financial-risk-analysis-barclays

November 17, 2025

1 Task 1: Data Cleaning and Formatting

[1]:
```
import pandas as pd
df = pd.read_csv('/content/Barclays_data.csv',skipinitialspace = True)
```

[2]:
```
df['TransactionAmount'] = df['TransactionAmount'].astype(str).str.
↪replace('[^0-9.-]', '', regex=True)
df['TransactionAmount'] = pd.to_numeric(df['TransactionAmount'],␣
↪errors='coerce')
```

[3]:
```
df['date_clean'] = pd.to_datetime(df.TransactionDate, errors = 'coerce')
```

[4]:
```
df['AccountType'] = df['AccountType'].str.strip().str.title()
df['TransactionType'] = df['TransactionType'].str.strip().str.upper()
```

[5]:
```
df = df.dropna(subset=['TransactionAmount','date_clean'])
```

[6]:
```
df
```

[6]:
```
     TransactionID CustomerID AccountID AccountType TransactionType  \
0              118   CUST3810  ACC49774     Savings         DEPOSIT
12              53   CUST5920  ACC49422      Credit      WITHDRAWAL
15             169   CUST5705  ACC42710     Current      WITHDRAWAL
16             185   CUST5705  ACC92360      Credit         PAYMENT
20             176   CUST5610  ACC25811        Loan         PAYMENT
..             …          …         …          …               …
785            159   CUST3015  ACC92558     Savings         PAYMENT
786            129   CUST4794  ACC49364      Credit        TRANSFER
794            157   CUST8660  ACC58078        Loan      WITHDRAWAL
796            106   CUST6937  ACC65144     Savings        TRANSFER
797             61   CUST3725  ACC70741        Loan         DEPOSIT

             Product    Firm   Region    Manager TransactionDate  \
0        Credit Card  Firm D     West  Manager 4      08-01-2024
12       Mutual Fund  Firm B    South  Manager 3      06-11-2023
15     Personal Loan  Firm D    North  Manager 1      12-05-2023
16   Savings Account  Firm C     East  Manager 3      06-09-2023
```

```
20        Mutual Fund  Firm B    South  Manager 2      06-02-2024
..                …      …       …        …             …
785  Savings Account  Firm A  Central  Manager 3      05-05-2023
786  Savings Account  Firm E    North  Manager 3      01-06-2023
794    Personal Loan  Firm A    North  Manager 1      12-02-2023
796      Mutual Fund  Firm D     East  Manager 3      06-07-2023
797      Mutual Fund  Firm E    North  Manager 4      02-01-2023

     TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths  \
0          20664.40982     88483.42208   0.483333           522            29
12         65215.76119     42285.97578   0.234974           837           227
15        101996.56660     83829.28291   0.185980           833           169
16         14658.77585    114622.94470   0.231351           395           157
20         33936.64367     79341.49720   0.620230           589            41
..                 …              …          …            …             …
785       101394.49730     26763.90303   0.387198           624            34
786        86674.52798     90166.74624   0.589847           647           158
794        68043.00322    127252.70430   0.632127           523           239
796        57508.00185     19847.81739   0.909006           748            72
797        77193.68065     30102.94832   0.655215           438           142

     date_clean
0    2024-08-01
12   2023-06-11
15   2023-12-05
16   2023-06-09
20   2024-06-02
..          …
785  2023-05-05
786  2023-01-06
794  2023-12-02
796  2023-06-07
797  2023-02-01

[322 rows x 16 columns]
```

2 Task 2: Descriptive Transactional Analysis

[7]:
```python
# monthly and yearly summaries of total credits, debits, and net transaction␣
↪volume

df['Month'] = df.date_clean.dt.to_period('M')
monthly_summary = df.groupby(['Month','TransactionType'])['TransactionAmount'].
↪sum().unstack().fillna(0)
print(monthly_summary)
```

```
TransactionType         DEPOSIT         PAYMENT        TRANSFER      WITHDRAWAL
Month
2023-01           102230.777000   396805.528330   513565.017980   216778.919470
2023-02           217868.116620    26053.329650    79537.164140        0.000000
2023-03           241474.616656     9488.942966   248537.787530    86566.271639
2023-04            87843.639073   133136.680141   403550.134090   218107.002100
2023-05           172541.331860   497248.214379   321364.717550   107696.799800
2023-06           416404.199180   420125.325190   525830.825482   532541.996616
2023-07           198972.624190   153024.036150   298699.014620        0.000000
2023-08           324188.385040   247024.374560   227742.811410   514315.115470
2023-09                0.000000   135823.722210    69011.597061    53861.137520
2023-10           309536.745680   584782.014370   190722.597000   189547.260700
2023-11           175926.341710   269261.476570   385045.992060   246308.520622
2023-12                0.000000   195928.864820   375420.492320   318325.461220
2024-01           228761.909890   163683.035030   269540.872120   246974.498689
2024-02           170014.437630    57762.903550    63160.236250   306502.307290
2024-04           186108.407092    95599.623240   104562.494450   290771.366781
2024-05            51341.593610   109852.803100   175556.727700   364910.784940
2024-06           278885.757140    86440.491340   216796.182450        0.000000
2024-07            75353.750360        0.000000   100617.686600        0.000000
2024-08           369808.172410   295788.149910   218219.082720   146651.547190
2024-09            65620.063336    34124.281540     7497.952844   122375.097090
2024-11            33799.770492    43362.123256   112160.831750    -2836.618108
2024-12           181101.468280   111307.781630    69016.657070    47162.331840
```

