PREDICTING LOAN DEFAULTS USING LOGISTIC REGRESSION

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Approach and method

- Project
- Dataset
- Data exploration
- Feature engineering
- Classification
  - Building basic logistic regression model
  - Optimising model parameters
- Results
- Conclusion
- Appendix

Project

- Predict customers' creditworthiness
  (i.e. whether they will complete or default on a loan)
- Build and test a logistic regression model
- Use 70% of the data to build the model and then test the model using the remaining 30%

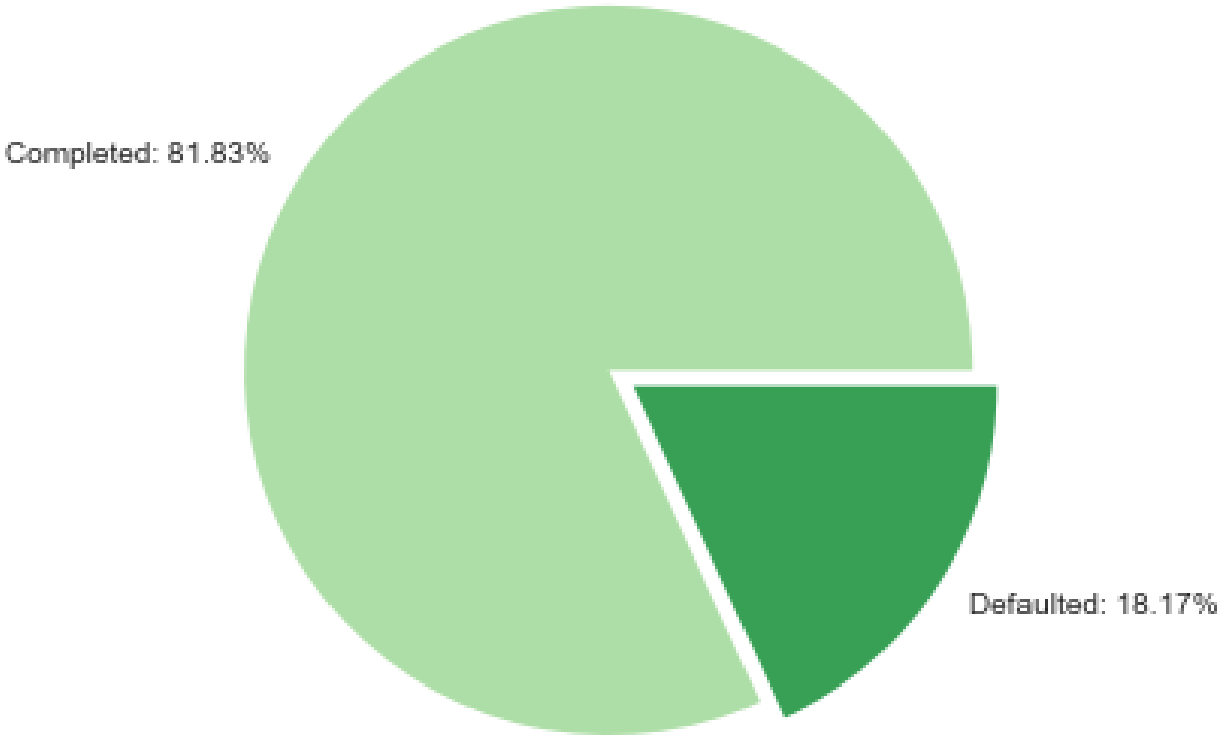
Lending Club dataset

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24776 entries, 0 to 24775
Data columns (total 21 columns):
Loan Amount                          24776 non-null int64
Loan Term                            24776 non-null object
Employment Length                    24776 non-null float64
Home Ownership                       24776 non-null object
Annual Income                        24776 non-null float64
Loan Purpose                         24776 non-null object
Address State                        24775 non-null object
Debt To Income Ratio                 24775 non-null float64
