Assumptions, Robustness, and Conditions for Valid CIs & T-Tests

- T-tests and CIs are based on the assumption that the population values being studied have a Normal distribution.
- In reality, populations may be anywhere from slightly non-normal to very non-normal.

Robustness of the T-procedures

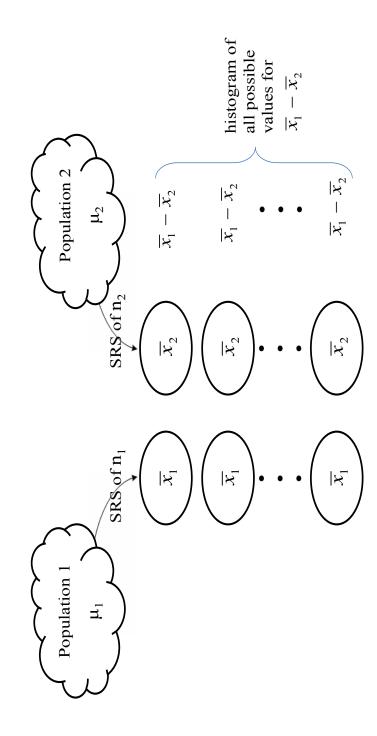
• The T-test and CI are called <u>robust</u> to the assumption of normality because p-values and confidence levels are not greatly affected by violations of this assumption of normally distributed populations, especially if sample sizes are large enough.

Conditions for a Valid 1-Sample CI and T-Test

- The data are a SRS from the population.
- The population must be large enough (at least 10 times larger than the sample size).
- The population is normally distributed.
 - \circ If n is small (n < 15), the data should not be grossly non-normal or contain outliers.
 - o If n is "medium" $(15 \le n < 40)$, the data should not have strong skewness or outliers.
 - o If n is large ($n \ge 40$), the *T*-procedures are robust to non-normality.

Checking if the conditions are met in your sample

• Always make a plot of the data to check for skewness and outliers before relying on T-procedures in small samples.



Comparing Two Independent Samples

The sampling distribution for ...

$$\overline{X}_1$$
 is approximately Normal with Mean= μ_1 , $SD = \frac{C}{N}$

$$\overline{X}_2$$
 is approximately Normal with Mean= μ_2 , $SD = \frac{\sigma_2}{\sqrt{n_2}}$

$$\overline{X}_1 - \overline{X}_2$$
 is approx Normal with $Mean = \mu_1 - \mu_2$, $SD = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$

$$z_{s} = \frac{\left(\overline{X}_{1} - \overline{X}_{2}\right) - \left(\mu_{1} - \mu_{2}\right)}{SD_{\overline{X}_{1} - \overline{X}_{2}}} \rightarrow t_{s} = \frac{\left(\overline{X}_{1} - \overline{X}_{2}\right) - \left(\mu_{1} - \mu_{2}\right)}{SE_{\overline{X}_{1} - \overline{X}_{2}}}$$

Example: 30 mice given one of two diets for 21 days.

Reduction in cholesterol in mg/dl is measured on day 22

$$H_o: \mu_1 - \mu_2 = D_0$$

$$t_s = \frac{(\overline{x}_1 - \overline{x}_2) - D_0}{SE_{\overline{x}_1 - \overline{x}_2}}$$

$$\sigma_1 = \sigma_2 \qquad \Rightarrow \qquad t_s = \frac{(\overline{x}_1 - \overline{x}_2) - D_0}{\sqrt{s_p^2 \left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \quad \text{with} \quad df = n_1 + n_2 - 2 \quad \text{(Equal Variance T-test)}$$

Rejection Region at the α level of significance:

Reject Ho in favor of
$$H_a: \mu_1 - \mu_2 > D_0 \quad \text{if} \quad t_s \ge t_\alpha$$

$$H_a: \mu_1 - \mu_2 < D_0 \quad \text{if} \quad t_s \le -t_\alpha$$

$$H_a: \mu_1 - \mu_2 \ne D_0 \quad \text{if} \quad |t_s| \ge t_{\alpha/2}$$

$$\sigma_1 \neq \sigma_2$$
 \rightarrow $t_s' = \frac{(\overline{x}_1 - \overline{x}_2) - D_0}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$ (Unpooled or Unequal Variance *T*-test)

Satterthwaite's approximation for the degrees of freedom:

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\left(\frac{s_1^2}{n_1}\right)^2 + \left(\frac{s_2^2}{n_2}\right)^2}$$
$$\frac{\left(\frac{s_1^2}{n_1}\right)^2}{(n_1 - 1)} + \frac{\left(\frac{s_2^2}{n_2}\right)^2}{(n_2 - 1)}$$