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## Exercises

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### 1. binomial logit

for the following data ( $X$  group variable)

	$Y$	
	0	1
$X$	$x_1$	$n_{11}$ $n_{12}$
	$\vdots$	
	$x_J$	$n_{J1}$ $n_{J2}$

a) write a binary regression model

*solution:*

general:

$$\log(\mathbb{P}(y = j | x) / \mathbb{P}(y = 1 | x)) = \alpha_j + \sum_{i=1}^I \beta_{ij} I(x \in \text{group}(i))$$
$$\alpha_1 = \beta_{1j} = \beta_{i1} = 0$$

binomial ( $j = 0, 1$ ):

$$\text{logit}(\mathbb{P}(y = 1 | x)) = \alpha + \sum_{i>1}^I \beta_i I(x \in \text{group}(i))$$

or

$$\mathbb{P}(y | x) = \begin{cases} \frac{\exp \alpha + \sum_{i>1}^I \beta_i I(x \in \text{group}(i))}{1 + \exp \alpha + \sum_{i>1}^I \beta_i I(x \in \text{group}(i))} & \text{for } y = 1 \\ \frac{1}{1 + \exp \alpha + \sum_{i>1}^I \beta_i I(x \in \text{group}(i))} & \text{for } y = 0 \end{cases}$$

b) interpret the regression coefficients for the logit model

*solution:*

general

$$\beta_{ij} = \underbrace{\text{logit}(\mathbb{P}(y = j | \text{group}(i)))}_{\alpha_j + \beta_{ij}} - \underbrace{\text{logit}(\mathbb{P}(y = 1 | \text{group}(1)))}_{\alpha_j}$$
$$= \log \left( \frac{\mathbb{P}(y = j | \text{group}(i)) / \mathbb{P}(y = 1 | \text{group}(i))}{\mathbb{P}(y = j | \text{group}(1)) / \mathbb{P}(y = 1 | \text{group}(1))} \right)$$

binomial ( $j = 0, 1$ ):

$$\beta_i = \underbrace{\text{logit}(\mathbb{P}(y = 1 \mid \text{group}(i)))}_{\alpha + \beta_i} - \underbrace{\text{logit}(\mathbb{P}(y = 1 \mid \text{group}(1)))}_{\alpha}$$

$$= \log \left( \frac{\mathbb{P}(y = 1 \mid \text{group}(i)) / \mathbb{P}(y = 0 \mid \text{group}(i))}{\mathbb{P}(y = 1 \mid \text{group}(1)) / \mathbb{P}(y = 0 \mid \text{group}(1))} \right)$$

in short form

$$\beta_i = \log \frac{p_{1|i} / p_{0|i}}{p_{1|1} / p_{0|1}}$$

c) write an equivalent log-linear model

*solution:*

$$\log \mu_{ij} = \mu_0 + \alpha_i + \beta_j + (\alpha\beta)_{ij}$$

$$\alpha_1 = \beta_1 = (\alpha\beta)_{1j} = (\alpha\beta)_{i1} = 0$$

equivalence

$$\mu_{ij} = \mu p_{ij}$$

$$\mu = \sum_{ij} \mu_{ij}$$

$\Rightarrow$

$$\text{logit} p_{2/i} = \log \frac{p_{2/i}}{p_{1/i}} = \log \frac{p_{i2}}{p_{i1}} = \log \frac{\mu_{2i}}{\mu_{1i}} = \alpha_2 + \beta_j + (\alpha\beta)_{2j} - \beta_j = \alpha_2 + (\alpha\beta)_{2j}$$

$\Rightarrow$

$$\log \frac{p_{2j}}{p_{1j}} - \log \frac{p_{21}}{p_{11}} = (\alpha\beta)_{2j}$$

$\Rightarrow$

$$(\alpha\beta)_{2j} = \log \left( \frac{\mathbb{P}(y = 1 \mid \text{group}(j)) / \mathbb{P}(y = 0 \mid \text{group}(j))}{\mathbb{P}(y = 1 \mid \text{group}(1)) / \mathbb{P}(y = 0 \mid \text{group}(1))} \right)$$

d) compare the coefficients for the log-linear and for the logit model

*solution:*

$$\log \mu_{ij} = \mu_0 + \alpha_i + \beta_j + (\alpha\beta)_{ij}$$

$$\alpha_1 = \beta_1 = (\alpha\beta)_{1j} = (\alpha\beta)_{i1} = 0$$

hence (see manuscript)

$$\begin{aligned}\log(p_{j|i} / p_{1|i}) &= \alpha_j^* + \beta_{ij}^* \\ \alpha_j^* &= \beta_j \\ \beta_{ij}^* &= (\alpha\beta)_{ij}\end{aligned}$$

special case binomial( $j = 0, 1$ )

