

# What to do today (Feb 6)?

1. *Introduction and Preparation*

## 2. **Analysis with Binary Variables (Chp1-2)**

- ▶ *2.1 Analysis with binary variables I (Chp 1)*
- ▶ **2.2 Analysis with binary response (Chp 2)**
  - ▶ *2.2.1 Regression models (Chp2.1, Chp2.2.1)*
  - ▶ *2.2.2 Simple logistic regression analysis (Chp2.2.2-7)*
  - ▶ **2.2.3 Multiple logistic regression analysis (Chp2.2.2-7)**
- ▶ **2.3 Generalized linear models (Chp2.3)**

3. *Analysis with Multicategory Variables (Chp3)*

## 2.2.3C Interactions and transformations of predictors

**When to consider two predictors  $X_1, X_2$**

the logistic regression model I:

$$\text{logit}[\pi(x_1, x_2)] = \log \left[ \frac{\pi(x_1, x_2)}{1 - \pi(x_1, x_2)} \right] = \alpha + \beta_1 x_1 + \beta_2 x_2$$

- ▶ **What if the interaction of  $X_1, X_2$  is of interest?**  $\implies$  to add the term for  $X_3 = X_1 X_2$  to the model:

$$\text{logit}[\pi(x_1, x_2)] = \log \left[ \frac{\pi(x_1, x_2)}{1 - \pi(x_1, x_2)} \right] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2$$

- ▶ **What if the effect of  $h(X_2)$  is of interest, instead of  $X_2$ ?**  $\implies$  to replace  $X_2$  with  $X_2^* = h(X_2)$  in to the model:

$$\text{logit}[\pi(x_1, x_2)] = \log \left[ \frac{\pi(x_1, x_2)}{1 - \pi(x_1, x_2)} \right] = \alpha + \beta_1 x_1 + \beta_2 h(x_2)$$

## 2.2.3D Qualitative explanatory variables

**Example.** AZT Use and AIDS (NY Times, 1991): a clinical trial with  $n=338$  HIV infected subjects

Race	AZT Use	AIDS Symptoms	
		yes	no
white	yes	14	93
	no	32	81
black	yes	11	52
	no	12	43

- ▶ binary response  $Y$ : AIDS developed or not
- ▶ two factors  $X = \text{AZT Use}$ : received immediately or not, and  $Z = \text{Race}$ : white or black
- ▶ multiple logistic model:  $\text{logit}[\pi(x, z)] = \alpha + \beta_1 X + \beta_2 Z$

## Multiple logistic regression model:

$$\text{logit}[\pi(x, z)] = \alpha + \beta_1 X + \beta_2 Z$$

$\Leftrightarrow \pi(x, z) = \pi(i, k)$ ,  $i = 1, 2$  and  $k = 1, 2$ :

**ANOVA Representation**  $\text{logit}[\pi(i, k)] = \alpha + \beta_i^X + \beta_k^Z$

- ▶ Coding Scheme I (eg. SAS):  $\beta_1^X = \beta_1$ , the coef to  $X$ ;  $\beta_2^X = 0$ ;  
The log OR of AIDS with AZT use vs not is  $\beta_1^X - \beta_2^X = \beta_1$ .
- ▶ Coding Scheme II (eg. R):  $\beta_1^X = 0$  and  $\beta_2^X = \beta_1$ , the coef to  $X$ ;  
The log OR of AIDS with AZT use vs not is  $\beta_1^X - \beta_2^X = -\beta_1$ .
- ▶ Coding Scheme III (eg. ANOVA-type):  $\beta_1^X = -\beta_2^X \Leftrightarrow$   
 $\beta_1^X + \beta_2^X = 0$ , and  $\beta_1^X = \beta_1$ , the coef to  $X$ ;  
The log OR of AIDS with AZT use vs not is  $\beta_1^X - \beta_2^X = 2\beta_1$ .

If consider two factor interactions ... ..

### Multiple logistic regression model:

$$\text{logit}[\pi(x, z)] = \alpha + \beta_1 X + \beta_2 Z + \beta_{12} XZ$$

$\pi(x, z) = P(Y = 1|X = x, Z = z) \Leftrightarrow \pi(x, z) = \pi(i, k), i = 1, 2$   
and  $k = 1, 2$ :

### ANOVA Representation

$$\text{logit}[\pi(i, k)] = \alpha + \beta_i^X + \beta_k^Z + \beta_{ik}^{XZ}$$

## 2.2.3E Example of the crab study (cont'd)

### Revisit II: A multiple logistic regression analysis

- ▶ Using Color and Width Predictors –  $X_1 = \text{width}$ ,  $X_2 = \text{color}$ : (a surrogate for age) light (not sampled), medium light, medium, medium dark, dark:
  - ▶  $X_{21} = 1$  for medium, = 0 otherwise
  - ▶  $X_{22} = 1$  for medium dark, = 0 otherwise
  - ▶  $X_{23} = 1$  for dark, = 0 otherwise
- ▶ Consider  $\text{logit}(\pi) = \alpha + \beta_1 x_1 + \beta_{21} x_{21} + \beta_{22} x_{22} + \beta_{23} x_{23}$
- ▶ For  $x_1 = 26.3$ , a medium-light crab's predicted probability is  $\hat{\pi}(26.3, 0, 0, 0) = .715$  and 95% CI (.392, .908):

