PREDICTING STUDENT DAYLY ALCOHOL CONSUMPTION
By Pavel Dudin, Charlotte 2016

OBJECTIVE

Although we think of college as a time when young adults experiment with alcohol, the college years are rarely the first time students have faced decisions about alcohol. According to the nationally representative “Monitoring the Future Study”, in 2012, 42 percent of high school seniors reported having had alcohol (more than just a few sips) within 30 days prior to the survey, and 24 percent reported binge drinking within the previous two weeks. During childhood and teenage years, the brain is still developing. Alcohol consumption showed negative associations with motivation for and subjectively achieved academic performance. Drinking could a ect child’s performance at school and prevent them from reaching their full potential.

University alcohol prevention activities might have positive impact on students’ academic success.(Walid El Ansari, Christiane Stock ,Int J Prev Med. 2013 Oct; 4(10): 1175–1188. Is Alcohol Consumption Associated with Poor Academic Achievement in University Students?). Modeling student alcohol consumption is an important tool for both educators and students, since it can help a better understanding of this problem and improve it. For instance, school professionals could perform corrective measures for the students.

The present work intends to approach student alcohol consumption in secondary education using regression models with “R”. The final goal is to find the best predicting model and correlation between alcohol consumption over the week. Weekly consumption was chosen because it is more significant than over the weekend.

DATABASE

Students Alcohol Consumption
https://archive.ics.uci.edu/ml/datasets/STUDENT+ALCOHOL+CONSUMPTION

Variables :
1 school - student's school (binary: "GP" - Gabriel Pereira or "MS" - Mousinho da Silveira)
2 sex - student's sex (binary: "F" - female or "M" - male)
3 age - student's age (numeric: from 15 to 22)
4 address - student's home address type (binary: "U" - urban or "R" - rural)
5 famsize - family size (binary: "LE3" - less or equal to 3 or "GT3" - greater than 3)
6 Pstatus - parent's cohabitation status (binary: "T" - living together or "A" - apart)
7 Medu - mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 - 5th to 9th grade, 3 - secondary education or 4 - higher education)
8 Fedu - father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 - 5th to 9th grade, 3 - secondary education or 4 - higher education)
9 Mjob - mother's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at_home" or "other")
10 Fjob - father's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at_home" or "other")
11 reason - reason to choose this school (nominal: close to "home", school "reputation", "course" preference or "other")
12 guardian - student's guardian (nominal: "mother", "father" or "other")
13 travel+time - home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
14 studytime - weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)

15 failures - number of past class failures (numeric: n if 1<=n<3, else 4)
16 schoolsup - extra educational support (binary: yes or no)
17 famsup - family educational support (binary: yes or no)
18 paid - extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
19 activities - extra-curricular activities (binary: yes or no)
20 nursery - attended nursery school (binary: yes or no)
21 higher - wants to take higher education (binary: yes or no)
22 internet - Internet access at home (binary: yes or no)
23 romantic - with a romantic relationship (binary: yes or no)
24 famrel - quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
25 freetime - free time after school (numeric: from 1 - very low to 5 - very high)
26 goout - going out with friends (numeric: from 1 - very low to 5 - very high)
27 Dalc - workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
28 Walc - weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
29 health - current health status (numeric: from 1 - very bad to 5 - very good)
30 absences - number of school absences (numeric: from 0 to 93)
31 G1 - first period grade (numeric: from 0 to 20)
31 G2 - second period grade (numeric: from 0 to 20)
32 G3 - final grade (numeric: from 0 to 20, output target)

There are several students that belong to both datasets .
These students can be identified by searching for identical attributes
that characterize each student.

