Final Model

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Usual Data Cleaning

```r
library(NHANES)  # NHANES dataset
library(dplyr)   # Data wrangling
library(ggplot2) # Visualization
library(car)     # Multicollinearity check (VIF)
library(ggResidpanel) # Advanced diagnostic plots
library(knitr) #for kable
library(gridExtra) #for scatterplot matrix

options(scipen = 999)

# if you don't have it installed, do install_packages("NHANES")
data("NHANES")
nrow(NHANES) #10,000 observations
```

```
## [1] 10000
```

```r
# remove babies (ages 0-3)
nhanes_filtered <- NHANES %>% filter(Age > 20,
                                     Height > 0,
                                     Weight > 0,
                                     BPDia1 > 10,
                                     BPDia2 > 10,
                                     BPDia3 > 10,
                                     BPDiaAve > 10,
                                     BPSys1 > 10,
                                     BPSys2 > 10,
                                     BPSys3 > 10,
                                     BPSysAve > 10,
                                     TotChol > 0)

nrow(nhanes_filtered) #7094 observations
```

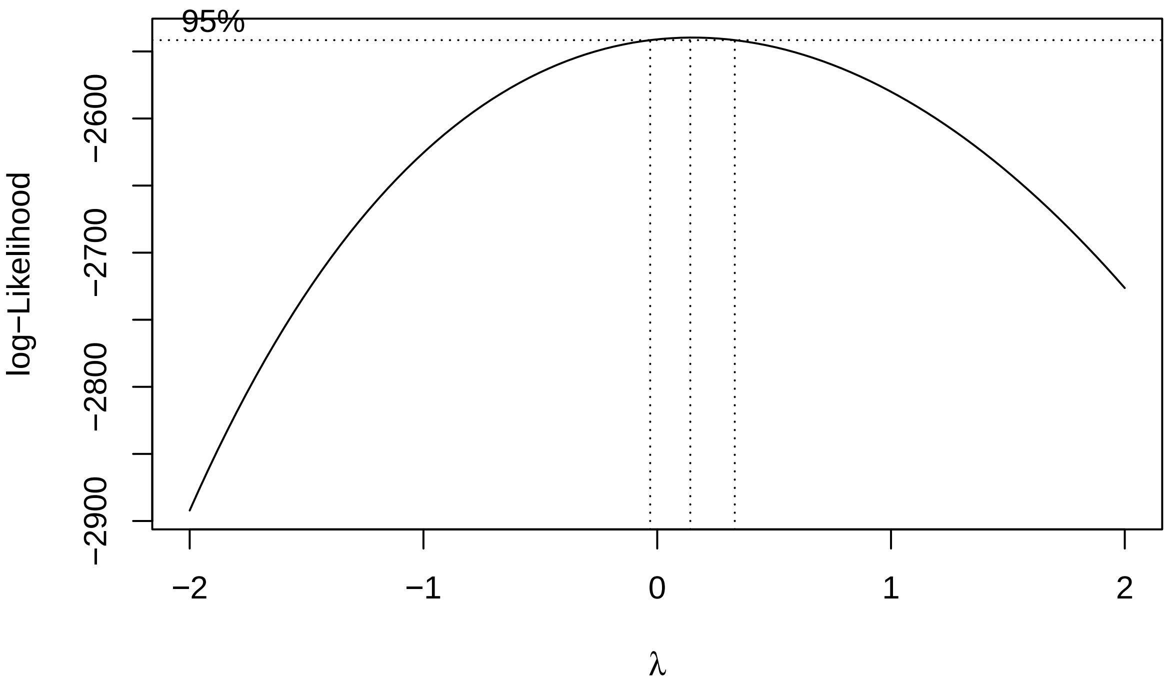
```
## [1] 5989
```

```r
# remove NA entries and only select columns of interest
nhanes_data <- nhanes_filtered %>%
  dplyr::select(Height, Age, Weight, BPSysAve, BPDiaAve,
                TotChol, SmokeNow, PhysActiveDays) %>%
  na.omit()


# categorical predictors
```

```r
nhanes_data$SmokeNow <- as.factor(nhanes_data$SmokeNow)
nhanes_data <- data.frame(nhanes_data)

# fit the model
model <- lm(TotChol ~ Age + Weight + Height + BPSysAve + BPDiaAve + SmokeNow +
              PhysActiveDays,
            data = nhanes_data)

n <- nrow(nhanes_data)
```

Box-Cox Transformation and Polynomial Term

```r
#POLYNOMIAL "AGE" TERM
pb_data <- nhanes_data %>%
  dplyr::select(Height, Age, Weight, BPSysAve, BPDiaAve,
                TotChol, SmokeNow, PhysActiveDays) %>%
  mutate(pb.Age2 = Age^2)

pb_model <- lm(TotChol~Age+pb.Age2+Height+Weight+BPSysAve+BPDiaAve+
                 SmokeNow+PhysActiveDays, data=pb_data)

#BOX COX TRANSFORMATION
library(MASS)

pb.b <- boxcox(pb_model)
```



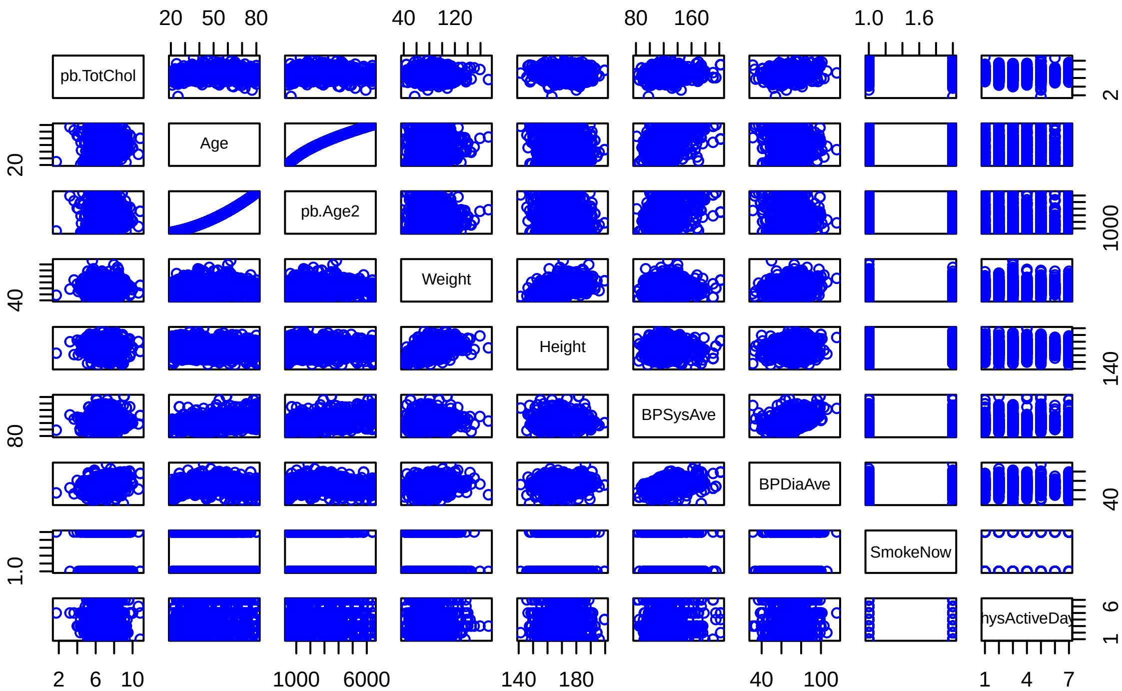

```r
pb.lambda <- pb.b$x[which.max(pb.b$y)]

pb.log_product <- sum(log(pb_data$TotChol))
pb.geo_mean <- exp(pb.log_product/n)
```

```r
pb.TotChol <- pb.geo_mean^(1-pb.lambda)*(pb_data$TotChol^pb.lambda - 1)/pb.lambda


p.BXCX.frame <- pb_data %>%
  dplyr::select(-TotChol) %>%
  mutate(pb.TotChol = pb.TotChol)

p.BXCX.model <- lm(pb.TotChol ~ Age + pb.Age2 + Weight + Height + BPSysAve +
                          BPDiaAve + SmokeNow + PhysActiveDays,
                        data = p.BXCX.frame)

summary(p.BXCX.model)
```

```
##
## Call:
## lm(formula = pb.TotChol ~ Age + pb.Age2 + Weight + Height + BPSysAve +
##     BPDiaAve + SmokeNow + PhysActiveDays, data = p.BXCX.frame)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5764 -0.6158 -0.0084  0.6574  3.8416
##
## Coefficients:
##                  Estimate Std. Error t value             Pr(>|t|)
## (Intercept)     4.6682540  0.6104391   7.647   0.0000000000000401 ***
## Age             0.0993535  0.0112143   8.860 < 0.0000000000000002 ***
## pb.Age2        -0.0009453  0.0001135  -8.331 < 0.0000000000000002 ***
## Weight         -0.0006614  0.0016858  -0.392              0.69487
## Height         -0.0087700  0.0033509  -2.617              0.00897 **
## BPSysAve        0.0057045  0.0019803   2.881              0.00404 **
## BPDiaAve        0.0128515  0.0028416   4.523   0.0000066733181871 ***
## SmokeNowYes     0.0127777  0.0596913   0.214              0.83053
## PhysActiveDays -0.0128377  0.0154387  -0.832              0.40583
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9849 on 1280 degrees of freedom
## Multiple R-squared:  0.1264, Adjusted R-squared:  0.121
## F-statistic: 23.15 on 8 and 1280 DF,  p-value: < 0.00000000000000022
```

