

Stat 4620: Day 22

(4/11)

Sec. 6.5: Multiparameter testing

Let x_1, \dots, x_n be a random sample from a distribution with density $f(x; \boldsymbol{\theta})$, where $\boldsymbol{\theta} \in \Omega \subset R^p$, i.e. $\boldsymbol{\theta} = [\theta_1, \dots, \theta_p]'$. We want to test

$$H_0 : \boldsymbol{\theta} \in \omega \text{ versus } H_1 : \boldsymbol{\theta} \in \omega^c$$

where ω is a proper subset of Ω . The **likelihood ratio test** is generalized to vector parameters as follows: Reject H_0 if

$$\Lambda = \frac{\max_{\boldsymbol{\theta} \in \omega} L(\boldsymbol{\theta})}{\max_{\boldsymbol{\theta} \in \Omega} L(\boldsymbol{\theta})} = \frac{L(\hat{\boldsymbol{\theta}}_\omega)}{L(\hat{\boldsymbol{\theta}}_\Omega)} \leq c$$

where c is such that

$$\max_{\boldsymbol{\theta} \in \omega} P[\Lambda \leq c] = \alpha$$

Example 6.5.1 (Test on mean of normal distribution)

Let x_1, \dots, x_n be a random sample from $N(\mu, \sigma^2)$. Test

$$H_0 : \mu = \mu_0 \text{ versus } H_1 : \mu \neq \mu_0$$

Solution. Here, we have a two-dimensional parameter vector $\boldsymbol{\theta} = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} = \begin{bmatrix} \mu \\ \sigma^2 \end{bmatrix}$. The null and alternative hypotheses may be written as

$$H_0 : \mu = \mu_0, \sigma^2 \text{ unrestricted} \text{ versus } H_1 : \mu \text{ unrestricted, } \sigma^2 \text{ unrestricted}$$

First, we find $\max_{\boldsymbol{\theta} \in \Omega} L(\boldsymbol{\theta})$:

$$f(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$
$$L(\mu, \sigma^2) = \left(\frac{1}{2\pi\sigma^2} \right)^{\frac{n}{2}} e^{-\frac{\sum(x_i-\mu)^2}{2\sigma^2}}$$
$$l(\mu, \sigma^2) = -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 - \frac{\sum(x_i - \mu)^2}{2\sigma^2}$$

The *normal equations* are

1. $\frac{\partial}{\partial \mu} l(\mu, \sigma^2) = \frac{1}{\sigma^2} \sum (x_i - \mu) = 0$
2. $\frac{\partial}{\partial \sigma^2} l(\mu, \sigma^2) = -\frac{n}{2\sigma^2} + \frac{1}{(\sigma^2)^2} \frac{\sum(x_i - \mu)^2}{2} = 0$

Solving simultaneously for μ and σ^2 , we get

$$\hat{\boldsymbol{\theta}}_{\Omega} = \begin{bmatrix} \hat{\mu} \\ \hat{\sigma}^2 \end{bmatrix} = \begin{bmatrix} \bar{x} \\ \frac{\sum(x_i - \bar{x})^2}{n} \end{bmatrix}$$

Plugging into the likelihood,

$$\begin{aligned} L(\hat{\boldsymbol{\theta}}_{\Omega}) &= L\left(\bar{x}, \frac{\sum(x_i - \bar{x})^2}{n}\right) = \left(\frac{1}{2\pi \frac{\sum(x_i - \bar{x})^2}{n}}\right)^{\frac{n}{2}} e^{-\frac{\sum(x_i - \bar{x})^2}{2 \frac{\sum(x_i - \bar{x})^2}{n}}} \\ &= \left(\frac{1}{2\pi \frac{\sum(x_i - \bar{x})^2}{n}}\right)^{\frac{n}{2}} e^{-\frac{n}{2}} \end{aligned}$$

