Introduction:

☞ In real time the loan qualifying procedure based on information given by customers while filling out an online application form. It is expected that the development of machine learning models that can help the company predict loan approval in generate decision-making process for determining whether an applicant is eligible for a loan or not.

☞ Below link is for selected loan_data_set

https://www.kaggle.com/datasets/burak3ergun/loan-data-set

☞ Importing libraries that will be used in this notebook.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Reading Data Set:

☞ After importing libraries, we will also import the dataset that will be used.

```
df = pd.read_csv("D:/PYTHON/ML/01_Loan_Data.csv")
```

```
df.shape
```

```
(614, 13)
```

☞ As can be seen in the data set 614 rows and 13 columns are present.

Data Exploration :

```
df.head()

    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0

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

df.tail()

      Loan_ID  Gender Married Dependents Education Self_Employed  \
609  LP002978  Female      No          0  Graduate            No
610  LP002979    Male     Yes         3+  Graduate            No
611  LP002983    Male     Yes          1  Graduate            No
612  LP002984    Male     Yes          2  Graduate            No
613  LP002990  Female      No          0  Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term
\
609             2900                0.0        71.0             360.0

610             4106                0.0        40.0             180.0

611             8072              240.0       253.0             360.0

612             7583                0.0       187.0             360.0

613             4583                0.0       133.0             360.0


     Credit_History Property_Area Loan_Status
609             1.0         Rural           Y
610             1.0         Rural           Y
```

```
611              1.0         Urban           Y
612              1.0         Urban           Y
613              0.0     Semiurban           N
```

```
df.describe().transpose()
```

```
                   count         mean          std    min     25%
50%  \
ApplicantIncome    614.0  5403.459283  6109.041673  150.0  2877.5
3812.5
CoapplicantIncome  614.0  1621.245798  2926.248369    0.0     0.0
1188.5
LoanAmount         592.0   146.412162    85.587325    9.0   100.0
128.0
Loan_Amount_Term   600.0   342.000000    65.120410   12.0   360.0
360.0
Credit_History     564.0     0.842199     0.364878    0.0     1.0
1.0

                       75%      max
ApplicantIncome    5795.00  81000.0
CoapplicantIncome  2297.25  41667.0
LoanAmount          168.00    700.0
Loan_Amount_Term    360.00    480.0
Credit_History        1.00      1.0
```

```
#check for any other unusable values
print(pd.isnull(df).sum())
```

```
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
```

☞so as we can see there is some null values in dataset

```
df['Gender'] = df['Gender'].map({'Male': 0,'Female': 1})
df['Married'] = df['Married'].map({'No': 0,'Yes': 1})
df['Education'] = df['Education'].map({'Not Graduate': 0,'Graduate':
1})
```

```
df['Self_Employed'] = df['Self_Employed'].map({'No': 0,'Yes': 1})
df['Loan_Status'] = df['Loan_Status'].map({'N': 0,'Y': 1})
```

☞ Unecessary variables will be dropped in this section.

```
df = df.drop([ 'Loan_ID', 'Property_Area'], axis=1)
```

```
df['Dependents']=df['Dependents'].replace('3+',4)
```

```
df
```

```
     Gender  Married Dependents  Education  Self_Employed
ApplicantIncome  \
0       0.0      0.0          0          1            0.0
5849
1       0.0      1.0          1          1            0.0
4583
2       0.0      1.0          0          1            1.0
3000
3       0.0      1.0          0          0            0.0
2583
4       0.0      0.0          0          1            0.0
6000
..      ...      ...        ...        ...            ...
...
609     1.0      0.0          0          1            0.0
2900
610     0.0      1.0          4          1            0.0
4106
611     0.0      1.0          1          1            0.0
8072
612     0.0      1.0          2          1            0.0
7583
613     1.0      0.0          0          1            1.0
4583

     CoapplicantIncome  LoanAmount  Loan_Amount_Term
Credit_History  \
0                  0.0         NaN             360.0             1.0

1               1508.0       128.0             360.0             1.0

2                  0.0        66.0             360.0             1.0

3               2358.0       120.0             360.0             1.0

4                  0.0       141.0             360.0             1.0

..                 ...         ...               ...             ...

609                0.0        71.0             360.0             1.0
```

```
610                 0.0         40.0             180.0             1.0

611               240.0        253.0             360.0             1.0

612                 0.0        187.0             360.0             1.0

613                 0.0        133.0             360.0             0.0


     Loan_Status
0              1
1              0
2              1
3              1
4              1
..           ...
609            1
610            1
611            1
612            1
613            0

[614 rows x 11 columns]
```

