

Lab 8 - Jackson Nahom

October 19, 2021

```
[1]: import pandas as pd
import numpy as np
import statsmodels.api as sm
from sklearn import metrics
```

```
[2]: ld = pd.read_csv('data/lendingclub_2015-2018.csv')
ld.head()
tmp = ld.tail()
display(tmp)
```

C:\ProgramData\Anaconda3\lib\site-

packages\IPython\core\interactiveshell.py:3165: DtypeWarning: Columns
(20,60,119,130,131,132,135,136,137,140,146,147,148) have mixed types.Specify
dtype option on import or set low_memory=False.

has_raised = await self.run_ast_nodes(code_ast.body, cell_name,

	index	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	\
249990	249991	145635719	NaN	35000.0	35000.0	35000.0	
249991	249992	145635974	NaN	7500.0	7500.0	7500.0	
249992	249993	145637006	NaN	30000.0	30000.0	30000.0	
249993	249994	145641258	NaN	22650.0	22650.0	22650.0	
249994	249995	145642272	NaN	1000.0	1000.0	1000.0	

	term	int_rate	installment	grade	...	\
249990	60 months	18.94	906.77	D	...	
249991	36 months	10.72	244.55	B	...	
249992	60 months	27.27	920.91	E	...	
249993	36 months	10.72	738.54	B	...	
249994	36 months	18.94	36.63	D	...	

	hardship_last_payment_amount	disbursement_method	debt_settlement_flag	\
249990	NaN	Cash	N	
249991	NaN	Cash	N	
249992	NaN	Cash	N	
249993	NaN	Cash	N	
249994	NaN	Cash	N	

	debt_settlement_flag_date	settlement_status	settlement_date	\
249990	NaN	NaN	NaN	

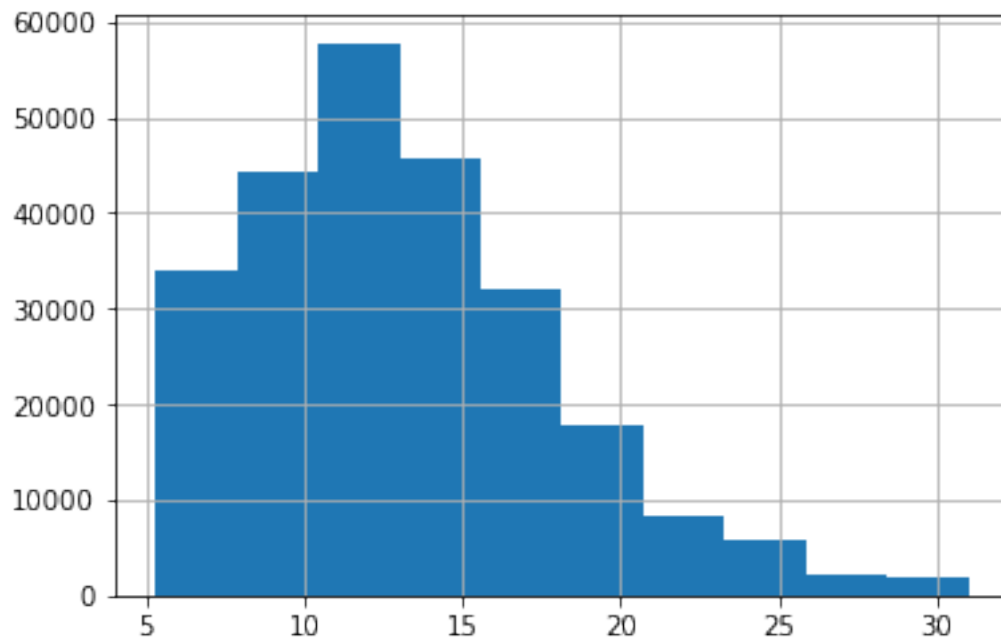
249991	NaN	NaN	NaN
249992	NaN	NaN	NaN
249993	NaN	NaN	NaN
249994	NaN	NaN	NaN

	settlement_amount	settlement_percentage	settlement_term	duration
249990	NaN	NaN	NaN	60
249991	NaN	NaN	NaN	36
249992	NaN	NaN	NaN	60
249993	NaN	NaN	NaN	36
249994	NaN	NaN	NaN	36

[5 rows x 153 columns]

```
[3]: ld['int_rate'].hist()
```

[3]: <AxesSubplot:>



```
[4]: # view unique values
ld['term'].unique()

# split rows into parts
term_split = ld['term'].str.split(' ')

# view first five rows
print(term_split[:5])
```

```

0    [, 36, months]
1    [, 36, months]
2    [, 36, months]
3    [, 36, months]
4    [, 36, months]
Name: term, dtype: object

```

```

[5]: # the str function can retrieve a specific list element for all rows
term_split.str[1]
ld['duration'] = term_split.str[1]

# add this to the dataframe
display(ld['duration'].head())
# this column is not in integer format. Must fix!

