Binary Classifier Project Detail

In machine learning, there are many methods used for binary classification. The most common are:

1.Logistic Regression

2.Naive Bayes

3.Decision Trees

4.Nearest Neighbor

5.Neural Networks

Hence, we'll be using some of these algorithms!

Importing & installing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import GridSearchCV
```

Preparing Data

In [4]:

```
df=pd.read_csv("World_Bank_Projects_downloaded_6_15_2022.csv",encoding =('ISO-8859-1'),low_
```

In [5]:

```
df
```

Out[5]:

	World Bank Projects, data as of 03/29/2022 22:00:01 EST	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Un
0	Project ID	Region	Country	Project Status	Project Name	Project Development Objective	Imp
1	id	regionname	countryname	projectstatusdisplay	project_name	pdo	ir
2	P169983	Africa East	Republic of Angola	Active	Third Angola Growth and Inclusion Development ...	The development objective is to support the Go...	I F the
3	P173711	Africa East	Republic of Madagascar	Active	Connecting Madagascar for Inclusive Growth	The Project Development Objective is to improv...	Roa
4	P175747	Middle East and North Africa	Kingdom of Morocco	Active	Resilient and Sustainable Water in Agriculture	The project development objectives (PDO) are t...	I Ag Dire
...	...	...	...	...	...	...	
21484	P006578	Latin America and Caribbean	Republic of Chile	Closed	Power and Irrigation Project	NaN	
21485	P037451	Europe and Central Asia	Grand Duchy of Luxembourg	Closed	Steel Mill and Railway Project	NaN	
21486	P037362	Europe and Central Asia	Kingdom of Denmark	Closed	Post War Reconstruction Project	NaN	
21487	P037452	Europe and Central Asia	Kingdom of the Netherlands	Closed	Post-war Reconstruction Project	NaN	
21488	P037383	Europe and Central Asia	French Republic	Closed	Reconstruction Project	NaN	

21489 rows × 26 columns

In [7]:

```
df.head(5)
```

Out[7]:

	World Bank Projects, data as of 03/29/2022 22:00:01 EST	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamec
0	Project ID	Region	Country	Project Status	Project Name	Project Development Objective	Implement Agei
1	id	regionname	countryname	projectstatusdisplay	project_name	pdo	impagei
2	P169983	Africa East	Republic of Angola	Active	Third Angola Growth and Inclusion Development ...	The development objective is to support the Go...	Ministry Finance the Repu of Ang
3	P173711	Africa East	Republic of Madagascar	Active	Connecting Madagascar for Inclusive Growth	The Project Development Objective is to improv...	Road Agei
4	P175747	Middle East and North Africa	Kingdom of Morocco	Active	Resilient and Sustainable Water in Agriculture	The project development objectives (PDO) are t...	Ministry Agricultu Directorate Irri

5 rows × 26 columns

In [8]:

```
df = df.rename(columns = {'World Bank Projects, data as of 03/29/2022 22:00:01 EST':'Projec
                          'Unnamed: 1':'Region',
                          'Unnamed: 2':'Country',
                          'Unnamed: 3':'Project Status',
                          'Unnamed: 4':'Project Name',
                          'Unnamed: 5':'Project Development Objective',
                          'Unnamed: 6':'Implementing Agency',
                          'Unnamed: 7':'Consultant Services Required',
                          'Unnamed: 8':'Project URL',
                          'Unnamed: 9':'Board Approval Date',
                           'Grant Amount':'Project Closing Date',
                           'Unnamed: 11':'Financing Type',
                           'Unnamed: 12':'Current Project Cost',
                           'Unnamed: 13':'IBRD Commitment',
                           'Unnamed: 14':'IDA Commitment',
                           'Unnamed: 15':'Total IDA and IBRD Commitment',
                          'Unnamed: 16':'Grant Amount',
                          'Unnamed: 17':'Borrower',
                          'Unnamed: 18':'Lending Instrument',
                          'Unnamed: 19':'Environmental Assessment Category',
                          'Unnamed: 20':'Environmental and Social Risk'})

