Predict Loan Eligibility for Dream Housing Finance company

Dream Housing Finance company deals in all kinds of home loans. They have presence across all urban, semi urban and rural areas. Customer first applies for home loan and after that company validates the customer eligibility for loan.

Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have provided a dataset to identify the customers segments that are eligible for loan amount so that they can specifically target these customers.

```
import pandas as pd
import numpy as np
import os,re,datetime
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import time
%matplotlib inline
```

```
train=pd.read_csv('train.csv')
```

```
train.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849
1	LP001003	Male	Yes	1	Graduate	No	4583
2	LP001005	Male	Yes	0	Graduate	Yes	3000
3	LP001006	Male	Yes	0	Not Graduate	No	2583
4	LP001008	Male	No	0	[illegible]	No	6000

\+ Code + Text

```
(train.isna().sum()/train.shape[0])*100
```

```
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
```

As we can see there are many columns with nan values Credit_History having 8% nan values, Self_Employed with 5.2% by dropping nan we might lose around 15% data. We will try to impute values

```
#checking duplicates
train.duplicated().sum()
```

```
0
```

```
train.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
```

```
train.Gender.unique()
```

```
array(['Male', 'Female', nan], dtype=object)
```

```
train.Gender.value_counts()
```

```
Male      489
Female    112
Name: Gender, dtype: int64
```

```
train[train.Gender.isnull()][['Gender','Loan_Status']]
```

	Gender	Loan_Status
23	NaN	N
126	NaN	Y
171	NaN	Y
188	NaN	Y
314	NaN	N
334	NaN	Y
460	NaN	Y
467	NaN	Y
477	NaN	N
507	NaN	N

```
#Filling missing values
train.Gender.fillna(value=train.Gender.mode()[0],inplace=True)
```

```
train.LoanAmount.median(),train.Credit_History.mode()[0]
```

```
(128.0, 1.0)
```

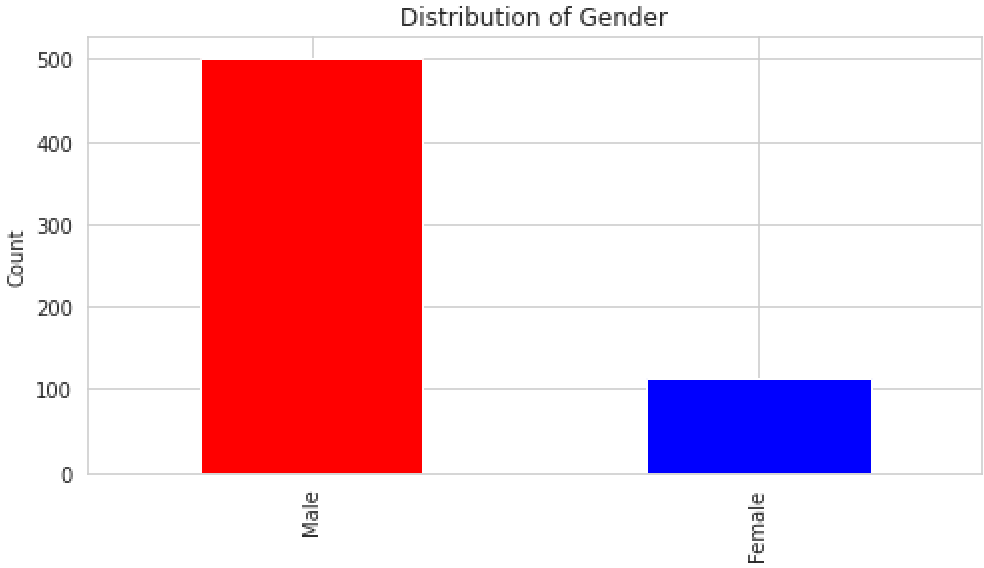
```
#Filling missing values
train.Married.fillna(value=train.Married.mode()[0],inplace=True)
train.Dependents.fillna(value=train.Dependents.mode()[0],inplace=True)
train.Self_Employed.fillna(value=train.Self_Employed.mode()[0],inplace=True)
train.LoanAmount.fillna(value=train.LoanAmount.median(),inplace=True)
train.Loan_Amount_Term.fillna(value=train.Loan_Amount_Term.median(),inplace=True)
train.Credit_History.fillna(value=train.Credit_History.mode()[0],inplace=True)
```

```
train.isna().sum()
```

```
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
```

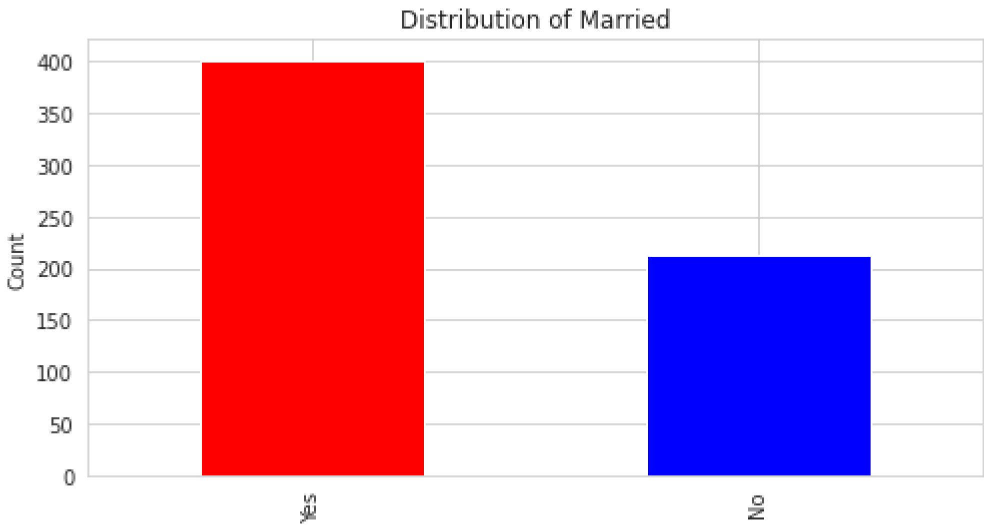
```
plt.figure(figsize=(8,4))
colors = ['r','b','b','b','b']
ax=train.Gender.value_counts().plot(kind='bar',color=colors)
plt.title('Distribution of Gender')
```

```
plt.title('Distribution of Gender')
plt.ylabel('Count')
plt.show()
train.Gender.value_counts()
```




```
Male      502
Female    112
Name: Gender, dtype: int64
```

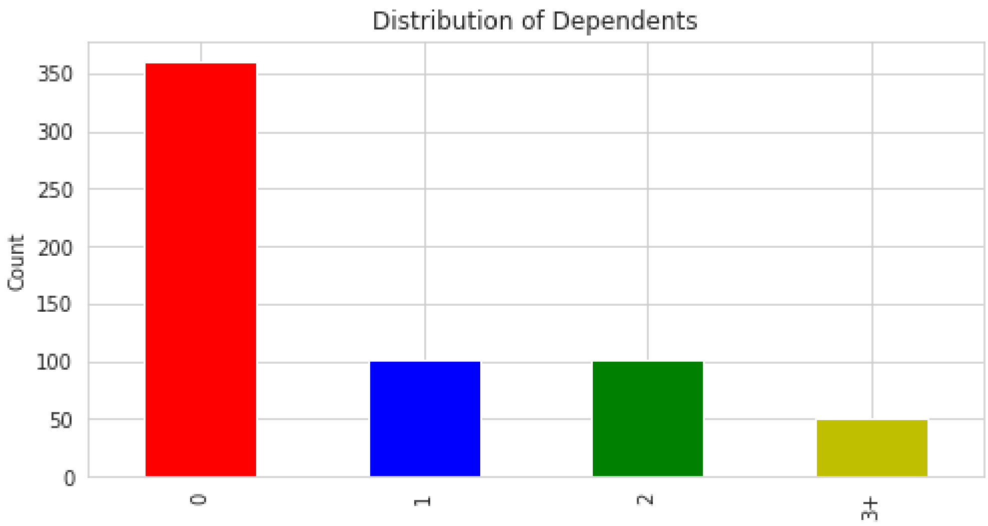
```
#Married PLOT
plt.figure(figsize=(8,4))
colors = ['r','b','b','b','b']
ax=train.Married.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Married')
plt.ylabel('Count')
plt.show()
train.Married.value_counts()
```




