Experimentation

Lecture 4

Psychology of Clothing

- High school students clothing style influence perceptions of academic prowess among peers and teachers (Behling & Williams, 1991)

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Reports

Enclothed cognition

Hajo Adam, Adam D. Galinsky *

Northwestern University, Evanston, IL 60208, USA

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ABSTRACT

We introduce the term "enclothed cognition" to describe the systematic influence that clothes have on the wearer's psychological processes. We offer a potentially unifying framework to integrate past findings and capture the diverse impact that clothes can have on the wearer by proposing that enclothed cognition involves the co-occurrence of two independent factors—the symbolic meaning of the clothes *and* the physical experience of wearing them. As a first test of our enclothed cognition perspective, the current research explored the effects of wearing a lab coat. A pretest found that a lab coat is generally associated with attentiveness and carefulness. We therefore predicted that wearing a lab coat would increase performance on attention-related tasks. In Experiment 1, physically wearing a lab coat increased selective attention compared to not wearing a lab coat. In Experiments 2 and 3, wearing a lab coat described as a doctor's coat increased sustained attention compared to wearing a lab coat described as a painter's coat, and compared to simply seeing or even identifying with a lab coat described as a doctor's coat. Thus, the current research suggests a basic principle of enclothed cognition—it depends on both the symbolic meaning and the physical experience of wearing the clothes.

Clothes change opinions

- High school students clothing style influence perceptions of academic prowess among peers and teachers (Behling & Williams, 1991)

Clothes change opinions

- Teaching assistants who wear formal clothes are perceived as more intelligent, but as less interesting than teaching assistants who wear less formal clothes (Morris, Gorham, Cohen, & Huffman, 1996)

Clothes change opinions

- When women dress in a masculine fashion during a recruitment interview, they are more likely to be hired (Forsythe, 1990), and when they dress sexily in prestigious jobs, they are perceived as less competent (Glick, Larsen, Johnson, & Branstiter, 2005)

Clothes change opinions

- Clients are more likely to return to formally dressed therapists than to casually dressed therapists (Dacy & Brodsky, 1992)

- Appropriately dressed customer service agents elicit stronger purchase intentions than inappropriately dressed ones (Shao, Baker, & Wagner, 2004)

Clothes change your own behavior

- Wearing large hoods and capes makes people more likely to administer electrical shocks to others (Zimbardo, 1969)

- Wearing a nurses uniform makes people less likely to administer shocks to others (Johnson & Downing, 1979)

Clothes change your own behavior

- Sports teams wearing black uniforms are more aggressive than teams wearing non-black uniforms (Frank & Gilovich, 1988)

Clothes change your own behavior

- Wearing a bikini makes women feel ashamed, eat less, and perform worse at math (Frederickson, Roberts, Noll, Quinn, & Twenge, 1998)

Enclothed cognition

- Hypothesis:
- Wearing a piece of clothing and **embodying** its symbolic meaning will trigger associated psychological processes.

Wearing a white lab coat

White lab coats...

- Are associated with Science and Doctors
- May induce a scientific focus and an emphasis on being careful and attentive, and not making errors

Experiment 1: physically wearing a lab coat

Method

Design and participants

Fifty-eight undergraduates (41 females, 19 males; average age: 20.29 years) at a large university in the Midwestern United States participated in the experiment. They were randomly assigned to one of two conditions: wearing a lab coat vs. not wearing a lab coat.

Procedure and experimental manipulation

In the *wearing-a-lab-coat condition*, participants were asked to wear a disposable white lab coat. To provide a cover story, the experimenter told participants that other participants in prior sessions of this experiment had been wearing lab coats during lab construction. Although the construction had been completed, the experimenter told participants that they still needed to wear the lab coat so all participants in the experiment would be in the same situation. In the *not-wearing-a-lab-coat condition*, participants completed the tasks in their own clothes.

Stroop experiment to measure attention

- RED
- BLUE
- GREEN
- BLUE

Congruent - fast

Incongruent - slow

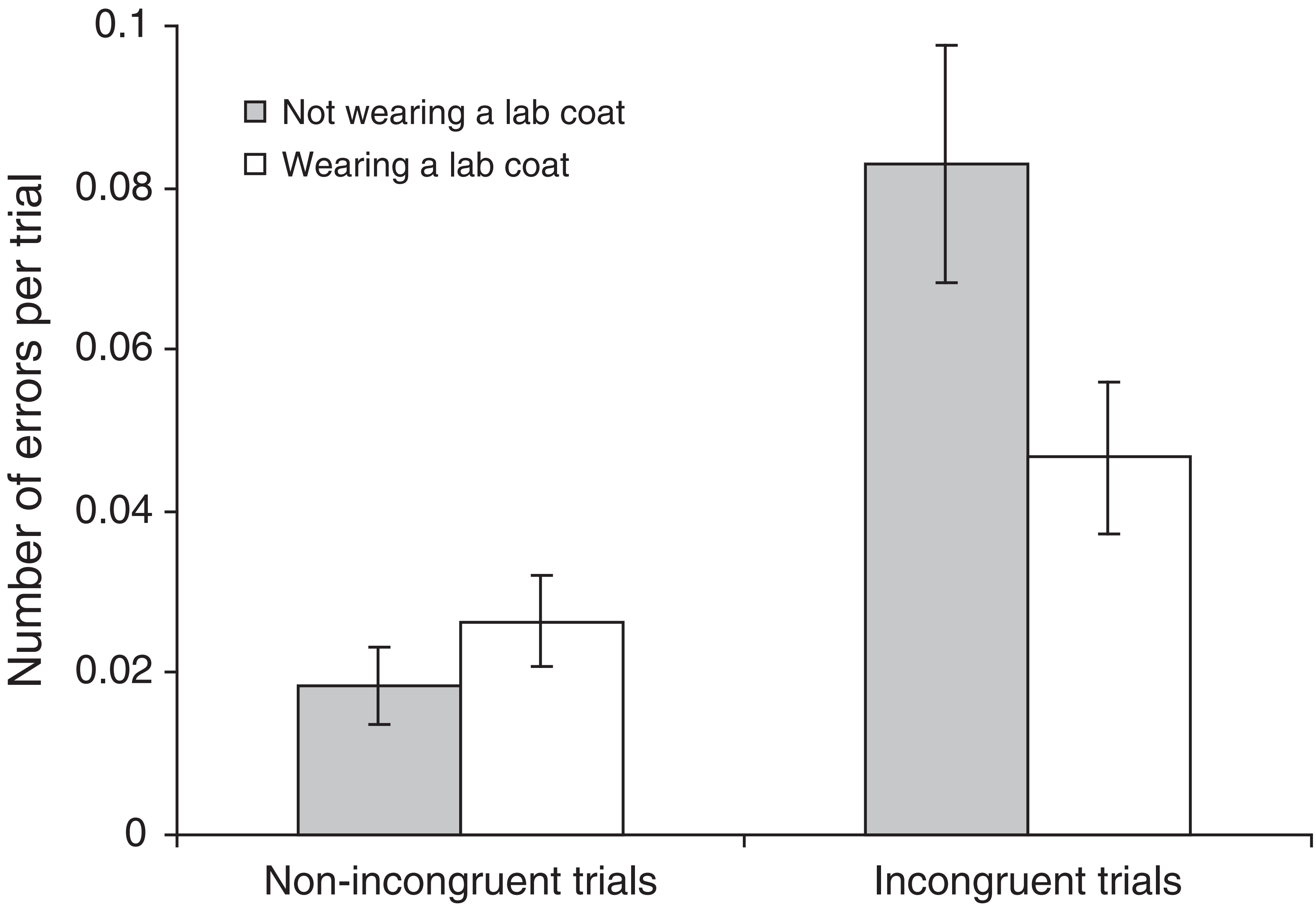


Fig. 1. Selective attention (number of errors per trial in the Stroop task) as a function of experimental condition and trial type. Error bars represent ± 1 SEM.

E2: Wearing vs. symbolic meaning

- Wearing the lab coat, and the symbolic meaning of the lab coat were confounded in E1

E2: Wearing vs. symbolic meaning

- 3 new conditions
- 1: Wearing a doctor’s coat
- 2: Seeing a doctor’s coat only
- 3: Wearing a coat, but told it’s a painters coat

