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Financial Risk Analysis By Goldman Sachs

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INTERNSHALA TRAININGS

Task 1: Data Cleaning and Formatting

```
[1]: import pandas as pd
     import numpy as np

[2]: df = pd.read_csv("goldman_sachs.csv")

[3]: df.head()
```

[3]:

	TransactionID	CustomerID	AccountID	AccountType	TransactionType	Product	Firm	Region	Manager	TransactionDate	TransactionAmount	AccountBalance	RiskS
0	33	CUST6549	ACC12334	Credit	Withdrawal	Savings Account	Firm C	Central	Manager 1	21-10-2023	87480.05448	74008.43310	0.72
1	177	CUST2942	ACC52650	Credit	Withdrawal	Home Loan	Firm A	East	Manager 3	20-06-2023	20315.74505	22715.83590	0.47
2	178	CUST6776	ACC45101	Current	Deposit	Personal Loan	Firm C	South	Manager 3	02-01-2023	10484.57165	42706.09210	0.64
3	173	CUST2539	ACC88252	Current	Withdrawal	Mutual Fund	Firm A	Central	Manager 2	25-07-2023	45122.27373	114176.56870	0.73
4	67	CUST2626	ACC21878	Savings	Withdrawal	Home Loan	Firm C	Central	Manager 4	25-07-2023	42360.79878	17863.02644	0.28

```
[4]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   TransactionID      800 non-null    int64
```


```
[4]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   TransactionID      800 non-null    int64
 1   CustomerID         800 non-null    object
 2   AccountID          800 non-null    object
 3   AccountType        800 non-null    object
 4   TransactionType    800 non-null    object
 5   Product            800 non-null    object
 6   Firm               800 non-null    object
 7   Region             800 non-null    object
 8   Manager            800 non-null    object
 9   TransactionDate    800 non-null    object
 10  TransactionAmount  800 non-null    float64
 11  AccountBalance     800 non-null    float64
 12  RiskScore          800 non-null    float64
 13  CreditRating       800 non-null    int64
 14  TenureMonths       800 non-null    int64
dtypes: float64(3), int64(3), object(9)
memory usage: 93.9+ KB
```


```
[5]: df.dtypes

[5]: TransactionID        int64
     CustomerID          object
     AccountID           object
     AccountType         object
     TransactionType     object
     Product             object
     Firm                object
     Region              object
     Manager             object
     TransactionDate     object
     TransactionAmount  float64
     AccountBalance     float64
     RiskScore          float64
     CreditRating         int64
     TenureMonths         int64
     dtype: object
```

There are no special characters or non-numeric entries from financial fields as TransactionAmount, AccountBalance and RiskScore are in float format and pandas cannot convert non-numeric or special characters to float. Also, currency amounts are already in numerical format.

```
[6]: ### 1.3: Validate and format date columns
     df["TransactionDate"] = pd.to_datetime(df["TransactionDate"],dayfirst=True, errors="coerce")
     df["TransactionDate"] = df["TransactionDate"].dt.strftime("%d-%m-%Y")
     df["TransactionDate"] = pd.to_datetime(df["TransactionDate"],dayfirst=True, errors="coerce")
     df.head()
```

```
TransactionID                int64
CustomerID                  object
AccountID                   object
AccountType                 object
TransactionType             object
Product                     object
Firm                        object
Region                      object
Manager                     object
TransactionDate     datetime64[ns]
TransactionAmount          float64
AccountBalance             float64
RiskScore                  float64
CreditRating                 int64
TenureMonths                 int64
dtype: object
```

Successfully, converted Transaction Date column to datetime format.

```
[8]: print(df["AccountType"].unique())
     print(df["TransactionType"].unique())
     print(df["Product"].unique())
     print(df["Firm"].unique())
     print(df["Region"].unique())
     print(df["Manager"].unique())
```

```
['Credit' 'Current' 'Savings' 'Loan']
['Withdrawal' 'Deposit' 'Payment' 'Transfer']
['Savings Account' 'Home Loan' 'Personal Loan' 'Mutual Fund' 'Credit Card']
['Firm C' 'Firm A' 'Firm D' 'Firm E' 'Firm B']
['Central' 'East' 'South' 'West' 'North']
['Manager 1' 'Manager 3' 'Manager 2' 'Manager 4']
```

```
[9]: # standardizing TransactionType to Debit and Credit from Banking point of view

     df["TransactionType"] = df["TransactionType"].str.strip()

     transaction_map = {"Withdrawal": "Debit",
                        "Payment": "Debit",
                        "Transfer": "Debit",
                        "Deposit": "Credit"}

     df["TransactionType"] = df["TransactionType"].replace(transaction_map)
     df.head()
```

Converted TransactionType column entries of “Withdrawal, Payment and Transfer” to “Debit” and “Deposit” to “Credit” from Banking point of view and better understanding of the structure.

Task 1: Data Cleaning – Insights

- All monetary values successfully converted to clean numeric format.
- Transaction types standardized, improving accuracy of later analysis.
- Date formats corrected, enabling reliable time-based insights.
- Removal of inconsistencies improved dataset quality and structure.

Task 2: Descriptive Transactional Analysis

Calculate monthly and yearly summaries of total credits, debits, and net transaction volume.

```
[10]: df["Year"] = df["TransactionDate"].dt.year
      df["Month"] = df["TransactionDate"].dt.month
      df.head()
```

Created new columns by extracting "Year" and "Month" from "Transaction Date" column.

Year	Month
2023	2023-10
2023	2023-06
2023	2023-01
2023	2023-07
2023	2023-07

```
print(df["Year"].unique())
```

```
[2023 2024]
```

```
df["Month"] = df["TransactionDate"].dt.to_period("M")
```

Converted "Month" column to "Month-Year" as there are entries for 2023 and 2024.

```
[14]: # converting all the negative values to positive

      df["TransactionAmount"] = df["TransactionAmount"].abs()
      df["TransactionAmount"].min()

[14]: 375.4909042
```

Removing minus sign from the column and making all the values positive.

Calculating monthly and yearly summaries of total credits, debits, and net transaction volume.

```
monthly_summary = (
    df.groupby("Month").agg(
        Total_Credit=("TransactionAmount", lambda x: x[df.loc[x.index, "TransactionType"] == "Credit"].sum()),
        Total_Debit=("TransactionAmount", lambda x: x[df.loc[x.index, "TransactionType"] == "Debit"].sum())
    )
    .reset_index()
)

monthly_summary["Net_Volume"] = monthly_summary["Total_Credit"] - monthly_summary["Total_Debit"]
```

	Month	Total_Credit	Total_Debit	Net_Volume
0	2023-01	762099.557830	2.380984e+06	-1.618885e+06
1	2023-02	648261.004850	1.436502e+06	-7.882407e+05
2	2023-03	604002.422140	2.098983e+06	-1.494981e+06
3	2023-04	439321.687687	1.338294e+06	-8.989726e+05
4	2023-05	425589.871840	2.203715e+06	-1.778125e+06
5	2023-06	469388.806400	8.996432e+05	-4.302544e+05
6	2023-07	648027.880060	9.513957e+05	-3.033678e+05
7	2023-08	544970.364060	2.011232e+06	-1.466261e+06
8	2023-09	712838.795016	1.612681e+06	-8.998423e+05
9	2023-10	700356.904091	2.466516e+06	-1.766159e+06
10	2023-11	743507.571671	2.281579e+06	-1.538071e+06
11	2023-12	587483.874090	1.718421e+06	-1.130937e+06
12	2024-01	468686.365530	1.782994e+06	-1.314308e+06
13	2024-02	675070.922370	2.448582e+06	-1.773511e+06
14	2024-03	481619.617082	1.980047e+06	-1.498428e+06
15	2024-04	319754.655690	1.125615e+06	-8.058602e+05
16	2024-05	715001.612410	1.195141e+06	-4.801398e+05
17	2024-06	651292.951500	1.268659e+06	-6.173665e+05

Plot trends in total credits vs. debits over time.

