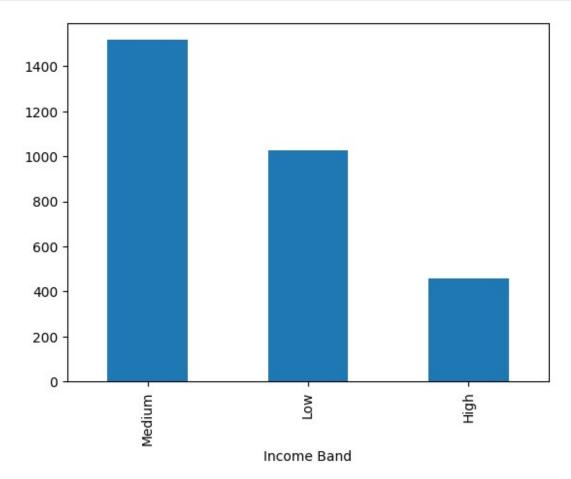
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
df = pd.read csv('/banking-clients.csv')
df.head(5)
{"type":"dataframe", "variable_name":"df"}
df.shape
(3000, 25)
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 25 columns):
#
     Column
                               Non-Null Count
                                               Dtype
     -----
                                               ----
 0
     Client ID
                               3000 non-null
                                               object
 1
     Name
                               3000 non-null
                                               object
 2
                               3000 non-null
     Age
                                               int64
 3
                               3000 non-null
     Location ID
                                               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
                               3000 non-null
    Loyalty Classification
                                               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
# Genrate discriptive statistics for the dataframe
df.describe()
```

```
{"summary":"{\n \"name\": \"df\",\n \"rows\": 8,\n \"fields\": [\n
 \"dtype\": \"number\",\n \"std\": 1044.4070732954572,\n \"min\": 17.0,\n \"max\": 3000.0,\n
\"num_unique_values\": 8,\n \"samples\": [\n 51.03966666666667,\n 51.0,\n 3000.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"Location ID\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 14612.18148735417,\n \"min\": 12.0,\n \"max\": 43369.0,\
n 171305.034263333333,\n 142313.47999999998,\n 3000.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"Superannuation Savings\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 23834.521347506627,\n \"min\": 1482.03,\n \"max\": 75963.9,\n \"num unique values\": 8 \n \"scmples\": [\n \"comples\": [\n \"]
\"num_unique_values\": 8,\n \"samples\": [\n 25531.59967333333,\n 22357.355000000003,\n 3000.0\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
}\n },\n {\n \"column\": \"Amount of Credit Cards\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
1060.1482852588065,\n \"min\": 0.6763867645368546,\n
\"max\": 3000.0,\n \"num_unique_values\": 6,\n
\"samples\": [\n 3000.0,\n 1.46366666666666667,\n
3.0\n ],\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n {\n \"column\":
\"Credit Card Balance\",\n \"properties\": {\n \"dtype\":
\"number\",\n \"std\": 4303.156900678545,\n \"min\":
1.17 \n \"max\": 13991.99.\n \"num_unique_values\": 8.\n
1.17,\n \"max\": 13991.99,\n \"num_unique_values\": 8,\n
0.0,\n \"max\": 3890598.08,\n \"num_unique_values\": 8,\n \"samples\": [\n 671560.1939233334,\n
```

