

VE401 Probabilistic Methods in Eng. Solution Manual for RC 6

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Assignment 5.2

Let X_1, \ldots, X_n be i.i.d. exponential random variables with parameter β . Recall that $Y = X_1 + X_2 + \cdots + X_n$ follows a Gamma distribution with parameters $\alpha = n$ and β . Transform this expression further to yield a chi-squared random variable.

Let X be an exponential random variable with parameter β . Devise a test statistic for testing $H_0: \beta = \beta_0$ and $H_0: \beta \leq \beta_0$ in a Fisher test.

Solution. Since Y follows a Gamma distribution with parameters $\alpha = n$ and β , we have the density function

$$f_Y(y) = \frac{\beta^n}{\Gamma(n)} y^{n-1} e^{-\beta y}, \qquad y > 0$$

and $f_Y(y) = 0$ when $y \le 0$. Let $u = \varphi(y) = 2\beta y$, then

$$y = \varphi^{-1}(u) = \frac{u}{2\beta} \quad \Rightarrow \quad \frac{\mathrm{d}}{\mathrm{d}u}\varphi^{-1}(u) = \frac{1}{2\beta}.$$

Then using transformation of variable, we have

$$f_U(u) = f_Y \circ \varphi^{-1}(u) \cdot \left| \frac{\mathrm{d}}{\mathrm{d}u} \varphi^{-1}(u) \right|$$
$$= \frac{\beta^n}{\Gamma(n)} \frac{u^{n-1}}{(2\beta)^{n-1}} e^{-u/2} \cdot \frac{1}{2\beta}$$
$$= \frac{1}{2^n \Gamma(n)} u^{n-1} e^{-u/2} \qquad u > 0,$$

and $f_U(u) = 0$ when $u \leq 0$, which is a chi-squared distribution with 2n degrees of freedom. Therefore, we have the distribution

$$Y \sim \frac{1}{2\beta} \chi_{2n}^2.$$

Given samples X_1, \ldots, X_n with size n, we can use test statistic

$$\chi_{2n}^2 = 2\beta_0 \sum_{i=1}^n X_i = 2n\beta_0 \overline{X}.$$

We see that a maximum likelihood estimator for β is given by

$$L(\beta) = \prod_{i=1}^{n} f_{X_i}(x_i) = \beta^n e^{\beta \sum_{i=1}^{n} X_i} \quad \Rightarrow \quad \ell(\beta) = n \ln \beta - \beta \sum_{i=1}^{n} X_i$$
$$\Rightarrow \quad \widehat{\beta} = \frac{1}{\overline{X}}.$$

With larger true parameter β , we would expect a smaller test statistic. Or

$$2n\beta \overline{x} = 2n\beta_0 \overline{x} \cdot \frac{\beta}{\beta_0} \le 2n\beta_0 \overline{x}$$

if $\beta \leq \beta_0$.

• For one-tailed test $\beta \leq \beta_0$, "more extreme data" means smaller \overline{X} . Therefore, the p-value is given by

$$P$$
-value = $F_{\chi^2_{2n}} \left(2n\beta_0 \overline{X} \right)$,

where $F_{\chi^2_{2n}}$ is the cumulative distribution function of chi-squared distribution with 2n degrees of freedom.

• For two-tailed test $\beta = \beta_0$, the p-value is given by

$$P-\text{value} = 2\min\left(F_{\chi_{2n}^2}\left(2n\beta_0\overline{X}\right), 1 - F_{\chi_{2n}^2}\left(2n\beta_0\overline{X}\right)\right).$$

If we want to have a critical region for the tests, with the test statistic χ^2_{2n} defined above, we reject H_0 at significance level α

- $H_0: \beta = \beta_0 \text{ if } \chi^2_{2n} < \chi^2_{2n,1-\alpha/2} \text{ or } \chi^2_{2n} > \chi^2_{2n,\alpha/2},$
- $H_0: \beta \le \beta_0 \text{ if } \chi^2_{2n} < \chi^2_{2n,1-\alpha}$
- $H_0: \beta \ge \beta_0 \text{ if } \chi^2_{2n} > \chi^2_{2n,\alpha}$.

Critical Region and Confidence Interval

Suppose we have a sample X_1, \ldots, X_n of size n from a normal population X with mean μ and known variance σ^2 . We would like to test the hypotheses

$$H_0: \mu \leq \mu_0, \qquad H_1: \mu > \mu_0.$$

Then for such one-tailed tests, what is the corresponding confidence interval? We know that we reject H_0 at significance level α if

$$Z = \frac{\overline{X} - \mu_0}{\sigma / \sqrt{n}} > z_{\alpha},$$

which can be rewritten as

$$\mu_0 < \overline{X} - z_\alpha \frac{\sigma}{\sqrt{n}}.$$

Since we know that if the inequality above holds, we will reject H_0 , in which case the null value μ_0 falls <u>outside</u> of the confidence interval. Therefore, the corresponding confidence interval is

given by

$$CI = \left[\overline{X} - z_{\alpha} \frac{\sigma}{\sqrt{n}}, \infty \right].$$

