

# EXERCISE 2 (exam practice)

$$n=30 \quad (y_1, \dots, y_{10}, y_{11}, \dots, y_{30})$$

$$x_i = \begin{cases} 1 & i=1, \dots, 10 \\ 0 & i=11, \dots, 30 \end{cases}$$

$$Y_i \sim \text{Ber}(\pi_i) \quad \text{logit}(\pi_i) = \beta_1 + \beta_2 x_i$$

$$\Leftrightarrow \log \frac{\pi_i}{1-\pi_i} = \beta_1 + \beta_2 x_i \quad \Leftrightarrow \pi_i = \frac{e^{\beta_1 + \beta_2 x_i}}{1 + e^{\beta_1 + \beta_2 x_i}}$$

$$a) \quad p(y_i; \pi_i) = \pi_i^{y_i} (1-\pi_i)^{1-y_i}$$

$$p(y_1, \dots, y_{30}; \underline{\beta}) = \prod_{i=1}^{30} \pi_i^{y_i} (1-\pi_i)^{1-y_i} \quad \text{with } \pi_i = \frac{e^{\beta_1 + \beta_2 x_i}}{1 + e^{\beta_1 + \beta_2 x_i}}$$

likelihood function

$$L(\underline{\beta}) = \prod_{i=1}^{30} \pi_i^{y_i} (1-\pi_i)^{1-y_i} \rightarrow L(\underline{\beta}) = \left( \frac{e^{\beta_1 + \beta_2 x_i}}{1 + e^{\beta_1 + \beta_2 x_i}} \right)^{y_i} \left( \frac{1}{1 + e^{\beta_1 + \beta_2 x_i}} \right)^{1-y_i}$$

log-likelihood function

$$\ell(\underline{\beta}) = \log L(\underline{\beta})$$

$$= \sum_{i=1}^{30} y_i \log \pi_i + (1-y_i) \log (1-\pi_i)$$

$$= \sum_{i=1}^{30} y_i \log \left( \frac{e^{\beta_1 + \beta_2 x_i}}{1 + e^{\beta_1 + \beta_2 x_i}} \right) + \sum_{i=1}^{30} (1-y_i) \log \left( \frac{1}{1 + e^{\beta_1 + \beta_2 x_i}} \right)$$

$$= \sum_{i=1}^{30} y_i (\beta_1 + \beta_2 x_i) - \sum_{i=1}^{30} \log (1 + e^{\beta_1 + \beta_2 x_i})$$

hence

$$\ell(\underline{\beta}) = \sum_{i=1}^{30} y_i (\beta_1 + \beta_2 x_i) - \sum_{i=1}^{30} \log (1 + e^{\beta_1 + \beta_2 x_i})$$

$$= \sum_{i=1}^{30} \left\{ y_i (\beta_1 + \beta_2 x_i) - \log (1 + e^{\beta_1 + \beta_2 x_i}) \right\}$$

$$= \beta_1 \sum_{i=1}^{30} y_i + \beta_2 \sum_{i=1}^{30} x_i y_i - \sum_{i=1}^{30} \log (1 + e^{\beta_1 + \beta_2 x_i})$$

Finally, the score function is

$$e_j(\underline{\beta}) = \frac{\partial \ell(\underline{\beta})}{\partial \beta_j} \quad j=1,2$$

$$= \begin{cases} \frac{\partial \ell(\underline{\beta})}{\partial \beta_1} = \sum_{i=1}^{30} y_i - \sum_{i=1}^{30} \frac{1}{1 + e^{\beta_1 + \beta_2 x_i}} \cdot e^{\beta_1 + \beta_2 x_i} = 30 \bar{y} - \sum_{i=1}^{30} \frac{e^{\beta_1 + \beta_2 x_i}}{1 + e^{\beta_1 + \beta_2 x_i}} + \sum_{i=11}^{30} \frac{e^{\beta_1}}{1 + e^{\beta_1}} \\ \frac{\partial \ell(\underline{\beta})}{\partial \beta_2} = \sum_{i=1}^{30} x_i y_i - \sum_{i=1}^{30} \frac{1}{1 + e^{\beta_1 + \beta_2 x_i}} \cdot e^{\beta_1 + \beta_2 x_i} \cdot x_i = \sum_{i=1}^{10} y_i - \sum_{i=1}^{10} \frac{e^{\beta_1 + \beta_2}}{1 + e^{\beta_1 + \beta_2}} \end{cases}$$

