Credit Risk Analysis - ML models

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Aim

The aim of this analysis is to determine credit risk based on customer behaviour regarding engagement with financial products as well as a variety of demographic attributes that may be informative.

Data source

In this analysis I'm using a **Kaggle credit risk dataset** described here

The data is structured in two csv files:

1. File 1 - **Payment data** contains customer's credit card payment history and has the following fields:

- id: customer id
- OVD_t1: number of times overdue type 1
- OVD_t2: number of times overdue type 2
- OVD_t3: number of times overdue type 3
- OVD_sum: total overdue days
- pay_normal: number of times normal payment
- prod_code: credit product code
- prod_limit: credit limit of product
- update_date: account update date
- new_balance: current balance of product
- highest_balance: highest balance in history
- report_date: date of recent payment

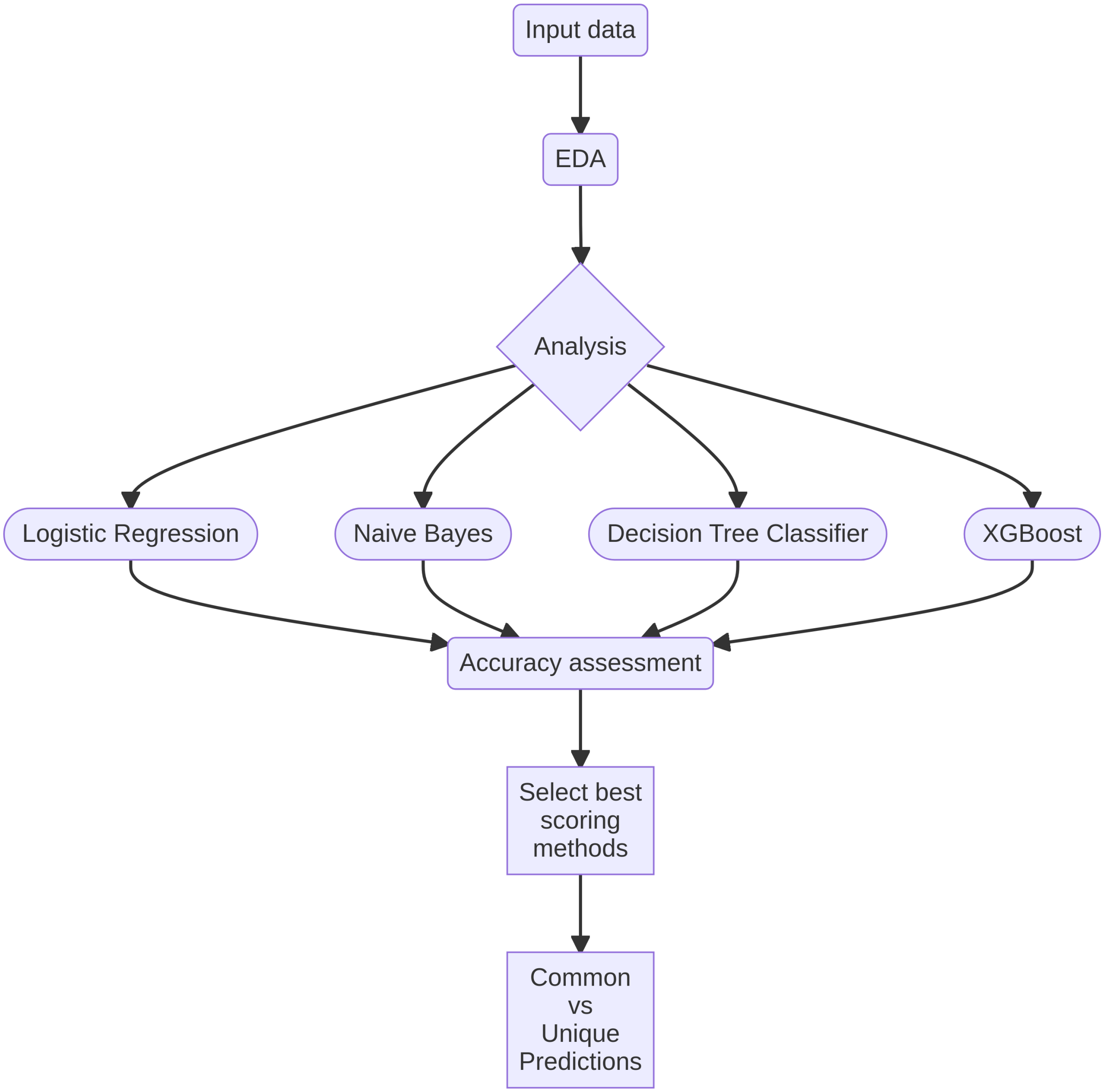
2. File 2 - **Customer data** which contains demographic data and category attributes that have been anonymised as follows:

