## **Lending Club Loan Data Analysis**

## Import libraries

2

3

4

debt\_consolidation

debt\_consolidation

credit\_card

1

0.1357

0.1008

0.1426

366.86

162.34

102.92

10.373491 11.63

11.299732 14.97

11.350407

682

712

8.10

4710.000000

2699.958333

4066.000000

```
In [1]:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.model selection import train test split
         from sklearn.preprocessing import MinMaxScaler
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense, Dropout
         from tensorflow.keras.callbacks import EarlyStopping
         from tensorflow.keras.models import load_model
         from sklearn.metrics import confusion_matrix, classification_report
         from pickle import dump, load
         %matplotlib inline
In [2]:
         df = pd.read_csv('loan_data.csv')
In [3]:
         df.info()
         df.head()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 9578 entries, 0 to 9577
        Data columns (total 14 columns):
         #
                                Non-Null Count Dtype
             Column
                                 _____
         0
             credit.policy
                                9578 non-null
                                                 int64
         1
             purpose
                                9578 non-null
                                                 object
         2
                                                 float64
             int.rate
                                9578 non-null
             installment
                                9578 non-null
                                                 float64
                               9578 non-null
                                                 float64
         4
             log.annual.inc
         5
                                9578 non-null
                                                 float64
             dti
         6
                                9578 non-null
                                                 int64
         7
             days.with.cr.line 9578 non-null
                                                 float64
         8
             revol.bal
                                9578 non-null
                                                 int64
             revol.util
                                9578 non-null
                                                 float64
         10 inq.last.6mths
                                9578 non-null
                                                 int64
         11 deling.2yrs
                                9578 non-null
                                                 int64
         12
             pub.rec
                                9578 non-null
                                                 int64
         13 not.fully.paid
                                9578 non-null
                                                 int64
        dtypes: float64(6), int64(7), object(1)
        memory usage: 1.0+ MB
           credit.policy
Out[3]:
                              purpose int.rate installment log.annual.inc
                                                                        dti fico days.with.cr.line
        0
                    1 debt_consolidation
                                        0.1189
                                                   829.10
                                                             11.350407
                                                                      19.48
                                                                            737
                                                                                    5639.958333
                             credit_card
                                        0.1071
                                                                            707
                                                                                    2760.000000
        1
                    1
                                                   228.22
                                                             11.082143 14.29
```

```
df.describe().transpose()
Out[4]:
                                                                                     25%
                                                                                                   50%
                            count
                                           mean
                                                            std
                                                                        min
              credit.policy
                           9578.0
                                        0.804970
                                                       0.396245
                                                                    0.000000
                                                                                 1.000000
                                                                                               1.000000
                                                                                                              1.000
                   int.rate
                            9578.0
                                        0.122640
                                                       0.026847
                                                                    0.060000
                                                                                 0.103900
                                                                                               0.122100
                                                                                                              0.140
               installment 9578.0
                                      319.089413
                                                     207.071301
                                                                   15.670000
                                                                               163.770000
                                                                                             268.950000
                                                                                                            432.762
            log.annual.inc 9578.0
                                       10.932117
                                                       0.614813
                                                                    7.547502
                                                                                10.558414
                                                                                              10.928884
                                                                                                             11.29
                       dti 9578.0
                                       12.606679
                                                       6.883970
                                                                    0.000000
                                                                                 7.212500
                                                                                              12.665000
                                                                                                             17.950
                           9578.0
                                                                 612.000000
                                                                               682.000000
                      fico
                                      710.846314
                                                      37.970537
                                                                                             707.000000
                                                                                                            737.000
          days.with.cr.line
                                     4560.767197
                                                    2496.930377
                           9578.0
                                                                 178.958333
                                                                              2820.000000
                                                                                            4139.958333
                                                                                                           5730.000
                 revol.bal 9578.0
                                    16913.963876
                                                  33756.189557
                                                                    0.000000
                                                                              3187.000000
                                                                                            8596.000000
                                                                                                         18249.500
                 revol.util 9578.0
                                       46.799236
                                                      29.014417
                                                                    0.000000
                                                                                22.600000
                                                                                              46.300000
                                                                                                             70.900
            inq.last.6mths 9578.0
                                        1.577469
                                                       2.200245
                                                                    0.000000
                                                                                 0.000000
                                                                                               1.000000
                                                                                                              2.000
               delinq.2yrs 9578.0
                                        0.163708
                                                       0.546215
                                                                    0.000000
                                                                                 0.000000
                                                                                               0.000000
                                                                                                              0.000
                   pub.rec 9578.0
                                        0.062122
                                                       0.262126
                                                                    0.000000
                                                                                 0.000000
                                                                                               0.000000
                                                                                                              0.000
             not.fully.paid 9578.0
                                        0.160054
                                                       0.366676
                                                                    0.000000
                                                                                 0.000000
                                                                                               0.000000
                                                                                                              0.000
In [5]:
           df['not.fully.paid'].isnull().mean()
          0.0
Out[5]:
In [6]:
           df1=pd.get_dummies(df, columns=['purpose'])
In [7]:
           df1['log.annual.inc'] = np.exp(df1['log.annual.inc'])
In [8]:
           df1.head()
Out[8]:
              credit.policy
                           int.rate installment
                                                  log.annual.inc
                                                                    dti
                                                                        fico
                                                                              days.with.cr.line revol.bal
                                                                                                          revol.ut
          0
                             0.1189
                                          829.10
                                                   85000.000385
                                                                 19.48
                                                                         737
                                                                                  5639.958333
                                                                                                   28854
                                                                                                               52.
                        1
          1
                             0.1071
                                          228.22
                                                   65000.000073
                                                                         707
                                                                                  2760.000000
                        1
                                                                 14.29
                                                                                                   33623
                                                                                                               76.
          2
                                                                                                               25.
                        1
                             0.1357
                                          366.86
                                                   31999.999943
                                                                 11.63
                                                                         682
                                                                                  4710.000000
                                                                                                    3511
          3
                             0.1008
                                          162.34
                                                   85000.000385
                                                                         712
                                                                                  2699.958333
                                                                                                               73.
                                                                   8.10
                                                                                                   33667
          4
                                                                                  4066.000000
                                                                                                               39.
                            0.1426
                                          102.92
                                                   80799.999636
                                                                 14.97
                                                                         667
                                                                                                    4740
                                                                                                                \triangleright
In [9]:
           df.groupby('not.fully.paid')['not.fully.paid'].count()/len(df)
          not.fully.paid
Out[9]:
                0.839946
```

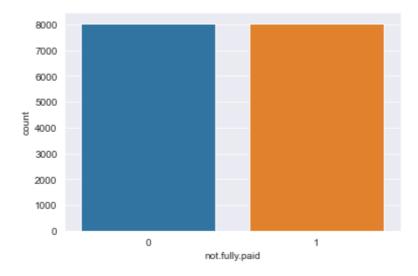
In [4]:

```
Name: not.fully.paid, dtype: float64
```

```
In [10]:
          sns.set_style('darkgrid')
          sns.countplot(x='not.fully.paid', data=df)
          <AxesSubplot:xlabel='not.fully.paid', ylabel='count'>
Out[10]:
            8000
            7000
            6000
            5000
            4000
            3000
            2000
            1000
                                     not.fully.paid
In [11]:
          count_class_0, count_class_1 = df['not.fully.paid'].value_counts()
In [12]:
          df_0 = df[df['not.fully.paid'] == 0]
          df_1 = df[df['not.fully.paid'] == 1]
In [13]:
          df_1_over = df_1.sample(count_class_0, replace=True)
          df_test_over = pd.concat([df_0, df_1_over], axis=0)
In [14]:
          print('Random over-sampling:')
          print(df_test_over['not.fully.paid'].value_counts())
          Random over-sampling:
          0
               8045
               8045
          1
         Name: not.fully.paid, dtype: int64
In [15]:
          sns.set_style('darkgrid')
          sns.countplot(x='not.fully.paid', data=df_test_over)
```

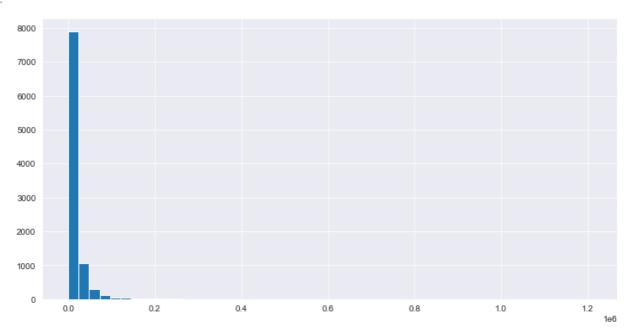
<AxesSubplot:xlabel='not.fully.paid', ylabel='count'>

