Loan Approval Prediction

May 23, 2023

1 Importing Necessary Libraries

[1]:
```
import pandas as pd,numpy as np # For Data Manipulation
import matplotlib.pyplot as pp,seaborn as sb # For Data Visualisation
from category_encoders import OrdinalEncoder # For Categorical Encoding
from sklearn.model_selection import train_test_split # For Model Validation sets
from sklearn.naive_bayes import GaussianNB # Model 1 : Naive Bayes -␣
↪Probablistic Model
from sklearn.tree import DecisionTreeClassifier as DTC # Model 2 : Decision␣
↪Tree - Determministic Model
import sklearn.tree as tree # For Decision Tree Visualisation
from sklearn.ensemble import RandomForestClassifier # Model 3 : Random Forest -␣
↪Ensemble Model (Bagging)
from sklearn.metrics import␣
↪accuracy_score,classification_report,roc_curve,roc_auc_score #Model␣
↪Validation
```

2 Importing our data

[2]:
```
data = pd.read_csv('data.csv')
```

3 Exploring our data - Descriptive

3.1 Getting first 5 rows

[3]:
```
data.head()
```

[3]:
```
    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
```

3.2 Getting first 'n' rows

[4]:
```
data.head(10)
```

[4]:
```
    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
5  LP001011   Male     Yes          2      Graduate           Yes
6  LP001013   Male     Yes          0  Not Graduate            No
7  LP001014   Male     Yes         3+      Graduate            No
8  LP001018   Male     Yes          2      Graduate            No
9  LP001020   Male     Yes          1      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
5             5417             4196.0       267.0             360.0
6             2333             1516.0        95.0             360.0
7             3036             2504.0       158.0             360.0
8             4006             1526.0       168.0             360.0
9            12841            10968.0       349.0             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
5             1.0         Urban           Y
```

```
6               1.0         Urban           Y
7               0.0     Semiurban           N
8               1.0         Urban           Y
9               1.0     Semiurban           N
```

3.3 Getting last 5 rows

[5]:
```
data.tail()
```

[5]:
```
      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
```

3.4 Getting last 'n' rows

[6]:
```
data.tail(10)
```

[6]:
```
      Loan_ID  Gender Married Dependents     Education Self_Employed  \
604  LP002959  Female     Yes          1      Graduate            No
605  LP002960    Male     Yes          0  Not Graduate            No
606  LP002961    Male     Yes          1      Graduate            No
607  LP002964    Male     Yes          2  Not Graduate            No
608  LP002974    Male     Yes          0      Graduate            No
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  \
```

```
604          12000                0.0       496.0             360.0
605           2400             3800.0         NaN             180.0
606           3400             2500.0       173.0             360.0
607           3987             1411.0       157.0             360.0
608           3232             1950.0       108.0             360.0
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
604             1.0     Semiurban           Y
605             1.0         Urban           N
606             1.0     Semiurban           Y
607             1.0         Rural           Y
608             1.0         Rural           Y
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
```

3.5 Looking at the description

[7]:
```
data.describe()
```

[7]:
```
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

3.6 Looking at its shape

[8]:
```
data.shape
```

[8]:
```
(614, 13)
```

4 Data Preperation

4.1 Checking for Null Values

[9]:
```
data.isnull().sum()
```

[9]:
```
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
```

4.2 Handling Null values

4.2.1 Handling Null Values in Categorical Features

[10]:
```
data['Gender'].fillna(method='ffill',inplace=True)
data['Self_Employed'].fillna(method='bfill',inplace=True)
data['Married'].fillna(method='ffill',inplace=True)
```

[11]:
```
data.isnull().sum()
```

[11]:
```
Loan_ID              0
Gender               0
Married              0
Dependents          15
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount          22
Loan_Amount_Term    14
Credit_History      50
```

