

Applied statistics with applications in R (and SAS)

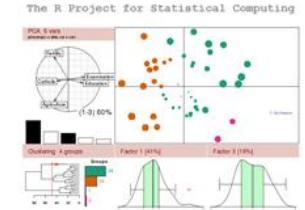
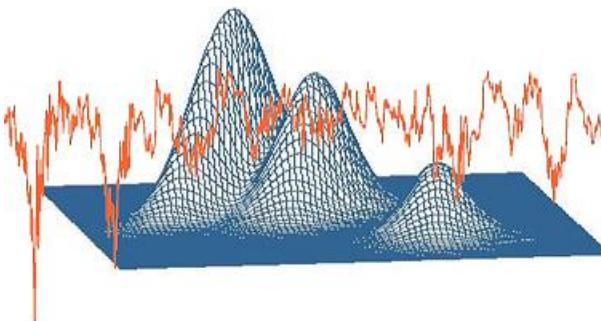
Alessio Cecchinato

Hugo Toledo Alvarado

DAFNAE - Department of Agronomy, Food

Natural resources, Animals and Environment

University of Padova



Overview

- o We will cover analysis of variance and analysis of covariance. The emphasis will be placed on selected practical tools using R software (and SAS) rather than on the mathematical manipulations. Want to understand the theory so that we can apply it appropriately



Overview

1. Introduction to hypothesis testing
2. How to state a null hypothesis and alternative hypothesis
3. How to identify errors and interpret the level of significance
4. Analysis of variance (ANOVA):
 5. One-way ANOVA
 6. Two-way ANOVA
 7. Two-way ANOVA and interactions
 8. ANCOVA
9. Exercises and applications with R software

Overview

Team Project:

- Data will be provided to a team composed of two to three students and asked to employ techniques learned throughout this course to analyze the data set, interpret and report results

Final Exam:

- Written examinations. A written examination consists of exercises designed to test the basic knowledge acquired during the course

References

R users:

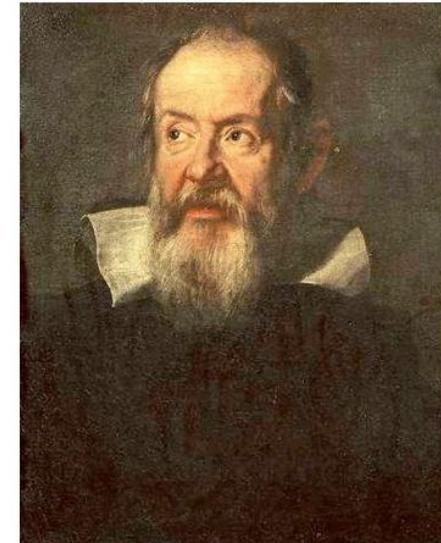
- Crawley, M. J. (2012). *The R book*. John Wiley & Sons.
- Kabacoff, R. I. (2010). *R in Action*. Manning.

SAS users:

- Text: *Applied Linear Statistical Models*, (4th ed.) by Neter, Kutner, Nachtsheim and Wasserman
- *SAS System for Regression* (2nd ed.) by Freund and Little
- *SAS/STAT User's Guide Vol. 1 and 2*

A brief introduction: Scientific Method

- a) Review and Research the problem
- ↓
- b) Formulate Hypothesis
- ↓
- c) Design experiment that will allow test of hypothesis
- ↓
- d) Evaluate the hypothesis
- ↓
- e) Draw Conclusions



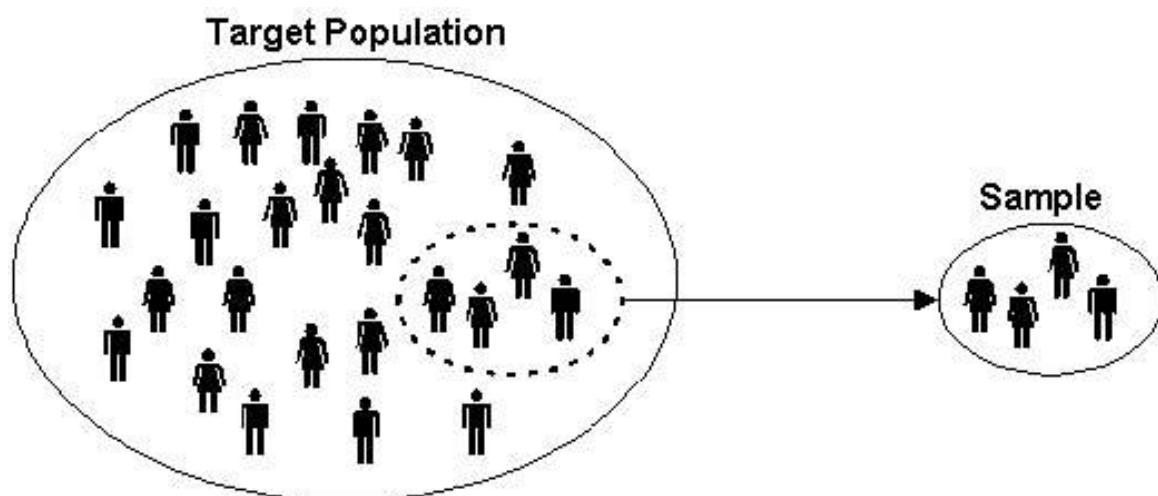
Galileo Galilei 1564-1642

How does statistical inference work?

- Infer upon the characteristics of a large population based on data from a finite random sample
- Mechanics (part of the scientific method):
 - Design and collect data from an experiment (e.g blood pressure)
 - Assess the probability of getting the experimental results assuming a true null hypothesis (status quo knowledge..e.g. no treatment difference)
 - Common investigator objective: disprove the status quo in favor of an alternative hypothesis (there is a treatment effect)
- Conclusions never made with absolute certainty...must establish proof beyond a reasonable doubt

Terminology

- **Population:** The collection of all responses, measurements, or counts that are of interest
- **Sample:** A portion or subset of the population



Population:

μ = mean

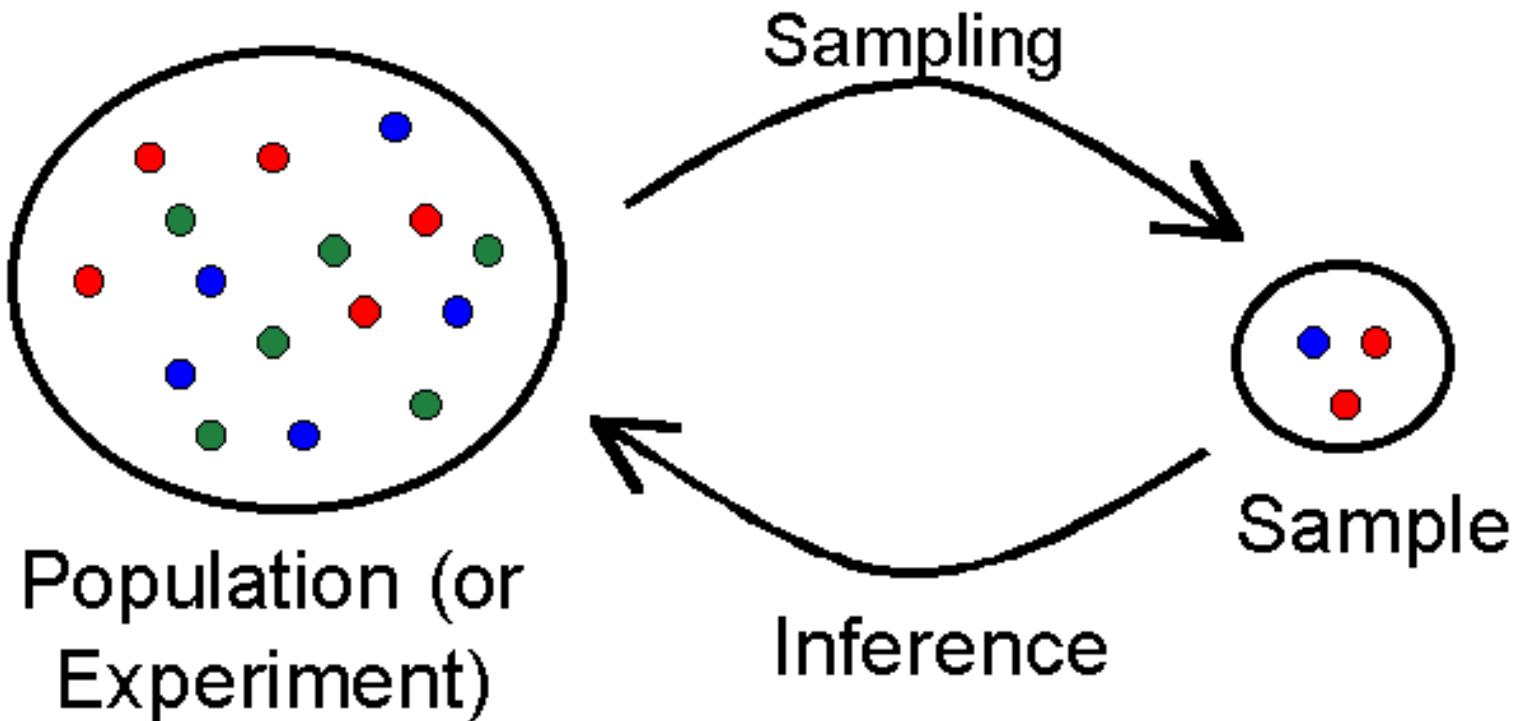
σ = standard deviation

Sample:

\bar{x} = mean

s = standard deviation

Populations and samples



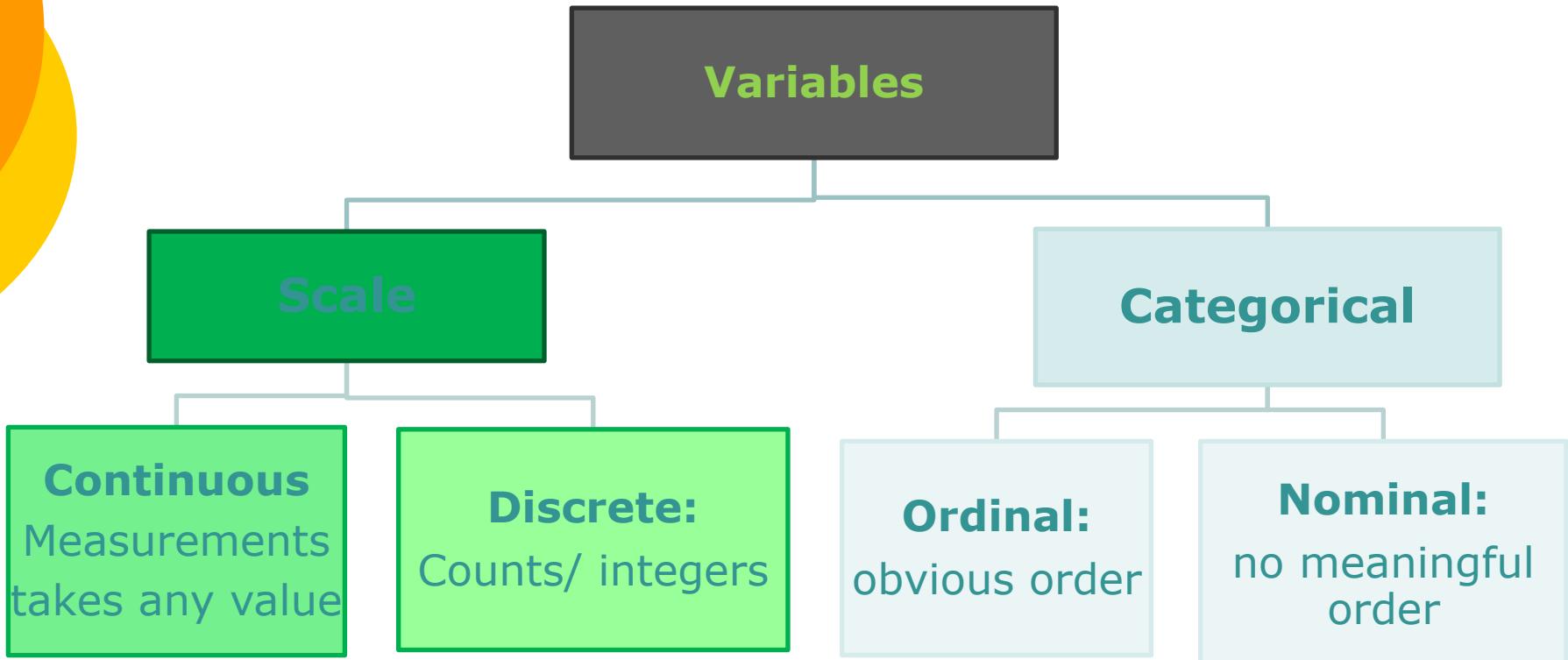
Do it yourself ...

- Identify the population and the sample in the following example: In a recent survey 2000 European Boxer dogs owners were asked if they submitted their dogs to x-ray screening for hip dysplasia. Eight hundred of the owners answered yes
- What is the population ?
- What is the sample ?
- What is the data set

Variables, Variables!!!

- Quantitative variables:
 - Due to a true numerical measurement
 - Ratio scale (e.g. weight) versus Interval Scale (e.g. temperature)
 - Discrete (countable) versus Continuous
- Qualitative variables:
 - Nominal scale (classification or group) **GENOTYPE, SEX**
 - Ordinal scale (ranked variables..small, medium, large)

Data types



Questionnaire

What data types relate to following questions?

- Q1: What is your favourite subject?

Nominal

Maths

English

Science

Art

French

- Q2: Gender:

Male

Female

Binary/ Nominal

- Q3: I consider myself to be good in statistics:

Strongly Disagree

Disagree

Not Sure

Agree

Strongly Agree

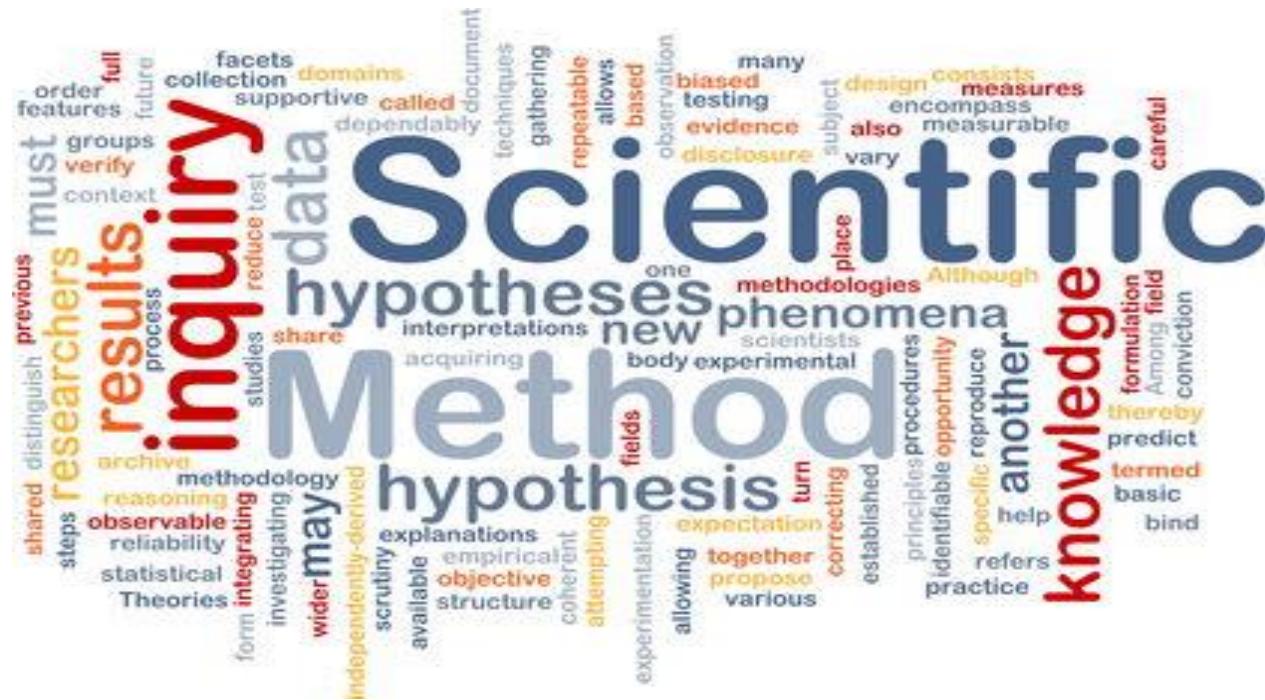
Ordinal

- Q4: Score in a recent exam:

Score between 0% and 100%

Scale

A (practical) introduction to hypothesis testing

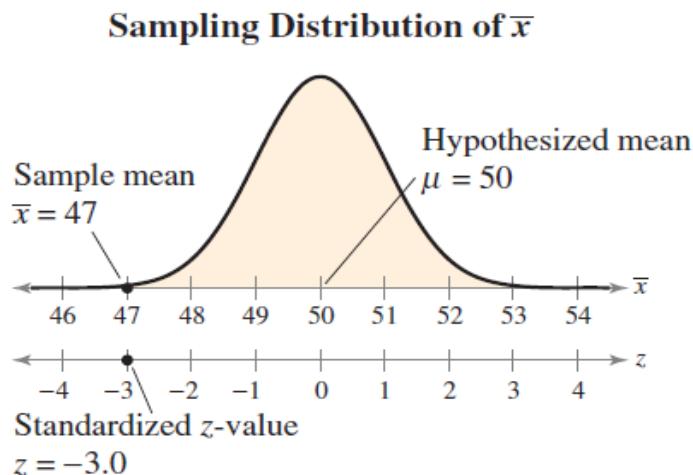


Hypothesis tests

- A hypothesis test is a process that uses sample statistics to test a claim about the value of population parameter
- Example: suppose an automobile manufacturer advertises that its new hybrid car has a mean gas mileage of 50 miles per gallon.
- If you suspect that the mean mileage is not 50 miles per gallon, how could you show that the advertisement is false?
- Obviously, you cannot test *all* the vehicles, so we draw a sample from the population ...
- There is a large probability that the value of the sample statistic differs from the that of the claim. Is it enough to conclude that the claim is wrong ?

