

Regression Analysis

Logistic Regression

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Model Description and Estimation



About This Lesson



Logistic Regression Model

Data: $\{(X_{1,1}, X_{1,2}, \dots, X_{1,p}), Y_1\}, \{(X_{2,1}, X_{2,2}, \dots, X_{2,p}), Y_2\}, \dots, \{(X_{n,1}, X_{n,2}, \dots, X_{n,p}), Y_n\}$
 where Y_1, \dots, Y_n are *binary* responses

Model: We model the *probability of success given the predictor(s)*

$$p = p(X_1, \dots, X_p) = \Pr(Y = 1 \mid X_1, \dots, X_p)$$

by linking p to the predicting variables through the **logit link function** g :

$$g(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$$

OR

$$p(X_1, \dots, X_p) = \frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}$$



Model Interpretation

- The probability of success given one predicting variable $X = x$ is
 $p = p(x) = \Pr(Y = 1 \mid x)$
- The logit function $\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x$ is the **log odds** function.
- The exponential of the logit function $\frac{p(X)}{1-p(X)} = e^{\beta_0 + \beta_1 x}$ is the **odds** of $Y = 1$ at $X = x$
- The odds at $X = a$ versus $X = b$ is equal to the **odds ratio**:

$$\frac{e^{\beta_0 + \beta_1 a}}{e^{\beta_0 + \beta_1 b}} = e^{\beta_1(a-b)}$$



Model Interpretation

If we calculate the odds ratio of the odds at $X = b + 1$ versus $X = b$, we have

$$\frac{e^{\beta_0 + \beta_1(b+1)}}{e^{\beta_0 + \beta_1 b}} = e^{\beta_1}$$

- The regression coefficient β_1 can be interpreted as the **log of the odds ratio for an increase of one unit in the predicting variable.**
- If X a **dummy** variable of a categorical factor, interpret as the **log of odds ratio of one category versus baseline.**
- Interpret β with respect to the odds of success, not directly with respect to the response variable.



Model Estimation

Model the probability of success given predictor(s):

$$\text{Logit}(\Pr(Y = 1 | X_1, \dots, X_p)) = \text{Logit}(p(X_1, \dots, X_p)) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$$

Parameters: $\beta_0, \beta_1, \dots, \beta_p$

Approach: Maximum Likelihood Estimation

$$\max_{\beta_0, \beta_1, \dots, \beta_p} \mathcal{L}(\beta_0, \beta_1, \dots, \beta_p) = \prod_{i=1}^n p(X_{i,1}, X_{i,2}, \dots, X_{i,p})^{Y_i} (1 - p(X_{i,1}, X_{i,2}, \dots, X_{i,p}))^{1-Y_i}$$

or

$$\begin{aligned} \max_{\beta_0, \beta_1, \dots, \beta_p} \ell(\beta_0, \beta_1, \dots, \beta_p) &= \max_{\beta_0, \beta_1, \dots, \beta_p} \log(\mathcal{L}(\beta_0, \beta_1, \dots, \beta_p)) \\ &= \max_{\beta_0, \beta_1, \dots, \beta_p} \sum_{i=1}^n \left(Y_i \log \left(\frac{e^{\beta_0 + \beta_1 X_{i,1} + \dots + \beta_p X_{i,p}}}{1 + e^{\beta_0 + \beta_1 X_{i,1} + \dots + \beta_p X_{i,p}}} \right) + (1 - Y_i) \log \left(\frac{1}{1 + e^{\beta_0 + \beta_1 X_{i,1} + \dots + \beta_p X_{i,p}}} \right) \right) \end{aligned}$$



Model Estimation (cont'd)

Approach: Maximum Likelihood Estimation

$$\max_{\beta_0, \beta_1, \dots, \beta_p} \sum_{i=1}^n \left(Y_i \log \left(\frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}} \right) + (1 - Y_i) \log \left(\frac{1}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}} \right) \right)$$

- Maximizing the (log-)likelihood function with respect to $\beta_0, \beta_1, \dots, \beta_p$ in closed form expression is not possible because the (log-)likelihood function is a non-linear function in the model parameters.
- Use numerical algorithm to estimate $\beta_0, \beta_1, \dots, \beta_p \Rightarrow \hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_p$

Upshot: The estimated parameters and their standard errors are approximate estimates. Do not attempt to do it yourself! Use statistical software to derive the estimated regression coefficients.



Summary