☞ we see how much columns are present in the loan data set

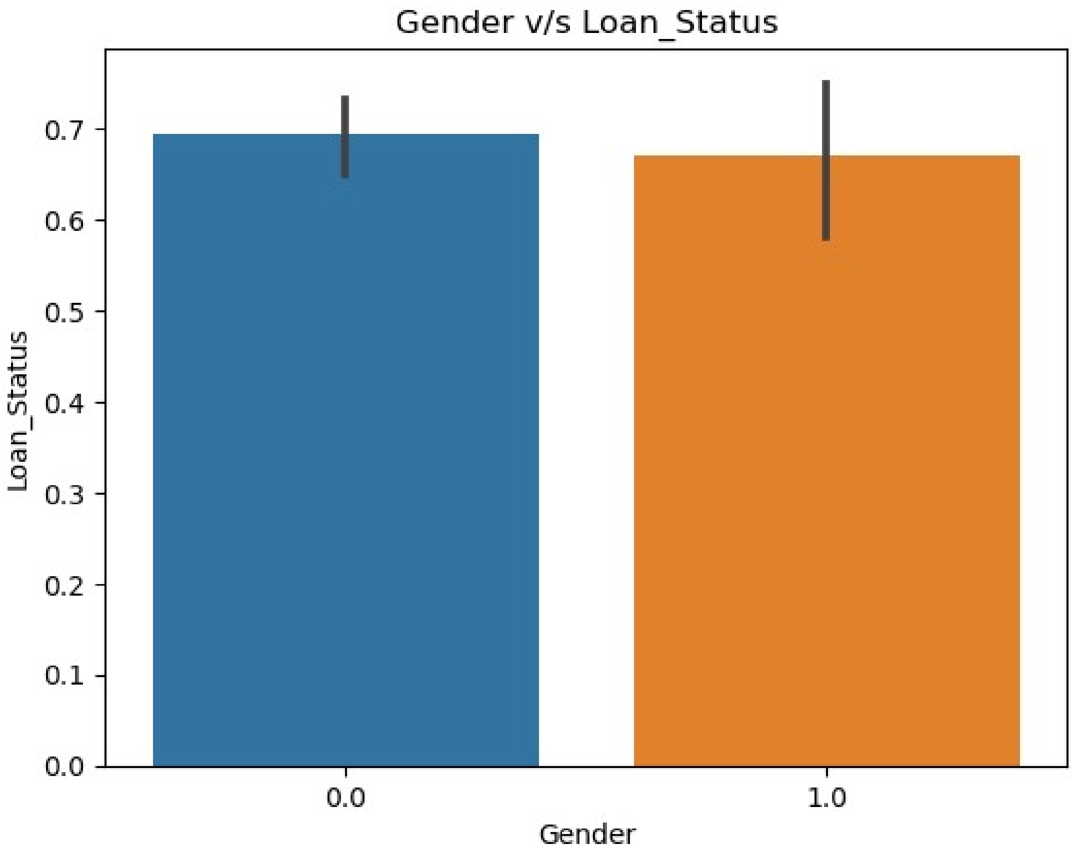
```
df.columns
```

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

Data Visualization:

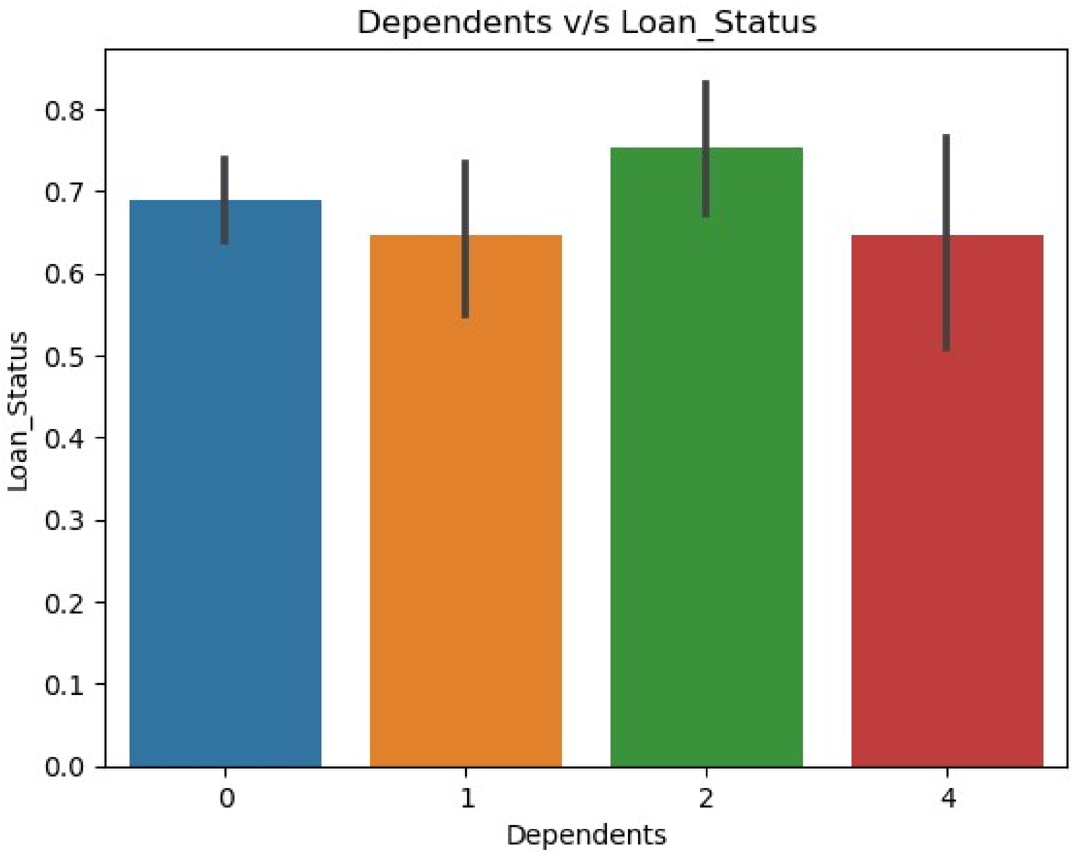
```
#draw a bar plot for Gender vs Loan_Status

plt.title('Gender v/s Loan_Status')

sns.barplot(x="Gender", y="Loan_Status", data=df)
```

```
<AxesSubplot:title={'center':'Gender v/s Loan_Status'},
xlabel='Gender', ylabel='Loan_Status'>
```



