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PROJECT-HOUSE LOAN DATA ANALYSIS

OBJECTIVE-

Create a model that predicts whether or not an applicant will be able to repay a loan using historical data.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#Load the dataset
df=pd.read_csv("loan_data1.csv")
df.head()
```

Out[2]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	...	FLAG_DOCUMEN
0	100002	1	Cash loans	M	N	Y	0	202500.0	406597.5	24700.5	...	
1	100003	0	Cash loans	F	N	N	0	270000.0	1293502.5	35698.5	...	
2	100004	0	Revolving loans	M	Y	Y	0	67500.0	135000.0	6750.0	...	
3	100006	0	Cash loans	F	N	Y	0	135000.0	312682.5	29686.5	...	
4	100007	0	Cash loans	M	N	Y	0	121500.0	513000.0	21865.5	...	

5 rows × 122 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

In [4]:
```
df.describe()
```

Out[4]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	...
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	307499.000000	3.072330e+05	307511.000000	307511.000000	307511.000000	...
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	27108.573909	5.383962e+05	0.020868	-16036.995067	63815.045904	...
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	14493.737315	3.694465e+05	0.013831	4363.988632	141275.766519	...
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.500000	4.050000e+04	0.000290	-25229.000000	-17912.000000	...
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16524.000000	2.385000e+05	0.010006	-19682.000000	-2760.000000	...
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	24903.000000	4.500000e+05	0.018850	-15750.000000	-1213.000000	...
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596.000000	6.795000e+05	0.028663	-12413.000000	-289.000000	...
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	258025.500000	4.050000e+06	0.072508	-7489.000000	365243.000000	...

8 rows × 106 columns

In [5]:
```
#Check for null values in the dataset
df.isna().sum()
```

Out[5]:
```
SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                              ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 122, dtype: int64
```

In [6]:
```
df.head()
```

Out[6]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	...	FLAG_DOCUMEN
0	100002	1	Cash loans	M	N	Y	0	202500.0	406597.5	24700.5	...	
1	100003	0	Cash loans	F	N	N	0	270000.0	1293502.5	35698.5	...	
2	100004	0	Revolving loans	M	Y	Y	0	67500.0	135000.0	6750.0	...	
3	100006	0	Cash loans	F	N	Y	0	135000.0	312682.5	29686.5	...	
4	100007	0	Cash loans	M	N	Y	0	121500.0	513000.0	21865.5	...	

5 rows × 122 columns

Print percentage of default to payer of the dataset for the TARGET column

In [7]:
```
defaulters=(df["TARGET"]==1).sum()
payers=(df["TARGET"]==0).sum()
defaulter_percent=(defaulters/payers)*100
print("Percentage of default to payer is ",defaulter_percent)
```