- id
- label: if it equals 1 it indicates the customer is high risk, if it equals 0 the customer is low risk
- fea_1
- fea_2
- fea_3
- fea_4
- fea_5
- fea_6
- fea_7
- fea_8
- fea_9
- fea_10
- fea_11

Methodology

I have decided to make a second report where I concentrate on ML models because neural networks offered no significant improvement in accuracy of prediction for far more computational cost.

Below is the amended flowchart



Input data pre-processing

Note:

After some standard pre-processing (renaming columns, concatenating data frames, and checking for missing data) I decided that data imputation was not appropriate while low credit risk customers might pay their full balance or higher amounts consistently on the same date, high risk customers would exhibit far more variance on both the date of balance closing and last payments made. I personally feel the variable 'pay_normal' (i.e. the number of times a customer does not default on payments) captures this information in a discretised manner that does not rely on following a Poisson distribution of events.

In short, I have decided that dropping update_date, and report_date variables was justified. I did however use KNN imputation to fill missing values for feature_2, prod_limit (the credit limit), and highest_balance features, the data for feature 2 appears to be normally distributed, while the prod_limit appears to be close to normally distributed but has a small number of outliers. The highest_balance variable exhibits most values centered close to zero but extremely long tail all the way out to 150,000,000.

It would be good to visualise how the different variables correlate with one another.