Spot the difference

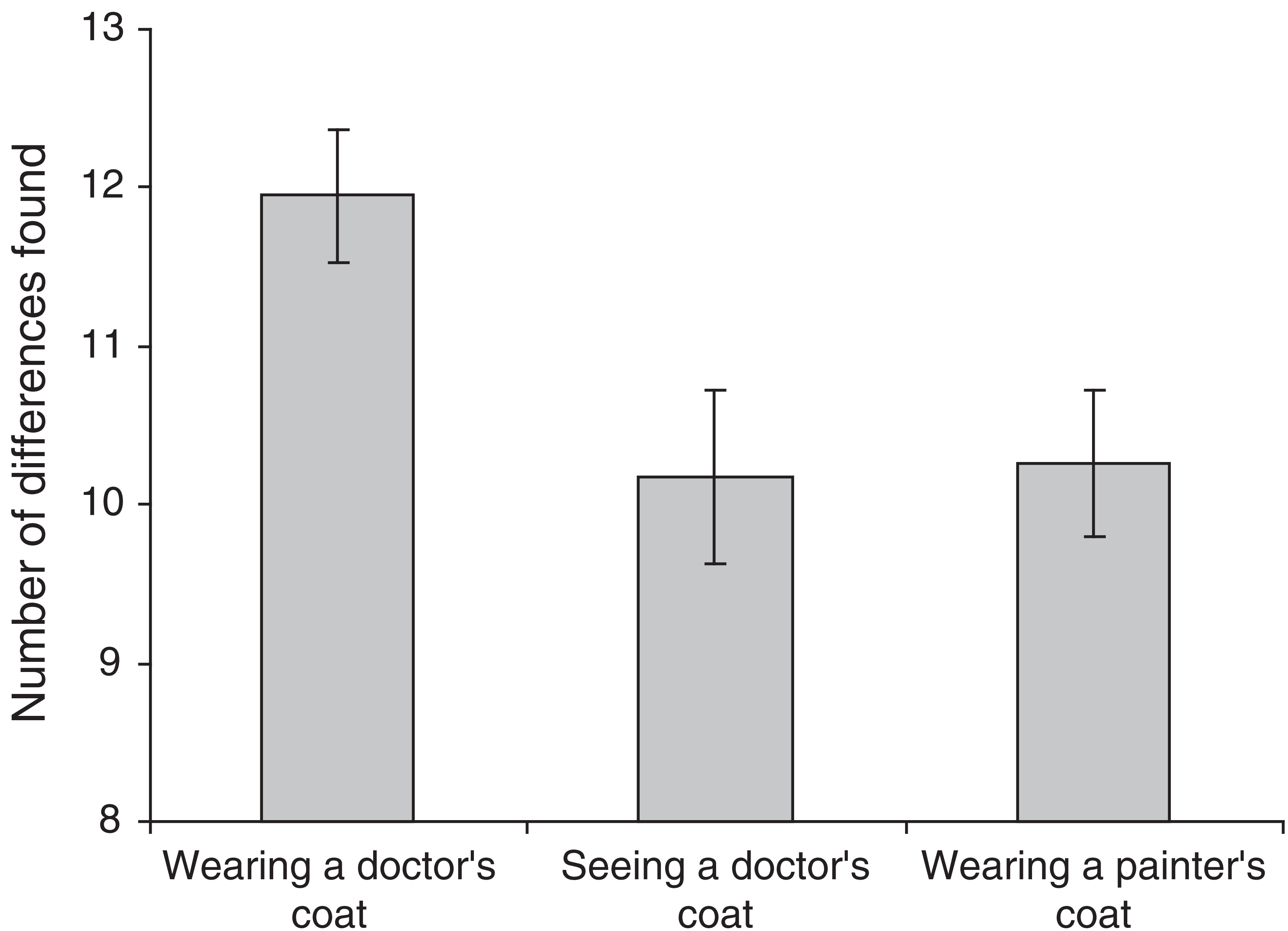


Fig. 2. Sustained attention (number of differences found in the comparative visual search tasks) as a function of experimental condition. Error bars represent ± 1 SEM.

E3: Wearing vs. personally identifying

- All participants wrote a paragraph about what the coat means to them
- 1: Wearing a doctor’s coat
- 2: Identifying with a doctor’s coat
- 3: Wearing a coat, but told it’s a painters coat

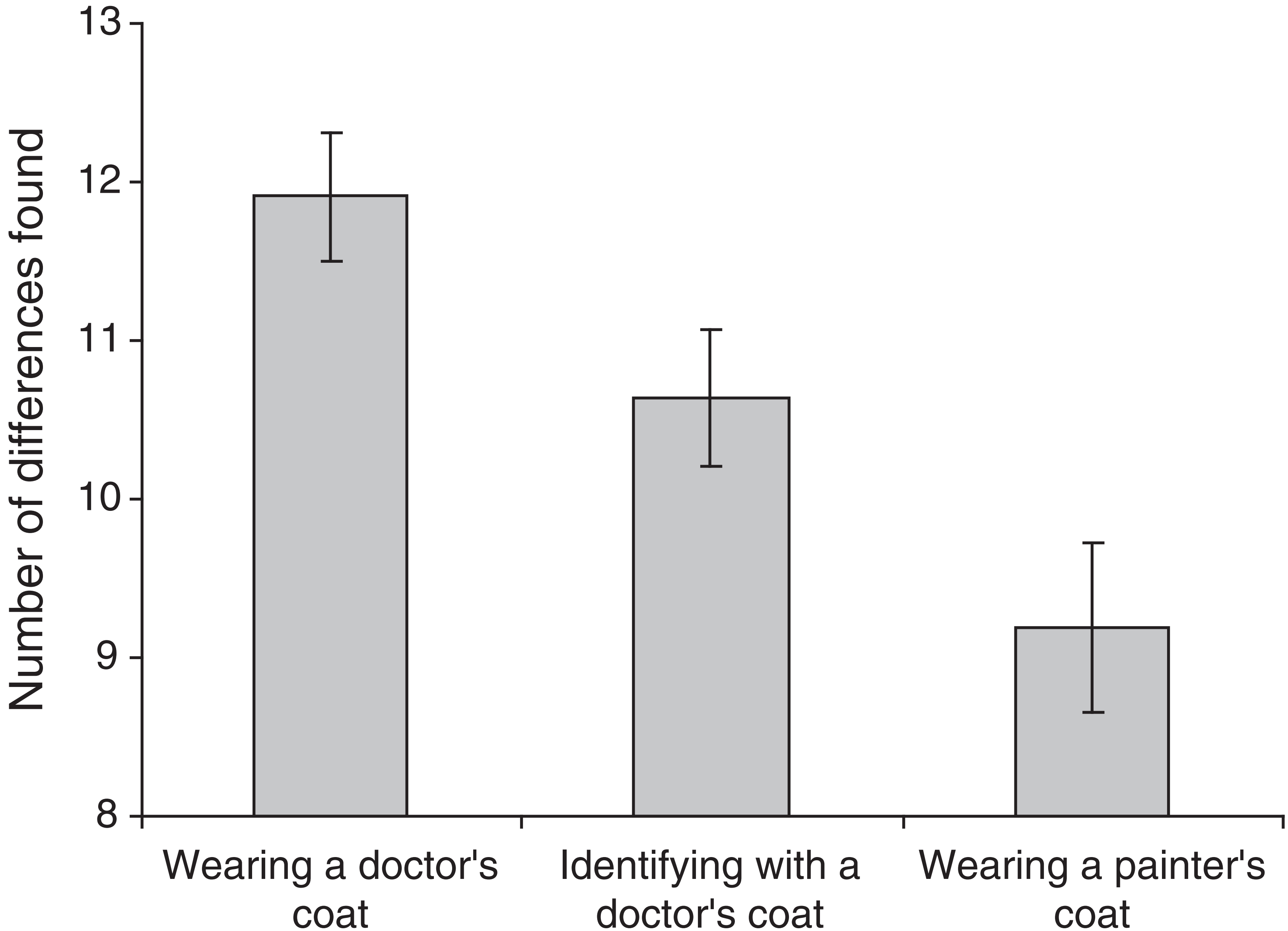


Fig. 3. Sustained attention (number of differences found in the comparative visual search tasks) as a function of experimental condition. Error bars represent ± 1 *SEM*.

Lecture #4

Read Chapter 3 -Getting started with Experiments

Definition of Experiments and basic terminology

Single-factor Experiments with 2 levels

Single-factor Experiments with more than 2 levels

One-way ANOVAs

What is an experiment?

- Manipulate something
- Measure the consequences of the manipulation
- Purpose: To determine if the manipulation **causes** a change in the measurement

Independent Variable (IV)

- The experimental manipulation
- Must have at least 2 levels

Dependent Variable (DV)

- What we measure
- The data

Factors vs. Levels

- Factor = Independent Variable
- Levels = the different conditions tested by the IV

Single factor Experiment with 2 levels

	Independent Variable	
	Level 1	Level 2
DV	data	data

Between-Subjects Designs

Different subjects in each experimental group

Subject	Group 1
1	
2	
3	
4	
5	
6	
7	
8	
9	
10	

Subject	Group 2
11	
12	
13	
14	
15	
16	
17	
18	
19	
20	

Between-Subjects Designs

- **Advantages:** Each subject contributes data only once, so it is not possible for measurement to be influenced by their previous experience with other conditions in the design
- **Disadvantages:**
  - Requires more subjects
  - Lower statistical power
  - Differences between conditions are confounded with subject, so differences could emerge because different people did different things in each of the conditions

Within-Subjects Designs

Same subjects participate in both conditions

Subject	Condition 1	Condition 2
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		

