## Tufts University Department of Mathematics Spring 2022

## MA 166: Statistics

## Homework 6 (v1.1) 1

Assigned Monday 28 February 2022 Due Monday 7 March 2022 at 11:59 pm EDT.

1. Larsen & Marx, Section 6.4, Problem 6.4.4, page 373: Construct a power curve for the  $\alpha = 0.05$  test of  $H_0$ :  $\mu = 60$  versus  $H_1$ :  $\mu \neq 60$  if the data consist of a random sample of size 16 from a normal distribution having  $\sigma = 4$ .

The upper and lower cutoffs  $\mu_{c\pm}$  for incurring a Type I error by rejecting a valid  $H_0$  are given by

$$\frac{\mu_{c\pm} - \mu_0}{\sigma / \sqrt{n}} = \pm z_{\alpha/2},$$

so that

$$\mu_{c\pm} = \mu_0 \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}.$$

In other words, assuming that  $H_0$  is true, a Type I error will be made if the sample mean is greater than  $\mu_{c+}$  or less than  $\mu_{c-}$ .

If  $H_0$  is not true, on the other hand, and the actual mean is located at some value  $\mu'$ , a Type II error will be made with probability

$$\beta = P\left(\mu_{c-} \leq \overline{\mu} \leq \mu_{c+} \mid \overline{\mu} \text{ is } N(\mu', \sigma/\sqrt{n}) \text{ r.v.}\right)$$

$$= \int_{\mu_{c-}}^{\mu_{c+}} d\xi \, \frac{1}{\sqrt{2\pi} \, \sigma/\sqrt{n}} \exp\left[-\frac{(\xi - \mu')^2}{2\sigma^2/n}\right]$$

$$= \int_{\frac{\mu_{c-} - \mu'}{\sigma/\sqrt{n}}}^{\frac{\mu_{c+} - \mu'}{\sigma/\sqrt{n}}} dz \, \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$$

$$= \int_{\frac{\mu_{c-} - \mu'}{\sigma/\sqrt{n}}}^{\infty} dz \, \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) - \int_{\frac{\mu_{c+} - \mu'}{\sigma/\sqrt{n}}}^{\infty} dz \, \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$$

$$= \int_{\frac{\mu_{0-} - \mu'}{\sigma/\sqrt{n}} - z_{\alpha/2}}^{\infty} dz \, \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) - \int_{\frac{\mu_{0-} - \mu'}{\sigma/\sqrt{n}} + z_{\alpha/2}}^{\infty} dz \, \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right).$$

Going forward, let us define the function  $Z^{-1}$  by  $\forall \beta \in [0,1]$ :  $Z^{-1}(z_{\beta}) = \beta$ . Then we can satisfy the above equation by taking

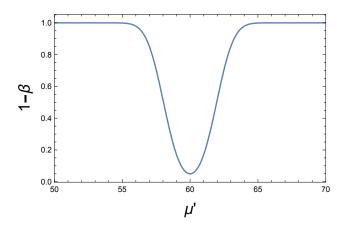
$$Z^{-1} \left( \frac{\mu_0 - \mu'}{\sigma/\sqrt{n}} - z_{\alpha/2} \right) = \frac{\gamma + \beta}{2}$$
$$Z^{-1} \left( \frac{\mu_0 - \mu'}{\sigma/\sqrt{n}} + z_{\alpha/2} \right) = \frac{\gamma - \beta}{2},$$

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whence

$$\beta = Z^{-1} \left( \frac{\mu_0 - \mu'}{\sigma / \sqrt{n}} - z_{\alpha/2} \right) - Z^{-1} \left( \frac{\mu_0 - \mu'}{\sigma / \sqrt{n}} + z_{\alpha/2} \right).$$

Given  $\alpha$ ,  $\sigma$ , n and  $\mu_0$ , the above equation allows us to make a plot of  $1-\beta$  as a function of  $\mu'$ , which is the power curve. In our case,  $\alpha = 0.05$ ,  $\sigma = 4$ , n = 16 and  $\mu_0 = 60$ , and the above relationship between  $1 - \beta$  and  $\mu'$  is plotted below



