

## Lecture 4

# Statistical background review (III)

MCB 416A/516A

Statistical Bioinformatics and Genomic Analysis

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## ■ Last time we reviewed:

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- Hypothesis testing

  - ❖ One- two- sided tests

  - ❖ One- two- sample test

  - ❖ Pvalue and interpretation

- Relationship between hypothesis test and confidence interval

- Type I and II errors

# Summary of hypothesis tests

## Tests on Means with Variance Known

	Hypothesis	Test Statistic	Fixed Significance Level Criteria for Rejection	P-Value
One sample	$H_0: \mu = \mu_0$	$Z_0 = \frac{\bar{y} - \mu_0}{\sigma/\sqrt{n}}$	$ Z_0  > Z_{\alpha/2}$	$P = 2[1 - \Phi( Z_0 )]$
	$H_1: \mu \neq \mu_0$			
	$H_0: \mu = \mu_0$		$Z_0 < -Z_\alpha$	$P = \Phi(Z_0)$
	$H_1: \mu < \mu_0$			
	$H_0: \mu = \mu_0$		$Z_0 > Z_\alpha$	$P = 1 - \Phi(Z_0)$
	$H_1: \mu > \mu_0$			
two samples	$H_0: \mu_1 = \mu_2$	$Z_0 = \frac{\bar{y}_1 - \bar{y}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$	$ Z_0  > Z_{\alpha/2}$	$P = 2[1 - \Phi( Z_0 )]$
	$H_1: \mu_1 \neq \mu_2$			
	$H_0: \mu_1 = \mu_2$		$Z_0 < -Z_\alpha$	$P = \Phi(Z_0)$
	$H_1: \mu_1 < \mu_2$			
	$H_0: \mu_1 = \mu_2$		$Z_0 > Z_\alpha$	$P = 1 - \Phi(Z_0)$
	$H_1: \mu_1 > \mu_2$			

# Tests on Means of Normal Distributions Variance Unknown

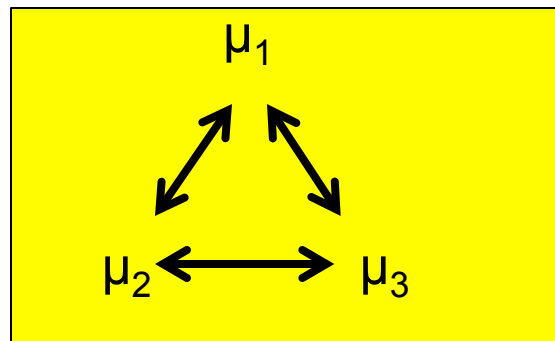
	Hypothesis	Test Statistic	Fixed Significance Level Criteria for Rejection	P-Value
One sample	$H_0: \mu = \mu_0$ $H_1: \mu \neq \mu_0$	$t_0 = \frac{\bar{y} - \mu_0}{S/\sqrt{n}}$	$ t_0  > t_{\alpha/2, n-1}$	sum of the probability above $t_0$ and below $-t_0$
	$H_0: \mu = \mu_0$ $H_1: \mu < \mu_0$		$t_0 < -t_{\alpha, n-1}$	probability below $t_0$
	$H_0: \mu = \mu_0$ $H_1: \mu > \mu_0$		$t_0 > t_{\alpha, n-1}$	probability above $t_0$
two samples		if $\sigma_1^2 = \sigma_2^2$		
	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 \neq \mu_2$	$t_0 = \frac{\bar{y}_1 - \bar{y}_2}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$	$ t_0  > t_{\alpha/2, v}$	sum of the probability above $t_0$ and below $-t_0$
		$v = n_1 + n_2 - 2$		
		if $\sigma_1^2 \neq \sigma_2^2$		
	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 < \mu_2$	$t_0 = \frac{\bar{y}_1 - \bar{y}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$	$t_0 < -t_{\alpha, v}$	probability below $t_0$
	$H_0: \mu_1 = \mu_2$ $H_1: \mu_1 > \mu_2$	$v = \frac{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2}{\frac{(S_1^2/n_1)^2}{n_1 - 1} + \frac{(S_2^2/n_2)^2}{n_2 - 1}}$	$t_0 > t_{\alpha, v}$	probability above $t_0$

or  $\min(n_1, n_2)$

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- We discussed method for comparing ***two*** conditions or treatments.
  - But how about compare more than two conditions or levels of a factor?
  - The *t*-test does not directly apply
    - Pairwise comparisons will inflate type I error

# Why pairwise comparisons inflates type I error?

- Each time a hypothesis test is performed at significance level  $\alpha$ , there is probability  $\alpha$  of rejecting in error.
- Performing multiple tests increases the chances of rejecting in error *at least once*.
- For example:
  - if you did 3 independent hypothesis tests at the  $\alpha = 0.05$
  - If, in truth,  $H_0$  were true for all three.
  - The probability that *at least one* test rejects  $H_0$  is 14.3%
  - ❖  $P(\text{at least one rejection}) = 1 - P(\text{no rejections}) = 1 - .95^3 = 0.143$



# ANOVA - Analysis of Variance

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- Extends independent-samples t test
- Compares the means of groups of independent observations.
  - Don't be fooled by the name.
  - ANOVA does not compare variances.
  - The name “analysis of variance” stems from a **partitioning** of the total variability in the response variable into components
  - Can compare more than two groups
- The ANOVA was developed by Fisher in the early 1920s, and initially applied to agricultural experiments.

