deepen-ml-project-1

September 20, 2024

1 Project Name: Loan Status Prediction

The following are variables in the Dataset:

- Loan_ID: A unique loan ID.
- Gender: Either male or female.
- Married: Weather Married(yes) or Not Marttied(No).
- Dependents: Number of persons depending on the client.
- Education: Applicant Education(Graduate or Undergraduate).
- Self_Employed: Self-employed (Yes/No).
- Applicant Income: Applicant income.
- CoapplicantIncome: Co-applicant income.
- LoanAmount: Loan amount in thousands.
- Loan_Amount_Term: The terms of the loan are in months.
- Credit_History: Credit history meets guidelines.
- Property_Area: Applicants are living either Urban, Semi-Urban or Rural.
- Loan_Status: Loan approved (Y/N).

2 Data Reading and Reviewing

[ ]:

```

```

[1]:

```python
import pandas as pd
```

[2]:

```python
df=pd.read_csv(r'C:\Users\l\Downloads\Loan Status Prediction.csv')
df
```

[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
..        …       …       …          …             …             …
376  LP002953    Male     Yes         3+      Graduate            No
377  LP002974    Male     Yes          0      Graduate            No
378  LP002978  Female      No          0      Graduate            No
```

```
379  LP002979    Male     Yes          3+      Graduate            No
380  LP002990  Female      No           0      Graduate           Yes

     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 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
..              …             …          …
376             1.0         Urban           Y
377             1.0         Rural           Y
378             1.0         Rural           Y
379             1.0         Rural           Y
380             0.0     Semiurban           N

[381 rows x 13 columns]
```

Observation:

- We can see that in the data Gender, Education, employment status and thier respective credit scores are most important variables to predict of the people are getting thier loans approved or not? i.e loan_status will be our target variable to predict

```
[ ]:
```

3 Data Cleaning

```
[ ]:
```

3.0.1 Checking Datatype of Variables

[ ]:

```

```

[4]:

```
df.describe
```

[4]:

```
<bound method NDFrame.describe of       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
..        …       …      …          …            …             …
376  LP002953    Male     Yes         3+      Graduate            No
377  LP002974    Male     Yes          0      Graduate            No
378  LP002978  Female      No          0      Graduate            No
379  LP002979    Male     Yes         3+      Graduate            No
380  LP002990  Female      No          0      Graduate           Yes

     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 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
..              …           …         …
376             1.0         Urban           Y
377             1.0         Rural           Y
378             1.0         Rural           Y
379             1.0         Rural           Y
380             0.0     Semiurban           N

[381 rows x 13 columns]>
```

[ ]:

Observation: - Column 'Dependents' have some values in strings (3+) we have to convert them into numerical

[ ]:

[34]:
```python
df['Dependents'] = df['Dependents'].replace('3+', 3)

df['Dependents'] = pd.to_numeric(df['Dependents'])

print(df)
```

```
     Loan_ID  Gender  Married  Dependents  Education  Self_Employed  \
0          0       1        1           1          0              0
1          1       1        1           0          0              1
2          2       1        1           0          1              0
3          3       1        0           0          0              0
4          4       1        1           0          1              0
..       …       …        …           …          …              …
376      376       1        1           3          0              0
377      377       1        1           0          0              0
378      378       0        0           0          0              0
379      379       1        1           3          0              0
380      380       0        0           0          0              1

     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  Property_Area  Loan_Status
0               1.0              0            0
1               1.0              2            1
2               1.0              2            1
3               1.0              2            1
4               1.0              2            1
..              …             …          …
376             1.0              2            1
377             1.0              0            1
```

```
378               1.0               0             1
379               1.0               0             1
380               0.0               1             0

[381 rows x 13 columns]
```

[ ]:

3.0.2 Checking Null Values

[ ]:

[5]:
```
df.isnull().sum()
```

[5]:
```
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
```

[ ]:

[6]:
```
import pandas as pd
import numpy as np
```

[11]:
```
df['Dependents'] = df.groupby('Married')['Dependents'].transform(lambda x: x.
 ↪fillna(x.mode()[0] if not x.mode().empty else x.dropna().max()))
df['Loan_Amount_Term'] = df.groupby(['Education',␣
 ↪'Property_Area'])['Loan_Amount_Term'].transform(lambda x: x.fillna(x.
 ↪median()))
df['Credit_History'] = df.groupby('Property_Area')['Credit_History'].
 ↪transform(lambda x: x.fillna(x.mode()[0] if not x.mode().empty else 0))

mode_gender = df['Gender'].mode()[0]
mode_self_employed = df['Self_Employed'].mode()[0]

df['Gender'].fillna(mode_gender, inplace=True)
df['Self_Employed'].fillna(mode_self_employed, inplace=True)
```

