Discovery_dataset

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Here, I recapitulate the main step related in the research paper with the graphs associated

The first step is data cleansing :

```
training_data=read.csv("data/Data_User_Modeling_training_Dataset.csv")
test_data=read.csv("data/Data_User_Modeling_test_Dataset.csv")
library(gplots)
```

```
##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess
```

```
library(ggplot2)
library(partykit)
```

```
## Loading required package: grid

## Loading required package: libcoin

## Loading required package: mvtnorm
```

```
library(rpart) # Popular decision tree algorithm
library(hier.part)
```

```
## Loading required package: gtools
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ipred)
library(randomForest)
```

```
## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
#library(rattle) # GUI for building trees and fancy tree plot #Doesn't work
library(rpart.plot) # Enhanced tree plots
library(party) # Alternative decision tree algorithm
```

```
## Loading required package: modeltools

## Loading required package: stats4

## Loading required package: strucchange

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: sandwich

##
## Attaching package: 'party'

## The following objects are masked from 'package:partykit':
##
##     cforest, ctree, ctree_control, edge_simple, mob, mob_control,
##     node_barplot, node_bivplot, node_boxplot, node_inner,
##     node_surv, node_terminal, varimp
```

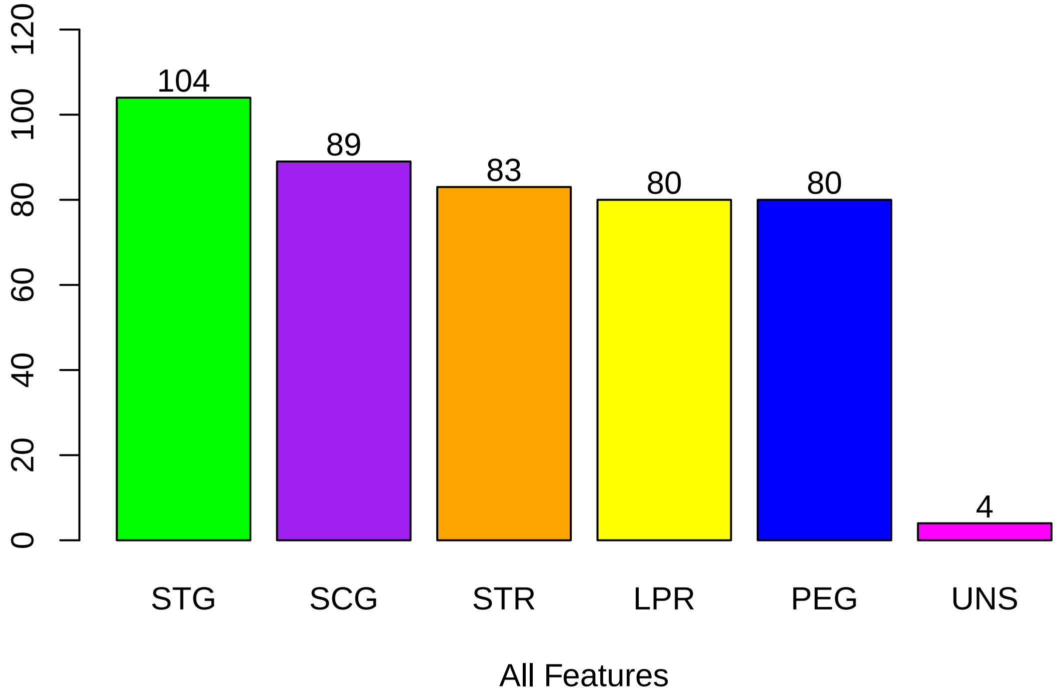
```
library(partykit) # Convert rpart object to BinaryTree
#library(RWeka) # Weka decision tree J48.
library(C50) # Original C5.0 implementation.