Next, we find $\max_{\boldsymbol{\theta} \in \omega} L(\boldsymbol{\theta})$:

$$\begin{aligned} \max_{\boldsymbol{\theta} \in \omega} L(\boldsymbol{\theta}) &= \max_{\sigma^2 > 0} L(\mu_0, \sigma^2) \\ &= \max_{\sigma^2 > 0} L(\mu_0, \sigma^2) = \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{n}{2}} e^{-\frac{\sum(x_i - \mu_0)^2}{2\sigma^2}} \end{aligned}$$

$$\begin{aligned} \ln L(\mu_0, \sigma^2) &= -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{\sum(x_i - \mu_0)^2}{2\sigma^2} \\ \frac{\partial}{\partial \sigma^2} \ln L(\mu_0, \sigma^2) &= -\frac{n}{2\sigma^2} + \frac{\sum(x_i - \mu_0)^2}{2(\sigma^2)^2} \end{aligned}$$

Equating to 0,

$$\frac{n}{2\hat{\sigma}^2} = \frac{\sum(x_i - \mu_0)^2}{2(\hat{\sigma}^2)^2} \Rightarrow \hat{\sigma}^2 = \frac{\sum(x_i - \mu_0)^2}{n} =$$

Plugging into the likelihood,

$$\begin{aligned} L(\hat{\boldsymbol{\theta}}_{\omega}) &= L\left(\mu_0, \frac{\sum(x_i - \mu_0)^2}{n}\right) = \left(\frac{1}{2\pi \frac{\sum(x_i - \mu_0)^2}{n}}\right)^{\frac{n}{2}} e^{-\frac{\sum(x_i - \mu_0)^2}{2 \frac{\sum(x_i - \mu_0)^2}{n}}} \\ &= \left(\frac{1}{2\pi \frac{\sum(x_i - \mu_0)^2}{n}}\right)^{\frac{n}{2}} e^{-\frac{n}{2}} \end{aligned}$$

The test statistic is

$$\begin{aligned} \Lambda &= \frac{L(\hat{\boldsymbol{\theta}}_{\omega})}{L(\hat{\boldsymbol{\theta}}_{\Omega})} = \frac{\left(\frac{1}{2\pi \frac{\sum(x_i - \mu_0)^2}{n}}\right)^{\frac{n}{2}} e^{-\frac{n}{2}}}{\left(\frac{1}{2\pi \frac{\sum(x_i - \bar{x})^2}{n}}\right)^{\frac{n}{2}} e^{-\frac{n}{2}}} = \left(\frac{\sum(x_i - \bar{x})^2}{\sum(x_i - \mu_0)^2}\right)^{\frac{n}{2}} \\ &= \left(\frac{\sum(x_i - \bar{x})^2}{\sum(x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2}\right)^{\frac{n}{2}} = \left(\frac{\sum(x_i - \bar{x})^2}{\sum(x_i - \bar{x})^2 + n(\bar{x} - \mu_0)^2}\right)^{-\frac{n}{2}} \\ &= \left(1 + \frac{n(\bar{x} - \mu_0)^2}{\sum(x_i - \bar{x})^2}\right)^{-\frac{n}{2}} \leq c \end{aligned}$$

if and only if

$$\frac{n(\bar{x} - \mu_0)^2}{\sum(x_i - \bar{x})^2} \geq c^{-\frac{2}{n}} - 1$$

if and only if

$$\left| \frac{n(\bar{x} - \mu_0)^2}{S} \right| \geq \sqrt{(n-1) \left(c^{-\frac{2}{n}} - 1 \right)}$$

The random variable on the left side has a t distribution with $n - 1$ degrees of freedom if H_0 is true. If we let the right side equal $t_{.975, n-1}$, then

$$P(\Lambda \leq c) = P\left(\left| \frac{n(\bar{x} - \mu_0)^2}{S} \right| \geq t_{.975, n-1} \right) = .05$$

So the likelihood ratio test rejects $H_0 : \mu = \mu_0$ if

$$\left| \frac{n(\bar{x} - \mu_0)^2}{S} \right| \geq t_{.975, n-1}$$

or equivalently,

$$\Lambda \leq \left(\frac{t_{.975, n-1}^2}{n-1} + 1 \right)^{-\frac{n}{2}}$$

■

Example 6.5.3 (Equality of proportions)

