Habits

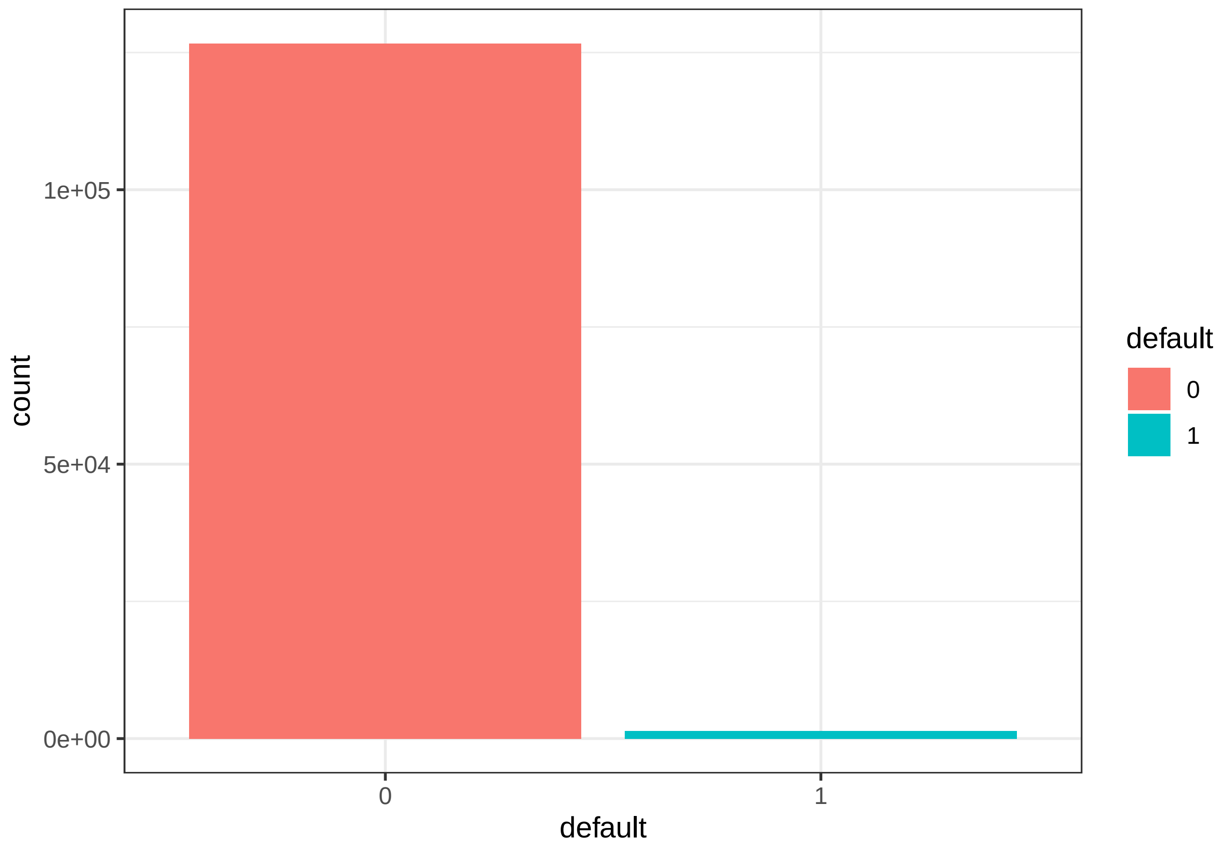
Contents

1. Setting up the data

An overview of the data shows us tha we have to change the structure of some of the variabels. Moreover, there are many extreme values in the data set and observations of defaulting companies are higly under-represented in the data set. We will deal with all these problems prior to implementing our prediction models.

Table 1:

Statistic	Min	Max
default	0	1
profit_margin	−10,000,000,000,000,000,000.000	25,553.330
gross_operating_inc_perc	0.000	1.000
operating_margin	−10,000,000,000,000,000,000.000	586.175
EBITDA_margin	−10,000,000,000,000,000,000.000	586.171
interest_coverage_ratio	−10,000,000,000,000,000,000.000	10,000,000,000,000,000,000.000
cost_of_debt	−8,131.722	165,944.600
interest_bearing_debt	−10,000,000,000,000,000,000.000	7,523.000
revenue_stability	−10,000,000,000,000,000,000.000	4,473.242
equity_ratio	−10,000,000,000,000,000,000.000	168.999
equity_ratio_stability	−10,000,000,000,000,000,000.000	168.000
liquidity_ratio_1	−2,473.828	10,000,000,000,000,000,000.000
liquidity_ratio_2	−2,473.790	10,000,000,000,000,000,000.000
liquidity_ratio_3	−2,473.809	10,000,000,000,000,000,000.000
equity	−771,200	182,466,000
total_assets	−9,685	544,267,000
revenue	−2,883,588	588,422,000
age_of_company	2	22
unpaid_debt_collection	−5.000	10,000,000,000,000,000,000.000
paid_debt_collection	−5.500	10,000,000,000,000,000,000.000
adverse_audit_opinion	0	6
industry	0	11
amount_unpaid_debt	−121,226	10,000,000,000,000,000,000
payment_reminders	0	3



Factor variables: Then we recategorize som of the factor variables. Adverse audit is coded as a dummy, where 1 indicates that there has been an adverse audit opinion, and 0 indicates no adverse audit.

The tables below show the distribution of the companies along the factor variables, depending on wether they have defaulted or not.

	0	1	2	3	4	5	6
0	86937	1029	87	12435	3305	22340	536
1	293	22	1	147	59	825	54

	0	1
0	86937	39732
1	293	1108

	0	1	2	3	4	5	7	8	9	10	11
0	50541	916	842	12627	13255	639	37287	4391	3286	2279	606
1	369	10	7	178	171	13	501	82	48	7	15

Let's have a look of the distribution of the variables in the data set. The figure below contains density plots for all the numeric variables. Due to the presence of outliers, these figures do not provide much information.

#Handling missing observations and outliers

We observe that the number xx appears throughout the data set, and assume that these are missing observations. In total, these extreme values account for xx percent of our observations.

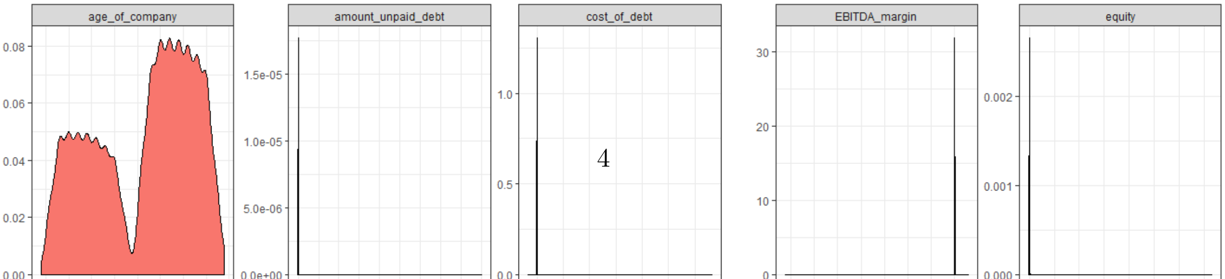
We choose to replace these values with NA to begin with.