```
Percentage of default to payer is  8.781828601345662
```

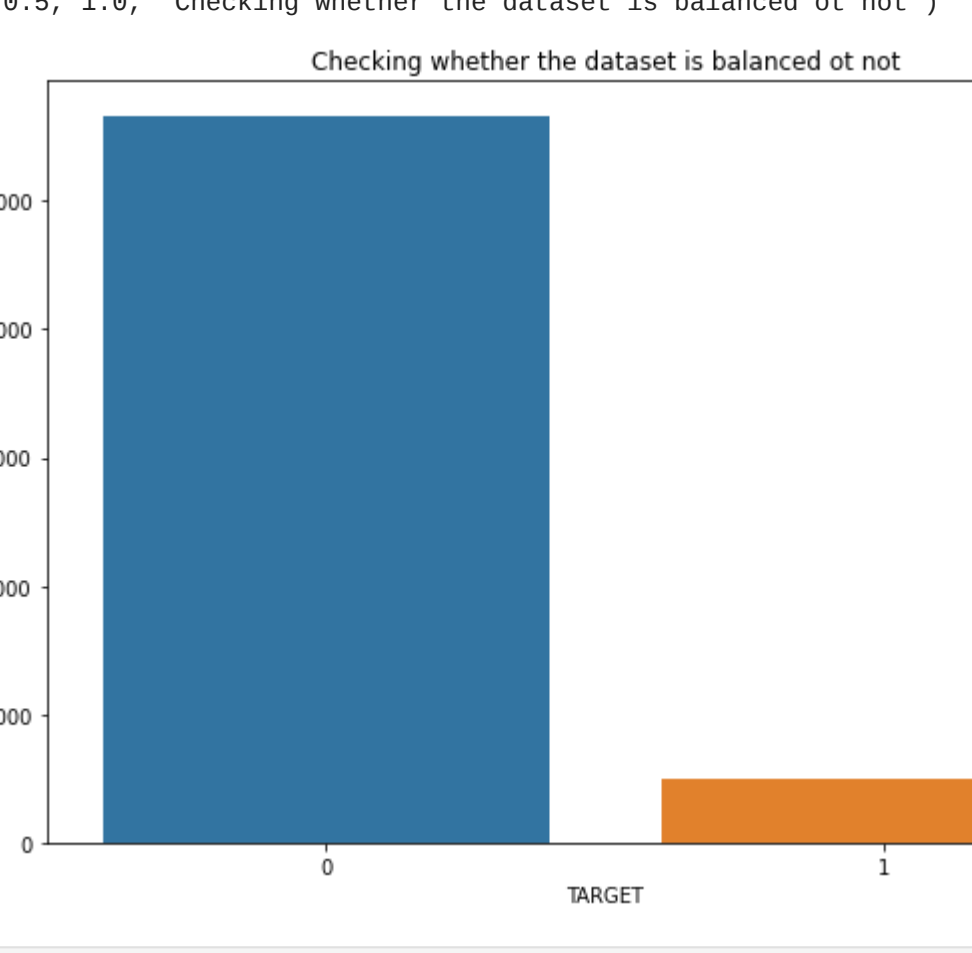
Balance the dataset if the data is imbalanced

In [8]:
```
df["TARGET"].value_counts()
```

Out[8]:
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

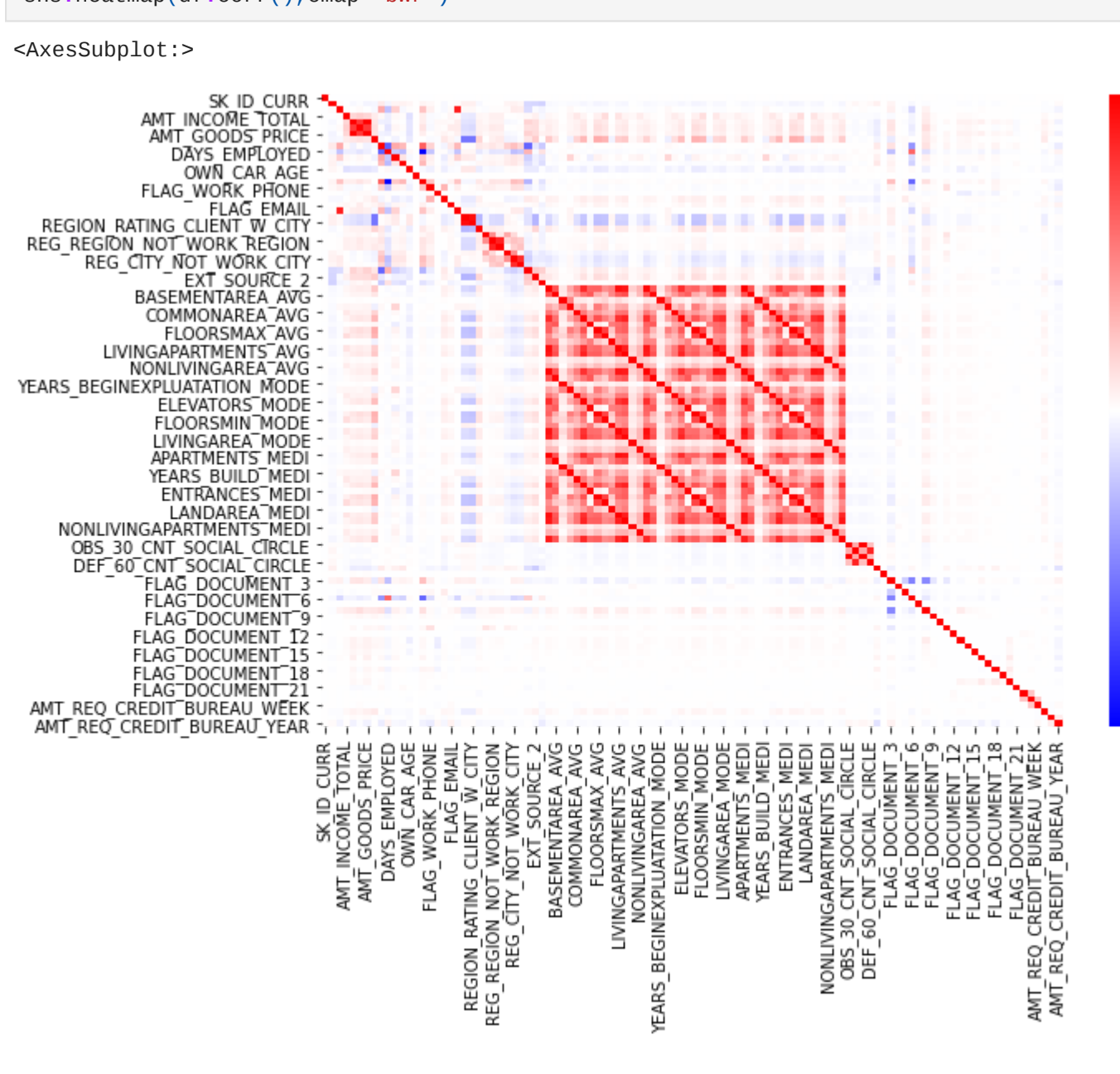
In [9]:
```
plt.figure(figsize=(10,7))
sns.countplot(df["TARGET"])
plt.title("Checking whether the dataset is balanced ot not")
```

Out[9]:
```
Text(0.5, 1.0, 'Checking whether the dataset is balanced ot not')
```



In [10]:
```
plt.figure(figsize=(10,7))
sns.heatmap(df.corr(),cmap="bwr")
```

Out[10]:
```
<AxesSubplot:>
```

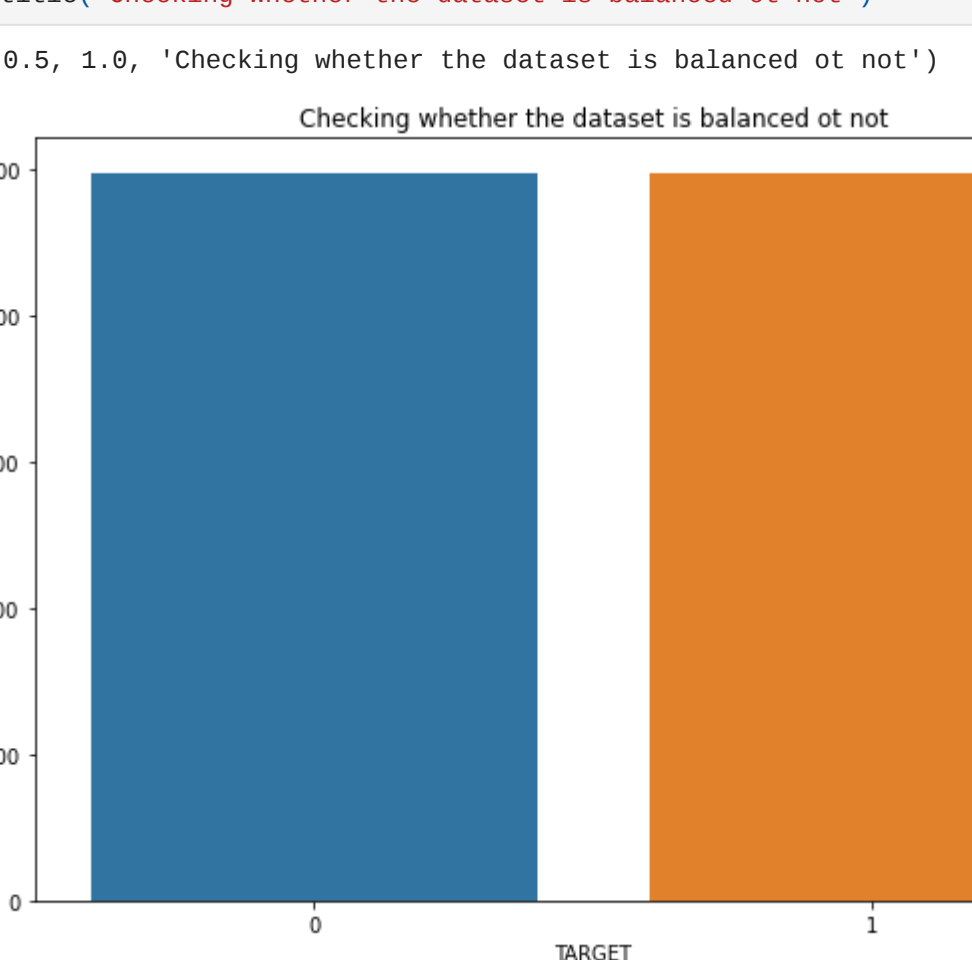


Balance the dataset using under-fitting random sampling

In [11]:
```
shuffled_df=df.sample(frac=1,random_state=25)
fraud_df=shuffled_df[shuffled_df["TARGET"]==1]
nonfraud_df=shuffled_df[shuffled_df["TARGET"]==0].sample(n=24825,random_state=25)
balanced_df=pd.concat([fraud_df,nonfraud_df])
```

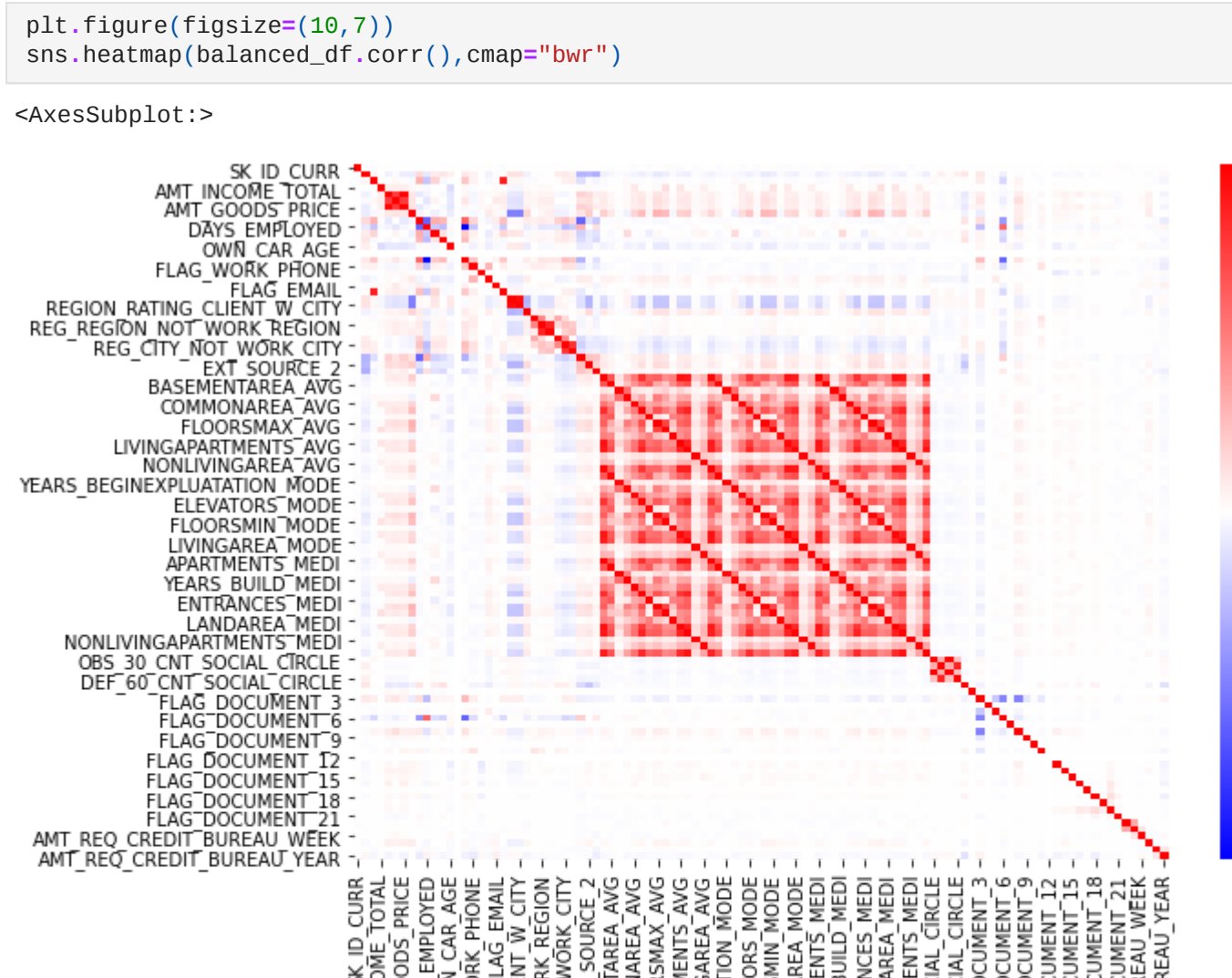
In [12]:
```
plt.figure(figsize=(10,7))
sns.countplot(balanced_df["TARGET"])
