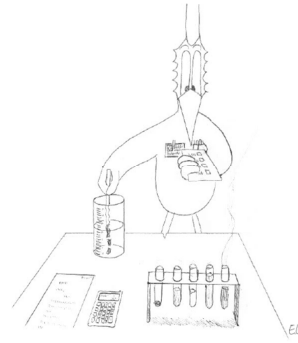


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## PERFORMANCE EVALUATION EXERCISES

### TESTS

With Solutions Jean-Yves Le Boudec, Spring 2021



1. If the data is in the critical region we...
  - (a) ☐ Accept  $H_0$
  - (b) ☒ Reject  $H_0$
  - (c) ☐ It depends on the nature of the test
  - (d) ☐ It depends on the size of the test
2. Saying that a test is of size 5% means that...
  - (a) ☐ The probability to accept  $H_0$  when  $H_0$  does not hold is  $\leq 0.05$
  - (b) ☒ The probability to reject  $H_0$  when  $H_0$  it holds is  $\leq 0.05$
  - (c) ☐ Both
3. If the  $p$ -value of a test is small we ...
  - (a) ☐ Accept  $H_0$
  - (b) ☒ Reject  $H_0$
  - (c) ☐ It depends on the nature of the test
  - (d) ☐ It depends on the size of the test
4. We have a collection of random variables  $X_i, Y_i$  which correspond to non paired simulation results with configuration 1 or 2. How can you test whether the configuration plays a role or not ?
  - (a) ☐ With a Wilcoxon Rank Sum test
  - (b) ☐ With an ANOVA test
  - (c) ☒ With either
  - (d) ☒ With none

**Solution.** (a) is robust and can be used if we can ensure that the simulation runs are independent and that the two distributions differ by a location shift, i.e. have same variance.

(b) is applicable if, in addition,  $X_i$  and  $Y_i$  can be assumed gaussian with same variance.

5. We test whether a distribution is gaussian using a Kolmogorov-Smirnov test against the fitted distribution. We obtain a  $p$ -value.
  - (a) ☒ The true  $p$ -value is smaller

- (b) ☐ We have obtained the true  $p$ -value
- (c) ☐ The true  $p$ -value is larger
- (d) ☐ It depends on the data

**Solution.** The KS test applies if we are testing against a fixed, non fitted distribution  $F$ . By using a fitted distribution, we are biasing the test, we are making it more likely than should be to accept the distribution  $F$ , i.e. to accept  $H_0$ . The  $p$ -value should therefore be higher (since a small  $p$ -value means rejecting  $H_0$ ).

6. We have two data sets  $X_i$  and  $Y_j$  believed to be iid and from one exponential distribution each. We want to test whether the parameter of their exponential distribution is the same.

Give the design of a corresponding likelihood ratio test. Give a formula for the  $p$ -value when  $m, n$  are large.

**Solution.** The generic model is  $X_i \sim \text{iid Exp}(\lambda)$ ,  $Y_j \sim \text{iid Exp}(\mu)$  and  $X_i, Y_j$  independent for  $i = 1 : m, j = 1 : n$  and for some  $\lambda, \mu > 0$ . The parameter is  $\theta = (\lambda, \mu)$  and  $\Theta = \{(\lambda, \mu) : \lambda > 0 \text{ and } \mu > 0\}$   $H_0$  corresponds to  $\lambda = \mu$ .

The PDF of the  $\text{Exp}(\lambda)$  distribution is  $f_X(x) = \lambda e^{-\lambda x}$  hence the likelihood of the data  $(\vec{x}, \vec{y})$  is

$$f_{\vec{X}, \vec{Y}}(\vec{x}, \vec{y}) = \prod_{i=1}^m (\lambda e^{-\lambda x_i}) \times \prod_{j=1}^n (\mu e^{-\mu y_j}) \quad (1)$$

and the log-likelihood is

$$m \log \lambda + n \log \mu - \lambda \sum_{i=1}^m x_i - \mu \sum_{j=1}^n y_j \quad (2)$$

We use the following notation:  $x^* = \frac{1}{m} \sum_i x_i$ ,  $y^* = \frac{1}{n} \sum_j y_j$  and  $z^* = \frac{1}{m+n} (\sum_i x_i + \sum_j y_j)$ .

