Predicting Student Success Usuing Machine Learning

2022-07-29 by Norah Rayfield

```
#Final Analysis

#All code can be found in Github at https://github.com/RayfieldNorah/CIND-820.git.

# Get the data, check data types of the attributes and install all needed packages and libraries
#install.packages("ggplot2")
#install.packages("ggcorrplot")
#install.packages("dplyr")
#install.packages("rlang")
#install.packages("magrittr")
#install.packages("caret")
#install.packages("psych")

library(InformationValue)
```

```
## Warning: package 'InformationValue' was built under R version 4.1.3
```

```
library(ISLR)
```

```
## Warning: package 'ISLR' was built under R version 4.1.3
```

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.1.3
```

```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following objects are masked from 'package:InformationValue':
##
##     confusionMatrix, precision, sensitivity, specificity
```

```
library(ggcorrplot)
library(ggplot2)
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
library(rlang)
```

```
## Warning: package 'rlang' was built under R version 4.1.3
```

```
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.1.3
```

```
##
## 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(psych)
```

```
## Warning: package 'psych' was built under R version 4.1.3
```

```
##
## Attaching package: 'psych'
```

```
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```
library(magrittr)
```

```
##
## Attaching package: 'magrittr'
```

```
## The following object is masked from 'package:rlang':
##
##     set_names
```

```
library(tidyr)
```

```
## Warning: package 'tidyr' was built under R version 4.1.3
```

```
##
## Attaching package: 'tidyr'
```

```
## The following object is masked from 'package:magrittr':
##
##     extract
```

```
library(factoextra)
```

```
## Warning: package 'factoextra' was built under R version 4.1.3
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
library(devtools)
```

```
## Warning: package 'devtools' was built under R version 4.1.3
```

```
## Loading required package: usethis
```

```
## Warning: package 'usethis' was built under R version 4.1.3
```

```
library(mlbench)
```

```
## Warning: package 'mlbench' was built under R version 4.1.3
```

```
library(car)
```

```
## Warning: package 'car' was built under R version 4.1.3
```

```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 4.1.3
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:psych':
##
##     logit
```

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

```
library(class)
library(rpart)
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 4.1.3
```

```
library(RColorBrewer)
library(rattle)
```

```
## Warning: package 'rattle' was built under R version 4.1.3
```

```
## Loading required package: tibble
```

```
## Loading required package: bitops
```

```
##
## Attaching package: 'bitops'
```

```
## The following object is masked from 'package:rlang':
##
##     %|%
```

```
## Rattle: A free graphical interface for data science with R.
## Version 5.5.1 Copyright (c) 2006-2021 Togaware Pty Ltd.
## Type 'rattle()' to shake, rattle, and roll your data.
```

```
library(performance)
```

```
## Warning: package 'performance' was built under R version 4.1.3
```

```
library(pROC)
```

```
## Warning: package 'pROC' was built under R version 4.1.3
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
library(Metrics)
```

```
## Warning: package 'Metrics' was built under R version 4.1.3
```

```
##
## Attaching package: 'Metrics'
```

```
## The following object is masked from 'package:pROC':
##
##     auc
```

```
## The following objects are masked from 'package:performance':
##
##     mae, mse, rmse
```

```
## The following object is masked from 'package:rlang':
##
##     ll
```

```
## The following objects are masked from 'package:caret':
##
##     precision, recall
```

```
## The following object is masked from 'package:InformationValue':
##
##     precision
```

```
mathdata=read.table("student-mat.csv",sep=";",header=TRUE,
                    stringsAsFactors = TRUE)
langdata=read.table("student-por.csv",sep=";",header=TRUE, stringsAsFactors = TRUE)

str(mathdata)
```

```
## 'data.frame':    395 obs. of  33 variables:
##  $ school    : Factor w/ 2 levels "GP","MS": 1 1 1 1 1 1 1 1 1 1 ...
##  $ sex       : Factor w/ 2 levels "F","M": 1 1 1 1 1 2 2 1 2 2 ...
##  $ age       : int  18 17 15 15 16 16 16 17 15 15 ...
##  $ address   : Factor w/ 2 levels "R","U": 2 2 2 2 2 2 2 2 2 2 ...
##  $ famsize   : Factor w/ 2 levels "GT3","LE3": 1 1 2 1 1 2 2 1 2 1 ...
##  $ Pstatus   : Factor w/ 2 levels "A","T": 1 2 2 2 2 2 2 1 1 2 ...
##  $ Medu      : int  4 1 1 4 3 4 2 4 3 3 ...
##  $ Fedu      : int  4 1 1 2 3 3 2 4 2 4 ...
##  $ Mjob      : Factor w/ 5 levels "at_home","health",..: 1 1 1 2 3 4 3 3 4 3 ...
##  $ Fjob      : Factor w/ 5 levels "at_home","health",..: 5 3 3 4 3 3 3 5 3 3 ...
##  $ reason    : Factor w/ 4 levels "course","home",..: 1 1 3 2 2 4 2 2 2 2 ...
##  $ guardian  : Factor w/ 3 levels "father","mother",..: 2 1 2 2 1 2 2 2 2 2 ...
##  $ traveltime: int  2 1 1 1 1 1 1 2 1 1 ...
##  $ studytime : int  2 2 2 3 2 2 2 2 2 2 ...
##  $ failures  : int  0 0 3 0 0 0 0 0 0 0 ...
##  $ schoolsup : Factor w/ 2 levels "no","yes": 2 1 2 1 1 1 1 2 1 1 ...
##  $ famsup    : Factor w/ 2 levels "no","yes": 1 2 1 2 2 2 1 2 2 2 ...
##  $ paid      : Factor w/ 2 levels "no","yes": 1 1 2 2 2 2 1 1 2 2 ...
##  $ activities: Factor w/ 2 levels "no","yes": 1 1 1 2 1 2 1 1 1 2 ...
##  $ nursery   : Factor w/ 2 levels "no","yes": 2 1 2 2 2 2 2 2 2 2 ...
##  $ higher    : Factor w/ 2 levels "no","yes": 2 2 2 2 2 2 2 2 2 2 ...
##  $ internet  : Factor w/ 2 levels "no","yes": 1 2 2 2 1 2 2 1 2 2 ...
##  $ romantic  : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 1 1 ...
##  $ famrel    : int  4 5 4 3 4 5 4 4 4 5 ...
##  $ freetime  : int  3 3 3 2 3 4 4 1 2 5 ...
##  $ goout     : int  4 3 2 2 2 2 4 4 2 1 ...
##  $ Dalc      : int  1 1 2 1 1 1 1 1 1 1 ...
##  $ Walc      : int  1 1 3 1 2 2 1 1 1 1 ...
##  $ health    : int  3 3 3 5 5 5 3 1 1 5 ...
##  $ absences  : int  6 4 10 2 4 10 0 6 0 0 ...
##  $ G1        : int  5 5 7 15 6 15 12 6 16 14 ...
##  $ G2        : int  6 5 8 14 10 15 12 5 18 15 ...
##  $ G3        : int  6 6 10 15 10 15 11 6 19 15 ...
```

```
str(langdata)
```

```
## 'data.frame':    649 obs. of  33 variables:
##  $ school    : Factor w/ 2 levels "GP","MS": 1 1 1 1 1 1 1 1 1 1 ...
##  $ sex       : Factor w/ 2 levels "F","M": 1 1 1 1 1 2 2 1 2 2 ...
##  $ age       : int  18 17 15 15 16 16 16 17 15 15 ...
##  $ address   : Factor w/ 2 levels "R","U": 2 2 2 2 2 2 2 2 2 2 ...
##  $ famsize   : Factor w/ 2 levels "GT3","LE3": 1 1 2 1 1 2 2 1 2 1 ...
##  $ Pstatus   : Factor w/ 2 levels "A","T": 1 2 2 2 2 2 2 1 1 2 ...
##  $ Medu      : int  4 1 1 4 3 4 2 4 3 3 ...
##  $ Fedu      : int  4 1 1 2 3 3 2 4 2 4 ...
##  $ Mjob      : Factor w/ 5 levels "at_home","health",..: 1 1 1 2 3 4 3 3 4 3 ...
##  $ Fjob      : Factor w/ 5 levels "at_home","health",..: 5 3 3 4 3 3 3 5 3 3 ...
##  $ reason    : Factor w/ 4 levels "course","home",..: 1 1 3 2 2 4 2 2 2 2 ...
##  $ guardian  : Factor w/ 3 levels "father","mother",..: 2 1 2 2 1 2 2 2 2 2 ...
##  $ traveltime: int  2 1 1 1 1 1 1 2 1 1 ...
##  $ studytime : int  2 2 2 3 2 2 2 2 2 2 ...
##  $ failures  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ schoolsup : Factor w/ 2 levels "no","yes": 2 1 2 1 1 1 1 2 1 1 ...
##  $ famsup    : Factor w/ 2 levels "no","yes": 1 2 1 2 2 2 1 2 2 2 ...
##  $ paid      : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ activities: Factor w/ 2 levels "no","yes": 1 1 1 2 1 2 1 1 1 2 ...
##  $ nursery   : Factor w/ 2 levels "no","yes": 2 1 2 2 2 2 2 2 2 2 ...
##  $ higher    : Factor w/ 2 levels "no","yes": 2 2 2 2 2 2 2 2 2 2 ...
##  $ internet  : Factor w/ 2 levels "no","yes": 1 2 2 2 1 2 2 1 2 2 ...
##  $ romantic  : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 1 1 ...
##  $ famrel    : int  4 5 4 3 4 5 4 4 4 5 ...
##  $ freetime  : int  3 3 3 2 3 4 4 1 2 5 ...
##  $ goout     : int  4 3 2 2 2 2 4 4 2 1 ...
##  $ Dalc      : int  1 1 2 1 1 1 1 1 1 1 ...
##  $ Walc      : int  1 1 3 1 2 2 1 1 1 1 ...
##  $ health    : int  3 3 3 5 5 5 3 1 1 5 ...
##  $ absences  : int  4 2 6 0 0 6 0 2 0 0 ...
##  $ G1        : int  0 9 12 14 11 12 13 10 15 12 ...
##  $ G2        : int  11 11 13 14 13 12 12 13 16 12 ...
##  $ G3        : int  11 11 12 14 13 13 13 13 17 13 ...
```

```
# Check for any missing values.

colSums(is.na(mathdata))
```

```
##     school        sex        age    address    famsize    Pstatus       Medu
##          0          0          0          0          0          0          0
##       Fedu       Mjob       Fjob     reason   guardian traveltime  studytime
##          0          0          0          0          0          0          0
##   failures  schoolsup     famsup       paid activities    nursery     higher
##          0          0          0          0          0          0          0
##   internet   romantic     famrel   freetime      goout       Dalc       Walc
##          0          0          0          0          0          0          0
##     health   absences         G1         G2         G3
##          0          0          0          0          0
```

```
colSums(is.na(langdata))
```

```
##     school        sex        age    address    famsize    Pstatus       Medu
##          0          0          0          0          0          0          0
##       Fedu       Mjob       Fjob     reason   guardian traveltime  studytime
##          0          0          0          0          0          0          0
##   failures  schoolsup     famsup       paid activities    nursery     higher
##          0          0          0          0          0          0          0
##   internet   romantic     famrel   freetime      goout       Dalc       Walc
##          0          0          0          0          0          0          0
##     health   absences         G1         G2         G3
##          0          0          0          0          0
```

```
# There are no missing values.
```

```
#Look at descriptive stats for the data
summary(mathdata)
```

```
##  school   sex          age       address famsize   Pstatus      Medu
##  GP:349   F:208   Min.   :15.0   R: 88   GT3:281   A: 41   Min.   :0.000
##  MS: 46   M:187   1st Qu.:16.0   U:307   LE3:114   T:354   1st Qu.:2.000
##                   Median :17.0                             Median :3.000
##                   Mean   :16.7                             Mean   :2.749
##                   3rd Qu.:18.0                             3rd Qu.:4.000
##                   Max.   :22.0                             Max.   :4.000
##       Fedu             Mjob           Fjob            reason      guardian
##  Min.   :0.000   at_home : 59   at_home : 20   course    :145   father: 90
##  1st Qu.:2.000   health  : 34   health  : 18   home      :109   mother:273
##  Median :2.000   other   :141   other   :217   other     : 36   other : 32
##  Mean   :2.522   services:103   services:111   reputation:105
##  3rd Qu.:3.000   teacher : 58   teacher : 29
##  Max.   :4.000
##    traveltime      studytime        failures      schoolsup famsup     paid
##  Min.   :1.000   Min.   :1.000   Min.   :0.0000   no :344   no :153   no :214
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:0.0000   yes: 51   yes:242   yes:181
##  Median :1.000   Median :2.000   Median :0.0000
##  Mean   :1.448   Mean   :2.035   Mean   :0.3342
##  3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:0.0000
##  Max.   :4.000   Max.   :4.000   Max.   :3.0000
##  activities nursery   higher    internet  romantic      famrel
##  no :194    no : 81   no : 20   no : 66   no :263   Min.   :1.000
##  yes:201    yes:314   yes:375   yes:329   yes:132   1st Qu.:4.000
##                                                     Median :4.000
##                                                     Mean   :3.944
##                                                     3rd Qu.:5.000
##                                                     Max.   :5.000
##     freetime         goout           Dalc            Walc
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000
##  1st Qu.:3.000   1st Qu.:2.000   1st Qu.:1.000   1st Qu.:1.000
##  Median :3.000   Median :3.000   Median :1.000   Median :2.000
##  Mean   :3.235   Mean   :3.109   Mean   :1.481   Mean   :2.291
##  3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:2.000   3rd Qu.:3.000
##  Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000
##      health         absences            G1              G2
##  Min.   :1.000   Min.   : 0.000   Min.   : 3.00   Min.   : 0.00
##  1st Qu.:3.000   1st Qu.: 0.000   1st Qu.: 8.00   1st Qu.: 9.00
##  Median :4.000   Median : 4.000   Median :11.00   Median :11.00
##  Mean   :3.554   Mean   : 5.709   Mean   :10.91   Mean   :10.71
##  3rd Qu.:5.000   3rd Qu.: 8.000   3rd Qu.:13.00   3rd Qu.:13.00
##  Max.   :5.000   Max.   :75.000   Max.   :19.00   Max.   :19.00
##        G3
##  Min.   : 0.00
##  1st Qu.: 8.00
##  Median :11.00
##  Mean   :10.42
##  3rd Qu.:14.00
##  Max.   :20.00
```

```
summary(langdata)
```

```
##  school   sex          age        address famsize   Pstatus      Medu
##  GP:423   F:383   Min.   :15.00   R:197   GT3:457   A: 80   Min.   :0.000
##  MS:226   M:266   1st Qu.:16.00   U:452   LE3:192   T:569   1st Qu.:2.000
##                   Median :17.00                             Median :2.000
##                   Mean   :16.74                             Mean   :2.515
##                   3rd Qu.:18.00                             3rd Qu.:4.000
##                   Max.   :22.00                             Max.   :4.000
##       Fedu             Mjob           Fjob            reason      guardian
##  Min.   :0.000   at_home :135   at_home : 42   course    :285   father:153
##  1st Qu.:1.000   health  : 48   health  : 23   home      :149   mother:455
##  Median :2.000   other   :258   other   :367   other     : 72   other : 41
##  Mean   :2.307   services:136   services:181   reputation:143
##  3rd Qu.:3.000   teacher : 72   teacher : 36
##  Max.   :4.000
##    traveltime      studytime        failures      schoolsup famsup     paid
##  Min.   :1.000   Min.   :1.000   Min.   :0.0000   no :581   no :251   no :610
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:0.0000   yes: 68   yes:398   yes: 39
##  Median :1.000   Median :2.000   Median :0.0000
##  Mean   :1.569   Mean   :1.931   Mean   :0.2219
##  3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:0.0000
##  Max.   :4.000   Max.   :4.000   Max.   :3.0000
##  activities nursery   higher    internet  romantic      famrel
##  no :334    no :128   no : 69   no :151   no :410   Min.   :1.000
##  yes:315    yes:521   yes:580   yes:498   yes:239   1st Qu.:4.000
##                                                     Median :4.000
##                                                     Mean   :3.931
##                                                     3rd Qu.:5.000
##                                                     Max.   :5.000
##     freetime        goout            Dalc            Walc          health
##  Min.   :1.00   Min.   :1.000   Min.   :1.000   Min.   :1.00   Min.   :1.000
##  1st Qu.:3.00   1st Qu.:2.000   1st Qu.:1.000   1st Qu.:1.00   1st Qu.:2.000
##  Median :3.00   Median :3.000   Median :1.000   Median :2.00   Median :4.000
##  Mean   :3.18   Mean   :3.185   Mean   :1.502   Mean   :2.28   Mean   :3.536
##  3rd Qu.:4.00   3rd Qu.:4.000   3rd Qu.:2.000   3rd Qu.:3.00   3rd Qu.:5.000
##  Max.   :5.00   Max.   :5.000   Max.   :5.000   Max.   :5.00   Max.   :5.000
##     absences            G1              G2              G3
##  Min.   : 0.000   Min.   : 0.0   Min.   : 0.00   Min.   : 0.00
##  1st Qu.: 0.000   1st Qu.:10.0   1st Qu.:10.00   1st Qu.:10.00
##  Median : 2.000   Median :11.0   Median :11.00   Median :12.00
##  Mean   : 3.659   Mean   :11.4   Mean   :11.57   Mean   :11.91
##  3rd Qu.: 6.000   3rd Qu.:13.0   3rd Qu.:13.00   3rd Qu.:14.00
##  Max.   :32.000   Max.   :19.0   Max.   :19.00   Max.   :19.00
```

```
describe(mathdata)
```

```
##             vars   n  mean   sd median trimmed  mad min max range  skew
## school*        1 395  1.12 0.32      1    1.02 0.00   1   2     1  2.38
## sex*           2 395  1.47 0.50      1    1.47 0.00   1   2     1  0.11
## age            3 395 16.70 1.28     17   16.63 1.48  15  22     7  0.46
## address*       4 395  1.78 0.42      2    1.85 0.00   1   2     1 -1.33
## famsize*       5 395  1.29 0.45      1    1.24 0.00   1   2     1  0.93
## Pstatus*       6 395  1.90 0.31      2    1.99 0.00   1   2     1 -2.59
## Medu           7 395  2.75 1.09      3    2.82 1.48   0   4     4 -0.32
## Fedu           8 395  2.52 1.09      2    2.53 1.48   0   4     4 -0.03
## Mjob*          9 395  3.17 1.23      3    3.21 1.48   1   5     4 -0.33
## Fjob*         10 395  3.28 0.86      3    3.32 0.00   1   5     4 -0.36
## reason*       11 395  2.26 1.21      2    2.20 1.48   1   4     3  0.41
## guardian*     12 395  1.85 0.54      2    1.84 0.00   1   3     2 -0.11
## traveltime    13 395  1.45 0.70      1    1.31 0.00   1   4     3  1.59
## studytime     14 395  2.04 0.84      2    1.96 0.00   1   4     3  0.63
## failures      15 395  0.33 0.74      0    0.14 0.00   0   3     3  2.37
## schoolsup*    16 395  1.13 0.34      1    1.04 0.00   1   2     1  2.20
## famsup*       17 395  1.61 0.49      2    1.64 0.00   1   2     1 -0.46
## paid*         18 395  1.46 0.50      1    1.45 0.00   1   2     1  0.17
## activities*   19 395  1.51 0.50      2    1.51 0.00   1   2     1 -0.04
## nursery*      20 395  1.79 0.40      2    1.87 0.00   1   2     1 -1.46
## higher*       21 395  1.95 0.22      2    2.00 0.00   1   2     1 -4.08
## internet*     22 395  1.83 0.37      2    1.91 0.00   1   2     1 -1.78
## romantic*     23 395  1.33 0.47      1    1.29 0.00   1   2     1  0.70
## famrel        24 395  3.94 0.90      4    4.04 1.48   1   5     4 -0.94
## freetime      25 395  3.24 1.00      3    3.23 1.48   1   5     4 -0.16
## goout         26 395  3.11 1.11      3    3.09 1.48   1   5     4  0.12
## Dalc          27 395  1.48 0.89      1    1.27 0.00   1   5     4  2.17
## Walc          28 395  2.29 1.29      2    2.15 1.48   1   5     4  0.61
## health        29 395  3.55 1.39      4    3.69 1.48   1   5     4 -0.49
## absences      30 395  5.71 8.00      4    4.24 5.93   0  75    75  3.64
## G1            31 395 10.91 3.32     11   10.80 4.45   3  19    16  0.24
## G2            32 395 10.71 3.76     11   10.84 2.97   0  19    19 -0.43
## G3            33 395 10.42 4.58     11   10.84 4.45   0  20    20 -0.73
##             kurtosis   se
## school*         3.68 0.02
## sex*           -1.99 0.03
## age            -0.03 0.06
## address*       -0.24 0.02
## famsize*       -1.14 0.02
## Pstatus*        4.71 0.02
## Medu           -1.10 0.06
## Fedu           -1.21 0.05
## Mjob*          -0.69 0.06
## Fjob*           0.98 0.04
## reason*        -1.40 0.06
## guardian*       0.15 0.03
## traveltime      2.27 0.04
## studytime      -0.04 0.04
## failures        4.89 0.04
## schoolsup*      2.86 0.02
## famsup*        -1.79 0.02
```

```
## paid*          -1.98 0.03
## activities*    -2.00 0.03
## nursery*        0.12 0.02
## higher*        14.71 0.01
## internet*       1.16 0.02
## romantic*      -1.51 0.02
## famrel          1.09 0.05
## freetime       -0.33 0.05
## goout          -0.79 0.06
## Dalc            4.65 0.04
## Walc           -0.81 0.06
## health         -1.03 0.07
## absences       21.31 0.40
## G1             -0.71 0.17
## G2              0.59 0.19
## G3              0.37 0.23
```

