

STAT 525 FALL 2018

Chapter 17

Analysis of Factor Level Means

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The Cell Means Model

- Expressed numerically

$$Y_{ij} = \mu_i + \varepsilon_{ij}$$

where μ_i is the theoretical mean of all observations at level i (or in cell i)

- The ε_{ij} are iid $N(0, \sigma^2)$ which implies the Y_{ij} are independent $N(\mu_i, \sigma^2)$
- Parameters
 - $\mu_1, \mu_2, \dots, \mu_r$
 - σ^2

Estimates

- Estimate μ_i by the sample mean of the observations at level i

$$\hat{\mu}_i = \bar{Y}_i.$$

- Pool s_i^2 using weights proportional to sample size (i.e., df) to get s^2

$$\begin{aligned}s^2 &= \frac{\sum (n_i - 1)s_i^2}{\sum (n_i - 1)} \\ &= \frac{\sum (n_i - 1)s_i^2}{n_T - r}\end{aligned}$$

Confidence Intervals of μ_i 's

- From model

$$\bar{Y}_{i\cdot} \sim N(\mu_i, \sigma^2/n_i)$$

- Confidence interval

$$\bar{Y}_{i\cdot} \pm t(1 - \alpha/2; n_T - r)s/\sqrt{n_i}$$

- Degrees of freedom larger than $n_i - 1$ because pooling variance estimates across treatments (i.e., borrowing information from other groups)

Example (Page 685)

```
options nocenter;
data a1;
    infile 'u:\.www\datasets525\CH16TA01.TXT';
    input cases design store;

proc means data=a1
    mean std stderr clm maxdec=2;
    class design;
    var cases;
run; quit;
```

Analysis Variable : cases

Des	N	Mean	Std Dev	Std Err	Lower 95%	Upper 95%
					CL for Mean	CL for Mean
1	5	14.60	2.30	1.03	11.74	17.46
2	5	13.40	3.65	1.63	8.87	17.93
3	4	19.50	2.65	1.32	15.29	23.71
4	5	27.20	3.96	1.77	22.28	32.12

- $4 \times 2.30^2 + 4 \times 3.65^2 + 3 \times 2.65^2 + 4 \times 3.96^2 = 158.24$. Except for rounding, this is equal to SSE.
- $19-4=15$, which is the df error in the ANOVA table.
- There is no pooling of error (or df) when computing these confidence intervals.

```

proc glm data=a1;
  class design;
  model cases=design;
  means design/t clm;
run; quit;

```

t Confidence Intervals for cases

Alpha	0.05
Error Degrees of Freedom	15
Error Mean Square	10.54667
Critical Value of t	2.13145

design	N	Mean	95% Confidence	
			Limits	
4	5	27.200	24.104	30.296
3	4	19.500	16.039	22.961
1	5	14.600	11.504	17.696
2	5	13.400	10.304	16.496

- Very important for there to be a common variance.
 - These confidence intervals are often narrower due to the increase of degrees of freedom.

Multiplicity

- Have generates r confidence intervals
- Overall confidence level (all intervals contain its true mean) is less than $1 - \alpha$
- Many different approaches have been proposed
- Previously discussed the Bonferroni

Example (Page 685)

```
proc glm data=a1;
  class design;
  model cases=design;
  means design/bon clm;
run; quit;
```

Bonferroni t Confidence Intervals for cases

Alpha	0.05
Error Degrees of Freedom	15
Error Mean Square	10.54667
Critical Value of t	2.83663

design	N	Mean	Simultaneous 95%	
			Confidence	Limits
4	5	27.200	23.080	31.320
3	4	19.500	14.894	24.106
1	5	14.600	10.480	18.720
2	5	13.400	9.280	17.520

Hypothesis Tests on μ_i 's

- Not usually done
- SAS often gives output for $H_0 : \mu_i = 0$ which rarely is of any interest
- If interested in $H_0 : \mu_i = c$, it is easiest to subtract of c from all observations in a data step and then test whether the new mean is equal to zero.

