

# **Week Eleven**

## **Last Week**

- Exam Recap
- Probability Distributions for Count Data
- Count Regression

## **This Week: GLMs for Count Data & Multicategory data**

- Bike Data

## **Next Week: Multicategory Regression**

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## Multicategory Logit Models

Recall Logistic regression for binary data

$$Y \sim \text{Binomial}(n, \pi)$$
$$\text{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right) = X\beta$$

What is an example of multicategory data? Can we come up with both nominal and ordinal categories?

- What is a probability distribution that is appropriate for this setting? Multinomial(n,  $\pi$ )
- What are some predictors for this variable?
- Let's think about a GLM
  1.  $Y \sim \text{Multinomial}(n, \pi)$
  2. Linear combination (functional form)
  3. Link function

## Baseline-Category Logits

Let's arbitrarily set category J to be the baseline. Then we can define a baseline category logit as

$$\log \left( \frac{\pi_i}{\pi_J} \right)$$

this can be formulated in a model as

$$\log \left( \frac{\pi_i}{\pi_J} \right) = \alpha_i + \beta_j x$$

This approach requires  $J - 1$  equations; however, these equations can be used for any pair of categories

$$\log \left( \frac{\pi_a}{\pi_b} \right) = \log \left( \frac{\pi_a/\pi_J}{\pi_b/\pi_J} \right) = \log \left( \frac{\pi_a}{\pi_J} \right) - \log \left( \frac{\pi_b}{\pi_J} \right) = (\alpha_a + \beta_a x) - (\alpha_b + \beta_b x)$$

from which we can find coefficients ( $\alpha$  and  $\beta$  for this categories a and b)

- this can give us odds ratios between two categories
- We can also directly estimate  $\pi_j(x)$  for any set of covariates.

$$\pi_j = \frac{\exp(\alpha_j + \beta_j x)}{\sum_h \exp(\alpha_h + \beta_h x)},$$

where  $\alpha_h$  and  $\beta_h = 0$  for the reference category.

- Add curve here

## Ordinal Data

Now let's consider ordinal responses.

- With this scenario, we are often interested in cumulative probability, the probability that  $Y$  falls at or below a particular point

$$P(Y < J) = \pi_1 + \dots + \pi_J$$

$$\text{logit}[P(Y < J)] = \alpha_j + \beta x$$

note that  $\beta$  does not have a subscript here (fairly strong assumption).

add cumulative logit figure here

add category probability curve too

### **Latent variable interpretation**

A common way to think about (and formulate) ordinal models is with a latent variable approach.

Let  $Y$  be some continuous latent variable that has cut points that map to the ordinal values.

A common approach for this model is to assume the latent variable has a standard normal distribution, this results in what is referred to as a probit model.