from IPython.display import Image
Image(filename='Capture.png')



Predicting Loan Defaults using Deep Learning with Keras & Tensorflow

import libraries

```
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 #pip uninstall h5py
#conda install -c anaconda h5py
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

df = pd.read_csv(r"C:/Users/Nageswaran
B/Documents/machine_learning/machine_learning_project/simplilearn/
Lending_Club_Loan_Data_Analysis/loan_data.csv")
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):

```
5
     dti
                         9578 non-null
                                         float64
                                         int64
 6
     fico
                         9578 non-null
                         9578 non-null
 7
     days.with.cr.line
                                         float64
 8
     revol.bal
                         9578 non-null
                                         int64
     revol.util
                         9578 non-null
                                         float64
 9
                         9578 non-null
 10
     ing.last.6mths
                                         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
df.head()
   credit.policy
                              purpose int.rate installment
log.annual.inc
                  debt consolidation
                                         0.1189
                                                       829.10
11.350407
               1
                          credit_card
                                         0.1071
                                                       228.22
1
11.082143
               1
                  debt_consolidation
                                         0.1357
                                                       366.86
10.373491
                  debt consolidation
               1
                                         0.1008
                                                       162.34
11.350407
               1
                          credit card
                                         0.1426
                                                       102.92
11.299732
                days.with.cr.line revol.bal
                                                revol.util
     dti
          fico
ing.last.6mths
   19.48
                      5639.958333
                                        28854
           737
                                                      52.1
1
   14.29
           707
                      2760.000000
                                        33623
                                                      76.7
0
2
                                                      25.6
   11.63
           682
                      4710.000000
                                         3511
1
3
    8.10
           712
                       2699.958333
                                        33667
                                                      73.2
1
4
   14.97
           667
                      4066.000000
                                         4740
                                                      39.5
   deling.2yrs
                pub.rec
                          not.fully.paid
0
             0
                       0
                                       0
1
2
             0
                       0
                                       0
3
             0
                       0
                                       0
```

0

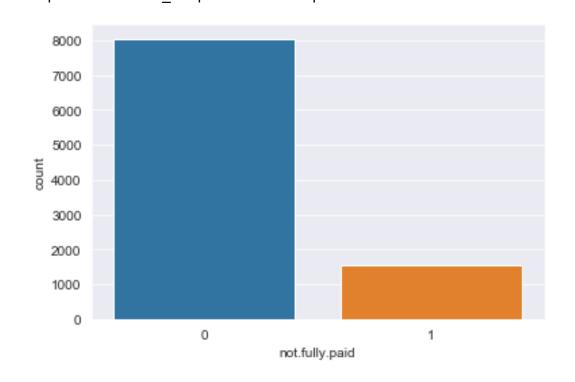
1

The "Purpose" data column is categorical, "Annual income" is log value, which needs to be converted back to exponential. The rest of the columns are numerical. Transpose the data frame to understand the std and mean.

df.describe().transpose()

credit.policy int.rate installment log.annual.inc dti fico days.with.cr.line revol.bal revol.util inq.last.6mths delinq.2yrs pub.rec not.fully.paid	count 9578.0 9578.0 9578.0 9578.0 9578.0 9578.0 9578.0 9578.0 9578.0 9578.0 9578.0	31 1 71 456 1691 4	mean 0.804970 0.122640 9.089413 0.932117 2.606679 0.846314 0.767197 3.963876 6.799236 1.577469 0.163708 0.062122 0.160054	24 337	std 0.396245 0.026847 07.071301 0.614813 6.883970 37.970537 96.930377 56.189557 29.014417 2.200245 0.546215 0.262126 0.366676	0 15 7 0 612 178 0 0 0	min .000000 .060000 .547502 .000000 .000000 .958333 .000000 .000000 .000000 .000000	\
ma\/		25%		50%		75%		
max credit.policy	1.00	0000	1.000	000	1.000	000		
1.000000e+00 int.rate	0.10	3900	0.122	100	0.140	700	2.16400)0e-
01							2120.00	
installment 9.401400e+02	163.77	0000	268.956	0000	432.762	500		
log.annual.inc 1.452835e+01	10.55	8414	10.928	8884	11.291	.293		
dti	7.21	2500	12.665	000	17.950	000		
2.996000e+01 fico	682.00	0000	707.000	000	737.000	000		
8.270000e+02								
days.with.cr.line 1.763996e+04	2820.00	0000	4139.958	3333	5730.000	000		
revol.bal 1.207359e+06	3187.00	0000	8596.000	0000	18249.500	000		
revol.util	22.60	0000	46.300	000	70.900	000		
1.190000e+02 inq.last.6mths	0.00	0000	1.000	000	2.000	000		
3.300000e+01								
delinq.2yrs 1.300000e+01	0.00	0000	0.000	0000	0.000	000		
pub.rec 5.000000e+00	0.00	0000	0.000	000	0.000	000		
not.fully.paid 1.000000e+00	0.00	9000	0.000	0000	0.000	000		

```
Check the label "no.fully.paid" distribution in the dataset.
df['not.fully.paid'].isnull().mean()
df.groupby('not.fully.paid')['not.fully.paid'].count()/len(df)
not.fully.paid
0     0.839946
1     0.160054
Name: not.fully.paid, dtype: float64
sns.set_style('darkgrid')
sns.countplot(x='not.fully.paid', data=df)
<matplotlib.axes._subplots.AxesSubplot at 0x2a40177aa90>
```



The above shows, This dataset is highly imbalanced and includes features that make this problem more challenging. If we do model training with this data, the prediction will be biased since the "not.fully.paid =0" has 83.9% filled, and only 16% is the "not.fully.paid=1"

There were multiple methods to handle imbalanced data; here are a few techniques.

1. Resample the training set

There are two approaches to make a balanced dataset out of an imbalanced one are undersampling and over-sampling.

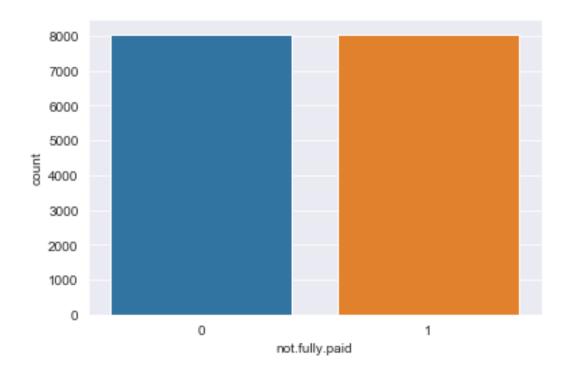
Under-sampling

Under-sampling balances the dataset by reducing the size of the abundant class. This method is used when the quantity of data is sufficient.

Over-sampling

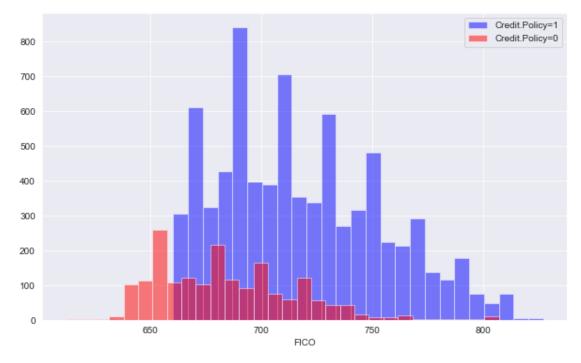
Oversampling is used when the quantity of data is insufficient. It tries to balance the dataset by increasing the size of rare samples.

