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# Estimating and Testing a Mean

ADM 2304

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# Review of Sampling Distributions

- If a population has mean  $\mu$  and stdev  $\sigma$ , then the sample mean ( $X$ -bar) from a “large” sample will have a normal distribution with mean  $\mu$  and standard deviation  $\sigma/\sqrt{n}$ .
- Provided the original population is not extremely skewed, a sample size of  $n > 30$  is “large” enough.

# Probability Intervals

- The probability that **X-bar** falls inside  $\mu \pm z_{\alpha/2} * \sigma/\sqrt{n}$ , is  $1 - \alpha$ .  
(meaning  $100(1 - \alpha)\%$  of all sample means will fall inside this interval )
- $(\mu - z_{\alpha/2} * \sigma/\sqrt{n} , \mu + z_{\alpha/2} * \sigma/\sqrt{n})$  is a fixed **probability interval**, because there is a fixed probability that the sample mean falls inside it, for given fixed values of  $\mu$  **and**  $\sigma$ .

# Confidence Interval for $\mu$

- **$\bar{X} \pm z_{\alpha/2} * \sigma/\sqrt{n}$**  is a  $100(1 - \alpha)$  % **confidence interval**. It covers the mean  $\mu$  if and only if  **$\bar{X}$**  falls inside the probability interval:  **$\mu \pm z_{\alpha/2} * \sigma/\sqrt{n}$** .
- This confidence interval can be calculated only when sample data are available to calculate the sample mean. However, it assumes that  $\sigma$  is known, even though  $\mu$  may be unknown.

# Confidence Interval for a (population) mean ( $\sigma$ known)

The  $100(1-\alpha)\%$  confidence interval is:

$$\bar{X} \pm z_{\alpha/2} * \sigma/\sqrt{n},$$

where  $z_{\alpha/2}$  is the upper  $\alpha/2$  point of the standard normal distribution.

(For  $n \leq 30$ , the original population must be approximately normally distributed as the CLT does not apply;

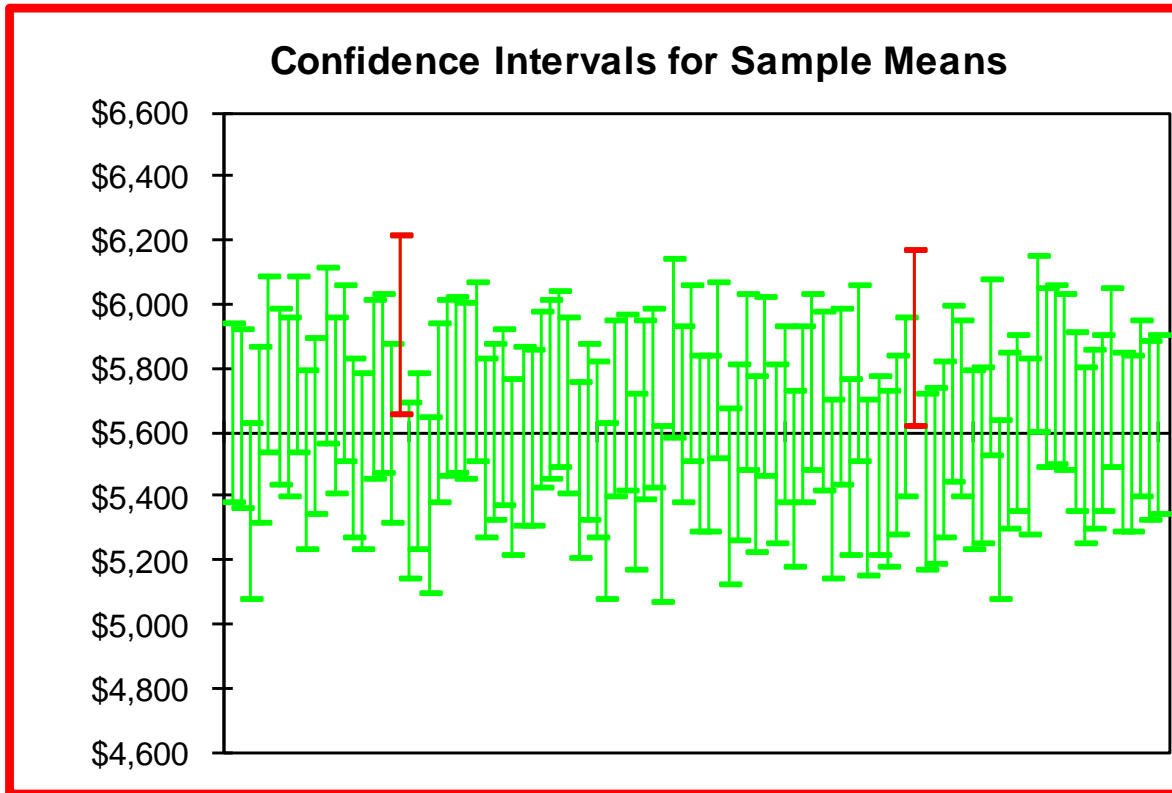
If the original population is not extremely skewed, then  $n > 30$  is large enough for the CLT to apply.)

