CS147 50-5102

CS 147: Computer Systems Performance Analysis Fractional Factorial Designs

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Overview



2^{k-p} Designs

Example Preparing the Sign Table Confounding Algebra of Confounding Design Resolution

Introductory Example of a 2^{k-p} Design

Exploring 7 factors in only 8 experiments:





Analysis of 2^{7–4} Design

- ▶ Column sums are zero: $\sum_i x_{ij} = 0 \quad \forall j$
- Sum of 2-column product is zero:

$$\sum_{i} x_{ij} x_{il} = 0 \quad \forall j \neq l$$

- Sum of column squares is $2^{7-4} = 8$
- Orthogonality allows easy calculation of effects:

$$q_{A} = \frac{-y_{1} + y_{2} - y_{3} + y_{4} - y_{5} + y_{6} - y_{7} + y_{8}}{8}$$

etc.



^{k-p} Designs Examp

Effects and Confidence Intervals for 2^{k-p} Designs

• Effects are as in 2^k designs:

$$q_{\alpha} = \frac{1}{2^{k-p}} \sum_{i} y_{i} x_{\alpha i}$$

- % variation proportional to squared effects
- For standard deviations & confidence intervals:
 - Use formulas from full-factorial designs
 - Replace 2^k with 2^{k-p}



2^{*k*-*p*} Designs Preparing the Sign Table

Preparing the Sign Table for a $2^{k-\rho}$ Design



- Prepare sign table for k p factors
- Assign remaining factors

Sign Table for k - p Factors



Same as table for experiment with k − p factors

 La, 2^{k+p} table
 2^{k+p} rows and 2^{k+p} columns
 Finit k − p columns get k − p chosen factors.
 Finit k − p columns get k − p colu

ion Table for k - p Factors

- Same as table for experiment with k p factors
 - ▶ I.e., 2^(*k*-*p*) table
 - 2^{k-p} rows and 2^{k-p} columns
 - First k p columns get k p chosen factors
 - Rest are interactions (products of previous columns)
 - "I" column can be included or omitted as desired

Assigning Remaining Factors



2^{k-p} - (k - p) - 1 interaction (product) columns will remain
 Choose any p columns
 Assign remaining p factors to them
 Any dhows sitys as-k, measuring interactions

signing Remaining Factors

- > $2^{k-p} (k-p) 1$ interaction (product) columns will remain
- Choose any p columns
 - Assign remaining p factors to them
 - Any others stay as-is, measuring interactions

Example of Preparing a Sign Table

A 2⁴⁻¹ design:

Run	А	В	С	
1	-1	-1	-1	
2	1	-1	-1	
3	-1	1	-1	
4	1	1	-1	
5	-1	-1	1	
6	1	-1	1	
7	-1	1	1	
8	1	1	1	

CS147	Example of Preparing a Sign Table
L^{k-p} Designs L^{k-p} De	A 24-1 design: Test A B C 1 - 1 - 1 - 1 2 - 1 - 1 - 1 4 - 1 - 1 5 - 1 - 1 5 - 1 - 1 7 - 1 - 1 8 - 1 -

Example of Preparing a Sign Table

A 2⁴⁻¹ design:

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Run	Α	В	С	AB	AC	BC	ABC
1	-1	-1	-1	1	1	1	-1
2	1	-1	-1	-1	-1	1	1
3	-1	1	-1	-1	1	-1	1
4	1	1	-1	1	-1	-1	-1
5	-1	-1	1	1	-1	-1	1
6	1	-1	1	-1	1	-1	-1
7	-1	1	1	-1	-1	1	-1
8	1	1	1	1	1	1	1



Example of Preparing a Sign Table

A 2⁴⁻¹ design:

Run	Α	В	С	AB	AC	BC	D
1	-1	-1	-1	1	1	1	-1
2	1	-1	-1	-1	-1	1	1
3	-1	1	-1	-1	1	-1	1
4	1	1	-1	1	-1	-1	-1
5	-1	-1	1	1	-1	-1	1
6	1	-1	1	-1	1	-1	-1
7	-1	1	1	-1	-1	1	-1
8	1	1	1	1	1	1	1

CS147	Example of Preparing a Sign Table		
$\frac{1}{2} - 2^{k-p}$ Designs	A 2 ⁴⁻¹ design:		
Preparing the Sign Table	1 -1 -1 -1 1 1 1 -1 2 1 -1 -1 -1 1 1 1 1 -1 3 -1 1 -1 -1 1 1 1 1		
Example of Preparing a Sign Table	5 -1 -1 1 1 -1 -1 1 8 1 -1 1 -1 1 -1 -1 7 -1 1 1 -1 -1 1 -1		
N I I O O			

Why did we choose the ABC column to rename as D? In one sense, the choice is completely arbitrary. But in reality, this leads to a discussion of confounding. ^{k – p} Designs Confo

Confounding



Confounding

The confounding problem
 An example of confounding
 Confounding notation
 Choices in fractional factorial design

