# Model4

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## Model 4

```
rm(list = ls())
gc()
```

```
##          used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 472187 25.3    1018675 54.5   660860 35.3
## Vcells 896951  6.9    8388608 64.0  1800812 13.8
```

```
set.seed(123)
library(car)
```

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

```
library(ggplot2)
library(olsrr)
```

```
##
## Attaching package: 'olsrr'
```

```
## The following object is masked from 'package:datasets':
##
##     rivers
```

```
################ (1) Data cleaning ########################################
## select variables
library(NHANES)
df0 <- NHANES
df <- NHANES[NHANES$Age >= 18 & NHANES$Age < 60,]
# colSums(is.na(df)) / nrow(df)
df <- df[, which(colSums(is.na(df)) / nrow(df) < 0.3)]
# exclude duplication
df <- df[!duplicated(df),]
names(df)
```

```
##  [1] "ID"              "SurveyYr"        "Gender"          "Age"
##  [5] "AgeDecade"       "Race1"           "Education"       "MaritalStatus"
##  [9] "HHIncome"        "HHIncomeMid"     "Poverty"         "HomeRooms"
## [13] "HomeOwn"         "Work"            "Weight"          "Height"
## [17] "BMI"             "BMI_WHO"         "Pulse"           "BPSysAve"
## [21] "BPDiaAve"        "BPSys1"          "BPDia1"          "BPSys2"
## [25] "BPDia2"          "BPSys3"          "BPDia3"          "DirectChol"
## [29] "TotChol"         "UrineVol1"       "UrineFlow1"      "Diabetes"
## [33] "HealthGen"       "DaysPhysHlthBad" "DaysMentHlthBad" "LittleInterest"
```

```
## [37] "Depressed"       "SleepHrsNight"   "SleepTrouble"    "PhysActive"
## [41] "Alcohol12PlusYr" "AlcoholYear"     "Smoke100"        "Smoke100n"
## [45] "Marijuana"       "RegularMarij"    "HardDrugs"       "SexEver"
## [49] "SexAge"          "SexNumPartnLife" "SexNumPartYear"  "SameSex"
## [53] "SexOrientation"
```

```
# df$BPSysAve
library(dplyr)
```

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

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

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

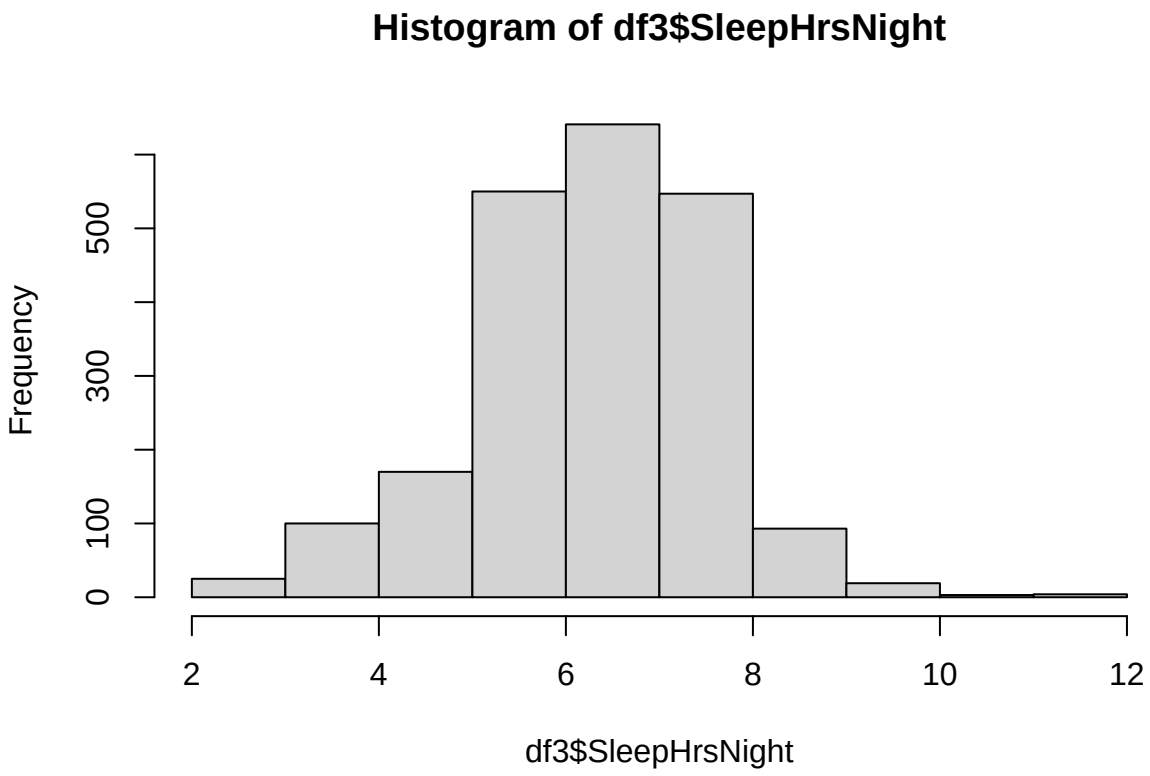
```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
df2 <- df %>% select(
  SleepHrsNight,
  BMI,
  DirectChol,
  Age,
  Gender,
  Race1,
  TotChol,
  BPDiaAve,
  BPSysAve,
  AlcoholYear,
  Poverty,
  SexNumPartnLife,
  SexNumPartYear,
  DaysMentHlthBad,
  UrineFlow1,
  PhysActive,
  DaysPhysHlthBad,
  Smoke100,
  Depressed,
  HealthGen,
  SexAge
)

df3 <- na.omit(df2)
#df3$SleepHrsNight <- df3$SleepHrsNight * 60
#df3 <- df3[, -which(names(df3) %in% "SleepHrsNight")]
# cor(df3$BPSysAve,df3$BPDiaAve)
psych::describe(df3)
```

```
##                vars    n   mean    sd median trimmed   mad   min     max
## SleepHrsNight     1 2152   6.78  1.31   7.00    6.85  1.48  2.00   12.00
## BMI               2 2152  28.77  6.75  27.60   28.09  5.78 15.02   69.00
```

```
## DirectChol         3 2152   1.35  0.41   1.29    1.31  0.39  0.39    3.83
## Age                4 2152  39.18 11.33  39.00   39.15 14.83 20.00   59.00
## Gender*            5 2152   1.53  0.50   2.00    1.54  0.00  1.00    2.00
## Race1*             6 2152   3.43  1.15   4.00    3.57  0.00  1.00    5.00
## TotChol            7 2152   5.07  1.05   4.99    5.01  1.04  1.53   13.65
## BPDiaAve           8 2152  71.19 11.84  71.00   71.28 10.38  0.00  116.00
## BPSysAve           9 2152 117.43 14.28 116.00  116.50 13.34 78.00  209.00
## AlcoholYear       10 2152  70.59 94.22  24.00   50.94 35.58  0.00  364.00
## Poverty           11 2152   2.84  1.69   2.78    2.89  2.49  0.00    5.00
## SexNumPartnLife   12 2152  16.73 66.13   7.00    8.91  5.93  0.00 2000.00
## SexNumPartYear    13 2152   1.38  2.59   1.00    1.04  0.00  0.00   69.00
## DaysMentHlthBad   14 2152   4.47  8.02   0.00    2.40  0.00  0.00   30.00
## UrineFlow1        15 2152   1.07  0.97   0.81    0.91  0.60  0.00   10.14
## PhysActive*       16 2152   1.58  0.49   2.00    1.60  0.00  1.00    2.00
## DaysPhysHlthBad   17 2152   3.16  7.19   0.00    1.12  0.00  0.00   30.00
## Smoke100*         18 2152   1.46  0.50   1.00    1.45  0.00  1.00    2.00
## Depressed*        19 2152   1.30  0.58   1.00    1.16  0.00  1.00    3.00
## HealthGen*        20 2152   2.64  0.94   3.00    2.65  1.48  1.00    5.00
## SexAge            21 2152  17.10  3.39  17.00   16.80  2.97  9.00   44.00
##                   range  skew kurtosis   se
## SleepHrsNight     10.00 -0.30     0.69 0.03
## BMI               53.98  1.28     2.96 0.15
## DirectChol         3.44  1.09     2.27 0.01
## Age               39.00  0.02    -1.15 0.24
## Gender*            1.00 -0.12    -1.99 0.01
## Race1*             4.00 -1.13     0.08 0.02
## TotChol           12.12  0.92     3.47 0.02
## BPDiaAve         116.00 -0.39     3.13 0.26
## BPSysAve         131.00  1.00     2.94 0.31
## AlcoholYear      364.00  1.66     1.98 2.03
## Poverty            5.00 -0.01    -1.47 0.04
## SexNumPartnLife 2000.00 18.82   456.62 1.43
## SexNumPartYear    69.00 14.07   293.16 0.06
## DaysMentHlthBad   30.00  2.16     3.76 0.17
## UrineFlow1        10.14  2.89    14.06 0.02
## PhysActive*        1.00 -0.32    -1.90 0.01
## DaysPhysHlthBad   30.00  2.80     7.06 0.15
## Smoke100*          1.00  0.15    -1.98 0.01
## Depressed*         2.00  1.83     2.21 0.01
## HealthGen*         4.00  0.11    -0.33 0.02
## SexAge            35.00  1.51     5.56 0.07
```

```
# psych::pairs.panels(df3)
hist(df3$SleepHrsNight)
```




```
# colSums(is.na(df2)) / nrow(df2)
fit0 <-
  lm(SleepHrsNight ~ .,
     data = df3)
#data type
df3$Gender <- ifelse(df3$Gender == "male", 0, 1)
df3$Smoke100 <- ifelse(df3$Smoke100 == "No", 0, 1)
df3$PhysActive <- ifelse(df3$PhysActive == "No", 0, 1)
df3 <- df3 %>%
  mutate(
    Race1 = case_when(
      Race1 == 'Black' ~ 1,
      Race1 == 'Hispanic' ~ 2,
      Race1 == 'Mexican' ~ 3,
      Race1 == 'White' ~ 4,
      Race1 == 'Other' ~ 5,
      TRUE ~ NA_integer_  # Default value if none of the conditions are met
    )
  )
df3 <- df3 %>%
  mutate(
    HealthGen = case_when(
      HealthGen == 'Poor' ~ 1,
      HealthGen == 'Fair' ~ 2,
      HealthGen == 'Good' ~ 3,
      HealthGen == 'Vgood' ~ 4,
```

```
      HealthGen == 'Excellent' ~ 5,
      TRUE ~ NA_integer_  # Default value if none of the conditions are met
    )
  )
## model_4 add additional risk factors ##
m_full = lm(
  BMI ~ SleepHrsNight + Age + Gender + factor(Race1)  + Poverty + TotChol + BPDiaAve + BPSysAve + Alcoho
    DaysPhysHlthBad + factor(HealthGen) + PhysActive + SleepHrsNight*Age + SleepHrsNight*Gender + Sleepl
  df3
)
summary(m_full)
```