```
Yes    401
No     213
Name: Married, dtype: int64
```

```
#Dependents PLOT
plt.figure(figsize=(8,4))
colors = ['r','b','g','y','b']
ax=train.Dependents.value_counts().plot(kind='bar',color= colors)
```

```
ax=train.Dependents.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Dependents')
plt.ylabel('Count')
plt.show()
train.Dependents.value_counts()
```



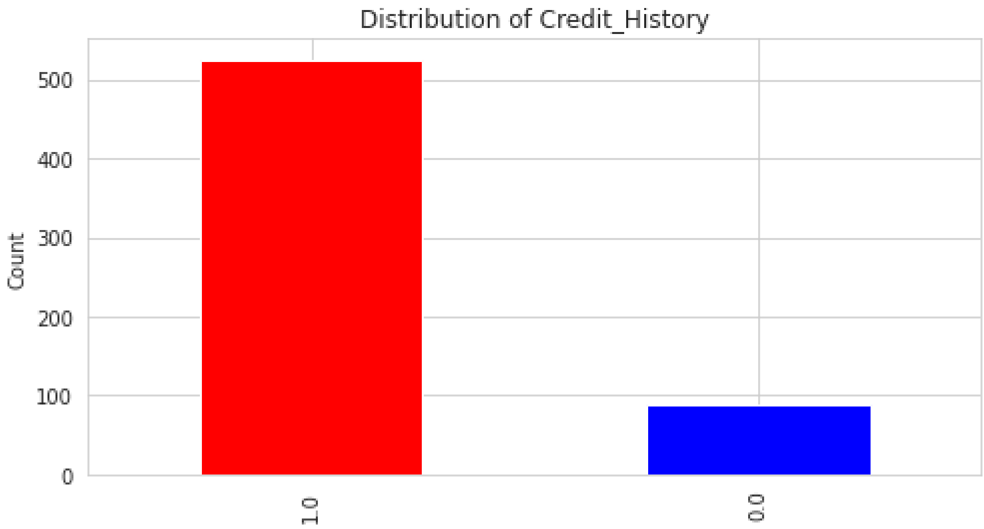

```
0      360
1      102
2      101
3+      51
Name: Dependents, dtype: int64
```

```
#Self_Employed PLOT
plt.figure(figsize=(8,4))
colors = ['r','b','b','b','b']
ax=train.Self_Employed.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Self_Employed')
plt.ylabel('Count')
plt.show()
train.Self_Employed.value_counts()
```


```
No     532
Yes     82
Name: Self_Employed, dtype: int64
```

```
#Credit_History PLOT
plt.figure(figsize=(8,4))
```

```
colors = ['r','b','b','b','b']
ax=train.Credit_History.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Credit_History')
plt.ylabel('Count')
plt.show()
train.Credit_History.value_counts()
```

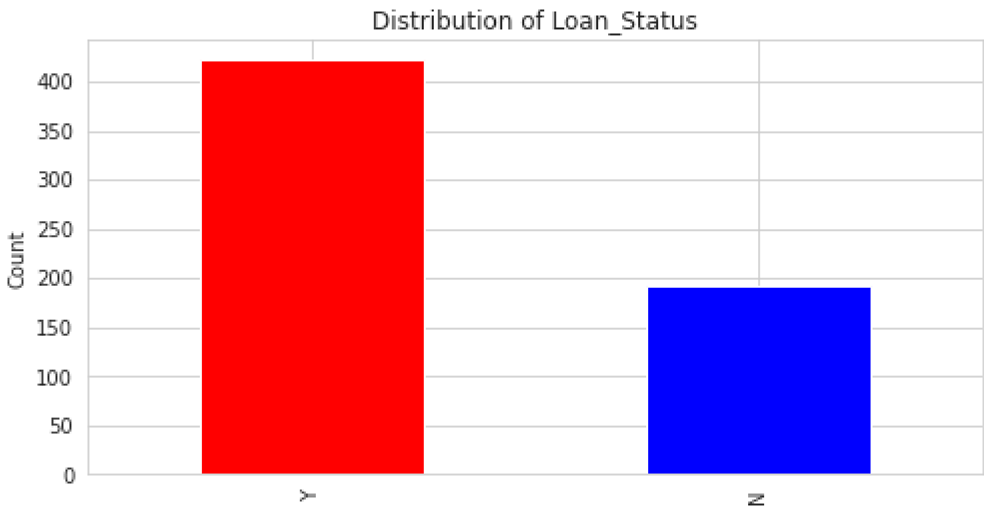



```
1.0    525
0.0     89
Name: Credit_History, dtype: int64
```

```
#Property_Area PLOT
plt.figure(figsize=(8,4))
colors = ['r','b','g','b','b']
ax=train.Property_Area.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Property_Area')
plt.ylabel('Count')
plt.show()
train.Property_Area.value_counts()
```


