C5_Project_Financial Risk Analysis with Python_Goldman Sachs

January 2, 2026

1 Financial Risk Analysis by Goldman Sachs

1.0.1 Task 1: Data Cleaning and Formatting

1. Remove/treat any special characters or non-numeric entries from financial fields.
2. Convert currency amounts into numerical format.
3. Validate and format date columns.
4. Ensure account types and transaction categories are standardized.

[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  \
0             33   CUST6549  ACC12334      Credit      Withdrawal
1            177   CUST2942  ACC52650      Credit      Withdrawal
2            178   CUST6776  ACC45101     Current         Deposit
3            173   CUST2539  ACC88252     Current      Withdrawal
4             67   CUST2626  ACC21878     Savings      Withdrawal

           Product    Firm   Region    Manager TransactionDate  \
0  Savings Account  Firm C  Central  Manager 1      21-10-2023
1        Home Loan  Firm A     East  Manager 3      20-06-2023
2    Personal Loan  Firm C    South  Manager 3      02-01-2023
3      Mutual Fund  Firm A  Central  Manager 2      25-07-2023
4        Home Loan  Firm C  Central  Manager 4      25-07-2023

   TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths
0        87480.05448     74008.43310   0.729101           319           200
1        20315.74505     22715.83590   0.472424           692            47
2        10484.57165     42706.09210   0.648784           543           109
3        45122.27373    114176.56870   0.734832           430           103
4        42360.79878     17863.02644   0.289304           468           234
```

[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
```

1.1: 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.

1.2: Also, currency amounts are already in numerical format.

[6]:
```python
### 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()
```

[6]:
```
   TransactionID CustomerID AccountID AccountType TransactionType  \
0             33   CUST6549  ACC12334      Credit      Withdrawal
1            177   CUST2942  ACC52650      Credit      Withdrawal
2            178   CUST6776  ACC45101     Current         Deposit
3            173   CUST2539  ACC88252     Current      Withdrawal
4             67   CUST2626  ACC21878     Savings      Withdrawal

           Product    Firm   Region    Manager TransactionDate  \
0  Savings Account  Firm C  Central  Manager 1      2023-10-21
1        Home Loan  Firm A     East  Manager 3      2023-06-20
2    Personal Loan  Firm C    South  Manager 3      2023-01-02
3      Mutual Fund  Firm A  Central  Manager 2      2023-07-25
4        Home Loan  Firm C  Central  Manager 4      2023-07-25

   TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths
0        87480.05448     74008.43310   0.729101           319           200
1        20315.74505     22715.83590   0.472424           692            47
2        10484.57165     42706.09210   0.648784           543           109
3        45122.27373    114176.56870   0.734832           430           103
4        42360.79878     17863.02644   0.289304           468           234
```

[7]:
```python
df.dtypes
```

[7]:
```
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
```

[8]:
```python
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]:
```python
# 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()
```

[9]:
```
   TransactionID CustomerID AccountID AccountType TransactionType  \
0             33   CUST6549  ACC12334      Credit           Debit
1            177   CUST2942  ACC52650      Credit           Debit
2            178   CUST6776  ACC45101     Current          Credit
3            173   CUST2539  ACC88252     Current           Debit
4             67   CUST2626  ACC21878     Savings           Debit

           Product    Firm   Region    Manager TransactionDate  \
0  Savings Account  Firm C  Central  Manager 1      2023-10-21
1        Home Loan  Firm A     East  Manager 3      2023-06-20
2    Personal Loan  Firm C    South  Manager 3      2023-01-02
3      Mutual Fund  Firm A  Central  Manager 2      2023-07-25
4        Home Loan  Firm C  Central  Manager 4      2023-07-25

   TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths
0        87480.05448     74008.43310   0.729101           319           200
1        20315.74505     22715.83590   0.472424           692            47
2        10484.57165     42706.09210   0.648784           543           109
3        45122.27373    114176.56870   0.734832           430           103
4        42360.79878     17863.02644   0.289304           468           234
```

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.

1.0.2 Task 2: Descriptive Transactional Analysis

2.1: 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()
```

[10]:
```
   TransactionID CustomerID AccountID AccountType TransactionType  \
0             33   CUST6549  ACC12334      Credit           Debit
1            177   CUST2942  ACC52650      Credit           Debit
2            178   CUST6776  ACC45101     Current          Credit
3            173   CUST2539  ACC88252     Current           Debit
4             67   CUST2626  ACC21878     Savings           Debit

           Product    Firm   Region    Manager TransactionDate  \
0  Savings Account  Firm C  Central  Manager 1      2023-10-21
1        Home Loan  Firm A     East  Manager 3      2023-06-20
2    Personal Loan  Firm C    South  Manager 3      2023-01-02
3      Mutual Fund  Firm A  Central  Manager 2      2023-07-25
4        Home Loan  Firm C  Central  Manager 4      2023-07-25

   TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths  \
0        87480.05448     74008.43310   0.729101           319           200
1        20315.74505     22715.83590   0.472424           692            47
2        10484.57165     42706.09210   0.648784           543           109
3        45122.27373    114176.56870   0.734832           430           103
4        42360.79878     17863.02644   0.289304           468           234

   Year  Month
0  2023     10
1  2023      6
2  2023      1
3  2023      7
4  2023      7
```

