392

Step4: Display unique rows

%python

distinct_count = df.distinct().count()

display(distinct_count)

(3) Spark Jobs

286392

Step5: Create a new table "cus_info" with columns "cust_id", "order_date","price"

df.select("cust_id", "order_date", "price").createOrReplaceTempView("cus_info")

display(spark.sql("SELECT * FROM cus_info"))

Table

	1.2 cust_id	order_date	1.2 price
1	60124	2020-10-01	89.9
2	60124	2020-10-01	19
3	60124	2020-10-01	149.9
4	60124	2020-10-01	79.9
5	60124	2020-11-13	99.9
6	60124	2020-11-13	39.9
7	60124	2020-11-13	47.6
8	42485	2020-10-01	49
9	42485	2020-10-01	135
10	42485	2020-10-01	549.9
11	42485	2020-10-08	549.9
12	42485	2020-10-21	549.9
13	42485	2020-12-24	254.8
14	42485	2020-12-24	315.5
15	42485	2020-12-24	69.8

10,000+ rows | Truncated data due to row limit | 0.88 seconds runtime   Refreshed 23 hours ago

Step6: Checking for missing data

```
null_count = spark.sql("""
    SELECT
        COUNT(*) AS null_count
    FROM
        cus_info
    WHERE
        cust_id IS NULL OR
        order_date IS NULL OR
        price IS NULL
""")
display(null_count)
```

null_count: pyspark.sql.dataframe.DataFrame = [null_count: long]

Table

	null_count
1	0

1 row | 1.55 seconds runtime

Step7: Creating new table "rfm_info" with unique cust_id from "cus_info"

rfm_info = spark.sql("SELECT DISTINCT cust_id FROM cus_info ORDER BY cust_id ASC")

rfm_info.createOrReplaceTempView("rfm_info")

display(spark.sql("SELECT * FROM rfm_info"))

Table

	1.2 cust_id
1	4
2	15
3	16
4	20
5	21
6	23
7	28
8	32
9	33
10	41
11	44
12	47
13	54
14	56
15	58

10,000+ rows | Truncated data due to row limit | 1.50 seconds runtime

Step8: Creating a new column recency in the table "rfm_info"

rfm_info = spark.sql("""

SELECT

```
        r.cust_id,
        MAX(c.order_date) AS Recency
    FROM
        rfm_info r
    JOIN
        cus_info c
    ON
        r.cust_id = c.cust_id
    GROUP BY
        r.cust_id
    ORDER BY
        r.cust_id ASC
""")
rfm_info.createOrReplaceTempView("rfm_info")
display(spark.sql("SELECT * FROM rfm_info"))
```

Table

	1.2 cust_id	Recency
1	4	2021-09-29
2	15	2021-02-11
3	16	2020-11-12
4	20	2021-09-29
5	21	2021-02-03
6	23	2021-08-07
7	28	2021-05-21
8	32	2021-09-18
9	33	2021-08-21
10	41	2020-11-18
11	44	2021-07-08
12	47	2021-07-26
13	54	2021-08-14
14	56	2021-08-06
15	58	2021-06-30

10,000+ rows | Truncated data due to row limit | 3.70 seconds runtime

Step9: Creating a new column for Frequency in the table "rfm_info"

```
rfm_info = spark.sql("""
    SELECT
        r.cust_id,
        MAX(c.order_date) AS Recency,
        COUNT(c.cust_id) AS Frequency
    FROM
        rfm_info r
    JOIN
        cus_info c
    ON
        r.cust_id = c.cust_id
    GROUP BY
        r.cust_id
```

```
    ORDER BY
        r.cust_id ASC
""")
rfm_info.createOrReplaceTempView("rfm_info")
display(spark.sql("SELECT * FROM rfm_info"))
```

Table

	1.2 cust_id	Recency	Frequency
1	4	2021-09-29	41
2	15	2021-02-11	6
3	16	2020-11-12	20
4	20	2021-09-29	11
5	21	2021-02-03	1
6	23	2021-08-07	6
7	28	2021-05-21	11
8	32	2021-09-18	230
9	33	2021-08-21	132
10	41	2020-11-18	1
11	44	2021-07-08	9
12	47	2021-07-26	32
13	54	2021-08-14	72
14	56	2021-08-06	233
15	58	2021-06-30	17

10,000+ rows | Truncated data due to row limit | 3.88 seconds runtime

Step10: Creating a new column Monetary in the table "rfm_info"

```
rfm_info = spark.sql("""
    SELECT
        r.cust_id,
        MAX(c.order_date) AS Recency,
        COUNT(c.cust_id) AS Frequency,
        SUM(c.price) AS Monetary
    FROM
```

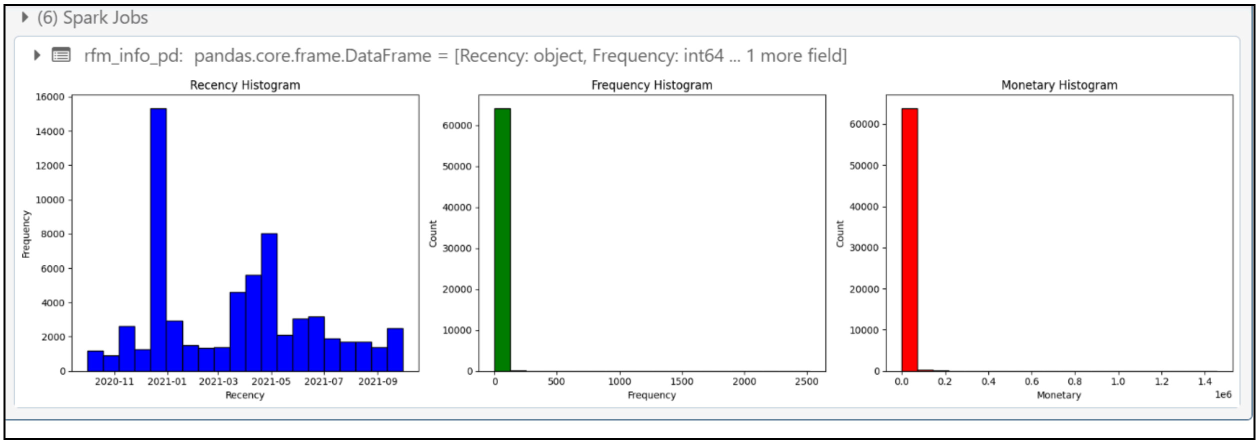
```
    rfm_info r
  JOIN
    cus_info c
  ON
    r.cust_id = c.cust_id
  GROUP BY
    r.cust_id
  ORDER BY
    r.cust_id ASC
""")
rfm_info.createOrReplaceTempView("rfm_info")
display(spark.sql("SELECT * FROM rfm_info"))
```