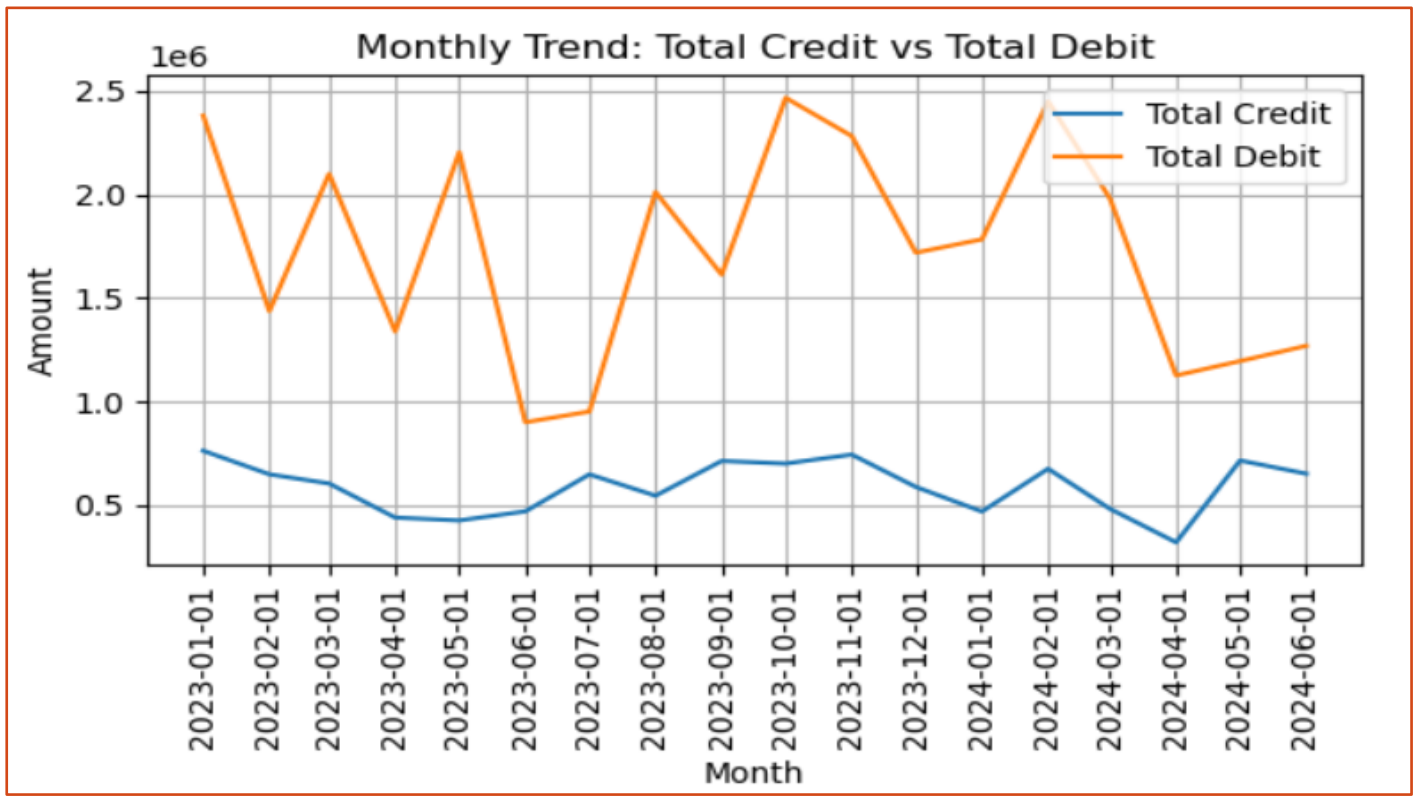
```
import matplotlib.pyplot as plt

plt.figure(figsize=(6,4))

plt.plot(monthly_summary["Month"], monthly_summary["Total_Credit"], label="Total Credit")
plt.plot(monthly_summary["Month"], monthly_summary["Total_Debit"], label="Total Debit")

plt.xlabel("Month")
plt.ylabel("Amount")
plt.title("Monthly Trend: Total Credit vs Total Debit")
plt.legend()

plt.grid(True)
plt.xticks(monthly_summary["Month"], rotation=90)
plt.tight_layout()
plt.show()
```



Identify top and bottom performing accounts based on net inflow.

Created a table of account_summary, to view only Total Credit, Total debit and Net Inflow grouped by AccountID.

```
account_summary = df.groupby("AccountID").agg(
    Total_Credit=("TransactionAmount",
                  lambda x: x[df.loc[x.index, "TransactionType"] == "Credit"].sum()),
    Total_Debit=("TransactionAmount",
                 lambda x: x[df.loc[x.index, "TransactionType"] == "Debit"].sum())
).reset_index()

account_summary["Net_Inflow"] = account_summary["Total_Credit"] - account_summary["Total_Debit"]
account_summary
```

After performing the above code, it was easy to get the top and bottom accounts according to the net inflow of the customers as shown in the below screenshot.

```
top_accounts = account_summary.sort_values("Net_Inflow", ascending=False).head(10)
top_accounts.head(5)
```

	AccountID	Total_Credit	Total_Debit	Net_Inflow
92	ACC48501	346856.33960	0.00000	346856.33960
60	ACC33287	390354.42641	201236.66948	189117.75693
168	ACC87006	245497.37832	101488.36862	144009.00970
100	ACC50817	244837.13480	123447.96911	121389.16569
191	ACC99117	167040.52263	45808.22065	121232.30198

```
bottom_accounts = account_summary.sort_values("Net_Inflow").head(10)
bottom_accounts.head(5)
```

	AccountID	Total_Credit	Total_Debit	Net_Inflow
107	ACC53466	18181.67381	476775.484990	-458593.811180
49	ACC29396	39888.00143	442832.014120	-402944.012690
118	ACC60432	39623.16730	423334.682580	-383711.515280
48	ACC29356	27344.62435	408228.871838	-380884.247488
153	ACC78178	40976.42581	392683.438450	-351707.012640