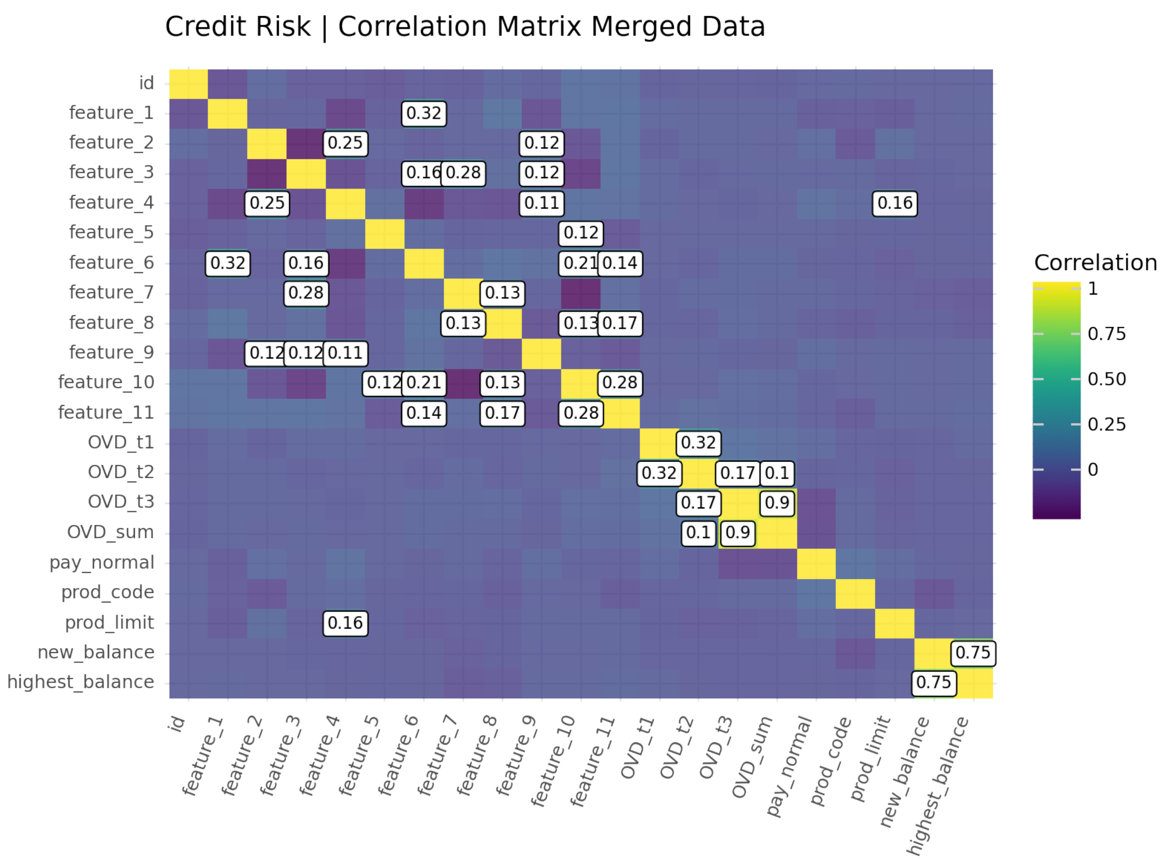


Figure 1: Correlation between different variables in the credit risk customer dataset

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Analyses

First thing here is to store the label used to classify a customer as high or low credit risk and store it as the response variable for all our models while keeping everything else as our predictor variables

ML models

Four methods will be used, Logistic Regression (LR), Naive Bayes (NB), a Decision Tree Classifier (DT), and XGBoost (XGB). The dataset is split into training and test sets, **70%** is kept for the training set and **30%** will be used as a test set.

Hyperparameter tuning was performed for both the DT and XGB models

The code is not shown but the prediction accuracy is reported below

```
Best random state after hyperparameter tuning for the Decision Tree Classifier
