Udemy_Data_Science_Neural_Networks_Project

March 27, 2021

1 Keras API Project Exercise - Tilemachos' Solution

1.1 The Data

LendingClub is a US peer-to-peer lending company, headquartered in San Francisco, California.[3] It was the first peer-to-peer lender to register its offerings as securities with the Securities and Exchange Commission (SEC), and to offer loan trading on a secondary market. LendingClub is the world's largest peer-to-peer lending platform.

1.1.1 Our Goal

Given historical data on loans given out with information on whether or not the borrower defaulted (charge-off), can we build a model thatcan predict wether or nor a borrower will pay back their loan? This way in the future when we get a new potential customer we can assess whether or not they are likely to pay back the loan. Keep in mind classification metrics when evaluating the performance of your model!

The "loan_status" column contains our label.

Using Subset of LendingClub DataSet obtained from Kaggle: https://www.kaggle.com/wordsforthewise/lending-club

1.1.2 Data Overview

1.2 —-

There are many LendingClub data sets on Kaggle. Here is the information on this particular data set:

LoanStatNew

Description

0

loan_amnt

The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

1

term

The number of payments on the loan. Values are in months and can be either 36 or 60.

2

int_rate

Interest Rate on the loan

3

installment

The monthly payment owed by the borrower if the loan originates.

4

grade

LC assigned loan grade

5

sub_grade

LC assigned loan subgrade

6

emp_title

The job title supplied by the Borrower when applying for the loan.*

7

emp_length

Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.

8

home_ownership

The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are: RENT, OWN, MORTGAGE, OTHER

9

annual_inc

The self-reported annual income provided by the borrower during registration.

10

verification_status

Indicates if income was verified by LC, not verified, or if the income source was verified

11

issue_d

The month which the loan was funded

12

loan_status

Current status of the loan

13

purpose

A category provided by the borrower for the loan request.

14

title

The loan title provided by the borrower

15

zip_code

The first 3 numbers of the zip code provided by the borrower in the loan application.

16

addr_state

The state provided by the borrower in the loan application

17

dti

A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.

18

earliest_cr_line

The month the borrower's earliest reported credit line was opened

19

open_acc

The number of open credit lines in the borrower's credit file.

20

pub_rec

Number of derogatory public records

21

revol_bal

Total credit revolving balance

22

revol_util

Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.

23

total_acc

The total number of credit lines currently in the borrower's credit file

24

initial_list_status

The initial listing status of the loan. Possible values are – W, F

25

application_type

Indicates whether the loan is an individual application or a joint application with two co-borrowers

26

mort_acc

Number of mortgage accounts.

27

pub_rec_bankruptcies

Number of public record bankruptcies

1.3 —

[1]:
```
#%% -*- coding: utf-8 -*-
"""
Created on Mon Oct  5 09:42:57 2020

@author: Tilemachos
"""

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import pandas as pd
from os import chdir
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import classification_report, confusion_matrix
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

2 Data Loading

[2]:
```
chdir('E:/MyProjects/Udemy_DataScience/Refactored_Py_DS_ML_Bootcamp-master/
 ↪DATA')

info = pd.read_csv('lending_club_info.csv', index_col = 'LoanStatNew')
df = pd.read_csv('lending_club_loan_two.csv')

