prediction-using-machine-learning

February 1, 2024

1 Loan Eligibility prediction using Machine Learning Models in Python

I will develop a model that can predict whether or not one can get a loan aproval. the model will use past data of the applicant and information like gender, marital status and income etc to predict their probability of getting a loan

1.0.1 Importing Libraries

[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.preprocessing  import LabelEncoder, StandardScaler
from sklearn import metrics
from sklearn.svm import SVC
from imblearn.over_sampling import RandomOverSampler

import warnings
warnings.filterwarnings('ignore')
```

1.0.2 Loading the dataset

[2]:
```
# Using this to load the file from my External Hard drive AND Saving it to␣
 ↪Uploaded
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving loan_data.csv to loan_data.csv
```

[3]:
```
# I will use this io.BytesIO(uploaded['loan_data.csv']) to read the csv file␣
 ↪from the io that i uploaded the file.
import io
df = pd.read_csv(io.BytesIO(uploaded['loan_data.csv']),encoding = 'latin-1').
 ↪dropna(axis = 1)
```

```
df.head()
```

[3]:

	Gender	Married	ApplicantIncome	LoanAmount	Loan_Status
0	Male	Yes	4583	128000.0	N
1	Male	Yes	3000	66000.0	Y
2	Male	Yes	2583	120000.0	Y
3	Male	No	6000	141000.0	Y
4	Male	Yes	5417	267000.0	Y

[4]:
```
## Shape of the dataset
df.shape
```

[4]: (577, 5)

[5]:
```
# Info() About the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 577 entries, 0 to 576
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Gender           577 non-null    object
 1   Married          577 non-null    object
 2   ApplicantIncome  577 non-null    int64
 3   LoanAmount       577 non-null    float64
 4   Loan_Status      577 non-null    object
dtypes: float64(1), int64(1), object(3)
memory usage: 22.7+ KB
```

To get values like the mean, count and min of the column

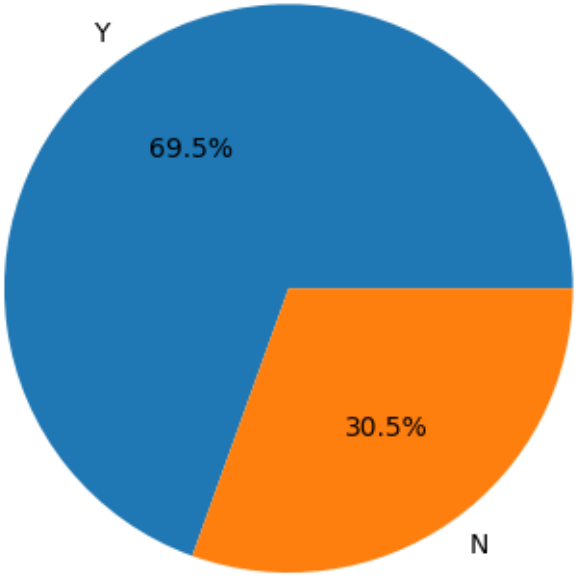
[6]:
```
df.describe().T
```

[6]:

	count	mean	std	min	25%	50%	75%	max
ApplicantIncome	577.0	5297.119584	5853.236196	150.0	2889.0	3800.0	5746.0	81000.0
LoanAmount	577.0	144968.804159	82704.181660	9000.0	100000.0	127000.0	167000.0	650000.0

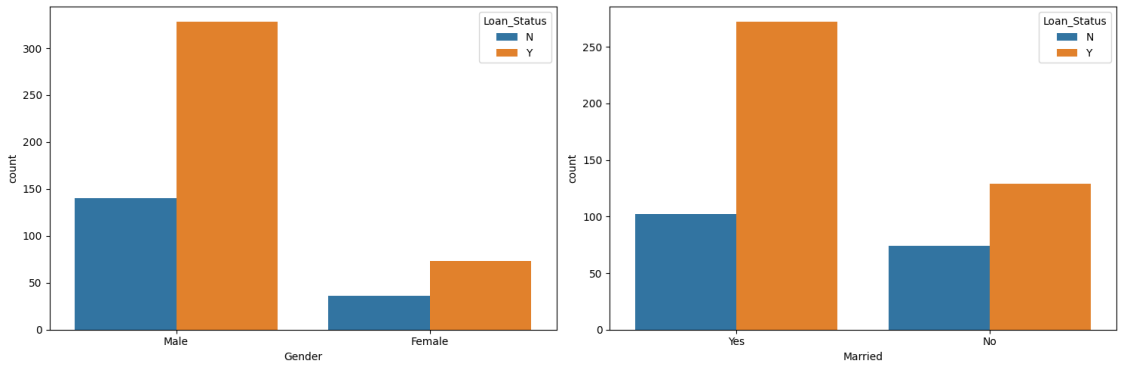
1.0.3 Exploratory Data Analysis

[7]:
```
# Plot the piechart of loanStatus column
temp = df['Loan_Status'].value_counts()
plt.pie(temp.values, labels = temp.index, autopct = '%1.1f%%')
plt.show()
```



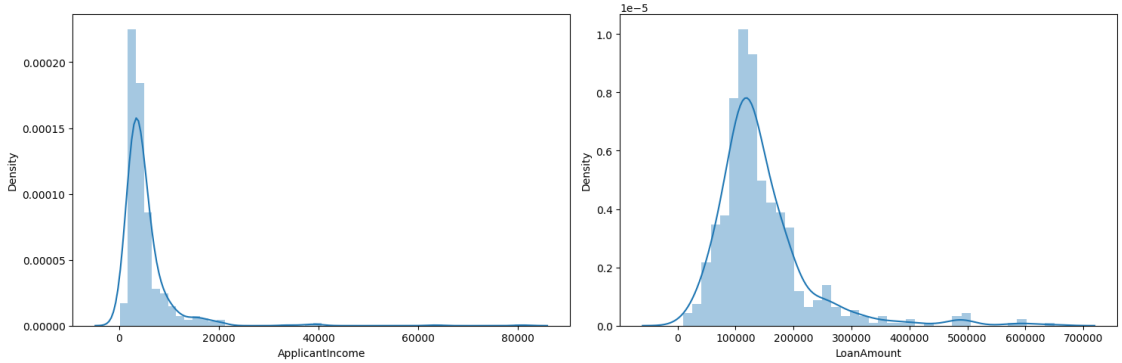
we have an imbalanced Dataset. I will have to balance it before training.

[8]:
```
# I will Plot a CountPlot
plt.subplots(figsize = (15, 5))
for i, col in enumerate(['Gender','Married']):
  plt.subplot(1, 2, i+1)
  sns.countplot(data = df, x = col, hue ='Loan_Status')

