Project2

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Importing in R

```
Student.mat<-read.table('~/Desktop/Shipwreck/student-mat.csv',sep = ",")
student.mat<-read.csv('~/Desktop/Shipwreck/student-mat.csv',sep = ",")
head(Student.mat)
```

```
##       V1  V2  V3      V4      V5      V6   V7   V8      V9      V10    V11
## 1 school sex age address famsize Pstatus Medu Fedu    Mjob     Fjob reason
## 2     GP   F  18       U     GT3       A    4    4 at_home  teacher course
## 3     GP   F  17       U     GT3       T    1    1 at_home    other course
## 4     GP   F  15       U     LE3       T    1    1 at_home    other  other
## 5     GP   F  15       U     GT3       T    4    2  health services   home
## 6     GP   F  16       U     GT3       T    3    3   other    other   home
##        V12        V13       V14      V15       V16     V17  V18        V19
## 1 guardian traveltime studytime failures schoolsup famsup paid activities
## 2   mother          2         2        0       yes      no   no         no
## 3   father          1         2        0        no     yes   no         no
## 4   mother          1         2        3       yes      no  yes         no
## 5   mother          1         3        0        no     yes  yes        yes
## 6   father          1         2        0        no     yes  yes         no
##       V20    V21      V22      V23    V24      V25    V26  V27  V28    V29
## 1 nursery higher internet romantic famrel freetime goout Dalc Walc health
## 2     yes    yes       no       no      4        3     4    1    1      3
## 3      no    yes      yes       no      5        3     3    1    1      3
## 4     yes    yes      yes       no      4        3     2    2    3      3
## 5     yes    yes      yes      yes      3        2     2    1    1      5
## 6     yes    yes       no       no      4        3     2    1    2      5
##        V30 V31 V32 V33
## 1 absences  G1  G2  G3
## 2        6   5   6   6
## 3        4   5   5   6
## 4       10   7   8  10
## 5        2  15  14  15
## 6        4   6  10  10
```

Q1. Investigation into G3

Goal:-Predict students ability to pass and their grades based on certain variables and find which variable(s) is the best predictor.Dataset used is student-mat.csv

Student dataset has G3 variable which is used for classifying Pass/Fail and for actegorising student's grades into Fail,Sufficient,Satisfactory,Good and Excellent.These classifications will be predicted based on some independent variables.

Predictors are:- 1. ParentStatus(living together or not) 2. Mother??? s education(factors:- none, upto 4th grade, upto 9th grade, secondary education and higher education) 3. Travel time to school 4. Romantic status of the student 5. G1 - score from test1 6. G2 - score from test2

Different methods used for prediction :- 1. Linear regression 2. Decision Tree 3. Naive Bayes Method

1. Linear regression is used on variables G1 and G2 individually to predict G3
2. Decision tree is used on variables G1 and G2 together to predict pass-ability and Grades
3. Naive Bayes method is used on categorical variables - ParentStatus, MotherEducation, TravelTime and Romantic Status to predict pass-ability and grades.

1. Load students data

```
students<-read.table('~/Desktop/Shipwreck/student-mat.csv',header = TRUE,sep = ",")
```

2. Extract necessary columns for analysis

```
students<- students[,c(6,7,13,23,31,32,33)]
```

3. Calculate pass or fail variable and store it in variable Pass

```
Pass <- ifelse(students$G3>9,'PASS','FAIL')
students <- data.frame(students,Pass)
```

4. Calculate Grade variable

```
Grade <- ifelse(students$G3<=9,'FAIL','PASS')
Grade <- ifelse(students$G3>=10 & students$G3<=11,'Sufficient',Grade)
Grade <- ifelse(students$G3>=12 & students$G3<=13,'Satisfactory',Grade)
Grade <- ifelse(students$G3>=14 & students$G3<=15,'Good',Grade)
Grade <- ifelse(students$G3>=16 & students$G3<=20,'Excellent',Grade)
students <- data.frame(students,Grade)
```

5. Exploration of data

Dimensions

```
dim(students)
```

```
## [1] 395   9
```

Number of rows in data

```r
nrow(students)
```

```
## [1] 395
```

Number of columns

```r
ncol(students)
```

```
## [1] 9
```

Structure

```r
str(students)
```

```
## 'data.frame':    395 obs. of  9 variables:
##  $ 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 ...
##  $ traveltime: int  2 1 1 1 1 1 1 2 1 1 ...
##  $ romantic  : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 1 1 ...
##  $ 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 ...
##  $ Pass      : Factor w/ 2 levels "FAIL","PASS": 1 1 2 2 2 2 2 1 2 2 ...
##  $ Grade     : Factor w/ 5 levels "Excellent","FAIL",..: 2 2 5 3 5 3 5 2 1 3 ...
```

Variable or column names

```r
names(students)
```

```
## [1] "Pstatus"    "Medu"       "traveltime" "romantic"   "G1"
## [6] "G2"         "G3"         "Pass"       "Grade"
```

Attributes

```r
attributes(students)
```

```
## $names
## [1] "Pstatus"    "Medu"       "traveltime" "romantic"   "G1"
## [6] "G2"         "G3"         "Pass"       "Grade"
##
## $row.names
##   [1]   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
##  [18]  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34
##  [35]  35  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51
##  [52]  52  53  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68
##  [69]  69  70  71  72  73  74  75  76  77  78  79  80  81  82  83  84  85
```

```
##  [86]  86  87  88  89  90  91  92  93  94  95  96  97  98  99 100 101 102
## [103] 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119
## [120] 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136
## [137] 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153
## [154] 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170
## [171] 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187
## [188] 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204
## [205] 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221
## [222] 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238
## [239] 239 240 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255
## [256] 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272
## [273] 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287 288 289
## [290] 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306
## [307] 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323
## [324] 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340
## [341] 341 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357
## [358] 358 359 360 361 362 363 364 365 366 367 368 369 370 371 372 373 374
## [375] 375 376 377 378 379 380 381 382 383 384 385 386 387 388 389 390 391
## [392] 392 393 394 395
##
## $class
## [1] "data.frame"
```

Top 10 rows

```r
head(students,n=10)
```

```
##    Pstatus Medu traveltime romantic G1 G2 G3 Pass      Grade
## 1        A    4          2       no  5  6  6 FAIL       FAIL
## 2        T    1          1       no  5  5  6 FAIL       FAIL
## 3        T    1          1       no  7  8 10 PASS Sufficient
## 4        T    4          1      yes 15 14 15 PASS       Good
## 5        T    3          1       no  6 10 10 PASS Sufficient
## 6        T    4          1       no 15 15 15 PASS       Good
## 7        T    2          1       no 12 12 11 PASS Sufficient
## 8        A    4          2       no  6  5  6 FAIL       FAIL
## 9        A    3          1       no 16 18 19 PASS  Excellent
## 10       T    3          1       no 14 15 15 PASS       Good
```

Variable distribution before factorisation

```r
summary(students)
```

```
##  Pstatus      Medu         traveltime    romantic        G1
##  A: 41   Min.   :0.000   Min.   :1.000   no :263   Min.   : 3.00
##  T:354   1st Qu.:2.000   1st Qu.:1.000   yes:132   1st Qu.: 8.00
##          Median :3.000   Median :1.000             Median :11.00
##          Mean   :2.749   Mean   :1.448             Mean   :10.91
##          3rd Qu.:4.000   3rd Qu.:2.000             3rd Qu.:13.00
##          Max.   :4.000   Max.   :4.000             Max.   :19.00
##        G2              G3           Pass              Grade
##  Min.   : 0.00   Min.   : 0.00   FAIL:130   Excellent   : 40
```

```
## 1st Qu.: 9.00   1st Qu.: 8.00   PASS:265   FAIL        :130
## Median :11.00   Median :11.00              Good        : 60
## Mean   :10.71   Mean   :10.42              Satisfactory: 62
## 3rd Qu.:13.00   3rd Qu.:14.00              Sufficient  :103
## Max.   :19.00   Max.   :20.00
```

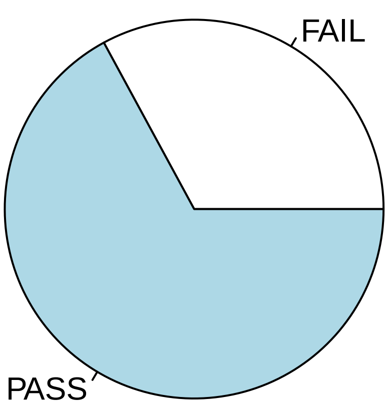
Factorize continuous predictor variables

Variable distribution after necessary factorisation

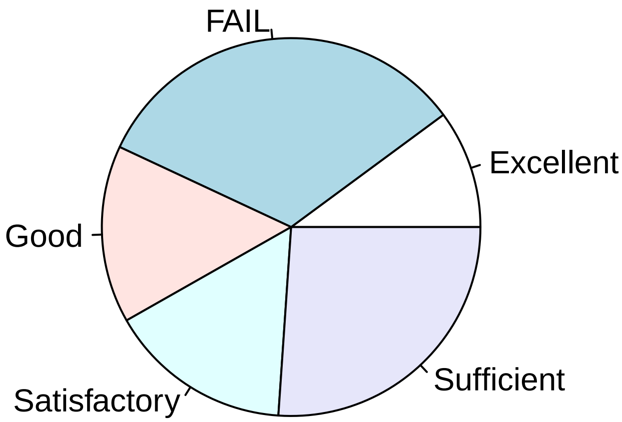
```
students$Medu <- factor(students$Medu)
students$traveltime <- factor(students$traveltime)
summary(students)
```

```
## Pstatus Medu    traveltime romantic       G1              G2
## A: 41   0:  3   1:257      no :263   Min.   : 3.00   Min.   : 0.00
## T:354   1: 59   2:107      yes:132   1st Qu.: 8.00   1st Qu.: 9.00
##         2:103   3: 23                Median :11.00   Median :11.00
##         3: 99   4:  8                Mean   :10.91   Mean   :10.71
##         4:131                        3rd Qu.:13.00   3rd Qu.:13.00
##                                      Max.   :19.00   Max.   :19.00
##       G3          Pass              Grade
## Min.   : 0.00   FAIL:130   Excellent   : 40
## 1st Qu.: 8.00   PASS:265   FAIL        :130
## Median :11.00              Good        : 60
## Mean   :10.42              Satisfactory: 62
## 3rd Qu.:14.00              Sufficient  :103
## Max.   :20.00
```