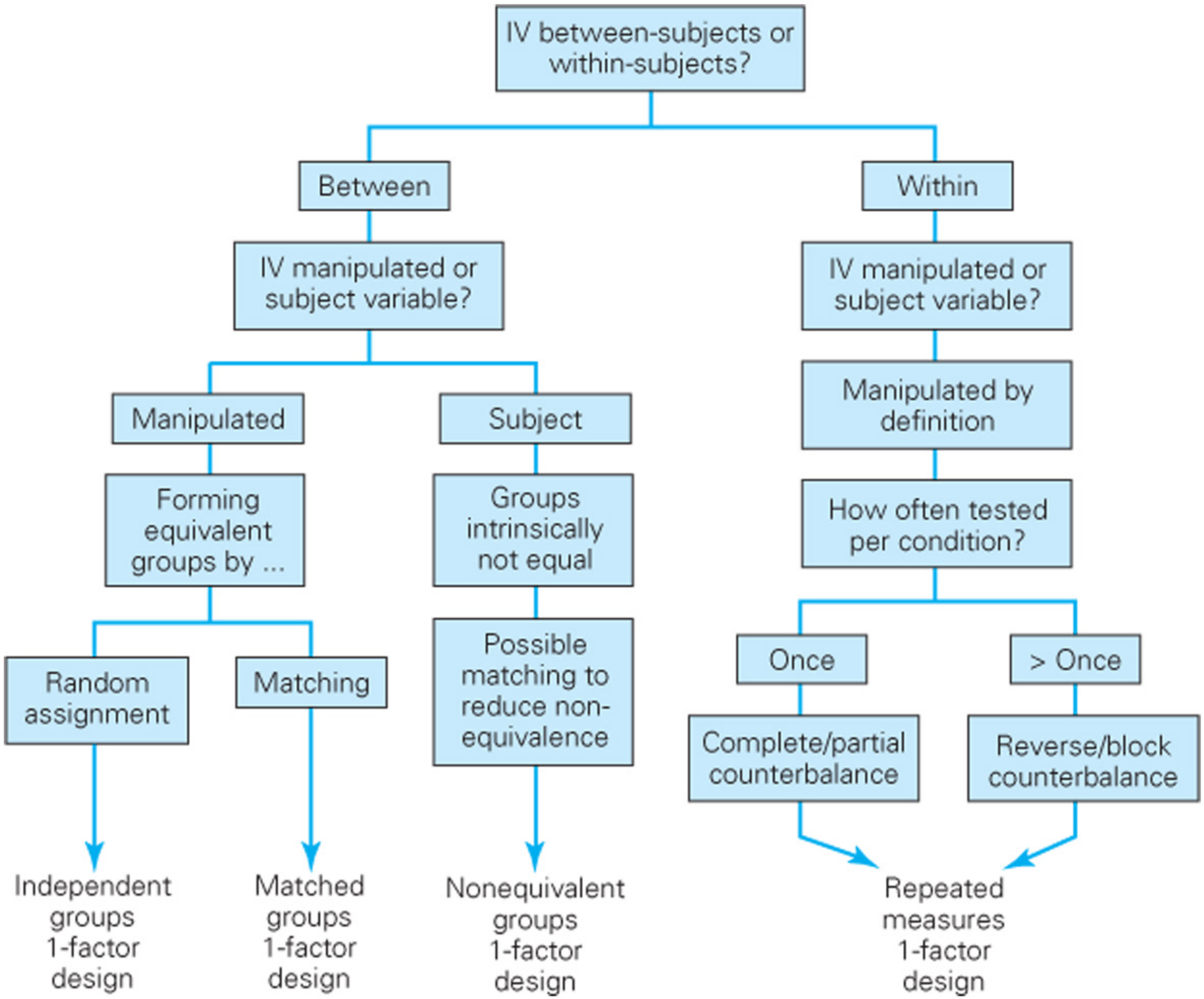
Within-Subjects Designs

- **Advantages:**
  - Requires fewer subjects
  - Higher Statistical Power
  - Capable of measuring changes that occur within an individual
- **Disadvantages:**
  - Possible carry-over effects from one condition to another

Between vs. Within and inferential statistics

- Your choice of design determines which statistical tests you should use to analyze your results
- For a single factor design with 2-levels use t-tests
- Between-subjects design = Independent samples t-test
- Within-subjects design = Paired samples t-test

Kinds of Designs



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One-way ANOVAs

Research Topic

Curing headaches

Theory

X causally influences Y

Theory

Tylenol (does a bunch of things) that reduce headache pain

Logical implication of Theory

More X should lead to less Y

Logical implication of theory

Taking Tylenol should reduce headache pain

Research Design

Groups	X	~X
Data	measure Y	measure Y

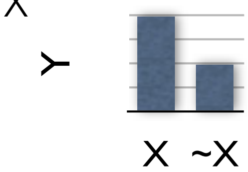
~ = not X or absence of X

Research Design

Groups	Tylenol	~Tylenol
Data	measure pain	measure pain

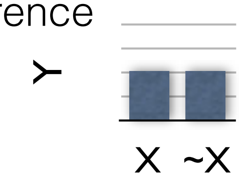
Possible Outcomes and Inferences

X>~X



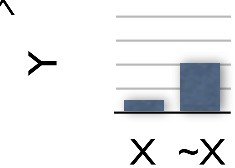
X causally increases Y

No Difference



X does not influence Y

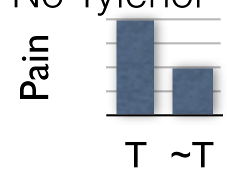
X<~X



X causally decreases Y

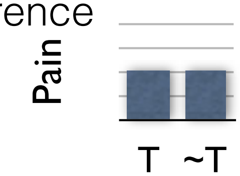
Possible Outcomes and Inferences

Tylenol > No Tylenol



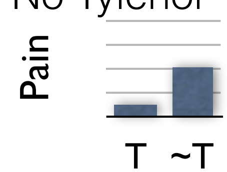
Tylenol increases headache pain

No Difference



Tylenol does not change headache pain

Tylenol < No Tylenol



Tylenol decreases headache pain

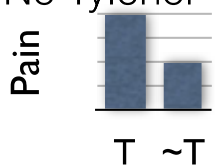
Inferential problems

- When we conduct an experiment, we want to make inferences about our hypothesis based on the data
- If our hypothesis says there should be a difference between conditions, then we want to look at the data to find out if there is or is not a difference
- However, there can be multiple issues with interpreting data that constrain our ability to make an inference

These are the possible patterns we could find,
along with the inferences we would like to make about each pattern

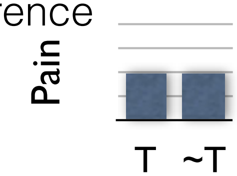
Possible Outcomes and Inferences

Tylenol > No Tylenol



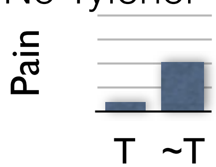
Tylenol increases headache pain

No Difference



Tylenol does not change headache pain

Tylenol < No Tylenol



Tylenol decreases headache pain

Problem	**Constraint on Inference**
Pattern could be produced by chance	?
Pattern could be produced by a confounding variable	?
Pattern might be real, but not shown in the data	?
Pattern could have occurred because of measurement error	?
Poor design choices could have produced the pattern	?

Goal of Good Experimental Design is to eliminate inferential problems

- If we conduct a “good” experiment we can eliminate or greatly reduce:
  - the influence of chance
  - the role of confounding variables
  - measurement error
  - bad design choices
- **If we can be confident in the pattern of our data, we can be confident about the inferences we make about our hypotheses**

“TO CALL IN THE STATISTICIAN AFTER THE EXPERIMENT IS DONE MAY BE NO MORE THAN ASKING HIM TO PERFORM A POST-MORTEM EXAMINATION: HE MAY BE ABLE TO SAY WHAT THE EXPERIMENT DIED OF..”

–Sir Ronald Fisher

tldr: the data is only as good as the experiment it comes from

So how do we run “good” experiments?

- **Start by eliminating chance**
    - increase n (number of subjects)
    - increase cell-size (number of measurements per subject in each condition)
    - Run higher-powered experiments
- Address potential control problems (more on this in the second half of the semester)

2 level experiment simulator

- This web-app allows you to simulate basic experiments with 2 levels.
  - You can choose the mean and standard deviation for condition 1 and 2
  - You can choose the number of subject to run in each condition
  - You receive the output of a t-test (independent samples), and a bar-graph showing the means in each condition
  - You receive a histogram showing how many times the experiment you simulated would produce a significant result ($p<.05$)

2 level experiment simulator

- We will use the simulator to:
  - examine the influence of n (number of subjects) on finding significant effects
  - examine the concept of the null-hypothesis
  - examine how the size of the difference between means influences the results
  - examine how the amount of variance in each condition influences the results

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Single-factor Experiments with more than 2 levels

One-way ANOVAs

Single factor Experiments with more than two levels

- All of the general principles that we have learned so far will apply to single-factor experiments with more than two levels.

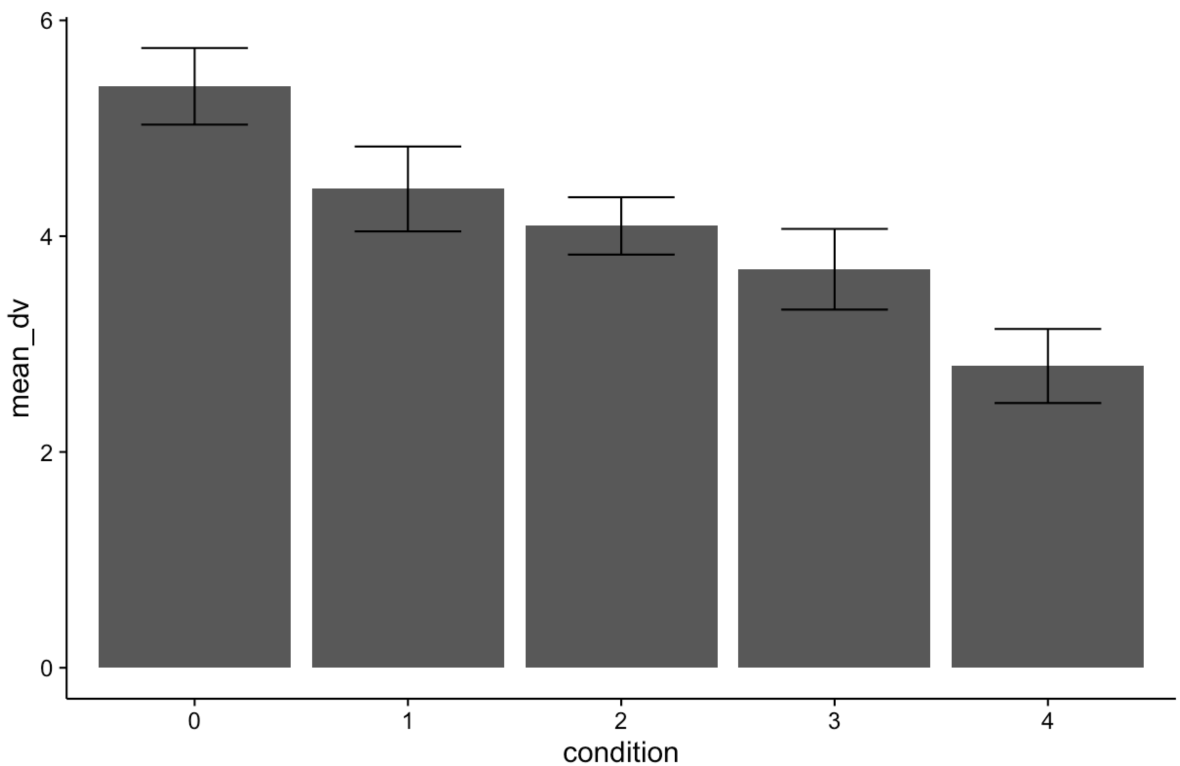
Single factor Experiment with more than 2 levels

	Independent Variable			
	Level 1	Level 2	Level 3	Level …n
DV	data	data	data	data

What is different about a 2-level design versus a multi-level design?