Table

	1.2 cust_id	Recency	Frequency	1.2 Monetary
1	4	2021-09-29	41	47400.2999999999...
2	15	2021-02-11	6	198.3
3	16	2020-11-12	20	16106.9
4	20	2021-09-29	11	31594.7
5	21	2021-02-03	1	21
6	23	2021-08-07	6	677.14
7	28	2021-05-21	11	4335.3
8	32	2021-09-18	230	171271.899999999...
9	33	2021-08-21	132	82769.20000000007
10	41	2020-11-18	1	219.9
11	44	2021-07-08	9	13813.4999999999...
12	47	2021-07-26	32	25298.40000000001
13	54	2021-08-14	72	29055.9999999999...
14	56	2021-08-06	233	162885.7999999996
15	58	2021-06-30	17	16536.7399999999...

Step11: Generate histograms to visualize the distributions of "Recency," "Frequency," and "Monetary" metrics

```
# Convert Spark DataFrame to Pandas DataFrame for plotting

rfm_info_pd = rfm_info.select("Recency", "Frequency", "Monetary").toPandas()

# Plot histograms

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Recency histogram

axes[0].hist(rfm_info_pd['Recency'], bins=20, color='blue', edgecolor='black')

axes[0].set_title('Recency Histogram')

axes[0].set_xlabel('Recency')

axes[0].set_ylabel('Frequency')

# Frequency histogram

axes[1].hist(rfm_info_pd['Frequency'], bins=20, color='green', edgecolor='black')

axes[1].set_title('Frequency Histogram')

axes[1].set_xlabel('Frequency')

axes[1].set_ylabel('Count')

# Monetary histogram

axes[2].hist(rfm_info_pd['Monetary'], bins=20, color='red', edgecolor='black')

axes[2].set_title('Monetary Histogram')

axes[2].set_xlabel('Monetary')

axes[2].set_ylabel('Count')

plt.tight_layout()

plt.show()
```



Recency Histogram:

- Most values are concentrated around specific dates, with a significant spike around early 2021. This suggests that many customers made recent purchases during that timeframe.
- Recency values are distributed unevenly, indicating varying activity levels among customers

Frequency Histogram:

- Many customers have very low purchase frequencies, indicating that most have made purchases only a few times.
- The distribution is highly skewed, with very few customers having high frequencies.

Monetary Histogram:

- Most monetary values are very small, indicating that the majority of customers spend relatively low.
- The graph shows an extreme right skew, with a few outliers contributing significantly higher amounts.

Step12 : Apply log transformation to normalize data in "rfm_info" table

rfm_info = rfm_info.withColumn("Log_Frequency", log("Frequency"))

rfm_info = rfm_info.withColumn("Log_Monetary", log("Monetary"))

rfm_info.createOrReplaceTempView("rfm_info")

display(spark.sql("SELECT * FROM rfm_info"))

Table

	cust_id	Recency	Frequency	Monetary	Log_Frequency	Log_Monetary
1	4	2021-09-29	41	47400.30000000002	3.713572066704308	10.766383836777063
2	15	2021-02-11	6	198.3	1.791759469228055	5.28978103552575
3	16	2020-11-12	20	16106.9000000000...	2.995732273553991	9.687003030590622
4	20	2021-09-29	11	31594.7000000000...	2.3978952727983707	10.36074466398919
5	21	2021-02-03	1	21	0	3.044522437723423
6	23	2021-08-07	6	677.14	1.791759469228055	6.517878046215625
7	28	2021-05-21	11	4335.299999999999	2.3978952727983707	8.374546090972395
8	32	2021-09-18	230	171271.899999999...	5.438079308923196	12.051007631159788
9	33	2021-08-21	132	82769.20000000001	4.882801922586371	11.32381129049505
10	41	2020-11-18	1	219.9	0	5.393172897560715
11	44	2021-07-08	9	13813.5	2.1972245773362196	9.533401653829532
12	47	2021-07-26	32	25298.4	3.4657359027997265	10.13849643160909
13	54	2021-08-14	72	29056	4.276666119016055	10.27698028140102
14	56	2021-08-06	233	162885.7999999999	5.4510384535657	12.000804620747635
15	58	2021-06-30	17	16536.7399999999...	2.833213344056216	9.713339851206953

10,000+ rows | Truncated data due to row limit | 3.65 seconds runtime   Refreshed 23 hours a

Step 13: Visualize normalized data

Add Log_Frequency and Log_Monetary columns

rfm_info = rfm_info.withColumn("Log_Frequency", F.log(F.col("Frequency") + 1))

rfm_info = rfm_info.withColumn("Log_Monetary", F.log(F.col("Monetary") + 1))

Convert Spark DataFrame to Pandas DataFrame for plotting

rfm_info_pd = rfm_info.select("Recency", "Log_Frequency", "Log_Monetary").toPandas()

Plot histograms

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

Recency histogram

axes[0].hist(rfm_info_pd['Recency'], bins=20, color='blue', edgecolor='black')

axes[0].set_title('Recency Histogram')

axes[0].set_xlabel('Recency')

axes[0].set_ylabel('Frequency')

