Regression Models: Assignment 1

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Importing libraries

```
library(dplyr)
library(MuMIn)
```

Exercise 1

Simulation

```
sim = list()
for (j in 1:1000) {
    vals = c()
    for (i in 1:100) {
        run = 3 + 3*cos(i/10 + 50) + rnorm(1, mean=0, sd=1)
            vals = c(vals, run)
    }
    sim[[j]] = vals
}
sim
```

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</pre>
```

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

$$l(\sigma^{2}|X) = \sum_{i=1}^{n} log(\frac{1}{\sqrt{2\pi\sigma^{2}}} - \frac{(Y_{i} - (\beta_{0} + \beta_{1}x_{ik} + \dots + \beta_{k}x_{ik}))^{2}}{2\sigma^{2}})$$

$$\propto -\frac{n}{2}log(\sigma^2) - \frac{(Y-X\beta)\prime(Y-X\beta)}{2\sigma^2}$$

Differentiating the second expression:

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

We get:

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

We reduce the expression further:

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

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

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

And solving for σ^2 we get:

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

Which is our maximum likelihood estimator for σ^2

```
bodyfat <- data.frame(read.table('../data/bodyfat.txt', header=TRUE))</pre>
modall <- lm(hwfat ~., data = bodyfat)</pre>
summary(modall)
##
## Call:
## lm(formula = hwfat ~ ., data = bodyfat)
## Residuals:
##
      Min
              1Q Median
                             30
                                   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
               -0.32893
                            0.32158 -1.023
                                               0.3098
## age
## 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 ***
                                               0.0063 **
                0.38743
                            0.13761
                                      2.815
## triceps
                0.11405
                            0.14193
                                      0.804
                                               0.4243
## subscap
## ---
## Signif. codes: 0 '***' 0.001 '**' 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))</pre>
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
```

```
# rsq \leftarrow function(x,y) cor(x,y)^2
# cols <- names(bodyfat)[1:length(names(bodyfat))-1]</pre>
\# r_2 \leftarrow c()
\# names(r_2) \leftarrow cols
# for (i in 1:length(cols)) {
   modall <- lm(hwfat ~ cols[i], bodyfat)</pre>
    r_2 \leftarrow rsq(predict(hwfat))
# }
# r2
options(na.action = "na.fail")
modall <- lm(hwfat ~., data = bodyfat)</pre>
combs <- dredge(modall, extra = "R^2")</pre>
## Fixed term is "(Intercept)"
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
     (Intrc) abs age
                               ht sbscp trcps wt R^2 df logLik
AICc delta weight
## 64 404.9 5.58 1
## Models ranked by AICc(x)
```

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)</pre>
```

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()</pre>
pvalues <- c()
amount of vars <- length(names(bodyfat))-1
for (i in 1:amount_of_vars) {
    anovas[[i]] <- anova(models[[i]],modall)</pre>
    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
               -0.06730905 0.16050751 -0.4193514 6.762255e-01
## ht
## 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).