Loan Eligibility Prediction

- Introduction:

We are going to apply multiple models in order to

we are going to work on binary classification problem, where we got some information about sample of peoples , and we need to predict whether we should give some one a loan or not depending on his information . we actually have a few sample size (614 rows), so we will go with machine learning techniques to solve our problem .

Steps : basics of visualizing the data . how to compare between feature importance (at less in this data) .

feature selection

feature engineer

some simple techniques to process the data . handling missing data . how to deal with categorical and numerical data . outliers data detection but the most important thing that you will learn , is how to evaluate your model at every step you take .

some important libraries like sklearn, matplotlib, numpy, pandas, seaborn, scipy fill the values using backward 'bfill' method for numerical columns , and most frequent value for categorical columns (simple techniques) 4 different models to train your data, so we can compare between them

a) logistic regression

b) KNeighborsClassifier

C) SVC

d) DecisionTreeClassifier

In [273...

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
```

In [274...

```
df = pd.read_csv("C:/Users/ROSHAN D K/Desktop/Python Projects/Data_mining_asses_2/train_lo
# test =  pd.read_csv("C:/Users/ROSHAN D K/Desktop/Python Projects/Data_mining_asses_2/tes
# Loan_ID = test.Loan_ID
# df = train.append(test) --Ask
df.head()
```

Out[274...

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAı
0	LP001002	Male	No	0	Graduate	No	5849	0.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	

Describing the data

In [275…
```
df.shape
```
Out[275…
```
(614, 13)
```
In [276…
```
df.isna().sum()
```
Out[276…
```
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
```
In [277…
```
df.isna().sum()* 100/len(df)
# In most of the columns missing data is less than 5%
```
Out[277…
```
Loan_ID              0.000000
Gender               2.117264
Married              0.488599
Dependents           2.442997
Education            0.000000
Self_Employed        5.211726
ApplicantIncome      0.000000
CoapplicantIncome    0.000000
LoanAmount           3.583062
Loan_Amount_Term     2.280130
Credit_History       8.143322
Property_Area        0.000000
Loan_Status          0.000000
dtype: float64
```
In [278…
```
df.nunique()
```
Out[278…
```
Loan_ID              614
Gender                 2
Married                2
Dependents             4
Education              2
Self_Employed          2
ApplicantIncome      505
CoapplicantIncome    287
LoanAmount           203
Loan_Amount_Term      10
Credit_History         2
Property_Area          3
Loan_Status            2
dtype: int64
```
In [279…
```
categorical_var = df[['Gender','Married','Dependents', 'Education', 'Self_Employed', 'Cred
numerical_var = df[['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term']
```

```
for i, col in enumerate(categorical_var.columns):
  print(categorical_var.columns[i].upper(), '\n', categorical_var[str(col)].unique(), '\n'
```

```
GENDER
 ['Male' 'Female' nan]

MARRIED
 ['No' 'Yes' nan]

DEPENDENTS
 ['0' '1' '2' '3+' nan]

EDUCATION
 ['Graduate' 'Not Graduate']

SELF_EMPLOYED
 ['No' 'Yes' nan]

CREDIT_HISTORY
 [ 1.  0. nan]

PROPERTY_AREA
 ['Urban' 'Rural' 'Semiurban']

LOAN_STATUS
 ['Y' 'N']
```

In [280…

```
df.describe()
```

Out[280…

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

Formating the data

In [282…

```
df.drop(["Loan_ID"], axis = 1, inplace = True)
df.head()
```

Out[282…

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loa
0	Male	No	0	Graduate	No	5849	0.0	NaN	
1	Male	Yes	1	Graduate	No	4583	1508.0	128.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	
4	Male	No	0	Graduate	No	6000	0.0	141.0	

In [283…
```
df['Dependents'] = df['Dependents'].str.replace("+","", regex = True)
df['Dependents'] = df['Dependents'].str.replace("3","4", regex = True)
df.Dependents.unique()
```
Out[283…
```
array(['0', '1', '2', '4', nan], dtype=object)
```

Handling missing values

In [284…
```
# applying mode method to deal with the missing values in the categorical varaiables
df.Gender.fillna(df.Gender.mode()[0],inplace = True)
df.Gender.isna().sum()
```
Out[284…
```
0
```

In [285…
```
df.Married.fillna(df.Married.mode()[0],inplace = True)
df.Married.isna().sum()
```
Out[285…
```
0
```

In [286…
```
df.Dependents.fillna(df.Dependents.mode()[0],inplace = True)
df.Dependents.isna().sum()
```
Out[286…
```
0
```

In [287…
```
# This contains more than 5% missing values
df.Self_Employed.fillna(df.Self_Employed.mode()[0],inplace = True)
df.Self_Employed.isna().sum()
```
Out[287…
```
0
```

In [288…
```
# This contains more than 5% missing values
df.Credit_History.fillna(df.Credit_History.mode()[0],inplace = True)
df.Credit_History.isna().sum()
```
Out[288…
```
0
```

In [289…
```
# applying median method to deal with the missing values in the numerical varaiables
df.LoanAmount.fillna(df.LoanAmount.median(),inplace = True)
df.LoanAmount.isna().sum()
```
Out[289…
```
0
```

In [290…
```
# df.dropna(axis=0, subset=['Loan_Status'],inplace = True)
# # df.Loan_Status.fillna(df.Loan_Status.mode()[0],inplace = True)
# df.Loan_Status.isna().sum()
```

In [291…
```
df.Loan_Amount_Term.fillna(df.Loan_Amount_Term.median(),inplace = True)
df.Loan_Amount_Term.isna().sum()
df.isna().sum()
#Any missing value present in the data
```
```
Gender                  0
```

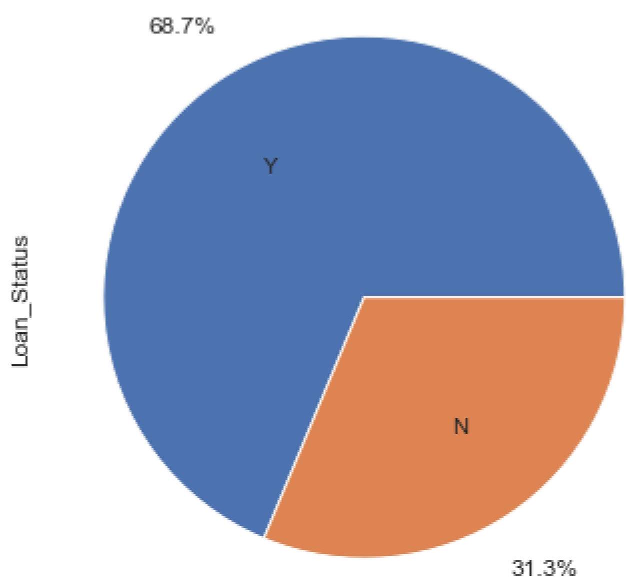
```
Out[291… Married              0
         Dependents           0
         Education            0
         Self_Employed        0
         ApplicantIncome      0
         CoapplicantIncome    0
         LoanAmount           0
         Loan_Amount_Term     0
         Credit_History       0
         Property_Area        0
         Loan_Status          0
         dtype: int64
```