	0	1	2	3
0	80182	26677	13775	6035
1	328	229	292	552

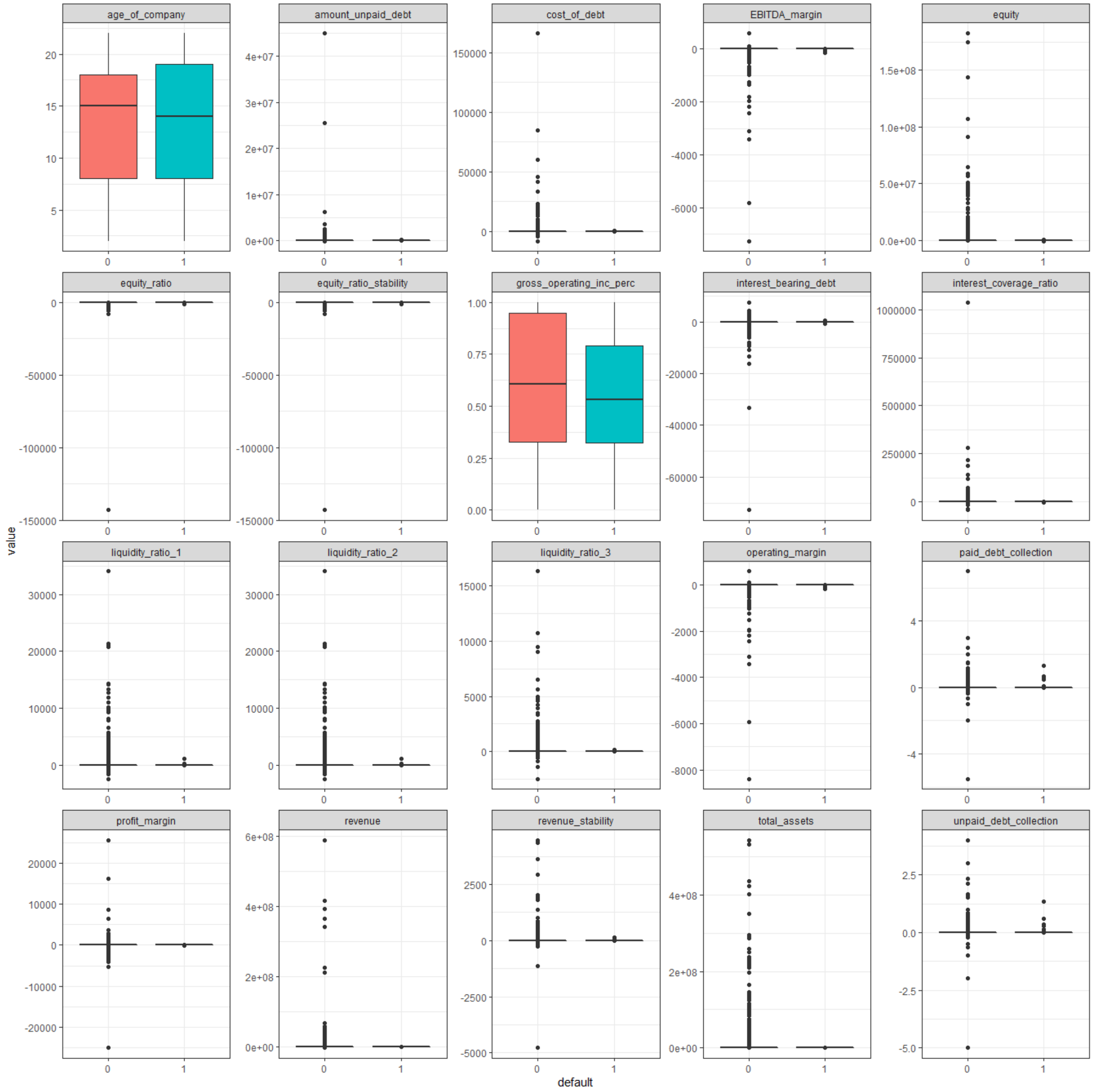
	key	value
1	profit__margin	0.10
2	gross__operating__inc__perc	0.00
3	operating__margin	0.10
4	EBITDA__margin	0.10
5	interest__coverage__ratio	0.17
6	cost__of__debt	0.00
7	interest__bearing__debt	0.00
8	revenue__stability	0.23
9	equity__ratio	0.01
10	equity__ratio__stability	0.14
11	liquidity__ratio__1	0.02
12	liquidity__ratio__2	0.02
13	liquidity__ratio__3	0.02
14	equity	0.00
15	total__assets	0.00
16	revenue	0.00
17	age__of__company	0.00
18	unpaid__debt__collection	0.01
19	paid__debt__collection	0.01
20	amount__unpaid__debt	0.01

Table 2:

Statistic	Min	Max	Mean	St. Dev.
profit__margin	−25,001.000	25,553.330	0.382	128.950
gross__operating__inc__perc	0.000	1.000	0.588	0.339
operating__margin	−8,391.346	586.175	−0.641	37.493
EBITDA__margin	−7,259.521	586.171	−0.536	34.862
interest__coverage__ratio	−41,488.830	1,037,285.000	85.094	3,551.132
cost__of__debt	−8,131.722	165,944.600	13.098	616.227
interest__bearing__debt	−72,702.900	7,523.000	−1.827	247.353
revenue__stability	−4,775.143	4,473.242	0.682	35.810
equity__ratio	−143,015.000	168.999	−2.899	405.043
equity__ratio__stability	−143,016.000	168.000	−4.151	435.700
liquidity__ratio__1	−2,473.828	34,126.680	8.238	201.297
liquidity__ratio__2	−2,473.790	34,126.590	7.901	201.280
liquidity__ratio__3	−2,473.809	16,330.310	3.378	87.779
equity	−771,200	182,466,000	32,016.920	1,090,415.000
total__assets	−9,685	544,267,000	122,994.800	4,352,257.000
revenue	−2,883,588	588,422,000	60,941.350	2,890,611.000
age__of__company	2	22	13.167	5.455
unpaid__debt__collection	−5.000	4.000	0.001	0.030
paid__debt__collection	−5.500	7.000	0.001	0.035
amount__unpaid__debt	−121,225.600	45,000,000.000	957.351	147,363.800



The figures below show the distribution after replacing xxx with NA. As shown, we still have an issue with outliers.



We assume that many of these values are error measurements. Applying a treshold of 2,5 percent at each end of the variables' distribution, we replace values exceeding this treshold with NAs.