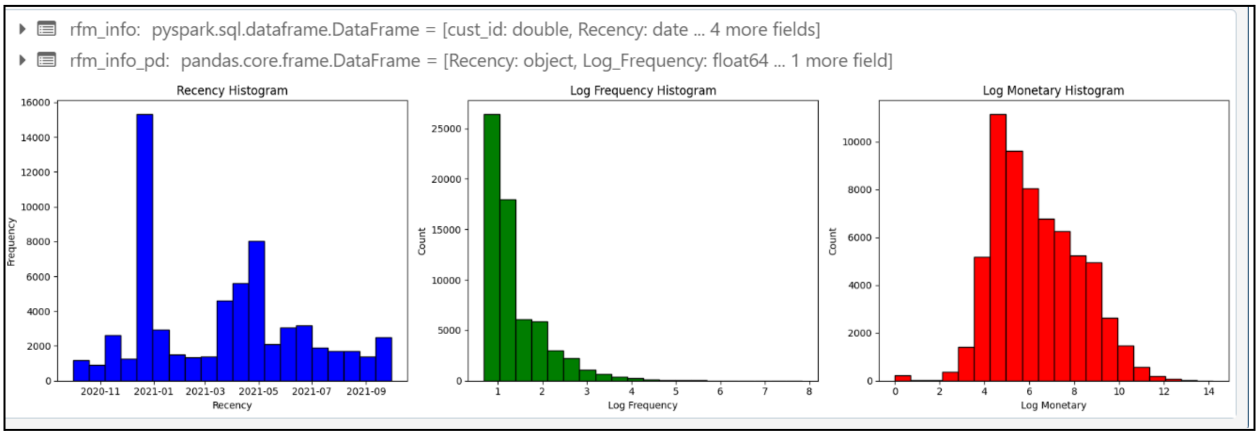
Log_Frequency histogram

axes[1].hist(rfm_info_pd['Log_Frequency'], bins=20, color='green', edgecolor='black')

axes[1].set_title('Log Frequency Histogram')

axes[1].set_xlabel('Log Frequency')

```
axes[1].set_ylabel('Count')

# Log_Monetary histogram

axes[2].hist(rfm_info_pd['Log_Monetary'], bins=20, color='red', edgecolor='black')

axes[2].set_title('Log Monetary Histogram')

axes[2].set_xlabel('Log Monetary')

axes[2].set_ylabel('Count')

plt.tight_layout()

plt.show()
```



Step 14: Renaming the columns

```
rfm_info = rfm_info.withColumnRenamed("Frequency", "Actual Frequency") \
            .withColumnRenamed("Monetary", "Actual Monetary") \
            .withColumnRenamed("Log_Frequency", "Frequency") \
            .withColumnRenamed("Log_Monetary", "Monetary")

rfm_info.createOrReplaceTempView("rfm_info")
```

Step 15: Reordering columns

```
rfm_info = rfm_info.select("cust_id", "Recency", "Frequency", "Monetary", "Actual Frequency", "Actual Monetary")
```

Step 16: Calculate percentile rank and rank customers by Recency and assign them into any one of the four tiers based on their percentile rank

```
from pyspark.sql import functions as F

from pyspark.sql.window import Window

# Calculate the quartiles for Recency

window = Window.orderBy(F.col("Recency").desc())

rfm_info = rfm_info.withColumn("Recency_rank", F.percent_rank().over(window))

# Assign Recency_tier based on quartiles

rfm_info = rfm_info.withColumn(

    "Recency_tier",

    F.when(F.col("Recency_rank") <= 0.25, "R-Tier-1")

    .when((F.col("Recency_rank") > 0.25) & (F.col("Recency_rank") <= 0.50), "R-Tier-2")

    .when((F.col("Recency_rank") > 0.50) & (F.col("Recency_rank") <= 0.75), "R-Tier-3")

    .otherwise("R-Tier-4")

).drop("Recency_rank")

rfm_info.createOrReplaceTempView("rfm_info")

display(spark.sql("SELECT * FROM rfm_info"))
```

Table

	Recency	1.2 Frequency	1.2 Monetary	Actual Frequency	1.2 Actual Monetary	Recency_tier
17	-09-30	2.48490664978800...	8.198144283214956	11	3633.2	R-Tier-1
18	-09-30	4.23410650459726	10.93765198262336	68	56254.1	R-Tier-1
19	-09-30	4.882801922586371	10.07597339690797	131	23764.100000000006	R-Tier-1
20	-09-30	1.09861228866810...	4.751864565138895	2	114.80000000000001	R-Tier-1
21	-09-30	1.38629436111989...	7.872607577470722	3	2623.4	R-Tier-1
22	-09-30	4.060443010546419	10.4170145243737...	57	33422.500000000015	R-Tier-1
23	-09-30	3.85014760171005...	12.8117546188623...	46	366499.3000000001	R-Tier-1
24	-09-30	5.41164605185503...	14.1910251951387...	223	1455739.3999999997	R-Tier-1
25	-09-30	1.94591014905531...	7.373123179823344	6	1591.5999999999997	R-Tier-1
26	-09-30	2.302585092994046	9.746827894520436	9	17098.899999999998	R-Tier-1
27	-09-30	1.38629436111989...	5.518656990529513	3	248.3	R-Tier-1
28	-09-30	2.772588722239781	6.75762982040449...	15	859.5999999999999	R-Tier-1
29	-09-30	1.09861228866810...	5.88860091164874...	2	359.9	R-Tier-1
30	-09-30	1.791759469228055	9.050230303547448	5	8519.5	R-Tier-1

