

Loan Prediction on LendingClub Issued Loans Dataset

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Visual Analytics

**20th December 2021
Final Project**

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Introduction and Motivation



Description, objectives and expected benefits

DESCRIPTION

- Project applying good visualisation techniques to find good loans.

OBJECTIVES

- Develop a classification model
- Create a training dataset
- Create a cluster method
- Identify the most important causes

EXPECTED BENEFITS

- Assess whether or not a new customer is likely to pay back the loan.



LendingClub Bank, N.A.

DATASET

- Lending Club, a US peer-to-peer lending company.
- Issued Loans between 2007 and 2017.
- 1,646,717 rows
- 74 columns

REQUIRED DATA

- **Customer data:** Home ownership, annual income, loan purpose
- **Loan data:** Loan amount, term, interest rate, grade, loan status, ...
- **Location**

Visualization

Good visualisations of the data so that it is easy and fast to understand the underlying characteristics of the data



MATPLOTLIB/SEABORN



PANDAS PROFILING



TABLEAU DASHBOARD



Python Code in Jupyter Notebook


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1646717 entries, 0 to 1646716
Data columns (total 74 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   id                                     1646717 non-null  int64
1   member_id                             887379 non-null   float64
2   loan_amnt                             1646717 non-null   float64
3   funded_amnt                           1646717 non-null   float64
4   funded_amnt_inv                       1646717 non-null   float64
5   term                                  1646717 non-null   object
6   int_rate                              1646717 non-null   float64
7   installment                           1646717 non-null   float64
8   grade                                 1646717 non-null   object
9   sub_grade                             1646717 non-null   object
10  emp_title                             1544285 non-null   object
11  emp_length                             1551529 non-null   object
12  home_ownership                         1646717 non-null   object
13  annual_inc                             1646713 non-null   float64
14  verification_status                   1646717 non-null   object
15  issue_d                               1646717 non-null   object
16  loan_status                           1646717 non-null   object
17  pymnt_plan                             1646717 non-null   object
18  url                                    887379 non-null   object
19  desc                                  126045 non-null   object
20  purpose                               1646717 non-null   object
21  title                                 1623392 non-null   object
22  zip_code                              1646716 non-null   object
23  addr_state                             1646717 non-null   object
24  dti                                    1646362 non-null   float64
25  delinq_2yrs                           1646688 non-null   float64
26  earliest_cr_line                       1646688 non-null   object
27  inq_last_6mths                         1646687 non-null   float64
28  mths_since_last_delinq                 829700 non-null   float64
29  mths_since_last_record                 278232 non-null   float64
30  open_acc                               1646688 non-null   float64
31  pub_rec                               1646688 non-null   float64
32  revol_bal                              1646717 non-null   float64
33  revol_util                             1645698 non-null   float64
34  total_acc                              1646688 non-null   float64
35  initial_list_status                   1646717 non-null   object
36  out_prncp                              1646717 non-null   float64
37  out_prncp_inv                         1646717 non-null   float64
38  total_pymnt                             1646717 non-null   float64
39  total_pymnt_inv                       1646717 non-null   float64
40  total_rec_prncp                       1646717 non-null   float64
41  total_rec_int                         1646717 non-null   float64
42  total_rec_late_fee                    1646717 non-null   float64
43  recoveries                             1646717 non-null   float64
44  collection_recovery_fee               1646717 non-null   float64
45  last_pymnt_d                           1628110 non-null   object
46  last_pymnt_amnt                       1646717 non-null   float64
47  next_pymnt_d                           1225831 non-null   object
48  last_credit_pull_d                     1646646 non-null   object
49  collections_12_mths_ex_med            1646572 non-null   float64
50  mths_since_last_major_derog           436808 non-null   float64
51  policy_code                            1646717 non-null   float64
52  application_type                       1646717 non-null   object
53  annual_inc_joint                       34514 non-null    float64
54  dti_joint                              34510 non-null    float64
55  verification_status_joint             34514 non-null    object
56  acc_now_delinq                         1646688 non-null   float64
57  tot_coll_amt                           1576441 non-null   float64
58  tot_cur_bal                            1576441 non-null   float64
59  open_acc_6m                           780648 non-null    float64
60  open_il_6m                             21372 non-null    float64
61  open_il_12m                           780649 non-null    float64
62  open_il_24m                           780649 non-null    float64
63  mths_since_rcnt_il                    759605 non-null    float64
64  total_bal_il                           780649 non-null    float64
65  il_util                                677360 non-null    float64
66  open_rv_12m                           780649 non-null    float64
67  open_rv_24m                           780649 non-null    float64
68  max_bal_bc                             780649 non-null    float64
69  all_util                                780596 non-null    float64
70  total_rev_hi_lim                       1576441 non-null   float64
71  inq_fi                                 780649 non-null    float64
72  total_cu_tl                            780648 non-null    float64
73  inq_last_12m                          780648 non-null    float64

