

## 5. Model Choice

(1) Basic asymptotic result of maximum likelihood estimation. Suppose the observations  $Y_i \sim \text{Bin}(n_i, p_i(\beta))$ ,  $i = 1, \dots, n$  are independent, then (under some further assumptions) the MLE  $\hat{\beta}$  is consistent, and satisfies

$$\hat{\beta} \sim N(\beta, (\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1}),$$

as  $n \rightarrow +\infty$ . Here  $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_n]^T$  is the  $n \times (k+1)$  design matrix, and  $\mathbf{W} = \text{Cov}(\mathbf{Y}) = \text{diag}(\text{Var}(Y_1), \dots, \text{Var}(Y_n))$ .

(2) The value of  $(\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1}$  is computed as an intermediate term in Newton's method.

(3) The diagonals yield the estimates of  $\text{Var}(\hat{\beta}_j)$ ,  $j = 0, 1, \dots, k$ .

(4) 95 % confidence intervals for individual coefficients can be computed approximately as

$$\hat{\beta}_j \pm 1.96 \sqrt{\text{Var}(\hat{\beta}_j)}$$

(5) 95 % confidence interval for an arbitrary linear combination of the coefficients:  $\mathbf{L}^T \beta = L_0 \beta_0 + \dots + L_k \beta_k$ , is approximately

$$\mathbf{L}^T \hat{\beta} \pm 1.96 \sqrt{\mathbf{L}^T \text{Cov}(\hat{\beta}) \mathbf{L}}$$

(6) Further formulas are available for approximate *simultaneous* confidence intervals.

(7) *Saturated model* has as many parameters as there are units of observation ( $= n$ ). It fits the data perfectly. N.B. there is a distinction here between Bernoulli and Binomial observations.

(8) Write the resulting probability estimates as  $p_i^*, i = 1, \dots, n$ , and the corresponding loglikelihood as  $\ell^*$

(9) Write the loglikelihood corresponding to the MLE as  $\ell(\hat{\beta})$ .

(10) Def.  $D(\hat{\beta}) = 2(\ell^* - \ell(\hat{\beta}))$  is the so-called *deviance*.

(11) Deviance does not have a known distribution, in general. An exception: the  $n_i$ 's are large.

(12) On the other hand, write  $\beta = (\beta_{(0)}^T, \beta_{(1)}^T)^T$ , where  $\beta_{(0)} = (\beta_0, \dots, \beta_r)^T$ , and  $\beta_{(1)} = (\beta_{r+1}, \dots, \beta_k)^T$ . Consider the hypothesis  $H_0 : \beta_{(1)} = \mathbf{0}$ .

(13) When  $H_0$  is true, then (under some regularity conditions)

$$D(\tilde{\beta}, \mathbf{0}) - D(\hat{\beta}) \sim \chi_{k-r}^2$$

asymptotically, as  $n \rightarrow +\infty$ .

(14) Change in deviance, or the *likelihood ratio test*, is the preferred way of testing adequacy of *nested* submodels.

- (15) Causal research: keep variables of scientific interest in the model at least as long as to see what their maximal influence in the data at hand are. Report this.
- (16) If there is a small number of candidate variables, one can put them all in the model to see what their combined explanatory power might be.
- (17) An essential question: in what scale would the explanatory variables to exert an influence that conforms to the theory.
- (18) There are non-parametric formulations for logistic regression, but they require a lot of data.
- (19) In descriptive studies automated, stepwise procedures can be useful.
- (20) *Information criteria* (AIC, BIC, DIC, NIC,...) can be used to distinguish models that are not nested, but only as rough guides, because their performance is inadequately known.