IISPS-INT-2394-EDA-Loan-Status-Prediction

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1) Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2) Importing Dataset

In [2]:
```
data = pd.read_csv("train.csv")
```

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

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
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

In [4]:
```
#Data Info
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
Loan_ID              614 non-null object
Gender               601 non-null object
Married              611 non-null object
Dependents           599 non-null object
Education            614 non-null object
Self_Employed        582 non-null object
ApplicantIncome      614 non-null int64
CoapplicantIncome    614 non-null float64
LoanAmount           592 non-null float64
Loan_Amount_Term     600 non-null float64
Credit_History       564 non-null float64
Property_Area        614 non-null object
Loan_Status          614 non-null object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

3) Taking care of null values

In [5]:
```
#Showing count of missing values in each column
data.apply(lambda x: sum(x.isnull()),axis=0)
```

Out[5]:
```
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 [6]:
```
data['Gender'].value_counts()
```

Out[6]:
```
Male      489
Female    112
Name: Gender, dtype: int64
```

In [7]:
```
data.Gender = data.Gender.fillna('Male')
```

In [8]:
```
data['Married'].value_counts()
```

Out[8]:
```
Yes    398
No     213
Name: Married, dtype: int64
```

In [9]:
```
data.Married = data.Married.fillna('Yes')
```

In [10]:
```
data['Dependents'].value_counts()
```

Out[10]:
```
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```

In [11]:
```
data.Dependents = data.Dependents.fillna('0')
```

In [12]:
```
data['Self_Employed'].value_counts()
```

Out[12]:
```
No     500
Yes     82
Name: Self_Employed, dtype: int64
```

In [13]:
```
data.Self_Employed = data.Self_Employed.fillna('No')
```

In [14]:
```
data.LoanAmount = data.LoanAmount.fillna(data.LoanAmount.mean())
```

In [15]:
```
data['Loan_Amount_Term'].value_counts()
```

Out[15]:
```
360.0    512
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
```

In [16]:
```
data.Loan_Amount_Term = data.Loan_Amount_Term.fillna(360.0)
```

In [17]:
```
data['Credit_History'].value_counts()
```

Out[17]:
```
1.0    475
0.0     89
Name: Credit_History, dtype: int64
```

In [18]:
```
data.Credit_History = data.Credit_History.fillna(1.0)
```

In [19]:
```
data.apply(lambda x: sum(x.isnull()),axis=0)
```

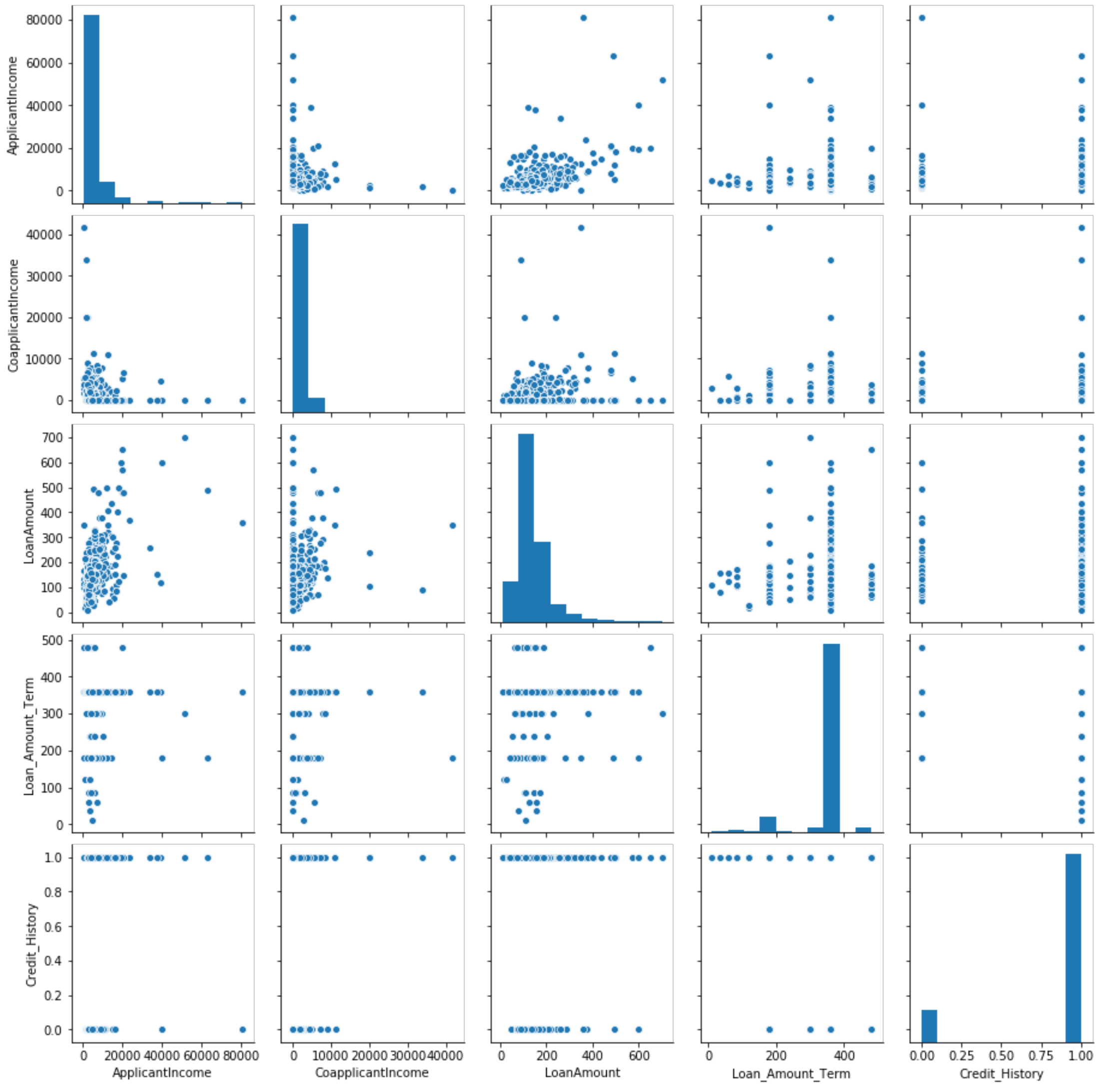
Out[19]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

All null values removed

4) Data Visualization

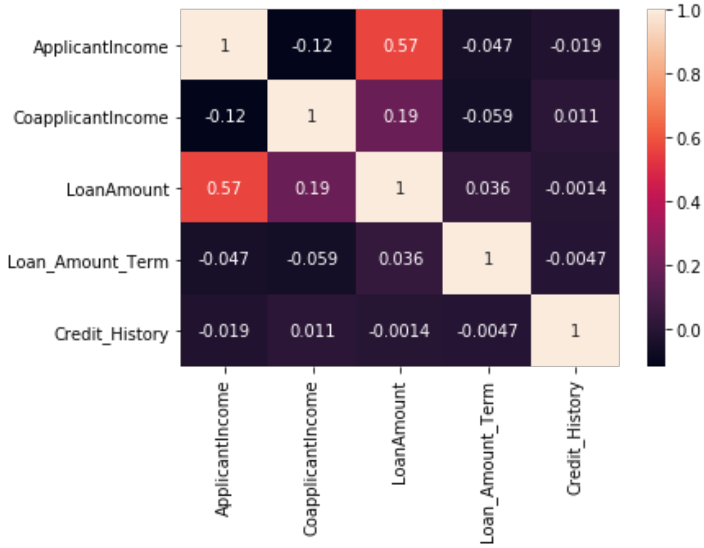
In [20]:
```
sns.pairplot(data)
```

Out[20]: <seaborn.axisgrid.PairGrid at 0x7f37064bd810>



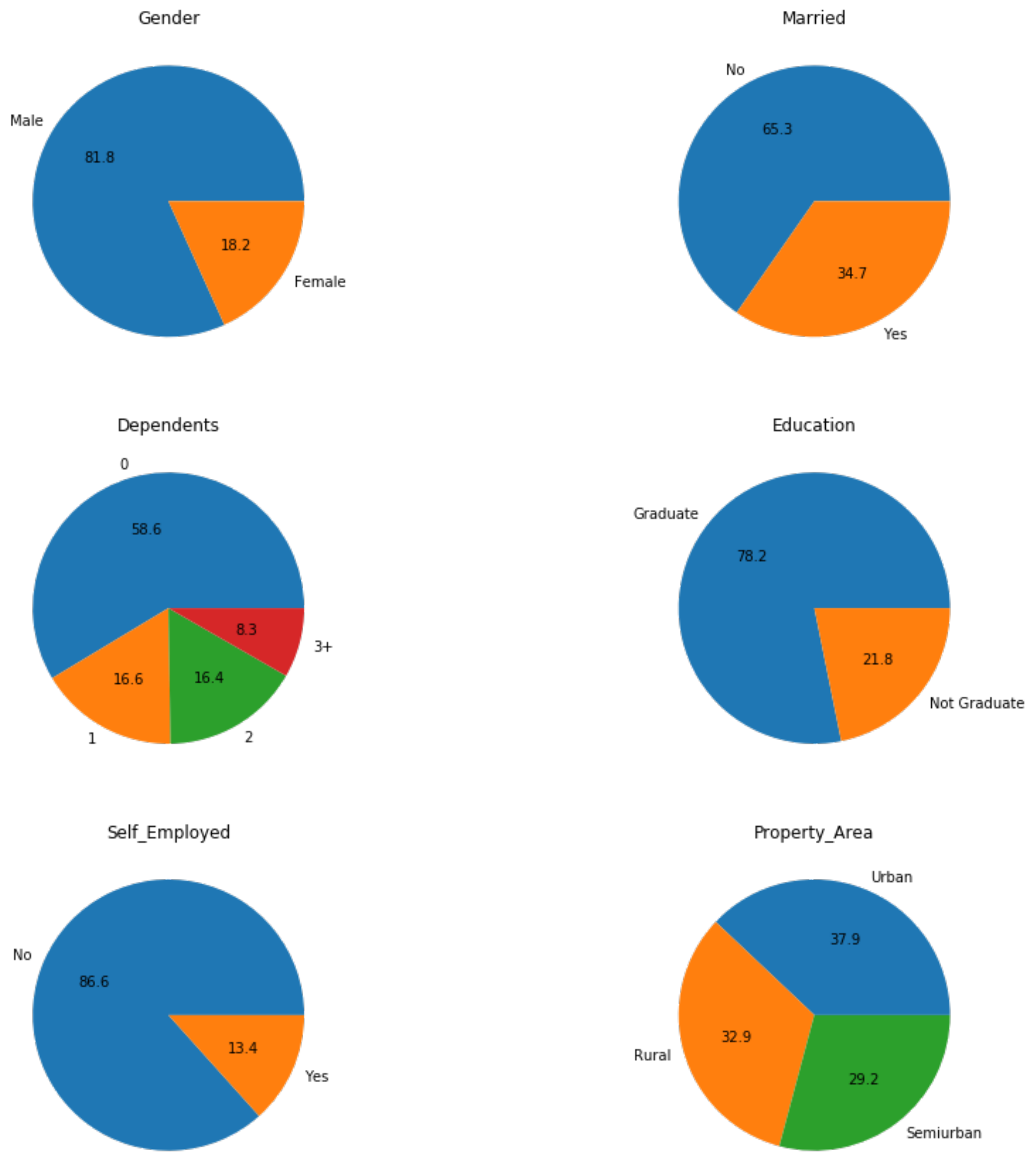
In [21]:
```
sns.heatmap(data.corr(), annot = True)
```

Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f37035b19d0>
```



