hw_ulugbek_OvsO_and_OvsR

November 10, 2024

1 One vs One and One vs Rest

Dataset: https://www.kaggle.com/datasets/burak3ergun/loan-data-set

1. Load the dataset – 0.5 marks
2. Analyze the dataset – 0.5 marks
3. Clean the dataset – 0.5 marks
4. EDA – 1 mark
5. Split, standarzdize and encode – 4 marks
6. Perform OvsO and OvsR – 0.5 marks
7. Evaluate – 0.5 marks
8. Analyze – 2.5 marks

1.0.1 Documentation:

OnevsOne: https://scikit-learn.org/dev/modules/generated/sklearn.multiclass.OneVsOneClassifier.html

One vs Rest: https://scikit-learn.org/1.5/modules/generated/sklearn.multiclass.OneVsRestClassifier.html

Reference: https://machinelearningmastery.com/one-vs-rest-and-one-vs-one-for-multi-class-classification/

[ ]:
```
!pip install kagglehub
```

```
Requirement already satisfied: kagglehub in /usr/local/lib/python3.10/dist-
packages (0.3.3)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from kagglehub) (24.1)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from kagglehub) (2.32.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from kagglehub) (4.66.6)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->kagglehub) (3.4.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->kagglehub) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->kagglehub) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->kagglehub) (2024.8.30)
```

[ ]:
```
import kagglehub

path = kagglehub.dataset_download("burak3ergun/loan-data-set")

print("Path to dataset files:", path)
```

```
Downloading from
https://www.kaggle.com/api/v1/datasets/download/burak3ergun/loan-data-
set?dataset_version_number=1…

100%|      | 7.80k/7.80k [00:00<00:00, 4.44MB/s]

Extracting files…
Path to dataset files: /root/.cache/kagglehub/datasets/burak3ergun/loan-data-
set/versions/1
```

[ ]:
```
!mv /root/.cache/kagglehub/datasets/burak3ergun/loan-data-set/versions/1/* .
```

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

from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer

from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier, OneVsOneClassifier
```

[ ]:
```
df = pd.read_csv('loan_data_set.csv')
df.head()
```

[ ]:
```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
```

```
4             6000                 0.0       141.0              360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

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

[ ]:
```
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
```

```
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

[ ]:
```
print(f"Shape of dataset: {df.shape}")
print("Null values:\n", df.isnull().sum())
```

```
Shape of dataset: (614, 13)
Null values:
 Loan_ID              0
Gender              13
Married              3
Dependents          15
Education            0
Self_Employed       32
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount          22
Loan_Amount_Term    14
Credit_History      50
Property_Area        0
Loan_Status          0
dtype: int64
```

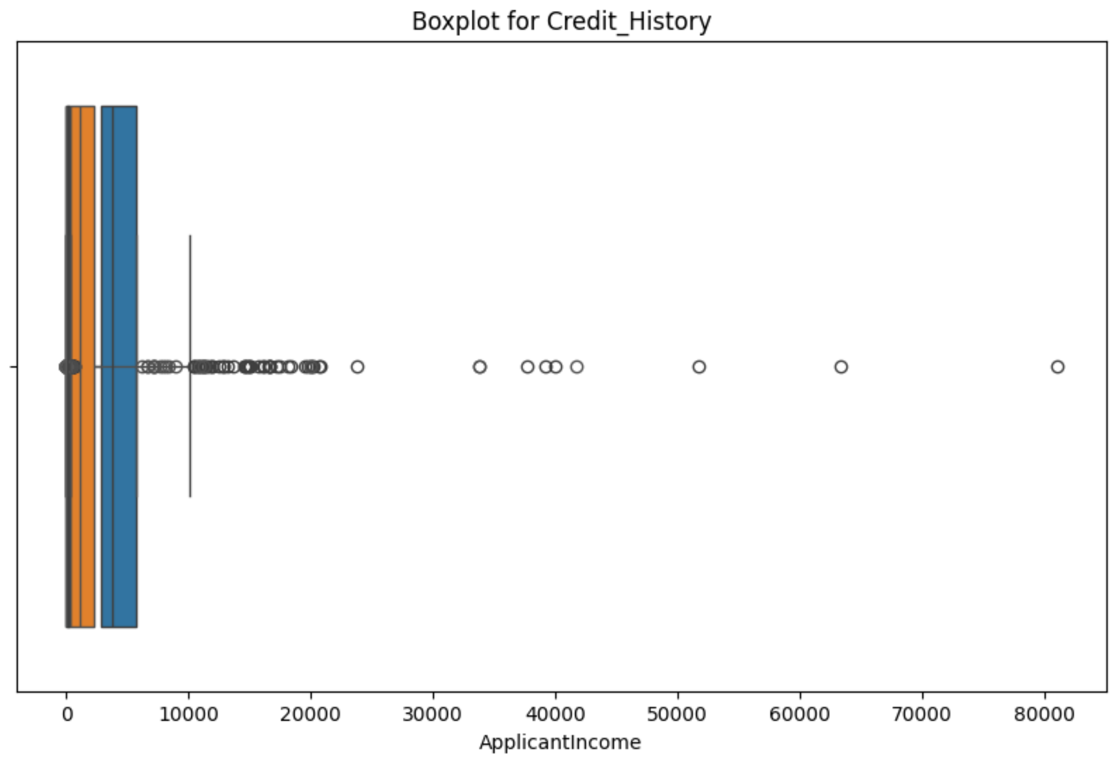
[ ]:
```
duplicate_rows = df.duplicated().sum()
print(f"Number of duplicate rows: {duplicate_rows}")
```