is 0 for  $i=11, \dots, 30$

If I denote with  $\bar{y}_1$  the mean of the first 10 observations, and  $\bar{y}_2$  the mean of the last 20, I get:

$$30 \bar{y} = \sum_{i=1}^{30} y_i = 10 \bar{y}_1 + 20 \bar{y}_2$$

$$\sum_{i=1}^{10} y_i = 10 \bar{y}_1$$

$$= \begin{cases} 10 \bar{y}_1 + 20 \bar{y}_2 - 10 \frac{e^{\beta_1 + \beta_2}}{1 + e^{\beta_1 + \beta_2}} - 20 \frac{e^{\beta_1}}{1 + e^{\beta_1}} \\ 10 \bar{y}_1 - 10 \frac{e^{\beta_1 + \beta_2}}{1 + e^{\beta_1 + \beta_2}} \end{cases}$$

likelihood equations:  $e_j(\underline{\beta}) = 0$

we can solve them analytically and find the MLE in this case

$$\begin{cases} 10 \bar{y}_1 + 20 \bar{y}_2 - 10 \frac{e^{\beta_1 + \beta_2}}{1 + e^{\beta_1 + \beta_2}} - 20 \frac{e^{\beta_1}}{1 + e^{\beta_1}} = 0 \\ 10 \bar{y}_1 - 10 \frac{e^{\beta_1 + \beta_2}}{1 + e^{\beta_1 + \beta_2}} = 0 \end{cases}$$

$$(eq. 2): \quad \bar{y}_1 = \frac{e^{\beta_1 + \beta_2}}{1 + e^{\beta_1 + \beta_2}} \Rightarrow \hat{\beta}_1 + \hat{\beta}_2 = \log \frac{\bar{y}_1}{1 - \bar{y}_1} = \log \frac{\hat{\pi}_1}{1 - \hat{\pi}_1}$$

proportion of successes in the first 10 obs.

with  $\hat{\pi}_1 = \bar{y}_1$  estimate of the probability for observations in the first group ( $i=1, \dots, 10$ )

$$(eq. 1): \quad 10 \bar{y}_1 + 20 \bar{y}_2 - 10 \frac{e^{\hat{\beta}_1 + \hat{\beta}_2}}{1 + e^{\hat{\beta}_1 + \hat{\beta}_2}} - 20 \frac{e^{\hat{\beta}_1}}{1 + e^{\hat{\beta}_1}} = 0$$

$$10 \bar{y}_1 + 20 \bar{y}_2 - 10 \bar{y}_1 - 20 \frac{e^{\hat{\beta}_1}}{1 + e^{\hat{\beta}_1}} = 0 \Rightarrow \frac{e^{\hat{\beta}_1}}{1 + e^{\hat{\beta}_1}} = \bar{y}_2 \Rightarrow \hat{\beta}_1 = \log \frac{\bar{y}_2}{1 - \bar{y}_2} = \log \frac{\hat{\pi}_2}{1 - \hat{\pi}_2}$$

Hence

$$\hat{\beta}_1 = \text{logit}(\bar{y}_2)$$

$$\hat{\beta}_1 + \hat{\beta}_2 = \text{logit}(\bar{y}_1) \Rightarrow \hat{\beta}_2 = \text{logit}(\bar{y}_1) - \text{logit}(\bar{y}_2)$$

The fitted model is

$$Y_i \sim \text{Ber}(\hat{\pi}_i) \quad \text{logit}(\hat{\pi}_i) = 1.3863 - 2.0794 x_i$$

$$b) \quad \hat{\pi}_i \text{ when } x_i=0 \text{ is}$$

$$P(Y_i=1 | x_i=0) = \frac{e^{\hat{\beta}_2}}{1 + e^{\hat{\beta}_2}} = 0.800$$

$$\hat{\pi}_i \text{ when } x_i=1 \text{ is}$$

$$P(Y_i=1 | x_i=1) = \frac{e^{\hat{\beta}_1 + \hat{\beta}_2}}{1 + e^{\hat{\beta}_1 + \hat{\beta}_2}} = 0.333$$

