House Loan Data Analysis

```
# import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from imblearn.over_sampling import SMOTE
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score, confusion_matrix,
precision_recall_curve, roc_curve, auc, average_precision_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping

import warnings
warnings.filterwarnings('ignore')
```

Load the dataset that is given to you

```
loan_df = pd.read_csv('loan_data.csv')
loan_df.head()
```

```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT
AMT_ANNUITY  \
0               Y             0          202500.0    406597.5
24700.5
1               N             0          270000.0   1293502.5
35698.5
2               Y             0           67500.0    135000.0
6750.0
3               Y             0          135000.0    312682.5
29686.5
4               Y             0          121500.0    513000.0
21865.5

   ...  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
```

```
0  ...                 0                 0                 0
0
1  ...                 0                 0                 0
0
2  ...                 0                 0                 0
0
3  ...                 0                 0                 0
0
4  ...                 0                 0                 0
0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                        0.0
1                        0.0                        0.0
2                        0.0                        0.0
3                        NaN                        NaN
4                        0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]
```

```
loan_df.shape
```

```
(307511, 122)
```

Check for null values in the dataset

```
nan_counts = loan_df.isna().sum()
nan_counts[nan_counts > 0].size
```

```
67
```

There are 67 columns with NaN values.

```
nan_cols = nan_counts[nan_counts > 0].index.tolist()
```

```
loan_df[nan_cols].dtypes.unique()
```

```
array([dtype('float64'), dtype('O')], dtype=object)
```

```
for col in nan_cols:
    if loan_df[col].dtype == 'float64':
        val = loan_df[col].median()
    elif loan_df[col].dtype == 'O':
        val = loan_df[col].mode()[0]

    loan_df[col] = loan_df[col].fillna(val)
```

```
loan_df.isna().sum().sum()
```

```
0
```

Now all NaN values got resolved.

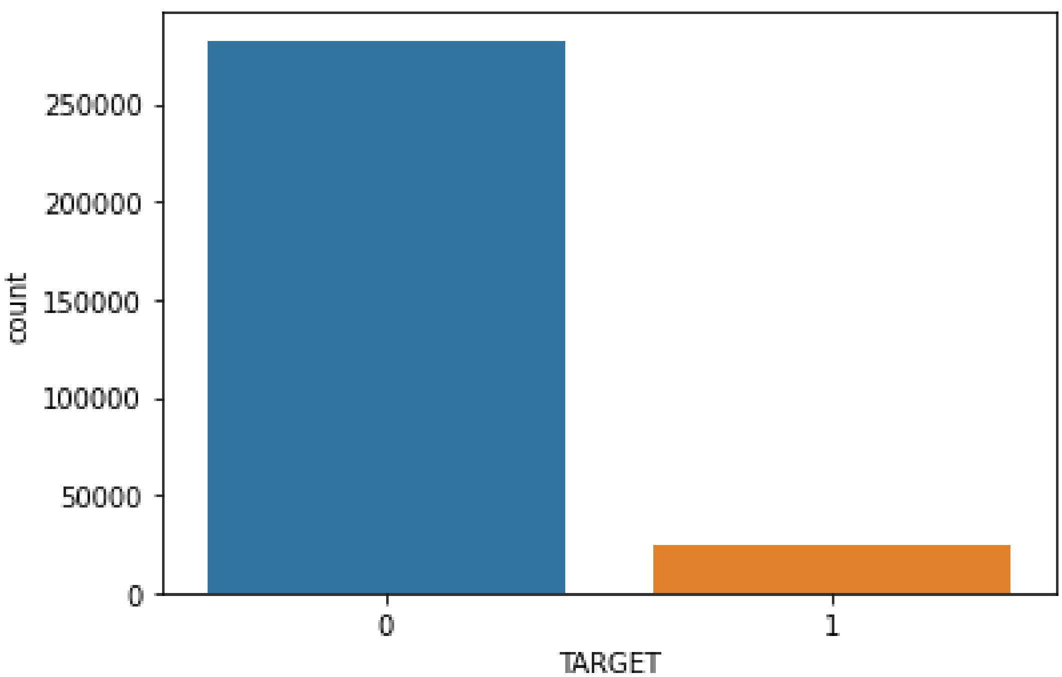
Print percentage of default to payer of the dataset for the TARGET column

```
loan_df['TARGET'].value_counts() / loan_df['TARGET'].size * 100
```

```
0    91.927118
1     8.072882
Name: TARGET, dtype: float64
```

So we have 92% data with target label as 0 and 8% as 1.

```
sns.countplot(loan_df['TARGET'])
plt.show()
```

