

# Final Exam

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2022-12-13

#Loading the package

*#Load packages to convert file in PDF.*

```
if(!require(tinytex)){install.packages("tinytex")}
```

```
## Loading required package: tinytex
```

This section is for the basic set up. It will clear all the plots, the console and the workspace. It also sets the overall format for numbers.

```
if(!is.null(dev.list())) dev.off()
```

```
## null device
```

```
##          1
```

```
cat("\014")
```

```
rm(list=ls())
options(scipen=9)
```

#To read Excel file in R data frame.

```
if(!require(readxl)){install.packages("readxl")}
## Loading required package: readxl
library("readxl")

if(!require(pastecs)){install.packages("pastecs")}
## Loading required package: pastecs
library("pastecs")

if(!require(lattice)){install.packages("lattice")}
## Loading required package: lattice
library("lattice")

if(!require(vcd)){install.packages("vcd")}
## Loading required package: vcd
## Loading required package: grid
library("vcd")

if(!require(HSAUR)){install.packages("HSAUR")}
## Loading required package: HSAUR
## Loading required package: tools
library("HSAUR")

if(!require(rmarkdown)){install.packages("rmarkdown")}
## Loading required package: rmarkdown
library("rmarkdown")

if(!require(ggplot2)){install.packages("ggplot2")}
## Loading required package: ggplot2
library("ggplot2")

if(!require(klaR)){install.packages("klaR")}
```

```
## Loading required package: klaR
## Loading required package: MASS
library("klaR")

if(!require(partykit)){install.packages("partykit")}

## Loading required package: partykit
## Loading required package: libcoin
## Loading required package: mvtnorm
library("partykit")
```

## To get working directory

To read PROG8430\_Assign04\_22F.txt file located at

**“D:/Final Assignment/DATA/Assignment5”**

```
getwd()

## [1] "D:/Final Assignment/DATA/FINAL EXAM"

Train_AP <- read_excel("PROG8430_Final_22F_train.xlsx")

head(Train_AP)

## # A tibble: 6 × 8
##   Cancer   Age   HW Hst     Exe Smk   Drk   Hlth
##   <chr>   <dbl> <dbl> <chr> <dbl> <chr> <chr> <chr>
## 1 0       43 1.13  1      53 0     0     VG
## 2 0       39 1.21  0      38 0     0     A
## 3 1       49 0.898 0      18 1     1     P
## 4 0       59 1.03  0       9 1     1     P
## 5 0       45 1.08  0     127 0     0     VG
## 6 0       53 1.06  1      11 0     0     A

str(Train_AP)

## tibble [695 × 8] (S3: tbl_df/tbl/data.frame)
## $ Cancer: chr [1:695] "0" "0" "1" "0" ...
## $ Age   : num [1:695] 43 39 49 59 45 53 69 50 40 50 ...
## $ HW    : num [1:695] 1.127 1.214 0.898 1.028 1.082 ...
## $ Hst   : chr [1:695] "1" "0" "0" "0" ...
## $ Exe   : num [1:695] 53 38 18 9 127 11 8 7 51 11 ...
## $ Smk   : chr [1:695] "0" "0" "1" "1" ...
```

```
## $ Drk : chr [1:695] "0" "0" "1" "1" ...
## $ Hlth : chr [1:695] "VG" "A" "P" "P" ...
```

Rename all variables with your initials appended.

# to change all column name by appending my initials (Ajay Patel = AP) and separate it by “\_”.

```
colnames(Train_AP) <- paste(colnames(Train_AP), "AP", sep = "_")
head(Train_AP)
```

```
## # A tibble: 6 × 8
##   Cancer_AP Age_AP HW_AP Hst_AP Exe_AP Smk_AP Drk_AP Hlth_AP
##   <chr>      <dbl> <dbl> <chr>   <dbl> <chr>   <chr>   <chr>
## 1 0          43 1.13  1       53 0       0       VG
## 2 0          39 1.21  0       38 0       0       A
## 3 1          49 0.898 0       18 1       1       P
## 4 0          59 1.03  0       9 1       1       P
## 5 0          45 1.08  0      127 0       0       VG
## 6 0          53 1.06  1       11 0       0       A
```

```
str(Train_AP)
```

```
## tibble [695 × 8] (S3: tbl_df/tbl/data.frame)
## $ Cancer_AP: chr [1:695] "0" "0" "1" "0" ...
## $ Age_AP : num [1:695] 43 39 49 59 45 53 69 50 40 50 ...
## $ HW_AP : num [1:695] 1.127 1.214 0.898 1.028 1.082 ...
## $ Hst_AP : chr [1:695] "1" "0" "0" "0" ...
## $ Exe_AP : num [1:695] 53 38 18 9 127 11 8 7 51 11 ...
## $ Smk_AP : chr [1:695] "0" "0" "1" "1" ...
## $ Drk_AP : chr [1:695] "0" "0" "1" "1" ...
## $ Hlth_AP : chr [1:695] "VG" "A" "P" "P" ...
```

Convert Character variables into factor variables.

```
Train_AP$Cancer_AP <- as.factor(Train_AP$Cancer_AP)
Train_AP$Hst_AP <- as.factor(Train_AP$Hst_AP)
Train_AP$Smk_AP <- as.factor(Train_AP$Smk_AP)
Train_AP$Drk_AP <- as.factor(Train_AP$Drk_AP)
Train_AP$Hlth_AP <- as.factor(Train_AP$Hlth_AP)
```

```
str(Train_AP)
```

```
## tibble [695 × 8] (S3: tbl_df/tbl/data.frame)
## $ Cancer_AP: Factor w/ 2 levels "0","1": 1 1 2 1 1 1 2 1 1 1 ...
## $ Age_AP : num [1:695] 43 39 49 59 45 53 69 50 40 50 ...
## $ HW_AP : num [1:695] 1.127 1.214 0.898 1.028 1.082 ...
## $ Hst_AP : Factor w/ 2 levels "0","1": 2 1 1 1 1 2 2 1 1 1 ...
## $ Exe_AP : num [1:695] 53 38 18 9 127 11 8 7 51 11 ...
## $ Smk_AP : Factor w/ 2 levels "0","1": 1 1 2 2 1 1 2 1 1 1 ...
## $ Drk_AP : Factor w/ 2 levels "0","1": 1 1 2 2 1 1 2 1 1 1 ...
```

```
## $ Hlth_AP : Factor w/ 5 levels "A","G","P","VG",...: 4 1 3 3 4 1 3 1 1 3
...
```

