# STA305/1004 - Class 11

February 13, 2017

► ANOVA table

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- ► ANOVA identity

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- ▶ F statistic
- Assumptions

#### Comparing more than two treatments

If interest is in designing an experiment to compare more than two treatments then the previous designs will need to modified.

A clinical trial comparing three drugs A, B, C to reduce duration of intubation for patients on mechanical ventilation.

What are the null and alternative hypotheses in these two scenarios?

#### Comparing more than two treatments

If interest is in designing an experiment to compare more than two treatments then the previous designs will need to modified.

- A clinical trial comparing three drugs A, B, C to reduce duration of intubation for patients on mechanical ventilation.
- Coagulation time of blood samples for animals receiving four different diets A, B, C, D.

What are the null and alternative hypotheses in these two scenarios?

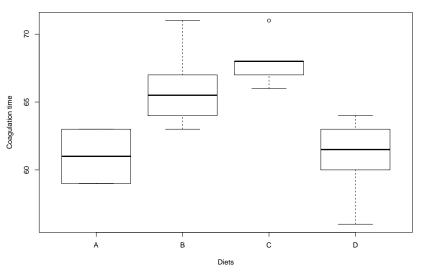
▶ 24 animals were randomized to four treatments with 6 animals in each group.

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- ▶ How many possible treatment assignments?

► The data for coagulation times for blood samples drawn from 24 animals receiving four different diets A, B, C, and D are shown below.

Α	В	C	D	
60	65	71	62	
63	66	66	60	
59	67	68	61	
63	63	68	64	
62	64	67	63	
59	71	68	56	
Treatment Average	61	66	68	61
Grand Average	64	64	64	64
Difference	-3	2	4	-3
-				

Coagulation time from 24 animals randomly allocated to four diets



Do the boxplots show evidence of a difference between diets?

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- An idea due to Fisher is to compare the variation in mean coagulation times between the diets to the variation of coagulation times within a diet. These two measures of variation are often summarized in an analysis of variance (ANOVA) table.
- Fisher introduced the method in his 1925 book "Statistical Methods for Research Workers".
- The statistical procedure enables experimenters to answer several questions at once.
- ► The prevailing method at the time was to test one factor at a time in an experiment.

► The between treatments variation and within treatment variation are two components of the total variation in the response.

$$y_{ij}-ar{y}_{\cdot\cdot}=\underbrace{\left(y_{i\cdot}-ar{y}_{\cdot\cdot}
ight)}_{ ext{treatment deviation}}+\underbrace{\left(y_{ij}-ar{y}_{i\cdot}
ight)}_{ ext{residual deviation}}$$
 $y_{i\cdot}=\sum_{i=1}^{n}y_{ij}, \qquad ar{y}_{i\cdot}=y_{i\cdot}/n,$ 

$$y_{..} = \sum_{i=1}^{a} \sum_{i=1}^{n} y_{ij}, \quad \bar{y}_{..} = y_{..}/N,$$

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- In the coagulation study data we can break up each observation's deviation from the grand mean into two components: treatment deviations; and residuals within treatment deviations.

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- Let  $y_{ij}$  be the jth (j=1,....,6) observation taken under treatment i=1,2,3,4.

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▶ Let  $y_{ij}$  be the jth observation taken under treatment i = 1, ..., a.

$$E(y_{ii}) = \mu_i = \mu + \tau_i,$$

and  $Var(y_{ij}) = \sigma^2$  and the observations are mutually independent.

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- ▶ The parameter  $\tau_i$  is the *ith* treatment effect.
- $\blacktriangleright$  The parameter  $\mu$  is the overall mean.

We are interested in testing if the a treatment means are equal.

$$H_0: \mu_1 = \cdots = \mu_a$$
 vs.  $H_1: \mu_i \neq \mu_j, i \neq j$ .

