

# homework03

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Question1:

```
rm(list = ls())
data <- read.csv("boxers.csv", header = TRUE, sep = ",")
x = data$reach
y = data$height
model = lm(y ~ x)
row1 <- rep(1, 19)
X1 <- rbind(row1, data$reach)
X1 = t(X1)
L <- t(X1) %*% X1
y_hat = fitted(model)
e = y - y_hat
s = sqrt(sum(e^2) / (19 - 2))

beta_hat = c(model$coefficients[1], model$coefficients[2])
beta_0 <- seq(30, 65, length.out = 500)

F_value <- qf(0.95, df1=2, df2=17, lower.tail=TRUE)

s_y = 2 * s^2 * F_value
y_lower = rep(0,500)
y_upper = rep(0,500)

#Solve quadratic equations with one variable
getroot = function(a,b,c){
  x1 = (-b + (b^2 - 4 * a * c)^0.5) / 2 / a
  x2 = (-b - (b^2 - 4 * a * c)^0.5) / 2 / a
  ans=c(x1,x2)
  return(ans)
}

for (i in 1:500) {
  solutions <- getroot(L[2,2], (L[1,2] + L[2,1]) * (beta_hat[1] - beta_0[i]), L[1,1] * (beta_hat[1] - beta_0[i]))
  y_lower[i] = beta_hat[2] - max(solutions)
  y_upper[i] = beta_hat[2] - min(solutions)
}

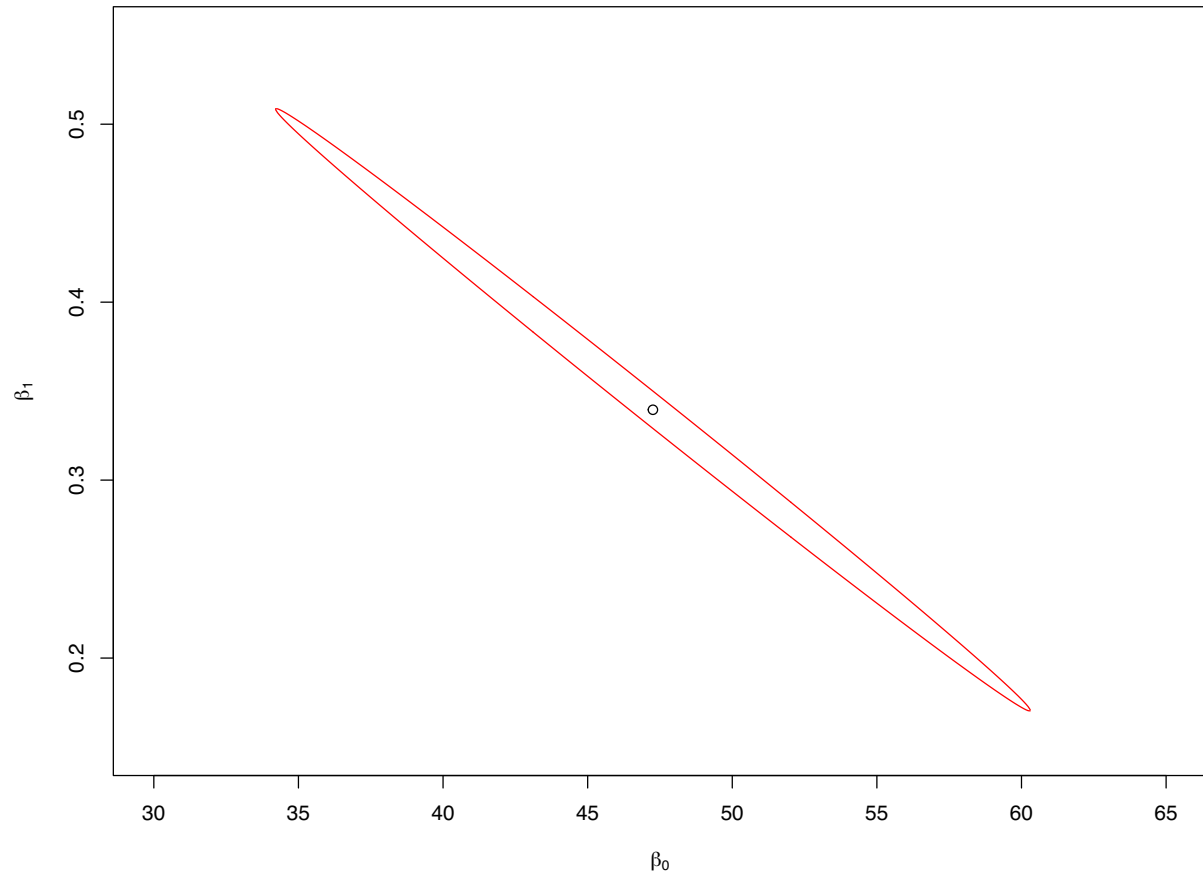
plot(beta_hat[1], beta_hat[2],
     main = expression(paste('95% confidence region for (', beta[0], ',', beta[1], ') from fitting height')),
     xlab = expression(paste(beta[0])),
     ylab = expression(paste(beta[1])),
```

```

xlim = c(30,65),
ylim = c(0.15,0.55))
lines(beta_0, y_lower, col='red', lty = 1)
lines(beta_0, y_upper, col='red', lty = 1)