In [22]:
```
a = data["Gender"].value_counts().to_numpy()
b = data["Married"].value_counts().to_numpy()
c = data["Dependents"].value_counts().to_numpy()
d = data["Education"].value_counts().to_numpy()
e = data["Self_Employed"].value_counts().to_numpy()
f = data["Property_Area"].value_counts().to_numpy()

fig, axs = plt.subplots(3, 2, figsize = (15, 15))
_ = axs[0, 0].pie(a, labels = data["Gender"].unique(), autopct = '%0.1f')
axs[0, 0].set_title('Gender')
_ = axs[0, 1].pie(b, labels = data["Married"].unique(), autopct = '%0.1f')
axs[0, 1].set_title('Married')
_ = axs[1, 0].pie(c, labels = data["Dependents"].unique(), autopct = '%0.1f')
axs[1, 0].set_title('Dependents')
_ = axs[1, 1].pie(d, labels = data["Education"].unique(), autopct = '%0.1f')
axs[1, 1].set_title('Education')
_ = axs[2, 0].pie(e, labels = data["Self_Employed"].unique(), autopct = '%0.1f
')
axs[2, 0].set_title('Self_Employed')
_ = axs[2, 1].pie(f, labels = data["Property_Area"].unique(), autopct = '%0.1f
')
_ = axs[2, 1].set_title('Property_Area')
```