summary(training_data)
```

```
##       STG              SCG              STR              LPR
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.2407   1st Qu.:0.2100   1st Qu.:0.2913   1st Qu.:0.2500
##  Median :0.3270   Median :0.3025   Median :0.4900   Median :0.3300
##  Mean   :0.3711   Mean   :0.3557   Mean   :0.4680   Mean   :0.4327
##  3rd Qu.:0.4950   3rd Qu.:0.4975   3rd Qu.:0.6900   3rd Qu.:0.6475
##  Max.   :0.9900   Max.   :0.9000   Max.   :0.9500   Max.   :0.9900
##       PEG              UNS
##  Min.   :0.0000   High    :63
##  1st Qu.:0.2500   Low     :83
##  Median :0.5000   Middle  :88
##  Mean   :0.4585   very_low:24
##  3rd Qu.:0.6600
##  Max.   :0.9300
```

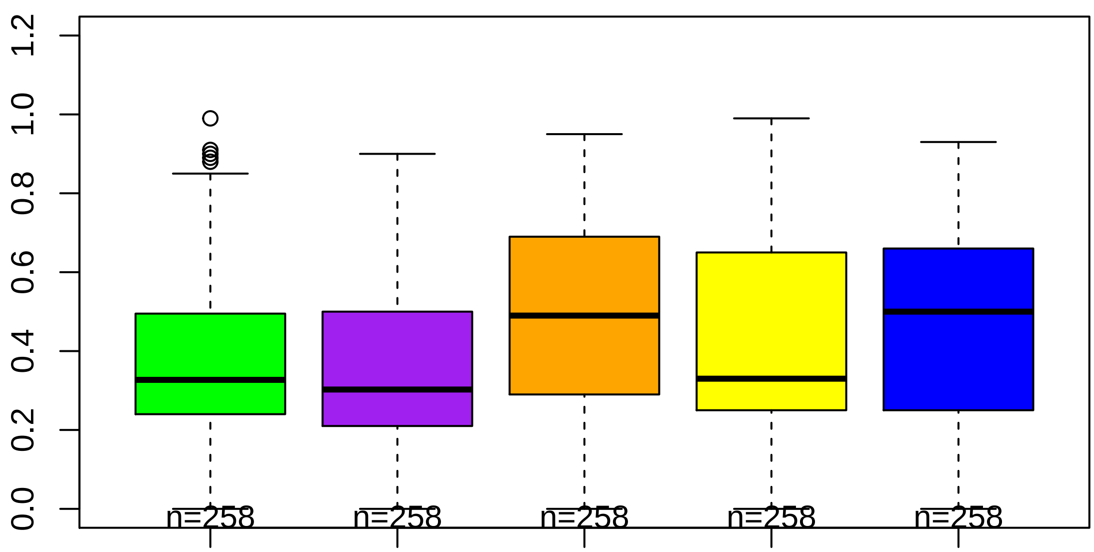
```
attach(training_data)
```

```
# Number of distinct values in each feture
a = n_distinct(STG)
b = n_distinct(SCG)
c = n_distinct(STR)
```

