House Loan Data Analysis

Deep Learning Project_01

In [1]:
```
# Lets first import the important libaray.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Let ignore the un necessary warnings
import warnings
warnings.filterwarnings("ignore")
```

Load the dataset that is given to you

In [3]:
```
df = pd.read_csv('loan_data.csv')
```

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

Out[4]:

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

5 rows × 122 columns

In [5]:
```
df.shape
```

Out[5]:
```
(307511, 122)
```

Check for null values in the dataset

In [6]:
```
pd.set_option('display.max_rows', 500)
```

In [7]:
```
((df.isnull().sum()/df.shape[0])*100)
```

Out[7]:
```
SK_ID_CURR                    0.000000
TARGET                        0.000000
NAME_CONTRACT_TYPE            0.000000
CODE_GENDER                   0.000000
FLAG_OWN_CAR                  0.000000
FLAG_OWN_REALTY               0.000000
CNT_CHILDREN                  0.000000
AMT_INCOME_TOTAL              0.000000
AMT_CREDIT                    0.000000
AMT_ANNUITY                   0.003902
AMT_GOODS_PRICE               0.090403
NAME_TYPE_SUITE               0.420148
NAME_INCOME_TYPE              0.000000
NAME_EDUCATION_TYPE           0.000000
NAME_FAMILY_STATUS            0.000000
NAME_HOUSING_TYPE             0.000000
REGION_POPULATION_RELATIVE    0.000000
DAYS_BIRTH                    0.000000
DAYS_EMPLOYED                 0.000000
```

In [8]:
```
# Lets drop the colums in which max of the data point is missed.
loan_df = df.drop(['OWN_CAR_AGE', 'EXT_SOURCE_1', 'APARTMENTS_AVG', 'BASEMENTAREA_AVG','YEARS_BI
                  'YEARS_BUILD_AVG','COMMONAREA_AVG', 'ELEVATORS_AVG','ENTRANCES_AVG','FLOORSMA
                  'LANDAREA_AVG','LIVINGAPARTMENTS_AVG','LIVINGAREA_AVG','NONLIVINGAPARTMENTS_A
                  'APARTMENTS_MODE','BASEMENTAREA_MODE','YEARS_BEGINEXPLUATATION_MODE','YEARS_BI
                  'ELEVATORS_MODE','ENTRANCES_MODE','FLOORSMAX_MODE','FLOORSMIN_MODE','LANDAREA_
                  'LIVINGAREA_MODE','NONLIVINGAPARTMENTS_MODE','NONLIVINGAREA_MODE','APARTMENTS_
                  'YEARS_BEGINEXPLUATATION_MEDI','YEARS_BUILD_MEDI','COMMONAREA_MEDI','ELEVATOR
                  'FLOORSMAX_MEDI','FLOORSMIN_MEDI','LANDAREA_MEDI','LIVINGAPARTMENTS_MEDI','LI
                  'NONLIVINGAPARTMENTS_MEDI','NONLIVINGAREA_MEDI','FONDKAPREMONT_MODE','HOUSETYI
                  'WALLSMATERIAL_MODE','EMERGENCYSTATE_MODE','SK_ID_CURR'], axis=1)
```

In [9]:
```
loan_df = loan_df.dropna(subset=['OCCUPATION_TYPE','AMT_REQ_CREDIT_BUREAU_HOUR','EXT_SOURCE_3',
                                 'EXT_SOURCE_2','NAME_TYPE_SUITE','AMT_ANNUITY'])
```

In [10]:
```
loan_df.isnull().sum()
```

Out[10]:
```
TARGET                         0
NAME_CONTRACT_TYPE             0
CODE_GENDER                    0
FLAG_OWN_CAR                   0
FLAG_OWN_REALTY                0
CNT_CHILDREN                   0
AMT_INCOME_TOTAL               0
AMT_CREDIT                     0
AMT_ANNUITY                    0
AMT_GOODS_PRICE                0
NAME_TYPE_SUITE                0
NAME_INCOME_TYPE               0
NAME_EDUCATION_TYPE            0
NAME_FAMILY_STATUS             0
NAME_HOUSING_TYPE              0
REGION_POPULATION_RELATIVE     0
DAYS_BIRTH                     0
DAYS_EMPLOYED                  0
DAYS_REGISTRATION              0
```