[11]:
```
print(df["Year"].unique())
```

```
[2023 2024]
```

[12]:
```
df["Month"] = df["TransactionDate"].dt.to_period("M")
```

[13]:
```
df.head()
```

[13]:
```
   TransactionID CustomerID AccountID AccountType TransactionType  \
0             33   CUST6549  ACC12334      Credit           Debit
1            177   CUST2942  ACC52650      Credit           Debit
2            178   CUST6776  ACC45101     Current          Credit
3            173   CUST2539  ACC88252     Current           Debit
4             67   CUST2626  ACC21878     Savings           Debit

           Product    Firm   Region    Manager TransactionDate  \
0  Savings Account  Firm C  Central  Manager 1      2023-10-21
1        Home Loan  Firm A     East  Manager 3      2023-06-20
2    Personal Loan  Firm C    South  Manager 3      2023-01-02
3      Mutual Fund  Firm A  Central  Manager 2      2023-07-25
4        Home Loan  Firm C  Central  Manager 4      2023-07-25

   TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths  \
0        87480.05448     74008.43310   0.729101           319           200
1        20315.74505     22715.83590   0.472424           692            47
2        10484.57165     42706.09210   0.648784           543           109
3        45122.27373    114176.56870   0.734832           430           103
4        42360.79878     17863.02644   0.289304           468           234

   Year    Month
0  2023  2023-10
1  2023  2023-06
2  2023  2023-01
3  2023  2023-07
4  2023  2023-07
```

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

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

[14]: 375.4909042

[15]:
```
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"]
```

[16]:
```
monthly_summary
```

[16]:

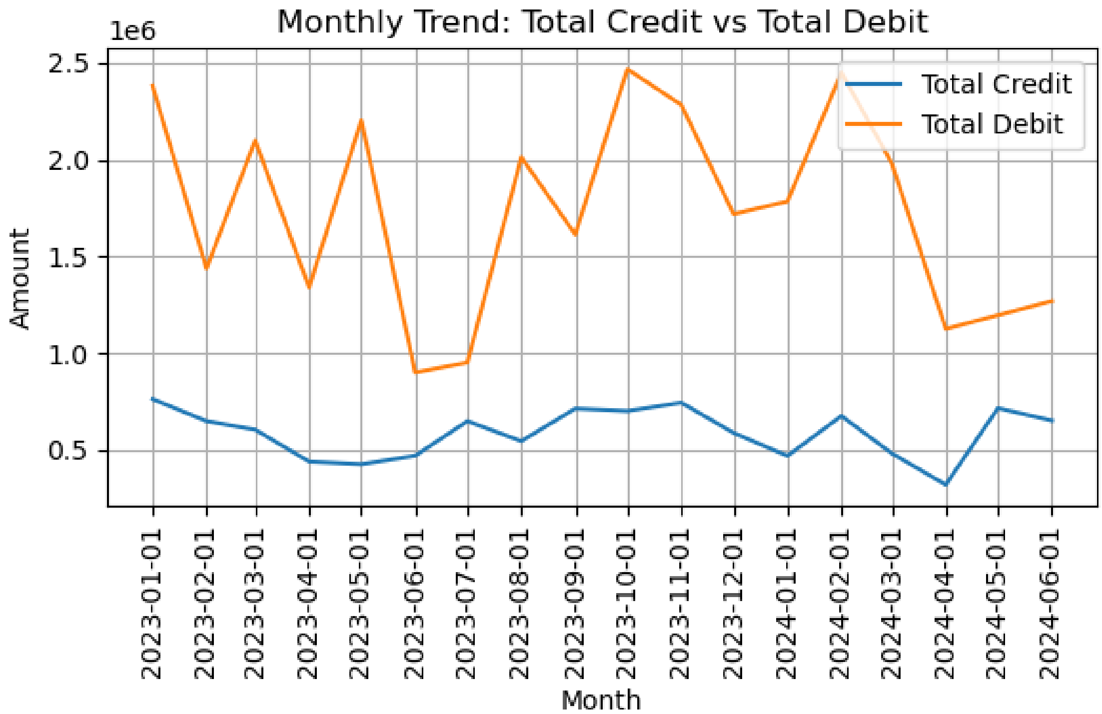
	Month	Total_Credit	Total_Debit	Net_Volume
0	2023-01	762099.557830	2.380984e+06	-1.618885e+06
1	2023-02	648261.004850	1.436502e+06	-7.882407e+05
2	2023-03	604002.422140	2.098983e+06	-1.494981e+06
3	2023-04	439321.687687	1.338294e+06	-8.989726e+05
4	2023-05	425589.871840	2.203715e+06	-1.778125e+06
5	2023-06	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

2.2: Plot trends in total credits vs. debits over time.

