In [37]: # import libraries import os 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 [38]: loan = pd.read csv('C:/Users/User/Downloads/sda/AI/step 4/loan data.csv',encoding = "ISO-8859-1", low memory=False) In [39]: loan.shape Out[39]: (9578, 14)In [40]: loan.describe() Out[40]: credit.policy int.rate installment log.annual.inc dti fico days.with.cr.line revol.bal revol.util 9578.000000 9578.000000 9578.000000 9578.000000 9.578000e+03 9578.000000 9578.000000 9578.000000 9578.000000 count 0.804970 0.122640 10.932117 12.606679 4560.767197 1.691396e+04 319.089413 710.846314 46.799236 mean 0.396245 0.026847 207.071301 0.614813 6.883970 37.970537 2496.930377 3.375619e+04 std 29.014417 0.000000 0.060000 15.670000 7.547502 0.000000 612.000000 0.000000 min 25% 1.000000 0.103900 163.770000 10.558414 7.212500 682.000000 2820.000000 3.187000e+03 22.600000 12.665000 50% 1.000000 0.122100 707.000000 4139.958333 8.596000e+03 268.950000 10.928884 46.300000 75% 1.000000 0.140700 432.762500 11.291293 17.950000 737.000000 5730.000000 1.824950e+04 70.900000 1.000000 0.216400 940.140000 14.528354 29.960000 827.000000 17639.958330 1.207359e+06 119.000000 max In [41]:

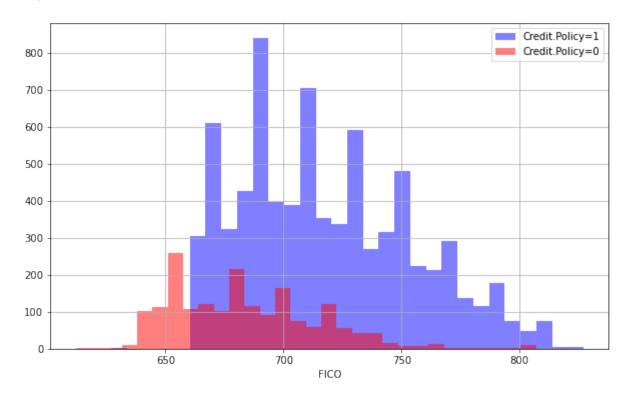
loan.head(10)

Out[41]:

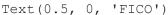
	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6n
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	

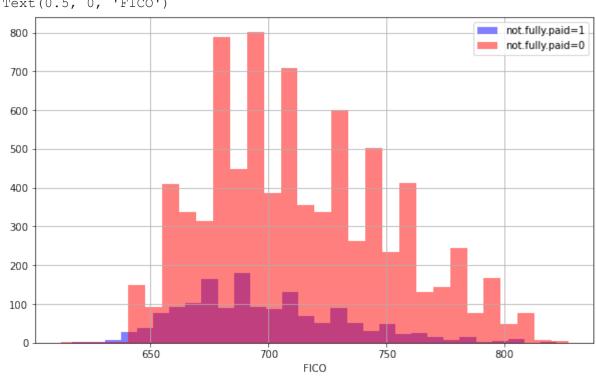
Lending	g club loan											
2		1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	
3		1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	
4		1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	
5		1	credit_card	0.0788	125.13	11.904968	16.98	727	6120.041667	50807	51.0	
6		1	debt_consolidation	0.1496	194.02	10.714418	4.00	667	3180.041667	3839	76.8	
7		1	all_other	0.1114	131.22	11.002100	11.08	722	5116.000000	24220	68.6	
8		1	home_improvement	0.1134	87.19	11.407565	17.25	682	3989.000000	69909	51.1	
9		1	debt_consolidation	0.1221	84.12	10.203592	10.00	707	2730.041667	5630	23.0	
lo	an.dtype	es										In [42]:
pur int ins log dti fic day rev inc del pub		t .i cr mt	objection float float float float into float into float into float float into float into float into into into into into into into int	264 264 264 264 264 264								Out[42]:
<pre>dtype: object #Transform categorical values into numerical values obj_loan = loan.select_dtypes(include=['object']).copy() obj_loan.head() Out[43]:</pre>												
	рι	ırp	ose									
0	debt_consol	ida	tion									
1	cred	lit_c	card									
2	debt_consol	ida	tion									
3	debt_consol	ida	tion									
4	cred	lit_c	card									
<pre>#obj_loan[obj_loan.isnull().any(axis=1)] obj_loan["purpose"].value_counts()</pre>										In [44]: In [45]:		
all	ot_conso _other edit_care		dation 3957 2333 1262	1								Out[45]:

```
home_improvement
                        629
small business
                        619
                        437
major_purchase
                        343
educational
Name: purpose, dtype: int64
                                                                                              In [46]:
obj loan = obj loan.fillna({"purpose" : "credit card"})
                                                                                              In [47]:
cleanup nums = {"purpose": {"credit card": 1, "debt consolidation": 2 }}
                                                                                             In [48]:
obj loan=obj loan.replace(cleanup nums)
obj loan.head()
                                                                                             Out[48]:
   purpose
        2
        1
        2
        2
        1
                                                                                              In [49]:
 #clean loan = loan[:]#pd.read csv('clean loan.csv',encoding='utf-8')
                                                                                              In [50]:
 #clean loan.nunique().sort values()
                                                                                              In [51]:
#EDA
plt.figure(figsize=(10,6))
loan[loan['credit.policy']==1]
['fico'].hist(alpha=0.5,color='blue',bins=30,label='Credit.Policy=1')
loan[loan['credit.policy']==0]
['fico'].hist(alpha=0.5,color='red',bins=30,label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
                                                                                             Out[51]:
Text(0.5, 0, 'FICO')
```



```
plt.figure(figsize=(10,6))
loan[loan['not.fully.paid']==1]
['fico'].hist(alpha=0.5,color='blue',bins=30,label='not.fully.paid=1')
loan[loan['not.fully.paid']==0]
['fico'].hist(alpha=0.5,color='red',bins=30,label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
```





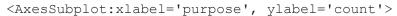
In [52]:

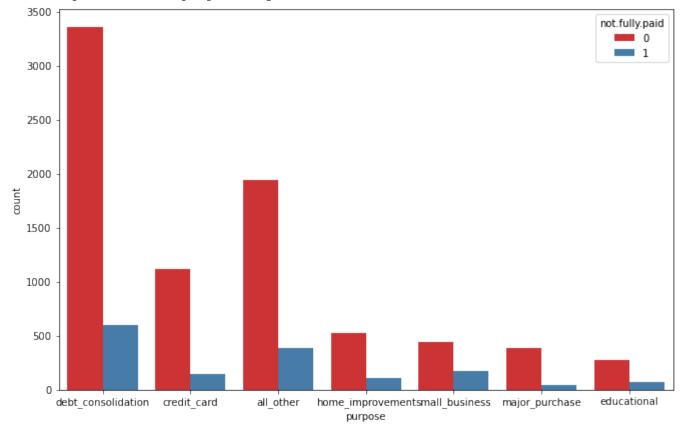
Out[52]:

In [53]:

```
plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=loan,palette='Set1')
```

Out[53]:



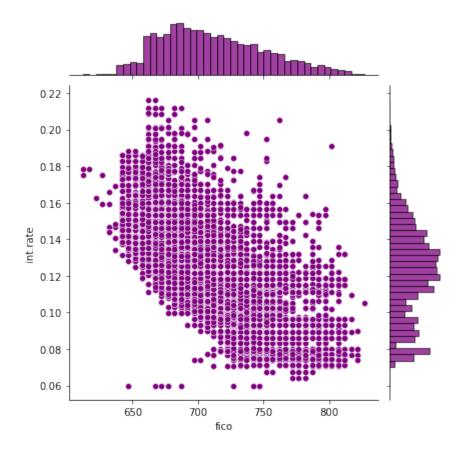


In [54]:

sns.jointplot(x='fico',y='int.rate',data=loan,color='purple')

Out[54]:

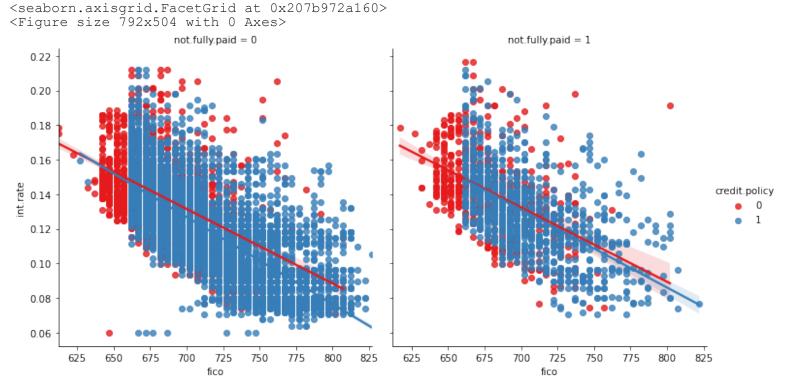
<seaborn.axisgrid.JointGrid at 0x207b8b55cd0>



Out[55]:

In [56]:

In [55]:



loan_num = loan.select_dtypes(include = ['float64','int64'])

loan num.head()

```
Out[56]:
   credit.policy int.rate installment log.annual.inc
                                           dti fico days.with.cr.line revol.bal revol.util inq.last.6mths delinq.2yrs p
0
              0.1189
                        829.10
                                 11.350407 19.48
                                               737
                                                      5639.958333
                                                                  28854
                                                                           52.1
                                                                                         0
                                                                                                  0
                        228.22
                                                                                         0
              0.1071
                                 11.082143 14.29
                                               707
                                                      2760.000000
                                                                  33623
                                                                           76.7
                                                                                                  0
1
              0.1357
                        366.86
                                               682
                                                                           25.6
2
           1
                                 10.373491 11.63
                                                      4710.000000
                                                                   3511
                                                                                         1
                                                                                                  0
              0.1008
                        162.34
                                 11.350407
                                               712
                                                      2699.958333
                                                                           73.2
                                                                                         1
                                                                                                  0
3
                                          8.10
                                                                  33667
                                                                           39.5
              0.1426
                        102.92
                                 11.299732 14.97 667
                                                      4066.000000
                                                                   4740
                                                                                         \cap
                                                                                                  1
                                                                                                In [57]:
#loan_num.hist(figsize=(16,20), bins=50, xlabelsize=8, ylabelsize=8);
                                                                                                In [58]:
#for i in range(0, len(loan num.columns),5):
     #sns.pairplot(data=loan num, x vars=loan num.columns[i:i+5],y vars=['log.annual.inc'])
                                                                                                In [59]:
#loan num corr = loan num.corr()['int.rate'][:-1] # -1 because the latest row is SalePrice
#golden features list = loan num corr[abs(loan num corr) >
0.5].sort values(ascending=False)
#print("There is {} strongly correlated values with
rate:\n{}".format(len(golden features list), golden features list))
                                                                                                In [60]:
#correlation
cor matrix = loan.corr().abs()
print(cor matrix)
                                               installment
                     credit.policy
                                     int.rate
                                                               log.annual.inc
                          1.000000
                                     0.294089
                                                    0.058770
                                                                     0.034906
credit.policy
                          0.294089
                                     1.000000
                                                    0.276140
                                                                     0.056383
int.rate
installment
                          0.058770
                                     0.276140
                                                    1.000000
                                                                     0.448102
log.annual.inc
                          0.034906
                                     0.056383
                                                    0.448102
                                                                     1.000000
                          0.090901
                                     0.220006
                                                    0.050202
                                                                     0.054065
                          0.348319
                                     0.714821
                                                    0.086039
                                                                     0.114576
days.with.cr.line
                          0.099026
                                     0.124022
                                                    0.183297
                                                                     0.336896
revol.bal
                          0.187518
                                     0.092527
                                                    0.233625
                                                                     0.372140
revol.util
                          0.104095
                                     0.464837
                                                    0.081356
                                                                     0.054881
ing.last.6mths
                          0.535511
                                     0.202780
                                                    0.010419
                                                                     0.029171
                          0.076318
                                     0.156079
                                                    0.004368
                                                                     0.029203
deling.2yrs
                          0.054243
                                     0.098162
                                                    0.032760
                                                                     0.016506
pub.rec
not.fully.paid
                          0.158119
                                     0.159552
                                                    0.049955
                                                                     0.033439
                          dti
                                    fico
                                           days.with.cr.line revol.bal
                     0.090901
                                0.348319
                                                               0.187518
credit.policy
                                                     0.099026
int.rate
                     0.220006
                               0.714821
                                                     0.124022
                                                                 0.092527
installment
                     0.050202
                                0.086039
                                                     0.183297
                                                                 0.233625
                     0.054065
                               0.114576
                                                     0.336896
                                                                 0.372140
log.annual.inc
dti
                     1.000000
                               0.241191
                                                     0.060101
                                                                 0.188748
                     0.241191
fico
                               1.000000
                                                    0.263880
                                                                 0.015553
days.with.cr.line 0.060101
                                0.263880
                                                    1.000000
                                                                 0.229344
                     0.188748
                               0.015553
                                                                 1.000000
                                                    0.229344
revol.bal
revol.util
                     0.337109
                                0.541289
                                                    0.024239
                                                                 0.203779
                    0.029189
                                0.185293
inq.last.6mths
                                                    0.041736
                                                                 0.022394
                     0.021792
                                0.216340
                                                    0.081374
                                                                 0.033243
delinq.2yrs
                     0.006209
                                0.147592
                                                     0.071826
                                                                 0.031010
pub.rec
not.fully.paid
                     0.037362
                                0.149666
                                                     0.029237
                                                                 0.053699
```

```
revol.util inq.last.6mths delinq.2yrs pub.rec credit.policy 0.104095 0.535511 0.076318 0.054243 int.rate 0.464837 0.202780 0.156079 0.098162 installment 0.081356 0.010419 0.004368 0.032760 log.annual.inc 0.054881 0.029171 0.029203 0.016506 dti 0.337109 0.029189 0.021792 0.006209 fico 0.541289 0.185293 0.216340 0.147592 days.with.cr.line revol.bal 0.203779 0.022394 0.033243 0.031010 revol.util 1.000000 0.013880 0.042740 0.066717 inq.last.6mths 0.013880 1.000000 0.021245 0.072673 delinq.2yrs 0.042740 0.021245 1.000000 0.009184 pub.rec 0.066717 0.072673 0.008881 0.048634
                                         not.fully.paid
                                           0.158119
 credit.policy
                                                        0.159552
 int.rate
 installment
                                                       0.049955
 log.annual.inc dti
                                                       0.033439
                                                      0.037362
                                                       0.149666
 days.with.cr.line
                                                      0.029237
                                                      0.053699
 revol.bal revol.util
                                                      0.082088
inq.last.6mths
delinq.2yrs
pub.rec
                                                      0.149452
                                                     0.008881
                                                      0.048634
 not.fully.paid
                                                        1.000000
  upper tri = cor matrix.where(np.triu(np.ones(cor matrix.shape), k=1).astype(np.bool))
  print(upper tri)
                                            credit.policy int.rate installment log.annual.inc \
 credit.policy
                                            NaN 0.294089 0.05877 0.034906
                                                                 NaN NaN
                                                                                                           0.27614
 int.rate
                                                                                                                                              0.056383
 installment

        Nan
        0.27614

        Nan
        Nan

                                                               NaN
                                                                                                                                             0.448102

        NaN
        NaN
        NaN

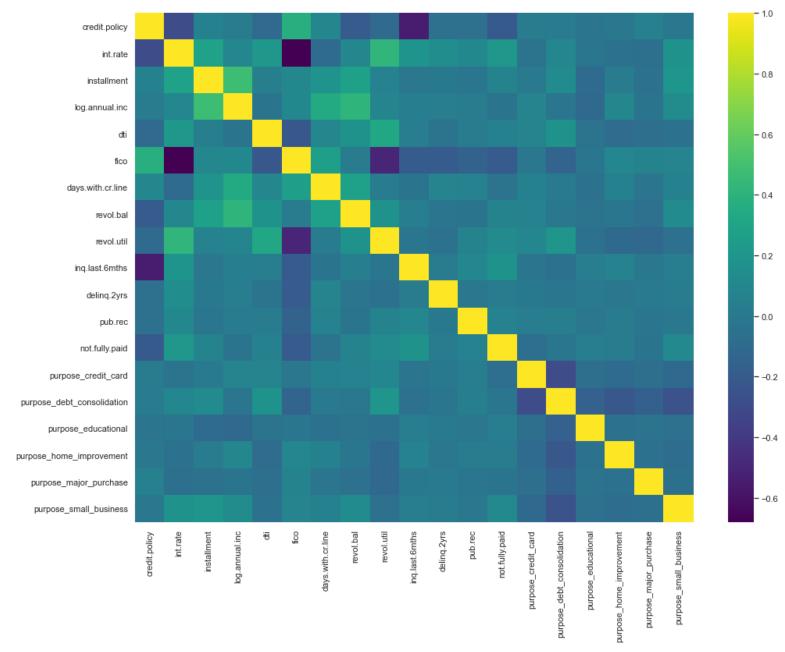
        NaN
        NaN
        NaN

 log.annual.inc
                                                                                                                                                           NaN
 dti
                                                                                                                                                          NaN
 fico
                                                                                                                                                          NaN
 days.with.cr.line
                                                                                                                                                          NaN
 revol.bal
                                                                                                                                                          NaN
                                                                                                                                                          NaN
 revol.util
 inq.last.6mths
                                                                                                                                                          NaN
 delinq.2yrs
                                                                                                                                                          NaN
                                                                                                                                                          NaN
 pub.rec
dti fico days.with.cr.line revol.bal \
credit.policy 0.090901 0.348319 0.099026 0.187518 
int.rate 0.220006 0.714821 0.124022 0.092527 
installment 0.050202 0.086039 0.183297 0.233625 
log.annual.inc 0.054065 0.114576 0.336896 0.372140 
dti NaN 0.241191 0.060101 0.188748 
fico NaN NaN NaN NaN 0.241191 0.060101 0.188748
not.fully.paid
                                                                                                          0.060101 0.188748
0.263880 0.015553
NaN 0.229344
NaN
                                                                                                                                                  NaN
                                                                                                                         NaN
                                                                                                                                                  NaN
                                                                                                                         NaN
                                                                                                                                                  NaN
                                                                                                                         NaN
                                                                                                                                                  NaN
                                                                                                                         NaN
                                                                                                                                                  NaN
                                                                                                                         NaN
                                                                                                                                                  NaN
                                         revol.util inq.last.6mths delinq.2yrs pub.rec 0.104095 0.535511 0.076318 0.054243 0.464837 0.202780 0.156079 0.098162
 credit.policy
 int.rate
installment
 installment 0.081356 log.annual.inc 0.054881
                                                                                                                 0.004368 0.032760
                                                                                    0.010419
                                                                                                                0.029203 0.016506
                                                                                   0.029171
```