In [11]:
```
loan_df['NAME_CONTRACT_TYPE'].value_counts()
```

Out[11]:
```
Cash loans         151480
Revolving loans     16252
Name: NAME_CONTRACT_TYPE, dtype: int64
```

In [12]:
```
loan_df['CODE_GENDER'].value_counts()
```

Out[12]:
```
F      103737
M       63993
XNA         2
Name: CODE_GENDER, dtype: int64
```

In [13]:
```
loan_df['FLAG_OWN_CAR'].value_counts()
```

Out[13]:
```
N    102179
Y     65553
Name: FLAG_OWN_CAR, dtype: int64
```

In [14]:
```
loan_df['FLAG_OWN_REALTY'].value_counts()
```

Out[14]:
```
Y    113749
N     53983
Name: FLAG_OWN_REALTY, dtype: int64
```

In [15]:
```
loan_df['NAME_TYPE_SUITE'].value_counts()
```

Out[15]:
```
Unaccompanied      137289
Family              21103
Spouse, partner      6312
Children             1502
Other_B               928
Other_A               455
Group of people       143
Name: NAME_TYPE_SUITE, dtype: int64
```

In [16]:
```
loan_df['NAME_INCOME_TYPE'].value_counts()
```

Out[16]:
```
Working                 106020
Commercial associate     46553
State servant            15144
Student                     10
Businessman                  3
Pensioner                    2
Name: NAME_INCOME_TYPE, dtype: int64
```

In [17]:
```
loan_df['NAME_EDUCATION_TYPE'].value_counts()
```

Out[17]:
```
Secondary / secondary special    115722
Higher education                  44477
Incomplete higher                  6010
Lower secondary                    1433
Academic degree                      90
Name: NAME_EDUCATION_TYPE, dtype: int64
```

In [18]:
```
loan_df['NAME_FAMILY_STATUS'].value_counts()
```

Out[18]:
```
Married                 111844
Single / not married     24171
Civil marriage           16515
Separated                10769
Widow                     4433
Name: NAME_FAMILY_STATUS, dtype: int64
```

In [19]:
```
loan_df['NAME_HOUSING_TYPE'].value_counts()
```

Out[19]:
```
House / apartment      147526
With parents             9172
Municipal apartment      5916
Rented apartment         2909
Office apartment         1517
Co-op apartment           692
Name: NAME_HOUSING_TYPE, dtype: int64
```

In [20]:
```
loan_df['OCCUPATION_TYPE'].value_counts()
```

Out[20]:
```
Laborers                 43437
Sales staff              24254
Core staff               22669
Managers                 17787
Drivers                  14546
High skill tech staff     9264
Accountants               8135
Medicine staff            7223
Security staff            5218
Cooking staff             4633
Cleaning staff            3637
Private service staff     1975
Low-skill Laborers        1443
Secretaries               1047
Waiters/barmen staff      1010
Realty agents              569
HR staff                   460
IT staff                   425
Name: OCCUPATION_TYPE, dtype: int64
```

In [21]:
```
loan_df['WEEKDAY_APPR_PROCESS_START'].value_counts()
```

Out[21]:
```
WEDNESDAY    28655
TUESDAY      28469
THURSDAY     27600
FRIDAY       27536
MONDAY       27298
SATURDAY     19159
SUNDAY        9015
Name: WEEKDAY_APPR_PROCESS_START, dtype: int64
```

In [22]:
```
loan_df['ORGANIZATION_TYPE'].value_counts()
```

Out[22]:
```
Business Entity Type 3    42113
Self-employed             25892
Other                      9194
Medicine                   8548
Government                 6958
Business Entity Type 2     6893
School                     6316
Trade: type 7              5608
Kindergarten               5327
Construction               4675
Business Entity Type 1     3830
Transport: type 4          3540
Trade: type 3              2584
Industry: type 9           2403
Security                   2397
Industry: type 3           2325
Housing                    2061
Bank                       1867
Police                     1824
```

