# Loan Approval Prediction System

July 5, 2025

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
```

```
/Users/hinalpanchal/opt/anaconda3/lib/python3.9/site-
packages/scipy/__init__.py:155: UserWarning: A NumPy version >=1.18.5 and
<1.25.0 is required for this version of SciPy (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

[2]:
```
loan_data = pd.read_csv('Loan Data.csv')
loan_data.head()
```

[2]:
```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001003   Male     Yes          1      Graduate            No
1  LP001005   Male     Yes          0      Graduate           Yes
2  LP001006   Male     Yes          0  Not Graduate            No
3  LP001008   Male      No          0      Graduate            No
4  LP001013   Male     Yes          0  Not Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             4583             1508.0       128.0             360.0
1             3000                0.0        66.0             360.0
2             2583             2358.0       120.0             360.0
3             6000                0.0       141.0             360.0
4             2333             1516.0        95.0             360.0

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

[3]:
```
loan_data.isna().sum()
```

[3]:
```
Loan_ID               0
Gender                5
Married               0
Dependents            8
Education             0
Self_Employed        21
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     11
Credit_History       30
Property_Area         0
Loan_Status           0
dtype: int64
```

[4]:
```
loan_data.dropna(inplace=True)
```

[5]:
```
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 308 entries, 0 to 380
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            308 non-null    object
 1   Gender             308 non-null    object
 2   Married            308 non-null    object
 3   Dependents         308 non-null    object
 4   Education          308 non-null    object
 5   Self_Employed      308 non-null    object
 6   ApplicantIncome    308 non-null    int64
 7   CoapplicantIncome  308 non-null    float64
 8   LoanAmount         308 non-null    float64
 9   Loan_Amount_Term   308 non-null    float64
 10  Credit_History     308 non-null    float64
 11  Property_Area      308 non-null    object
 12  Loan_Status        308 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 33.7+ KB
```

[6]:
```
loan_data.duplicated().sum()
```

[6]:
```
0
```

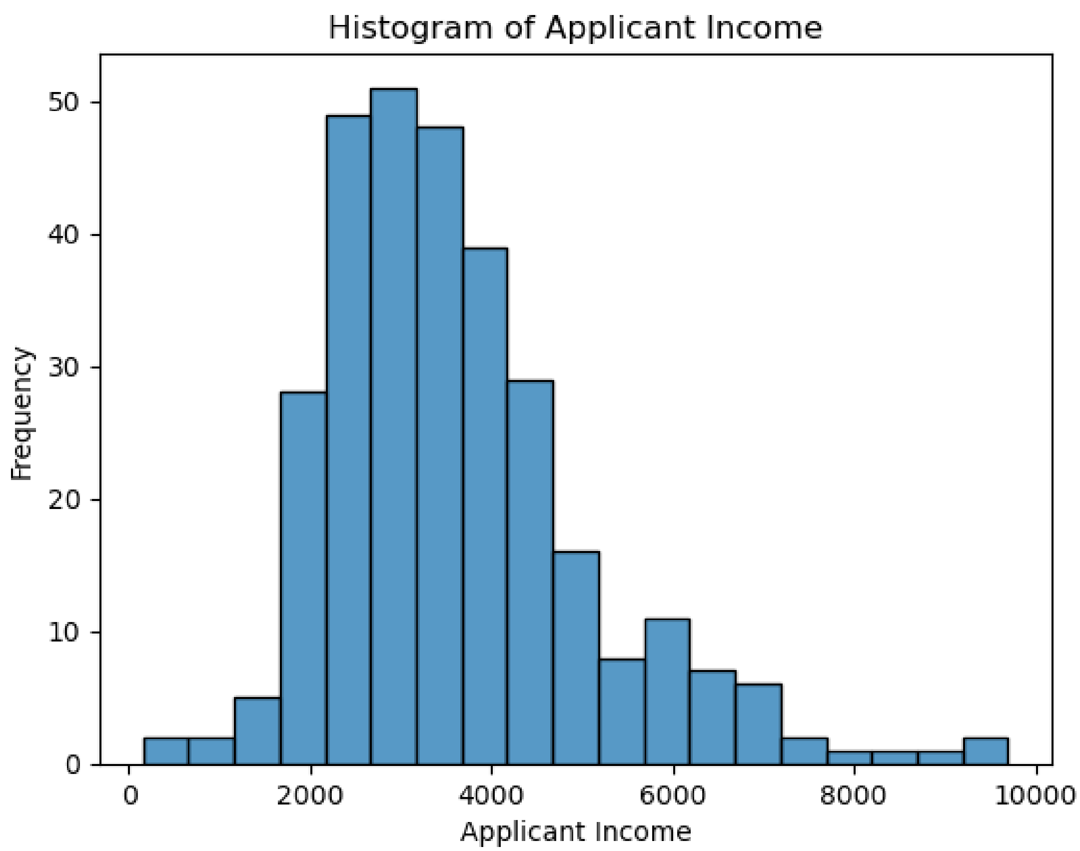
[7]:
```
loan_data.columns
```

[7]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
```