# Helper function to quickly get feature info
def feat_info(col_name):
    print(info.loc[col_name]['Description'])
```

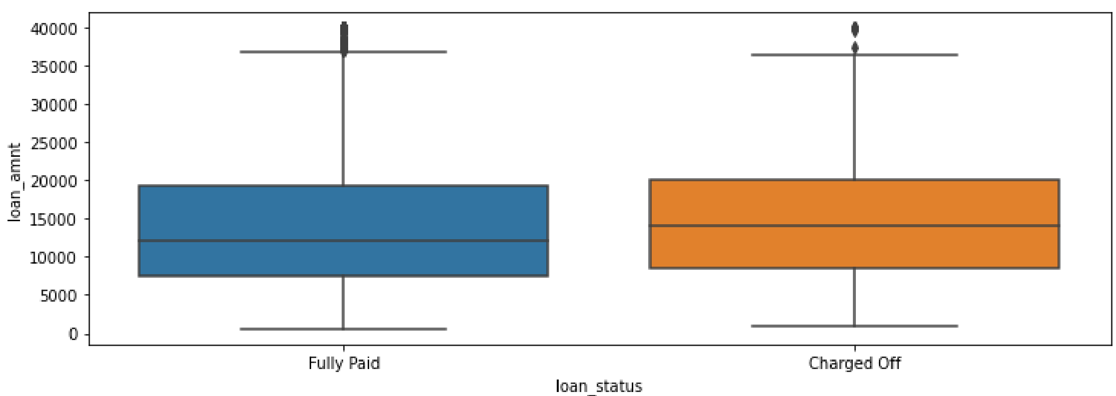
3 Preemptive Exploratory Data Analysis

3.0.1 First of all we want to explore our data, find important features, duplicate information, correlations, missing data etc. We can also use our limited domain knowledge to infer relations between the features.

3.0.2 Is there any relationship between expensive loans, and not being able to pay them off, or the opposite?

[3]:
```
plt.figure(figsize=(12,4))
sns.boxplot(x='loan_status', y = 'loan_amnt', data = df)
```

[3]:
```
<AxesSubplot:xlabel='loan_status', ylabel='loan_amnt'>
```



3.0.3 There is a slight increase of charged off large loans, but not much.

3.0.4 We can also check that by examining the numbers:

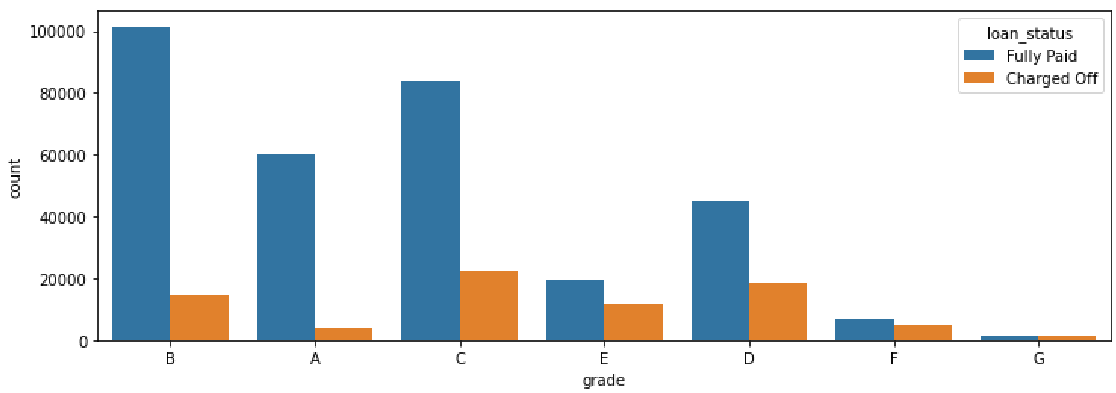
[4]:
```
df.groupby('loan_status')['loan_amnt'].describe()
```

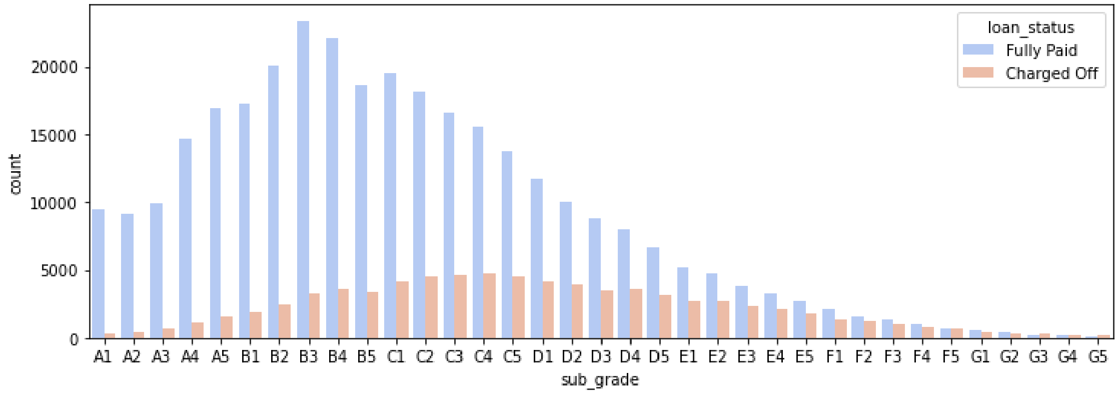
[4]:
```
                  count          mean          std     min     25%      50%  \
loan_status
Charged Off    77673.0  15126.300967  8505.090557  1000.0  8525.0  14000.0
Fully Paid    318357.0  13866.878771  8302.319699   500.0  7500.0  12000.0

                  75%      max
loan_status
Charged Off   20000.0  40000.0
Fully Paid    19225.0  40000.0
```

3.0.5 Now, let's investigate the grades and subgrades.

[5]:
```python
# How does grade affect the label?
plt.figure(figsize=(12,4))
sns.countplot(x='grade', data=df, hue='loan_status')