There will be *n* observations under the *ith* treatment.

$$y_{i\cdot} = \sum_{j=1}^n y_{ij}, \qquad \bar{y}_{i\cdot} = y_{i\cdot}/n,$$

$$y_{\cdot \cdot} = \sum_{i=1}^{a} \sum_{j=1}^{n} y_{ij}, \qquad \bar{y}_{\cdot \cdot} = y_{\cdot \cdot}/N,$$

where N=an is the total number of observations. The "dot" subscript notation means sum over the subscript that it replaces.

## The ANOVA identity

The total sum of squares  $SS_T = \sum_{i=1}^a \sum_{j=1}^n (y_{ij} - \bar{y}_{\cdot \cdot})^2$  can be written as

$$\sum_{i=1}^a \sum_{j=1}^n \left[ \left( ar{y}_{i\cdot} - ar{y}_{\cdot\cdot} 
ight) + \left( y_{ij} - ar{y}_{i\cdot} 
ight) 
ight]^2$$

by adding and subtracting  $\bar{y}_i$  to  $SS_T$ .

It can be shown that

$$SS_{T} = \sum_{i=1}^{a} \sum_{j=1}^{n} (y_{ij} - \bar{y}_{..})^{2} = \underbrace{n \sum_{i=1}^{a} (y_{i.} - \bar{y}_{..})^{2}}_{\text{Sum of Squares Due to Treatment}} + \underbrace{\sum_{i=1}^{a} \sum_{j=1}^{n} (y_{ij} - \bar{y}_{i.})^{2}}_{\text{Sum of Squares Due to Error}}$$
$$= SS_{Treat} + SS_{E}.$$

#### The ANOVA identity

This is sometimes called the analysis of variance identity. It shows how the total sum of squares can be split into two sum of squares: one part that is due to differences between treatments; and one part due to differences within treatments.

The ANOVA identity

	Α	В	C	D
	60	65	71	62
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Treatment Average	61	66	68	61
Grand Average	64	64	64	64
Difference	-3	2	4	-3

▶ The decomposition of the first observation  $y_{11} = 60$  in diet A is

$$y_{11} - \bar{y}_{\cdot \cdot} = (y_1 - \bar{y}_{\cdot \cdot}) + (y_{11} - \bar{y}_{1 \cdot})$$
  

$$60 - 64 = (61 - 64) + (60 - 61)$$
  

$$-4 = -3 + -1$$

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$$60 - 64 = (61 - 64) + (60 - 61)$$
  

$$-4 = -3 + -1$$

If each observation is decomposed in this manner then there will be three tables of residuals: total residuals; between treatment residuals; and within treatment residuals.

# Example - Blood coagulation study $(SS_T)$

The deviations from the grand average  $(y_{ij} - \bar{y}_{..})$  are in the table below:

- A B C D
- -4 1 7 -2
- -1 22-4
- -5 3 4 -3
- -1 -1 4 0
- -2 0 3 -1
- -5 7 4 -8

The total sum of squares is obtained by squaring all the entries in this table and summing:  $SS_T = (-4)^2 + (-1)^2 + \cdots + (-8)^2 = 340$ .

# Example - Blood coagulation study $(SS_{Treat})$

The between treatment deviations  $(y_i - \bar{y}_{\cdot \cdot})$  are in the table below:

- A B C D
- -3 2 4 -3 -3 2 4 -3
- -3 2 4 -3
- 0240
- -3 2 4 -3
- -3 2 4 -3
- -3 2 4 -3

The sum of squares due to treatment is obtained by squaring all the entries in this table and summing:  $SS_{Treat} = (-3)^2 + (2)^2 + \cdots + (-3)^2 = 228$ .

