

## Exercises 26.01.2005

### Exercise 1

Each time the experiment is conducted a certain number of Poisson distributed events occur. We know that for one hypothesis the mean value of events is  $m_0$  and for the other  $m_1$ . The distributions follow Poisson distribution on both hypotheses.

Our observation is just number of samples and it ranges from 0 to  $\infty$ . Find the loglikelihood ratio?

### Solution 1

The Poisson distribution is characterized as

$$\Pr(n \text{ events}) = \frac{(m_i)^n}{n!} e^{-m_i}, n = 0, 1, \dots, i = 0, 1.$$

Where the  $m_i$  is the parameter which specifies the average number of events:  $E(n) = m_i$ .

The parameter  $m_i$  is different in the two hypothesis. We have the two hypothesis:

$$H_1 : p_r(n \text{ events}) = \frac{m_1^n}{n!} e^{-m_1} \quad n = 0, 1, 2, \dots$$

$$H_0 : p_r(n \text{ events}) = \frac{m_0^n}{n!} e^{-m_0}$$

The likelihood ratio test is:

$$\Lambda(n) = \frac{\overbrace{m_1^n / n! e^{-m_1}}^{H_1}}{\overbrace{m_0^n / n! e^{-m_0}}^{H_0}} = \frac{m_1^n}{m_0^n} \exp\left(-\left(m_1 - m_0\right)\right) \stackrel{H_1}{\underset{H_0}{\gtrless}} \ln \eta$$

or equivalently,

$$n \stackrel{H_1}{\underset{H_0}{\gtrless}} \frac{\ln \eta + m_1 - m_0}{\ln m_1 - \ln m_0} \text{ if } m_1 > m_0,$$

$$n \stackrel{H_0}{\underset{H_1}{\gtrless}} \frac{\ln \eta + m_1 - m_0}{\ln m_1 - \ln m_0} \text{ if } m_0 > m_1.$$

### Exercise 2

A sample function of a simple Poisson counting process  $N(t)$  is observed over the interval  $T$ :

Hypothesis  $H_1$  : the mean rate is  $k_1$  :  $\Pr(H_1) = \frac{1}{2}$ ,

Hypothesis  $H_0$  : the mean rate is  $k_0$  :  $\Pr(H_0) = \frac{1}{2}$ .

1. Prove that the number of events in the interval  $T$  is a “sufficient statistic” to choose hypothesis  $H_0$  or  $H_1$ .
2. Assuming equal costs for the possible errors, derive the appropriate likelihood ratio test and the threshold.

### Solution 2

Let  $R$  denote the number of events over the interval  $T$ .

$$P_{r|H_1}(R|H_1) = \frac{(k_1 T)^R}{R!} e^{-k_1 T} \Rightarrow \Lambda(R) = \frac{P_{r|H_0}(R|H_0)}{P_{r|H_1}(R|H_1)} = \left(\frac{k_1}{k_0}\right)^R e^{-(k_1 - k_0)T}$$

$$P_{r|H_0}(R|H_0) = \frac{(k_0 T)^R}{R!} e^{-k_0 T}$$

$l(R) = \log(\Lambda(R)) = R + C$  is trivially a sufficient statistics since it is the observation itself.

### Exercise 3

We observe the i.i.d. samples  $r$  for  $n = 0, 1, \dots, N-1$  from the Rayleigh pdf.

$$p_{r_i|H_k}(R_i | H_k) = \frac{R_i}{\sigma_k^2} \exp\left(-\frac{1}{2} \frac{R_i^2}{\sigma_k^2}\right).$$

Derive the Neyman-Pearson test for the hypothesis-testing problem:

$$\begin{aligned} H_0 &: \sigma_0^2 \\ H_1 &: \sigma_1^2 > \sigma_0^2 \end{aligned}$$

