# Loan Approval Prediction - Exploratory Data Analysis

## **Step 1: Import Necessary Libraries**

```
In [1]: import pandas as pd
        import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
        from sklearn.preprocessing import StandardScaler
         from sklearn.preprocessing import LabelEncoder
         import category_encoders as ce
        from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LogisticRegression
        from sklearn.svm import SVC
        from sklearn.neighbors import KNeighborsClassifier
        from xgboost import XGBClassifier
        from sklearn.neural_network import MLPClassifier
        from sklearn.metrics import roc_curve, auc
        from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_sco
        from sklearn.model_selection import train_test_split, GridSearchCV
        from sklearn.model selection import RandomizedSearchCV
         from sklearn.model_selection import cross_val_score
```

#### **Step 2: Import Loan Dataset**

```
In [2]: df = pd.read_csv(r'prosperLoanDataCleaned.csv')
          df.head()
Out[2]:
            Term MonthsOfEmployementExperience IsHomeowner OpenCreditLines TotalInquiries AvailableBankcardCredit DebtTol
         0
                                          2.000000
                                                                          4.000000
                                                                                              3
                                                                                                            1500.000000
               36
                                                               1
                                                               0
                                                                          9.260164
               36
                                         96.071582
                                                                                                            11210.225447
                                          19.000000
                                                               0
                                                                          2.000000
                                                                                              5
                                                                                                            2580.000000
         2
               36
               36
                                          1.000000
                                                                          7.000000
                                                                                                            3626.000000
                                                               1
                                                                                              1
               36
                                        121.000000
                                                                          9.000000
                                                                                                             178.000000
In [3]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55106 entries, 0 to 55105
Data columns (total 17 columns):
# Column
                                  Non-Null Count Dtype
0
    Term
                                  55106 non-null int64
    MonthsOfEmployementExperience 55106 non-null float64
1
    IsHomeowner
                                  55106 non-null int64
2
    OpenCreditLines
                                  55106 non-null float64
                                  55106 non-null int64
    TotalInquiries
                                  55106 non-null float64
    AvailableBankcardCredit
    DebtToIncomeRatio
                                  55106 non-null float64
                                  55106 non-null int64
    IncomeVerifiable
                                  55106 non-null float64
8
    StatedMonthlyIncome
                                  55106 non-null int64
9
    LoanNumber
10 LoanAmount
                                  55106 non-null int64
                                  55106 non-null float64
11 MonthlyInstallment
                                  55106 non-null float64
12 InterestRate
13 IsEmployed
                                 55106 non-null int64
14 AverageCreditScore
                                 55106 non-null int64
15 AnyDelinquencies
                                  55106 non-null int64
16 GoodLoan
                                  55106 non-null int64
dtypes: float64(7), int64(10)
memory usage: 7.1 MB
```

