
LendingClub

Lending Club Loan Status

2019 Data Analysis Report for Fontys University

Version number: 1

Prepared by: Borislav Pavlov

CONTENTS

01 FOREWORD

Lending Club is a US peer-to-peer lending company, headquartered in San Francisco, California. 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. Lending Club is the world's largest peer-to-peer lending platform. The company claims that $ 15.98 billion in loans had been originated through its platform up to December 31, 2015.

Lending Club enables borrowers to create unsecured personal loans between $ 1,000 and $ 40,000. The standard loan period is three years. Investors can search and browse the loan listings on Lending Club website and select loans that they want to invest in based on the information supplied about the borrower, amount of loan, loan grade, and loan purpose. Investors make money from interest. Lending Club makes money by charging borrowers an origination fee and investors a service fee.

02

INTRODUCTION

If you're following the news in the world of online marketplace lending then you maybe heard about the internal scandal in Lending Club's company which resulted the resignation of its founder, chairman, and chief executive, Renaud Laplanche.

Let me tell you what happened in a few words. On Monday, after an internal review, Lending Club announced that $22 million in subprime loans that had been sold in March and April of this year to a single investor, went against the investor's expressed terms.

This situation is a sign that frauds like this must be prevented and this is the purpose of this report too.

Could the disaster from 2016 for the company be prevented?

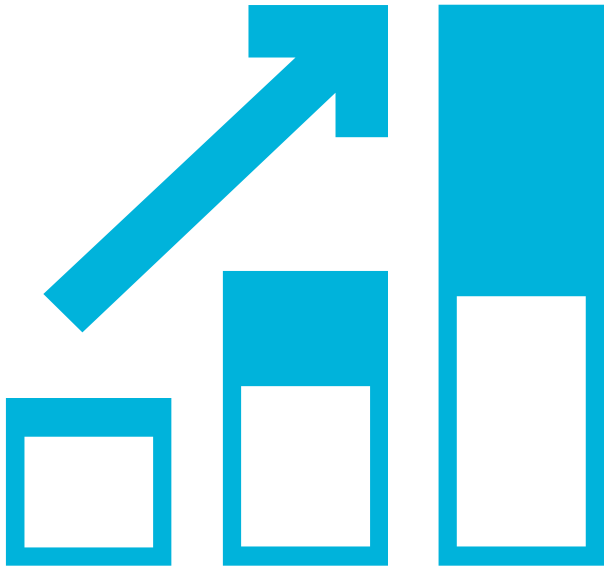
Is there any relation with the customer's data and the target question if they are going to return their loan?

The goal of this project will be to answer these questions.

If you want to read more about what happened with the company 2016 check the web pages.

https://www.nytimes.com/2018/09/28/technology/lendingclub-renaud-laplanche-fraud.html

https://www.marketwatch.com/story/goldman-jefferies-stopped-buying-lendingclub-loans-2016-05-10



03 DATA AND METHODOLOGY

3.1 Lending Club Data

There are available files containing complete loan data for all loans issued through the 2007-2019, including the current loan status (Current, Late, Fully Paid, etc.) and latest payment information. The file containing loan data through the "present" contains complete loan data for all loans issued through the previous completed calendar quarter. Additional features include credit scores, number of finance inquiries, address including zip codes, and state, and collections among others. The file is a matrix of about 890 thousand observations and 75 variables.

Our main focus will be on the years from 2007 to 2018. Furthermore, a data dictionary is provided in a separate file.

3.2 Methods

All of the data is e publicly available at LendingClub.com.

We will use the data from 2007-2018 year which can be downloaded from here.

The analysis was made in Python programming language supported by Anaconda environment and more precisely Jupyter Notebook, which is attached at bottom of the document.

First of all, all of the data had to be cleaned. Once we had the data cleaned and ready we started exploring it by plotting different distributions of the features.

After the whole exploratory data analysis, we were ready to choose which features to use for our prediction and they were the following:

- loan_amount: 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.
- Interest_rate: Interest Rate on the loan.
- annual_income: The self-reported annual income provided by the borrower during registration.
- delinq_2yrs: The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years.
- 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.
- 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.
- tot_cur_bal: Total current balance of all accounts.
- purpose: A category provided by the borrower for the loan request.

- home_ownership: The home ownership status provided by the borrower during registration. Our values are: RENT, OWN, MORTGAGE, OTHER.

- recoveries: Post charge of gross recovery.
- total_rec_prncp: Principal received to date.
- out_prncp: Remaining outstanding principal for total amount funded.
- last_pymnt_d: Last month payment was received.

For making our predictive model a reality, we decided to use the following algorithms:

- Decision tree classifier,
- Random Forest (tree based model) Neural Network algorithms were used.

3.3 Data analysis

Through our Exploratory Data Analysis, we tried to find if there is any kind of relation between any of the features in the dataset.

For the purpose, we used different libraries which helped us to better visualize the features that we are exploring and see if there were any trends and correlations.

The Figure below are the conclusions that we found by distributing some of the features which we think can give us some insights and help us with the prediction later.

LOANS ISSUED PER YEAR

1

- Most of the **loans issued** were in the range of 10,000 to 20,000 USD.
- The **year of 2018** was the year were most loans were issued.
- Loans were issued in an **incremental manner**. (Possible due to a recovery in the U.S economy)

DISTRIBUTION OF THE STATES

2

- **California, Texas, New York and Florida** are the states in which the highest amount of loans were issued.
- Interesting enough, all four states have an approximate **interest rate of 13%** which is at the same level of the average interest rate for all states (13.24%)
- California, Texas and New York are **all above the average annual income** (with the exclusion of Florida), this might give possible indication why most loans are issued in these states.

DISTRIBUTION OF THE LOAN STATUS

3

The conclusions that we can get from this chart are that we have a lot of loans which are fully paid with fair amount of current loans. Other categories (including) default have a really low number. This means the data is imbalanced and we might need to do something about this later in the analysis.

The approach that we are going to use is to replace all kind of “Late” loans,” Charged Off”, "Does not meet the credit policy. Status: Charged Off", "In Grace Period" and “Default” status with “Bad Loan” status and the rest with “Good Loan” status. In this way we have only 2 options for the loan status and we increase the balance of the data.

DISTRIBUTION BY ICOME

4

- Borrowers that made part of the **high income category** took higher loan amounts than people from **low** and **medium income categories.** Of course, people with higher annual incomes are more likely to pay loans with a higher amount. (First row to the left of the subplots)
- Loans that were borrowed by the **Low income category** had a slightly higher change of becoming a bad loan. (First row to the right of the subplots)
- Borrowers with **High** and **Medium** annual incomes had a longer employment length than people with lower incomes (Second row to the left of the subplots)

DISTRIBUTION OF THE INTEREST RATE

5

- Loans that have a **high interest rate** (above 13.23%) are more likely to become a **bad loan.**
- Loans that have a longer **maturity date (60 months)** are more likely to be a bad loan.

DISTRIBUTION OF THE HOME OWNERSHIP

6

- The types of bad loans in the last year are having a tendency to decline, except for not meeting credit policy.
- Mortgage was the variable from the home ownership column that used the highest amount borrowed within loans that were considered to be bad.
- There is a slight **increase** on people who have mortgages that are applying for a loan.

DISTRIBUTION BY THE PURPOSE OF THE LOAN

7

- **Bad Loans Count:** People that apply for educational and small business purposed tend to have a higher risk of being a bad loan. (% wise)
- **Most frequent Purpose:** The reason that clients applied the most for a loan was to consolidate debt.
- **Less frequent purpose:** Clients applied less for educational purposes for all three income categories.
- **Interest Rates:** In all reasons for application except (medical, small business and credit card), the low income category has a higher interest rate. Something that could possibly explain this is the amount of capital that is needed from other income categories that might explain why the low income categories interest rate for these purposes are lower.

DISTRIBUTION BY THE 20 MOST COMMON EMPLOYEE TITLES

8

We can see that Director, Engineer, President, Vice President are the category's with highest incidence in Grade A.

Analyzing this we can get some insights about the profile of grades and professionals.

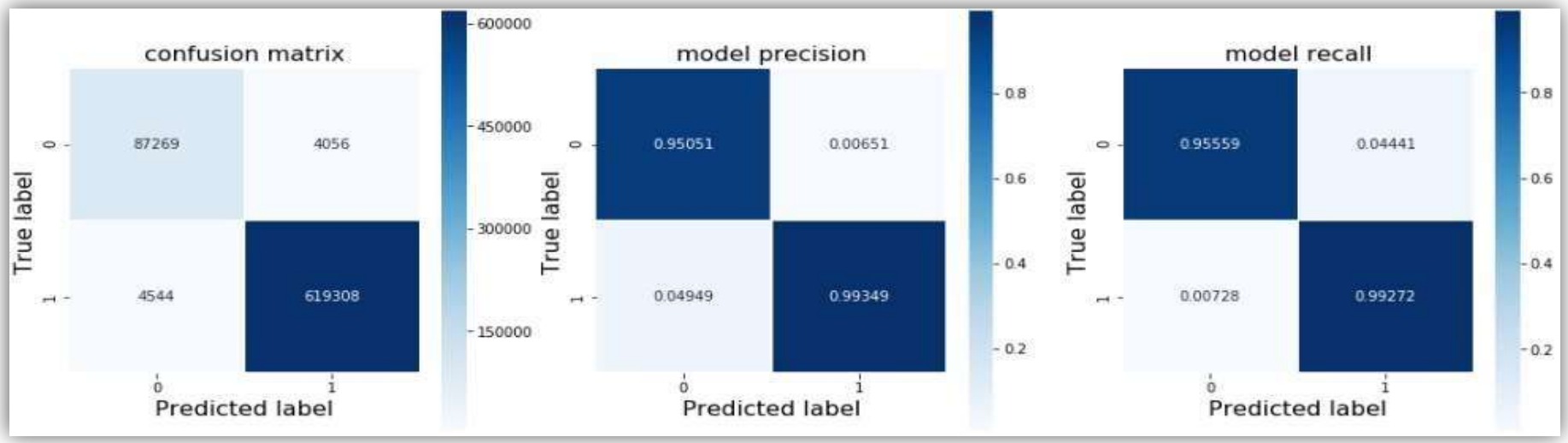
Fig.1: Features Analysis

3. 4 Results

After we applied the algorithms that we said we are going to us in the “Methods” section, we displayed in a graph and compared their results with each other.

