

Lecture 20

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- 1 Review two sample binomial results
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Two sample binomials results

Recall $X \sim \text{Bin}(n_1, p_1)$ and $Y \sim \text{Bin}(n_2, p_2)$. Also this information is often arranged in a 2×2 table:

$n_{11} = x$	$n_{12} = n_1 - x$	n_1
$n_{21} = y$	$n_{22} = n_2 - y$	n_2

$$\text{var}(\bar{X}) = \frac{p}{n}$$

$$\bullet \hat{RD} = \hat{p}_1 - \hat{p}_2$$

$$\text{var}(\bar{X}) = \frac{p}{n}$$

$$\text{var} = \text{var}_1 + \text{var}_2$$

$$\hat{SE}_{\hat{RD}} = \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$$

$$\bullet \hat{RR} = \frac{\hat{p}_1}{\hat{p}_2} \quad \log \hat{p}_1 - \log \hat{p}_2$$

$$f(\text{odds}) = \frac{p}{1-p}$$

$$\hat{SE}_{\log \hat{RR}} = \sqrt{\frac{(1-\hat{p}_1)}{\hat{p}_1 n_1} + \frac{(1-\hat{p}_2)}{\hat{p}_2 n_2}}$$

$$\bullet \hat{OR} = \frac{\hat{p}_1/(1-\hat{p}_1)}{\hat{p}_2/(1-\hat{p}_2)} = \frac{n_{11}n_{22}}{n_{12}n_{21}}$$

$$f'(0) \cdot SE(\theta) = \frac{1}{p} \sqrt{\frac{(1-p)p}{n}}$$

$$\hat{SE}_{\log \hat{OR}} = \sqrt{\frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}}}$$

$$CI = \text{Estimate} \pm Z_{1-\alpha/2} SE_{\text{Est}}$$

Standard errors

- **delta method** can be used to obtain large sample standard errors
- Formally, the delta method states that if

$$\frac{\hat{\theta} - \theta}{\hat{SE}_{\hat{\theta}}} \rightarrow N(0, 1)$$

then

$$\frac{f(\hat{\theta}) - f(\theta)}{f'(\hat{\theta})\hat{SE}_{\hat{\theta}}} \rightarrow N(0, 1)$$

这是定理

- Asymptotic mean of $f(\hat{\theta})$ is $f(\theta)$
- Asymptotic standard error of $f(\hat{\theta})$ can be estimated with $f'(\hat{\theta})\hat{SE}_{\hat{\theta}}$

Example

- $\theta = p_1$
- $\hat{\theta} = \hat{p}_1$
- $\hat{SE}_{\hat{\theta}} = \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1}}$
- $f(x) = \log(x)$
- $f'(x) = 1/x$
- $\frac{\hat{\theta} - \theta}{\hat{SE}_{\hat{\theta}}} \rightarrow N(0, 1)$ by the CLT
- Then $\hat{SE}_{\log \hat{p}_1} = f'(\hat{\theta}) \hat{SE}_{\hat{\theta}}$

$$= \frac{1}{\hat{p}_1} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1}} = \sqrt{\frac{(1-\hat{p}_1)}{\hat{p}_1 n_1}}$$

- And

$$\frac{\log \hat{p}_1 - \log p_1}{\sqrt{\frac{(1-\hat{p}_1)}{\hat{p}_1 n_1}}} \rightarrow N(0, 1)$$

Putting it all together

- Asymptotic standard error

$$\begin{aligned}\text{Var}(\log \hat{R}) &= \text{Var}\{\log(\hat{p}_1/\hat{p}_2)\} \\ &= \text{Var}(\log \hat{p}_1) + \text{Var}(\log \hat{p}_2) \\ &\approx \frac{(1 - \hat{p}_1)}{\hat{p}_1 n_1} + \frac{(1 - \hat{p}_2)}{\hat{p}_2 n_2}\end{aligned}$$

- The last line following from the delta method
- The approximation requires large sample sizes
- The delta method can be used similarly for the log odds ratio

Motivation for the delta method

$$x = \hat{\theta} \sim N(\theta, \Sigma)$$

$$y = h(\hat{\theta}) \quad \text{cdf } y? \quad p(Y \leq y) = p(h(x) \leq y) = p(x \leq h^{-1}(y))$$

- If $\hat{\theta}$ is close to θ then

$$= f_x(h^{-1}(y))$$

$$\frac{f(\hat{\theta}) - f(\theta)}{\hat{\theta} - \theta} \approx f'(\hat{\theta}) \quad \text{pdf} = p'(Y \leq y)$$

- So

$$\frac{f(\hat{\theta}) - f(\theta)}{f'(\hat{\theta})} \approx \hat{\theta} - \theta$$

$$= \frac{\partial}{\partial y} F_x(h^{-1}(y))$$

$$= f_x(h^{-1}(y)) \cdot \frac{\partial}{\partial y}(h^{-1}(y))$$

- Therefore

$$\frac{f(\hat{\theta}) - f(\theta)}{f'(\hat{\theta}) \hat{SE}_{\hat{\theta}}} \approx \frac{\hat{\theta} - \theta}{\hat{SE}_{\hat{\theta}}}$$