



**LLK Intelligence**

# **Predicting Credit-worthy Applicants**

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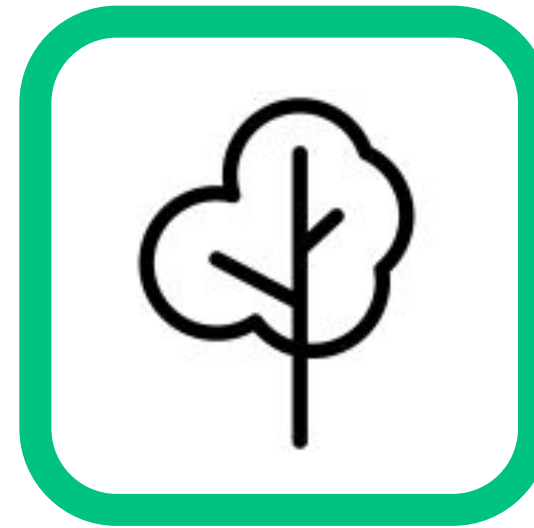


# Meet our team



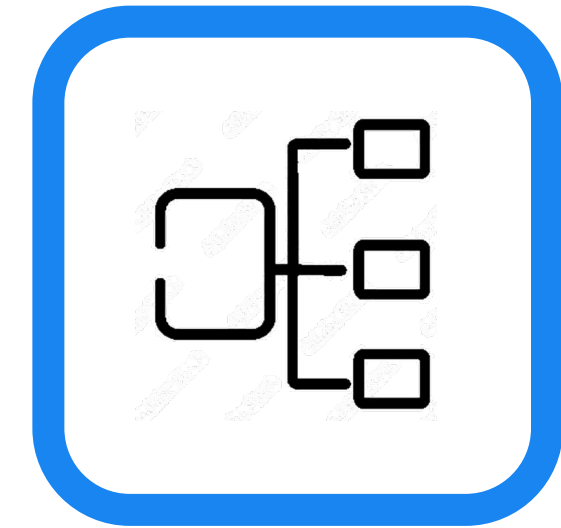
**Aidan**

- Data Exploration and Preparation



**Matthew**

- Predictive Modelling:
  - Decision Tree



**Kai**

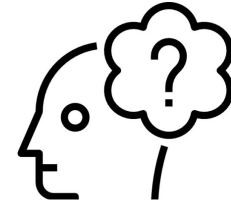
- Predictive Modelling
  - Naive Bayes
- Further exploratory Analysis
  - Linear regression
  - Correlation matrix

## Team

Developed analysis and presentation materials



# Introduction



## **Problem statement**

Which credit customers should get approval for a loan?



## **Our task**

Recommend a strategy based on available credit data that will help bank managers decide whether to approve a loan for new applicants

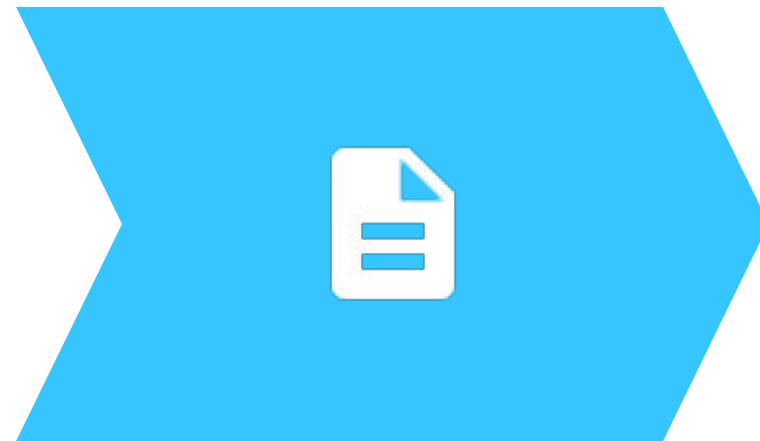


## **Our conclusion**

WEKA-based Naive Bayes model based four attributes performs the best, while satisfying model objectives

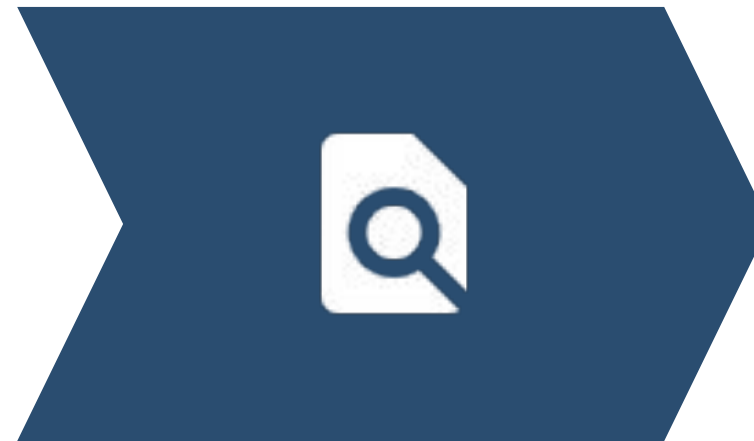


# Data Exploration and Preparation



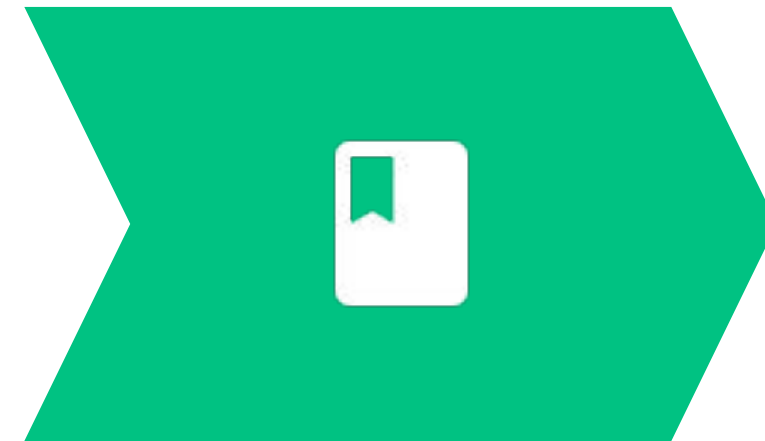
STEP 1

Check for  
missing data



STEP 2

Complete  
distributional  
analysis



STEP 3

Detect  
notable data  
outliers






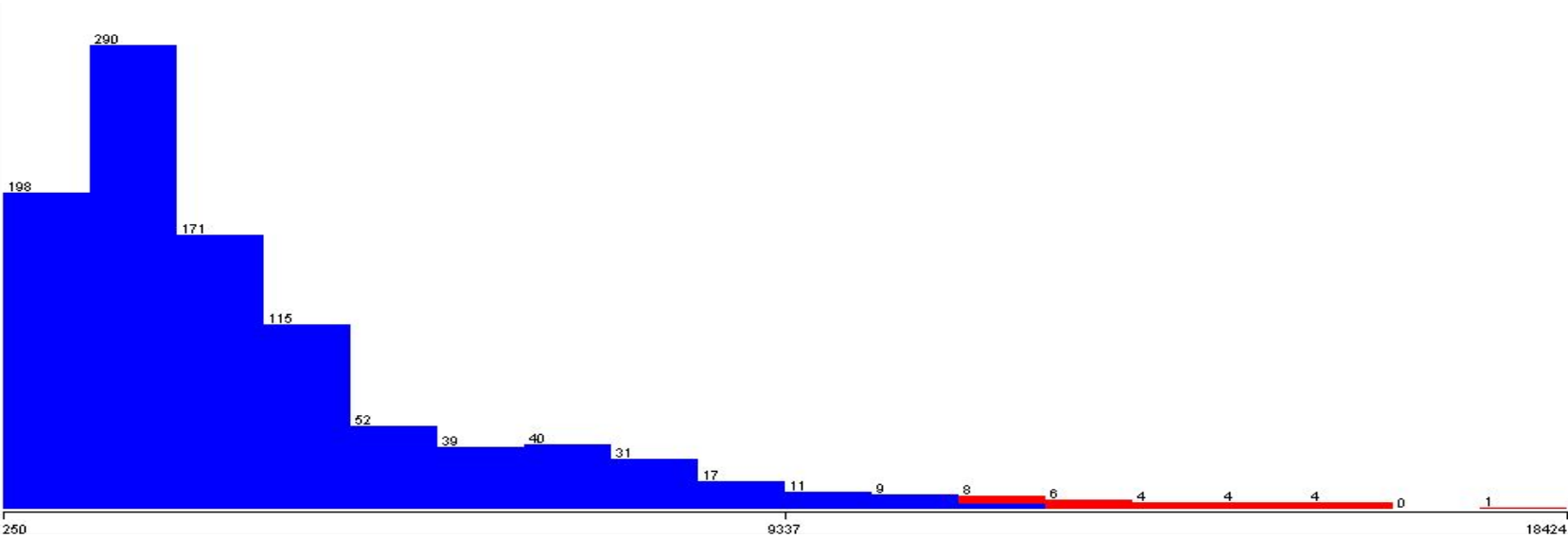
# Data Preparation Highlights

Quartile Distribution of Most Relevant Fields

	Duration of Credit (mos)	Credit Amount
Min	4	250
25th Percentile	12	1,366
Median	18	2,320
75th Percentile	24	3,972
Max	72	18,424

Credit Amount Distribution

 Outliers removed in the prepared dataset



- Most fields in dataset are qualitative classes despite quantitative in nature
- Focused on preparing data for ‘**numeric**’ fields
- Notable outliers in **Credit Amount** and removed those records in the prepared dataset



# Data Analysis



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# Predictive Modelling Approach

## CONSERVATIVE APPROACH

**Keep money safe first, then profit**

Assume a traditional loan business that is risk averse

## PRECISION MOST IMPORTANT

**Most important:**

- to correctly identify clients with good credit
- to minimize approving applicants with bad credit

		PREDICTED	
		Positive <i>Good Creditability</i>	Negative <i>Bad Creditability</i>
ACTUAL	Positive <i>Good Creditability</i>	True Positive	False Negative
	Negative <i>Bad Creditability</i>	False Positive	True Negative

**MOST IMPORTANT**

## MINIMIZE DATA FIELDS IN MODEL

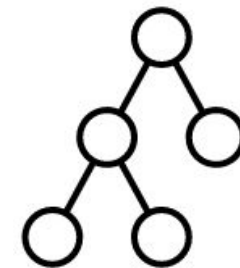
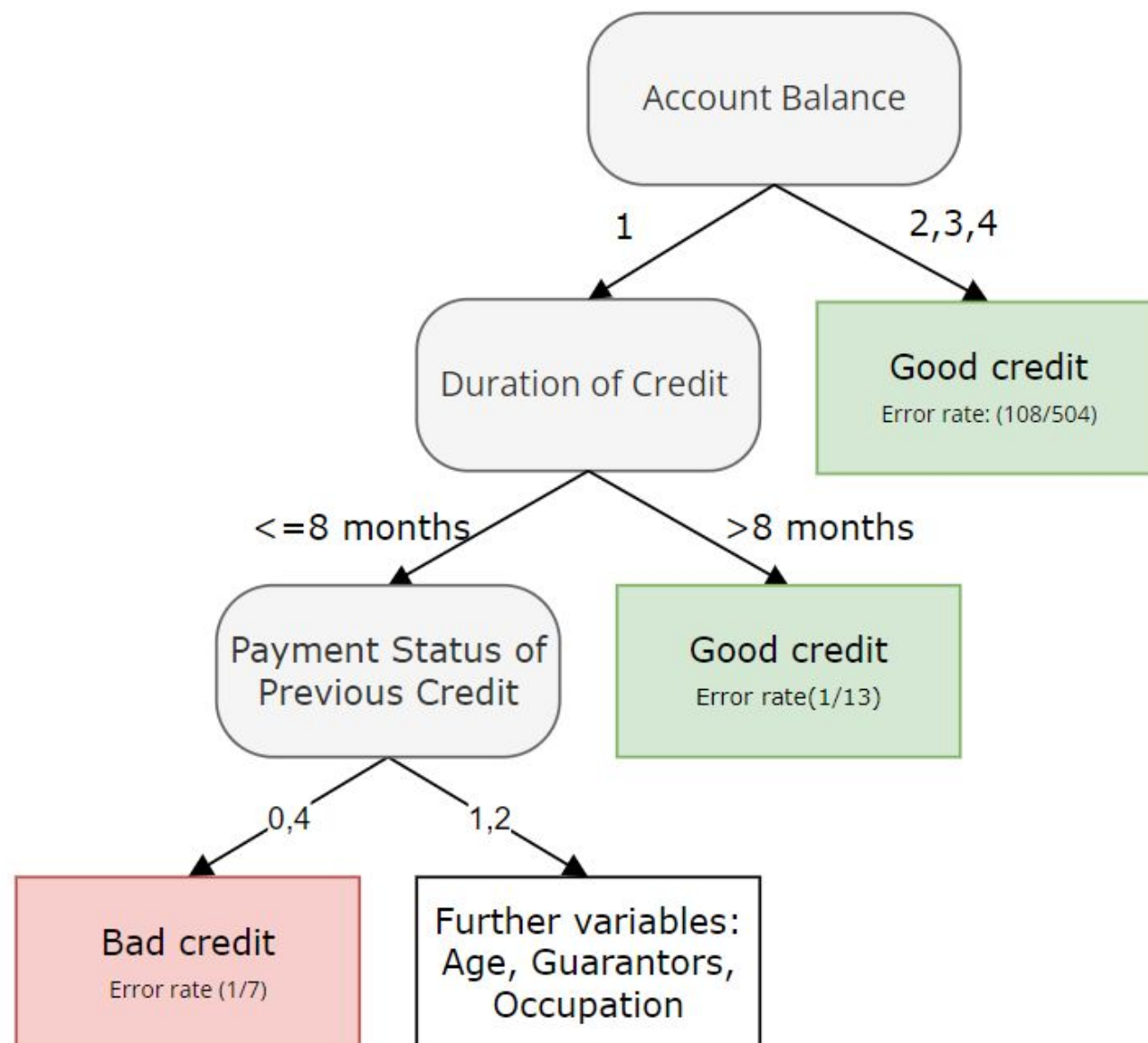
**... but only if it does not affect precision**

Limit the amount of fields in the model will allow for faster response times to applicants



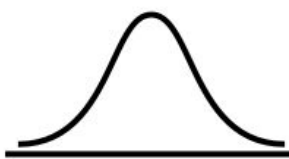
# Predictive Modelling Methods

## Decision Tree Output Example



## Decision Tree Method

- Predicts the value of a target variable by learning simple decision rules inferred from the data features
- Key variables that predict good credit applicants:
  - Account balance, Value of Savings / Stocks, Payment Status of Previous Credit, Duration of Credit, Age, Guarantors



## Naive Bayes Method

- Most important conditional probabilities:
  - Account balance, Payment Status of Previous Credit, Duration of Credit





# Predictive Modelling Results

Most Important			
	Precision	Accuracy	Recall
Pre-prepared data - Baseline [n = 300]			
Decision Tree	0.70	0.65	0.80
Naive Bayes	0.76	0.75	0.90
Prepared data [n = 293]			
Decision Tree	0.82	0.75	0.81
Naive Bayes	0.84	0.76	0.81

Removal of outliers led to improved Precision figures

Naive Bayes performed marginally better than Decision Tree and process to next step






# Predictive Modelling Refinement

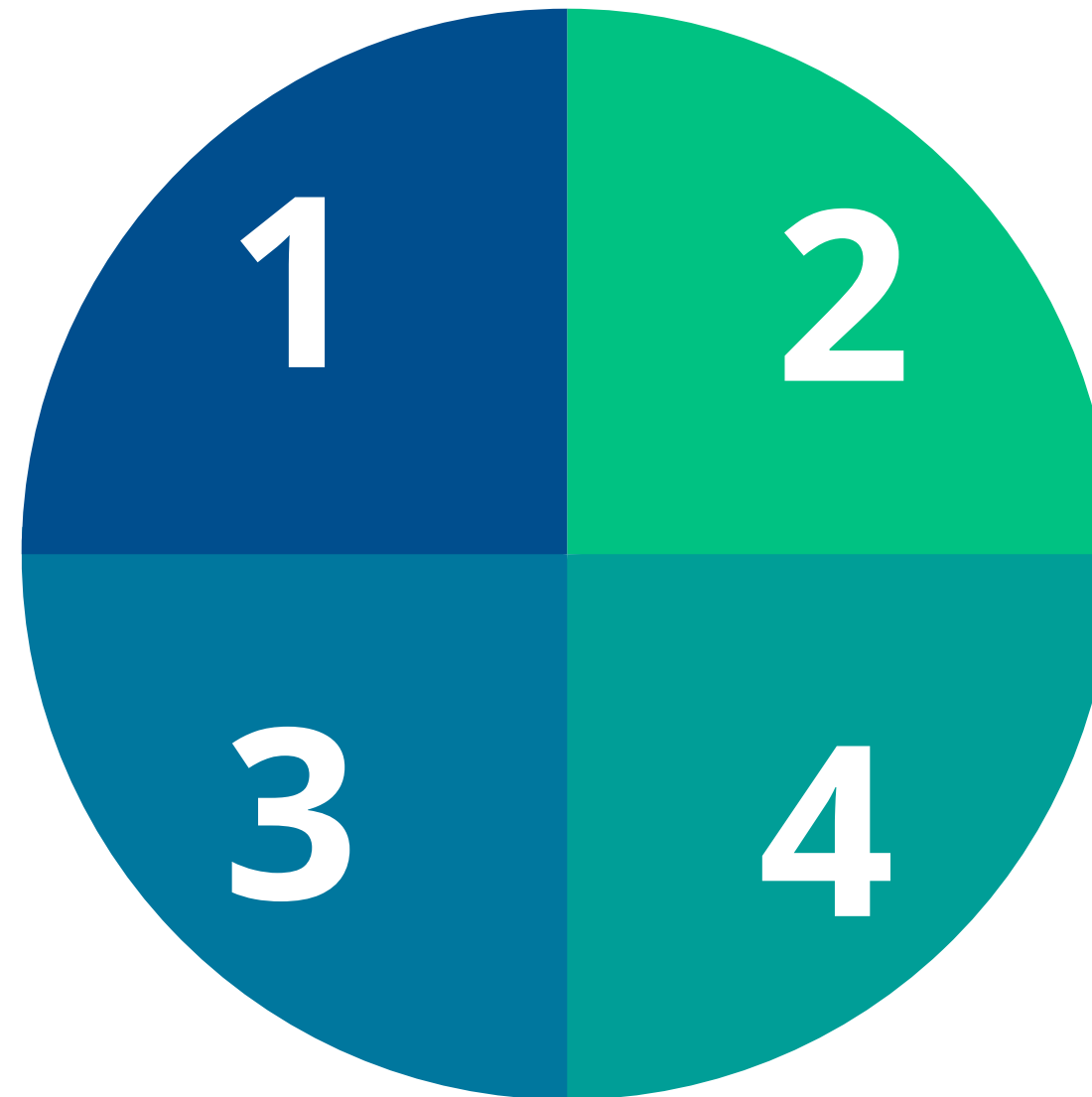
- Recommend the Naive Bayes classification method
- Selected the commonly recurring field in all classification models and re-ran the model

Account Balance

 Payment Status of  
Previous Credit

Duration of Credit

Value Savings and  
Stock





# Predictive Modelling Refinement

## Naive Bayes Model

	Most Important		
	Precision	Accuracy	Recall
Pre-prepared data Baseline [n = 300]	0.76	0.75	0.90
Prepared data All variables [n = 293]	0.84	0.76	0.81
Prepared data Four variables [n = 293]	0.82	0.76	0.84

Marginal impact to Precision by isolating to only four variables

Simplifying the model is worthwhile to reduce complexity and improve decision response times

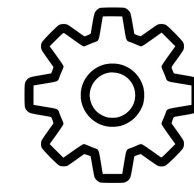


# Recommendations



Apply the Naive Bayes classification model based on the following criteria:

- Account Balance
- Duration of Credit
- Payment Status of Previous Credit
- Value Savings/Stocks



Require further training of the model



Seek expanded dataset with more numeric fields, allowing the model to identify its own classification 'bins'





# Appendices

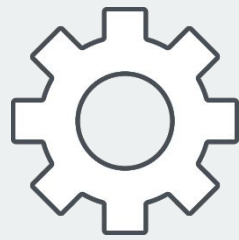
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# Predictive Model Development and Selection



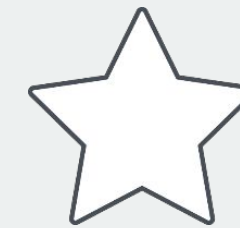
Run Decision Tree and Naive Bayes classifiers using the WEKA application

1



Run based on a ratio 70/30 train and test sets on the raw and prepared datasets

2



Choose the classification model and isolate the model to smaller set of variables where possible

3



# Metrics selection logic

bank



Money safe first, then profit



In all predict 1(+) datapoints, the number of actual 1(+) datapoints should as large as possible



Precision should as high as possible



We can tolerate a certain amount of FN, but we have zero tolerance for FP.  
Cause FP means we provide loans to class 0 and then we cannot get money back.

True Class	Predicted Class	
	True Positive (TP)	False Negative (FN)
False Positive (FP)		True Negative (TN)

We assume the bank belongs to the risk-averse type (cause just the traditional loan business, not risk-seeking type like doing hedge fund), So Precision is our main consideration.

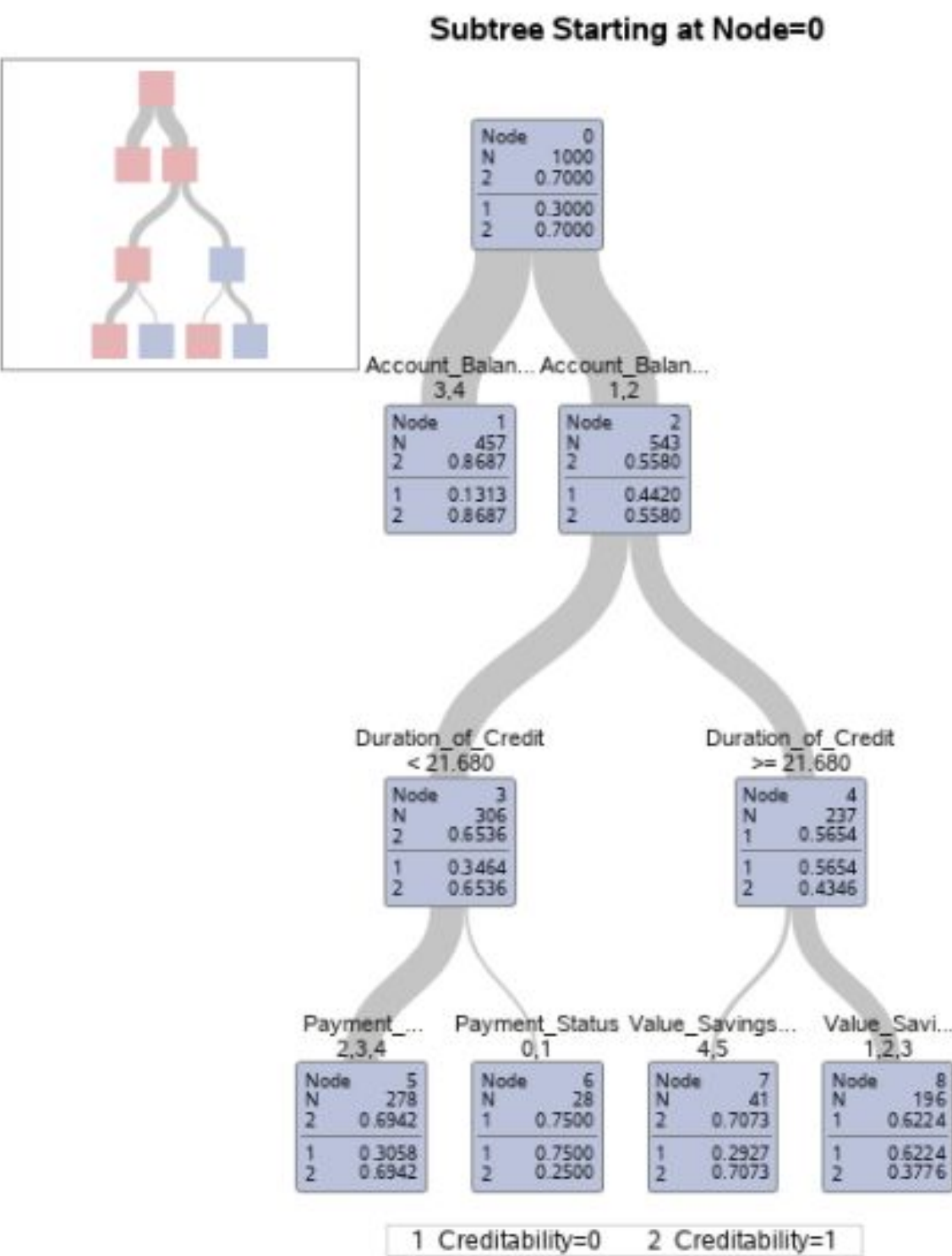
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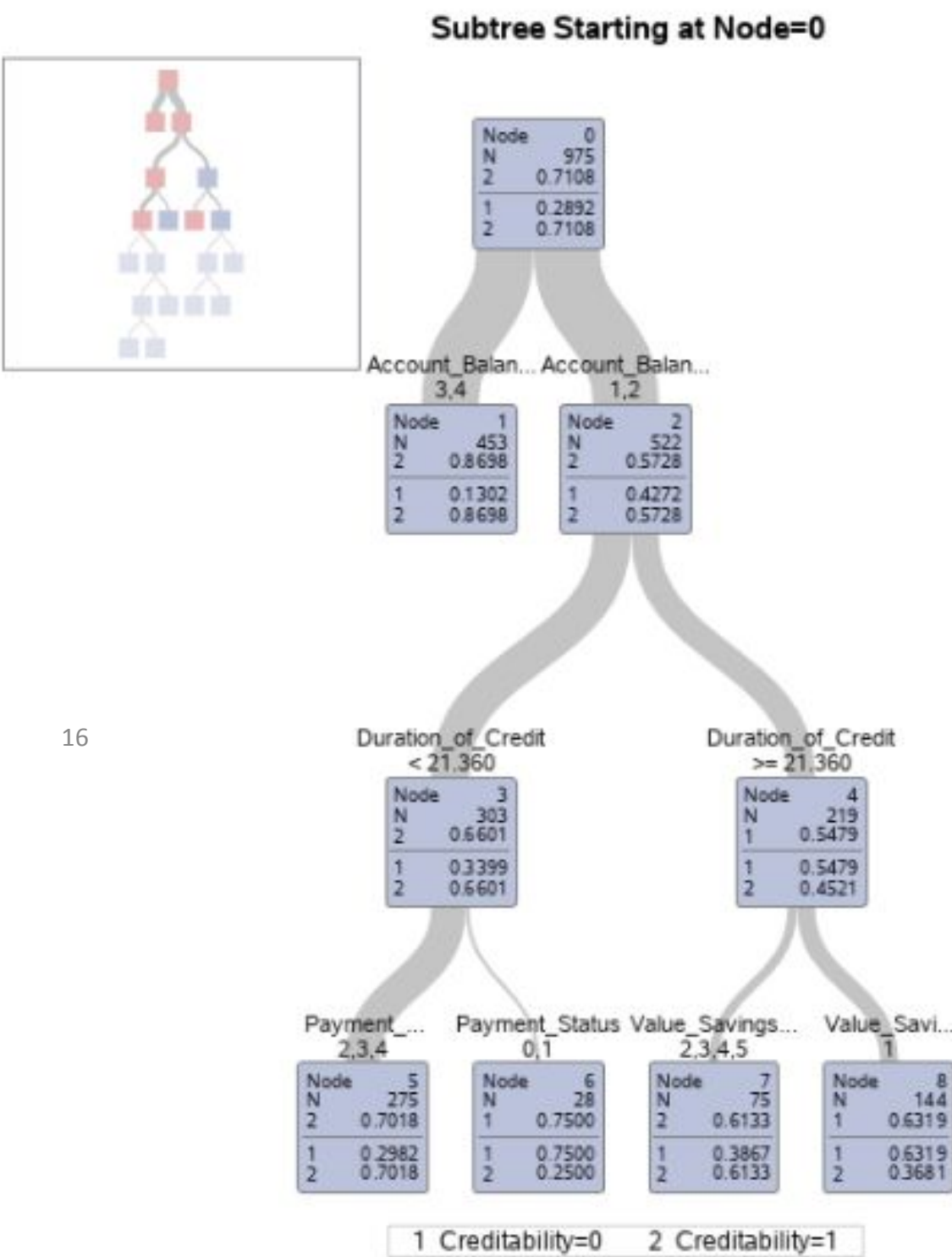


# Predictive Modelling - Decision Tree

Pre-processed data



Processed data



# Predictive Modelling - Decision Tree

Based on ALL variables 0.1 trim					
Pre-prepared data			Prepared data		
Generated confusion matrix			Generated confusion matrix		
	0	1		0	1
0	38	68	0	35	49
1	16	178	1	24	185
Positive represents 1			Positive represents 1		
	+	-		+	-
+	178	16	+	185	24
-	68	38	-	49	35
Accuracy	0.72		Accuracy	0.750853	
Recall	0.917526		Recall	0.885167	
Precision	0.723577		Precision	0.790598	
F1 Score	0.809091		F1 Score	0.835214	

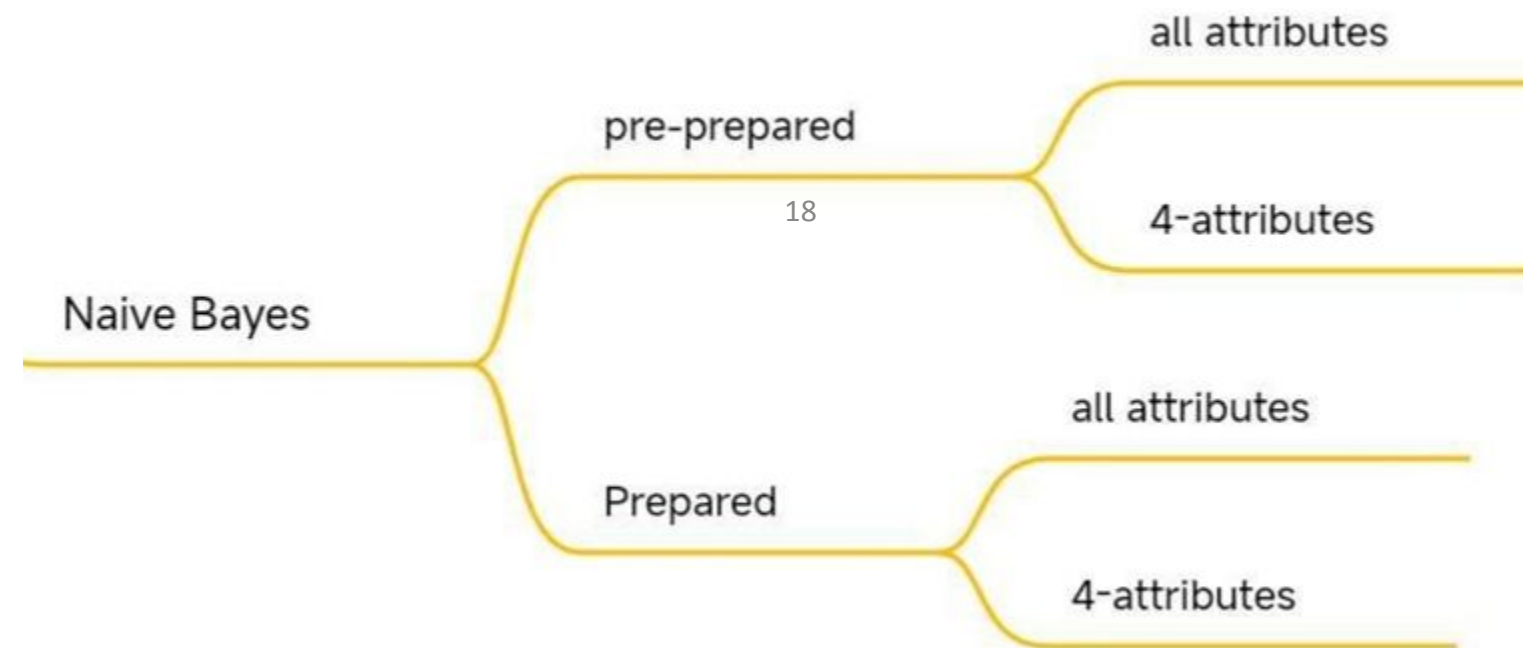
Based on ALL variables 0.25 trim					
Pre-prepared data			Prepared data		
Generated confusion matrix			Generated confusion matrix		
	0	1		0	1
0	40	66	0	49	35
1	39	155	1	39	170
Positive represents 1			Positive represents 1		
	+	-		+	-
+	155	39	+	170	39
-	66	40	-	35	49
Accuracy	0.65		Accuracy	0.74744	
Recall	0.798969		Recall	0.813397	
Precision	0.701357		Precision	0.829268	
F1 Score	0.746988		F1 Score	0.821256	

Based on 4 variables 0.25 trim					
Pre-prepared data			Prepared data		
Generated confusion matrix			Generated confusion matrix		
	0	1		0	1
0	52	54	0	40	44
1	20	174	1	31	178
Positive represents 1			Positive represents 1		
	+	-		+	-
+	174	20	+	178	31
-	54	52	-	44	40
Accuracy	0.753333		Accuracy	0.744027	
Recall	0.896907		Recall	0.851675	
Precision	0.763158		Precision	0.801802	
F1 Score	0.824645		F1 Score	0.825986	



# Predictive Modeling

- Evaluation method: Naïve Bayes(Weka)
- The Split method:
- Train : Test = 70% : 30%



# Predictive Modelling - Naive Bayes

- Explain the Naïve Bayes model
- Bayes' theorem:  $posterior = \frac{prior * likelihood}{evidence}$
- Naïve Bayes learnt the priors  $P_{class1}=0.7$ ,  $P_{class0}=0.3$ . In our model:

## Naive Bayes Classifier

Attribute	Class	
	0 (0.29)	1 (0.71)
=====		
Account Balance		
1	91.0	89.0
2	64.0	105.0
3	10.0	37.0
4	37.0	257.0
[total]	202.0	488.0
Duration of Credit (month)		
mean	23.8801	19.0948
std. dev.	12.7811	10.8691
weight sum	198	484
precision	1.8667	1.8667
Payment Status of Previous Credit		
0	16.0	9.0
1	19.0	16.0
2	113.0	245.0
3	21.0	39.0
4	34.0	180.0
[total]	203.0	489.0
Value Savings/Stocks		
1	149.0	271.0
2	19.0	46.0
3	10.0	36.0
4	5.0	32.0
5	20.0	104.0
[total]	203.0	489.0



# Predictive Modelling - Naive Bayes

- Likelihood/Conditional Probabilities:
- Basically calculate each situation in each attributes given class 1 or class 0. using smoothing technology. +1 in molecular, +V in denominator, V means in the attribute, the number of all distinct situations in class1+ class0.
- Coose a class:
- Calculate each tuple as prior \* all likelihood in two classes then compare.

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# Predictive Modelling - Naive Bayes

Based on ALL variables NB						
pre-prepared data			<u>11.19%</u>	Prepared data		
	0	1			0	1
0	50	56		0	52	32
1	19	175		1	38	171
	1	0			1	0
1	175	19		1	171	38
0	56	50		0	32	52
TP	0.902062	0.902062		TP	0.818182	0.818182
precision	0.757576	0.757576		precision	0.842365	0.842365
FP	0.528302	0.528302		FP	0.380952	0.380952
recall	0.902062	0.902062		recall	0.818182	0.818182
Accuracy	0.75	0.75		Accuracy	0.761092	0.761092

Based on 4 variables NB						
pre-prepared data			12.85%	Prepared data		
	0	1			0	1
0	40	66		0	46	38
1	16	178		1	32	177
	1	0			1	0
1	178	16		1	177	32
0	66	40		0	38	46
TP	0.917526	0.917526		TP	0.84689	0.84689
precision	0.729508	0.729508		precision	0.823256	0.823256
FP	0.622642	0.622642		FP	0.452381	0.452381
recall	0.917526	0.917526		recall	0.84689	0.84689
Accuracy	0.726667	0.726667		Accuracy	0.761092	0.761092

**precision:** Among the customers who are able to borrow in our predicted model, how many customers are actually able to borrow, and the rest are actually unable to lend

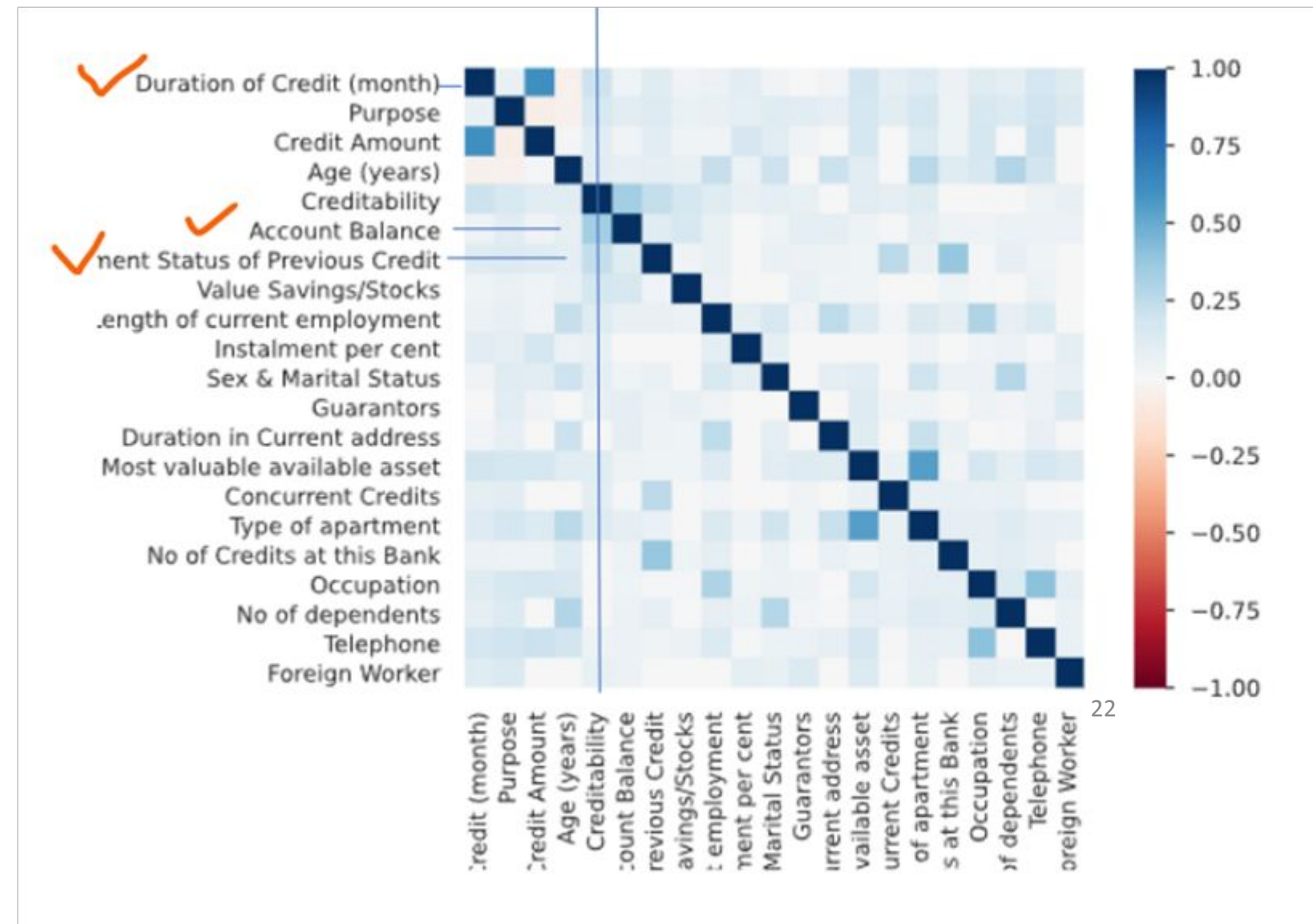
**TP/Recall:** Among all the customers who are actually able to borrow money, how many customers have we predicted(provide loan)





# Exploratory Analysis

- Correlation Matrix(sk-learn)



Also shown the data after prepared, The most related attributes with the class attribute.



# Exploratory Analysis

- Linear regression(R studio)

```
lm(formula = Creditability ~ Account + Duration + Payment + Value,
    data = bank)

Residuals:
    Min       1Q   Median       3Q      Max
-1.1053 -0.3861  0.1168  0.3047  0.7222

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.359636   0.049057   7.331 4.81e-13 ***
Account      0.100836   0.010861   9.285 < 2e-16 ***
Duration     -0.007214   0.001148  -6.284 4.99e-10 ***
Payment      0.064876   0.012440   5.215 2.24e-07 ***
Value        0.033884   0.008560   3.958 8.10e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4094 on 970 degrees of freedom
Multiple R-squared:  0.189,    Adjusted R-squared:  0.1856
F-statistic: 56.51 on 4 and 970 DF,  p-value: < 2.2e-16
```

R-squared is much lower than 0.7, so they are not a good linear regression model.