```
Number of duplicate rows: 0
```

[ ]:
```
def find_outliers_IQR(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
    return outliers

plt.figure(figsize=(10, 6))
numerical_columns = df.select_dtypes(include=['float64', 'int64'])
for col in numerical_columns.columns:
    outliers = find_outliers_IQR(df, col)
    print(f"Number of outliers in {col}: {len(outliers)}")

    sns.boxplot(x=df[col])
    plt.title(f"Boxplot for {col}")
```

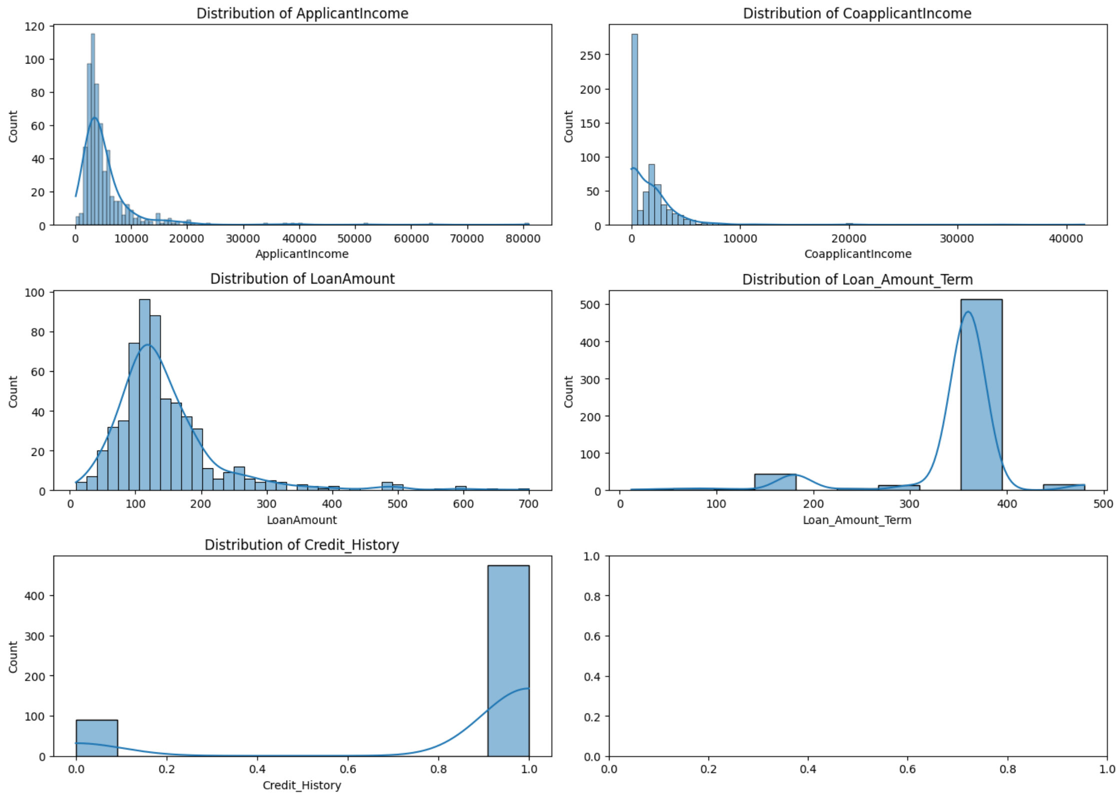
```
plt.show()
```