Dimension reduction process.

let's check missing factor variables.

```
summary(Train_AP)
```

```
## Cancer_AP Age_AP HW_AP Hst_AP Exe_AP Smk_AP
## 0:344 Min. :22.00 Min. :0.678 0:447 Min. : 1.00 0:342
## 1:351 1st Qu.:42.00 1st Qu.:0.948 1:248 1st Qu.: 15.00 1:353
## Median :48.00 Median :1.031 Median : 26.00
## Mean :47.09 Mean :1.040 Mean : 31.45
## 3rd Qu.:52.00 3rd Qu.:1.115 3rd Qu.: 42.00
## Max. :70.00 Max. :8.500 Max. :140.00
## Drk_AP Hlth_AP
## 0:319 A :209
## 1:376 G :163
## P :151
## VG:114
## VP: 58
##
```

*#there is no missing values in all the variables.*

```
stat.desc(Train_AP)
```

```
## Cancer_AP Age_AP HW_AP Hst_AP Exe_AP Smk_AP
## nbr.val NA 695.0000000 695.0000000 NA 695.0000000 NA
## nbr.null NA 0.0000000 0.0000000 NA 0.0000000 NA
## nbr.na NA 0.0000000 0.0000000 NA 0.0000000 NA
## min NA 22.0000000 0.67800000 NA 1.0000000 NA
## max NA 70.0000000 8.50000000 NA 140.0000000 NA
## range NA 48.0000000 7.82200000 NA 139.0000000 NA
## sum NA 32731.0000000 722.46700000 NA 21858.0000000 NA
## median NA 48.0000000 1.03100000 NA 26.0000000 NA
## mean NA 47.0949640 1.03952086 NA 31.4503597 NA
## SE.mean NA 0.3030735 0.01169660 NA 0.8477562 NA
## CI.mean NA 0.5950510 0.02296496 NA 1.6644745 NA
## var NA 63.8382311 0.09508318 NA 499.4899674 NA
## std.dev NA 7.9898830 0.30835561 NA 22.3492722 NA
## coef.var NA 0.1696547 0.29663244 NA 0.7106206 NA
## Drk_AP Hlth_AP
## nbr.val NA NA
## nbr.null NA NA
## nbr.na NA NA
## min NA NA
## max NA NA
## range NA NA
## sum NA NA
## median NA NA
```

```
## mean      NA      NA
## SE.mean   NA      NA
## CI.mean   NA      NA
## var       NA      NA
## std.dev   NA      NA
## coef.var  NA      NA
```

*#There is no low variance after inspection of Coef.var of all variables  
#(for numeric).*

Apply the High Correlation Filter to remove appropriate columns of data.

High correlation between two variables means they have similar trends and are likely to carry similar information.

No correlation available between numerical and nominal columns.

pearson, spearman, kendall methods can be used to measure the degree of association between two variables.

can only check for numerical and we have 3 columns with numeric data so  $n(n-1)/2$  ( $3*2/2 = 3$ ) combinations should be checked.

*#by spearman method  
#Spearman is non-parametric and therefore makes no normality assumption*

```
cor(Train_AP$Age_AP, Train_AP$HW_AP, method = "spearman")
## [1] -0.1572284
cor(Train_AP$Age_AP, Train_AP$Exe_AP, method = "spearman")
## [1] 0.03219058
cor(Train_AP$HW_AP, Train_AP$Exe_AP, method = "spearman")
## [1] -0.04108865
```

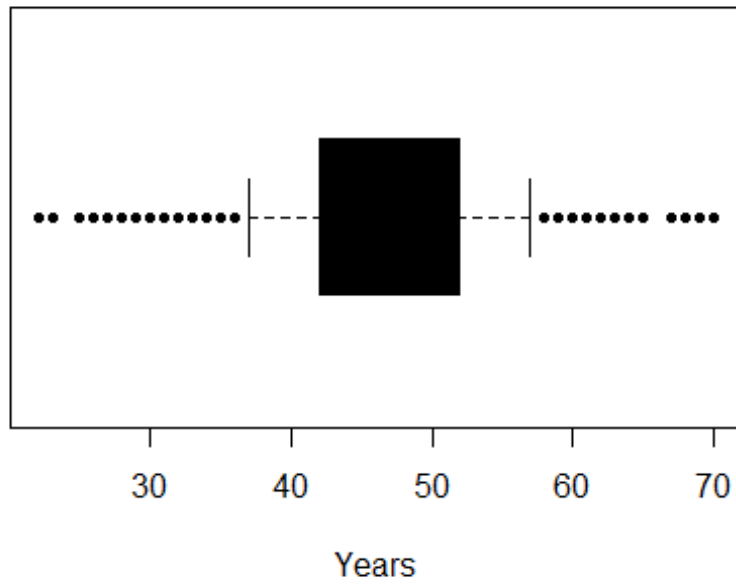
Conclusion: There is no correlation between numeric variables. Moreover, 4 variables are binary so we cannot plot

There is no single variable which is not useful in analytic purpose.

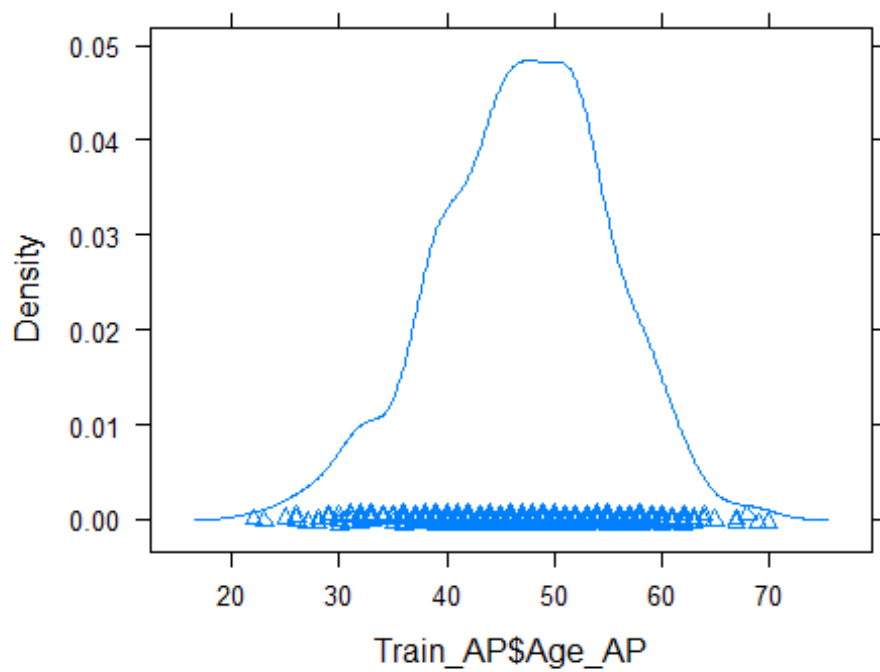
Let's check for the outliers.

```
boxplot(Train_AP$Age_AP,
        main="Box Plot of Age in years",
        xlab="Years",
        col=1, horizontal=TRUE, pch=20, range = 0.5)
```