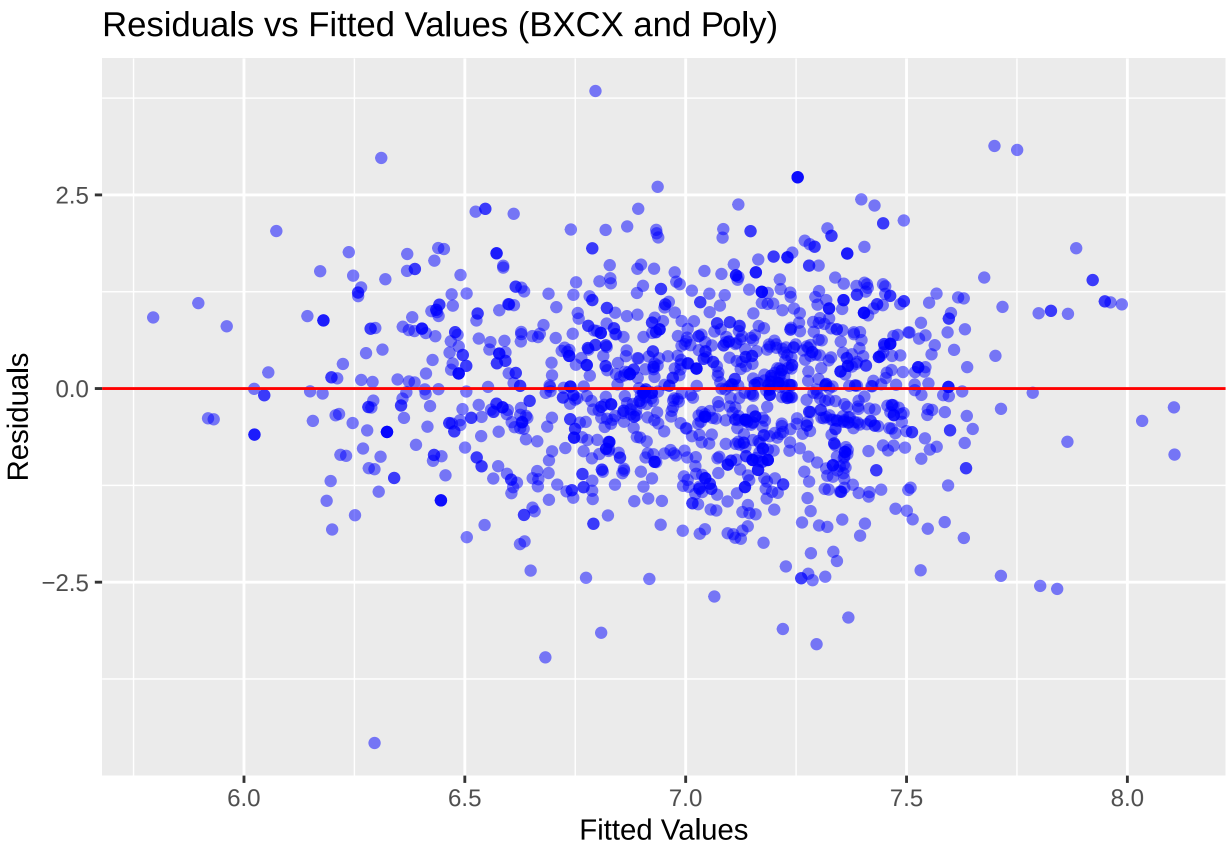
```r
#FITTED AND RESIDUAL VALUES FROM TRANSFORMED
pb.fitted <- fitted(p.BXCX.model)
pb.residuals <- resid(p.BXCX.model)

#DATA FRAME FOR PLOTTING
pb.plot_data <- data.frame(pb.fitted = pb.fitted, pb.residuals = pb.residuals)

#PAIRWISE PLOTS OF ORIGINAL MODEL
pairs(~pb.TotChol+Age+pb.Age2+Weight+Height+
        BPSysAve+BPDiaAve+SmokeNow+PhysActiveDays,
      data = p.BXCX.frame,
      main = "Pairwise ScatterPlots of Transformed Polynomial Model",
      col = "blue")
```

Pairwise ScatterPlots of Transformed Polynomial Model

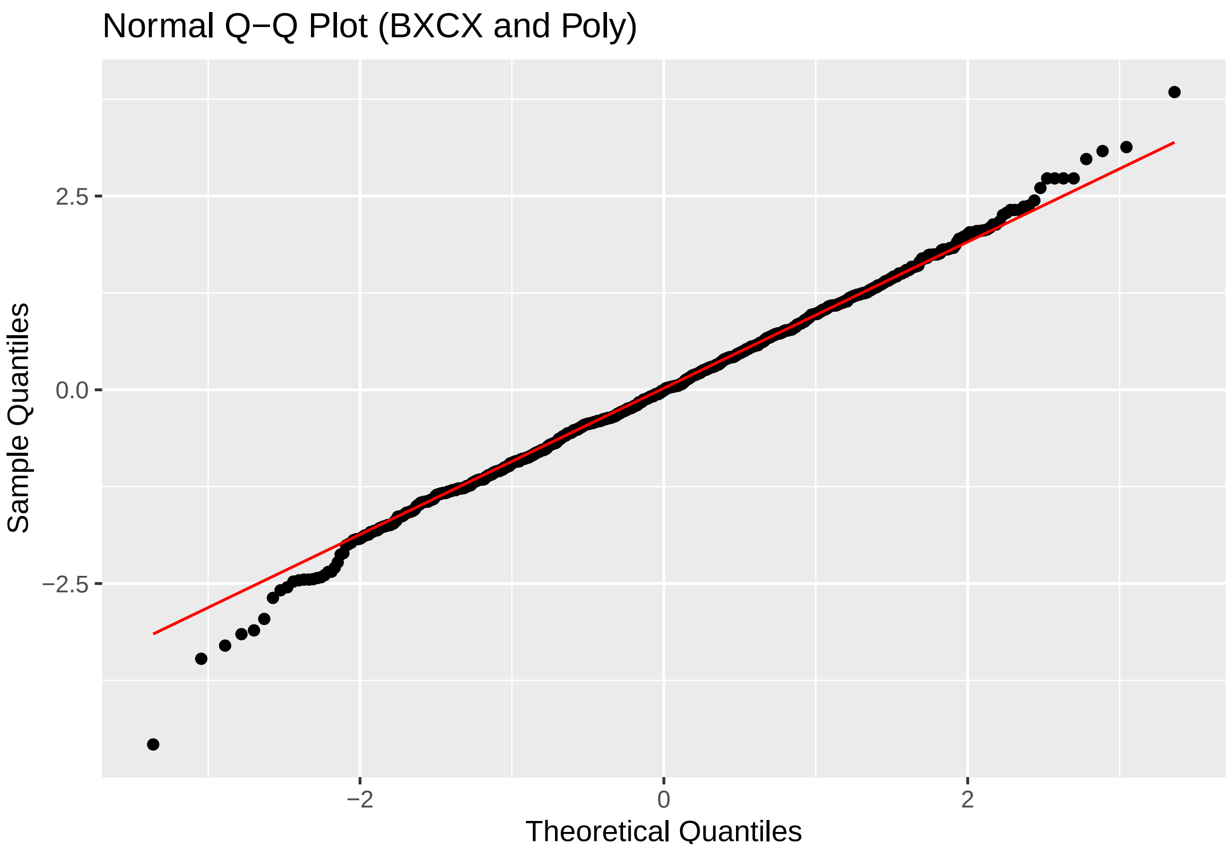


Residual Plots

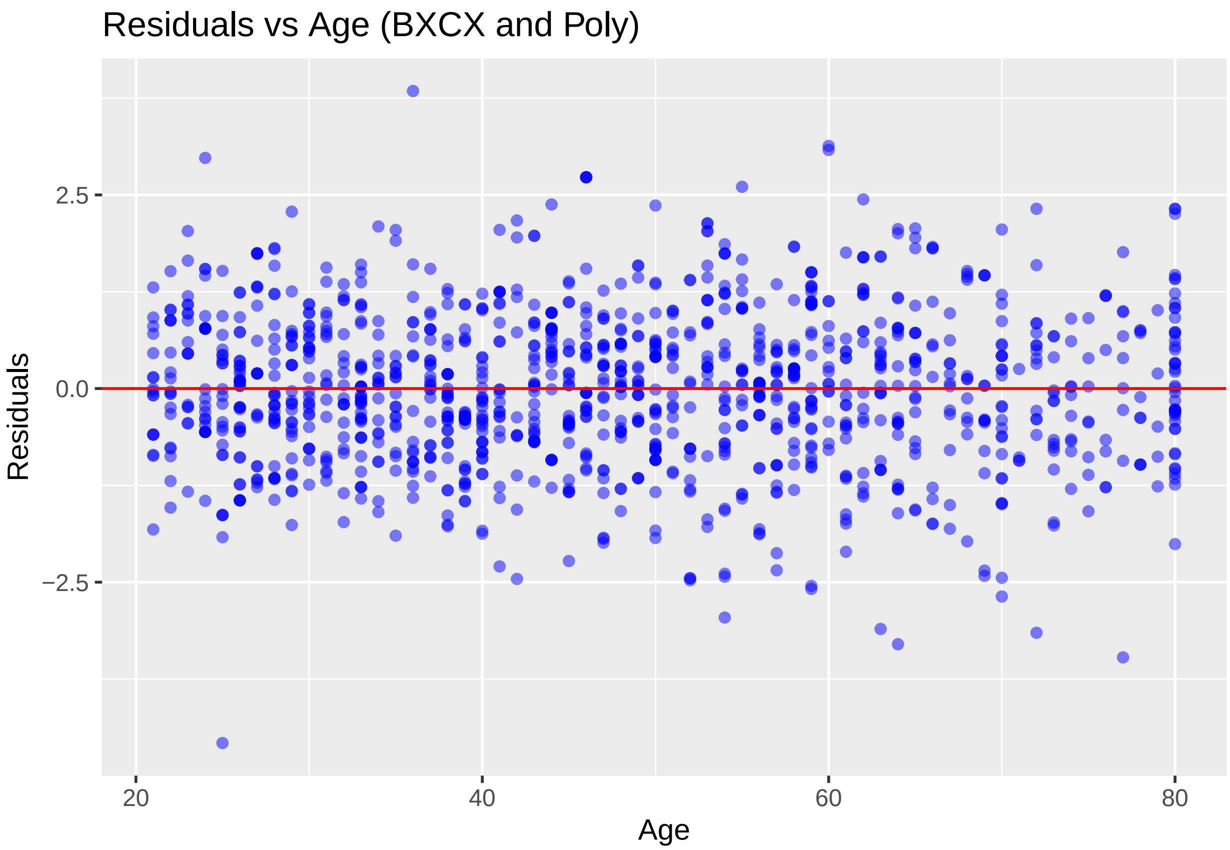
```
#RESIDUALS VS FITTED
res_fitted_plot <- ggplot(data = pb.plot_data,
                          aes(x = pb.fitted, y = pb.residuals)) +
  geom_point(color = "blue", alpha = 0.5) +
  geom_hline(yintercept = 0, color = "red") +
  labs(title = "Residuals vs Fitted Values (BXCX and Poly)",
       x = "Fitted Values", y = "Residuals")

print(res_fitted_plot)
```


Residuals vs Fitted Values (BXCX and Poly)
Residuals
2.5
0.0
−2.5
6.0
6.5
7.0
7.5
8.0
Fitted Values