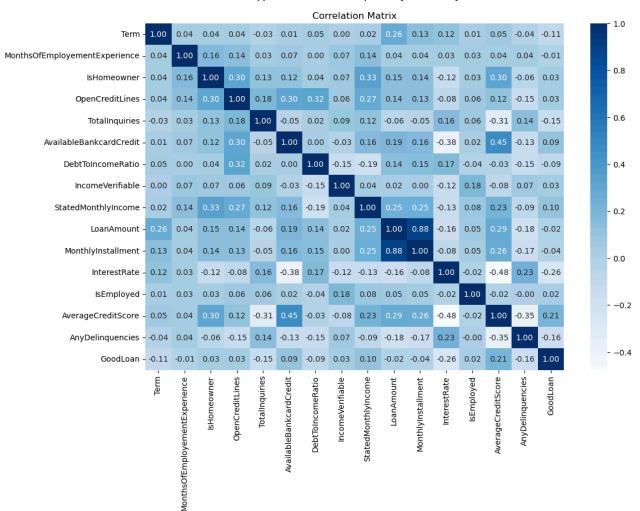
#### Step 3: Data Pre-processing

```
In [4]: df = df.drop(['LoanNumber'], axis=1)
         categorical = ['Term','IsHomeowner','IsEmployed','AnyDelinquencies','IncomeVerifiable']
         numerical = ['LoanAmount','InterestRate','MonthlyInstallment','MonthsOfEmployementExperience','AverageCr
                      ,'OpenCreditLines','TotalInquiries','AvailableBankcardCredit','DebtToIncomeRatio','StatedMo
        df[numerical].skew()
In [5]:
        LoanAmount
                                           1.646822
Out[5]:
                                           0.115913
        InterestRate
        MonthlyInstallment
                                           1.953124
        MonthsOfEmployementExperience
                                          1.834853
        AverageCreditScore
                                          -1.351894
        OpenCreditLines
                                          1.131160
        TotalInquiries
                                          6.574083
        AvailableBankcardCredit
                                          7.593415
        DebtToIncomeRatio
                                          12.416432
                                         44.534218
        StatedMonthlyIncome
        dtype: float64
        skewed_features = ['TotalInquiries', 'AvailableBankcardCredit', 'DebtToIncomeRatio', 'StatedMonthlyIncom
In [6]:
         for feature in skewed_features:
             df[feature] = np.log1p(df[feature])
        Q1 = df[numerical].quantile(0.25)
         Q3 = df[numerical].quantile(0.75)
         IQR = Q3 - Q1
         # Calculate median
        median = df[numerical].median()
         # Identify outliers
         outliers_lower = (df[numerical] < (Q1 - 1.5 * IQR))</pre>
         outliers_upper = (df[numerical] > (Q3 + 1.5 * IQR))
         # Replace outliers with median
         df[numerical] = df[numerical].mask(outliers_lower, median, axis=1)
         df[numerical] = df[numerical].mask(outliers upper, median, axis=1)
        df[numerical].skew()
In [8]:
```

```
1.106712
        LoanAmount
Out[8]:
        InterestRate
                                          0.115913
                                         0.980513
        MonthlyInstallment
        MonthsOfEmployementExperience
                                         0.856838
        AverageCreditScore
                                         -0.158725
        OpenCreditLines
                                         0.453486
        TotalInquiries
                                         -0.074052
        AvailableBankcardCredit
                                         -0.734401
        DebtToIncomeRatio
                                         0.325207
        StatedMonthlyIncome
                                         -0.044581
        dtype: float64
```

## Step 4: Performing Exploratory Data Analysis

```
In [9]:
         df.describe()
Out[9]:
                       Term MonthsOfEmployementExperience
                                                           IsHomeowner OpenCreditLines TotalInquiries AvailableBankcardCre
          count 55106.000000
                                              55106.000000
                                                            55106.000000
                                                                           55106.000000
                                                                                        55106.000000
                                                                                                              55106.0000
                   37.248213
                                                 66.350954
          mean
                                                                0.479240
                                                                               8.093467
                                                                                            1.729962
                                                                                                                  8.1995
            std
                    7.800320
                                                 50.984545
                                                                0.499573
                                                                               4.059213
                                                                                            0.824806
                                                                                                                  1.7880
           min
                   12.000000
                                                  0.000000
                                                                0.000000
                                                                               0.000000
                                                                                            0.000000
                                                                                                                  2.3025
           25%
                   36.000000
                                                 24.000000
                                                                0.000000
                                                                               5.000000
                                                                                            1.098612
                                                                                                                  7.1800
           50%
                   36.000000
                                                 63.000000
                                                                0.000000
                                                                               8.000000
                                                                                            1.791759
                                                                                                                  8.3824
           75%
                   36.000000
                                                 96.071582
                                                                1.000000
                                                                              10.000000
                                                                                            2.302585
                                                                                                                  9.3246
           max
                   60.000000
                                                 224.000000
                                                                1.000000
                                                                              20.000000
                                                                                            4.094345
                                                                                                                 13.3789
In [10]: df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 55106 entries, 0 to 55105
         Data columns (total 16 columns):
          # Column
                                               Non-Null Count Dtype
          0 Term
                                               55106 non-null int64
              MonthsOfEmployementExperience 55106 non-null float64
             IsHomeowner
                                               55106 non-null int64
          3
             OpenCreditLines
                                               55106 non-null float64
          4
              TotalInquiries
                                               55106 non-null float64
             AvailableBankcardCredit
                                             55106 non-null float64
          5
                                               55106 non-null float64
              DebtToIncomeRatio
                                               55106 non-null int64
              IncomeVerifiable
          8
              StatedMonthlyIncome
                                               55106 non-null float64
          9
              LoanAmount
                                               55106 non-null int64
          10 MonthlyInstallment
                                               55106 non-null float64
          11 InterestRate
                                               55106 non-null float64
          12 IsEmployed
                                               55106 non-null int64
                                               55106 non-null int64
          13
              AverageCreditScore
              AnyDelinquencies
                                               55106 non-null
              GoodLoan
                                               55106 non-null int64
         dtypes: float64(8), int64(8)
         memory usage: 6.7 MB
In [11]:
         corr_matrix = df.corr()
          plt.figure(figsize=(12, 8))
          sns.heatmap(corr_matrix, annot=True, cmap='Blues', fmt=".2f")
          plt.title('Correlation Matrix')
          plt.show()
```