plt.tight_layout()
plt.show()
```



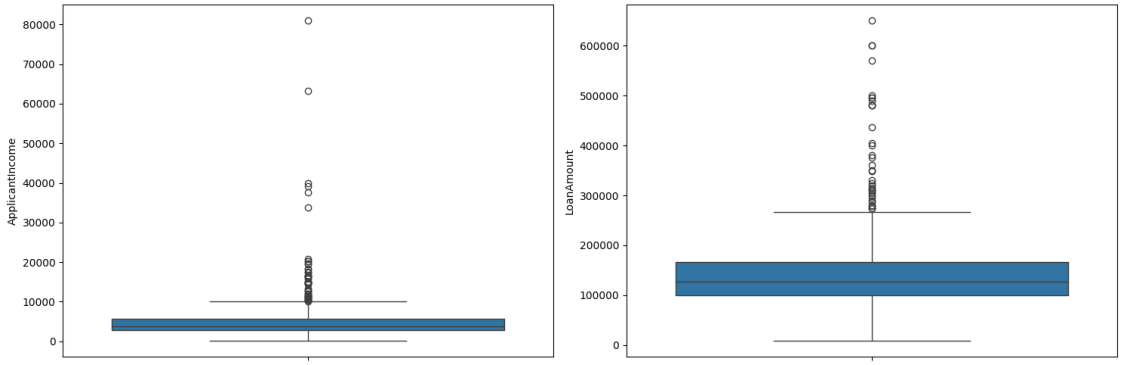
one observation we can see is that Chances of getting a loan approved for married people is quite low

[9]:
```
plt.subplots(figsize=(15, 5))
for i, col in enumerate(['ApplicantIncome', 'LoanAmount']):
  plt.subplot(1, 2, i+1)
  sns.distplot(df[col])

