

Regression Models: Assignment 1

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Installing libraries used

```
packages = c("dplyr", "MuMIn", "MASS", "leaps", "glmnet", "car")
for (package in packages) {
  install.packages(package)
}
```

Importing libraries

```
library(dplyr)
library(MuMIn)
library(MASS)
library(leaps)
library(glmnet)
library(car)
```

Exercise 1

Simulation

```
# terms
s = list()
X = list()

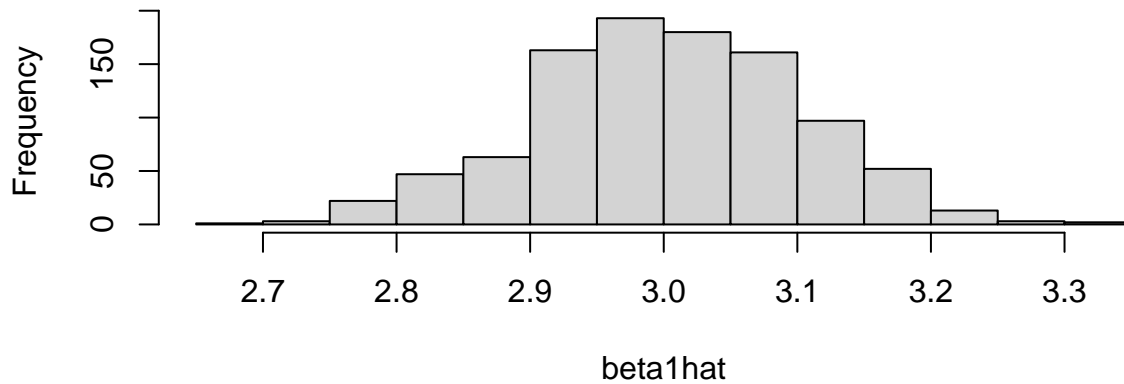
# betas estimation
beta_est = list()
beta1hat = c()
beta2hat = c()

# variables
phi = 50
beta1 = 3
beta2 = 3
x1 = matrix(rep(1,100),nrow=100,byrow=T)

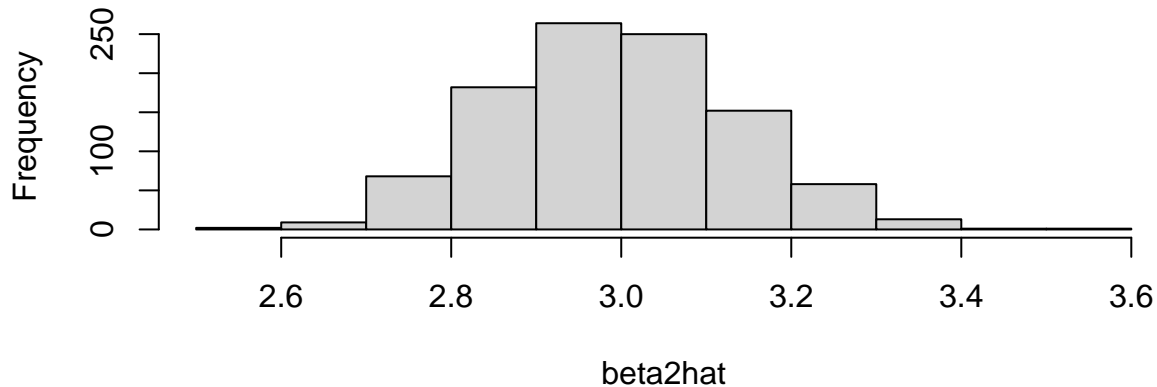
# simulation
simulation <- function(mean,sd,phi,beta1,beta2,itors,size) {
  for (j in 1:itors) {
    loop_s = matrix(rep(0,size),nrow=size,byrow=T)
    loop_x2 = matrix(rep(0,size),nrow=size,byrow=T)
    for (i in 1:size) {
      e = rnorm(1, mean=mean, sd=sd)
      loop_x2[i] = cos(i/10 + phi)
      loop_s[i] = beta1 + beta2*loop_x2[i] + e
    }
    X[[j]] = cbind(x1,loop_x2)
    s[[j]] = loop_s
    beta_est[[j]] = ginv(t(X[[j]])%*%X[[j]])%*%t(X[[j]])%*%loop_s
    beta1hat = c(beta1hat, beta_est[[j]][1])
    beta2hat = c(beta2hat, beta_est[[j]][2])
  }
  # plotting beta1hat and beta2hat
  par(mfrow=c(2,1))
  hist(beta1hat)
  hist(beta2hat)
  return(c(mean(beta1hat),mean(beta2hat)))
}
```

```
means <- simulation(mean=0, sd=1, phi=phi, beta1=beta1, beta2=beta2, iters=1000, size=100)
```

Histogram of beta1hat



Histogram of beta2hat



We know that the estimate is unbiased if its expected value of our estimators is equal to the real value of our estimators (in this case $E[\hat{\beta}_1] = \beta_1$ and $E[\hat{\beta}_2] = \beta_2$ as the sample size $n \rightarrow \infty$).