```
\"min\": 0.0,\n \"max\": 1969923.08,\n \"num_unique_values\": 8,\n \"samples\": [\n 321092.94912666664,\n 242815.655,\n 3000.0\
 n ],\n \"semantic type\": \"\",\n
0.0,\n \"max\": 1724118.36,\n \"num_unique_values\": 8,\n \"samples\": [\n 232908.3534833333,\n 164086.555,\n 3000.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"Foreign Currency Account\",\n \"properties\": {\n \""}
\"dtype\": \"number\",\n \"std\": 39821.13354767674,\n \"min\": 45.0,\n \"max\": 124704.87,\n
\"num_unique_values\": 8,\n \"samples\": [\n 29883.529993333334,\n 24341.190000000002,\n 3000.0\n
],\n \"semantic_type\": \"\",\n \"description\": \"\"\n
[\n 866759.8084066667,\n 711314.65999999999,\n 3000.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"Properties Owned\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 1060.1241040744355,\n \"min\":
"number\",\n \"std\": 1059.8841634225845,\n \"num_unique_values\": 7,\n \"samples\": [\n 3000.0,\n 2.24933333333333334,\n 3.0\n ],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"BRId\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 1059.8239053751968,\n \"min\": 1.0,\n \"max\": 2000.0 \" "max\": \"num unique_values\": 7\n \"samples\": [\n \"comples\": [\n \"comples\": [\n \"comples\": [\n \"min\": 1.0,\n \"max\": 2000.0 \" "max\": [\n \"min\": 1.0,\n \"max\": [\n \"min\": [\n \"max\": [\n \"min\": [\n \"max\": [\n \\ max\": 
3000.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 3000.0,\n 2.55933333333335,\n 3.0\n ],\n
 \"semantic_type\": \"\",\n \"description\": \"\"\n }\
n },\n {\n \"column\": \"GenderId\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\":
1060.1550392950937,\n \"min\": 0.5000673512490724,\n \"max\": 3000.0,\n \"num_unique_values\": 5,\n \"samples\": [\n 1.504,\n 2.0,\n
```