- Basically the same except:
  - Obviously, more than two levels
  - Two kinds of empirical questions:
    1. Omnibus question: Are there any differences?
    2. Specific questions: Which specific conditions are different from one another.
  - Statistical Analysis usually involves:
    3. ANOVA to answer Omnibus question
    4. Follow-up t-tests for specific comparisons

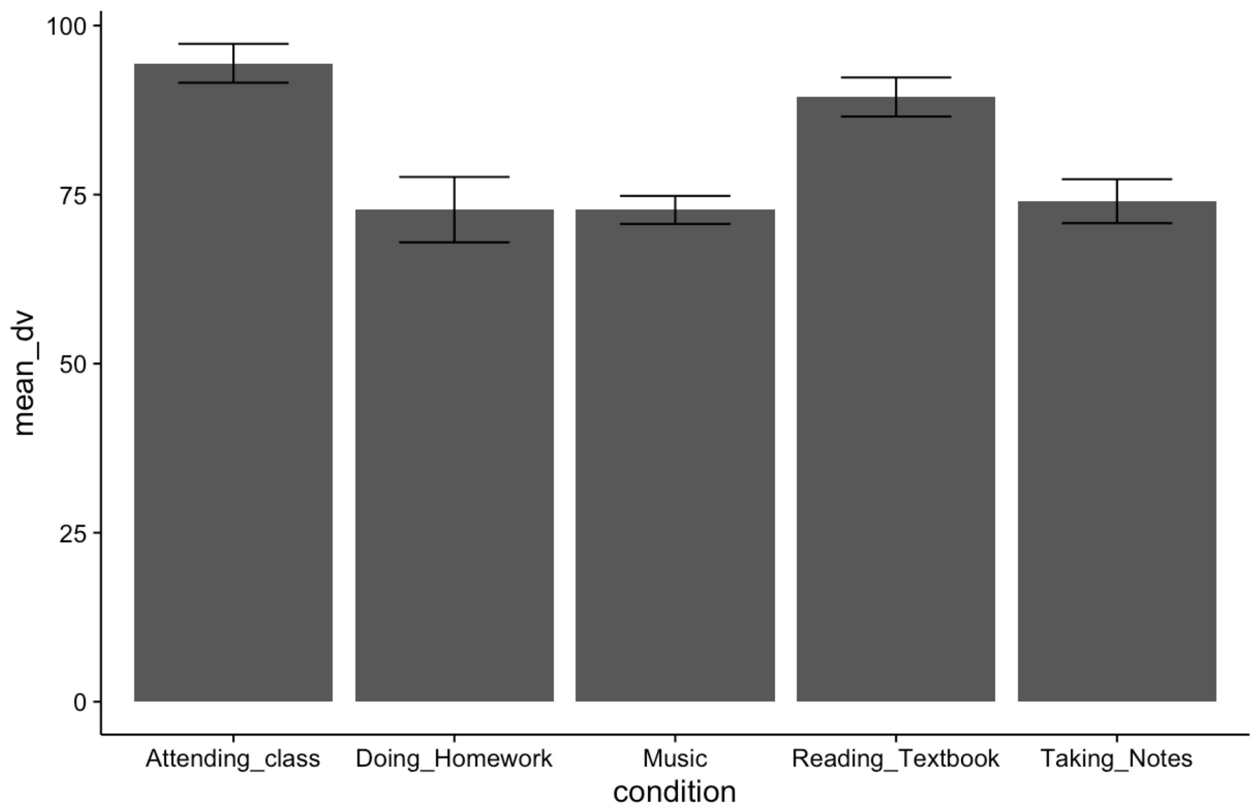
Multi-level designs with parametric IVs



Parametric IVs are continuous variables

(the above could be number of tylenols in a headache pain experiment)

Multi-level designs with categorical IVs



Categorical IVs are qualitatively different conditions
(E.g., which study habits have the biggest influence on class average)

Why run multi-level designs?

- Advantages:
  - You can test more conditions, allowing more opportunity to find effects of interest
  - Vary the strength of the manipulation
  - Test more complicated hypotheses that predict specific patterns across the levels
- Disadvantages:
  - More complicated to analyze, especially when conducting comparisons between specific conditions (the number of possible comparisons is always ((# of levels)*(#of levels-1))/2
    - 3 levels = (3*2)/2 = 3 comparisons; 10 levels = (10*9)/2 = 45 comparisons

Multi-level experiment simulator

- This web-app allows you to simulate single experiments with multiple levels
  - You can choose the mean and standard deviation for each condition
  - You can choose the number of subject to run in each condition
  - You receive the output of an ANOVA (between-subjects), a bar graph plot, table of means, and the option to conduct follow-up tests
  - You receive a histogram showing how many times the experiment you simulated would produce a significant result ($p<.05$)

Multi-level experiment simulator

- We will use the simulator to:
  - Get a feel for what results from multi-level designs look like
  - Examine how changing n (number of subjects), mean differences, and variances change our results
  - Examine ways in which chance can influence our results

Chance, Type 1 and 2 errors

- Because we sample data from distributions when we take measurements, there is always some possibility that chance could influence our results.

- **Type 1 Error:** Incorrectly rejecting the Null, or the data show a difference (because of chance), but there is no true difference

- **Type 2 Error:** Incorrectly concluding the Null, or the data show no difference (because of chance), but there really is a difference

Reporting results

1. Conduct the ANOVA, report the F value, DFs, MSE and p-value: $F(2,18) = 3.15$, $MSE = 345.23$, $p<.05$.

2. Report the mean values in each condition, or use a table or figure to show the means

3. Report follow-up t-tests for specific comparisons of interest.

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Single-factor Experiments with more than 2 levels

One-way ANOVAs

ANOVA (things you should already know because you took statistics and didn't forget what you learned…)

- What the acronym ANOVA stands for
- How to calculate the ANOVA for a set of data (by hand, or by pressing buttons in SPSS)
- How to interpret the output of the ANOVA table
- What each of these terms means: F-value, SS, MSE, p-value

Example ANOVA table

	DF	SS	MSE	F	p
Condition	2	14183	7091	5.58	0.00934
Residuals	27	34284	1270		

Example ANOVA table

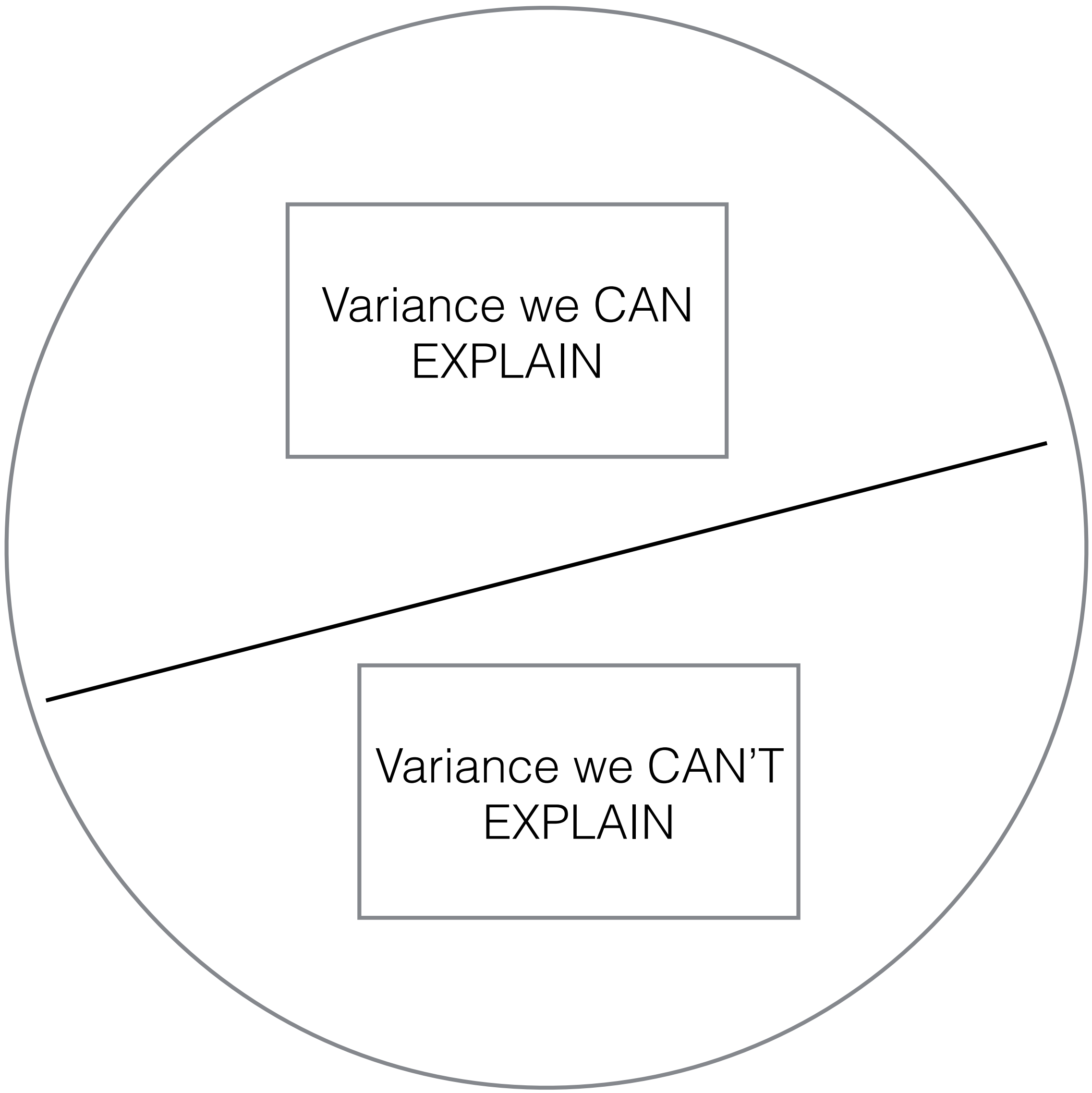
	Degrees of Freedom	Sums of Squares	Mean Squared Error	F-value	p-value
	DF	SS	MSE	F	p
Condition	2	14183	7091	5.58	0.00934
Residuals	27	34284	1270		

What are those things, what do they mean, and where do they come from?

The big idea: How much of the variance (or change in the data) can we explain?

