Lending Club Loan Data Analysis

Project 2

You can see the source code more clearly here:

https://github.com/rayas711/Lending-Club-Loan-Data-Analysis/blob/master/lending-club-loan-data-analysis-raya.ipynb

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Lending Club Loan Data Analysis

DESCRIPTION

Create a model that predicts whether or not a loan will be default using the historical data.

Problem Statement:

For companies like Lending Club correctly predicting whether or not a loan will be a default is very important. In this project, using the historical data from 2007 to 2015, you have to build a deep learning model to predict the chance of default for future loans. As you will see later this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Domain: Finance

Analysis to be done: Perform data preprocessing and build a deep learning prediction model.

Content:

Dataset columns and definition:

- **credit.policy:** 1 if the customer meets the credit underwriting criteria of LendingClub.com, and 0 otherwise.
- **purpose:** The purpose of the loan (takes values "credit_card", "debt_consolidation", "educational", "major_purchase", "small_business", and "all_other").
- **int.rate:** The interest rate of the loan, as a proportion (a rate of 11% would be stored as 0.11). Borrowers judged by LendingClub.com to be more risky are assigned higher interest rates.
- **installment:** The monthly installments owed by the borrower if the loan is funded.
- **log.annual.inc:** The natural log of the self-reported annual income of the borrower.
- **dti:** The debt-to-income ratio of the borrower (amount of debt divided by annual income).
- **fico:** The FICO credit score of the borrower.
- **days.with.cr.line:** The number of days the borrower has had a credit line.
- **revol.bal:** The borrower's revolving balance (amount unpaid at the end of the credit card billing cycle).
- **revol.util:** The borrower's revolving line utilization rate (the amount of the credit line used relative to total credit available).
- **inq.last.6mths:** The borrower's number of inquiries by creditors in the last 6 months.
- **delinq.2yrs:** The number of times the borrower had been 30+ days past due on a payment in the past 2 years.
- **pub.rec:** The borrower's number of derogatory public records (bankruptcy filings, tax liens, or judgments).

Steps to perform:

Perform exploratory data analysis and feature engineering and then apply feature engineering. Follow up with a deep learning model to predict whether or not the loan will be default using the historical data.

Tasks:

1. Feature Transformation

- Transform categorical values into numerical values (discrete)

2. Exploratory data analysis of different factors of the dataset.

3. Additional Feature Engineering

- You will check the correlation between features and will drop those features which have a strong correlation
- This will help reduce the number of features and will leave you with the most relevant features

4. Modeling

- After applying EDA and feature engineering, you are now ready to build the predictive models
- In this part, you will create a deep learning model using Keras with Tensorflow backend

Screen shots:

Lending Club Loan Data Analysis_Raya Draft saved

File Edit View Run Add-ons Help

Run All Code Draft Session (1h:5m)

Share Save Version 0

Data Add data

input (733.65 KB)

lending-club-loan-data-analysis

loan_data.csv

output (44.2MB / 19.6GB)

/kaggle/working

my_model_lending_club.h5

scaler.pkl

Settings

Language Python

Environment Preferences

Accelerator None

Internet

Code Help

[1]:

```python
#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
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
```

[2]:

```python
df = pd.read_csv('../input/lending-club-loan-data-analysis/loan_data.csv')
```

[3]:

```python
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   credit.policy      9578 non-null   int64
 1   purpose            9578 non-null   object
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64
 11  delinq.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
```

[3]:

	credit.policy	purpose	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
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

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.

[4]:

```python
df.describe().transpose()
```

[4]:

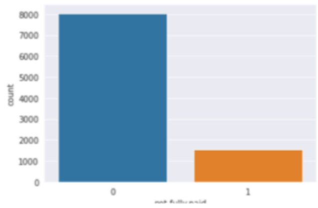
	count	mean	std	min	25%	50%	75%	max
credit.policy	9578.0	0.804970	0.396245	0.000000	1.000000	1.000000	1.000000	1.000000e+00
int.rate	9578.0	0.122640	0.026847	0.060000	0.103900	0.122100	0.140700	2.164000e-01
installment	9578.0	319.089413	207.071301	15.670000	163.770000	268.950000	432.762500	9.401400e+02
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
fico	9578.0	710.846314	37.970537	612.000000	682.000000	707.000000	737.000000	8.270000e+02
days.with.cr.line	9578.0	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
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
delinq.2yrs	9578.0	0.163708	0.546215	0.000000	0.000000	0.000000	0.000000	1.300000e+01
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

