Optimize LendingClub's Profit by Predicting Borrower's Repayment Capability

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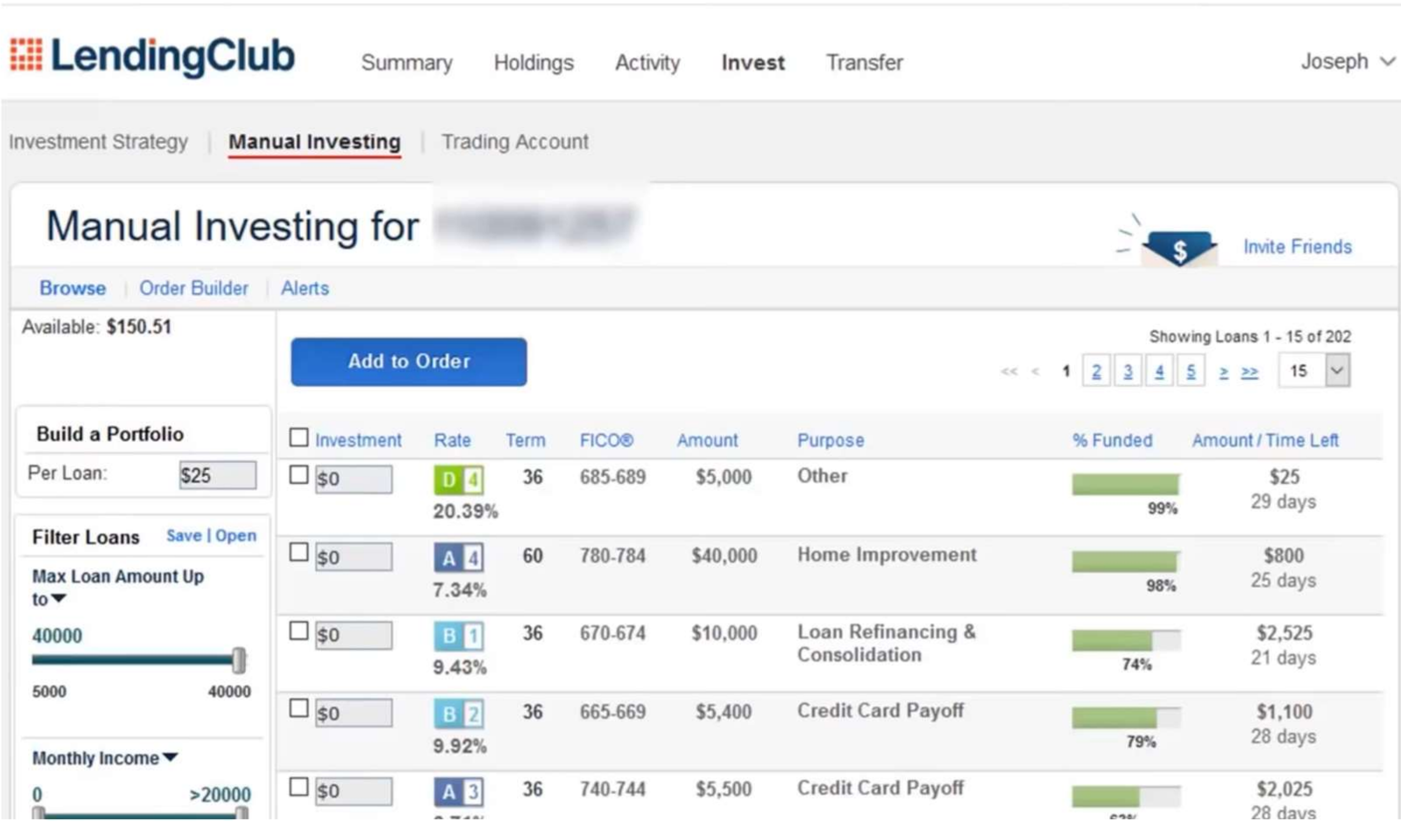
LendingClub Overview

01

LendingClub (LC) is a United States peer-to-peer (p2p) lending company, headquartered in San Fransisco, California. LC is the world's largest p2p lending platform. Over the last 10 years, they've helped millions of people take control of their debt, grow their small businesses, and invest for the future.



Investors made money from the interest on these loans. LC made money by charging borrowers an origination fee and investors a service fee.

Details for 5506713

Tradeable Notes ▸

Note Status

Status	Principal
Not Yet Issued (0)	$0.00
Issued & Current (1,124)	$21,615.06
In Grace Period (26)	$424.42
Late 16 - 30 days (9)	$239.18
Late 31 - 120 days (41)	$800.30
Fully Paid* (1,071)	$0.00
Default (4)	$75.55
Total (2,275):	**$23,154.50**
Charged Off* (385)	$8,132.06

Composition ** ($)

Term | Grade

A (8.6%) B (17.8%) C (23.4%)
D (25.1%) E (13.5%) F *** (8.4%) G *** (3.3%)

Details

Weighted Average Rate	15.13%
Accrued Interest	$269.33
Payments to Date	$60,198.22
Principal	$47,013.43
Interest	$13,176.39
Late Fees Received	$8.40

Table of Content

02

Investors were able to search and browse the loan listings on LC website and select loans that they wanted to invest in based on the information supplied about the borrower, amount of loan, loan grade, and loan purpose.

Problems

03

If the borrower can't pay the loan, investors won't get interests. If the investors don't get interests, LendingClub (LC) can't charged the service fee to investors. Means LC don't get their money and might costs a debt collection agencies.

://www.4thway.co.uk/guides/seven-key-peer-peer-lending-risks/

P2P lending risk 3: losing money due to bad debts (credit risk)

Now we're halfway through the list and we've got to the most "commonplace" reason for losing money on some loans: when your borrowers aren't good enough and can't pay all your money back. This is called "credit risk".

P2P lending risk 7: losses because you can't sell early (liquidity risk)

The ability to sell your loans early – before your borrowers repay them naturally – is not a God-given right.

Peer-to-peer lending returns are stable because most lenders hold onto loans until they're repaid. If lending became like the stock market, where people dip in and out all the time, it would start leading to similarly wild price swings. In lending, that means swings in interest earned or returns made.

What tools does LendingClub have to deal with delinquent borrowers?

Delinquencies are a natural component of investing in Notes. When borrowers are delinquent, LendingClub makes significant efforts to contact the delinquent borrowers, collect outstanding payments, and bring the loans back to current status. LendingClub has a robust internal servicing team and works with several external collection agencies on a regular basis. We use a statistical risk model to identify which loans to outsource to external collection agencies with the goal of maximizing the returns to our investors. These third party agencies have extensive experience and sophisticated tools to track borrowers who have changed locations.

Once loans become delinquent, we attempt to contact borrowers via email, phone, and letter to collect any past due payments. We often review recent credit reports to understand the current credit status of the delinquent borrowers. Depending on the circumstances, we may work with the borrowers to arrange for payment to be made immediately, structure a new payment plan, or take other appropriate action, all in an attempt to prevent the loan status from deteriorating further. For

01

Characteristics?

What are the characteristics of the borrowers who stop repaying the loan?

02

How to Optimize Profit?

How to optimize LendingClub's profit since LendingClub made money by charging borrowers and investors a fee?

Goals

04

Investors made money from the interest on these loans. LC made money by charging borrowers an origination fee and investors a service fee.

01

Find Out the Main Characteristics

Find out the main characteristics what make borrowers to stop repaying the loan.

02

Ensure LendingClub's Profit

Using Machine Learning Model to ensure LendingClub's profit especially for investor so we can certainly charge a service fee to them.

Project Limitation

05

In this project, we will focus on the range of loan amount between $ 25 until $ 10,000. Because, borrowers who have loan amount above $10,000 has many consideration to be picked. Right?

The other reason that this limitation exists is to minimize unwanted errors of Machine Learning later. So, the rest of loan amount will be handled by LC's proffesionals.

Dataset

06

LendingClub dataset consists of 27 columns and 16,4337 rows. This dataset is from Pierian Data which contains loan amount, loan term, interest rate, installment, grade, home ownership, purpose of the loan, loan status and many more. Basically, this dataset is available from their site which anyone can scrape from there.

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	verification_status	issue_d	loan_stat
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	Not Verified	Jan-2015	Fully Paid
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	Not Verified	Jan-2015	Fully Paid
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	Not Verified	Nov-2014	Fully Paid
10	10000.0	36 months	13.11	337.47	B	B4	Sodexo	2 years	RENT	95000.0	Verified	Jun-2013	Fully Paid
12	7500.0	36 months	9.17	239.10	B	B2	Social Work/Care Manager	7 years	OWN	55000.0	Not Verified	Dec-2015	Fully Paid