Strategy: Create a ratio by dividing the variance into two parts

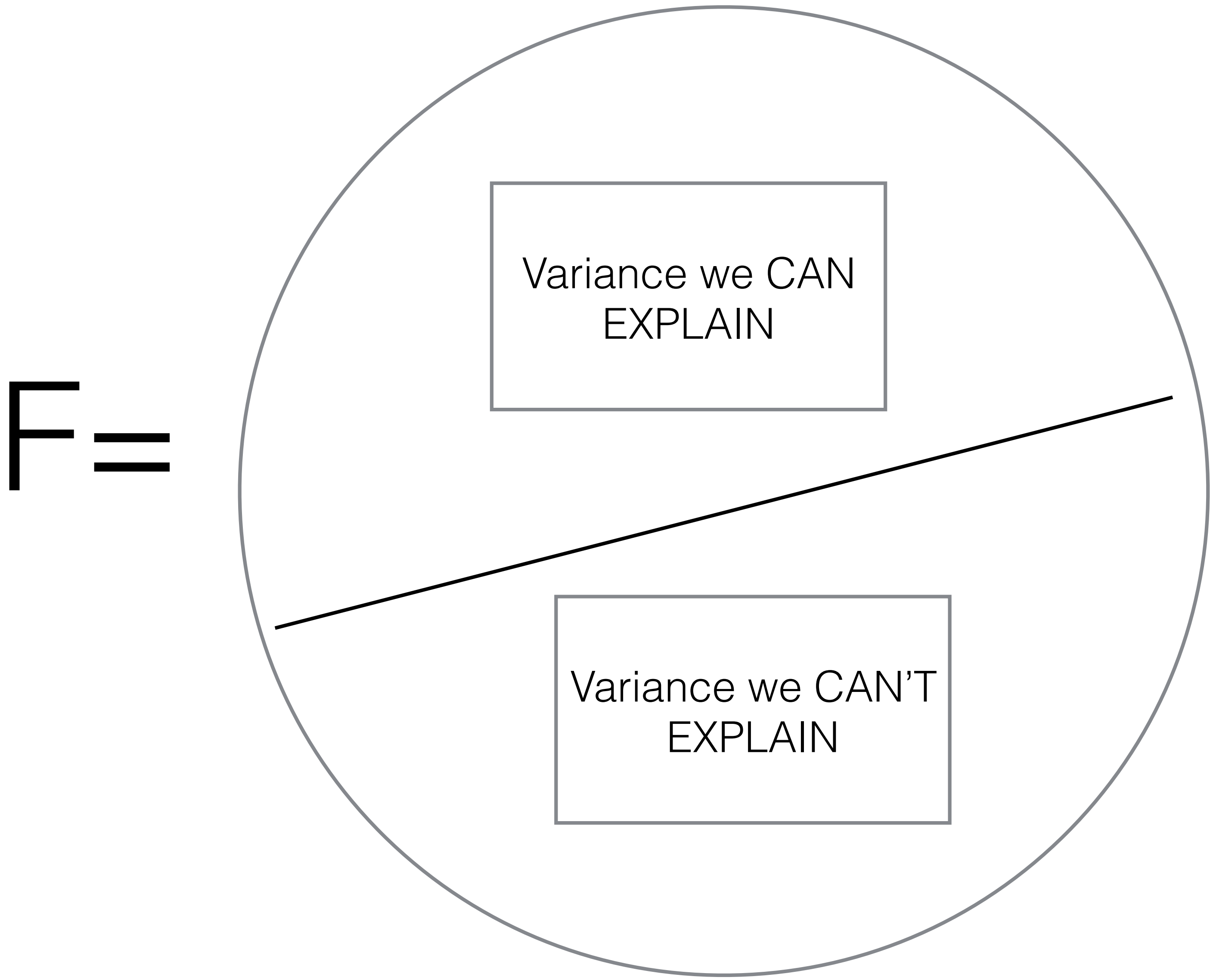
F=



What happens to F when the variance we can explain is **larger** than the variance we can't explain?

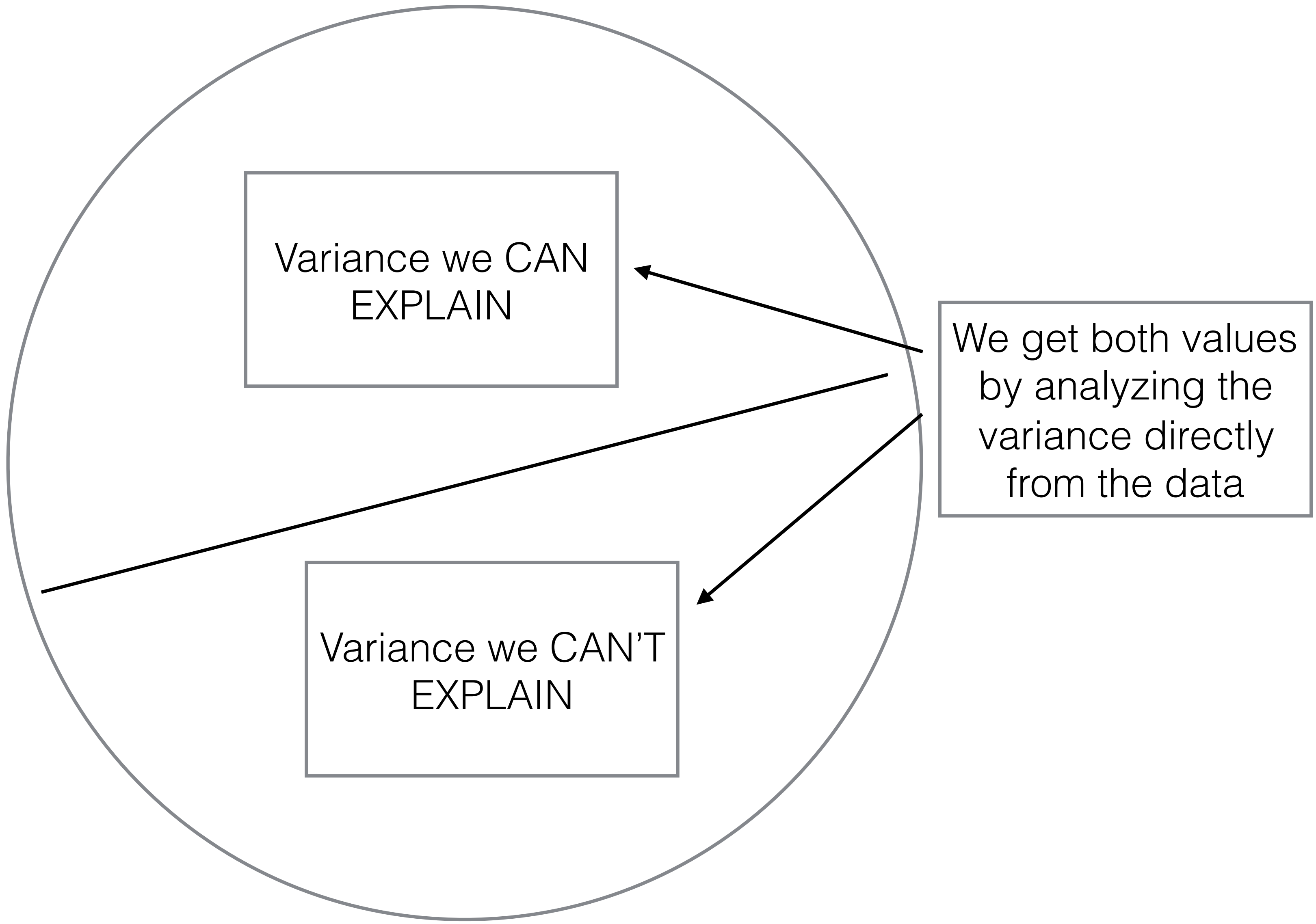
$$F = \frac{\text{Variance we CAN EXPLAIN}}{\text{Variance we CAN'T EXPLAIN}}$$

What happens to F when the variance we can explain is **smaller** than the variance we can't explain?



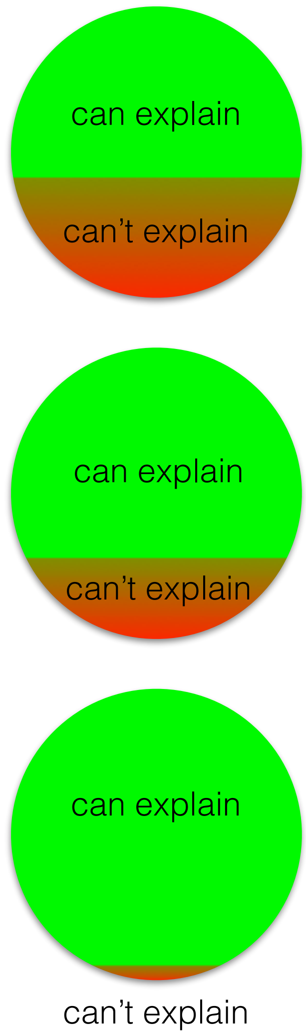
How can we estimate the variances?

