Prediction of Default Rates for Peer-to-Peer Loaning Companies

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Meet The Team

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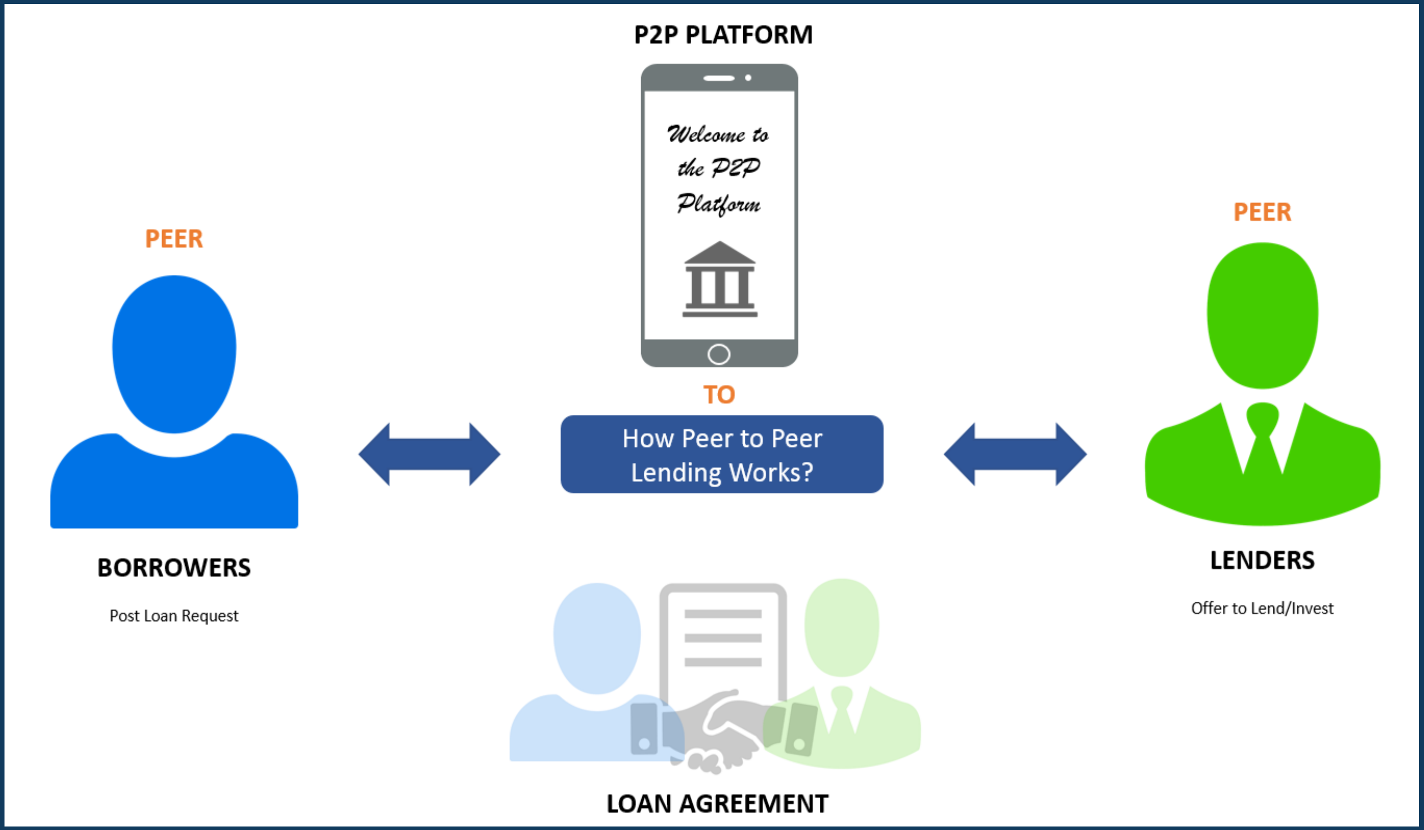
Background

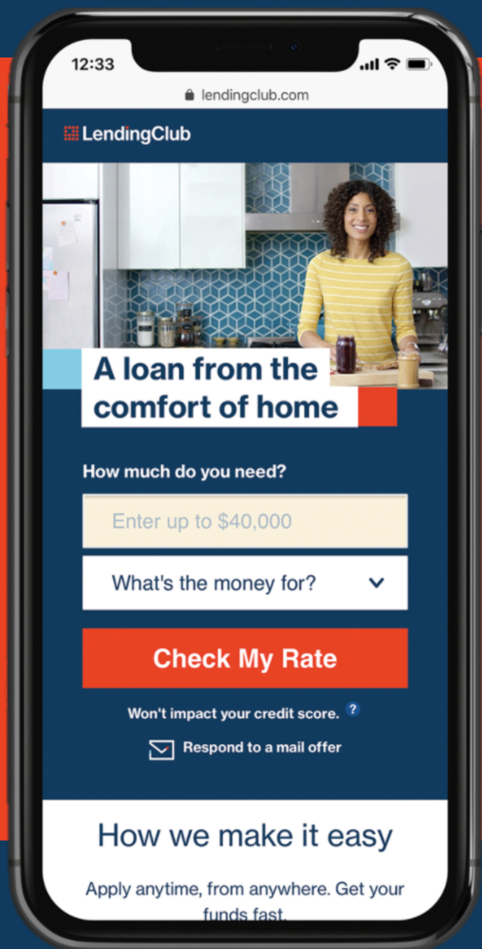
What is a P2P company?