# And subgrade?
subgrade_order = sorted(df['sub_grade'].unique())
plt.figure(figsize=(12,4))
sns.countplot(x='sub_grade', data=df, order=subgrade_order,palette='coolwarm',␣
↪hue='loan_status')
```

[5]: <AxesSubplot:xlabel='sub_grade', ylabel='count'>



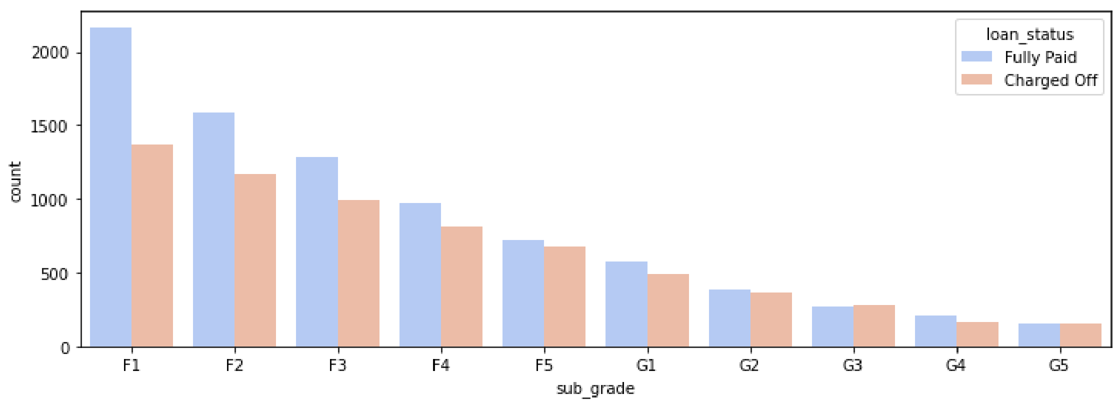


3.0.6 F and G grade loans are paid off almost 50% of the time, so maybe it's not even worth giving these loans.

3.0.7 Let us examine the F and G grades in a more granular manner.

[6]:
```
f_and_g = df[ (df['grade'] == 'G') | (df['grade'] == 'F') ]
plt.figure(figsize=(12,4))
sns.countplot(x='sub_grade', data=f_and_g, order=sorted(f_and_g['sub_grade'].
↪unique()), hue='loan_status',palette='coolwarm')
```

[6]: <AxesSubplot:xlabel='sub_grade', ylabel='count'>

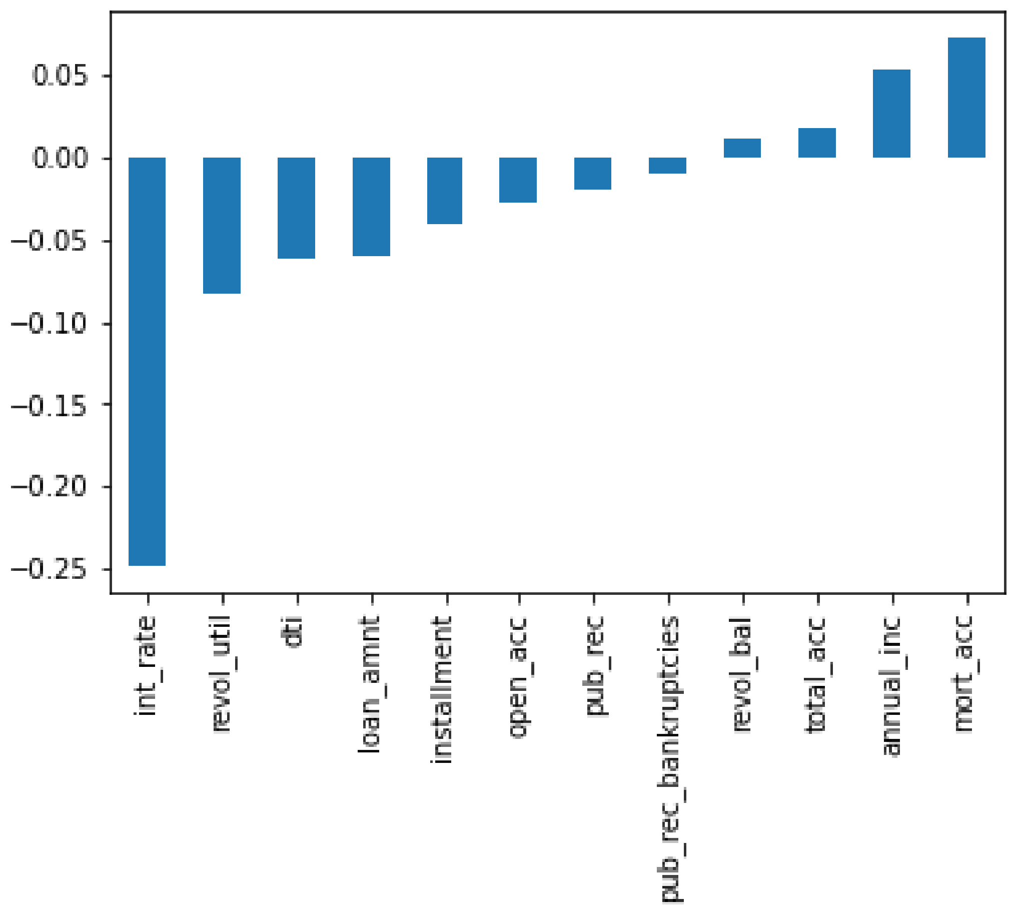


3.0.8 It seems that only the highest subgrades of the "F-G" group have some small value.

3.0.9 Let us now examine how numerical features affect the label.

[9]:
```
# Convert loan_status column to numerical
df['loan_repaid'] = df['loan_status'].map({'Fully Paid':1, 'Charged Off':0})
df.drop('loan_status',axis=1,inplace=True)