Note that, unlike the power curve shown in Fig. 6.4.4 of the Larsen and Marx text, the graph of the above power curve is symmetric about  $\mu_0$ , owing to the two-sided nature of the test. On the other hand, it remains true that  $\lim_{\mu'\to\mu_0}(1-\beta)=\alpha$ , since

$$1 - \beta = 1 - Z^{-1} (-z_{\alpha/2}) + Z^{-1} (z_{\alpha/2})$$

$$= 1 - Z^{-1} (z_{1-\alpha/2}) + Z^{-1} (z_{\alpha/2})$$

$$= 1 - (1 - \alpha/2) + (\alpha/2)$$

$$= \alpha.$$

2. Larsen & Marx, Section 6.5, Problem 6.5.2, page 377: Let  $y_1, y_2, \ldots, y_{10}$  be a random sample from an exponential pdf with unknown parameter  $\lambda$ . Find the form of the GLRT for  $H_0: \lambda = \lambda_0$  versus  $H_1: \lambda \neq \lambda_0$ . What integral would have to be evaluated to determine the critical value if  $\alpha$  were equal to 0.05?

The exponential distribution is  $f_Y(y; \lambda) = \lambda e^{-\lambda y}$  for y > 0. Here we must have  $\lambda > 0$ , else  $f_Y$  will not be normalizable. The likelihood function is then

$$L(\lambda) = \prod_{j=1}^{n} \lambda e^{-\lambda y_j} = \lambda^n e^{-n\lambda \overline{y}},$$

and the log likelihood is

$$\log L(\lambda) = n \log \lambda - n\lambda \overline{y}.$$

The maximum likelihood occurs when

$$0 = \frac{\partial \log L(\lambda)}{\partial \lambda} = \frac{n}{\lambda} - n\overline{y}$$

or 
$$\lambda = \lambda_e := 1/\overline{y}$$
.

The set of  $\lambda$  values consistent with the null hypothesis is  $\omega = {\lambda_0}$ , while the set of all possible  $\lambda$  values is  $\Omega = \mathbb{R}^+$ . Hence we have

$$\max_{\lambda \in \omega} L(\lambda) = L(\lambda_0) = \lambda_0^n e^{-n\lambda_0 \overline{y}} = \lambda_0^n e^{-n\lambda_0/\lambda_e}$$

and

$$\max_{\lambda \in \Omega} L(\lambda) = L(\lambda_e) = \lambda_e^n e^{-n}$$

The GLR is usually denoted by  $\lambda$ , but we can not use that here because we are already using  $\lambda$  to denote the parameter. So let us denote the GLR by the next letter in the Greek alphabet,  $\mu$ . We have

$$\mu = \frac{\max_{\lambda \in \omega} L(\lambda)}{\max_{\lambda \in \Omega} L(\lambda)} = \left(\frac{\lambda_0}{\lambda_e}\right)^n \exp\left[n\left(1 - \frac{\lambda_0}{\lambda_e}\right)\right] = (\lambda_0 \overline{y})^n \exp\left[n\left(1 - \lambda_0 \overline{y}\right)\right],$$

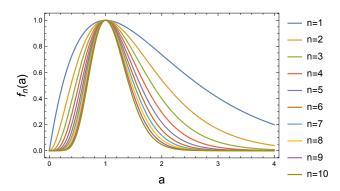
and so the GLRT is that we reject  $H_0$  whenever

$$\mu = (\lambda_0 \overline{y})^n \exp\left[n\left(1 - \lambda_0 \overline{y}\right)\right] \le \mu^*.$$

If we define  $a = \lambda_0 \overline{y}$ , this criterion becomes

$$f_n(a) := a^n \exp[n(1-a)] \le \mu^*.$$

The function  $f_n(a)$  is plotted against a for various values of n below.



