

GradProject_R

May 18, 2019

1 Introduction

Many institutions use different statistical and machine learning algorithms on a prepared dataset in order to obtain efficient and useful results. In this thesis, we are going to apply some statistical and machine learning algorithms to a given dataset and criticize their results.

Dataset contains confidential information about different people who acquired credit from a bank, and whether they are paid their credit back or not. Dataset can be accessed via this [link](#), and we will try to build a solid model for making a classification for credit approvals.

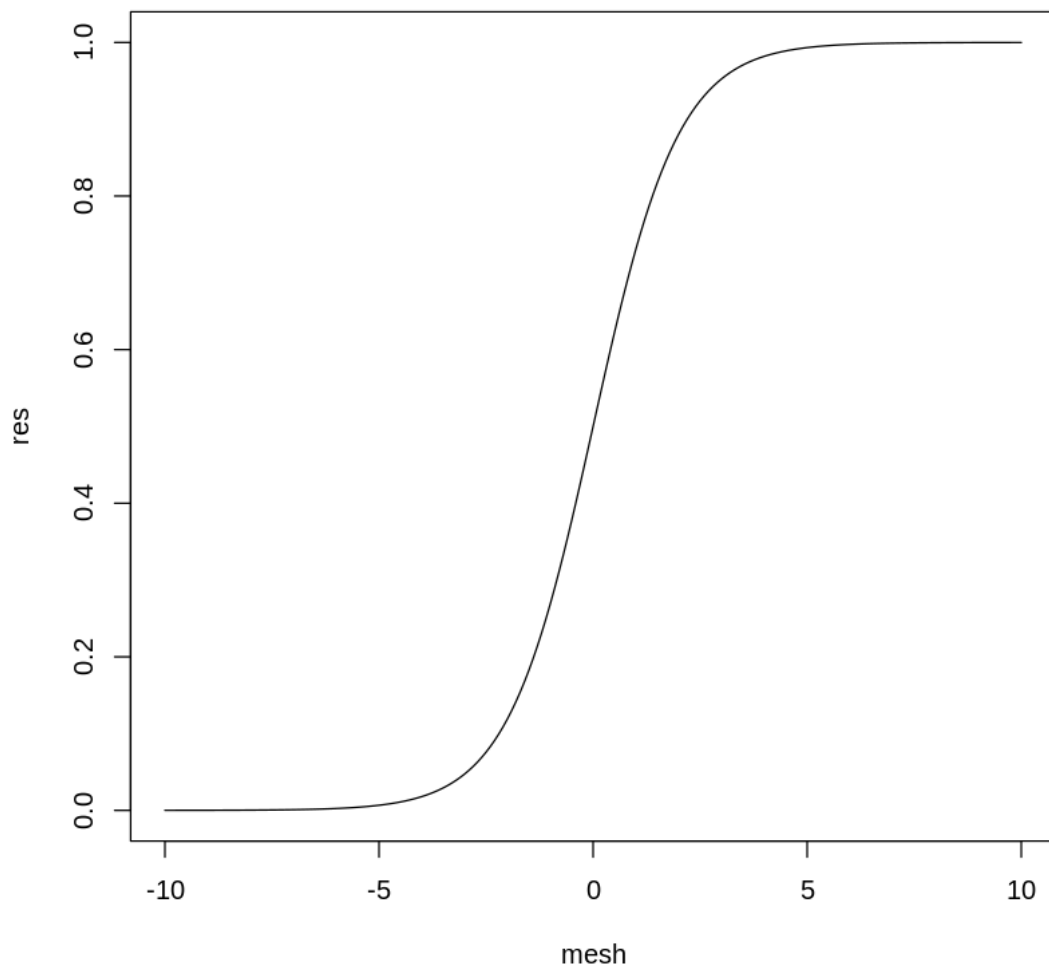
"**Classification problem**" considers the about giving predictions on a defined discrete result. Each instance belongs to one element of result set, and we will try to arrange dataset properly for making predictions by scaling them, applying statistical algortihms etc. Then, we will test algorithms such as logistic regression, multinomial logistic regression and support vector machine to find out if they are accurate or not; then we will make evaluations about outputs.

1.1 Logistic Regression

Logistic regression is a classification method for finding an answer to "classification" problem.

For logistic regression problems, the response variable has to be binary: 0 or 1, or YES or NO. The usual way of converting numerical values to binary classes is to interpret it as probabilities which takes values between 0 and 1. In converting probabilities we use cetain functions. The sigmoid function is most commonly used.

```
In [1]: sigmoid <- function(x) {  
      1/(1+exp(-x))  
}  
mesh <- seq(-10, 10, 0.1)  
res <- sigmoid(mesh)  
plot(mesh, res, type="l")
```



Passing parameters to a function returns a probability value. Since sigmoid function is bounded between 0 and 1, it is wise to choose for calculating probability. Usually selecting a $P(Y = y|X = x_{(1)}, \dots, x_{(n)}) \geq 0.5$ as a label and other values as another label. This concludes the binary classification problem.

Theoretical explanations below are taken from [CMU 36-402, Undergraduate Advanced Data Analysis, Lecture 13, Logistic Regression](#).

Solving a classification problem is hard with linear regression. One way to solve might be selecting a linear function for making classification, but it is not useful due to "diminishing returns" problem and being unbounded from function's nature. On the other hand, logarithmic transformation might be useful, but, logarithmic functions are bounded from one direction.

Lastly, a useful concept might be making nuance adjustments as called "**logistic transformation**", which can be made as $\log(\frac{p}{1-p})$. This adjustment makes possible to have reasonable results.

This method is called as logistic regression. We can accomplish this as solving the equation below for $P(x)$.

$$\log\left(\frac{P(x)}{1-P(x)}\right) = \beta_0 + x.\beta$$

Solving for $P(x)$, we conclude:

$$P(x; b; w) = \frac{e^{\beta_0 + x.\beta}}{1 + e^{\beta_0 + x.\beta}} = \frac{1}{1 + e^{-(\beta_0 + x.\beta)}}$$

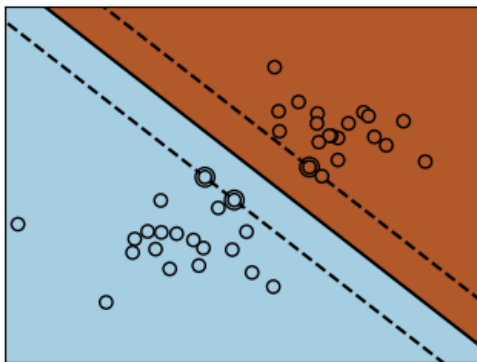
For reducing classification error rate, it should be predicted $Y = 1$ when $P \geq 0.5$ and $Y = 0$ when $P < 0.5$. This means that whenever $\beta_0 + x.\beta$ is greater than zero Y should be classified as 1 and 0 on other conditions. As a conclusion, logistic regression returns a "**linear classifier**".

$$\beta_0 + x.\beta = 0$$

can be considered as the "**decision boundary**", which is a point or line if x is one dimensional or two, and so on.

1.2 Support Vector Machine

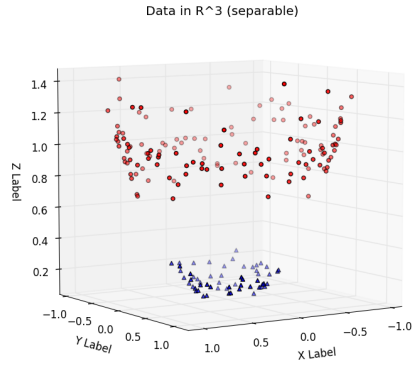
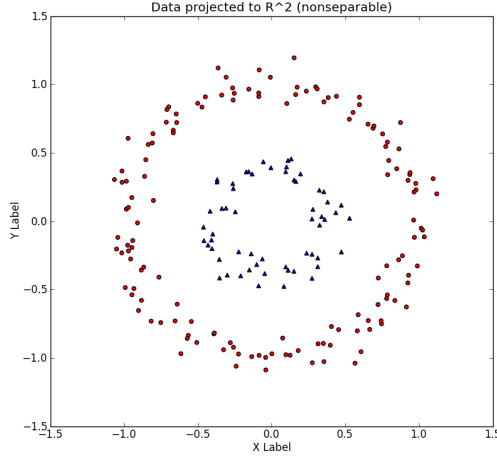
Support Vector Machine (SVM) is also a classification algorithm. Name comes from a term called as "support vector" which defines a classifier from using it. Support vector machine uses hyperplanes for making classifications. But on a space, there can be infinitely many hyperplanes, and SVM tries to calculate most efficient and accurate hyper plane to use as a classifier. On a given space, for example \mathbb{R}^n , algorithm tries to find the hardest points to classify. After that, by using these points, generates support vectors in order to create a classifier, then by using these support vectors SVM creates hyperplanes and tries to maximizing margin between these hyperplanes. In the middle of those hyperplanes, algorithm obtains most efficient hyperplane. Easiest way to apply or show this is on using linear separators:



[Taken from scikit-learn.org](https://scikit-learn.org)

Dotted lines are called support vectors, black line is hyperplane. There can be infinitely many hyperplane, but when we are choosing we need to do this by maximizing the margin between our support vectors so that we can use the best classifier.

SVM also has a kernel "**trick**". One can change kernel to be used in order to making classifications possible. For example:



Taken from to-

wardsdatascience.com

A non-separable data can be made separable by usage of different kernels.

But, how does SVM makes as best prediction as possible? Let us dive in to some theory. Theoretical explanations below taken from [Computer Image Processing and Analysis \(E161\)](#) and [R. Berwick, An Idiot's guide to Support vectormachines \(SVMs\)](#).

From linear algebra, we simply know that a hyperplane can be written as

$$w^T * x + \beta_0 = 0$$

Any vector $x = x_1, \dots, x_{(n)}$ in a given dataset belongs a certain class which defined as $y = y_1, \dots, y_{(n)}$. Thus, we need to define a condition for making classifications. For talking binary classification on a linearly separable dataset on \mathbb{R}^2 , we can say that there are two classes, and each data point must belong either one. Define data points as (x_i, y_i) where x_i is the feature, y_i is the class. and two hyper planes such as

$$H_1 : w.x_i + b = +1$$

$$H_2 : w.x_i + b = -1,$$

assuming $y_i = +1$ for $w.x_i + b > +1$ and $y_i = -1$ for $w.x_i + b < -1$. These support vectors are created from critical points, which means changing any of their position would affect the position of the vectors.

SVM is pursuing the idea of maximizing the margin between these support vectors, also called as "**street**".

Maximizing the margin of street is a problem that concerns optimization, which called as "Constrained Optimization Problem"; to minimize $\|w\|$.

Kernel Trick If data is not linearly separable, "**Kernel Mapping**" is also a solution. Simply, it is possible to map samples to higher dimensions:

$$x \rightarrow \phi(x)$$

where $\phi(x)$ is linearly separable. Decision number on new space becomes as:

$$f(x) = \phi(x)^T w + b = \sum_{j=1}^m \alpha_j y_j \phi(x_j)$$

where

$$w = \sum_{j=1}^m \alpha_j y_j \phi(x_j)$$

Definition: Kernel function is a function that taking two vector and returns an inner product.

Let x_i, x_j be two vectors and $\phi(x_i)$ and $\phi(x_j)$ be their images, a kernel function is represented as:

$$K(x_1, x_2) = \phi(x_1)^T \phi(x_2)$$

Since kernel function returns a result of inner product, dimension of space does not matter.

Kernel space's "learning algorithm" can be derived by changing all inner products of the original space to new kernel:

$$f(x) = \phi(x)^T w + b = \sum_{j=1}^m \alpha_j y_j K(x, x_j) + b$$

And parameter b can be found from any support vector x .

2 Experiment

First we are importing necessary libraries and dataset. Then we are assigning dataset to a variable "myData"

```
In [3]: library(rpart)
library(rpart.plot)
library(e1071)
library(caret)
library(ROSE)
library(foreign)
library(nnet)
```

```
In [4]: myData <- read.csv("http://archive.ics.uci.edu/ml/machine-learning-databases/statlog/a
```

As explained on the web page of the dataset, because of confidentiality, column names, instance names and other characteristics of features are obscured except type of feature (either continuous or numerical) and dependend variable V15 is should be predicted. We are going to investigate other characteristics of features. V1, V4, V5, V6, V8, V9, V11, V12 are categorical features, other features are continuous features. Categorical features are also encoded with numbers.

```
In [5]: head(myData)
```

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
1	22.08	11.460	2	4	4	1.585	0	0	0	1	2	100	1213	0
0	22.67	7.000	2	8	4	0.165	0	0	0	0	2	160	1	0
0	29.58	1.750	1	4	4	1.250	0	0	0	1	2	280	1	0
0	21.67	11.500	1	5	3	0.000	1	1	11	1	2	0	1	1
1	20.17	8.170	2	6	4	1.960	1	1	14	0	2	60	159	1
0	15.83	0.585	2	8	8	1.500	1	1	2	0	2	100	1	1

2.1 Data Normalization, Feature Selection and Sampling

Adjusting dataset for categorical variables. Here R's factor function is used in order to tell R kernel that given certain columns should be treated as categorical features. The reason we are doing this is since categorical features are encoded as numbers, by default R will try to behave those features continuously and make calculations by that assumption. We would not be doing this if categorical features would be encoded as strings.

```
In [6]: myData$V1 <- factor(myData$V1)
myData$V4 <- factor(myData$V4)
myData$V5 <- factor(myData$V5)
myData$V6 <- factor(myData$V6)
myData$V8 <- factor(myData$V8)
myData$V9 <- factor(myData$V9)
myData$V11 <- factor(myData$V11)
myData$V12 <- factor(myData$V12)
myData$V15 <- factor(myData$V15)
```

For an easier implementation, we created a vector called `numerical_features` and `categorical_features`. It contains names of numerical features and categorical features by only themselves.

```
In [7]: numerical_features <- c("V2", "V3", "V7", "V10", "V13", "V14")
categorical_features <- c("V1", "V4", "V5", "V6", "V8", "V9", "V11", "V12")
```

After factorization, we are going to split the dataset to train and test parts. Here we are taking random row number with using `nrow`. Then creating a train and test samples from dataset with %75 train to %25 test ratio.

```
In [8]: n <- nrow(myData)
test <- sample(1:n, n*0.25)
train <- -test
```

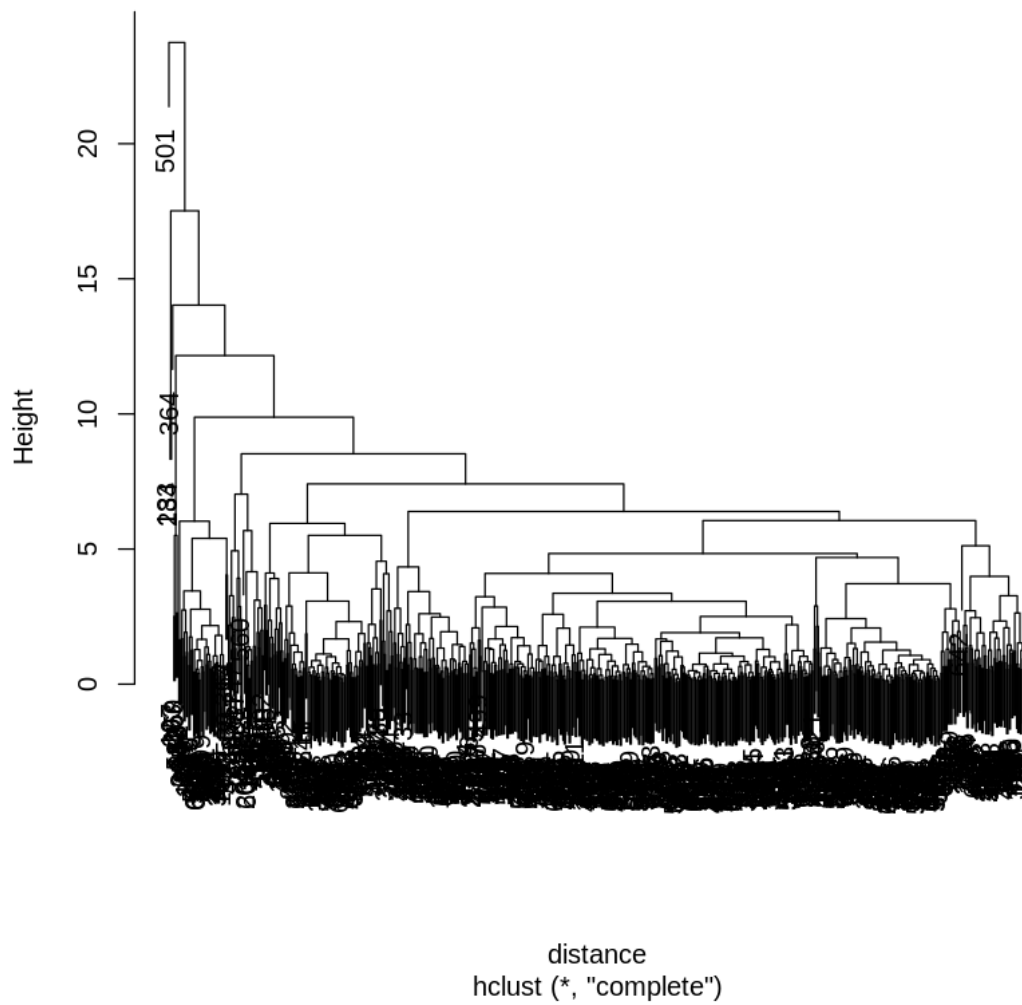
In order to make accurate predictions, we must normalize his data if range of magnitude differs. Here we are scaling our data in order to make more accurate predictions. If we do not apply this operation, columns with bigger numbers might have an effect so that columns with smaller numerical values might not be considered for algorithms. This might create a problem if a column with a smaller number have vast amount of effect on predictions.

```
In [9]: myData[,numerical_features] <- scale(myData[,numerical_features])
```

Other than normalization problem, some of categorical features might create a problem. For example, 5th column is categorical but there are 14 different categories. It is better to check if 5th column is important, or able to prune it with hierarchical clustering; because there might some problems occur whilst splitting data into train and test. Let's take a look at dendrogram.

```
In [128]: distance <- dist(myData[,numerical_features])
cluster <- hclust(distance)
plot(cluster, label = myData$V15)
```

Cluster Dendrogram



```
In [11]: sd <- split(myData$V5,cutree(cluster, 4))
         for(i in 1:4) {
           print(table(sd[i]))
         }
```

```
 1  2  3  4  5  6  7  8  9 10 11 12 13 14
52 30 59 51 10 54 38 144 64 25 78  3 40 38
```

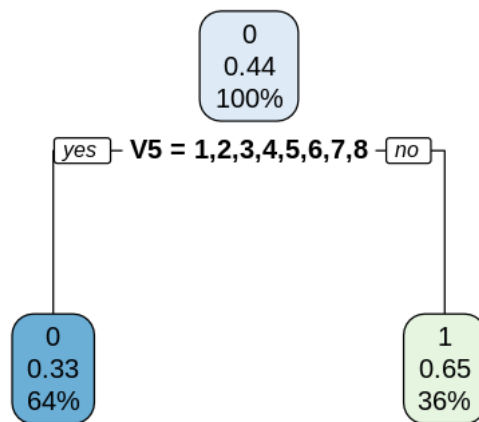
```
 1  2  3  4  5  6  7  8  9 10 11 12 13 14
0  0  0  0  0  0  0  1  0  0  0  0  1  0
```

```
 1  2  3  4  5  6  7  8  9 10 11 12 13 14
```

0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
1	2	3	4	5	6	7	8	9	10	11	12	13	14	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

We can conclude from the results that majority of instances will take part on cluster 1, so cutting tree on fourth level might not be a valuable operation. Now let's take a look at decision tree if we can observe anything significant from entropy values.

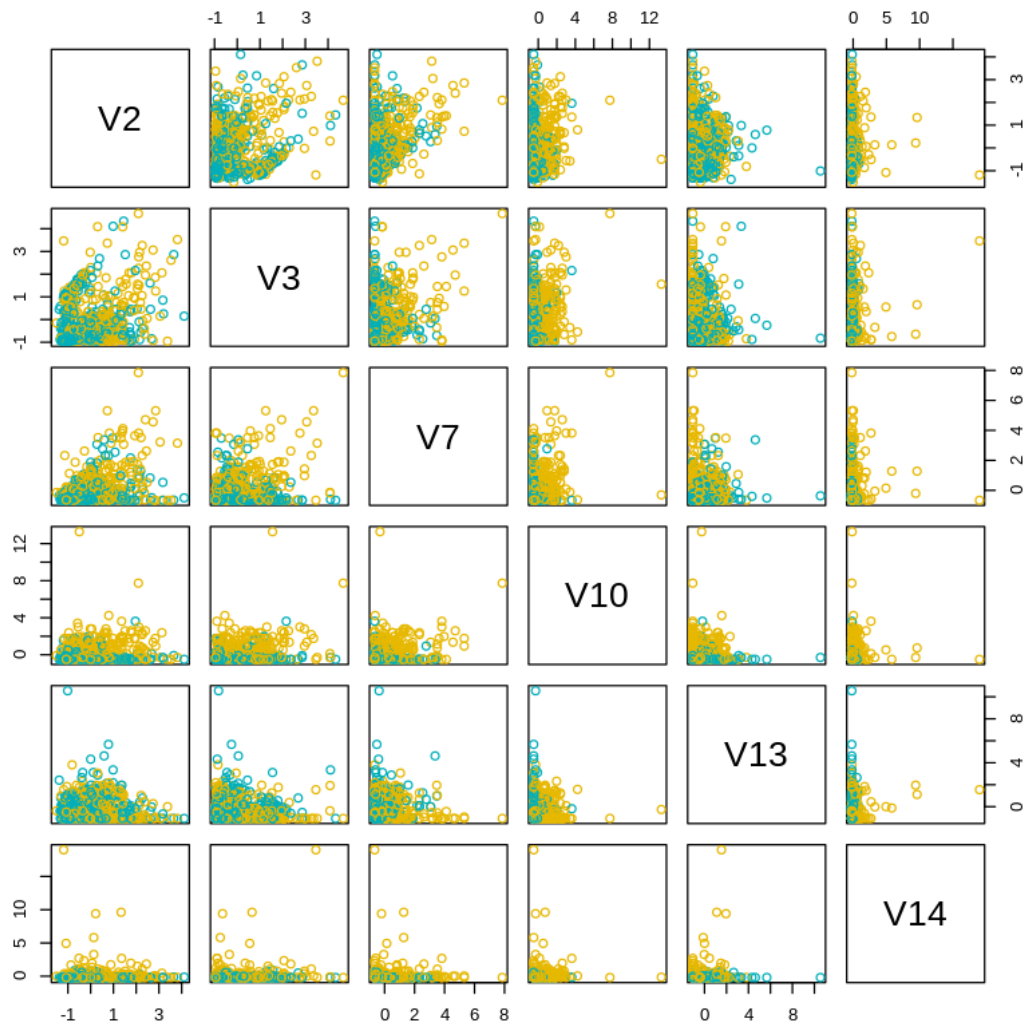
```
In [12]: treeModel.model <- rpart(V15 ~ V5, data=myData, method='class')
         rpart.plot(treeModel.model)
```

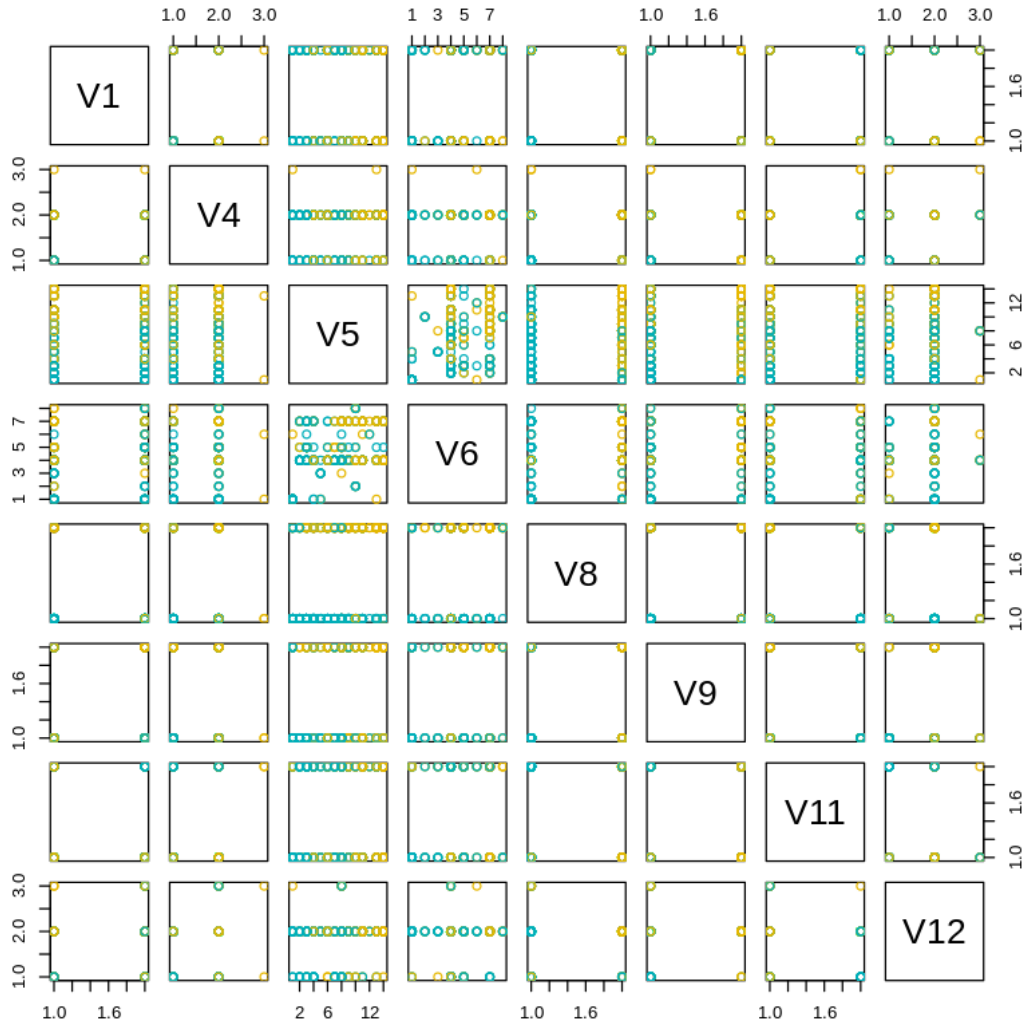


As we can see, decision tree could not give satisfying results for evaluation on feature V5. Because we can see that 0.33 of the data is 64% accurate and 0.65 of data is 36% accurate. These values are not reliable enough for consideration.

Now let's take a look from a visual perspective to our data. We are going to use R's pairs function in order to determine if there is something significant between features as pairs.

```
In [13]: my_cols <- c("#00AFBB", "#E7B800")
pairs(myData[,numerical_features], col=my_cols[myData$V15])
pairs(myData[,categorical_features], col=my_cols[myData$V15])
```





From these graphs, we can conclude that finance statlog data set is applicable and safe for regression functions. We might need to arrange features, maybe subtracting certain ones if we would observe some linear pattern. These kinds of linearity means that features who behaves as such have non-colinear behavior.

2.2 Contingency matrix

From visual methods, making comments about categorical data is rather difficult. We do not know weights on each possible values and can not tell their behaviour by looking graphics. Instead, we are going to look at contingency matrix on some features. Apparently, calculating all contingency tables for all features is not feasible so we are going to look several features' contingency tables. After this, we will look at chi-square tests to see if each selected features are independent from each other or not.

```
In [142]: table(myData$V8, myData$V12)
          chisq.test(myData$V8, myData$V12, simulate.p.value = TRUE)

table(myData$V8, myData$V5)
          chisq.test(myData$V8, myData$V5, simulate.p.value = TRUE)

table(myData$V9, myData$V11)
          chisq.test(myData$V9, myData$V11)
```

	1	2	3
0	36	285	8
1	21	340	0

Pearson's Chi-squared test with simulated p-value (based on 2000 replicates)

```
data: myData$V8 and myData$V12
X-squared = 15.336, df = NA, p-value = 0.0004998
```

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	41	20	39	31	6	24	18	73	28	10	20	1	12	6
1	12	10	20	20	4	30	20	73	36	15	58	2	29	32

Pearson's Chi-squared test with simulated p-value (based on 2000 replicates)

```
data: myData$V8 and myData$V5
X-squared = 73.222, df = NA, p-value = 0.0004998
```

	0	1
0	217	178
1	157	138

Pearson's Chi-squared test with Yates' continuity correction

```
data: myData$V9 and myData$V11
```

X-squared = 0.13724, df = 1, p-value = 0.711

From chi-square tests, we can say that at third test, by looking X-squared value and p-value, so we accept the null hypothesis, which means those features are independent from each other. Test solution is opposite on first two tests, which means they are dependent. To be more explanatory, V12 and V5 are dependent to V8.

2.3 Covariance Matrix

Now let's take a look at covariance matrix. We should observe that result of matrix have a value 1 on diagonal axis and not 1 on others.

```
In [129]: # Numerical features:
# V2, V3, V7, V13, V14
cov(myData[,numerical_features])
```

	V2	V3	V7	V10	V13	V14
V2	1.00000000	0.2013152	0.39278787	0.18557383	-0.07715894	0.01853870
V3	0.20131524	1.00000000	0.29890156	0.27120674	-0.22234629	0.12312115
V7	0.39278787	0.2989016	1.00000000	0.32232967	-0.07638852	0.05134493
V10	0.18557383	0.2712067	0.32232967	1.00000000	-0.11980806	0.06369244
V13	-0.07715894	-0.2223463	-0.07638852	-0.11980806	1.00000000	0.06560887
V14	0.01853870	0.1231212	0.05134493	0.06369244	0.06560887	1.00000000

2.4 Logistic Regression

We will use R's glm function for creating a generalized linear model. Parameters are placed as:

Feature to predict ~ Features that will be used for predicting (adding them with addition means using them together), data to use, family.

After that, we simply test our model and make predictions; then print it on a confusion matrix. Below, we are testing our dataset for all features on logistic regression.

```
In [36]: model <- glm(V15 ~ . , data=myData[train,], binomial)
oddsratio <- exp(predict(model,myData[test,]))
predicted <- ifelse(oddsratio > 0.7,1,0)
confusionMatrix(table(predicted,real=myData[test,15]))
```

Warning message:

glm.fit: fitted probabilities numerically 0 or 1 occurred

Confusion Matrix and Statistics

```
      real
predicted 0  1
0      88  4
1      14 66
```

```

Accuracy : 0.8953
95% CI : (0.8397, 0.9368)
No Information Rate : 0.593
P-Value [Acc > NIR] : < 2e-16

Kappa : 0.7879
McNemar's Test P-Value : 0.03389

Sensitivity : 0.8627
Specificity : 0.9429
Pos Pred Value : 0.9565
Neg Pred Value : 0.8250
Prevalence : 0.5930
Detection Rate : 0.5116
Detection Prevalence : 0.5349
Balanced Accuracy : 0.9028

'Positive' Class : 0

```

Using all features gave a good result. Now let's take a look at anova and summary of model that includes all features to see if we can make any deductions.

After executing the cell above, we came across a warning that says:

Warning message: "glm.fit: fitted probabilities numerically 0 or 1 occurred"

This warning means logistic regression acquired a probability either exactly ONE or ZERO. So R is gently warning us in case of making over fitting.

```

In [33]: anova(model)
summary(model)

```

	Df	Deviance	Resid. Df	Resid. Dev
NULL	NA	NA	517	714.3585
V1	1	0.03223381	516	714.3263
V2	1	11.75240978	515	702.5739
V3	1	9.54742828	514	693.0264
V4	2	12.57345747	512	680.4530
V5	13	85.84356258	499	594.6094
V6	7	6.84781907	492	587.7616
V7	1	21.87411565	491	565.8875
V8	1	197.07862224	490	368.8089
V9	1	19.32813512	489	349.4807
V10	1	5.04040619	488	344.4403
V11	1	1.37543596	487	343.0649
V12	2	10.88824204	485	332.1767
V13	1	5.83671496	484	326.3399
V14	1	17.23341401	483	309.1065

```
Call:
glm(formula = V15 ~ ., family = binomial, data = myData[train,
])
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.4619	-0.3062	-0.1205	0.4591	3.2022

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-4.49470	1.05377	-4.265	2e-05	***
V11	-0.08313	0.34722	-0.239	0.81078	
V2	0.14810	0.18268	0.811	0.41752	
V3	-0.19938	0.16128	-1.236	0.21638	
V42	0.51299	0.37297	1.375	0.16900	
V43	14.19758	1023.60423	0.014	0.98893	
V52	5.09061	2.44231	2.084	0.03713	*
V53	4.44189	2.35201	1.889	0.05895	.
V54	4.23610	2.24173	1.890	0.05880	.
V55	0.25699	2.24326	0.115	0.90879	
V56	4.47178	2.31202	1.934	0.05310	.
V57	4.71659	2.34789	2.009	0.04455	*
V58	4.62698	2.27924	2.030	0.04235	*
V59	5.44701	2.31905	2.349	0.01883	*
V510	6.18767	2.56691	2.411	0.01593	*
V511	4.65402	2.28358	2.038	0.04155	*
V512	3.32147	4.34320	0.765	0.44442	
V513	5.83584	2.37887	2.453	0.01416	*
V514	7.83342	2.51088	3.120	0.00181	**
V62	-4.54778	3.24751	-1.400	0.16140	
V63	1.18367	2.23884	0.529	0.59702	
V64	-2.97156	2.14409	-1.386	0.16577	
V65	-3.45244	2.22952	-1.549	0.12150	
V67	-0.72115	2.48415	-0.290	0.77159	
V68	-2.38023	2.16438	-1.100	0.27145	
V69	-6.25786	2.82279	-2.217	0.02663	*
V7	0.22136	0.18490	1.197	0.23123	
V81	3.78872	0.40479	9.360	< 2e-16	***
V91	0.71305	0.42217	1.689	0.09122	.
V10	0.44779	0.29768	1.504	0.13250	
V111	-0.01509	0.31340	-0.048	0.96160	
V122	-0.26169	0.52245	-0.501	0.61644	
V123	3.62320	1.13231	3.200	0.00138	**
V13	-0.42914	0.17042	-2.518	0.01180	*
V14	3.44539	1.11492	3.090	0.00200	**

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 714.36 on 517 degrees of freedom
Residual deviance: 309.11 on 483 degrees of freedom
AIC: 379.11

Number of Fisher Scoring iterations: 15

From anova table, we can observe that deviance values of V1, V11 are significantly low, this means these features have equally small amounts of effect on model. Therefore we can subtract these two columns.

We can observe that using factor function creates one-hot encoded feature columns on background. We can see that some categories of V12 are reliable and should be considered whilst making predictions, with V8's first category. In addition, we can see that estimate values of feature V6 are relatively low and high on standard error.

Before changing our model, let us try to change the classification ratio to see if the accuracy will be increased.

```
In [44]: model <- glm(V15 ~ . , data=myData[train,], binomial)
         oddsratio <- exp(predict(model,myData[test,]))
         predicted <- ifelse(oddsratio > 0.5,1,0)
         confusionMatrix(table(predicted,real=myData[test,15]))
```

Warning message:

glm.fit: fitted probabilities numerically 0 or 1 occurred

Confusion Matrix and Statistics

	real	
predicted	0	1
0	84	3
1	18	67

Accuracy : 0.8779
95% CI : (0.8194, 0.9228)
No Information Rate : 0.593
P-Value [Acc > NIR] : < 2e-16

Kappa : 0.7553
McNemar's Test P-Value : 0.00225

Sensitivity : 0.8235
Specificity : 0.9571
Pos Pred Value : 0.9655
Neg Pred Value : 0.7882
Prevalence : 0.5930
Detection Rate : 0.4884

```
Detection Prevalence : 0.5058
Balanced Accuracy : 0.8903
```

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

Changing ratio declined the accuracy. Now we will remove some features to observe differences on accuracy.

```
In [67]: model <- glm(V15 ~ . - V6, data=myData[train,], binomial)
         oddsratio <- exp(predict(model,myData[test,]))
         predicted <- ifelse(oddsratio > 0.75,1,0)
         confusionMatrix(table(predicted,real=myData[test,15]))
```

Warning message:

glm.fit: fitted probabilities numerically 0 or 1 occurred

Confusion Matrix and Statistics

```
      real
predicted 0  1
0      88  3
1      14 67
```

```
Accuracy : 0.9012
95% CI : (0.8465, 0.9414)
No Information Rate : 0.593
P-Value [Acc > NIR] : < 2e-16
```

```
Kappa : 0.8002
McNemar's Test P-Value : 0.01529
```

```
Sensitivity : 0.8627
Specificity : 0.9571
Pos Pred Value : 0.9670
Neg Pred Value : 0.8272
Prevalence : 0.5930
Detection Rate : 0.5116
Detection Prevalence : 0.5291
Balanced Accuracy : 0.9099
```

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

Subtracting V6 increased accuracy a little bit. 0.9012 accuracy is a great ratio. We are going to take a look at precision of numerical features.


```
In [73]: model <- glm(V15 ~ V2 + V3 + V7 + V10 + V13 + V14, data=myData[train,], binomial)
         oddsratio <- exp(predict(model,myData[test,]))
         predicted <- ifelse(oddsratio > 0.7,1,0)
         confusionMatrix(table(predicted,real=myData[test,15]))
```

Warning message:

glm.fit: fitted probabilities numerically 0 or 1 occurred

Confusion Matrix and Statistics

```
      real
predicted 0  1
      0 80 13
      1 22 57
```

```
      Accuracy : 0.7965
      95% CI   : (0.7285, 0.854)
No Information Rate : 0.593
P-Value [Acc > NIR] : 1.138e-08
```

```
      Kappa : 0.5868
McNemar's Test P-Value : 0.1763
```

```
      Sensitivity : 0.7843
      Specificity : 0.8143
Pos Pred Value   : 0.8602
Neg Pred Value   : 0.7215
Prevalence       : 0.5930
Detection Rate   : 0.4651
Detection Prevalence : 0.5407
Balanced Accuracy : 0.7993
```

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

From result of the model above, we can conclude that categorical features have a significant effect on predictions, and they should be emphasized. Below we are going to look numerical model's anova table and summary.

```
In [70]: anova(model)
         summary(model)
```

	Df	Deviance	Resid. Df	Resid. Dev
NULL	NA	NA	517	714.3585
V2	1	11.7838443	516	702.5747
V3	1	9.5430836	515	693.0316
V7	1	45.8632337	514	647.1684
V10	1	81.0050763	513	566.1633
V13	1	0.1897627	512	565.9735
V14	1	33.0455169	511	532.9280

Call:

```
glm(formula = V15 ~ V2 + V3 + V7 + V10 + V13 + V14, family = binomial,
    data = myData[train, ])
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.8653	-0.7896	-0.6808	0.8448	1.8441

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	0.27653	0.14224	1.944	0.051888 .
V2	-0.02429	0.11683	-0.208	0.835283
V3	0.01772	0.11478	0.154	0.877338
V7	0.76582	0.16771	4.566	4.96e-06 ***
V10	1.30421	0.21837	5.972	2.34e-09 ***
V13	-0.08993	0.11674	-0.770	0.441103
V14	2.38945	0.62143	3.845	0.000121 ***

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 714.36 on 517 degrees of freedom
Residual deviance: 532.93 on 511 degrees of freedom
AIC: 546.93

Number of Fisher Scoring iterations: 7

From results of anova and summary values, we can see that V7, V10 and V14 are reliable, also lack of deviance tells us that V13 is not necessary for consideration. Below, we will construct our model from using only reliable features.

```
In [74]: model <- glm(V15 ~ V7 + V10 + V14, data=myData[train,], binomial)
         oddsratio <- exp(predict(model,myData[test,]))
         predicted <- ifelse(oddsratio > 0.7,1,0)
         confusionMatrix(table(predicted,real=myData[test,15]))
```

Warning message:
glm.fit: fitted probabilities numerically 0 or 1 occurred

Confusion Matrix and Statistics

```
      real
predicted 0  1
      0 80 15
      1 22 55
```

```
      Accuracy : 0.7849
      95% CI : (0.7159, 0.8438)
No Information Rate : 0.593
P-Value [Acc > NIR] : 7.814e-08
```

```
      Kappa : 0.5612
McNemar's Test P-Value : 0.3239
```

```
      Sensitivity : 0.7843
      Specificity : 0.7857
      Pos Pred Value : 0.8421
      Neg Pred Value : 0.7143
      Prevalence : 0.5930
      Detection Rate : 0.4651
      Detection Prevalence : 0.5523
      Balanced Accuracy : 0.7850
```

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

Using only reliable numerical features can give pretty good solution too. If the dataset would be bigger, it might be useful to use only these reliable features in order to obtain faster calculations, but it is definitely preferable to include categorical variables. Lastly, for showing untrustable features, we are going to create a model using V2, V3 and V13 and observe its accuracy.

```
In [76]: model <- glm(V15 ~ V2 + V3 + V13, data=myData[train,], binomial)
      oddsratio <- exp(predict(model,myData[test,]))
      predicted <- ifelse(oddsratio > 0.7,1,0)
      confusionMatrix(table(predicted,real=myData[test,15]))
```

Confusion Matrix and Statistics

```
      real
predicted 0  1
      0 40 12
      1 62 58
```

```
      Accuracy : 0.5698
```

```

          95% CI : (0.4922, 0.6449)
No Information Rate : 0.593
P-Value [Acc > NIR] : 0.7583

          Kappa : 0.1985
McNemar's Test P-Value : 1.226e-08

Sensitivity : 0.3922
Specificity : 0.8286
Pos Pred Value : 0.7692
Neg Pred Value : 0.4833
Prevalence : 0.5930
Detection Rate : 0.2326
Detection Prevalence : 0.3023
Balanced Accuracy : 0.6104

'Positive' Class : 0

```

Clearly, result is not good and should not be applied.

2.5 Support Vector Machine

Now let's try to implement Support Vector Machine (SVM) algorithm.

First, we will try to implement SVM for all features to see if categorical features.

We are creating a model from R's svm function. After that we are making predictions, showing our results on a confusion matrix after testing the predictions.

```

In [91]: model <- svm(V15 ~ ., data=myData[train,])
          predictions <- predict(model, myData[test,])
          confusionMatrix(table(predictions, myData[test,15]))

```

Confusion Matrix and Statistics

```

predictions  0  1
            0 85  4
            1 17 66

          Accuracy : 0.8779
          95% CI : (0.8194, 0.9228)
No Information Rate : 0.593
P-Value [Acc > NIR] : < 2.2e-16

          Kappa : 0.7542
McNemar's Test P-Value : 0.008829

Sensitivity : 0.8333

```

```

        Specificity : 0.9429
        Pos Pred Value : 0.9551
        Neg Pred Value : 0.7952
        Prevalence : 0.5930
        Detection Rate : 0.4942
        Detection Prevalence : 0.5174
        Balanced Accuracy : 0.8881

'Positive' Class : 0

```

SVM gave results just as good as logistic regression on all data. A model that has 0.8779 can be considered as a successful model if over fitting has not been made. After this result, we can compare results from all features and only numerical features to have an idea of how categorical features are beneficial, whilst measuring the goodness of numerical features.

```

In [97]: model <- svm(V15 ~ V2 + V3 + V7 + V10 + V13 + V14, data=myData[train,])
        predictions <- predict(model, myData[test,])
        confusionMatrix(table(predictions, myData[test,15]))

```

Confusion Matrix and Statistics

```

predictions  0  1
            0 89 17
            1 13 53

```

```

        Accuracy : 0.8256
        95% CI : (0.7605, 0.8791)
        No Information Rate : 0.593
        P-Value [Acc > NIR] : 4.938e-11

```

```

        Kappa : 0.6354
        Mcnemar's Test P-Value : 0.5839

```

```

        Sensitivity : 0.8725
        Specificity : 0.7571
        Pos Pred Value : 0.8396
        Neg Pred Value : 0.8030
        Prevalence : 0.5930
        Detection Rate : 0.5174
        Detection Prevalence : 0.6163
        Balanced Accuracy : 0.8148

'Positive' Class : 0

```

Numerical features also makes creating a solid model possible since confusion matrix has 0.8256 accuracy value.

Now, let us go further and make predictions with using different kernels.

```
In [99]: model <- svm(V15 ~ ., data=myData[train,], kernel="polynomial")
         predictions <- predict(model, myData[test,])
         confusionMatrix(table(predictions, myData[test,15]))
```

Confusion Matrix and Statistics

```
predictions  0  1
             0 102 55
             1   0 15

              Accuracy : 0.6802
              95% CI : (0.605, 0.7492)
    No Information Rate : 0.593
    P-Value [Acc > NIR] : 0.01144

              Kappa : 0.2444
  McNemar's Test P-Value : 3.305e-13

              Sensitivity : 1.0000
              Specificity : 0.2143
    Pos Pred Value : 0.6497
    Neg Pred Value : 1.0000
    Prevalence : 0.5930
    Detection Rate : 0.5930
    Detection Prevalence : 0.9128
    Balanced Accuracy : 0.6071

    'Positive' Class : 0
```

Using a different kernel does not supposed to be a useful idea all the time. From the code snippet above, we see that using a polynomial kernel on all features created a worse model than radial kernel (Default kernel on SVM is radial kernel). Some other kernels:

```
In [102]: model <- svm(V15 ~ ., data=myData[train,], kernel="linear")
          predictions <- predict(model, myData[test,])
          confusionMatrix(table(predictions, myData[test,15]))
```

Confusion Matrix and Statistics

```
predictions  0  1
             0 86  3
```

1 16 67

Accuracy : 0.8895
95% CI : (0.8329, 0.9322)
No Information Rate : 0.593
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.7776
McNemar's Test P-Value : 0.005905

Sensitivity : 0.8431
Specificity : 0.9571
Pos Pred Value : 0.9663
Neg Pred Value : 0.8072
Prevalence : 0.5930
Detection Rate : 0.5000
Detection Prevalence : 0.5174
Balanced Accuracy : 0.9001

'Positive' Class : 0

```
In [103]: model <- svm(V15 ~ ., data=myData[train,], kernel="sigmoid")
          predictions <- predict(model, myData[test,])
          confusionMatrix(table(predictions, myData[test,15]))
```

Confusion Matrix and Statistics

```
predictions  0  1
            0 86  4
            1 16 66
```

Accuracy : 0.8837
95% CI : (0.8261, 0.9275)
No Information Rate : 0.593
P-Value [Acc > NIR] : < 2e-16

Kappa : 0.7654
McNemar's Test P-Value : 0.01391

Sensitivity : 0.8431
Specificity : 0.9429
Pos Pred Value : 0.9556
Neg Pred Value : 0.8049
Prevalence : 0.5930
Detection Rate : 0.5000

```
Detection Prevalence : 0.5233
Balanced Accuracy : 0.8930
```

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

Other kernels seem to be just as good as radial kernel.

3 Analysis

3.0.1 Distribution of algorithms

In this section, we are going to test each algorithm for same train and test data splits for several time and take a look at their distributions.

We are going to create random train and test groups, and test each algorithm with same groups. Then we will pass each result to an array and check what their distribution looks like, then we are going to evaluate results.

Logistic Regression

```
In [41]: results_numerical <- c()
         results_all <- c()
         for(i in 1:15){
           n <- nrow(myData)
           test <- sample(1:n, n*0.25)
           train <- -test
           model_numerical <- glm(V15 ~ V2 + V3 + V7 + V10 + V13 + V14, data=myData[train,],
                                oddsratio_numerical <- exp(predict(model_numerical,myData[test,]))
                                predicted_numerical <- ifelse(oddsratio_numerical > 0.75,1,0)
                                cm_numerical <- confusionMatrix(table(predicted_numerical,real=myData[test,15]))
                                results_numerical <- c(results_numerical, cm_numerical$overall['Accuracy'])

           model_all<- glm(V15 ~ ., data=myData[train,], binomial)
           oddsratio_all <- exp(predict(model_all,myData[test,]))
           predicted_all <- ifelse(oddsratio_all > 0.75,1,0)
           cm_all <- confusionMatrix(table(predicted_all,real=myData[test,15]))
           results_all <- c(results_all, cm_all$overall['Accuracy'])

         }

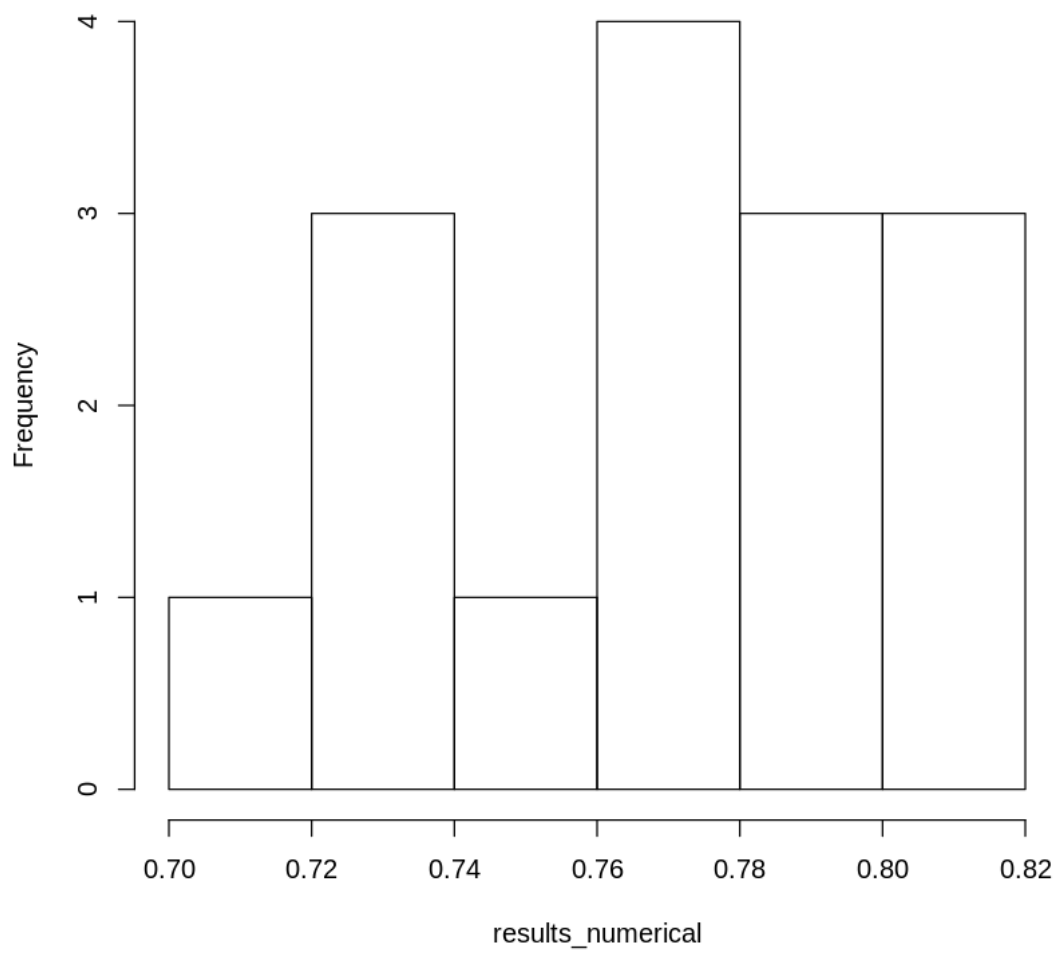
         hist(results_numerical)
         hist(results_all)
```

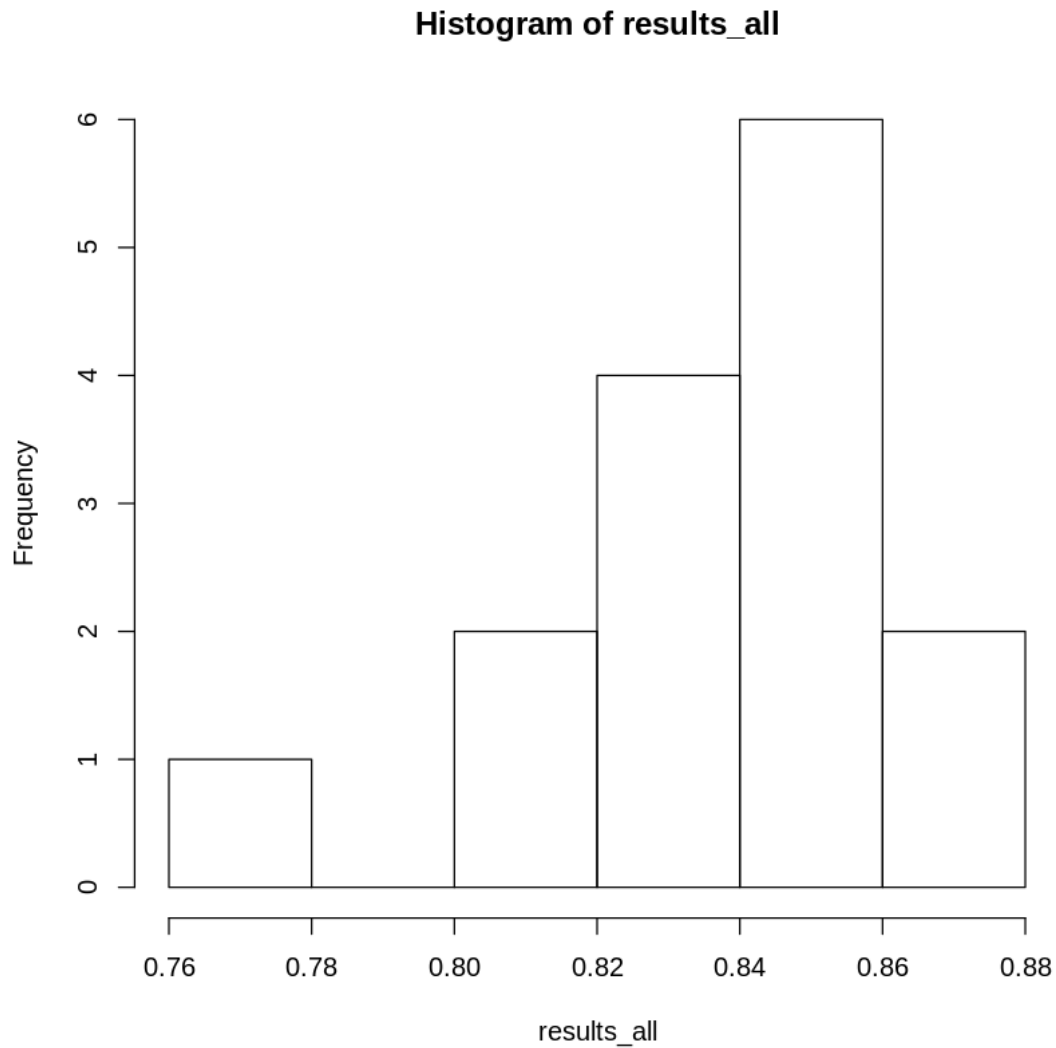
Warning message:

glm.fit: fitted probabilities numerically 0 or 1 occurredWarning message:

[illegible]

Histogram of results_numerical





Results of numerical features show us that there are more than one model to converge, so this might create problem for some specific occasions. For example, for a certain random dataset, model might converge to very different solutions even for the smallest nuances. Results for all features looks more consistent on histogram.

Support Vector Machine

```
In [127]: results_numerical <- c()
          results_all <- c()
          for(i in 1:50){
            n <- nrow(myData)
            test <- sample(1:n, n*0.25)
            train <- -test
            model_numerical <- svm(V15 ~ V2 + V3 + V7 + V10 + V13 + V14, data=myData[train,])
```

```

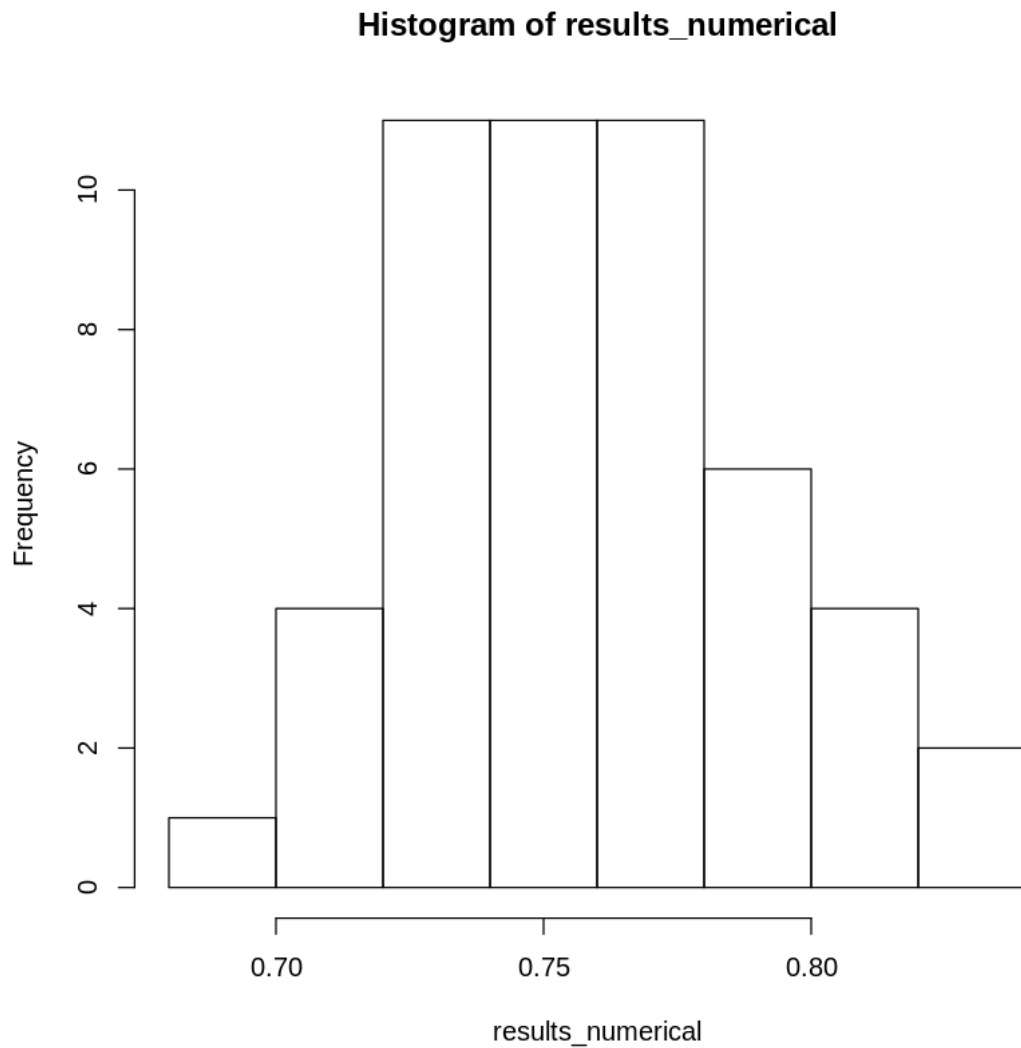
predictions_numerical <- predict(model_numerical, myData[test,])
cm_numerical <- confusionMatrix(table(predictions_numerical, myData[test,15]))
results_numerical <- c(results_numerical, cm_numerical$overall['Accuracy'])

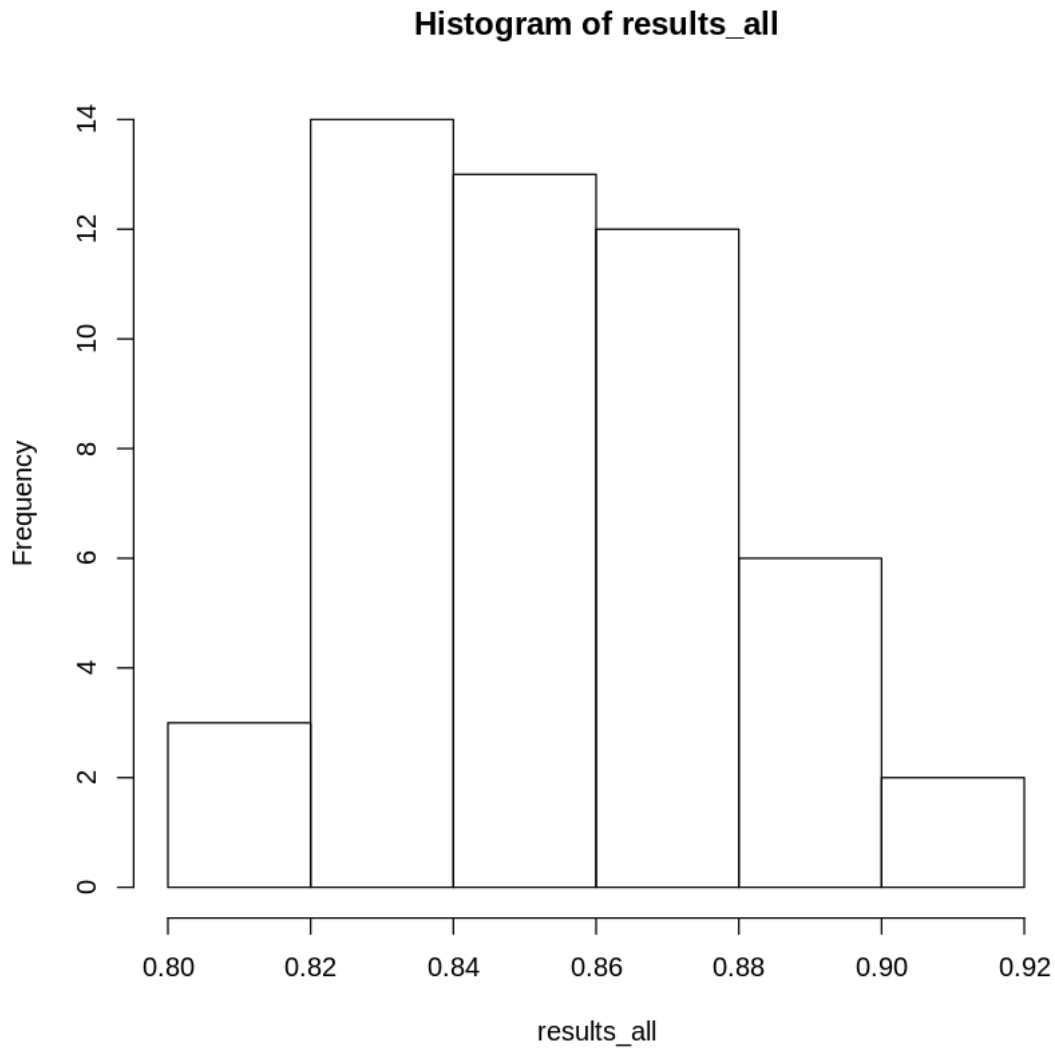
model_all <- svm(V15 ~ ., data=myData[train,])
predictions_all <- predict(model_all, myData[test,])
cm_all <- confusionMatrix(table(predictions_all, myData[test,15]))
results_all <- c(results_all, cm_all$overall['Accuracy'])

}

hist(results_numerical)
hist(results_all)

```





We can observe that SVM is more reliable upon convergence, its shape looks like t-distribution as should be.

4 Conclusion

On this thesis, we have worked on a finance dataset and tested logistic regression and SVM algorithms. We investigated the nature of dataset, features' specifications and behaviours; and we tried to derive relations and meanings in between. Also we tested logistic regression and SVM's nature, studied specialties on a classification problem and came across several different conclusions about their methodology.

To take this study one step further, deep learning could be discussed; by its nature, deep learning could be an efficient approach for handling this certain classification problem, but we did not surround that on this thesis.