df = df.drop(['Unnamed: 21','Unnamed: 22','Unnamed: 23','Unnamed: 24','Unnamed: 25'],axis=1
df = df.drop([0,1],axis=0)
df.reset_index(inplace=True)
df = df.drop(['index'],axis=1)
df['Grant Amount'] = df['Grant Amount'].astype(float)
df['Total IDA and IBRD Commitment'] = df['Total IDA and IBRD Commitment'].astype(float)
df['IDA Commitment'] = df['IDA Commitment'].astype(float)
df['IBRD Commitment'] = df['IBRD Commitment'].astype(float)
df['Current Project Cost'] = df['Current Project Cost'].astype(float)
df["Project Status"].replace({'Active':0,'Pipeline':0,'Closed':1, 'Dropped':1 }, inplace=Tr
```

In [10]:

```
df.head(3)
```

Out[10]:

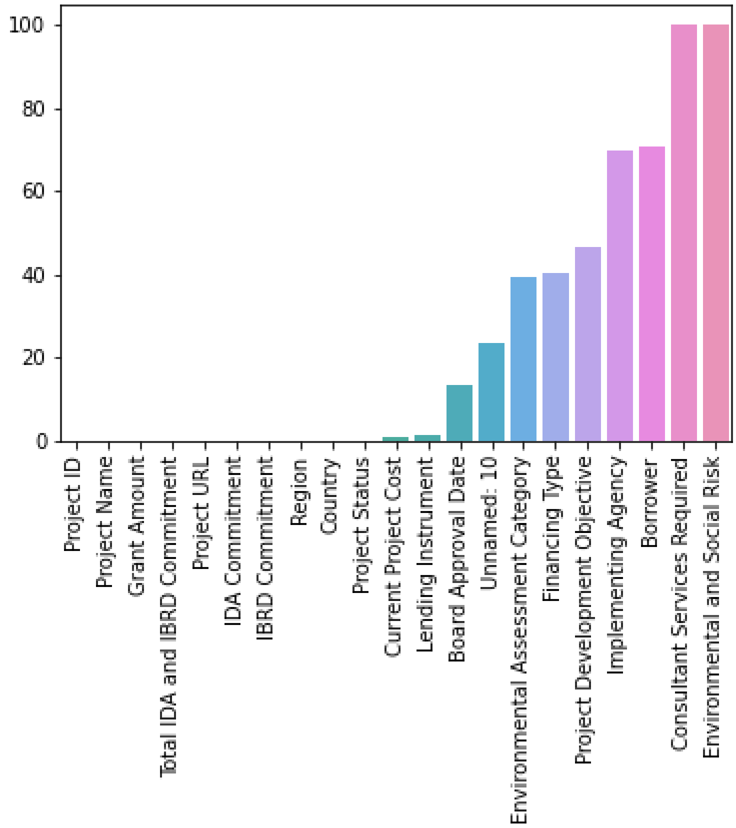
	Project ID	Region	Country	Project Status	Project Name	Project Development Objective	Implementing Agency	Consultant Services Required
0	P169983	Africa East	Republic of Angola	0.0	Third Angola Growth and Inclusion Development ...	The development objective is to support the Go...	Ministry of Finance of the Republic of Angola	NaN
1	P173711	Africa East	Republic of Madagascar	0.0	Connecting Madagascar for Inclusive Growth	The Project Development Objective is to improv...	Road Agency	NaN
2	P175747	Middle East and North Africa	Kingdom of Morocco	0.0	Resilient and Sustainable Water in Agriculture	The project development objectives (PDO) are t...	Ministry of Agriculture - Directorate of Irrig...	NaN

3 rows × 21 columns

Cleaning Data

In [11]:

```
percent_nan = 100* df.isnull().sum() / len(df)
percent_nan = percent_nan.sort_values()

sns.barplot(x=percent_nan.index,y=percent_nan)
plt.xticks(rotation=90);
```



In [12]:

```
df.isnull().sum()
```

Out[12]:

```
Project ID                              0
Region                                  2
Country                                 2
Project Status                          3
Project Name                            0
Project Development Objective        9962
Implementing Agency                 14938
Consultant Services Required        21459
Project URL                             0
Board Approval Date                  2870
Unnamed: 10                          5029
Financing Type                       8611
Current Project Cost                  147
IBRD Commitment                         0
IDA Commitment                          0
Total IDA and IBRD Commitment           0
Grant Amount                            0
Borrower                            15170
Lending Instrument                    248
Environmental Assessment Category    8404
Environmental and Social Risk       21460
dtype: int64
```

In [13]:

```
df = df.drop(['Consultant Services Required','Environmental and Social Risk'],axis=1)
```

Hence, more than 4 columns have 60+ percentage of nan values. We will clean the rest of the columns as per the algorithmic requirements.

Filling nan values in Project Status & Project Development Objective column, which will be our target label & feature.

In [14]:

```
df['Project Status'].value_counts()
```

Out[14]:

```
1.0    17425
0.0     4059
Name: Project Status, dtype: int64
```

In [15]:

```
df['Project Status'] = df['Project Status'].fillna(1)
```

In [16]:

```
data = df[['Project Status','Project Development Objective']]
data.isnull().sum()
data.dropna(axis=0,inplace=True)
```

Training Models

Training and Data

In [17]:

```
X = data['Project Development Objective']
y = data['Project Status']
```

In [18]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)
```

1. Naive Bayes

In [19]:

```
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import MultinomialNB

pipe = Pipeline([('tfidf', TfidfVectorizer()),('svc', LinearSVC()),])
```

In [20]:

```
# Feed the training data through the pipeline
pipe.fit(X_train, y_train)
```

Out[20]:

```
Pipeline(steps=[('tfidf', TfidfVectorizer()), ('svc', LinearSVC())])
```

In [21]:

```
from sklearn.metrics import classification_report,plot_confusion_matrix
preds = pipe.predict(X_test)
print(classification_report(y_test,preds))
```

```
              precision    recall  f1-score   support

         0.0       0.71      0.67      0.69       807
         1.0       0.83      0.86      0.84      1498

    accuracy                           0.79      2305
   macro avg       0.77      0.76      0.77      2305
weighted avg       0.79      0.79      0.79      2305
```

In [22]:

```
from sklearn.metrics import classification_report,plot_confusion_matrix
preds = pipe.predict(X_test)
print(classification_report(y_test,preds))
```

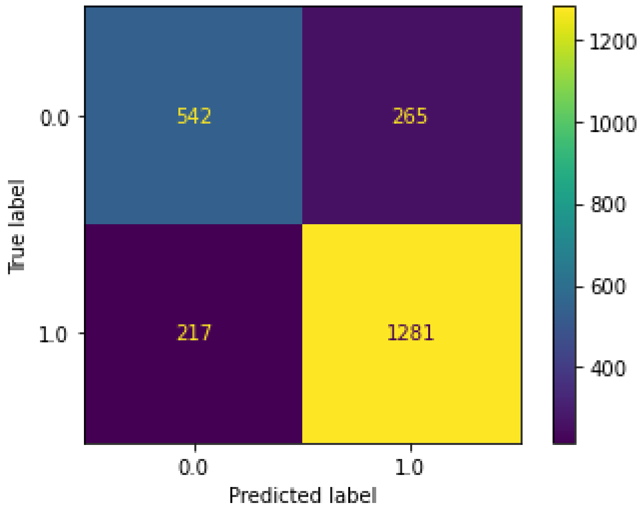
```
              precision    recall  f1-score   support

         0.0       0.71      0.67      0.69       807
         1.0       0.83      0.86      0.84      1498

    accuracy                           0.79      2305
   macro avg       0.77      0.76      0.77      2305
weighted avg       0.79      0.79      0.79      2305
```