Encode the columns that is required for the model

In [23]:
```
# Now We have some categorical column that we will encode foe the model building.
from sklearn.preprocessing import LabelEncoder
```

In [24]:
```
le = LabelEncoder()
```

In [25]:
```
loan_df['NAME_CONTRACT_TYPE'] = le.fit_transform(loan_df['NAME_CONTRACT_TYPE'])
loan_df['CODE_GENDER'] = le.fit_transform(loan_df['CODE_GENDER'])
loan_df['FLAG_OWN_CAR'] = le.fit_transform(loan_df['FLAG_OWN_CAR'])
loan_df['FLAG_OWN_REALTY'] = le.fit_transform(loan_df['FLAG_OWN_REALTY'])
loan_df['NAME_TYPE_SUITE'] = le.fit_transform(loan_df['NAME_TYPE_SUITE'])
loan_df['NAME_INCOME_TYPE'] = le.fit_transform(loan_df['NAME_INCOME_TYPE'])
loan_df['NAME_EDUCATION_TYPE'] = le.fit_transform(loan_df['NAME_EDUCATION_TYPE'])
loan_df['NAME_FAMILY_STATUS'] = le.fit_transform(loan_df['NAME_FAMILY_STATUS'])
loan_df['NAME_HOUSING_TYPE'] = le.fit_transform(loan_df['NAME_HOUSING_TYPE'])
loan_df['OCCUPATION_TYPE'] = le.fit_transform(loan_df['OCCUPATION_TYPE'])
loan_df['WEEKDAY_APPR_PROCESS_START'] = le.fit_transform(loan_df['WEEKDAY_APPR_PROCESS_START'])
loan_df['ORGANIZATION_TYPE'] = le.fit_transform(loan_df['ORGANIZATION_TYPE'])
```

In [26]:
```
loan_df['OCCUPATION_TYPE'].value_counts()
```

Out[26]:
```
8     43437
14    24254
3     22669
10    17787
4     14546
6      9264
0      8135
11     7223
16     5218
2      4633
1      3637
12     1975
9      1443
15     1047
17     1010
13      569
5       460
7       425
Name: OCCUPATION_TYPE, dtype: int64
```

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

In [27]:
```
loan_df.TARGET.value_counts()
```

Out[27]:
```
0    153525
1     14207
Name: TARGET, dtype: int64
```

In [28]:
```
((loan_df['TARGET']==1).sum() / loan_df.shape[0])*100
```

Out[28]:
```
8.470059380440226
```

From above code its clear that dataset is highly imbalanced, so we will balanced the dataset.

Balance the dataset if the data is imbalanced

In [29]:
```
# Lets apply the smote oversampling thechnique
from imblearn.over_sampling import SMOTE
```

In [35]:
```
x = loan_df.drop(['TARGET'], axis=1)
y = loan_df[['TARGET']]
```

In [36]:
```
smt = SMOTE()
```

In [37]:
```
x_sm, y_sm = smt.fit_resample(x, y)
```

In [39]:
```
print(y_sm.shape)
print(y_sm.value_counts())
```

```
(307050, 1)
TARGET
0         153525
1         153525
dtype: int64
```

Now dataset is balanced.

In [40]:
```
loan_df = pd.concat([x_sm,y_sm], axis=1)
```

In [50]:
```
loan_df.head()
```

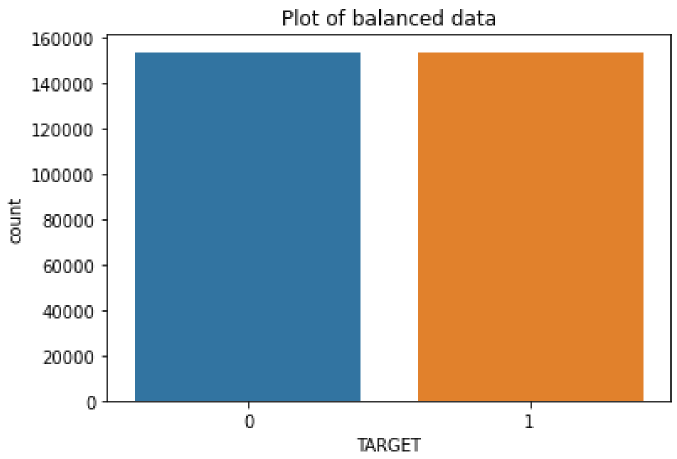
Out[50]:

	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_
0	0	1	0	1	0	20
1	1	1	1	1	0	6
2	0	1	0	1	0	9
3	0	0	1	1	1	17
4	0	1	1	1	0	36

5 rows × 72 columns

Plot the balanced data or imbalanced data

In [47]:
```
sns.countplot(loan_df['TARGET'])
plt.title('Plot of balanced data')
plt.show()
```



In [51]:
```
x = loan_df.drop(["TARGET"], axis = 1)
y = loan_df[["TARGET"]]
```

In [49]:
```
# Now lets split the data set
from sklearn.model_selection import train_test_split
```

In [52]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=.25, random_state=10)
```

In [53]:
```
from sklearn.preprocessing import StandardScaler
```

In [54]:
```
sc = StandardScaler()
```

In [56]:
```
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

In [58]:
```
x_train.shape
```

Out[58]: (230287, 71)

In [48]:
```
# Now lets create the ANN model for this problem
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LeakyReLU,PReLU,ELU, ReLU
from tensorflow.keras.layers import Dropout
```

In [57]:
```
classifier = Sequential()
```

In [59]:
```
# lets First introducing the input layer
classifier.add(Dense(units=71, activation='relu'))
```

In [60]:
```
# now lets introduce the first hidden layer
classifier.add(Dense(units=50, activation='relu'))
```

In [61]:
```
# now lets introduce the second hidden layer
classifier.add(Dense(units=35, activation='relu'))
```

In [62]:
```
# Adding the output layer
classifier.add(Dense(1, activation='sigmoid'))
```

In [63]:
```
import tensorflow
opt = tensorflow.keras.optimizers.Adam(learning_rate = 0.01)
```

In [64]:
```
classifier.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
```

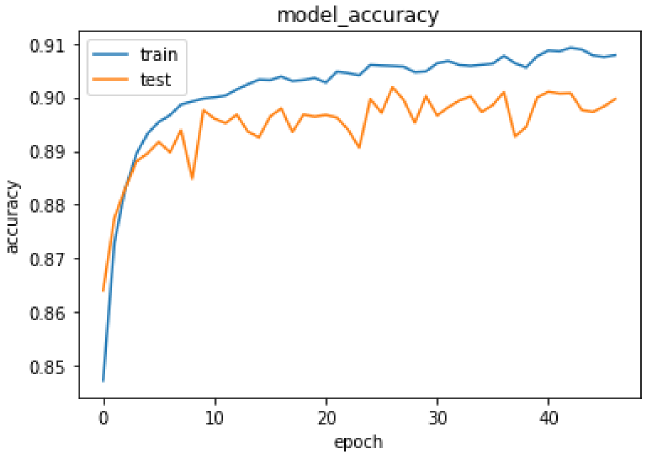
In [65]:
```
# early stoping
import tensorflow as tf
early_stoping = tf.keras.callbacks.EarlyStopping(
monitor = 'val_loss',
min_delta=0.0001,
patience=20,
verbose=1,
mode='auto',
baseline=None,
restore_best_weights=False)
```