Out[15]:



```
In [16]: df['revol.bal'].hist(figsize=[12,6], bins=50)
```

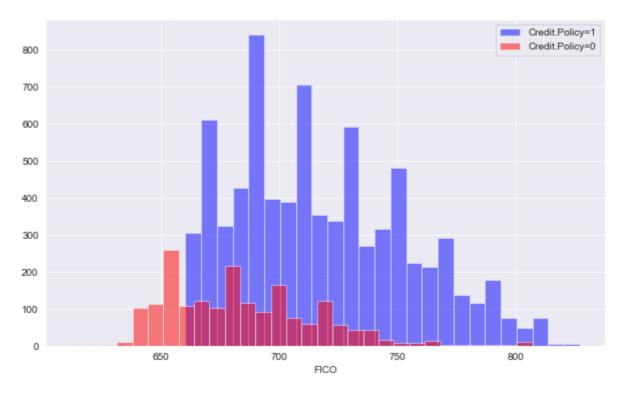
Out[16]: <AxesSubplot:>



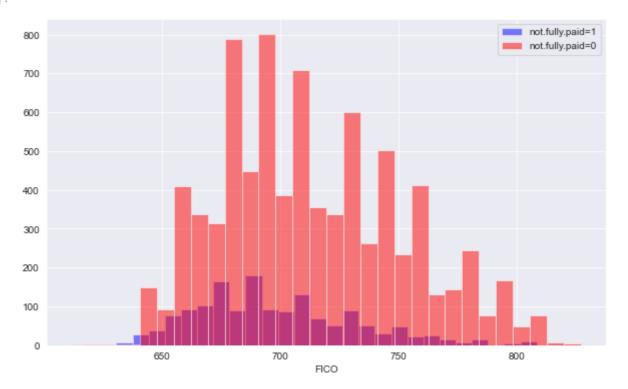
```
In [17]: df1=pd.get_dummies(df, columns=['purpose'])
```

```
plt.figure(figsize=(10,6))
    df[df['credit.policy']==1]['fico'].hist(alpha=0.5,color='blue',bins=30,label='Credit
    df[df['credit.policy']==0]['fico'].hist(alpha=0.5,color='red',bins=30,label='Credit.
    plt.legend()
    plt.xlabel('FICO')
```

Out[18]: Text(0.5, 0, 'FICO')

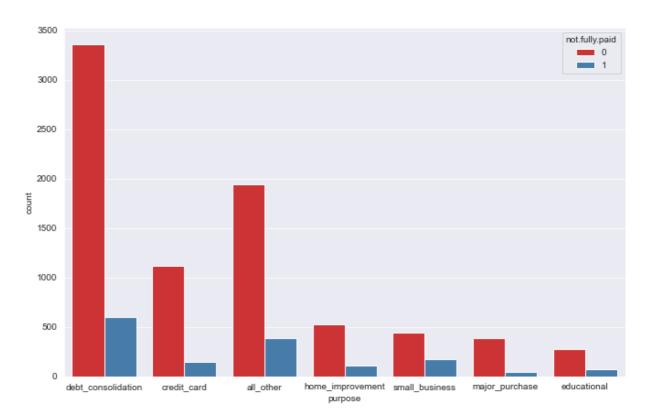


Out[19]: Text(0.5, 0, 'FICO')



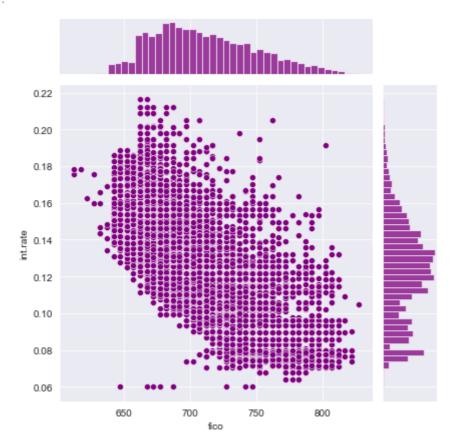
```
In [20]:
    plt.figure(figsize=(11,7))
    sns.countplot(x='purpose',hue='not.fully.paid',data=df,palette='Set1')
```

Out[20]: <AxesSubplot:xlabel='purpose', ylabel='count'>



In [21]: sns.jointplot(x='fico',y='int.rate',data=df,color='purple')

Out[21]: <seaborn.axisgrid.JointGrid at 0x208261bd460>



Out[22]: <seaborn.axisgrid.FacetGrid at 0x2082785c850> <Figure size 792x504 with 0 Axes>



```
In [23]: cat_feats = ['purpose']
```

In [24]: final\_data = pd.get\_dummies(df\_test\_over,columns=cat\_feats,drop\_first=True)

final\_data.info()
final\_data.head()

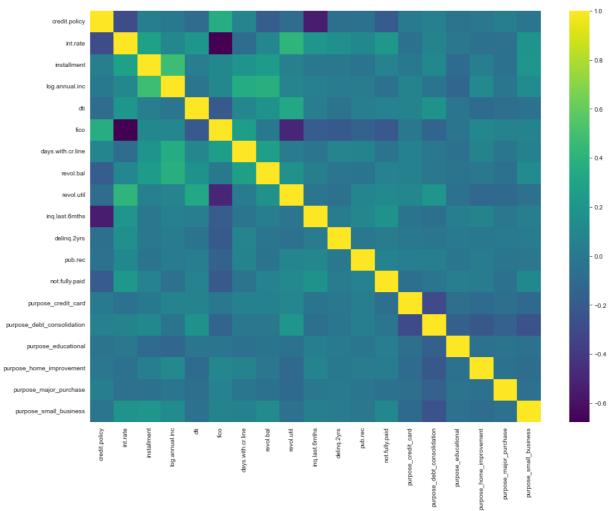
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16090 entries, 0 to 5248
Data columns (total 19 columns):

memory usage: 2.3 MB

Ducu	cordinis (cocar is cordinis).				
#	Column	Non-Null Count	Dtype		
0	credit.policy	16090 non-null	int64		
1	int.rate	16090 non-null	float64		
2	installment	16090 non-null	float64		
3	log.annual.inc	16090 non-null	float64		
4	dti	16090 non-null	float64		
5	fico	16090 non-null	int64		
6	days.with.cr.line	16090 non-null	float64		
7	revol.bal	16090 non-null	int64		
8	revol.util	16090 non-null	float64		
9	inq.last.6mths	16090 non-null	int64		
10	delinq.2yrs	16090 non-null	int64		
11	pub.rec	16090 non-null	int64		
12	not.fully.paid	16090 non-null	int64		
13	purpose_credit_card	16090 non-null	uint8		
14	<pre>purpose_debt_consolidation</pre>	16090 non-null	uint8		
15	purpose_educational	16090 non-null	uint8		
16	purpose_home_improvement	16090 non-null	uint8		
17	purpose_major_purchase	16090 non-null	uint8		
18	purpose_small_business	16090 non-null	uint8		
dtypes: float64(6), int64(7), uint8(6)					

Out[25]: credit.policy int.rate installment log.annual.inc dti fico days.with.cr.line revol.bal revol.ut 0 0.1189 829.10 11.350407 19.48 737 28854 52. 5639.958333 1 0.1071 228.22 11.082143 14.29 707 2760.000000 33623 76. 2 366.86 10.373491 682 4710.000000 25. 1 0.1357 11.63 3511 0.1008 3 162.34 11.350407 8.10 712 2699.958333 33667 73.