**Box Plot of Age in years**

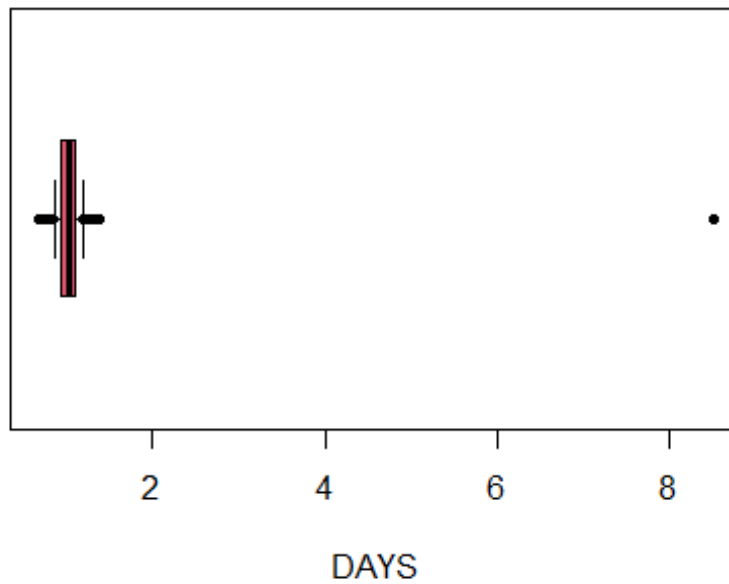


```
densityplot( ~ Train_AP$Age_AP, pch=2)
```



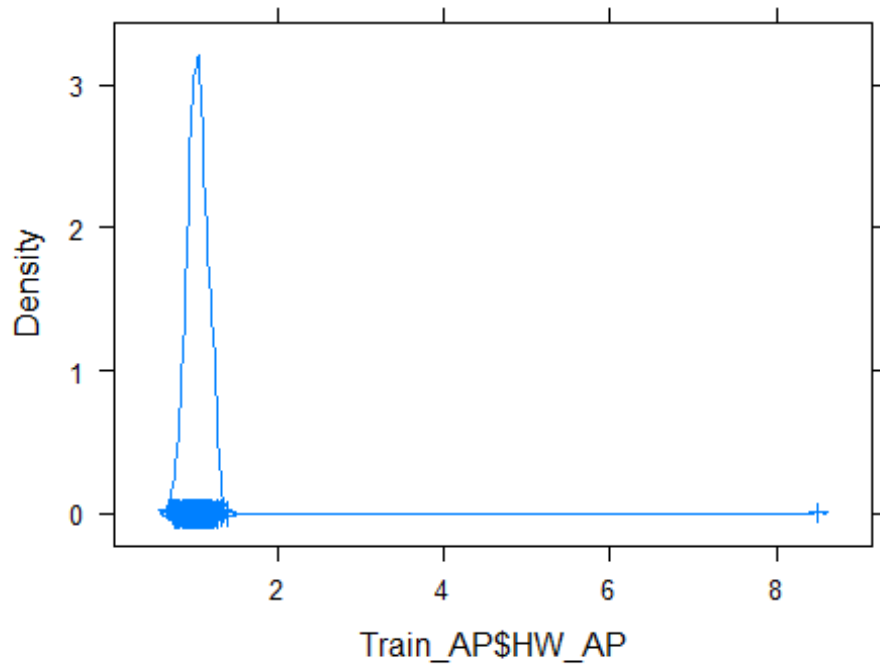
```
boxplot(Train_AP$HW_AP,  
        main="Box Plot of A ratio of Height to Weight",  
        xlab="DAYS",  
        col=2, horizontal=TRUE, pch=20, range = 0.5)
```

### Box Plot of A ratio of Height to Weight



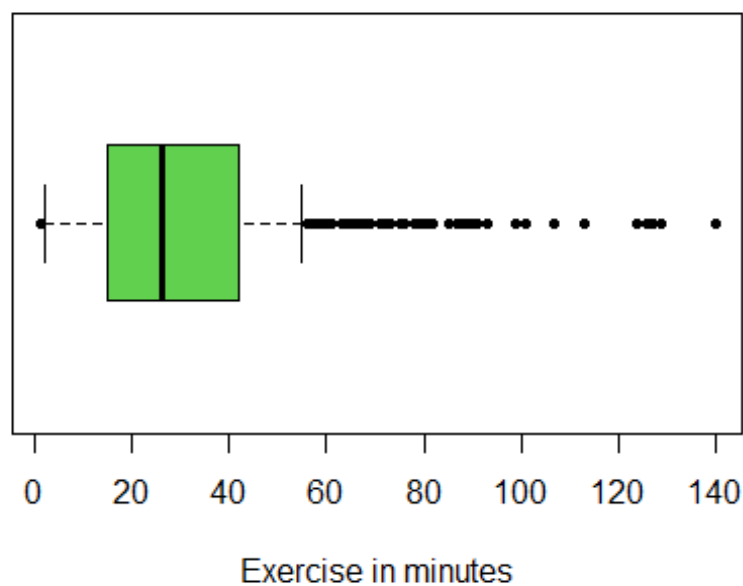
```
densityplot( ~ Train_AP$HW_AP, pch=3)
```