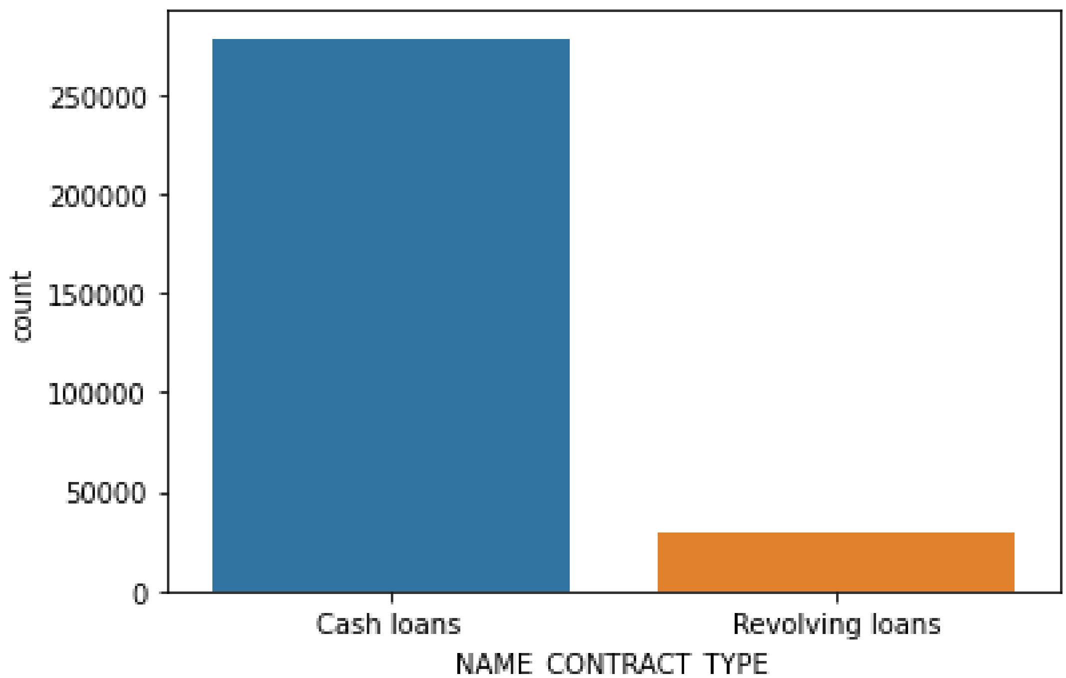


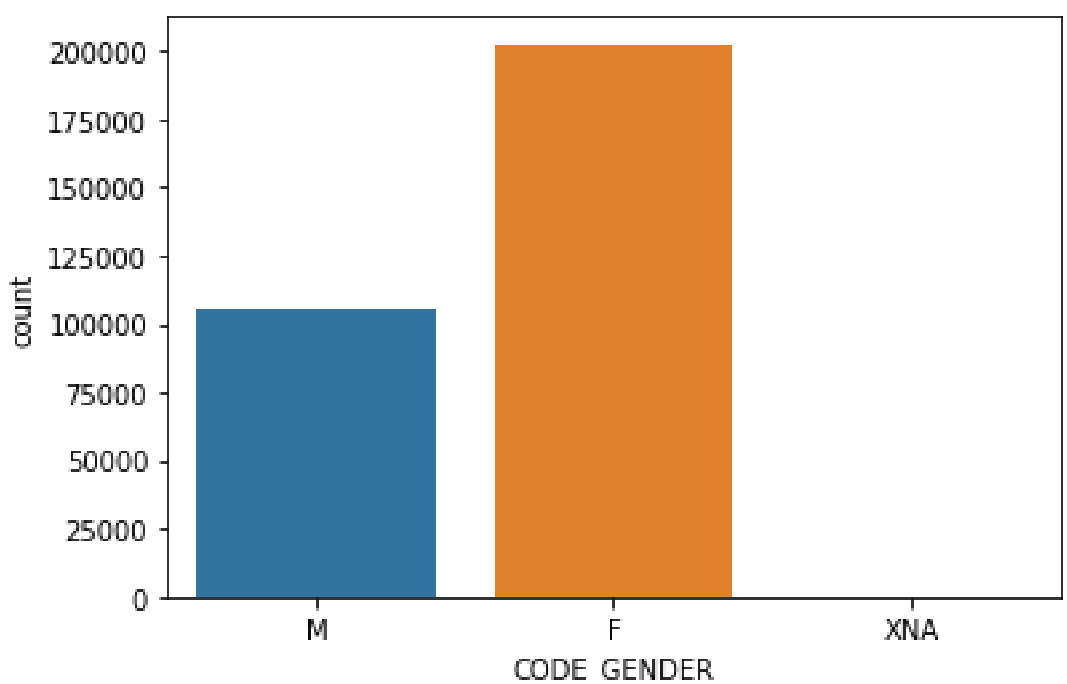
Lets extract the categorical values.

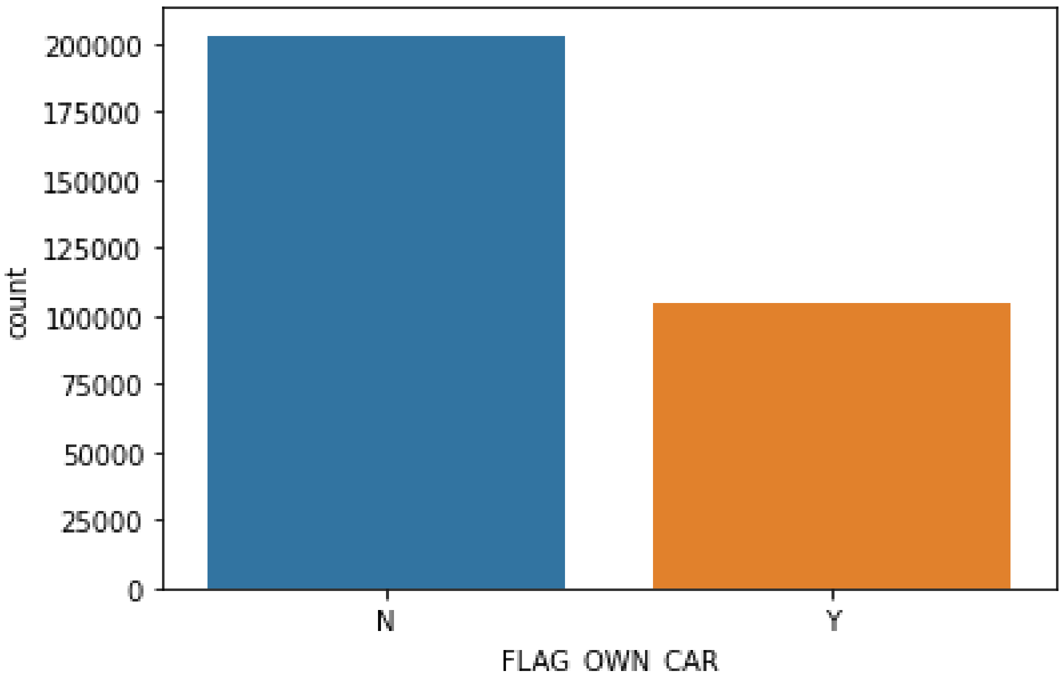
```
cat_cols = loan_df.columns[loan_df.dtypes == 'O']
len(cat_cols)
```