```
There is no absolute advantage of one resampling method over another.
count class 0, count class 1 = df['not.fully.paid'].value counts()
df 0 = df[df['not.fully.paid'] == 0]
df 1 = df[df['not.fully.paid'] == 1]
df 1 over = df 1.sample(count class 0, replace=True)
df test over = pd.concat([df 0, df 1 over], axis=0)
print('Random over-sampling:')
print(df test over['not.fully.paid'].value counts())
sns.set style('darkgrid')
sns.countplot(x='not.fully.paid', data=df test over)
Random over-sampling:
     8045
1
     8045
Name: not.fully.paid, dtype: int64
<matplotlib.axes. subplots.AxesSubplot at 0x2a401ad3e48>
```

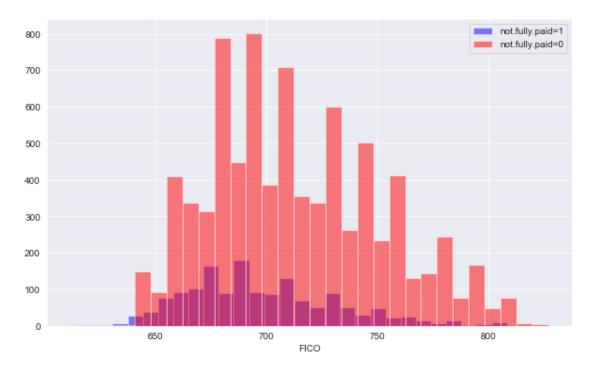


Exploratory Data Analysis

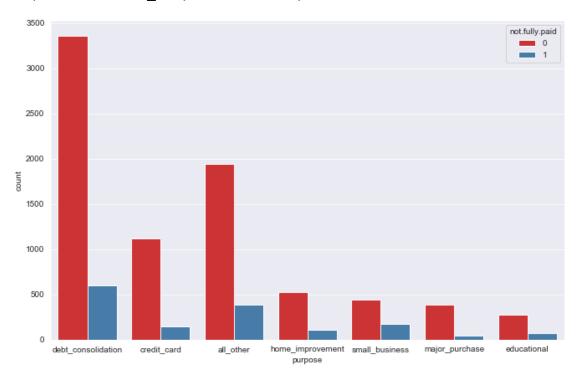
```
plt.figure(figsize=(10,6))
df[df['credit.policy']==1]
['fico'].hist(alpha=0.5,color='blue',bins=30,label='Credit.Policy=1')
df[df['credit.policy']==0]
['fico'].hist(alpha=0.5,color='red',bins=30,label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
Text(0.5, 0, 'FICO')
```



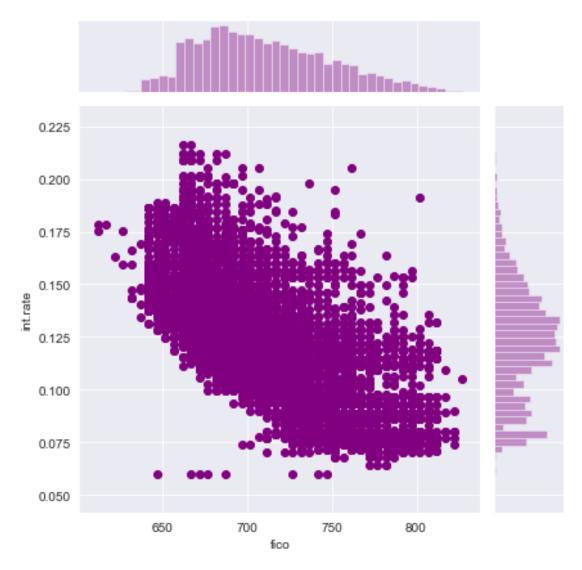
```
plt.figure(figsize=(10,6))
df[df['not.fully.paid']==1]
['fico'].hist(alpha=0.5,color='blue',bins=30,label='not.fully.paid=1')
df[df['not.fully.paid']==0]
['fico'].hist(alpha=0.5,color='red',bins=30,label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
Text(0.5, 0, 'FICO')
```



plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=df,palette='Set1')
<matplotlib.axes._subplots.AxesSubplot at 0x2a402dc3940>

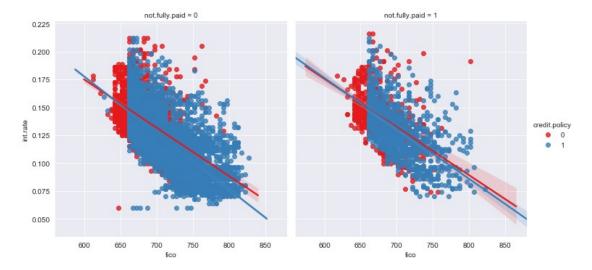


sns.jointplot(x='fico',y='int.rate',data=df,color='purple')
<seaborn.axisgrid.JointGrid at 0x2a402e13208>



<seaborn.axisgrid.FacetGrid at 0x2a4031a34e0>

<Figure size 792x504 with 0 Axes>



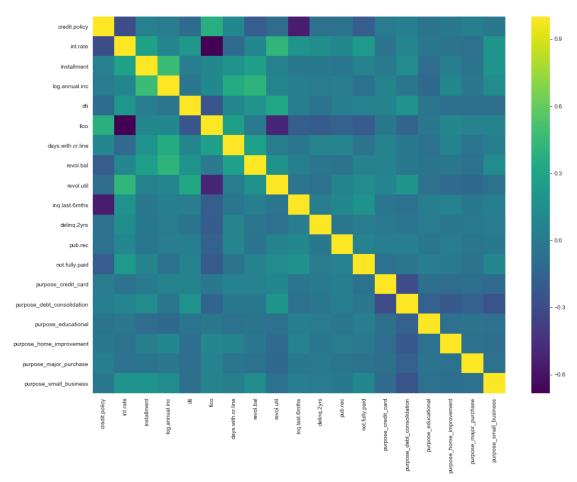
The above visuals gave us an idea of how the data is and what we will work with. Nest step is to prepare the data for model training and test as the first step converts the categorical values to numeric. Here in this dataset "purpose" column is a critical data point for the model as per our analysis above, and it is categorical.