plt.title("Checking whether the dataset is balanced ot not")
```

Out[12]:
```
Text(0.5, 1.0, 'Checking whether the dataset is balanced ot not')
```



In [13]:
```
plt.figure(figsize=(10,7))
sns.heatmap(balanced_df.corr(),cmap="bwr")
```

Out[13]:
```
<AxesSubplot:>
```



In [14]:
```
balanced_df.head()
```

Out[14]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	...	FLAG_DOC
122136	241602	1	Cash loans	F	N	Y	0	66600.0	808650.0	31464.0	...	
32365	137520	1	Cash loans	M	Y	Y	0	135000.0	512064.0	25033.5	...	
95288	210632	1	Cash loans	M	Y	N	0	180000.0	1078200.0	31522.5	...	
243096	381398	1	Cash loans	F	Y	Y	1	117000.0	539100.0	27652.5	...	
61628	171473	1	Cash loans	M	N	Y	0	180000.0	900000.0	57649.5	...	

5 rows × 122 columns

In [15]:
```
balanced_df.describe(include="object")
```

Out[15]:

	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	NAME_TYPE_SUITE	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSIN
count	49650	49650	49650	49650	49470	49650	49650	49650	
unique	2	2	2	2	7	6	5	5	
top	Cash loans	F	N	Y	Unaccompanied	Working	Secondary / secondary special	Married	House / a