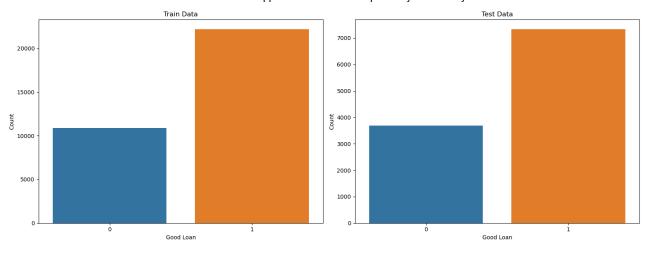
The target variable is GoodLoan, which is a binary classification of whether a loan is good or not. Based on the correlation matrix in the image, here are some of the variables that are related to GoodLoan:

- Interest rate: This has a negative correlation of -0.25 with GoodLoan. Low-interest rates are associated with an increased likelihood of a good loan.
- AverageCreditScore: This has a positive correlation of 0.22 with GoodLoan. This means a higher credit score is associated with an increased likelihood of a good loan.
- AnyDelinquencies: This has a weak negative correlation of -0.13 with GoodLoan. Fewer delinquencies are associated with an increased likelihood of a good loan.
- Term: This has a weak negative correlation of -0.11 with GoodLoan. This means a lower, shorter term is associated with an increased likelihood of a good loan.
- DebtToIncomeRatio: This has a weak negative correlation of -0.10 with GoodLoan. This means a lower debt-to-income ratio is associated with an increased likelihood of a good loan.
- StatedMonthlyIncome: This has a weak positive correlation of 0.10 with GoodLoan. This means that a higher stated monthly income is associated with an increased likelihood of a good loan.
- AvailableBankcardCredit: This has a weak positive correlation of 0.10 with GoodLoan. This means a higher available bankcard credit limit is associated with an increased likelihood of a good loan.

Other variables related to GoodLoan include LoanAmount, InterestRate, MonthlyInstallment, IsEmployed, MonthsOfEmployementExperience, and IsHomeowner. However, the strength of their correlations is lower than those mentioned above.

```
df = df.sample(frac=1, random_state=42)
In [12]:
                       MonthsOfEmployementExperience IsHomeowner OpenCreditLines TotalInquiries AvailableBankcardCredit De
Out[12]:
                 Term
           2098
                    36
                                             60.000000
                                                                   1
                                                                            8.000000
                                                                                          1.791759
                                                                                                                 5.894403
          43905
                                              9.000000
                                                                   0
                                                                            5.000000
                                                                                                                 8.382404
                    36
                                                                                          2.302585
          46310
                                                                   0
                    36
                                             96.071582
                                                                            9.260164
                                                                                          0.693147
                                                                                                                 9.324671
          53388
                    36
                                             63.000000
                                                                            6.000000
                                                                                          1.791759
                                                                                                                 7.556951
          32128
                    36
                                             11.000000
                                                                   1
                                                                            9.000000
                                                                                          2.197225
                                                                                                                 4.934474
              •••
          44732
                    36
                                             49.000000
                                                                   1
                                                                            4.000000
                                                                                          1.791759
                                                                                                                 8.860357
          54343
                                                                                                                 8.382404
                    36
                                             22.000000
                                                                   0
                                                                            2.000000
                                                                                          1.945910
          38158
                    36
                                             87.000000
                                                                  0
                                                                            6.000000
                                                                                          2.639057
                                                                                                                 6.198479
            860
                    36
                                             18.000000
                                                                   1
                                                                            8.000000
                                                                                          2.708050
                                                                                                                 8.889170
          15795
                    36
                                             16.000000
                                                                   0
                                                                            6.000000
                                                                                          1.098612
                                                                                                                10.297420
         55106 rows × 16 columns
In [13]:
          train,test = train_test_split(df, test_size=0.2, random_state=42)
           train,val = train_test_split(train, test_size=0.25, random_state=42)
In [14]:
          fig, axes = plt.subplots(1, 2, figsize=(16, 6)) # 1 row, 2 columns
          # Plot the first count plot on the left subplot
          sns.countplot(x='GoodLoan', data=train, ax=axes[0])
          axes[0].set_title('Train Data')
           axes[0].set_xlabel('Good Loan')
          axes[0].set_ylabel('Count')
          # Plot the second count plot on the right subplot
          sns.countplot(x='GoodLoan', data=test, ax=axes[1])
          axes[1].set_title('Test Data')
          axes[1].set_xlabel('Good Loan')
          axes[1].set_ylabel('Count')
          # Adjust layout to prevent overlap
          plt.tight_layout()
          # Show the plots
```