16

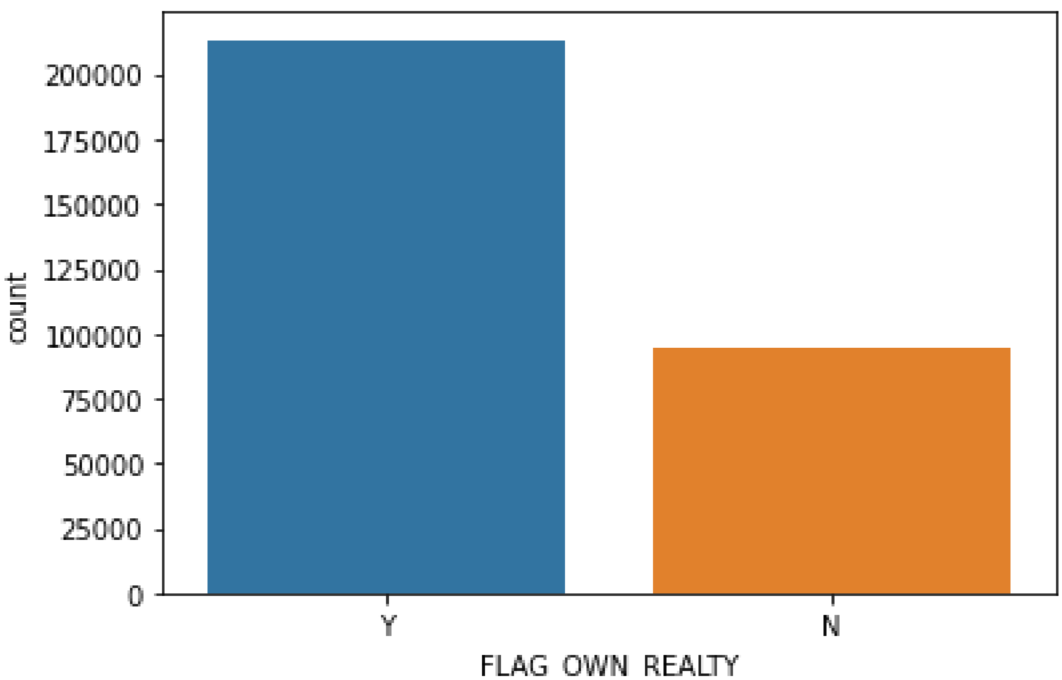
```
for col in cat_cols[:5]:
    sns.countplot(loan_df[col])
    plt.show()
```



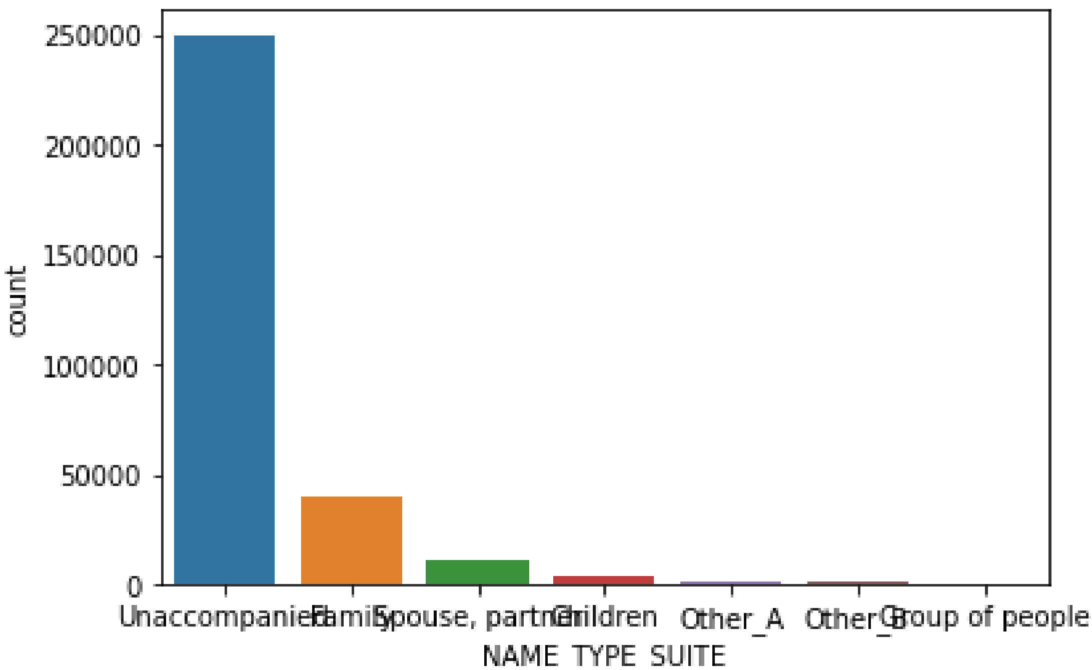




count
200000
175000
150000
125000
100000
75000
50000
25000
0
N
Y
FLAG_OWN_CAR



count
200000
175000
150000
125000
100000
75000
50000
25000
0
Y
N
FLAG_OWN_REALTY



Encode the columns that is required for the model

```
loan_df_en = pd.get_dummies(loan_df, columns = cat_cols,
drop_first=True)
```

```
loan_df_en.shape
```

```
(307511, 230)
```