freq	45558	30740	33534	34232	40400	27857	36986	30843	

In [16]:
```
balanced_df.drop(columns=(["WEEKDAY_APPR_PROCESS_START","FLAG_OWN_REALTY","NAME_TYPE_SUITE","FONDKAPREMONT_MODE","EMERGENCYSTATE_MODE"]),inplace=True)
balanced_df.describe(include="object")
```

Out[16]:

	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	OCCUPATION_TYPE	ORGANIZATI
count	49650	49650	49650	49650	49650	49650	49650	35402	
unique	2	2	2	6	5	5	6	18	
top	Cash loans	F	N	Working	Secondary / secondary special	Married	House / apartment	Laborers	Business En
freq	45558	30740	33534	27857	36986	30843	43361	10110	

Encode the columns that is required for the model

In [17]:
```
from sklearn.preprocessing import LabelEncoder
```

In [18]:
```
le=LabelEncoder()
balanced_df["NAME_CONTRACT_TYPE"]=le.fit_transform(balanced_df["NAME_CONTRACT_TYPE"])
balanced_df["CODE_GENDER"]=le.fit_transform(balanced_df["CODE_GENDER"])
balanced_df["FLAG_OWN_CAR"]=le.fit_transform(balanced_df["FLAG_OWN_CAR"])
balanced_df["NAME_INCOME_TYPE"]=le.fit_transform(balanced_df["NAME_INCOME_TYPE"])