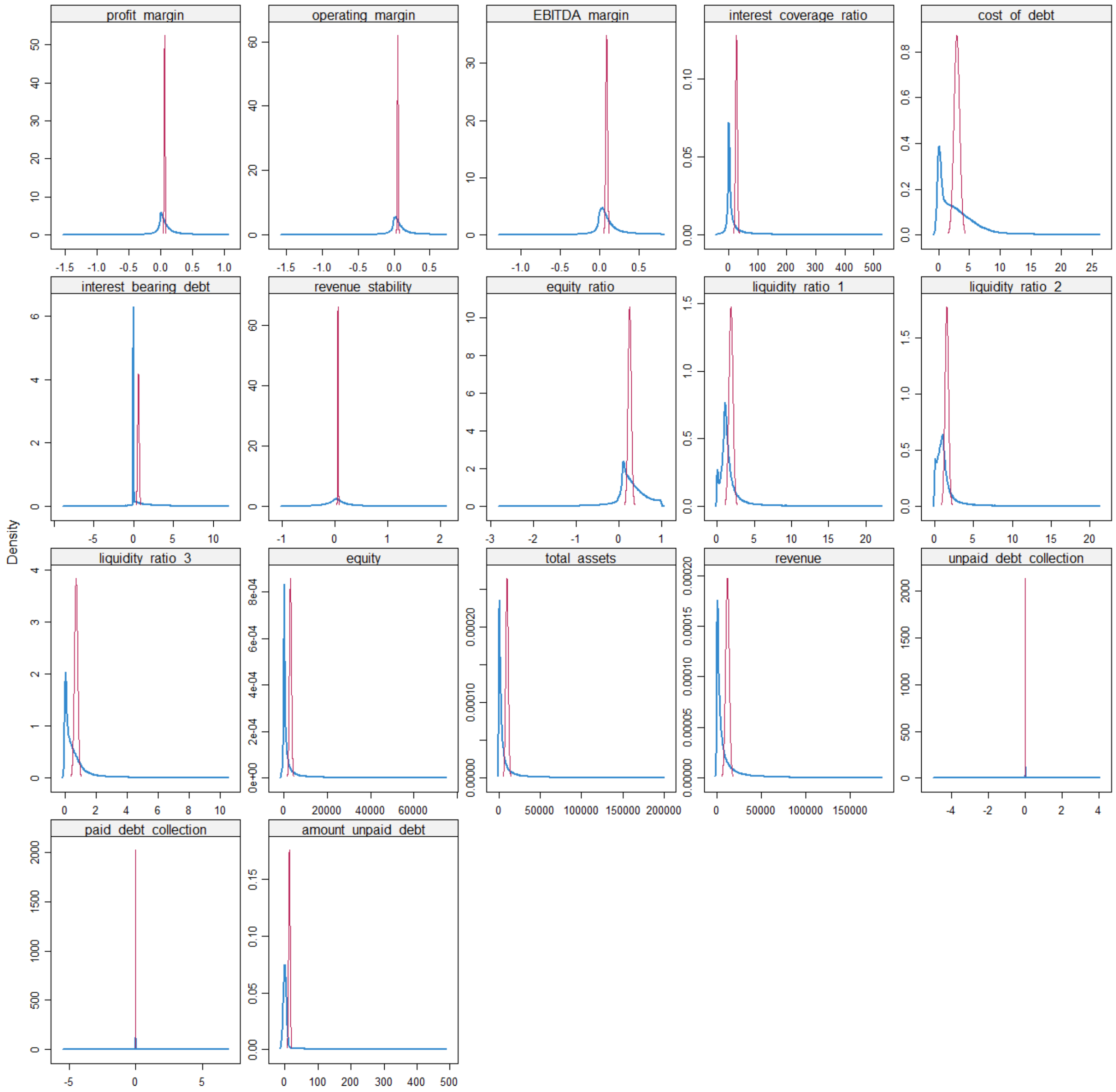
Mia: Might mention that equity ratio stability seems to have exactly same distribution as equity ratio. We test for correlation etc etc and end up removing this variable moving forward. Saves some computation time for r when imputing.

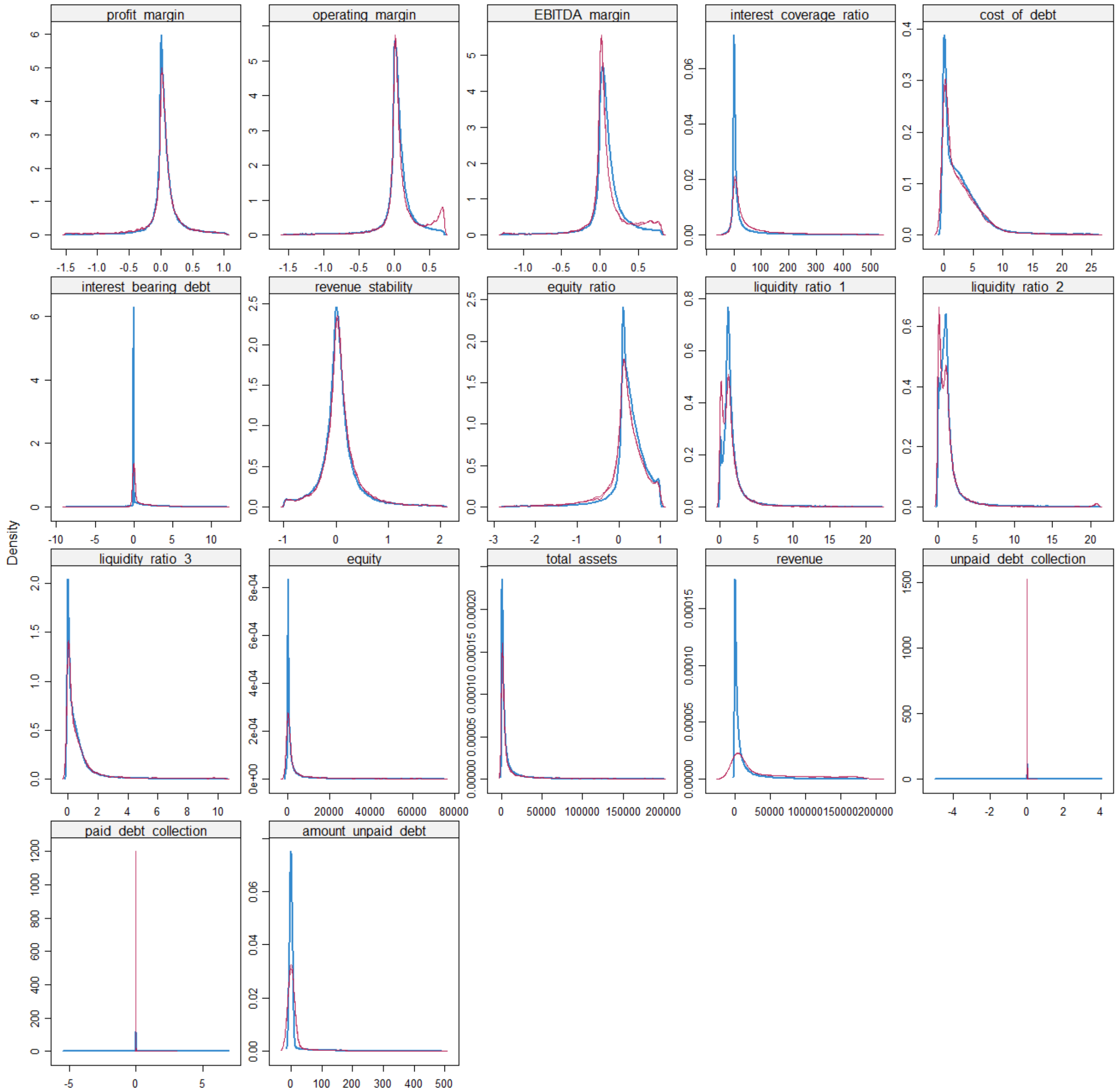
Imputation

As we have as much as xxx NA's, we choose not to delete these values, but rather impute them using the MICE package.

We deploy two methods for imputation: mean and ppm. Explain: - ppm and why it is good - why imputation can introduce challenges -

The tables below show how the distributions change when we apply different imputation methods. The original data is shown in the blue line, the mean imoutation in xxx line, and the pmm method in the xxx line.





	1	2
Orginal	128070	23
Imputed	128070	23

As shown in the distribtion plots, there is not much variation in the variables measuring paid and unpaid debt collection. We generate two new dummy variables that provide two binary measures of paid and unpaid debt. Moreover,