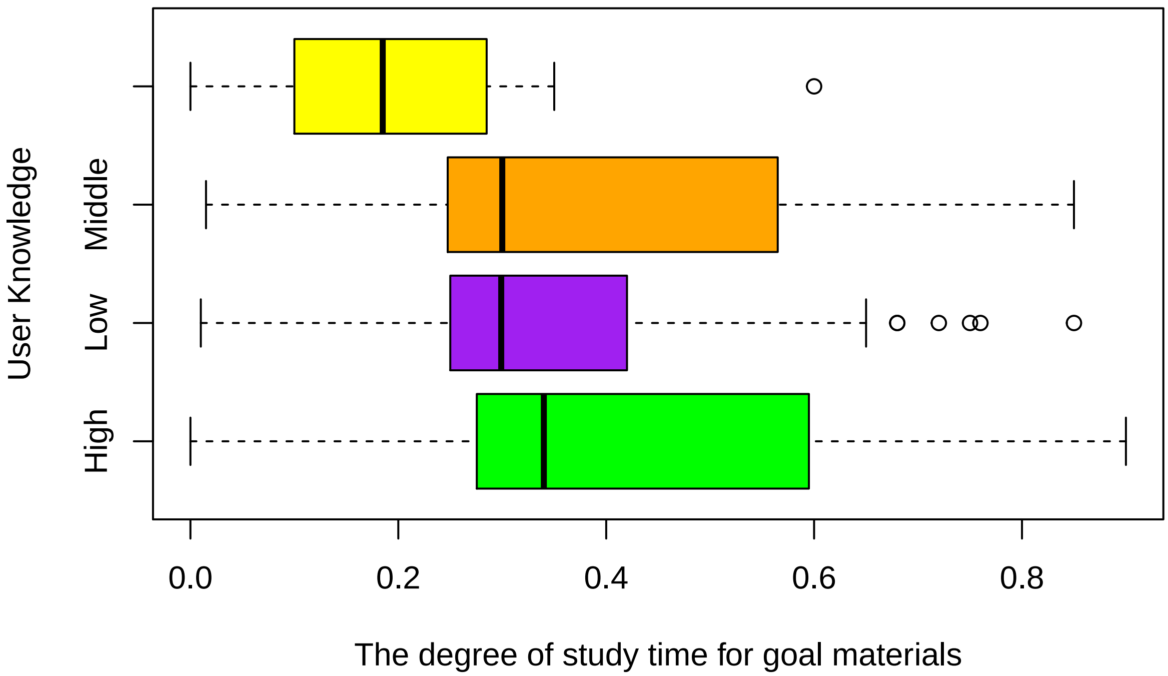
```
d = n_distinct(LPR)
e = n_distinct(PEG)
f = n_distinct(UNS)
num_distinct = c(a,b,c,d,e,f)

plot = barplot(num_distinct, names = c("STG", "SCG", "STR", "LPR", "PEG", "UNS"), ylim=c(0,120), xlab="
text(plot,num_distinct + 4,labels=as.character(num_distinct))
```



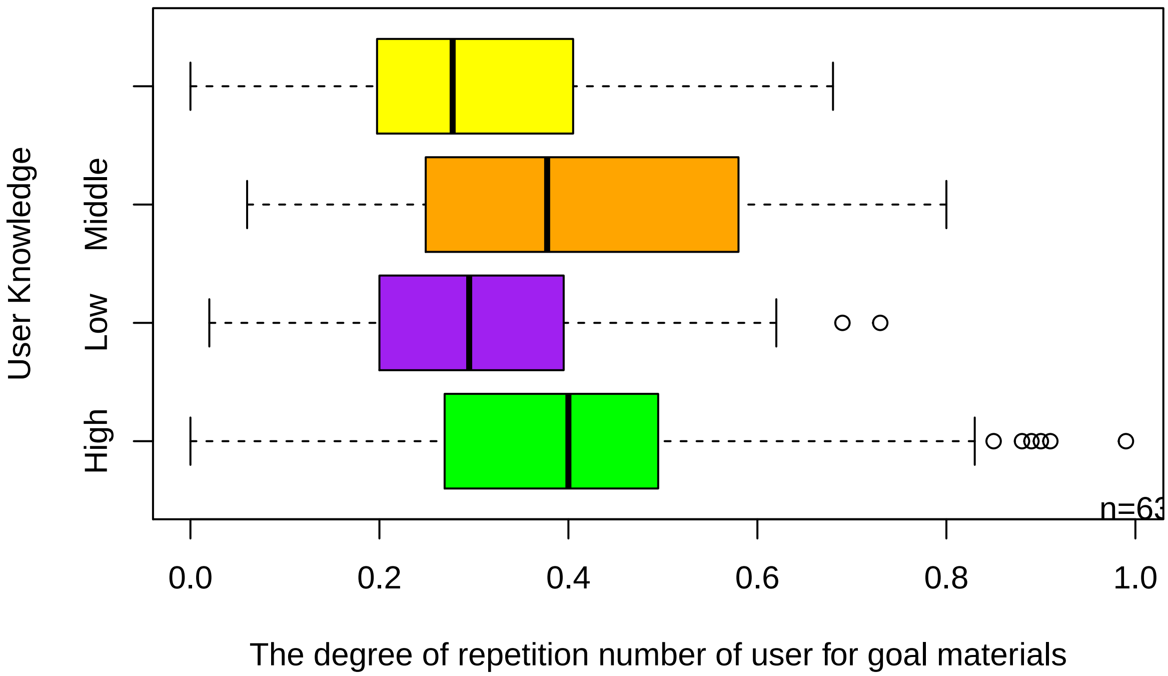

```
# boxplot of all data
boxplot2(STG,SCG,STR,LPR,PEG, col=c("green", "purple", "orange", "yellow", "blue", "magenta"), ylim=c(0
```



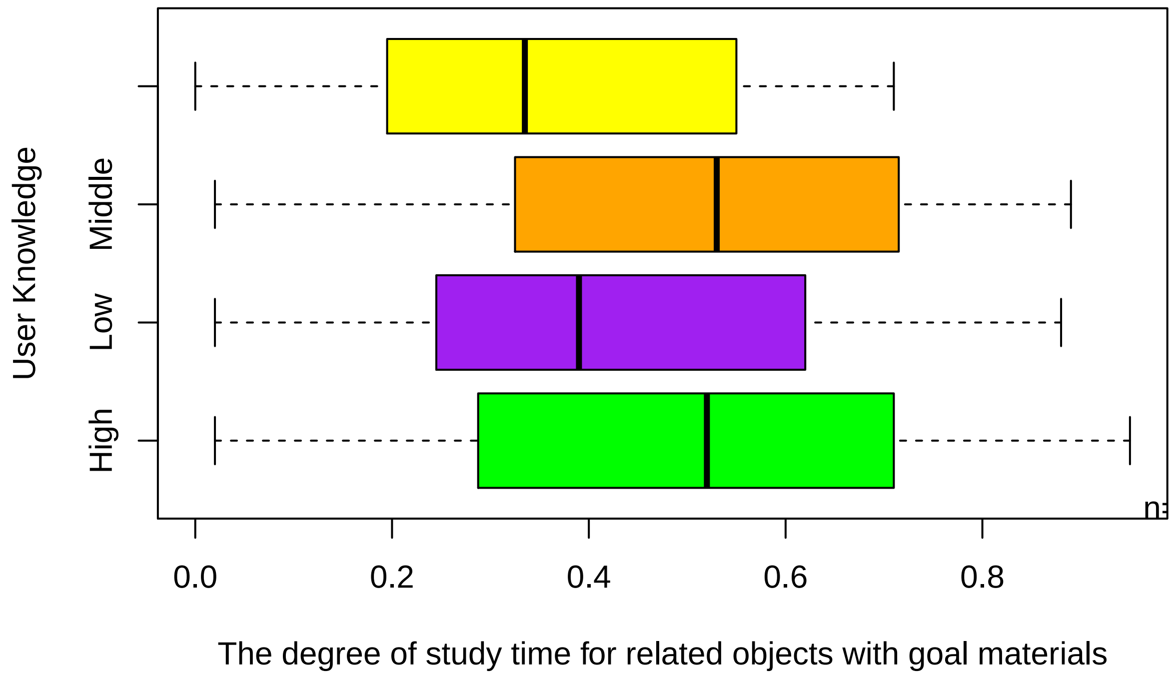

```
# boxplot of SCG divided accross UNS values
boxplot2(SCG~UNS,data=training_data, horizontal = TRUE,
     xlab="The degree of study time for goal materials", ylab="User Knowledge", col=c("green", "purple"
```



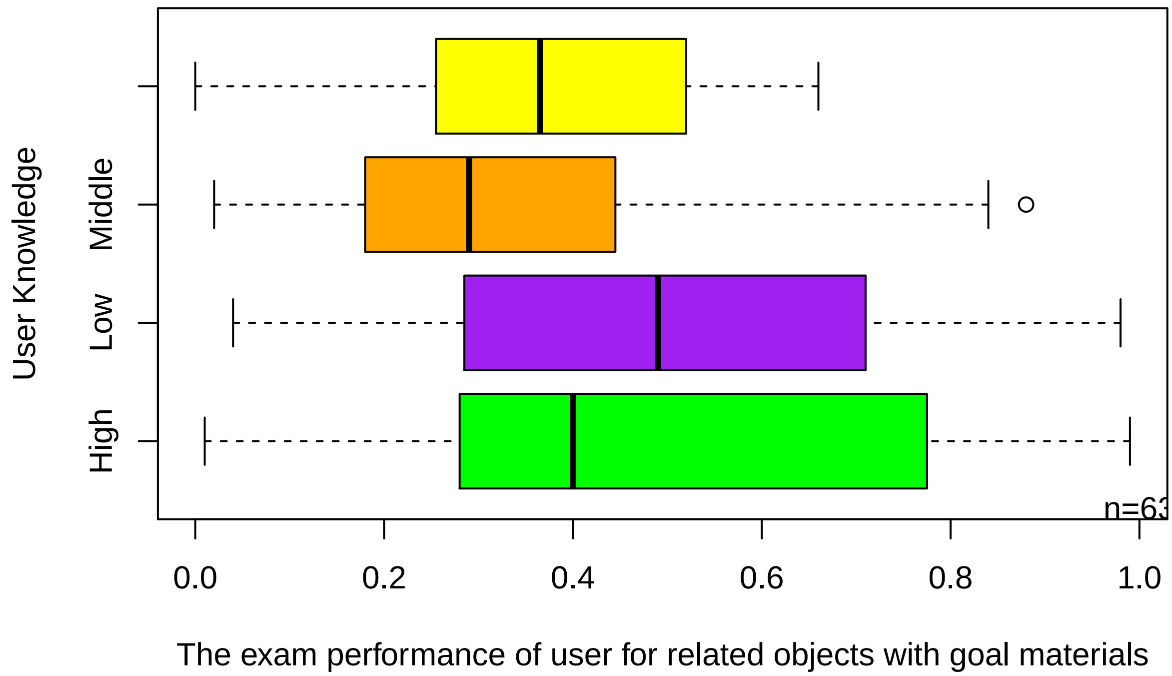

```r
# boxplot of STG divided accross UNS values
boxplot2(STG~UNS,data=training_data, horizontal = TRUE,