Hypothesis tests

- Let's **assume the claim is correct!**
- you could take a random sample of 30 vehicles and measure the mileage of each ($\bar{x}=47$ miles/gallon and $s = 5.5$ miles/gallon)
- Recalling CLT, we know that the sampling distribution of the sample mean is normal with a mean of 47 and a standard error of $5.5/\sqrt{30} \approx 1$



- So either the sample is very unusual or the claim is false

Hypothesis tests

- This is an unusual event!
- Your assumption that the company's advertisement is correct has led you to an improbable result. So, either you had a very unusual sample, or the advertisement is probably false.
- **The logical conclusion is that the advertisement is probably false**



Stating a hypothesis

- A claim about a population parameter is called a statistical hypothesis
- To test a statistical hypothesis, we must carefully state a pair of hypotheses:
 - ***the claim***
 - ***its complement***
- When the first is true, the other is false
- Of the two hypotheses, the one that contains a statement of equality ($=, \leq, \geq$) is called the **null hypothesis (H_0)**, the other one ($\neq, <, >$) is the **alternative hypothesis (H_a)**

Examples

Write the claim as a mathematical sentence. State the null and alternative hypotheses, and identify which represents the claim

- A school publicizes that the proportion of its students who are involved in at least one extracurricular activity is 61%.
 - $H_0 : p = 0.61$ Claim: "the proportion is 61%"
 - $H_0 : p \neq 0.61$
- A car dealership announces that the mean time for an oil change is less than 15 minutes
 - $H_0 : \mu \geq 15 \text{ minutes}$ Claim: "the mean is less than 15 minutes"
 - $H_0 : \mu < 15 \text{ minutes}$
- A company advertises that the mean life of its furnaces is more than 18 years
 - $H_0 : \mu \leq 18 \text{ years}$
 - $H_0 : \mu > 18 \text{ years}$ Claim: "the mean is more than 18 years"

Types of errors and level of significance

- We always test the null hypothesis H_0
- So, after the test, we make one of two possible decisions:
 - **reject the null hypothesis or**
 - **fail to reject the null hypothesis**
- Because the decision is based on incomplete information (the sample) there is always the chance of making the wrong decision
- There are two types of errors we can make:
 - **A type I error** occurs if the null hypothesis is rejected when it is true
 - **A type II error** occurs if the null hypothesis is not rejected when it is false

Types of errors and level of significance

Decision	Truth of H_0	
	H_0 is true.	H_0 is false.
Do not reject H_0 .	Correct decision Type I error	Type II error Correct decision
Reject H_0 .		

Typically restrict to a 5% Risk
= level of significance

Prob of this = Power of test

Controlled via sample size
 $(=1-\text{Power of test})$

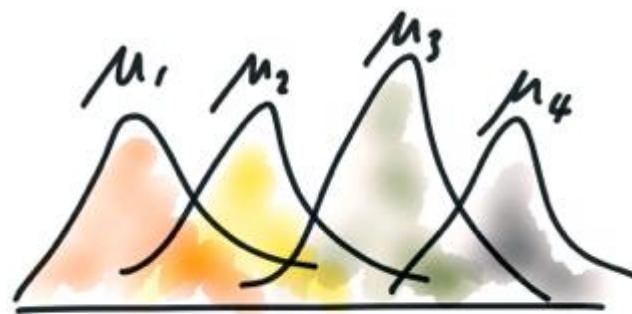
- In a hypothesis test, the **level of significance α** is your maximum allowable probability of making a type I error
- By setting the level of significance at a small value, we say that we want the probability of rejecting a true null hypothesis to be small
- Commonly used level of significance are $\alpha = 0.1$, $\alpha = 0.05$ and $\alpha = 0.01$

Summary for hypothesis testing

- ① State the claim mathematically and verbally. Identify the null and alternative hypotheses ($H_0 = ?$, $H_a = ?$)
- 2. Choose the level of significance $\alpha = ?$
- 3. Identify the type of test (left-, right-, or two-tailed) and identify the standardized sampling distribution (z, t, etc)
- 4. Determine critical values (z_0, t_0 , etc)
- 5. Determine rejection regions
- 6. Calculate the test statistic and its standardized value
- 7. Decision rule:
Is the standardized test statistic in the rejection region ?


Yes No
Reject H_0 Fail to reject H_0
- 8. Interpret the decision in the context of the original claim

Analysis of variance (ANOVA)



ANOVA

$\mu_1 = \mu_2 = \mu_3 = \mu_4 ?$

Analysis of variance (ANOVA)

- Analysis of variance (ANOVA) is a hypothesis-testing technique that is used to compare means from three or more populations
- The response variable Y is continuous
- The explanatory variable is categorical
 - We call it a factor
 - The possible values are called levels
- This approach is a generalization of the *independent two-sample t-test*
- In other words, it can be used when there are more than two treatments

Analysis of variance (ANOVA)

- A **factor** refers to a categorical quantity under examination in an experiment as a possible cause of variation in the response variable
- **Levels** refer to the categories, measurements, or strata of a factor of interest in the experiment

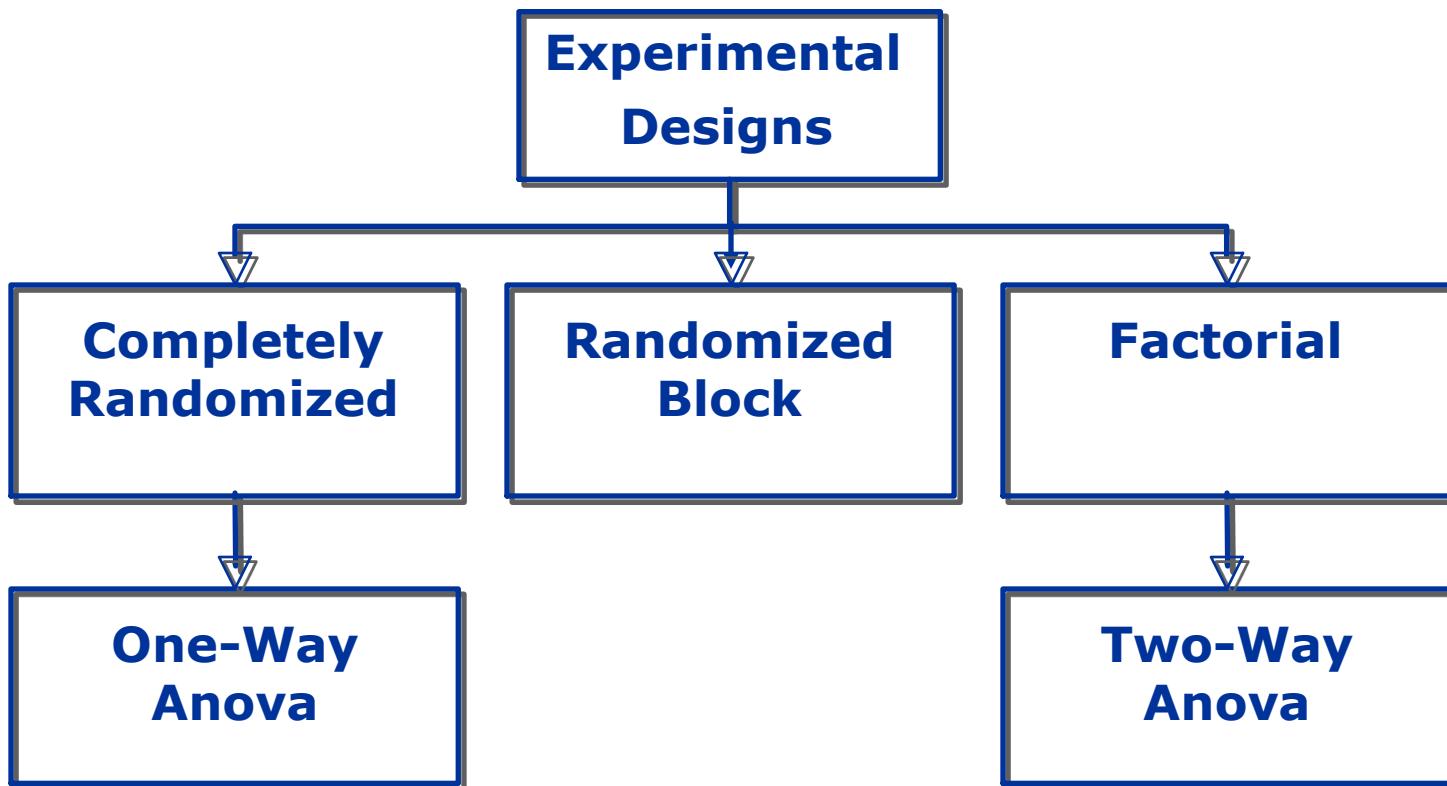
Data for One-Way ANOVA

- Y is the response variable
- X is the factor (it is qualitative/discrete)
 - r is the number of levels
 - often refer to these levels as groups or treatments
- Y_{ij} is the j^{th} observation in the i^{th} group

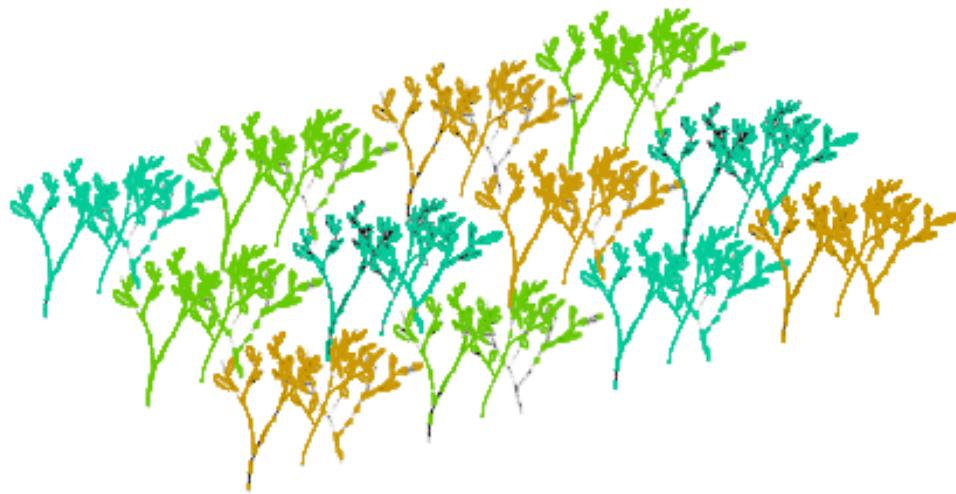
Notation

- For $Y_{i,j}$ we use
 - i to denote the level of the factor
 - j to denote the j^{th} observation at factor level i
- $i = 1, \dots, r$ levels of factor X
- $j = 1, \dots, n_i$ observations for level i of factor X

Types of Experimental Designs

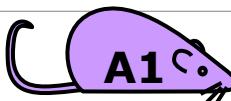


Completely Randomized Design



Blood cholesterol example

- Experimental study with randomization:
 - 6 rats assigned at random to one of 2 treatments ($n=3$ rats per treatment)
- Blood Cholesterol Data collected (mg/dl):

New Treatment (A)	Control Treatment (B)
$y_{A1} = 144$ 	$y_{B1} = 149$ 
$y_{A2} = 148$ 	$y_{B2} = 148$ 
$y_{A3} = 146$ 	$y_{B3} = 159$ 

- Would you conclude the treatments lead to different mean blood cholesterol levels ????

$$\text{Ave } \bar{y}_A = 146$$

$$\text{Ave } \bar{y}_B = 152$$



A mean treatment difference is found!

Statistical
inference

But is it.....

Due to mere chance (biological noise) ???

Or...

The real thing (beyond reasonable doubt)?

Completely Randomized Design

- Experimental units (subjects) are assigned randomly to treatments
 - Subjects are assumed homogeneous
- One factor or independent variable
 - 2 or more treatment levels or groups
- Analyzed by one-way ANOVA

One-Way ANOVA F-Test

- Tests the equality of 2 or more (p) population means
- Variables
 - One nominal independent variable
 - One continuous dependent variable



One-Way ANOVA F-Test Assumptions

- Randomness & independence of errors
- Normality
 - Populations (for each condition) are normally distributed
- Homogeneity of variance
 - Populations (for each condition) have equal variances

Assumption

$$(1) \quad y_i = \alpha + \beta_1 x_{1i} + \dots + \beta_n x_{ni} + \varepsilon_i$$

y is a linear function of $\alpha, \beta, x_1, \dots, x_n$ and ε (residual)

$$(2) \quad E(\varepsilon_i) = 0$$

ε does not depend on x_1, \dots, x_n (ε and x_1, \dots, x_n are not correlated)

$$(3) \quad \text{Var}(\varepsilon_i) = \sigma_e^2$$

Omocedasticity assumption: the variance of ε is equal for all the observations

$$(4) \quad \text{Cov}(\varepsilon_i, \varepsilon_j) = 0 \text{ dove } i \neq j$$

The residual of each observation is not related with the residual of other observations

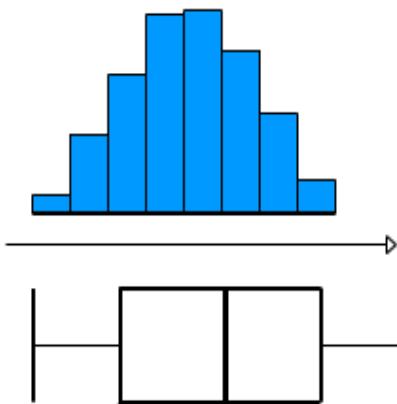
$$(5) \quad \varepsilon_i \sim N(0, \sigma_e^2)$$

The residuals are normally distributed

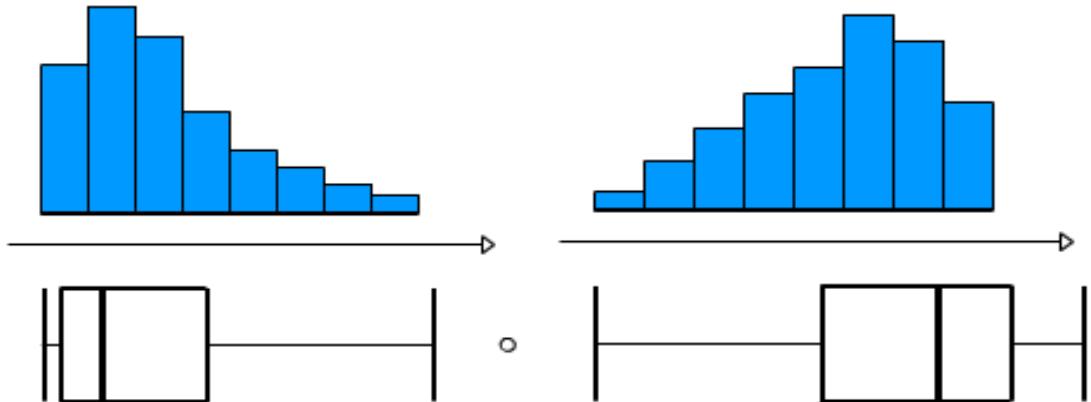
Assessing Normality

Charts can be used to **informally** assess whether data is:

Normally
distributed



Or....Skewed



**The mean and median are very
different for skewed data**

Normality test

- Wide variety of tests we can perform to test if the data follows a normal distribution
- Mardia (1980) provides an extensive list for both the univariate and multivariate cases, categorizing them into two types
 - Properties of normal distribution, more specifically, the first four moments of the normal distribution
 - Shapiro-Wilk's W (compares the ratio of the standard deviation to the variance multiplied by a constant to one)
 - Goodness-of-fit tests,
 - Kolmogorov-Smirnov D
 - Cramer-von Mises W^2
 - Anderson-Darling A^2

Mardia, K.V. (1980): Tests of univariate and multivariate normality. In P.R. Krishnaiah (ed.), *Handbook of statistics* (vol. 1; pp 279-320). Amsterdam: North Holland.