```
Property_Area         0
Loan_Status           0
dtype: int64
```

4.2.2 Handling Null Values in Dependents by mean

[12]:
```
data['Dependents'].value_counts()
```

[12]:
```
0      345
1      102
2      101
3+      51
Name: Dependents, dtype: int64
```

Converting the data into numerical

[13]:
```
def convert_to_str(x):
    if x == '3+':
        return float(x[:-1])
    return float(x)
```

[14]:
```
data['Dependents']=data['Dependents'].apply(convert_to_str)
```

[15]:
```
data['Dependents'].fillna(data['Dependents'].mean(),inplace=True)
```

[16]:
```
data['Dependents'] = data['Dependents'].apply(float)
data['Dependents'].isnull().sum()
```

[16]:
```
0
```

4.2.3 Handling Null Values in Numerical Features

[17]:
```
data['LoanAmount'].fillna(data['LoanAmount'].mean(),inplace=True)
data['Loan_Amount_Term'].fillna(data['Loan_Amount_Term'].mean(),inplace=True)
data['Credit_History'].fillna(data['Credit_History'].mean(),inplace=True)
```

[18]:
```
data.isnull().sum()
```

[18]:
```
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
```

4.3 Looking for duplicates

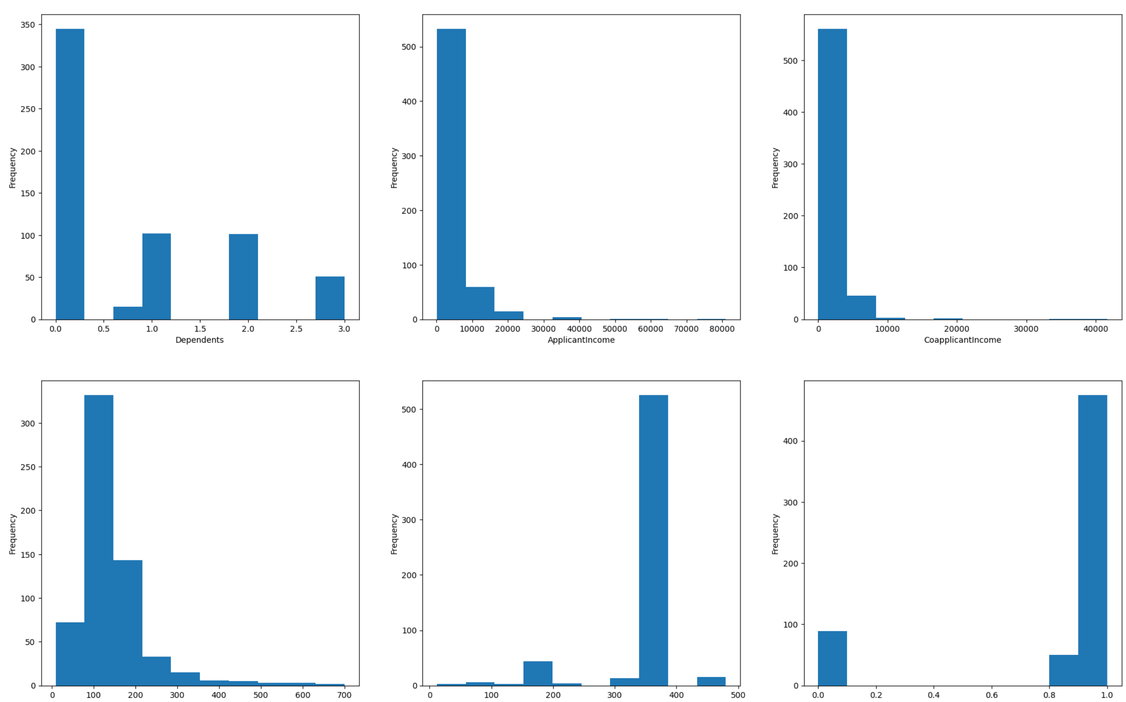
[19]:
```python
data.duplicated().sum()
```

[19]:
```
0
```

5 Exploring our data - Graphical

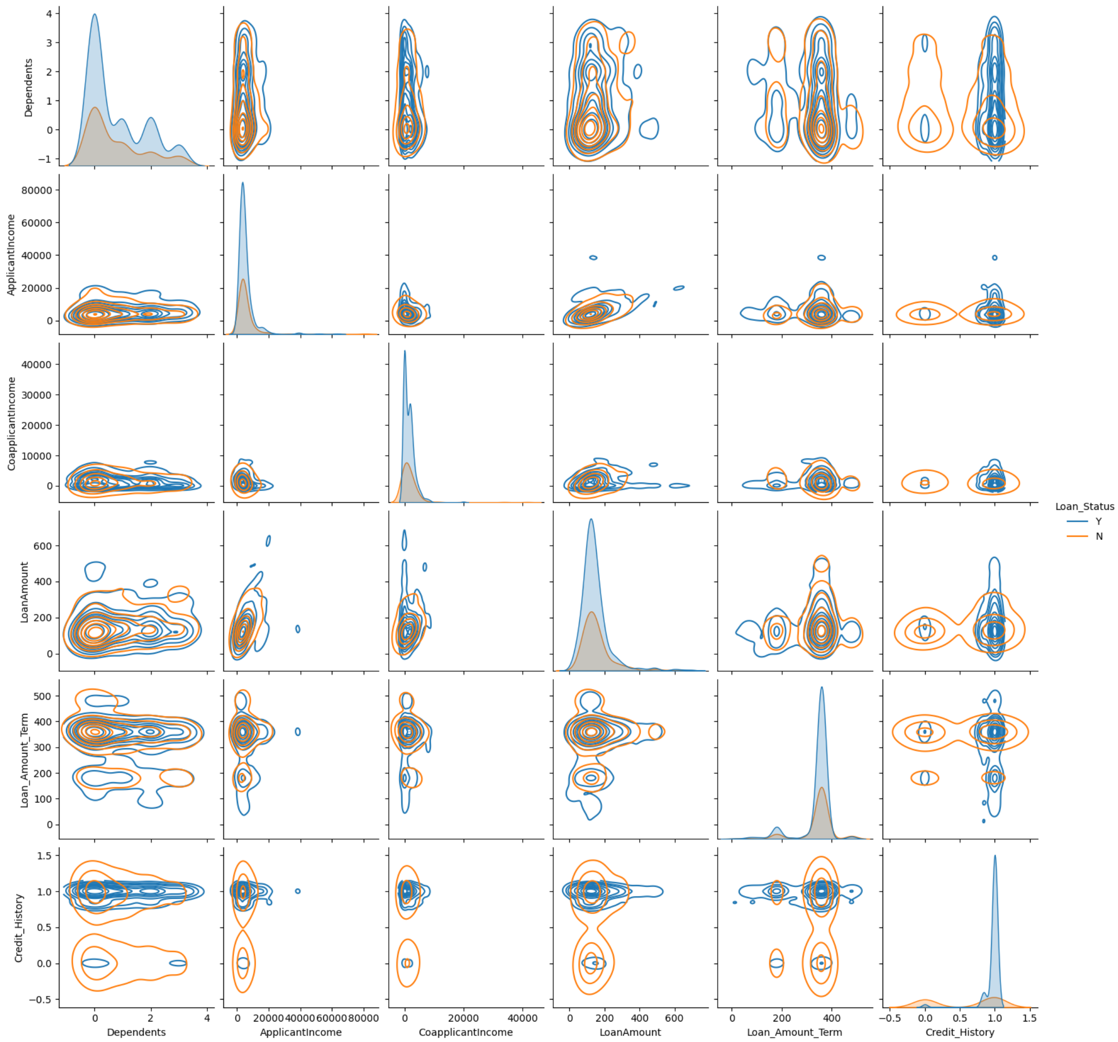
5.1 Histograms

[20]:
```python
numeric_vars =  ['Dependents', 'ApplicantIncome', 'CoapplicantIncome',␣
 ↪'LoanAmount',
       'Loan_Amount_Term', 'Credit_History']
# create histograms for each numeric variable
fig = pp.figure(figsize=(24, 15))
for i in range(len(numeric_vars)):
    var = numeric_vars[i]
    sub = fig.add_subplot(2, 3, i + 1)
    sub.set_xlabel(var)
    data[var].plot(kind = 'hist')