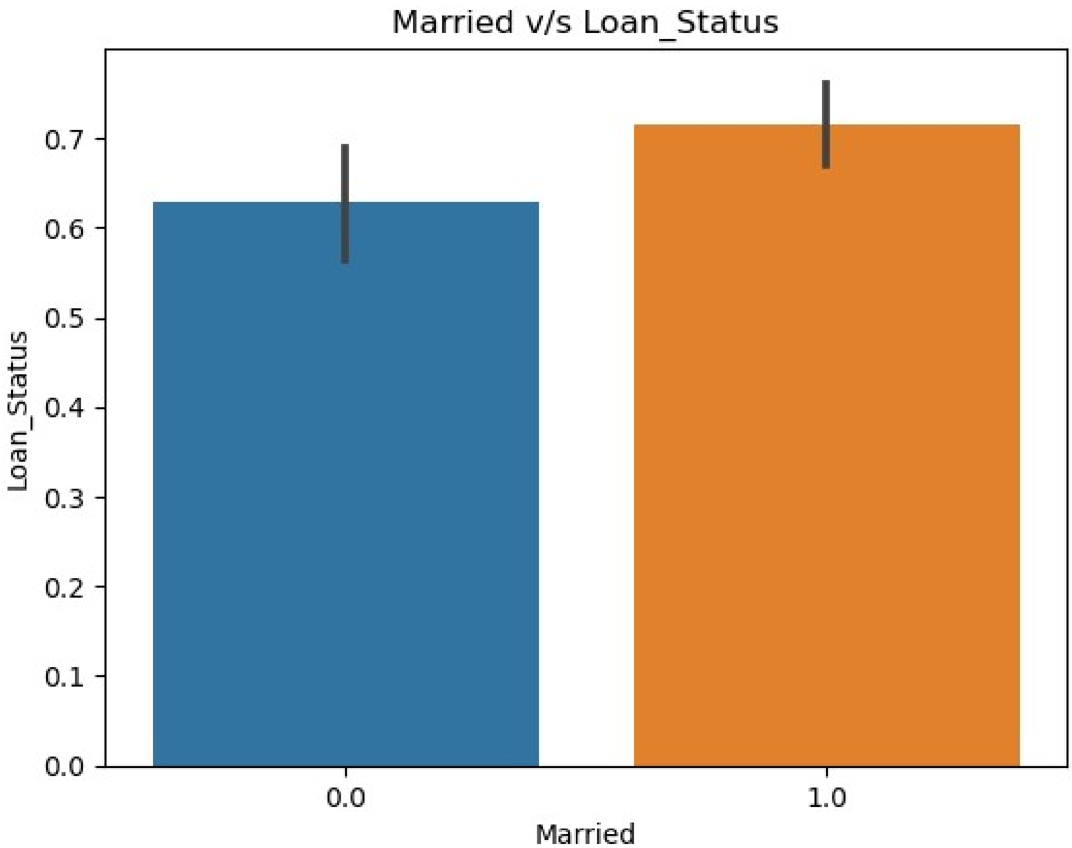

```
#draw a bar plot for Dependents vs. Loan_Status

plt.title('Dependents v/s Loan_Status')

sns.barplot(x="Dependents", y="Loan_Status", data=df)
```

```
<AxesSubplot:title={'center':'Dependents v/s Loan_Status'},
xlabel='Dependents', ylabel='Loan_Status'>
```