In [23]:

```
plot_confusion_matrix(pipe,X_test,y_test)
```

Out[23]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x11696682
370>
```



2. Logistic Regression

In [24]:

```
data2 = df[['Project Status','Region','Country','Current Project Cost','IBRD Commitment','I
data2 = data2.dropna(axis=0)

data2.select_dtypes(include='object')
df_nums = data2.select_dtypes(exclude='object')
df_objs = data2.select_dtypes(include='object')

df_objs = pd.get_dummies(df_objs,drop_first=True)

data2 = pd.concat([df_nums,df_objs],axis=1)
data2 = data2.astype(float)
```

In [27]:

```
X = data2.drop(['Project Status'],axis=1)
y = data2['Project Status']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_X_train = scaler.fit_transform(X_train)
scaled_X_test = scaler.transform(X_test)
```

In [29]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Depending on warnings you may need to adjust max iterations allowed
# Or experiment with different solvers
log_model = LogisticRegression(solver='saga',multi_class="ovr",max_iter=5000)
log_model.fit(X_train,y_train)
```

Out[29]:

```
LogisticRegression(max_iter=5000, multi_class='ovr', solver='saga')
```

GridSearch for Best Hyper-Parameters

Tried GridSearch but it kept showing error. Will try to solve the problem later but the deadline was closing in so I submitted.

Model Performance on Classification Tasks

In [30]:

```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,plot_conf
y_pred = log_model.predict(X_test)
y_pred
```

Out[30]:

```
array([1., 1., 1., ..., 1., 1., 1.])
```

In [31]:

```
accuracy_score(y_test,y_pred)
```

Out[31]:

```
0.8020149953139644
```

In [32]:

```
confusion_matrix(y_test,y_pred)
```

Out[32]:

```
array([[  10,  818],
       [  27, 3413]], dtype=int64)
```

3. AdaBoost

In [33]:

```
data2 = df[['Project Status','Region','Country','Current Project Cost','IBRD Commitment','I
data2 = data2.dropna(axis=0)

data2.select_dtypes(include='object')
df_nums = data2.select_dtypes(exclude='object')
df_objs = data2.select_dtypes(include='object')

df_objs = pd.get_dummies(df_objs,drop_first=True)

data2 = pd.concat([df_nums,df_objs],axis=1)
data2 = data2.astype(float)

X = data2.drop(['Project Status'],axis=1)
y = data2['Project Status']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_X_train = scaler.fit_transform(X_train)
scaled_X_test = scaler.transform(X_test)
```

In [34]:

```
param_grid = {"n_estimators":[40,41],
              'learning_rate':[0.2,0.3]}

from sklearn.ensemble import AdaBoostClassifier

from sklearn.model_selection import GridSearchCV
model = AdaBoostClassifier()

Grad_Boost_model = GridSearchCV(model,param_grid)

Grad_Boost_model.fit(X_train,y_train)
```

Out[34]:

```
GridSearchCV(estimator=AdaBoostClassifier(),
             param_grid={'learning_rate': [0.2, 0.3], 'n_estimators': [40, 4
1]})
```