Pie chart for pass

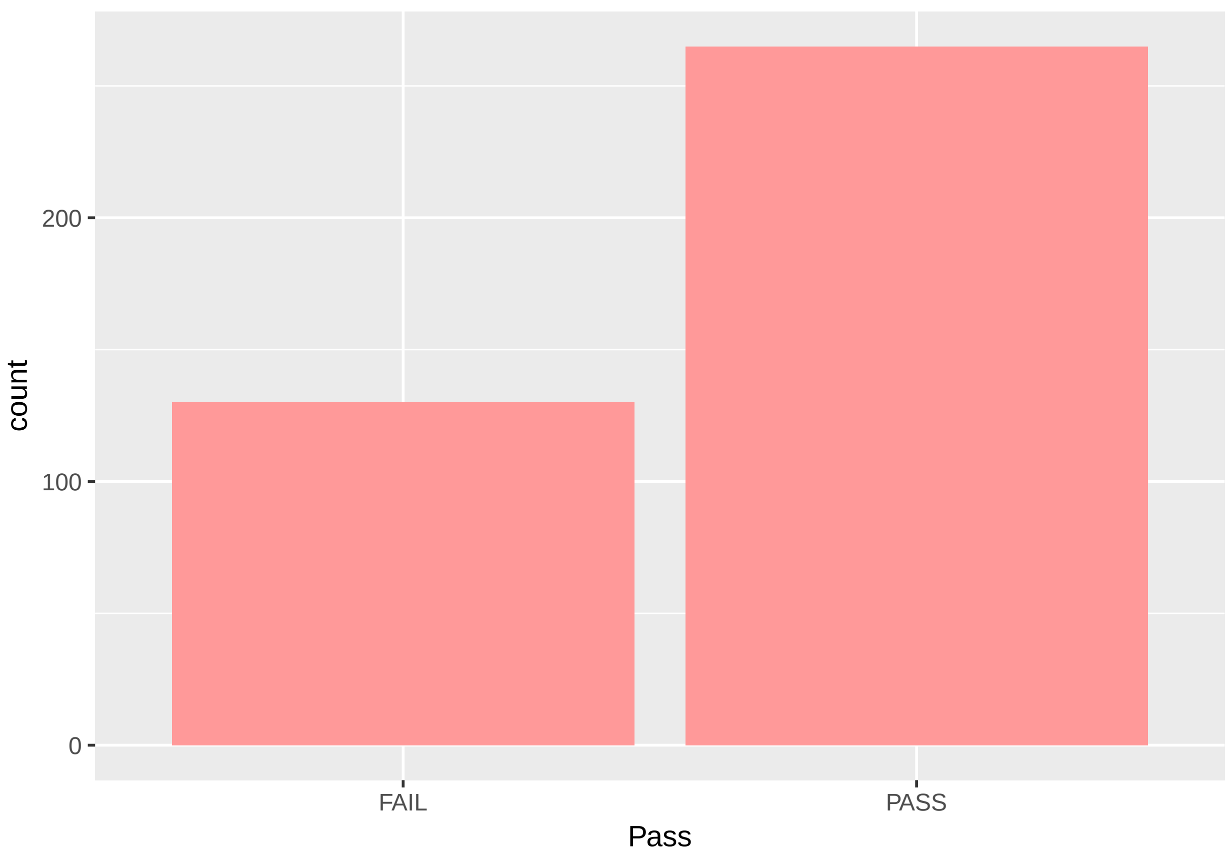


Pie chart for grade

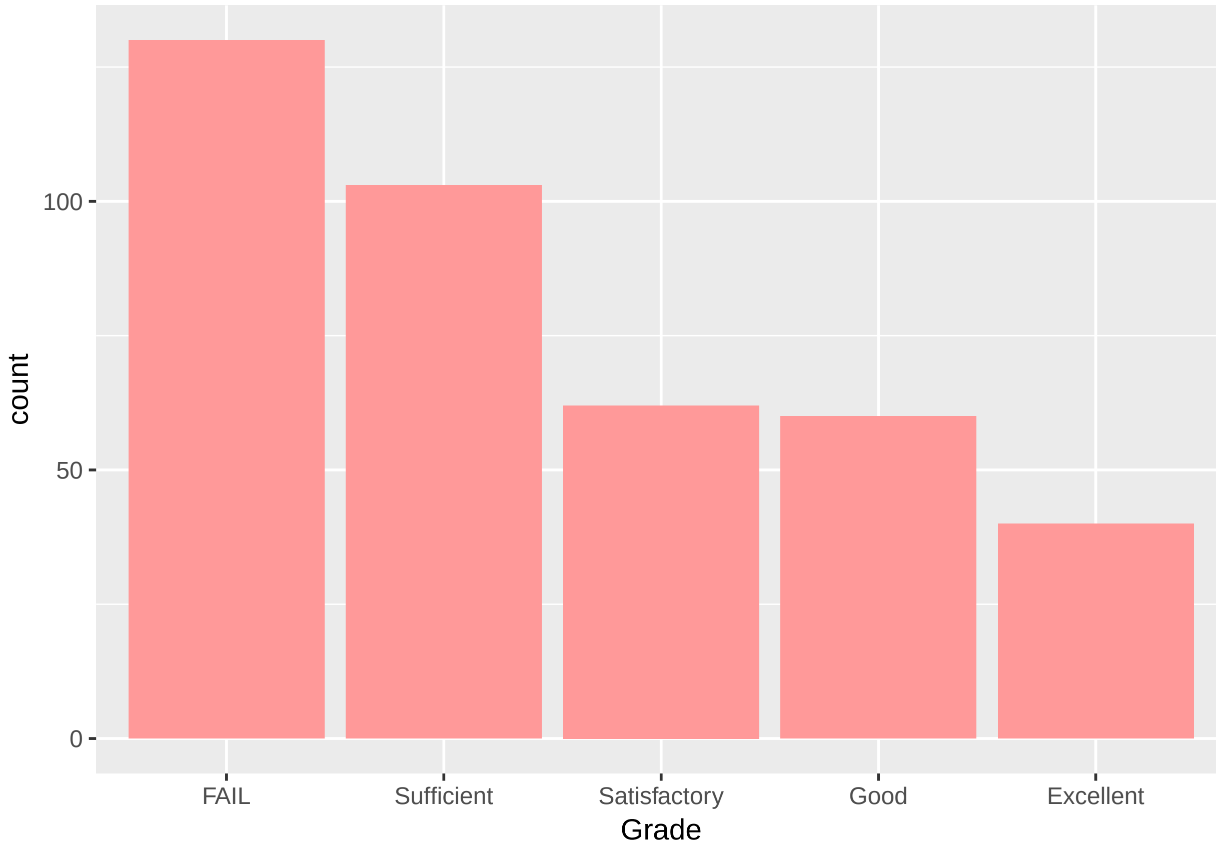


Bar graph for pass

```
## Warning: package 'ggplot2' was built under R version 3.3.2
```



Bar graph for grade



Statistical data of G3

```r
summary(with(students,G3))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    8.00   11.00   10.42   14.00   20.00
```

```r
sprintf('variance is %f',var(with(students,G3)))
```

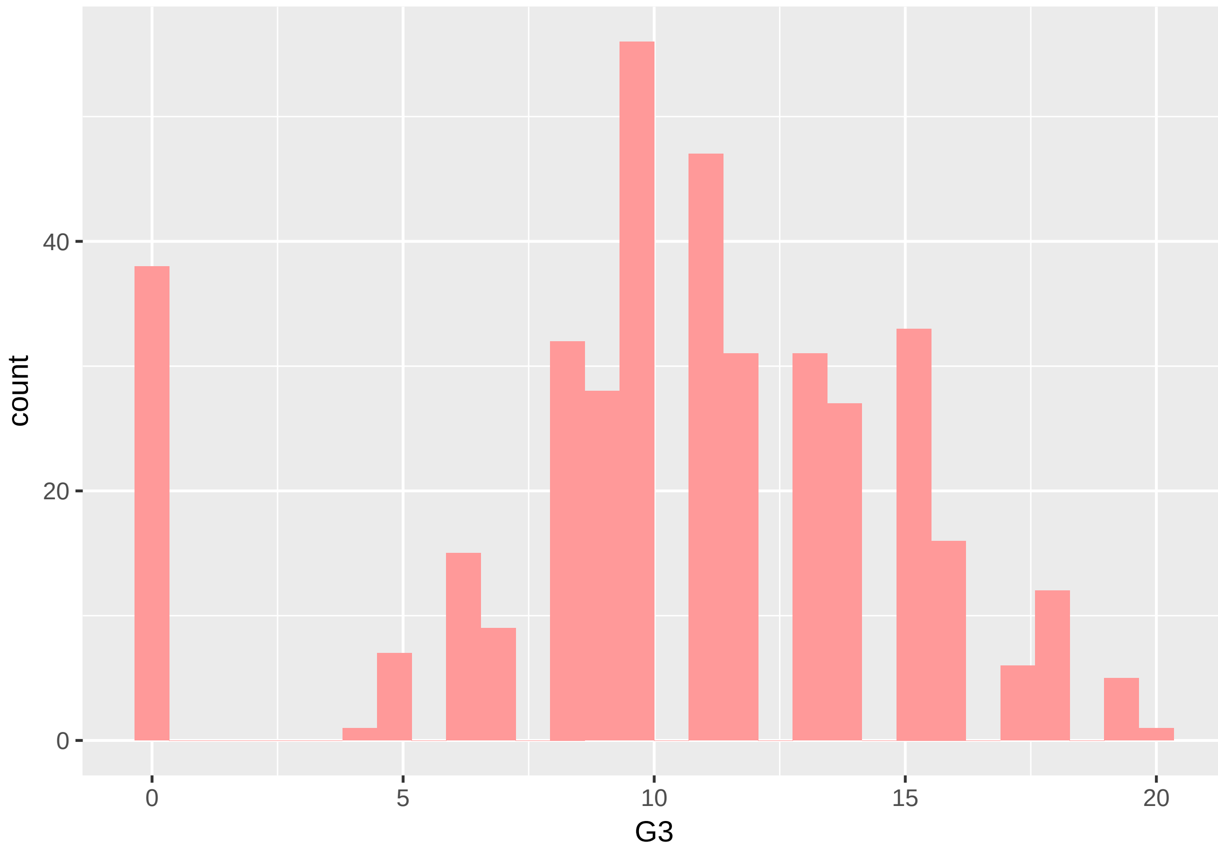
```
## [1] "variance is 20.989616"
```

```r
sprintf('standard deviation is %f',sd(with(students,G3)))
```

```
## [1] "standard deviation is 4.581443"
```

Histogram for G3

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



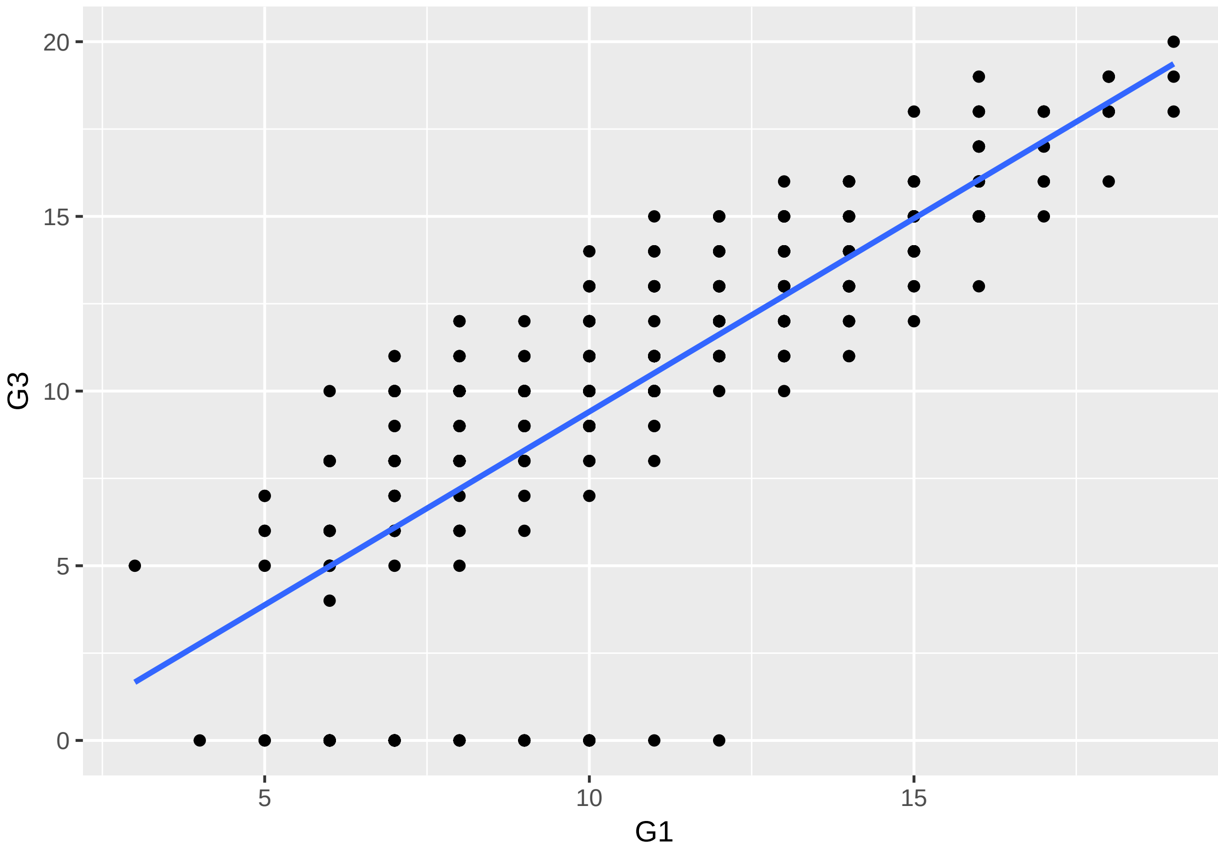
Predicting G3 using G1

Correlation between G1 and G3

```
r <- cor(with(students,G1), with(students,G3))
sprintf("G3 shows a positive correllation with G1")
```

```
## [1] "G3 shows a positive correllation with G1"
```

Scatterplot of G1, G3



Fit linear regression using G1 as predictor to predict G3

```
fit <- with(students,lm(G3 ~ G1))
fit
```

```
##
## Call:
## lm(formula = G3 ~ G1)
##
## Coefficients:
## (Intercept)           G1
##      -1.653        1.106
```

