STA305/1004 - Design of Scientific Studies

Lin Zhang

Department of Statistical Sciences, University of Toronto

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Agenda Today

- Blocking in factorial design
- Fractional factorial design
- Split plot design

- ▶ In a trial conducted using a 2³ design it might be desirable to use the same batch of raw material to make all 8 runs.
- ► Suppose that batches of raw material were only large enough to make 4 runs.

What can we do?

- ▶ In a trial conducted using a 2³ design it might be desirable to use the same batch of raw material to make all 8 runs.
- ► Suppose that batches of raw material were only large enough to make 4 runs.

What can we do? Blocking!

Consider a 2^3 design.

Run	1	2	3	12	13	23	123
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

Runs	Block
1, 4, 6, 7	ı
2, 3, 5, 8	Ш

How are the runs assigned to the blocks?

Consider a 2^3 design.

Run	1	2	3	12	13	23	123
							4
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

Runs	Block	4
1, 4, 6, 7		_
2, 3, 5, 8	П	+

- ▶ 4 is the block variable, denoted by B
- The blocking is said to be **generated** by the relationship $4 = 1 \times 2 \times 3$.

- Any systematic differences between the two blocks of four runs will be eliminated from all the main effects and two factor interactions.
- ► However, the three factor interaction is confounded with any batch (block) difference.
- ► The ability to estimate the three factor interaction separately from the block effect is lost.

Blocking Factorial Design - Effect Hierarchy Principle

Effect hierarchy principle

- Lower-order effects are more likely to be important than higher-order effects.
- ▶ Effects of the same order are equally likely to be important.

Why effect hierarchy principle?

- Higher order interactions are more difficult to interpret or justify physically.
- Investigators are less interested in estimating the magnitudes of these effects even when they are statistically significant.

Orthogonal Blocks

Why is x_4 a good blocking variable?

Run	1	2	3	4=123
	x_1	x_2	<i>X</i> ₃	<i>X</i> ₄
1	-1	-1	-1	-1
2	1	-1	-1	1
3	-1	1	-1	1
4	1	1	-1	-1
5	-1	-1	1	1
6	1	-1	1	-1
7	-1	1	1	-1
8	1	1	1	1

- ▶ It can be shown that $\mathbf{x}_1 \cdot \mathbf{x}_4 = 0$, $\mathbf{x}_2 \cdot \mathbf{x}_4 = 0$ and $\mathbf{x}_3 \cdot \mathbf{x}_4 = 0$.
- ▶ 4 does not interact with any main effect, namely, 1, 2 or 3.

- ► Suppose a researcher wants to arrange the 2³ design into four blocks.
- ▶ Two blocking variable: $B_1 = x_1x_2x_3$, $B_2 = x_2x_3$.

Run	1	2	3	4=123	5=23
	x_1	<i>X</i> ₂	<i>X</i> 3	X4	<i>X</i> 5
1	-1	-1	-1	-1	1
2	1	-1	-1	1	1
3	-1	1	-1	1	-1
4	1	1	-1	-1	-1
5	-1	-1	1	1	-1
6	1	-1	1	-1	-1
7	-1	1	1	-1	1
8	1	1	1	1	1

Exercise: What effects are B_1 and B_2 associated with?

Suppose a researcher wants to arrange the 2^3 design into four blocks.

Run	1	2	3	4=123	5=23
	x_1	<i>X</i> ₂	<i>X</i> ₃	<i>X</i> ₄	<i>X</i> ₅
1	-1	-1	-1	-1	1
2	1	-1	-1	1	1
3	-1	1	-1	1	-1
4	1	1	-1	-1	-1
5	-1	-1	1	1	-1
6	1	-1	1	-1	-1
7	-1	1	1	-1	1
8	1	1	1	1	1

Runs	Block	4	5
4, 6		_	_
1, 7	П	_	+
3, 5	Ш	+	_
2, 8	IV	+	+

Is there a problem with this block design? It is confounded with the main effect 1.