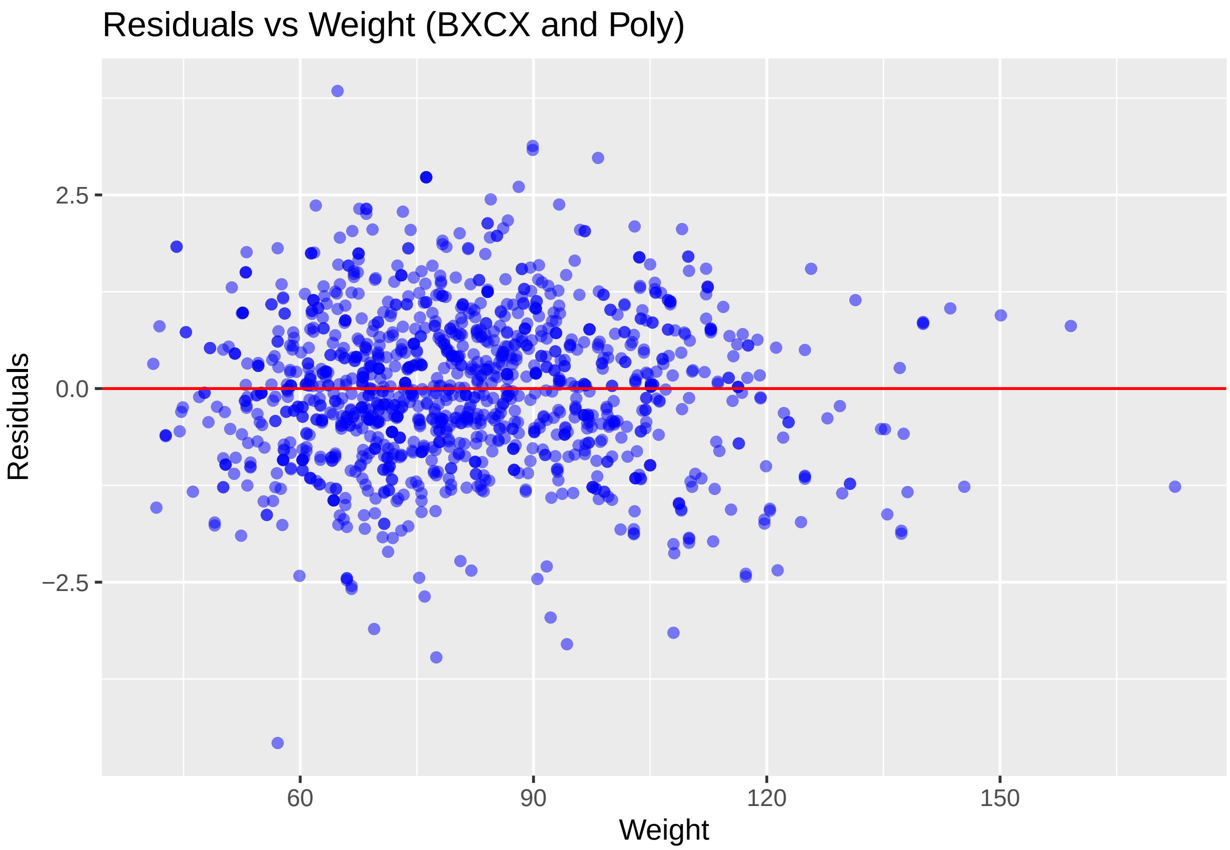
```r
#NORMAL QQ PLOT
qq_plot <- ggplot(data = data.frame(pb.residuals = pb.residuals),
                  aes(sample = pb.residuals)) +
  stat_qq() +
  stat_qq_line(color = "red") +
  labs(title = "Normal Q-Q Plot (BXCX and Poly)",
       x = "Theoretical Quantiles", y = "Sample Quantiles")

print(qq_plot)
```



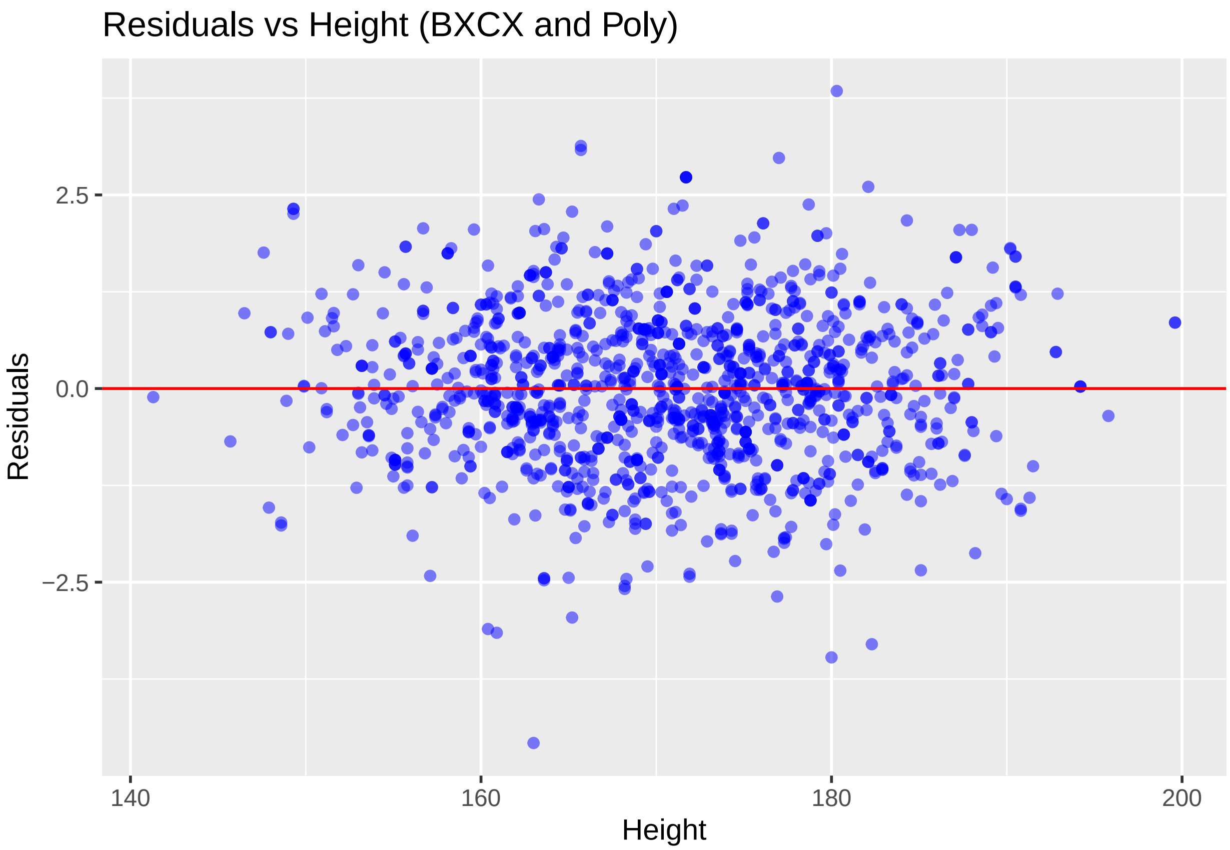

```r
#RESIDUALS VS AGE
res_age_plot <- ggplot(p.BXCX.frame,
                       aes(x = Age, y = pb.residuals)) +
  geom_point(color = "blue", alpha = 0.5) +
  geom_hline(yintercept = 0, color = "red") +
  labs(title = "Residuals vs Age (BXCX and Poly)",
       x = "Age", y = "Residuals")

print(res_age_plot)
```



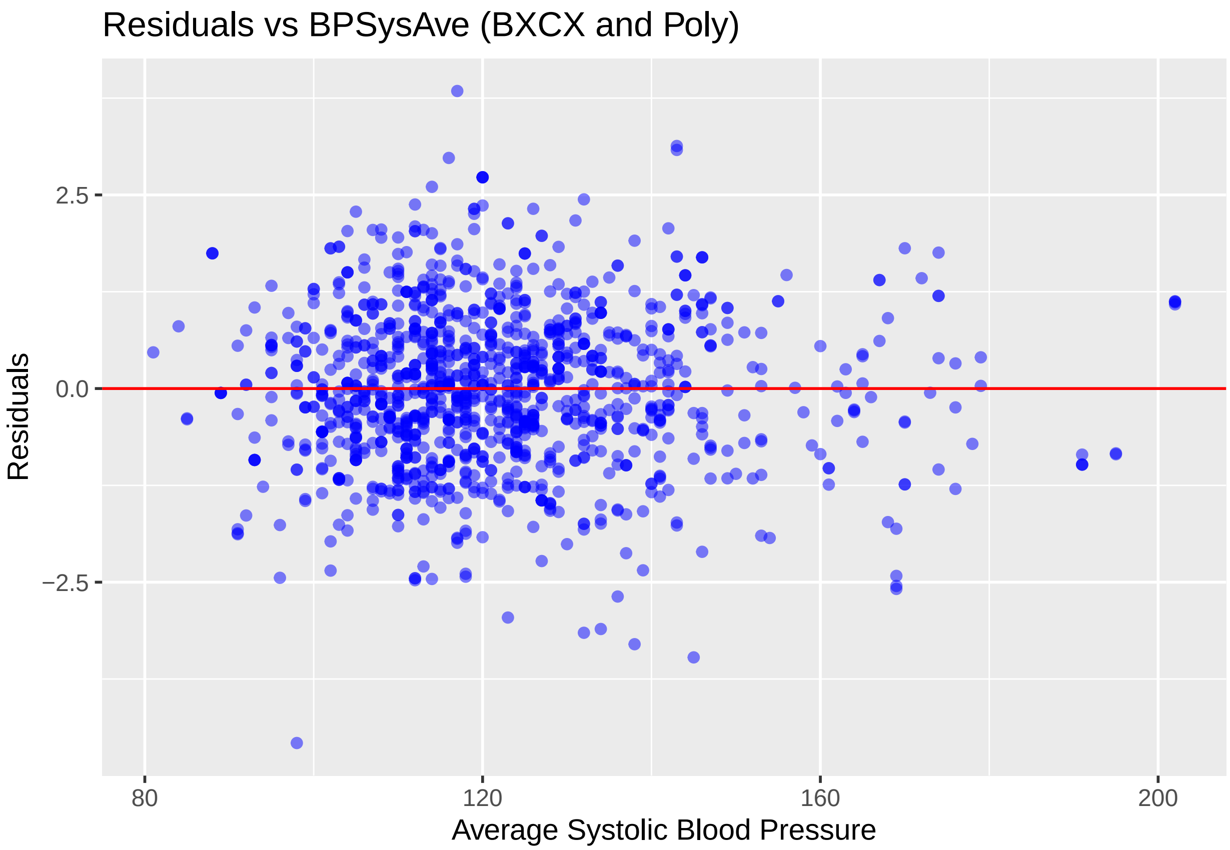

```r
#RESIDUALS VS WEIGHT
res_weight_plot <- ggplot(p.BXCX.frame,
                          aes(x = Weight, y = pb.residuals)) +
  geom_point(color = "blue", alpha = 0.5) +
  geom_hline(yintercept = 0, color = "red") +
  labs(title = "Residuals vs Weight (BXCX and Poly)",
       x = "Weight", y = "Residuals")

print(res_weight_plot)
```