# ANOVA – Null and Alternative Hypotheses

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Say the sample contains  $K$  independent groups

- ANOVA tests the null hypothesis

$$H_0: \mu_1 = \mu_2 = \dots = \mu_K$$

— That is, “the group means are all equal”

- The alternative hypothesis is

$$H_1: \mu_i \neq \mu_j \text{ for some } i, j$$

— or, “the group means are *not* all equal”

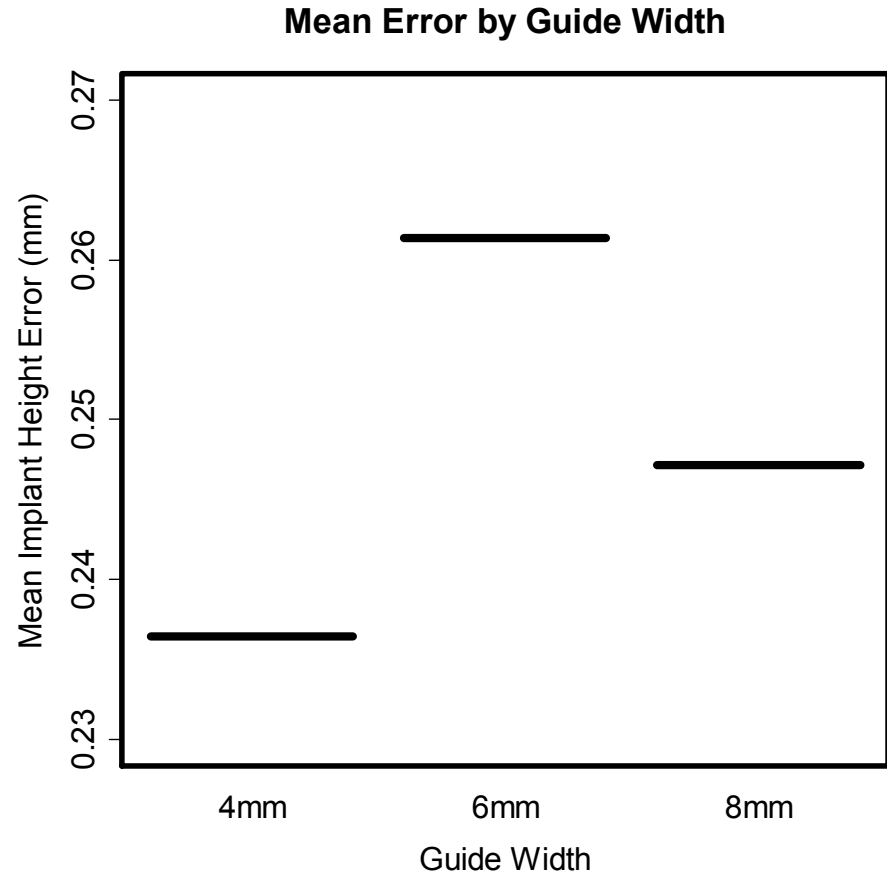


# Example: Accuracy of Implant Placement

Implants were placed in a manikin using placement guides of various widths.

15 implants were placed using each guide.

Error (discrepancies with a reference implant) was measured for each implant.