First of all, necessary packages need to be installed:

```
#installing packages

wants <- c("mlogit","mgcv", "nnet","e1071"
,"VGAM","nnet","rpart.plot","ROCR","randomForest",

"caret","lift","nnet","ggplot2","reshape2","caTools","mlbench","SDMTools","pR
OC")

has   <- wants %in% rownames(installed.packages())

if(any(!has)) install.packages(wants[!has])
```

Loading data from two .csv files:

```
#loading data

setwd("C:/Users/111/Desktop/Alcohol-master")

d1=read.table("student-mat.csv",sep=";",header=TRUE)
d2=read.table("student-por.csv",sep=";",header=TRUE)

#there are severalstudents that belong to both datasets .
#These students can be identified by searching for identical attributes
#that characterize each student.

#binding datasets
```

```
df=rbind(d1, d2)
```

creating the unique index using “mgcv”, and getting the final data set d3:

```
library(mgcv)

unique=uniquecombs(df[1:13]) #columnes to identify the unique subjects by.

uniqueIndex<-attributes(unique)

d3=df[uniqueIndex$row.names,]
```

Structure d3:

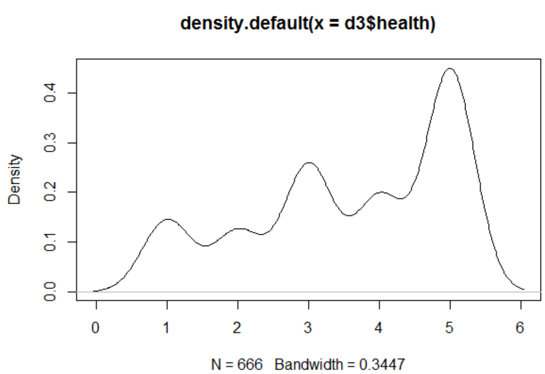
```
'data.frame':	666 obs. of  33 variables:
 $ school    : Factor w/ 2 levels "GP","MS": 1 1 1 1 1 1 1 1 1 1 ...
 $ sex       : Factor w/ 2 levels "F","M": 1 1 1 1 1 2 2 1 2 2 ...
 $ age       : int  18 17 15 15 16 16 16 17 15 15 ...
 $ address   : Factor w/ 2 levels "R","U": 2 2 2 2 2 2 2 2 2 2 ...
 $ 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 ...
```

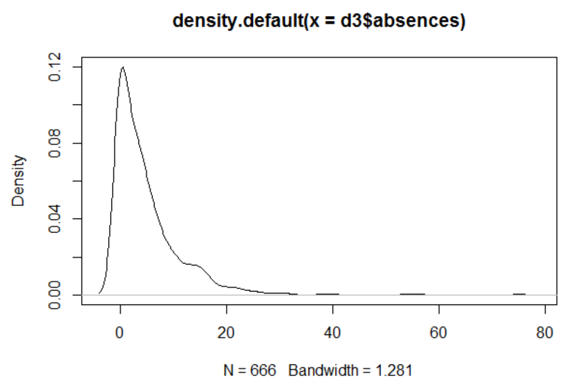
ANALIZING THE DATA

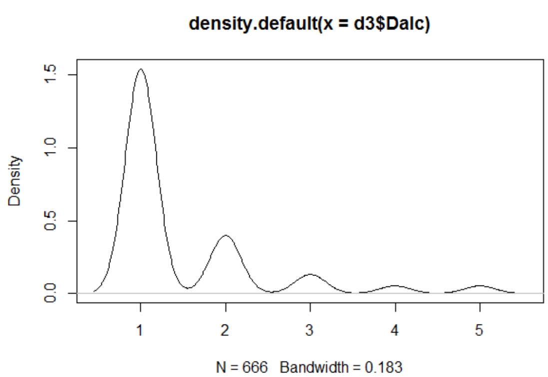
```
#storing my themes
library(ggplot2)

mytheme1=theme_bw(base_size = 12, base_family = "")

mytheme2=theme(panel.grid.major = element_line(colour = "white")) +
  theme(panel.border =
   element_rect(linetype = "solid", colour = "white"))
```