```
\"semantic type\": \"\",\n
                                    {\n \"column\":
                                    \"dtype\": \"number\",\n
\"IAId\",\n \"properties\": {\n
                               \"min\": 1.0,\n
\"std\": 1057.1739338184325,\n
                                                   \"max\":
3000.0,\n \"num_unique_values\": 8,\n \"samples\": [\n
3000.0\n
                                                    ],\n
\"semantic_type\": \"\",\n
                           \"description\": \"\"\n
                                                    }\
    }\n \[ \lambda\rangle\", "type": "dataframe"}
bins = [0,100000,300000,float('inf')]
labels = ['Low','Medium','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 distrubution of unique categories 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
     1352
3
1
      660
2
      495
4
      493
Name: count, dtype: int64
Value Counts for 'GenderId':
GenderId
     1512
1
     1488
Name: count, dtype: int64
Value Counts for'IAId':
IAId
1
      177
2
      177
3
      177
4
      177
8
      177
9
      176
13
      176
12
      176
10
      176
11
      176
14
      176
15
      176
6
       89
5
       89
7
       89
16
       88
       88
17
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
              1309
European
Asian
               754
               507
American
               254
Australian
African
               176
Name: count, dtype: int64
Value Counts for 'Occupation':
Occupation
Associate Professor
                                 28
Structural Analysis Engineer
                                 28
Recruiter
                                 25
Account Coordinator
                                 24
                                 24
Human Resources Manager
                                 . .
Office Assistant IV
                                  8
Automation Specialist I
                                  7
Computer Systems Analyst I
                                  6
                                  5
Developer III
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':
```

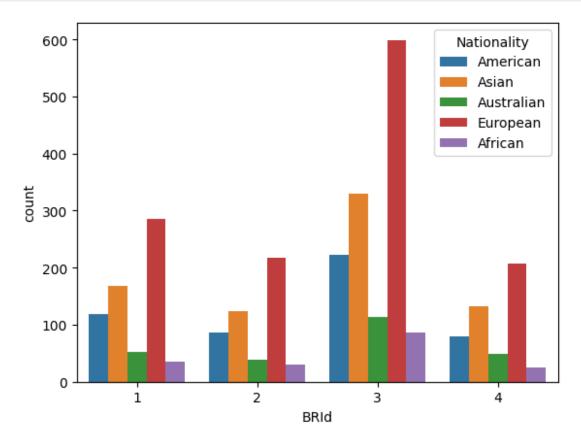
```
Properties Owned
2
     777
1
     776
3
     742
     705
Name: count, dtype: int64
Value Counts for 'Risk Weighting':
Risk Weighting
2
     1222
1
      836
3
      460
4
      322
5
      160
Name: count, dtype: int64
Value Counts for'Income Band':
Income Band
Medium
          1517
Low
          1027
Hiah
           456
Name: count, dtype: int64
```

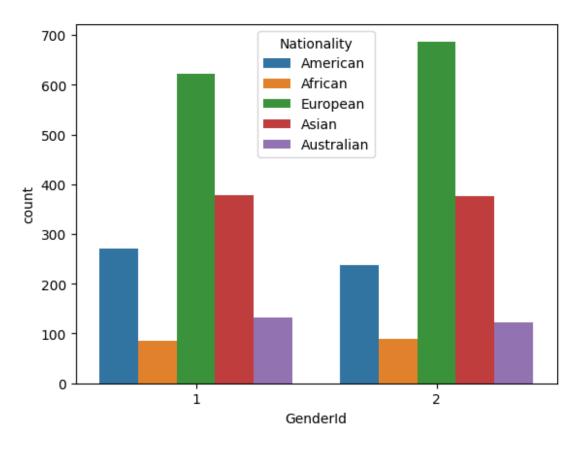
Univariate Analysis

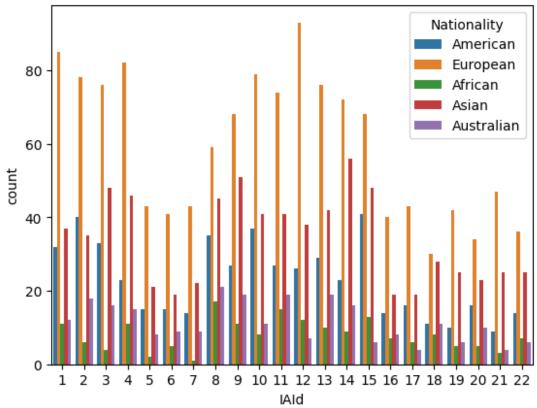
```
for i, predictor in enumerate(df[["BRId", "GenderId", "IAId", "Amount of
Credit Cards", "Nationality", "Occupation", "Fee Structure", "Loyalty
Classification", "Properties Owned", "Risk Weighting", "Income
Band"]].columns):
  plt.figure(i)
  sns.countplot(data = df, x = predictor)
                                                      Traceback (most recent call
NameError
last)
<ipython-input-1-533aad80979d> in <cell line: 0>()
----> 1 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)
       2
             sns.countplot(data = df, x = predictor)
NameError: name 'df' is not defined
```

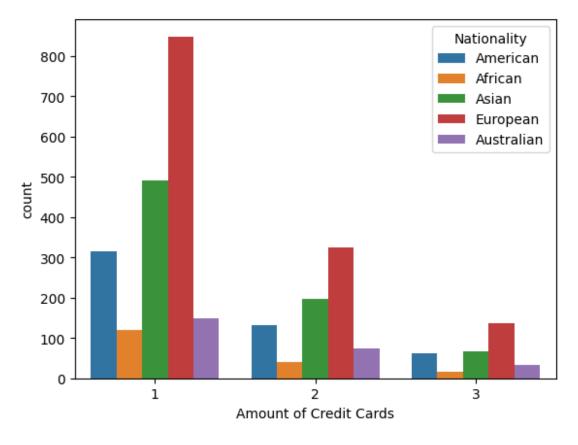
Bivariate Analysis

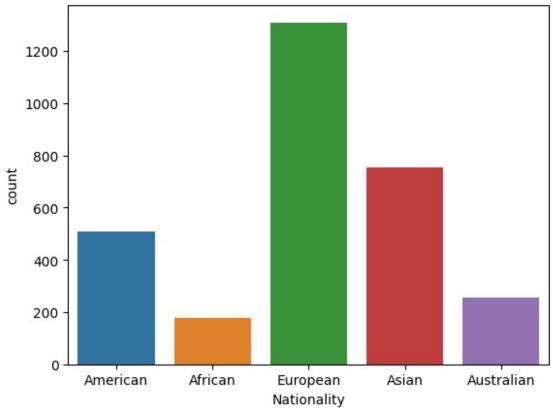
```
for i, predictor in enumerate(df[["BRId","GenderId","IAId", "Amount of
Credit Cards", "Nationality","Occupation", "Fee Structure", "Loyalty
Classification","Properties Owned","Risk Weighting", "Income
Band"]].columns):
   plt.figure(i)
   sns.countplot(data = df, x = predictor, hue='Nationality')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