No. 06 —— Dataset

	Column	Dtype	Null	Null (%)	nUnique	Unique	Description
0	loan_amnt	float64	0	0.00	368	[10000.0, 8000.0, 7200.0, 7500.0, 9200.0, 7350...	The listed amount of the loan applied for by t...
1	term	object	0	0.00	2	[36 months, 60 months]	The number of payments on the loan. Values are...
2	int_rate	float64	0	0.00	524	[11.44, 11.99, 6.49, 13.11, 9.17, 6.62, 6.99, ...	Interest Rate on the loan
3	installment	float64	0	0.00	19765	[329.48, 265.68, 220.65, 337.47, 239.1, 282.48...	The monthly payment owed by the borrower if th...
4	grade	object	0	0.00	7	[B, A, D, C, E, F, G]	LC assigned loan grade
5	sub_grade	object	0	0.00	35	[B4, B5, A2, B2, A3, D1, C2, C1, A1, C5, B3, D...	LC assigned loan subgrade
6	emp_title	object	12495	7.60	83379	[Marketing, Credit analyst , Client Advocate, ...	The job title supplied by the Borrower when ap...
7	emp_length	object	10586	6.44	11	[10+ years, 4 years, 6 years, 2 years, 7 years...	Employment length in years. Possible values ar...
8	home_ownership	object	0	0.00	6	[RENT, MORTGAGE, OWN, OTHER, NONE, ANY]	The home ownership status provided by the borr...
9	annual_inc	float64	0	0.00	13588	[117000.0, 65000.0, 54000.0, 95000.0, 55000.0,...	The self-reported annual income provided by th...
10	verification_status	object	0	0.00	3	[Not Verified, Verified, Source Verified]	Indicates if income was verified by LC, not ve...
11	issue_d	object	0	0.00	115	[Jan-2015, Nov-2014, Jun-2013, Dec-2015, Apr-2...	The month which the loan was funded
12	loan_status	object	0	0.00	2	[Fully Paid, Charged Off]	Current status of the loan
13	purpose	object	0	0.00	14	[vacation, debt_consolidation, credit_card, ot...	A category provided by the borrower for the lo...
14	title	object	678	0.41	26652	[Vacation, Debt consolidation, Credit card ref...	The loan title provided by the borrower
15	dti	float64	0	0.00	4125	[26.24, 22.05, 2.6, 12.04, 28.21, 10.81, 7.47,...	A ratio calculated using the borrower's total ...
16	earliest_cr_line	object	0	0.00	639	[Jun-1990, Jul-2004, Sep-2006, Dec-1990, Apr-1...	The month the borrower's earliest reported cre...
17	open_acc	float64	0	0.00	54	[16.0, 17.0, 6.0, 5.0, 13.0, 12.0, 10.0, 9.0, ...	The number of open credit lines in the borrowe...
18	pub_rec	float64	0	0.00	16	[0.0, 1.0, 2.0, 3.0, 4.0, 8.0, 5.0, 6.0, 10.0,...	Number of derogatory public records
19	revol_bal	float64	0	0.00	32194	[36369.0, 20131.0, 5472.0, 4702.0, 17838.0, 64...	Total credit revolving balance
20	revol_util	float64	170	0.10	1141	[41.8, 53.3, 21.5, 64.4, 54.9, 22.9, 37.2, 0.0...	Revolving line utilization rate, or the amount...
21	total_acc	float64	0	0.00	100	[25.0, 27.0, 13.0, 26.0, 35.0, 23.0, 36.0, 7.0...	The total number of credit lines currently in ...
22	initial_list_status	object	0	0.00	2	[w, f]	The initial listing status of the loan. Possib...
23	application_type	object	0	0.00	3	[INDIVIDUAL, JOINT, DIRECT_PAY]	Indicates whether the loan is an individual ap...
24	mort_acc	float64	20887	12.71	27	[0.0, 3.0, 4.0, 6.0, nan, 5.0, 2.0, 1.0, 7.0, ...	Number of mortgage accounts.
25	pub_rec_bankruptcies	float64	349	0.21	9	[0.0, 1.0, nan, 2.0, 3.0, 5.0, 4.0, 6.0, 7.0, ...	Number of public record bankruptcies
26	address	object	0	0.00	163893	[0174 Michelle Gateway\nMendozaberg, OK 22690,...	The state provided by the borrower in the loan...

Handling Missing Values

There are some features which have missing values.

01

emp_title

This feature is about employment title.

02

emp_length

This feature is about employment length in years.

03

title

This feature is about employment title of the borrower's reason.

04

revol_util

This feature is about revolving utilization rate.

05

mort_acc

This feature is about number of mortgage account.

06

Pub_rec_bankruptcies

This feature is about number of public record of bankruptcies.

01

emp_title

This feature is about employment title.

```
In [ ]: lendclub['emp_title'].nunique()

        # there are 173105 job title in this data

Out[ ]: 83379

In [ ]: lendclub['emp_title'].value_counts()

Out[ ]: Teacher                         1679
        Manager                         1490
        Supervisor                       726
        Sales                            622
        Driver                           593
                                        ...
        City of Hopewell Schools           1
        Commonwealth Management co.        1
        Senior Ticket Agent                1
        Afc                                1
        HEALTH SERVICES MANAGEMENT         1
        Name: emp_title, Length: 83379, dtype: int64
```

```
In [ ]: lendclub.stb.freq(['emp_length'], cum_cols = False)

        # based on the table below, the most frequent employee's length is '10+ years',
        # let's impute the missing value with '10+ years'
```

Out[ ]:

	emp_length	count	percent
0	10+ years	44827	29.155583
1	2 years	16055	10.442209
2	< 1 year	14799	9.625303
3	3 years	14037	9.129697
4	1 year	12030	7.824339
5	5 years	11393	7.410033
6	4 years	10377	6.749224
7	6 years	8732	5.679313
8	7 years	8207	5.337851
9	8 years	7435	4.835741
10	9 years	5859	3.810707

```
In [ ]: lendclub['emp_length'].describe()

Out[ ]: count        153751
        unique           11
        top       10+ years
        freq          44827
        Name: emp_length, dtype: object
```

02

emp_length

This feature is about employment length in years.

```
In [ ]: lendclub.stb.freq(['title'], cum_cols = False)

        # there's a lot reasons that have same meaning, but python read it's different cause of lower-upper case.
        # we could re-categorize it with the correct one,
        # before we do that, better to check on 'purpose' column.
```

Out[ ]:

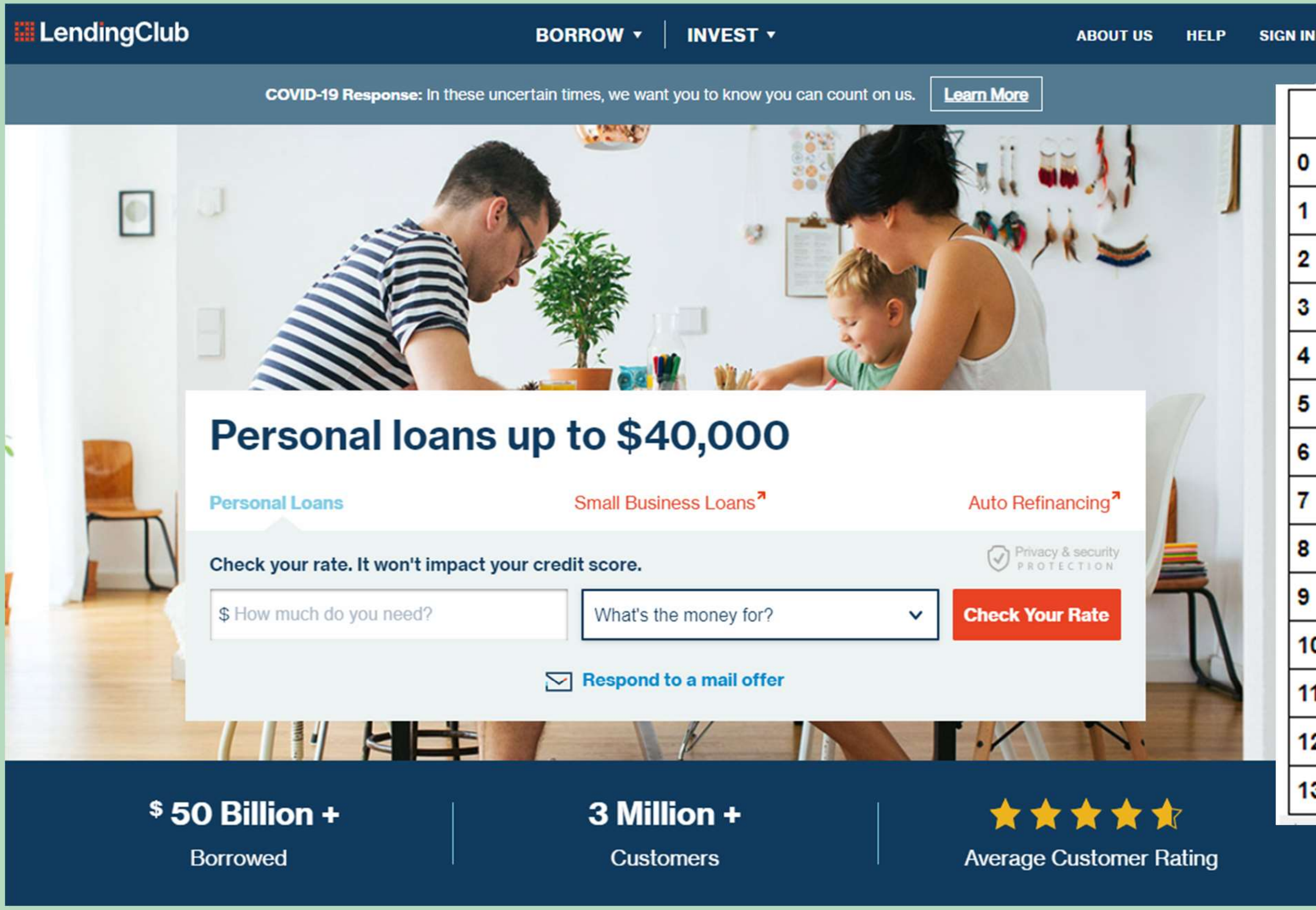
	title	count	percent
0	Debt consolidation	53738	32.835347
1	Credit card refinancing	18998	11.608283
2	Other	8302	5.072743
3	Home improvement	6410	3.916680
4	Debt Consolidation	3825	2.337177
...	...	...	...
26647	to pay of my bill,and one 22apr loand	1	0.000611
26648	Personal loan	1	0.000611
26649	HITEK EQUIPMENT	1	0.000611
26650	\tdebt_consolidation	1	0.000611
26651	\tcredit_card	1	0.000611

26652 rows × 3 columns

03

title

This feature is about employment title of the borrower's reason.



	purpose	count	percent
0	debt_consolidation	85754	52.181797
1	credit_card	32468	19.756963
2	other	14241	8.665730
3	home_improvement	10919	6.644274
4	major_purchase	5447	3.314531
5	car	3577	2.176625
6	medical	2940	1.789007
7	small_business	2235	1.360010
8	moving	2217	1.349057
9	vacation	2127	1.294292
10	wedding	1159	0.705258
11	house	826	0.502626
12	educational	214	0.130220
13	renewable_energy	213	0.129612

03

title

This feature is about employment title of the borrower’s reason.

```
In [ ]: lendclub.stb.freq(['revol_util'], cum_cols = False)
```