*If  $n/N > .05$ , the Finite Population Correction (FPC) =  $\sqrt{[(N-n)/(N-1)]}$  should be used to adjust the standard deviation.*

# Sampling Interpretation

- For example, if we define an interval within 2 standard deviations on either side of **X-bar**, we are 95% “confident” the interval will cover  $\mu$  because 95% of **all such intervals** will cover the true population mean  $\mu$ .
- Demo using *conf.xlt* to show the “sampling interpretation of confidence intervals”.

# Simulation of Confidence Intervals



|                     |                |
|---------------------|----------------|
| <b>True Mean</b>    | <b>\$5,600</b> |
| <b>Sigma</b>        | <b>1000</b>    |
| <b># of Samples</b> | <b>100</b>     |
| <b>Sample Size</b>  | <b>50</b>      |

|                            |
|----------------------------|
| <b>Confidence Interval</b> |
| <b>95.0 %</b>              |

|                                 |
|---------------------------------|
| <b>Size of Interval</b>         |
| <b>xbar ( + or - ) \$277.18</b> |

|              |                                |
|--------------|--------------------------------|
| <b>Alpha</b> | <b>Z<sub>(1-alpha/2)</sub></b> |
| <b>5.0%</b>  | <b>1.960</b>                   |

**Generate Random  
Sample Means**

**% of Intervals That Include the True Mean      98%**

# What if the variance is not known?

- We replace the unknown  $\sigma$  by its estimate  $s$ , the sample standard deviation;
- For small samples, the critical value  $z_{\alpha/2}$  must be replaced by a similar value from the t-distribution;
- This is symmetric like the normal distribution but with more probability in the tails; however, it approaches the normal shape as  $n$  gets large (meaning  $n > 30$ ).

# t-distribution

- For different sample sizes  $n$ , the value of  $t_{\alpha/2}$  allows for more uncertainty than the value of  $z_{\alpha/2}$  does. For example, where the confidence coefficient is 95%,

|                     |                                       |
|---------------------|---------------------------------------|
| $n=5$ uses d.f.=4   | $t_{\alpha/2} = 2.776,$               |
| $n=10$ uses d.f.=9  | $t_{\alpha/2} = 2.262,$               |
| $n=20$ uses d.f.=19 | $t_{\alpha/2} = 2.093,$               |
| $n=30$ uses d.f.=29 | $t_{\alpha/2} = 2.045,$               |
| $n$ infinite        | $t_{\alpha/2} = z_{\alpha/2} = 1.96.$ |
- $n-1$  represents the degrees of freedom for the sample standard deviation  $s$  (that's why we divide by  $n-1$  in the formula for  $s$ );
- When the number of degrees of freedom is large, the distribution of  $t$  approaches the standard normal  $z$  distribution (see bottom row of Table T on page A-58 in Appendix B or the t-table tab of "ProbabilityTables.xls").

# Confidence Interval for a (population) mean ( $\sigma$ unknown)

The  $100(1-\alpha)\%$  confidence interval is:

$$\bar{X} \pm t_{\alpha/2} * (s/\sqrt{n}) * FPC,$$

where  $t_{\alpha/2}$  is the upper  $\alpha/2$  point of the t- distribution with  $n-1$  degrees of freedom.

For  $n \leq 30$ , the original population must be approximately normally distributed;

For  $n > 30$ , the original population must not be extremely skewed and  $t_{\alpha/2} \cong z_{\alpha/2}$

# Example

- Take a sample of male student heights and estimate the average male height using a 95% confidence interval.

# Using Minitab

- Click on the **Stat** Menu, and select **Basic Statistics**.
- Select the **1-sample t** choice (only select **1-sample z** if the population standard deviation “sigma” is known).
- You can specify a column that contains the individual data values or specify the sample size **n**, sample mean **X-bar** and sample standard deviation **s**. Note that the interval assumes an infinite population.
- **Options** -- specify confidence level (default is 95%). For a 2-sided confidence interval, leave the default “**not equal**” “alternative”; for 1-sided confidence interval, specify the “less than” or “greater than” alternative, depending on which alternative you believe.

# Sample Size Determination for Estimating a Population Mean

- To determine the sample size requirement for a survey to estimate a population mean, we need to know or to guess at the variability of the data (as measured by the standard deviation  $\sigma$ ), as well as to determine the confidence level  $(1 - \alpha)$  and the margin of error ( $\pm M$ ).
- Since  $\pm z_{\alpha/2} * \sigma / \sqrt{n} = \pm M$ , solve for  $n = (z_{\alpha/2} * \sigma / M)^2$ ; we use  $z_{\alpha/2}$  instead of  $t_{\alpha/2}$ , in expectation of a sample size requirement greater than 30. If  $\sigma$  is not known, then we need to estimate it using the standard deviation  $s$  from a small sample.
- The more variable the data, the larger the sample size required to achieve a given margin of error for estimating the mean.

# Example

- We wish to estimate the mean male student height using a 95% confidence interval with a margin of error of  $\pm 0.5$  in.
- What sample size would be required?

# Testing a Mean

We have the weight loss in pounds (negative values denote weight gains) for a random sample of 15 individuals who were selected to go on a special 4-week diet.

# Setting the alternative

If we think (before seeing the data) that the diet is effective, then we should do a 1-sided test:

$$H_0: \mu = \mu_0 \text{ or } \mu \leq \mu_0$$

$$H_a: \mu > \mu_0$$

For this example, the hypothesized value  $\mu_0$  is zero, and we have:

$$H_0: \mu = 0 \text{ or } \mu \leq 0$$

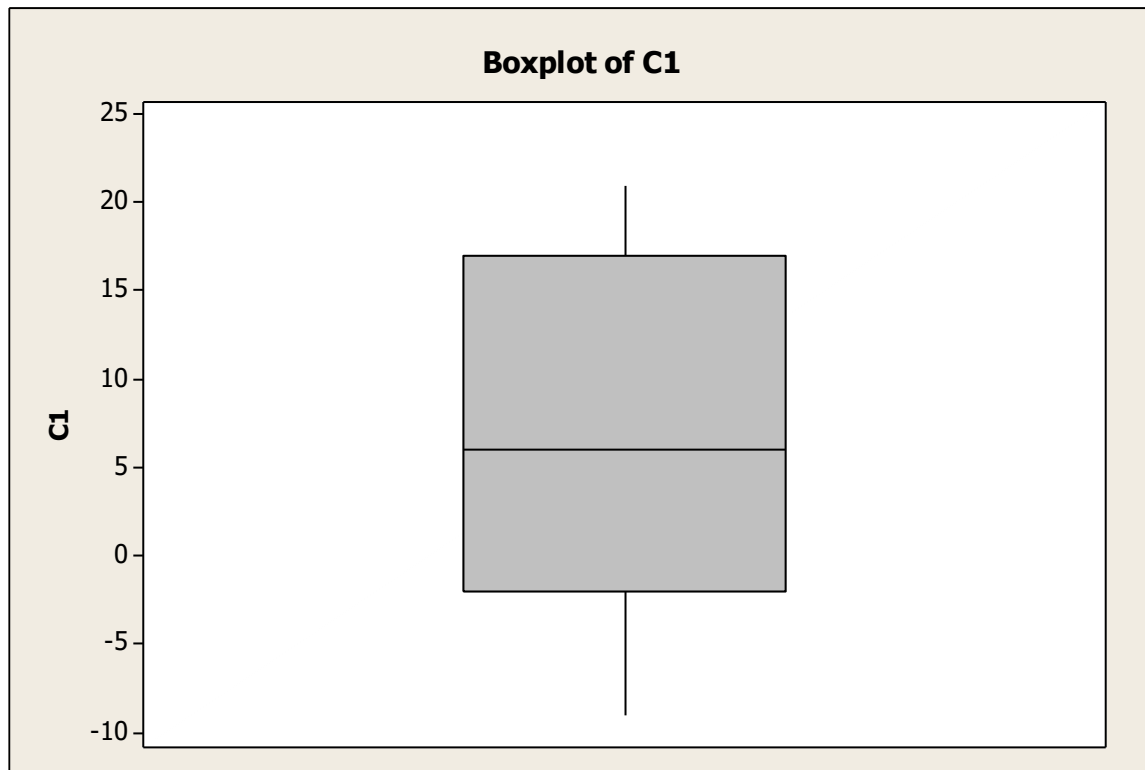
$$H_a: \mu > 0$$

# Data

Suppose the fifteen weight losses are:

|    |    |   |    |    |    |    |    |
|----|----|---|----|----|----|----|----|
| 20 | -8 | 6 | 20 | 15 | -3 | 0  | 21 |
| 3  | -2 | 7 | 9  | -9 | -2 | 17 |    |

The boxplot shows the data can be assumed to come from an approximately normal distribution (since the data are symmetric and there are no outliers):



# How do we proceed?

- To estimate the mean, we use the sample mean **x-bar**, based on a sample of  $n$ .
- If we assume the null hypothesis is true, then the sample mean has mean  $\mu_0$  and standard deviation  $\sigma/\sqrt{n}$ . Since the data come from a normal distribution, the sample mean is normally distributed. (If  $n > 30$ , then the sampling distribution is normal provided the population is not extremely skewed.)
- If the value of the population standard deviation  $\sigma$  is known, we can standardize the sample mean by calculating the z-statistic:

$$z_{\text{stat}} = (\bar{x} - \mu_0) / (\sigma/\sqrt{n}).$$

# Decision Rule

- The rejection region is  $z_{\text{stat}} > z_{\alpha}$ , because only large positive values of  $z_{\text{stat}}$  argue for the alternative hypothesis and against the null hypothesis.
- Similarly the p-value is the probability that we would obtain a Z-value *larger* than the one we obtained in the sample, given that the null hypothesis is true, i.e.  $P(Z > z_{\text{stat}})$ .

# What if $\sigma$ is not known?

- If the value of the population standard deviation  $\sigma$  is not known, then we calculate the t-statistic:

$$t_{\text{stat}} = (\bar{x} - \mu_0) / (s/\sqrt{n}).$$

- The rejection region becomes  $t_{\text{stat}} > t_{\alpha}$  and we look up the t-distribution with  $n-1$  degrees of freedom. The p-value is  $P(t > t_{\text{stat}})$ .

# 2-sided test

A 2-sided test would be reasonable if, prior to seeing the data, we think the diet does something, but we are not sure whether it results in a weight loss or a weight gain:

$$H_0: \mu = 0$$

$$H_a: \mu \neq 0 \quad (\mu < 0 \quad \text{or} \quad \mu > 0)$$

# 2-sided test (cont'd)

- Here we use a 2-tailed rejection region because both very large positive values and very large negative values (the sign does not matter) of the t-statistic argue against the null hypothesis.
- For a test restricting the probability of the Type I error to alpha, we divide alpha by 2 and define a “2-tailed” or “2-sided” rejection region, each with probability  $\alpha/2$  under the null hypothesis:

We reject the null hypothesis if

$$t_{\text{stat}} < -t_{\alpha/2} \text{ or } t_{\text{stat}} > t_{\alpha/2} , \\ \text{or } |t_{\text{stat}}| > t_{\alpha/2} .$$

# p-value

- The p-value for a 2-sided test is

$$\begin{aligned} & P(t < - | t_{\text{stat}} | \text{ or } t > | t_{\text{stat}} | ) \\ & = 2 P(t > | t_{\text{stat}} | ) \text{ or } 2 P(t < - | t_{\text{stat}} | ) \end{aligned}$$

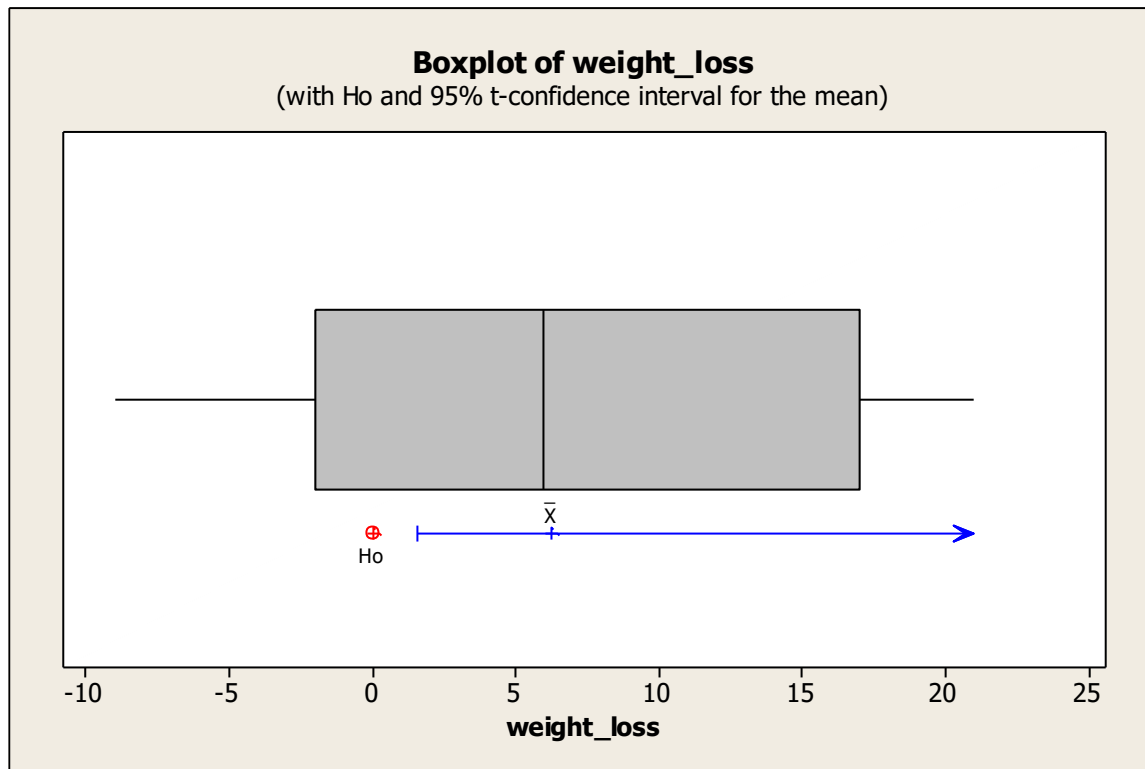
since the sign of the t-statistic does not matter.

- Only the absolute value counts as a measure of how far the sample result is from 0 and we calculate the probability that the t distribution is more extreme than  $| t_{\text{stat}} |$  in both the positive and the negative direction.

# Using Minitab

- Go to the **Stat** Menu, select **Basic Statistics** and **1-sample t**
- (select **1-sample z** if the population standard deviation is known)

The 1-sided confidence interval  
“at least 1.55477” is shown in blue; it does not cover  
the hypothesized mean of 0, as indicated in red.



### One-Sample T: weight\_loss

Test of mu = 0 vs > 0

| Variable    | N  | Mean    | StDev    | SE Mean | 95% Lower Bound | T    | P            |
|-------------|----|---------|----------|---------|-----------------|------|--------------|
| weight_loss | 15 | 6.26667 | 10.36110 | 2.67522 | 1.55477         | 2.34 | <b>0.017</b> |

### One-Sample T: weight\_loss

Test of mu = 0 vs < 0

| Variable    | N  | Mean    | StDev    | SE Mean | 95% Upper Bound | T    | P            |
|-------------|----|---------|----------|---------|-----------------|------|--------------|
| weight_loss | 15 | 6.26667 | 10.36110 | 2.67522 | 10.97857        | 2.34 | <b>0.983</b> |

### One-Sample T: weight\_loss

Test of mu = 0 vs not = 0

| Variable    | N  | Mean    | StDev    | SE Mean | 95% CI              | T    | P            |
|-------------|----|---------|----------|---------|---------------------|------|--------------|
| weight_loss | 15 | 6.26667 | 10.36110 | 2.67522 | (0.52888, 12.00445) | 2.34 | <b>0.034</b> |

If we take the perspective of the weight loss clinic, then the appropriate test is the first one since we would expect a positive weight loss if the diet is effective. The second test is not necessary since the positive z-statistic is clearly not inconsistent with the null hypothesis ( $\mu \geq 0$ ). If we did not know what to expect, then the third test might be appropriate.