No. Delinquencies In Last 2 Years    24775 non-null object
Earliest Credit Line Opened          24776 non-null float64
FICO Credit Score                    24775 non-null float64
No. Inquiries In Last 6 Months       24775 non-null float64
Months Since Last Delinquency        24776 non-null int64
No. Of Credit Lines                  24775 non-null float64
No. Adverse Public Records           24775 non-null object
Total Credit Balance                 24775 non-null float64
Use Of Credit Line                   24724 non-null float64
Total Number Of Credit Lines         24775 non-null float64
Loan Application Description         24776 non-null int64
No. Of Public Record Bankruptcies    24776 non-null object
Class                                24776 non-null object
dtypes: float64(10), int64(3), object(8)
memory usage: 4.0+ MB
```

The data contains rows of customers, with each column showing the features for loan applications that have been approved, together with outcomes of the loans (in the final column ‘Class’).

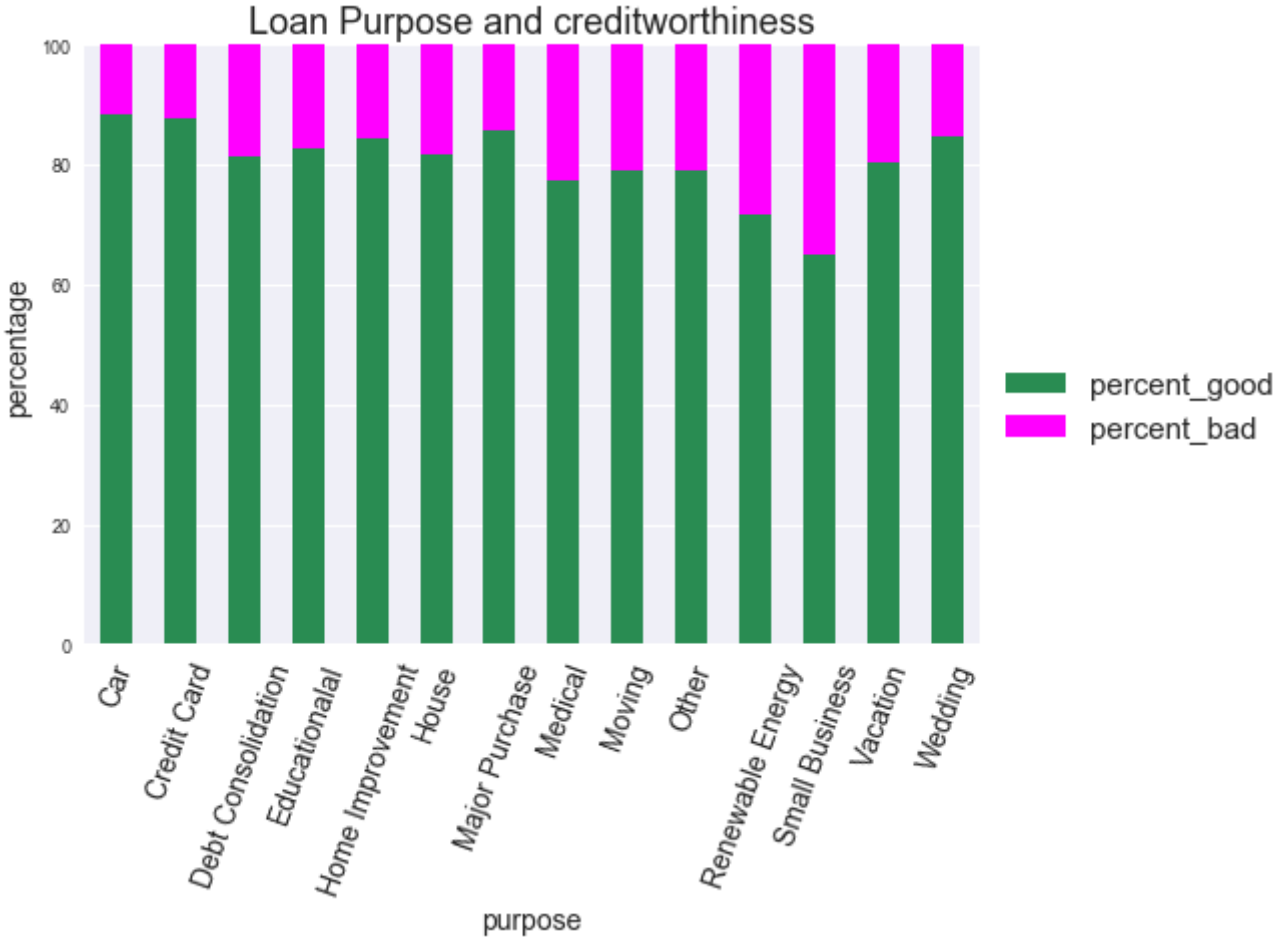
The outcomes show that each customer has either defaulted or completed their loan.