Out[ ]:

	revol_util	count	percent
0	0.00	1242	0.756547
1	55.00	313	0.190660
2	47.00	313	0.190660
3	60.00	311	0.189441
4	61.00	310	0.188832
...	...	...	...
1136	0.54	1	0.000609
1137	0.49	1	0.000609
1138	0.16	1	0.000609
1139	0.05	1	0.000609
1140	0.04	1	0.000609

1141 rows × 3 columns

```
In [ ]: lendclub['revol_util'].describe()

        # let's impute the missing value with mean value
```

```
Out[ ]: count    164167.000000
        mean         51.096413
        std          25.304787
        min           0.000000
        25%          31.900000
        50%          51.300000
        75%          70.800000
        max         892.300000
        Name: revol_util, dtype: float64
```

04

revol_util

This feature is about revolving utilization rate.

```
In [ ]: lendclub['mort_acc'].describe()

        # because 'mort_acc' have an integer value, we will im

Out[ ]: count    143450.000000
        mean          1.397128
        std           1.931071
        min           0.000000
        25%           0.000000
        50%           1.000000
        75%           2.000000
        max          31.000000
        Name: mort_acc, dtype: float64
```

```
In [ ]: lendclub.stb.freq(['mort_acc'], cum_cols = False)
Out[ ]:
```

	mort_acc	count	percent
0	0.0	70146	48.899268
1	1.0	23556	16.421053
2	2.0	17487	12.190310
3	3.0	12352	8.610666
4	4.0	8437	5.881492
5	5.0	5131	3.576856
6	6.0	3018	2.103869
7	7.0	1636	1.140467
8	8.0	779	0.543046
9	9.0	396	0.276054
10	10.0	211	0.147090
11	11.0	113	0.078773
12	12.0	62	0.043221
13	13.0	39	0.027187
14	14.0	30	0.020913
15	15.0	15	0.010457
16	16.0	11	0.007668
17	24.0	7	0.004880
18	19.0	5	0.003486
19	18.0	5	0.003486
20	17.0	5	0.003486
21	22.0	3	0.002091
22	23.0	2	0.001394
23	31.0	1	0.000697
24	26.0	1	0.000697
25	21.0	1	0.000697
26	20.0	1	0.000697

05

mort_acc

This feature is about number of mortgage account.

```
In [ ]: lendclub.stb.freq(['pub_rec_bankruptcies'], cum_cols = False)
```

Out[ ]:

	pub_rec_bankruptcies	count	percent
0	0.0	139795	85.247091
1	1.0	22884	13.954680
2	2.0	1044	0.636632
3	3.0	197	0.120131
4	4.0	43	0.026221
5	5.0	17	0.010367
6	6.0	5	0.003049
7	7.0	2	0.001220
8	8.0	1	0.000610

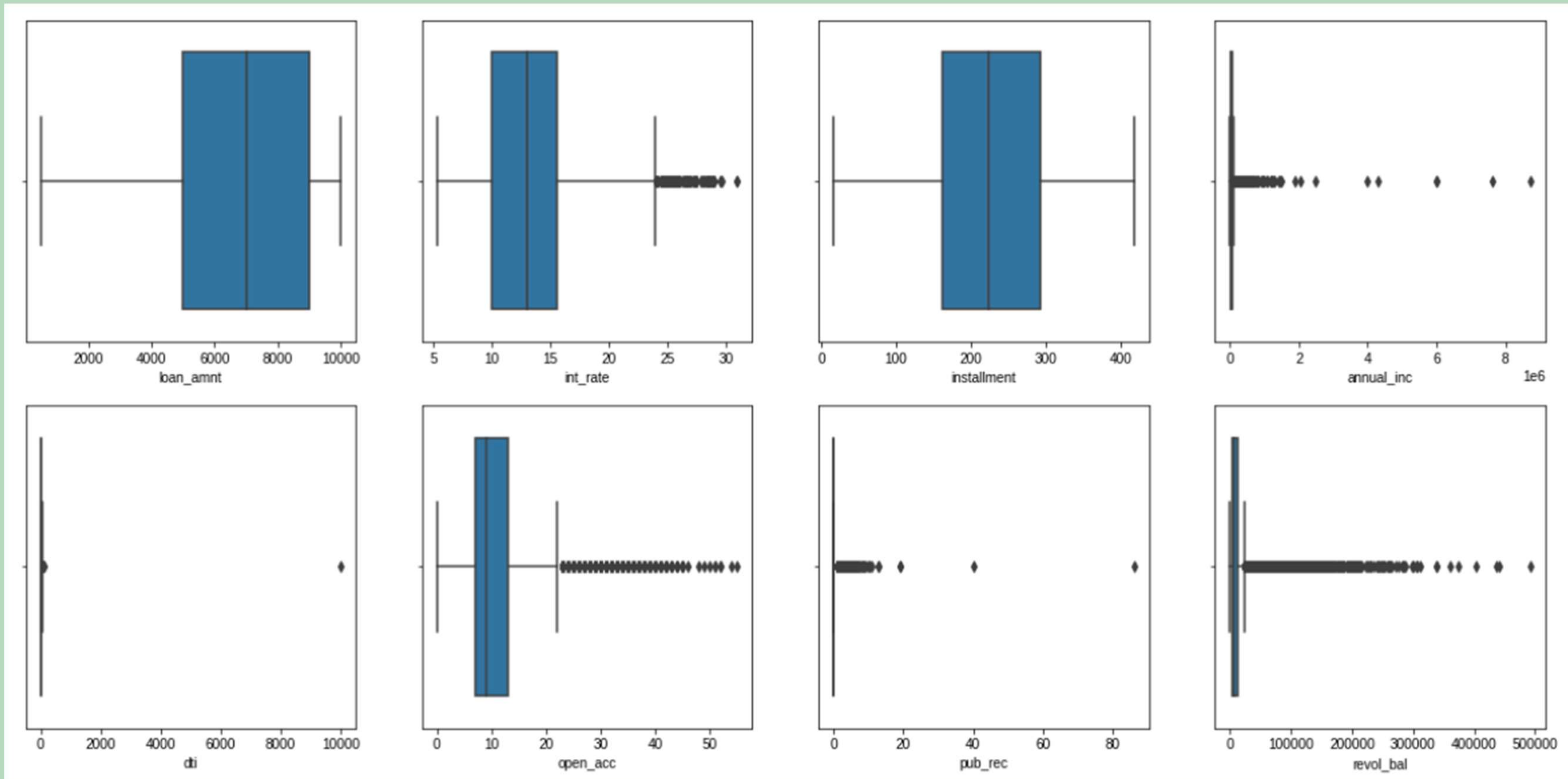
```
In [ ]: lendclub['pub_rec_bankruptcies'].describe()

        # we see that the value either mean, Q1, Q2 (median), or Q3 is '0'.
        # so we impute the missing value with '0'.
```

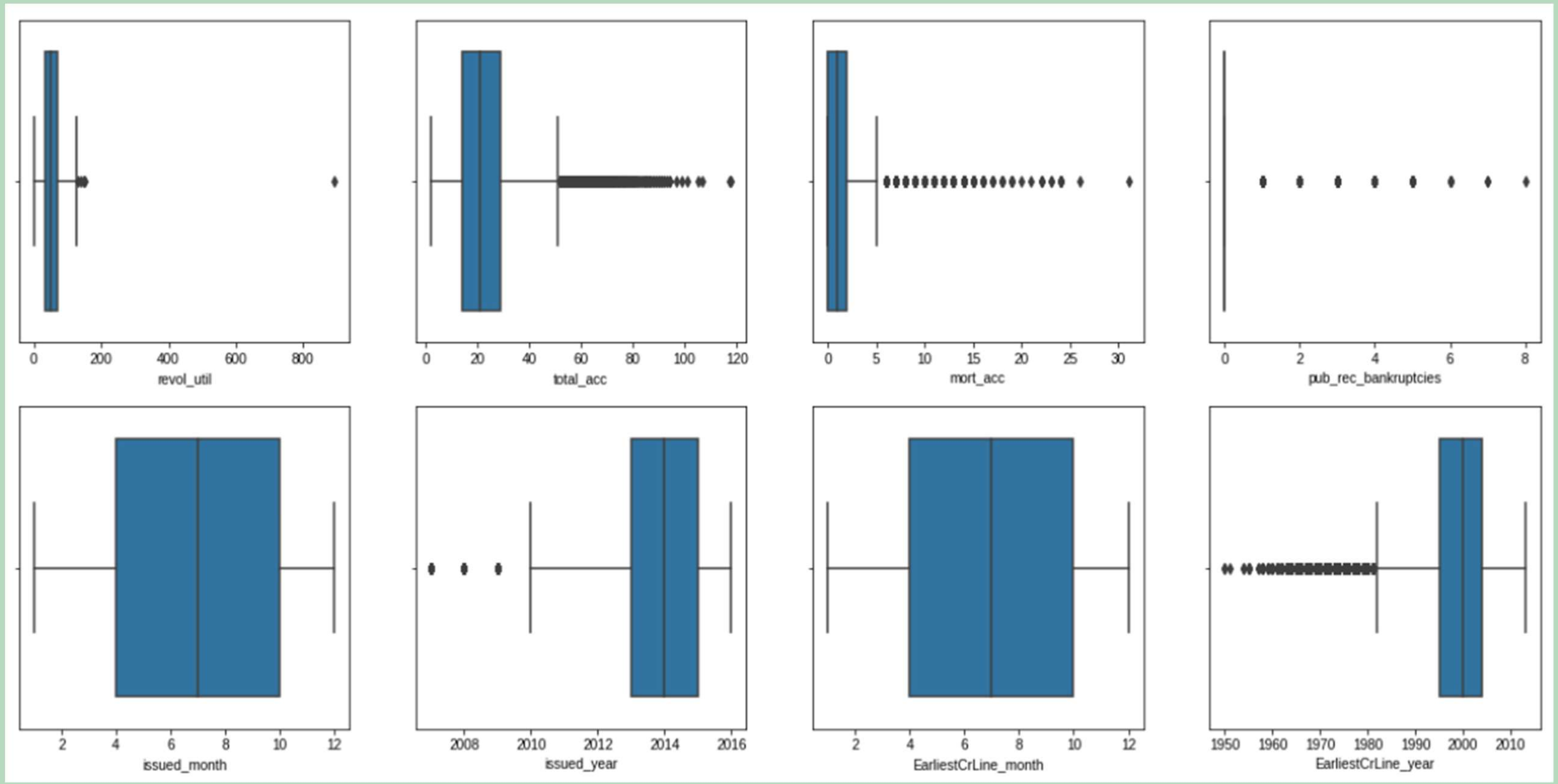
```
Out[ ]: count    163988.000000
        mean          0.157768
        std           0.399758
        min           0.000000
        25%           0.000000
        50%           0.000000
        75%           0.000000
        max           8.000000
        Name: pub_rec_bankruptcies, dtype: float64
```

06

Pub_rec_bankruptcies

This feature is about number of public record of bankruptcies.