The results are the following:

DECISION TREE CLASSIFIER RESULTS



As you can see, this model had predicted right 87269 “Bad Loans” and 619308 “Good Loans”. However, it had wrong

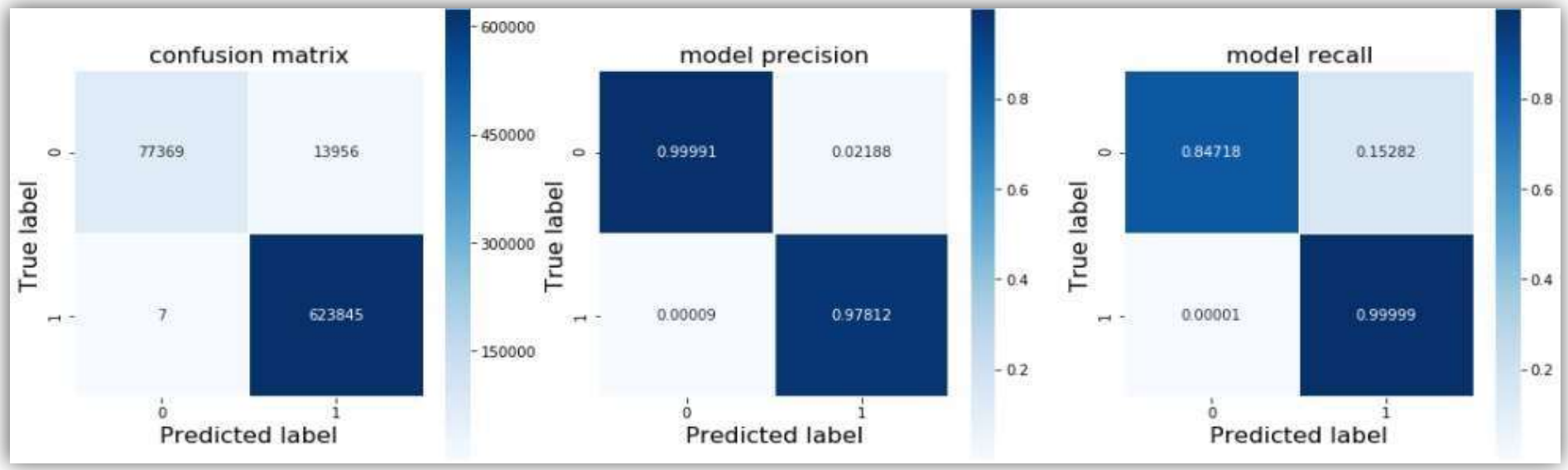
4056 “Bad Loans” and 4544 “Good Loans”. The total model precision for the “Bad Loans” is 0.95 % and for the “Good Loans” is 0.99 %. The overall accuracy score for this model is 0.98% which is really good.

NEURAL NETWORKS RESULTS

For our neural networks model we used TensorFlow and we tried two not so different approaches:

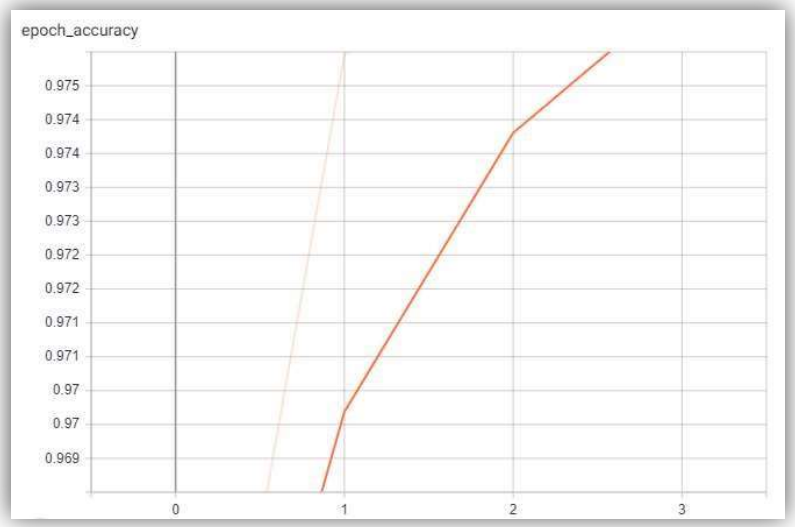
- Using one of the build in TensorFlow estimators
- Using a Keras Model

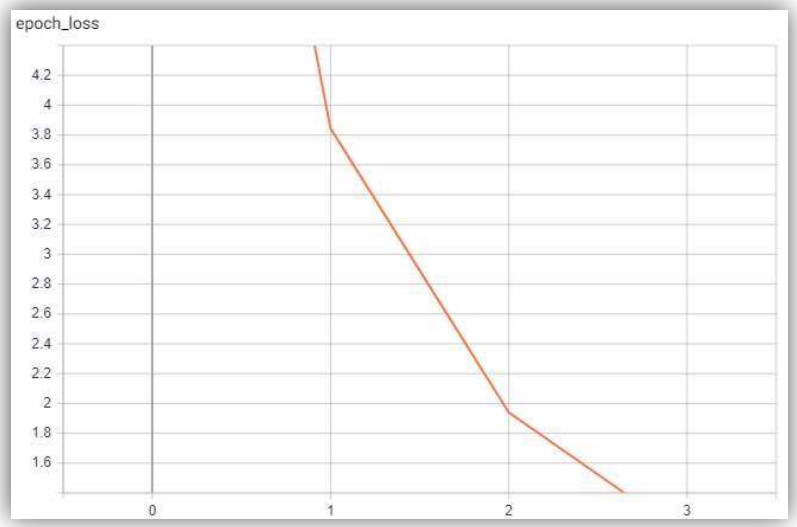
For our first approach, since we are trying to classify if the loan is going to be “Bad Loan” or “Good Loan”, we used a DNNClassifier estimator. Defining one hidden layer with 1500 neurons, we trained the model and the results that we got are the following.

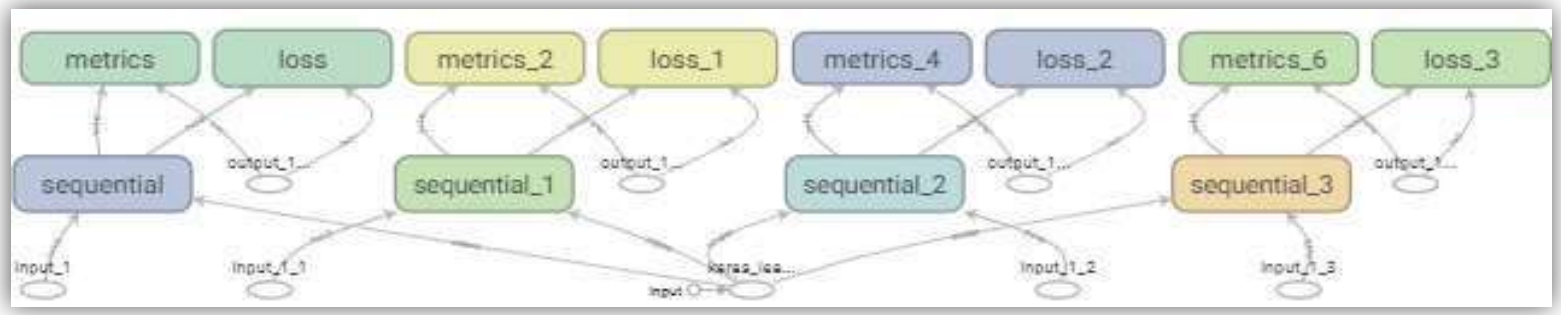


As you can see we have a 0.999 % accuracy in predicting whether the loan is going to be “Bad” and 0.97% whether it is going to be “Good”. The overall accuracy score for this model is again 0.98% which also a very good model.

The second approach, with defining a keras model, we have got an overall accuracy of 0.979% in 4 epochs.
We used the tensor board so we can see a visualization of the epoch accuracy, epoch loss and the main graph of the model.

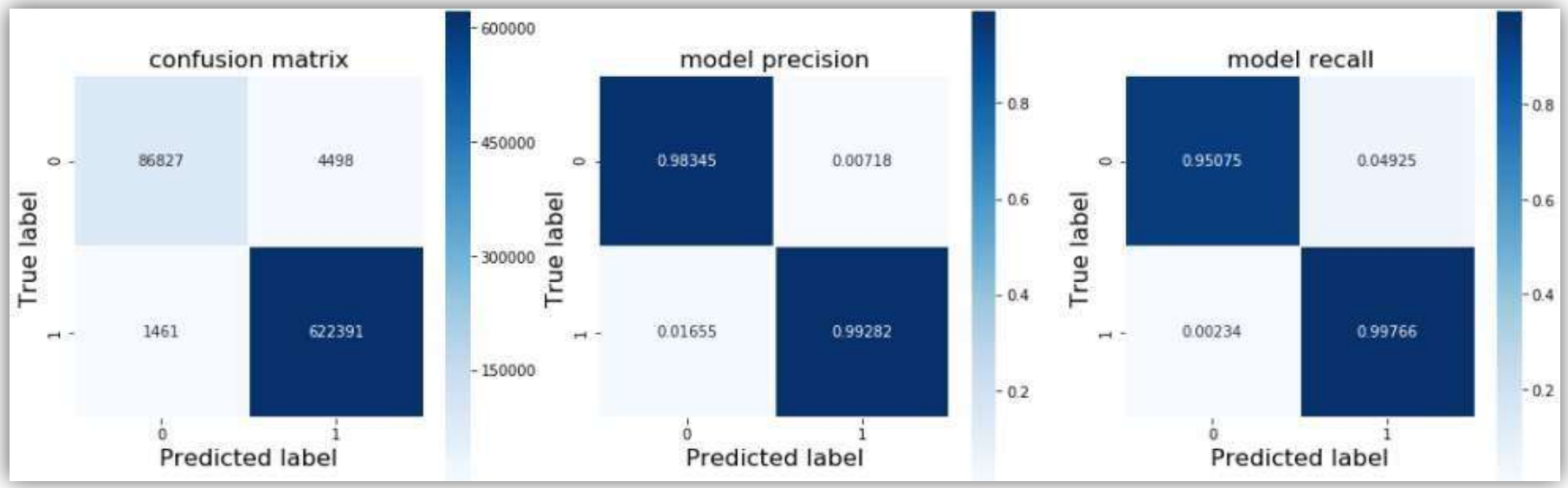






Data and Methodology

RANDOM FOREST CLASSIFIER RESULTS



Our final model had overall accuracy score of 0.99% which make it the best. It is noticeable that only 1461 samples were got wrong for predicting if they are “Good Loans” which is 4 times better than the Decision Tree Classifier.

04 CONCLUSION

We can say that all of the models are very good with accuracy score 0.98% for the Decision Tree Classifier, Neural Networks algorithms and 0.99% for the Random Forest Classifier.

However, if we have to choose one of the models it will not be that easy. It really depends on which metrics you want to optimize. For instance, we can see that the precision of predicting “Bad Loans” using the Neural Networks is the highest – 0.99% but the recall is 0.84% and for the Random Forest Classifier the precision for predicting “Bad Loans” is 0.98% but the recall is 0.95% and that is 0.11% more than the Neural Networks.

In conclusion, I can say that we successfully build a machine learning predictive model with almost perfect accuracy which predicts whether a person will return his/her loan, which can be used further by Lending Club for their analysis.

05 APPENDICES

- BUSINESS PROPOSAL
- JUPYTER NOTEBOOK

Lending Club Loan Status

2019 Business Proposal

Version number: 3

Prepared by: Borislav Pavlov

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01 COMPANY INFORMATION

Lending Club is a US peer-to-peer lending company, headquartered in San Francisco, California. 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. Lending Club is the world's largest peer-to-peer lending platform. The company claims that $ 15.98 billion in loans had been originated through its platform up to December 31, 2015

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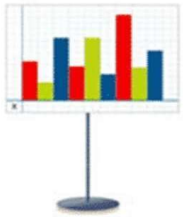
HOW LENDING CLUB WORKS

Borrowers apply for loans.
Investors open an account.

Borrowers get funded.
Investors build a portfolio.



Borrowers repay automatically.
Investors earn & reinvest.