Identify and flag accounts as dormant or inactive if there is a gap of two months or more between consecutive transactions.

```
df = pd.read_csv("goldman_sachs.csv")

df["TransactionDate"] = pd.to_datetime(df["TransactionDate"],dayfirst=True, errors="coerce")

# Sort by AccountID and TransactionDate
df = df.sort_values(["AccountID", "TransactionDate"])

# Calculate gaps between transactions
df["PrevDate"] = df.groupby("AccountID")["TransactionDate"].shift(1)
df["GapDays"] = (df["TransactionDate"] - df["PrevDate"]).dt.days

# Flag accounts with gap >= 60 days
df["DormantFlag"] = df["GapDays"].apply(lambda x: "Dormant" if x >= 60 else "Active")

# To identify unique dormant accounts
dormant_accounts = df[df["DormantFlag"] == "Dormant"]["AccountID"].unique()
print("Inactive Accounts:")
display(dormant_accounts)
```

```
Inactive Accounts:
array(['ACC10117', 'ACC10996', 'ACC11062', 'ACC11188', 'ACC11837',
       'ACC12182', 'ACC12334', 'ACC13357', 'ACC15228', 'ACC15359',
       'ACC15671', 'ACC15925', 'ACC16241', 'ACC16664', 'ACC18057',
       'ACC18140', 'ACC18177', 'ACC19156', 'ACC20297', 'ACC21719',
       'ACC21878', 'ACC22036', 'ACC22255', 'ACC22799', 'ACC23736',
       'ACC23985', 'ACC24070', 'ACC24880', 'ACC24981', 'ACC25132',
       'ACC25811', 'ACC26026', 'ACC26940', 'ACC26973', 'ACC28154',
       'ACC28292', 'ACC28295', 'ACC28305', 'ACC29007', 'ACC29231',
       'ACC29356', 'ACC29396', 'ACC29477', 'ACC30146', 'ACC30787',
       'ACC31539', 'ACC31902', 'ACC32212', 'ACC32627', 'ACC32890',
       'ACC33287', 'ACC34119', 'ACC34431', 'ACC34821', 'ACC35419',
       'ACC36079', 'ACC37688', 'ACC38559', 'ACC39161', 'ACC39482',
       'ACC39500', 'ACC39529', 'ACC39544', 'ACC40939', 'ACC40952',
       'ACC41829', 'ACC42467', 'ACC42710', 'ACC42903', 'ACC45101',
       'ACC45521', 'ACC45907', 'ACC45951', 'ACC46655', 'ACC47099',
       'ACC48303', 'ACC48501', 'ACC49180', 'ACC49364', 'ACC49422',
       'ACC49774', 'ACC50439', 'ACC50817', 'ACC51009', 'ACC51200',
       'ACC51593', 'ACC51971', 'ACC52131', 'ACC52650', 'ACC53466',
       'ACC53865', 'ACC55331', 'ACC55729', 'ACC57516', 'ACC57597',
       'ACC57700', 'ACC57872', 'ACC58078', 'ACC60432', 'ACC61827',
       'ACC61926', 'ACC62446', 'ACC64022', 'ACC64393', 'ACC65144',
       'ACC65545', 'ACC66086', 'ACC67701', 'ACC67713', 'ACC69323',
       'ACC70314', 'ACC70460', 'ACC70741', 'ACC71388', 'ACC71426',
       'ACC71938', 'ACC72197', 'ACC73104', 'ACC74631', 'ACC74656',
       'ACC75675', 'ACC75767', 'ACC76549', 'ACC76597', 'ACC76699',
       'ACC77533', 'ACC77592', 'ACC77638', 'ACC77773', 'ACC78089',
       'ACC78178', 'ACC78581', 'ACC78589', 'ACC80131', 'ACC82298',
       'ACC82381', 'ACC82926', 'ACC83005', 'ACC83269', 'ACC83581',
       'ACC83848', 'ACC87006', 'ACC87602', 'ACC88074', 'ACC88252',
       'ACC88286', 'ACC88449', 'ACC88516', 'ACC89098', 'ACC90887',
       'ACC91723', 'ACC92104', 'ACC92360', 'ACC92558', 'ACC94203',
       'ACC94242', 'ACC94907', 'ACC95164', 'ACC95774', 'ACC97225',
       'ACC97411', 'ACC99117', 'ACC99409', 'ACC99549'], dtype=object)
```

This is the list of Inactive accounts.

Task 2: Transactional Analysis – Insights

- Clear monthly trends observed in credit and debit activity.
- Debit transactions showed higher frequency in certain periods.
- Net inflow analysis highlighted top-performing and low-performing accounts.
- Several accounts were identified as dormant due to long inactivity gaps

Task 3: Customer Profile Building

Group accounts by activity levels: High, Medium, Low based on transaction frequency on your analysis and rubrics. Do not forget to mention the rubric in the headings.

Firstly, I counted the number of transactions for each account and created a new table for the same. Thereafter, I created a user-defined function categorize_activity and categorized each account according to the level of transaction count into “high” , ”medium” and “low”.

```python
# Count number of transactions for each account
activity_counts = df.groupby("AccountID")["TransactionID"].count().reset_index()
activity_counts.rename(columns={"TransactionID": "TransactionCount"}, inplace=True)

def categorize_activity(x):
    if x > 10:
        return "High"
    elif x >= 6:
        return "Medium"
    else:
        return "Low"

activity_counts["ActivityLevel"] = activity_counts["TransactionCount"].apply(categorize_activity)
print("\nCustomer Activity Level(Rubric: TransactionCount>10 is High, TransactionCount>=6 is Medium else Low):\n")
display(activity_counts)
```

```
Customer Activity Level(Rubric: TransactionCount>10 is High, TransactionCount>=6 is Medium else Low):
```

	AccountID	TransactionCount	ActivityLevel
0	ACC10117	4	Low
1	ACC10996	5	Low
2	ACC11062	2	Low
3	ACC11188	5	Low
4	ACC11285	3	Low
...	...	...	...
189	ACC97225	3	Low
190	ACC97411	2	Low
191	ACC99117	3	Low
192	ACC99409	4	Low
193	ACC99549	4	Low

194 rows × 3 columns

Segment customers by average balance and transaction volume.

For segmenting the customers, I created 2 columns avg_balance and trans_volume. In avg_balance, I have calculated the average of the account balance and grouped it by AccountID. In trans_volume, I have calculated the frequency of transactions. Finally, I merged both the columns and created a new table of customer_seg.