In [66]:
```
model = classifier.fit(x_train, y_train, validation_split=0.33,batch_size=10, epochs=1000, calll
```

```
Epoch 1/1000
15430/15430 [==============================] - 144s 9ms/step - loss: 0.3602 - accuracy: 0.8473
- val_loss: 0.3223 - val_accuracy: 0.8640
Epoch 2/1000
15430/15430 [==============================] - 181s 12ms/step - loss: 0.3084 - accuracy: 0.872
8 - val_loss: 0.2987 - val_accuracy: 0.8775
Epoch 3/1000
15430/15430 [==============================] - 235s 15ms/step - loss: 0.2902 - accuracy: 0.883
1 - val_loss: 0.2872 - val_accuracy: 0.8831
Epoch 4/1000
15430/15430 [==============================] - 167s 11ms/step - loss: 0.2766 - accuracy: 0.889
5 - val_loss: 0.2775 - val_accuracy: 0.8881
Epoch 5/1000
15430/15430 [==============================] - 120s 8ms/step - loss: 0.2761 - accuracy: 0.8933
- val_loss: 0.2748 - val_accuracy: 0.8896
Epoch 6/1000
15430/15430 [==============================] - 133s 9ms/step - loss: 0.2656 - accuracy: 0.8954
- val_loss: 0.2722 - val_accuracy: 0.8917
Epoch 7/1000
15430/15430 [==============================] - 134s 9ms/step - loss: 0.2648 - accuracy: 0.8967
- val_loss: 0.2808 - val_accuracy: 0.8897
Epoch 8/1000
15430/15430 [==============================] - 119s 8ms/step - loss: 0.2610 - accuracy: 0.8986
- val_loss: 0.2760 - val_accuracy: 0.8938
Epoch 9/1000
15430/15430 [==============================] - 116s 8ms/step - loss: 0.2608 - accuracy: 0.8992
- val_loss: 0.2873 - val_accuracy: 0.8848
Epoch 10/1000
15430/15430 [==============================] - 124s 8ms/step - loss: 0.2605 - accuracy: 0.8997
- val_loss: 0.2631 - val_accuracy: 0.8976
Epoch 11/1000
15430/15430 [==============================] - 147s 10ms/step - loss: 0.2618 - accuracy: 0.900
0 - val_loss: 0.2704 - val_accuracy: 0.8960
Epoch 12/1000
15430/15430 [==============================] - 146s 9ms/step - loss: 0.2621 - accuracy: 0.9003
- val_loss: 0.2954 - val_accuracy: 0.8952
Epoch 13/1000
15430/15430 [==============================] - 147s 10ms/step - loss: 0.2581 - accuracy: 0.901
5 - val_loss: 0.2639 - val_accuracy: 0.8968
Epoch 14/1000
15430/15430 [==============================] - 151s 10ms/step - loss: 0.2592 - accuracy: 0.902
4 - val_loss: 0.2715 - val_accuracy: 0.8936
Epoch 15/1000
15430/15430 [==============================] - 167s 11ms/step - loss: 0.2570 - accuracy: 0.903
3 - val_loss: 0.2760 - val_accuracy: 0.8925
Epoch 16/1000
15430/15430 [==============================] - 152s 10ms/step - loss: 0.2551 - accuracy: 0.903
2 - val_loss: 0.2673 - val_accuracy: 0.8964
Epoch 17/1000
15430/15430 [==============================] - 172s 11ms/step - loss: 0.2559 - accuracy: 0.903
8 - val_loss: 0.2720 - val_accuracy: 0.8979
Epoch 18/1000
15430/15430 [==============================] - 153s 10ms/step - loss: 0.2592 - accuracy: 0.903
0 - val_loss: 0.3138 - val_accuracy: 0.8935
Epoch 19/1000
15430/15430 [==============================] - 153s 10ms/step - loss: 0.2573 - accuracy: 0.903
2 - val_loss: 0.2728 - val_accuracy: 0.8968
Epoch 20/1000
15430/15430 [==============================] - 191s 12ms/step - loss: 0.2567 - accuracy: 0.903
6 - val_loss: 0.2710 - val_accuracy: 0.8964
Epoch 21/1000
15430/15430 [==============================] - 156s 10ms/step - loss: 0.2614 - accuracy: 0.902
7 - val_loss: 0.2786 - val_accuracy: 0.8967
Epoch 22/1000
15430/15430 [==============================] - 169s 11ms/step - loss: 0.2563 - accuracy: 0.904
8 - val_loss: 0.2691 - val_accuracy: 0.8962
Epoch 23/1000
15430/15430 [==============================] - 166s 11ms/step - loss: 0.2570 - accuracy: 0.904
5 - val_loss: 0.2726 - val_accuracy: 0.8940
Epoch 24/1000
```

```