02 ABOUT THE DATASET

There are available files containing complete loan data for all loans issued through the 2007-2019, including the current loan status (Current, Late, Fully Paid, etc.) and latest payment information. The file containing loan data through the "present" contains complete loan data for all loans issued through the previous completed calendar quarter. Additional features include credit scores, number of finance inquiries, address including zip codes, and state, and collections among others. The file is a matrix of about 890 thousand observations and 75 variables.

Our main focus will be on the years from 2007 to 2018, because most of the data for 2019 year is still in the process and most of the loans are just issued.

Furthermore, a data dictionary is provided in a separate file.

03 EXPLORATORY DATA ANALYSIS

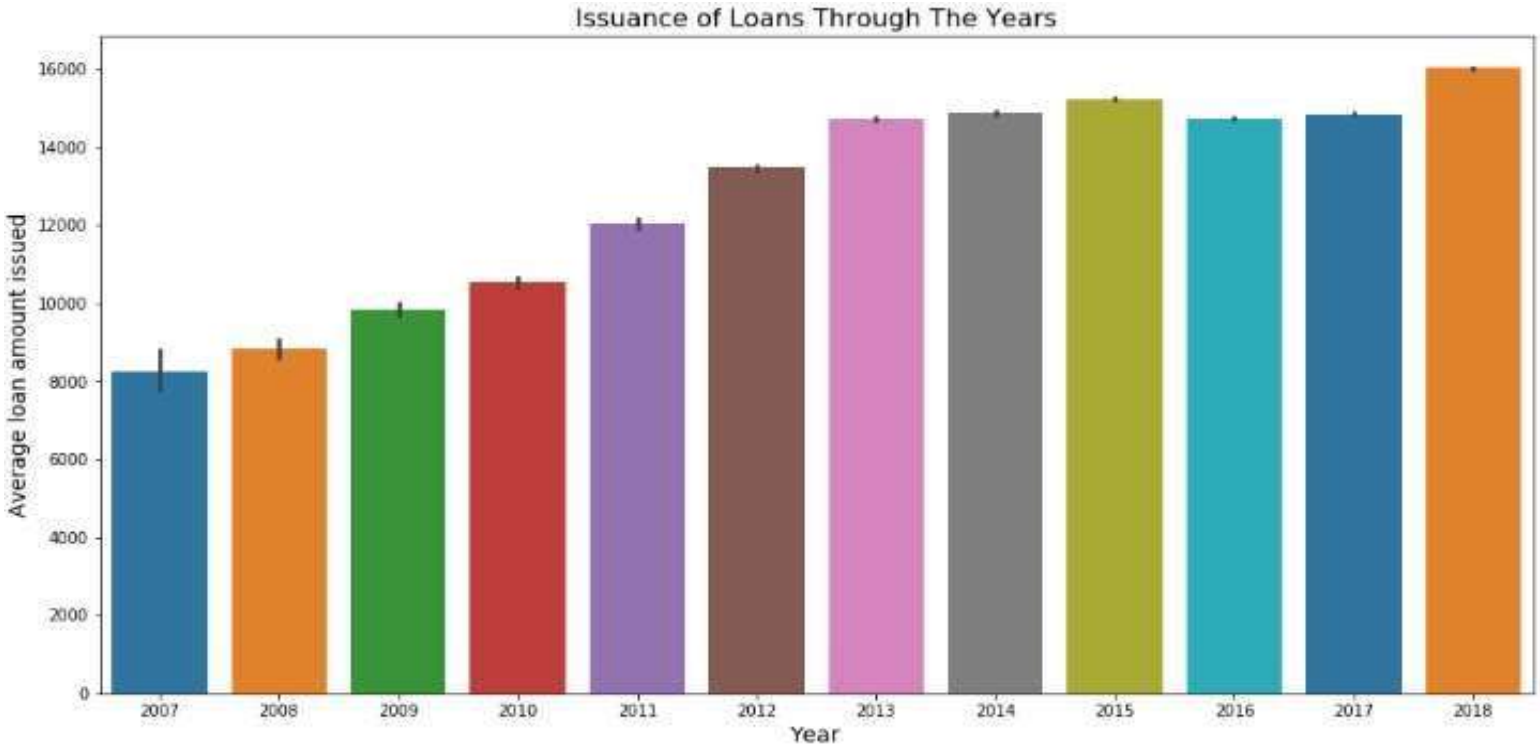
id	2260668	100.000000
member_id	2260668	100.000000
url	2260668	100.000000
desc	2134601	94.423462
mths_since_last_delinq	1158502	51.246003
mths_since_last_record	1901512	84.112837
next_pymnt_d	1303607	57.664681
mths_since_last_major_derog	1679893	74.309585
annual_inc_joint	2139958	94.660428
dti_joint	2139962	94.660605
verification_status_joint	2144938	94.880717
mths_since_recent_bc_dlq	1740957	77.011175
mths_since_recent_revol_delinq	1520309	67.250432
revol_bal_joint	2152648	95.221766
sec_app_earliest_cr_line	2152647	95.221722
sec_app_inq_last_6mths	2152647	95.221722
sec_app_mort_acc	2152647	95.221722
sec_app_open_acc	2152647	95.221722
sec_app_revol_util	2154484	95.302981
sec_app_open_act_il	2152647	95.221722
sec_app_num_rev_accts	2152647	95.221722
sec_app_chargeoff_within_12_mths	2152647	95.221722
sec_app_collections_12_mths_ex_med	2152647	95.221722
sec_app_mths_since_last_major_derog	2224726	98.410116
hardship_type	2250055	99.530537
hardship_reason	2250055	99.530537
hardship_status	2250055	99.530537
deferral_term	2250055	99.530537
hardship_amount	2250055	99.530537
hardship_start_date	2250055	99.530537
hardship_end_date	2250055	99.530537
payment_plan_start_date	2250055	99.530537
hardship_length	2250055	99.530537
hardship_dpd	2250055	99.530537
hardship_loan_status	2250055	99.530537
orig_projected_additional_accrued_interest	2252242	99.627278
hardship_payoff_balance_amount	2250055	99.530537

Our exploring of the data will

begin by looking of the number and percentage of missing values.

As you can see, there are a lot of columns which have huge chunk of data missing. These columns are not necessary for our analysis. Next step is to drop any columns where 50% or more data is missing. This will help us clean the Dataset a little bit. We continue by displaying all of the loans issued per each year we understood from the chart that:

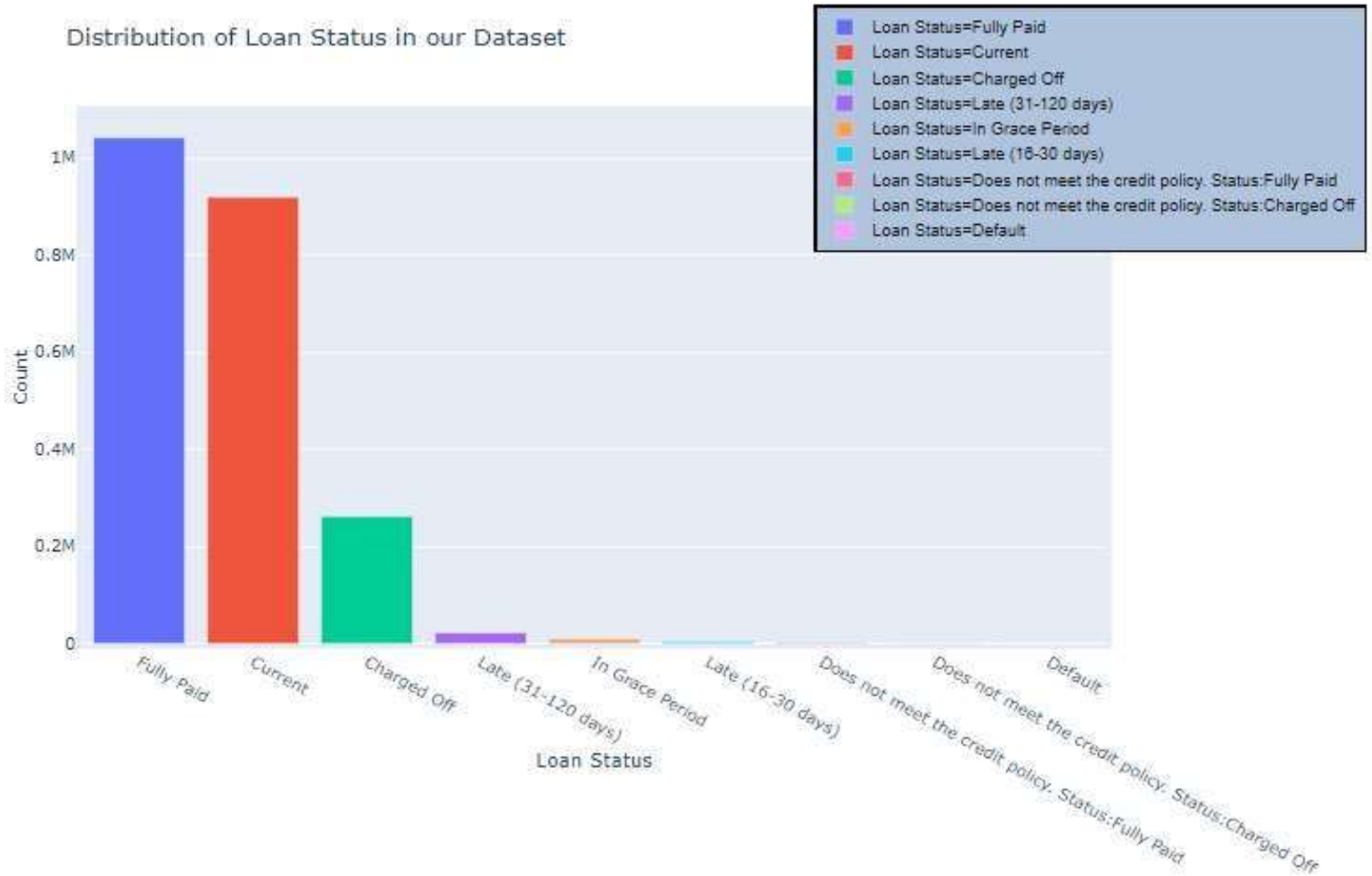
- Most of the loans issued were in the range of 10,000 to 20,000 USD.
- The year of 2018 was the year were most loans were issued.
- Loans were issued in an incremental manner. (Possible due to a recovery in the U.S economy)


Issuance of Loans Through The Years
Average loan amount issued
0
2000
4000
6000
8000
10000
12000
14000
16000
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
Year

By using histogram, we can see the distribution of the loan status column.

The conclusions that we can get from this chart are that we have a lot of loans which are fully paid with fair amount of current loans. Other categories (including) default have a really low number. This means the data is imbalanced and we might need to do something about this later in the analysis.