Normality test

Descriptive Statistics and Normality Test

```
milk<-cows$milk      # Select the variable
summary(milk)         # Basic statistics

##      Min. 1st Qu. Median   Mean 3rd Qu.   Max.
##  15.30    24.88   29.05   30.09   35.30   50.90

sd(milk)              # Standard Deviation function

## [1] 7.614805

range(milk)            # Range function

## [1] 15.3 50.9

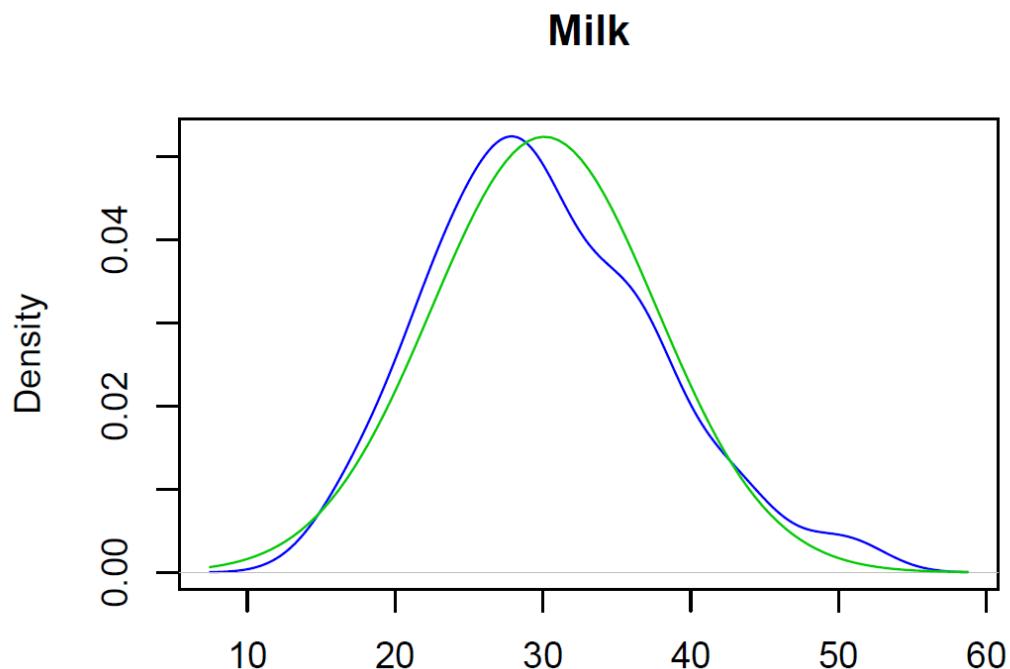
shapiro.test(milk)    # Shapiro - Wilk normality test

##
## Shapiro-Wilk normality test
##
## data: milk
## W = 0.97876, p-value = 0.04779
```

Normality test

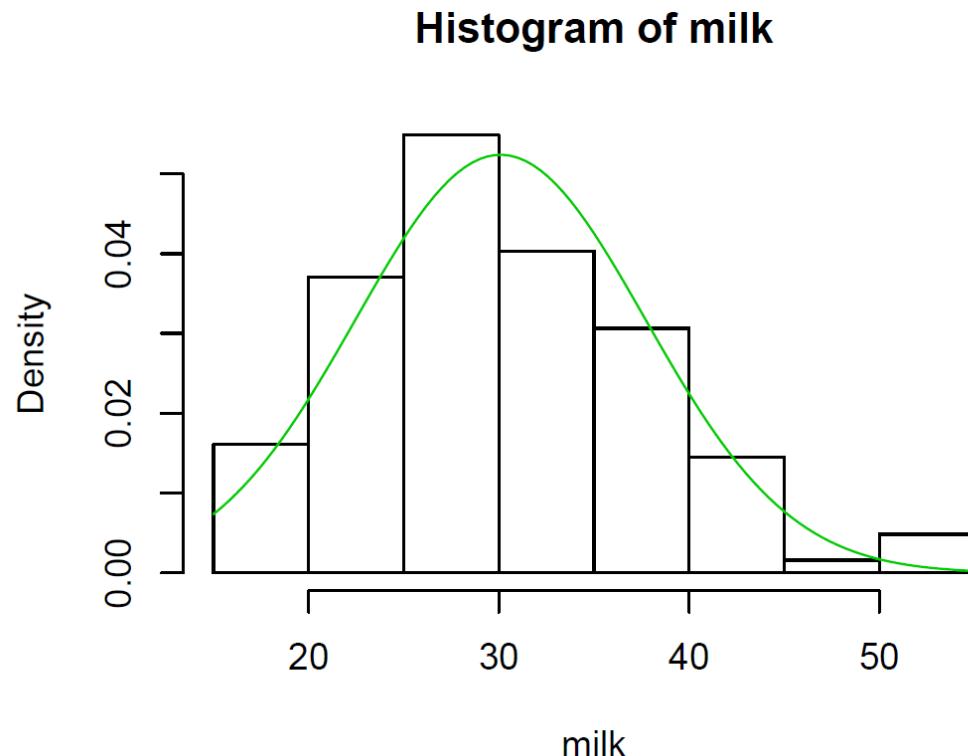
Density plot with normal distribution curve

```
plot(density(milk), col=4, main="Milk") # Create a density plot  
curve(dnorm(x,mean=mean(milk),sd = sd(milk)),add = T,col=3) # Add normal dist.
```



Normality test

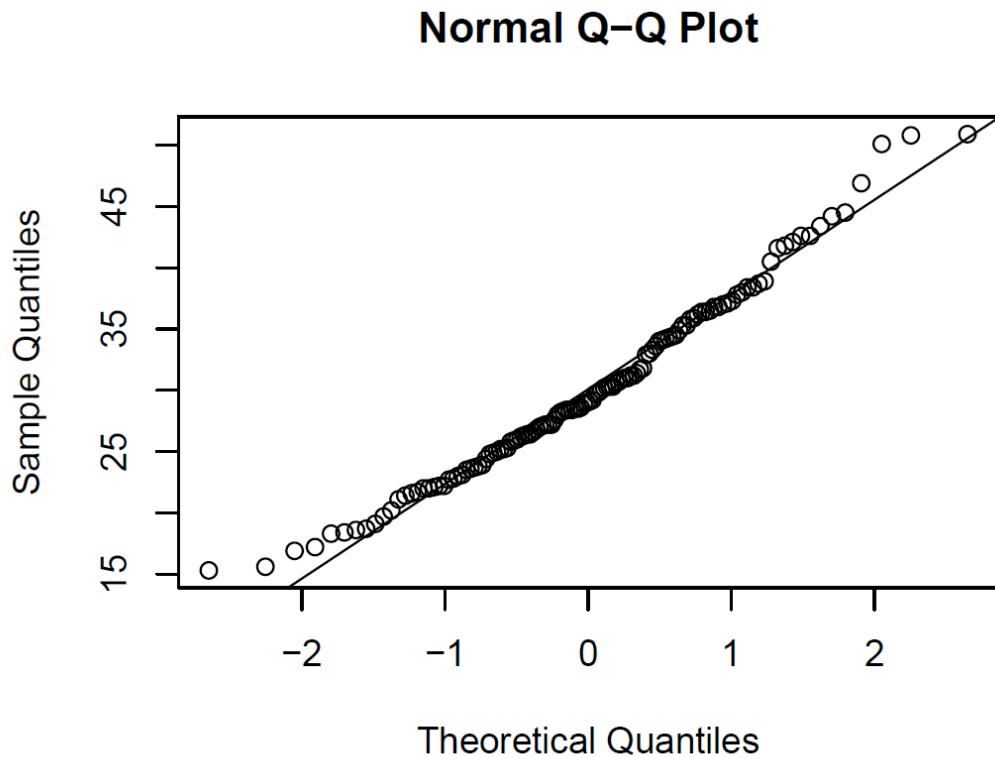
```
hist(milk, breaks = 10, freq = FALSE) # Create histogram  
curve(dnorm(x,mean=mean(milk),sd = sd(milk)),add = T,col=3) # Add normal dist.
```



Normality test

Q-Q Plot

```
qqnorm(cows$milk) # Create a qq-plot  
qqline(cows$milk) # Add line
```



Normality test

```
*****verifica normalità*****;
```

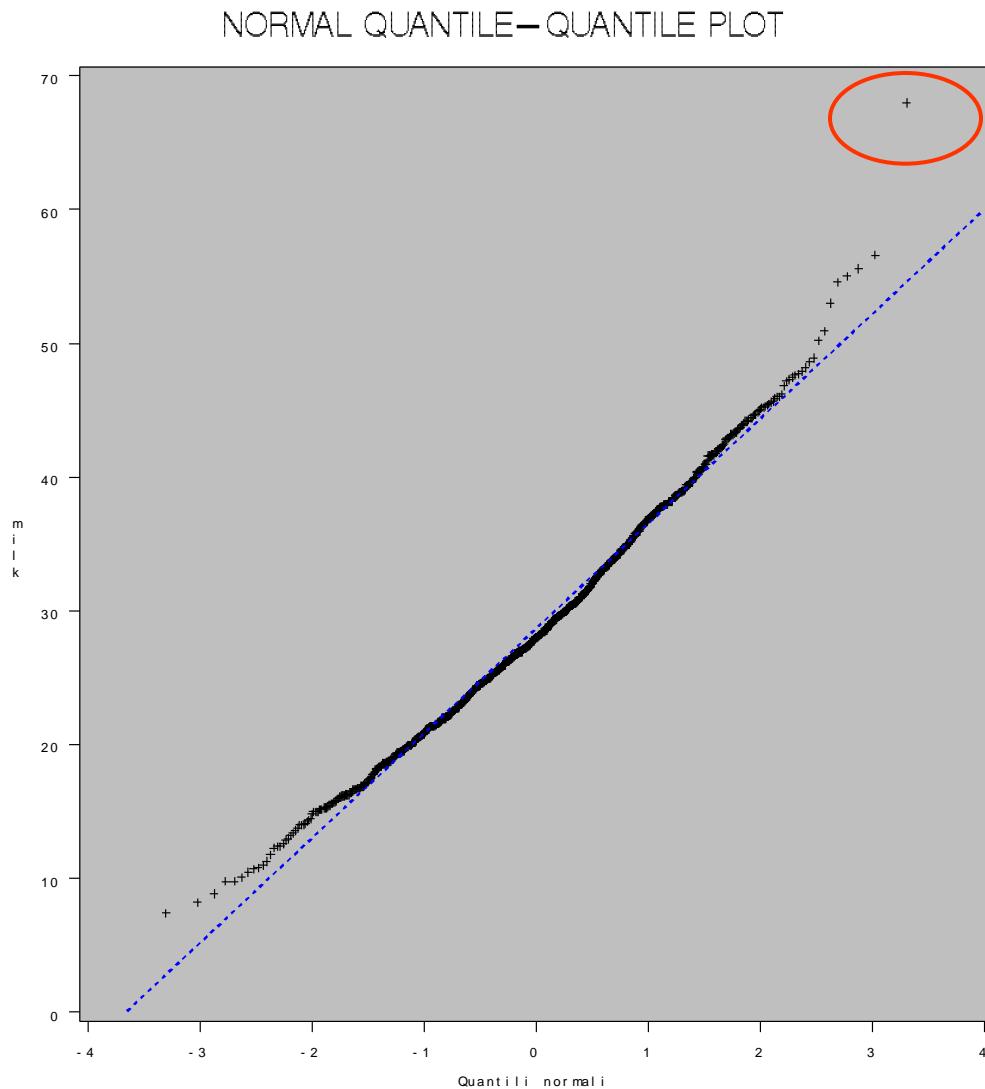
```
PROC UNIVARIATE DATA=brown NOPRINT;  
VAR milk grs prt cellu scs casein indcas r k20 a30 sh ph pnc;  
HISTOGRAM milk grs prt cellu scs casein indcas r k20 a30 sh ph pnc/NORMAL;  
INSET NORMAL(AD ADPVAL CVM CVMPVAL KSD KSDPVAL);  
RUN;
```

```
SYMBOL1 v=PLUS;  
TITLE 'NORMAL QUANTILE-QUANTILE PLOT';  
PROC UNIVARIATE DATA=brown NOPRINT;  
QQPLOT milk grs prt cellu scs casein indcas r indcas k20 a30 sh ph pnc/ normal(mu=est sigma=est color=blue  
l=2 w=2 nowrap)  
square cframe = ligr;
```

```
RUN;
```

```
GOPTIONS RESET=ALL;
```

Normality test

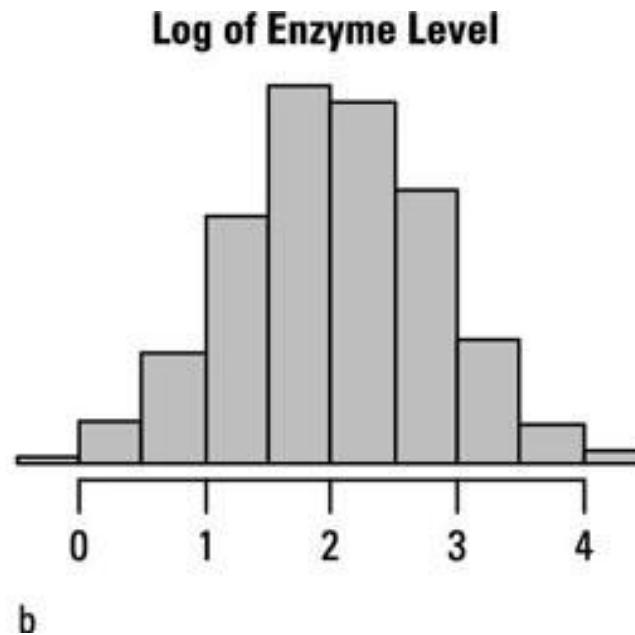
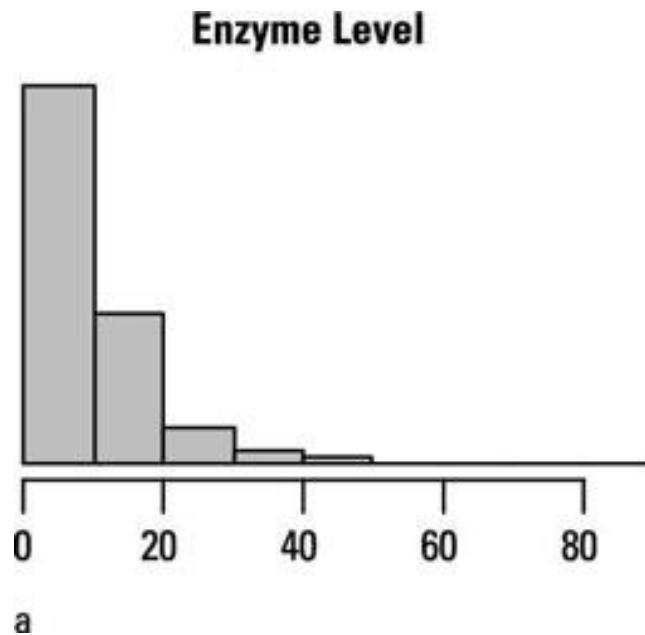


Consequences of Non-Normality

- F-test is very robust against non-normal data, especially in a fixed-effects model
- Large sample size will approximate normality by Central Limit Theorem (recommended sample size > 50)
- Simulations have shown unequal sample sizes between treatment groups magnify any departure from normality
- A large deviation from normality leads to hypothesis test conclusions that are too liberal and a decrease in power and efficiency

Remedial Measures for Non-Normality

- Data transformation (log, square root, etc...)
- Be aware - transformations may lead to a fundamental change in the relationship between the dependent and the independent variable and is not always recommended



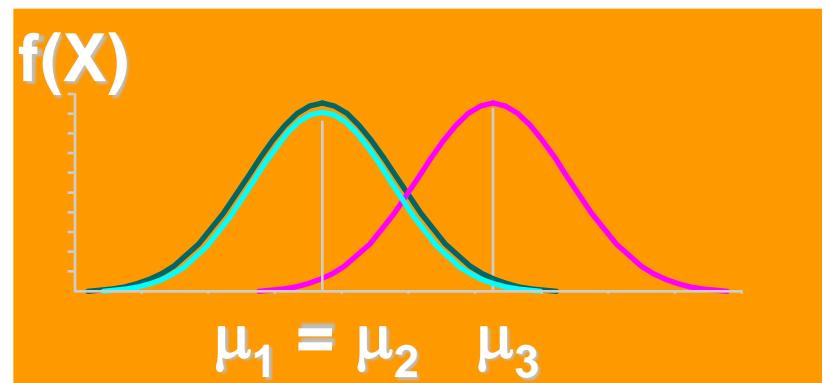
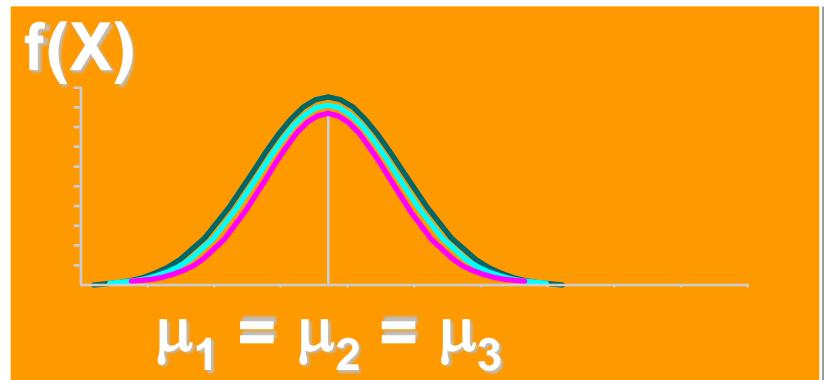
One-Way ANOVA F-Test Hypotheses

$$H_0: \mu_1 = \mu_2 = \mu_3 = \dots = \mu_p$$

- All Population Means are Equal
- No Treatment Effect

$$H_a: \text{Not All } \mu_j \text{ Are Equal}$$

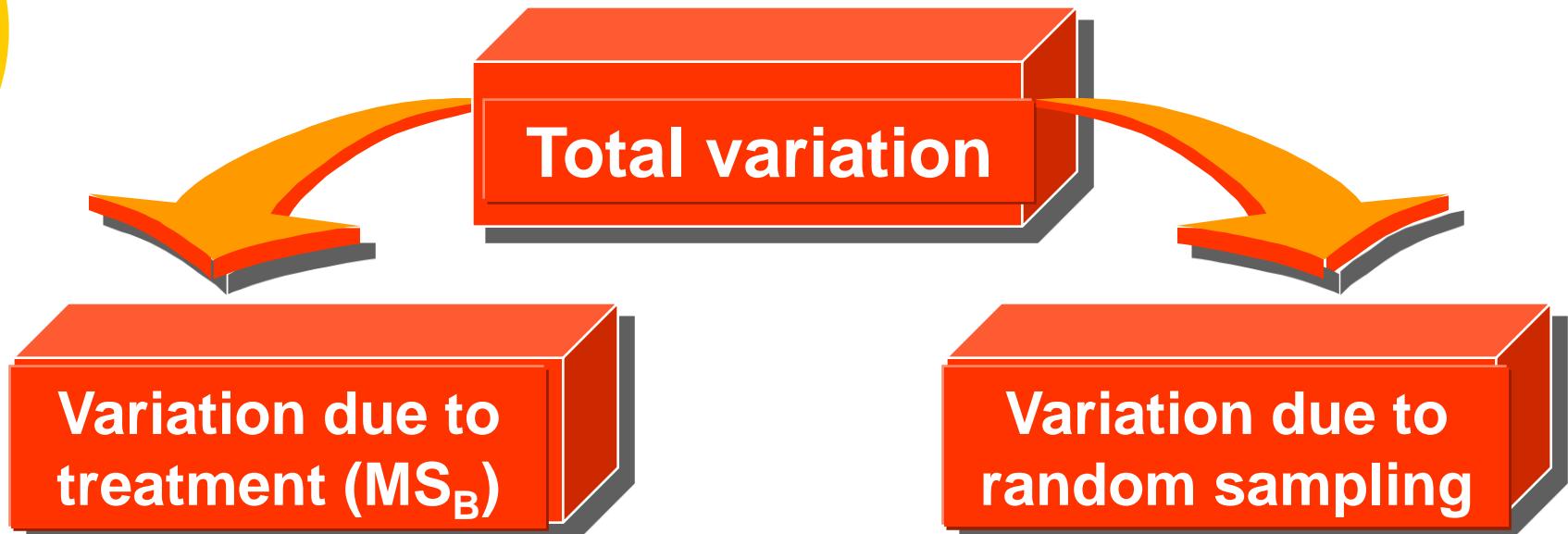
- At Least 1 Pop. Mean is Different
- Treatment Effect
- NOT $\mu_1 \neq \mu_2 \neq \dots \neq \mu_p$