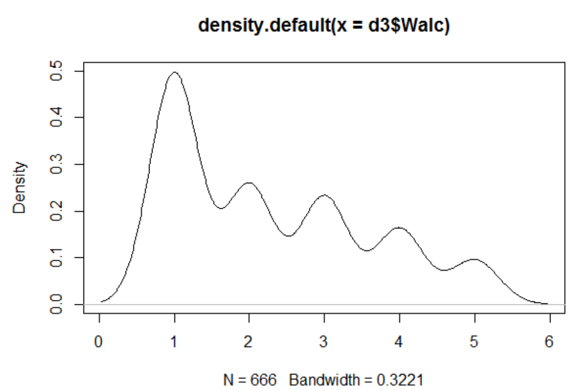
Simple density plots of the dependent variables will be plotted:

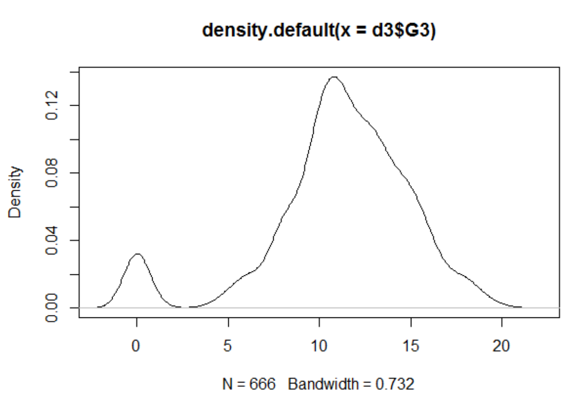
```
#plotting dependent variables
```











As we see there are 2 different alcohol consumption variables: Dalc and Walc, daily and weekends prospectively.

```
table(d2$Dalc) #weekday alcohol consumption 1-5 score
1   2   3   4   5
451 121  43  17  17 =34

table(d2$Walc) #weekend alcohol consumption 1-5 score
  1   2   3   4   5
247 150 120  87  45 = 132
```

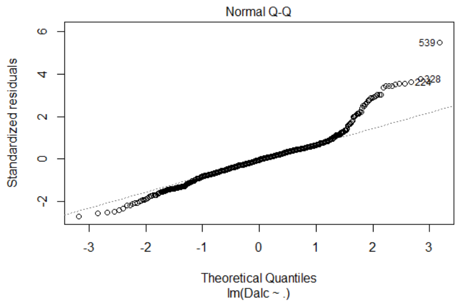
As observed high level drinking (4-5) is greater on the weekends and it is not so significant for everyday performance in the schools as daily drinking. Hence "Dalc" variable will be used for the next models as a dependent variable.