## Example - Blood coagulation study $(SS_E)$

The within treatment deviations  $(y_{ij} - \bar{y}_{i.})$  are in the table below:

A B C D
-1 -1 3 1
2 0 -2 -1
-2 1 0 0
2 -3 0 3
1 -2 -1 2
-2 5 0 -5

The sum of squares due to error  $(y_{ij} - \bar{y}_{i\cdot})$  is obtained by squaring the entries in this table and summing:  $SS_E = (-1)^2 + (2)^2 + \cdots + (-5)^2 = 112$ .

$$\underbrace{340}_{SS_T} = \underbrace{228}_{SS_{Treat}} + \underbrace{112}_{SS_E}.$$

Which illustrates the ANOVA identity for the blood coagulation study.

#### ANOVA - degrees of freedom

#### The deviations

▶  $SS_{Treat}$  is called the sum of squares due to treatments (i.e., between treatments), and  $SS_E$  is called the sum of squares due to error (i.e., within treatments).

#### ANOVA - degrees of freedom

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- ▶ There are a treatment levels so  $SS_{Treat}$  has a-1 degrees of freedom.

#### ANOVA - degrees of freedom

#### The deviations

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- ▶ There are an = N total observations. So  $SS_T$  has N-1 degrees of freedom.
- ▶ There are a treatment levels so  $SS_{Treat}$  has a-1 degrees of freedom.
- ▶ Within each treatment there are n replicates with n-1 degrees of freedom. There are a treatments. So, there are a(n-1) = an a = N a degrees of freedom for error.

A B C D

-4 17-2 -1 22-4

-5 3 4 -3

-1 -1 4 0 -2 0 3 -1

-5 7 4 -8

A B C D

-3 2 4 -3 -3 2 4 -3

-3 2 4 -3

-3 2 4 -3

-3 2 4 -3 -3 2 4 -3

A B C D

-1 -1 3 1 2 0 -2 -1

-2 1 0 0  $2 - 3 \quad 0 \quad 3$ 

1 -2 -1 2 -2 5 0 -5

▶ Let a be the vector of deviations from the grand mean,

$$a = (-4, -1, -5, -1, -2, -5, 1, 2, 3, -1, 0, 7, 7, 2, 4, 4, 3, 4, -2, -4, -3, 0, -1, -8),$$
 
$$b = (-3, -3, -3, -3, -3, -3, 2, 2, 2, 2, 2, 2, 4, 4, 4, 4, 4, 4, -3, -3, -3, -3, -3, -3, -3),$$
 
$$c = (-1, 2, -2, 2, 1, -2, -1, 0, 1, -3, -2, 5, 3, -2, 0, 0, -1, 0, 1, -1, 0, 3, 2, -5).$$

- Let a be the vector of deviations from the grand mean,
- ▶ Let *b* be the vector of deviations of treatment deviations

```
 a = (-4, -1, -5, -1, -2, -5, 1, 2, 3, -1, 0, 7, 7, 2, 4, 4, 3, 4, -2, -4, -3, 0, -1, -8),   b = (-3, -3, -3, -3, -3, -3, 2, 2, 2, 2, 2, 2, 4, 4, 4, 4, 4, 4, -3, -3, -3, -3, -3, -3, -3),   c = (-1, 2, -2, 2, 1, -2, -1, 0, 1, -3, -2, 5, 3, -2, 0, 0, -1, 0, 1, -1, 0, 3, 2, -5).
```

- Let a be the vector of deviations from the grand mean,
- Let b be the vector of deviations of treatment deviations
- Let *c* be the vector of within-treatment deviations.

```
 a = (-4, -1, -5, -1, -2, -5, 1, 2, 3, -1, 0, 7, 7, 2, 4, 4, 3, 4, -2, -4, -3, 0, -1, -8),   b = (-3, -3, -3, -3, -3, -3, 2, 2, 2, 2, 2, 2, 4, 4, 4, 4, 4, 4, -3, -3, -3, -3, -3, -3, -3),   c = (-1, 2, -2, 2, 1, -2, -1, 0, 1, -3, -2, 5, 3, -2, 0, 0, -1, 0, 1, -1, 0, 3, 2, -5).
```

▶ The dot product of b and c,  $b \cdot c$ , is

```
b*c
```

```
A B C D

3 -2 12 -3

-6 0 -8 3

6 2 0 0

-6 -6 0 -9

-3 -4 -4 -6

6 10 0 15
```

```
[1] 0
```

sum(b\*c)

▶ The dot product of b and c,  $b \cdot c$ , is

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▶ Therefore, the vectors b and c are orthogonal.