F=



Getting a feel for F

What happens to F when there are real differences between conditions



Small effect $F = 1 - 2$

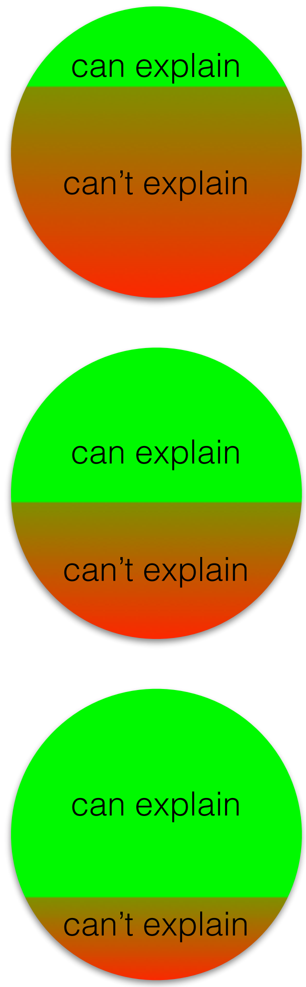
Medium effect $F > 3$

Big effect $F > 10$

Getting a feel for F

What happens to F when there are no differences between conditions

Because of chance, F can range from small to large

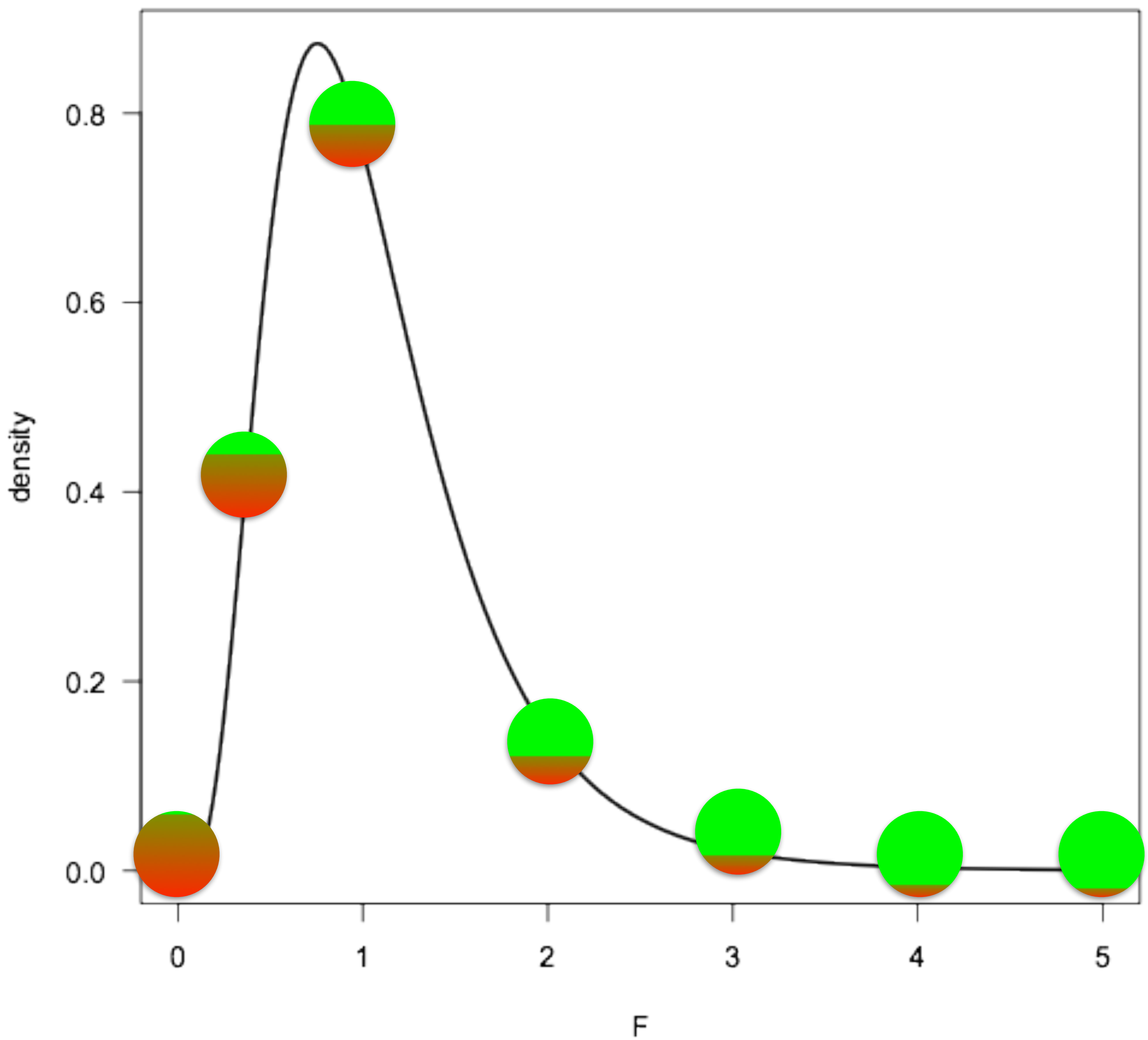


$F < 1$

$F = 1$

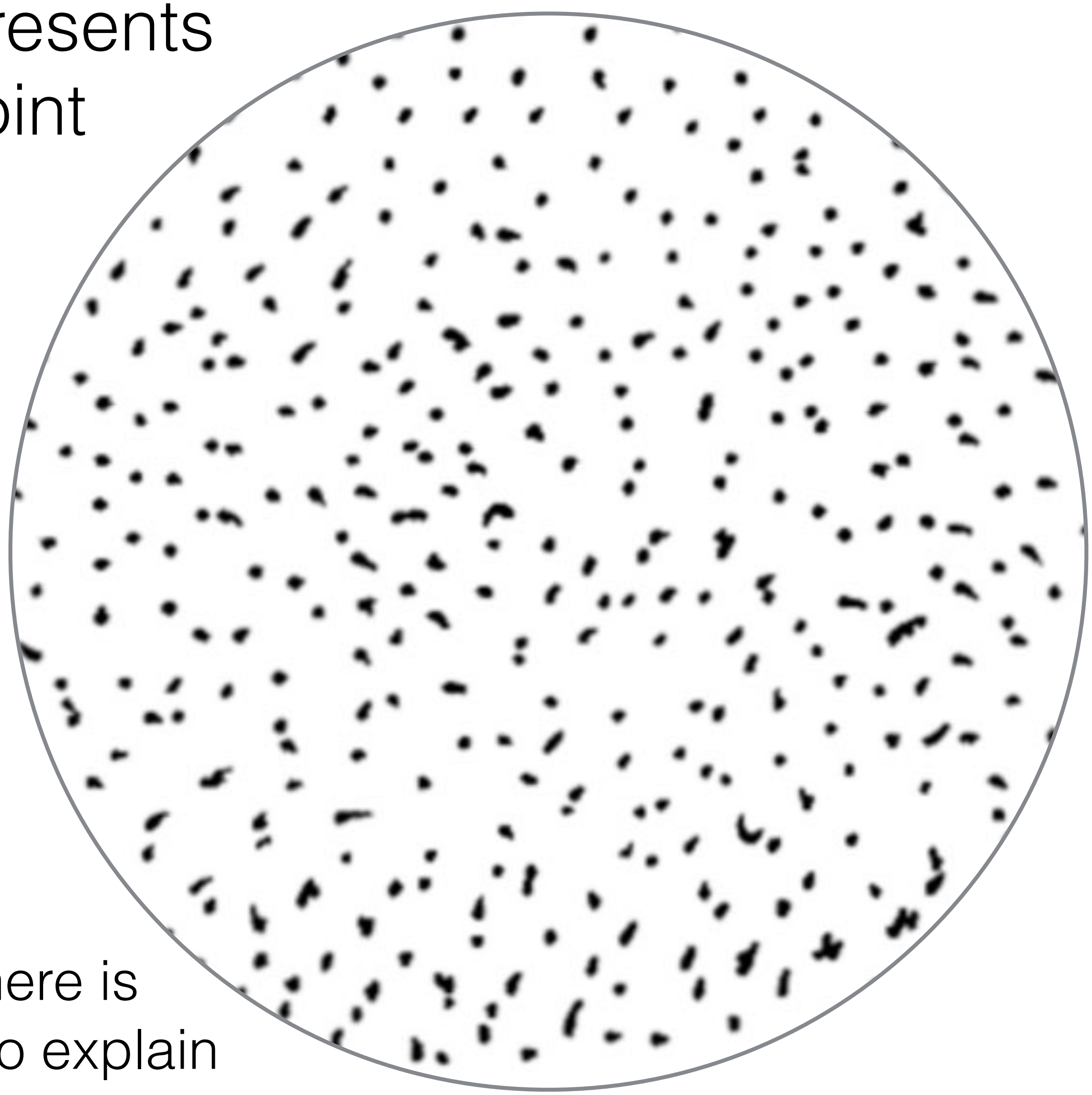
$F > 1$

The F-distribution (how F- behaves by chance alone)