plt.show()



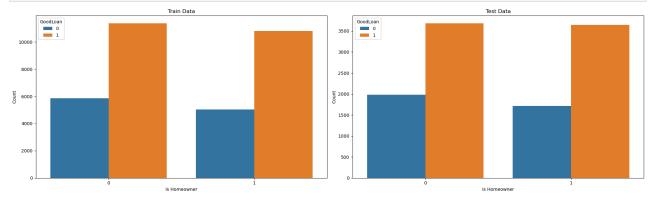
```
In [15]: fig, axes = plt.subplots(1, 2, figsize=(20, 6)) # 1 row, 2 columns

# Plot on the first subplot
sns.countplot(x='IsHomeowner', hue='GoodLoan', data=train, ax=axes[0])
axes[0].set_title('Train Data')
axes[0].set_xlabel('Is Homeowner')
axes[0].set_ylabel('Count')

# Plot on the second subplot
sns.countplot(x='IsHomeowner', hue='GoodLoan', data=test, ax=axes[1])
axes[1].set_title('Test Data')
axes[1].set_xlabel('Is Homeowner')
axes[1].set_ylabel('Count')

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



```
In [16]: fig, axes = plt.subplots(1, 2, figsize=(18, 6))

# Plot the first count plot on the first subplot
sns.countplot(x='AnyDelinquencies', hue='GoodLoan', data=train, ax=axes[0])
axes[0].set_title('Train Data')
axes[0].set_xlabel('Any Delinquencies')
axes[0].set_ylabel('Count')

# Plot the second count plot on the second subplot
sns.countplot(x='AnyDelinquencies', hue='GoodLoan', data=test, ax=axes[1])
axes[1].set_title('Test Data')
axes[1].set_xlabel('Any Delinquencies')
axes[1].set_ylabel('Count')

# Adjust Layout to prevent overlap
plt.tight_layout()
```

```
# Show the plots
plt.show()
                                     Train Data
                                                                                                                   Test Data
                                                                     GoodLoan
0
 17500
                                                                               5000
 15000
                                                                               4000
                                                                              3000
                                                                               2000
                                                                               1000
  2500
                                   Any Delinquencies
                                                                                                                 Any Delinquencies
# Plot the first count plot on the first subplot
```

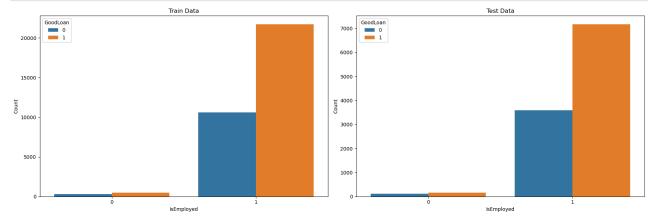
```
In [17]: fig, axes = plt.subplots(1, 2, figsize=(18, 6))

# Plot the first count plot on the first subplot
sns.countplot(x='IsEmployed', hue='GoodLoan', data=train, ax=axes[0])
axes[0].set_title('Train Data')
axes[0].set_xlabel('IsEmployed')
axes[0].set_ylabel('Count')