```
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```

```
#Loan_Status PLOT
plt.figure(figsize=(8,4))
colors = ['r','b','g','b','b']
ax=train.Loan_Status.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Loan_Status')
plt.ylabel('Count')
plt.show()
train.Loan_Status.value_counts()
```




```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

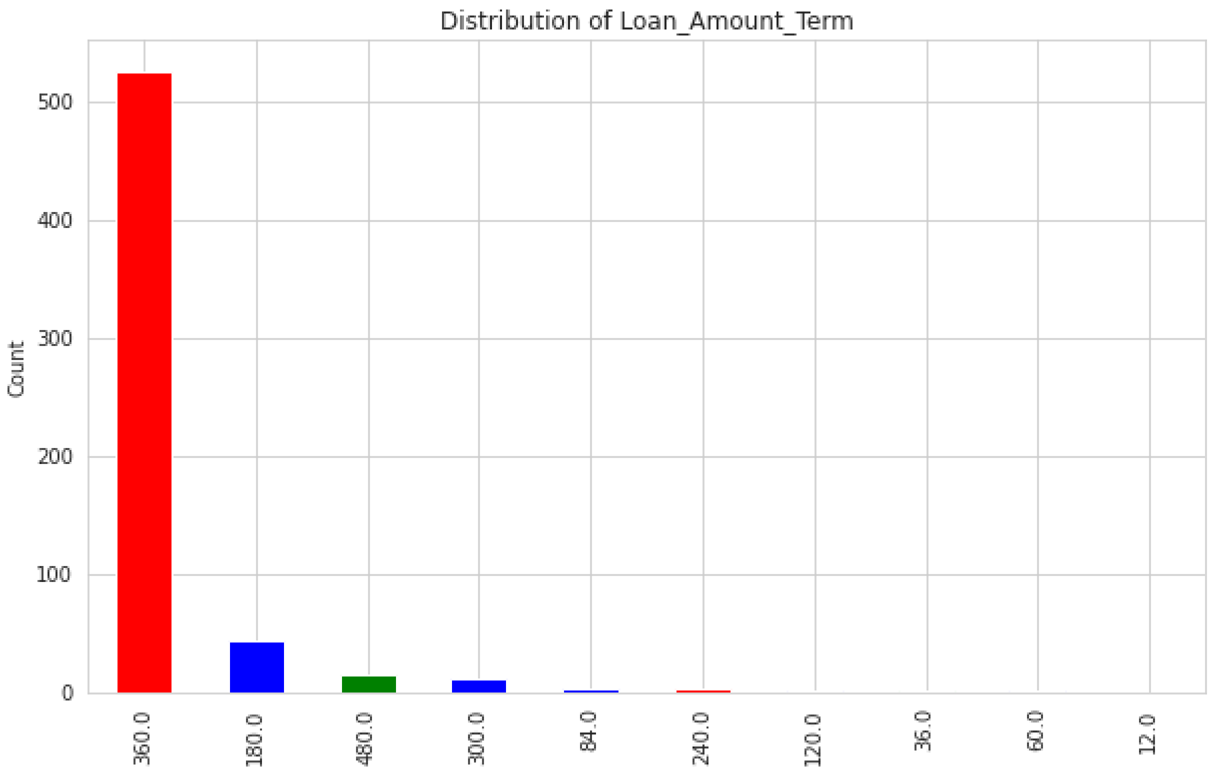
```
train.head()
```

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

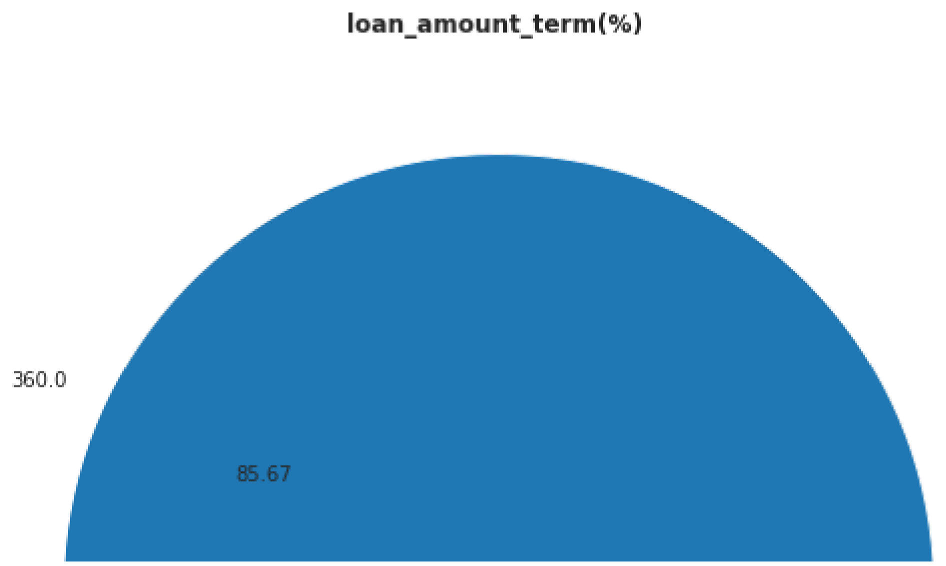
```
train.Loan_Amount_Term.value_counts()
```

```
360.0    526
180.0     44
480.0     15
300.0     13
84.0       4
240.0      4
120.0      3
36.0       2
60.0       2
12.0       1
Name: Loan_Amount_Term, dtype: int64
```

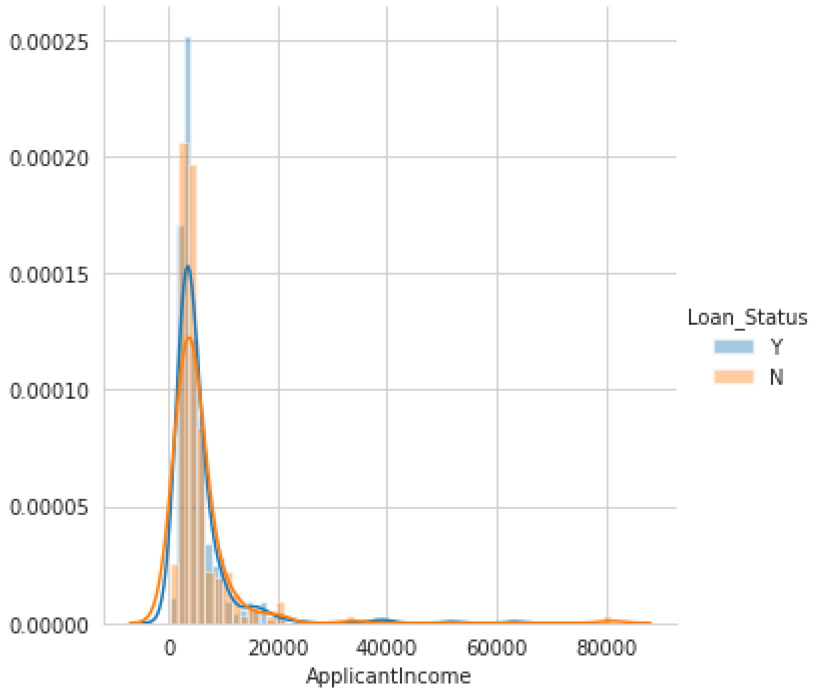
```
#Loan_Amount_Term PLOT
plt.figure(figsize=(10,6))
colors = ['r','b','g','b','b']
ax=train.Loan_Amount_Term.value_counts().plot(kind='bar',color= colors)
plt.title('Distribution of Loan_Amount_Term')
plt.ylabel('Count')
plt.show()
```




```
#pie chart for loan_amount_term
plt.figure(figsize=(20,10))
values=train.Loan_Amount_Term.value_counts()
labels=train.Loan_Amount_Term.value_counts().index
plt.pie(values,labels=labels,autopct='%.2f')
plt.title('loan_amount_term(%) ', weight='bold')
plt.show()
```




```
sns.set_style==('whitegrid');
sns.FacetGrid(train,hue='Loan_Status',size=5).map(sns.distplot,'ApplicantIncome').add_lege
plt.show()
```

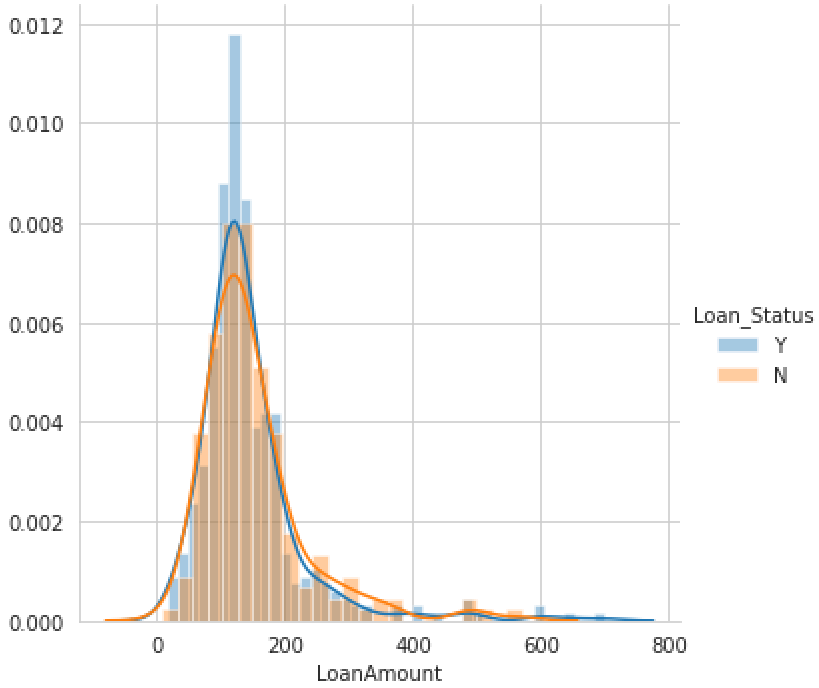



