

project

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2023-11-21

(1) Data cleaning

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

##          used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 469578 25.1   1011221 54.1   660860 35.3
## Vcells 877810  6.7    8388608 64.0  1800812 13.8

set.seed(123)
##### (1) Data cleaning #####
library(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)]
df <- df[!duplicated(df), ]
# colSums(is.na(df)) / nrow(df)
# df$BPSysAve
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

library(car)

## Loading required package: carData

##
## Attaching package: 'car'

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

df2 <- df %>% select(
  SleepHrsNight,
  BMI,
```

```

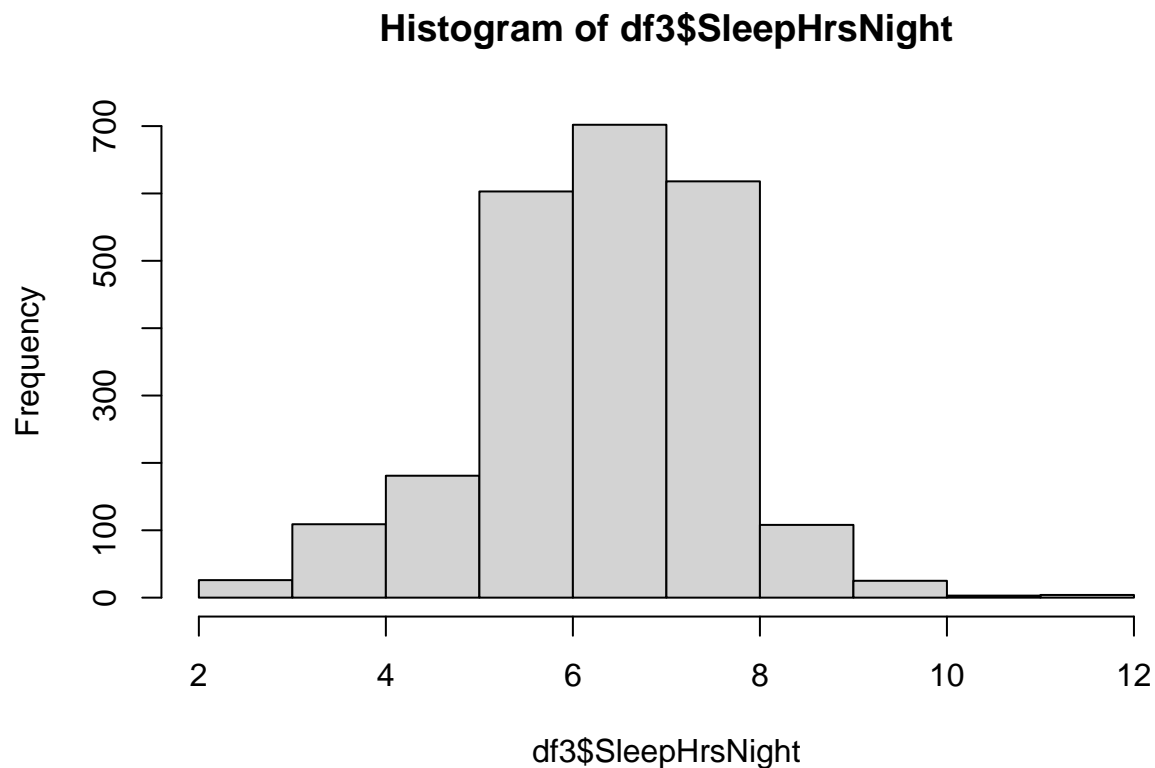
DirectChol,
Age,
Gender,
Race1,
TotChol,
BPDiaAve,
BPSysAve,
AlcoholYear,
Poverty,
HomeRooms,
SexNumPartnLife,
SexNumPartYear,
DaysMentHlthBad
)

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	2379	6.81	1.31	7.00	6.87	1.48	2.00	12.00
## BMI	2	2379	28.78	6.79	27.52	28.10	5.95	15.02	69.00
## DirectChol	3	2379	1.34	0.41	1.27	1.30	0.39	0.39	3.83
## Age	4	2379	38.65	11.58	39.00	38.60	14.83	18.00	59.00
## Gender*	5	2379	1.54	0.50	2.00	1.55	0.00	1.00	2.00
## Race1*	6	2379	3.43	1.16	4.00	3.56	0.00	1.00	5.00
## TotChol	7	2379	5.06	1.05	4.99	5.00	1.04	1.53	13.65
## BPDiaAve	8	2379	71.25	11.63	71.00	71.33	10.38	0.00	116.00
## BPSysAve	9	2379	117.55	14.40	116.00	116.59	13.34	78.00	226.00
## AlcoholYear	10	2379	68.91	93.00	24.00	49.33	35.58	0.00	364.00
## Poverty	11	2379	2.79	1.69	2.71	2.83	2.42	0.00	5.00
## HomeRooms	12	2379	6.02	2.24	6.00	5.88	1.48	1.00	13.00
## SexNumPartnLife	13	2379	15.97	63.17	6.00	8.52	5.93	0.00	2000.00
## SexNumPartYear	14	2379	1.37	2.76	1.00	1.00	0.00	0.00	69.00
## DaysMentHlthBad	15	2379	4.42	7.98	0.00	2.35	0.00	0.00	30.00
##	range	skew	kurtosis	se					
## SleepHrsNight	10.00	-0.30	0.64	0.03					
## BMI	53.98	1.23	2.65	0.14					
## DirectChol	3.44	1.14	2.57	0.01					
## Age	41.00	0.02	-1.16	0.24					
## Gender*	1.00	-0.15	-1.98	0.01					
## Race1*	4.00	-1.10	0.06	0.02					
## TotChol	12.12	0.88	3.24	0.02					
## BPDiaAve	116.00	-0.36	3.11	0.24					
## BPSysAve	148.00	1.12	3.93	0.30					
## AlcoholYear	364.00	1.70	2.16	1.91					
## Poverty	5.00	0.03	-1.48	0.03					
## HomeRooms	12.00	0.64	0.43	0.05					
## SexNumPartnLife	2000.00	19.57	497.14	1.30					
## SexNumPartYear	69.00	13.35	250.92	0.06					
## DaysMentHlthBad	30.00	2.19	3.88	0.16					

```
# 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 <- 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
    )
  )
```

(2) Baseline characteristics

```
Hmisc::describe(df3)
```

```
## df3
##
## 15 Variables      2379 Observations
## -----
## SleepHrsNight
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      11      0.94      6.807      1.417      4      5
##      .25      .50      .75      .90      .95
##      6      7      8      8      9
##
## lowest : 2 3 4 5 6, highest: 8 9 10 11 12
##
## Value      2      3      4      5      6      7      8      9      10      11      12
## Frequency      3      23      109      181      603      702      618      108      25      3      4
## Proportion 0.001 0.010 0.046 0.076 0.253 0.295 0.260 0.045 0.011 0.001 0.002
## -----
## BMI
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      1139      1      28.78      7.297      20.15      21.39
##      .25      .50      .75      .90      .95
##    23.97      27.52      32.20      37.47      41.46
##
## lowest : 15.02 15.80 15.98 16.51 16.70, highest: 62.80 63.30 63.91 67.83 69.00
## -----
## DirectChol
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      99      0.999      1.34      0.4424      0.80      0.88
##      .25      .50      .75      .90      .95
##    1.06      1.27      1.55      1.86      2.07
##
## lowest : 0.39 0.41 0.52 0.54 0.57, highest: 3.41 3.44 3.59 3.72 3.83
## -----
## Age
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      42      0.999      38.65      13.37      21      23
##      .25      .50      .75      .90      .95
##    29      39      48      55      57
##
## lowest : 18 19 20 21 22, highest: 55 56 57 58 59
## -----
## Gender
##      n missing distinct      Info      Sum      Mean      Gmd
##    2379      0      2      0.746      1102      0.4632      0.4975
##
## -----
## Race1
##      n missing distinct      Info      Mean      Gmd
##    2379      0      5      0.77      3.427      1.127
##
```

```

## lowest : 1 2 3 4 5, highest: 1 2 3 4 5
##
## Value      1      2      3      4      5
## Frequency  318   160   271  1447   183
## Proportion 0.134 0.067 0.114 0.608 0.077
## -----
## TotChol
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      212      1    5.057    1.15    3.54    3.83
##      .25      .50      .75      .90      .95
##    4.32    4.99    5.69    6.36    6.83
##
## lowest :  1.53  2.43  2.59  2.69  2.74, highest:  9.31  9.34  9.90 12.28 13.65
## -----
## BPDiaAve
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      84    0.999    71.25    12.62     53     58
##      .25      .50      .75      .90      .95
##      64      71      78      85      89
##
## lowest :    0  20  21  22  25, highest: 108 109 110 114 116
## -----
## BPSysAve
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      99    0.999    117.6    15.47    98.0   101.8
##      .25      .50      .75      .90      .95
##   108.0   116.0   125.0   134.0   142.0
##
## lowest :  78  83  84  85  86, highest: 184 191 202 209 226
## -----
## AlcoholYear
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      56    0.993    68.91    90.19      0      0
##      .25      .50      .75      .90      .95
##      4      24     104     208     260
##
## lowest :    0    1    2    3    4, highest: 260 300 312 360 364
## -----
## Poverty
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      398    0.989     2.794    1.932    0.329    0.658
##      .25      .50      .75      .90      .95
##    1.225    2.710    4.710    5.000    5.000
##
## lowest : 0.00 0.02 0.03 0.04 0.05, highest: 4.95 4.96 4.97 4.99 5.00
## -----
## HomeRooms
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    2379      0      13    0.978     6.024    2.459      3      4
##      .25      .50      .75      .90      .95
##      4      6      7      9     10
##
## lowest :  1  2  3  4  5, highest:  9 10 11 12 13
##