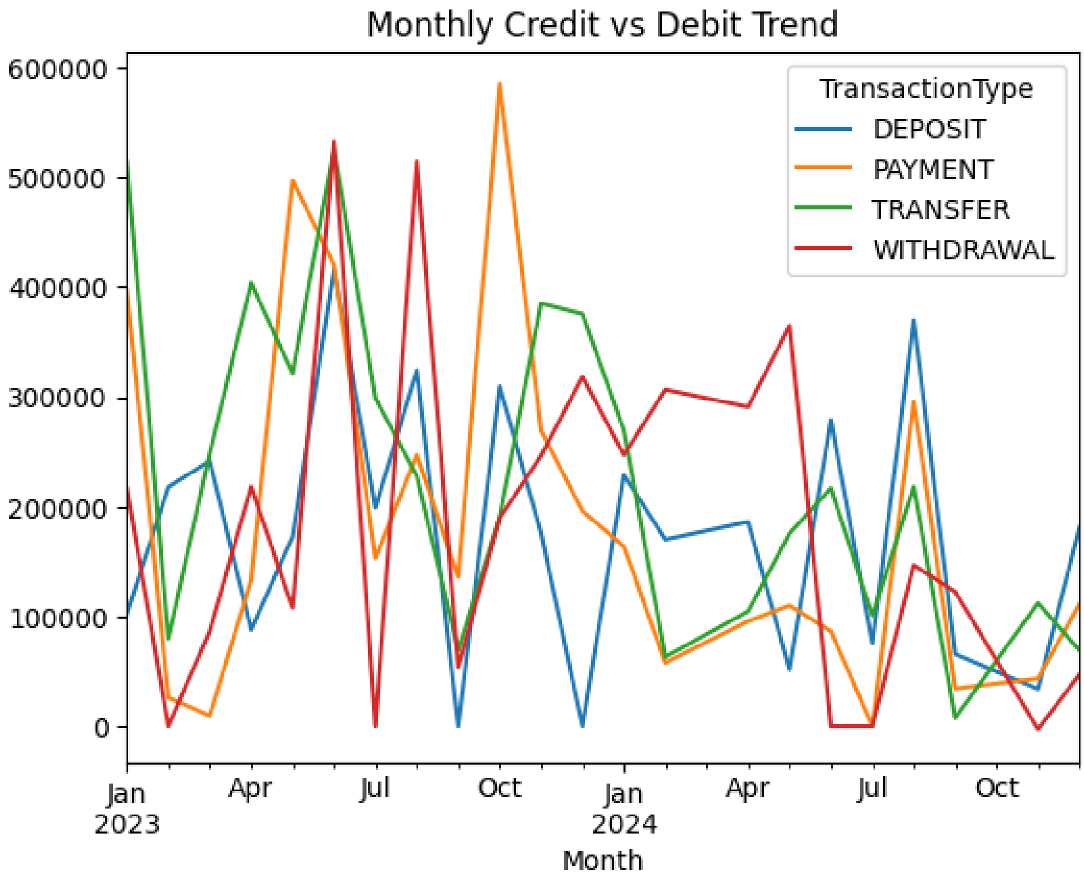
[8]:

```python
# Yearly summary

df['Year'] = df['date_clean'].dt.year
yearly_summary = df.groupby(['Year','TransactionType'])['TransactionAmount'].
 ↪sum().unstack().fillna(0)
print(yearly_summary)
```

```
TransactionType       DEPOSIT       PAYMENT      TRANSFER    WITHDRAWAL
Year
2023             2.246987e+06  3.068703e+06  3.639028e+06  2.484048e+06
2024             1.640795e+06  9.979212e+05  1.337129e+06  1.522511e+06
```

[9]:

```python
# Plotting trends over time
import matplotlib.pyplot as plt
monthly_summary.plot(kind='line')
plt.title("Monthly Credit vs Debit Trend")
plt.show()
```



[10]:

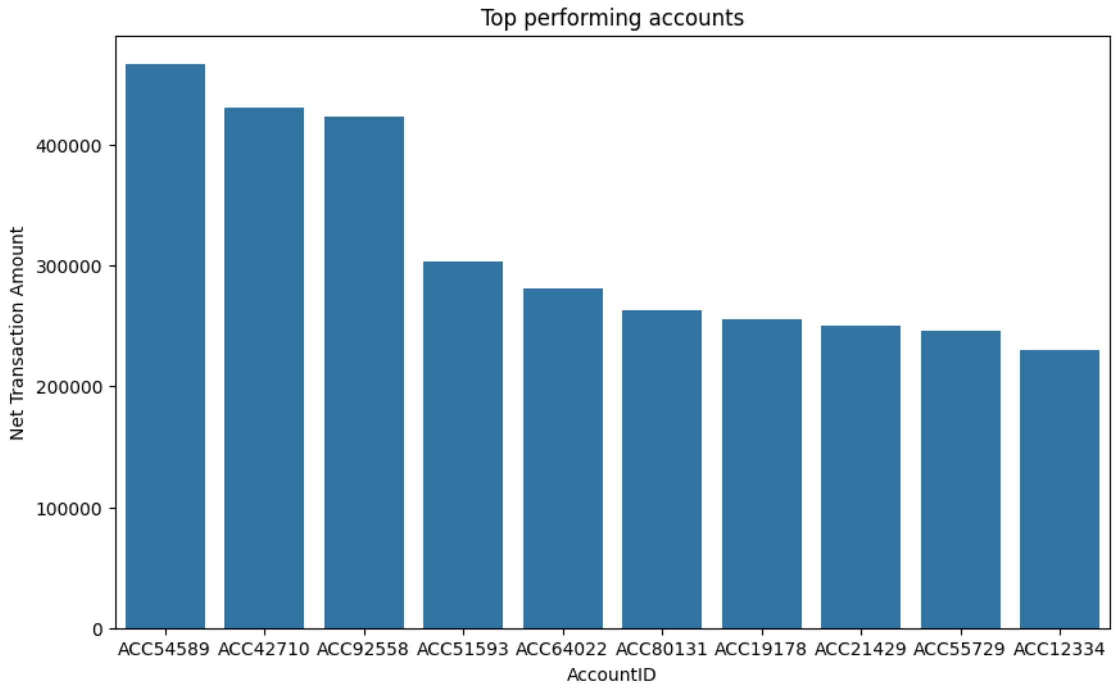
```python
# Top performing accounts based on net inflow
acct_net = df.groupby('AccountID')['TransactionAmount'].sum().
    ↪sort_values(ascending=False)
top10 = acct_net.head(10)
print(top10)
```

```
AccountID
ACC54589    466994.02713
ACC42710    430992.46852
ACC92558    423546.82565
ACC51593    302956.35635
ACC64022    280704.62307
ACC80131    262810.52358
ACC19178    255599.36727
ACC21429    250567.97260
ACC55729    245539.40399
ACC12334    230513.36771
Name: TransactionAmount, dtype: float64
```