15430/15430 [==============================] - 153s 10ms/step - loss: 0.2585 - accuracy: 0.904
1 - val_loss: 0.2848 - val_accuracy: 0.8906
Epoch 25/1000
15430/15430 [==============================] - 167s 11ms/step - loss: 0.2538 - accuracy: 0.906
0 - val_loss: 0.2698 - val_accuracy: 0.8997
Epoch 26/1000
15430/15430 [==============================] - 153s 10ms/step - loss: 0.2541 - accuracy: 0.905
9 - val_loss: 0.2792 - val_accuracy: 0.8971
Epoch 27/1000
15430/15430 [==============================] - 148s 10ms/step - loss: 0.2540 - accuracy: 0.905
8 - val_loss: 0.2617 - val_accuracy: 0.9019
Epoch 28/1000
15430/15430 [==============================] - 149s 10ms/step - loss: 0.2538 - accuracy: 0.905
7 - val_loss: 0.2621 - val_accuracy: 0.8995
Epoch 29/1000
15430/15430 [==============================] - 131s 8ms/step - loss: 0.2566 - accuracy: 0.9047
- val_loss: 0.2733 - val_accuracy: 0.8953
Epoch 30/1000
15430/15430 [==============================] - 141s 9ms/step - loss: 0.2581 - accuracy: 0.9048
- val_loss: 0.2685 - val_accuracy: 0.9002
Epoch 31/1000
15430/15430 [==============================] - 140s 9ms/step - loss: 0.2561 - accuracy: 0.9063
- val_loss: 0.2729 - val_accuracy: 0.8966
Epoch 32/1000
15430/15430 [==============================] - 131s 8ms/step - loss: 0.2538 - accuracy: 0.9067
- val_loss: 0.2778 - val_accuracy: 0.8981
Epoch 33/1000
15430/15430 [==============================] - 133s 9ms/step - loss: 0.2556 - accuracy: 0.9060
- val_loss: 0.2680 - val_accuracy: 0.8994
Epoch 34/1000
15430/15430 [==============================] - 145s 9ms/step - loss: 0.2561 - accuracy: 0.9058
- val_loss: 0.2655 - val_accuracy: 0.9002
Epoch 35/1000
15430/15430 [==============================] - 154s 10ms/step - loss: 0.2542 - accuracy: 0.906
0 - val_loss: 0.2722 - val_accuracy: 0.8973
Epoch 36/1000
15430/15430 [==============================] - 146s 9ms/step - loss: 0.2552 - accuracy: 0.9062
- val_loss: 0.2675 - val_accuracy: 0.8985
Epoch 37/1000
15430/15430 [==============================] - 141s 9ms/step - loss: 0.2520 - accuracy: 0.9077
- val_loss: 0.2634 - val_accuracy: 0.9010
Epoch 38/1000
15430/15430 [==============================] - 143s 9ms/step - loss: 0.2567 - accuracy: 0.9063
- val_loss: 0.2817 - val_accuracy: 0.8927
Epoch 39/1000
15430/15430 [==============================] - 144s 9ms/step - loss: 0.2585 - accuracy: 0.9055
- val_loss: 0.2759 - val_accuracy: 0.8945
Epoch 40/1000
15430/15430 [==============================] - 147s 10ms/step - loss: 0.2537 - accuracy: 0.907
6 - val_loss: 0.2709 - val_accuracy: 0.9000
Epoch 41/1000
15430/15430 [==============================] - 148s 10ms/step - loss: 0.2508 - accuracy: 0.908
7 - val_loss: 0.2691 - val_accuracy: 0.9010
Epoch 42/1000
15430/15430 [==============================] - 135s 9ms/step - loss: 0.2516 - accuracy: 0.9085
- val_loss: 0.2692 - val_accuracy: 0.9007
Epoch 43/1000
15430/15430 [==============================] - 103s 7ms/step - loss: 0.2502 - accuracy: 0.9092
- val_loss: 0.2662 - val_accuracy: 0.9008
Epoch 44/1000
15430/15430 [==============================] - 103s 7ms/step - loss: 0.2519 - accuracy: 0.9089
- val_loss: 0.2788 - val_accuracy: 0.8976
Epoch 45/1000
15430/15430 [==============================] - 104s 7ms/step - loss: 0.2546 - accuracy: 0.9078
- val_loss: 0.2718 - val_accuracy: 0.8973
Epoch 46/1000
15430/15430 [==============================] - 103s 7ms/step - loss: 0.2536 - accuracy: 0.9075
- val_loss: 0.2758 - val_accuracy: 0.8983
Epoch 47/1000
15430/15430 [==============================] - 103s 7ms/step - loss: 0.2547 - accuracy: 0.9078
- val_loss: 0.2637 - val_accuracy: 0.8997
Epoch 47: early stopping
```