Step 17 : Divide customers into quartiles based on their purchase Frequency and assign them to any one of the four tiers

```
%python

from pyspark.sql.functions import ntile, col, when

from pyspark.sql.window import Window

# Define a window specification

window_spec = Window.orderBy(col("Frequency").desc())

# Add a new column "Frequency_Tier" with ntile function to divide into 4 quartiles

rfm_info = rfm_info.withColumn("Frequency_Tier", ntile(4).over(window_spec))

# Map the quartile numbers to the desired tier labels

rfm_info = rfm_info.withColumn("Frequency_Tier",

                         when(col("Frequency_Tier") == 1, "F-Tier-1")

                         .when(col("Frequency_Tier") == 2, "F-Tier-2")

                         .when(col("Frequency_Tier") == 3, "F-Tier-3")

 .otherwise("F-Tier-4"))
```

display(rfm_info)

	cy	1.2 Monetary	1²₃ Actual Frequency	1.2 Actual Monetary	ABC Recency_tier	ABC Frequency_Tier
1	34170946	11.1555159655974...	2524	69947.59999999992	R-Tier-1	F-Tier-1
2	09369372	11.24974216518487	707	76859.10000000049	R-Tier-1	F-Tier-1
3	57709897	11.3084773105517...	608	81508.70000000046	R-Tier-1	F-Tier-1
4	19509559	10.81867137200873	436	49943.684999999976	R-Tier-2	F-Tier-1
5	05284438	14.0777425829192...	397	1299827.0999999975	R-Tier-1	F-Tier-1
6	54460526	8.873845855106767	329	7141.697999999998	R-Tier-1	F-Tier-1
7	47587197	10.0152102167385...	306	22363.053999999993	R-Tier-1	F-Tier-1
8	76607412	13.00474162124171	304	444515.1300000007	R-Tier-1	F-Tier-1
9	10819852	10.4103002753746...	285	33198.83800000006	R-Tier-1	F-Tier-1
10	13690637	12.518543478389	277	273358.61499999993	R-Tier-1	F-Tier-1
11	03146316	9.238120894986912	263	10280.700000000037	R-Tier-2	F-Tier-1
12	26156687	10.2301558154505...	241	27725.830000000027	R-Tier-1	F-Tier-1
13	33490655	12.67361820306645	240	319213.3829999998	R-Tier-1	F-Tier-1
14	15357702	12.0008107599993...	233	162885.7999999999	R-Tier-1	F-Tier-1

Step 18 : Segment customers into four Monetary based tiers based on their spending

```
window = Window.orderBy(F.col("Monetary").desc())

rfm_info = rfm_info.withColumn("Monetary_rank", F.percent_rank().over(window))

# Assign Monetary_tier based on quartiles

rfm_info = rfm_info.withColumn(

    "Monetary_tier",

    F.when(F.col("Monetary_rank") <= 0.25, "M-Tier-1")

    .when((F.col("Monetary_rank") > 0.25) & (F.col("Monetary_rank") <= 0.50), "M-Tier-2")

    .when((F.col("Monetary_rank") > 0.50) & (F.col("Monetary_rank") <= 0.75), "M-Tier-3")

    .otherwise("M-Tier-4")

).drop("Monetary_rank")

rfm_info.createOrReplaceTempView("rfm_info")

display(spark.sql("SELECT * FROM rfm_info"))
```

		Actual Frequency	Actual Monetary	Recency_tier	Frequency_Tier	Monetary_tier
9	29207	116	593717.5000000008	R-Tier-1	F-Tier-1	M-Tier-1
10	788...	59	551750.6000000003	R-Tier-1	F-Tier-1	M-Tier-1
11	24171	304	444515.1300000007	R-Tier-1	F-Tier-1	M-Tier-1
12	30719	211	436156.2000000003	R-Tier-1	F-Tier-1	M-Tier-1
13	41009	47	432130.1000000003	R-Tier-1	F-Tier-1	M-Tier-1
14	255...	52	407645.2000000001	R-Tier-1	F-Tier-1	M-Tier-1
15	735...	36	401852.4	R-Tier-1	F-Tier-1	M-Tier-1
16	576...	47	398604.9000000001	R-Tier-1	F-Tier-1	M-Tier-1
17	354...	54	394199.3000000001	R-Tier-1	F-Tier-1	M-Tier-1
18	353...	123	391904.9000000002	R-Tier-1	F-Tier-1	M-Tier-1
19	285...	41	384152.9000000002	R-Tier-1	F-Tier-1	M-Tier-1
20	896...	136	372842.0000000003	R-Tier-1	F-Tier-1	M-Tier-1
21	819...	212	369709.199999999	R-Tier-1	F-Tier-1	M-Tier-1
22	623...	46	366499.3000000001	R-Tier-1	F-Tier-1	M-Tier-1

Step 19: Summarize the Recency distribution for each tier

```
query = """
SELECT
  Recency_tier,
  MIN(Recency) AS min_date,
  MAX(Recency) AS max_date
FROM rfm_info
GROUP BY Recency_tier
ORDER BY Recency_tier
"""
result = spark.sql(query)
display(result)
```

▸ (8) Spark Jobs

▸ result: pyspark.sql.dataframe.DataFrame = [Recency_tier: string, min_date: date ... 1 more field]

Table

	Recency_tier	min_date	max_date
1	R-Tier-1	2021-05-20	2021-09-30
2	R-Tier-2	2021-03-27	2021-05-19
3	R-Tier-3	2020-12-27	2021-03-26
4	R-Tier-4	2020-10-01	2020-12-26

4 rows | 3.82 seconds runtime

Step 20: Summarise the Frequency distribution for each tier

```
query = """
SELECT
  Frequency_Tier,
  MIN(Frequency) AS min_frequency,
  MIN(`Actual Frequency`) AS min_actual_frequency,
  MAX(Frequency) AS max_frequency,
  MAX(`Actual Frequency`) AS max_actual_frequency
FROM rfm_info
GROUP BY Frequency_Tier
ORDER BY Frequency_Tier
"""
result = spark.sql(query)
display(result)
```

▸ result: pyspark.sql.dataframe.DataFrame = [Frequency_Tier: string, min_frequency: double ... 3 more fields]

Table

	Frequency_Tier	min_frequency	min_actual_frequency	max_frequency	max_actual_frequency
1	F-Tier-1	1.6094379124341003	4	7.83399634170946	252
2	F-Tier-2	1.0986122886681096	2	1.6094379124341003	
3	F-Tier-3	0.6931471805599453	1	1.0986122886681096	
4	F-Tier-4	0.6931471805599453	1	0.6931471805599453	