- ► The confounding problem
- An example of confounding
- Confounding notation
- Choices in fractional factorial design

The Confounding Problem



he Confounding Problem

Fundamental to fractional factorial designs
 Some effects produce combined influences
 Limited experiments means only combination can be co.
 Problem of combined influence is confounding
 Inseparable effects called confounded

- Fundamental to fractional factorial designs
- Some effects produce combined influences
 - Limited experiments means only combination can be counted
- Problem of combined influence is confounding
 - Inseparable effects called confounded

^{- p} Designs Confoundi

An Example of Confounding

- ► Consider this 2³⁻¹ table:

 I
 A
 B
 C

 1
 -1
 -1
 1

 1
 1
 -1
 -1

 1
 -1
 1
 -1

 1
 1
 1
 1
- Extend it with an AB column:

 I
 A
 B
 C
 AB

 1
 -1
 -1
 1
 1

 1
 1
 -1
 -1
 -1

-1 1 -1 -1

1 1

1

1

1

CS147 CS147 2^{k−p} Designs Confounding Confounding Confounding
 An Example of Contouridary

 - Consider this 2³⁻¹ safe:
 1
 A
 B
 C

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^{- p} Designs Confoundi

An Example of Confounding

- ► Consider this 2³⁻¹ table:

 I
 A
 B
 C

 1
 -1
 -1
 1

 1
 1
 -1
 -1

 1
 -1
 1
 -1

 1
 1
 1
 1
- Extend it with an AB column:
 I A B C AB

 1
 -1
 -1
 1

-1 -1

-1 1 -1 -1

1 1

-1

1

1

1

1

 $\begin{array}{c} & \text{CS147} \\ & -2^{k-p} \text{ Designs} \\ & & -\text{Confounding} \\ & & & -\text{An Example of Confounding} \end{array}$

 An Example of Contourding

 - Consider this 2^{k-1} table:
 1
 1
 1

 1
 1
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 1
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 1
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 2
 Extend table and Brothers
 A
 B
 C
 AB

 1
 1
 1
 1
 1
 1
 1
 1

 2
 Extend table and B
 Colume 1
 A
 B
 C
 AB

Analyzing the Confounding Example

Effect of C is same as that of AB:

 $q_C = (y_1 - y_2 - y_3 + y_4)/4$ $q_{AB} = (y_1 - y_2 - y_3 + y_4)/4$

Formula for q_C really gives combined effect:

 $q_{C} + q_{AB} = (y_{1} - y_{2} - y_{3} + y_{4})/4$

 $\begin{array}{c} \text{CS147} \\ \begin{array}{c} 2^{k-p} \text{ Designs} \\ \begin{array}{c} -\text{Confounding} \\ -\text{Analyzing the Confounding Example} \end{array} \end{array} \qquad \begin{array}{c} \text{-Back to c, s-r, s+h}^{k} \\ \begin{array}{c} -\text{Confounding} \\ \hline \\ \end{array} \qquad \begin{array}{c} \text{-Confounding} \\ \hline \end{array} \qquad \begin{array}{c} \text{-Confounding} \end{array} \qquad \begin{array}{c} \text{-Confounding} \\ \hline \end{array} \qquad \begin{array}{c} \text{-Confounding} \end{array} \qquad \begin{array}{c} \text{-Confounding}$

Analyzing the Confounding Example

Effect of C is same as that of AB:

 $q_C = (y_1 - y_2 - y_3 + y_4)/4$ $q_{AB} = (y_1 - y_2 - y_3 + y_4)/4$

Formula for q_C really gives combined effect:

 $q_C + q_{AB} = (y_1 - y_2 - y_3 + y_4)/4$

- No way to separate q_C from q_{AB}
 - Not problem if q_{AB} is known to be small

CS147 Confounding Analyzing the Confounding Example Confounding the Confounding Example

Confounding Notation



 Previous confounding is denoted by equating confounded effects: C = AB
 Other effects are also confounded in this design: A = BC, B = AC, C = AB, I = ABC
 Last entry indicates ABC is confounded with overall mean, it
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nfounding Notation

- Previous confounding is denoted by equating confounded effects: C = AB
- Other effects are also confounded in this design: A = BC, B = AC, C = AB, I = ABC
 - Last entry indicates ABC is confounded with overall mean, or q₀

Choices in Fractional Factorial Design



- Many fractional factorial designs possible
 - Chosen when assigning remaining p signs
 - > 2^p different designs exist for 2^{k-p} experiments
- Some designs better than others
 - Desirable to confound significant effects with insignificant ones
 - Usually means low-order with high-order

Rules of Confounding Algebra



 Particular design can be characterized by single contoundir Teditocnity, us / = wyz...confordunding Oftans can be loand by multiplying by various terms / rad as unity (e.g., I × A = A) Souwell terms disasser (APC becomes AC)

ules of Confounding Algebra

- Particular design can be characterized by single confounding
 - ► Traditionally, use *I* = *wxyz*... confounding
- Others can be found by multiplying by various terms
 - *I* acts as unity (e.g., $I \times A = A$)
 - Squared terms disappear (AB²C becomes AC)

Example: 2^{3–1} Confoundings

- Design is characterized by I = ABC
- Multiplying by A gives $A = A^2 B C = B C$
- ▶ Multiplying by *B*, *C*, *AB*, *AC*, *BC*, and *ABC*:
 - $B = AB^{2}C = AC$ $C = ABC^{2} = AB$ $AB = A^{2}B^{2}C = C$ $AC = A^{2}BC^{2} = B$ $BC = AB^{2}C^{2} = A$ $ABC = A^{2}B^{2}C^{2} = I$
- Note that only first two lines are unique in this case



Generator Polynomials



 Polynomial I = wnyz... is called generator polynomial the contourding
 A 2ⁿ-9 dissign contourds 2ⁿ effects together
 So enventor cohormatin has 2ⁿ terms

nerator Polynon

Can be found by considering interactions replaced in sign tai

- Polynomial *I* = wxyz... is called generator polynomial for the confounding
- A 2^{k-p} design confounds 2^p effects together
 - ► So generator polynomial has 2^p terms
 - Can be found by considering interactions replaced in sign table

Example of Finding Generator Polynomial

CS147 2^{k-p} Designs Algebra of Confounding Example of Finding Generator Polynomial

- ► Consider 2⁷⁻⁴ design
- Sign table has $2^3 = 8$ rows and columns
- First 3 columns represent A, B, and C
- Columns for D, E, F, and G replace AB, AC, BC, and ABC columns respectively
 - So confoundings are necessarily: D = AB, E = AC, F = BC, and G = ABC

Turning Basic Terms into Generator Polynomial



- ► Basic confoundings are D = AB, E = AC, F = BC, and G = ABC
- Multiply each equation by left side: I = ABD, I = ACE, I = BCF, and I = ABCG

or I = ABD = ACE = BCF = ABCG

Finishing Generator Polynomial



Any subset of above terms also multiplies out to 1 • E.g., ABD × ACE = APBCDE = BCDE Expanding all possible combinations gives 16 term generations (book may be wring): 1 = ABD = ACE = BCF = ABCG = BCDE = ACD = CBD = ABE = CBE = ABC = ABCG

hing Generator Polynom

- Any subset of above terms also multiplies out to I
 - E.g., $ABD \times ACE = A^2BCDE = BCDE$
- Expanding all possible combinations gives 16-term generator (book may be wrong): I = ABD = ACE = BCF = ABCG = BCDE = ACDF = CDG = ABEF = BEG = AFG = DEF = ADEG = BDFG = CEFG = ABCDEFG

Design Resolution



Design Resolution

Definitions leading to resolution
 Definition of resolution
 Finding resolution
 Choosing a resolution

- Definitions leading to resolution
- Definition of resolution
- Finding resolution
- Choosing a resolution

Definitions Leading to Resolution



Design is characterized by its resolution
 Resolution measured by order of contounded effects
 Order of effect is number of factors in it
 E.p. / Is order 0.4820b coster 4.4
 Order of a contounding is sum of effect orders
 E.n. 4.9 = COR words the order 4.5

itions Leading to Resolution

- Design is characterized by its resolution
- Resolution measured by order of confounded effects
- Order of effect is number of factors in it
 - E.g., *I* is order 0, *ABCD* is order 4
- Order of a confounding is sum of effect orders
 - E.g., AB = CDE would be of order 5

Definition of Resolution



efinition of Resolution

Resolution is minimum order of any confounding in design
 Denoted by uppercase Roman numerals

 E.g. 2⁸⁻¹ with resolution of 3 is called R₀
 Or more compactly 2_m

- Resolution is minimum order of any confounding in design
- Denoted by uppercase Roman numerals
 - E.g, 2^{5-1} with resolution of 3 is called R_{III}
 - Or more compactly, 2_{III}

Finding Resolution



 Find minimum order of effects confounded with mean

 Le., search generator polynomial
 Onnider earlier example: I = ABD = ACE = BCF = ABCG = BCCE = ACPE = CDG = ABG = ABFG = BEG = AFG DEF = ADEG = BDFG = ABDG = CEFG = ABCDEFG
 Solfs an A desion

- > Find minimum order of effects confounded with mean
 - I.e., search generator polynomial
- Consider earlier example: I = ABD = ACE = BCF = ABCG = BCDE = ACDF = CDG = ABEF = BEG = AFG = DEF = ADEG = BDFG = ABDG = CEFG = ABCDEFG
- ► So it's an *R*_{III} design

Choosing a Resolution



Generally, higher resolution is better
 Gecause usually higher-order interactions are smaller
 Exception: when low-order interactions are known to be small
 Then chose design that confounds trees with important
 interactions
 Even if resolution is over

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- Generally, higher resolution is better
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- Exception: when low-order interactions are known to be small
 - Then choose design that confounds those with important interactions
 - Even if resolution is lower