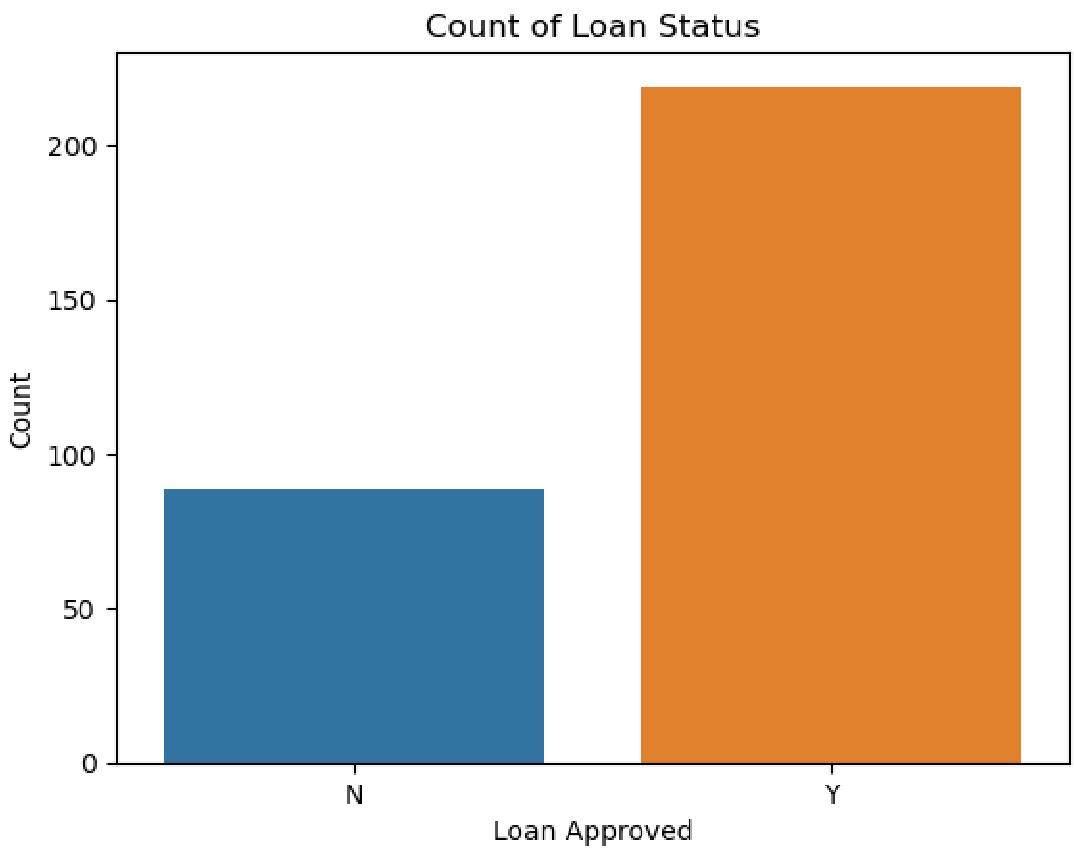
```
 'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
dtype='object')
```

# 1 Create Visualization Understand the Data

[8]:
```python
sns.histplot(loan_data['ApplicantIncome'])
plt.title('Histogram of Applicant Income')
plt.xlabel('Applicant Income')
plt.ylabel('Frequency')
plt.show()
```




[9]:
```python
sns.countplot(x='Loan_Status', data = loan_data)
plt.title('Count of Loan Status')
plt.xlabel('Loan Approved')
plt.ylabel('Count')
plt.show()
```