$$\log(p_{1|i} / p_{0|i}) = \text{logit} p_{1|i} = \alpha^* + \beta_i^*$$

with  $\text{logit}(p_{j|i}) - \text{logit}(p_{j|1}) = \beta_i^*$

## 2. continuous regressors multinomial logit

For the following data

case	age( $x^{(1)}$ )	inc( $x^{(2)}$ )	cat1( $y^{(1)}$ )	cat2( $y^{(2)}$ )	cat3( $y^{(3)}$ )
1	$x_1^{(1)}$	$x_1^{(2)}$	$y_1^{(1)}$	$y_1^{(2)}$	$y_1^{(3)}$
2	$x_2^{(1)}$	$x_2^{(2)}$	$y_2^{(1)}$	$y_2^{(2)}$	$y_2^{(3)}$
$\vdots$					
$I$	$x_I^{(1)}$	$x_I^{(2)}$	$y_I^{(1)}$	$y_I^{(2)}$	$y_I^{(3)}$

a) specify multinomial reg and interpret the regression coefficients

*solution:*

$$\mathbb{P}(y = j | x^{(1)}, x^{(2)}) = \begin{cases} \frac{\exp(\alpha_j + \beta_j^{(1)} x^{(1)} + \beta_j^{(2)} x^{(2)})}{1 + \sum_{k>1} \exp(\alpha_k + \beta_k^{(1)} x^{(1)} + \beta_k^{(2)} x^{(2)})} & \text{if } j > 1 \\ \frac{1}{1 + \sum_{k>1} \exp(\alpha_k + \beta_k^{(1)} x^{(1)} + \beta_k^{(2)} x^{(2)})} & \text{if } j = 1 \end{cases}$$

or, alternatively as log-odds-ratio

$$\log \frac{\mathbb{P}(y = j | x^{(1)}, x^{(2)})}{\mathbb{P}(y = 1 | x^{(1)}, x^{(2)})} = \alpha_j + \beta_j^{(1)} x^{(1)} + \beta_j^{(2)} x^{(2)}$$

more generally

$$\mathbb{P}(y = j | x^{(1)}, x^{(2)}) = \begin{cases} \frac{\exp(\alpha_j + \sum_i \beta_j^{(i)} x^{(i)})}{1 + \sum_{k>1} \exp(\alpha_k + \sum_i \beta_k^{(i)} x^{(i)})} & \text{if } j > 1 \\ \frac{1}{1 + \sum_{k>1} \exp(\alpha_k + \sum_i \beta_k^{(i)} x^{(i)})} & \text{if } j = 1 \end{cases}$$

b) write log-likelihood function.

*solution:* Introduce notation  $d_{ij} = I(y_i = j)$   
 $\implies$

$$L(\alpha, \beta) = \prod_{i=1}^n \prod_{j=1}^J \mathbb{P}\left(y_i = j \mid x_i^{(1)}, x_i^{(2)}\right)^{d_{ij}}$$

$$= \frac{\prod_{i=1}^n \prod_{j=1}^J \exp\left(\alpha_j + \sum_i \beta_j^{(i)} x_i^{(i)}\right)^{d_{ij}}}{\left(1 + \sum_{k>1} \exp\left(\alpha_k + \sum_i \beta_k^{(i)} x_i^{(i)}\right)\right)^n}$$

with  $\alpha_1 = \beta_1^{(i)} = 0$   
 $\implies$

$$\log L(\alpha, \beta) = \sum_i^n \sum_j^n d_{ij} \left( \alpha_j + \sum_i \beta_j^{(i)} x_i^{(i)} \right) - n \log \left( 1 + \sum_{k>1} \exp \left( \alpha_k + \sum_i \beta_k^{(i)} x_i^{(i)} \right) \right)$$

c) write likelihood-ratio test for hypothesis of age independence of cat  
 $df_{full} = 3(J - 1)$ ,  $df_{red} = 2(J - 1)$

### 3 multinomial for aggregate data (contingency table)

for the following data:

age-group	cat1( $y^{(1)}$ )	cat2( $y^{(2)}$ )	cat3( $y^{(3)}$ )
1	$y_1^{(1)}$	$y_1^{(2)}$	$y_1^{(3)}$
2	$y_2^{(1)}$	$y_2^{(2)}$	$y_2^{(3)}$
$\vdots$			
$I$	$y_I^{(1)}$	$y_I^{(2)}$	$y_I^{(3)}$

a) specify multinomial reg model and interpret the coefficients:

*solution:* specify multinomial reg on indicator functions  $x^{(i)} = I(\text{observation} \in \text{group}(i))$

$$\mathbb{P}\left(y = j \mid x^{(2)}, \dots, x^{(I)}\right) = \begin{cases} \frac{\exp\left(\alpha_j + \sum_{i>1} \beta_j^{(i)} x_i^{(i)}\right)}{1 + \sum_{k>1} \exp\left(\alpha_k + \sum_{i>1} \beta_k^{(i)} x_i^{(i)}\right)} & \text{if } j > 1 \\ \frac{1}{1 + \sum_{k>1} \exp\left(\alpha_k + \sum_{i>1} \beta_k^{(i)} x_i^{(i)}\right)} & \text{if } j = 1 \end{cases}$$

or, in ANOVA-notation  $\left(\beta_j^{(i)} x_i^{(i)} = \beta_{ij}, \beta_{1j} = 0\right)$