```
print(df)
```

```
      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
..        …       …       …        …            …           …
376  LP002953    Male     Yes         3+      Graduate            No
377  LP002974    Male     Yes          0      Graduate            No
378  LP002978  Female      No          0      Graduate            No
379  LP002979    Male     Yes         3+      Graduate            No
380  LP002990  Female      No          0      Graduate           Yes

     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 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
..              …           …         …
376             1.0         Urban           Y
377             1.0         Rural           Y
378             1.0         Rural           Y
379             1.0         Rural           Y
380             0.0     Semiurban           N

[381 rows x 13 columns]
```

[ ]:

[12]:
```
df.isnull().sum()
```

[12]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

[ ]:

Obversation: - Dataset has many columns and rows with categorical data and we have to convert them into numerical using label encoding method, and also Dependents, Loan_Amount_Term, Credit_History, Gender and Self_Employed columns had missing values. By using the mean, mode and median imputers we have filled the missing values and Data is clean now.

4 Label Encoding

[ ]:

[21]:
```python
import pandas as pd
from sklearn.preprocessing import LabelEncoder
```

[31]:
```python
label_encoder = LabelEncoder()

columns_to_encode = ['Gender', 'Married', 'Education',␣
↪'Self_Employed','Property_Area', 'Loan_Status', 'Loan_ID']

for column in columns_to_encode:
    df[column] = label_encoder.fit_transform(df[column])
```

[32]:
```python
print(df)
```

```
     Loan_ID  Gender  Married Dependents  Education  Self_Employed  \
0          0       1        1          1          0              0
1          1       1        1          0          0              1
2          2       1        1          0          1              0
3          3       1        0          0          0              0
4          4       1        1          0          1              0
..       …       …        …          …          …              …
376      376       1        1         3+          0              0
```

```
377      377      1      1       0       0          0
378      378      0      0       0       0          0
379      379      1      1      3+       0          0
380      380      0      0       0       0          1

     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  Property_Area  Loan_Status
0               1.0              0            0
1               1.0              2            1
2               1.0              2            1
3               1.0              2            1
4               1.0              2            1
..              …             …          …
376             1.0              2            1
377             1.0              0            1
378             1.0              0            1
379             1.0              0            1
380             0.0              1            0