```
col_fea = ['purpose']
final_data =
pd.get_dummies(df_test_over,columns=col_fea,drop_first=True)
final_data.info()
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 16090 entries, 0 to 8012
Data columns (total 19 columns):

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

<matplotlib.axes._subplots.AxesSubplot at 0x2a403280ac8>



We only focus on the grids of yellow or very light green. After comparing with the feature description again, I decided to drop:'revol.bal', 'days.with.cr.line', 'installment', 'revol.bal'

revol.bal, day.with.cr.line, installment can represent by annual income. revol.util can represent by int.rate.

Modeling

Deep Learning Implementation

```
Finally, do the train test split and fit the model with the data shape we created above, since
there are 19 features, I chose the first layer of the neural network with 19 nodes.
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
accuracy: 0.5401 - val loss: 0.6884 - val accuracy: 0.5844
Epoch 2/200
accuracy: 0.6041 - val loss: 0.6794 - val accuracy: 0.6002
Epoch 3/200
accuracy: 0.6135 - val loss: 0.6677 - val accuracy: 0.6051
Epoch 4/200
accuracy: 0.6145 - val loss: 0.6575 - val accuracy: 0.6105
Epoch 5/200
accuracy: 0.6203 - val loss: 0.6530 - val accuracy: 0.6130
Epoch 6/200
accuracy: 0.6230 - val_loss: 0.6517 - val_accuracy: 0.6169
Epoch 7/200
accuracy: 0.6220 - val loss: 0.6511 - val accuracy: 0.6109
Epoch 8/200
accuracy: 0.6261 - val loss: 0.6513 - val accuracy: 0.6101
Epoch 9/200
accuracy: 0.6219 - val loss: 0.6501 - val accuracy: 0.6093
Epoch 10/200
accuracy: 0.6258 - val loss: 0.6494 - val accuracy: 0.6128
Epoch 11/200
```

```
accuracy: 0.6259 - val loss: 0.6483 - val accuracy: 0.6145
Epoch 12/200
accuracy: 0.6275 - val loss: 0.6489 - val accuracy: 0.6122
Epoch 13/200
accuracy: 0.6274 - val loss: 0.6479 - val accuracy: 0.6153
Epoch 14/200
accuracy: 0.6293 - val loss: 0.6472 - val accuracy: 0.6163
Epoch 15/200
accuracy: 0.6311 - val loss: 0.6485 - val accuracy: 0.6085
Epoch 16/200
accuracy: 0.6313 - val loss: 0.6454 - val accuracy: 0.6182
Epoch 17/200
accuracy: 0.6306 - val loss: 0.6459 - val accuracy: 0.6178
Epoch 18/200
accuracy: 0.6298 - val loss: 0.6458 - val accuracy: 0.6182
Epoch 19/200
accuracy: 0.6295 - val loss: 0.6448 - val accuracy: 0.6169
Epoch 20/200
accuracy: 0.6320 - val loss: 0.6446 - val accuracy: 0.6184
Epoch 21/200
accuracy: 0.6298 - val loss: 0.6439 - val accuracy: 0.6165
Epoch 22/200
accuracy: 0.6346 - val loss: 0.6439 - val accuracy: 0.6165
Epoch 23/200
accuracy: 0.6359 - val loss: 0.6429 - val accuracy: 0.6194
Epoch 24/200
accuracy: 0.6346 - val loss: 0.6439 - val accuracy: 0.6213
Epoch 25/200
accuracy: 0.6326 - val loss: 0.6433 - val accuracy: 0.6203
Epoch 26/200
accuracy: 0.6355 - val loss: 0.6426 - val accuracy: 0.6169
Epoch 27/200
accuracy: 0.6337 - val loss: 0.6423 - val accuracy: 0.6269
```

```
Epoch 28/200
accuracy: 0.6370 - val loss: 0.6428 - val accuracy: 0.6273
Epoch 29/200
accuracy: 0.6348 - val loss: 0.6467 - val accuracy: 0.6194
Epoch 30/200
accuracy: 0.6339 - val loss: 0.6415 - val accuracy: 0.6230
Epoch 31/200
accuracy: 0.6352 - val loss: 0.6411 - val accuracy: 0.6232
Epoch 32/200
accuracy: 0.6367 - val_loss: 0.6415 - val_accuracy: 0.6238
Epoch 33/200
accuracy: 0.6364 - val_loss: 0.6408 - val_accuracy: 0.6209
Epoch 34/200
accuracy: 0.6365 - val loss: 0.6405 - val accuracy: 0.6225
Epoch 35/200
accuracy: 0.6366 - val loss: 0.6404 - val accuracy: 0.6184
Epoch 36/200
accuracy: 0.6382 - val_loss: 0.6410 - val_accuracy: 0.6236
Epoch 37/200
accuracy: 0.6361 - val_loss: 0.6395 - val_accuracy: 0.6219
Epoch 38/200
accuracy: 0.6362 - val loss: 0.6400 - val accuracy: 0.6265
Epoch 39/200
accuracy: 0.6369 - val loss: 0.6395 - val accuracy: 0.6246
Epoch 40/200
accuracy: 0.6380 - val loss: 0.6396 - val accuracy: 0.6184
Epoch 41/200
accuracy: 0.6384 - val loss: 0.6397 - val accuracy: 0.6242
Epoch 42/200
accuracy: 0.6369 - val loss: 0.6395 - val accuracy: 0.6248
Epoch 43/200
accuracy: 0.6401 - val loss: 0.6390 - val accuracy: 0.6271
Epoch 44/200
```

```
accuracy: 0.6389 - val loss: 0.6399 - val accuracy: 0.6256
Epoch 45/200
accuracy: 0.6430 - val loss: 0.6397 - val accuracy: 0.6269
Epoch 46/200
accuracy: 0.6412 - val loss: 0.6384 - val accuracy: 0.6254
Epoch 47/200
accuracy: 0.6396 - val loss: 0.6399 - val accuracy: 0.6269
Epoch 48/200
accuracy: 0.6407 - val loss: 0.6388 - val accuracy: 0.6236
Epoch 49/200
accuracy: 0.6400 - val loss: 0.6417 - val accuracy: 0.6238
Epoch 50/200
accuracy: 0.6375 - val loss: 0.6383 - val accuracy: 0.6298
Epoch 51/200
accuracy: 0.6382 - val loss: 0.6382 - val accuracy: 0.6292
Epoch 52/200
accuracy: 0.6401 - val loss: 0.6388 - val accuracy: 0.6265
Epoch 53/200
accuracy: 0.6442 - val loss: 0.6382 - val accuracy: 0.6265
Epoch 54/200
accuracy: 0.6412 - val loss: 0.6403 - val accuracy: 0.6275
Epoch 55/200
accuracy: 0.6426 - val loss: 0.6374 - val accuracy: 0.6275
Epoch 56/200
accuracy: 0.6428 - val loss: 0.6379 - val accuracy: 0.6319
Epoch 57/200
accuracy: 0.6406 - val loss: 0.6382 - val accuracy: 0.6304
Epoch 58/200
accuracy: 0.6420 - val loss: 0.6372 - val accuracy: 0.6288
Epoch 59/200
accuracy: 0.6414 - val_loss: 0.6368 - val_accuracy: 0.6281
Epoch 60/200
accuracy: 0.6458 - val loss: 0.6374 - val accuracy: 0.6292
Epoch 61/200
```