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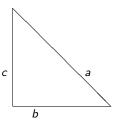
- ▶ Therefore, the vectors *b* and *c* are orthogonal.
- ightharpoonup Thus, the vector a is the hypotenuse of a right triangle with sides b and c.

Pythagoras' theorem in n dimensions is  $|a|^2 = |b|^2 + |c|^2$ , where  $|a| = \sqrt{a_1^2 + \cdots + a_n^2}$ .

The ANOVA identity can be seen using Pythagoras' theorem since

$$\left|a\right|^2 = SS_T, \left|b\right|^2 = SS_{Treat}, \left|c\right|^2 = SS_E.$$

If there were only three observations then the vectors would be as shown below.



The degrees of freedom are the dimensions in which the vectors are free to move given the constraints.

# The ANOVA identity SST=SSTreat+SSE assumes that the data follow a normal distribution?

Respond at PollEv.com/nathantaback
Text NATHANTABACK to 37607 once to join, then A or B

Yes, it requires the normality assumption

No, it does not require the normality assumption.

Figure 1:

$$SS_E = \sum_{i=1}^{a} \left[ \sum_{j=1}^{n} (y_{ij} - \bar{y}_{i.})^2 \right]$$

If the term inside the brackets is divided by n-1 then it is the sample variance for the ith treatment

$$S_i^2 = \frac{\sum_{j=1}^n (y_{ij} - \bar{y}_{i.})^2}{n-1},$$
  $1 = 1,...,a.$ 

Combining these a variances to give a single estimate of the common population variance

$$\frac{(n-1)S_1^2 + \cdots + (n-1)S_a^2}{(n-1) + \cdots + (n-1)} = \frac{SS_E}{N-a}.$$

Thus,  $SS_E$  is a pooled estimate of the common variance  $\sigma^2$  within each of the a treatments.

If there were no differences between the a treatment means  $\bar{y}_i$ , we could use the variation of the treatment averages from the grand average to estimate  $\sigma^2$ .

$$\frac{n\sum_{i=1}^{a}(y_{i\cdot}-\bar{y}_{\cdot\cdot})^{2}}{a-1}=\frac{SS_{Treat}}{a-1}$$

is an estimate of  $\sigma^2$  when the treatment means are all equal.

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- One is based on the variability within treatments and one based on the variability between treatments.
- ▶ If there are no differences in the treatment means then these two estimates should be similar.
- If these estimates are different then this could be evidence that the difference is due to differences in the treatment means.

## ANOVA - Mean square error

The mean square for treatment is defined as

$$MS_{Treat} = \frac{SS_{Treat}}{a-1}$$

and the mean square for error is defined as

$$MS_E = \frac{SS_E}{N-a}.$$

#### ANOVA - F statistic

▶  $SS_{Treat}$  and  $SS_E$  are independent.

$$F = rac{MS_{Treat}}{MS_E} \sim F_{a-1,N-a}.$$

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- ▶  $SS_{Treat}$  and  $SS_E$  are independent.
- ▶ It can be shown that  $SS_{Treat}/\sigma^2 \sim \chi^2_{a-1}$  and  $SS_E/\sigma^2 \sim \chi^2_{N-a}$ .
- ▶ Thus, if  $H_0: \mu_1 = \cdots = \mu_a$  is true then the ratio

$$F = rac{MS_{Treat}}{MS_F} \sim F_{a-1,N-a}.$$