[17]:
```
monthly_summary["Month"] = monthly_summary["Month"].dt.to_timestamp()
```

[18]:
```
import matplotlib.pyplot as plt
```

[19]:
```
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()
```



2.3: Identify top and bottom performing accounts based on net inflow

[20]:
```
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
```

[20]:

	AccountID	Total_Credit	Total_Debit	Net_Inflow
0	ACC10117	142170.20378	57310.763650	84859.440130
1	ACC10996	62580.86356	188158.687390	-125577.823830
2	ACC11062	0.00000	27189.136160	-27189.136160
3	ACC11188	45748.34156	211828.262030	-166079.920470
4	ACC11285	0.00000	96729.609841	-96729.609841
..	…	…	…	…
189	ACC97225	87320.05768	72962.656600	14357.401080

```
190  ACC97411       0.00000  174551.560470 -174551.560470
191  ACC99117  167040.52263   45808.220650  121232.301980
192  ACC99409   39893.63471   94227.858580  -54334.223870
193  ACC99549   70443.88751  118498.523760  -48054.636250

[194 rows x 4 columns]
```

[21]:
```
top_accounts = account_summary.sort_values("Net_Inflow", ascending=False).
 ↪head(10)
top_accounts.head(5)
```

[21]:
```
    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
```

[22]:
```
bottom_accounts = account_summary.sort_values("Net_Inflow").head(10)
bottom_accounts.head(5)
```

[22]:
```
    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
```

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

[23]:
```
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
```

```python
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)
```

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

1.0.3 Task 3: Customer Profile Building

3.1 : 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.

[24]:
```
# 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 x 3 columns]
```

[25]:
```
activity_counts["TransactionCount"].max()
```

[25]: 14

3.2 - Segment customers by average balance and transaction volume.

[26]:
```python
avg_balance = df.groupby("AccountID")["AccountBalance"].mean().reset_index()
avg_balance.rename(columns={"AccountBalance": "AvgBalance"}, inplace=True)
```

[27]:
```python
trans_volume = df.groupby("AccountID")["TransactionID"].count().reset_index()
trans_volume.rename(columns={"TransactionID": "TransactionCount"}, inplace=True)
```

[28]:
```python
customer_seg = pd.merge(avg_balance, trans_volume, on="AccountID")
customer_seg.head()
```

[28]:

	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

[29]:
```python
avg_balance["AvgBalance"].max()
```

[29]: 128085.50099999999

[30]:
```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)
```

[31]:
```python
customer_seg["TransactionCount"].max()
```

[31]: 14

[32]:
```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)
```

[33]:
```python
print(f"\nCustomer Segmentation(Rubric: AvgBalance>70000 is High Balance,␣
↪AvgBalance>=30000 is Medium Balance Else Low Balance.\n\t\t\t      ␣
↪TransactionCount>10 is High Volume, TransactionCount>=6 is Medium Volume␣
↪Else Low Volume.)\n")
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

[194 rows x 5 columns]

3.3: Create Customer Profiles: * High-net inflow accounts * High-frequency low-balance accounts * Accounts with negative or near-zero balances

[34]:
```python
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())
```

```
Accounts with High Net-Inflow


Empty DataFrame
```

```
Columns: [AccountID, NetInflow]
Index: []
```

[35]:
```
activity_counts
```

[35]:
```
    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 x 3 columns]
```

[36]:
```
avg_balance
```

[36]:
```
    AccountID    AvgBalance
0    ACC10117  70107.007957
1    ACC10996  43568.008084
2    ACC11062  38137.132610
3    ACC11188  69652.151044
4    ACC11285  97401.348560
..        …            …
189  ACC97225  38652.306677
190  ACC97411  55978.315635
191  ACC99117  47228.185087
192  ACC99409  83743.915565
193  ACC99549  68641.201433

[194 rows x 2 columns]
```

[37]:
```
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

[38]:
```
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:
```

[38]:

	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 behavior 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.

1.0.4 Task 4: Financial Risk Identification

4.1: Track accounts with frequent large withdrawals or overdrafts

[39]:
```
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:


Empty DataFrame
Columns: [AccountID, LargeWithdrawalCount, RiskLevel]
Index: []
```

4.2: Calculate balance volatility using standard deviation or coefficient of variation

[40]:
```
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()
```

```
vol_threshold = balance_volatility["BalanceStdDev"].quantile(0.75)

# High volatility accounts
high_vol_accounts = balance_volatility[balance_volatility["BalanceStdDev"] >␣
↪vol_threshold][["AccountID"]]

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 x 5 columns]
```

4.3: Use IQR or z-score methods to detect anomalies.