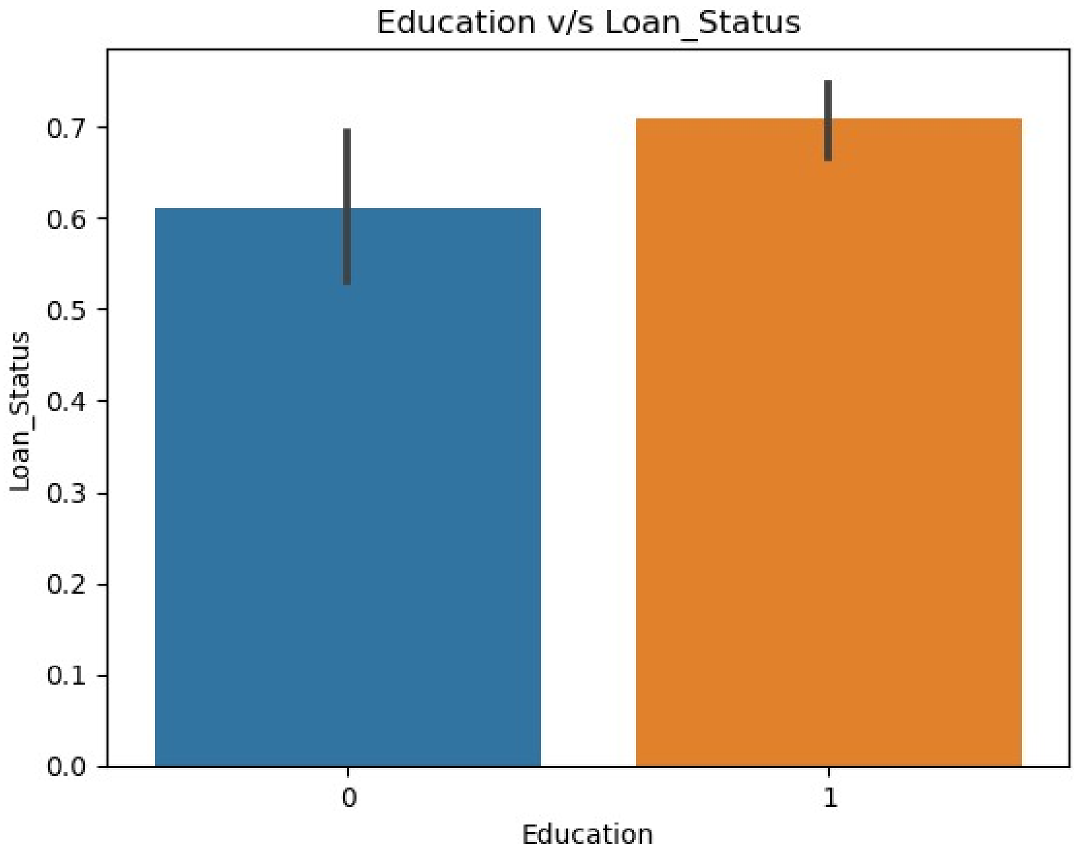

```
#draw a bar plot for Married vs. Loan_Status

plt.title('Married v/s Loan_Status')

sns.barplot(x="Married", y="Loan_Status", data=df)
```

```
<AxesSubplot:title={'center':'Married v/s Loan_Status'},
xlabel='Married', ylabel='Loan_Status'>
```



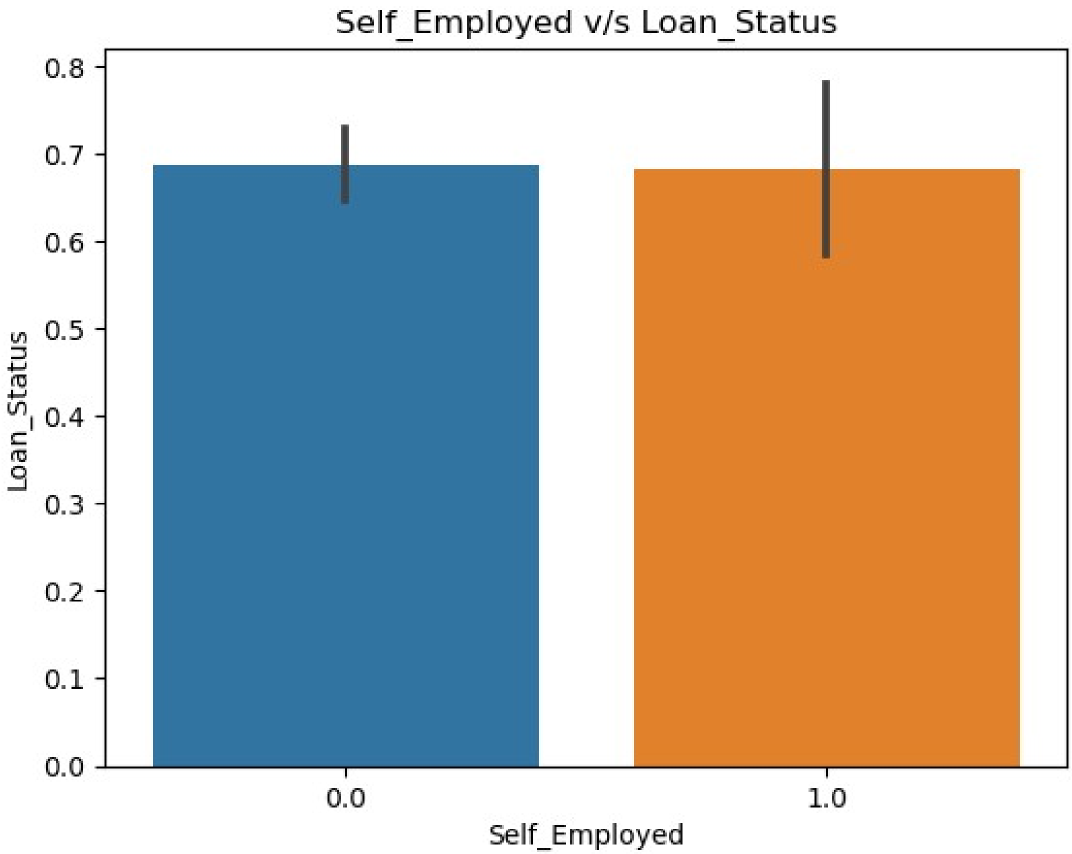

```
#draw a bar plot for Education vs. Loan_Status

plt.title('Education v/s Loan_Status')

sns.barplot(x="Education", y="Loan_Status", data=df)
```

```
<AxesSubplot:title={'center':'Education v/s Loan_Status'},
xlabel='Education', ylabel='Loan_Status'>
```