Let $\mathbf{x} = (x_1, \dots, x_{n_1})$ be a random sample of size n_1 from $\text{Bernoulli}(p_1)$, i.e. the $\{x_i\}$ are independent with probability mass function

$$\begin{array}{c|cc} x_i & 1 & 0 \\ \hline p(x_i) & p_1 & 1 - p_1 \end{array}$$

or $p(x_i) = p_1^{x_i} (1 - p_1)^{1-x_i}$, $x_i = 0, 1$. Similarly, let $\mathbf{y} = (y_1, \dots, y_{n_2})$ be a random sample of size n_2 from $\text{Bernoulli}(p_2)$. The hypotheses of interest are

$$H_0 : p_1 = p_2 \text{ versus } H_1 : p_1 \neq p_2$$

The combined sample has likelihood

$$\begin{aligned} L(\boldsymbol{\theta}) &= L(p_1, p_2; \mathbf{x}, \mathbf{y}) = \prod_{i=1}^{n_1} p(x_i) \prod_{j=1}^{n_2} p(y_j) \\ &= p_1^{\sum x_i} (1 - p_1)^{n_1 - \sum x_i} p_2^{\sum y_j} (1 - p_2)^{n_2 - \sum y_j} \end{aligned}$$

$$\ln L(\boldsymbol{\theta}) = \sum x_i \ln p_1 + \left(n_1 - \sum x_i \right) \ln(1 - p_1) + \sum y_j \ln p_2 + \left(n_2 - \sum y_j \right) \ln(1 - p_2)$$

The normal equations are

1. $\frac{\partial}{\partial p_1} \ln L(\boldsymbol{\theta}) = \frac{\sum x_i}{p_1} - \frac{n_1 - \sum x_i}{1 - p_1}$
2. $\frac{\partial}{\partial p_2} \ln L(\boldsymbol{\theta}) = \frac{\sum y_j}{p_2} - \frac{n_2 - \sum y_j}{1 - p_2}$

Equating (1) to 0,

$$\frac{\sum x_i}{\hat{p}_1} = \frac{n_1 - \sum x_i}{1 - \hat{p}_1} \text{ implies } (1 - \hat{p}_1) \sum x_i = \hat{p}_1 \left(n_1 - \sum x_i \right)$$

or $\hat{p}_1 = \frac{\sum x_i}{n_1} = \bar{x}$. Similarly, equating (2) to 0 gives $\hat{p}_2 = \frac{\sum y_j}{n_2} = \bar{y}$. Therefore

$$\hat{\boldsymbol{\theta}}_{\Omega} = \begin{pmatrix} \hat{p}_1 \\ \hat{p}_2 \end{pmatrix} = \begin{pmatrix} \bar{x} \\ \bar{y} \end{pmatrix}$$

Then,

$$\begin{aligned} L(\hat{\boldsymbol{\theta}}_{\Omega}) &= L(\hat{p}_1, \hat{p}_2) = \hat{p}_1^{\sum x_i} (1 - \hat{p}_1)^{n_1 - \sum x_i} \hat{p}_2^{\sum y_j} (1 - \hat{p}_2)^{n_2 - \sum y_j} \\ &= \left(\frac{\hat{p}_1}{1 - \hat{p}_1} \right)^{\sum x_i} (1 - \hat{p}_1)^{n_1} \left(\frac{\hat{p}_2}{1 - \hat{p}_2} \right)^{\sum y_j} (1 - \hat{p}_2)^{n_2} \\ &= \left(\frac{\hat{p}_1}{1 - \hat{p}_1} \right)^{n_1 \hat{p}_1} (1 - \hat{p}_1)^{n_1} \left(\frac{\hat{p}_2}{1 - \hat{p}_2} \right)^{n_2 \hat{p}_2} (1 - \hat{p}_2)^{n_2} \end{aligned}$$

To find $\hat{\boldsymbol{\theta}}_{\omega}$, note that under H_0 , we have $p_1 = p_2 = p$, so that we are maximizing the likelihood

$$\begin{aligned} L(\boldsymbol{\theta}) &= p^{\sum x_i} (1 - p)^{n_1 - \sum x_i} p^{\sum y_j} (1 - p)^{n_2 - \sum y_j} \\ &= p^{\sum x_i + \sum y_j} (1 - p)^{n_1 + n_2 - \sum x_i - \sum y_j} \end{aligned}$$