95
Best random state after hyperparameter tuning for XGBoost
0
```

Reporting the results of our models

Selecting the best methods based on the accuracy scores

The reason why one would want to consider selecting the results of more than one method are many. For one, the way a given classifier method might choose a given outcome may be affected by specific statistical quirks of each method, for closely scoring methods one may want to see what predicted IDs are common to both methods and which ones aren't in order to better understand what parameters might be more relevant to each model.

Visualising differences between the predicted customers common to both models and those that are unique to either model

Plot all high risk cases predicted by both XGBoost and DT models

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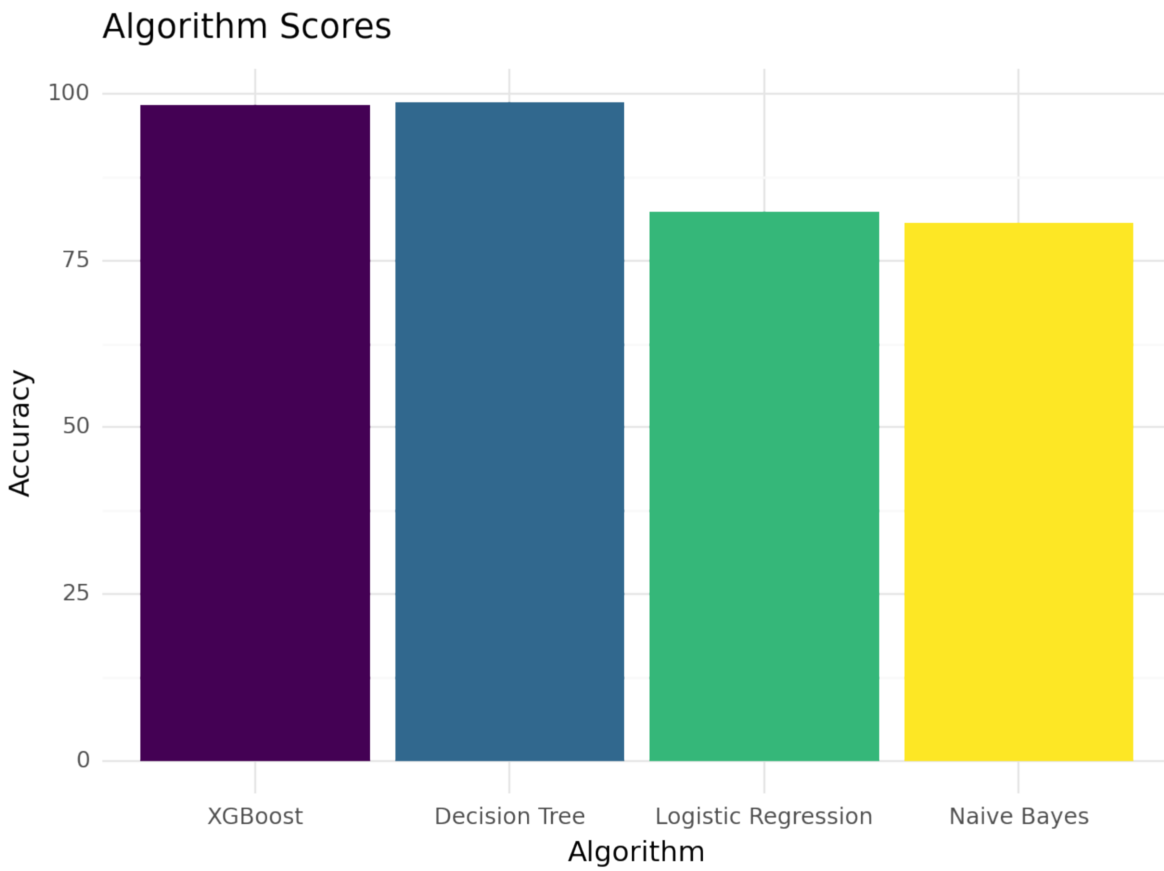

