Stat 571B Experimental Design

Topic 14: 2^K factorial design (II)

Montgomery: chapter 6

Prof. Lingling An University of Arizona

Outline

- General 2^k factorial design
- Unreplicated factorial design

General 2^k Design

- k factors: A, B, \ldots, K each with 2 levels (+,-)
- ullet consists of all possible level combinations (2^k treatments) each with n replicates
- Classify factorial effects:

type of effect	label	the number of effects
main effects (of order 1)	A, B, C, \ldots, K	k
2-factor interactions (of order 2)	AB, AC,, JK	$\begin{pmatrix} k \\ 2 \end{pmatrix}$
3-factor interactions (of order 3)	ABC,ABD,\ldots,IJK	$\begin{pmatrix} k \\ 3 \end{pmatrix}$
• • •		
k-factor interaction (of order k)	$ABC\cdots K$	$\left(\begin{array}{c} k \\ k \end{array}\right)$

- In total, how many effects?
- ullet Each effect (main or interaction) has 1 degree of freedom full model (i.e. model consisting of all the effects) has 2^k-1 degrees of freedom.
- Error component has $2^k(n-1)$ degrees of freedom (why?).
- One-to-one correspondence between effects and contrasts:
 - For main effect: convert the level column of a factor using $-\Rightarrow -1$ and $+\Rightarrow 1$
 - For interactions: multiply the contrasts of the main effects of the involved factors, componentwisely.

General 2^k Design: Analysis

Estimates:

grand mean :
$$\frac{\sum \bar{y}_{i.}}{2^k}$$

For effect with contrast $C = (c_1, c_2, \dots, c_{2^k})$, its estimate is

$$\text{effect} = \frac{\sum c_i \bar{y}_i}{2^{(k-1)}}$$

Variance

$$Var(effect) = \frac{\sigma^2}{n2^{k-2}}$$

what is the standard error of the effect?

• t-test for H_0 : effect=0. Using the confidence interval approach,

$$\mathsf{effect} \pm t_{\alpha/2,2^k(n-1)}\mathsf{S.E.}(\mathsf{effect})$$

Using ANOVA model:

Sum of Squares due to an effect, using its contrast,

$$SS_{\text{effect}} = \frac{\left(\sum c_i \bar{y}_{i.}\right)^2}{2^k/n} = n2^{k-2} (\text{effect})^2$$

• SS_T and SS_E can be calculated as before and a ANOVA table including SS due to the effects and SS_E can be constructed and the effects can be tested by F-tests.

Using regression:

• Introducing variables x_1, \ldots, x_k for main effects, their products are used for interactions, the following regression model can be fitted

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k + \ldots + \beta_{12\cdots k} x_1 x_2 \cdots x_k + \epsilon$$

The coefficients are estimated by half of effects they represent, that is,

$$\hat{\beta} = \frac{\text{effect}}{2}$$

Unreplicated 2^k Design -- Filtration Rate Experiment

	factor								
A	B	C	D	filtration					
_	_	_	_	45					
+	_	_	_	71					
_	+	_	_	48					
+	+	_	_	65					
_	_	+	_	68					
+	_	+	_	60					
_	+	+	_	80					
+	+	+	_	65					
_	_	_	+	43					
+	_	_	+	100					
_	+	_	+	45					
+	+	_	+	104					
_	_	+	+	75					
+	_	+	+	86					
_	+	+	+	70					
+	+	+	+	96					

Unreplicated 2^k Design

- No degree of freedom left for error component if full model is fitted.
- Formulas used for estimates and contrast sum of squares are given in Slides
 5-6 with n=1
- No error sum of squares available, cannot estimate σ^2 and test effects in both the ANOVA and Regression approaches.
- Approach 1: pooling high-order interactions
 - Often assume 3 or higher interactions do not occur
 - Pool estimates together for error
 - Warning: may pool significant interaction

Unreplicated 2^k Design

- Approach 2: Using the normal probability plot (QQ plot) to identify significant effects.
 - Recall

$$Var(effect) = \frac{\sigma^2}{2^{(k-2)}}$$

If the effect is not significant (=0), then the effect estimate follows $N(0,\frac{\sigma^2}{2^{(k-2)}})$