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

Out[23]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
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

5) Splitting in X and Y

In [24]:
```
# Splitting traing data into X and Y
X = data.iloc[:, 1: 12].values
y = data.iloc[:, 12].values
```

In [25]:
```
X
```

Out[25]:
```
array([['Male', 'No', '0', ..., 360.0, 1.0, 'Urban'],
       ['Male', 'Yes', '1', ..., 360.0, 1.0, 'Rural'],
       ['Male', 'Yes', '0', ..., 360.0, 1.0, 'Urban'],
       ...,
       ['Male', 'Yes', '1', ..., 360.0, 1.0, 'Urban'],
       ['Male', 'Yes', '2', ..., 360.0, 1.0, 'Urban'],
       ['Female', 'No', '0', ..., 360.0, 0.0, 'Semiurban']], dtype=object)
```

```
In [26]: y
```

```
Out[26]: array(['Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y',
               'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'N', 'N', 'N', 'Y',
               'Y', 'Y', 'N', 'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y',
               'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
               'N', 'N', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'N',
               'N', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N',
               'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
               'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
               'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N',
               'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'N', 'N', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'N', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N',
               'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N',
               'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y',
               'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
               'Y', 'N', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N',
               'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
               'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y',
               'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N', 'N',
               'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y',
               'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N',
               'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'Y', 'Y', 'Y',
               'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
               'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
               'N', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
               'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y',
               'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
               'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'N', 'Y',
               'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'N', 'Y',
               'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y',
               'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'N', 'Y', 'N', 'Y', 'Y',
               'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y',
               'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
               'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
               'N', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'N', 'N', 'N',
               'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
               'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
               'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y',
               'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'N',
               'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N',
               'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N',
               'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
               'Y', 'Y', 'N'], dtype=object)
```

6) Label Encoding

```
In [27]: from sklearn.preprocessing import LabelEncoder
         le = LabelEncoder()
```

In [28]:
```
for i in range(0, 5):
    X[:,i] = le.fit_transform(X[:,i])

X[:,10] = le.fit_transform(X[:,10])
y = le.fit_transform(y)
```

In [29]:
```
X.shape
```

Out[29]: (614, 11)

7) Splitting into train and test

In [30]:
```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1/3, rand
om_state = 0)
```

In [31]:
```
X_train.shape
```

Out[31]: (409, 11)

In [32]:
```
X_test.shape
```

Out[32]: (205, 11)

In [33]:
```
y_train.shape
```

Out[33]: (409,)

In [34]:
```
y_test.shape
```

Out[34]: (205,)

8) Feature Scaling

In [35]:
```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

Applying Principal Component analysis (PCA)

Using to emphasize variation and bring out strong patterns in the dataset and make data easy to explore and visualize further in training and testing

In [36]:
```
# Applying PCA
from sklearn.decomposition import PCA
pca = PCA(n_components = 2)
X_train = pca.fit_transform(X_train)
X_test = pca.fit_transform(X_test)
explained_variance = pca.explained_variance_ratio_
```

Done

Decision Tree Classification

In [37]:
```
# Fitting Decision Tree Classification to the Training set
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)
```

Out[37]:
```
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

In [38]:
```
# Predicting the Test set results
y_pred = classifier.predict(X_test)
y_pred
```

Out[38]:
```
array([0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1,
       1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0,
       1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0,
       0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0,
       1, 0, 1, 1, 0, 1, 1])
```

In [39]:
```
# Measuring Accuracy
from sklearn import metrics
print('The accuracy of Decision Tree Classifier is: ', metrics.accuracy_score(y
_test, y_pred))
```

```
The accuracy of Decision Tree Classifier is:  0.5365853658536586
```

In [40]:
```
# Making confusion matrix
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_test, y_pred))
```

```
[[20 40]
 [55 90]]
```

In [41]:
```
import sklearn.metrics as metrics
fpr,tpr,threshold = metrics.roc_curve(y_test, y_pred)
roc_auc = metrics.auc(fpr, tpr)
```