In [35]:

```
Grad_Boost_model.best_params_
```

Out[35]:

```
{'learning_rate': 0.3, 'n_estimators': 41}
```

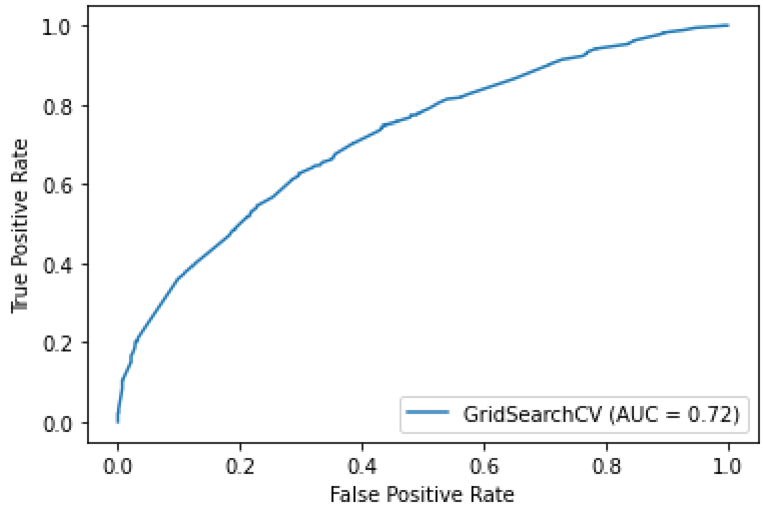
Performance Evaluation

In [36]:

```
from sklearn.metrics import precision_recall_curve,plot_precision_recall_curve,plot_roc_cur
plot_roc_curve(Grad_Boost_model,X_test,y_test)
```

Out[36]:

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x11682665cd0>
```



In [37]:

```
#Ada Boost
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,plot_conf
y_Grad_Boost_model_pred = Grad_Boost_model.predict(X_test)
confusion_matrix(y_test,y_Grad_Boost_model_pred)
```

Out[37]:

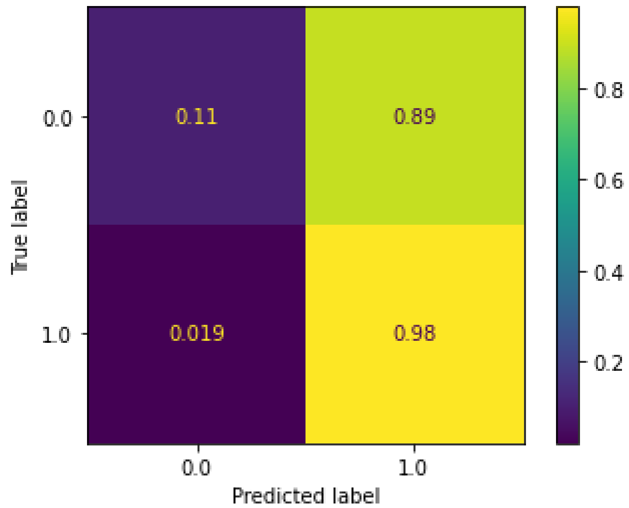
```
array([[  87,   741],
       [  65,  3375]], dtype=int64)
```

In [38]:

```
plot_confusion_matrix(Grad_Boost_model,X_test,y_test,normalize='true')
```

Out[38]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x116956d1
2b0>
```



In [39]:

```
print(classification_report(y_test,y_Grad_Boost_model_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.57      0.11      0.18       828
         1.0       0.82      0.98      0.89      3440

    accuracy                           0.81      4268
   macro avg       0.70      0.54      0.54      4268
weighted avg       0.77      0.81      0.75      4268
```

Concluding the models

1. Logistic Regression

In [40]:

```
b = np.array(X_test.iloc[953])
(log_model.predict_proba([b])[0][0]) * 100
```

Out[40]:

```
49.678632795139
```

In [41]:

```
def predict(Val):
    a = np.round(((log_model.predict_proba([Val])[0][0]) * 100),3)
    print('Chances of Cancellation are:',a,'%')
```

In [42]:

```
predict(np.array(X_test.iloc[953]))
```

```
Chances of Cancellation are: 49.679 %
```

2. AdaBoost

In [43]:

```
d = np.array(X_test.iloc[953])
(Grad_Boost_model.predict_proba([d])[0][0]) * 100
```

Out[43]:

```
45.712074653804734
```

In [44]:

```
def predict(Val):
    d = np.round(((Grad_Boost_model.predict_proba([Val])[0][0]) * 100),3)
    print('Chances of Cancellation are:',d,'%')
```

In [45]:

```
predict(np.array(X_test.iloc[953]))
```

```
Chances of Cancellation are: 45.712 %
```

Hence, we can predict the probability whether a project will be “closed” or “canceled/distressed”.