Arrange the 2^3 design into four blocks.

Run	1	2	3	4=123	5=23
	x_1	x_2	<i>X</i> ₃	<i>X</i> ₄	<i>X</i> ₅
1	-1	-1	-1	-1	1
2	1	-1	-1	1	1
3	-1	1	-1	1	-1
4	1	1	-1	-1	-1
5	-1	-1	1	1	-1
6	1	-1	1	-1	-1
7	-1	1	1	-1	1
8	1	1	1	1	1

- This blocking is confounded with the interaction term 123 and 23 by design.
- $x_4 = x_1x_2x_3$, $x_5 = x_2x_3$, the blocking is also confounded with $x_4x_5 = x_1x_2x_3x_2x_3 = x_1$
- \triangleright x_i 's are indicators, that is, $x_i = 1$ or -1. $x_i^2 = 1$.

- Any blocking scheme that confounds main effects with blocks should not be used.
- ▶ This is based on the assumption:

The block-by-treatment interactions are negligible.

- ► This assumption states that treatment effects do not vary from block to block.
- Without this assumption estimability of the factorial effects will be very complicated.

Two block variable $B_1 = 12$ and $B_2 = 13$.

Run	1	2	3	4=12	5=13
	x_1	<i>X</i> ₂	<i>X</i> 3	<i>X</i> 4	<i>X</i> 5
1	-1	-1	-1	1	1
2	1	-1	-1	-1	-1
3	-1	1	-1	-1	1
4	1	1	-1	1	-1
5	-1	-1	1	1	-1
6	1	-1	1	-1	1
7	-1	1	1	-1	-1
8	1	1	1	1	1

Runs	Block	4	5
2, 7	ı	_	_
3, 6	П	_	+
4, 5	Ш	+	_
1, 8	IV	+	+

Exercise: What effects is this blocking confounded with?

Generators and Defining Relations

- ▶ For a 2^k factorial design, to arrange it into 2^q blocks, we need q block variables and each block has 2^{k-1} factorial combinations.
- ▶ Let $B_1, B_2, ..., B_q$ be the block variables.
- ▶ Define $B_i = v_i$, where v_i is the factorial effect confounded with the *i*th blocking factor.
- The block design is confounded with all the possible products produced by B₁, B₂,..., B_q.
- ▶ There are $(2^q 1)$ possible combinations

In the arrange 2^3 factorial design into 4 blocks example:

- ▶ k = 3 and q = 2. Each block has $2^{3-2} = 2$ factorial combinations.
- \triangleright $B_1 = 12, B_2 = 13$
- ▶ The block design is confounded with $B_1 = 12$, $B_2 = 13$ and $B_1 \cdot B_2 = 23$

Generators and Defining Relations

Exercise: Consider a 2^5 factorial design. To arrange it into 8 blocks, consider the following two blocking schemes:

- \triangleright $B_1 = 135, B_2 = 235, B_3 = 1234$
- \triangleright $B_1 = 12, B_2 = 13, B_3 = 45$

Questions:

- 1. What are the effects that are confounded with each blocking scheme?
- 2. Which design is better?

Generators and Defining Relations

Exercise: Consider a 2^5 factorial design. To arrange it into 8 blocks, consider the following two blocking schemes:

- \triangleright $B_1 = 135, B_2 = 235, B_3 = 1234$
- \triangleright $B_1 = 12, B_2 = 13, B_3 = 45$

Fractional Factorial Design

Fractional Factorial Design

- ▶ A 2^k full factorial requires 2^k runs.
- ▶ Full factorials are seldom used in practice for large k ($k \ge 7$).
- ► For economic reasons, fractional factorial designs that consist of a fraction of the full factorial designs, are used.

- A chemist in an industrial development lab was trying to formulate a household liquid product using a new process.
- ► The liquid had good properties but was unstable.
- The chemist wanted to synthesize the product in hope of hitting conditions that would give stability, but without success.
- ► The chemist identified four important influences:
 - A: acid concentration
 - B: catalyst concentration
 - ► C: temperature
 - ▶ D: monomer concentration
- ▶ A full factorial design requires $2^4 = 16$ runs.
- ▶ The chemist can only afford 8 runs.

The chemist's 8 run fractional factorial design.

test	Α	В	С	D	у
1	-1	-1	-1	-1	20
2	1	-1	-1	1	14
3	-1	1	-1	1	17
4	1	1	-1	-1	10
5	-1	-1	1	1	19
6	1	-1	1	-1	13
7	-1	1	1	-1	14
8	1	1	1	1	10

- ▶ The signs of the ABC interaction is used to accommodate factor D.
- The column for D is to estimate the main effect of D and also for interaction effect of ABC.
- ▶ The main factor D is said to be **aliased** with the ABC interaction.
- ► This is called a 2^{3-1} design. In general, a 2^{k-p} design is a $\frac{1}{2^p}$ fraction of a 2^k design using 2^{k-p} runs.

The aliasing relation is denoted by

$$D = ABC$$

- Aliasing of the effects is a price one must pay for choosing a smaller design.
- ► The 2⁴⁻¹ design has only 7 degrees of freedom for estimating factorial effects, it cannot estimate all 15 factorial effects among the factors A, B, C, D.

- ► A simple calculus is available to show the consequences of any proposed blocking arrangement.
- ▶ If any column in a 2^k design are multiplied by themselves a column of plus signs is obtained. This is denoted by the symbol *I*.

$$I = 11 = 22 = 33 = 44 = 55,$$

where, for example, 22 means the product of the elements of column 2 with itself.

Any column multiplied by I leaves the elements unchanged. So, I3 = 3.

- ▶ The equation I = ABCD is called the **defining relation** of the 2^{4-1} design.
- The design is said to have resolution IV because the defining relation consists of the "word" ABCD, which has "length" 4.
- ▶ Multiplying both sides of I = ABCD by column A

$$A = A \times I = A \times ABCD = BCD$$
,

the relation A = BCD is obtained.

▶ A is aliased with the BCD interaction. Following the same method all 7 aliasing relations can be obtained.

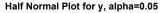
Example - 2⁴ design for studying a chemical reaction

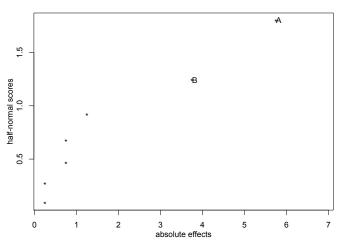
```
fact.prod <- lm(y~A*B*C*D,data=tab0602)
fact.prod1 <- aov(y~A*B*C*D,data=tab0602)
round(2*fact.prod$coefficients,2)</pre>
```

```
(Intercept)
                          В
                                                           A:B
     29.25
                                  -1.25
                                                           0.25
              -5.75
                       -3.75
                                               0.75
       B:C
                A:D
                        B:D
                                    C:D
                                              A:B:C
                                                          A:B:D
     -0.25
                 NΑ
                         NΑ
                                                            NΑ
                                     NΑ
                                                 NΑ
     B:C:D
           A:B:C:D
        NΑ
                 NA
```

Example - 2⁴ design for studying a chemical reaction

DanielPlot(fact.prod,half = T)

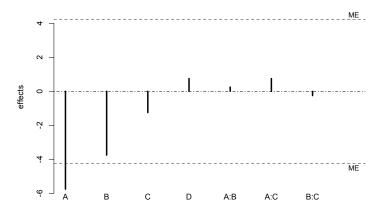




Example - 2⁴ design for studying a chemical reaction

LenthPlot(fact.prod1)

alpha PSE ME SME 0.050000 1.125000 4.234638 10.134346



Split Plot Design

Split Plot Design

Split plot designs were originally developed for agriculture by R.A. Fisher and F. Yates.

- ▶ Some factors need to be applied to larger plots as compared to other factors.
- For example, if type of irrigation method and the type of fertilizer used are two factors, then irrigation requires a larger plot.

Split Plot Design

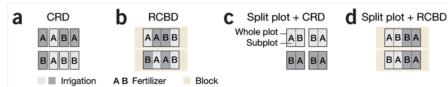
From

Points of Significance: Split plot design

Naomi Altman & Martin Krzywinski

Nature Methods 12, 165-166 (2015) | doi:10.1038/nmeth.3293

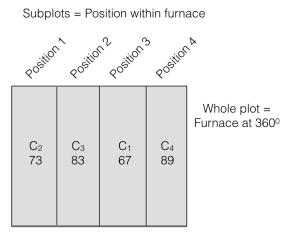
Published online 26 February 2015



(a) In CRD, levels of irrigation and fertilizer are assigned to plots of land (experimental units) in a random and balanced fashion. (b) In RCBD, similar experimental units are grouped (for example, by field) into blocks and treatments are distributed in a CRD fashion within the block. (c) If irrigation is more difficult to vary on a small scale and fields are large enough to be split, a split plot design becomes appropriate. Irrigation levels are assigned to whole plots by CRD and fertilizer is assigned to subplots using RCBD (irrigation is the block). (d) If the fields are large enough, they can be used as blocks for two levels of irrigation. Each field is composed of two whole plots, each composed of two subplots using RCBD (blocked by field) and fertilizer assigned to subplots using RCBD (blocked by irrigation).

- ▶ An experiment of corrosion resistance of steel bars treated with four different coatings *C*₁, *C*₂, *C*₃, *C*₄ was conducted.
- ► Three furnace temperatures were investigated.
- Four differently coated bars randomly arranged in the furnace within each heat.
- ▶ Positions of the coated steel bars in the furnace randomized within each heat.
- ► Furnace temperature was difficult to change so heats were run in systematic order shown.
- ▶ The primary interests were the comparison of coatings and how they interacted with temperature.

The split-plot experiment of corrosion resistance is shown for the first replicate at 360° .



- ▶ There are I = 3 furnace temperatures arranged in n = 2 replications.
- Each furnace temperature is called a whole plot.
- ▶ The whole plot treatments are $T_1 = 360^\circ$, $T_2 = 370^\circ$, $T_3 = 380^\circ$.
- ▶ Within each furnace temperature there are J = 4 subplots.
- ▶ The four sub plot treatments C_1 , C_2 , C_3 , C_4 are randomly applied to the sub plots within each whole plot.

Temperature	Position 1	Position 2	Position 3	Position 4
360°	C_2	<i>C</i> ₃	C_1	C ₄
370°	C_1	<i>C</i> ₃	C ₄	C_2
380°	<i>C</i> ₃	C_1	C_2	C_4

Temperature	Position 1	Position 2	Position 3	Position 4
380°	C ₄	<i>C</i> ₃	C_2	C_1
370°	C_4	C_1	C_3	C_2
360°	C_1	C_4	C_2	<i>C</i> ₃

Analysis of the whole plots:

df
2 - 1
3 - 1
(3-1)(2-1)
$3 \cdot 2 - 1$

Analysis of the sub plots:

Source	df
Between whole plots	$3 \cdot 2 - 1$
Coatings	4 - 1
Coatings $ imes$ Temperature	(4-1)(3-1)
Sub plot Error	3(2-1)(4-1)
Total	$3 \cdot 2 \cdot 4 - 1$

head(tab0901)

	run	${\tt heats}$	coating	position	replication	resistance
1	r1	T360	C2	1	1	73
2	r1	T360	C3	2	1	83
3	r1	T360	C1	3	1	67
4	r1	T360	C4	4	1	89
5	r2	T370	C1	1	1	65
6	r2	T370	C3	2	1	87

- ▶ The numerical calculations for the ANOVA of a split-plot design are the same as for other balanced designs (designs where all treatment combinations have the same number of observations) and can be performed in R or with other statistical software.
- Experimenters sometimes have difficulty identifying appropriate error terms.

spfurcoat1 <- aov(resistance~ replication*heats*coating,data=tab0901)
summary(spfurcoat1)</pre>

	Df	Sum Sq	Mean Sq
replication	1	782	782
heats	2	26519	13260
coating	3	4289	1430
replication:heats	2	13658	6829
replication:coating	3	254	85
heats:coating	6	3270	545
replication:heats:coating	6	867	144

spfurcoat1 <- aov(resistance~ replication*heats*coating,data=tab0901)
summary(spfurcoat1)</pre>

	\mathtt{Df}	Sum Sq	Mean Sq
replication	1	782	782
heats	2	26519	13260
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replication:heats	2	13658	6829
replication:coating	3	254	85
heats:coating	6	3270	545
replication:heats:coating	6	867	144

The whole plot effects are 'replication' and 'replication:heats'. The ANOVA table for the whole plots is:

Source	DF	SS	MS
replication	1	782	782
heats	2	26519	13260
replication: heats(whole plot error)	2	13658	6829

The whole plot mean square error is 6829, which measures the differences between the replicated heats at the three different temperatures.

spfurcoat1 <- aov(resistance~ replication*heats*coating,data=tab0901)
summary(spfurcoat1)</pre>

\mathtt{Df}	${\tt Sum} \ {\tt Sq}$	Mean Sq
1	782	782
2	26519	13260
3	4289	1430
2	13658	6829
3	254	85
6	3270	545
6	867	144
	1 2 3 2 3 6	2 26519 3 4289 2 13658 3 254 6 3270

The subplot effects are:

Source	DF	SS	MS
coating	3	4289	1430
coating:heats	6	3270	545
Sub plot error	9	1121	124.6

- ► The subplot mean square error is (254 + 867)/(3 + 6) = 124.6.
- The subplot error measures to what extent the coatings give dissimilar results within each of the replicated temperatures.

```
spfurcoat <- aov(resistance~ replication + heats + replication:heats</pre>
               + coating + heats:coating
               +Error(heats/replication),data=tab0901)
summary(spfurcoat)
Error: heats
     Df Sum Sq Mean Sq
heats 2 26519 13260
Error: heats:replication
                Df Sum Sq Mean Sq
                      782
                             782
replication 1
replication:heats 2 13658
                            6829
Error: Within
             Df Sum Sq Mean Sq F value Pr(>F)
             3 4289 1429.7 11.480 0.00198 **
coating
heats:coating 6 3270 545.0 4.376 0.02407 *
Residuals 9 1121 124.5
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
```

The values for the split plot experiment can be put into one ANOVA table.

Source	DF	SS	MS	F	<i>P</i> (> <i>F</i>)
Whole plot:					
replication	1	782	782	782/6829 = 0.12	0.77
heats	2	26519	13260	13260/6829=1.9	0.34
replication $ imes$ heats	2	13658	6829		
(whole plot error)					
Subplot:					
coating	3	4289	1430	11.48	0.002
coating imes heats	6	3270	545	4.376	0.02
Subplot error	9	1121	124.5		

ANOVA table - General Form

- ► Suppose that a split plot experiment is conducted with whole factor plot *A* with *I* levels and sub plot factor *B* with *J* levels.
- ▶ The experiment is replicated *n* times.

Source	DF	SS
Whole plot:		
replication	n-1	SS_{Rep}
Α	I-1	SS_A
replication \times A	(n-1)(I-1)	SS_W
(whole plot error)		
Subplot:		
В	J-1	SS_B
$A \times B$	(I-1)(J-1)	$SS_{A \times B}$
Subplot error	I(J-1)(n-1)	SSs

Split plot - WRONG ANOVA

furcoatanova <- aov(resistance~heats*coating,data=tab0901)</pre> summary(furcoatanova)

```
Df Sum Sq Mean Sq F value Pr(>F)
             2 26519 13260 10.226 0.00256 **
heats
           3 4289 1430 1.103 0.38602
coating
heats:coating 6 3270 545 0.420 0.85180
Residuals 12 15560 1297
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
```

The two-way ANOVA shows that there is no evidence of a difference in the four coatings, evidence of a difference between temperatures, and no evidence of an interaction between temperature and coating.

Split plot - WRONG ANOVA

What happened?

- ▶ The two factors temperature and coating use different randomization schemes and the number of replicates is different for each factor.
- ► The subplot factor, coating, restricted randomization to the four positions within a given temperature (whole plot).
- Therefore, the error should consist of two parts: whole plot error and subplot error.
- In order to test the significance of the whole plot factor and the subplot factor, we need the mean squares with the whole plot error component and subplot error component, respectively.

Split plot - WRONG ANOVA

The (incorrect) two-way ANOVA model is

$$y_{ijk} = \eta + \alpha_i + \beta_j + (\alpha \beta)_{ij} + \epsilon_{ijk}, \ \epsilon_{ijk} \sim N(0, \sigma^2)$$

 y_{ijk} is the observation for the kth replicate of the ith level of factor A and the jth level of factor B. (adapted from Wu and Hamada)

Split plot ANOVA

The correct model is

$$y_{ijk} = \eta + \tau_k + \alpha_i + (\tau \alpha)_{ki} + \beta_j + (\alpha \beta)_{ij} + (\tau \beta)_{kj} + (\tau \alpha \beta)_{kij} + \epsilon'_{ijk}, \ \epsilon'_{ijk} \sim N(0, \sigma^2)$$

$$i = 1, ..., I; j = 1, ..., J; k = 1, ..., n.$$

 y_{ijk} is the observation for the kth replicate of the ith level of factor A and the jth level of factor B.

Whole plot effects

- $ightharpoonup au_k$ is the effect of the kth replicate.
- $\triangleright \alpha_i$ is the *i*th main effect for A
- $(\tau \alpha)_{ki}$ is the (k, i)th interaction effect between replicate and A. This is the whole plot error term.

Subplot effects

- \triangleright β_i is the *j*th main effect of B
- $(\alpha\beta)_{ij}$ is the (i,j)th interaction between A and B.
- $(\tau\beta)_{ki}$ is the (k,j)th interaction between the replicate and B.
- $(\tau \alpha \beta)_{kij}$ is the (k, i, j)th interaction between the replicate, A, and B.
- $ightharpoonup \epsilon'_{ijk}$ is the error term.

The term $\epsilon_{kij} = (\tau \beta)_{kj} + (\tau \alpha \beta)_{kij} + \epsilon'_{ijk}$ is the subplot error term.

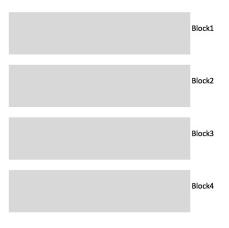
What is a split plot?

- A split-plot can be thought of as a blocked experiment where the blocks themselves serve as experimental units for a subset of the factors.
- Corresponding to two levels of experimental units are two levels of randomization.
- One randomization to determine assignment to whole plots.
- ► The randomization of treatments to split-plot experimental units occurs within each plot.

Randomizing a split plot experiment

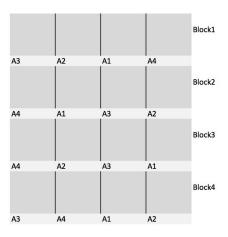
The three steps in randomizing a basic split-plot experiment consisting of 5 blocks (replicates), 4 levels of whole plot factor A, and 8 levels of split-plot factor B are:

1. Division of experimental area or material into five blocks



Randomizing a split plot experiment

2. Randomization of four levels of whole plot factor A to each of the five blocks.



Randomizing a split plot experiment

3. Randomization of eight levels of split plot factor B within each level of whole plot factor A.

B3	B6	B8	B8	
B7	B7	B7	B7	Block1
B6	B5	B1	B4	
B2	B3	B6	B3]
B4	B1	B3	B6]
B1	B2	B4	B5	
B5	B4	B2	B1]
B8	B8	B5	B2	
A3	A2	A1	A4	
B7	B7	B5	B4	
B8	B5	B2	B7	Block2
B3	B6	B1	B8	
B1	B1	B7	B1	
B2	B4	B4	B5	
B5	B8	B6	B2	
B6	B2	B8	B6	
B4	B3	B3	B3	
A4	A1	A3	A2	
B2	B4	B6	B8	
B5	B2	B3	B3	Block3
B3	B3	B5	B4	
B6	B1	B7	B2]
B8	B8	B4	B1	
B7	B5	B2	B5	
B1	B6	B8	B7	
B4	B7	B1	B6	

Split-plot designs versus Factorial Designs

How does the split-plot design compare with a $3\cdot 4$ factorial design of coating and temperature?

In the factorial design:

- An oven temperature-coating combination would be randomly selected then we would obtain a corrosion resistance measure.
- Then randomly select another oven temperature-coating combination and obtain another corrosion resistance measure until we have a resistance measure for all 12 oven temperature-coating combinations.
- ▶ To run each combination in random order would require adjusting the furnace temperature up to 24 times (since there were two replicates) and would have resulted in a much larger variance.

Split plot

- is like a randomized block design (with whole plots as blocks) in which the opportunity is taken to introduce additional factors between blocks.
- ▶ In this design there is only one source of error influencing the resistance.

Split-plot designs versus Factorial Designs

There are two different experimental units:

- ► The six different furnace heats, called whole plots.
- The four positions within each furnace heat, called subplots, where the differently coated bars could be placed in the furnace.
- Misleading to treat as if only one error source and one variance.
- Two different experimental units: six furnace heats (whole plots); and four positions (subplots) where different coated bars are placed in furnace.
- ▶ Two different variances: σ_W^2 for whole plots and σ_S^2 for subplots.
- It would be misleading to treat as if only one error source and one variance.

Split-plot designs versus Factorial Designs

- Achieving and maintaining a given temperature in this furnace was very imprecise.
- ► The whole plot variance, measuring variation from one heat to another, was expected to be large.
- ► The subplot variance measuring variation from position to position, within a given heat, was expected to be small.
- ► The subplot effects and subplot-main plot interaction are estimated using with the same subplot error.

Why choose a split plot design?

- ► Two considerations important in choosing an experimental design are feasibility and efficiency.
- ▶ In industrial experimentation a split-plot design is often convenient and the only practical possibility.
- This is the case whenever there are certain factors that are difficult to change and others that are easy to change.
- In this example changing the furnace temperature was difficult to change; rearranging the positions of the coated bars in the furnace was easy to change.

Take-home Message

- Fractional factorial design
- ► Split plot
- Run and understand the R code in the notes
- ▶ Work on the exercises in the lecture notes and online notes.
- Online notes:

```
http://utstat.toronto.edu/~nathan/teaching/STA305/classnotes/week10/sta305-classnotes-week10.html
http://utstat.toronto.edu/~nathan/teaching/STA305/classnotes/week11/sta305-week11-classnotes.html
```

Information on the Final Exam

- ► Time: 19:00 22:00, Thursday, August 16, 2018
- ▶ Location: EX 100
- ► The final exam is cumulative, covering material from Lecture 1 - Lecture 11 inclusive.
- ► Five questions, each worth 30 marks.
- Aid sheet will be posted on Thursday (August 9) before lecture
- You will only be tested on the materials that Tiffany and I covered, including (but not limited to) concepts, formulas, proofs, derivations, R code, applications and exercises.

Information on the Final Exam

Office hours for the final:

- ▶ Location: SS 623B
- ► Lin: Tue 10a-1p (Aug 14); Thur 10a-12p (Aug 16).
- ▶ Jimmy: Wed 3-5p (Aug 15).
- ▶ Bo: Thur 4-6p (Aug 16).

Regular office hours on Tue and Thur for the week of August 13 are canceled.

Thank you and best luck on final!