Peer-to-peer (P2P) lenders are secondary marketplaces for loans that connect individual borrowers and lenders over an online platform. Lenders and borrowers never directly interact with each other; the P2P platform acts instead as a middleman. The most common type of P2P loan is a personal or business loan.

LendingClub

How LendingClub works



1

Apply

Apply on LC App or website based on user questionnaire

2

Choose a Loan Offer

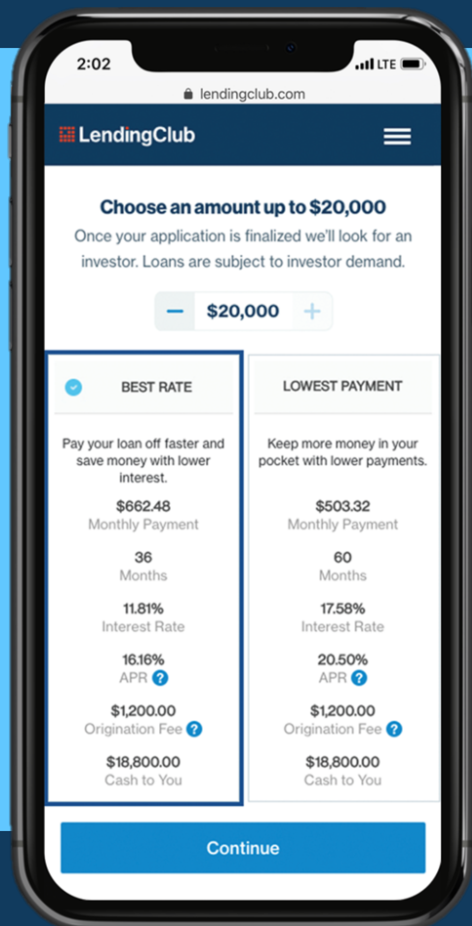
3

Get Funded

How LendingClub works

1

Apply



2

Choose a Loan Offer

Select rate, term, and payment options

3

Get Funded

How LendingClub works

1

Apply

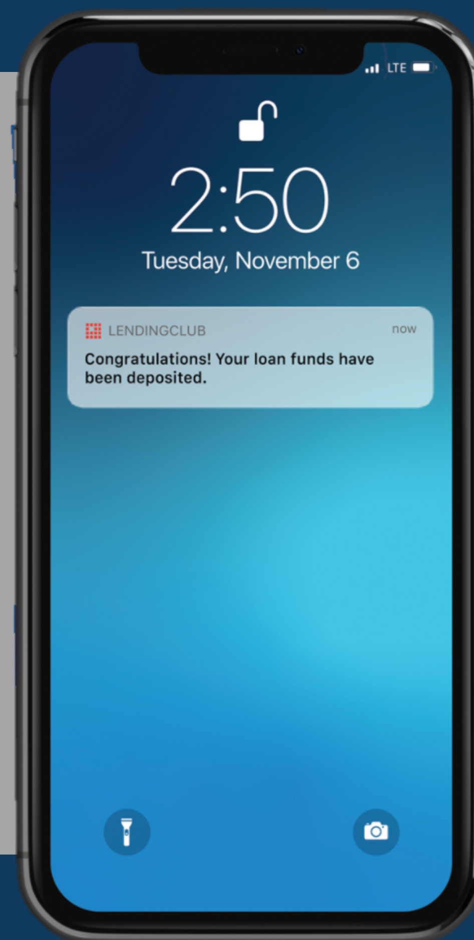
2

Choose a Loan Offer

3

Get Funded

After evaluation and matching an investor, loan can be sent directly to the borrower's account



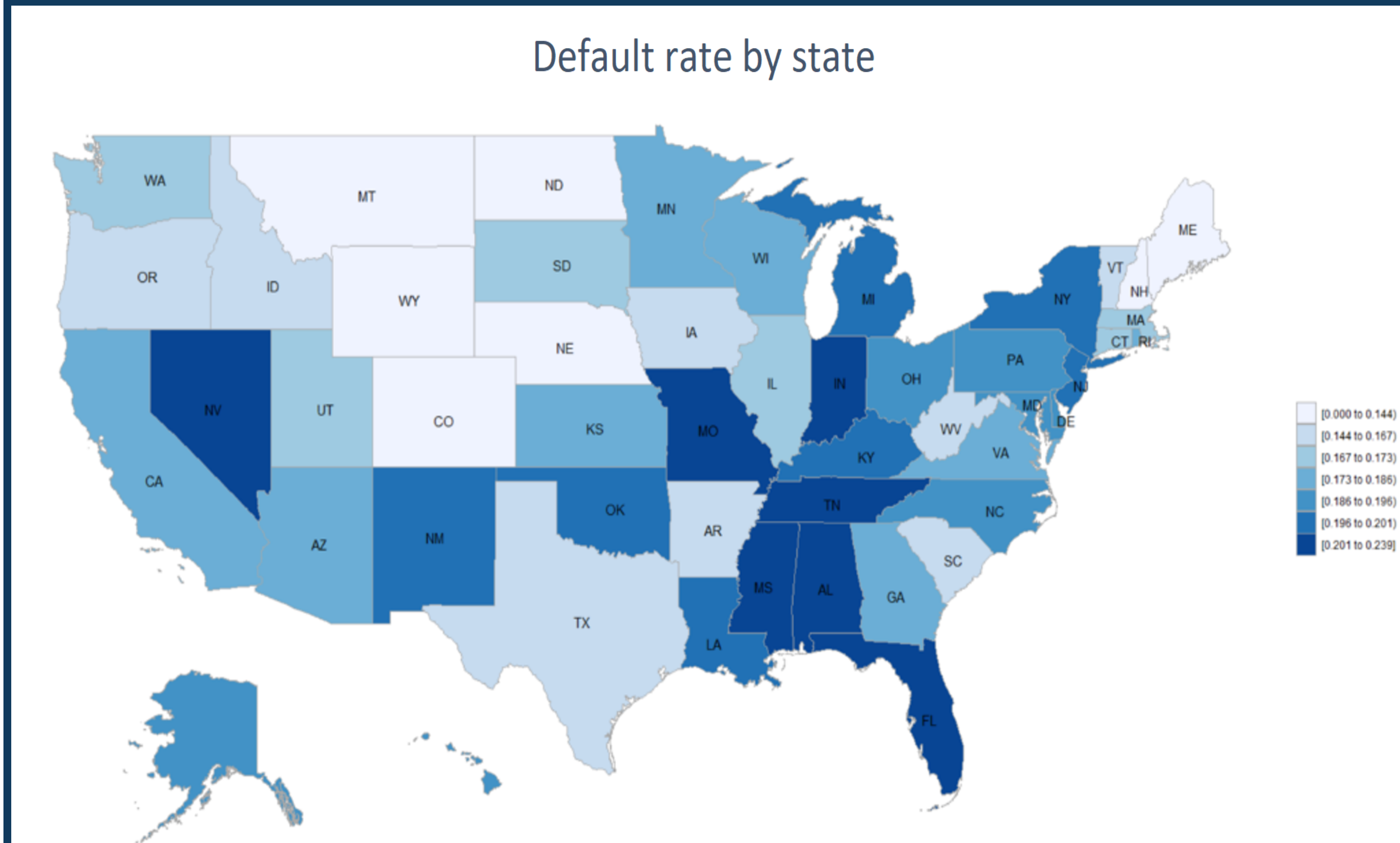
Why predicting default rate?