dtypes: float64(50), int64(1), object(23)
memory usage: 929.7+ MB
```

Exploratory Data Analysis (EDA)

- Current loans
- NaN
- Non-relevant features
- Formatting
- Data leakage
- Bad/Good loan definition

Result:

- 1,646,717 → 370,702 rows
- 74 → 50 columns

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	total_bal_il	il_util	open_rv_12m	open.
0	1077501	1296599.0	5000.0	5000.0	4975.0	36 months	10.65	162.87	B	B2	...	NaN	NaN	NaN	
1	1077430	1314167.0	2500.0	2500.0	2500.0	60 months	15.27	59.83	C	C4	...	NaN	NaN	NaN	
2	1077175	1313524.0	2400.0	2400.0	2400.0	36 months	15.96	84.33	C	C5	...	NaN	NaN	NaN	
3	1076863	1277178.0	10000.0	10000.0	10000.0	36 months	13.49	339.31	C	C1	...	NaN	NaN	NaN	
4	1075358	1311748.0	3000.0	3000.0	3000.0	60 months	12.69	67.79	B	B5	...	NaN	NaN	NaN	

5 rows × 74 columns

Data Wrangling

Data pre-processing

- One Hot Encoding
- Label Encoding

Over-sampling

- SMOTE

Down-sampling