```
Number of outliers in ApplicantIncome: 50
Number of outliers in CoapplicantIncome: 18
Number of outliers in LoanAmount: 39
Number of outliers in Loan_Amount_Term: 88
Number of outliers in Credit_History: 89
```

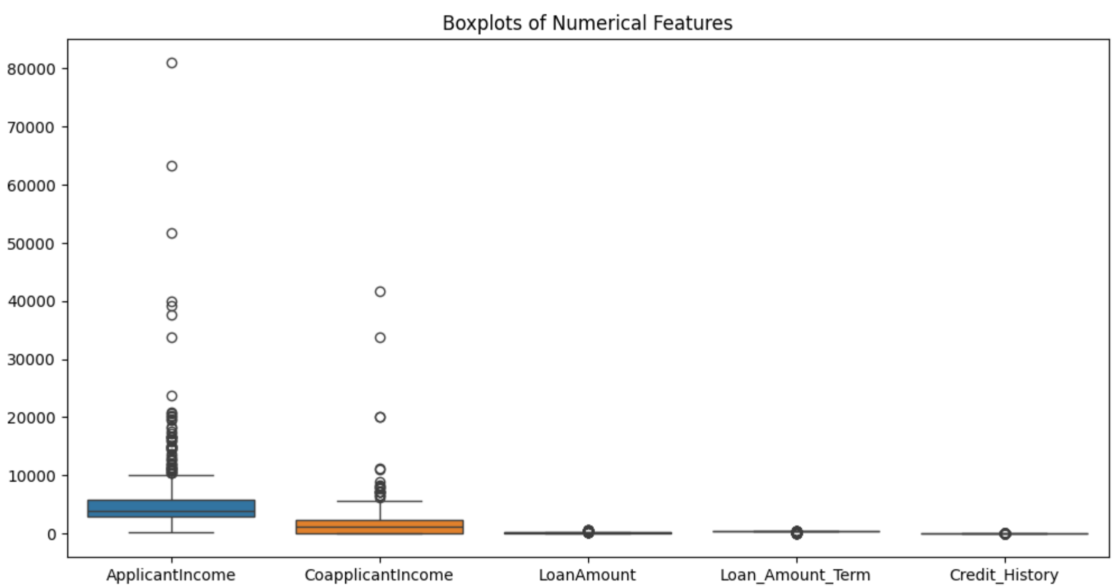


[ ]:
```
numerical_features = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',␣
↪'Loan_Amount_Term', 'Credit_History']
fig, axes = plt.subplots(3, 2, figsize=(14, 10))
axes = axes.flatten()

for i, feature in enumerate(numerical_features):
    sns.histplot(df[feature].dropna(), kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {feature}')

plt.tight_layout()

# Boxplots to detect outliers
plt.figure(figsize=(12, 6))
sns.boxplot(data=df[numerical_features])
plt.title("Boxplots of Numerical Features")
```