[11]:
```python
import seaborn as sns
```

[12]:
```python
plt.figure(figsize=(10,6))
plt.title("Top performing accounts")
plt.xlabel("AccountID")
plt.ylabel("Net Transaction Amount")
sns.barplot(x=top10.index, y=top10.values)
```

[12]:
```
<Axes: title={'center': 'Top performing accounts'}, xlabel='AccountID',
ylabel='Net Transaction Amount'>
```



[13]:
```python
# Bottom performing accounts based on net inflow:
Bottom10 = acct_net.tail(10)
print(Bottom10)
```

```
AccountID
ACC96868    20346.625400
ACC52650    19904.777256
ACC35419    18969.706802
ACC76699    15533.680530
ACC48501    14881.167950
ACC61926     7835.672309
ACC43309     7674.262152
ACC42467     5847.832762
ACC65545     4120.984679
```

```
ACC90887     1086.210765
Name: TransactionAmount, dtype: float64
```

[14]:
```
# Identifying and flag accounts as dormant or inactive if there is a gap of two␣
↪months or more
# between consecutive transactions:
df_sorted = df.sort_values(['AccountID','date_clean'])
df_sorted['gap_days'] = df_sorted.groupby('AccountID')['date_clean'].diff().dt.
↪days
dormant_accounts = df_sorted[df_sorted['gap_days'] > 60]['AccountID'].unique()
print(dormant_accounts)
```

```
['ACC10117' 'ACC11062' 'ACC12334' 'ACC15228' 'ACC19156' 'ACC19178'
 'ACC21429' 'ACC21719' 'ACC21878' 'ACC22036' 'ACC22255' 'ACC23985'
 'ACC25132' 'ACC26940' 'ACC26956' 'ACC29007' 'ACC29396' 'ACC29477'
 'ACC30787' 'ACC31539' 'ACC31902' 'ACC32627' 'ACC33287' 'ACC34431'
 'ACC34568' 'ACC34821' 'ACC39482' 'ACC39529' 'ACC40939' 'ACC42467'
 'ACC42710' 'ACC45101' 'ACC45521' 'ACC45907' 'ACC46655' 'ACC47099'
 'ACC49180' 'ACC49364' 'ACC49422' 'ACC49774' 'ACC51593' 'ACC54589'
 'ACC58078' 'ACC60432' 'ACC64022' 'ACC66086' 'ACC67701' 'ACC69323'
 'ACC70314' 'ACC70460' 'ACC71388' 'ACC71938' 'ACC72197' 'ACC75675'
 'ACC76549' 'ACC76597' 'ACC77592' 'ACC77773' 'ACC78089' 'ACC78581'
 'ACC78589' 'ACC80131' 'ACC82298' 'ACC82381' 'ACC83005' 'ACC83269'
 'ACC83581' 'ACC83848' 'ACC88286' 'ACC88449' 'ACC90887' 'ACC92360'
 'ACC92558' 'ACC95164' 'ACC97225' 'ACC99409']
```

3 *Task 3: Customer Profile Building*

[15]:
```
# Grouping accounts by activity levels:
# Rubrics:
# Low --> Total Transactions<=2
# Medium ---> Total Transactions >2 and <=4
# High ---> Total Transaction >=5

profile = df.groupby('AccountID').agg(
    total_transactions=('TransactionID', 'count'),
    total_inflow = ('TransactionAmount', 'sum'),
    avg_balance = ('AccountBalance', 'mean')
).reset_index()

profile['activity_level'] = pd.cut(profile['total_transactions'],
                                   bins=[-1,2,4,1e9],
                                   labels=['Low','Medium','High'])
profile.head(30)
```

[15]:

	AccountID	total_transactions	total_inflow	avg_balance	activity_level
0	ACC10117	3	177550.151550	100686.898200	Medium
1	ACC10996	1	70136.967170	25464.127790	Low
2	ACC11062	2	110594.783980	65947.316965	Low
3	ACC11188	1	20835.546350	86796.680310	Low
4	ACC12334	3	230513.367710	27143.265607	Medium
5	ACC15228	4	169094.207541	93709.956587	Medium
6	ACC15359	2	50011.889380	66401.687335	Low
7	ACC15925	1	66974.968290	49648.462570	Low
8	ACC16241	1	48633.263000	15180.432510	Low
9	ACC16664	1	107144.803400	73757.355750	Low
10	ACC18057	1	65322.161190	66933.085960	Low
11	ACC18177	1	28894.675830	60440.182510	Low
12	ACC19156	3	139436.637030	88611.499527	Medium
13	ACC19178	6	255599.367270	79438.676415	High
14	ACC21264	1	28595.325890	47767.707370	Low
15	ACC21429	4	250567.972600	67914.810115	Medium
16	ACC21719	3	136661.203080	69424.634163	Medium
17	ACC21878	4	225271.849390	67497.561915	Medium
18	ACC22036	2	34620.171763	100935.461625	Low
19	ACC22255	3	105431.874740	50863.581503	Medium
20	ACC23736	1	93934.325730	113590.769900	Low
21	ACC23985	3	176671.315090	78987.177790	Medium
22	ACC24070	2	125816.913310	74899.140470	Low
23	ACC24508	1	79121.421540	64104.814780	Low
24	ACC24981	1	87135.500040	79579.949240	Low
25	ACC25132	4	174008.034610	71133.281755	Medium
26	ACC25811	1	33936.643670	79341.497200	Low
27	ACC26026	1	39410.843180	128196.612200	Low
28	ACC26940	2	85770.721560	33578.516058	Low
29	ACC26956	2	126842.127660	63624.542840	Low

[16]:

```
# Segmenting customers by average balance and transaction volume:

customer_segments = df.groupby("CustomerID").agg(
    avg_balance=('AccountBalance', 'mean'),
    avg_txn_amount=('TransactionAmount', 'mean'),
    total_txn=('TransactionID', 'count')
).reset_index()
```