Taking derivative with respect to p and equating to 0, we get

$$\hat{p} = \frac{\sum x_i + \sum y_j}{n_1 + n_2}$$

Note that $\sum x_i + \sum y_j = (n_1 + n_2)\hat{p}$. Now

$$\begin{aligned} L(\hat{\boldsymbol{\theta}}_{\omega}) &= \hat{p}^{\sum x_i + \sum y_j} (1 - \hat{p})^{n_1 + n_2 - \sum x_i - \sum y_j} \\ &= \left(\frac{\hat{p}}{1 - \hat{p}} \right)^{\sum x_i + \sum y_j} (1 - \hat{p})^{n_1 + n_2} \\ &= \left(\frac{\hat{p}}{1 - \hat{p}} \right)^{(n_1 + n_2)\hat{p}} (1 - \hat{p})^{n_1 + n_2} \end{aligned}$$

The likelihood ratio test is

$$\begin{aligned} \Lambda &= \frac{L(\hat{\boldsymbol{\theta}}_{\omega})}{L(\hat{\boldsymbol{\theta}}_{\Omega})} = \frac{\left(\frac{\hat{p}}{1 - \hat{p}} \right)^{(n_1 + n_2)\hat{p}} (1 - \hat{p})^{n_1 + n_2}}{\left(\frac{\hat{p}_1}{1 - \hat{p}_1} \right)^{n_1 \hat{p}_1} (1 - \hat{p}_1)^{n_1} \left(\frac{\hat{p}_2}{1 - \hat{p}_2} \right)^{n_2 \hat{p}_2} (1 - \hat{p}_2)^{n_2}} \\ &= \left(\frac{\hat{p}}{1 - \hat{p}} \right)^{n_1 \hat{p}_1} \left(\frac{\hat{p}}{1 - \hat{p}} \right)^{n_2 \hat{p}_2} \left(\frac{1 - \hat{p}}{1 - \hat{p}_1} \right)^{n_1} \left(\frac{1 - \hat{p}}{1 - \hat{p}_2} \right)^{n_2} \leq c \end{aligned}$$

Theorem 6.5.1. Let x_1, \dots, x_n be a random sample from a distribution $f(x; \boldsymbol{\theta})$ for $\boldsymbol{\theta} \in \Omega$ with dimension p . Let ω be a proper subset of Ω with dimension $p - q$. Assume the regularity conditions hold, including existence of unique mle solutions $\hat{\boldsymbol{\theta}}_{\Omega}$ and $\hat{\boldsymbol{\theta}}_{\omega}$. Under $H_0 : \boldsymbol{\theta} \in \omega$,

$$-2 \ln \Lambda \xrightarrow{D} \chi_q^2$$

Comments:

1. The degrees of freedom q is the difference between the dimensions of Ω and ω .

- Another interpretation: q is the number of constraints represented by the null hypothesis, hence the term *degrees of freedom*.
- Since the LRT rejects for small values of Λ (or large values of $-2 \ln \Lambda$), Theorem 6.5.1 says that the LRT with (approximate) size α is

$$-2 \ln \Lambda \geq \chi_{1-\alpha, q}^2$$

or equivalently, $\Lambda \leq e^{-\frac{\chi_{1-\alpha, q}^2}{2}}$

Example 6.5.3 con't The full model parameter space (p_1, p_2) has dimension $p = 2$. The reduced H_0 parameter space p has dimension $p - q = 1$. The difference is $q = 1$. This is also the number of constraints imposed by $H_0 : p_1 = p_2$. So the likelihood ratio test with size $\alpha = .05$ is

$$-2 \ln \Lambda \geq \chi_{.95, 1df}^2 = 3.841$$

or equivalently

$$\left(\frac{\hat{p}}{1-\hat{p}} \right)^{n_1 \hat{p}_1} \left(\frac{\hat{p}}{1-\hat{p}} \right)^{n_2 \hat{p}_2} \left(\frac{1-\hat{p}}{1-\hat{p}_1} \right)^{n_1} \left(\frac{1-\hat{p}}{1-\hat{p}_2} \right)^{n_2} \leq .1465$$