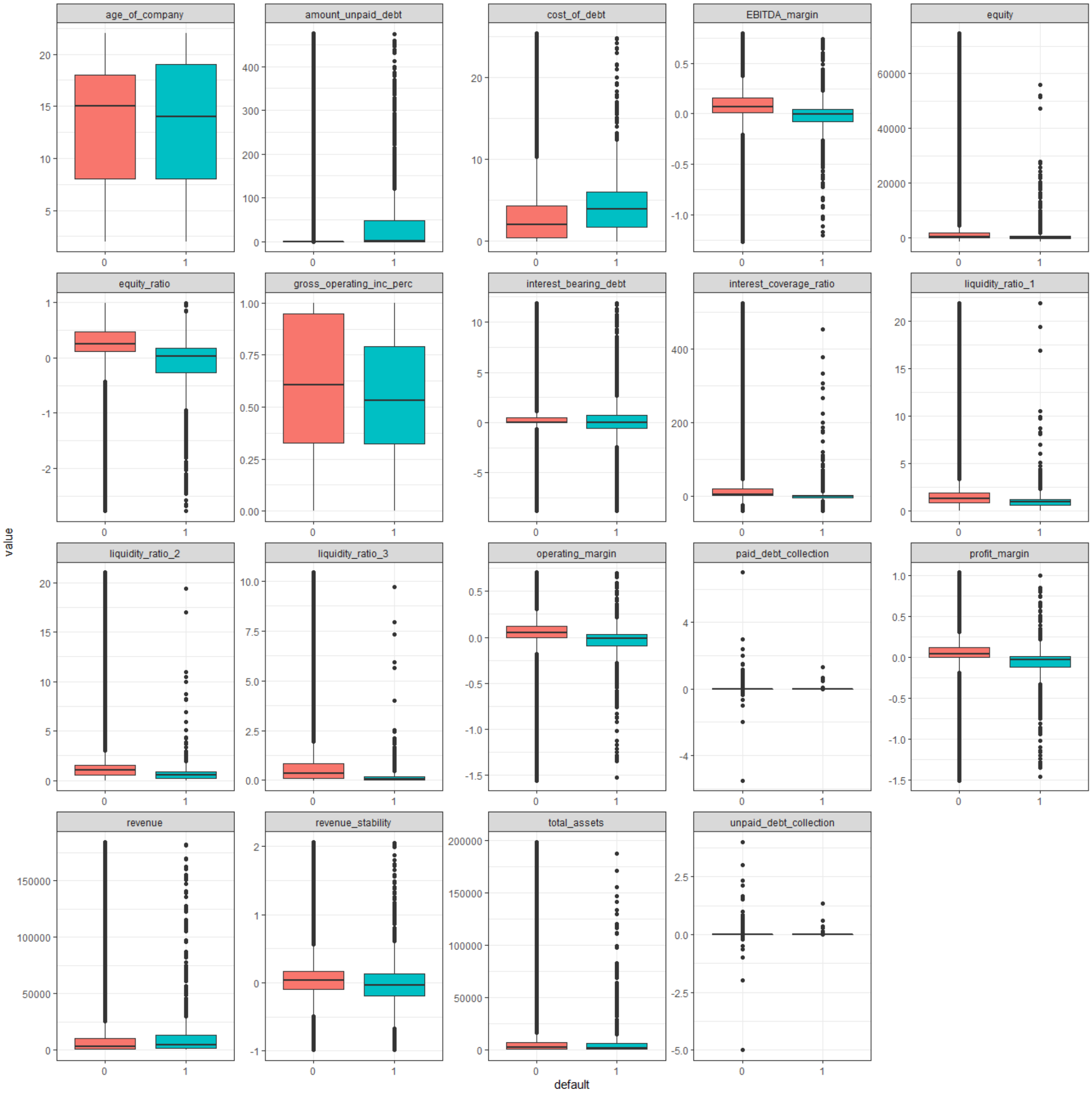
The table below shows how this variable is distributed. As shown, defaulting firms are more frequently represented among those with debt collection. Moreover, firms who have reported paying down previous debt are less frequently represented among defaulters.

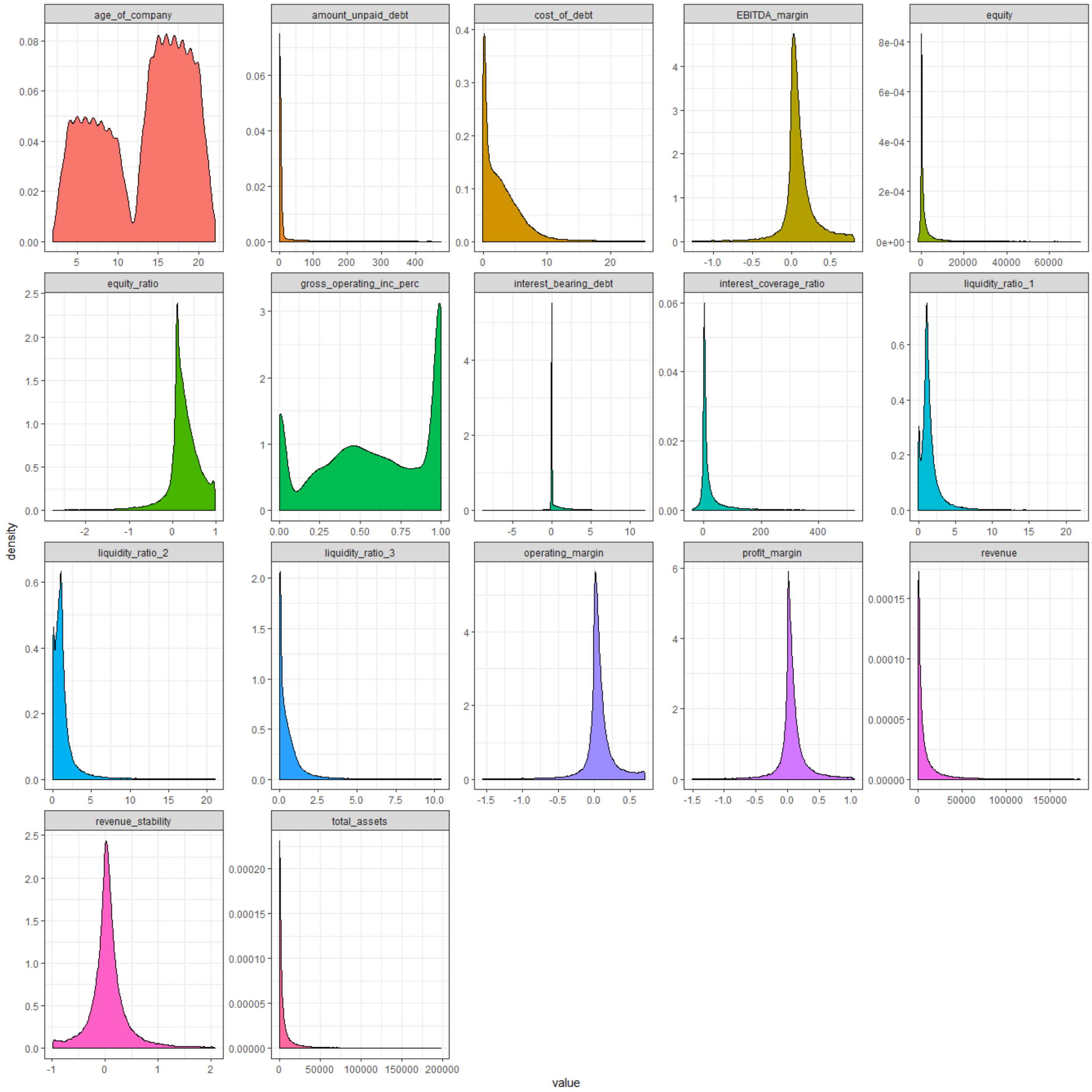
Mia: Might need to work on the reasoning behind generating this dummy a bit more. Could we do without it?

	0	1
0	97469	29200
1	449	952

	0	1
0	109170	17499
1	922	479

After cleaning, imputing and restructuring our data set is better suited for prediciton modelling, see density plots below.





#Modelling preparations A few more steps before we are ready to start modelling:

We split the data frame into a training and test set. The variables total_assets, revenue, industry and paid_debt_collection are removed as they correlate with other independent variables.

[1] TRUE

	1
Train defaults	0.01
Test defaults	0.01

Dealing with data imbalance

As mentioned, defaulting firms are highly underrepresentated in the data set. We deal with this by implementing the oversamlpling technique “smote”. - Writ some sentences about smote.