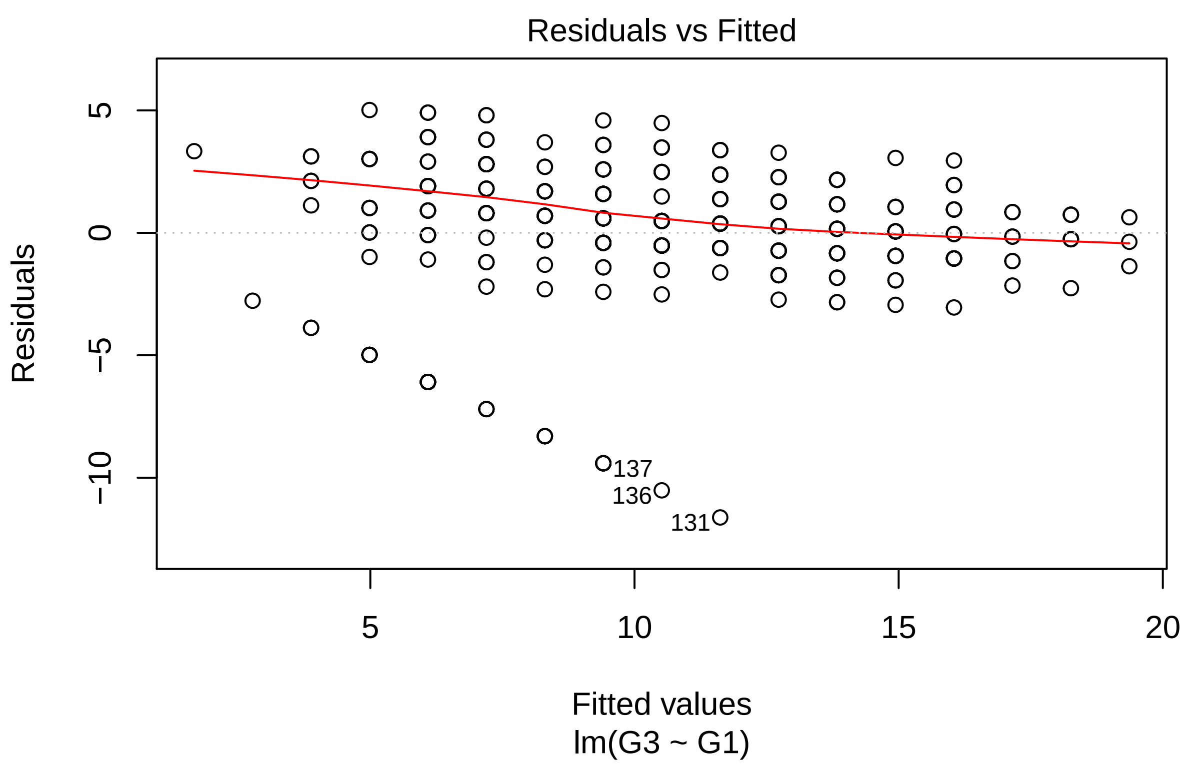
```
attributes(fit)
```

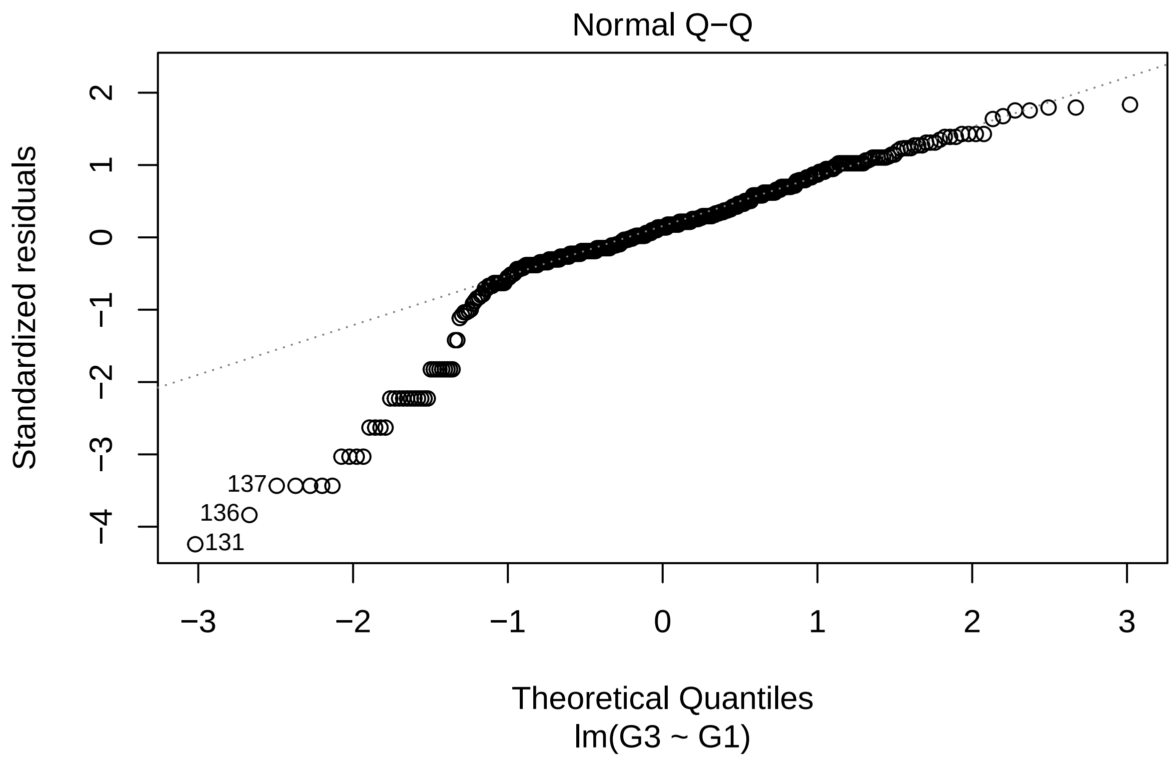
```
## $names
##  [1] "coefficients"  "residuals"     "effects"       "rank"
##  [5] "fitted.values" "assign"        "qr"            "df.residual"
##  [9] "xlevels"       "call"          "terms"         "model"
##
## $class
## [1] "lm"
```

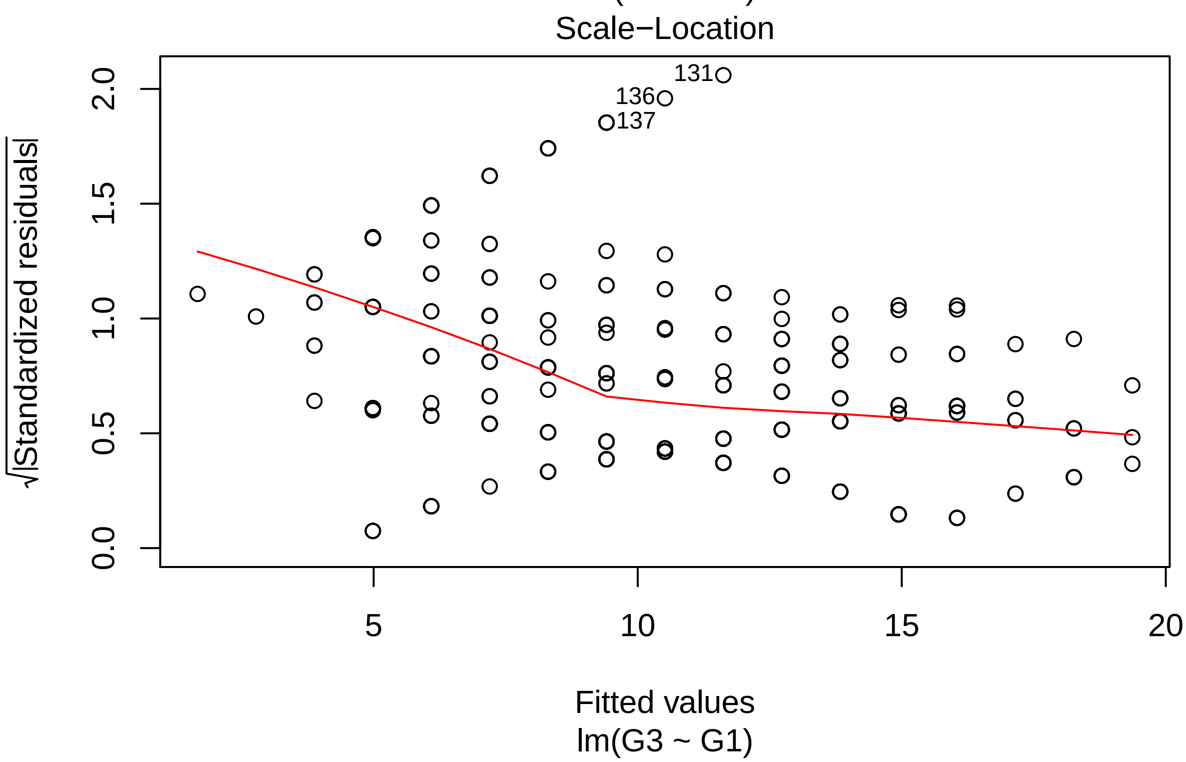
```
summary(fit)
```

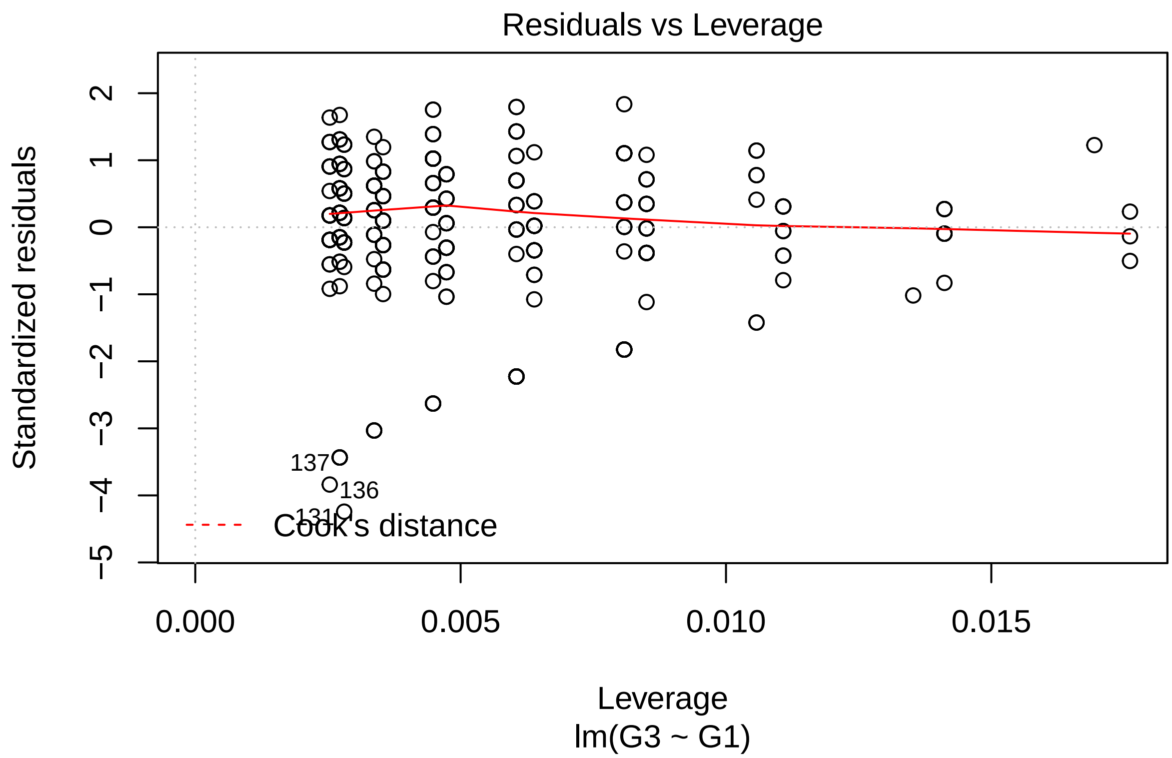
```
##
## Call:
## lm(formula = G3 ~ G1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.6223  -0.8348   0.3777   1.6965   5.0153
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.65280    0.47475  -3.481 0.000555 ***
## G1           1.10626    0.04164  26.568  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.743 on 393 degrees of freedom
## Multiple R-squared:  0.6424, Adjusted R-squared:  0.6414
## F-statistic: 705.8 on 1 and 393 DF,  p-value: < 2.2e-16
```

Plotting line of best fit




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(G3 ~ G1)
137
136
131
−4
−3
−2
−1
0
1
2
3


Scale−Location
√|Standardized residuals|
Fitted values
lm(G3 ~ G1)
131
136
137
0.0
0.5
1.0
1.5
2.0
5
10
15
20




```
## [1] "Residual graph is random in nature suggesting linear regression is not a bad choice for this da
```

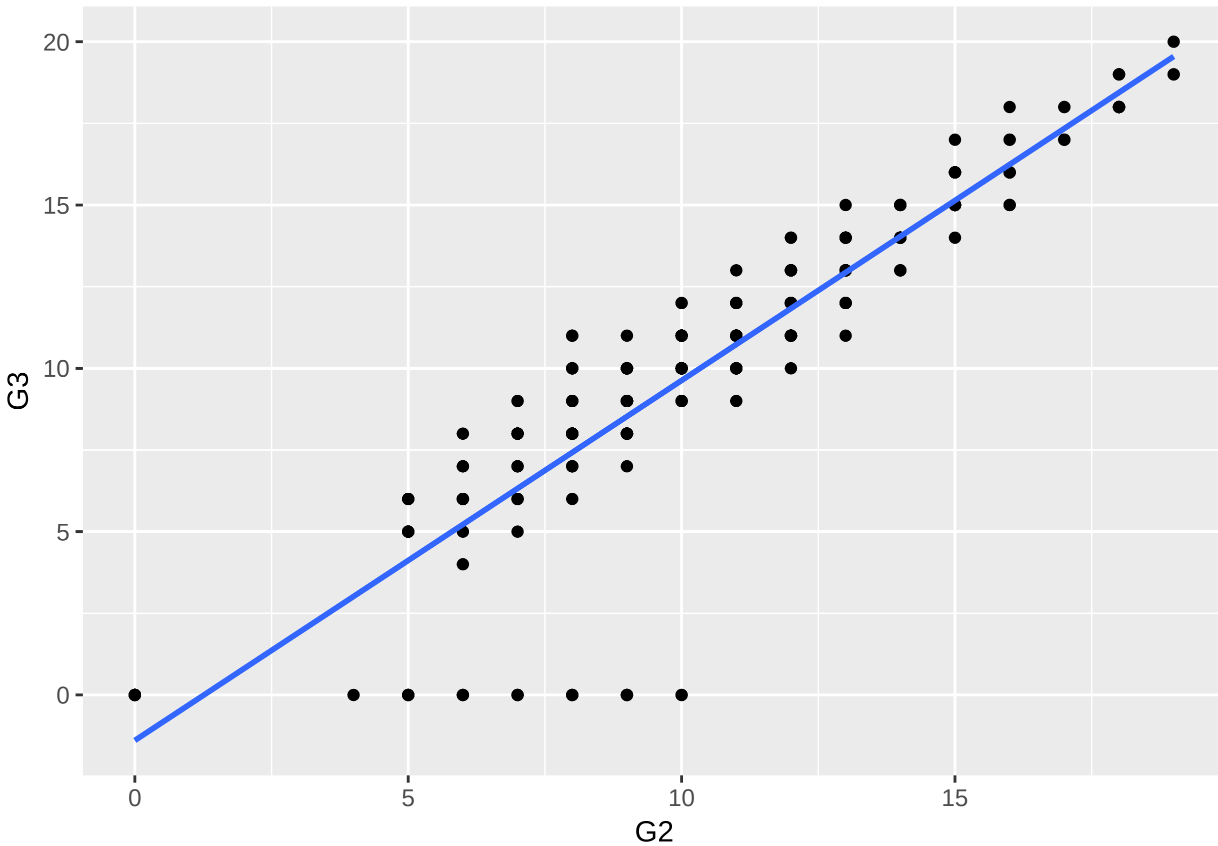
Predicting G3 using G2

Correlation between G2 and G3

```r
r <- cor(with(students,G2), with(students,G3))
sprintf('Correlation between G2 and G3 is %f and the coefficient of determination is %f',r, r^2)
```

```
## [1] "Correlation between G2 and G3 is 0.904868 and the coefficient of determination is 0.818786"
```