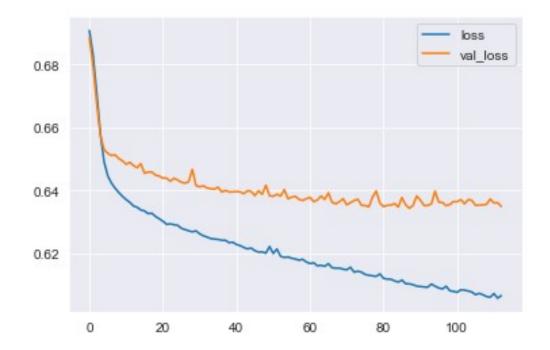
```
accuracy: 0.6444 - val loss: 0.6378 - val accuracy: 0.6294
Epoch 62/200
accuracy: 0.6422 - val loss: 0.6364 - val accuracy: 0.6256
Epoch 63/200
accuracy: 0.6463 - val loss: 0.6370 - val accuracy: 0.6302
Epoch 64/200
accuracy: 0.6436 - val loss: 0.6382 - val accuracy: 0.6294
Epoch 65/200
accuracy: 0.6463 - val loss: 0.6372 - val accuracy: 0.6310
Epoch 66/200
accuracy: 0.6449 - val loss: 0.6393 - val accuracy: 0.6327
Epoch 67/200
accuracy: 0.6444 - val loss: 0.6362 - val accuracy: 0.6277
Epoch 68/200
accuracy: 0.6463 - val_loss: 0.6357 - val_accuracy: 0.6308
Epoch 69/200
accuracy: 0.6449 - val loss: 0.6364 - val accuracy: 0.6271
Epoch 70/200
accuracy: 0.6454 - val loss: 0.6374 - val accuracy: 0.6312
Epoch 71/200
accuracy: 0.6455 - val loss: 0.6354 - val accuracy: 0.6279
Epoch 72/200
accuracy: 0.6472 - val loss: 0.6361 - val accuracy: 0.6246
Epoch 73/200
accuracy: 0.6463 - val loss: 0.6368 - val accuracy: 0.6290
Epoch 74/200
accuracy: 0.6437 - val loss: 0.6372 - val accuracy: 0.6337
Epoch 75/200
accuracy: 0.6456 - val loss: 0.6353 - val_accuracy: 0.6250
Epoch 76/200
accuracy: 0.6476 - val loss: 0.6352 - val accuracy: 0.6298
Epoch 77/200
accuracy: 0.6484 - val loss: 0.6348 - val accuracy: 0.6298
```

```
Epoch 78/200
accuracy: 0.6466 - val loss: 0.6379 - val accuracy: 0.6300
Epoch 79/200
accuracy: 0.6471 - val loss: 0.6398 - val accuracy: 0.6285
Epoch 80/200
accuracy: 0.6476 - val loss: 0.6360 - val accuracy: 0.6327
Epoch 81/200
accuracy: 0.6477 - val loss: 0.6349 - val accuracy: 0.6341
Epoch 82/200
accuracy: 0.6489 - val loss: 0.6353 - val accuracy: 0.6308
Epoch 83/200
accuracy: 0.6493 - val_loss: 0.6354 - val_accuracy: 0.6310
Epoch 84/200
accuracy: 0.6514 - val loss: 0.6358 - val accuracy: 0.6312
Epoch 85/200
accuracy: 0.6478 - val loss: 0.6347 - val accuracy: 0.6337
Epoch 86/200
accuracy: 0.6459 - val loss: 0.6378 - val accuracy: 0.6323
Epoch 87/200
accuracy: 0.6517 - val_loss: 0.6355 - val_accuracy: 0.6323
Epoch 88/200
accuracy: 0.6504 - val loss: 0.6343 - val accuracy: 0.6296
Epoch 89/200
accuracy: 0.6504 - val loss: 0.6352 - val accuracy: 0.6304
Epoch 90/200
44/44 [============== ] - 0s 1ms/step - loss: 0.6097 -
accuracy: 0.6495 - val loss: 0.6382 - val_accuracy: 0.6310
Epoch 91/200
accuracy: 0.6508 - val loss: 0.6369 - val accuracy: 0.6302
Epoch 92/200
accuracy: 0.6485 - val loss: 0.6352 - val accuracy: 0.6335
Epoch 93/200
accuracy: 0.6492 - val loss: 0.6352 - val accuracy: 0.6302
Epoch 94/200
```

```
accuracy: 0.6516 - val loss: 0.6358 - val accuracy: 0.6319
Epoch 95/200
accuracy: 0.6518 - val loss: 0.6398 - val accuracy: 0.6358
Epoch 96/200
accuracy: 0.6512 - val loss: 0.6363 - val accuracy: 0.6306
Epoch 97/200
accuracy: 0.6495 - val loss: 0.6362 - val accuracy: 0.6354
Epoch 98/200
accuracy: 0.6514 - val loss: 0.6352 - val accuracy: 0.6319
Epoch 99/200
accuracy: 0.6519 - val loss: 0.6355 - val accuracy: 0.6310
Epoch 100/200
accuracy: 0.6526 - val loss: 0.6365 - val accuracy: 0.6343
Epoch 101/200
accuracy: 0.6508 - val loss: 0.6365 - val accuracy: 0.6323
Epoch 102/200
accuracy: 0.6539 - val loss: 0.6371 - val accuracy: 0.6306
Epoch 103/200
accuracy: 0.6525 - val loss: 0.6358 - val accuracy: 0.6354
Epoch 104/200
accuracy: 0.6547 - val loss: 0.6371 - val accuracy: 0.6335
Epoch 105/200
accuracy: 0.6513 - val loss: 0.6369 - val accuracy: 0.6333
Epoch 106/200
accuracy: 0.6535 - val loss: 0.6353 - val accuracy: 0.6298
Epoch 107/200
accuracy: 0.6519 - val loss: 0.6354 - val accuracy: 0.6354
Epoch 108/200
accuracy: 0.6548 - val loss: 0.6354 - val accuracy: 0.6337
Epoch 109/200
accuracy: 0.6551 - val_loss: 0.6356 - val_accuracy: 0.6323
Epoch 110/200
accuracy: 0.6549 - val loss: 0.6373 - val accuracy: 0.6339
Epoch 111/200
```