Balance the dataset if the data is imbalanced

```
x = loan_df_en.drop(['TARGET'], axis=1)
y = loan_df_en['TARGET']

x_train, x_test, y_train, y_test = train_test_split(x, y,
random_state=0)
```

```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(230633, 229)
(76878, 229)
(230633,)
(76878,)
```

```
print('Before balancing, train 1:', sum(y_train == 1))
print('Before balancing, train 0:', sum(y_train == 0))
```

```
Before balancing, train 1: 18734
Before balancing, train 0: 211899
```

```
sm = SMOTE(random_state=0)

x_train_blc, y_train_blc = sm.fit_resample(x_train, y_train)

print('After balancing, train 1:', sum(y_train_blc == 1))
print('After balancing, train 0:', sum(y_train_blc == 0))
```

```
After balancing, train 1: 211899
After balancing, train 0: 211899
```

```
y_train_blc.shape
```

```
(423798,)
```

Plot the balanced data or imbalanced data

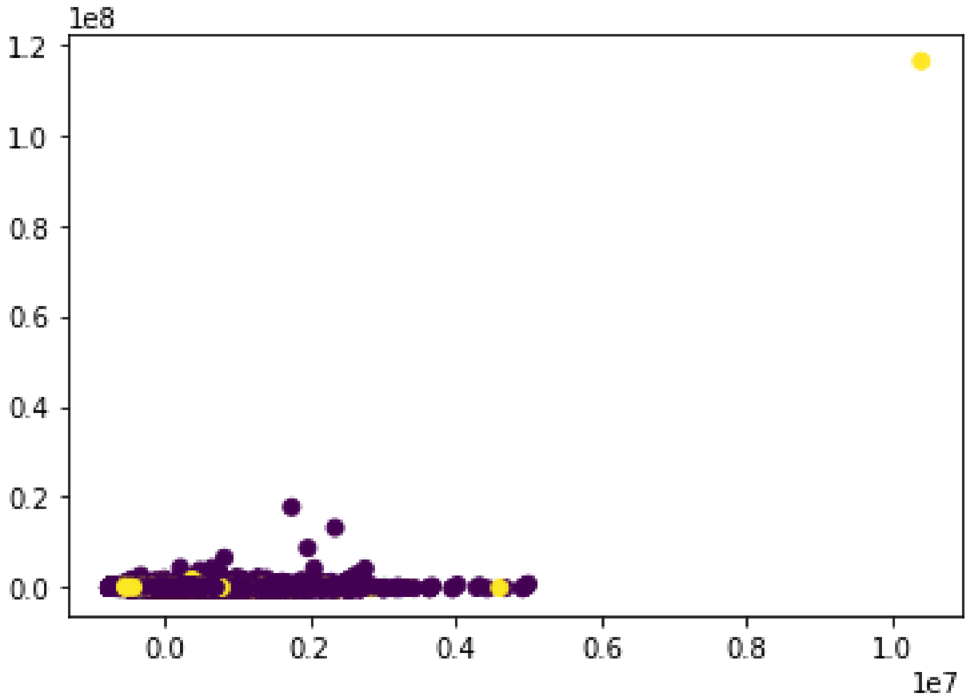
Lets plot x_train and x_train_blc. Now we have 229 dimension.

So we can use PCA to get 2D data and can plot it.

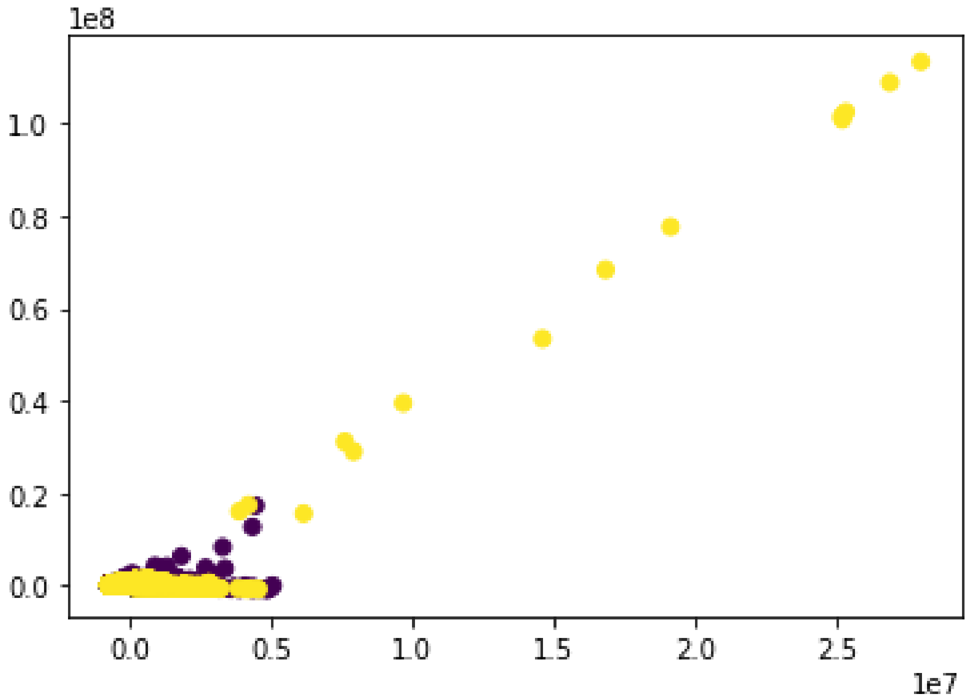
```
pca = PCA(n_components= 2)
x_train_pca = pca.fit_transform(x_train)
x_train_blc_pca = pca.fit_transform(x_train_blc)

print(x_train_pca.shape)
print(x_train_blc_pca.shape)
```

```
(230633, 2)
(423798, 2)
```

```
plt.scatter(x_train_pca[:, 0], x_train_pca[:, 1], c= y_train)
plt.show()
```




```
plt.scatter(x_train_blc_pca[:, 0], x_train_blc_pca[:, 1], c=
y_train_blc)
plt.show()
```



Lets find out the important features based on correlation with Target.