```

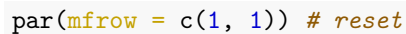
```
## Value      1      2      3      4      5      6      7      8      9     10     11
## Frequency   25     34    168   408   441   438   331   213   134    93    42
## Proportion 0.011 0.014 0.071 0.172 0.185 0.184 0.139 0.090 0.056 0.039 0.018
##
## Value      12     13
## Frequency   26     26
## Proportion 0.011 0.011
## -----
## SexNumPartnLife
##      n missing distinct      Info      Mean      Gmd      .05      .10
##  2379      0      81    0.996    15.97    21.68      1      1
##    .25    .50    .75    .90    .95
##      3      6     15     30     50
##
## lowest :    0    1    2    3    4, highest:  600  800  999 1000 2000
## -----
## SexNumPartYear
##      n missing distinct      Info      Mean      Gmd      .05      .10
##  2379      0      22    0.683     1.374    1.258      0      0
##    .25    .50    .75    .90    .95
##      1      1      1      2      3
##
## lowest :  0  1  2  3  4, highest: 19 20 30 50 69
## -----
## DaysMentHlthBad
##      n missing distinct      Info      Mean      Gmd      .05      .10
##  2379      0      28    0.842     4.422    6.829      0      0
##    .25    .50    .75    .90    .95
##      0      0      5     15     30
##
## lowest :  0  1  2  3  4, highest: 25 26 27 29 30
## -----
```

(3) linear regression model

```
model1 = lm(df3$SleepHrsNight ~ df3$BMI, data = df3)
summary(model1)
```

```
##
## Call:
## lm(formula = df3$SleepHrsNight ~ df3$BMI, data = df3)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.8366 -0.8209  0.1606  1.1457  5.2593
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.089190   0.116862  60.663  <2e-16 ***
## df3$BMI      -0.009790   0.003953  -2.477   0.0133 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
par(mfrow = c(2, 3)) #read more from ?plot.lm
plot(model1, which = 1)
plot(model1, which = 2)
plot(model1, which = 3)
plot(model1, which = 4)
plot(model1, which = 5)
plot(model1, which = 6)
```



```
m_initial = lm(SleepHrsNight ~ BMI + Age + Gender + factor(Race1), df3)
summary(m_initial)
```

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```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.926204   0.165453  41.862 < 2e-16 ***
## BMI          -0.006542   0.003986  -1.641  0.10086
## Age          -0.008653   0.002331  -3.712  0.00021 ***
## Gender        0.190406   0.053607   3.552  0.00039 ***
## factor(Race1)2 0.219456   0.126253   1.738  0.08230 .
## factor(Race1)3 0.463251   0.107923   4.292 1.84e-05 ***
## factor(Race1)4 0.364311   0.081381   4.477 7.94e-06 ***
## factor(Race1)5 0.346075   0.121784   2.842  0.00453 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.298 on 2371 degrees of freedom
## Multiple R-squared:  0.02277, Adjusted R-squared:  0.01988
## F-statistic: 7.892 on 7 and 2371 DF, p-value: 1.734e-09

m_knrisk = lm(
  SleepHrsNight ~ BMI + Age + Gender + factor(Race1) + TotChol + BPDiaAve +
    BPSysAve + AlcoholYear + DaysMentHlthBad,
  df3
)
summary(m_knrisk)

##
## Call:
## lm(formula = SleepHrsNight ~ BMI + Age + Gender + factor(Race1) +
##     TotChol + BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad,
##     data = df3)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.9890 -0.8396  0.0721  0.9860  5.3001
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.0320813  0.2778091  25.313 < 2e-16 ***
## BMI          -0.0044747  0.0040584  -1.103  0.270326
## Age          -0.0094332  0.0024860  -3.794  0.000152 ***
## Gender        0.2375920  0.0557852   4.259 2.13e-05 ***
## factor(Race1)2 0.2194679  0.1252138   1.753 0.079775 .
## factor(Race1)3 0.4198626  0.1074580   3.907 9.60e-05 ***
## factor(Race1)4 0.3457651  0.0809536   4.271 2.02e-05 ***
## factor(Race1)5 0.3059503  0.1211322   2.526 0.011610 *
## TotChol       0.0047497  0.0266203   0.178 0.858404
## BPDiaAve      0.0005694  0.0027009   0.211 0.833058
## BPSysAve     -0.0010233  0.0022623  -0.452 0.651072
## AlcoholYear   0.0004989  0.0002951   1.691 0.091045 .
## DaysMentHlthBad -0.0263313  0.0033210  -7.929 3.38e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.281 on 2366 degrees of freedom
## Multiple R-squared:  0.0491, Adjusted R-squared:  0.04427
```



```
## F-statistic: 10.18 on 12 and 2366 DF, p-value: < 2.2e-16
```

```
m_full = lm(
  SleepHrsNight ~ BMI + Age + Gender + factor(Race1) + TotChol + BPDiaAve +
  BPSysAve + AlcoholYear + DaysMentHlthBad + HomeRooms + SexNumPartnLife +
  SexNumPartYear + Poverty,
  df3
)
summary(m_full)
```

```
##
```

```
## Call:
```

```
## lm(formula = SleepHrsNight ~ BMI + Age + Gender + factor(Race1) +
##     TotChol + BPDiaAve + BPSysAve + AlcoholYear + DaysMentHlthBad +
##     HomeRooms + SexNumPartnLife + SexNumPartYear + Poverty, data = df3)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -4.8773 -0.8413  0.0550  0.9634  5.3687
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6.7900913   0.2880350   23.574 < 2e-16 ***
## BMI            -0.0040314   0.0040533   -0.995 0.320044
## Age            -0.0108102   0.0025767   -4.195 2.82e-05 ***
## Gender          0.2295409   0.0559260    4.104 4.19e-05 ***
## factor(Race1)2  0.2329616   0.1249975    1.864 0.062483 .
## factor(Race1)3  0.4443994   0.1077464    4.124 3.84e-05 ***
## factor(Race1)4  0.3135085   0.0815958    3.842 0.000125 ***
## factor(Race1)5  0.2899386   0.1211140    2.394 0.016746 *
## TotChol         0.0053548   0.0265885    0.201 0.840408
## BPDiaAve        0.0006679   0.0026998    0.247 0.804627
## BPSysAve       -0.0005452   0.0022628   -0.241 0.809634
## AlcoholYear     0.0003952   0.0002967    1.332 0.182986
## DaysMentHlthBad -0.0247441   0.0033503   -7.386 2.09e-13 ***
## HomeRooms       0.0213263   0.0127462    1.673 0.094431 .
## SexNumPartnLife -0.0009946   0.0004243   -2.344 0.019168 *
## SexNumPartYear  0.0149274   0.0097588    1.530 0.126243
## Poverty         0.0372512   0.0173927    2.142 0.032314 *
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 1.278 on 2362 degrees of freedom
```