We can test for this with our 1000 simulation sample:

```
print(means)
#> [1] 3.003231 2.995873
```

Calculating a relative error for each one of these values:

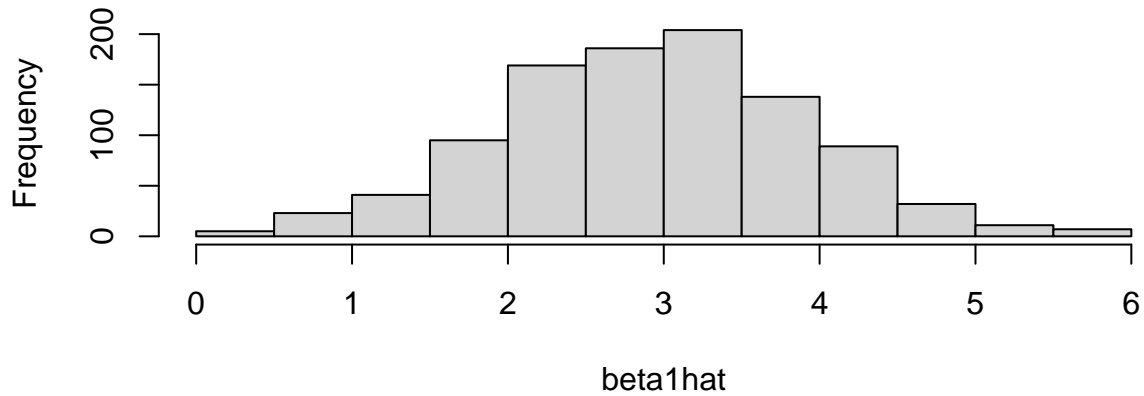
```
betas = c(beta1,beta2)
for (i in 1:length(means)) {
  print(paste("beta ",i, " hat has a relative error of: ", abs(means[i]-betas[i])/betas[i]))
}
#> [1] "beta 1 hat has a relative error of: 0.00107715176850961"
#> [1] "beta 2 hat has a relative error of: 0.00137580030629625"
```

Which are <1% incorrect versus the real betas, therefore, these estimators are unbiased.

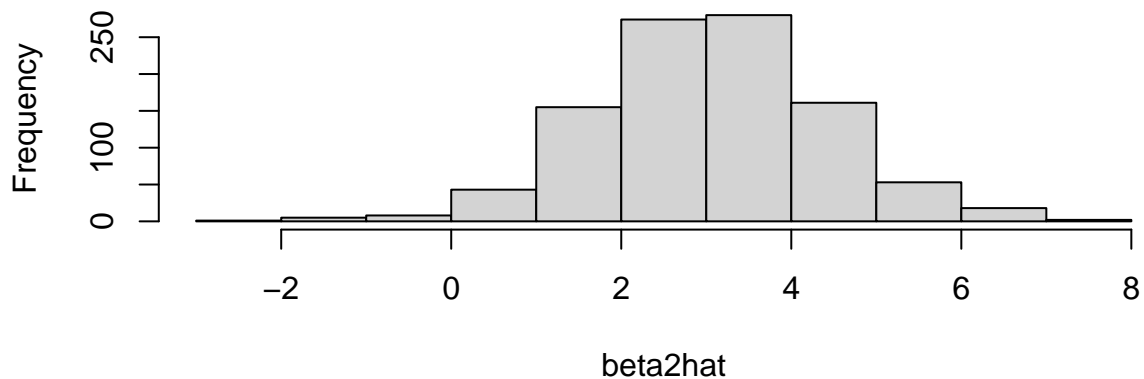
If we increase the value of sigma by ~10x the original value ($\sigma = 1$):

```
means <- simulation(mean=0, sd=10, phi=phi, beta1=beta1, beta2=beta2, iters=1000, size=100)
```

Histogram of beta1hat



Histogram of beta2hat



```
print(means)
#> [1] 2.934653 3.041834

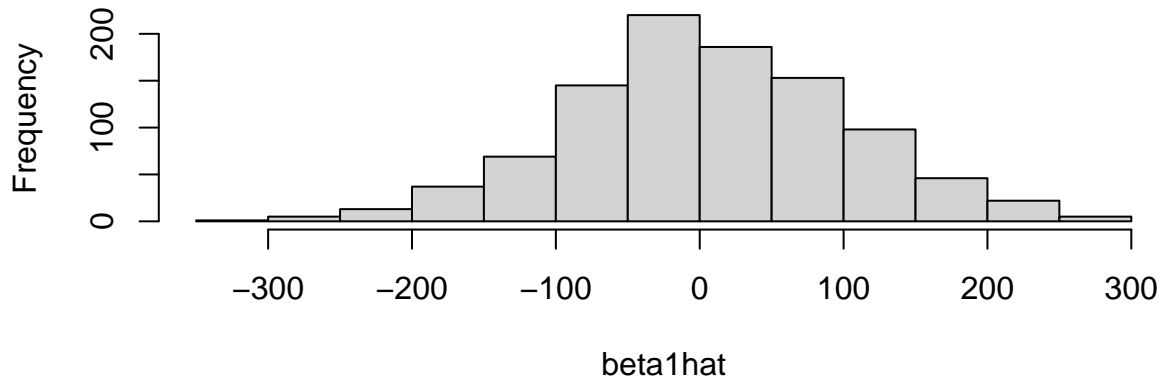
betas = c(beta1,beta2)
for (i in 1:length(means)) {
  print(paste("beta ",i, " hat has a relative error of: ", abs(means[i]-betas[i])/betas[i]))
}
#> [1] "beta 1 hat has a relative error of: 0.0217823161811492"
#> [1] "beta 2 hat has a relative error of: 0.0139447893946369"
```

We can see that our relative error increases, therefore our estimation would either require a significantly larger amount of iterations to reach the same estimation accuracy. So then we could say that our residuals being a lot more dispersed can measurably affect the accuracy of our prediction.