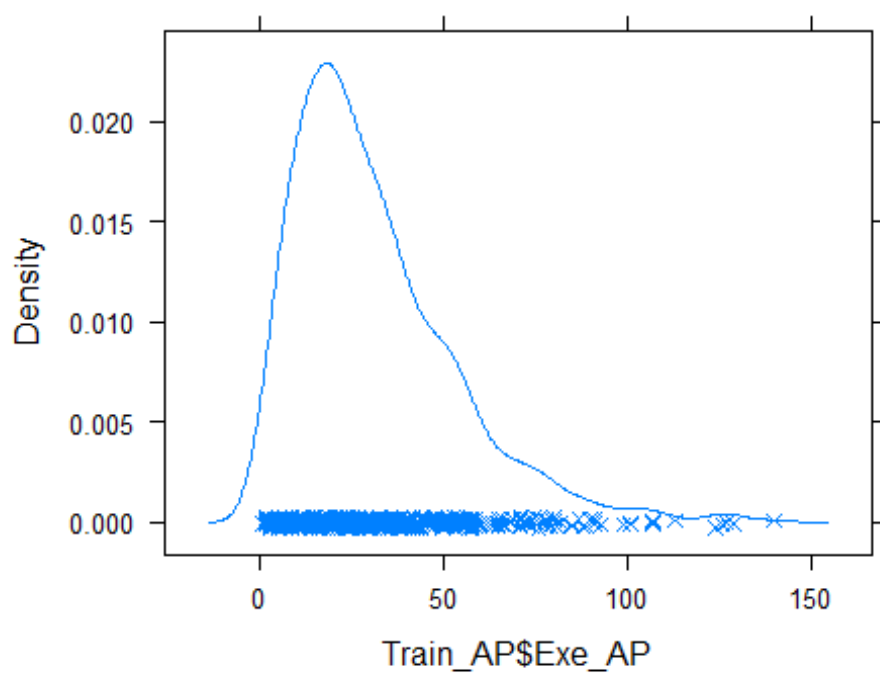


```
boxplot(Train_AP$Exe_AP,  
        main="Box Plot of Time spent exercising each week",  
        xlab="Exercise in minutes",  
        col=3, horizontal=TRUE, pch=20, range = 0.5)
```

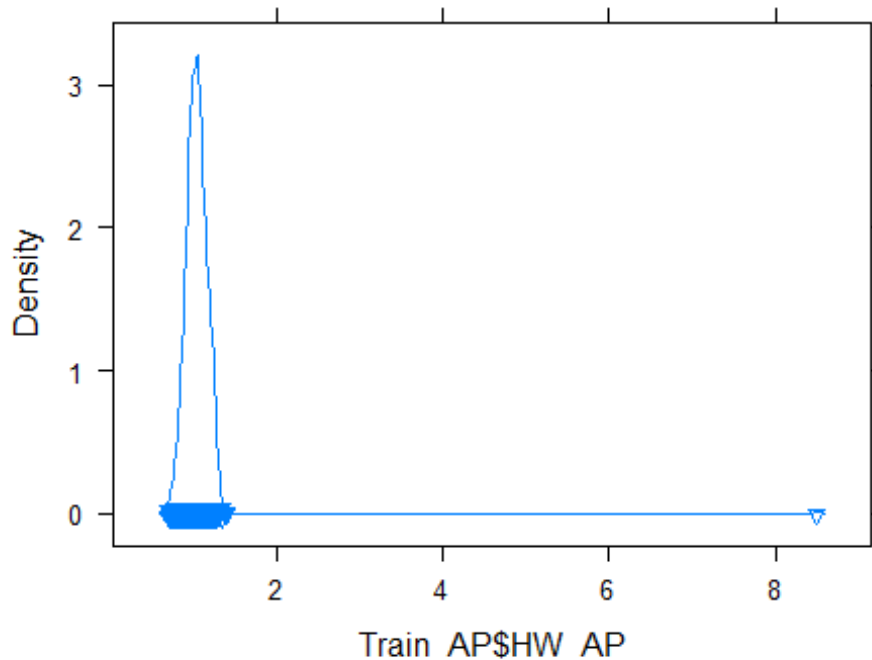
## Box Plot of Time spent exercising each week



```
densityplot( ~ Train_AP$Exe_AP, pch=4)
```



```
densityplot( ~ Train_AP$HW_AP, pch=6)
```



```
nr <- which(Train_AP$HW_AP == max(Train_AP$HW_AP))#to see which row has max value
nr
## [1] 257
```

From Density plot and boxplot we can say all the variables are seem fine. However, HW\_AP has outlier which has value 8.5 but I am keep this variables as it is at this moment because it is possible that that person has height or weight more compared to each other so ratio is high.