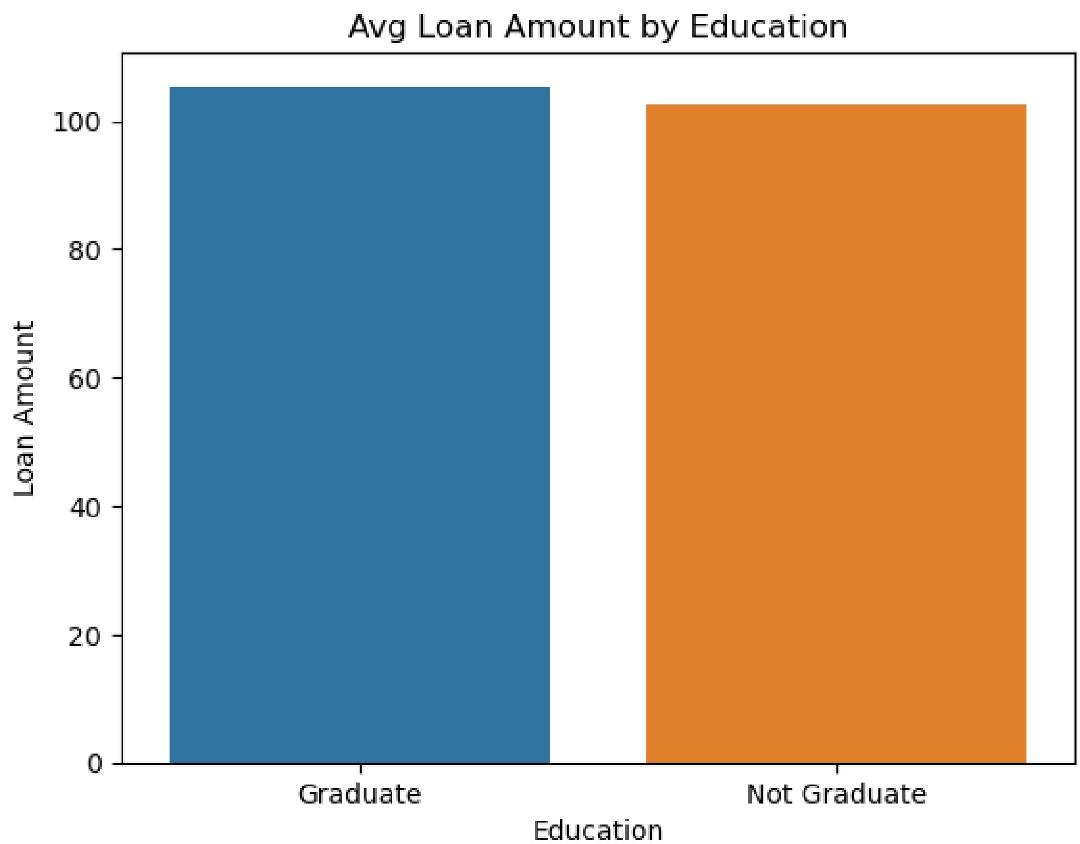



[10]:
```
avg_loan_amount_by_education = loan_data.groupby('Education')['LoanAmount'].
  ↪mean().reset_index()
avg_loan_amount_by_education
```