balanced_df["NAME_EDUCATION_TYPE"]=le.fit_transform(balanced_df["NAME_EDUCATION_TYPE"])
balanced_df["NAME_FAMILY_STATUS"]=le.fit_transform(balanced_df["NAME_FAMILY_STATUS"])
balanced_df["NAME_HOUSING_TYPE"]=le.fit_transform(balanced_df["NAME_HOUSING_TYPE"])
balanced_df["OCCUPATION_TYPE"]=le.fit_transform(balanced_df["OCCUPATION_TYPE"])
balanced_df["ORGANIZATION_TYPE"]=le.fit_transform(balanced_df["ORGANIZATION_TYPE"])
balanced_df["HOUSETYPE_MODE"]=le.fit_transform(balanced_df["HOUSETYPE_MODE"])
balanced_df["NAME_CONTRACT_TYPE"]=le.fit_transform(balanced_df["NAME_CONTRACT_TYPE"])
balanced_df["WALLSMATERIAL_MODE"]=le.fit_transform(balanced_df["WALLSMATERIAL_MODE"])
```

In [19]:
```
balanced_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 49650 entries, 122136 to 68357
Columns: 117 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(10), int64(42)
memory usage: 43.8 MB
```

In [20]:
```
balanced_df.head()
```

Out[20]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	...	FLAG_DOC
122136	241602	1	0	0	0	0	66600.0	808650.0	31464.0	675000.0	...	