4  In [26]: fin  Out[26]:	1 0.1426  nal_data.corr()  credit.policy int.rate installment log.annual.inc dti fico days.with.cr.line	102.92  credit.policy 1.000000 -0.292936 0.041604 -0.001350 -0.090071 0.369161	int.rate -0.292936 1.000000 0.276567 0.096911 0.204188	14.97 667  install  0.0↓1604  0.2√6567  1.0∪0000  0.4√4633	4066.000000  log.annual.inc -0.001350 0.096911 0.474633 1.000000	4740 dti -0.090071 0.204188 0.026456	fica 0.36916° -0.678610 0.108112
+11	credit.policy int.rate installment log.annual.inc dti fico	1.000000 -0.292936 0.041604 -0.001350 -0.090071	-0.292936 1.000000 0.276567 0.096911	0.041604 0.276567 1.000000	-0.001350 0.096911 0.474633	-0.090071 0.204188	fice 0.36916 -0.678610
+11	credit.policy int.rate installment log.annual.inc dti fico	1.000000 -0.292936 0.041604 -0.001350 -0.090071	-0.292936 1.000000 0.276567 0.096911	0.041604 0.276567 1.000000	-0.001350 0.096911 0.474633	-0.090071 0.204188	0.36916
Out[26]:	int.rate installment log.annual.inc dti fico	1.000000 -0.292936 0.041604 -0.001350 -0.090071	-0.292936 1.000000 0.276567 0.096911	0.041604 0.276567 1.000000	-0.001350 0.096911 0.474633	-0.090071 0.204188	0.36916
	int.rate installment log.annual.inc dti fico	-0.292936 0.041604 -0.001350 -0.090071	1.000000 0.276567 0.096911	0.276567 1.000000	0.096911 0.474633	0.204188	-0.678610
	installment log.annual.inc dti fico	0.041604 -0.001350 -0.090071	0.276567 0.096911	1.000000	0.474633		
	log.annual.inc dti fico	-0.001350 -0.090071	0.096911			0.026456	0.108117
	dti	-0.090071		0.474633	1.000000		
	fico		0.204188			-0.027900	0.10105
		0.369161		0.026456	-0.027900	1.000000	-0.21840
	days.with.cr.line		-0.678610	0.108112	0.101053	-0.218408	1.000000
	,	0.083334	-0.088130	0.187013	0.351656	0.101006	0.24754
	revol.bal	-0.192345	0.089382	0.244833	0.383079	0.167429	0.002748
	revol.util	-0.092568	0.413014	0.048807	0.075584	0.327976	-0.49831!
	inq.last.6mths	-0.548311	0.193937	-0.008135	0.045589	0.029469	-0.190399
	delinq.2yrs	-0.067099	0.150418	-0.003552	0.019765	-0.037132	-0.208084
	pub.rec	-0.053369	0.103463	-0.034209	0.012777	0.024347	-0.16018
	not.fully.paid	-0.199075	0.215752	0.066307	-0.045227	0.057253	-0.21514
	purpose_credit_card	0.004447	-0.046707	-0.003196	0.070919	0.073972	-0.00765
pur	rpose_debt_consolidation	0.047619	0.069952	0.107542	-0.034128	0.178502	-0.137804
	purpose_educational	-0.036258	-0.013537	-0.096777	-0.122052	-0.026607	-0.02306
purp	pose_home_improvement	-0.012949	-0.049965	0.033758	0.110007	-0.095456	0.09893
	purpose_major_purchase	0.040188	-0.056724	-0.047970	-0.018209	-0.073832	0.059664
	purpose_small_business	-0.023047	0.186254	0.195330	0.122265	-0.051991	0.074590
4							•
sns	<pre>t.figure(figsize=[16, s.heatmap(</pre>	.corr(),					



```
In [28]:
          to_drop2 = ['revol.bal', 'days.with.cr.line', 'installment', 'revol.bal']
          final_data.drop(to_drop2, axis=1, inplace=True)
In [29]:
          final_data.isnull().mean()
         credit.policy
                                        0.0
Out[29]:
                                        0.0
         int.rate
         log.annual.inc
                                        0.0
         dti
                                        0.0
         fico
                                        0.0
         revol.util
                                        0.0
         inq.last.6mths
                                        0.0
         delinq.2yrs
                                        0.0
         pub.rec
                                        0.0
         not.fully.paid
                                        0.0
         purpose_credit_card
                                        0.0
         purpose_debt_consolidation
                                        0.0
         purpose_educational
                                        0.0
         purpose_home_improvement
                                        0.0
         purpose_major_purchase
                                        0.0
         purpose_small_business
                                        0.0
         dtype: float64
In [30]:
          to_train = final_data[final_data['not.fully.paid'].isin([0,1])]
          to_pred = final_data[final_data['not.fully.paid'] == 2]
```

X = to\_train.drop('not.fully.paid', axis=1).values

y = to\_train['not.fully.paid'].values

In [31]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_stat
In [32]:
      scaler = MinMaxScaler()
      X_train = scaler.fit_transform(X_train)
      X_test = scaler.transform(X_test)
In [33]:
      X train.shape
Out[33]: (11263, 15)
In [34]:
      model = Sequential()
      model.add(Dense(94, activation='relu'))
      model.add(Dense(30, activation='relu'))
      model.add(Dense(15, activation='relu'))
      model.add(Dense(1, activation='sigmoid'))
      model.compile(
            optimizer='adam',
            loss='binary_crossentropy',
           metrics=['accuracy'])
In [35]:
      early_stop = EarlyStopping(
           monitor='val_loss',
           mode='min',
           verbose=1,
            patience=25)
      model.fit(
           X_train,
           y_train,
           epochs=200,
           batch size=256,
           validation_data=(X_test, y_test),
            callbacks=[early_stop])
      Epoch 1/200
      655 - val_loss: 0.6681 - val_accuracy: 0.6045
      Epoch 2/200
      02 - val_loss: 0.6507 - val_accuracy: 0.6049
      Epoch 3/200
      41 - val_loss: 0.6480 - val_accuracy: 0.6134
      Epoch 4/200
      62 - val_loss: 0.6457 - val_accuracy: 0.6161
      Epoch 5/200
      282 - val loss: 0.6433 - val accuracy: 0.6147
      Epoch 6/200
      16 - val_loss: 0.6427 - val_accuracy: 0.6261
      Epoch 7/200
      13 - val_loss: 0.6413 - val_accuracy: 0.6196
      Epoch 8/200
      25 - val_loss: 0.6420 - val_accuracy: 0.6184
      Epoch 9/200
```

```
54 - val_loss: 0.6385 - val_accuracy: 0.6232
Epoch 10/200
54 - val loss: 0.6423 - val accuracy: 0.6225
Epoch 11/200
55 - val_loss: 0.6373 - val_accuracy: 0.6248
Epoch 12/200
80 - val_loss: 0.6360 - val_accuracy: 0.6277
Epoch 13/200
94 - val loss: 0.6360 - val accuracy: 0.6283
Epoch 14/200
44/44 [============] - 0s 9ms/step - loss: 0.6259 - accuracy: 0.63
69 - val_loss: 0.6380 - val_accuracy: 0.6252
Epoch 15/200
08 - val_loss: 0.6340 - val_accuracy: 0.6325
Epoch 16/200
49 - val_loss: 0.6348 - val_accuracy: 0.6285
Epoch 17/200
03 - val_loss: 0.6339 - val_accuracy: 0.6310
Epoch 18/200
15 - val_loss: 0.6323 - val_accuracy: 0.6339
Epoch 19/200
43 - val_loss: 0.6319 - val_accuracy: 0.6321
Epoch 20/200
30 - val_loss: 0.6349 - val_accuracy: 0.6248
Epoch 21/200
476 - val_loss: 0.6330 - val_accuracy: 0.6314
Epoch 22/200
438 - val_loss: 0.6329 - val_accuracy: 0.6321
Epoch 23/200
44/44 [============] - 0s 10ms/step - loss: 0.6162 - accuracy: 0.6
425 - val_loss: 0.6297 - val_accuracy: 0.6346
Epoch 24/200
17 - val_loss: 0.6297 - val_accuracy: 0.6292
Epoch 25/200
73 - val loss: 0.6288 - val accuracy: 0.6350
44/44 [============] - 0s 8ms/step - loss: 0.6127 - accuracy: 0.64
93 - val_loss: 0.6328 - val_accuracy: 0.6343
Epoch 27/200
39 - val_loss: 0.6291 - val_accuracy: 0.6288
Epoch 28/200
503 - val_loss: 0.6293 - val_accuracy: 0.6292
Epoch 29/200
44/44 [============] - 0s 10ms/step - loss: 0.6090 - accuracy: 0.6
503 - val_loss: 0.6295 - val_accuracy: 0.6290
Epoch 30/200
44/44 [=============] - 0s 11ms/step - loss: 0.6070 - accuracy: 0.6
```

```
523 - val_loss: 0.6295 - val_accuracy: 0.6352
Epoch 31/200
56 - val_loss: 0.6255 - val_accuracy: 0.6339
Epoch 32/200
50 - val_loss: 0.6271 - val_accuracy: 0.6356
Epoch 33/200
88 - val_loss: 0.6257 - val_accuracy: 0.6325
Epoch 34/200
84 - val_loss: 0.6258 - val_accuracy: 0.6360
Epoch 35/200
15 - val_loss: 0.6243 - val_accuracy: 0.6391
Epoch 36/200
648 - val_loss: 0.6236 - val_accuracy: 0.6406
Epoch 37/200
15 - val_loss: 0.6226 - val_accuracy: 0.6451
Epoch 38/200
48 - val_loss: 0.6251 - val_accuracy: 0.6420
Epoch 39/200
26 - val_loss: 0.6218 - val_accuracy: 0.6395
44/44 [==============] - 0s 8ms/step - loss: 0.5977 - accuracy: 0.66
60 - val loss: 0.6210 - val accuracy: 0.6462
Epoch 41/200
24 - val_loss: 0.6187 - val_accuracy: 0.6486
Epoch 42/200
13 - val_loss: 0.6198 - val_accuracy: 0.6437
Epoch 43/200
706 - val_loss: 0.6213 - val_accuracy: 0.6387
Epoch 44/200
42 - val_loss: 0.6224 - val_accuracy: 0.6455
Epoch 45/200
44/44 [============] - 0s 8ms/step - loss: 0.5904 - accuracy: 0.67
21 - val_loss: 0.6193 - val_accuracy: 0.6433
Epoch 46/200
19 - val loss: 0.6210 - val accuracy: 0.6352
Epoch 47/200
44/44 [============] - 0s 8ms/step - loss: 0.5882 - accuracy: 0.67
66 - val_loss: 0.6230 - val_accuracy: 0.6443
Epoch 48/200
72 - val_loss: 0.6225 - val_accuracy: 0.6428
Epoch 49/200
05 - val_loss: 0.6177 - val_accuracy: 0.6447
Epoch 50/200
36 - val_loss: 0.6145 - val_accuracy: 0.6493
Epoch 51/200
24 - val_loss: 0.6169 - val_accuracy: 0.6542
```