[5]:
```python
#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)
```

[5]:
```
not.fully.paid
0    0.839946
1    0.160054
Name: not.fully.paid, dtype: float64
```

```python
sns.set_style('darkgrid')
sns.countplot(x='not.fully.paid', data=df)
```

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



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"

[7]:
```python
df1=pd.get_dummies(df, columns=['purpose'])
```

[8]:
```python
df1['log.annual.inc'] = np.exp(df1['log.annual.inc'])
```

[9]:
```python
df1.head()
```

[9]:

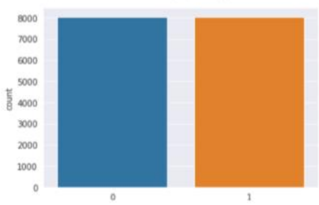
	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid	purpose_all_other	purpose_credit_card	purpose_debt_consolidation	purpc
0	1	0.1189	829.10	85000.000385	19.48	737	5639.958333	28854	52.1	0	0	0	0	0	0	1	
1	1	0.1071	228.22	65000.000073	14.29	707	2760.000000	33623	76.7	0	0	0	0	0	1	0	
2	1	0.1357	366.86	31999.999943	11.63	682	4710.000000	3511	25.6	1	0	0	0	0	0	1	
3	1	0.1008	162.34	85000.000385	8.10	712	2699.958333	33667	73.2	1	0	0	0	0	0	1	
4	1	0.1426	102.92	80799.999636	14.97	667	4066.000000	4740	39.5	0	1	0	0	0	1	0	

```python
#The dataset used here is minimal; I chose to try oversampling to balance this dataset.
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)
```

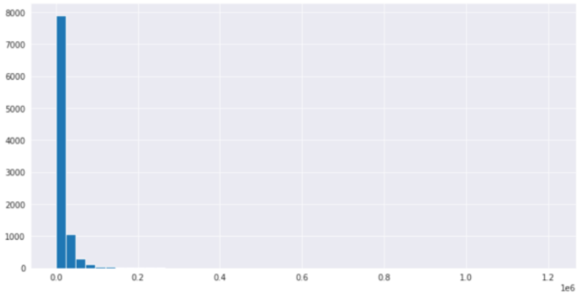
```
Random over-sampling:
0    8045
1    8045
Name: not.fully.paid, dtype: int64
```

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



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

[11]: <AxesSubplot:>

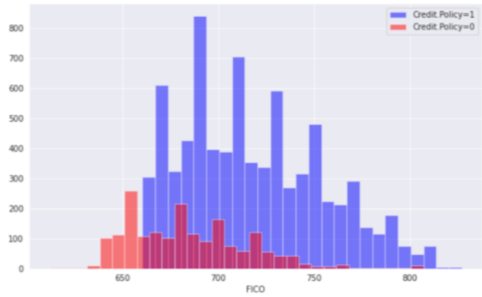


+ Code + Markdown

[12]:
```python
df1=pd.get_dummies(df, columns=['purpose'])
```

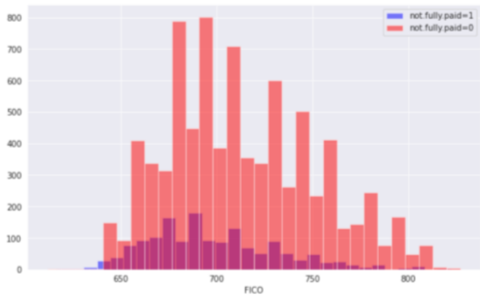
```python
#Create a histogram of two FICO distributions on top of each other, one for each credit.policy outcome
plt.figure(figsize=(10,6))
df[df['credit.policy']==1]['fico'].hist(alpha=0.5,color='blue',bins=30,label='Credit.Policy=1')
df[df['credit.policy']==0]['fico'].hist(alpha=0.5,color='red',bins=30,label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
```

[13]: Text(0.5, 0, 'FICO')