Scatterplot of G2, G3



Fit linear regression using G1 as predictor to predict G3

```
fit <- with(students,lm(G3 ~ G2))
fit
```

```
##
## Call:
## lm(formula = G3 ~ G2)
##
## Coefficients:
## (Intercept)           G2
##      -1.393        1.102
```

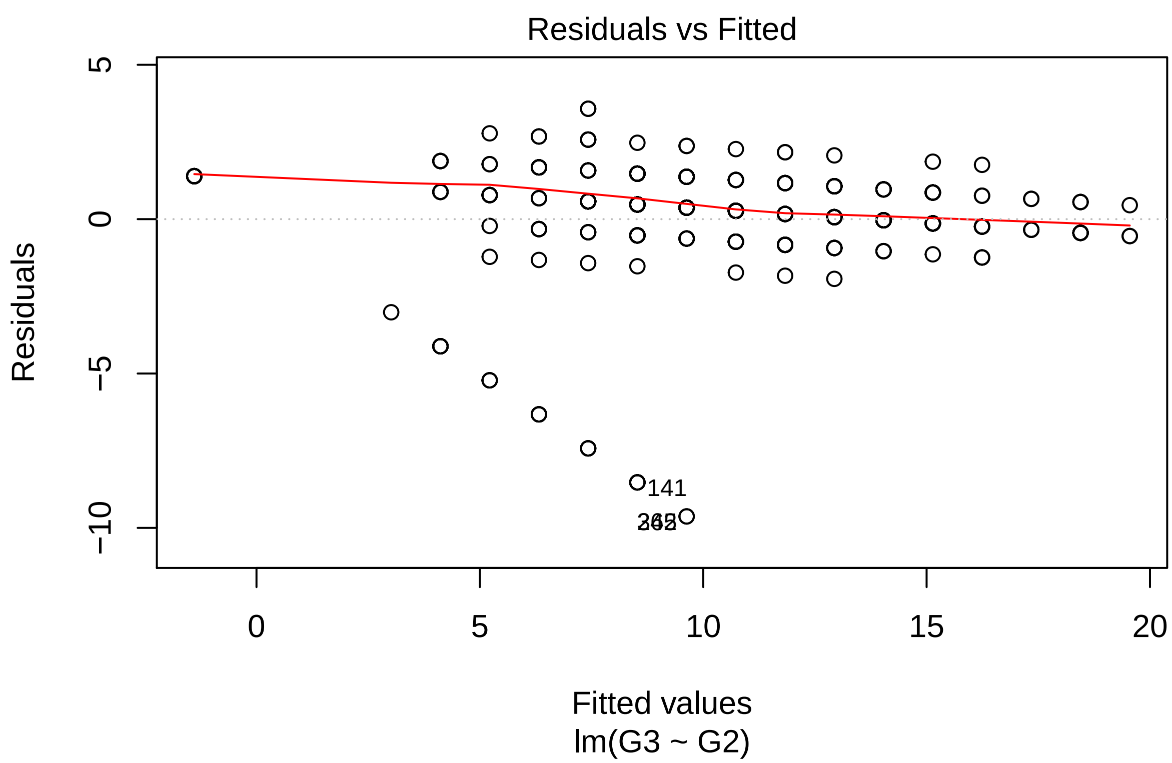
```
attributes(fit)
```

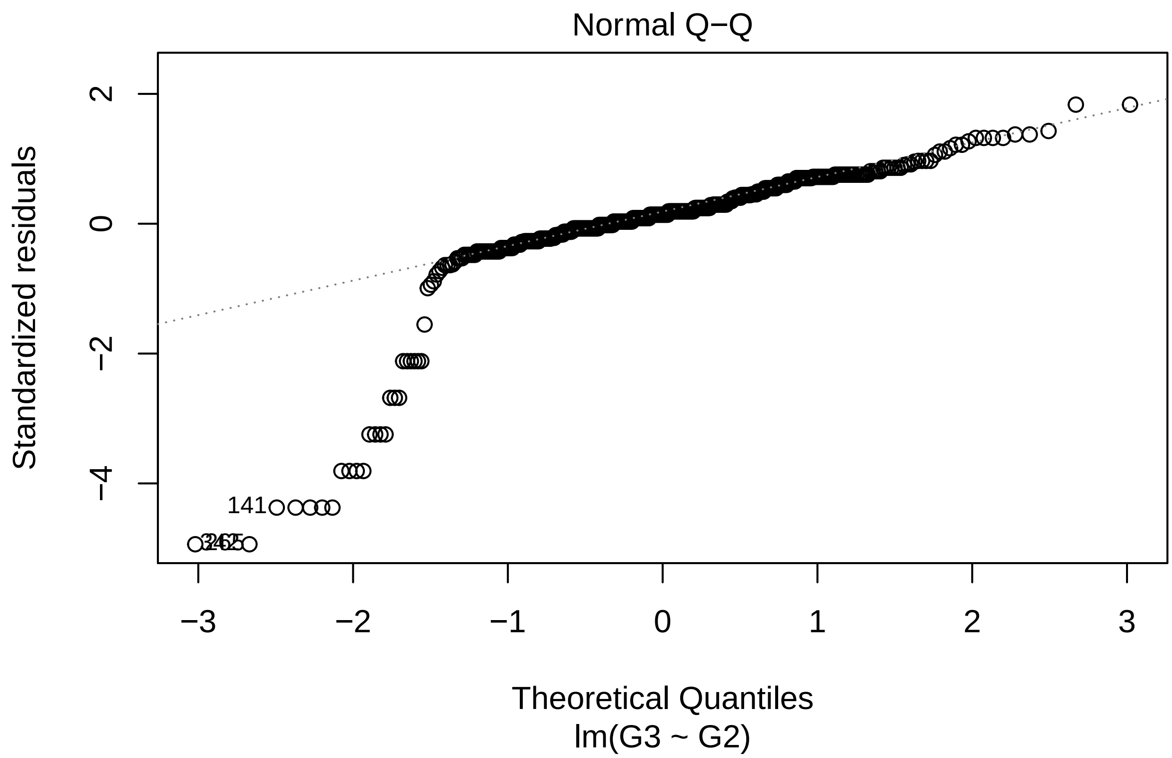
```
## $names
##  [1] "coefficients"  "residuals"     "effects"       "rank"
##  [5] "fitted.values" "assign"        "qr"            "df.residual"
##  [9] "xlevels"       "call"          "terms"         "model"
##
## $class
## [1] "lm"
```

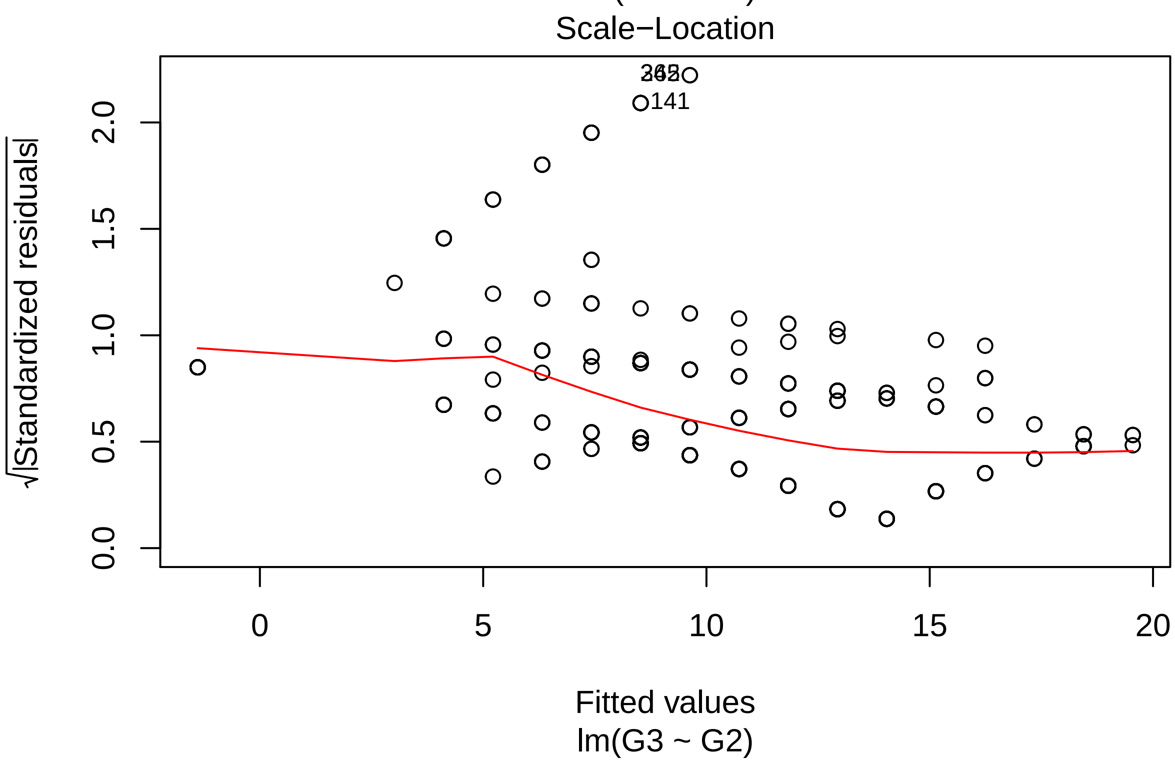
```
summary(fit)
```

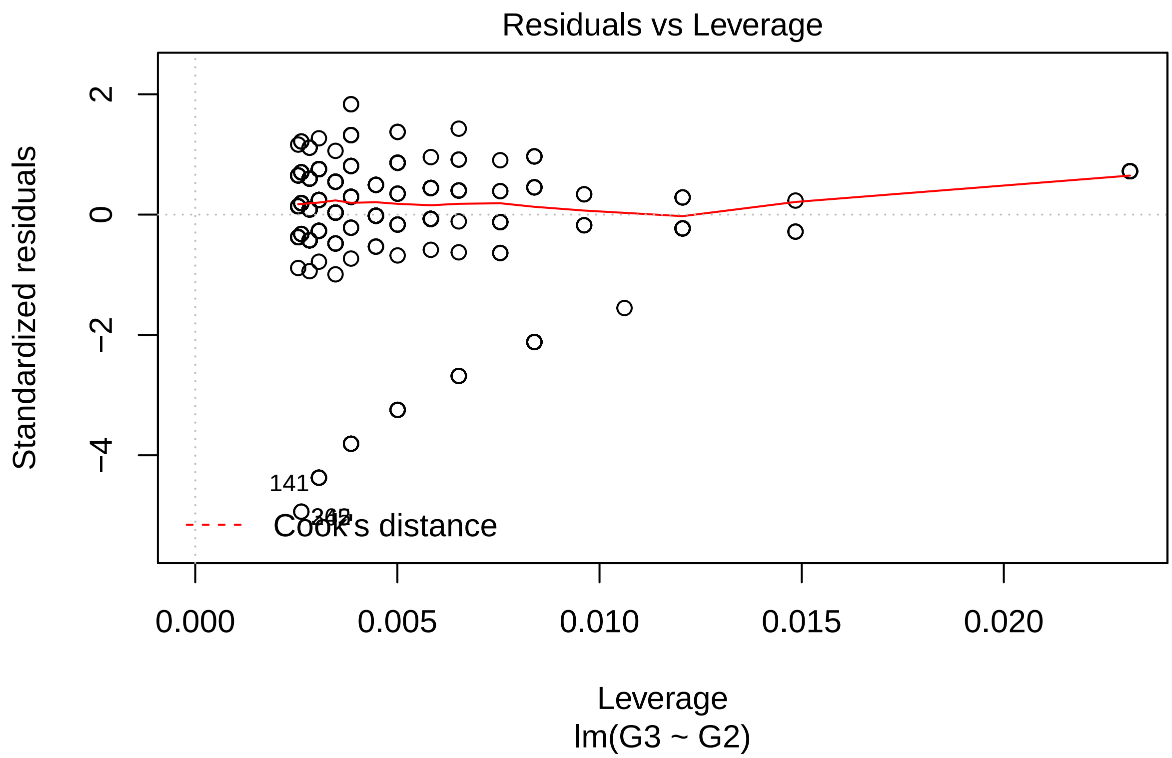
```
##
## Call:
## lm(formula = G3 ~ G2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.6284 -0.3326  0.2695  1.0653  3.5759
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.39276    0.29694   -4.69 3.77e-06 ***
## G2           1.10211    0.02615   42.14  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.953 on 393 degrees of freedom
## Multiple R-squared:  0.8188, Adjusted R-squared:  0.8183
## F-statistic:  1776 on 1 and 393 DF,  p-value: < 2.2e-16
```

Plotting line of best fit




Normal Q−Q
Standardized residuals
141
Theoretical Quantiles
lm(G3 ~ G2)


Scale−Location
√|Standardized residuals|
141
Fitted values
lm(G3 ~ G2)




```
## [1] "Residual graph is random in nature suggesting linear regression is not a bad choice for this da
```