We compute the optimal value of the log likelihood under  $H_0$ , namely under the constraint  $\lambda = \mu$ :

$$\min_{\lambda > 0} \left( m \log \lambda + n \log \lambda - \lambda \sum_{i=1}^m x_i - \lambda \sum_{j=1}^n y_j \right)$$

Taking the derivative we find that the optimum is for  $\lambda = \mu = \frac{\sum_i x_i + \sum_j y_j}{m+n} = \frac{1}{z^*}$  and the value of the optimal log-likelihood under  $H_0$  is

$$\begin{aligned} \ell_0 &= (m+n) \log \frac{1}{z^*} - m - n \\ &= -(m+n) (\log z^* + 1) \end{aligned}$$

Under  $H_1$  the optimal is for  $\lambda = \frac{1}{x^*}$  and  $\mu = \frac{1}{y^*}$ . The value of the optimal log-likelihood under  $H_1$  is

$$\begin{aligned} \ell_1 &= m \left( \log \frac{1}{x^*} - 1 \right) + n \left( \log \frac{1}{y^*} - 1 \right) \\ &= -m (\log x^* + 1) - n (\log y^* + 1) \end{aligned}$$

The log-likelihood ratio statistic is

$$lrs = \ell_1 - \ell_0 = (m+n) \log z^* - m \log x^* - n \log y^*$$

Apply theorem 4.3:  $q_2 = 2 - 1 = 1$  hence the distribution of  $2lrs$  under  $H_0$  is approximately  $\chi_1^2$  and the  $p$  value is approximately

$$p = 1 - F_{\chi_1^2}(2lrs)$$

where  $F_{\chi_1^2}$  is the CDF of  $\chi_1^2$ .

7. We have some data set  $\vec{Y} = Y_{i=1:I}$  modelled with a parametric model with  $\theta \in \Theta$ . Let  $f_{\vec{Y}}(\vec{y}|\theta)$  be the PDF of the observation  $\vec{y} = y_{1:I}$ . We assume that we have a method to compute  $\hat{\theta}(\vec{y})$ , the maximum likelihood estimator of  $\theta$  for value of the data set  $\vec{y}$ .

- (a) Give a likelihood ratio test for the test

$$H_0 : \theta = \theta_0 \text{ versus } H_1 : \theta \in \Theta$$

- (b) Give the pseudo-code of an algorithm to compute the  $p$ -value of this test using Monte-Carlo simulation with  $R$  runs.  
(c) We run this algorithm with  $R = 10'000$  and find  $p = 0$ . Give a 99% confidence for the true  $p$ -value. What can we conclude at a size of 5% ?

**Solution.**

- (a) Under  $H_0$  the MLE is  $\hat{\theta} = \theta_0$  (a fixed value) and the log-likelihood is

$$\ell_0 = \log f_{\vec{Y}}(\vec{y}|\theta_0)$$

Under  $H_1$  the optimal likelihood is obtained for  $\theta = \hat{\theta}(\vec{y})$  and thus

$$\ell_1 = \log f_{\vec{Y}}(\vec{y}|\hat{\theta}(\vec{y}))$$

and

$$lrs(\vec{y}) = \log f_{\vec{Y}}(\vec{y}|\hat{\theta}(\vec{y})) - \log f_{\vec{Y}}(\vec{y}|\theta_0)$$

The test has a rejection region of the form  $lrs(\vec{y}) > C$  for some constant  $C$  that depends on the size of the test. The  $p$ -value is thus

$$p = \mathbb{P} \left( lrs(\vec{Y}) > lrs(\vec{y}) \right) \quad (3)$$

where  $\vec{Y}$  is a random sequence that has PDF  $f_{\vec{Y}}(\cdot|\theta_0)$