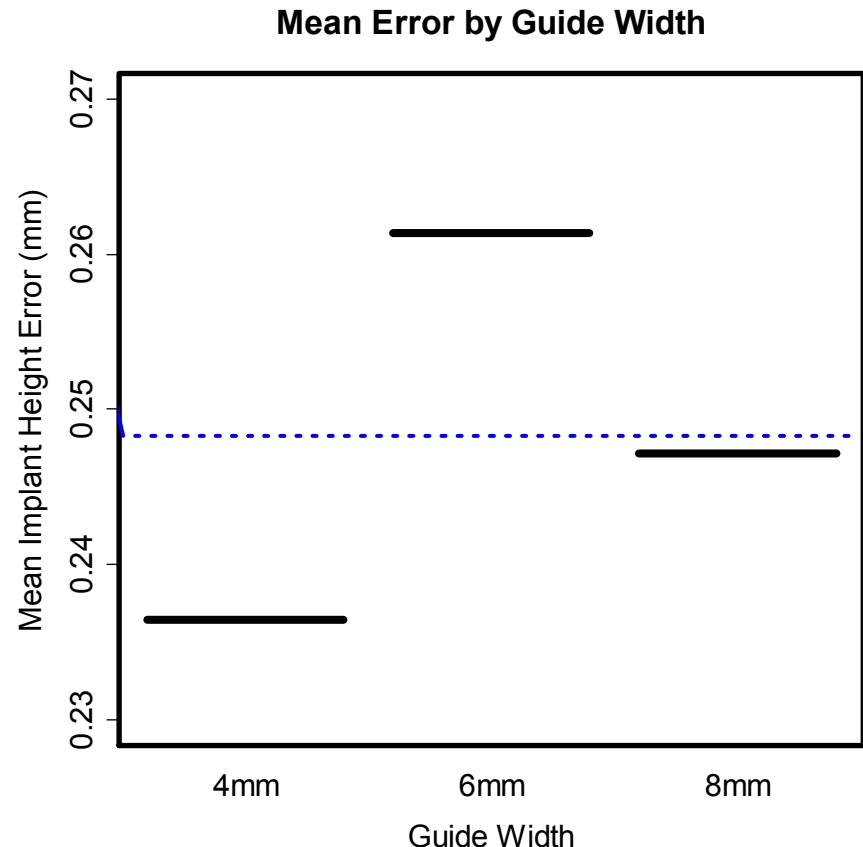


# Example: Accuracy of Implant Placement -2

The overall mean of the entire sample was 0.248 mm.

This is called the “grand” mean, and is often denoted by  $\bar{X}$  or  $\bar{X}_{||}$

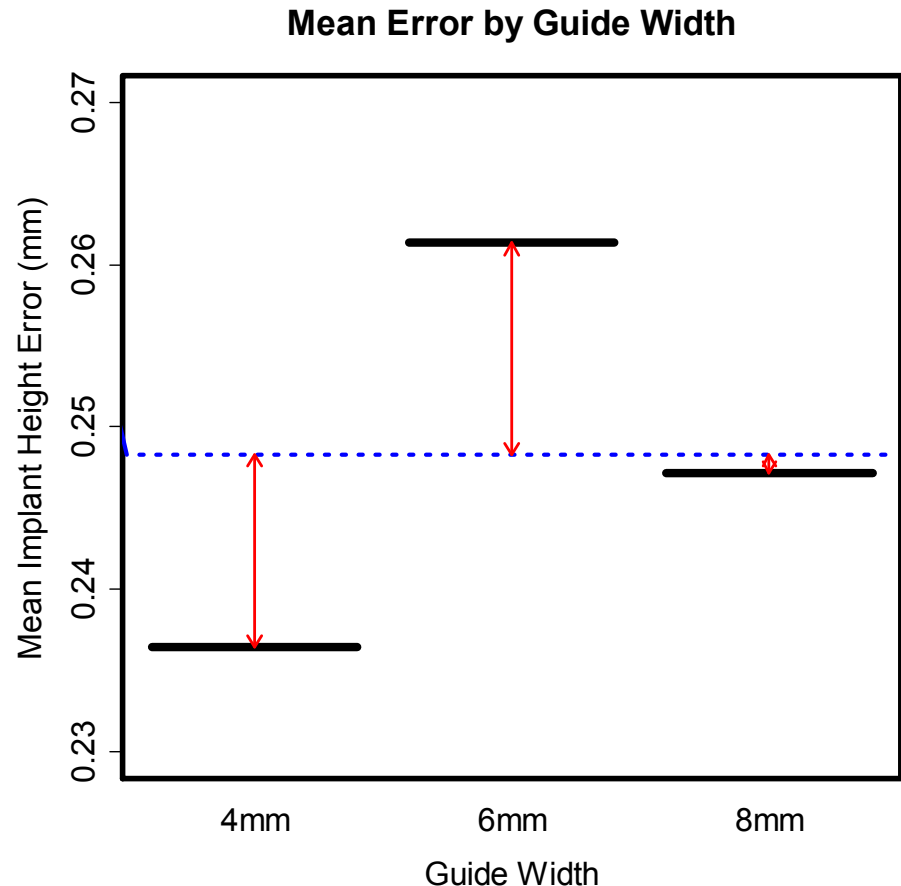
If  $H_0$  were true then we'd expect the group means to be close to the grand mean.



# Example: Accuracy of Implant Placement -3

The ANOVA test is based on the combined distances from  $\bar{\bar{X}}$ .

If the combined distances are large, that indicates we should reject  $H_0$ .



# The Anova Statistic

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To combine the differences from the grand mean we

- Square the differences
- Multiply by the numbers of observations in the groups
- Sum over the groups

$$SSB = 15(\bar{X}_{4mm} - \bar{\bar{X}})^2 + 15(\bar{X}_{6mm} - \bar{\bar{X}})^2 + 15(\bar{X}_{8mm} - \bar{\bar{X}})^2$$

where the  $\bar{X}_*$  are the group means.