[17]:

```
balance_bins = customer_segments['avg_balance'].quantile([0, 0.33, 0.66, 1]).
 ↪values
amount_bins = customer_segments['avg_txn_amount'].quantile([0, 0.33, 0.66, 1]).
 ↪values

customer_segments['balance_segment'] = pd.cut(
    customer_segments['avg_balance'],
```

```
    bins=balance_bins,
    labels=['Low Balance', 'Medium Balance', 'High Balance'],
    include_lowest=True,
    duplicates='drop'
)

customer_segments['amount_segment'] = pd.cut(
    customer_segments['avg_txn_amount'],
    bins=amount_bins,
    labels=['Low Spender', 'Medium Spender', 'High Spender'],
    include_lowest=True,
    duplicates='drop'
)
```

[18]:
```
customer_segments['combined_segment'] = (
    customer_segments['balance_segment'].astype(str)
    + " | "
    + customer_segments['amount_segment'].astype(str)
)
```

[19]:
```
customer_segments
```

[19]:
```
    CustomerID    avg_balance  avg_txn_amount  total_txn balance_segment  \
0     CUST1042  111660.679000    59642.065170          1    High Balance
1     CUST1114   99018.533450    39721.284650          1    High Balance
2     CUST1121   83103.736320    13783.954250          1  Medium Balance
3     CUST1189   48001.048005    96525.228050          2     Low Balance
4     CUST1223   46609.716930    86652.652360          1     Low Balance
..         …            …             …        …             …
142   CUST9564   96467.981205   104645.762800          2    High Balance
143   CUST9666   63959.895530    65853.519200          1  Medium Balance
144   CUST9731   80384.574728    73121.140433          4  Medium Balance
145   CUST9843   70513.535370    54301.392025          2  Medium Balance
146   CUST9962   57648.720385    40527.835033          4     Low Balance

     amount_segment                 combined_segment
0    Medium Spender    High Balance | Medium Spender
1       Low Spender       High Balance | Low Spender
2       Low Spender     Medium Balance | Low Spender
3      High Spender      Low Balance | High Spender
4      High Spender      Low Balance | High Spender
..             …                              …
142    High Spender     High Balance | High Spender
143    High Spender   Medium Balance | High Spender
144    High Spender   Medium Balance | High Spender
145  Medium Spender  Medium Balance | Medium Spender
146     Low Spender        Low Balance | Low Spender
```

[147 rows x 7 columns]

[20]:
```
plt.figure(figsize=(8,6))
plt.scatter(customer_segments['avg_balance'],
            customer_segments['avg_txn_amount'],
            c=customer_segments['balance_segment'].cat.codes, alpha=0.7)
plt.xlabel("Average Balance")
plt.ylabel("Average Transaction Amount")
plt.title("Customer Segmentation: Balance vs Spending")
plt.show()
```

[21]:
```
# High net inflow accounts:
high_inflow = profile.sort_values(by = 'total_inflow', ascending = False).
  ↪head(50)
high_inflow
```

[21]:

	AccountID	total_transactions	total_inflow	avg_balance	activity_level
82	ACC54589	6	466994.027130	54916.744670	High
58	ACC42710	7	430992.468520	59338.567807	High

148	ACC92558	5	423546.825650	63110.498334	High
78	ACC51593	4	302956.356350	96361.553762	Medium
95	ACC64022	4	280704.623070	77527.760875	Medium
126	ACC80131	4	262810.523580	76470.034708	Medium
13	ACC19178	6	255599.367270	79438.676415	High
15	ACC21429	4	250567.972600	67914.810115	Medium
84	ACC55729	4	245539.403990	56327.446467	Medium
4	ACC12334	3	230513.367710	27143.265607	Medium
67	ACC46655	4	229673.138370	77844.932950	Medium
106	ACC70741	3	229127.916810	75428.887777	Medium
17	ACC21878	4	225271.849390	67497.561915	Medium
151	ACC95164	3	210511.537760	85680.685150	Medium
110	ACC72197	3	203072.722740	74640.068737	Medium
63	ACC45521	4	202909.324510	74555.164237	Medium
46	ACC34568	3	202526.270780	69148.729560	Medium
134	ACC83581	4	201273.441070	60761.724078	Medium
147	ACC92360	4	194393.619970	101427.500845	Medium
73	ACC49422	5	189282.999300	53789.003897	High
36	ACC29477	2	178295.776800	91336.529580	Low
0	ACC10117	3	177550.151550	100686.898200	Medium
21	ACC23985	3	176671.315090	78987.177790	Medium
25	ACC25132	4	174008.034610	71133.281755	Medium
122	ACC78089	3	173808.609890	93973.739357	Medium
64	ACC45907	2	170412.882330	41547.218861	Low
114	ACC75675	4	169786.466700	63342.764867	Medium
5	ACC15228	4	169094.207541	93709.956587	Medium
117	ACC76597	3	168320.477790	54953.011026	Medium
133	ACC83269	2	161897.365300	66499.699790	Low
116	ACC76549	3	157764.699940	60815.007063	Medium
70	ACC49180	3	155846.553112	63932.824007	Medium
47	ACC34821	2	154644.985900	68095.037580	Low
109	ACC71938	2	154547.571630	22700.657765	Low
141	ACC88449	3	154285.839930	67391.872663	Medium
40	ACC31539	3	153573.800540	66968.426810	Medium
158	ACC99409	3	150389.377740	92689.093310	Medium
149	ACC94203	2	149005.749790	75375.340970	Low
89	ACC58078	3	146339.660120	84984.071697	Medium
74	ACC49774	3	145267.649060	120070.127927	Medium
52	ACC39500	2	141181.043100	61531.340035	Low
140	ACC88286	4	140453.172832	81444.181712	Medium
12	ACC19156	3	139436.637030	88611.499527	Medium
16	ACC21719	3	136661.203080	69424.634163	Medium
51	ACC39482	2	135077.094350	83574.382980	Low
42	ACC32627	2	133732.515390	94185.435270	Low
112	ACC74631	1	128558.970700	36149.543470	Low
44	ACC33287	2	127071.689330	80712.027330	Low
29	ACC26956	2	126842.127660	63624.542840	Low

```
22   ACC24070                    2  125816.913310   74899.140470           Low
```

