# Feedback — Quiz 3

Help

Thank you. Your submission for this quiz was received.

You submitted this quiz on Fri 26 Dec 2014 9:54 AM PST. You got a score of 7.00 out of 7.00.

# **Question 1**

Consider the mtcars data set. Fit a model with mpg as the outcome that includes number of cylinders as a factor variable and weight as confounder. Give the adjusted estimate for the expected change in mpg comparing 8 cylinders to 4.

Your Answer		Score	Explanation
3.206			
• -6.071	~	1.00	
-4.256			
33.991			
Total		1.00 / 1.00	

### **Question Explanation**

```
fit <- lm(mpg ~ factor(cyl) + wt, data = mtcars)
summary(fit)$coef

## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 33.991 1.8878 18.006 6.257e-17
## factor(cyl)6 -4.256 1.3861 -3.070 4.718e-03
## factor(cyl)8 -6.071 1.6523 -3.674 9.992e-04
## wt -3.206 0.7539 -4.252 2.130e-04
```

Consider the mtcars data set. Fit a model with mpg as the outcome that includes number of cylinders as a factor variable and weight as a possible confounding variable. Compare the effect of 8 versus 4 cylinders on mpg for the adjusted and unadjusted by weight models. Here, adjusted means including the weight variable as a term in the regression model and unadjusted means the model without weight included. What can be said about the effect comparing 8 and 4 cylinders after looking at models with and without weight included?.

Your Answer	Score	Explanation
○ Holding weight constant, cylinder appears to have more of an impact on mpg than if weight is disregarded.		
Holding weight constant, cylinder appears to have less of an impact on mpg than if weight is disregarded.	<b>✓</b> 1.00	It is both true and sensible that including weight would attenuate the effect of number of cylinders on mpg.
Within a given weight, 8 cylinder vehicles have an expected 12 mpg drop in fuel efficiency.		
Including or excluding weight does not appear to change anything regarding the estimated impact of number of cylinders on mpg.		
Total	1.00 /	

### **Question Explanation**

```
fit1 <- lm(mpg ~ factor(cyl), data = mtcars)
fit2 <- lm(mpg ~ factor(cyl) + wt, data = mtcars)
summary(fit1)$coef</pre>
```

```
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 26.664
                         0.9718 27.437 2.688e-22
## factor(cyl)6 -6.921 1.5583 -4.441 1.195e-04
## factor(cyl)8 -11.564 1.2986 -8.905 8.568e-10
summary(fit2)$coef
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 33.991 1.8878 18.006 6.257e-17
## factor(cyl)6 -4.256 1.3861 -3.070 4.718e-03
## factor(cyl)8 -6.071
                         1.6523 -3.674 9.992e-04
                -3.206
## wt
                          0.7539 -4.252 2.130e-04
c(summary(fit1)$coef[3, 1], summary(fit2)$coef[3, 1])
## [1] -11.564 -6.071
```

Consider the mtcars data set. Fit a model with mpg as the outcome that considers number of cylinders as a factor variable and weight as confounder. Now fit a second model with mpg as the outcome model that considers the interaction between number of cylinders (as a factor variable) and weight. Give the P-value for the likelihood ratio test comparing the two models and suggest a model using 0.05 as a type I error rate significance benchmark.

# Your Answer The P-value is larger than 0.05. So, according to our criterion, we would fail to reject, which suggests that the interaction terms is necessary. The P-value is small (less than 0.05). So, according to our criterion, we reject, which suggests that the interaction term is necessary

The P-value is small (less than 0.05). Thus it is surely true that there is no interaction term in the true model.
The P-value is larger than 0.05. So, according to our criterion, we would fail to reject, which suggests that the interaction terms may not be necessary.
The P-value is small (less than 0.05). Thus it is surely true that there is an interaction term in the true model.
The P-value is small (less than 0.05). So, according to our criterion, we reject, which suggests that the interaction term is not necessary.

