**First we fit a linear model using “uptake” as the response and “conc” as the predictor:**

> model <- lm(uptake ~ conc , data = CO2)

**Next we report the summary of the linear model:**

> summary(model)

Call:

lm(formula = uptake ~ conc, data = CO2)

Residuals:

Min 1Q Median 3Q Max

-22.831 -7.729 1.483 7.748 16.394

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 19.500290 1.853080 10.523 < 2e-16 \*\*\*

conc 0.017731 0.003529 5.024 2.91e-06 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.514 on 82 degrees of freedom

Multiple R-squared: 0.2354, Adjusted R-squared: 0.2261

F-statistic: 25.25 on 1 and 82 DF, p-value: 2.906e-06

**Now we find the critical value for the 90% confidence interval:**

> (alpha = .1)

[1] 0.1

> (n = length(CO2$uptake))

[1] 84

> (critical\_value <- qt(1-alpha/2,n-2))

[1] 1.663649

**Now we can compute the confidence interval. Above I highlighted the information we need, which are the estimates for the slope and its standard error:**

> (B1\_hat <- .017731)

[1] 0.017731

> (SE\_hat <- .003529)

[1] 0.003529

> (lower\_ci <- B1\_hat - critical\_value \* SE\_hat)

[1] 0.01185998

> (upper\_ci <- B1\_hat + critical\_value \* SE\_hat)

[1] 0.02360202

**Therefore the 90% confidence interval for the true value of the slope is (.0119, .0236).**

**Finally, for the situation described in part c) we would build a prediction interval. This is because we are interested in predicting a new observation when X = 100. Therefore, we have uncertainty with respect to estimating the mean AND the random error of future observations.**