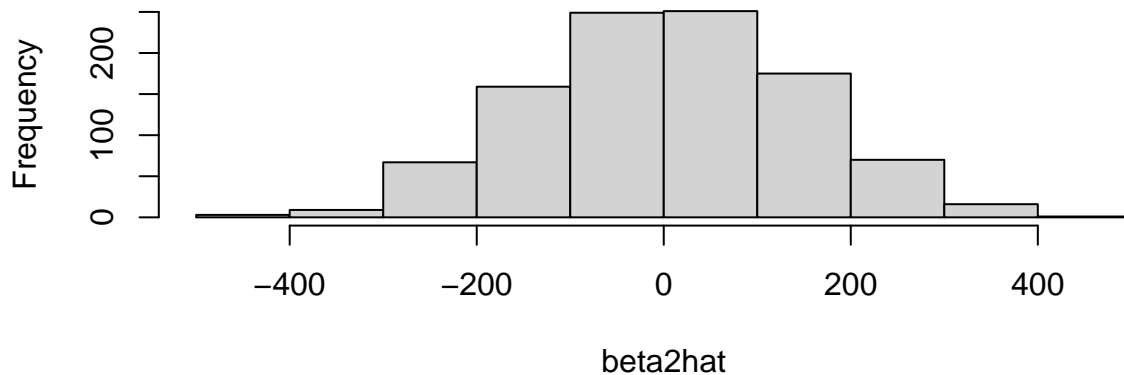
If we increase the value of sigma by ~1000x the original value ($\sigma = 1$):

```
means <- simulation(mean=0, sd=1000, phi=phi, beta1=beta1, beta2=beta2, iters=1000, size=100)
```

Histogram of beta1hat



Histogram of beta2hat



```
print(means)
#> [1] 6.856831 5.014018

betas = c(beta1,beta2)
for (i in 1:length(means)) {
  print(paste("beta ",i, " hat has a relative error of: ", abs(means[i]-betas[i])/betas[i]))
}
#> [1] "beta 1 hat has a relative error of: 1.28561024902312"
#> [1] "beta 2 hat has a relative error of: 0.671339263905679"
```

In an attempt to show a waaaaay worse scenario, here we can see our relative error is not only large but, having tried running this a few times, the relative error can reach massive amounts, being, at times, more than 100% wrong.

Exercise 2

Importing the data

```
d <- data.frame(read.table('../data/index.txt', header=TRUE))
```

```
X = d$PovPct  
Y = d$Brth15to17  
beta1 = cov(X, Y)/var(X)  
beta0 = mean(Y) - beta1*mean(X)
```

```
beta1  
#> [1] 1.373345  
beta0  
#> [1] 4.267293
```

Exercise 3

First we have the log-likelihood function for β and σ^2

$$l(\sigma^2|X) = \sum_{i=1}^n \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} - \frac{(Y_i - (\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}))^2}{2\sigma^2}\right) \\ \propto -\frac{n}{2} \log(\sigma^2) - \frac{(Y - X\beta)'(Y - X\beta)}{2\sigma^2}$$

Differentiating the second expression:

$$\frac{\partial l}{\partial \sigma} \left(-\frac{n}{2} \log(\sigma^2) - \frac{(Y - X\beta)'(Y - X\beta)}{2\sigma^2} \right) = 0$$

We get:

$$-\frac{n}{2} \left(\frac{1}{\sigma^2} \right) (2\sigma) - (Y - X\beta)'(Y - X\beta) * (-2)(2\sigma^{-3}) = 0$$

We reduce the expression further:

$$-\frac{n}{\sigma} + \frac{(Y - X\beta)'(Y - X\beta)}{\sigma^3} = 0$$

We multiply both sides by σ^3 and we get:

$$-n\sigma^2 + (Y - X\beta)'(Y - X\beta) = 0$$

And solving for σ^2 we get:

$$\hat{\sigma}^2 = \frac{(Y - X\beta)'(Y - X\beta)}{n}$$

Which is our maximum likelihood estimator for σ^2

Exercise 4

Exercise 5

```
bodyfat <- data.frame(read.table('../data/bodyfat.txt', header=TRUE))
modall <- lm(hwfat ~., data = bodyfat)
summary(modall)
#>
#> Call:
#> lm(formula = hwfat ~ ., data = bodyfat)
#>
#> Residuals:
#>      Min       1Q   Median       3Q      Max
#> -6.162 -1.858 -0.464  2.502  8.177
#>
#> Coefficients:
#>              Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 13.29370     9.63027   1.380  0.1718
#> age         -0.32893     0.32158  -1.023  0.3098
#> ht          -0.06731     0.16051  -0.419  0.6762
#> wt          -0.01365     0.02591  -0.527  0.5999
#> abs          0.37142     0.08837   4.203 7.55e-05 ***
#> triceps      0.38743     0.13761   2.815  0.0063 **
#> subscap      0.11405     0.14193   0.804  0.4243
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 3.028 on 71 degrees of freedom
#> Multiple R-squared:  0.8918, Adjusted R-squared:  0.8827
#> F-statistic: 97.54 on 6 and 71 DF,  p-value: < 2.2e-16
```

The sum of residuals is zero:

```
residuals <- sum(resid(modall))
```

The sum of the observed data is equal to the sum of the fitted values

```
Y_hat <- predict(modall, bodyfat[1:length(names(bodyfat))-1])
sum(bodyfat$hwfat) - sum(Y_hat)
#> [1] 4.547474e-13
```