[41]:
```
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  \
266             14   CUST3015  ACC21719        Loan         Deposit

             Product    Firm Region    Manager TransactionDate  \
266  Savings Account  Firm D  North  Manager 3      2024-05-22

     TransactionAmount  AccountBalance  RiskScore  CreditRating  TenureMonths  \
266       -30721.24789     113801.0737   0.378442           360           222

      PrevDate  GapDays DormantFlag
266 2024-02-06    106.0     Dormant
```

In financial datasets, IQR is usually preferred, because large transactions are not normally distributed.

4.4: Highlight customers with irregular or suspicious transaction behavior

[42]:
```
balance_volatility
```

[42]:

	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 x 5 columns]
```

[43]:

```
large_withdrawal_counts
```

[43]:

```
Empty DataFrame
Columns: [AccountID, LargeWithdrawalCount, RiskLevel]
Index: []
```

[44]:

```
# 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)
)

# 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
```

[44]:

```
    AccountID  HighVolatility  FrequentWithdrawals  LowBalance  AnomalousTxn  \
0    ACC10117           False                False       False         False
1    ACC10996           False                False        True         False
2    ACC11062           False                False        True         False
3    ACC11188           False                False       False         False
4    ACC11285            True                False       False         False
..        …               …                  …          …             …
189  ACC97225           False                False        True         False
190  ACC97411           False                False        True         False
191  ACC99117           False                False        True         False
192  ACC99409           False                False       False         False
193  ACC99549           False                False       False         False

     SuspicionScore FinalRiskCategory
0                 0          Low Risk
1                 1       Medium Risk
2                 1       Medium Risk
3                 0          Low Risk
4                 1       Medium Risk
..              …               …
189               1       Medium Risk
190               1       Medium Risk
191               1       Medium Risk
192               0          Low Risk
193               0          Low Risk

[194 rows x 7 columns]
```

[55]:

```
risk_flags["SuspicionScore"].max()
```

[55]: 2

[56]:
```
risk_flags[risk_flags["SuspicionScore"] == 2]
```

[56]:
```
    AccountID  HighVolatility  FrequentWithdrawals  LowBalance  AnomalousTxn  \
40   ACC26973            True                False        True         False
50   ACC29477            True                False        True         False
60   ACC33287            True                False        True         False
79   ACC42710            True                False        True         False
87   ACC45968            True                False        True         False
98   ACC49774            True                False        True         False
110  ACC55331            True                False        True         False
117  ACC58667            True                False        True         False
133  ACC70314            True                False        True         False