- ▶ calculate 95% CI for  $\text{logit}(\pi) = \alpha + \beta_1 26.3$ :

$$(\hat{\alpha} + \hat{\beta}_1 26.3) \pm 1.96 * \sqrt{\hat{\text{var}}(\hat{\alpha}) + \hat{\text{var}}(\hat{\beta}_1) * 26.3^2 + 2\hat{\text{cov}}(\hat{\alpha}, \hat{\beta}_1) * 26.3}$$

$$\implies (-.44, 2.28)$$

- ▶ calculate 95% CI for  $\pi$ :

$$\left( \frac{e^{-.44}}{1 + e^{-.44}}, \frac{e^{2.28}}{1 + e^{2.28}} \right) = (.392, .908)$$

## Revisit II: A multiple logistic regression analysis – using the regression outcome

- ▶ For  $x_1 = 26.3$  (average width) and a medium-light crab, its odds is  $.715/.285 = 2.51$
- ▶ For  $x_1 = 26.3$  and a dark crab, its prob of having satellites is  $.399$  and odds is  $.399/(1 - .399) = 0.66$
- ▶ The odds ratio of having satellites for medium-light vs dark crabs with average width is  $2.51/.66 = 3.8$   
⇒ a dark crab of average width is less likely than a medium-light crab to have satellites.

## Revisit II: An alternative multiple logistic regression analysis (Quantitative Treatment of the Ordinal Predictor, color)

$color = x_2 = 1, 2, 3, 4$  for the color categories and fit  
 $logit(\pi) = \alpha + \beta_1 x_1 + \beta_2 x_2$

- ▶ using the regression outcome  
The estm for  $\beta_1$  and  $\beta_2$  along with their ASE values show strong evidence of an effect for each.
- ▶ goodness-of-it?

**to add in more predictors? how about two predictors'  
interactions**

### Revisit III: Model selection (Backward Elimination)

Consider the multiple logistic regression with different sets of predictors:

Model	Predictors	Deviance	DF	AIC	Models Compared	Deviance Difference
1	C * S + C * W + S * W	173.7	155	209.7	-	-
2	C + S + W	186.6	166	200.6	(2)-(1)	12.9 (df = 11)
3a	C + S	208.8	167	220.8	(3a)-(2)	22.2 (df = 1)
3b	S + W	194.4	169	202.4	(3b)-(2)	7.8 (df = 3)
3c	C + W	187.5	168	197.5	(3c)-(2)	0.9 (df = 2)
4a	C	212.1	169	220.1	(4a)-(3c)	24.6 (df = 1)
4b	W	194.5	171	198.5	(4b)-(3c)	7.0 (df = 3)
5	C = dark + W	188.0	170	194.0	(5)-(3c)	0.5 (df = 2)
6	None	225.8	172	227.8	(6)-(5)	37.8 (df = 2)

C=color; S=spine condition; W=width.

Note: A strong linear correlation between width and weight: sample corr=0.887.

So weight is not included.

**To be studied in Chp 5 systematically.**

## 2.3A Generalized linear models: Introduction

- ▶ Ordinary Linear Regression Models (OLM)

To study  $Y \leftarrow X, Z$ ? with continuous response  $Y$  and two explanatory variables:  $Y = \alpha + \beta X + \gamma Z + \eta XZ + \epsilon$  with  $E(\epsilon) = 0$  and  $V(\epsilon) = \sigma^2$

- ▶ *R*: `glmout <- glm(Y~X*Z, family=gaussian)`

- ▶ Logistic Regression Models (Logit)

To study  $Y \leftarrow X, Z$ ? with binary response  $Y = 1$ , or 0:

$\text{logit}[\pi(x, z)] = \alpha + \beta X + \gamma Z + \eta XZ$  with

$P(Y = 1|X = x, Z = z) = \pi(x, z)$  and

$Y \sim \text{Bernoulli}(\pi(x, z))$

- ▶ *R*: `glmout <- glm(Y~X*Z, family=binomial)`

## 2.3B Generalized linear models: Components

**What common features in the examples of regression models, OLM, Logit?** Recall how to conduct the analysis with  $R$ :  
 $glm(formula, family) \implies$

**GOAL:** to study how  $Y \leftarrow X_1, \dots, X_K$

### Generalized Linear Models:

- ▶ **Random Component.** response r.v.  $Y$  with  $\mu(x_1, \dots, x_k) = E(Y|x_1, \dots, x_k)$  to be examined
- ▶ **Systematic Component.**  $\alpha + \beta_1 x_1 + \dots + \beta_K x_K$   
Some  $x_k$  can be based on others: e.g.  $x_3 = x_1 x_2$ .
- ▶ **Link Function.**  $g(\mu) = \alpha + \beta_1 x_1 + \dots + \beta_K x_K$   
The link function  $g(\cdot)$  links the *random component* through its mean and the *systematic component*. **More on GLM later**

## What will we study next?

- 1. Introduction and Preparation*
- 2. Analysis with Binary Variables (Chp1-2)*
- 3. Analysis with Multicategory Variables (Chp 3)**
  - ▶ 3.1 Revisit to Analysis with Contingency Table (Chp 3.1-2)**
    - ▶ 3.1.1 Review of two-way contingency tables**
    - ▶ 3.1.2 Analysis of  $I \times J$  contingency table**
    - ▶ 3.1.3 Multi-way contingency tables (supplementary)**
  - ▶ 3.2 Analysis with Multicategory Response (Chp 3.3-5)**