The residuals are orthogonal to the predictors

```
sum(residuals*bodyfat[1:length(names(bodyfat))-1])
#> [1] -3.077268e-10
```

The residuals are orthogonal to the fitted values

```
sum(residuals*Y_hat)
#> [1] -1.568657e-11
```


Exercise 6

We use `regsubsets` to find the best model combinations by adjusted R^2

```
options(na.action = "na.fail")
modall <- lm(hwfat ~., data = bodyfat)
combs <- leaps::regsubsets(bodyfat[,1:6], bodyfat[,7])
summary(combs)
#> Subset selection object
#> 6 Variables (and intercept)
#>          Forced in Forced out
#> age          FALSE      FALSE
#> ht           FALSE      FALSE
#> wt           FALSE      FALSE
#> abs          FALSE      FALSE
#> triceps      FALSE      FALSE
#> subscap      FALSE      FALSE
#> 1 subsets of each size up to 6
#> Selection Algorithm: exhaustive
#>          age ht wt abs triceps subscap
#> 1 ( 1 ) " " " " " " "*" " " " "
#> 2 ( 1 ) " " " " " " "*" "*" " "
#> 3 ( 1 ) "*" " " " " "*" "*" " "
#> 4 ( 1 ) "*" "*" " " "*" "*" " "
#> 5 ( 1 ) "*" " " "*" "*" "*" "*"
#> 6 ( 1 ) "*" "*" "*" "*" "*" "*"

```

And their corresponding R^2 values:

```
summary(combs)$adjr2
#> [1] 0.8409068 0.8801014 0.8849817 0.8846381 0.8840129 0.8826699

```

We can see the best model is the one with the following R^2

```
max(summary(combs)$adjr2)
#> [1] "NULL"

```

Which corresponds to the model which uses the variables **age**, **ht**, **abs** and **triceps**.

We can also do this same calculation using the function `dredge` (albeit less efficiently):

```
combs <- dredge(modall, extra = "R^2")
print("best model")
#> [1] "best model"
combs[combs$"R^2" == max(combs$"R^2")]
#> Global model call: lm(formula = hwfat ~ ., data = bodyfat)
#> ---
#> Model selection table
#>   (Intercept)  abs    age    ht  sbscp  trcps    wt    R^2 df logLik
#> 64    13.29 0.3714 -0.3289 -0.06731 0.1141 0.3874 -0.01365 0.8918  8 -193.43
#>   AICc delta weight
#> 64 404.9  5.58      1
#> Models ranked by AICc(x)

```

Exercise 7

We know that:

$$\begin{aligned} SST &= \sum_{i=1}^n (y_i - \bar{y})^2 \\ &= \sum_{i=1}^n (y_i - \hat{y}_i + \hat{y}_i - \bar{y})^2 \\ &= \sum_{i=1}^n (y_i - \hat{y}_i)^2 + 2 \sum_{i=1}^n (y_i - \hat{y}_i)(\hat{y}_i - \bar{y}) + \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 \\ &= SSE + SSR + 2 \sum_{i=1}^n (y_i - \hat{y}_i)(\hat{y}_i - \bar{y}) \end{aligned}$$

No we must prove that:

$$2 \sum_{i=1}^n (y_i - \hat{y}_i)(\hat{y}_i - \bar{y}) = 0$$

So then we have:

$$\sum_{i=1}^n (y_i - \hat{y}_i)(\hat{y}_i - \bar{y}) = \sum_{i=1}^n (y_i - \hat{y}_i)\hat{y}_i - \sum_{i=1}^n (y_i - \hat{y}_i)\bar{y} = 0$$

Because we know that:

$$\sum_{i=1}^n (y_i - \hat{y}_i)\hat{y}_i = 0$$

Given that the residuals must be orthogonal to the fitted values.

And:

$$\sum_{i=1}^n (y_i - \hat{y}_i)\bar{y} = 0$$

Because the sum of the observed data is equal to the sum of the fitted values:

$$\sum_{i=1}^n y_i = \sum_{i=1}^n \hat{y}_i$$

Exercise 8

We define a list with all the models excluding, in each one, a single variable.

```
models <- list()
vars <- c("age", "ht", "wt", "abs", "triceps", "subscap")
models[[1]] <- update(modall, ~.-age)
models[[2]] <- update(modall, ~.-ht)
models[[3]] <- update(modall, ~.-wt)
models[[4]] <- update(modall, ~.-abs)
models[[5]] <- update(modall, ~.-triceps)
models[[6]] <- update(modall, ~.-subscap)
```

We run ANOVA with both the models without each variable and the main model including all the other variables.

