

## S620 - Introduction To Statistical Theory - Homework 5

**Enrique Areyan**  
**March 13, 2014**

1. Suppose that  $x_1, \dots, x_5 \sim \text{Poisson}(\lambda)$ , i.e.,  $P(X_i = r) = \frac{e^{-\lambda} \lambda^r}{r!}$  for  $r = 0, 1, 2, \dots$ . Compare the following two tests of  $H_0 : \lambda = 1/2$  versus  $H_1 : \lambda = 1$

- (a) Let  $y = x_1 + \dots + x_5$  and reject  $H_0$  iff  $y \geq 4$ . Note that  $Y \sim \text{Poisson}(5\lambda)$ .  
 (b) Reject  $H_0$  iff at least three of the  $x_i$  are nonzero.

**Solution:** For each test, let us compute its size and power:

- (a) *Size:* Since this is a non-randomized test, take:

$$P_{\lambda=\frac{1}{2}}(\text{reject } H_0) = P_{\lambda=\frac{1}{2}}(y \geq 4) = 1 - P_{\lambda=\frac{1}{2}}(y < 4) = 1 - \sum_{i=0}^3 P_{\lambda=\frac{1}{2}}(y = i)$$

Since  $y \sim \text{Pois}(5\lambda) = \text{Pois}(\frac{5}{2})$ , we have that  $P_{\lambda=\frac{1}{2}}(y = i) = \frac{e^{-5/2} (\frac{5}{2})^i}{i!}$ , and hence:

$$1 - \sum_{i=0}^3 P_{\lambda=\frac{1}{2}}(y = i) = 1 - \left[ e^{-5/2} \left( \frac{(\frac{5}{2})^0}{0!} + \frac{(\frac{5}{2})^1}{1!} + \frac{(\frac{5}{2})^2}{2!} + \frac{(\frac{5}{2})^3}{3!} \right) \right] = 1 - \left[ e^{-5/2} \left( 1 + \frac{5}{2} + \frac{5^2}{2^3} + \frac{5^3}{2^4 \cdot 3} \right) \right] = 0.242423867$$

And so the size of the test is 0.242423867. Hence, there is approximately a 24.24% chance of rejecting the null given that is true, i.e., committing a type I error.

*Power:* we would need to do the same computation under the alternative hypothesis:

$$P_{\lambda=1}(\text{reject } H_0) = P_{\lambda=1}(y \geq 4) = 1 - P_{\lambda=1}(y < 4) = 1 - \sum_{i=0}^3 P_{\lambda=1}(y = i)$$

Since  $y \sim \text{Pois}(5\lambda) = \text{Pois}(5)$ , we have that  $P_{\lambda=1}(y = i) = \frac{e^{-5} 5^i}{i!}$ , and hence:

$$1 - \sum_{i=0}^3 P_{\lambda=1}(y = i) = 1 - \left[ e^{-5} \left( \frac{5^0}{0!} + \frac{5^1}{1!} + \frac{5^2}{2!} + \frac{5^3}{3!} \right) \right] = 1 - \left[ e^{-5} \left( 1 + 5 + \frac{5^2}{2} + \frac{5^3}{3 \cdot 2} \right) \right] = 0.734974085$$

This test has high power. In other words, there is approximately a 73.49% chance of rejecting the null hypothesis when the alternative is the true state of nature.

- (b) For this test, let us define for  $i = 1, 2, 3, 4, 5$ :

$$z_i = \begin{cases} 1 & \text{if } x_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

Now,  $Pr_{\theta}\{z_i = 1\} = Pr_{\theta}\{x_i > 0\} = 1 - Pr_{\theta}\{x_i = 0\} = 1 - \frac{e^{-\theta} (\frac{5}{2})^0}{0!} = 1 - e^{-\theta}$ .

Thus,  $z_i \sim \text{Bernoulli}(1 - e^{-\theta})$ . Define  $T_{\theta} = z_1 + z_2 + \dots + z_5$ . Then,  $T_{\theta} \sim \text{Bin}(5, 1 - e^{-\theta})$ .

*Size:* Since this is a non-randomized test, take:

$$\begin{aligned} Pr_{\lambda=\frac{1}{2}}(\text{reject } H_0) &= P(T_{\frac{1}{2}} \geq 3) \\ &= 1 - \left[ P(T_{\frac{1}{2}} = 0) + P(T_{\frac{1}{2}} = 1) + P(T_{\frac{1}{2}} = 2) \right] \\ &= 1 - \left[ \binom{5}{0} (1 - e^{-1/2})^0 (e^{-1/2})^5 + \binom{5}{1} (1 - e^{-1/2})^1 (e^{-1/2})^4 + \binom{5}{2} (1 - e^{-1/2})^2 (e^{-1/2})^3 \right] \\ &= 1 - \left[ (e^{-1/2})^5 + 5(1 - e^{-1/2})(e^{-1/2})^4 + 10(1 - e^{-1/2})^2 (e^{-1/2})^3 \right] \\ &= 0.306217655 \end{aligned}$$

And so the size of the test is 0.306217655. Hence, there is approximately a 30.621% chance of rejecting the null given that is true, i.e., committing a type I error.