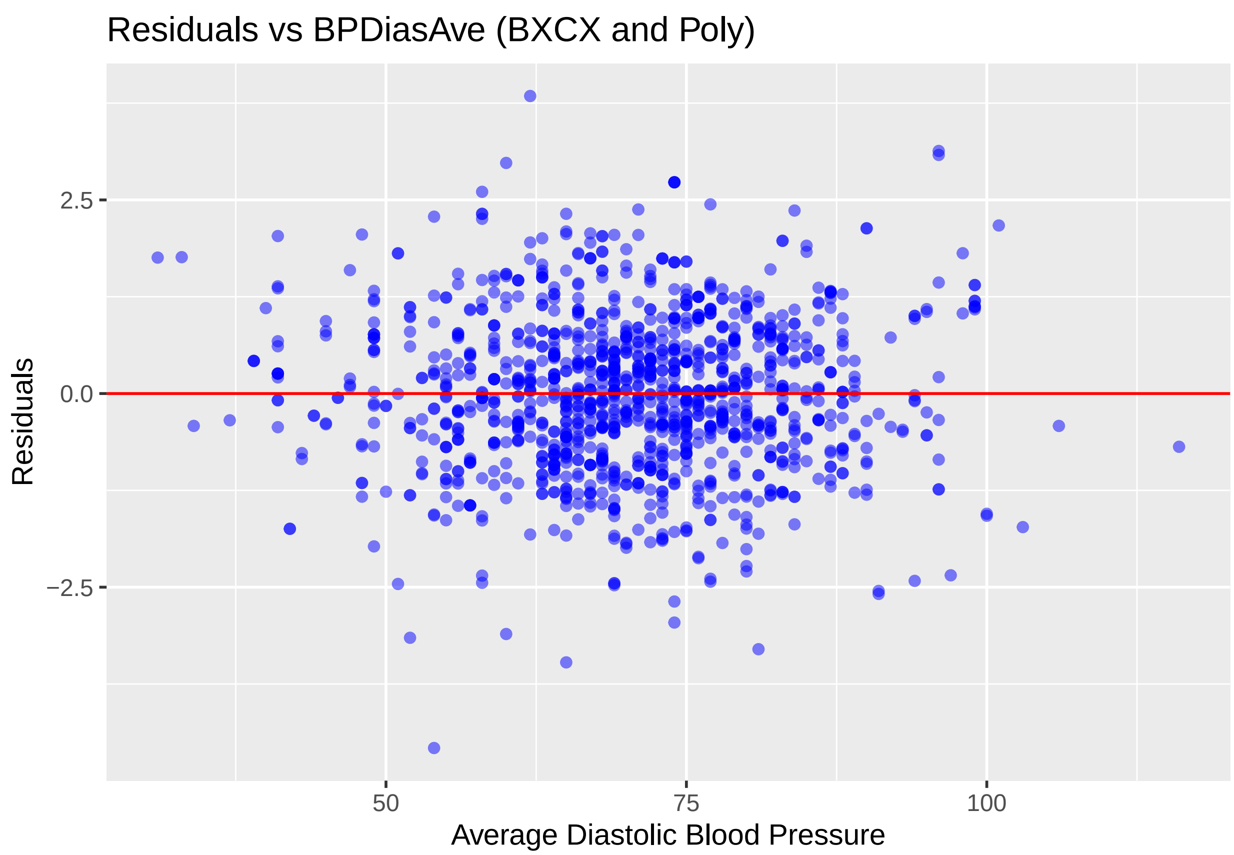

```
#RESIDUALS VS HEIGHT
res_height_plot <- ggplot(p.BXCX.frame,
                         aes(x = Height, y = pb.residuals)) +
  geom_point(color = "blue", alpha = 0.5) +
  geom_hline(yintercept = 0, color = "red") +
  labs(title = "Residuals vs Height (BXCX and Poly)",
       x = "Height", y = "Residuals")

print(res_height_plot)
```



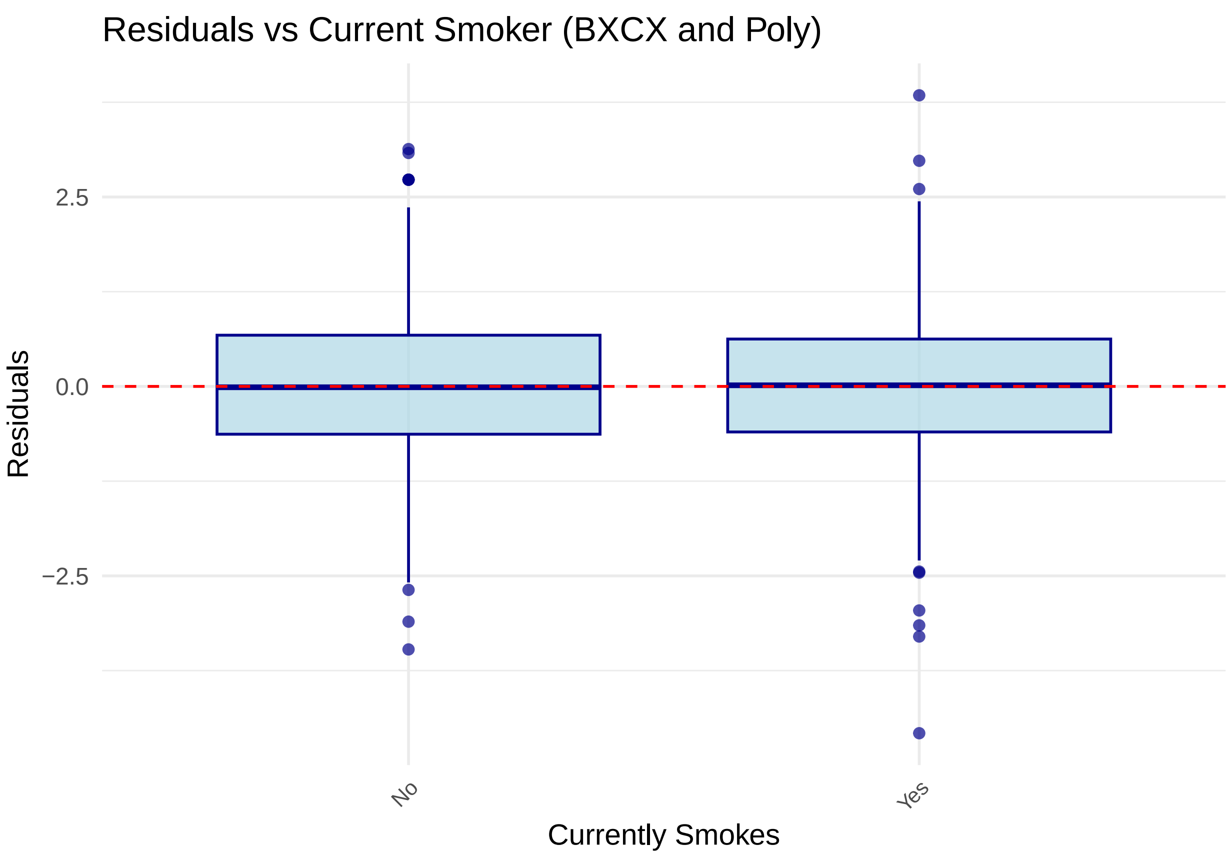

```
#RESIDUALS VS BPSysAve
res_BPSysAve_plot <- ggplot(p.BXCX.frame,
                            aes(x = BPSysAve, y = pb.residuals)) +
  geom_point(color = "blue", alpha = 0.5) +
  geom_hline(yintercept = 0, color = "red") +
  labs(title = "Residuals vs BPSysAve (BXCX and Poly)",
       x = "Average Systolic Blood Pressure", y = "Residuals")

print(res_BPSysAve_plot)
```



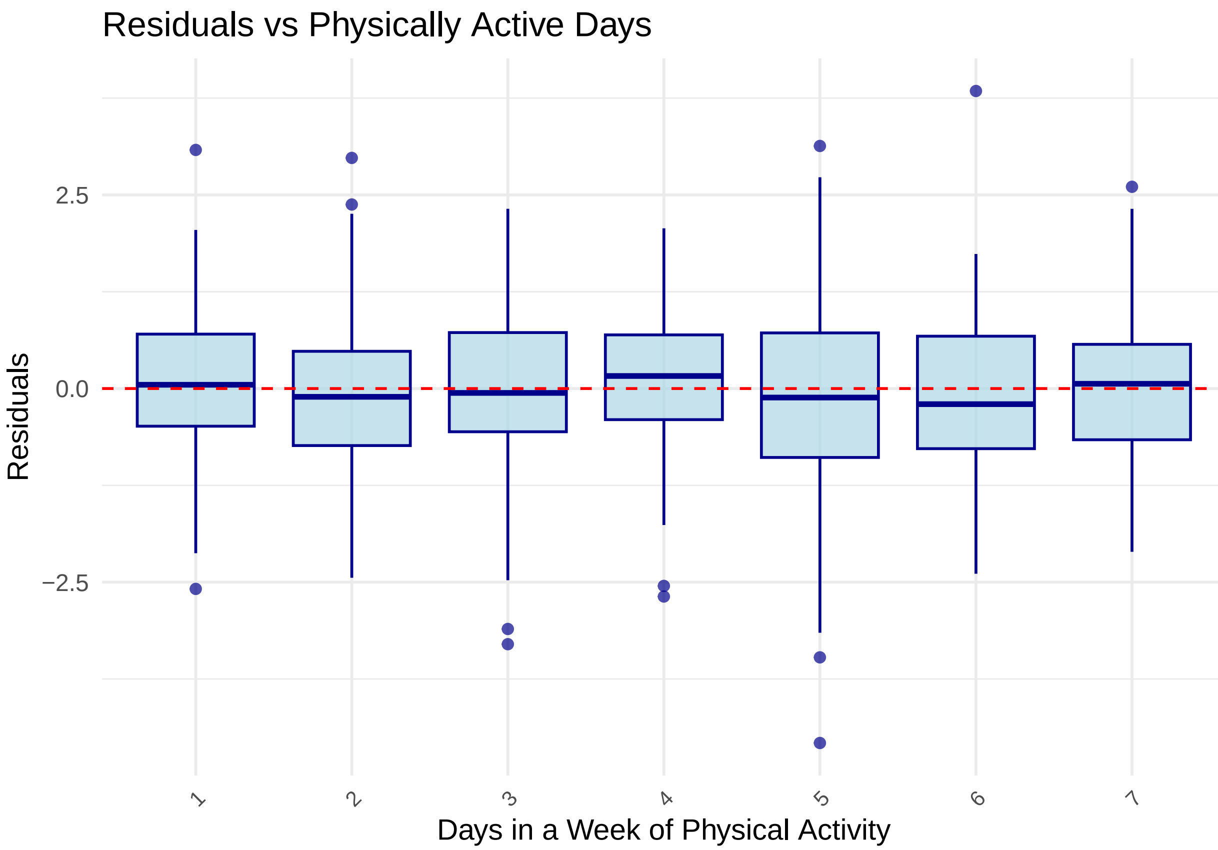

```r
#RESIDUALS VS BPDiaAve
res_BPDiaAve_plot <- ggplot(p.BXCX.frame,
                            aes(x = BPDiaAve, y = pb.residuals)) +
  geom_point(color = "blue", alpha = 0.5) +
  geom_hline(yintercept = 0, color = "red") +
  labs(title = "Residuals vs BPDiasAve (BXCX and Poly)",
       x = "Average Diastolic Blood Pressure", y = "Residuals")

print(res_BPDiaAve_plot)
```