$$\mathbb{P}(y = j \mid \text{group}(i)) = \begin{cases} \frac{\exp(\alpha_j + \beta_{ij})}{1 + \sum_{k>1} \exp(\alpha_k + \beta_{ik})} & \text{if } j > 1 \\ \frac{1}{1 + \sum_{k>1} \exp(\alpha_k + \beta_{ik})} & \text{if } j = 1 \end{cases}$$

or, alternatively as log-odds-ratio

$$\log \frac{\mathbb{P}(y = j \mid \text{group}(i))}{\mathbb{P}(y = 1 \mid \text{group}(i))} = \alpha_j + \beta_{ij}$$

$$\alpha_1 = \beta_{1j} = \beta_{i1} = 0$$

or, as odds-ratio:

$$\log \frac{\mathbb{P}(y = j \mid \text{group}(i))}{\mathbb{P}(y = 1 \mid \text{group}(i))} - \log \frac{\mathbb{P}(y = j \mid \text{group}(1))}{\mathbb{P}(y = 1 \mid \text{group}(1))} = \beta_{ij}$$

hence

$$\beta_{ij} = \log \left( \frac{\mathbb{P}(y = j \mid \text{group}(i))}{\mathbb{P}(y = 1 \mid \text{group}(i))} \bigg/ \frac{\mathbb{P}(y = j \mid \text{group}(1))}{\mathbb{P}(y = 1 \mid \text{group}(1))} \right)$$

(see `mlogit` in STATA [R])

**b)** write likelihood function

*solution:* see notes on multinomial regression.

**c)** write likelihood-ratio test for hypothesis of age-group independenc of cat

#### 4. multinomial output

Interpreting output from a multinomial logit model  
according to the data

	x			
y	A	B	C	D
Y1	9	8	4	4
Y2	4	13	9	3
Y3	7	3	10	5
Y4	5	1	2	13

consider the model

$$\mathbb{P}(Y = j \mid x = k) = \begin{cases} \frac{1}{1 + \sum_{j=2}^J \exp(\alpha_j + \beta_{jk})} & \text{for } j = 1 \\ \frac{\exp(\alpha_j + \beta_{jk})}{1 + \sum_{j=2}^J \exp(\alpha_j + \beta_{jk})} & \text{for } 1 < j \leq J \end{cases} \quad \text{with } \alpha_1 = \beta_{j1} = 0$$

$$\log \frac{\mathbb{P}(Y = j | x = k)}{\mathbb{P}(Y = 1 | x = k)} = \begin{cases} \alpha_j + \beta_{jk} & \text{if } k > 1 \\ \alpha_j & \text{if } k = 1 \end{cases}$$

hence

$$\beta_{jk} = \begin{cases} \log \frac{p_{jk}}{p_{1k}} / \log \frac{p_{j1}}{p_{11}} & \text{if } 1 < j \leq J, 1 < k \leq K \\ 0 & \text{if } j = 1 \end{cases}$$

and

$$\alpha_j = \begin{cases} \log \frac{p_{j1}}{p_{11}} & \text{if } 1 < j \leq J \\ 0 & \text{if } j = 1 \end{cases}$$

obtain estimates

multinom(formula = y ~x)

Coefficients:

	(Intercept)	xB	xC	xD
Y2	-0.81	1.30	1.62	0.52
Y3	-0.25	-0.73	1.17	0.47
Y4	-0.59	-1.49	-0.11	1.77

Std. Errors:

	(Intercept)	xB	xC	xD
Y2	0.60	0.75	0.85	0.97
Y3	0.50	0.84	0.78	0.84
Y4	0.56	1.20	1.03	0.80

Residual Deviance: 243

means

$$\mathbb{P}(Y = Y4 | x = xD) = \frac{\exp(-0.59 + 1.77)}{1 + \exp(-0.81 + 0.52) + \exp(-0.25 + 0.47) + \exp(-0.59 + 1.77)} = 0.52081$$

$$\frac{\mathbb{P}(Y = Y4 | x = xA)}{\mathbb{P}(Y = Y1 | x = xA)} = \exp(-0.59)$$

$$\frac{\mathbb{P}(Y = Y4 | x = xD)}{\mathbb{P}(Y = Y1 | x = xD)} = \underbrace{\exp(1.77)}_{5.8709} \frac{\mathbb{P}(Y = Y4 | x = xA)}{\mathbb{P}(Y = Y1 | x = xA)}$$

fitted values

	XA	XB	XC	XD
Y1	0.36	0.32	0.16	0.16
Y2	0.16	0.52	0.36	0.12
Y3	0.28	0.12	0.40	0.20
Y4	0.20	0.04	0.08	0.52

check:  $p_{44} = 0.52\dots$

$$(52/20) / (16/36) = 5.85 = (p_{44}/p_{14}) / (p_{41}/p_{11}) = \exp(\beta_{44})$$

$$p_{41}/p_{11} = 20/36 = 0.555\ 56 = \exp(-0.59)$$

true values:

	[,1]	[,2]	[,3]	[,4]
[1,]	0.4	0.2	0.2	0.2
[2,]	0.2	0.4	0.2	0.2
[3,]	0.2	0.2	0.4	0.2
[4,]	0.2	0.2	0.2	0.4

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