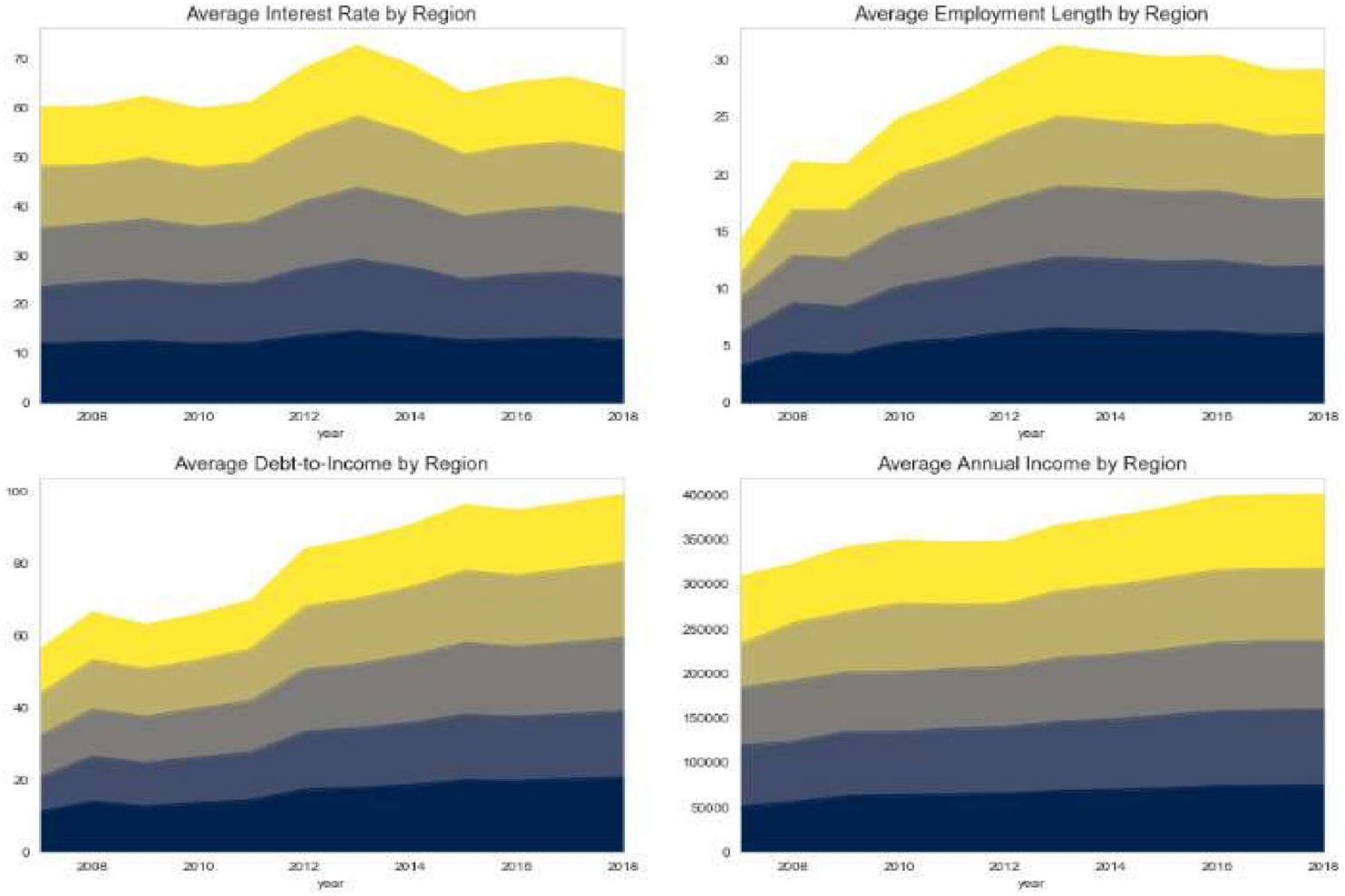
The approach that we are going to use is to replace all kind of “Late” loans,” Charged Off”, "Does not meet the credit policy. Status: Charged Off", "In Grace Period" and “Default” status with “Bad Loan” status and the rest with “Good Loan” status. In this way we have only 2 options for the loan status and we increase the balance of the data.

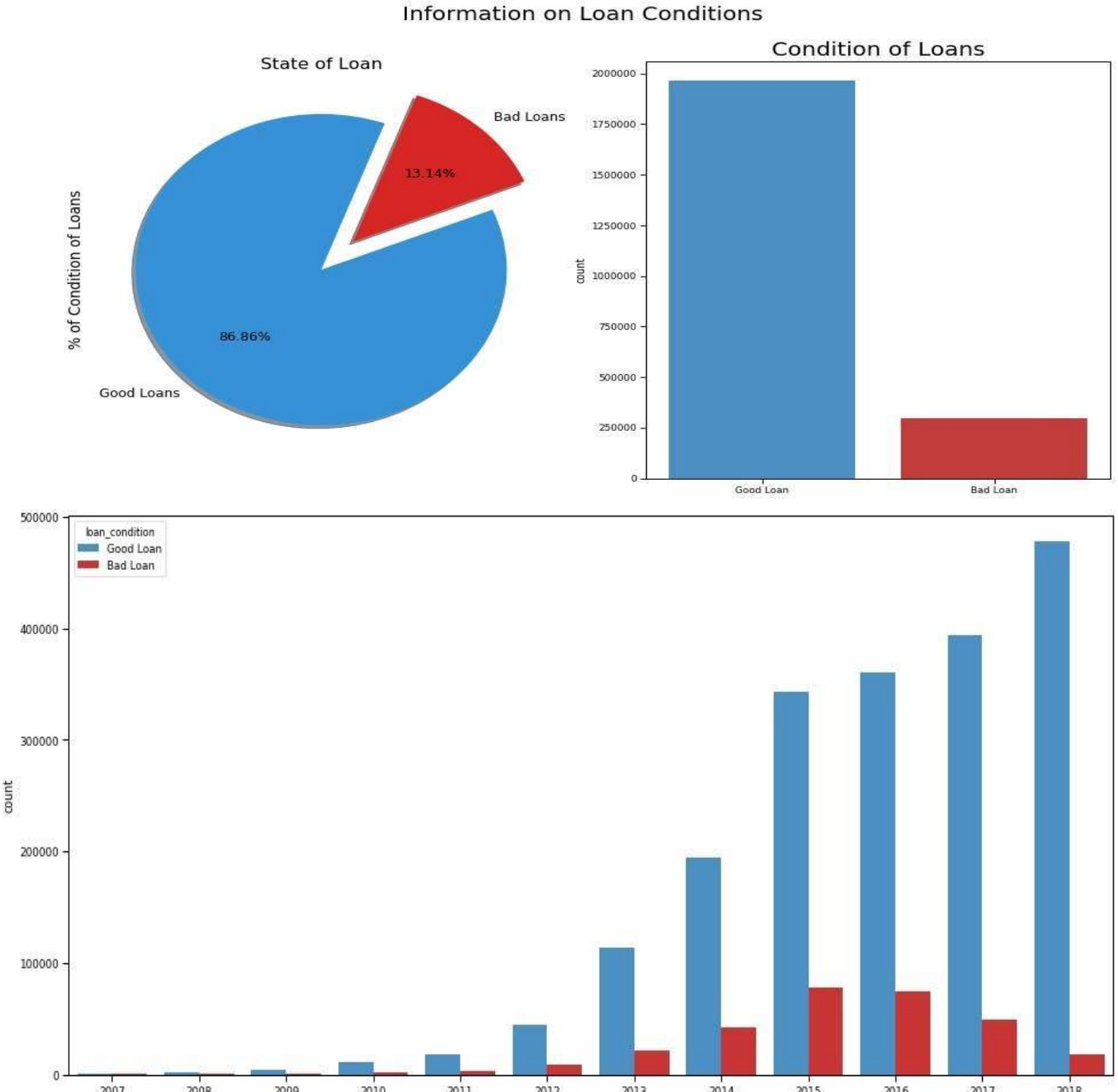


The summary from the charts below is as follow:

- Currently, bad loans consist 13.14% of total loans but remember that we still have current loans which have the risk of becoming bad loans. (So this percentage is subjected to possible changes.)
- The South West and West regions have experienced a slight increase in the "median income" in the past years.
- Average interest rates have declined since 2012 but this might explain the increase in the volume of loans.

- Employment Length tends to be greater in the regions of the South West and West
- Clients located in the regions of Northeast and Midwest have not experienced a drastic increase in debt-to-income(dti) as compared to the other regions.

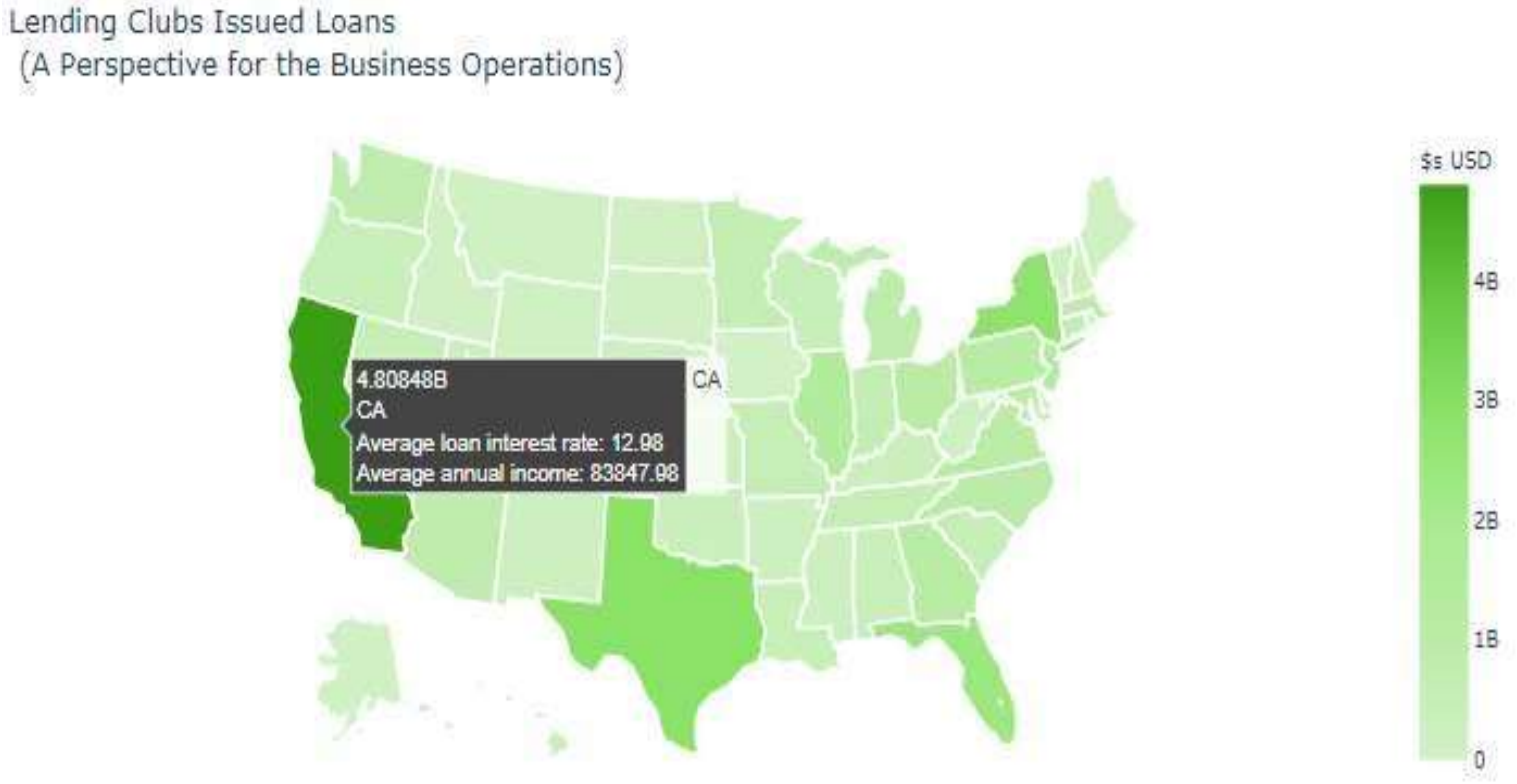

Average Interest Rate by Region
70
60
50
40
30
20
10
0
2008
2010
2012
2014
2016
2018
year
Average Employment Length by Region
30
25
20
15
10
5
0
2008
2010
2012
2014
2016
2018
year
Average Debt-to-Income by Region
100
80
60
40
20
0
2008
2010
2012
2014
2016
2018
year
Average Annual Income by Region
400000
350000
300000
250000
200000
150000
100000
50000
0
2008
2010
2012
2014
2016
2018
year