```
describe(langdata)
```

```
##             vars   n  mean   sd median trimmed  mad min max range  skew
## school*        1 649  1.35 0.48      1    1.31 0.00   1   2     1  0.64
## sex*           2 649  1.41 0.49      1    1.39 0.00   1   2     1  0.37
## age            3 649 16.74 1.22     17   16.70 1.48  15  22     7  0.41
## address*       4 649  1.70 0.46      2    1.74 0.00   1   2     1 -0.85
## famsize*       5 649  1.30 0.46      1    1.25 0.00   1   2     1  0.89
## Pstatus*       6 649  1.88 0.33      2    1.97 0.00   1   2     1 -2.29
## Medu           7 649  2.51 1.13      2    2.53 1.48   0   4     4 -0.03
## Fedu           8 649  2.31 1.10      2    2.27 1.48   0   4     4  0.21
## Mjob*          9 649  2.94 1.25      3    2.93 1.48   1   5     4 -0.19
## Fjob*         10 649  3.22 0.86      3    3.29 0.00   1   5     4 -0.53
## reason*       11 649  2.11 1.19      2    2.02 1.48   1   4     3  0.56
## guardian*     12 649  1.83 0.52      2    1.83 0.00   1   3     2 -0.20
## traveltime    13 649  1.57 0.75      1    1.43 0.00   1   4     3  1.24
## studytime     14 649  1.93 0.83      2    1.85 1.48   1   4     3  0.70
## failures      15 649  0.22 0.59      0    0.07 0.00   0   3     3  3.08
## schoolsup*    16 649  1.10 0.31      1    1.01 0.00   1   2     1  2.57
## famsup*       17 649  1.61 0.49      2    1.64 0.00   1   2     1 -0.46
## paid*         18 649  1.06 0.24      1    1.00 0.00   1   2     1  3.69
## activities*   19 649  1.49 0.50      1    1.48 0.00   1   2     1  0.06
## nursery*      20 649  1.80 0.40      2    1.88 0.00   1   2     1 -1.52
## higher*       21 649  1.89 0.31      2    1.99 0.00   1   2     1 -2.55
## internet*     22 649  1.77 0.42      2    1.83 0.00   1   2     1 -1.26
## romantic*     23 649  1.37 0.48      1    1.34 0.00   1   2     1  0.55
## famrel        24 649  3.93 0.96      4    4.05 1.48   1   5     4 -1.10
## freetime      25 649  3.18 1.05      3    3.19 1.48   1   5     4 -0.18
## goout         26 649  3.18 1.18      3    3.20 1.48   1   5     4 -0.01
## Dalc          27 649  1.50 0.92      1    1.28 0.00   1   5     4  2.13
## Walc          28 649  2.28 1.28      2    2.14 1.48   1   5     4  0.63
## health        29 649  3.54 1.45      4    3.67 1.48   1   5     4 -0.50
## absences      30 649  3.66 4.64      2    2.80 2.97   0  32    32  2.01
## G1            31 649 11.40 2.75     11   11.38 2.97   0  19    19  0.00
## G2            32 649 11.57 2.91     11   11.56 2.97   0  19    19 -0.36
## G3            33 649 11.91 3.23     12   12.04 2.97   0  19    19 -0.91
##             kurtosis   se
## school*        -1.60 0.02
## sex*           -1.87 0.02
## age             0.05 0.05
## address*       -1.28 0.02
## famsize*       -1.21 0.02
## Pstatus*        3.23 0.01
## Medu           -1.27 0.04
## Fedu           -1.12 0.04
## Mjob*          -0.83 0.05
## Fjob*           1.17 0.03
## reason*        -1.25 0.05
## guardian*       0.17 0.02
## traveltime      1.08 0.03
## studytime       0.02 0.03
## failures        9.70 0.02
## schoolsup*      4.64 0.01
## famsup*        -1.79 0.02
```

```
## paid*          11.66 0.01
## activities*    -2.00 0.02
## nursery*        0.31 0.02
## higher*         4.50 0.01
## internet*      -0.41 0.02
## romantic*      -1.71 0.02
## famrel          1.32 0.04
## freetime       -0.41 0.04
## goout          -0.87 0.05
## Dalc            4.28 0.04
## Walc           -0.78 0.05
## health         -1.13 0.06
## absences        5.70 0.18
## G1              0.02 0.11
## G2              1.63 0.11
## G3              2.66 0.13
```

```
write.csv(summary(mathdata),"mathsummary.csv")
write.csv(summary(langdata),"langsummary.csv")
```

```
# Calculating frequency of multiple variables
mod_frame <- apply(mathdata, 2 , table)

print ("Math Frequencies")
```

```
## [1] "Math Frequencies"
```

```
print (mod_frame)
```

```
## $school
##
##  GP  MS
## 349  46
##
## $sex
##
##   F   M
## 208 187
##
## $age
##
##  15  16  17  18  19  20  21  22
##  82 104  98  82  24   3   1   1
##
## $address
##
##   R   U
##  88 307
##
## $famsize
##
## GT3 LE3
## 281 114
##
## $Pstatus
##
##   A   T
##  41 354
##
## $Medu
##
##   0   1   2   3   4
##   3  59 103  99 131
##
## $Fedu
##
##   0   1   2   3   4
##   2  82 115 100  96
##
## $Mjob
##
##  at_home   health    other services  teacher
##       59       34      141      103       58
##
## $Fjob
##
##  at_home   health    other services  teacher
##       20       18      217      111       29
##
## $reason
##
```

```
##     course       home      other reputation
##        145        109         36        105
##
## $guardian
##
## father mother  other
##     90    273     32
##
## $traveltime
##
##   1   2   3   4
## 257 107  23   8
##
## $studytime
##
##   1   2   3   4
## 105 198  65  27
##
## $failures
##
##   0   1   2   3
## 312  50  17  16
##
## $schoolsup
##
##  no yes
## 344  51
##
## $famsup
##
##  no yes
## 153 242
##
## $paid
##
##  no yes
## 214 181
##
## $activities
##
##  no yes
## 194 201
##
## $nursery
##
##  no yes
##  81 314
##
## $higher
##
##  no yes
##  20 375
```

```
##
## $internet
##
##  no yes
##  66 329
##
## $romantic
##
##  no yes
## 263 132
##
## $famrel
##
##   1   2   3   4   5
##   8  18  68 195 106
##
## $freetime
##
##   1   2   3   4   5
##  19  64 157 115  40
##
## $goout
##
##   1   2   3   4   5
##  23 103 130  86  53
##
## $Dalc
##
##   1   2   3   4   5
## 276  75  26   9   9
##
## $Walc
##
##   1   2   3   4   5
## 151  85  80  51  28
##
## $health
##
##   1   2   3   4   5
##  47  45  91  66 146
##
## $absences
##
##   0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18  19
## 115   3  65   8  53   5  31   7  22   3  17   3  12   3  12   3   7   1   5   1
##  20  21  22  23  24  25  26  28  30  38  40  54  56  75
##   4   1   3   1   1   1   1   1   1   1   1   1   1   1
##
## $G1
##
##  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19
##  1  1  7 24 37 41 31 51 39 35 33 30 24 22  8  8  3
```

```
##
## $G2
##
##  0  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19
## 13  1 15 14 21 32 50 46 35 41 37 23 34 13  5 12  3
##
## $G3
##
##  0  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20
## 38  1  7 15  9 32 28 56 47 31 31 27 33 16  6 12  5  1
```

```
modl_frame <- apply(langdata, 2 , table)

print ("Language Frequencies")
```

```
## [1] "Language Frequencies"
```

```
print (modl_frame)
```

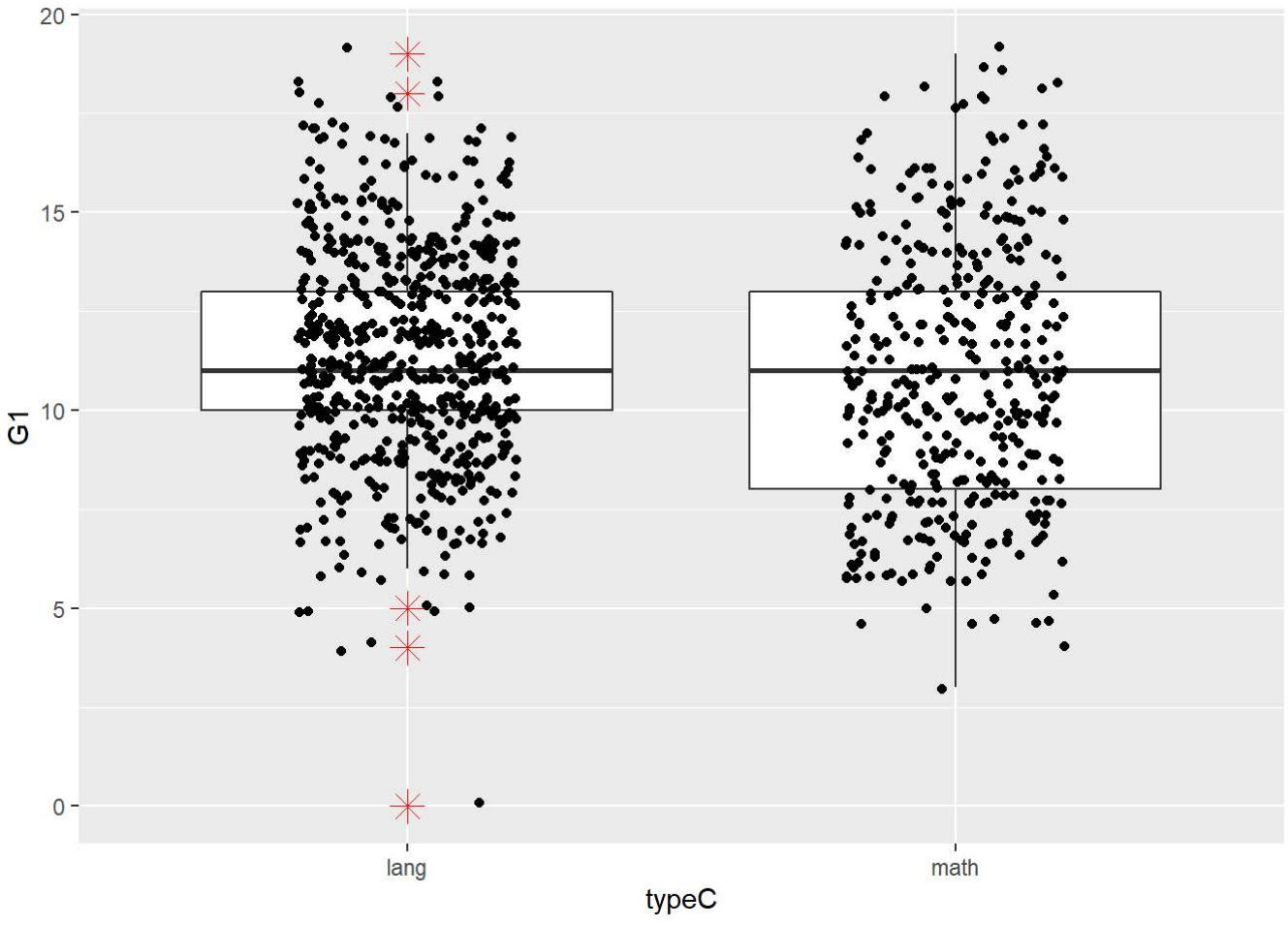
```
## $school
##
##  GP  MS
## 423 226
##
## $sex
##
##   F   M
## 383 266
##
## $age
##
##  15  16  17  18  19  20  21  22
## 112 177 179 140  32   6   2   1
##
## $address
##
##   R   U
## 197 452
##
## $famsize
##
## GT3 LE3
## 457 192
##
## $Pstatus
##
##   A   T
##  80 569
##
## $Medu
##
##   0   1   2   3   4
##   6 143 186 139 175
##
## $Fedu
##
##   0   1   2   3   4
##   7 174 209 131 128
##
## $Mjob
##
##  at_home   health    other services  teacher
##      135       48      258      136       72
##
## $Fjob
##
##  at_home   health    other services  teacher
##       42       23      367      181       36
##
## $reason
##
```

```
##     course       home      other reputation
##        285        149         72        143
##
## $guardian
##
## father mother  other
##    153    455     41
##
## $traveltime
##
##   1   2   3   4
## 366 213  54  16
##
## $studytime
##
##   1   2   3   4
## 212 305  97  35
##
## $failures
##
##   0   1   2   3
## 549  70  16  14
##
## $schoolsup
##
##  no yes
## 581  68
##
## $famsup
##
##  no yes
## 251 398
##
## $paid
##
##  no yes
## 610  39
##
## $activities
##
##  no yes
## 334 315
##
## $nursery
##
##  no yes
## 128 521
##
## $higher
##
##  no yes
##  69 580
```

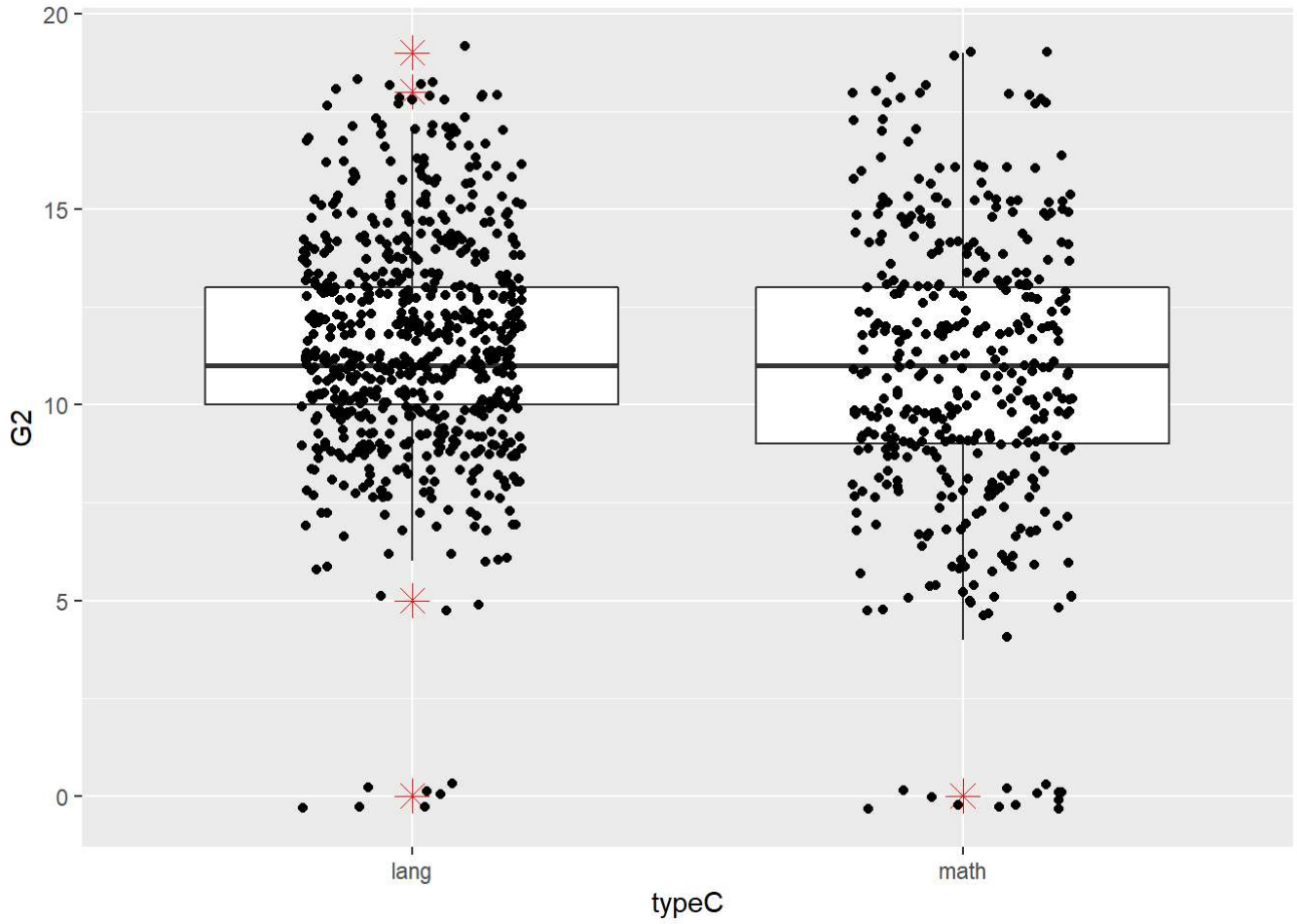
```
##
## $internet
##
##  no yes
## 151 498
##
## $romantic
##
##  no yes
## 410 239
##
## $famrel
##
##   1   2   3   4   5
##  22  29 101 317 180
##
## $freetime
##
##   1   2   3   4   5
##  45 107 251 178  68
##
## $goout
##
##   1   2   3   4   5
##  48 145 205 141 110
##
## $Dalc
##
##   1   2   3   4   5
## 451 121  43  17  17
##
## $Walc
##
##   1   2   3   4   5
## 247 150 120  87  45
##
## $health
##
##   1   2   3   4   5
##  90  78 124 108 249
##
## $absences
##
##   0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  18  21  22
## 244  12 110   7  93  12  49   3  42   7  21   5  12   1   8   2  10   3   2   2
##  24  26  30  32
##   1   1   1   1
##
## $G1
##
##  0  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19
##  1  2  5  9 33 42 65 95 91 82 72 71 35 22 16  7  1
```

```
##
## $G2
##
##   0   5   6   7   8   9  10  11  12  13  14  15  16  17  18  19
##   7   3   7  16  40  72  83 103  86  80  54  38  25  20  14   1
##
## $G3
##
##   0   1   5   6   7   8   9  10  11  12  13  14  15  16  17  18  19
##  15   1   1   3  10  35  35  97 104  72  82  63  49  36  29  15   2
```

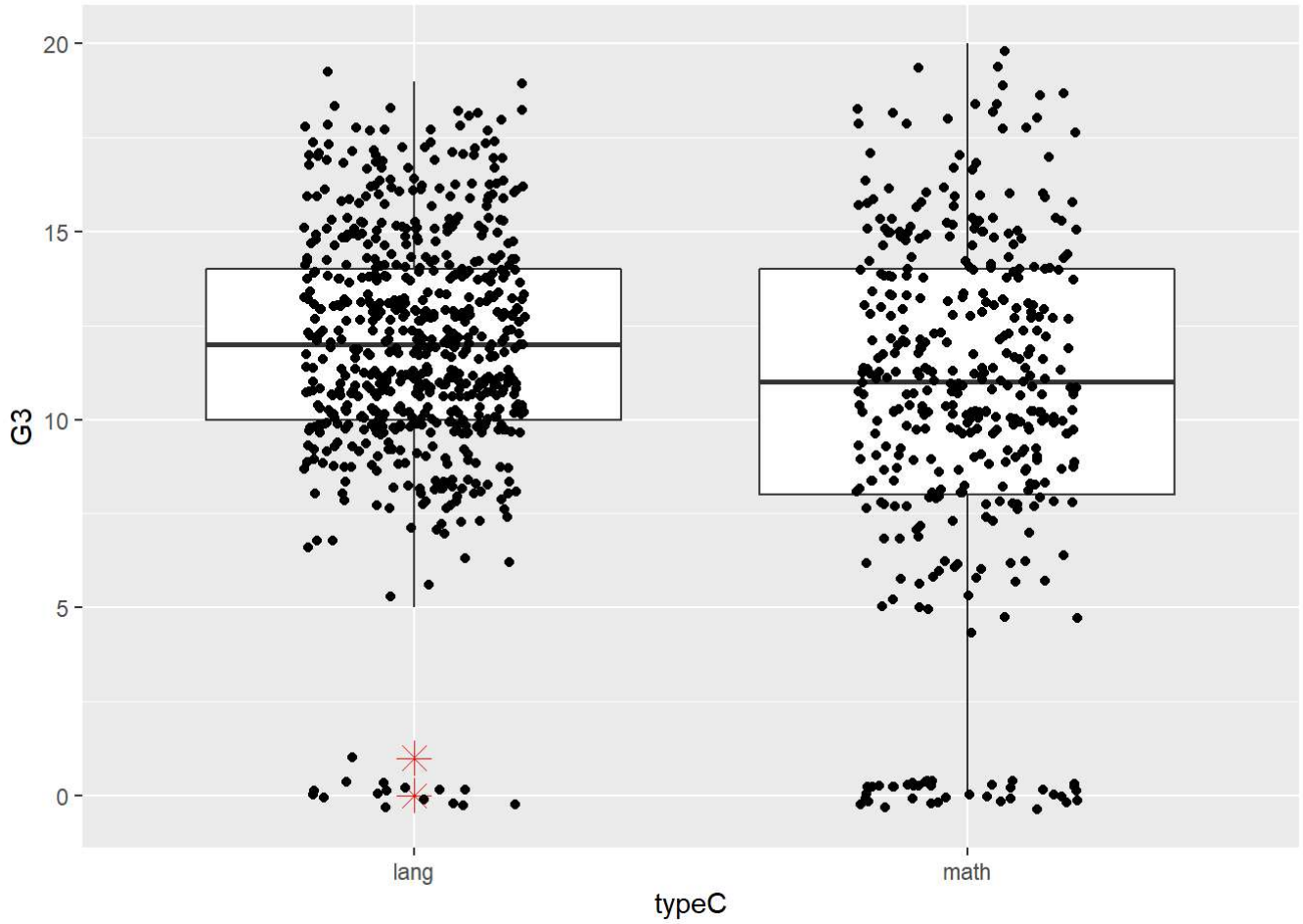
```
#Exploratory Analysis and Visualizations

#Add type column and append both files
langdata$typeC <- 'lang'
mathdata$typeC <- 'math'
appendedDf <- rbind(mathdata, langdata)

#Take a closer look at the continuous variables
continuousgr <- (appendedDf[,c(31,32,33,34)])