```



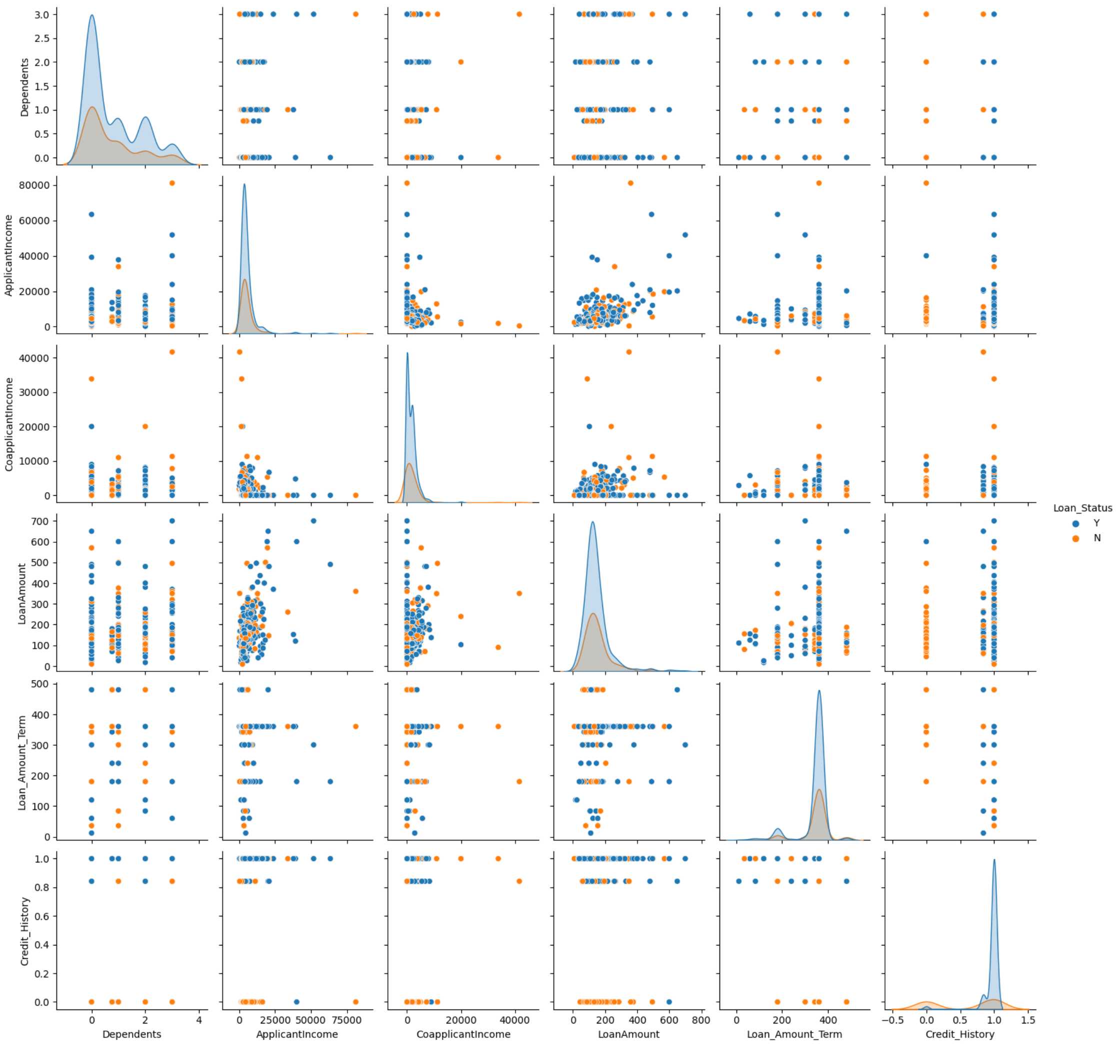
5.2 Kde Plot

[21]:
```
sb.pairplot(data,hue='Loan_Status',kind='kde')
pp.show()
```



5.3 Pair Plot

[22]:
```
sb.pairplot(data,hue='Loan_Status')
pp.show()
```



6 Encoding Categorical Features

[23]:
```
data.head()
```

[23]:
```
    Loan_ID Gender Married  Dependents     Education Self_Employed  \
0  LP001002   Male      No         0.0      Graduate            No
1  LP001003   Male     Yes         1.0      Graduate            No
2  LP001005   Male     Yes         0.0      Graduate           Yes
3  LP001006   Male     Yes         0.0  Not Graduate            No
4  LP001008   Male      No         0.0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0  146.412162             360.0
1             4583             1508.0  128.000000             360.0
```