32365	137520	1	0	1	1	0	135000.0	512064.0	25033.5	360000.0	...	
95288	210632	1	0	1	1	0	180000.0	1078200.0	31522.5	900000.0	...	
243096	381398	1	0	0	1	1	117000.0	539100.0	27652.5	450000.0	...	
61628	171473	1	0	1	0	0	180000.0	900000.0	57649.5	900000.0	...	

5 rows × 117 columns

In [21]:
```
x=balanced_df.drop(["TARGET"],axis=1)
y=balanced_df[["TARGET"]]
```

In [22]:
```
x.head()
```

Out[22]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	NAME_INCOME_TYPE	...
122136	241602	0	0	0	0	66600.0	808650.0	31464.0	675000.0	2	...
32365	137520	0	1	1	0	135000.0	512064.0	25033.5	360000.0	0	...
95288	210632	0	1	1	0	180000.0	1078200.0	31522.5	900000.0	5	...
243096	381398	0	0	1	1	117000.0	539100.0	27652.5	450000.0	5	...
61628	171473	0	1	0	0	180000.0	900000.0	57649.5	900000.0	5	...

5 rows × 116 columns

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

Out[23]:

	TARGET
122136	1
32365	1
95288	1
243096	1
61628	1

In [24]:
```
from sklearn.model_selection import train_test_split
```

In [25]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=25)
```