One-Way ANOVA Basic Idea

- Compares 2 types of variation to test equality of means
- If treatment variation is significantly greater than random variation then means are not equal
- Variation measures are obtained by 'partitioning' total variation

One-Way ANOVA Partitions Total Variation



Sum of squares due to treatment **SST**
(i.e., between groups)

Sum of squares error **SSE** (i.e.,
within groups)

One-Way ANOVA Partitions Total Variation

$$SS_{ERROR} = \sum_j \sum_i (Y_{ij} - \hat{Y}_{ij})^2$$

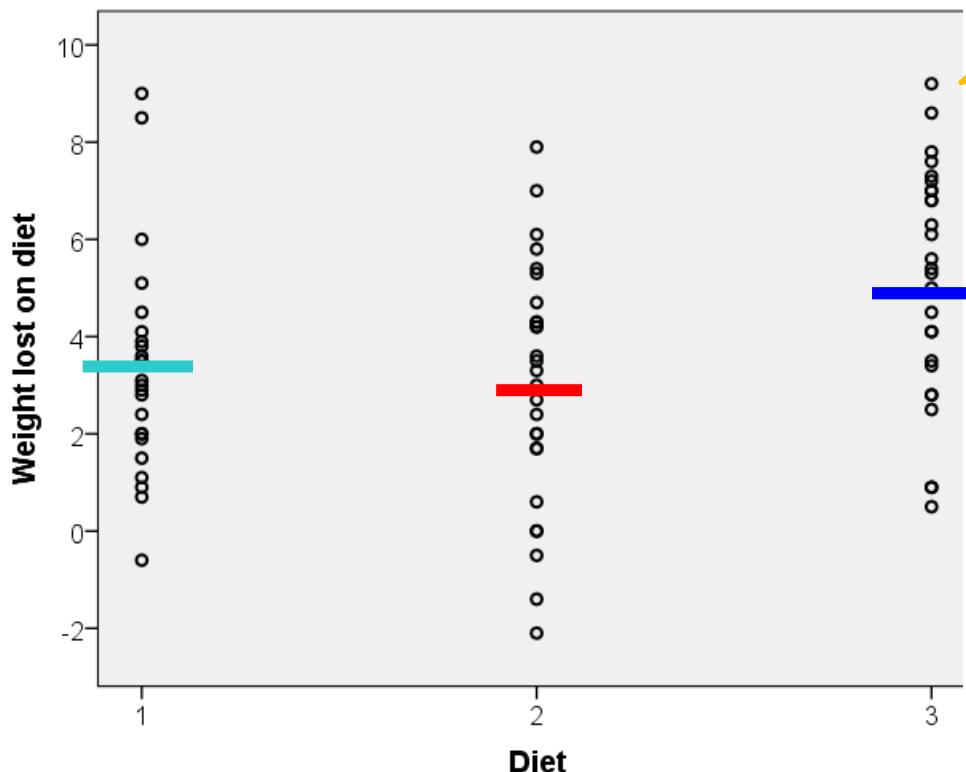
$$+ \quad SS_{TREAT} = \sum_j \sum_i (\hat{Y}_{ij} - \bar{Y})^2$$

$$SS_{TOTAL} = \sum_j \sum_i (Y_{ij} - \bar{Y})^2$$

Within group variation

Residual = difference between an individual and their group mean

$$SS_{ERROR} = \sum_j \sum_i (Y_{ij} - \hat{Y}_{ij})^2$$



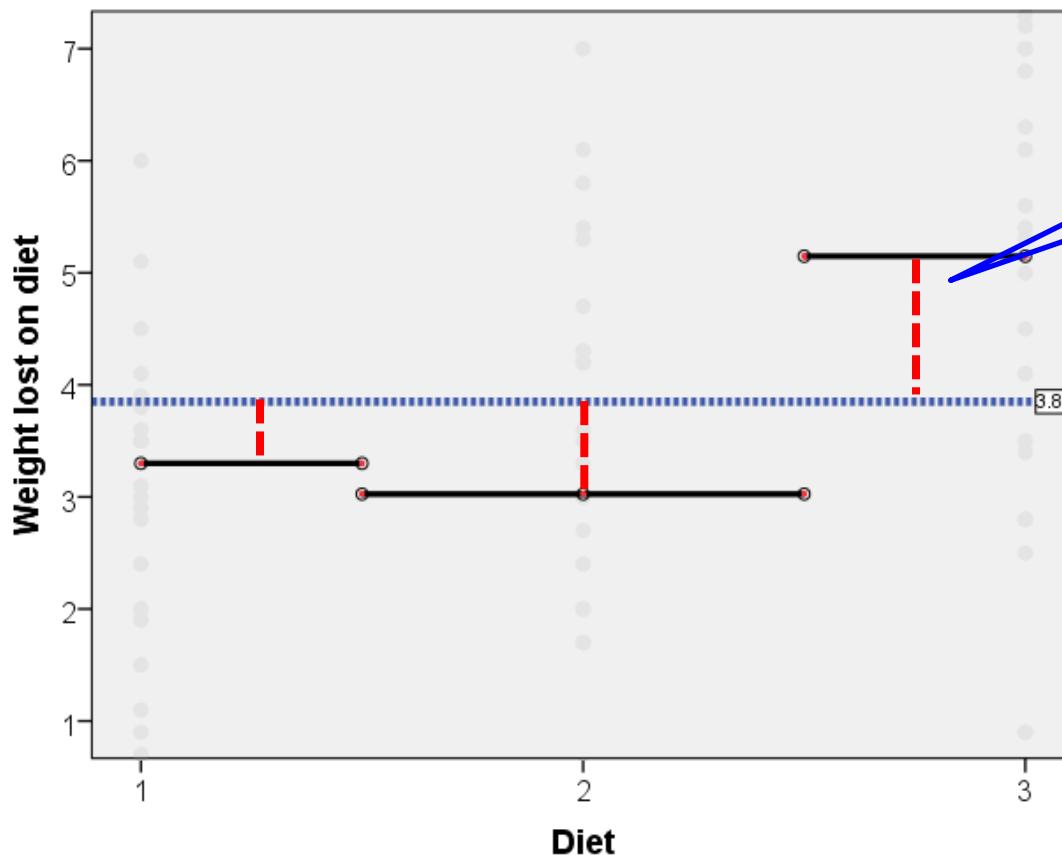
Person lost 9.2kg so residual = 9.2 - 5.15 = 4.05

Mean weight lost on diet 3 = 5.15kg

Between group variation

Differences between each group mean and the overall mean

$$SS_{TREAT} = \sum_j \sum_i (\hat{Y}_{ij} - \bar{Y})^2$$



Diet 3 difference
 $= 5.15 - 3.85 = 1.3$

Overall I mean
 $= 3.85$

One-Way ANOVA F-Test

- 1. Test Statistic

- $F = MST / MSE$

$$= \frac{SST / (p - 1)}{SSE / (n - p)}$$

- MST Is Mean Square for Treatment

- MSE Is Mean Square for Error

- 2. Degrees of Freedom

- $df_1 = p - 1$

- $df_2 = n - p$

- $p = \# \text{ Populations, Groups}$

- $n = \text{Total Sample Size}$

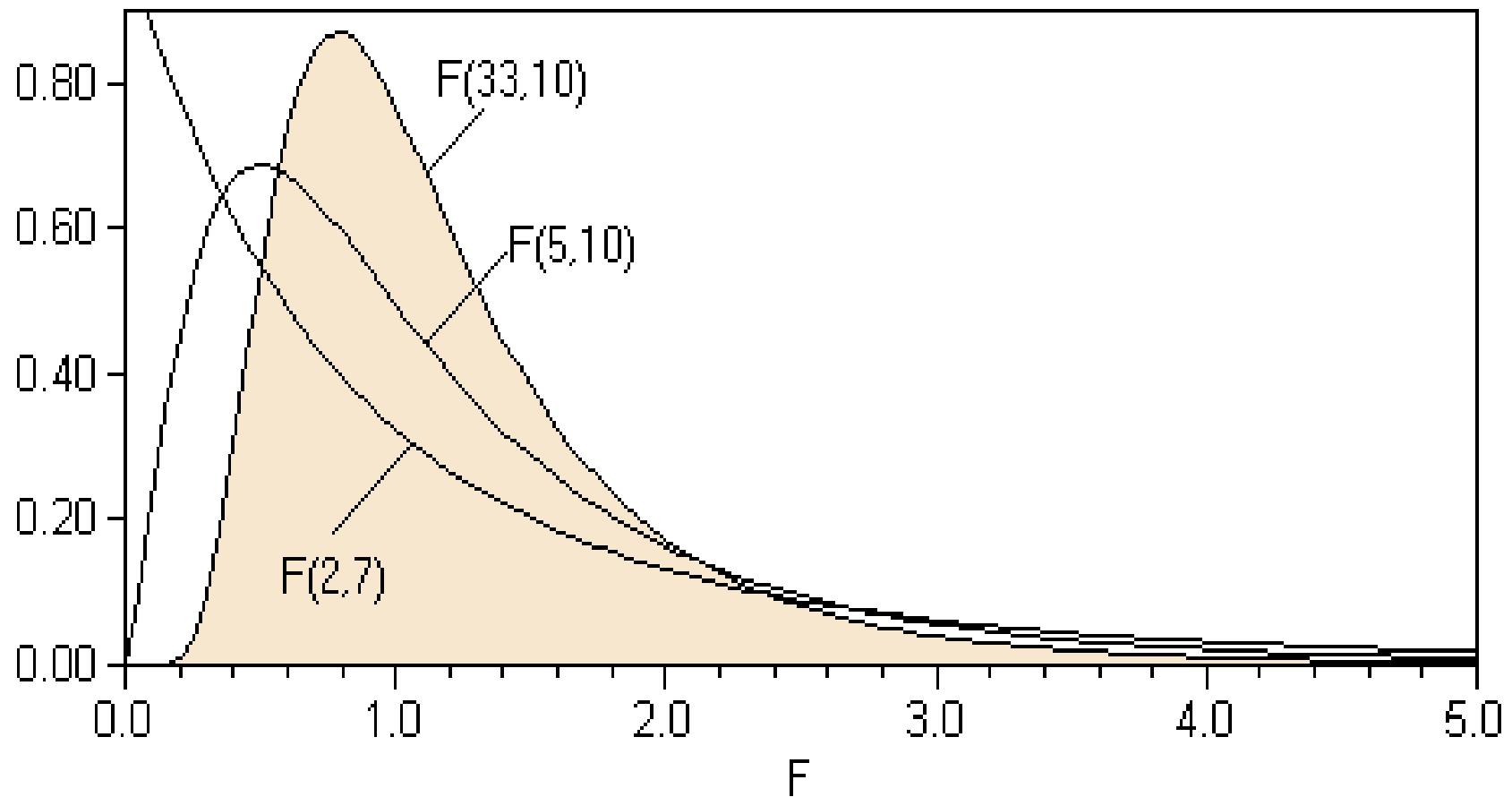
One-Way ANOVA - Summary Table

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square (Variance)	F
Treatment	$p - 1$	SST	$MST = \frac{SST}{p - 1}$	$\frac{MST}{MSE}$
Error	$n - p$	SSE	$MSE = \frac{SSE}{n - p}$	
Total	$n - 1$	$SS(\text{Total}) = SST + SSE$		

ANOVA – the sampling distribution for F

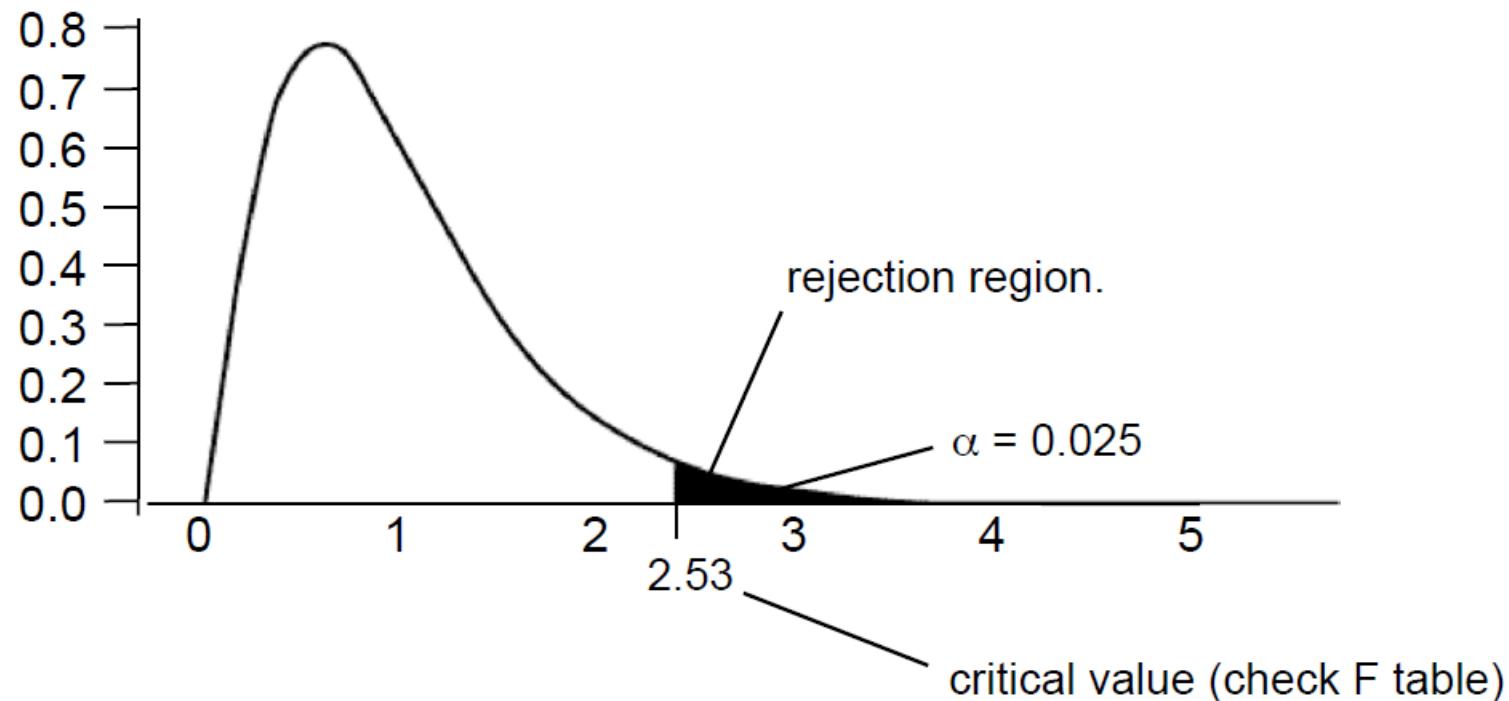
- The sampling distribution for the test statistic F is an F (Snedecor) distribution with $k-1$ degrees of freedom (df_N) for the numerator (df_N) and $N-k$ degrees of freedom for the denominator (df_D)
- The F distribution :
 - is a family of curve each of which determined by the df of the numerator and by the df of the denominator
 - is positively skewed
 - has a total area under the curve equal to 1
 - F-values are greater than or equal to zero
 - Its mean value is approximately equal to 1

ANOVA – the sampling distribution for F



ANOVA – reject region

Example : an F distribution with $df_N=15$, $df_d = 21$



One-Way ANOVA F-Test Example

- As a PhD student in animal and food science you want to see if 3 food supplements have different mean milk yields. You assign 15 cows, 5 per food supplement (CRD)
- Question: At the .05 level, is there a difference in mean yields?

