Banking_EDA

May 5, 2025

0.1 Exploratory Data Analysis of banking data

Problem Statement : Develop a basic understanding of risk analytics in banking and financial services and understand how data is used to minimise the risk of losing money while lending to customers.

EDA Techniques Used: - Data Overview and Summary

- Univariate Analysis
- Bivariate Analysis
- Categorical Feature Analysis
- Data Visualization
- Correlation Analysis

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

[ ]:
```
df = pd.read_csv('/content/Banking.csv')
df.head(5)
```

[ ]:
```
  Client ID            Name  Age  Location ID Joined Bank   Banking Contact  \
0  IND81288    Raymond Mills   24        34324  06-05-2019    Anthony Torres
1  IND65833    Julia Spencer   23        42205  10-12-2001  Jonathan Hawkins
2  IND47499   Stephen Murray   27         7314  25-01-2010     Anthony Berry
3  IND72498   Virginia Garza   40        34594  28-03-2019        Steve Diaz
4  IND60181  Melissa Sanders   46        41269  20-07-2012        Shawn Long

  Nationality            Occupation Fee Structure Loyalty Classification  …  \
0    American  Safety Technician IV          High                   Jade  …
1     African   Software Consultant          High                   Jade  …
2    European    Help Desk Operator          High                   Gold  …
3    American          Geologist II           Mid                 Silver  …
4    American   Assistant Professor           Mid               Platinum  …

   Bank Deposits  Checking Accounts  Saving Accounts  \
```

```
0     1485828.64          603617.88        607332.46
1      641482.79          229521.37        344635.16
2     1033401.59          652674.69        203054.35
3     1048157.49         1048157.49        234685.02
4      487782.53          446644.25        128351.45

   Foreign Currency Account  Business Lending  Properties Owned  \
0                  12249.96        1134475.30                 1
1                  61162.31        2000526.10                 1
2                  79071.78         548137.58                 1
3                  57513.65        1148402.29                 0
4                  30012.14        1674412.12                 0

   Risk Weighting  BRId  GenderId  IAId
0               2     1         1     1
1               3     2         1     2
2               3     3         2     3
3               4     4         1     4
4               3     1         2     5

[5 rows x 25 columns]
```

[ ]:
```
df.shape
```

[ ]:
```
(3000, 25)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 25 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Client ID                 3000 non-null   object
 1   Name                      3000 non-null   object
 2   Age                       3000 non-null   int64
 3   Location ID               3000 non-null   int64
 4   Joined Bank               3000 non-null   object
 5   Banking Contact           3000 non-null   object
 6   Nationality               3000 non-null   object
 7   Occupation                3000 non-null   object
 8   Fee Structure             3000 non-null   object
 9   Loyalty Classification    3000 non-null   object
 10  Estimated Income          3000 non-null   float64
 11  Superannuation Savings    3000 non-null   float64
 12  Amount of Credit Cards    3000 non-null   int64
 13  Credit Card Balance       3000 non-null   float64
```

```
 14  Bank Loans                3000 non-null   float64
 15  Bank Deposits             3000 non-null   float64
 16  Checking Accounts         3000 non-null   float64
 17  Saving Accounts           3000 non-null   float64
 18  Foreign Currency Account  3000 non-null   float64
 19  Business Lending          3000 non-null   float64
 20  Properties Owned          3000 non-null   int64
 21  Risk Weighting            3000 non-null   int64
 22  BRId                      3000 non-null   int64
 23  GenderId                  3000 non-null   int64
 24  IAId                      3000 non-null   int64
dtypes: float64(9), int64(8), object(8)
memory usage: 586.1+ KB
```

[ ]:
```python
# Generate descriptive statistics for the dataframe
df.describe()
```

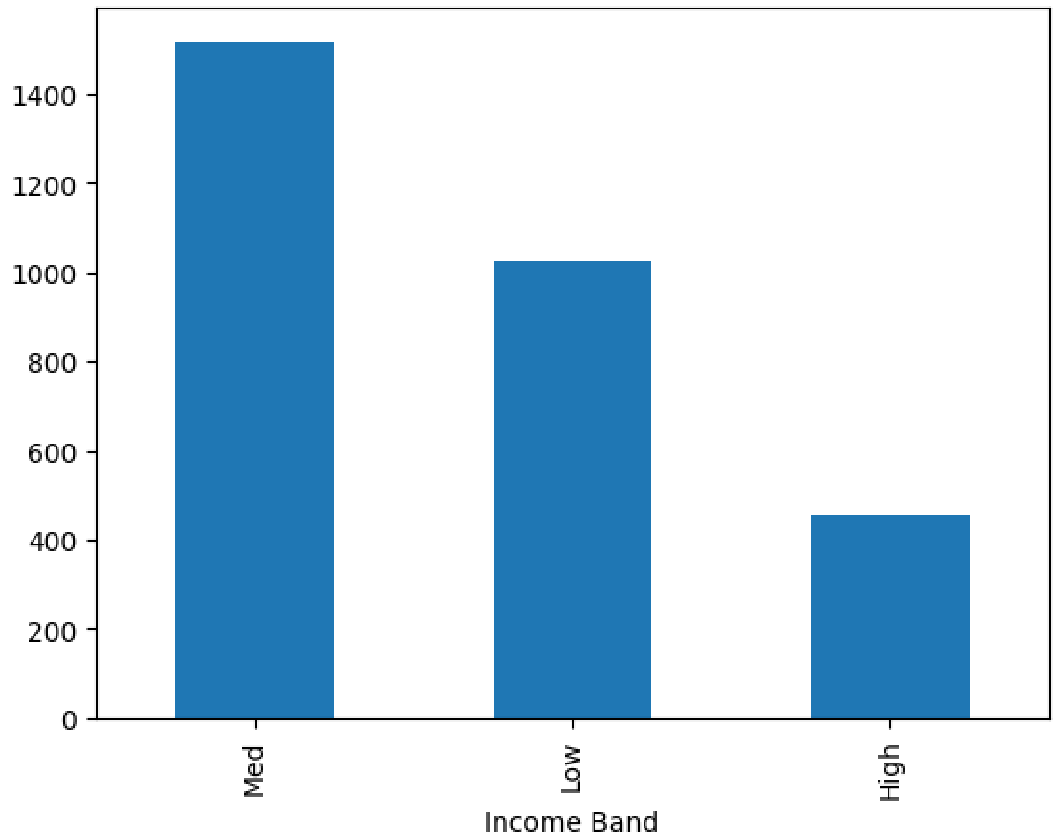
[ ]:
```
               Age   Location ID  Estimated Income  Superannuation Savings  \
count  3000.000000   3000.000000       3000.000000             3000.000000
mean     51.039667  21563.323000     171305.034263            25531.599673
std      19.854760  12462.273017     111935.808209            16259.950770
min      17.000000     12.000000      15919.480000             1482.030000
25%      34.000000  10803.500000      82906.595000            12513.775000
50%      51.000000  21129.500000     142313.480000            22357.355000
75%      69.000000  32054.500000     242290.305000            35464.740000
max      85.000000  43369.000000     522330.260000            75963.900000

       Amount of Credit Cards  Credit Card Balance    Bank Loans  \
count             3000.000000          3000.000000  3.000000e+03
mean                 1.463667          3176.206943  5.913862e+05
std                  0.676387          2497.094709  4.575570e+05
min                  1.000000             1.170000  0.000000e+00
25%                  1.000000          1236.630000  2.396281e+05
50%                  1.000000          2560.805000  4.797934e+05
75%                  2.000000          4522.632500  8.258130e+05
max                  3.000000         13991.990000  2.667557e+06

       Bank Deposits  Checking Accounts  Saving Accounts  \
count   3.000000e+03       3.000000e+03     3.000000e+03
mean    6.715602e+05       3.210929e+05     2.329084e+05
std     6.457169e+05       2.820796e+05     2.300078e+05
min     0.000000e+00       0.000000e+00     0.000000e+00
25%     2.044004e+05       1.199475e+05     7.479440e+04
50%     4.633165e+05       2.428157e+05     1.640866e+05
75%     9.427546e+05       4.348749e+05     3.155750e+05
max     3.890598e+06       1.969923e+06     1.724118e+06
```

```
       Foreign Currency Account  Business Lending  Properties Owned  \
count               3000.000000      3.000000e+03       3000.000000
mean               29883.529993      8.667598e+05          1.518667
std                23109.924010      6.412303e+05          1.102145
min                   45.000000      0.000000e+00          0.000000
25%                11916.542500      3.748251e+05          1.000000
50%                24341.190000      7.113147e+05          2.000000
75%                41966.392500      1.185110e+06          2.000000
max               124704.870000      3.825962e+06          3.000000

       Risk Weighting         BRId     GenderId         IAId
count     3000.000000  3000.000000  3000.000000  3000.000000
mean         2.249333     2.559333     1.504000    10.425333
std          1.131191     1.007713     0.500067     5.988242
min          1.000000     1.000000     1.000000     1.000000
25%          1.000000     2.000000     1.000000     5.000000
50%          2.000000     3.000000     2.000000    10.000000
75%          3.000000     3.000000     2.000000    15.000000
max          5.000000     4.000000     2.000000    22.000000
```

[ ]:
```
bins = [0, 100000, 300000, float('inf')]
labels = ['Low', 'Med', 'High']

df['Income Band'] = pd.cut(df['Estimated Income'], bins=bins, labels=labels,␣
 ↪right=False)
```

[ ]:
```
df['Income Band'].value_counts().plot(kind='bar')
```

[ ]: <Axes: xlabel='Income Band'>



[ ]:
```
# Examine the distribution of unique cataegories in categorical columns
categorical_cols = df[["BRId", "GenderId", "IAId", "Amount of Credit Cards",␣
 ↪"Nationality", "Occupation", "Fee Structure", "Loyalty Classification",␣
 ↪"Properties Owned", "Risk Weighting", "Income Band"]].columns

for col in categorical_cols:
  print(f"Value Counts for '{col}':")
  display(df[col].value_counts())
```

```
Value Counts for 'BRId':

BRId
3    1352
1     660
2     495
4     493
Name: count, dtype: int64

Value Counts for 'GenderId':

GenderId
2    1512
```

```
1    1488
Name: count, dtype: int64
```

```
Value Counts for 'IAId':
```

```
IAId
1     177
3     177
4     177
8     177
2     177
11    176
15    176
14    176
13    176
12    176
10    176
9     176
7      89
6      89
5      89
16     88
17     88
18     88
19     88
20     88
21     88
22     88
Name: count, dtype: int64
```

```
Value Counts for 'Amount of Credit Cards':
```

```
Amount of Credit Cards
1    1922
2     765
3     313
Name: count, dtype: int64
```

```
Value Counts for 'Nationality':
```

```
Nationality
European      1309
Asian          754
American       507
Australian     254
African        176
Name: count, dtype: int64
```

```
Value Counts for 'Occupation':
```

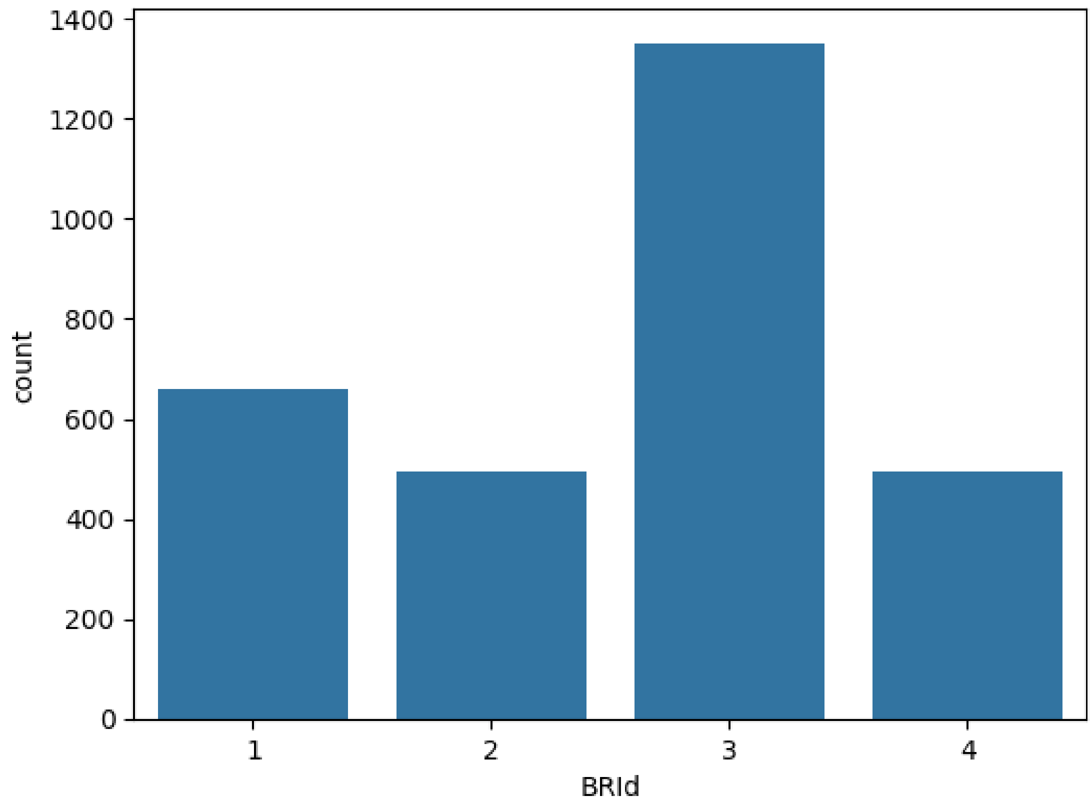
```
Occupation
Structural Analysis Engineer    28
```