```
Epoch 52/200
823 - val loss: 0.6153 - val accuracy: 0.6526
Epoch 53/200
42 - val_loss: 0.6132 - val_accuracy: 0.6534
Epoch 54/200
81 - val_loss: 0.6142 - val_accuracy: 0.6511
Epoch 55/200
75 - val_loss: 0.6120 - val_accuracy: 0.6565
Epoch 56/200
44/44 [============] - 0s 9ms/step - loss: 0.5730 - accuracy: 0.68
99 - val_loss: 0.6126 - val_accuracy: 0.6528
Epoch 57/200
16 - val_loss: 0.6156 - val_accuracy: 0.6501
Epoch 58/200
79 - val_loss: 0.6128 - val_accuracy: 0.6586
Epoch 59/200
86 - val_loss: 0.6083 - val_accuracy: 0.6586
Epoch 60/200
42 - val_loss: 0.6118 - val_accuracy: 0.6493
Epoch 61/200
44/44 [============] - 0s 8ms/step - loss: 0.5667 - accuracy: 0.69
61 - val_loss: 0.6109 - val_accuracy: 0.6557
Epoch 62/200
02 - val_loss: 0.6076 - val_accuracy: 0.6629
Epoch 63/200
13 - val_loss: 0.6075 - val_accuracy: 0.6559
Epoch 64/200
32 - val_loss: 0.6105 - val_accuracy: 0.6609
19 - val loss: 0.6068 - val accuracy: 0.6515
Epoch 66/200
70 - val_loss: 0.6010 - val_accuracy: 0.6700
Epoch 67/200
59 - val loss: 0.6029 - val accuracy: 0.6617
Epoch 68/200
20 - val_loss: 0.6027 - val_accuracy: 0.6600
Epoch 69/200
43 - val_loss: 0.6011 - val_accuracy: 0.6712
Epoch 70/200
12 - val_loss: 0.6047 - val_accuracy: 0.6576
Epoch 71/200
64 - val loss: 0.6035 - val accuracy: 0.6594
Epoch 72/200
43 - val_loss: 0.6024 - val_accuracy: 0.6582
```

Epoch 73/200

```
22 - val_loss: 0.6014 - val_accuracy: 0.6569
Epoch 74/200
48 - val loss: 0.5988 - val accuracy: 0.6642
Epoch 75/200
06 - val_loss: 0.5988 - val_accuracy: 0.6671
Epoch 76/200
07 - val_loss: 0.5959 - val_accuracy: 0.6631
Epoch 77/200
26 - val loss: 0.6009 - val accuracy: 0.6663
Epoch 78/200
44/44 [============] - 0s 8ms/step - loss: 0.5458 - accuracy: 0.70
91 - val_loss: 0.5968 - val_accuracy: 0.6723
Epoch 79/200
42 - val_loss: 0.5991 - val_accuracy: 0.6629
Epoch 80/200
08 - val_loss: 0.5970 - val_accuracy: 0.6752
Epoch 81/200
47 - val_loss: 0.5927 - val_accuracy: 0.6694
Epoch 82/200
66 - val_loss: 0.6038 - val_accuracy: 0.6663
Epoch 83/200
07 - val_loss: 0.5967 - val_accuracy: 0.6685
Epoch 84/200
99 - val_loss: 0.5909 - val_accuracy: 0.6741
Epoch 85/200
78 - val_loss: 0.5901 - val_accuracy: 0.6750
Epoch 86/200
20 - val_loss: 0.5921 - val_accuracy: 0.6704
Epoch 87/200
49 - val_loss: 0.5945 - val_accuracy: 0.6766
Epoch 88/200
09 - val_loss: 0.5958 - val_accuracy: 0.6675
Epoch 89/200
80 - val loss: 0.5954 - val accuracy: 0.6685
44/44 [============] - 0s 8ms/step - loss: 0.5292 - accuracy: 0.72
57 - val_loss: 0.5916 - val_accuracy: 0.6756
Epoch 91/200
49 - val_loss: 0.5871 - val_accuracy: 0.6760
Epoch 92/200
82 - val_loss: 0.5880 - val_accuracy: 0.6820
Epoch 93/200
79 - val_loss: 0.5877 - val_accuracy: 0.6791
Epoch 94/200
44/44 [============] - 0s 8ms/step - loss: 0.5255 - accuracy: 0.72
```

```
57 - val_loss: 0.5894 - val_accuracy: 0.6737
Epoch 95/200
96 - val_loss: 0.5973 - val_accuracy: 0.6710
Epoch 96/200
05 - val_loss: 0.5880 - val_accuracy: 0.6814
Epoch 97/200
36 - val_loss: 0.5856 - val_accuracy: 0.6766
Epoch 98/200
38 - val_loss: 0.5897 - val_accuracy: 0.6826
Epoch 99/200
49 - val_loss: 0.5897 - val_accuracy: 0.6768
Epoch 100/200
21 - val_loss: 0.6001 - val_accuracy: 0.6750
Epoch 101/200
44/44 [=============] - 0s 9ms/step - loss: 0.5192 - accuracy: 0.73
05 - val_loss: 0.5881 - val_accuracy: 0.6874
Epoch 102/200
46 - val_loss: 0.5866 - val_accuracy: 0.6880
Epoch 103/200
69 - val_loss: 0.5881 - val_accuracy: 0.6797
44/44 [=============] - 0s 9ms/step - loss: 0.5130 - accuracy: 0.73
63 - val loss: 0.5827 - val accuracy: 0.6843
Epoch 105/200
60 - val_loss: 0.5820 - val_accuracy: 0.6822
Epoch 106/200
99 - val_loss: 0.5928 - val_accuracy: 0.6797
Epoch 107/200
88 - val_loss: 0.5816 - val_accuracy: 0.6814
Epoch 108/200
406 - val_loss: 0.5858 - val_accuracy: 0.6930
Epoch 109/200
44/44 [===============] - 0s 9ms/step - loss: 0.5091 - accuracy: 0.74
01 - val_loss: 0.5831 - val_accuracy: 0.6795
Epoch 110/200
68 - val loss: 0.5823 - val accuracy: 0.6888
Epoch 111/200
44/44 [============] - 0s 9ms/step - loss: 0.5060 - accuracy: 0.74
27 - val_loss: 0.5852 - val_accuracy: 0.6899
Epoch 112/200
24 - val_loss: 0.5810 - val_accuracy: 0.6851
Epoch 113/200
33 - val_loss: 0.5779 - val_accuracy: 0.6915
Epoch 114/200
31 - val_loss: 0.5814 - val_accuracy: 0.6762
Epoch 115/200
14 - val_loss: 0.5800 - val_accuracy: 0.6924
```