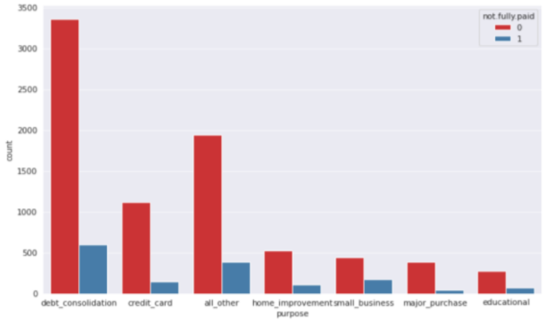

```python
#Let's see a similar chart for "not.fully.paid" column
plt.figure(figsize=(10,6))
df[df['not.fully.paid']==1]['fico'].hist(alpha=0.5,color='blue',
                                          bins=30,label='not.fully.paid=1')
df[df['not.fully.paid']==0]['fico'].hist(alpha=0.5,color='red',
                                          bins=30,label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
```

[14]: Text(0.5, 0, 'FICO')



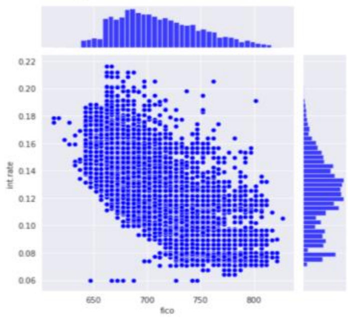
[15]:
```python
#Now, check the dataset group by loan purpose. Create a countplot with the color hue defined by not.fully.paid
plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=df,palette='Set1')
```

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




```python
#The next visual we will pull part of EDA in this dataset is the trend between FICO score and interest rate
sns.jointplot(x='fico',y='int.rate',data=df,color='blue')
```

[16]: <seaborn.axisgrid.JointGrid at 0x7f811ca18650>



[17]:
```python
#To compare the trend between not.fully.paid and credit.policy, create seaborn lmplot
plt.figure(figsize=(11,7))
sns.lmplot(y='int.rate',x='fico',data=df,hue='credit.policy',
           col='not.fully.paid',palette='Set1')
```

[17]: <seaborn.axisgrid.FacetGrid at 0x7f811c526f10>
<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.

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16090 entries, 0 to 7142
Data columns (total 19 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   credit.policy               16090 non-null  int64
 1   int.rate                    16090 non-null  float64
 2   installment                 16090 non-null  float64
 3   log.annual.inc              16090 non-null  float64
 4   dti                         16090 non-null  float64
 5   fico                        16090 non-null  int64
 6   days.with.cr.line           16090 non-null  float64
 7   revol.bal                   16090 non-null  int64
 8   revol.util                  16090 non-null  float64
 9   inq.last.6mths              16090 non-null  int64
 10  delinq.2yrs                 16090 non-null  int64
 11  pub.rec                     16090 non-null  int64
 12  not.fully.paid              16090 non-null  int64
 13  purpose_credit_card         16090 non-null  uint8
 14  purpose_debt_consolidation  16090 non-null  uint8
 15  purpose_educational         16090 non-null  uint8
```

memory usage: 2.1 MB

[18]:

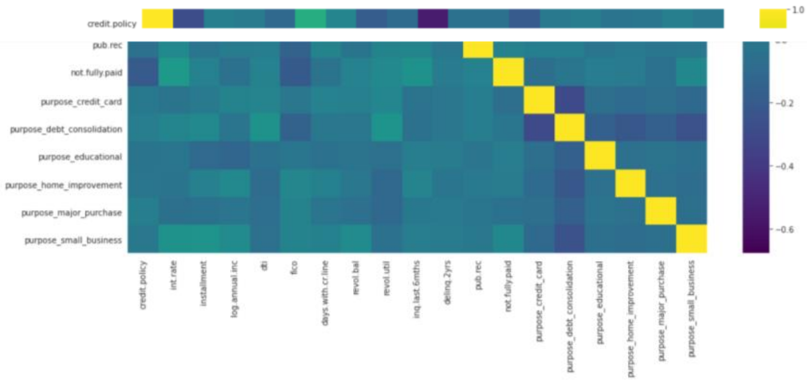
	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid	purpose_credit_card	pu
0	1	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0	0	
1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0	1	
2	1	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0	0	
3	1	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0	0	
4	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0	1	

+ Code + Markdown

[19]:
```python
final_data.corr()
plt.figure(
        figsize=[16,12]
)

