

### 6.3 Some applications involving binary data:

Combination of several  $2 \times 2$  tables:

Suppose there are  $m$  centres participating in the clinical trial. Then, the following tables can be obtained,  $j = 1, \dots, m$ ,

	Success	Failure	
Treatment	$y_{1j}$	$n_{1j} - y_{1j}$	$n_{1j}$
Control	$y_{2j}$	$n_{2j} - y_{2j}$	$n_{2j}$
	$s_{1j}$	$s_{2j}$	$n_j$

We may consider  $Y_{1j} \sim B(n_{1j}, \pi_{1j})$  and  $Y_{2j} \sim B(n_{2j}, \pi_{2j})$  with

$$\text{logit}(\pi_{1j}) = \lambda_j + \Delta,$$

$$\text{logit}(\pi_{2j}) = \lambda_j.$$

The main difficulty based on the full likelihood is that it contains  $m + 1$  parameters  $\lambda_1, \lambda_2, \dots, \lambda_m, \Delta$ , to be estimated. In such circumstances, maximum likelihood needs not be consistent or efficient for large  $m$ . However, if we used the conditional likelihood based on  $Y_{1j}|Y_{1j} + Y_{2j} = s_{1j}$ , the likelihood then depends on only one parameter  $\Delta$ . The conditional log-likelihood for  $\Delta$  is

$$\begin{aligned} l_c(\Delta) &\propto \sum_{j=1}^m \log \left[ \frac{\varphi^{y_{1j}}}{P_0(\varphi)} \right] = \sum_{j=1}^m \{y_{1j} \cdot \log(\varphi) - \log[P_0(\varphi)]\} \\ &= \sum_{j=1}^m \{y_{1j}\Delta - \log[P_0(\exp(\Delta))]\} \end{aligned}$$

where

$$\varphi = \frac{\left( \frac{\pi_{1j}}{1 - \pi_{1j}} \right)}{\left( \frac{\pi_{2j}}{1 - \pi_{2j}} \right)},$$

$$\Delta = \text{logit}(\pi_{1j}) - \text{logit}(\pi_{2j}) = \log \left( \frac{\pi_{1j}}{1 - \pi_{1j}} \right) - \log \left( \frac{\pi_{2j}}{1 - \pi_{2j}} \right) = \log(\varphi),$$

and

$$P_0(\varphi) = \sum_{k=a}^b \binom{n_{1j}}{k} \binom{n_{2j}}{s_{1j} - k} \varphi^k.$$

Thus, the maximum conditional likelihood estimate is the solution of

$$\frac{dl_c(\Delta)}{d\Delta} = 0.$$

In addition, provided the total conditional Fisher information is sufficiently large,

standard large-sample likelihood theory applies to the conditional likelihood. To test  $H_0: \Delta = 0$ , we can use the score statistic under  $H_0$ :

$$U = \left[ \frac{dl_c(\Delta)}{d\Delta} \right]_{\Delta=0} = \sum_{j=1}^m \left[ y_{1j} - \frac{n_{1j}(y_{1j} + y_{2j})}{n_j} \right] = \sum_{j=1}^m \left( y_{1j} - \frac{n_{1j}s_{1j}}{n_j} \right),$$

where the conditional expectation  $Y_{1j}$  is

$$\frac{n_{1j}}{n_j} \cdot s_{1j}.$$

In addition,

$$Var(U) = \sum_{j=1}^m \frac{n_{1j}n_{2j}s_{1j}(n_j - s_{1j})}{n_j^2(n_j - 1)}.$$

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Then, the test statistic is

$$Z^- = \frac{U - 1/2}{\sqrt{Var(U)}}$$

for one-sided hypothesis. The test is known as the **Mantel-Haenszel** test.

### Note:

There is the probability that  $\Delta$  varies from centre to centre. That is,  $\Delta$  might not be constant over different centres. Such interactions require careful investigation and detailed plausible explanation.