#Model 1: GLM

Our first prediction model is a logistic regression model. - Some words about variable selection

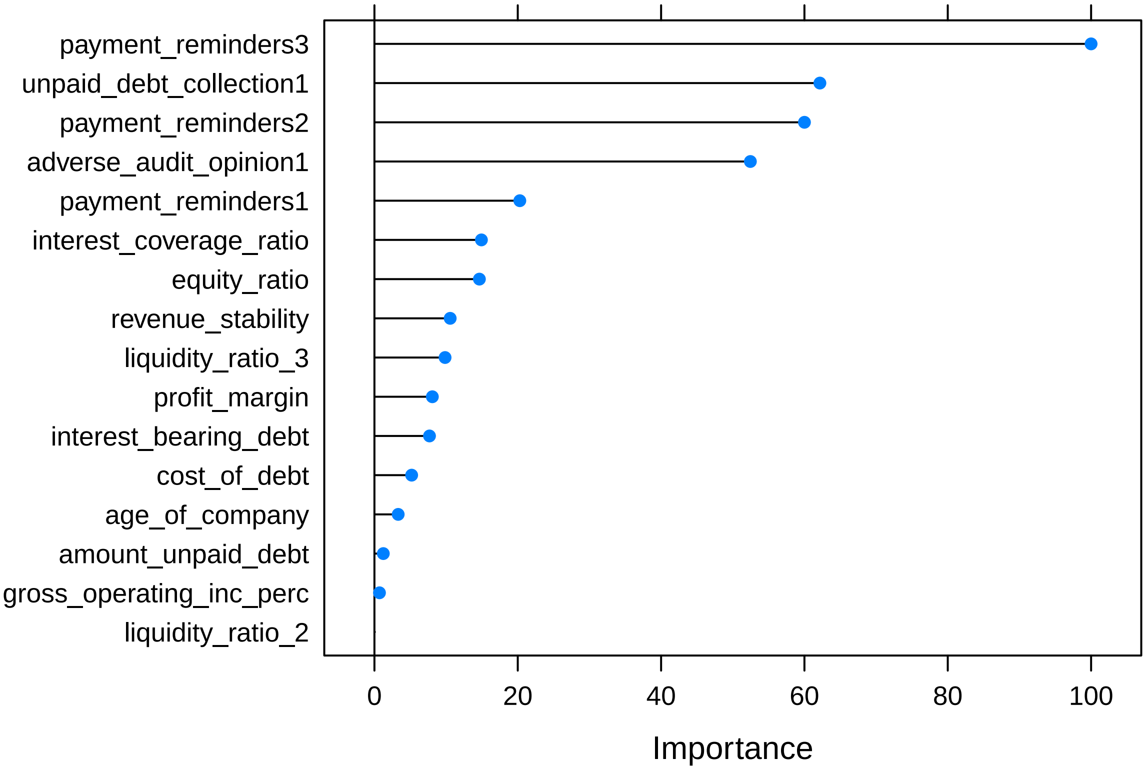
Summary statistics are presented below.

Comments:

- What variables are significant?
- Do they make economically sense?

The plot below shows the variable importance of the independent variables in the glm model. - Comments: what variables perform well

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.4972	0.1450	-17.22	0.0000
profit__margin	-0.7085	0.1700	-4.17	0.0000
gross__operating__inc__perc	-0.2626	0.1183	-2.22	0.0264
interest__coverage__ratio	-0.0071	0.0012	-5.97	0.0000
cost__of__debt	0.0375	0.0110	3.41	0.0007
interest__bearing__debt	-0.0602	0.0148	-4.06	0.0000
revenue__stability	-0.4814	0.0998	-4.82	0.0000
equity__ratio	-0.5196	0.0881	-5.90	0.0000
liquidity__ratio__2	-0.0874	0.0430	-2.03	0.0419
liquidity__ratio__3	-0.4105	0.0886	-4.63	0.0000
age__of__company	0.0194	0.0067	2.91	0.0036
unpaid__debt__collection1	1.4323	0.0777	18.44	0.0000
adverse__audit__opinion1	1.2293	0.0774	15.88	0.0000
amount__unpaid__debt	0.0012	0.0005	2.36	0.0182
payment__reminders1	0.6615	0.0895	7.39	0.0000
payment__reminders2	1.7179	0.0961	17.87	0.0000
payment__reminders3	3.1267	0.1100	28.42	0.0000



Confusion Matrix and Statistics

```
      Reference
```

Prediction 0 1 0 32849 93 1 5151 327

```
          Accuracy : 0.8635
            95% CI : (0.86, 0.8669)
No Information Rate : 0.9891
P-Value [Acc > NIR] : 1

             Kappa : 0.0925
```

Mcnemar's Test P-Value : <2e-16

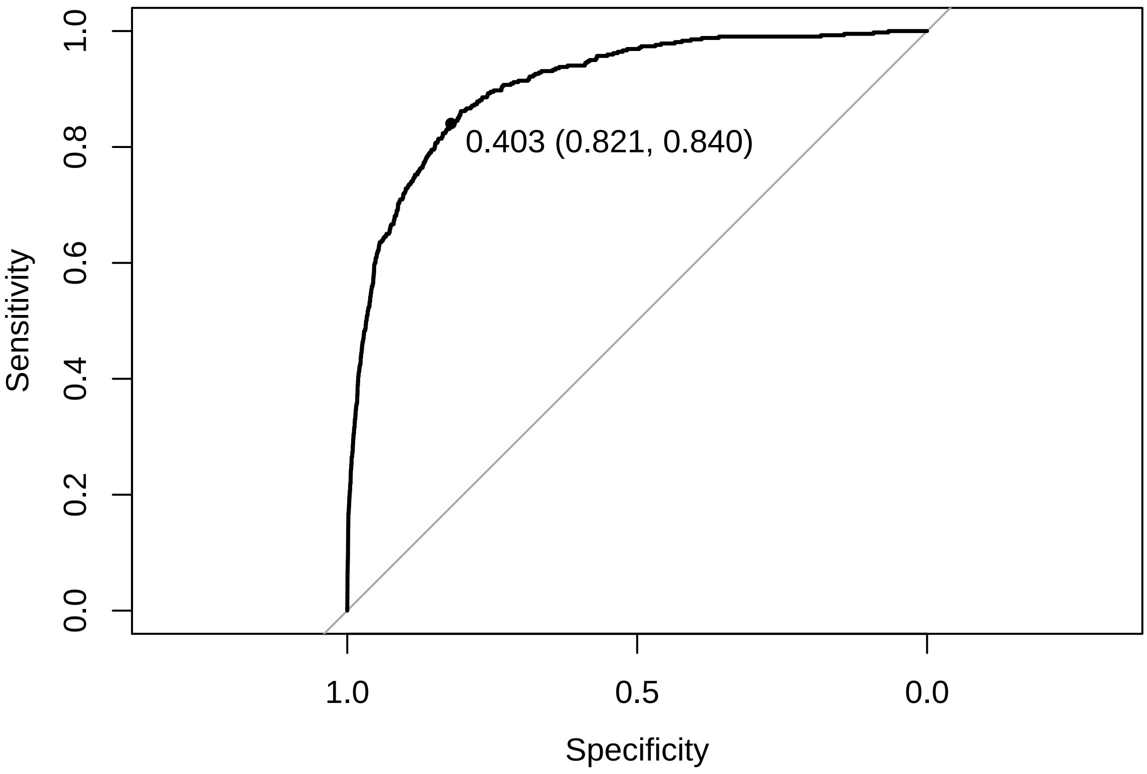
```
       Sensitivity : 0.86445
       Specificity : 0.77857
    Pos Pred Value : 0.99718
    Neg Pred Value : 0.05969
        Prevalence : 0.98907
    Detection Rate : 0.85500
```

Detection Prevalence : 0.85742
Balanced Accuracy : 0.82151

```
   'Positive' Class : 0
```