Model Evaluation and Validation

```
pd.DataFrame(model.history.history)[['loss','val_loss']].plot()
<matplotlib.axes. subplots.AxesSubplot at 0x2a4033789b0>
```



0	0.63	0.68	0.65	2437
1	0.64	0.59	0.62	2390
accuracy			0.64	4827
macro avg	0.64	0.64	0.64	4827
weighted avg	0.64	0.64	0.64	4827

The model's overall f1-score for accuracy is 0.65. Still, there are type 2 errors (972) in the prediction.

Model Refinement

Two ways of refining the model we will try here. Add Dropout layers to bring down the overfitting OR Lower the cut-off line in binary prediction to reduce the Type 2 error, at the cost of increasing Type 1 error. In the LendingClub case, Type 2 error is the more serious problem because it devastates its balance sheet, while Type 1 error is not a very big deal. 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
binary accuracy: 0.5380 - val loss: 0.6896 - val binary accuracy:
0.5780
Epoch 2/200
binary_accuracy: 0.5537 - val_loss: 0.6832 - val_binary_accuracy:
0.5927
Epoch 3/200
binary accuracy: 0.5649 - val loss: 0.6749 - val binary accuracy:
0.6070
Epoch 4/200
binary accuracy: 0.5788 - val loss: 0.6666 - val binary accuracy:
0.6091
Epoch 5/200
binary accuracy: 0.5957 - val loss: 0.6624 - val binary accuracy:
0.6070
Epoch 6/200
binary accuracy: 0.5934 - val loss: 0.6605 - val binary accuracy:
0.6118
Epoch 7/200
binary accuracy: 0.6029 - val loss: 0.6589 - val binary accuracy:
0.6095
Epoch 8/200
binary accuracy: 0.6087 - val loss: 0.6586 - val binary accuracy:
0.6145
Epoch 9/200
binary_accuracy: 0.6093 - val_loss: 0.6585 - val_binary_accuracy:
0.6078
Epoch 10/200
binary accuracy: 0.6062 - val loss: 0.6573 - val binary accuracy:
```

```
0.6053
Epoch 11/200
binary accuracy: 0.6156 - val loss: 0.6564 - val binary accuracy:
0.6087
Epoch 12/200
binary accuracy: 0.6133 - val loss: 0.6561 - val binary accuracy:
0.6107
Epoch 13/200
binary_accuracy: 0.6206 - val_loss: 0.6556 - val_binary_accuracy:
0.6095
Epoch 14/200
binary accuracy: 0.6175 - val loss: 0.6555 - val binary accuracy:
0.6116
Epoch 15/200
binary accuracy: 0.6148 - val loss: 0.6551 - val binary accuracy:
0.6138
Epoch 16/200
binary accuracy: 0.6172 - val loss: 0.6541 - val binary accuracy:
0.6153
Epoch 17/200
binary accuracy: 0.6181 - val loss: 0.6535 - val binary accuracy:
0.6165
Epoch 18/200
binary accuracy: 0.6204 - val loss: 0.6530 - val binary accuracy:
0.6153
Epoch 19/200
binary accuracy: 0.6203 - val loss: 0.6530 - val binary accuracy:
0.6178
Epoch 20/200
binary accuracy: 0.6189 - val loss: 0.6523 - val binary accuracy:
0.6165
Epoch 21/200
binary accuracy: 0.6188 - val loss: 0.6514 - val binary accuracy:
0.6165
Epoch 22/200
binary accuracy: 0.6182 - val loss: 0.6511 - val binary accuracy:
0.6116
Epoch 23/200
```

```
binary accuracy: 0.6200 - val loss: 0.6510 - val binary accuracy:
0.6163
Epoch 24/200
binary_accuracy: 0.6198 - val_loss: 0.6505 - val_binary_accuracy:
0.6169
Epoch 25/200
binary accuracy: 0.6169 - val loss: 0.6501 - val binary accuracy:
0.6174
Epoch 26/200
binary accuracy: 0.6229 - val loss: 0.6495 - val binary accuracy:
0.6172
Epoch 27/200
binary_accuracy: 0.6184 - val_loss: 0.6500 - val_binary_accuracy:
0.6169
Epoch 28/200
binary accuracy: 0.6176 - val loss: 0.6503 - val binary accuracy:
0.6138
Epoch 29/200
binary accuracy: 0.6247 - val loss: 0.6495 - val_binary_accuracy:
0.6134
Epoch 30/200
binary accuracy: 0.6239 - val loss: 0.6494 - val binary accuracy:
0.6213
Epoch 31/200
binary accuracy: 0.6197 - val loss: 0.6495 - val binary accuracy:
0.6225
Epoch 32/200
binary accuracy: 0.6266 - val loss: 0.6487 - val binary accuracy:
0.6174
Epoch 33/200
binary accuracy: 0.6212 - val loss: 0.6486 - val binary accuracy:
0.6230
Epoch 34/200
binary_accuracy: 0.6243 - val_loss: 0.6490 - val_binary_accuracy:
0.6215
Epoch 35/200
binary accuracy: 0.6213 - val loss: 0.6489 - val binary accuracy:
```

```
0.6151
Epoch 36/200
binary accuracy: 0.6217 - val loss: 0.6483 - val binary accuracy:
0.6236
Epoch 37/200
binary accuracy: 0.6303 - val loss: 0.6485 - val binary accuracy:
0.6230
Epoch 38/200
binary_accuracy: 0.6259 - val_loss: 0.6479 - val_binary_accuracy:
0.6207
Epoch 39/200
binary accuracy: 0.6276 - val loss: 0.6475 - val binary accuracy:
0.6240
Epoch 40/200
binary accuracy: 0.6295 - val loss: 0.6477 - val binary accuracy:
0.6219
Epoch 41/200
binary accuracy: 0.6266 - val loss: 0.6473 - val binary accuracy:
0.6244
Epoch 42/200
binary accuracy: 0.6231 - val loss: 0.6470 - val binary accuracy:
0.6275
Epoch 43/200
binary accuracy: 0.6272 - val loss: 0.6470 - val binary accuracy:
0.6261
Epoch 44/200
binary accuracy: 0.6290 - val loss: 0.6469 - val binary accuracy:
0.6246
Epoch 45/200
binary accuracy: 0.6291 - val loss: 0.6472 - val binary accuracy:
0.6248
Epoch 46/200
binary accuracy: 0.6267 - val loss: 0.6470 - val binary accuracy:
0.6203
Epoch 47/200
binary accuracy: 0.6279 - val loss: 0.6466 - val binary accuracy:
0.6223
Epoch 48/200
```