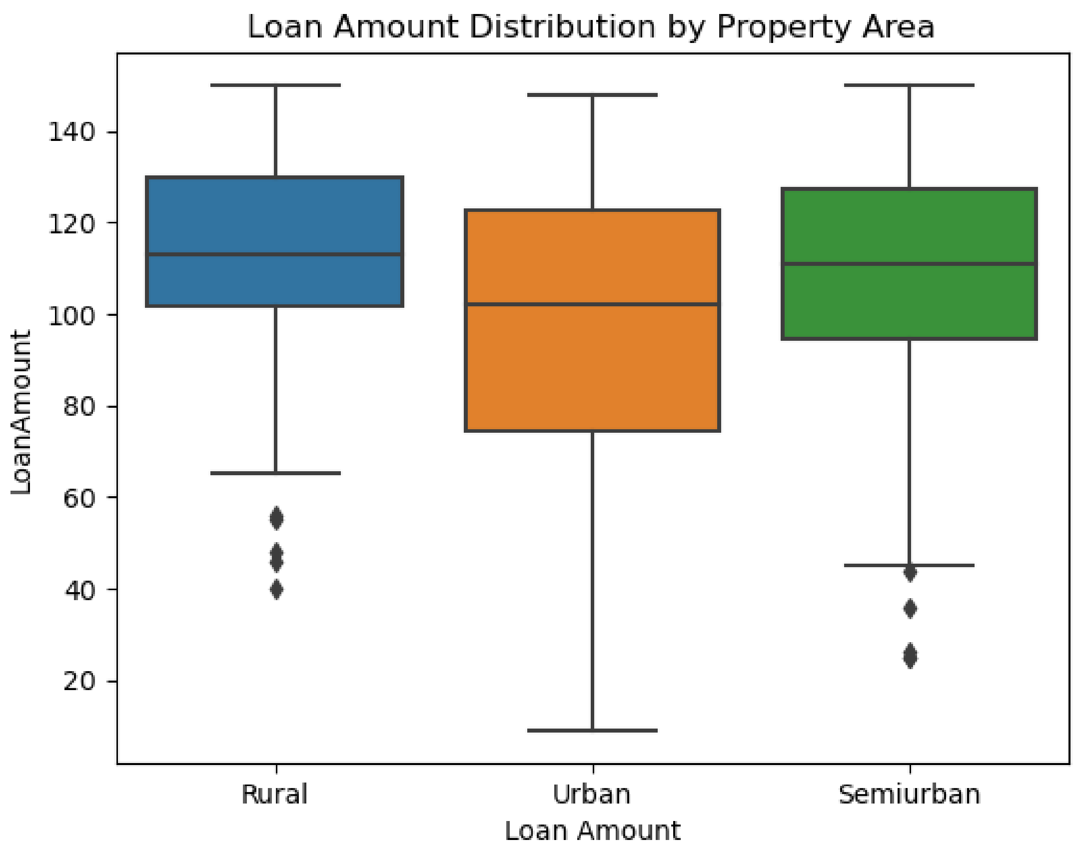
[10]:

| | Education | LoanAmount |
|---|---|---|
| 0 | Graduate | 105.344978 |
| 1 | Not Graduate | 102.531646 |

[11]:
```
sns.barplot(x='Education', y='LoanAmount', data=avg_loan_amount_by_education)
plt.title('Avg Loan Amount by Education')
plt.xlabel('Education')
plt.ylabel('Loan Amount')
plt.show()
```