```
## Multiple R-squared:  0.05601, Adjusted R-squared:  0.04962
```

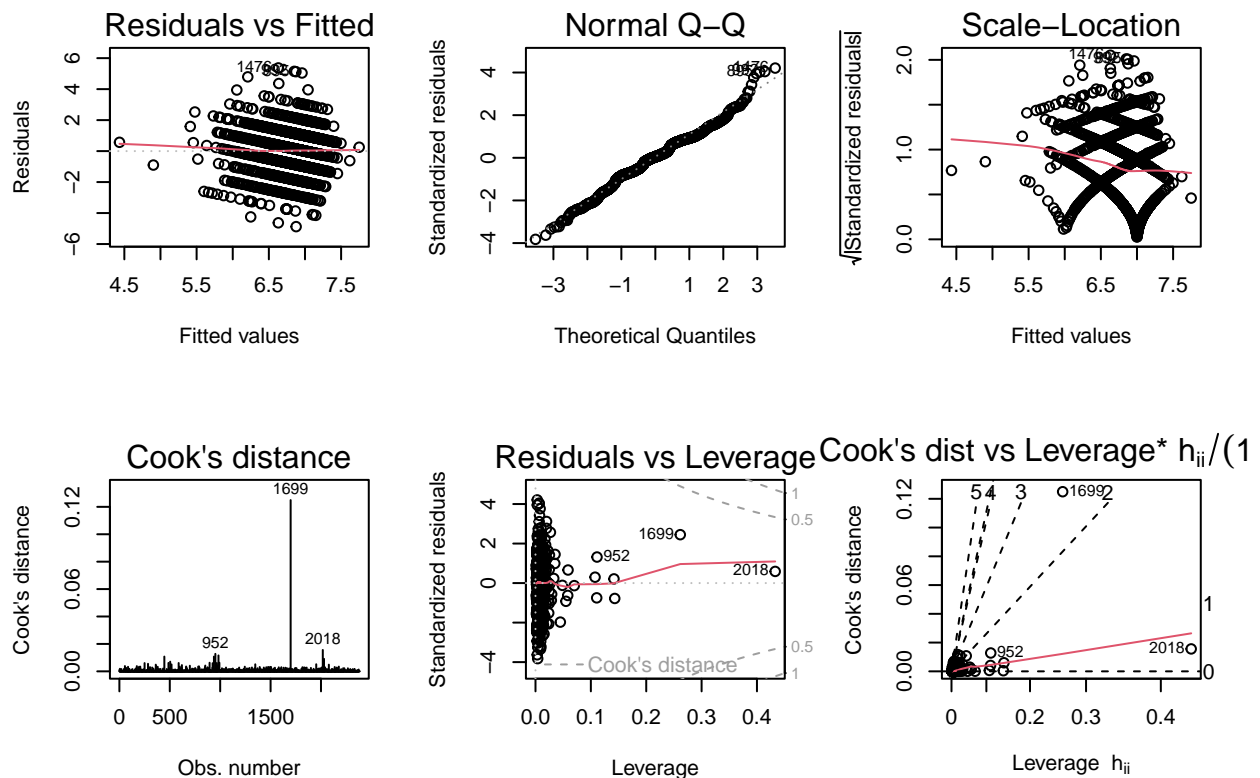
```
## F-statistic: 8.759 on 16 and 2362 DF, p-value: < 2.2e-16
```

```
vif(m_full)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## BMI          1.104174 1      1.050797
## Age          1.296882 1      1.138807
## Gender       1.133022 1      1.064435
## factor(Race1) 1.208657 4      1.023972
## TotChol      1.133282 1      1.064557
## BPDiaAve     1.436892 1      1.198704
```

```
## BPSysAve      1.545631  1      1.243234
## AlcoholYear   1.108683  1      1.052940
## DaysMentHlthBad 1.041358  1      1.020469
## HomeRooms     1.182949  1      1.087635
## SexNumPartnLife 1.046533  1      1.023002
## SexNumPartYear 1.053685  1      1.026491
## Poverty       1.261580  1      1.123201
```

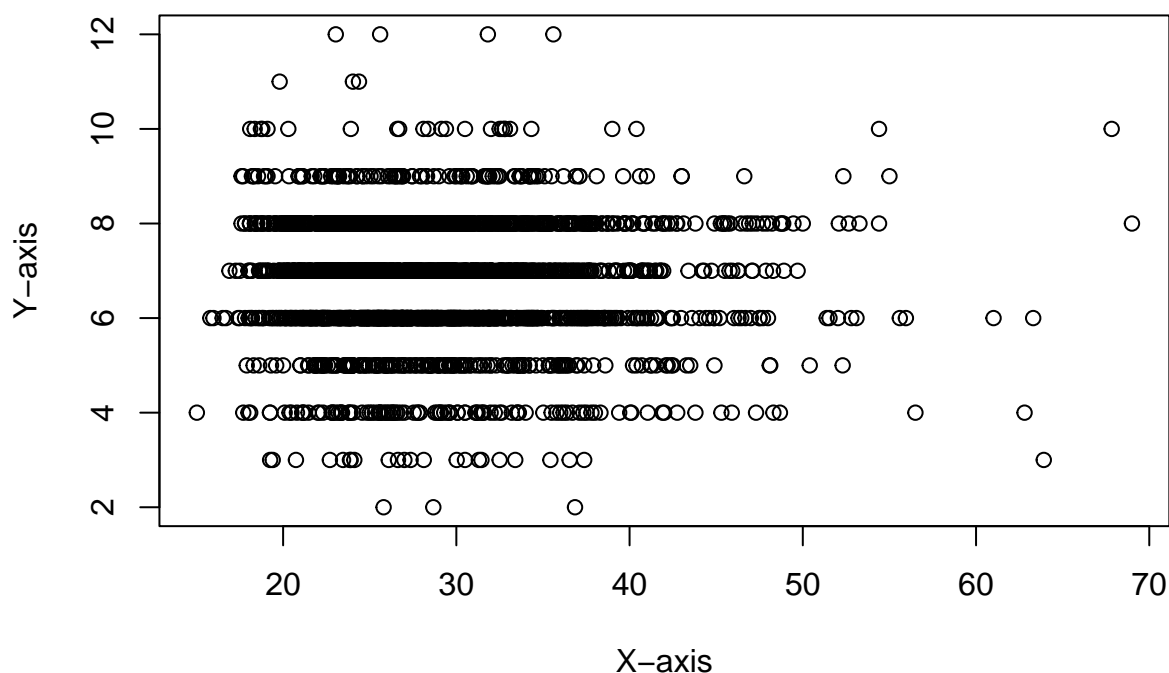
```
par(mfrow = c(2, 3)) #read more from ?plot.lm
plot(m_full, which = 1)
plot(m_full, which = 2)
plot(m_full, which = 3)
plot(m_full, which = 4)
plot(m_full, which = 5)
plot(m_full, which = 6)
```



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

plot(
  df3$BMI,
  df3$SleepHrsNight,
  main = "Scatter Plot with Linear Regression Line",
  xlab = "X-axis",
  ylab = "Y-axis"
)
```