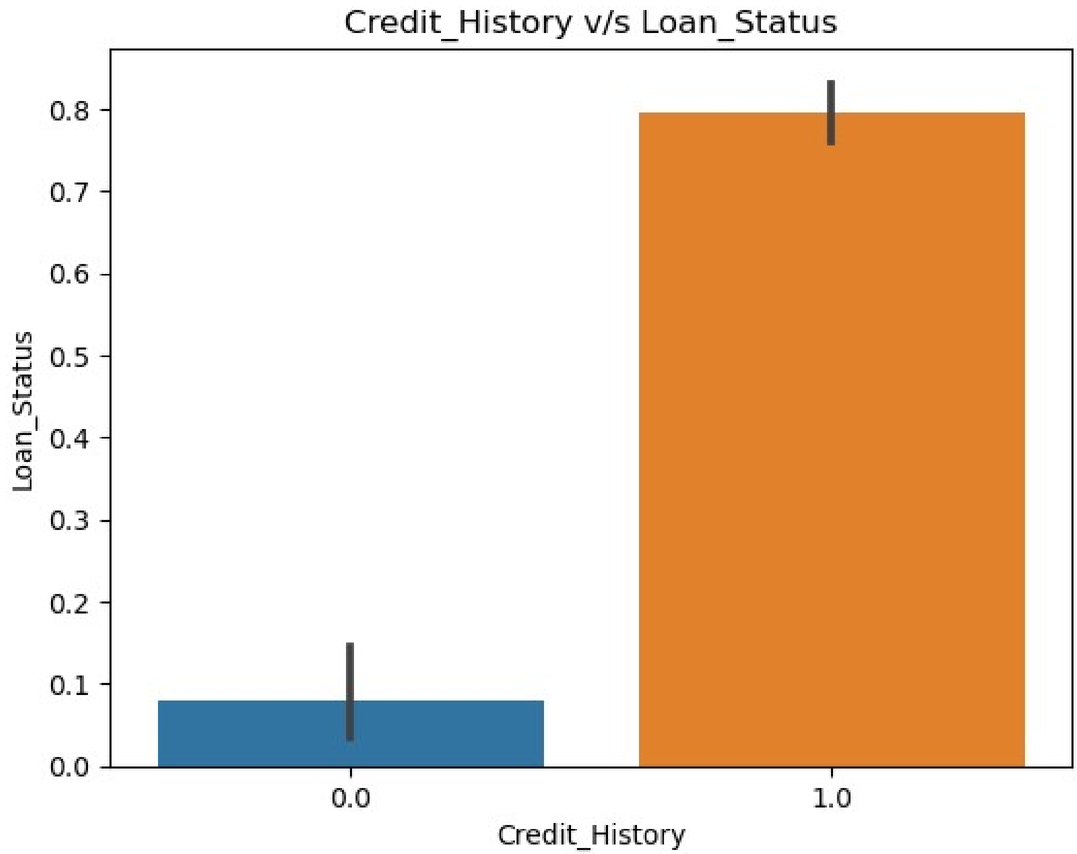

```
#draw a bar plot for Self_Employed  vs. Loan_Status

plt.title('Self_Employed v/s Loan_Status')

sns.barplot(x="Self_Employed", y="Loan_Status", data=df)
```

```
<AxesSubplot:title={'center':'Self_Employed v/s Loan_Status'},
xlabel='Self_Employed', ylabel='Loan_Status'>
```