- (b) To compute the  $p$ -value by Monte-Carlo simulation with  $R$  runs we draw  $R$  replicates of the sequence  $\vec{Y}$  from the PDF  $f_{\vec{Y}}(\cdot|\theta_0)$  and evaluate  $p$  as the empirical mean:

tot = 0

for  $r = 1 : R$  do

draw  $\vec{y}^r$  from the distribution with PDF  $f_{\vec{Y}}(\cdot|\theta_0)$

if  $\{lrs(\vec{y}^r) > lrs(\vec{y})\}$  tot = tot+1

end

return  $\left( \frac{\text{tot}}{R} \right)$

- (c) By Theorem 2.4, a 99% confidence interval for  $p$  is  $[0, p_0]$  with  $p_0 = 5.3 \times 10^{-4}$ . Since the upper bound on the estimated  $p$ -value is very small, much smaller than 5%, we reject  $H_0$ .

8. We consider again the case in the previous question. Using Monte-Carlo simulation, we have obtained a 99% confidence interval  $[\ell(\vec{y}), u(\vec{y})]$  for the  $p$ -value. We reject  $H_0$  if the true  $p$  is small, but since we don't know the true  $p$ -value, we use the rejection condition  $u(\vec{y}) < \alpha$ . What value of  $\alpha$  should we choose to ensure that this way of doing provides a test of size 5% ?

**Solution.** Let  $Z$  represent the sequence of all random numbers we have used to estimate the  $p$ -value  $p(\vec{y})$ . The sequence  $Z$  is independent of the data  $\vec{y}$ . The upper bound  $u(\vec{y}, Z)$  is true with confidence 99%, therefore

$$\mathbb{P}(u(\vec{y}, Z) \leq p(\vec{y})) \leq 1\% \quad (4)$$

Furthermore, let  $\vec{Y}_0$  be a random variable that has the distribution of  $\vec{Y}$  under  $H_0$ . By definition of a  $p$ -value we know that:

$$\mathbb{P}(p(\vec{Y}_0) < \alpha) = \alpha \quad (5)$$

Also, observe that (4) should hold for any realization of  $\vec{y}$ , therefore

$$\mathbb{P}(u(\vec{Y}_0, Z) \leq p(\vec{Y}_0)) \leq 1\% \quad (6)$$

Now our test consists in rejecting  $H_0$  whenever  $u(\vec{y}, Z) < \alpha$ . The probability  $p_I$  of a type-I error is the probability of rejection when  $\vec{y}$  is a sample of  $\vec{Y}_0$ :

$$\begin{aligned} p_I &= \mathbb{P}(u(\vec{Y}_0, Z) < \alpha) \\ &= \mathbb{E}(\mathbf{1}_{\{u(\vec{Y}_0, Z) < \alpha\}}) \\ &= \mathbb{E}(\mathbf{1}_{\{u(\vec{Y}_0, Z) < \alpha\}} \mathbf{1}_{\{u(\vec{Y}_0, Z) > p(\vec{Y}_0)\}} + \mathbf{1}_{\{u(\vec{Y}_0, Z) < \alpha\}} \mathbf{1}_{\{u(\vec{Y}_0, Z) \leq p(\vec{Y}_0)\}}) \\ &= \mathbb{E}(\mathbf{1}_{\{u(\vec{Y}_0, Z) < \alpha\}} \mathbf{1}_{\{u(\vec{Y}_0, Z) > p(\vec{Y}_0)\}}) + \mathbb{E}(\mathbf{1}_{\{u(\vec{Y}_0, Z) < \alpha\}} \mathbf{1}_{\{u(\vec{Y}_0, Z) \leq p(\vec{Y}_0)\}}) \\ &\leq \mathbb{E}(\mathbf{1}_{\{p(\vec{Y}_0) < \alpha\}}) + \mathbb{E}(\mathbf{1}_{\{u(\vec{Y}_0, Z) \leq p(\vec{Y}_0)\}}) \\ &= \mathbb{P}(p(\vec{Y}_0) < \alpha) + \mathbb{P}(u(\vec{Y}_0, Z) \leq p(\vec{Y}_0)) \\ &\leq \alpha + 1\% \end{aligned}$$

Therefore, we need to take  $\alpha = 4\%$  to obtain a test of size 5%. The uncertainty due to the Monte Carlo estimation needs to be added to  $\alpha$ .