# Show correlation bars of features to loan_repaid label
df.corr()['loan_repaid'].sort_values().iloc[:-1].plot(kind='bar')
```

[9]: <AxesSubplot:>



3.0.10 Seems like the interest rate is one of the strongest predictors, which makes sense, since it is usually related to risk.

4 Data Cleaning - Missing Data

4.1 Check what percentage of each feature is missing.

[10]:
```
print(100*df.isnull().sum() / len(df))
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
address                 0.000000
loan_repaid             0.000000
dtype: float64
```

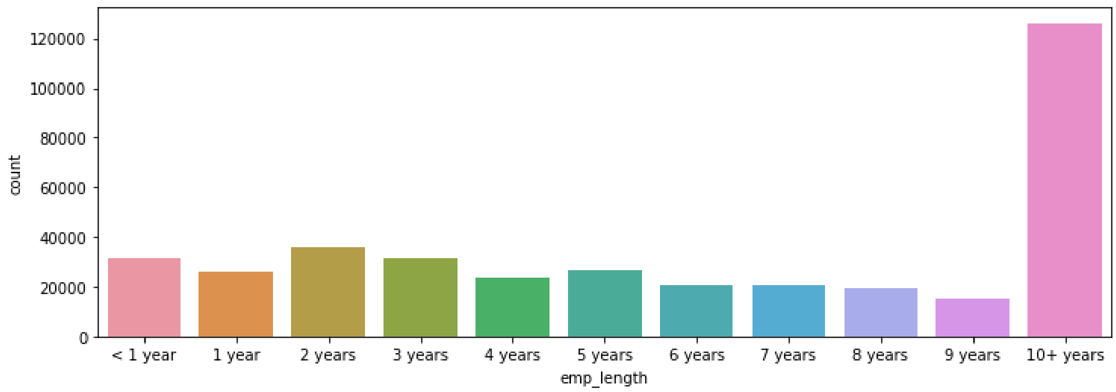
4.1.1 Let us examine how employment length affects loan repayments.

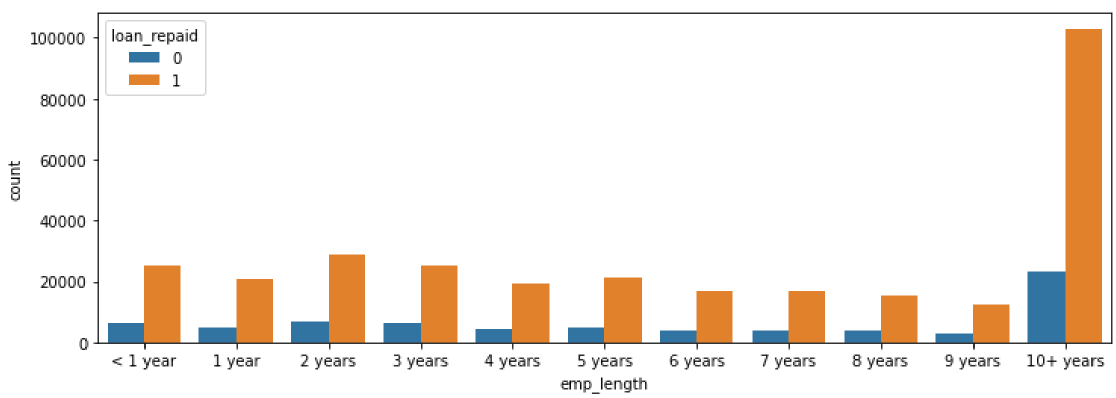
4.1.2 Plot employment length (ignoring the 4.6% missing) against loan repayment status

[11]:
```
sorted(df['emp_length'].dropna().unique())
emp_length_order = ['< 1 year',
 '1 year',
 '2 years',
 '3 years',
 '4 years',
 '5 years',
 '6 years',
 '7 years',
 '8 years',
```

```
 '9 years',
 '10+ years']

plt.figure(figsize=(12,4))
sns.countplot(data=df, x='emp_length',order = emp_length_order)
plt.figure(figsize=(12,4))
sns.countplot(data=df, x='emp_length',order =␣
↪emp_length_order,hue='loan_repaid')
```

[11]: <AxesSubplot:xlabel='emp_length', ylabel='count'>



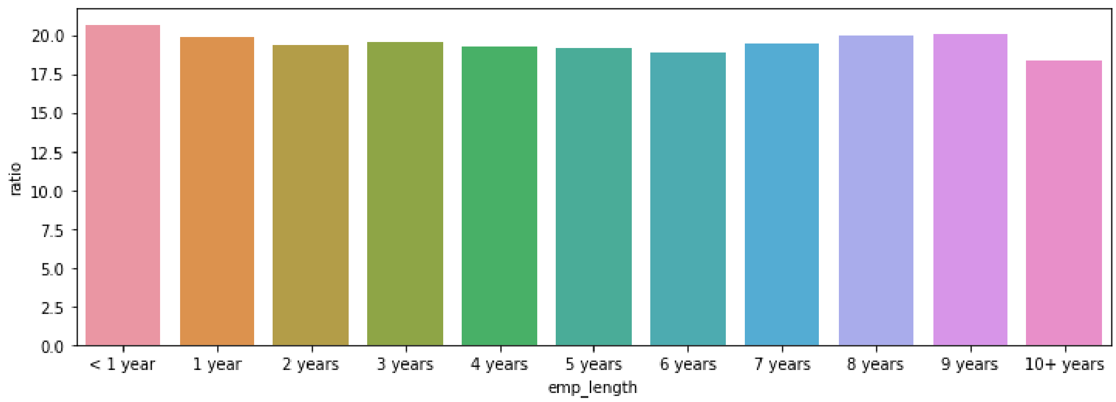


4.1.3 It seems that most subjects have been employed for 10 or more years. Let us examine the ratios over each employment length category.

[12]:
```
# Get value counts of repaid and not repaid loans, for each employment length␣
↪category
my_pivot = df.groupby('emp_length')['loan_repaid'].value_counts()
```

