## STA 674

Regression Analysis And Design Of Experiments

Treatment Comparisons – Lecture 3

# STA 674, RA Design Of Experiments: Treatment Comparisons

- Last time, we did some inference in SAS with contrasts and brought to consciousness the increased risk of Type I error when doing multiple comparisons.
- This time, we will look at one mathematically simple (but conservative) method of working against this phenomenon.

### Treatment Comparisons

#### Bonferroni's Inequality

• If n tests are conducted each with a comparisonwise error rate of  $\alpha_C$  then the experimentwise error rate always satisfies:

$$n\alpha_C \leq \alpha_E$$

#### **Bonferroni Correction**

The experimentwise error rate for a set of n tests will be less than or equal to a desired level,  $\alpha_E$ , if:

$$\alpha_C \leq \frac{\alpha_E}{n}$$

We can ensure that the experimentwise error rate is no bigger than  $\alpha_E$  by setting  $\alpha_C = \frac{\alpha_E}{n}$ .

### Treatment Comparisons

#### Example exercise: tomato growth

Consider the experiment tomato plant experiment with four treatments and suppose that the researcher wants to compare every treatment with every other treatment. This entails

$$n = (4 \times 3)/2 = 6$$

different tests.

- 1. Explain the difference between the comparison-wise and experiment-wise error rates. Experiment-wise error = out of 6 comparisons, the likelihood that any of the 6 (1 or more) comparisons were type 1 errors (mistakenly rejected null hypothesis) was less than 0.05
- 2. Use Bonferroni's method to compute a comparison-wise error rate that ensures an experiment-wise error rate of  $\alpha_E = 0.05$ . 0.05/6 = ~1% = alpha c = prob. that mistakenly reject null on any individual comparison

#### Example exercise: tomato growth

comparing P to bonferoni's estimate of alpha c

#### The GLM Procedure

Dependent Variable: growth

```
DF | Contrast SS | Mean Square | F Value | Pr > F
Contrast
                      1 435.6000000 435.6000000
                                                    63.36 < .0001
Control vs Glucose
Control vs Fructose
                      1 532.9000000 532.9000000
                                                    77.51 < .0001
                      1 168.1000000 168.1000000
                                                    24.45 0.0001
Control vs Sucrose
                                                     0.71 0.4110
Fructose vs Glucose
                          4.9000000
                                       4.9000000
                      1 102.4000000 102.4000000
                                                    14.89 0.0014
Fructose vs Sucrose
                                                     9.09 0.0082
                         62.5000000
                                      62.5000000
Glucose vs Sucrose
```

```
/* all possible comparisons -- Bonferroni correction */;
PROC GLM DATA=TOMATO;
CLASS treatment;
MODEL growth=treatment;
MEANS treatment / clm lsd;
CONTRAST "Control vs Glucose" treatment -1 0 1 0;
CONTRAST "Control vs Fructose" treatment -1 1 0 0;
CONTRAST "Control vs Sucrose" treatment -1 0 0 1;
CONTRAST "Fructose vs Glucose" treatment 0 -1 1 0;
CONTRAST "Fructose vs Sucrose" treatment 0 -1 0 1;
CONTRAST "Glucose vs Sucrose" treatment 0 0 -1 1;
```

not significant

significant but close to insignificant

### Treatment Comparisons

#### Simultaneous Confidence Intervals

- Suppose that we are going to conduct an experiment with *t* treatments and plan to compute 95% confidence intervals for the mean response of each treatment.
- What is the probability that the confidence intervals will *all* cover their respective treatment means?

For regular CI of each mean...the probability of missing the mean (e.g., for 95% CI, 5% probability that mean is outside that range) adds up for each mean...so for 3 95% means/CI = 0.05+0.05+0.05 = 0.15 probability of at least one missing the mean

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### Treatment Comparisons

#### Simultaneous Confidence Intervals

- If we wish to construct confidence intervals for the treatment means such that the probability that all t intervals cover their respective means is  $(1 \alpha_E)$ , then we need to increase the probability that any one interval covers its respective mean,  $(1 \alpha_C)$ .
- Confidence intervals constructed so that *all* treatment means are covered with probability  $(1 \alpha_E)$  are called  $(1 \alpha_E)$  100% simultaneous confidence intervals.
- If we repeated the experiment many, many times and constructed confidence intervals in this way then  $(1 \alpha_E)$  100% of the time all t intervals would cover their respective means.

### Treatment Comparisons

#### Simultaneous Confidence Intervals with Bonferroni's Correction

• We can construct a set of  $(1 - \alpha_E)$  100% simultaneous confidence intervals for t treatment means by constructing  $(1 - \alpha_C)$  100% for each mean where:

$$\alpha_C = \frac{\alpha_E}{n}$$

### Treatment Comparisons

#### Example exercise: tomato growth

Consider the tomato experiment again and suppose we wish to construct 95% simultaneous confidence intervals for the means of each treatment.

Use the Bonferroni correction to compute a value of  $\alpha_C$  such that if we compute  $(1-\alpha_C)$  100% confidence intervals for each mean then the intervals will form simultaneous 95% confidence intervals.  $\alpha_C = 0.05/4 = 0.0125$ ...use this for P value for individual CI

- 2. Provide an interpretation of the single interval for the control treatment.
- 3. Provide an interpretation for all 4 intervals together.

#### Example exercise: tomato growth

```
/* Comparisons of each alternative with control -- Bonferroni correction */;
PROC GLM DATA=TOMATO;
CLASS treatment;
MODEL growth=treatment;
MEANS treatment / CLM LSD alpha = .0166666666;
CONTRAST "Control vs Glucose" treatment -1 0 1 0;
CONTRAST "Control vs Fructose" treatment -1 1 0 0;
CONTRAST "Control vs Sucrose" treatment -1 0 0 1;
RUN;
```

treatment	N	Mean	95% Confid	ence Limits
Control	5	42.200	39.714	44.686
Sucrose	5	34.000	31.514	36.486
Glucose	5	29.000	26.514	31.486
Fructose	5	27.600	25.114	30.086

tr	reatment	N	Mean	98.33333% Lin			
C	ontrol	5	42.200	39.066	45.334		
S	ucrose	5	34.000	30.866	37.134		
G	lucose	5	29.000	25.866	32.134		
F	ructose	5	27.600	24.466	30.734		

#### The SAS System

The GLM Procedure

Dependent Variable: growth

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F	
Control vs Glucose	1	435.6000000	435.6000000	63.36	<.0001	
<b>Control vs Fructose</b>	1	532.9000000	532.9000000	77.51	<.0001	
Control vs Sucrose	1	168.1000000	168.1000000	24.45	0.0001	

#### The SAS System

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