To predict Pass and Fail using G1 + G2

Using Decision Tree

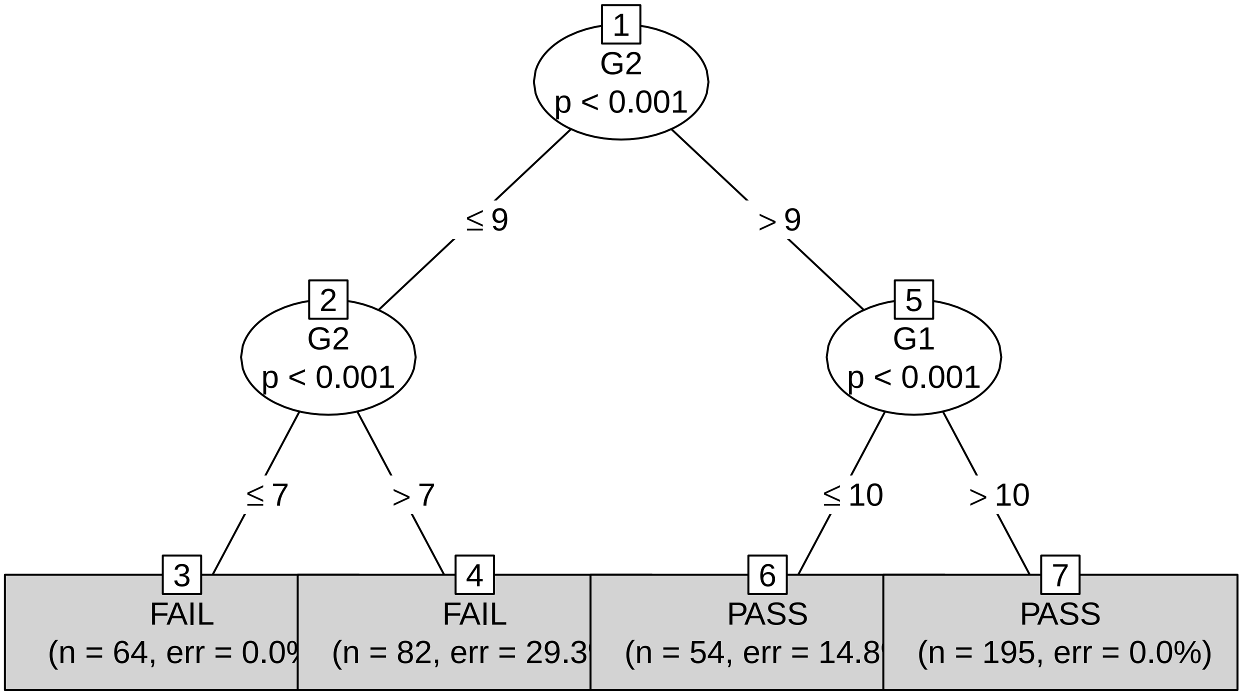
```r
library(partykit)
```

```
## Loading required package: grid
```

```r
formula <- Pass ~ G1 + G2
tree <- ctree(formula, data=students)
print(tree)
```

```
##
## Model formula:
## Pass ~ G1 + G2
##
## Fitted party:
## [1] root
## |   [2] G2 <= 9
## |   |   [3] G2 <= 7: FAIL (n = 64, err = 0.0%)
## |   |   [4] G2 > 7: FAIL (n = 82, err = 29.3%)
## |   [5] G2 > 9
## |   |   [6] G1 <= 10: PASS (n = 54, err = 14.8%)
## |   |   [7] G1 > 10: PASS (n = 195, err = 0.0%)
##
## Number of inner nodes:    3
## Number of terminal nodes: 4
```

```r
plot(tree,type = "simple")
```




```r
sprintf('Errors-on-predictions Matrix')
```

```
## [1] "Errors-on-predictions Matrix"
```

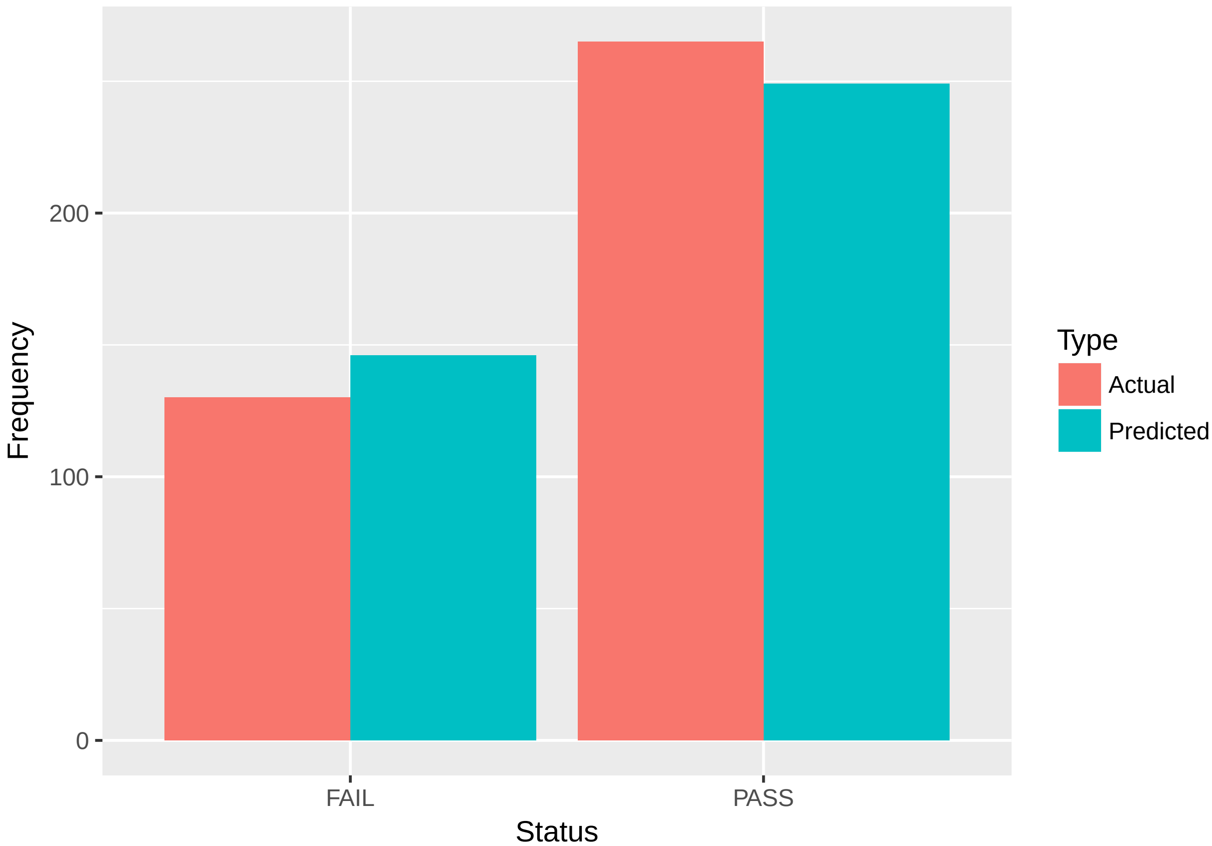
```r
table(predict(tree, newdata=students), students$Pass,dnn=c('Predicted','Actual'))
```

```
##          Actual
## Predicted FAIL PASS
##      FAIL  122   24
##      PASS    8  241
```

```r
df.confmatrix <- data.frame(table(predict(tree, newdata=students), students$Pass,dnn=c('Predicted','Actu
library(tidyr)
data_long <- gather(df.confmatrix, Type, Status, Predicted:Actual)
library(dplyr)
```

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

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

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

```r
data_long <- data_long %>% group_by(Status,Type) %>% summarise(Frequency=sum(Freq))
ggplot(data_long, aes(x=Status,y=Frequency,fill=Type)) + geom_bar(stat='identity', position='dodge')
```



Using Naive-Bayes Prediction

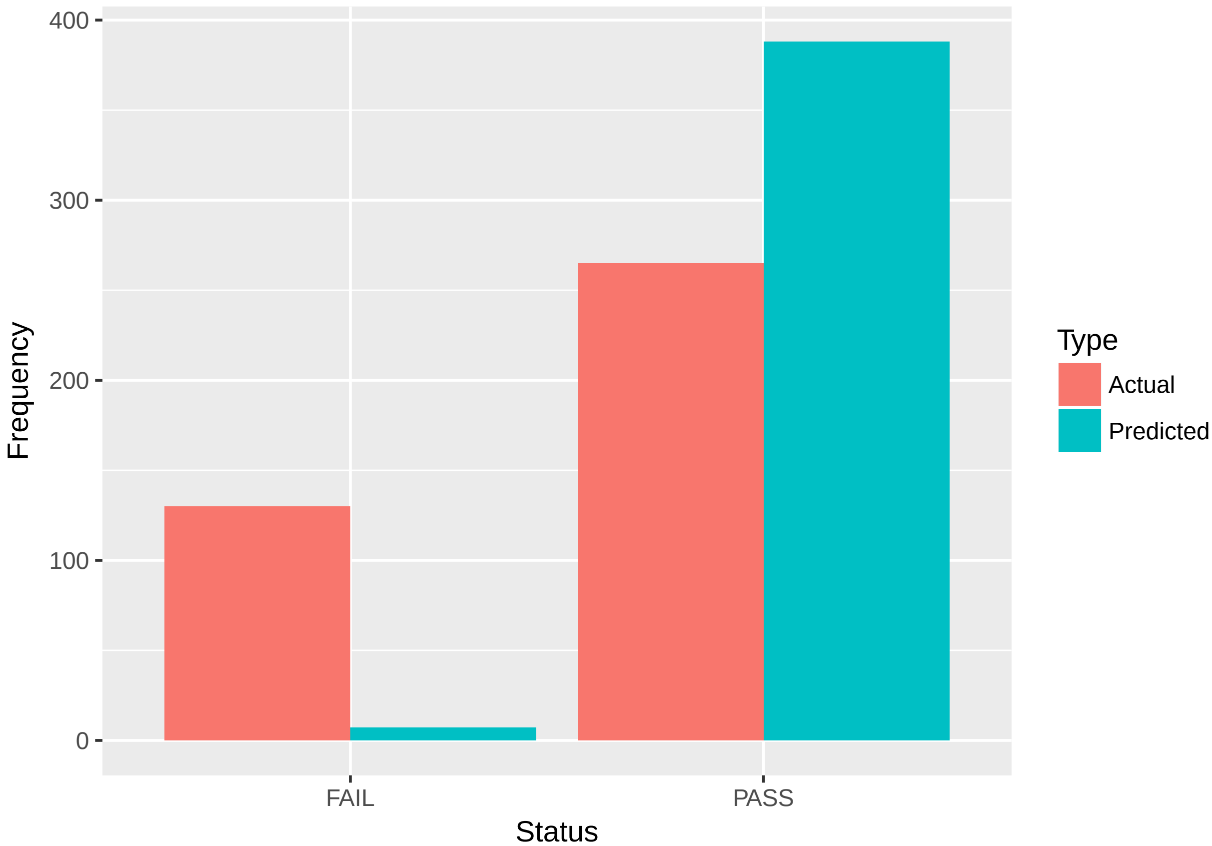
```
library(e1071)
```

```
## Warning: package 'e1071' was built under R version 3.3.2
```

```
classifier<-naiveBayes(students[,1:4], students[,8])
table(predict(classifier, students[,1:4]), students[,8], dnn = c('Predicted','Actual'))
```

```
##          Actual
## Predicted FAIL PASS
##      FAIL    3    4
##      PASS  127  261
```

```
df.confmatrix <- data.frame(table(predict(classifier, students[,1:4]), students[,8], dnn = c('Predicted
data_long <- gather(df.confmatrix, Type, Status, Predicted:Actual)
data_long <- data_long %>% group_by(Status,Type) %>% summarise(Frequency=sum(Freq))
ggplot(data_long, aes(x=Status,y=Frequency,fill=Type)) + geom_bar(stat='identity', position='dodge')
```