Figure 2: Model performance - accuracy of predictions

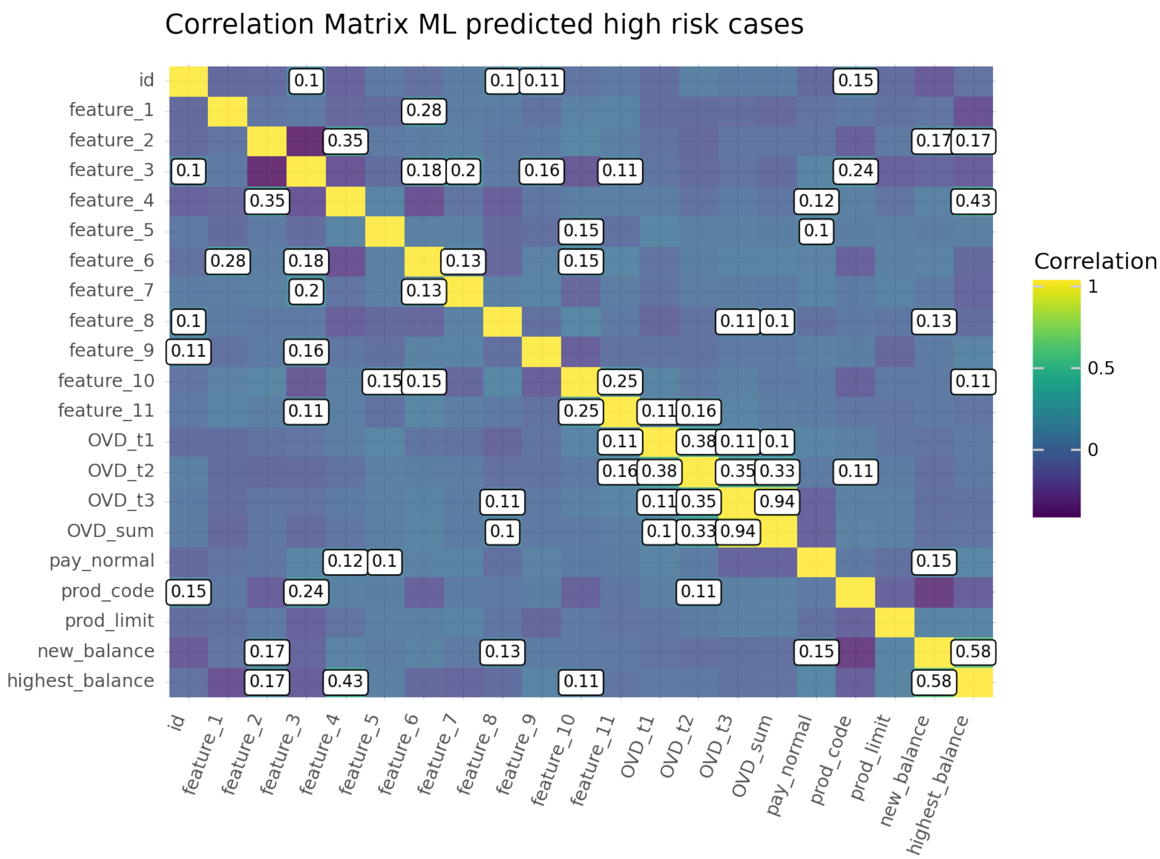

Figure 3: Correlation plot - Common set of predicted high risk customers by both XGBoost and Decision Tree Classifier

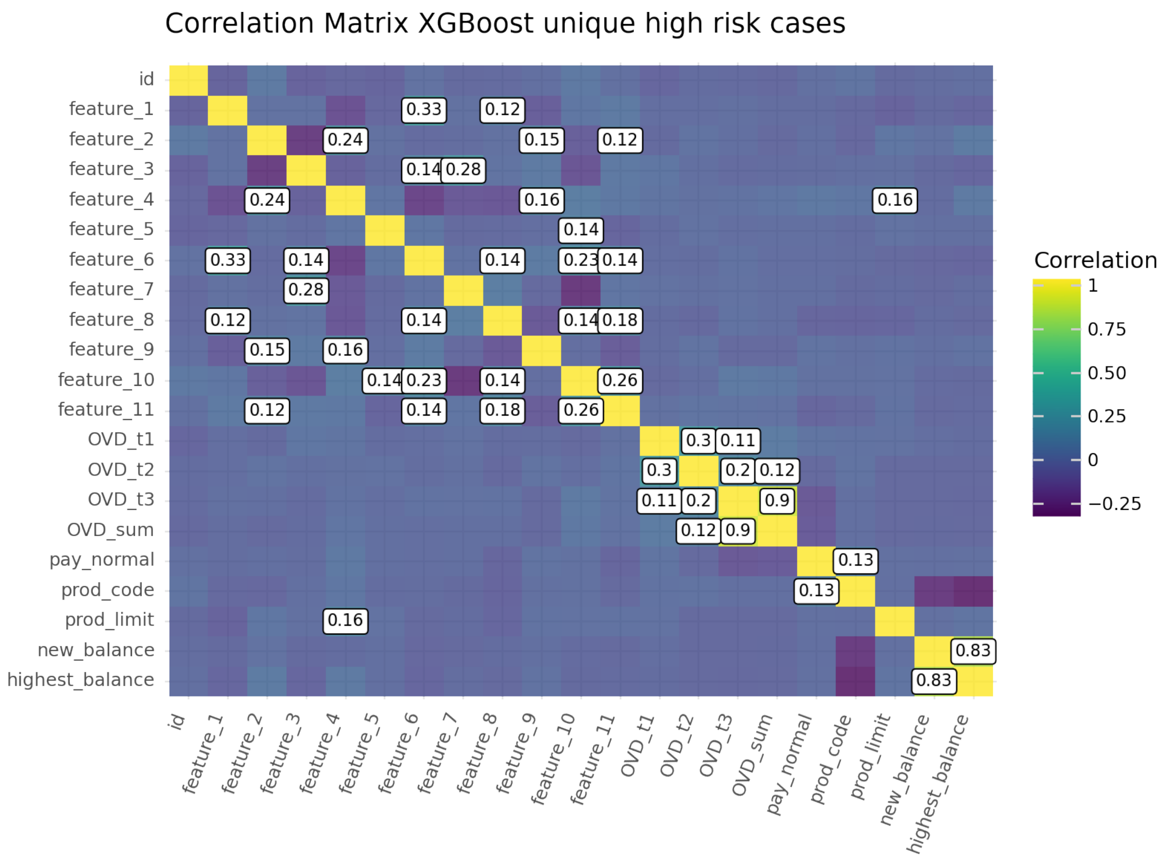

Figure 4: Correlation plot - high risk customers predicted by XGBoost alone

And those predicted by XGBoost but not the Decision Tree Classifier model

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Finally, those predictions made by the Decision Tree Classifier model but not XGBoost