```
Epoch 116/200
44/44 [===============] - 0s 10ms/step - loss: 0.4987 - accuracy: 0.7
485 - val loss: 0.5785 - val accuracy: 0.6866
Epoch 117/200
09 - val_loss: 0.5797 - val_accuracy: 0.6870
Epoch 118/200
81 - val_loss: 0.5845 - val_accuracy: 0.6853
Epoch 119/200
442 - val_loss: 0.5814 - val_accuracy: 0.6882
Epoch 120/200
44/44 [============] - 0s 11ms/step - loss: 0.4973 - accuracy: 0.7
470 - val_loss: 0.5848 - val_accuracy: 0.6866
Epoch 121/200
463 - val_loss: 0.5759 - val_accuracy: 0.6948
Epoch 122/200
72 - val_loss: 0.5741 - val_accuracy: 0.6957
Epoch 123/200
495 - val_loss: 0.6200 - val_accuracy: 0.6718
Epoch 124/200
13 - val_loss: 0.5830 - val_accuracy: 0.6977
Epoch 125/200
44/44 [============] - 0s 9ms/step - loss: 0.4949 - accuracy: 0.75
22 - val_loss: 0.5823 - val_accuracy: 0.6961
Epoch 126/200
568 - val_loss: 0.5844 - val_accuracy: 0.6955
Epoch 127/200
10 - val_loss: 0.5891 - val_accuracy: 0.6874
Epoch 128/200
491 - val_loss: 0.5798 - val_accuracy: 0.6926
563 - val_loss: 0.5735 - val_accuracy: 0.6986
Epoch 130/200
536 - val_loss: 0.5751 - val_accuracy: 0.6967
Epoch 131/200
549 - val loss: 0.5780 - val accuracy: 0.6928
Epoch 132/200
56 - val_loss: 0.5725 - val_accuracy: 0.7033
Epoch 133/200
557 - val_loss: 0.5698 - val_accuracy: 0.6973
Epoch 134/200
60 - val_loss: 0.5738 - val_accuracy: 0.6959
Epoch 135/200
533 - val loss: 0.5696 - val accuracy: 0.7000
Epoch 136/200
73 - val_loss: 0.5875 - val_accuracy: 0.6926
Epoch 137/200
```

```
93 - val_loss: 0.5700 - val_accuracy: 0.6994
Epoch 138/200
13 - val loss: 0.5767 - val accuracy: 0.6953
Epoch 139/200
05 - val_loss: 0.5708 - val_accuracy: 0.7000
Epoch 140/200
00 - val_loss: 0.5716 - val_accuracy: 0.6977
Epoch 141/200
78 - val loss: 0.5687 - val accuracy: 0.7027
Epoch 142/200
44/44 [============] - 0s 9ms/step - loss: 0.4876 - accuracy: 0.75
16 - val_loss: 0.5906 - val_accuracy: 0.6963
Epoch 143/200
32 - val_loss: 0.5684 - val_accuracy: 0.6988
Epoch 144/200
57 - val_loss: 0.5691 - val_accuracy: 0.7000
Epoch 145/200
44 - val_loss: 0.5683 - val_accuracy: 0.7008
Epoch 146/200
64 - val_loss: 0.5687 - val_accuracy: 0.7037
Epoch 147/200
630 - val_loss: 0.5868 - val_accuracy: 0.6973
Epoch 148/200
33 - val_loss: 0.5713 - val_accuracy: 0.6973
Epoch 149/200
25 - val_loss: 0.5684 - val_accuracy: 0.7054
Epoch 150/200
47 - val_loss: 0.5716 - val_accuracy: 0.6977
Epoch 151/200
50 - val_loss: 0.5732 - val_accuracy: 0.7037
Epoch 152/200
84 - val_loss: 0.5765 - val_accuracy: 0.7035
Epoch 153/200
88 - val_loss: 0.5637 - val_accuracy: 0.7058
44/44 [============] - 0s 8ms/step - loss: 0.4675 - accuracy: 0.77
21 - val_loss: 0.6008 - val_accuracy: 0.6897
Epoch 155/200
03 - val_loss: 0.5621 - val_accuracy: 0.7089
Epoch 156/200
21 - val_loss: 0.5722 - val_accuracy: 0.7054
Epoch 157/200
44/44 [============] - 0s 8ms/step - loss: 0.4694 - accuracy: 0.76
68 - val_loss: 0.5822 - val_accuracy: 0.7011
Epoch 158/200
44/44 [===============] - 0s 7ms/step - loss: 0.4681 - accuracy: 0.76
```

```
63 - val_loss: 0.5666 - val_accuracy: 0.7077
Epoch 159/200
80 - val_loss: 0.5656 - val_accuracy: 0.7054
Epoch 160/200
00 - val_loss: 0.5794 - val_accuracy: 0.6992
Epoch 161/200
44 - val_loss: 0.5675 - val_accuracy: 0.7044
Epoch 162/200
41 - val_loss: 0.5740 - val_accuracy: 0.7050
Epoch 163/200
30 - val_loss: 0.5746 - val_accuracy: 0.7011
Epoch 164/200
90 - val_loss: 0.5824 - val_accuracy: 0.7019
Epoch 165/200
44/44 [=============] - 0s 9ms/step - loss: 0.4642 - accuracy: 0.77
11 - val_loss: 0.5623 - val_accuracy: 0.7037
Epoch 166/200
02 - val_loss: 0.5617 - val_accuracy: 0.7102
Epoch 167/200
96 - val_loss: 0.5913 - val_accuracy: 0.6969
Epoch 168/200
44/44 [=============] - 0s 9ms/step - loss: 0.4630 - accuracy: 0.77
30 - val loss: 0.5597 - val accuracy: 0.7118
Epoch 169/200
42 - val_loss: 0.5689 - val_accuracy: 0.7093
Epoch 170/200
24 - val_loss: 0.5691 - val_accuracy: 0.7046
Epoch 171/200
46 - val_loss: 0.5649 - val_accuracy: 0.7158
Epoch 172/200
70 - val_loss: 0.5827 - val_accuracy: 0.7079
Epoch 173/200
44/44 [============] - 0s 8ms/step - loss: 0.4609 - accuracy: 0.77
10 - val_loss: 0.5633 - val_accuracy: 0.7081
Epoch 174/200
45 - val loss: 0.5604 - val accuracy: 0.7154
Epoch 175/200
03 - val_loss: 0.5644 - val_accuracy: 0.7089
Epoch 176/200
80 - val_loss: 0.5587 - val_accuracy: 0.7116
Epoch 177/200
08 - val_loss: 0.5665 - val_accuracy: 0.7077
Epoch 178/200
05 - val loss: 0.5599 - val_accuracy: 0.7077
Epoch 179/200
74 - val_loss: 0.5859 - val_accuracy: 0.7073
```

```
Epoch 180/200
78 - val loss: 0.5647 - val accuracy: 0.7110
Epoch 181/200
58 - val_loss: 0.5660 - val_accuracy: 0.7145
Epoch 182/200
24 - val_loss: 0.5790 - val_accuracy: 0.7125
Epoch 183/200
03 - val_loss: 0.5739 - val_accuracy: 0.7104
Epoch 184/200
44/44 [============] - 0s 8ms/step - loss: 0.4524 - accuracy: 0.77
93 - val_loss: 0.5699 - val_accuracy: 0.7108
Epoch 185/200
24 - val_loss: 0.5578 - val_accuracy: 0.7261
Epoch 186/200
92 - val_loss: 0.5634 - val_accuracy: 0.7156
Epoch 187/200
76 - val_loss: 0.5603 - val_accuracy: 0.7220
Epoch 188/200
48 - val_loss: 0.5665 - val_accuracy: 0.7137
Epoch 189/200
63 - val_loss: 0.5589 - val_accuracy: 0.7201
Epoch 190/200
79 - val_loss: 0.5571 - val_accuracy: 0.7230
Epoch 191/200
18 - val_loss: 0.5915 - val_accuracy: 0.7050
Epoch 192/200
00 - val_loss: 0.5596 - val_accuracy: 0.7236
01 - val_loss: 0.5589 - val_accuracy: 0.7154
Epoch 194/200
95 - val_loss: 0.5777 - val_accuracy: 0.7102
Epoch 195/200
50 - val loss: 0.5602 - val accuracy: 0.7265
Epoch 196/200
60 - val_loss: 0.5635 - val_accuracy: 0.7176
Epoch 197/200
67 - val_loss: 0.5624 - val_accuracy: 0.7149
Epoch 198/200
44 - val_loss: 0.5566 - val_accuracy: 0.7212
Epoch 199/200
50 - val loss: 0.5741 - val accuracy: 0.7122
Epoch 200/200
82 - val_loss: 0.5571 - val_accuracy: 0.7170
```

<keras.callbacks.History at 0x20828fecc70>

0.55

0.50

0.45

25

```
In [40]:
          predictions = (model.predict(X_test) > 0.5).astype("int32")
          print(confusion_matrix(y_test,predictions),'\n',classification_report(y_test,predict
         [[1781 656]
          [ 710 1680]]
                         precision
                                      recall f1-score
                                                          support
                     0
                             0.71
                                       0.73
                                                 0.72
                                                            2437
                             0.72
                                                            2390
                     1
                                       0.70
                                                 0.71
             accuracy
                                                  0.72
                                                            4827
                             0.72
                                       0.72
                                                 0.72
                                                            4827
            macro avg
                                                 0.72
         weighted avg
                             0.72
                                       0.72
                                                            4827
```

```
In [48]:
          model_new = Sequential()
          model_new.add(Dense(94, activation='relu'))
          model_new.add(Dropout(0.2))
          model_new.add(Dense(30, activation='relu'))
          model new.add(Dropout(0.2))
          model_new.add(Dense(15, activation='relu'))
          model_new.add(Dropout(0.2))
          model_new.add(
                  Dense(1, activation='sigmoid'))
          model_new.compile(
                  optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['binary accuracy'])
          model_new.fit(
                  X_train,
                  y_train,
                  epochs=200,
                  batch_size=256,
                  validation_data=(X_test, y_test),
                   callbacks=[early_stop])
```