- Higher default rate compared to bank

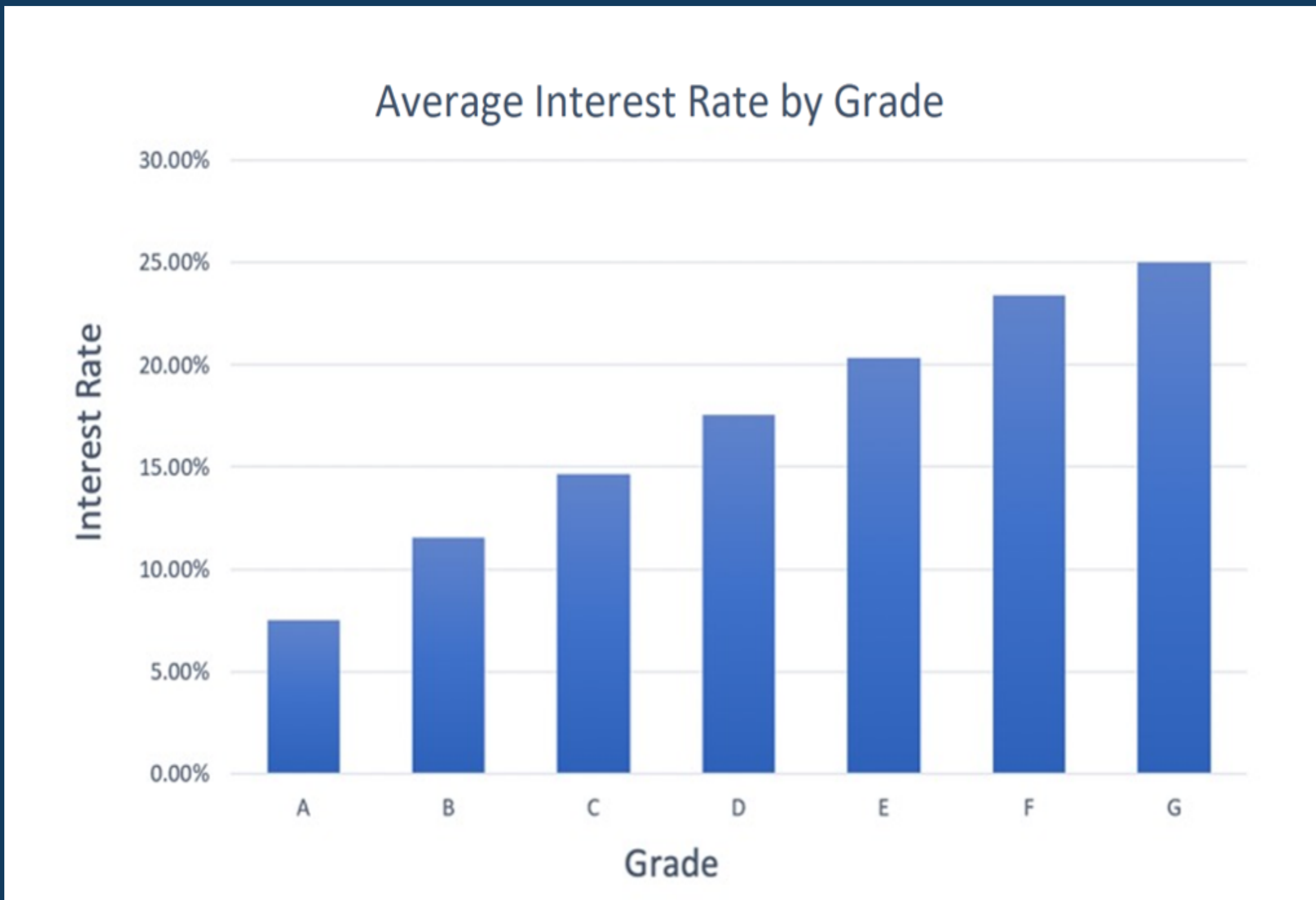
- As a prediction model for P2P companies

