

17.

THE K-FACTOR DESIGN

17.1 INTRODUCTION

Suppose we have k factors, factor i takes a_i levels and we take n observations from treatment (i_1, i_2, \dots, i_k) . Then for a single observation we have

$$E[y] = \sum_{i_1=1}^{a_1} \sum_{i_k=1}^{a_k} \beta_{i_1 \dots i_k} X_{i_1 \dots i_k}$$

where $X_{i_1 \dots i_k} = 1$ if y is a response from treatment (i_1, i_2, \dots, i_k) and is 0 otherwise. Listing the observations in natural order we have

$$E[y] = \mathbf{X}\boldsymbol{\beta} = (X_{11\dots 1} \dots X_{a_1 \dots a_k}) \boldsymbol{\beta}$$

where $X_{1\dots 1}$ has 1 in the first n+1 through 2n entries and 0 elsewhere, etc.

$$\text{Note that } \mathbf{b} = (\mathbf{X}\mathbf{X})^{-1}\mathbf{X}y = \left(\frac{T_{11\dots 1}}{n}, \dots, \frac{T_{a_1 \dots a_k}}{n} \text{right} \right)'$$

and $T_{i_1 \dots i_k}$ is the total of all observations from treatment (i_1, \dots, i_k) .

(a) The model with k-factors is

$$A_1: A_{11}, \dots, A_{a_1}$$

$$A_2: A_{12}, \dots, A_{a_22}$$

.

.

.

$$A_k: A_{1k}, \dots, A_{a_kk}$$

which gives the linear model

$$E[y] = \beta_{1\dots 1} x_{1\dots 1} + \beta_{21\dots 1} x_{21\dots 1} + \dots + \beta_{abc} X_{abc}$$

Where $x_{i_1 \dots i_k} = 1$ if treatment $A_{i_1} \dots A_{i_k}$ is applied and is 0 otherwise.

If we apply $A_{i_1 i} \dots A_{i_k k}$, n times we obtain

$$E[y] = \mathbf{X}\beta \text{ where}$$

$$\mathbf{X} = \begin{pmatrix} 1 & 0 & \cdot & \cdot & \cdot & 0 \\ 1 & 0 & \cdot & \cdot & \cdot & 0 \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ n & 0 & & & & \cdot \\ 0 & 1 & & & & \cdot \\ 0 & 1 & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ & n & & & & 0 \\ & \cdot & & & & 1 \\ & \cdot & & & & 1 \\ & \cdot & & & & \cdot \\ & \cdot & & & & \cdot \\ & \cdot & & & & \cdot \\ & \cdot & & & & \cdot \\ 0 & 0 & & & & n \end{pmatrix}$$

and

$$\mathbf{y} = \begin{pmatrix} n & \text{obs} & \text{from} & A_{11} \\ n & \text{obs} & \text{from} & A_{12} \\ & & \cdot & \\ & & \cdot & \\ & & \cdot & \\ n & \text{obs} & \text{from} & A_{a_kk} \end{pmatrix}$$

the least squares estimator is given by

$$\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} = \begin{bmatrix} \frac{T_{1\dots 1}}{n} \\ \cdot \\ \cdot \\ \cdot \\ \frac{T_{21\dots 1}}{n} \end{bmatrix} = \begin{bmatrix} \bar{y}_{1\dots 1} \\ \cdot \\ \cdot \\ \cdot \\ \bar{y}_{21\dots 1} \end{bmatrix}$$

and $\alpha = \mathbf{C}\beta$ where $a_{i_1 \dots i_k} = (\mathbf{C}_{i_1 i} \times \dots \times \mathbf{C}_{i_k k}) \beta$

First test for interactions of order $k-1$, then $k-2$, etc. Then obtain the following ANOVA for single degrees of freedom.

ANOVA (coarse table)

Source	DF	SS
Mean	1	$na^2_{1\dots 1}$
Main Effects		
·		
·		
·		
First order Interactions		
·		
·		
·		
(k-1) order Interactions		
Error	$(n-1) a_1 \cdots a_k$	
	$na_1 \cdots a_k$	$\mathbf{y'y}$

If we collect appropriate degrees of freedom together we obtain the

ANOVA (fine table)