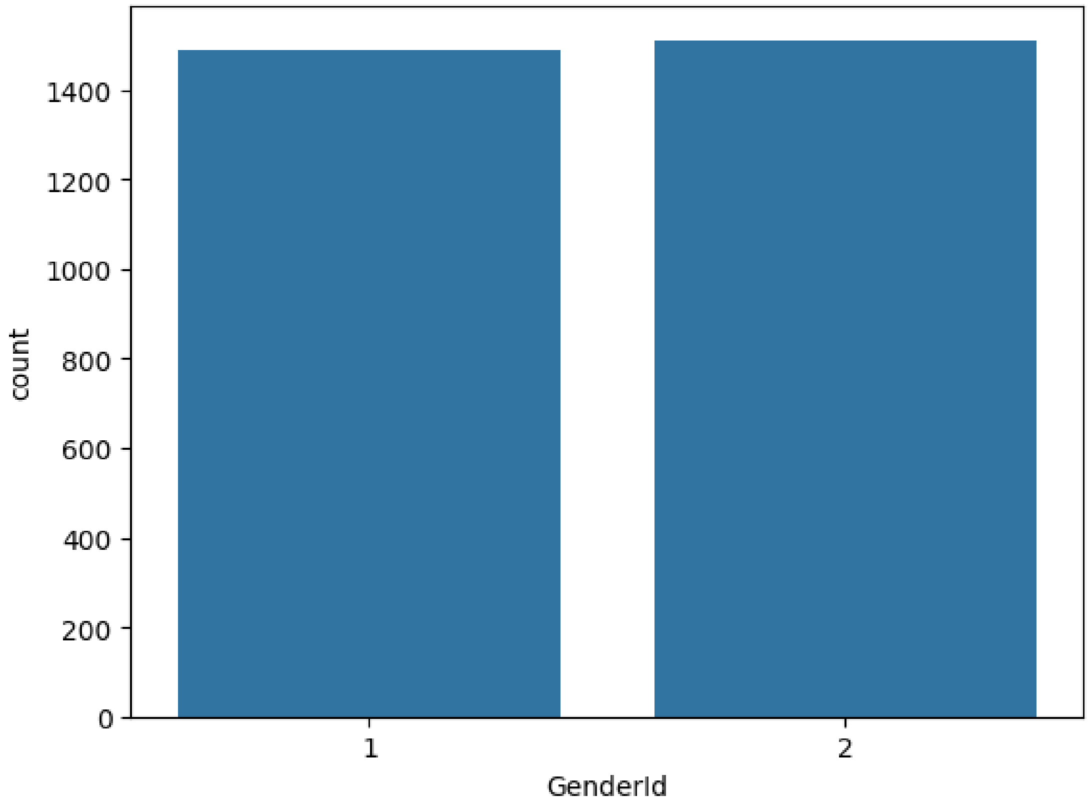
```
Associate Professor            28
Recruiter                      25
Human Resources Manager        24
Account Coordinator            24
                               ..
Office Assistant IV             8
Automation Specialist I         7
Computer Systems Analyst I      6
Developer III                   5
Senior Sales Associate          4
Name: count, Length: 195, dtype: int64

Value Counts for 'Fee Structure':

Fee Structure
High    1476
Mid      962
Low      562
Name: count, dtype: int64

Value Counts for 'Loyalty Classification':

Loyalty Classification
Jade        1331
Silver       767
Gold         585
Platinum     317
Name: count, dtype: int64

Value Counts for 'Properties Owned':

Properties Owned
2    777
1    776
3    742
0    705
Name: count, dtype: int64

Value Counts for 'Risk Weighting':

Risk Weighting
2    1222
1     836
3     460
4     322
5     160
Name: count, dtype: int64

Value Counts for 'Income Band':

Income Band
Med     1517
Low     1027
```

```
High     456
Name: count, dtype: int64
```

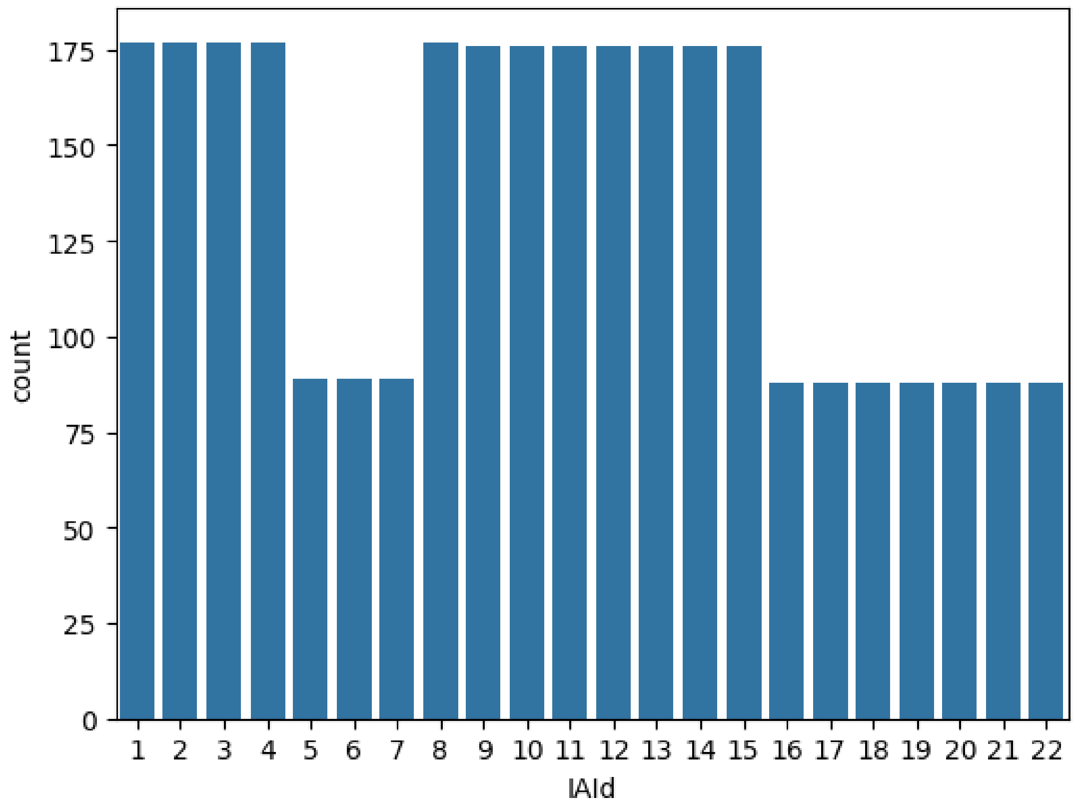
0.2 Univariate Analysis

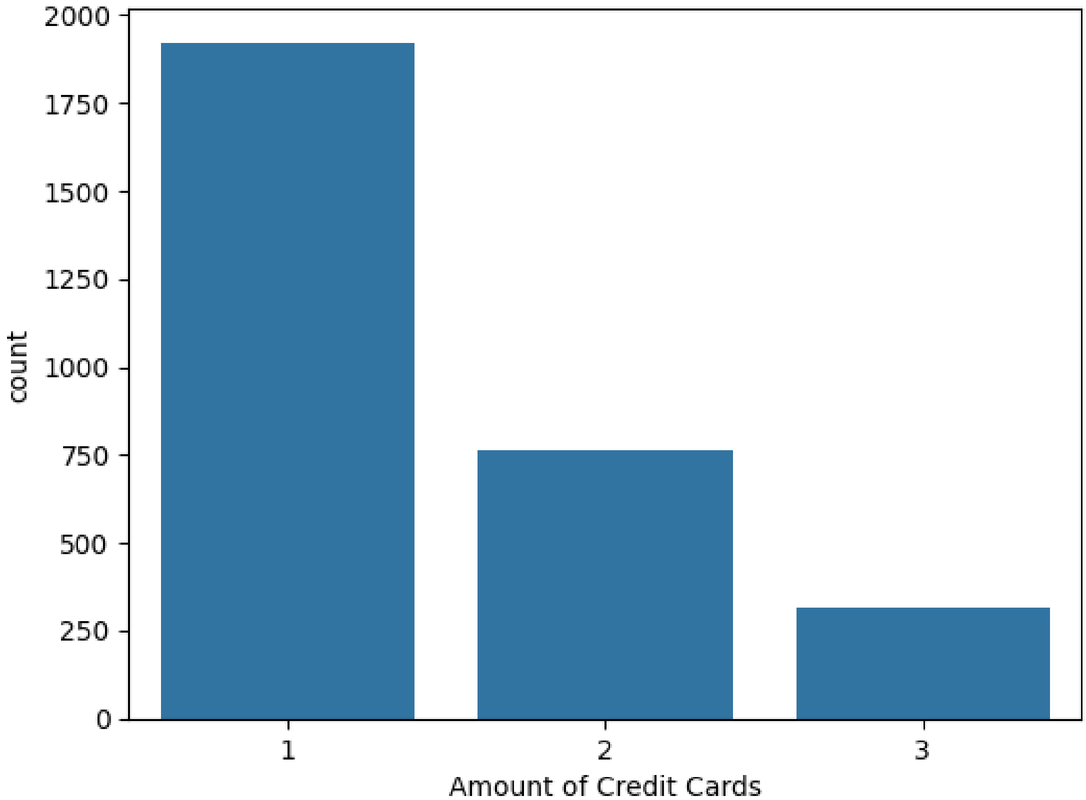
[ ]:
```
for i, predictor in enumerate(df[["BRId", "GenderId", "IAId", "Amount of Credit␣
↪Cards", "Nationality", "Occupation", "Fee Structure", "Loyalty␣
↪Classification", "Properties Owned", "Risk Weighting", "Income Band"]].
↪columns):
    plt.figure(i)
    sns.countplot(data=df, x=predictor)
```

