Lab 5 - Computational Statistics (732A89)

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2025-02-20

QUESTION 1 Bootstrap for regression

First, we use lm() to fit a cubic regression model

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \epsilon$$

, where x represents the concentration of the fertilizer (%) and y represents the yield (mg).

```
##
## Call:
## lm(formula = Yield ~ poly(Fertilizer, 3, raw = TRUE), data = data)
##
## Residuals:
##
      Min
                10 Median
                                3Q
                                       Max
  -58.893 -17.142 -3.893 17.716
                                    58.107
##
## Coefficients:
##
                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                                     199.284
                                                  5.442 36.616
                                                                  <2e-16 ***
## poly(Fertilizer, 3, raw = TRUE)1
                                      62.634
                                                 72.165
                                                          0.868
                                                                  0.3881
                                                165.952
## poly(Fertilizer, 3, raw = TRUE)2 -298.766
                                                         -1.800
                                                                  0.0757 .
## poly(Fertilizer, 3, raw = TRUE)3 158.664
                                                 91.587
                                                          1.732
                                                                  0.0872 .
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## Residual standard error: 26.47 on 77 degrees of freedom
## Multiple R-squared: 0.646, Adjusted R-squared: 0.6322
## F-statistic: 46.84 on 3 and 77 DF, p-value: < 2.2e-16
```

To reduce model complexity, we remove the cubic term and fit a $quardic\ model$

$$y = \beta_0 + \beta_1 x + \beta_2 x^2$$

We then estimate the coefficients with their 95% confidence intervals. The regression curve plot and confidence intervals for the coefficients are shown below:

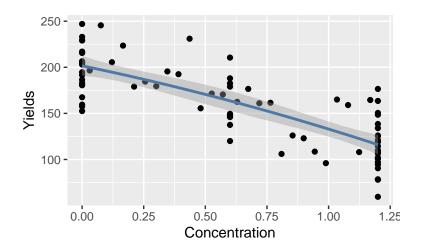


Figure 1: Yields vs Concentration

Table 1: 95% Confidence Interval of parameters

	2.5 %	97.5 %
(Intercept)	190.97432	212.242998
poly(Fertilizer, 2, raw = TRUE)1	-103.16614	-7.791748
$\underline{\text{poly}}(\text{Fertilizer}, 2, \text{raw} = \text{TRUE})2$	-51.57084	25.228592

We now use the **bootstrap method** with 10,000 replicates to derive a 95% confidence interval for β_1 using percentile method. The histogram and the 95% confidence interval are shown below:

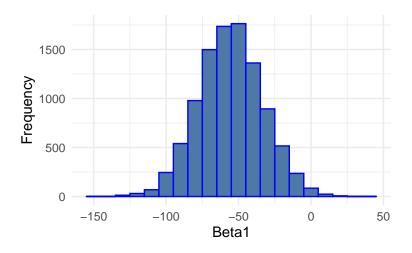


Figure 2: Bootstrap Coefficient Distribution

95% CI for beta 1 : -98.47781 -11.3802

Now we use the package boot to compute a 95% confidence interval for β_1 using both percentile method and BCa(bias-corrected and accelerated) method. The table below summarizes the 95% confidence intervals obtained using different methods:

Table 2: 95% Confidence Interval of different methods

	Lower Bound	Upper Bound	Interval Width
lm	-103.16614	-7.791748	95.3744
bootstrap	-98.47781	-11.380203	87.0976
boot_percentile	-99.46221	-12.067414	87.3948
$boot_BCa$	-98.38221	-10.665462	87.7167

Discussion of Confidence Interval Differences

From the results, we observe the following:

- 1. The confidence interval(CI) using lm() is wider than the bootstrap CIs. This is because lm() assumes that data follows a normal distribution. If the data sample size is small or the data is not normally distributed this assumption may not hold, leading to a less accurate CI.
- 2. The bootstrap method produces narrower confidence interval without distributional assumption. This allows it to better adapt to the actual data distribution.
- 3. The CIs obtained using the manual bootstrap method and the boot package with the percentile method are similar. However, the CI from the boot package with the BCa method is slightly different. This difference may be due to the BCa method correcting for bias, suggesting that the data may have some skewness.

Appendix

Question 1

```
library(ggplot2)
library(boot)
data <- read.csv("kresseertrag.dat",header=FALSE,sep = "")</pre>
colnames(data) <- c("Number", "Fertilizer", "Yield")</pre>
data <- as.data.frame(data)</pre>
modelA <- lm(Yield~poly(Fertilizer,3,raw = TRUE),data = data)</pre>
summary(modelA)
confint(modelA,level = 0.95)
#b
#remove a term
modelB <- lm(Yield~poly(Fertilizer,2,raw = TRUE),data = data)</pre>
summary(modelB)
#coefficients with 95% confidence interval
confint(modelB,level = 0.95)
#plot
#plot(data$Fertilizer,data$Yield,main="Yields vs Concentration",
# xlab = "Concentration", ylab = "Yields")
```

```
#lines(data$Fertilizer, fitted(modelB), col="blue")
ggplot(data,aes(x=Fertilizer,y=Yield))+
  geom_point()+
  labs(title = "Yields vs Concentration",x="Concentration",y="Yields")+
  geom_line(aes(y=fitted(modelB)),color="#4E79A7")
  #geom_line(aes(y=fitted(modelA)),color="red")
#c bootstrap for beta
bo <- 10000
                                       #bootstrasp replicates
bs <- c()
set.seed(12345)
#save the results
for (i in 1:bo) {
  #sampling using indcies
  indices <- sample(1:nrow(data),size=nrow(data),replace = TRUE)</pre>
  bootstrapData <- data[indices,]</pre>
  model_bootstrap <- lm(Yield~poly(Fertilizer,2,raw = TRUE),data = bootstrapData)</pre>
  bs <- c(bs,coef(model_bootstrap)[2])</pre>
}
hist(bs)
bss <- sort(bs)</pre>
ci95 <- c(bss[round(bo*0.25)],bss[round(bo*0.975)])</pre>
ci95
#d bootstrap using boot package
beta1 <- function(data,i){</pre>
  model <- lm(Yield~poly(Fertilizer,2,raw = TRUE),subset=i,data = data)</pre>
  coef(model)[2]
}
cb <- boot(data,beta1,R=10000)
perc <- boot.ci(cb,type = "perc")</pre>
bca <- boot.ci(cb,type = "bca")</pre>
perc
result <- c(CI[2,],95.3744,ci95,87.0976,perc$percent[4],perc$percent[5],87.3948,bca$bca[4],bca$bca[5],
 result_mt <- matrix(result,byrow = TRUE,ncol=3)</pre>
 rownames(result_mt) <- c("lm", "bootstrap", "boot_percentile", "boot_BCa")</pre>
 colnames(result_mt) <- c("Lower Bound", "Upper Bound", "Interval Width")</pre>
 kable(result_mt,caption = "95% Confidence Interval of different methods")
```