Scatter Plot with Linear Regression Line

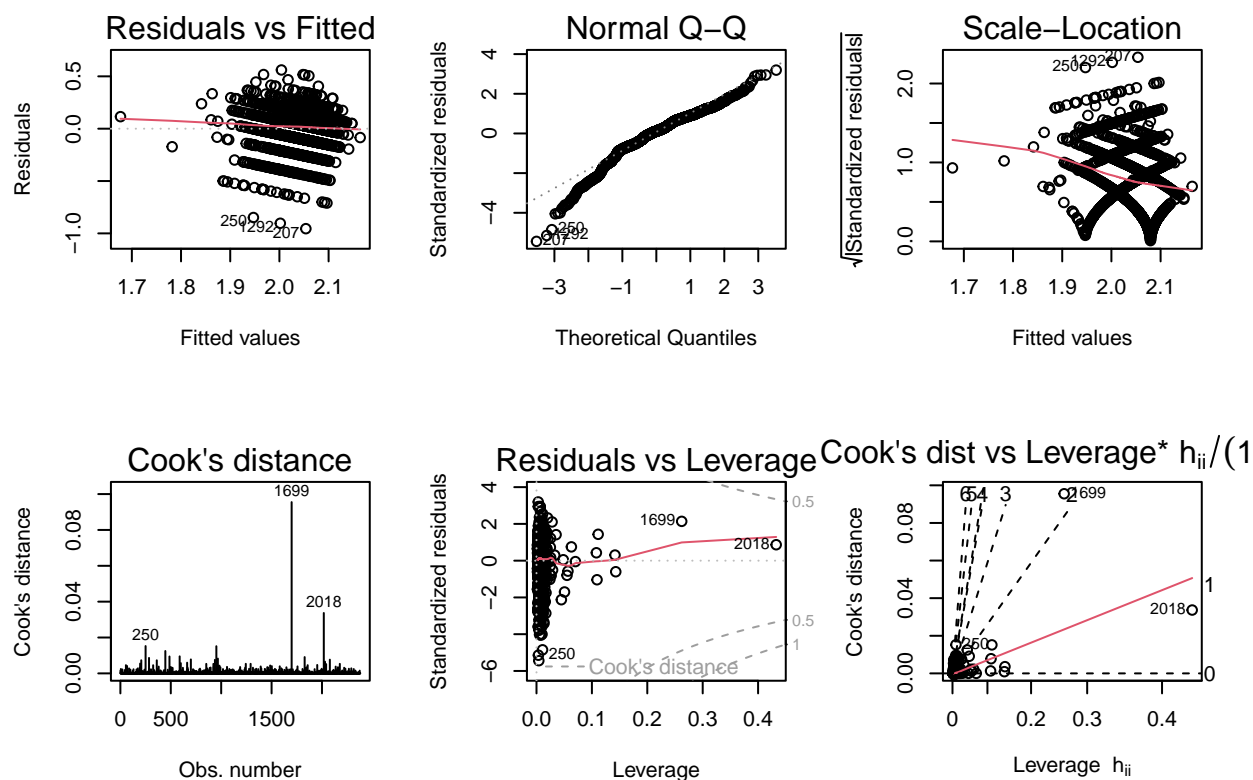


```
#log x
df3$logBMI = log(df3$BMI + 1)
df3$logSleepHrsNight = log(df3$SleepHrsNight + 1)
df3$logDaysMentHlthBad = log(df3$DaysMentHlthBad + 1)
df3$invTotChol = 1 / df3$TotChol
df3$sqrtDaysMentHlthBad = sqrt(df3$DaysMentHlthBad)
df3$sqBMI = (df3$BMI - mean(df3$BMI)) ^ 2
m_logfull_2 = lm(
  logSleepHrsNight ~ Age + Gender + factor(Race1) + logBMI + invTotChol +
  BPDiaAve + BPSysAve + AlcoholYear + sqrtDaysMentHlthBad + HomeRooms + SexNumPartnLife +
  SexNumPartYear + Poverty,
  df3
)
summary(m_logfull_2)
```

```
##
## Call:
## lm(formula = logSleepHrsNight ~ Age + Gender + factor(Race1) +
##     logBMI + invTotChol + BPDiaAve + BPSysAve + AlcoholYear +
##     sqrtDaysMentHlthBad + HomeRooms + SexNumPartnLife + SexNumPartYear +
##     Poverty, data = df3)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.95516 -0.09798  0.01973  0.12503  0.56082
##
```

```
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    2.091e+00  7.094e-02  29.476 < 2e-16 ***
## Age           -1.567e-03  3.540e-04  -4.427 9.99e-06 ***
## Gender         3.130e-02  7.727e-03   4.050 5.28e-05 ***
## factor(Race1)2  3.462e-02  1.719e-02   2.014 0.04416 *
## factor(Race1)3  6.283e-02  1.482e-02   4.239 2.33e-05 ***
## factor(Race1)4  4.723e-02  1.121e-02   4.212 2.63e-05 ***
## factor(Race1)5  4.506e-02  1.666e-02   2.705 0.00688 **
## logBMI        -2.052e-02  1.776e-02  -1.156 0.24797
## invTotChol    -1.352e-02  8.866e-02  -0.152 0.87885
## BPDiaAve       1.927e-04  3.715e-04   0.519 0.60410
## BPSysAve      -5.826e-05  3.116e-04  -0.187 0.85168
## AlcoholYear     6.167e-05  4.089e-05   1.508 0.13167
## sqrtDaysMentHlthBad -1.748e-02  2.215e-03  -7.891 4.55e-15 ***
## HomeRooms       3.031e-03  1.755e-03   1.727 0.08428 .
## SexNumPartnLife -1.467e-04  5.844e-05  -2.511 0.01211 *
## SexNumPartYear   1.880e-03  1.344e-03   1.399 0.16203
## Poverty         6.249e-03  2.396e-03   2.608 0.00917 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1759 on 2362 degrees of freedom
## Multiple R-squared:  0.06159,    Adjusted R-squared:  0.05523
## F-statistic: 9.689 on 16 and 2362 DF,  p-value: < 2.2e-16

par(mfrow = c(2, 3)) #read more from ?plot.lm
plot(m_logfull_2, which = 1)
plot(m_logfull_2, which = 2)
plot(m_logfull_2, which = 3)
plot(m_logfull_2, which = 4)
plot(m_logfull_2, which = 5)
plot(m_logfull_2, which = 6)
```



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

(4) Diagnosis: 10-fold CV

```
library(caret)

## Loading required package: ggplot2
## Loading required package: lattice

splitIndex <-
  createDataPartition(df3$SleepHrsNight, p = 0.7, list = FALSE)
trainData <- df3[splitIndex, ]
testData <- df3[-splitIndex, ]
predictions <- predict(m_logfull_2, newdata = testData)
mse <- mean((testData$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
##
## 2379 samples
## 20 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 2141, 2140, 2141, 2141, 2142, 2142, ...
## Resampling results:
##
## RMSE      Rsquared  MAE
## 0.1900161  0.979765  0.1266116
##
## 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 0.1900161 0.979765 0.1266116 0.03595476 0.005748305 0.00897214

```

(4) Diagnosis: Normality Assumption

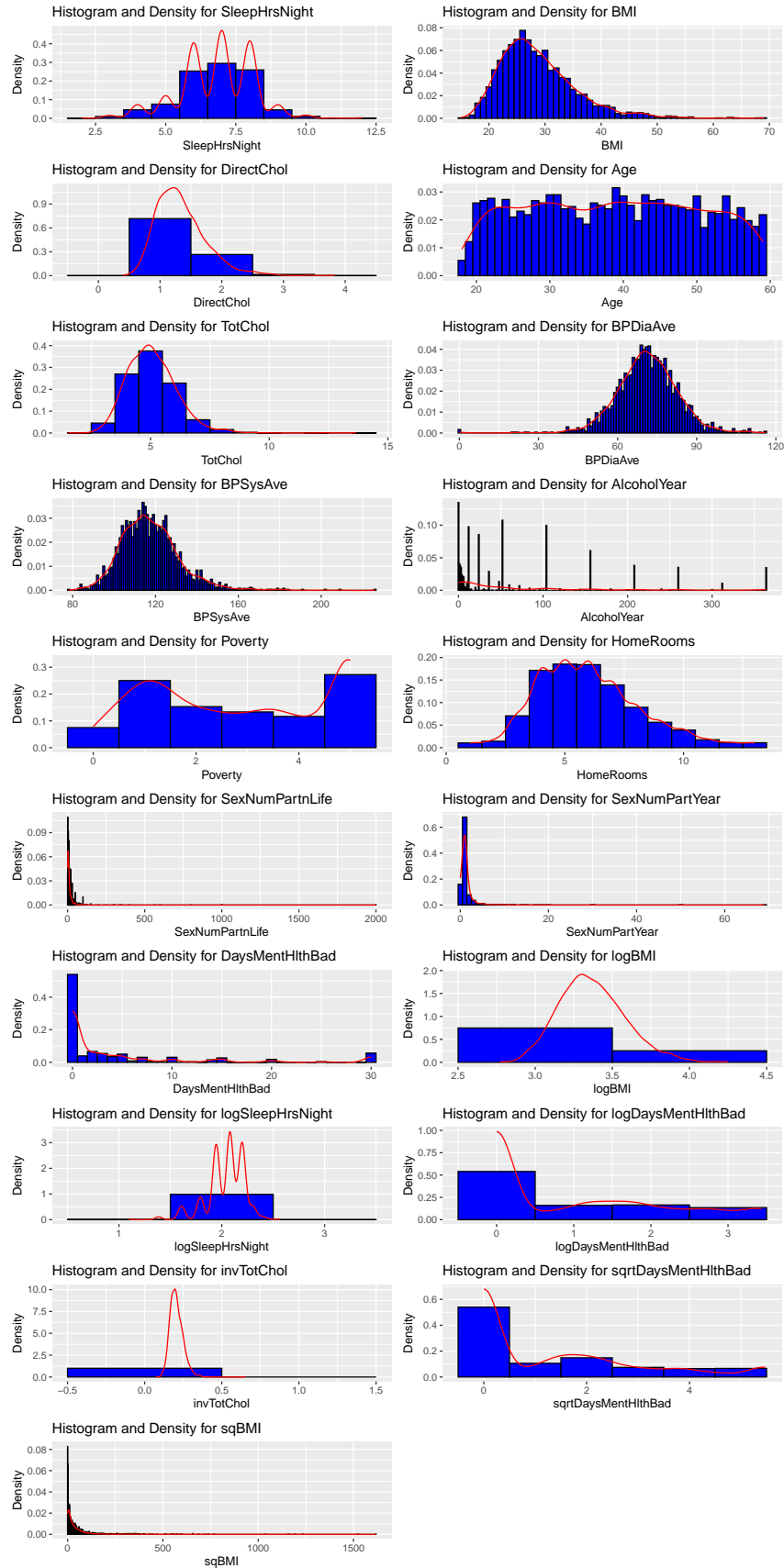
```

library(ggplot2)
library(patchwork)
# Initializes an empty patchwork object
plot_list <- list()

# Draw a histogram for each numeric variable (except Race1 and Gender) and add it to the list
for (var in names(df3)) {
  if (is.numeric(df3[[var]]) && !(var %in% c("Race1", "Gender"))) {
    p <- ggplot(df3, aes(x = .data[[var]])) +
      geom_histogram(
        aes(y = after_stat(density)),
        binwidth = 1,
        fill = "blue",
        color = "black"
      ) +
      geom_density(col = "red") +
      ggtitle(paste("Histogram and Density for", var)) +
      xlab(var) +
      ylab("Density")
    plot_list[[length(plot_list) + 1]] <- p
  }
}

# Use patchwork to put all the charts together
combined_plot <- wrap_plots(plot_list, ncol = 2)
print(combined_plot)