4 rows | 2.84 seconds runtime Refreshed 23 hours ago

Step 21 : Summarize the Monetary distribution for each tier

```
%python

query = """

SELECT

  Monetary_tier,

  MIN(Monetary) AS min_monetary,

  MIN(`Actual Monetary`) AS min_actual_monetary,

  MAX(Monetary) AS max_monetary,

  MAX(`Actual Monetary`) AS max_actual_monetary

FROM rfm_info

GROUP BY Monetary_tier

ORDER BY Monetary_tier

"""

result = spark.sql(query)

display(result)
```

Table

	Monetary_tier	min_monetary	min_actual_monetary	max_monetary	max_actual_monetary
1	M-Tier-1	7.680637427560936	2165	14.191025195138725	1455739.3999999997
2	M-Tier-2	5.993961427306569	399.9999999999999	7.68059125844345	2164.9
3	M-Tier-3	4.793308128103486	119.69999999999999	5.993712019648461	399.9
4	M-Tier-4	0	0	4.792479284293085	119.60000000000001

4 rows | 3.76 seconds runtime

Refreshed 23 hours ago

Step 22 : Divide customers into different segments based on RFM tiers

```
from pyspark.sql.functions import when

rfm_info = rfm_info.withColumn(
    "cust_segment",
    when(
        (rfm_info.Recency_tier == "R-Tier-1") &
        (rfm_info.Frequency_Tier == "F-Tier-1") &
        (rfm_info.Monetary_tier == "M-Tier-1"), "Champions"
    ).when(
        (rfm_info.Frequency_Tier == "F-Tier-1"), "Loyal Customers"
    ).when(
        (rfm_info.Recency_tier == "R-Tier-1") &
        ((rfm_info.Monetary_tier == "M-Tier-1") | (rfm_info.Monetary_tier == "M-Tier-2")),
"Potential loyalist"
    ).when(
        (rfm_info.Recency_tier == "R-Tier-1") &
        (rfm_info.Frequency_Tier == "F-Tier-3"), "New Customers"
    ).when(
        (rfm_info.Frequency_Tier == "F-Tier-1") &
```

```
        ((rfm_info.Monetary_tier == "M-Tier-2") | (rfm_info.Monetary_tier == "M-Tier-3")),
"Promising"

    ).when(

        (rfm_info.Recency_tier == "R-Tier-4") &

        (rfm_info.Frequency_Tier == "F-Tier-4") &

        (rfm_info.Monetary_tier == "M-Tier-4"), "Lost"

    ).when(

        (rfm_info.Recency_tier == "R-Tier-4") &

        ((rfm_info.Frequency_Tier == "F-Tier-3") | (rfm_info.Frequency_Tier == "F-Tier-4")) &

        ((rfm_info.Monetary_tier == "M-Tier-3") | (rfm_info.Monetary_tier == "M-Tier-4")),
"Hibernate"

    ).when(

        ((rfm_info.Recency_tier == "R-Tier-3") | (rfm_info.Recency_tier == "R-Tier-4")) &

        ((rfm_info.Frequency_Tier == "F-Tier-3") | (rfm_info.Frequency_Tier == "F-Tier-4")) &

        ((rfm_info.Monetary_tier == "M-Tier-1") | (rfm_info.Monetary_tier == "M-Tier-2")), "At
Risk"

    ).when(

        (rfm_info.Recency_tier == "R-Tier-4") &

        ((rfm_info.Frequency_Tier == "F-Tier-3") | (rfm_info.Frequency_Tier == "F-Tier-4")) &

        (rfm_info.Monetary_tier == "M-Tier-1"), "Can't loose them"

    ).when(

        ((rfm_info.Recency_tier == "R-Tier-3") | (rfm_info.Recency_tier == "R-Tier-4")) &

        ((rfm_info.Frequency_Tier == "F-Tier-2") | (rfm_info.Frequency_Tier == "F-Tier-3") |
(rfm_info.Frequency_Tier == "F-Tier-4")) &

        ((rfm_info.Monetary_tier == "M-Tier-2") | (rfm_info.Monetary_tier == "M-Tier-3") |
(rfm_info.Monetary_tier == "M-Tier-4")), "Needs attention"

    ).otherwise("Unknown")
```

)

rfm_info.createOrReplaceTempView("rfm_info")

display(spark.sql("SELECT * FROM rfm_info"))

rfm_info: pyspark.sql.dataframe.DataFrame = [cust_id: double, Recency: date ... 8 more fields]

Table

	ncy	1.2 Actual Monetary	Recency_tier	Frequency_Tier	Monetary_tier	cust_segment
1	223	1455739.3999999997	R-Tier-1	F-Tier-1	M-Tier-1	Champions
2	397	1299827.0999999975	R-Tier-1	F-Tier-1	M-Tier-1	Champions
3	142	1154207.6000000006	R-Tier-1	F-Tier-1	M-Tier-1	Champions
4	110	1033606.3000000013	R-Tier-1	F-Tier-1	M-Tier-1	Champions
5	122	1002832.6000000011	R-Tier-1	F-Tier-1	M-Tier-1	Champions
6	108	722789.3000000002	R-Tier-1	F-Tier-1	M-Tier-1	Champions
7	55	656946.2000000003	R-Tier-1	F-Tier-1	M-Tier-1	Champions
8	78	599366.8000000002	R-Tier-1	F-Tier-1	M-Tier-1	Champions
9	116	593717.5000000008	R-Tier-1	F-Tier-1	M-Tier-1	Champions
10	59	551750.6000000003	R-Tier-1	F-Tier-1	M-Tier-1	Champions
11	304	444515.1300000007	R-Tier-1	F-Tier-1	M-Tier-1	Champions
12	211	436156.2000000003	R-Tier-1	F-Tier-1	M-Tier-1	Champions
13	47	432130.1000000003	R-Tier-1	F-Tier-1	M-Tier-1	Champions
14	52	407645.2000000001	R-Tier-1	F-Tier-1	M-Tier-1	Champions

Step 23: The RFM segmentation results for the customers with IDs: 60149, 2844, 60767 and 39707 (answer to the requirement)

query = """

SELECT *

FROM rfm_info

WHERE cust_id IN (60149, 2844, 60767, 39707)

"""

result = spark.sql(query)

display(result)