```
In [292…
sns.set_style("whitegrid")
sns.set(rc={'figure.figsize':(10,6)})
```

Checking Data Distribution

```
In [281…
ex = df['Loan_Status'].value_counts()
ex.plot(kind='pie', figsize=(10,6), autopct='%1.1f%%',
       pctdistance=1.25, labeldistance=.6);
print('The percentage of Y class : %.2f' % (df['Loan_Status'].value_counts()[0] / len(df)*
print('The percentage of N class : %.2f' % (df['Loan_Status'].value_counts()[1] / len(df)*
```

```
The percentage of Y class : 68.73
The percentage of N class : 31.27
```

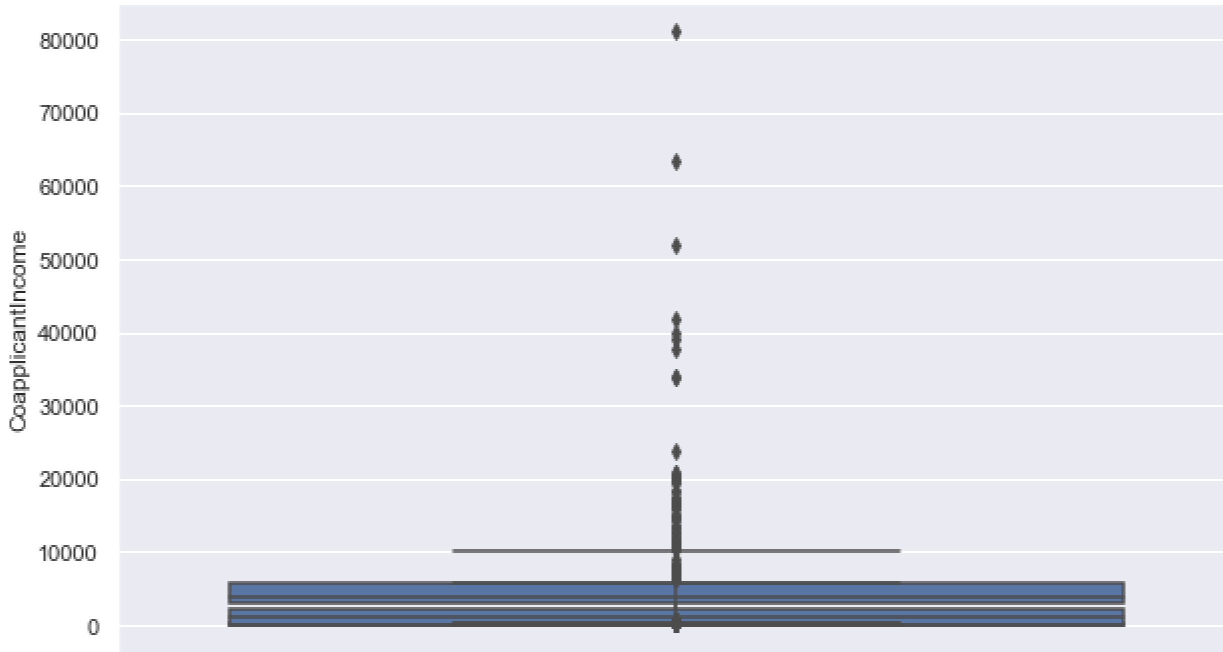



```
In [293…
# Dealing with outliers and normalization --> boxplot, log
```

```
In [294…
# MAke it a function
# plt.hist(df.ApplicantIncome, bins = 10);
# sns.displot(data=df, x="ApplicantIncome", kde = True, bins = 20);
# plt.hist(df.LoanAmount, bins = 10);
# sns.displot(data=df, x="LoanAmount", kde = True, bins = 20);
# plt.hist(df.CoapplicantIncome, bins = 10);
# sns.displot(data=df, x="CoapplicantIncome", kde = True, bins = 20);
```