- Random under sampling

Correlation analysis

- Deletion of high correlated variables

Grade:

{A, B, C, D, E, F, G} → {0, 1, 2, 3, 4, 5, 6, 7}

Payment Plan:

{'y', 'n'} → {0,1}

Before:

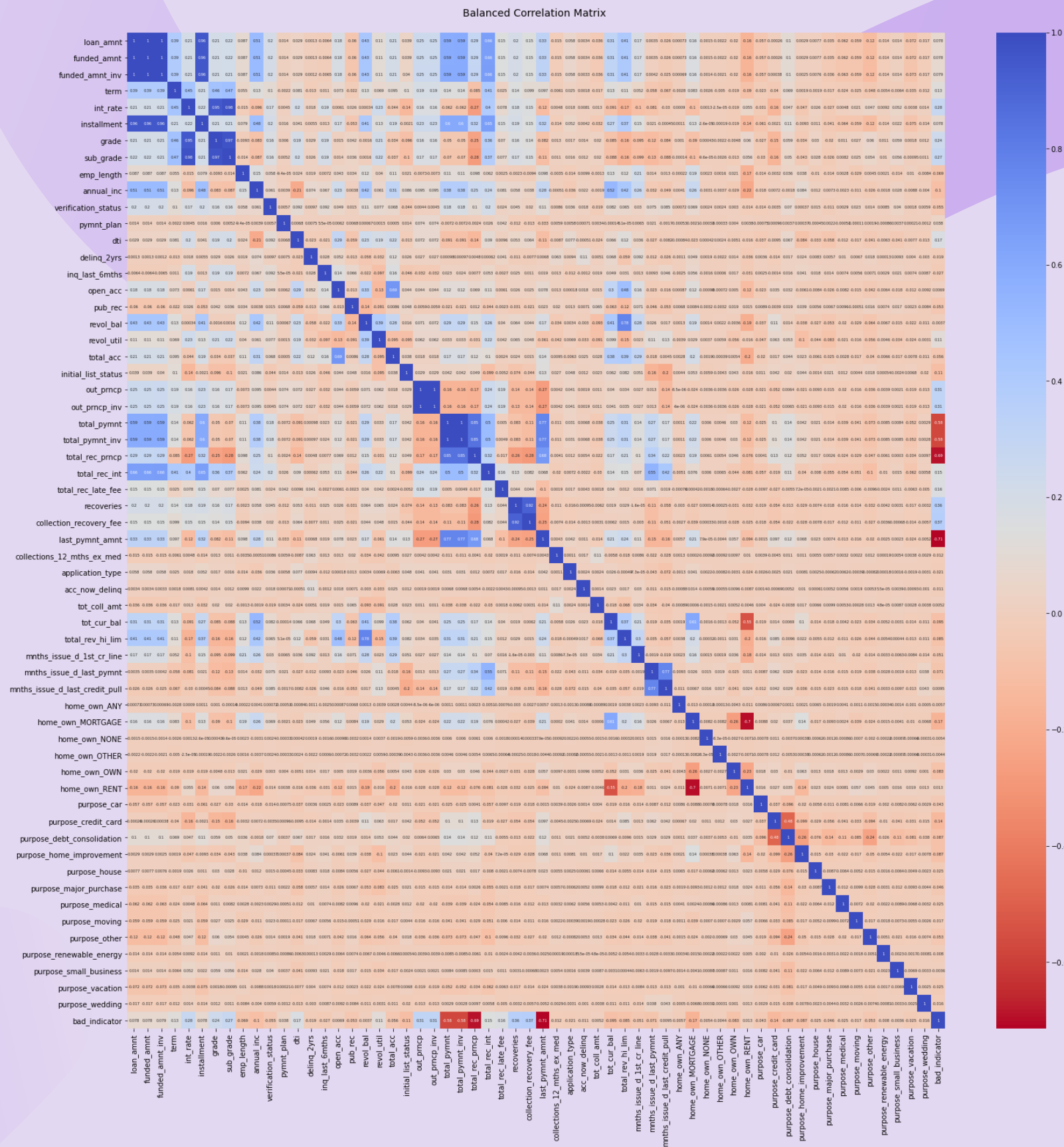
75% Good loans - 25% Bad loans

After:

52% Good loans - **48%** Bad loans

Data Wrangling

10 Most Correlated



Pandas profiling

Overview

Overview

Alerts

40

Reproduction

Dataset statistics

Number of variables	49
Number of observations	409072
Missing cells	0
Missing cells (%)	0.0%
Total size in memory	148.2 MiB
Average record size in memory	380.0 B

Variable types

Numeric	49
---------	----

- General dataset's overview
- Variable distribution
- Irrelevant variable (All values the same, 0, ...)

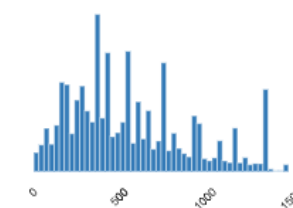
Variables

loan_amnt

Real number ($\mathbb{R}_{\geq 0}$)

Distinct	1481
Distinct (%)	0.4%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Mean	559.0586792

