



## Quiz 4

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1 / 1  
points

1.

Consider the space shuttle data `?shuttle` in the `MASS` library. Consider modeling the use of the autolander as the outcome (variable name `use`). Fit a logistic regression model with autolander (variable `auto`) use (labeled as "auto" 1) versus not (0) as predicted by wind sign (variable `wind`). Give the estimated odds ratio for autolander use comparing head winds, labeled as "head" in the variable `headwind` (numerator) to tail winds (denominator).



1.327



0.969

**Correct**

```
1 library(MASS)
2 data(shuttle)
3 ## Make our own variables just for illustration
4 shuttle$auto <- 1 * (shuttle$use == "auto")
5 shuttle$headwind <- 1 * (shuttle$wind == "head")
6 fit <- glm(auto ~ headwind, data = shuttle, family = binomial)
7 exp(coef(fit))
8
```

```
1 ## (Intercept)    headwind
2 ##      1.3273      0.9687
3
```

```
1 ## Another way without redefining variables
2 fit <- glm(relevel(use, "noauto") ~ relevel(wind, "tail"), data =
3 shuttle, family = binomial)
4 exp(coef(fit))
```

```
1 ##              (Intercept) relevel(wind, "tail")head
2 ##              1.3273      0.9687
```



-0.031



0.031

1 / 1  
points

2.

Consider the previous problem. Give the estimated odds ratio for autolander use comparing head winds (numerator) to tail winds (denominator) adjusting for wind strength from the variable magn.

☐ 0.684☐ 1.485☒ 0.969**Correct**

The estimate doesn't change with the inclusion of wind strength

```
1 shuttle$auto <- 1 * (shuttle$use == "auto")
2 shuttle$headwind <- 1 * (shuttle$wind == "head")
3 fit <- glm(auto ~ headwind + magn, data = shuttle, family = binomial)
4 exp(coef(fit))
5
```

```
1 ## (Intercept)    headwind  magnMedium    magnOut  magnStrong
2 ##      1.4852      0.9685      1.0000      0.6842      0.9376
3
```

```
1 ## Another way without redifing variables
2 fit <- glm(relevel(use, "noauto") ~ relevel(wind, "tail") + magn, data
3         = shuttle,
4         family = binomial)
5 exp(coef(fit))
6
```

```
1 ## (Intercept) relevel(wind, "tail")head
2 ##      1.4852      0.9685
3 ##      magnMedium      magnOut
4 ##      1.0000      0.6842
5 ##      magnStrong
6 ##      0.9376
```

☐ 1.001 / 1  
points

3.

If you fit a logistic regression model to a binary variable, for example use of the autolander, then fit a logistic regression model for one minus the outcome (not using the autolander) what happens to the coefficients?

- ☐ The intercept changes sign, but the other coefficients don't.
- ☐ The coefficients get inverted (one over their previous value).
- ☐ The coefficients change in a non-linear fashion.
- ☒ The coefficients reverse their signs.

**Correct**

Remember that the coefficients are on the log scale. So changing the sign changes the numerator and denominator for the exponent.



1 / 1  
points

4.

Consider the insect spray data `InsectSprays`. Fit a Poisson model using spray as a factor level. Report the estimated relative rate comparing spray A (numerator) to spray B (denominator).

- ☐ 0.321
- ☐ 0.136
- ☐ -0.056
- ☒ 0.9457

**Correct**

```
1 fit <- glm(count ~ relevel(spray, "B"), data = InsectSprays, family =
  poisson)
2 exp(coef(fit))[2]
```

```
1 ## relevel(spray, "B")A
2 ##                0.9457
```



1 / 1  
points

5.

Consider a Poisson glm with an offset,  $t$ . So, for example, a model of the form `glm(count ~ x + offset(t), family = poisson)` where  $x$  is a factor variable comparing a treatment (1) to a control (0) and  $t$  is the natural log of a monitoring time. What is impact of the coefficient for  $x$  if we fit the model `glm(count ~ x + offset(t2), family = poisson)` where  $2 <- \log(10) + t$ ? In other words, what happens to the coefficients if we change the units of the offset variable. (Note, adding  $\log(10)$  on the log scale is multiplying by 10 on the original scale.)



The coefficient estimate is unchanged



**Correct**

Note, the coefficients are unchanged, except the intercept, which is shifted by  $\log(10)$ . Recall that, except the intercept, all of the coefficients are interpreted as log relative rates when holding the other variables or offset constant. Thus, a unit change in the offset would cancel out. This is not true of the intercept, which is interpreted as the log rate (not relative rate) with all of the covariates set to 0.



The coefficient estimate is divided by 10.



The coefficient estimate is multiplied by 10.



The coefficient is subtracted by  $\log(10)$ .



1 / 1  
points

6.

Consider the data

```
1 x <- -5:5
2 y <- c(5.12, 3.93, 2.67, 1.87, 0.52, 0.08, 0.93, 2.05, 2.54, 3.87, 4.97)
```

Using a knot point at 0, fit a linear model that looks like a hockey stick with two lines meeting at  $x=0$ . Include an intercept term,  $x$  and the knot point term. What is the estimated slope of the line after 0?



2.037



-0.183



-1.024



1.013



**Correct**

```
1 z <- (x > 0) * x
2 fit <- lm(y ~ x + z)
3 sum(coef(fit)[2:3])
```

```
1 ## [1] 1.013
```