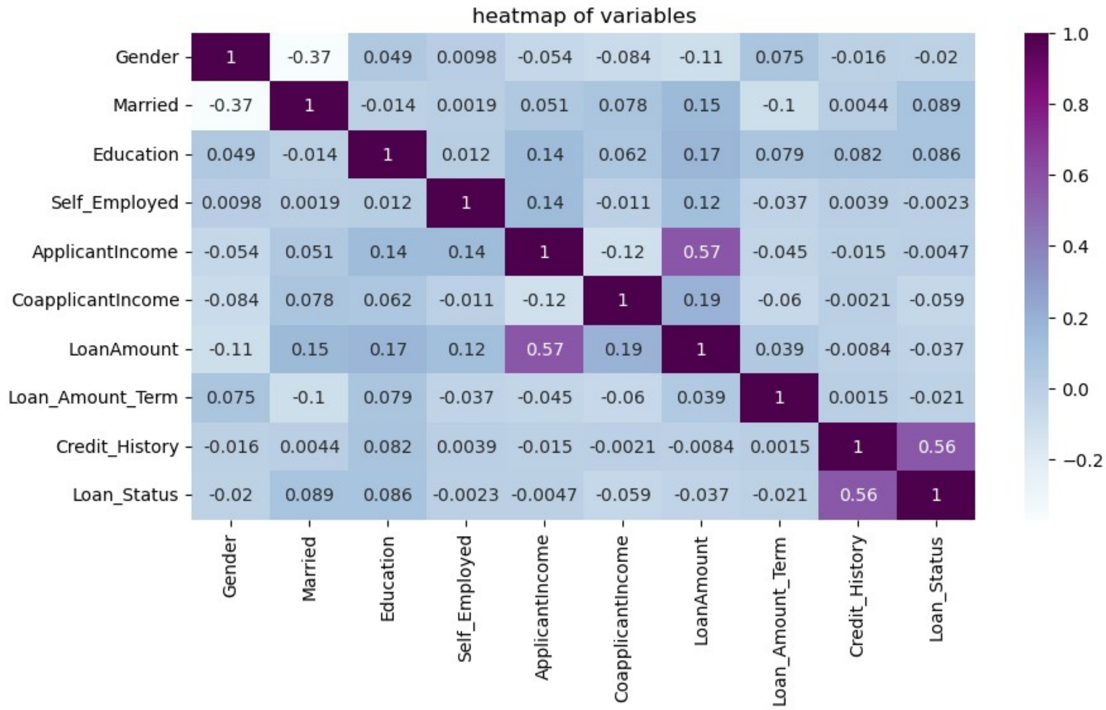

```
#draw a bar plot for Credit_History  vs. Loan_Status

plt.title('Credit_History v/s Loan_Status')

sns.barplot(x="Credit_History", y="Loan_Status", data=df)
```

```
<AxesSubplot:title={'center':'Credit_History v/s Loan_Status'},
xlabel='Credit_History', ylabel='Loan_Status'>
```




```
correlation=df.corr()
plt.figure(figsize=(10,5))
plt.title("heatmap of variables")
sns.heatmap(correlation, annot = True, cmap = 'BuPu')
```

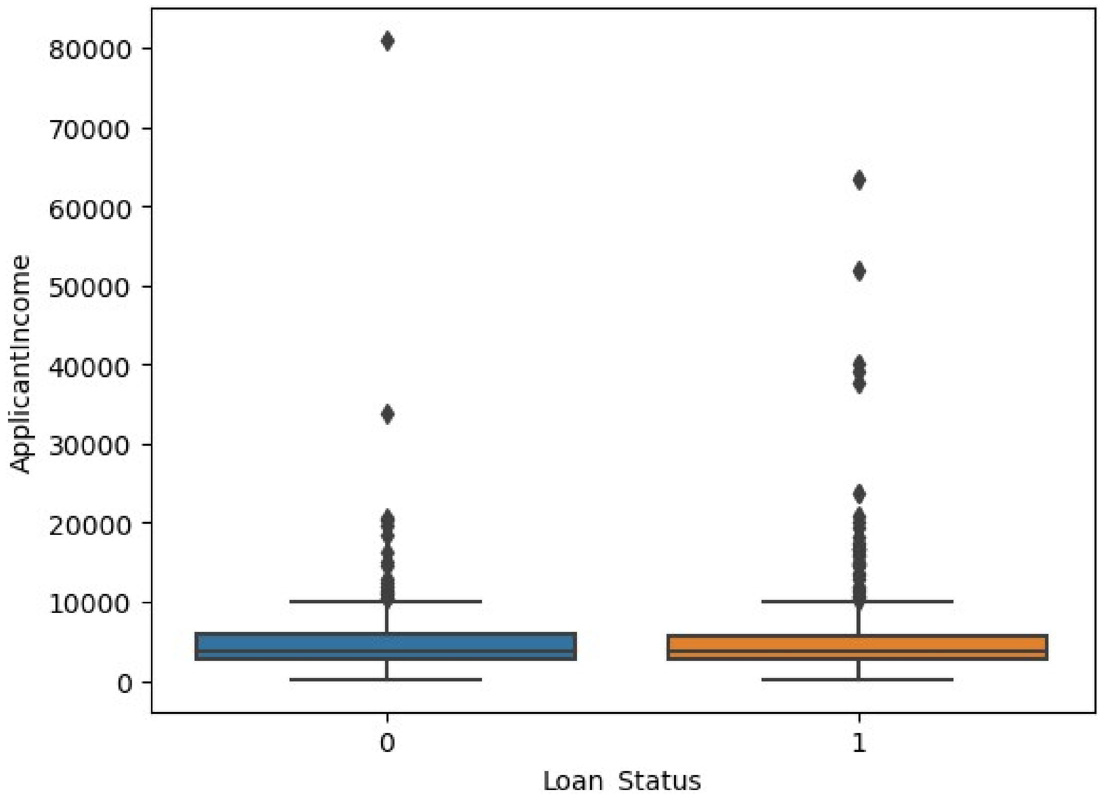
```
<AxesSubplot:title={'center':'heatmap of variables'}>
```