```
In [295…
# make it a function
sns.boxplot(y = df.ApplicantIncome);
```

```
sns.boxplot(y = df.LoanAmount);
sns.boxplot(y = df.CoapplicantIncome);
```



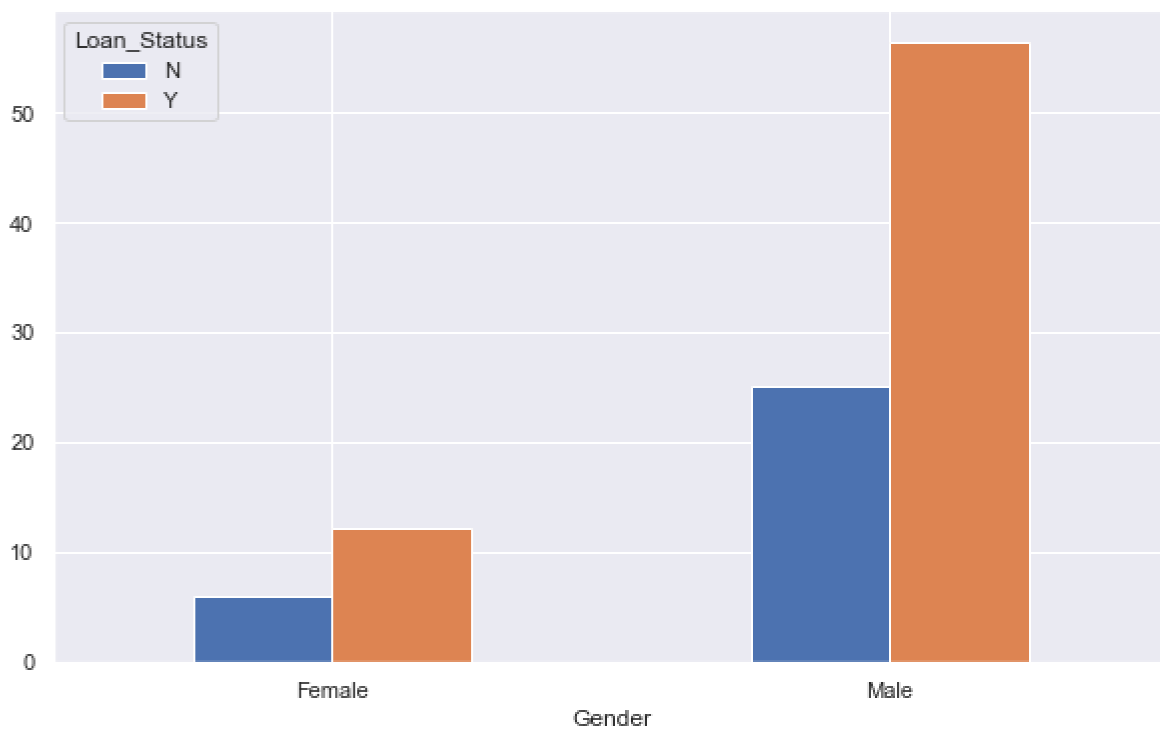
Bivariate analysis

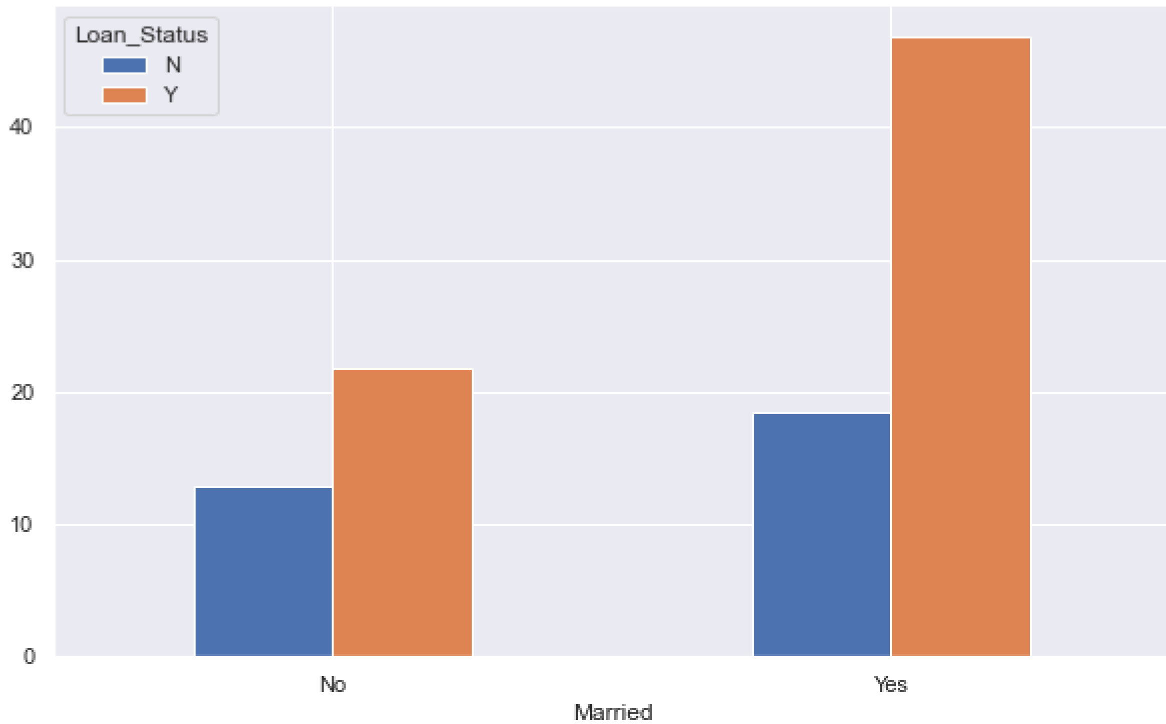
In [296…

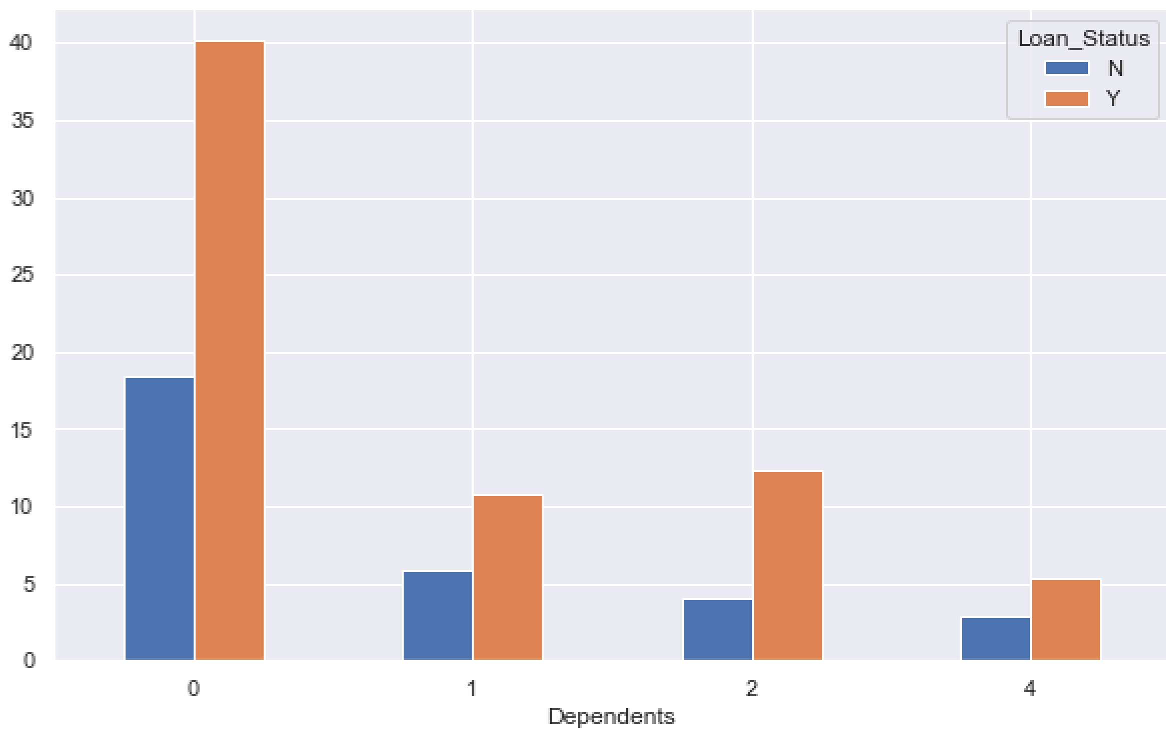
```
def plot_all_cols(df, column_col, normalize=False):