[381 rows x 13 columns]
```

[ ]:

Observation: - Many columns in dataset like 'Gender', 'Married', 'Education', 'Self_Employed','Property_Area', 'Loan_Status', 'Loan_ID' had categorical values by using label incoding the values are turned into numerical

[ ]:

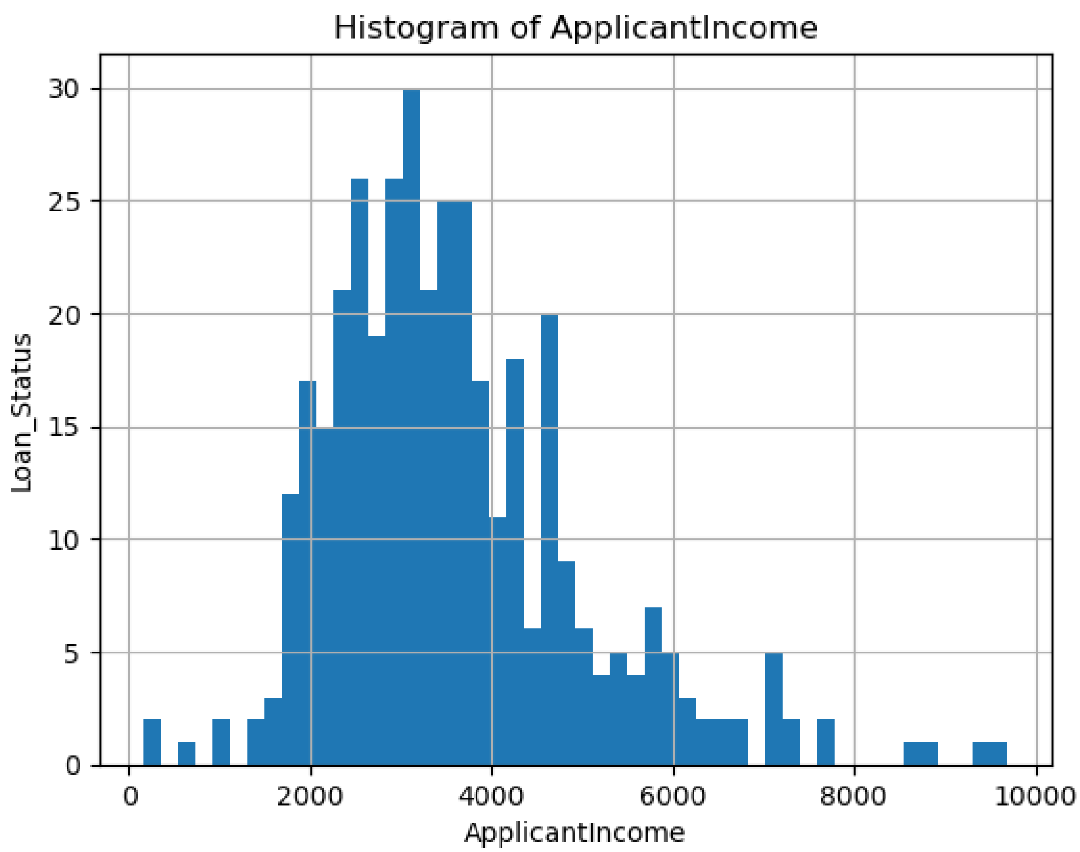
5 Exploratory Data Analysis

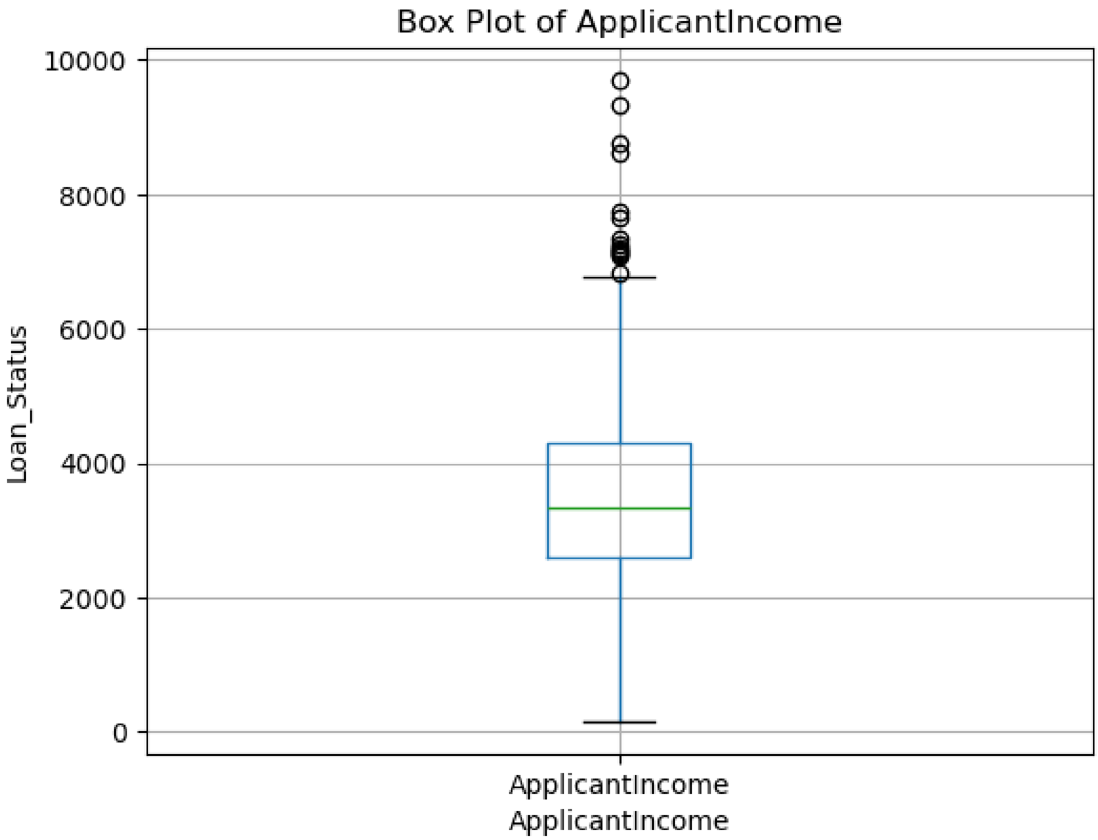
5.0.1 1. Histograms and Box Plots

[15]:
```
import pandas as pd
import matplotlib.pyplot as plt

df['ApplicantIncome'].hist(bins=50)
plt.title('Histogram of ApplicantIncome')
plt.xlabel('ApplicantIncome')
plt.ylabel('Loan_Status')
plt.show()

df.boxplot(column='ApplicantIncome')
plt.title('Box Plot of ApplicantIncome')
plt.xlabel('ApplicantIncome')
plt.ylabel('Loan_Status')
plt.show()
```






```
[ ]:
```

Observation: - After using histplot and Box Plot we can observe that applicants with income of more than 6000 are the significant outliers in our data

```
[ ]:
```

5.0.2 Checking Skewness

```
[ ]:
```

```
[35]: skewness = df.skew()
      print(skewness)
```

```
Loan_ID               0.000000
Gender               -1.335495
Married              -0.403147
Dependents            1.169190
Education             1.038274
Self_Employed         2.837288
```