“SSB” = **S**um of **S**quares **B**etween groups

Note: This looks a bit like a variance.

# How big is big?

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- For the Implant Accuracy Data,  $SSB = 0.0047$
- Is that big enough to reject  $H_0$ ?
- As with the  $t$  test, we compare the statistic to the variability of the individual observations.
- In ANOVA the variability is estimated by the Mean Square Error, or MSE

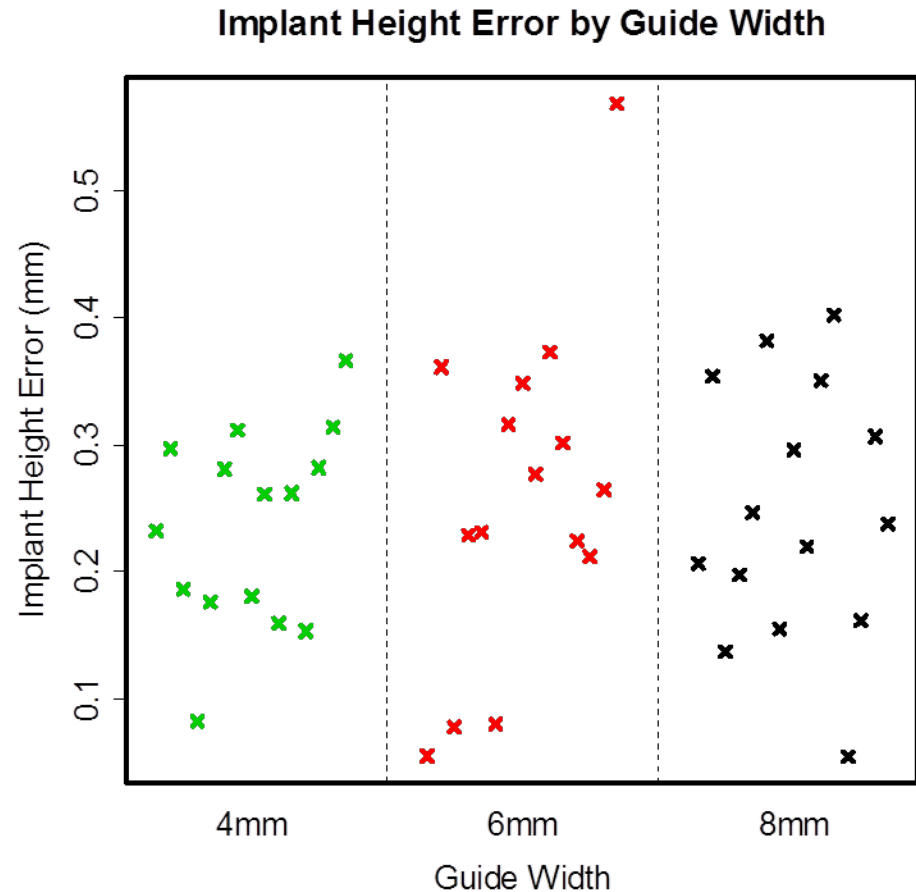
# MSE: Mean Square Error

The Mean Square Error is a measure of the variability after the group effects have been taken into account.

$$MSE = \frac{1}{N - K} \sum_j \sum_i (x_{ij} - \bar{X}_j)^2$$

where  $x_{ij}$  is the  $j^{th}$  observation in the  $j^{th}$  group.