Information on Loan Conditions
State of Loan
Bad Loans
13.14%
86.86%
Good Loans
% of Condition of Loans
Condition of Loans
count
2000000
1750000
1500000
1250000
1000000
750000
500000
250000
0
Good Loan
Bad Loan
loan_condition
Good Loan
Bad Loan
count
500000
400000
300000
200000
100000
0
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018

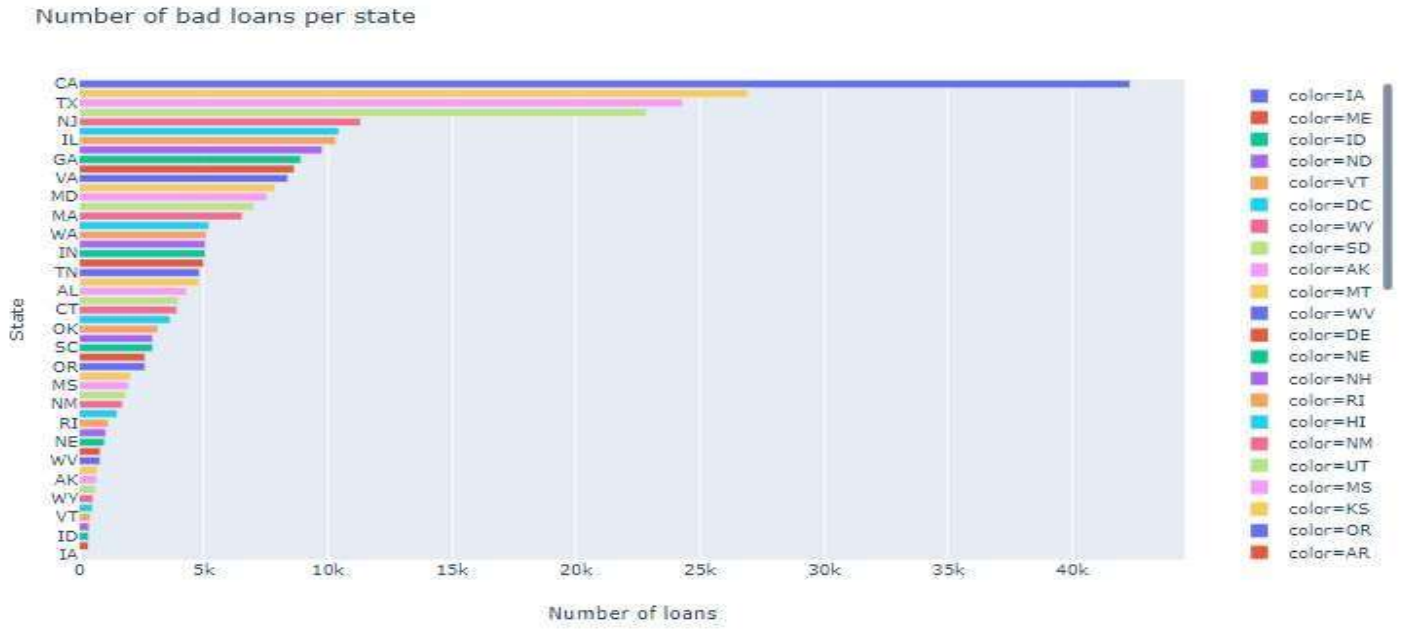
The next chart is distribution of the states by focusing on three key metrics: Loans issued by state (Total Sum), Average interest rates charged to customers and average annual income of all customers.

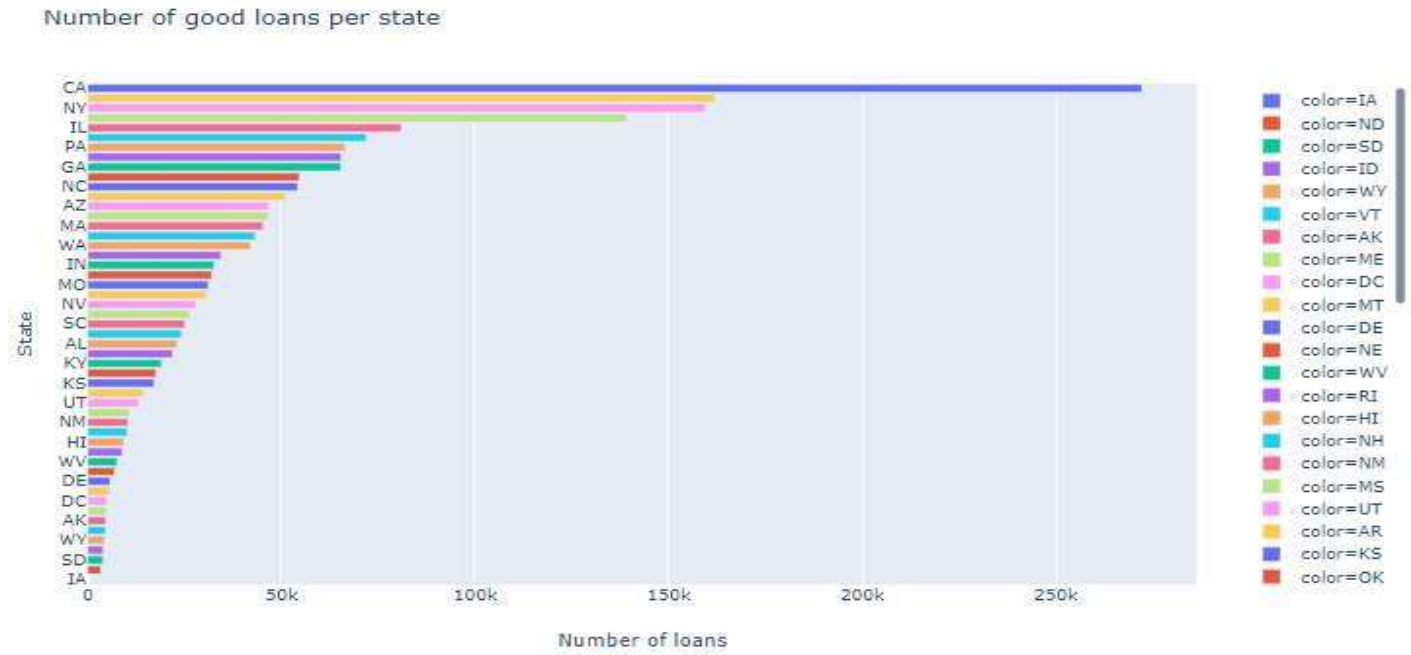
The conclusions that we can get from here are that:

- California, Texas, New York and Florida are the states in which the highest amount of loans were issued.
- Interesting enough, all four states have an approximate interest rate of 13% which is at the same level of the average interest rate for all states (13.24%)
- California, Texas and New York are all above the average annual income (with the exclusion of Florida), this might give possible indication why most loans are issued in these states.



Using the states will not contribute much in our prediction, because as you can see from the graphs below, most of the states are symmetrical in the comparison between the good and the bad loans.


Number of bad loans per state
State
CA
TX
NJ
IL
GA
VA
MD
MA
WA
IN
TN
AL
CT
OK
SC
OR
MS
NM
RI
NE
WV
AK
WY
VT
ID
IA
0
5k
10k
15k
20k
25k
30k
35k
40k
Number of loans
color=IA
color=ME
color=ID
color=ND
color=VT
color=DC
color=WY
color=SD
color=AK
color=MT
color=WV
color=DE
color=NE
color=NH
color=RI
color=HI
color=NM
color=UT
color=MS
color=KS
color=OR
color=AR

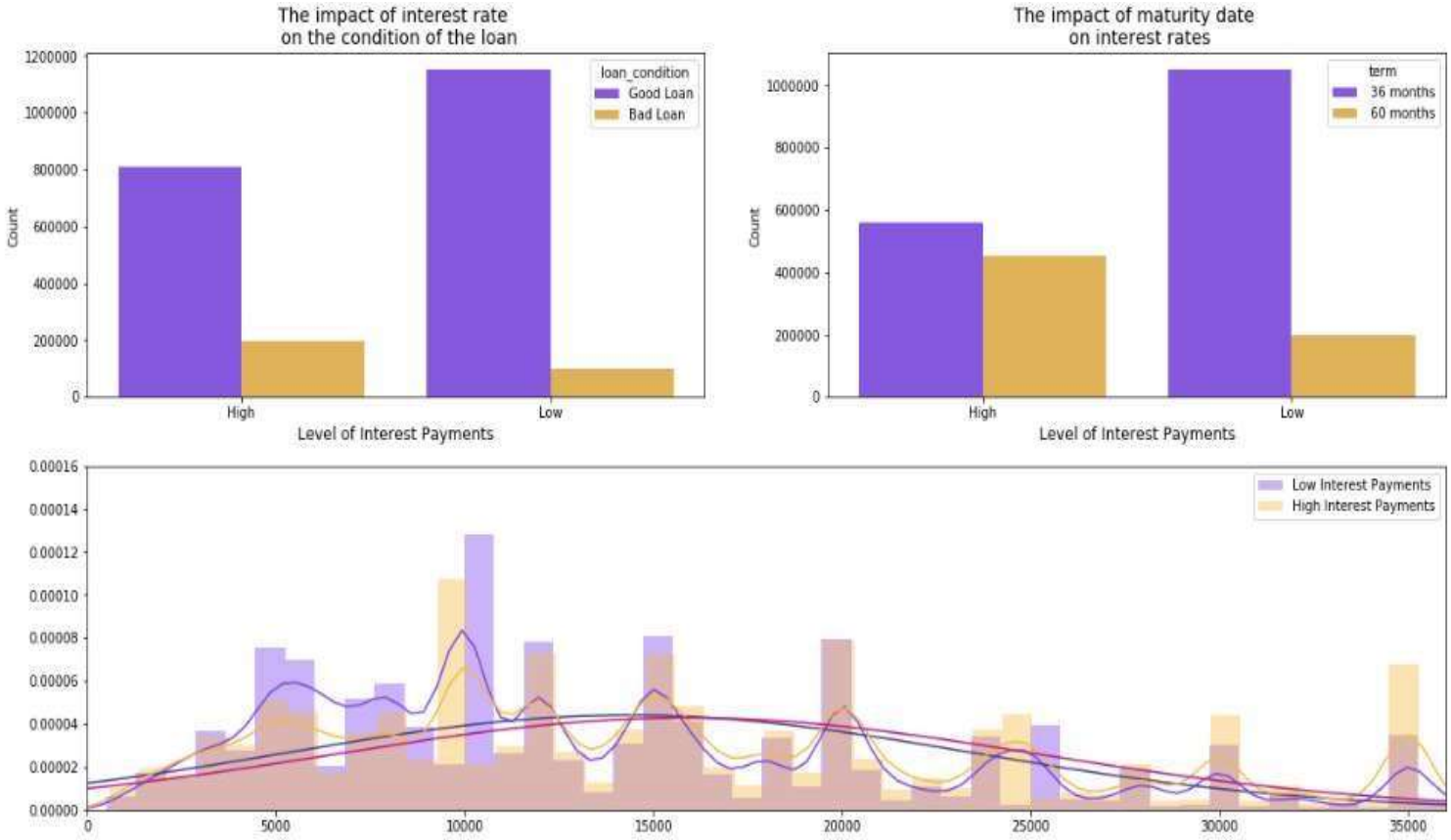

Number of good loans per state
State
CA
NY
IL
PA
GA
NC
AZ
MA
WA
IN
MO
NV
SC
AL
KY
KS
UT
NM
HI
WV
DE
DC
AK
WY
SD
IA
0
50k
100k
150k
200k
250k
Number of loans
color=IA
color=ND
color=SD
color=ID
color=WY
color=VT
color=AK
color=ME
color=DC
color=MT
color=DE
color=NE
color=WV
color=RI
color=HI
color=NH
color=NM
color=MS
color=UT
color=AR
color=KS
color=OK

