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Lecture 7c: Practice Problem Solutions

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Death in the ICU: Patients with Sepsis

1. Let's again consider the sample of 106 patients admitted to the ICU at a large U.S. hospital
   - All patients in sample had sepsis (blood infection) at time of admission to ICU; information was collected on whether a patient died while in the ICU, the patient's age at admission (range 17-94 years), and whether the patient was in shock at time of admission, and whether patient was suffering from malnutrition at time of admission
   - Now using malnutrition as the *x*, let's use logistic regression to relate death to malnutrition status

Death in the ICU: Patients with Sepsis

- Results from logistic regression using Stata

Variable	Estimated Coefficient	Standard Error
Malnutrition (1 = "yes")	1.21	0.05
Constant	-1.86	0.34

a) Using this result, estimate the odds ratio of death for patients who were malnourished (at the time of ICU admission) compared to patients who were not malnourished

Recall, the slope estimates the *ln odds ratio* of death for those with *x* value of 1 compared to those with an *x* value of 0; so to get the estimated odds ratio, we need to exponentiate: i.e.,

$$O\hat{R} = e^{1.21} \approx 3.5$$

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Constant	-1.86	0.34

b) What is the interpretation of the intercept in the above model? Does it potentially have scientific relevance?

Well, the intercept is the estimated *ln odds* of death for those with x = 0. In this case, this represents an actual group in our sample, those who were not malnourished at the time of ICU admission. The *ln odds* estimate is -1.86, so the resulting odds estimate is found by exponentiating: $\widehat{odds} = e^{-1.86} \approx .16.$ Note, this is not an odds ratio, just an odds for a single group—we'll see how to turn it into an estimated probability (proportion) in lecture 7e.

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c) Suppose we have coded the *x* as 1 if a patient was not malnourished, and 0 if the patient was malnourished; if we re-ran the logistic model what would the resulting slope and odds ratio be?

The slope would -1.21 and the resulting odds ratio estimate:

$$O\hat{R} = e^{-1.21} \approx 0.3 = \frac{1}{e^{1.21}}$$

Example: Breast Feeding Status and Age

2. Recall results from logistic regression using Stata relating breast feeding status to age for the sample of Nepali children < 36 months

Variable	Estimated Coefficient	Standard Error
Age of Child (mos)	-0.25	0.04
Constant	7.43	1.04

– In the lecture, we showed that the difference in breast feeding status between two groups of children who differed by more than one unit (month) in age was additive on the log odds scale:

$$ln(Odds of\ bf, x_1 = 24) - ln(Odds of\ bf, x_1 = 18) = 6\hat{\beta}_1$$

– This same difference was multiplicative on the odds ratio scale:

$$(0.78)^6 = .78 \times .78 \times .78 \times .78 \times .78 \times .78$$

Example: Breast Feeding Status and Age

a) What is the mathematical reason that quantities that are additive on the log scale are multiplicative when exponentiated?

The pure "mathplanation": $e^{(6\times\hat{\beta}_1)} = (e^{\hat{\beta}_1})^6 = (\hat{OR})^6$

Example: Breast Feeding Status and Age

b) What is a more "intuitive" explanation of why the odds ratio for a six-month difference in age involved multiplying the odds ratio for a one-month difference in age times itself six times?

Here's one thought: Suppose I line up the groups in descending order of age:

24

23

22

Etc.

Example: Breast Feeding Status and Age

b) What is a more "intuitive" explanation of why the odds ratio for a six-month difference in age involved multiplying the odds ratio for a one-month difference in age times itself six times?

Now input the odds ratio for the one month differences in age groups:

24

23 $\rightarrow \hat{OR}_{24\ to\ 23} = 0.78$

22 $\rightarrow \hat{OR}_{23\ to\ 22} = 0.78$

Etc.

Example: Breast Feeding Status and Age

b) What is a more "intuitive" explanation of why the odds ratio for a six-month difference in age involved multiplying the odds ratio for a one-month difference in age times itself six times?

Now compute the odds ratio for the two month difference; extend this reasoning to a six month difference!

24

$\hat{OR}_{24\ to\ 23} = 0.78$

23

$$\hat{OR}_{24\ to\ 22} = \hat{OR}_{24\ to\ 23} \times \hat{OR}_{23\ to\ 22} = .78 \times .78$$

$\hat{OR}_{23\ to\ 22} = 0.78$

22

Etc.