Project 3: Predicting Default Risk

Step 1: Business and Data Understanding

Key Decisions:

1. What decisions needs to be made?

   Due to a financial scandal that hit a competitive bank last week, our bank suddenly has an influx of nearly 500 new customers applying for loans for our bank instead of the other bank in our city. As a loan officer at a young and small bank (been in operations for two years), I need to come up with an efficient solution to classify new customers on whether they can be approved for a loan or not. I'll use a series of classification models to figure out the best model and provide a list of creditworthy customers to bank manager.

2. What data is needed to inform those decisions?

   We have two datasets, one for current customers data stored in 'credit-data-training.xlsx' file and another for new customers data stored in 'customers-to-score.xlsx' file.

Variables for the two datasets

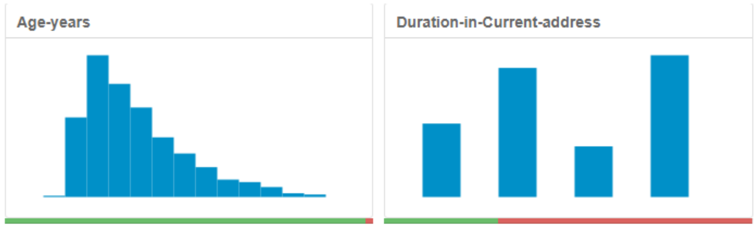
	'credit-data-training.xlsx'	*'customers-to-score.xlsx'*
Joint Fields	*Account-Balance*	*Account-Balance*
	Duration-of-Credit-Month	*Duration-of-Credit-Month*
	Payment-Status-of-Previous-Credit	*Payment-Status-of-Previous-Credit*
	Purpose	*Purpose*
	Credit-Amount	*Credit-Amount*
	Value-Savings-Stocks	*Value-Savings-Stocks*
	Length-of-current-employment	*Length-of-current-employment*
	Instalment-per-cent	*Instalment-per-cent*
	Guarantors	*Guarantors*
	Duration-in-Current-address	*Duration-in-Current-address*
	Most-valuable-available-asset	*Most-valuable-available-asset*
	Age-years	*Age-years*
	Concurrent-Credits	*Concurrent-Credits*
	Type-of-apartment	*Type-of-apartment*
	No-of-Credits-at-this-Bank	*No-of-Credits-at-this-Bank*
	Occupation	*Occupation*
	No-of-dependents	*No-of-dependents*
	Telephone	*Telephone*
	Foreign-Worker	*Foreign-Worker*
	Credit-Application-Result	

3. What kind of model (Continuous, Binary, Non-Binary, Time-Series) do we need to use to help make these decisions?

   Since we are interested in answering the question whether a customer is qualified to be approved for a loan or not, such problem needs a binary model building to answer it. The target field is 'Credit-Application-Result' contains two possible values (Creditworthy/Non- Creditworthy). I will compare 4 different binary classification models (Logistic, Decision Tree, Random Forest, and Boosted) to choose the one that best fit data.

Step 2: Data Preparation

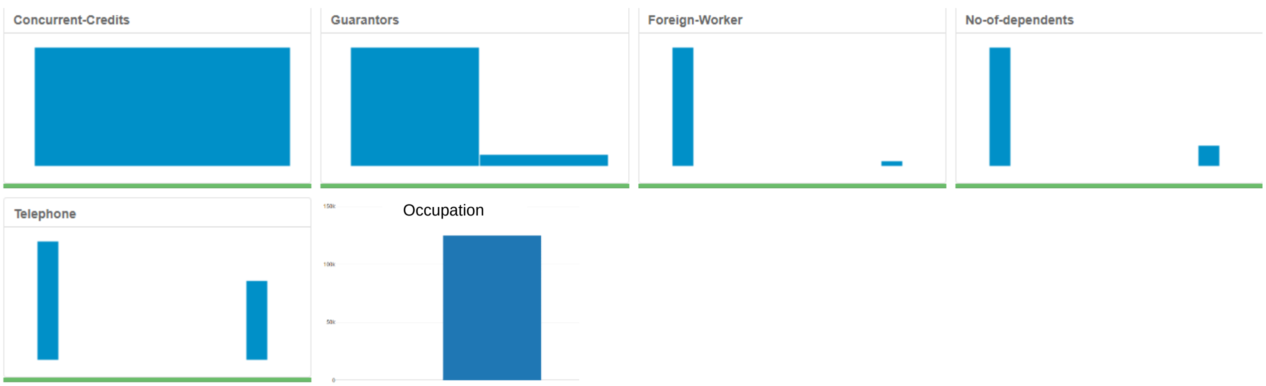
1. Fields with Missing Data



The above visualization identifies missing data with two fields:

- *'Duration-in-Current-address' field has about 69% of its data are missing, so with a high missing data we should remove this field forever.*
- *'Age-years' field has about 2% of its data are missing, by taking into consideration the logical impact of age as a variable in our decision, we should impute the missing ages by replacing them with age median.*

2. Fields with Low Variability



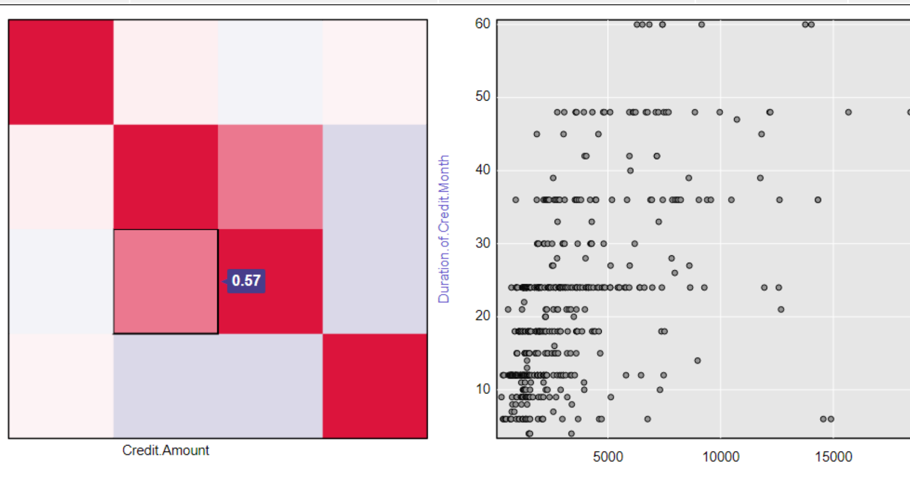
The above visualization identifies low variability with 6 fields in which we should remove all of them.

3. Multicollinearity Identification

We need to check whether any group of the possible predictors are highly correlated or not. The correlation plot matrix between all possible predictor variable is given below

Full Correlation Matrix

	Credit.Application.Result.num	Duration.of.Credit.Month	Credit.Amount	Age.years
Credit.Application.Result.num	1.000000	-0.202504	-0.201946	0.052914
Duration.of.Credit.Month	-0.202504	1.000000	0.573980	-0.064197
Credit.Amount	-0.201946	0.573980	1.000000	0.069316
Age.years	0.052914	-0.064197	0.069316	1.000000



It is clear that there isn't a high correlation between any two possible predictor variables.

Step 3: Training Classification Models

First, I have randomly split dataset into two subsets (70% Estimation and 30% Validation). Then I have trained the 4 models (Logistic, Decision Tree, Random Forest, and Boosted) on Estimation group. Finally, I have used the validation group to test each model accuracy.

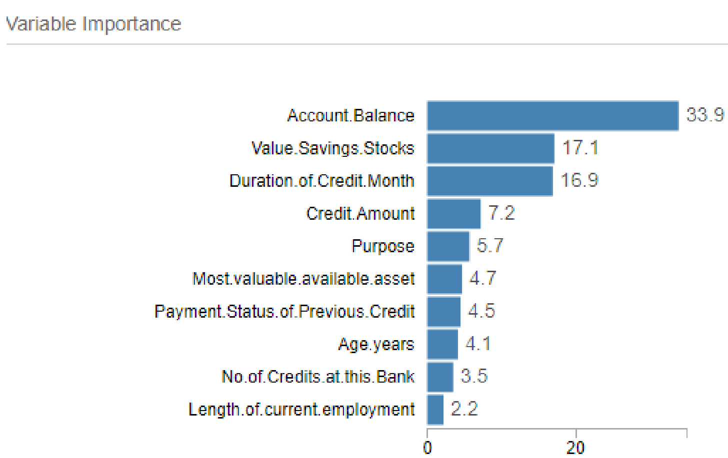
1. Which predictor variables are significant or the most important?

- *with **Logistic Model**: 'Account Balance', 'Credit Amount', and 'Purpose' are the top significant variables descendingly.*

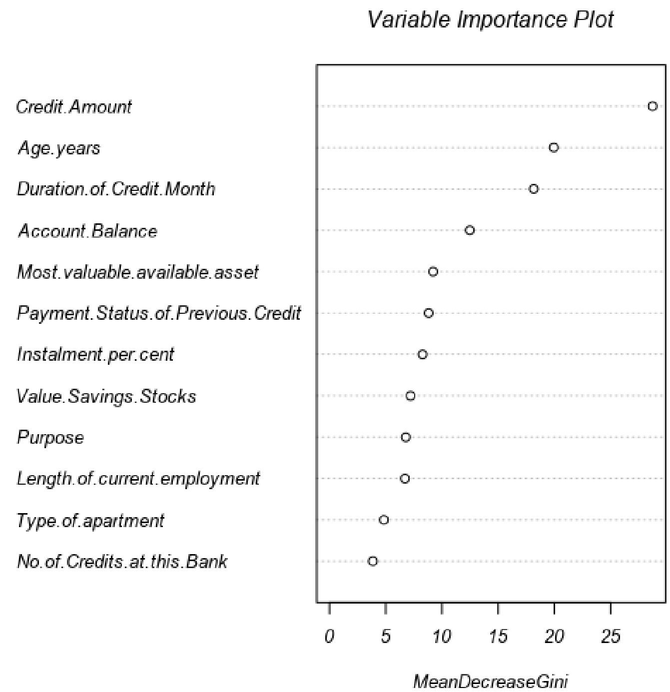
	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-2.9621914	6.837e-01	-4.3326	1e-05	***
Account.BalanceSome Balance	-1.6053228	3.067e-01	-5.2344	1.65e-07	***
Payment.Status.of.Previous.CreditPaid Up	0.2360857	2.977e-01	0.7930	0.42775	
Payment.Status.of.Previous.CreditSome Problems	1.2154514	5.151e-01	2.3595	0.0183	*
PurposeNew car	-1.6993164	6.142e-01	-2.7668	0.00566	**
PurposeOther	-0.3257637	8.179e-01	-0.3983	0.69042	
PurposeUsed car	-0.7645820	4.004e-01	-1.9096	0.05618	.
Credit.Amount	0.0001704	5.733e-05	2.9716	0.00296	**
Length.of.current.employment4-7 yrs	0.3127022	4.587e-01	0.6817	0.49545	
Length.of.current.employment< 1yr	0.8125785	3.874e-01	2.0973	0.03596	*
Instalment.per.cent	0.3016731	1.350e-01	2.2340	0.02549	*
Most.valuable.available.asset	0.2650267	1.425e-01	1.8599	0.06289	.

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

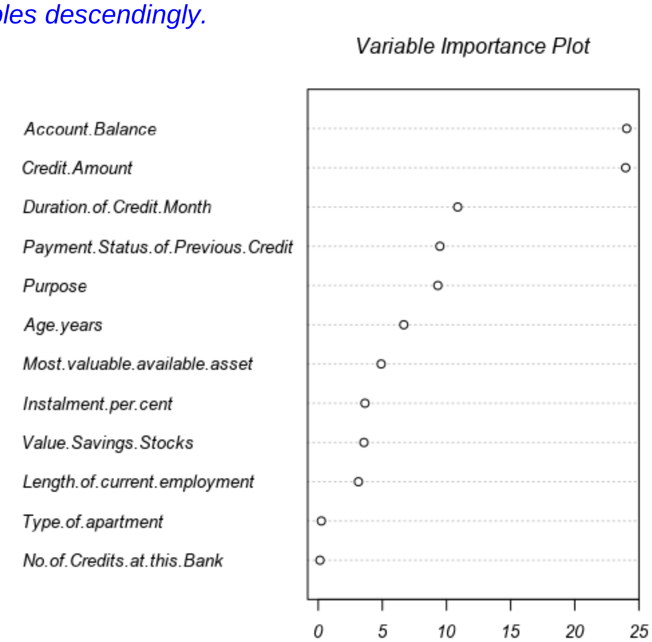
- *with **Decision Tree**: 'Account Balance', 'Value Savings Stocks', and 'Duration of Credit Month' are the top important variables descendingly.*



- *with **Forest Model**: 'Credit Amount', 'Age Years', and 'Duration of Credit Month' are the top important variables descendingly.*



- *with **Boosted Model**: 'Account Balance', 'Credit Amount', and 'Duration of Credit Month' are the top important variables descendingly.*



2. What was the overall percent accuracy? Are there any bias seen in the model's predictions?
   - *with **Logistic Model**: the overall accuracy is 76% while the accuracy of predicting Creditwothy is 88% and the accuracy of predicting Non-Creditwothy is 49%. In such case, we can say that this model is biased to Creditwothy than Non-Creditwothy.*

Fit and error measures

Model	Accuracy	F1	AUC	Accuracy_Creditworthy	Accuracy_Non-Creditworthy
LR_Approval	0.7600	0.8364	0.7306	0.8762	0.4889

Confusion matrix of LR_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	92	23
Predicted_Non-Creditworthy	13	22

- *with **Decision Tree**: the overall accuracy is 75% while the accuracy of predicting Creditwothy is 89% and the accuracy of predicting Non-Creditwothy is 42%. In such case, we can say that this model is biased to Creditworthy than Non-Creditwothy.*

Fit and error measures

Model	Accuracy	F1	AUC	Accuracy_Creditworthy	Accuracy_Non-Creditworthy
DT_Approval	0.7467	0.8304	0.7035	0.8857	0.4222

Confusion matrix of DT_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	93	26
Predicted_Non-Creditworthy	12	19

- *with **Forest Model**: the overall accuracy is 79% while the accuracy of predicting Creditwothy is 97% and the accuracy of predicting Non-Creditwothy is 38%. In such case, we can say that this model is mostly biased to Creditworthy than Non-Creditwothy.*

Fit and error measures

Model	Accuracy	F1	AUC	Accuracy_Creditworthy	Accuracy_Non-Creditworthy
FT_Approval	0.7933	0.8681	0.7368	0.9714	0.3778

Confusion matrix of FT_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	102	28
Predicted_Non-Creditworthy	3	17

- *with **Boosted Model**: the overall accuracy is 79% while the accuracy of predicting Creditwothy is 96% and the accuracy of predicting Non-Creditwothy is 40%. In such case, we can say that this model is mostly biased to Creditworthy than Non-Creditwothy.*

Fit and error measures

Model	Accuracy	F1	AUC	Accuracy_Creditworthy	Accuracy_Non-Creditworthy
BM_Approval	0.7933	0.8670	0.7505	0.9619	0.4000

Confusion matrix of BM_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	101	27
Predicted_Non-Creditworthy	4	18

Step 4: Writeup

1-Which model did I choose to use?

We can compare all 4 models side by side by looking to the following

Model Comparison Report

Fit and error measures

Model	Accuracy	F1	AUC	Accuracy_Creditworthy	Accuracy_Non-Creditworthy
BM_Approval	0.7933	0.8670	0.7505	0.9619	0.4000
FT_Approval	0.7933	0.8681	0.7368	0.9714	0.3778
DT_Approval	0.7467	0.8304	0.7035	0.8857	0.4222
LR_Approval	0.7600	0.8364	0.7306	0.8762	0.4889

Confusion matrix of BM_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	101	27
Predicted_Non-Creditworthy	4	18

Confusion matrix of DT_Approval

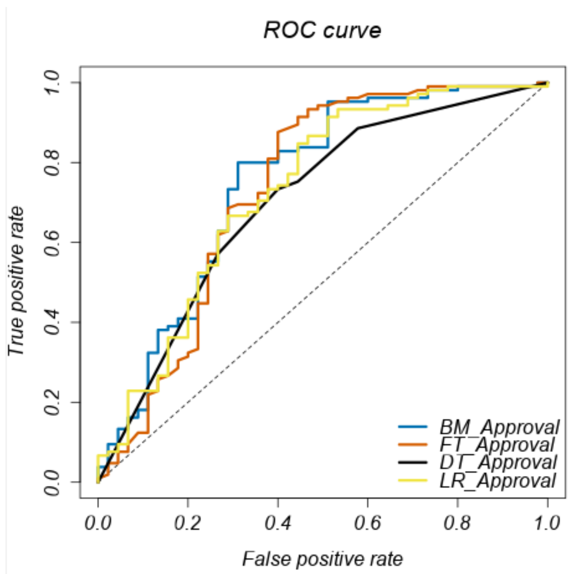
	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	93	26
Predicted_Non-Creditworthy	12	19

Confusion matrix of FT_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	102	28
Predicted_Non-Creditworthy	3	17

Confusion matrix of LR_Approval

	Actual_Creditworthy	Actual_Non-Creditworthy
Predicted_Creditworthy	92	23
Predicted_Non-Creditworthy	13	22



Taking into consideration the overall accuracy, both Forest and Boosted models have the highest overall accuracy of 79.33%, as well we can see that Forest model has the highest Accuracy of predicting Creditworthy at 97.14%, while Boosted model is more accurate in predicting Non-Creditworthy than Forest do.

Also using ROC graph, we can say that Forest model has the highest value with top true positive side of the graph.

Since we are interested in predicting Creditworthy we should choose Forest as the best fit model.

2-How many individuals are creditworthy?

Once we have come up to the best fit model, we could apply that model with our new dataset and the results as follows:

Sum_Score_Creditworthy	Sum_Score_Non-Creditworthy
408	92
81.6%	18.4%

408 customers will be approved and 92 customers will be disapproved