```
2            3000              0.0   66.000000             360.0
3            2583           2358.0  120.000000             360.0
4            6000              0.0  141.000000             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
```

6.1 Encoding for non continuous features

[24]:
```
data.drop('Loan_ID',axis=1,inplace=True)
```

6.2 Encoding other features

6.2.1 Looking at our categorical Features in detail

[25]:
```
cf = ['Gender','Married','Education','Self_Employed','Property_Area','Loan_Status']
for i in cf:
    print('----------',i,'----------')
    print(data[i].value_counts())
    print('\n')
```

```
---------- Gender ----------
Male      500
Female    114
Name: Gender, dtype: int64



---------- Married ----------
Yes    400
No     214
Name: Married, dtype: int64



---------- Education ----------
Graduate        480
Not Graduate    134
Name: Education, dtype: int64



---------- Self_Employed ----------
No     528
Yes     86
Name: Self_Employed, dtype: int64
```

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


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

6.2.2 Defining custom mapping

[26]:
```
maps = [{'col':'Gender',
'mapping':{'Male':1,'Female':0}},
        {'col':'Married',
'mapping':{'Yes':1,'No':0}},
        {'col':'Education',
'mapping':{'Graduate':1,'Not Graduate':0}},
        {'col':'Self_Employed',
'mapping':{'Yes':1,'No':0}},
        {'col':'Property_Area',
'mapping':{'Rural':0,'Semiurban':1,'Urban':2}},
        {'col':'Loan_Status',
'mapping':{'Y':1,'N':0}}]
```

6.2.3 Encoding our data

[27]:
```
oc = OrdinalEncoder(cols=cf,return_df=True,
                           mapping=maps)
data[cf] = oc.fit_transform(data[cf])
```

6.2.4 Verifying our data

[28]:
```
data.head()
```

[28]:
```
   Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
0       1        0         0.0          1              0             5849
1       1        1         1.0          1              0             4583
2       1        1         0.0          1              1             3000
3       1        1         0.0          0              0             2583
4       1        0         0.0          1              0             6000
```