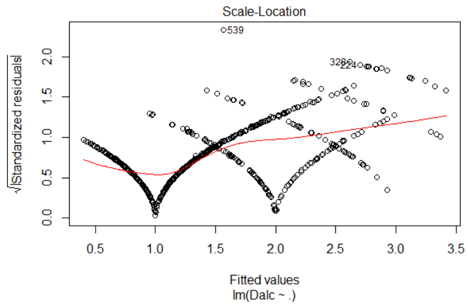
To find out the most influential variables the linear logistic regression will be build.

```
#building linear regression model
linear<-lm(Dalc ~ ., d3)

summary(linear)

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.170797   0.565495  -0.302 0.762729
schoolMS          0.041222   0.116969   0.352 0.724646
sexM              0.183566   0.059005   3.111 0.001950 **
age               0.019120   0.027873   0.686 0.492989
addressU         -0.013894   0.073109  -0.190 0.849337
famsizeLE3        0.072926   0.060021   1.215 0.224828
PstatusT         -0.139556   0.084718  -1.647 0.100001
Medu              0.127691   0.039199   3.258 0.001185 **
Fedu             -0.065954   0.033547  -1.966 0.049737 *
Mjobhealth       -0.409413   0.136727  -2.994 0.002859 **
Mjobother         0.056958   0.087009   0.655 0.512950
Mjobservices     -0.067699   0.098598  -0.687 0.492576
Mjobteacher      -0.124710   0.126670  -0.985 0.325240
Fjobhealth       -0.066378   0.178882  -0.371 0.710711
Fjobother        -0.327085   0.130334  -2.510 0.012339 *
Fjobservices     -0.050507   0.135782  -0.372 0.710039
Fjobteacher      -0.113211   0.162857  -0.695 0.487217
reasonhome        0.047930   0.066920   0.716 0.474123
reasonother       0.345565   0.102068   3.386 0.000755 ***
reasonreputation -0.045160   0.070091  -0.644 0.519611
guardianmother   -0.032562   0.066193  -0.492 0.622950
guardianother     0.176591   0.129999   1.358 0.174826
traveltime        0.063482   0.040474   1.568 0.117286
studytime         0.008953   0.035211   0.254 0.799380
failures          0.017393   0.044753   0.389 0.697667
schoolsupyes      0.144666   0.079771   1.814 0.070232 .
famsupyes         0.059651   0.057192   1.043 0.297351
paidyes           0.067767   0.059867   1.132 0.258087
activitiesyes    -0.079941   0.054266  -1.473 0.141224
nurseryyes       -0.116294   0.067679  -1.718 0.086235 .
higheryes         0.196401   0.124626   1.576 0.115551
internetyes       0.076681   0.074830   1.025 0.305885
romanticyes       0.055150   0.057877   0.953 0.341014
famrel           -0.030495   0.029792  -1.024 0.306417
freetime          0.088547   0.028698   3.085 0.002122 **
goout            -0.019645   0.027212  -0.722 0.470603
```

```
Walc                 0.410729   0.024550  16.730  < 2e-16 ***
health               0.019348   0.019413   0.997 0.319321
absences             0.002600   0.003961   0.656 0.511829
G1                  -0.004112   0.017563  -0.234 0.814944
G2                   0.012143   0.022047   0.551 0.581984
G3                  -0.011537   0.015813  -0.730 0.465926
```

```
plot(linear)
```






```
#plotting independent variables

ggplot (aes(x = Dalc,fill=sex),data = d3) + geom_histogram(binwidth = 1,na.rm
= T) +
  facet_grid(sex~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Dalc,fill=age),data = d3) + geom_histogram(binwidth = 1,na.rm
= T) +
  facet_grid(age~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Dalc,fill=Medu),data = d3) + geom_histogram(binwidth =
1,na.rm = T) +
  facet_grid(Medu~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Dalc,fill=Mjob),data = d3) + geom_histogram(binwidth =
1,na.rm = T) +
  facet_grid(Mjob~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Dalc,fill=Fedu),data = d3) + geom_histogram(binwidth =
1,na.rm = T) +
  facet_grid(Fedu~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Dalc,fill=Fjob),data = d3) + geom_histogram(binwidth =
1,na.rm = T) +
  facet_grid(Fjob~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Dalc,fill=freetime),data = d3) + geom_histogram(binwidth =
1,na.rm = T) +
  facet_grid(freetime~.,scale="free") +mytheme1+mytheme2

ggplot (aes(x = Walc,y=Dalc),data = d3) + geom_point()+geom_jitter(alpha =
0.2)
```