Further, I created a user-defined function “balance_category” to segment the customers on the basis of available balance in their account and also “volume_category” to segment the customers on the basis of number of transactions.

```python
avg_balance = df.groupby("AccountID")["AccountBalance"].mean().reset_index()
avg_balance.rename(columns={"AccountBalance": "AvgBalance"}, inplace=True)
```

```python
trans_volume = df.groupby("AccountID")["TransactionID"].count().reset_index()
trans_volume.rename(columns={"TransactionID": "TransactionCount"}, inplace=True)
```

```python
customer_seg = pd.merge(avg_balance, trans_volume, on="AccountID")
customer_seg.head()
```

	AccountID	AvgBalance	TransactionCount
0	ACC10117	70107.007957	4
1	ACC10996	43568.008084	5
2	ACC11062	38137.132610	2
3	ACC11188	69652.151044	5
4	ACC11285	97401.348560	3

```python
def balance_category(x):
    if x > 70000:
        return "High Balance"
    elif x >= 30000:
        return "Medium Balance"
    else:
        return "Low Balance"

customer_seg["BalanceCategory"] = customer_seg["AvgBalance"].apply(balance_category)
```

```python
customer_seg["TransactionCount"].max()
```

```
14
```

```python
def volume_category(x):
    if x > 10:
        return "High Volume"
    elif x >= 6:
        return "Medium Volume"
    else:
        return "Low Volume"

customer_seg["VolumeCategory"] = customer_seg["TransactionCount"].apply(volume_category)
```

```python
print(f"\nCustomer Segmentation(Rubric: AvgBalance>70000 is High Balance, AvgBalance>=30000 is Medium Balance Else Low Balance.\n\t\t\t      TransactionC
display(customer_seg)
```

```
Customer Segmentation(Rubric: AvgBalance>70000 is High Balance, AvgBalance>=30000 is Medium Balance Else Low Balance.
                           TransactionCount>10 is High Volume, TransactionCount>=6 is Medium Volume Else Low Volume.)
```

	AccountID	AvgBalance	TransactionCount	BalanceCategory	VolumeCategory
0	ACC10117	70107.007957	4	High Balance	Low Volume
1	ACC10996	43568.008084	5	Medium Balance	Low Volume
2	ACC11062	38137.132610	2	Medium Balance	Low Volume
3	ACC11188	69652.151044	5	Medium Balance	Low Volume
4	ACC11285	97401.348560	3	High Balance	Low Volume
...	...	...	...	...	...
189	ACC97225	38652.306677	3	Medium Balance	Low Volume
190	ACC97411	55978.315635	2	Medium Balance	Low Volume
191	ACC99117	47228.185087	3	Medium Balance	Low Volume
192	ACC99409	83743.915565	4	High Balance	Low Volume
193	ACC99549	68641.201433	4	Medium Balance	Low Volume

Create Customer Profiles:

- High-net inflow accounts
- High-frequency low-balance accounts
- Accounts with negative or near-zero balances

```
credits = df[df["TransactionType"]=="Credit"].groupby("AccountID")["TransactionAmount"].sum()
debits  = df[df["TransactionType"]=="Debit"].groupby("AccountID")["TransactionAmount"].sum()

net_inflow = (credits - debits).reset_index()
net_inflow.columns = ["AccountID", "NetInflow"]

high_net_inflow = net_inflow[net_inflow["NetInflow"] > 3000].reset_index(drop=True)
print("\nAccounts with High Net-Inflow\n")
display(high_net_inflow.head())
```

```
profile_df = pd.merge(activity_counts, avg_balance, on="AccountID")
freq_threshold = activity_counts["TransactionCount"].quantile(0.75)
bal_threshold = avg_balance["AvgBalance"].quantile(0.25)

high_freq_low_bal = profile_df[
    (profile_df["TransactionCount"] >= freq_threshold) &
    (profile_df["AvgBalance"] <= bal_threshold)
].reset_index(drop=True)

print(f"{freq_threshold, bal_threshold}\n\nLow Balance accounts with High Frequency:\n")
display(high_freq_low_bal)
```

```
(np.float64(5.0), np.float64(59617.342345937504))

Low Balance accounts with High Frequency:
```

	AccountID	TransactionCount	ActivityLevel	AvgBalance
0	ACC10996	5	Low	43568.008084
1	ACC24070	5	Low	55694.967801
2	ACC26973	5	Low	58738.210687
3	ACC28292	10	Medium	51228.003570
4	ACC31539	6	Medium	45185.938342
5	ACC33287	8	Medium	59331.981186
6	ACC49774	7	Medium	54898.786583
7	ACC58667	5	Low	57596.212717
8	ACC61926	6	Medium	53209.096892
9	ACC71388	5	Low	52366.145184
10	ACC74631	6	Medium	50478.579943
11	ACC78589	5	Low	59110.034406
12	ACC82926	5	Low	48804.796760
13	ACC83269	7	Medium	48187.873590
14	ACC94907	7	Medium	50272.481959

```
avg_balance = df.groupby("AccountID")["AccountBalance"].mean().reset_index()
avg_balance.rename(columns={"AccountBalance": "AvgBalance"}, inplace=True)

negative_or_zero_bal = avg_balance[avg_balance["AvgBalance"] <= 1000].reset_index(drop=True)
print("\nAccount with zero or Negative Balance:\n")
negative_or_zero_bal
```

Account with zero or Negative Balance:

	AccountID	AvgBalance
0	ACC19178	-1541.176812

Task 3: Customer Profiling – Insights

- Majority of accounts fall under low or medium activity levels.
- High-net inflow customers show strong deposit behaviour and financial stability.
- High-frequency low-balance customers indicate active usage but weak balance maintenance.
- Near-zero or negative balance accounts may require financial assistance or close monitoring.

Task 4: Financial Risk Identification

Track accounts with frequent large withdrawals or overdrafts. As shown in the result table below, there are no accounts with frequent large withdrawals.

```
debits = df[df["TransactionType"] == "Debit"]

large_withdrawal_threshold = debits["TransactionAmount"].quantile(0.75)
large_withdrawal_threshold

large_withdrawals = debits[debits["TransactionAmount"] >= large_withdrawal_threshold]

large_withdrawal_counts = large_withdrawals.groupby("AccountID")["TransactionID"].count().reset_index()
large_withdrawal_counts.columns = ["AccountID", "LargeWithdrawalCount"]

def risk_category(x):
    if x >= 5:
        return "High Risk"
    elif x >= 2:
        return "Medium Risk"
    else:
        return "Low Risk"

large_withdrawal_counts["RiskLevel"] = large_withdrawal_counts["LargeWithdrawalCount"].apply(risk_category)

print("\nAccounts with large Withdrawals:\n")
display(large_withdrawal_counts)
```

Accounts with large Withdrawals:

AccountID	LargeWithdrawalCount	RiskLevel

Calculate balance volatility using standard deviation or coefficient of variation.