# Plot the second count plot on the second subplot
sns.countplot(x='IsEmployed', hue='GoodLoan', data=test, ax=axes[1])
axes[1].set_title('Test Data')
axes[1].set_xlabel('IsEmployed')
axes[1].set_ylabel('Count')

# Adjust Layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



```
In [18]: fig, axes = plt.subplots(1, 2, figsize=(18, 6))

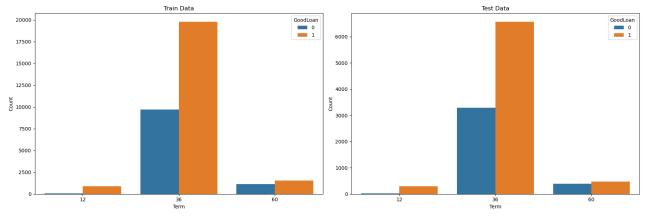
# Plot the first count plot on the first subplot
sns.countplot(x='Term', hue='GoodLoan', data=train, ax=axes[0])
axes[0].set_title('Train Data')
axes[0].set_xlabel('Term')
axes[0].set_ylabel('Count')

# Plot the second count plot on the second subplot
sns.countplot(x='Term', hue='GoodLoan', data=test, ax=axes[1])
axes[1].set_title('Test Data')
axes[1].set_xlabel('Term')
axes[1].set_ylabel('Count')

# Adjust Layout to prevent overlap
```

```
plt.tight_layout()

# Show the plots
plt.show()
```



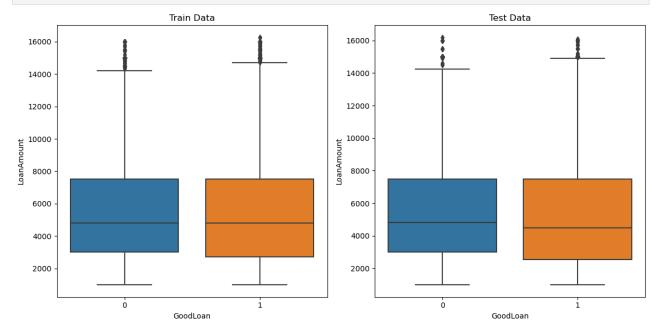
```
In [19]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='LoanAmount', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='LoanAmount', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



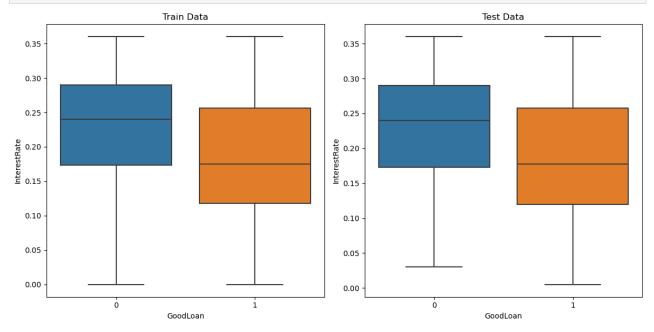
```
In [20]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='InterestRate', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='InterestRate', data=test, ax=axes[1])
axes[1].set_title('Test Data')
```

```
# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



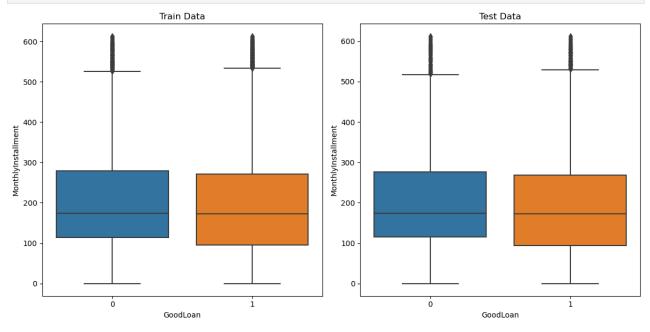
```
In [21]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='MonthlyInstallment', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='MonthlyInstallment', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



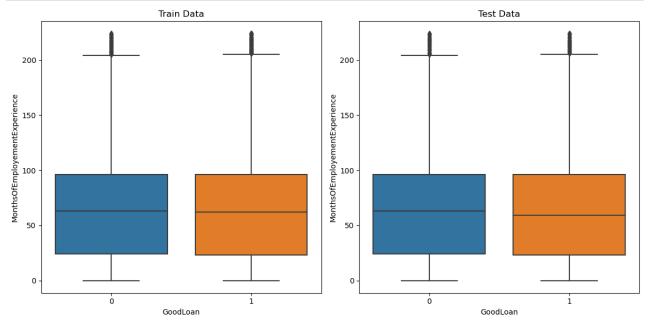
```
fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='MonthsOfEmployementExperience', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='MonthsOfEmployementExperience', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust Layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