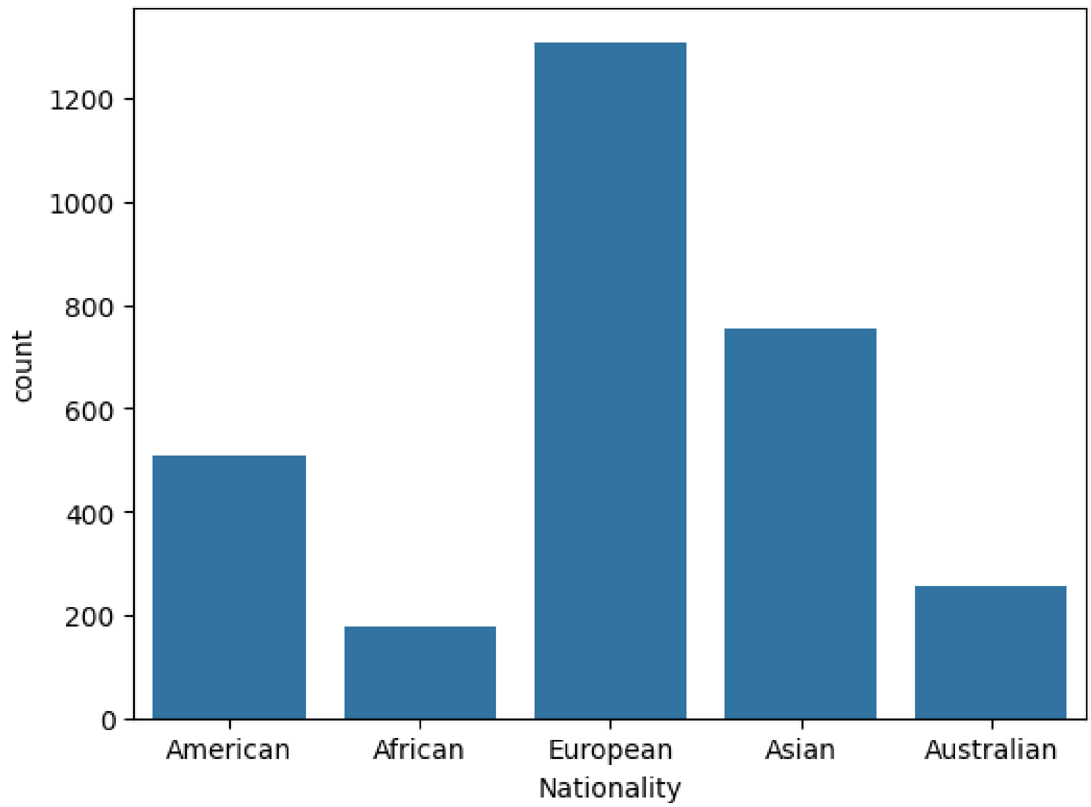




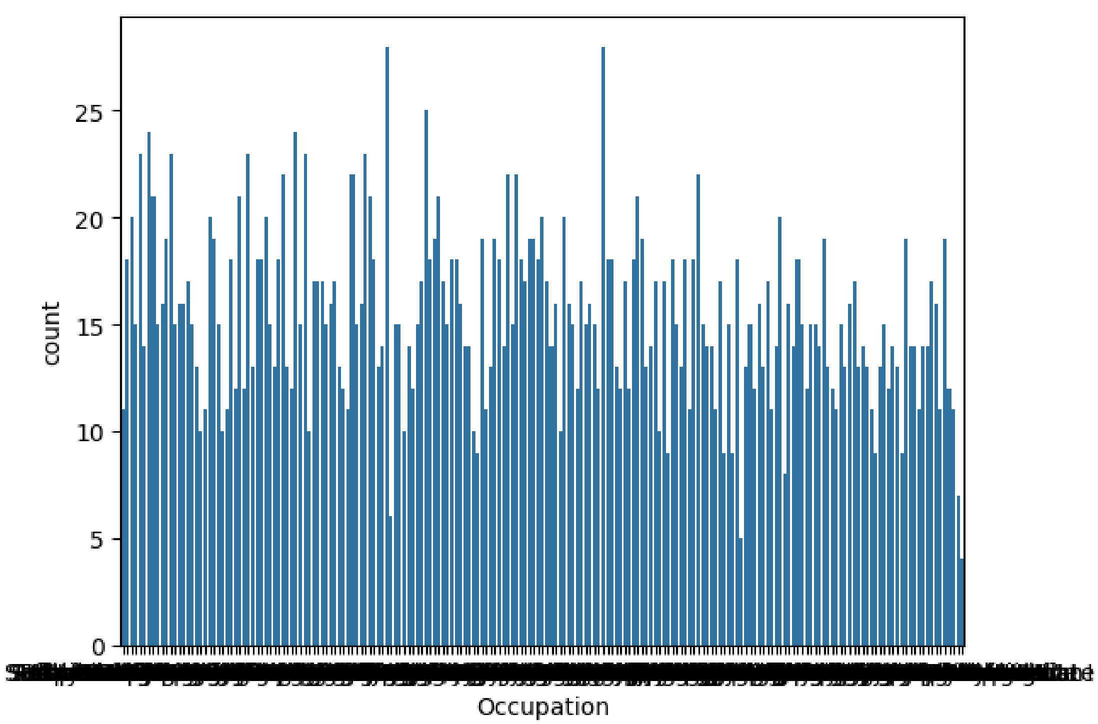
1400
1200
1000
800
600
400
200
0
count
1
2
GenderId


count
0
25
50
75
100
125
150
175
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22
IAId

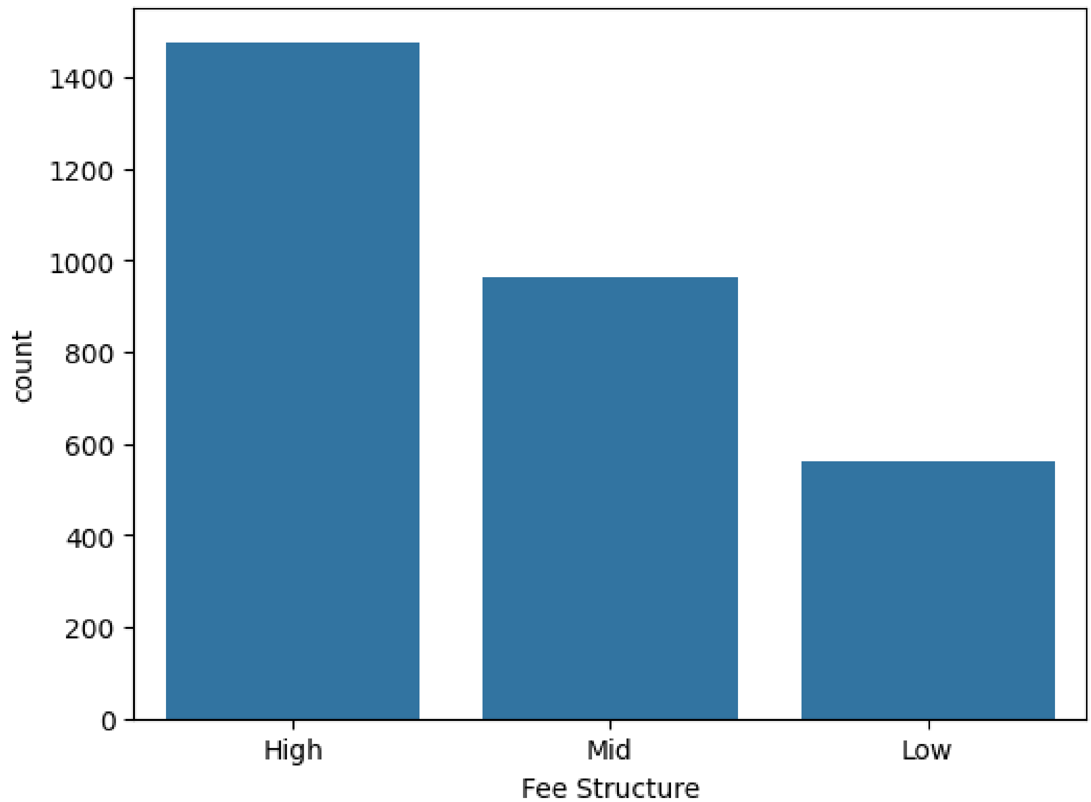

2000
1750
1500
1250
1000
750
500
250
0
count
1
2
3
Amount of Credit Cards

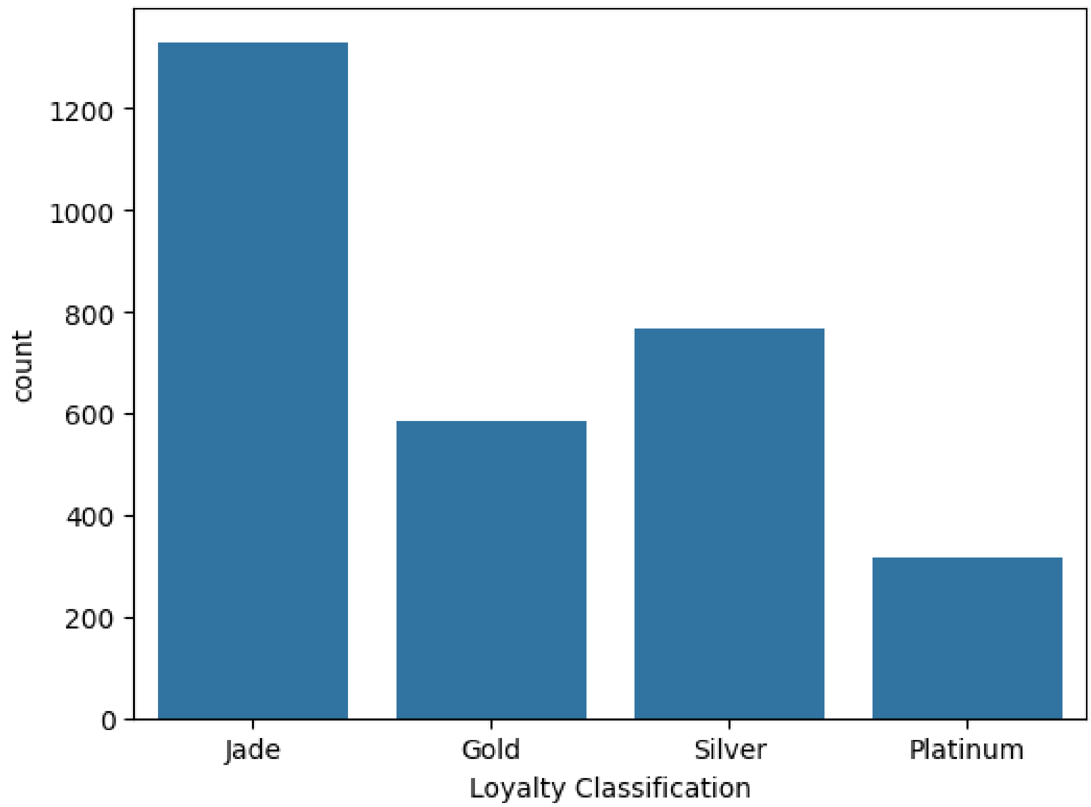


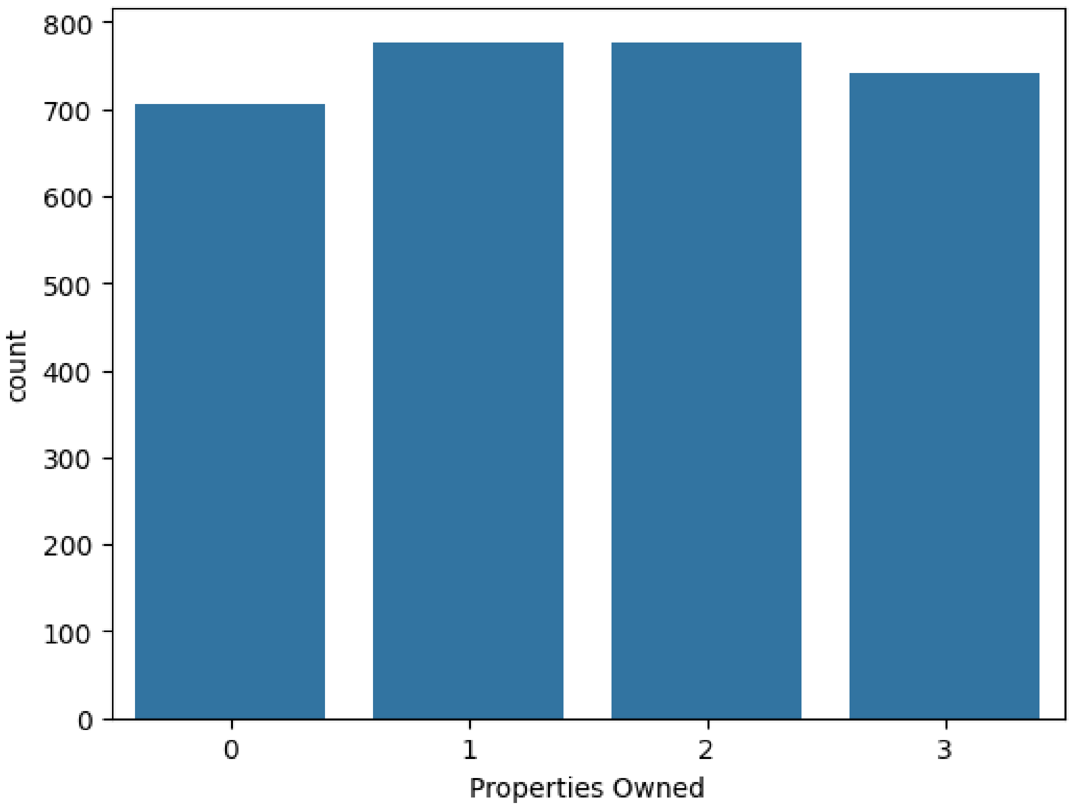
count
Nationality
American
African
European
Asian
Australian
0
200
400
600
800
1000
1200