```

```

0    36
1    36
2    36
3    36
4    36
Name: duration, dtype: object

```

```

[6]: # convert column to integer
ld['duration'] = ld['duration'].apply(int)
display(ld['duration'].head())

```

```

0    36
1    36
2    36
3    36
4    36
Name: duration, dtype: int64

```

```

[7]: ld['log_loan_amnt'] = np.log(ld['loan_amnt'])
ld['log_annual_inc'] = np.log(ld['annual_inc']+1)

```

```

[8]: cols = ['int_rate', 'log_loan_amnt', 'installment', 'log_annual_inc',
    ↪ 'duration', 'fico_range_low', 'revol_util', 'dti']
corr = ld[cols].corr()
corr.style.background_gradient(cmap='coolwarm')

# ld[cols].corr() # <--- use this if you just want the table in non-graphical
    ↪ format

```

```

[8]: <pandas.io.formats.style.Styler at 0x1e306c92cd0>

```

```

[9]: pred_vars = ['log_loan_amnt', 'log_annual_inc', 'fico_range_low', 'revol_util',
    ↪ 'dti', 'duration']

```

```
[10]: print("before dropping rows with missing data", len(ld))
      ld = ld.dropna(subset=pred_vars)
      print("after dropping rows with missing data", len(ld))
```

before dropping rows with missing data 249995
 after dropping rows with missing data 249582

```
[11]: from sklearn.model_selection import train_test_split

      # use index-based sampling since we have time series data
      train, test = train_test_split(ld, test_size=0.25, shuffle=False)
```

```
[12]: # earliest and latest dates in train
      print("training data starts\n", train['issue_d'].head())
      print("training data ends\n", train['issue_d'].tail())
      # earliest and latest in test
      print("testing data starts\n", test['issue_d'].head())
      print("testing data ends\n", test['issue_d'].tail())
```

training data starts
 0 Jul-2007
 1 Jul-2007
 2 Jul-2007
 3 Jul-2007
 4 Jul-2007
 Name: issue_d, dtype: object
 training data ends
 187369 Nov-2017
 187370 Nov-2017
 187371 Nov-2017
 187372 Nov-2017
 187373 Nov-2017
 Name: issue_d, dtype: object
 testing data starts
 187374 Nov-2017
 187375 Nov-2017
 187376 Nov-2017
 187377 Nov-2017
 187378 Nov-2017
 Name: issue_d, dtype: object
 testing data ends
 249990 Dec-2018
 249991 Dec-2018
 249992 Dec-2018
 249993 Dec-2018
 249994 Dec-2018
 Name: issue_d, dtype: object

```
[13]: reg_fico = sm.OLS(train['int_rate'], train['fico_range_low']).fit()
reg_fico.summary()
```

```
[13]: <class 'statsmodels.iolib.summary.Summary'>
```

```

"""
                                OLS Regression Results
=====
Dep. Variable:                  int_rate    R-squared (uncentered):
0.873
Model:                          OLS        Adj. R-squared (uncentered):
0.873
Method:                        Least Squares    F-statistic:
1.287e+06
Date:                          Tue, 19 Oct 2021    Prob (F-statistic):
0.00
Time:                          16:59:49    Log-Likelihood:
-5.6714e+05
No. Observations:              187186    AIC:
1.134e+06
Df Residuals:                  187185    BIC:
1.134e+06
Df Model:                      1
Covariance Type:               nonrobust
=====
==
                                coef    std err          t      P>|t|      [0.025
0.975]
-----
--
fico_range_low      0.0188    1.66e-05   1134.408    0.000    0.019
0.019
=====
Omnibus:                 10997.634    Durbin-Watson:           1.948
Prob(Omnibus):            0.000    Jarque-Bera (JB):        13259.038
Skew:                     0.605    Prob(JB):                 0.00
Kurtosis:                 3.483    Cond. No.                 1.00
=====

Notes:
[1] R2 is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""