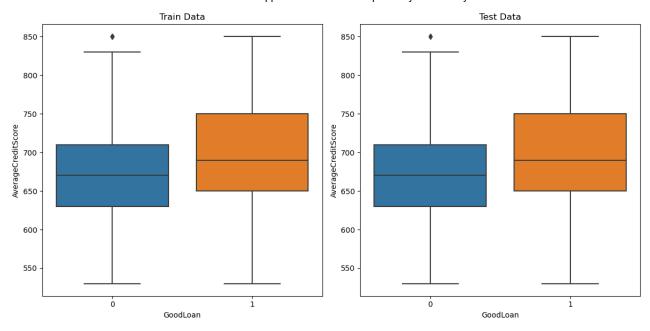
```
In [23]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='AverageCreditScore', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='AverageCreditScore', data=test, ax=axes[1])
axes[1].set_title('Test Data')

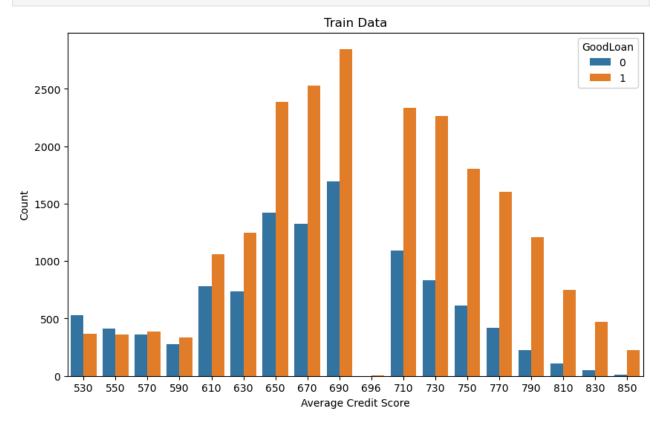
# Adjust Layout to prevent overlap
plt.tight_layout()

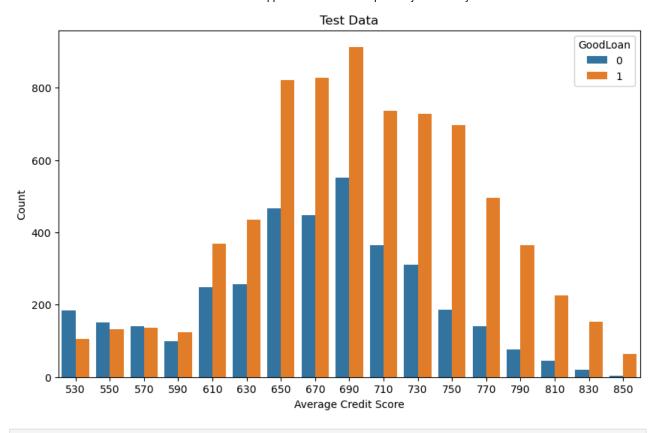
# Show the plots
plt.show()
```