By distributing the income category, this what we can get out of the charts:

- Borrowers that made part of the high income category took higher loan amounts than people from low and medium income categories. Of course, people with higher annual incomes are more likely to pay loans with a higher amount. (First row to the left of the subplots)
- Loans that were borrowed by the Low income category had a slightly higher change of becoming a bad loan. (First row to the right of the subplots)
- Borrowers with High and Medium annual incomes had a longer employment length than people with lower incomes (Second row to the left of the subplots)
- Borrowers with a lower income had on average higher interest rates while people with a higher annual income had lower interest rates on their loans. (Second row to the right of the subplots)

By distribution the interest rate combined with high and low level payments with the loan status and the impact of maturity date we can say that:

- Loans that have a high interest rate (above 13.23%) are more likely to become a bad loan.
- Loans that have a longer maturity date (60 months) are more likely to be a bad loan.

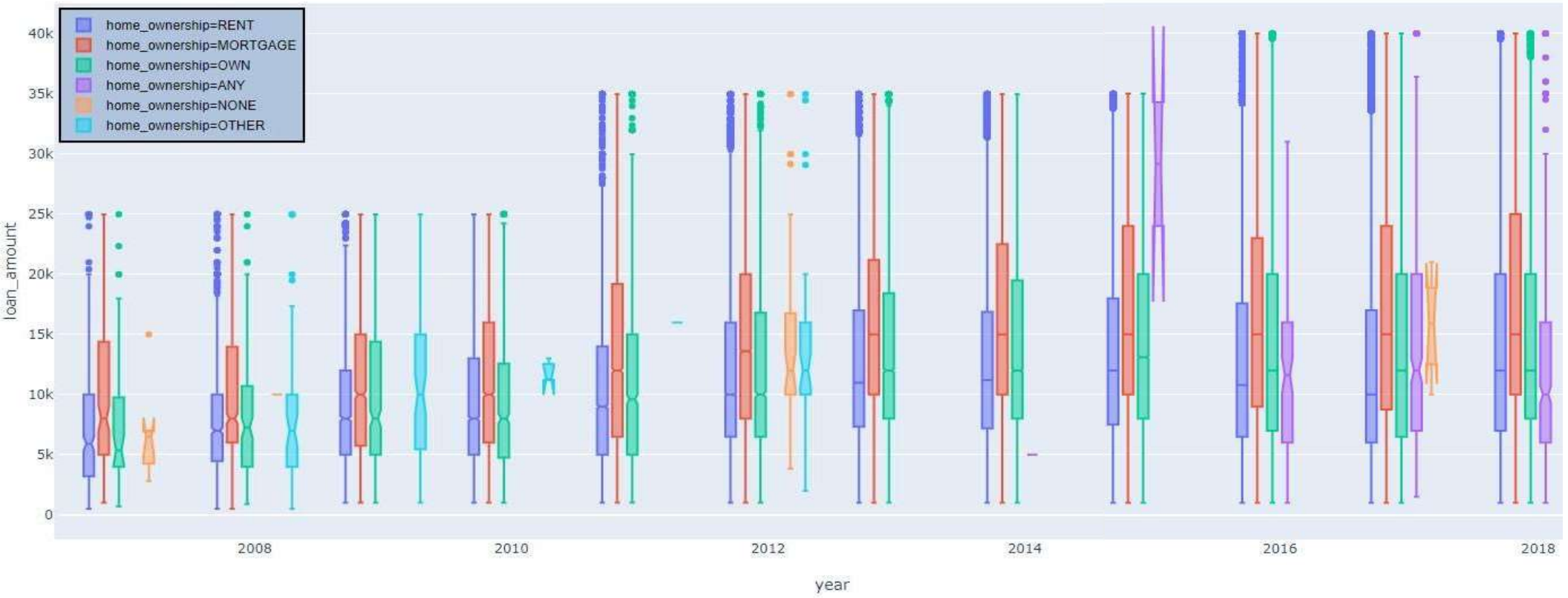


The main aim in here is to find the main factors that causes for a loan to be considered a "Bad Loan". Features like low credit grade or a high debt to income could be possible contributors in determining whether a loan is at a high risk of being bad.

From the charts below, we can see that:

- The types of bad loans in the last year are having a tendency to decline, except for not meeting credit policy.
- Mortgage was the variable from the home ownership column that used the highest amount borrowed within loans that were considered to be bad.
- There is a slight increase on people who have mortgages that are applying for a loan.

- People who have a mortgage (depending on other factors as well within the mortgage) are more likely to ask for



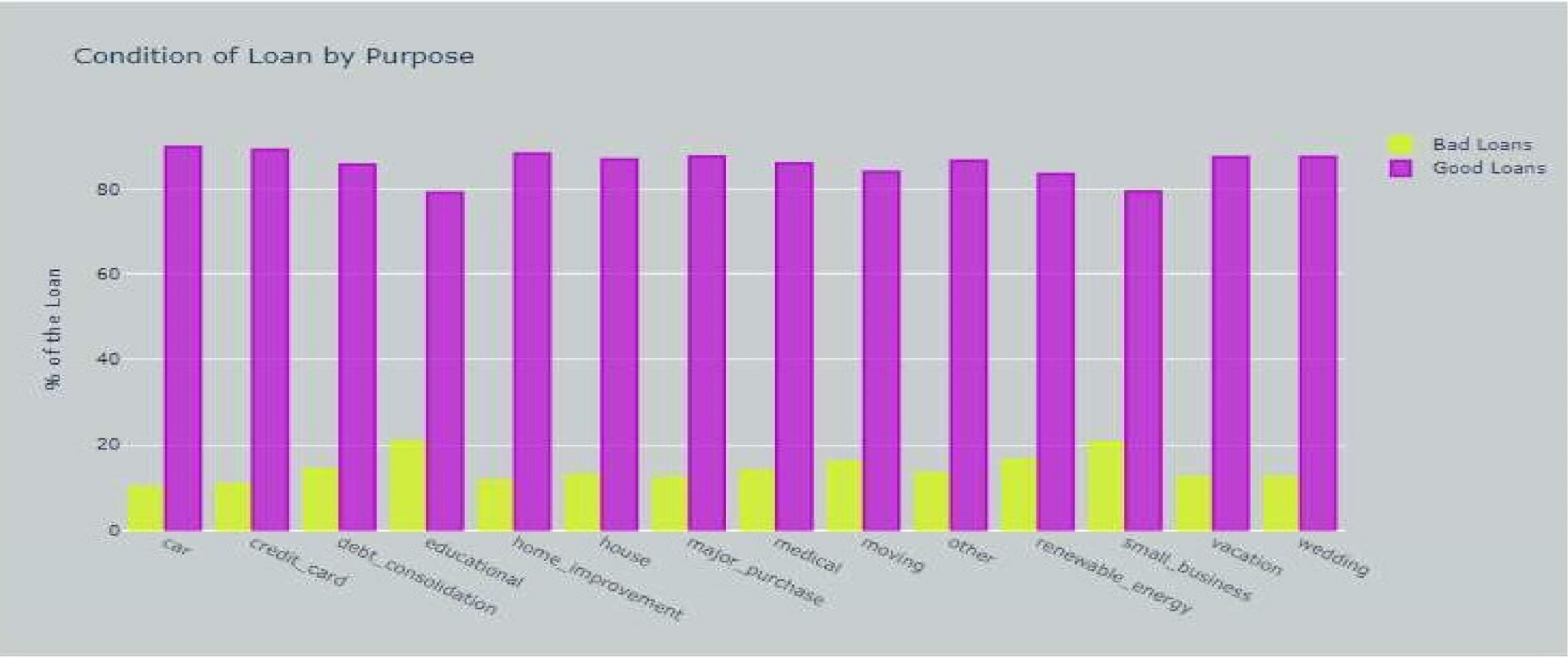

Types of Bad Loans
(Amount Borrowed Throughout the Years)
Amount Issued
40k
35k
30k
25k
20k
15k
10k
5k
0
2008
2010
2012
2014
2016
2018
Year
A. Charged Off
A. Defaults
Not Meet C.P
A. Graced Period
Late (16-30 days)
Late (31-120 days)

contribute to a "higher " risk whether the loan will be repaid or not.

Our next step is to go into depth regarding the reasons for clients to apply for a loan. Our main aim is to see if there are purposes that

Summary:

- Bad Loans Count: People that apply for educational and small business purposed tend to have a higher risk of being a bad loan. (% wise)
  Most frequent Purpose: The reason that clients applied the most for a loan was to consolidate debt.