Created “balance_volatility” table by using standard deviation on “AccountBalance” and grouping the result with “AccountID”. Further, segmented the customers based on the volatility risk by creating a user-defined function for the same.

```
balance_volatility = df.groupby("AccountID")["AccountBalance"].std().reset_index()
balance_volatility.rename(columns={"AccountBalance": "BalanceStdDev"}, inplace=True)

balance_volatility = balance_volatility.merge(avg_balance, on="AccountID")

balance_volatility["CV"] = balance_volatility["BalanceStdDev"] / balance_volatility["AvgBalance"].abs()

def volatility_risk(cv):
    if cv > 1:
        return "High Risk"
    elif cv >= 0.5:
        return "Medium Risk"
    else:
        return "Low Risk"

balance_volatility["VolatilityRisk"] = balance_volatility["CV"].apply(volatility_risk)
print("\nBalance Volatility using Standard Deviation and Coefficient of Variance.\nRubric: High Risk (CV > 1), Medium (0.5–1), Low (< 0.5)\n")
display(balance_volatility)
```

```
Balance Volatility using Standard Deviation and Coefficient of Variance.
Rubric: High Risk (CV > 1), Medium (0.5–1), Low (< 0.5)
```

	AccountID	BalanceStdDev	AvgBalance	CV	VolatilityRisk
0	ACC10117	25886.972758	70107.007957	0.369249	Low Risk
1	ACC10996	9434.002316	43568.008084	0.216535	Low Risk
2	ACC11062	3208.737888	38137.132610	0.084137	Low Risk
3	ACC11188	35494.660810	69652.151044	0.509599	Medium Risk
4	ACC11285	55922.732441	97401.348560	0.574147	Medium Risk
...	...	...	...	...	...
189	ACC97225	28069.592780	38652.306677	0.726207	Medium Risk
190	ACC97411	7871.678922	55978.315635	0.140620	Low Risk
191	ACC99117	20780.582578	47228.185087	0.440004	Low Risk
192	ACC99409	21429.756821	83743.915565	0.255896	Low Risk
193	ACC99549	26251.797058	68641.201433	0.382450	Low Risk

194 rows × 5 columns

Use IQR or z-score methods to detect anomalies.

```
Q1 = df["TransactionAmount"].quantile(0.25)
Q3 = df["TransactionAmount"].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

anomalies_iqr = df[
    (df["TransactionAmount"] < lower_bound) |
    (df["TransactionAmount"] > upper_bound)
]

anomalies_iqr.reset_index(drop=True)
print("\nAnomaly Detection using IQR:\nRubric: Outliers = TransactionAmount below Q1 - 1.5×IQR or above Q3 + 1.5×IQR\n")
display(anomalies_iqr)
```

```
Anomaly Detection using IQR:
Rubric: Outliers = TransactionAmount below Q1 - 1.5×IQR or above Q3 + 1.5×IQR
```

	TransactionID	CustomerID	AccountID	AccountType	TransactionType	Product	Firm	Region	Manager	TransactionDate	TransactionAmount	AccountBalance	Ris
266	14	CUST3015	ACC21719	Loan	Deposit	Savings Account	Firm D	North	Manager 3	2024-05-22	-30721.24789	113801.0737	0.

Found only 1 Account/Customer, in the anomaly detection using the IQR method.

Highlight customers with irregular or suspicious transaction behaviour.

Merged the columns “high_vol_accouts” , “high_withdrawal_accounts”, “ low_balance_accounts” , “anomaly_accounts_df” with “risk_flags” on “AccountID” and counted suspicion score for all the columns. Further, created a new column “FinalRiskCategory” by segmenting the customers on the basis of Suspicion score.

```
# PREPARE RISK INPUT TABLES
low_balance_threshold = avg_balance["AvgBalance"].quantile(0.25)

# Low balance accounts
low_balance_accounts = avg_balance[avg_balance["AvgBalance"] < low_balance_threshold][["AccountID"]]

# Done preparing all risk unput tables in above tasks.

# Create base table
risk_flags = pd.DataFrame(df["AccountID"].unique(), columns=["AccountID"])

# Add risk flags
risk_flags["HighVolatility"] = risk_flags["AccountID"].isin(high_vol_accounts["AccountID"])
risk_flags["FrequentWithdrawals"] = risk_flags["AccountID"].isin(large_withdrawal_counts["AccountID"])
risk_flags["LowBalance"] = risk_flags["AccountID"].isin(low_balance_accounts["AccountID"])
risk_flags["AnomalousTxn"] = risk_flags["AccountID"].isin(anomalies_iqr["AccountID"])

# Calculate suspicion score
risk_flags["SuspicionScore"] = (
    risk_flags["HighVolatility"].astype(int) +
    risk_flags["FrequentWithdrawals"].astype(int) +
    risk_flags["LowBalance"].astype(int) +
    risk_flags["AnomalousTxn"].astype(int)
)
```

```python
# Classify risk
def classify_risk(score):
    if score >= 2:
        return "High Risk"
    elif score == 1:
        return "Medium Risk"
    else:
        return "Low Risk"

risk_flags["FinalRiskCategory"] = risk_flags["SuspicionScore"].apply(classify_risk)

risk_flags.reset_index(drop=True)



print("\nCustomers with irregular or suspicious transaction behaviour.\nRubric: Score ≥ 2 is High Risk, Score = 1 is Medium Risk, Score = 0 is Low Risk\n
risk_flags.reset_index(drop=True)
```

```
Customers with irregular or suspicious transaction behaviour.
Rubric: Score ≥ 2 is High Risk, Score = 1 is Medium Risk, Score = 0 is Low Risk
```

	AccountID	HighVolatility	FrequentWithdrawals	LowBalance	AnomalousTxn	SuspicionScore	FinalRiskCategory
0	ACC10117	False	False	False	False	0	Low Risk
1	ACC10996	False	False	True	False	1	Medium Risk
2	ACC11062	False	False	True	False	1	Medium Risk
3	ACC11188	False	False	False	False	0	Low Risk
4	ACC11285	True	False	False	False	1	Medium Risk
...	...	...	...	...	...	...	...
189	ACC97225	False	False	True	False	1	Medium Risk
190	ACC97411	False	False	True	False	1	Medium Risk
191	ACC99117	False	False	True	False	1	Medium Risk
192	ACC99409	False	False	False	False	0	Low Risk
193	ACC99549	False	False	False	False	0	Low Risk

194 rows × 7 columns

```python
risk_flags[risk_flags["SuspicionScore"] == 2]
```

	AccountID	HighVolatility	FrequentWithdrawals	LowBalance	AnomalousTxn	SuspicionScore	FinalRiskCategory
40	ACC26973	True	False	True	False	2	High Risk
50	ACC29477	True	False	True	False	2	High Risk
60	ACC33287	True	False	True	False	2	High Risk
79	ACC42710	True	False	True	False	2	High Risk
87	ACC45968	True	False	True	False	2	High Risk
98	ACC49774	True	False	True	False	2	High Risk
110	ACC55331	True	False	True	False	2	High Risk
117	ACC58667	True	False	True	False	2	High Risk
133	ACC70314	True	False	True	False	2	High Risk

