

# Lesson 17: Wrap-up and other regressions

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# Animals of the day



# Today

- Let's zoom out a little and see what types of regressions we can do
- You should have the main tools to perform these regressions
  - Each has some nuances, but I'll give you sources that help walk you through them

# Types of regressions

Dist'n of Y	Typical uses	Link name	Link function	Common name
<u>Normal</u> 5/2	Linear-response data	Identity	$g(\mu) = \mu$	Linear regression
<u>Bernoulli / Binomial</u> 5/3	outcome of single yes/no occurrence	Logit	$g(\mu) = \text{logit}(\mu)$	Logistic regression
Poisson 5/3	count of occurrences in fixed amount of time/space	Log	$g(\mu) = \log(\mu)$	Poisson regression
<u>Bernoulli / Binomial</u>	outcome of single yes/no occurrence	Log	$g(\mu) = \log(\mu)$	Log-binomial regression
Multinomial	outcome of single occurrence with $K > 2$ options, <i>nominal</i>	Logit	$g(\mu) = \text{logit}(\mu)$	Multinomial logistic regression
Multinomial	outcome of single occurrence with $K > 2$ options, <i>ordinal</i>	Logit	$g(\mu) = \text{logit}(\mu)$	Ordinal logistic regression



# Linear regression

- **Outcome type:** continuous
- **Example outcomes:**
  - Height
  - IAT score
  - Heart rate

- **Population model**

$$\underline{E(Y | X)} = \underline{\mu} = \underline{\beta_0 + \beta_1 X}$$

↓  
sys

- **Interpretations**
  - The change in average  $Y$  for every 1 unit increase in  $X$

# Linear regression resources

- 512/612 class site!!
- [Online textbook by Dr. Nahhas](#)

# Logistic regression

- **Outcome type:** binary, yes or no

- **Example outcomes:**

- Food insecurity —
- Disease diagnosis for patient —
- Fracture —

- **Population model**

$$\log\left(\frac{\mu}{1-\mu}\right)$$
$$\text{logit}(\mu) = \beta_0 + \beta_1 X$$

SYS

- **Interpretations**

- The  $\beta_1$  log-odds ratio for every 1 unit increase in  $X$

# Logistic regression resources

- [Online textbook by Dr. Nahhas](#)

# Poisson Regression

- **Outcome type:** Counts or rates

- **Example outcomes:**

- Number of children in household
- Number of hospital admissions
- Rate of incidence for COVID in US counties

- **Population model**

$$\log(\mu) = \beta_0 + \beta_1 X$$

- **Interpretations**

- The count (or rate) ratio for every 1 unit increase in  $X$

$\exp(\beta_1)$

$\beta_1$ : log count ratio

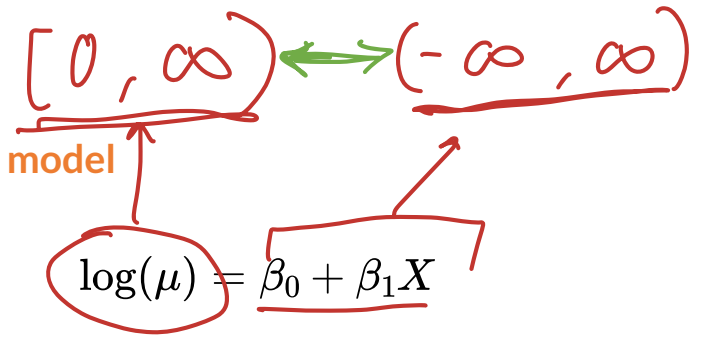
# Poisson Regression resources

- [PennState 504 website](#)
- [Online textbook by Dr. Nahhas](#)
- [YouTube video on R tutorial for Poisson Regression](#)
  - Dr. Fogerty is a professor in Political Science, so just beware they may not have formal statistical training
- [Guided R tutorial page on Poisson regression](#)
- [Online textbook by Dr. Werth](#)
  - Social scientist, so just beware they may not have formal statistical training

# Log-binomial Regression

- **Outcome type:** binary, yes or no
- **Example outcomes:**
  - Food insecurity
  - Disease diagnosis for patient
  - Fracture

- **Population model**



- **Interpretations**

- We have log of probability on the left
- So exponential of our coefficients will be **risk ratio**


log risk ratio

$$\beta_1 = \log(P(Y | X = x+1)) - \log(P(Y | X = x))$$

$$\beta_1 = \log\left(\frac{P(Y | X = x+1)}{P(Y | X = x)}\right)$$



# Log-binomial Regression resources

- Online textbook by Dr. Nahhas 
- Article on `logbin` package that is used to fit log-binomial regression

# Multinomial logistic regression

- **Outcome type:** multi-level categorical, no inherent order
- **Example outcomes:**
  - Blood type
  - US region (from WBNS)
  - Primary site of lung cancer (upper lobe, lower lobe, overlapped, etc.)
- We have additional restriction that the multiple group probabilities sum to 1

$$P(Y=0) + P(Y=1) + P(Y=2) = 1$$

- **Population models**

$$\log \left( \frac{\mu_{\text{group 2}}}{\mu_{\text{group 1}}} \right) = \beta_0 + \beta_1 X$$

$$\log \left( \frac{\mu_{\text{group 3}}}{\mu_{\text{group 1}}} \right) = \beta_0 + \beta_1 X$$

gp 3 vs gp 2

- **Interpretations**

- Basically fitting two binary logistic regressions at same time!
- First equation: how a one unit change in X changes the log-odds of going from group 1 to group 2
- Second equation: how a one unit change in X changes the log-odds of going from group 1 to group 3

$$\text{logit}(\mu_{gp2}) \rightarrow \log \left( \frac{\mu_{gp2}}{1 - \mu_{gp2}} \right)$$