We can see the pvalues for the ANOVA where each specific variable was excluded:

```
anovas <- list()
pvalues <- c()
amount_of_vars <- length(names(bodyfat))-1
for (i in 1:amount_of_vars) {
  anovas[[i]] <- anova(models[[i]], modall)
  pvalues <- c(pvalues, sum(anovas[[i]][2, "Pr(>F)"]))
}
for (i in 1:length(vars)) {
  print(paste("excluding: ", vars[i], ": ", pvalues[i], sep=""))
}
#> [1] "excluding: age: 0.30983932449522"
#> [1] "excluding: ht: 0.67622546378066"
#> [1] "excluding: wt: 0.599878887504826"
#> [1] "excluding: abs: 7.54898491342447e-05"
#> [1] "excluding: triceps: 0.00630111253287972"
#> [1] "excluding: subscap: 0.424314507846979"
```

Then we compare with summary:

```
summary(modall)[4]
#> $coefficients
#>
#> Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 13.29369860 9.63026704 1.3804081 1.717917e-01
#> age -0.32893403 0.32157778 -1.0228755 3.098393e-01
#> ht -0.06730905 0.16050751 -0.4193514 6.762255e-01
#> wt -0.01365183 0.02590783 -0.5269385 5.998789e-01
#> abs 0.37141976 0.08836595 4.2032001 7.548985e-05
#> triceps 0.38742647 0.13761017 2.8153912 6.301113e-03
#> subscap 0.11405213 0.14192779 0.8035927 4.243145e-01
```

And we can see we get the same pvalues in the summary. Therefore viewing the summary can be a much faster version of performing such testing.

as a result we get that the least meaningful variable (the variable that explains the lowest variance of the model) is the variable ht (height) followed by the variable wt (weight).

Exercise 9

Given that $E[\hat{Y}|X_h] = \hat{Y}_h \sim N(X_h\beta, \sigma^2 X_h(X'X)^{-1}X_h')$

$$\Rightarrow \hat{y}_h \pm t_{n-(k+1), \frac{\alpha}{2}} * \hat{\sigma} \sqrt{h_{ii}}$$

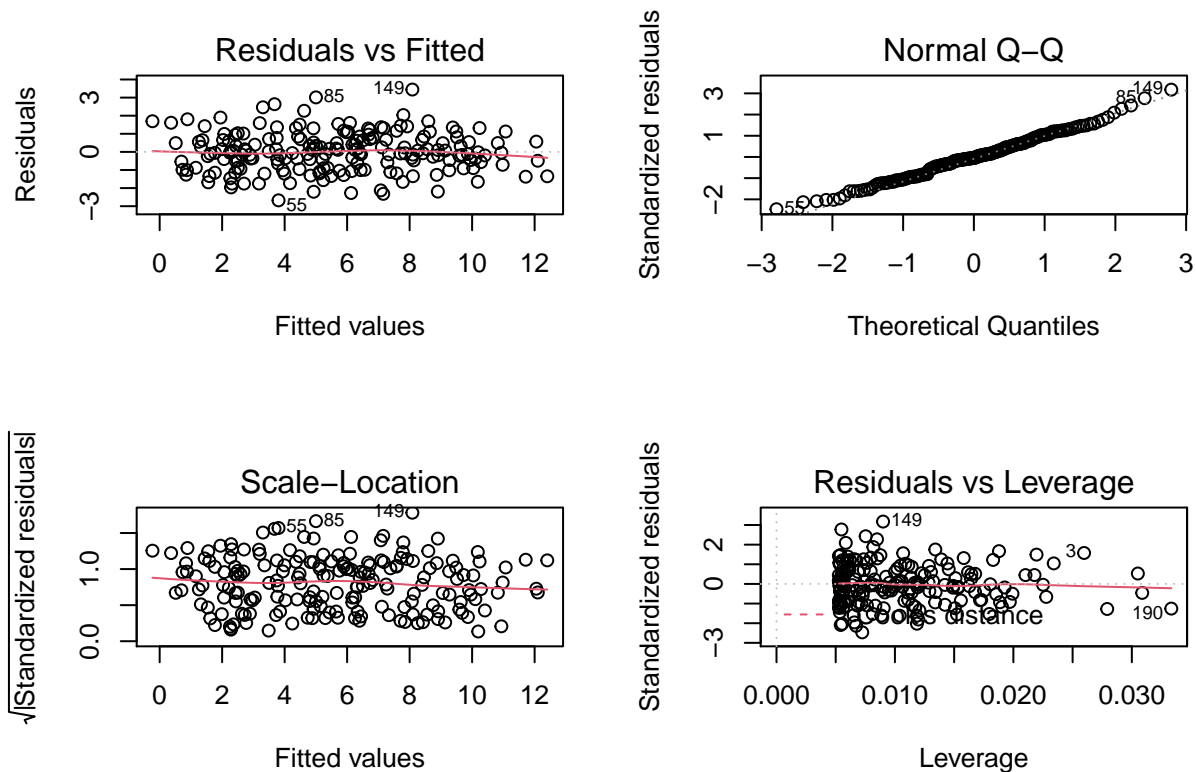
where h_{ii} is the diagonal of our H matrix.

is our expression for the $(1 - \alpha)\%$ confidence interval for \hat{Y}_h when σ^2 is unknown.

