

## ORTHOGONAL POLYNOMIAL CONTRASTS

### INDIVIDUAL DF COMPARISONS: EQUALLY SPACED TREATMENTS

- Many treatments are equally spaced (incremented).
- This provides us with the opportunity to look at the response curve of the data (form of multiple regression).
- Regression analysis could be performed using the data; however, when there are equal increments between successive levels of a factor, a simple coding procedure may be used to accomplish the analysis with much less effort.
- This technique is related to the one we will use for linear contrasts.
- We will partition the factor in the ANOVA table into separate single degree of freedom comparisons.
- The number of possible comparisons is equal to the number of levels of a factor minus one.
- For example, if there are three levels of a factor, there are two possible comparisons.
- The comparisons are called orthogonal polynomial contrasts or comparisons.
- Orthogonal polynomials are equations such that each is associated with a power of the independent variable (e.g.  $X$ , linear;  $X^2$ , quadratic;  $X^3$ , cubic, etc.).
  - 1<sup>st</sup> order comparisons measure linear relationships.
  - 2<sup>nd</sup> order comparisons measures quadratic relationships.
  - 3<sup>rd</sup> order comparisons measures cubic relationships.

#### Example 1

- We wish to determine the effect of drying temperature on germination of barley, we can set up an experiment that uses three equally space temperatures (90°F, 100°F, 110°F) and four replicates.
- The ANOVA would look like:

Sources of variation	df
Rep	$r-1=3$
Treatment	$t-1=2$
Error	$(r-1)(t-1)=6$
Total	$rt-1=11$

- Since there are three treatments equally spaced by 10°F, treatment can be partitioned into two single df polynomial contrasts (i.e. linear and quadratic).
- The new ANOVA table would look like:

Sources of variation	df
Replicate	r-1
Treatment	t-1
Linear	1
Quadratic	1
Error	(r-1)(t-1)
Total	rt-1

- Sum of squares can be calculated for each of the comparisons using the formula:  $Q^2 / (k*r)$  where  $Q = \sum c_i Y_i$ ,  $k = \sum c_i^2$ ,  $c$ =coefficients, and  $r$ =number of replicates.
- $F$ -tests can be calculated for each of the polynomial contrasts.

The coefficients used for calculating sums of squares are:

Number of treatment	Degree of polynomial	Treatment totals						Divisor $k = \sum c_i^2$
		T1	T2	T3	T4	T5	T6	
2	1	-1	+1					2
3	1	-1	0	+1				2
	2	+1	-2	+1				6
4	1	-3	-1	+1	+3			20
	2	+1	-1	-1	+1			4
	3	-1	+3	-3	+1			20
5	1	-2	-1	0	+1	+2		10
	2	+2	-1	-2	-1	+2		14
	3	-1	+2	0	-2	+1		10
	4	+1	-4	+6	-4	+1		70
6	1	-5	-3	-1	+1	+3	+5	70
	2	+5	-1	-4	-4	-1	+5	84
	3	-5	+7	+4	-4	-7	+5	180
	4	+1	-3	+2	+2	-3	+1	28
	5	-1	+5	-10	+10	-5	+1	252

- Coefficients for these comparisons would be as follows:

	Drying temperature		
	90°	100°	110°
Linear	-1	0	1
Quadratic	1	-2	1

Using the formulas  $SS = Q^2 / (\mathbf{k} * \mathbf{r})$   $Q = \sum c_i Y_i$  and  $k = \sum c_i^2$

$$SS_{\text{Linear}} = [(-1)(Y_{1.}) + (0)(Y_{2.}) - (1)(Y_{3.})]^2 \div (2 * 4)$$

$$SS_{\text{Quadratic}} = [(1)(Y_{1.}) + (-2)(Y_{2.}) - (1)(Y_{3.})]^2 \div (6 * 4)$$

### Example 2

Effect of row spacing on yield (bu/ac) of soybean.

Block	Row spacing (inches)					$\sum Y_{.j}$
	18	24	30	36	42	
1	33.6	31.1	33.0	28.4	31.4	157.5
2	37.1	34.5	29.5	29.9	28.3	159.3
3	34.1	30.5	29.2	31.6	28.9	154.3
4	34.6	32.7	30.7	32.3	28.6	158.9
5	35.4	30.7	30.7	28.1	29.6	154.5
6	36.1	30.3	27.9	26.9	33.4	154.6
$Y_{.i}$	210.9	189.8	181.0	177.2	180.2	939.1
$\bar{Y}_{.i}$	35.15	31.63	30.17	29.53	30.03	31.3

Step 1. ANOVA of data as an RCBD:

SOV	Df	SS	MS	F
Rep	5	5.41		
Treatment	4	125.66	31.415	8.4997**
Error	20	73.92	3.696	
Total	29	204.99		

Step 2. Partition Treatment of source of variation into four single degree of freedom orthogonal polynomial contrasts.