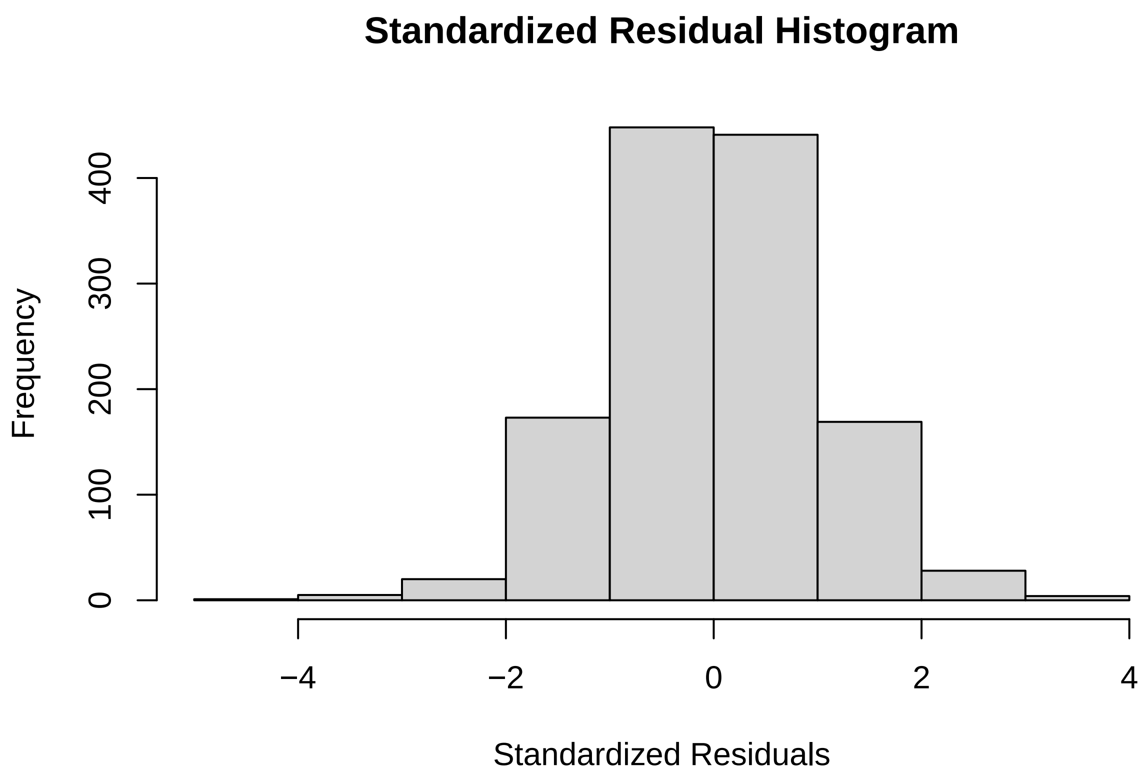

```r
#RESIDUALS VS SmokeNow (BOXPLOT)
res_smoke_plot <- ggplot(
  p.BXCX.frame, aes(x = as.factor(SmokeNow), y = pb.residuals)) +
  geom_boxplot(fill = "lightblue", color = "darkblue", alpha = 0.7) +
  geom_hline(yintercept = 0, color = "red", linetype = "dashed") +
  theme_minimal() +
  ggtitle("Residuals vs Current Smoker (BXCX and Poly)") +
  xlab("Currently Smokes") +
  ylab("Residuals") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8))

print(res_smoke_plot)
```




```
#RESIDUALS VS PhysActiveDays (BOXPLOT)
res_active_plot <- ggplot(
  p.BXCX.frame,
  aes(x = as.factor(PhysActiveDays), y = pb.residuals)) +
  geom_boxplot(fill = "lightblue", color = "darkblue", alpha = 0.7) +
  geom_hline(yintercept = 0, color = "red", linetype = "dashed") +
  theme_minimal() +
  ggtitle("Residuals vs Physically Active Days") +
  xlab("Days in a Week of Physical Activity") +
  ylab("Residuals") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1, size = 8))

print(res_active_plot)
```




```r
tr_stres_values <- rstandard(p.BXCX.model)

tr_stres_plot <- hist(tr_stres_values,
                      xlab = "Standardized Residuals",
                      main = "Standardized Residual Histogram")
```




```
leverage <- hatvalues(p.BXCX.model)


##LEVERAGE POINTS
p <- 8
high_lev <- 2*(p+1)/n

leverage_points <- p.BXCX.frame[leverage > high_lev,]
leverage_points <- leverage_points %>%
  mutate(row = row.names(leverage_points))


#FINDING OUTLIERS
st.residuals <- rstandard(p.BXCX.model)

outlier_points <- p.BXCX.frame[abs(st.residuals) > 4,]

#COOKS DISTANCE
cooks_value <- cooks.distance(p.BXCX.model)

f_value <- qf(0.50, 8, 1280)

cooks_points <- p.BXCX.frame[cooks_value > f_value,]

#DFFITS
dffits_cutoff <- 2*(sqrt((p+1)/n))

dffits_value = dffits(p.BXCX.model)

dffits_points <- p.BXCX.frame[(abs(dffits_value) > dffits_cutoff),]
```

```r
dffits_points <- dffits_points %>%
  mutate(row = row.names(dffits_points))

#DFBETAS
dfbetas_cutoff <- 2/sqrt(n)

dfbeta_frame <- as.data.frame(dfbetas(p.BXCX.model))

dfbeta_points <- round(dfbeta_frame[apply(
  abs(dfbeta_frame)>dfbetas_cutoff,1,any),],4)
dfbeta_points <- dfbeta_points %>%
  mutate(row = row.names(dfbeta_points))

#Problematic observations
influential_points <- c(728,823)
p.BXCX.frame[influential_points, ]
```

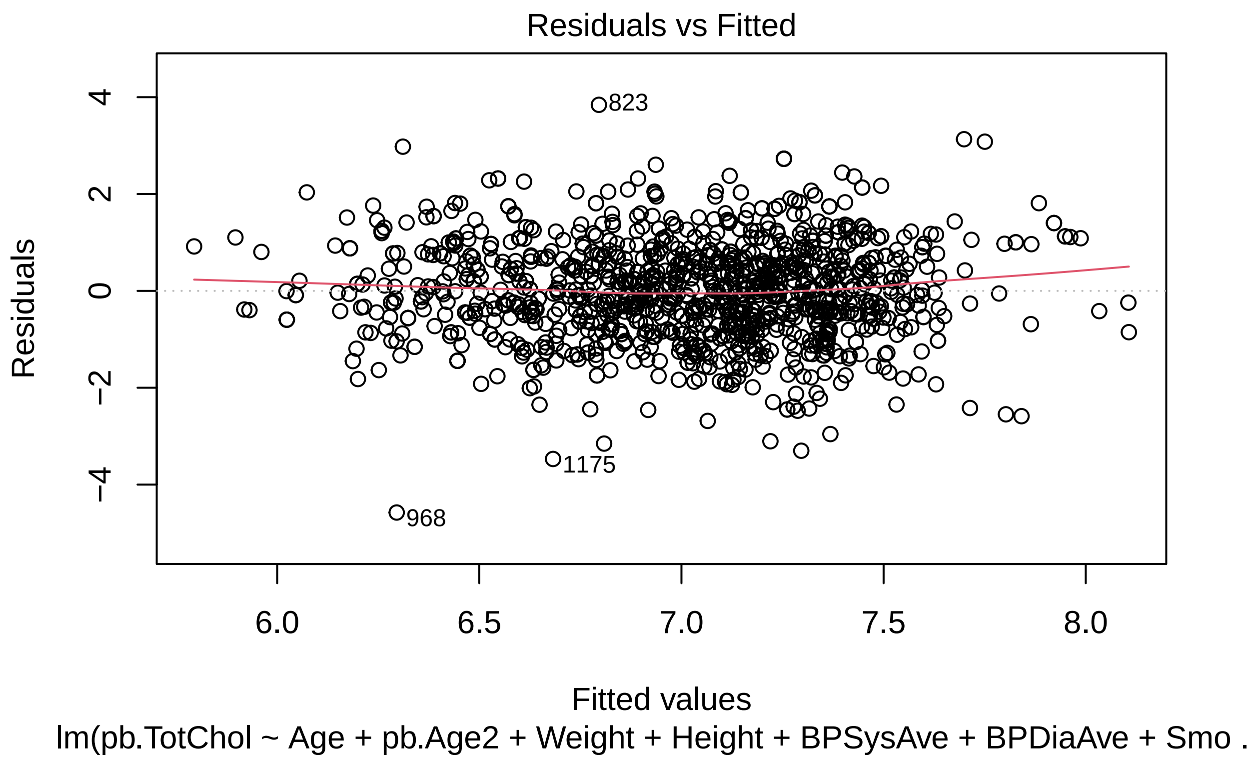
```
##     Height Age Weight BPSysAve BPDiaAve SmokeNow PhysActiveDays pb.Age2
## 728  160.9  72  108.0      132       52      Yes              5    5184
## 823  180.3  36   64.8      117       62      Yes              6    1296
##     pb.TotChol
## 728    3.65555
## 823   10.63743
```

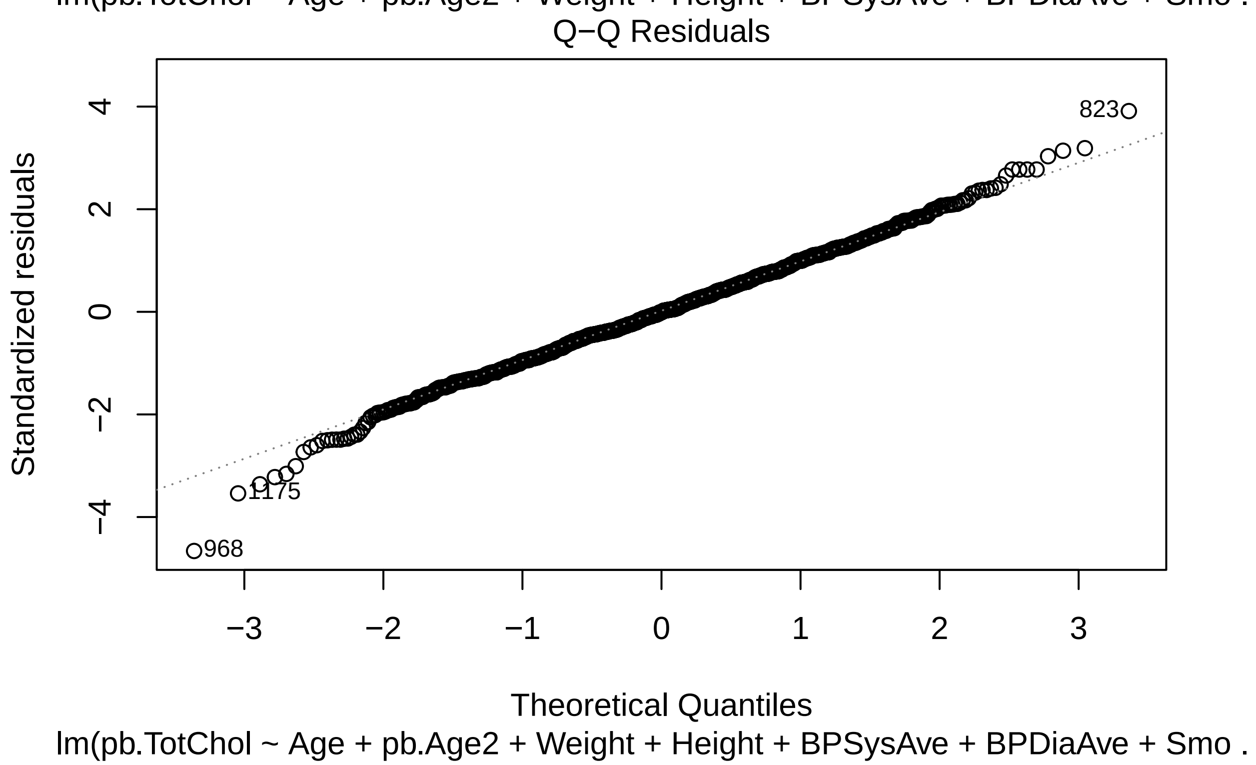
```r
clean.frame <- p.BXCX.frame %>%
dplyr::filter(!row_number() %in% influential_points)

clean_model <- lm(pb.TotChol ~ Age + pb.Age2 + Weight + Height + BPSysAve +
    BPDiaAve + SmokeNow + PhysActiveDays, data = clean.frame)

summary(clean_model)
```