```
   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

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

[29]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gender             614 non-null    int32
 1   Married            614 non-null    int32
 2   Dependents         614 non-null    float64
 3   Education          614 non-null    int32
 4   Self_Employed      614 non-null    int32
 5   ApplicantIncome    614 non-null    int64
 6   CoapplicantIncome  614 non-null    float64
 7   LoanAmount         614 non-null    float64
 8   Loan_Amount_Term   614 non-null    float64
 9   Credit_History     614 non-null    float64
 10  Property_Area      614 non-null    int32
 11  Loan_Status        614 non-null    int32
dtypes: float64(5), int32(6), int64(1)
memory usage: 43.3 KB
```

7 Splitting our data set

[30]:
```
x = data.drop('Loan_Status',axis=1)
y = data['Loan_Status']
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.33,␣
 ↪random_state=42)
```

[31]:
```
x_train.head()
```

[31]:
```
     Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
244       1        1         0.0          0              0             3406
393       1        1         2.0          0              0             1993
310       0        0         0.0          1              0             2917
408       1        1         1.0          1              0             8300
572       1        1         2.0          1              0            16666

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
244             4417.0       123.0             360.0             1.0
393             1625.0       113.0             180.0             1.0
310                0.0        84.0             360.0             1.0
408                0.0       152.0             300.0             0.0
572                0.0       275.0             360.0             1.0

     Property_Area
244              1
393              1
310              1
408              1
572              2
```

[32]:
```
x_test.head()
```

[32]:
```
     Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
350       1        1         0.0          1              0             9083
377       1        1         0.0          1              0             4310
163       1        1         2.0          1              0             4167
609       0        0         0.0          1              0             2900
132       1        0         0.0          1              0             2718

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
350                0.0       228.0             360.0        1.000000
377                0.0       130.0             360.0        0.842199
163             1447.0       158.0             360.0        1.000000
609                0.0        71.0             360.0        1.000000
132                0.0        70.0             360.0        1.000000

     Property_Area
350              1
377              1
163              0
609              0
132              1
```

[33]:
```
y_train.head()
```

[33]:
```
244    1
393    1
310    1
408    0
572    1
Name: Loan_Status, dtype: int32
```

[34]:
```
y_test.head()
```

[34]:
```
350    1
377    1
163    1
609    1
132    1
Name: Loan_Status, dtype: int32
```

8 Training our models

8.1 Model 1 : Naive Bayes (Gaussian Naive Bayes)

[35]:
```
nb = GaussianNB()
nb.fit(x_train,y_train)
```

[35]:
```
GaussianNB()
```

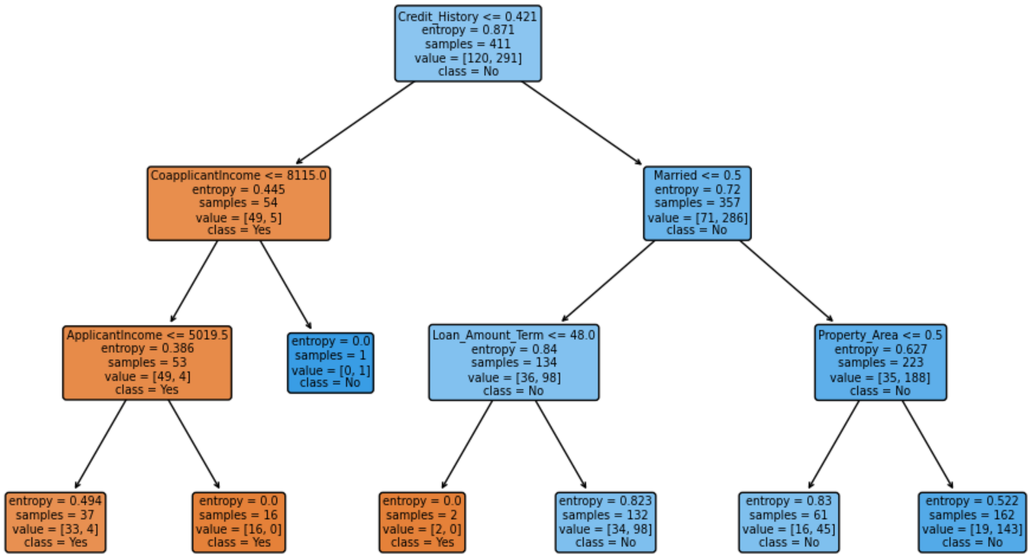
8.2 Model 2 : Decision Tree Classifier

[36]:
```
dtc = DTC(criterion="entropy", max_depth=3)
dtc.fit(x_train,y_train)
```

[36]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3)
```

