Confidence Intervals for Means -Unknown Variance

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We have seen that when \overline{x} is the mean of a random sample $x = \{x_1, x_2, \dots, x_n\}$ from a normal population $N(\mu, \sigma^2)$ with **known** variance σ^2 , the quantity

$$z = \frac{\overline{x} - \mu}{\sigma / \sqrt{n}}$$

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Based on this fact, a $100(1 - \alpha)\%$ confidence interval for the parameter μ is:

$$\left[\overline{x} - z_{\alpha/2}\sqrt{\frac{\sigma^2}{n}}, \overline{x} + z_{\alpha/2}\sqrt{\frac{\sigma^2}{n}}\right]$$

In practice, the population variance σ^2 is seldom known, and usually must be estimated from the sample.

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We will see that the following is an unbiased estimate of the population variance σ^2 :

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The square root of S^2 is denoted by S and called the sample standard deviation

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In so doing, Gosset proved that unlike its counterpart

$$z = \frac{\overline{x} - \mu}{\sigma / \sqrt{n}},$$

t does **not** have a normal distribution.

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Like the normal distribution, the t distribution is bell-shaped and centered at zero.

As the sample size n and degrees of freedom n-1 become large, the t curve becomes indistinguishable from the normal curve.

Confidence intervals for the population mean μ are obtained from the *t* distribution in a manner similar to those used when the variance σ^2 is known, except:

- σ is replaced by S
- $z_{\alpha/2}$ is replaced by $t_{\alpha/2,n-1}$

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Values of $t_{\alpha/2,n-1}$ can be obtained from a table of the Student-t distribution or from a spreadsheet using

$$t_{\alpha/2,n-1} = = \mathsf{TINV}(\alpha, n-1)$$

where *n* is the sample size and α is the desired alpha level.

Theorem: If

$$x_i \sim N(\mu, \sigma^2), \quad i = 1, \dots, n$$

with μ and σ^2 unknown, then $100(1-\alpha)\%$ of the time the interval

$$\left[\overline{x} - t_{\alpha/2, n-1} \sqrt{\frac{S^2}{n}}, \quad \overline{x} + t_{\alpha/2, n-1} \sqrt{\frac{S^2}{n}}\right]$$

will contain the (unknown) population mean μ .

Example: A sample of 12 fifth-grade students found an average weight \overline{x} of 83.4 pounds with a sample variance of 17.0.

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In this case $S^2 = 17.0$ and $t_{.025,11} = 2.20$ so the 95% confidence interval for μ is

$$\left[\overline{x} - t_{\alpha/2, n-1} \sqrt{\frac{S^2}{n}}, \quad \overline{x} + t_{\alpha/2, n-1} \sqrt{\frac{S^2}{n}} \right]$$
$$= \left[83.4 - 2.20 \sqrt{\frac{17}{12}}, \quad 83.4 + 2.20 \sqrt{\frac{17}{12}} \right] = \left[80.7, \ 86.0 \right]$$