[22]:
```python
# High-frequency low-balance accounts:
# Calculating the threshold average balance
threshold_avg_balance = profile.loc[profile['activity_level'] == 'High',␣
 ↪'avg_balance'].mean()
threshold_avg_balance
Hf_low_bal_accounts = profile[(profile['activity_level'] == 'High') &␣
 ↪(profile['avg_balance'] < threshold_avg_balance)]
Hf_low_bal_accounts
```

[22]:

	AccountID	total_transactions	total_inflow	avg_balance	activity_level
58	ACC42710	7	430992.46852	59338.567807	High
73	ACC49422	5	189282.99930	53789.003897	High
82	ACC54589	6	466994.02713	54916.744670	High

[23]:
```python
# Accounts with negative or near zero balances:
negative_accounts = profile[profile.avg_balance < 0]
negative_accounts
```

[23]:

	AccountID	total_transactions	total_inflow	avg_balance	activity_level
56	ACC41829	1	23800.71917	-2531.437176	Low

4 *Task 4: Financial Risk Identification*

[24]:
```python
# Large withdrawals:
# Calculating first the threshold value:
threshold = df.loc[df.TransactionType == 'WITHDRAWAL', 'TransactionAmount'].
 ↪quantile(0.95)
threshold

# Accounts with frequent large withdrawals:
large_withdrawals = df.loc[(df.TransactionType == 'WITHDRAWAL') & (df.
 ↪TransactionAmount > threshold)]
large_withdrawals
```

[24]:

	TransactionID	CustomerID	AccountID	AccountType	TransactionType	\
121	180	CUST2842	ACC49180	Current	WITHDRAWAL	
251	157	CUST2871	ACC43771	Credit	WITHDRAWAL	
434	23	CUST2464	ACC34568	Loan	WITHDRAWAL	
492	111	CUST8028	ACC40939	Loan	WITHDRAWAL	

	Product	Firm	Region	Manager	TransactionDate	\
121	Home Loan	Firm C	North	Manager 3	01-04-2024	
251	Mutual Fund	Firm D	East	Manager 4	11-05-2023	
434	Mutual Fund	Firm C	East	Manager 2	12-05-2023	

```
492  Savings Account  Firm A   West  Manager 1      05-05-2023

     TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths  \
121        109356.8390     45153.93637   0.560205           388           162
251        117259.1168     45725.22114   0.596077           380           181
434        109238.6461     91912.41131   0.332623           561           147
492        107696.7998     41353.73521   0.522655           726           155

    date_clean    Month  Year
121 2024-01-04  2024-01  2024
251 2023-11-05  2023-11  2023
434 2023-12-05  2023-12  2023
492 2023-05-05  2023-05  2023
```

[25]:
```
# Calculating balance volatility using standard deviation:
volatility = df.groupby('AccountID')['AccountBalance'].std().
↪rename('BalanceVolatility')
volatility
```

[25]:
```
AccountID
ACC10117     8996.864497
ACC10996             NaN
ACC11062    22572.552392
ACC11188             NaN
ACC12334     7710.352740
                 …
ACC97225    17885.106696
ACC97411             NaN
ACC99117             NaN
ACC99409    52199.191215
ACC99549             NaN
Name: BalanceVolatility, Length: 160, dtype: float64
```

[26]:
```
# Calculating IQR:
Q1 = df.TransactionAmount.quantile(0.25)
Q3 = df.TransactionAmount.quantile(0.75)
IQR = Q3 - Q1
IQR
```

[26]:
```
np.float64(40866.4893025)
```

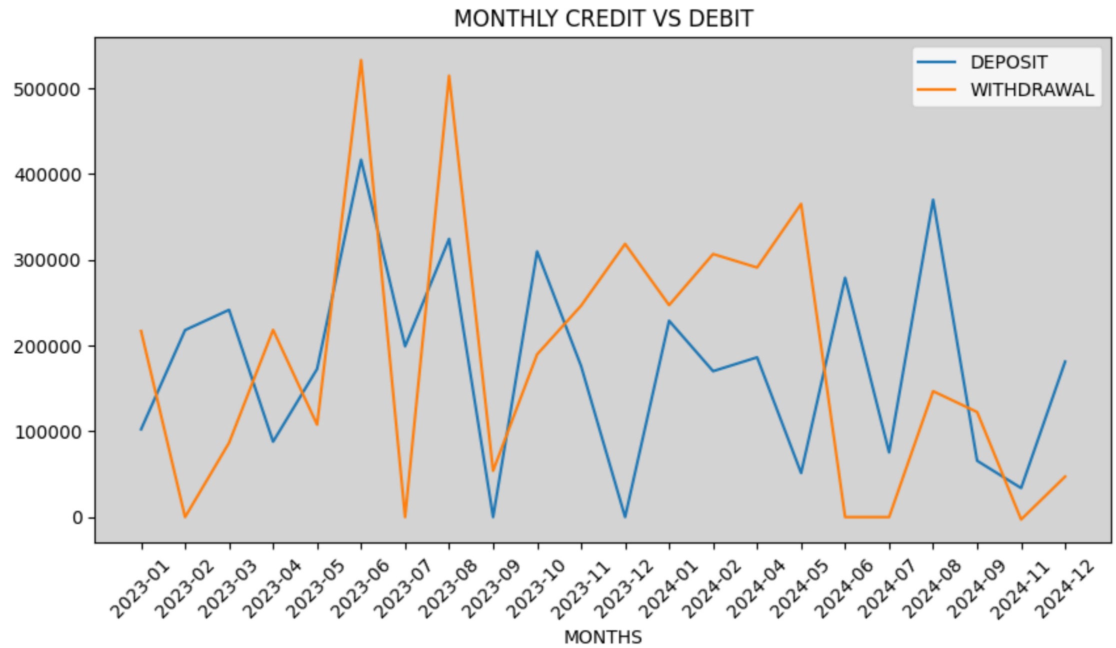
[27]:
```
# Calculating the account with anomalies

L_b = Q1 - 1.5*IQR
U_b = Q3 + 1.5*IQR
anomalies = df[(df.TransactionAmount < L_b) | (df.TransactionAmount > U_b)]
anomalies
```