```
# Currently every row (employment length) has two rows - one for each loan␣
↪outcome
# Unstack so that we get two columns for each row (one column for each outcome)
# Now we can calculate the ratio of not repaid loans
emp_length_ratio = 100*my_pivot.unstack(level=-1)[0]/df.
↪groupby('emp_length')['loan_repaid'].count()
emp_length_ratio = pd.DataFrame(emp_length_ratio, columns = ['ratio'])

plt.figure(figsize=(12,4))
sns.barplot(data=emp_length_ratio.reset_index(),x='emp_length',y='ratio',order␣
↪= emp_length_order)
```

[12]: <AxesSubplot:xlabel='emp_length', ylabel='ratio'>



4.1.4 We can see that the ratio is almost evenly distributed among all employment lengths (with a +/- 2% deviation). We can therefore drop this feature.

[13]:
```
# This feature doesn't really affect the label, so we can ignore it.
df.drop('emp_length',axis=1,inplace=True)
```

4.1.5 If we examine 'title' and 'purpose' more carefully, is contains duplicated information.

[14]:
```
# Drop Title columns, as it contains duplicate information
df.drop('title', axis=1, inplace=True)
```

4.1.6 Examining the employment titles, we see that realistically there are too many unique job titles to convert to a dummy variable, so we'll just drop it.

Alternatively, with a bit of domain knowledge a clustering of some of the most frequent jobs could be done.

[15]:
```
df['emp_title'].value_counts()
```

[15]:
```
Teacher                           4389
Manager                           4250
Registered Nurse                  1856
RN                                1846
Supervisor                        1830
                                  …
Moen Incorporated                    1
Products Development                 1
service station installation         1
Campaign Director                    1
SEVEN HILLS FOUNDATION               1
Name: emp_title, Length: 173105, dtype: int64
```

[16]:
```
df.drop('emp_title', axis=1, inplace=True)
```

4.1.7 We examine the mortgage account column, which as we saw above has almost 10% missing data. This means that if we drop these rows, we lose 10% of our data, so this is not an option. We could also just drop this feature, but let's think of an alternative.

[17]:
```
# Examine mort_acc
df['mort_acc'].value_counts()
```

[17]:
```
0.0     139777
1.0      60416
2.0      49948
3.0      38049
4.0      27887
5.0      18194
6.0      11069
7.0       6052
8.0       3121
9.0       1656
10.0       865
11.0       479
12.0       264
13.0       146
14.0       107
15.0        61
16.0        37
17.0        22
18.0        18
19.0        15
20.0        13
24.0        10
22.0         7
21.0         4
```

```
25.0          4
27.0          3
23.0          2
32.0          2
26.0          2
31.0          2
30.0          1
28.0          1
34.0          1
Name: mort_acc, dtype: int64
```

4.1.8 Which columns are most highly correlated with mort_acc?

[18]:
```python
# Which columns are most highly correlated with mort_acc?
df.corr()['mort_acc'].sort_values(ascending=False).iloc[1:]
```

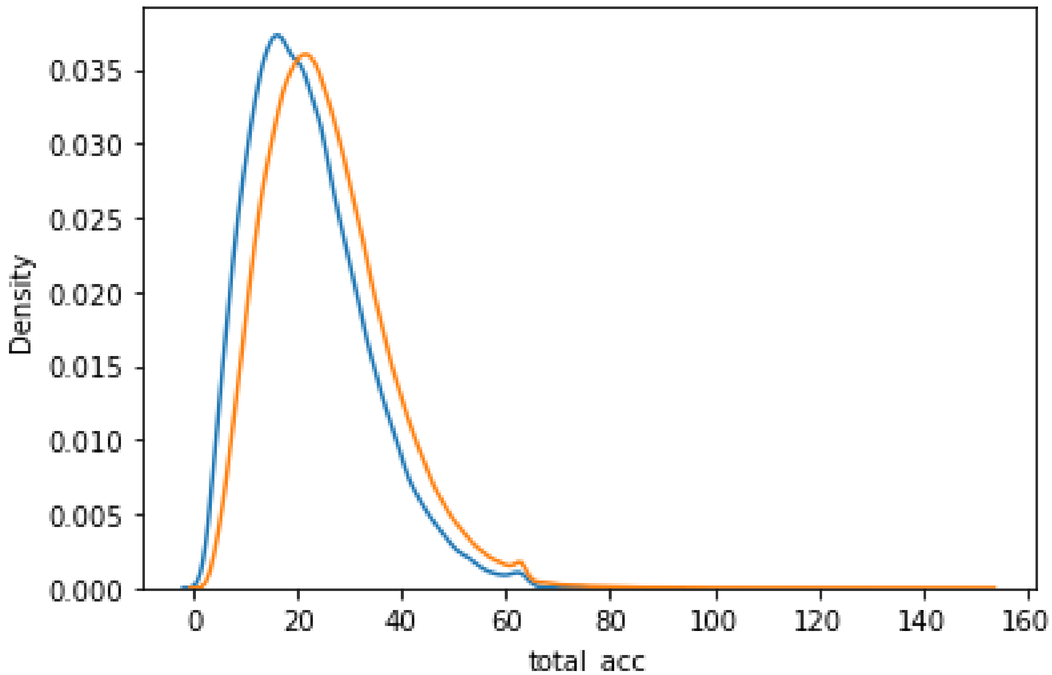
[18]:
```
total_acc               0.381072
annual_inc              0.236320
loan_amnt               0.222315
revol_bal               0.194925
installment             0.193694
open_acc                0.109205
loan_repaid             0.073111
pub_rec_bankruptcies    0.027239
pub_rec                 0.011552
revol_util              0.007514
dti                    -0.025439
int_rate               -0.082583
Name: mort_acc, dtype: float64
```

4.1.9 Perhaps unsurprisingly, this is the total account column (as it is a sum of, among others, the mortgage accounts)

4.1.10 Let's plot the distributions of the 'total_acc' column for the missing and present data to see how the statistics are affected

[19]:
```python
# Plot distribution for the 'total_acc' column of rows that contain 'mort_acc'␣
↪values,
# and then those that are missing 'mort_acc' values
sns.kdeplot(df[df['mort_acc'].isnull()]['total_acc'])
sns.kdeplot(df[~df['mort_acc'].isnull()]['total_acc'])
```

[19]:
```
<AxesSubplot:xlabel='total_acc', ylabel='Density'>
```



4.1.11 There is a very similar distribution in the total_acc values of both groups of rows. We can calculate what is the mean number of mortgage accounts for all entries with a specific number of total accounts. Then, we can fill in the missing 'mort_acc' values using the mean of their equivalent 'total_acc' cluster. This way we are practically 'predicting' the expected value of 'mort_acc', since the missing data follow the same distribution as the ones used for the prediction.

[20]:
```
# Let's get the mean mort_acc value for each total_acc
total_acc_avg = df.groupby('total_acc').mean()['mort_acc']
# We can use this as a lookup to fill in the missing values
def fill_mort_acc(total_acc, mort_acc):
    if np.isnan(mort_acc):
        return total_acc_avg[total_acc]
    else:
        return mort_acc
df['mort_acc'] = df.apply(lambda x:
 ↪fill_mort_acc(x['total_acc'],x['mort_acc']),axis = 1)
```

[21]:
```
#Check again how much of each feature is missing
print(100*df.isnull().sum() / len(df))
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
```