```
plt.figure(figsize=(15,8))
sns.set_style==('whitegrid');
sns.FacetGrid(train,hue='Loan_Status',size=5).map(sns.distplot,'CoapplicantIncome').add_le
plt.show()
```

<Figure size 1080x576 with 0 Axes>


```
plt.figure(figsize=(15,8))
sns.set_style==('whitegrid');
sns.FacetGrid(train,hue='Loan_Status',size=5).map(sns.distplot,'LoanAmount').add_legend();
plt.show()
```

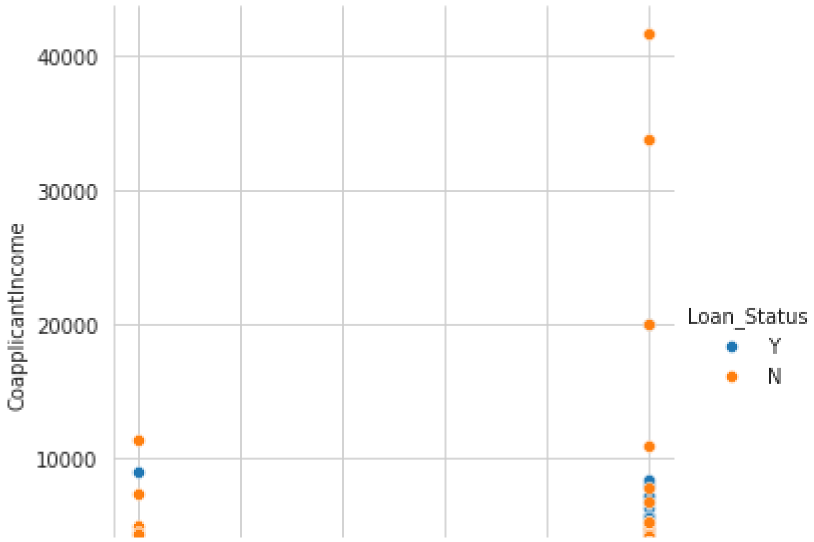
<Figure size 1080x576 with 0 Axes>



By looking at the pdf plots of LoanAmount,CoapplicantIncome,ApplicantIncome we can see a lot of overlapping.

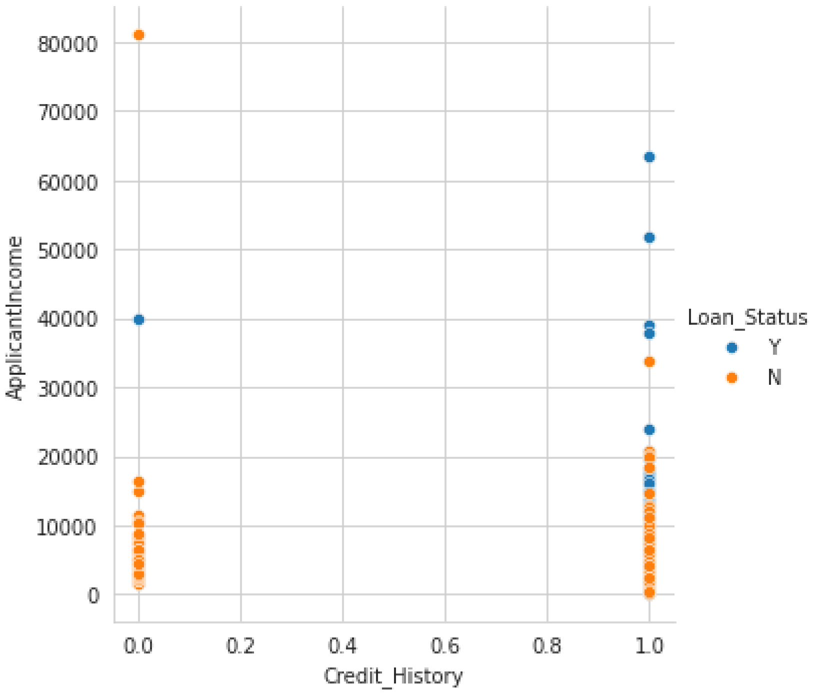
```
plt.figure(figsize=(15,8))
sns.set_style==('whitegrid');
sns.FacetGrid(train,hue='Loan_Status',size=5).map(sns.scatterplot,'Credit_History','Coappl
plt.show()
```

<Figure size 1080x576 with 0 Axes>



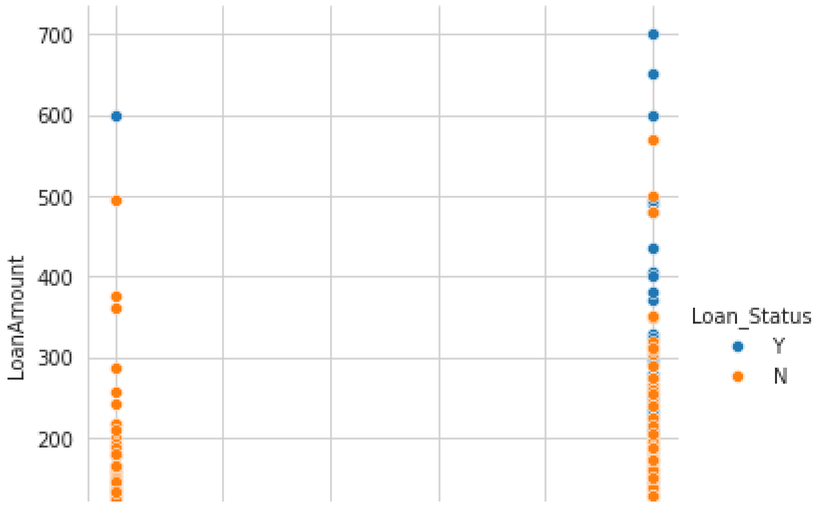