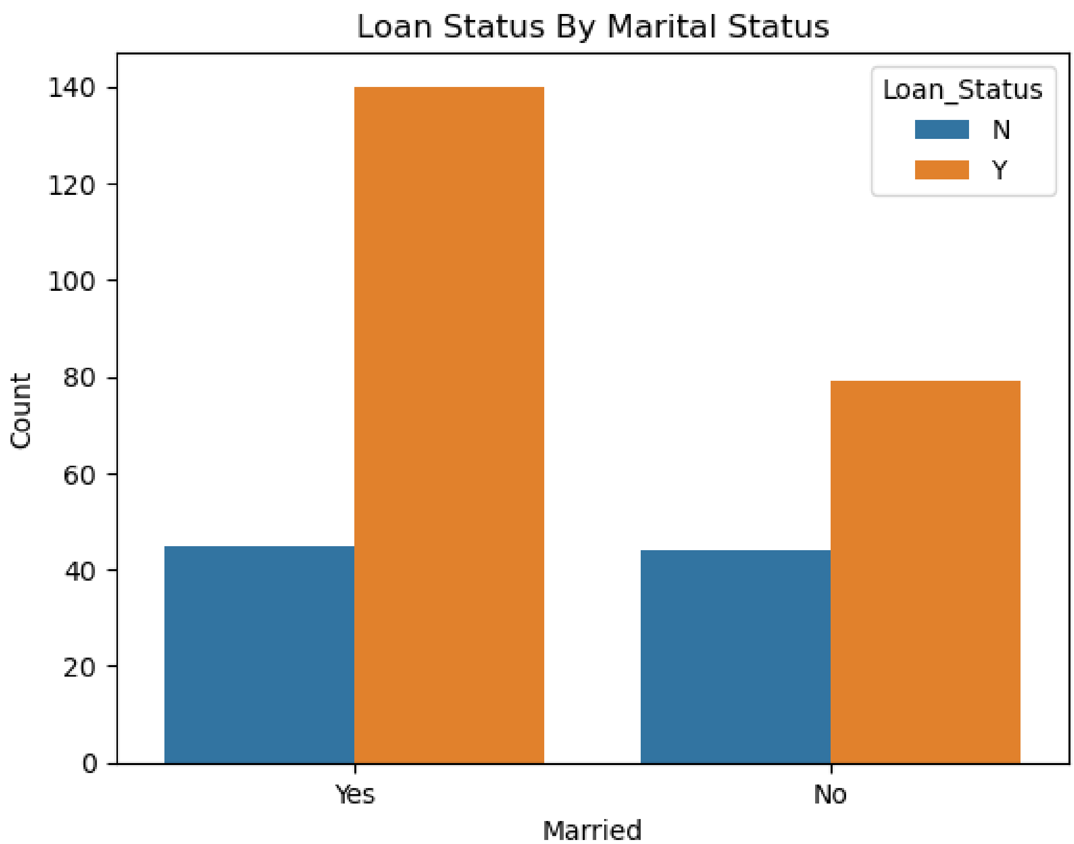



[12]:
```
sns.boxplot(x='Property_Area',y='LoanAmount', data= loan_data)
plt.title('Loan Amount Distribution by Property Area')
plt.xlabel('Property Area')
plt.xlabel('Loan Amount')
plt.show()
```

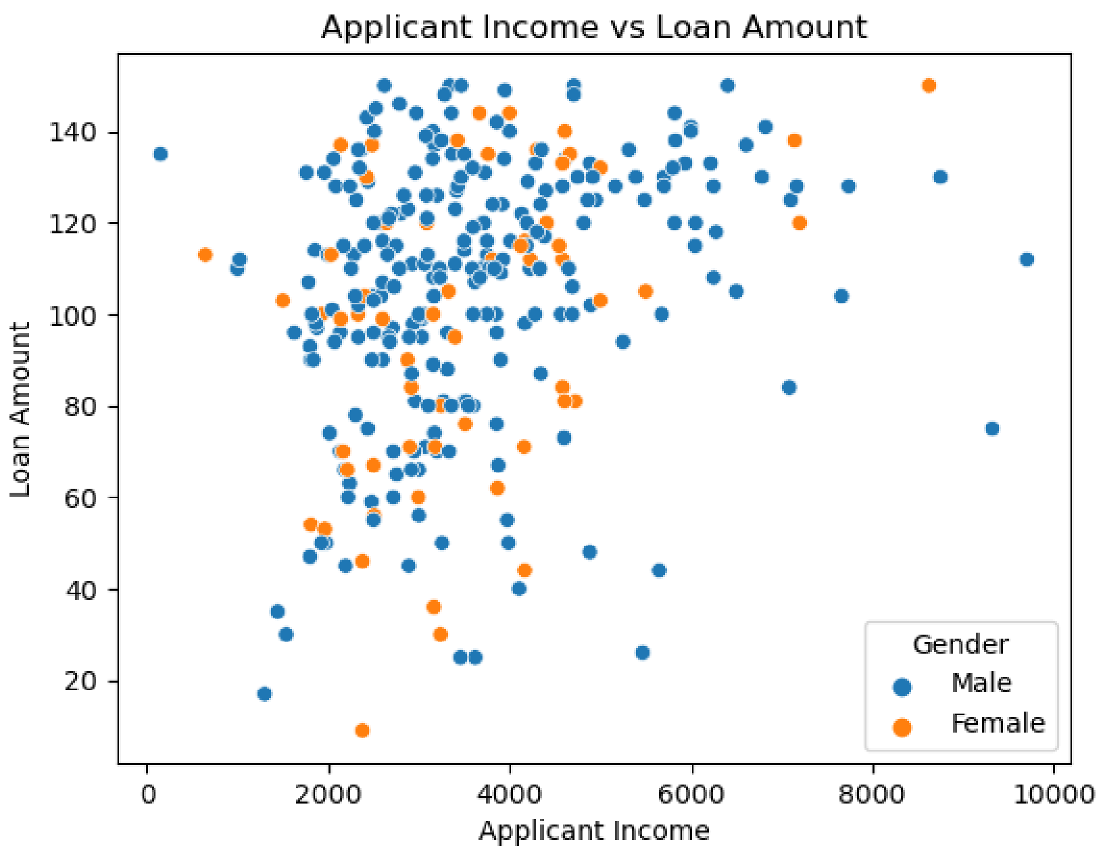



[13]:
```
sns.countplot(x='Loan_Status', hue= 'Gender', data = loan_data)
plt.title('Count of Loan Status By Gender')
plt.xlabel('Loan Approved')
plt.ylabel('Count')
plt.show()
```