2000
4000
6000
8000
10000
loan_amnt
5
10
15
20
25
30
int_rate
0
100
200
300
400
installment
0
2
4
6
8
1e6
annual_inc
0
2000
4000
6000
8000
10000
dti
0
10
20
30
40
50
open_acc
0
20
40
60
80
pub_rec
0
100000
200000
300000
400000
500000
revol_bal

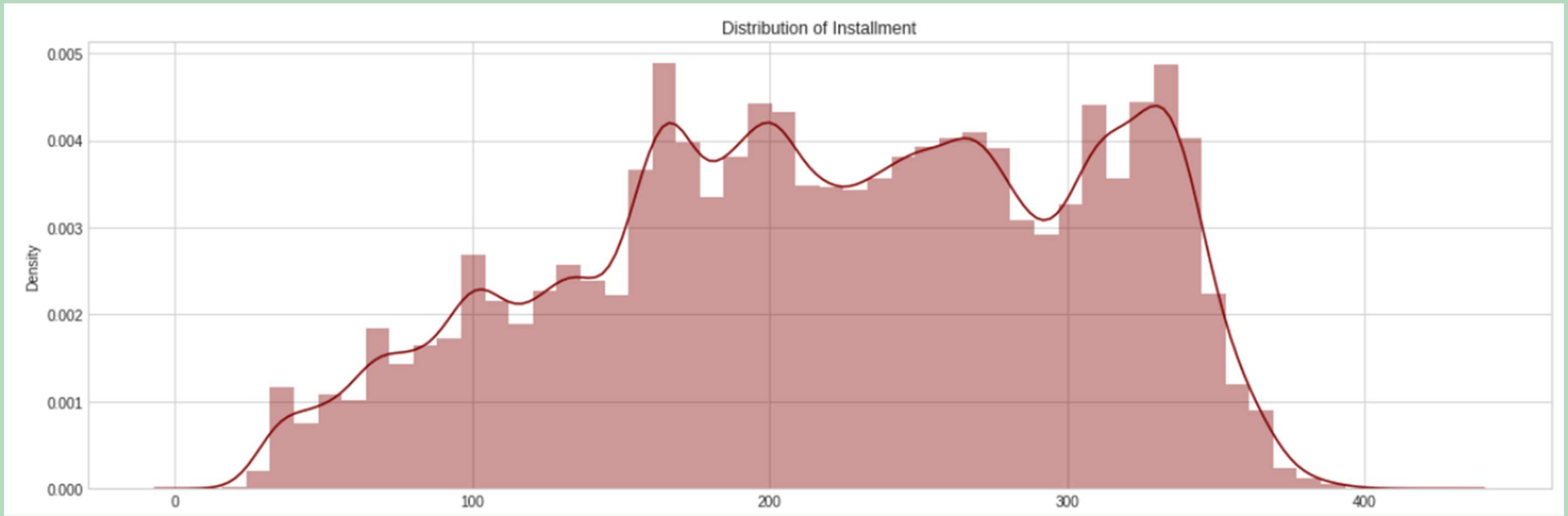


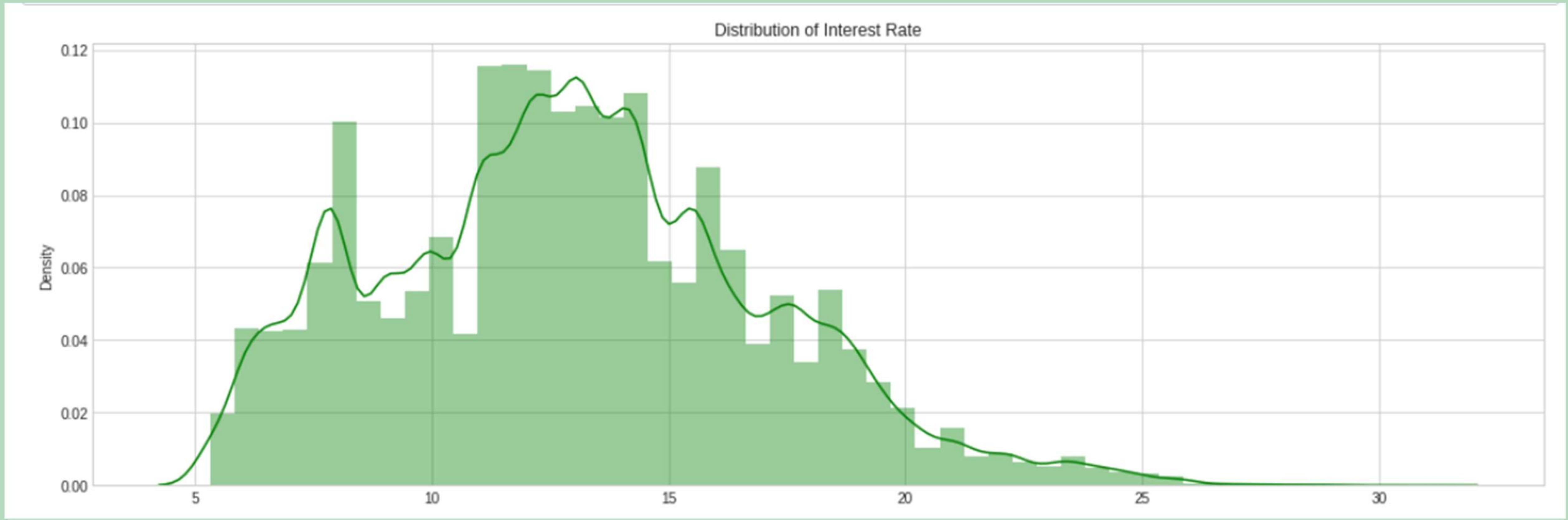
0 200 400 600 800
revol_util
0 20 40 60 80 100 120
total_acc
0 5 10 15 20 25 30
mort_acc
0 2 4 6 8
pub_rec_bankruptcies
2 4 6 8 10 12
issued_month
2008 2010 2012 2014 2016
issued_year
2 4 6 8 10 12
EarliestCrLine_month
1950 1960 1970 1980 1990 2000 2010
EarliestCrLine_year

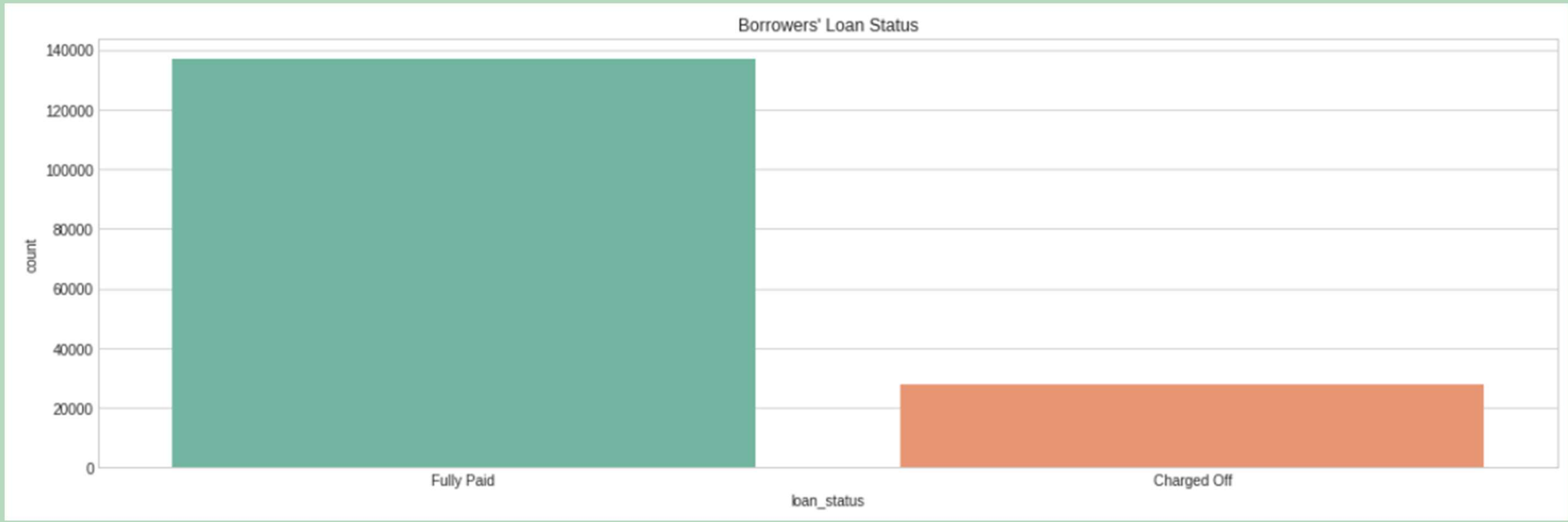
Exploratory Data Analysis

07

This section consists of data analysis and visualization including some insights from the LendingClub dataset.