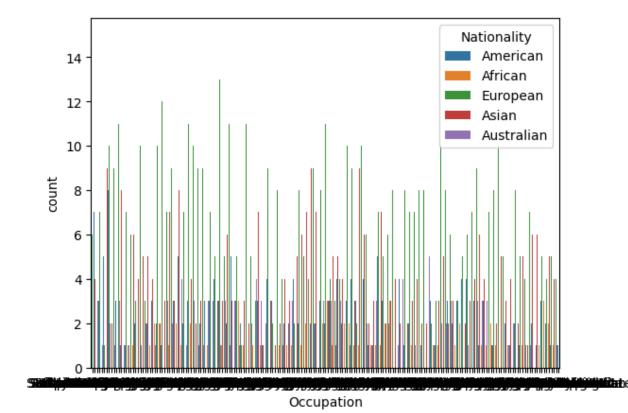


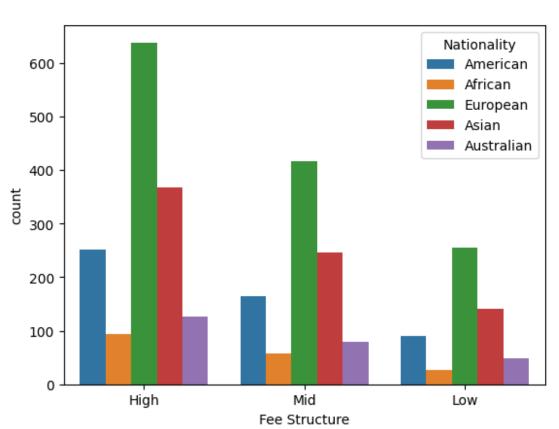


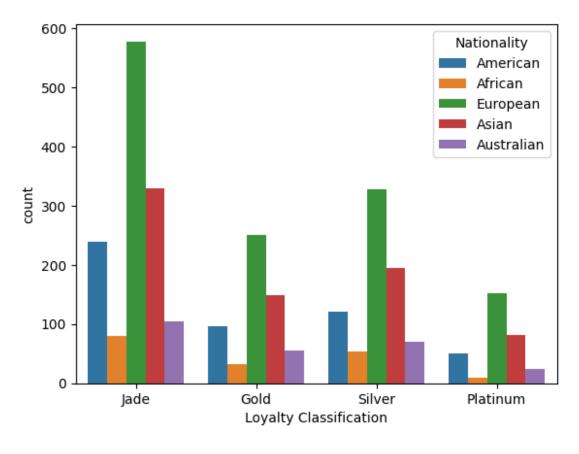


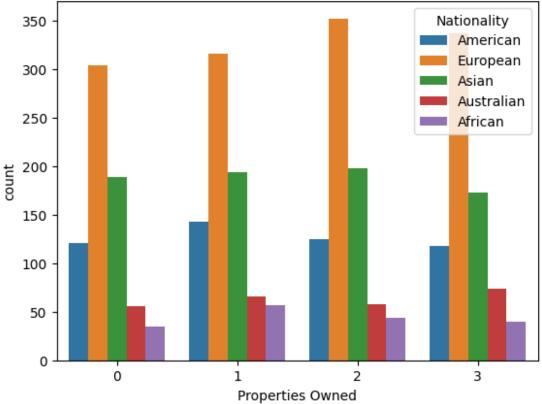


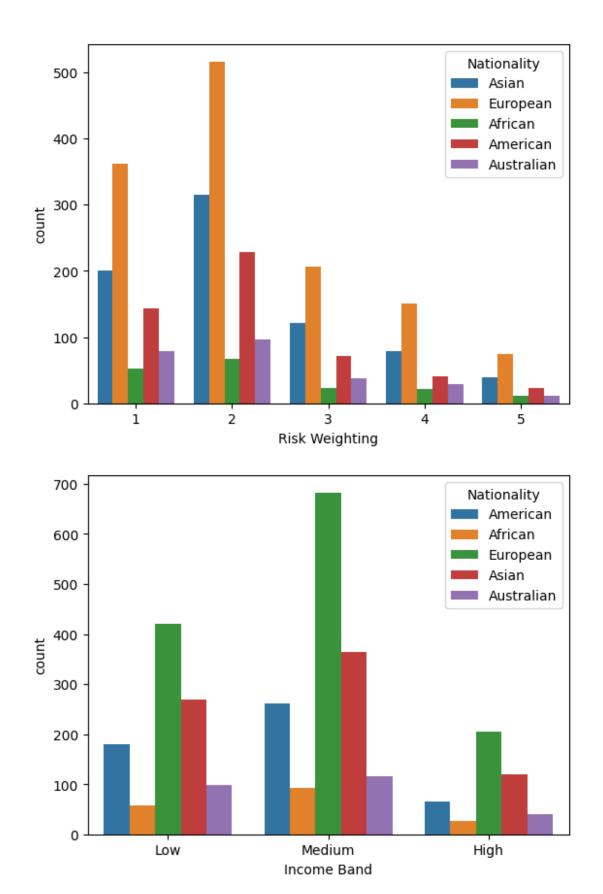






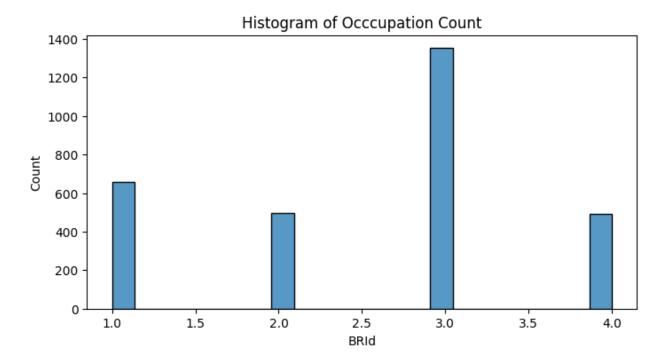


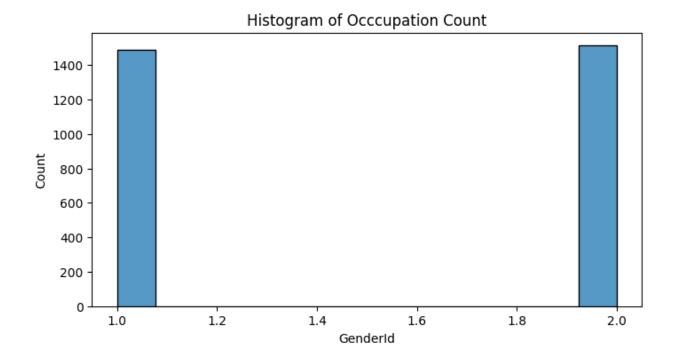


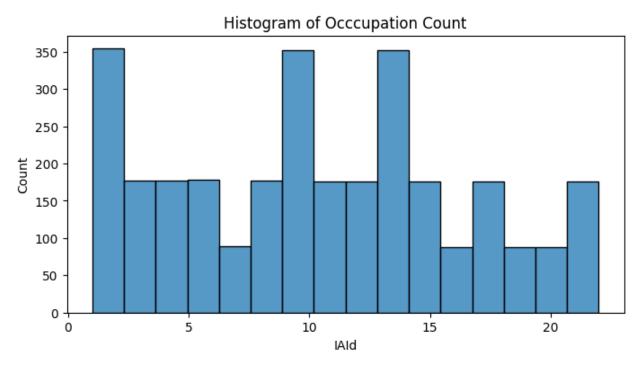