#let's create glm model as our dependent variable is in binary so here we will apply logistic regression.

```
glmstart_time_AP <- Sys.time()
glm_AP <- glm(Train_AP$Cancer_AP ~ ., data=Train_AP, family = "binomial")
summary(glm_AP)

##
## Call:
## glm(formula = Train_AP$Cancer_AP ~ ., family = "binomial", data =
Train_AP)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.94946  -0.46807   0.05306   0.43762   2.83234
##
```

```
## Coefficients:
##           Estimate Std. Error z value      Pr(>|z|)
## (Intercept)  10.132190   1.638007   6.186 0.0000000006183 ***
## Age_AP       0.056034   0.016007   3.501   0.000464 ***
## HW_AP        -14.018355   1.428407  -9.814   < 2e-16 ***
## Hst_AP1      1.777051   0.268118   6.628 0.0000000000341 ***
## Exe_AP       -0.006979   0.005379  -1.298   0.194417
## Smk_AP1      2.976943   0.657854   4.525 0.0000060328439 ***
## Drk_AP1      -0.575130   0.661089  -0.870   0.384315
## Hlth_AP1     0.006291   0.321522   0.020   0.984389
## Hlth_APP     0.194847   0.340547   0.572   0.567213
## Hlth_APVG    0.022065   0.363307   0.061   0.951570
## Hlth_APVP    0.416644   0.496110   0.840   0.401008
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 963.40  on 694  degrees of freedom
## Residual deviance: 459.55  on 684  degrees of freedom
## AIC: 481.55
##
## Number of Fisher Scoring iterations: 6

glmend_time_AP <- Sys.time()
glm_Time_AP <- glmend_time_AP - glmstart_time_AP

str(Train_AP)

## tibble [695 × 8] (S3: tbl_df/tbl/data.frame)
##  $ Cancer_AP: Factor w/ 2 levels "0","1": 1 1 2 1 1 1 2 1 1 1 ...
##  $ Age_AP   : num [1:695] 43 39 49 59 45 53 69 50 40 50 ...
##  $ HW_AP    : num [1:695] 1.127 1.214 0.898 1.028 1.082 ...
##  $ Hst_AP   : Factor w/ 2 levels "0","1": 2 1 1 1 1 2 2 1 1 1 ...
##  $ Exe_AP   : num [1:695] 53 38 18 9 127 11 8 7 51 11 ...
##  $ Smk_AP   : Factor w/ 2 levels "0","1": 1 1 2 2 1 1 2 1 1 1 ...
##  $ Drk_AP   : Factor w/ 2 levels "0","1": 1 1 2 2 1 1 2 1 1 1 ...
##  $ Hlth_AP  : Factor w/ 5 levels "A","G","P","VG",...: 4 1 3 3 4 1 3 1 1 3
##  ...

#just experimenting
#glm1_AP <- glm(Train_AP$Cancer_AP ~ Age_AP + HW_AP + Hst_AP +
#  Smk_AP+Drk_AP, data=Train_AP, family = "binomial")
#summary(glm1_AP)
#-----
resp_glm_AP <- predict(glm_AP, type="response")
Class_glm_AP <- ifelse(resp_glm_AP > 0.5, "1", "0")
CF_GLM_AP <- table(Train_AP$Cancer_AP, Class_glm_AP,
  dnn=list("Act ", "Predicted") )
CF_GLM_AP
```

```

##      Predicted
## Act    0    1
##      0 292  52
##      1  47 304

glmTP_AP <- CF_GLM_AP[2,2]
glmTN_AP <- CF_GLM_AP[1,1]
glmFP_AP <- CF_GLM_AP[1,2]
glmFN_AP <- CF_GLM_AP[2,1]

GLMAccuracy_AP <- (glmTP_AP + glmTN_AP) / 695
GLMAccuracy_AP

## [1] 0.857554

#let's see by applying backward

backstart_time_AP <- Sys.time()
glm_AP <- glm(Train_AP$Cancer_AP ~ ., data=Train_AP, family = "binomial")
Backstep.fit_AP <- step(glm_AP, direction = "backward", trace = 0)
backend_time_AP <- Sys.time()
back_Time_AP <- backend_time_AP - backstart_time_AP
summary(Backstep.fit_AP)

##
## Call:
## glm(formula = Train_AP$Cancer_AP ~ Age_AP + HW_AP + Hst_AP +
##      Smk_AP, family = "binomial", data = Train_AP)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.00105  -0.46973   0.05708   0.45025   2.86729
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  10.02415    1.61313   6.214 0.00000000051625 ***
## Age_AP       0.05456    0.01573   3.469  0.000523 ***
## HW_AP      -14.02958    1.42152  -9.869 < 2e-16 ***
## Hst_AP1      1.80988    0.26535   6.821 0.00000000000906 ***
## Smk_AP1      2.43806    0.24161  10.091 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 963.4  on 694  degrees of freedom
## Residual deviance: 463.2  on 690  degrees of freedom
## AIC: 473.2
##
## Number of Fisher Scoring iterations: 6

```

*#confusion matrix for backward*

```
resp_glm_AP <- predict(Backstep.fit_AP, type="response")
Class_glm_AP <- ifelse(resp_glm_AP > 0.5, "1", "0")
CF_bGLM_AP <- table(Train_AP$Cancer_AP, Class_glm_AP,
                    dnn=list("Act ", "Predicted") )
CF_bGLM_AP
```

```
##      Predicted
## Act    0    1
##    0 292  52
##    1  46 305
```

```
BackTP_AP <- CF_bGLM_AP[2,2]
BackTN_AP <- CF_bGLM_AP[1,1]
BackFP_AP <- CF_bGLM_AP[1,2]
BackFN_AP <- CF_bGLM_AP[2,1]
```

```
BackAccuracy_AP <- (BackTP_AP + BackTN_AP) / 695
BackAccuracy_AP
```

```
## [1] 0.8589928
```

```
back_Time_AP
```

```
## Time difference of 0.157881 secs
```

Conclusion: I am selecting backward model as a the best model because it has low AIC all the variables are significant, residuals are symmetrical. However, there is slightly high differenece between NULL and residuals deviance compared to normal glm model but from other factors backward model is the best.

Naïve-Bayes Classification

```
NBstart_time_AP <- Sys.time()
```

```
NB.fit_AP <- NaiveBayes(Train_AP$Cancer_AP ~ . ,data = Train_AP,
na.action=na.omit)
```

```
NBend_time_AP <- Sys.time()
```

```
NB_Time_AP <- NBend_time_AP - NBstart_time_AP
```

```
NB_Time_AP
```

```
## Time difference of 0.005084038 secs
```

```
pred_bay_AP <- predict(NB.fit_AP,Train_AP)
```

*#Creates Confusion Matrix*

```
CF_NB_AP <- table(Actual=Train_AP$Cancer_AP, Predicted=pred_bay_AP$class)
```

*#Confusion matrix of Naïve-Bayesian classification.*

```
CF_NB_AP
```

```
##          Predicted
## Actual    0     1
##          0 263   81
##          1   55  296
```

```
NB_TP_AP <- CF_NB_AP[2,2]
```

```
NB_TN_AP <- CF_NB_AP[1,1]
```

```
NB_FP_AP <- CF_NB_AP[1,2]
```

```
NB_FN_AP <- CF_NB_AP[2,1]
```

```
NBAccuracy_AP <- (NB_TP_AP + NB_TN_AP) / 695
```

```
NBAccuracy_AP
```

```
## [1] 0.8043165
```

## Linear Discriminant Analysis

```
LDAstart_time_AP <- Sys.time()
```

```
LDA.fit_AP <- lda(Train_AP$Cancer_AP ~ ., data = Train_AP, na.action=na.omit)
```

```
LDAend_time_AP <- Sys.time()
```

```
LDA_Time_AP <- LDAend_time_AP - LDAstart_time_AP
```

```
LDA_Time_AP
```

```
## Time difference of 0.008917093 secs
```

*#Predicting LDA Model*

```
LDApred_AP <- predict(LDA.fit_AP, data=Train_AP)
```

*#Confusion matrix for LDA Model.*

```
CF_LDA_AP <- table(Actual=Train_AP$Cancer_AP, Predicted=LDApred_AP$class)
```

```
CF_LDA_AP
```

```
##          Predicted
## Actual    0     1
##          0 272   72
##          1   63  288
```

```
LDA_TP_AP <- CF_LDA_AP[2,2]
LDA_TN_AP <- CF_LDA_AP[1,1]
LDA_FP_AP <- CF_LDA_AP[1,2]
LDA_FN_AP <- CF_LDA_AP[2,1]

LDA_Accuracy_AP <- (LDA_TP_AP + LDA_TN_AP) / 695
LDA_Accuracy_AP

## [1] 0.8057554
```

Conclusion: here we can see the backward model has the lowest false positives, false negatives, and high accuracy. However, model processing time is high compared to others but I am choosing backward model as the best model.