Exercise 10

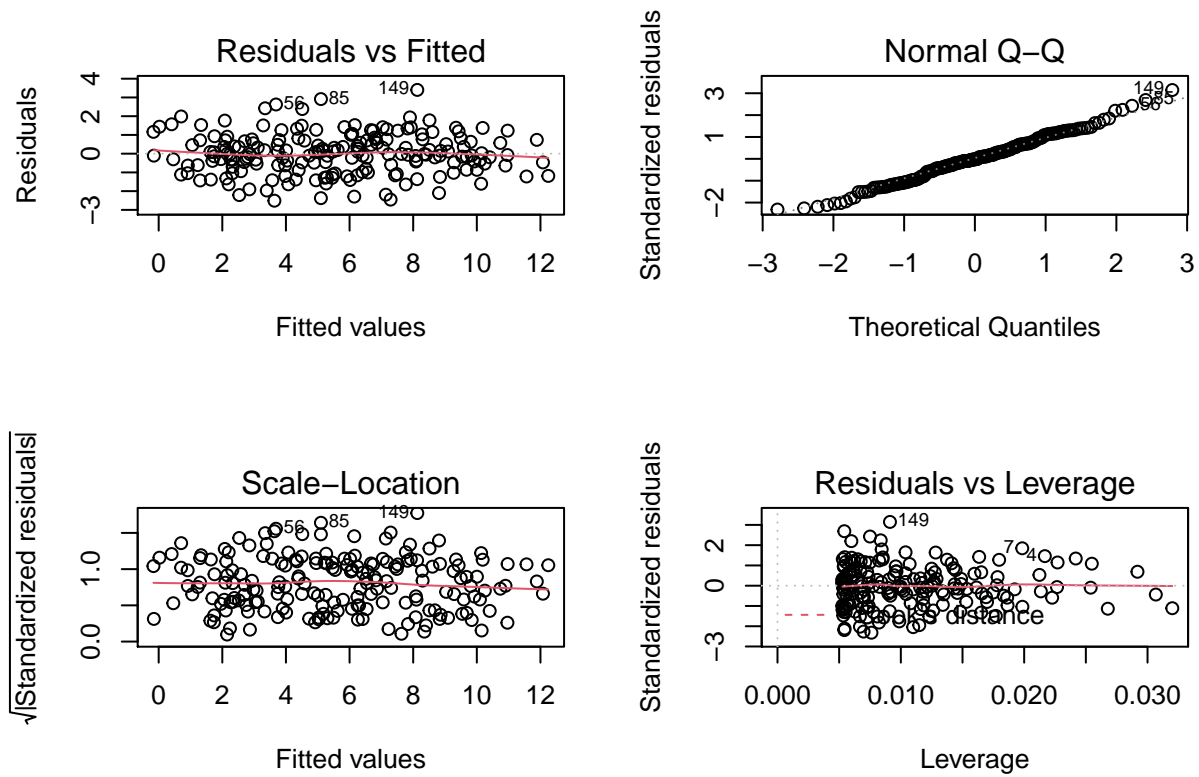
```
minmax_scaler <- function(x) {
  return((x-min(x))/(max(x)-min(x)))
}
```

```
transform <- data.frame(read.table('../data/Transform_V2.txt', header=TRUE))
trm1 <- lm(y ~ sqrt(x2+1), data=transform)
trm2 <- lm(y ~ I(x3^(2)), data=transform)
par(mfrow=c(2,2))
plot(trm1)
```



We can see that the square root transformation is appropriate for the X_2 variable

```
par(mfrow=c(2,2))
plot(trm2)
```