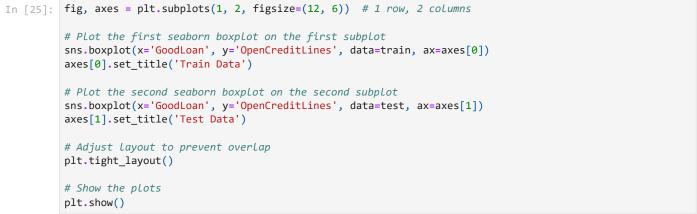


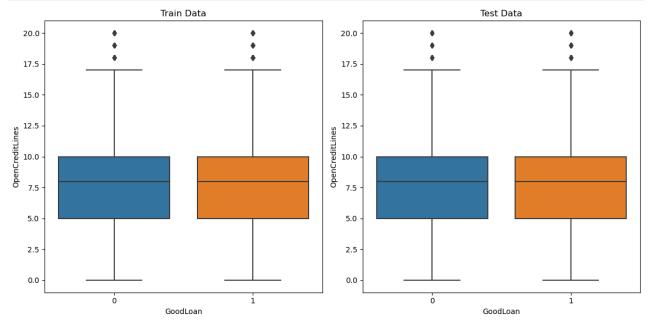
```
In [24]:
    plt.figure(figsize=(10, 6))
    sns.countplot(x='AverageCreditScore', hue='GoodLoan', data=train)
    plt.title('Train Data')
    plt.xlabel('Average Credit Score')
    plt.ylabel('Count')
    plt.show()

    plt.figure(figsize=(10, 6))
    sns.countplot(x='AverageCreditScore', hue='GoodLoan', data=test)
    plt.title('Test Data')
    plt.xlabel('Average Credit Score')
    plt.ylabel('Count')
    plt.show()
```









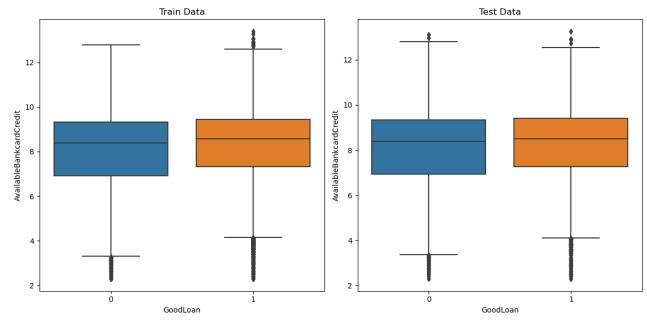
```
In [26]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='AvailableBankcardCredit', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='AvailableBankcardCredit', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust Layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



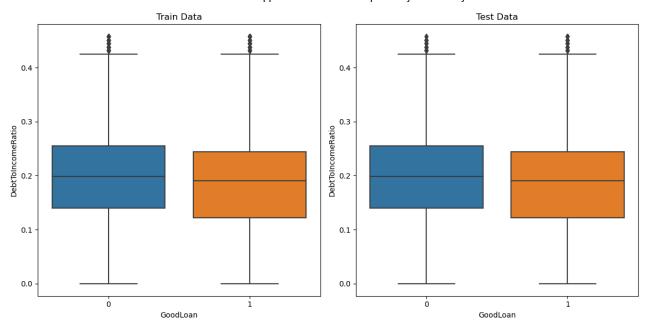
```
In [27]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='DebtToIncomeRatio', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='DebtToIncomeRatio', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



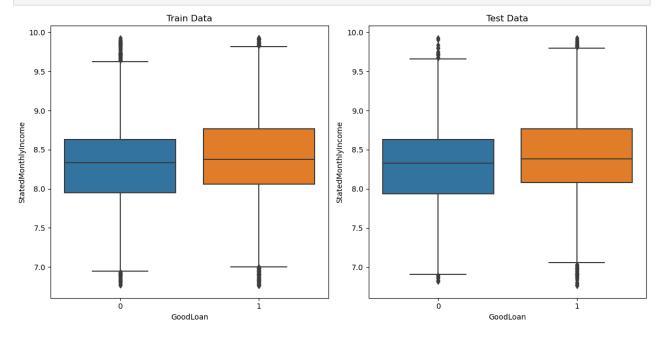
```
In [28]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='StatedMonthlyIncome', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
sns.boxplot(x='GoodLoan', y='StatedMonthlyIncome', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```



```
In [29]: fig, axes = plt.subplots(1, 2, figsize=(12, 6)) # 1 row, 2 columns

# Plot the first seaborn boxplot on the first subplot
sns.boxplot(x='GoodLoan', y='TotalInquiries', data=train, ax=axes[0])
axes[0].set_title('Train Data')

# Plot the second seaborn boxplot on the second subplot
```

```
sns.boxplot(x='GoodLoan', y='TotalInquiries', data=test, ax=axes[1])
axes[1].set_title('Test Data')

# Adjust Layout to prevent overlap
plt.tight_layout()

# Show the plots
plt.show()
```