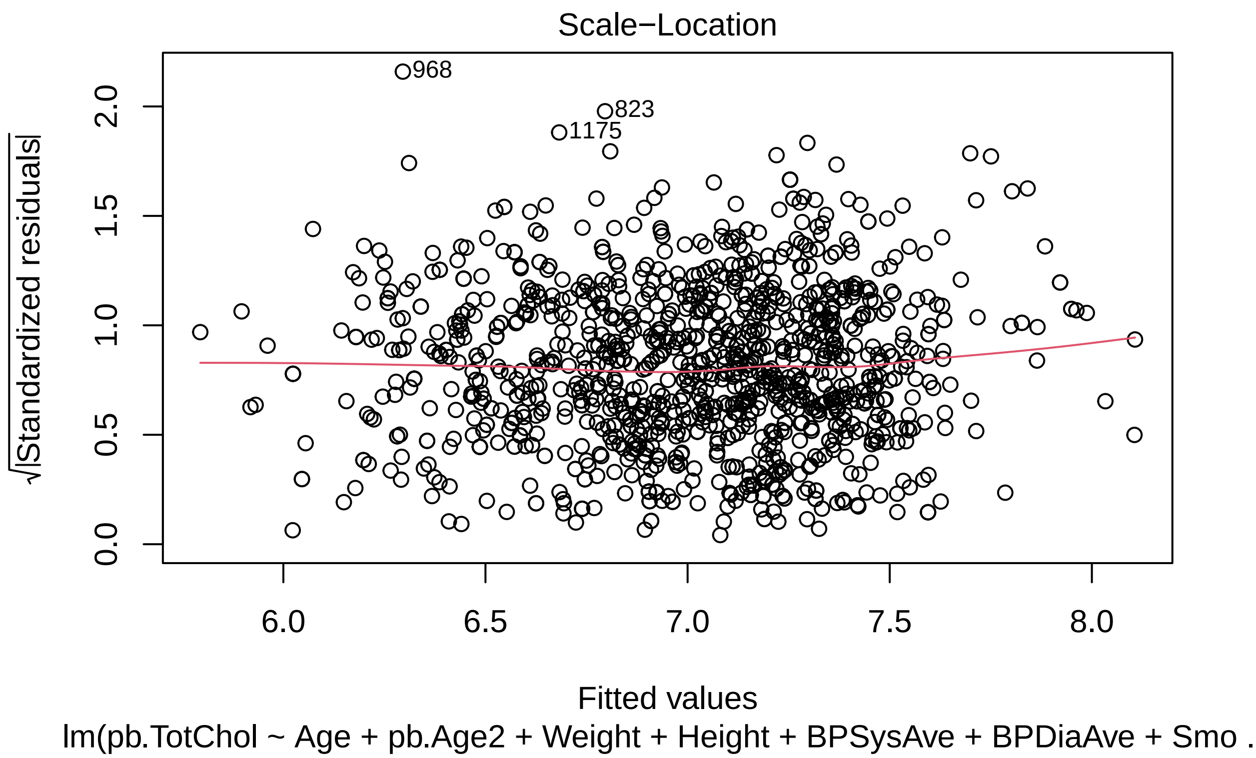
```
##
## Call:
## lm(formula = pb.TotChol ~ Age + pb.Age2 + Weight + Height + BPSysAve +
##     BPDiaAve + SmokeNow + PhysActiveDays, data = clean.frame)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5691 -0.6185  0.0030  0.6555  3.1272
##
## Coefficients:
##                   Estimate  Std. Error t value             Pr(>|t|)
## (Intercept)     4.82829934  0.60556204   7.973 0.000000000000003403 ***
## Age             0.09839179  0.01111150   8.855 < 0.0000000000000002 ***
## pb.Age2        -0.00093174  0.00011244  -8.287 0.000000000000000291 ***
## Weight         -0.00003742  0.00167529  -0.022              0.98218
## Height         -0.00984142  0.00332638  -2.959              0.00315 **
## BPSysAve        0.00564643  0.00196213   2.878              0.00407 **
## BPDiaAve        0.01274747  0.00281842   4.523 0.000006665615466859 ***
## SmokeNowYes     0.01780620  0.05923101   0.301              0.76375
## PhysActiveDays -0.01413432  0.01530911  -0.923              0.35604
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

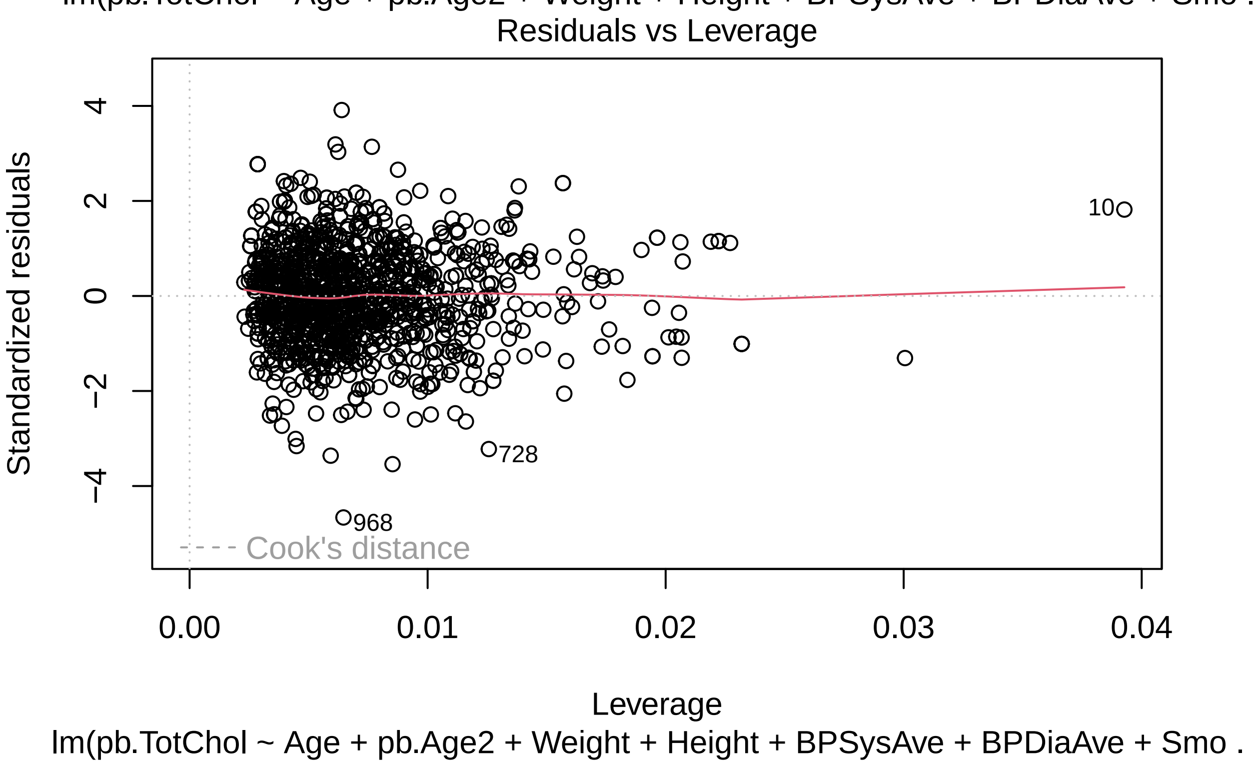
```
##
## Residual standard error: 0.9757 on 1278 degrees of freedom
## Multiple R-squared:  0.129,  Adjusted R-squared:  0.1236
## F-statistic: 23.66 on 8 and 1278 DF,  p-value: < 0.00000000000000022
```

```r
plots <- plot(p.BXCX.model)
```







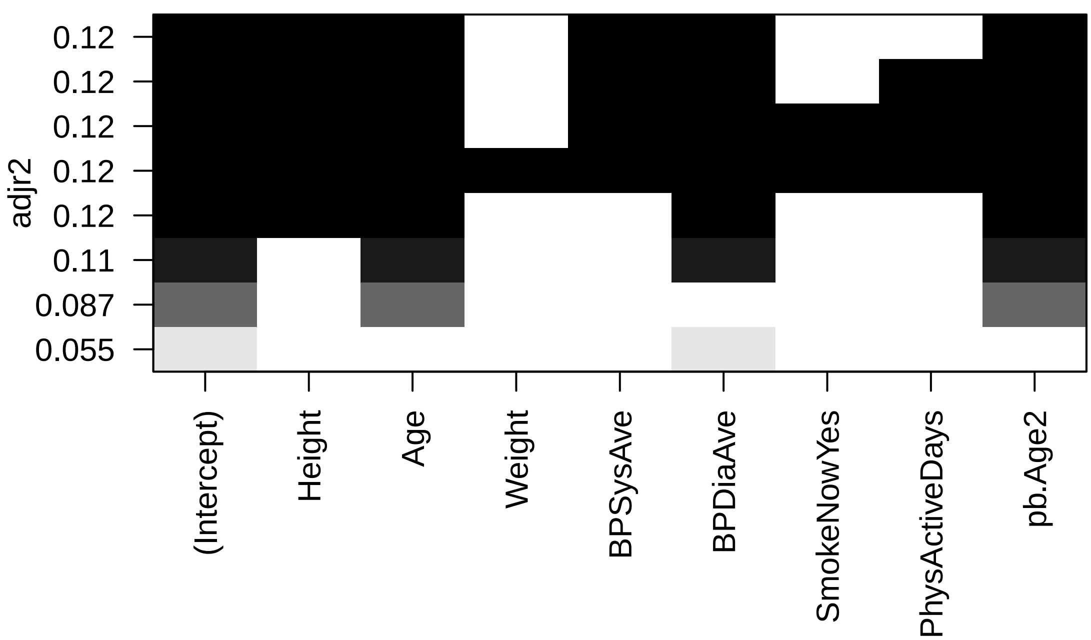