plt.tight_layout()
plt.show()
```



Now to get the Outliers we use Boxplot

[10]:
```
plt.subplots(figsize=(15,5))
for i, col in enumerate(['ApplicantIncome', 'LoanAmount']):
  plt.subplot(1, 2, i+1)
  sns.boxplot(df[col])

plt.tight_layout()
plt.show()
```



1.0.4 We remove the Extreme outliers

[11]:
```
df = df[df['ApplicantIncome'] < 25000]
df = df[df['LoanAmount'] < 400000]
```

1.0.5 Now lets see the mean amount of the loan granted to males as well as females

[12]:
```
df.groupby('Gender').mean()['LoanAmount']
```

[12]:
```
Gender
Female    118822.429907
Male      139289.823009
Name: LoanAmount, dtype: float64
```

nOW WE SEE the mean amount of the loan granted to Married, and gender

[13]:
```
df.groupby(['Married','Gender']).mean()['LoanAmount']
```

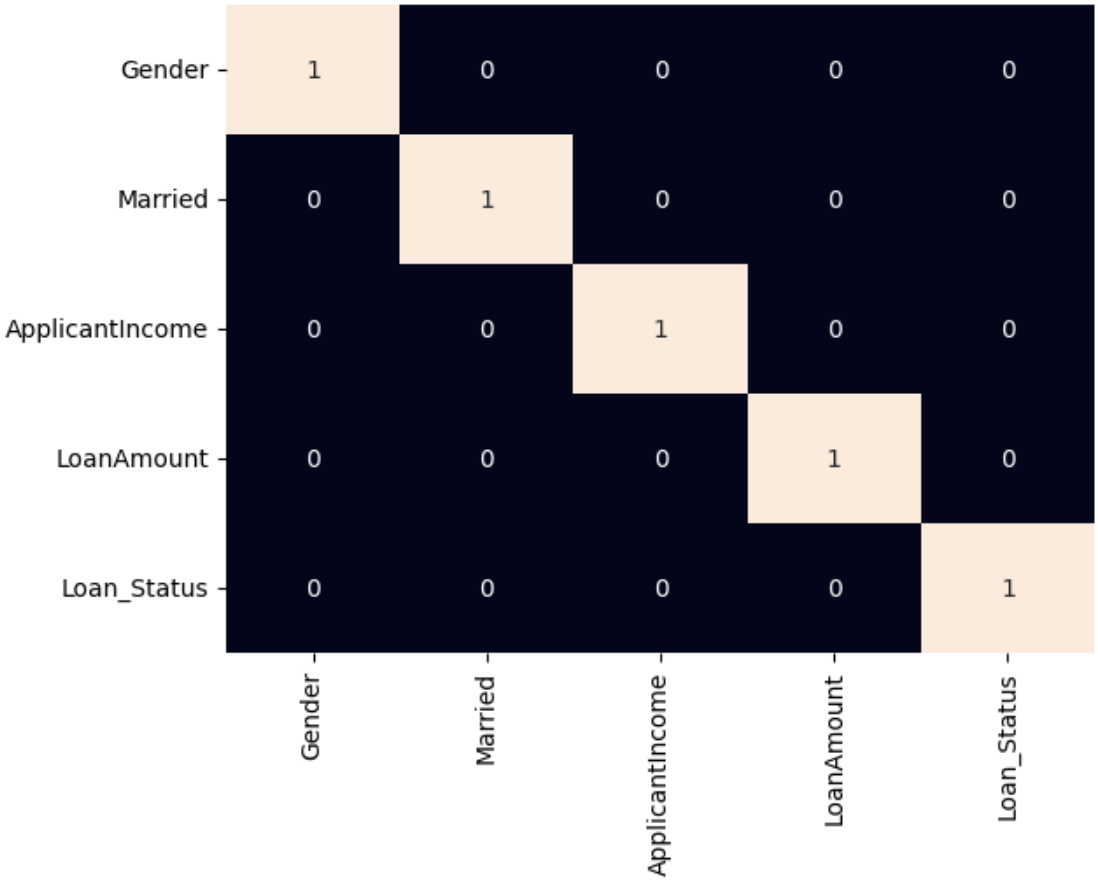
[13]:
```
Married  Gender
No       Female    116115.384615
         Male      126644.628099
Yes      Female    126103.448276
         Male      143912.386707
Name: LoanAmount, dtype: float64
```

one more interesting observation in addition to the previous one that the married people requested loan amount is generally higher than that of the unmarried.

[14]:
```
by ='Joseph Gathithi Wathome'
```

1.0.6 Function to perform a label encoding

[15]:
```
def encode_labels(data):
  for col in data.columns:
    if data[col].dtype == 'object':
      le = LabelEncoder()
      data[col] = le.fit_transform(data[col])
  return data

