

# **MAT2377**

Catalin Rada

Version June 2, 2009

## 8-3 Estimating the mean of a normal population ( $\sigma$ unknown)

In the special case of a normal population, it is possible to construct a C.I. for the mean even when  $\sigma$  is unknown.

**Definition:** Consider the random variable  $T$  with probability density function

$$f(t) = \frac{\Gamma[(\nu + 1)/2]}{\sqrt{\pi\nu}\Gamma(\nu/2)} \left[ (t^2/\nu) + 1 \right]^{-(\nu+1)/2}$$

for  $-\infty < t < \infty$ , where  $\Gamma(r) = \int_0^\infty x^{r-1} e^{-x} dx$  for  $r > 0$  is the gamma function. Properties of gamma function:

— when  $r$  is integer,  $\Gamma(r) = (r - 1)!$ , so  $\Gamma(1) = 0! = 1$ ;  $\Gamma(1/2) = \pi^{1/2}$ .

We say that  $T$  follows a  $t$  distribution with  $\nu$  degrees of freedom. The mean and variance of  $T$  are **zero** and  $k/(k-2)$ , for  $k > 2$ . More Properties: Consider a  $t$  distribution with  $\nu$  degrees of freedom.

— as for the normal we define the percentile  $t_{\alpha,\nu}$ ; and we find them in Table V;

— the density  $f(t)$  is symmetric about  $t = 0$ , hence  $t_{1-\alpha,\nu} = -t_{\alpha,\nu}$ ;

— if  $\nu \rightarrow \infty$ , then the  $t$  distribution is a standard normal, hence  $z_{\alpha} = t_{\alpha,\infty}$ . So we can use table V to find percentiles for the  $N(0,1)$  distribution. For example,  $z_{0.025} = t_{0.025,\infty} = 1.96$ .

**Theorem:** Let  $X_1, \dots, X_n$  is a random sample from a normal population with mean  $\mu$  and variance  $\sigma^2$ . The random variable  $T = \frac{\bar{X} - \mu}{S/\sqrt{n}}$  has a  $t$  distribution with  $\nu = n - 1$  degrees of freedom ( $S^2$  is the sample variance).

Therefore, if the population is normal, then a  $100(1 - \alpha)\%$  confidence

interval for  $\mu$  is:  $\bar{x} \pm t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$ .

EXC: A SuperCola beverage machine is made up such that it releases a certain amount of sugar into a chamber where it is mixed with soda. A random sample of 25 beverages was found to have a mean sugar content of  $\bar{x} = 1.10$  and a stand deviation of  $s = 0.015$ . Find a 95% CI on the mean of sugar dispensed.

**Sol** We are given only  $n = 25$ ,  $\bar{x} = 1.10$ ,  $s = 0.015$ , so  $95 = (1 - \alpha)100$ , hence  $\alpha = 0.05$ . The interval is:  $[\bar{x} - t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}, \bar{x} + t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}] = [1.10 - t_{0.025, 24} \frac{0.015}{\sqrt{25}}, 1.10 + t_{0.025, 24} \frac{0.015}{\sqrt{25}}] = [1.10 - 2.064 \frac{0.015}{\sqrt{25}}, 1.10 + 2.064 \frac{0.015}{\sqrt{25}}] = [1.094, 1.106]$ . We used table V, and moreover we assumed normal distribution (half of the exercises ...)!

As in the previous lecture: the one sided  $100(1 - \alpha)\%$  confidence bounds/intervals are defined via:  $\bar{x} - t_{\alpha, n-1} \frac{s}{\sqrt{n}}$  — lower-confidence bound,

$\bar{x} + t_{\alpha, n-1} \frac{s}{\sqrt{n}}$  — upper-confidence bound;

Remember:  $t$  distribution IS used only in the case of **normal** population with **unknown** variance!

Do at the blackboard **8-24**/page 272.

## Last Example

Nine measurements of ozone concentration are obtained during a year:

3.5 5.1 6.6 6.0 4.2 4.4 5.3 5.6 4.4

Assuming the measurements are normally distributed, provide two 95% confidence intervals for the population mean  $\mu$ :

- one assuming that the population variance  $\sigma^2 = 1.21$ ;
- another *relaxing this assumption*.

First,  $\alpha = 1 - 0.95$ . Second, the sample mean is 5.01.

Assuming the population variance is 1.21:

$$5.01 \pm (1.96 \times \sqrt{1.21}/\sqrt{9}) \Rightarrow 5.01 \pm 0.72 \text{ or } (4.29, 5.73).$$

If we relax the assumption, we have to compute

$$\begin{aligned}\bar{x} \pm t_{\alpha/2, n-1} \frac{s}{\sqrt{n}} &= 5.01 \pm 2.306 \frac{0.97}{\sqrt{9}} \\ &= (4.26, 5.76),\end{aligned}$$

where the pleasure of computing  $s$  belongs to ...

## Summary of confidence intervals for $\mu$ when $\sigma$ **known**

- If  $\bar{x}$  is the size- $n$ -sample mean from a **normal** population with **known** variance  $\sigma^2$ , the *exact*  $(1 - \alpha)$  C.I. for  $\mu$ :

$$\bar{x} \pm z_{\alpha/2}\sigma / \sqrt{n};$$

- If  $\bar{x}$  is the size- $n$ -sample mean from a **non-normal** population with **known** variance  $\sigma^2$  and  $n$  is '**big**', the *approximate*  $(1 - \alpha)$  C.I. for  $\mu$ :

$$\bar{x} \pm z_{\alpha/2}\sigma / \sqrt{n};$$



## Summary of confidence intervals for $\mu$ when $\sigma$ **unknown**

- If  $\bar{x}$  is the size- $n$ -sample mean from a **normal** population with **unknown** variance, the *exact*  $(1 - \alpha)$  C.I. for  $\mu$ :

$$\bar{x} \pm t_{\alpha/2, n-1} s / \sqrt{n};$$

- If  $\bar{x}$  is the size- $n$ -sample mean from a **normal** or **non-normal** population with **unknown** variance and  $n$  is '**big**', the *approximate*  $(1 - \alpha)$  C.I. is:

$$\bar{x} \pm z_{\alpha/2} s / \sqrt{n};$$

## 8-5 Estimating a population **proportion**, confidence interval

Consider the sample proportion  $\hat{P} = X/n$ , where  $X$  is the number of successes among the  $n$  trials. (For us: belonging to a class of interest.)

$X$  follows a binomial distribution with parameters  $n$  and  $p$ . If  $n$  is large then  $X$  follows approximately a normal distribution. Since  $\hat{P}$  is a linear function of  $X$ , then it is also approximately normal. Hence:

$\hat{P}$  follows  $N(p, \frac{p(1-p)}{n})$  distribution approximately, i.e.,  $Z = \frac{\hat{P}-p}{\sqrt{\frac{p(1-p)}{n}}}$  is standard normal. Thus  $1 - \alpha = P(-z_{\alpha/2} \leq Z \leq z_{\alpha/2}) = P(-z_{\alpha/2} \leq \frac{\hat{P}-p}{\sqrt{\frac{p(1-p)}{n}}} \leq z_{\alpha/2}) = P(\hat{P} - z_{\alpha/2}\sqrt{\frac{p(1-p)}{n}} \leq p \leq \hat{P} + z_{\alpha/2}\sqrt{\frac{p(1-p)}{n}})$ .

Therefore, for large  $n$ , a  $100(1 - \alpha)\%$  C.I. for the true proportion  $p$  is:  
$$\left[ \hat{p} - z_{\alpha/2} \sqrt{\frac{p(1-p)}{n}}, \hat{p} + z_{\alpha/2} \sqrt{\frac{p(1-p)}{n}} \right].$$

**Problem:** The confidence interval involves  $p$ , which is an unknown quantity. In practice, we simply replace  $p$  with its point estimate  $\hat{p}$  to obtain an approximate confidence interval. For large  $n$ , that is:  $n\hat{p} > 5$  and  $n(1 - \hat{p}) > 5$ , a  $100(1 - \alpha)\%$  confidence interval for  $p$  is:

$$\left[ \hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}, \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \right]$$

One-sided confidence bounds are given by:

— lower bound:  $\hat{p} - z_{\alpha} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \leq p;$

— upper bound:  $p \leq \hat{p} + z_\alpha \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$ .

Do 8-47 at the blackboard! a)  $n = 300$ ,  $\hat{p} = \frac{13}{300}$ ,  $100(1 - \alpha) = 95$ , so  $\alpha = 0.05$ , hence  $\alpha/2 = 0.025$ . The CI is  $[\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}, \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}]$   
 $= [0.04333 - 1.96 \sqrt{\frac{0.04333(0.95667)}{300}}, 0.04333 + 1.96 \sqrt{\frac{0.04333(0.95667)}{300}}] = [0.02029, 0.06637]$ .

b) The CI is  $(-\infty, \hat{p} + z_\alpha \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}] = (-\infty, 0.04333 + z_{0.05} \sqrt{\frac{0.04333(0.95667)}{300}}] = (-\infty, 0.06273]$ , since  $z_{0.05} \cong 1.65$ .

**SAMPLE SIZE:** If  $\hat{p}$  is used as an estimate of  $p$ , we can be  $100(1 - \alpha)\%$  confident that the error  $|\hat{p} - p|$  will not exceed a specified amount  $E$  when the sample size is  $n = (\frac{z_{\alpha/2}}{E})^2 \times p(1 - p)$ , convince yourself by plugging in the C.I.!!! **BUT Problem:** The latter formula involves the unknown

parameter  $p$ . Using the maximization of  $p(1 - p)$  one gets:

**RULE:** If  $\hat{p}$  is used as an estimate of  $p$ , we can be at least  $100(1 - \alpha)\%$  confident that the error  $|\hat{p} - p|$  will not exceed a specified amount  $E$  when the sample size is  $n = \left(\frac{z_{\alpha/2}}{E}\right)^2 \times (0.25)$

**Do** 8-54/page 281. SOL:  $99 = (1 - \alpha)100$  implies that  $\alpha = 0.01$ , so  $z_{0.005} \cong 2.58$ , note that  $E = 0.017$ , so  $n = \left(\frac{z_{\alpha/2}}{E}\right)^2 \times (0.25) = 5758.13$ , so we may take  $n = 5759$ .

## 8-4 Confidence interval for the variance

DEF: Consider a rv  $\chi^2$  whose p.d.f. is given by  $f(x) = \frac{1}{2^{k/2}\Gamma(k/2)}x^{(k/2)-1}e^{-x/2}$  for  $x > 0$ . We say that  $\chi^2$  has a chi-square ( $\chi^2$ ) distribution with  $k - 1$  degrees of freedom. Properties:

1) the expectation is  $k$ , variance is  $2k$ ;

2) NOT symmetric, in fact skewed to the right; bigger  $k$  implies more symmetric;

3) the percentile  $P(\chi^2 > \chi_{\alpha,k}^2) = \alpha$  (an integral, right?) are found in table IV/714. For example:  $\chi_{0.95,6}^2 = 1.64$  and  $\chi_{0.05,6}^2 = 12.59$ .

**Theorem:** Let  $X_1, \dots, X_n$  be a random sample from a NORMAL distribution with mean  $\mu$  and variance  $\sigma^2$ , let  $S^2$  be the sample variance.

Then the rv  $\frac{(n-1)S^2}{\sigma^2}$  has a chi-square ( $\chi^2$ ) distribution with  $n - 1$  degrees of freedom.

Hence a  $100(1 - \alpha)$  CONFIDENCE interval for  $\sigma^2$  is

$$\left[ \frac{(n-1)s^2}{\chi_{\alpha/2, n-1}^2}, \frac{(n-1)s^2}{\chi_{1-\alpha/2, n-1}^2} \right]$$

. To get a C.I. for  $\sigma$  just take radicals!

ONE-SIDED bounds of variance:

— lower bound for  $\sigma^2$  is  $\frac{(n-1)s^2}{\chi_{\alpha, n-1}^2}$ , or the C.I. is  $\left[ \frac{(n-1)s^2}{\chi_{\alpha, n-1}^2}, \infty \right)$

— upper bound for  $\sigma^2$  is  $\frac{(n-1)s^2}{\chi_{1-\alpha, n-1}^2}$ , or the C.I. is  $(-\infty, \frac{(n-1)s^2}{\chi_{1-\alpha, n-1}^2}]$

Do exc 8-41/page 276 SOL: We get  $n = 51$ ,  $s = 0.37$ ,  $100(1 - \alpha) = 95$ ; so  $\alpha/2 = 0.025$ . We get first a C.I. for  $\sigma^2$ , and then for  $\sigma$ . We have 
$$\left[ \frac{(n-1)s^2}{\chi_{\alpha/2, n-1}^2}, \frac{(n-1)s^2}{\chi_{1-\alpha/2, n-1}^2} \right] = \left[ \frac{(51-1)(0.37)^2}{\chi_{0.025, 50}^2}, \frac{(51-1)(0.37)^2}{\chi_{0.975, 50}^2} \right] = \left[ \frac{(51-1)(0.37)^2}{71.42}, \frac{(51-1)(0.37)^2}{32.36} \right] = [0.096, 0.2115],$$
 so a C.I. for  $\sigma$  is  $[\sqrt{0.096}, \sqrt{0.2115}]$ , or  $[0.31, 0.46]$ .