```
Epoch 2/200
44/44 [=======================] - 0s 5ms/step - loss: 0.6620 - binary_accurac
y: 0.6080 - val_loss: 0.6564 - val_binary_accuracy: 0.6033
Epoch 3/200
y: 0.6141 - val_loss: 0.6548 - val_binary_accuracy: 0.6039
Epoch 4/200
y: 0.6204 - val_loss: 0.6513 - val_binary_accuracy: 0.6076
Epoch 5/200
y: 0.6179 - val_loss: 0.6506 - val_binary_accuracy: 0.6095
Epoch 6/200
y: 0.6191 - val_loss: 0.6474 - val_binary_accuracy: 0.6089
y: 0.6194 - val_loss: 0.6479 - val_binary_accuracy: 0.6099
Epoch 8/200
y: 0.6214 - val_loss: 0.6472 - val_binary_accuracy: 0.6124
Epoch 9/200
44/44 [=============] - 0s 5ms/step - loss: 0.6461 - binary_accurac
y: 0.6227 - val_loss: 0.6436 - val_binary_accuracy: 0.6140
Epoch 10/200
y: 0.6335 - val_loss: 0.6425 - val_binary_accuracy: 0.6188
Epoch 11/200
y: 0.6271 - val_loss: 0.6428 - val_binary_accuracy: 0.6213
y: 0.6258 - val_loss: 0.6412 - val_binary_accuracy: 0.6227
Epoch 13/200
y: 0.6306 - val_loss: 0.6415 - val_binary_accuracy: 0.6190
Epoch 14/200
y: 0.6298 - val_loss: 0.6393 - val_binary_accuracy: 0.6184
y: 0.6368 - val_loss: 0.6394 - val_binary_accuracy: 0.6194
Epoch 16/200
y: 0.6330 - val_loss: 0.6385 - val_binary_accuracy: 0.6201
Epoch 17/200
y: 0.6342 - val loss: 0.6385 - val binary accuracy: 0.6246
y: 0.6291 - val_loss: 0.6380 - val_binary_accuracy: 0.6242
Epoch 19/200
44/44 [============] - 0s 6ms/step - loss: 0.6351 - binary_accurac
y: 0.6314 - val_loss: 0.6373 - val_binary_accuracy: 0.6246
Epoch 20/200
y: 0.6357 - val_loss: 0.6367 - val_binary_accuracy: 0.6252
Epoch 21/200
y: 0.6333 - val_loss: 0.6366 - val_binary_accuracy: 0.6275
Epoch 22/200
y: 0.6308 - val_loss: 0.6363 - val_binary_accuracy: 0.6292
```

Epoch 23/200

```
cy: 0.6387 - val_loss: 0.6387 - val_binary_accuracy: 0.6190
Epoch 24/200
cy: 0.6345 - val_loss: 0.6374 - val_binary_accuracy: 0.6256
Epoch 25/200
cy: 0.6374 - val_loss: 0.6353 - val_binary_accuracy: 0.6285
Epoch 26/200
y: 0.6380 - val_loss: 0.6349 - val_binary_accuracy: 0.6285
Epoch 27/200
y: 0.6389 - val_loss: 0.6349 - val_binary_accuracy: 0.6271
Epoch 28/200
y: 0.6406 - val_loss: 0.6355 - val_binary_accuracy: 0.6343
Epoch 29/200
y: 0.6419 - val_loss: 0.6340 - val_binary_accuracy: 0.6327
Epoch 30/200
44/44 [============] - 0s 8ms/step - loss: 0.6291 - binary_accurac
y: 0.6406 - val_loss: 0.6340 - val_binary_accuracy: 0.6256
Epoch 31/200
y: 0.6414 - val_loss: 0.6325 - val_binary_accuracy: 0.6385
y: 0.6444 - val_loss: 0.6320 - val_binary_accuracy: 0.6356
Epoch 33/200
y: 0.6401 - val_loss: 0.6315 - val_binary_accuracy: 0.6314
Epoch 34/200
y: 0.6431 - val_loss: 0.6332 - val_binary_accuracy: 0.6327
Epoch 35/200
cy: 0.6394 - val_loss: 0.6315 - val_binary_accuracy: 0.6327
Epoch 36/200
y: 0.6429 - val_loss: 0.6316 - val_binary_accuracy: 0.6358
Epoch 37/200
y: 0.6448 - val_loss: 0.6305 - val_binary_accuracy: 0.6360
Epoch 38/200
y: 0.6477 - val_loss: 0.6312 - val_binary_accuracy: 0.6337
Epoch 39/200
y: 0.6390 - val_loss: 0.6308 - val_binary_accuracy: 0.6341
y: 0.6454 - val_loss: 0.6324 - val_binary_accuracy: 0.6348
Epoch 41/200
y: 0.6465 - val_loss: 0.6298 - val_binary_accuracy: 0.6375
Epoch 42/200
y: 0.6484 - val_loss: 0.6312 - val_binary_accuracy: 0.6323
y: 0.6457 - val_loss: 0.6307 - val_binary_accuracy: 0.6356
Epoch 44/200
44/44 [============] - 0s 7ms/step - loss: 0.6195 - binary_accurac
```

```
y: 0.6476 - val_loss: 0.6303 - val_binary_accuracy: 0.6389
Epoch 45/200
y: 0.6484 - val_loss: 0.6291 - val_binary_accuracy: 0.6375
y: 0.6474 - val_loss: 0.6281 - val_binary_accuracy: 0.6358
Epoch 47/200
y: 0.6489 - val_loss: 0.6285 - val_binary_accuracy: 0.6393
Epoch 48/200
y: 0.6484 - val_loss: 0.6298 - val_binary_accuracy: 0.6375
44/44 [=============] - 0s 9ms/step - loss: 0.6155 - binary_accurac
y: 0.6512 - val_loss: 0.6274 - val_binary_accuracy: 0.6354
Epoch 50/200
cy: 0.6515 - val_loss: 0.6272 - val_binary_accuracy: 0.6368
Epoch 51/200
y: 0.6536 - val_loss: 0.6304 - val_binary_accuracy: 0.6319
Epoch 52/200
y: 0.6471 - val_loss: 0.6264 - val_binary_accuracy: 0.6383
Epoch 53/200
y: 0.6518 - val_loss: 0.6260 - val_binary_accuracy: 0.6377
Epoch 54/200
y: 0.6557 - val_loss: 0.6271 - val_binary_accuracy: 0.6377
Epoch 55/200
44/44 [=============] - 0s 8ms/step - loss: 0.6144 - binary_accurac
y: 0.6498 - val_loss: 0.6279 - val_binary_accuracy: 0.6391
Epoch 56/200
y: 0.6552 - val_loss: 0.6255 - val_binary_accuracy: 0.6387
Epoch 57/200
y: 0.6555 - val_loss: 0.6271 - val_binary_accuracy: 0.6418
Epoch 58/200
y: 0.6496 - val_loss: 0.6252 - val_binary_accuracy: 0.6375
Epoch 59/200
y: 0.6512 - val_loss: 0.6259 - val_binary_accuracy: 0.6352
Epoch 60/200
y: 0.6563 - val loss: 0.6253 - val binary accuracy: 0.6346
Epoch 61/200
y: 0.6550 - val_loss: 0.6238 - val_binary_accuracy: 0.6370
Epoch 62/200
y: 0.6563 - val_loss: 0.6240 - val_binary_accuracy: 0.6352
Epoch 63/200
y: 0.6548 - val_loss: 0.6231 - val_binary_accuracy: 0.6366
Epoch 64/200
cy: 0.6586 - val_loss: 0.6254 - val_binary_accuracy: 0.6348
Epoch 65/200
y: 0.6596 - val_loss: 0.6233 - val_binary_accuracy: 0.6385
```