Food1	Food2	Food3
25.4	23.4	20
26.31	21.8	22.2
24.1	23.5	19.75
23.74	22.75	20.6
25.1	21.6	20.4

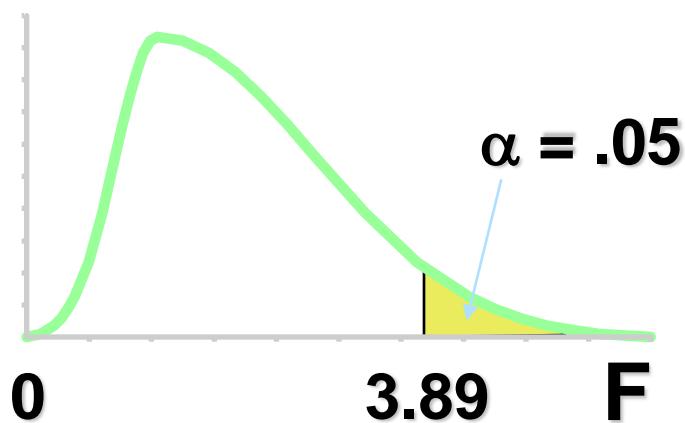


One-Way ANOVA F-Test Solution

- $H_0: \mu_1 = \mu_2 = \mu_3$
- $H_a: \text{Not All Equal}$
- $\alpha = .05$
- $df_1 = 2 \ df_2 = 12$
- Critical Value(s):

Test Statistic:

$$F = \frac{MST}{MSE} = \frac{23.5820}{.9211} = 25.6$$



Decision:
Reject at $\alpha = .05$

Conclusion:
There Is Evidence Pop. Means Are Different

ANOVA - calculations

$$MST = \frac{SST}{p-1} = \frac{\sum_{i=1}^p n_i \cdot (\hat{Y}_i - \bar{Y})^2}{p-1}$$

Where SST is the between groups sum of squares, p is the number of groups and n_i is the size group

$$MSE = \frac{SSE}{N-p} = \frac{\sum_{i=1}^p (n_i - 1) \cdot S^2_i}{p-1}$$

Where SSE is the within groups sum of squares (error), p is the number of groups, n_i is the size group, N is the sum of group sizes, S^2_i is the within group variance

ANOVA - Example

Our data set: $\bar{Y}_{(\text{grand mean})} = 22.71$

$$\hat{Y}_{Food1} = 24.93; \quad \hat{Y}_{Food2} = 22.61; \quad \hat{Y}_{Food3} = 20.59$$

$$S^2_{Food1} = 1.0648; \quad S^2_{Food2} = 0.778; \quad S^2_{Food3} = 0.9205$$

$$MST = \frac{SST}{p-1} = \frac{\sum_{i=1}^p n_i \cdot (\hat{Y}_i - \bar{Y})^2}{p-1} = \frac{5 \cdot (24.93 - 22.71)^2 + (22.61 - 22.71)^2 + (20.59 - 22.71)^2}{3-1} = 23.582$$

$$MSE = \frac{SSE}{N-p} = \frac{\sum_{i=1}^p (n_i - 1) \cdot S^2_i}{N-1} = \frac{(4 \cdot 1.0648) + (4 \cdot 0.778) + (4 \cdot 0.9295)}{15-3} = 0.9211$$

$$df_N = p - 1 = 3 - 1, \quad df_D = N - p = 15 - 3 = 12$$

Summary Table Solution

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square (Variance)	F
Food	$3 - 1 = 2$	47.1640	23.5820	25.60
Error	$15 - 3 = 12$	11.0532	.9211	
Total	$15 - 1 = 14$	58.2172		



R CODES FOR ANOVA

Create Dataframe

```
foods<-data.frame(milk=c(25.40,26.31,24.10,23.74,25.10,
                         23.40,21.80,23.50,22.75,21.60,
                         20.00,22.20,19.75,20.60,20.40),
                    food=c("Food1","Food1","Food1","Food1","Food1",
                           "Food2","Food2","Food2","Food2","Food2",
                           "Food3","Food3","Food3","Food3","Food3"),
                    stringsAsFactors = TRUE)

print(foods) #See the Data

##      milk   food
## 1  25.40 Food1
## 2  26.31 Food1
## 3  24.10 Food1
## 4  23.74 Food1
## 5  25.10 Food1
## 6  23.40 Food2
## 7  21.80 Food2
## 8  23.50 Food2
## 9  22.75 Food2
## 10 21.60 Food2
## 11 20.00 Food3
## 12 22.20 Food3
## 13 19.75 Food3
## 14 20.60 Food3
## 15 20.40 Food3
```



R OUTPUT - ANOVA

```
tm<-lm(milk ~ food, data = foods)      # Fit the linear model
summary(tm)                            # Linear Model Summary

##
## Call:
## lm(formula = milk ~ food, data = foods)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##   -1.19  -0.82   0.01   0.63   1.61
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 24.9300    0.4292  58.084 4.48e-16 ***
## foodFood2   -2.3200    0.6070  -3.822  0.00243 **
## foodFood3   -4.3400    0.6070  -7.150 1.16e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9597 on 12 degrees of freedom
## Multiple R-squared:  0.8101, Adjusted R-squared:  0.7785
## F-statistic: 25.6 on 2 and 12 DF,  p-value: 4.684e-05

fm<-aov(milk ~ food, data = foods)    # Fit the ANOVA
summary(fm)                          # ANOVA table SS I

##
## Df Sum Sq Mean Sq F value    Pr(>F)
## food          2  47.16  23.582   25.6 4.68e-05 ***
## Residuals    12  11.05   0.921
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

SAS CODES FOR ANOVA

```
Data Anova;  
input group$ milk @@;  
cards;  
food1 25.40      food2 23.40      food3 20.00  
food1 26.31      food2 21.80      food3 22.20  
food1 24.10      food2 23.50      food3 19.75  
food1 23.74      food2 22.75      food3 20.60  
food1 25.10      food2 21.60      food3 20.40  
;  
run;
```

```
proc anova; /* or PROC GLM */  
class group;  
model milk=group;  
run;
```

SAS OUTPUT - ANOVA

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La procedura GLM					
Variabile dipendente: milk					
Origine	DF	Somma dei quadrati	Media quadratica	Valore F	Pr > F
Modello	2	47.16400000	23.58200000	25.60	<.0001
Errore	12	11.05320000	0.92110000		
Totale corretto	14	58.21720000			
Riquadro					
Var coeff Radice MSE milk Media					
0.810139 4.226066 0.959740 22.71000					
Origine	DF	Tipo I SS	Media quadratica	Valore F	Pr > F
group	2	47.16400000	23.58200000	25.60	<.0001
Origine	DF	Tipo III SS	Media quadratica	Valore F	Pr > F
group	2	47.16400000	23.58200000	25.60	<.0001

Pair-wise comparison

- Needed when the overall F test is rejected
- Can be done without adjustment of type I error if other comparisons were planned in advance (least significant difference - LSD method)
- Type I error needs to be adjusted if other comparisons were not planned in advance (Bonferroni's and scheffe's methods)

Fisher's Least Significant Difference (LSD) Test

To compare level 1 and level 2

$$t = (\bar{y}_1 - \bar{y}_2) \Bigg/ \sqrt{MSE \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}$$

Compare this to $t_{\alpha/2}$ = Upper-tailed value or $-t_{\alpha/2}$ lower-tailed from Student's t-distribution for $\alpha/2$ and $(n - p)$ degrees of freedom

MSE = Mean square within from ANOVA table

n = Number of subjects

p = Number of levels

Bonferroni's method

To compare level 1 and level 2

$$t = (\bar{y}_1 - \bar{y}_2) \Bigg/ \sqrt{MSE \left(\frac{1}{n_1} + \frac{1}{n_2} \right)}$$

Adjust the significance level α by taking the new significance level α^*

$$\alpha^* = \alpha / \binom{p}{2}$$



R CODES FOR multiple comparisons

```
TukeyHSD(fm)                      # Tukey test for multiple comparisons

## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = milk ~ food, data = foods)
##
## $food
##      diff      lwr      upr     p adj
## Food2-Food1 -2.32 -3.939373 -0.7006265 0.0063517
## Food3-Food1 -4.34 -5.959373 -2.7206265 0.0000322
## Food3-Food2 -2.02 -3.639373 -0.4006265 0.0153900

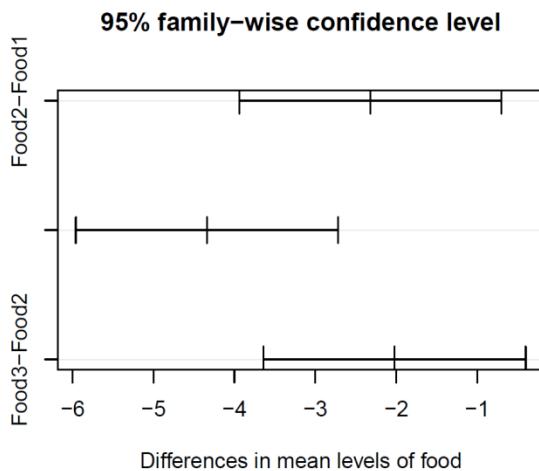
plot(TukeyHSD(fm))                # Plot for tukey test
aggregate(foods$milk, by=list(foods$food), FUN = mean) # Means by group

## Group.1      x
## 1 Food1 24.93
## 2 Food2 22.61
## 3 Food3 20.59
```

SAS OUTPUT - Tukey

```
TukeyHSD(fm)          # Tukey test for multiple comparisons

## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = milk ~ food, data = foods)
##
## $food
##      diff      lwr      upr   p adj
## Food2-Food1 -2.32 -3.939373 -0.7006265 0.0063517
## Food3-Food1 -4.34 -5.959373 -2.7206265 0.0000322
## Food3-Food2 -2.02 -3.639373 -0.4006265 0.0153900
plot(TukeyHSD(fm))      # Plot for tukey test
```

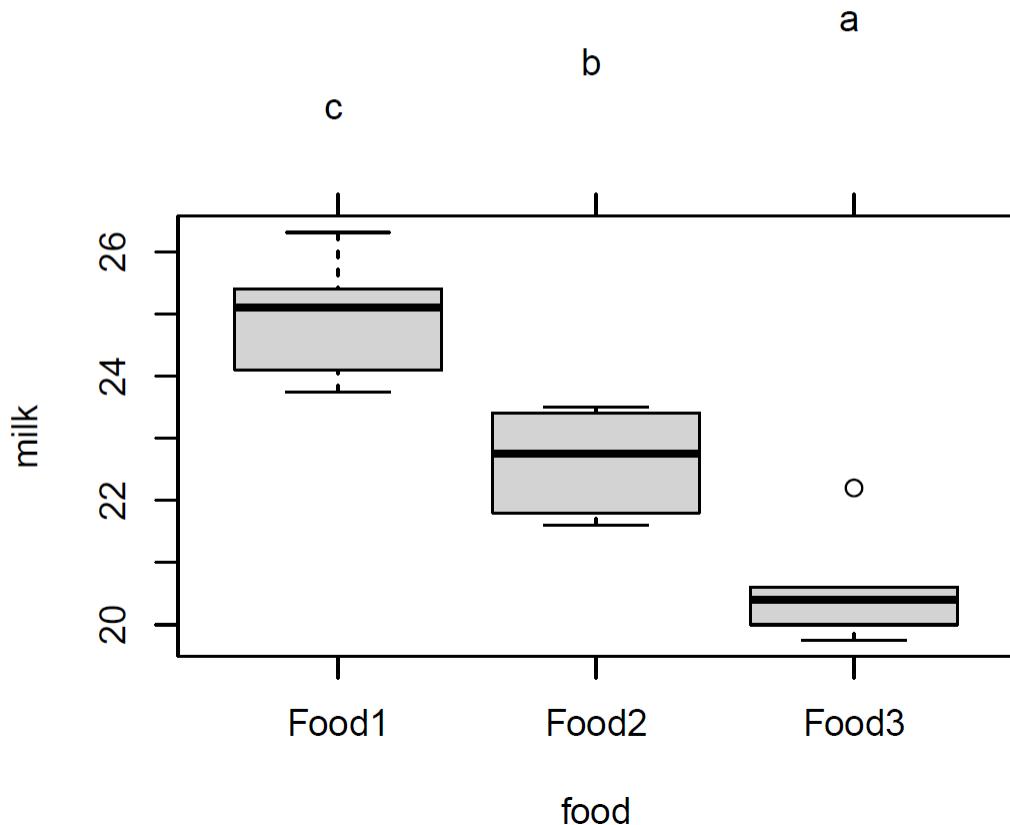


```
aggregate(foods$milk, by=list(foods$food), FUN = mean) # Means by group

## Group.1      x
## 1 Food1 24.93
## 2 Food2 22.61
## 3 Food3 20.59
```

R Plot– Tukey differences

```
#install.packages("multcomp")
library(multcomp)
par(mar=c(4,4,6,2))           # Change parameters for the plot margins
tuk <- glht(fm, linfct=mcp(food="Tukey")) # Fit the general Linear Hypotheses
plot(cld(tuk, level=0.05), col="lightgrey")   # Plot the mean differences
```



SAS CODES FOR multiple comparisons