```
ApplicantIncome       1.119751
CoapplicantIncome     8.660692
LoanAmount           -0.804282
Loan_Amount_Term     -2.253633
Credit_History       -1.972497
Property_Area        -0.091709
Loan_Status          -0.936181
dtype: float64
```

[ ]:

Observation: - We can see numerical columns like ApplicantIncome, CoapplicantIncome, Dependents, and Loan_Amount_Term. have higher skewness

[ ]:

5.0.3 Handling Skewness

1. Log Transformation: for ApplicantIncome, CoapplicantIncome, Dependents, and Loan_Amount_Term.

[ ]:

[37]:
```
import numpy as np

df['ApplicantIncome_log'] = np.log(df['ApplicantIncome'] + 1)
df['CoapplicantIncome_log'] = np.log(df['CoapplicantIncome'] + 1)
df['LoanAmount_log'] = np.log(df['LoanAmount'] + 1)
df['Dependents_log'] = np.log(df['Dependents'] + 1)
```

[40]:
```
New_skewness = df[['ApplicantIncome_log', 'CoapplicantIncome_log',␣
 ↪'LoanAmount_log', 'Dependents_log']].skew()
print(New_skewness)
```

```
ApplicantIncome_log     -1.642001
CoapplicantIncome_log   -0.120231
LoanAmount_log          -2.181560
Dependents_log           0.852382
dtype: float64
```

[ ]:

Observation: - We can see the skewness is quite balanced compared to before

[ ]:

5.0.4 Transformation of Old Variables in New

[ ]:

[42]:
```
df['ApplicantIncome'] = df['ApplicantIncome_log']
df['CoapplicantIncome'] = df['CoapplicantIncome_log']
df['LoanAmount'] = df['LoanAmount_log']
df['Dependents'] = df['Dependents_log']

df.drop(['ApplicantIncome_log', 'CoapplicantIncome_log', 'LoanAmount_log',␣
 ↪'Dependents_log'], axis=1, inplace=True)
```

[ ]:

6 Data Preprocessing for Model Building

6.0.1 Splitting the Data to Get Training and Testing Data

[ ]:

[48]:
```
X = df.drop(['Loan_Status', 'Loan_ID'], axis=1)
print(X.head())
```

```
   Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
0       1        1    0.693147          0              0         8.430327
1       1        1    0.000000          0              1         8.006701
2       1        1    0.000000          1              0         7.857094
3       1        0    0.000000          0              0         8.699681
4       1        1    0.000000          1              0         7.755339

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0           7.319202    4.859812             360.0             1.0
1           0.000000    4.204693             360.0             1.0
2           7.765993    4.795791             360.0             1.0
3           0.000000    4.955827             360.0             1.0
4           7.324490    4.564348             360.0             1.0

   Property_Area
0              0
1              2
2              2
3              2
4              2
```

[51]:
```
y= df['Loan_Status']
y
```

[51]:
```
0      0
1      1
2      1
3      1
4      1
      ..
376    1
377    1
378    1
379    1
380    0
Name: Loan_Status, Length: 381, dtype: int64
```

[ ]:

6.0.2 Model Building

[ ]:

[49]:
```python
from sklearn.model_selection import train_test_split
```

[54]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
print(X_train.shape, X_test.shape)
```

```
(304, 11) (77, 11)
```

[55]:
```python
from sklearn.linear_model import LogisticRegression
```

[57]:
```python
lr=LogisticRegression()
lr
```

[57]:
```
LogisticRegression()
```

6.0.3 Prediction

[59]:
```python
lr.fit(X_train,y_train)
lr
```

```
C:\ProgramData\anaconda3\Lib\site-
packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
```

```
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[59]:
```
LogisticRegression()
```

[62]:
```
y_pred=lr.predict(X_test)
y_pred
```

[62]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1,
       0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int64)
```

6.0.4 Scoring

[66]:
```
lr.score(X_train, y_train)
```

[66]:
```
0.8519736842105263
```

[67]:
```
lr.score(X_test, y_test)
```

[67]:
```
0.8181818181818182
```

6.0.5 Model Evaluation

[68]:
```
from sklearn.metrics import  accuracy_score, confusion_matrix
```

[69]:
```
accuracy_score(y_test,y_pred)
```

[69]:
```
0.8181818181818182
```

[70]:
```
confusion_matrix(y_test, y_pred)
```

[70]:
```
array([[ 7, 14],
       [ 0, 56]], dtype=int64)
```

7 Final Analysis:

- After checking the model score and model evaluation the Machine Learning testing model is 80% accurate

[ ]:
```

```