     SuspicionScore FinalRiskCategory
40                2         High Risk
50                2         High Risk
60                2         High Risk
79                2         High Risk
87                2         High Risk
98                2         High Risk
110               2         High Risk
117               2         High Risk
133               2         High Risk
```

Task 4: Financial Risk Identification – Insights

- Large withdrawal patterns detected among a subset of customers.
- High volatility accounts show unstable financial behavior 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.

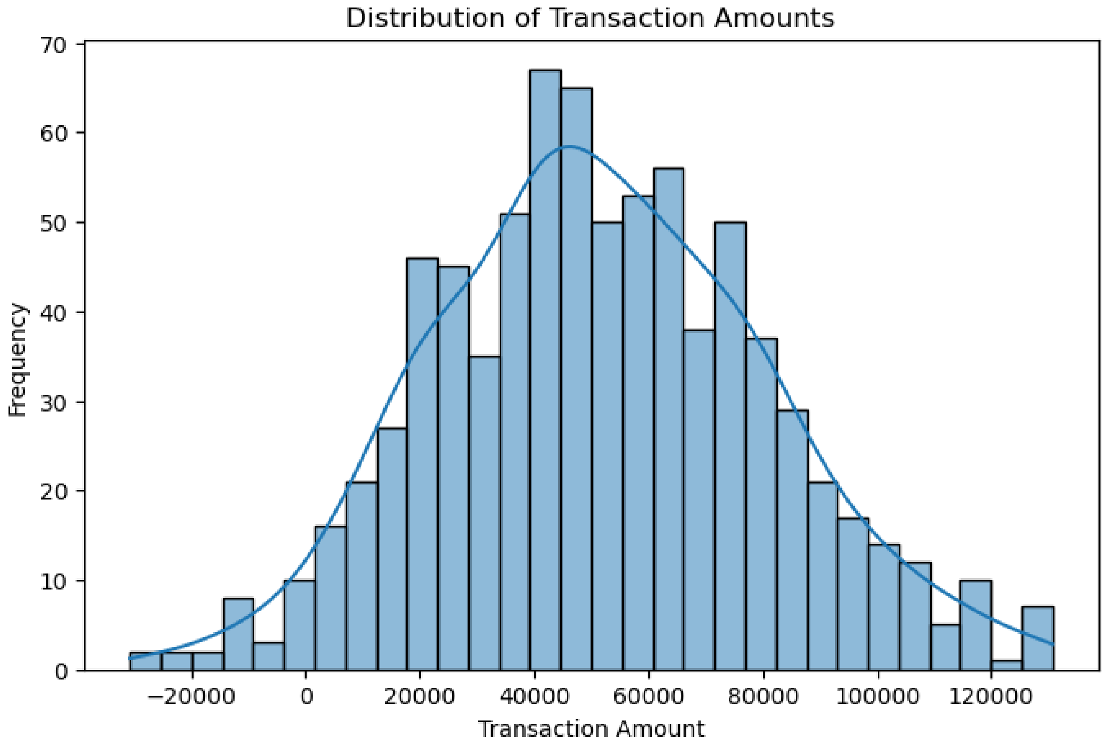
1.0.5 Task 5: Visualisation

5.1: Conduct extensive exploratory data analysis with attractive visualizations for your findings