```



```

df3 <- data.frame(df3)
library(dplyr)
# Shapiro-Wilk normality test is performed for each numerical variable in df3
results <- sapply(df3, function(x) {
  if (is.numeric(x)) {
    shapiro_test <- shapiro.test(x)
    return(c(shapiro_test$statistic, shapiro_test$p.value))
  } else {
    return(c(NA, NA))
  }
})
# Convert the result to a data box and name the column
results_df <- as.data.frame(t(results))
names(results_df) <- c("W", "p.value")
# Add a variable name as a new column
results_df$Variable <- rownames(results_df)
# Rearrange the order of columns
results_df <- results_df[, c("Variable", "W", "p.value")]
# Calculate the corrected P-value (for example, using Bonferroni correction)
results_df$p.adjusted <-
  p.adjust(results_df$p.value, method = "bonferroni")
print(results_df)

```

	Variable	W	p.value	p.adjusted
## SleepHrsNight	SleepHrsNight	0.9354644	6.065754e-31	1.273808e-29
## BMI	BMI	0.9301559	5.692561e-32	1.195438e-30
## DirectChol	DirectChol	0.9405789	6.876212e-30	1.444005e-28
## Age	Age	0.9582706	1.360245e-25	2.856515e-24
## Gender	Gender	0.6346474	1.545071e-57	3.244648e-56
## Race1	Race1	0.7427298	1.802728e-51	3.785730e-50
## TotChol	TotChol	0.9663542	3.785914e-23	7.950419e-22
## BPDiaAve	BPDiaAve	0.9726214	6.250883e-21	1.312685e-19
## BPSysAve	BPSysAve	0.9484045	3.946229e-28	8.287082e-27
## AlcoholYear	AlcoholYear	0.7403964	1.270928e-51	2.668949e-50
## Poverty	Poverty	0.8951549	1.570942e-37	3.298979e-36
## HomeRooms	HomeRooms	0.9553923	2.237881e-26	4.699550e-25
## SexNumPartnLife	SexNumPartnLife	0.1509787	1.499112e-73	3.148134e-72
## SexNumPartYear	SexNumPartYear	0.2545353	5.992229e-71	1.258368e-69
## DaysMentHlthBad	DaysMentHlthBad	0.6076574	8.193380e-59	1.720610e-57
## logBMI	logBMI	0.9877235	1.946304e-13	4.087239e-12
## logSleepHrsNight	logSleepHrsNight	0.8984084	4.408251e-37	9.257327e-36
## logDaysMentHlthBad	logDaysMentHlthBad	0.7729598	2.157265e-49	4.530256e-48
## invTotChol	invTotChol	0.9572292	7.005059e-26	1.471062e-24
## sqrtDaysMentHlthBad	sqrtDaysMentHlthBad	0.7619387	3.557376e-50	7.470490e-49
## sqBMI	sqBMI	0.4152373	3.203569e-66	6.727494e-65

Standardized residuals, Studentized residuals

```

# Regular residuals
residual_1 <- fit0$residuals

# Standardized residuals

```



```

residual_2 <- rstandard(fit0)

# Studentized residuals
residual_3 <- rstudent(fit0)

# Externally studentized residuals
# Note: Externally studentized residuals are the same as studentized residuals in most cases
residual_4 <- rstudent(fit0)

# Creating a data frame to summarize these residuals
residual_summary <- data.frame(
  Residuals = c("Regular", "Standardized", "Studentized", "Externally Studentized"),
  Mean = c(mean(residual_1), mean(residual_2), mean(residual_3), mean(residual_4)),
  SD = c(sd(residual_1), sd(residual_2), sd(residual_3), sd(residual_4)),
  Min = c(min(residual_1), min(residual_2), min(residual_3), min(residual_4)),
  Max = c(max(residual_1), max(residual_2), max(residual_3), max(residual_4))
)

# Display the summary
print(residual_summary)

##           Residuals      Mean      SD      Min      Max
## 1           Regular 7.060476e-17 1.273554 -4.878636 5.368822
## 2      Standardized 1.960572e-04 1.000639 -3.826002 4.207084
## 3        Studentized 1.585968e-04 1.001202 -3.837105 4.222048
## 4 Externally Studentized 1.585968e-04 1.001202 -3.837105 4.222048

# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model
# fit0 <- lm(SleepMinNight ~ ., data = df3)

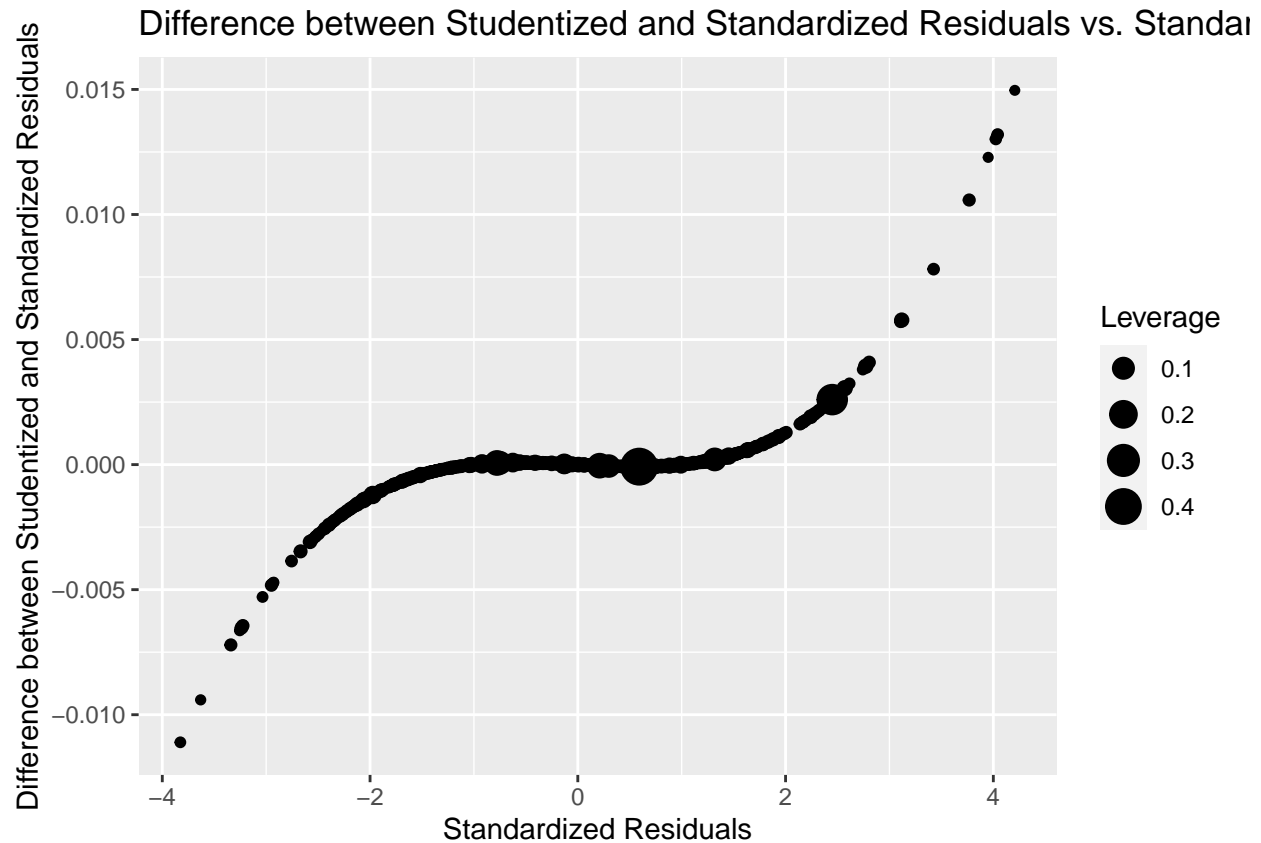
# Calculate standardized and studentized residuals
residual_2 <- rstandard(fit0)
residual_3 <- rstudent(fit0)

# Calculate leverage values
leverage_values <- hatvalues(fit0)

# Create a data frame for plotting
plot_data <- data.frame(
  Standardized_Residuals = residual_2,
  Difference = residual_3 - residual_2,
  Leverage = leverage_values
)

# Create the plot
ggplot(plot_data, aes(x = Standardized_Residuals, y = Difference)) +
  geom_point(aes(size = Leverage)) +
  ggtitle("Difference between Studentized and Standardized Residuals vs. Standardized Residuals") +
  xlab("Standardized Residuals") +
  ylab("Difference between Studentized and Standardized Residuals")