ggplot(continuousgr, aes(x=typeC, y=G1)) +
  geom_boxplot(outlier.colour="red", outlier.shape=8,
               outlier.size=4) + geom_jitter(shape=16, position=position_jitter(0.2))
```



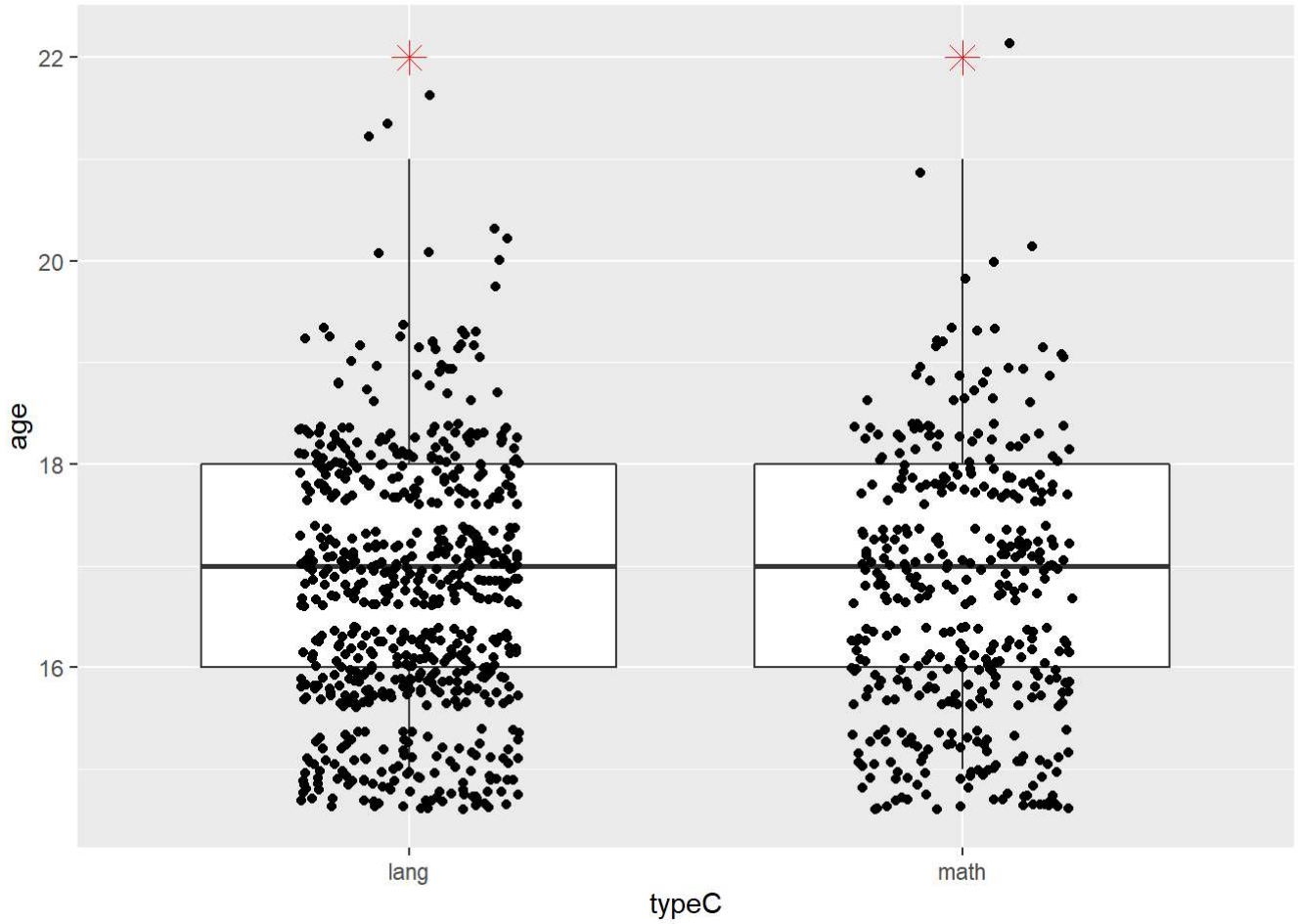
```
ggplot(continuousgr, aes(x=typeC, y=G2)) +
  geom_boxplot(outlier.colour="red", outlier.shape=8,
               outlier.size=4) + geom_jitter(shape=16, position=position_jitter(0.2))
```



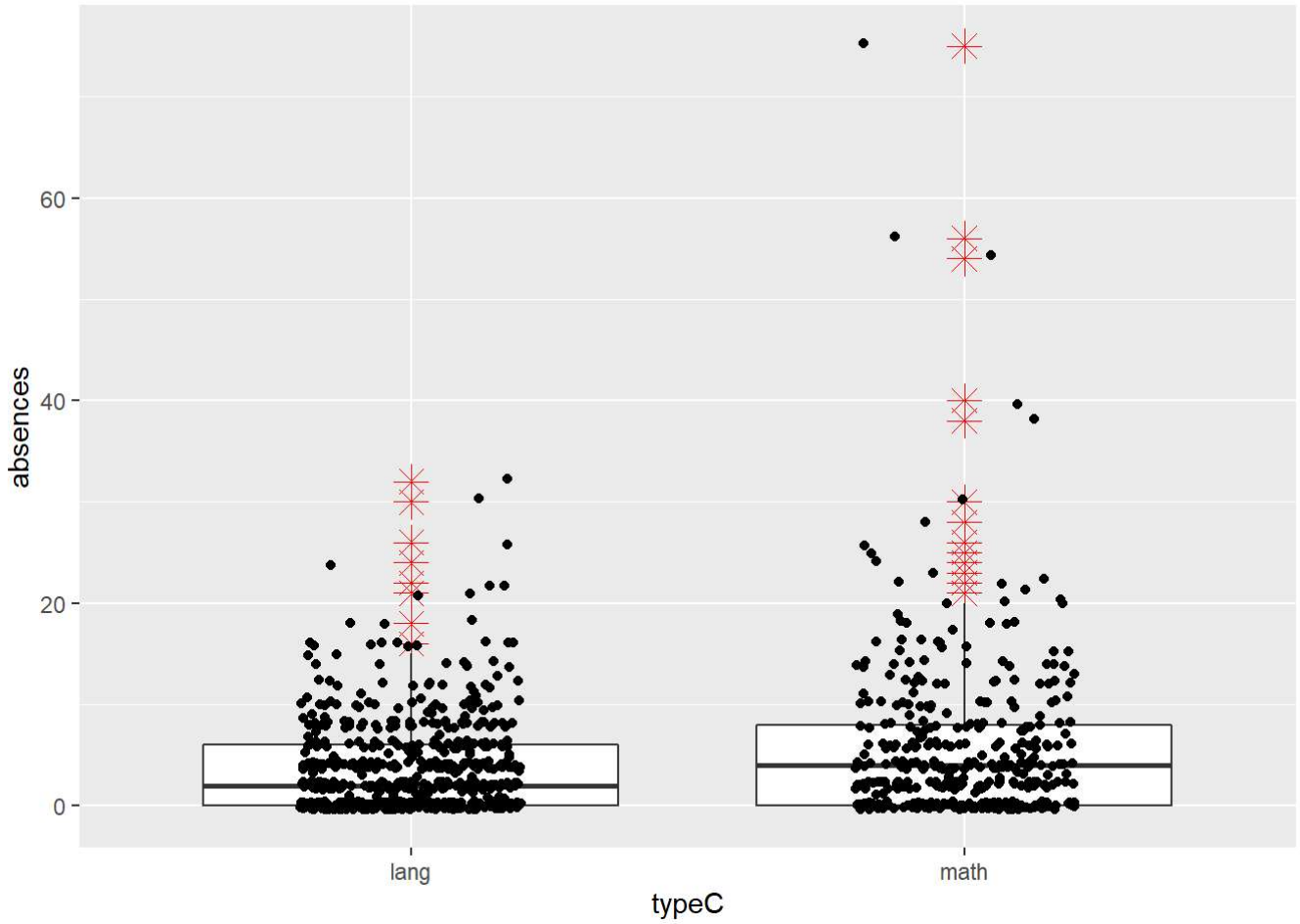

```
ggplot(continuousgr, aes(x=typeC, y=G3)) +
  geom_boxplot(outlier.colour="red", outlier.shape=8,
               outlier.size=4) + geom_jitter(shape=16, position=position_jitter(0.2))
```




```
continuousa <- (appendedDf[,c(3,30,34)])
ggplot(continuousa, aes(x=typeC, y=age)) +
  geom_boxplot(outlier.colour="red", outlier.shape=8,
               outlier.size=4) + geom_jitter(shape=16, position=position_jitter(0.2))
```

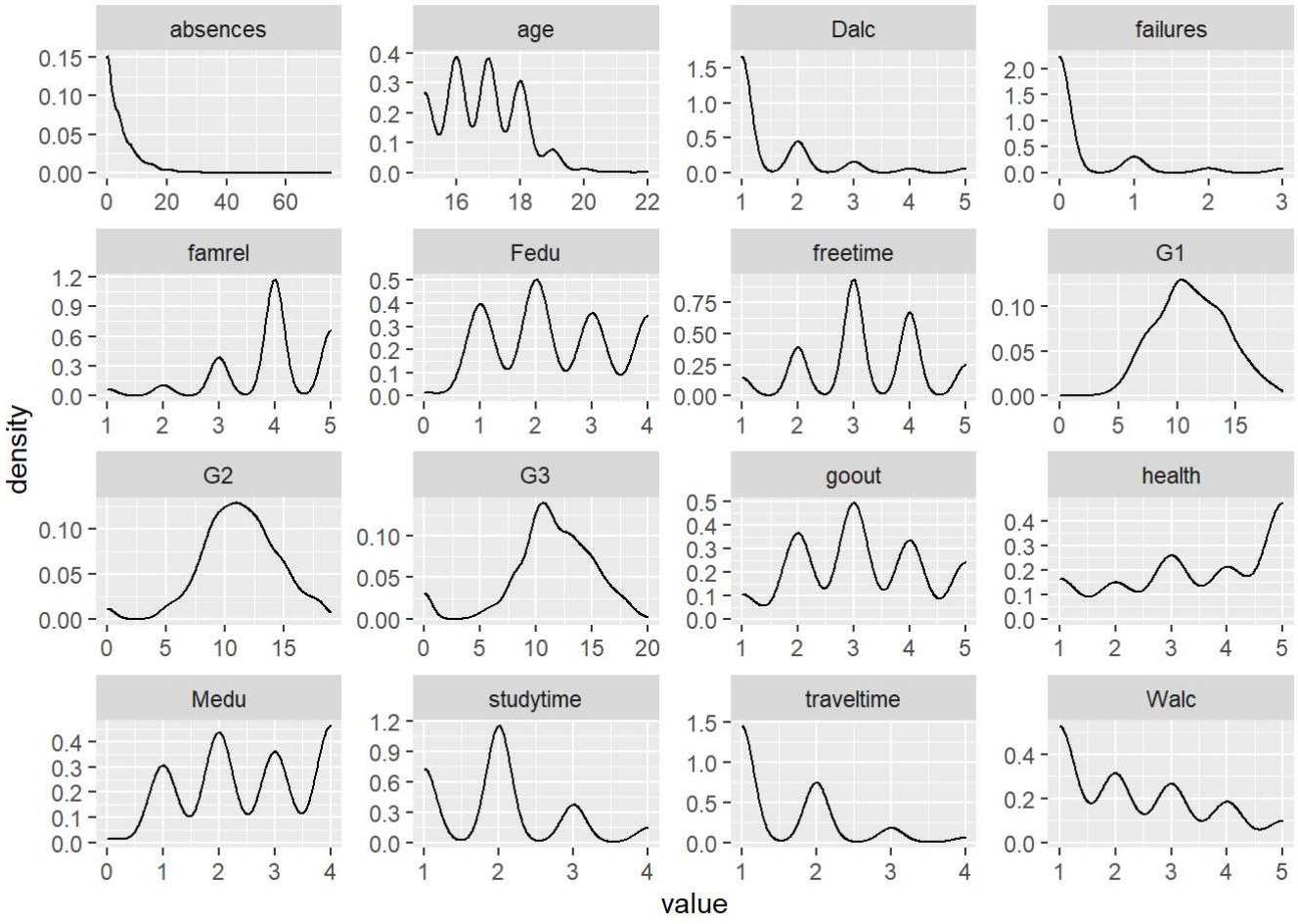



```
ggplot(continuousa, aes(x=typeC, y=absences)) +
  geom_boxplot(outlier.colour="red", outlier.shape=8,
               outlier.size=4) + geom_jitter(shape=16, position=position_jitter(0.2))
```



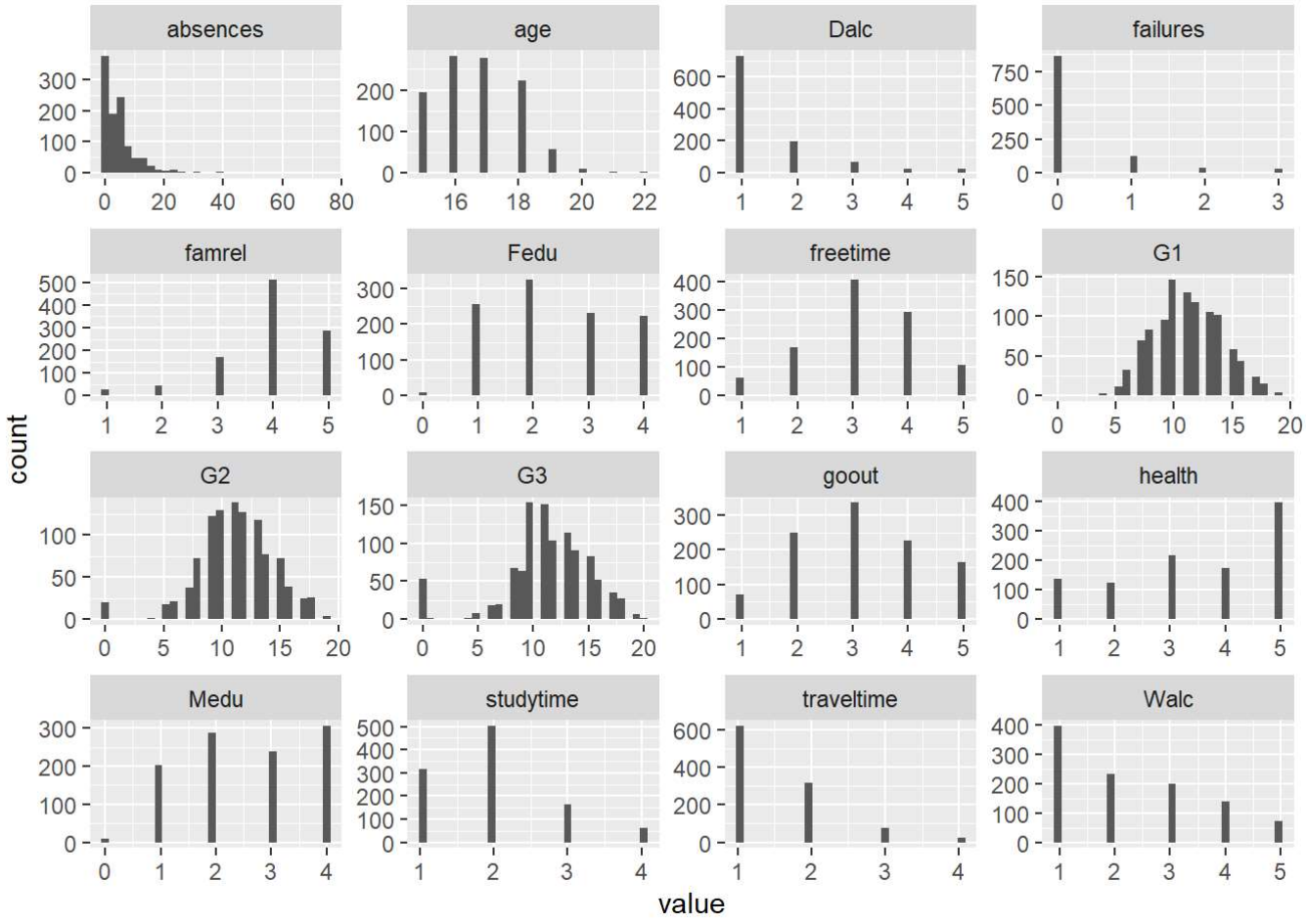

```
#some outliers were identified
```

```
#Look at the discrete variables

appendedDf %>%
  select_if(is.numeric) %>%
  gather() %>%
  ggplot(aes(x = value)) +
    geom_density() +
    facet_wrap(~key, scales = 'free')
```



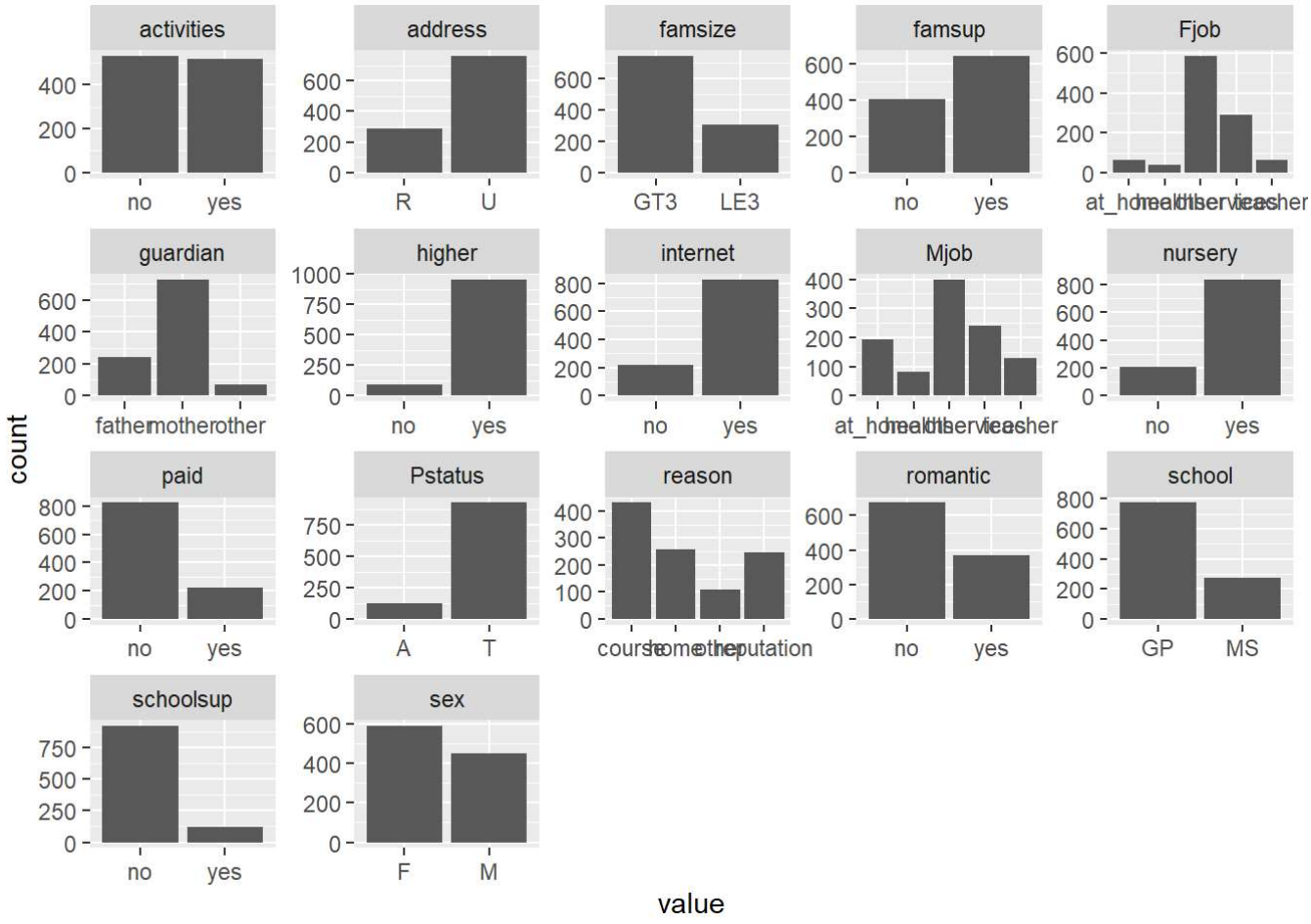

```
appendedDf %>%
  select_if(is.numeric) %>%
  gather() %>%
  ggplot(aes(x = value)) +
    geom_histogram() +
    facet_wrap(~key, scales = 'free')
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
appendedDf %>%
  select_if(is.factor) %>%
  gather() %>%
  ggplot(aes(x = value)) +
    geom_bar() +
    facet_wrap(~key, scales = 'free')
```

```
## Warning: attributes are not identical across measure variables;
## they will be dropped
```



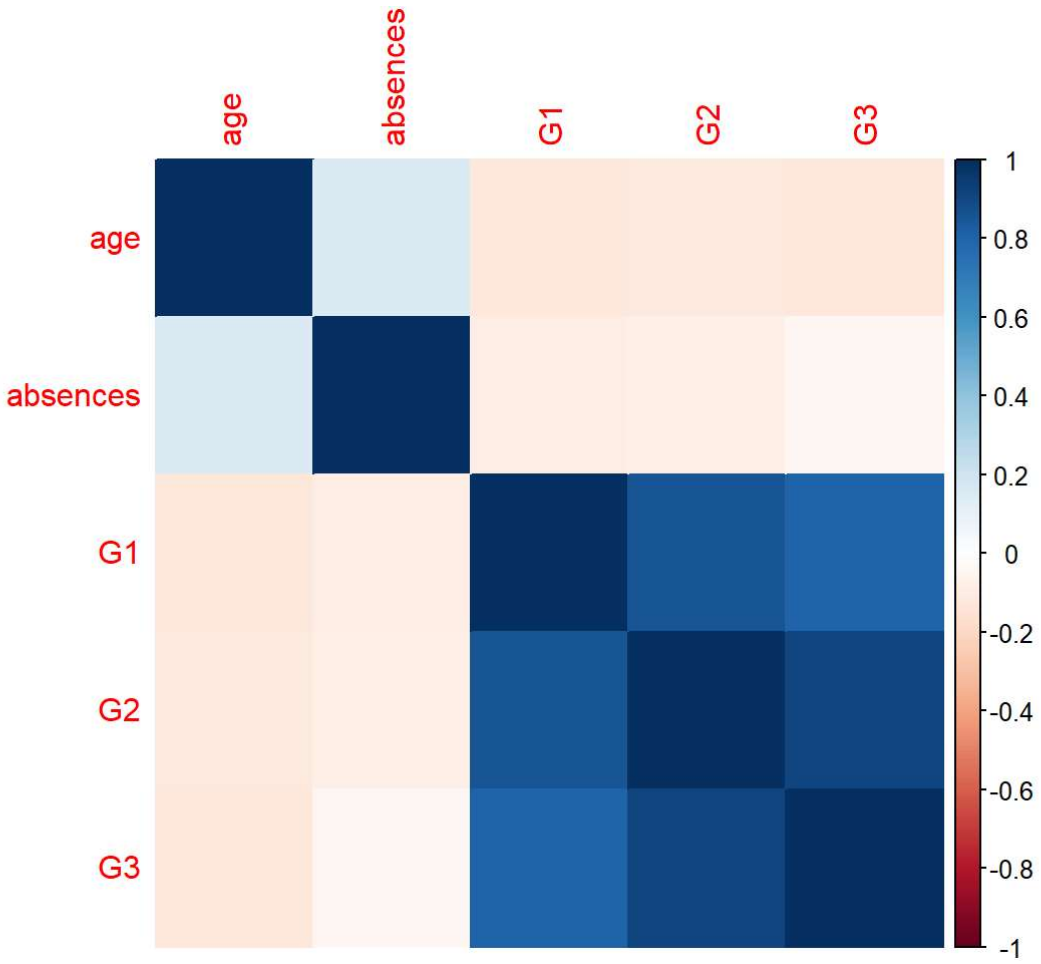

```
#change binary values to numeric
appendedDf$schoolsup<-ifelse(appendedDf$schoolsup=="yes",1,0)
appendedDf$sex<-ifelse(appendedDf$sex=="F",1,0)
appendedDf$address<-ifelse(appendedDf$address=="U",1,0)
appendedDf$famsize<-ifelse(appendedDf$famsize=="GT3",1,0)
appendedDf$school<-ifelse(appendedDf$school=="GP",1,0)
appendedDf$famsup<-ifelse(appendedDf$famsup=="yes",1,0)
appendedDf$paid<-ifelse(appendedDf$paid=="yes",1,0)
appendedDf$activities<-ifelse(appendedDf$activities=="yes",1,0)
appendedDf$nursery<-ifelse(appendedDf$nursery=="yes",1,0)
appendedDf$higher<-ifelse(appendedDf$higher=="yes",1,0)
appendedDf$internet<-ifelse(appendedDf$internet=="yes",1,0)
appendedDf$romantic<-ifelse(appendedDf$romantic=="yes",1,0)
appendedDf$Pstatus<-ifelse(appendedDf$Pstatus=="T",1,0)
appendedDf$typeC<-ifelse(appendedDf$typeC=="math",1,0)
str(appendedDf)
```

