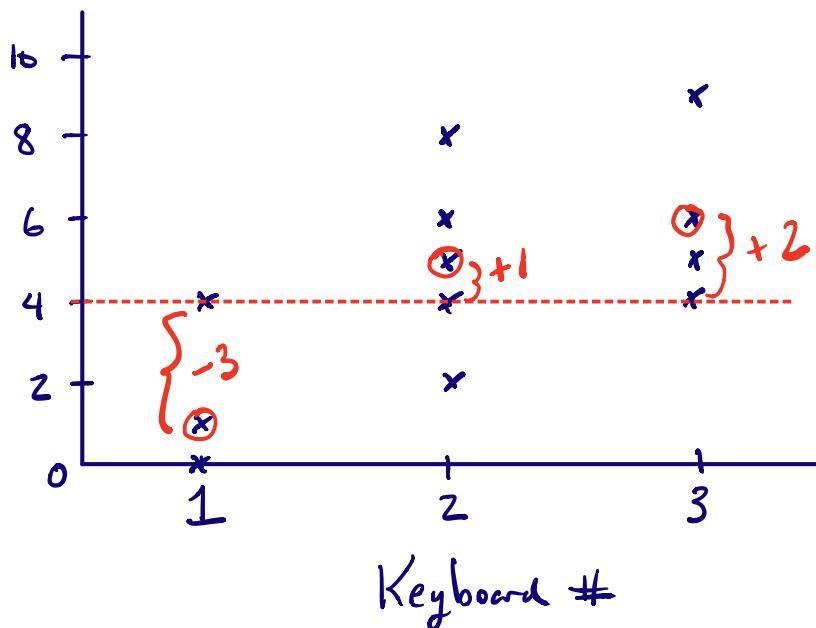


## Lecture 4 - Repeated Measures Designs.

From last time: An 110 psychologist studied three computer keyboard designs. Subjects were randomly assigned to type on one of the three designs, and the # of errors was recorded.

	Keyboard 1	Keyboard 2	Keyboard 3
0	6	6	
4	8	5	
0	5	9	
1	4	4	
0	2	6	
<hr/>		M = 1	5
<hr/>		6	$\bar{X} = 4$
d <sub>j</sub>	-3	+1	+2



General principle of experimental design:

Data are nonsense without an underlying model to impose structure

Structure = "data story"

↳ how can we generate each data point?

Linear model:

$$X_{ij} = \mu + \alpha_j + \varepsilon_{ij}$$

Translation: each score  $X_{ij}$  can be obtained by:

- (1) starting with the **grand mean**  $\mu$
- (2) adding the relevant **treatment effect**  $\alpha_j$
- (3) adding the remaining **residual error**  $\varepsilon_{ij}$   
that is not already accounted for  
by  $\mu$  and  $\alpha_j$

So I can write the full model of these data

as:

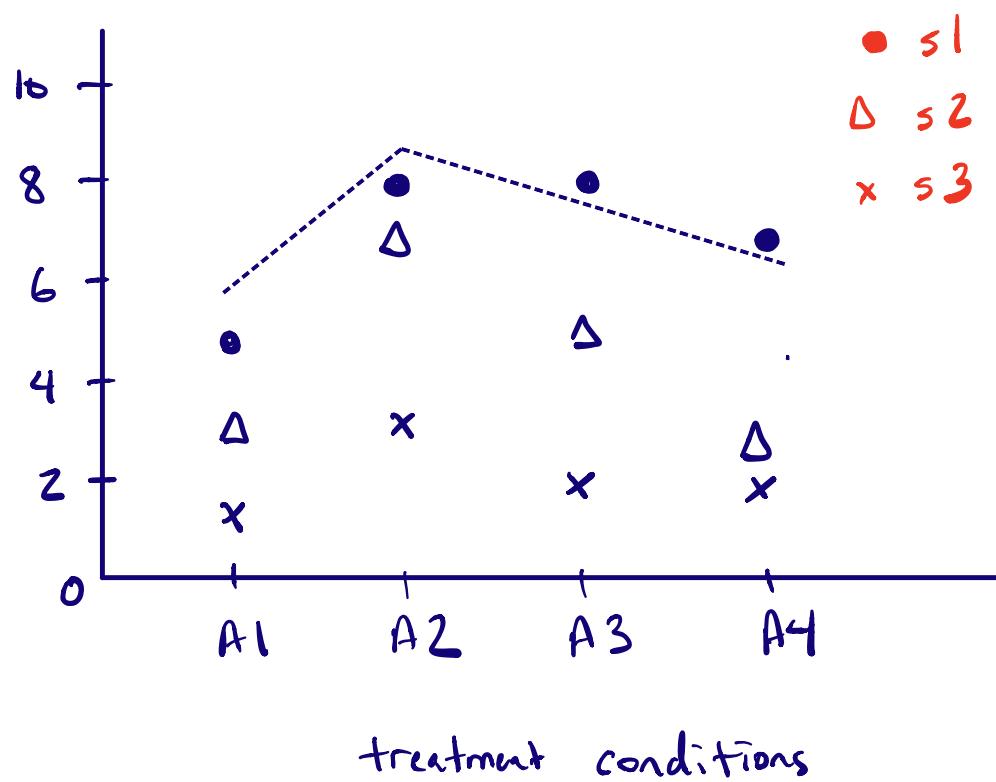
$$\begin{aligned} X_{ij} &= \mu + \alpha_j + \varepsilon_{ij} \\ &= 4 + \begin{bmatrix} -3 \\ 1 \\ 2 \end{bmatrix} + \varepsilon_{ij} \end{aligned}$$