[14]:
```
sns.countplot(x='Married', hue= 'Loan_Status', data = loan_data)
plt.title('Loan Status By Marital Status')
plt.xlabel('Married')
plt.ylabel('Count')
plt.show()
```




[15]:
```
sns.scatterplot(x='ApplicantIncome', y='LoanAmount', hue ='Gender', data =␣
↪loan_data)
plt.title('Applicant Income vs Loan Amount')
plt.xlabel('Applicant Income')
plt.ylabel('Loan Amount')
plt.show()
```




[16]:
```
numeric_data =loan_data.select_dtypes(include=['int64','float64'])
```

[17]:
```
numeric_data
```

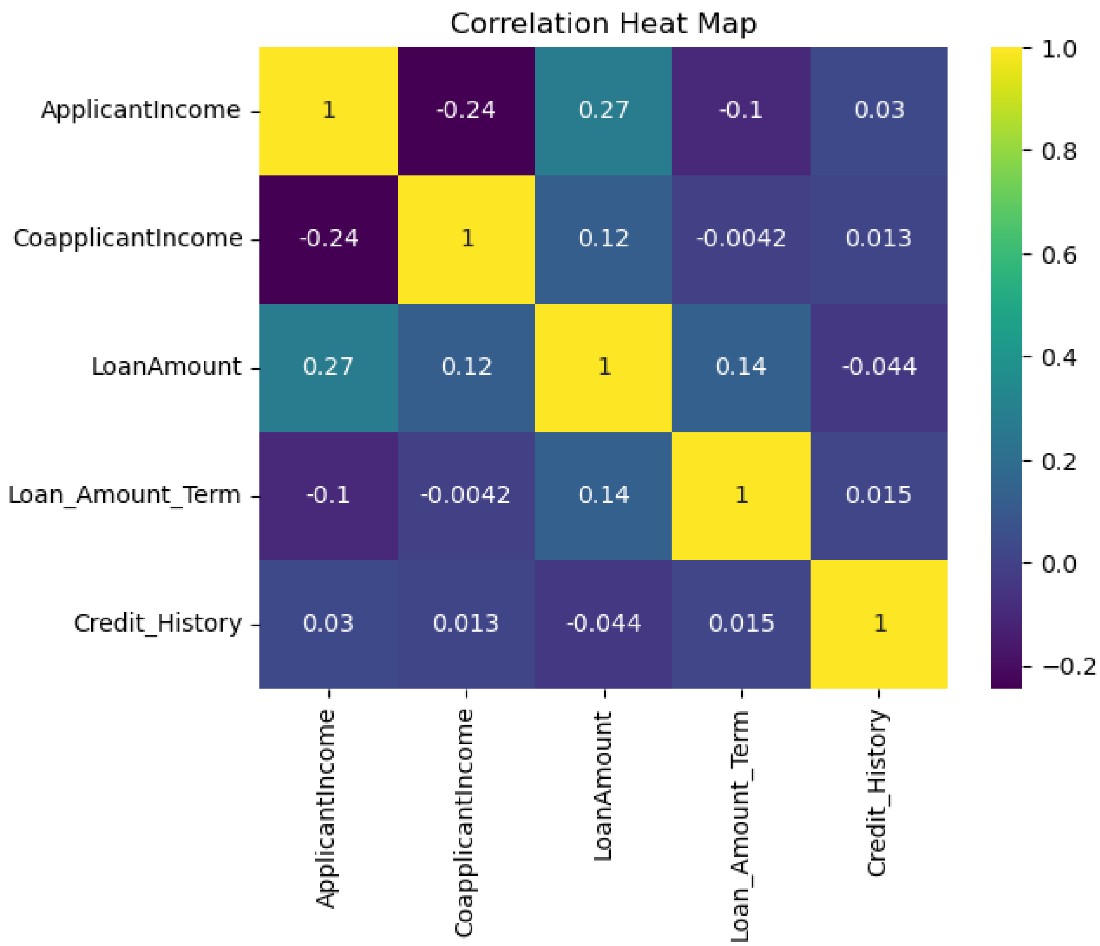
[17]:
```
     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               4583             1508.0       128.0             360.0
1               3000                0.0        66.0             360.0
2               2583             2358.0       120.0             360.0
3               6000                0.0       141.0             360.0
4               2333             1516.0        95.0             360.0
..               …                  …          …                 …
376             5703                0.0       128.0             360.0
377             3232             1950.0       108.0             360.0
378             2900                0.0        71.0             360.0
379             4106                0.0        40.0             180.0
380             4583                0.0       133.0             360.0

     Credit_History
0               1.0
1               1.0
```

```
2              1.0
3              1.0
4              1.0
..             …
376            1.0
377            1.0
378            1.0
379            1.0
380            0.0

[308 rows x 5 columns]
```