    for index_col in df.columns:
        if index_col != column_col:
                crosstab_result = pd.crosstab(index=df[index_col], columns=df[column_col],
                crosstab_result.mul(100).plot.bar(rot=0)
```

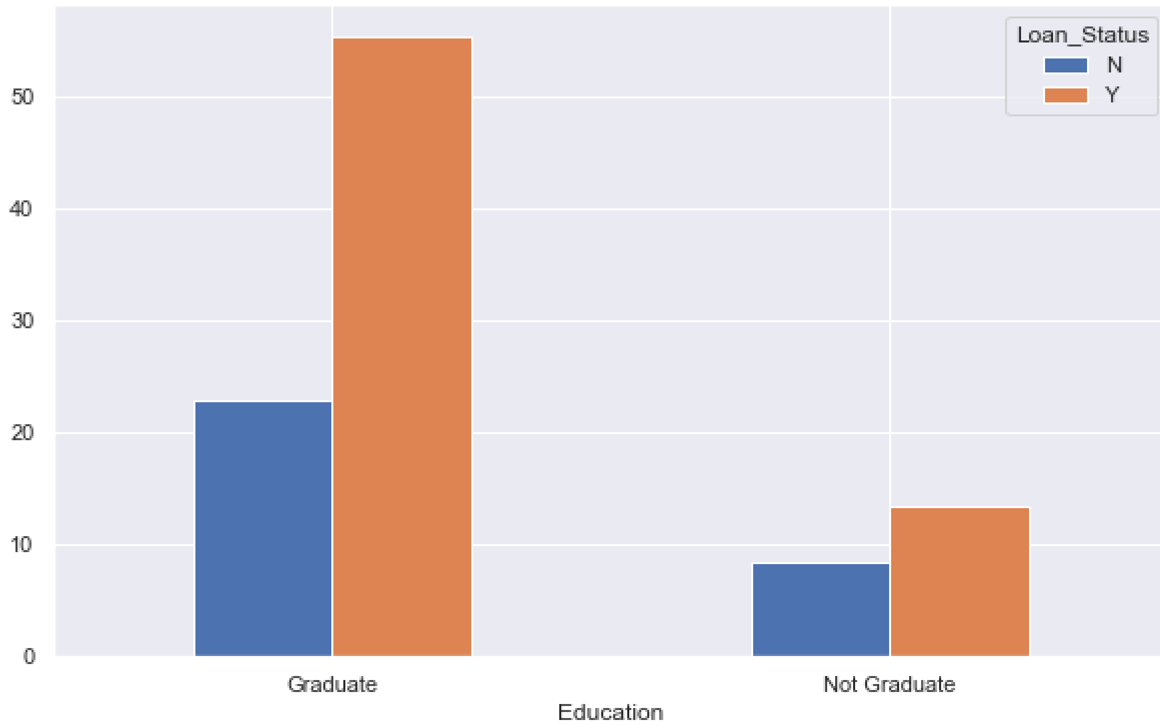
In [297…

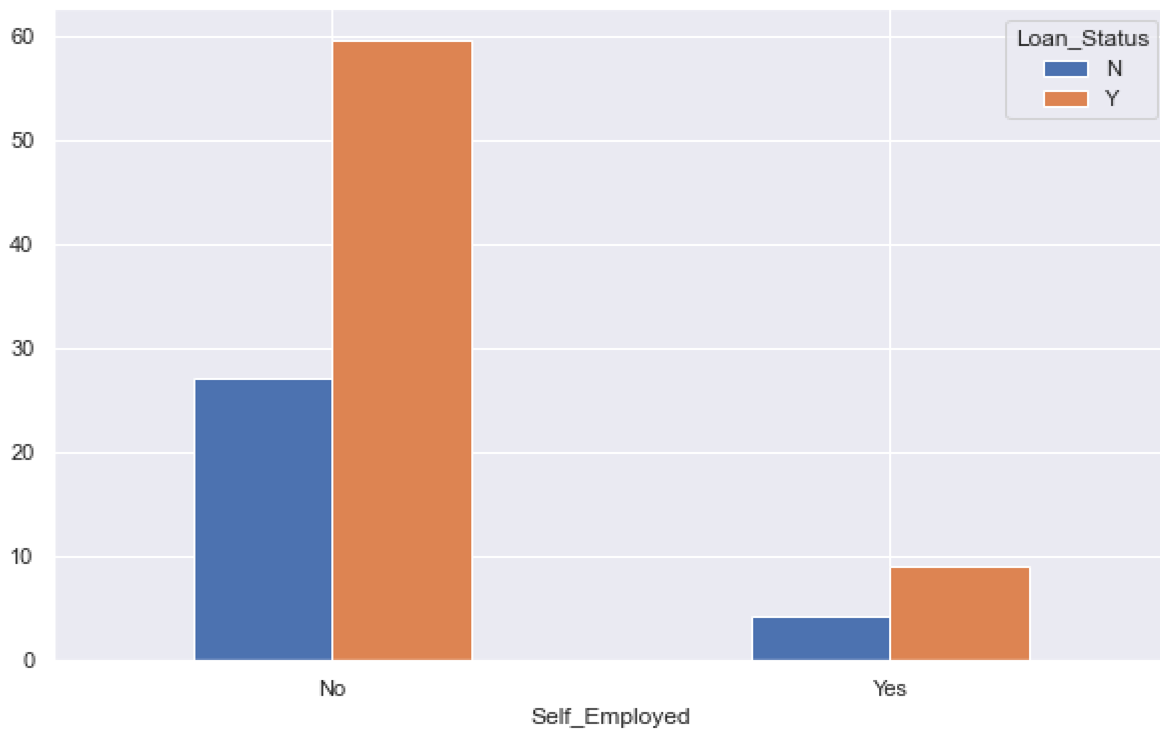