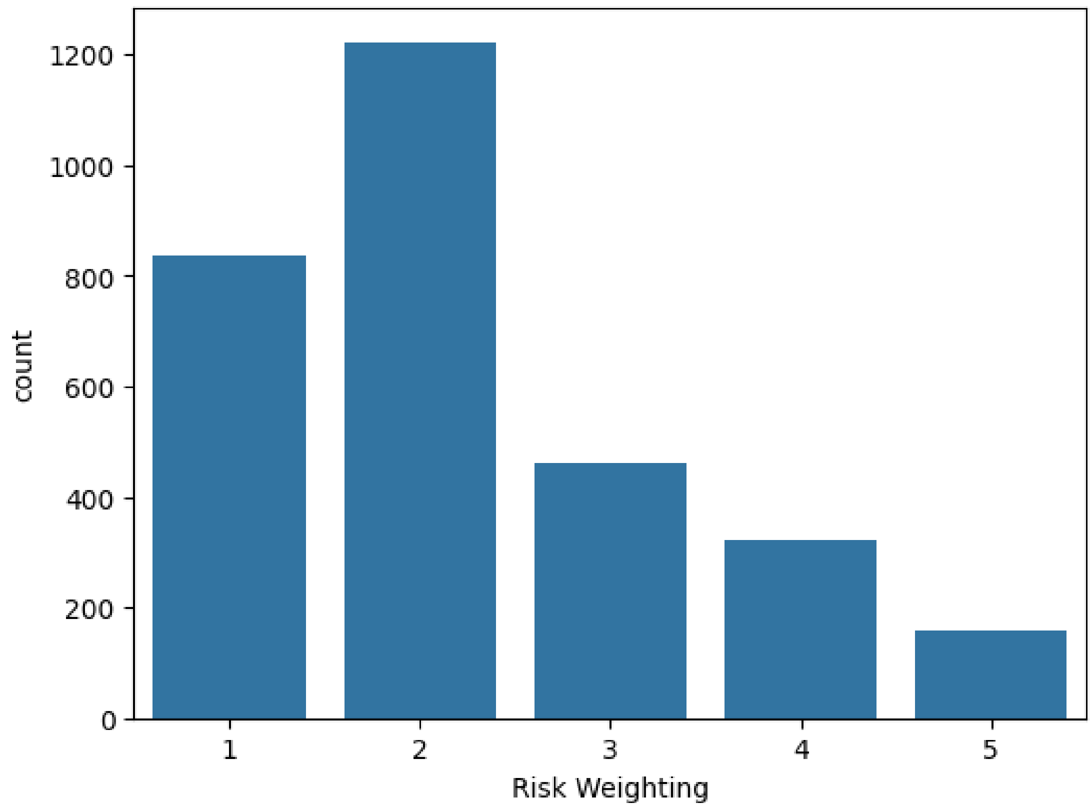
count
Occupation
0
5
10
15
20
25

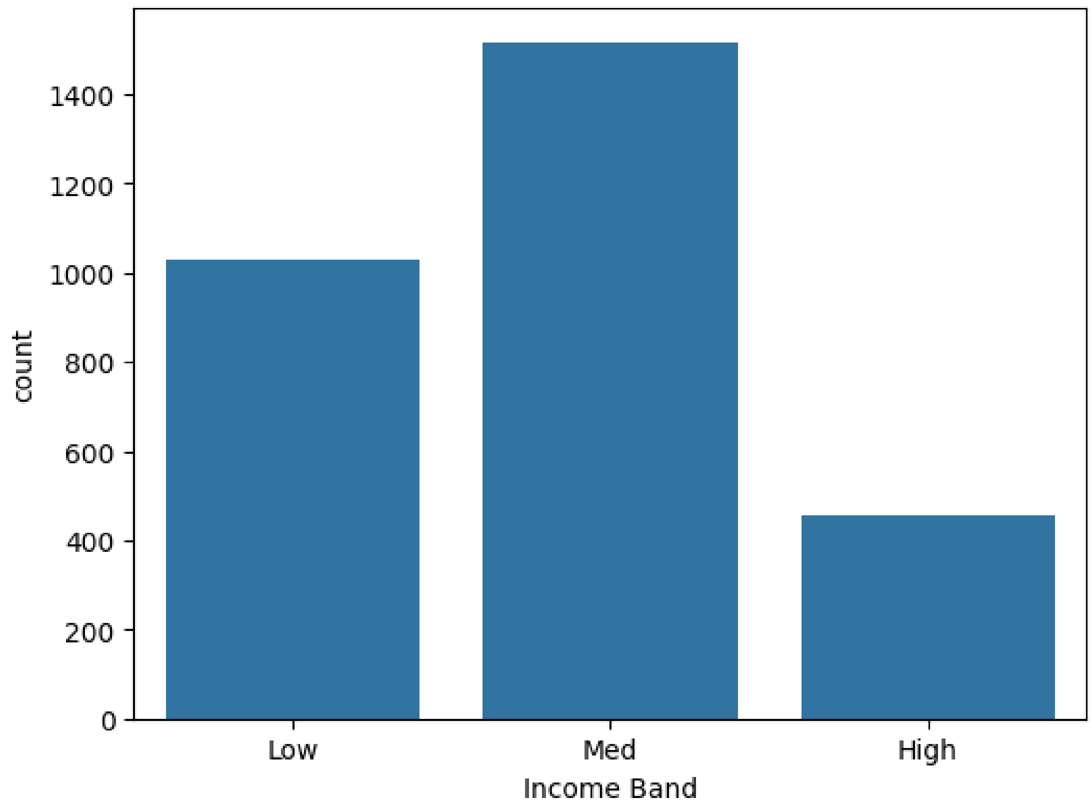

1400
1200
1000
800
600
400
200
0
count
High
Mid
Low
Fee Structure


count
1200
1000
800
600
400
200
0
Jade
Gold
Silver
Platinum
Loyalty Classification



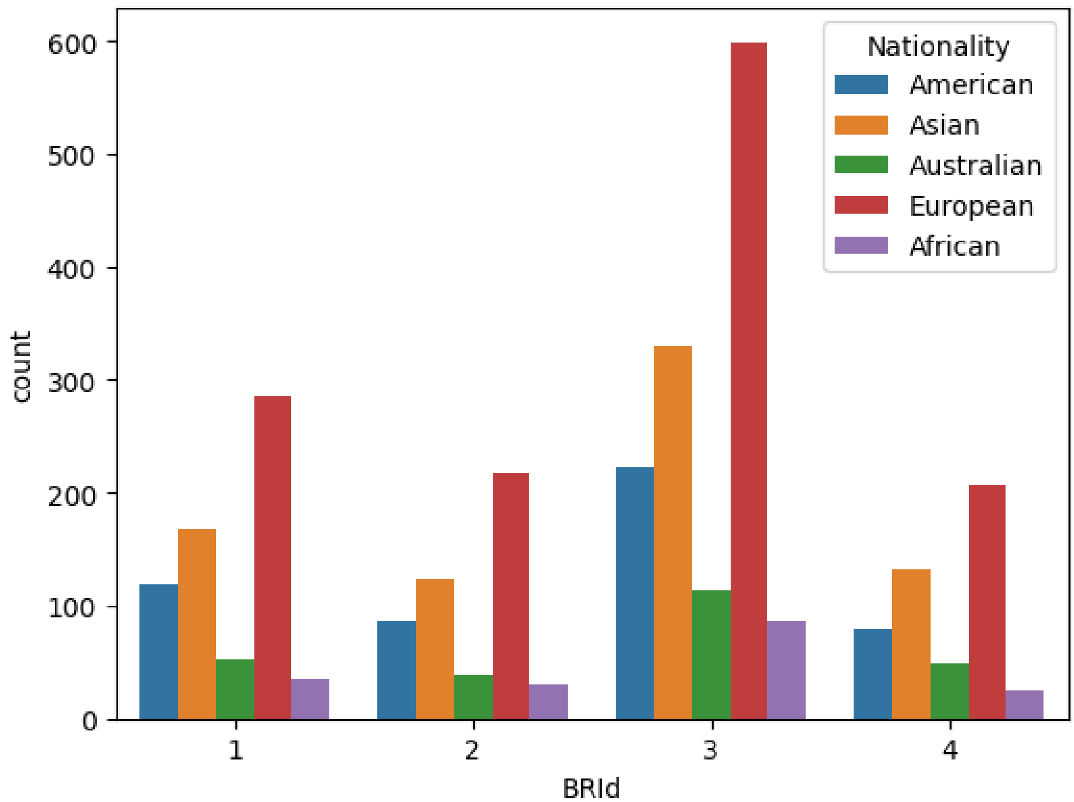
800
700
600
500
400
300
200
100
0
count
0
1
2
3
Properties Owned