### Solution 3

Decide  $H_1$  if

$$\frac{\prod_{n=0}^{N-1} \frac{r_n}{\sigma_1^2} e^{-\frac{1}{2} \frac{r_n^2}{\sigma_1^2}}}{\prod_{n=0}^{N-1} \frac{r_n}{\sigma_0^2} e^{-\frac{1}{2} \frac{r_n^2}{\sigma_0^2}}} = \frac{\sigma_1^{2N}}{\sigma_0^{2N}} e^{-\frac{1}{2} \left( \frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2} \right) \sum_{n=0}^{N-1} r_n^2} > \eta$$

$$\ln\left(\frac{\sigma_1^{2N}}{\sigma_0^{2N}}\right) - \frac{1}{2}\left(\frac{1}{\sigma_1^2} - \frac{1}{\sigma_0^2}\right)\sum_{n=0}^{N-1} r_n^2 > \ln(\eta)$$

$$\sum_{n=0}^{N-1} r_n^2 < \frac{2(\sigma_0^2 \sigma_1^2)}{(\sigma_1^2 - \sigma_0^2)} \left( \ln\left(\frac{\sigma_1^{2N}}{\sigma_0^{2N}}\right) - \ln(\eta) \right)$$

$$P_F = 1 - \int_{\frac{2(\sigma_0^2 \sigma_1^2)}{(\sigma_1^2 - \sigma_0^2)} \left( \ln\left(\frac{\sigma_1^{2N}}{\sigma_0^{2N}}\right) - \ln(\eta) \right)}^{\infty} l_r dl_r$$

$$\text{where } l_r = \sum_{n=0}^{N-1} r_n^2$$

### Exercise 4

The probability density of  $\mathbf{r}$  on the three hypotheses is

$$p_{r_1, r_2 | H_k} (R_1, R_2 | H_k) = \left( 2\pi\sigma_{0k}\sigma_{1k} \right)^{-1} \exp \left[ -\frac{1}{2} \left( \frac{R_1^2}{\sigma_{0k}^2} + \frac{R_2^2}{\sigma_{1k}^2} \right) \right],$$

where  $-\infty < R_1, R_2 < \infty$ ,  $k = 1, 2, 3$ .

$$\sigma_{00}^2 = \sigma_{10}^2 = \sigma_n^2,$$

$$\sigma_{01}^2 = \sigma_s^2 + \sigma_n^2, \quad \sigma_{11}^2 = \sigma_n^2,$$

$$\sigma_{02}^2 = \sigma_n^2, \quad \sigma_{12}^2 = \sigma_s^2 + \sigma_n^2.$$

The cost matrix is

$$\begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & \alpha \\ 1 & \alpha & 0 \end{bmatrix},$$

where  $0 \leq \alpha < 1$  and  $\Pr(H_1) = \Pr(H_2) \triangleq p$ . Define  $l_1 = R_1^2$  and  $l_2 = R_2^2$ .

1. Find the optimum test and indicate the decision regions in the  $l_1, l_2$ -plane.
2. Write an expression for the error probabilities. (Do not evaluate the integrals.)

### Solution 4

Let  $\Lambda_1(R)$  denote the likelihood ratio between the second and the first hypothesis and  $\Lambda_2(R)$  between the third and first.

$$\Lambda_1(R) = \frac{P(R|H_1)}{P(R|H_0)} = \frac{\sigma_n}{\sqrt{\sigma_s^2 + \sigma_n^2}} \exp \left[ \frac{R_1^2}{2} \frac{\sigma_s^2}{\sigma_n^2 (\sigma_s^2 + \sigma_n^2)} \right]$$

$$\Lambda_2(R) = \frac{P(R|H_2)}{P(R|H_0)} = \frac{\sigma_n}{\sqrt{\sigma_s^2 + \sigma_n^2}} \exp \left[ \frac{R_2^2}{2} \frac{\sigma_s^2}{\sigma_n^2 (\sigma_s^2 + \sigma_n^2)} \right]$$

Optimum test becomes

$$P_1(C_{01} - C_{11}) \Lambda_1(R) \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_2}{\gtrless}} P_0(C_{10} - C_{00}) + P_2(C_{12} - C_{02}) \Lambda_2(R)$$

$$P_2(C_{02} - C_{22}) \Lambda_2(R) \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\gtrless}} P_0(C_{20} - C_{00}) + P_1(C_{21} - C_{01}) \Lambda_1(R)$$

$$P_2(C_{12} - C_{22}) \Lambda_2(R) \stackrel{H_0 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\gtrless}} P_0(C_{20} - C_{10}) + P_1(C_{21} - C_{11}) \Lambda_1(R)$$

