Regression_HW3_Warren_Geither

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10/4/2020

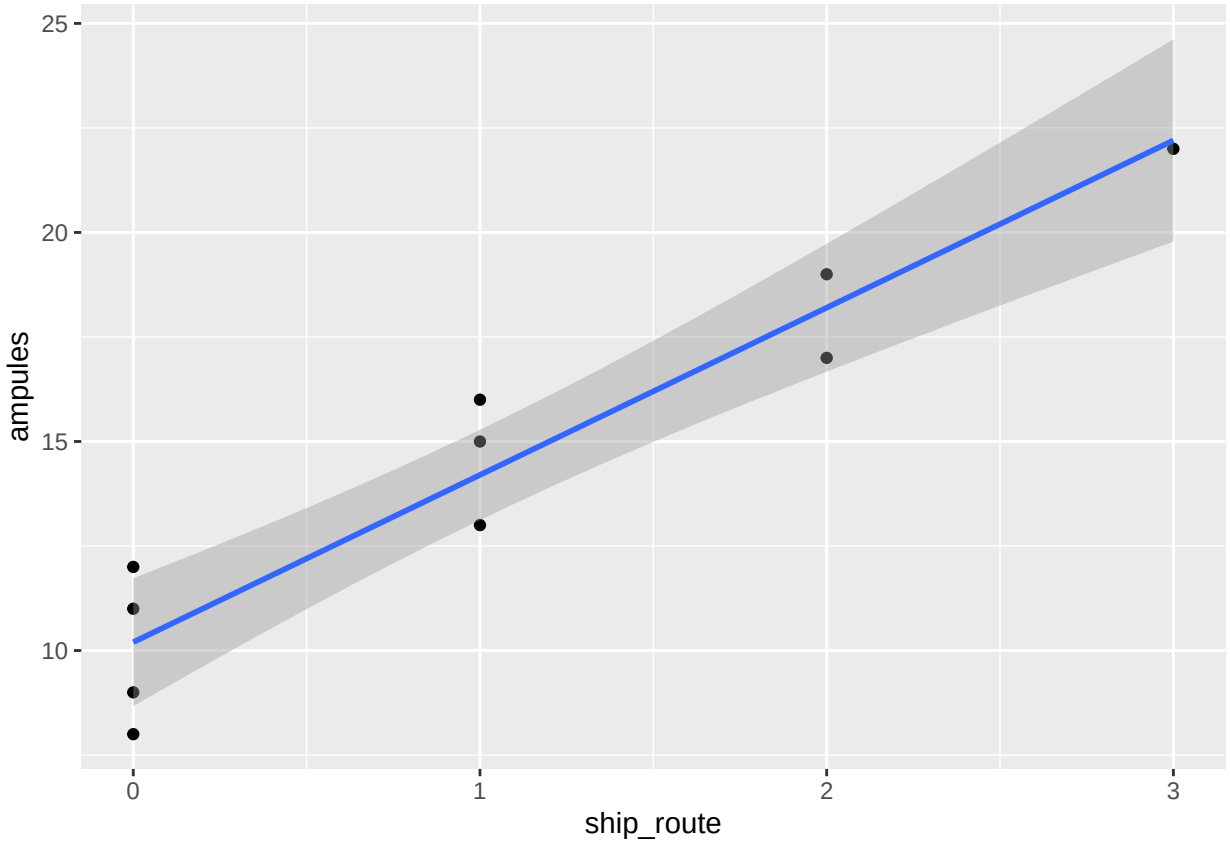
Problem 1

a.)

```
# create dataframe
freight_data_df <- data.frame(ship_route = c(1,0,2,0,3,1,0,1,2,0)
                              , ampules = c(16,9,17,12,22,13,8,15,19,11))

lmfit <- lm(ampules~ship_route, freight_data_df)
# plot scatterplot and estimated regression line
ggplot(freight_data_df, aes(x=ship_route, y=ampules)) +
  geom_point()+
  geom_smooth(method=lm)
```

```
## `geom_smooth()` using formula 'y ~ x'
```



The linear regression function does appear to have a good fit

b.)

```
# print summary to get coeffienient estimates
summary(lmfit)
```

```
##
## Call:
## lm(formula = ampules ~ ship_route, data = freight_data_df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##   -2.2   -1.2    0.3    0.8    1.8
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  10.2000     0.6633  15.377 3.18e-07 ***
## ship_route    4.0000     0.4690   8.528 2.75e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.483 on 8 degrees of freedom
## Multiple R-squared:  0.9009, Adjusted R-squared:  0.8885
## F-statistic: 72.73 on 1 and 8 DF,  p-value: 2.749e-05
```

```r
# plug in values for beta_hats
b_0 <- 10.2
b_1 <- 4

# estimate value at x=1
x1 <- b_0 + b_1*1

# print results
print(paste0("Point estimate for X=1: ", x1))
```

```
## [1] "Point estimate for X=1: 14.2"
```