Comments:

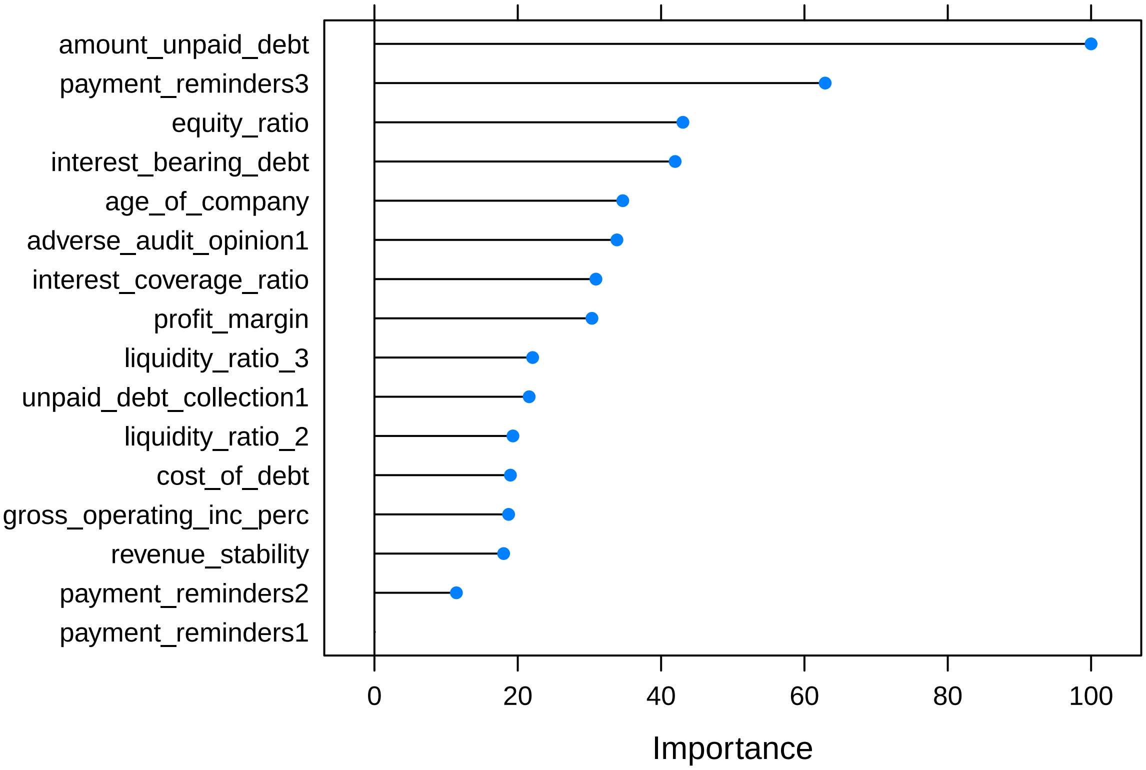
Discuss the confusion matrix.



threshold accuracy 0.4028848 0.8213170

Random forest

Our second predicion model is a random forest model.



Confusion Matrix and Statistics

```
      Reference
```

Prediction 0 1 0 34738 139 1 3262 281

```
               Accuracy : 0.9115
                 95% CI : (0.9086, 0.9143)
    No Information Rate : 0.9891
    P-Value [Acc > NIR] : 1

                  Kappa : 0.1247
```

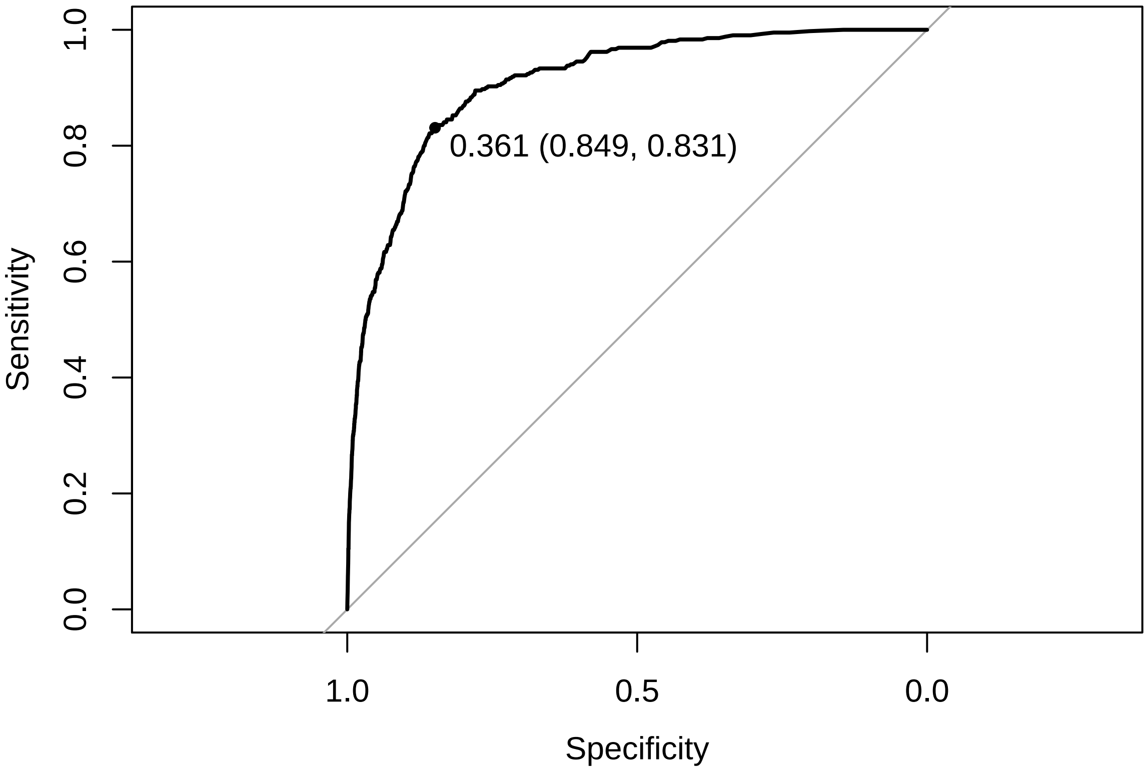
Mcnemar's Test P-Value : <2e-16

```
            Sensitivity : 0.91416
            Specificity : 0.66905
         Pos Pred Value : 0.99601
         Neg Pred Value : 0.07931
             Prevalence : 0.98907
         Detection Rate : 0.90416
```