```
proc glm;
class group;
model milk=group;
means group/ lsd bon;
run;
```

SAS OUTPUT - LSD



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La procedura GLM

Test t (LSD) per milk

NOTA: Questo test controlla il tasso di errore di confronto di tipo I, non il tasso di errore sperimentale.

Alfa	0.05
Gradi di libertà per l'errore	12
Errore quadratico medio	0.9211
Valore critico di t	2.17881
Minore differenza significativa	1.3225

Le medie con la stessa lettera non sono significativamente diverse.

t Raggruppamento	Media	N	group
A	24.9300	5	food1
B	22.6100	5	food2
C	20.5900	5	food3

SAS OUTPUT - Bonferroni

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La procedura GLM

Test t di Bonferroni (Dunn) per milk

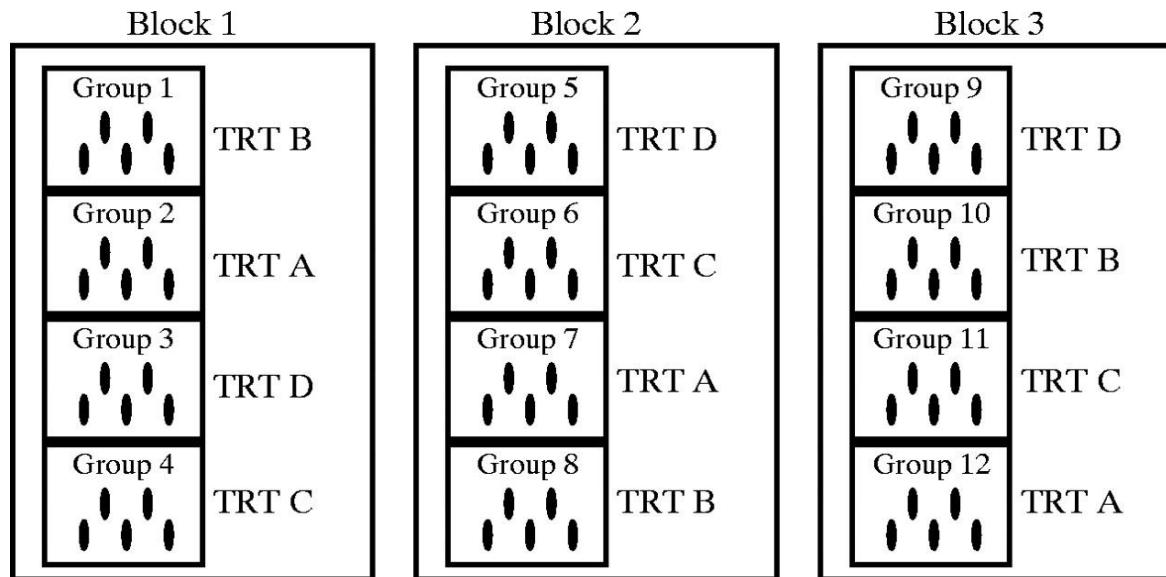
NOTA: Questo test controlla il tasso di errore sperimentale di tipo I, ma generalmente ha un tasso di errore di tipo II maggiore rispetto a REGWQ.

Alfa	0.05
Gradi di libertà per l'errore	12
Errore quadratico medio	0.9211
Valore critico di t	2.77947
Minima differenza significativa	1.6871

Le medie con la stessa lettera non sono significativamente diverse.

Bon Raggruppamento	Media	N	group
A	24.9300	5	food1
B	22.6100	5	food2
C	20.5900	5	food3

Randomized Block Design



Randomized Block Design

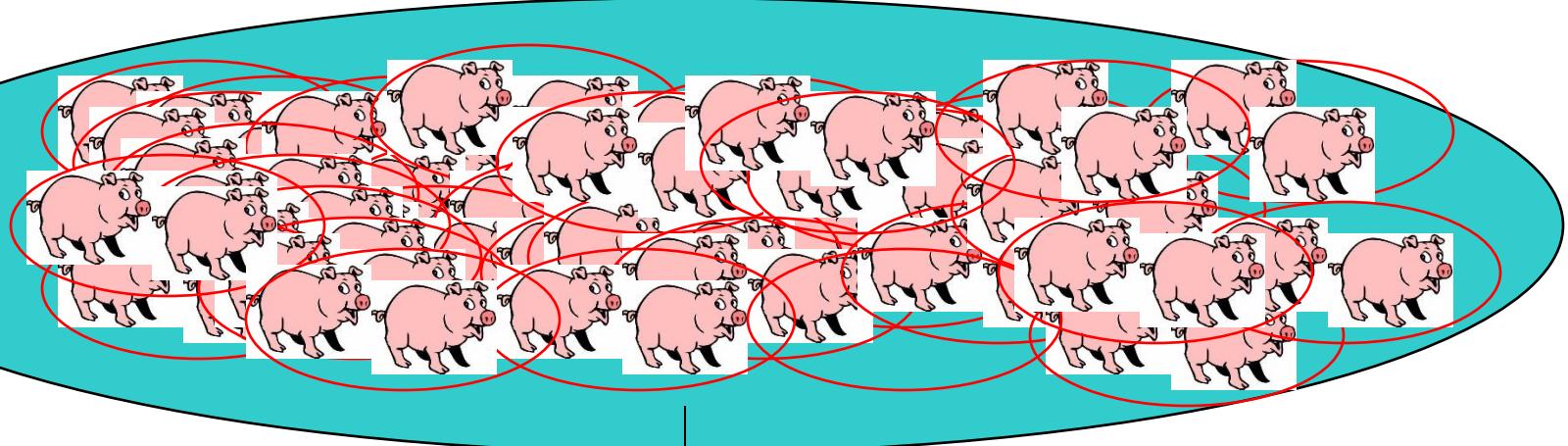
- Experimental Units (Subjects) Are Assigned Randomly within Blocks
 - Blocks are Assumed Homogeneous
- One Factor or Independent Variable of Interest
 - 2 or More Treatment Levels or Classifications
- One Blocking Factor

Randomized Block Design

Factor Levels: (Treatments)		A, B, C, D			
Experimental Units		Treatments are randomly assigned within blocks			
Block 1		A	C	D	B
Block 2		C	D	B	A
Block 3		B	A	D	C
⋮		⋮	⋮	⋮	⋮
		⋮	⋮	⋮	⋮
		⋮	⋮	⋮	⋮
Block b		D	C	A	B

The Randomized Complete Block Design (RCBD)

Population of litters of size 2



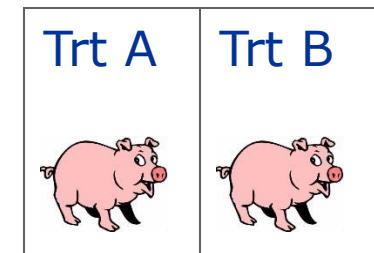
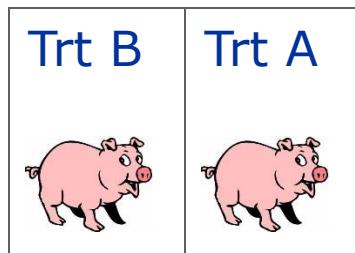
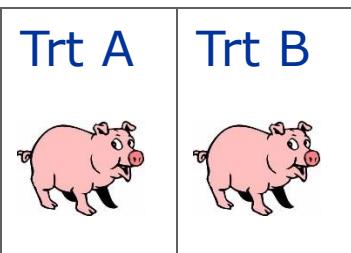
Draw random sample of litters

Litter 1

Litter 2

Litter n

...



Randomly assign treatments to piglets within litters

Randomized Block F-Test

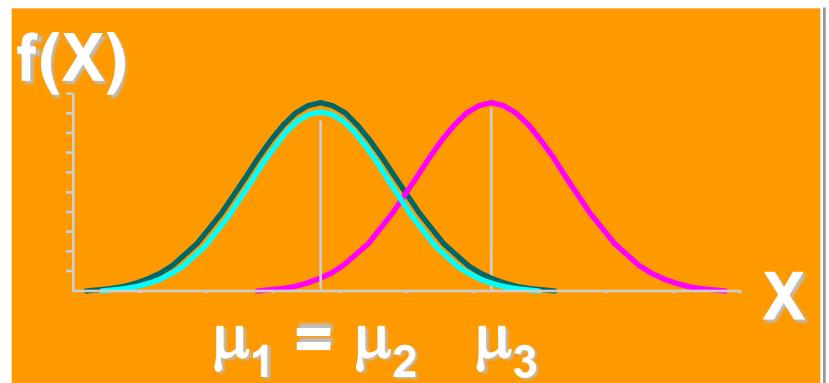
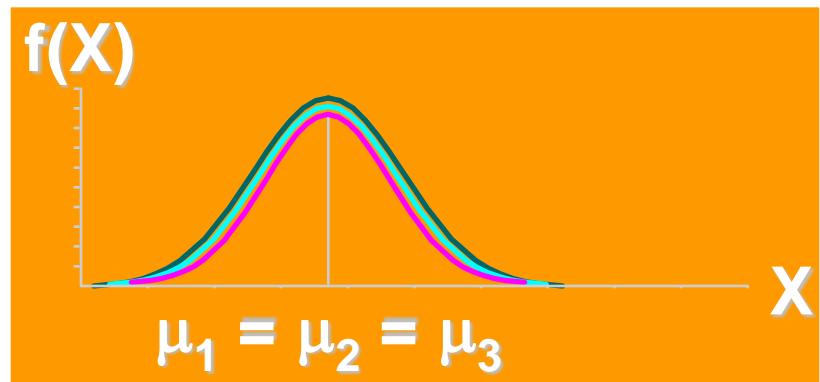
- Tests the Equality of 2 or More (p) Population Means
- Variables
 - One Nominal Independent Variable
 - One Nominal Blocking Variable
 - One Continuous Dependent Variable

Randomized Block F-Test Assumptions

- Normality
 - Probability distribution of each block-treatment combination is normal
- Homogeneity of variance
 - Probability distributions of all block-treatment combinations have equal variances

Randomized Block F-Test Hypotheses

- $H_0: \mu_1 = \mu_2 = \mu_3 = \dots = \mu_p$
 - All Population Means are Equal
 - No Treatment Effect
- $H_a:$ Not All μ_j Are Equal
 - At Least 1 Pop. Mean is Different
 - Treatment Effect
 - $\mu_1 \neq \mu_2 \neq \dots \neq \mu_p$ Is wrong



Two-Way ANOVA - Summary Table

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F
Treatment (a)	$a - 1$	$SS(A)$	$MS(A)$	$\frac{MS(A)}{MSE}$
Blocks (b)	$b - 1$	$SS(B)$	$MS(B)$	$\frac{MS(B)}{MSE}$
Error	$(a-1)(b-1)$	$SS(E)$	$MS(E)$	
Total	$N-1$	$SS(T)$		

Randomized Block F-Test

Test Statistic

- Test Statistic

- $F = MST / MSE$

- MST Is Mean Square for Treatment

- MSE Is Mean Square for Error

- Degrees of Freedom

- $df_N = p - 1$

- $df_D = n - b - p + 1 \text{ or } (p-1)(b-1)$

- $p = \# \text{ Treatments}, b = \# \text{ Blocks}, N = \text{Total Sample Size}$

Example: 15 piglets; weaned in 5 litters; treated with 3 treatments

EXAMPLE and SAS CODE

Litter	T1	T2	T3
1	7.86	7.76	7.46
2	8.00	7.73	7.68
3	7.93	7.74	7.51
4	7.62	7.43	7.21
5	7.81	7.44	7.42

Alternatives: PROC ANOVA, GLM, MIXED,
ANALYST, INTERACTIVE DATA ANALYSIS

```
□ data rcbd;
  input trt $ litter y @@;
  cards;
T1 1 7.86 T2 1 7.76 T3 1 7.46
T1 2 8.00 T2 2 7.73 T3 2 7.68
T1 3 7.93 T2 3 7.74 T3 3 7.51
T1 4 7.62 T2 4 7.43 T3 4 7.21
T1 5 7.81 T2 5 7.44 T3 5 7.42
;
run;

□ proc print data=rcbd;
run;

□ proc anova data=rcbd;
class litter trt;
model y = litter trt;
means trt;
run;

□ proc glm data=rcbd;
class litter trt;
model y = litter trt;
lsmeans trt / stderr;
run;

□ proc mixed data=rcbd;
class litter trt;
model y = trt;
random litter;
lsmeans trt;
run; .
```

RESULTS (PROC ANOVA)

(Test for Fixed Effects)

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	0.65649333	0.10941556	24.51	<.0001
Error	8	0.03570667	0.00446333		
Corrected Total	14	0.69220000			
R-Square	Coeff Var	Root MSE	y Mean		
0.948416	0.874453	0.066808	7.640000		
Source	DF	Anova SS	Mean Square	F Value	Pr > F
litter	4	0.27713333	0.06928333	15.52	0.0008
trt	2	0.37936000	0.18968000	42.50	<.0001

RESULTS (PROC GLM)

(Test for Fixed Effects)

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	0.65649333	0.10941556	24.51	<.0001
Error	8	0.03570667	0.00446333		
Corrected Total	14	0.69220000			

R-Square	Coeff Var	Root MSE	y Mean
0.948416	0.874453	0.066808	7.640000

Source	DF	Type I SS	Mean Square	F Value	Pr > F
litter	4	0.27713333	0.06928333	15.52	0.0008
trt	2	0.37936000	0.18968000	42.50	<.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
litter	4	0.27713333	0.06928333	15.52	0.0008
trt	2	0.37936000	0.18968000	42.50	<.0001

EXAMPLE and R CODE



Litter	T1	T2	T3
1	7.86	7.76	7.46
2	8.00	7.73	7.68
3	7.93	7.74	7.51
4	7.62	7.43	7.21
5	7.81	7.44	7.42

```
pigs<-data.frame(trt=c("T1","T1","T1","T1","T1",
                        "T2","T2","T2","T2","T2",
                        "T3","T3","T3","T3","T3"),
                   litter=c("1","2","3","4","5",
                           "1","2","3","4","5",
                           "1","2","3","4","5"),
                   y=c(7.86,8.00,7.93,7.62,7.81,
                       7.76,7.73,7.74,7.43,7.44,
                       7.46,7.68,7.51,7.21,7.42),
                   stringsAsFactors = TRUE)
print(pigs) #See the Data
```



(Test for Fixed Effects)

```
tm<-lm(y ~ trt + litter, data = pigs) # Fit the linear model
summary(tm) # Linear Model Summary

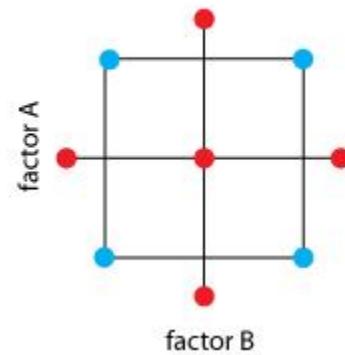
##
## Call:
## lm(formula = y ~ trt + litter, data = pigs)
##
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -0.09667 -0.03500 -0.00400  0.04033  0.08667
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 7.89733   0.04564 173.040 1.39e-15 ***
## trtT2       -0.22400   0.04225 -5.301 0.000727 ***
## trtT3       -0.38800   0.04225 -9.183 1.60e-05 ***
## litter2      0.11000   0.05455  2.017 0.078477 .  
## litter3      0.03333   0.05455  0.611 0.558109    
## litter4      -0.27333   0.05455 -5.011 0.001039 ** 
## litter5      -0.13667   0.05455 -2.505 0.036632 *  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06681 on 8 degrees of freedom
## Multiple R-squared:  0.9484, Adjusted R-squared:  0.9097 
## F-statistic: 24.51 on 6 and 8 DF,  p-value: 9.763e-05

fm<-aov(y ~ trt + litter, data = pigs) # Fit the ANOVA
summary(fm) # ANOVA Table SS I

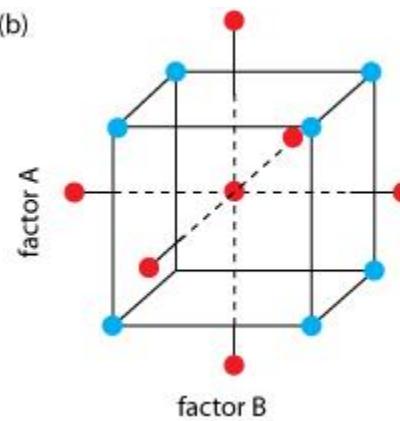
##           Df Sum Sq Mean Sq F value    Pr(>F)    
## trt          2 0.3794 0.18968  42.50 5.48e-05 ***
## litter        4 0.2771 0.06928  15.52 0.000771 ***
## Residuals     8 0.0357 0.00446
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Factorial Design

(a)



(b)



Factorial Design

- Experimental units (subjects) are assigned randomly to treatments
 - Subjects are assumed homogeneous
- Two or more **factors** or independent variables
 - Each has 2 or more treatments (levels)
- Analyzed by two-way ANOVA

Advantages of Factorial Designs

- Saves time & effort
 - e.g., Could use separate completely randomized designs for each variable
- Controls confounding effects by putting other variables into model
- Can explore interaction between variables

Two-Way ANOVA

- Tests the equality of 2 or more population means when several independent variables are used
- Same results as separate one-way anova on each variable
 - But interaction can be tested

Two-Way ANOVA Assumptions

- Normality
 - Populations are Normally Distributed
- Homogeneity of Variance
 - Populations have Equal Variances
- Independence of Errors
 - Independent Random Samples are Drawn

Two-Way ANOVA Data Table

Factor A		Factor B			
		1	2	...	b
1	1	Y_{111}	Y_{121}	...	Y_{1b1}
	2	Y_{112}	Y_{122}	...	Y_{1b2}
2	1	Y_{211}	Y_{221}	...	Y_{2b1}
	2	Y_{212}	Y_{222}	...	Y_{2b2}
:	:	:	:	:	:
a	1	Y_{a11}	Y_{a21}	...	Y_{ab1}
	2	Y_{a12}	Y_{a22}	...	Y_{ab2}

Observation k

Y_{ijk}

Level i Level j

Factor A Factor B

The two factor factorial Experiment

The model for a factorial experiment with two factors A and B is:

$$y_{ijk} = \mu + A_i + B_j + (AB)_{ij} + \varepsilon_{ijk} \quad i = 1, \dots, a; j = 1, \dots, b; k = 1, \dots, n$$

Where:

y_{ijk} = observation k in level i of factor A and level j of factor B

μ = the overall mean

A_i = the effect of level i of factor A

B_j = the effect of level j of factor B

$(AB)_{ij}$ = the effect of the interaction of level i of factor A with level j of factor B

ε_{ijk} = random error with mean 0 and variance σ^2

a = number of levels of factor A; b = number of levels of factor B; n = number of observations for each $A \times B$ combination