c.)

```r
# get point estimate for x2
x2 <- b_0 + b_1*2

# get increase
delta <- x2 - x1

print(paste0("Increase from X=1 to X=2: ", delta))
```

```
## [1] "Increase from X=1 to X=2: 4"
```

d.)

```r
# find x_bar
x_bar <- mean(freight_data_df$ship_route)

print(paste0("x_bar: ", x_bar))
```

```
## [1] "x_bar: 1"
```

```r
# find y_bar
y_bar <- mean(freight_data_df$ampules)

print(paste0("y_bar: ", y_bar))
```

```
## [1] "y_bar: 14.2"
```

As shown in the plot in part a and the calculation in part b. The line does run through this point.

Problem 2

a.)

```r
# 95% confidence interval for beta_1
confint(lmfit, "ship_route", level=0.95)
```

```
##                2.5 %   97.5 %
## ship_route 2.918388 5.081612
```

Interpretation of interval: We are 95% confident that true beta_1 lies within this interval. Meaning if we drew 100 samples from the same experiment, 95% of the samples would generate intervals that contain the true beta_1

b.)

```
# print summary which includes a 2-sided t-test
model_sum <- summary(lmfit)
model_sum
```

```
##
## Call:
## lm(formula = ampules ~ ship_route, data = freight_data_df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##   -2.2   -1.2    0.3    0.8    1.8
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  10.2000     0.6633  15.377 3.18e-07 ***
## ship_route    4.0000     0.4690   8.528 2.75e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.483 on 8 degrees of freedom
## Multiple R-squared:  0.9009, Adjusted R-squared:  0.8885
## F-statistic: 72.73 on 1 and 8 DF,  p-value: 2.749e-05
```

Ho: beta_1 = 0 Ha: beta_1 != 0 alpha = .05 p_val = 0.0000275

The p value is the probability of viewing results at least as extreme as what we observed under the assumption that the null is true. i.e. if there was no linear relationship, there would be a 0.00275% chance of seeing these results or more extreme results.

Since the p value is less than our alpha of 0.05, we can reject the null hypothesis and say there is statistically significant evidence to believe in a linear relationship between ship route changes and number of ampules broken.

c.)

```
# one sided t-test, gets p-values for coefficients
pt(coef(model_sum)[, 3], lmfit$df, lower = FALSE)
```

```
##  (Intercept)   ship_route
## 1.589137e-07 1.374335e-05
```

```
# https://stats.stackexchange.com/questions/325354/if-and-how-to-use-one-tailed-testing-in-multiple-reg
```

Ho: beta_1 = 0 Ha: beta_1 > 0 alpha = .05 p_val = 0.0000137

The p value is the probability of viewing results at least as extreme as what we observed under the assumption that the null is true. i.e. if there was no linear relationship, there would be a 0.00137% chance of seeing these results or more extreme results.

Since the p value is less than our alpha of 0.05, we can reject the null hypothesis and say there is statistically significant evidence to believe there does exist a postive linear relationship between ship route changes and number of ampules broken.

d.)

```
# 95% confidence interval for beta_0
confint(lmfit, "(Intercept)", level=0.95)
```

```
##                2.5 %   97.5 %
## (Intercept) 8.67037 11.72963
```

Interpretation of interval: We are 95% confident that true mean of broken ampules lies within this interval (8.6, 11.7). Meaning if we drew 100 samples from the same experiment, 95% of the samples would generate intervals that contain the true beta_0.

e.)

Ho: b_0 = 9.0 Ha: b_0 > 9.0

Problem 3

a.)

```
# get data ready for x=2
new_data1 <- data.frame(ship_route=2)

# 99% condifence interval for data
predict(lmfit, new_data1, interval = "confidence", level = 0.99)
```

```
##    fit      lwr      upr
## 1 18.2 15.97429 20.42571
```

```
# settoing x = 4
new_data2 <- data.frame(ship_route=4)

# 99% c.i. for x = 2
predict(lmfit, new_data2, interval = "confidence", level = 0.99)
```

```
##    fit      lwr      upr
## 1 26.2 21.22316 31.17684
```

b.)

```
# set data for preditcion
predict_data <- data.frame(ship_route=2)

# make prediction
predict(lmfit, predict_data, interval = "predict", level = 0.99)
```

```
##    fit      lwr      upr
## 1 18.2 12.74814 23.65186
```

Given that there will be 2 transfers, we are 99% confident that the number of ampules broken will be between 12.7 to 23.65.

c.)

```r
# set data for preditcion
predict_data <- data.frame(ship_route=2)

# make prediction
3*predict(lmfit, predict_data, interval = "predict", level = 0.99)
```

```
##    fit      lwr      upr
## 1 54.6 38.24442 70.95558
```