

Primer on Analysis of Experimental Data and Design of Experiments

Lecture 8. Statistical Design of Experiments

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Outline

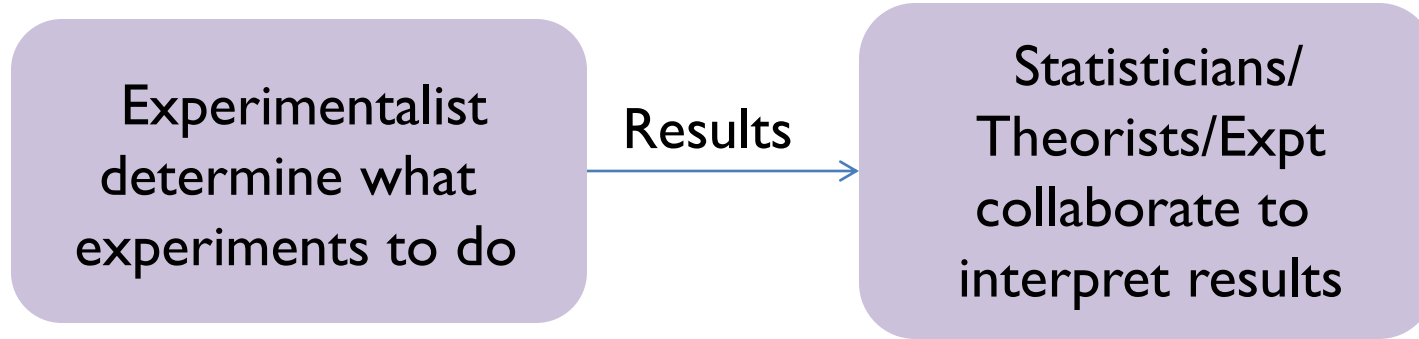
1. Context and background
2. Full factorial DOE explained by a toy model
3. Taguchi and fractional factorial experiments to reduce the number of experiments
4. Conclusions

Design of Experiments

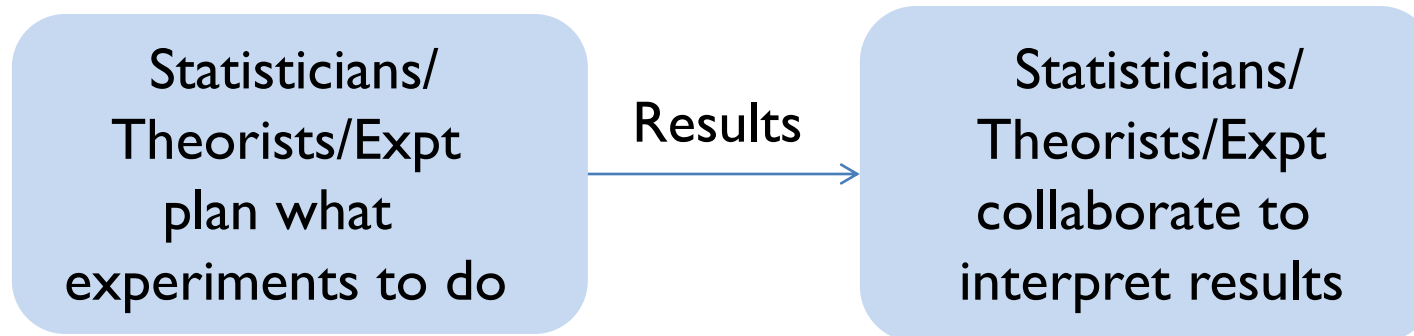
- Set of guidelines for designing, conducting and analyzing experiments for system optimization
- Foundations of DOE were laid by Sir. R.A. Fisher in early 1920s (Analysis of Farm data, output as good as input).
- Concepts of Orthogonal arrays were introduced by Taguchi in 1950s. (Formalized the whole analysis)
- DOE has revolutionized quality control/reliability in all fields of science and technology (Toyota was one of the early adopter, most semiconductor companies use the method).

Philosophical shift with DOE

Before Fisher ...

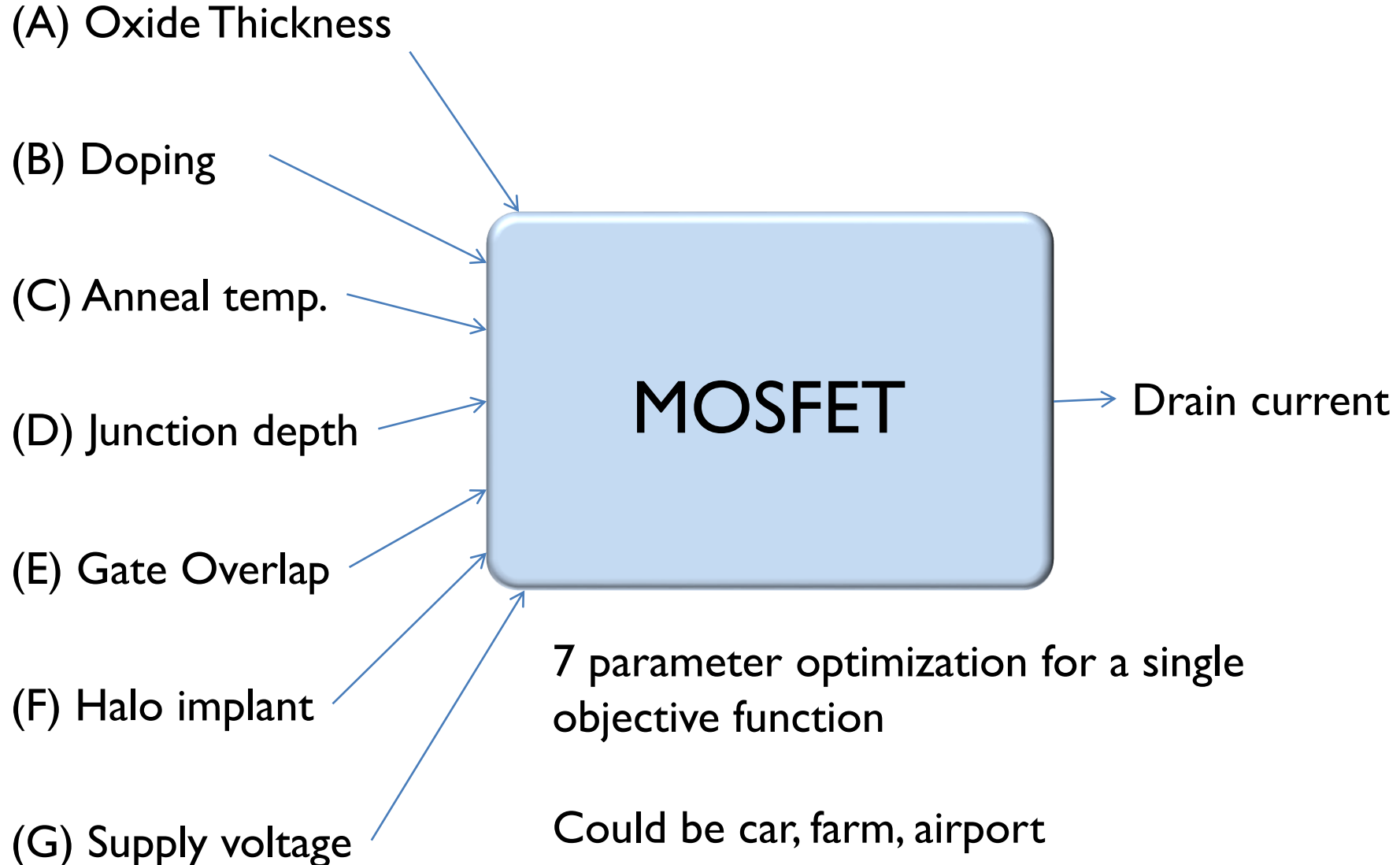


After Fisher ...



Output cannot be greater than input

Problem definition (7 factor problem)



Definition of terms

Factor	Level	Run/trial/replicate
Tox	1, 2, 3 nm	(2 nm, 10^{17} cm ⁻³ , 4 μm) _{rep}
Doping	10^{16} , 10^{17} cm ⁻³	
Lch	2, 3, 4 μm	

- 1 factor, 3 level, 4 replicate experiment
- 2 factor, 2 level, 3 replicate experiment
- 8 factor, 2 level, 1 replicate experiment

7 Factor, 2 level: One factor at a time

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \epsilon$$

	A	B	C	D	E	F	G	Output
Run 1	1	1	1	1	1	1	1	10
Run 2	2	1	1	1	1	1	1	15
Run 3	2	2	1	1	1	1	1	12
Run 4	2	1	2	1	1	1	1	9
Run 5	2	1	1	2	1	1	1	18
Run 6	2	1	1	2	2	1	1	19
Run 7	2	1	1	2	2	2	1	17
Run 8	2	1	1	2	2	1	2	13
Final	2	1	1	2	2	1	1	19