```
plt.figure(figsize=(15,8))
sns.set_style==('whitegrid');
sns.FacetGrid(train,hue='Loan_Status',size=5).map(sns.scatterplot,'Credit_History','Applic
plt.show()
```

<Figure size 1080x576 with 0 Axes>



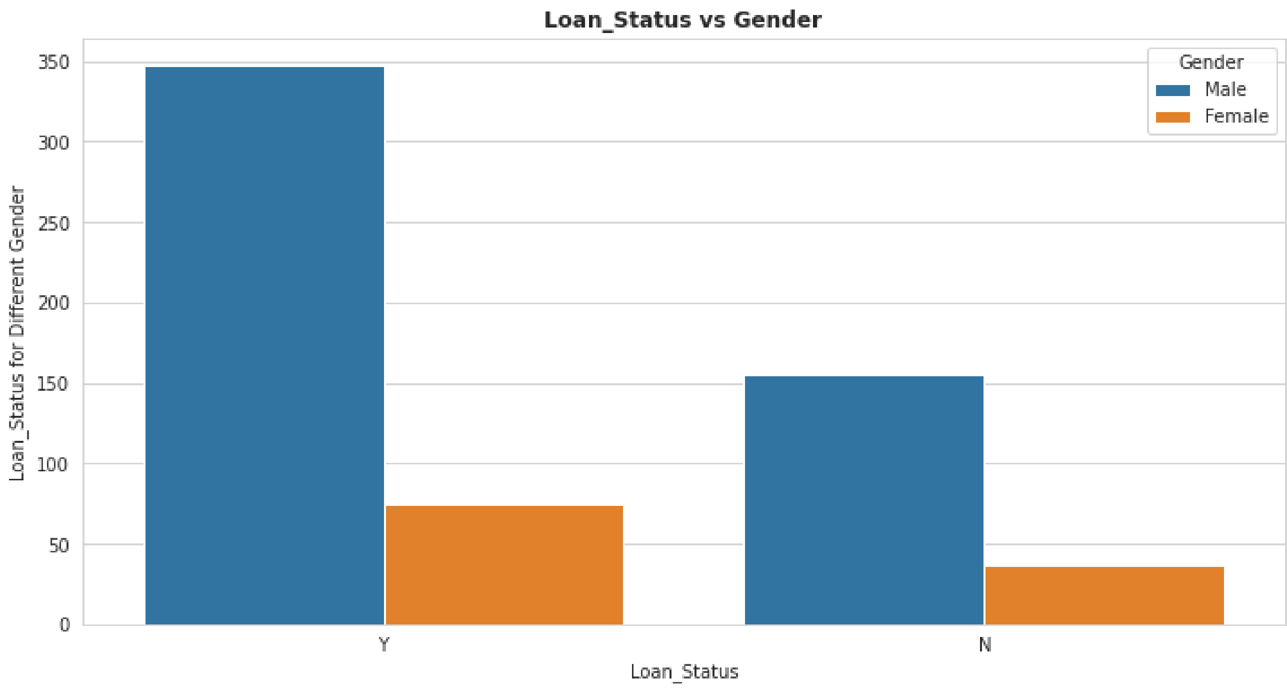

```
plt.figure(figsize=(15,8))
sns.set_style==('whitegrid');
sns.FacetGrid(train,hue='Loan_Status',size=5).map(sns.scatterplot,'Credit_History','LoanAm
plt.show()
```

```
<Figure size 1080x576 with 0 Axes>
```




```
plt.figure(figsize = (12,6))
sns.countplot(x=train['Loan_Status'], hue = train['Gender'])
plt.ylabel("Loan_Status for Different Gender")
plt.title("Loan_Status vs Gender",weight = 'bold')
```

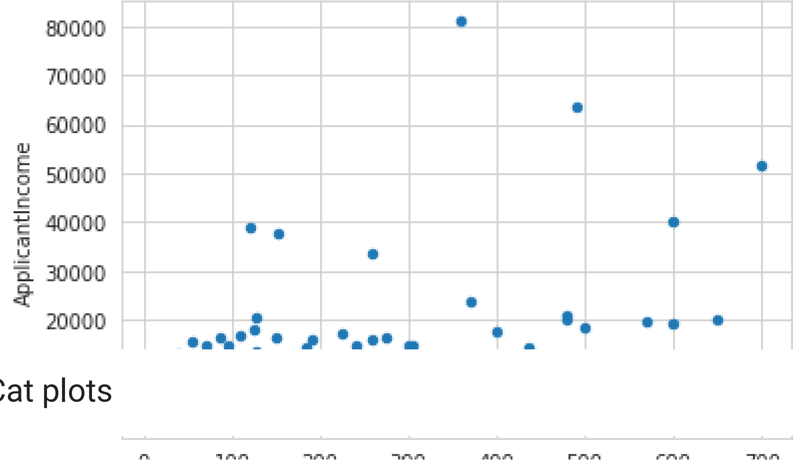
```
Text(0.5, 1.0, 'Loan_Status vs Gender')
```



Rejection and approval of female applicants are low as compared to male applicants

```
# Scatter plot of ApplicantIncome and LoanAmount
train.plot('LoanAmount','ApplicantIncome', kind ='scatter')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f574c29b4a8>



Cat-Cat plots

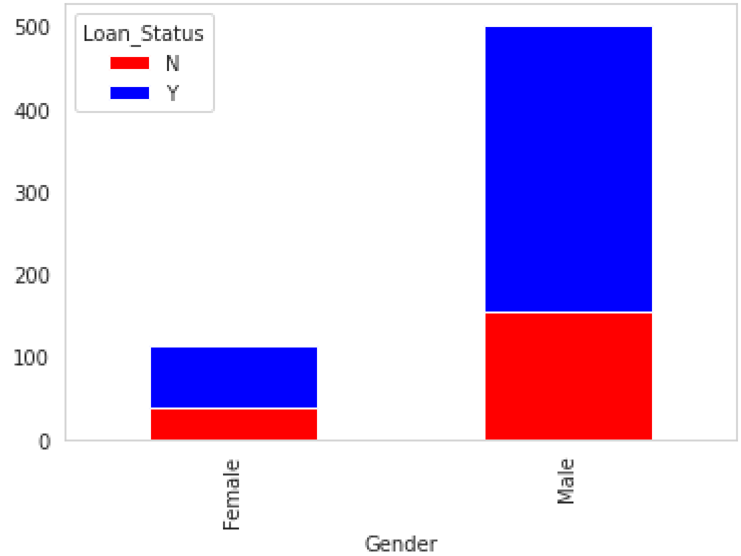
```
# print the cross-tabulation

ct=pd.crosstab(train.Gender,train.Loan_Status,margins=True)
print(ct)
```

```
Loan_Status     N    Y  All
Gender
Female         37   75  112
Male          155  347  502
All           192  422  614
```

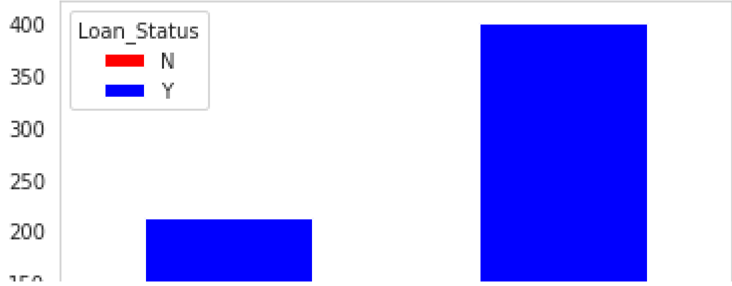
```
ct.iloc[:-1,:-1].plot(kind = 'bar', stacked = True, color = ['red','blue'], grid = False)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f574c096fd0>

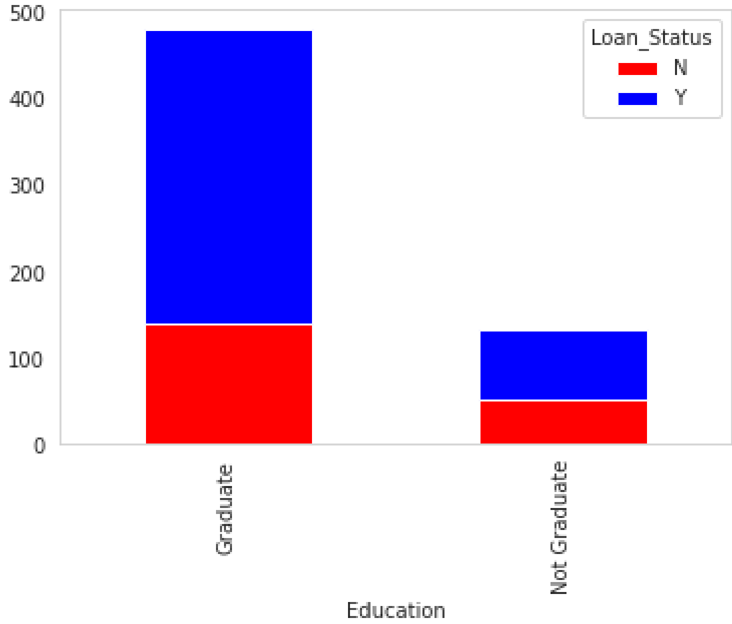