Minimum	0
Maximum	1480
Zeros	1258
Zeros (%)	0.3%
Negative	0
Negative (%)	0.0%
Memory size	3.1 MiB



Toggle details

Classification Modelling

Logistic Regression (x2)

Random Forest

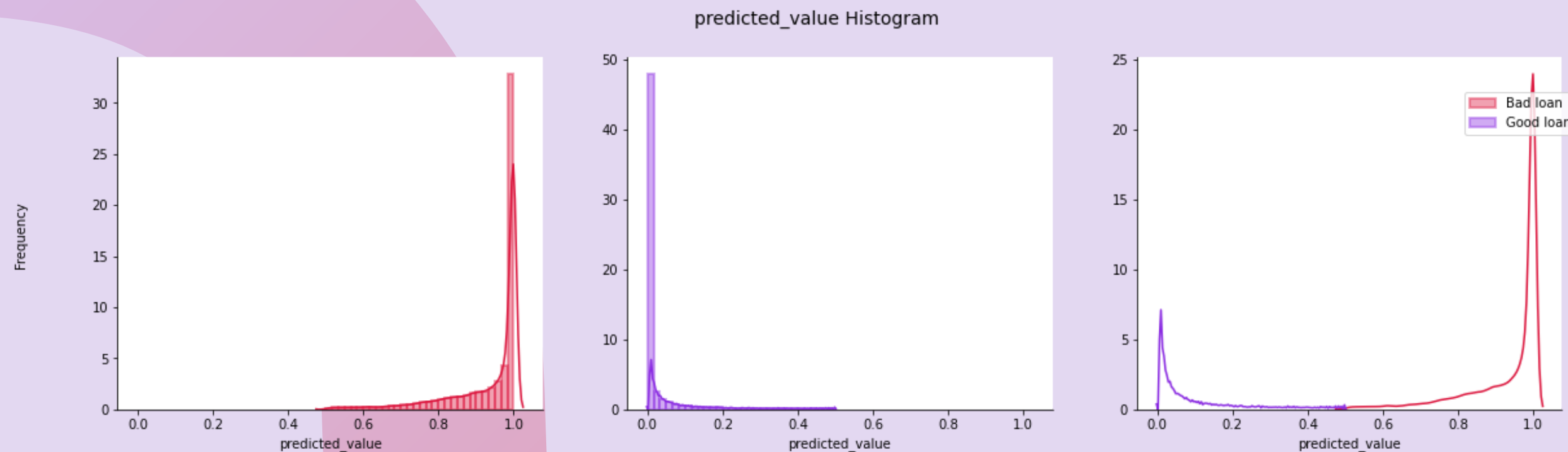
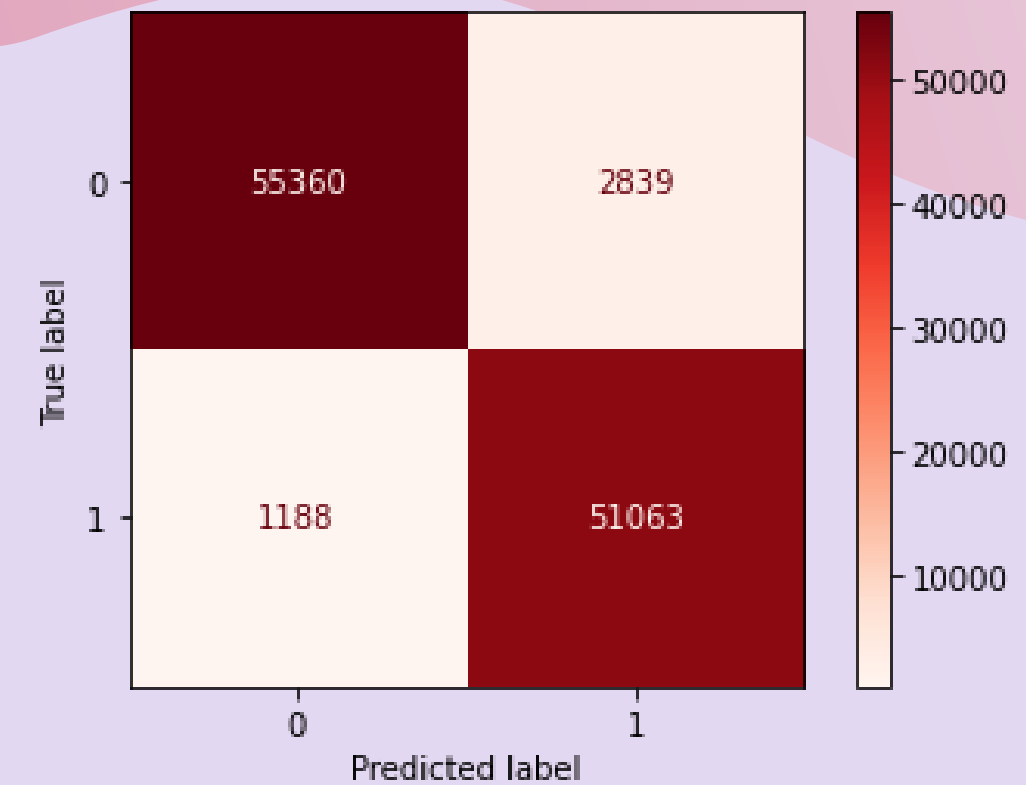
AdaBoost

Classification Modelling

Logistic Regression 1

LogisticRegression(C=1.0, max_iter=100, solver='liblinear')

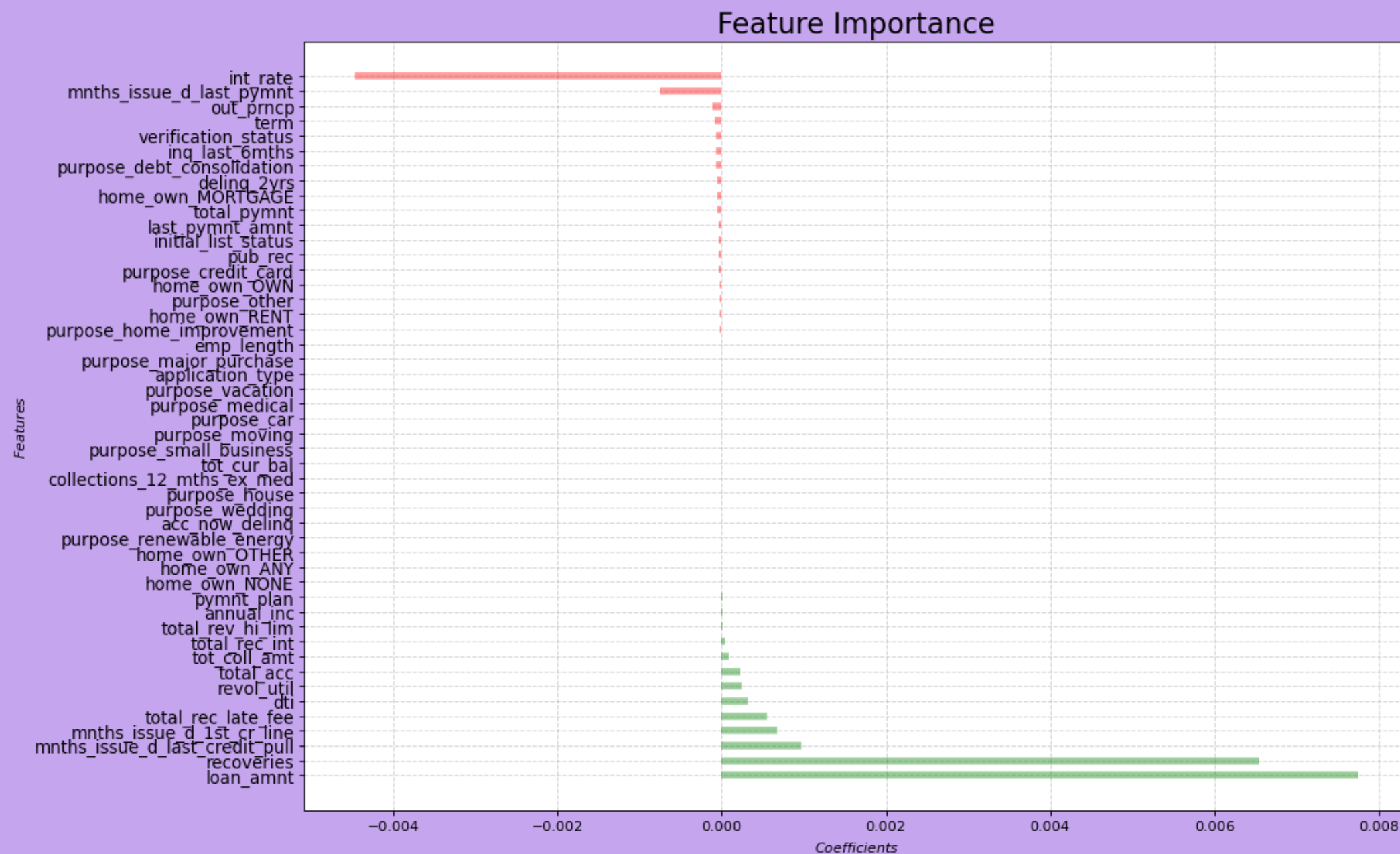
Classification report:				
	precision	recall	f1-score	support
0	0.98	0.95	0.96	58199
1	0.95	0.98	0.96	52251
accuracy			0.96	110450
macro avg	0.96	0.96	0.96	110450
weighted avg	0.96	0.96	0.96	110450



Classification Modelling

Logistic Regression 1

LogisticRegression(C=1.0, max_iter=100, solver='liblinear')



Top features:

- Loan amount
- Recoveries
- Months issue and credit pull
- Months issue and 1st credit
- Total recoveries late fee

Data Leakage:

- recoveries