```
## 'data.frame':    1044 obs. of  34 variables:
##  $ school    : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ sex       : num  1 1 1 1 1 0 0 1 0 0 ...
##  $ age       : int  18 17 15 15 16 16 16 17 15 15 ...
##  $ address   : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ famsize   : num  1 1 0 1 1 0 0 1 0 1 ...
##  $ Pstatus   : num  0 1 1 1 1 1 1 0 0 1 ...
##  $ Medu      : int  4 1 1 4 3 4 2 4 3 3 ...
##  $ Fedu      : int  4 1 1 2 3 3 2 4 2 4 ...
##  $ Mjob      : Factor w/ 5 levels "at_home","health",..: 1 1 1 2 3 4 3 3 4 3 ...
##  $ Fjob      : Factor w/ 5 levels "at_home","health",..: 5 3 3 4 3 3 3 5 3 3 ...
##  $ reason    : Factor w/ 4 levels "course","home",..: 1 1 3 2 2 4 2 2 2 2 ...
##  $ guardian  : Factor w/ 3 levels "father","mother",..: 2 1 2 2 1 2 2 2 2 2 ...
##  $ traveltime: int  2 1 1 1 1 1 1 2 1 1 ...
##  $ studytime : int  2 2 2 3 2 2 2 2 2 2 ...
##  $ failures  : int  0 0 3 0 0 0 0 0 0 0 ...
##  $ schoolsup : num  1 0 1 0 0 0 0 1 0 0 ...
##  $ famsup    : num  0 1 0 1 1 1 0 1 1 1 ...
##  $ paid      : num  0 0 1 1 1 1 0 0 1 1 ...
##  $ activities: num  0 0 0 1 0 1 0 0 0 1 ...
##  $ nursery   : num  1 0 1 1 1 1 1 1 1 1 ...
##  $ higher    : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ internet  : num  0 1 1 1 0 1 1 0 1 1 ...
##  $ romantic  : num  0 0 0 1 0 0 0 0 0 0 ...
##  $ famrel    : int  4 5 4 3 4 5 4 4 4 5 ...
##  $ freetime  : int  3 3 3 2 3 4 4 1 2 5 ...
##  $ goout     : int  4 3 2 2 2 2 4 4 2 1 ...
##  $ Dalc      : int  1 1 2 1 1 1 1 1 1 1 ...
##  $ Walc      : int  1 1 3 1 2 2 1 1 1 1 ...
##  $ health    : int  3 3 3 5 5 5 3 1 1 5 ...
##  $ absences  : int  6 4 10 2 4 10 0 6 0 0 ...
##  $ G1        : int  5 5 7 15 6 15 12 6 16 14 ...
##  $ G2        : int  6 5 8 14 10 15 12 5 18 15 ...
##  $ G3        : int  6 6 10 15 10 15 11 6 19 15 ...
##  $ typeC     : num  1 1 1 1 1 1 1 1 1 1 ...
```

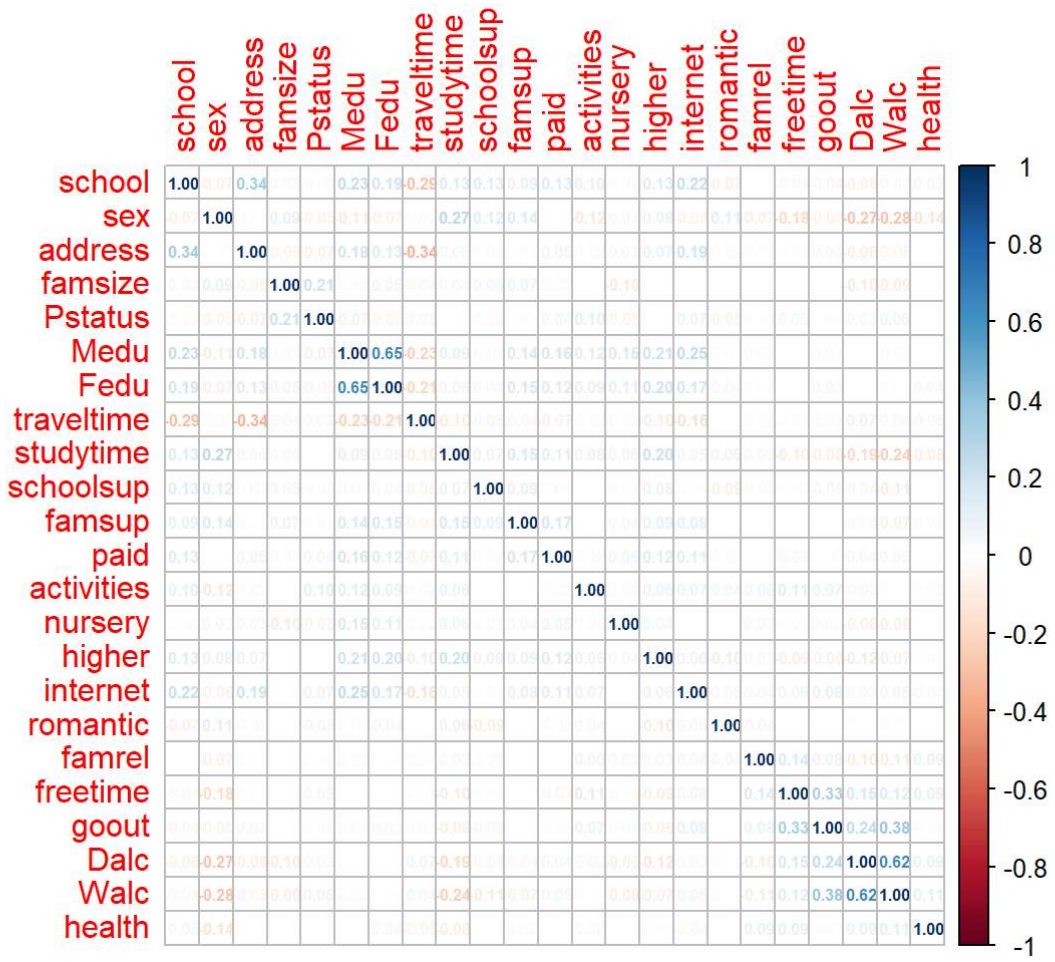
```
allnums <- (appendedDf[,c(1,2,3,4,5,6,7,8,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,
31,32,33,34)])
head(allnums)
```

```
##   school sex age address famsize Pstatus Medu Fedu traveltime studytime
## 1      1   1  18       1       1       0    4    4          2         2
## 2      1   1  17       1       1       1    1    1          1         2
## 3      1   1  15       1       0       1    1    1          1         2
## 4      1   1  15       1       1       1    4    2          1         3
## 5      1   1  16       1       1       1    3    3          1         2
## 6      1   0  16       1       0       1    4    3          1         2
##   failures schoolsup famsup paid activities nursery higher internet romantic
## 1        0         1      0    0          0       1      1        0        0
## 2        0         0      1    0          0       0      1        1        0
## 3        3         1      0    1          0       1      1        1        0
## 4        0         0      1    1          1       1      1        1        1
## 5        0         0      1    1          0       1      1        0        0
## 6        0         0      1    1          1       1      1        1        0
##   famrel freetime goout Dalc Walc health absences G1 G2 G3 typeC
## 1      4        3     4    1    1      3        6  5  6  6     1
## 2      5        3     3    1    1      3        4  5  5  6     1
## 3      4        3     2    2    3      3       10  7  8 10     1
## 4      3        2     2    1    1      5        2 15 14 15     1
## 5      4        3     2    1    2      5        4  6 10 10     1
## 6      5        4     2    1    2      5       10 15 15 15     1
```

```
#Look at correlations between continuous variables
corrdf <- (appendedDf[,c(3,30,31,32,33)])
myplot = cor(corrdf)
corrplot(myplot, method = 'color')
```




```
#Look at correlations between categorical variables
corrdf2 <- (appendedDf[,c(1, 2, 4, 5,6,7, 8, 13,14,16,17,18, 19, 20, 21, 22, 23,24,25,26,27,28,
29)])
myplot2 = cor(corrdf2, method = 'spearman')
corrplot(myplot2, method = 'number', number.cex = 0.5)
```




```
#The grade variables, G1, G2 and G3 are highly positively correlated
#absences and age show some correlation
```

```
#normalize numeric attributes
min_max_norm <- function(x){
  (x - min(x)) / (max(x) - min(x))
}

datanorm <- allnums %>%
  mutate(across(c(3,7,8,9,10,11,20,21,22,23,24,25,26,27,28),min_max_norm))




#Dimensionality reduction
#PCA
dataMatrix <- data.matrix(datanorm[,c(1:28,30)])
data_PCA <- princomp(dataMatrix )
summary(data_PCA, loading = T)
```

```
## Importance of components:
##                           Comp.1     Comp.2     Comp.3     Comp.4     Comp.5
## Standard deviation     0.6357896 0.57702940 0.51305614 0.50349052 0.48864428
## Proportion of Variance 0.1159827 0.09553492 0.07552593 0.07273591 0.06850968
## Cumulative Proportion  0.1159827 0.21151761 0.28704354 0.35977945 0.42828913
##                            Comp.6     Comp.7     Comp.8     Comp.9    Comp.10
## Standard deviation     0.46745478 0.45973252 0.39706605 0.38898417 0.36755530
## Proportion of Variance 0.06269682 0.06064245 0.04523679 0.04341403 0.03876249
## Cumulative Proportion  0.49098595 0.55162840 0.59686519 0.64027923 0.67904172
##                           Comp.11    Comp.12    Comp.13    Comp.14    Comp.15
## Standard deviation     0.35232605 0.34016364 0.33324504 0.31022173 0.30692421
## Proportion of Variance 0.03561687 0.03320031 0.03186352 0.02761282 0.02702891
## Cumulative Proportion  0.71465859 0.74785890 0.77972241 0.80733523 0.83436414
##                           Comp.16    Comp.17    Comp.18    Comp.19    Comp.20
## Standard deviation     0.29392149 0.27496059 0.26334861 0.24498790 0.21890642
## Proportion of Variance 0.02478729 0.02169238 0.01989887 0.01722089 0.01374939
## Cumulative Proportion  0.85915143 0.88084381 0.90074268 0.91796357 0.93171295
##                           Comp.21    Comp.22    Comp.23     Comp.24     Comp.25
## Standard deviation     0.21185506 0.20681283 0.20061719 0.172991986 0.163746861
## Proportion of Variance 0.01287787 0.01227217 0.01154789 0.008586541 0.007693293
## Cumulative Proportion  0.94459082 0.95686299 0.96841087 0.976997416 0.984690709
##                            Comp.26     Comp.27     Comp.28    Comp.29
## Standard deviation     0.153228376 0.143044479 0.076275739 0.05998360
## Proportion of Variance 0.006736661 0.005870951 0.001669318 0.00103236
## Cumulative Proportion  0.991427370 0.997298321 0.998967640 1.00000000
##
## Loadings:
##            Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8 Comp.9
## school      0.473                0.234         0.154  0.150         0.325
## sex        -0.111 -0.723                0.154  0.225 -0.178  0.216 -0.178
## age
## address     0.337                0.506  0.216         0.211  0.133  0.106
## famsize           -0.197  0.120 -0.324 -0.269  0.376  0.645 -0.342
## Pstatus                         -0.156 -0.127         0.136        -0.146
## Medu        0.207         0.105                                -0.227 -0.109
## Fedu        0.173                                              -0.193
## traveltime -0.135               -0.125
## studytime         -0.169
## failures
## schoolsup         -0.104                                             0.149
## famsup      0.216 -0.399  0.191        -0.417 -0.652         0.178  0.177
## paid        0.352        -0.195 -0.358        -0.120 -0.137        -0.173
## activities  0.186  0.252  0.754 -0.223         0.270 -0.336  0.195
## nursery                         0.130        -0.119 -0.360 -0.766
## higher      0.121
## internet    0.272         0.155  0.144  0.109 -0.136  0.217        -0.651
## romantic   -0.105 -0.123  0.333 -0.221  0.752 -0.273  0.244 -0.117  0.201
## famrel
## freetime           0.117
## goout              0.108                      -0.122               -0.188
## Dalc               0.155                      -0.163
## Walc               0.274                      -0.220  0.129  0.114 -0.132
```

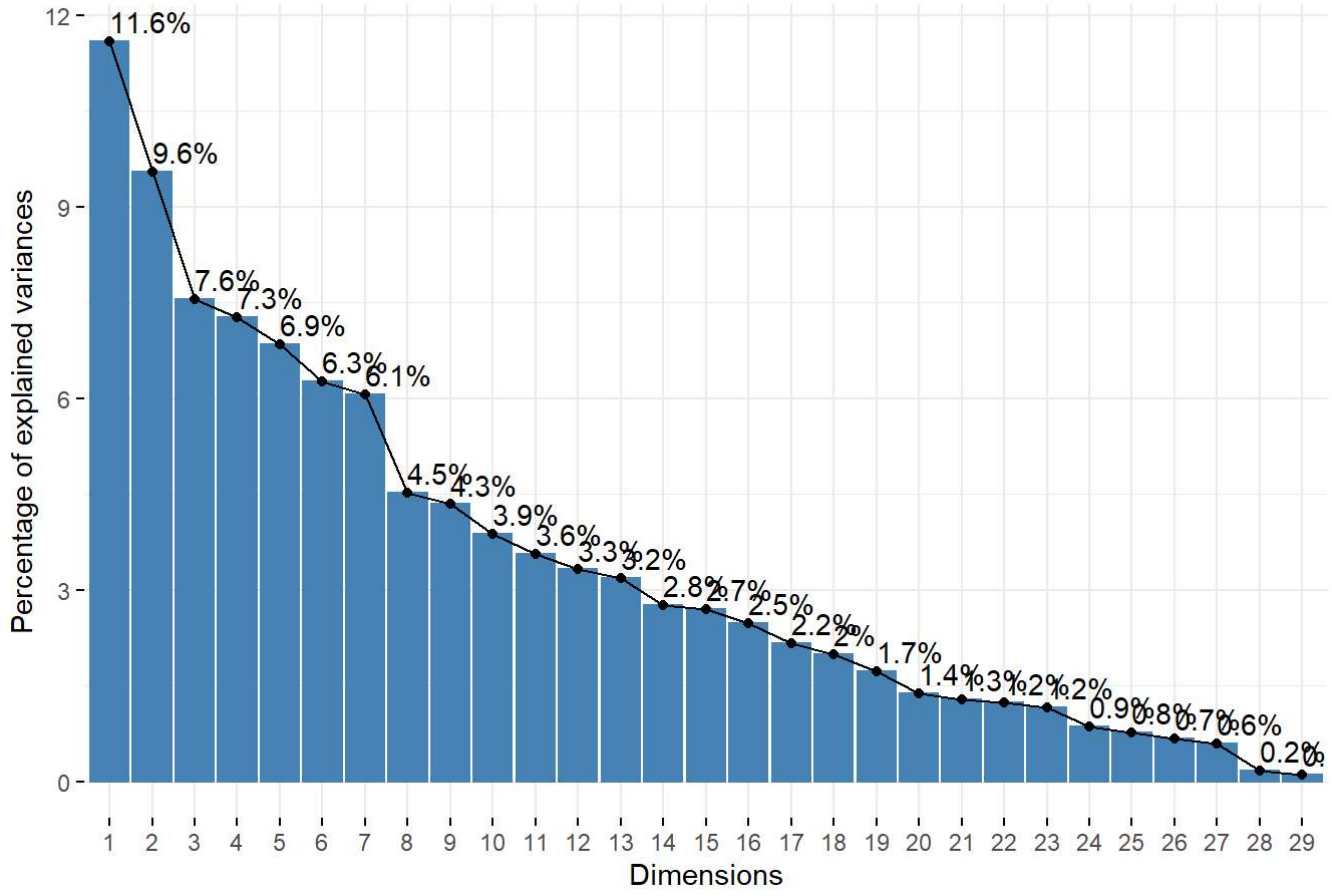
```
## health             0.113                                          0.429
## absences
## G1
## G2                              0.109
## typeC       0.479        -0.391 -0.461  0.214  0.122 -0.153
##            Comp.10 Comp.11 Comp.12 Comp.13 Comp.14 Comp.15 Comp.16 Comp.17
## school      0.179   0.426   0.346   0.149   0.330   0.163   0.174
## sex        -0.260   0.299  -0.172   0.123           0.138          -0.149
## age                                                 0.102
## address    -0.475  -0.416  -0.135  -0.165
## famsize    -0.139                                          0.139
## Pstatus                            -0.360   0.504          -0.609  -0.195
## Medu        0.125          -0.117   0.348  -0.187          -0.103  -0.149
## Fedu                       -0.145   0.383  -0.222          -0.183  -0.218
## traveltime                  0.105
## studytime   0.114                             0.169                  0.379
## failures   -0.129           0.115  -0.130  -0.121           0.132  -0.108
## schoolsup           0.281   0.193          -0.244  -0.790  -0.286
## famsup             -0.140   0.128  -0.125           0.111
## paid               -0.176  -0.223           0.401  -0.381   0.391   0.129
## activities -0.140                                                  -0.101
## nursery    -0.331   0.178   0.175  -0.201
## higher      0.153          -0.200   0.218   0.101          -0.340   0.240
## internet    0.233   0.302          -0.369  -0.183           0.145
## romantic    0.123                                          -0.127
## famrel                             -0.119                          0.393
## freetime   -0.169                                 -0.194   0.112          0.466
## goout      -0.409   0.197           0.201           0.159  -0.107   0.403
## Dalc       -0.159   0.110           0.184                          -0.114
## Walc       -0.328   0.233           0.343   0.196                  -0.210
## health              0.388  -0.749  -0.167
## absences
## G1          0.122
## G2          0.122                              0.113
## typeC                              -0.108  -0.330   0.259  -0.251
##            Comp.18 Comp.19 Comp.20 Comp.21 Comp.22 Comp.23 Comp.24 Comp.25
## school      0.132
## sex                                                 0.108
## age                -0.179                   0.162   0.135  -0.404
## address                     0.120
## famsize    -0.169
## Pstatus     0.308
## Medu        0.254  -0.157                           0.118          -0.648
## Fedu        0.291  -0.102   0.137                                   0.637
## traveltime -0.172   0.123   0.582   0.642  -0.303   0.205
## studytime  -0.287  -0.785                           0.108   0.159
## failures           -0.133                   0.509   0.420  -0.419   0.134
## schoolsup                                                  -0.162
## famsup
## paid        0.219
## activities
## nursery    -0.112
```

```
## higher     -0.433   0.451                   0.435   0.246
## internet   -0.162
## romantic
## famrel      0.228   0.154   0.487  -0.603  -0.178   0.299
## freetime    0.301          -0.533   0.284  -0.222   0.354
## goout       0.114           0.231           0.284  -0.528
## Dalc       -0.151  -0.101          -0.112  -0.197   0.311          -0.318
## Walc       -0.269                  -0.218  -0.158   0.111           0.172
## health
## absences
## G1                                         -0.263  -0.114  -0.493
## G2                                         -0.303  -0.127  -0.578
## typeC      -0.159                          -0.107
##            Comp.26 Comp.27 Comp.28 Comp.29
## school
## sex
## age         0.501   0.664
## address
## famsize
## Pstatus
## Medu       -0.251   0.161
## Fedu        0.206  -0.124
## traveltime
## studytime
## failures   -0.322  -0.326
## schoolsup
## famsup
## paid
## activities
## nursery
## higher
## internet
## romantic
## famrel
## freetime            0.131
## goout              -0.146
## Dalc        0.552  -0.490
## Walc       -0.420   0.289
## health
## absences                   -0.992
## G1                 -0.109          -0.750
## G2         -0.109  -0.110           0.658
## typeC
```

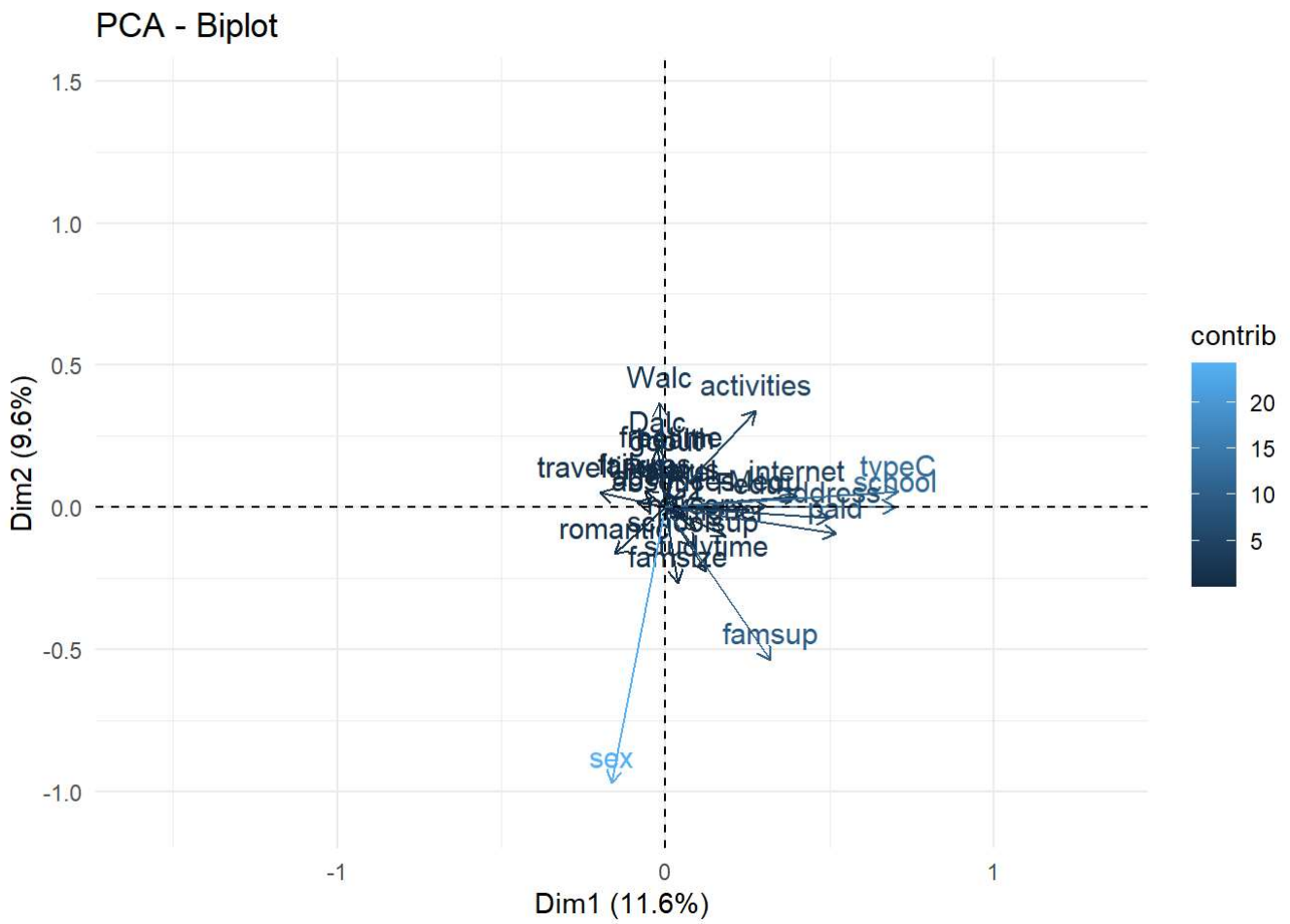
```
score <- data_PCA$scores
head(score)
```