Data exploration



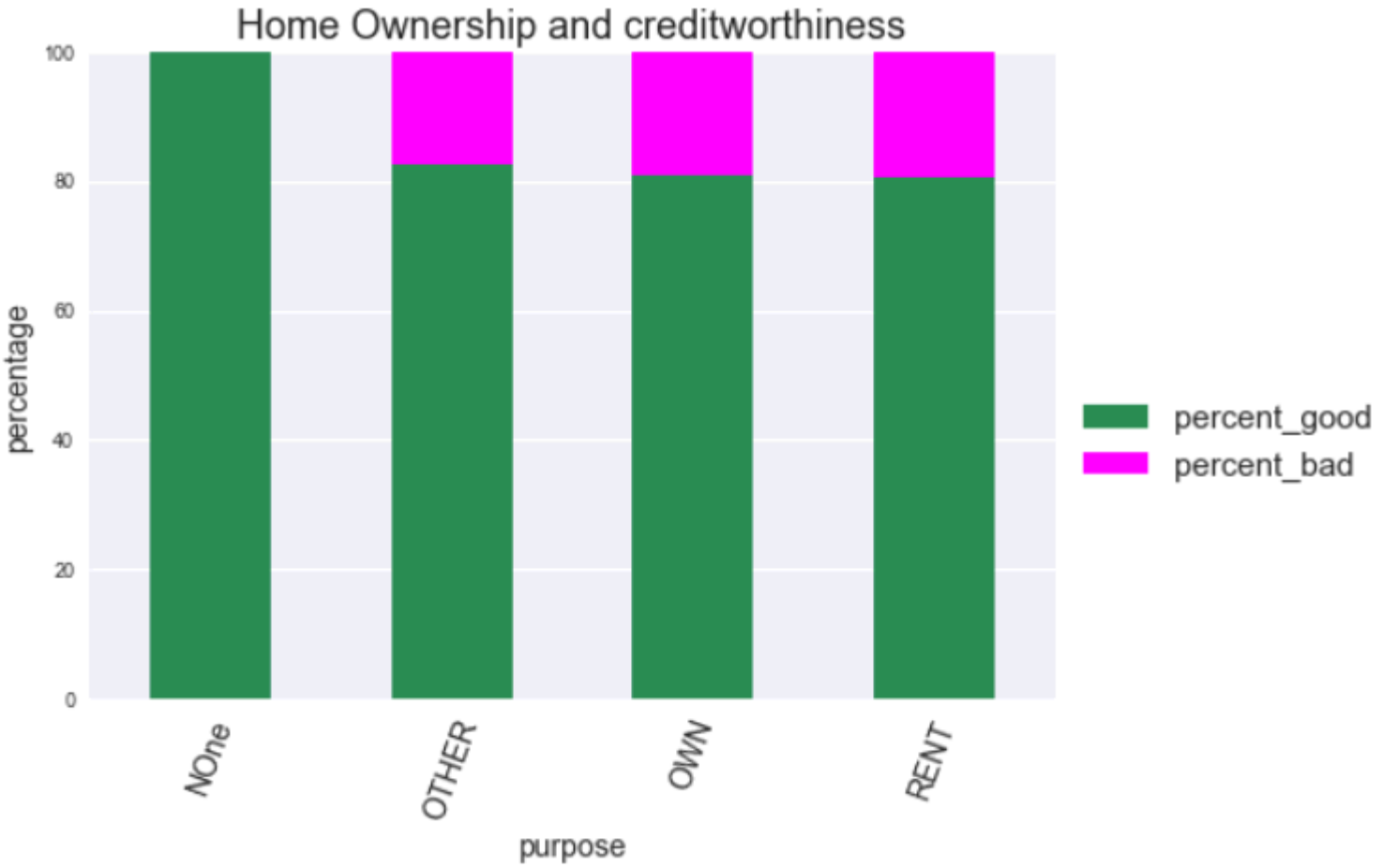
- The dataset is unbalanced, with defaulted loans only accounting for 18.17%.
- The unbalanced nature of the data will have to be considered when making predictions.

Data exploration



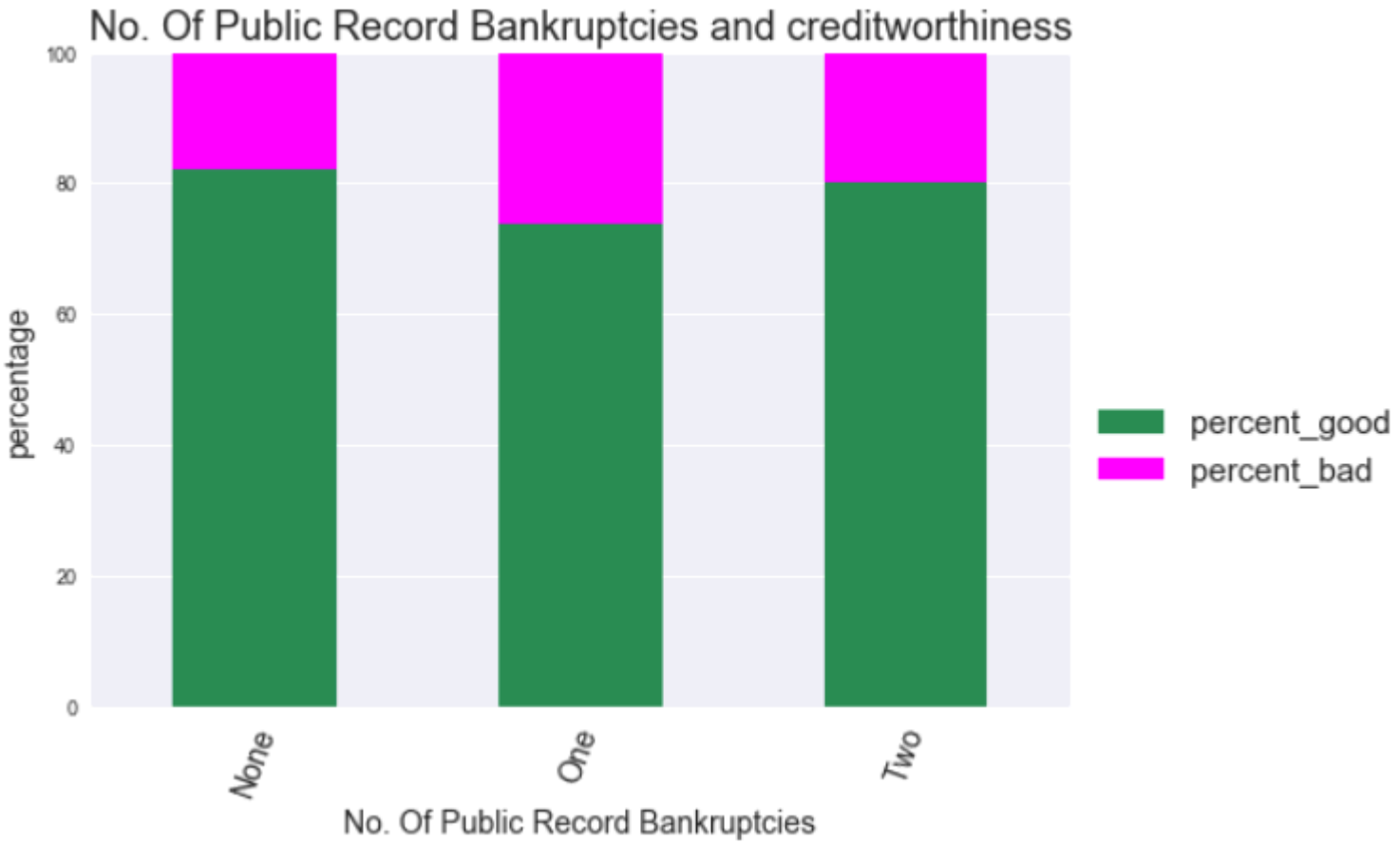
Loan purposes ‘Renewable Energy’ and ‘Small Business’ have the highest percentage of bad loans.

Data exploration



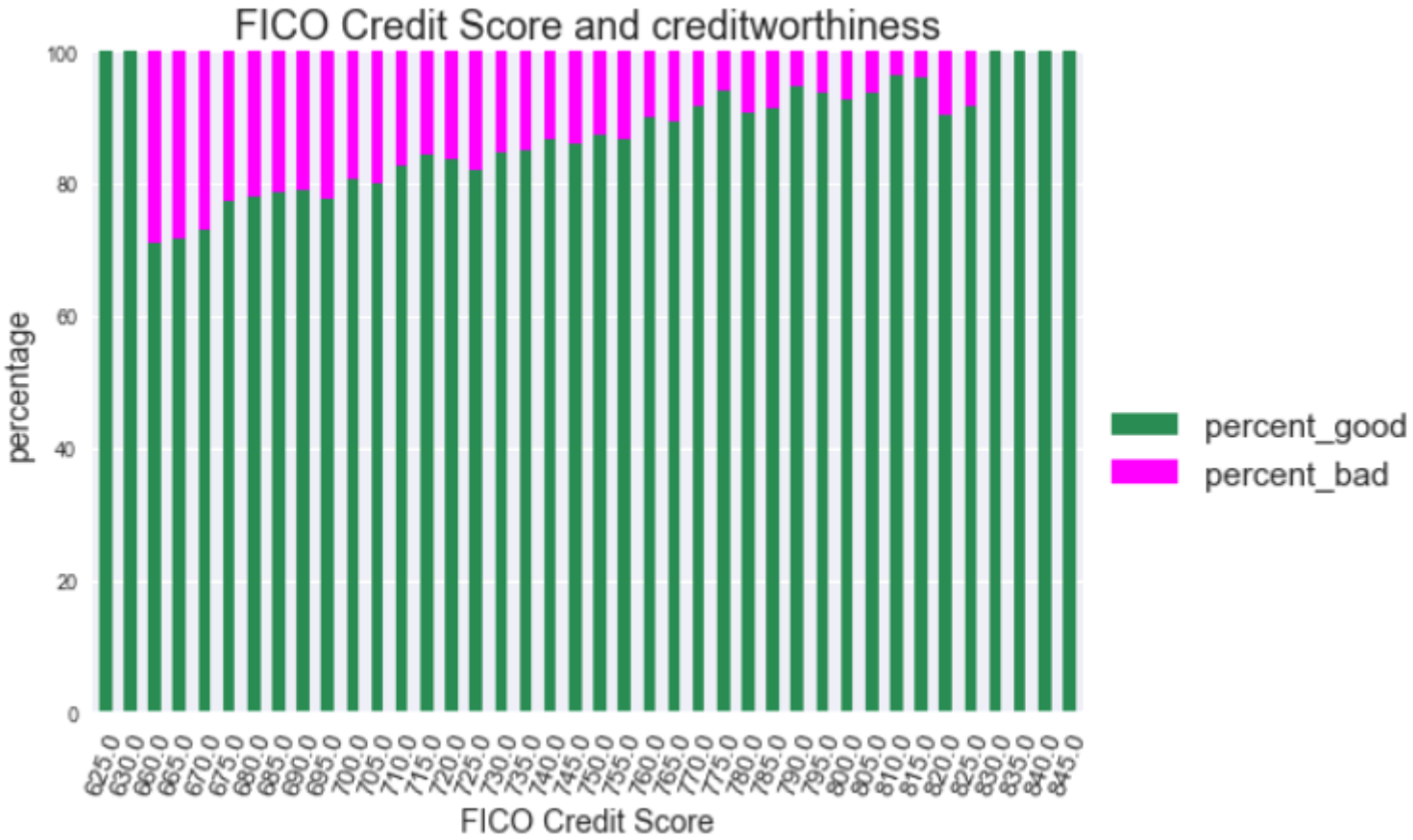
Category ‘None’ only contains completed loans.
Defaults in category ‘Rent’ are marginally higher than in ‘Other and ‘Own’.

Data exploration



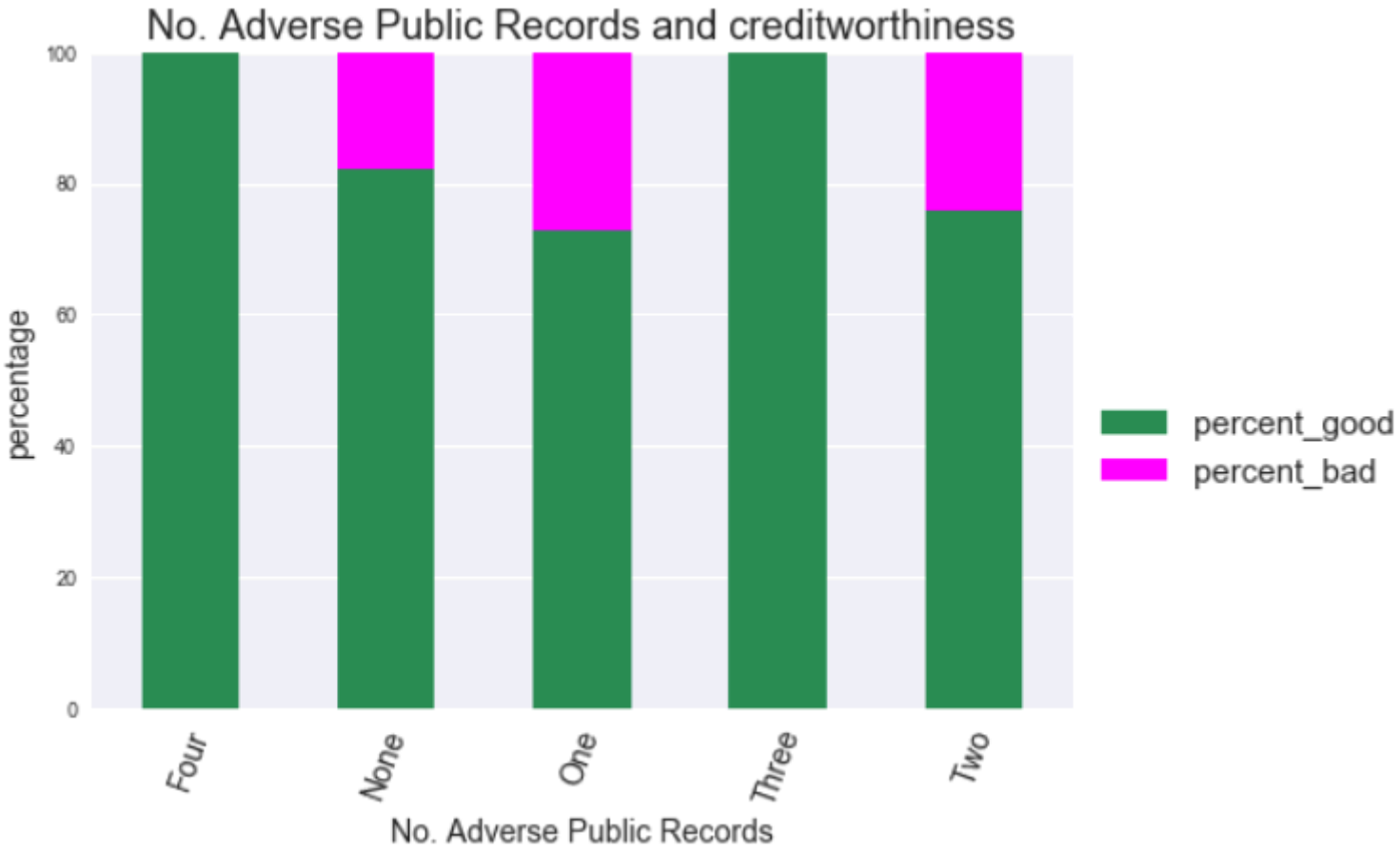
One public record bankruptcy has the highest percentage of bad loans.

Data exploration



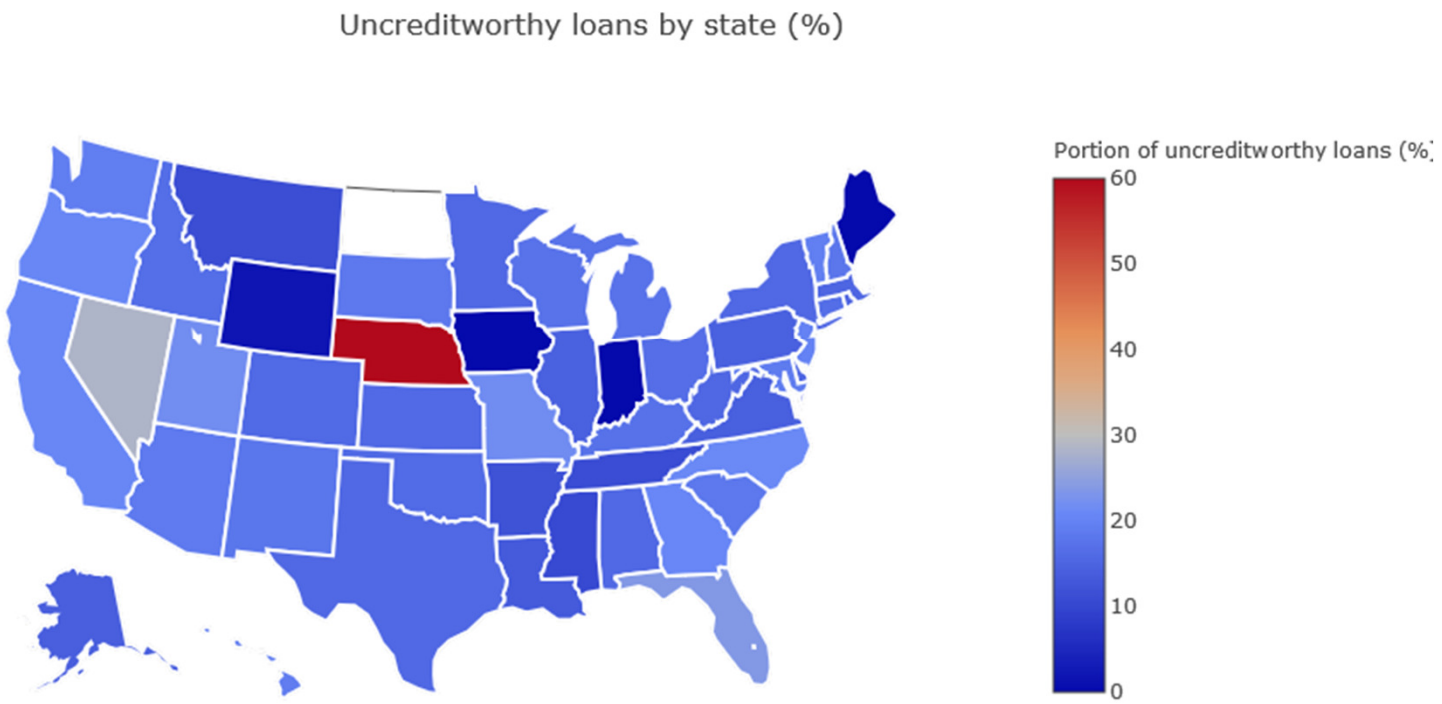
The lowest and the highest FICO scores do not contain bad loans, otherwise bad loans decrease with increase in score.

Data exploration



One adverse public record has the highest percentage of bad loans, while three only contain good loans.

Data exploration



- NE stands out as having 60% of bad loans, or 5 bad loans in absolute numbers.
- NV has 28.43% of bad loans, or 306 bad loans in absolute numbers.