In [42]:
```
threshold
```

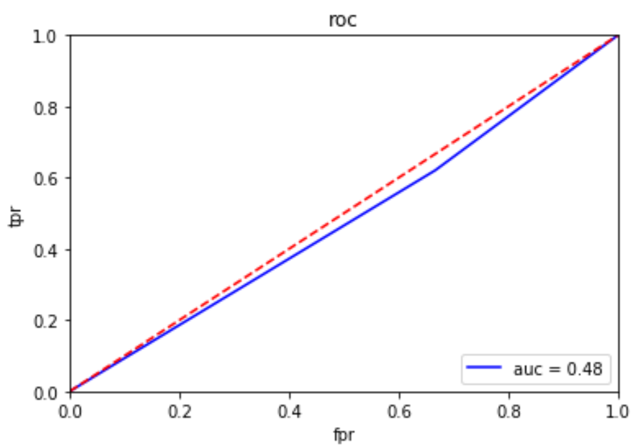
Out[42]:
```
array([2, 1, 0])
```

In [43]:
```
fpr
```

Out[43]:
```
array([0.        , 0.66666667, 1.        ])
```

In [44]:
```
tpr
```
Out[44]:
```
array([0.        , 0.62068966, 1.        ])
```

In [45]:
```
plt.title("roc")
plt.plot(fpr,tpr,'b',label = 'auc = %0.2f'%roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('tpr')
plt.xlabel('fpr')
```
Out[45]:
```
Text(0.5, 0, 'fpr')
```



Random Forest

In [46]:
```
# Fitting Random Forest Classification to the Training set
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', r
andom_state = 0)
classifier.fit(X_train, y_train)
```
Out[46]:
```
RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=0)
```

In [47]:
```
# Predicting the Test set results
y_pred = classifier.predict(X_test)
y_pred
```
Out[47]:
```
array([1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0,
       1, 0, 1, 1, 1, 1, 1])
```

In [48]:
```
# Measuring Accuracy
from sklearn import metrics
print('The accuracy of Random Forest Classification is: ', metrics.accuracy_sco
re(y_pred, y_test))
```

```
The accuracy of Random Forest Classification is:  0.5853658536585366
```

In [49]:
```
# Making confusion matrix
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_test, y_pred))
```

```
[[22 38]
 [47 98]]
```

In [50]:
```
import sklearn.metrics as metrics
fpr,tpr,threshold = metrics.roc_curve(y_test, y_pred)
roc_auc = metrics.auc(fpr, tpr)
```

In [51]:
```
threshold
```

Out[51]:
```
array([2, 1, 0])
```

In [52]:
```
fpr
```

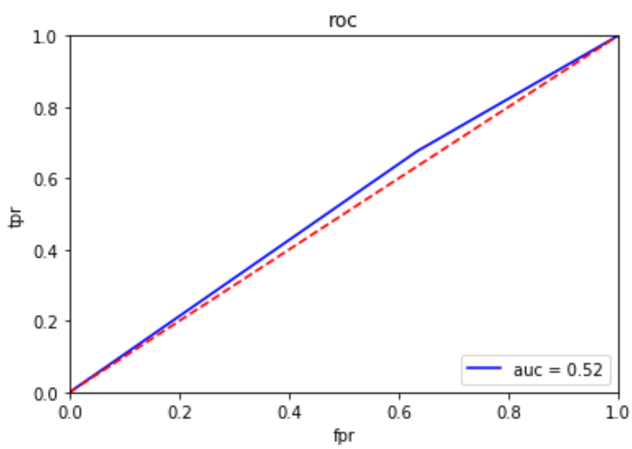
Out[52]:
```
array([0.        , 0.63333333, 1.        ])
```

In [53]:
```
tpr
```

Out[53]:
```
array([0.        , 0.67586207, 1.        ])
```

In [54]:
```
plt.title("roc")
plt.plot(fpr,tpr,'b',label = 'auc = %0.2f'%roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('tpr')
plt.xlabel('fpr')
```

Out[54]:
```
Text(0.5, 0, 'fpr')
```



SVM

In [55]:
```
from sklearn.svm import SVC
svm=SVC(kernel="linear")
svm.fit(X_train,y_train)
```

Out[55]:
```
SVC(kernel='linear')
```

In [56]:
```
# Predicting test data
y_pred_svm=svm.predict(X_test)
```

In [57]:
```
# Accuracy score
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred_svm)
```