```
binary accuracy: 0.6332 - val loss: 0.6472 - val binary accuracy:
0.6167
Epoch 49/200
binary_accuracy: 0.6295 - val_loss: 0.6456 - val_binary_accuracy:
0.6265
Epoch 50/200
binary accuracy: 0.6309 - val loss: 0.6458 - val binary accuracy:
0.6248
Epoch 51/200
binary accuracy: 0.6283 - val loss: 0.6461 - val binary accuracy:
0.6178
Epoch 52/200
binary_accuracy: 0.6301 - val_loss: 0.6455 - val_binary_accuracy:
0.6240
Epoch 53/200
binary accuracy: 0.6311 - val loss: 0.6449 - val binary accuracy:
0.6236
Epoch 54/200
binary accuracy: 0.6339 - val loss: 0.6444 - val binary accuracy:
0.6213
Epoch 55/200
binary accuracy: 0.6279 - val loss: 0.6444 - val binary accuracy:
0.6254
Epoch 56/200
binary accuracy: 0.6343 - val loss: 0.6441 - val binary accuracy:
0.6242
Epoch 57/200
binary accuracy: 0.6335 - val loss: 0.6431 - val binary accuracy:
0.6285
Epoch 58/200
binary accuracy: 0.6321 - val loss: 0.6430 - val binary accuracy:
0.6277
Epoch 59/200
binary_accuracy: 0.6258 - val_loss: 0.6433 - val_binary_accuracy:
0.6236
Epoch 60/200
binary accuracy: 0.6330 - val loss: 0.6427 - val binary accuracy:
```

```
0.6271
Epoch 61/200
binary accuracy: 0.6323 - val loss: 0.6426 - val binary accuracy:
0.6271
Epoch 62/200
binary accuracy: 0.6340 - val loss: 0.6422 - val binary accuracy:
0.6244
Epoch 63/200
binary accuracy: 0.6307 - val loss: 0.6418 - val binary accuracy:
0.6238
Epoch 64/200
binary accuracy: 0.6329 - val loss: 0.6420 - val binary accuracy:
0.6290
Epoch 65/200
binary accuracy: 0.6300 - val loss: 0.6415 - val binary accuracy:
0.6242
Epoch 66/200
binary accuracy: 0.6343 - val loss: 0.6416 - val binary accuracy:
0.6252
Epoch 67/200
binary accuracy: 0.6352 - val loss: 0.6411 - val binary accuracy:
0.6252
Epoch 68/200
binary accuracy: 0.6326 - val loss: 0.6415 - val binary accuracy:
0.6269
Epoch 69/200
binary accuracy: 0.6348 - val loss: 0.6409 - val binary accuracy:
0.6232
Epoch 70/200
binary accuracy: 0.6312 - val loss: 0.6411 - val binary accuracy:
0.6254
Epoch 71/200
binary accuracy: 0.6358 - val loss: 0.6411 - val binary accuracy:
0.6288
Epoch 72/200
binary accuracy: 0.6367 - val loss: 0.6405 - val binary accuracy:
0.6252
Epoch 73/200
```

```
binary accuracy: 0.6328 - val loss: 0.6411 - val binary accuracy:
0.6256
Epoch 74/200
binary_accuracy: 0.6365 - val_loss: 0.6406 - val_binary_accuracy:
0.6273
Epoch 75/200
binary accuracy: 0.6364 - val loss: 0.6408 - val binary accuracy:
0.6275
Epoch 76/200
binary accuracy: 0.6324 - val loss: 0.6404 - val binary accuracy:
0.6279
Epoch 77/200
binary_accuracy: 0.6359 - val_loss: 0.6402 - val_binary_accuracy:
0.6271
Epoch 78/200
binary accuracy: 0.6308 - val loss: 0.6393 - val binary accuracy:
0.6254
Epoch 79/200
binary accuracy: 0.6348 - val loss: 0.6398 - val binary accuracy:
0.6261
Epoch 80/200
binary accuracy: 0.6369 - val loss: 0.6394 - val binary accuracy:
0.6290
Epoch 81/200
binary accuracy: 0.6356 - val loss: 0.6389 - val binary accuracy:
0.6275
Epoch 82/200
binary accuracy: 0.6330 - val loss: 0.6391 - val binary accuracy:
0.6265
Epoch 83/200
binary accuracy: 0.6393 - val loss: 0.6388 - val binary accuracy:
0.6281
Epoch 84/200
binary_accuracy: 0.6356 - val_loss: 0.6391 - val_binary_accuracy:
0.6273
Epoch 85/200
binary accuracy: 0.6394 - val loss: 0.6402 - val binary accuracy:
```

```
0.6292
Epoch 86/200
binary accuracy: 0.6368 - val loss: 0.6392 - val binary accuracy:
0.6300
Epoch 87/200
binary accuracy: 0.6358 - val loss: 0.6388 - val binary accuracy:
0.6298
Epoch 88/200
binary accuracy: 0.6413 - val loss: 0.6385 - val binary accuracy:
0.6304
Epoch 89/200
binary accuracy: 0.6349 - val loss: 0.6382 - val binary accuracy:
0.6294
Epoch 90/200
binary accuracy: 0.6354 - val loss: 0.6384 - val binary accuracy:
0.6263
Epoch 91/200
binary_accuracy: 0.6370 - val_loss: 0.6384 - val binary accuracy:
0.6269
Epoch 92/200
binary accuracy: 0.6375 - val loss: 0.6377 - val binary accuracy:
0.6331
Epoch 93/200
binary accuracy: 0.6394 - val loss: 0.6383 - val binary accuracy:
0.6275
Epoch 94/200
binary accuracy: 0.6408 - val loss: 0.6386 - val binary accuracy:
0.6261
Epoch 95/200
binary accuracy: 0.6368 - val loss: 0.6371 - val binary accuracy:
0.6263
Epoch 96/200
binary accuracy: 0.6375 - val loss: 0.6375 - val binary accuracy:
0.6271
Epoch 97/200
binary accuracy: 0.6410 - val loss: 0.6374 - val binary accuracy:
0.6329
Epoch 98/200
```