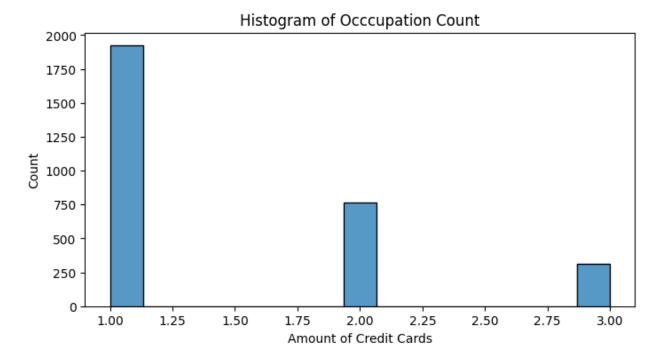
```
# Hisplot of Value Counts for different Occupations

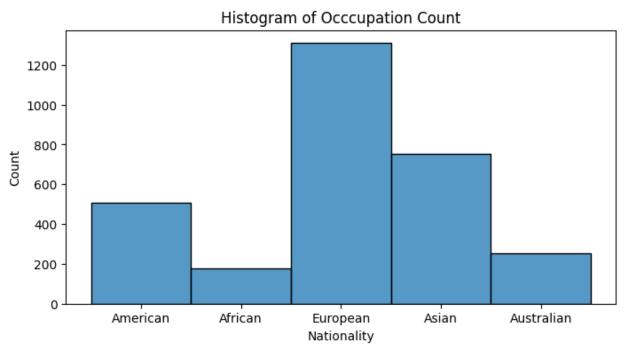
for col in categorical_cols:
    if col == "Occupation":
        continue
    plt.figure(figsize=(8,4))
    sns.histplot(df[col])
    plt.title('Histogram of Occcupation Count')
    plt.xlabel(col)
    plt.ylabel("Count")
    plt.show()
```