```



```
# Display the plot
print(ggplot)
```

```
## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##   UseMethod("ggplot")
## }
## <bytecode: 0x4e12680>
## <environment: namespace:ggplot2>
```

```
# Load necessary library
library(ggplot2)
```

```
# Assuming fit0 is your linear model
# fit0 <- lm(SleepMinNight ~ ., data = df3)
```

```
# Calculate studentized and externally studentized residuals
```

```
residual_3 <- rstudent(fit0)
```

```
residual_4 <- rstudent(fit0) # Externally studentized residuals are typically the same as studentized
```

```
# Regular residuals
```

```
residual_1 <- fit0$residuals
```

```
# Create a data frame for plotting
```

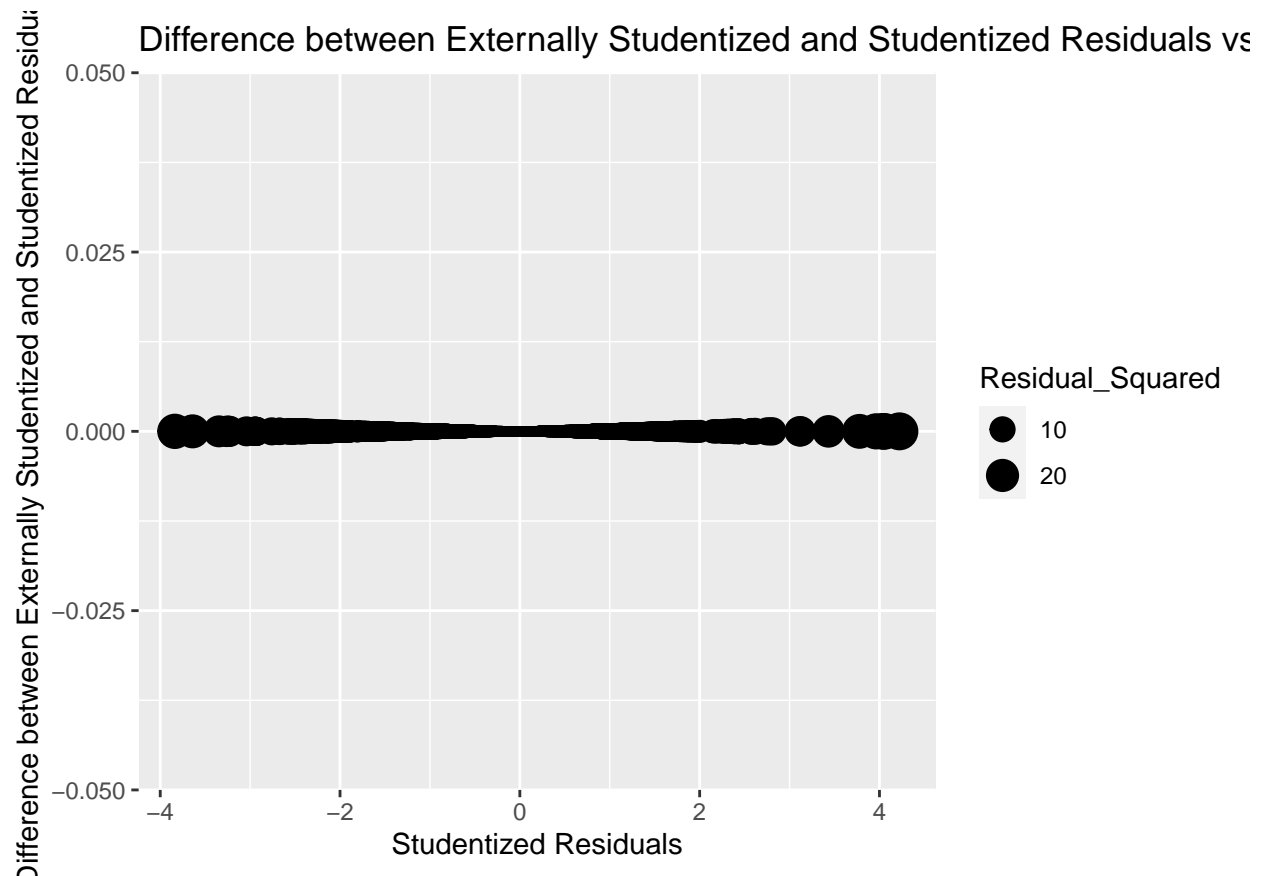
```
plot_data <- data.frame(
  Studentized_Residuals = residual_3,
  Difference = residual_4 - residual_3,
```

```

Residual_Squared = residual_1^2
)

# Create the plot
ggplot(plot_data, aes(x = Studentized_Residuals, y = Difference)) +
  geom_point(aes(size = Residual_Squared)) +
  ggtitle("Difference between Externally Studentized and Studentized Residuals vs. Studentized Residuals") +
  xlab("Studentized Residuals") +
  ylab("Difference between Externally Studentized and Studentized Residuals")

```



```

# Display the plot
print(ggplot)

## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##   UseMethod("ggplot")
## }
## <bytecode: 0x4e12680>
## <environment: namespace:ggplot2>

# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model
# fit0 <- lm(SleepMinNight ~ ., data = df3)

# Calculate regular residuals

```

```

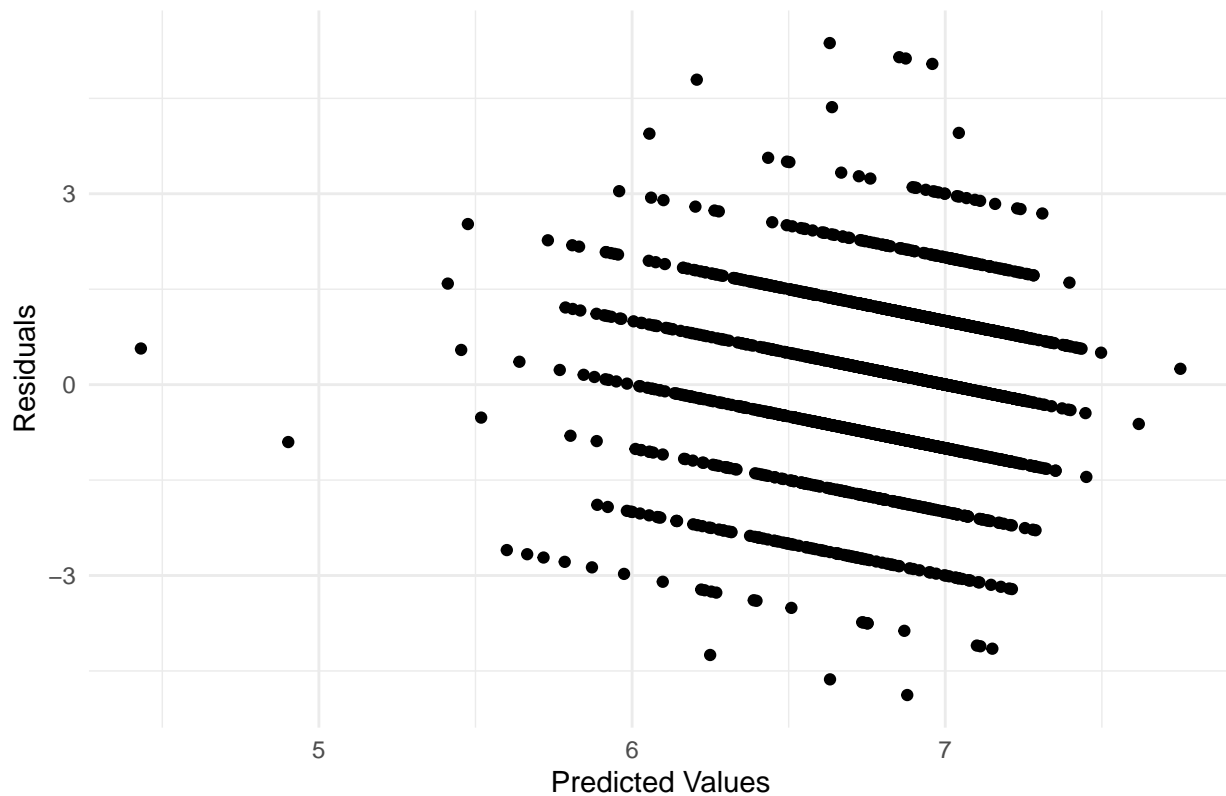
residual_1 <- fit0$residuals

# Get predicted values from the model
predicted_values <- predict(fit0)

# Create the plot
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_1)) +
  ggtitle("Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Residuals") +
  theme_minimal()

