Predicting Loan Approval Using Random Forests

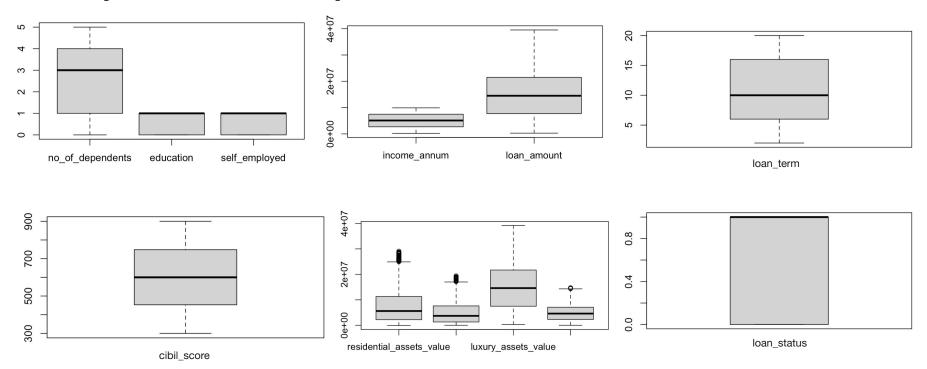
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> summary(Loandata)

> Summary(Loandata)								
loan_id	no_of_de	pendents	educa ⁻	tion	self_em	ployed	income	_annum
Min. :	1 Min. :	0.000 M	1in.	:0.0000	Min.	:0.0000	Min.	: 200000
1st Qu.:10	68 1st Qu.:	1.000 1	st Qu.	:0.0000	1st Qu.	:0.0000	1st Qu.	:2700000
Median :21	35 Median :	3.000 M	Median	:1.0000	Median	:1.0000	Median	:5100000
Mean :21	35 Mean :	2.499 M	l ean	:0.5022	Mean	:0.5036	Mean	:5059124
3rd Qu.:32	02 3rd Qu.:	4.000 3	Brd Qu.	:1.0000	3rd Qu.	:1.0000	3rd Qu.	:7500000
Max. :42	69 Max. :	5.000 M	lax.	:1.0000	Max.	:1.0000	Max.	:9900000
loan_amount loan_term cibil_score residential_assets_value								
Min. :	300000 Min.	: 2.0	Min.	:300.0	Min.	: -10000	00	
1st Qu.: 7	700000 1st	Qu.: 6.0	1st Q	u.:453.0	1st Qu	.: 220000	00	
Median :14	500000 Medi	an :10.0	Media	n :600.0	Median	: 560000	00	
Mean :15	133450 Mear	:10.9	Mean	:599.9	Mean	: 747261	.7	
3rd Qu.:21	500000 3rd	Qu.:16.0	3rd Qu	u.:748.0	3rd Qu	.:1130000	10	
Max. :39	500000 Max.	:20.0	Max.	:900.0	Max.	:2910000	00	
commercial_assets_value luxury_assets_value bank_asset_value loan_status								
Min. :	0	Min. :	300000	Ø Min.	:	0 Mi	n. :0.	0000
1st Qu.: 1	300000	1st Qu.:	7500000	0 1st (u.: 230	0000 1s	t Qu.:0.	0000
Median : 3	700000	Median :1	460000	0 Media	ın : 460	0000 Me	dian :1.	0000
Mean : 4	973155	Mean :1	512630	6 Mean	: 497	6692 Me	an :0.	6222
3rd Qu.: 7	600000	3rd Qu.:2	21700000	∂ 3rd Q	u.: 710	0000 3r	d Qu.:1.	0000
Max. :19	400000	Max. :3	39200000	Max.	:1470	0000 Ma	ıx. :1.	0000

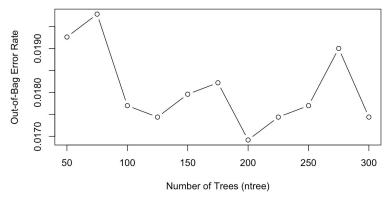
- Our dataset is the "Loan Approval Dataset" from Kaggle
- Loan status is our dependent variable
- We will exclude loan ID
- Most outcomes have very large means. Self employed has the lowest with 0.50 and residential assets has the highest of 74,726,617.

Boxplots of all Independent Variables



Random Forest



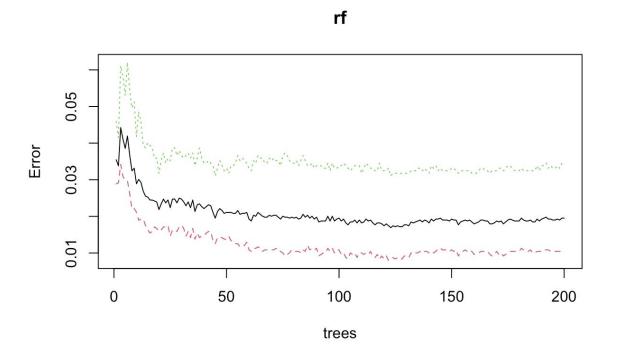


OOB Error Rate VS Number of trees shows that 200 trees gives the lowest OOB

```
Call:
randomForest(formula = loan_status ~ . - loan_id, data = loan_train,
ntree = 200, mtry = 3, oob.prox = TRUE)
               Type of random forest: classification
                    Number of trees: 200
No. of variables tried at each split: 3
       00B estimate of error rate: 1.95%
Confusion matrix:
                    Rejected class.error
          Approved
               2369
                           25 0.01044277
Approved
Rejected
                 50
                        1398 0.03453039
```

Running the model using 200 trees and an mtry of 3 because the square root of 10 is approximately 3

Plot of the Random Forests



- The plot of the random forests shows the error rates at each tree number
- Range from 0-200

Confusion Matrix

Training Set

Confusion Matrix and Statistics

Reference

Prediction Approved Rejected Approved 2394 0 Rejected 0 1448

Accuracy: 1

Test Set

Confusion Matrix and Statistics

Reference

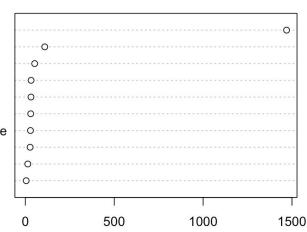
Prediction Approved Rejected
Approved 261 5
Rejected 1 160

Accuracy : 0.9859

Our model accuracy for our training set is 100% while our model accuracy for our test set is 98.59%, which proves to be a good model

Variable Importance

cibil_score
loan_term
loan_amount
luxury_assets_value
income_annum
residential_assets_value
commercial_assets_value
bank_asset_value
no_of_dependents
self_employed



Top 10 - Variable Importance

- Cibil score is the most important factor in determining whether a loan will be approved or not, valued at 1470
- The next most important is loan term at 109
- Based on the mean decrease impurity

Logistic Regression Coefficients

For the original model, we ran logistic regression with all variables besides loan ID because it was just a count. Their coefficients are shown below.

```
Call: qlm(formula = loan_status ~ . - loan_id, family = binomial, data = loan_train)
Coefficients:
             (Intercept)
                                  no_of_dependents
                                                      education Not Graduate
               1.136e+01
                                         1.384e-02
                                                                   1.470e-01
       self_employed Yes
                                      income annum
                                                                 loan amount
              -1.110e-01
                                         5.825e-07
                                                                  -1.410e-07
               loan_term
                                       cibil_score
                                                    residential_assets_value
                                        -2.483e-02
              1.496e-01
                                                                  -5.167e-09
commercial_assets_value
                               luxury_assets_value
                                                            bank_asset_value
                                        -2.423e-08
              -1.513e-08
                                                                  -5.718e-08
```

Forward Selection and AIC

The most efficient variables based on forward selection are cibil score, loan term, loan amount and annual income.

```
Step: AIC=1893.77
loan_status ~ cibil_score + loan_term + loan_amount + income_annum

The AIC for the optimal model was 1724, which is lower than the AIC > AIC(model_1)
for model 1, making the optimal model the better model.

[1] 1730.85

AIC(model_opt_train)
[1] 1724.181
```

Misclassification Matrix

Training Set

(171 + 156) / (2238 + 156 + 171 + 1277) =0.085 Error rate 8.5%

Predicted

Truth 0 1 Approved 2238 156 Rejected 171 1277

Test set

(16 + 19) / (243 + 19 + 16 + 149) = 0.082Error rate 8.2%

Predicted

Truth 0 1 Approved 243 19 Rejected 16 149

Conclusion

- Based on our findings random forest is more accurate for this dataset based on accuracy, but both methods have high accuracy
- Cibil score is the most important factor for both random forest and logistic regression

Thank you. Any questions?