In [61]:

<AxesSubplot:>

```
0.021792 0.006209
0.216340 0.147592
0.081374 0.071826
0.033243 0.031010
0.042740 0.066717
0.021245 0.072673
NaN 0.009184
                       0.337109
dti
                                        0.029189
                                        0.185293
fico
                       0.541289
                                        0.041736
days.with.cr.line 0.024239 revol.bal 0.203779
revol.bal
                                        0.022394
                         NaN
                                        0.013880
revol.util
inq.last.6mths
                            NaN
                                              NaN
delinq.2yrs
                            NaN
                                               NaN
                                                             NaN 0.009184
                            NaN
                                               NaN
                                                             NaN
                                                                        NaN
pub.rec
not.fully.paid
                            NaN
                                               NaN
                                                             NaN
                                                                         NaN
                    not.fully.paid
credit.policy
                           0.158119
int.rate
                           0.159552
installment
                           0.049955
log.annual.inc
                           0.033439
dti
                           0.037362
fico
                           0.149666
days.with.cr.line
                           0.029237
revol.bal
                          0.053699
revol.util
                           0.082088
inq.last.6mths
                          0.149452
                          0.008881
delinq.2yrs
                          0.048634
pub.rec
not.fully.paid
                                 NaN
                                                                                                  In [95]:
final data.corr()
plt.figure(
         figsize=[16,12]
)
sns.heatmap(
         data=final data.corr(),
         cmap='viridis',
         annot=False,
         fmt='.2q'
)
                                                                                                 Out[95]:
```



loan.describe().transpose()

std 25% 50% 75% count min max mean 9578.0 0.804970 0.396245 0.000000 1.000000 1.000000 1.000000 1.000000e+00 credit.policy int.rate 9578.0 0.122640 0.026847 0.060000 0.103900 0.122100 0.140700 2.164000e-01 installment 9578.0 319.089413 207.071301 15.670000 163.770000 268.950000 432.762500 9.401400e+02 log.annual.inc 9578.0 10.932117 0.614813 7.547502 10.558414 10.928884 11.291293 1.452835e+01 dti 9578.0 12.606679 6.883970 0.000000 7.212500 12.665000 17.950000 2.996000e+01 9578.0 fico 710.846314 37.970537 612.000000 682.000000 707.000000 737.000000 8.270000e+02 9578.0 days.with.cr.line 4560.767197 2496.930377 178.958333 2820.000000 4139.958333 5730.000000 1.763996e+04 revol.bal 9578.0 16913.963876 33756.189557 0.000000 3187.000000 8596.000000 18249.500000 1.207359e+06 In [62]:

Out[62]:

```
revol.util 9578.0
                       46.799236
                                   29.014417
                                              0.000000
                                                        22.600000
                                                                   46.300000
                                                                              70.900000
                                                                                        1.190000e+02
  inq.last.6mths 9578.0
                        1.577469
                                    2.200245
                                              0.000000
                                                        0.000000
                                                                    1.000000
                                                                               2.000000
                                                                                        3.300000e+01
                                             0.000000
                                                        0.000000
                                                                                        1.300000e+01
    delinq.2yrs 9578.0
                        0.163708
                                    0.546215
                                                                   0.000000
                                                                               0.000000
       pub.rec 9578.0
                        0.062122
                                    0.262126
                                             0.000000
                                                        0.000000
                                                                   0.000000
                                                                               0.000000
                                                                                       5.000000e+00
  not.fully.paid 9578.0
                        0.160054
                                    0.366676
                                             0.000000
                                                        0.000000
                                                                   0.000000
                                                                               0.000000
                                                                                       1.000000e+00
                                                                                                        In [63]:
loan['not.fully.paid'].isnull().mean()
loan.groupby('not.fully.paid')['not.fully.paid'].count()/len(loan)
                                                                                                       Out[63]:
not.fully.paid
     0.839946
1
      0.160054
Name: not.fully.paid, dtype: float64
                                                                                                        In [64]:
sns.set style('darkgrid')
sns.countplot(x='not.fully.paid', data=loan)
                                                                                                       Out[64]:
<AxesSubplot:xlabel='not.fully.paid', ylabel='count'>
  8000
  7000
  6000
  5000
  4000
  3000
  2000
  1000
     0
                  0
                                          1
                           not.fully.paid
                                                                                                        In [65]:
count class 0, count class 1 = loan['not.fully.paid'].value counts()
loan 0 = loan[loan['not.fully.paid'] == 0]
loan 1 = loan[loan['not.fully.paid'] == 1]
loan 1 over = loan 1.sample(count class 0, replace=True)
loan test over = pd.concat([loan 0, loan 1 over], axis=0)
print('Random over-sampling:')
print(loan test over['not.fully.paid'].value counts())
sns.set style('darkgrid')
sns.countplot(x='not.fully.paid', data=loan test over)
Random over-sampling:
1
     8045
\Omega
     8045
Name: not.fully.paid, dtype: int64
```

Out[65]:

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

```
8000

7000

6000

5000

3000

2000

1000

0

0

1

not.fully.paid
```

```
In [66]:
col fea = ['purpose']
final data = pd.get dummies(loan test over, columns=col fea, drop first=True)
final data.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16090 entries, 0 to 1885
Data columns (total 19 columns):
    Column
                                 Non-Null Count Dtype
0
                                 16090 non-null int64
    credit.policy
                                 16090 non-null float64
    int.rate
    installment
                                 16090 non-null float64
   log.annual.inc
                                 16090 non-null float64
   dti
                                 16090 non-null float64
 5
    fico
                                 16090 non-null int64
 6 days.with.cr.line
                                16090 non-null float64
 7
                                16090 non-null int64
   revol.bal
 8 revol.util
                                16090 non-null float64
 9
                                16090 non-null int64
    ing.last.6mths
 10 deling.2yrs
                                16090 non-null int64
 11 pub.rec
                                16090 non-null int64
 12 not.fully.paid
                                16090 non-null int64
12 not.fully.paid 16090 non-null int64
13 purpose credit card 16090 non-null uint8
 14 purpose debt consolidation 16090 non-null uint8
 15 purpose educational
                                16090 non-null uint8
16 purpose home improvement
                                 16090 non-null uint8
17 purpose_major_purchase
18 purpose small business
                                 16090 non-null uint8
                                 16090 non-null uint8
dtypes: float64(6), int64(7), uint8(6)
memory usage: 2.1 MB
                                                                                         In [67]:
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
X train, X test, y train, y test = train test split(X, y, test size=0.3, random state =
101)
scaler = MinMaxScaler()
X train = scaler.fit transform(X train)
X test = scaler.transform(X test)
model = Sequential()
```

```
model.add(
    Dense(19, activation='relu')
model.add(
    Dense(10, activation='relu')
model.add(
    Dense(5, activation='relu')
model.add(
    Dense(1, activation='sigmoid')
model.compile(
    optimizer='adam',
    loss='binary crossentropy',
    metrics=['accuracy']
)
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
loss: 0.6860 - val accuracy: 0.5728
Epoch 2/200
al loss: 0.6788 - val accuracy: 0.6008
Epoch 3/200
al loss: 0.6728 - val accuracy: 0.6068
Epoch 4/200
al loss: 0.6679 - val accuracy: 0.6089
Epoch 5/200
al loss: 0.6593 - val accuracy: 0.6018
Epoch 6/200
al loss: 0.6531 - val accuracy: 0.6027
Epoch 7/200
al loss: 0.6506 - val accuracy: 0.6116
```

```
Epoch 8/200
al loss: 0.6497 - val accuracy: 0.6091
Epoch 9/200
al loss: 0.6485 - val accuracy: 0.6087
Epoch 10/200
al loss: 0.6473 - val accuracy: 0.6124
Epoch 11/200
al loss: 0.6475 - val accuracy: 0.6060
Epoch 12/200
al loss: 0.6460 - val accuracy: 0.6167
Epoch 13/200
al loss: 0.6470 - val accuracy: 0.6157
Epoch 14/200
al loss: 0.6450 - val accuracy: 0.6153
Epoch 15/200
al loss: 0.6450 - val accuracy: 0.6122
Epoch 16/200
al loss: 0.6441 - val accuracy: 0.6169
Epoch 17/200
al loss: 0.6434 - val accuracy: 0.6182
Epoch 18/200
al loss: 0.6431 - val accuracy: 0.6201
Epoch 19/200
al loss: 0.6434 - val accuracy: 0.6240
Epoch 20/200
al loss: 0.6427 - val accuracy: 0.6159
Epoch 21/200
al loss: 0.6425 - val accuracy: 0.6143
Epoch 22/200
al loss: 0.6424 - val accuracy: 0.6198
Epoch 23/200
loss: 0.6414 - val accuracy: 0.6176
Epoch 24/200
al loss: 0.6420 - val accuracy: 0.6178
Epoch 25/200
al loss: 0.6407 - val accuracy: 0.6238
Epoch 26/200
al loss: 0.6415 - val accuracy: 0.6196
Epoch 27/200
al loss: 0.6400 - val accuracy: 0.6252
Epoch 28/200
al loss: 0.6395 - val accuracy: 0.6306
Epoch 29/200
al loss: 0.6394 - val accuracy: 0.6225
Epoch 30/200
al loss: 0.6394 - val accuracy: 0.6238
```

```
Epoch 31/200
al loss: 0.6383 - val accuracy: 0.6263
Epoch 32/200
al loss: 0.6398 - val accuracy: 0.6292
Epoch 33/200
al loss: 0.6386 - val accuracy: 0.6290
Epoch 34/200
al loss: 0.6381 - val accuracy: 0.6259
Epoch 35/200
al loss: 0.6391 - val accuracy: 0.6267
Epoch 36/200
al loss: 0.6369 - val accuracy: 0.6290
Epoch 37/200
al loss: 0.6365 - val accuracy: 0.6321
Epoch 38/200
al loss: 0.6374 - val accuracy: 0.6321
Epoch 39/200
al loss: 0.6374 - val accuracy: 0.6317
Epoch 40/200
al loss: 0.6359 - val accuracy: 0.6329
Epoch 41/200
al loss: 0.6357 - val accuracy: 0.6348
Epoch 42/200
al loss: 0.6371 - val accuracy: 0.6312
Epoch 43/200
al loss: 0.6361 - val accuracy: 0.6352
Epoch 44/200
al loss: 0.6358 - val accuracy: 0.6352
Epoch 45/200
al loss: 0.6357 - val accuracy: 0.6350
Epoch 46/200
al loss: 0.6365 - val accuracy: 0.6321
Epoch 47/200
al loss: 0.6353 - val accuracy: 0.6377
Epoch 48/200
al loss: 0.6343 - val accuracy: 0.6399
Epoch 49/200
al loss: 0.6339 - val accuracy: 0.6414
Epoch 50/200
al loss: 0.6340 - val accuracy: 0.6381
Epoch 51/200
al loss: 0.6338 - val accuracy: 0.6385
Epoch 52/200
al loss: 0.6344 - val accuracy: 0.6414
Epoch 53/200
al loss: 0.6335 - val accuracy: 0.6393
```

```
Epoch 54/200
al loss: 0.6345 - val accuracy: 0.6414
Epoch 55/200
al loss: 0.6339 - val accuracy: 0.6453
Epoch 56/200
al loss: 0.6375 - val accuracy: 0.6275
Epoch 57/200
al loss: 0.6334 - val accuracy: 0.6401
Epoch 58/200
al loss: 0.6331 - val accuracy: 0.6453
Epoch 59/200
al loss: 0.6336 - val accuracy: 0.6404
Epoch 60/200
al loss: 0.6336 - val accuracy: 0.6459
Epoch 61/200
al loss: 0.6326 - val accuracy: 0.6443
Epoch 62/200
al loss: 0.6333 - val accuracy: 0.6420
Epoch 63/200
al loss: 0.6332 - val accuracy: 0.6443
Epoch 64/200
al loss: 0.6320 - val accuracy: 0.6478
Epoch 65/200
al loss: 0.6333 - val accuracy: 0.6372
Epoch 66/200
al loss: 0.6322 - val accuracy: 0.6459
Epoch 67/200
al loss: 0.6318 - val accuracy: 0.6459
Epoch 68/200
al loss: 0.6319 - val accuracy: 0.6466
Epoch 69/200
al loss: 0.6333 - val accuracy: 0.6491
Epoch 70/200
al loss: 0.6324 - val accuracy: 0.6464
Epoch 71/200
al loss: 0.6338 - val accuracy: 0.6358
Epoch 72/200
al loss: 0.6315 - val accuracy: 0.6424
Epoch 73/200
al loss: 0.6320 - val accuracy: 0.6499
Epoch 74/200
al loss: 0.6331 - val accuracy: 0.6466
Epoch 75/200
al loss: 0.6311 - val accuracy: 0.6443
Epoch 76/200
al loss: 0.6316 - val accuracy: 0.6418
```

```
Epoch 77/200
al loss: 0.6304 - val accuracy: 0.6453
Epoch 78/200
al loss: 0.6306 - val accuracy: 0.6507
Epoch 79/200
al loss: 0.6313 - val accuracy: 0.6377
Epoch 80/200
al loss: 0.6316 - val accuracy: 0.6385
Epoch 81/200
al loss: 0.6301 - val accuracy: 0.6455
Epoch 82/200
al loss: 0.6303 - val accuracy: 0.6416
Epoch 83/200
al loss: 0.6301 - val accuracy: 0.6489
Epoch 84/200
al loss: 0.6301 - val accuracy: 0.6520
Epoch 85/200
al loss: 0.6302 - val accuracy: 0.6439
Epoch 86/200