```
plt.show()
```

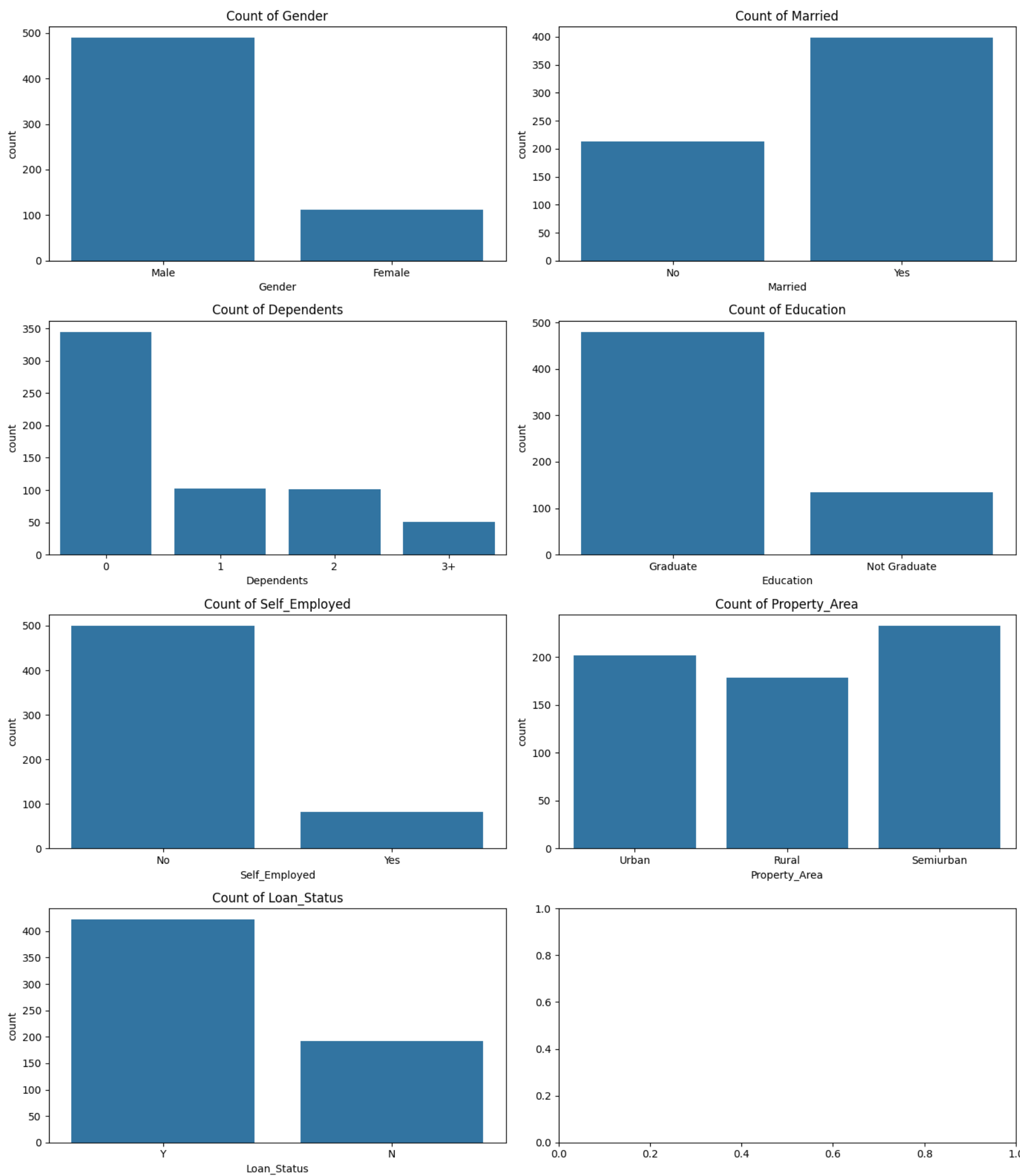


Distribution of ApplicantIncome
Count
ApplicantIncome
Distribution of CoapplicantIncome
CoapplicantIncome
Distribution of LoanAmount
LoanAmount
Distribution of Loan_Amount_Term
Loan_Amount_Term
Distribution of Credit_History
Credit_History

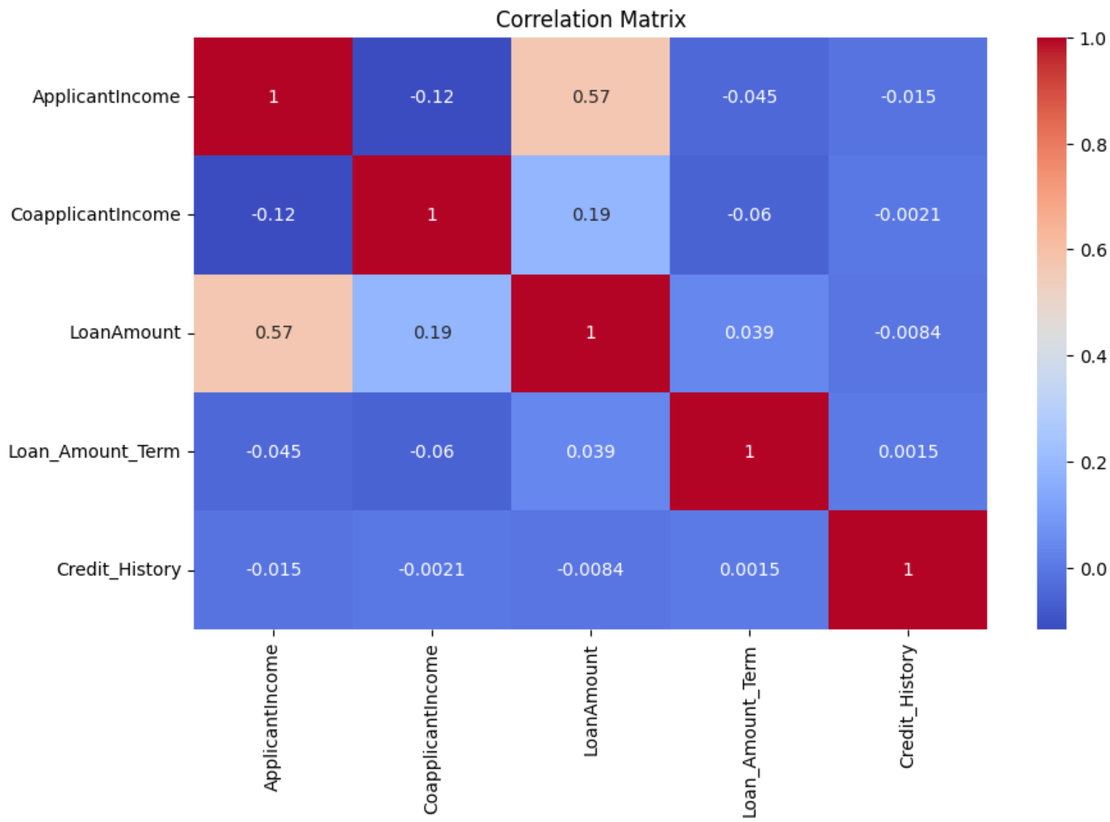