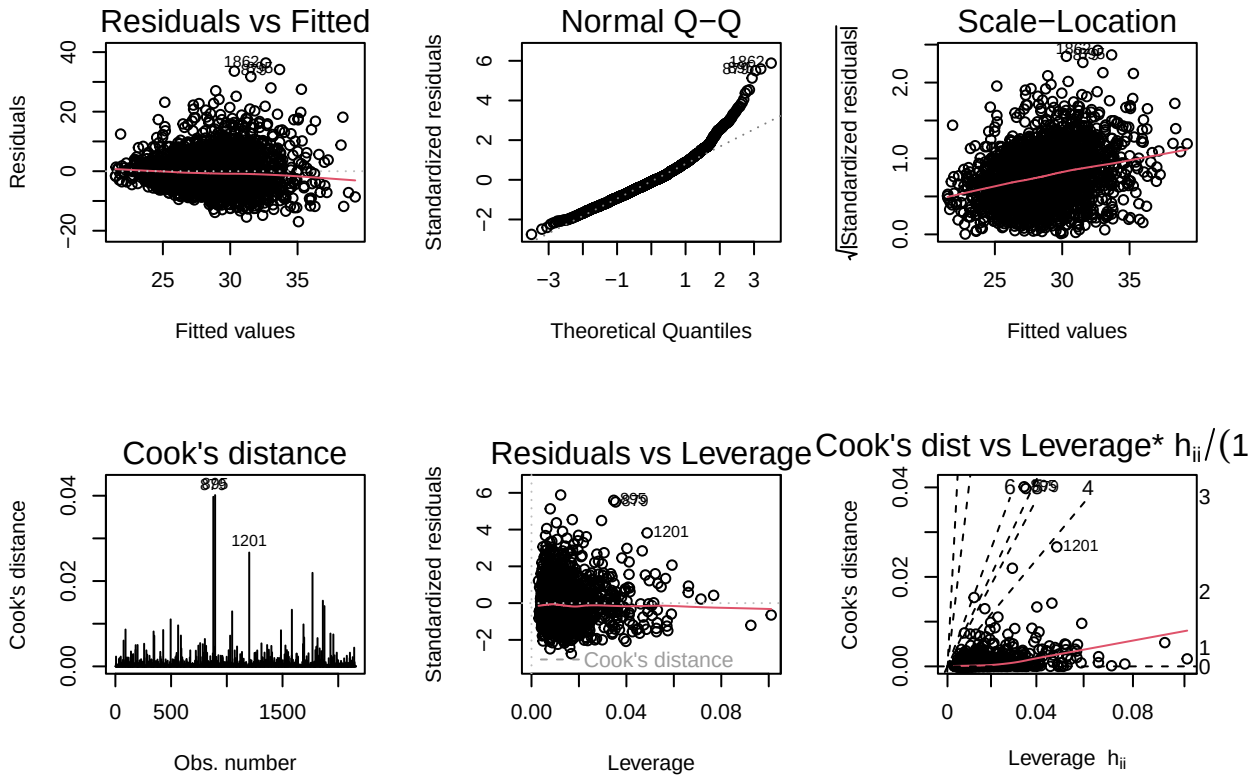
```
##
## Call:
## lm(formula = BMI ~ SleepHrsNight + Age + Gender + factor(Race1) +
##     Poverty + TotChol + BPDiaAve + BPSysAve + AlcoholYear + Smoke100 +
##     UrineFlow1 + DaysMentHlthBad + DaysPhysHlthBad + factor(HealthGen) +
##     PhysActive + SleepHrsNight * Age + SleepHrsNight * Gender +
##     SleepHrsNight * factor(Race1), data = df3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -16.958  -4.088  -0.576   3.191  36.357
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   29.960505   3.507260   8.542  < 2e-16 ***
## SleepHrsNight                 -0.672481   0.440017  -1.528  0.12658
## Age                           -0.080205   0.063471  -1.264  0.20649
## Gender                         3.956938   1.441705   2.745  0.00611 **
## factor(Race1)2                -0.876564   3.071088  -0.285  0.77535
## factor(Race1)3                -3.407567   2.778060  -1.227  0.22011
## factor(Race1)4                -5.099534   1.932348  -2.639  0.00838 **
## factor(Race1)5                 1.067095   3.249451   0.328  0.74265
## Poverty                        0.054070   0.091689   0.590  0.55544
## TotChol                        0.012933   0.135840   0.095  0.92416
## BPDiaAve                       0.057750   0.013676   4.223 2.52e-05 ***
## BPSysAve                       0.052227   0.011793   4.429 9.96e-06 ***
## AlcoholYear                   -0.009047   0.001517  -5.966 2.84e-09 ***
## Smoke100                      -0.847770   0.287236  -2.951  0.00320 **
## UrineFlow1                    -0.088739   0.142102  -0.624  0.53238
## DaysMentHlthBad               -0.032621   0.017991  -1.813  0.06993 .
## DaysPhysHlthBad                0.014998   0.020905   0.717  0.47319
## factor(HealthGen)2            -2.171783   1.002132  -2.167  0.03033 *
## factor(HealthGen)3            -3.905240   0.993873  -3.929 8.79e-05 ***
## factor(HealthGen)4            -5.635919   1.018732  -5.532 3.55e-08 ***
## factor(HealthGen)5            -7.518320   1.075750  -6.989 3.69e-12 ***
## PhysActive                    -0.891431   0.294530  -3.027  0.00250 **
## SleepHrsNight:Age              0.012971   0.009134   1.420  0.15574
## SleepHrsNight:Gender          -0.508514   0.207897  -2.446  0.01453 *
## SleepHrsNight:factor(Race1)2 -0.160437   0.452870  -0.354  0.72317
## SleepHrsNight:factor(Race1)3  0.334059   0.403929   0.827  0.40832
## SleepHrsNight:factor(Race1)4  0.544607   0.287394   1.895  0.05823 .
## SleepHrsNight:factor(Race1)5 -0.629379   0.475731  -1.323  0.18599
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.217 on 2124 degrees of freedom
## Multiple R-squared:  0.1631, Adjusted R-squared:  0.1525
## F-statistic: 15.33 on 27 and 2124 DF,  p-value: < 2.2e-16
```

```
car::Anova(m_full, type = "III")
```

```
## Anova Table (Type III tests)
##
## Response: BMI
##                              Sum Sq   Df F value    Pr(>F)
## (Intercept)                    2821    1 72.9730 < 2.2e-16 ***
## SleepHrsNight                    90    1  2.3357  0.126585
## Age                              62    1  1.5968  0.206493
## Gender                          291    1  7.5330  0.006109 **
## factor(Race1)                   409    4  2.6474  0.031870 *
## Poverty                          13    1  0.3478  0.555444
## TotChol                           0    1  0.0091  0.924157
## BPDiaAve                        689    1 17.8308 2.516e-05 ***
## BPSysAve                        758    1 19.6127 9.965e-06 ***
## AlcoholYear                    1376    1 35.5910 2.844e-09 ***
## Smoke100                        337    1  8.7112  0.003197 **
## UrineFlow1                       15    1  0.3900  0.532385
## DaysMentHlthBad                 127    1  3.2879  0.069935 .
## DaysPhysHlthBad                  20    1  0.5147  0.473188
## factor(HealthGen)              4622    4 29.8917 < 2.2e-16 ***
## PhysActive                      354    1  9.1605  0.002503 **
## SleepHrsNight:Age                78    1  2.0165  0.155745
## SleepHrsNight:Gender            231    1  5.9828  0.014526 *
## SleepHrsNight:factor(Race1)     430    4  2.7841  0.025329 *
## Residuals                     82107 2124
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
########### model 4 diagnosis ###########
par(mfrow = c(2, 3)) #read more from ?plot.lm
plot(m_full, which = 1)
plot(m_full, which = 2)
plot(m_full, which = 3)
plot(m_full, which = 4)
plot(m_full, which = 5)
plot(m_full, which = 6)
```




```
par(mfrow = c(1, 1)) # reset

m_full.yhat = m_full$fitted.values
m_full.res = m_full$residuals
m_full.h = hatvalues(m_full)
m_full.r = rstandard(m_full)
m_full.rr = rstudent(m_full)
#which subject is most outlying with respect to the x space
Hmisc::describe(m_full.h)
```

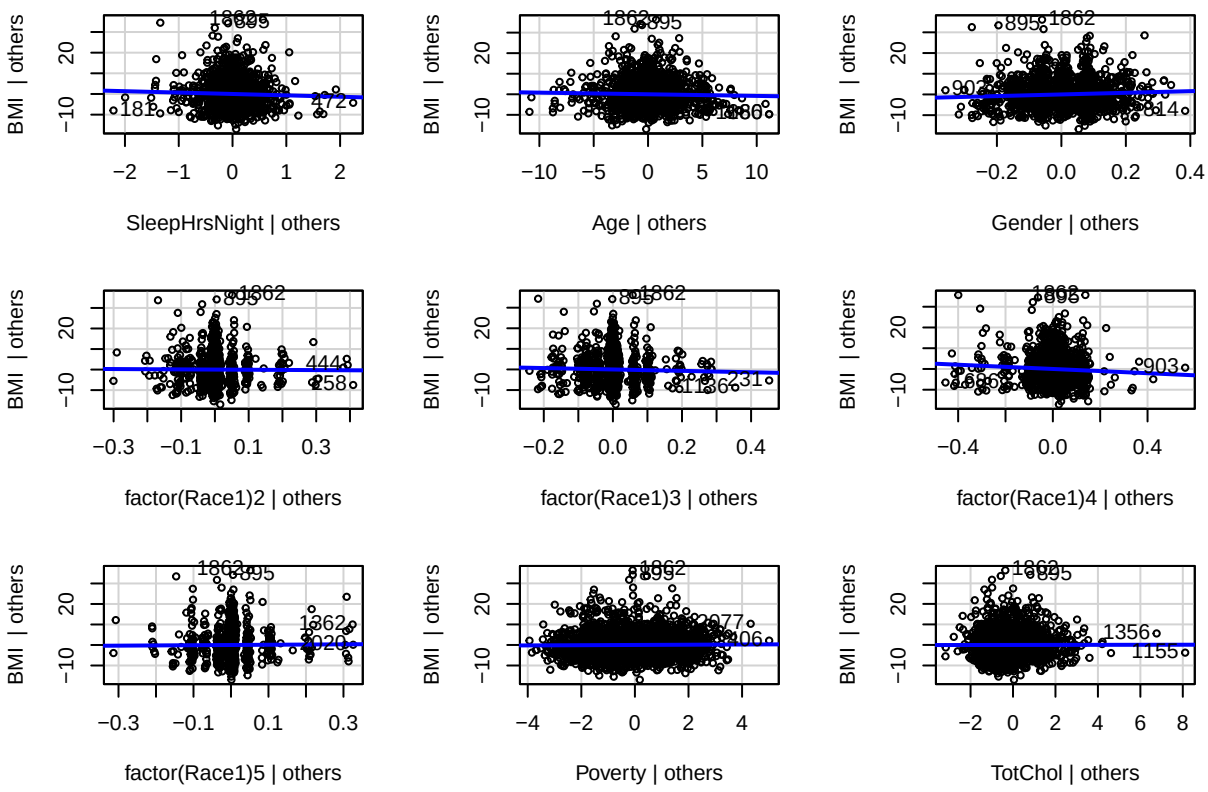
```
## m_full.h
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     2152        0     2152        1  0.01301 0.008551 0.004865 0.005528
##      .25      .50      .75      .90      .95
## 0.007242 0.010523 0.015295 0.023125 0.031581
##
## lowest : 0.002972138 0.003170460 0.003312764 0.003418926 0.003468613
## highest: 0.066174863 0.071440848 0.076776919 0.092465730 0.101033382
```