sns.heatmap(
        data=final_data.corr(),
        cmap='viridis',
        annot=False,
        fmt='.2g'
)
```

[19]: <AxesSubplot:>



+ Code + Markdown

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.

[20]:
```python
to_drop2 = ['revol.bal', 'days.with.cr.line', 'installment', 'revol.bal']

final_data.drop(to_drop2, axis=1, inplace=True)
```

[21]:
```python
final_data.isnull().mean()
```

[21]:
```
credit.policy                 0.0
int.rate                      0.0
log.annual.inc                0.0
dti                           0.0
fico                          0.0
revol.util                    0.0
inq.last.6mths                0.0
delinq.2yrs                   0.0
pub.rec                       0.0
not.fully.paid                0.0
purpose_credit_card           0.0
purpose_debt_consolidation    0.0
purpose_educational           0.0
purpose_home_improvement      0.0
purpose_major_purchase        0.0
purpose_small_business        0.0
dtype: float64
```

+ Code + Markdown

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.

[22]:

```python
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)
X_train.shape

model = Sequential()

model.add(
        Dense(94, activation='relu')
)

model.add(
        Dense(30, activation='relu')
)

model.add(
        Dense(15, activation='relu')
)


model.add(
        Dense(1, activation='sigmoid')
)

model.compile(
        optimizer='adam',
        loss='binary_crossentropy',
        metrics=['accuracy']
)
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]
)
```

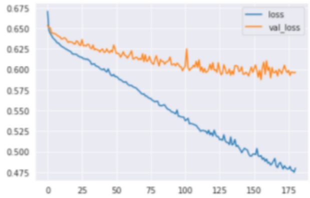
```
Epoch 1/200
44/44 [==============================] - 1s 16ms/step - loss: 0.6809 - accuracy: 0.5745 - val_loss: 0.6536 - val_accuracy: 0.6161
Epoch 2/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6497 - accuracy: 0.6213 - val_loss: 0.6505 - val_accuracy: 0.6132
Epoch 3/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6412 - accuracy: 0.6248 - val_loss: 0.6503 - val_accuracy: 0.6136
Epoch 4/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6436 - accuracy: 0.6180 - val_loss: 0.6440 - val_accuracy: 0.6225
Epoch 5/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6389 - accuracy: 0.6322 - val_loss: 0.6438 - val_accuracy: 0.6180
Epoch 6/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6376 - accuracy: 0.6304 - val_loss: 0.6434 - val_accuracy: 0.6223
Epoch 7/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6359 - accuracy: 0.6302 - val_loss: 0.6427 - val_accuracy: 0.6240
Epoch 8/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6306 - accuracy: 0.6397 - val_loss: 0.6412 - val_accuracy: 0.6292
Epoch 9/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6278 - accuracy: 0.6422 - val_loss: 0.6400 - val_accuracy: 0.6227
Epoch 10/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6300 - accuracy: 0.6353 - val_loss: 0.6394 - val_accuracy: 0.6306
Epoch 11/200
44/44 [==============================] - 0s 4ms/step - loss: 0.6257 - accuracy: 0.6387 - val_loss: 0.6369 - val_accuracy: 0.6248
Epoch 12/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6266 - accuracy: 0.6371 - val_loss: 0.6370 - val_accuracy: 0.6290
Epoch 13/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6234 - accuracy: 0.6459 - val_loss: 0.6383 - val_accuracy: 0.6273
Epoch 14/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6280 - accuracy: 0.6413 - val_loss: 0.6376 - val_accuracy: 0.6296
Epoch 15/200
44/44 [==============================] - 0s 3ms/step - loss: 0.6234 - accuracy: 0.6460 - val_loss: 0.6353 - val_accuracy: 0.6321
Epoch 16/200
```

Model Evaluation and Validation

[23]:

```
pd.DataFrame(model.history.history)[['loss','val_loss']].plot() #over fitting
```

[23]: <AxesSubplot:>



This validation result, the Loss plot, shows us the model is overfitted.

[24]:

```
predictions = model.predict_classes(X_test)

print(
        confusion_matrix(y_test,predictions),
        '\n',
        classification_report(y_test,predictions)
)
```

```
/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/sequential.py:450: UserWarning: `model.predict_classes()` is deprecated and wil
l be removed after 2021-01-01. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi-class classification   (e.g. i
f it uses a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it u
ses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
[[1784  653]
 [ 889 1501]]
              precision    recall  f1-score   support