- Assume all effects not significant, their estimates can be considered as a random sample from $N(0,\frac{\sigma^2}{2^{(k-2)}})$
- QQ plot of the estimates is expected to be a linear line
- Deviation from a linear line indicates significant effects

Using SAS to generate QQ plot for effects - data

```
data filter;
 do D = -1 to 1 by 2; do C = -1 to 1 by 2;
 do B = -1 to 1 by 2; do A = -1 to 1 by 2;
 input y @@; output;
 end; end; end; end;
datalines:
45 71 48 65 68 60 80 65 43 100 45 104 75 86 70 96
proc print data=filter;
run;
data inter;  /* Define Interaction Terms */
 set filter:
AB=A*B; AC=A*C; AD=A*D; BC=B*C; BD=B*D; CD=C*D; ABC=AB*C; ABD=AB*D;
 ACD=AC*D; BCD=BC*D; ABCD=ABC*D;
 run;
proc print data=inter;
run;
```

Obs	D	С	В	Α	У	AB	AC	AD	ВС	BD	CD	ABC	ABD	ACD	BCD	ABCD
1	-1	-1	-1	-1	45	1	1	1	1	1	1	-1	-1	-1	-1	1
2	-1	-1	-1	1	71	-1	-1	-1	1	1	1	1	1	1	-1	-1
3	-1	-1	1	-1	48	-1	1	1	-1	-1	1	1	1	-1	1	-1
4	-1	-1	1	1	65	1	-1	-1	-1	-1	1	-1	-1	1	1	1
5	-1	1	-1	-1	68	1	-1	1	-1	1	-1	1	-1	1	1	-1
6	-1	1	-1	1	60	-1	1	-1	-1	1	-1	-1	1	-1	1	1
7	-1	1	1	-1	80	-1	-1	1	1	-1	-1	-1	1	1	-1	1
8	-1	1	1	1	65	1	1	-1	1	-1	-1	1	-1	-1	-1	-1
9	1	-1	-1	-1	43	1	1	-1	1	-1	-1	-1	1	1	1	-1
10	1	-1	-1	1	100	-1	-1	1	1	-1	-1	1	-1	-1	1	1
11	1	-1	1	-1	45	-1	1	-1	-1	1	-1	1	-1	1	-1	1
12	1	-1	1	1	104	1	-1	1	-1	1	-1	-1	1	-1	-1	-1
13	1	1	-1	-1	75	1	-1	-1	-1	-1	1	1	1	-1	-1	1
14	1	1	-1	1	86	-1	1	1	-1	-1	1	-1	-1	1	-1	-1
15	1	1	1	-1	70	-1	-1	-1	1	1	1	-1	-1	-1	1	-1
16	1	1	1	1	96	1	1	1	1	1	1	1	1	1	1	1

```
proc glm data=inter; /* GLM Proc to Obtain
Effects */
 class A B C D AB AC AD BC BD CD ABC ABD ACD BCD
ABCD;
 model y=A B C D AB AC AD BC BD CD ABC ABD ACD
BCD ABCD;
 estimate 'A' A -1 1; estimate 'AC' AC -1 1;
 run;
proc reg outest=effects data=inter;    /* REG
Proc to Obtain Effects */
model y=A B C D AB AC AD BC BD CD ABC ABD ACD
BCD ABCD;
 run;
```

Source	DF	Sum of Squares	Mean Square	e F Value	Pr > F
Model	15	5730.93750	382.062500		
Frror	0 Course	DE Tun	a III CC Maan	E Value Dr. >	

Error	0	Source	DF	Type III SS	_	F Value
Corrected Total	15				Square	
	. •	Α	1	1870.5625	1870.5625	