	1.2 cust_id	Recency	1.2 Frequency	1.2 Monetary
1	39707	2021-09-29	5.986452005284438	14.0777425829192...
2	2844	2021-09-29	4.532599493153256	12.2508648284123...
3	60767	2020-10-12	2.39789527279837...	11.1302145064806...
4	60149	2020-10-01	1.09861228866810...	6.187442430349423

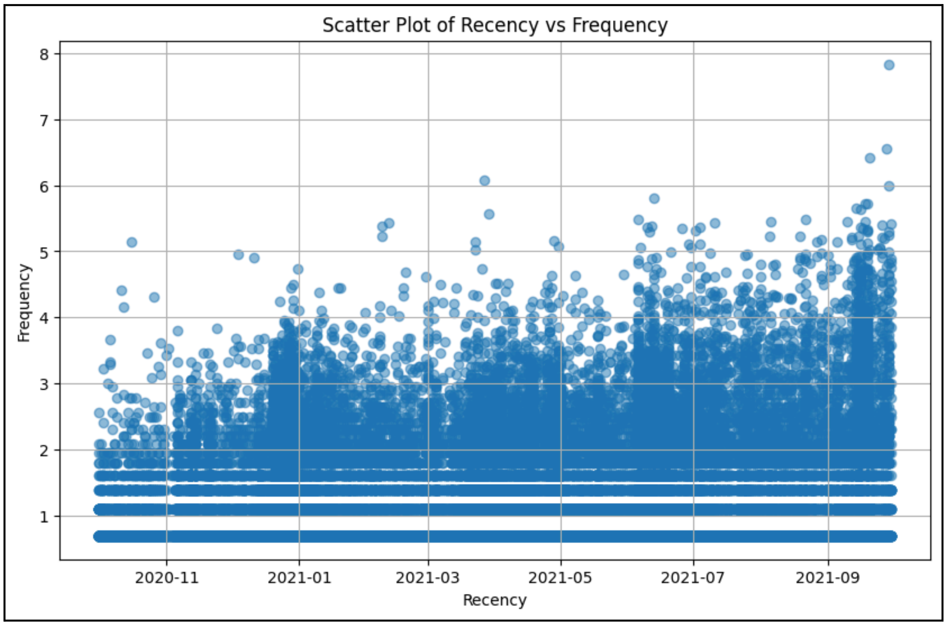
Recency_tier	Frequency_Tier	Monetary_tier	cust_segment
R-Tier-1	F-Tier-1	M-Tier-1	Champions
R-Tier-1	F-Tier-1	M-Tier-1	Champions
R-Tier-4	F-Tier-1	M-Tier-1	Loyal Customers
R-Tier-4	F-Tier-3	M-Tier-2	At Risk

Step 24: Generate a scatter plot to visualize the relationship between the "Recency" and "Frequency"

```
# Select relevant columns

recency_frequency_df = rfm_info.select("Recency", "Frequency")

# Convert to Pandas DataFrame for plotting

recency_frequency_pd = recency_frequency_df.toPandas()

# Create scatter plot

plt.figure(figsize=(10, 6))

plt.scatter(recency_frequency_pd["Recency"], recency_frequency_pd["Frequency"], alpha=0.5)

plt.title("Scatter Plot of Recency vs Frequency")

plt.xlabel("Recency")

plt.ylabel("Frequency")
```

plt.grid(True)

plt.show()



The scatter plot shows that a slightly higher number of customers are engaged with the company in recent times compared to the past. “Recency” trends appear to be stable over time, with no clear seasonal spikes.

Step 25 : Generate a scatter plot to visualize the relationship between Frequency and Monetary values

Select relevant columns

frequency_monetary_df = rfm_info.select("Frequency", "Monetary")

Convert to Pandas DataFrame for plotting

frequency_monetary_pd = frequency_monetary_df.toPandas()

Create scatter plot

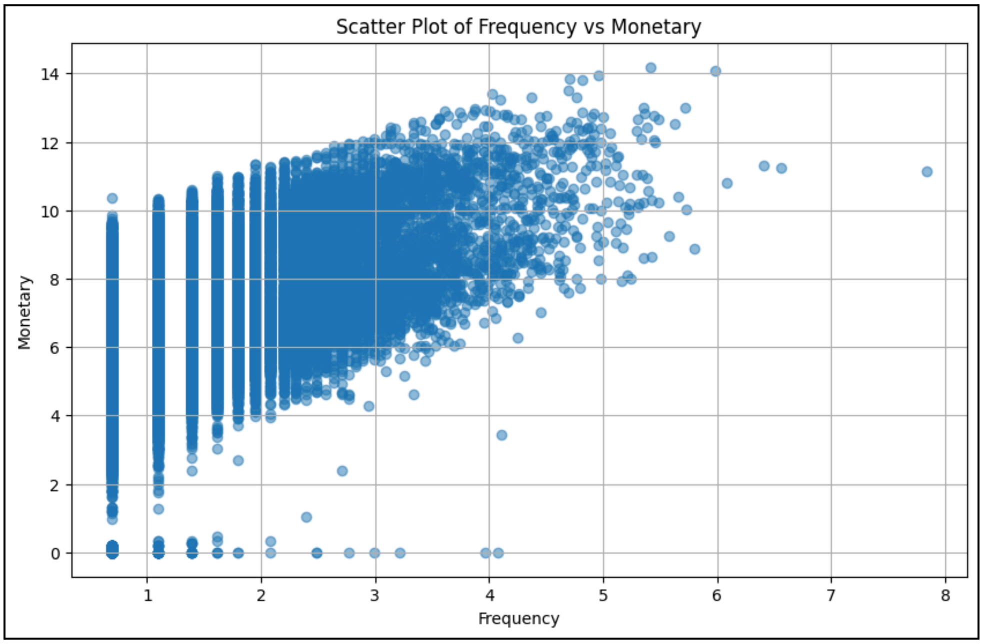
plt.figure(figsize=(10, 6))

plt.scatter(frequency_monetary_pd["Frequency"], frequency_monetary_pd["Monetary"], alpha=0.5)

plt.title("Scatter Plot of Frequency vs Monetary")

plt.xlabel("Frequency")

```
plt.ylabel("Monetary")

plt.grid(True)

plt.show()
```



The scatter plot shows a positive correlation between frequency and monetary value, with frequent customers contributing more revenue.