# Applying the funtion in whole column
df = encode_labels(df)

# Generate Heatmap
sns.heatmap(df.corr() > 0.8, annot = True, cbar = False)
plt.show()
```



1.1 Data Preprocessing

here we will split the data for training and testing

[16]:
```
features = df.drop('Loan_Status',axis = 1)
target = df['Loan_Status'].values
X_train, X_val, Y_train, Y_val = train_test_split(features, target,
                                                  test_size = 0.2,
                                                  random_state = 10)

#  As the data was highly  imbalanced we will balance it by adding repetitive␣
 ↪rows of minority class
ros = RandomOverSampler(sampling_strategy = 'minority', random_state = 0)
X, Y = ros.fit_resample(X_train, Y_train)

X_train.shape, X.shape
```

[16]:
```
((447, 4), (616, 4))
```

1.1.1 nOW BY USING sTANDARD sCALING I WILL NORMALIZING THE DATA

[17]:
```
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_val = scaler.transform(X_val)
```

1.2 Model Development

[19]:
```
from sklearn.metrics import roc_auc_score
model = SVC(kernel= 'rbf')
model.fit(X,Y)

print('Training Accuracy: ', metrics.roc_auc_score(Y, model.predict(X)))
print('Validation Accuracy: ', metrics.roc_auc_score(Y_val, model.
 ↪predict(X_val)))
print()
```