```

95% confidence region for  $(\beta_0, \beta_1)$  from fitting height vs reach in boxer data



2. Show that the Box-Cox  $\lambda$  can be computed as follows:

- (a) Let  $\bar{y} = \sqrt[n]{y_1 y_2 \dots y_n}$  denote the geometric mean of the  $y$  observations
- (b) For each  $\lambda$ , transform the  $y_i$  to

$$z_i(\lambda) = \begin{cases} \frac{y_i^\lambda - 1}{\lambda \bar{y}^{\lambda-1}}, & \lambda \neq 0 \\ \bar{y} \log y_i, & \lambda = 0 \end{cases}$$

- (c) Fit the desired linear regression model to  $z_1(\lambda), z_2(\lambda), \dots, z_n(\lambda)$  and compute its residual sum of squares  $S(\lambda)$
- (d) The Box-Cox  $\lambda$  minimizes  $S(\lambda)$

We already have maximum likelihood way to estimate  $\lambda$ , the likelihood function is  $\frac{1}{(2\pi)^{n/2} \sigma^n} \exp \left\{ -\frac{(y^{(\lambda)} - X\beta)' (y^{(\lambda)} - X\beta)}{2\sigma^2} \right\} J(\lambda, y)$  where  $J = \prod_{i=1}^n y_i^{\lambda-1}$

Using this we could find that  $\hat{\beta}_{MLE} = (X'X)^{-1} X' y^{(\lambda)}$ ,  $\hat{\sigma}_{MLE}^2 = \frac{1}{n} y^{(\lambda)'} (I - X(X'X)^{-1} X') y^{(\lambda)}$   
 Then,  $\log L_{max}(\lambda) = \log L(\hat{\beta}_{MLE}, \hat{\sigma}_{MLE}^2) = -\frac{n}{2} \log \left( y^{(\lambda)'} (I - X(X'X)^{-1} X') y^{(\lambda)} \right) + \log J$   
 $= -\frac{n}{2} \log \left( \frac{y^{(\lambda)'}}{J^{\frac{1}{n}}} \cdot (I - X(X'X)^{-1} X') \frac{y^{(\lambda)}}{J^{\frac{1}{n}}} \right)$

And we suppose:  
 $z_i(\lambda) = \frac{1}{J^{\frac{1}{n}}} y_i^{(\lambda)}$ ,  $S(\lambda)$  is residual sum of squares for  $z_i(\lambda)$   
 So  $\log L_{max}(\lambda) = -\frac{n}{2} \log (S(\lambda))$

Thus we minimize  $S(\lambda) \Leftrightarrow$  we find the MLE of  $\lambda$   
 So Box-Cox  $\lambda$  can be computed by minimizing  $S(\lambda)$ .

□