```
plot_all_cols(df, 'Loan_Status', normalize=True)
```

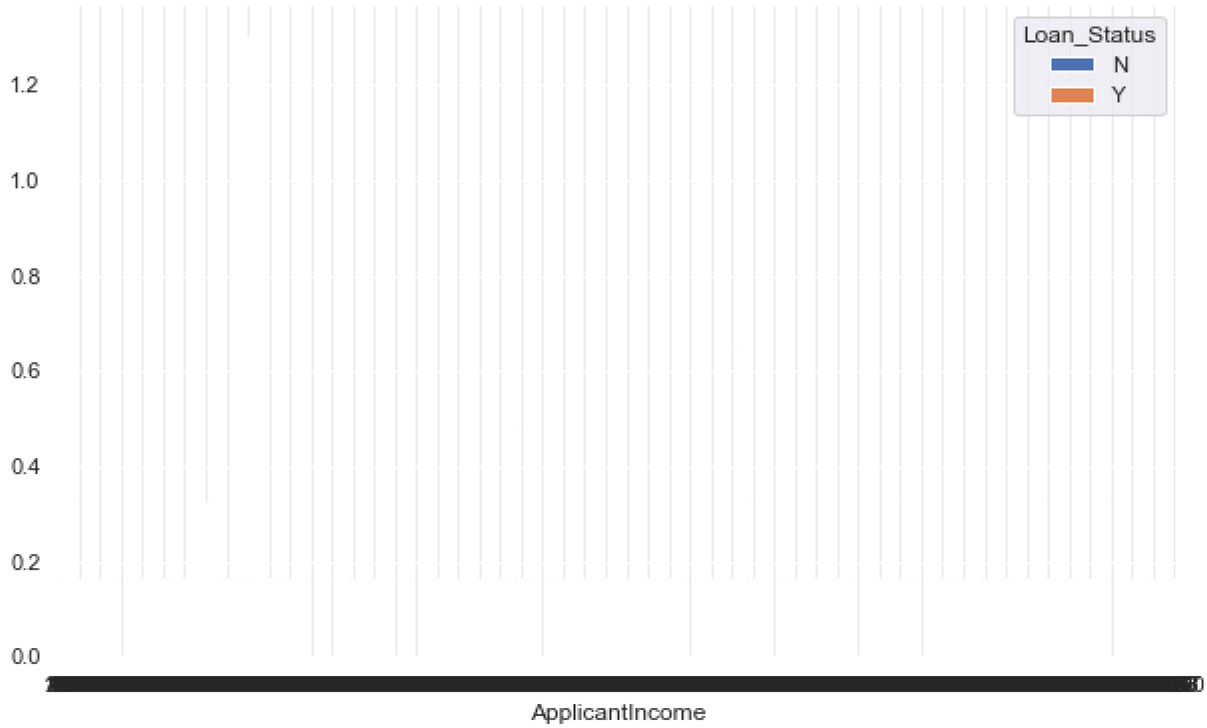


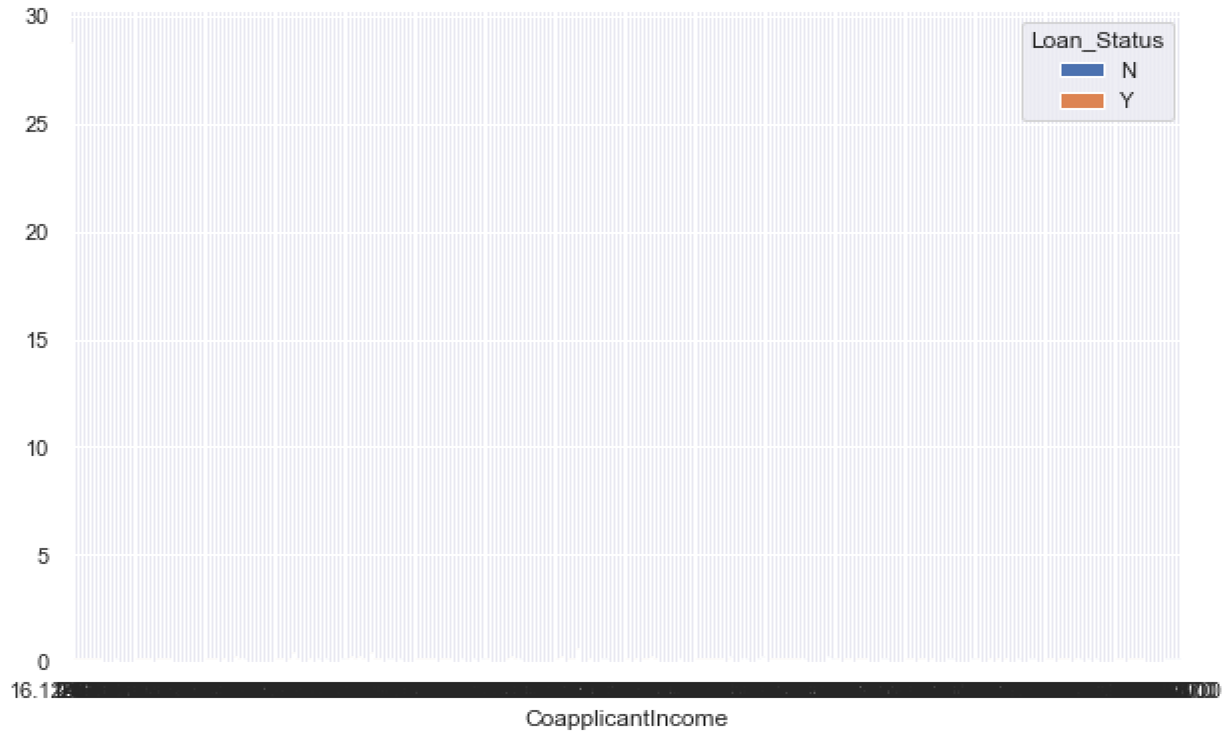

Loan_Status
N
Y
40
30
20
10
0
No
Yes
Married

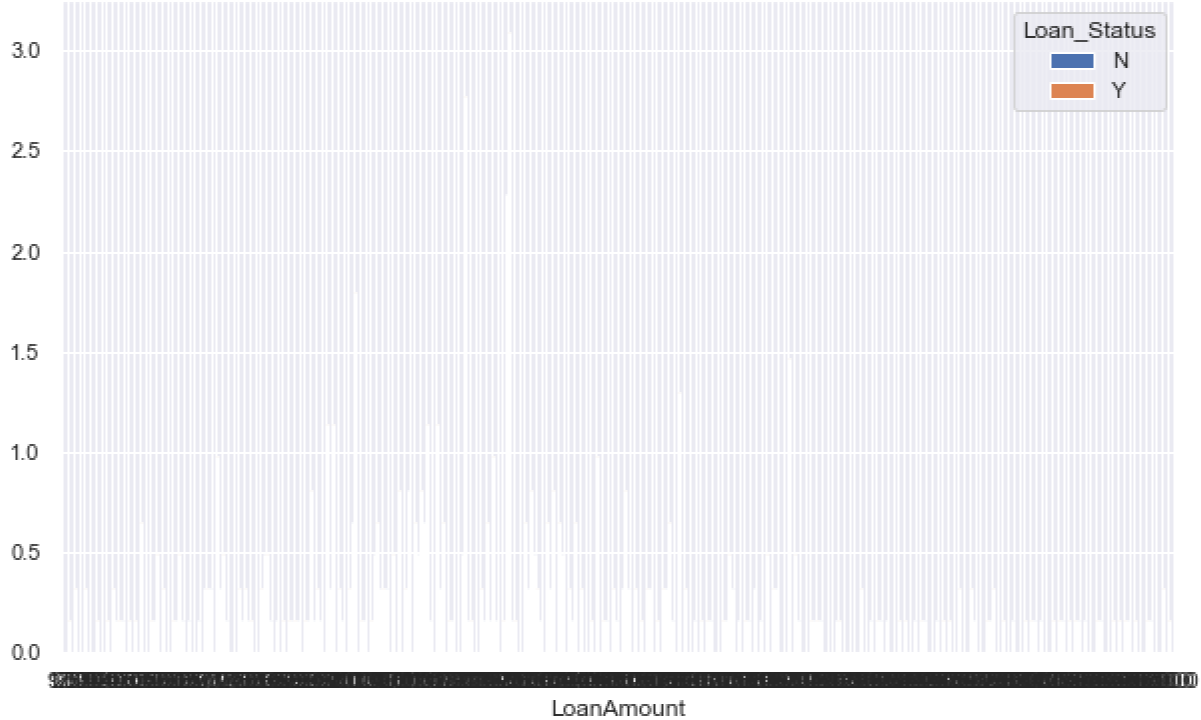

Loan_Status
N
Y
40
35
30
25
20
15
10
5
0
0
1
2
4
Dependents