```

```
[14]: reg_multi = sm.OLS(train['int_rate'], train[pred_vars], hasconst=False).fit()
reg_multi.summary()
```

```
[14]: <class 'statsmodels.iolib.summary.Summary'>
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          int_rate    R-squared (uncentered):
0.910
Model:                  OLS        Adj. R-squared (uncentered):
0.909
Method:                 Least Squares    F-statistic:
3.135e+05
Date:                   Tue, 19 Oct 2021    Prob (F-statistic):
0.00
Time:                   16:59:51    Log-Likelihood:
-5.3544e+05
No. Observations:       187186    AIC:
1.071e+06
Df Residuals:           187180    BIC:
1.071e+06
Df Model:                6
Covariance Type:        nonrobust
=====
==
                        coef      std err          t      P>|t|      [0.025
0.975]
-----
--
log_loan_amnt          0.4867      0.018      27.573      0.000      0.452
0.521
log_annual_inc          0.4736      0.019      25.196      0.000      0.437
0.510
fico_range_low        -0.0094      0.000     -38.372      0.000     -0.010
-0.009
revol_util              0.0350      0.000      79.704      0.000      0.034
0.036
dti                    0.0454      0.001      52.977      0.000      0.044
0.047
duration               0.1685      0.001     169.180      0.000      0.167
0.170
=====
Omnibus:                20040.090    Durbin-Watson:           1.920
Prob(Omnibus):           0.000    Jarque-Bera (JB):       33725.942
Skew:                    0.755    Prob(JB):                0.00
Kurtosis:                4.429    Cond. No.                1.62e+03

```

=====
Notes:

- [1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
 - [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 - [3] The condition number is large, $1.62e+03$. This might indicate that there are strong multicollinearity or other numerical problems.
- """

```
[15]: print(reg_fico.aic)
      print(reg_multi.aic)
```

```
1134288.3080747342
1070889.1563837891
```

```
[16]: sm.stats.anova_lm(reg_fico, reg_multi)
```

```
[16]:
```

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
0	187185.0	4.693344e+06	0.0	NaN	NaN	NaN
1	187180.0	3.344763e+06	5.0	1.348581e+06	15093.884858	0.0

```
[17]: fico_pred = reg_fico.predict(test['fico_range_low'])

fico_rmse = metrics.mean_squared_error(test['int_rate'], fico_pred,
    ↪squared=False)
print("RMSE:", fico_rmse)
```

```
RMSE: 5.4935559541762
```

```
[18]: multi_pred = reg_multi.predict(test[pred_vars])

multi_rmse = metrics.mean_squared_error(test['int_rate'], multi_pred,
    ↪squared=False)
print("RMSE:", multi_rmse)
```

```
RMSE: 4.706613506113946
```

1 Tasks

1. Can you build a model that performs significantly better than the models already built? Train the model and compare it. Which variables did you use and why do you think they improved the model?
2. What level of RMSE would you consider acceptable would you consider appropriate in this situation?

1.1 Task 1

Can you build a model that performs significantly better than the models already built? Train the model and compare it. Which variables did you use and why do you think they improved the model?

```
[51]: ld = pd.read_csv('data/lendingclub_2015-2018.csv')
ld.head()
tmp = ld.tail()
display(tmp)
```

C:\ProgramData\Anaconda3\lib\site-

packages\IPython\core\interactiveshell.py:3165: DtypeWarning: Columns
(20,60,119,130,131,132,135,136,137,140,146,147,148) have mixed types.Specify
dtype option on import or set low_memory=False.

```
has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

	index	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	\
249990	249991	145635719	NaN	35000.0	35000.0	35000.0	
249991	249992	145635974	NaN	7500.0	7500.0	7500.0	
249992	249993	145637006	NaN	30000.0	30000.0	30000.0	
249993	249994	145641258	NaN	22650.0	22650.0	22650.0	
249994	249995	145642272	NaN	1000.0	1000.0	1000.0	

	term	int_rate	installment	grade	...	\
249990	60 months	18.94	906.77	D	...	
249991	36 months	10.72	244.55	B	...	
249992	60 months	27.27	920.91	E	...	
249993	36 months	10.72	738.54	B	...	
249994	36 months	18.94	36.63	D	...	

	hardship_last_payment_amount	disbursement_method	debt_settlement_flag	\
249990	NaN	Cash	N	
249991	NaN	Cash	N	
249992	NaN	Cash	N	
249993	NaN	Cash	N	
249994	NaN	Cash	N	

	debt_settlement_flag_date	settlement_status	settlement_date	\
249990	NaN	NaN	NaN	
249991	NaN	NaN	NaN	
249992	NaN	NaN	NaN	
249993	NaN	NaN	NaN	
249994	NaN	NaN	NaN	

	settlement_amount	settlement_percentage	settlement_term	duration
249990	NaN	NaN	NaN	60
249991	NaN	NaN	NaN	36
249992	NaN	NaN	NaN	60

249993	NaN	NaN	NaN	36
249994	NaN	NaN	NaN	36

[5 rows x 153 columns]