Data exploration: Initial insights

- Relationships between predictor and target variable are not always linear.

- Observations of features ‘FICO Credit Score’ and ‘Address State’ can be grouped in order to increase predictive power.

Feature engineering

- convert 'Class' feature (=target) into numerical values
  - Assign ‘0’ to ‘creditworthy’
  - Assign ‘1’ to ‘uncreditworthy’

Feature engineering

- summarise address states into geographic regions:
  - East_Coast: 7731 observations
  - South: 6885 observations
  - West_Coast: 4485 observations
  - Middle: 3461 observations
  - North: 2213 observations

- summarise FICO scores into categories
  - Very Good: 15950 observations
  - Exceptional: 5208 observations
  - Good: 3337 observations

Feature engineering

- create dummy variables for categorical features
  - 'Loan Term',
  - 'Home Ownership',
  - 'Loan Purpose',
  - 'FICO Credit Score',
  - 'Address State'

Feature engineering

- encode remaining columns containing object data types
  - 'No. Delinquencies In Last 2 Years‘
  - 'No. Adverse Public Records‘
  - 'No. Of Public Records

  - The above columns contain strings (e.g. one, two, three, …) describing numbers from 0 to 9
  - Change strings into numerical format (e.g. 1, 2, 3, …)

Feature engineering

- drop redundant feature
  - Drop ‘Class’ feature
- deal with nan values
  - Replace ‘nan’ with median values for each feature
- remove outliers
  - See appendix

Classification

- Define predictor variables (X) and target variable (y)
  - y = ‘Class_new’ column containing ‘0’ for completed and ‘1’ for defaulted loan
  - X = transformed features excluding y
- Implement train test split on X and y
- 70% train, 30% test
- Stratify target y as data may not be normally distributed

Classification: Evaluation metric

- AUC ('area under the curve') score
  - The AUC score equals the probability that a randomly chosen positive example ranks above (is deemed to have a higher probability of being positive than) a randomly chosen negative example.
- TPR (also called Recall or Sensitivity) = sum total positives/sum of condition positive = TP/(TP+FN)
- FPR (also called Fall-out) = sum of false positives/sum of condition negative = FP/(FP+TN)
- The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

Source: www.wikipedia.com

Classification: Build model