- total_rec_late_fee
- total_rec_int
- total_pymnt
- last_pymnt_d
- last_pymt_amnt
- mnths_issue_d_last_pymnt
- mnths_issue_d_last_credit_pull
- out_prncp

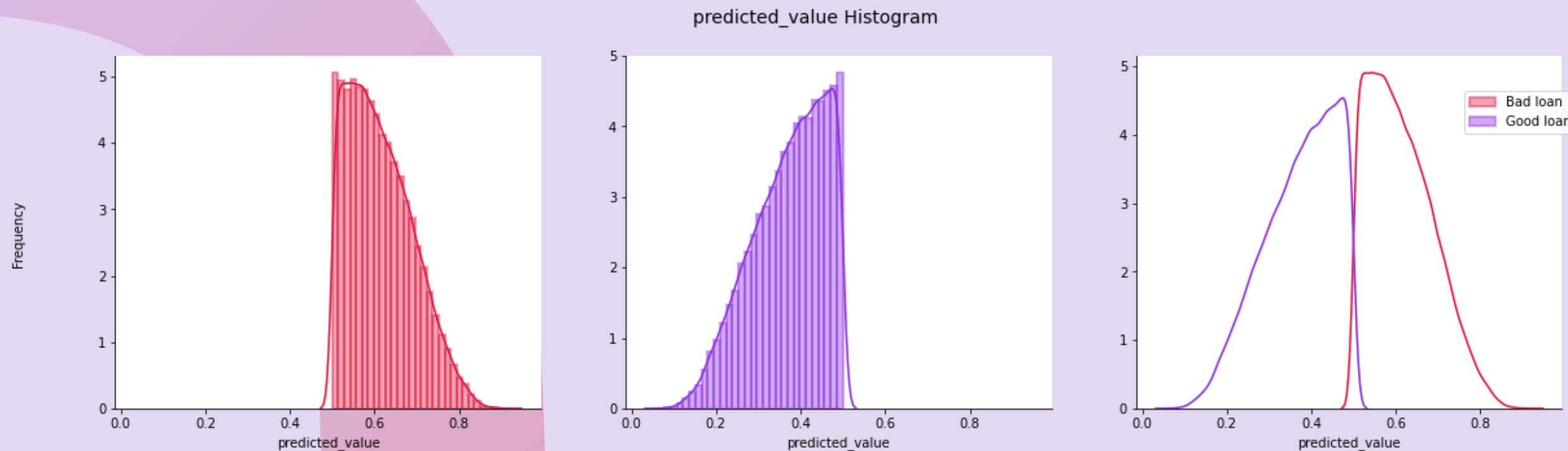
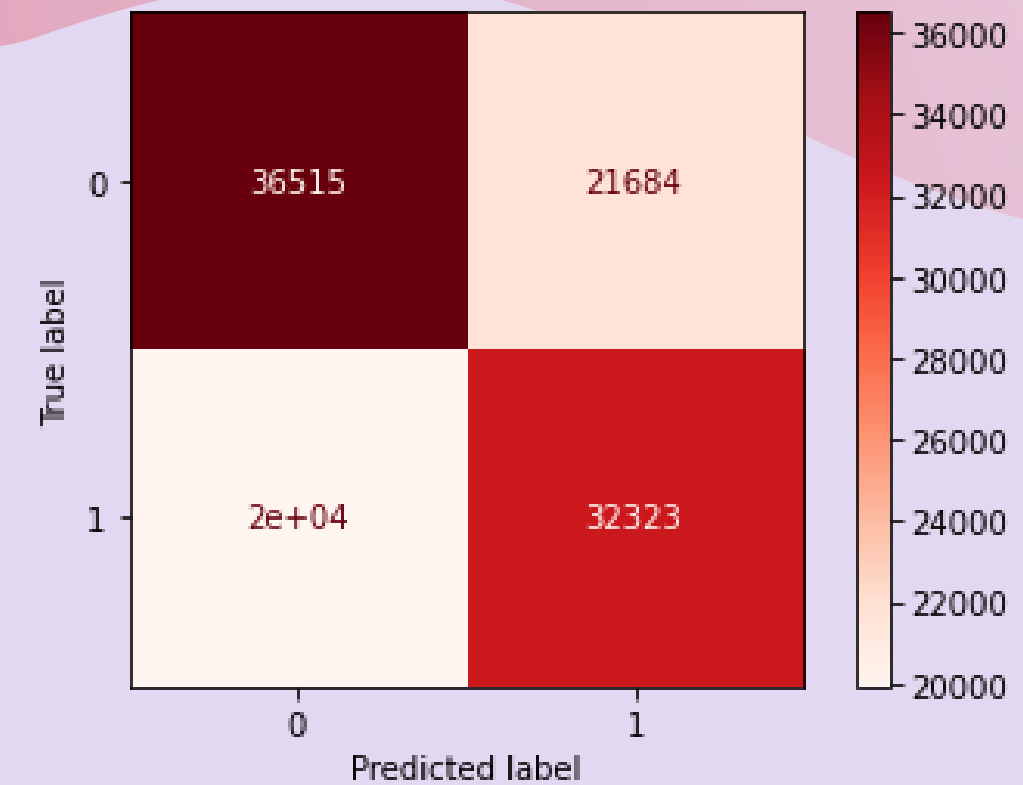
Classification Modelling

Logistic Regression 2

LogisticRegression(C=1.0, max_iter=100, solver='liblinear')

Classification report:

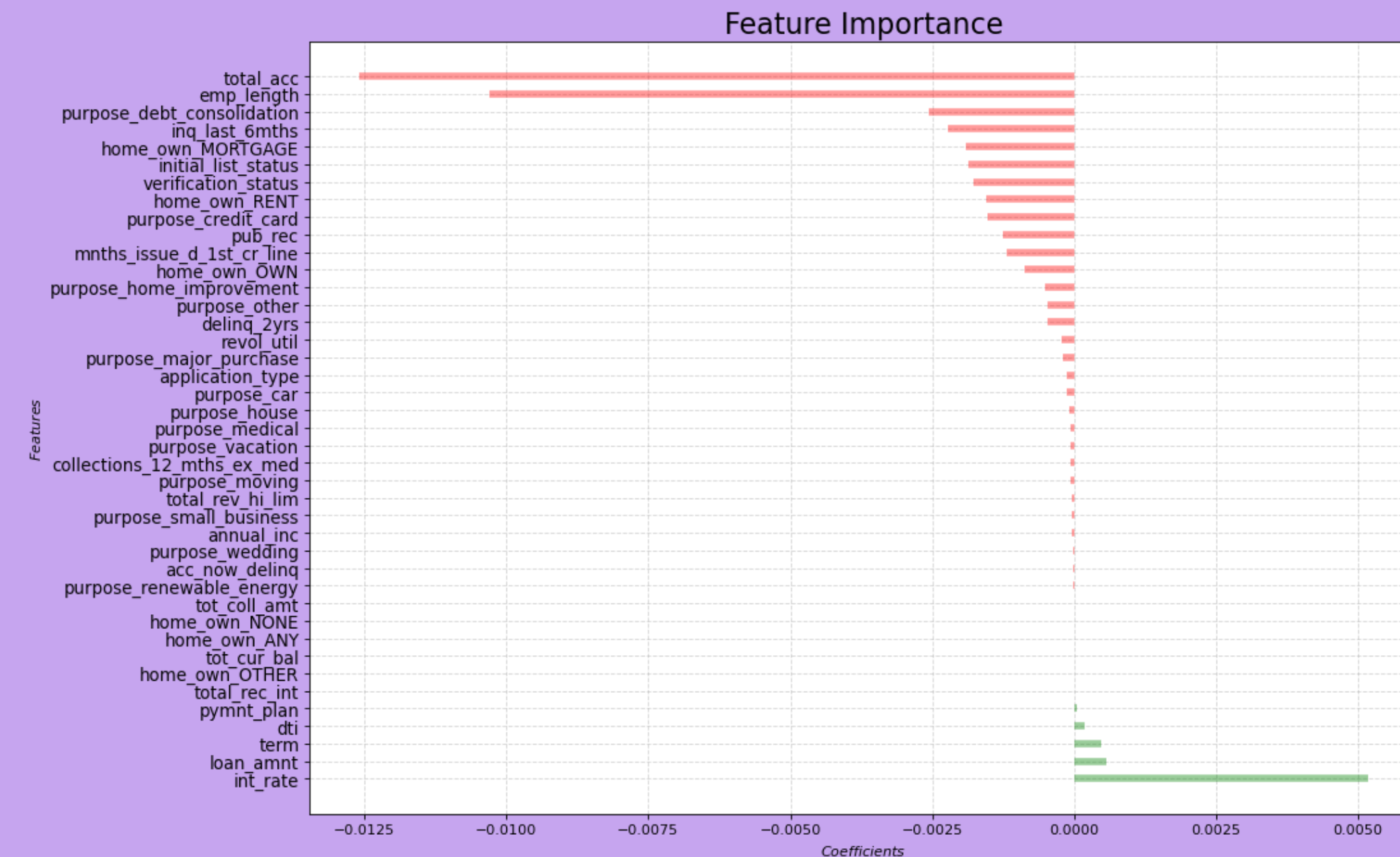
	precision	recall	f1-score	support
0	0.65	0.63	0.64	58199
1	0.60	0.62	0.61	52251
accuracy			0.62	110450
macro avg	0.62	0.62	0.62	110450
weighted avg	0.62	0.62	0.62	110450



Classification Modelling

Logistic Regression 2

LogisticRegression(C=1.0, max_iter=100, solver='liblinear')



Top features:

- Interest rate
- Loan amount
- Term
- DTI

Classification Modelling

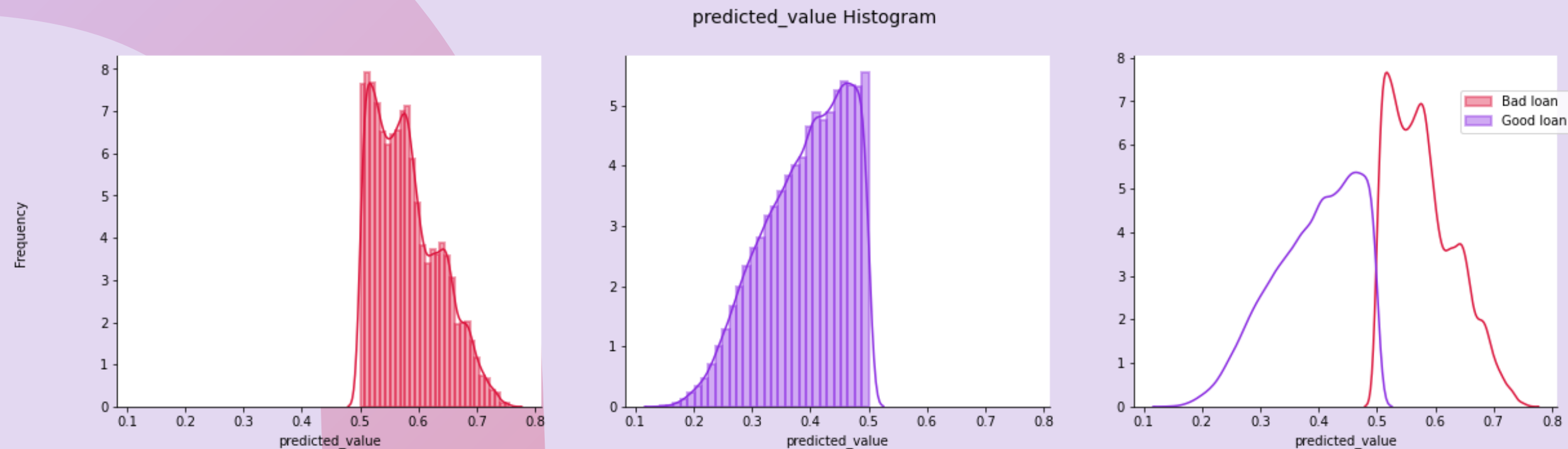
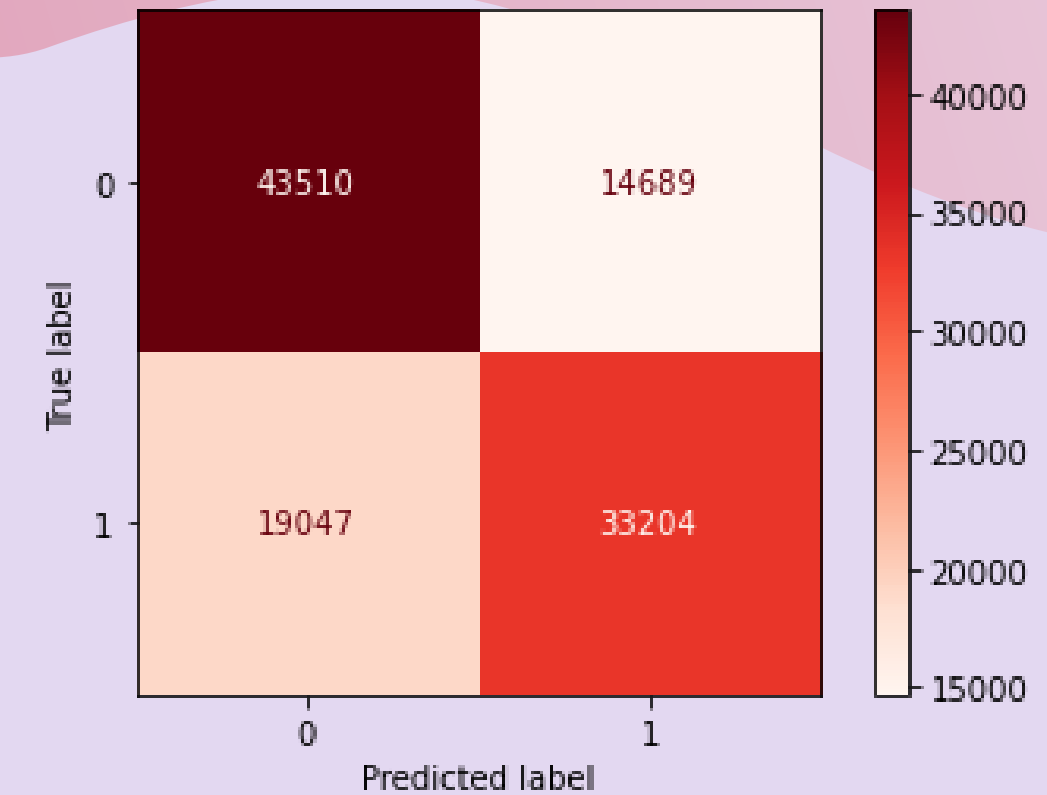
Random Forest

RandomForestClassifier(max_depth=5)