```
Epoch 66/200
44/44 [=======================] - 0s 7ms/step - loss: 0.6056 - binary_accurac
y: 0.6592 - val_loss: 0.6234 - val_binary_accuracy: 0.6348
Epoch 67/200
y: 0.6629 - val_loss: 0.6240 - val_binary_accuracy: 0.6412
Epoch 68/200
y: 0.6565 - val_loss: 0.6232 - val_binary_accuracy: 0.6422
Epoch 69/200
y: 0.6609 - val_loss: 0.6205 - val_binary_accuracy: 0.6462
Epoch 70/200
y: 0.6615 - val_loss: 0.6197 - val_binary_accuracy: 0.6482
Epoch 71/200
y: 0.6616 - val_loss: 0.6207 - val_binary_accuracy: 0.6464
Epoch 72/200
y: 0.6608 - val_loss: 0.6217 - val_binary_accuracy: 0.6439
Epoch 73/200
44/44 [=============] - 0s 6ms/step - loss: 0.6054 - binary_accurac
y: 0.6614 - val_loss: 0.6185 - val_binary_accuracy: 0.6470
Epoch 74/200
y: 0.6656 - val_loss: 0.6195 - val_binary_accuracy: 0.6459
Epoch 75/200
y: 0.6592 - val_loss: 0.6196 - val_binary_accuracy: 0.6505
y: 0.6636 - val_loss: 0.6189 - val_binary_accuracy: 0.6493
Epoch 77/200
y: 0.6667 - val_loss: 0.6199 - val_binary_accuracy: 0.6424
Epoch 78/200
y: 0.6615 - val_loss: 0.6184 - val_binary_accuracy: 0.6495
y: 0.6662 - val_loss: 0.6172 - val_binary_accuracy: 0.6557
Epoch 80/200
y: 0.6705 - val_loss: 0.6194 - val_binary_accuracy: 0.6470
Epoch 81/200
y: 0.6656 - val loss: 0.6179 - val binary accuracy: 0.6489
y: 0.6644 - val_loss: 0.6156 - val_binary_accuracy: 0.6534
Epoch 83/200
44/44 [============] - 0s 7ms/step - loss: 0.5972 - binary_accurac
y: 0.6673 - val_loss: 0.6143 - val_binary_accuracy: 0.6503
Epoch 84/200
cy: 0.6641 - val_loss: 0.6140 - val_binary_accuracy: 0.6567
Epoch 85/200
y: 0.6675 - val_loss: 0.6179 - val_binary_accuracy: 0.6486
Epoch 86/200
cy: 0.6650 - val_loss: 0.6134 - val_binary_accuracy: 0.6511
```

Epoch 87/200

```
cy: 0.6714 - val_loss: 0.6135 - val_binary_accuracy: 0.6542
Epoch 88/200
44/44 [=============] - 0s 8ms/step - loss: 0.5940 - binary_accurac
y: 0.6668 - val loss: 0.6144 - val binary accuracy: 0.6480
Epoch 89/200
y: 0.6680 - val_loss: 0.6127 - val_binary_accuracy: 0.6551
Epoch 90/200
y: 0.6732 - val_loss: 0.6135 - val_binary_accuracy: 0.6571
Epoch 91/200
y: 0.6725 - val_loss: 0.6113 - val_binary_accuracy: 0.6515
Epoch 92/200
y: 0.6694 - val_loss: 0.6113 - val_binary_accuracy: 0.6563
Epoch 93/200
y: 0.6712 - val_loss: 0.6086 - val_binary_accuracy: 0.6582
Epoch 94/200
44/44 [============] - 0s 7ms/step - loss: 0.5933 - binary_accurac
y: 0.6723 - val_loss: 0.6130 - val_binary_accuracy: 0.6493
Epoch 95/200
y: 0.6727 - val_loss: 0.6096 - val_binary_accuracy: 0.6563
Epoch 96/200
y: 0.6781 - val_loss: 0.6089 - val_binary_accuracy: 0.6571
Epoch 97/200
y: 0.6750 - val_loss: 0.6082 - val_binary_accuracy: 0.6522
Epoch 98/200
y: 0.6760 - val_loss: 0.6075 - val_binary_accuracy: 0.6615
Epoch 99/200
y: 0.6776 - val_loss: 0.6074 - val_binary_accuracy: 0.6549
Epoch 100/200
y: 0.6792 - val_loss: 0.6110 - val_binary_accuracy: 0.6594
Epoch 101/200
y: 0.6776 - val_loss: 0.6074 - val_binary_accuracy: 0.6549
Epoch 102/200
cy: 0.6709 - val_loss: 0.6097 - val_binary_accuracy: 0.6619
Epoch 103/200
cy: 0.6747 - val_loss: 0.6069 - val_binary_accuracy: 0.6569
44/44 [============] - 0s 7ms/step - loss: 0.5861 - binary_accurac
y: 0.6766 - val_loss: 0.6057 - val_binary_accuracy: 0.6617
Epoch 105/200
y: 0.6759 - val_loss: 0.6063 - val_binary_accuracy: 0.6644
Epoch 106/200
y: 0.6803 - val_loss: 0.6061 - val_binary_accuracy: 0.6588
y: 0.6802 - val_loss: 0.6049 - val_binary_accuracy: 0.6615
Epoch 108/200
44/44 [============] - 0s 7ms/step - loss: 0.5832 - binary_accurac
```

```
y: 0.6806 - val_loss: 0.6053 - val_binary_accuracy: 0.6629
Epoch 109/200
y: 0.6766 - val_loss: 0.6065 - val_binary_accuracy: 0.6617
44/44 [============] - 0s 7ms/step - loss: 0.5835 - binary_accurac
y: 0.6820 - val_loss: 0.6026 - val_binary_accuracy: 0.6648
Epoch 111/200
y: 0.6875 - val_loss: 0.6041 - val_binary_accuracy: 0.6617
Epoch 112/200
y: 0.6841 - val_loss: 0.6041 - val_binary_accuracy: 0.6611
44/44 [=============] - 0s 7ms/step - loss: 0.5797 - binary_accurac
y: 0.6841 - val_loss: 0.6058 - val_binary_accuracy: 0.6615
Epoch 114/200
y: 0.6810 - val_loss: 0.6027 - val_binary_accuracy: 0.6640
Epoch 115/200
y: 0.6811 - val_loss: 0.6036 - val_binary_accuracy: 0.6714
Epoch 116/200
cy: 0.6817 - val_loss: 0.6036 - val_binary_accuracy: 0.6663
Epoch 117/200
cy: 0.6846 - val_loss: 0.6015 - val_binary_accuracy: 0.6667
Epoch 118/200
44/44 [============] - 0s 7ms/step - loss: 0.5790 - binary_accurac
y: 0.6867 - val loss: 0.6019 - val binary accuracy: 0.6623
Epoch 119/200
y: 0.6897 - val_loss: 0.6022 - val_binary_accuracy: 0.6654
Epoch 120/200
y: 0.6861 - val_loss: 0.6044 - val_binary_accuracy: 0.6667
Epoch 121/200
y: 0.6877 - val_loss: 0.6020 - val_binary_accuracy: 0.6667
Epoch 122/200
y: 0.6860 - val_loss: 0.6006 - val_binary_accuracy: 0.6652
Epoch 123/200
y: 0.6864 - val_loss: 0.5996 - val_binary_accuracy: 0.6692
Epoch 124/200
y: 0.6850 - val loss: 0.5984 - val binary accuracy: 0.6654
Epoch 125/200
y: 0.6886 - val_loss: 0.5997 - val_binary_accuracy: 0.6675
Epoch 126/200
y: 0.6864 - val_loss: 0.6008 - val_binary_accuracy: 0.6627
Epoch 127/200
y: 0.6900 - val_loss: 0.5973 - val_binary_accuracy: 0.6708
Epoch 128/200
y: 0.6899 - val_loss: 0.6024 - val_binary_accuracy: 0.6721
Epoch 129/200
y: 0.6879 - val_loss: 0.6035 - val_binary_accuracy: 0.6692
```

```
Epoch 130/200
44/44 [=======================] - 0s 7ms/step - loss: 0.5767 - binary_accurac
y: 0.6848 - val_loss: 0.5999 - val_binary_accuracy: 0.6685
Epoch 131/200
y: 0.6922 - val_loss: 0.5990 - val_binary_accuracy: 0.6706
Epoch 132/200
y: 0.6929 - val_loss: 0.5973 - val_binary_accuracy: 0.6696
Epoch 133/200
y: 0.6900 - val_loss: 0.5978 - val_binary_accuracy: 0.6801
Epoch 134/200
y: 0.6903 - val_loss: 0.5995 - val_binary_accuracy: 0.6679
Epoch 135/200
y: 0.6893 - val_loss: 0.5968 - val_binary_accuracy: 0.6689
Epoch 136/200
y: 0.6845 - val_loss: 0.5981 - val_binary_accuracy: 0.6708
Epoch 137/200
y: 0.6961 - val_loss: 0.5969 - val_binary_accuracy: 0.6689
Epoch 138/200
y: 0.6941 - val_loss: 0.5931 - val_binary_accuracy: 0.6700
Epoch 139/200
y: 0.6933 - val_loss: 0.5993 - val_binary_accuracy: 0.6694
Epoch 140/200
y: 0.6893 - val_loss: 0.5966 - val_binary_accuracy: 0.6714
Epoch 141/200
y: 0.6884 - val_loss: 0.5947 - val_binary_accuracy: 0.6692
Epoch 142/200
y: 0.6932 - val_loss: 0.5926 - val_binary_accuracy: 0.6741
y: 0.6962 - val_loss: 0.5944 - val_binary_accuracy: 0.6733
Epoch 144/200
44/44 [============] - 0s 7ms/step - loss: 0.5697 - binary_accurac
y: 0.6931 - val_loss: 0.5972 - val_binary_accuracy: 0.6737
Epoch 145/200
y: 0.6948 - val loss: 0.5938 - val binary accuracy: 0.6739
y: 0.7006 - val_loss: 0.5938 - val_binary_accuracy: 0.6698
Epoch 147/200
44/44 [===========] - 0s 7ms/step - loss: 0.5655 - binary_accurac
y: 0.6952 - val_loss: 0.5971 - val_binary_accuracy: 0.6750
Epoch 148/200
y: 0.6983 - val loss: 0.5984 - val binary accuracy: 0.6710
Epoch 149/200
y: 0.6971 - val_loss: 0.5919 - val_binary_accuracy: 0.6754
Epoch 150/200
y: 0.6987 - val_loss: 0.5945 - val_binary_accuracy: 0.6679
```

Epoch 151/200

