

Likelihood ratio tests

Recap: likelihood ratio test

Let X_1, \dots, X_n be a sample from a distribution with parameter $\theta \in \mathbb{R}^d$. We wish to test $H_0 : \theta \in \Theta_0$ vs. $H_A : \theta \in \Theta_1$.

The **likelihood ratio test** (LRT) rejects H_0 when

$$\frac{\sup_{\theta \in \Theta_1} L(\theta | \mathbf{X})}{\sup_{\theta \in \Theta_0} L(\theta | \mathbf{X})} > k,$$

where k is chosen such that $\sup_{\theta \in \Theta_0} \beta_{LR}(\theta) \leq \alpha$.

\uparrow power of LRT

Example: linear regression with normal data

Suppose we observe $(X_1, Y_1), \dots, (X_n, Y_n)$, where

$$Y_i = \beta^T X_i + \varepsilon_i \text{ and } \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2). \text{ Partition } \beta = (\beta_{(1)}, \beta_{(2)})^T.$$

We wish to test $H_0 : \beta_{(2)} = 0$ vs. $H_A : \beta_{(2)} \neq 0$.

Full model (H_A): $Y_i = \beta^T X_i + \varepsilon_i$

$$SSE_{full} = \sum_{i=1}^n (Y_i - \hat{\beta}_{full}^T X_i)^2 \quad \hat{\beta}_{full} = (X^T X)^{-1} X^T Y$$

MLE for σ^2 : $\hat{\sigma}_{full}^2 = \frac{1}{n} SSE_{full}$

Reduced model (H_0): $Y_i = \beta_{(1)}^T X_{i(1)} + \varepsilon_i$

$$SSE_{reduced} = \sum_{i=1}^n (Y_i - \hat{\beta}_{(1)reduced}^T X_{i(1)})^2$$

MLE for σ^2 : $\frac{1}{n} SSE_{reduced}$

$$\hat{\beta}_{(1)reduced} = (X_{(1)}^T X_{(1)})^{-1} X_{(1)}^T Y$$

Test statistic: $F = \frac{(SSE_{reduced} - SSE_{full}) / q}{SSE_{full} / (n - p)}$

$q = \# \text{ elements in } \beta_{(2)}$

$p = \# \text{ elements in } \beta$

$$\text{LRT: rejects } H_0 \text{ if } \frac{\sup_{\beta, \sigma^2} L(\beta, \sigma^2 | X, Y)}{\sup_{\substack{\beta, \sigma^2 \\ \beta(2)=0}} L(\beta, \sigma^2 | X, Y)} > K$$

$$\Leftrightarrow \frac{L(\hat{\beta}_{\text{full}}, \hat{\sigma}_{\text{full}}^2 | X, Y)}{L(\hat{\beta}_{\text{reduced}}, \hat{\sigma}_{\text{reduced}}^2 | X, Y)} > K \Leftrightarrow \log L(\hat{\beta}_{\text{full}}, \hat{\sigma}_{\text{full}}^2 | X, Y) - \log L(\hat{\beta}_{\text{red.}}, \hat{\sigma}_{\text{red.}}^2 | X, Y) > \log(K)$$

$$\begin{aligned} \log L(\hat{\beta}, \hat{\sigma}^2 | X, Y) &= \log \left(\left(\frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \right)^n \exp \left\{ -\frac{1}{2\hat{\sigma}^2} \sum_{i=1}^n (y_i - \hat{\beta}^T x_i)^2 \right\} \right) \\ &= -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\hat{\sigma}^2) - \frac{1}{2\hat{\sigma}^2} \text{SSE} \quad (\text{SSE} = n\hat{\sigma}^2) \\ &= -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\hat{\sigma}^2) - \frac{n}{2} \end{aligned}$$

$$\text{So LRT rejects } H_0 \text{ if } \frac{n}{2} \log(\hat{\sigma}_{\text{reduced}}^2) - \frac{n}{2} \log(\hat{\sigma}_{\text{full}}^2) > \log(K)$$

$$\Leftrightarrow \frac{n}{2} \log \left(\frac{\text{SSE}_{\text{reduced}}}{\text{SSE}_{\text{full}}} \right) > \log(K)$$

$$\Leftrightarrow \frac{(\text{SSE}_{\text{reduced}} - \text{SSE}_{\text{full}}) / q}{\text{SSE}_{\text{full}} / (n-p)} > \left(\exp \left(\frac{2 \log K}{n} \right) - 1 \right) \left(\frac{n-p}{q} \right)$$

$$\sup_{\lambda \neq \lambda_0} L(\lambda | X) = \sup_{\lambda} L(\lambda | X)$$

$$\text{MLE: } \hat{\lambda} = \frac{1}{n} \sum_{i=1}^n x_i$$

Example: Poisson sample

Let $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poisson}(\lambda)$. We wish to test $H_0 : \lambda = \lambda_0$ vs. $H_A : \lambda \neq \lambda_0$.

Write down the LRT statistic, and simplify as much as possible.

$$L(\lambda | X) = \prod_{i=1}^n \frac{\lambda^{x_i} e^{-\lambda}}{x_i!} = \frac{\lambda^{\sum x_i} e^{-n\lambda}}{\prod_i x_i!}$$

$$\sup_{\lambda = \lambda_0} L(\lambda | X) = L(\lambda_0 | X)$$

$$\sup_{\lambda} L(\lambda | X) = L(\hat{\lambda} | X)$$

LRT rejects when

$$\left(\frac{\hat{\lambda}}{\lambda_0} \right)^{\sum x_i} e^{n(\lambda_0 - \hat{\lambda})} > k$$

$$\frac{\hat{\lambda}^{\sum x_i} e^{-n\hat{\lambda}}}{\lambda_0^{\sum x_i} e^{-n\lambda_0}} > k$$

$$\hat{\theta} = \text{MLE}$$

Asymptotics of the LRT

Suppose we observe iid data X_1, \dots, X_n and want to test

$$H_0: \theta = \theta_0 \quad \text{vs.} \quad H_A: \theta \neq \theta_0 \quad (\theta \in \mathbb{R})$$

$$\begin{aligned} \text{Under } H_0, \quad & \underbrace{-2(\log L(\theta_0 | X) - \log L(\hat{\theta} | X))}_{= 2 \log \left(\frac{L(\hat{\theta} | X)}{L(\theta_0 | X)} \right)} \xrightarrow{d} \chi^2_1 \end{aligned}$$

Proof: (let $\ell(\theta) = \log L(\theta | X)$)

① using Taylor expansion: $2\ell(\hat{\theta}) - 2\ell(\theta_0) \approx -\ell''(\hat{\theta})(\hat{\theta} - \theta_0)^2$

② $-\frac{1}{n} \ell''(\hat{\theta}) \xrightarrow{P} ?$, $\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} ?$

③ Apply Slutsky's & continuous mapping theorem

Generalization to higher dimensions