For Test data

```
Test_AP <- read_excel("PROG8430_Final_22F_test.xlsx")

head(Test_AP)

## # A tibble: 6 × 7
##   Age   HW Hst   Exe Smk   Drk   Hlth
##   <dbl> <dbl> <chr> <dbl> <chr> <chr> <chr>
## 1    43 0.99  0     19  0     0    VG
## 2    50 0.847 0     29  1     1    A
## 3    62 0.792 0     20  1     1    G
## 4    44 0.857 0      5  0     0    VG
## 5    52 1.06  1    149  0     0    P
## 6    55 0.963 0     10  0     0    P

str(Test_AP)

## tibble [705 × 7] (S3: tbl_df/tbl/data.frame)
## $ Age : num [1:705] 43 50 62 44 52 55 43 51 50 41 ...
## $ HW  : num [1:705] 0.99 0.847 0.792 0.857 1.065 ...
## $ Hst : chr [1:705] "0" "0" "0" "0" ...
## $ Exe : num [1:705] 19 29 20 5 149 10 21 31 19 15 ...
## $ Smk : chr [1:705] "0" "1" "1" "0" ...
## $ Drk : chr [1:705] "0" "1" "1" "0" ...
## $ Hlth: chr [1:705] "VG" "A" "G" "VG" ...

#initials

colnames(Test_AP) <- paste(colnames(Test_AP), "AP", sep = "_")
head(Test_AP)

## # A tibble: 6 × 7
##   Age_AP HW_AP Hst_AP Exe_AP Smk_AP Drk_AP Hlth_AP
##   <dbl> <dbl> <chr>   <dbl> <chr> <chr> <chr>
## 1    43 0.99  0     19  0     0    VG
## 2    50 0.847 0     29  1     1    A
```



```
## 3      62 0.792 0          20 1      1      G
## 4      44 0.857 0          5 0      0      VG
## 5      52 1.06  1        149 0      0      P
## 6      55 0.963 0         10 0      0      P
```

```
str(Test_AP)
```

```
## tibble [705 × 7] (S3: tbl_df/tbl/data.frame)
## $ Age_AP : num [1:705] 43 50 62 44 52 55 43 51 50 41 ...
## $ HW_AP  : num [1:705] 0.99 0.847 0.792 0.857 1.065 ...
## $ Hst_AP : chr [1:705] "0" "0" "0" "0" ...
## $ Exe_AP : num [1:705] 19 29 20 5 149 10 21 31 19 15 ...
## $ Smk_AP : chr [1:705] "0" "1" "1" "0" ...
## $ Drk_AP : chr [1:705] "0" "1" "1" "0" ...
## $ Hlth_AP: chr [1:705] "VG" "A" "G" "VG" ...
```

*# converting characters into the factors*

```
Test_AP$Hst_AP <- as.factor(Test_AP$Hst_AP)
Test_AP$Smk_AP <- as.factor(Test_AP$Smk_AP)
Test_AP$Drk_AP <- as.factor(Test_AP$Drk_AP)
Test_AP$Hlth_AP <- as.factor(Test_AP$Hlth_AP)
```

```
str(Test_AP)
```

```
## tibble [705 × 7] (S3: tbl_df/tbl/data.frame)
## $ Age_AP : num [1:705] 43 50 62 44 52 55 43 51 50 41 ...
## $ HW_AP  : num [1:705] 0.99 0.847 0.792 0.857 1.065 ...
## $ Hst_AP : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 2 1 1 1 ...
## $ Exe_AP : num [1:705] 19 29 20 5 149 10 21 31 19 15 ...
## $ Smk_AP : Factor w/ 2 levels "0","1": 1 2 2 1 1 1 1 1 1 1 ...
## $ Drk_AP : Factor w/ 2 levels "0","1": 1 2 2 1 1 1 1 1 2 1 ...
## $ Hlth_AP: Factor w/ 5 levels "A","G","P","VG",...: 4 1 2 4 3 3 4 3 1 4
## ...
```

```
summary(Test_AP)
```

```
##      Age_AP      HW_AP      Hst_AP      Exe_AP      Smk_AP      Drk_AP
## Min.   :24.00   Min.   :0.654   0:465   Min.    :  0.0   0:345   0:324
## 1st Qu.:42.00   1st Qu.:0.922   1:240   1st Qu.: 15.0   1:360   1:381
## Median :48.00   Median :1.024           Median : 25.0
## Mean   :47.79   Mean   :1.021           Mean   : 30.2
## 3rd Qu.:53.00   3rd Qu.:1.108           3rd Qu.: 41.0
## Max.   :80.00   Max.   :1.356           Max.   :149.0
## Hlth_AP
## A :198
## G :177
## P :138
## VG:119
## VP: 73
##
```

*#there is no missing values in all the variables.*

stat.desc(Test\_AP)