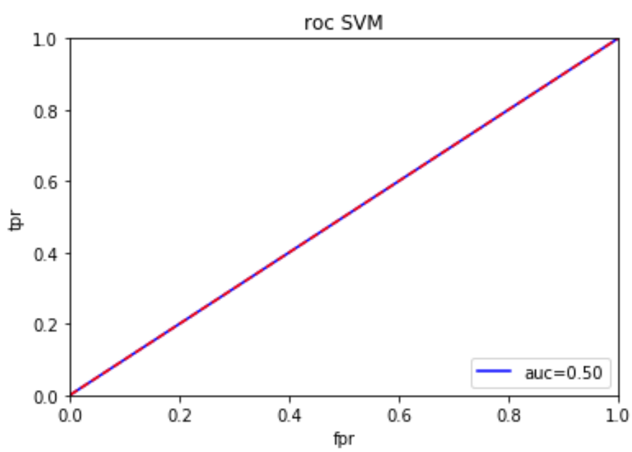
Out[57]:
```
0.7073170731707317
```

In [58]:
```
import sklearn.metrics as metrics
fpr_svm,tpr_svm,thrrshold_svm=metrics.roc_curve(y_test,y_pred_svm)
roc_auc_svm=metrics.auc(fpr_svm,tpr_svm)
roc_auc_svm
```

Out[58]:
```
0.5
```

In [59]:
```
import matplotlib.pyplot as plt
plt.title('roc SVM')
plt.plot(fpr_svm,tpr_svm,'b',label='auc=%0.2f'%roc_auc_svm)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('tpr')
plt.xlabel('fpr')
```

Out[59]:
```
Text(0.5, 0, 'fpr')
```



KNN

In [60]:
```
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5,metric="minkowski")
knn.fit(X_train,y_train)
```

Out[60]: KNeighborsClassifier()

In [61]:
```
# Predicting test data
y_pred_knn=knn.predict(X_test)
```

In [62]:
```
# Accuracy score
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred_knn)
```

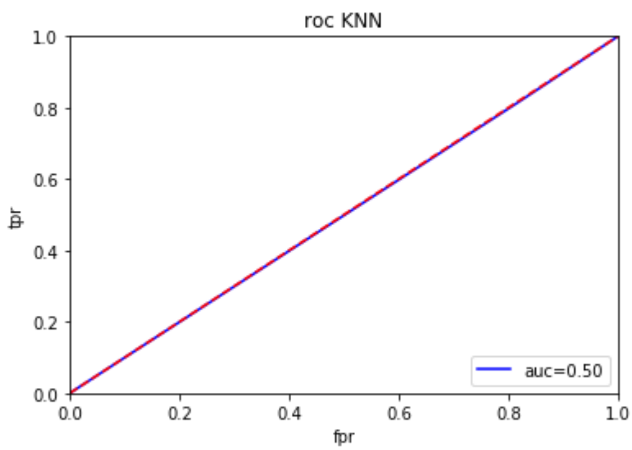
Out[62]: 0.6292682926829268

In [63]:
```
# roc auc
import sklearn.metrics as metrics
fpr_knn,tpr_knn,thrrshold_knn=metrics.roc_curve(y_test,y_pred_knn)
roc_auc_knn=metrics.auc(fpr_knn,tpr_knn)
roc_auc_knn
```

Out[63]: 0.4985632183908046

In [64]:
```
# Visualising roc auc
import matplotlib.pyplot as plt
plt.title('roc KNN')
plt.plot(fpr_knn,tpr_knn,'b',label='auc=%0.2f'%roc_auc_knn)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('tpr')
plt.xlabel('fpr')
```

Out[64]: Text(0.5, 0, 'fpr')



Logistic Regression

In [65]:
```
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression()
lgr.fit(X_train,y_train)
```

Out[65]:
```
LogisticRegression()
```

In [66]:
```
# Predicting test data
y_pred_log=lgr.predict(X_test)
```

In [67]:
```
# Accuracy score
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred_log)
```