- Visualization 1 — Distribution of Transaction Amounts

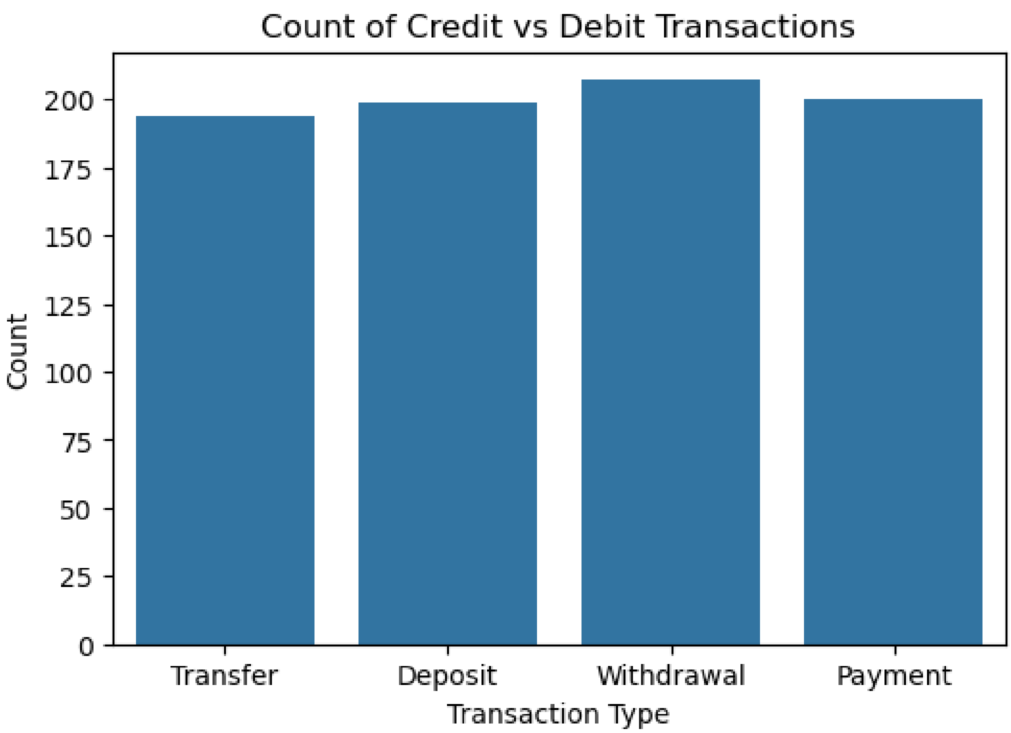
[46]:
```
import seaborn as sns
```

[47]:
```
plt.figure(figsize=(8,5))
sns.histplot(df["TransactionAmount"], bins=30, kde=True)
plt.title("Distribution of Transaction Amounts")
plt.xlabel("Transaction Amount")
plt.ylabel("Frequency")
plt.show()
```



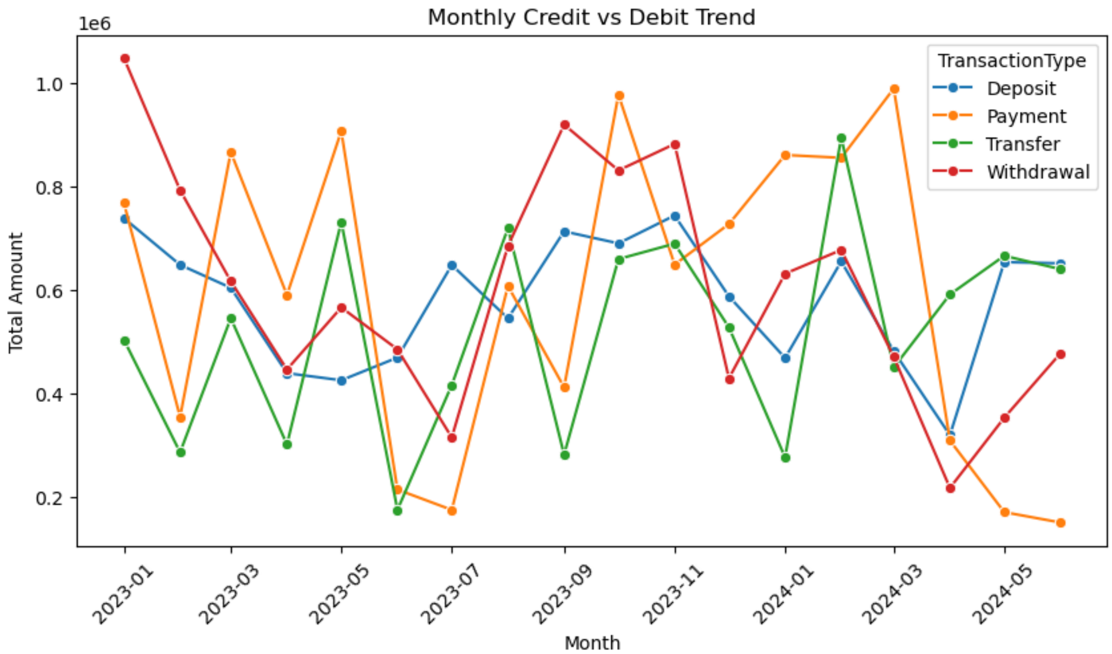
- Visualization 2 — Credit vs Debit Count

[48]:
```
plt.figure(figsize=(6,4))
sns.countplot(data=df, x="TransactionType")
plt.title("Count of Credit vs Debit Transactions")
plt.xlabel("Transaction Type")
plt.ylabel("Count")
plt.show()
```



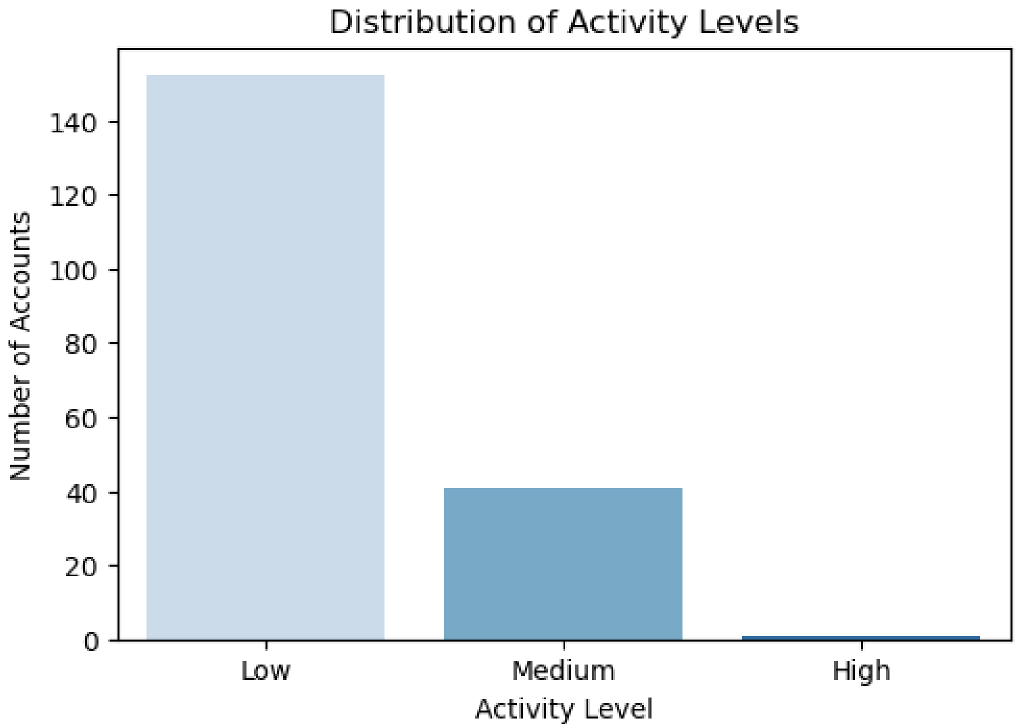
- Visualization 3 — Monthly Credit vs Debit Trend

[49]:
```
df["Month"] = pd.to_datetime(df["TransactionDate"]).dt.to_period("M").dt.
    ↪to_timestamp()