- Help customers to understand their chance of getting loan

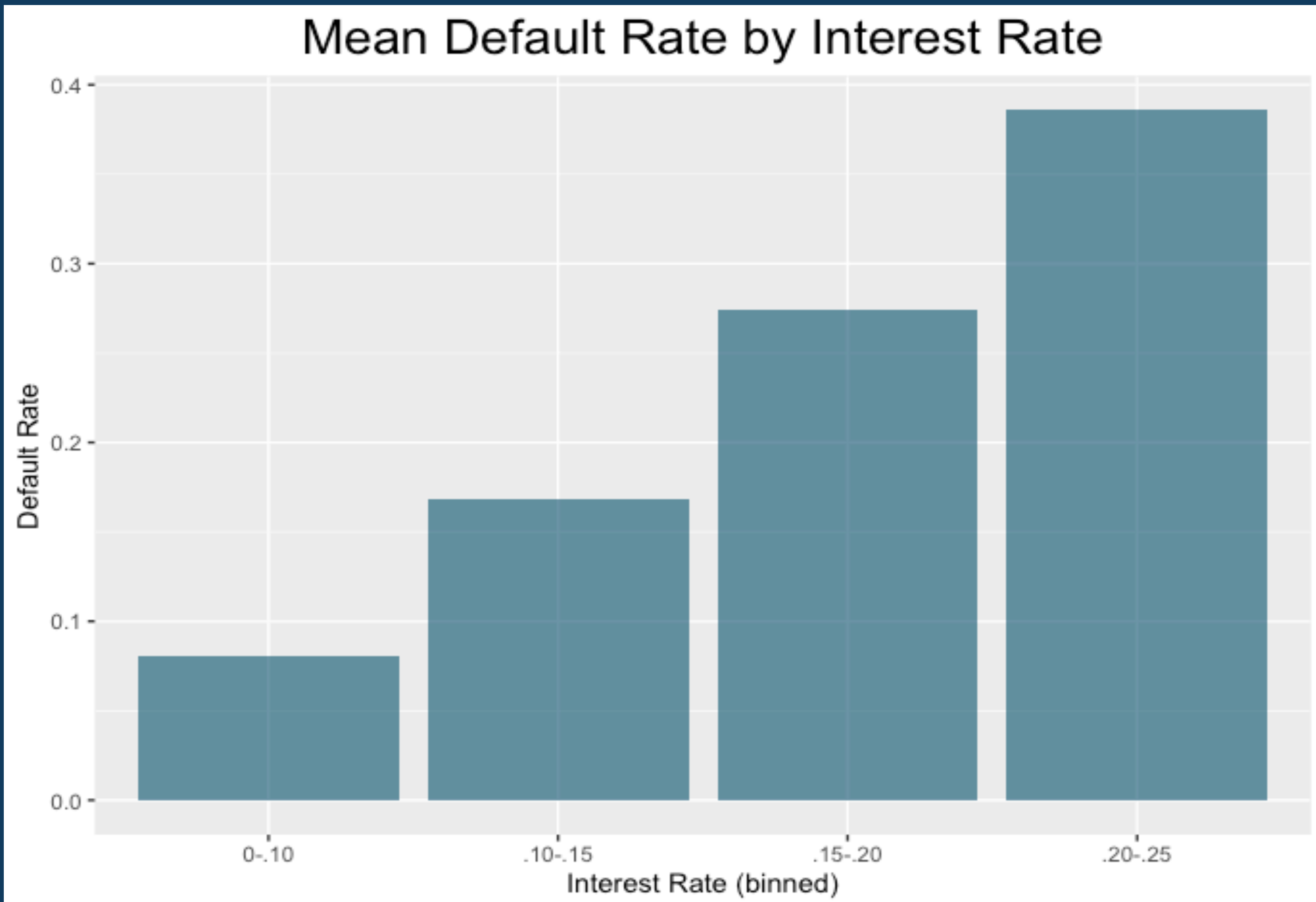
Data Visualization

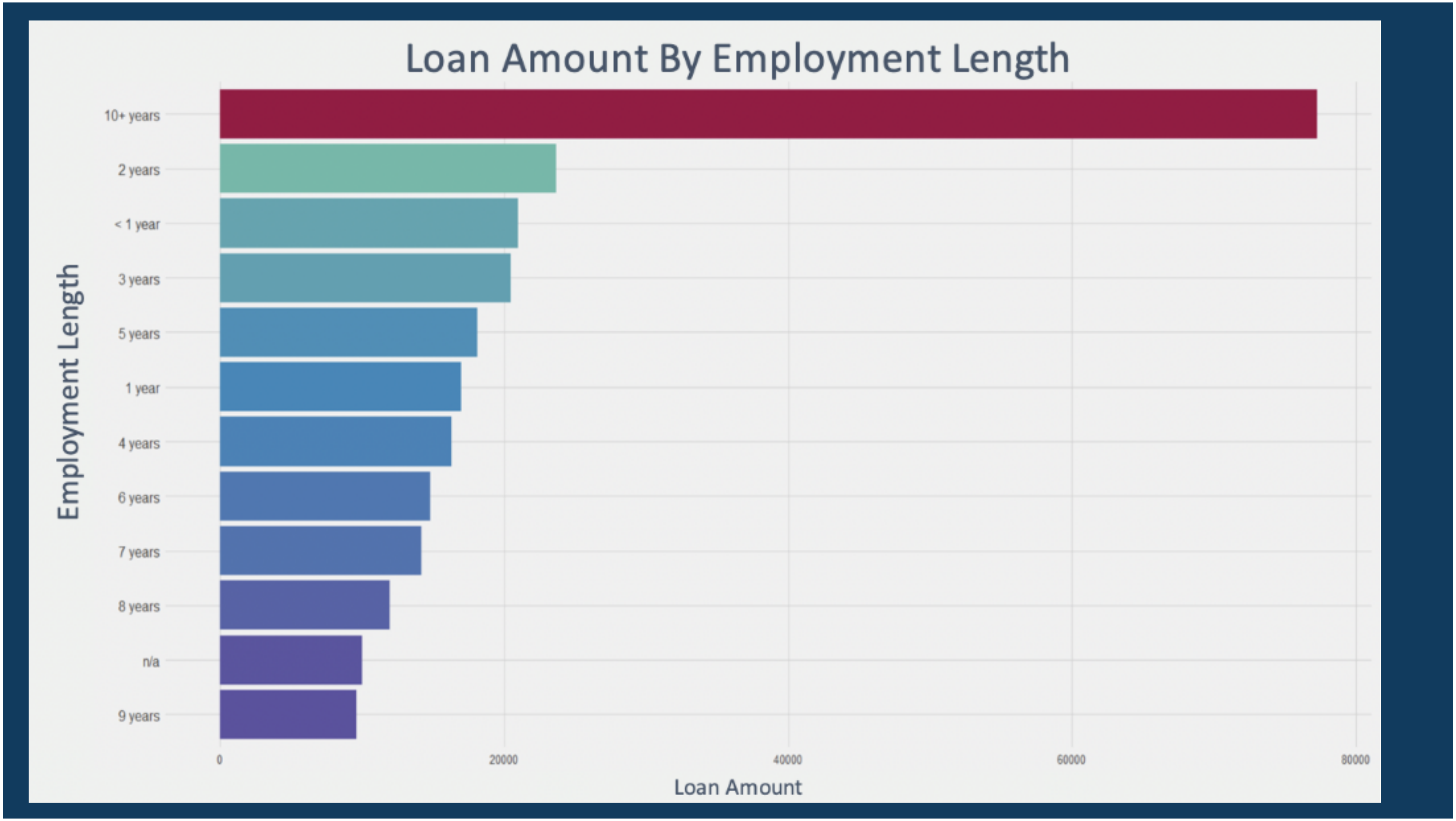


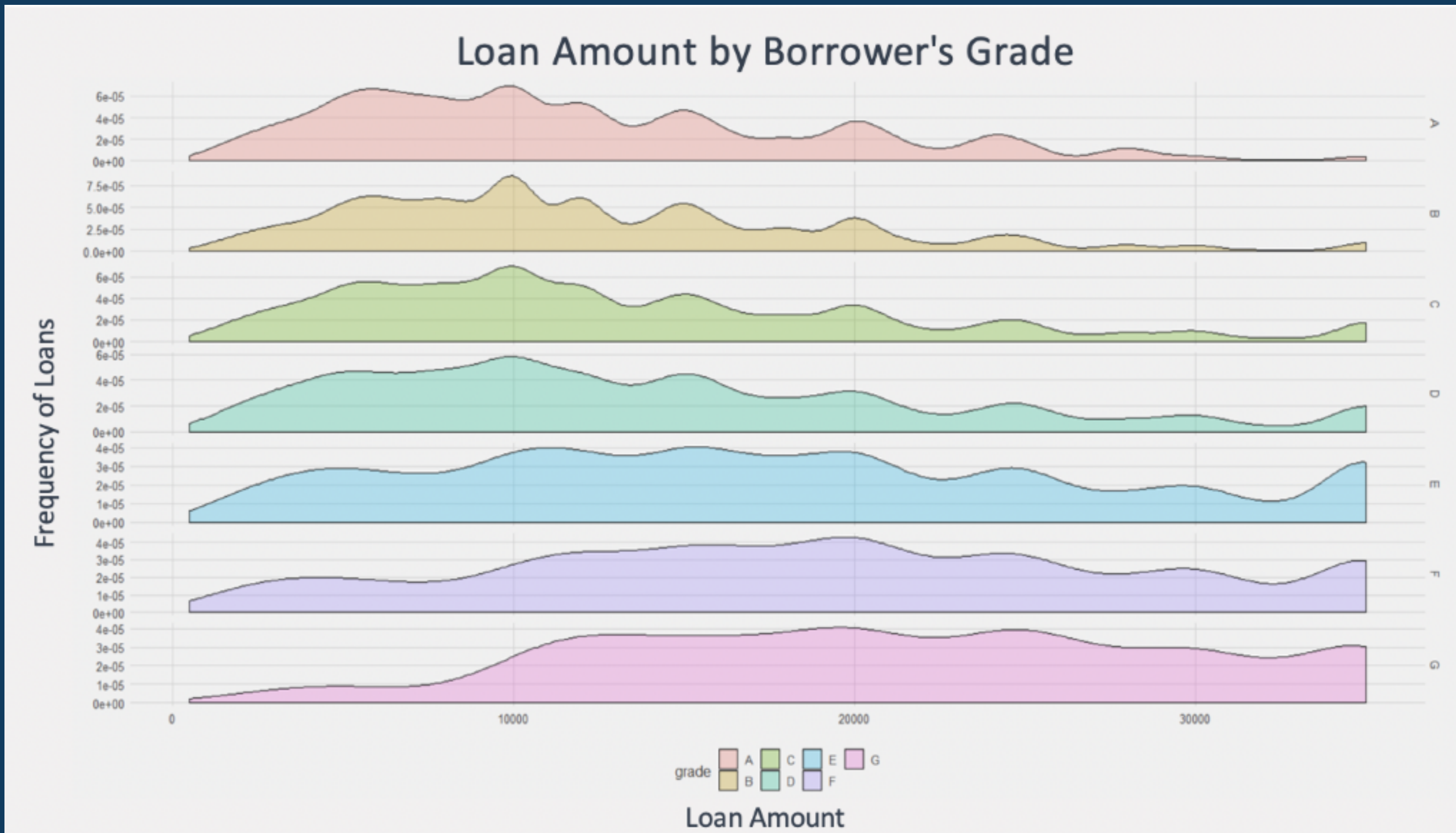
This chart shows the default rate per state. Darker colors indicate a higher average default rate. California sits in the middle, with Nevada, Florida, Alabama, Missouri, Indiana, Tennessee, and Mississippi holding the biggest default rates.