8.2.1 Visualisng the decision Tree

[37]:
```
pp.figure(figsize=(12,7))
tree.plot_tree(dtc.fit(x_train,y_train),feature_names = x_train.
 ↪columns,class_names=['Yes','No'],
               filled=True,rounded=True)
pp.show()
```



8.3 Model 3 : Random Forest Classifier

[38]:
```
rfc = RandomForestClassifier(criterion='entropy',max_depth=3,random_state=42,n_jobs=-1)
rfc.fit(x_train,y_train)
```

[38]:
```
RandomForestClassifier(criterion='entropy', max_depth=3, n_jobs=-1,
                       random_state=42)
```

9 Evaluationg our models

9.1 Accuracy Scores

[39]:
```
models = ["Naive Bayes","Decision Tree","Random Forest"]
acc = pd.DataFrame({
    "train" : [accuracy_score(y_train,nb.predict(x_train))*100,accuracy_score(y_train,dtc.predict(x_train))*100,
              accuracy_score(y_train,rfc.predict(x_train))*100],
    "test" : [accuracy_score(y_test,nb.predict(x_test))*100,accuracy_score(y_test,dtc.predict(x_test))*100,
              accuracy_score(y_test,rfc.predict(x_test))*100]
},index=models)
```

[40]:
```
acc
```

[40]:

	train	test
Naive Bayes	81.265207	79.802956
Decision Tree	82.238443	79.310345
Random Forest	81.508516	79.802956

9.2 Classification Reports

9.2.1 Naive Bayes

[41]:
```
print(classification_report(y_train,nb.
    ↪predict(x_train),target_names=["Yes","No"]))
```

```
              precision    recall  f1-score   support

         Yes       0.81      0.47      0.59       120
          No       0.81      0.96      0.88       291

    accuracy                           0.81       411
   macro avg       0.81      0.71      0.74       411
weighted avg       0.81      0.81      0.79       411
```

9.3 Decision Tree

[42]:
```
print(classification_report(y_train,dtc.
    ↪predict(x_train),target_names=["Yes","No"]))
```

```
              precision    recall  f1-score   support

         Yes       0.93      0.42      0.58       120
          No       0.81      0.99      0.89       291

    accuracy                           0.82       411
   macro avg       0.87      0.71      0.74       411
weighted avg       0.84      0.82      0.80       411
```

9.4 Random Forest

[43]:
```
print(classification_report(y_train,rfc.
    ↪predict(x_train),target_names=["Yes","No"]))
```

```
              precision    recall  f1-score   support

         Yes       0.91      0.41      0.56       120
          No       0.80      0.98      0.88       291

    accuracy                           0.82       411
   macro avg       0.85      0.70      0.72       411
```

```
weighted avg       0.83      0.82      0.79       411
```