In [26]:
```
x_train.shape,x_test.shape
```

Out[26]:
```
((37237, 116), (12413, 116))
```

In [27]:
```
y_train.shape,y_test.shape
```

Out[27]:
```
((37237, 1), (12413, 1))
```

In [28]:
```
from sklearn.preprocessing import StandardScaler
```

In [29]:
```
scaler=StandardScaler()
x_train=scaler.fit_transform(x_train)
x_test=scaler.transform(x_test)
```

Architect the Deep learning Model

In [30]:
```
import tensorflow as tf
```

In [31]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout
```

In [32]:
```
model=Sequential()
model.add(Dense(256,activation="relu",input_shape=(x_train.shape[1],)))
model.add(Dropout(0.3))
model.add(Dense(128,activation="relu"))
model.add(Dropout(0.3))
model.add(Dense(64,activation="relu"))
model.add(Dropout(0.3))
model.add(Dense(1,activation="sigmoid"))
```

In [33]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 256)               29952

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 dropout_1 (Dropout)         (None, 128)               0

 dense_2 (Dense)             (None, 64)                8256

 dropout_2 (Dropout)         (None, 64)                0

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 71,169
Trainable params: 71,169
Non-trainable params: 0
_________________________________________________________________
```

In [34]:
```
model.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
```

In [35]:
```
model.fit(x_train,y_train,validation_data=(x_test,y_test),epochs=100)
```

```
Epoch 1/100
1164/1164 [==============================] - 7s 5ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 2/100
1164/1164 [==============================] - 6s 5ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 3/100
1164/1164 [==============================] - 6s 5ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 4/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 5/100
1164/1164 [==============================] - 5s 5ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 6/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 7/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 8/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 9/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 10/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 11/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 12/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 13/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 14/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 15/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 16/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 17/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 18/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 19/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 20/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 21/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 22/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 23/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 24/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 25/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 26/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 27/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 28/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 29/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 30/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 31/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 32/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 33/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 34/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 35/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 36/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 37/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 38/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 39/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 40/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 41/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 42/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 43/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 44/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 45/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 46/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 47/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 48/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 49/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 50/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 51/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 52/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 53/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 54/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 55/100
1164/1164 [==============================] - 4s 3ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 56/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 57/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 58/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 59/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 60/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 61/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 62/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 63/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 64/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 65/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 66/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 67/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 68/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 69/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 70/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 71/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 72/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 73/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 74/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 75/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 76/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 77/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 78/100
1164/1164 [==============================] - 5s 5ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 79/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 80/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 81/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 82/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 83/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 84/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 85/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 86/100
1164/1164 [==============================] - 5s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 87/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 88/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 89/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 90/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 91/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 92/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 93/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 94/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 95/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 96/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 97/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 98/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 99/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
Epoch 100/100
1164/1164 [==============================] - 4s 4ms/step - loss: nan - accuracy: 0.5005 - val_loss: nan - val_accuracy: 0.4984
```

Out[35]:
```
<keras.callbacks.History at 0x29c504b2fa0>
```

In [36]:
```
pred=(model.predict(x_test)>0.5)*1.0
pred
```

Out[36]:
```
array([[0.],
       [0.],
       [0.],
       ...,
       [0.],
       [0.],
       [0.]])
```

In [37]:
```
from sklearn.metrics import confusion_matrix,classification_report
```

In [38]:
```
print(confusion_matrix(pred,y_test))
```

```
[[6187 6226]
 [   0    0]]
```

In [39]:
```
print(classification_report(pred,y_test))
```

```
              precision    recall  f1-score   support

         0.0       1.00      0.50      0.67     12413
         1.0       0.00      0.00      0.00         0

    accuracy                           0.50     12413
   macro avg       0.50      0.25      0.33     12413
weighted avg       1.00      0.50      0.67     12413
```

Calculate Sensitivity as a metrics

Sensitivity=TP/(FN+TP)

Specificity=TN/(FP+TN)

In [40]:
```
print("Sensitivity of the dataset is",6187/(0+6187))
```

```
Sensitivity of the dataset is 1.0
```

Calculate area under receiver operating characteristics curve

In [41]:
```
from sklearn.metrics import roc_curve
```

In [42]:
```
fpr,tpr,thresholds=roc_curve(pred,y_test)
print(fpr)
print("\n")
print(tpr)
print("\n")
print(thresholds)
```

```
[0.         0.50157093 1.        ]


[nan nan nan]


[2 1 0]
```

THANK YOU...!!!