count
1200
1000
800
600
400
200
0
1
2
3
4
5
Risk Weighting

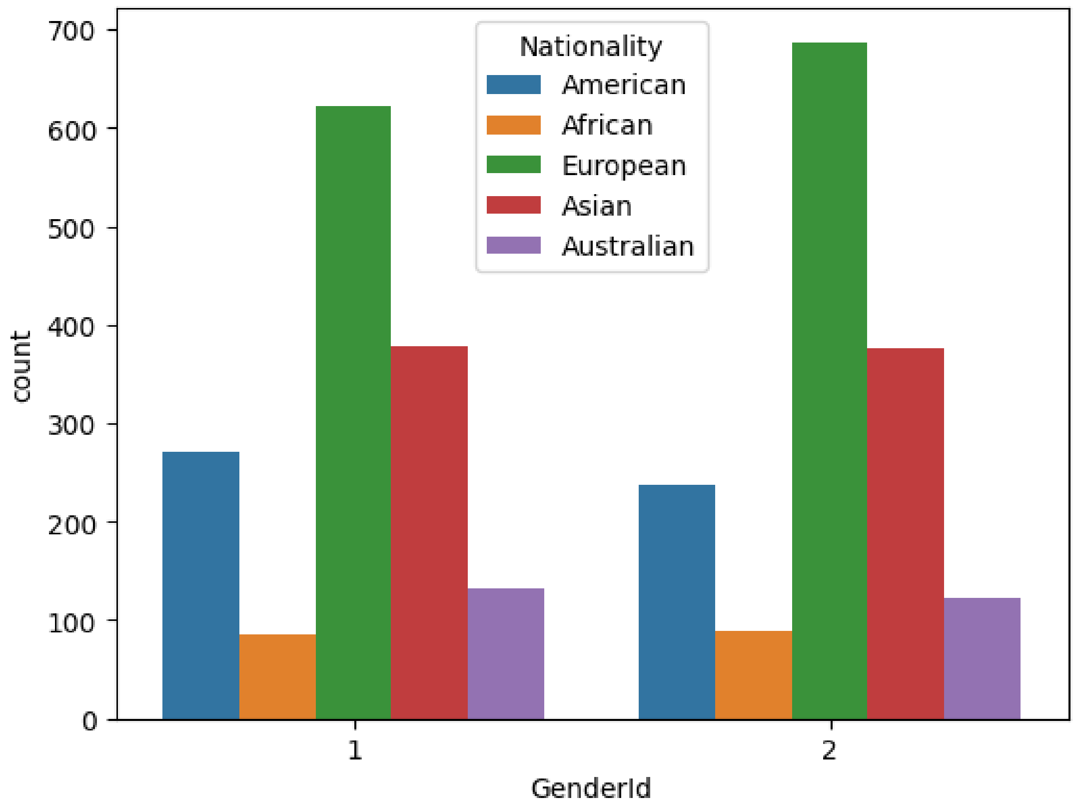


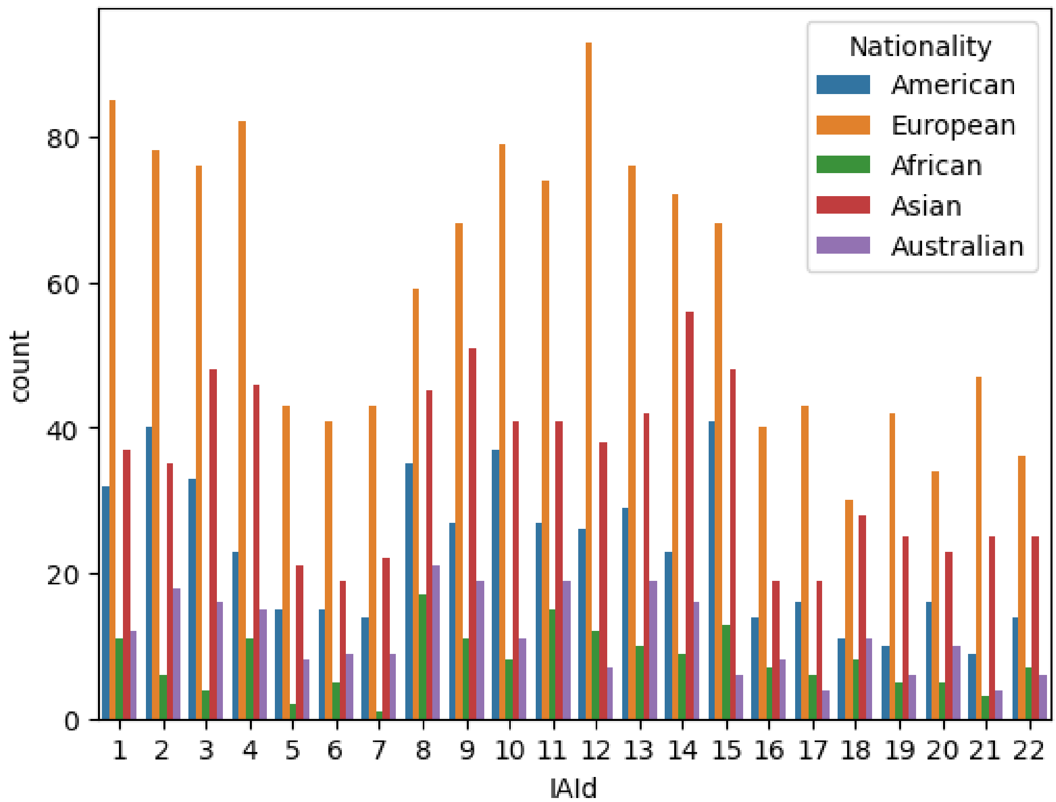
0.3 Bivariate Analysis

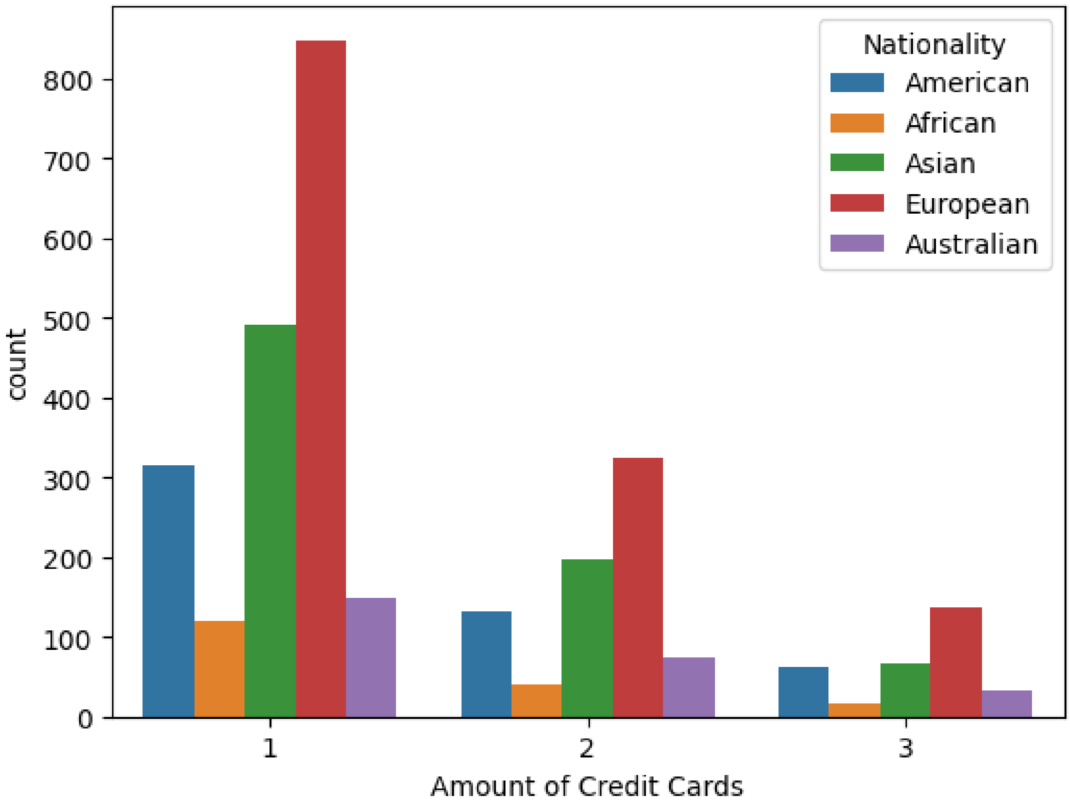
```
[ ]: for i, predictor in enumerate(df[["BRId", "GenderId", "IAId", "Amount of Credit␣
     ↪Cards", "Nationality", "Occupation", "Fee Structure", "Loyalty␣
     ↪Classification", "Properties Owned", "Risk Weighting", "Income Band"]].
     ↪columns):
         plt.figure(i)
         sns.countplot(data=df, x=predictor, hue='Nationality')
```

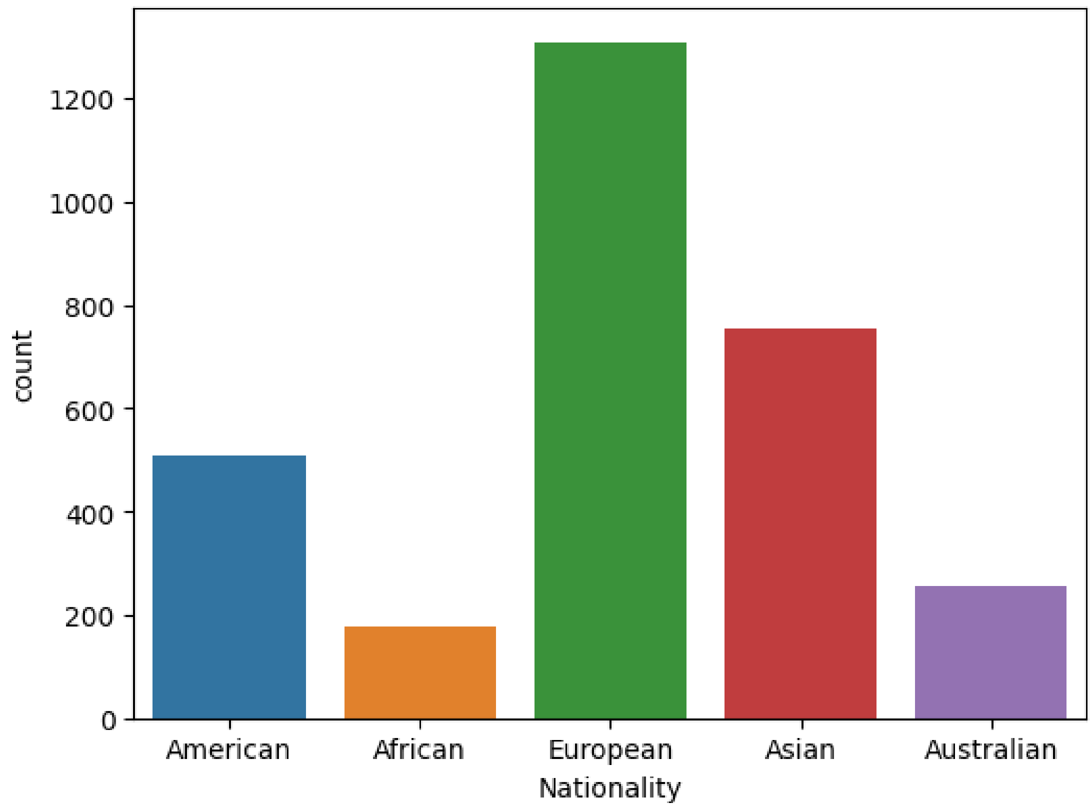


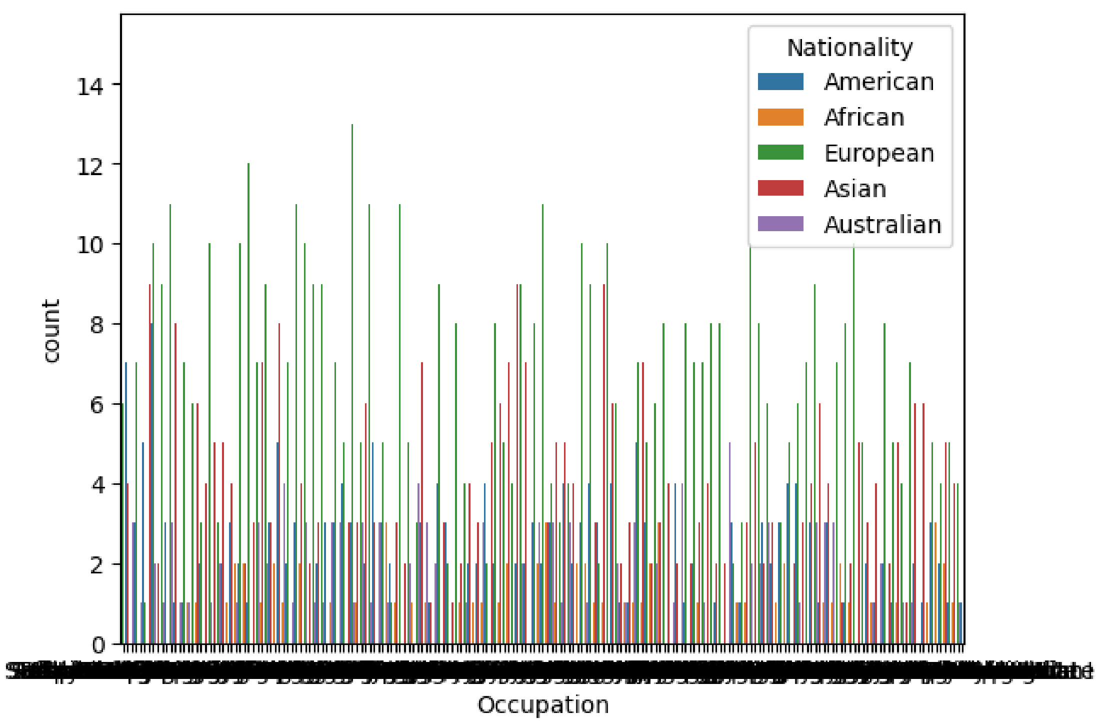
Nationality
American
Asian
Australian
European
African
600
500
400
300
200
100
0
count
1
2
3
4
BRId

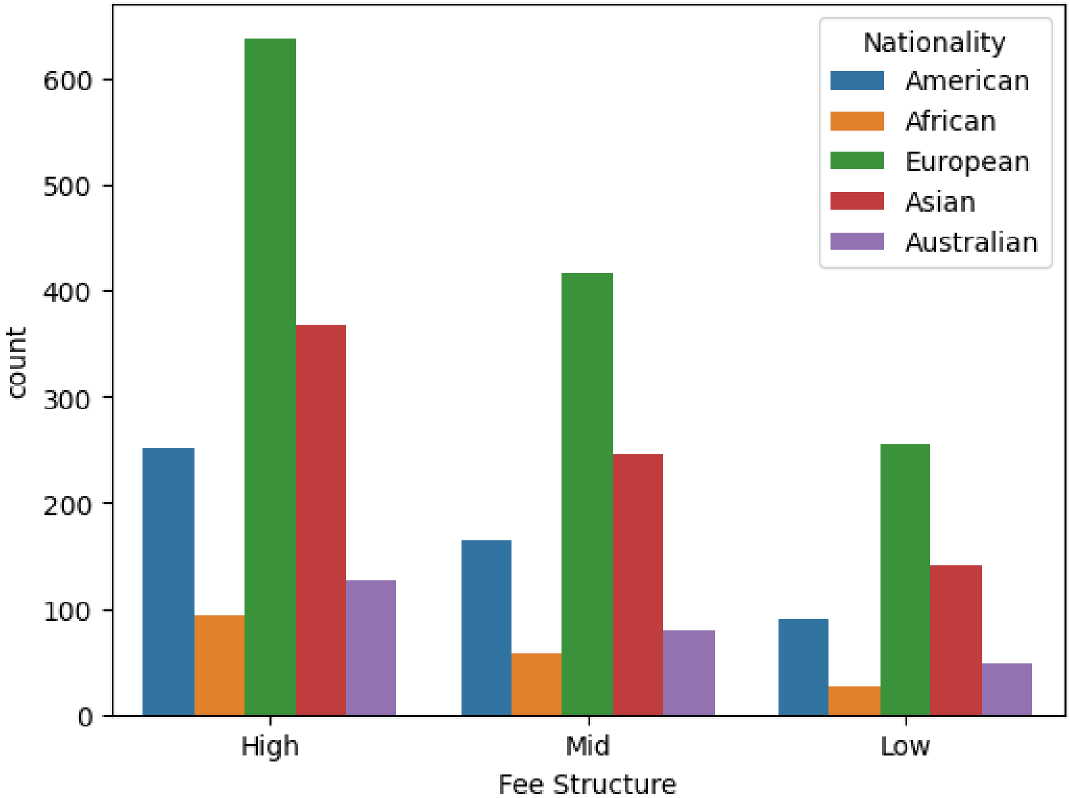

Nationality
American
African
European
Asian
Australian
700
600
500
400
300
200
100
0
count
1
2
GenderId

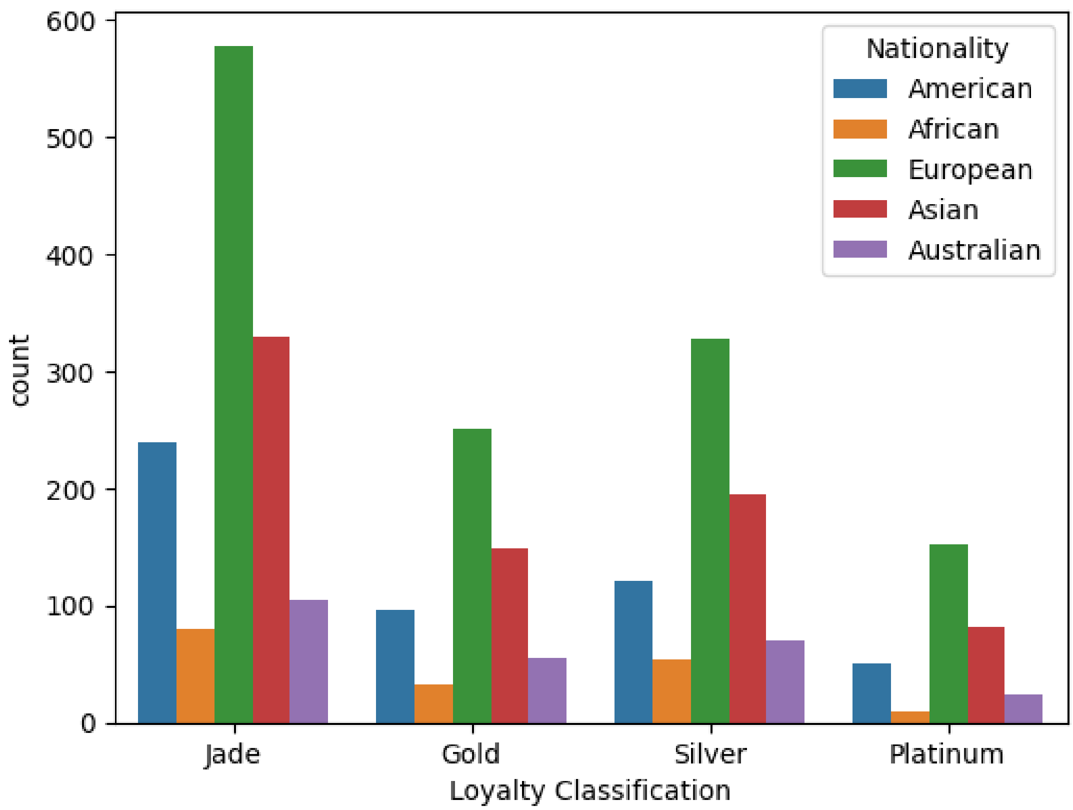

Nationality
American
European
African
Asian
Australian
count
0
20
40
60
80
IAId
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22