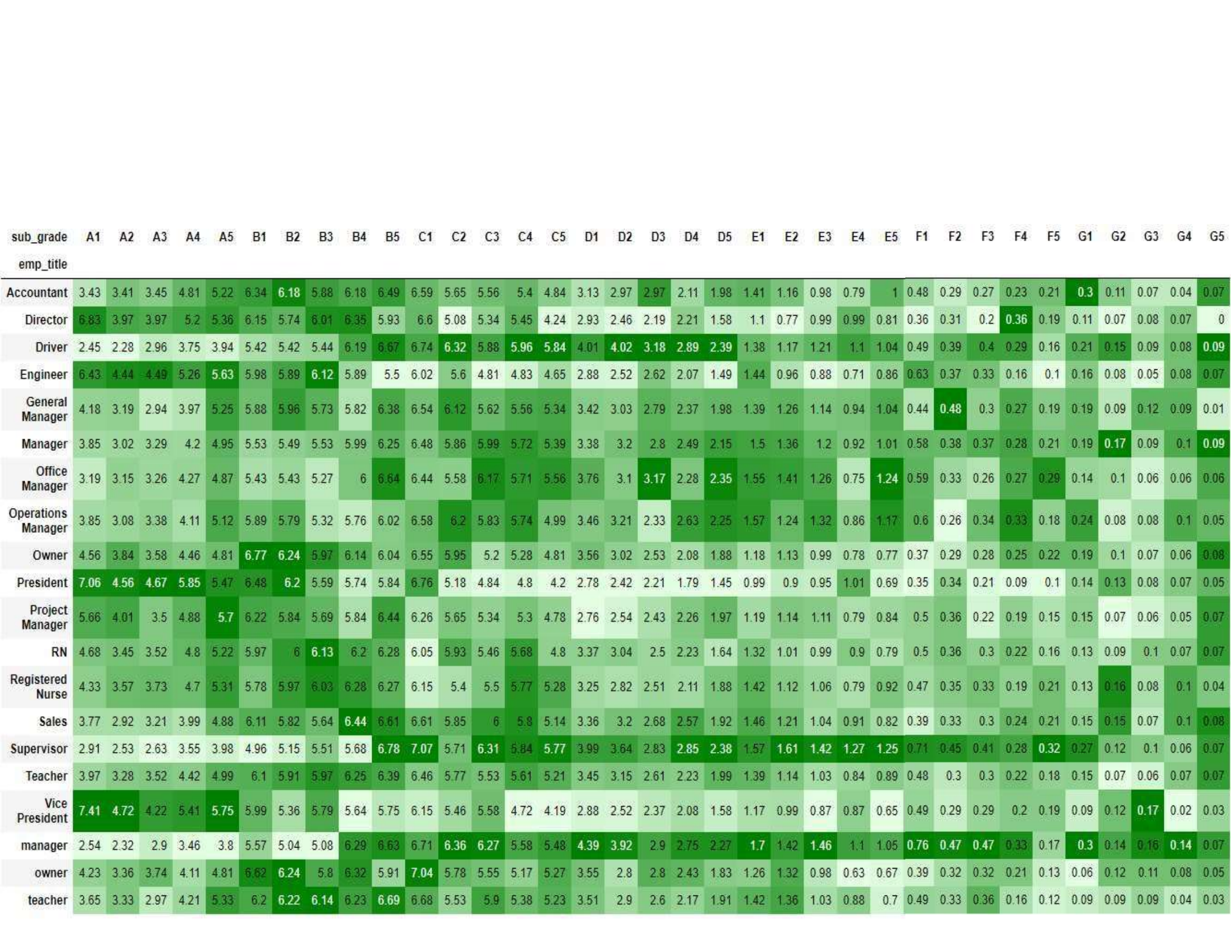
- Less frequent purpose: Clients applied less for educational purposes for all three income categories.
- Interest Rates: In all reasons for application except (medical, small business and credit card), the low income category has a higher interest rate. Something that could possibly explain this is the amount of capital that is needed from other income categories that might explain why the low income categories interest rate for these purposes are lower.
- Bad/Good Ratio: Except for educational purposes (we see a spike in high income this is due to the reasons that only two loans were issued and one was a bad loan which caused this ratio to spike to 50%.), but we can see that in all other purposed the bad good ratio is lower the higher your income category.

	income_category	purpose	interest_rate	total_loan_amount	good_loans_count	bad_loans_count	total_loans_issued	bad/good ratio (%)
0	High	car	10.7707	18261.8	371	27	398	6.78
6	High	major_purchase	11.865	23518.8	1225	108	1333	8.1
1	High	credit_card	10.483	26483.8	11502	814	12316	6.61
2	High	debt_consolidation	11.9964	26566.3	23924	2392	26316	9.09
4	High	home_improvement	11.4999	25283.3	6341	619	6960	8.89
5	High	house	13.4026	27674.7	497	47	544	8.64
10	High	renewable_energy	13.9004	23222.9	22	2	24	8.33
3	High	educational	11.42	11000	1	1	2	50
8	High	moving	13.4618	20310.1	297	26	323	8.05
9	High	other	13.0708	22356.9	2824	293	3117	9.4
11	High	small_business	14.047	26298.4	1086	202	1288	15.68
12	High	vacation	12.1724	13601.4	161	19	180	10.56
13	High	wedding	14.3942	20600.7	32	4	36	11.11
7	High	medical	12.7023	18812	499	56	555	10.09
19	Low	house	14.7226	13679	9208	1500	10708	14.01
14	Low	car	12.3811	8621.24	18244	2147	20391	10.53
15	Low	credit_card	11.8892	13575	366007	47160	413167	11.41
16	Low	debt_consolidation	13.732	14366.5	880262	155070	1035332	14.98
17	Low	educational	12.1935	6037.17	302	80	382	20.94
18	Low	home_improvement	12.8863	12544.2	94178	13284	107462	12.36
20	Low	major_purchase	12.9778	11151.7	34864	5104	39968	12.77
21	Low	medical	13.7637	8542.1	19420	3275	22695	14.43
23	Low	other	14.4278	9271.68	100342	16144	116486	13.86
24	Low	renewable_energy	14.9076	9409.65	998	202	1200	16.83
25	Low	small_business	15.5867	14115.7	13747	3808	17555	21.69
26	Low	vacation	13.5781	5827.6	11522	1700	13222	12.86
27	Low	wedding	14.0828	9727.41	1766	250	2016	12.4
22	Low	moving	14.9422	7338.68	10738	2189	12927	16.93
28	Medium	car	11.0979	13184.7	2991	233	3224	7.23
29	Medium	credit_card	10.9895	21696.2	84226	7262	91488	7.94
30	Medium	debt_consolidation	12.7093	22338.7	192183	24046	216229	11.12
40	Medium	vacation	12.7658	9047.15	1911	212	2123	9.99
32	Medium	home_improvement	12.0465	18943.5	32469	3566	36035	9.9
31	Medium	educational	11.6883	11910	33	7	40	17.5
36	Medium	moving	13.7073	12919.8	1917	236	2153	10.96
35	Medium	medical	13.0493	13269	3762	476	4238	11.23
33	Medium	house	13.372	20984.1	2602	282	2884	9.78
37	Medium	other	13.2897	15718.8	17749	2084	19833	10.51
38	Medium	renewable_energy	13.8434	16719.3	188	33	221	14.93
39	Medium	small_business	14.5619	21259	4790	1056	5846	18.06
34	Medium	major_purchase	11.9599	17793.7	8165	979	9144	10.71
41	Medium	wedding	14.603	14252.7	265	38	303	12.54

Considering only the 20 most common Employer Titles we can see how the grades are distributed by different professionals.

Summary:

We can see that Director, Engineer, President, Vice President are the category's with highest incidence in Grade A; Analyzing this table we can get some insights about the profile of grades and professionals.



sub_grade	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	C1	C2	C3	C4	C5	D1	D2	D3	D4	D5	E1	E2	E3	E4	E5	F1	F2	F3	F4	F5	G1	G2	G3	G4	G5
emp_title																																			
Accountant	3.43	3.41	3.45	4.81	5.22	6.34	6.18	5.88	6.18	6.49	6.59	5.65	5.56	5.4	4.84	3.13	2.97	2.97	2.11	1.98	1.41	1.16	0.98	0.79	1	0.48	0.29	0.27	0.23	0.21	0.3	0.11	0.07	0.04	0.07
Director	6.83	3.97	3.97	5.2	5.36	6.15	5.74	6.01	6.35	5.93	6.6	5.08	5.34	5.45	4.24	2.93	2.46	2.19	2.21	1.58	1.1	0.77	0.99	0.99	0.81	0.36	0.31	0.2	0.36	0.19	0.11	0.07	0.08	0.07	0
Driver	2.45	2.28	2.96	3.75	3.94	5.42	5.42	5.44	6.19	6.67	6.74	6.32	5.88	5.96	5.84	4.01	4.02	3.18	2.89	2.39	1.38	1.17	1.21	1.1	1.04	0.49	0.39	0.4	0.29	0.16	0.21	0.15	0.09	0.08	0.09
Engineer	6.43	4.44	4.49	5.26	5.63	5.98	5.89	6.12	5.89	5.5	6.02	5.6	4.81	4.83	4.65	2.88	2.52	2.62	2.07	1.49	1.44	0.96	0.88	0.71	0.86	0.63	0.37	0.33	0.16	0.1	0.16	0.08	0.05	0.08	0.07
General Manager	4.18	3.19	2.94	3.97	5.25	5.88	5.96	5.73	5.82	6.38	6.54	6.12	5.62	5.56	5.34	3.42	3.03	2.79	2.37	1.98	1.39	1.26	1.14	0.94	1.04	0.44	0.48	0.3	0.27	0.19	0.19	0.09	0.12	0.09	0.01
Manager	3.85	3.02	3.29	4.2	4.95	5.53	5.49	5.53	5.99	6.25	6.48	5.86	5.99	5.72	5.39	3.38	3.2	2.8	2.49	2.15	1.5	1.36	1.2	0.92	1.01	0.58	0.38	0.37	0.28	0.21	0.19	0.17	0.09	0.1	0.09
Office Manager	3.19	3.15	3.26	4.27	4.87	5.43	5.43	5.27	6	6.64	6.44	5.58	6.17	5.71	5.56	3.76	3.1	3.17	2.28	2.35	1.55	1.41	1.26	0.75	1.24	0.59	0.33	0.26	0.27	0.29	0.14	0.1	0.06	0.06	0.06
Operations Manager	3.85	3.08	3.38	4.11	5.12	5.89	5.79	5.32	5.76	6.02	6.58	6.2	5.83	5.74	4.99	3.46	3.21	2.33	2.63	2.25	1.57	1.24	1.32	0.86	1.17	0.6	0.26	0.34	0.33	0.18	0.24	0.08	0.08	0.1	0.05
Owner	4.56	3.84	3.58	4.46	4.81	6.77	6.24	5.97	6.14	6.04	6.55	5.95	5.2	5.28	4.81	3.56	3.02	2.53	2.08	1.88	1.18	1.13	0.99	0.78	0.77	0.37	0.29	0.28	0.25	0.22	0.19	0.1	0.07	0.06	0.08
President	7.06	4.56	4.67	5.85	5.47	6.48	6.2	5.59	5.74	5.84	6.76	5.18	4.84	4.8	4.2	2.78	2.42	2.21	1.79	1.45	0.99	0.9	0.95	1.01	0.69	0.35	0.34	0.21	0.09	0.1	0.14	0.13	0.08	0.07	0.05
Project Manager	5.66	4.01	3.5	4.88	5.7	6.22	5.84	5.69	5.84	6.44	6.26	5.65	5.34	5.3	4.78	2.76	2.54	2.43	2.26	1.97	1.19	1.14	1.11	0.79	0.84	0.5	0.36	0.22	0.19	0.15	0.15	0.07	0.06	0.05	0.07
RN	4.68	3.45	3.52	4.8	5.22	5.97	6	6.13	6.2	6.28	6.05	5.93	5.46	5.68	4.8	3.37	3.04	2.5	2.23	1.64	1.32	1.01	0.99	0.9	0.79	0.5	0.36	0.3	0.22	0.16	0.13	0.09	0.1	0.07	0.07
Registered Nurse	4.33	3.57	3.73	4.7	5.31	5.78	5.97	6.03	6.28	6.27	6.15	5.4	5.5	5.77	5.28	3.25	2.82	2.51	2.11	1.88	1.42	1.12	1.06	0.79	0.92	0.47	0.35	0.33	0.19	0.21	0.13	0.16	0.08	0.1	0.04
Sales	3.77	2.92	3.21	3.99	4.88	6.11	5.82	5.64	6.44	6.61	6.61	5.85	6	5.8	5.14	3.36	3.2	2.68	2.57	1.92	1.46	1.21	1.04	0.91	0.82	0.39	0.33	0.3	0.24	0.21	0.15	0.15	0.07	0.1	0.08
Supervisor	2.91	2.53	2.63	3.55	3.98	4.96	5.15	5.51	5.68	6.78	7.07	5.71	6.31	5.84	5.77	3.99	3.64	2.83	2.85	2.38	1.57	1.61	1.42	1.27	1.25	0.71	0.45	0.41	0.28	0.32	0.27	0.12	0.1	0.06	0.07
Teacher	3.97	3.28	3.52	4.42	4.99	6.1	5.91	5.97	6.25	6.39	6.46	5.77	5.53	5.61	5.21	3.45	3.15	2.61	2.23	1.99	1.39	1.14	1.03	0.84	0.89	0.48	0.3	0.3	0.22	0.18	0.15	0.07	0.06	0.07	0.07
Vice President	7.41	4.72	4.22	5.41	5.75	5.99	5.36	5.79	5.64	5.75	6.15	5.46	5.58	4.72	4.19	2.88	2.52	2.37	2.08	1.58	1.17	0.99	0.87	0.87	0.65	0.49	0.29	0.29	0.2	0.19	0.09	0.12	0.17	0.02	0.03
manager	2.54	2.32	2.9	3.46	3.8	5.57	5.04	5.08	6.29	6.63	6.71	6.36	6.27	5.58	5.48	4.39	3.92	2.9	2.75	2.27	1.7	1.42	1.46	1.1	1.05	0.76	0.47	0.47	0.33	0.17	0.3	0.14	0.16	0.14	0.07
owner	4.23	3.36	3.74	4.11	4.81	6.62	6.24	5.8	6.32	5.91	7.04	5.78	5.55	5.17	5.27	3.55	2.8	2.8	2.43	1.83	1.26	1.32	0.98	0.63	0.67	0.39	0.32	0.32	0.21	0.13	0.06	0.12	0.11	0.08	0.05
teacher	3.65	3.33	2.97	4.21	5.33	6.2	6.22	6.14	6.23	6.69	6.68	5.53	5.9	5.38	5.23	3.51	2.9	2.6	2.17	1.91	1.42	1.36	1.03	0.88	0.7	0.49	0.33	0.36	0.16	0.12	0.09	0.09	0.09	0.04	0.03