           0       0.67      0.73      0.70      2437
           1       0.70      0.63      0.66      2390

    accuracy                           0.68      4827
   macro avg       0.68      0.68      0.68      4827
weighted avg       0.68      0.68      0.68      4827
```

The model's overall f1-score for accuracy is 0.70. Still, there are type 2 errors (889) 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.

[25]:

```
model_new = Sequential()

model_new.add(
        Dense(94, activation='relu')
)

model_new.add(Dropout(0.2))

model_new.add(
        Dense(30, activation='relu')
)

model_new.add(Dropout(0.2))

model_new.add(
        Dense(15, activation='relu')
)

model_new.add(Dropout(0.2))
model_new.add(
        Dense(1, activation='sigmoid')
)

model_new.compile(
        optimizer='adam',
        loss='binary_crossentropy',
        metrics=['binary_accuracy']
)


model_new.fit(
        X_train,
        y_train,
        epochs=200,
        batch_size=256,
        validation_data=(X_test, y_test),
         callbacks=[early_stop]
)
```

```
Epoch 1/200
44/44 [==============================] - 1s 8ms/step - loss: 0.6916 - binary_accuracy: 0.5177 - val_loss: 0.6681 - val_binary_accuracy: 0.6165
Epoch 2/200
44/44 [==============================] - 0s 4ms/step - loss: 0.6698 - binary_accuracy: 0.5884 - val_loss: 0.6538 - val_binary_accuracy: 0.6184
Epoch 3/200
44/44 [==============================] - 0s 4ms/step - loss: 0.6584 - binary_accuracy: 0.6038 - val_loss: 0.6516 - val_binary_accuracy: 0.6134
Epoch 4/200
44/44 [==============================] - 0s 4ms/step - loss: 0.6554 - binary_accuracy: 0.6036 - val_loss: 0.6491 - val_binary_accuracy: 0.6182
Epoch 5/200
44/44 [==============================] - 0s 4ms/step - loss: 0.6512 - binary_accuracy: 0.6197 - val_loss: 0.6484 - val_binary_accuracy: 0.6134
Epoch 6/200
```

```
44/44 [==============================] - 0s 4ms/step - loss: 0.5404 - binary_accuracy: 0.7150 - val_loss: 0.5709 - val_binary_accuracy: 0.6957
```

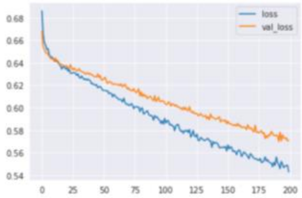
[25]: <tensorflow.python.keras.callbacks.History at 0x7f81102f3790>

+ Code + Markdown

[26]:

```
pd.DataFrame(model_new.history.history)[['loss','val_loss']].plot()
```

[26]: <AxesSubplot:>



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

[27]:

```
predictions_new = (model_new.predict_proba(X_test) >= 0.2).astype('int')

print(
        confusion_matrix(y_test,predictions_new),
        '\n',
        classification_report(y_test,predictions_new)
)
```

```
[[ 490 1947]
 [  28 2362]]
              precision    recall  f1-score   support

           0       0.95      0.20      0.33      2437
           1       0.55      0.99      0.71      2390

    accuracy                           0.59      4827
   macro avg       0.75      0.59      0.52      4827
weighted avg       0.75      0.59      0.52      4827
```

```
/opt/conda/lib/python3.7/site-packages/tensorflow/python/keras/engine/sequential.py:425: UserWarning: `model.predict_proba()` is deprecated and will be removed after 2021-01-01. Please use `model.predict()` instead.
  warnings.warn('`model.predict_proba()` is deprecated and '
```

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

[28]:

```
#Save the model and scalar
dump(scaler, open('scaler.pkl', 'wb'))
model_new.save('my_model_lending_club.h5')
```

Model Use Case

We will use the model on "not.fully.paid = 0" records; when these loans are matured, we will get it as the Out-Of-Time sample validation results.

[29]:

```
later_scaler = load(open('scaler.pkl', 'rb'))
later_model = load_model('my_model_lending_club.h5')

X_OOT = to_pred.drop('not.fully.paid', axis=1).values
to_pred.drop('not.fully.paid', axis=1).values

print(X_OOT.shape)
```

```
(0, 15)
```

All the write up is included with the code “python file”.