In this lecture, we consider designs where participants are measured **multiple times**

↳ "repeated measures designs"

Ex:

subject	treatment conditions			
	A1	A2	A3	A4
s1	5	8	8	7
s2	3	7	5	3
s3	1	3	2	2



What is our data story?

- not only is there variability between treatments, but there is also variability between subjects
- let us obtain each data point  $X_{ij}$  as:
  - (1) grand mean  $\mu$
  - (2) plus a treatment effect  $\alpha_j$
  - (3) plus a subject effect  $\pi_i$
  - (4) plus residual error

Model:

$$X_{ij} = \mu + \alpha_j + \pi_i + \epsilon_{ij}$$

let's estimate these effects  
from our data.

Estimating our model:

subject	treatment conditions				M	$\pi_i$
	A1	A2	A3	A4		
s1	5	8	8	7	7	+2.5
s2	3	7	5	3	4.5	0
s3	1	3	2	2	2	-2.5
M	3	6	5	4	4.5	
$\alpha_j$	-1.5	+1.5	+0.5	-0.5		

So we can write

$$X_{ij} = \mu + \alpha_j + \pi_i + \varepsilon_{ij}$$

$$= 4.5 + \begin{bmatrix} -1.5 \\ 1.5 \\ 0.5 \\ 0.5 \end{bmatrix} + \begin{bmatrix} 2.5 \\ 0 \\ -2.5 \end{bmatrix} + \varepsilon_{ij}$$