```
[52]: # view unique values
ld['term'].unique()

# split rows into parts
term_split = ld['term'].str.split(' ')

# view first five rows
print(term_split[:5])
```

```
0    [, 36, months]
1    [, 36, months]
2    [, 36, months]
3    [, 36, months]
4    [, 36, months]
Name: term, dtype: object
```

```
[53]: # the str function can retrieve a specific list element for all rows
term_split.str[1]
ld['duration'] = term_split.str[1].apply(int)

# add this to the dataframe
display(ld['duration'].head())
```

```
0    36
1    36
2    36
3    36
4    36
Name: duration, dtype: int64
```

```
[54]: ld['log_funded_amnt'] = np.log(ld['funded_amnt'])
ld['log_last_pymnt_amnt'] = np.log(ld['last_pymnt_amnt']+1)
```

```
[55]: pred_vars = ['log_funded_amnt', 'inq_last_6mths', 'open_acc', 'bc_util',
↳ 'log_last_pymnt_amnt'
        , 'duration']
```

```
[56]: print("before dropping rows with missing data", len(ld))
ld = ld.dropna(subset=pred_vars)
print("after dropping rows with missing data", len(ld))
```

before dropping rows with missing data 249995
after dropping rows with missing data 241305

```
[57]: # use index-based sampling since we have time series data
train, test = train_test_split(ld, test_size=0.25, shuffle=False)

[58]: reg_multi = sm.OLS(train['int_rate'], train[pred_vars], hasconst=False).fit()
reg_multi.summary()
```

```
[58]: <class 'statsmodels.iolib.summary.Summary'>
"""
                                OLS Regression Results
=====
=====
Dep. Variable:                  int_rate    R-squared (uncentered):
0.915
Model:                          OLS      Adj. R-squared (uncentered):
0.915
Method:                        Least Squares    F-statistic:
3.242e+05
Date:                          Tue, 19 Oct 2021    Prob (F-statistic):
0.00
Time:                          17:08:09    Log-Likelihood:
-5.1239e+05
No. Observations:              180978    AIC:
1.025e+06
Df Residuals:                  180972    BIC:
1.025e+06
Df Model:                      6
Covariance Type:               nonrobust
=====
=====
                                coef    std err          t      P>|t|      [0.025
0.975]
-----
log_funded_amnt                0.2840      0.007     39.156      0.000      0.270
0.298
inq_last_6mths                 1.2735      0.011    117.876      0.000      1.252
1.295
open_acc                      -0.0311      0.002    -17.298      0.000     -0.035
-0.028
bc_util                       0.0438      0.000    125.490      0.000      0.043
0.044
log_last_pymnt_amnt           0.0117      0.006      2.020     0.043      0.000
0.023
duration                      0.1726      0.001    177.848      0.000      0.171
0.174
=====
Omnibus:                       21085.333    Durbin-Watson:                   1.935
```

Prob(Omnibus):	0.000	Jarque-Bera (JB):	32356.254
Skew:	0.852	Prob(JB):	0.00
Kurtosis:	4.178	Cond. No.	89.4

=====

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

"""

```
[59]: #print(high_fico.aic)
print(reg_multi.aic)
```

1024786.7440574181

```
[60]: multi_pred = reg_multi.predict(test[pred_vars])

multi_rmse = metrics.mean_squared_error(test['int_rate'], multi_pred,
    ↪squared=False)
print("RMSE:", multi_rmse)
```

RMSE: 4.578078326741005

My OLS Regression model is improved from our lab example. Using `log_funded_amnt`, `inq_last_6mths`, `open_acc`, `bc_util`, `log_last_pymnt_amnt`, and `duration` I achieved and adjusted R^2 of 0.915 compared to 0.909 in class. My model's AIC and RMSE were 1024786.74 and 4.5781 respectively. While the model we did in class the AIC and RMSE were 1070889.16 and 4.7066 respectively. My model had lower AIC and RMSE showing that it is better fitted than the model we did in class.

2 Task 2

What level of RMSE would you consider acceptable would you consider appropriate in this situation?

I don't believe there is a standard acceptable level of RMSE. In this case we are looking at interest rates on loans and trying to predict them. RMSE is the standard deviation the actual interest rate is away from predicted interest rate. In my model's case on average I was 4.5781 standard deviations away from the actual interest rate. Since interest rates of loans is so important and could impact a person's financial future I would be more comfortable with an RMSE under 2, meaning on average my predictions were 2 less than 2 standard deviations away from the actual.

```
[ ]:
```