```
library(leaps)

best_subset <- regsubsets(pb.TotChol~., data=clean.frame,nvmax=8,                    nbest=1,really.big=T

summary(best_subset)
```

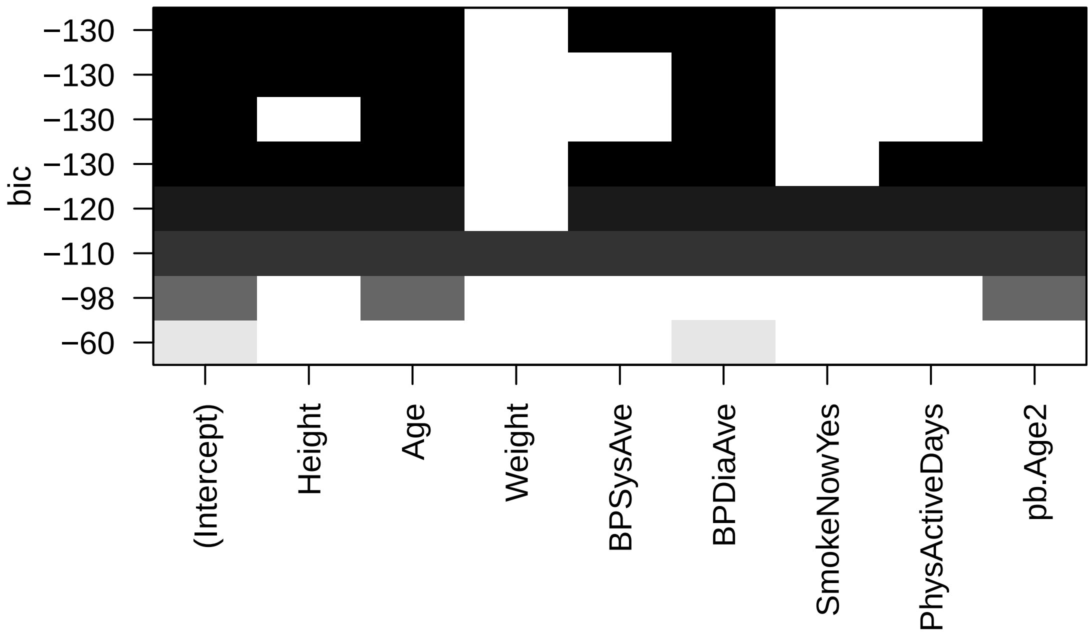
```
## Subset selection object
```

```
## Call: regsubsets.formula(pb.TotChol ~ ., data = clean.frame, nvmax = 8,
##     nbest = 1, really.big = TRUE, method = "exhaustive")
## 8 Variables  (and intercept)
##                Forced in Forced out
## Height             FALSE      FALSE
## Age                FALSE      FALSE
## Weight             FALSE      FALSE
## BPSysAve           FALSE      FALSE
## BPDiaAve           FALSE      FALSE
## SmokeNowYes        FALSE      FALSE
## PhysActiveDays     FALSE      FALSE
## pb.Age2            FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##          Height Age Weight BPSysAve BPDiaAve SmokeNowYes PhysActiveDays pb.Age2
## 1  ( 1 ) " "    " " " "    " "      "*"      " "         " "            " "
## 2  ( 1 ) " "    "*" " "    " "      " "      " "         " "            "*"
## 3  ( 1 ) " "    "*" " "    " "      "*"      " "         " "            "*"
## 4  ( 1 ) "*"    "*" " "    " "      "*"      " "         " "            "*"
## 5  ( 1 ) "*"    "*" " "    "*"      "*"      " "         " "            "*"
## 6  ( 1 ) "*"    "*" " "    "*"      "*"      " "         "*"            "*"
## 7  ( 1 ) "*"    "*" " "    "*"      "*"      "*"         "*"            "*"
## 8  ( 1 ) "*"    "*" "*"    "*"      "*"      "*"         "*"            "*"
```

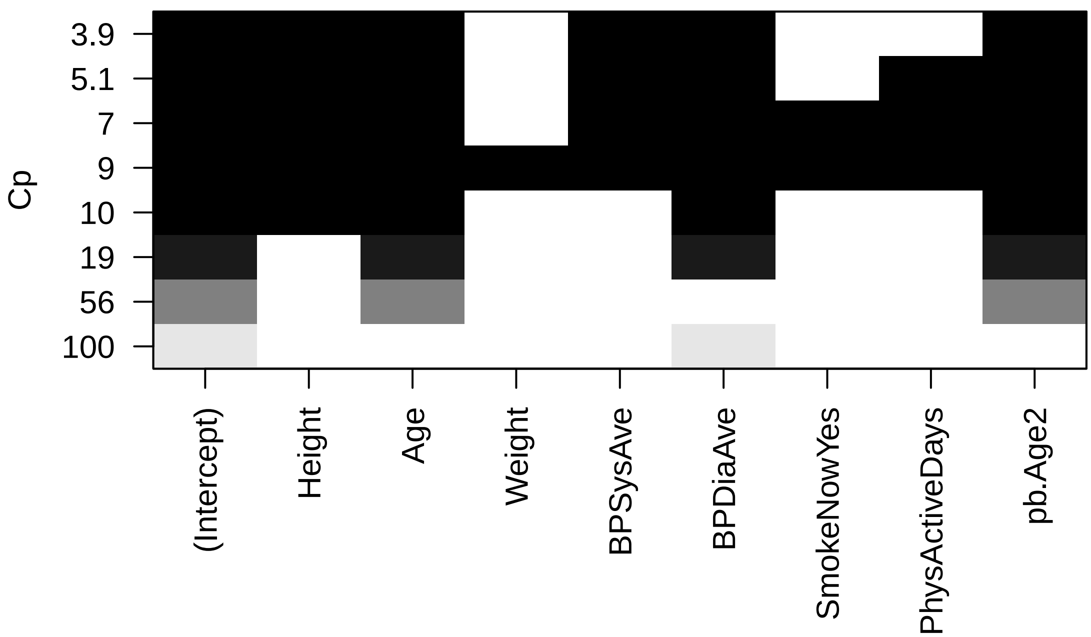
```r
plot(best_subset,scale='adjr2')
```




```r
plot(best_subset,scale='bic');
```




```r
plot(best_subset,scale='Cp')
```




```r
AIC <- step(clean_model, direction="both")
```

```
## Start:  AIC=-54.33
## pb.TotChol ~ Age + pb.Age2 + Weight + Height + BPSysAve + BPDiaAve +
##     SmokeNow + PhysActiveDays
##
##                  Df Sum of Sq    RSS     AIC
## - Weight          1     0.000 1216.7 -56.334
## - SmokeNow        1     0.086 1216.8 -56.244
## - PhysActiveDays  1     0.811 1217.5 -55.476
## <none>                        1216.7 -54.335
## - BPSysAve        1     7.884 1224.5 -48.022
```

```
## - Height          1     8.333 1225.0 -47.550
## - BPDiaAve        1    19.475 1236.1 -35.897
## - pb.Age2         1    65.377 1282.0  11.028
## - Age             1    74.647 1291.3  20.300
##
## Step:  AIC=-56.33
## pb.TotChol ~ Age + pb.Age2 + Height + BPSysAve + BPDiaAve + SmokeNow +
##     PhysActiveDays
##
##                  Df Sum of Sq    RSS     AIC
## - SmokeNow        1     0.088 1216.8 -58.241
## - PhysActiveDays  1     0.811 1217.5 -57.476
## <none>                        1216.7 -56.334
## + Weight          1     0.000 1216.7 -54.335
## - BPSysAve        1     7.936 1224.6 -49.967
## - Height          1    10.536 1227.2 -47.237
## - BPDiaAve        1    19.546 1236.2 -37.823
## - pb.Age2         1    65.904 1282.6   9.557
## - Age             1    75.216 1291.9  18.868
##
## Step:  AIC=-58.24
## pb.TotChol ~ Age + pb.Age2 + Height + BPSysAve + BPDiaAve + PhysActiveDays
##
##                  Df Sum of Sq    RSS     AIC
## - PhysActiveDays  1     0.811 1217.6 -59.384
## <none>                        1216.8 -58.241
## + SmokeNow        1     0.088 1216.7 -56.334
## + Weight          1     0.003 1216.8 -56.244
## - BPSysAve        1     8.071 1224.8 -51.731
## - Height          1    10.615 1227.4 -49.062
## - BPDiaAve        1    19.459 1236.2 -39.821
## - pb.Age2         1    66.037 1282.8   7.779
## - Age             1    75.131 1291.9  16.872
##
## Step:  AIC=-59.38
## pb.TotChol ~ Age + pb.Age2 + Height + BPSysAve + BPDiaAve
##
##                  Df Sum of Sq    RSS     AIC
## <none>                        1217.6 -59.384
## + PhysActiveDays  1     0.811 1216.8 -58.241
## + SmokeNow        1     0.088 1217.5 -57.476
## + Weight          1     0.000 1217.6 -57.384
## - BPSysAve        1     7.982 1225.5 -52.974
## - Height          1    10.444 1228.0 -50.391
## - BPDiaAve        1    19.562 1237.1 -40.870
## - pb.Age2         1    65.411 1283.0   5.965
## - Age             1    74.398 1292.0  14.949
```

```
summary(AIC)
```

```
##
## Call:
## lm(formula = pb.TotChol ~ Age + pb.Age2 + Height + BPSysAve +
##     BPDiaAve, data = clean.frame)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5880 -0.6170 -0.0140  0.6438  3.1057
##
## Coefficients:
##               Estimate Std. Error t value             Pr(>|t|)
## (Intercept)  4.8098341  0.5741846   8.377 < 0.0000000000000002 ***
## Age          0.0974977  0.0110200   8.847 < 0.0000000000000002 ***
## pb.Age2     -0.0009263  0.0001117  -8.296  0.00000000000000027 ***
## Height      -0.0098211  0.0029628  -3.315             0.000943 ***
## BPSysAve     0.0056469  0.0019487   2.898             0.003821 **
## BPDiaAve     0.0127101  0.0028016   4.537  0.00000624991387098 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9749 on 1281 degrees of freedom
## Multiple R-squared:  0.1284, Adjusted R-squared:  0.125
## F-statistic: 37.73 on 5 and 1281 DF,  p-value: < 0.00000000000000022
```

```r
final_model <- lm(pb.TotChol ~ Age+pb.Age2+Height+BPSysAve+BPDiaAve,
                    data=clean.frame)
```

```r
#PREDICTION ACCURACY
set.seed(123)
train_index <- sample(1:nrow(clean.frame), 0.7 * nrow(clean.frame))
train_data <- clean.frame[train_index, ]
test_data <- clean.frame[-train_index, ]

validation_model <- lm(pb.TotChol ~ Age + pb.Age2 + Height + BPSysAve + BPDiaAve,
                        data = train_data)
predictions <- predict(validation_model, newdata = test_data)