Step 26: Generate a scatter plot to visualize the relationship between Recency and Monetary values

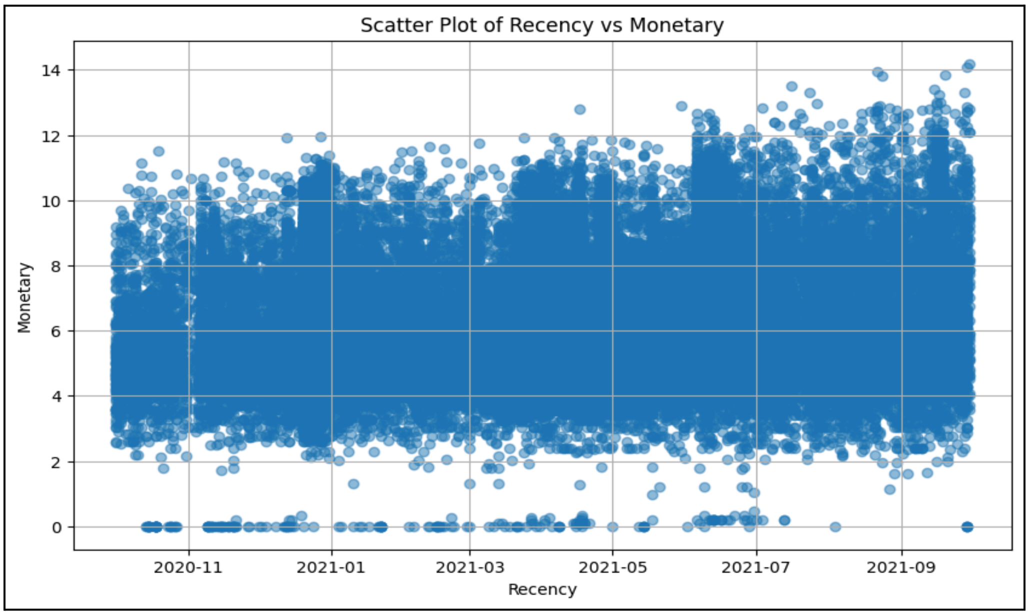
```
# Select relevant columns

recency_monetary_df = rfm_info.select("Recency", "Monetary")

# Convert to Pandas DataFrame for plotting

recency_monetary_pd = recency_monetary_df.toPandas()

# Create scatter plot

plt.figure(figsize=(10, 6))

plt.scatter(recency_monetary_pd["Recency"], recency_monetary_pd["Monetary"], alpha=0.5)

plt.title("Scatter Plot of Recency vs Monetary")
```

plt.xlabel("Recency")

plt.ylabel("Monetary")

plt.grid(True)

plt.show()



The scatter plot of Recency vs. Monetary shows that customers with recent interactions have slightly contributed more towards monetary values. The dense clustering over the time around the similar range of "Monetary" values suggests many customers have moderate spending behaviour.

Step 27 :Create a 3D scatter plot to visualize the relationship between Recency, Frequency and Monetary values

Convert Spark DataFrame to Pandas DataFrame

rfm_info_pd = rfm_info.toPandas()

Convert 'Recency' column to numeric values (days since a reference date)

reference_date = pd.to_datetime('2024-11-23')

rfm_info_pd['Recency'] = (reference_date - pd.to_datetime(rfm_info_pd['Recency'])).dt.days

Create 3D scatter plot

fig = plt.figure()

ax = fig.add_subplot(111, projection='3d')

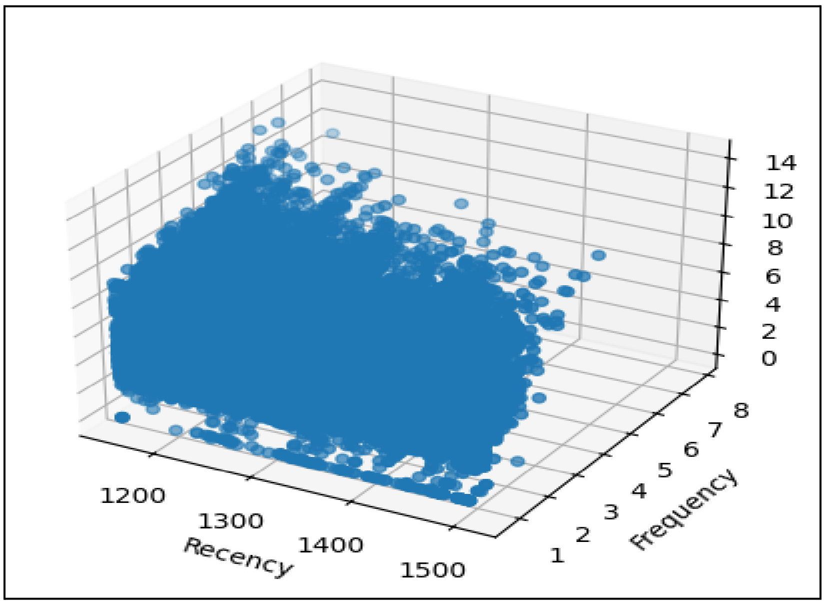
ax.scatter(rfm_info_pd['Recency'], rfm_info_pd['Frequency'], rfm_info_pd['Monetary'])

ax.set_xlabel('Recency')

ax.set_ylabel('Frequency')

ax.set_zlabel('Monetary')

plt.show()



The graph suggests a dominant group of low-frequency, low-spending customers who haven't shopped recently, with a smaller group of valuable, high-spending customers worth focusing on for retention or engagement strategies

Step 28 : Create a 3D scatter plot with 'Recency', 'Frequency', and 'Monetary' as the axes to visualize the data for the 'Champions' segment.