To predict Grades using G1+G3

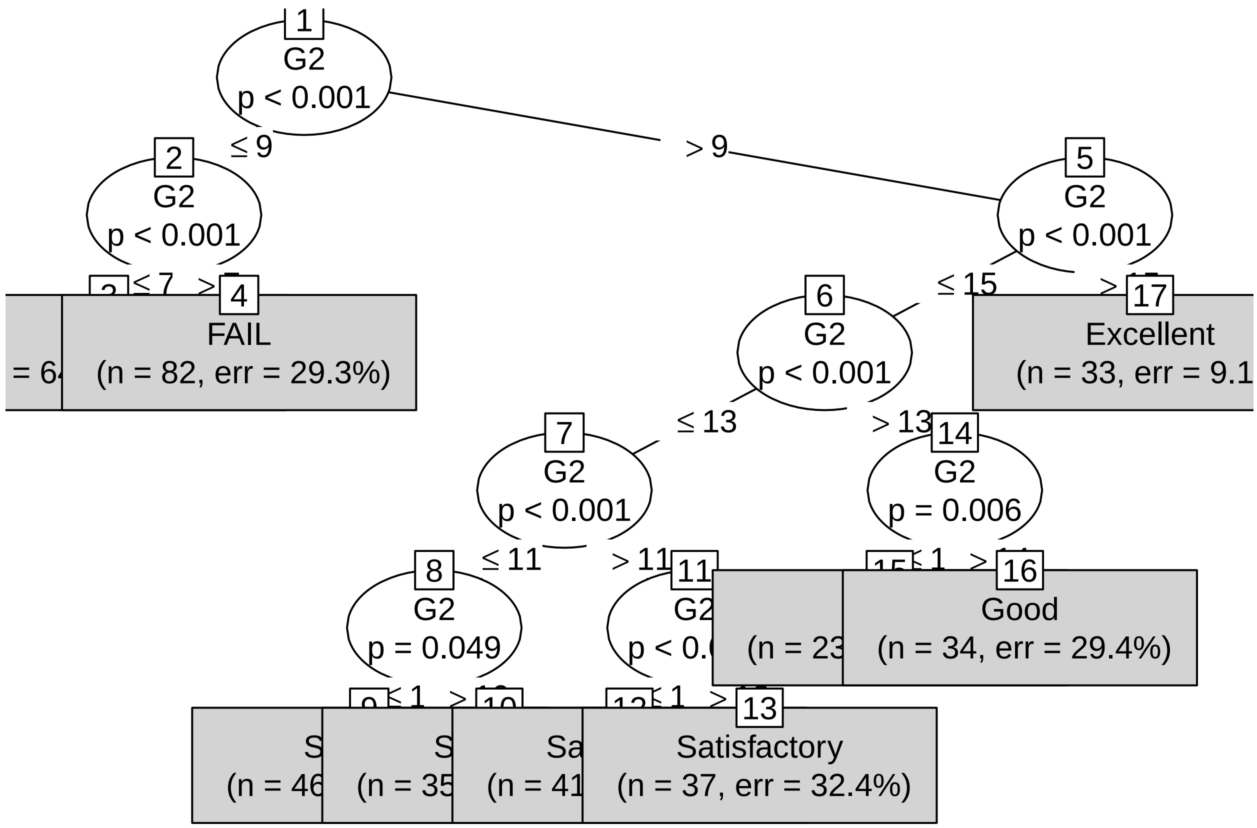
Using Decision Tree

```
formula <- Grade ~ G1 + G2
tree <- ctree(formula, data=students)
print(tree)
```

```
##
## Model formula:
## Grade ~ G1 + G2
##
## Fitted party:
## [1] root
## |   [2] G2 <= 9
## |   |   [3] G2 <= 7: FAIL (n = 64, err = 0.0%)
## |   |   [4] G2 > 7: FAIL (n = 82, err = 29.3%)
## |   [5] G2 > 9
## |   |   [6] G2 <= 15
## |   |   |   [7] G2 <= 13
## |   |   |   |   [8] G2 <= 11
## |   |   |   |   |   [9] G2 <= 10: Sufficient (n = 46, err = 19.6%)
## |   |   |   |   |   [10] G2 > 10: Sufficient (n = 35, err = 22.9%)
## |   |   |   |   [11] G2 > 11
## |   |   |   |   |   [12] G2 <= 12: Satisfactory (n = 41, err = 39.0%)
```

```
## |   |   |   |   |   [13] G2 > 12: Satisfactory (n = 37, err = 32.4%)
## |   |   |   [14] G2 > 13
## |   |   |   |   [15] G2 <= 14: Good (n = 23, err = 13.0%)
## |   |   |   |   [16] G2 > 14: Good (n = 34, err = 29.4%)
## |   |   [17] G2 > 15: Excellent (n = 33, err = 9.1%)
##
## Number of inner nodes:    8
## Number of terminal nodes: 9
```

```r
plot(tree,type = "simple")
```



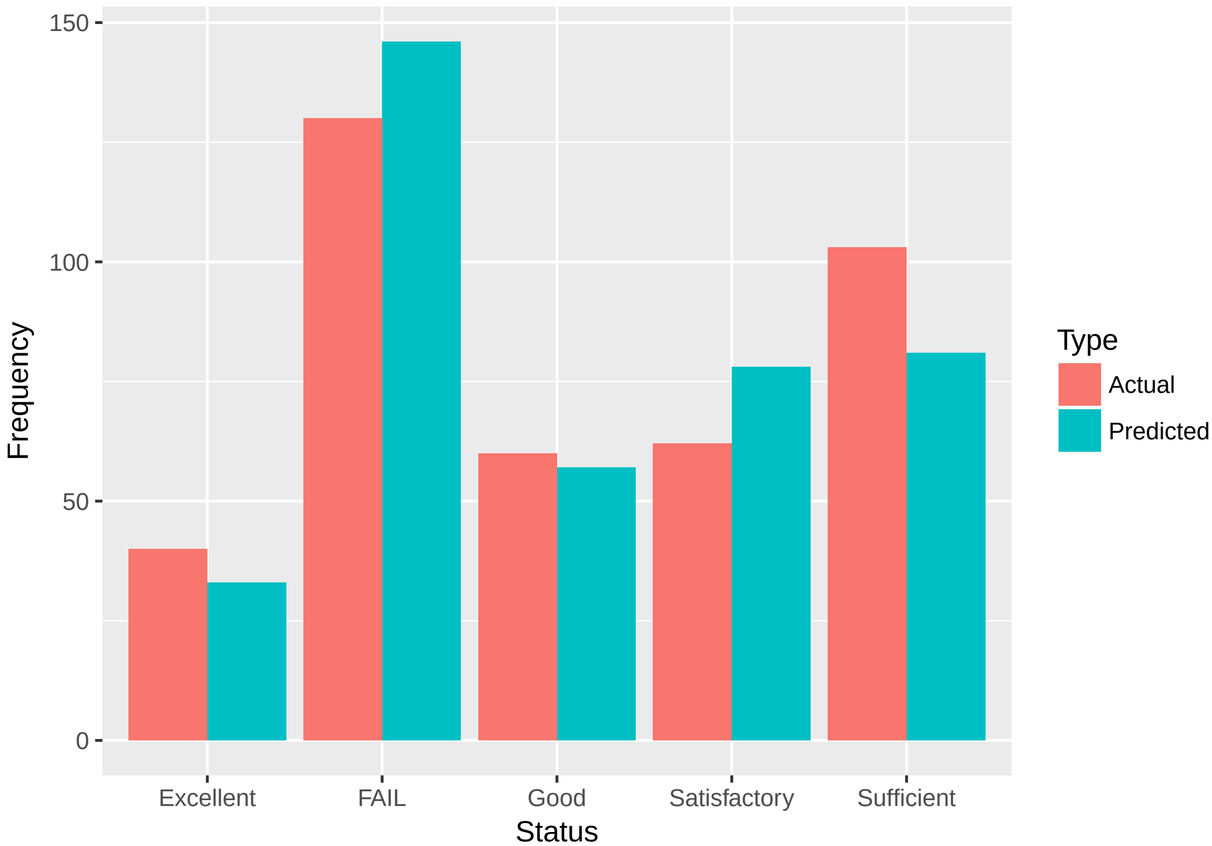

```r
sprintf('Errors-on-predictions Matrix')
```

```
## [1] "Errors-on-predictions Matrix"
```

```r
table(predict(tree, newdata=students), students$Grade,dnn=c('Predicted','Actual'))
```

```
##                Actual
## Predicted       FAIL Sufficient Satisfactory Good Excellent
##   FAIL           122         24            0    0         0
##   Sufficient       8         64            9    0         0
##   Satisfactory     0         15           50   13         0
##   Good             0          0            3   44        10
##   Excellent        0          0            0    3        30
```

```r
df.confmatrix <- data.frame(table(predict(tree, newdata=students), students$Grade,dnn=c('Predicted','Ac
data_long <- gather(df.confmatrix, Type, Status, Predicted:Actual)
data_long <- data_long %>% group_by(Status,Type) %>% summarise(Frequency=sum(Freq))
ggplot(data_long, aes(x=Status,y=Frequency,fill=Type)) + geom_bar(stat='identity', position='dodge')
```



Using Naive-Bayes Prediction

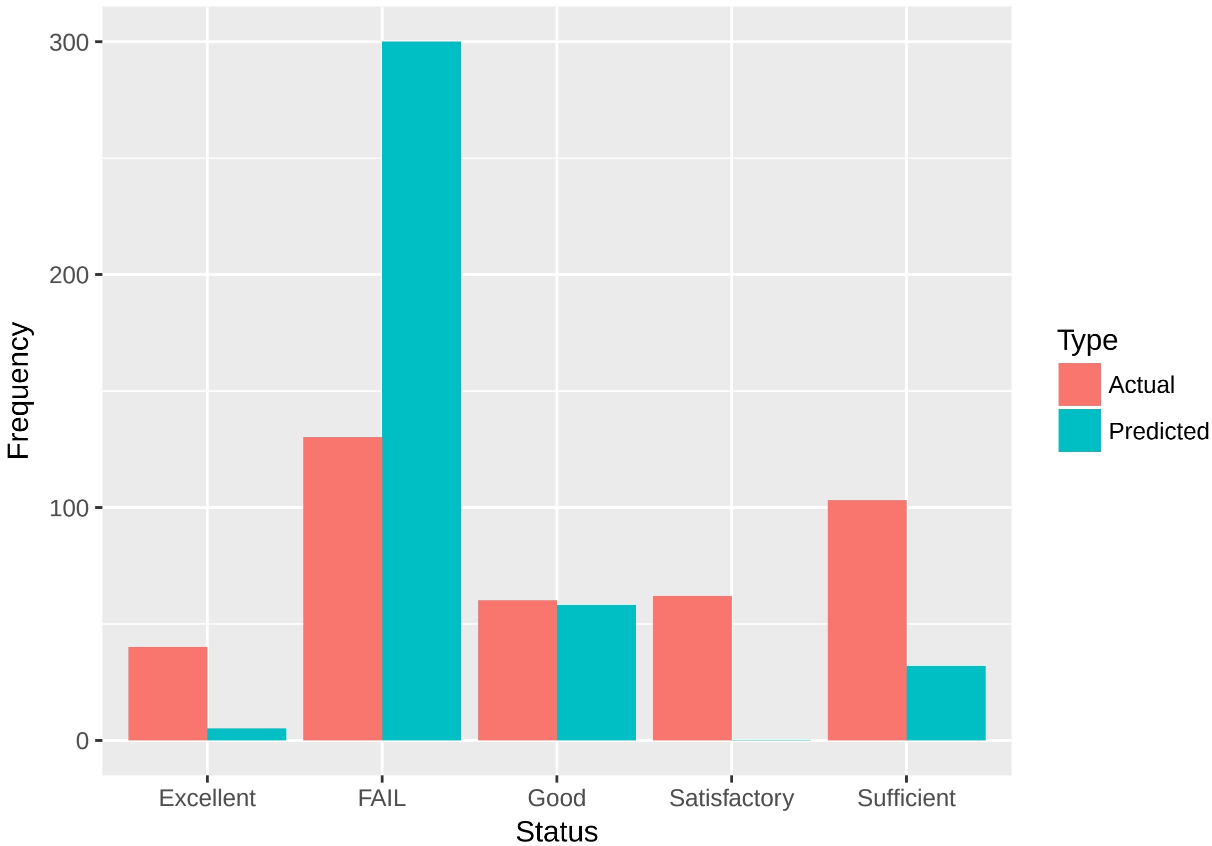
```
classifier<-naiveBayes(students[,1:4], students[,9])
sprintf('Errors-on-predictions Matrix')
```

```
## [1] "Errors-on-predictions Matrix"
```

```
table(predict(classifier, students[,1:4]), students[,9], dnn = c('Predicted','Actual'))
```

```
##                Actual
## Predicted       FAIL Sufficient Satisfactory Good Excellent
##   FAIL           111         78           51   37        23
##   Sufficient       7         12            5    3         5
##   Satisfactory     0          0            0    0         0
##   Good            11         12            6   18        11
##   Excellent        1          1            0    2         1
```

```
df.confmatrix <- data.frame(table(predict(classifier, students[,1:4]), students[,9], dnn = c('Predicted
data_long <- gather(df.confmatrix, Type, Status, Predicted:Actual)
data_long <- data_long %>% group_by(Status,Type) %>% summarise(Frequency=sum(Freq))
ggplot(data_long, aes(x=Status,y=Frequency,fill=Type)) + geom_bar(stat='identity', position='dodge')
```



Conclusion

Linear regression showed strong relationship between G3 and G2. G1 also showed positive relationship but not as strong as G2. Decision tree prediction on the same dataset showed very less errors on predictions making G1 and G2 suitable for predicting Grades and Pass-ability of students Naive Bayes method showed large errors on predictions. So, either the those four variables are not good predictors or Naive Bayes method is not a good predicting model for this dataset. Based on all the analysis, G2 is the strongest predictor for G3, which in turn, for pass-ability and grades.

```r
# A small function to check for missing values within a vector.
na.test <- function (x) {
  output <- any(is.na(x)== TRUE)
return(output)
}
sprintf('Applying the function to every column');
```

```
## [1] "Applying the function to every column"
```

```r
apply(student.mat, 2, 'na.test')
```

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

Q2. What is the impact of age and the sex on performance(G3) ?