```
##         Comp.1      Comp.2      Comp.3      Comp.4     Comp.5      Comp.6
## [1,] 0.1515054 -0.42893630 -0.86881252  0.22253378  0.1277206  0.79282786
## [2,] 0.3046240 -0.63415222 -0.64655447 -0.10651901 -0.1798919  0.31372047
## [3,] 0.5053699 -0.09127951 -1.18218724  0.01433697  0.5047999  0.28988917
## [4,] 1.0784900 -0.72547551  0.44613394 -0.58030810  0.5112759  0.05716699
## [5,] 0.6594463 -0.71035163 -0.85236982 -0.38754134 -0.3005554  0.07830783
## [6,] 1.2942678  0.51509143 -0.01910466 -0.06012887 -0.1628791 -0.39522528
##          Comp.7       Comp.8      Comp.9     Comp.10     Comp.11    Comp.12
## [1,] -0.2493474 -0.315565487  0.60308622 -0.36238805  0.18365708  0.3218368
## [2,]  0.5327917  0.841900948 -0.01198026  0.12618812 -0.03023202  0.1115188
## [3,] -0.5814766  0.361614179 -0.14506020 -0.37499463  0.58984346  0.2020173
## [4,] -0.1024558 -0.212525634  0.21270159  0.09564712 -0.17417632 -0.4523031
## [5,] -0.1237801 -0.233653456  0.62890691 -0.37202669 -0.23050015 -0.3911324
## [6,] -0.7198779  0.007348327  0.10984067  0.20791205 -0.25198423 -0.4400668
##         Comp.13    Comp.14      Comp.15     Comp.16     Comp.17     Comp.18
## [1,]  0.8109409 -0.9700917 -0.344777183 -0.07830307  0.17976451  0.10019092
## [2,] -0.4707217 -0.2182965  0.365347413 -0.08163834  0.15307318 -0.09279067
## [3,] -0.4190188  0.1754499 -0.926633870  0.02173663 -0.13458111  0.11587085
## [4,] -0.1633238  0.2743132 -0.052148170  0.15380196 -0.19921495 -0.18166765
## [5,]  0.1641277  0.2983074  0.117507891  0.05713624 -0.14312025  0.24781614
## [6,] -0.3134001  0.1303550 -0.001214135  0.05616535  0.05029108  0.26397352
##          Comp.19     Comp.20     Comp.21     Comp.22      Comp.23     Comp.24
## [1,] -0.09330423  0.38239680  0.14536747  0.07591153  0.000933532  0.13149269
## [2,]  0.17899469  0.08713509 -0.26417304  0.13036238 -0.003550461  0.37130927
## [3,] -0.03852080 -0.14863968 -0.08252605  0.39158903  0.533315745 -0.18452994
## [4,] -0.11302976 -0.10272564  0.10987585 -0.07391771 -0.185166712 -0.06255147
## [5,]  0.06288130 -0.07669153 -0.03884803 -0.02098507  0.104390782  0.24010403
## [6,]  0.03366414 -0.09345173 -0.07196474 -0.16630561  0.098305958 -0.11462794
##          Comp.25     Comp.26     Comp.27     Comp.28     Comp.29
## [1,] -0.07547432  0.25365485  0.25106201  0.03427193  0.06262378
## [2,] -0.06292082  0.19796233  0.06269895  0.02298925  0.03771086
## [3,]  0.13886383 -0.36539676 -0.37171150 -0.07411728  0.01877965
## [4,] -0.27310959 -0.17933860 -0.17068202  0.03009817 -0.04059137
## [5,] -0.00339791 -0.02322869  0.04878757 -0.00215762  0.16728716
## [6,] -0.04864251 -0.13699433  0.05502544 -0.08849720 -0.02340240
```

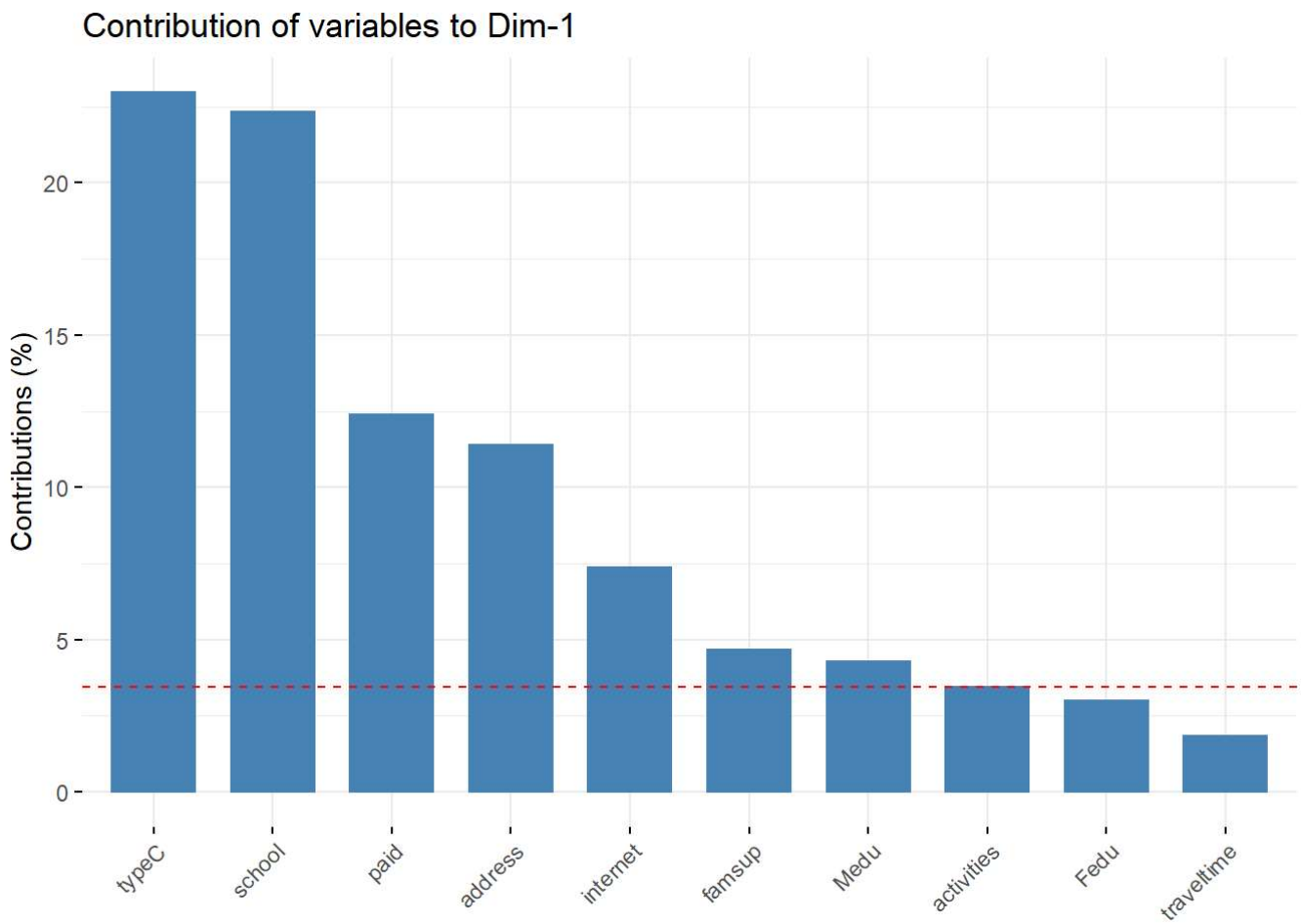
```
# Plot the dimensions
fviz_screeplot(data_PCA, main=" ",ncp=50, addlabels = TRUE)
```



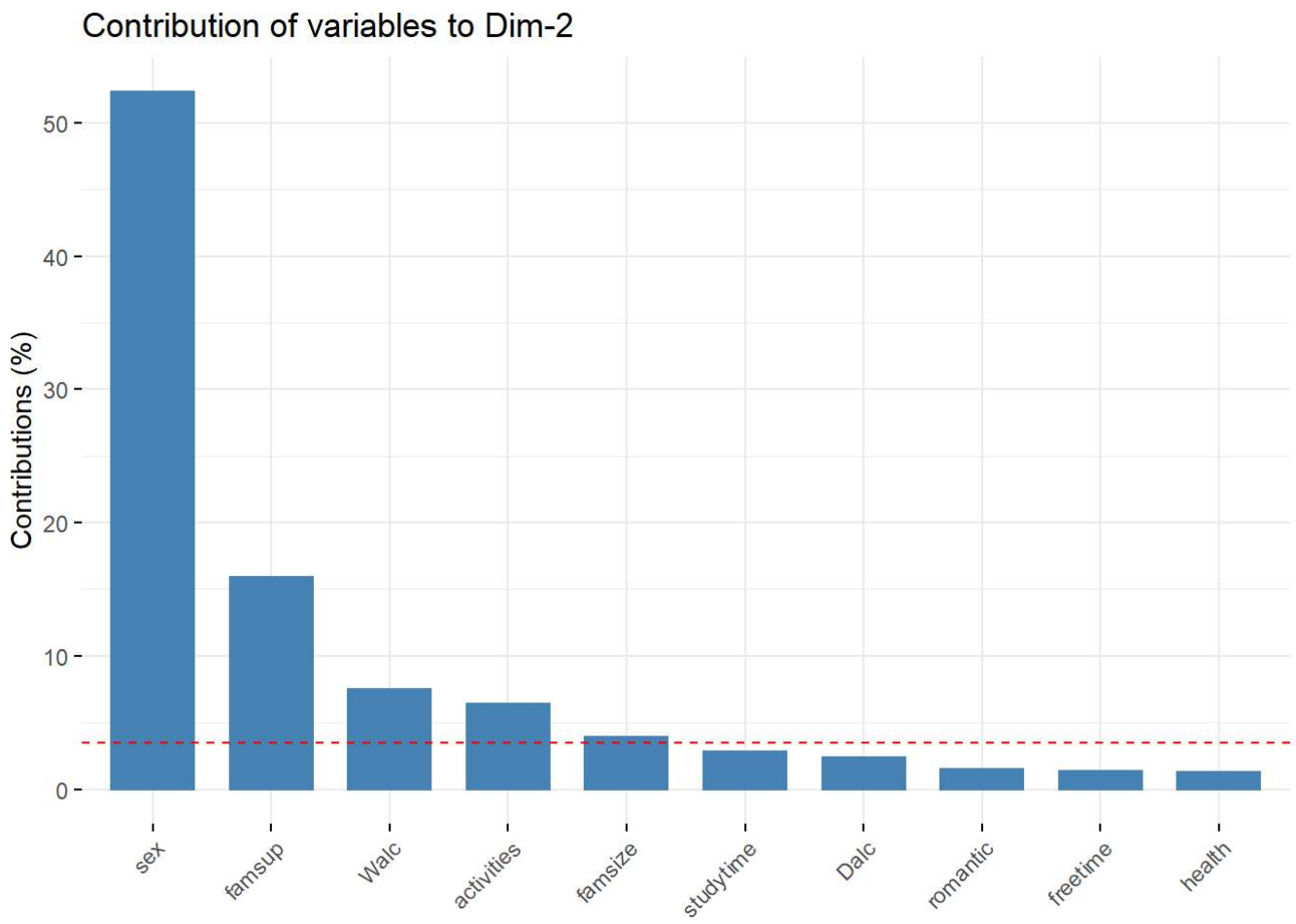

```
# Plot the Principal Components:
fviz_pca_biplot(data_PCA,col.var="contrib", invisible = "ind", habillage ="none", geom = "text",
labelsize=4) + theme_minimal()
```




```
# show the contributions of the variables for PC1
fviz_contrib(data_PCA, choice = "var", axes = 1, top = 10)
```




```
# show the contributions of the variables for PC2
fviz_contrib(data_PCA, choice = "var", axes = 2, top = 10)
```




```
#Recursive Feature Elimination

dataR<-(datanorm[,c(1:30)])


#add the target column called FinalGradeR
#grades less than 10 are a failure and assigned a zero and #grades more than or equal to 10 will
be considered pass and #assigned 1

dataR <- dataR %>%
  mutate(FinalGradeR = case_when(
    G3 < 10 ~ 0,
    G3 > 9 ~ 1
  ))

head(dataR)
```

```
##   school sex       age address famsize Pstatus Medu Fedu traveltime studytime
## 1      1   1 0.4285714       1       1       0 1.00 1.00  0.3333333 0.3333333
## 2      1   1 0.2857143       1       1       1 0.25 0.25  0.0000000 0.3333333
## 3      1   1 0.0000000       1       0       1 0.25 0.25  0.0000000 0.3333333
## 4      1   1 0.0000000       1       1       1 1.00 0.50  0.0000000 0.6666667
## 5      1   1 0.1428571       1       1       1 0.75 0.75  0.0000000 0.3333333
## 6      1   0 0.1428571       1       0       1 1.00 0.75  0.0000000 0.3333333
##   failures schoolsup famsup paid activities nursery higher internet romantic
## 1        0         1      0    0          0       1      1        0        0
## 2        0         0      1    0          0       0      1        1        0
## 3        1         1      0    1          0       1      1        1        0
## 4        0         0      1    1          1       1      1        1        1
## 5        0         0      1    1          0       1      1        0        0
## 6        0         0      1    1          1       1      1        1        0
##   famrel freetime goout Dalc Walc health   absences        G1        G2 G3
## 1   0.75     0.50  0.75 0.00 0.00    0.5 0.08000000 0.2631579 0.3157895  6
## 2   1.00     0.50  0.50 0.00 0.00    0.5 0.05333333 0.2631579 0.2631579  6
## 3   0.75     0.50  0.25 0.25 0.50    0.5 0.13333333 0.3684211 0.4210526 10
## 4   0.50     0.25  0.25 0.00 0.00    1.0 0.02666667 0.7894737 0.7368421 15
## 5   0.75     0.50  0.25 0.00 0.25    1.0 0.05333333 0.3157895 0.5263158 10
## 6   1.00     0.75  0.25 0.00 0.25    1.0 0.13333333 0.7894737 0.7894737 15
##   typeC FinalGradeR
## 1     1           0
## 2     1           0
## 3     1           1
## 4     1           1
## 5     1           1
## 6     1           1
```

```
dataR<-(dataR[,c(1:28, 30, 31)])


head(dataR)
```

```
##   school sex       age address famsize Pstatus Medu Fedu traveltime studytime
## 1      1   1 0.4285714       1       1       0 1.00 1.00  0.3333333 0.3333333
## 2      1   1 0.2857143       1       1       1 0.25 0.25  0.0000000 0.3333333
## 3      1   1 0.0000000       1       0       1 0.25 0.25  0.0000000 0.3333333
## 4      1   1 0.0000000       1       1       1 1.00 0.50  0.0000000 0.6666667
## 5      1   1 0.1428571       1       1       1 0.75 0.75  0.0000000 0.3333333
## 6      1   0 0.1428571       1       0       1 1.00 0.75  0.0000000 0.3333333
##   failures schoolsup famsup paid activities nursery higher internet romantic
## 1        0         1      0    0          0       1      1        0        0
## 2        0         0      1    0          0       0      1        1        0
## 3        1         1      0    1          0       1      1        1        0
## 4        0         0      1    1          1       1      1        1        1
## 5        0         0      1    1          0       1      1        0        0
## 6        0         0      1    1          1       1      1        1        0
##   famrel freetime goout Dalc Walc health   absences        G1        G2 typeC
## 1   0.75     0.50  0.75 0.00 0.00    0.5 0.08000000 0.2631579 0.3157895     1
## 2   1.00     0.50  0.50 0.00 0.00    0.5 0.05333333 0.2631579 0.2631579     1
## 3   0.75     0.50  0.25 0.25 0.50    0.5 0.13333333 0.3684211 0.4210526     1
## 4   0.50     0.25  0.25 0.00 0.00    1.0 0.02666667 0.7894737 0.7368421     1
## 5   0.75     0.50  0.25 0.00 0.25    1.0 0.05333333 0.3157895 0.5263158     1
## 6   1.00     0.75  0.25 0.00 0.25    1.0 0.13333333 0.7894737 0.7894737     1
##   FinalGradeR
## 1           0
## 2           0
## 3           1
## 4           1
## 5           1
## 6           1
```

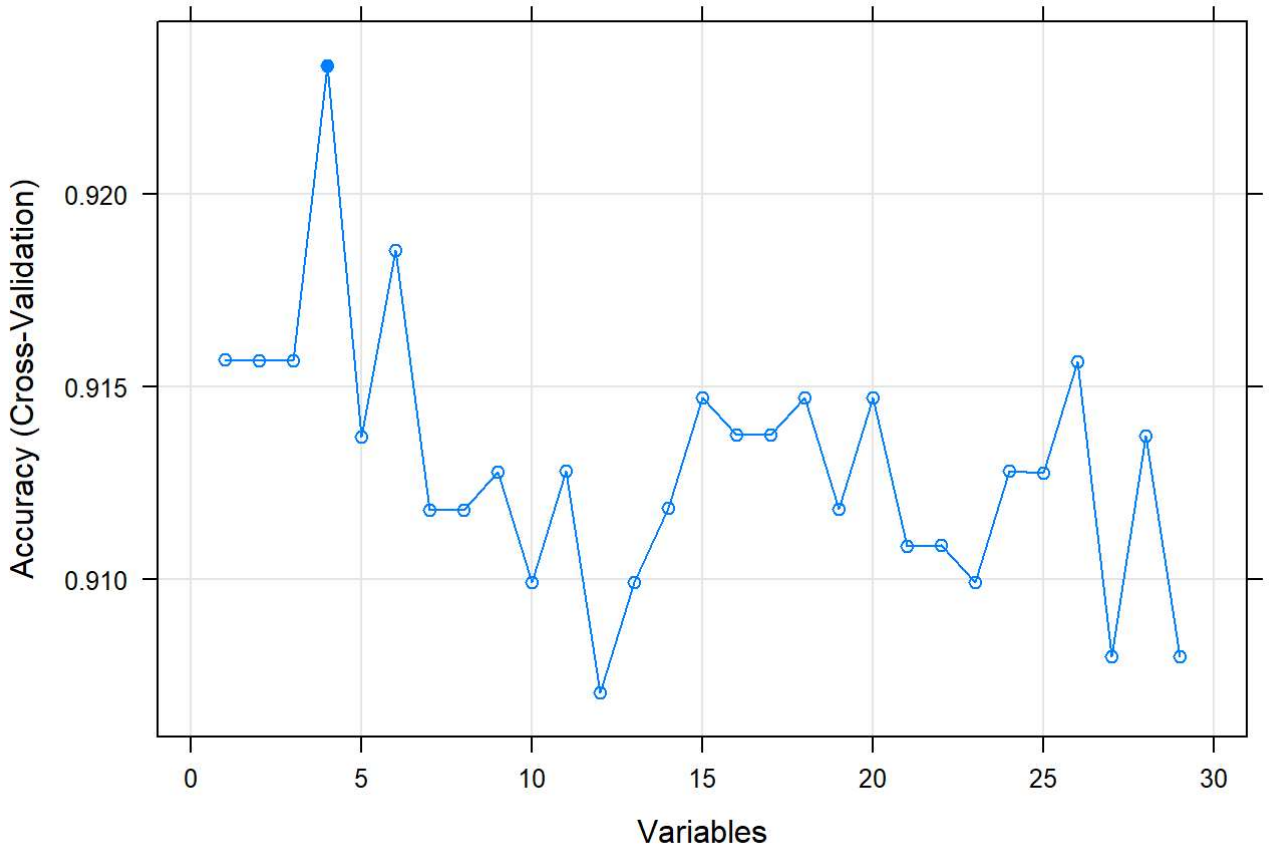
```
for (i in colnames(dataR)){
   dataR[[i]] = factor(dataR[[i]])
}


set.seed(2022)


# definethe control using a RF selection function
control <- rfeControl(functions=rfFuncs, method="cv", number=10)
# run the algorithm
results <- rfe(dataR[,1:29], dataR[,30], sizes=c(1:29), rfeControl=control)
# Look at the results
print(results)
```

```
##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (10 fold)
##
## Resampling performance over subset size:
##
##  Variables Accuracy  Kappa AccuracySD KappaSD Selected
##          1   0.9157 0.7275    0.01739 0.05989
##          2   0.9157 0.7379    0.01639 0.05138
##          3   0.9157 0.7417    0.01923 0.05762
##          4   0.9233 0.7681    0.01824 0.05516        *
##          5   0.9137 0.7386    0.02774 0.08223
##          6   0.9185 0.7531    0.01900 0.05718
##          7   0.9118 0.7264    0.01882 0.06156
##          8   0.9118 0.7277    0.01652 0.05231
##          9   0.9128 0.7315    0.01912 0.06191
##         10   0.9099 0.7208    0.01062 0.03599
##         11   0.9128 0.7285    0.01399 0.05065
##         12   0.9071 0.7121    0.01378 0.03963
##         13   0.9099 0.7216    0.01467 0.04856
##         14   0.9119 0.7235    0.01275 0.04065
##         15   0.9147 0.7328    0.01481 0.04752
##         16   0.9138 0.7314    0.01650 0.05106
##         17   0.9138 0.7297    0.01218 0.04326
##         18   0.9147 0.7334    0.01474 0.04862
##         19   0.9118 0.7240    0.01814 0.05828
##         20   0.9147 0.7341    0.01851 0.06087
##         21   0.9109 0.7201    0.01997 0.06649
##         22   0.9109 0.7201    0.02035 0.06723
##         23   0.9099 0.7170    0.01602 0.05285
##         24   0.9128 0.7243    0.01949 0.06444
##         25   0.9128 0.7280    0.02021 0.06524
##         26   0.9157 0.7383    0.02032 0.06561
##         27   0.9080 0.7114    0.01609 0.05029
##         28   0.9137 0.7294    0.01997 0.06645
##         29   0.9080 0.7101    0.01607 0.05226
##
## The top 4 variables (out of 4):
##    G2, G1, failures, typeC
```

```
# list the chosen predictors
predictors(results)
```

```
## [1] "G2"       "G1"       "failures" "typeC"
```

```
# plot the results
plot(results, type=c("g", "o"))
```




```
#normalize numeric attributes
min_max_norm <- function(x){
  (x - min(x)) / (max(x) - min(x))
}
dataN<-(appendedDf[,c(1,2,3,4,5,6,7,8,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,3
2,33,34)])
head(dataN)
```

```
##   school sex age address famsize Pstatus Medu Fedu traveltime studytime
## 1      1   1  18       1       1       0    4    4          2         2
## 2      1   1  17       1       1       1    1    1          1         2
## 3      1   1  15       1       0       1    1    1          1         2
## 4      1   1  15       1       1       1    4    2          1         3
## 5      1   1  16       1       1       1    3    3          1         2
## 6      1   0  16       1       0       1    4    3          1         2
##   failures schoolsup famsup paid activities nursery higher internet romantic
## 1        0         1      0    0          0       1      1        0        0
## 2        0         0      1    0          0       0      1        1        0
## 3        3         1      0    1          0       1      1        1        0
## 4        0         0      1    1          1       1      1        1        1
## 5        0         0      1    1          0       1      1        0        0
## 6        0         0      1    1          1       1      1        1        0
##   famrel freetime goout Dalc Walc health absences G1 G2 G3 typeC
## 1      4        3     4    1    1      3        6  5  6  6     1
## 2      5        3     3    1    1      3        4  5  5  6     1
## 3      4        3     2    2    3      3       10  7  8 10     1
## 4      3        2     2    1    1      5        2 15 14 15     1
## 5      4        3     2    1    2      5        4  6 10 10     1
## 6      5        4     2    1    2      5       10 15 15 15     1
```