[27]:
```
     TransactionID CustomerID AccountID AccountType TransactionType  \
710            117   CUST3041  ACC95164      Credit         DEPOSIT

         Product    Firm Region    Manager TransactionDate  TransactionAmount  \
710  Credit Card  Firm A   West  Manager 3      06-04-2024         142081.629

     AccountBalance  RiskScore  CreditRating  TenureMonths date_clean  \
710     60296.30589   0.368576           560           104 2024-06-04

       Month  Year
710  2024-06  2024
```

5 Task 5: Visualisation

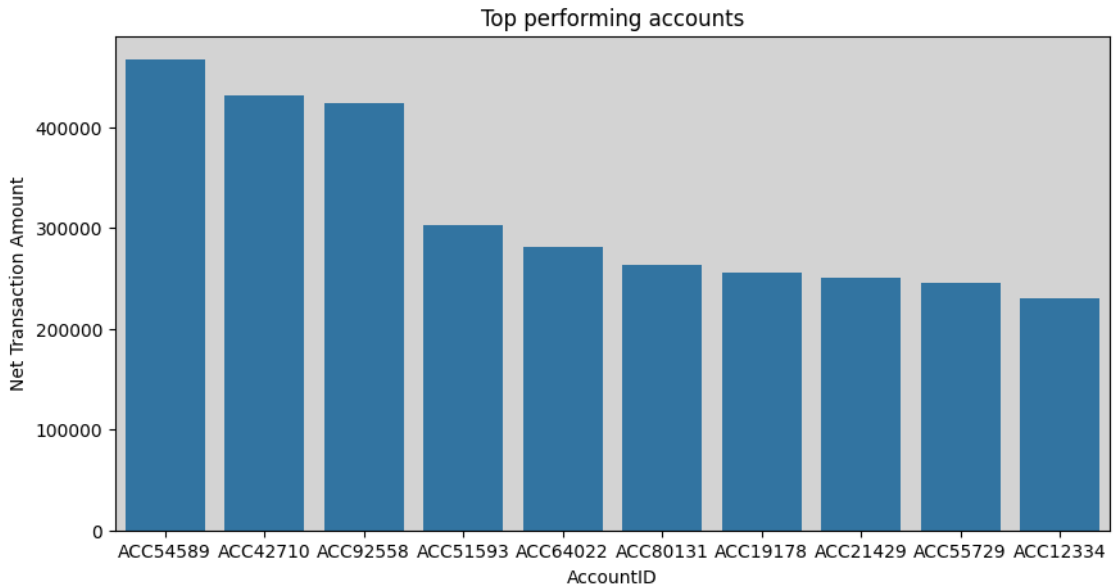
[28]:
```python
# Calculating monthly Deposit vs Withdrawal trend:
fig, cn = plt.subplots(figsize=(10,5))
cn.set_facecolor("lightgray")
# plt.figure(figsize=(10,5))
plt.plot(monthly_summary.index.astype(str), monthly_summary['DEPOSIT'],␣
 ↪label='DEPOSIT')
plt.plot(monthly_summary.index.astype(str), monthly_summary['WITHDRAWAL'],␣
 ↪label='WITHDRAWAL')
plt.legend();
plt.xticks(rotation=45);
plt.xlabel("MONTHS")
plt.title("MONTHLY CREDIT VS DEBIT")
```

[28]:
```
Text(0.5, 1.0, 'MONTHLY CREDIT VS DEBIT')
```



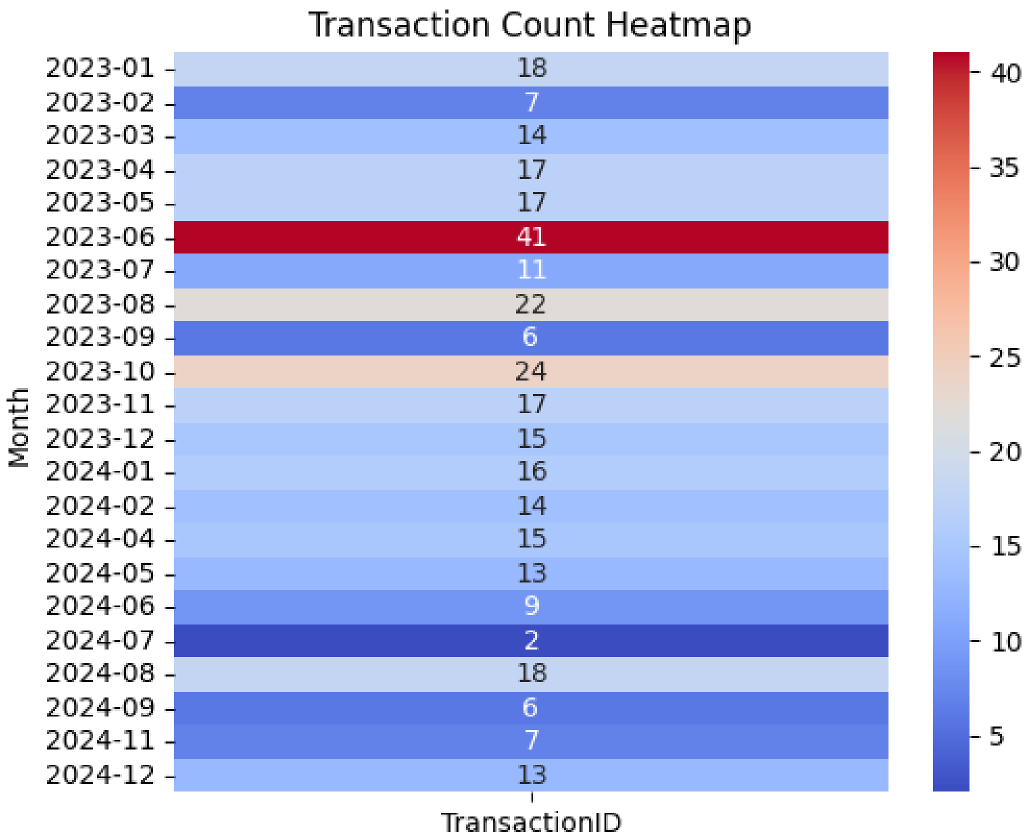
[29]:
```python
# Top 10 accounts by net inflow:
fig,cn = plt.subplots(figsize=(10,5))
cn.set_facecolor("lightgrey")
plt.title("Top performing accounts")
plt.xlabel("AccountID")
plt.ylabel("Net Transaction Amount")
sns.barplot(x=top10.index, y=top10.values)
```