Two-Way ANOVA - Null Hypotheses

No Difference in Means Due to Factor A

$$\triangleright H_0: \mu_{1\cdot} = \mu_{2\cdot} = \dots = \mu_{a\cdot}$$

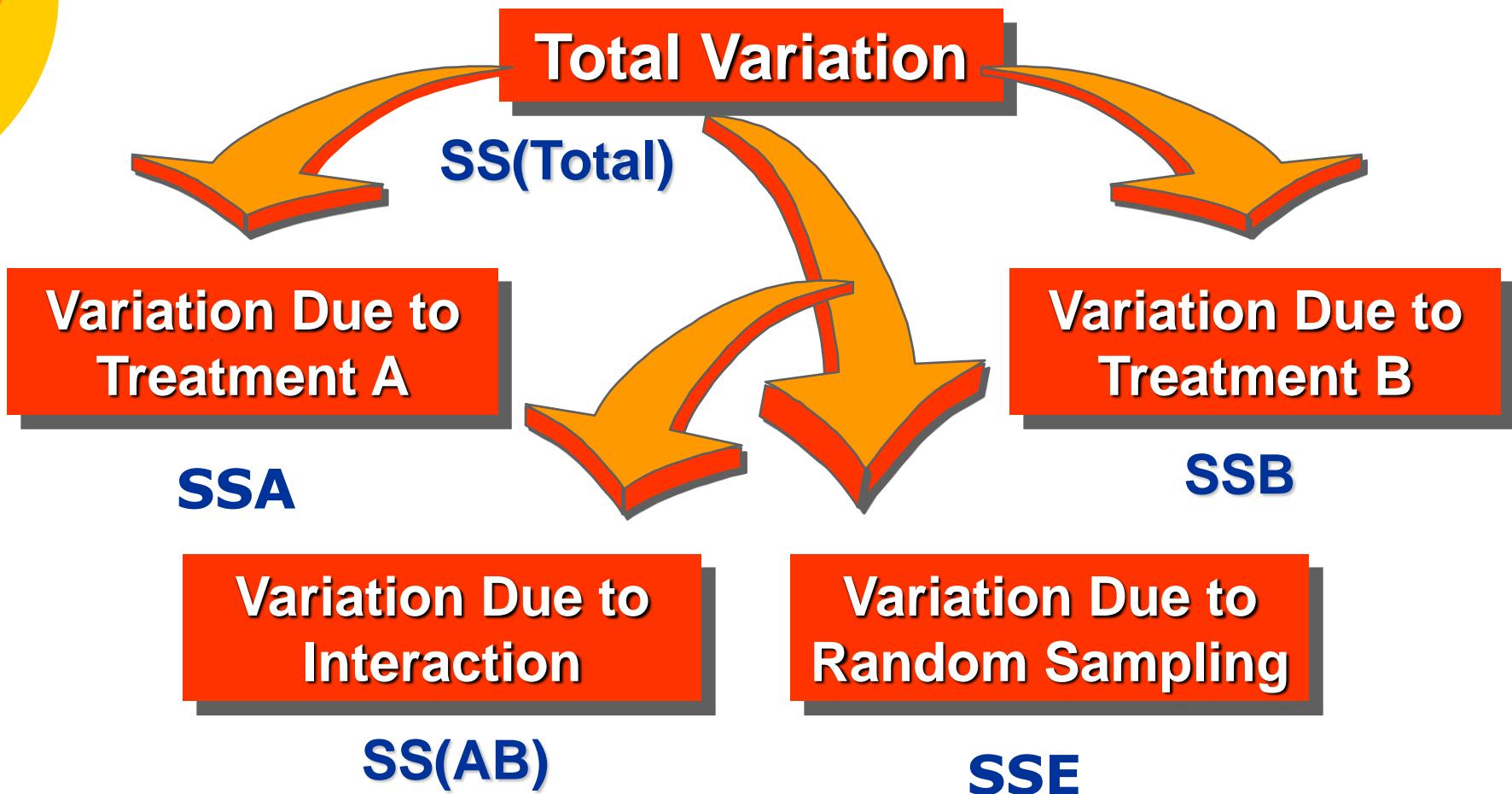
No Difference in Means Due to Factor B

$$\triangleright H_0: \mu_{\cdot 1} = \mu_{\cdot 2} = \dots = \mu_{\cdot b}$$

No Interaction of Factors A & B

$$\triangleright H_0: AB_{ij} = 0$$

Two-Way ANOVA - Total Variation Partitioning



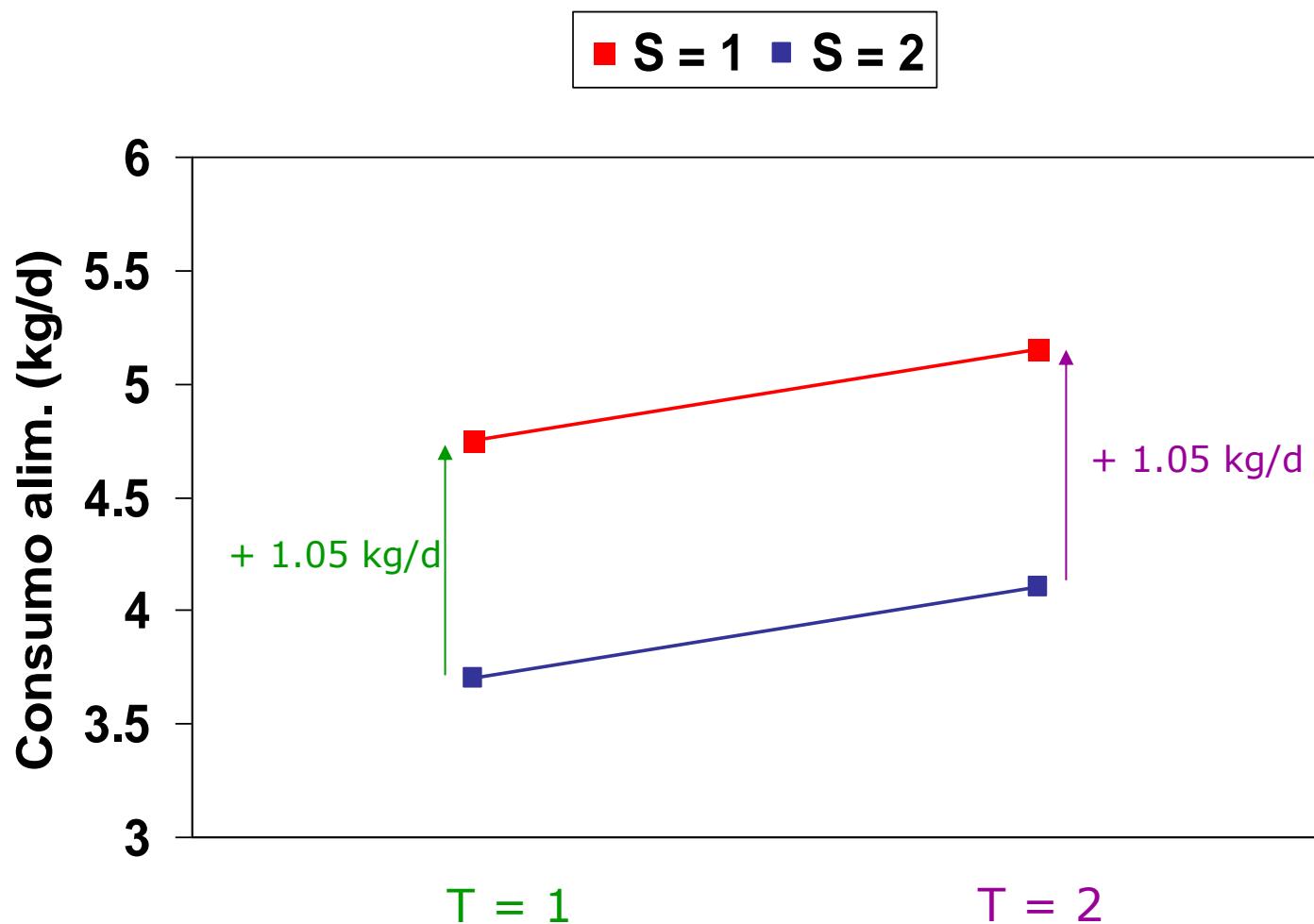
Two-Way ANOVA - Summary Table

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Square	F
A (Row)	$a - 1$	$SS(A)$	$MS(A)$	<u>$MS(A)$</u> MSE
B (Column)	$b - 1$	$SS(B)$	$MS(B)$	<u>$MS(B)$</u> MSE
AB (Interaction)	$(a-1)(b-1)$	$SS(AB)$	$MS(AB)$	<u>$MS(AB)$</u> MSE
Error	$ab(n-1)$	SSE	MSE	
Total	$abn-1$	$SS(Total)$		Same as Other Designs

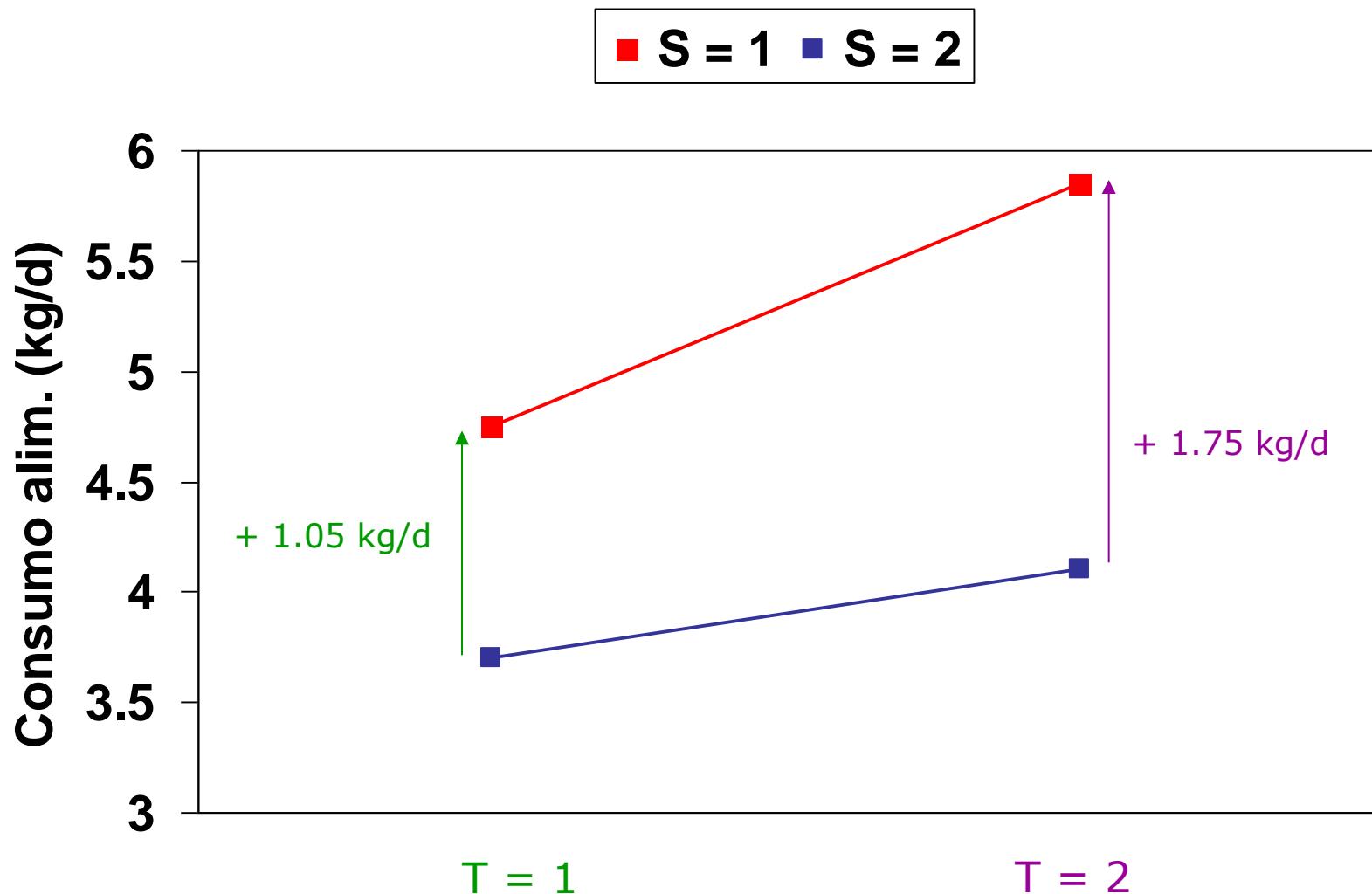
Interaction

- Occurs when effects of one factor vary according to levels of other factor
- When significant, interpretation of main effects (A & B) is complicated
- Can be detected
 - In data table, pattern of cell means in one row differs from another row
 - In graph of cell means, lines cross

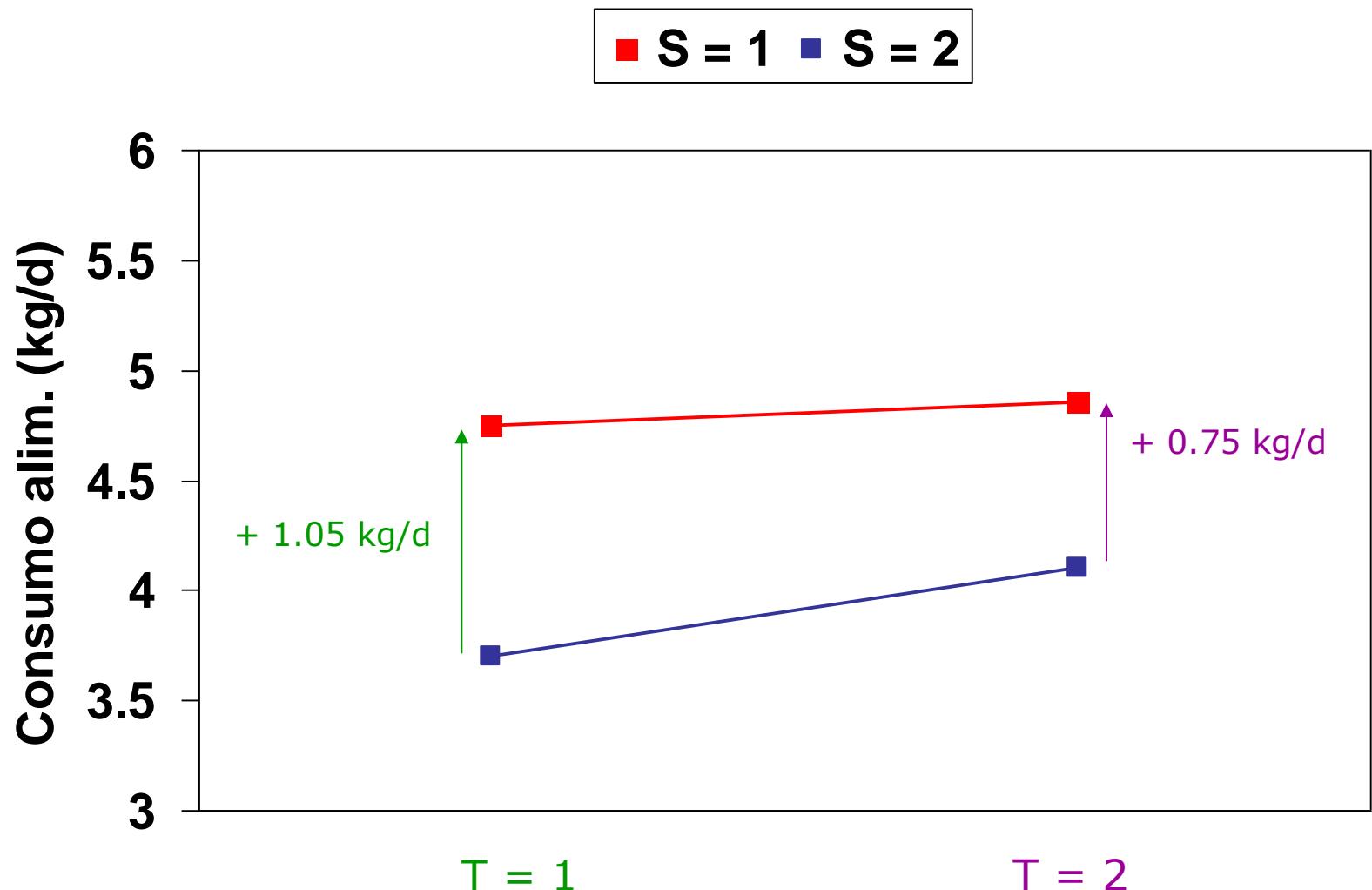
Example: graphs of interaction – **no** interaction



Example: graphs of Interaction – **positive** interaction



Example: graphs of Interaction – **negative** interaction



Two-Way ANOVA F - Test Example



Vitamin I	0 mg		4 mg	
Vitamin II	0 mg	5mg	0 mg	5 mg
	0.585	0.567	0.473	0.684
	0.536	0.545	0.450	0.702
	0.458	0.589	0.869	0.900
	0.486	0.536	0.473	0.698
	0.536	0.549	0.464	0.693

```
data gain;
  input vitI vitII gain @@;
  datalines;
  1 1 0.585 2 1 0.473
  1 1 0.536 2 1 0.450
  1 1 0.458 2 1 0.869
  1 1 0.486 2 1 0.473
  1 1 0.536 2 1 0.464
  1 2 0.567 2 2 0.684
  1 2 0.545 2 2 0.702
  1 2 0.589 2 2 0.900
  1 2 0.536 2 2 0.698
  1 2 0.549 2 2 0.693
;

proc glm;
  class vitI vitII;
  model gain=vitI vitII vitI*vitII;
  lsmeans vitI*vitII/ tdiff pdiff stderr adjust=tukey;
  run;
```

SAS OUTPUT - ANOVA



La procedura GLM

Variabile dipendente: gain

Origine	DF	Somma dei quadrati	Media quadratica	Valore F	Pr > F
Modello	3	0.14521095	0.04840365	4.39	0.0196
Errore	16	0.17648360	0.01103023		
Totale corretto	19	0.32169455			

R-squared	Var coeff	Radice MSE	gain Media
0.451394	17.81139	0.105025	0.589650

Origine	DF	Tipo I SS	Media quadratica	Valore F	Pr > F
vitI	1	0.05191805	0.05191805	4.71	0.0454
vitII	1	0.06418445	0.06418445	5.82	0.0282
vitI*vitII	1	0.02910845	0.02910845	2.64	0.1238

Origine	DF	Tipo III SS	Media quadratica	Valore F	Pr > F
vitI	1	0.05191805	0.05191805	4.71	0.0454
vitII	1	0.06418445	0.06418445	5.82	0.0282
vitI*vitII	1	0.02910845	0.02910845	2.64	0.1238

SAS OUTPUT - ANOVA

La procedura GLM
Medie dei minimi quadrati
Correzione per i confronti multipli: Tukey

vit I	vit II	gain LSMEAN	Errore standard	Pr > t	Numero LSMEAN
1	1	0.52020000	0.04696855	<.0001	1
1	2	0.55720000	0.04696855	<.0001	2
2	1	0.54580000	0.04696855	<.0001	3
2	2	0.73540000	0.04696855	<.0001	4

Medie dei minimi quadrati per l'effetto vitI*vitII
t per H0: LSMean(i)=LSMean(j) / Pr > |t|

Variabile dipendente: gain

i/j	1	2	3	4
1		-0.55703 0.9433	-0.38541 0.9799	-3.23981 0.0238
2	0.557031 0.9433		0.171626 0.9981	-2.68278 0.0701
3	0.385405 0.9799	-0.17163 0.9981		-2.85441 0.0506
4	3.239814 0.0238	2.682783 0.0701	2.854409 0.0506	