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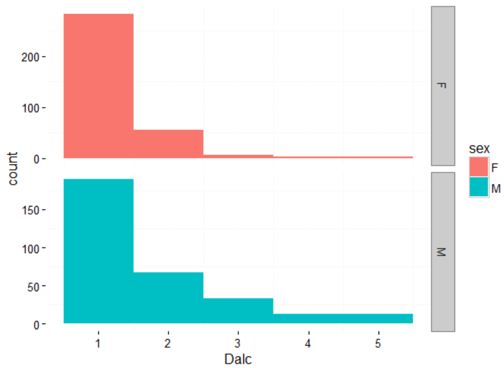
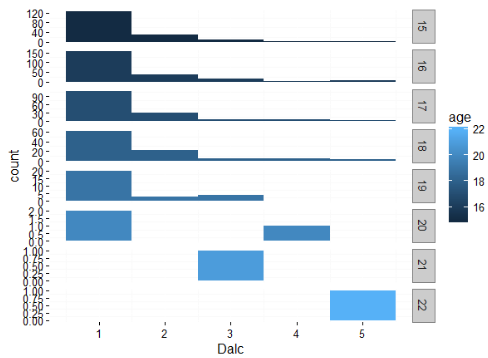
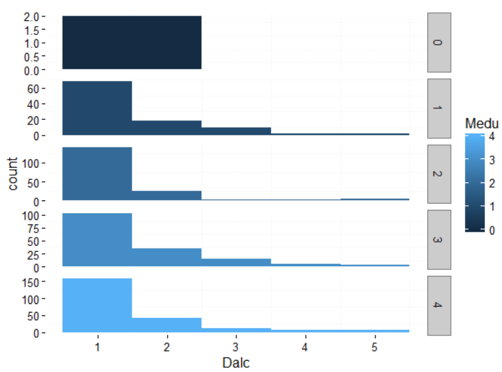
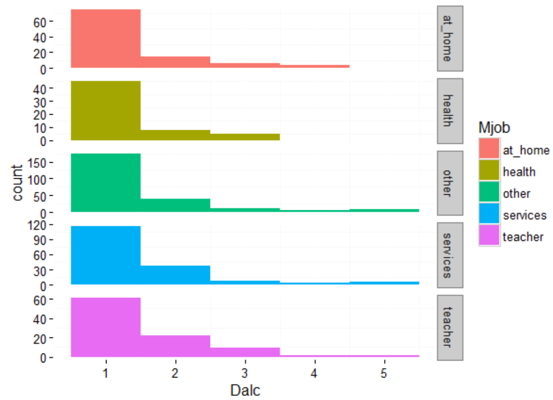
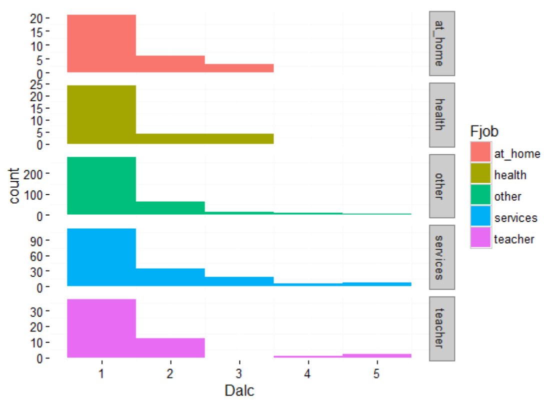
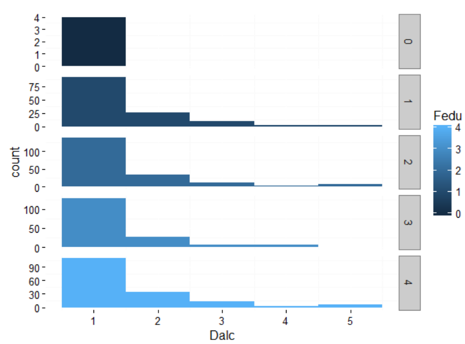