Suppose that

$$n_1 = 50, n_2 = 50, \hat{p}_1 = .30, \hat{p}_2 = .34$$

will the LRT reject $H_0 : p_1 = p_2$?

```
> n1<-50
> n2<-50
> x1<-15
> x2<-17
> p1hat<-x1/n1
> p2hat<-x2/n2
> phat<-(n1*p1hat+n2*p2hat)/(n1+n2)
> phat
[1] 0.32
> Lambda<-((phat*(1-p1hat))/(p1hat*(1-phat)))^(n1*p1hat)*((phat*(1-p2hat))/(p2hat*(1-phat)))^(n2*p2hat)
> Lambda
[1] 0.9121446
```

So the test does not reject. How far do the two proportions need to be for the test to reject?

```
> p2hat<-seq(.32, .50, by=.01)
> Lambda<-((phat*(1-p1hat))/(p1hat*(1-phat)))^(n1*p1hat)*((phat*(1-p2hat))/(p2hat*(1-phat)))^(n2*p2hat)
> cbind(p2hat, Lambda)
   p2hat   Lambda
[1,] 0.32 0.95457795
[2,] 0.33 0.94373208
[3,] 0.34 0.91214459
[4,] 0.35 0.86218570
[5,] 0.36 0.79724542
[6,] 0.37 0.72136912
[7,] 0.38 0.63886128
[8,] 0.39 0.55390847
```

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[9,] 0.40 0.47026321
[10,] 0.41 0.39101685
[11,] 0.42 0.31847291
[12,] 0.43 0.25411761
[13,] 0.44 0.19867208
[14,] 0.45 0.15220380
[15,] 0.46 0.11427202
[16,] 0.47 0.08408371
[17,] 0.48 0.06064095
[18,] 0.49 0.04286666
[19,] 0.50 0.02970185
> n1<-200
> n2<-200
> Lambda2<-((phat*(1-p1hat))/(p1hat*(1-phat)))^(n1*p1hat)*((phat*(1-p2hat))/(p2hat*(1-phat)))^
> n1<-2000
> n2<-2000
> Lambda3<-((phat*(1-p1hat))/(p1hat*(1-phat)))^(n1*p1hat)*((phat*(1-p2hat))/(p2hat*(1-phat)))^
> cbind(p2hat,Lambda,Lambda<.1465,Lambda2,Lambda2<.1465, Lambda3, Lambda3<.1465)
      p2hat      Lambda      Lambda2      Lambda3
[1,] 0.32 0.95457795 0 8.303202e-01 0 1.557600e-01 0
[2,] 0.33 0.94373208 0 7.932222e-01 0 9.861630e-02 1
[3,] 0.34 0.91214459 0 6.922369e-01 0 2.526664e-02 1
[4,] 0.35 0.86218570 0 5.525903e-01 0 2.654805e-03 1
[5,] 0.36 0.79724542 0 4.039877e-01 0 1.157927e-04 1
[6,] 0.37 0.72136912 0 2.707885e-01 0 2.119834e-06 1
[7,] 0.38 0.63886128 0 1.665813e-01 0 1.645367e-08 1
[8,] 0.39 0.55390847 0 9.413520e-02 1 5.464121e-11 1
[9,] 0.40 0.47026321 0 4.890621e-02 1 7.827811e-14 1
[10,] 0.41 0.39101685 0 2.337663e-02 1 4.873252e-17 1
[11,] 0.42 0.31847291 0 1.028703e-02 1 1.327089e-20 1
[12,] 0.43 0.25411761 0 4.170029e-03 1 1.589976e-24 1
[13,] 0.44 0.19867208 0 1.557928e-03 1 8.423130e-29 1
[14,] 0.45 0.15220380 0 5.366634e-04 1 1.981616e-33 1
[15,] 0.46 0.11427202 1 1.705138e-04 1 2.077763e-38 1
[16,] 0.47 0.08408371 1 4.998590e-05 1 9.738112e-44 1
[17,] 0.48 0.06064095 1 1.352272e-05 1 2.044745e-49 1
[18,] 0.49 0.04286666 1 3.376593e-06 1 1.926582e-55 1
[19,] 0.50 0.02970185 1 7.782763e-07 1 0.000000e+00 1

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