Simple, widely used, but non-optimum solutions

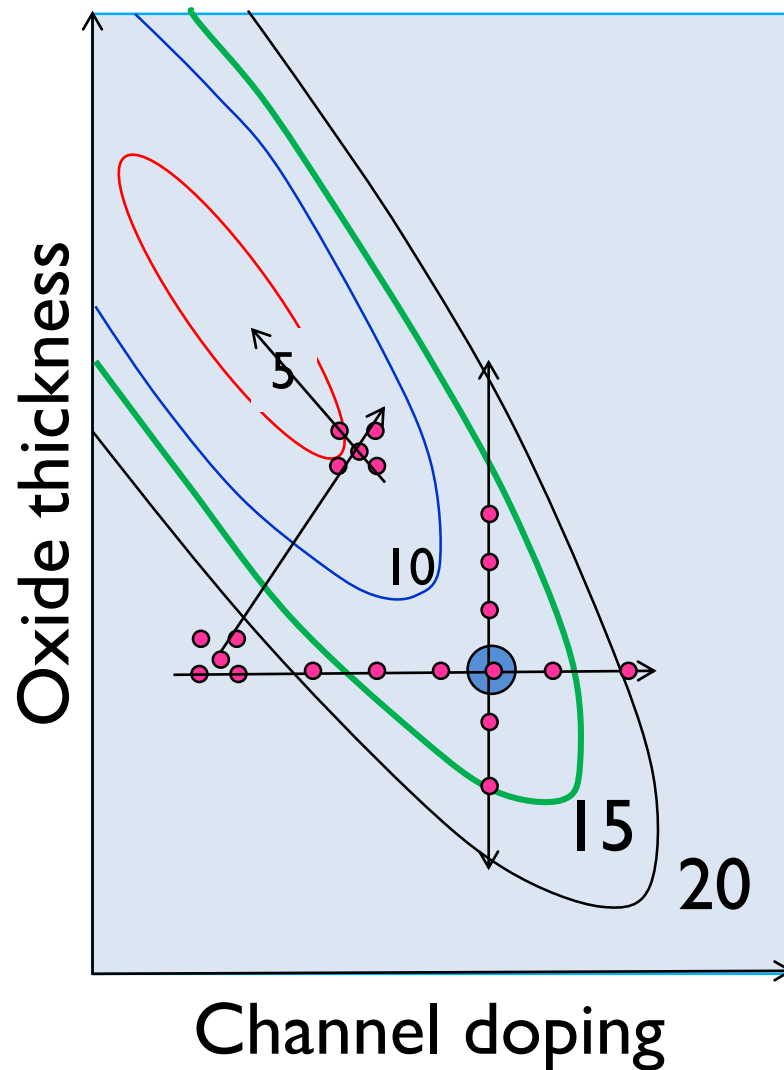
7 Factor, 2 Level: Full factorial analysis

$$Level^{factor} = L^F = 2^7 = 128$$

				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
D ₁	E ₁	F ₁	G ₁	R-1 (10)				R-2 (15)		R-3 (12)	
			G ₂								
		F ₂	G ₁						R-4 (9)		
			G ₂								
	E ₂	F ₁	G ₁								
			G ₂								
		F ₂	G ₁								
			G ₂								
D ₂	E ₁	F ₁	G ₁					R-5 (18)			
			G ₂								
		F ₂	G ₁								
			G ₂								
	E ₂	F ₁	G ₁					R-6 (19)			
			G ₂					R-8 (13)			
		F ₂	G ₁					R-7 (17)			
			G ₂								

Single parameter method is a fractional non-optimal factorial method: After A₂ win, will never visit A₁. After B₂ loss, will never visit B₂. Same for C₂ Column, etc.

The problem with one-at-a-time approach

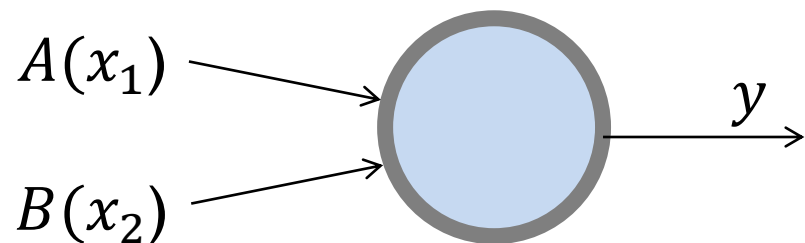


Response surface
Orthogonal sampling

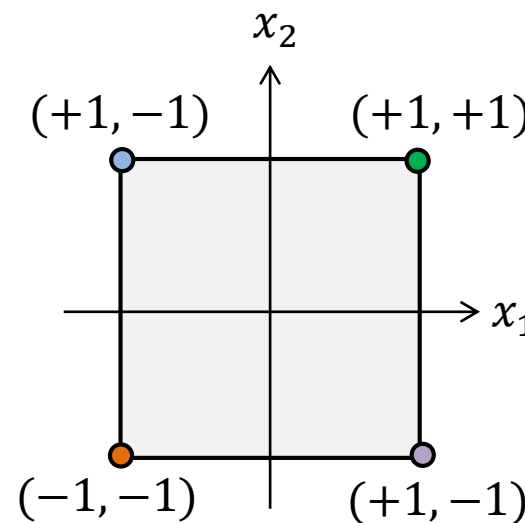
Outline

1. Context and background
2. Full factorial DOE explained by a toy model
3. Taguchi and fractional factorial experiments to reduce the number of experiments
4. Conclusions

A Toy Problem with two factors and two levels



$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \epsilon$$



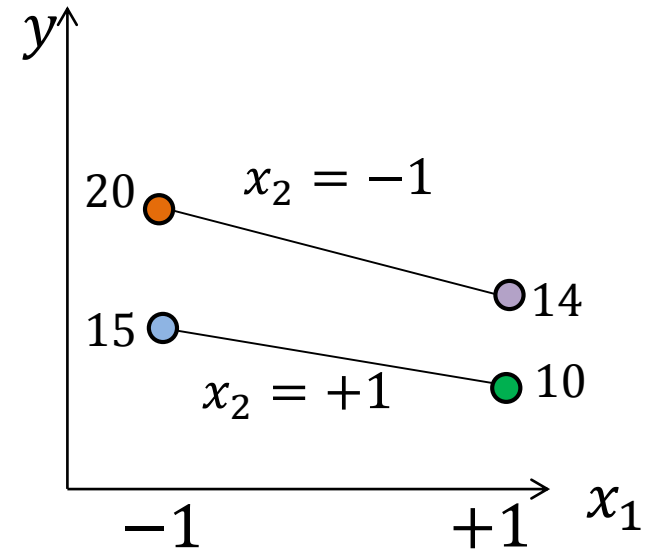
A	200 ($x_1 = -1$)	300 ($x_1 = +1$)
B	0 ($x_2 = -1$)	> 1 ($x_2 = +1$)

	x_1	x_2	$x_1 x_2$		y
●	-1	-1	+1	(1)	20
●	+1	-1	-1	a	14
●	-1	+1	-1	b	15
●	+1	+1	+1	ab	10

A toy problem with two factors

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \epsilon$$

	x_1	x_2	$x_1 x_2$		y
●	-1	-1	+1	(1)	20
●	+1	-1	-1	a	14
●	-1	+1	-1	b	15
●	+1	+1	+1	ab	10



$$\text{Effect of A} = [(a + ab) - ((1) + b)]/2 = -5.5$$

$$\text{Effect of B} = [(b + ab) - ((1) + a)]/2 = -4.5$$

$$\text{AB interaction} = [((1) + ab) - (a + b)]/2 = 0.5$$

Regression coefficient
 $= \text{Effect} / (+1 - (-1)) = \text{Effect} / 2 = \text{slope}$

Randomization: Importance of the error term

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \epsilon$$

Sample selection is critical

For the existing problem, randomize over unknown variables such as sub-areas, gender, fall/winter session, etc.

For dielectric breakdown, choose samples from multiple tools, days of the week, randomize test equipment, etc.

Don't trust yourself: use a random number generator.

A Toy Problem with two factors: Fractional factorial experiments

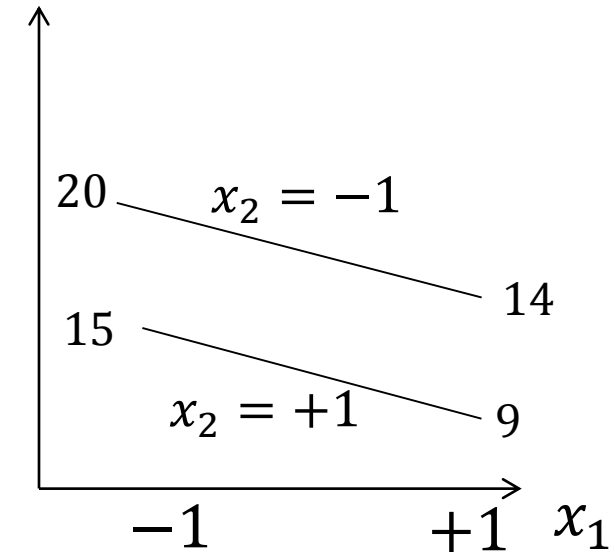
$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cancel{\beta_{12} x_1 x_2} + \epsilon$$

Choose $x_1 x_2 = +1$ OR $x_1 x_2 = -1$

	x_1	x_2	$x_1 x_2$		y	
●	-1	-1	+1	(1)	20	0
○	+1	-1	-1	a	14	-6
○	-1	+1	-1	b	15	-5
●	+1	+1	+1	ab	10	

Effect of A=[a]/1 = -6

Effect of B=[b]/1 = -5



Regression coefficient
= Effect/(+1 - (-1)) = Effect/2 = slope

A Toy Problem with 3 factors, 2 levels

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{13} x_1 x_3 + \beta_{123} x_1 x_2 x_3 + \epsilon$$

x_1	x_2	x_3	$x_1 x_2$	$x_2 x_3$	$x_1 x_3$	$x_1 x_2 x_3$		y
-1	-1	-1	+1	+1	+1	-1	(1)	67
+1	-1	-1	-1	+1	-1	+1	a	79
-1	+1	-1	-1	-1	+1	+1	b	61
+1	+1	-1	+1	-1	-1	-1	ab	75
-1	-1	+1	+1	-1	-1	+1	c	59
+1	-1	+1	-1	-1	+1	-1	ac	90
-1	+1	+1	-1	+1	-1	-1	bc	52
+1	+1	+1	+1	+1	+1	+1	abc	87

Step 1: Choose full-factorial
and randomize order,

Step 3: For data analysis,
prepare the signs for cross-terms

Step 2: Do the experiments
and collect the results.