By inserting into the equations  $\Pr(H_1) = \Pr(H_2) \triangleq p$  and  $\Pr(H_0) \triangleq 1 - 2p$

$$p\Lambda_1(R) \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_2}{\lessgtr}} (1 - 1p) + p(\alpha - 1)\Lambda_2(R)$$

$$p\Lambda_2(R) \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\lessgtr}} (1 - 2p)$$

$$p\alpha\Lambda_2(R) \stackrel{H_0 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\lessgtr}} p\Lambda_1(R)$$

The second equation

$$p\Lambda_2(R) \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\lessgtr}} (1 - 2p)$$

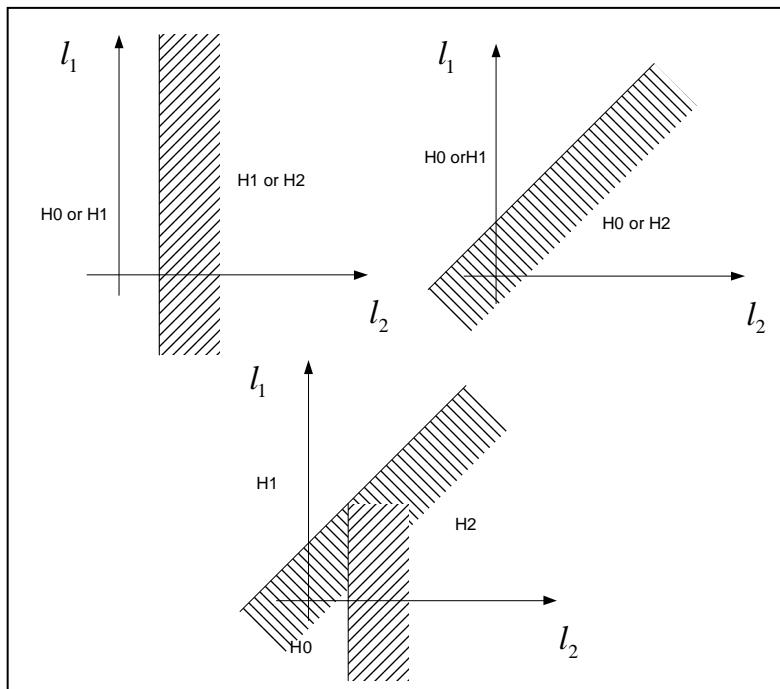
$$\log(p) + \log(\Lambda_2(R)) \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\lessgtr}} \log(1 - 2p)$$

$$l_2 \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\lessgtr}} \frac{2\sigma_n^2(\sigma_s^2 + \sigma_n^2)}{\sigma_s^2} \left[ \ln\left(\frac{1 - 2p}{p}\right) + \ln\left(\frac{\sqrt{\sigma_s^2 + \sigma_n^2}}{\sigma_n}\right) \right]$$

First part always bigger than zero, second part also. The equation does not depend on the  $l_1$  value.

The third equation

$$\ln \alpha + l_1 \frac{\sigma_s^2}{2\sigma_n^2(\sigma_s^2 + \sigma_n^2)} \stackrel{H_1 \text{ or } H_2}{\underset{H_0 \text{ or } H_1}{\lessgtr}} l_2 \frac{\sigma_s^2}{2\sigma_n^2(\sigma_s^2 + \sigma_n^2)}$$



$$l_1 \stackrel{H_1 \text{ or } H_2}{\leqslant} l_2 - \frac{2\sigma_n^2 (\sigma_s^2 + \sigma_n^2)}{\sigma_s^2} \ln \alpha$$

## 2. Error probabilities

$$\Pr(H_1 H_2 | H_0) = \int_{Z_0} \left[ p P_{r_1 r_2 | H_2} (R_1, R_2 | H_2) + p P_{r_1 r_2 | H_1} (R_1, R_2 | H_1) \right] dR_1 dR_2$$

$$\Pr(H_0 H_2 | H_1) = \int_{Z_1} \left[ (1 - 2p) P_{r_1 r_2 | H_0} (R_1, R_2 | H_0) + p \alpha P_{r_1 r_2 | H_2} (R_1, R_2 | H_2) \right] dR_1 dR_2$$

$$\Pr(H_0 H_1 | H_2) = \int_{Z_2} \left[ (1 - 2p) P_{r_1 r_2 | H_0} (R_1, R_2 | H_0) + p \alpha P_{r_1 r_2 | H_1} (R_1, R_2 | H_1) \right] dR_1 dR_2$$

Where  $Z_i$  are the decision regions associated with the hypothesis  $H_i$ .