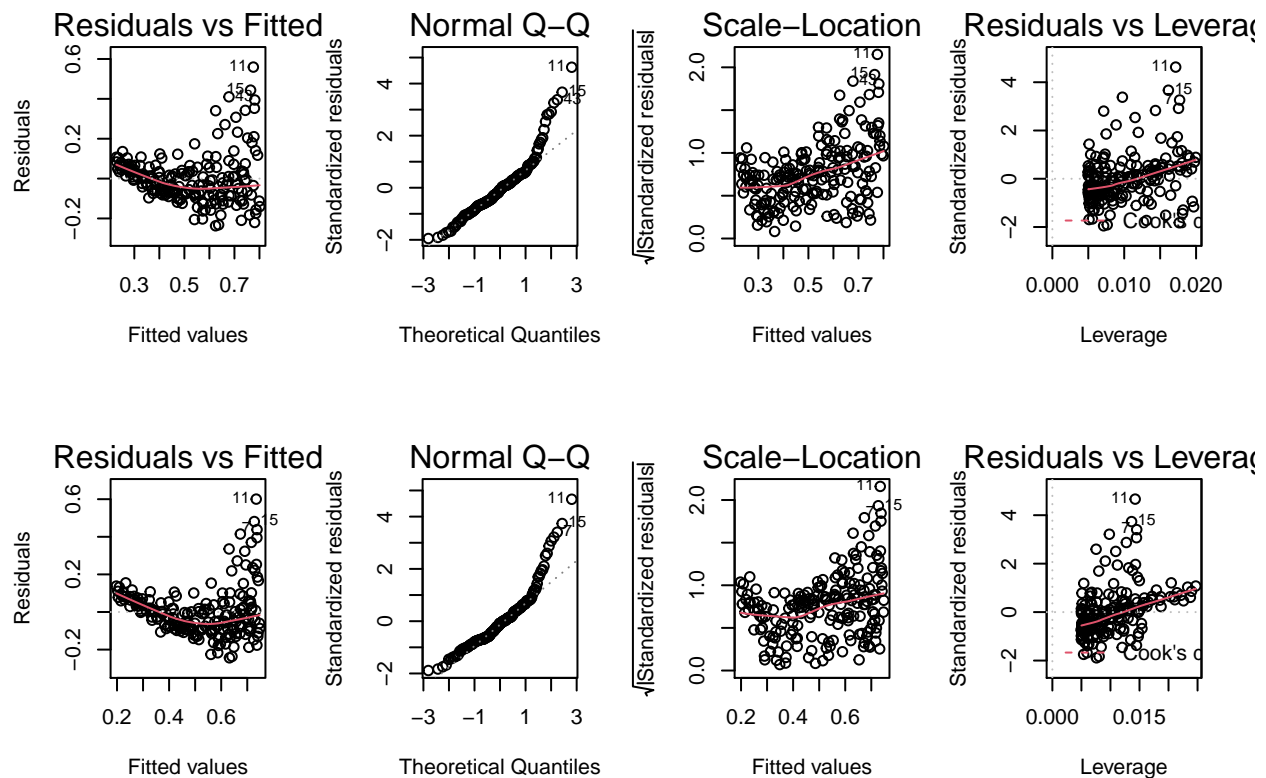


We can see that the X^2 transformation is appropriate for the X_3 variable

Exercise 11

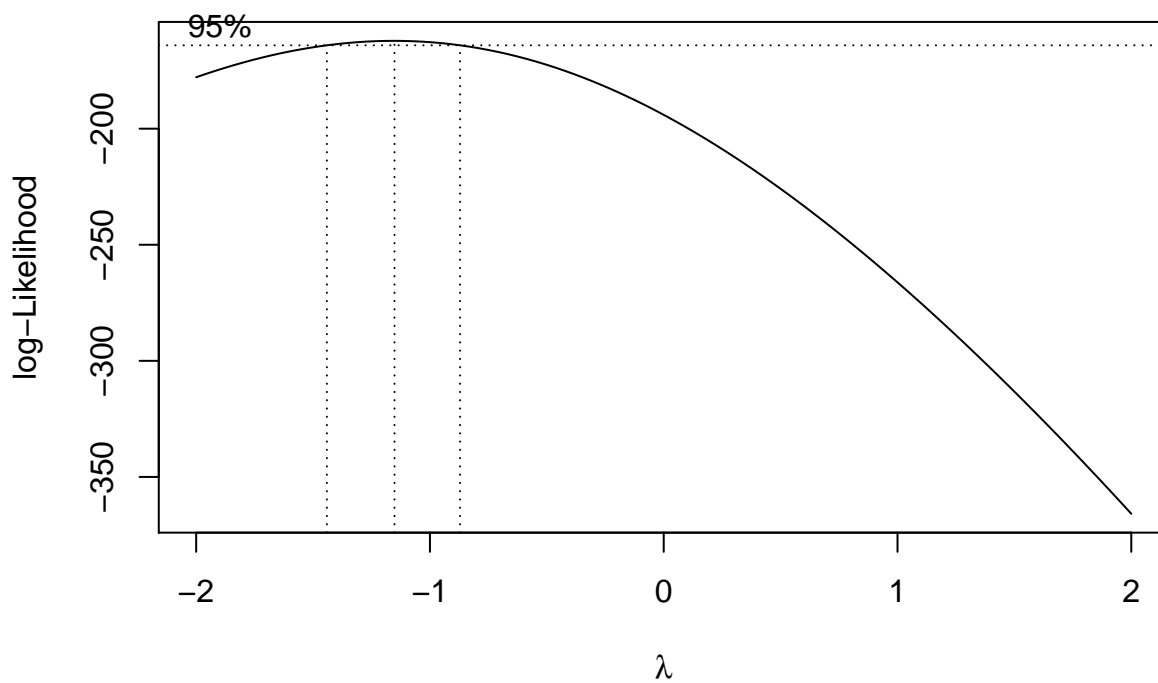
```
boxcox_transf <- function(x, lambda) {
  if (lambda == 0) {
    return(log(x))
  } else {
    return((x^(lambda)-1)/lambda)
  }
}
```

```
transform2 <- data.frame(read.table('../data/Transform2_V2.txt', header=TRUE))
trm1 <- lm(y2 ~ x1, data=transform2)
trm2 <- lm(y2 ~ x2, data=transform2)
par(mfrow=c(2,4))
plot(trm1)
plot(trm2)
```