K = number of groups  
N = total number of obs

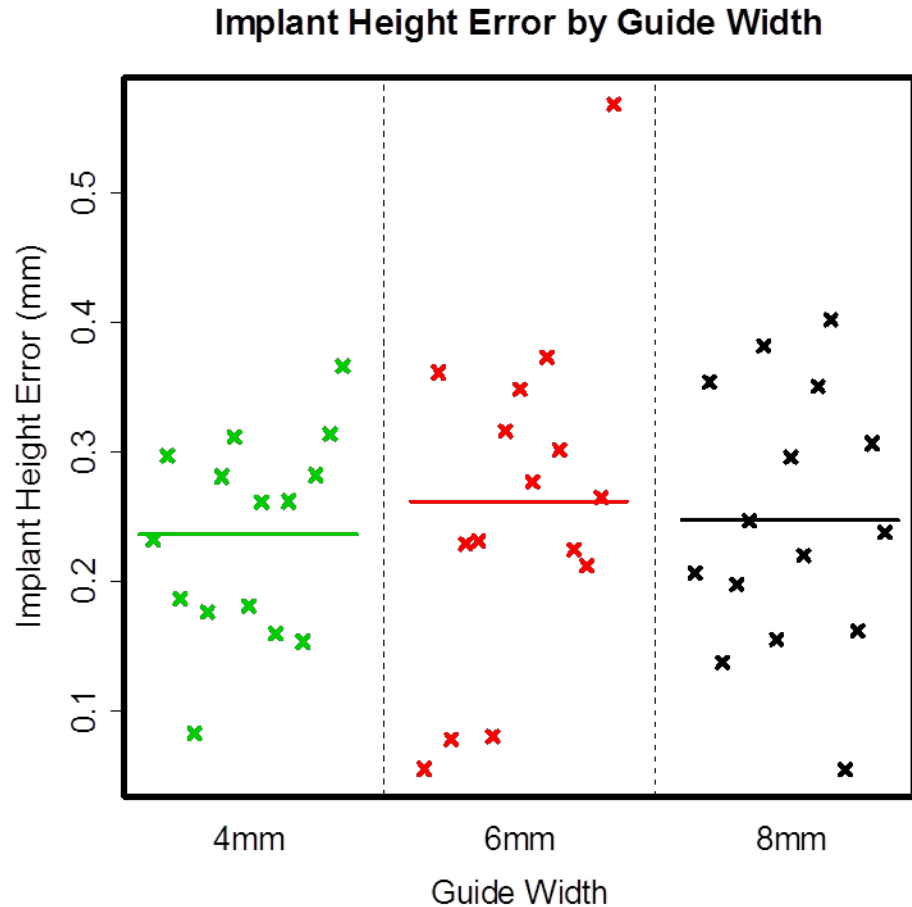


# MSE: Mean Square Error -2

The Mean Square Error is a measure of the variability after the group effects have been taken into account.

$$MSE = \frac{1}{N - K} \sum_j \sum_i (x_{ij} - \bar{X}_j)^2$$

where  $x_{ij}$  is the  $j^{th}$  observation in the  $j^{th}$  group.

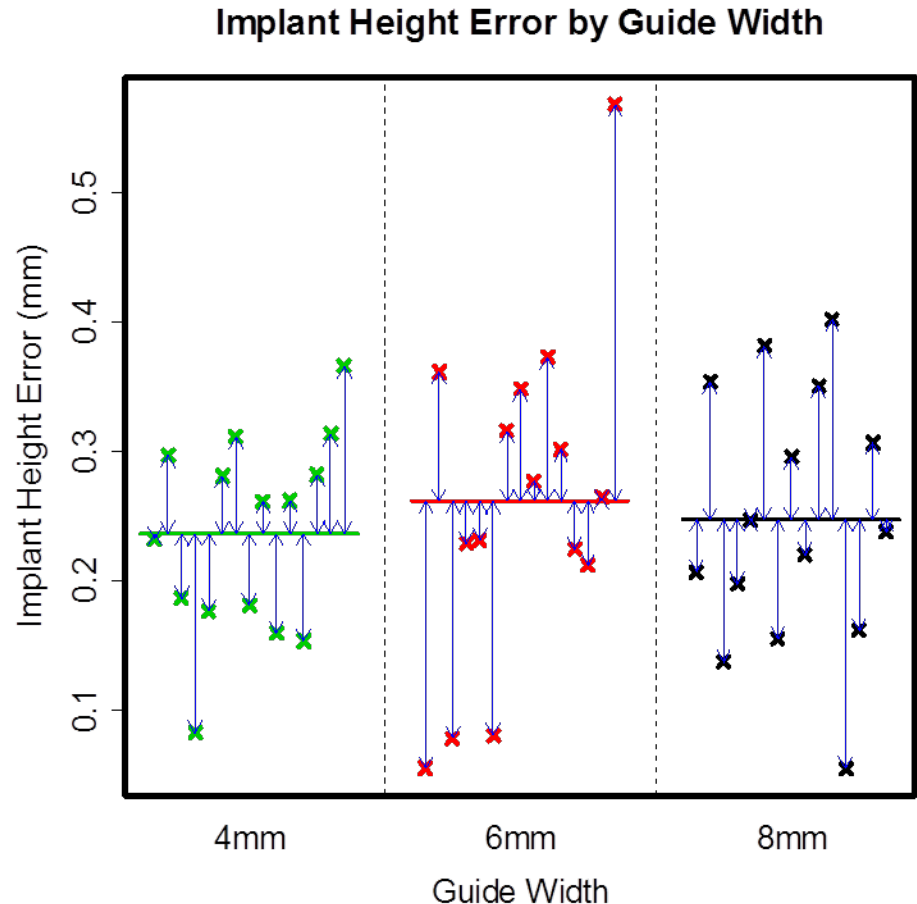


# MSE: Mean Square Error -3

The Mean Square Error is a measure of the variability after the group effects have been taken into account.

$$MSE = \frac{1}{N-K} \sum_j \sum_i (x_{ij} - \bar{X}_j)^2$$

Note that the variation of the means seems quite small compared to the variance of observations within groups





## Notes on *MSE*

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- If there are only two groups, the *MSE* is equal to the pooled estimate of variance used in the equal-variance *t* test.
- ANOVA assumes that all the group variances are equal.
- Other options should be considered if group variances differ by a factor of 2 or more.