Boxplots of Numerical Features
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History

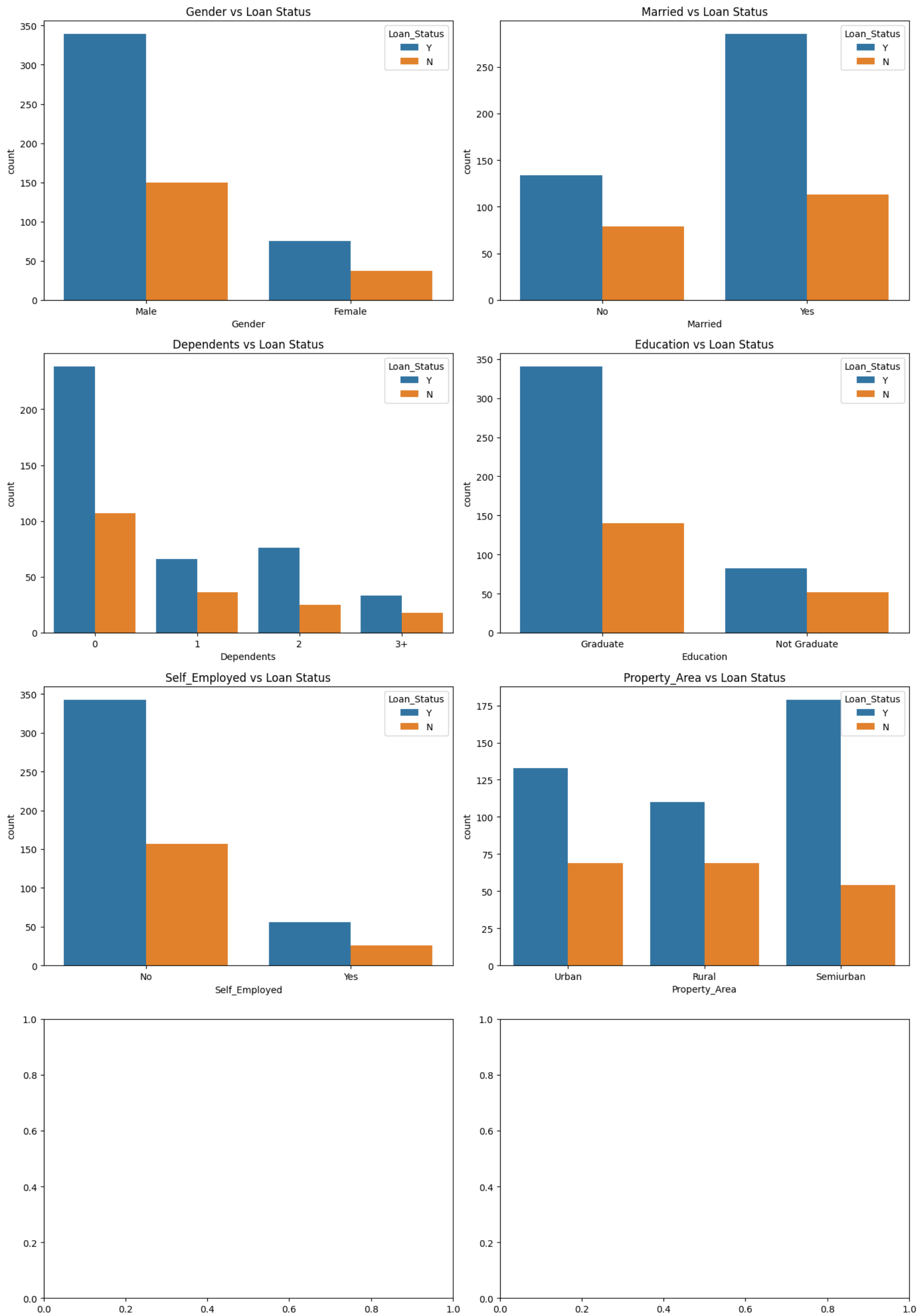
[ ]:
```
categorical_features = ['Gender', 'Married', 'Dependents', 'Education',␣
↪'Self_Employed', 'Property_Area', 'Loan_Status']
fig, axes = plt.subplots(4, 2, figsize=(14, 16))
axes = axes.flatten()