First of all, I checked whether there is a difference in performance between boys and girls.

```
gender.dif <- t.test(student.mat$G3~student.mat$sex,var.equal = TRUE)
library(apa)
apa(gender.dif)
```

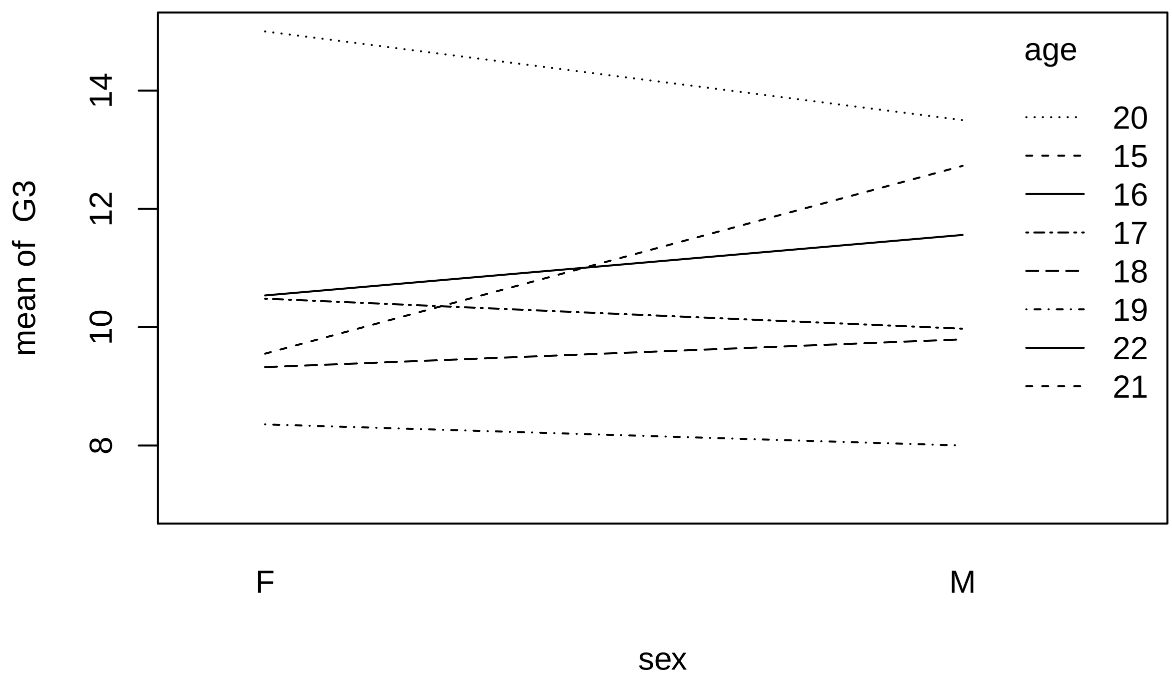
```
## [1] "*t*(393) = -2.06, *p* = .040, *d* = -0.21"
```

The mean values between the genders is not equal.Now, I go a step further and take also the age into consideration.

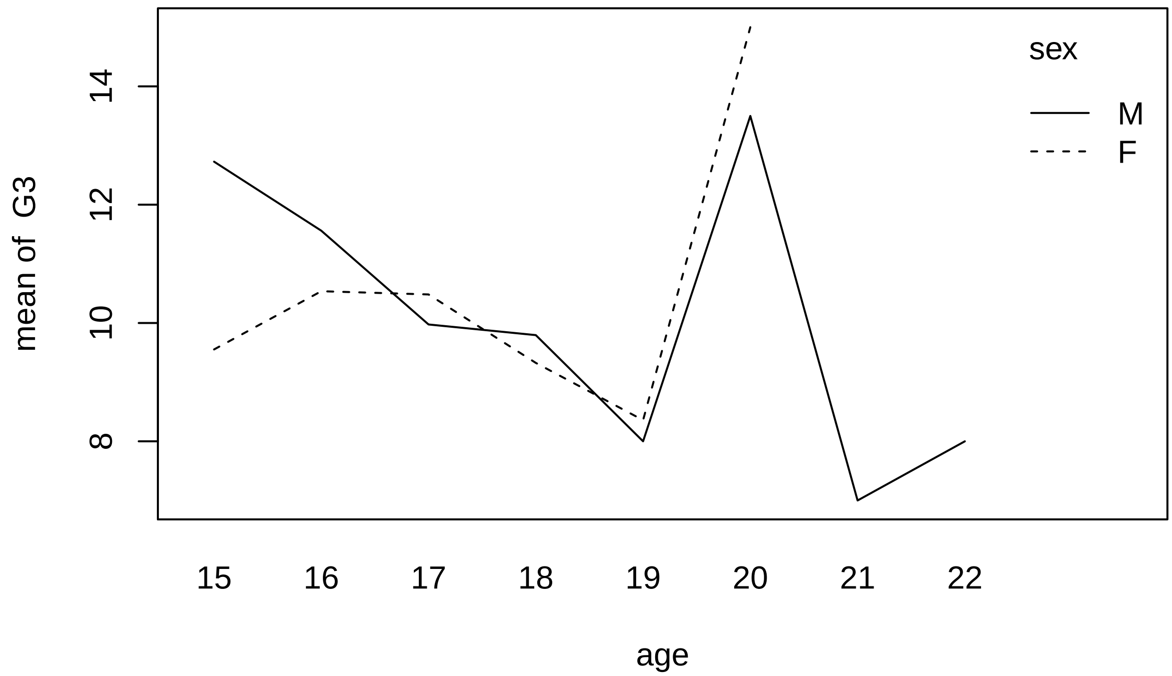
```
summary(with(student.mat, aov(G3 ~ sex + age + sex*age)))
```

```
##              Df Sum Sq Mean Sq F value  Pr(>F)
## sex           1     89   88.51   4.385 0.03690 *
## age           1    208  208.24  10.317 0.00143 **
## sex:age       1     81   80.74   4.000 0.04619 *
## Residuals   391   7892   20.19
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
with(student.mat, interaction.plot(sex, age, G3))
```




```
with(student.mat, interaction.plot(age, sex, G3))
```




```r
table(student.mat$age)
```

```
##
##  15  16  17  18  19  20  21  22
##  82 104  98  82  24   3   1   1
```

```r
student.mat.2 <- subset(student.mat, age < 20)
table(student.mat.2$age)
```

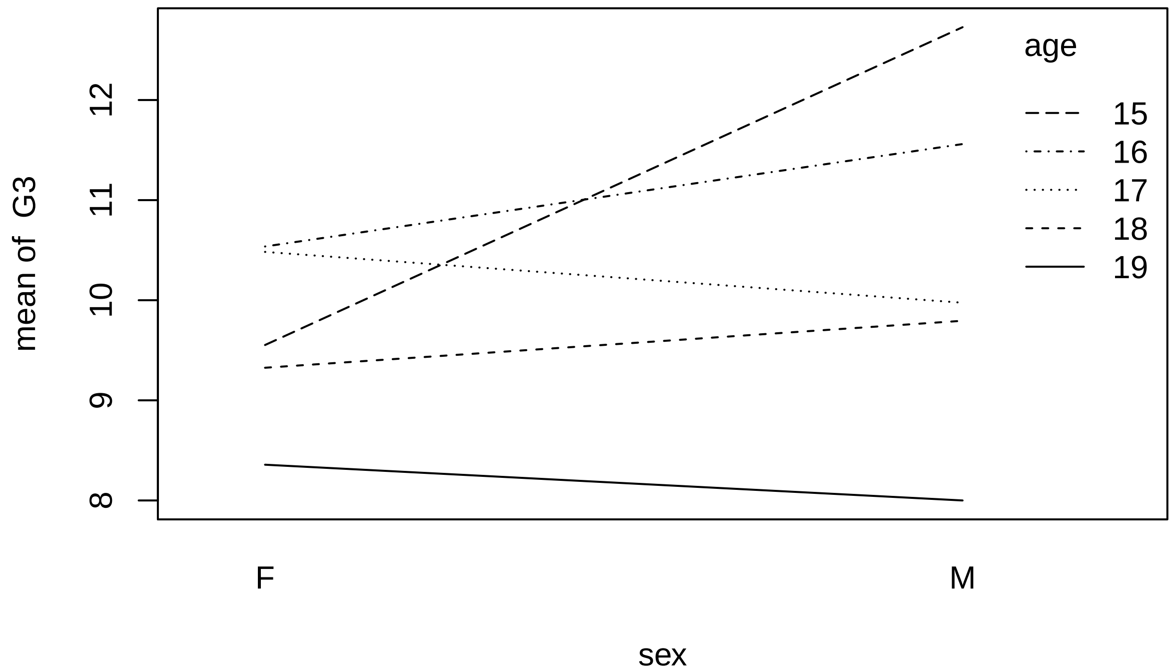
```
##
##  15  16  17  18  19
##  82 104  98  82  24
```

```r
summary(with(student.mat.2, aov(G3 ~ sex + age + sex*age)))
```

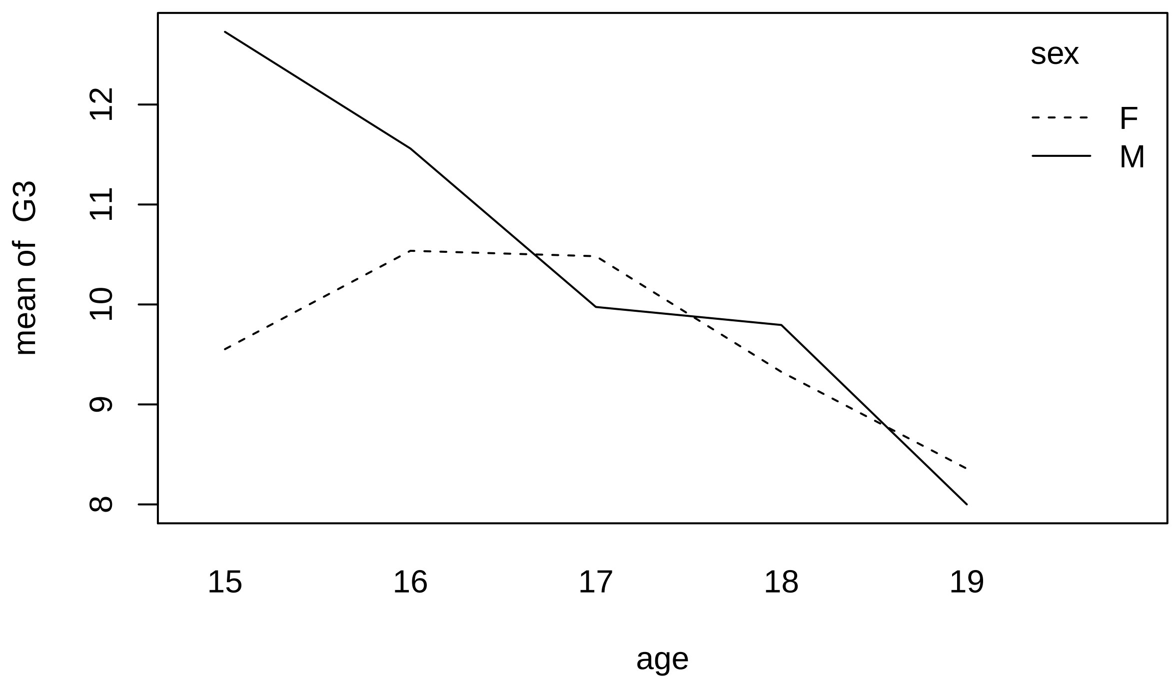
```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## sex           1     94   93.56   4.665 0.031406 *
## age           1    240  240.21  11.975 0.000599 ***
## sex:age       1     95   95.50   4.761 0.029714 *
## Residuals   386   7743   20.06
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

While eliminating the outliers, the probability that the treatment means differ became less likely for every factor. Now, I redo the interaction plots, too.

```r
with(student.mat.2, interaction.plot(sex, age, G3))
```




```r
with(student.mat.2, interaction.plot(age, sex, G3))
```



Especially the last plot looks better. But as it seems, the interaction is more difficult to understand. I was wondering why the performance of boys gradually (linearly) decreases when boys grow older and why the performance of girls stays more constant with reference to the age. Looking at the mean values this thought is reinforced.

```r
library(tidyverse)
```

```
## Loading tidyverse: tibble
## Loading tidyverse: readr
## Loading tidyverse: purrr
```

```
## Conflicts with tidy packages ----------------------------------------------

## filter(): dplyr, stats
## lag():    dplyr, stats
```

```r
student.mat.2 %>%
  group_by(age, sex) %>%
  summarise(
    a.mean = mean(G3)
  )
```

```
## Source: local data frame [10 x 3]
## Groups: age [?]
##
##      age    sex    a.mean
##    <int> <fctr>     <dbl>
## 1     15      F  9.552632
## 2     15      M 12.727273
## 3     16      F 10.537037
## 4     16      M 11.560000
## 5     17      F 10.482759
## 6     17      M  9.975000
## 7     18      F  9.325581
## 8     18      M  9.794872
## 9     19      F  8.357143
## 10    19      M  8.000000
```

Consequently, I checked the correlation between age and the performance for two subsets holding boys and girls separately.