[18]:
```
correlation_matrix = numeric_data.corr()
correlation_matrix
```

[18]:
```
                   ApplicantIncome  CoapplicantIncome  LoanAmount  \
ApplicantIncome           1.000000          -0.243677    0.267628
CoapplicantIncome        -0.243677           1.000000    0.123028
LoanAmount                0.267628           0.123028    1.000000
Loan_Amount_Term         -0.099571          -0.004158    0.135069
Credit_History            0.030307           0.012715   -0.043853

                   Loan_Amount_Term  Credit_History
ApplicantIncome           -0.099571        0.030307
CoapplicantIncome         -0.004158        0.012715
LoanAmount                 0.135069       -0.043853
Loan_Amount_Term           1.000000        0.015269
Credit_History             0.015269        1.000000
```

[19]:
```
sns.heatmap(correlation_matrix, annot=True, cmap='viridis')
plt.title('Correlation Heat Map')
plt.show()
```




[20]:
```
loan_data.columns
```

[20]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

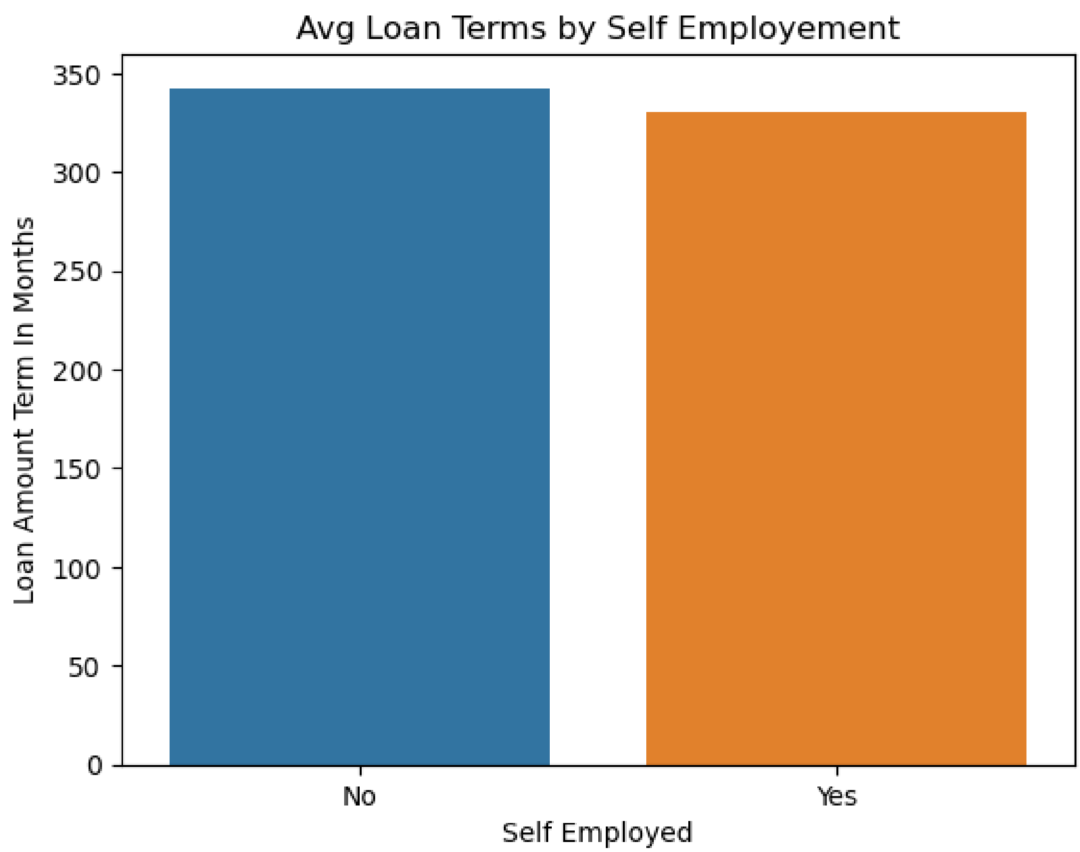
[21]:
```
Avg_loan_term_by_employeed = loan_data.
 ↪groupby('Self_Employed')['Loan_Amount_Term'].mean().reset_index()
Avg_loan_term_by_employeed
```