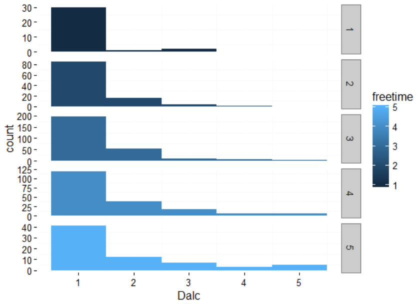


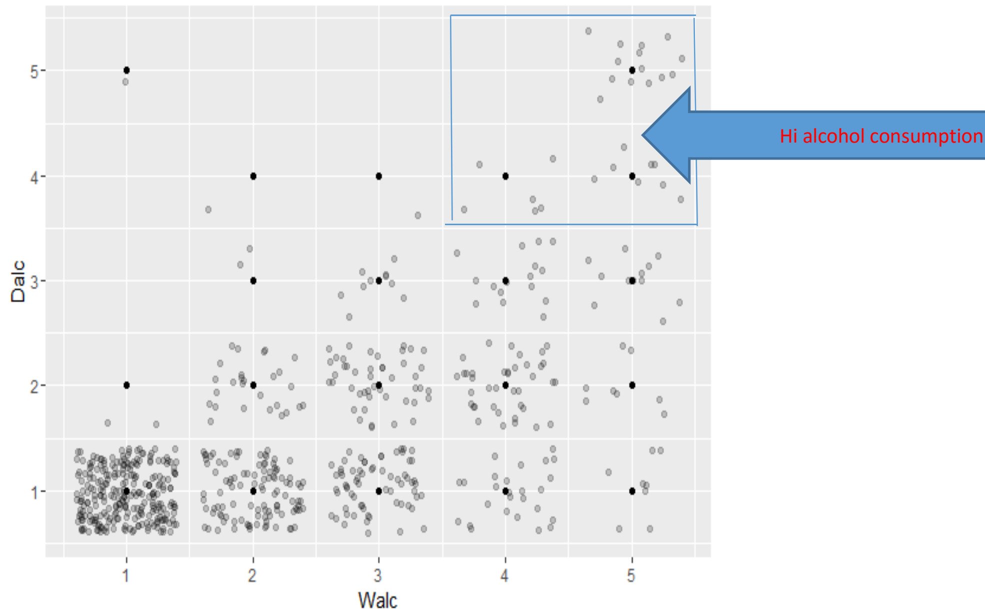













```
#preparing  training and testing sets for the future work

library(caTools)

set.seed(76)

sample.d3 = sample.split(d3$Dalc, SplitRatio=0.7,group = NULL )

trainIdx = which(sample.d3 == TRUE)

trainData = d3[trainIdx,]

testIdx = which(sample.d3 == FALSE)

testData = d3[testIdx,]

#Display of distributed data

dim(trainData) [1] 465  33

dim(testData) [1] 201  33


#Logistic regression

set.seed(123)

#creating logistic regression model

train.glm<- glm(Dalc~ ., data=trainData,family= gaussian)

summary(train.glm)

plot(train.glm)
```

```
#predicting the

predicted.glm=predict(train.glm,type="response")

head(predicted.glm)
  1         2         3         4         5         6 
1.1628075 0.6538965 1.9595075 0.7408622 1.2479522 1.4182362 

summary(predicted.glm)

tapply(predicted.glm,d3$Dalc,mean)
   1        2        3        4        5 
1.197307 1.906120 2.334112 2.682862 2.877123 

table(d3$Dalc, predicted.glm >2.5) #with threshold 2.5

FALSE TRUE
  1   467    5
  2   111   11
  3    22   18
  4     6   10
  5     1   15
```

For the Daily alcohol consumption, we will use Multinomial Regression Model

We have a multilevel variable Dalc

```
levels(as.factor(d3$Dalc)) "1" "2" "3" "4" "5"

#multinomial regression

require(foreign)
require(nnet)
require(ggplot2)
require(reshape2)
```

Executing a multinomial regression with independent variables on train data.

```
mult.regression <-  multinom(as.factor(Dalc )~ . , data = trainData)

summary(mult.regression)
```

We'll calculate Z score and p-Value for the variables in the model.

```
z <summary(mult.regression)$coefficients/
summary(mult.regression)$standard.errors

p <- (1 - pnorm(abs(z), 0, 1))*2

predict.test.multinom<-predict(mult.regression,newdata = testData)

predict.test.multinom.prob<- predict(mult.regression, newdata = testData,
"probs")
```

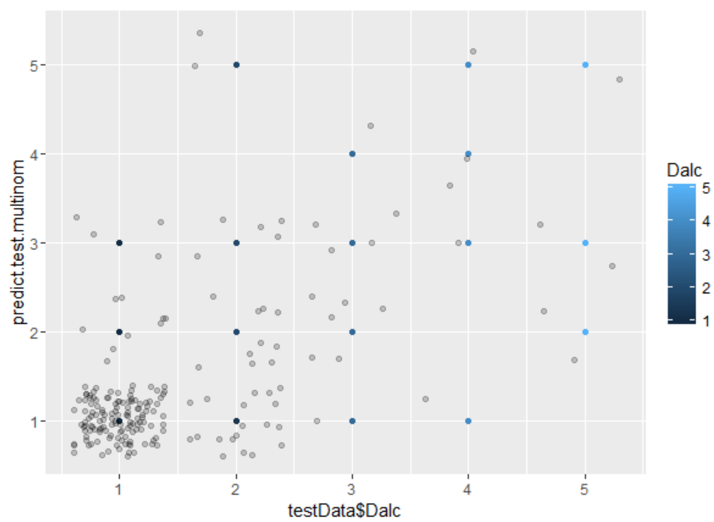
```
summary(predict.train.multinom.prob)

table(testData$Dalc,predict.test.multinom)

mean(as.character(predict.test.multinom) != as.character(testData$Dalc))
#misclassification error  27.3% low

ggplot(testData, aes(x=testData$Dalc, y=predict.test.multinom)) +
geom_point(aes(colour=Dalc))+geom_jitter(alpha = 0.2)
```