```

Residuals vs. Predicted Values



```

# Display the plot
print(ggplot)

## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##   UseMethod("ggplot")
## }
## <bytecode: 0x4e12680>
## <environment: namespace:ggplot2>

# Load necessary library
library(ggplot2)

# Assuming fit0 is your linear model

```

```

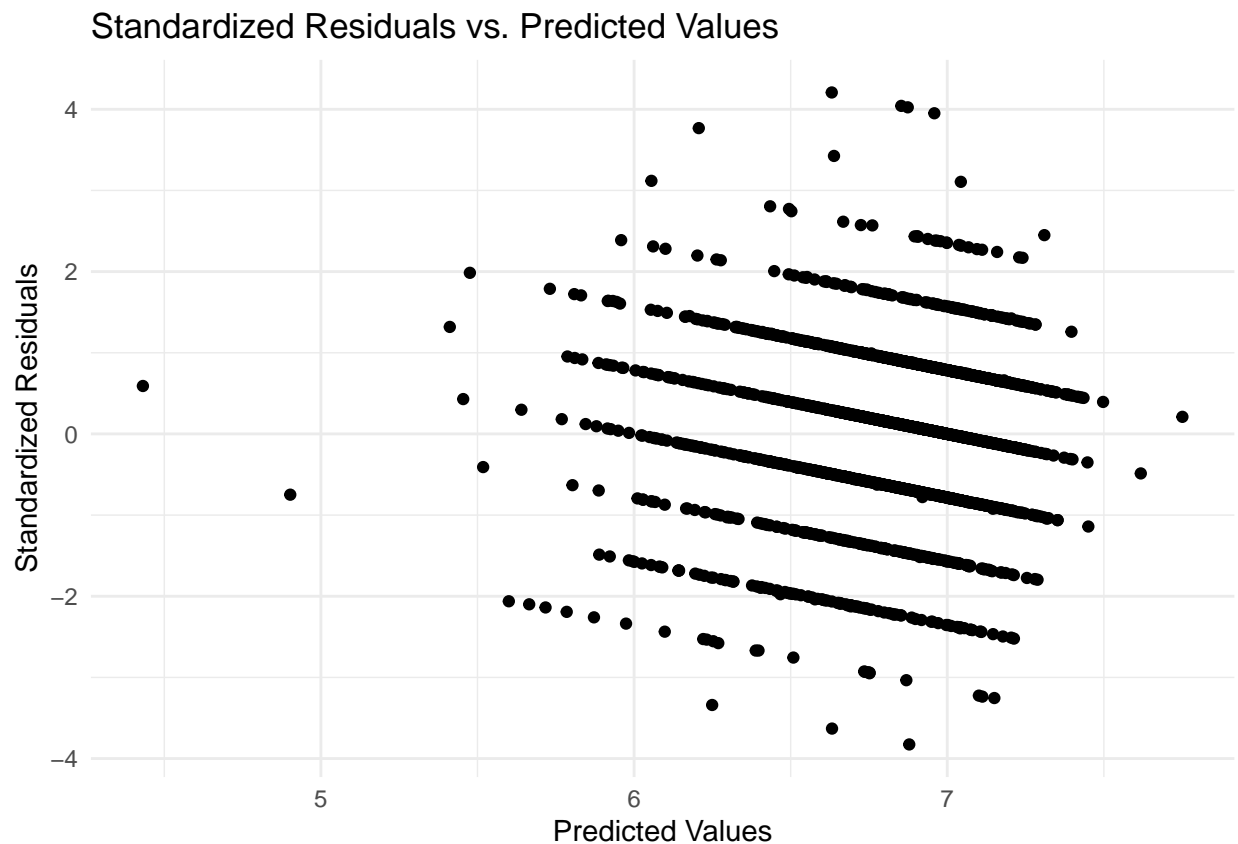
# fit0 <- lm(SleepMinNight ~ ., data = df3)

# Calculate different types of residuals
residual_2 <- rstandard(fit0)
residual_3 <- rstudent(fit0)
residual_4 <- rstudent(fit0) # Externally studentized residuals

# Get predicted values from the model
predicted_values <- predict(fit0)

# Plot for Standardized Residuals
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_2)) +
  ggtitle("Standardized Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Standardized Residuals") +
  theme_minimal()

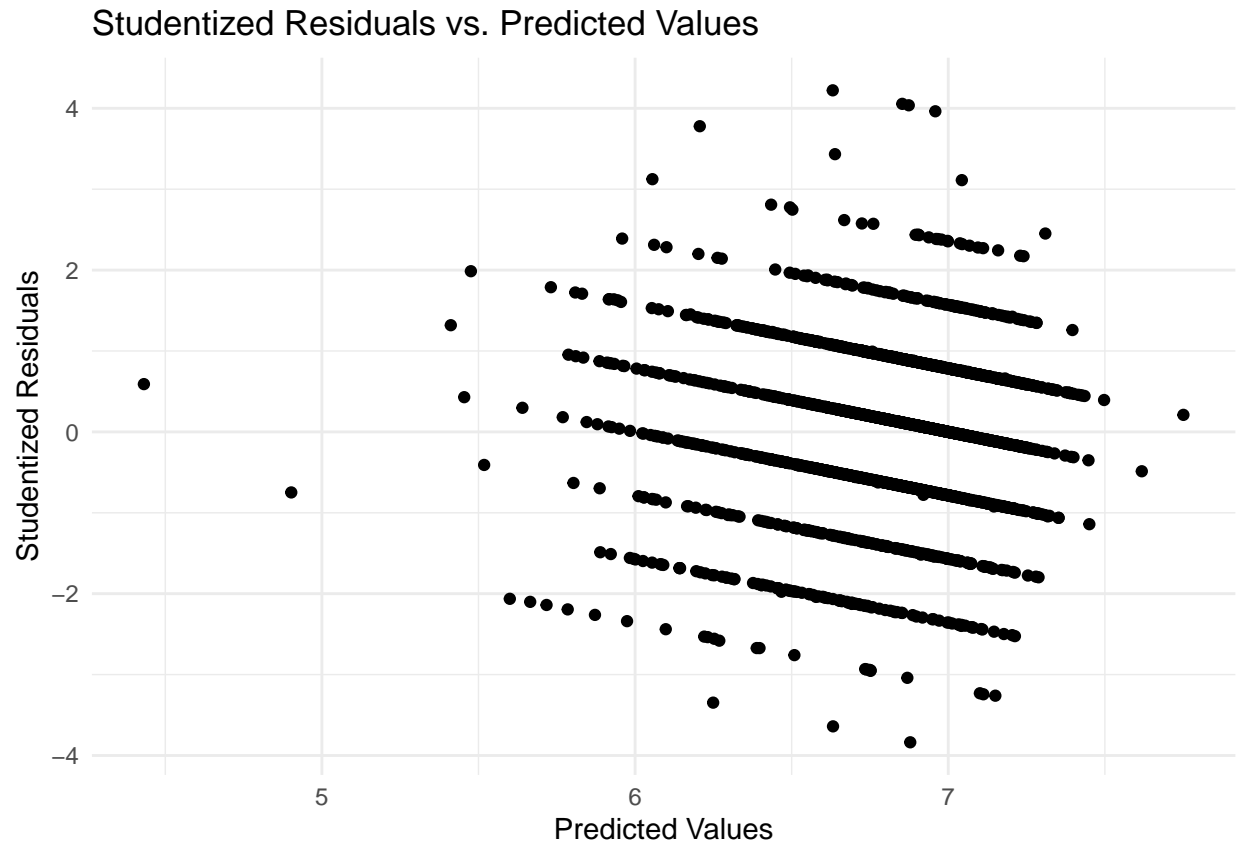
```