Differences in Means

- From model

$$\bar{Y}_{i\cdot} - \bar{Y}_{k\cdot} \sim N \left(\mu_i - \mu_k, \sigma^2 \left(\frac{1}{n_i} + \frac{1}{n_k} \right) \right)$$

- Confidence interval

$$\bar{Y}_{i\cdot} - \bar{Y}_{k\cdot} \pm t(1 - \alpha/2; n_T - r) s \sqrt{1/n_i + 1/n_k}$$

- In this case $H_0 : \mu_i - \mu_k = 0$ is of interest
- Similar multiplicity problem
- Now have $\frac{r(r-1)}{2}$ pairwise comparisons

Multiplicity Adjustment

- Approaches adjust multiplier of the SE
 - Alter α level (e.g., Bonferroni)
 - Use different distribution
- Conservative \rightarrow strong control of overall Type I error - avoids false positives
- Powerful \rightarrow able to pick up differences that exist - avoids false negatives
- All approaches try to strike a balance

Least Significant Difference

- Simply ignores multiplicity issue
- Uses $t(1 - \alpha/2; n_T - r)$ to determine multiplier
- Called T or LSD in SAS

Tukey Multiple Comparison Procedure

- Based on studentized range distribution q
- Range is $\max(\bar{Y}_i) - \min(\bar{Y}_i)$ in r levels
- Accounts for any possible pair being furthest apart
- Controls overall experimentwise error rate
- Uses $q(1 - \alpha; r, n_T - r)/\sqrt{2}$ to determine multiplier
- Called TUKEY in SAS

Scheffé Multiple Comparison Procedure

- Based on the F distribution
- Accounts for multiplicity for all linear combinations of means, not just pairwise comparisons
- Protects against data snooping
- Uses $\sqrt{(r - 1)F(1 - \alpha; r - 1, n_T - r)}$ to determine multiplier
- Called SCHEFFE in SAS

Bonferroni Multiple Comparison Procedure

- Replaces α by

$$\alpha^* = \frac{\alpha}{r(r-1)/2}$$

- Uses $t(1 - \alpha^*/2; n_T - r)$ to determine multiplier
- Called BON in SAS

Holm Multiple Comparison Procedure

- Refinement of Bonferroni
- Instead of using

$$\alpha^* = \frac{\alpha}{g}$$

for all comparisons

- Rank P-values from smallest to largest

$$p(1) \leq p(2) \leq \cdots \leq p(g)$$

- Continue to reject until $p(k) \geq \alpha/(g - k + 1)$
- Available in PROC MULTTEST in SAS

False Discovery Rate

- FDR defined as expected proportion of false positives in the collection of rejected null hypotheses
- Becoming more popular, especially when # of tests in the thousands
- Rank P-values from smallest to largest

$$p(1) \leq p(2) \leq \cdots \leq p(g)$$

- Continue to reject until $p_{(k)} \geq k\alpha/g$
- Available in PROC MULTTEST in SAS

Example (Page 685)

```
/* Compare all pairs */
proc glm data=a1;
  class design;
  model cases=design;
  means design/lsd tukey bon scheffe;
run; quit;
```

t Tests (LSD) for cases

NOTE: This test controls the Type I comparisonwise error rate, not the experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	15
Error Mean Square	10.54667
Critical Value of t	2.13145

Comparisons significant at the 0.05 level are indicated by ***.

Comparison	design	Difference		
		Between Means	95% Confidence Limits	
4 - 3		7.700	3.057	12.343 ***
4 - 1		12.600	8.222	16.978 ***
4 - 2		13.800	9.422	18.178 ***
3 - 4		-7.700	-12.343	-3.057 ***
3 - 1		4.900	0.257	9.543 ***
3 - 2		6.100	1.457	10.743 ***
1 - 4		-12.600	-16.978	-8.222 ***
1 - 3		-4.900	-9.543	-0.257 ***
1 - 2		1.200	-3.178	5.578
2 - 4		-13.800	-18.178	-9.422 ***
2 - 3		-6.100	-10.743	-1.457 ***
2 - 1		-1.200	-5.578	3.178

Tukey's Studentized Range (HSD) Test for cases

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	15
Error Mean Square	10.54667
Critical Value of Studentized Range	4.07597

Comparisons significant at the 0.05 level are indicated by ***.

		Difference		
design	Comparison	Between Means	Simultaneous 95% Confidence Limits	
4	- 3	7.700	1.421	13.979 ***
4	- 1	12.600	6.680	18.520 ***
4	- 2	13.800	7.880	19.720 ***
3	- 4	-7.700	-13.979	-1.421 ***
3	- 1	4.900	-1.379	11.179
3	- 2	6.100	-0.179	12.379
1	- 4	-12.600	-18.520	-6.680 ***
1	- 3	-4.900	-11.179	1.379
1	- 2	1.200	-4.720	7.120
2	- 4	-13.800	-19.720	-7.880 ***
2	- 3	-6.100	-12.379	0.179
2	- 1	-1.200	-7.120	4.720

Bonferroni (Dunn) t Tests for cases

NOTE: This test controls the Type I experimentwise error rate,
but it generally has a higher Type II error rate than
Tukey's for all pairwise comparisons.

Alpha	0.05
Error Degrees of Freedom	15
Error Mean Square	10.54667
Critical Value of t	3.03628

Comparisons significant at the 0.05 level are indicated by ***.

		Difference		
design	Comparison	Between Means	Simultaneous Confidence Limits	95% Limits
4	- 3	7.700	1.085	14.315 ***
4	- 1	12.600	6.364	18.836 ***
4	- 2	13.800	7.564	20.036 ***
3	- 4	-7.700	-14.315	-1.085 ***
3	- 1	4.900	-1.715	11.515
3	- 2	6.100	-0.515	12.715
1	- 4	-12.600	-18.836	-6.364 ***
1	- 3	-4.900	-11.515	1.715
1	- 2	1.200	-5.036	7.436
2	- 4	-13.800	-20.036	-7.564 ***
2	- 3	-6.100	-12.715	0.515
2	- 1	-1.200	-7.436	5.036

Scheffe's Test for cases

NOTE: This test controls the Type I experimentwise error rate,
but it generally has a higher Type II error rate than
Tukey's for all pairwise comparisons.

Alpha	0.05
Error Degrees of Freedom	15
Error Mean Square	10.54667
Critical Value of F	3.28738

Comparisons significant at the 0.05 level are indicated by ***.

		Difference	Simultaneous 95%		
design	Comparison	Between Means	Confidence	Limits	
4	- 3	7.700	0.859	14.541	***
4	- 1	12.600	6.150	19.050	***
4	- 2	13.800	7.350	20.250	***
3	- 4	-7.700	-14.541	-0.859	***
3	- 1	4.900	-1.941	11.741	
3	- 2	6.100	-0.741	12.941	
1	- 4	-12.600	-19.050	-6.150	***
1	- 3	-4.900	-11.741	1.941	
1	- 2	1.200	-5.250	7.650	
2	- 4	-13.800	-20.250	-7.350	***
2	- 3	-6.100	-12.941	0.741	
2	- 1	-1.200	-7.650	5.250	

```
/* LINES: group factor levels based on test results */
proc glm data=a1;
  class design;
  model cases=design;
  means design/lines tukey;
run;
```

Tukey's Studentized Range (HSD) Test for cases

NOTE: Cell sizes are not equal.

Means with the same letter are not significantly different.

	Mean	N	design
A	27.200	5	4
B	19.500	4	3
B			
B	14.600	5	1
B			
B	13.400	5	2

Linear Combination of Means

- Would like to test $H_0 : L = \sum c_i \mu_i = L_0$
- Hypotheses usually planned but can be “after the fact”
- Can use statistical model to construct t-test

$$\begin{aligned}\hat{L} &= \sum c_i \bar{Y}_{i\cdot} \\ Var(\hat{L}) &= Var(\sum c_i \bar{Y}_{i\cdot}) = \sum c_i^2 Var(\bar{Y}_{i\cdot}) \\ \implies \widehat{Var}(\hat{L}) &= MSE \sum (c_i^2 / n_i) \\ \implies t^* &= \frac{\hat{L} - L_0}{\sqrt{\widehat{Var}(\hat{L})}}\end{aligned}$$

- Under H_0 : $t^* \sim t_{n_T - r}$

Contrasts

- Special case of linear combination
 - Requires $\sum c_i = 0$
- Example 1: $\mu_1 - \mu_2 = 0$
- Example 2: $\mu_1 - (\mu_2 + \mu_3)/2 = 0$
- Example 3: $(\mu_1 + \mu_2) - (\mu_3 + \mu_4) = 0$

Example (Page 685)

```
proc glm data=a1;
  class design;
  model cases=design;
  contrast '1&2 v 3&4' design .5 .5 -.5 -.5;
  estimate '1&2 v 3&4' design .5 .5 -.5 -.5;
run; quit;
```

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1&2 v 3&4	1	411.4000000	411.4000000	39.01	<.0001

Parameter	Estimate	Error	t Value	Pr > t
1&2 v 3&4	-9.3500000	1.49705266	-6.25	<.0001

- Contrast does an F test while estimate does a t-test and gives an estimate of the linear combination.
- Contrast allows you to simultaneously test a collection of contrasts.

```

/* Joint test of several contrasts */
proc glm data=a1;
  class design;
  model cases=design;
  contrast '1 v 2&3&4' design 1 -.3333 -.3333 -.3333;
  estimate '1 v 2&3&4' design 3 -1 -1 -1 /divisor=3;
  contrast '2 v 3 v 4' design 0 1 -1 0,
             design 0 0 1 -1;
run; quit;

```

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
1 v 2&3&4	1	108.4739502	108.4739502	10.29	0.0059
2 v 3 v 4	2	477.9285714	238.9642857	22.66	<.0001

Parameter	Estimate	Standard			Pr > t
		Error	t Value	Pr > t	
1 v 2&3&4	-5.43333333	1.69441348	-3.21	0.0059	

```

/* HOLM & FDR */
proc multtest data=a1 holm fdr out=out1 noprint;
  class design;
  contrast '12' 1 -1 0 0;
  contrast '13' 1 0 -1 0;
  contrast '14' 1 0 0 -1;
  contrast '23' 0 1 -1 0;
  contrast '24' 0 1 0 -1;
  contrast '34' 0 0 1 -1;
  test mean(cases);

proc print data=out1; quit;

```

contrast	_value_	_se_	_nval_	raw_p	stpbond_p	fdr_p
12	22.8	39.0248	15	0.56774	0.56774	0.56774
13	-93.1	41.3921	15	0.03995	0.07990	0.04794
14	-239.4	39.0248	15	0.00002	0.00010	0.00006
23	-115.9	41.3921	15	0.01346	0.04038	0.02019
24	-262.2	39.0248	15	0.00001	0.00004	0.00004
34	-146.3	41.3921	15	0.00300	0.01201	0.00601

- Instead of comparing each raw p -value to a different α level, the p -values are adjusted based on the procedure.

```

/* HOLM & FDR */
proc multtest data=a1 holm fdr out=out2 noprint;
  class design;
  contrast '12vs34' 1 1 -1 -1;
  contrast '13vs24' 1 -1 1 -1;
  contrast '12' 1 -1 0 0;
  contrast '13' 1 0 -1 0;
  contrast '24' 0 1 0 -1;
  contrast '34' 0 0 1 -1;
  test mean(cases);

proc print data=out2; run; quit;

```

contrast	_value_	_se_	_nval_	raw_p	stpbond_p	fdr_p
12vs34	-355.3	56.8880	15	0.00002	0.00008	0.00005
13vs24	-123.5	56.8880	15	0.04639	0.11984	0.05567
12	22.8	39.0248	15	0.56774	0.56774	0.56774
13	-93.1	41.3921	15	0.03995	0.11984	0.05567
24	-262.2	39.0248	15	0.00001	0.00004	0.00004
34	-146.3	41.3921	15	0.00300	0.01201	0.00601

- Instead of comparing each raw p -value to a different α level, the p -values are adjusted based on the procedure.
 - $stpbond_p(k) = raw_p(k) \times (g - k + 1)$
 - $fdr_p(k) = raw_p(k) \times g/k$

Chapter Review

- Inference for
 - Means
 - Differences in cell means
 - Contrasts
- Multiplicity
 - The Tukey procedure can be modified to handle general contrasts of factor level means
 - If only pairwise comparisons are to be made, the Tukey procedure gives narrower confidence limits and is therefore the preferred method than the Sheffé procedure
 - For general contrasts of factor level means, the Sheffé procedure is preferred than the Tukey procedure
 - Bonferroni, Sheffé and Tukey procedures are of the form “estimator \pm multiplier \times SE” with different multipliers. For any given problem, one may select the one with the smallest multiplier