Total 1.00 / 1.00

### **Question Explanation**

```
fit1 <- lm(mpg ~ factor(cyl) + wt, data = mtcars)
fit2 <- lm(mpg ~ factor(cyl) * wt, data = mtcars)
summary(fit1)$coef</pre>
```

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

## (Intercept) 33.991 1.8878 18.006 6.257e-17

## factor(cyl)6 -4.256 1.3861 -3.070 4.718e-03

## factor(cyl)8 -6.071 1.6523 -3.674 9.992e-04

## wt -3.206 0.7539 -4.252 2.130e-04
```

### summary(fit2)\$coef

```
## (Intercept) 39.571 3.194 12.3895 2.058e-12
## factor(cyl)6 -11.162 9.355 -1.1932 2.436e-01
## factor(cyl)8 -15.703 4.839 -3.2448 3.223e-03
## wt -5.647 1.359 -4.1538 3.128e-04
## factor(cyl)6:wt 2.867 3.117 0.9197 3.662e-01
## factor(cyl)8:wt 3.455 1.627 2.1229 4.344e-02
```

```
anova(fit1, fit2)
```

```
## Analysis of Variance Table
```

Consider the mtcars data set. Fit a model with mpg as the outcome that includes number of cylinders as a factor variable and weight inlcuded in the model as

```
lm(mpg ~ I(wt * 0.5) + factor(cyl), data = mtcars)
```

How is the wt coefficient interpretted?

Your Answer	Score	Explanation
The estimated expected change in MPG per half ton increase in weight for the average number of cylinders.		
<ul> <li>The estimated expected change in MPG per half ton increase in weight for for a specific number of cylinders (4, 6, 8).</li> </ul>		
The estimated expected change in MPG per one ton increase in weight for a specific number of cylinders (4, 6, 8).	<b>✓</b> 1.00	
The estimated expected change in MPG per half ton increase in weight.		
The estimated expected change in MPG per one ton increase in weight.		
Total	1.00 / 1.00	

Consider the following data set

```
x <- c(0.586, 0.166, -0.042, -0.614, 11.72)
y <- c(0.549, -0.026, -0.127, -0.751, 1.344)
```

Give the hat diagonal for the most influential point

Your Answer		Score	Explanation
0.2287			
0.2025			
0.9946	~	1.00	
0.2804			
Total		1.00 / 1.00	

## **Question Explanation**

```
influence(lm(y \sim x))$hat
```

```
## 1 2 3 4 5
## 0.2287 0.2438 0.2525 0.2804 0.9946
```

```
## showing how it's actually calculated
xm <- cbind(1, x)
diag(xm %*% solve(t(xm) %*% xm) %*% t(xm))</pre>
```

## [1] 0.2287 0.2438 0.2525 0.2804 0.9946

# **Question 6**

Consider the following data set

```
x <- c(0.586, 0.166, -0.042, -0.614, 11.72)
y <- c(0.549, -0.026, -0.127, -0.751, 1.344)
```

Give the slope dfbeta for the point with the highest hat value.

Your Answer		Score	Explanation
-134	~	1.00	
0.673			
-0.378			
00134			
Total		1.00 / 1.00	

```
Question Explanation
```

```
influence.measures(lm(y ~ x))

## Influence measures of

## lm(formula = y ~ x) :

##

## dfb.1_ dfb.x dffit cov.r cook.d hat inf

## 1 1.0621 -3.78e-01 1.0679 0.341 2.93e-01 0.229 *

## 2 0.0675 -2.86e-02 0.0675 2.934 3.39e-03 0.244

## 3 -0.0174 7.92e-03 -0.0174 3.007 2.26e-04 0.253 *

## 4 -1.2496 6.73e-01 -1.2557 0.342 3.91e-01 0.280 *

## 5 0.2043 -1.34e+02 -149.7204 0.107 2.70e+02 0.995 *
```

# **Question 7**

Consider a regression relationship between Y and X with and without adjustment for a third variable Z. Which of the following is true about comparing the regression coefficient between Y and X with and without adjustment for Z.

Your Answer		Score	Explanation
It is possible for the coefficient to reverse sign after adjustment. For example, it can be strongly significant and positive before adjustment and strongly significant and negative after adjustment.	*	1.00	
For the the coefficient to change sign, there must be a significant interaction term.			
<ul> <li>Adjusting for another variable can only attenuate the coefficient toward zero. It can't materially change sign.</li> </ul>			
○ The coefficient can't change sign after adjustment, except for slight numerical pathological cases.			
Total		1.00 /	
		1.00	
Question Explanation			
See lecture 02_03 for various examples.			