# ANOVA F Test

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- The ANOVA F test is based on the  $F$  statistic

$$F = \frac{SSB/(K - 1)}{MSE}$$

where  $K$  is the number of groups.

- Under  $H_0$  the  $F$  statistic has an “F” distribution, with  $K-1$  and  $N-K$  degrees of freedom ( $N$  is the total number of observations)  
— In this case  $N=45$

# Implant Data: F test p-value

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To get a p-value we compare our  $F$  statistic to an  $F(2, 42)$  distribution.

$F(2,42)$  distribution

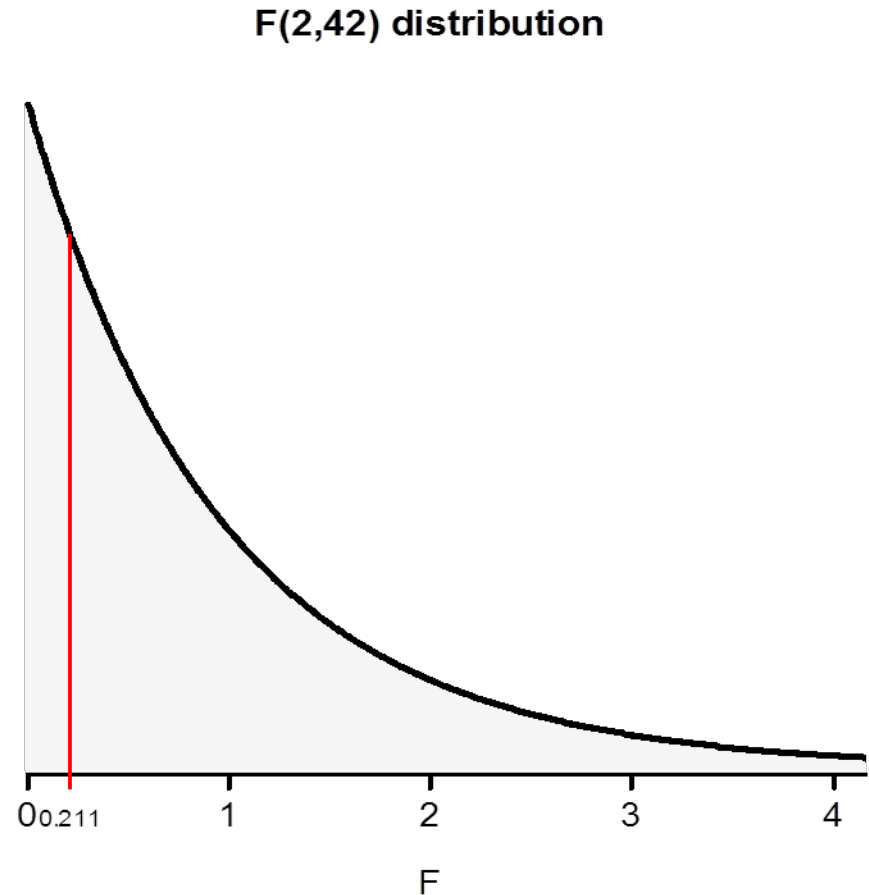


# Implant Data: F test p-value -2

To get a p-value we compare our  $F$  statistic to an  $F(2, 42)$  distribution.

In our example

$$F = \frac{.0047/2}{.0467/42} = .211$$



# Implant Data: F test p-value -3

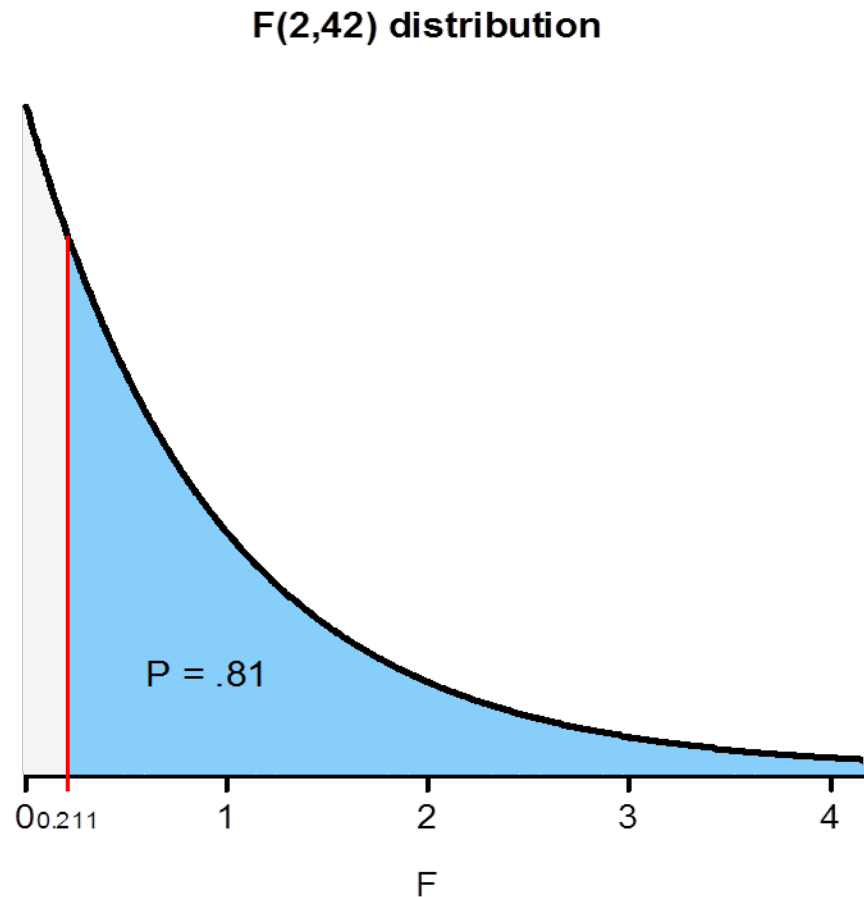
To get a p-value we compare our  $F$  statistic to an  $F(2, 42)$  distribution.

