

## Topic 21 - Two Factor ANOVA

STAT 525 - Fall 2013

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## Outline

- Data
- Model
- Parameter Estimates
  - Equal Sample Size
  - One replicate per cell
  - Unequal Sample size

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## Overview

- Now have two factors ( $A$  and  $B$ )
- Suppose each factor has two levels
- Could analyze as one factor with 4 levels
  - Trt 1:  $A$  high,  $B$  high
  - Trt 2:  $A$  high,  $B$  low
  - Trt 3:  $A$  low,  $B$  high
  - Trt 4:  $A$  low,  $B$  low
- Use contrasts to test for main effects an interaction

$$A \text{ main effect} = \frac{\text{Trt1} + \text{Trt2}}{2} - \frac{\text{Trt3} + \text{Trt4}}{2}$$

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## Example

An experiment is conducted to study the effect of hormones injected into test rats. There are two distinct hormones ( $A, B$ ) each with two distinct levels. For purposes here, we will consider this to be four different treatments labeled  $\{A, a, B, b\}$ . Each treatment is applied to six rats with the response being the amount of glycogen (in mg) in the liver.

Treatment	Responses					
A	106	101	120	86	132	97
a	51	98	85	50	111	72
B	103	84	100	83	110	91
b	50	66	61	72	85	60

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## Example

Three contrasts are of interest. They are:

Comparison	A	a	B	b
Hormone A vs Hormone B	1	1	-1	-1
Low level vs High level	1	-1	1	-1
Equivalence of level effect	1	-1	-1	1

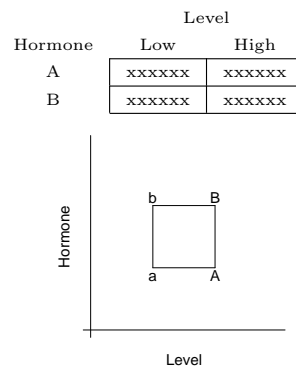
Can we reanalyze the experiment in such a way that these sum of squares are already separated?

## Two-way Factorial

- Break up the treatments into the two factors
- Example also known as a  $2^2$  factorial
- Investigates all combos of factor levels
- Single “replicate” involves  $ab$  trials

## Two-way Factorial Layout

- Often presented as table or plot



## Data for Two Factor ANOVA

- $Y$  is the response variable
- Factor  $A$  has levels  $i = 1, 2, \dots, a$
- Factor  $B$  has levels  $j = 1, 2, \dots, b$
- $Y_{ijk}$  is the  $k^{\text{th}}$  observation from cell  $(i, j)$
- Chapter 19 assumes  $n_{ij} = n$
- Chapter 20 assumes  $n_{ij} = 1$
- Chapter 23 allows  $n_{ij}$  to vary

## Example Page 833

- Castle Bakery supplies wrapped Italian bread to a large number of supermarkets
- Bakery interested in the set up of their store display
  - Height of display shelf (top, middle, bottom)
  - Width of display shelf (regular, wide)
- Twelve stores equal in sales volume were selected
- Randomly assigned equally to each of 6 combinations
- $Y$  is the sales of the bread
  - $i = 1, 2, 3$  and  $j = 1, 2$
  - $n_{ij} = n = 2$

## SAS Commands

```
data a1; infile 'u:\.www\datasets525\CH19TA07.txt';
  input sales height width;

proc print;
run;

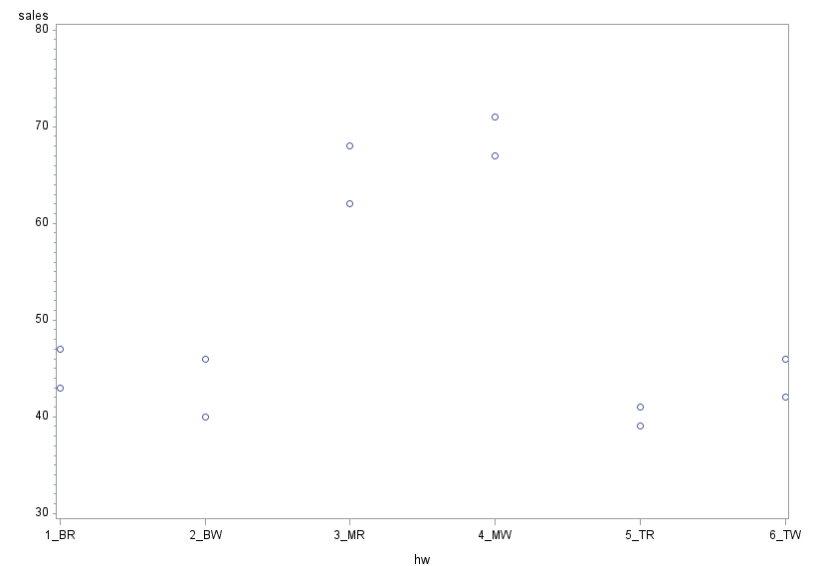
data a1; set a1;
  if height eq 1 and width eq 1 then hw='1_BR';
  if height eq 1 and width eq 2 then hw='2_BW';
  if height eq 2 and width eq 1 then hw='3_MR';
  if height eq 2 and width eq 2 then hw='4_MW';
  if height eq 3 and width eq 1 then hw='5_TR';
  if height eq 3 and width eq 2 then hw='6_TW';

symbol1 v=circle i=none;
proc gplot data=a1;
  plot sales*hw/frame;
```