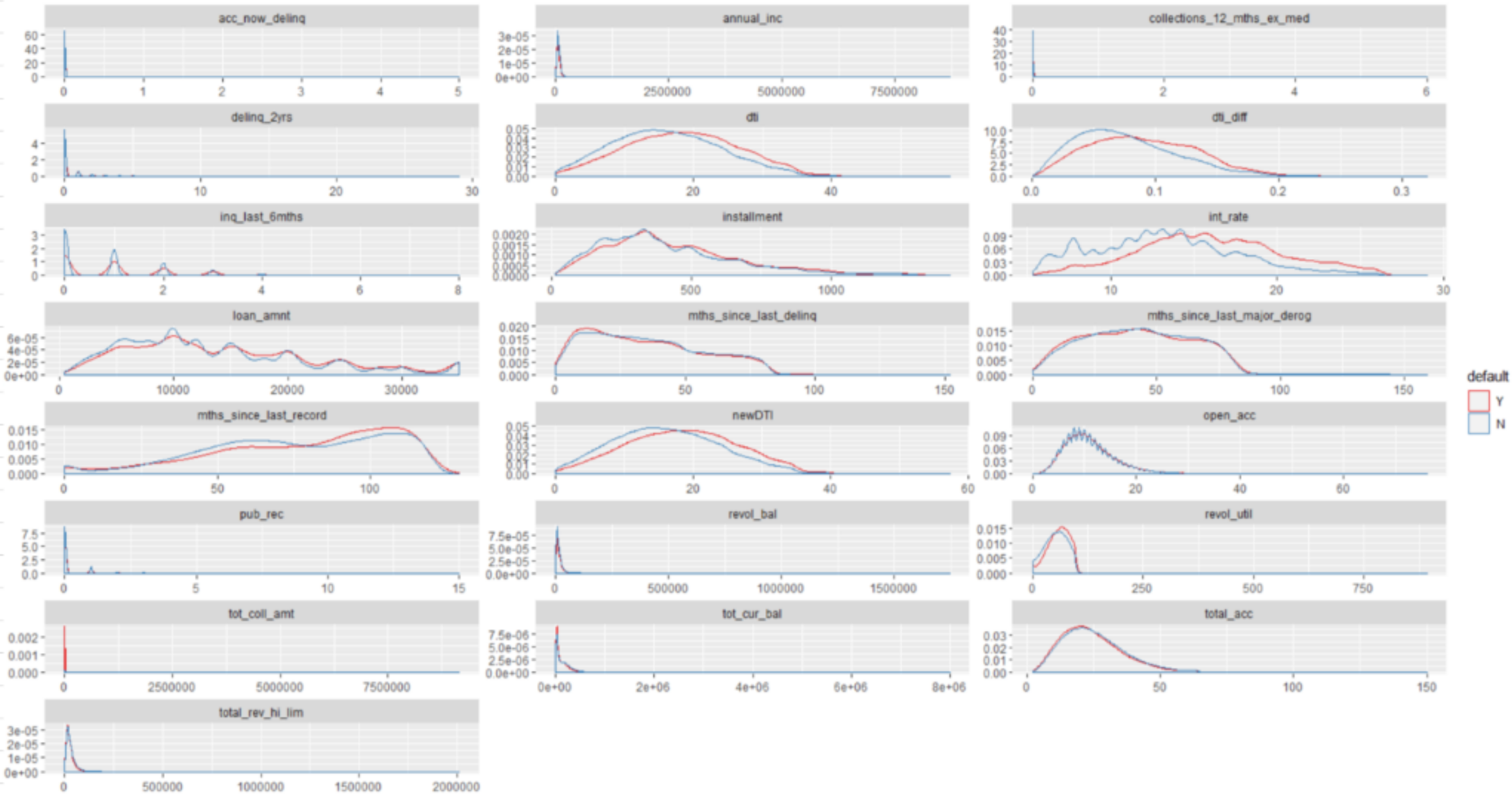
Average Interest Rate by Grade
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Interest Rate
A
B
C
D
E
F
G
Grade


Mean Default Rate by Interest Rate
Default Rate
0.4
0.3
0.2
0.1
0.0
0-.10
.10-.15
.15-.20
.20-.25
Interest Rate (binned)


Loan Amount By Employment Length
Employment Length
10+ years
2 years
< 1 year
3 years
5 years
1 year
4 years
6 years
7 years
8 years
n/a
9 years
0
20000
40000
60000
80000
Loan Amount