for i, feature in enumerate(categorical_features):
    sns.countplot(x=feature, data=df, ax=axes[i])
    axes[i].set_title(f'Count of {feature}')

plt.tight_layout()
```



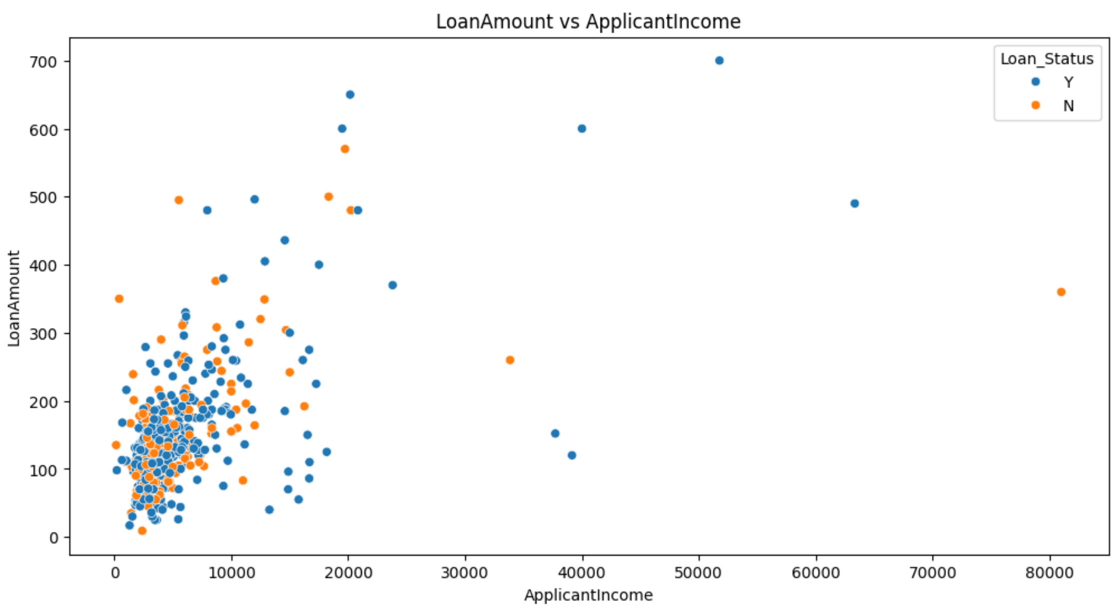
[ ]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(df[numerical_features].corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()

# Pairplot for selected features to check relationships and clustering
sns.pairplot(df, vars=numerical_features, hue='Loan_Status', diag_kind="kde")
plt.suptitle("Pairplot of Numerical Features")
plt.show()
```