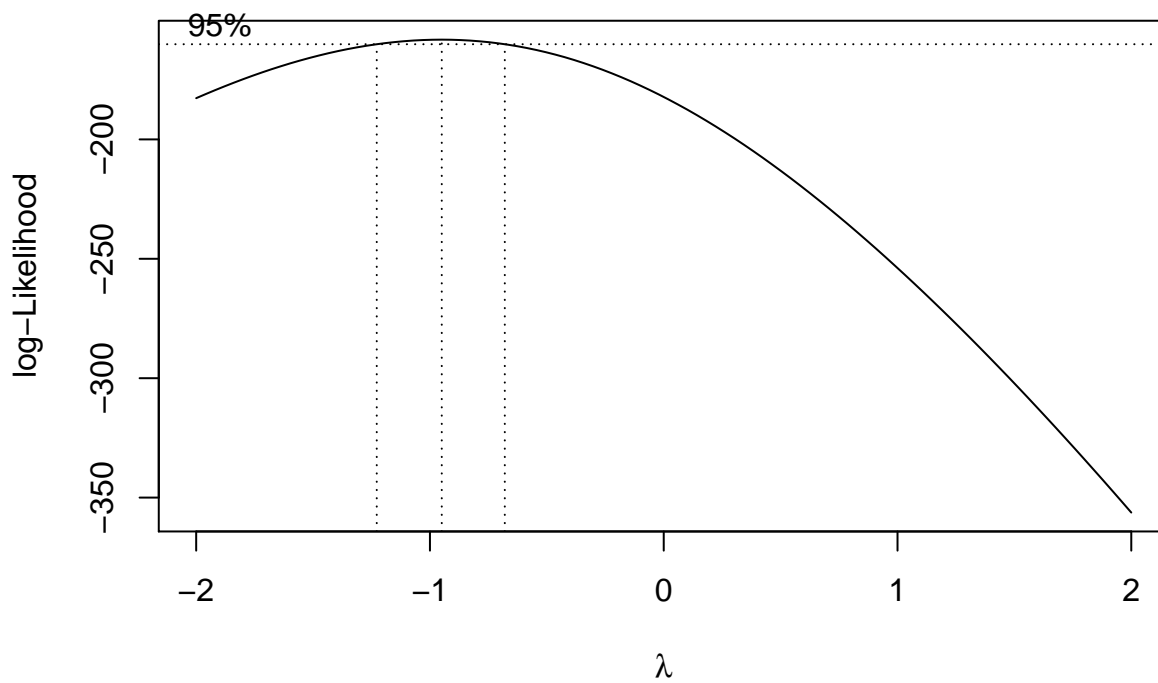


Neither variable has constant variance, therefore we apply a boxcox transformation to both X_2 and X_3 .

```
boxcox(trm2)
```

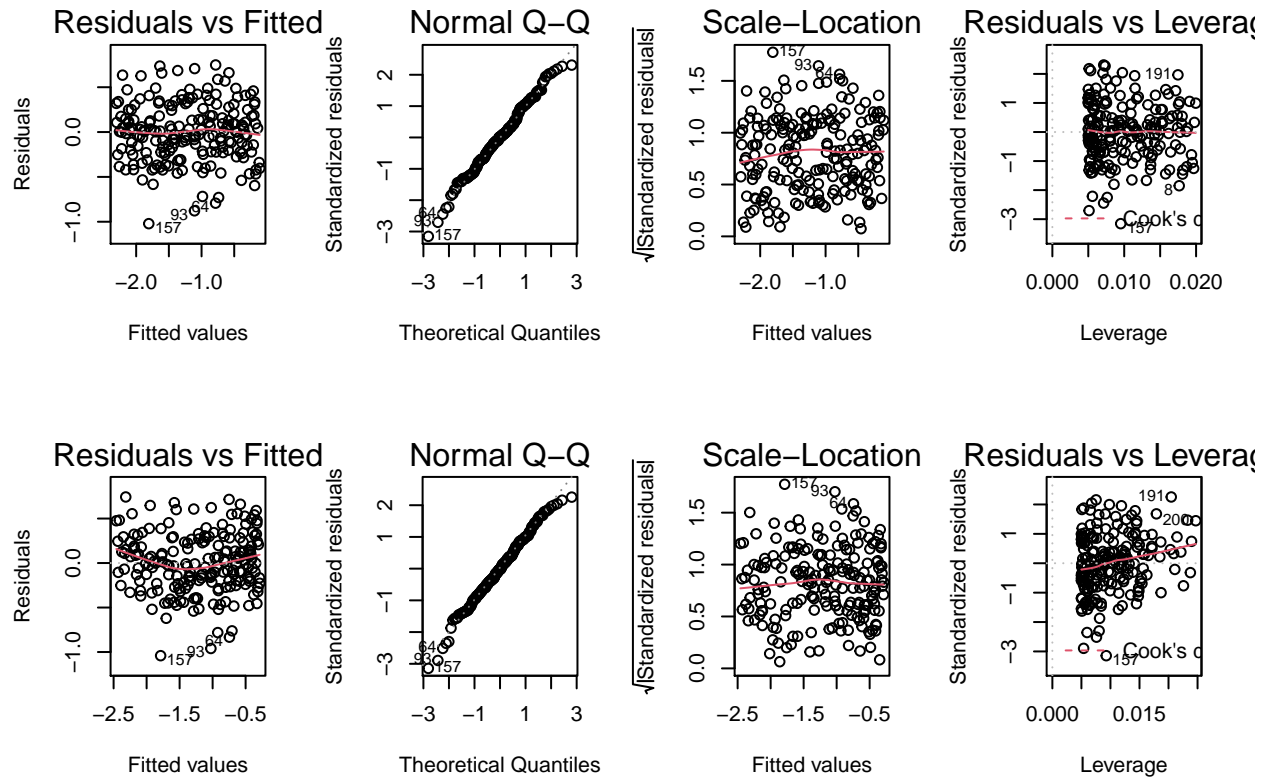


```
boxcox(trm1)
```



As -1 is in the confidence interval for both models, we will apply a boxcox transformation using $\lambda = -1$.

```
transform2 <- data.frame(read.table('../data/Transform2_V2.txt', header=TRUE))
trm1 <- lm(bxcx_transf(y2,-1) ~ x1, data=transform2)
trm2 <- lm(bxcx_transf(y2,-1) ~ x2, data=transform2)
par(mfrow=c(2,4))
plot(trm1)
plot(trm2)
```



Here we see the situation has improved significantly and we now have constant variance.

Exercise 12

Exercise 13

Using R's function to calculate VIF for our model:

```
vif(modall)
#>      age      ht      wt      abs  triceps  subscap
#> 1.553994 2.582940 10.194274 10.799321 10.951090 14.114459
```

We can see that the VIF score for **triceps**, **abs**, **wt** and **subscap** are all above 10 and therefore very high.

Programming my own VIF function:

```
vif_mc <- function(X) {
  for (i in 1:(length(names(X)))) {
    preds <- 1:length(names(X))
    preds <- preds[preds != i]
    model <- lm(X[,i] ~ X[,preds])
    print(model)
  }
}
```