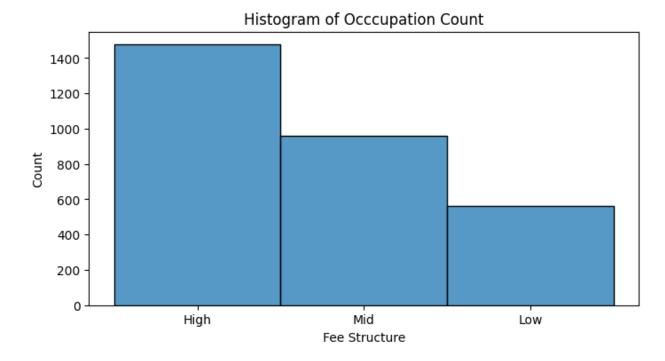


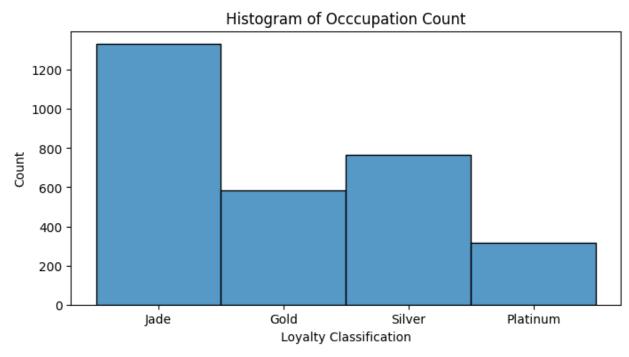


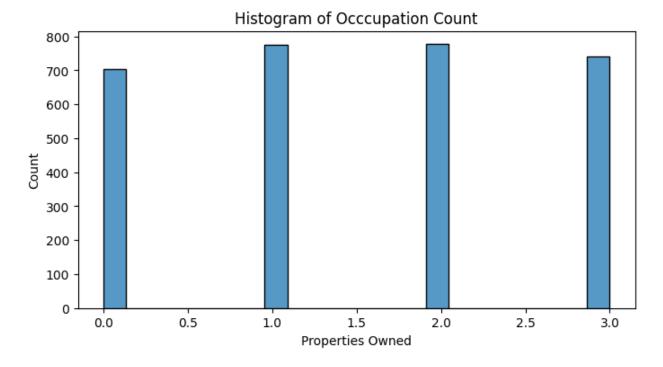


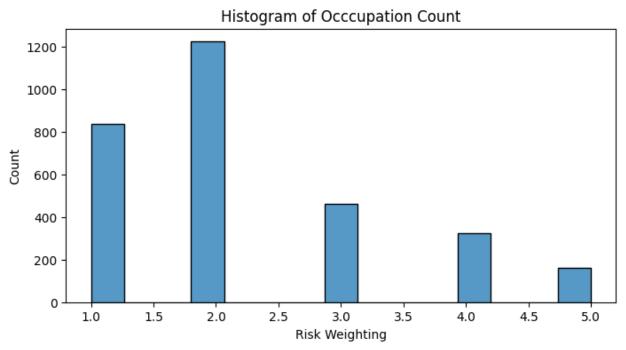




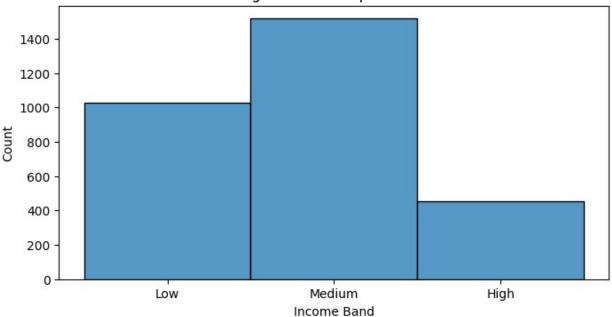








Histogram of Occcupation Count

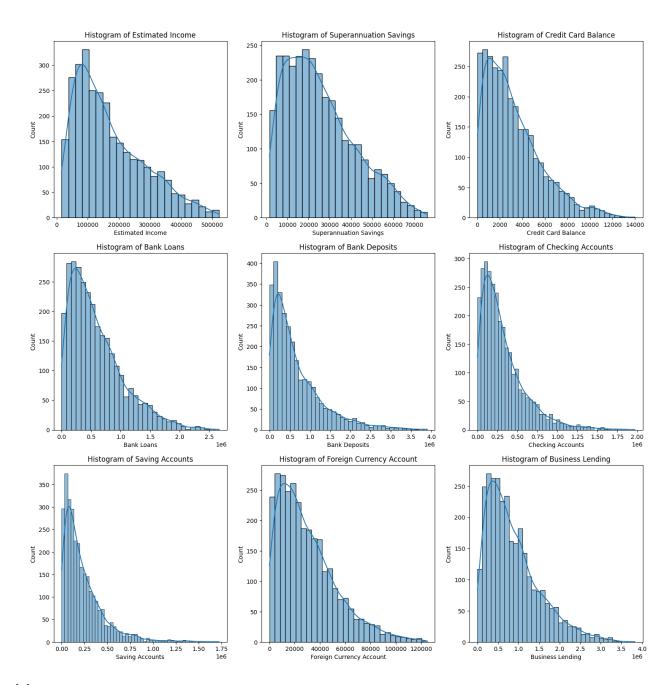


Numerical Analysis

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

# Univariate analysis and visualization

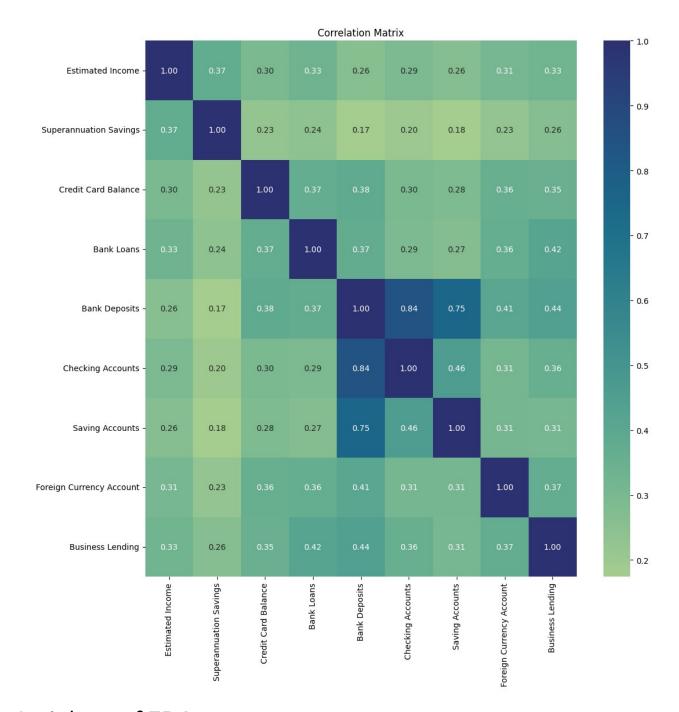
plt.figure(figsize=(18,25))
for i,col in enumerate(numerical_col):
   plt.subplot(4,3,i+1)
   sns.histplot(df[col],kde=True)
   plt.title(f'Histogram of {col}')
plt.show()
```



Heatmaps

```
numerical_col =['Estimated Income', 'Superannuation Savings','Credit
Card Balance','Bank Loans','Bank Deposits','Checking Accounts','Saving
Accounts','Foreign Currency Account','Business Lending']
correlation_matrix = df[numerical_col].corr()
```

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



Insightes of EDA:

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