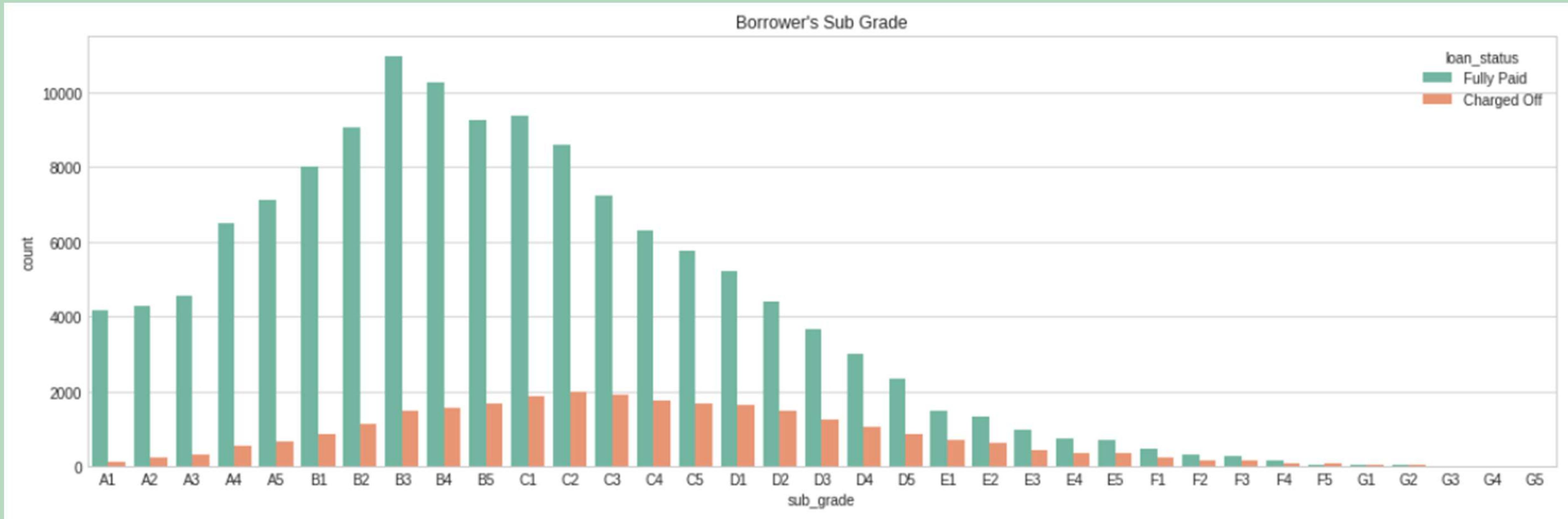

Distribution of Installment
Density
0.005
0.004
0.003
0.002
0.001
0.000
0
100
200
300
400


Distribution of Interest Rate
Density
0.00
0.02
0.04
0.06
0.08
0.10
0.12
5
10
15
20
25
30



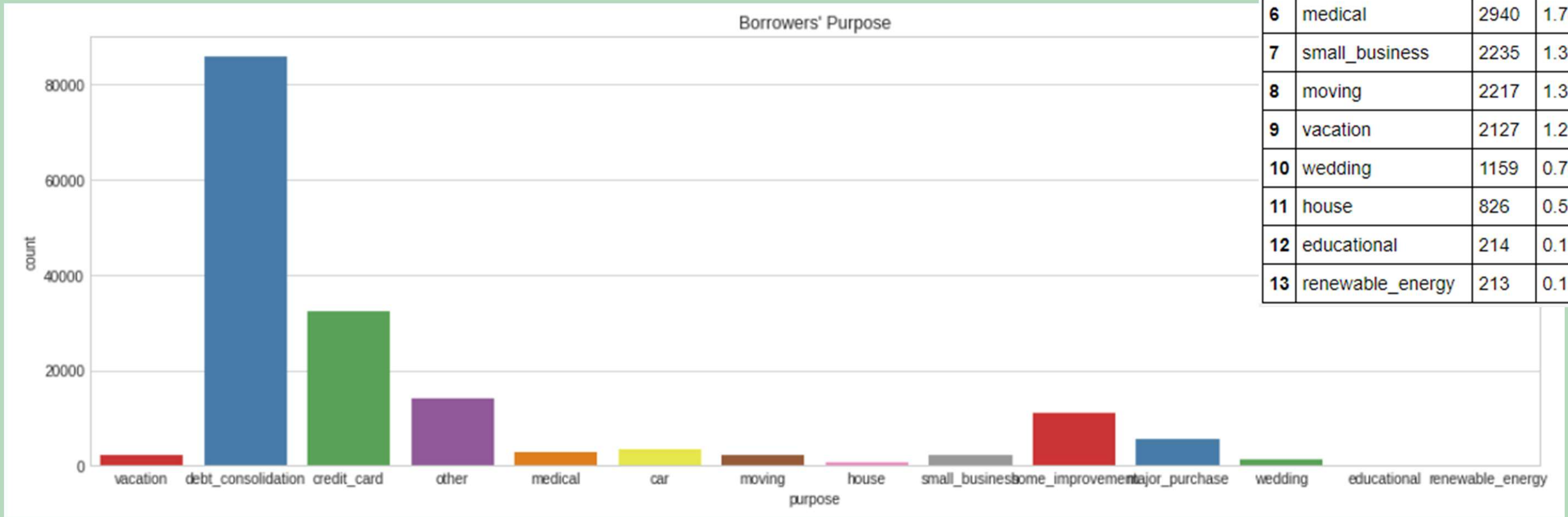
	loan_status	count	percent
0	Fully Paid	136690	83.176643
1	Charged Off	27647	16.823357

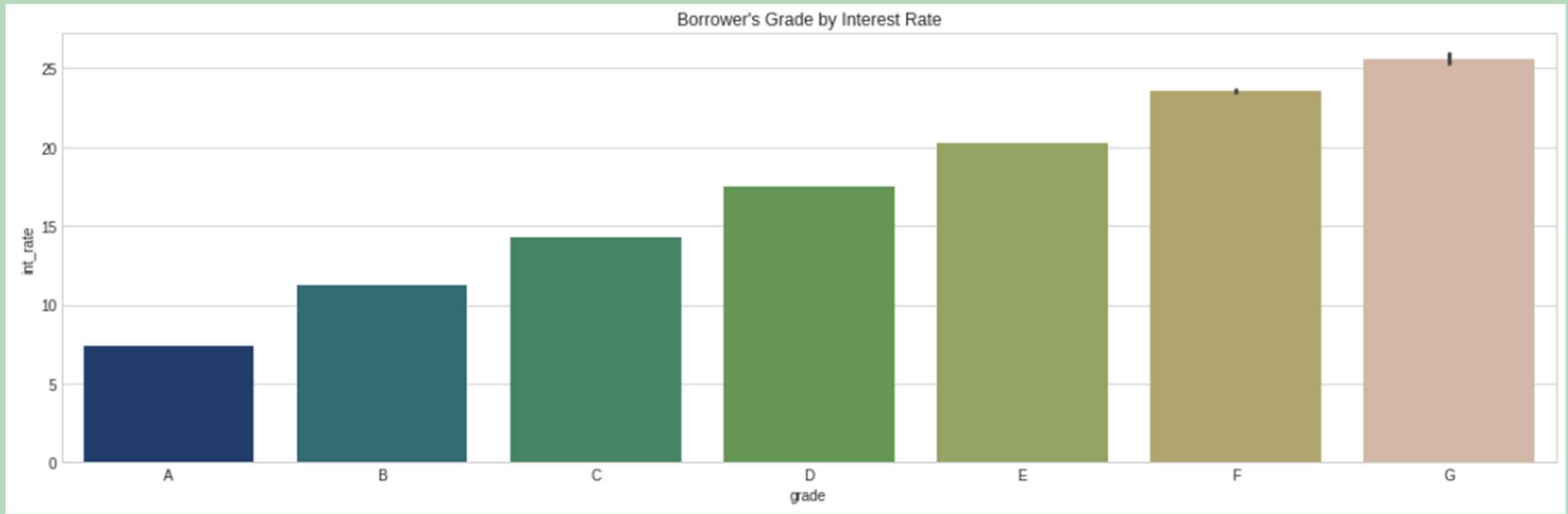
No. 07 —— Exploratory Data Analysis



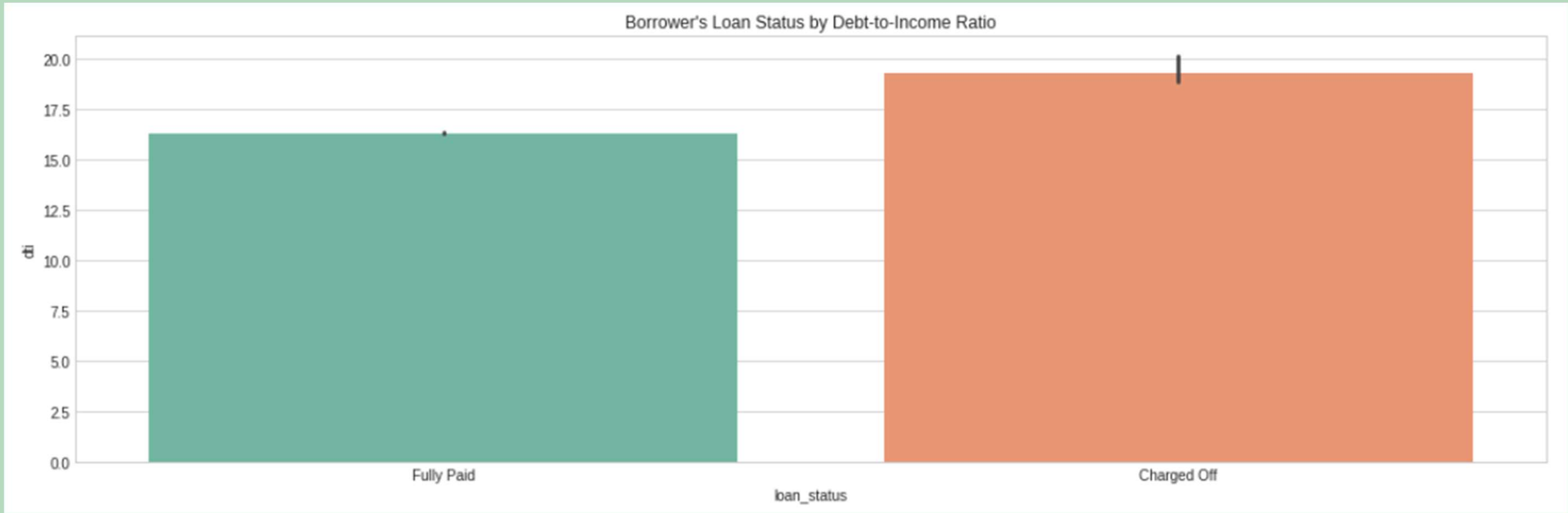
sub_grade	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	C1	C2	C3	C4	C5	D1	D2	D3	D4	D5	E1	E2	E3	E4	E5	F1	F2	F3	F4	F5	G1	G2	G3	G4	G5
loan_status																																			
Charged Off	2.786	5.23	6.66	7.831	8.808	9.728	11.12	12.071	13.242	15.223	16.594	18.813	21.088	21.787	22.672	24.026	25.36	25.299	26.236	27.346	31.622	32.319	31.847	33.48	34.652	33.242	36.97	38.816	36.719	55.072	47.321	55.263	47.368	51.852	55.0
Fully Paid	97.214	94.77	93.34	92.169	91.192	90.272	88.88	87.929	86.758	84.777	83.406	81.187	78.912	78.213	77.328	75.974	74.64	74.701	73.764	72.654	68.378	67.681	68.153	66.52	65.348	66.758	63.03	61.184	63.281	44.928	52.679	44.737	52.632	48.148	45.0