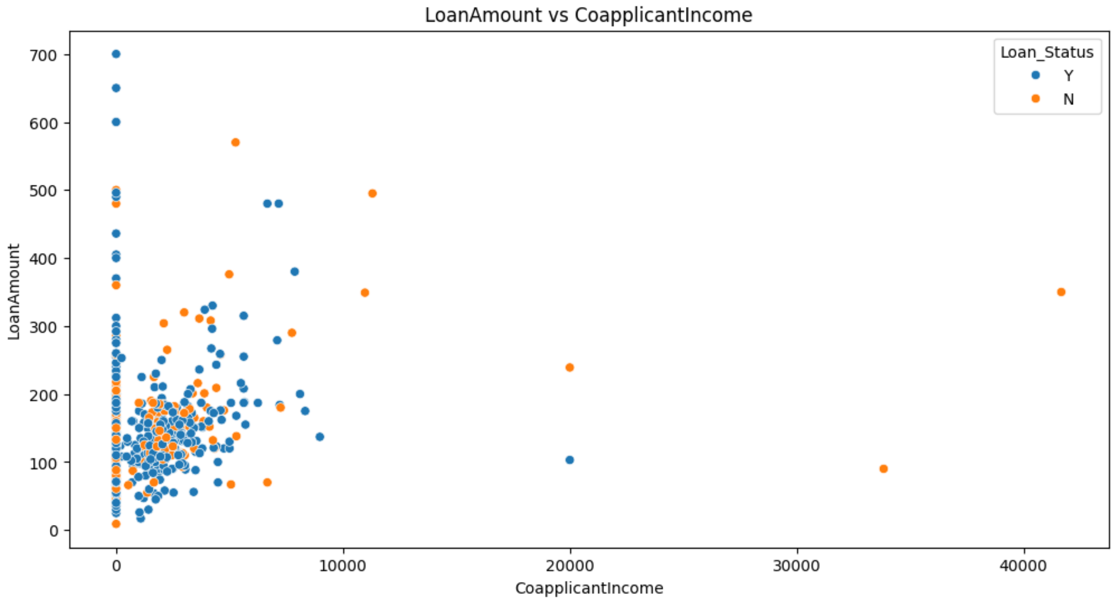


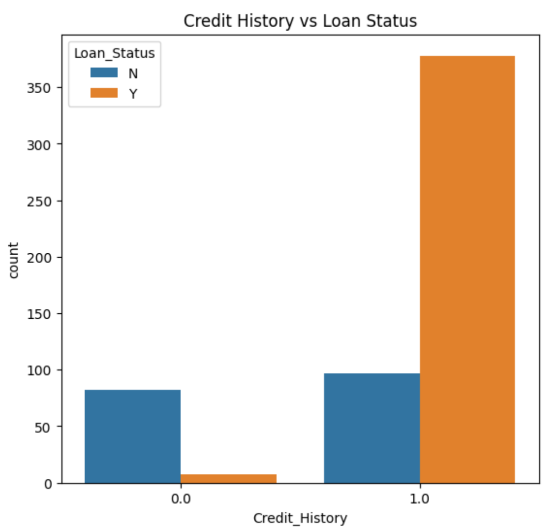

```
[ ]: fig, axes = plt.subplots(4, 2, figsize=(14, 20))
     axes = axes.flatten()

     for i, feature in enumerate(categorical_features[:-1]):  # Exclude Loan_Status
         sns.countplot(x=feature, hue="Loan_Status", data=df, ax=axes[i])
         axes[i].set_title(f'{feature} vs Loan Status')

     plt.tight_layout()
```

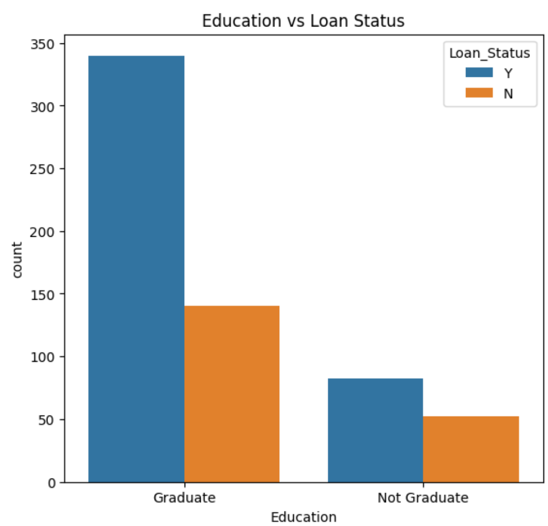

Gender vs Loan Status
count
Gender
Male
Female
Loan_Status
Y
N
Married vs Loan Status
count
Married
No
Yes
Dependents vs Loan Status
count
Dependents
0
1
2
3+
Education vs Loan Status
count
Education
Graduate
Not Graduate
Self_Employed vs Loan Status
count
Self_Employed
No
Yes
Property_Area vs Loan Status
count
Property_Area
Urban
Rural
Semiurban