☞In the above heatmap as we can analise max value is 1 and min value is -1 so which parameter is contributing and affecting the loan status.higher value of the loan_status contents to lower loan amount term. The value of the loan represents the intensity of the data.

```
sns.boxplot(x="Loan_Status", y="ApplicantIncome", data=df)
```

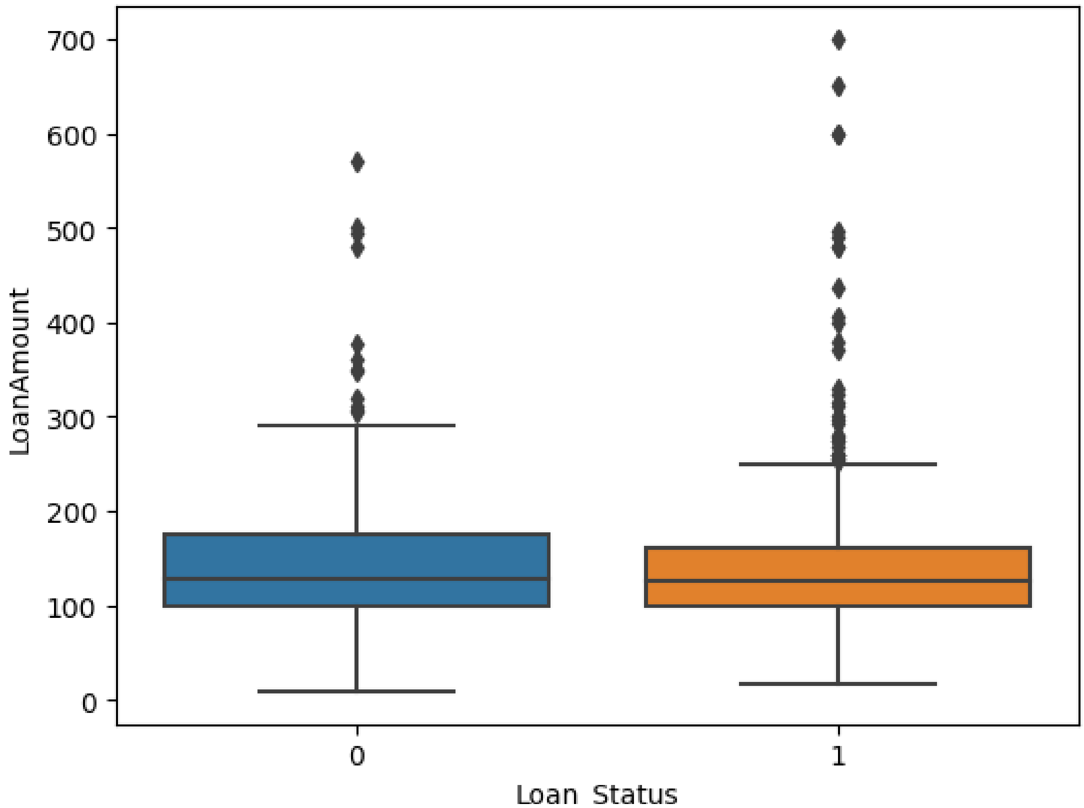
```
<AxesSubplot:xlabel='Loan_Status', ylabel='ApplicantIncome'>
```



☞ It can be seen that there are lots of outliers in Applicant Income, and the distribution also positively skewed.

```
sns.boxplot(x="Loan_Status", y="LoanAmount", data=df)
```

```
<AxesSubplot:xlabel='Loan_Status', ylabel='LoanAmount'>
```