     xlab="The degree of repetition number of user for goal materials", ylab="User Knowledge", col=c("g
```



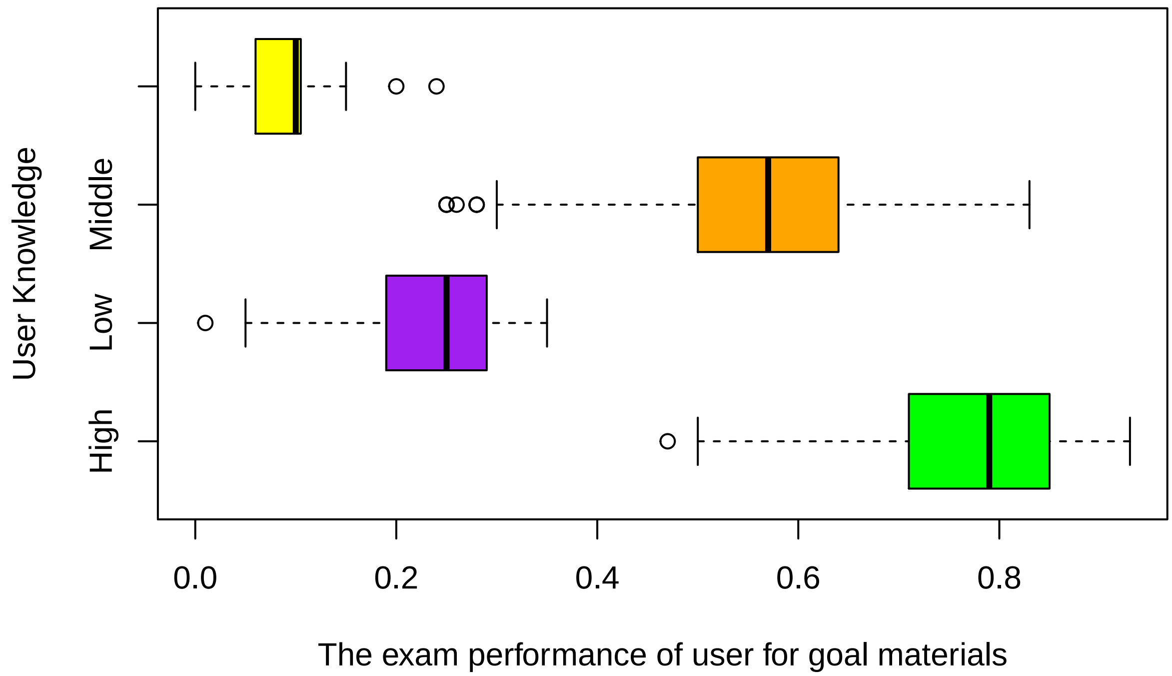

```r
# boxplot of STR divided accross UNS values
boxplot2(STR~UNS,data=training_data, horizontal = TRUE,
     xlab="The degree of study time for related objects with goal materials", ylab="User Knowledge", col
```



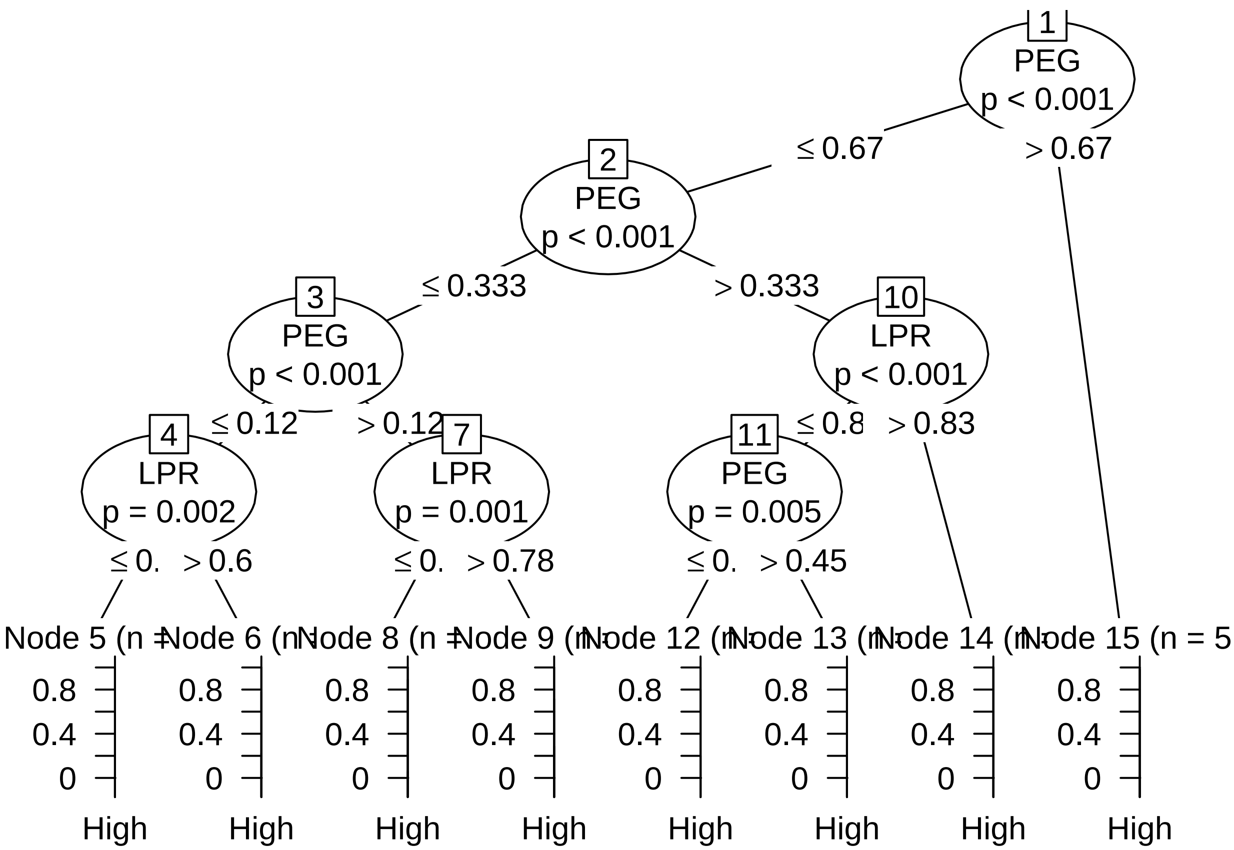

```r
# boxplot of LPR divided accross UNS values
boxplot2(LPR~UNS,data=training_data, horizontal = TRUE,
     xlab="The exam performance of user for related objects with goal materials", ylab="User Knowledge"
```




```r
# boxplot of PEG divided accross UNS values
boxplot2(PEG~UNS,data=training_data, horizontal = TRUE,
     xlab="The exam performance of user for goal materials", ylab="User Knowledge", col=c("green", "pur
```



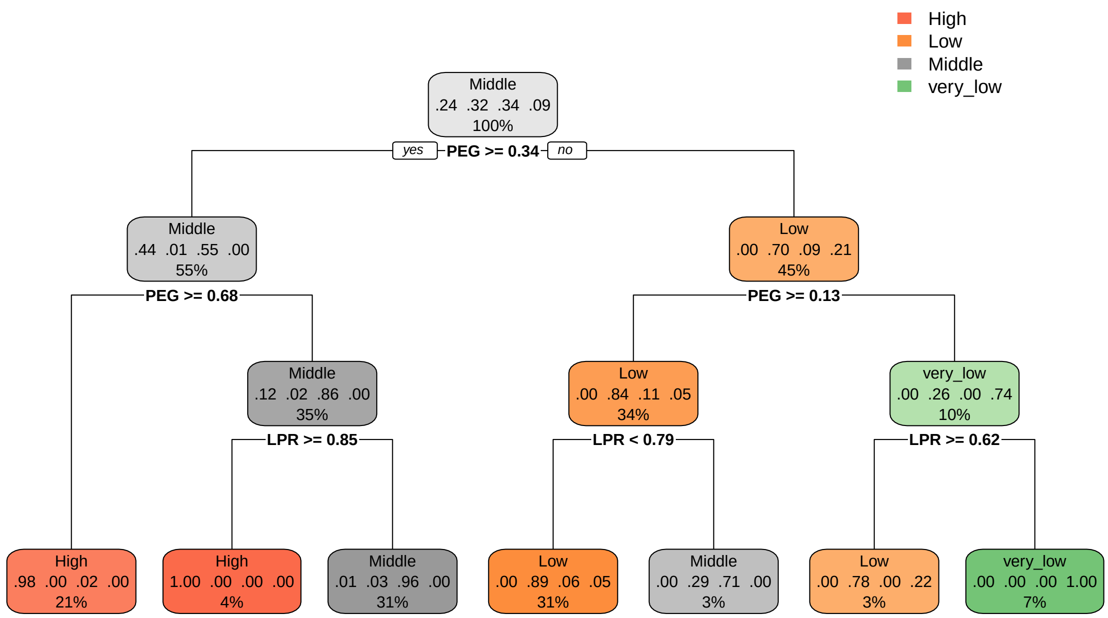

```r