[ ]:
```
plt.figure(figsize=(12, 6))
sns.scatterplot(x='ApplicantIncome', y='LoanAmount', hue='Loan_Status', data=df)
plt.title("LoanAmount vs ApplicantIncome")

plt.figure(figsize=(12, 6))
sns.scatterplot(x='CoapplicantIncome', y='LoanAmount', hue='Loan_Status',␣
↪data=df)
plt.title("LoanAmount vs CoapplicantIncome")
plt.show()

# Credit History and Education vs Loan Status
fig, axes = plt.subplots(1, 2, figsize=(14, 6))
sns.countplot(x='Credit_History', hue="Loan_Status", data=df, ax=axes[0])
axes[0].set_title("Credit History vs Loan Status")

sns.countplot(x='Education', hue="Loan_Status", data=df, ax=axes[1])
axes[1].set_title("Education vs Loan Status")
plt.show()
```









[ ]:
```
df.drop(columns=['Loan_ID'], inplace=True)
df.columns
```

[ ]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[ ]:
```python
X = df.drop("Loan_Status", axis=1)
y = df['Loan_Status'].map({'Y': 1, 'N': 0})

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
X_train.shape, X_test.shape
```

[ ]:
```
((491, 12), (123, 12))
```

[ ]:
```python
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X.select_dtypes(include=['object']).columns

numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ]
)

X_train = preprocessor.fit_transform(X_train)
X_test = preprocessor.transform(X_test)

X_train[0]
```

[ ]:
```
<1x511 sparse matrix of type '<class 'numpy.float64'>'
        with 12 stored elements in Compressed Sparse Row format>
```

[ ]:
```python
base_classifier = LogisticRegression(max_iter=1000, random_state=42)

# One-vs-Rest (OvR) classification
ovr_classifier = OneVsRestClassifier(base_classifier)
ovr_classifier.fit(X_train, y_train)
ovr_score = ovr_classifier.score(X_test, y_test)

# One-vs-One (OvO) classification
ovo_classifier = OneVsOneClassifier(base_classifier)
ovo_classifier.fit(X_train, y_train)
```

```
ovo_score = ovo_classifier.score(X_test, y_test)

print(f"OvR Accuracy: {ovr_score:.4f}")
print(f"OvO Accuracy: {ovo_score:.4f}")
```

```
OvR Accuracy: 0.7886
OvO Accuracy: 0.7886
```

[ ]:
```
from sklearn.metrics import classification_report

y_pred_ovr = ovr_classifier.predict(X_test)
y_pred_ovo = ovo_classifier.predict(X_test)

print("OvR Classification Report:\n", classification_report(y_test, y_pred_ovr))
print("\nOvO Classification Report:\n", classification_report(y_test,␣
↪y_pred_ovo))
```

```
OvR Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.42      0.58        43
           1       0.76      0.99      0.86        80

    accuracy                           0.79       123
   macro avg       0.85      0.70      0.72       123
weighted avg       0.83      0.79      0.76       123


OvO Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.42      0.58        43
           1       0.76      0.99      0.86        80

    accuracy                           0.79       123
   macro avg       0.85      0.70      0.72       123
weighted avg       0.83      0.79      0.76       123
```

Step 4: Analysis

Performance Summary

We got the same result for both classifiers since our dataset only has two classes -> Loan_Status = 'Y' and 'N'.

But usually, both methods have the following:

One-vs-Rest (OvR):

- OvR will generally have higher recall as it focuses on distinguishing each class against all others. If the dataset is imbalanced, OvR can suffer because it tries to make a binary decision for each class.

- The accuracy and F1-scores in the OvR classification report provide insights into each class's predictive strength.

One-vs-One (OvO):

- OvO tends to have better precision because it compares each pair of classes independently. It is often more accurate on balanced datasets with multiple classes but can be computationally intensive for large numbers of classes.
- OvO can be beneficial when classes have subtle differences, as it avoids generalization across all classes.