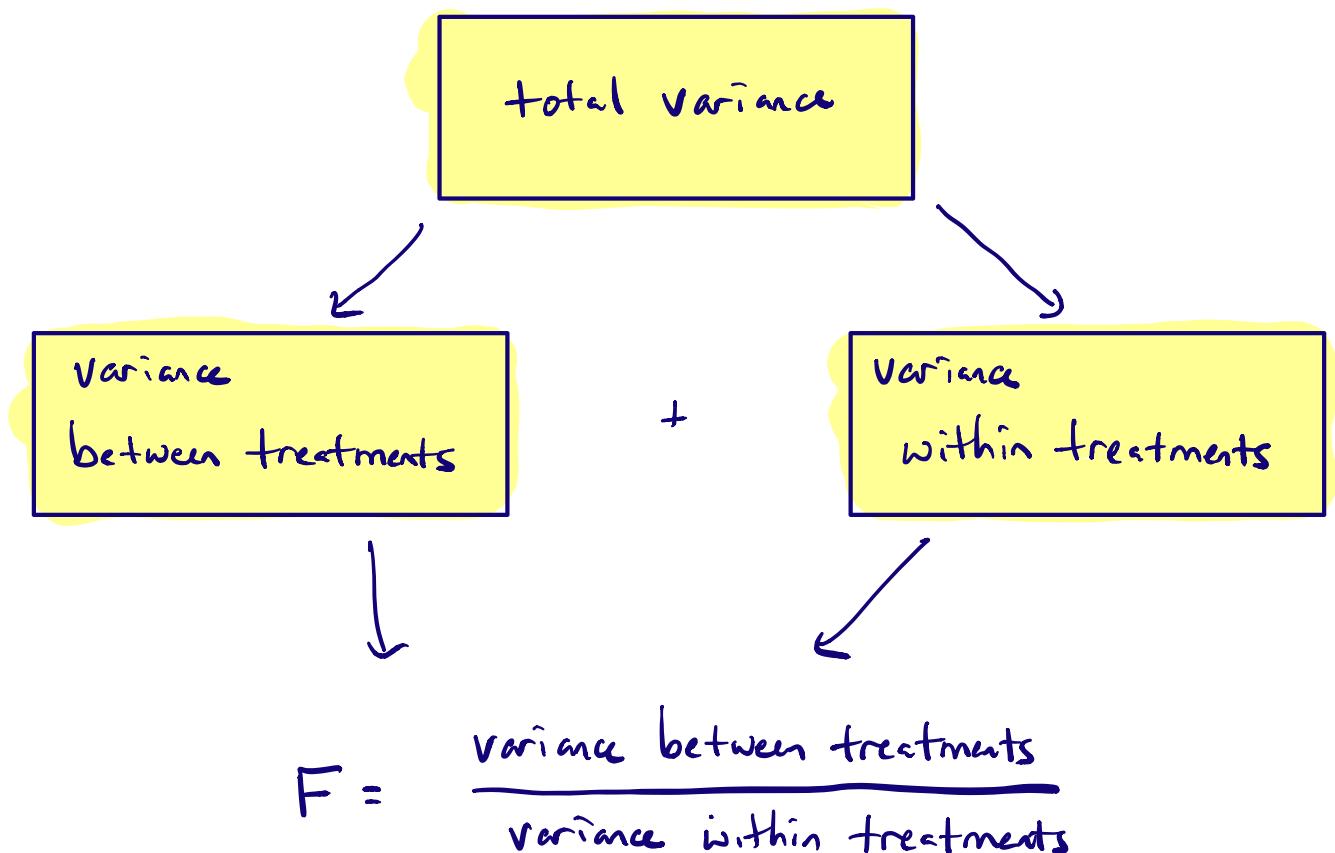
## Hypothesis testing:

$$H_0: \alpha_j = 0 \quad \text{"constrained model"}$$

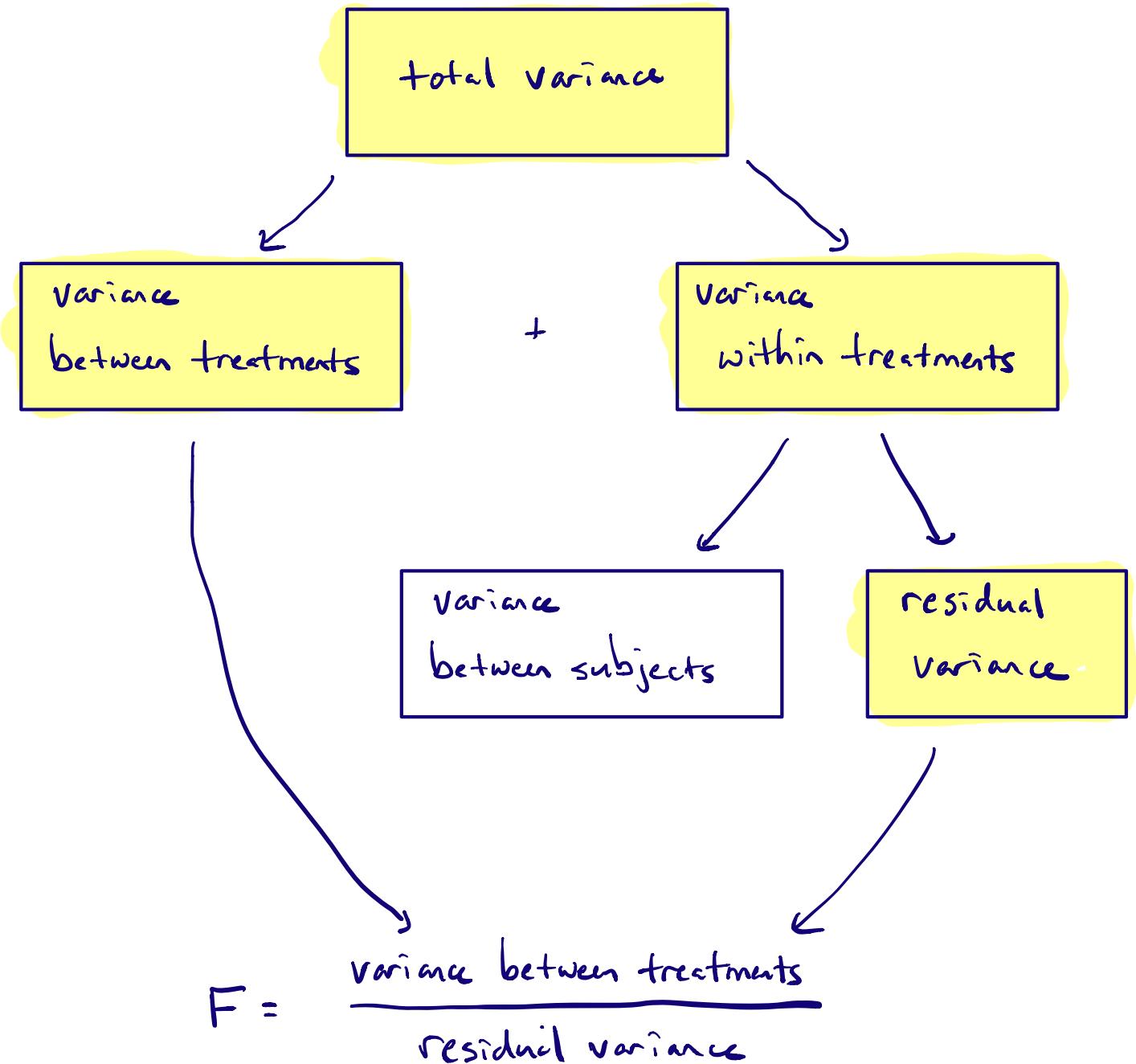
$$H_1: \text{some } \alpha_j \neq 0$$

Which better predicts the observed data?

Recall: ANOVA works by partitioning variance



In repeated measures designs, we further partition the variance within treatments



## ANOVA computations

Just like before we calculate

$$* SS_{\text{total}} = \sum x^2 - \frac{(\sum x)^2}{N}$$

$$* SS_{\text{bet trnts}} = N \sum_{j=1}^4 (\bar{x}_{\text{trnt}_j} - \bar{x})^2$$

We also need to compute:

$$* SS_{\text{bet subj}} = N \sum_{i=1}^3 (\bar{x}_{\text{subj}_i} - \bar{x})^2$$

Then  $SS_{\text{resid}} = \text{whatever is left over}$

$$= SS_{\text{total}} - SS_{\text{bet trnts}} - SS_{\text{bet subj}}$$

## Computations

$$\begin{aligned} SS_{\text{bet trnts}} &= N \sum_{j=1}^4 (\bar{x}_{\text{tmt } j} - \bar{x})^2 \\ &= 3 \left[ (3-4.5)^2 + (6-4.5)^2 + (5-4.5)^2 + (4-4.5)^2 \right] \\ &= 3 (2.25 + 2.25 + 0.25 + 0.25) \\ &= 15 \end{aligned}$$

$$\begin{aligned} SS_{\text{bet subj}} &= N \sum_{i=1}^3 (\bar{x}_{\text{subj } i} - \bar{x})^2 \\ &= 4 \left[ (7-4.5)^2 + (4.5-4.5)^2 + (2-4.5)^2 \right] \\ &= 4 (6.25 + 0 + 6.25) \\ &= 50 \end{aligned}$$

$$\begin{aligned} SS_{\text{total}} &= \sum x^2 - \frac{(\sum x)^2}{N} \\ &= 312 - \frac{54^2}{12} = 69 \end{aligned}$$

## ANOVA table:

source	SS	df	MS	F
bet trnts	15	3	5	7.5
residual	4	6	0.67	
bet subj	50	2	25	
total	69	11		

Report:  $F(3, 6) = 7.50$ ,  $P = 0.0187$ ,

$$BF_{10} = 41.09$$

What if we didn't account for subject variability?

source	SS	df	MS	F	
bet. trnts	15	3	5	0.74	$\leftarrow p = 0.557$
residual	54	8	6.75		$BF_{01} = 9.56$
total	69	11			

Moral: by accounting for subject variability,  
repeated measures ANOVA can better  
uncover latent treatment effects