```
ct=pd.crosstab(train.Married,train.Loan_Status,margins=True)
ct.iloc[:-1,:-1].plot(kind='bar',stacked=True,color=['red','blue'],grid=False)
```

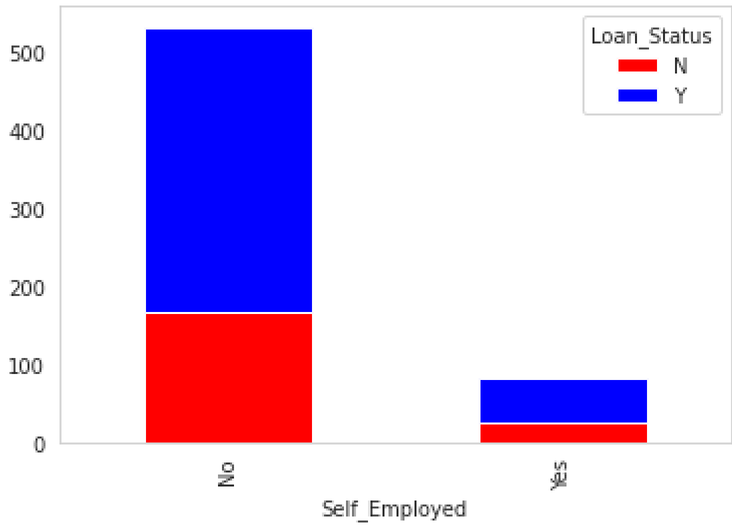
<matplotlib.axes._subplots.AxesSubplot at 0x7f574c0a2160>



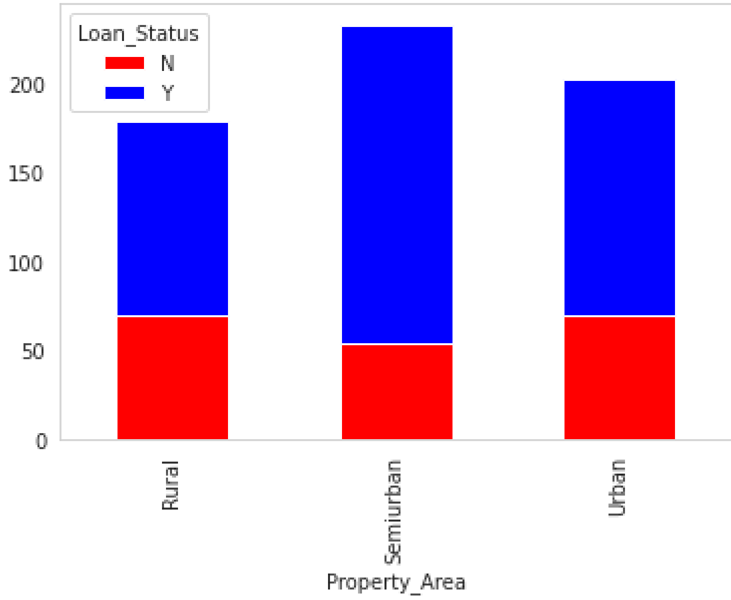

```
ct=pd.crosstab(train.Education,train.Loan_Status,margins=True)
ct.iloc[:-1,:-1].plot(kind='bar',stacked=True,color=['red','blue'],grid=False)
plt.show()
```



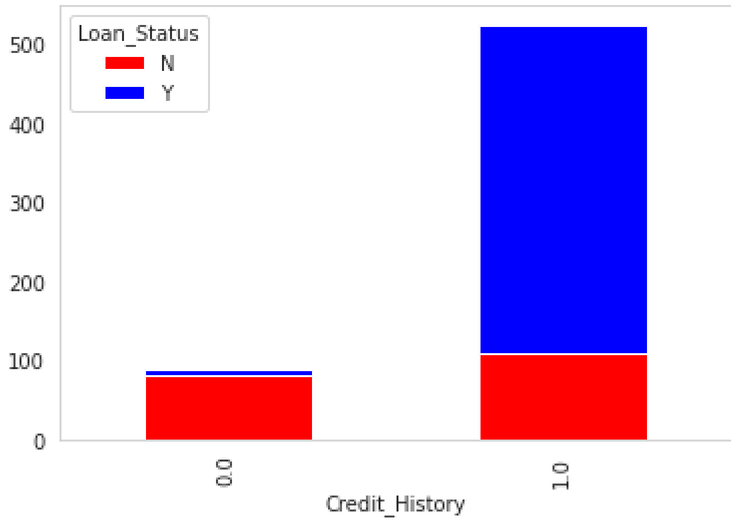

```
ct=pd.crosstab(train.Self_Employed,train.Loan_Status,margins=True)
ct.iloc[:-1,:-1].plot(kind='bar',stacked=True,color=['red','blue'],grid=False)
plt.show()
```




```
ct=pd.crosstab(train.Property_Area,train.Loan_Status,margins=True)
ct.iloc[:-1,:-1].plot(kind='bar',stacked=True,color=['red','blue'],grid=False)
plt.show()
```




```
ct=pd.crosstab(train.Credit_History,train.Loan_Status,margins=True)
ct.iloc[:-1,:-1].plot(kind='bar',stacked=True,color=['red','blue'],grid=False)
plt.show()
```




```
train.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001002	Male	No	0	Graduate	No	5849
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3	LP001006	Male	Yes	0	Not Graduate	No	2583
4	LP001008	Male	No	0	Graduate	No	6000

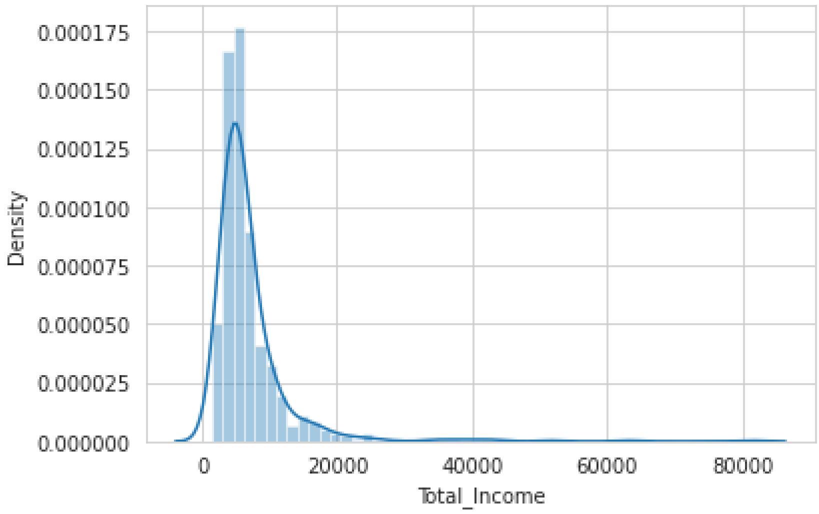
Getting new Data Columns

We have two columns named applicant income and co-applicant income. It may be the case that total income might have a great impact on Loan Status. This is just a guess. It may or may not work. Also It may be the case that EMI would have a greater impact on Loan Status as it combines Loan Amount and Loan Amount Term. So I am just using some common sense to find new variables that can impact. Well this concept in short is known as Feature Engineering. (It's not as easy as what is explained here….But to make our model better ..we are approaching this way…..)

```
train['Total_Income']=train.ApplicantIncome+train.CoapplicantIncome
```