```
datanorm <- dataN %>%
  mutate(across(c(3,7,8,9,10,11,20,21,22,23,24,25,26,27,28),min_max_norm))

head(datanorm)
```

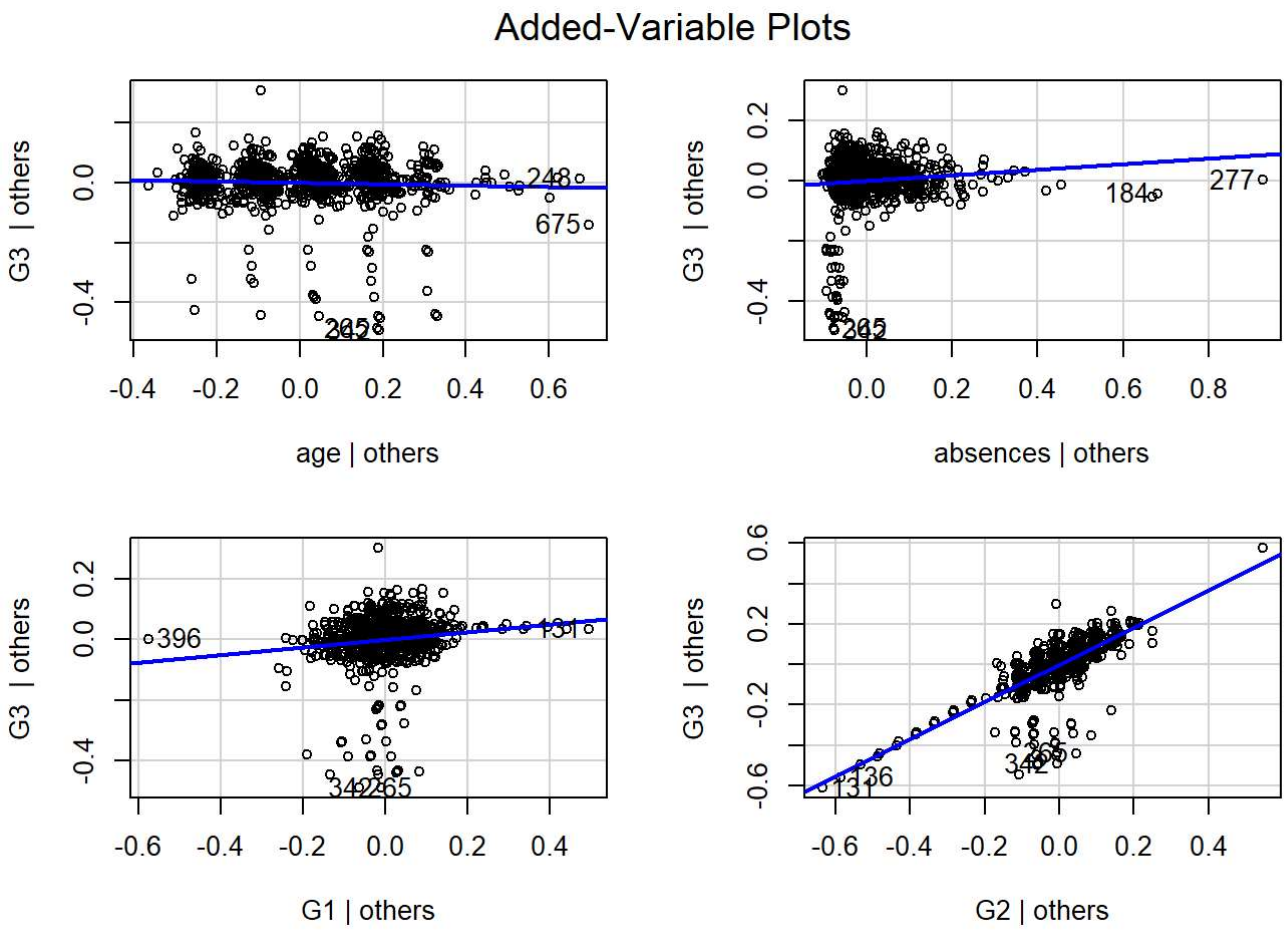
```
##   school sex       age address famsize Pstatus Medu Fedu traveltime studytime
## 1      1   1 0.4285714       1       1       0 1.00 1.00  0.3333333 0.3333333
## 2      1   1 0.2857143       1       1       1 0.25 0.25  0.0000000 0.3333333
## 3      1   1 0.0000000       1       0       1 0.25 0.25  0.0000000 0.3333333
## 4      1   1 0.0000000       1       1       1 1.00 0.50  0.0000000 0.6666667
## 5      1   1 0.1428571       1       1       1 0.75 0.75  0.0000000 0.3333333
## 6      1   0 0.1428571       1       0       1 1.00 0.75  0.0000000 0.3333333
##   failures schoolsup famsup paid activities nursery higher internet romantic
## 1        0         1      0    0          0       1      1        0        0
## 2        0         0      1    0          0       0      1        1        0
## 3        1         1      0    1          0       1      1        1        0
## 4        0         0      1    1          1       1      1        1        1
## 5        0         0      1    1          0       1      1        0        0
## 6        0         0      1    1          1       1      1        1        0
##   famrel freetime goout Dalc Walc health   absences        G1        G2 G3
## 1   0.75     0.50  0.75 0.00 0.00    0.5 0.08000000 0.2631579 0.3157895  6
## 2   1.00     0.50  0.50 0.00 0.00    0.5 0.05333333 0.2631579 0.2631579  6
## 3   0.75     0.50  0.25 0.25 0.50    0.5 0.13333333 0.3684211 0.4210526 10
## 4   0.50     0.25  0.25 0.00 0.00    1.0 0.02666667 0.7894737 0.7368421 15
## 5   0.75     0.50  0.25 0.00 0.25    1.0 0.05333333 0.3157895 0.5263158 10
## 6   1.00     0.75  0.25 0.00 0.25    1.0 0.13333333 0.7894737 0.7894737 15
##   typeC
## 1     1
## 2     1
## 3     1
## 4     1
## 5     1
## 6     1
```

```
#create different sub groups of variables for the ml models

#add the target column
datagroupB <- datanorm %>%
  mutate(FinalGradeR = case_when(
    G3 < 10 ~ 0,
    G3 > 9 ~ 1
  ))

datagroupA <- (datanorm)

datagroupA <- datagroupA %>%
  mutate(FinalGradeR = case_when(
    G3 < 10 ~ 0,
    G3 > 9 ~ 1
  ))
datagroupA <- datagroupA[,c(1:28,30,31)]


datagroupB<-(datanorm[,c(11,27,28,29,30)])

#add the target column
datagroupB <- datagroupB %>%
  mutate(FinalGradeR = case_when(
    G3 < 10 ~ 0,
    G3 > 9 ~ 1
  ))
datagroupB <- datagroupB[,c(1:3,5,6)]


datagroupC <- (datanorm[,c(30,1,14,4,18,13,7,15,8,9,29)])
datagroupC <- datagroupC %>%
  mutate(FinalGradeR = case_when(
    G3 < 10 ~ 0,
    G3 > 9 ~ 1
  ))
datagroupC <- datagroupC[,c(1:10,12)]


datagroupLR <- dataN %>%
  mutate(across(c(3,26,27,28,29),min_max_norm))
datagroupLR <- (datagroupLR[,c(3,26,27,28,29)])
```

```
#Linear regression model
lm<-lm(G3 ~ age + absences + G1 + G2, data = datagroupLR)
summary(lm)
```

```
##
## Call:
## lm(formula = G3 ~ age + absences + G1 + G2, data = datagroupLR)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.48900 -0.01997  0.00336  0.04108  0.30467
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.05274    0.01078  -4.893 1.15e-06 ***
## age         -0.02215    0.01404  -1.577  0.11503
## absences     0.09460    0.02994   3.160  0.00162 **
## G1           0.12773    0.03039   4.203 2.86e-05 ***
## G2           0.91962    0.02758  33.345  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07887 on 1039 degrees of freedom
## Multiple R-squared:  0.834,  Adjusted R-squared:  0.8334
## F-statistic:  1305 on 4 and 1039 DF,  p-value: < 2.2e-16
```

```
avPlots(lm)
```

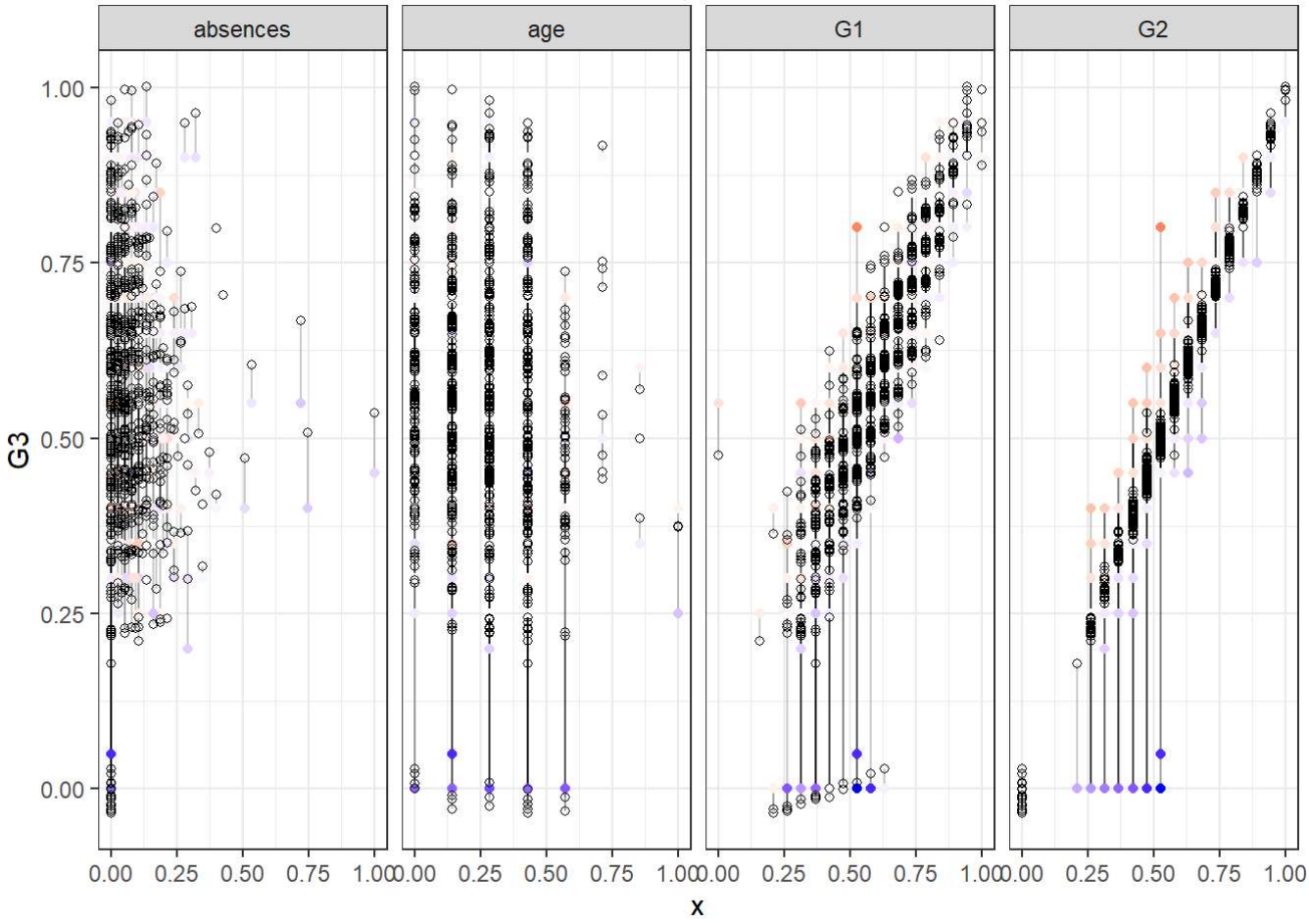


```
datagroupLR$predicted <- predict(lm)
datagroupLR$residuals <- residuals(lm)
head(datagroupLR)
```

```
##         age   absences        G1        G2   G3 predicted   residuals
## 1 0.4285714 0.08000000 0.2631579 0.3157895 0.30 0.2693511  0.03064887
## 2 0.2857143 0.05333333 0.2631579 0.2631579 0.30 0.2215919  0.07840807
## 3 0.0000000 0.13333333 0.3684211 0.4210526 0.50 0.3941362  0.10586380
## 4 0.0000000 0.02666667 0.7894737 0.7368421 0.75 0.7282299  0.02177010
## 5 0.1428571 0.05333333 0.3157895 0.5263158 0.50 0.4734828  0.02651722
## 6 0.1428571 0.13333333 0.7894737 0.7894737 0.75 0.7835573 -0.03355731
```

```
#plot the residuals

datagroupLR %>%
  gather(key = "iv", value = "x", -G3, -predicted, -residuals) %>%

  ggplot(aes(x = x, y = G3)) +
  geom_segment(aes(xend = x, yend = predicted), alpha = .2) +
  geom_point(aes(color = residuals)) +
  scale_color_gradient2(low = "blue", mid = "white", high = "red") +
  guides(color = FALSE) +
  geom_point(aes(y = predicted), shape = 1) +
  facet_grid(~ iv, scales = "free_x") +
  theme_bw()
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```




```
#split data into train and test sets
train_index <- sample(1:nrow(datagroupA), 0.7 * nrow(datagroupA))
train.setA <- datagroupA[train_index,]
test.setA <- datagroupA[-train_index,]

train_index <- sample(1:nrow(datagroupB), 0.7 * nrow(datagroupB))
train.setB <- datagroupB[train_index,]
test.setB <- datagroupB[-train_index,]

train_index <- sample(1:nrow(datagroupC), 0.7 * nrow(datagroupC))
train.setC <- datagroupC[train_index,]
test.setC <- datagroupC[-train_index,]
```

```
#build logistic regression models
glm_modelA <- glm(FinalGradeR ~ ., family = "binomial" (link=logit), data = train.setA)
summary(glm_modelA)
```

```
##
## Call:
## glm(formula = FinalGradeR ~ ., family = binomial(link = logit),
##     data = train.setA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.7718   0.0000   0.0093   0.1253   2.1496
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -19.787987   2.690112  -7.356 1.90e-13 ***
## school        0.881952   0.480217   1.837   0.0663 .
## sex           0.556339   0.465283   1.196   0.2318
## age           1.290172   1.184388   1.089   0.2760
## address      -0.300619   0.423801  -0.709   0.4781
## famsize       0.406928   0.419358   0.970   0.3319
## Pstatus      -0.975515   0.739024  -1.320   0.1868
## Medu          1.615800   0.944574   1.711   0.0872 .
## Fedu         -1.920646   0.925007  -2.076   0.0379 *
## traveltime    0.388077   0.781142   0.497   0.6193
## studytime    -1.347233   0.833561  -1.616   0.1060
## failures      0.363988   0.719521   0.506   0.6129
## schoolsup     0.648974   0.533544   1.216   0.2239
## famsup       -0.009491   0.397175  -0.024   0.9809
## paid         -0.545610   0.514314  -1.061   0.2888
## activities   -0.531775   0.387334  -1.373   0.1698
## nursery       0.147902   0.448228   0.330   0.7414
## higher        0.534187   0.552998   0.966   0.3341
## internet      0.239603   0.457583   0.524   0.6005
## romantic     -0.571870   0.414829  -1.379   0.1680
## famrel       -0.669258   0.804552  -0.832   0.4055
## freetime      0.609520   0.790567   0.771   0.4407
## goout        -1.592999   0.770191  -2.068   0.0386 *
## Dalc         -1.489725   0.986027  -1.511   0.1308
## Walc          2.087572   0.857832   2.434   0.0150 *
## health       -0.461938   0.558120  -0.828   0.4079
## absences     -5.947909   2.914228  -2.041   0.0413 *
## G1           10.919820   2.529942   4.316 1.59e-05 ***
## G2           34.076336   4.479684   7.607 2.81e-14 ***
## typeC        -0.866669   0.492285  -1.761   0.0783 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 777.80  on 729  degrees of freedom
## Residual deviance: 215.66  on 700  degrees of freedom
## AIC: 275.66
##
## Number of Fisher Scoring iterations: 9
```

```
glm_modelB <- glm(FinalGradeR ~ ., family = "binomial" (link=logit), data = train.setB)
summary(glm_modelB)
```

```
##
## Call:
## glm(formula = FinalGradeR ~ ., family = binomial(link = logit),
##     data = train.setB)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.4700   0.0004   0.0203   0.1732   2.2423
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -17.7145     1.9740  -8.974  < 2e-16 ***
## failures      0.5704     0.7424   0.768   0.4423
## G1            8.6592     2.1259   4.073 4.64e-05 ***
## G2           29.6387     3.8221   7.755 8.86e-15 ***
## typeC        -0.8404     0.3494  -2.405   0.0162 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 760.07  on 729  degrees of freedom
## Residual deviance: 224.48  on 725  degrees of freedom
## AIC: 234.48
##
## Number of Fisher Scoring iterations: 8
```

```
glm_modelC <- glm(FinalGradeR ~ ., family = "binomial"(link=logit), data = train.setC)
summary(glm_modelC)
```

```
##
## Call:
## glm(formula = FinalGradeR ~ ., family = binomial(link = logit),
##     data = train.setC)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3057   0.3589   0.4908   0.7850   1.4697
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.42664    0.35240   1.211    0.226
## typeC       -1.59059    0.23074  -6.893 5.45e-12 ***
## school       1.01950    0.24986   4.080 4.50e-05 ***
## paid         0.29320    0.24836   1.181    0.238
## address      0.07596    0.22471   0.338    0.735
## internet     0.17243    0.23257   0.741    0.458
## famsup      -0.30036    0.20323  -1.478    0.139
## Medu         0.44347    0.45163   0.982    0.326
## activities   0.13604    0.18882   0.720    0.471
## Fedu         0.55842    0.45390   1.230    0.219
## traveltime   0.32654    0.41505   0.787    0.431
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 777.80  on 729  degrees of freedom
## Residual deviance: 706.99  on 719  degrees of freedom
## AIC: 728.99
##
## Number of Fisher Scoring iterations: 4
```

```
test.setA$pred <- predict(glm_modelA, newdata = test.setA, type = 'response')

ProbabilityCutoff <- 0.5
test.setA$pred.probs <- 1-test.setA$pred

test.setA$pred.passed <- ifelse(test.setA$pred > ProbabilityCutoff, 1, 0)

confusionMatrix(as.factor(test.setA$FinalGradeR), as.factor(test.setA$pred.passed))
```

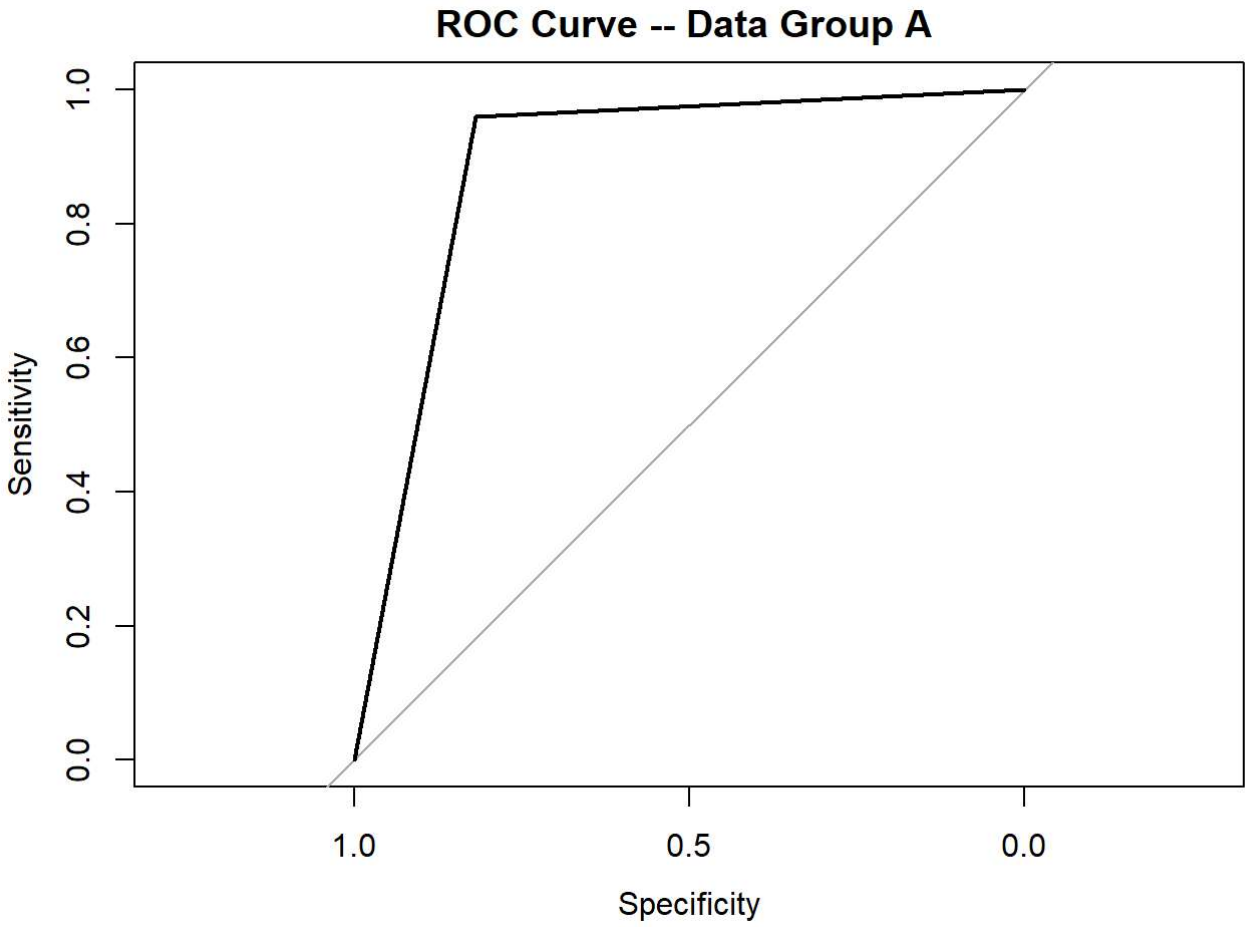
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  54  12
##          1  10 238
##
##                Accuracy : 0.9299
##                  95% CI : (0.8958, 0.9556)
##     No Information Rate : 0.7962
##     P-Value [Acc > NIR] : 3.986e-11
##
##                   Kappa : 0.7866
##
##  Mcnemar's Test P-Value : 0.8312
##
##             Sensitivity : 0.8438
##             Specificity : 0.9520
##          Pos Pred Value : 0.8182
##          Neg Pred Value : 0.9597
##              Prevalence : 0.2038
##          Detection Rate : 0.1720
##    Detection Prevalence : 0.2102
##       Balanced Accuracy : 0.8979
##
##        'Positive' Class : 0
##
```

```
#plot the ROC curve
roc_score=roc(test.setA$FinalGradeR, test.setA$pred.passed) #AUC score
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```
plot(roc_score ,main ="ROC Curve -- Data Group A ")
```




```
auc(test.setA$FinalGradeR, test.setA$pred.passed)
```

```
## [1] 0.8889296
```

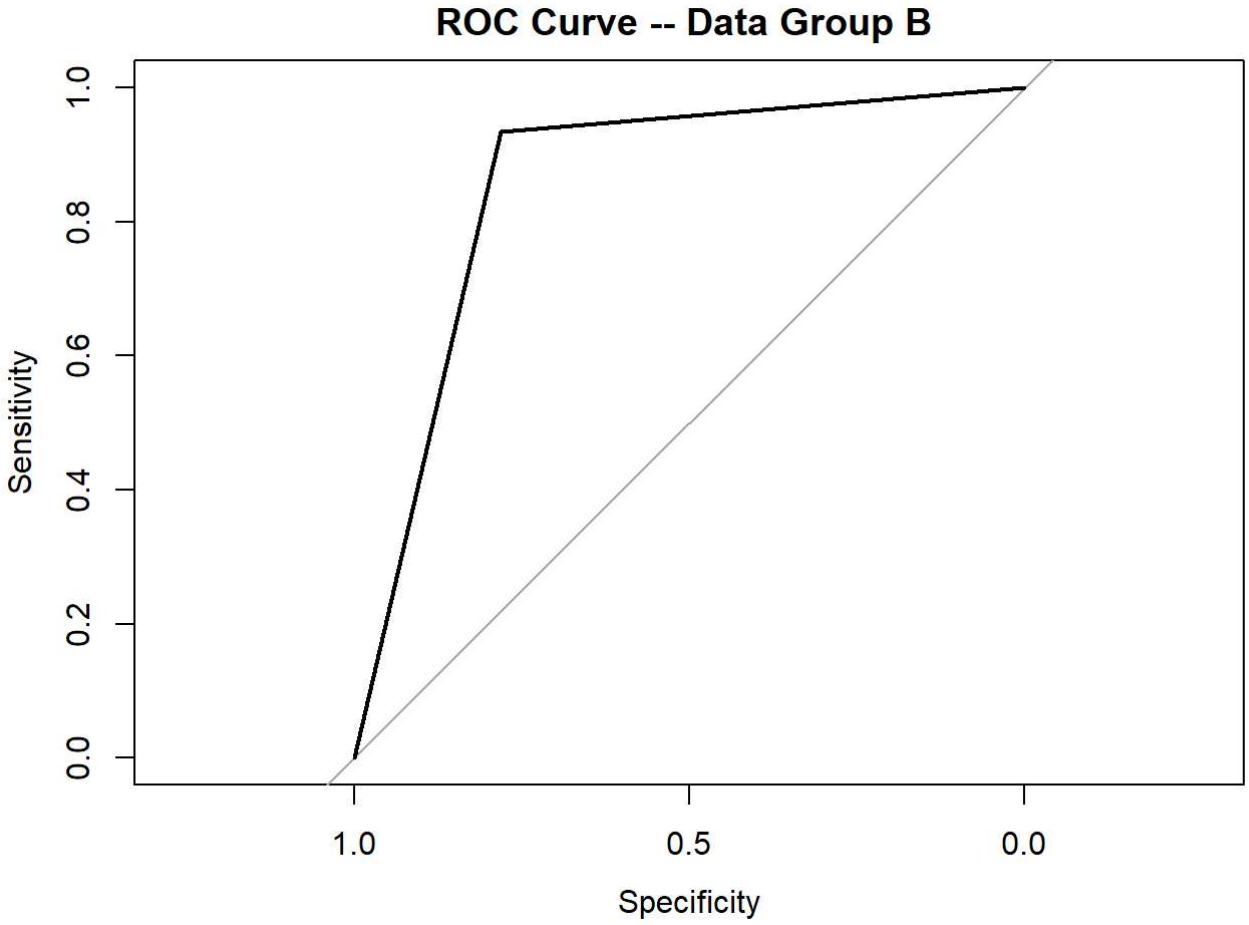
```
test.setB$pred <- predict(glm_modelB, newdata = test.setB, type = 'response')

test.setB$pred.probs <- 1-test.setB$pred

test.setB$pred.passed <- ifelse(test.setB$pred > ProbabilityCutoff, 1, 0)

confusionMatrix(as.factor(test.setB$FinalGradeR), as.factor(test.setB$pred.passed))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  57  16
##          1  16 225
##
##                Accuracy : 0.8981
##                  95% CI : (0.8592, 0.9292)
##     No Information Rate : 0.7675
##     P-Value [Acc > NIR] : 1.943e-09
##
##                   Kappa : 0.7144
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.7808
##             Specificity : 0.9336
##          Pos Pred Value : 0.7808
##          Neg Pred Value : 0.9336
##              Prevalence : 0.2325
##          Detection Rate : 0.1815
##    Detection Prevalence : 0.2325
##       Balanced Accuracy : 0.8572
##
##        'Positive' Class : 0
##
```

