

EXERCISE 2

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

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

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

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

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

$$p(y_1, \dots, y_{30}; \pi) = \prod_{i=1}^n \pi_i^{y_i} (1-\pi_i)^{1-y_i}$$

likelihood function

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

log-likelihood function

$$\ell(\pi) = \log L(\pi)$$

$$= \sum_{i=1}^n y_i \underbrace{\log \pi_i}_{\beta_1 + \beta_2 x_i} + (1-y_i) \underbrace{\log(1-\pi_i)}_{\log(1+e^{\beta_1 + \beta_2 x_i})} - \log(1+e^{\beta_1 + \beta_2 x_i})$$

hence

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

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

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

Finally, the score function is

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

$$= \begin{cases} \frac{\partial \ell(\beta)}{\partial \beta_1} = \sum_{i=1}^n y_i - \sum_{i=1}^n \frac{1}{1+e^{\beta_1 + \beta_2 x_i}} \cdot e^{\beta_1 + \beta_2 x_i} \\ \frac{\partial \ell(\beta)}{\partial \beta_2} = \sum_{i=1}^n x_i y_i - \sum_{i=1}^n \frac{1}{1+e^{\beta_1 + \beta_2 x_i}} \cdot e^{\beta_1 + \beta_2 x_i} \cdot x_i \end{cases}$$

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

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

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

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

when $x_i=0$ 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

when $x_i=1$ 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) $H_0: \beta_2 = -1$
 $H_1: \beta_2 < -1$

The test statistic $Z = \frac{\hat{\beta}_2 - (-1)}{\sqrt{[\hat{j}(\hat{\beta})]_{2,2}}} \stackrel{H_0}{\sim} N(0,1)$

from the summary

$$\sqrt{[\hat{j}(\hat{\beta})]_{2,2}} = 0.4926 \quad \hat{\beta}_2 = -2.0794$$

$$Z_{\text{obs}} = \frac{-2.0794 + 1}{0.4926} = -2.3792$$



The reject region here is for negative values

Using a significance level α , I reject H_0 if $Z_{\text{obs}} < -2\alpha$

$\alpha = 5\% \quad -2\alpha = -2 \cdot 0.05 = -2 \cdot 0.95 = -1.64 \quad$ I do not reject H_0 at 5% level

$\alpha = 10\% \quad -2\alpha = -2 \cdot 0.10 = -2 \cdot 0.90 = -1.28 \quad$ I reject H_0 at 10% level

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

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

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

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

The null deviance is

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

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