Loan Amount by Borrower's Grade
Frequency of Loans
Loan Amount
grade
A
B
C
D
E
F
G
0
10000
20000
30000

Density plot for Default



Features With The Most Information Gain

=== Attribute selection 10 fold cross-validation (stratified), seed: 1 ===

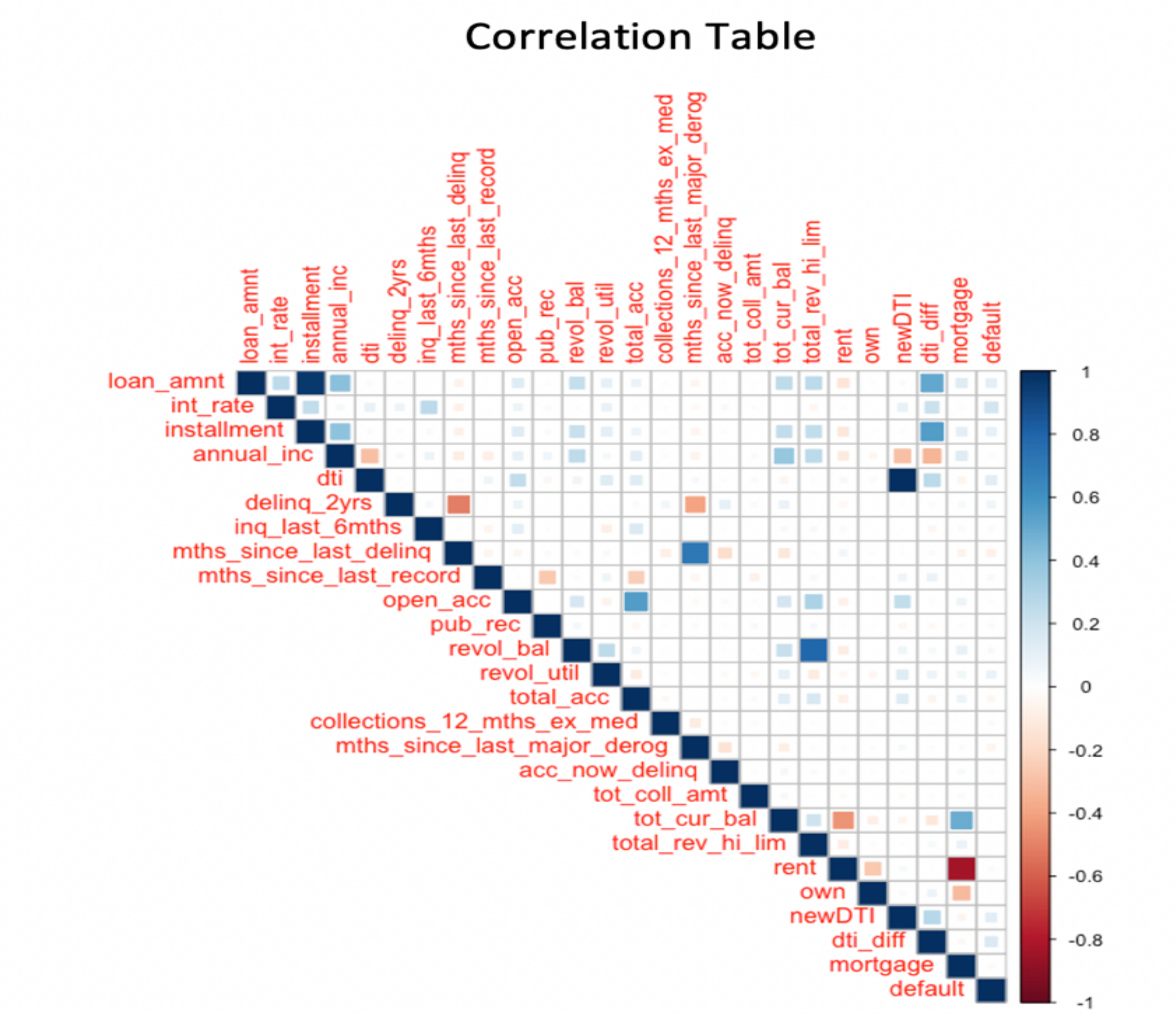
average merit	average rank	attribute
0.05 +- 0	1 +- 0	2 int_rate
0.017 +- 0	2.2 +- 0.6	29 grade_a
0.016 +- 0	3.3 +- 0.64	57 dti_diff
0.013 +- 0	6 +- 0	6 dti
0.011 +- 0	7 +- 0	52 thirtysix_mo
0.009 +- 0	8 +- 0	30 grade_b
0.008 +- 0	9 +- 0	32 grade_e
0.007 +- 0	10.4 +- 0.49	12 revol_util
0.007 +- 0	10.6 +- 0.49	4 annual_inc
0.006 +- 0	12.2 +- 0.4	17 tot_cur_bal
0.006 +- 0	12.9 +- 0.54	33 grade_f
0.005 +- 0	13.9 +- 0.3	1 loan_amnt
0.005 +- 0	15 +- 0	5 verification_status
0.004 +- 0	16.5 +- 0.5	22 mortgage _
0.004 +- 0	18.1 +- 0.54	20 rent
0.004 +- 0	18.5 +- 1.02	3 installment
0.003 +- 0	20 +- 0	18 total_rev_hi_lim
0.002 +- 0	21 +- 0	8 inq_last_6mths
0.002 +- 0	22 +- 0	34 grade_g
0.001 +- 0	23 +- 0	48 credit_age
0.001 +- 0	24 +- 0	13 total_acc
0.001 +- 0	25 +- 0	51 application_type_dummy
0.001 +- 0	26.4 +- 0.49	53 Last_Record
0.001 +- 0	27.2 +- 0.87	37 Small_Business
0.001 +- 0	27.4 +- 0.66	27 emp_length_10plus
0.001 +- 0	29 +- 0	50 Derog
0.001 +- 0	30.2 +- 0.4	49 Delinq

These features are kept in the final analysis.