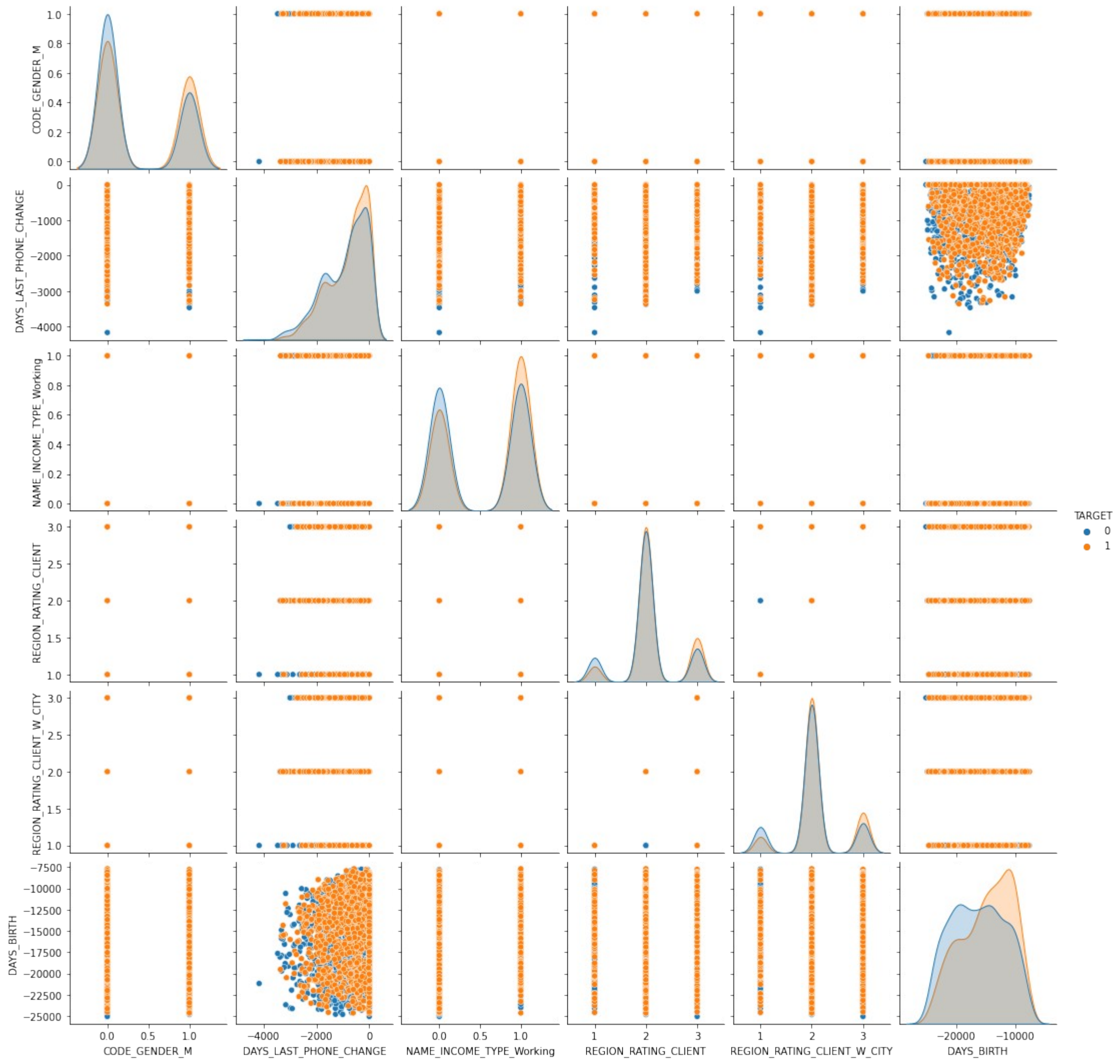
```
col_idx = np.argsort(loan_df_en.corr()['TARGET'])[-7:-1]
corr_cols = loan_df_en.columns[col_idx].tolist()
corr_cols
```

```
['CODE_GENDER_M',
 'DAYS_LAST_PHONE_CHANGE',
 'NAME_INCOME_TYPE_Working',
 'REGION_RATING_CLIENT',
 'REGION_RATING_CLIENT_W_CITY',
 'DAYS_BIRTH']
```

```
vals = x_train_blc.loc[:, corr_cols]
vals['TARGET'] = y_train_blc
vals1 = vals[vals['TARGET'] == 0][:1000]
vals2 = vals[vals['TARGET'] == 1][:1000]

vals = pd.concat([vals1, vals2])
vals.shape
```

```
(2000, 7)
```

```
sns.pairplot(vals, hue= 'TARGET')
plt.show()
```




```
# Standardize data
sc = StandardScaler()
x_train_blc = sc.fit_transform(x_train_blc)
x_test = sc.transform(x_test)
```