##	Age_AP	HW_AP	Hst_AP	Exe_AP	Smk_AP
Drk_AP					
## nbr.val	705.0000000	705.000000000	NA	705.0000000	NA
NA					
## nbr.null	0.0000000	0.000000000	NA	1.0000000	NA
NA					
## nbr.na	0.0000000	0.000000000	NA	0.0000000	NA
NA					
## min	24.0000000	0.654000000	NA	0.0000000	NA
NA					
## max	80.0000000	1.356000000	NA	149.0000000	NA
NA					
## range	56.0000000	0.702000000	NA	149.0000000	NA
NA					
## sum	33689.0000000	719.929000000	NA	21294.0000000	NA
NA					
## median	48.0000000	1.024000000	NA	25.0000000	NA
NA					
## mean	47.7858156	1.021175887	NA	30.2042553	NA
NA					
## SE.mean	0.3116863	0.004901292	NA	0.8260822	NA
NA					
## CI.mean.0.95	0.6119459	0.009622900	NA	1.6218796	NA
NA					
## var	68.4895712	0.016935980	NA	481.1002660	NA
NA					
## std.dev	8.2758426	0.130138313	NA	21.9339979	NA
NA					
## coef.var	0.1731862	0.127439665	NA	0.7261890	NA
NA					
##	Hlth_AP				
## nbr.val	NA				
## nbr.null	NA				
## nbr.na	NA				
## min	NA				
## max	NA				
## range	NA				
## sum	NA				
## median	NA				
## mean	NA				
## SE.mean	NA				
## CI.mean.0.95	NA				
## var	NA				
## std.dev	NA				
## coef.var	NA				

```

#There is no low variance after inspection of Coef.var of all variables
#(for numeric).
#by spearman method
#Speaman is non-parametric and therefore makes no normalacy assumption

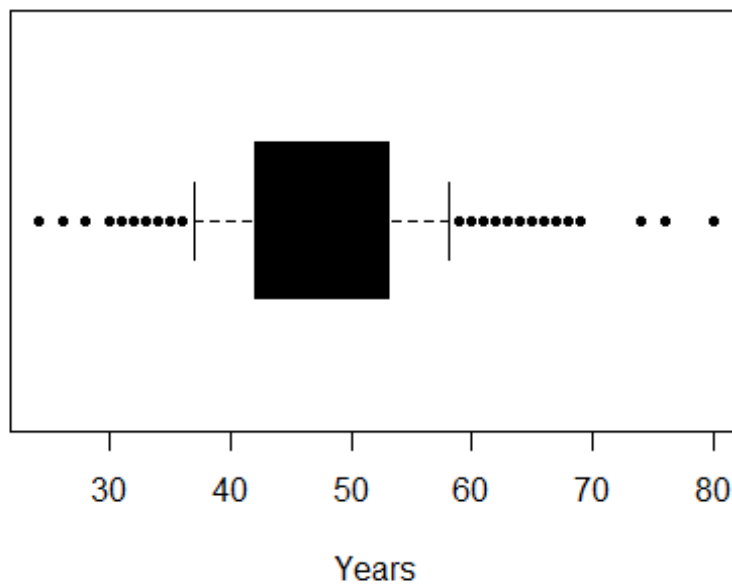
cor(Train_AP$Age_AP,Train_AP$HW_AP,method = "spearman")
## [1] -0.1572284
cor(Train_AP$Age_AP,Train_AP$Exe_AP,method = "spearman")
## [1] 0.03219058
cor(Train_AP$HW_AP,Train_AP$Exe_AP,method = "spearman")
## [1] -0.04108865

#There is no correlation between numeric variables

boxplot(Test_AP$Age_AP,
        main="Box Plot of Age in years",
        xlab="Years",
        col=1, horizontal=TRUE, pch=20, range = 0.5)

```

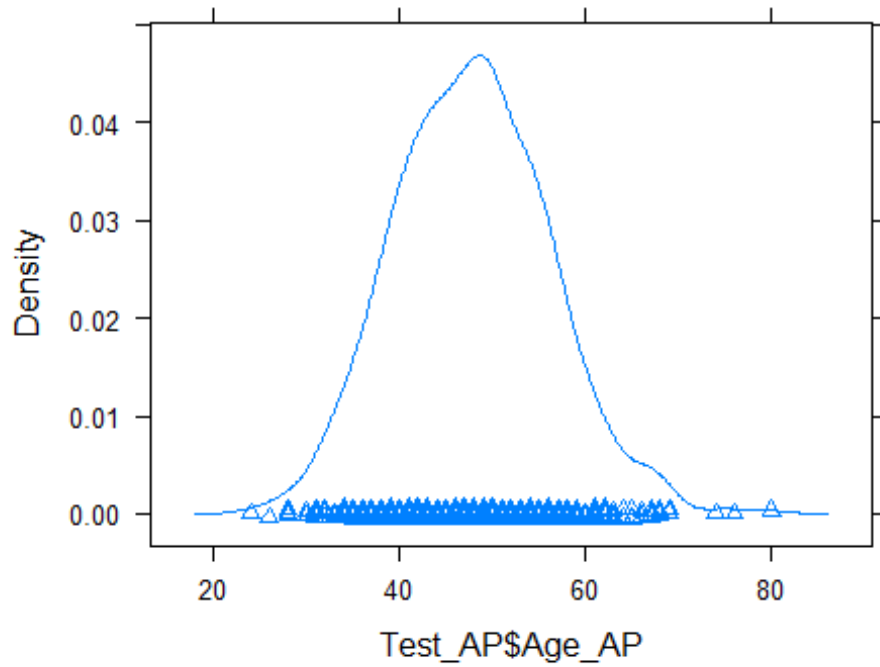
**Box Plot of Age in years**



```

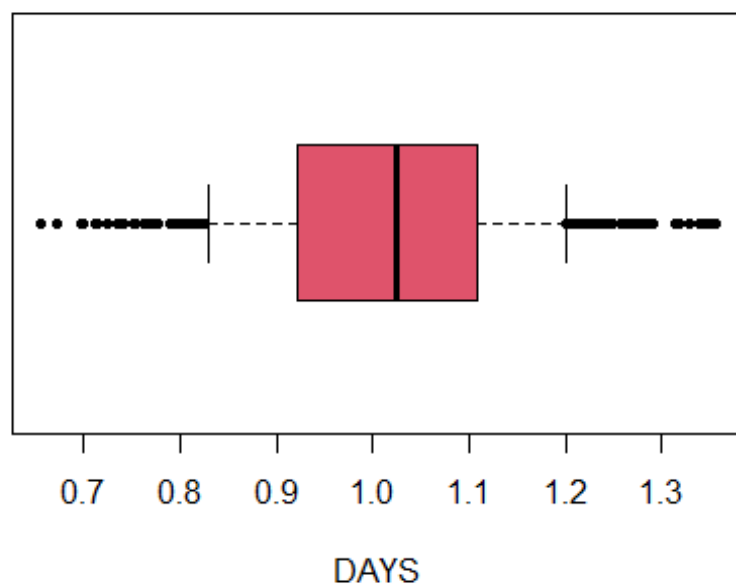
densityplot( ~ Test_AP$Age_AP, pch=2)