```
y: 0.6943 - val_loss: 0.5936 - val_binary_accuracy: 0.6743
Epoch 152/200
44/44 [============== ] - 0s 7ms/step - loss: 0.5657 - binary_accurac
y: 0.6975 - val_loss: 0.5910 - val_binary_accuracy: 0.6727
Epoch 153/200
y: 0.6949 - val_loss: 0.5922 - val_binary_accuracy: 0.6766
Epoch 154/200
y: 0.7011 - val_loss: 0.5893 - val_binary_accuracy: 0.6824
Epoch 155/200
y: 0.6967 - val_loss: 0.5916 - val_binary_accuracy: 0.6750
Epoch 156/200
y: 0.7000 - val_loss: 0.5906 - val_binary_accuracy: 0.6824
Epoch 157/200
y: 0.6990 - val_loss: 0.5889 - val_binary_accuracy: 0.6745
Epoch 158/200
y: 0.6986 - val_loss: 0.5897 - val_binary_accuracy: 0.6801
Epoch 159/200
y: 0.6924 - val_loss: 0.5857 - val_binary_accuracy: 0.6750
Epoch 160/200
y: 0.6947 - val_loss: 0.5885 - val_binary_accuracy: 0.6801
Epoch 161/200
y: 0.6979 - val_loss: 0.5894 - val_binary_accuracy: 0.6824
Epoch 162/200
y: 0.7040 - val_loss: 0.5881 - val_binary_accuracy: 0.6795
Epoch 163/200
y: 0.7040 - val_loss: 0.5882 - val_binary_accuracy: 0.6805
Epoch 164/200
y: 0.6995 - val_loss: 0.5900 - val_binary_accuracy: 0.6828
Epoch 165/200
y: 0.6986 - val_loss: 0.5872 - val_binary_accuracy: 0.6783
Epoch 166/200
y: 0.6967 - val_loss: 0.5873 - val_binary_accuracy: 0.6820
Epoch 167/200
y: 0.7043 - val_loss: 0.5864 - val_binary_accuracy: 0.6830
y: 0.7052 - val_loss: 0.5878 - val_binary_accuracy: 0.6808
Epoch 169/200
44/44 [============== ] - 0s 7ms/step - loss: 0.5607 - binary_accurac
y: 0.6970 - val_loss: 0.5809 - val_binary_accuracy: 0.6847
Epoch 170/200
y: 0.7017 - val_loss: 0.5856 - val_binary_accuracy: 0.6824
y: 0.7002 - val_loss: 0.5857 - val_binary_accuracy: 0.6754
Epoch 172/200
44/44 [============] - 0s 7ms/step - loss: 0.5550 - binary_accurac
```

```
y: 0.7003 - val_loss: 0.5843 - val_binary_accuracy: 0.6861
Epoch 173/200
y: 0.6995 - val_loss: 0.5838 - val_binary_accuracy: 0.6855
Epoch 174/200
y: 0.6968 - val_loss: 0.5825 - val_binary_accuracy: 0.6830
Epoch 175/200
y: 0.7052 - val_loss: 0.5829 - val_binary_accuracy: 0.6859
Epoch 176/200
y: 0.7069 - val_loss: 0.5800 - val_binary_accuracy: 0.6888
44/44 [============] - 0s 10ms/step - loss: 0.5534 - binary_accura
cy: 0.7043 - val_loss: 0.5856 - val_binary_accuracy: 0.6874
Epoch 178/200
cy: 0.6971 - val_loss: 0.5838 - val_binary_accuracy: 0.6857
Epoch 179/200
y: 0.7032 - val_loss: 0.5859 - val_binary_accuracy: 0.6810
Epoch 180/200
y: 0.7035 - val_loss: 0.5864 - val_binary_accuracy: 0.6805
Epoch 181/200
y: 0.7052 - val_loss: 0.5848 - val_binary_accuracy: 0.6851
Epoch 182/200
44/44 [============] - 0s 9ms/step - loss: 0.5543 - binary_accurac
y: 0.7047 - val loss: 0.5801 - val binary accuracy: 0.6839
Epoch 183/200
44/44 [=============] - 0s 7ms/step - loss: 0.5530 - binary_accurac
y: 0.7066 - val_loss: 0.5821 - val_binary_accuracy: 0.6872
Epoch 184/200
y: 0.7077 - val_loss: 0.5818 - val_binary_accuracy: 0.6915
Epoch 185/200
y: 0.7074 - val_loss: 0.5786 - val_binary_accuracy: 0.6868
Epoch 186/200
y: 0.7051 - val_loss: 0.5785 - val_binary_accuracy: 0.6903
Epoch 187/200
y: 0.7120 - val_loss: 0.5841 - val_binary_accuracy: 0.6797
Epoch 188/200
y: 0.7024 - val loss: 0.5778 - val binary accuracy: 0.6878
Epoch 189/200
y: 0.7097 - val_loss: 0.5769 - val_binary_accuracy: 0.6849
Epoch 190/200
y: 0.7088 - val_loss: 0.5790 - val_binary_accuracy: 0.6868
Epoch 191/200
cy: 0.7051 - val_loss: 0.5786 - val_binary_accuracy: 0.6901
Epoch 192/200
y: 0.7057 - val_loss: 0.5802 - val_binary_accuracy: 0.6884
Epoch 193/200
```

y: 0.7104 - val\_loss: 0.5804 - val\_binary\_accuracy: 0.6932

```
Epoch 194/200
      y: 0.7089 - val_loss: 0.5772 - val_binary_accuracy: 0.6882
      Epoch 195/200
      y: 0.7034 - val_loss: 0.5813 - val_binary_accuracy: 0.6859
      Epoch 196/200
      y: 0.7090 - val_loss: 0.5754 - val_binary_accuracy: 0.6859
      Epoch 197/200
      y: 0.7066 - val_loss: 0.5784 - val_binary_accuracy: 0.6870
      Epoch 198/200
      y: 0.7109 - val_loss: 0.5796 - val_binary_accuracy: 0.6907
      Epoch 199/200
      y: 0.7129 - val_loss: 0.5730 - val_binary_accuracy: 0.6928
      Epoch 200/200
      y: 0.7124 - val_loss: 0.5759 - val_binary_accuracy: 0.6919
      <keras.callbacks.History at 0x2082e087850>
Out[48]:
In [42]:
      pd.DataFrame(model_new.history.history)[['loss','val_loss']].plot()
      <AxesSubplot:>
Out[42]:
                                  loss
      0.68
                                  val loss
      0.66
      0.64
      0.62
      0.60
      0.58
      0.56
      0.54
                          125
In [44]:
      predictions new = (model.predict(X test) >= 0.2).astype("int")
      print(confusion matrix(y test,predictions new),'\n',classification report(y test,pre
      [[ 874 1563]
      [ 73 2317]]
               precision
                        recall f1-score
                                    support
                  0.92
             0
                        0.36
                               0.52
                                     2437
                        0.97
                               0.74
                                     2390
             1
                  0.60
        accuracy
                               0.66
                                     4827
```

```
In [45]:
    dump(scaler, open('scaler.pkl', 'wb'))
    model_new.save('my_model_lending_club.h5')
```

0.63

0.63

4827

4827

0.66

0.66

0.76

0.76

macro avg

weighted avg

```
In [46]: later_scaler = load(open('scaler.pkl', 'rb'))
later_model = load_model('my_model_lending_club.h5')

In [47]: 
X_00T = to_pred.drop('not.fully.paid', axis=1).values
to_pred.drop('not.fully.paid', axis=1).values
print(X_00T.shape)

(0, 15)
```