```
#plot the ROC curve
roc_score=roc(test.setB$FinalGradeR, test.setB$pred.passed) #AUC score
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
plot(roc_score ,main ="ROC Curve -- Data Group B ")
```




```
auc(test.setB$FinalGradeR, test.setB$pred.passed)
```

```
## [1] 0.8572159
```

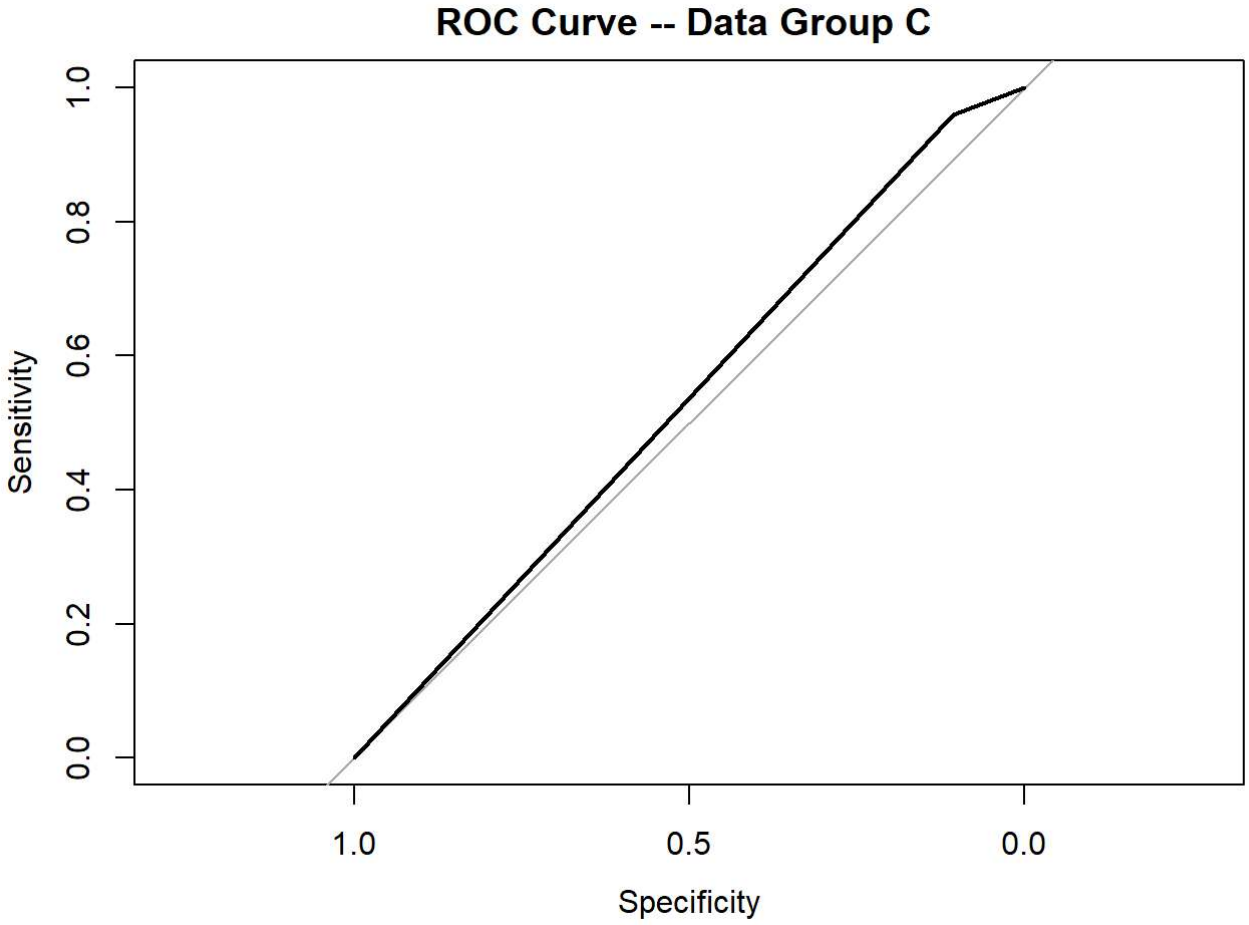
```
test.setC$pred <- predict(glm_modelC, newdata = test.setC, type = 'response')
test.setC$pred.probs <- 1-test.setC$pred

test.setC$pred.passed <- ifelse(test.setC$pred > ProbabilityCutoff, 1, 0)

confusionMatrix(as.factor(test.setC$FinalGradeR), as.factor(test.setC$pred.passed))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0   7  59
##          1  10 238
##
##                Accuracy : 0.7803
##                  95% CI : (0.7303, 0.8248)
##     No Information Rate : 0.9459
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0904
##
##  Mcnemar's Test P-Value : 7.536e-09
##
##             Sensitivity : 0.41176
##             Specificity : 0.80135
##          Pos Pred Value : 0.10606
##          Neg Pred Value : 0.95968
##              Prevalence : 0.05414
##          Detection Rate : 0.02229
##    Detection Prevalence : 0.21019
##       Balanced Accuracy : 0.60656
##
##        'Positive' Class : 0
##
```

```
#plot the ROC curve

roc_score=roc(test.setC$FinalGradeR, test.setC$pred.passed) #AUC score
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```
plot(roc_score ,main ="ROC Curve -- Data Group C ")
```




```
auc(test.setC$FinalGradeR, test.setC$pred.passed)
```

```
## [1] 0.532869
```

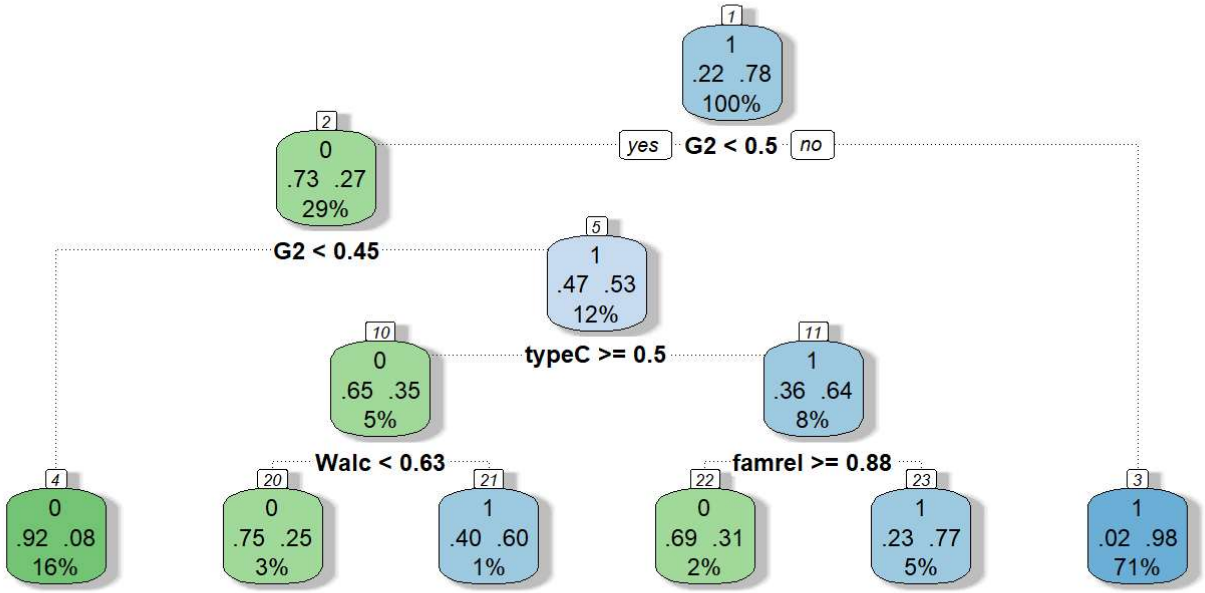
```
#build decision tree models
treeA <- rpart(FinalGradeR ~ ., data=train.setA, method="class", control = rpart.control(minspli
t = 30, minbucket = 10, cp = 0.001))

summary(treeA)
```

```
## Call:
## rpart(formula = FinalGradeR ~ ., data = train.setA, method = "class",
##     control = rpart.control(minsplit = 30, minbucket = 10, cp = 0.001))
##   n= 730
##
##           CP nsplit rel error    xerror       xstd
## 1 0.57926829      0 1.0000000 1.0000000 0.06875826
## 2 0.04573171      1 0.4207317 0.4756098 0.05089391
## 3 0.03658537      3 0.3292683 0.4634146 0.05031418
## 4 0.01219512      4 0.2926829 0.3658537 0.04524887
## 5 0.00100000      5 0.2804878 0.3231707 0.04274910
##
## Variable importance
##       G2       G1 failures   higher   famrel    typeC      age     Walc
##       51       27        9        6        2        1        1        1
##     paid
##        1
##
## Node number 1: 730 observations,    complexity param=0.5792683
##   predicted class=1  expected loss=0.2246575  P(node) =1
##     class counts:   164   566
##    probabilities: 0.225 0.775
##   left son=2 (209 obs) right son=3 (521 obs)
##   Primary splits:
##       G2       < 0.5        to the left,  improve=147.956000, (0 missing)
##       G1       < 0.4473684  to the left,  improve=111.337300, (0 missing)
##       failures < 0.1666667  to the right, improve= 32.323040, (0 missing)
##       higher   < 0.5        to the left,  improve= 15.651810, (0 missing)
##       typeC    < 0.5        to the right, improve=  8.972684, (0 missing)
##   Surrogate splits:
##       G1       < 0.5        to the left,  agree=0.871, adj=0.550, (0 split)
##       failures < 0.1666667  to the right, agree=0.773, adj=0.206, (0 split)
##       higher   < 0.5        to the left,  agree=0.749, adj=0.124, (0 split)
##       age      < 0.9285714  to the right, agree=0.716, adj=0.010, (0 split)
##       absences < 0.2866667  to the right, agree=0.715, adj=0.005, (0 split)
##
## Node number 2: 209 observations,    complexity param=0.04573171
##   predicted class=0  expected loss=0.2727273  P(node) =0.2863014
##     class counts:   152    57
##    probabilities: 0.727 0.273
##   left son=4 (120 obs) right son=5 (89 obs)
##   Primary splits:
##       G2       < 0.4473684  to the left,  improve=20.216210, (0 missing)
##       G1       < 0.3947368  to the left,  improve=11.142000, (0 missing)
##       typeC    < 0.5        to the right, improve= 5.108027, (0 missing)
##       absences < 0.14       to the right, improve= 2.090096, (0 missing)
##       health   < 0.125      to the left,  improve= 1.783799, (0 missing)
##   Surrogate splits:
##       G1        < 0.4473684  to the left,  agree=0.732, adj=0.371, (0 split)
##       Fedu      < 0.875      to the left,  agree=0.589, adj=0.034, (0 split)
##       studytime < 0.5        to the left,  agree=0.589, adj=0.034, (0 split)
##       age       < 0.07142857 to the right, agree=0.584, adj=0.022, (0 split)
```

```
##       paid      < 0.5        to the left,  agree=0.584, adj=0.022, (0 split)
##
## Node number 3: 521 observations
##   predicted class=1  expected loss=0.02303263  P(node) =0.7136986
##     class counts:    12   509
##    probabilities: 0.023 0.977
##
## Node number 4: 120 observations
##   predicted class=0  expected loss=0.08333333  P(node) =0.1643836
##     class counts:   110    10
##    probabilities: 0.917 0.083
##
## Node number 5: 89 observations,    complexity param=0.04573171
##   predicted class=1  expected loss=0.4719101  P(node) =0.1219178
##     class counts:    42    47
##    probabilities: 0.472 0.528
##   left son=10 (34 obs) right son=11 (55 obs)
##   Primary splits:
##       typeC     < 0.5        to the right, improve=3.375593, (0 missing)
##       absences  < 0.14       to the right, improve=2.425373, (0 missing)
##       studytime < 0.5        to the right, improve=2.145265, (0 missing)
##       famrel    < 0.875      to the right, improve=1.512176, (0 missing)
##       Walc      < 0.625      to the left,  improve=1.488583, (0 missing)
##   Surrogate splits:
##       paid      < 0.5        to the right, agree=0.764, adj=0.382, (0 split)
##       famrel    < 0.375      to the left,  agree=0.663, adj=0.118, (0 split)
##       studytime < 0.5        to the right, agree=0.640, adj=0.059, (0 split)
##       Walc      < 0.875      to the right, agree=0.640, adj=0.059, (0 split)
##       absences  < 0.2533333  to the right, agree=0.640, adj=0.059, (0 split)
##
## Node number 10: 34 observations,    complexity param=0.01219512
##   predicted class=0  expected loss=0.3529412  P(node) =0.04657534
##     class counts:    22    12
##    probabilities: 0.647 0.353
##   left son=20 (24 obs) right son=21 (10 obs)
##   Primary splits:
##       Walc   < 0.625      to the left,  improve=1.7294120, (0 missing)
##       health < 0.875      to the left,  improve=1.2053010, (0 missing)
##       G1     < 0.5        to the right, improve=0.9523367, (0 missing)
##       age    < 0.2142857  to the right, improve=0.6943240, (0 missing)
##       famrel < 0.625      to the left,  improve=0.6627451, (0 missing)
##   Surrogate splits:
##       Dalc       < 0.375      to the left,  agree=0.853, adj=0.5, (0 split)
##       traveltime < 0.5        to the left,  agree=0.765, adj=0.2, (0 split)
##       sex        < 0.5        to the right, agree=0.735, adj=0.1, (0 split)
##       Pstatus    < 0.5        to the right, agree=0.735, adj=0.1, (0 split)
##       studytime  < 0.1666667  to the right, agree=0.735, adj=0.1, (0 split)
##
## Node number 11: 55 observations,    complexity param=0.03658537
##   predicted class=1  expected loss=0.3636364  P(node) =0.07534247
##     class counts:    20    35
##    probabilities: 0.364 0.636
```

```
##   left son=22 (16 obs) right son=23 (39 obs)
##   Primary splits:
##       famrel   < 0.875      to the right, improve=4.733392, (0 missing)
##       G1       < 0.5        to the left,  improve=2.845850, (0 missing)
##       age      < 0.3571429  to the left,  improve=2.457469, (0 missing)
##       absences < 0.02       to the right, improve=1.498501, (0 missing)
##       health   < 0.875      to the right, improve=1.473064, (0 missing)
##   Surrogate splits:
##       age        < 0.07142857 to the left,  agree=0.782, adj=0.250, (0 split)
##       G1         < 0.3947368  to the left,  agree=0.745, adj=0.125, (0 split)
##       traveltime < 0.8333333  to the right, agree=0.727, adj=0.063, (0 split)
##       schoolsup  < 0.5        to the right, agree=0.727, adj=0.063, (0 split)
##       health     < 0.125      to the left,  agree=0.727, adj=0.063, (0 split)
##
## Node number 20: 24 observations
##   predicted class=0  expected loss=0.25  P(node) =0.03287671
##     class counts:    18     6
##    probabilities: 0.750 0.250
##
## Node number 21: 10 observations
##   predicted class=1  expected loss=0.4  P(node) =0.01369863
##     class counts:     4     6
##    probabilities: 0.400 0.600
##
## Node number 22: 16 observations
##   predicted class=0  expected loss=0.3125  P(node) =0.02191781
##     class counts:    11     5
##    probabilities: 0.688 0.312
##
## Node number 23: 39 observations
##   predicted class=1  expected loss=0.2307692  P(node) =0.05342466
##     class counts:     9    30
##    probabilities: 0.231 0.769
```

```
fancyRpartPlot(treeA,caption = "Classification Tree")
```



Classification Tree

```
predictA <-predict(treeA, test.setA, type = 'class')

table_A<- table(test.setA$FinalGradeR, predictA)
table_A
```

```
##    predictA
##       0   1
##   0  53  13
##   1   9 239
```

```
accuracy_Test <- sum(diag(table_A)) / sum(table_A)
print(paste('Accuracy for tree A', accuracy_Test))
```

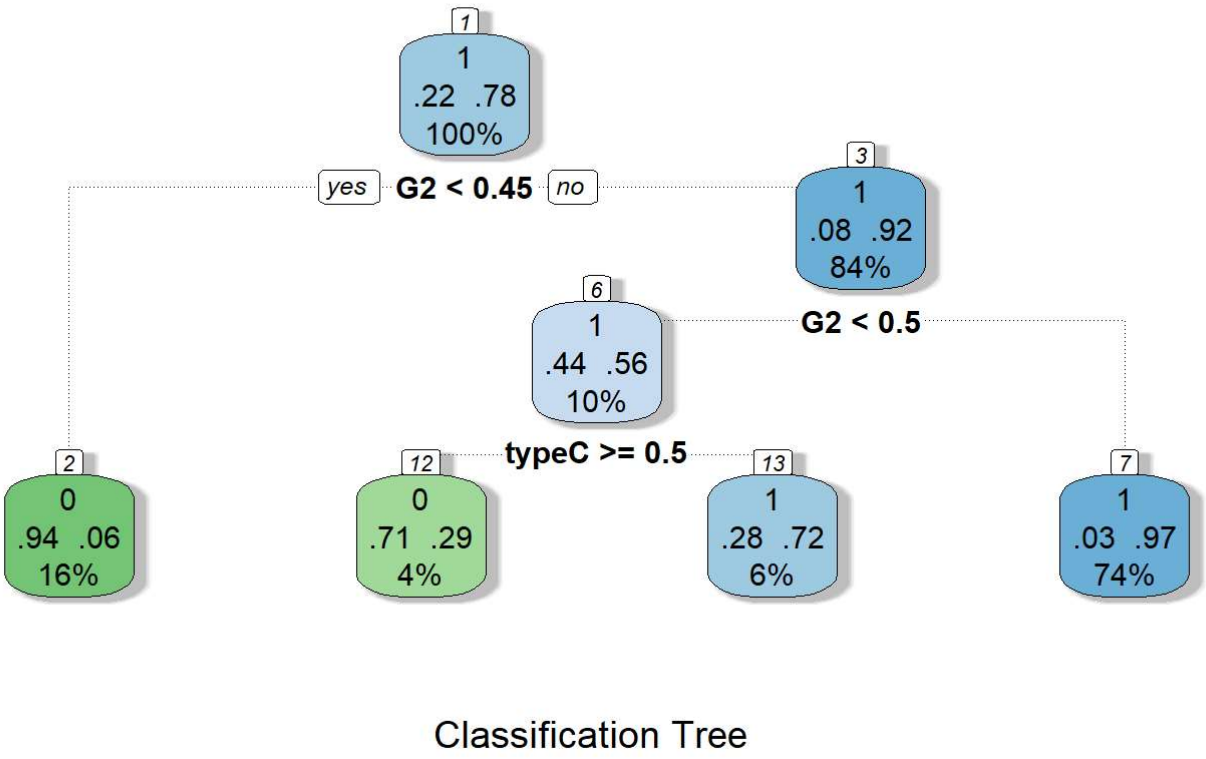
```
## [1] "Accuracy for tree A 0.929936305732484"
```

```
treeB <- rpart(FinalGradeR ~ ., data =train.setB, method = 'class', control = rpart.control(mins
plit = 30, minbucket = 10, cp = 0.001))
summary(treeB)
```

```
## Call:
## rpart(formula = FinalGradeR ~ ., data = train.setB, method = "class",
##     control = rpart.control(minsplit = 30, minbucket = 10, cp = 0.001))
##   n= 730
##
##           CP nsplit rel error    xerror       xstd
## 1 0.64968153      0 1.0000000 1.0000000 0.07070759
## 2 0.03821656      1 0.3503185 0.4394904 0.05034591
## 3 0.00100000      3 0.2738854 0.2738854 0.04051833
##
## Variable importance
##       G2       G1 failures    typeC
##       66       26        6        3
##
## Node number 1: 730 observations,    complexity param=0.6496815
##   predicted class=1  expected loss=0.2150685  P(node) =1
##     class counts:   157   573
##    probabilities: 0.215 0.785
##   left son=2 (116 obs) right son=3 (614 obs)
##   Primary splits:
##       G2       < 0.4473684 to the left,  improve=144.81820, (0 missing)
##       G1       < 0.4473684 to the left,  improve=120.53060, (0 missing)
##       failures < 0.1666667 to the right, improve= 25.71011, (0 missing)
##       typeC    < 0.5       to the right, improve= 11.66517, (0 missing)
##   Surrogate splits:
##       G1       < 0.4473684 to the left,  agree=0.911, adj=0.440, (0 split)
##       failures < 0.8333333 to the right, agree=0.858, adj=0.103, (0 split)
##
## Node number 2: 116 observations
##   predicted class=0  expected loss=0.06034483  P(node) =0.1589041
##     class counts:   109     7
##    probabilities: 0.940 0.060
##
## Node number 3: 614 observations,    complexity param=0.03821656
##   predicted class=1  expected loss=0.0781759  P(node) =0.8410959
##     class counts:    48   566
##    probabilities: 0.078 0.922
##   left son=6 (75 obs) right son=7 (539 obs)
##   Primary splits:
##       G2       < 0.5       to the left,  improve=22.369990, (0 missing)
##       G1       < 0.5526316 to the left,  improve=13.522330, (0 missing)
##       failures < 0.5       to the right, improve= 1.399248, (0 missing)
##       typeC    < 0.5       to the right, improve= 1.156212, (0 missing)
##   Surrogate splits:
##       G1 < 0.3947368 to the left,  agree=0.889, adj=0.093, (0 split)
##
## Node number 6: 75 observations,    complexity param=0.03821656
##   predicted class=1  expected loss=0.44  P(node) =0.1027397
##     class counts:    33    42
##    probabilities: 0.440 0.560
##   left son=12 (28 obs) right son=13 (47 obs)
##   Primary splits:
```