Similarly, if the null hypothesis is $H_0: \mu \geq \mu_0$, the corresponding one-sided confidence interval is given by

$$CI = \left(-\infty, \overline{X} + z_{\alpha} \frac{\sigma}{\sqrt{n}}\right].$$

Mean and Variance for Rank Sum

<u>Wilcoxon rank-sum test statistic</u>. Let X_1, \ldots, X_m and Y_1, \ldots, Y_n , where $m \leq n$, be random samples from two continuous populations X and Y and associate the rank R_i , $i = 1, \ldots, m+n$, to the R_i th smallest among the m+n total observations. The test statistic is given by

$$W_m = \text{sum of the ranks of } X_1, \dots, X_m$$

with

$$E[W_m] = \frac{m(m+n+1)}{2}, \quad Var[W_m] = \frac{mn(m+n+1)}{12}.$$

Proof. The rank of the m+n random variables follows a uniform discrete distribution. Namely,

$$P[R_i = k] = \frac{1}{m+n},$$
 for $k = 1, ..., m+n$.

Therefore, the expectation of each rank is given by

$$E[R_i] = \frac{1}{m+n} \sum_{k=1}^{m+n} k = \frac{m+n+1}{2},$$

giving

$$E[W_m] = E\left[\sum_{i=1}^{m} R_i\right] = \frac{m(m+n+1)}{2}.$$

Denote N = m + n. We know that

$$\sum_{i=1}^{N} i^2 = \frac{N(N+1)(2N+1)}{6}, \qquad \sum_{i=1}^{N} \sum_{j=1}^{N} ij = \left(\sum_{i=1}^{N} i\right)^2 = \frac{N^2(N+1)^2}{4}.$$

Therefore,

$$\sum_{i\neq j}^{N} ij = \frac{N^2(N+1)^2}{4} - \frac{N(N+1)(2N+1)}{6}.$$

By properties of variance, we have

$$\operatorname{Var}[W_m] = \operatorname{Var}\left[\sum_{i=1}^m R_i\right] = \sum_{i=1}^m \operatorname{Var}[R_i] + \sum_{i \neq j}^m \operatorname{Cov}[R_i, R_j],$$

where

$$\operatorname{Var}[R_{i}] = \operatorname{E}[R_{i}^{2}] - \operatorname{E}[R_{i}]^{2}$$

$$= \frac{(N+1)(2N+1)}{6} - \left(\frac{N+1}{2}\right)^{2}$$

$$= \frac{N^{2}-1}{12},$$

$$\operatorname{Cov}[R_{i}, R_{j}] = \operatorname{E}[R_{i}R_{j}] - \operatorname{E}[R_{i}]\operatorname{E}[R_{j}]$$

$$= \sum_{i \neq j}^{N} \frac{ij}{N(N-1)} - \left(\frac{N+1}{2}\right)^{2}$$

$$= \frac{N(N+1)^{2}}{4(N-1)} - \frac{(N+1)(2N+1)}{6(N-1)} - \frac{(N+1)^{2}}{4}$$

$$= -\frac{N+1}{12}.$$

Therefore,

$$Var[W_m] = \sum_{i=1}^{m} Var[R_i] + \sum_{i \neq j}^{m} Cov[R_i, R_j]$$

$$= \frac{m(N^2 - 1)}{12} - m(m - 1) \cdot \frac{N+1}{12}$$

$$= \frac{m(N - m)(N+1)}{12}$$

$$= \frac{mn(m+n+1)}{12}.$$

Comparison of Means

Exercise 1.

Suppose we have two normally distributed populations $X^{(1)}$ and $X^{(2)}$ with mean μ_1, μ_2 and variances σ_1^2, σ_2^2 , respectively. A sample of size n = 20 is gathered for each of these populations

$$X^{(1)}$$
 3.73 2.90 2.58 3.33 3.34 2.80 3.84 3.01 2.91 0.83 4.54 3.49 1.12 0.78 0.67 2.32 2.42 3.21 3.09 1.16

and

$$X^{(2)}$$
 1.30 2.55 3.03 1.71 2.45
 $X^{(2)}$ 2.58 2.68 1.07 2.45 2.72
2.54 2.59 2.35 2.42 2.87
4.13 1.73 2.42 3.03 1.23

We want to test the hypotheses

$$H_0: \mu_1 = \mu_2, \qquad H_1: |\mu_1 - \mu_2| \ge 0.5,$$

with significance level $\alpha = 0.05$ in the following cases.

1. We know the variances are $\sigma_1^2 = \sigma_2^2 = 1$. Perform the test. What is the required sample size for the power of the test to be at least 80%?

Solution. We calculate

$$\overline{x}^{(1)} = 2.604, \quad \overline{x}^{(2)} = 2.343.$$

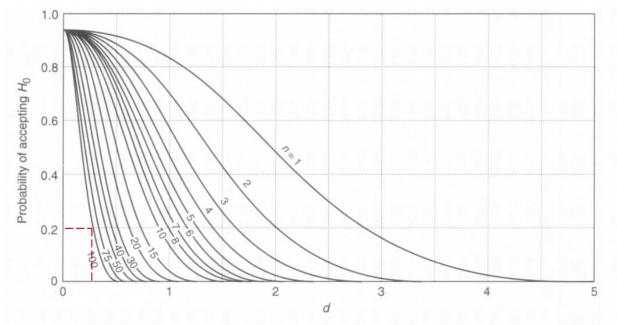
Then the test statistic is given by

$$z = \frac{\overline{x}^{(1)} - \overline{x}^{(2)}}{\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}} = \frac{2.604 - 2.343}{\sqrt{1/20 + 1/20}} = 0.8254.$$

The critical value is given by $z_{\alpha/2} = 1.96 > z$. Therefore, we fail to reject H_0 . We calculate

$$d = \frac{|\mu_1 - \mu_2|}{\sqrt{2\sigma^2}} = 0.35,$$

and read from OC curve for normal tests. We would require a sample size of at least 100.



(a) OC curves for different values of n for the two-sided normal test for a level of significance $\alpha = 0.05$.

2. The variances are unknown but equal $\sigma^2 = \sigma_1^2 = \sigma_2^2$. Perform the test. What is the required sample size for the power of the test to be at least 70%?

Solution. We calculate the variances

$$s_1^2 = 1.263,$$
 $s_2^2 = 0.534,$ $s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} = \frac{s_1^2 + s_2^2}{2} = 0.899.$

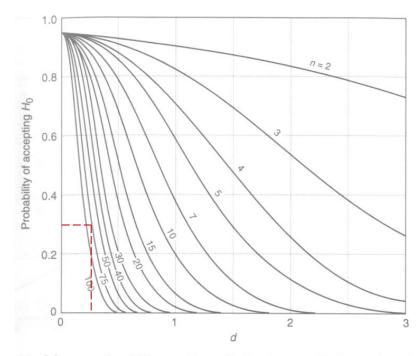
Then the test statistic is given by

$$t_{38} = \frac{\overline{x}^{(1)} - \overline{x}^{(2)}}{\sqrt{s_p^2(1/n_1 + 1/n_2)}} = 0.871.$$

The critical value is given by $t_{\alpha/2,38} = 2.024 > t_{38}$. Therefore, we fail to reject H_0 . We calculate

$$d = \frac{|\mu_1 - \mu_2|}{2s_p} = \frac{0.5}{2\sqrt{0.899}} = 0.264,$$

where we estimate the variance using pooled variance, and read from OC curve for normal tests. We would require a modified sample size of at least $n^* = 2n - 1 = 75$, giving n = 38.



- (e) OC curves for different values of n for the two-sided t test for a level of significance $\alpha = 0.05$.
- 3. The variances are unknown and not necessarily equal. Perform the hypothesis test. **Solution.** We calculate

$$\gamma = \frac{(s_1^2/n_1 + s_2^2/n_2)^2}{\frac{(s_1^2/n_1)^2}{n_1 - 1} + \frac{(s_2^2/n_2)^2}{n_2 - 1}} = 32.64 \approx 32$$

and thus the test statistic

$$t_{32} = \frac{\overline{x}^{(1)} - \overline{x}^{(2)}}{\sqrt{s_1^2/n_1 + s_2^2/n_2}} = 0.871$$

with critical value $t_{\alpha/2,32} = 2.04 > t_{32}$. Therefore, we fail to reject H_0 .

Pearson Statistic

Exercise 2.

Let X denote the number of defective components from a pack of 12 such components. 100 such packs are observed, and the corresponding values of X are as follows.

Perform a test to analyze whether a binomial distribution is an appropriate model for the distribution of X.

Solution. We set up the hypothesis

 $H_0: X$ follows a binomial distribution with parameters n=12 and p,

where p is unknown and requires an estimate

$$\widehat{p} = \frac{1}{12 \times 100} (42 + 2 \times 36 + 3 \times 5 + 4 \times 1) = 0.1108.$$

Then we calculate

$$P[X = 0] = {12 \choose 0} (1 - \widehat{p})^{12} = 0.244,$$

$$P[X = 1] = {12 \choose 1} \widehat{p} (1 - \widehat{p})^{11} = 0.365,$$

$$P[X = 2] = {12 \choose 2} \widehat{p}^2 (1 - \widehat{p})^{10} = 0.250,$$

$$P[X = 3] = {12 \choose 3} \widehat{p}^3 (1 - \widehat{p})^9 = 0.104,$$

$$P[X \ge 4] = 1 - P[X < 4] = 0.036.$$

Therefore, the observations and expectations can be listed as follows.

We check that Cochran's rule is satisfied. The Pearson statistic is then given by

$$\chi_3^2 = \sum_{i=1}^5 \frac{(O_i - E_i)^2}{E_i} = 13.197,$$

with critical value $\chi_{0.05,3} = 7.81 < \chi_3^2$ and 5 - 1 - 1 = 3 degrees of freedom. Therefore, we reject H_0 with significance level 0.05. There is evidence that X does not follow a binomial distribution.