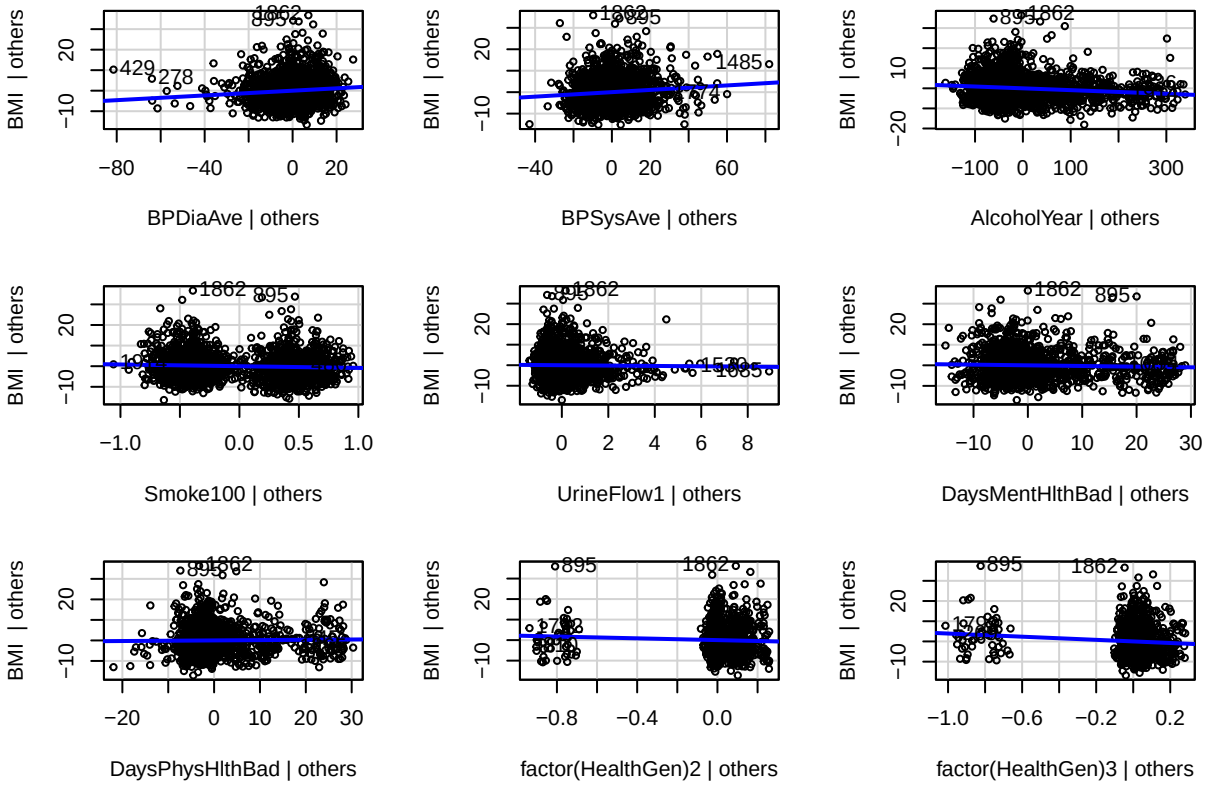
```
m_full.h[which.max(m_full.h)]
```

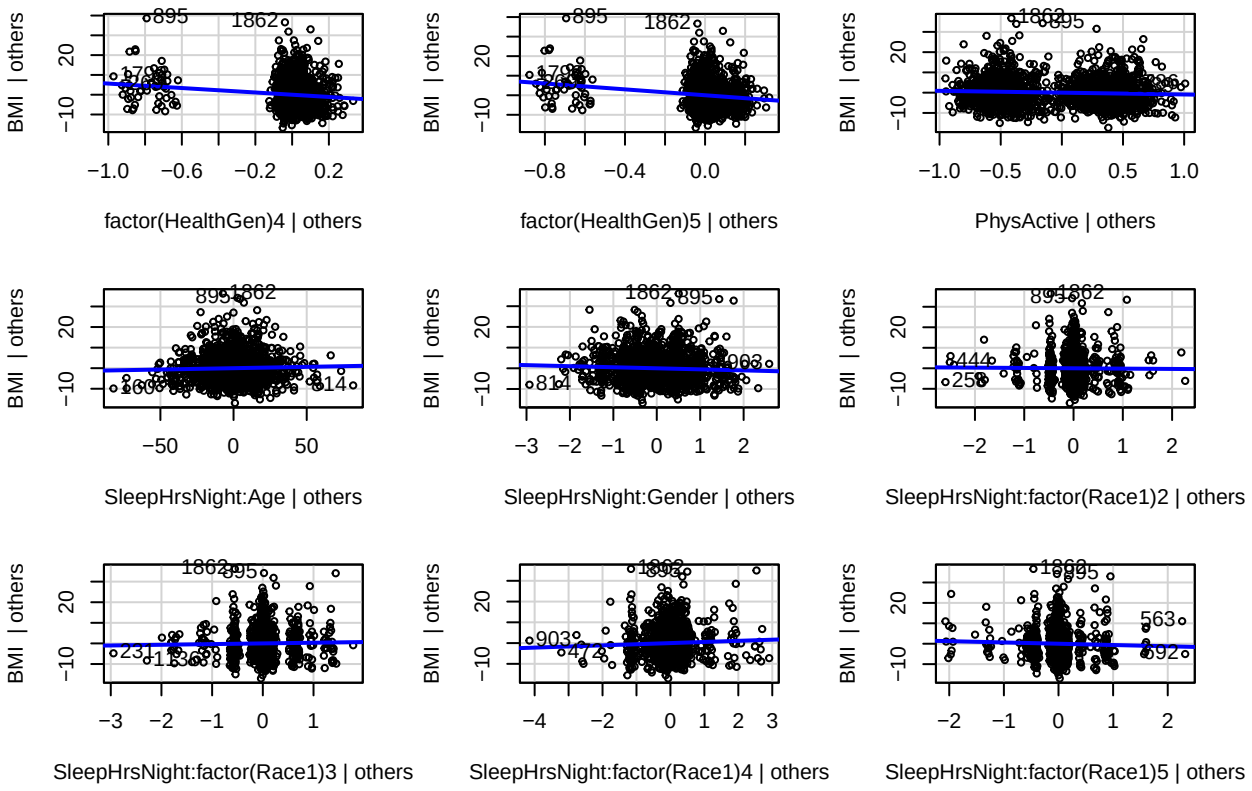
```
##       231
## 0.1010334
```

```
###################### Assumption:LINE ##############################

#(1)Linear: 2 approaches
```

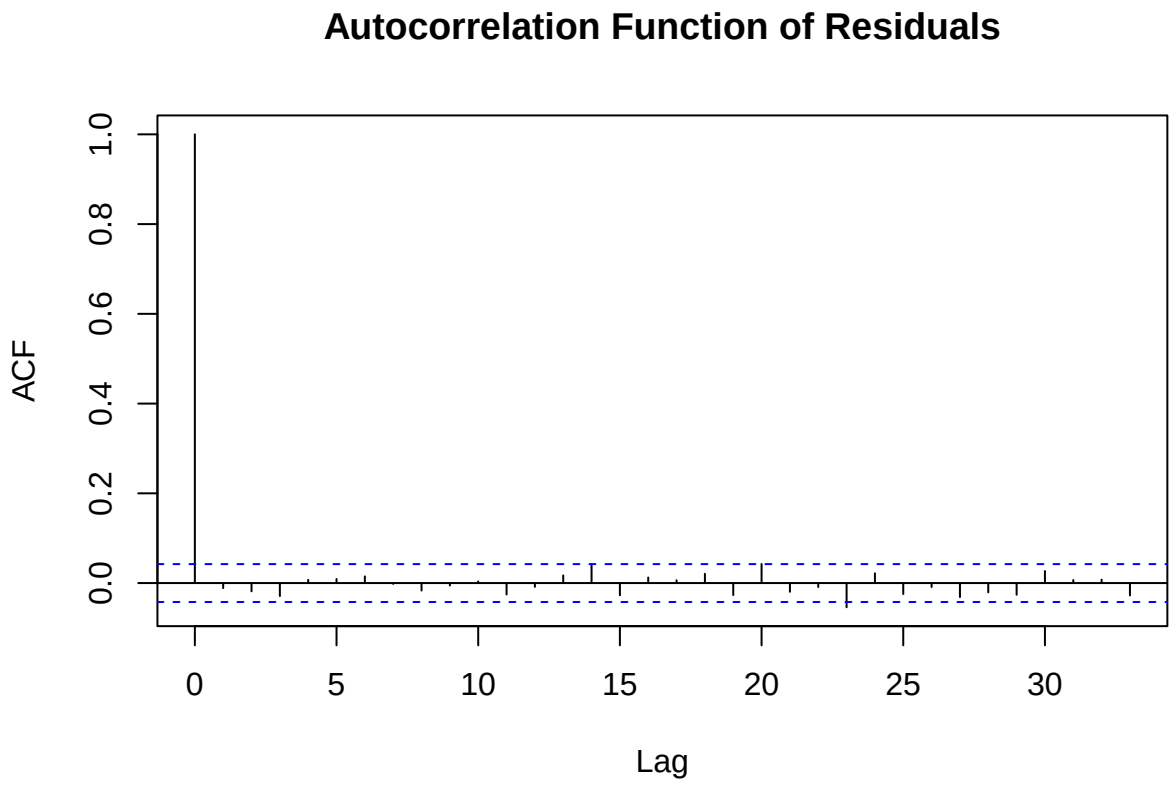
```r
# partial regression plots
car::avPlots(m_full)
```



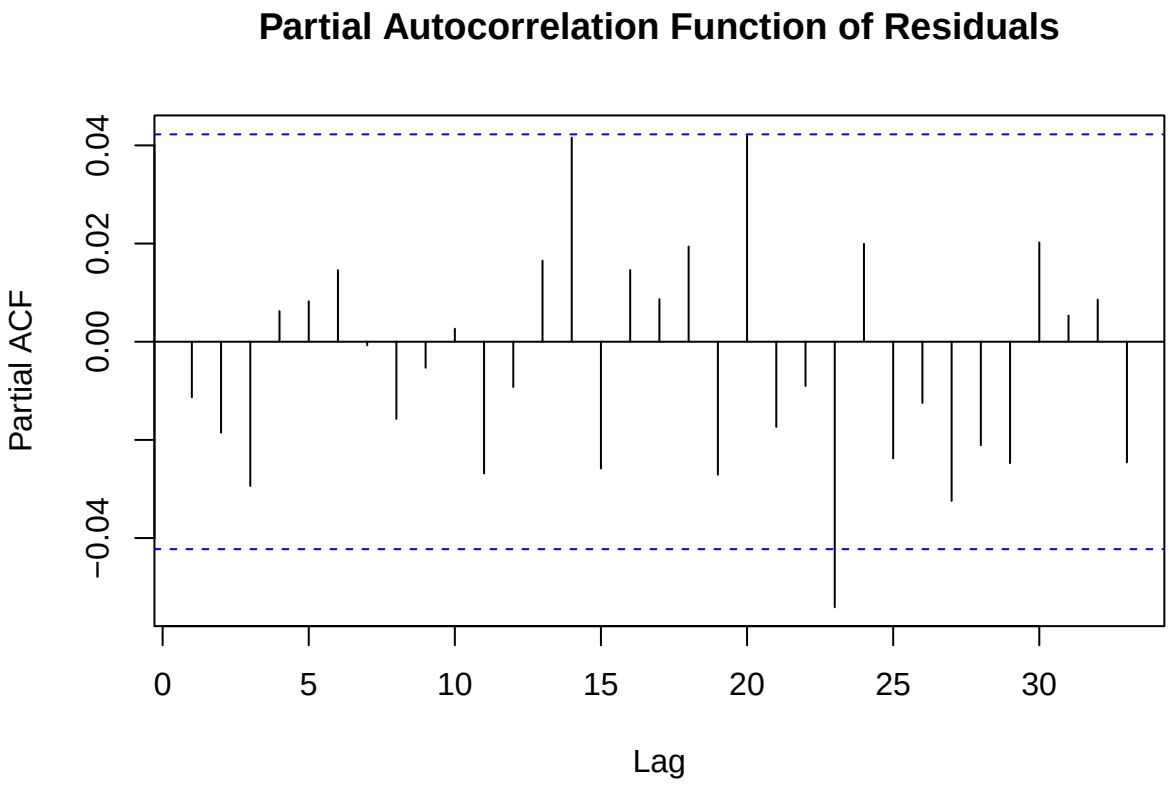

BMI | others
BPDiaAve | others
BPSysAve | others
AlcoholYear | others
Smoke100 | others
UrineFlow1 | others
DaysMentHlthBad | others
DaysPhysHlthBad | others
factor(HealthGen)2 | others
factor(HealthGen)3 | others



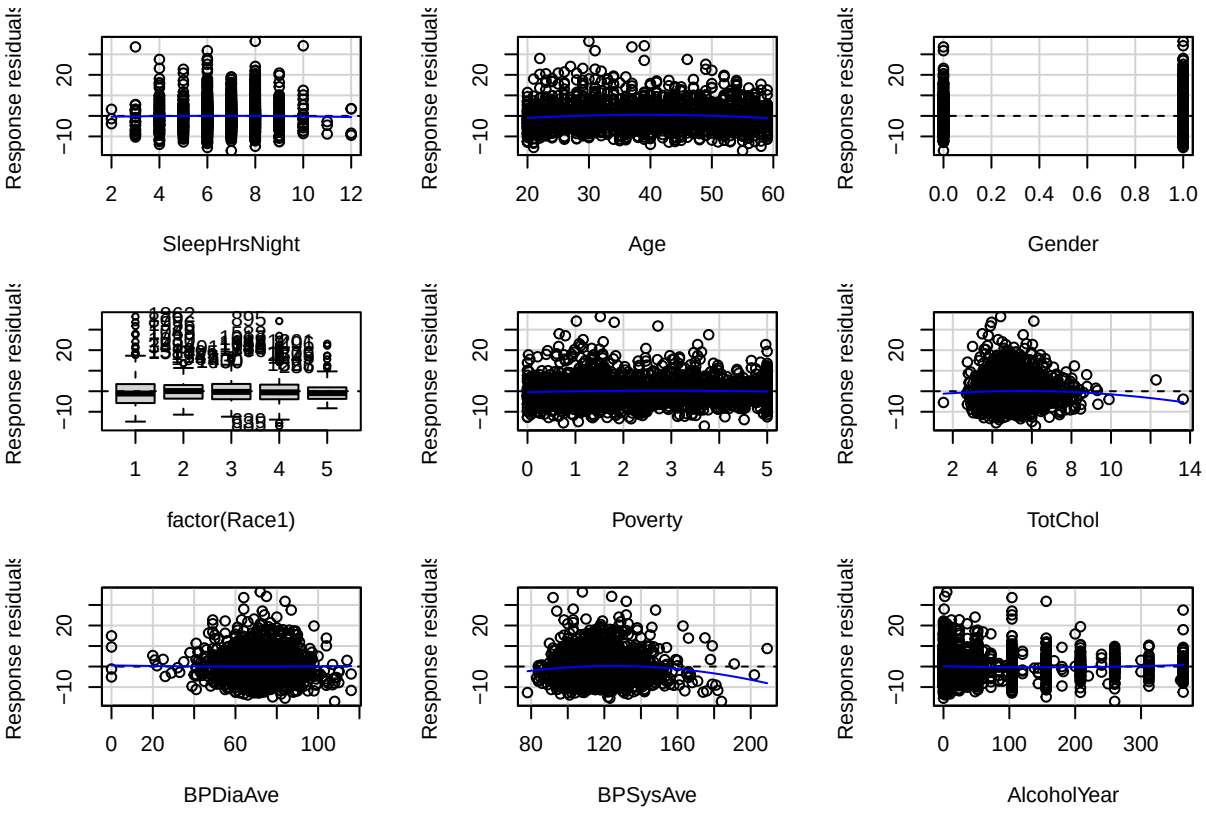

```
#(2)Independence:

residuals <- resid(m_full)
acf(residuals, main = "Autocorrelation Function of Residuals")
```