```
##       typeC    < 0.5       to the right, improve=6.72291800, (0 missing)
##       G1       < 0.3947368 to the left,  improve=2.00218400, (0 missing)
##       failures < 0.1666667 to the left,  improve=0.03505071, (0 missing)
##
## Node number 7: 539 observations
##   predicted class=1  expected loss=0.02782931  P(node) =0.7383562
##     class counts:    15   524
##    probabilities: 0.028 0.972
##
## Node number 12: 28 observations
##   predicted class=0  expected loss=0.2857143  P(node) =0.03835616
##     class counts:    20     8
##    probabilities: 0.714 0.286
##
## Node number 13: 47 observations
##   predicted class=1  expected loss=0.2765957  P(node) =0.06438356
##     class counts:    13    34
##    probabilities: 0.277 0.723
```

```
fancyRpartPlot(treeB, caption = "Classification Tree")
```



```
predictB <-predict(treeB, test.setB, type = 'class')

table_B<- table(test.setB$FinalGradeR, predictB)
table_B
```

```
##    predictB
##       0   1
##   0  59  14
##   1  16 225
```

```
accuracy_Test <- sum(diag(table_B)) / sum(table_B)
print(paste('Accuracy for tree B', accuracy_Test))
```

```
## [1] "Accuracy for tree B 0.904458598726115"
```

```
treeC <- rpart(FinalGradeR ~ ., data =train.setC, method = 'class', control = rpart.control(mins
plit = 10, minbucket = 10, cp = 0.001))

summary(treeC)
```

```
## Call:
## rpart(formula = FinalGradeR ~ ., data = train.setC, method = "class",
##     control = rpart.control(minsplit = 10, minbucket = 10, cp = 0.001))
##   n= 730
##
##            CP nsplit rel error   xerror       xstd
## 1 0.008130081      0 1.0000000 1.000000 0.06875826
## 2 0.006097561      6 0.9390244 1.085366 0.07074150
## 3 0.003810976      7 0.9329268 1.091463 0.07087565
## 4 0.001000000     15 0.9024390 1.115854 0.07140258
##
## Variable importance
##      typeC     school       paid       Medu       Fedu     famsup   internet
##         24         19         13         10          9          7          6
## traveltime activities    address
##          5          4          4
##
## Node number 1: 730 observations,    complexity param=0.008130081
##   predicted class=1  expected loss=0.2246575  P(node) =1
##     class counts:   164   566
##    probabilities: 0.225 0.775
##   left son=2 (278 obs) right son=3 (452 obs)
##   Primary splits:
##       typeC    < 0.5       to the right, improve=12.306760, (0 missing)
##       school   < 0.5       to the left,  improve= 3.020075, (0 missing)
##       Medu     < 0.875     to the left,  improve= 2.405894, (0 missing)
##       Fedu     < 0.375     to the left,  improve= 2.066714, (0 missing)
##       internet < 0.5       to the left,  improve= 1.372363, (0 missing)
##   Surrogate splits:
##       paid < 0.5       to the right, agree=0.748, adj=0.338, (0 split)
##
## Node number 2: 278 observations,    complexity param=0.008130081
##   predicted class=1  expected loss=0.3417266  P(node) =0.3808219
##     class counts:    95   183
##    probabilities: 0.342 0.658
##   left son=4 (152 obs) right son=5 (126 obs)
##   Primary splits:
##       paid       < 0.5       to the left,  improve=2.3816750, (0 missing)
##       Medu       < 0.375     to the left,  improve=1.4243150, (0 missing)
##       famsup     < 0.5       to the right, improve=0.8333849, (0 missing)
##       Fedu       < 0.375     to the left,  improve=0.6338959, (0 missing)
##       activities < 0.5       to the left,  improve=0.1875245, (0 missing)
##   Surrogate splits:
##       famsup < 0.5       to the left,  agree=0.622, adj=0.167, (0 split)
##       Medu   < 0.875     to the left,  agree=0.608, adj=0.135, (0 split)
##       Fedu   < 0.875     to the left,  agree=0.554, adj=0.016, (0 split)
##
## Node number 3: 452 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.1526549  P(node) =0.6191781
##     class counts:    69   383
##    probabilities: 0.153 0.847
##   left son=6 (153 obs) right son=7 (299 obs)
```

```
##   Primary splits:
##       school   < 0.5       to the left,  improve=9.257059, (0 missing)
##       Fedu     < 0.625     to the left,  improve=3.354053, (0 missing)
##       Medu     < 0.875     to the left,  improve=3.098157, (0 missing)
##       address  < 0.5       to the left,  improve=2.188422, (0 missing)
##       internet < 0.5       to the left,  improve=2.043080, (0 missing)
##   Surrogate splits:
##       address    < 0.5       to the left,  agree=0.732, adj=0.209, (0 split)
##       internet   < 0.5       to the left,  agree=0.695, adj=0.098, (0 split)
##       Medu       < 0.375     to the left,  agree=0.679, adj=0.052, (0 split)
##       traveltime < 0.5       to the right, agree=0.666, adj=0.013, (0 split)
##
## Node number 4: 152 observations,    complexity param=0.008130081
##   predicted class=1  expected loss=0.4013158  P(node) =0.2082192
##     class counts:    61    91
##    probabilities: 0.401 0.599
##   left son=8 (30 obs) right son=9 (122 obs)
##   Primary splits:
##       Medu     < 0.375     to the left,  improve=2.0438450, (0 missing)
##       famsup   < 0.5       to the right, improve=1.9579150, (0 missing)
##       Fedu     < 0.375     to the left,  improve=0.8399571, (0 missing)
##       internet < 0.5       to the left,  improve=0.4743396, (0 missing)
##       school   < 0.5       to the left,  improve=0.3482972, (0 missing)
##   Surrogate splits:
##       school < 0.5       to the left,  agree=0.816, adj=0.067, (0 split)
##
## Node number 5: 126 observations
##   predicted class=1  expected loss=0.2698413  P(node) =0.1726027
##     class counts:    34    92
##    probabilities: 0.270 0.730
##
## Node number 6: 153 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.2941176  P(node) =0.209589
##     class counts:    45   108
##    probabilities: 0.294 0.706
##   left son=12 (118 obs) right son=13 (35 obs)
##   Primary splits:
##       Fedu       < 0.625     to the left,  improve=2.9352230, (0 missing)
##       Medu       < 0.375     to the left,  improve=1.1557000, (0 missing)
##       paid       < 0.5       to the right, improve=0.9070341, (0 missing)
##       traveltime < 0.1666667 to the left,  improve=0.4022532, (0 missing)
##       internet   < 0.5       to the left,  improve=0.2794118, (0 missing)
##   Surrogate splits:
##       Medu < 0.875     to the left,  agree=0.804, adj=0.143, (0 split)
##
## Node number 7: 299 observations
##   predicted class=1  expected loss=0.08026756  P(node) =0.409589
##     class counts:    24   275
##    probabilities: 0.080 0.920
##
## Node number 8: 30 observations,    complexity param=0.006097561
##   predicted class=0  expected loss=0.4333333  P(node) =0.04109589
```

```
##     class counts:    17    13
##    probabilities: 0.567 0.433
##   left son=16 (13 obs) right son=17 (17 obs)
##   Primary splits:
##       activities < 0.5       to the right, improve=0.72428360, (0 missing)
##       famsup     < 0.5       to the right, improve=0.16874000, (0 missing)
##       Fedu       < 0.375     to the left,  improve=0.13333330, (0 missing)
##       traveltime < 0.1666667 to the left,  improve=0.03650075, (0 missing)
##       internet   < 0.5       to the left,  improve=0.03333333, (0 missing)
##   Surrogate splits:
##       famsup     < 0.5       to the right, agree=0.733, adj=0.385, (0 split)
##       school     < 0.5       to the right, agree=0.667, adj=0.231, (0 split)
##       address    < 0.5       to the right, agree=0.667, adj=0.231, (0 split)
##       traveltime < 0.5       to the right, agree=0.600, adj=0.077, (0 split)
##
## Node number 9: 122 observations,    complexity param=0.008130081
##   predicted class=1  expected loss=0.3606557  P(node) =0.1671233
##     class counts:    44    78
##    probabilities: 0.361 0.639
##   left son=18 (66 obs) right son=19 (56 obs)
##   Primary splits:
##       famsup     < 0.5       to the right, improve=2.5350220, (0 missing)
##       traveltime < 0.5       to the left,  improve=1.0016890, (0 missing)
##       Fedu       < 0.625     to the left,  improve=0.3100563, (0 missing)
##       internet   < 0.5       to the left,  improve=0.2574874, (0 missing)
##       Medu       < 0.875     to the left,  improve=0.2221948, (0 missing)
##   Surrogate splits:
##       school   < 0.5       to the right, agree=0.598, adj=0.125, (0 split)
##       Fedu     < 0.375     to the right, agree=0.598, adj=0.125, (0 split)
##       Medu     < 0.875     to the right, agree=0.590, adj=0.107, (0 split)
##       internet < 0.5       to the right, agree=0.557, adj=0.036, (0 split)
##
## Node number 12: 118 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.3474576  P(node) =0.1616438
##     class counts:    41    77
##    probabilities: 0.347 0.653
##   left son=24 (59 obs) right son=25 (59 obs)
##   Primary splits:
##       Fedu       < 0.375     to the left,  improve=0.8305085, (0 missing)
##       activities < 0.5       to the right, improve=0.3589282, (0 missing)
##       traveltime < 0.5       to the left,  improve=0.3020352, (0 missing)
##       address    < 0.5       to the left,  improve=0.1308275, (0 missing)
##       Medu       < 0.375     to the left,  improve=0.1130985, (0 missing)
##   Surrogate splits:
##       Medu       < 0.375     to the left,  agree=0.712, adj=0.424, (0 split)
##       internet   < 0.5       to the right, agree=0.585, adj=0.169, (0 split)
##       activities < 0.5       to the right, agree=0.542, adj=0.085, (0 split)
##       traveltime < 0.1666667 to the right, agree=0.534, adj=0.068, (0 split)
##       paid       < 0.5       to the left,  agree=0.525, adj=0.051, (0 split)
##
## Node number 13: 35 observations
##   predicted class=1  expected loss=0.1142857  P(node) =0.04794521
```

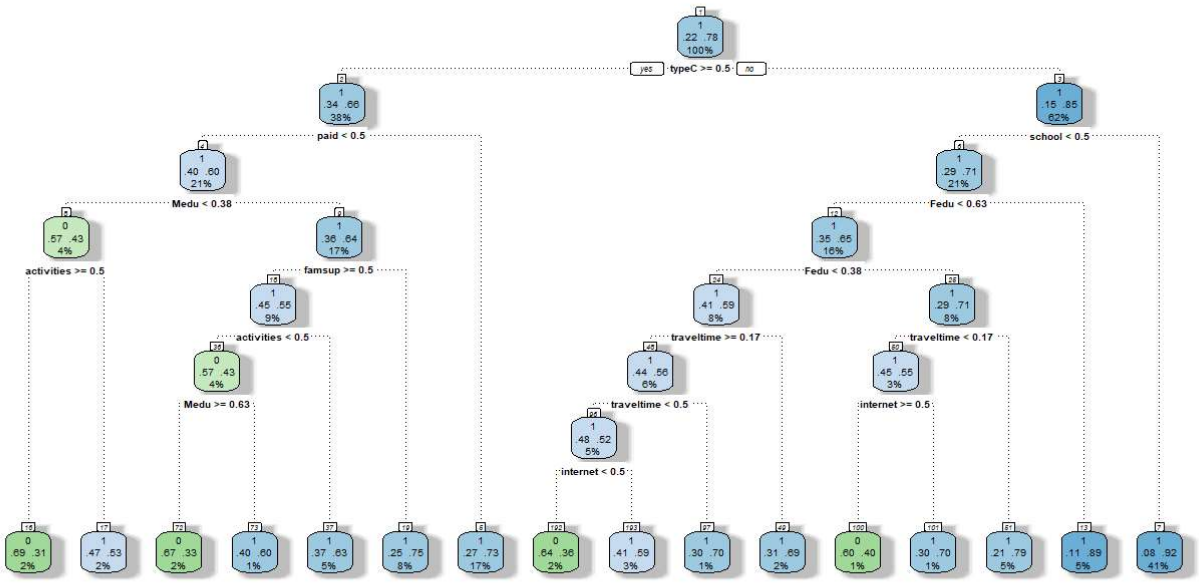
```
##     class counts:     4    31
##    probabilities: 0.114 0.886
##
## Node number 16: 13 observations
##   predicted class=0  expected loss=0.3076923  P(node) =0.01780822
##     class counts:     9     4
##    probabilities: 0.692 0.308
##
## Node number 17: 17 observations
##   predicted class=1  expected loss=0.4705882  P(node) =0.02328767
##     class counts:     8     9
##    probabilities: 0.471 0.529
##
## Node number 18: 66 observations,    complexity param=0.008130081
##   predicted class=1  expected loss=0.4545455  P(node) =0.09041096
##     class counts:    30    36
##    probabilities: 0.455 0.545
##   left son=36 (28 obs) right son=37 (38 obs)
##   Primary splits:
##       activities < 0.5       to the left,  improve=1.3287760, (0 missing)
##       Medu       < 0.875     to the left,  improve=0.6475006, (0 missing)
##       internet   < 0.5       to the left,  improve=0.4865320, (0 missing)
##       Fedu       < 0.625     to the left,  improve=0.3448337, (0 missing)
##       traveltime < 0.1666667 to the left,  improve=0.3336219, (0 missing)
##   Surrogate splits:
##       internet < 0.5       to the left,  agree=0.606, adj=0.071, (0 split)
##       Medu     < 0.625     to the left,  agree=0.591, adj=0.036, (0 split)
##       Fedu     < 0.375     to the left,  agree=0.591, adj=0.036, (0 split)
##
## Node number 19: 56 observations
##   predicted class=1  expected loss=0.25  P(node) =0.07671233
##     class counts:    14    42
##    probabilities: 0.250 0.750
##
## Node number 24: 59 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.4067797  P(node) =0.08082192
##     class counts:    24    35
##    probabilities: 0.407 0.593
##   left son=48 (43 obs) right son=49 (16 obs)
##   Primary splits:
##       traveltime < 0.1666667 to the right, improve=0.39027390, (0 missing)
##       internet   < 0.5       to the left,  improve=0.31417530, (0 missing)
##       Medu       < 0.625     to the left,  improve=0.27457630, (0 missing)
##       famsup     < 0.5       to the right, improve=0.13198370, (0 missing)
##       address    < 0.5       to the left,  improve=0.08171913, (0 missing)
##   Surrogate splits:
##       Medu < 0.875     to the left,  agree=0.78, adj=0.188, (0 split)
##
## Node number 25: 59 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.2881356  P(node) =0.08082192
##     class counts:    17    42
##    probabilities: 0.288 0.712
```

```
##   left son=50 (20 obs) right son=51 (39 obs)
##   Primary splits:
##       traveltime < 0.1666667 to the left,  improve=1.58544100, (0 missing)
##       activities < 0.5       to the right, improve=0.80242360, (0 missing)
##       Medu       < 0.625     to the right, improve=0.50338980, (0 missing)
##       internet   < 0.5       to the right, improve=0.11813640, (0 missing)
##       famsup     < 0.5       to the left,  improve=0.03555766, (0 missing)
##   Surrogate splits:
##       paid < 0.5       to the right, agree=0.678, adj=0.05, (0 split)
##
## Node number 36: 28 observations,    complexity param=0.008130081
##   predicted class=0  expected loss=0.4285714  P(node) =0.03835616
##     class counts:    16    12
##    probabilities: 0.571 0.429
##   left son=72 (18 obs) right son=73 (10 obs)
##   Primary splits:
##       Medu < 0.625     to the right, improve=0.91428570, (0 missing)
##       Fedu < 0.625     to the right, improve=0.05274725, (0 missing)
##   Surrogate splits:
##       Fedu < 0.625     to the right, agree=0.75, adj=0.3, (0 split)
##
## Node number 37: 38 observations
##   predicted class=1  expected loss=0.3684211  P(node) =0.05205479
##     class counts:    14    24
##    probabilities: 0.368 0.632
##
## Node number 48: 43 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.4418605  P(node) =0.05890411
##     class counts:    19    24
##    probabilities: 0.442 0.558
##   left son=96 (33 obs) right son=97 (10 obs)
##   Primary splits:
##       traveltime < 0.5       to the left,  improve=0.52445380, (0 missing)
##       internet   < 0.5       to the left,  improve=0.43102180, (0 missing)
##       famsup     < 0.5       to the right, improve=0.01449713, (0 missing)
##       activities < 0.5       to the left,  improve=0.01449713, (0 missing)
##       Medu       < 0.375     to the right, improve=0.01443053, (0 missing)
##
## Node number 49: 16 observations
##   predicted class=1  expected loss=0.3125  P(node) =0.02191781
##     class counts:     5    11
##    probabilities: 0.312 0.688
##
## Node number 50: 20 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.45  P(node) =0.02739726
##     class counts:     9    11
##    probabilities: 0.450 0.550
##   left son=100 (10 obs) right son=101 (10 obs)
##   Primary splits:
##       internet < 0.5       to the right, improve=0.9, (0 missing)
##       famsup   < 0.5       to the right, improve=0.1, (0 missing)
##   Surrogate splits:
```

```
##       Medu       < 0.375     to the left,  agree=0.65, adj=0.3, (0 split)
##       famsup     < 0.5       to the left,  agree=0.60, adj=0.2, (0 split)
##       paid       < 0.5       to the right, agree=0.55, adj=0.1, (0 split)
##       activities < 0.5       to the right, agree=0.55, adj=0.1, (0 split)
##
## Node number 51: 39 observations
##   predicted class=1  expected loss=0.2051282  P(node) =0.05342466
##     class counts:     8    31
##    probabilities: 0.205 0.795
##
## Node number 72: 18 observations
##   predicted class=0  expected loss=0.3333333  P(node) =0.02465753
##     class counts:    12     6
##    probabilities: 0.667 0.333
##
## Node number 73: 10 observations
##   predicted class=1  expected loss=0.4  P(node) =0.01369863
##     class counts:     4     6
##    probabilities: 0.400 0.600
##
## Node number 96: 33 observations,    complexity param=0.003810976
##   predicted class=1  expected loss=0.4848485  P(node) =0.04520548
##     class counts:    16    17
##    probabilities: 0.485 0.515
##   left son=192 (11 obs) right son=193 (22 obs)
##   Primary splits:
##       internet   < 0.5       to the left,  improve=0.757575800, (0 missing)
##       activities < 0.5       to the left,  improve=0.729292900, (0 missing)
##       address    < 0.5       to the left,  improve=0.431002300, (0 missing)
##       famsup     < 0.5       to the right, improve=0.129292900, (0 missing)
##       Medu       < 0.375     to the right, improve=0.008658009, (0 missing)
##
## Node number 97: 10 observations
##   predicted class=1  expected loss=0.3  P(node) =0.01369863
##     class counts:     3     7
##    probabilities: 0.300 0.700
##
## Node number 100: 10 observations
##   predicted class=0  expected loss=0.4  P(node) =0.01369863
##     class counts:     6     4
##    probabilities: 0.600 0.400
##
## Node number 101: 10 observations
##   predicted class=1  expected loss=0.3  P(node) =0.01369863
##     class counts:     3     7
##    probabilities: 0.300 0.700
##
## Node number 192: 11 observations
##   predicted class=0  expected loss=0.3636364  P(node) =0.01506849
##     class counts:     7     4
##    probabilities: 0.636 0.364
##
```

```
## Node number 193: 22 observations
##   predicted class=1  expected loss=0.4090909  P(node) =0.03013699
##     class counts:     9    13
##    probabilities: 0.409 0.591
```

```
fancyRpartPlot(treeC, caption = "Classification Tree")
```



Classification Tree

```
predictC <-predict(treeC, test.setC, type = 'class')

table_C<- table(test.setC$FinalGradeR, predictC)
table_C
```

```
##    predictC
##       0   1
##   0  12  54
##   1  13 235
```

```
accuracy_Test <- sum(diag(table_C)) / sum(table_C)
print(paste('Accuracy for tree C', accuracy_Test))
```

```
## [1] "Accuracy for tree C 0.786624203821656"
```

```
# buid kNN model

target_category <- train.setA[,30]
test_category <- test.setA[,30]
test.setA <- test.setA[,1:30]


knnmodel <- knn(train.setA, test.setA, cl=target_category, k = 10)
tab <- table(knnmodel,test_category)
accuracy <- function(x){sum(diag(x)/(sum(rowSums(x)))) * 100}
accuracy(tab)
```

```
## [1] 96.17834
```

```
confusionMatrix(table(knnmodel ,test_category))
```

```
## Confusion Matrix and Statistics
##
##         test_category
## knnmodel   0   1
##        0  54   0
##        1  12 248
##
##                Accuracy : 0.9618
##                  95% CI : (0.9342, 0.9801)
##     No Information Rate : 0.7898
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.8767
##
##  Mcnemar's Test P-Value : 0.001496
##
##             Sensitivity : 0.8182
##             Specificity : 1.0000
##          Pos Pred Value : 1.0000
##          Neg Pred Value : 0.9538
##              Prevalence : 0.2102
##          Detection Rate : 0.1720
##    Detection Prevalence : 0.1720
##       Balanced Accuracy : 0.9091
##
##        'Positive' Class : 0
##
```

```
target_category <- train.setB[,5]
test_category <- test.setB[,5]
test.setB <- test.setB[,1:5]

knnmodelB <- knn(train.setB, test.setB, cl=target_category, k = 10)
tab <- table(knnmodelB,test_category)
accuracy <- function(x){sum(diag(x)/(sum(rowSums(x)))) * 100}
accuracy(tab)
```

```
## [1] 100
```

```
confusionMatrix(table(knnmodelB ,test_category))
```

```
## Confusion Matrix and Statistics
##
##          test_category
## knnmodelB   0   1
##         0  73   0
##         1   0 241
##
##                Accuracy : 1
##                  95% CI : (0.9883, 1)
##     No Information Rate : 0.7675
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##
##  Mcnemar's Test P-Value : NA
##
##             Sensitivity : 1.0000
##             Specificity : 1.0000
##          Pos Pred Value : 1.0000
##          Neg Pred Value : 1.0000
##              Prevalence : 0.2325
##          Detection Rate : 0.2325
##    Detection Prevalence : 0.2325
##       Balanced Accuracy : 1.0000
##
##        'Positive' Class : 0
##
```

```
target_category <- train.setC[,11]
test_category <- test.setC[,11]
test.setC <- test.setC[,1:11]

knnmodelC <- knn(train.setC, test.setC, cl=target_category, k = 10)
tab <- table(knnmodelC,test_category)
accuracy <- function(x){sum(diag(x)/(sum(rowSums(x)))) * 100}
accuracy(tab)
```

```
## [1] 98.40764
```

```
confusionMatrix(table(knnmodelC ,test_category))
```

```
## Confusion Matrix and Statistics
##
##          test_category
## knnmodelC   0   1
##         0  61   0
##         1   5 248
##
##                Accuracy : 0.9841
##                  95% CI : (0.9632, 0.9948)
##     No Information Rate : 0.7898
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.9507
##
##  Mcnemar's Test P-Value : 0.07364
##
##             Sensitivity : 0.9242
##             Specificity : 1.0000
##          Pos Pred Value : 1.0000
##          Neg Pred Value : 0.9802
##              Prevalence : 0.2102
##          Detection Rate : 0.1943
##    Detection Prevalence : 0.1943
##       Balanced Accuracy : 0.9621
##
##        'Positive' Class : 0
##
```