[29]:
```
<Axes: title={'center': 'Top performing accounts'}, xlabel='AccountID',
ylabel='Net Transaction Amount'>
```

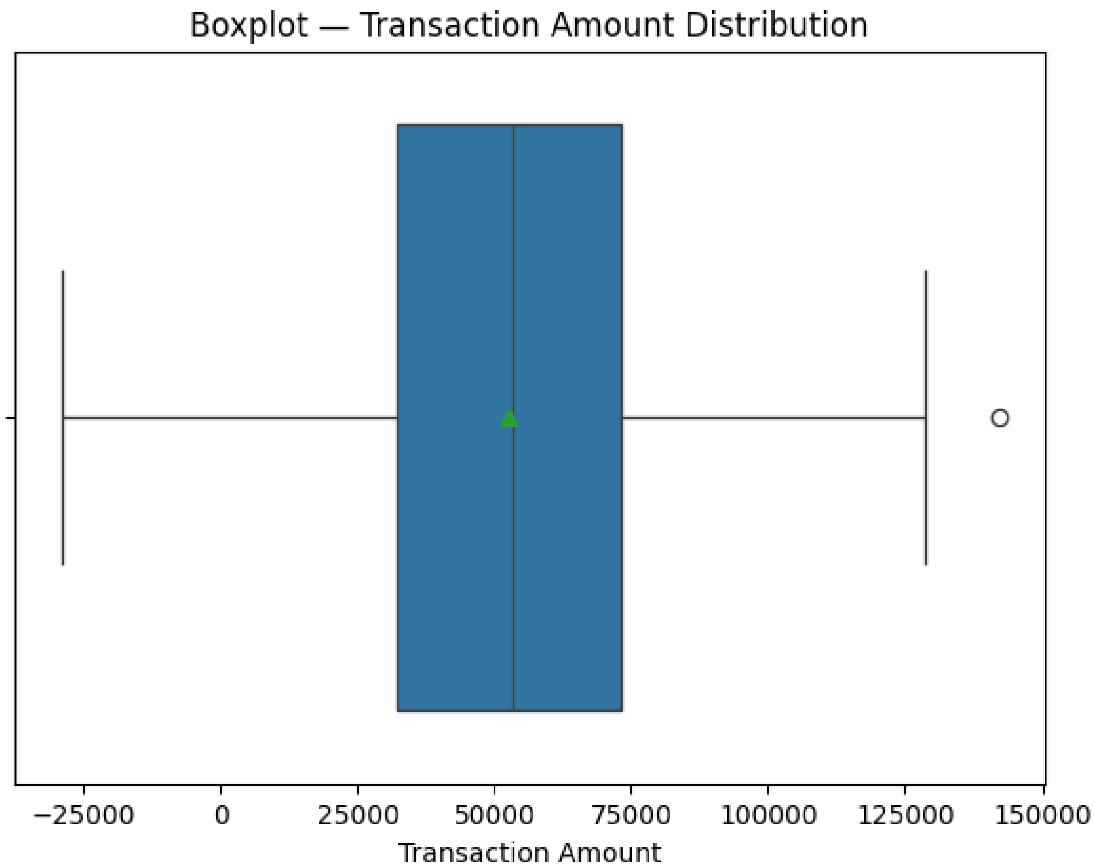


[30]:

```
# Heatmap for monthly Transaction Volume:

monthly_txn = df.groupby(['Month'])['TransactionID'].count().reset_index()
monthly_txn_pivot = monthly_txn.pivot_table(index='Month',␣
 ↪values='TransactionID')
monthly_txn
plt.figure(figsize=(6,5))
sns.heatmap(monthly_txn_pivot, annot=True, cmap='coolwarm')
plt.title("Transaction Count Heatmap")
plt.show()
```

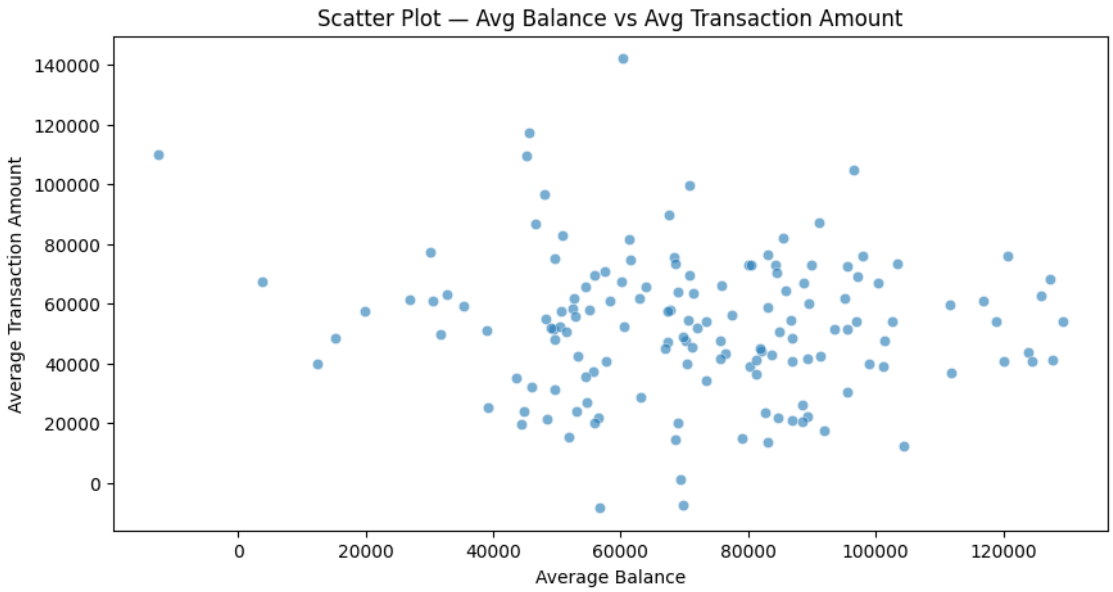


[31]:
```python
# Transaction Amount Distribution (BOXPLOT):

plt.figure(figsize=(7,5))
sns.boxplot(x=df['TransactionAmount'], showmeans = True)
plt.title("Boxplot - Transaction Amount Distribution")
plt.xlabel("Transaction Amount")
plt.show()
```