```
binary accuracy: 0.6369 - val loss: 0.6376 - val binary accuracy:
0.6248
Epoch 99/200
binary_accuracy: 0.6387 - val_loss: 0.6367 - val_binary_accuracy:
0.6323
Epoch 100/200
binary accuracy: 0.6356 - val loss: 0.6374 - val binary accuracy:
0.6290
Epoch 101/200
binary accuracy: 0.6418 - val loss: 0.6367 - val binary accuracy:
0.6310
Epoch 102/200
binary_accuracy: 0.6399 - val_loss: 0.6366 - val_binary_accuracy:
0.6292
Epoch 103/200
binary accuracy: 0.6354 - val loss: 0.6360 - val binary accuracy:
0.6312
Epoch 104/200
binary accuracy: 0.6345 - val loss: 0.6370 - val binary accuracy:
0.6275
Epoch 105/200
binary accuracy: 0.6421 - val loss: 0.6365 - val binary accuracy:
0.6288
Epoch 106/200
binary accuracy: 0.6394 - val loss: 0.6356 - val binary accuracy:
0.6304
Epoch 107/200
binary accuracy: 0.6422 - val loss: 0.6360 - val binary accuracy:
0.6306
Epoch 108/200
binary accuracy: 0.6433 - val loss: 0.6360 - val binary accuracy:
0.6275
Epoch 109/200
binary_accuracy: 0.6389 - val_loss: 0.6360 - val_binary_accuracy:
0.6273
Epoch 110/200
binary accuracy: 0.6387 - val loss: 0.6358 - val binary accuracy:
```

```
0.6304
Epoch 111/200
binary accuracy: 0.6379 - val loss: 0.6359 - val binary accuracy:
0.6296
Epoch 112/200
binary accuracy: 0.6346 - val loss: 0.6354 - val binary accuracy:
0.6343
Epoch 113/200
binary_accuracy: 0.6443 - val_loss: 0.6354 - val_binary_accuracy:
0.6343
Epoch 114/200
binary accuracy: 0.6389 - val loss: 0.6348 - val binary accuracy:
0.6331
Epoch 115/200
binary accuracy: 0.6457 - val loss: 0.6351 - val binary accuracy:
0.6346
Epoch 116/200
binary accuracy: 0.6466 - val loss: 0.6352 - val binary accuracy:
0.6333
Epoch 117/200
binary accuracy: 0.6374 - val loss: 0.6352 - val binary accuracy:
0.6323
Epoch 118/200
binary accuracy: 0.6406 - val loss: 0.6345 - val binary accuracy:
0.6321
Epoch 119/200
binary accuracy: 0.6448 - val loss: 0.6345 - val binary accuracy:
0.6375
Epoch 120/200
binary accuracy: 0.6371 - val loss: 0.6345 - val binary accuracy:
0.6352
Epoch 121/200
binary accuracy: 0.6377 - val loss: 0.6349 - val binary accuracy:
0.6372
Epoch 122/200
binary accuracy: 0.6413 - val loss: 0.6336 - val binary accuracy:
0.6350
Epoch 123/200
```

```
binary accuracy: 0.6378 - val loss: 0.6339 - val binary accuracy:
0.6379
Epoch 124/200
binary_accuracy: 0.6432 - val_loss: 0.6338 - val_binary_accuracy:
0.6406
Epoch 125/200
binary accuracy: 0.6435 - val loss: 0.6337 - val binary accuracy:
0.6381
Epoch 126/200
binary accuracy: 0.6412 - val loss: 0.6334 - val binary accuracy:
0.6308
Epoch 127/200
binary_accuracy: 0.6419 - val_loss: 0.6333 - val_binary_accuracy:
0.6317
Epoch 128/200
binary accuracy: 0.6471 - val loss: 0.6331 - val binary accuracy:
0.6412
Epoch 129/200
binary accuracy: 0.6380 - val loss: 0.6333 - val binary accuracy:
0.6368
Epoch 130/200
binary accuracy: 0.6446 - val loss: 0.6332 - val binary accuracy:
0.6360
Epoch 131/200
binary accuracy: 0.6422 - val loss: 0.6327 - val binary accuracy:
0.6383
Epoch 132/200
binary accuracy: 0.6457 - val loss: 0.6333 - val binary accuracy:
0.6333
Epoch 133/200
binary accuracy: 0.6423 - val loss: 0.6326 - val binary accuracy:
0.6366
Epoch 134/200
binary_accuracy: 0.6436 - val_loss: 0.6324 - val_binary_accuracy:
0.6348
Epoch 135/200
binary accuracy: 0.6473 - val loss: 0.6327 - val binary accuracy:
```

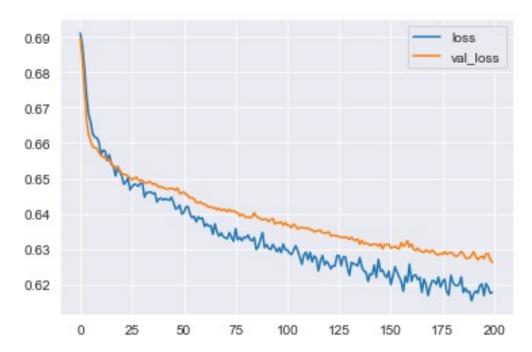
```
0.6300
Epoch 136/200
binary accuracy: 0.6402 - val loss: 0.6313 - val binary accuracy:
0.6379
Epoch 137/200
binary accuracy: 0.6439 - val loss: 0.6324 - val binary accuracy:
0.6356
Epoch 138/200
binary accuracy: 0.6457 - val loss: 0.6314 - val binary accuracy:
0.6350
Epoch 139/200
binary accuracy: 0.6477 - val loss: 0.6317 - val binary accuracy:
0.6350
Epoch 140/200
binary accuracy: 0.6447 - val_loss: 0.6315 - val_binary_accuracy:
0.6356
Epoch 141/200
binary accuracy: 0.6504 - val loss: 0.6309 - val binary accuracy:
0.6397
Epoch 142/200
binary accuracy: 0.6418 - val loss: 0.6313 - val binary accuracy:
0.6381
Epoch 143/200
binary accuracy: 0.6453 - val loss: 0.6313 - val binary accuracy:
0.6352
Epoch 144/200
binary accuracy: 0.6511 - val loss: 0.6313 - val binary accuracy:
0.6352
Epoch 145/200
binary accuracy: 0.6427 - val loss: 0.6307 - val binary accuracy:
0.6397
Epoch 146/200
binary accuracy: 0.6535 - val loss: 0.6315 - val binary accuracy:
0.6366
Epoch 147/200
binary accuracy: 0.6475 - val loss: 0.6300 - val binary accuracy:
0.6399
Epoch 148/200
```