al loss: 0.6307 - val accuracy: 0.6509
Epoch 87/200
al loss: 0.6314 - val accuracy: 0.6499
Epoch 88/200
al loss: 0.6294 - val accuracy: 0.6495
Epoch 89/200
al loss: 0.6297 - val accuracy: 0.6520
Epoch 90/200
al loss: 0.6294 - val accuracy: 0.6484
Epoch 91/200
al loss: 0.6303 - val accuracy: 0.6499
Epoch 92/200
al loss: 0.6297 - val accuracy: 0.6491
Epoch 93/200
al loss: 0.6294 - val accuracy: 0.6534
Epoch 94/200
al loss: 0.6297 - val accuracy: 0.6466
Epoch 95/200
al loss: 0.6303 - val accuracy: 0.6426
Epoch 96/200
al loss: 0.6285 - val accuracy: 0.6540
Epoch 97/200
al loss: 0.6297 - val accuracy: 0.6435
Epoch 98/200
al loss: 0.6281 - val accuracy: 0.6472
Epoch 99/200
al loss: 0.6290 - val accuracy: 0.6420
```

```
Epoch 100/200
al loss: 0.6298 - val accuracy: 0.6401
Epoch 101/200
al loss: 0.6272 - val accuracy: 0.6464
Epoch 102/200
al loss: 0.6268 - val accuracy: 0.6536
Epoch 103/200
al loss: 0.6272 - val accuracy: 0.6466
Epoch 104/200
al loss: 0.6273 - val accuracy: 0.6424
Epoch 105/200
al loss: 0.6272 - val accuracy: 0.6451
Epoch 106/200
al loss: 0.6289 - val accuracy: 0.6399
Epoch 107/200
al loss: 0.6272 - val accuracy: 0.6486
Epoch 108/200
al loss: 0.6263 - val accuracy: 0.6476
Epoch 109/200
al loss: 0.6267 - val accuracy: 0.6567
Epoch 110/200
al loss: 0.6276 - val accuracy: 0.6526
Epoch 111/200
al loss: 0.6269 - val accuracy: 0.6513
Epoch 112/200
step - loss: 0.5997 - accuracy: 0.6686 - val loss: 0.6257 - val accuracy: 0.6532
Epoch 113/200
al loss: 0.6264 - val accuracy: 0.6578
Epoch 114/200
al loss: 0.6257 - val accuracy: 0.6495
Epoch 115/200
al loss: 0.6270 - val accuracy: 0.6401
Epoch 116/200
al loss: 0.6265 - val accuracy: 0.6536
Epoch 117/200
al loss: 0.6260 - val accuracy: 0.6478
Epoch 118/200
al loss: 0.6258 - val accuracy: 0.6571
Epoch 119/200
al loss: 0.6243 - val accuracy: 0.6522
Epoch 120/200
al loss: 0.6269 - val accuracy: 0.6420
Epoch 121/200
al loss: 0.6261 - val accuracy: 0.6534
Epoch 122/200
al loss: 0.6255 - val accuracy: 0.6470
```

```
Epoch 123/200
al loss: 0.6253 - val accuracy: 0.6534
Epoch 124/200
al loss: 0.6256 - val accuracy: 0.6555
Epoch 125/200
al loss: 0.6249 - val accuracy: 0.6530
Epoch 126/200
al loss: 0.6276 - val accuracy: 0.6567
Epoch 127/200
al loss: 0.6269 - val accuracy: 0.6457
Epoch 128/200
al loss: 0.6245 - val accuracy: 0.6544
Epoch 129/200
al loss: 0.6243 - val accuracy: 0.6522
Epoch 130/200
al loss: 0.6254 - val accuracy: 0.6507
Epoch 131/200
al loss: 0.6263 - val accuracy: 0.6540
Epoch 132/200
al loss: 0.6241 - val accuracy: 0.6578
Epoch 133/200
al loss: 0.6241 - val accuracy: 0.6536
Epoch 134/200
al loss: 0.6241 - val accuracy: 0.6470
Epoch 135/200
al loss: 0.6240 - val accuracy: 0.6505
Epoch 136/200
al loss: 0.6263 - val accuracy: 0.6559
Epoch 137/200
al loss: 0.6248 - val accuracy: 0.6559
Epoch 138/200
al loss: 0.6237 - val accuracy: 0.6480
Epoch 139/200
al loss: 0.6260 - val accuracy: 0.6424
Epoch 140/200
al loss: 0.6252 - val accuracy: 0.6468
Epoch 141/200
al loss: 0.6242 - val accuracy: 0.6497
Epoch 142/200
al loss: 0.6242 - val accuracy: 0.6457
Epoch 143/200
al loss: 0.6242 - val accuracy: 0.6528
Epoch 144/200
al loss: 0.6240 - val accuracy: 0.6497
Epoch 145/200
al loss: 0.6260 - val accuracy: 0.6428
```

```
Epoch 146/200
al loss: 0.6249 - val accuracy: 0.6509
Epoch 147/200
al loss: 0.6252 - val accuracy: 0.6453
Epoch 148/200
al loss: 0.6249 - val accuracy: 0.6482
Epoch 149/200
al loss: 0.6223 - val accuracy: 0.6524
Epoch 150/200
al loss: 0.6234 - val accuracy: 0.6470
Epoch 151/200
al loss: 0.6237 - val accuracy: 0.6449
Epoch 152/200
al loss: 0.6233 - val accuracy: 0.6497
Epoch 153/200
al loss: 0.6229 - val accuracy: 0.6526
Epoch 154/200
al loss: 0.6225 - val accuracy: 0.6507
Epoch 155/200
al loss: 0.6265 - val accuracy: 0.6433
Epoch 156/200
al loss: 0.6264 - val accuracy: 0.6447
Epoch 157/200
al loss: 0.6229 - val accuracy: 0.6505
Epoch 158/200
al loss: 0.6231 - val accuracy: 0.6459
Epoch 159/200
al loss: 0.6237 - val accuracy: 0.6547
Epoch 160/200
al loss: 0.6235 - val accuracy: 0.6526
Epoch 161/200
al loss: 0.6238 - val accuracy: 0.6470
Epoch 162/200
al loss: 0.6224 - val accuracy: 0.6530
Epoch 163/200
al loss: 0.6233 - val accuracy: 0.6470
Epoch 164/200
al loss: 0.6229 - val accuracy: 0.6449
Epoch 165/200
al loss: 0.6231 - val accuracy: 0.6482
Epoch 166/200
al loss: 0.6226 - val accuracy: 0.6478
Epoch 167/200
al loss: 0.6217 - val accuracy: 0.6499
Epoch 168/200
al loss: 0.6223 - val accuracy: 0.6544
```

```
Epoch 169/200
al loss: 0.6215 - val accuracy: 0.6559
Epoch 170/200
al loss: 0.6206 - val accuracy: 0.6482
Epoch 171/200
al loss: 0.6214 - val accuracy: 0.6518
Epoch 172/200
al loss: 0.6228 - val accuracy: 0.6464
Epoch 173/200
al loss: 0.6196 - val accuracy: 0.6528
Epoch 174/200
al loss: 0.6207 - val accuracy: 0.6571
Epoch 175/200
al loss: 0.6250 - val accuracy: 0.6559
Epoch 176/200
al loss: 0.6210 - val accuracy: 0.6499
Epoch 177/200
al loss: 0.6202 - val accuracy: 0.6534
Epoch 178/200
al loss: 0.6196 - val accuracy: 0.6547
Epoch 179/200
al loss: 0.6204 - val accuracy: 0.6559
Epoch 180/200
al loss: 0.6243 - val accuracy: 0.6470
Epoch 181/200
al loss: 0.6209 - val accuracy: 0.6474
Epoch 182/200
al loss: 0.6193 - val accuracy: 0.6582
Epoch 183/200
al loss: 0.6205 - val accuracy: 0.6484
Epoch 184/200
al loss: 0.6201 - val accuracy: 0.6547
Epoch 185/200
al loss: 0.6218 - val accuracy: 0.6474
Epoch 186/200
al loss: 0.6213 - val accuracy: 0.6507
Epoch 187/200
al loss: 0.6218 - val accuracy: 0.6497
Epoch 188/200
al loss: 0.6195 - val accuracy: 0.6522
Epoch 189/200
al loss: 0.6198 - val accuracy: 0.6536
Epoch 190/200
al loss: 0.6189 - val accuracy: 0.6559
Epoch 191/200
al loss: 0.6195 - val accuracy: 0.6491
```

```
Epoch 192/200
al loss: 0.6203 - val accuracy: 0.6495
Epoch 193/200
al loss: 0.6202 - val accuracy: 0.6453
Epoch 194/200
al loss: 0.6186 - val accuracy: 0.6561
Epoch 195/200
al loss: 0.6184 - val accuracy: 0.6584
Epoch 196/200
al loss: 0.6187 - val accuracy: 0.6524
Epoch 197/200
al loss: 0.6196 - val accuracy: 0.6567
Epoch 198/200
al loss: 0.6173 - val accuracy: 0.6578
Epoch 199/200
al loss: 0.6179 - val accuracy: 0.6565
Epoch 200/200
al loss: 0.6186 - val accuracy: 0.6489
                                               Out[67]:
<tensorflow.python.keras.callbacks.History at 0x207bb50c850>
                                                In [68]:
pd.DataFrame(model.history.history)[['loss','val loss']].plot()
                                               Out[68]:
<AxesSubplot:>
                     loss
                     val loss
0.68
0.66
0.64
0.62
0.60
0.58
   0
     25
       50
          75
            100
               125
                 150
                    175
                      200
                                                In [69]:
predictions = model.predict classes(X test)
print(
    confusion matrix(y test, predictions),
    '\n',
    classification report(y test, predictions)
)
[[1437 1000]
[ 695 1695]]
        precision
               recall
                   f1-score
                          support
```