```
Classification report:
              precision    recall  f1-score   support

     0       0.70      0.75      0.72     58199
     1       0.69      0.64      0.66     52251

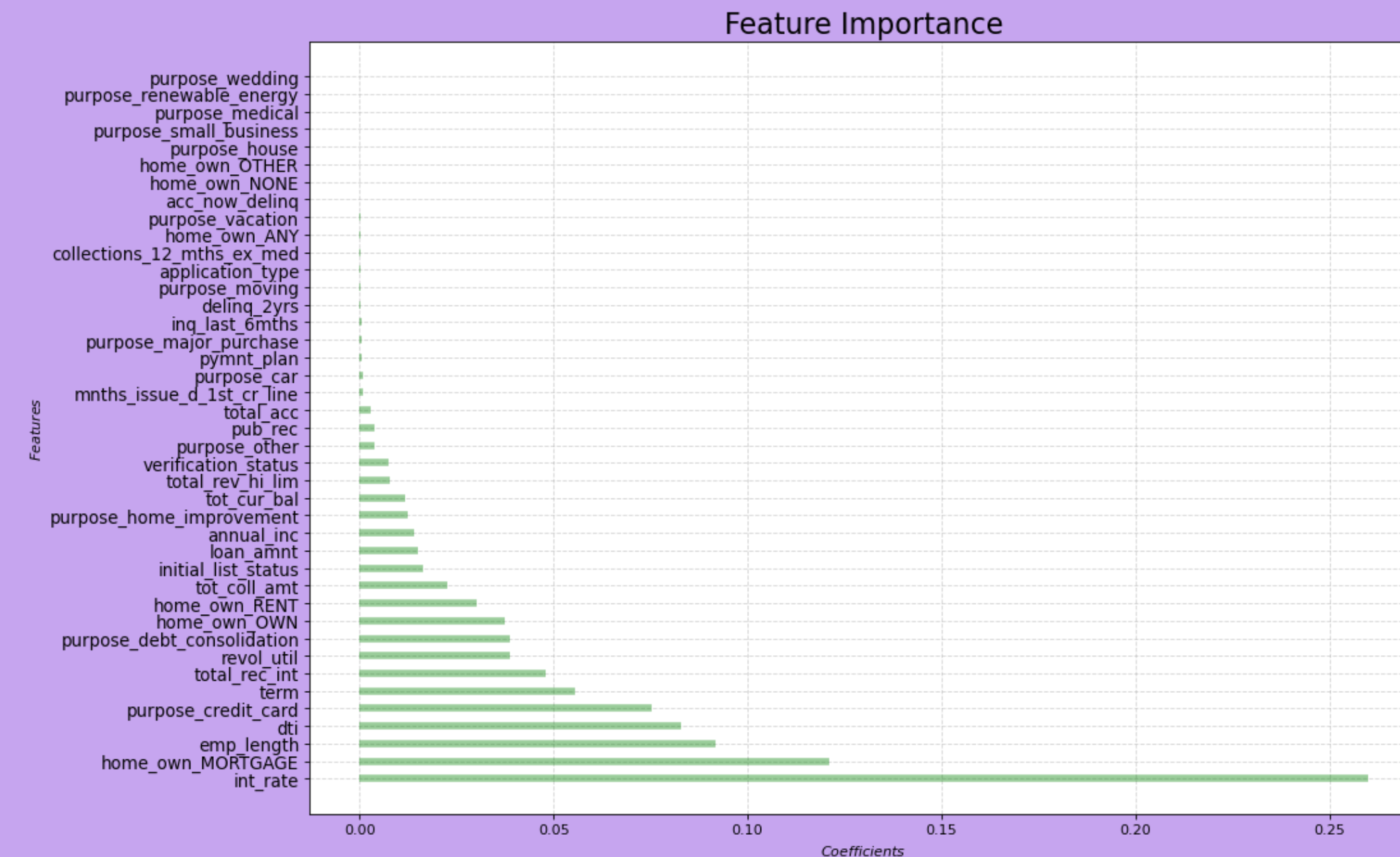
 accuracy      0.69      0.69      0.69     110450
 macro avg     0.69      0.69      0.69     110450
 weighted avg  0.69      0.69      0.69     110450
```



Classification Modelling

Random Forest

RandomForestClassifier(max_depth=5)



Top features:

- Interest rate
- Home ownership: Mortgage
- Employment length
- DTI
- Purpose: Credit card
- Term

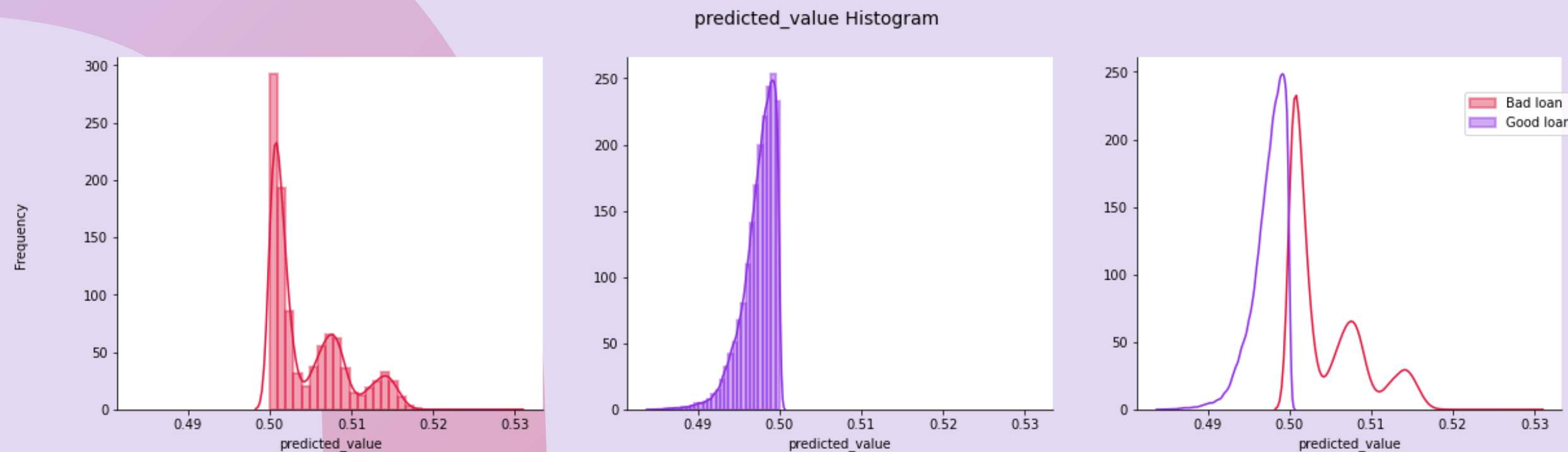