In our example

$$F = \frac{.0047/2}{.0467/42} = .211$$

The p-value is

$$P(F(2,42) > .211) = 0.81$$



# ANOVA Table

Results are often displayed using an ANOVA Table

Source of Variation	Sum of Squares	df	Mean Square	F	P-value
Between Groups	.005	2	.002	.211	.811
Within Groups	.466	42	.011		
Total	.470	44			

Pop Quiz!: Where are the following quantities presented in this table?

Sum of Squares  
Between (*SSB*)

Mean Square  
Error (*MSE*)

F Statistic

p value

# ANOVA Table -2

Results are often displayed using an ANOVA Table

Source of Variation	Sum of Squares	df	Mean Square	F	P-value
Between Groups	.005	2	.002	.211	.811
Within Groups	.466	42	.011		
Total	.470	44			

Sum of Squares  
Between (*SSB*)

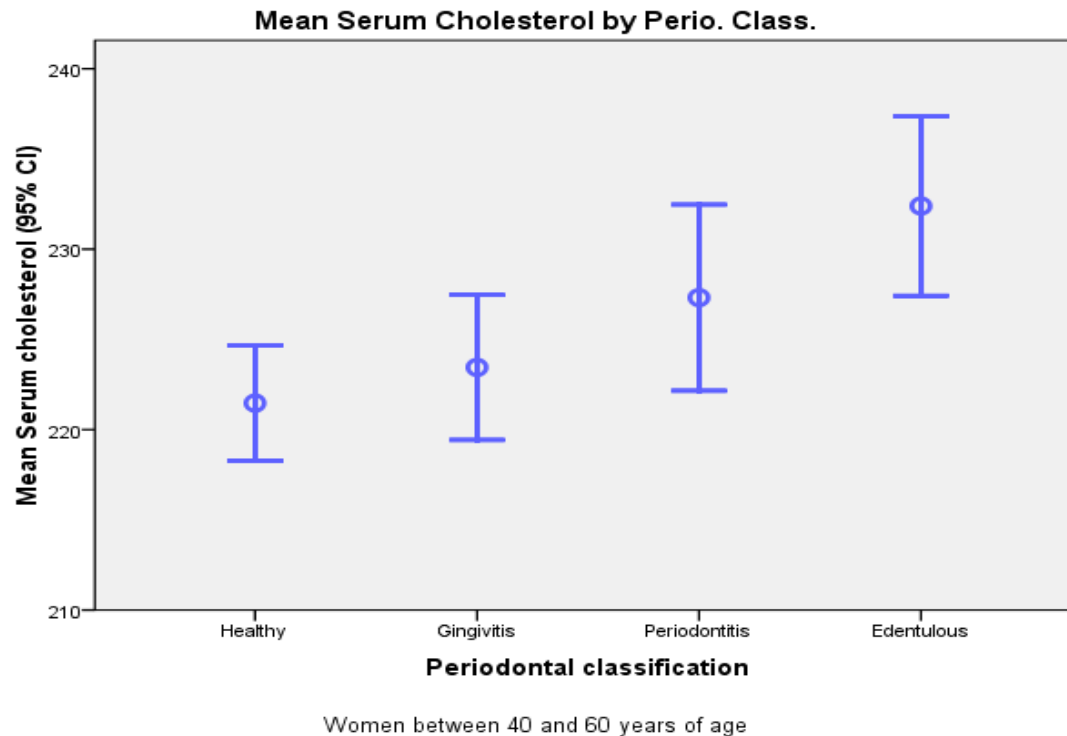
Mean Square  
Error (*MSE*)

F Statistic

p value

fail to reject at .811

# Post Hoc Tests



Compare cholesterol between periodontal groups. 40-60 yrs old women.