0.63

2437

0.59

0

0.67

```
0.63
                         0.71
                                  0.67
                                           2390
   accuracy
                                  0.65
                                           4827
                0.65
                         0.65
  macro avg
                                  0.65
                                           4827
weighted avg
                0.65
                         0.65
                                  0.65
                                           4827
C:\Users\User\anaconda3\lib\site-packages\tensorflow\python\keras\engine\sequential.py:455:
UserWarning: `model.predict classes()` is deprecated and will be removed after 2021-01-01. P
lease use instead: * `np.argmax(model.predict(x), axis=-1)`, if your model does multi-class
              (e.g. if it uses a `softmax` last-layer activation).* `(model.predict(x) >
classification
0.5).astype("int32")`, if your model does binary classification (e.g. if it uses a `sig
moid` last-layer activation).
 warnings.warn('`model.predict classes()` is deprecated and '
                                                                             In [70]:
model new = Sequential()
model new.add(
       Dense(19, activation='relu')
model new.add(Dropout(0.2))
model new.add(
       Dense(10, activation='relu')
model new.add(Dropout(0.2))
model new.add(
       Dense(5, 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 1/200
6 - val loss: 0.6886 - val binary accuracy: 0.5859
Epoch 27200
0 - val loss: 0.6803 - val binary accuracy: 0.5975
```

```
Epoch 3/200
7 - val loss: 0.6767 - val binary accuracy: 0.6002
Epoch 4/200
700 - val loss: 0.6741 - val binary accuracy: 0.6020
Epoch 5/2\overline{0}0
838 - val loss: 0.6699 - val binary accuracy: 0.6093
Epoch 6/2\overline{0}0
896 - val loss: 0.6676 - val binary accuracy: 0.6078
Epoch 7/2\overline{0}0
899 - val loss: 0.6650 - val binary accuracy: 0.6101
Epoch 8/2\overline{0}0
978 - val loss: 0.6632 - val binary accuracy: 0.6111
Epoch 9/2\overline{0}0
977 - val loss: 0.6604 - val binary accuracy: 0.6194
Epoch 10/\overline{2}00
991 - val loss: 0.6597 - val binary accuracy: 0.6130
Epoch 11/\overline{2}00
036 - val loss: 0.6581 - val binary accuracy: 0.6149
Epoch 12/\overline{2}00
012 - val loss: 0.6570 - val binary accuracy: 0.6147
Epoch 13/\overline{2}00
035 - val loss: 0.6569 - val binary accuracy: 0.6120
Epoch 14/\overline{2}00
034 - val loss: 0.6552 - val binary accuracy: 0.6130
Epoch 15/\overline{2}00
098 - val loss: 0.6539 - val binary accuracy: 0.6126
Epoch 16/\overline{2}00
108 - val loss: 0.6530 - val binary accuracy: 0.6097
Epoch 17/\overline{2}00
015 - val loss: 0.6531 - val binary accuracy: 0.6099
Epoch 18/\overline{2}00
083 - val loss: 0.6514 - val binary accuracy: 0.6124
Epoch 19/\overline{2}00
103 - val loss: 0.6517 - val binary accuracy: 0.6111
Epoch 20/\overline{2}00
108 - val loss: 0.6502 - val binary accuracy: 0.6190
Epoch 21/\overline{2}00
132 - val loss: 0.6504 - val binary accuracy: 0.6196
Epoch 22/200
130 - val loss: 0.6489 - val binary accuracy: 0.6174
Epoch 23/\overline{2}00
148 - val loss: 0.6485 - val binary accuracy: 0.6172
Epoch 24/\overline{2}00
147 - val loss: 0.6483 - val binary accuracy: 0.6203
Epoch 25/\overline{2}00
128 - val loss: 0.6477 - val binary accuracy: 0.6155
```

```
Epoch 26/200
163 - val loss: 0.6471 - val binary accuracy: 0.6196
Epoch 27/200
164 - val loss: 0.6472 - val binary accuracy: 0.6151
Epoch 28/\overline{2}00
146 - val loss: 0.6465 - val binary accuracy: 0.6147
Epoch 29/\overline{2}00
138 - val loss: 0.6461 - val binary accuracy: 0.6192
Epoch 30/\overline{2}00
222 - val loss: 0.6453 - val binary accuracy: 0.6165
Epoch 31/\overline{2}00
160 - val loss: 0.6445 - val binary accuracy: 0.6205
Epoch 32/\overline{2}00
197 - val loss: 0.6440 - val binary accuracy: 0.6259
Epoch 33/\overline{2}00
205 - val loss: 0.6438 - val binary accuracy: 0.6256
Epoch 34/\overline{2}00
179 - val loss: 0.6429 - val binary accuracy: 0.6275
Epoch 35/\overline{2}00
216 - val loss: 0.6436 - val binary accuracy: 0.6201
Epoch 36/\overline{2}00
250 - val loss: 0.6430 - val binary accuracy: 0.6242
Epoch 37/\overline{2}00
218 - val loss: 0.6434 - val binary accuracy: 0.6256
Epoch 38/\overline{2}00
192 - val loss: 0.6426 - val binary accuracy: 0.6186
Epoch 39/\overline{2}00
209 - val loss: 0.6420 - val binary accuracy: 0.6277
Epoch 40/\overline{2}00
245 - val loss: 0.6420 - val binary accuracy: 0.6246
Epoch 41/\overline{2}00
292 - val loss: 0.6411 - val binary accuracy: 0.6219
Epoch 42/\overline{2}00
219 - val loss: 0.6414 - val binary accuracy: 0.6279
Epoch 43/\overline{2}00
256 - val loss: 0.6407 - val binary accuracy: 0.6273
Epoch 44/\overline{2}00
275 - val loss: 0.6403 - val binary accuracy: 0.6242
Epoch 45/\overline{2}00
235 - val loss: 0.6407 - val binary accuracy: 0.6296
Epoch 46/\overline{2}00
280 - val loss: 0.6401 - val binary accuracy: 0.6285
Epoch 47/\overline{2}00
256 - val loss: 0.6401 - val binary accuracy: 0.6294
Epoch 48/\overline{2}00
283 - val loss: 0.6394 - val binary accuracy: 0.6302
```

```
Epoch 49/200
235 - val loss: 0.6394 - val binary accuracy: 0.6273
Epoch 50/\overline{2}00
323 - val loss: 0.6381 - val binary accuracy: 0.6304
Epoch 51/\overline{2}00
296 - val loss: 0.6385 - val binary accuracy: 0.6244
Epoch 52/\overline{2}00
278 - val loss: 0.6380 - val binary accuracy: 0.6230
Epoch 53/\overline{2}00
313 - val loss: 0.6388 - val binary accuracy: 0.6302
Epoch 54/\overline{2}00
229 - val loss: 0.6371 - val binary accuracy: 0.6298
Epoch 55/\overline{2}00
284 - val loss: 0.6373 - val binary accuracy: 0.6302
Epoch 56/\overline{2}00
339 - val loss: 0.6364 - val binary accuracy: 0.6250
Epoch 57/\overline{2}00
366 - val loss: 0.6372 - val binary accuracy: 0.6252
Epoch 58/\overline{2}00
321 - val loss: 0.6364 - val binary accuracy: 0.6259
Epoch 59/\overline{2}00
334 - val loss: 0.6359 - val binary accuracy: 0.6292
