

## 2-sample t-test

$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  Estimates the population mean  $\mu$ .  $S^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$  Estimates the variance  $\sigma^2$ . The Hypothesis test is:  $H_0: \mu_1 = \mu_2$ ;  $H_a: \mu_1 \neq \mu_2$ , or  $<$  (left-tailed) or  $>$  (right-tailed).

**Known Variances** use the  $z$  test;  $Z = (\bar{y}_1 - \bar{y}_2) / \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$  (two population means), or  $Z = (\bar{y} - \mu_0) / \frac{\sigma}{\sqrt{n}}$  (one).  $100(1-\alpha\%)$  C.I. for  $\mu_1 - \mu_2$ :  $(\bar{y}_1 - \bar{y}_2) \pm Z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$ . C.R. where  $H_a: \neq \implies Z_{\alpha/2}$ .  $< \implies -Z_{\alpha}$ .  $> \implies Z_{\alpha}$

**Unknown Variances** ( $\sigma_1^2 = \sigma_2^2$ )  $t = (\bar{y}_1 - \bar{y}_2) / S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$ ,  $d.f = v = n_1 + n_2 - 2$ .  $S_p^2 = \frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{n_1 + n_2 - 2}$  ( $S_p = \sqrt{S_p^2}$ )  $100(1-\alpha)\%$  C.I. for  $\mu_1 - \mu_2$ :  $(\bar{y}_1 - \bar{y}_2) \pm t_{\alpha/2, v} S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$  (two means), or  $\bar{y} \pm t_{\alpha, n-1} \frac{\sigma}{\sqrt{n}}$  (one mean).

**Unknown Variances** ( $\sigma_1^2 \neq \sigma_2^2$ )  $t = (\bar{y}_1 - \bar{y}_2) / \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}$ ,  $d.f = v = \frac{((S_1^2/n_1) + (S_2^2/n_2))^2}{(S_1^2/n_1)^2 + (S_2^2/n_2)^2}$ . (round down  $v$  to the nearest int.) C.R. where  $H_a: \neq \implies t_{\alpha/2, v}$ .  $H_a: < \implies -t_{\alpha, v}$ .  $H_a: > \implies t_{\alpha, v}$

**Tests on Variances** The Hypothesis test is:  $H_0: \sigma_1^2 = \sigma_2^2$ ;  $H_a: \sigma_1^2 \neq \sigma_2^2$ , or  $<$  (left-tailed) or  $>$  (right-tailed).

**two-tailed( $\neq$ ):**  $F = \frac{S_1^2}{S_2^2} > F_{\alpha/2, n_1-1, n_2-1}$ , **left-tail( $<$ ):**  $F = \frac{S_2^2}{S_1^2} > F_{\alpha, n_2-1, n_1-1}$ , **right-tail ( $>$ ):**  $F = \frac{S_1^2}{S_2^2} > F_{\alpha, n_1-1, n_2-1}$ .

## Paired t-test (2 measurements from each exp unit)

Advantage: less variability than a design with 2 separate samples, test is more sensitive, ie more powerful.

Hypothesis:  $H_0: \mu_d = 0$ .  $H_a: \mu_d \neq 0$ . Where  $\mu_d = \mu_2 - \mu_1$  (before - after). Test statistic:  $t = \frac{\bar{d}}{S_d / \sqrt{n}}$  Where  $\bar{d} = \frac{1}{n} \sum_{j=1}^n d_j$  is the sample mean. And  $S_d^2 = \frac{1}{n-1} \sum_{j=1}^n (d_j - \bar{d})^2$ . (note: use  $S_d = \sqrt{S_d^2}$ ) Reject  $H_0$  if  $|t| > t_{\alpha/2, n-1}$ .

## ANOVA

The overall mean  $\mu$  is  $\frac{1}{a} \sum_{i=1}^a \mu_i$ . Note that  $\sum_{i=1}^a \tau_i = 0$ .

LS estimates:  $\hat{\mu} = \bar{y}_{..}$ ,  $\hat{\mu}_i = \bar{y}_{i.}$ ,  $\hat{\tau} = \bar{y}_{i.} - \bar{y}_{..}$ , to estimate common population variances  $\sigma^2$ , use  $S_p^2 = \frac{\sum_{i=1}^a (n_i-1)s_i^2}{\sum_{i=1}^a (n_i-1)}$

## Anova table (one-way layout)

Source	df	SS	MS	F
Treatments	$a - 1$	$SSTr$	$MSTr = \frac{SSTr}{a-1}$	$F = \frac{MSTr}{MSE}$
Error	$N - a$	$SSE$	$MSE = \frac{SSE}{N-a}$	
Total	$N - 1$	$SST$		

Note:  $N$  is the total number of observations, Pooled sample variance  $S_p^2 = \frac{SSE}{N-a} = MSE$ . Reject  $H_0$  if  $F > F_{\alpha, a-1, N-a}$ , or p-value  $< \alpha$ .

Hypotheses:  $H_0: \mu_1 = \mu_2 = \dots = \mu_a$ .  $H_a$ : Not all  $\mu_i$  are equal. Or  $H_0: \tau_1 = \tau_2 = \dots = \tau_a = 0$ .  $H_a$ : Not all  $\tau_i = 0$ .

$100(1-\alpha)\%$  C.I. for  $\mu_i$ :  $\bar{y}_{i.} \pm t_{\alpha/2, N-a} \sqrt{\frac{MSE}{n}}$

To check model assumptions use a normal probability plot and normality test (Anderson-Darling or some other), and a plot of residuals vs. predicted value (residual plot). The residuals should look like they are from a normal distribution if the model assumptions were met. If the model assumptions were met, the residual plot should look like a random scatter. if the plot shows a 'funnel' shape, this is an indication of non-constant variance (heteroscedasticity). The remedy is typically a transformation of the response.

## Normal probability plot

To estimate the standard deviation  $\sigma$ , note that the slope  $\approx \frac{1}{\sigma}$ , only with z-score. Or you can estimate the distance from 16% to 50% as one standard deviation. To estimate the mean  $\mu$  look at the 50<sup>th</sup> percentile. Hypotheses:  $H_0$ : The data are drawn from a normal distribution.  $H_a$ : The data are not drawn from a normal distribution. Large p-value means normal.

Standard to Percentile:	Standard Deviations	-2	-1	0	1	2
	Percentile	2.27%	15.88%	50%	84.23%	97.72%

Note that  $\Phi(\text{standard deviation}) = \text{percentile}$ , and  $\Phi^{-1}(\text{percentile}) = \text{standard deviation}$ .

## Contrasts

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$\Gamma = \sum_{i=1}^a c_i \mu_i$ , where  $c_i$ 's are constants such that  $\sum_{i=1}^a c_i = 0$ . To estimate  $\Gamma$  use  $\hat{\Gamma} = \sum_{i=1}^a c_i \bar{y}_i$ .

Hypotheses:  $H_0: \sum_{i=1}^a c_i \mu_i = 0$ .  $H_a: \sum_{i=1}^a c_i \mu_i \neq 0$ . (or  $<$  or  $>$ ).

Test statistic:  $t = (\sum_{i=1}^a c_i \bar{y}_i) / (\sqrt{\frac{MSE}{n} \sum_{i=1}^a c_i^2})$ . Reject  $H_0$  if  $t$  in C.R. of  $t_{\alpha, N-a}$  (or  $\alpha/2$  for 2-tail) or if p-value  $< \alpha$ .

Note:  $F = (\sum_{i=1}^a c_i \bar{y}_i)^2 / (\frac{MSE}{n} \sum_{i=1}^a c_i^2)$  can be used to test 2-tailed. Reject  $H_0$  if  $F > F_{\alpha, 1, N-a}$  or if p-value  $< \alpha$ .

## Pairwise comparisons

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Note: LSD is most powerful, but worst at guarding against Type I errors. Tukey's is most balanced for equal sample sizes. And Bonferroni's is least likely to make a Type I error.

**Fishers LSD** For every pair of treatments test the hypothesis at  $\alpha$ .  $H_0: \mu_i = \mu_j$ .  $H_a: \mu_i \neq \mu_j$ .

Test statistic  $t = |\bar{y}_i - \bar{y}_j| / \sqrt{MSE \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$ . Reject  $H_0$  is  $|t| > t_{\alpha/2, N-a}$ .

Therefore, The two treatment means are significantly different if  $|\bar{y}_i - \bar{y}_j| > t_{\alpha/2, N-a} \sqrt{MSE \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$ .

**Bonferroni's Method** Denote the FWE by  $\alpha$ . Identical to Fisher's LSD except that

$|\bar{y}_i - \bar{y}_j| > t_{\alpha/2k, N-a} \sqrt{MSE \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$ . Where  $k = \binom{a}{2}$ .

**Tukey's Method** Means are significantly different at  $FWE\alpha$  when:  $|\bar{y}_i - \bar{y}_j| > q_{\alpha, a, N-a} \sqrt{\frac{MSE}{2} \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$ .

100(1 -  $\alpha$ )% Simultaneous C.I's for all possible treatment differences  $\mu_i - \mu_j$  using Tukeys Method:

$\bar{y}_i - \bar{y}_j \pm q_{\alpha, a, N-a} \sqrt{\frac{MSE}{2} \left( \frac{1}{n_i} + \frac{1}{n_j} \right)}$

**Graphical results** Note that a line under the treatments indicates that they are not significantly different.

(2)            (1)            (4)            (3)            (5)      Treatments should be ordered from the smallest sample mean to the largest sample mean. This graph indicates that treatment 2 and 1 are not significantly different, and 4 and 3, and 5 are not significantly different.

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## Test of equality of variances

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Hypothesis:  $H_0: \sigma_1^2 = \sigma_2^2 = \dots = \sigma_a^2$ .  $H_a$ : at least one  $\sigma_i^2$  is different.

**Bartlett's test** (use if data is normal) assumes normality for each treatment. Very sensitive to non-normality.

**Modified Levene's test** (use if data  $\approx$  normal) robust for non-normality. For data from a normal dist, not as powerful as Bartlett's.

## Conclusions

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**Rejection Methods** Reject  $H_0$  if p-value  $\leq \alpha$ . Reject  $H_0$  if the test statistic falls within the critical region.

100(1 -  $\alpha$ )% **C.I** "We are 100(1 -  $\alpha$ )% confident that the true {test} is between {upper bound} and {lower bound}."

**Reject  $H_0$**  "There is enough statistical evidence to support (the statement of  $H_a$ )."

**Fail to reject  $H_0$**  "There is not enough statistical evidence to support (the statement of  $H_a$ ).\" or \"The evidence from the data is consistent with (the statement of  $H_0$ )\""