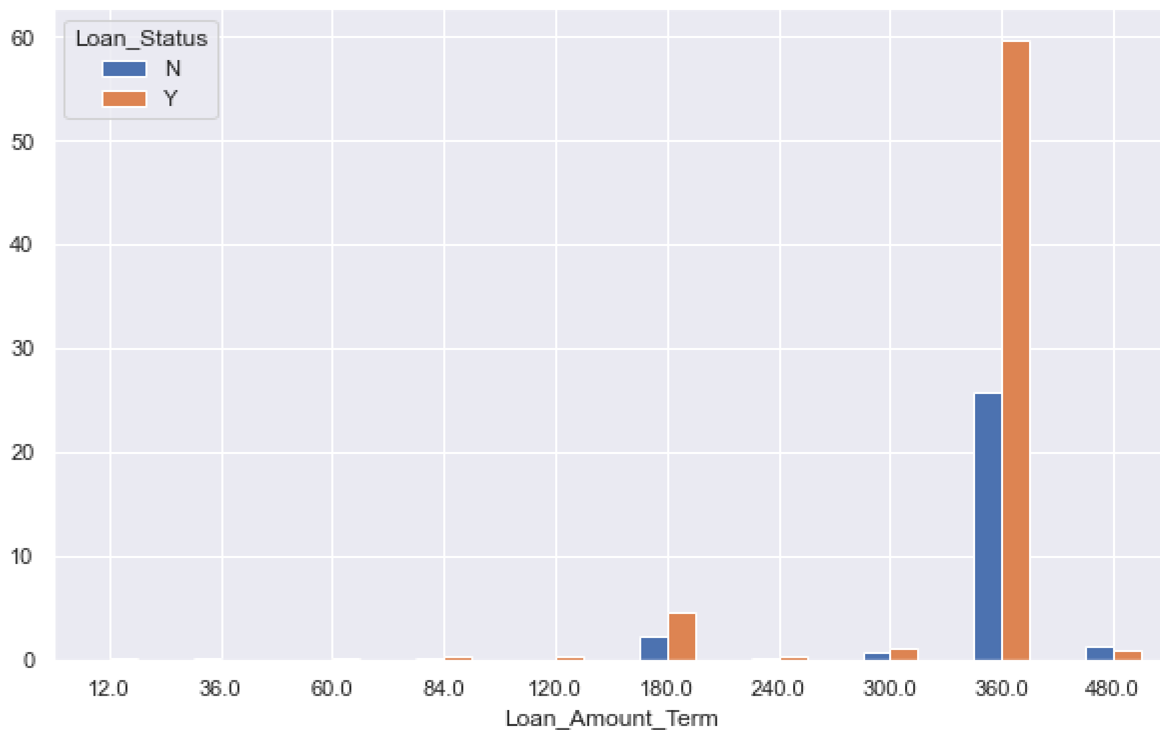

Loan_Status
N
Y
0
10
20
30
40
50
Graduate
Not Graduate
Education

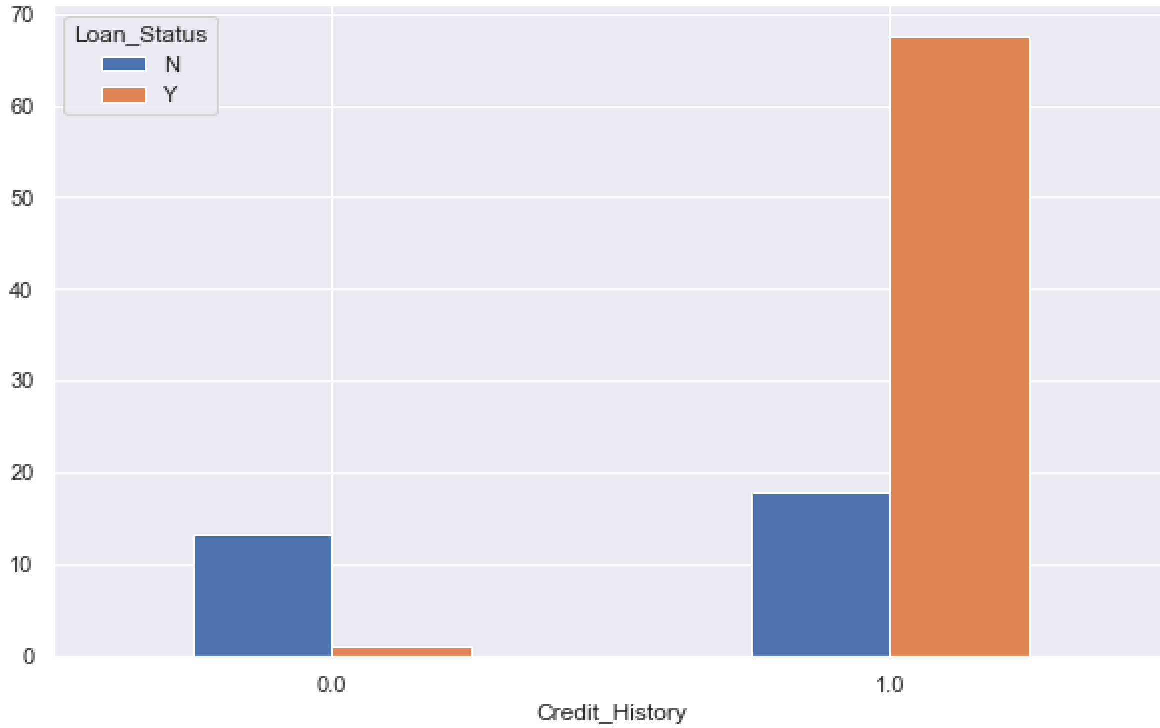

Loan_Status
N
Y
0
10
20
30
40
50
60
No
Yes
Self_Employed

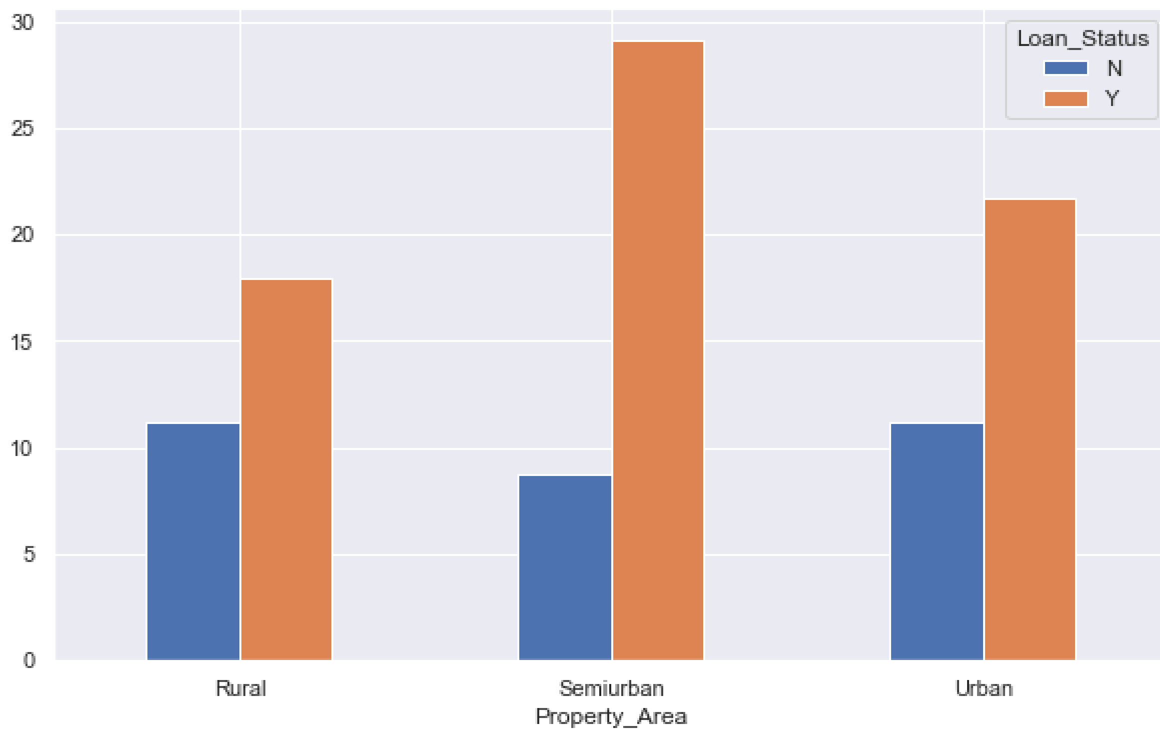

Loan_Status
N
Y
1.2
1.0
0.8
0.6
0.4
0.2
0.0
ApplicantIncome


Loan_Status
N
Y
30
25
20
15
10
5
0
CoapplicantIncome


Loan_Status
N
Y
3.0
2.5
2.0
1.5
1.0
0.5
0.0
LoanAmount


Loan_Status
N
Y
60
50
40
30
20
10
0
12.0
36.0
60.0
84.0
120.0
180.0
240.0
300.0
360.0
480.0
Loan_Amount_Term





Handling Categorical variables - Label encoding

In [298…