```
# build logistic regression model
# address unbalanced classes with parameter 'class_weights'

from sklearn import linear_model
from sklearn.metrics import roc_auc_score

estimator = linear_model.LogisticRegression(random_state=42, class_weight={0:0.1817, 1:0.8183})

estimator.fit(X_train, y_train)

y_pred_regr = estimator.predict_proba(X_test)

y_pred_regr = pd.DataFrame(y_pred_regr, index=y_test.index)

# how does the basic model perform?

AUC = roc_auc_score(y_test, y_pred_regr[1])
print("The AUC score for a simple Logistic Regression model is {:.4f}.".format(AUC))
```

```
The AUC score for a simple Logistic Regression model is 0.7207.
```

Add class weights to account for unbalanced classes

Initial AUC score: 0.7207

Classification: Optimise model

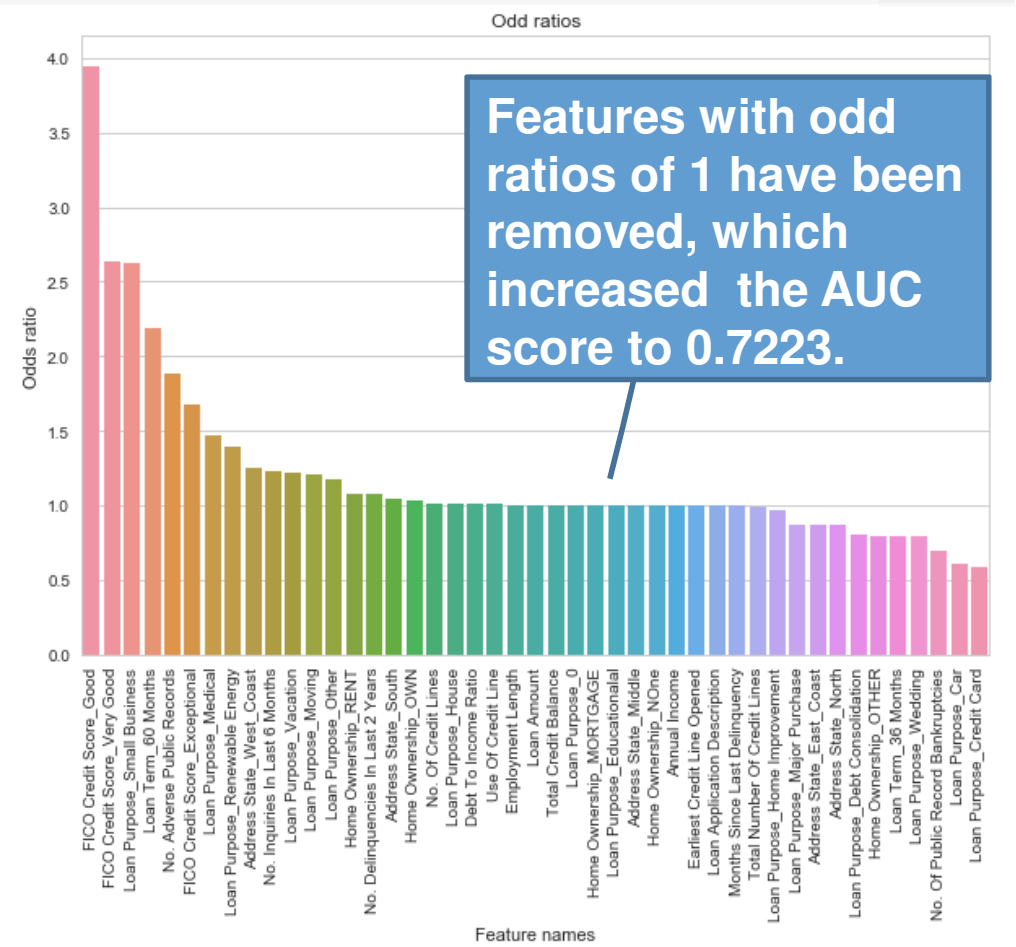
```
# tuning model parameters

from sklearn.model_selection import GridSearchCV


param_grid = {'C': [0.01, 1, 2, 3], 'penalty':['l1', 'l2']}

gsregr = GridSearchCV(estimator, param_grid, cv=9)

gsregr.fit(X_train, y_train)

y_pred_opt = gsregr.predict_proba(X_test)
y_pred_opt = pd.DataFrame(y_pred_opt, index = y_test.index)

# how does the optimised model perform?

AUC_opt = roc_auc_score(y_test, y_pred_opt[1])
print("The AUC score for an optimised Logistic Regression model is {:.4f}.".format(AUC_opt))
```