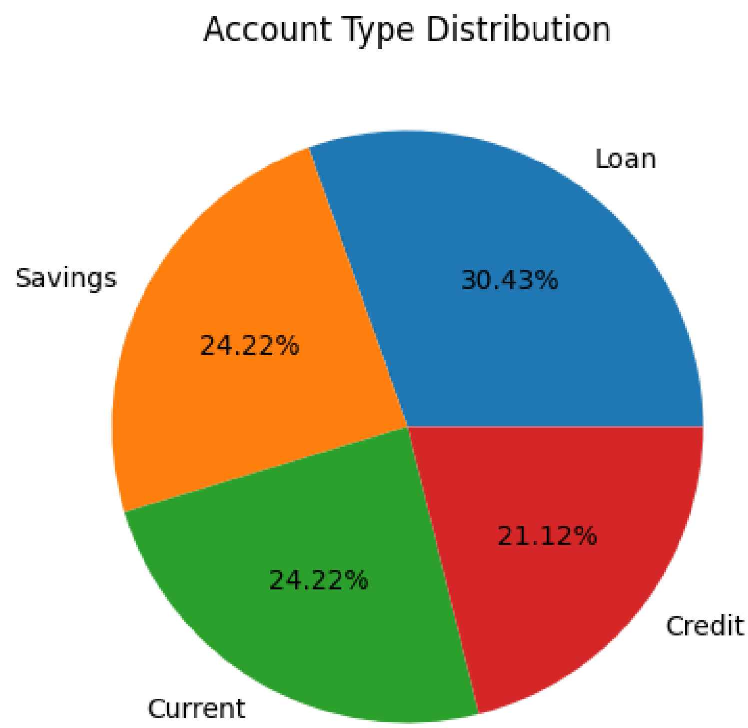


[32]:
```
# Average Balance vs Average Transaction Amount:

cust = df.groupby('CustomerID').agg(
    avg_balance = ('AccountBalance', 'mean'),
    avg_transaction_amount = ('TransactionAmount', 'mean')
).reset_index()

fig, cn = plt.subplots(figsize=(10,5))
sns.scatterplot(x = cust['avg_balance'], y = cust['avg_transaction_amount'],␣
 ↪alpha=0.6)
plt.title("Scatter Plot - Avg Balance vs Avg Transaction Amount")
plt.xlabel("Average Balance")
plt.ylabel("Average Transaction Amount")
```

[32]:
```
Text(0, 0.5, 'Average Transaction Amount')
```



[33]:
```
# Account Type Distribution:
plt.figure(figsize = (10,5))
plt.title("Account Type Distribution")
plt.pie(df.AccountType.value_counts(), labels = df.AccountType.value_counts().
 ↪keys(), autopct = "%1.2f%%")
plt.show()
```



6 Task 6: Hypothesis Testing

[34]:
```
# Test whether high-volume transaction accounts have statistically higher␣
↪average
# balances than low-volume accounts.
import numpy as np
from scipy.stats import ttest_ind, mannwhitneyu, levene

acct = df.groupby('AccountID').agg(
    txn_count=('TransactionID','count'),
    avg_balance=('AccountBalance','mean')
).reset_index()

# Remove NA / infinite
acct = acct.replace([np.inf, -np.inf], np.nan).
↪dropna(subset=['txn_count','avg_balance'])

# ---- Grouping: median split ----
median_txn = acct['txn_count'].median()
high = acct.loc[acct['txn_count'] >  median_txn, 'avg_balance']
```

```python
low  = acct.loc[acct['txn_count'] <= median_txn, 'avg_balance']

print(f"High n={len(high)}, Low n={len(low)}")

# Quick sanity: need some data in both groups
assert len(high) > 10 and len(low) > 10, "Groups too small; adjust rule or use␣
↪quantiles."

# ---- Variance check (optional) ----
w_stat, w_p = levene(high, low, center='median')
print(f"Levene variance test p={w_p:.4f} (p<0.05 means variances differ)")

# ---- Welch t-test (safe default) ----
t_stat, p_val = ttest_ind(high, low, equal_var=False, nan_policy='omit')
print(f"Welch t-test: t={t_stat:.3f}, p={p_val:.5f}")

# One-sided p-value (High > Low)
p_one_sided = p_val / 2 if t_stat > 0 else 1 - (p_val / 2)
print(f"One-sided p-value (High > Low) = {p_one_sided:.5f}")

alpha = 0.05
if p_one_sided < alpha:
    print("Conclusion: Reject H0 → High-volume accounts have significantly␣
↪higher average balance.")
else:
    print("Conclusion: Fail to reject H0 → No significant evidence that␣
↪High_volume accounts have significantly higher average balance than␣
↪Low_volume accounts")

# ---- Effect size (Cohen's d using pooled SD) ----
def cohens_d(x, y):
    nx, ny = len(x), len(y)
    vx, vy = np.var(x, ddof=1), np.var(y, ddof=1)
    sp2 = ((nx-1)*vx + (ny-1)*vy) / (nx+ny-2)
    return (np.mean(x) - np.mean(y)) / np.sqrt(sp2)

d = cohens_d(high.values, low.values)
print(f"Cohen's d = {d:.3f}  (0.2=small, 0.5=medium, 0.8=large)")
```

```
High n=45, Low n=115
Levene variance test p=0.0359 (p<0.05 means variances differ)
Welch t-test: t=0.388, p=0.69878
One-sided p-value (High > Low) = 0.34939
Conclusion: Fail to reject H0 → No significant evidence that High_volume
accounts have significantly higher average balance than Low_volume accounts
Cohen's d = 0.060  (0.2=small, 0.5=medium, 0.8=large)
```

7 Task 7: Video Presentation

Video Link —-> https://www.loom.com/share/56af54df97dd4a28967712c26e668c42