## Sales Data

Obs	sales	height	width
1	47	1	1
2	43	1	1
3	46	1	2
4	40	1	2
5	62	2	1
6	68	2	1
7	67	2	2
8	71	2	2
9	41	3	1
10	39	3	1
11	42	3	2
12	46	3	2

## Scatterplot



## The Model

- All observations assumed independent
- All observations normally distributed with
  - a mean that may depend on levels of factors A and B
  - constant variance
- Often presented in terms of cell means or factor effects

## The Cell Means Model

- Expressed mathematically

$$Y_{ijk} = \mu_{ij} + \varepsilon_{ijk}$$

where  $\mu_{ij}$  is the theoretical mean or expected value of all observations in cell  $(i, j)$

- The  $\varepsilon_{ijk}$  are iid  $N(0, \sigma^2)$  which implies the  $Y_{ijk}$  are independent  $N(\mu_{ij}, \sigma^2)$
- Parameters
  - $\{\mu_{ij}\}$ ,  $i = 1, 2, \dots, a$ ,  $j = 1, 2, \dots, b$
  - $\sigma^2$

## Estimates / Inference

- Estimate  $\mu_{ij}$  by the sample mean of the observations in cell  $(i, j)$

$$\hat{\mu}_{ij} = \bar{Y}_{ij.}$$

- Can also estimate variance using observations in cell  $(i, j)$

$$s_{ij}^2 = \sum (Y_{ijk} - \bar{Y}_{ij.})^2 / (n - 1)$$

- These  $s_{ij}^2$  are combined for single estimate of  $\sigma^2$

## ANOVA Table : $n_{ij} = n$

- Similar ANOVA table construction ( $\bar{Y}_{ij.}$  is fitted value)

Source of Variation	df	SS
Model	$ab - 1$	$n \sum \sum (\bar{Y}_{ij.} - \bar{Y}_{...})^2$
Error	$ab(n - 1)$	$\sum \sum \sum (Y_{ijk} - \bar{Y}_{ij.})^2$
Total	$abn - 1$	$\sum \sum \sum (Y_{ijk} - \bar{Y}_{...})^2$

$$\bar{Y}_{...} = \sum \sum \sum Y_{ijk} / abn$$

$$\bar{Y}_{ij.} = \sum Y_{ijk} / n$$

- Can further break down into Factor A, Factor B and interaction effects using contrasts

## Factor Effects Model

- Breaks down cell means

$$\mu = \sum_i \sum_j \mu_{ij} / (ab)$$

$$\mu_{i.} = \sum_j \mu_{ij} / b \text{ and } \mu_{.j} = \sum_i \mu_{ij} / a$$

$$\alpha_i = \mu_{i.} - \mu \text{ and } \beta_j = \mu_{.j} - \mu$$

$$(\alpha\beta)_{ij} = \mu_{ij} - (\mu + \alpha_i + \beta_j)$$

- Interaction effect is the difference between the cell mean and the additive or main effects model. Explains variation not explained by main effects.