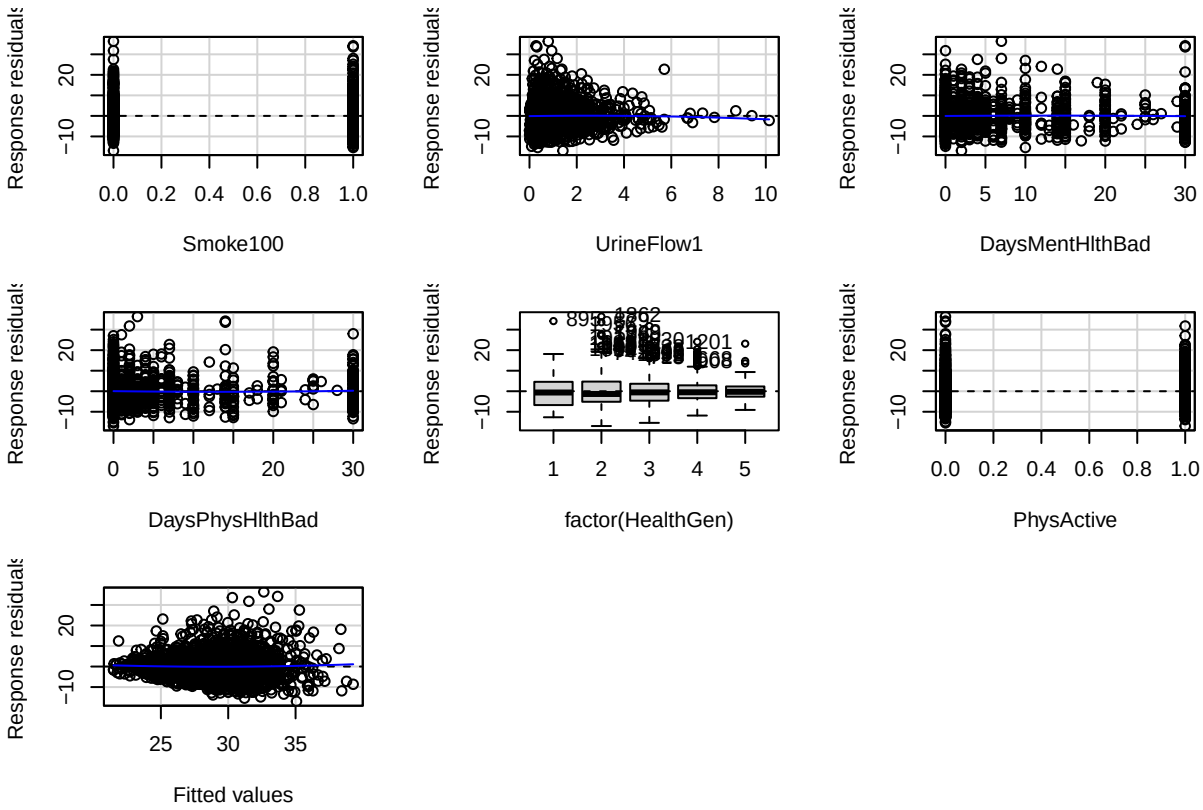



```
pacf(residuals, main = "Partial Autocorrelation Function of Residuals")
```



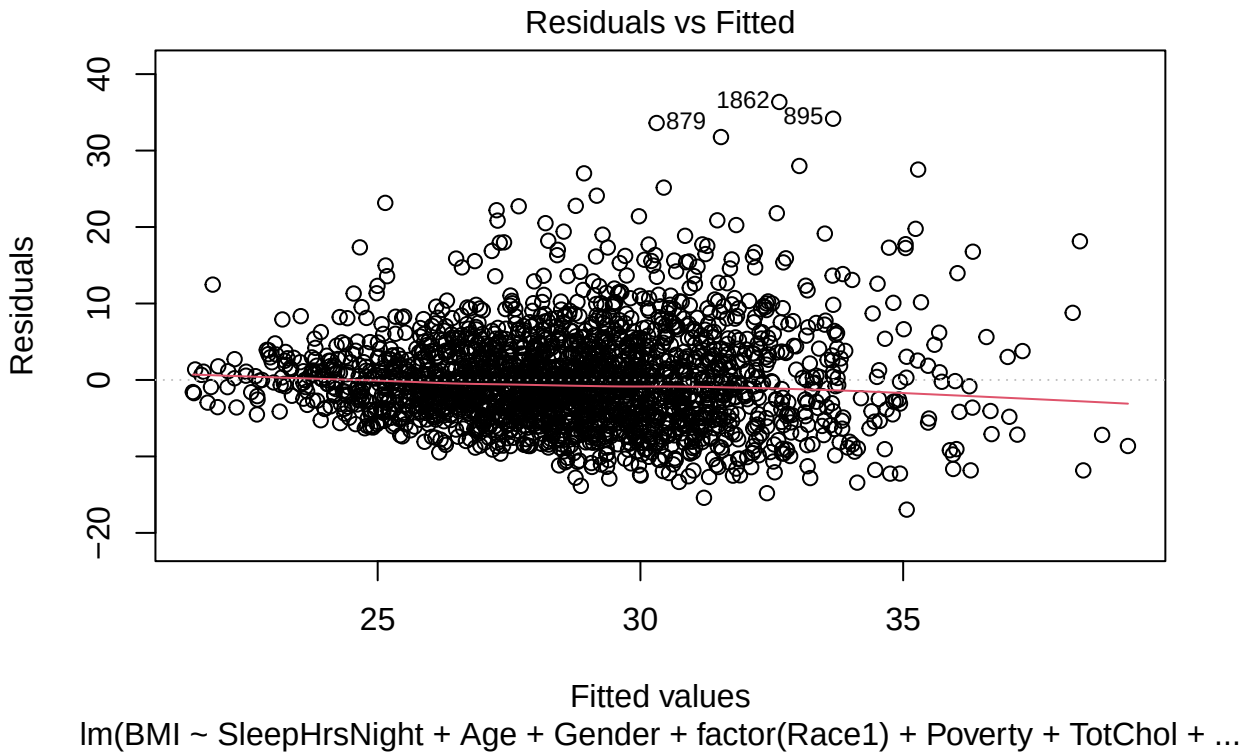

```
#(3)E: constant var: residuals-fitted values; transform for variance-stable...(total: 4 solutions)

car::residualPlots(m_full, type = "response")
```


Response residuals
SleepHrsNight
Age
Gender
factor(Race1)
Poverty
TotChol
BPDiaAve
BPSysAve
AlcoholYear

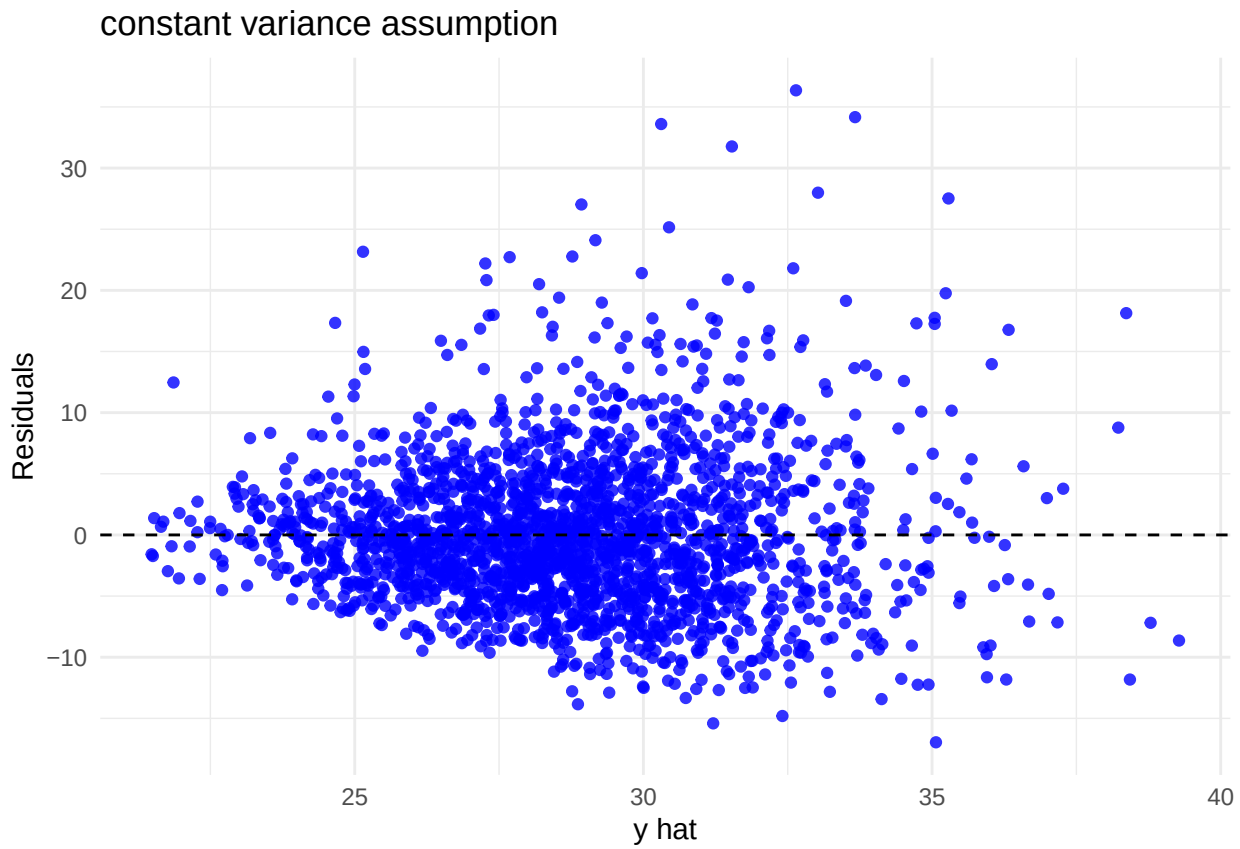



```
##                    Test stat Pr(>|Test stat|)
## SleepHrsNight        -0.4613        0.6446186
## Age                  -3.7447        0.0001854 ***
## Gender                0.3845        0.7006805
## factor(Race1)
## Poverty              -1.4419        0.1494722
## TotChol              -1.4869        0.1371842
## BPDiaAve              0.3082        0.7579352
## BPSysAve             -3.6531        0.0002654 ***
## AlcoholYear           1.9135        0.0558163 .
## Smoke100              0.0927        0.9261142
## UrineFlow1           -0.6018        0.5473911
## DaysMentHlthBad      -0.4951        0.6205792
## DaysPhysHlthBad       0.7946        0.4269417
## factor(HealthGen)
## PhysActive           -0.4795        0.6315971
## Tukey test            1.2073        0.2273166
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(m_full, which = 1)
```




```
#or
ggplot(m_full, aes(x = m_full.yhat, y = m_full.res)) +
  geom_point(color = "blue", alpha = 0.8) +
  geom_hline(yintercept = 0,
             linetype = "dashed",
             color = "black") +
  labs(title = "constant variance assumption",
       x = "y hat",
       y = "Residuals") +
  theme_minimal()
```



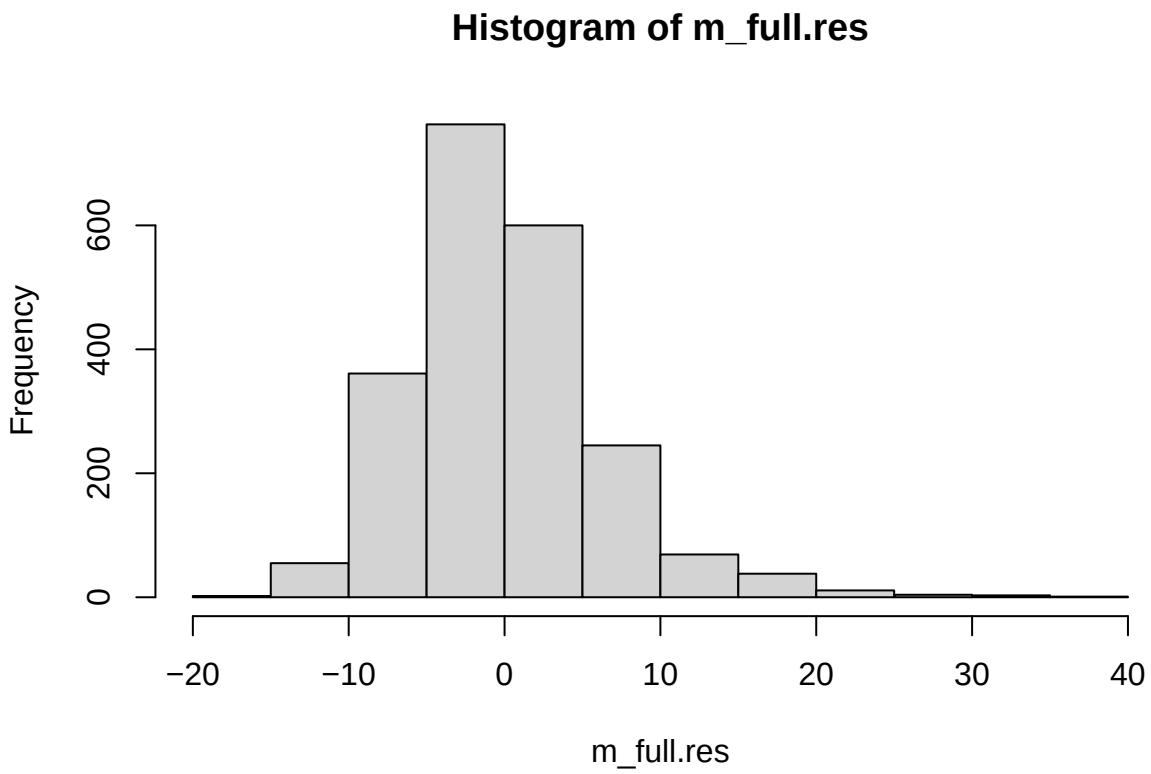

```
#conclusion: the constant variance assumption is basically not violated. The spread of the residuals ap


#(4)Normality: residuals freq - residuals (4 plots: his, box, Q-Q, shapiro); transform

#exam quartiles of the residuals
Hmisc::describe(m_full.res)
```

```
## m_full.res
##          n    missing   distinct       Info       Mean        Gmd        .05
##       2152          0       2152          1 -2.195e-17      6.655    -8.6296
##        .10        .25        .50        .75        .90        .95
##    -7.0359    -4.0879    -0.5759     3.1910     7.5243    10.4454
##
## lowest : -16.95814 -15.40920 -14.80810 -13.84646 -13.42587
## highest:  27.98564  31.76705  33.60166  34.16306  36.35676
```