Create DL model

```
model = Sequential()
model.add(Dense(128, activation= 'tanh', input_shape=(229,),
kernel_initializer='he_normal', kernel_regularizer='L2'))
model.add(BatchNormalization())
model.add(Dense(64, activation= 'relu',
kernel_initializer='he_normal', kernel_regularizer='L2'))
model.add(BatchNormalization())
model.add(Dense(32, activation= 'relu',
kernel_initializer='he_normal', kernel_regularizer='L2'))
model.add(BatchNormalization())
model.add(Dense(1, activation= 'sigmoid'))

model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_8 (Dense)             (None, 128)               29440     
                                                                 
 batch_normalization_6 (Batc  (None, 128)              512       
 hNormalization)                                                 
                                                                 
 dense_9 (Dense)             (None, 64)                8256      
                                                                 
 batch_normalization_7 (Batc  (None, 64)               256       
 hNormalization)                                                 
                                                                 
 dense_10 (Dense)            (None, 32)                2080      
                                                                 
 batch_normalization_8 (Batc  (None, 32)               128       
 hNormalization)                                                 
                                                                 
 dense_11 (Dense)            (None, 1)                 33        
                                                                 
=================================================================
Total params: 40,705
Trainable params: 40,257
Non-trainable params: 448
_________________________________________________________________
```

Calculate Sensitivity as a metrice

```
model.compile(optimizer='adam',
loss=tf.keras.losses.binary_crossentropy,
metrics=[tf.keras.metrics.AUC()])

callback = EarlyStopping(monitor='val_loss', patience=3)

history = model.fit(
    x_train_blc, y_train_blc,
    validation_data=(x_test, y_test),
    batch_size= 50,
    epochs= 20,
    verbose=1,
    callbacks=[callback]
)
```

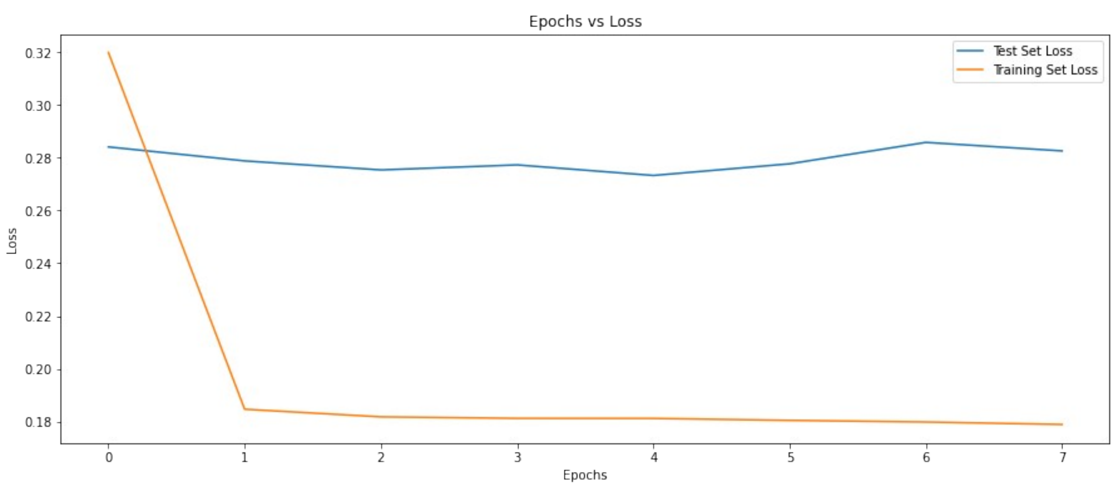
```
Epoch 1/20
8476/8476 [==============================] - 32s 4ms/step - loss:
0.3198 - auc_2: 0.9640 - val_loss: 0.2840 - val_auc_2: 0.7020
Epoch 2/20
8476/8476 [==============================] - 29s 3ms/step - loss:
0.1847 - auc_2: 0.9691 - val_loss: 0.2787 - val_auc_2: 0.7073
Epoch 3/20
8476/8476 [==============================] - 30s 4ms/step - loss:
```

```
0.1818 - auc_2: 0.9692 - val_loss: 0.2753 - val_auc_2: 0.7137
Epoch 4/20
8476/8476 [==============================] - 30s 3ms/step - loss:
0.1813 - auc_2: 0.9692 - val_loss: 0.2772 - val_auc_2: 0.7073
Epoch 5/20
8476/8476 [==============================] - 28s 3ms/step - loss:
0.1812 - auc_2: 0.9691 - val_loss: 0.2732 - val_auc_2: 0.7111
Epoch 6/20
8476/8476 [==============================] - 28s 3ms/step - loss:
0.1805 - auc_2: 0.9694 - val_loss: 0.2776 - val_auc_2: 0.7134
Epoch 7/20
8476/8476 [==============================] - 27s 3ms/step - loss:
0.1799 - auc_2: 0.9695 - val_loss: 0.2857 - val_auc_2: 0.7039
Epoch 8/20
8476/8476 [==============================] - 27s 3ms/step - loss:
0.1789 - auc_2: 0.9699 - val_loss: 0.2825 - val_auc_2: 0.6921
```