## Factor Effects Model

- Statistical model is

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk} \quad \begin{cases} i = 1, 2, \dots, a \\ j = 1, 2, \dots, b \\ k = 1, 2, \dots, n \end{cases}$$

$\mu$  - grand mean

$\alpha_i$  -  $i$ th level effect of factor A (ignores B)

$\beta_j$  -  $j$ th level effect of factor B (ignores A)

$(\alpha\beta)_{ij}$  - interaction effect of combination  $ij$

- Like one-way model this is over-parameterized.
- Must include  $a + b + 1$  model constraints.

$$\sum_i \alpha_i = 0 \quad \sum_j \beta_j = 0 \quad \sum_i (\alpha\beta)_{ij} = 0 \quad \sum_j (\alpha\beta)_{ij} = 0$$

## Factor Effects Estimates

- Constraints on previous page result in

$$\hat{\mu} = \bar{Y} \dots$$

$$\hat{\alpha}_i = \bar{Y}_{i..} - \bar{Y} \dots$$

$$\hat{\beta}_j = \bar{Y}_{.j.} - \bar{Y} \dots$$

$$\widehat{(\alpha\beta)}_{ij} = \bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y} \dots$$

- The predicted value and residual are

$$\hat{Y}_{ijk} = \bar{Y}_{ij.}$$

$$e_{ijk} = Y_{ijk} - \bar{Y}_{ij.}$$

## Questions about our Example

- Does the height of the display affect sales?
  - If yes, will need to do pairwise comparisons
- Does the width of the display affect sales?
  - If yes, will need to do pairwise comparisons
- Does the effect of height depend on the width?
- Does the effect of width depend on the height?
  - If yes to either of these last two, we have an interaction

## Partitioning the Sum of Squares

$$Y_{ijk} - \bar{Y}... = (\bar{Y}_{i..} - \bar{Y}...) + (\bar{Y}_{.j.} - \bar{Y}...) + (\bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}...) + (Y_{ijk} - \bar{Y}_{ij.})$$

- Consider  $\sum \sum \sum (Y_{ijk} - \bar{Y}...)^2$
- Right hand side simplifies to

$$\begin{aligned} & bn \sum_i (\bar{Y}_{i..} - \bar{Y}...)^2 + \\ & an \sum_j (\bar{Y}_{.j.} - \bar{Y}...)^2 + \\ & n \sum_i \sum_j (\bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}...)^2 + \\ & \sum_i \sum_j \sum_k (Y_{ijk} - \bar{Y}_{ij.})^2 \end{aligned}$$

## Partitioning the Sum of Squares

- Can be written as  

$$SSTO = SSA + SSB + SSAB + SSE$$
- Degrees of freedom also broken down
- Under normality, all  $SS/\sigma^2$  independent

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square
Factor A	SSA	$a - 1$	MSA
Factor B	SSB	$b - 1$	MSB
Interaction	SSAB	$(a - 1)(b - 1)$	MSAB
Error	SSE	$ab(n - 1)$	MSE
Total	SSTO	$abn - 1$	

## Hypothesis Testing

- Can show: Fixed Case  

$$E(MSE) = \sigma^2$$

$$E(MSA) = \sigma^2 + bn \sum \alpha_i^2 / (a - 1)$$

$$E(MSB) = \sigma^2 + an \sum \beta_j^2 / (b - 1)$$

$$E(MSAB) = \sigma^2 + n \sum (\alpha\beta)_{ij}^2 / (a - 1)(b - 1)$$
- Use F-test to test for A, B, and AB effects

$$F^* = \frac{SSA/(a - 1)}{SSE/(ab(n - 1))}$$

$$F^* = \frac{SSB/(b - 1)}{SSE/(ab(n - 1))}$$

$$F^* = \frac{SSAB/(a - 1)(b - 1)}{SSE/(ab(n - 1))}$$

## SAS Commands

```
proc glm data=a1;
  class height width;
  model sales=height width height*width;
  means height width height*width;

proc means data=a1;
  var sales; by height width;
  output out=a2 mean=avsales;

symbol1 v=square i=join c=black;
symbol2 v=diamond i=join c=black;
proc gplot data=a2;
  plot avsales*height=width/frame;
run;
```

# Output

The GLM Procedure

Class Level Information		
Class	Levels	Values
height	3	1 2 3
width	2	1 2

Number of observations 12

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	1580.000000	316.000000	30.58	0.0003
Error	6	62.000000	10.333333		
Corrected Total	11	1642.000000			

R-Square	Coeff Var	Root MSE	sales Mean
0.962241	6.303040	3.214550	51.00000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
height	2	1544.000000	772.000000	74.71	<.0001
width	1	12.000000	12.000000	1.16	0.3226
height*width	2	24.000000	12.000000	1.16	0.3747