A Toy Problem with 3 factors, 2 levels

x_1	x_2	x_3	x_1x_2	x_2x_3	x_1x_3	$x_1x_2x_3$		y
-1	-1	-1	+1	+1	+1	-1	(1)	67
+1	-1	-1	-1	+1	-1	+1	a	79
-1	+1	-1	-1	-1	+1	+1	b	61
+1	+1	-1	+1	-1	-1	-1	ab	75
-1	-1	+1	+1	-1	-1	+1	c	59
+1	-1	+1	-1	-1	+1	-1	ac	90
-1	+1	+1	-1	+1	-1	-1	bc	52
+1	+1	+1	+1	+1	+1	+1	abc	87

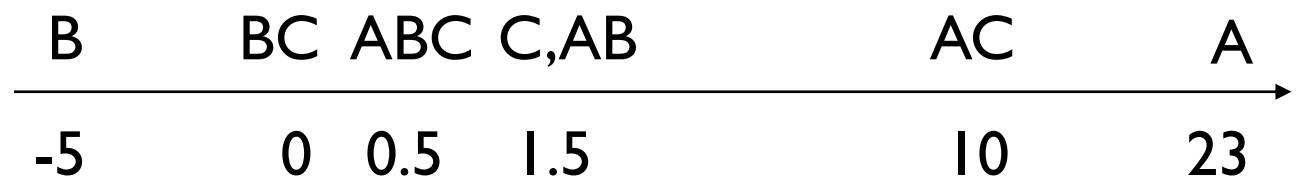
Effect of C=1.5
 Effect of AC = 10.0
 Effect of AB = 1.5
 Effect of BC = 0.0
 Effect of ABC=0.5

$$\text{Effect of A} = [(a + ab + ac + abc) - ((1) + b + c + bc)]/4 = 23$$

$$\text{Effect of B} = [(b + ab + bc + abc) - ((1) + a + c + ac)]/4 = -5$$

$$\text{Effect of AB} = [((1) + ab + c + abc) - (a + b + bc + ac)]/4 = 1.5$$

Importance of factors by Normal Q-Q plot: Step 1



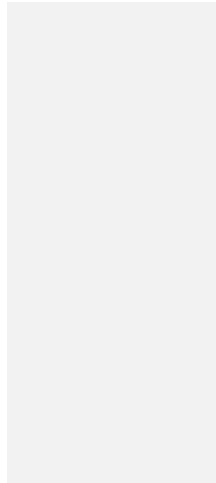
Step 1: Order effect of A, B, C, AC, AB, BC, ABC = 23, -5, 1.5, 10, 1.5, 0.0, 0.5

Importance of factors by Normal Plot: Step 2

Step 2 : Determine F_i

$$i \mid f_i = (i - 0.5)/7 \quad Z_i$$

1		0.071428
2		0.214286
3		0.357143
4		0.500000
5		0.642857
6		0.785714
7		0.928571

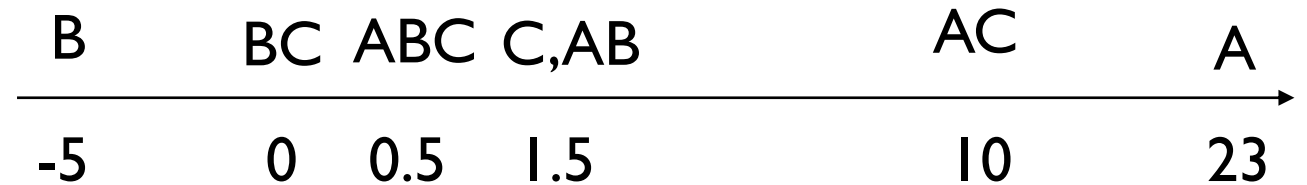
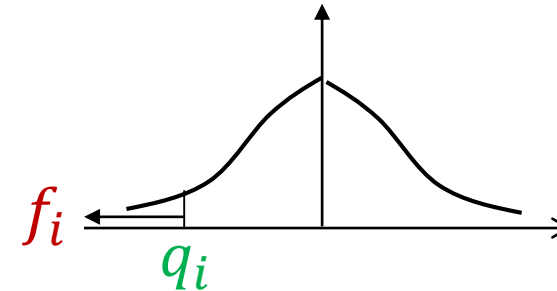


Importance of factors by Normal plots: Step 3

Step 3 : Find $P(q_i) < f_i$

Normal table $q_i = 4.91 [f_i^{0.14} - (1 - f_i)^{0.14}]$

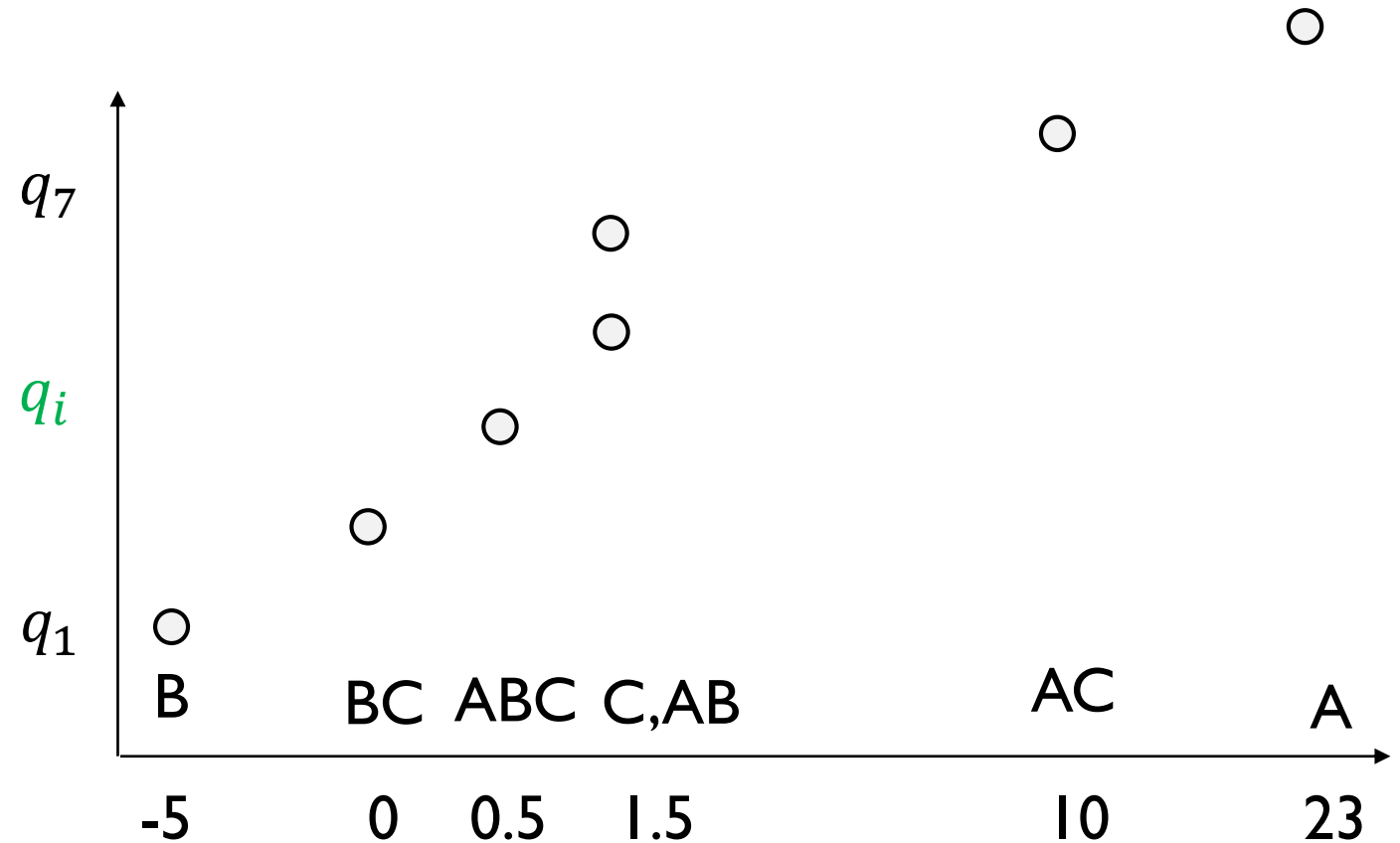
i	f_i	q_i
1 - 5.0	0.071428	- 1.47
2 + 0.0	0.214286	- 0.79
3 + 0.5	0.357143	- 0.36
4 + 1.5	0.500000	+ 0.00
5 + 1.5	0.642857	+ 0.36
6 + 10	0.785714	+ 0.79
7 + 23	0.928571	+ 1.47