```
grade                   0.000000
sub_grade               0.000000
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
purpose                 0.000000
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                0.000000
pub_rec_bankruptcies    0.135091
address                 0.000000
loan_repaid             0.000000
dtype: float64
```

4.1.12 Now less than 0.5% of data are missing, and we can remove those entries without significant problems.

[22]:
```
df.dropna(inplace=True)
print(100*df.isnull().sum() / len(df))
```

```
loan_amnt               0.0
term                    0.0
int_rate                0.0
installment             0.0
grade                   0.0
sub_grade               0.0
home_ownership          0.0
annual_inc              0.0
verification_status     0.0
issue_d                 0.0
purpose                 0.0
dti                     0.0
earliest_cr_line        0.0
open_acc                0.0
pub_rec                 0.0
revol_bal               0.0
revol_util              0.0
total_acc               0.0
initial_list_status     0.0
application_type        0.0
```

```
mort_acc                0.0
pub_rec_bankruptcies    0.0
address                 0.0
loan_repaid             0.0
dtype: float64
```

5 Data preprocessing

5.1 Term feature

[23]:
```
#Term feature

feat_info('term')
df['term'].value_counts()
```

```
The number of payments on the loan. Values are in months and can be either 36 or
60.
```

[23]:
```
 36 months    301247
 60 months     93972
Name: term, dtype: int64
```

5.1.1 2 choices here: Convert them to numeric or one-hot encode into '60 months' or 'not 60 months'.

5.1.2 However, converting to numeric also preserves the temporal relationship between the two, so it might be a good idea to keep that.

[24]:
```
# Convert term months to float
df['term'] = df['term'].apply(lambda x: int(x.split()[0]))
```

5.2 Grade feature

[25]:
```
# Grade feature
# grade is a part of subgrade, so we can drop it (duplicate information)
df.drop('grade',axis=1,inplace=True)
```

5.2.1 Subgrade is categorical, so we convert it into dummy variables.

[26]:
```
# Convert subgrade into dummy variables

dummies = pd.get_dummies(df['sub_grade'], drop_first=True)
df = pd.concat([df.drop('sub_grade', axis=1),dummies], axis=1)
```

5.2.2 Similarly for verification_status, application_type, initial_list_status and purpose. They also have very few categories.

[27]:
```
# Similarly for verification_status, application_type, initial_list_status and
# purpose. They also have very few categories.

dummies = pd.get_dummies(df[['verification_status', 'application_type',
                  'initial_list_status','purpose']], drop_first=True)
df = pd.concat([df.drop(['verification_status', 'application_type',
                  'initial_list_status','purpose'], axis=1),dummies], axis=1)
```

5.3 Home ownership feature

[28]:
```
# Home ownership feature
df['home_ownership'].value_counts()
```

[28]:
```
MORTGAGE    198022
RENT        159395
OWN          37660
OTHER          110
NONE            29
ANY              3
Name: home_ownership, dtype: int64
```

5.3.1 Most people have the first few categories, so classify all the others as 'other'

[29]:
```
# Most people have the first few categories, so classify all the others as␣
↪'other'
df['home_ownership'] = df['home_ownership'].replace(['NONE','ANY'],'OTHER')
dummies = pd.get_dummies(df['home_ownership'], drop_first=True)
df = pd.concat([df.drop('home_ownership', axis=1),dummies], axis=1)
```

5.4 Address

[30]:
```
# Address
print(df['address'])
```

```
0              0174 Michelle Gateway\nMendozaberg, OK 22690
1           1076 Carney Fort Apt. 347\nLoganmouth, SD 05113
2           87025 Mark Dale Apt. 269\nNew Sabrina, WV 05113
3                     823 Reid Ford\nDelacruzside, MA 00813
4                      679 Luna Roads\nGreggshire, VA 11650
                                ...
396025       12951 Williams Crossing\nJohnnyville, DC 30723
396026    0114 Fowler Field Suite 028\nRachelborough, LA…
396027     953 Matthew Points Suite 414\nReedfort, NY 70466
396028    7843 Blake Freeway Apt. 229\nNew Michael, FL 2…
```