```
binary accuracy: 0.6484 - val loss: 0.6312 - val binary accuracy:
0.6379
Epoch 149/200
binary_accuracy: 0.6489 - val_loss: 0.6311 - val_binary_accuracy:
0.6428
Epoch 150/200
binary accuracy: 0.6468 - val loss: 0.6313 - val binary accuracy:
0.6383
Epoch 151/200
binary accuracy: 0.6478 - val loss: 0.6302 - val binary accuracy:
0.6397
Epoch 152/200
binary_accuracy: 0.6487 - val_loss: 0.6305 - val_binary_accuracy:
0.6401
Epoch 153/200
binary accuracy: 0.6420 - val loss: 0.6307 - val binary accuracy:
0.6391
Epoch 154/200
binary accuracy: 0.6470 - val loss: 0.6302 - val binary accuracy:
0.6426
Epoch 155/200
binary accuracy: 0.6453 - val loss: 0.6300 - val binary accuracy:
0.6393
Epoch 156/200
binary accuracy: 0.6496 - val loss: 0.6317 - val binary accuracy:
0.6387
Epoch 157/200
binary accuracy: 0.6494 - val loss: 0.6307 - val binary accuracy:
0.6435
Epoch 158/200
binary accuracy: 0.6446 - val loss: 0.6312 - val binary accuracy:
0.6391
Epoch 159/200
binary_accuracy: 0.6452 - val_loss: 0.6323 - val_binary_accuracy:
0.6354
Epoch 160/200
binary accuracy: 0.6400 - val loss: 0.6305 - val binary accuracy:
```

```
0.6389
Epoch 161/200
binary accuracy: 0.6505 - val loss: 0.6313 - val binary accuracy:
0.6383
Epoch 162/200
binary accuracy: 0.6410 - val loss: 0.6298 - val binary accuracy:
0.6368
Epoch 163/200
binary accuracy: 0.6472 - val loss: 0.6295 - val binary accuracy:
0.6387
Epoch 164/200
binary accuracy: 0.6494 - val loss: 0.6302 - val binary accuracy:
0.6414
Epoch 165/200
binary accuracy: 0.6448 - val loss: 0.6295 - val binary accuracy:
0.6383
Epoch 166/200
binary accuracy: 0.6536 - val loss: 0.6292 - val binary accuracy:
0.6375
Epoch 167/200
binary accuracy: 0.6522 - val loss: 0.6290 - val binary accuracy:
0.6451
Epoch 168/200
binary accuracy: 0.6469 - val loss: 0.6297 - val binary accuracy:
0.6399
Epoch 169/200
binary accuracy: 0.6559 - val loss: 0.6293 - val binary accuracy:
0.6343
Epoch 170/200
binary accuracy: 0.6486 - val loss: 0.6290 - val binary accuracy:
0.6387
Epoch 171/200
binary accuracy: 0.6527 - val loss: 0.6297 - val binary accuracy:
0.6395
Epoch 172/200
binary accuracy: 0.6489 - val loss: 0.6291 - val binary accuracy:
0.6370
Epoch 173/200
```

```
binary accuracy: 0.6496 - val loss: 0.6284 - val binary accuracy:
0.6389
Epoch 174/200
binary_accuracy: 0.6448 - val_loss: 0.6283 - val_binary_accuracy:
0.6412
Epoch 175/200
binary accuracy: 0.6510 - val loss: 0.6287 - val binary accuracy:
0.6410
Epoch 176/200
binary accuracy: 0.6490 - val loss: 0.6285 - val binary accuracy:
0.6393
Epoch 177/200
binary_accuracy: 0.6467 - val_loss: 0.6292 - val_binary_accuracy:
Epoch 178/200
binary accuracy: 0.6500 - val loss: 0.6284 - val binary accuracy:
0.6408
Epoch 179/200
binary accuracy: 0.6515 - val loss: 0.6288 - val binary accuracy:
0.6414
Epoch 180/200
binary accuracy: 0.6484 - val loss: 0.6290 - val binary accuracy:
0.6418
Epoch 181/200
binary accuracy: 0.6528 - val loss: 0.6286 - val binary accuracy:
0.6383
Epoch 182/200
binary accuracy: 0.6475 - val loss: 0.6280 - val binary accuracy:
0.6420
Epoch 183/200
binary accuracy: 0.6497 - val loss: 0.6279 - val binary accuracy:
0.6387
Epoch 184/200
binary_accuracy: 0.6540 - val_loss: 0.6285 - val_binary_accuracy:
0.6399
Epoch 185/200
binary accuracy: 0.6480 - val loss: 0.6292 - val binary accuracy:
```

```
0.6383
Epoch 186/200
binary accuracy: 0.6528 - val loss: 0.6286 - val binary accuracy:
0.6383
Epoch 187/200
binary accuracy: 0.6484 - val loss: 0.6274 - val binary accuracy:
0.6443
Epoch 188/200
binary accuracy: 0.6551 - val loss: 0.6273 - val binary accuracy:
0.6428
Epoch 189/200
binary accuracy: 0.6530 - val loss: 0.6274 - val binary accuracy:
0.6401
Epoch 190/200
binary accuracy: 0.6581 - val loss: 0.6282 - val binary accuracy:
0.6358
Epoch 191/200
binary accuracy: 0.6551 - val loss: 0.6292 - val binary accuracy:
0.6360
Epoch 192/200
binary accuracy: 0.6527 - val loss: 0.6279 - val binary accuracy:
0.6422
Epoch 193/200
binary accuracy: 0.6496 - val loss: 0.6269 - val binary accuracy:
0.6430
Epoch 194/200
binary accuracy: 0.6520 - val loss: 0.6275 - val binary accuracy:
0.6408
Epoch 195/200
binary accuracy: 0.6533 - val loss: 0.6279 - val binary accuracy:
0.6383
Epoch 196/200
binary accuracy: 0.6545 - val loss: 0.6272 - val binary accuracy:
0.6389
Epoch 197/200
binary accuracy: 0.650 - 0s 2ms/step - loss: 0.6201 - binary accuracy:
0.6481 - val loss: 0.6286 - val binary accuracy: 0.6401
Epoch 198/200
```



The graph shows that, by adding in Dropout layers, we have reduced the overfitting issue compared with the old model.

```
classification_report(y_test,predictions_new)
)
[[ 245 2192]
[ 39 2351]]
                            recall f1-score
               precision
                                               support
           0
                   0.86
                             0.10
                                       0.18
                                                 2437
                   0.52
                             0.98
           1
                                       0.68
                                                 2390
                                       0.54
                                                 4827
    accuracy
  macro avg
                   0.69
                             0.54
                                       0.43
                                                 4827
weighted avg
                                                 4827
                   0.69
                             0.54
                                       0.43
```

By changing the cut-off line to 0.2 (default is 0.5), we have dramatically brought down the Type 2 error.