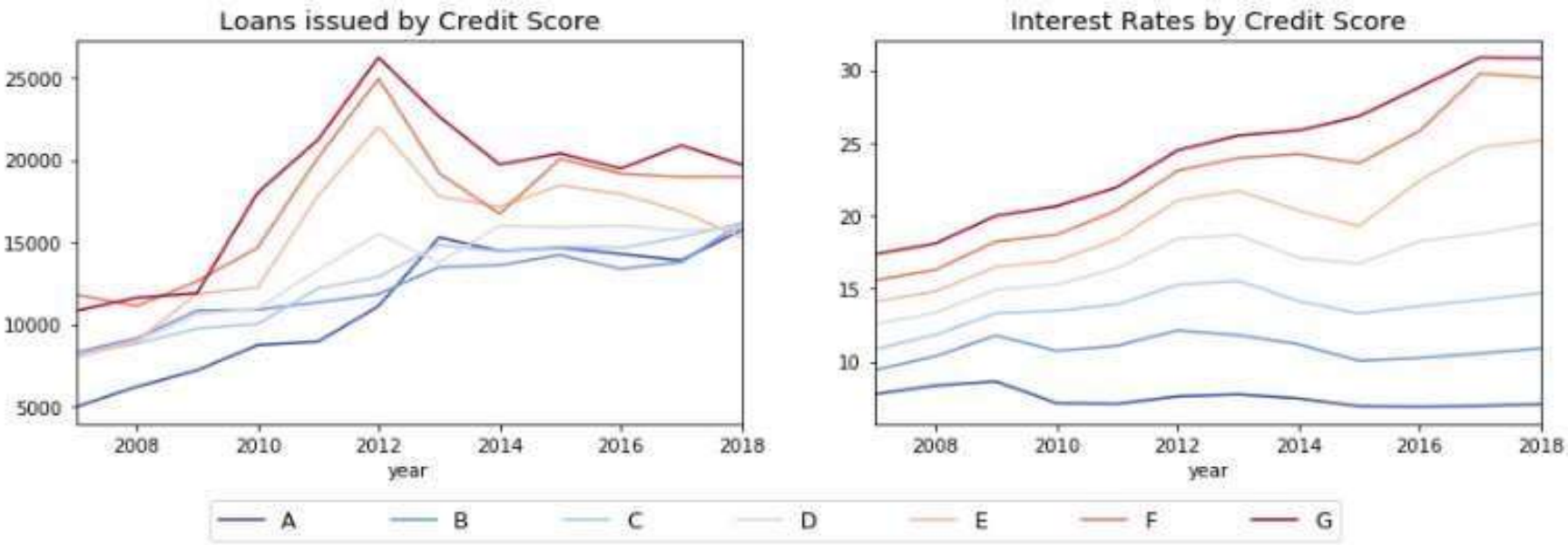
04 RISK ANALYTICS

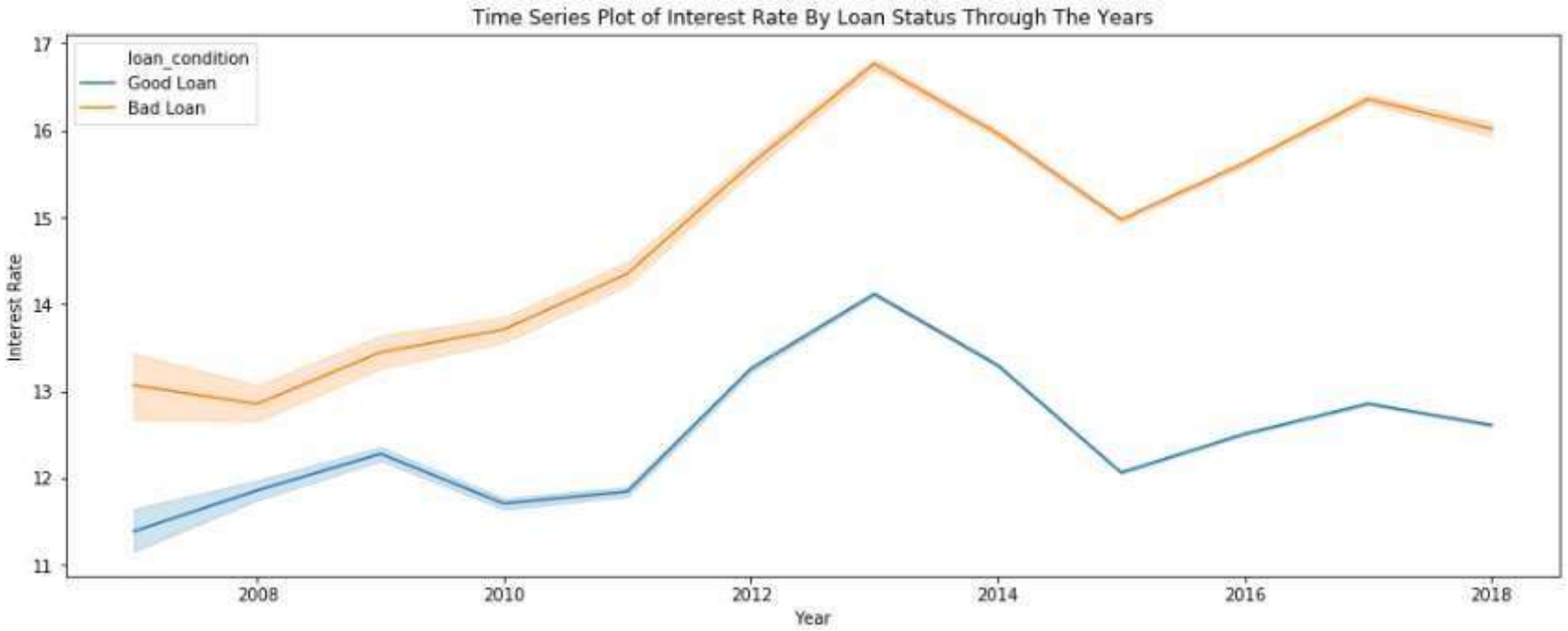
Credit scores are important metrics for assessing the overall level of risk.

By plotting the loans issued by credit score, the interest rates by credit score and the interest rate through the years the conclusions that we made are that:

- The scores that has a lower grade received a larger amounts of loans (which might had contributed to a higher level of risk).
- Logically, the lower the grade the higher the interestthe customer had to pay back to investors.

- Remember also, most loan statuses are“Current” so there is a risk that at the end of maturity some of these loans might become bad loans.


Loans issued by Credit Score
25000
20000
15000
10000
5000
2008
2010
2012
2014
2016
2018
year
Interest Rates by Credit Score
30
25
20
15
10
2008
2010
2012
2014
2016
2018
year
A
B
C
D
E
F
G



In the figure below, the risk analyses of the project have been made.

The factors mentioned could have a severe impact on the project, if no action would be taken in case they would occur.

ID	Risks	Chance	Impact	Rate	Actions
1	Co-worker is sick	M	M	14	Contact with a doctor
2	Algorithm not trained well	M	H	12	Use more data to train the algorithm or select different algorithm.
3	Internet down unexpected	L	M	4	Call the maintenance team and ask for help.
4	Data breach	L	H	6	Call customers and inform them.

05 MODELING

As it can be seen from the graph, approximately 14% of the loans are “Bad Loans”.

Also, it was expected that the company will take some kind of actions after the scandal and the fraud that happened on 2016 and the “Bad Loans” will decrease but still it is noticeable that there is again slight increase after 2017.

The goal of this project will be to create a model which predict whether a loan is most likely to be return. A binary classification system is used, in which the values for the loan status field are classified into two categories:

1: "Fully Paid" or "Current" – Good Loan

0: "Late" (for any time period) or "Charged Off" – Bad Loan

The data has 145 features but the following have the most relation with our may goal and they will be used to predict the loan status category (descriptions are from the "LCDataDictionary.xlsx" file):

- loan_amount: 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.
- Interest_rate: Interest Rate on the loan.
- annual_income: The self-reported annual income provided by the borrower during registration.
- delinq_2yrs: The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years.
- 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.
- 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.
- tot_cur_bal: Total current balance of all accounts.
- purpose: A category provided by the borrower for the loan request.
- home_ownership: The home ownership status provided by the borrower during registration. Our values are: RENT, OWN, MORTGAGE, OTHER.
- recoveries: Post charge of gross recovery.
- total_rec_prncp: Principal received to date.
- out_prncp: Remaining outstanding principal for total amount funded.
- last_pymnt_d: Last month payment was received.

Finally, for the purpose, we are going to classify if the loan status will be a “Good” one or “Bad” one by using and comparing the following algorithms:

- Decision tree classifier
- Random Forest (tree based model)

- Neural Network

REFERENCES

Lending Club. (n.d.). Retrieved from Wikipedia: https://en.wikipedia.org/wiki/LendingClub