```
from sklearn.preprocessing import LabelEncoder

# create label encoder
label_encoder = LabelEncoder()

cat = ['Gender','Married','Dependents', 'Education', 'Self_Employed', 'Credit_History','Pr
for cats in cat:
    df[cats] = label_encoder.fit_transform(df[cats])
df.head()
```

Out[298…

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loa
0	1	0	0	0	0	5849	0.0	128.0	

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loa
1	1	1	1	0	0	4583	1508.0	128.0	
2	1	1	0	0	1	3000	0.0	66.0	
3	1	1	0	1	0	2583	2358.0	120.0	
4	1	0	0	0	0	6000	0.0	141.0	

Feature scaling - For ML model

In [299…

```
X = df.drop('Loan_Status', axis = 1)
y = df.Loan_Status
```

In [300…

```
# Feature scaling
scale = ['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term']
from sklearn.preprocessing import StandardScaler
st = StandardScaler()
X[scale] = st.fit_transform(X[scale])
X.head()
```

Out[300…

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loa
0	1	0	0	0	0	0.072991	-0.554487	-0.211241	
1	1	1	1	0	0	-0.134412	-0.038732	-0.211241	
2	1	1	0	0	1	-0.393747	-0.554487	-0.948996	
3	1	1	0	1	0	-0.462062	0.251980	-0.306435	
4	1	0	0	0	0	0.097728	-0.554487	-0.056551	

Splitting the dataset

In [301…

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
```

In [302…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
print(X.shape,X_train.shape,X_test.shape)
```

```
(614, 11) (491, 11) (123, 11)
```

Training the Model

In [303…

```
lr = LogisticRegression()
lr.fit(X_train, y_train)
lr_pred = lr.predict(X_test)
lr_acc = accuracy_score(y_test, lr_pred)
print("Logistic Regression Accuracy:", lr_acc)
# average cross validation score yet to print
```

```
Logistic Regression Accuracy: 0.7886178861788617
```

In [304…
```
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_pred = knn.predict(X_test)
knn_acc = accuracy_score(y_test, knn_pred)
print("K-Nearest Neighbors Accuracy:", knn_acc)
```

```
K-Nearest Neighbors Accuracy: 0.7073170731707317
```

In [305…
```
svc = SVC()
svc.fit(X_train, y_train)
svc_pred = svc.predict(X_test)
svc_acc = accuracy_score(y_test, svc_pred)
print("Support Vector Machine Accuracy:", svc_acc)
```

```
Support Vector Machine Accuracy: 0.7804878048780488
```

In [306…
```
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
dt_pred = dt.predict(X_test)
dt_acc = accuracy_score(y_test, dt_pred)
print("Decision Tree Accuracy:", dt_acc)
```

```
Decision Tree Accuracy: 0.6910569105691057
```

In [307…
```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
rf_pred = rf.predict(X_test)
rf_acc = accuracy_score(y_test, rf_pred)
print("Random Forest Accuracy:", rf_acc)
```

```
Random Forest Accuracy: 0.7723577235772358
```

In [ ]: