



School of Computer Science & Software Engineering

Bachelor of Computer Science

INFO411

Assignment 1

Name: Sivathorn Siralert

UOW ID: 6738564

Part 1

I first load in all the data and describe the columns

```
> describe(data)
data
```

```
46 Variables      2500 Observations
-----
functionary
      n missing distinct      Info      Sum      Mean      Gmd
2500      0         2      0.603      696      0.2784      0.4019
-----
re.balanced..paid.back..a.recently.overdrawn.current.account
      n missing distinct      Info      Sum      Mean      Gmd
2500      0         2      0.379      2129      0.8516      0.2529
-----
FI30.credit.score
      n missing distinct      Info      Sum      Mean      Gmd
2500      0         2      0.444      2049      0.8196      0.2958
-----
gender
      n missing distinct      Info      Sum      Mean      Gmd
2500      0         2      0.75      1235      0.494      0.5001
-----
X0..accounts.at.other.banks
      n missing distinct      Info      Mean      Gmd
2500      0         5      0.96      3.048      1.606

Value      1      2      3      4      5
Frequency    490    467    499    521    523
Proportion 0.196 0.187 0.200 0.208 0.209
```

For the frequency table, variable is rounded to the nearest 0

```
-----
credit.refused.in.past.
      n missing distinct      Info      Sum      Mean      Gmd
2500      0         2      0.347      334      0.1336      0.2316
```

```

-----
years.employed
      n  missing distinct      Info      Mean      Gmd
2500      0          5      0.96    3.011    1.588

```

```

Value      1      2      3      4      5
Frequency  489   495   503   526   487
Proportion 0.196 0.198 0.201 0.210 0.195

```

For the frequency table, variable is rounded to the nearest 0

```

-----
savings.on.other.accounts
      n  missing distinct      Info      Mean      Gmd
2500      0          6    0.959    3.142    2.014

```

```

Value      1      2      3      4      5      6
Frequency  585   559   490    36   443   387
Proportion 0.234 0.224 0.196 0.014 0.177 0.155

```

For the frequency table, variable is rounded to the nearest 0

```

-----
self.employed.
      n  missing distinct      Info      Sum      Mean      Gmd
2500      0          2    0.474    492    0.1968    0.3163

```

```

-----
max..account.balance.12.months.ago
      n  missing distinct      Info      Mean      Gmd
2500      0          5      0.96    2.958    1.577

```

```

Value      1      2      3      4      5
Frequency  490   544   517   479   470
Proportion 0.196 0.218 0.207 0.192 0.188

```

For the frequency table, variable is rounded to the nearest 0

```

-----
min..account.balance.12.months.ago
      n  missing distinct      Info      Mean      Gmd
2500      0          5      0.96    2.972    1.596

```

```

Value      1      2      3      4      5
Frequency  518   481   539   476   486
Proportion 0.207 0.192 0.216 0.190 0.194

```

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.12.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.985	1.594

Value	1	2	3	4	5
Frequency	500	510	506	495	489
Proportion	0.200	0.204	0.202	0.198	0.196

For the frequency table, variable is rounded to the nearest 0

max..account.balance.11.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.99	1.607

Value	1	2	3	4	5
Frequency	514	498	481	514	493
Proportion	0.206	0.199	0.192	0.206	0.197

For the frequency table, variable is rounded to the nearest 0

min..account.balance.11.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.964	1.597

Value	1	2	3	4	5
Frequency	523	493	508	502	474
Proportion	0.209	0.197	0.203	0.201	0.190

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.11.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.989	1.58

Value	1	2	3	4	5
Frequency	503	481	518	537	461
Proportion	0.201	0.192	0.207	0.215	0.184

For the frequency table, variable is rounded to the nearest 0

max..account.balance.10.months.ago

n	missing	distinct	Info	Mean	Gmd
---	---------	----------	------	------	-----

2500 0 5 0.96 2.95 1.614

Value	1	2	3	4	5
Frequency	529	532	466	482	491
Proportion	0.212	0.213	0.186	0.193	0.196

For the frequency table, variable is rounded to the nearest 0

min..account.balance.10.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.003	1.595

Value	1	2	3	4	5
Frequency	487	521	487	507	498
Proportion	0.195	0.208	0.195	0.203	0.199

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.10.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.027	1.583

Value	1	2	3	4	5
Frequency	464	517	512	502	505
Proportion	0.186	0.207	0.205	0.201	0.202

For the frequency table, variable is rounded to the nearest 0

max..account.balance.9.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.014	1.63

Value	1	2	3	4	5
Frequency	516	487	483	474	540
Proportion	0.206	0.195	0.193	0.190	0.216

For the frequency table, variable is rounded to the nearest 0

min..account.balance.9.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.986	1.604

Value	1	2	3	4	5
Frequency	495	538	479	483	505
Proportion	0.198	0.215	0.192	0.193	0.202

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.9.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.971	1.605

Value	1	2	3	4	5
Frequency	526	492	490	512	480
Proportion	0.210	0.197	0.196	0.205	0.192

For the frequency table, variable is rounded to the nearest 0

max..account.balance.8.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.046	1.619

Value	1	2	3	4	5
Frequency	488	492	484	488	548
Proportion	0.195	0.197	0.194	0.195	0.219

For the frequency table, variable is rounded to the nearest 0

min..account.balance.8.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.019	1.586

Value	1	2	3	4	5
Frequency	481	489	531	499	500
Proportion	0.192	0.196	0.212	0.200	0.200

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.8.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.989	1.601

Value	1	2	3	4	5
Frequency	501	510	506	481	502
Proportion	0.200	0.204	0.202	0.192	0.201

For the frequency table, variable is rounded to the nearest 0

max..account.balance.7.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.004	1.606

Value	1	2	3	4	5
Frequency	498	519	457	526	500
Proportion	0.199	0.208	0.183	0.210	0.200

For the frequency table, variable is rounded to the nearest 0

min..account.balance.7.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.028	1.582

Value	1	2	3	4	5
Frequency	476	491	508	536	489
Proportion	0.190	0.196	0.203	0.214	0.196

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.7.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.03	1.613

Value	1	2	3	4	5
Frequency	493	497	480	502	528
Proportion	0.197	0.199	0.192	0.201	0.211

For the frequency table, variable is rounded to the nearest 0

max..account.balance.6.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.997	1.602

Value	1	2	3	4	5
Frequency	507	494	493	512	494
Proportion	0.203	0.198	0.197	0.205	0.198

For the frequency table, variable is rounded to the nearest 0

min..account.balance.6.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.028	1.606

Value	1	2	3	4	5
Frequency	471	535	484	474	536

Proportion 0.188 0.214 0.194 0.190 0.214

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.6.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.049	1.596

Value	1	2	3	4	5
Frequency	480	470	516	515	519
Proportion	0.192	0.188	0.206	0.206	0.208

For the frequency table, variable is rounded to the nearest 0

max..account.balance.5.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.003	1.61

Value	1	2	3	4	5
Frequency	511	484	500	496	509
Proportion	0.204	0.194	0.200	0.198	0.204

For the frequency table, variable is rounded to the nearest 0

min..account.balance.5.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.99	1.597

Value	1	2	3	4	5
Frequency	499	505	515	483	498
Proportion	0.200	0.202	0.206	0.193	0.199

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.5.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.979	1.612

Value	1	2	3	4	5
Frequency	513	524	468	493	502
Proportion	0.205	0.210	0.187	0.197	0.201

For the frequency table, variable is rounded to the nearest 0


```
max..account.balance.4.months.ago
      n  missing distinct      Info      Mean      Gmd
    2500      0      5      0.96      3.03      1.605
```

```
Value      1      2      3      4      5
Frequency   492   484   500   505   519
Proportion 0.197 0.194 0.200 0.202 0.208
```

For the frequency table, variable is rounded to the nearest 0

```
min..account.balance.4.months.ago
      n  missing distinct      Info      Mean      Gmd
    2500      0      5      0.96      3.006      1.601
```

```
Value      1      2      3      4      5
Frequency   496   505   489   509   501
Proportion 0.198 0.202 0.196 0.204 0.200
```

For the frequency table, variable is rounded to the nearest 0

```
avrg..account.balance.4.months.ago
      n  missing distinct      Info      Mean      Gmd
    2500      0      5      0.96      3.038      1.58
```

```
Value      1      2      3      4      5
Frequency   460   504   527   500   509
Proportion 0.184 0.202 0.211 0.200 0.204
```

For the frequency table, variable is rounded to the nearest 0

```
max..account.balance.3.months.ago
      n  missing distinct      Info      Mean      Gmd
    2500      0      5      0.96      3.021      1.609
```

```
Value      1      2      3      4      5
Frequency   501   482   497   503   517
Proportion 0.200 0.193 0.199 0.201 0.207
```

For the frequency table, variable is rounded to the nearest 0

```
min..account.balance.3.months.ago
      n  missing distinct      Info      Mean      Gmd
    2500      0      5      0.96      3.019      1.574
```

```
Value      1      2      3      4      5
```

Frequency 473 496 520 532 479
Proportion 0.189 0.198 0.208 0.213 0.192

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.3.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.04	1.606

Value	1	2	3	4	5
Frequency	488	487	483	522	520
Proportion	0.195	0.195	0.193	0.209	0.208

For the frequency table, variable is rounded to the nearest 0

max..account.balance.2.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	2.996	1.578

Value	1	2	3	4	5
Frequency	482	507	531	498	482
Proportion	0.193	0.203	0.212	0.199	0.193

For the frequency table, variable is rounded to the nearest 0

min..account.balance.2.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.011	1.623

Value	1	2	3	4	5
Frequency	515	481	497	475	532
Proportion	0.206	0.192	0.199	0.190	0.213

For the frequency table, variable is rounded to the nearest 0

avrg..account.balance.2.months.ago

n	missing	distinct	Info	Mean	Gmd
2500	0	5	0.96	3.02	1.594

Value	1	2	3	4	5
Frequency	473	528	481	511	507
Proportion	0.189	0.211	0.192	0.204	0.203

For the frequency table, variable is rounded to the nearest 0

```

-----
-----
max..account.balance.1.months.ago
      n missing distinct      Info      Mean      Gmd
2500      0          5      0.96    2.973    1.591

```

```

Value      1      2      3      4      5
Frequency  508    507    503    508    474
Proportion 0.203 0.203 0.201 0.203 0.190

```

For the frequency table, variable is rounded to the nearest 0

```

-----
-----
min..account.balance.1.months.ago
      n missing distinct      Info      Mean      Gmd
2500      0          5      0.959    2.952    1.589

```

```

Value      1      2      3      4      5
Frequency  492    568    492    463    485
Proportion 0.197 0.227 0.197 0.185 0.194

```

For the frequency table, variable is rounded to the nearest 0

```

-----
-----
avrg..account.balance.1.months.ago
      n missing distinct      Info      Mean      Gmd
2500      0          5      0.96    3.011    1.576

```

```

Value      1      2      3      4      5
Frequency  469    524    498    528    481
Proportion 0.188 0.210 0.199 0.211 0.192

```

For the frequency table, variable is rounded to the nearest 0

```

-----
-----
credit.rating
      n missing distinct      Info      Mean      Gmd
2500      0          4      0.916    1.58    1.146

```

```

Value      0      1      2      3
Frequency  538    483    970    509
Proportion 0.215 0.193 0.388 0.204

```

For the frequency table, variable is rounded to the nearest 0

Next i do some data cleaning and then examine the corelation

```
> head(corTable,6)

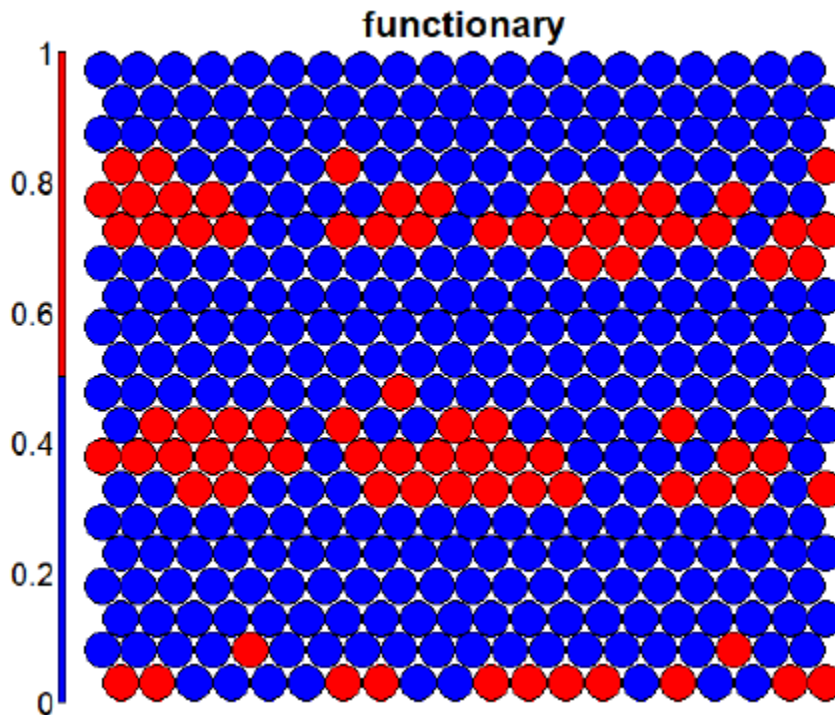
                                [,1]
credit.rating                    1.00000000
functionary                      0.31728279
FI30.credit.score                0.27988701
re.balanced..paid.back..a.recently.overdrawn.current.acount 0.21822314
credit.refused.in.past.          0.21783847
gender
```

This allows me to conclude that i need to use functionary, FI30 credit score, rebalanced (paid back) a recently overdrawn current account, credit refused in past and gender as they have the highest correlation compared to the other attributes.

Part 2

Using those 5 attributes, i plot a SOM for each attribute.

Functionary



Legend:

red-0/non functional

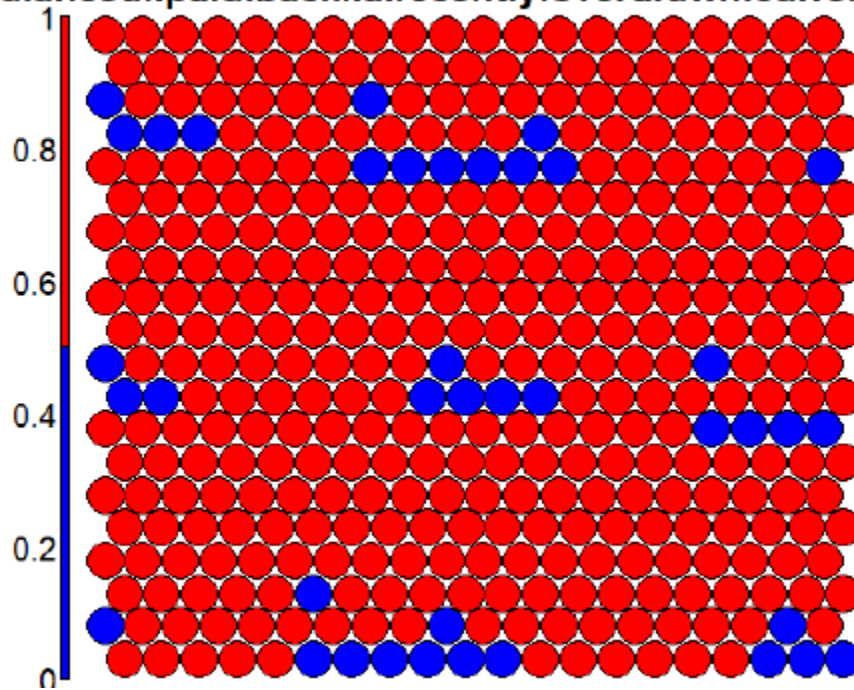
blue-1/fucntional

Most circles are blue, and are more clustered tgt compared to red, showing that most account are functional

functioning=likely to have higher credit rating

Paid back overdrawn current account

re.balanced..paid.back..a.recently.overdrawn.current.acount



Legend:

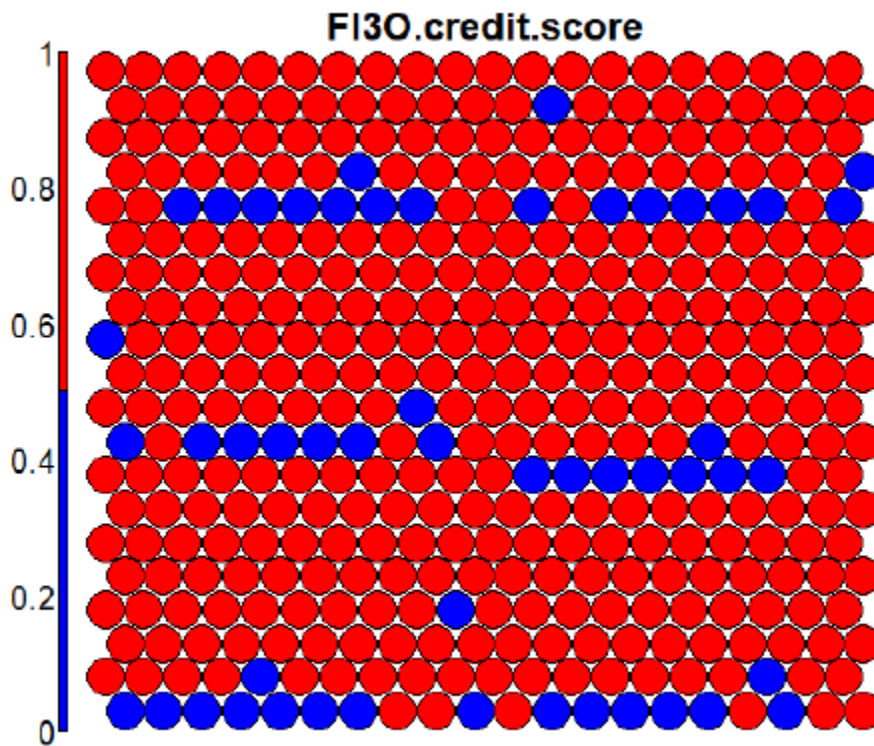
red-1/paid back

Blue-0/not paid back

Most circles are red, and are more clustered compared to blue, showing that most users paid back overdrawn current account

Paid back=likely to have higher credit rating

FI3O creit score



Legend:

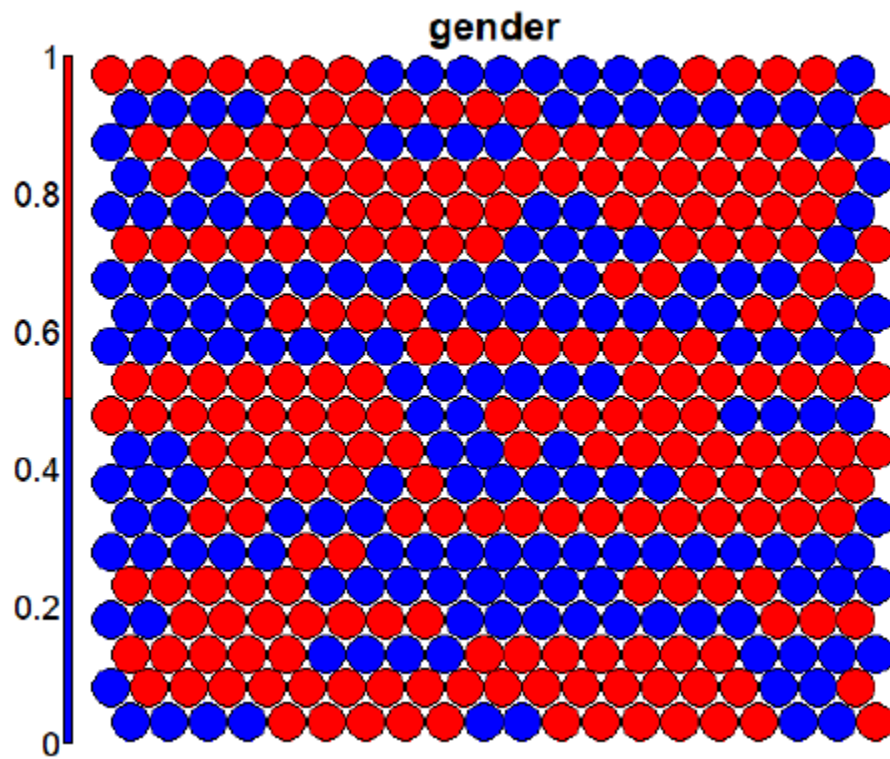
red-1/credit

Blue-0/no credit

Most circles are red, and are more clustered than blue, showing that most users have high credit

High credit score=likely to have higher credit rating

Gender



Legend:

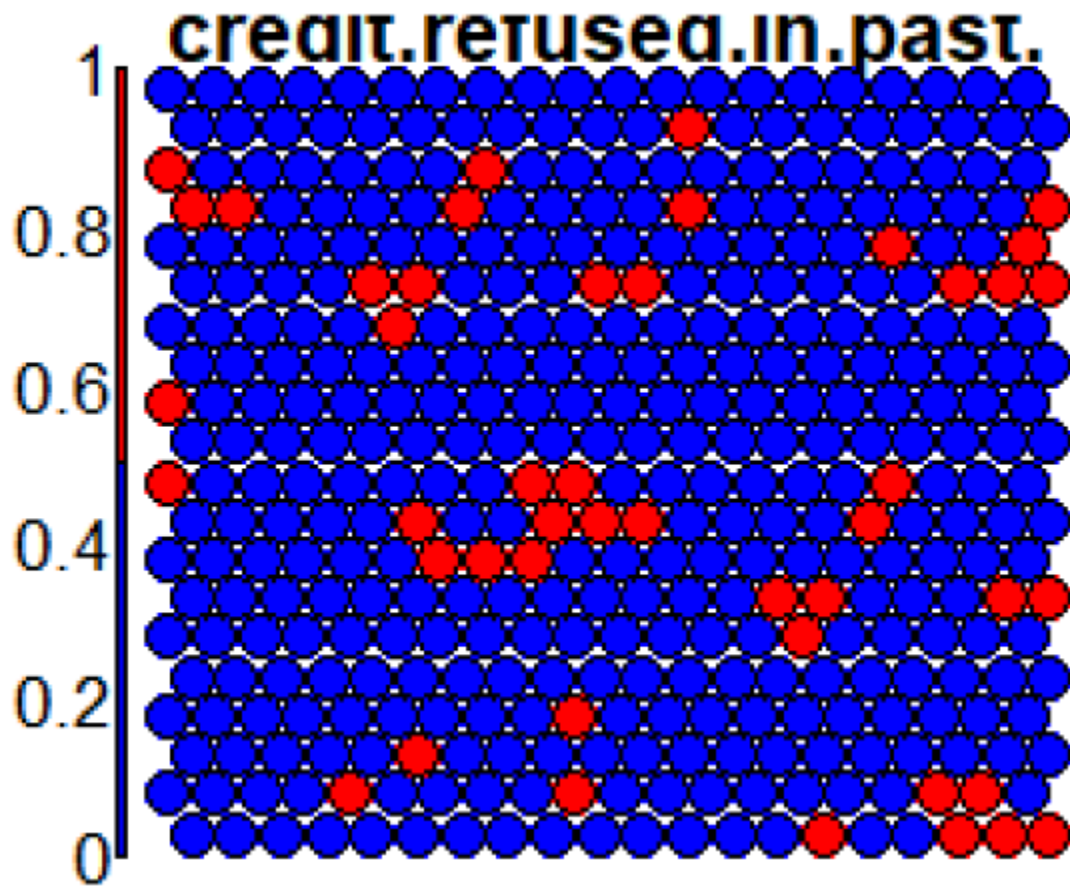
red-1/female

Blue-0/male

There is even spread of blue and red(looks like even)

Shows that theres equal chance for male or female to have high credit rating

Credit refused in the apst



Legend:

red-1/refused

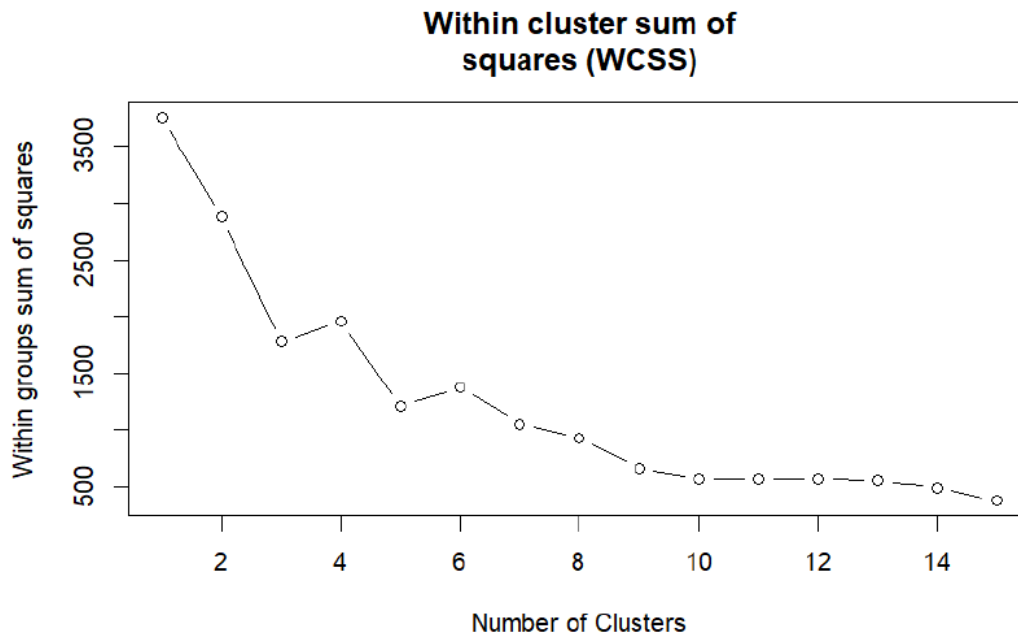
Blue-0/not refused

Most fo the map is blue, and are more clustered than red, showing that most ppl have no credit refused

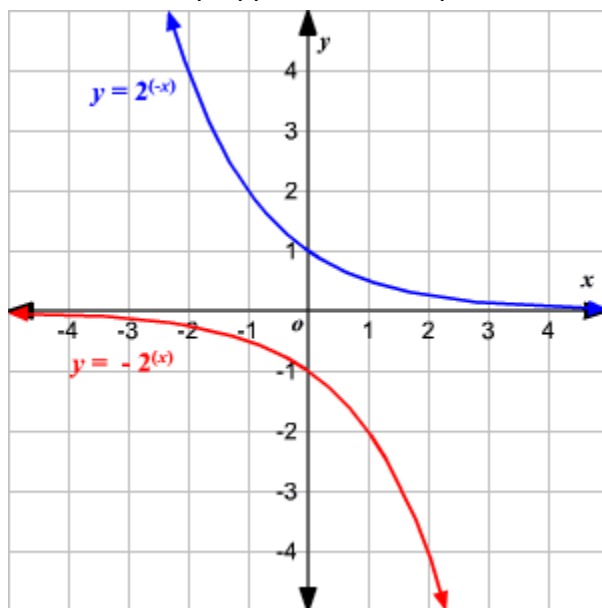
No credit refused= more likely to have higher credit rating

Part 3

I will now visualise the dataset using k mean clustering to demo the relationship b/w the WCSS(y axis) and the number of clusters(x axis)



The relationship appears to be exponential looking like this

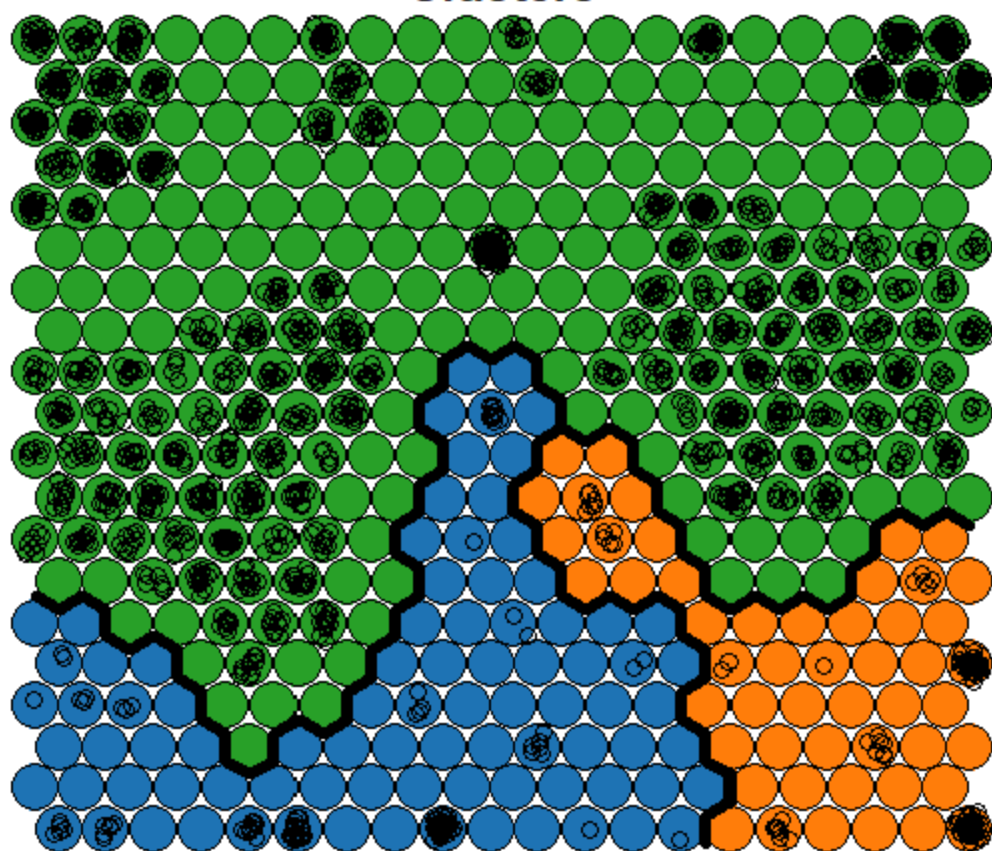


(just an example of exponential graph)

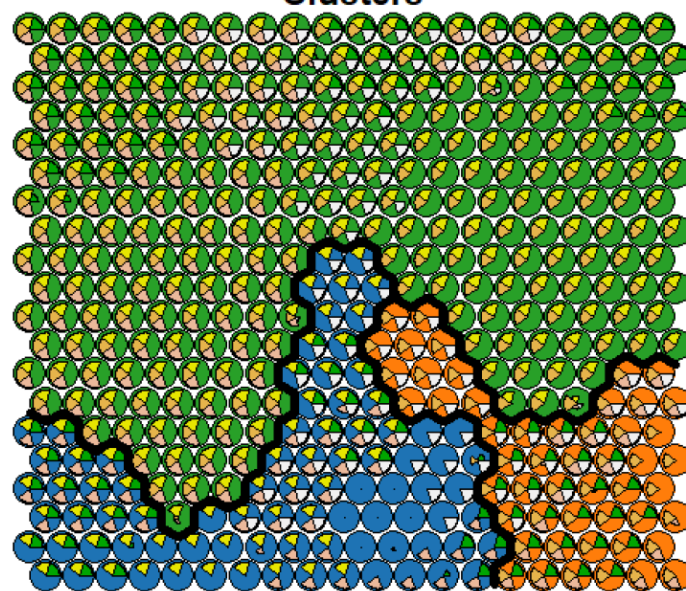
When number of clusters increase, there is an exponential drop in WCSS.

From this we determine that 3 is the best number of clusters to use.

Clusters



Clusters



■ functional	■ FICO credit score	□ credit refused in past
■ re-balanced, paid back, a recently overdrawn current account	■ gender	

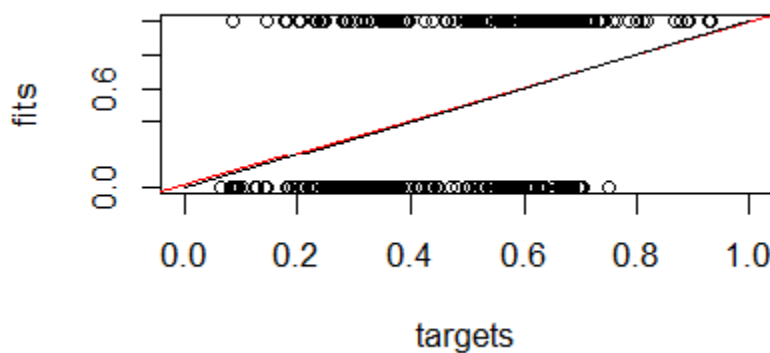
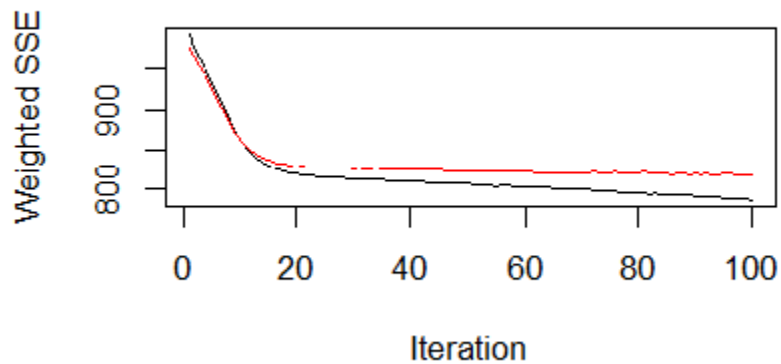
From all this information, we can deduce that kohonen is not 100% accurate. I hypothesise that this is because the input quality affects the SOM topology, affecting their ability to map vectors, as well as how many times we iterate and many more

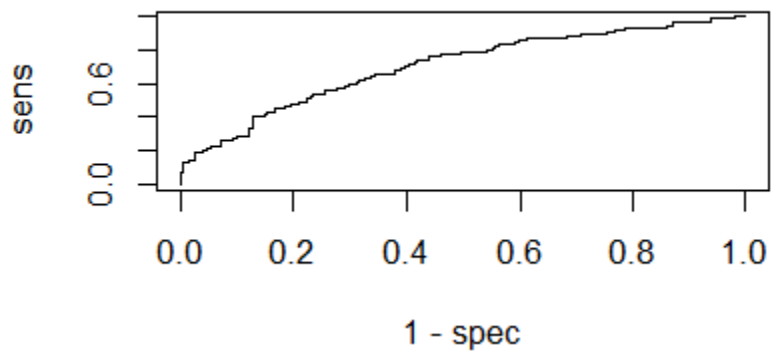
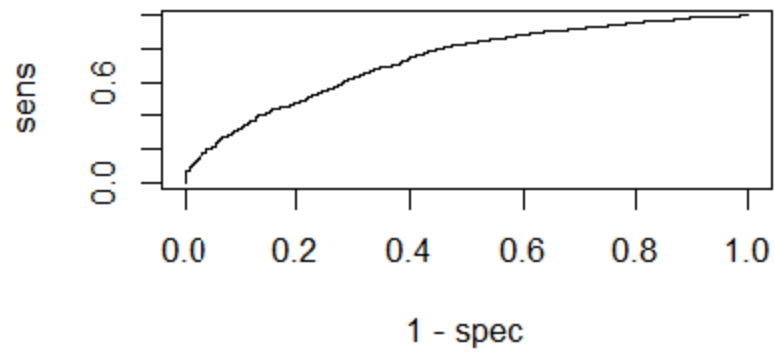
Part 4

We will conduct the MLP with 100 iterations, learning parameter to 0.01, number of nodes to 20 after splitting the dataset to a ratio of 0.2

```
# Train the MLP model
model = mlp(trainSet$inputsTrain,
            trainSet$targetsTrain,
            size=c(20),
            learnFuncParams=c(0.001),
            maxit=100,
            inputsTest = trainSet$inputsTest,
            targetsTest = trainSet$targetsTest)

#
# Predict the test
# The predict() function in R is used to predict the values
# based on the input data.
predictTestSet = predict(model, trainSet$inputsTest)
```





After fine tuning, we perform the following

```
>confusionMatrix(trainSet$targetsTrain, fitted.values(model))
```

```
      Predictions
Targets 1      2      3
      1 214    164    22
      2 120    612    51
      3  44    175   178
```

```
>confusionMatrix(trainSet$targetsTest, predictTestSet)
```

```
      Predictions
Targets 1      2      3
      1  52    19     2
      2  27   150    21
      3  14    50    40
```

accuracy: $(52+150+40)/(52+19+2+27+150+21+14+50+40)=240/375=64\%$

Code

```
# Preprocessing
library(kohonen)
library(dummies)
library(ggplot2)
library(sp)
library(maptools)
library(reshape2)
library(rgeos)
library(sf)
library(terra)
library(MASS)
library(Hmisc)
library(RSNNS)

# Colour palette definition
pretty_palette <- c("#1f77b4", "#ff7f0e", "#2ca02c", "#d62728", "#9467bd",
"#8c564b", "#e377c2")

### DATA PREPARATION
data <- read.csv("./creditworthiness.csv")
describe(data)
classifiedData = subset(data, data[,46] > 0)
unknownData = subset(data, data[,46] == 0)
corTable = abs(cor(classifiedData, y=classifiedData$credit.rating))
corTable = corTable[order(corTable, decreasing = TRUE),,drop = FALSE]
head(corTable,6)

# ----- SOM TRAINING -----

#choose the variables with which to train the SOM
#the following selects column 1,2,3,4,6
interestedFeatures <- data[, c(1,2,3,4,6)]

#data_train <- data[, c(1:45)]
data_train <- classifiedData[, c(1:45)]

# now train the SOM using the Kohonen method
data_train_matrix <- as.matrix(scale(data_train))
names(data_train_matrix) <- names(data_train)
require(kohonen)
x_dim=20
y_dim=20
small_areas <-FALSE
if (small_areas){
  # larger grid for the small areas example (more samples)
  som_grid <- somgrid(xdim = x_dim, ydim=y_dim, topo="hexagonal")
} else {
```



```

    som_grid <- somgrid(xdim = x_dim/2, ydim=y_dim/2, topo="hexagonal")
  }
  # Train the SOM model!
  if (packageVersion("kohonen") < 3){
    system.time(som_model <- som(data_train_matrix,
                                grid=som_grid,
                                rlen=1000,
                                alpha=c(0.8,0.01),
                                n.hood = "circular",
                                keep.data = TRUE ))
  }else{
    system.time(som_model <- som(data_train_matrix,
                                grid=som_grid,
                                rlen=1000,
                                alpha=c(0.8,0.01),
                                mode="online",
                                normalizeDataLayers=false,
                                keep.data = TRUE ))
  }
  summary(som_model)
  rm(som_grid, data_train_matrix)

  # ----- SOM VISUALISATION -----

  source('./coolBlueHotRed.R')
  # Plot the heatmap for a variable at scaled / normalised values
  var <- 1 # Functionary
  var_unscaled <- aggregate(as.numeric(data_train[,var]),
                            by=list(som_model$unit.classif), FUN=mean, simplify=TRUE)[,2]
  plot(som_model, type = "property", property=var_unscaled,
       main=names(data_train)[var], palette.name=coolBlueHotRed)
  rm(var_unscaled, var)

  var <- 2 # FI30.credit.score
  var_unscaled <- aggregate(as.numeric(data_train[,var]),
                            by=list(som_model$unit.classif), FUN=mean, simplify=TRUE)[,2]
  plot(som_model, type = "property", property=var_unscaled,
       main=names(data_train)[var], palette.name=coolBlueHotRed)
  rm(var_unscaled, var)

  var <- 3 # Rebalance.payback
  var_unscaled <- aggregate(as.numeric(data_train[,var]),
                            by=list(som_model$unit.classif), FUN=mean, simplify=TRUE)[,2]
  plot(som_model, type = "property", property=var_unscaled,
       main=names(data_train)[var], palette.name=coolBlueHotRed)
  rm(var_unscaled, var)

  var <- 4 # credit.refused.in.past.

```

```

var_unscaled <- aggregate(as.numeric(data_train[,var]),
by=list(som_model$unit.classif), FUN=mean, simplify=TRUE)[,2]
plot(som_model, type = "property", property=var_unscaled,
main=names(data_train)[var], palette.name=coolBlueHotRed)
rm(var_unscaled, var)

var <- 6 #Gender
var_unscaled <- aggregate(as.numeric(data_train[,var]),
by=list(som_model$unit.classif), FUN=mean, simplify=TRUE)[,2]
plot(som_model, type = "property", property=var_unscaled,
main=names(data_train)[var], palette.name=coolBlueHotRed)
rm(var_unscaled, var)

source('./plotHeatMap.R')
plotHeatMap(som_model, classifiedData, variable=0)

genderT = with(classifiedData, table(credit.rating, gender))
barplot(genderT, beside = TRUE,
        legend = c("Credit Rating A", "Credit Rating B", "Credit Rating
C"),
        col = c("darkgreen","yellow", "red"),
        main = "Gender vs Credit Rating",
        sub="0 = Male, 1 = Female")
selfEmployed = with(classifiedData, table(credit.rating, self.employed.))
barplot(selfEmployed, beside = TRUE,
        legend = c("Credit Rating A", "Credit Rating B", "Credit Rating
C"),
        col = c("darkgreen","yellow", "red"),
        main = "Self Employed vs Credit Rating",
        sub="0 = No, 1 = Yes")
functional = with(classifiedData, table(credit.rating, functionary))
barplot(functional, beside = TRUE,
        legend = c("Credit Rating A", "Credit Rating B", "Credit Rating
C"),
        col = c("darkgreen","yellow", "red"),
        main = "Functionary vs Credit Rating",
        sub="0 = No, 1 = Yes")
genderT = with(classifiedData, table(credit.rating, gender))
genderT
barplot(genderT, beside = TRUE,
        legend = c("Credit Rating A", "Credit Rating B", "Credit Rating
C"),
        col = c("darkgreen","yellow", "red"),
        main = "Gender vs Credit Rating",
        sub="0 = Male, 1 = Female")
selfEmployed = with(classifiedData, table(credit.rating, self.employed.))
barplot(selfEmployed, beside = TRUE,
        legend = c("Credit Rating A", "Credit Rating B", "Credit Rating
C"),

```

```

        col = c("darkgreen","yellow", "red"),
        main = "Self Employed vs Credit Rating",
        sub="0 = No, 1 = Yes")
# generate a contingency table and plot a barplot
FI30T = with(classifiedData, table(credit.rating, FI30.credit.score))
FI30T
barplot(genderT, beside = TRUE,
        legend = c("Credit Rating A", "Credit Rating B", "Credit Rating
C"),
        col = c("darkgreen","yellow", "red"),
        main = "FI30 vs Credit Rating",
        sub="0 = Not OK, 1 = Ok")

# show the WCSS metric for kmeans for different clustering sizes.
# Can be used as a "rough" indicator of the ideal number of clusters
mydata <- matrix(unlist(som_model$codes), ncol = length(data_train),
                byrow = FALSE)
wss <- (nrow(mydata)-1)*sum(apply(mydata,2,var))
for (i in 2:15) wss[i] <- sum(kmeans(mydata,
                                    centers=i)$withinss)

par(mar=c(5.1,4.1,4.1,2.1))
plot(1:15, wss, type="b", xlab="Number of Clusters",
     ylab="Within groups sum of squares", main="Within cluster sum of
squares (WCSS)")

# Form clusters on grid
## use hierarchical clustering to cluster the codebook vectors
som_cluster <- cutree(hclust(dist(mydata)), 3)
# Show the map with different colours for every cluster

plot(som_model, type="mapping", bgcol = pretty_palette[som_cluster], main
     = "Clusters")
add.cluster.boundaries(som_model, som_cluster)
#show the same plot with the codes instead of just colours
plot(som_model, type="codes", bgcol = pretty_palette[som_cluster], main =
     "Clusters")
add.cluster.boundaries(som_model, som_cluster)

# ----- Clustering SOM results -----

# show the WCSS metric for kmeans for different clustering sizes.
# Can be used as a "rough" indicator of the ideal number of clusters
mydata <- matrix(unlist(som_model$codes), ncol = length(data_train),
                byrow = FALSE)
wss <- (nrow(mydata)-1)*sum(apply(mydata,2,var))
for (i in 2:15) wss[i] <- sum(kmeans(mydata,
                                    centers=i)$withinss)

par(mar=c(5.1,4.1,4.1,2.1))

```

```

plot(1:15, wss, type="b", xlab="Number of Clusters",
     ylab="Within groups sum of squares", main="Within cluster sum of
squares (WCSS)")

# Form clusters on grid
## use hierarchical clustering to cluster the codebook vectors
som_cluster <- cutree(hclust(dist(mydata)), 3)
# Show the map with different colours for every cluster

plot(som_model, type="mapping", bgcol = pretty_palette[som_cluster], main
     = "Clusters")
add.cluster.boundaries(som_model, som_cluster)
#show the same plot with the codes instead of just colours
plot(som_model, type="codes", bgcol = pretty_palette[som_cluster], main =
     "Clusters")
add.cluster.boundaries(som_model, som_cluster)


# To train the MLP model to classified based on the following
# interested columns.
interestedColumns = c(1, 2, 3, 4, 6, 9)
# Seperate value from targets
trainValues = classifiedData[,interestedColumns]
unknownValues = unknownData[,interestedColumns]
# Use decodeClassLabels() to decode class labels from a
# numerical or levels vector to a binary matrix.
trainTargets = decodeClassLabels(classifiedData[,46])
# Split the data into training and testing data set
trainSet = splitForTrainingAndTest(trainValues, trainTargets, ratio =
                                0.2)

# Normalized the training data set
trainSet = normTrainingAndTestSet(trainSet)
# Train the MLP model
model = mlp(trainSet$inputsTrain,
            trainSet$targetsTrain,
            size=c(20),
            learnFuncParams=c(0.001),
            maxit=100,
            inputsTest = trainSet$inputsTest,
            targetsTest = trainSet$targetsTest)

#
# Predict the test
# The predict() function in R is used to predict the values
# based on the input data.
predictTestSet = predict(model, trainSet$inputsTest)
# Predict the unknown set
predictUnknownSet = predict(model, unknownValues)

```

```
# Compute the confusion matrix
confusionMatrix(trainSet$targetsTrain, fitted.values(model))
confusionMatrix(trainSet$targetsTest, predictTestSet)
# interpreting the unknown data set (prediction)
head(trainTargets)
head(classifiedData[,46])
head(predictUnknownSet)
# Plot
par(mar=c(5.1,4.1,4.1,2.1))
par(mfrow=c(2,2))
plotIterativeError(model)
plotRegressionError(predictTestSet[,2], trainSet$targetsTest[,2])
plotROC(fitted.values(model)[,2], trainSet$targetsTrain[,2])
plotROC(predictTestSet[,2],trainSet$targetsTest[,2])
summary(model)
model
weightMatrix(model)
extractNetInfo(model)
```