The confusion matrix looks like this

table `predict.test.multinom`

	1	2	3	4	5
1	129	9	4	0	0
2	20	10	5	0	2
3	1	6	4	1	0
4	1	0	1	2	1
5	0	2	2	0	1

misclassification error 27.3% ,low.



```
#CVM regression

library(caret)

library(e1071)


trainModels=list()

#forming set of 60 different values of cost and gamma
#and applying to SVM to finding the best model


train_svmBest<-svm(as.factor(Dalc) ~ sex+ age+famsize+Pstatus+ Medu+Fedu +
        studytime +failures+ schoolsup+ activities+ higher +romantic
        +famrel+freetime+goout, data = trainData,type= "C", kernel="radial",
        cost=901,gamma = 181,probability=TRUE)


#predicting the test data

svmmodel.predict<-
predict(train_svmBest,subset(testData,decision.values=TRUE))

svmmodel.class<-predict(train_svmBest,testData,type="class")

svmmodel.labels<-testData$Dalc


#analyzing result

library(SDMTools)

svmmodel.confusion<-confusionMatrix(svmmodel.labels,svmmodel.class)

svmmodel.confusion #Accuracy : 0.8408
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   2   3   4   5
         1 142   0   0   0   0
         2  22  15   0   0   0
         3   5   0   7   0   0
         4   1   0   0   4   0
         5   4   0   0   0   1

Overall Statistics

               Accuracy : 0.8408
                 95% CI : (0.7827, 0.8885)
    No Information Rate : 0.8657
```

```
    P-Value [Acc > NIR] : 0.8712

                  Kappa : 0.572
 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
Sensitivity            0.8161  1.00000  1.00000  1.00000 1.000000
Specificity            1.0000  0.88172  0.97423  0.99492 0.980000
Pos Pred Value         1.0000  0.40541  0.58333  0.80000 0.200000
Neg Pred Value         0.4576  1.00000  1.00000  1.00000 1.000000
Prevalence             0.8657  0.07463  0.03483  0.01990 0.004975
Detection Rate         0.7065  0.07463  0.03483  0.01990 0.004975
Detection Prevalence   0.7065  0.18408  0.05970  0.02488 0.024876
Balanced Accuracy      0.9080  0.94086  0.98711  0.99746 0.990000
```

#SVM with cross validation in R using caret

```
ctrl <- trainControl(method = "repeatedcv", repeats = 10)#setting up control

set.seed(1500)

mod <- train(Dalc ~ sex+ age+famsize+Pstatus+ Medu+Fedu +
           +                 studytime +failures+ schoolsup+ activities+
higher +romantic
            +                famrel+freetime+goout, data=trainData, method
= "svmLinear", trControl = ctrl)

  RMSE         Rsquared
  0.9186448    0.09766363
Tuning parameter 'C' was held constant at a value of 1
```

As a result, we determined that the best model to predict daily alcohol consumption for student population is SVM prediction model with accuracy of 0.84 in comparison with multinomial prediction model of 0.725. After cross validation using caret package RMSE equals 0.91 .

Simple logistic regression gave us the most influential factors affected daily alcohol consumption. The key factors might be changed to decrease drinking are free time (positive correlation) and school support (positive correlation). Parents jobs and their educational level have a high impact although they are pretty stable and cannot be changed.