```
The AUC score for an optimised Logistic Regression model is 0.7216.
```

Use GridSearchCV to find best model parameters

Optimised AUC score: 0.7216

Classification: Feature selection



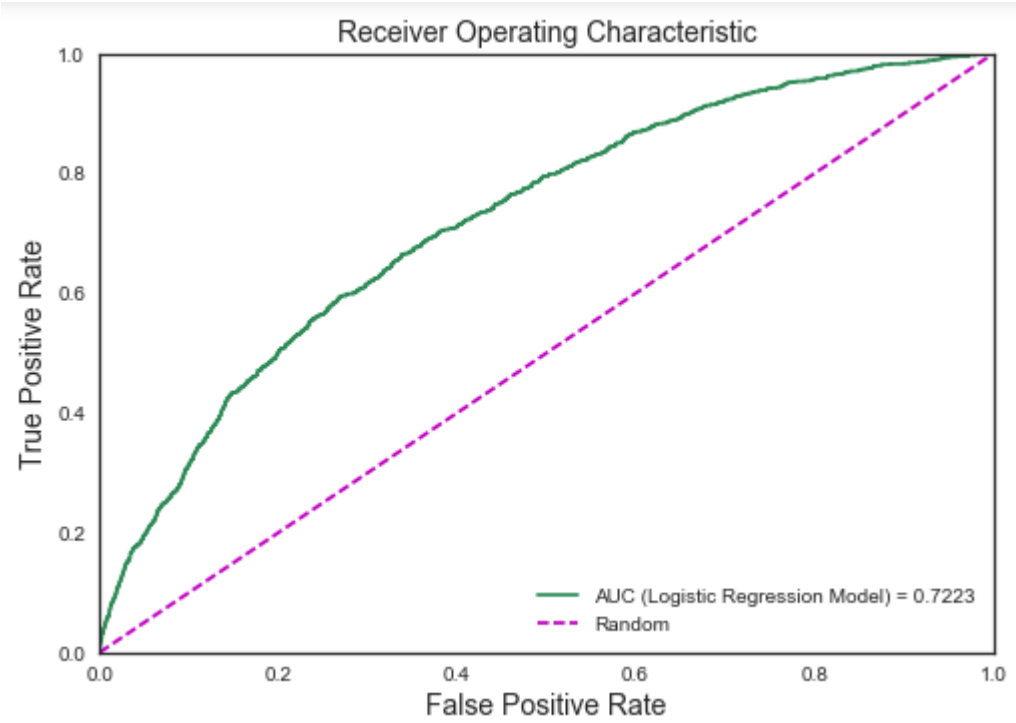
Highest odds for bad loans:

- FICO Credit Score Good
- FICO Credit Score Very Good
- Loan Purpose Small Business
- Loan Term 60 Months
- No. Adverse Public Records

Lowest odds for bad loans:

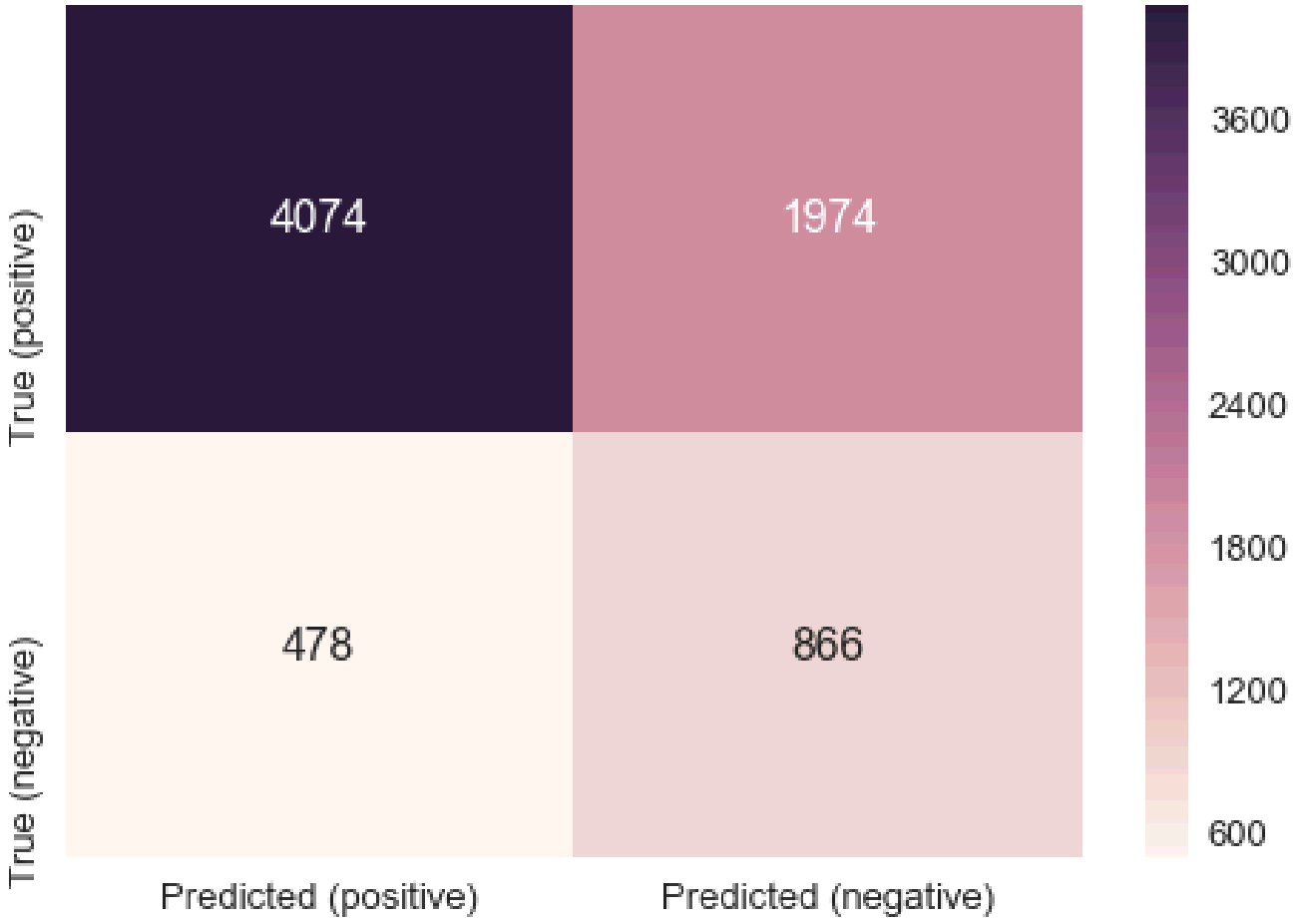
- Loan Purpose Credit Card
- Loan Purpose Car
- No. Of Public Record Bankruptcies
- Loan Purpose Wedding
- Loan Term 36 Months

Results: ROC Curve



- The optimised model delivered an AUC score of 0.7223.
- This can be interpreted as the probability that a randomly chosen positive example is deemed to have a higher probability of being positive than a randomly chosen negative example.
- Parameter tuning and feature selection improved the score.

Results: Confusion matrix



Conclusion

- The model outperforms random guessing in predicting loan defaults.
- The model identifies features with high and low odds for bad loans.