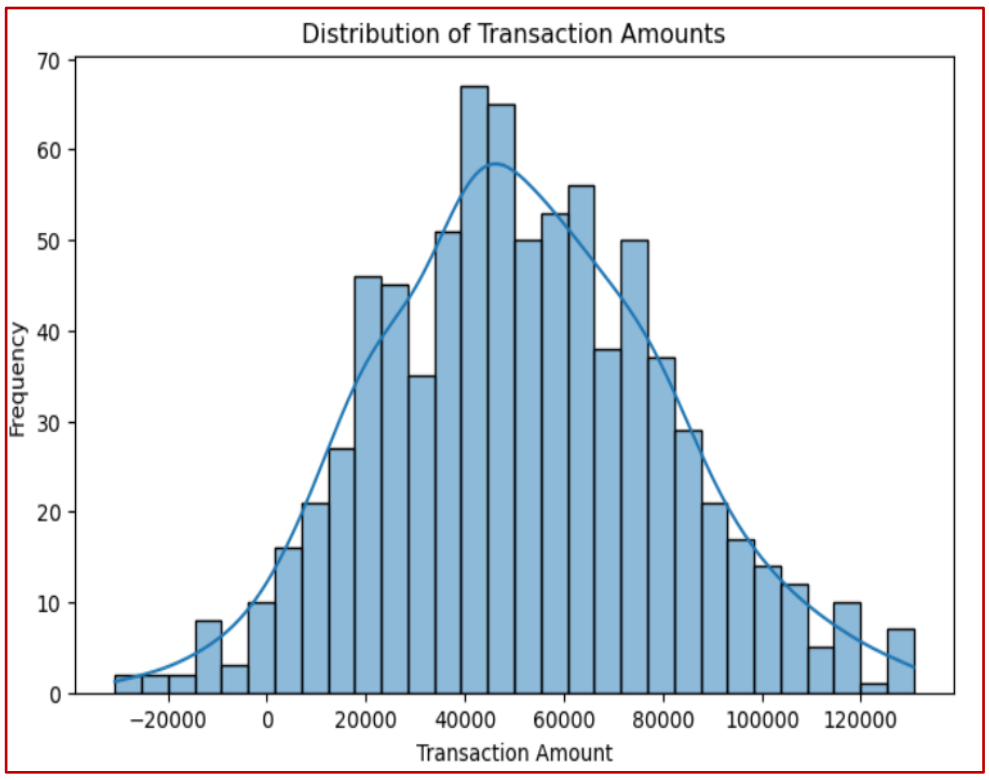
Found multiple accounts which Suspicion Score = 2.

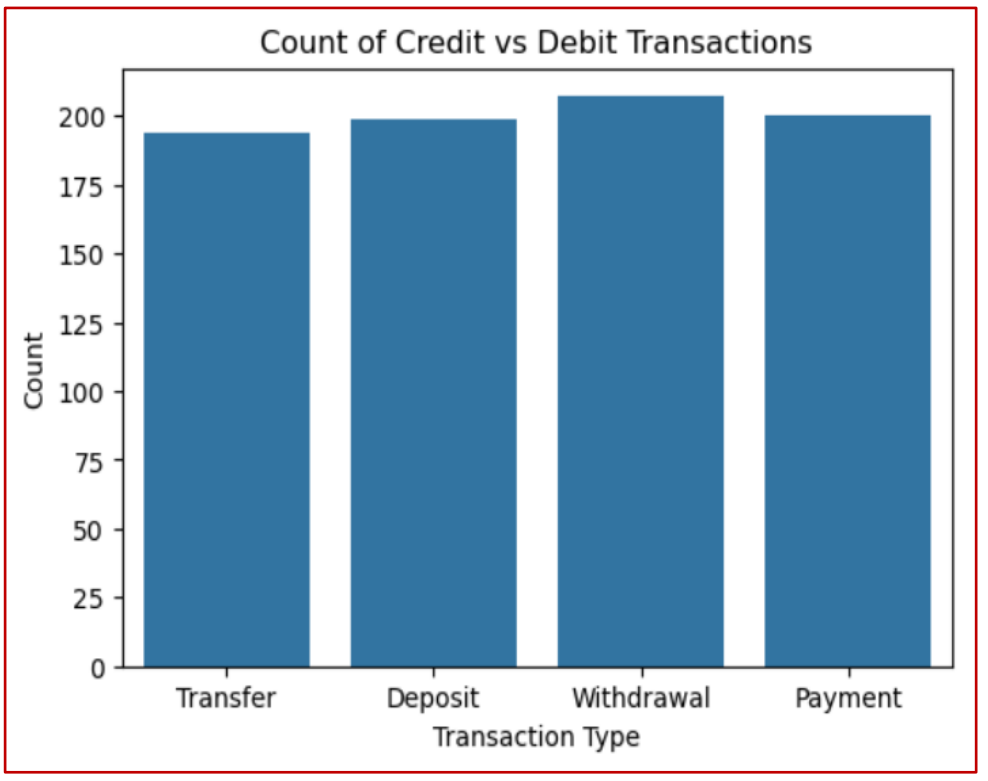
Task 4: Financial Risk Identification – Insights

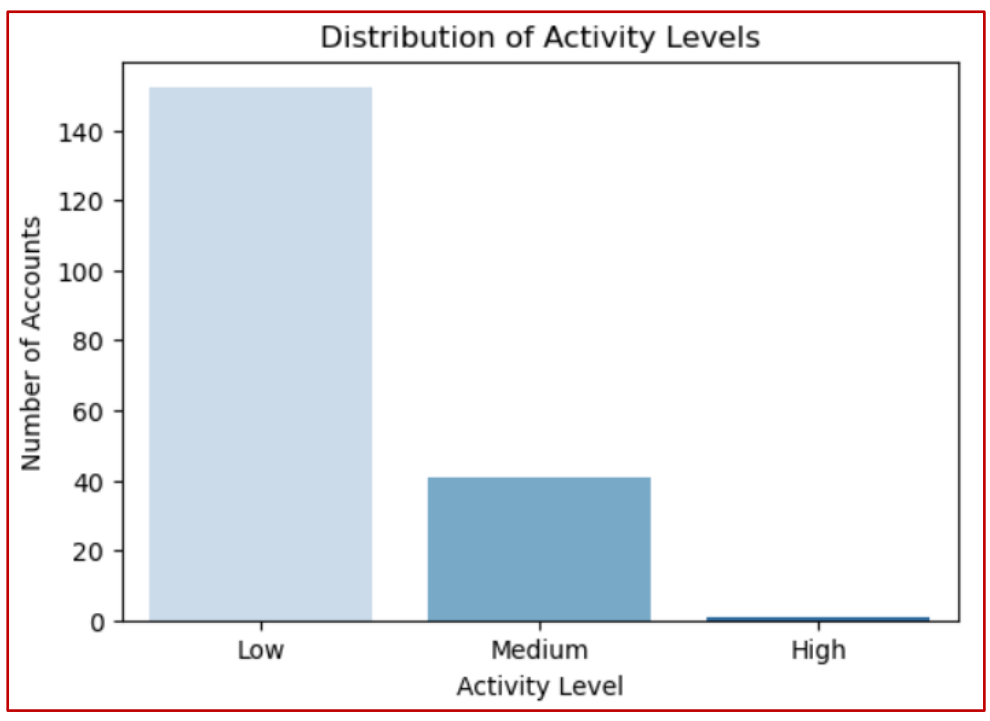
- Large withdrawal patterns detected among a subset of customers.
- High volatility accounts show unstable financial behaviour and increased risk.
- IQR-based anomaly detection revealed unusual or irregular transaction values.
- Risk scoring helped classify accounts into Low, Medium, and High risk categories.