```
Training Accuracy:  0.6136363636363635
Validation Accuracy:  0.4908403026682596
```

1.2.1 Model Evaluation

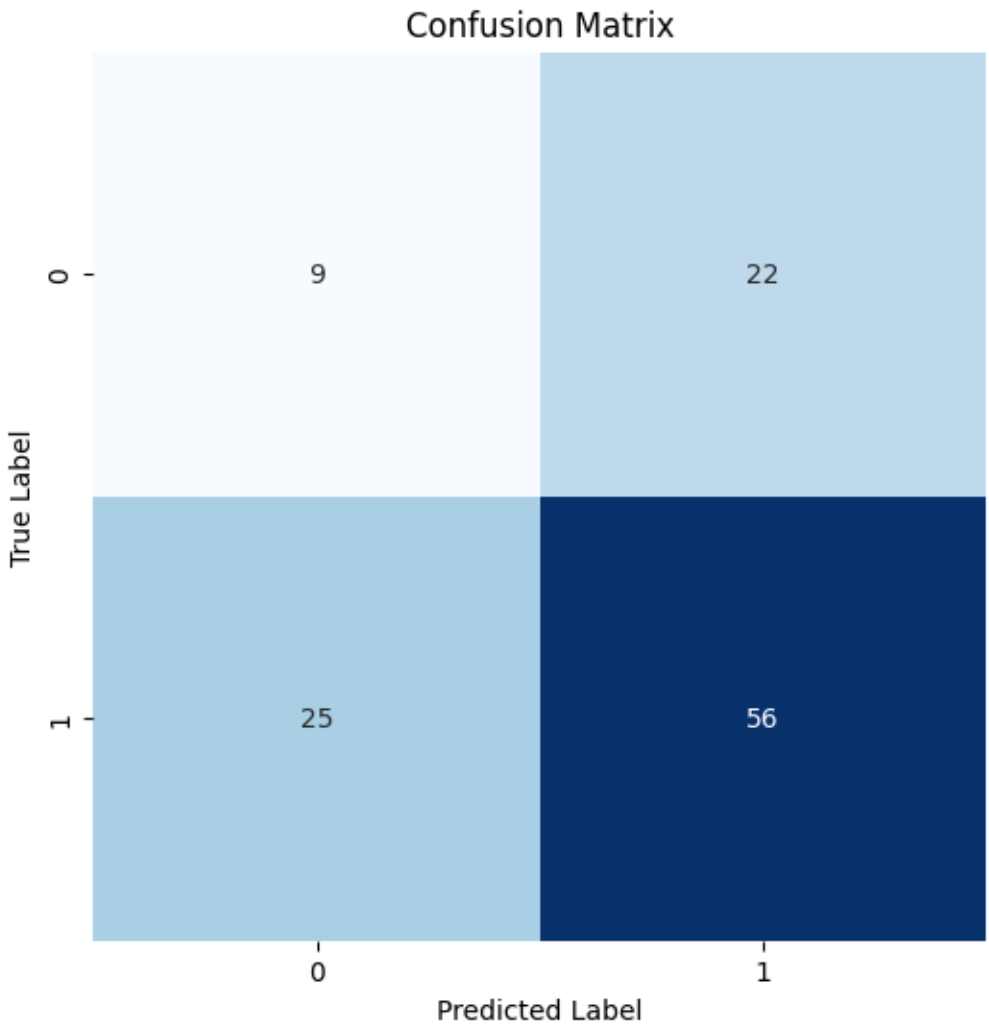
since its a clasification project we will be evaluating the model by using confusion matrix

I will first train the SVC model using the training data X and Y. Then, I will calculate the ROC AUC scores for both the training and validation datasets. The confusion matrix is built for the validation data by using the confusion_matrix function from sklearn.metrics. Finally, I will plot the confusion matrix using the plot_confusion_matrix function from the sklearn.metrics.plot_confusion_matrix submodule.

[20]:
```
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
training_roc_auc = roc_auc_score(Y, model.predict(X))
validation_roc_auc = roc_auc_score(Y_val, model.predict(X_val))

print('Training ROC AUC Score: ', training_roc_auc)
print('Validation ROC AUC Score: ', validation_roc_auc)
print()

cm = confusion_matrix(Y_val, model.predict(X_val))
```

```
Training ROC AUC Score:  0.6136363636363635
Validation ROC AUC Score:  0.4908403026682596
```

[21]:
```
plt.figure(figsize=(6,6))
sns.heatmap(cm, annot = True, fmt = 'd', cmap = 'Blues', cbar = False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



1.2.2 Classification Report

[24]:
```
from sklearn.metrics import classification_report
print(classification_report(Y_val, model.predict(X_val)))
print(by)
```

```
              precision    recall  f1-score   support

           0       0.26      0.29      0.28        31
           1       0.72      0.69      0.70        81

    accuracy                           0.58       112
   macro avg       0.49      0.49      0.49       112
weighted avg       0.59      0.58      0.59       112
```

Joseph Gathithi Wathome

As this dataset contains fewer features the performance of the model is not up to the mark maybe if we will use a better and big dataset we will be able to achieve better accuracy.