Nationality
American
African
Asian
European
Australian
count
0
100
200
300
400
500
600
700
800
1
2
3
Amount of Credit Cards

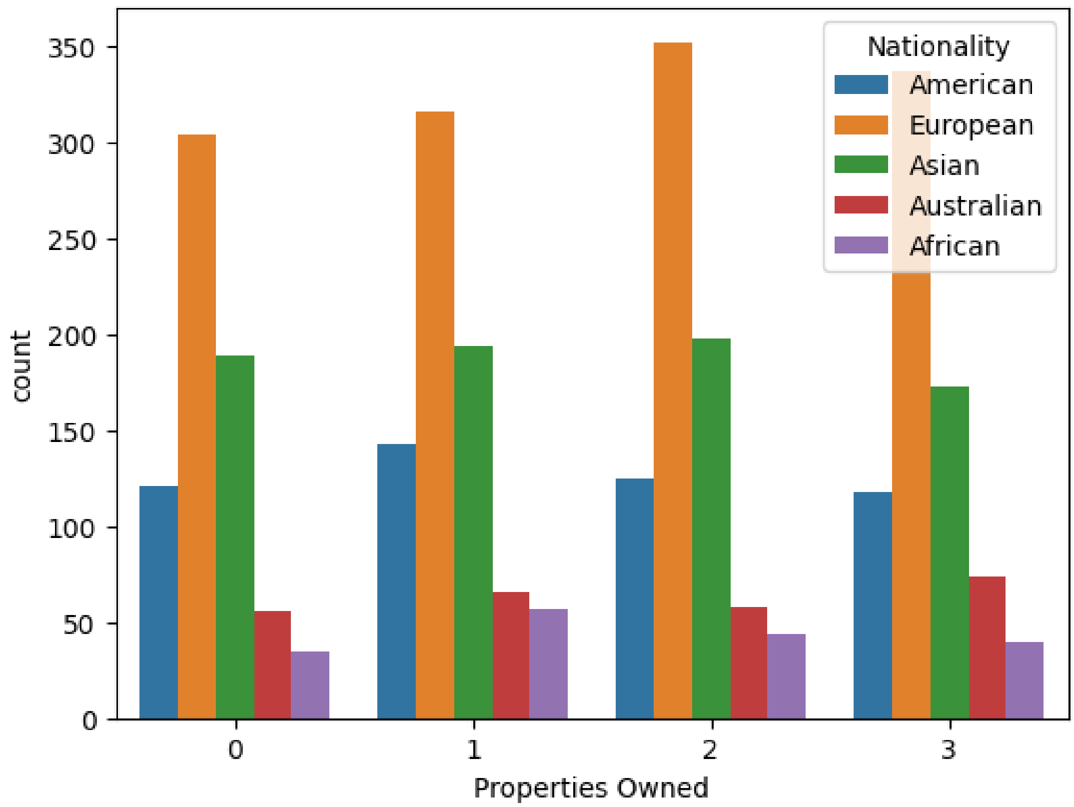

count
1200
1000
800
600
400
200
0
American
African
European
Asian
Australian
Nationality

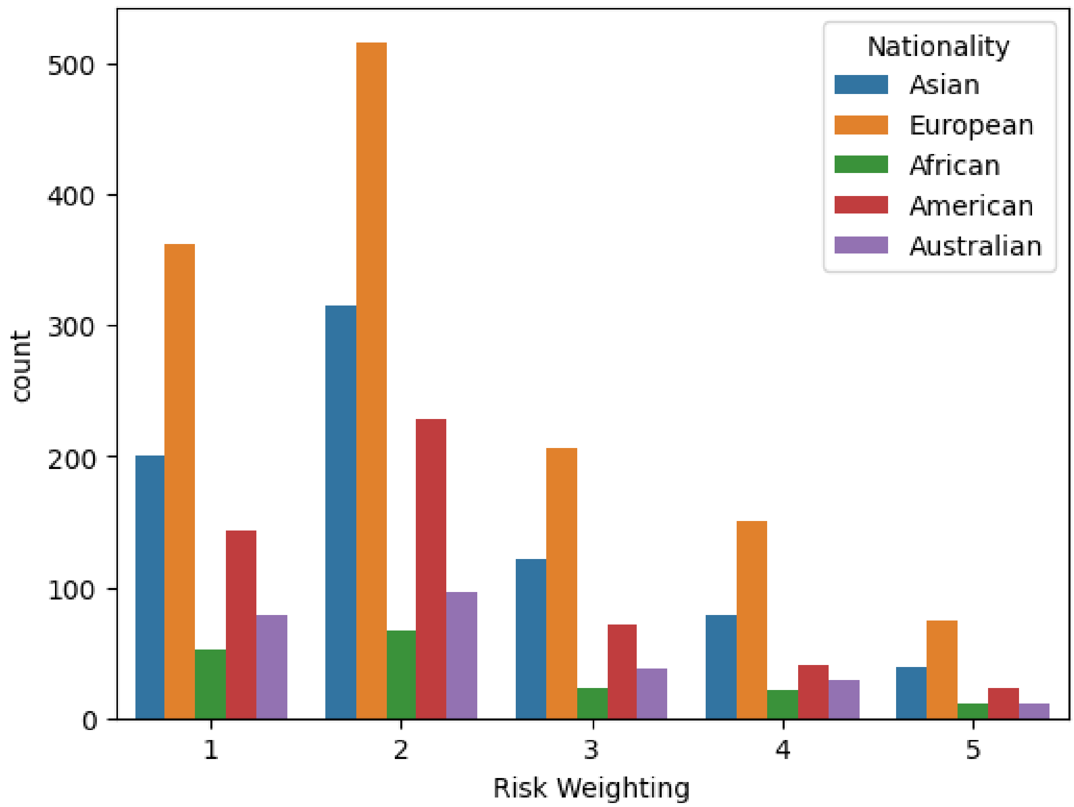

Nationality
American
African
European
Asian
Australian
count
14
12
10
8
6
4
2
0
Occupation

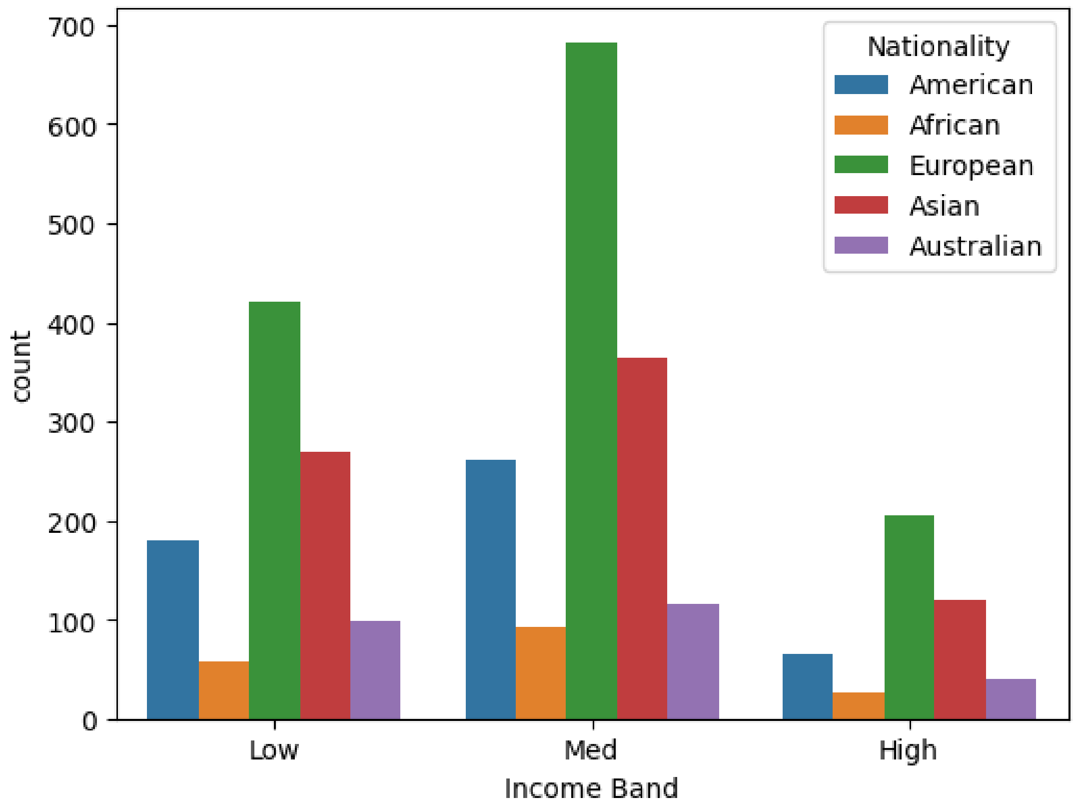

Nationality
American
African
European
Asian
Australian
count
0
100
200
300
400
500
600
High
Mid
Low
Fee Structure



600
500
400
300
200
100
0
count
Nationality
American
African
European
Asian
Australian
Jade
Gold
Silver
Platinum
Loyalty Classification

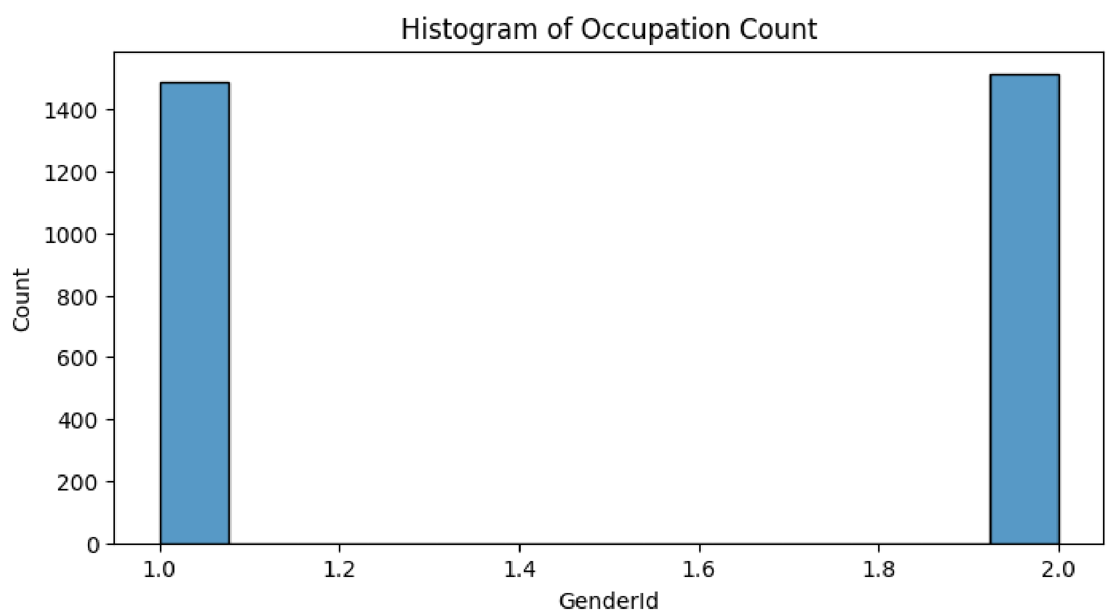

Nationality
American
European
Asian
Australian
African
count
0
50
100
150
200
250
300
350
0
1
2
3
Properties Owned