Calculating F

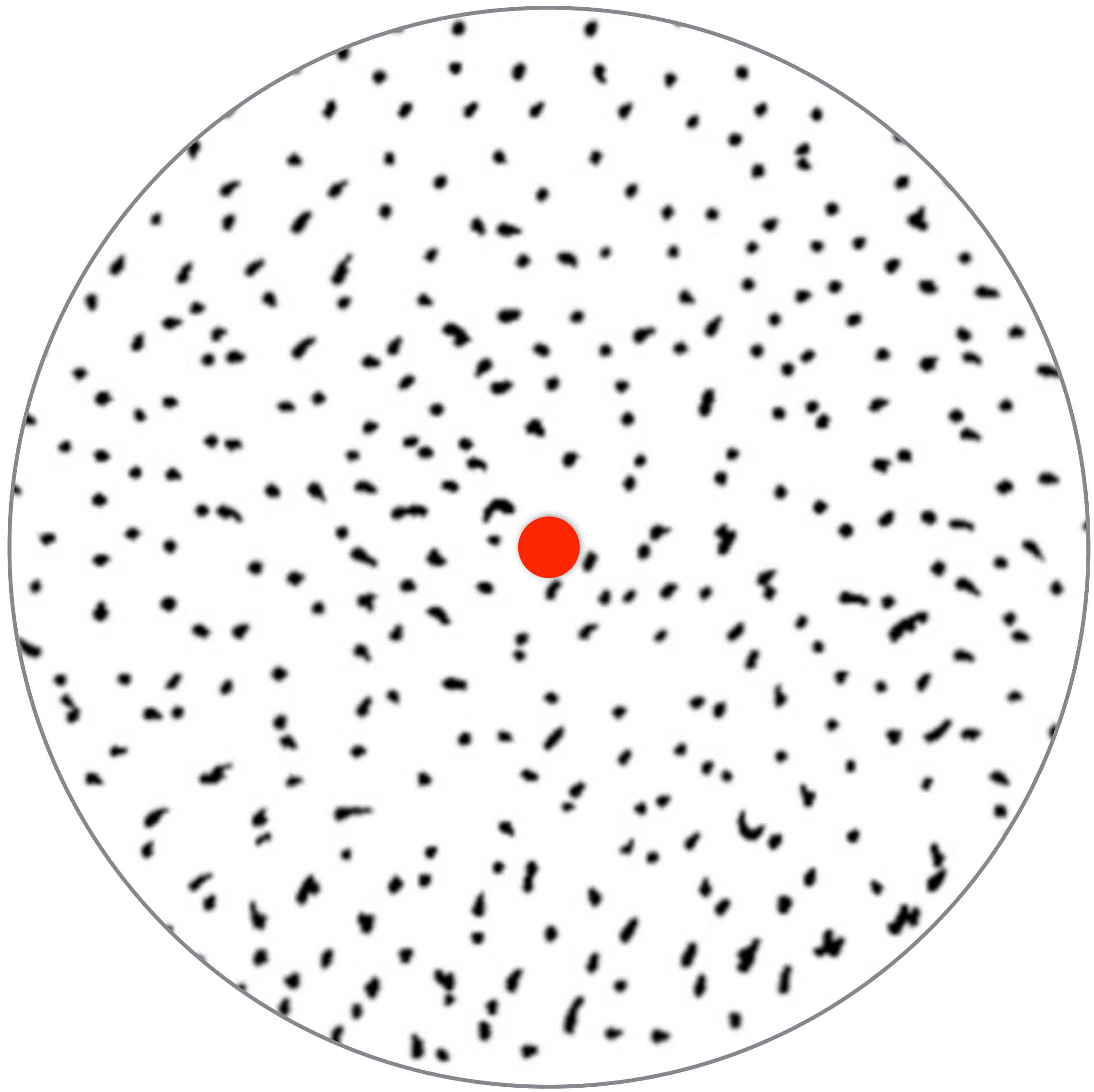
Each dot represents
a data-point



We can see there is
a lot of variance to explain

1) calculate the Grand Mean (the center of the data)

a) The center of the data is our best guess for any given data point



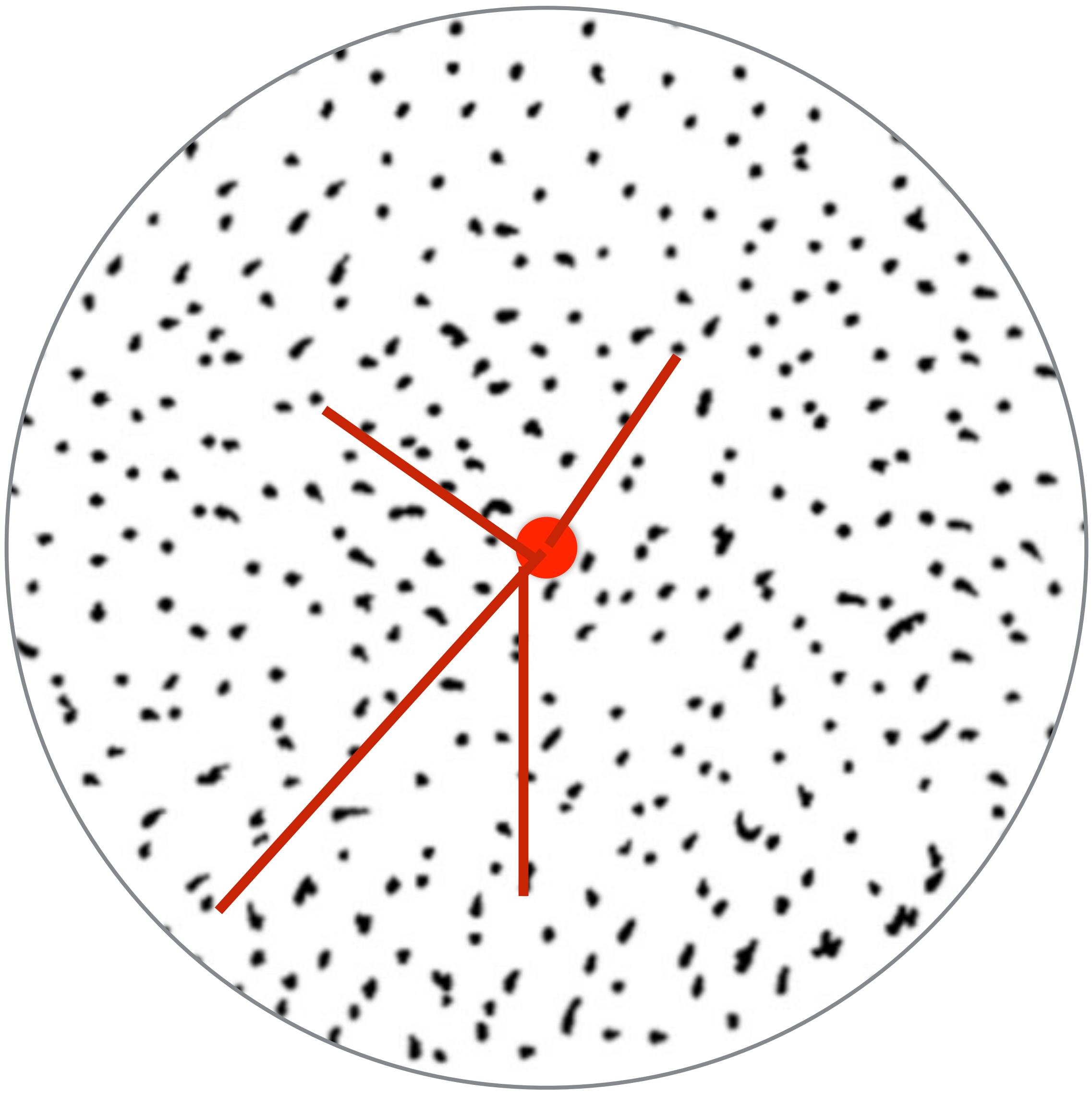
b) We use the center as a starting point to measure variance in the next step

c) The distance between the center and any data-point, tells us how far (different) that point is from the center

2) calculate the total amount of variance (SStotal)

a) Each line represents the difference between a data-point and the mean

b) We measure all of the lines for each data point, then Square them (so there are no negative numbers)

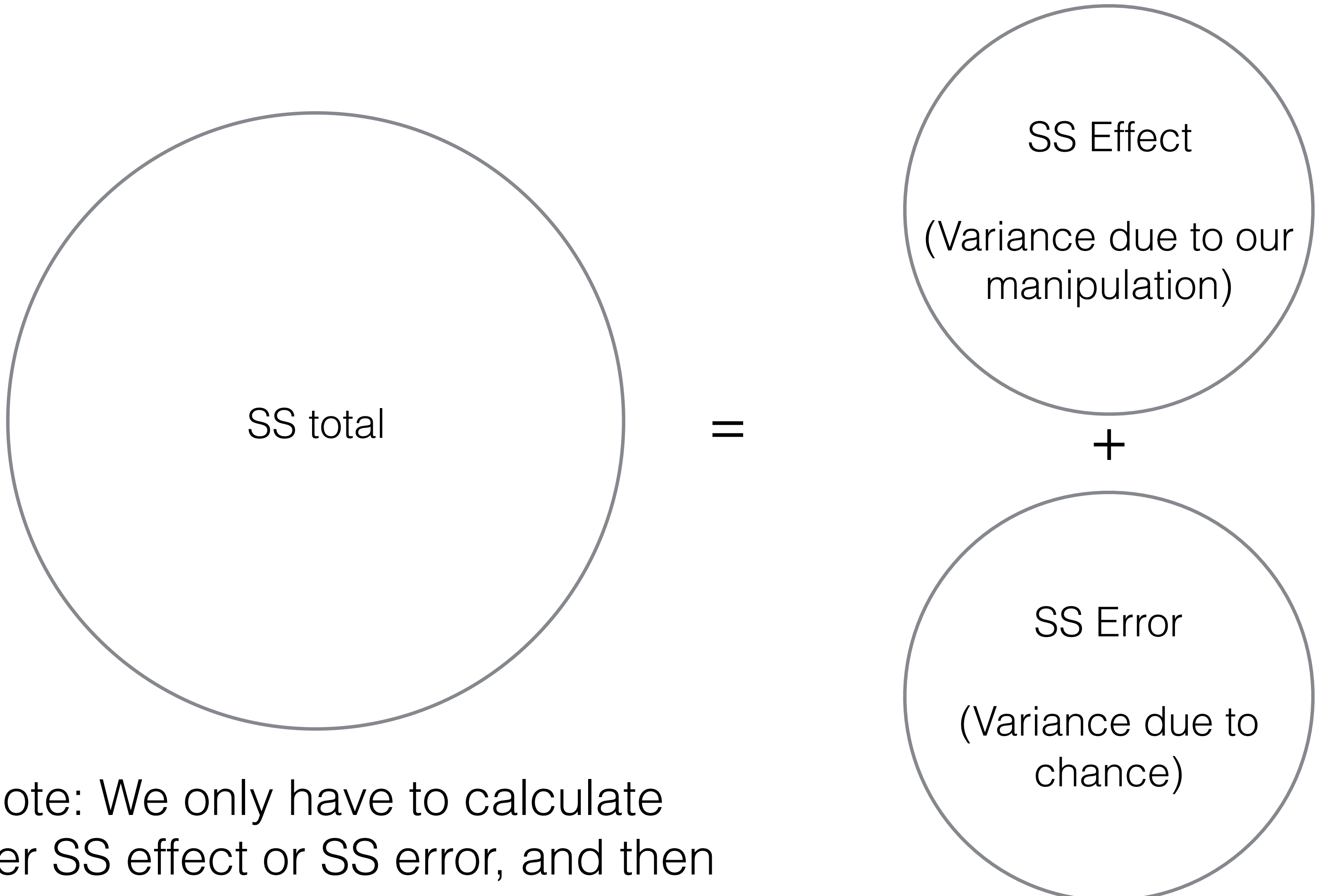


c) Then we add up all the numbers (the Squared Differences)…

That's called the SS (Sum of Squares)

