

Comparing two means

Goal: compare the means of two populations/treatments

- μ_1 & μ_2 represent two population means to compare
- σ_1 & σ_2 represent two population standard deviations
- Take a random sample from each population/treatment
- Two samples are *independent* (don't influence each other)
(recall: in matched pairs, two sets of observations *not* independent)
- Sample sizes: n_1 = sample 1 size; n_2 = sample 2 size
- Use $\bar{Y}_1, \bar{Y}_2, s_1, s_2$ to estimate population parameters
- **Sampling Distribution of $\bar{Y}_2 - \bar{Y}_1$**
 - Center/typical value is $\mu_2 - \mu_1$
 - Standard deviation: $SD(\bar{Y}_2 - \bar{Y}_1) = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$
 - If two population distributions are normal or sample sizes large $n_1, n_2 \geq 30$, then distribution of $\bar{Y}_2 - \bar{Y}_1$ is *normal*
 - If $\sigma_1 = \sigma_2 = \sigma$, then $SD(\bar{Y}_2 - \bar{Y}_1) = \sigma \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$

To compare 2 population/treatment means, we either give a *confidence interval* for their difference $\mu_2 - \mu_1$ or we test the hypothesis of no difference $H_0 : \mu_1 = \mu_2$

Standard Errors (*assuming* $\sigma_1 = \sigma_2 = \sigma$)

- To measure of how well $\bar{Y}_2 - \bar{Y}_1$ estimates $\mu_2 - \mu_1$, we estimate the spread $SD(\bar{Y}_2 - \bar{Y}_1) = \sigma\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$ with the **standard error of $\bar{Y}_2 - \bar{Y}_1$** given by

$$SE(\bar{Y}_2 - \bar{Y}_1) = s_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

- Estimate σ with *pooled* standard deviation: $s_p = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$
(s_1, s_2 both estimate same standard deviation σ)

- The ratio

$$t = \frac{(\bar{Y}_2 - \bar{Y}_1) - (\mu_2 - \mu_1)}{SE(\bar{Y}_2 - \bar{Y}_1)}$$

has an approximate t -distribution with $n_1 + n_2 - 2$ degrees of freedom

Confidence Intervals for $\mu_2 - \mu_1$ (*assuming* $\sigma_1 = \sigma_2 = \sigma$)

- A $100(1 - \alpha)\%$ confidence interval for $\mu_2 - \mu_1$ is given by:

$$\bar{Y}_2 - \bar{Y}_1 \pm t_{n_1+n_2-2}^{(1-\alpha/2)}SE(\bar{Y}_2 - \bar{Y}_1)$$

where $t_{n_1+n_2-2}^{(1-\alpha/2)}$ is the t -ratio larger than $100(1 - \alpha/2)\%$ of t -ratios from a t -distribution with $n_1 + n_2 - 2$ degrees of freedom

- Same use/interpretation as before except confidence interval is for the *difference* $\mu_2 - \mu_1$ in population/treatment means

Two sample t-tests

1. **State Hypotheses:** $H_0: \mu_1 = \mu_2$ (or $\mu_2 - \mu_1 = 0$) *null hypothesis*
 $H_a: \mu_2 > \mu_1$ (or $\mu_2 - \mu_1 > 0$) *alternatives*
 $H_a: \mu_2 < \mu_1$ (or $\mu_2 - \mu_1 < 0$)
 $H_a: \mu_2 \neq \mu_1$ (or $\mu_2 - \mu_1 \neq 0$)

2. **Test Statistic (t-ratio):** $t = \frac{(\bar{Y}_2 - \bar{Y}_1) - (\mu_2 - \mu_1)}{\text{SE}(\bar{Y}_2 - \bar{Y}_1)},$

substituting value of $\mu_2 - \mu_1$ (i.e., $\mu_2 - \mu_1 = 0$) under null hypothesis H_0

3. **p-value:** probability of getting more extreme test statistic (t -ratio) than our observed t if H_0 is true

Consider t -distribution having degrees of freedom $df = n_1 + n_2 - 2$

$$\begin{aligned} H_a: \mu_2 > \mu_1 \quad \text{p-value} &= \% \text{ of } t\text{-ratios larger than our } t \\ &= \text{area under } t\text{-curve to right of } t \\ &= 1 - \% \text{ of } t\text{-ratios smaller than our } t \end{aligned}$$

$$\begin{aligned} H_a: \mu_2 < \mu_1 \quad \text{p-value} &= \% \text{ of } t\text{-ratios smaller than our } t \\ &= \text{area under } t\text{-curve to left of } t \end{aligned}$$

$$\begin{aligned} H_a: \mu_2 \neq \mu_1 \quad \text{p-value} &= \% \text{ of } t\text{-ratios absolutely larger than our } |t| \\ &= \text{twice area under } t\text{-curve to right of } |t| \\ &= 2 \times (1 - \% \text{ of } t\text{-ratios smaller than our } |t|) \end{aligned}$$

4. **Interpretation of p-value:** Small p-values are evidence against H_0 (i.e., the t -ratio t we observe seems “unusual” under the null hypothesis or “unusually far” from the center of t -distribution at zero).

5. **Conclusion:** In terms of the problem and H_a , roughly again

small p-value \Rightarrow statistically significant evidence to prove H_a

large p-value \Rightarrow *no* statistically significant evidence to prove H_a

Note: It is possible to also test $H_0 : \mu_2 - \mu_1 = D$, that the difference in means $\mu_2 - \mu_1$ equals some specified value D , where D may not necessarily be zero. (See page 43 of text.) One would then substitute the hypothesized value D for $\mu_2 - \mu_1$ in the test statistic t or t -ratio in Step 3 above. Usually though, the value $D = 0$ (for “no difference in means”) is most common.