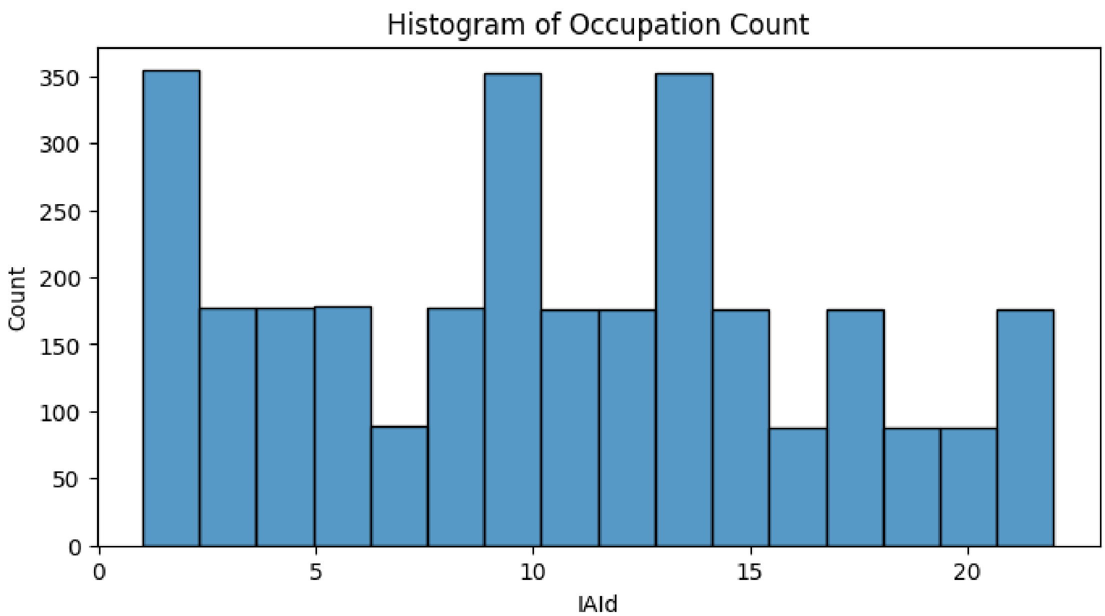

Nationality
Asian
European
African
American
Australian
count
500
400
300
200
100
0
1
2
3
4
5
Risk Weighting

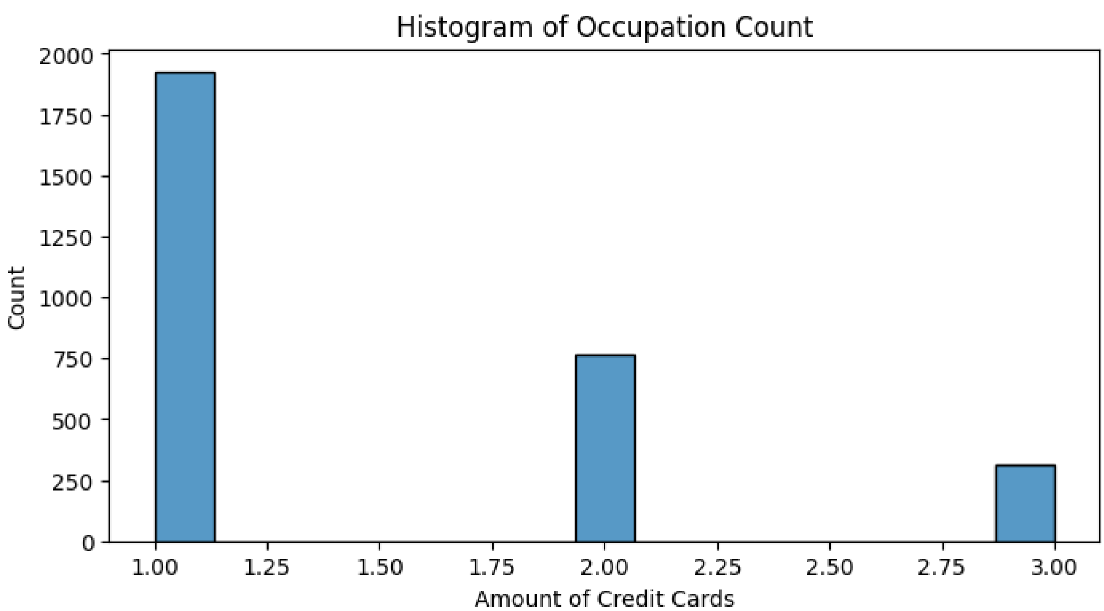


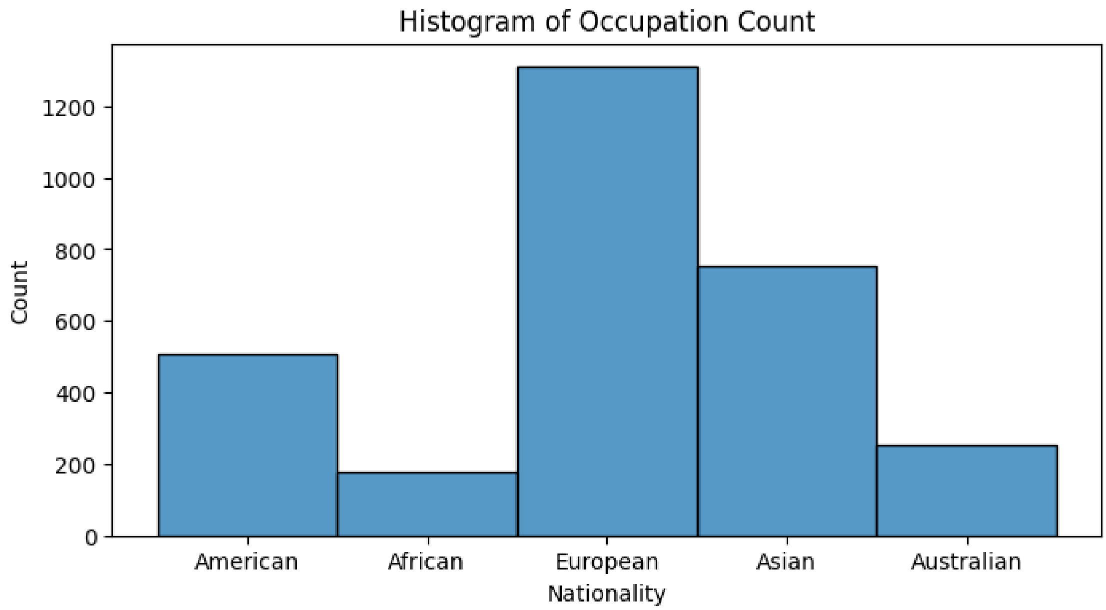
[ ]:
```python
# HIstplot of value counts for different Occupation

for col in categorical_cols:
  if col == "Occupation":
    continue
  plt.figure(figsize=(8,4))
  sns.histplot(df[col])
  plt.title('Histogram of Occupation Count')
  plt.xlabel(col)
  plt.ylabel("Count")
  plt.show()
```


Histogram of Occupation Count
Count
BRId
0
200
400
600
800
1000
1200
1400
1.0
1.5
2.0
2.5
3.0
3.5
4.0

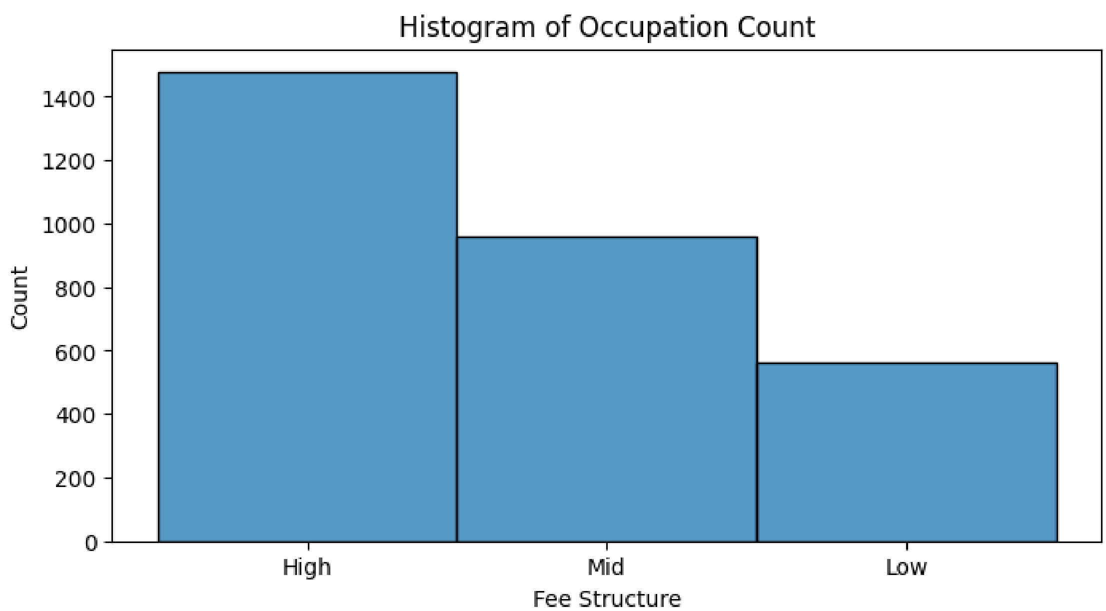

Histogram of Occupation Count
Count
GenderId
0
200
400
600
800
1000
1200
1400
1.0
1.2
1.4
1.6
1.8
2.0


Histogram of Occupation Count
Count
350
300
250
200
150
100
50
0
0
5
10
15
20
IAId

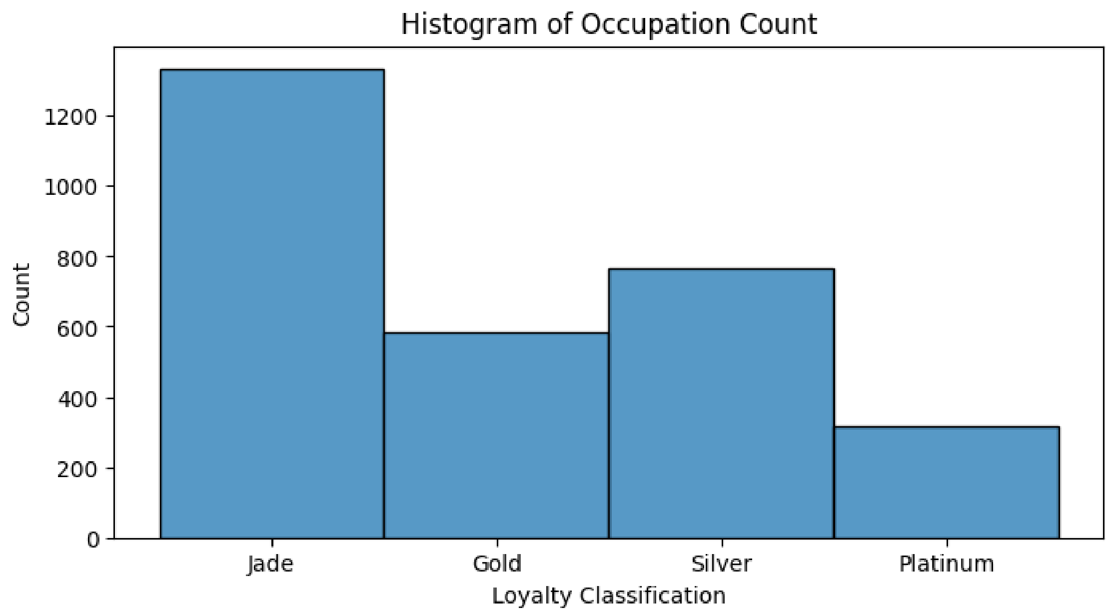

Histogram of Occupation Count
Count
2000
1750
1500
1250
1000
750
500
250
0
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Amount of Credit Cards