The ANOVA shows good evidence ( $p = 0.002$ ) that the means are not all the same.

Which means are different?

Can directly compare the subgroups using “post hoc” tests.

Source of Variation	Sum of Squares	df	Mean Square	F	P-value
Between Groups	33383	3	11128	5.1	.002
Within Groups	4417119	2007	2201		
Total	4450502	2010			



# Least Significant Difference test

	N	Mean	Std. Deviation
Healthy	802	221.5	46.2
Gingivitis	490	223.5	45.3
Periodontitis	347	227.3	48.9
Edentulous	372	232.4	48.8

The most simple post hoc test is called the *Least Significant Difference Test*.

The computation is very similar to the equal-variance *t* test.

	Sum of Squares	df	Mean Square	F	pvalue
Between Groups	33383	3	11128	5.1	.002
Within Groups	4417119	2007	2201		
Total	4450502	2010			

Compute an equal-variance *t* test, but replace the pooled variance ( $s^2$ ) with the *MSE*.

# Least Significant Difference Test: Examples

	N	Mean	Std. Deviation
Healthy	802	221.5	46.2
Gingivitis	490	223.5	45.3
Periodontitis	347	227.3	48.9
Edentulous	372	232.4	48.8

Compare Healthy group to Periodontitis group:

$$T = \frac{221.5 - 227.3}{\sqrt{2201(1/802 + 1/347)}} = -1.92$$

$$p = 2 \cdot P(t_{1147} > 1.92) = 0.055$$

	Sum of Squares	df	Mean Square	F	pvalue
Between Groups	33383	3	11128	5.1	.002
Within Groups	4417119	2007	2201		
Total	4450502	2010			

Compare Gingivitis group to Periodontitis group:

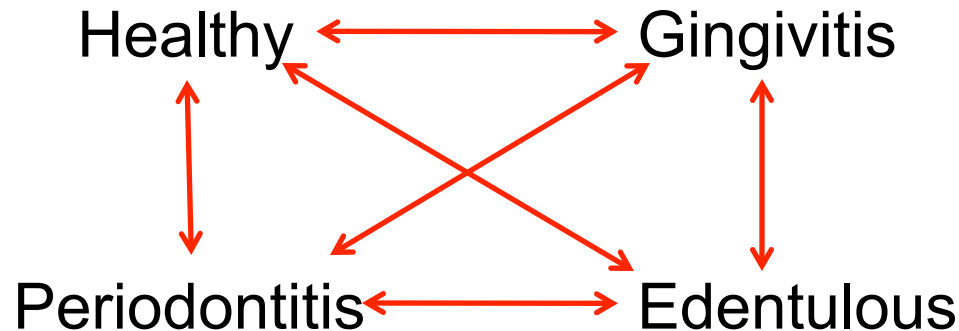
$$T = \frac{223.5 - 227.3}{\sqrt{2201(1/490 + 1/347)}} = -1.15$$

$$p = 2 \cdot P(t_{835} > 1.15) = 0.25$$

# Post Hoc Tests: Multiple Comparisons

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- Post-hoc testing usually involves multiple comparisons.
- For example, if the data contain 4 groups, then 6 different pairwise comparisons can be made



# Post Hoc Tests: Multiple Comparisons -2

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- Each time a hypothesis test is performed at significance level  $\alpha$ , there is probability  $\alpha$  of rejecting in error.
- Performing multiple tests increases the chances of rejecting in error *at least once*.
- For example:
  - if you did 6 independent hypothesis tests at the  $\alpha = 0.05$
  - If, in truth,  $H_0$  were true for all six.
  - The probability that *at least one* test rejects  $H_0$  is 26%
    - ❖  $P(\text{at least one rejection}) = 1 - P(\text{no rejections}) = 1 - .95^6 = .26$

# Bonferroni Correction for Multiple Comparisons

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- The Bonferroni correction is a simple way to adjust for the multiple comparisons.

very conservative only good for small numbers

## **Bonferroni Correction**

- Perform each test at significance level  $\alpha$ .
- Multiply each p-value by the number of tests performed.
- The overall significance level (chance of any of the tests rejecting in error) will be less than  $\alpha$ .

# Example: Cholesterol Data post-hoc comparisons

Group 1	Group 2	Mean Difference (Group 1 - Group 2)	Least Significant Difference p-value	Bonferroni p-value
Healthy	Gingivitis	-2.0	.46	1.0
Healthy	Periodontitis	-5.8	.055	.330
Healthy	Edentulous	-10.9	.00021	.00126
Gingivitis	Periodontitis	-3.9	.25	1.0
Gingivitis	Edentulous	-8.9	.0056	.0336
Periodontitis	Edentulous	-5.1	.147	.88

max = 1

Conclusion: The Edentulous group is significantly different than the Healthy group and the Gingivitis group ( $p < 0.05$ ), after adjustment for multiple comparisons