	purpose	count	percent
0	debt_consolidation	85754	52.181797
1	credit_card	32468	19.756963
2	other	14241	8.665730
3	home_improvement	10919	6.644274
4	major_purchase	5447	3.314531
5	car	3577	2.176625
6	medical	2940	1.789007
7	small_business	2235	1.360010
8	moving	2217	1.349057
9	vacation	2127	1.294292
10	wedding	1159	0.705258
11	house	826	0.502626
12	educational	214	0.130220
13	renewable_energy	213	0.129612





	int_rate
grade	
A	7.362835
B	11.230545
C	14.250424
D	17.488502
E	20.252314
F	23.554118
G	25.612088

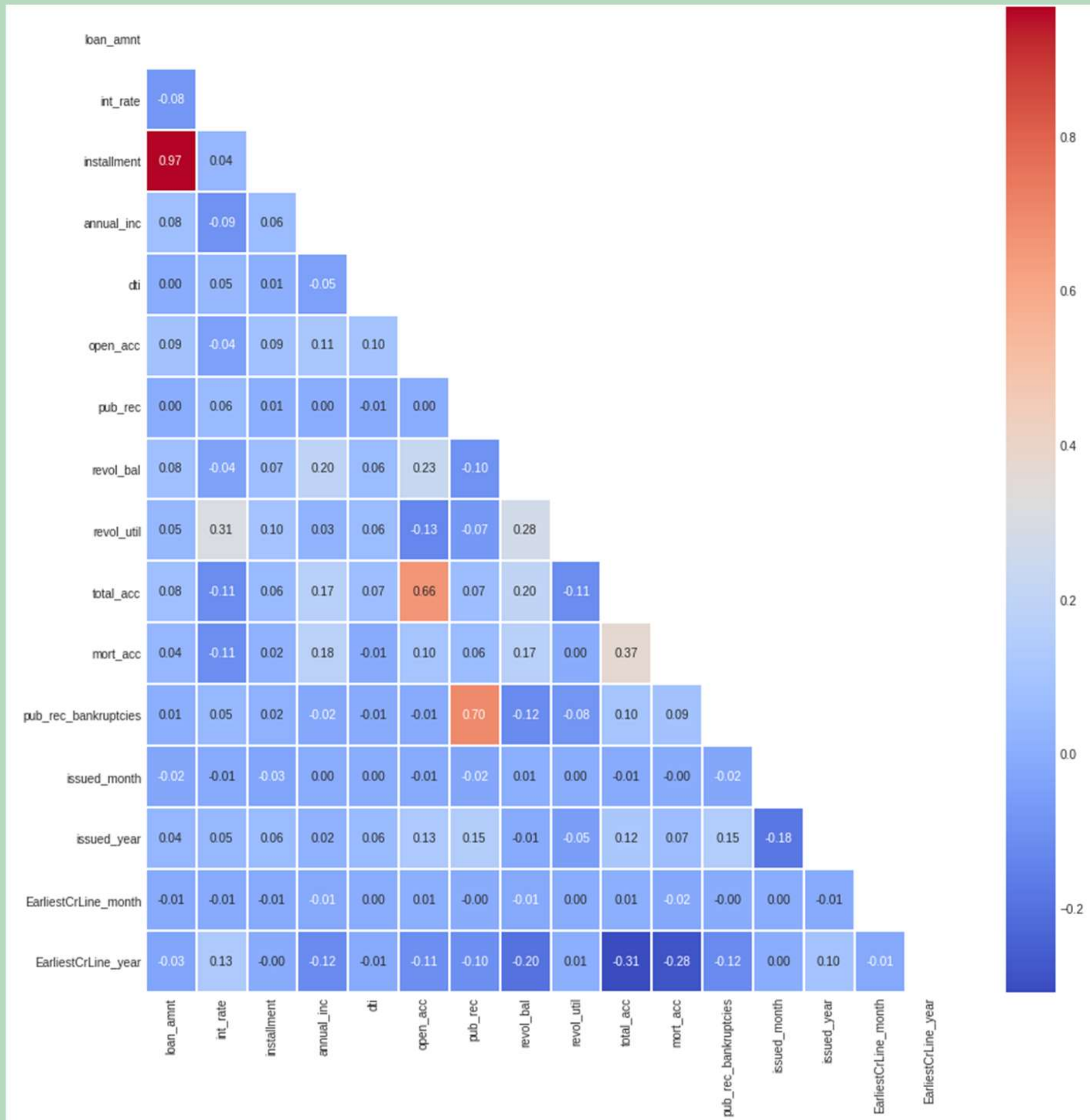


loan_status	Charged Off	Fully Paid
row_0		
Average of Debt-to-Income Ratio	19.305847	16.333995

Machine Learning Modelling

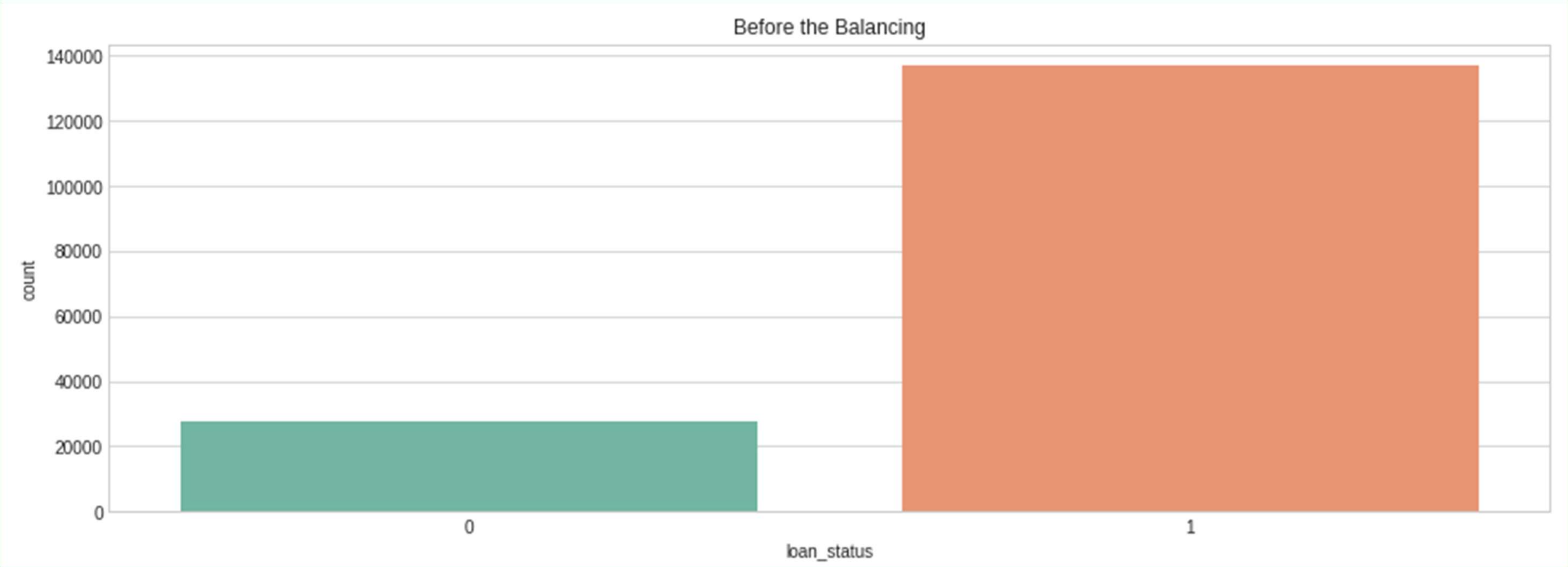
08

This section contains of the method of feature selection and models' performance.