☞ As can be seen, Co Applicant Income has a high number of outliers, and the distribution is also positively skewed.

```
data = df.dropna()
```

model building

Logistic Regression:

```
# standardization of data
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import preprocessing

# split the data into training and testing set
X_train, X_test, y_train, y_test =
train_test_split(data.drop(['Loan_Status'],axis=1),

data['Loan_Status'], test_size=0.2,
                                                     random_state=20)

logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
```

```
LogisticRegression()
```

```
predictions = logmodel.predict(X_test)
X_test.head()
```

```
     Gender  Married Dependents  Education  Self_Employed  
ApplicantIncome  \
15      0.0      0.0          0          1            0.0      
4950   
602     0.0      1.0          4          1            0.0      
5703   
78      0.0      1.0          4          1            0.0      
3167   
415     1.0      0.0          0          1            0.0      
2995   
472     0.0      1.0          4          1            0.0      
4691   

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  
15                 0.0       125.0             360.0             1.0  
602                0.0       128.0             360.0             1.0  
78              4000.0       180.0             300.0             0.0  
415                0.0        60.0             360.0             1.0  
472                0.0       100.0             360.0             1.0  
```

```
accuracy = logmodel.score(X_test,y_test)
print(accuracy*100,'%')
```

```
83.33333333333334 %
```

```
predictions
```

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

```
from sklearn.metrics import classification_report
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.85      0.57      0.68        30
           1       0.83      0.95      0.89        66

    accuracy                           0.83        96
   macro avg       0.84      0.76      0.78        96
```

```
weighted avg       0.84      0.83      0.82        96
```

```python
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, predictions)
```

```
array([[17, 13],
       [ 3, 63]], dtype=int64)
```

☞Logistic regression accuracy : 83.33 %

SVM (Support vector machine) classifier

```python
from sklearn.svm import SVC

# if the data is not linerarly seperable, the SVM use a kernal function to map the data into a higher-dimentional
#space where the classes are seperable. some common kernal function include linear, polynomiall and radial basis function.
model=SVC(kernel = 'linear', C = 1)
model.fit(X_train, y_train)
```

```
SVC(C=1, kernel='linear')
```

```python
svm_pred=model.predict(X_test)
```

```python
print(svm_pred)
```

```
[1 1 0 1 1 1 1 1 0 1 1 1 0 1 0 0 1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 1 0
 1 1 1 0 1 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 0 1 1 1
 1 1 1 1 1 1 1 0 1 0 1 1 1 1 1 0 0 0 1 0 1 0]
```

```python
# model accuracy for X_test
accuracy = model.score(X_test, y_test)
print(accuracy*100,'%')
```

```
84.375 %
```

```python
cm=confusion_matrix(y_test,svm_pred)
print(cm)
print()
print("clssification report\n")
print( classification_report(y_test,svm_pred))
```

```
[[17 13]
 [ 2 64]]

clssification report

              precision    recall  f1-score   support
```

```
              0       0.89      0.57      0.69        30
              1       0.83      0.97      0.90        66

       accuracy                           0.84        96
      macro avg       0.86      0.77      0.79        96
   weighted avg       0.85      0.84      0.83        96
```

☞SVM(support vector machine) classifier accuracy : 84.37%

KNN (k-nearest neighbours) classifier

```
from sklearn.neighbors import KNeighborsClassifier

# knn=KNeighbhorsClassifier(n_neighbors=42)
knn = KNeighborsClassifier(n_neighbors = 12)
knn.fit(X_train,y_train)
```

```
KNeighborsClassifier(n_neighbors=12)
```

```
# creating confusion matrix with the help of the following script we
can make predictions--
knn_prediction=knn.predict(X_test)

#next print result as follows
cm=confusion_matrix(y_test, knn_prediction)
print(classification_report(knn_prediction,y_test))
print(cm)
```

```
              precision    recall  f1-score   support

              0       0.10      0.33      0.15         9
              1       0.91      0.69      0.78        87

       accuracy                           0.66        96
      macro avg       0.50      0.51      0.47        96
   weighted avg       0.83      0.66      0.73        96

[[ 3 27]
 [ 6 60]]
```

```
# accuracy on x_test
accuracy=knn.score(X_test, y_test)
print(accuracy*100,'%')
```

```
65.625 %
```

☞KNN(k_nearest neighbours)classifier accuracy : 65.62%

naive bayes classifier

```
from sklearn.naive_bayes import GaussianNB

gnb = GaussianNB().fit(X_train, y_train)
gnb_predictions = gnb.predict(X_test)


accuracy=gnb.score(X_test, y_test)
print(accuracy*100,'%')
print()
print(classification_report(y_test,gnb_predictions))
print(confusion_matrix(y_test,gnb_predictions))
```

```
86.45833333333334 %

              precision    recall  f1-score   support

           0       0.87      0.67      0.75        30
           1       0.86      0.95      0.91        66

    accuracy                           0.86        96
   macro avg       0.87      0.81      0.83        96
weighted avg       0.87      0.86      0.86        96

[[20 10]
 [ 3 63]]
```

☞ we get accuracy is 86.45% that means as compare to other model navie bays model is bestfitted on the loan data set.In naive bayes theorem it handles both continuous and discrete data. It is highly scalable with the number of predictors and data points.It is not sensitive to irrelevant features that's why is more fit in the loan data set.

☞naive bayes classifier accuracy : 86.45 %

End