```
396029          787 Michelle Causeway\nBriannaton, AR 48052
Name: address, Length: 395219, dtype: object
```

5.4.1 This contains a full address. An efficient way to engineer this feature is to extract the zip code (more detailed than state, more generalized than street + number)

[31]:
```
# Extract the zip code and save as separate column
df['zipcode'] = df['address'].apply(lambda adrs: adrs.split()[-1])
df.drop('address', axis = 1, inplace = True)
```

5.5 Issue date

5.5.1 This column would leak to information leakage, as it tells us when (and therefore if) the loan was funded

[35]:
```
# issue_d
# The month in which the loan was funded
# This would be information leakage, as it tells us whether the loan was␣
↪funded, so drop it
feat_info('issue_d')
df['issue_d'].value_counts()
df.drop('issue_d', axis=1, inplace=True)
```

5.6 Earliest Credit Line

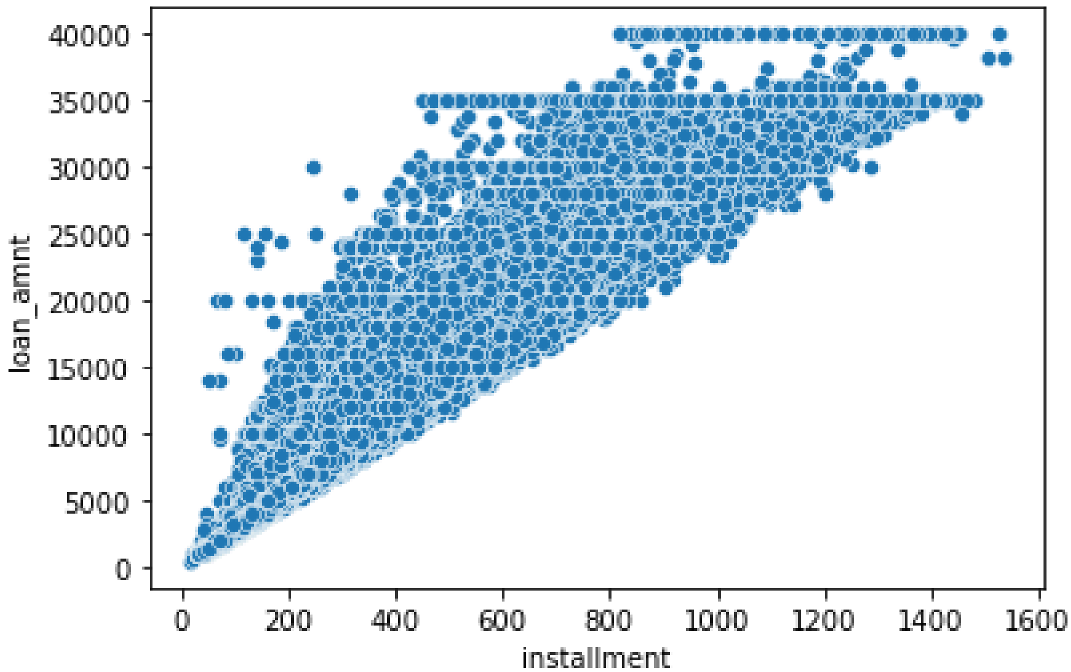
5.6.1 Simplify by just saving the year

[36]:
```
# earliest_cr_line

df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'],format='%b-%Y')
df['earliest_cr_line'] = df['earliest_cr_line'].apply(lambda x: x.year)
```

5.7 Instalment

[37]:
```
#The installment is 95% correlated with the loan amount, so it can be dropped
sns.scatterplot(data=df,x='installment',y='loan_amnt')
```

[37]:
```
<AxesSubplot:xlabel='installment', ylabel='loan_amnt'>
```



5.7.1 Highly correlated with loan amount, so can be dropped

[38]:
```
df.drop(['installment'], axis=1, inplace=True)
```

6 Training the neural network

[39]:
```
# Store values in the familiar X, y format for training data and label,␣
↪respectively (label = 'loan_repaid')
X = df.drop('loan_repaid', axis=1).values
y = df['loan_repaid'].values
```

[40]:
```
## Optional sampling for performance reasons
# df = df.sample(frac=0.1, random_state=101)
```

[41]:
```
# Train - test split the data (20%)
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,␣
↪random_state = 101)
```

6.1 Create network architecture and train

[42]:
```
# Use rectified linear unit activation function and adam optimizer
activation_function = 'relu'
optimizer = 'adam'
batch_size = 256
```

```
alpha = 2
N_h = X_train.shape[0]/(alpha*(X_train.shape[1]-1))
```

6.1.1 Scale the data using the MinMaxScaler

[43]:
```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

6.1.2 Define the neural network architecture (Sequential with 3 dense layers, second one half the input size)

6.1.3 A 20% Dropout rate was chosen to avoid overfitting to the data

[44]:
```
input_shape = X_train.shape[1]
model = Sequential([
    Dense(input_shape, activation = activation_function),
    Dropout(0.2),

    Dense(np.ceil(input_shape/2), activation = activation_function),
    Dropout(0.2),

    Dense(units = 1, activation='sigmoid')
    ])
```

```
WARNING:tensorflow:From E:\Anaconda3\envs\KTF_NN\lib\site-
packages\tensorflow\python\ops\init_ops.py:1251: calling
VarianceScaling.__init__ (from tensorflow.python.ops.init_ops) with dtype is
deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the
constructor
```

6.1.4 Since the problem is a binary classification problem, we use binary cross-entropy as a loss function. We also include an Early Stopping callback to avoid training after the validation loss stops decreasing