Epoch 60/\overline{2}00
330 - val loss: 0.6359 - val binary accuracy: 0.6296
Epoch 61/\overline{2}00
328 - val loss: 0.6356 - val binary accuracy: 0.6308
Epoch 62/\overline{2}00
317 - val loss: 0.6358 - val binary accuracy: 0.6339
Epoch 63/\overline{2}00
313 - val loss: 0.6351 - val binary accuracy: 0.6323
Epoch 64/\overline{2}00
322 - val loss: 0.6355 - val binary accuracy: 0.6294
Epoch 65/\overline{2}00
300 - val loss: 0.6357 - val binary accuracy: 0.6364
Epoch 66/\overline{2}00
324 - val loss: 0.6341 - val binary accuracy: 0.6358
Epoch 67/\overline{2}00
339 - val loss: 0.6359 - val binary accuracy: 0.6198
Epoch 68/200
391 - val loss: 0.6338 - val binary accuracy: 0.6375
Epoch 69/\overline{2}00
315 - val loss: 0.6338 - val binary accuracy: 0.6360
Epoch 70/\overline{2}00
330 - val loss: 0.6328 - val binary accuracy: 0.6350
Epoch 71/\overline{2}00
371 - val loss: 0.6337 - val binary accuracy: 0.6354
```

```
Epoch 72/200
322 - val loss: 0.6325 - val binary accuracy: 0.6385
Epoch 73/\overline{2}00
345 - val loss: 0.6327 - val binary accuracy: 0.6366
Epoch 74/\overline{2}00
393 - val loss: 0.6329 - val binary accuracy: 0.6379
Epoch 75/\overline{2}00
361 - val loss: 0.6322 - val binary accuracy: 0.6408
Epoch 76/\overline{2}00
402 - val loss: 0.6321 - val binary accuracy: 0.6352
Epoch 77/\overline{2}00
367 - val loss: 0.6332 - val binary accuracy: 0.6410
Epoch 78/\overline{2}00
397 - val loss: 0.6323 - val binary accuracy: 0.6395
Epoch 79/\overline{2}00
0 - val loss: 0.6321 - val binary accuracy: 0.6370
Epoch 80/200
387 - val loss: 0.6322 - val binary accuracy: 0.6339
Epoch 81/\overline{2}00
392 - val loss: 0.6313 - val binary accuracy: 0.6420
Epoch 82/\overline{2}00
412 - val loss: 0.6312 - val binary accuracy: 0.6406
Epoch 83/\overline{2}00
442 - val loss: 0.6305 - val binary accuracy: 0.6397
Epoch 84/\overline{2}00
417 - val loss: 0.6306 - val binary accuracy: 0.6439
Epoch 85/\overline{2}00
358 - val loss: 0.6306 - val binary accuracy: 0.6443
Epoch 86/\overline{2}00
420 - val loss: 0.6308 - val binary accuracy: 0.6430
Epoch 87/\overline{2}00
1 - val loss: 0.6304 - val binary accuracy: 0.6445
Epoch 8\overline{8}/200
441 - val loss: 0.6303 - val binary accuracy: 0.6437
Epoch 89/\overline{2}00
443 - val loss: 0.6305 - val binary accuracy: 0.6410
Epoch 90/\overline{2}00
417 - val loss: 0.6294 - val binary accuracy: 0.6428
Epoch 91/\overline{2}00
460 - val loss: 0.6296 - val binary accuracy: 0.6433
Epoch 92/\overline{2}00
452 - val loss: 0.6299 - val binary accuracy: 0.6472
Epoch 93/\overline{2}00
432 - val loss: 0.6293 - val binary accuracy: 0.6468
Epoch 94/\overline{2}00
417 - val loss: 0.6301 - val binary accuracy: 0.6399
```

```
Epoch 95/200
488 - val loss: 0.6288 - val binary accuracy: 0.6455
Epoch 96/200
428 - val loss: 0.6288 - val binary accuracy: 0.6420
Epoch 97/\overline{2}00
445 - val loss: 0.6278 - val binary accuracy: 0.6470
Epoch 98/\overline{2}00
498 - val loss: 0.6280 - val binary accuracy: 0.6468
Epoch 99/\overline{2}00
474 - val loss: 0.6290 - val binary accuracy: 0.6404
Epoch 100/200
459 - val loss: 0.6273 - val binary accuracy: 0.6497
Epoch 101\overline{7}200
438 - val loss: 0.6276 - val binary accuracy: 0.6515
Epoch 102\overline{7}200
452 - val loss: 0.6269 - val binary accuracy: 0.6513
Epoch 103\overline{7}200
441 - val loss: 0.6270 - val binary accuracy: 0.6437
Epoch 104\overline{7}200
455 - val loss: 0.6266 - val binary accuracy: 0.6505
Epoch 1057200
493 - val loss: 0.6264 - val binary accuracy: 0.6489
Epoch 1067200
458 - val loss: 0.6263 - val binary accuracy: 0.6522
Epoch 1077200
463 - val loss: 0.6269 - val binary accuracy: 0.6466
Epoch 108\overline{7}200
541 - val loss: 0.6255 - val binary accuracy: 0.6474
Epoch 1097200
469 - val loss: 0.6266 - val binary accuracy: 0.6449
Epoch 110\overline{7}200
477 - val loss: 0.6258 - val binary accuracy: 0.6513
Epoch 111\overline{7}200
435 - val loss: 0.6257 - val binary accuracy: 0.6495
Epoch 1127200
493 - val loss: 0.6258 - val binary accuracy: 0.6476
Epoch 1137200
551 - val loss: 0.6252 - val binary accuracy: 0.6520
Epoch 114/200
481 - val loss: 0.6253 - val binary accuracy: 0.6499
Epoch 115/200
453 - val loss: 0.6255 - val binary accuracy: 0.6509
Epoch 116/200
489 - val loss: 0.6245 - val binary accuracy: 0.6547
Epoch 117\overline{7}200
496 - val loss: 0.6244 - val binary accuracy: 0.6507
```

```
Epoch 118/200
474 - val loss: 0.6258 - val binary accuracy: 0.6509
Epoch 119/200
445 - val loss: 0.6247 - val binary accuracy: 0.6526
Epoch 1207200
461 - val loss: 0.6242 - val binary accuracy: 0.6524
Epoch 121/200
502 - val loss: 0.6248 - val binary accuracy: 0.6453
Epoch 122\overline{7}200
465 - val loss: 0.6246 - val binary accuracy: 0.6486
Epoch 123/200
2 - val loss: 0.6242 - val binary accuracy: 0.6542
Epoch 1\overline{2}4/200
433 - val loss: 0.6246 - val binary accuracy: 0.6509
Epoch 1257200
488 - val loss: 0.6247 - val binary accuracy: 0.6563
Epoch 126\overline{7}200
513 - val loss: 0.6244 - val binary accuracy: 0.6486
Epoch 1277200
474 - val loss: 0.6260 - val binary accuracy: 0.6443
Epoch 1287200
3 - val loss: 0.6235 - val binary_accuracy: 0.6561
Epoch 1\overline{2}9/200
494 - val loss: 0.6239 - val binary accuracy: 0.6497
Epoch 1307200
527 - val loss: 0.6238 - val binary accuracy: 0.6499
Epoch 1317200
512 - val loss: 0.6244 - val binary accuracy: 0.6518
Epoch 1327200
488 - val loss: 0.6242 - val binary accuracy: 0.6505
Epoch 1337200
501 - val loss: 0.6230 - val binary accuracy: 0.6555
Epoch 134/200
473 - val loss: 0.6243 - val binary accuracy: 0.6520
Epoch 1357200
472 - val loss: 0.6240 - val binary accuracy: 0.6466
Epoch 136\overline{7}200
521 - val loss: 0.6228 - val binary accuracy: 0.6515
Epoch 137/200
530 - val loss: 0.6239 - val binary accuracy: 0.6474
Epoch 138/200
518 - val loss: 0.6228 - val binary accuracy: 0.6499
Epoch 139/200
552 - val loss: 0.6232 - val binary accuracy: 0.6491
Epoch 140\overline{7}200
504 - val loss: 0.6227 - val binary accuracy: 0.6497