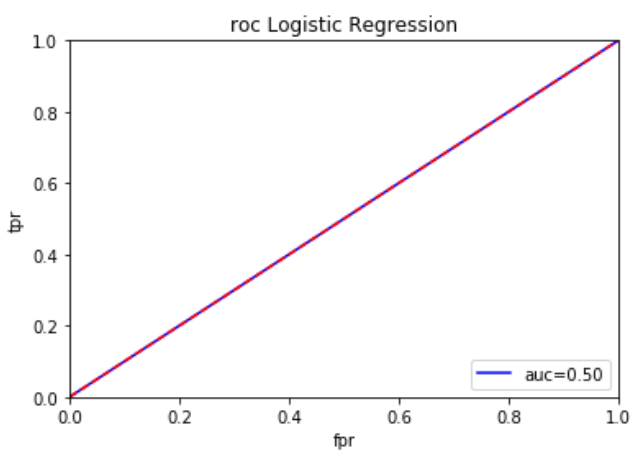
Out[67]:
```
0.7073170731707317
```

In [68]:
```
# roc auc
import sklearn.metrics as metrics
fpr_log,tpr_log,thrrshold_log=metrics.roc_curve(y_test,y_pred_log)
roc_auc_log=metrics.auc(fpr_log,tpr_log)
roc_auc_log
```

Out[68]:
```
0.5
```

In [69]:
```
# Visualising roc auc
import matplotlib.pyplot as plt
plt.title('roc Logistic Regression')
plt.plot(fpr_log,tpr_log,'b',label='auc=%0.2f'%roc_auc_log)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('tpr')
plt.xlabel('fpr')
```

Out[69]:
```
Text(0.5, 0, 'fpr')
```



Naive Bayes

In [70]:
```
# Fitting Naive Bayes to the Training set
from sklearn.naive_bayes import GaussianNB
naive = GaussianNB()
naive.fit(X_train, y_train)
```

Out[70]:
```
GaussianNB()
```

In [71]:
```
# Predicting the Test set results
y_pred = naive.predict(X_test)
```

In [72]:
```
y_pred
```

Out[72]:
```
array([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, 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, 1, 1, 1, 1, 1, 1, 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,
       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, 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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 1, 0])
```

In [73]:
```
# Measuring Accuracy
from sklearn.metrics import accuracy_score
print('The accuracy of Naive Bayes is: ', accuracy_score(y_test,y_pred))
```

```
The accuracy of Naive Bayes is:  0.7121951219512195
```

In [74]:
```
# Making confusion matrix
from sklearn.metrics import confusion_matrix
print(confusion_matrix(y_test, y_pred))
```

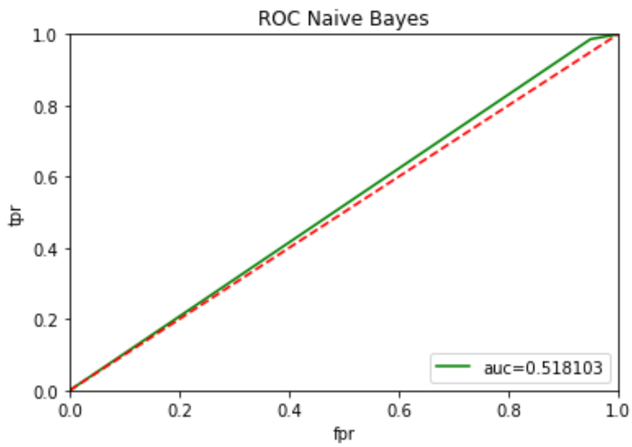
```
[[  3  57]
 [  2 143]]
```

In [75]:
```
import sklearn.metrics as metrics
fpr,tpr,threshold=metrics.roc_curve(y_test,y_pred)
```

In [76]:
```
roc_auc=metrics.auc(fpr,tpr)
```

In [77]:
```
import matplotlib.pyplot as plt
plt.title('ROC Naive Bayes')
plt.plot(fpr,tpr,'g',label='auc=%f'%roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('tpr')
plt.xlabel('fpr')
```

Out[77]: Text(0.5, 0, 'fpr')



Results:

The accuracy of Decision Tree Classifier is: 51.22 % and auc value = 0.56

The accuracy of Random Forest Classification is: 56.1 % and auc value = 0.57

The accuracy of SVM is: 70.7 % and auc value = 0.50

The accuracy of KNN is: 62.9 % and auc value = 0.50

The accuracy of Logistic is: 70.7 % and auc value = 0.50

The accuracy of Naive Bayes is: 71.2 % and auc value = 0.51

Selecting Navie Bayes

Accuracy value is also greater and auc is sufficient in comparison to others

In [81]:
```
import pickle
with open("FinalModel.pkl", "wb") as fid:
    pickle.dump(naive,fid)
```

Done

```
In [ ]:
```