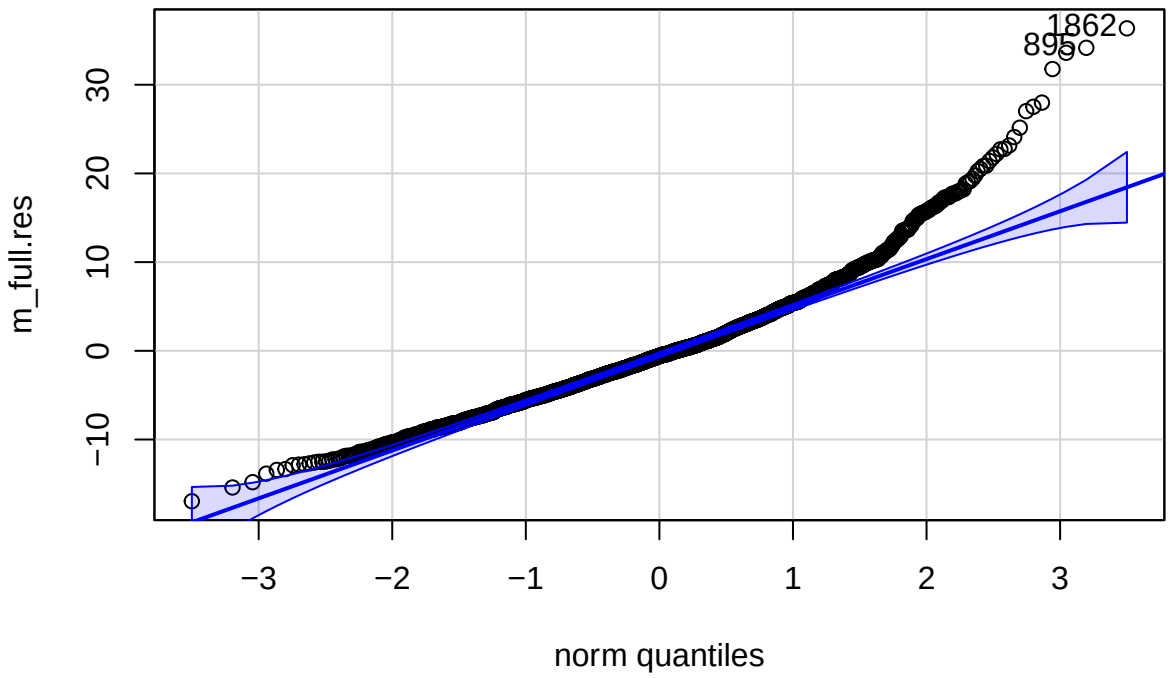
```
Hmisc::describe(m_full.res)$counts[c(".25", ".50", ".75")] #not symmetric
```

```
##       .25       .50       .75
## "-4.0879" "-0.5759" " 3.1910"
```

```
#histogram
par(mfrow = c(1, 1))
hist(m_full.res, breaks = 15)
```



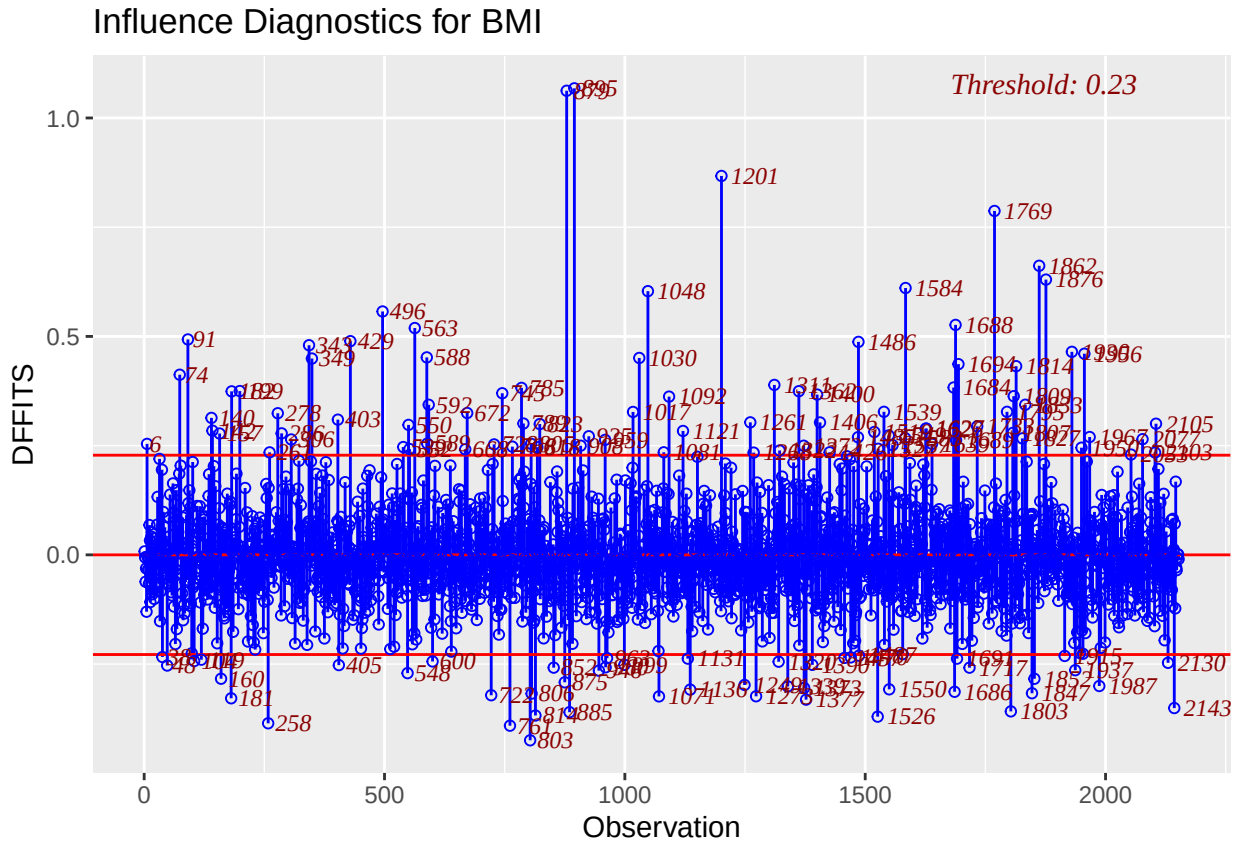

```
# Q-Q plot
qq.m_full.res = car::qqPlot(m_full.res)
```




```
m_full.res[qq.m_full.res]
```

```
##     1862      895
## 36.35676 34.16306
```

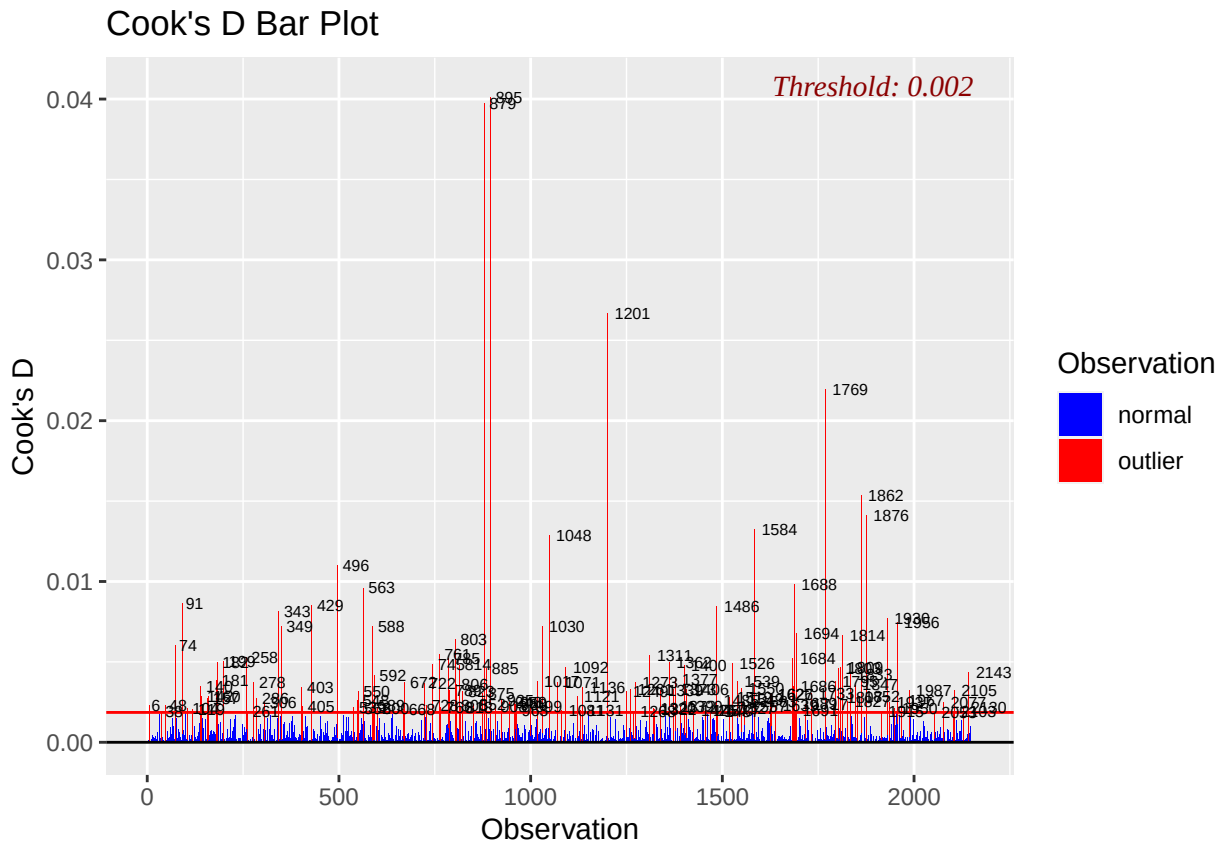
```
################ influential observations  ##################

influence4 = data.frame(
  Residual = resid(m_full),
  Rstudent = rstudent(m_full),
  HatDiagH = hat(model.matrix(m_full)),
  CovRatio = covratio(m_full),
  DFFITS = dffits(m_full),
  COOKsDistance = cooks.distance(m_full)
)
# DFFITS
ols_plot_dffits(m_full)
```




```
influence4[order(abs(influence4$DFFITS), decreasing = T), ] %>% head()
```

```
##      Residual Rstudent   HatDiagH  CovRatio    DFFITS COOKsDistance
## 895  34.16306 5.632875 0.03468934 0.6928884 1.0678114    0.04014143
## 879  33.60166 5.541168 0.03544669 0.7027303 1.0622481    0.03974315
## 1201 23.15612 3.830897 0.04875209 0.8783372 0.8672618    0.02669040
## 1769 27.51498 4.512694 0.02952588 0.7991973 0.7871278    0.02192759
## 1862 36.35676 5.930967 0.01229464 0.6475374 0.6617130    0.01539036
## 1876 17.25396 2.846975 0.04668488 0.9553282 0.6300187    0.01412858
```