```

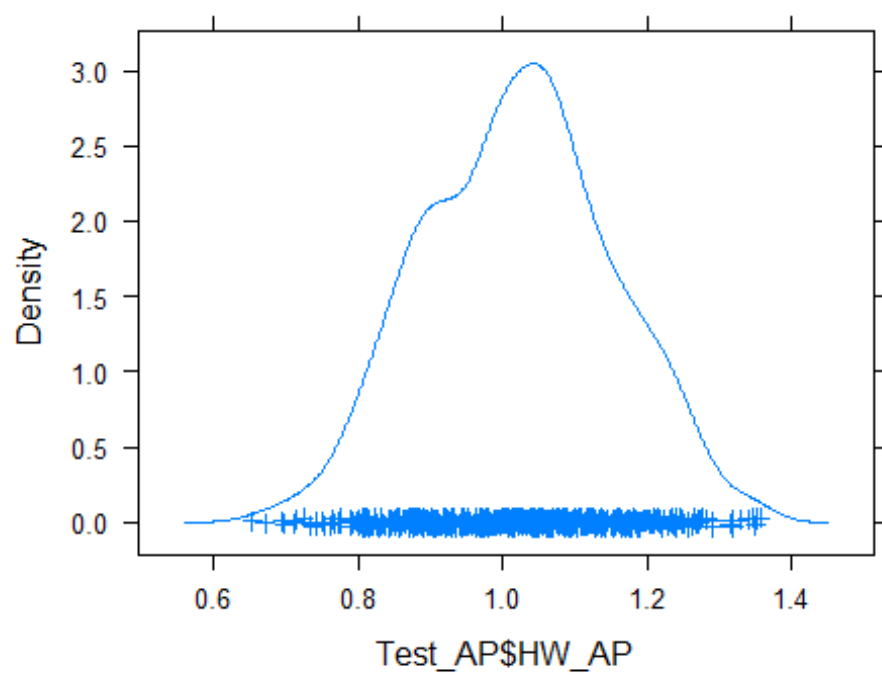


```
boxplot(Test_AP$HW_AP,  
        main="Box Plot of A ratio of Height to Weight",  
        xlab="DAYS",  
        col=2, horizontal=TRUE, pch=20, range = 0.5)
```

**Box Plot of A ratio of Height to Weight**

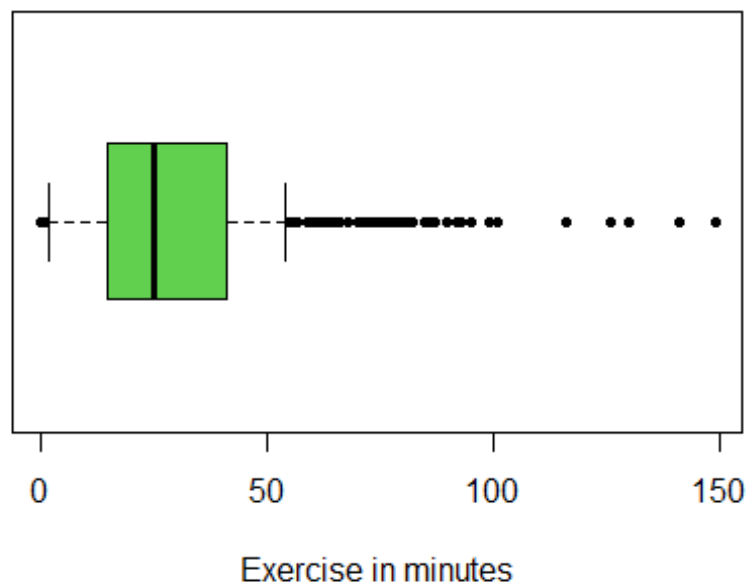


```
densityplot( ~ Test_AP$HW_AP, pch=3)
```

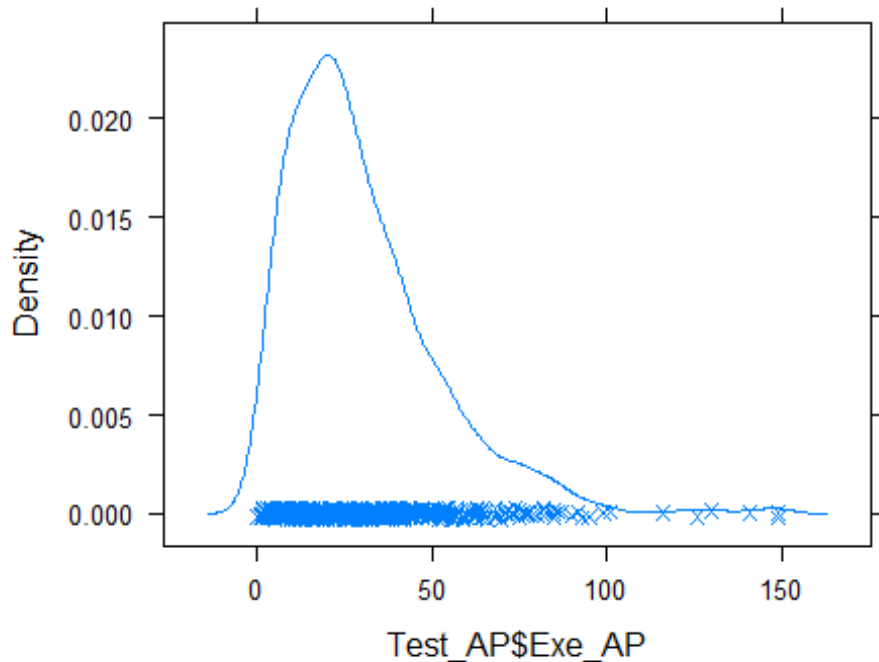


```
boxplot(Test_AP$Exe_AP,  
        main="Box Plot of Time spent exercising each week",  
        xlab="Exercise in minutes",  
        col=3, horizontal=TRUE, pch=20, range = 0.5)
```

### Box Plot of Time spent exercising each week



```
densityplot( ~ Test_AP$Exe_AP, pch=4)
```



From above graphs,

All variables seem reasonable.

```
if(!require(writexl)){install.packages("writexl")}
## Loading required package: writexl
library("writexl")

pred_AP <- predict(Backstep.fit_AP, newdata=Test_AP)
head(pred_AP)

##           1           2           3           4           5           6
## -1.5189399  3.3072872  4.7336655  0.4015572 -0.2702163 -0.4853899

test_fin_AP <- cbind(Test_AP,pred_AP)

write_xlsx(test_fin_AP, "PROG8430_22F_Final_Pred_AP.xlsx")
```

References:

David Marsh.(2022).[PROG8430-L10-22F].eConestoga.

David Marsh.(2022).[PROG8430-L11-22F].eConestoga.

David Marsh.(2022).[PROG8430-L12-22F].eConestoga.

David Marsh.(2022).[R Documents].eConestoga.