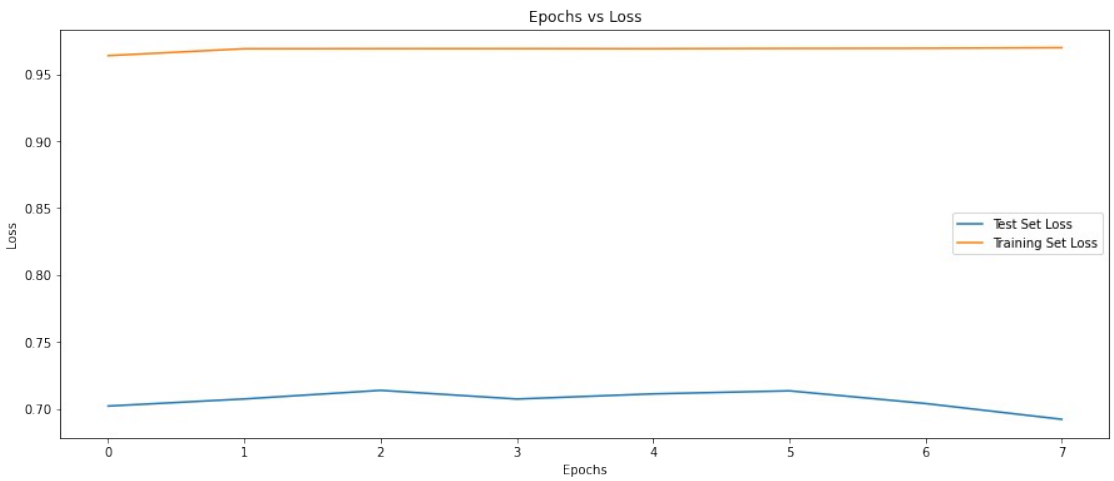
```
history = pd.DataFrame(history.history)
history.head()
```

	loss	auc_2	val_loss	val_auc_2
0	0.319780	0.963956	0.284033	0.702000
1	0.184721	0.969133	0.278740	0.707318
2	0.181829	0.969194	0.275317	0.713744
3	0.181271	0.969211	0.277223	0.707261
4	0.181243	0.969146	0.273222	0.711122

```
plt.figure(figsize = (15,6))
plt.plot(history.val_loss, label='Test Set Loss')
plt.plot(history.loss, label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
plt.figure(figsize = (15,6))
plt.plot(history.val_auc_2, label='Test Set Loss')
plt.plot(history.auc_2, label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



Calculate Sensitivity as a metrice

Calculate area under receiver operating characteristics curve

Lets test the model with train and test set and get confusion matrix, sensitivity and auc scores.

```
y_train_blc_pred = model.predict(x_train_blc)
```

```
cm1 = confusion_matrix(y_train_blc, y_train_blc_pred>0.5)
cm1
```

```
array([[210168,   1731],
       [ 20480, 191419]])
```

```
tn, fp, fn, tp = cm1.ravel()
sensitivity = tp / (tp+fn)
print(sensitivity)
```

```
0.9033501809824492
```

```
roc_auc_score(y_train_blc, y_train_blc_pred)
```

```
0.972218982736536
```

```
y_train_pred = model.predict(x_train)
```

```
cm2 = confusion_matrix(y_train, y_train_pred>0.5)
cm2
```

```
array([[ 51957, 159942],
       [  3394,  15340]])
```

```
tn, fp, fn, tp = cm2.ravel()
sensitivity = tp / (tp+fn)
print(sensitivity)
```

```
0.8188320700330949
```

```
roc_auc_score(y_train, y_train_pred)
```

```
0.5375519069958544
```

```
y_test_pred = model.predict(x_test)
```

```
cm3 = confusion_matrix(y_test, y_test_pred>0.5)
cm3
```

```
array([[70207,   580],
       [ 5980,   111]])
```

```
tn, fp, fn, tp = cm3.ravel()
sensitivity = tp / (tp+fn)
print(sensitivity)
```

```
0.018223608602856673
```

```
roc_auc_score(y_test, y_test_pred)
```

```
0.6924418195981503
```

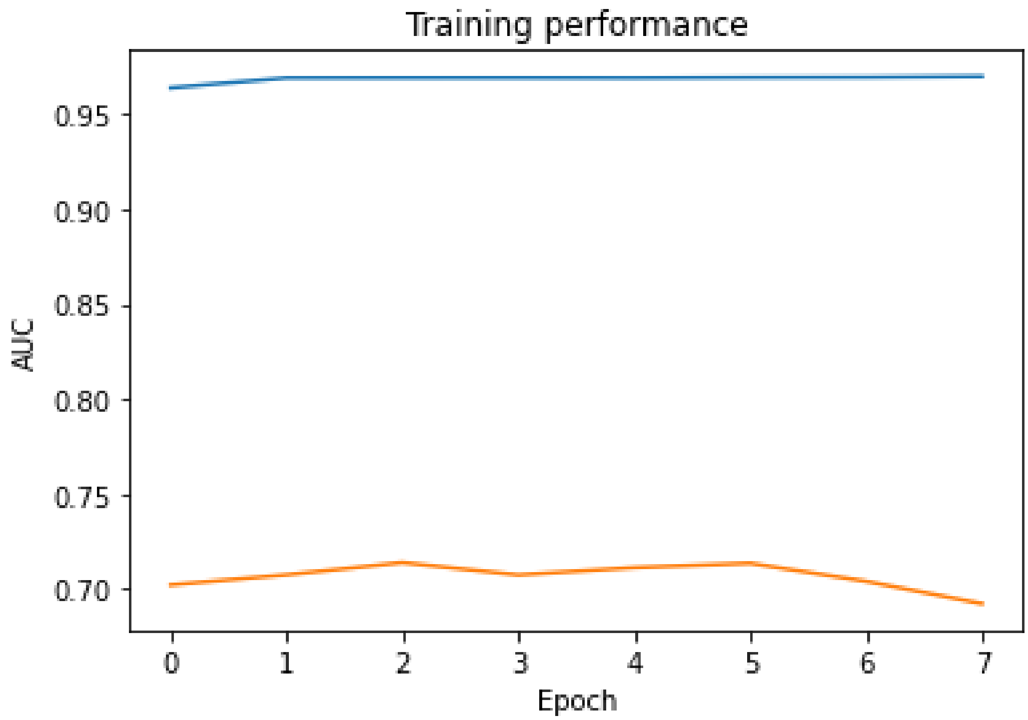
```
# test auc
fpr, tpr, thresholds = roc_curve(y_test, y_test_pred)
auc_score = auc(fpr, tpr)
print(auc_score)
```