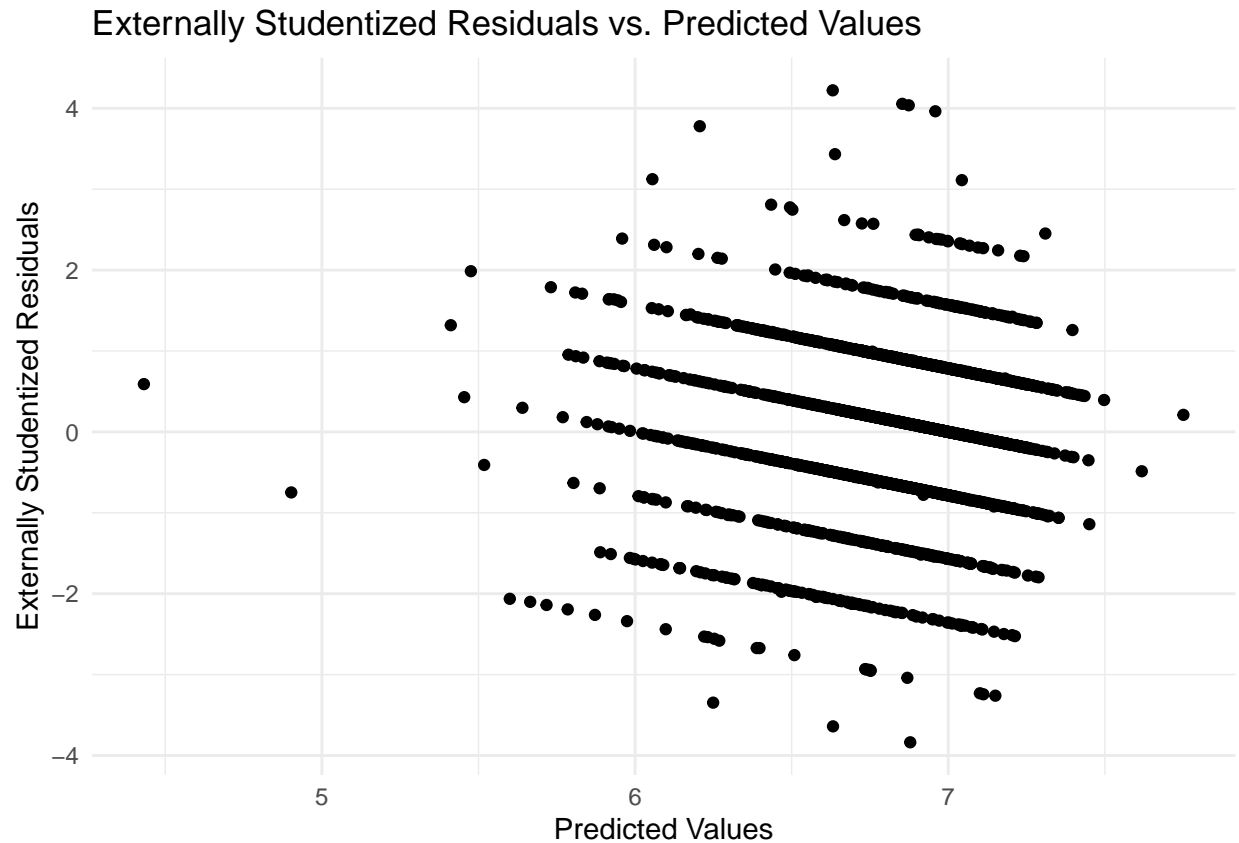
```

# Plot for Studentized Residuals
ggplot() +
  geom_point(aes(x = predicted_values, y = residual_3)) +
  ggtitle("Studentized Residuals vs. Predicted Values") +
  xlab("Predicted Values") +
  ylab("Studentized Residuals") +
  theme_minimal()

```



```
# Plot for Externally Studentized Residuals  
ggplot() +  
  geom_point(aes(x = predicted_values, y = residual_4)) +  
  ggtitle("Externally Studentized Residuals vs. Predicted Values") +  
  xlab("Predicted Values") +  
  ylab("Externally Studentized Residuals") +  
  theme_minimal()
```



(5) Model Selection

```
step(fit0)
```

```
## Start:  AIC=1185.54
## SleepHrsNight ~ BMI + DirectChol + Age + Gender + Race1 + TotChol +
##      BPDiaAve + BPSysAve + AlcoholYear + Poverty + HomeRooms +
##      SexNumPartnLife + SexNumPartYear + DaysMentHlthBad
##
##
```

	Df	Sum of Sq	RSS	AIC
## - DirectChol	1	0.003	3857.0	1183.5
## - TotChol	1	0.069	3857.0	1183.6
## - BPSysAve	1	0.093	3857.1	1183.6
## - BPDiaAve	1	0.098	3857.1	1183.6
## - BMI	1	1.435	3858.4	1184.4
## - AlcoholYear	1	2.773	3859.7	1185.2
## <none>			3857.0	1185.5
## - SexNumPartYear	1	3.823	3860.8	1185.9
## - HomeRooms	1	4.571	3861.5	1186.4
## - Poverty	1	7.466	3864.4	1188.1
## - SexNumPartnLife	1	8.973	3865.9	1189.1
## - Race1	4	32.638	3889.6	1197.6
## - Gender	1	23.929	3880.9	1198.2
## - Age	1	28.718	3885.7	1201.2

```
## - DaysMentHlthBad 1 89.039 3946.0 1237.8
##
## Step: AIC=1187.2
## SleepHrsNight ~ BMI + Age + Gender + Race1 + TotChol + BPDiaAve +
## BPSysAve + AlcoholYear + Poverty + HomeRooms + SexNumPartnLife +
## SexNumPartYear + DaysMentHlthBad
##
## Call:
## lm(formula = SleepHrsNight ~ BMI + Age + Gender + Race1 + TotChol +
## BPDiaAve + BPSysAve + AlcoholYear + Poverty + HomeRooms +
## SexNumPartnLife + SexNumPartYear + DaysMentHlthBad, data = df3)
##
## Coefficients:
## (Intercept) BMI Age Gender
## 6.8656069 -0.0040545 -0.0107790 0.2153535
## Race1 TotChol BPDiaAve BPSysAve
## 0.0766796 0.0095890 0.0003656 -0.0007014
## AlcoholYear Poverty HomeRooms SexNumPartnLife
## 0.0003533 0.0303914 0.0198583 -0.0010323
## SexNumPartYear DaysMentHlthBad
## 0.0146137 -0.0253312
```

```
library(olsrr)
```

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

```
ols_step_forward_p(m_full, penter = 0.1, details = F)
```

```
##
## Selection Summary
## -----
## Variable Adj.
## Step Entered R-Square R-Square C(p) AIC RMSE
## -----
## 1 DaysMentHlthBad 0.0242 0.0238 66.5525 7985.6561 1.2951
## 2 Gender 0.0311 0.0303 51.4035 7970.8875 1.2908
## 3 Age 0.0373 0.0361 37.8570 7957.5830 1.2869
## 4 factor(Race1) 0.0471 0.0443 15.3744 7941.2801 1.2815
## 5 Poverty 0.0507 0.0475 8.3826 7934.2917 1.2793
## 6 SexNumPartnLife 0.0525 0.0489 5.7740 7931.6716 1.2783
## 7 HomeRooms 0.0536 0.0496 4.9984 7930.8847 1.2779
## -----
```

```
ols_step_forward_p(m_full, penter = 0.05, details = F)
```

```
##
## Selection Summary
## -----
## Variable Adj.
## Step Entered R-Square R-Square C(p) AIC RMSE
## -----
```



```
##      1    DaysMentHlthBad      0.0242      0.0238      66.5525      7985.6561      1.2951
##      2      Gender            0.0311      0.0303      51.4035      7970.8875      1.2908
##      3      Age              0.0373      0.0361      37.8570      7957.5830      1.2869
##      4  factor(Race1)        0.0471      0.0443      15.3744      7941.2801      1.2815
##      5      Poverty          0.0507      0.0475       8.3826      7934.2917      1.2793
##      6  SexNumPartnLife      0.0525      0.0489       5.7740      7931.6716      1.2783
## -----
```

```
ols_mallows_cp(model = m_logfull_2, fullmodel = m_full) # Mallows' Cp
```

```
## [1] -2306.233
```