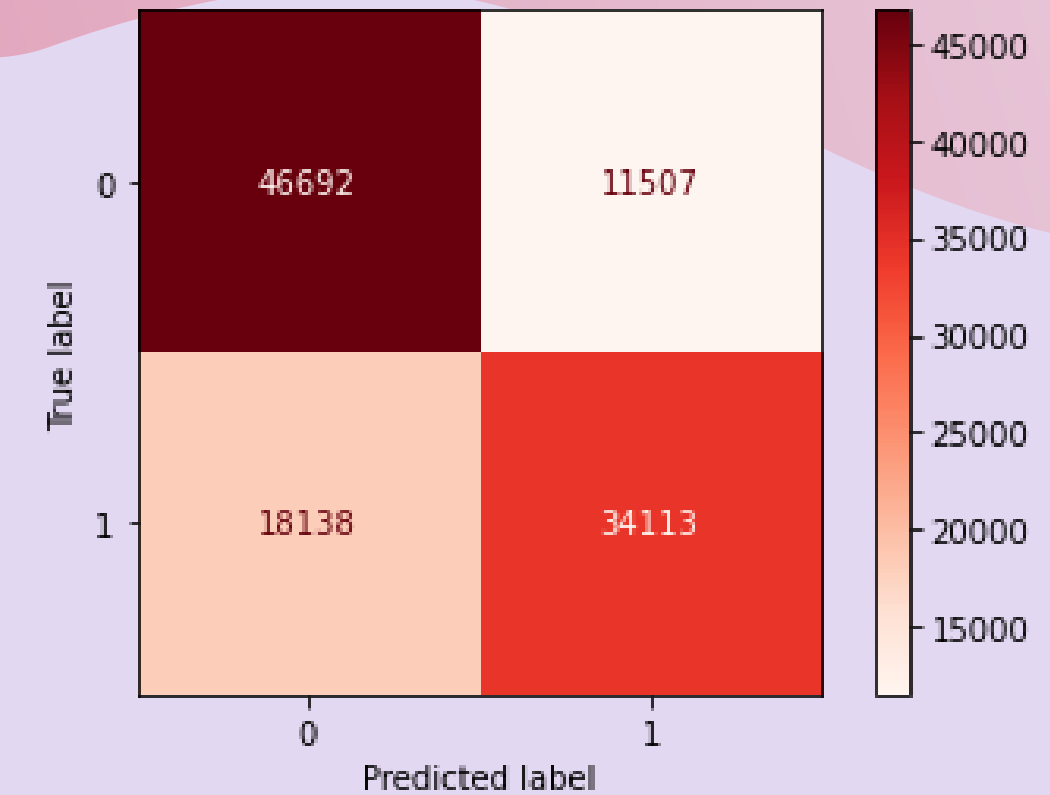
Classification Modelling

AdaBoost

AdaBoostClassifier(random_state=0, n_estimators=100)

Classification report:

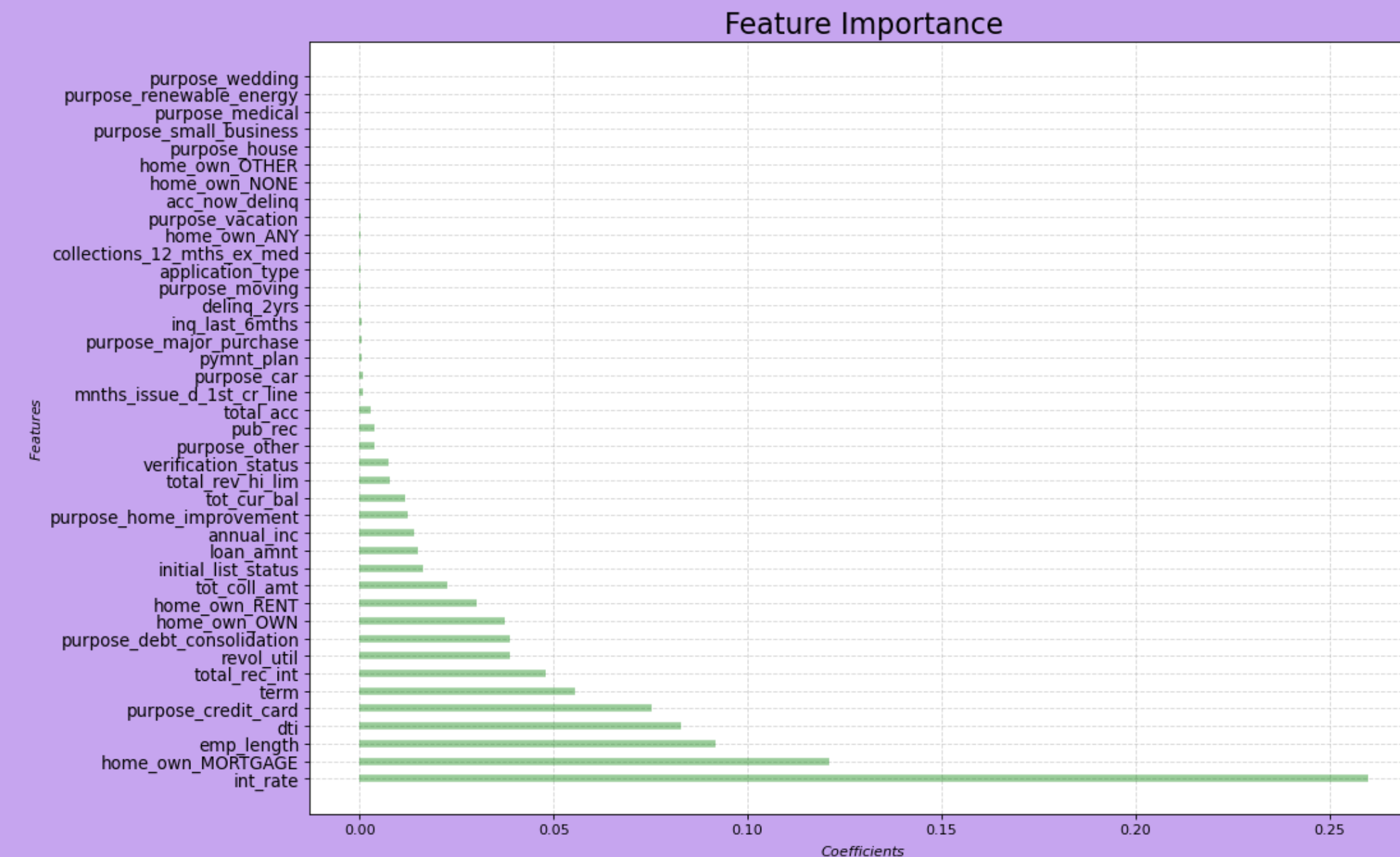
	precision	recall	f1-score	support
0	0.72	0.80	0.76	58199
1	0.75	0.65	0.70	52251
accuracy			0.73	110450
macro avg	0.73	0.73	0.73	110450
weighted avg	0.73	0.73	0.73	110450



Classification Modelling

AdaBoost

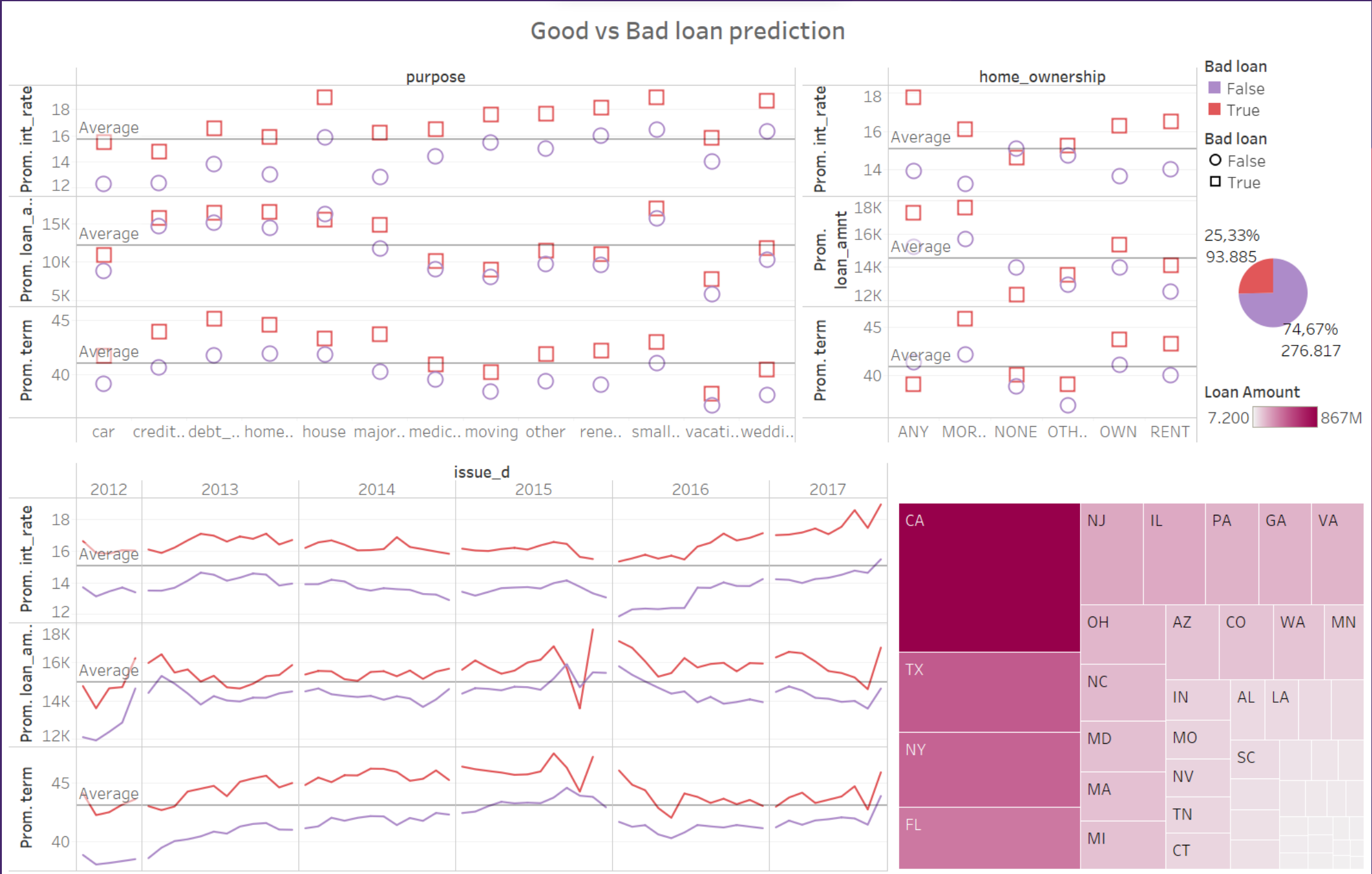
AdaBoostClassifier(random_state=0, n_estimators=100)



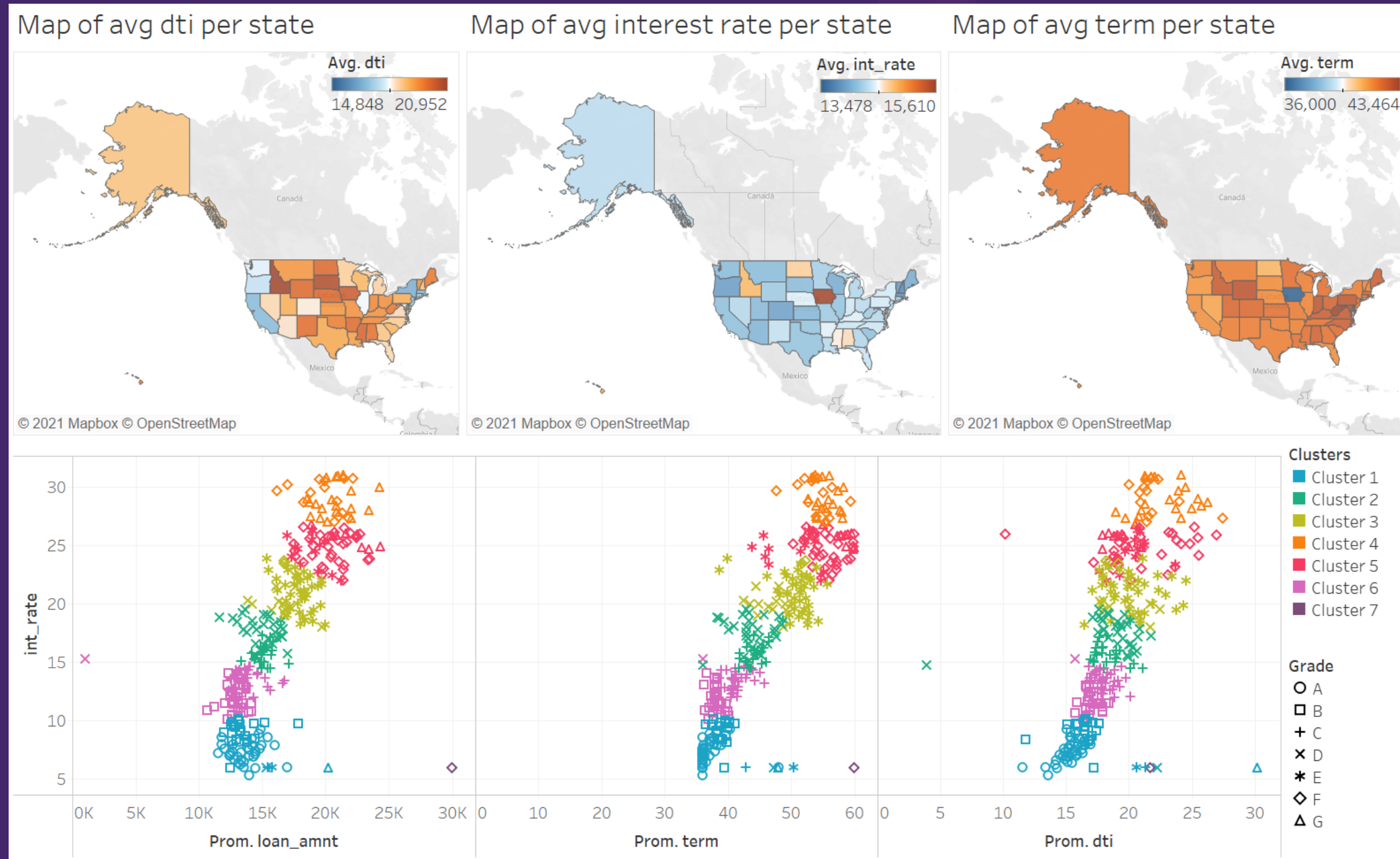
Top features:

- Home ownership: Mortgage
- Home ownership: Rent
- Purpose: Debit consolidation
- Home ownership: Own
- Interest rate

Dashboard



Dashboard



Results and Evaluation

Main features

- Interest Rate
- Loan Amount
- DTI
- Term
- Purpose
- Home ownership

Future work

- Cluster loans into ranges
- Parameter fine-tuning
- More/Different relevant features
- More/Different models

Bibliography

- <https://www.kaggle.com/husainsb/lendingclub-issued-loans>
- <https://www.kaggle.com/ethon0426/lending-club-20072020q1>



Thank you for your attention!

Any doubts?

VISUAL ANALYTICS FINAL PROJECT:
LOAN PREDICTION ON LENDINGCLUB ISSUED
LOANS DATASET

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20/12/2021