Source	DF	SS
Mean	1	$\frac{G^2}{na_1 \cdots a_k} = SL(M)$
A_1	$a_1 - 1$	$\sum_{i=1}^{a_1} \frac{T_i^2}{na_2 \cdots a_k} - SL(M) = SL(A)$
.	.	.
.	.	.
.	.	.
A_k	$a_k - 1$	$\sum_{i=1}^{a_k} \frac{T_i^2}{na_1 \cdots a_{k-1}} - SL(M) = SL(A_k)$
$A_1 \times A_2$	$(a_1 - 1)(a_2 - 1)$	$\sum_{i=1}^{a_1} \sum_{j=1}^{a_2} \frac{T_{ij}^2}{na_3 \cdots a_k} - SL(A_1) - SL(A_2) - SL(M)$
.	.	.
.	.	.
.	.	.
$A_1 \times A_2 \times A_3$	$(a_1 - 1)(a_2 - 1)(a_3 - 1)$	1 (see below)
.	.	.
.	.	.
.	.	.
$A_1 \times \cdots \times A_k$	$(a_1 - 1) \cdots (a_k - 1)$	2 (see below)
Error	$(n - 1)a_1 \cdots a_k$	subtraction
	$na_1 \cdots a_k$	$\mathbf{y}'\mathbf{y}$

where

$$1 = \sum_{i_1=1}^{a_1} \sum_{i_2=1}^{a_2} \sum_{i_3=1}^{a_3} \frac{T_{i_1 i_2 i_3}^2}{na_4 \cdots a_k} - SL(A_1 \times A_2) - SL(A_1 \times A_3) - SL(A_2 \times A_3) - SL(A_2) - SL(A_3) - SL(M)$$

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$$2 = \sum_{i_1=1}^{a_1} \cdots \sum_{i_k=1}^{a_k} \frac{T_{i_1}^2}{n} - SL(A_1 \times \cdots \times A_{k-1}) - \cdots - SL(M)$$

Note: If $n=1$ then we have no degrees of freedom for estimating error, however for $k \geq 4$ higher order interactions are sometimes assumed not to exist and these degrees of freedom become available for error.

Example of a 4 x 3 x 2 Factorial Experiment

A has 4 levels

B has 3 levels

C has 2 levels

Thus there are $4 \times 3 \times 2 = 24$ treatment combinations. Say there are 5 observations on each treatment. This gives the following table.

ANOVA

Source		DF
Main Effects	A	3
	B	2
	C	1
Interactions	A x B	6
	A x C	3
	B x C	2
	A x B x C	6
Error	(Within Treat)	96
Total (corrected for mean)		

where $\frac{G^2}{N} = 4296.03 = \frac{(718)^2}{120}$

with Error equal to 364.80

The steps necessary for a hand calculation are briefly summarized below.

Step 1: Form the following table.

Each cell is the total of 5 observations

		A_1	A_2	A_3	A_4	Σ
C_1	B_1	21	33	35	44	133
	B_2	24	32	36	41	133
	B_3	18	30	37	49	134
	Σ	63	95	108	134	400
C_2	B_1	16	28	35	36	115
	B_2	14	26	33	34	107
	B_3	13	23	27	33	96
	Σ	43	77	95	103	318
	Σ	106	172	203	237	718

Step 2: Perform the following calculations

$$SS_T = \frac{(21)^2}{5} + \frac{(33)^2}{5} + \dots + \frac{(33)^2}{5} - \frac{(718)^2}{120}$$

$$= 4691.20 - 4296.03 = 395.17$$

$$SS_C = \frac{(400)^2}{60} + \frac{(318)^2}{60} - \frac{(718)^2}{120}$$

$$= 4352.07 - 4296.03 = 56.04$$

$$SS_A = 4606.60 - 4296.03 = 310.57$$

To calculate the A x C interaction - look at cells of the A x C table.

$$SS_{cell} = \frac{(63)^2}{15} + \frac{(95)^2}{15} + \cdots + \frac{(103)^2}{15} - \frac{(718)^2}{120}$$

$$= 4668.40 - 4296.03 = 372.37$$

	A ₁	A ₂	A ₃	A ₄	Σ
C ₁	63	95	108	134	400
C ₂	43	77	95	103	318
Σ	106	172	203	237	718

$$SS_{AC} = SS_{cell} - SS_C - SS_A$$

$$= 372.37 - 56.04 - 310.57 = 5.76$$

For the A x B interaction follow the same technique.

$$SS_B = \frac{(248)^2}{40} + \frac{(240)^2}{40} + \frac{(230)^2}{40} - \frac{(718)^2}{120}$$

$$= 4300.10 - 4296.03 = 4.07$$

$$SS_{cell} = \frac{(37)^2}{10} + \frac{(61)^2}{10} + \cdots + \frac{(82)^2}{10} - \frac{(718)^2}{120}$$

$$= 4617.40 - 4296.03 = 321.37$$

$$SS_{AB} = 321.37 - 4.07 - 310.57 = 6.73$$

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for the B x C interaction

$$\begin{aligned}SS_{cell} &= \frac{(133)^2}{20} + \frac{(133)^2}{20} + \dots + \frac{(96)^2}{20} - \frac{(718)^2}{120} \\ &= 4361.21 - 4296.03 = 65.17\end{aligned}$$

Then by subtraction we have

$$SS_{B \times C} = 65.17 - 56.04 - 4.04 = 5.06$$

$$\begin{aligned}SS_{ABC} &= SS_T - SS_A - SS_B - SS_C - SS_{AB} - SS_{AC} - SS_{BC} \\ &= 395.17 - 310.57 - 4.07 - 56.04 - 6.73 - 5.76 - 5.06 \\ &= 395.17 - 388.23 = 6.94\end{aligned}$$

The complete ANOVA table is given below.

ANOVA

Source	DF	SS	MS	F
A	3	310.52	103.52	27.24
B	2	4.07	2.04	
C	1	56.04	56.04	14.75
AxB	6	6.73	1.12	
AxC	3	5.76	1.92	
BxC	2	5.06	2.57	
AxBxC	6	6.94	1.16	
Error	96	364.80	3.80	
Total		759.97		

where \cdot indicates the P-value if $< .05$. Note the above was an example using a hand calculation method. A computer implementation for the multifactor design will be given at the end of the chapter.

17.2 2^k FACTORIAL DESIGN

Consider a design where we have k factors each taking two (2) levels. For each factor there is essentially one contrast $\left(\frac{1}{\sqrt{2}} - \frac{-1}{\sqrt{2}} \right)$ and accordingly the analysis of such designs is relatively straightforward. Since such designs are of such importance a special notation has been developed. As before the factors are denoted by capitals $A:A_1,A_2; B:B_1,B_2; C:C_1,C_2$; etc. And the total of all observations receiving treatment $A_i B_j C_k$ is denoted by $a^{i-1} b^{j-1} c^{k-1}$ where $a^0=1$ and $a^1=a$. Level 1 of a factor is called the low level and level 2 called the high level.

Example 1 2^2 - factorial

There are a total of 4 treatments.

$$a^0 b^0 = (1)$$

$$a^1 b^0 = a$$

$$a^0 b^1 = b$$

$$a^1 b^1 = ab$$

Example 2 2^3 - factorial

There are a total of 8 treatments.

$$a^0 b^0 c^0 = (1)$$

$$a^1 b^0 c^0 = a$$

$$a^0 b^1 c^0 = b$$

$$a^1 b^1 c^0 = ab$$

$$a^0 b^0 c^1 = c$$

$$a^1 b^0 c^1 = ac$$

$$a^0 b^1 c^1 = bc$$

$$a^1 b^1 c^1 = abc$$

The treatment in the above examples are written in what is known as *natural order*.

As mentioned above the contrast matrix for the full design is of the form:

											Divisor	Source	
C =	1	1	1	1	1	1	1	1	...	1	1	$\sqrt{2}^k$	Mean
	1	-1	1	-1	1	-1			...	1	-1	$\sqrt{2}^k$	A
	1	1	-1	-1	1	-1						$\sqrt{2}^k$	B
	1	-1	1	-1	1	-1						$\sqrt{2}^k$	A x B
	.											.	.
	.											.	.
	.											.	.

Note that the rows of C are ± 1 's divided by $\sqrt{2}^{-k}$.

The quantities we wish to make inferences about are given by $\alpha = C\beta$ and the elements of α are often denoted (1, A, B, AB, ...)

Example 1 (cont'd)

Source					Divisor	
Mean		1	1	1	1	2
A	C =	1	-1	1	-1	2
B		1	1	1	-1	2
AxB		1	-1	-1	1	2

$$\alpha = (\beta_{11} + \beta_{21} + \beta_{12} + \beta_{22})/2$$

$$\alpha_{21} = (\beta_{11} - \beta_{21} + \beta_{12} - \beta_{22})/2$$

$$\alpha_{12} = (\beta_{11} + \beta_{21} - \beta_{12} - \beta_{22})/2$$

$$\alpha_{22} = (\beta_{11} + \beta_{21} - \beta_{12} + \beta_{22})/2$$

$$\alpha_{11} = ((1) + a + b + ab)/2n$$

$$\alpha_{21} = ((1) - a + b - ab)/2n$$

$$\alpha_{12} = ((1) + a - b - ab)/2n$$

$$\alpha_{22} = ((1) - a - b + ab)/2n$$

Then the ANOVA table takes the form

Source	DF	SS
Mean	1	na_{11}^2
A	1	na_{21}^2
B	1	na_{12}^2
AB	1	na_{22}^2
Error	4(n-1)	subtraction
Total	abn	$y'y$

17.3 YATES ALGORITHM

Yates Algorithm is a fast way of performing the calculations for a 2^k factorial. We illustrate the method with a 2^3 - factorial.

Step 1	Step 2	
write down totals in natural order	form first 4 entries by adding successive elements and last 4 by subtracting 2nd element from first	
(1)	(1) + a	
a	b + ab	
b	c + ac	
ab	bc + abc	
c	(1) - a	
ac	b - ab	
bc	c - ac	
abc	bc - abc	
Step 3 (repeat)	Step 4 (repeat)	Source
(1) + a + b + ab	(1) + a + b + ab + c + ac + bc + abc	(mean)
c + ac + bc + abc	(1) - a + b - ab + c - ac + bc - abc	(A)
(1) - a + b - ab	(1) + a - b - ab + c - ac - bc - abc	(B)
c - ac + bc - abc	(1) - a - b + ab + c - ac - bc - abc	(C)
(1) + a - b - ab	(1) + a + b + ab - c - ac - bc - abc	(AB)
c + ac - bc - abc	(1) - a + b - ab - c + ac - bc - abc	(AC)
(1) - a - b + ab	(1) + a - b - ab - c - ac + bc + abc	(BC)
c - ac - bc + abc	(1) - a - b + ab - c + ac + bc - abc	(ABC)

In general we are required to repeat the step k times.

17.4 Example : An experimental psychologist is interested in determining whether verbal retention is influenced by the following factors

- A: number of presentations: once, twice
- B: mode of presentation: visual, auditory
- C: time of presentation: immediate, delayed

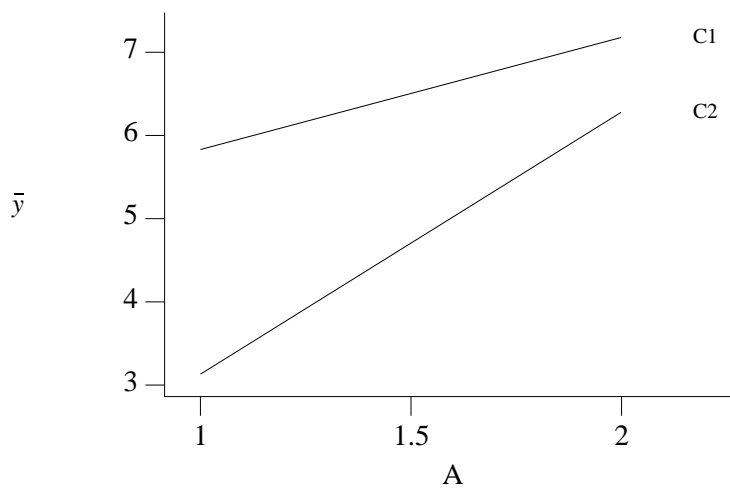
Ten subjects are run under each treatment condition. The results are listed below:

A ₁				A ₂			
B ₁		B ₂		B ₁		B ₂	
C ₁	C ₂	C ₁	C ₂	C ₁	C ₂	C ₁	C ₂
8	4	4	4	9	7	7	7
7	4	8	2	9	7	6	6
4	5	7	2	8	6	7	5
6	2	5	2	8	9	6	5
6	4	6	1	8	7	6	5
4	4	6	3	8	7	6	4
4	5	5	2	7	6	6	6
6	4	6	2	8	6	7	6
8	4	5	2	6	8	8	7
7	4	5	3	6	6	8	6
60	40	57	23	77	69	67	57

ANOVA	DF	SS	MS	F
A	1	101.25		
B	1	22.05		20.05*
C	1	64.80		
AxB	1	.05		
AxC	1	16.20		14.73*
BxC	1	3.20		2.91
AxBxC	1	1.80		1.64
Error	72	79.40	1.10	
Total	79	288.75		

where * indicates $p < .05$.

A graph of the A x C interaction is given below.



17.5 SPSSX COMPUTER PROGRAM

```
data list/ A 1 B 3 C 5 Y 7
begin data
1 1 1 8
1 1 1 7
....
....
....
2 2 2 6
end data
manova y by A B C (1,2)/
      design = A, B, C, A by B, A by C,
            B by C, A by B by C/
      print=cellinfo(means)
      omeans=TABLES(A,B,C,A by C)/
      residuals = casewise plot/
finish
```

*note that since there are only 2 levels to each factor we may omit the partition and contrast statements of SPSSX.

Cell Means and Standard Deviations

Variable .. Y

FACTOR	CODE	Mean	Std. Dev.	N	95 percent Conf. Interval	
A	1					
B	1					
C	1	6.000	1.563	10	4.882	7.118
C	2	4.000	.816	10	3.416	4.584
B	2					
C	1	5.700	1.160	10	4.871	6.529
C	2	2.300	.823	10	1.711	2.889
A	2					
B	1					
C	1	7.700	1.059	10	6.942	8.458
C	2	6.900	.994	10	6.189	7.611
B	2					
C	1	6.700	.823	10	6.111	7.289
C	2	5.700	.949	10	5.021	6.379
For entire sample		5.625	1.912	80	5.200	6.050

Combined Observed Means for A

Variable .. Y

A		Mean
1	WGT.	4.50000
	UNWGT.	4.50000
2	WGT.	6.75000
	UNWGT.	6.75000

Combined Observed Means for B

Variable .. Y

B		Mean
1	WGT.	6.15000
	UNWGT.	6.15000
2	WGT.	5.10000
	UNWGT.	5.10000

Combined Observed Means for C

Variable .. Y

C		Mean
1	WGT.	6.52500
	UNWGT.	6.52500
2	WGT.	4.72500
	UNWGT.	4.72500

Combined Observed Means for A BY C

Variable .. Y

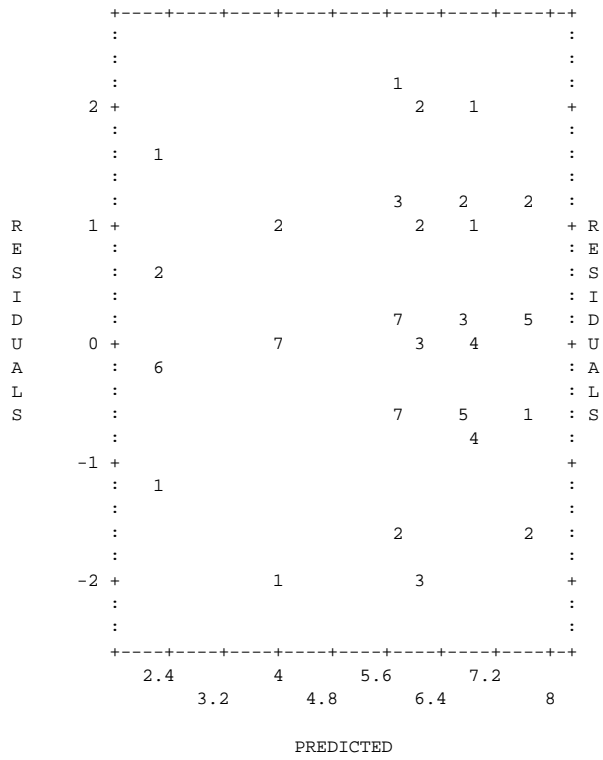
	A	1	2
C			
1	WGT.	5.85000	7.20000
	UNWGT.	5.85000	7.20000
2	WGT.	3.15000	6.30000
	UNWGT.	3.15000	6.30000

The ANOVA table for the model is given below. The A by C interaction is significant, $F(1,72) = 14.69$, $p < .001$. A graph of the means would indicate the type of interaction. The main effects of A, B, and C are also significant.

Tests of Significance for Y using UNIQUE sums of squares					
Source of Variation	SS	DF	MS	F	Sig of F
WITHIN CELLS	79.40	72	1.10		
A	101.25	1	101.25	91.81	.000
B	22.05	1	22.05	19.99	.000
C	64.80	1	64.80	58.76	.000
A BY B	.05	1	.05	.05	.832
A BY C	16.20	1	16.20	14.69	.000
B BY C	3.20	1	3.20	2.90	.093
A BY B BY C	1.80	1	1.80	1.63	.205

The residuals look reasonable.

Plots of Observed, Predicted, and Residual Case Values (CONT.)
 Predicted Values VS Std Resid. for Y



The normal probability plot looks reasonable.

Plots of Observed, Predicted, and Residual Case Values (CONT.)
Normal Plot

