2-sample t-test

$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ Estimates the population mean μ. $S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2$ Estimates the variance σ^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 ($\sigma_1^2 \neq \sigma_2^2$) $t = (\bar{y}_1 - \bar{y}_2)/\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}$, $d.f = v = \frac{((S_1^2/n_1)+(S_2^2/n_2))^2}{\frac{(S_1^2/n_1)^2}{n_1-1} + \frac{(S_2^2/n_2)^2}{n_2-1}}$. (round down v to nearest int.)
C.R. where H_a: $\neq \implies t_{\alpha/2,v}$. $< \implies -t_{\alpha,v}$. $> \implies t_{\alpha,v}$

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 seperate samples, test is more sensitive, ie more powerful.
Hypothesis: H_0: $\mu_\delta = 0$. H_a: $\mu_\delta \neq 0$. Where $\mu_\delta = \mu_2 - \mu_1$ (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 μ 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 variences σ^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: $\mu_1 = \mu_2 = \cdots = \mu_a$. H_a: Not all μ_i are equal. Or H_0: $\tau_1 = \tau_2 = \cdots = \tau_a = 0$. H_a: Not all $\tau_i = 0$.

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

To check model assumtions 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 σ, note that the slope $\approx \frac{1}{\sigma}$, only with z-score. Or you can estimate the distance from 16% to 50% as on standard deviation. To estimate the mean μ look at the 50^{th} percentile. Hypotheses: H_0: The data are drawn from a normal distribution. H_a: The data are not drawn froma normal disribution. 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 Φ(standard deviation) = percentile, and Φ^{-1}(percentile) = standard deviation.

Contrasts

$\Gamma = \sum_{i=1}^{a} c_i\mu_i$, where c_i's are constants such that $\sum_{i=1}^{a} c_i = 0$. To estimate Γ use $\hat{\Gamma} = \sum_{i=1}^{a} c_i\bar{y}_{i\cdot}$.
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: $t = (\sum_{i=1}^{a} c_i\bar{y}_{i\cdot})/(\sqrt{\frac{MSE}{n}\sum_{i=1}^{a} c_i^2})$. 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: $F = (\sum_{i=1}^{a} c_i\bar{y}_{i\cdot})^2/(\frac{MSE}{n}\sum_{i=1}^{a} c_i^2)$ can be used to test 2-tailed. Reject H_0 if $F > F_{\alpha,1,N-a}$ or if p-value $< \alpha$.

Pairwise comparisons

Note: LSD is most powerful, but worst at gaurding 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 hypotheis at α. H_0: $\mu_i = \mu_j$. H_a: $\mu_i \neq \mu_j$.
Test statistic $t = |\bar{y}_{i\cdot} - \bar{y}_{j\cdot}| / \sqrt{MSE\left(\frac{1}{n_i} + \frac{1}{n_j}\right)}$. Reject H_0 is $|t| > t_{\alpha/2,N-a}$.

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

Bonferroni's Method Denote the FWE by α. Identical to Fisher's LSD except that $|\bar{y}_{i\cdot} - \bar{y}_{j\cdot}| > t_{\alpha/2k,N-a}\sqrt{MSE\left(\frac{1}{n_i} + \frac{1}{n_j}\right)}$.
Where $k = \binom{a}{2}$.

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

$100(1-\alpha)\%$ Simultanious C.I's for all possible treatment differences $\mu_i - \mu_j$ using Tukeys Method: $\bar{y}_{i\cdot} - \bar{y}_{j\cdot} \pm q_{\alpha,a,N-a}\sqrt{\frac{MSE}{2}\left(\frac{1}{n_i} + \frac{1}{n_j}\right)}$

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 smallest sample mean to 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.

Conclusions

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)"

Test of equality of variances

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

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

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