Filter data for "Champions" segment

champions_df = rfm_info.filter(rfm_info.cust_segment == "Champions")

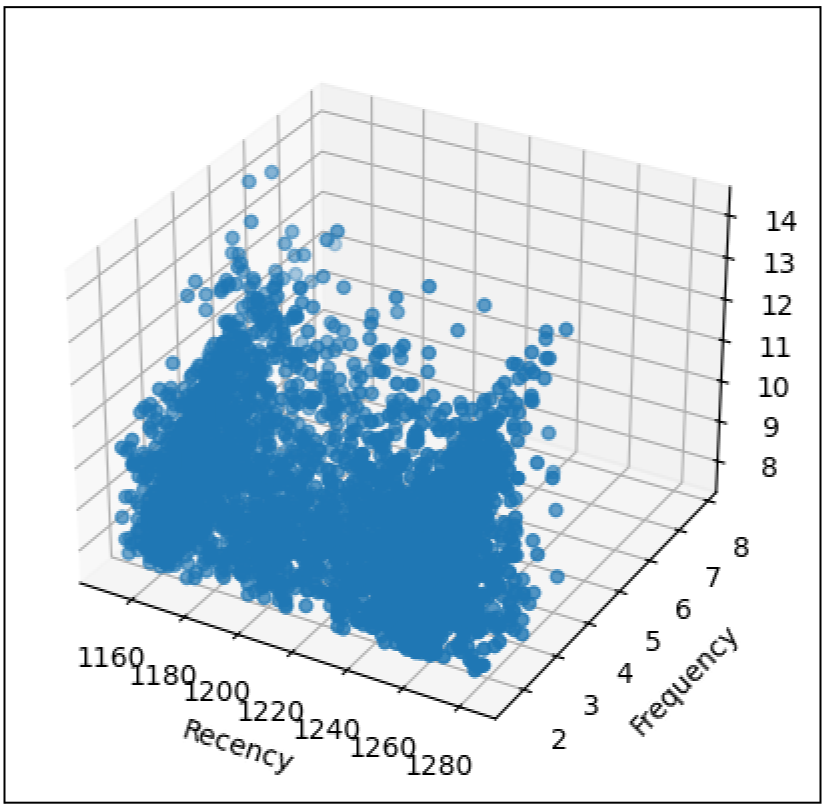
Convert Spark DataFrame to Pandas DataFrame

champions_pd = champions_df.toPandas()

Convert 'Recency' column to numeric values (days since a reference date)

reference_date = pd.to_datetime('2024-11-23')

```
champions_pd['Recency'] = (reference_date - pd.to_datetime(champions_pd['Recency'])).dt.days

# Create 3D scatter plot

fig = plt.figure()

ax = fig.add_subplot(111, projection='3d')

ax.scatter(champions_pd['Recency'], champions_pd['Frequency'], champions_pd['Monetary'])

ax.set_xlabel('Recency')

ax.set_ylabel('Frequency')

ax.set_zlabel('Monetary')

plt.show()
```



The graph for the "Champions" segment shows that these customers have made recent purchases, as indicated by recency values, and they exhibit high purchasing frequency. Their monetary contributions are significant, with some variability, suggesting that while most customers are consistent high spenders, a few stand out as exceptionally valuable.

Step 29 : Create a 3D scatter plot with 'Recency', 'Frequency', and 'Monetary' as the axes to visualize the data for the 'Lost' segment.

Filter the DataFrame for 'Lost' customer segment

rfm_lost_pd = rfm_info.filter(rfm_info['cust_segment'] == 'Lost').toPandas()

Convert 'Recency' column to numeric values (days since a reference date)

rfm_lost_pd['Recency'] = (reference_date - pd.to_datetime(rfm_lost_pd['Recency'])).dt.days

Create 3D scatter plot

fig = plt.figure()

ax = fig.add_subplot(111, projection='3d')

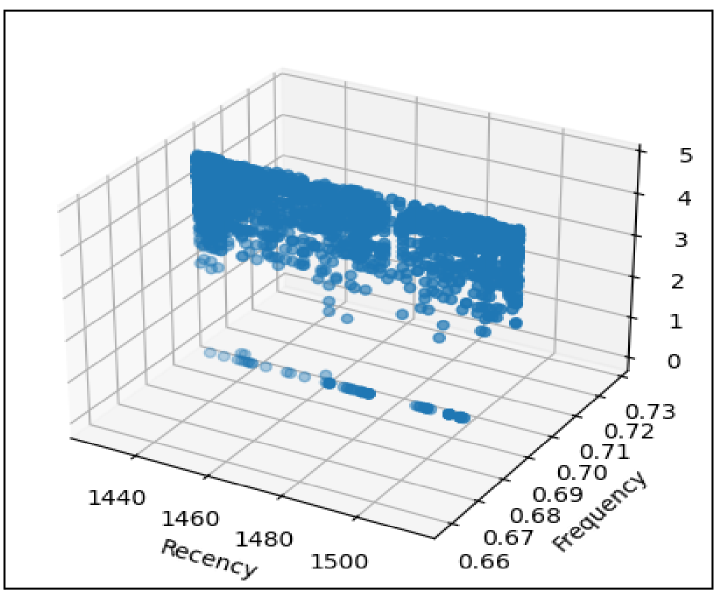
ax.scatter(rfm_lost_pd['Recency'], rfm_lost_pd['Frequency'], rfm_lost_pd['Monetary'])

ax.set_xlabel('Recency')

ax.set_ylabel('Frequency')

ax.set_zlabel('Monetary')

plt.show()



This scatter plot for the "Lost" customer segment highlights key behavioral patterns. The Recency axis shows high values, indicating that these customers haven't made purchases for a long time. The Frequency values are generally low, suggesting infrequent past purchases, and the

Monetary values are also low, reflecting minimal spending. These characteristics align with customers who have disengaged or churned, showing inactivity across all three metrics.

Conclusion

The RFM customer segmentation is successfully implemented in AWS Databricks. The customers of the given company are divided into 10 significant segments to facilitate better understanding of customer behaviour and pave the way for deeper analysis, understanding and forecasting for improved sales and profitability.

Note: The RFM segmentation results for given customer IDs are retrieved in Step 23.