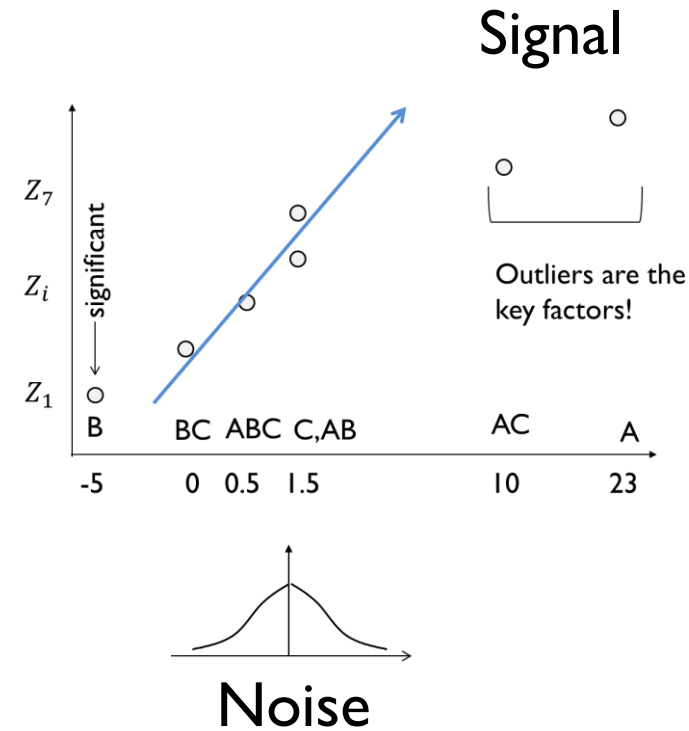
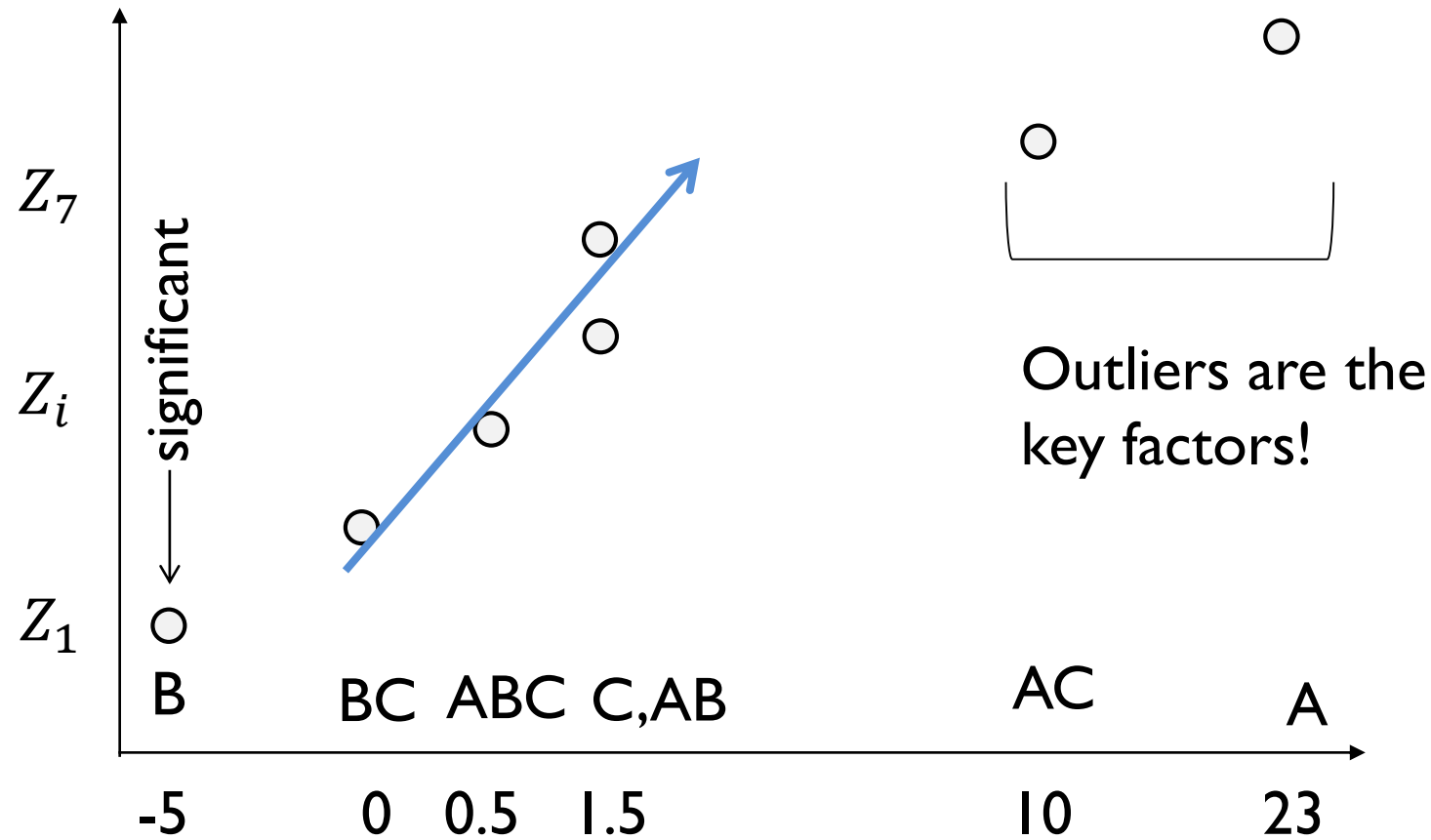
Importance of factors by Normal plots: Step 4

Step 3 : Find $P(q_i) < f_i$

i	F_i	q_i
1 - 5.0	0.071428	- 1.468
2 + 0.0	0.214286	- 0.793
3 + 0.5	0.357143	- 0.366
4 + 1.5	0.500000	+ 0.000
5 + 1.5	0.642857	+ 0.366
6 + 10	0.785714	+ 0.793
7 + 23	0.928571	+ 1.468



Importance of factors by Normal plots: Step 5



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1. Context and background
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A toy problem with 3 factors, 2 levels

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{13} x_1 x_3 + \beta_{123} x_1 x_2 x_3 + \epsilon$$

x_1	x_2	x_3	$x_1 x_2$	$x_2 x_3$	$x_1 x_3$	$x_1 x_2 x_3$		y
-1	-1	-1	+1	+1	+1	-1	(1)	67
+1	-1	-1	-1	+1	-1	+1	a	79
-1	+1	-1	-1	-1	+1	+1	b	61
+1	+1	-1	+1	-1	-1	-1	ab	75
-1	-1	+1	+1	-1	-1	+1	c	59
+1	-1	+1	-1	-1	+1	-1	ac	90
-1	+1	+1	-1	+1	-1	-1	bc	52
+1	+1	+1	+1	+1	+1	+1	abc	87

Step 1: Choose full-factorial
and randomize order,

Step 3: For data analysis,
prepare the signs for cross-terms

Step 2: Do the experiments
and collect the results.

Two approaches to reduce the number of experiments

Determine the number of variables and experiments you have time to do.

Fractional Factorial Approach: 4, 8, 16, 32, 64

Taguchi Orthogonal Array: 4, 8, 12, 20, 24, 28

Full factorial: 3 factors, 2 levels

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{13} x_1 x_3 + \beta_{123} x_1 x_2 x_3 + \epsilon$$

x_1	x_2	x_3	$x_1 x_2$	$x_2 x_3$	$x_1 x_3$	$x_1 x_2 x_3$		y
-1	-1	-1	+1	+1	+1	-1	(1)	67
+1	-1	-1	-1	+1	-1	+1	<i>a</i>	79
-1	+1	-1	-1	-1	+1	+1	<i>b</i>	61
+1	+1	-1	+1	-1	-1	-1	<i>ab</i>	75
-1	-1	+1	+1	-1	-1	+1	<i>c</i>	59
+1	-1	+1	-1	-1	+1	-1	<i>ac</i>	90
-1	+1	+1	-1	+1	-1	-1	<i>bc</i>	52
+1	+1	+1	+1	+1	+1	+1	<i>abc</i>	87

Effect of A = $[(ab + ac) - ((1) + bc)]/2 = ?$

Effect of B = $[(ab + bc) - ((1) + ac)]/2 = ?$

Half-factorial experiments

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{13} x_1 x_3 + \beta_{123} x_1 x_2 x_3 + \epsilon$$

x_1	x_2	x_3	$x_1 x_2$	$x_1 x_2 x_3$		y
-1	-1	-1	+1	-1	(1)	67
+1	-1	-1	-1	+1	a	79
-1	+1	-1	-1	+1	b	61
+1	+1	-1	+1	-1	ab	75
-1	-1	+1	+1	+1	c	59
+1	-1	+1	-1	-1	ac	90
-1	+1	+1	-1	-1	bc	52
+1	+1	+1	+1	+1	abc	87

The number of experiments must be greater than the number of variables.

The technique allows to determine the correlation experiments.

Fractional factorial tables are balanced. We have the same need for randomization.

$$\text{Effect of A} = [(ab + ac) - ((1) + bc)]/2 = ?$$

$$\text{Effect of B} = [(ab + bc) - ((1) + ac)]/2 = ?$$

Taguchi approach: 3 factors, 2 levels (P-B Matrix)

Generating vector

x_1	x_2	x_3
+1	-1	+1
+1	+1	-1
-1	∓ 1	+1
-1	-1	-1

Plackett-Burman design

Use the col 1
generating vector

Set bottom row -1

Roll the vector from
the first column to fill
other columns.

Another way: 7 factors, 2 levels (P-B Matrix)

Vector

x_1	x_2	x_3	x_4	x_5	x_6	x_7
+1	-1	-1	+1	-1	+1	+1
+1	+1	-1	-1	+1	-1	+1
+1	+1	+1	-1	-1	+1	-1
-1	+1	+1	+1	-1	-1	+1
+1	-1	+1	+1	+1	-1	-1
-1	+1	-1	+1	+1	+1	-1
-1	-1	+1	-1	+1	+1	+1
-1	-1	-1	-1	-1	-1	-1

Plackett-Burman design

Use the col 1
generating vector

Set bottom row -1

Roll the vector from
the first column to fill
other columns.

Another way: 11 factors, 2 levels (P-B Matrix)

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_{11}
+1	-1	+1	-1	-1				
+1	+1	-1						
-1	+1	+1						
+1	-1	+1						
+1	+1	+1						
+1	+1	+1						
-1	+1	+1						
-1	-1	+1						
-1	-1	-1						
+1	-1	-1						
-1	+1	-1	-1	-1				
-1	-1	-1	-1	-1	-1	-1	-1	-1

Plackett-Burman design

Use the col 1
generating vector

Set bottom row -1

Roll the vector from
the first column to fill
other columns.

Taguchi table: Continued

$$L_4(2^3)$$

Run	Columns		
	1	2	3
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

$$L_8(2^7)$$

Run	Columns						
	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

$$L_{12}(2^{11})$$

Run	Columns										
	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

$$L_N(S^M)$$

M ... Factors

S ... Levels

N ... experiment > DOF = 1 + M(S-1)

A 4-Factor, 2-Level experiment

Run	Columns						
	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

(col 1,A)



(col 3,C)



(col 4,D)



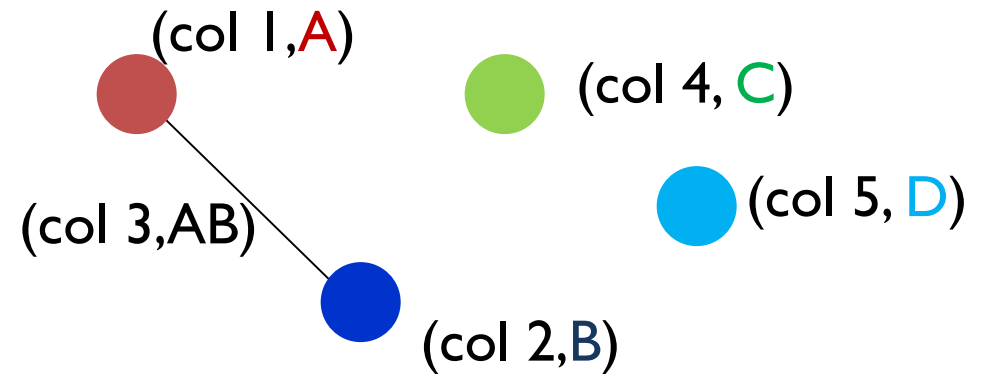
(col 2,B)



Only (AB) pair correlation found, no other correlation

Main effect and interactions

Run	A	B	AB	C	D	Columns	
	1	2	3	4	5	6	7
	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2



(AB) is a dummy column, without it the C and D would have different arrangements ...

Still need L8 array (4-7), other two-level arrays L4 (1-3) and L12(8-11)

Conclusions

1. Design of experiment is a powerful technique universally used in industry and in large scale field trials.
2. Taguchi/Fisher methods replace the older one-factor-at-a-time experiments with experiments based on orthogonal arrays; In this approach, only the effect of main factors remain; others are cancelled.
3. Understanding and analyzing correlation is important in design of experiments. Unless the correlation is well understood and incorporated through dummy variables, the analysis may lead to faulty conclusions.

Primer on Analysis of Experimental Data and Design of Experiments

Lecture 9. DOE Analysis by ANOVA

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Outline

1. Introduction to Analysis of Variance (Anova)
2. Single factor Analysis of Variance
3. Two factor Anova
4. Generalized Anova
5. Conclusions

Recall: A Toy Problem with 3 factors, 2 levels

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{13} x_1 x_3 + \beta_{123} x_1 x_2 x_3 + \epsilon$$

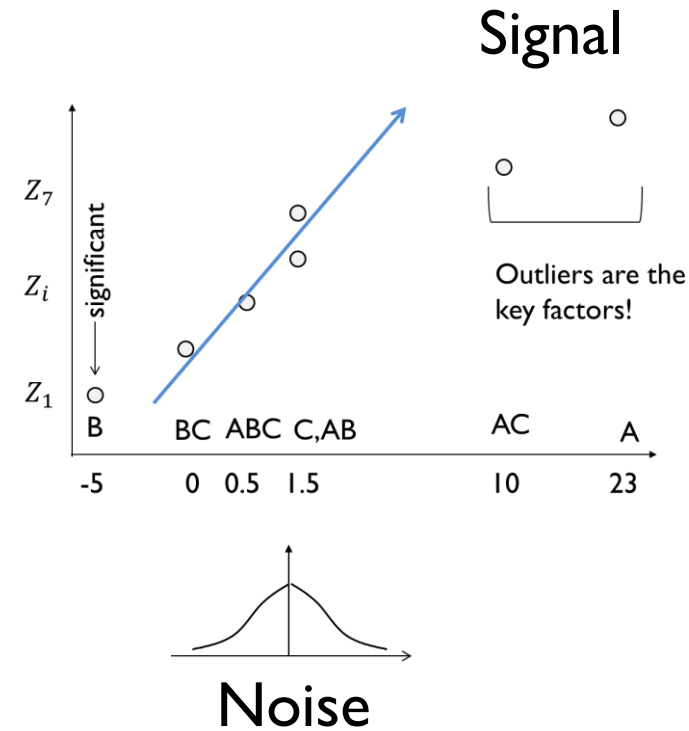
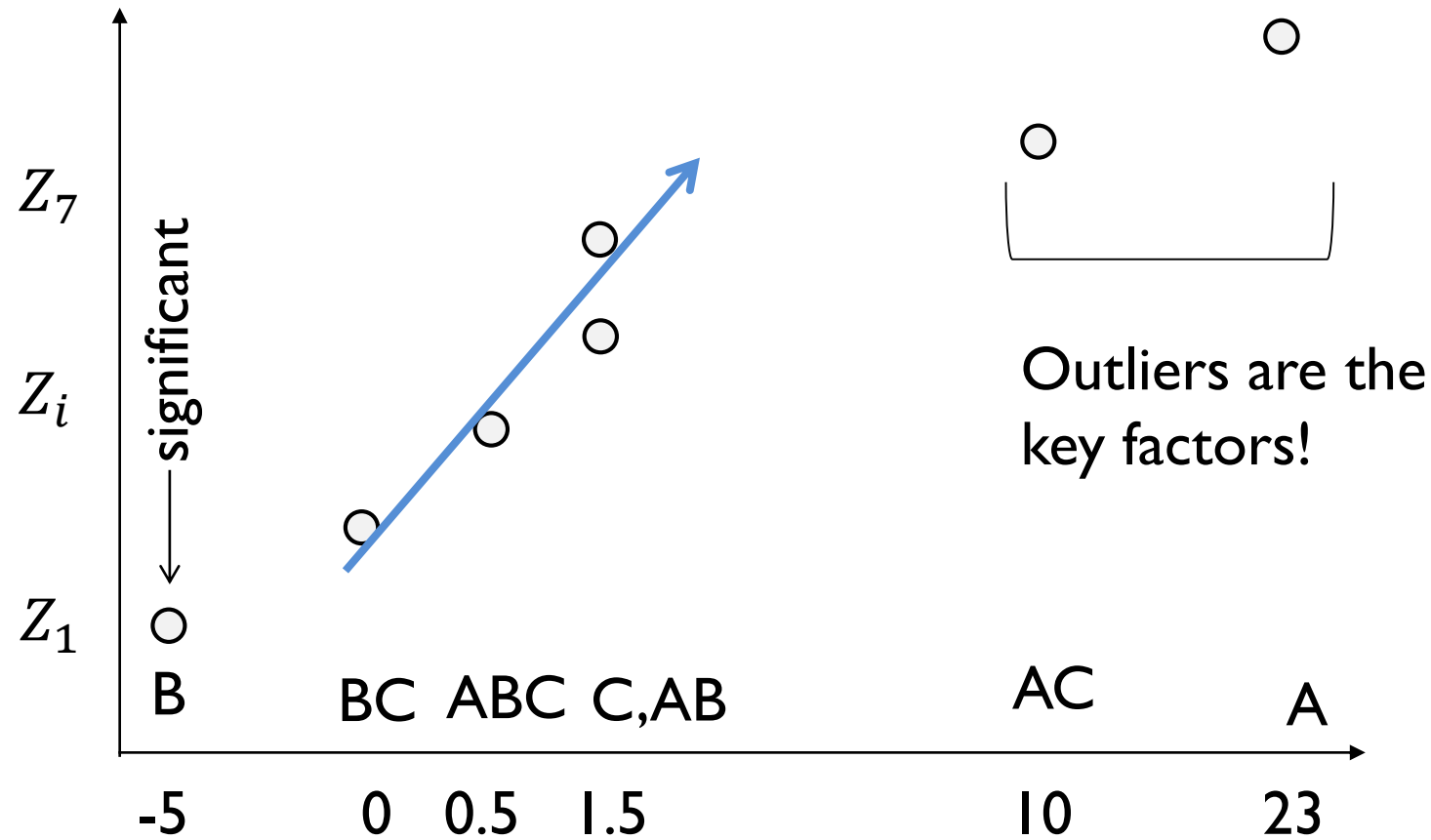
x_1	x_2	x_3	$x_1 x_2$	$x_2 x_3$	$x_1 x_3$	$x_1 x_2 x_3$		y
-1	-1	-1	+1	+1	+1	-1	(1)	67
+1	-1	-1	-1	+1	-1	+1	a	79
-1	+1	-1	-1	-1	+1	+1	b	61
+1	+1	-1	+1	-1	-1	-1	ab	75
-1	-1	+1	+1	-1	-1	+1	c	59
+1	-1	+1	-1	-1	+1	-1	ac	90
-1	+1	+1	-1	+1	-1	-1	bc	52
+1	+1	+1	+1	+1	+1	+1	abc	87

Step 1: Choose full-factorial
and randomize order,

Step 3: For data analysis,
prepare the signs for cross-terms

Step 2: Do the experiments
and collect the results.

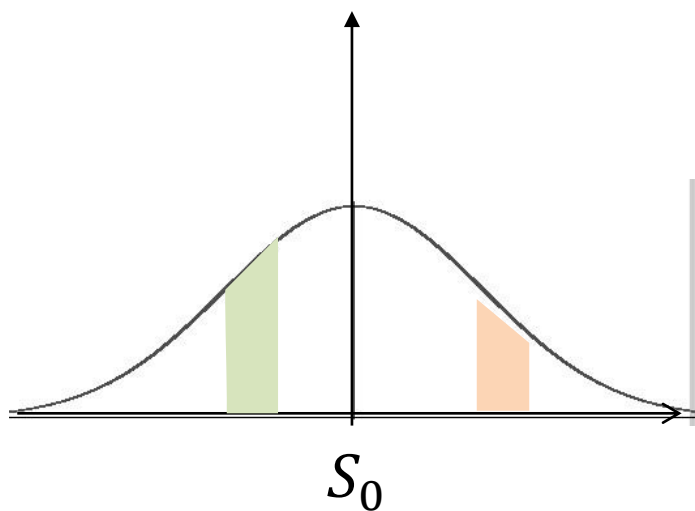
Recall: Importance of factors by Normal plots



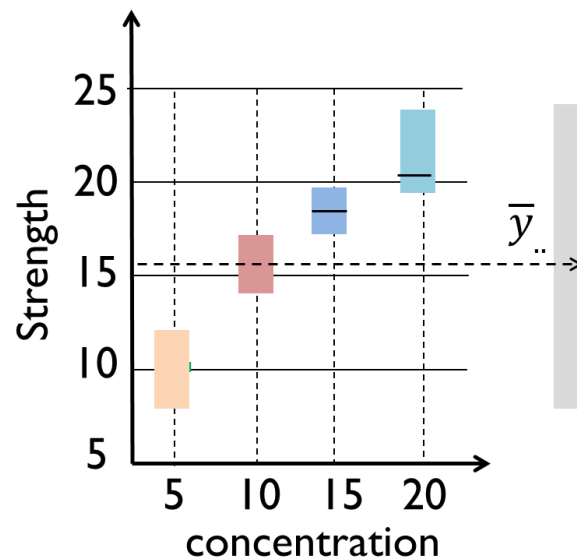
Single factor ANOVA: Treatment

	replicates					
	1	2	3	4	5	6
5	7	8	15	11	9	10
10	12	17	13	18	19	15
15	14	18	19	17	16	18
20	19	25	22	23	18	20

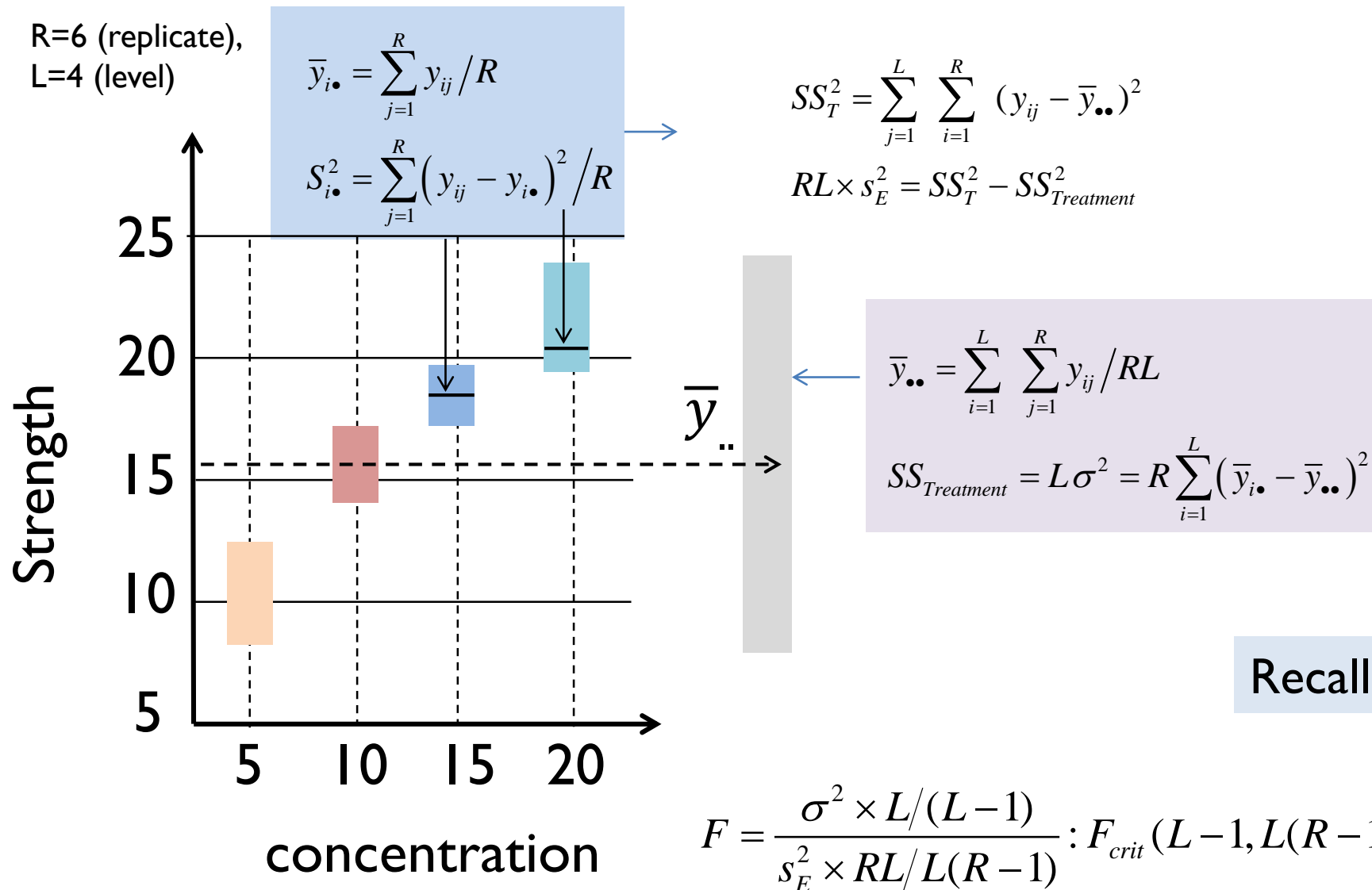
Treatments (levels)



In essence, no effect



Single factor Anova: Treatment Analysis



Single factor ANOVA (continued)

	1	2	3	4	5	6
5	7	8	15	11	9	10
10	12	17	13	18	19	15
15	14	18	19	17	16	18
20	19	25	22	23	18	20

1. Treatment number, $a = 4$; $\text{dof}_a = 3$; Sample number: $n = 6$
2. Global sample number: $a \times n = 24$, $\text{dof}_n = 23$, **AVG** (global)=15.96
3. Total “Sum of square” **SS_T** = $\sum_{24}(\text{data} - \text{AVG})^2 = 512.96$
4. Treatment sum: **$SS_{\text{treatment}}$** = $n \times \sum_4(\text{treat. avg} - \text{AVG})^2 = 382$.
5. **SS_{error}** = **SS_T** - **$SS_{\text{treatment}}$** = 130.62
6. **$ME_{\text{treatment}}$** = **$SS_{\text{treatment}}$** / dof_a , **ME_{Error}** = **SS_{error}** / $(\text{dof}_n - \text{dof}_a)$
7. Finally, $F = (\text{ME}_{\text{treatment}})/(\text{ME}_{\text{error}}) = \frac{382/3}{130.62/20} = 19.6$
8. Compare: $f(0.01, \text{dof}_a, \text{dof}_n)$, or $P(F_{3,20} > 19.6) = 3.59 \times 10^{-6}$

Single factor ANOVA: Wood Treatment

	→ replicates						
	1	2	3	4	5	6	
5	7	8	15	11	9	10	t.avg
10	12	17	13	18	19	15	(t. avg – AVG) ²
15	14	18	19	17	16	18	10.00
20	19	25	22	23	18	20	15.67
							17.00
							21.17
							15.96
							35.50174
							0.085069
							1.085069
							27.12674
							63.79861

↓ treatments

$\Sigma(\text{data} - \text{AVG})^2 = 512$

$6 \times 63.8 = 382.8$

Variation	SS	df	MS	F	P-value	F crit
Between Groups	382.7917	3	127.60	19.605	3.59E-06	4.94
Within Groups	130.1667	20	6.51			
Total	512.9583	23				

① → ③

② → ④

⑤ → ⑥

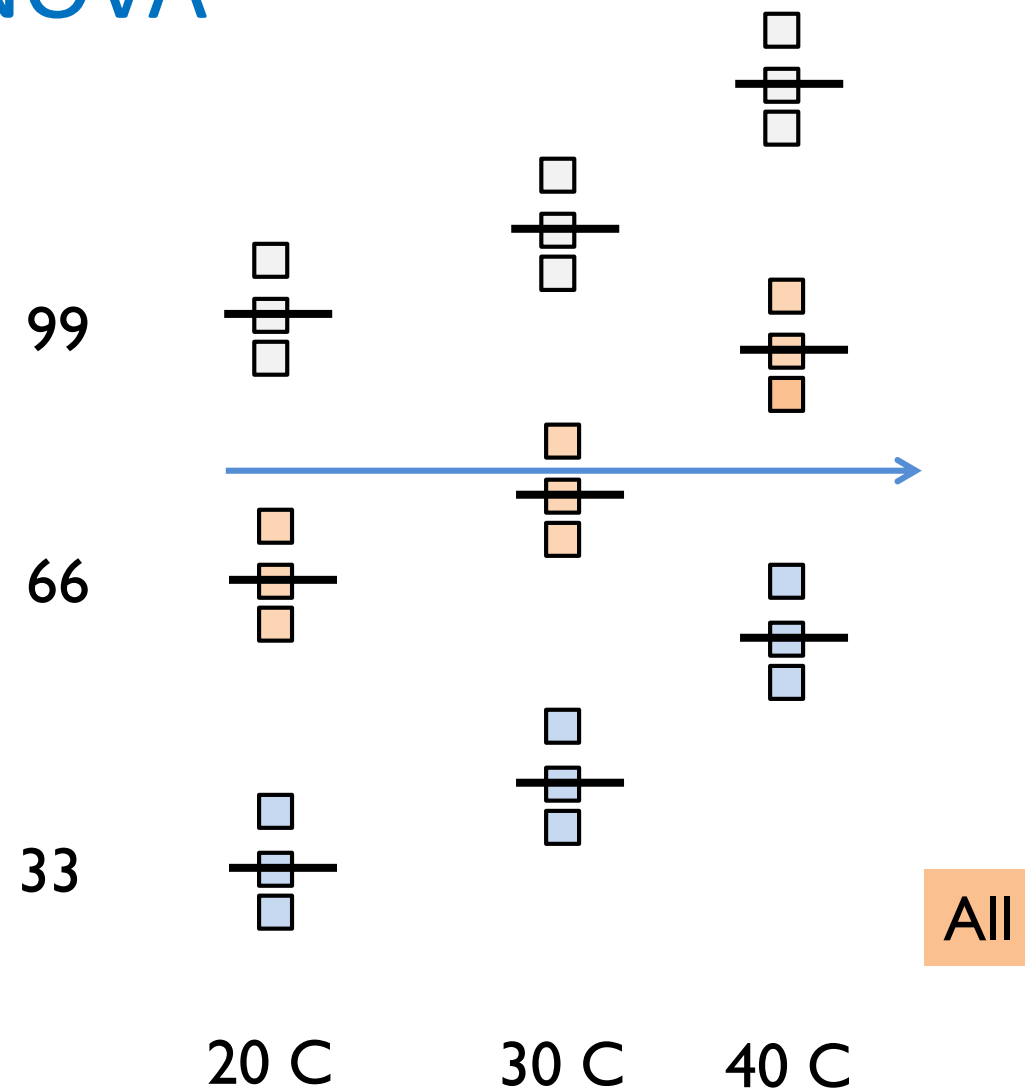
Outline

1. Introduction to Analysis of Variance (Anova)
2. Single factor Analysis of Variance
- 3. Generalized Anova**
4. Conclusions

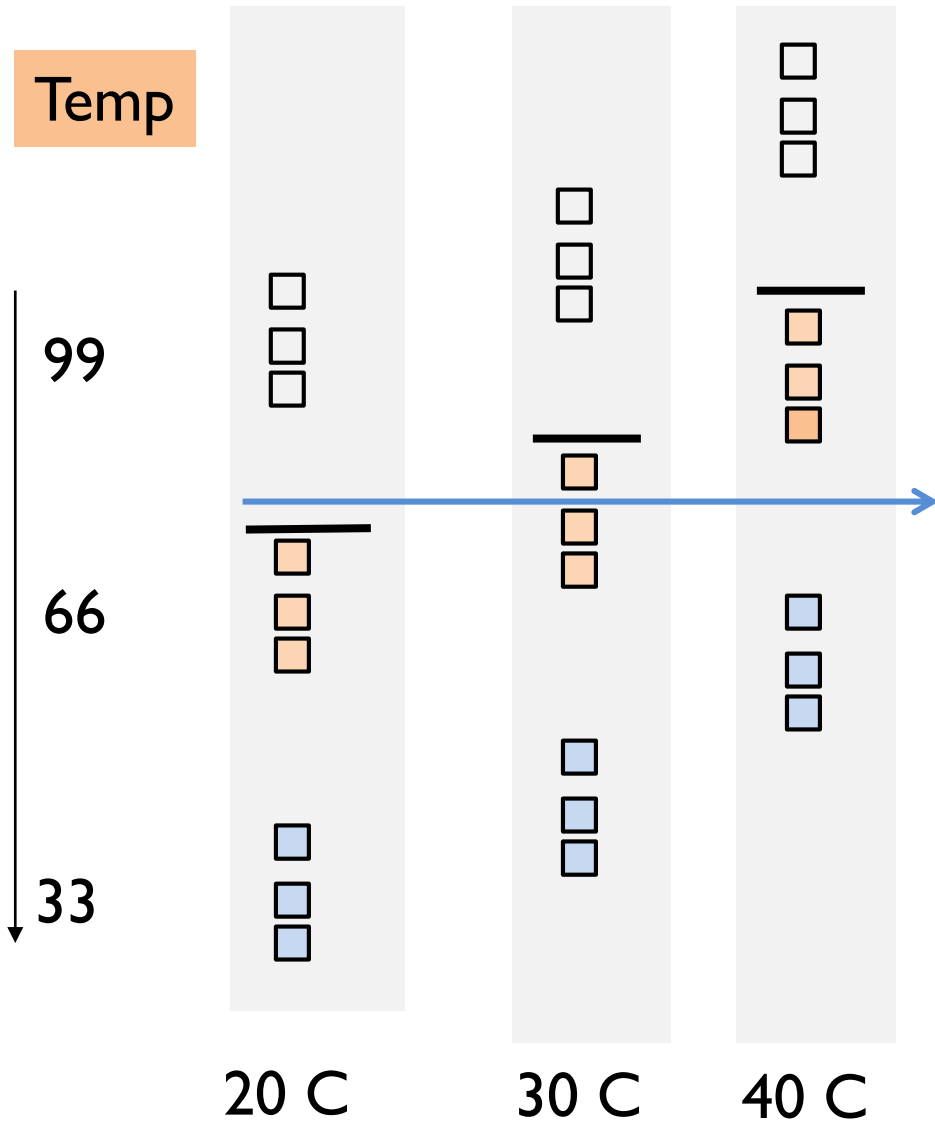
Two factor ANOVA

Full factorial:
2 factor, 3 level,
3 replicate experiment

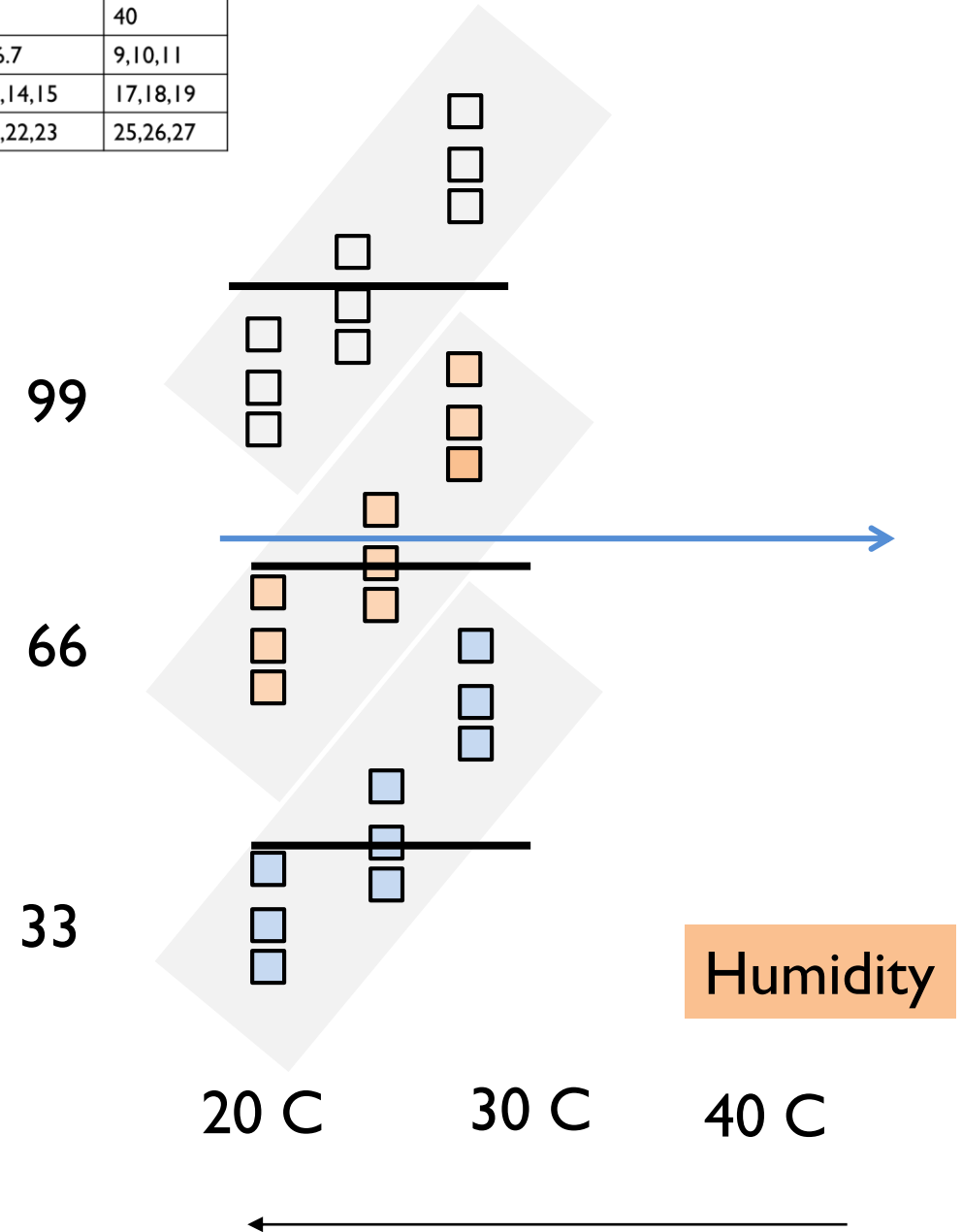
	Temperature (C)		
Humidity (%)	20	30	40
33	1,2,3	5,6,7	9,10,11
66	9,10,11	13,14,15	17,18,19
99	17,18,19	21,22,23	25,26,27



Two factor ANOVA



	Temperature (C)		
Humidity (%)	20	30	40
33	1,2,3	5,6,7	9,10,11
66	9,10,11	13,14,15	17,18,19
99	17,18,19	21,22,23	25,26,27



Two factor ANOVA

Full factorial:
2 factor, 3 level,
3 replicate experiment

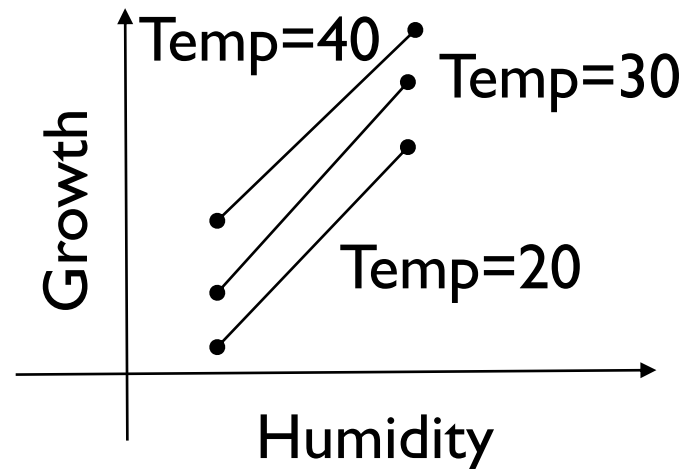
	Temperature (C)		
Humidity (%)	20	30	40
33	1,2,3	5,6,7	9,10,11
66	9,10,11	13,14,15	17,18,19
99	17,18,19	21,22,23	25,26,27

Excel/Minitab Analysis

	Sum of Squares	dof	Mean-square	F Ratio	Significance
Temp	312.66	3-1=2	312.66/2=156.33	156.33/1.0=156.33	0.000 (significant)
Humidity	1200.66	3-1=2	1200.66/2=600.33	600.66/1=600.33	0.000 (Significant)
Temp*Humidity	1.33	2x2=4	1.33/4=0.33	0.33/1.0=0.33	0.853 (insignificant)
Error	18.00	27-2-2-4=19	18.00/18=1		

Two factor ANOVA (Excel/Minitab Analysis)

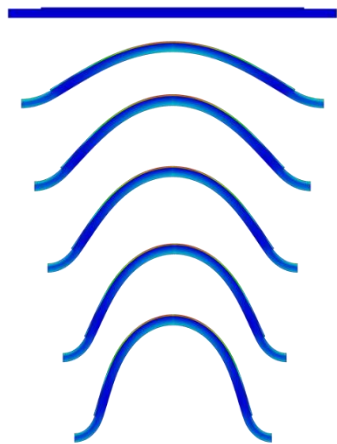
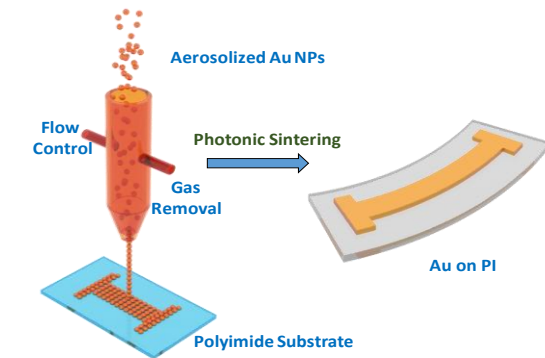
	Sum of Squares	dof	Mean-square	F Ratio	p-value
Temp	312.66	$3-1=2$	$312.66/2=156.33$	$156.33/1.0=156.33$	0.000 (significant)
Humidity	1200.66	$3-1=2$	$1200.66/2=600.33$	$600.66/1=600.33$	0.000 (Significant)
Temp*Humidity	1.33	$2 \times 2=4$	$1.33/4=0.33$	$0.33/1.0=0.33$	0.853 (insignificant)
Error	18.00	$27-2-2-4=19$	$18.00/18=1$		



No mutual interaction

Ref. Statistics Explained,
S. Mckillup, Cambridge Press

Multiple Factor ANOVA



Thickness (μm)	BR	BF	Resistance Change (Percent)				
			50	100	150	200	250
10	Half	Slow	46.5	52.61	66.3	91.58	149.6
10	Half	Fast	67.7	69.4	97.34	124.4	139.3
10	Full	Slow	92.975	174.45	232.45	252.64	275.3
10	Full	Fast	85.6	135.47	162.59	157.53	208.6
25	Half	Slow	22.4	23.57	24.87	29.14	28.9
25	Half	Fast	25.2	35.22	22.14	24.5	29.65
25	Full	Slow	24.7	32.89	54.68	78.23	95.63
25	Full	Fast	45.23	51.29	65.26	61.4	78.95

Field view

Thickness=2 (i.e. 10, 15), BR=2 (i.e. slow, fast)

BF=2 (Half and full), Cycles=5 (i.e. 50, 100, 150, 200, 250)

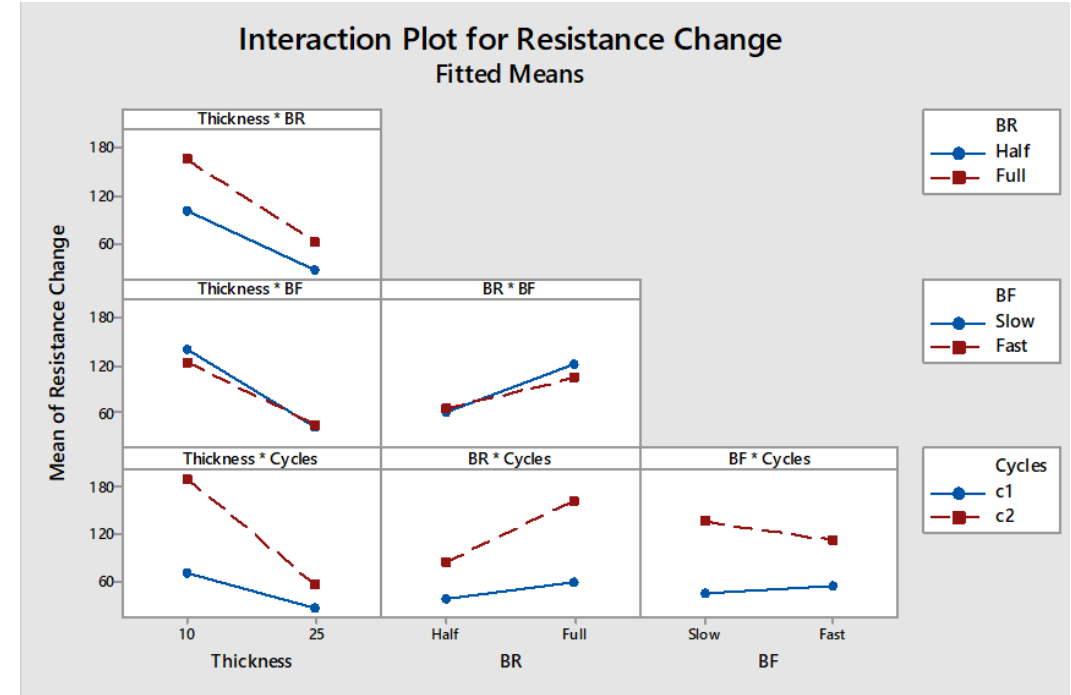
5 factors, (2,2,2,5) levels, single replicate DOE experiments

40 experiments (Need to use statistical package, e.g. Minitab)

Multiple Factor ANOVA (Continued)

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	79330.2	5666.4	1685.12	0.019
Linear	4	64198.5	16049.6	4772.93	0.011
Thickness	1	31944.0	31944.0	9499.67	0.007
BR	1	9887.1	9887.1	2940.27	0.012
BF	1	194.4	194.4	57.82	0.083
Cycles	1	22173.1	22173.1	6593.95	0.008
2-Way Interactions	6	14177.8	2363.0	702.71	0.029
Thickness*BR	1	915.3	915.3	272.19	0.039
Thickness*BF	1	311.3	311.3	92.58	0.066
Thickness*Cycles	1	8300.3	8300.3	2468.40	0.013
BR*BF	1	448.1	448.1	133.26	0.055
BR*Cycles	1	3145.1	3145.1	935.31	0.021
BF*Cycles	1	1057.6	1057.6	314.52	0.036
3-Way Interactions	4	953.8	238.5	70.91	0.089
Thickness*BR*BF	1	454.5	454.5	135.16	0.055
Thickness*BR*Cycles	1	85.2	85.2	25.34	0.125
Thickness*BF*Cycles	1	166.2	166.2	49.42	0.090
BR*BF*Cycles	1	247.9	247.9	73.74	0.074
Error	1	3.4	3.4		
Total	15	79333.5			



Check for p-values < 0.05

One way: Thickness, BR, and Cycles (BF does not matter on its own)

Two-way: Thickness/BR, Thickness/cycles, BR/cycles, BF/cycles

Three-way: Thickness, BR, BF (may be, close to 0.05, more experiments)

Conclusions

1. Design of experiment results are analyzed by ANOVA test to make sure that the effect of variables on the final result is statistically significant. Insignificant variables can be dropped to simplify analysis.
2. ANOVA generalizes hypothesis testing to continuous variables.
3. A positive test from Anova says one of the treatment is different from others – it does not say which one. With a positive result, one can do pair-wise comparison.
4. Simple Anova tests are easily done by calculator. More complicated Anova tests are best done by statistical packages, such as S or Minitab, etc.
5. With results of Anova at hand, the new design of experiments based on new Taguchi table must be performed.

Review Questions

1. What does the word ANOVA stand for? Who developed the technique?
2. How does ANOVA compare with standard hypothesis testing?
3. If an ANOVA test identifies correlation among the variables, how should one redo the Taguchi tables?
4. Can ANOVA analysis include discrete variables?
5. If there are 7 replicates and 5 treatments, how many samples are tested?
6. For 7 replicates and 5 treatments, what is the degree of freedom for the treatments? What about the samples?
7. An experiment involving single factor ANOVA can be analyzed by Excel. Is this correct?

References

The classical AVONA method is discussed in great detail in Chapter 13 and 14 of “Applied Statistics and Probability for Engineers, 3rd Edition, D.C. Montgomery and G. C. Runger, Wiley, 2003.

Hunter’s lectures on AVONA is also very enjoyable

<http://www.youtube.com/watch?v=k3n9iSB6Cns>

<http://www.youtube.com/watch?v=F05zZL3uyRo>

A slightly different approach that also reduces the number of experiments greatly is based on the response surface approach. It uses Newton-like algorithm to find the peaks/valleys of the response surface, see R. H. Myers and D.C. Montgomery, “Response Surface Methodology”, Wiley Interscience, 2002. This book discusses design of experiment in great detail.

For general reference see

Joan Fisher Box, “R.A. Fisher and the Design of Experiments, 1922-1926”, *The American Statistician*, vol. 34, no. 1, pp. 1-7, Feb. 1980.

F.Yates, “Sir Ronald Fisher and the Design of Experiments”, *Biometrics*, vol. 20, no. 2, In Memoriam: Ronald Aylmer Fisher, 1890-1962., pp. 307-321, (Jun. 1964.