In [67]:
```
# Summarize the history for accuracy
plt.plot(model.history['accuracy'])
plt.plot(model.history['val_accuracy'])
plt.title('model_accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','test'], loc='upper left')
plt.show()
```



In [80]:
```
# Making the prediction and evaluating the model.
y_pred = classifier.predict(x_test)
y_preds = (y_pred>=0.5)
```

```
2399/2399 [==============================] - 13s 5ms/step
```

In [81]:
```
y_preds
```

Out[81]:
```
array([[ True],
       [ True],
       [False],
       ...,
       [False],
       [ True],
       [ True]])
```

In [82]:
```
from sklearn.metrics import classification_report, confusion_matrix, auc,roc_curve,roc_auc_score
```

In [83]:
```
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.87      0.94      0.90     38389
           1       0.94      0.86      0.90     38374

    accuracy                           0.90     76763
   macro avg       0.90      0.90      0.90     76763
weighted avg       0.90      0.90      0.90     76763
```

Calculate Sensitivity as a metrice

In [84]:
```
confusion = confusion_matrix(y_test, y_preds)
```

In [85]:
```
confusion
```

Out[85]:
```
array([[36222,  2167],
       [ 5484, 32890]], dtype=int64)
```

In [86]:
```
# True Positive
TP = confusion[1,1]
# True Negatives
TN = confusion[0,0]
# False Positives
FP = confusion[0,1]
# False Negatives
FN = confusion[1,0]
```

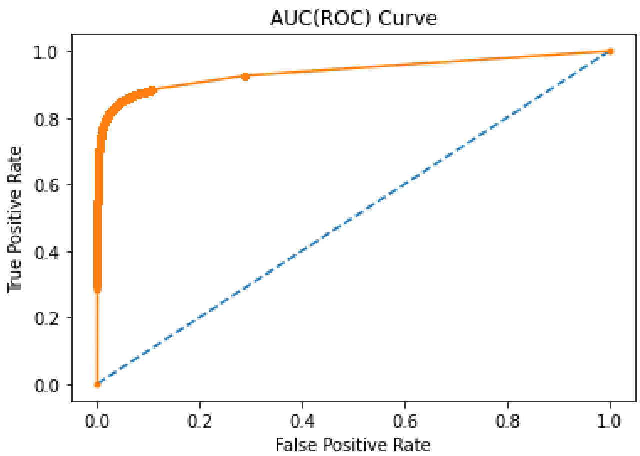
In [87]:
```
sensitivity = TP/(TP+FN)
print("Sensitivity: %.3f" %sensitivity)
```

```
Sensitivity: 0.857
```

Calculate area under receiver operating characteristics curve

In [90]:
```
# Let's compute the AUC(ROC) Receiver Operating Characteristics curve and also visualize by th
probs = classifier.predict(x_test)
# Area under the curve.
auc_cl = roc_auc_score(y_test, probs)
print("AUC: %.3f" %auc_cl)
# Calculating the roc curve.
fpr, tpr, thresholds = roc_curve(y_test, probs)
#plotting the auc(roc) curve.
plt.plot([0,1], [0,1], linestyle='--')
plt.plot(fpr,tpr, marker='.')
plt.title("AUC(ROC) Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```

```
2399/2399 [==============================] - 13s 5ms/step
AUC: 0.939
```



In [ ]:

In [ ]:

In [ ]: