

IMS Medallion Lecture, JSM, Washington DC, August 2009

From R. A. Fisher to Microarrays

Why 70 Year Old Theory is Relevant Today

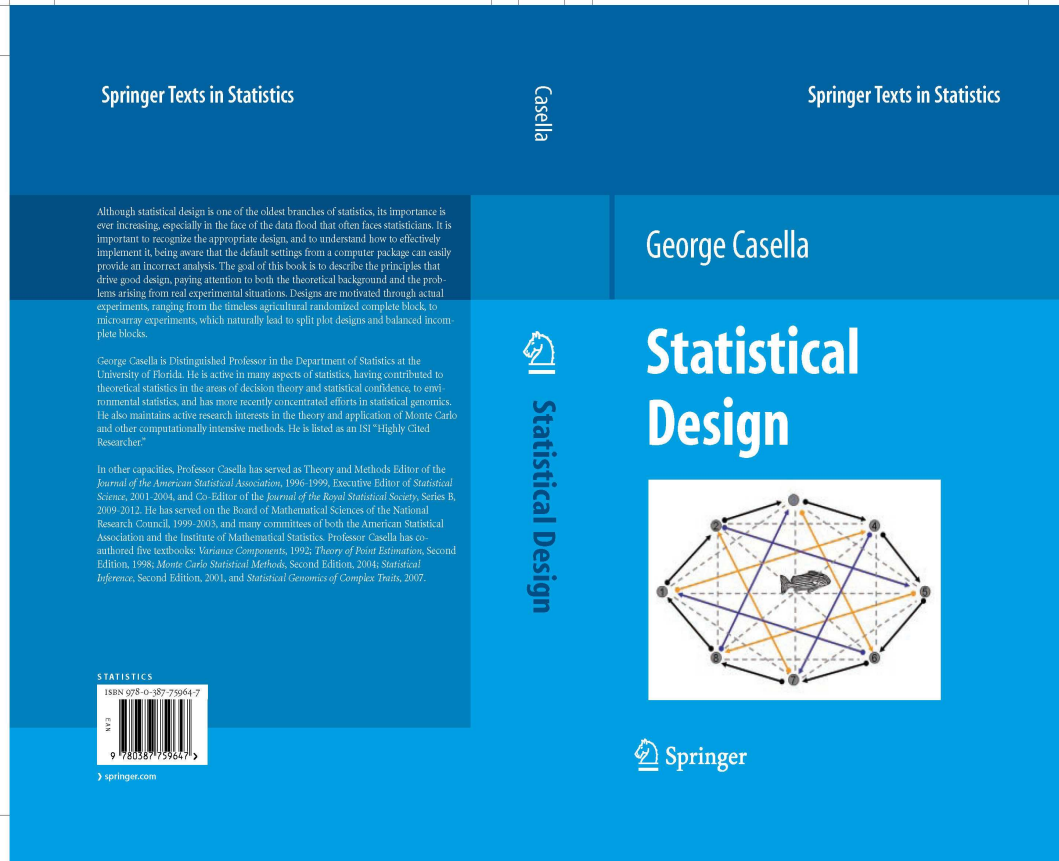
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Overview

- ▶ From the Field to the Lab
- ▶ Getting the Errors Correct
- ▶ Revisiting the Field and the Lab
- ▶ Replication - True and Technical
 - There is nothing here that you don't already know
 - (or knew)
 - but maybe not in this context
- ▶ BIBDs and Their Variations
- ▶ Splitting the Plot
- ▶ Lightning Round
- ▶ Conclusions

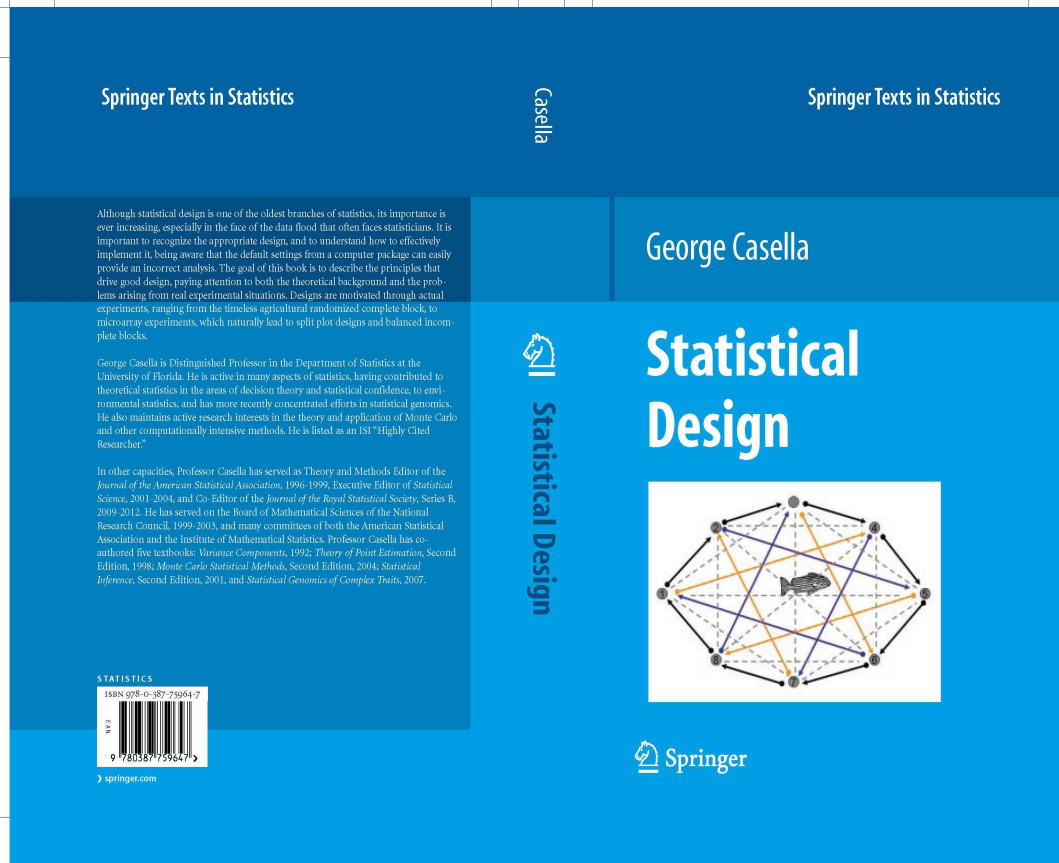
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This is stuff I learned when writing this

▷ Shameless Advertising



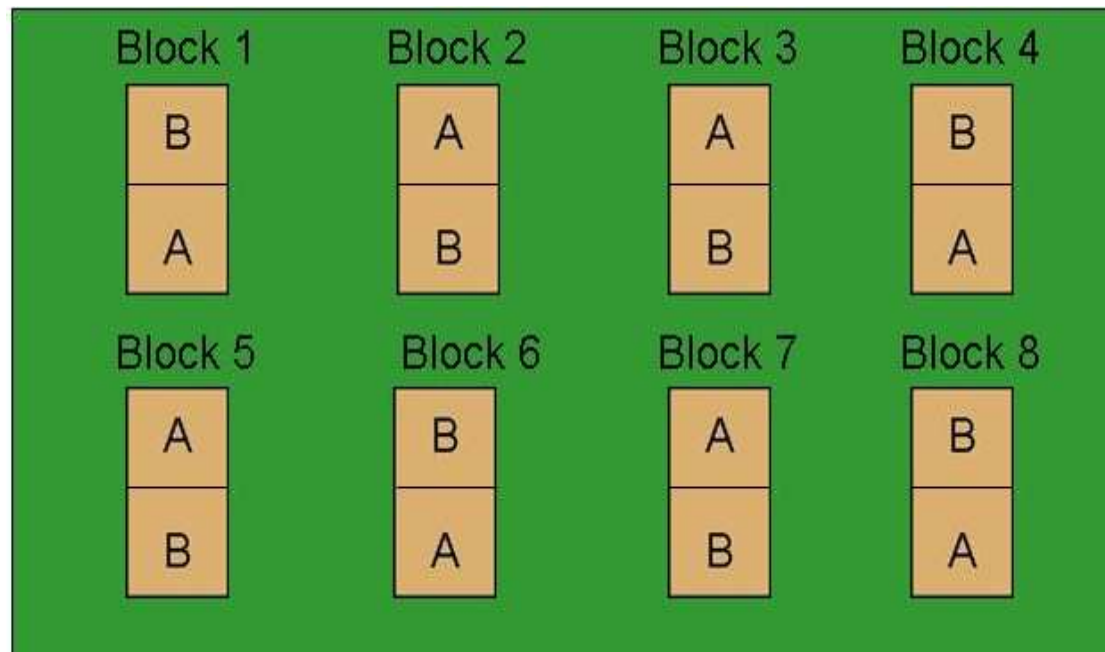
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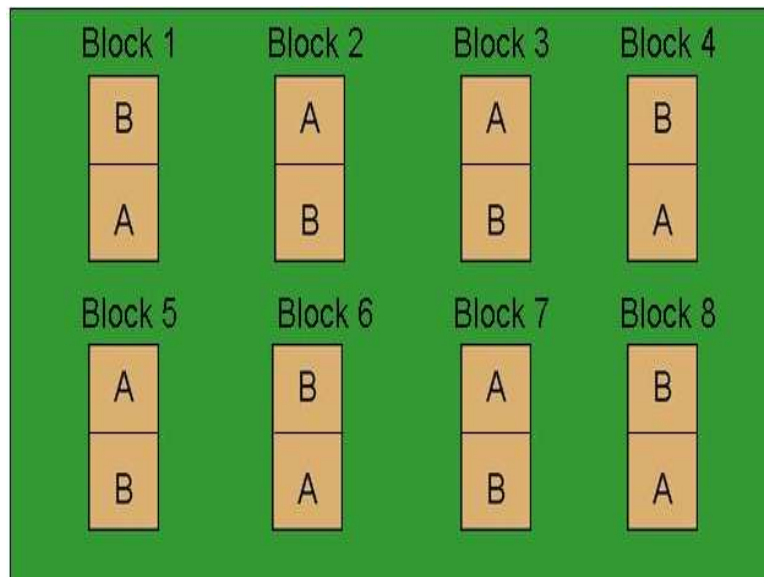
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A Classic Field Experiment

► The Field Plot Design might be



Analysis



Source	df
Blocks	7
Treatments	1
$T \times B$	7

H_0 : No Treatment Effect

$$F = \frac{MS(\text{Trts})}{MS(T \times B)}$$

The Denominator

- ▶ Although we talk of tests here
- ▶ It is all about the denominator

▷ If

$$F = \frac{MS(\text{Trts})}{MS(T \times B)}$$

▷ A confidence interval on treatment differences is

$$\text{Trt}_i - \text{Trt}_j \in \bar{Y}_i - \bar{Y}_j \pm t \sqrt{MS(T \times B)}$$

Where t is a t cutoff with $MS(T \times B)$ degrees of freedom

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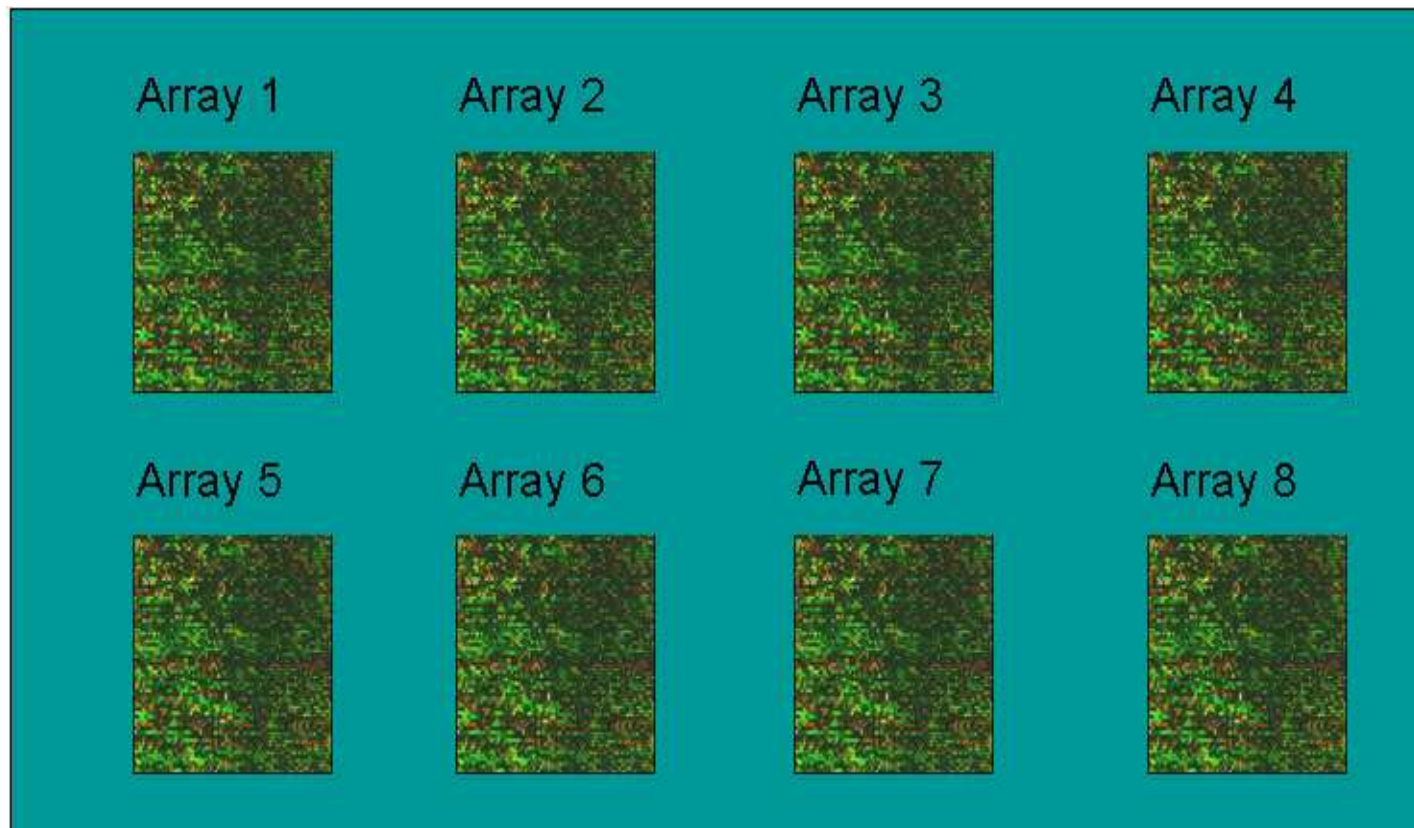
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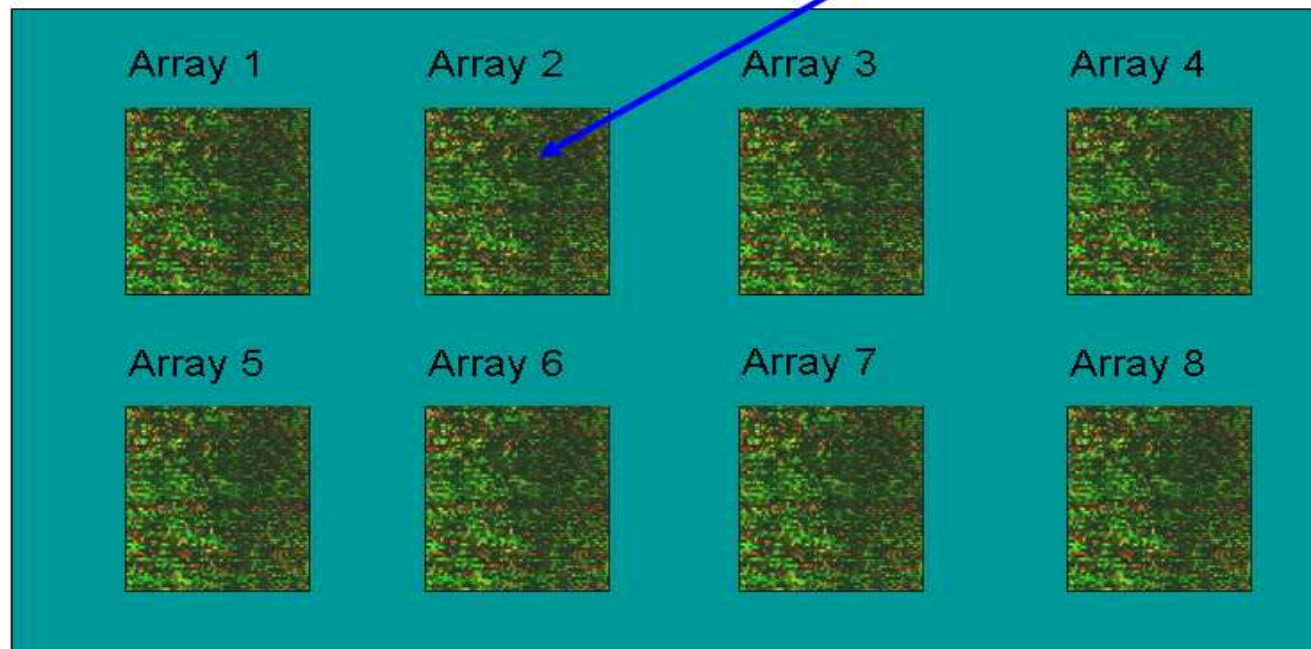
A (Now) Classic Microarray Experiment

► The Microarray Design might be



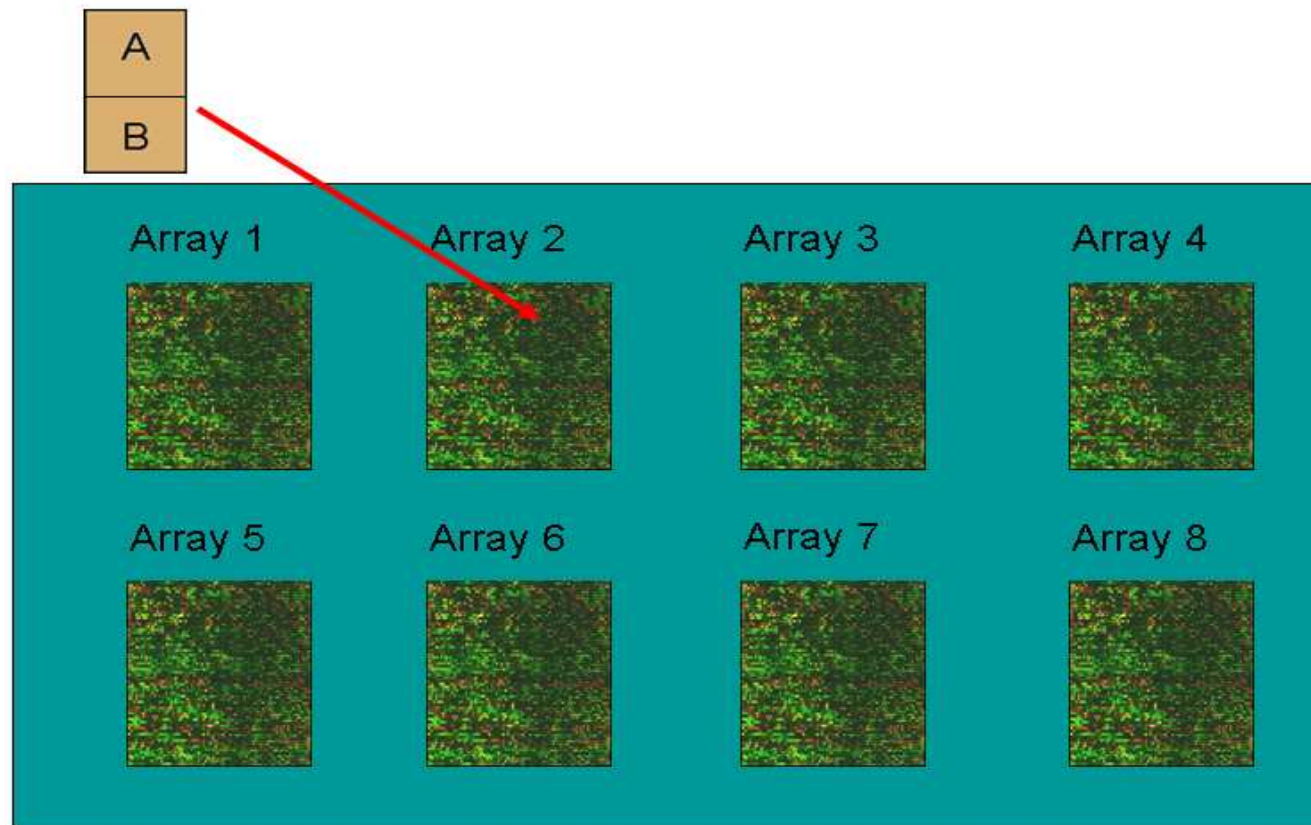
A Two-Dye Array

But what is in here??

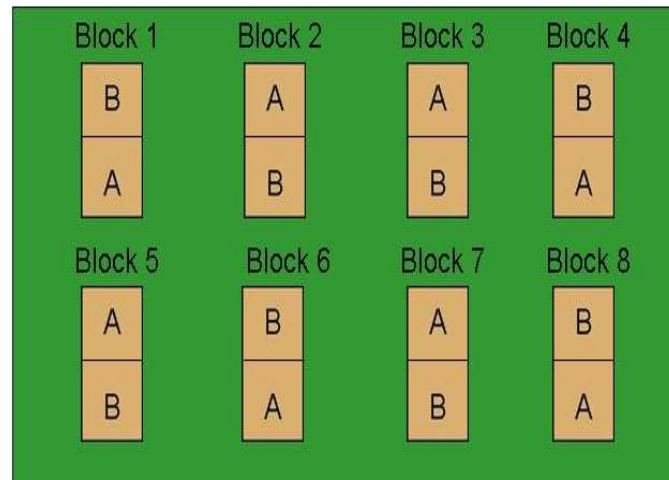


▷ The treatment comparisons!

A Randomized Block Design



▷ Look familiar?



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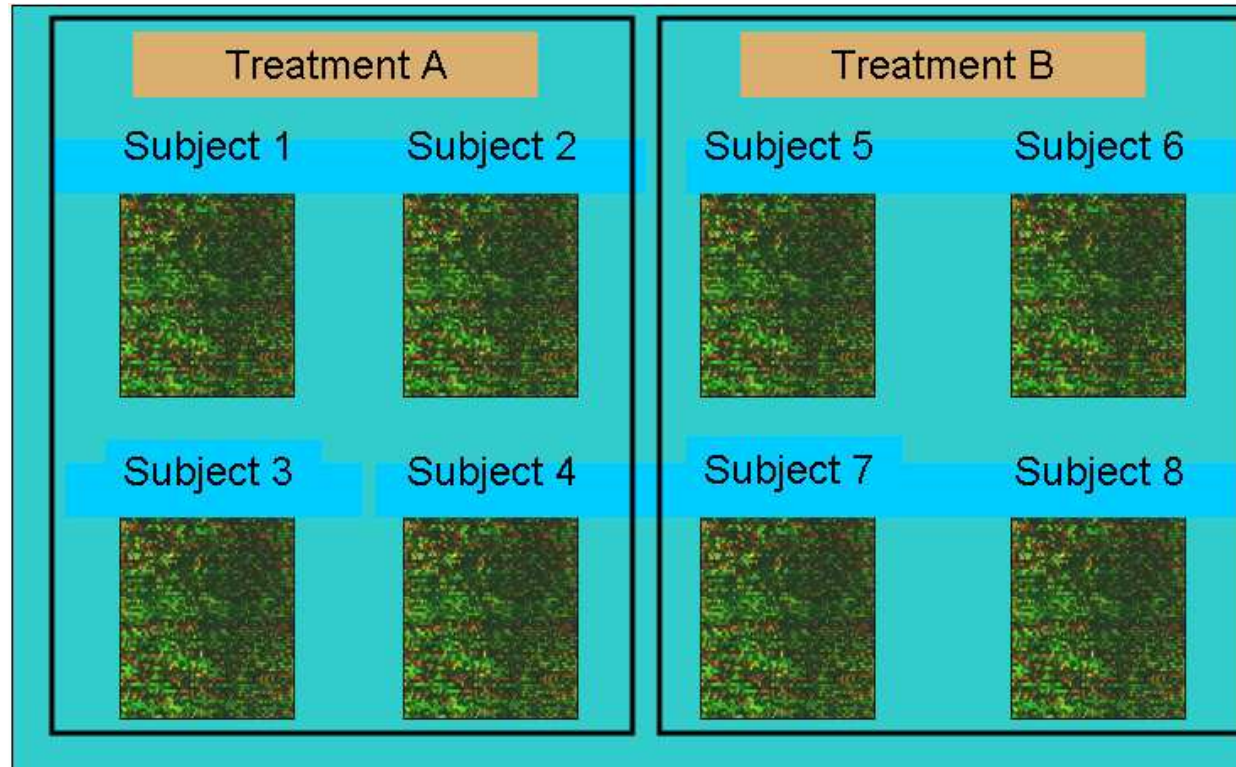
“Get it right for one gene”

Two-Dye Systems

- ▶ A two-dye system
 - ▷ Leads to a blocking design, with blocks = subjects
 - ▷ Each block can have two treatments
 - ▷ Error term is from the **Treatment \times Subject Interaction**

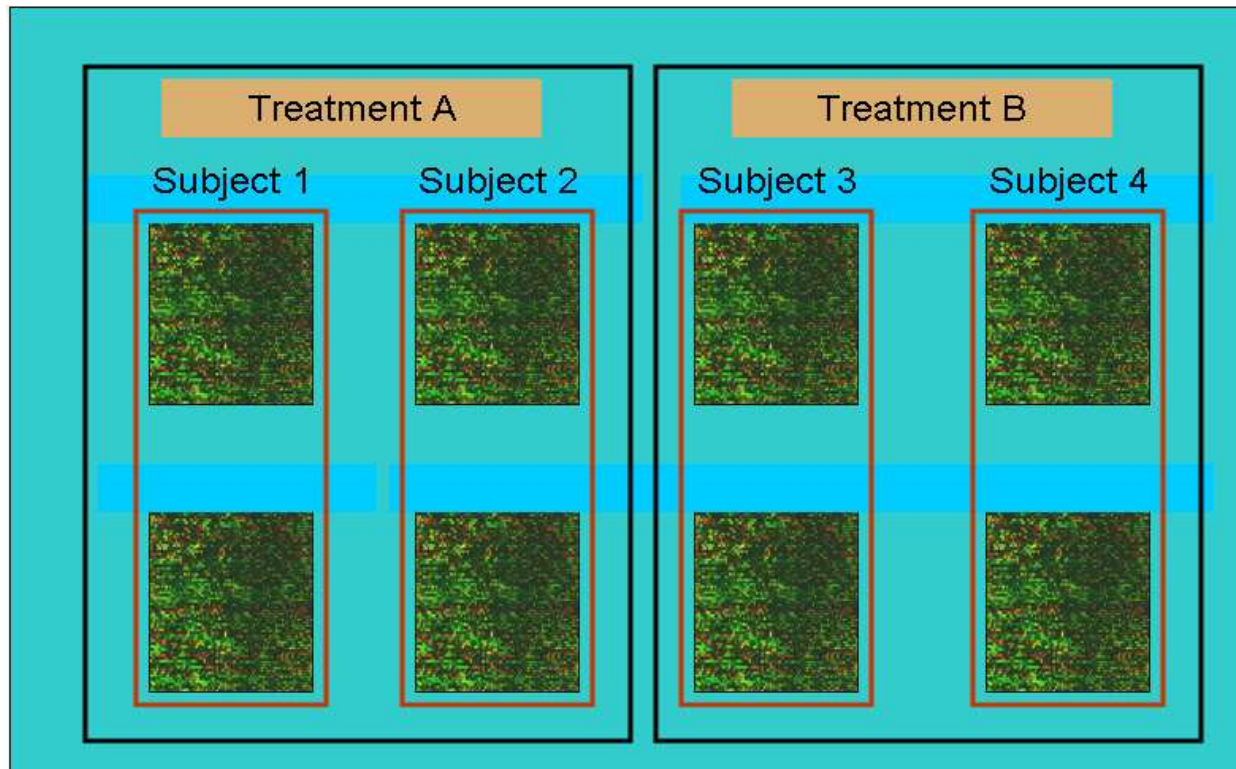
- ▶ Oligo arrays (Affymetrix) are a bit different.....

A Single Dye System

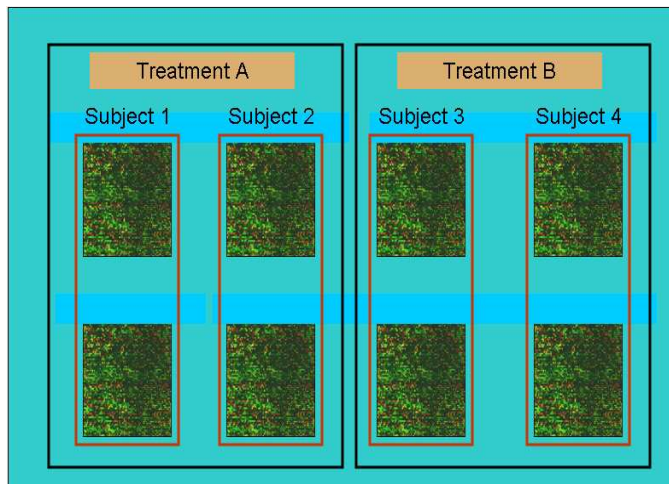
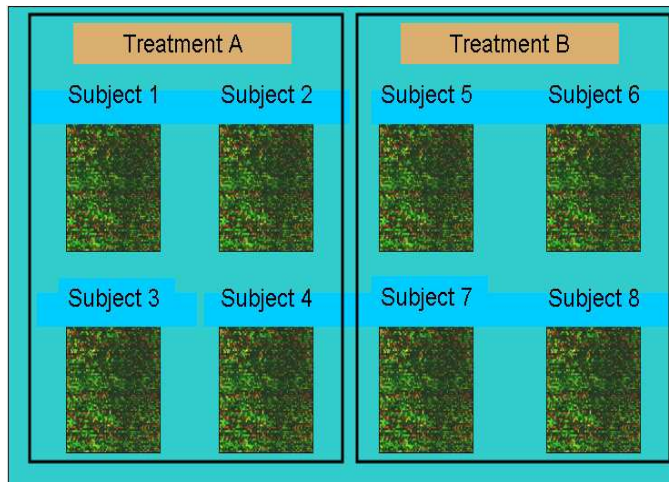


► A oneway anova

Avoid This Mistake



► A nested design - lost degrees of freedom



Oneway

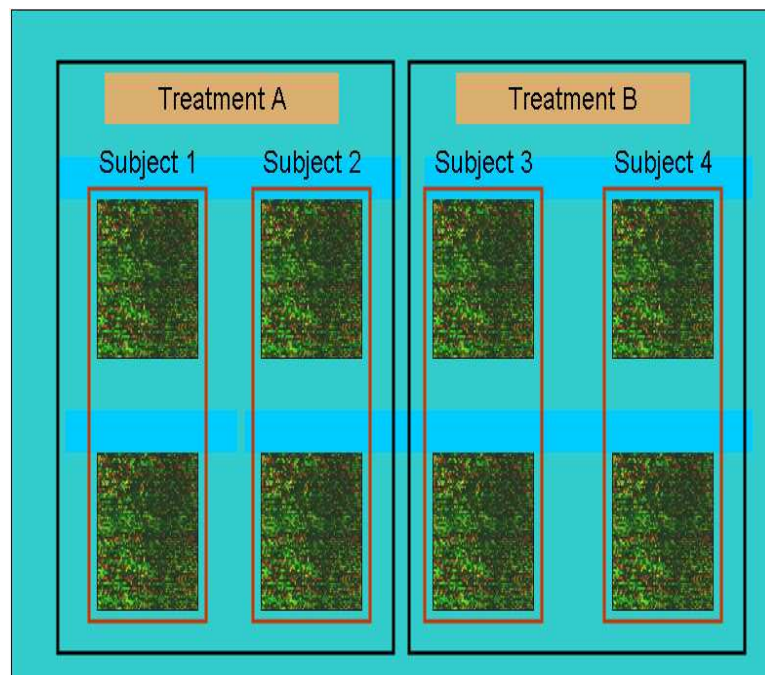
Source	df
Treatments	1
Subjects (in Treatments)	6

Nested

Source	df
Treatments	1
Subjects (in Treatments)	2
Arrays (in Subjects)	4

Error df in Red

Analysis of the Nested Design



Source	df
Treatments	1
Subjects (in Treatments)	2
Arrays (in Subjects)	4

- ▶ These are **Technical Reps**
- ▶ They measure **Array Variability**
- ▶ Useless for **Treatment Variability**

Design and Analysis

- ▶ Remember - We are talking of **Design**, not **Analysis**
 - ▷ We can design for one gene
 - ▷ Analysis is a bit more complicated
 - ▷ Often need to consider all (or a group of) genes
- ▶ But - a good design always helps the analysis
- ▶ Also - this talk is not just about microarrays
 - ▷ It is about Design Principles
 - ▷ Application in Life Sciences, Social Sciences, etc...

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WWSD

- ▶ OR, why do I need statistics when I have a computer?
- ▶ Watch out for the default analysis
- ▶ Even more scary when the computer becomes the teacher!
 - ▷ This is not the computer's fault
 - ▷ We need to get the correct error term!

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RCB models

► A “no interaction” RCB model

$$Y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij}, \quad i = 1, \dots, t, \quad j = 1, \dots, b,$$

$$\tau_i = \text{Treatments}$$

$$\beta_j = \text{Blocks}$$

(1) $\varepsilon_{ij} \sim \text{iid } N(0, \sigma_\varepsilon^2)$,

(2) β_1, \dots, β_b , are iid $N(0, \sigma_\beta^2)$,

(3) Everything is independent.

RCB models

► An “interaction” RCB model

$$Y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk},$$
$$i = 1, \dots, t, \quad j = 1, \dots, b, \quad k = 1, \dots, r,$$

- (1) $\varepsilon_{ijk} \sim \mathbf{N}(0, \sigma^2)$,
- (2) $\beta_1, \dots, \beta_b \sim \mathbf{N}(0, \sigma_\beta^2)$,
- (3) $(\tau\beta)_{11}, \dots, (\tau\beta)_{tb}$, are $\mathbf{N}(0, \sigma_{\tau\beta}^2)$,
- (4) Everything is independent

Interactions in RCB models

$$Y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij} \quad \text{or} \quad Y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk}$$

- ▶ Are These **Really** Different Models?
- ▶ Some Think So
- ▶ Some Textbooks Think So

As Seen in Some Textbooks

No interaction RCB model

Source	df
Blocks	b-1
Treatments	t-1
Residual	(b-1)(t-1)

H_0 : No Treatment Effect

$$F = \frac{MS(\text{Trts})}{MS(\text{Residual})}$$

Interaction RCB model

Source	df
Blocks	b-1
Treatments	t-1
Interaction	(b-1)(t-1)
Error	bt(r-1)

H_0 : No Treatment Effect

$$F = \frac{MS(\text{Trts})}{MS(\text{Error})} \text{ or } F = \frac{MS(\text{Trts})}{MS(\text{Pooled})}$$

“The case of the jumping denominator”



$$F = \frac{\text{MS(Trts)}}{\text{MS(Residual)}}$$

or

$$F = \frac{\text{MS(Trts)}}{\text{MS(Error)}}$$

- ▶ If the model changes does the truth change?
 - ▷ No interaction model \nRightarrow No interaction!

Expected Mean Squares - Randomized Complete Blocks

Source	df	EMS
Blocks	$b - 1$	$\sigma_{\varepsilon}^2 + r\sigma_{\tau\beta}^2 + rt\sigma_{\beta}^2$
Treatments	$t - 1$	$\sigma_{\varepsilon}^2 + r\sigma_{\tau\beta}^2 + \frac{rt}{t-1} \sum_i (\tau_i - \bar{\tau})^2$
T \times B	$(t - 1)(b - 1)$	$\sigma_{\varepsilon}^2 + r\sigma_{\tau\beta}^2$
Within	$bt(r - 1)$	σ_{ε}^2

► Works for

$$\triangleright Y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk}$$

$$\triangleright Y_{ijk} = \mu + \tau_i + \beta_j + \varepsilon_{ijk}$$

This is the error for
treatment estimates

Fisher knew the correct errors

► Fisher's Advice:

“We shall need to judge of the magnitude of the differences introduced by testing our treatments upon the different plots **by the discrepancies between the performances of the same treatment in different blocks.**”

R. A. Fisher *The Design of Experiments*, Section 26

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Revisiting the Field and the Lab

▶ Alfalfa Variety Trials

- ▷ Six Blocks
- ▷ Four Varieties
- ▷ Three Plants/ Variety/Block

▶ Varieties

- ▷ Ladak
- ▷ Narragansett
- ▷ DuPuits
- ▷ Flamand

▶ Objective: Increase Yield

▶ Microarray Experiment

- ▷ Six Subjects
- ▷ Four Treatments
- ▷ Three Arrays/Trt/Subject

▶ Treatment to Stem Cells

- ▷ Control
- ▷ Chemical
- ▷ GFP(Green Flor. Protein)
- ▷ GFP+transplant

▶ Convert Stem Cells to Neurons

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Alfalfa Variety Trial

		Blocks			
		1	2	...	6
1	y_{111}	y_{121}	...	y_{161}	
	y_{112}	y_{122}	...	y_{162}	
	y_{113}	y_{123}	...	y_{163}	
Varieties	⋮	⋮	⋮	⋮	
4	y_{411}	y_{421}	...	y_{461}	
	y_{412}	y_{422}	...	y_{462}	
	y_{413}	y_{423}	...	y_{463}	

Microarray Stem Cell

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Treatments	⋮	⋮	⋮	⋮	
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	y_{412}	y_{422}	...	y_{462}	
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Source	df	Sum Sq	Mean Sq	F	p
Block	5	3.98	1.33		
Variety	3	37.20	12.40	26.07	< .0001
$V \times B$	15	4.28	0.48	1.88	0.050
Within	48	8.10	0.25		

Source	df	Sum Sq	Mean Sq	F	p
Subjects	5	0.95	0.19		
Treatments	3	14.37	4.79	17.44	< .0001
$T \times S$	15	4.12	0.27	39.81	< .0001
Within	48	15.84	0.33	0.01	

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- Better Design Strategy:
Increase the Number of Blocks
- ▷ subjects
 - ▷ biological reps
 - ▷ arrays

What to do
with all of
those Within
Degrees of Freedom?

Revisiting the Field and the Lab

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Testing $H_0 : \sigma_{\tau\beta}^2 = 0?$

Pooling? – Better to avoid

► Maybe

▷ Type II error ↓

▷ Type I error ↑

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► For the RCB model

$$Y_{ijk} = \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk},$$

▷ we have

$$\text{Corr}(\varepsilon_{ijk}, \varepsilon_{i'jk'}) = \begin{cases} \rho_\varepsilon & \text{for technical replication} \\ 0 & \text{for true replication.} \end{cases}$$

▷ which affects the error term

► Look at the Expected Mean Squares

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► RCB anova - technical replication

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T \times B	$(t - 1)(b - 1)$	$\sigma_\varepsilon^2[1 + (r - 1)\rho_\varepsilon] + r\sigma_{\tau\beta}^2$
Within	$bt(r - 1)$	$(1 - \rho_\varepsilon)\sigma_\varepsilon^2$

► Treatment Test OK

► RCB anova - technical replication

Source	df	EMS
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Within	$bt(r - 1)$	$(1 - \rho_\varepsilon)\sigma_\varepsilon^2$

► Cannot test the interaction - often an important test

Example

- ▷ Microarray Experiment on **Unirradiated vs. Irradiated Cells**
- ▷ Twoway crossed treatment design

	Treatment	
	U	I
Line 1	x	x
	x	x
Line 2	x	x
	x	x

Independent
Replication?

Technical
Replication?

Cell Line Anova

- Technical Replication \Rightarrow No interaction test in RCB

			True Rep		Technical Rep	
Treatment			Source	df	Source	df
	U	I				
Line 1	x	x	Blocks(Lines)	1	Blocks(Lines)	1
	x	x	Treatments(U/I)	1	Treatments(U/I)	1
Line 2	x	x	$L \times T$	1	$L \times T$	1
	x	x	Within	4	Subsampling	4
			Total	7	Total	7

- Subsampling = Pseudoreplication = Technical Replication

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▶ **Balanced Incomplete Block Designs (BIBD)**

- ▷ Are needed when all treatments cannot fit in one block
- ▷ Arise naturally in microarray experiments

▶ Some Examples

- ▷ Two-Dye System \Rightarrow Block of Size 2
- ▷ GCP Example - Treatment applied to cells - Subject is block
- ▷ Other Technological advances

- ▶ **Balanced Incomplete Block Designs (BIBD)**
 - ▷ Are needed when all treatments cannot fit in one block
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- ▶ **Some Examples**
 - ▷ Two-Dye System \Rightarrow Block of Size 2
 - ▷ GCP Example - Treatment applied to cells - Subject is block
 - ▷ Other Technological advances

▶ The new Agilent arrays



▶ “Muiltplex formats enable hybridization of multiple samples on a single chip”

▶ Available formats

▷ 1x244K

▷ 2x105K

▷ 4x44K

▷ 8x15K

▶ A Statistical Design Nightmare?

▶ The new Agilent arrays



▶ “Muiltplex formats enable hybridization of multiple samples on a single chip”

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Properties of Balanced Incomplete Block Designs

$$Y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij},$$

▷ $\varepsilon_{ij} \sim \text{iid } \mathbf{N}(0, \sigma_\varepsilon^2)$.

▷ β_1, \dots, β_b , are iid $\mathbf{N}(0, \sigma_\beta^2)$

▶ Treatment contrasts are free of block effects

$$\text{Var} \left(\sum_{i=1}^t a_i \hat{\tau}_i \right) = \frac{k}{\lambda t} \sigma_\varepsilon^2 \sum_{i=1}^t a_i^2.$$

▷ no σ_β^2

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▷ no σ_β^2

What can go wrong?

- ▶ NASA Experiment on Substantiality of Crops (Potatoes)
 - ▷ Two Factors: Photoperiod (P), and bioactive Tuber Inducing Factor solution (TIF)
 - ▷ Each at two levels = Four Treatments
 - ▷ Agilent two-dye microarray chip \Rightarrow BIBD
- ▶ “I ran all four pairs”
- ▶ But $\binom{4}{2} = 6!!!$

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► He ran all four pairs

P-1/TIF1
P-2/TIF-1

P-1/TIF-1
P-1/TIF-2

P-1/TIF-1
P-2/TIF-2

P-2/TIF-1
P-2/TIF-2

The case of the missing pairs



► Damage Control - confounding - contrasts have block effects

► He ran all four pairs

P-1/TIF1
P-2/TIF-1

P-1/TIF-1
P-1/TIF-2

P-1/TIF-1
P-2/TIF-2

P-2/TIF-1
P-2/TIF-2

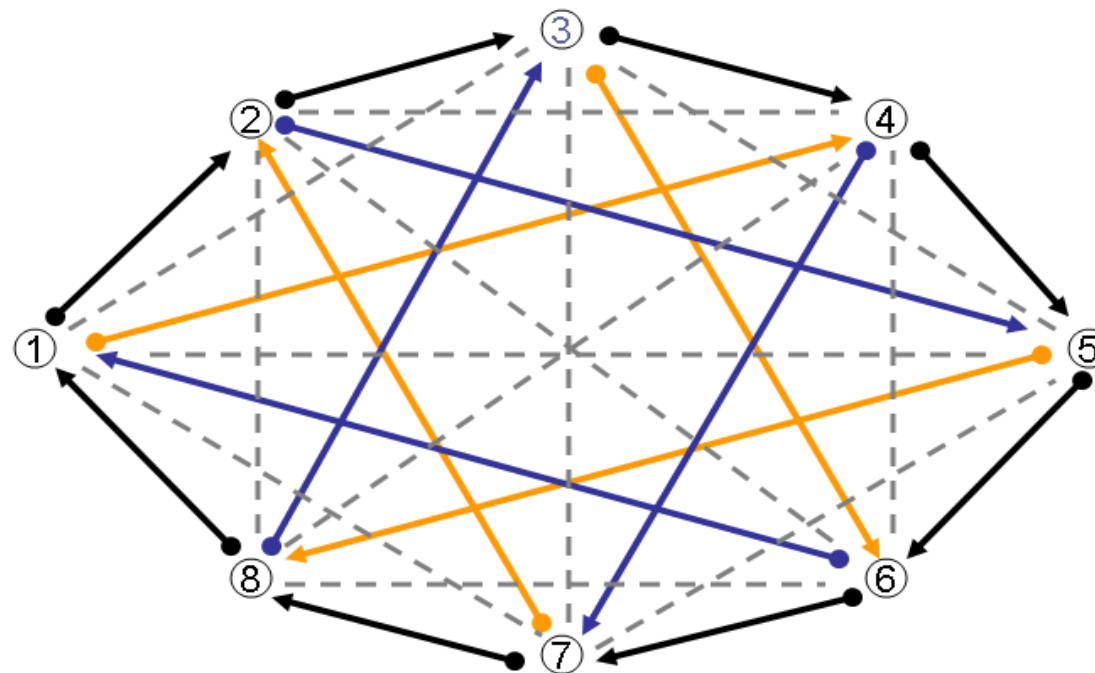
The case of the missing pairs



► **Damage Control** - confounding - contrasts have block effects

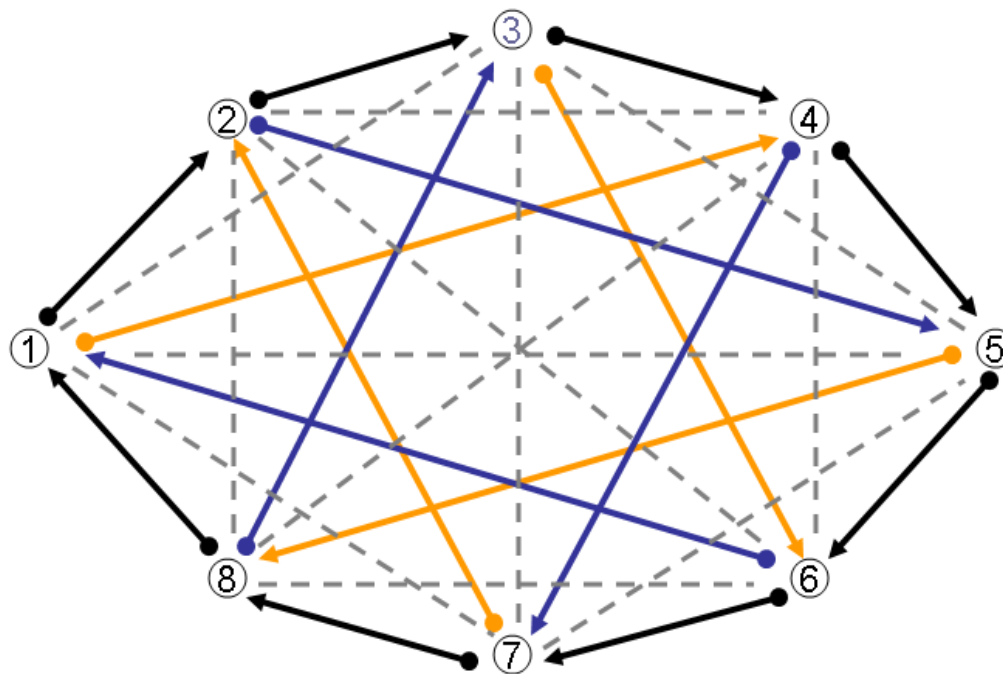
Loops, Augmented Loops, and BIBDs

▷ *Persea* (Avocado) Experiment-Eight Different Tissues



▷ Reducing Some Variances

Persea (Avocado) Experiment

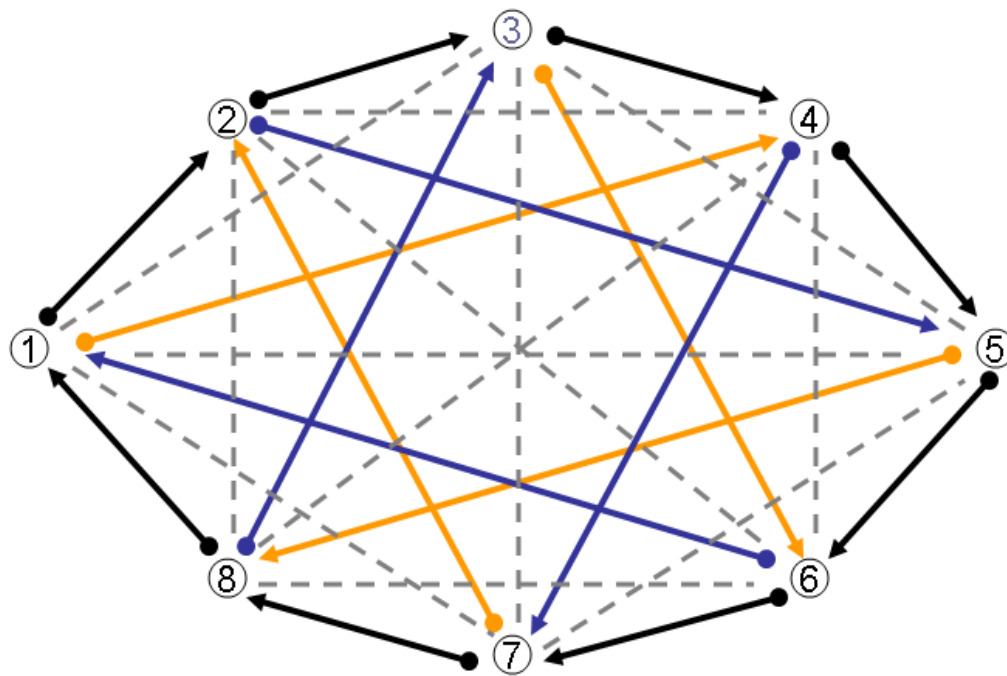


Outer Black Lines
= Loop Design

Outer Black Lines
+ Orange and Blue
= Augmented Loop

All Lines
= BIBD

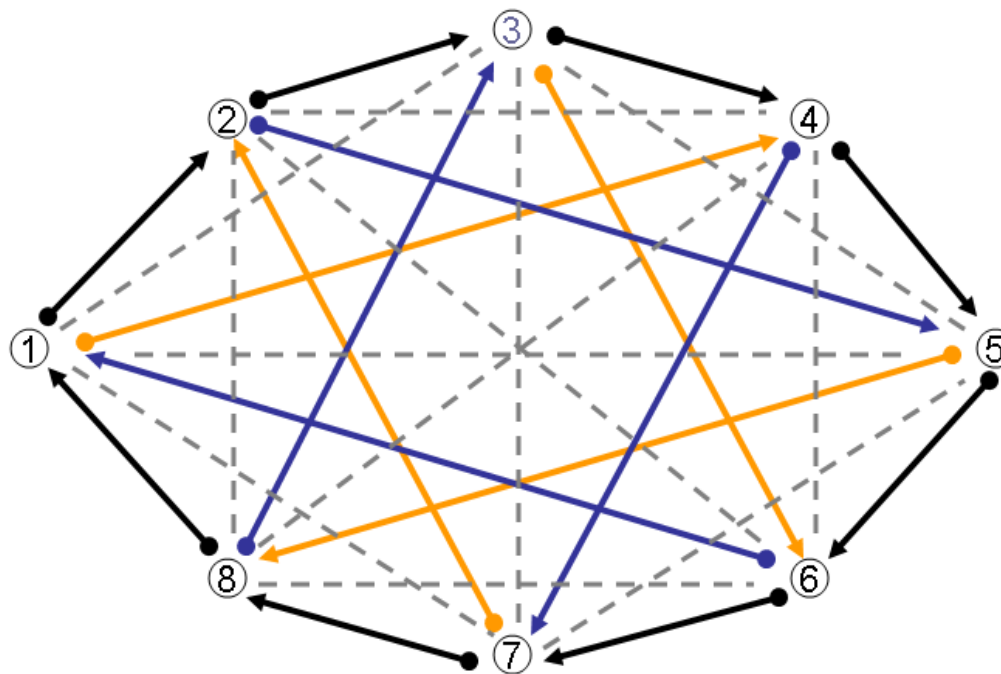
Persea (Avocado) Experiment



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All Lines
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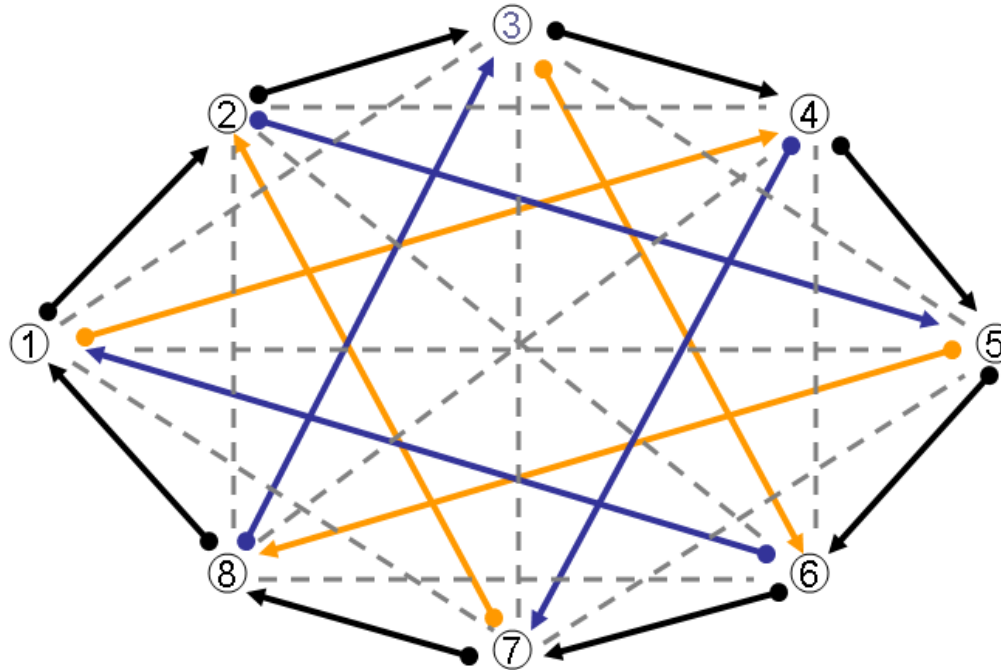
Persea (Avocado) Experiment

Outer Black Lines
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Loop Design Variances



Adjacent Treatments

$$\text{Var}(\hat{\tau}_i - \hat{\tau}_{i'}) = \sigma_\varepsilon^2 + \frac{1}{2}\sigma_\beta^2$$

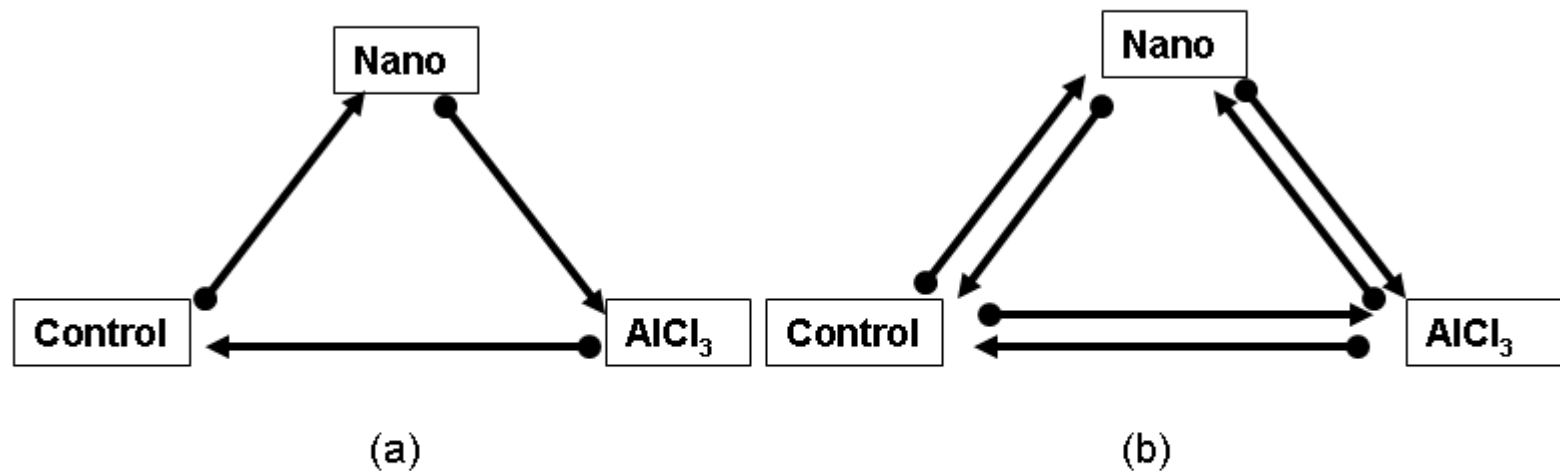
Non-Adjacent Treatments

$$\text{Var}(\hat{\tau}_i - \hat{\tau}_{i'}) = \sigma_\varepsilon^2 + \sigma_\beta^2$$

BIBD: No σ_β^2

A Word About Reference Designs

► Effect of Aluminum on Zebrafish



- ▷ Recommended: Loop (left) or Double Loop (right)
- ▷ Experimenters chose Reference Design

Reference or Loop?

Dye	Reference			Loop		
Green	Ref.	Ref.	Ref.	Cont.	Nano	AlCl ₃
Red	Cont.	AlCl ₃	Nano	Nano	AlCl ₃	Cont.

$$\text{Reference Design : } \text{Var}(\hat{\tau}_i - \hat{\tau}_{i'}) = 2\sigma_\varepsilon^2 + 2\sigma_\beta^2$$

$$\text{Loop Design : } \text{Var}(\hat{\tau}_i - \hat{\tau}_{i'}) = \sigma_\varepsilon^2 + \frac{1}{2}\sigma_\beta^2$$

- ▷ “Half of your observations are on a treatment that you don’t care about”

Reference or Loop?

Dye	Reference			Loop		
Green	Ref.	Ref.	Ref.	Cont.	Nano	AlCl ₃
Red	Cont.	AlCl ₃	Nano	Nano	AlCl ₃	Cont.

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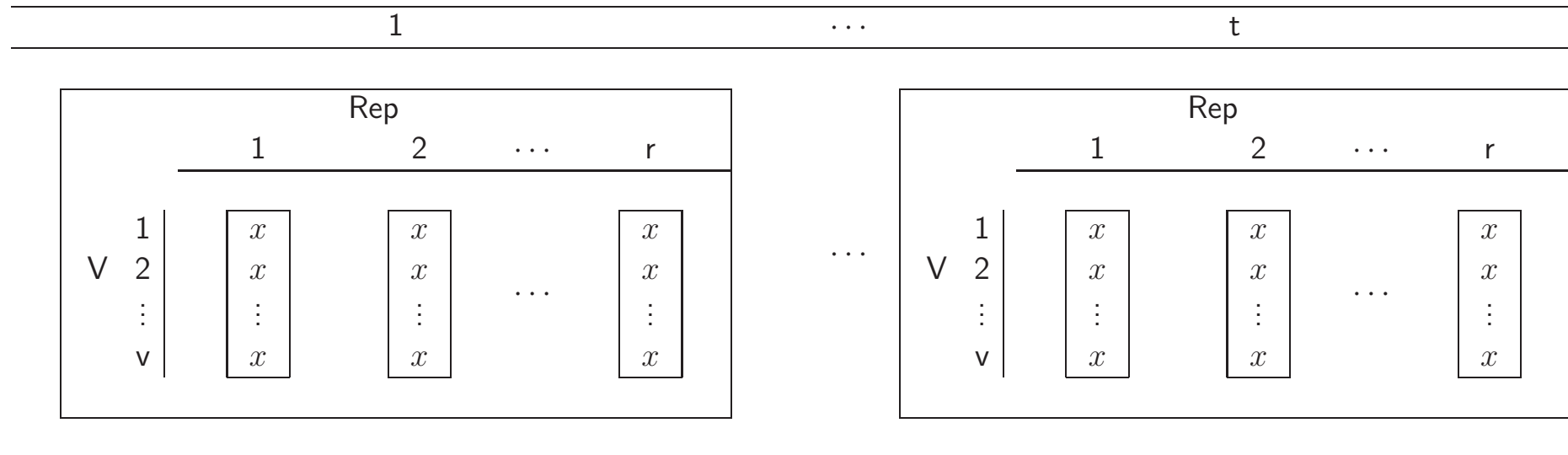
$$\text{Loop Design : } \text{Var}(\hat{\tau}_i - \hat{\tau}_{i'}) = \sigma_\varepsilon^2 + \frac{1}{2}\sigma_\beta^2$$

- ▷ “Half of your observations are on a treatment that you don’t care about”

- ▶ From the Field to the Lab
- ▶ Getting the Errors Correct
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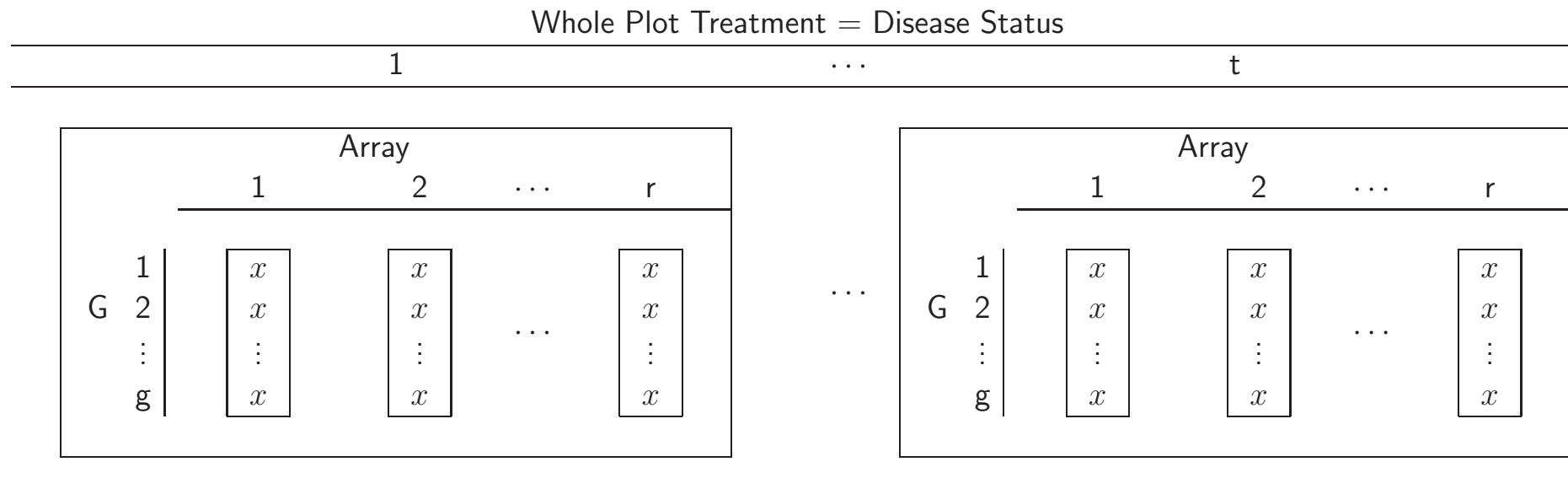
Split Plots - Agricultural Experiment

Whole Plot Treatment = Fertilizer



- ▷ Fertilizer applied to Whole Plots
- ▷ Varieties within Whole Plots = Split Plots

Split Plots - Microarray Experiment



- ▷ Arrays = Whole Plots
- ▷ Gene within Arrays = Split Plots

Split Plot Anova

Source	df	EMS
Whole Plot Trt	t-1	$\sigma_{\delta}^2 + g\sigma_{\varepsilon}^2 + \frac{rg}{t-1} \sum_i \tau_i^2$
Arrays (in Whole Plots)	t(r-1)	$\sigma_{\delta}^2 + g\sigma_{\varepsilon}^2$
Genes (Split Plot Trt)	g-1	$\sigma_{\delta}^2 + \frac{rt}{g-1} \sum_k \gamma_k^2$
Genes \times Whole Plot Trt	(g-1)(t-1)	$\sigma_{\delta}^2 + \frac{r}{(g-1)(t-1)} \sum_{ik} (\tau\gamma)_{ik}^2$
Error (Split Plot Trt \times Replication in Whole Plots)	t(g-1)(r-1)	σ_{δ}^2
Total	grt-1	

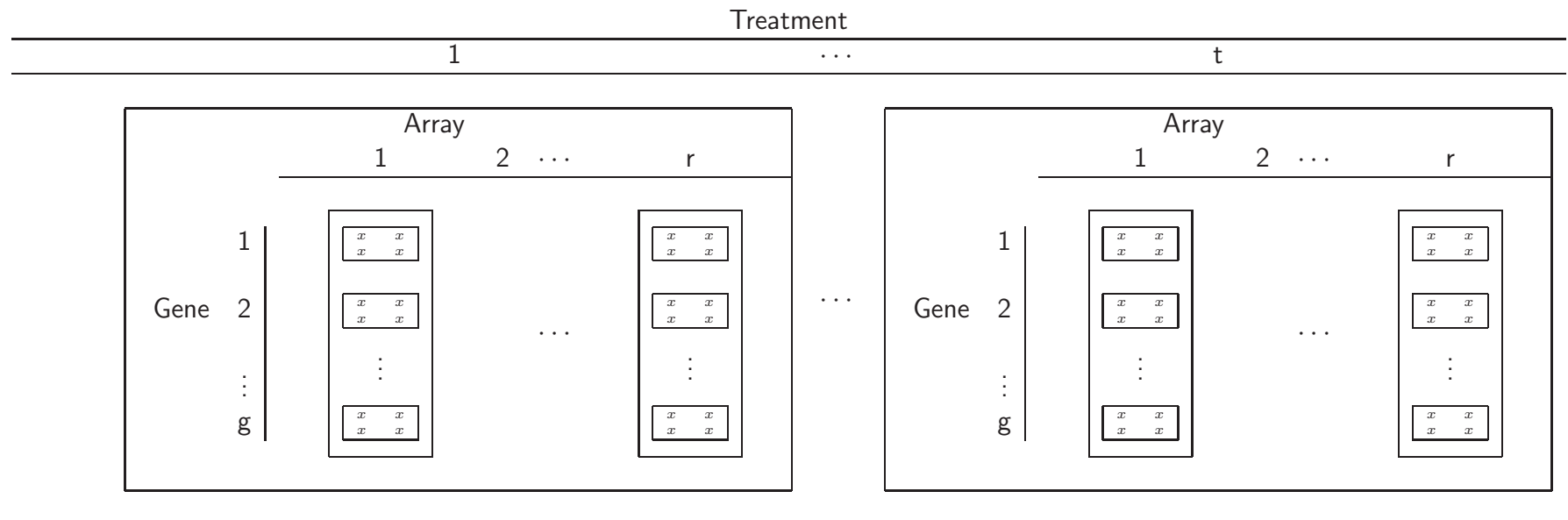
- ▷ Interest is at Split Plot level
- ▷ Genes \times Whole Plot Trt = Differential Expression
- ▷ Split Plot comparisons have smaller error
- ▷ Pooling Genes - Analysis Question

Split Plot Anova

Source	df	EMS
Whole Plot Trt	t-1	$\sigma_{\delta}^2 + g\sigma_{\varepsilon}^2 + \frac{rg}{t-1} \sum_i \tau_i^2$
Arrays (in Whole Plots)	t(r-1)	$\sigma_{\delta}^2 + g\sigma_{\varepsilon}^2$
Genes (Split Plot Trt)	g-1	$\sigma_{\delta}^2 + \frac{rt}{g-1} \sum_k \gamma_k^2$
Genes \times Whole Plot Trt	(g-1)(t-1)	$\sigma_{\delta}^2 + \frac{r}{(g-1)(t-1)} \sum_{ik} (\tau\gamma)_{ik}^2$
Error (Split Plot Trt \times Replication in Whole Plots)	t(g-1)(r-1)	σ_{δ}^2
Total	grt-1	

- ▷ Interest is at Split Plot level
- ▷ Genes \times Whole Plot Trt = Differential Expression
- ▷ Split Plot comparisons have smaller error
- ▷ Pooling Genes - Analysis Question

Splitting Even More



- ▷ Probes nested within Genes
- ▷ Probe \times Gene Interaction \Rightarrow SNP?
- ▷ Split Split Plot comparisons

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Pooling

- ▶ Should we pool RNA of Subjects?

$$\sigma^2 = \sigma_B^2 + \sigma_W^2 \quad \text{Between} + \text{Within Variance}$$

- ▶ Variance of Treatment Mean

$$\text{Var}(\bar{Y}_i) = \frac{1}{rp} \left(\sigma_B^2 + \frac{\sigma_W^2}{s} \right).$$

▷ r =True Rep, p =Pooling, s =Technical Rep

Pooling

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- ▷ r =True Rep, p =Pooling, s =Technical Rep

Conservative Tests

► Completely Randomized Design

Source	df	EMS
Treatment T	$t - 1$	$\sigma^2 + \frac{rg}{t-1} \sum_i \tau_i^2$
Treatment G	$g - 1$	$\sigma^2 + \frac{rt}{g-1} \sum_j \gamma_j^2$
T × G	$(t - 1)(g - 1)$	$\sigma^2 + \frac{r}{(t-1)(g-1)} \sum_{ij} (\tau\gamma)_{ij}^2$
Within	$tg(r - 1)$	σ^2

► Pooling \Rightarrow

- ▷ Lower Power
- ▷ Lower Type I Error

Conservative Tests

► Completely Randomized Design

Source	df	EMS
Treatment T	$t - 1$	$\sigma^2 + \frac{rg}{t-1} \sum_i \tau_i^2$
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Within	$tg(r - 1)$	σ^2

► Pooling \Rightarrow

▷ Lower Power

▷ Lower Type I Error

Anti-Conservative Tests

► Randomized Complete Block Design

Source	df	EMS
Blocks	$b - 1$	$\sigma_\varepsilon^2 + r\sigma_{\tau\beta}^2 + rt\sigma_\beta^2$
Treatments	$t - 1$	$\sigma_\varepsilon^2 + r\sigma_{\tau\beta}^2 + \frac{rt}{t-1} \sum_i (\tau_i - \bar{\tau})^2$
T × B	$(t - 1)(b - 1)$	$\sigma_\varepsilon^2 + r\sigma_{\tau\beta}^2$
Within	$bt(r - 1)$	σ_ε^2

► Pooling \Rightarrow

- ▷ Higher Power
- ▷ Higher Type I Error

Anti-Conservative Tests

► Randomized Complete Block Design

Source	df	EMS
Blocks	$b - 1$	$\sigma_\varepsilon^2 + r\sigma_{\tau\beta}^2 + rt\sigma_\beta^2$
Treatments	$t - 1$	$\sigma_\varepsilon^2 + r\sigma_{\tau\beta}^2 + \frac{rt}{t-1} \sum_i (\tau_i - \bar{\tau})^2$
T × B	$(t - 1)(b - 1)$	$\sigma_\varepsilon^2 + r\sigma_{\tau\beta}^2$
Within	$bt(r - 1)$	σ_ε^2

► Pooling \Rightarrow

- ▷ Higher Power
- ▷ Higher Type I Error

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 - ▷ Check the Denominator
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Thank You for Your Attention

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University of Florida Gators!