*Power:* we would need to do the same computation under the alternative hypothesis:

$$\begin{aligned} Pr_{\lambda=1}(\text{reject } H_0) = P(T_1 \geq 3) &= 1 - [P(T_1 = 0) + P(T_1 = 1) + P(T_1 = 2)] \\ &= 1 - \left[ \binom{5}{0}(1 - e^{-1})^0(e^{-1})^5 + \binom{5}{1}(1 - e^{-1})^1(e^{-1})^4 + \binom{5}{2}(1 - e^{-1})^2(e^{-1})^3 \right] \\ &= 1 - \left[ (e^{-1})^5 + 5(1 - e^{-1})(e^{-1})^4 + 10(1 - e^{-1})^2(e^{-1})^3 \right] \\ &= 0.736436218 \end{aligned}$$

This test has high power. In other words, there is approximately a 73.64% chance of rejecting the null hypothesis when the alternative is the true state of nature.

In summary we have:

	Test a	Test b
Size	0.242423867	0.306217655
Power	0.734974085	0.736436218

The test have virtually the same power. However, test (a) has smaller size and thus it is more conservative. In other words, for the same power as test (b) we have that test (a) has a smaller chance of committing type I error. It would make sense to choose test (a) instead of test (b).

3. Suppose that  $x_1, \dots, x_n \sim \text{Normal}(\mu, \sigma^2)$ , where  $\mu$  is unknown and  $\sigma^2 > 0$  is known. Show that the corresponding family of joint densities of  $x = (x_1, \dots, x_n)$  has monotone likelihood ratio. Given  $\alpha \in (0, 1)$  and  $\mu_0$ , construct a uniformly most powerful test of size  $\alpha$  for  $H_0 : \mu \leq \mu_0$  versus  $H_1 : \mu > \mu_0$ .

**Solution:** By definition, the family of densities  $\mathcal{F} = \{f(x; \theta) : \theta \in \Theta \subseteq \mathbb{R}\}$ , with real scalar parameter  $\theta$  is of monotone likelihood ratio (MLR) iff there exists a function  $t : \mathcal{X} \rightarrow \mathbb{R}$  such that

$$\Lambda(x) = \frac{f(x; \theta_2)}{f(x; \theta_1)}$$

is a nondecreasing function of  $t(x)$  for any  $\theta_1 \leq \theta_2$ .

Let us compute the likelihood ratio. First note that the joint densities of independent, i.i.d normal random variable is given by:

$$\begin{aligned} f(x_1, \dots, x_n; \theta) &= \left[ \frac{e^{-\frac{1}{2} \left( \frac{X_1 - \theta}{\sigma} \right)^2}}{\sigma \sqrt{2\pi}} \right] \left[ \frac{e^{-\frac{1}{2} \left( \frac{X_2 - \theta}{\sigma} \right)^2}}{\sigma \sqrt{2\pi}} \right] \dots \left[ \frac{e^{-\frac{1}{2} \left( \frac{X_n - \theta}{\sigma} \right)^2}}{\sigma \sqrt{2\pi}} \right] \\ &= \frac{1}{\sigma^n (2\pi)^{n/2}} e^{\left\{ -\frac{1}{2} \left( \frac{X_1 - \theta}{\sigma} \right)^2 \right\} + \left\{ -\frac{1}{2} \left( \frac{X_2 - \theta}{\sigma} \right)^2 \right\} + \dots + \left\{ -\frac{1}{2} \left( \frac{X_n - \theta}{\sigma} \right)^2 \right\}} \\ &= \left[ \sigma^n (2\pi)^{n/2} \right]^{-1} e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta)^2 \right]} \end{aligned}$$

So the likelihood ratio is (suppose  $\theta_1 \leq \theta_2$ ):

$$\begin{aligned}
\frac{f(x_1, \dots, x_n; \theta_2)}{f(x_1, \dots, x_n; \theta_1)} &= \frac{[\sigma^n (2\pi)^{n/2}]^{-1} e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_2)^2 \right]}}{[\sigma^n (2\pi)^{n/2}]^{-1} e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_1)^2 \right]}} \\
&= \frac{e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_2)^2 \right]}}{e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_1)^2 \right]}} \\
&= e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_2)^2 \right] + \frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_1)^2 \right]} \\
&= e^{\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_1)^2 - \sum_{i=1}^n (x_i - \theta_2)^2 \right]} \\
&= e^{\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_1)^2 - (x_i - \theta_2)^2 \right]}
\end{aligned}$$

Note that for any  $i$  we have:  $(x_i - \theta_1)^2 - (x_i - \theta_2)^2 = x_i^2 - 2x_i\theta_1 + \theta_1^2 - x_i^2 + 2x_i\theta_2 - \theta_2^2 = \theta_1^2 - \theta_2^2 + 2x_i(\theta_2 - \theta_1)$ . Hence,

$$\sum_{i=1}^n \theta_1^2 - \theta_2^2 + 2x_i(\theta_2 - \theta_1) = n(\theta_1^2 - \theta_2^2) + 2(\theta_2 - \theta_1) \sum_{i=1}^n x_i \cdot \frac{n}{n} = n\{(\theta_1^2 - \theta_2^2) + 2(\theta_2 - \theta_1)\bar{x}\}$$

And so the likelihood ratio is:

$$\begin{aligned}
\frac{f(x_1, \dots, x_n; \theta_2)}{f(x_1, \dots, x_n; \theta_1)} &= e^{\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \theta_1)^2 - (x_i - \theta_2)^2 \right]} \\
&= e^{[n\{(\theta_1^2 - \theta_2^2) + 2(\theta_2 - \theta_1)\bar{x}\} / 2\sigma^2]}
\end{aligned}$$

This calculation shows that that  $\Lambda(x)$  depends on  $x$  through  $\bar{x}$ . Since  $\theta_1 \leq \theta_2 \implies \theta_2 - \theta_1 \geq 0$ , we have that  $\Lambda(x)$  is an increasing function of  $\bar{x}$ . Hence, take  $t(x) = \bar{x}$  to conclude that the corresponding family of joint densities of  $x = (x_1, \dots, x_n)$  has monotone likelihood ratio.

Having showed that  $x = (x_1, \dots, x_n)$  has monotone likelihood ratio with respect to  $t(x) = \bar{x}$ , Theorem 4.2 applies and the test:

$$\phi_0(x) = \begin{cases} 1 & \text{if } t(x) = \bar{x} > t_0 \\ 0 & \text{otherwise} \end{cases}$$

Is UMP among all test of size  $\alpha$ . So the test that rejects whenever  $\bar{x} > t_0$  is our UMP. In this case we can actually find what  $t_0$  is (for convenience, we will find  $z_\alpha$  which corresponds to  $t_0$  after standardization of  $\bar{x}$ ). First note that:  $Z = \sqrt{n}(\bar{x} - \mu_0)/\sigma^2 \sim Normal(0, 1)$ . The probability of rejection under the null is:

$$Pr\{Z > z_\alpha\} = \alpha \implies 1 - \Phi(z_\alpha) = \alpha \implies \Phi(z_\alpha) = 1 - \alpha \implies z_\alpha = \Phi^{-1}(1 - \alpha)$$

And so we will reject the null if, after standardizing  $\bar{x}$  we observe a value  $z_\alpha \geq \Phi^{-1}(1 - \alpha)$ .

4. Suppose that  $x_1, \dots, x_n \sim \text{Normal}(\mu, \sigma^2)$ , where  $\mu$  is known and  $\sigma^2 > 0$  is unknown. Given  $\alpha \in (0, 1)$  and  $\sigma_0^2 > 0$ , construct a uniformly most powerful test of size  $\alpha$  for  $H_0 : \sigma^2 \leq \sigma_0^2$  versus  $H_1 : \sigma^2 > \sigma_0^2$ .

**Solution:** Let us compute the likelihood ratio. We already computed the joint density to be:

$$f(x_1, \dots, x_n; \mu, \sigma) = [\sigma^n (2\pi)^{n/2}]^{-1} e^{-\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 \right]}$$

So the likelihood ratio is:

$$\begin{aligned} \frac{f(x_1, \dots, x_n; \mu, \sigma_2)}{f(x_1, \dots, x_n; \mu, \sigma_1)} &= \frac{[\sigma_2^n (2\pi)^{n/2}]^{-1} e^{-\frac{1}{2\sigma_2^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 \right]}}{[\sigma_1^n (2\pi)^{n/2}]^{-1} e^{-\frac{1}{2\sigma_1^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 \right]}} \\ &= \left( \frac{\sigma_1}{\sigma_2} \right)^n e^{\left\{ -\frac{1}{2\sigma_2^2} \sum_{i=1}^n (x_i - \mu)^2 + \frac{1}{2\sigma_1^2} \sum_{i=1}^n (x_i - \mu)^2 \right\}} \\ &= \left( \frac{\sigma_1}{\sigma_2} \right)^n e^{\left\{ \sum_{i=1}^n (x_i - \mu)^2 \left( \frac{1}{2\sigma_1^2} - \frac{1}{2\sigma_2^2} \right) \right\}} \end{aligned}$$

Since  $\sigma_2 > \sigma_1 \implies \frac{1}{2\sigma_2^2} < \frac{1}{2\sigma_1^2}$  and so  $\frac{1}{2\sigma_1^2} - \frac{1}{2\sigma_2^2} > 0$ . Note that  $\mu$  is known and so  $\Lambda(x)$  depends on  $x$  through  $\sum_{i=1}^n (x_i - \mu)^2$ . Take  $t(x) = \sum_{i=1}^n (x_i - \mu)^2$ , and this family has monotone likelihood ratio ( $t(x)$  is increasing). Apply theorem 4.2 to conclude that the test:

$$\phi_0(x) = \begin{cases} 1 & \text{if } t(x) = \sum_{i=1}^n (x_i - \mu)^2 > t_0 \\ 0 & \text{otherwise} \end{cases}$$

Is UMP among all test of size  $\alpha$ .