_	Source	DF	Type III SS	Mean Square	F Value	Pr > F
5	A	1	1870.5625 00	1870.5625 00		
	В	1	39.062500	39.062500		
	С	1	390.06250 0	390.06250 0		
	D	1	855.56250 0	855.56250 0		
	AB	1	0.062500	0.062500		
	AC	1	1314.0625 00	1314.0625 00	-	
	AD	1	1105.5625 00	1105.5625 00	-	
	BC	1	22.562500	22.562500		
	BD	1	0.562500	0.562500		
	CD	1	5.062500	5.062500		
	ABC	1	14.062500	14.062500		
	ABD	1	68.062500	68.062500		
	V C D	1	10 562500	10 562500		

Parameter	Estimate	Standard Error	t Value	Pr > t
Α	21.6250000			
AC	-18.1250000			

Output (Proc reg)

Parameter Estimates									
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t				
Intercept	1	70.06250							
Α	1	10.81250							
В	1	1.56250							
С	1	4.93750							
D	1	7.31250							
AB	1	0.06250							
AC	1	-9.06250							
AD	1	8.31250							
BC	1	1.18750							
BD	1	-0.18750							
CD	1	-0.56250							
ABC	1	0.93750							
ABD	1	2.06250							
ACD	1	-0.81250							
BCD	1	-1.31250							
ABCD	1	0.68750							

```
data effect2; set effects;
 drop y intercept RMSE ;
 run;
proc transpose data=effect2 out=effect3;
run;
data effect4; set effect3; effect=col1*2;
run;
proc sort data=effect4; by effect;
run;
proc print data=effect4;
run;
```

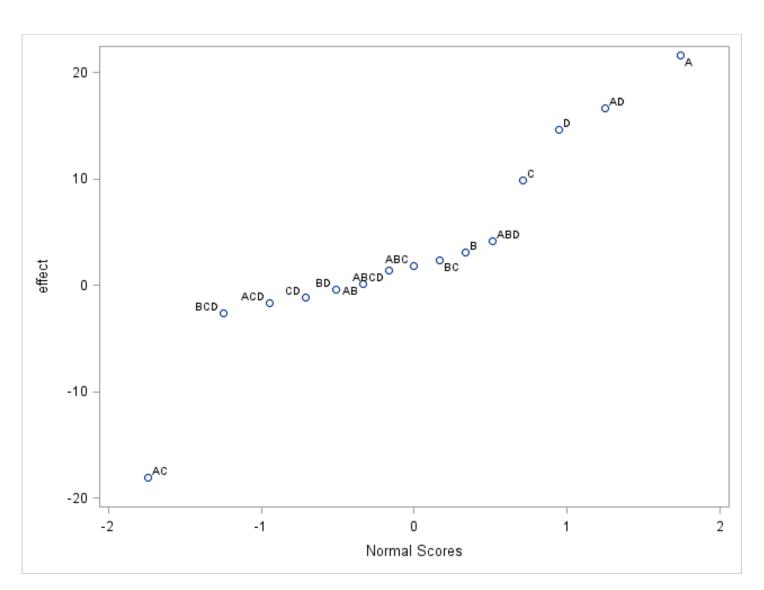
Obs	_NAME_	COL1	effect
1	AC	-9.0625	-18.125
2	BCD	-1.3125	-2.625
3	ACD	-0.8125	-1.625
4	CD	-0.5625	-1.125
5	BD	-0.1875	-0.375
6	AB	0.0625	0.125
7	ABCD	0.6875	1.375
8	ABC	0.9375	1.875
9	BC	1.1875	2.375
10	В	1.5625	3.125
11	ABD	2.0625	4.125
12	С	4.9375	9.875
13	D	7.3125	14.625
14	AD	8.3125	16.625
15	Α	10.8125	21.625

```
proc rank data=effect4 out=effect5
normal=blom;
 var effect; ranks neff;
 run;
proc print data=effect5;
run;
proc sgplot data=effect5;
scatter x=neff y=effect/datalabel= NAME ;
xaxis label='Normal Scores';
run;
```

Ranked effects

Obs	_NAME_	COL1	effect	neff
1	AC	-9.0625	-18.125	-1.73938
2	BCD	-1.3125	-2.625	-1.24505
3	ACD	-0.8125	-1.625	-0.94578
4	CD	-0.5625	-1.125	-0.71370
5	BD	-0.1875	-0.375	-0.51499
6	AB	0.0625	0.125	-0.33489
7	ABCD	0.6875	1.375	-0.16512
8	ABC	0.9375	1.875	0.00000
9	BC	1.1875	2.375	0.16512
10	В	1.5625	3.125	0.33489
11	ABD	2.0625	4.125	0.51499
12	С	4.9375	9.875	0.71370
13	D	7.3125	14.625	0.94578
14	AD	8.3125	16.625	1.24505
15	Α	10.8125	21.625	1.73938

Proc sgplot



Filtration Experiment Analysis

Fit a linear line based on small effects, identify the effects which are potentially significant, then use ANOVA or regression fit a sub-model with those effects.

- 1. Potentially significant effects: A, AD, C, D, AC.
- 2. Use main effect plot and interaction plot
- 3. ANOVA model involving only $A,\,C,\,D$ and their interactions (projecting the original unreplicated 2^4 experiment onto a replicated 2^3 experiment)
- 4. regression model only involving A, C, D, AC and AD.
- 5. Diagnostics using residuals.

ANOVA with A, C and D and their interactions

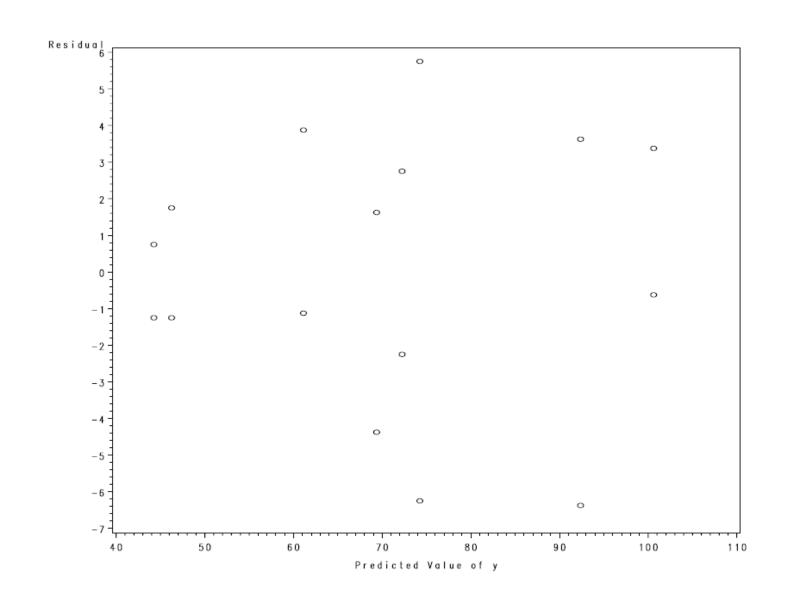
```
proc glm data=filter;
class A C D;
model y=A|C|D;
                Sum Squares Mean Square F Value Pr > F
Source
           DF
            7 5551.437500
                               793.062500
                                             35.35 <.0001
Model
          8 179.500000
                                22.437500
Error
Cor Total 15
                 5730.937500
                              Mean Square F Value Pr > F
Source
           DF
                   Type I SS
            1
                 1870.562500
                               1870.562500
                                             83.37 <.0001
Α
                  390.062500
                               390.062500
                                             17.38 0.0031
            1
C
            1 1314.062500
                               1314.062500
                                             58.57 <.0001
A*C
            1
                855.562500
                              855.562500
                                             38.13 0.0003
D
                 1105.562500
                               1105.562500
A \star D
            1
                                             49.27 0.0001
                    5.062500
                                 5.062500
                                              0.23 0.6475
C*D
            1
A*C*D
                   10.562500
                                10.562500
                                              0.47 0.5120
*ANOVA confirms that A, C, D, AC and AD are significant effects
```

Regression Model

```
* the same date step
data inter; set filter; AC=A*C; AD=A*D;
proc reg data=inter; model y=A C D AC AD;
output out=outres r=res p=pred;
proc gplot data=outres; plot res*pred; run;
   ______
Dependent Variable: y
                  Analysis of Variance
                       Sum of
                                      Mean
                                    Square F Value Pr > F
Source
             DF
                      Squares
                   5535.81250 1107.16250
                                               56.74
Model
                                                       <.0001
                    195.12500
Error
      10
                                  19.51250
Corrected Total 15 5730.93750
Root MSE
                   4.41730 R-Square
                                        0.9660
```

Dependent Mean Coeff Var		70.06250 6.30479	Adj R-Sq	0.9489	
		Paramete	r Estimates		
		Parameter	Standard		
Variable	DF	Estimate	Error	t Value	Pr > t
Intercept	1	70.06250	1.10432	63.44	<.0001
A	1	10.81250	1.10432	9.79	<.0001
C	1	4.93750	1.10432	4.47	0.0012
D	1	7.31250	1.10432	6.62	<.0001
AC	1	-9.06250	1.10432	-8.21	<.0001
AD	1	8.31250	1.10432	7.53	<.0001

Residual plot



Response Optimization / Best Setting Selection

Use x_1 , x_3 , x_4 for A, C, D; and x_1x_3 , x_1x_4 for AC, AD respectively. The regression model gives the following function for the response (filtration rate):

$$y = 70.06 + 10.81x_1 + 4.94x_3 + 7.31x_4 - 9.06x_1x_3 + 8.31x_1x_4$$

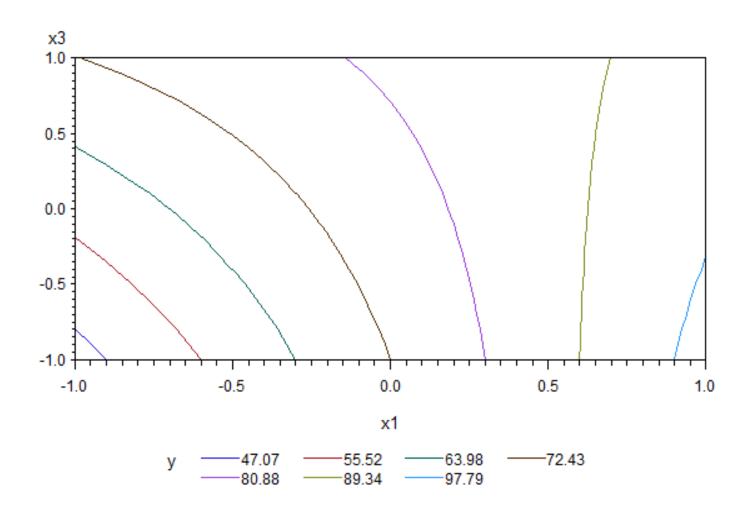
Want to maximize the response. Let D be set at high level ($x_4 = 1$)

$$y = 77.37 + 19.12x_1 + 4.94x_3 - 9.06x_1x_3$$

Contour plot

```
goption colors=(none);
data one;
do x1 = -1 to 1 by .1;
  do x3 = -1 to 1 by .1;
  y=77.37+19.12*x1 +4.94*x3 -9.06*x1*x3; output;
  end; end;
proc gcontour data=one; plot x3*x1=y;
run; quit;
```

Contour Plot for Response Given D (= +1)



D = -1

```
data one;

do x1 = -1 to 1 by .1;

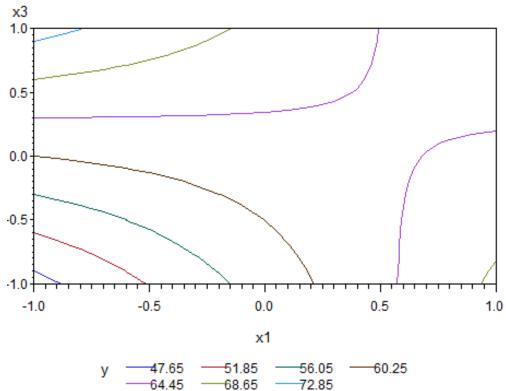
do x3 = -1 to 1 by .1;

y=62.75+2.5*x1 +4.94*x3 -9.06*x1*x3; output;

end; end;

proc gcontour data=one; plot x3*x1=y;

run;
```



Last slide

• Read Sections: 6.4-6.5