# Compare predictions to actual
mean((predictions - test_data$pb.TotChol)^2)  # MSE
```

```
## [1] 0.9542581
```

```r
sqrt(mean((predictions - test_data$pb.TotChol)^2))  # RMSE
```

```
## [1] 0.9768613
```

```r
#K-Fold (10-Fold) MODEL VALIDATION
library(caret)

#FINAL_MODEL VALIDATION
train_control <- trainControl(method = "cv", number = 10)
cv_model <- train(
  pb.TotChol ~ Age+pb.Age2+Height+BPSysAve+BPDiaAve,
  data = clean.frame,
  method = "lm",
  trControl = train_control
)

print(cv_model)
```

```
## Linear Regression
##
```

```
## 1287 samples
##    5 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1158, 1159, 1158, 1158, 1158, 1159, ...
## Resampling results:
##
##   RMSE       Rsquared   MAE
##   0.9751559  0.1373103  0.7694394
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```r
#FINAL_MODEL VALIDATION
train_control_full <- trainControl(method = "cv", number = 10)
cv_full_model <- train(
  pb.TotChol ~ .,
  data = clean.frame,
  method = "lm",
  trControl = train_control_full
)

print(cv_full_model)
```

```
## Linear Regression
##
## 1287 samples
##    8 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1159, 1160, 1160, 1157, 1159, 1158, ...
## Resampling results:
##
##   RMSE       Rsquared   MAE
##   0.9751863  0.1249023  0.7700059
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```r
#NULL_MODEL VALIDATION

train_control_null <- trainControl(method = "cv", number = 10)


cv_null_model <- train(
  pb.TotChol ~ SmokeNow,
  data = clean.frame,
  method = "lm",
  trControl = train_control_null
)

print(cv_null_model)
```

```
## Linear Regression
##
## 1287 samples
```

```
##    1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1159, 1159, 1159, 1159, 1158, 1158, ...
## Resampling results:
##
##   RMSE      Rsquared    MAE
##   1.040307  0.01430996  0.822368
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
#ORIGINAL MODEL VALIDATION
train_original <- trainControl(method = "cv", number = 10)
cv_original_model <- train(
  TotChol ~ Age+Height+BPSysAve+BPDiaAve,
  data = nhanes_data,
  method = "lm",
  trControl = train_original
)

print(cv_original_model)
```

```
## Linear Regression
##
## 1289 samples
##    4 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1161, 1159, 1162, 1160, 1160, 1159, ...
## Resampling results:
##
##   RMSE      Rsquared    MAE
##   1.040968  0.08495365  0.811146
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
#ORIGINAL FULL MODEL VALIDATION
train_full.og <- trainControl(method = "cv", number = 10)
cv_full.og_model <- train(
  TotChol ~ .,
  data = nhanes_data,
  method = "lm",
  trControl = train_full.og
)

print(cv_full.og_model)
```

```
## Linear Regression
##
## 1289 samples
##    7 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
```

```
## Summary of sample sizes: 1159, 1160, 1161, 1160, 1160, 1160, ...
## Resampling results:
##
##   RMSE      Rsquared    MAE
##   1.042695  0.07761385  0.8123572
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```r
library(glmnet)

lasso_model <- train(
  pb.TotChol ~ Age+pb.Age2+Height+BPSysAve+BPDiaAve,
  data = clean.frame,
  method = "glmnet",
  trControl = train_control,
  tuneGrid = expand.grid(
    alpha = 1,          # Lasso
    lambda = 10^seq(-4, 1, length = 100)  # Lambda grid
  )
)
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo,
## : There were missing values in resampled performance measures.
```

```r
print(lasso_model)
```

```
## glmnet
##
## 1287 samples
##    5 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1157, 1159, 1159, 1159, 1157, 1157, ...
## Resampling results across tuning parameters:
##
##   lambda        RMSE       Rsquared    MAE
##    0.0001000000  0.9739945  0.12976077  0.7691609
##    0.0001123324  0.9739945  0.12976077  0.7691609
##    0.0001261857  0.9739954  0.12976027  0.7691613
##    0.0001417474  0.9739968  0.12976110  0.7691633
##    0.0001592283  0.9739972  0.12976034  0.7691709
##    0.0001788650  0.9739984  0.12975948  0.7691810
##    0.0002009233  0.9739984  0.12975931  0.7691886
##    0.0002257020  0.9740001  0.12975727  0.7692012
##    0.0002535364  0.9740017  0.12975569  0.7692135
##    0.0002848036  0.9740038  0.12975328  0.7692262
##    0.0003199267  0.9740048  0.12975191  0.7692410
##    0.0003593814  0.9740075  0.12974927  0.7692584
##    0.0004037017  0.9740107  0.12974633  0.7692776
##    0.0004534879  0.9740149  0.12974168  0.7692999
##    0.0005094138  0.9740202  0.12973622  0.7693249
##    0.0005722368  0.9740262  0.12973035  0.7693532
##    0.0006428073  0.9740347  0.12972198  0.7693856
##    0.0007220809  0.9740448  0.12971192  0.7694221
```

```
##    0.0008111308  0.9740576  0.12969877  0.7694622
##    0.0009111628  0.9740733  0.12968324  0.7695082
##    0.0010235310  0.9740939  0.12966277  0.7695633
##    0.0011497570  0.9741190  0.12963730  0.7696274
##    0.0012915497  0.9741515  0.12960470  0.7697029
##    0.0014508288  0.9741919  0.12956313  0.7697917
##    0.0016297508  0.9742422  0.12951111  0.7698953
##    0.0018307383  0.9743054  0.12944533  0.7700177
##    0.0020565123  0.9743852  0.12936063  0.7701696
##    0.0023101297  0.9744860  0.12925250  0.7703542
##    0.0025950242  0.9746139  0.12911309  0.7705734
##    0.0029150531  0.9747736  0.12893521  0.7708222
##    0.0032745492  0.9749757  0.12870552  0.7711129
##    0.0036783798  0.9752300  0.12840816  0.7714521
##    0.0041320124  0.9755503  0.12802323  0.7718671
##    0.0046415888  0.9759544  0.12752228  0.7723643
##    0.0052140083  0.9764636  0.12686796  0.7729484
##    0.0058570208  0.9771052  0.12601114  0.7736473
##    0.0065793322  0.9779143  0.12488299  0.7745175
##    0.0073907220  0.9789321  0.12339687  0.7755773
##    0.0083021757  0.9802155  0.12142813  0.7768724
##    0.0093260335  0.9818310  0.11881896  0.7783836
##    0.0104761575  0.9838665  0.11535396  0.7801559
##    0.0117681195  0.9864259  0.11077160  0.7822815
##    0.0132194115  0.9896455  0.10474258  0.7848019
##    0.0148496826  0.9936933  0.09690608  0.7878965
##    0.0166810054  0.9981864  0.08815626  0.7914723
##    0.0187381742  0.9997776  0.08527529  0.7927283
##    0.0210490414  0.9999655  0.08514331  0.7928204
##    0.0236448941  1.0001619  0.08506055  0.7929176
##    0.0265608778  1.0004073  0.08495308  0.7930506
##    0.0298364724  1.0007142  0.08481231  0.7932449
##    0.0335160265  1.0010956  0.08463104  0.7935106
##    0.0376493581  1.0015596  0.08441208  0.7938228
##    0.0422924287  1.0021302  0.08413960  0.7942503
##    0.0475081016  1.0028260  0.08379719  0.7947584
##    0.0533669923  1.0036963  0.08331182  0.7953584
##    0.0599484250  1.0047968  0.08259402  0.7960685
##    0.0673415066  1.0061608  0.08156831  0.7969906
##    0.0756463328  1.0076835  0.08042130  0.7980031
##    0.0849753436  1.0092617  0.07970862  0.7991878
##    0.0954548457  1.0110954  0.07890115  0.8006928
##    0.1072267222  1.0134043  0.07743096  0.8026675
##    0.1204503540  1.0163388  0.07457984  0.8051721
##    0.1353047775  1.0197924  0.07010347  0.8080000
##    0.1519911083  1.0230368  0.06637875  0.8105885
##    0.1707352647  1.0260602  0.06605730  0.8126892
##    0.1917910262  1.0297810  0.06605634  0.8152489
##    0.2154434690  1.0344526  0.06605634  0.8184422
##    0.2420128265  1.0395529  0.03679097  0.8215551
##    0.2718588243  1.0403394         NaN  0.8219620
##    0.3053855509  1.0403394         NaN  0.8219620
##    0.3430469286  1.0403394         NaN  0.8219620
##    0.3853528594  1.0403394         NaN  0.8219620
```

```
##    0.4328761281  1.0403394         NaN  0.8219620
##    0.4862601580  1.0403394         NaN  0.8219620
##    0.5462277218  1.0403394         NaN  0.8219620
##    0.6135907273  1.0403394         NaN  0.8219620
##    0.6892612104  1.0403394         NaN  0.8219620
##    0.7742636827  1.0403394         NaN  0.8219620
##    0.8697490026  1.0403394         NaN  0.8219620
##    0.9770099573  1.0403394         NaN  0.8219620
##    1.0974987655  1.0403394         NaN  0.8219620
##    1.2328467394  1.0403394         NaN  0.8219620
##    1.3848863714  1.0403394         NaN  0.8219620
##    1.5556761439  1.0403394         NaN  0.8219620
##    1.7475284000  1.0403394         NaN  0.8219620
##    1.9630406500  1.0403394         NaN  0.8219620
##    2.2051307399  1.0403394         NaN  0.8219620
##    2.4770763560  1.0403394         NaN  0.8219620
##    2.7825594022  1.0403394         NaN  0.8219620
##    3.1257158497  1.0403394         NaN  0.8219620
##    3.5111917342  1.0403394         NaN  0.8219620
##    3.9442060594  1.0403394         NaN  0.8219620
##    4.4306214576  1.0403394         NaN  0.8219620
##    4.9770235643  1.0403394         NaN  0.8219620
##    5.5908101825  1.0403394         NaN  0.8219620
##    6.2802914418  1.0403394         NaN  0.8219620
##    7.0548023107  1.0403394         NaN  0.8219620
##    7.9248289835  1.0403394         NaN  0.8219620
##    8.9021508545  1.0403394         NaN  0.8219620
##   10.0000000000  1.0403394         NaN  0.8219620
##
## Tuning parameter 'alpha' was held constant at a value of 1
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were alpha = 1 and lambda = 0.0001123324.
```

```r
# Best lambda from caret model
best_lambda <- cv_model$bestTune$lambda

# Extract coefficients at that lambda
lasso_coefs <- round(coef(cv_model$finalModel, s = best_lambda),4)

# Convert to tidy format
as.matrix(lasso_coefs)
```

```
##                [,1]
## (Intercept)  4.8098
## Age          0.0975
## pb.Age2     -0.0009
## Height      -0.0098
## BPSysAve     0.0056
## BPDiaAve     0.0127
```