9.5 AUC ROC CURVE

9.6 Getting ROC Scores

[44]:
```python
pred_prob1 = nb.predict_proba(x_test)
pred_prob2 = dtc.predict_proba(x_test)
pred_prob3 = rfc.predict_proba(x_test)
fpr1, tpr1, thresh1 = roc_curve(y_test, pred_prob1[:,1], pos_label=1)
fpr2, tpr2, thresh2 = roc_curve(y_test, pred_prob2[:,1], pos_label=1)
fpr3, tpr3, thresh3 = roc_curve(y_test, pred_prob3[:,1], pos_label=1)
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

9.7 Getting AUC Scores

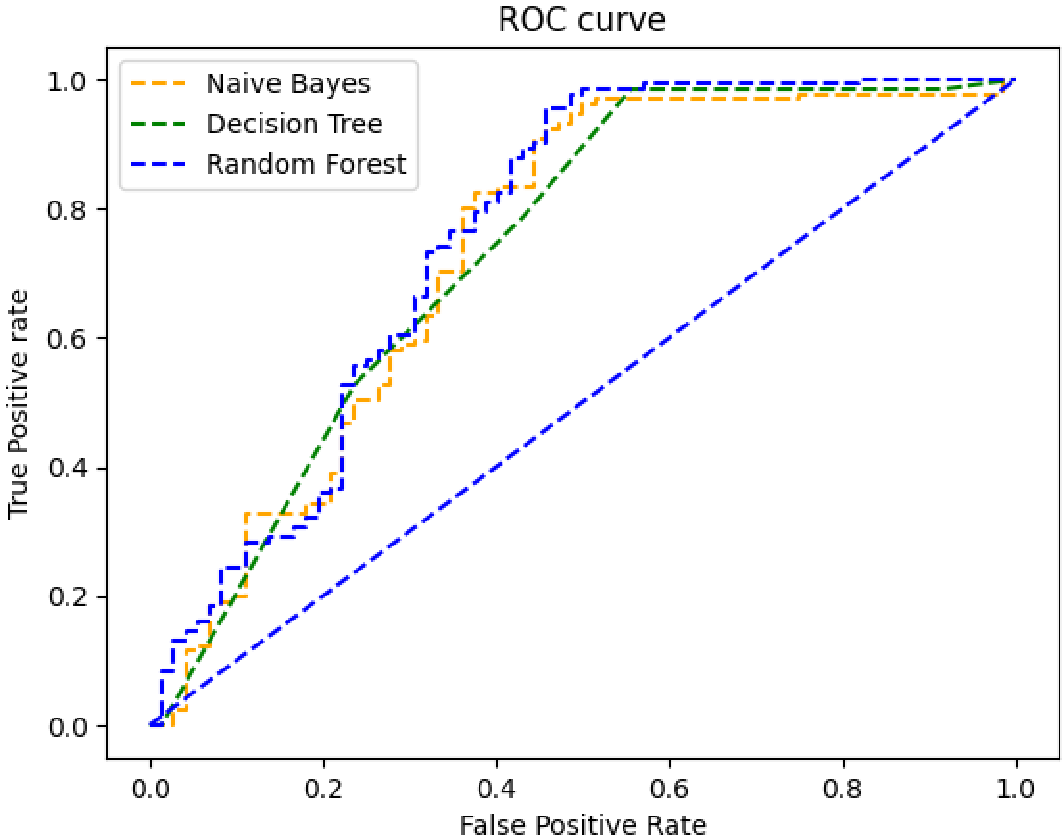
[45]:
```python
auc_score1 = roc_auc_score(y_test, pred_prob1[:,1])
auc_score2 = roc_auc_score(y_test, pred_prob2[:,1])
auc_score3 = roc_auc_score(y_test, pred_prob3[:,1])
auc = pd.DataFrame(data=[auc_score1, auc_score2,␣
 ↪auc_score3],index=models,columns=['AUC Score'])
auc
```

[45]:

	AUC Score
Naive Bayes	0.736959
Decision Tree	0.735157
Random Forest	0.757740

9.8 Plotting the ROC Curve

[46]:
```python
pp.plot(fpr1, tpr1, linestyle='--',color='orange', label='Naive Bayes')
pp.plot(fpr2, tpr2, linestyle='--',color='green', label='Decision Tree')
pp.plot(fpr3, tpr3, linestyle='--',color='blue', label='Random Forest')
pp.plot(p_fpr, p_tpr, linestyle='--', color='blue')
pp.title('ROC curve')
pp.xlabel('False Positive Rate')
pp.ylabel('True Positive rate')
pp.legend(loc='best')
pp.savefig('ROC',dpi=300)
pp.show()
```


ROC curve
Naive Bayes
Decision Tree
Random Forest
True Positive rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0