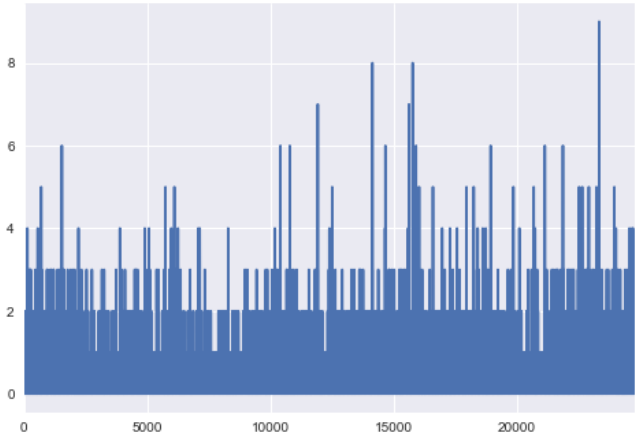
Limitations

- Relationships between predictor variables and target are not necessarily linear.
- The amount of features and observations is not very large.

Recommendations

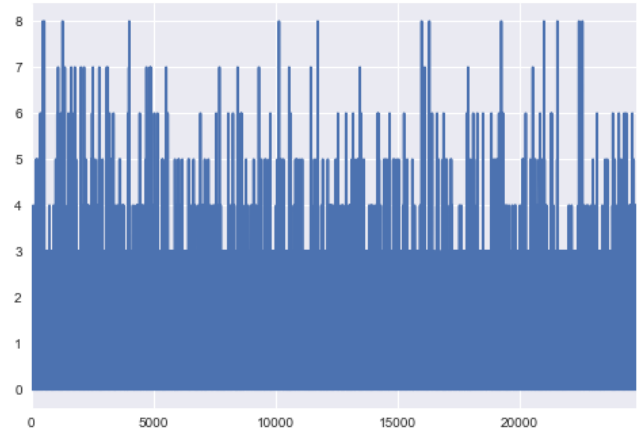
- Get more data.
- Build model using XG Boost, as this algorithm tends to perform well when variables exhibit non-linear relationships.

Appendix: Dealing with outliers



No. Delinquencies In Last 2 Years:

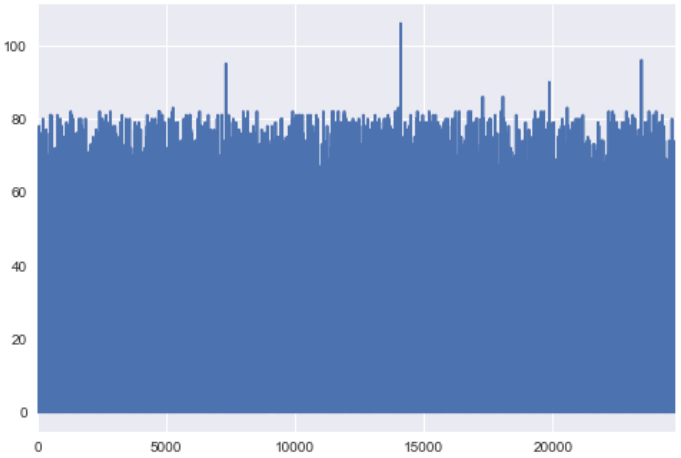
Take out values above 4



No. Inquiries In Last 6 Months:

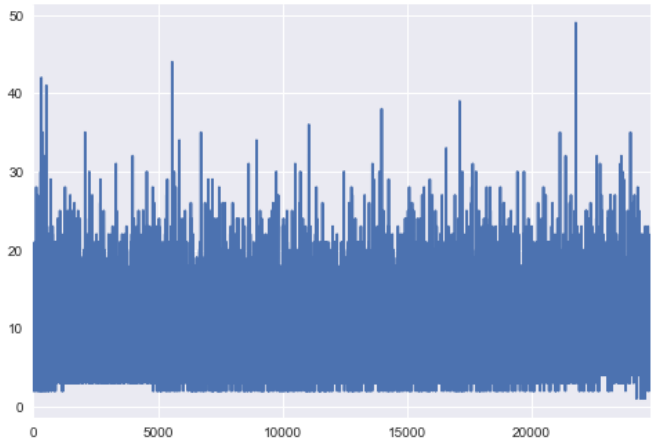
Take out values above 7

Appendix: Dealing with outliers



Months Since Last Delinquency:

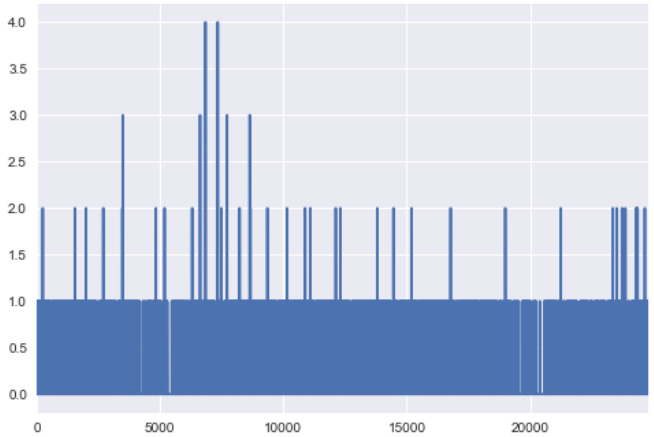
Take out values above 85



No. Of Credit Lines:

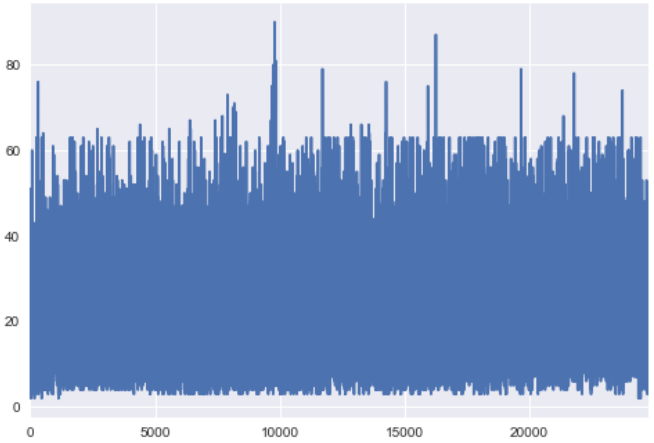
Take out values above 30

Appendix: Dealing with outliers



No. Adverse Public Records:

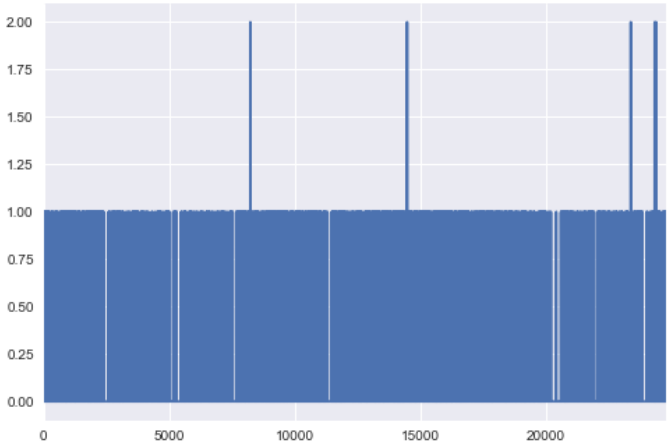
Take out values above 1



Total Number Of Credit Lines:

Take out values above 65

Appendix: Dealing with outliers



No. Of Public Record Bankruptcies:

Take out values above 1