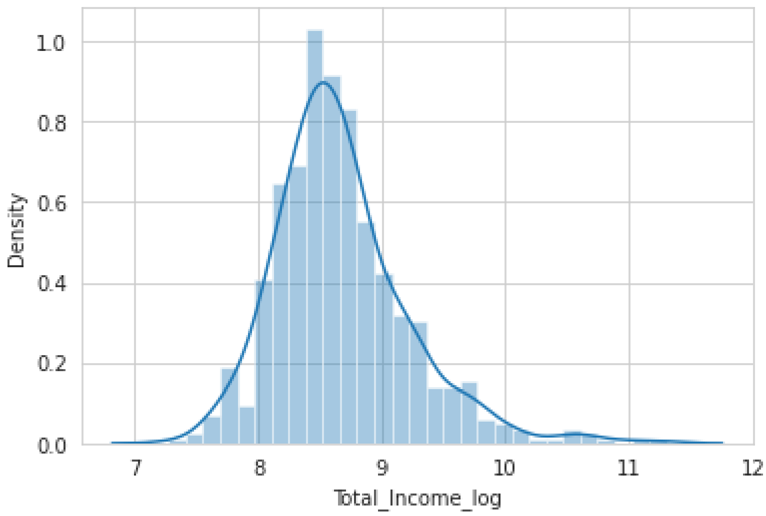
```
sns.distplot(train.Total_Income)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f574bfbdc50>
```




```
train['Total_Income_log']=np.log(train.Total_Income)
sns.distplot(train.Total_Income_log)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f574c4ba208>
```



Applying the log function removes the skewness of data and makes it normal. As total income is skewed i have applied log of that which makes it normal so that many machine learning algorithms can be applied smoothly.

Adding one more Feature: EMI

A = PxRx(1+R)^N

B = (1+R)^(N-1)

EMI = A/B.

ref: https://www.myloancare.in/home-loan-interest-rates/ EMI could be a big factor in determining the approval as high emi amount might lower chances of approval.

```
train['EMI']=(train.LoanAmount*0.09*(1.09**train.Loan_Amount_Term))/(1.09**(train.Loan_Amo
```

```
#pd.get_dummies ==> Convert categorical variable into dummy/indicator variables.(OneHot en
train.Gender=pd.get_dummies(train.Gender,drop_first=True)
train.Married=pd.get_dummies(train.Married,drop_first=True)
train.Dependents=pd.get_dummies(train.Dependents,drop_first=True)
train.Education=pd.get_dummies(train.Education,drop_first=True)
train.Self_Employed=pd.get_dummies(train.Self_Employed,drop_first=True)
train.Property_Area=pd.get_dummies(train.Property_Area,drop_first=True)
train.Loan_Amount_Term=pd.get_dummies(train.Loan_Amount_Term,drop_first=True)
```

```
train.drop(['Loan_ID'],axis=1,inplace=True)
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(train,train['Loan_Status'],stratify=train
```

```
from joblib import dump,load

dump(X_train, 'more_feature_X_train')
dump(X_test, 'more_feature_X_test')
dump(y_train, 'more_feature_y_train')
dump(y_test, 'more_feature_y_test')
```

```
from sklearn.preprocessing import MinMaxScaler
mms=MinMaxScaler(feature_range=(-1,1))
```

```
applicant_income=mms.fit_transform(np.array(X_train.ApplicantIncome).reshape(-1,1))
```

```
coapplicant_income=mms.fit_transform(np.array(X_train.CoapplicantIncome).reshape(-1,1))
loan_amount=mms.fit_transform(np.array(X_train.LoanAmount).reshape(-1,1))

emi=mms.fit_transform(np.array(X_train.EMI).reshape(-1,1))
total_amount=mms.fit_transform(np.array(X_train.Total_Income).reshape(-1,1))
```

```
total_amount_log=mms.fit_transform(np.array(X_train.Total_Income_log).reshape(-1,1))

applicant_income=mms.fit_transform(np.array(X_train.ApplicantIncome).reshape(-1,1))


applicant_income1=mms.fit_transform(np.array(X_test.ApplicantIncome).reshape(-1,1))
coapplicant_income1=mms.fit_transform(np.array(X_test.CoapplicantIncome).reshape(-1,1))
loan_amount1=mms.fit_transform(np.array(X_test.LoanAmount).reshape(-1,1))
emi1=mms.fit_transform(np.array(X_test.EMI).reshape(-1,1))
total_amount1=mms.fit_transform(np.array(X_test.Total_Income).reshape(-1,1))
total_amount_log1=mms.fit_transform(np.array(X_test.Total_Income_log).reshape(-1,1))




## combine all 'one-hot' encoded features as Te.
tr =pd.DataFrame(pd.np.column_stack([ applicant_income,coapplicant_income,loan_amount,tota

## CONCAT both dataframe ### ie Te and X_test(original dataframe)
## https://stackoverflow.com/questions/45963799/pandas-concat-resulting-in-nan-rows

l3=X_train.values.tolist()
l4=tr.values.tolist()
for i in range(len(l3)):
    l3[i].extend(l4[i])

X_train=pd.DataFrame(l3,columns=X_train.columns.tolist()+tr.columns.tolist())
X_train.shape


X_train.head()


# after onehot encoding DONE. 'location','rest_type','cuisines' are redundant features. RE

X_train =X_train.drop(['ApplicantIncome','CoapplicantIncome','LoanAmount','EMI','Total_Inc



## combine all 'one-hot' encoded features as Te.
te =pd.DataFrame(pd.np.column_stack([ applicant_income1,coapplicant_income1,loan_amount1,t

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l3=X_test.values.tolist()
l4=te.values.tolist()
for i in range(len(l3)):
    l3[i].extend(l4[i])

X_test=pd.DataFrame(l3,columns=X_test.columns.tolist()+te.columns.tolist())
X_test =X_test.drop(['ApplicantIncome','CoapplicantIncome','LoanAmount','EMI','Total_Incom
X_test.shape


y_train=X_train['Loan_Status']
```

```
X_train.drop('Loan_Status',axis=1,inplace=True)
```

```
y_train
```

MODELING

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV,KFold,StratifiedKFold
from sklearn import metrics
```

```
score1=0
i=1
params={'C':[10**i for i in range(-3,3)]}
kf=StratifiedKFold(n_splits=10,shuffle=True,random_state=95)
for tr,te in kf.split(X_train,y_train):
  print('{} of kfold {}'.format(i,kf.n_splits))
  #print(te)
  x1,x2=X_train.loc[tr],X_train.loc[te]
  y1,y2=y_train.loc[tr],y_train.loc[te]
  model2=GridSearchCV(LogisticRegression(random_state=95),param_grid=params,scoring='accur
  model2.fit(x1,y1)
  pred_test=model2.predict(x2)
  score=metrics.accuracy_score(y2,pred_test)
  score1+=score
  print('accuracy_score',score)
  i+=1
```