```
0.6924418195981503
```

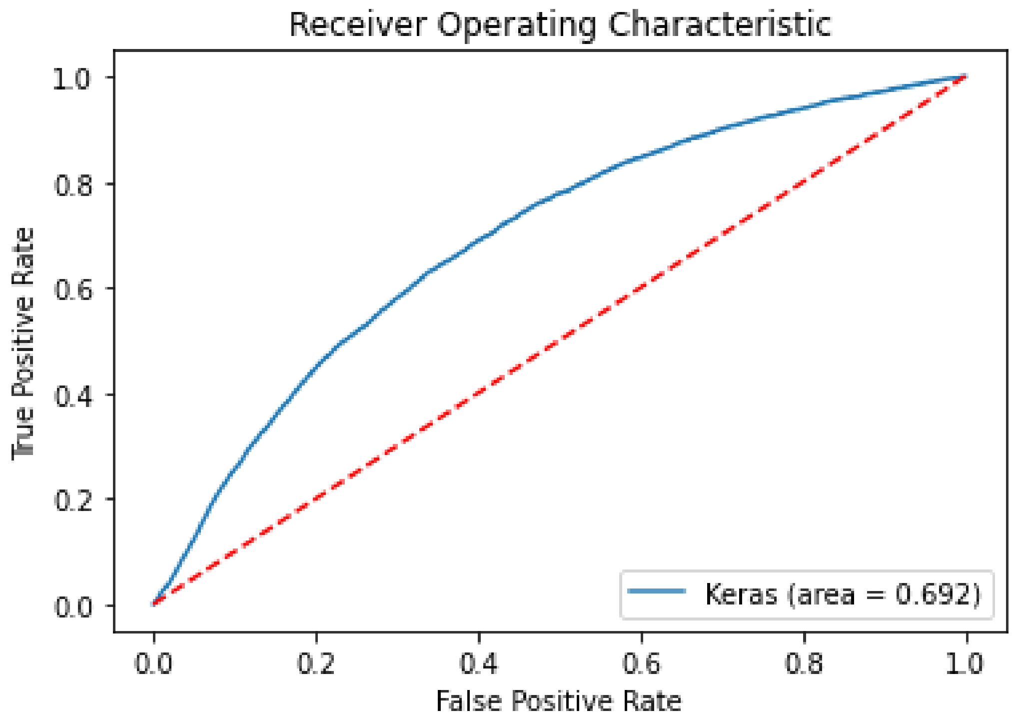
```
_, train_acc = model.evaluate(x_train_blc, y_train_blc, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train:{}%, Test: {} %'.format((train_acc*100), (test_acc*100)))
```

```
Train:97.2213089466095%, Test: 69.21027898788452 %
```

```
# Plot AUC score
plt.plot(history['auc_2'], label='Train')
plt.plot(history['val_auc_2'], label='Validation')
plt.xlabel('Epoch')
plt.ylabel('AUC')
plt.title('Training performance')
plt.show()
```




```
# Plot TPR FPR
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, label='Keras (area = {:.3f})'.format(auc))
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




```
# Plotting ROCAUC and PRAUC
f,(plt1, plt2) = plt.subplots(1, 2, sharey=True, figsize=(12, 4))
plt1.set_title('ROC Curve')
plt1.set_xlabel('FPR')
plt1.set_ylabel('TPR')
plt2.set_title('PR Curve')
plt2.set_xlabel('Precision')
plt2.set_ylabel('Recall')
# Training set
y_train_predicted = model.predict(x_train_blc).ravel()
fpr, tpr, thresholds = roc_curve(y_train_blc, y_train_predicted)
precision, recall, thresholds = precision_recall_curve(y_train_blc,
y_train_predicted)
plt1.scatter(fpr, tpr, color='b')
plt2.scatter(precision, recall,color='b')
print('Accuracy (Training): %f' % (train_acc*100))
print('ROCAUC Score (Training): %f' % roc_auc_score(y_train_blc,
y_train_predicted))
print('PRAUC Score (Training): %f' % auc(fpr, tpr))
# Validation set
y_valid_predicted = model.predict(x_test).ravel()
fpr, tpr, thresholds = roc_curve(y_test, y_valid_predicted)
precision, recall, thresholds = precision_recall_curve(y_test,
y_valid_predicted)
plt1.scatter(fpr, tpr, color='r')
plt2.scatter(precision, recall,color='r')
acc_score = model.evaluate(x_test, y_test)
print('Accuracy (Validation): %f' % (test_acc*100))
```

```
rocauc_score = roc_auc_score(y_test, y_valid_predicted)
print('ROCAUC Score (Validation): %f' % rocauc_score)
prauc_score = auc(fpr, tpr)
print('PRAUC Score (Validation): %f' % prauc_score)
plt.show()
```

```
Accuracy (Training): 97.221309
ROCAUC Score (Training): 0.972219
PRAUC Score (Training): 0.972219
2403/2403 [==============================] - 3s 1ms/step - loss:
0.2825 - auc_2: 0.6921
Accuracy (Validation): 69.210279
ROCAUC Score (Validation): 0.692442
PRAUC Score (Validation): 0.692442
```