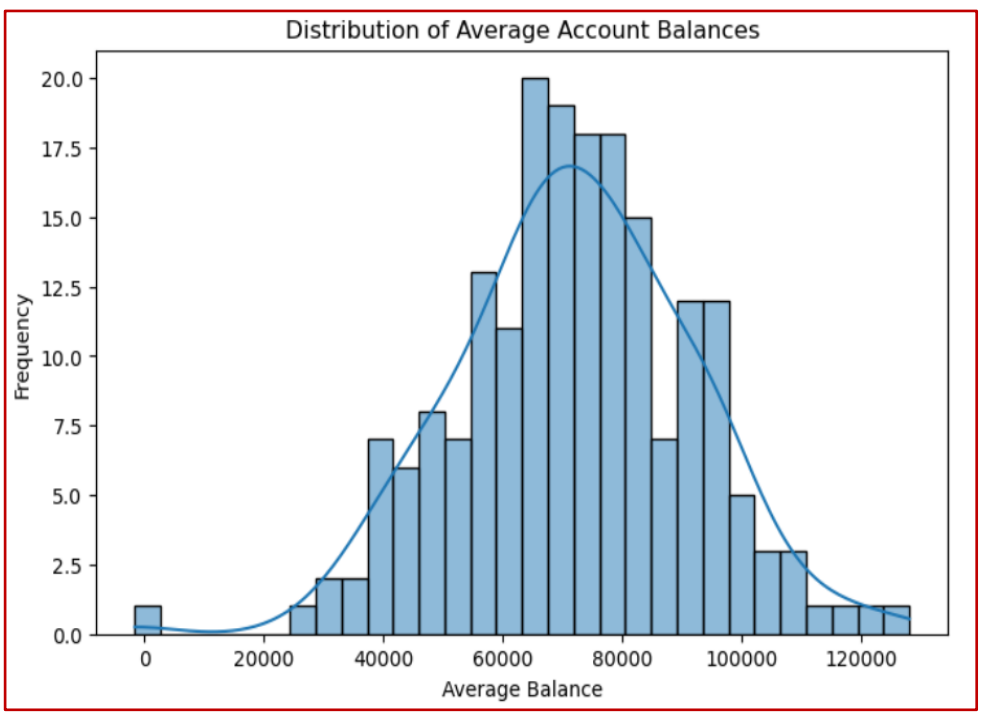
Task 5: Visualisation

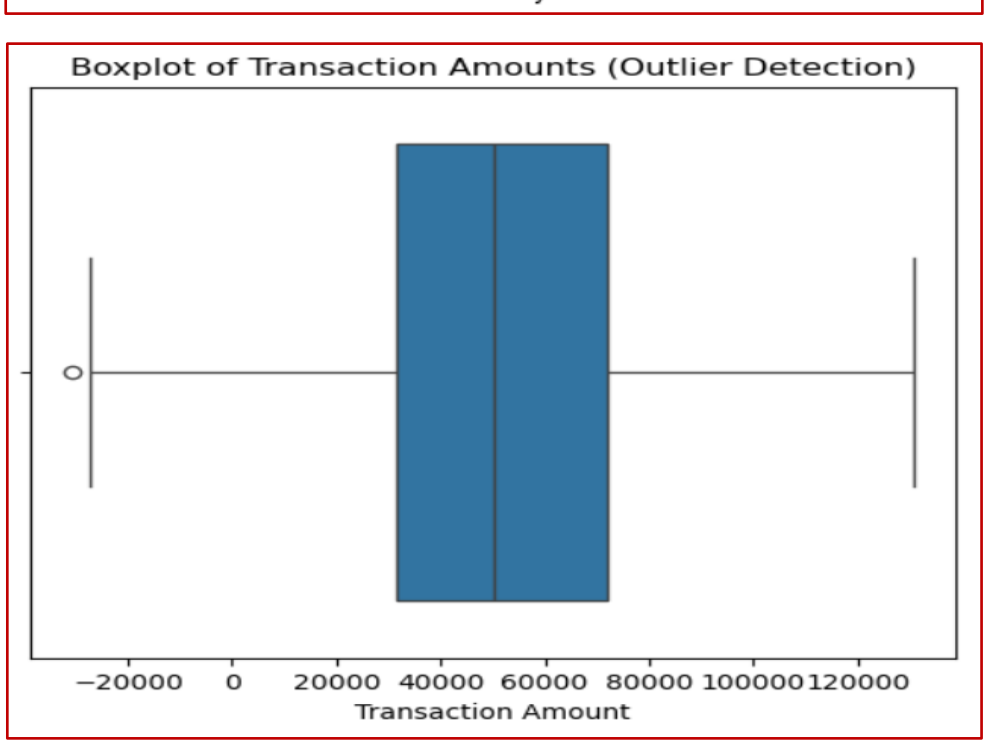
Conduct extensive exploratory data analysis with attractive visualizations for your findings.