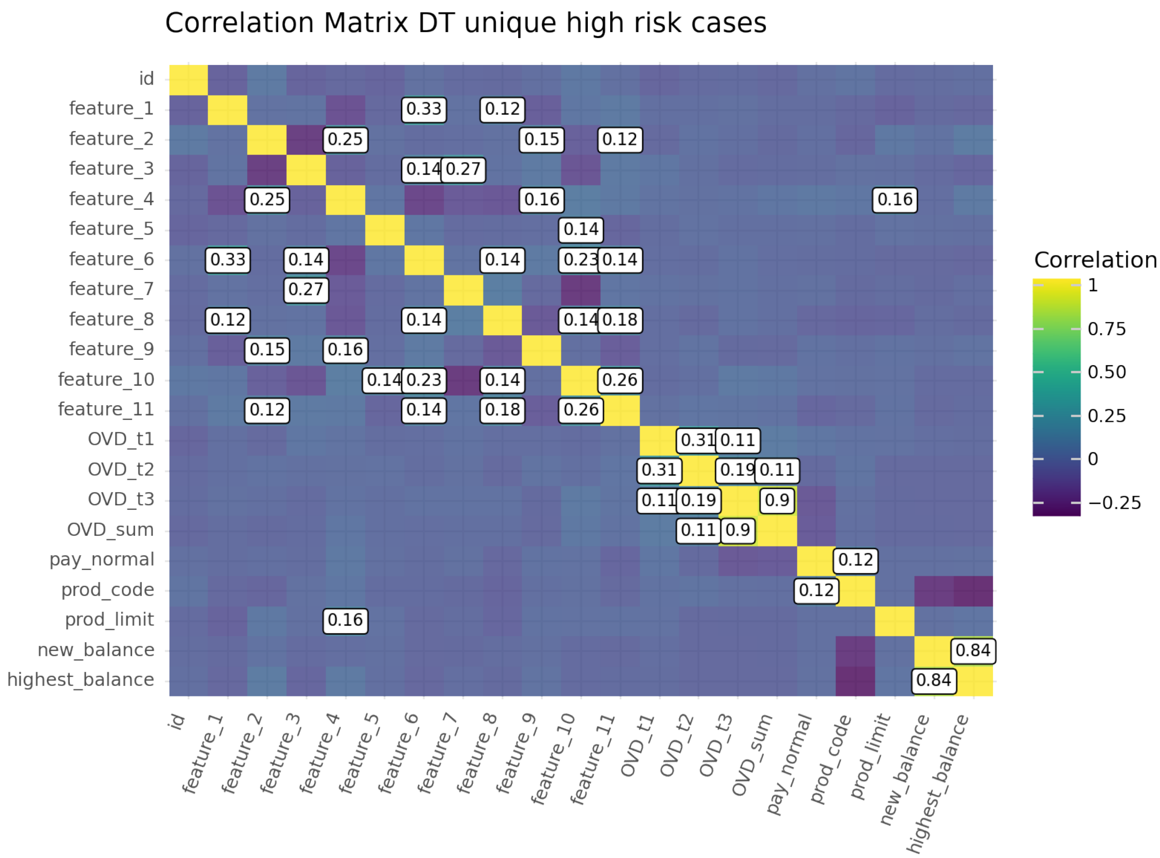

Figure 5: Correlation plot - high risk customers predicted by DT model alone

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We can see that the features that matter to predict high risk are the same for both XGBoost and DT models. However, there are some differences in the correlation values possibly arising from differences in sensitivity between ensemble models (XGBoost) and other classifier models such as decision tree classifiers. Whether the sensitivity threshold in making these predictions should be tweaked or not would depend on how much risk can be tolerated but both models perform well, although XGBoost shows marginally better performance.