```

```
Epoch 141/200
504 - val loss: 0.6226 - val binary accuracy: 0.6532
Epoch 142/200
506 - val loss: 0.6229 - val binary accuracy: 0.6497
Epoch 143/200
519 - val loss: 0.6232 - val binary accuracy: 0.6468
Epoch 144\overline{7}200
547 - val loss: 0.6221 - val binary accuracy: 0.6505
Epoch 1457200
562 - val loss: 0.6225 - val binary accuracy: 0.6551
Epoch 146\overline{7}200
573 - val loss: 0.6223 - val binary accuracy: 0.6559
Epoch 147\overline{7}200
492 - val loss: 0.6220 - val binary accuracy: 0.6542
Epoch 1487200
544 - val loss: 0.6222 - val binary accuracy: 0.6578
Epoch 149\overline{7}200
520 - val loss: 0.6218 - val binary accuracy: 0.6567
Epoch 1507200
497 - val loss: 0.6214 - val binary accuracy: 0.6576
Epoch 1517200
489 - val loss: 0.6214 - val binary accuracy: 0.6598
Epoch 1527200
503 - val loss: 0.6211 - val binary accuracy: 0.6586
Epoch 1537200
488 - val loss: 0.6217 - val binary accuracy: 0.6569
Epoch 154\overline{7}200
543 - val loss: 0.6220 - val binary accuracy: 0.6486
Epoch 1557200
576 - val loss: 0.6210 - val binary accuracy: 0.6536
Epoch 156\overline{7}200
578 - val loss: 0.6211 - val binary accuracy: 0.6518
Epoch 157\overline{7}200
528 - val loss: 0.6213 - val binary accuracy: 0.6551
Epoch 1587200
528 - val loss: 0.6206 - val binary accuracy: 0.6557
Epoch 159\overline{7}200
534 - val loss: 0.6206 - val binary accuracy: 0.6532
Epoch 160/200
525 - val loss: 0.6203 - val binary accuracy: 0.6563
Epoch 161/200
497 - val loss: 0.6208 - val binary accuracy: 0.6538
Epoch 162/200
520 - val loss: 0.6213 - val binary accuracy: 0.6578
Epoch 1637200
547 - val loss: 0.6205 - val binary accuracy: 0.6549
```

```
Epoch 164/200
522 - val loss: 0.6203 - val binary accuracy: 0.6578
Epoch 165/200
536 - val loss: 0.6203 - val binary accuracy: 0.6580
Epoch 166/200
505 - val loss: 0.6199 - val binary accuracy: 0.6536
Epoch 167/200
533 - val loss: 0.6212 - val binary accuracy: 0.6536
Epoch 1687200
565 - val loss: 0.6203 - val binary accuracy: 0.6584
Epoch 169\overline{7}200
506 - val loss: 0.6213 - val binary accuracy: 0.6513
Epoch 170\overline{7}200
537 - val loss: 0.6206 - val binary accuracy: 0.6540
Epoch 1717200
520 - val loss: 0.6204 - val binary accuracy: 0.6555
Epoch 172\overline{7}200
547 - val loss: 0.6206 - val binary accuracy: 0.6580
Epoch 1737200
553 - val loss: 0.6197 - val binary accuracy: 0.6551
Epoch 1747200
512 - val loss: 0.6194 - val binary accuracy: 0.6559
Epoch 1757200
572 - val loss: 0.6195 - val binary accuracy: 0.6540
Epoch 1767200
507 - val loss: 0.6199 - val binary accuracy: 0.6505
Epoch 177\overline{7}200
607 - val loss: 0.6193 - val binary accuracy: 0.6573
Epoch 1787200
564 - val loss: 0.6201 - val binary accuracy: 0.6555
Epoch 179\overline{7}200
509 - val loss: 0.6194 - val binary accuracy: 0.6565
Epoch 180/200
513 - val loss: 0.6186 - val binary accuracy: 0.6598
Epoch 1817200
530 - val loss: 0.6194 - val binary accuracy: 0.6555
Epoch 1827200
488 - val loss: 0.6197 - val binary accuracy: 0.6542
Epoch 183/200
552 - val loss: 0.6184 - val binary accuracy: 0.6594
Epoch 184/200
590 - val loss: 0.6205 - val binary accuracy: 0.6547
Epoch 185/200
536 - val loss: 0.6182 - val binary accuracy: 0.6613
Epoch 186\overline{7}200
610 - val loss: 0.6183 - val binary accuracy: 0.6598
```

```
Epoch 187/200
589 - val loss: 0.6187 - val binary accuracy: 0.6549
Epoch 188/200
603 - val loss: 0.6186 - val binary accuracy: 0.6602
Epoch 1897200
576 - val loss: 0.6186 - val binary accuracy: 0.6584
Epoch 190\overline{7}200
526 - val loss: 0.6193 - val binary accuracy: 0.6547
Epoch 191\overline{7}200
557 - val loss: 0.6182 - val binary accuracy: 0.6532
Epoch 192/200
521 - val loss: 0.6176 - val binary accuracy: 0.6567
Epoch 1937200
522 - val loss: 0.6179 - val binary accuracy: 0.6584
Epoch 1947200
598 - val loss: 0.6177 - val binary accuracy: 0.6600
Epoch 1957200
572 - val loss: 0.6176 - val binary accuracy: 0.6559
Epoch 1967200
516 - val loss: 0.6176 - val binary accuracy: 0.6619
Epoch 1977200
582 - val loss: 0.6178 - val binary accuracy: 0.6580
Epoch 1987200
573 - val loss: 0.6187 - val binary accuracy: 0.6596
Epoch 1997200
605 - val loss: 0.6182 - val binary accuracy: 0.6540
Epoch 2007200
524 - val loss: 0.6175 - val binary accuracy: 0.6582
                                        Out[70]:
<tensorflow.python.keras.callbacks.History at 0x207c3902f10>
                                         In [71]:
pd.DataFrame(model new.history.history)[['loss','val loss']].plot()
```

Out[71]:



<AxesSubplot:>

0.61

0

In [72]:

200

```
predictions new = (model new.predict proba(X test) >= 0.2).astype('int')
print(
        confusion matrix(y test, predictions new),
        classification report(y test, predictions new)
)
[[ 242 2195]
  30 2360]]
               precision
                          recall f1-score
                                                support
           0
                   0.89
                             0.10
                                        0.18
                                                  2437
                             0.99
                   0.52
                                        0.68
                                                  2390
                                        0.54
   accuracy
                                                  4827
                   0.70
                             0.54
                                        0.43
                                                  4827
  macro avq
                   0.71
                             0.54
                                        0.43
                                                  4827
weighted avg
```

C:\Users\User\anaconda3\lib\site-packages\tensorflow\python\keras\engine\sequential.py:430:
UserWarning: `model.predict_proba()` is deprecated and will be removed after 2021-01-01. Ple
ase use `model.predict()` instead.
 warnings.warn('`model.predict proba()` is deprecated and '

By: Abdullah Alwabel