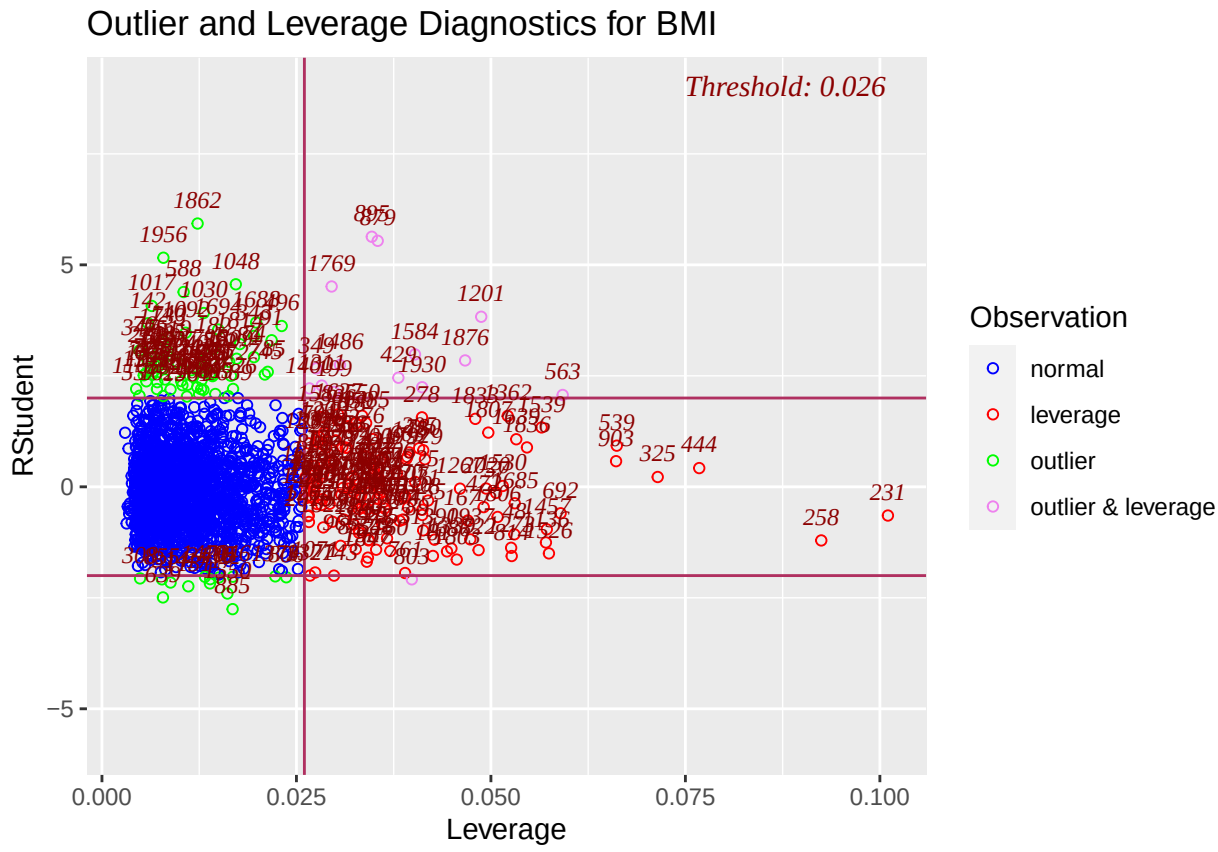
```
#From the plot above, we can see 2 observations with the largest (magnitude) of DFFITS, observation 879

# Cook's D
ols_plot_cooksd_bar(m_full)
```




```
influence4[order(influence4$COOKsDistance, decreasing = T), ] %>% head()
```

```
##      Residual Rstudent   HatDiagH  CovRatio    DFFITS COOKsDistance
## 895  34.16306 5.632875 0.03468934 0.6928884 1.0678114    0.04014143
## 879  33.60166 5.541168 0.03544669 0.7027303 1.0622481    0.03974315
## 1201 23.15612 3.830897 0.04875209 0.8783372 0.8672618    0.02669040
## 1769 27.51498 4.512694 0.02952588 0.7991973 0.7871278    0.02192759
## 1862 36.35676 5.930967 0.01229464 0.6475374 0.6617130    0.01539036
## 1876 17.25396 2.846975 0.04668488 0.9553282 0.6300187    0.01412858
```

```
#From the plot above, we can see that the observation 879 and 1769 also have the largest Cook's Distanc

#leverage
ols_plot_resid_lev(m_full)
```




```
#high leverage
influence4[order(influence4$HatDiagH, decreasing = T), ] %>% head()
```

```
##      Residual   Rstudent   HatDiagH CovRatio      DFFITS COOKsDistance
## 231 -3.813195 -0.6467635 0.10103338 1.120952 -0.21682342  0.0016794740
## 258 -7.153198 -1.2078235 0.09246573 1.095243 -0.38553371  0.0053072906
## 444  2.520223  0.4217833 0.07677692 1.094967  0.12163298  0.0005285825
## 325  1.326059  0.2212833 0.07144085 1.090527  0.06137863  0.0001346080
## 539  5.570046  0.9270421 0.06617486 1.072851  0.24678184  0.0021751896
## 903  3.470564  0.5775193 0.06608684 1.080214  0.15362814  0.0008431791
```

```
#high studentized residual
influence4[order(influence4$Rstudent, decreasing = T), ] %>% head()
```

```
##      Residual Rstudent    HatDiagH  CovRatio    DFFITS COOKsDistance
## 1862 36.35676 5.930967 0.012294639 0.6475374 0.6617130   0.015390364
## 895  34.16306 5.632875 0.034689340 0.6928884 1.0678114   0.040141432
## 879  33.60166 5.541168 0.035446686 0.7027303 1.0622481   0.039743153
## 1956 31.76705 5.160492 0.007897548 0.7204138 0.4604251   0.007480843
## 1048 27.98564 4.561499 0.017207050 0.7846276 0.6035730   0.012890516
## 1769 27.51498 4.512694 0.029525875 0.7991973 0.7871278   0.021927594
```

```
#From the plot above, we can see that the observation 1155 has the largest leverage (0.0368). Observati


#From the plot above, there is 7 observations(1048,1769,1684, 74, 72, 1689, 1311) located in the inters
#The thresholds for the externally studentized residual are -2 and 2, i.e. 2 in magnitude. The threshol
```

```r
#From (DFFITS), observations 879 and 1769 appear to be influential observations. Observation 1155 has es

rm4.df3 = df3[-c(879, 1769, 1155, 1048, 1769, 1684, 74, 72, 1689, 1311), ]
rm.m_full =  lm(
  BMI ~ SleepHrsNight + Age + Gender + factor(Race1)  + Poverty + TotChol + BPDiaAve + BPSysAve + Alcoho
    DaysPhysHlthBad + factor(HealthGen) + PhysActive + SleepHrsNight*Age + SleepHrsNight*Gender + Sleepl
  rm4.df3
)
## Before removing these observations, the estimated coefficients are:
summary(m_full)$coef
```

```
##                                    Estimate  Std. Error     t value     Pr(>|t|)
## (Intercept)                    29.960505073 3.507260454  8.54242377 2.466760e-17
## SleepHrsNight                  -0.672481427 0.440016672 -1.52830897 1.265847e-01
## Age                            -0.080204768 0.063470508 -1.26365410 2.064929e-01
## Gender                          3.956938092 1.441705429  2.74462315 6.109021e-03
## factor(Race1)2                 -0.876564287 3.071087624 -0.28542471 7.753466e-01
## factor(Race1)3                 -3.407566549 2.778060078 -1.22659930 2.201092e-01
## factor(Race1)4                 -5.099534349 1.932348034 -2.63903513 8.375006e-03
## factor(Race1)5                  1.067094548 3.249451033  0.32839225 7.426475e-01
## Poverty                         0.054070144 0.091688515  0.58971556 5.554441e-01
## TotChol                         0.012933319 0.135840431  0.09520965 9.241573e-01
## BPDiaAve                        0.057749909 0.013676197  4.22265846 2.516211e-05
## BPSysAve                        0.052226688 0.011792973  4.42862767 9.964814e-06
## AlcoholYear                    -0.009047472 0.001516551 -5.96582184 2.844035e-09
## Smoke100                       -0.847770435 0.287235608 -2.95148099 3.197186e-03
## UrineFlow1                     -0.088738883 0.142102264 -0.62447199 5.323847e-01
## DaysMentHlthBad                -0.032621346 0.017990576 -1.81324636 6.993492e-02
## DaysPhysHlthBad                 0.014998194 0.020905479  0.71742883 4.731884e-01
## factor(HealthGen)2             -2.171782863 1.002132374 -2.16716166 3.033334e-02
## factor(HealthGen)3             -3.905239626 0.993873382 -3.92931303 8.791217e-05
## factor(HealthGen)4             -5.635919387 1.018731903 -5.53228908 3.550503e-08
## factor(HealthGen)5             -7.518320187 1.075750186 -6.98890903 3.694385e-12
## PhysActive                     -0.891431344 0.294529536 -3.02662801 2.502685e-03
## SleepHrsNight:Age               0.012970832 0.009134171  1.42003383 1.557446e-01
## SleepHrsNight:Gender           -0.508514014 0.207897348 -2.44598605 1.452629e-02
## SleepHrsNight:factor(Race1)2   -0.160436519 0.452869868 -0.35426627 7.231745e-01
## SleepHrsNight:factor(Race1)3    0.334059261 0.403929165  0.82702436 4.083162e-01
## SleepHrsNight:factor(Race1)4    0.544606530 0.287394425  1.89497946 5.823080e-02
## SleepHrsNight:factor(Race1)5   -0.629379219 0.475730981 -1.32297295 1.859868e-01
```

```r
## After removing these observations, the estimated coefficients are:
summary(rm.m_full)$coef
```

```
##                                    Estimate  Std. Error     t value     Pr(>|t|)
## (Intercept)                    28.268008351 3.459409877  8.17133828 5.189771e-16
## SleepHrsNight                  -0.424021324 0.433321364 -0.97853778 3.279203e-01
## Age                            -0.079264749 0.062184319 -1.27467423 2.025646e-01
## Gender                          3.918842197 1.416789399  2.76600192 5.724139e-03
## factor(Race1)2                  1.368019475 3.022848671  0.45255970 6.509122e-01
## factor(Race1)3                 -0.913434900 2.739731420 -0.33340308 7.388631e-01
## factor(Race1)4                 -2.879953436 1.919328994 -1.50050015 1.336342e-01
## factor(Race1)5                  3.200399722 3.194996265  1.00169122 3.166073e-01
## Poverty                         0.055168101 0.089769348  0.61455387 5.389155e-01
```

```
## TotChol                       0.030174864 0.135186651  0.22320891 8.233945e-01
## BPDiaAve                      0.054810943 0.013401685  4.08985453 4.478056e-05
## BPSysAve                      0.053259584 0.011621651  4.58278995 4.855550e-06
## AlcoholYear                  -0.009863362 0.001492621 -6.60808052 4.912196e-11
## Smoke100                     -0.906976594 0.281453978 -3.22246856 1.290233e-03
## UrineFlow1                   -0.103228010 0.139065343 -0.74229861 4.579889e-01
## DaysMentHlthBad              -0.027067099 0.017667463 -1.53203084 1.256644e-01
## DaysPhysHlthBad              -0.006917921 0.020728014 -0.33374742 7.386033e-01
## factor(HealthGen)2           -2.860916730 0.983991462 -2.90746093 3.681707e-03
## factor(HealthGen)3           -4.310290167 0.973430101 -4.42794009 9.998425e-06
## factor(HealthGen)4           -6.058304209 0.998133224 -6.06963486 1.515217e-09
## factor(HealthGen)5           -7.927510866 1.053831429 -7.52256068 7.893859e-14
## PhysActive                   -0.802153028 0.288476385 -2.78065404 5.473008e-03
## SleepHrsNight:Age             0.013395759 0.008948908  1.49691548 1.345645e-01
## SleepHrsNight:Gender         -0.522213533 0.204157956 -2.55788970 1.060010e-02
## SleepHrsNight:factor(Race1)2 -0.423357311 0.445647906 -0.94998160 3.422301e-01
## SleepHrsNight:factor(Race1)3  0.036331910 0.398266905  0.09122503 9.273224e-01
## SleepHrsNight:factor(Race1)4  0.283662710 0.285240570  0.99446832 3.201087e-01
## SleepHrsNight:factor(Race1)5 -0.880859176 0.467706683 -1.88335811 5.978896e-02
```

```
#### change percent
abs((rm.m_full$coefficients - m_full$coefficients) / (m_full$coefficients) * 100)
```

```
##                   (Intercept)                 SleepHrsNight
##                      5.649093                     36.946761
##                           Age                        Gender
##                      1.172024                      0.962762
##                 factor(Race1)2                factor(Race1)3
##                    256.066075                     73.193923
##                 factor(Race1)4                factor(Race1)5
##                     43.525168                    199.917165
##                       Poverty                       TotChol
##                      2.030615                    133.311061
##                      BPDiaAve                      BPSysAve
##                      5.089126                      1.977715
##                    AlcoholYear                      Smoke100
##                      9.017876                      6.983749
##                    UrineFlow1                DaysMentHlthBad
##                     16.327823                     17.026419
##                DaysPhysHlthBad            factor(HealthGen)2
##                    146.125029                     31.731251
##            factor(HealthGen)3            factor(HealthGen)4
##                     10.371977                      7.494515
##            factor(HealthGen)5                    PhysActive
##                      5.442581                     10.015165
##             SleepHrsNight:Age          SleepHrsNight:Gender
##                      3.276022                      2.694030
## SleepHrsNight:factor(Race1)2 SleepHrsNight:factor(Race1)3
##                    163.878395                     89.124112
## SleepHrsNight:factor(Race1)4 SleepHrsNight:factor(Race1)5
##                     47.914192                     39.956826
```

```
#The estimated regression coefficients doesn't change slightly after removing these observations. 5 of

##################   multicollinearity   ######################
```

```r
#Pearson correlations
var4 = c(
  "BMI",
  "SleepHrsNight",
  "Age",
  "Gender",
  "Race1",
  "TotChol",
  "BPDiaAve",
  "BPSysAve",
  "AlcoholYear",
  "Smoke100",
  "DaysPhysHlthBad",
  "PhysActive",
  "Poverty",
  "UrineFlow1",
  "DaysMentHlthBad",
  "HealthGen"
)
newData4 = df3[, var4]
library("corrplot")
```

```
## corrplot 0.92 loaded
```

```r
par(mfrow = c(1, 2))
cormat4 = cor(as.matrix(newData4[, -c(1)], method = "pearson"))
p.mat4 = cor.mtest(as.matrix(newData4[, -c(1)]))$p
corrplot(
  cormat4,
  method = "color",
  type = "upper",
  number.cex = 1,
  diag = FALSE,
  addCoef.col = "black",
  tl.col = "black",
  tl.srt = 90,
  p.mat = p.mat4,
  sig.level = 0.05,
  insig = "blank",
)

#None of the covariates seem strongly correlated.There is no evidence of collinearity from the pair-wis

# collinearity diagnostics (VIF)
car::vif(m_full)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##                                     GVIF Df GVIF^(1/(2*Df))
## SleepHrsNight               1.849122e+01  1        4.300141
## Age                         2.879008e+01  1        5.365639
## Gender                      2.882194e+01  1        5.368607
## factor(Race1)               5.340628e+05  4        5.199350
## Poverty                     1.338183e+00  1        1.156799
```