```
1 of kfold 10
accuracy_score 0.74
2 of kfold 10
accuracy_score 0.8163265306122449
3 of kfold 10
accuracy_score 0.8775510204081632
4 of kfold 10
accuracy_score 0.7346938775510204
5 of kfold 10
accuracy_score 0.8571428571428571
6 of kfold 10
accuracy_score 0.8163265306122449
7 of kfold 10
accuracy_score 0.7755102040816326
8 of kfold 10
accuracy_score 0.7959183673469388
9 of kfold 10
accuracy_score 0.8571428571428571
10 of kfold 10
accuracy_score 0.8367346938775511
```

Naive bayes

```
from sklearn.naive_bayes import GaussianNB
score2=0
i=1
params={}
kf=StratifiedKFold(n_splits=10,shuffle=True,random_state=95)
for tr,te in kf.split(X_train,y_train):
  print('{} of kfold {}'.format(i,kf.n_splits))
  #print(te)
  x1,x2=X_train.loc[tr],X_train.loc[te]
  y1,y2=y_train.loc[tr],y_train.loc[te]
  model=GridSearchCV(GaussianNB(),param_grid=params,scoring='accuracy')
  model.fit(x1,y1)
  pred_test=model.predict(x2)
  score=metrics.accuracy_score(y2,pred_test)
  score2+=score
  print('accuracy_score',score)
  i+=1
```

```
1 of kfold 10
accuracy_score 0.72
2 of kfold 10
accuracy_score 0.8163265306122449
3 of kfold 10
accuracy_score 0.8775510204081632
4 of kfold 10
accuracy_score 0.7142857142857143
5 of kfold 10
accuracy_score 0.8571428571428571
6 of kfold 10
accuracy_score 0.8367346938775511
7 of kfold 10
accuracy_score 0.7755102040816326
8 of kfold 10
accuracy_score 0.7959183673469388
9 of kfold 10
accuracy_score 0.8571428571428571
10 of kfold 10
accuracy_score 0.8367346938775511
```

```
test=pd.read_csv('test.csv')
test.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001015	Male	Yes	0	Graduate	No	5720
1	LP001022	Male	Yes	1	Graduate	No	3076
2	LP001031	Male	Yes	2	Graduate	No	5000
3	LP001035	Male	Yes	2	Graduate	No	2340
4	LP001051	Male	No	0	Not Graduate	No	3276

```
test.drop('Loan_ID',axis=1,inplace=True)
```

```
test.isna().sum()

     Gender               11
     Married               0
     Dependents           10
     Education             0
     Self_Employed        23
     ApplicantIncome       0
     CoapplicantIncome     0
     LoanAmount            5
     Loan_Amount_Term      6
     Credit_History       29
     Property_Area         0
     dtype: int64
```

```
#Filling missing values
test.Married.fillna(value=test.Married.mode()[0],inplace=True)
test.Dependents.fillna(value=test.Dependents.mode()[0],inplace=True)
test.Self_Employed.fillna(value=test.Self_Employed.mode()[0],inplace=True)
test.LoanAmount.fillna(value=test.LoanAmount.median(),inplace=True)
test.Loan_Amount_Term.fillna(value=test.Loan_Amount_Term.median(),inplace=True)
test.Credit_History.fillna(value=test.Credit_History.mode()[0],inplace=True)
#Filling missing values
test.Gender.fillna(value=test.Gender.mode()[0],inplace=True)
#pd.get_dummies ==> Convert categorical variable into dummy/indicator variables.(OneHot en
test.Gender=pd.get_dummies(test.Gender,drop_first=True)
test.Married=pd.get_dummies(test.Married,drop_first=True)
test.Dependents=pd.get_dummies(test.Dependents,drop_first=True)
test.Education=pd.get_dummies(test.Education,drop_first=True)
test.Self_Employed=pd.get_dummies(test.Self_Employed,drop_first=True)
test.Property_Area=pd.get_dummies(test.Property_Area,drop_first=True)
test.Loan_Amount_Term=pd.get_dummies(test.Loan_Amount_Term,drop_first=True)
```

```
test['EMI']=(test.LoanAmount*0.09*(1.09**test.Loan_Amount_Term))/(1.09**(test.Loan_Amount_
test['Total_Income']=test.ApplicantIncome+test.CoapplicantIncome
test['Total_Income_log']=np.log(test.Total_Income)
```

```
coapplicant_income=mms.fit_transform(np.array(test.CoapplicantIncome).reshape(-1,1))
loan_amount=mms.fit_transform(np.array(test.LoanAmount).reshape(-1,1))

emi=mms.fit_transform(np.array(test.EMI).reshape(-1,1))
total_amount=mms.fit_transform(np.array(test.Total_Income).reshape(-1,1))
total_amount_log=mms.fit_transform(np.array(test.Total_Income_log).reshape(-1,1))

applicant_income=mms.fit_transform(np.array(test.ApplicantIncome).reshape(-1,1))
```

```
## combine all 'one-hot' encoded features as Te.
tr =pd.DataFrame(pd.np.column_stack([ applicant_income,coapplicant_income,loan_amount,tota

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l3=test.values.tolist()
```

```
l4=tr.values.tolist()
for i in range(len(l3)):
    l3[i].extend(l4[i])

test=pd.DataFrame(l3,columns=test.columns.tolist()+tr.columns.tolist())
test.shape
```

```
(367, 20)
```

```
test =test.drop(['ApplicantIncome','CoapplicantIncome','LoanAmount','EMI','Total_Income_lo
```

```
test.head()
```

	Gender	Married	Dependents	Education	Self_Employed	Loan_Amount_Term	Credit_H
0	1.0	1.0	0.0	0.0	0.0	0.0	
1	1.0	1.0	1.0	0.0	0.0	0.0	
2	1.0	1.0	0.0	0.0	0.0	0.0	
3	1.0	1.0	0.0	0.0	0.0	0.0	
4	1.0	0.0	0.0	1.0	0.0	0.0	

```
pred_test_sub=model.predict(test)
pred_test_prob=model.predict_proba(test)[:,1]
print('average accuracy',score1/10)
```

```
average accuracy 0.810734693877551
```

```
pred_test_sub2=model2.predict(test)
pred_test_prob2=model2.predict_proba(test)[:,1]
print('average accuracy',score2/10)
```

```
average accuracy 0.808734693877551
```

```
pred_test_sub
```

```
array(['Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y',
       'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N',
       'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y',
       'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
```

```
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y'], dtype=object)
```

```
submission=pd.read_csv('test.csv')
```

```
submission['Loan_Status']=pred_test_sub
```

```
subs=submission[['Loan_ID','Loan_Status']]
```

```
subs.head()
```

	Loan_ID	Loan_Status
0	LP001015	Y
1	LP001022	Y
2	LP001031	Y
3	LP001035	Y
4	LP001051	Y

```
subs.to_csv('sub_loan.csv',index=False)
```

```
submission2=pd.read_csv('test.csv')
submission2['Loan_Status']=pred_test_sub
```

```
subs2=submission2[['Loan_ID','Loan_Status']]
```

```
subs2.to_csv('sub_loan2.csv',index=False)
```