3 gps

# Multinomial logistic regression resources

- [YouTube video on R tutorial for Poisson Regression](#)
  - Again, Dr. Fogerty is a professor in Political Science
- [R-bloggers post with guided R code](#)
- [Online textbook by Dr. Werth with data and R script](#)

# Ordinal logistic regression

- **Outcome type:** multi-level categorical, with inherent order

- **Example outcomes:**

- Satisfaction level (likert scale)
- Pain level
- Stages of cancer

$$\log \left( \frac{P(Y \leq -3)}{P(Y > -3)} \right)$$

$$\log \left( \frac{P(Y \leq 3)}{P(Y > 3)} \right)$$

- **Population models**, with levels  $k = 1, 2, 3, \dots, K$

$$\log \left( \frac{P(Y \leq 1)}{P(Y > 1)} \right) = \beta_0 + \beta_1 X$$

$$\log \left( \frac{P(Y \leq k)}{P(Y > k)} \right) = \alpha_0 + \alpha_1 X$$

- When these variables are predictors, we are pretty lenient about treating them as continuous
  - We must be VERY STRICT when they are outcomes
  - They do not meet the assumptions we place on continuous outcomes in linear regression!!
- We have additional restriction that the multiple group probabilities sum to 1

- **Interpretations**

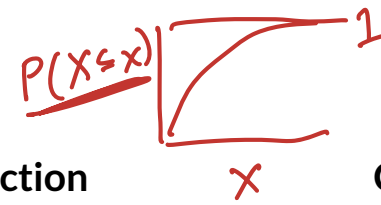
- Basically fitting  $K$  binary logistic regressions at same time!
- First equation: how a one unit change in  $X$  changes the log-odds of going from group 1 to any other group

*ratio of*
- Second equation: how a one unit change in  $X$  changes the log-odds of going from group 1 or 2 to group 3 or above

# Ordinal logistic regression resources

- [Online textbook by Dr. Nahhas](#)
- [Online textbook by Dr. Werth with data and R script](#)

## Even more regressions...



Dist'n of Y	Typical uses	Link name	Link function	Common name
<u>Bernoulli / Binomial</u>	outcome of single yes/no occurrence	<u>Probit</u>	$g(\mu) = \Phi^{-1}(\mu)$ <i>inverse CDF</i>	Probit regression
<u>Bernoulli / Binomial</u>	outcome of single yes/no occurrence	<u>Complementary log-log</u>	$g(\mu) = \log(-\log(1 - \mu))$	Complementary log-log regression
<u>Multinomial</u>	outcome of single occurrence with $K > 2$ options, <i>nominal</i>	Probit	$g(\mu) = \Phi^{-1}(\mu)$	Multinomial probit regression
<u>Multinomial</u>	outcome of single occurrence with $K > 2$ options, <i>ordinal</i>	Probit	$g(\mu) = \Phi^{-1}(\mu)$	Ordered probit regression

# More regression resources

- Probit regression
- Complementary log-log
- Multinomial probit
- Ordered probit



## General resources

- Dr. Fogerty's YouTube series
- Dr. Werth's Categorical Book
- Dr. Nahhas' Book
- The Epidemiologist R Handbook
  - Analysis AND R work *Biostatisticians*

# Moment of appreciation for your growth

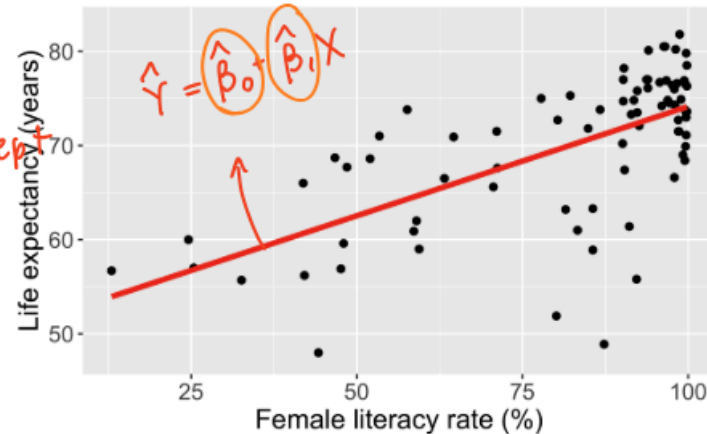
- Remember when we were learning simple linear regression...
- This was a slide from our second week together:

## Regression line = best-fit line

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X$$

- $\hat{Y}$  is the predicted outcome for a specific value of  $X$
- $\hat{\beta}_0$  is the intercept of the best-fit line → estimated intercept
- $\hat{\beta}_1$  is the slope of the best-fit line, i.e., the increase in  $\hat{Y}$  for every increase of one (unit increase) in  $X$ 
  - slope = rise over run

Relationship between life expectancy and the female literacy rate in 2011



- Even if you don't feel like you learned everything, you have learned a lot from the first time you saw the above slide