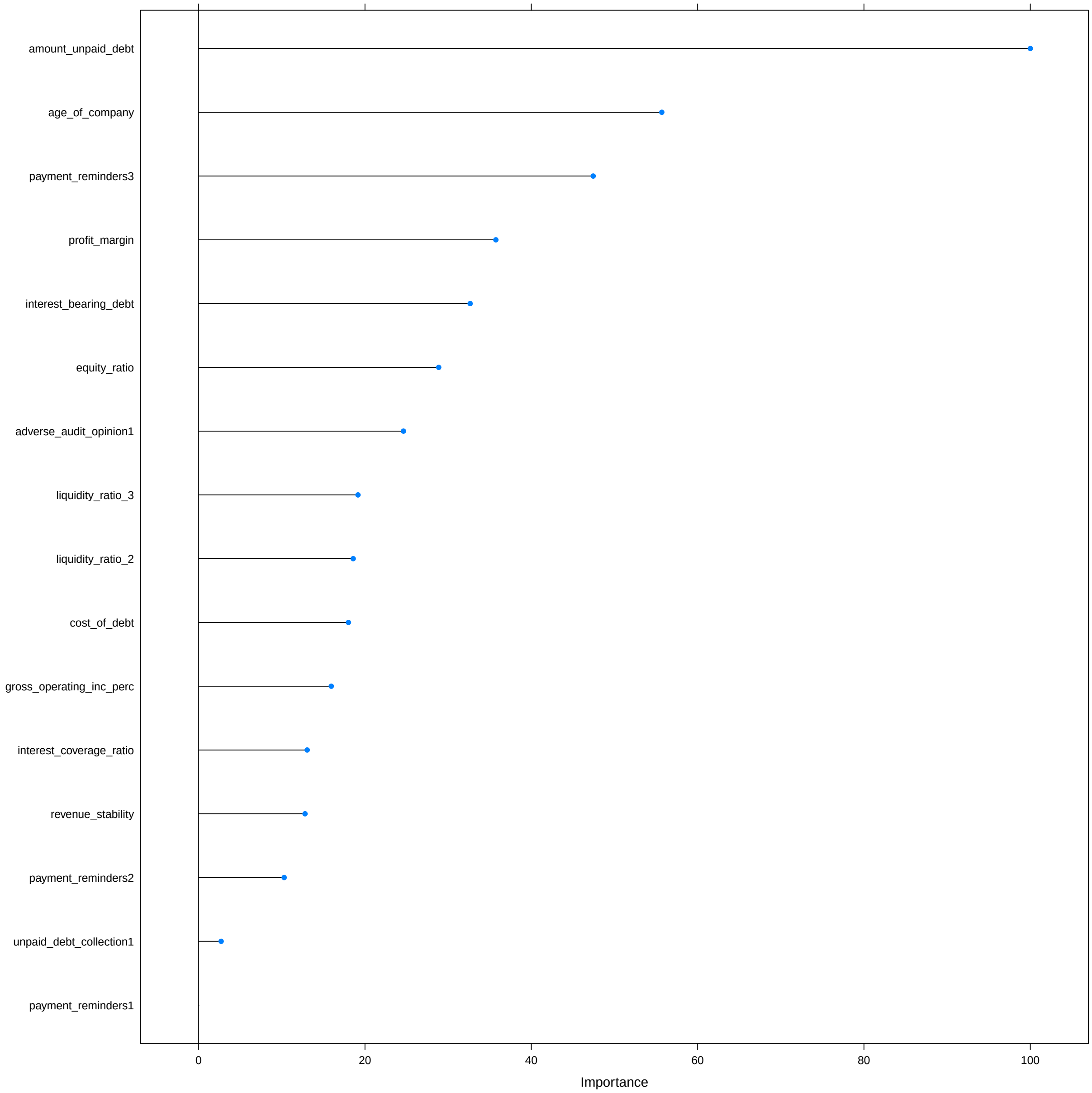
Detection Prevalence : 0.90778
Balanced Accuracy : 0.79160

```
'Positive' Class : 0
```

Comments: About the confustion matrix How well the model performs relative to glm Accuracy, specificity and sensitivity etc.



threshold accuracy 0.3610000 0.8484643



Confusion Matrix and Statistics

```
      Reference
```

Prediction 0 1 0 35184 144 1 2816 276

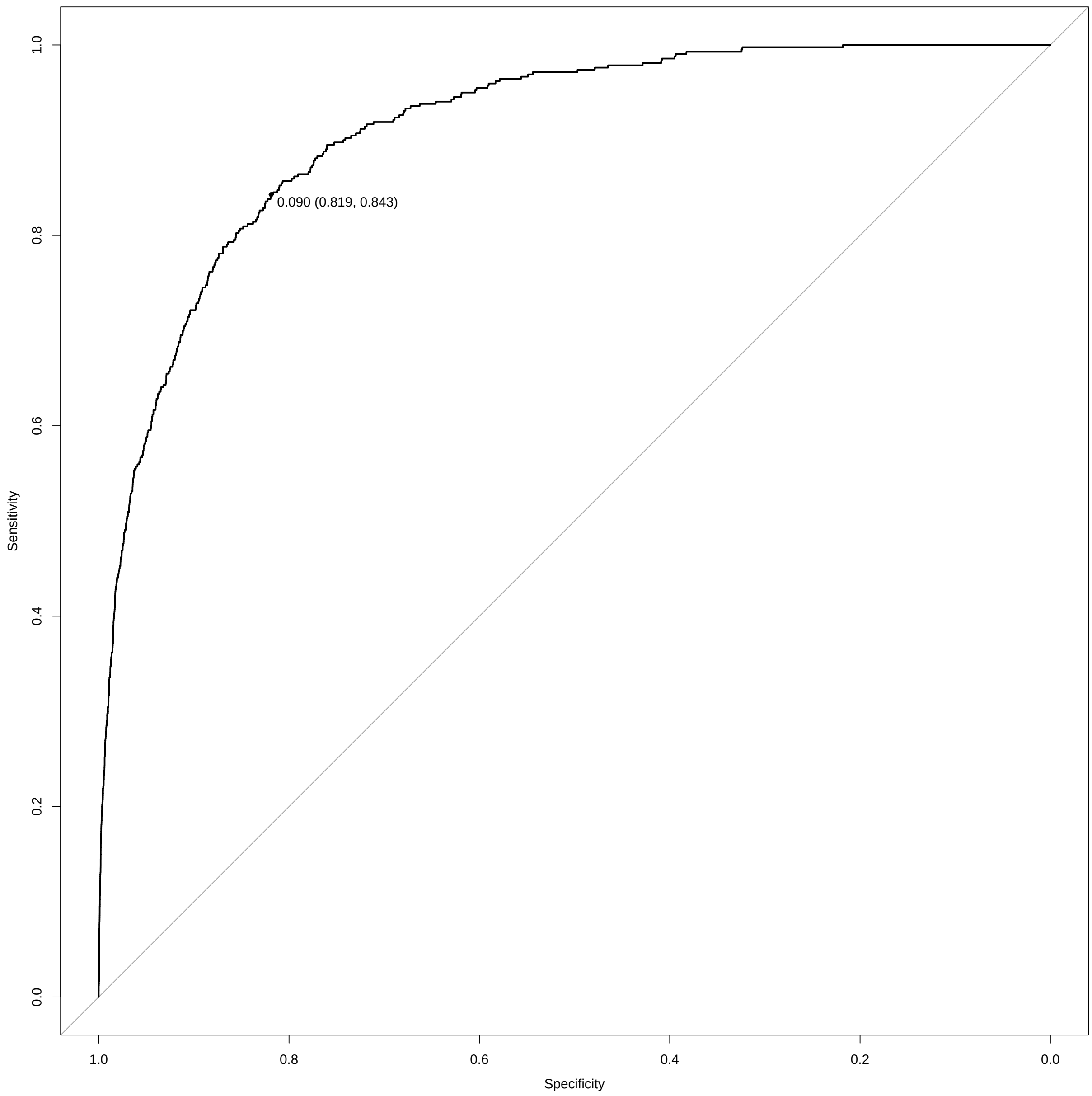
```
           Accuracy : 0.923
             95% CI : (0.9202, 0.9256)
No Information Rate : 0.9891
P-Value [Acc > NIR] : 1

              Kappa : 0.1406
```

Mcnemar's Test P-Value : <2e-16

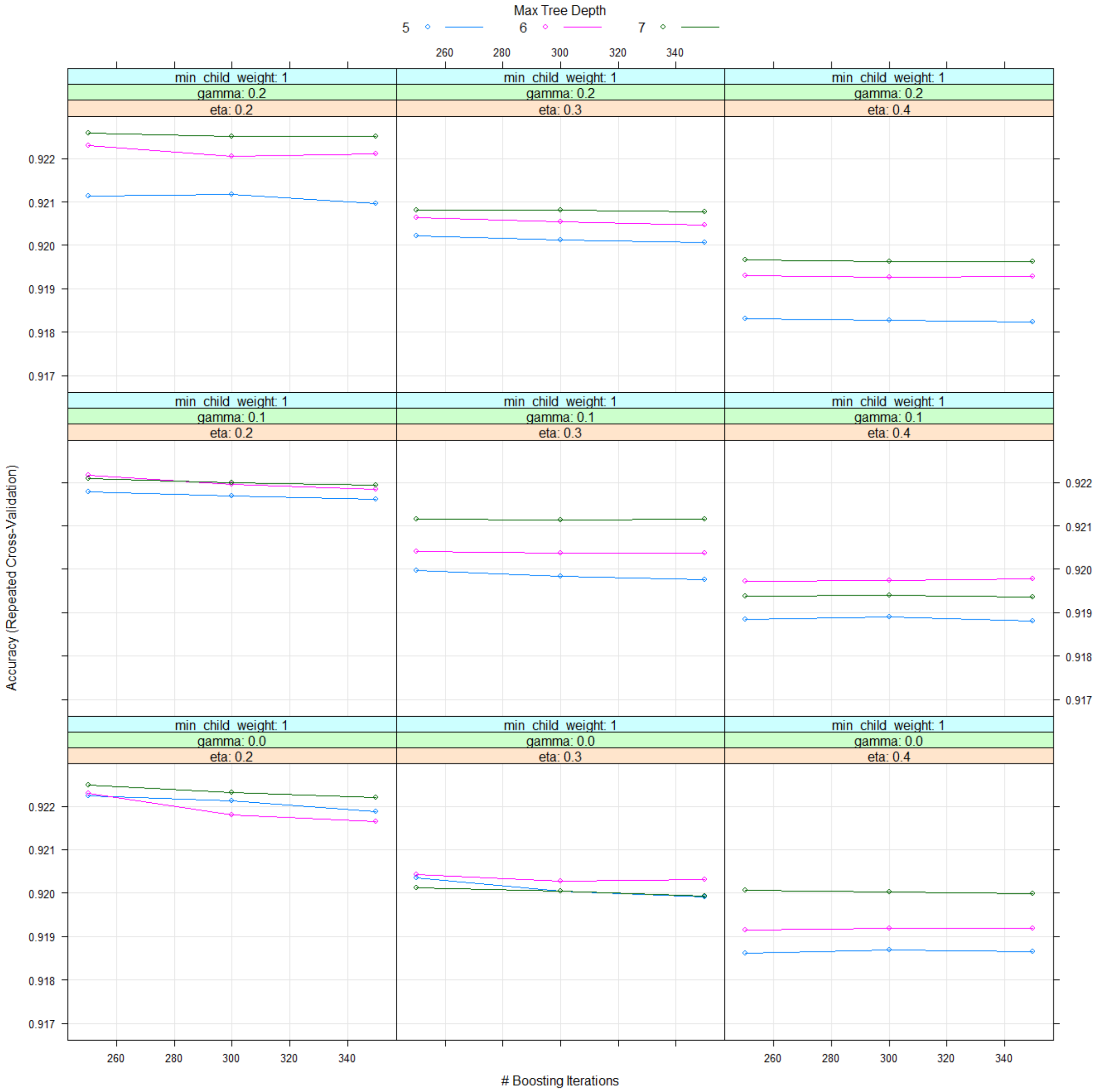
```
            Sensitivity : 0.92589
            Specificity : 0.65714
         Pos Pred Value : 0.99592
         Neg Pred Value : 0.08926
             Prevalence : 0.98907
         Detection Rate : 0.91577
```

Detection Prevalence : 0.91952
Balanced Accuracy : 0.79152

```
       'Positive' Class : 0
```



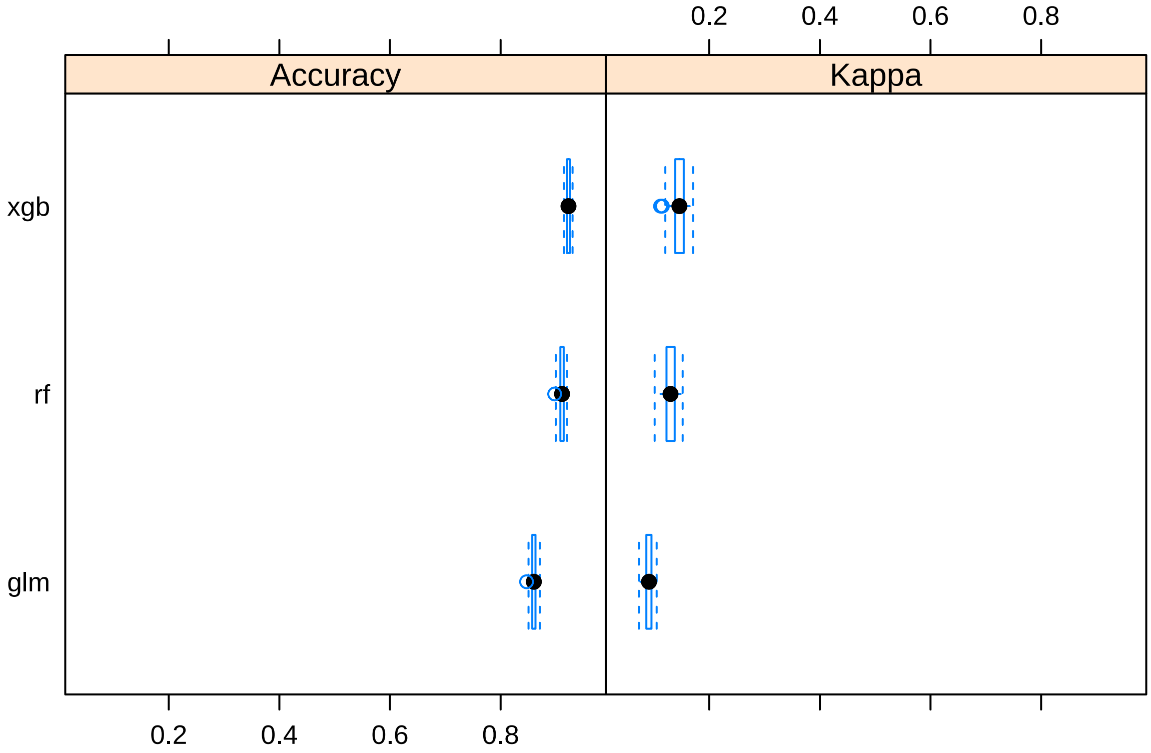
threshold accuracy 0.08979452 0.81907860



Accuracy and Kappa These are the default metrics used to evaluate algorithms on binary and multi-class classification datasets in caret.

Accuracy is the percentage of correctly classifies instances out of all instances. It is more useful on a binary classification than multi-class classification problems because it can be less clear exactly how the accuracy breaks down across those classes (e.g. you need to go deeper with a confusion matrix). Learn more about Accuracy here.

Kappa or Cohen's Kappa is like classification accuracy, except that it is normalized at the baseline of random chance on your dataset. It is a more useful measure to use on problems that have an imbalance in the classes (e.g. 70-30 split for classes 0 and 1 and you can achieve 70% accuracy by predicting all instances are for class 0). Learn more about Kappa here.



% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: søn., nov 03, 2019 - 16:57:51

Table 3:

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
glm	0.847	0.857	0.860	0.860	0.863	0.871	0
rf	0.898	0.908	0.911	0.911	0.914	0.920	0
xgb	0.915	0.920	0.923	0.923	0.925	0.930	0

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: søn., nov 03, 2019 - 16:57:51

Table 4:

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
glm	0.073	0.086	0.091	0.091	0.096	0.105	0
rf	0.101	0.123	0.130	0.130	0.137	0.152	0
xgb	0.112	0.139	0.146	0.146	0.154	0.171	0