```r
cor.test1 <- with(subset(student.mat.2, sex == "M"),
     cor.test(G3, age))
cor.test1
```

```
##
##  Pearson's product-moment correlation
##
## data:  G3 and age
## t = -4.13, df = 181, p-value = 5.535e-05
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.4206139 -0.1550039
## sample estimates:
##        cor
## -0.2934623
```

```r
apa(cor.test1)
```

```
## [1] "*r*(181) = -.29, *p* < .001"
```

```r
cor.test2 <- with(subset(student.mat.2, sex == "F"),
     (cor.test(G3, age)))
cor.test2
```

```
##
##  Pearson's product-moment correlation
##
## data:  G3 and age
```

```
## t = -0.93582, df = 205, p-value = 0.3505
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1998139  0.0717874
## sample estimates:
##         cor
## -0.06522112
```

```r
apa(cor.test2)
```

```
## [1] "*r*(205) = -.07, *p* = .350"
```

As expected, there is a correlation between age and performance for boys and none for girls. Therefore, I will focus on the boys. I calculate a linear regression analysis between age and performance in order to get further information.

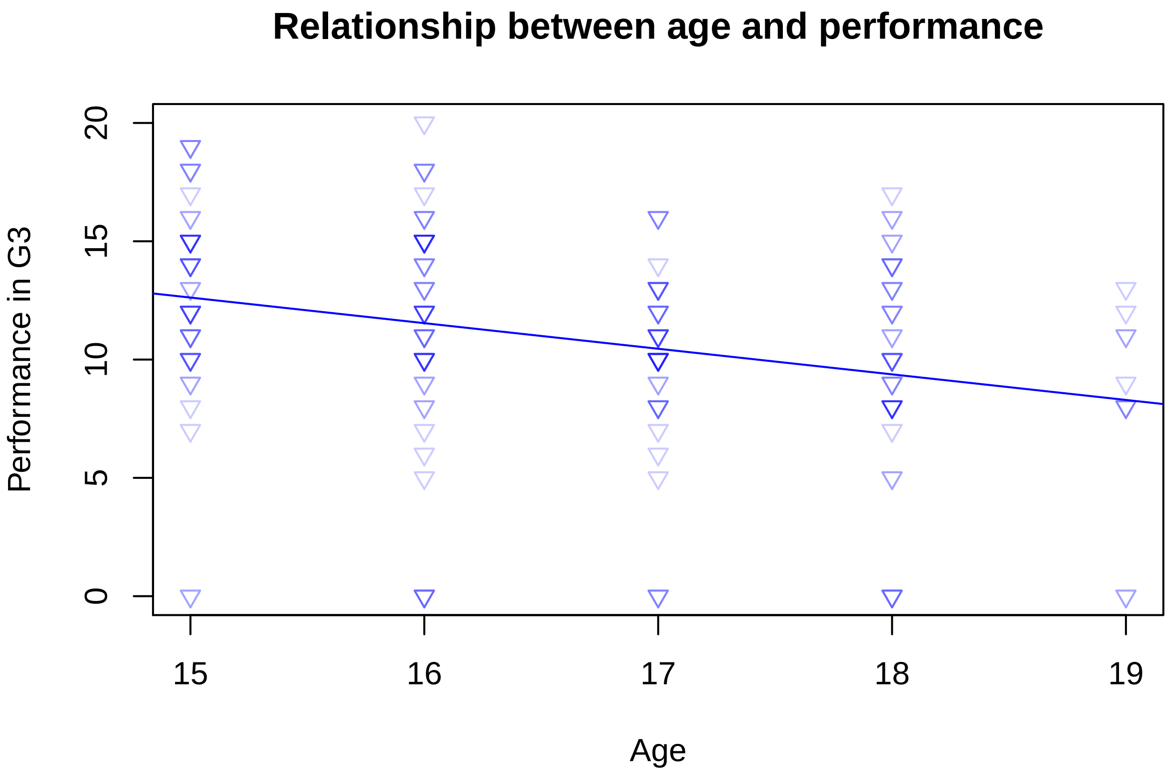
```r
with(subset(student.mat.2, sex == "M"),
     summary(lm(G3~ age)))
```

```
##
## Call:
## lm(formula = G3 ~ age)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.6200  -1.5383   0.4617   2.6252   8.4617
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  28.8464     4.3514   6.629 3.75e-10 ***
## age          -1.0818     0.2619  -4.130 5.53e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.311 on 181 degrees of freedom
## Multiple R-squared:  0.08612,    Adjusted R-squared:  0.08107
## F-statistic: 17.06 on 1 and 181 DF,  p-value: 5.535e-05
```

The probability that the group means are equal is, of course, the same as in the correlation analysis. However, with the linear regression we can predict values and show a tendency with a regression line. Last but not least, I show the results in a scatter plot:

```r
plot(1,
     xlim = c(15, 19),
     ylim = c(0, 20),
     type = "n",
     main = "Relationship between age and performance",
     xlab = "Age",
     ylab = "Performance in G3"
     )

#Now, I fill in the points.
with(subset(student.mat.2, sex == "M"),
     points(age,
            G3,
            pch = 25,
            col = alpha("blue", 0.2)
```

```
          ))

#Finally, I draw the regression line.
with(subset(student.mat.2, sex == "M"),
     abline(lm(G3 ~ age), col = "blue"))
```



Q3.What is the relationship between failures and performance with reference to the age?

While eliminating persons older than 20, I recognized that these persons have bad grades. So at first, I checked the correlation between failures and age.

```
cor.test3 <- with(student.mat, cor.test(age, failures))
apa(cor.test3)
```

```
## [1] "*r*(393) = .24, *p* < .001"
```

```
cor.test2 <- with(subset(student.mat.2, sex == "F"),
     (cor.test(G3, age)))
cor.test2
```

```
##
##  Pearson's product-moment correlation
##
## data:  G3 and age
## t = -0.93582, df = 205, p-value = 0.3505
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.1998139  0.0717874
## sample estimates:
##         cor
## -0.06522112
```

The results reveal a strong connection between failures and age. This maybe explains why there are people of 22 in a school class. Furthermore, I explored the relationship between age, failures and the performance

```
with(student.mat, summary(aov(G3 ~ age + failures + age*failures)))
```

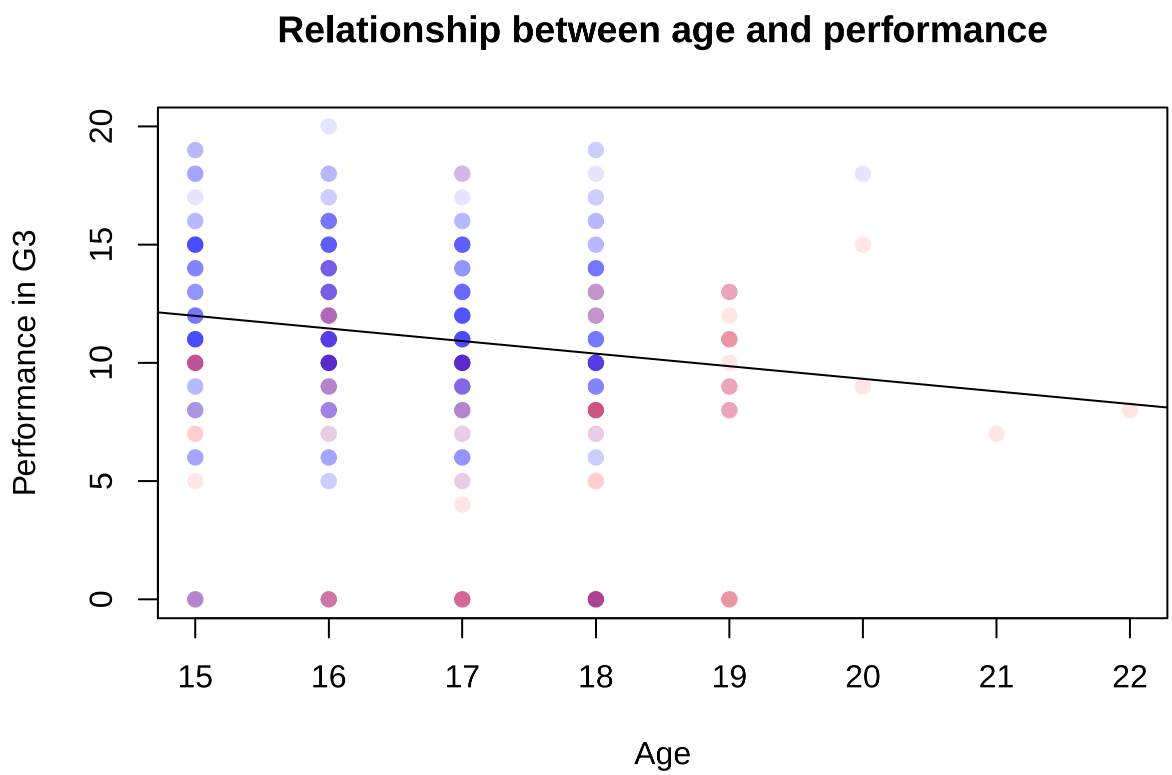
```
##               Df Sum Sq Mean Sq F value   Pr(>F)
## age            1    216   215.9  11.976 0.000598 ***
## failures       1    906   906.2  50.261 6.33e-12 ***
## age:failures   1     98    98.4   5.458 0.019986 *
## Residuals    391   7049    18.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The results show that all factors are significant. The older a person was and the more failures a person experienced, the more will the performance decrease. Finally, I plot the results:

```
plot(1,
     xlim = c(15, 22),
     ylim = c(0, 20),
     type = "n",
     main = "Relationship between age and performance",
     xlab = "Age",
     ylab = "Performance in G3"
     )

#People with no failures.
with(subset(student.mat, failures == 0),
     points(age,
            G3,
            pch = 21,
```

```r
            col = alpha("blue", 0.1),
            bg =alpha("blue", 0.1)
            ))

#People with more than one failure.
with(subset(student.mat, failures > 0),
     points(age,
            G3,
            pch = 21,
            col = alpha("red", 0.1),
            bg =alpha("red", 0.1)
            ))

with(student.mat, abline(lm(G3 ~ age + failures + age*failures)))
```

```
## Warning in abline(lm(G3 ~ age + failures + age * failures)): only using the
## first two of 4 regression coefficients
```



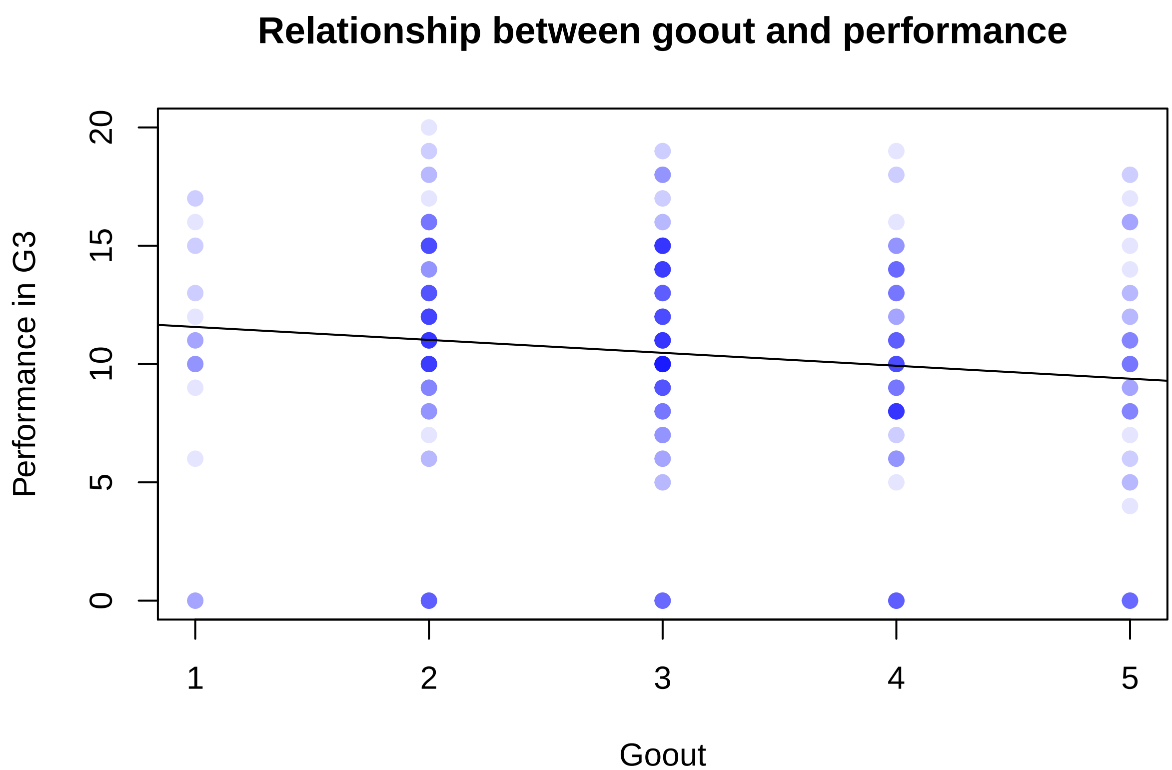
Q4. Relationship between goout and performance

```
lm1 <- with(student.mat, summary(lm(G3 ~ goout )))
lm1
```

```
##
## Call:
## lm(formula = G3 ~ goout)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.5676  -1.9282   0.4324   3.0718   9.0718
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  12.1141     0.6793  17.833  < 2e-16 ***
## goout        -0.5465     0.2057  -2.656  0.00823 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.547 on 393 degrees of freedom
## Multiple R-squared:  0.01763,    Adjusted R-squared:  0.01513
## F-statistic: 7.054 on 1 and 393 DF,  p-value: 0.008229
```

Going out is significantly related to the performance in the math course. I want to visualize this with a scatter plot:

```
plot(1,
     xlim = c(1, 5),
     ylim = c(0, 20),
     type = "n",
     main = "Relationship between goout and performance",
     xlab = "Goout",
     ylab = "Performance in G3"
     )


with(student.mat,
     points(goout,
            G3,
            pch = 21,
            col = alpha("blue", 0.1),
            bg =alpha("blue", 0.1)
            ))

with(student.mat, abline(lm(G3 ~ goout)))
```



After checking the plot I realized that the mean of the performance is low when the child is rarely going out. This is why I assumed another coherence. At first, I checked for the means:

```
aggregate(
  formula = G3 ~ goout,
  data= student.mat,
  FUN = mean)
```

```
##   goout        G3
## 1     1  9.869565
## 2     2 11.194175
## 3     3 10.961538
## 4     4  9.651163
## 5     5  9.037736
```

The means reveal what I assumed. The first mean is lower than the second or third one. Finally, I expected the relationship between performance and going out to be quadratic. I checked this with a regression analysis.

Conclusion

In comparison to that the result that going out is negatively correlated with your performance in a Math Class is totally intuitive. Additionally, the results revealed that older children which failed once or several times have lower performance rates.

While boys show lower performances when they grow older, girls remain relatively constant.