loan_amnt
int_rate -0.08
installment 0.97 0.04
annual_inc 0.08 -0.09 0.06
dti 0.00 0.05 0.01 -0.05
open_acc 0.09 -0.04 0.09 0.11 0.10
pub_rec 0.00 0.06 0.01 0.00 -0.01 0.00
revol_bal 0.08 -0.04 0.07 0.20 0.06 0.23 -0.10
revol_util 0.05 0.31 0.10 0.03 0.06 -0.13 -0.07 0.28
total_acc 0.08 -0.11 0.06 0.17 0.07 0.66 0.07 0.20 -0.11
mort_acc 0.04 -0.11 0.02 0.18 -0.01 0.10 0.06 0.17 0.00 0.37
pub_rec_bankruptcies 0.01 0.05 0.02 -0.02 -0.01 -0.01 0.70 -0.12 -0.08 0.10 0.09
issued_month -0.02 -0.01 -0.03 0.00 0.00 -0.01 -0.02 0.01 0.00 -0.01 -0.00 -0.02
issued_year 0.04 0.05 0.06 0.02 0.06 0.13 0.15 -0.01 -0.05 0.12 0.07 0.15 -0.18
EarliestCrLine_month -0.01 -0.01 -0.01 -0.01 0.00 0.01 -0.00 -0.01 0.00 0.01 -0.02 -0.00 0.00 -0.01
EarliestCrLine_year -0.03 0.13 -0.00 -0.12 -0.01 -0.11 -0.10 -0.20 0.01 -0.31 -0.28 -0.12 0.00 0.10 -0.01
loan_amnt
int_rate
installment
annual_inc
dti
open_acc
pub_rec
revol_bal
revol_util
total_acc
mort_acc
pub_rec_bankruptcies
issued_month
issued_year
EarliestCrLine_month
EarliestCrLine_year
0.8
0.6
0.4
0.2
0.0
-0.2

```
feat_coef = lendclub[['sub_grade', 'purpose_small_business', 'installment', 'int_rate',
                      'loan_amnt', 'purpose_wedding', 'purpose_house', 'purpose_medical',
                      'purpose_moving', 'home_ownership_OTHER', 'home_ownership_RENT', 'dti',
                      'purpose_home_improvement', 'purpose_educational', 'total_acc',
                      'home_ownership_OWN', 'purpose_other', 'open_acc',
                      'purpose_debt_consolidation', 'revol_util', 'purpose_renewable_energy',
                      'annual_inc', 'pub_rec_bankruptcies', 'loan_status']]
```

```
In [ ]: print(f"Total Features: {lendclub.shape[1]} columns.")
        print(f"Selected Features: {feat_coef.shape[1]-1} columns.")

        Total Features: 40 columns.
        Selected Features: 23 columns.
```



	loan_status	count	percent
0	1	136690	83.176643
1	0	27647	16.823357

	loan_status	count	percent
0	1.0	109352	50.0
1	0.0	109352	50.0

	Precision Score
Logistic Regression	0.895764
Tuned Logistic Regression	0.896274
SVC	0.834360
Tuned SVC	0.831588
Random Forest	0.839162
Tuned Random Forest	0.897117
XGBoost	0.838876
Tuned XGBoost	0.837845

	TruePositive	TrueNegative	FalsePositive	FalseNegative
Logistic Regression	17763	3463	2067	9575
Tuned Logistic Regression	17679	3484	2046	9659
SVC	17197	2116	3414	10141
Tuned SVC	19134	1655	3875	8204
Random Forest	26729	407	5123	609
Tuned Random Forest	14937	3817	1713	12401
XGBoost	26714	399	5131	624
Tuned XGBoost	27023	300	5230	315

Using Precision from classification report because we only focus to minimize False Positive which the actual is charged-off but the model predicts fully paid rather than the actual is fully paid but the model predicts charged-off. This is nightmare for lenders/ investors because the worst scenario is all lenders' money would be gone in no time.

The Best Model

09

After all, the selected model is tuned random forest algorithm. The specified parameters are:

- 'max_depth' : 2,
- 'min_samples_leaf': 0.07
- 'n_estimators' : 10
- Precision: 0.90
- False Positive: 1713

Conclusions

10

This sections tells the conclusions of the entire analysis. There are at least 10 points to summary this report.

1. 83.18 % borrowers are likely to complete their loan amount.
2. Borrowers who loan 60 months has higher interest rate (15.7%).
3. LendingClub is the healthy platform for investors.
4. High risk high return.
5. When it comes to proportion, the highest percentage of borrowers who complete their loan is 'A1' with 97.21%, meanwhile the 'B3' has 87.93% only.
6. Revolving balance about $11,106 tend to be charged off borrowers in 60 months of loan term.
7. Individual applications are tend to have high charged-off rate compare to joint application type (or with two co-borrowers).
8. Educational purpose borrowers who have 11.43 debt-to-income ratio (which is the lowest ratio) are the only one purpose which fully paid their loan, compare to other purposes.
9. The main characteristics of borrowers who stop repay their loans are have: high interest rate, high loan amount, high installment, high debt-to-income ratio, low grade and low sub grade.
10. Machine learning model which built with Random Forest algorithm has Precision score 0.90 of 1.0.

Recommendations

11

Recommendation for LendingClub to ensure the profit and minimize the risk and cost.

1. LendingClub could offer subscription services to lenders that will help them to choose borrowers wisely. Let's say educating them with the facts like "High risk isn't always high return, but high understanding leads to high return". Except if the lenders put their money into A grade borrowers, they don't need many informations.
2. Machine Learning model can be included in the subscription services which can help lenders easily to pick borrowers. Lenders only need to put the information of borrowers and then one 'click' away, they get the result of borrowers' repayment capability.