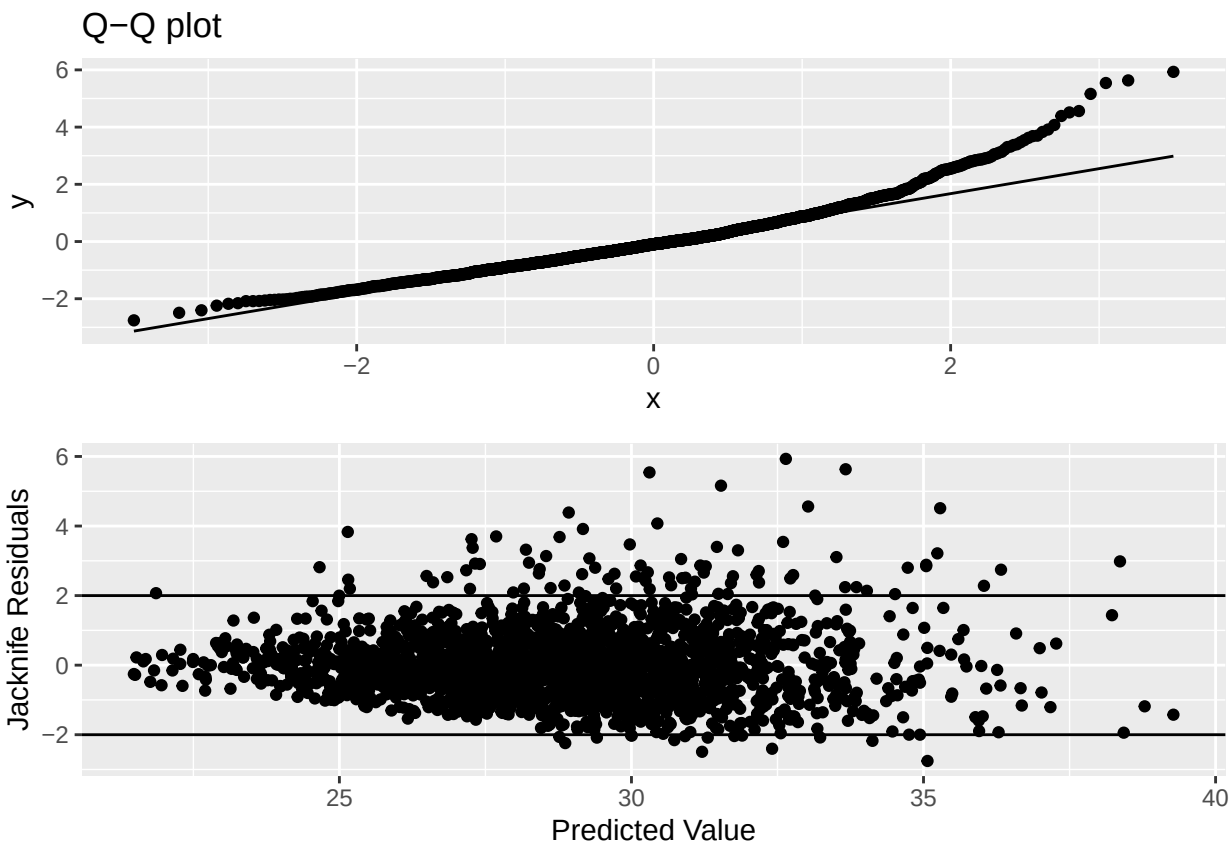
```
## TotChol                      1.135148e+00  1        1.065433
## BPDiaAve                     1.459656e+00  1        1.208162
## BPSysAve                     1.578347e+00  1        1.256323
## AlcoholYear                  1.136198e+00  1        1.065926
## Smoke100                     1.142055e+00  1        1.068670
## UrineFlow1                   1.049202e+00  1        1.024306
## DaysMentHlthBad              1.158938e+00  1        1.076540
## DaysPhysHlthBad              1.256335e+00  1        1.120864
## factor(HealthGen)            1.495098e+00  4        1.051559
## PhysActive                   1.177165e+00  1        1.084972
## SleepHrsNight:Age            3.875954e+01  1        6.225716
## SleepHrsNight:Gender         3.046426e+01  1        5.519444
## SleepHrsNight:factor(Race1) 6.995071e+05  4        5.377730
```

```
#From the VIF values in the output above, once again we do not observe any potential collinearity issue

################ using log-transformed BMI  ##################
# log BMI
df3$logBMI = log(df3$BMI + 1)
m_full.log = lm(
  logBMI ~ SleepHrsNight + Age + Gender + factor(Race1)  + Poverty + TotChol + BPDiaAve + BPSysAve + Al
    SleepHrsNight*Age+SleepHrsNight*Gender+SleepHrsNight*factor(Race1),
  df3
)
p41.log = ols_plot_resid_lev(m_full.log)
p42.log = ols_plot_cooksd_bar(m_full.log)
library(gridExtra)
```

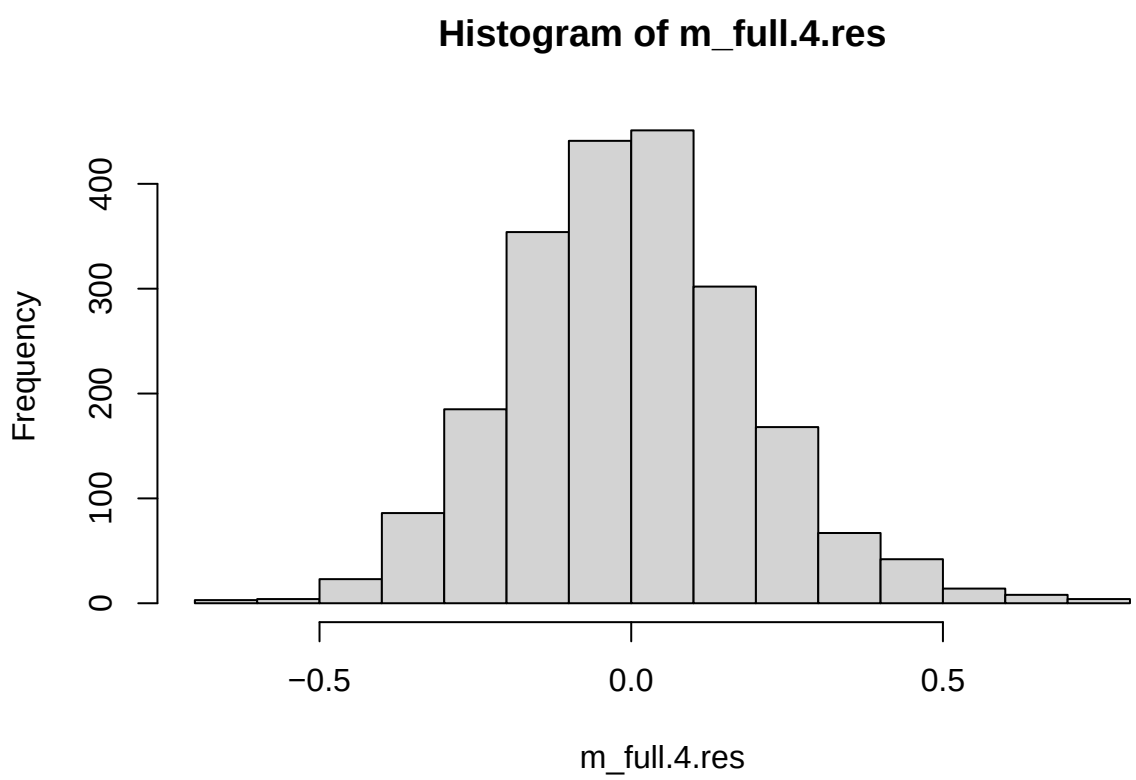
```
##
## Attaching package: 'gridExtra'
```

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

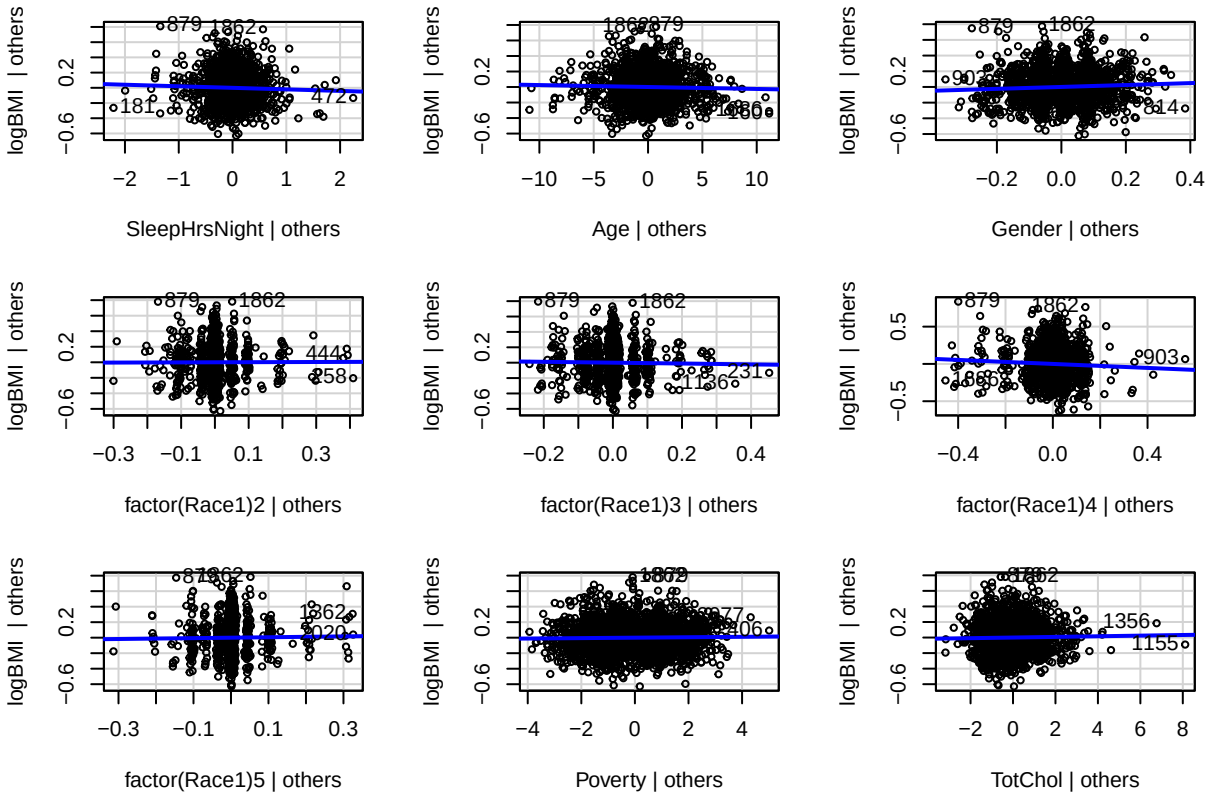
```
p43.log = ggplot(m_full.log, aes(sample = rstudent(m_full.log))) + geom_qq() + stat_qq_line() +
  labs(title = "Q-Q plot")
p44.log = ggplot() + geom_point(aes(y = rstudent(m_full.log), x = m_full.log$fitted.values)) + labs(x =
  geom_hline(yintercept = c(-2, 2))
grid.arrange(p43.log, p44.log, nrow = 2)


p43 = ggplot(m_full, aes(sample = rstudent(m_full))) + geom_qq() + stat_qq_line() +
  labs(title = "Q-Q plot")
p44 = ggplot() + geom_point(aes(y = rstudent(m_full), x = m_full$fitted.values)) + labs(x = "Predicted
  geom_hline(yintercept = c(-2, 2))
grid.arrange(p43, p44, nrow = 2)


m_full.4.yhat = m_full.log$fitted.values
m_full.4.res = m_full.log$residuals
m_full.4.h = hatvalues(m_full.log)
m_full.4.r = rstandard(m_full.log)
m_full.4.rr = rstudent(m_full.log)

par(mfrow = c(1, 1))
```