Features With The Least Information Gain

0 +- 0	31 +- 0.63	35 Credit_Card
0 +- 0	31.8 +- 0.4	11 revol_bal
0 +- 0	33.2 +- 0.4	16 tot_coll_amt
0 +- 0	34 +- 0.63	7 delinq_2yrs
0 +- 0	34.8 +- 0.4	41 Home_Improvement
0 +- 0	36.8 +- 0.98	9 open_acc
0 +- 0	37 +- 1	36 Car
0 +- 0	38.1 +- 0.83	31 grade_c
0 +- 0	38.1 +- 0.94	14 collections_12_mths_ex_med
0 +- 0	40 +- 0	38 Purpose_Other
0 +- 0	41.2 +- 0.6	44 Moving
0 +- 0	42.5 +- 0.92	43 Medical
0 +- 0	43.1 +- 0.83	10 pub_rec
0 +- 0	43.2 +- 0.75	24 emp_length_lessthan1
0 +- 0	45.2 +- 0.4	25 emp_length_1to5
0 +- 0	45.8 +- 0.4	42 Major_Purchase
0 +- 0	49 +- 0.63	47 Renewable
0 +- 0	49.9 +- 2.66	21 own
0 +- 0	50.4 +- 3.38	46 House
0 +- 0	50.8 +- 2.09	26 emp_length_6to9
0 +- 0	51.2 +- 2.75	40 Debt_Consolidation
0 +- 0	52.2 +- 1.78	45 Vacation
0 +- 0	52.5 +- 3.64	28 emp_length_is_NA
0 +- 0	52.8 +- 3.16	15 acc_now_delinq
0 +- 0	53 +- 2.37	39 Wedding
0 +- 0	53.2 +- 0.87	23 other

These features are removed in the final analysis.

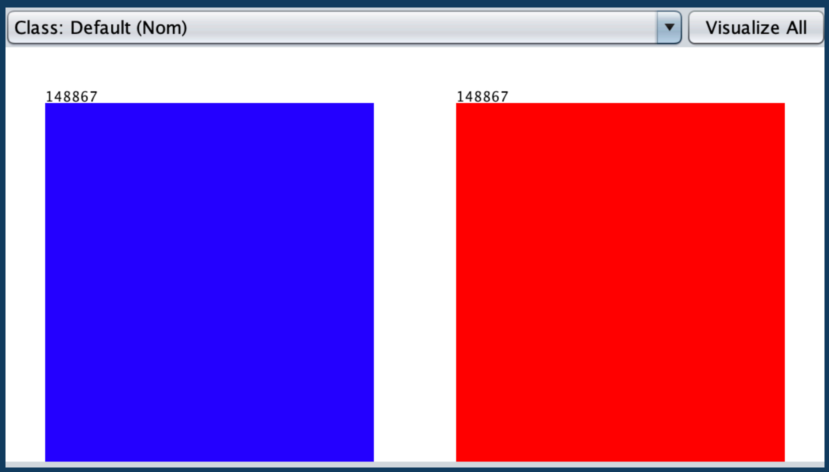


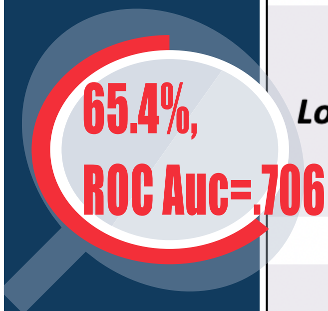
Interesting correlations between variables

- Dti (debt-to-income ratio)
- **Dti_diff (=difference between dti and the new dti)**
- **Int_rate**
- Loan_amnt
- Rent and tot_cur_bal (total current balance of all accounts)

Models

Oversampling





		Oversampling				No resampling	
		With *dti_diff*		Without *dti_diff*			
		Class: 1	Class: 0	Class: 1	Class: 0	Class:1	Class: 0
Logistic Regression	**precision:**	0.348	0.864	0.345	0.865	0.544	0.786
	recall:	0.637	0.659	0.647	0.649	0.058	0.986
	weighted accuracy:	65.41%		64.85%		78.00%	
	ROC Area	0.706		0.705			
J48 Decision Tree	**precision:**	0.333	0.865	0.332	0.864	0.583	0.784
	recall:	0.658	0.624	0.657	0.622	0.042	0.991
	weighted accuracy:	63.13%		63.00%		0.78%	
	ROC Area	0.684		0.684		0.641	
Random Forest	**precision:**	0.367	0.856	0.869	0.687	0.78	0.997
	recall:	0.577	0.716	0.605	0.687	0.692	0.0187
	weighted accuracy:	68.50%		66.90%		78%	
	ROC Area	0.396		0.412		0.3	
Naïve Bayes	**precision:**	0.338	0.865	0.333	0.866	0.835	0.384
	recall:	0.651	0.636	0.666	0.619	0.793	0.451
	weighted accuracy:	63.90%		62.90%		0.74%	
	ROC Area	0.695		0.693		0.69	

Conclusion

- Random Forest is the best model, followed by Logistic Regression.

- Recommendation for investors: buy loans which are in Grade A and have smaller loan amounts and from borrowers who have a low dti (debt-to-income ratio).

THANK YOU

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How to find us

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