monthly = df.groupby(["Month", "TransactionType"])["TransactionAmount"].sum().
    ↪reset_index()

plt.figure(figsize=(10,5))
sns.lineplot(data=monthly, x="Month", y="TransactionAmount",␣
    ↪hue="TransactionType", marker="o")
plt.title("Monthly Credit vs Debit Trend")
plt.xlabel("Month")
plt.ylabel("Total Amount")
plt.xticks(rotation=45)
plt.show()
```



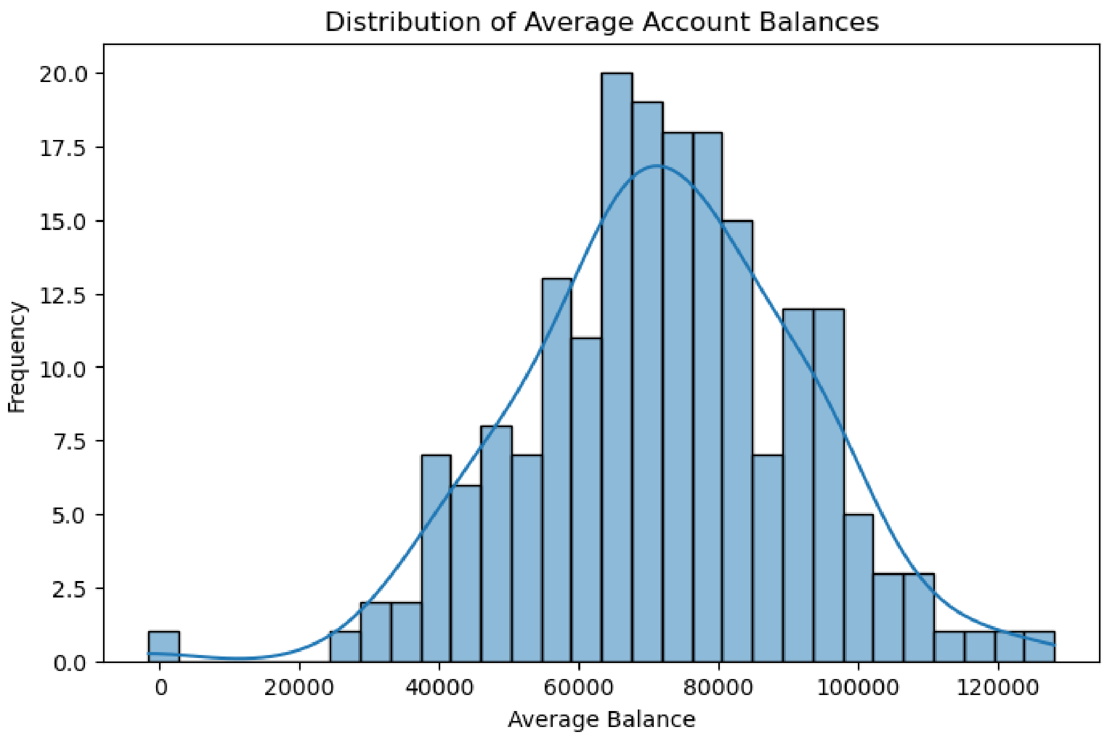
- Visualization 4 — Account Activity Levels (High / Medium / Low)

[50]:
```
plt.figure(figsize=(6,4))
sns.countplot(data=activity_counts, x="ActivityLevel", palette="Blues",
 ↪hue="ActivityLevel")
plt.title("Distribution of Activity Levels")
plt.xlabel("Activity Level")
plt.ylabel("Number of Accounts")
plt.show()
```



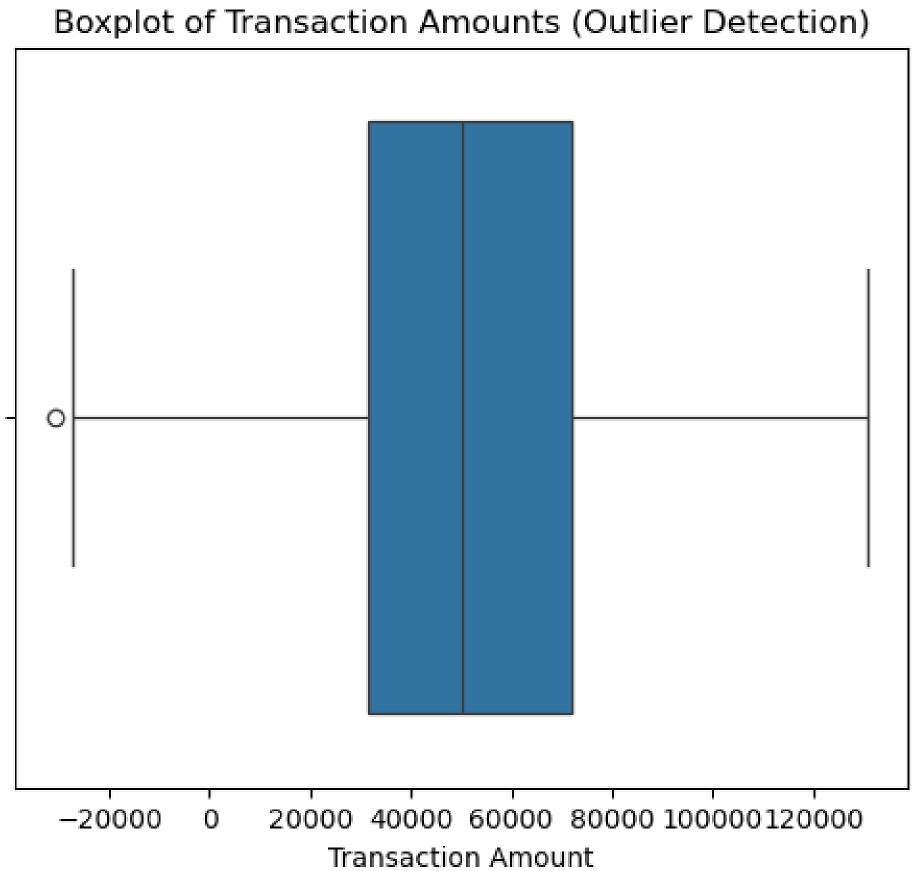
- Visualization 5 — Average Balance Distribution

[51]:
```
plt.figure(figsize=(8,5))
sns.histplot(avg_balance["AvgBalance"], bins=30, kde=True)
plt.title("Distribution of Average Account Balances")
plt.xlabel("Average Balance")
plt.ylabel("Frequency")
plt.show()
```



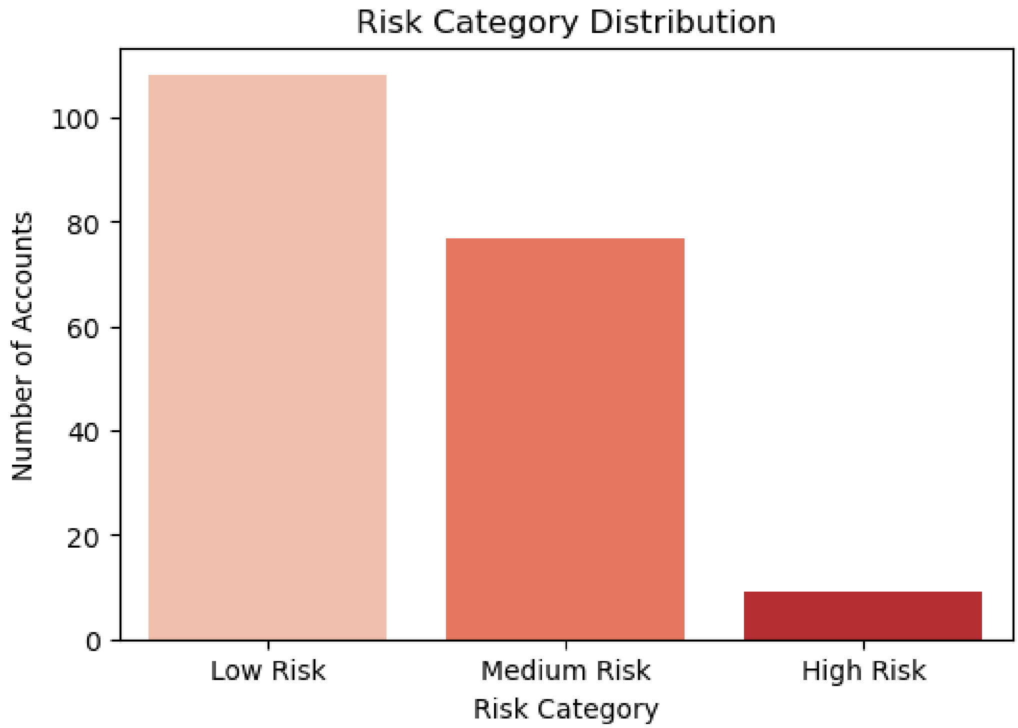
- Visualization 6 — Boxplot for Outlier Detection (IQR)

[52]:
```
plt.figure(figsize=(6,5))
sns.boxplot(x=df["TransactionAmount"])
plt.title("Boxplot of Transaction Amounts (Outlier Detection)")
plt.xlabel("Transaction Amount")
plt.show()
```



- Visualization 7 — Risk Category Distribution (from Task 4)

[53]:
```
plt.figure(figsize=(6,4))
sns.countplot(data=risk_flags, x="FinalRiskCategory", palette="Reds",␣
↪hue="FinalRiskCategory")
plt.title("Risk Category Distribution")
plt.xlabel("Risk Category")
plt.ylabel("Number of Accounts")
plt.show()
```



Task 5: Visualization – Insights

- Visual patterns clearly highlight behavior 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.

1.0.6 Task 6: Hypothesis Testing

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

[54]:
```
# --------------------------------
# Do high-volume accounts maintain higher average balances?
# --------------------------------

from scipy.stats import ttest_ind

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

```python
# -------------------------------
# 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
# H : High-volume accounts do NOT have higher average balances
# H : High-volume accounts DO have higher average balances
# -------------------------------

# -------------------------------
# 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 H ")
    print("High-volume accounts have significantly higher average balances.\n")
else:
    print("\nConclusion: Fail to Reject H ")
    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 H
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 behavior.
- 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.

1.1 Overall Project Insight

The end-to-end analysis revealed clear patterns in customer financial behavior, 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 behavior provided a structured method to classify accounts, enabling data-driven risk management.

Hypothesis testing validated key behavioral 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.

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```