It gives us a single number representing all of the variance in the data

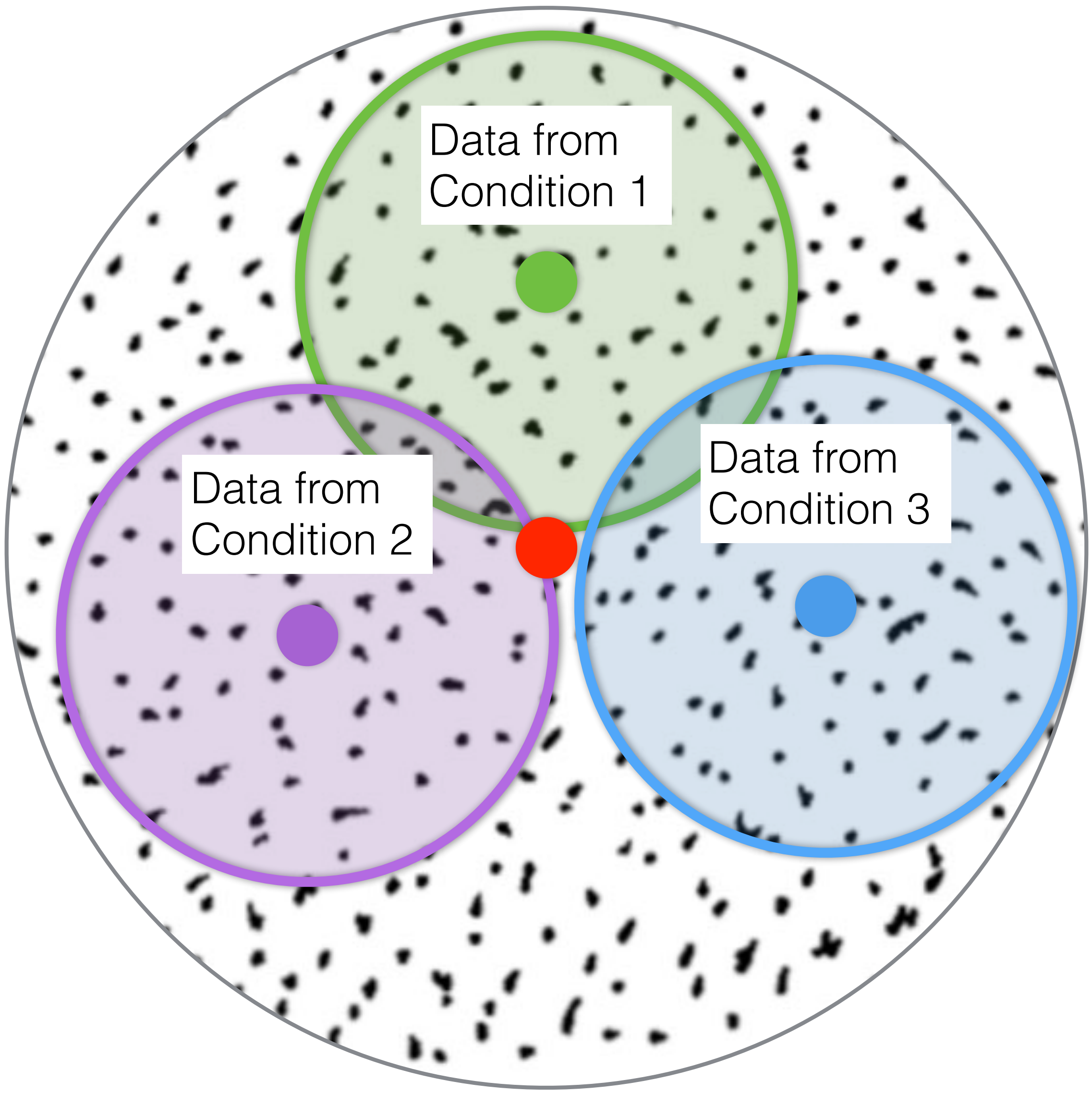
3) Split SS total into two parts



Note: We only have to calculate either SS effect or SS error, and then solve for the other one

4) calculate SS effect (the variance explained by our manipulation)

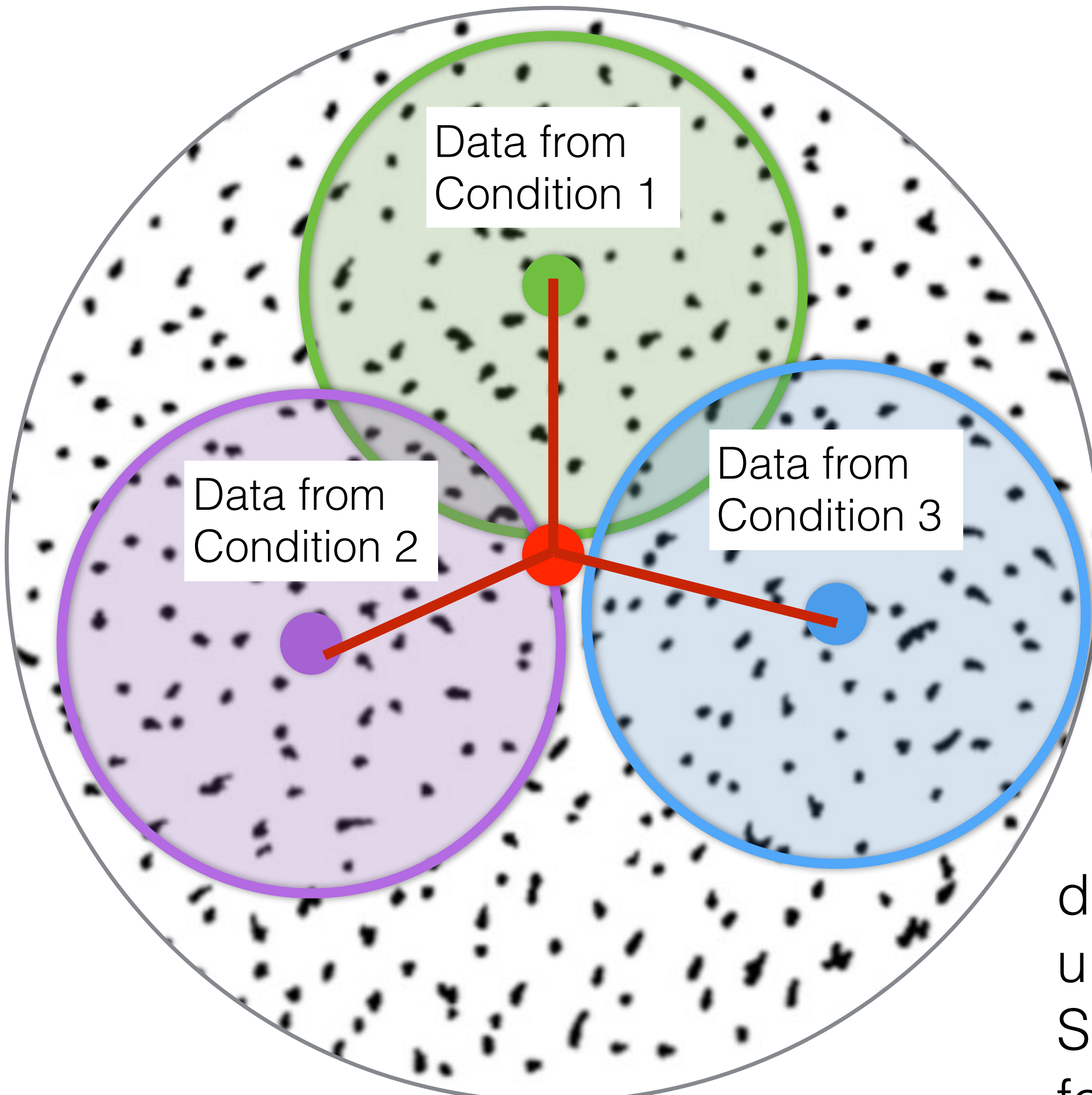
a) we find the means for our conditions



4) calculate SS effect (the variance explained by our manipulation)

a) we find the means for our conditions

b) we compute the distances between the Center (grand mean), and each of the condition means



c) We square the distances, and multiply by them by the number of observations in each condition (the mean represents that many numbers

d) We add them up, to get the Sum of Squares for the effect

5) Solve for SS Error

SS Error

(Variance due to chance)

=

SS total

-

SS Effect

(Variance due to our manipulation)

6) Normalize the SS effect and SS error (by the dfs) to get the MSE effect, and MSE error

$$F = \frac{\dfrac{\text{SS effect}}{\text{df effect}}}{\dfrac{\text{SS error}}{\text{df error}}}$$

$\dfrac{\text{SS effect}}{\text{df effect}} =$ Variance we CAN EXPLAIN

$\dfrac{\text{SS error}}{\text{df error}} =$ Variance we CAN'T EXPLAIN

7) Calculate F-value by dividing MSE effect/ MSE error

F=

MSE effect = Variance we CAN EXPLAIN

MSE error = Variance we CAN'T EXPLAIN

	The Data			SS Total			SS Effect		
	Condition 1	Condition 2	Condition 3	Squared Difference between each data point and Grand Mean			Squared Difference between each Condition Mean and Grand Mean		
	4	5	5	1.777777778	0.111111111	0.111111111	1.777777778	0.444444444	0.444444444
	3	6	6	5.444444444	0.444444444	0.444444444	1.777777778	0.444444444	0.444444444
	5	5	7	0.111111111	0.111111111	2.777777778	1.777777778	0.444444444	0.444444444
	4	6	6	1.777777778	0.444444444	0.444444444	1.777777778	0.444444444	0.444444444
	3	5	4	5.444444444	0.111111111	1.777777778	1.777777778	0.444444444	0.444444444
	4	4	3	1.777777778	1.777777778	5.444444444	1.777777778	0.444444444	0.444444444
	3	6	7	5.444444444	0.444444444	2.777777778	1.777777778	0.444444444	0.444444444
	5	7	9	0.111111111	2.777777778	13.44444444	1.777777778	0.444444444	0.444444444
	5	10	7	0.111111111	21.77777778	2.777777778	1.777777778	0.444444444	0.444444444
Means	4	6	6		SS total	80		SS effect	24
Grand Mean	5.333333333							SS error	56

	df	SS	MSE	F	p-value
effect	2	24	12	5.143	0.0096
error	24	56	2.333333		