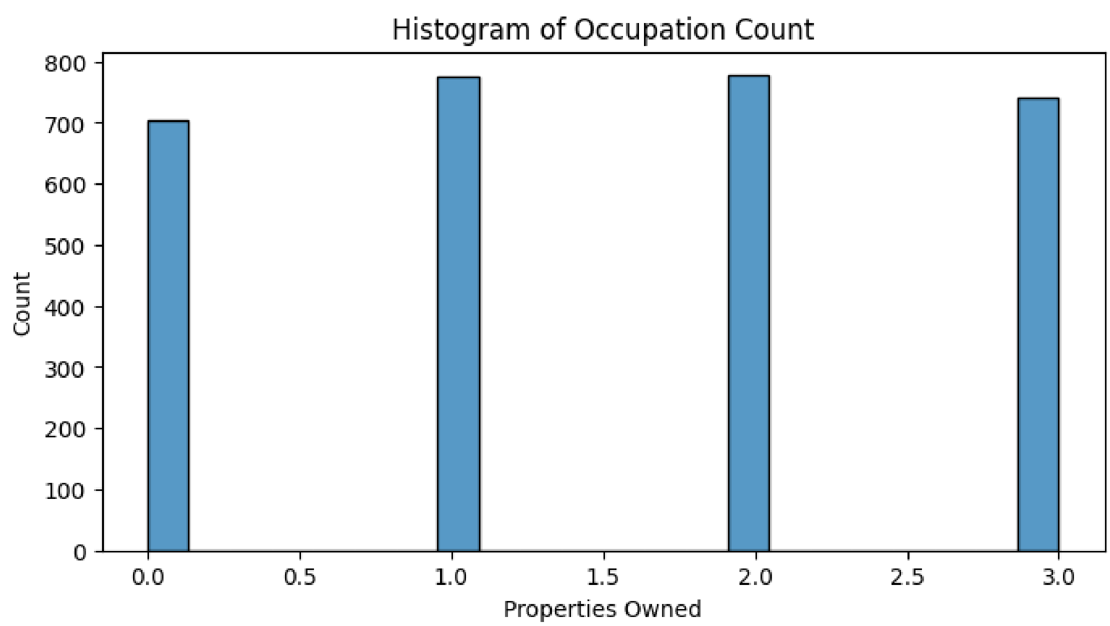


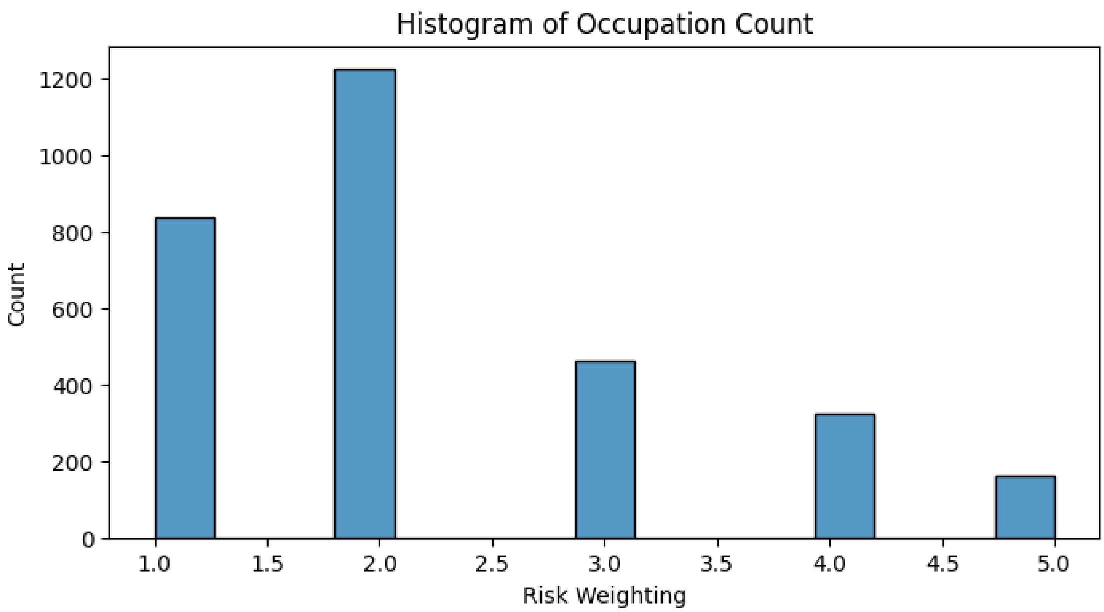
Histogram of Occupation Count
Count
1200
1000
800
600
400
200
0
American
African
European
Asian
Australian
Nationality

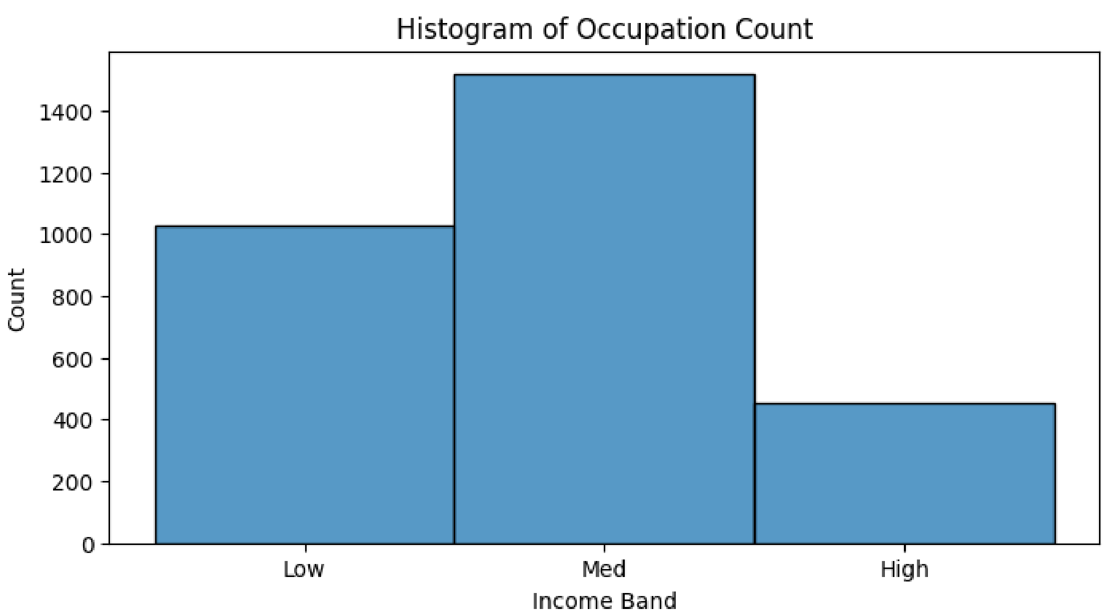


Histogram of Occupation Count
Count
1400
1200
1000
800
600
400
200
0
High
Mid
Low
Fee Structure


Histogram of Occupation Count
Count
0
200
400
600
800
1000
1200
Jade
Gold
Silver
Platinum
Loyalty Classification


Histogram of Occupation Count
Count
0
100
200
300
400
500
600
700
800
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Properties Owned

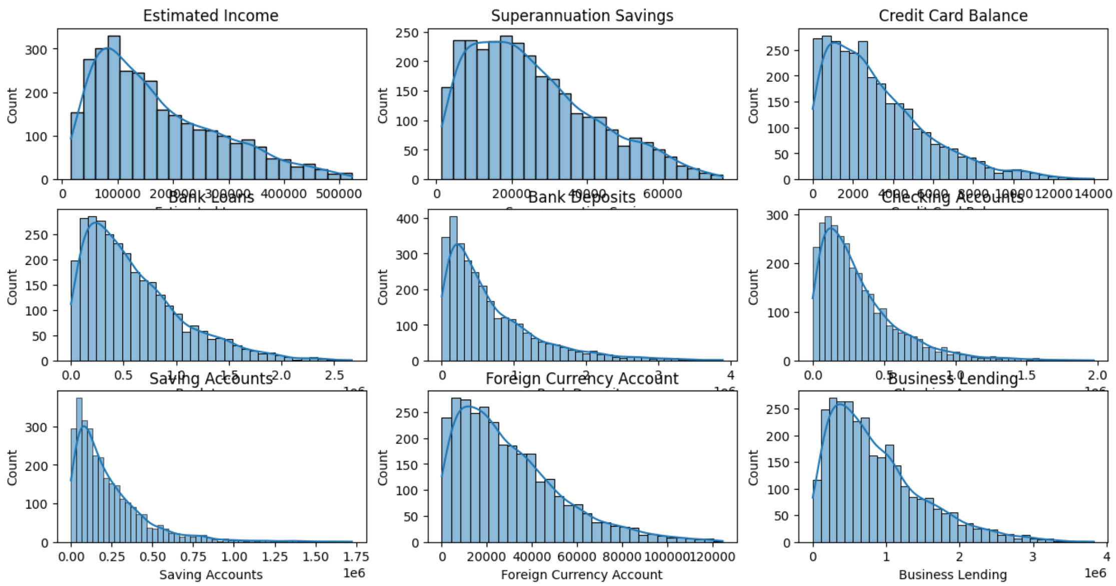




0.4 Numerical Analysis

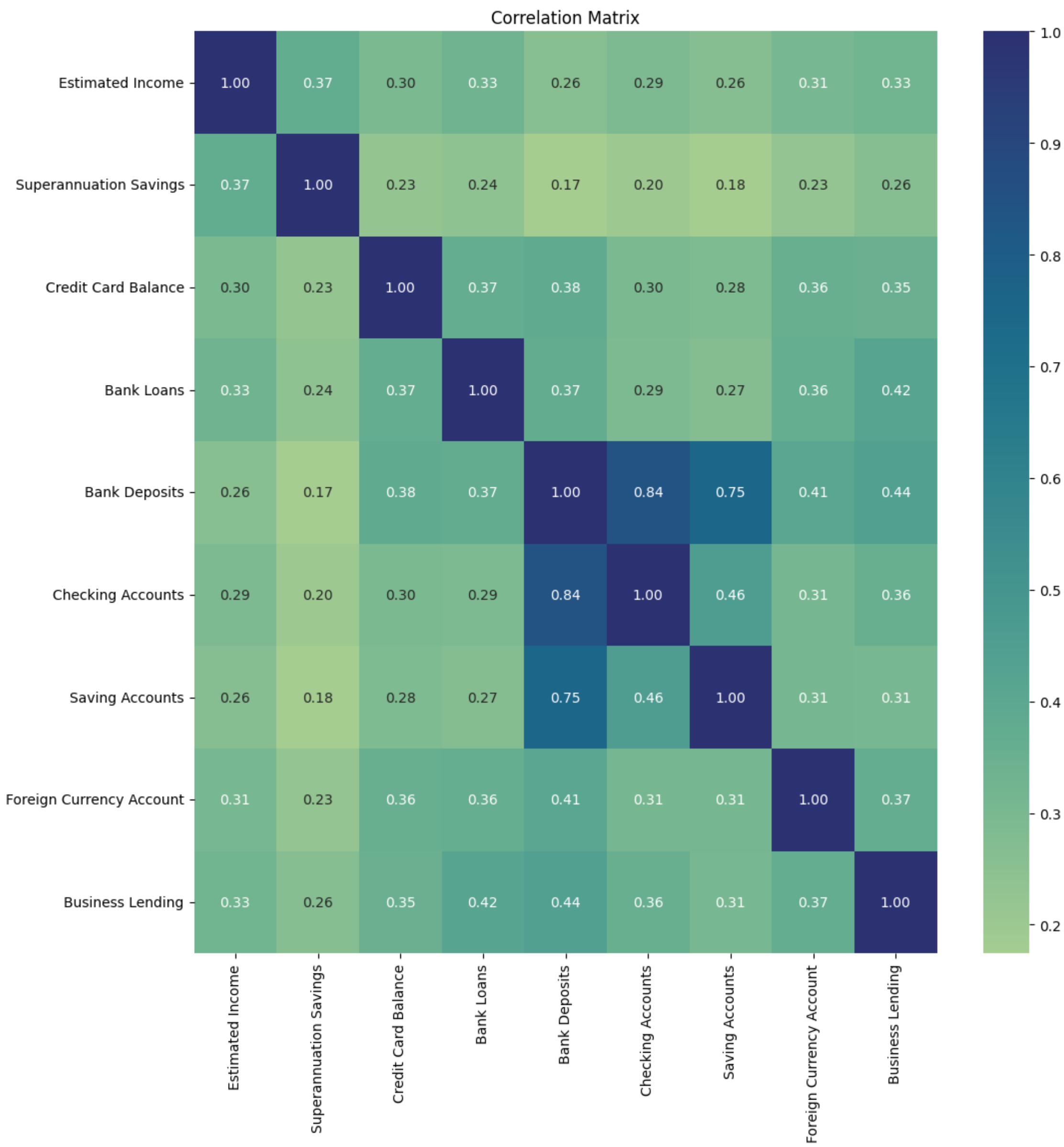
[ ]:
```
numerical_cols = ['Estimated Income', 'Superannuation Savings', 'Credit Card␣
↪Balance', 'Bank Loans', 'Bank Deposits', 'Checking Accounts', 'Saving␣
↪Accounts', 'Foreign Currency Account', 'Business Lending']
```

```python
# Univariate analysis and visualization
plt.figure(figsize=(15,10))
for i,col in enumerate(numerical_cols):
  plt.subplot(4,3,i+1)
  sns.histplot(df[col],kde=True)
  plt.title(col)
plt.show()
```



0.5 Heatmaps

[ ]:
```python
numerical_cols = ['Estimated Income', 'Superannuation Savings', 'Credit Card Balance', 'Bank Loans', 'Bank Deposits', 'Checking Accounts', 'Saving Accounts', 'Foreign Currency Account', 'Business Lending']

correlation_matrix = df[numerical_cols].corr()

plt.figure(figsize=(12,12))
sns.heatmap(correlation_matrix, annot=True, cmap='crest', fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
```



[ ]:

[ ]:

0.6 Insights of EDA:

- The strongest positive correlation occur among "Bank Deposits" with "Checking Accounts", "Saving Accounts" and "Foreign Currency Account" indicating that customers who maintain high balances in one account type often hold substantial amount/funds across other accounts as well.

- Moderate correlations of Age and Estimated Income with various balances (Superannuation, Savings, Checking) reflect a common financial lifecycle trend: higher income earners and older individuals often accumulate more savings, retirement funds, and may carry higher credit card balances or loans.
- Property ownership may depend on external factors (location, real estate market conditions, inheritance, etc.) that are not captured by these particular banking variables. Hence, we see weaker correlations here.
- Business Lending's moderate link to Bank Loans suggests some customers may have both personal and business debts. However, business lending is relatively uncorrelated with other deposit or property-related metrics, indicating it may serve a distinct subset of customers or needs. Income Banding helped categorize customers into financial segments, supporting better risk-based decision-making.
- Customer Profile Trends showed clustering around certain occupations and loyalty levels, indicating potential behavioral patterns.
- Correlations between features such as income, properties owned, and risk weighting provided hints at possible risk drivers.
- Categorical Distributions revealed imbalances (e.g., skewed gender representation or concentration in a few occupations), which may inform marketing or risk models.

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