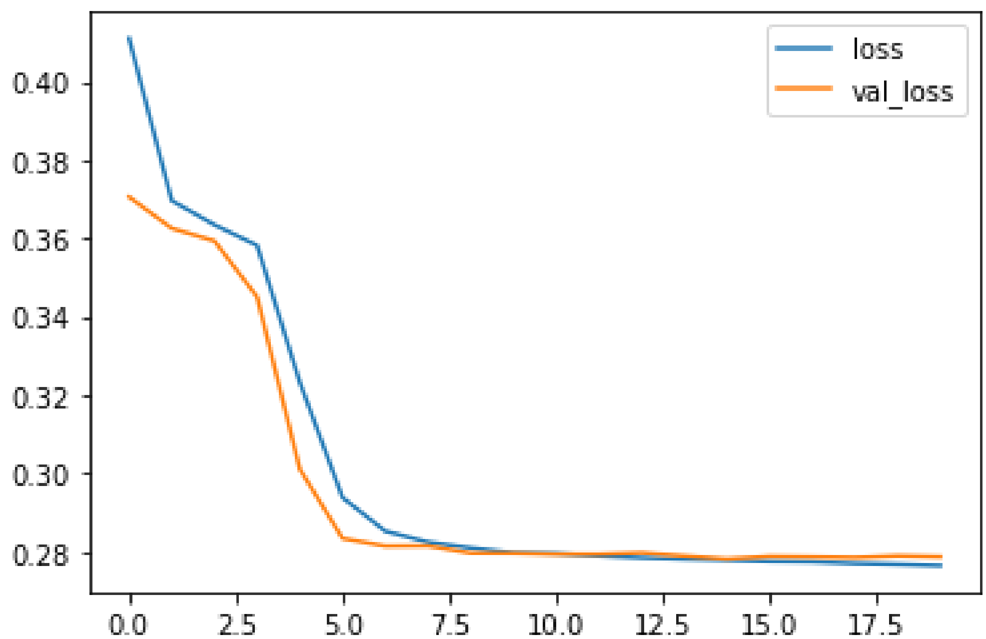
[45]:
```
model.compile(optimizer = 'adam', loss = 'binary_crossentropy' )
early_stop = EarlyStopping(monitor = 'val_loss', mode = 'min', verbose = 1,␣
 ↪patience = 5)
model.fit(x = X_train, y = y_train, validation_data = (X_test, y_test),␣
 ↪batch_size = batch_size, epochs = 25, callbacks = [early_stop])

model_loss = pd.DataFrame(model.history.history)
model_loss.plot()
```

```
WARNING:tensorflow:From E:\Anaconda3\envs\KTF_NN\lib\site-
packages\tensorflow\python\ops\nn_impl.py:180:
```

```
add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 316175 samples, validate on 79044 samples
Epoch 1/25
316175/316175 [==============================] - 7s 23us/sample - loss: 0.4111 -
val_loss: 0.3706
Epoch 2/25
316175/316175 [==============================] - 6s 20us/sample - loss: 0.3697 -
val_loss: 0.3626
Epoch 3/25
316175/316175 [==============================] - 6s 19us/sample - loss: 0.3635 -
val_loss: 0.3594
Epoch 4/25
316175/316175 [==============================] - 4s 13us/sample - loss: 0.3582 -
val_loss: 0.3451
Epoch 5/25
316175/316175 [==============================] - 3s 11us/sample - loss: 0.3233 -
val_loss: 0.3011
Epoch 6/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2938 -
val_loss: 0.2834
Epoch 7/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2853 -
val_loss: 0.2814
Epoch 8/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2825 -
val_loss: 0.2815
Epoch 9/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2810 -
val_loss: 0.2796
Epoch 10/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2797 -
val_loss: 0.2796
Epoch 11/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2796 -
val_loss: 0.2794
Epoch 12/25
316175/316175 [==============================] - 3s 10us/sample - loss: 0.2789 -
val_loss: 0.2794
Epoch 13/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2784 -
val_loss: 0.2797
Epoch 14/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2781 -
val_loss: 0.2789
Epoch 15/25
```

```
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2779 -
val_loss: 0.2781
Epoch 16/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2775 -
val_loss: 0.2788
Epoch 17/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2774 -
val_loss: 0.2787
Epoch 18/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2770 -
val_loss: 0.2785
Epoch 19/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2768 -
val_loss: 0.2789
Epoch 20/25
316175/316175 [==============================] - 3s 9us/sample - loss: 0.2765 -
val_loss: 0.2787
Epoch 00020: early stopping
```

[45]: <AxesSubplot:>



6.2 Evaluate the network

[46]:
```
# Print Confusion matrix and classification report
y_pred = model.predict_classes(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

# The labels are imbalanced, so Accuracy is not as important as Recall
print('Accuracy by just predicting "Fully Paid" every time: {perc:.2f}%'
      .format(perc = df['loan_repaid'].value_counts()[1]/len(df)*100))
```

```
              precision    recall  f1-score   support

           0       0.99      0.43      0.60     15658
           1       0.88      1.00      0.93     63386

    accuracy                           0.89     79044
   macro avg       0.94      0.72      0.77     79044
weighted avg       0.90      0.89      0.87     79044

[[ 6791  8867]
 [   45 63341]]
Accuracy by just predicting "Fully Paid" every time: 80.38%
```

6.3 The majority of people pay back the loans, and this imbalance in the data makes the prediction task more complicated. The current iteration is a first solution to this problem used in the Udemy Data Science and Machine Learning Bootcamp.