Contrast	Row spacing (inches)				
	18	24	30	36	42
$\Sigma Y_i$	210.9	189.8	181.0	177.2	180.0
Linear	-2	-1	0	1	2
Quadratic	2	-1	-2	-1	2
Cubic	-1	2	0	-2	1
Quartic	1	-4	6	-4	1

Step 3. Calculate Sum of Squares for each contrast.

Contrast	Row spacing (inches)					Q	$r \sum c_i^2$	SS
	18	24	30	36	42			
$\Sigma Y_i$	210.9	189.8	181.0	177.2	180.0			
Linear	-2	-1	0	1	2	-74.4	6(10)	92.25
Quadratic	2	-1	-2	-1	2	52.8	6(14)	33.19
Cubic	-1	2	0	-2	1	-5.7	6(10)	0.54
Quartic	1	-4	6	-4	1	8.9	6(70)	0.19

Remember:

$$Q = \sum c_i Y_i$$

e.g. Q for Linear =  $(-2)210.9 + (-1)189.8 + (0)181.0 + (1)177.2 + (2)180.0 = -74.4$

and  $SS = Q^2/rk$

Step 4. Rewrite ANOVA.

SOV	Df	SS	MS	F
Rep	5	5.41		
Treatment	4	126.17	31.54	TRT MS/Error MS = 8.59**
Linear	1	92.25	92.25	Lin. MS/Error MS = 24.14**
Quadratic	1	33.19	33.19	Quad. MS/Error MS = 9.04**
Cubic	1	0.54	0.54	Cubic MS/Error MS = 0.15
Quartic	1	0.19	0.19	Quart. MS/Error MS = 0.05
Error	20	73.41	3.67	
Total	29	204.99		

## Step 5. Conclusions

This analysis shows highly significant linear and quadratic effects for the row spacing treatments.

The linear component is the portion of the SS attributable to the linear regression of yield on spacing.

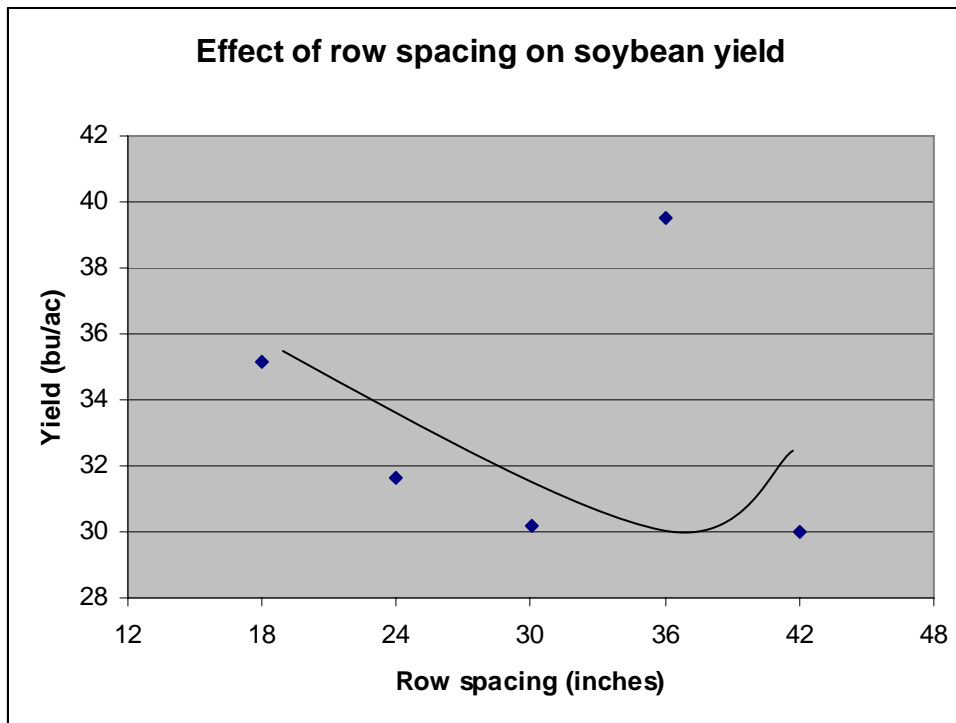
$$\text{i.e. } b_1 = \frac{SSCP}{r(SS X)} = \frac{\sum XY - \frac{\sum X \sum Y}{n}}{r(SS X)} = \frac{\sum XY}{r(SS X)} = \frac{Q}{r \sum c_i^2}$$

$$\text{Therefore } b_1 = -74.4/60 = -1.24$$

The quadratic component measures the additional improvement due to fitting the  $X^2$  component.

$$\text{i.e. } b_2 = \frac{SSCP}{r(SS X)} = \frac{\sum XY - \frac{\sum X \sum Y}{n}}{r(SS X)} = \frac{\sum XY}{r(SS X)} = \frac{Q}{r \sum c_i^2}$$

$$\text{Therefore } b_2 = 52.8/(6*14) = 0.63.$$



### Example 3

Given the following data set, partition the A and B main effects, and the AxB interaction using orthogonal polynomial contrasts.

Treatment	Rep 1	Rep 2	Rep 3	Trt Total
a <sub>0</sub> b <sub>0</sub>	10	12	14	36
a <sub>0</sub> b <sub>1</sub>	16	19	21	56
a <sub>0</sub> b <sub>2</sub>	24	27	32	82
a <sub>1</sub> b <sub>0</sub>	12	15	17	44
a <sub>1</sub> b <sub>1</sub>	19	23	29	71
a <sub>1</sub> b <sub>2</sub>	33	34	37	104
a <sub>2</sub> b <sub>0</sub>	24	27	29	80
a <sub>2</sub> b <sub>1</sub>	39	41	43	123
a <sub>2</sub> b <sub>2</sub>	45	47	52	144
Rep Total	222	245	273	740

Step 1. Complete the ANOVA as an RCBD.

SOV	df	SS	MS	F
Rep	2	144.9	72.5	60.4**
A	2	1790.3	895.2	746.0**
B	2	1607.4	803.7	669.8**
AxB	4	58.8	14.7	7.4**
Error	16	19.1	1.2	
Total	26	3620.5		

Step 2. Partition A, B, and AxB into their polynomial components.

Contrast	a <sub>0</sub> b <sub>0</sub>	a <sub>0</sub> b <sub>1</sub>	a <sub>0</sub> b <sub>2</sub>	a <sub>1</sub> b <sub>0</sub>	a <sub>1</sub> b <sub>1</sub>	a <sub>1</sub> b <sub>2</sub>	a <sub>2</sub> b <sub>0</sub>	a <sub>2</sub> b <sub>1</sub>	a <sub>2</sub> b <sub>2</sub>	Q	k
A <sub>L</sub>	-1	-1	-1	0	0	0	1	1	1	173	6
A <sub>Q</sub>	1	1	1	-2	-2	-2	1	1	1	83	18
B <sub>L</sub>	-1	0	1	-1	0	1	-1	0	1	170	6
B <sub>Q</sub>	1	-2	1	1	-2	1	1	-2	1	-10	18
A <sub>L</sub> B <sub>L</sub>	1	0	-1	0	0	0	-1	0	1	18	4
A <sub>L</sub> B <sub>Q</sub>	-1	2	-1	0	0	0	1	-2	1	-28	12
A <sub>Q</sub> B <sub>L</sub>	-1	0	1	2	0	-2	-1	0	1	-10	12
A <sub>Q</sub> B <sub>Q</sub>	1	-2	1	-2	4	-2	1	-2	1	-28	36

Step 3. Calculate SS for each contrast.

Contrast	$Q^2/rk$	SS
SS $A_L$	$173^2/(3 \times 6) =$	1662.7
SS $A_Q$	$83^2/(3 \times 18) =$	127.6
SS $B_L$	$170^2/(3 \times 6) =$	1605.6
SS $B_Q$	$-10^2/(3 \times 18) =$	1.9
SS $A_L B_L$	$18^2/(3 \times 4) =$	27.0
SS $A_L B_Q$	$-28^2/(3 \times 12) =$	21.8
SS $A_Q B_L$	$-10^2/(3 \times 12) =$	2.8
SS $A_Q B_Q$	$-28^2/(3 \times 36) =$	7.3

Step 4. Rewrite the ANOVA.

SOV	df	SS	MS	F (assuming A and B fixed)
Rep	2	144.9	72.5	60.4**
A	2	1790.3	895.2	746.0**
$A_L$	1	1662.7	1662.7	1385.6**
$A_Q$	1	127.6	127.6	106.3**
B	2	1607.4	803.7	669.8**
$B_L$	1	1605.6	1605.6	1338.0**
$B_Q$	1	1.9	1.9	1.6
AxB	4	58.8	14.7	7.4**
$A_L B_L$	1	27.0	27.0	22.5**
$A_L B_Q$	1	21.8	21.8	18.2**
$A_Q B_L$	1	2.8	2.8	2.3
$A_Q B_Q$	1	7.3	7.3	6.1*
Error	16	19.1	1.2	
Total	26	3620.5		

Step 5. Conclusions

The  $A_L$ ,  $B_L$ ,  $A_L B_L$ ,  $A_L B_Q$ , and  $A_Q B_Q$  sources of variation all contribute significantly to the model.

## Analysis of Orthogonal Polynomial Contrasts

### SAS Commands

```
options pageno=1;
data orthpoly;
input row rep yield;
datalines;
18 1 33.6
24 1 31.1
30 1 33
36 1 28.4
42 1 31.4
18 2 37.1
24 2 34.5
30 2 29.5
36 2 29.9
42 2 28.3
18 3 34.1
24 3 30.5
30 3 29.2
36 3 31.6
42 3 28.9
18 4 34.6
24 4 32.7
30 4 30.7
36 4 32.3
42 4 28.6
18 5 35.4
24 5 30.7
30 5 30.7
36 5 28.1
42 5 29.6
18 6 36.1
24 6 30.3
30 6 27.9
36 6 26.9
42 6 33.4
;;
ods rtf file='polynomial contrast SAS output.rtf';
proc print;
title 'Printout of Orthogonal Polynomial Data';
run;
Proc glm;
Class rep row;
Model yield=rep row;
*Treatment order-----18 24 30 36 42;
contrast 'linear' row -2 -1 0 1 2;
contrast 'quadratic' row 2 -1 -2 -1 2;
contrast 'cubic' row -1 2 0 -2 1;
contrast 'quartic' row 1 -4 6 -4 1;
title 'Anova with Polynomial Contrasts';
run;
ods rtf close;
run
```



*Printout of Orthogonal Polynomial Data*

<b>Obs</b>	<b>row</b>	<b>rep</b>	<b>yield</b>
1	18	1	33.6
2	24	1	31.1
3	30	1	33.0
4	36	1	28.4
5	42	1	31.4
6	18	2	37.1
7	24	2	34.5
8	30	2	29.5
9	36	2	29.9
10	42	2	28.3
11	18	3	34.1
12	24	3	30.5
13	30	3	29.2
14	36	3	31.6
15	42	3	28.9
16	18	4	34.6
17	24	4	32.7
18	30	4	30.7
19	36	4	32.3
20	42	4	28.6
21	18	5	35.4
22	24	5	30.7
23	30	5	30.7
24	36	5	28.1
25	42	5	29.6
26	18	6	36.1
27	24	6	30.3
28	30	6	27.9
29	36	6	26.9
30	42	6	33.4

## *Anova with Polynomial Contrasts*

### *The GLM Procedure*

Class Level Information		
Class	Levels	Values
rep	6	1 2 3 4 5 6
row	5	18 24 30 36 42

Number of Observations Read	30
Number of Observations Used	30

## *Anova with Polynomial Contrasts*

### *The GLM Procedure*

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
<b>Model</b>	9	131.0710000	14.5634444	3.94	0.0051
<b>Error</b>	20	73.9186667	3.6959333		
<b>Corrected Total</b>	29	204.9896667			

R-Square	Coeff Var	Root MSE	yield Mean
0.639403	6.141458	1.922481	31.30333

Source	DF	Type I SS	Mean Square	F Value	Pr > F
<b>rep</b>	5	5.4096667	1.0819333	0.29	0.9113
<b>row</b>	4	125.6613333	31.4153333	8.50	0.0004

Source	DF	Type III SS	Mean Square	F Value	Pr > F
<b>rep</b>	5	5.4096667	1.0819333	0.29	0.9113
<b>row</b>	4	125.6613333	31.4153333	8.50	0.0004

Contrast	DF	Contrast SS	Mean Square	F Value	Pr > F
<b>linear</b>	1	91.26666667	91.26666667	24.69	<.0001
<b>quadratic</b>	1	33.69333333	33.69333333	9.12	0.0068
<b>cubic</b>	1	0.50416667	0.50416667	0.14	0.7158
<b>quartic</b>	1	0.19716667	0.19716667	0.05	0.8197