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• Inference for contrast of factor level means.

$$L = \sum_{i=1}^r C_i \mu_i, \text{ where } \sum_{i=1}^r C_i = 0$$

$$\text{EX: } L = \mu_1 - \mu_2$$

$$L = \frac{\mu_1 + \mu_2}{2} - \frac{\mu_3 + \mu_4}{2}$$

$$L = \mu_1 - \frac{\mu_2 + \mu_3 + \mu_4}{3}$$

$$\text{Estimator: } \hat{L} = \sum_{i=1}^r C_i \bar{y}_{i\cdot}, \quad SE(\hat{L}) = \sqrt{\left(\sum_{i=1}^r \frac{C_i^2}{n_i}\right) MSE}$$

• Multiple comparisons and error rates

EX: 100 tests with sig-level .05, all  $H_0$  true

Then  $X = \#$  of times  $H_0$  rejected  $\sim \text{Binomial}(100, .05)$

$$EX = 100 \times .05 = 5$$

• Running multiple tests on the same data set at the same stage of an analysis increases the chance of obtaining at least one invalid ~~test~~ result.

Significance level  $\begin{cases} \text{due to real difference} \\ \text{due to chance} \end{cases}$

• Performing more than one stat inference procedure on the same data set without adjusting the type I error rate accordingly is a common error in practice.

"Data snooping".

test what "seems" to be significant.

"hunt around through the data for a big contrast and then pretend that you've only done one comparison".

• Now assume you perform 2 tests using the same data, both  $H_0$  are true, there is no ~~general~~ reason that the sample giving a type I error for one test will also give a type I error for the other test. So we need to consider the joint Type I error.

Def: experimentwise error rate / familywise error rate.

keep the familywise error rate at  $\alpha = .05$

$P(\exists \text{ in the experiment, } \exists \text{ at least one incorrect inference})$

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Given a family of null hypotheses  $H_{01}, H_{02}, \dots, H_{0K}$   
 a familywise type I error occurs if all  $H_{01}, \dots, H_{0K}$   
 are true, but at least one of them is rejected.

• Tukey's test

focus on the pairs of means

Tukey's procedure (balanced  $n_1 = n_2 = \dots = n_r = n$ )

$$q = \frac{\bar{y}_{\max} - \bar{y}_{\min}}{\sqrt{\frac{MSE}{n}}}$$

~ Tukey's Studentized range distr.  
 with parameters  $(r, n_T - r)$

Testing:  $H_0: \mu_i = \mu_{i'}, \text{ for all } i, i' = 1, \dots, r$

vs  $H_A: H_0 \text{ is not true}$

gives us the simultaneous testing result for

$H_0: \mu_i = \mu_{i'} \text{ for all } i, i'$

$1 - \alpha = 1 - \text{FWER (familywise error rate)}$

$= P(\text{none of the pair wise comparisons is rejected})$

$$= P\left(\frac{|\bar{y}_{i_0} - \bar{y}_{i_1}|}{\sqrt{MSE(\frac{1}{n} + \frac{1}{n})}} < \text{critical value for all } i, i'\right)$$

$$= P \left( \frac{\bar{y}_{\max} - \bar{y}_{\min}}{\sqrt{MSE \left( \frac{1}{n} + \frac{1}{n} \right)}} < c.v. \right)$$

$$\frac{\bar{y}_{\max} - \bar{y}_{\min}}{\sqrt{\frac{MSE}{n}} \sqrt{2}} = \frac{q}{\sqrt{2}}$$

$$= P \left( \frac{q}{\sqrt{2}} < \frac{q_{\alpha}(r, N_T - r)}{\sqrt{2}} \right)$$

$$= 1 - \alpha$$

If not balanced, approximately

~~Fall~~ For all  $1 \leq i, i' \leq r$ , the  $100(1-\alpha)\%$  Tukey simultaneous

C.I. for  $\mu_i - \mu_{i'}$  is

$$\bar{y}_{i.} - \bar{y}_{i'.} \pm \frac{q_{\alpha}(r, n_T - r)}{\sqrt{2}} SE(\bar{y}_{i.} - \bar{y}_{i'.})$$

$$SE(\bar{y}_{i.} - \bar{y}_{i'.}) = \sqrt{MSE \left( \frac{1}{n_i} + \frac{1}{n_{i'}} \right)}$$

For  $H_0: \mu_i - \mu_{i'} = 0$  vs  $H_A$   
for all  $i, i'$

$$\text{reject } H_0 \text{ if } \frac{|\bar{y}_{i.} - \bar{y}_{i'.}|}{SE(\bar{y}_{i.} - \bar{y}_{i'.})} > \frac{q_{\alpha}(r, n_T - r)}{\sqrt{2}}$$

EX: treatment

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A	B	C
5	3	1
2	3	0
5	0	1
4	2	2
2	2	1
$\bar{y}_{1.} = 3.6$	$\bar{y}_{2.} = 2$	$\bar{y}_{3.} = 1$

$$T = q \cdot \sqrt{\frac{MSE}{n}}$$

$$= 3.77 \sqrt{\frac{1.43}{5}} = 1.99$$

↑  
q(0.95, 3, 12)

group	1	2	3
	2	3	3
	$ \bar{y}_{1.} - \bar{y}_{2.} $	$ \bar{y}_{2.} - \bar{y}_{3.} $	$ \bar{y}_{1.} - \bar{y}_{3.} $
			$= 2.6 > T$

# Scheffé multiple comparison Procedure.

Suppose there are  $r$  factors in total

$$L = \sum_{i=1}^r c_i \mu_i \quad \left( \sum_i c_i = 0 \right)$$

$$\hat{L} = \sum_{i=1}^r c_i \bar{y}_{i..}, \quad SE(\hat{L}) = \sqrt{MSE \sum_{i=1}^r \frac{c_i^2}{n_i}}$$

$$100(1-\alpha)\% \text{ CI} \quad \hat{L} \pm \sqrt{(r-1) F_{\alpha, r-1, n_T-r}} \quad SE(\hat{L})$$

For testing  $H_0: L=0$  vs  $H_A: L \neq 0$

$$\text{test statistic } T = \frac{|\hat{L}|}{SE(\hat{L})} > \sqrt{(r-1) F_{\alpha, r-1, n_T-r}}$$

Most conservative (least powerful)

$$H_0: L=0$$

include infinite statements

Proof: Because  $\sum_{i=1}^r c_i = 0$

$$\hat{L} = \sum_i c_i \bar{y}_{i..} = \sum_i c_i (\bar{y}_{i..} - \bar{y}_{...})$$

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By the Cauchy-Schwarz inequality.

$$\left| \sum_i a_i b_i \right| \leq \sqrt{\sum_i a_i^2 \sum_i b_i^2}$$

We have

$$\begin{aligned} |\hat{L}| &= \left| \sum_i \frac{c_i}{\sqrt{n_i}} (\bar{y}_{i\cdot} - \bar{y}_{\cdot\cdot}) \right| \\ &\leq \sqrt{\sum_i \frac{c_i^2}{n_i} \sum_i n_i (\bar{y}_{i\cdot} - \bar{y}_{\cdot\cdot})^2} \\ &= \sqrt{\sum_i \frac{c_i^2}{n_i} SSTR} \end{aligned}$$

$$T = \frac{|\hat{L}|}{SE(\hat{L})} = \frac{|\hat{L}|}{\sqrt{MSE \sum_i \frac{c_i^2}{n_i}}} \leq \frac{\sqrt{\sum_i \frac{c_i^2}{n_i} SSTR}}{\sqrt{\sum_i \frac{c_i^2}{n_i} MSE}} = \sqrt{\frac{SSTR}{MSE}}$$

Recall  $F = \frac{MSTR}{MSE}$  is the ANOVA F-statistic

$$T \leq \sqrt{\frac{SSTR}{MSE}} = \sqrt{\frac{(r-1) MSTR}{MSE}} = \sqrt{(r-1) F}$$

We thus get a uniform upper bound for the test statistic for any contrast  $L$ .

$$T(L) \leq \sqrt{(r-1) F}$$

$\bar{F}$  has a  $\bar{F}$ -distr. with df.  $(r-1, n_T-r)$

$$P(\bar{F} > F_{\alpha, r-1, n_T-r}) = \alpha$$

FWER  $\uparrow$  =  $P(\text{any contrast } L \text{ is rejected})$

$$= P(\tau(L) > \sqrt{(r-1)} F_{\alpha, r-1, n_T-r} \text{ for some contrast})$$

$$\leq P(\sqrt{(r-1)} \bar{F} > \sqrt{(r-1)} F_{\alpha, r-1, n_T-r})$$

$$= P(\bar{F} > F_{\alpha, r-1, n_T-r})$$

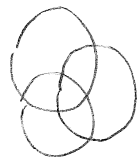
$$= \alpha$$

Bonferroni's method

$$\hat{L} \pm B \text{ SE}(\hat{L})$$

$$\downarrow t_{(1-\frac{\alpha}{2g}, n_T-r)} \quad g: \# \text{ of contrast}$$

$$P\left(\bigcap_{i=1}^g A_i^c\right) = 1 - P\left(\bigcup_{i=1}^g A_i^c\right)$$



$$\geq 1 - \sum_{i=1}^g P(A_i^c) = 1 - \sum_{i=1}^g (1 - P(A_i))$$



• Holm Method ( Refined Bonferroni Method ,  
more powerful than Bonferroni )

Order P-values  $P_{(1)} \leq P_{(2)} \leq \dots \leq P_{(k)}$

Then. if  $P_{(1)} > \frac{\alpha}{k} \Rightarrow$  accept  $H_0^{(1)}, \dots, H_0^{(k)}$

o.w. reject  $H_0^{(1)}$ , go to  $P_{(2)}$

If  $P_{(2)} > \frac{\alpha}{k-1} \Rightarrow$  accept  $H_0^{(2)}, \dots, H_0^{(k)}$

o.w. reject  $H_0^{(2)}$ , go to  $P_{(3)}$

If  $P_{(3)} > \frac{\alpha}{k-2} \Rightarrow$  accept  $H_0^{(3)}, \dots, H_0^{(k)}$

etc.

Proof: why Holm's method control ~~ex~~ FWER.

Denote  $J_T :=$  index set of true hypotheses

Define  $j :=$  first index of a true hypothesis.

$\Rightarrow H_0^{(1)}, \dots, H_0^{(j-1)}$  are all false

$$\Rightarrow (j-1) \leq k - |J_T| \quad |J_T| : \# \text{ of } \sqrt{J_T} \text{ index in}$$

$$j \leq k+1 - |J_T|$$

$$k+1-j \geq |J_T|$$

Now for  $\forall J_T$

$P(\text{at least 1 type I error})$

$$= P(\text{Reject } H_0^{(i)})$$

$$= P(P_j) \leq \frac{\alpha}{k+1-j} \leq P(P_j) \leq \frac{\alpha}{|J_T|}$$

$$= P\left(\min_{j \in J_T} P_j \leq \frac{\alpha}{|J_T|}\right) \leq \sum_{j \in J_T} \frac{\alpha}{|J_T|} = \alpha$$

$\swarrow \sim U(0,1)$

$$\swarrow P(\text{some } P_i \leq \frac{\alpha}{|J_T|} \text{ for some } i)$$

# Fisher's least significant Difference (LSD)

The LSD is the minimum amount by which two means must differ in order to be considered statistically different.

• a usual t-test

• No adjustment is made for multiple comparisons.

## Summary of multiple comparison adjustments

Method	family of contrast	C.V.
Fisher LSD	a single pairwise comparison	$t_{\frac{\alpha}{2}}, N_T - r$
Tukey	all pairwise comparison	$q_{\alpha}(r, N_T - r) / \sqrt{2}$
Bonferroni	varies	$t_{\frac{\alpha}{2k}}, N_T - r$ k: # of test
Scheffé	all contrasts	$\sqrt{(r-1) F_{\alpha, r-1, N_T - r}}$
Conservative		

powerful ↑

↓

Ex:

Recall treatment

A B C

 $n_i$  5 5 5 $\bar{y}_{i.}$  3.6 2 1

MSE = 1.43

$H_0: \mu_i = \mu_{i'}$  for all  $i, i'$   
 the C.V. at  $\alpha = .05$  are

 $> \alpha = .05$  $r \leftarrow 3$  $k \leftarrow \binom{3}{2} = 3$  $N_T \leftarrow 15$ 

$> qt(1 - \frac{\alpha}{2}, df = N_T - r)$  # Fisher's LSD

2.178813

$> qt(1 - \frac{\alpha}{k}, df = N_T - r)$  # Bonferroni

2.7794

$> qtukey(1 - \alpha, r, N_T - r) / \sqrt{2}$  # Tukey

2.6679

$> sqrt((r-1) * qt(1 - \alpha, r-1, N_T - r))$  # Scheffé

2.7876

C.I width

$$C.V \times SE(\bar{y}_i - \bar{y}_{i'})$$

$$C.V \cdot \sqrt{MSE(\frac{1}{5} + \frac{1}{5})} = C.V \cdot \sqrt{1.43 \times \frac{2}{5}} = C.V \cdot .7563$$

Power

Scheffé < Bonferroni < Tukey

Scheffé: conservative, works better for "many comparisons".

Tukey: pairwise (not work for contrast like  $\mu_1 - \frac{\mu_2 + \mu_3}{2}$ )

Bonferroni: conservative, works for smaller # of comparisons

In R

pairwise, t.test(y, x, p.adjust)

TukeyHSD: A B C  
"none", "holm", "bonferroni"

(AB) (AC), (BC)