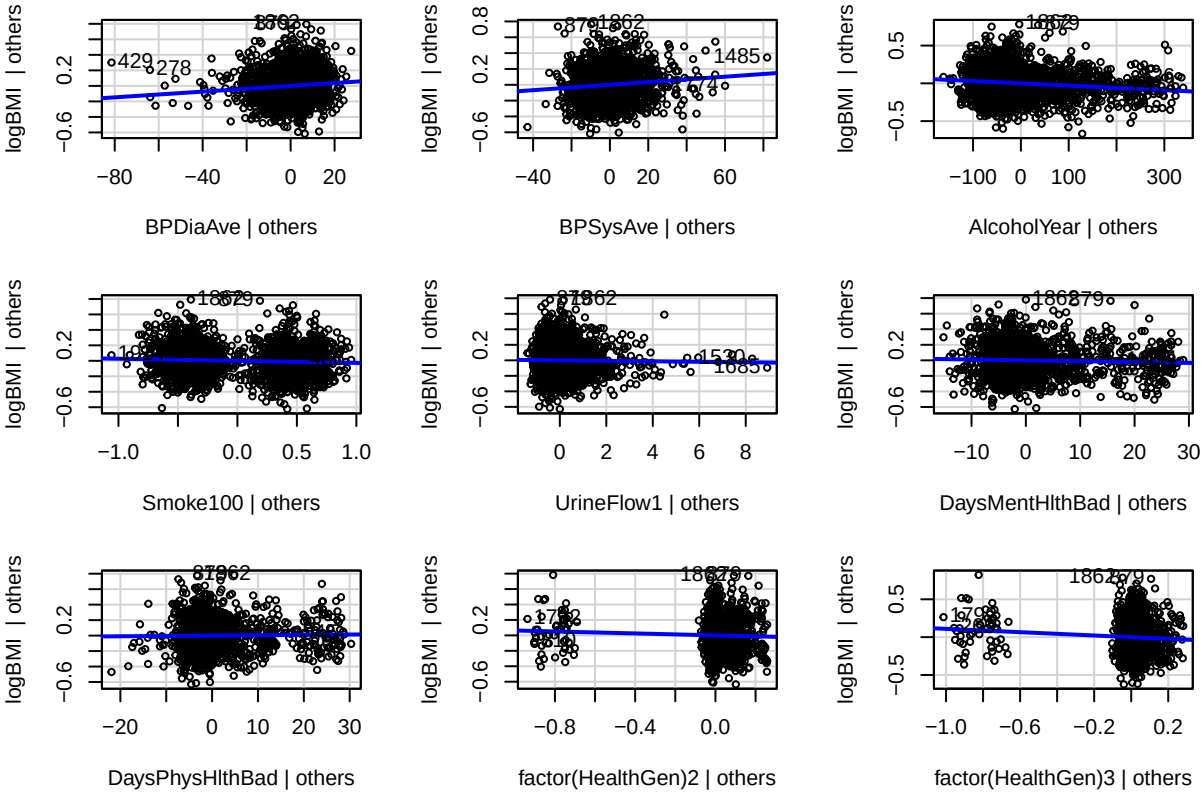


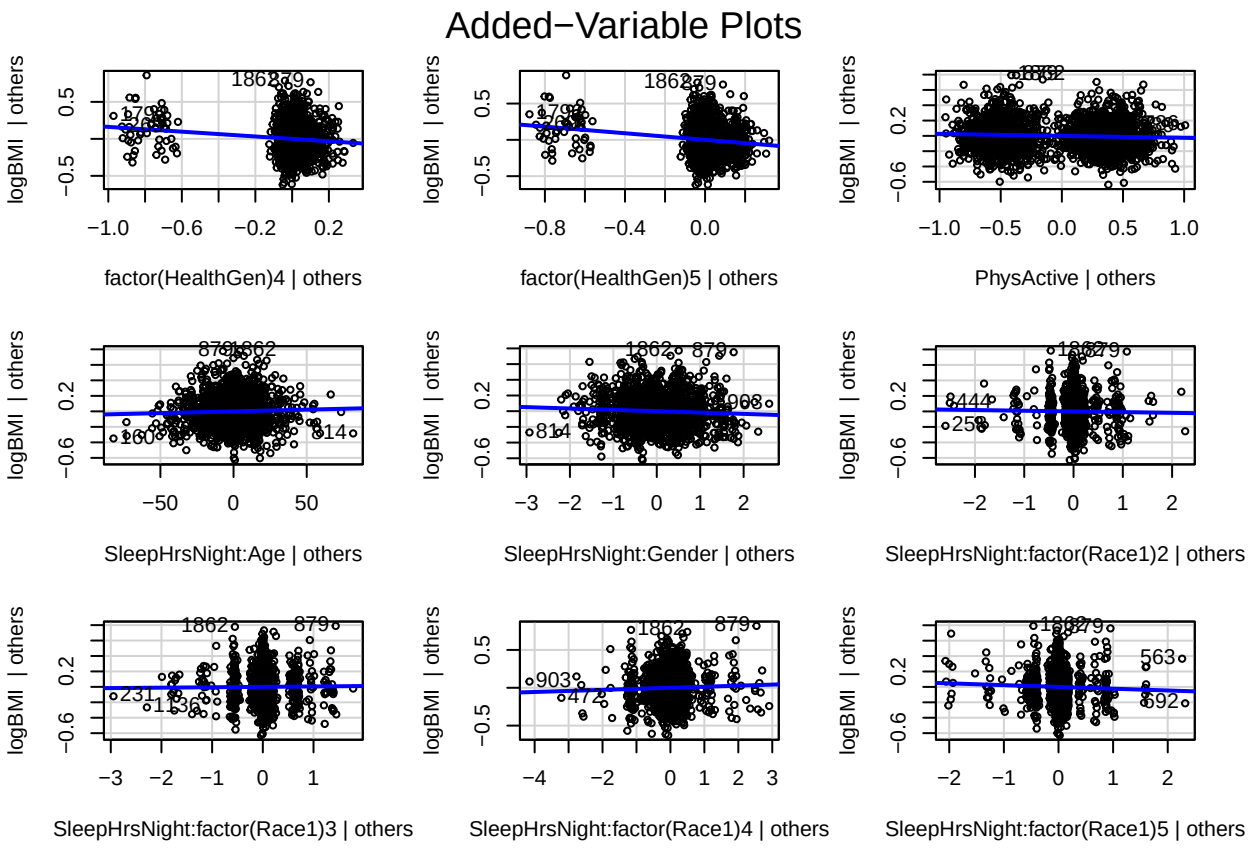

```
hist(m_full.4.res, breaks = 15)
```




```
car::avPlots(m_full.log)
```


logBMI | others
SleepHrsNight | others
Age | others
Gender | others
factor(Race1)2 | others
factor(Race1)3 | others
factor(Race1)4 | others
factor(Race1)5 | others
Poverty | others
TotChol | others


logBMI | others
BPDiaAve | others
BPSysAve | others
AlcoholYear | others
Smoke100 | others
UrineFlow1 | others
DaysMentHlthBad | others
DaysPhysHlthBad | others
factor(HealthGen)2 | others
factor(HealthGen)3 | others



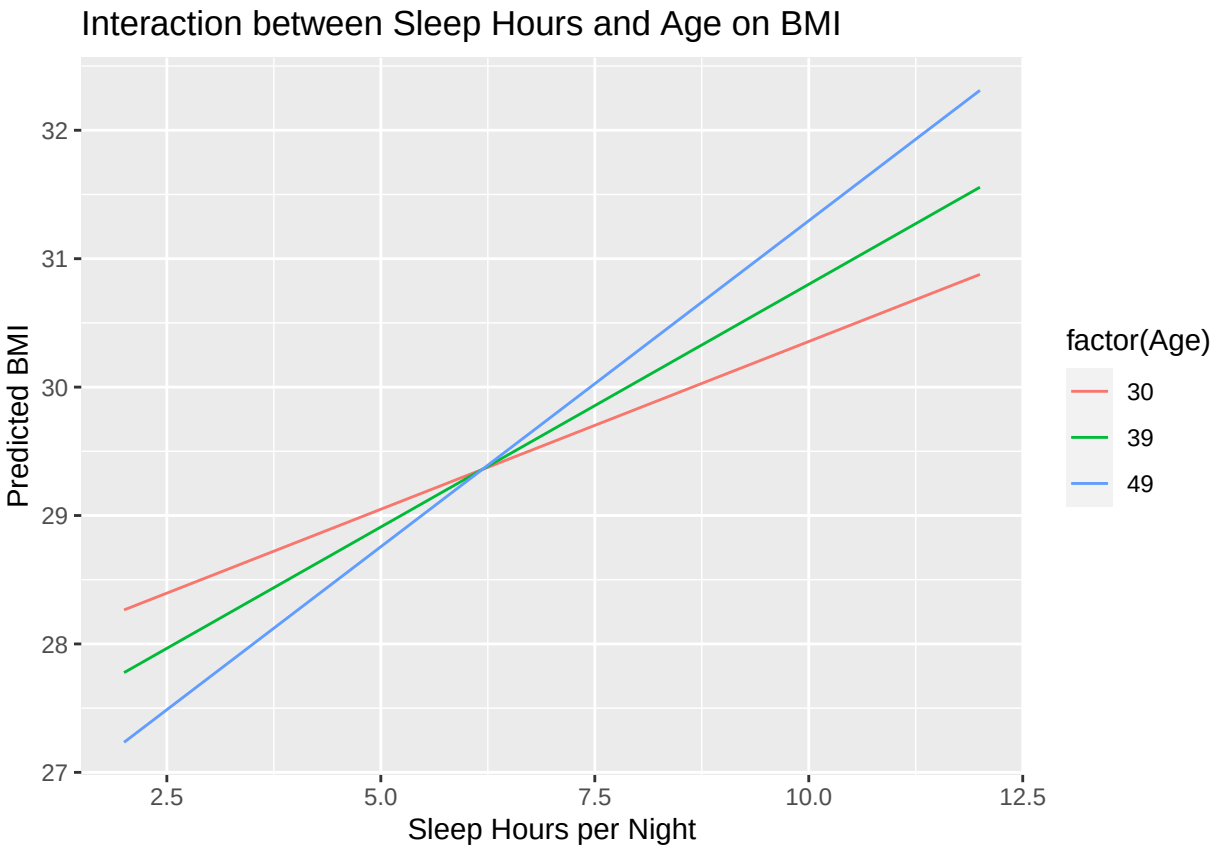

```
#After looking at residuals from models using the log-transformed (natural log scale) BMI adjusted for

#collinearity diagnostics

car::vif(m_full.log)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

| | GVIF | Df | GVIF^(1/(2*Df)) |
|---|---|---|---|
| SleepHrsNight | 1.849122e+01 | 1 | 4.300141 |
| Age | 2.879008e+01 | 1 | 5.365639 |
| Gender | 2.882194e+01 | 1 | 5.368607 |
| factor(Race1) | 5.340628e+05 | 4 | 5.199350 |
| Poverty | 1.338183e+00 | 1 | 1.156799 |
| TotChol | 1.135148e+00 | 1 | 1.065433 |
| BPDiaAve | 1.459656e+00 | 1 | 1.208162 |
| BPSysAve | 1.578347e+00 | 1 | 1.256323 |
| AlcoholYear | 1.136198e+00 | 1 | 1.065926 |
| Smoke100 | 1.142055e+00 | 1 | 1.068670 |
| UrineFlow1 | 1.049202e+00 | 1 | 1.024306 |
| DaysMentHlthBad | 1.158938e+00 | 1 | 1.076540 |
| DaysPhysHlthBad | 1.256335e+00 | 1 | 1.120864 |
| factor(HealthGen) | 1.495098e+00 | 4 | 1.051559 |
| PhysActive | 1.177165e+00 | 1 | 1.084972 |
| SleepHrsNight:Age | 3.875954e+01 | 1 | 6.225716 |
| SleepHrsNight:Gender | 3.046426e+01 | 1 | 5.519444 |

```
## SleepHrsNight:factor(Race1) 6.995071e+05  4        5.377730
```

```r
#The VIF from both the models are the same. None of the VIF values are greater than 10. So there are no
getMode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

new_data <- expand.grid(SleepHrsNight = seq(min(df3$SleepHrsNight), max(df3$SleepHrsNight), length.out =
                        Age = quantile(df3$Age, probs = c(0.25, 0.5, 0.75)),
                        Gender = median(df3$Gender, na.rm = TRUE),
                        Race1 = median(df3$Race1, na.rm = TRUE),
                        Poverty = median(df3$Poverty, na.rm = TRUE),
                        TotChol = median(df3$TotChol, na.rm = TRUE),
                        BPDiaAve = median(df3$BPDiaAve, na.rm = TRUE),
                        BPSysAve = median(df3$BPSysAve, na.rm = TRUE),
                        AlcoholYear = median(df3$AlcoholYear, na.rm = TRUE),
                        Smoke100 = getMode(df3$Smoke100),
                        UrineFlow1 = median(df3$UrineFlow1, na.rm = TRUE),
                        DaysMentHlthBad = median(df3$DaysMentHlthBad, na.rm = TRUE),
                        DaysPhysHlthBad = median(df3$DaysPhysHlthBad, na.rm = TRUE),
                        HealthGen = getMode(df3$HealthGen),
                        PhysActive = getMode(df3$PhysActive)
)

# predict
new_data$predicted_BMI <- predict(m_full, newdata = new_data)
# interaction
library(ggplot2)
ggplot(new_data, aes(x = SleepHrsNight, y = predicted_BMI, group = factor(Age))) +
  geom_line(aes(color = factor(Age))) +
  labs(title = "Interaction between Sleep Hours and Age on BMI",
       x = "Sleep Hours per Night",
       y = "Predicted BMI")
```




```
# cross validation
library(caret)
```

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

```
splitIndex <-
  createDataPartition(df3$SleepHrsNight, p = 0.7, list = FALSE)
trainData <- df3[splitIndex, ]
testData <- df3[-splitIndex, ]
predictions <- predict(m_full, newdata = testData)
mse <- mean((testData$SleepHrsNight - predictions) ^ 2)
control <-
  trainControl(method = "cv", number = 10)  # 10-fold cross-validation
cv_model <-
  train(
    SleepHrsNight ~ .,
    data = df3,
    method = "lm",
    trControl = control
  )
cv_model
```

```
## Linear Regression
##
## 2152 samples
##   21 predictor
##
```

```
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1937, 1938, 1936, 1937, 1937, 1937, ...
## Resampling results:
##
##   RMSE      Rsquared    MAE
##   1.280489  0.04937206  0.9968378
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
(cv_results <- cv_model$results)
```

```
##   intercept     RMSE   Rsquared       MAE    RMSESD RsquaredSD      MAESD
## 1      TRUE 1.280489 0.04937206 0.9968378 0.0466957 0.02498676 0.03037066
```