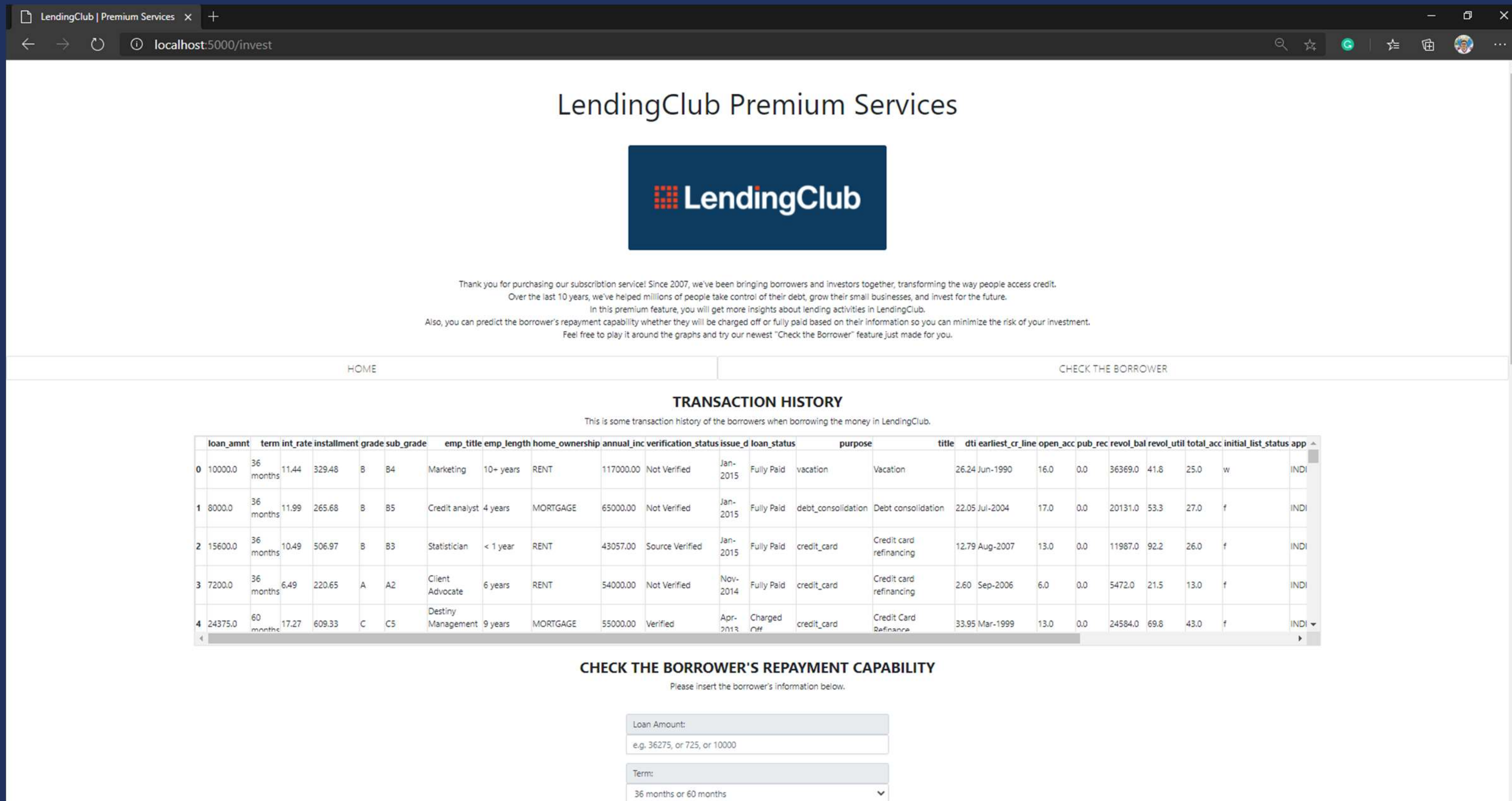
Dashboard

12

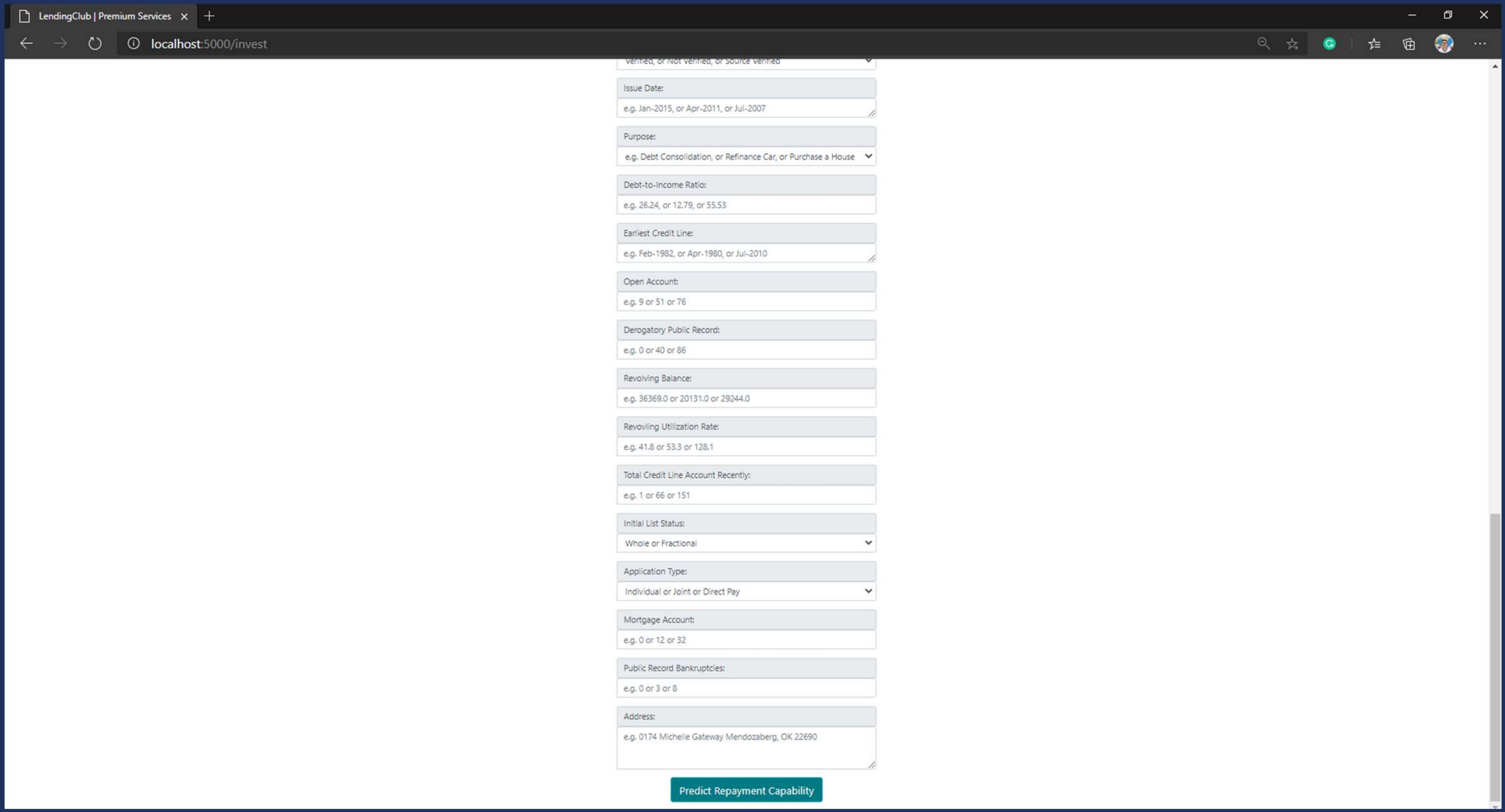
Dashboard shows us what subscription feature on LendingClub's page looks like.

No. 12 —— Dashboard

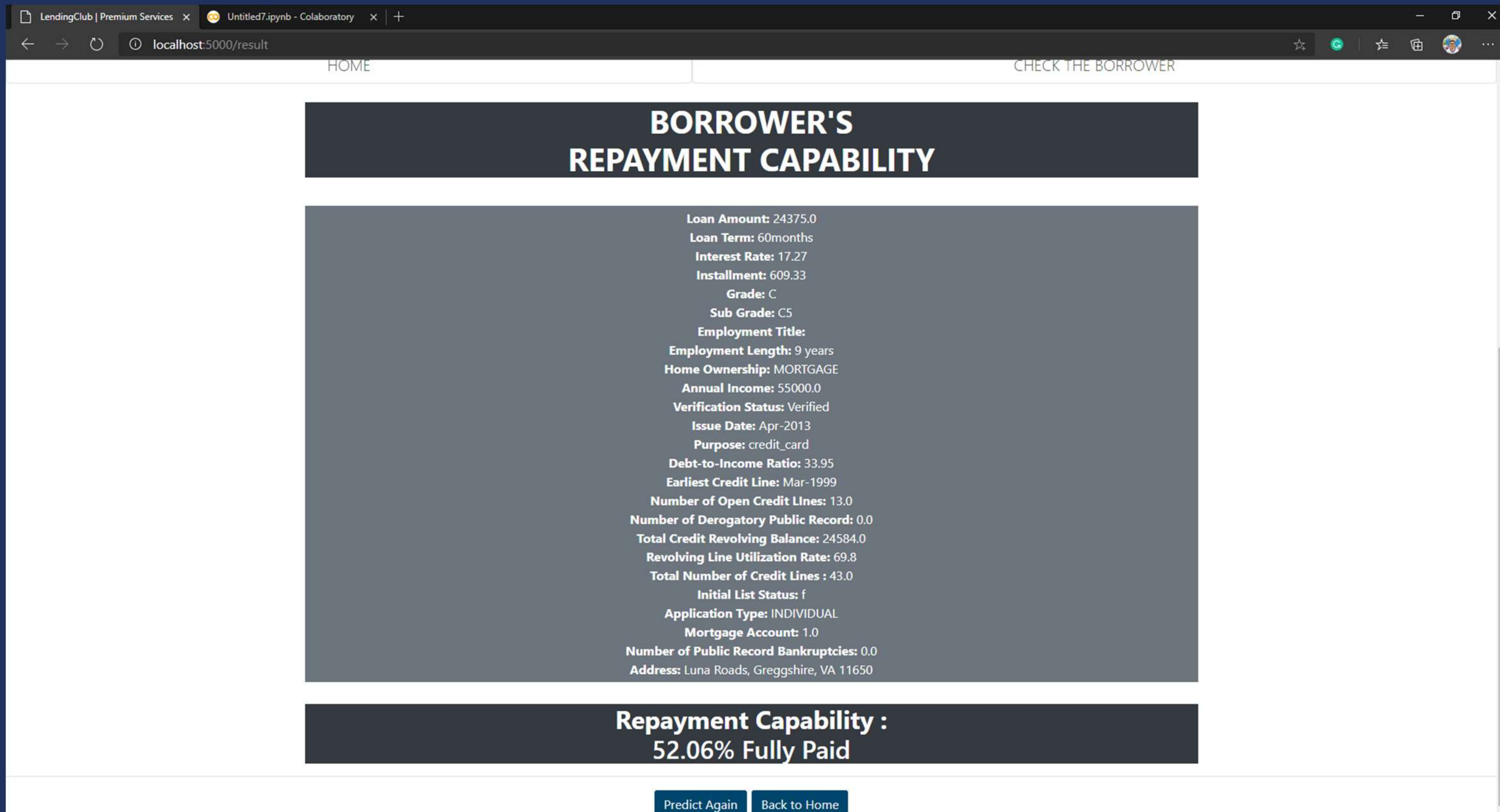
No. 12 — Dashboard

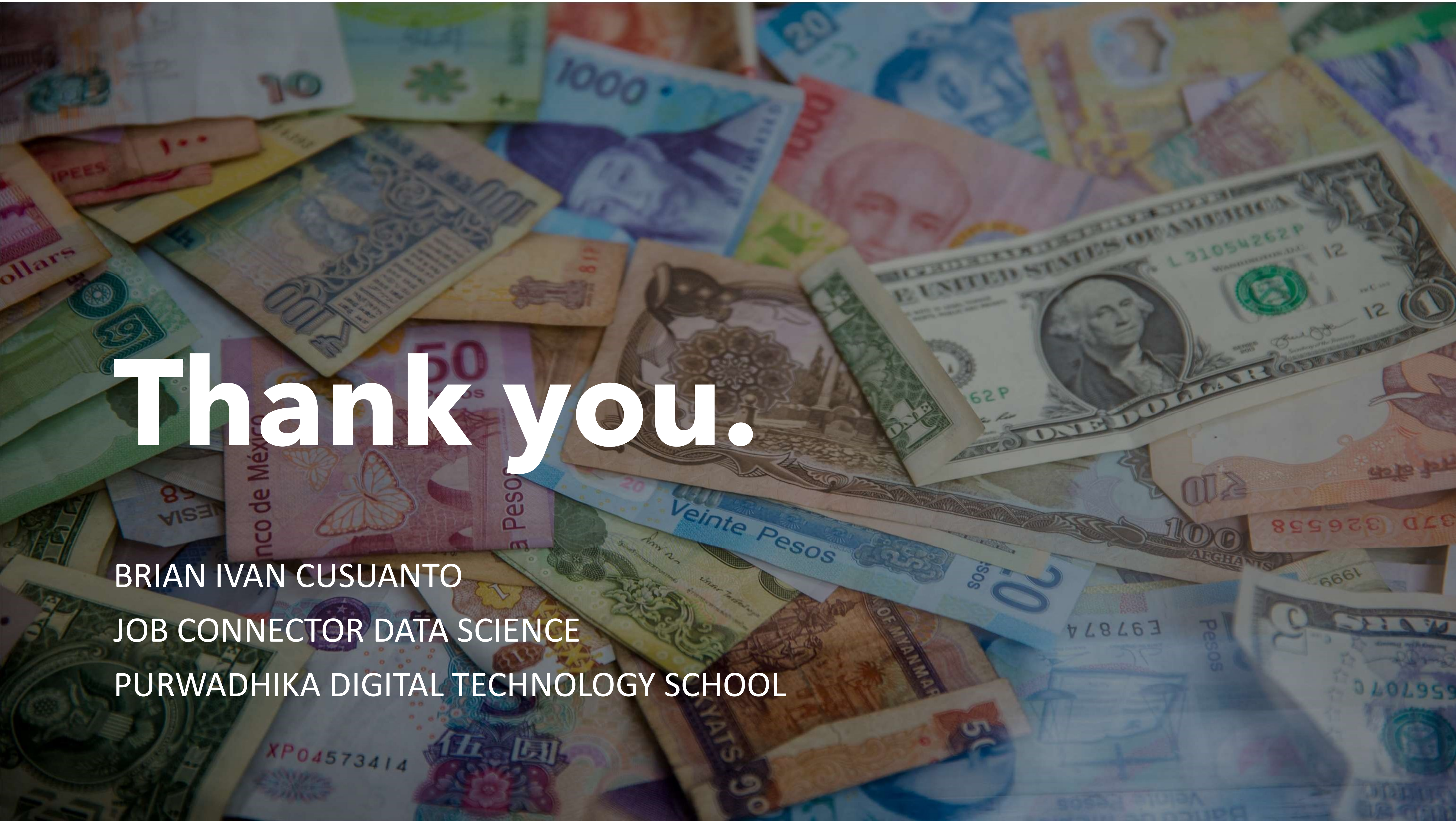


No. 12 Dashboard



No. 12 —— Dashboard





Thank you.

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