For low values of n, it is seen that  $f_n(a)$  is a skewed distribution, but for large values of n, it begins to resemble something more familiar. To see what it becomes, note that  $f_n(a) = e^{F_n(a)}$ , where

$$F_n(a) = \log [f_n(a)] = n \log a + n - na,$$

and that

$$F_n'(a) = \frac{n}{a} - n$$

$$F_n''(a) = -\frac{n}{a^2}.$$

From this, we see that

$$F_n(1) = 0$$
  
 $F'_n(a) = 0$   
 $F''_n(a) = -n$ 

and, in fact, this much is evident in the plots of  $f_n(a)$  provided above. Hence, the leading term in the Taylor expansion of  $F_n(a)$  about a = 1 is

$$F_n(a) \approx -\frac{n}{2}(a-1)^2,$$

whence

$$f_n(a) \approx C_n \exp\left[-\frac{n}{2}(a-1)^2\right],$$

where we have allowed for a proportionality constant  $C_n$ . To interpret  $f_n$  as a pdf for a, we need to choose the  $C_n$  so that  $f_n(a)$  is normalized, and this yields

$$f_n(a) \approx \frac{1}{\sqrt{2\pi/n}} \exp\left[-\frac{(a-1)^2}{2/n}\right],$$

This is a normal distribution with mean 1 and variance 1/n. In this limit then, the GLRT becomes

$$-z_{\alpha/2} \le \sqrt{n}(a-1) \le +z_{\alpha/2},$$

or

$$1 - \frac{z_{\alpha/2}}{\sqrt{n}} \le a \le 1 + \frac{z_{\alpha/2}}{\sqrt{n}},$$

or, since  $a = \lambda_0 \overline{y}$ , we reject  $H_0$  if

$$1 - \frac{z_{\alpha/2}}{\sqrt{n} \lambda_0} \le \overline{y} \le 1 + \frac{z_{\alpha/2}}{\sqrt{n} \lambda_0}.$$

It is seen that the GLRT reduces to a standard Z test in the large n limit.

3. Larsen & Marx, Section 7.3, Problem 7.3.2, page 388: Find the moment-generating function for a chi square random variable and use it to show that  $E(\chi_n^2) = n$  and  $Var(\chi_n^2) = 2n$ .

The chi squared pdf with n degrees of freedom is

$$f_U(u) = \frac{1}{2^{n/2}\Gamma(\frac{n}{2})}u^{(n/2)-1}e^{-u/2}$$

for  $u \geq 0$ . The moment generating function for this is given by

$$M_{U}(t) = \int_{0}^{\infty} du \ e^{tu} f_{U}(u)$$

$$= \int_{0}^{\infty} du \ e^{tu} \frac{1}{2^{n/2} \Gamma\left(\frac{n}{2}\right)} u^{(n/2)-1} e^{-u/2}$$

$$= \frac{1}{2^{n/2} \Gamma\left(\frac{n}{2}\right)} \int_{0}^{\infty} du \ u^{(n/2)-1} e^{-(1/2-t)u}$$

$$= \frac{1}{2^{n/2} (1/2 - t)^{n/2}} \left[ \frac{(1/2 - t)^{n/2}}{\Gamma\left(\frac{n}{2}\right)} \int_{0}^{\infty} du \ u^{(n/2)-1} e^{-(1/2-t)u} \right].$$

The quantity in square brackets is the integration of a gamma pdf with parameters  $^{n}/_{2}$  and (1/2-t), and hence is equal to one. (Really, this last conclusion is valid only for  $t < ^{1}/_{2}$ , but the variable in a moment generating function is usually regarded as a formal variable and not associated with a numerical value.) In any case, we are left with the moment generating function

$$M_U(t) = \frac{1}{(1-2t)^{n/2}},$$

for which the binomial expansion in t to second order is

$$M_U(t) = 1 + nt + \frac{n(n+2)}{2}t^2 + \cdots$$

From the definition of the moment generating function, we see that

$$M_U(t) = \int_0^\infty du \ e^{tu} f_U(u)$$

$$= \int_0^\infty du \ \left(\sum_{j=0}^\infty \frac{t^j u^j}{j!}\right) f_U(u)$$

$$= \sum_{j=0}^\infty \frac{t^j}{j!} \int_0^\infty du \ u^j f_U(u)$$

$$= \sum_{j=0}^\infty \frac{t^j}{j!} E(u^j).$$

Comparing this with the binomial expansion of  $M_U(t)$  given above, we identify

$$E(U) = n,$$

and

$$E(U^2) = n(n+2) = n^2 + 2n.$$

It follows that

$$Var(U) = E(U^2) - E(U)^2 = n^2 + 2n - n^2,$$

or

$$Var(U) = 2n,$$

as was to be shown.