Source	DF	Type III SS	Mean Square	F Value	Pr > F
height	2	1544.000000	772.000000	74.71	<.0001
width	1	12.000000	12.000000	1.16	0.3226
height*width	2	24.000000	12.000000	1.16	0.3747

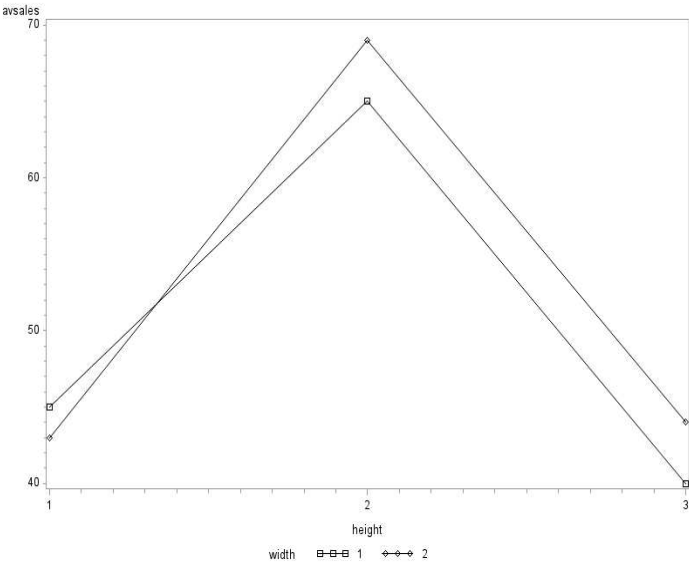
# Output

Level of		-----sales-----	
height	N	Mean	Std Dev
1	4	44.0000000	3.16227766
2	4	67.0000000	3.74165739
3	4	42.0000000	2.94392029

Level of		-----sales-----	
width	N	Mean	Std Dev
1	6	50.0000000	12.0664825
2	6	52.0000000	13.4313067

Level of	Level of	-----sales-----		
height	width	N	Mean	Std Dev
1	1	2	45.0000000	2.82842712
1	2	2	43.0000000	4.24264069
2	1	2	65.0000000	4.24264069
2	2	2	69.0000000	2.82842712
3	1	2	40.0000000	1.41421356
3	2	2	44.0000000	2.82842712

# Interaction Plot



# SAS Commands

```
proc glm data=a1;
  class height width;
  model sales=height|width;
  means height / tukey lines;

proc glm data=a1;
  class height width;
  model sales=height width;
  means height / tukey lines;
run;
```

## Results

- There appears to be no interaction between height and width ( $P=0.37$ )  $\rightarrow$  The effect of width (or height) is the same regardless of height (or width). Because of this, we can focus on the main effects (averages out the other effect).
- The main effect for width is not statistically significant ( $P=0.32$ )  $\rightarrow$  Width does not affect sales of bread
- The main effect for height is statistically significant ( $P < 0.0001$ ). From the scatterplot and interaction plot, it appears the middle location is better than the top and bottom. Pairwise testing (adjusting for multiple comparisons) can confirm this.

## Pooling Insignificant Terms

- Some argue that an insignificant interaction should be dropped from the model (i.e., pooled with error)
- See last GLM call
 
$$SSE^* = SSE + SSAB$$

$$df_E^* = ab(n-1) + (a-1)(b-1)$$
- This increases DF but could inflate  $\hat{\sigma}^2$
- Possibly result in a Type II error
- Rule of thumb: Only pool when dfe small (e.g.,  $< 5$ ) and P-value of the interaction is large (e.g.,  $> 0.25$ )

## Output

Tukey's Studentized Range (HSD) Test for sales

```
Error Degrees of Freedom      6
Error Mean Square             10.33333
Critical Value of Studentized Range  4.33902
Minimum Significant Difference    6.974
```

	Mean	N	height
A	67.000	4	2
B	44.000	4	1
B	42.000	4	3

\*\*\*\* POOLING \*\*\*\*

```
Error Degrees of Freedom      8
Error Mean Square             10.75
Critical Value of Studentized Range  4.04101
Minimum Significant Difference    6.6247
```

	Mean	N	height
A	67.000	4	2
B	44.000	4	1
B	42.000	4	3

## Background Reading

- KNNL Chapter 19
- knnl833.sas