[21]:

| | Self_Employed | Loan_Amount_Term |
|---|---|---|
| 0 | No | 342.3 |
| 1 | Yes | 330.0 |

[22]:
```
sns.barplot(x='Self_Employed', y= 'Loan_Amount_Term', data=␣
 ↪Avg_loan_term_by_employeed)
```

```
plt.title('Avg Loan Terms by Self Employement')
plt.xlabel('Self Employed')
plt.ylabel('Loan Amount Term In Months')
plt.show()
```




## 2 Creating the ML model to make Predictions

[23]:
```
#calling the data again for reference and select the needed columns for
↪predictions

loan_data.columns
```

[23]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[24]:

```
X=␣
  ↪loan_data[['Married','ApplicantIncome','Education','LoanAmount','Credit_History']].
  ↪copy()
y= loan_data['Loan_Status']
```

[25]:
```
# since Loan Status is in Y and N we need to convert it, so we do Encoding

labelencoder = preprocessing.LabelEncoder()
y = labelencoder.fit_transform(y) # n=o, y=1
```

[26]:
```
labelencoder = preprocessing.LabelEncoder()
X['Married'] = labelencoder.fit_transform(X['Married'].astype(str)) # 1= Y, 0=N
X['Education'] = labelencoder.fit_transform(X['Education'].astype(str)) #␣
  ↪graduate=0
```

[27]:
```
# Since the Applicant Income and Loan Amount are huge numbers, we want to␣
  ↪standarize them
from sklearn.preprocessing import StandardScaler
scaler= StandardScaler()

X = scaler.fit_transform(X)
```

[28]:
```
# for the fast API we need to dump the values

import joblib
joblib.dump(scaler,'Scaler.pkl')
```

[28]: ['Scaler.pkl']

# 3 Logistic Regression

[29]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.3)
```

[30]:
```
# Start with the Logistic regression model

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

LogisticReg = LogisticRegression()

LogisticReg.fit(X_train, y_train)

prediction= LogisticReg.predict(X_test)
```

[31]:
```
accuracy = accuracy_score(y_test, prediction)

print('Accuracy of the Logistic Regression model is :', accuracy)
```

```
Accuracy of the Logistic Regression model is : 0.8494623655913979
```

## 4 KNN

[32]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV

import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

param_grid = {'n_neighbors':[3,5,7],
                'weights':['uniform','distance']}

gridkn = GridSearchCV(KNeighborsClassifier(), param_grid)
```

[33]:
```
gridkn.fit(X_train, y_train)
```

[33]:
```
GridSearchCV(estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': [3, 5, 7],
                         'weights': ['uniform', 'distance']})
```

[34]:
```
gridkn.best_params_
```

[34]:
```
{'n_neighbors': 5, 'weights': 'uniform'}
```

[35]:
```
knpreds =gridkn.predict(X_test)
```

[36]:
```
accuracy = accuracy_score(y_test, knpreds)

print('Accuracy of the KNN model is :', accuracy)
```

```
Accuracy of the KNN model is : 0.7311827956989247
```

## 5 Support Vector Machine

[37]:
```
from sklearn.svm import SVC
```

[38]:
```
svm = SVC()
param_grid_svc = {'C':[0.01,0.1,0.5],'kernel':['linear','rbf','poly']}
```

[39]:
```
gridsvm= GridSearchCV(svm,param_grid_svc)
```

[40]:
```
gridsvm.fit(X_train,y_train)
```

[40]: GridSearchCV(estimator=SVC(),
             param_grid={'C': [0.01, 0.1, 0.5],
                         'kernel': ['linear', 'rbf', 'poly']})

[41]:
```
gridsvm.best_params_
```

[41]: {'C': 0.01, 'kernel': 'linear'}

[42]:
```
svm_prediction =gridsvm.predict(X_test)
```

[43]:
```
accuracy = accuracy_score(y_test, svm_prediction)

print('Accuracy of the KNN model is :', accuracy)
```

Accuracy of the KNN model is : 0.8494623655913979

[44]:
```
joblib.dump(gridsvm, 'model.pkl')
```

[44]: ['model.pkl']

[ ]:
```

```