# decision tree
tree1 <- ctree(UNS ~ .,data = training_data)
plot(tree1) #Review the design
```




```r
fit1 = predict(tree1, test_data)
table(fit1, test_data$UNS)
```

```
##
## fit1       High Low Middle Very Low
##   High       39   0      1        0
##   Low         0  42      3        5
##   Middle      0   4     30        0
##   very_low    0   0      0       21
```

```
#recursive partition tree
tree2 <- rpart(UNS ~ ., data = training_data)
rpart.plot(tree2)
```




```
rpart.rules(tree2)
```

```
##       UNS  High  Low Midd very
##      High [ .98  .00  .02  .00] when PEG >=         0.68
##      High [1.00  .00  .00  .00] when PEG is 0.34 to 0.68 & LPR >= 0.85
##       Low [ .00  .78  .00  .22] when PEG <  0.13         & LPR >= 0.62
##       Low [ .00  .89  .06  .05] when PEG is 0.13 to 0.34 & LPR <  0.79
##    Middle [ .00  .29  .71  .00] when PEG is 0.13 to 0.34 & LPR >= 0.79
##    Middle [ .01  .03  .96  .00] when PEG is 0.34 to 0.68 & LPR <  0.85
##  very_low [ .00  .00  .00 1.00] when PEG <  0.13         & LPR <  0.62
```

```
fit2 = predict(tree2, test_data, type = "class")
table(fit2, test_data$UNS)
```

```
##
## fit2       High Low Middle Very Low
##   High       39   0      1        0
##   Low         0  42      3        5
##   Middle      0   4     30        0
##   very_low    0   0      0       21
```

```
# J48 package issues

# PART package issues
```

```r
#hier.part(training_data$UNS, training_data)
```

```r
# Bagging tree NOTE: Interesting we did much better than them here, they did something wrong
tree3 = bagging(UNS ~., data=training_data, coob=TRUE)
fit3 = predict(tree3, test_data)
table(fit3, test_data$UNS)
```

```
##
## fit3       High Low Middle Very Low
##   High       35   0      1        0
##   Low         0  43      3        4
##   Middle      4   3     30        0
##   very_low    0   0      0       22
```

```r
# Random Forest
tree4 = randomForest(UNS ~., data=training_data)
fit4 = predict(tree4, test_data)
table(fit4, test_data$UNS)
```

```
##
## fit4       High Low Middle Very Low
##   High       39   0      0        0
##   Low         0  45      3        3
##   Middle      0   1     31        0
##   very_low    0   0      0       23
```

```r
# C5.0
tree5 <- C5.0(UNS ~., data=training_data)
fit5 = predict(tree5, test_data)
table(fit5, test_data$UNS)
```

```
##
## fit5       High Low Middle Very Low
##   High       39   0      1        0
##   Low         0  39      3        3
##   Middle      0   5     30        0
##   very_low    0   2      0       23
```

```r
# Aggregate Data - Add accuracy to each model, compile, add missing algorithms if possible
```

```r
# SVM classification
```