$$\text{when } x_i=0 \text{ the odds are}$$

$$\frac{\text{prob. success} | x_i=0}{\text{prob. failure} | x_i=0} = \frac{P(Y_i=1 | x_i=0)}{P(Y_i=0 | x_i=0)} = \frac{\left( \frac{e^{\hat{\beta}_2}}{1 + e^{\hat{\beta}_2}} \right)}{\left( \frac{1}{1 + e^{\hat{\beta}_2}} \right)} = \frac{0.800}{0.200} = 4.00 \quad (= e^{\hat{\beta}_2})$$

odds · 100 = 400 = number of expected successes every 100 failures  
 → when  $x=0$ , I expect 400 successes every 100 failures

$$\text{when } x_i=1 \text{ the odds are}$$

$$\frac{\text{prob. success} | x_i=1}{\text{prob. failure} | x_i=1} = \frac{P(Y_i=1 | x_i=1)}{P(Y_i=0 | x_i=1)} = \frac{\left( \frac{e^{\hat{\beta}_1 + \hat{\beta}_2}}{1 + e^{\hat{\beta}_1 + \hat{\beta}_2}} \right)}{\left( \frac{1}{1 + e^{\hat{\beta}_1 + \hat{\beta}_2}} \right)} = \frac{0.333}{0.666} = 0.500 \quad (= e^{\hat{\beta}_1 + \hat{\beta}_2})$$

→ when  $x=1$ , I expect 50 successes every 100 failures

Finally, the odds ratio is

$$\frac{\left( \frac{\pi_i}{1-\pi_i} \mid x_i=1 \right)}{\left( \frac{\pi_i}{1-\pi_i} \mid x_i=0 \right)} = \frac{e^{\hat{\beta}_1 + \hat{\beta}_2}}{e^{\hat{\beta}_2}} = e^{\hat{\beta}_1} = 0.1250$$

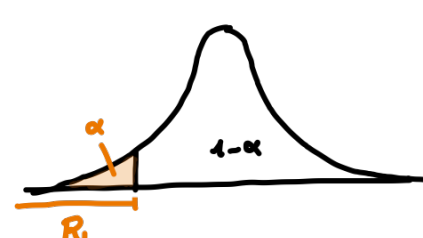
The odds for the group  $x_i=0$  are multiplied by 0.1250 to obtain the odds at  $x_i=1$

$$c) \quad \begin{cases} H_0: \beta_2 = -1 \\ H_1: \beta_2 < -1 \end{cases}$$

$$\text{The test statistic} \quad Z = \frac{\hat{\beta}_2 - (-1)}{\sqrt{j(\hat{\beta})_{22}^{-1}}} \stackrel{H_0}{\sim} N(0,1)$$

$$\text{From the summary} \quad \sqrt{j(\hat{\beta})_{22}^{-1}} = 0.7926 \quad \hat{\beta}_2 = -2.0794$$

$$z_{obs} = \frac{-2.0794 + 1}{0.7926} = -1.3792$$



The reject region here is for negative values

Using a significance level  $\alpha$ , I reject  $H_0$  if  $z_{obs} < z_\alpha$

$\alpha = 5\%$      $z_\alpha = z_{0.05} = -z_{0.95} = -1.64$     I do not reject  $H_0$  at 5% level

$\alpha = 10\%$      $z_\alpha = z_{0.10} = -z_{0.90} = -1.28$     I reject  $H_0$  at a 10% level

d) the residual deviance is the lik. ratio test between the saturated model and the proposed model:

$$D(\text{model}) = 2 \{ \tilde{\ell}(\text{saturated}) - \hat{\ell}(\text{model}) \}$$

where  $\tilde{\ell}(\text{saturated})$  is the maximum of the log-likelihood under a model with n parameters,

and  $\hat{\ell}(\text{model})$  is the maximum of the log-likelihood under the current model

The null deviance is

$$D(\text{null}) = 2 \{ \tilde{\ell}(\text{saturated}) - \tilde{\ell}(\text{null}) \}$$

where  $\tilde{\ell}(\text{null})$  is the maximum of the log-likelihood under a model with a single parameter  $\pi$