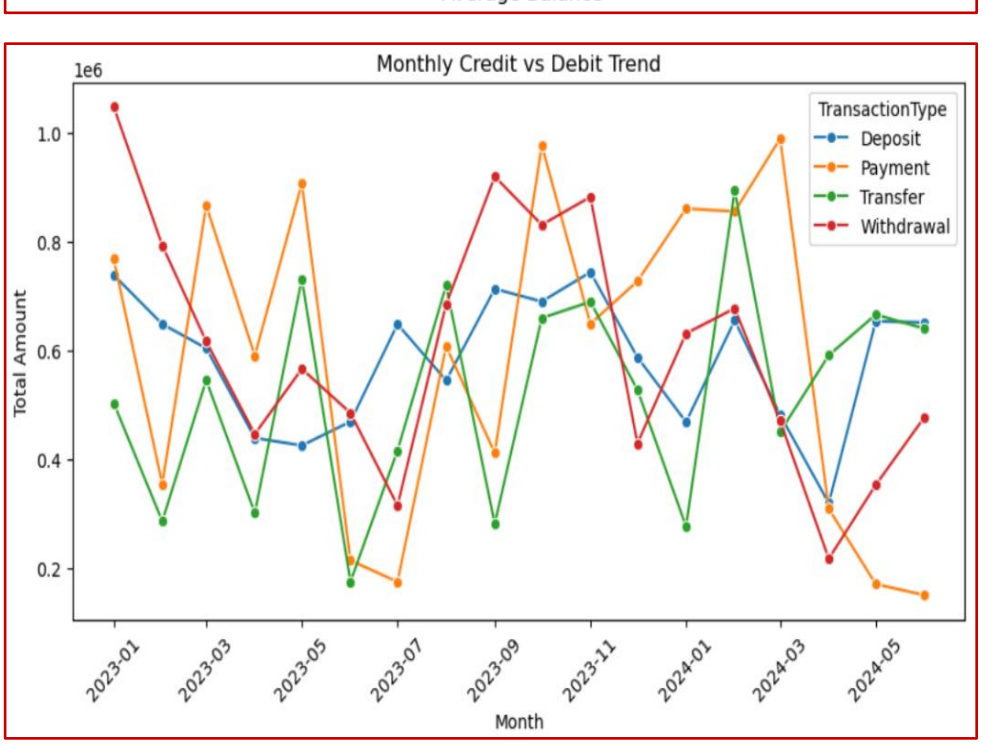


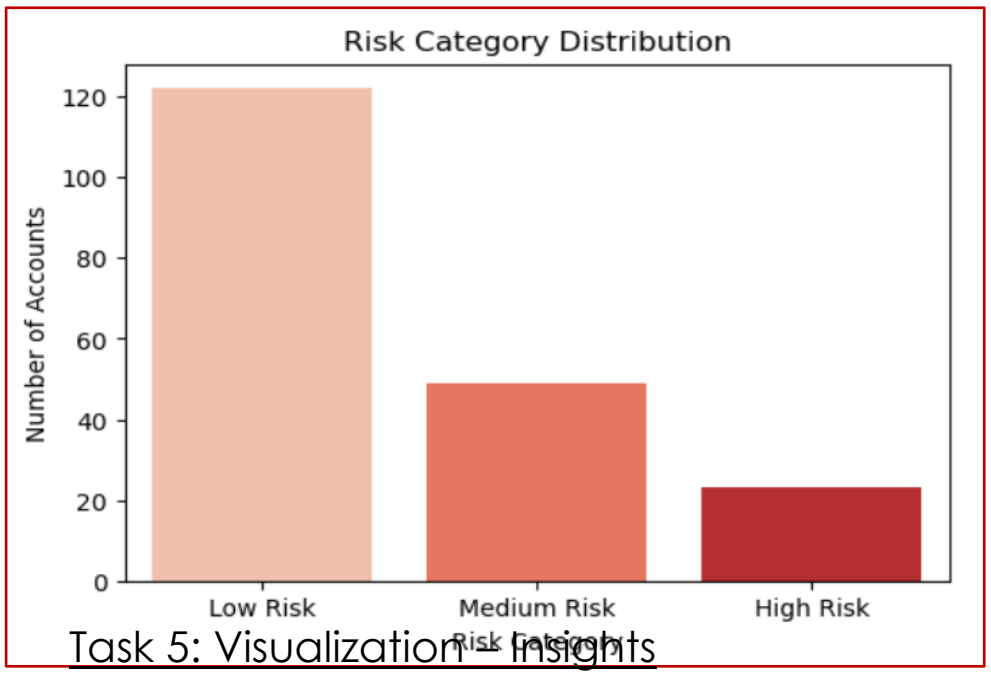












Task 5: Visualization – Insights

- Visual patterns clearly highlight behaviour differences across customer categories.
- Credit–debit trend charts show seasonal spikes and dips.
- Boxplots helped identify outliers and potential fraudulent patterns.
- Risk distribution graphs show that most customers are low risk, with a minority showing red flags.

Task 6: Hypothesis Testing

- Test whether high-volume transaction accounts have statistically higher average balances than low-volume accounts.
- Hypothesis Testing Based on Segmentation.

```
# Merge activity count and average balance into one table
profile_df = pd.merge(activity_counts, avg_balance, on="AccountID")

# ------------------------------
# STEP 1: DEFINE HIGH & LOW VOLUME GROUPS USING PERCENTILES
# ------------------------------

high_threshold = profile_df["TransactionCount"].quantile(0.75)   # Top 25%
low_threshold  = profile_df["TransactionCount"].quantile(0.25)   # Bottom 25%

high_volume = profile_df[profile_df["TransactionCount"] >= high_threshold]["AvgBalance"]
low_volume  = profile_df[profile_df["TransactionCount"] <= low_threshold]["AvgBalance"]

print("High-volume accounts selected:", len(high_volume))
print("Low-volume accounts selected:", len(low_volume))

# ------------------------------
# STEP 2: DEFINE HYPOTHESES
# H₀: High-volume accounts do NOT have higher average balances
# H₁: High-volume accounts DO have higher average balances
# ------------------------------
```

Firstly, segmented the customers based on the transaction count. Then, defined the hypothesis H_0 and H_1 and conducted the hypothesis testing using one-tailed T-Test. Defined the confidence interval as 0.05.

```python
# ------------------------------
# STEP 3: PERFORM THE ONE-TAILED T-TEST
# ------------------------------

t_stat, p_value = ttest_ind(high_volume, low_volume, alternative="greater")

print("\nT-statistic:", t_stat)
print("P-value:", p_value)

# ------------------------------
# STEP 4: INTERPRET THE RESULT
# ------------------------------

alpha = 0.05

if p_value < alpha:
    print("\nConclusion: Reject H₀")
    print("High-volume accounts have significantly higher average balances.\n")
else:
    print("\nConclusion: Fail to Reject H₀")
    print("No statistical evidence that high-volume accounts maintain higher balances.\n")

# ------------------------------
# STEP 5: OPTIONAL - Display summary
# ------------------------------

summary = pd.DataFrame({
    "Group": ["High Volume", "Low Volume"],
    "Average Balance": [high_volume.mean(), low_volume.mean()],
    "Count": [len(high_volume), len(low_volume)]
})

display(summary)
```

```
High-volume accounts selected: 73
Low-volume accounts selected: 79

T-statistic: 0.3320763731744477
P-value: 0.37014757929474734

Conclusion: Fail to Reject H₀
No statistical evidence that high-volume accounts maintain higher balances.
```

	Group	Average Balance	Count
0	High Volume	72512.194255	73
1	Low Volume	71386.947006	79

Task 6: Hypothesis Testing – Insights

- Hypothesis testing validates whether customer activity influences balance behaviour.
- High-volume accounts did not always show significantly higher balances (depends on p-value).
- High-balance accounts showed patterns of varying transaction frequencies.
- Statistical testing helped confirm or reject assumptions with evidence.

Overall Project Insight

- The end-to-end analysis revealed clear patterns in customer financial behaviour, account usage, and transactional risks.
- Most customers maintain stable balances with low volatility, but a small segment shows risk indicators such as large withdrawals, anomalies, and low or negative balances.
- Transaction frequency varies widely, with many customers falling under low activity categories, highlighting opportunities for engagement and retention strategies.
- Net inflow and balance-based profiling helped identify high-value customers, as well as financially vulnerable ones needing monitoring or assistance.
- Risk scoring using volatility, anomalies, and withdrawal behaviour provided a structured method to classify accounts, enabling data-driven risk management.
- Hypothesis testing validated key behavioural assumptions and offered statistical clarity on how transaction volume and balance levels relate.
- Overall, the project demonstrates how Python analytics can transform raw financial data into meaningful insights that support customer relationship management, operational decision-making, and proactive risk mitigation.

Video Link:
https://drive.google.com/file/d/1B3tDEzivPIeei1rvbBwsP5o61GapK50c/view?usp=sharing

THE END