Two-Way ANOVA F - Test Example

Create Dataframe

```
gain<-data.frame(vitI=c("1","1","1","1","1",
                         "1","1","1","1","1",
                         "2","2","2","2","2",
                         "2","2","2","2","2"),
                  vitII=c("1","1","1","1","1",
                         "2","2","2","2","2",
                         "1","1","1","1","1",
                         "2","2","2","2","2"),
                  gain=c(0.585,0.536,0.458,0.486,0.536,
                         0.567,0.545,0.589,0.536,0.549,
                         0.473,0.450,0.869,0.473,0.464,
                         0.684,0.702,0.900,0.698,0.693),
                  stringsAsFactors = TRUE)

print(gain) #See the Data
```

Vitamin I	0 mg		4 mg	
Vitamin II	0 mg	5mg	0 mg	5 mg
	0.585	0.567	0.473	0.684
	0.536	0.545	0.450	0.702
	0.458	0.589	0.869	0.900
	0.486	0.536	0.473	0.698
	0.536	0.549	0.464	0.693



R OUTPUT - ANOVA

```
tm<-lm(gain ~ vitI + vitII + vitI*vitII, data = gain) # Fit the linear model
summary(tm) # Linear Model Summary

##
## Call:
## lm(formula = gain ~ vitI + vitII + vitI * vitII, data = gain)
##
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -0.0958 -0.0541 -0.0273  0.0158  0.3232 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  0.52020   0.04697 11.075 6.51e-09 ***
## vitI2        0.02560   0.06642  0.385   0.705    
## vitII2       0.03700   0.06642  0.557   0.585    
## vitI2:vitII2 0.15260   0.09394  1.624   0.124    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.105 on 16 degrees of freedom
## Multiple R-squared:  0.4514, Adjusted R-squared:  0.3485 
## F-statistic: 4.388 on 3 and 16 DF,  p-value: 0.01958

fm<-aov(gain ~ vitI + vitII + vitI*vitII, data = gain) # Fit the ANOVA
summary(fm) # ANOVA Table

##
##          Df  Sum Sq Mean Sq F value Pr(>F)    
## vitI       1  0.05192 0.05192  4.707 0.0454 *  
## vitII      1  0.06418 0.06418  5.819 0.0282 *  
## vitI:vitII 1  0.02911 0.02911  2.639 0.1238  
## Residuals  16  0.17648 0.01103                        
## ---
```



R OUTPUT - LSM

```
library(lsmeans)
lsmeans(tm,"vitI")    #LSM for VitI

##   vitI lsmean          SE df lower.CL upper.CL
## 1    0.5387 0.03321178 16  0.4682942 0.6091058
## 2    0.6406 0.03321178 16  0.5701942 0.7110058
##
## Results are averaged over the levels of: vitII
## Confidence level used: 0.95

lsmeans(tm,"vitII")  #LSM for VitII

##   vitII lsmean          SE df lower.CL upper.CL
## 1    0.5330 0.03321178 16  0.4625942 0.6034058
## 2    0.6463 0.03321178 16  0.5758942 0.7167058
##
## Results are averaged over the levels of: vitI
## Confidence level used: 0.95

summary(ref.grid(tm))#This is the reference grid of the model

##   vitI vitII prediction          SE df
## 1    1      1     0.5202 0.04696855 16
## 2    1      2     0.5458 0.04696855 16
## 1    2      1     0.5572 0.04696855 16
## 2    2      2     0.7354 0.04696855 16

aggregate(gain$gain, by=list(gain$vitI,gain$vitII), FUN = mean) # Means by group

##   Group.1 Group.2      x
## 1        1      1 0.5202
## 2        2      1 0.5458
## 3        1      2 0.5572
## 4        2      2 0.7354
```



Multiple Comparisons

```
TukeyHSD(fm)          # Tukey test for multiple comparisons

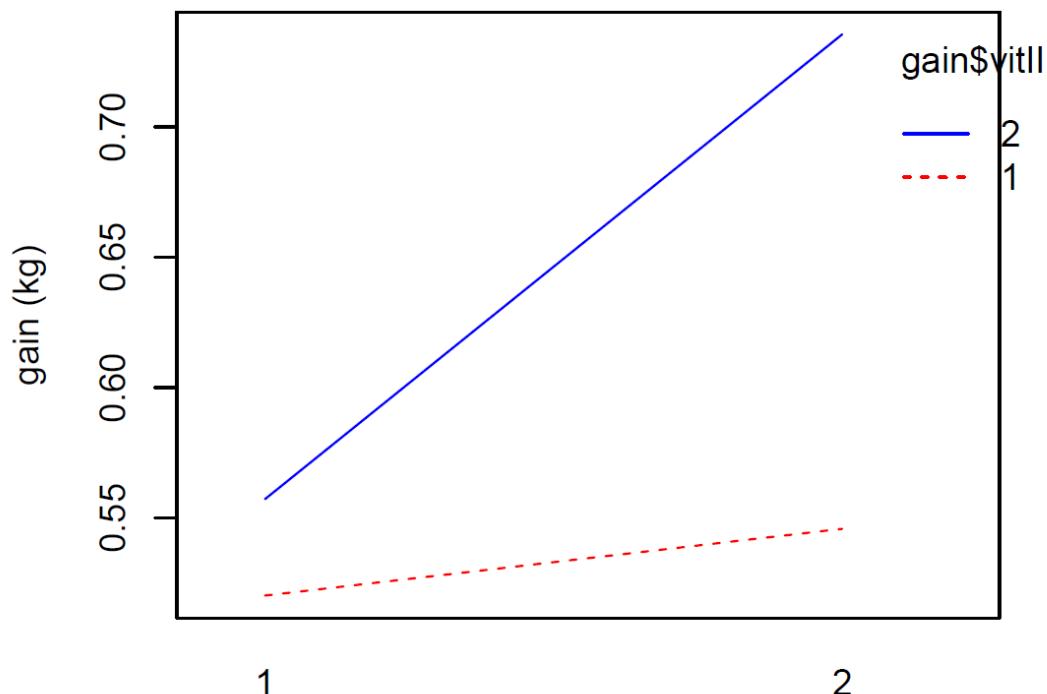
## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = gain ~ vitI + vitII + vitI * vitII, data = gain)
##
## $vitI
##      diff      lwr      upr     p adj
## 2-1 0.1019 0.002331117 0.2014689 0.0454479
##
## $vitII
##      diff      lwr      upr     p adj
## 2-1 0.1133 0.013731112 0.2128689 0.0282222
##
## $`vitI:vitII`
##      diff      lwr      upr     p adj
## 2:1-1:1 0.0256 -0.1644391365 0.2156391 0.9798534
## 1:2-1:1 0.0370 -0.1530391365 0.2270391 0.9432622
## 2:2-1:1 0.2152  0.0251608635 0.4052391 0.0238280
## 1:2-2:1 0.0114 -0.1786391365 0.2014391 0.9981254
## 2:2-2:1 0.1896 -0.0004391365 0.3796391 0.0506375
## 2:2-1:2 0.1782 -0.0118391365 0.3682391 0.0700704

plot(TukeyHSD(fm))  # Plot for tukey test
```

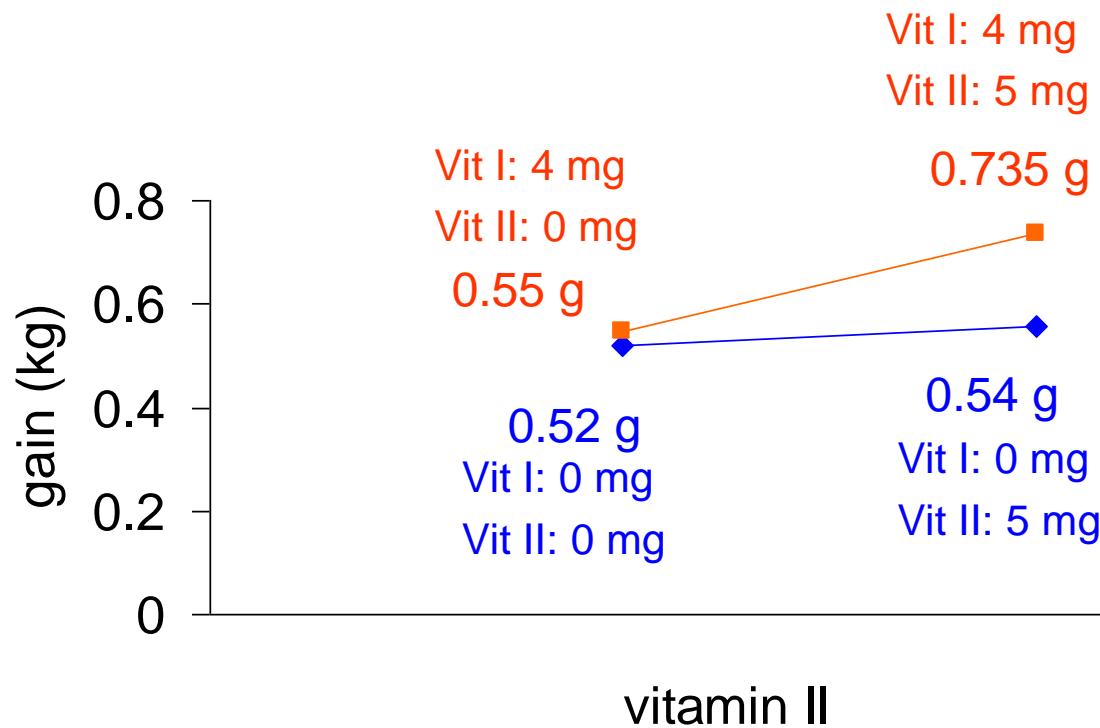
Interaction Plot

```
par(mar=c(3,4,3,2)) # Change parameters for the plot margins  
interaction.plot(gain$vitI,gain$vitII,response = gain$gain,  
                  col=c("red","blue"),pch = c(16,18),  
                  main="Interaction Between VitI and VitII",  
                  ylab = "gain (kg)")
```

Interaction Between VitI and VitII



Interaction



According to the figure interaction possibly exists, but probably the power is not enough to detect it. Most likely more than 5 measurement per group are needed

Analysis of covariance



Analysis of covariance

- Statistical procedure in which variability of a dependent variable is explained by both categorical and **continuous independent variables (covariate)**
- Common application of analysis of covariance is to adjust treatment means for known source of variability that can be explained by a continuous variable

Completely Randomized Design with a Covariate

In a CRD with a covariate the analysis of covariance is utilized for correcting treatment means, controlling the experimental error, and increase precision

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \tau_i + \varepsilon_{ij} \quad i = 1, \dots, a; j = 1, \dots, n$$

Where:

y_{ijk} = observation j in group i (treatment i)

β_0 = the intercept

x_{ij} = the regression coefficient

β_1 = a continuous independent variable with mean μ_x (covariate)

τ_i = the fixed effect of group or treatment i

ε_{ijk} = random error with mean 0 and variance σ^2

Assumptions

- Covariate is fixed and independent of treatments
- Error are independent each other
- Errors have a normal distribution with mean 0 and homogeneous variance σ^2

CRD with a Covariate - example

Diet A		Diet B		Diet C	
Initial weight (kg)	Gain (g/d)	Initial weight (kg)	Gain (g/d)	Initial weight (kg)	Gain (g/d)
350	970	390	990	400	990
400	1000	340	950	320	940
360	980	410	980	330	930
350	980	430	990	390	1000
340	970	390	980	420	1000

```

data gain;
input treatment $ initial gain @@;
datalines;
A 350 970 B 390 990 C 400 990
A 400 1000 B 340 950 C 320 940
A 360 980 B 410 980 C 330 930
A 350 980 B 430 990 C 390 1000
A 340 970 B 390 980 C 420 1000
;

proc print data=gain;
run;

proc glm;
class treatment;
model gain=initial treatment/solution;
lsmeans treatment/stderr pdiff tdiff adjust=tukey;
run;

```

SAS OUTPUT



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Oss	treatment	initial	gain
1	A	350	970
2	B	390	990
3	C	400	990
4	A	400	1000
5	B	340	950
6	C	320	940
7	A	360	980
8	B	410	980
9	C	330	930
10	A	350	980
11	B	430	990
12	C	390	1000
13	A	340	970
14	B	390	980
15	C	420	1000

La procedura GLM

Variabile dipendente: gain

Origine	DF	Somma dei quadrati	Media quadratica	Valore F	Pr > F
Modello	3	5492.014652	1830.671551	19.34	0.0001
Errore	11	1041.318681	94.665335		
Totale corretto	14	6533.333333			

R-quadro	Var coeff	Radice MSE	gain Media
0.840614	0.996206	9.729611	976.6667

SAS OUTPUT



Origine	DF	Tipo I SS	Media quadratica	Valore F	Pr > F
initial treatment	1	4441.252588	4441.252588	46.92	<.0001
	2	1050.762064	525.381032	5.55	0.0216
Origine	DF	Tipo III SS	Media quadratica	Valore F	Pr > F
initial treatment	1	5318.681319	5318.681319	56.18	<.0001
	2	1050.762064	525.381032	5.55	0.0216
Parametro	Stima	Errore standard	Valore t	Pr > t	
Interc	747.1648352 B	30.30956710	24.65	<.0001	
initial treatment A	0.6043956	0.08063337	7.50	<.0001	
treatment B	15.2527473 B	6.22915600	2.45	0.0323	
treatment C	-6.0879121 B	6.36135441	-0.96	0.3591	
	0.0000000 B	.	.	.	

NOTA: La matrice $X'X$ è singolare ed è stata utilizzata una inversa generalizzata per risolvere le equazioni normali. I termini le cui stime sono seguite dalla lettera 'B' non sono stimati in modo univoco.

SAS OUTPUT



La procedura GLM
Medie dei minimi quadrati
Correzione per i confronti multipli: Tukey-Kramer

treatment	gain LSMEAN	Errore standard	Pr > t	Numero LSMEAN
A	988.864469	4.509065	<.0001	1
B	967.523810	4.570173	<.0001	2
C	973.611722	4.356524	<.0001	3

Medie dei minimi quadrati per l'effetto treatment
t per H0: LSMean(i)=LSMean(j) / Pr > |t|

Variabile dipendente: gain

i/j	1	2	3
1	3.198241 0.0213	2.448606 0.0765	
2	-3.19824 0.0213		-0.95702 0.6175
3	-2.44861 0.0765	0.957015 0.6175	

CRD with a Covariate - example

```
gain<-data.frame(trt=c("A","A","A","A","A",
                      "B","B","B","B","B",
                      "C","C","C","C","C"),
                  in_weight=c(350,400,360,350,340,
                             390,340,410,430,390,
                             400,320,330,390,420),
                  gain=c(970,1000,980,980,970,
                        990, 950,980,990,980,
                        990,940,930,1000,1000),
                  stringsAsFactors = TRUE)

print(gain) #See the Data
```

Diet A		Diet B		Diet C	
Initial weight (kg)	Gain (g/d)	Initial weight (kg)	Gain (g/d)	Initial weight (kg)	Gain (g/d)
350	970	390	990	400	990
400	1000	340	950	320	940
360	980	410	980	330	930
350	980	430	990	390	1000
340	970	390	980	420	1000

R OUTPUT

```
contrasts(gain$trt)<-contr.SAS # Set contrasts like SAS?

tm<-lm(gain ~ in_weight + trt, data=gain) # Fit the linear model
summary(tm)

## 
## Call:
## lm(formula = gain ~ in_weight + trt, data = gain)
## 
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -16.615  -4.066   0.000   3.319  17.121 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 747.16484  30.30957  24.651 5.61e-11 ***
## in_weight    0.60440  -0.08063   7.496 1.21e-05 ***
## trt1        15.25275   6.22916   2.449  0.0323 *  
## trt2       -6.08791   6.36135  -0.957  0.3591  
## --- 
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 9.73 on 11 degrees of freedom
## Multiple R-squared:  0.8406, Adjusted R-squared:  0.7971 
## F-statistic: 19.34 on 3 and 11 DF,  p-value: 0.0001078
```

It must be interpreted
as 'standard' regression
coefficient



ANOVA tables

```
fm<-aov(gain ~ in_weight + trt, data=gain) # Fit the ANOVA
summary(fm) #ANOVA table SS I

##          Df Sum Sq Mean Sq F value    Pr(>F)
## in_weight     1   4441    4441  46.91 2.77e-05 ***
## trt          2   1051      525   5.55   0.0216 *
## Residuals   11   1041       95
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#install.packages("car")
car::Anova(tm,type="III") #Anova table with SS III

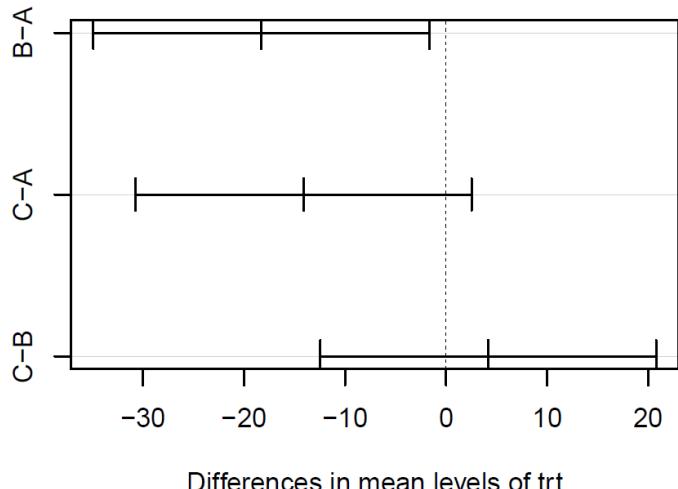
## Anova Table (Type III tests)
##
## Response: gain
##          Sum Sq Df  F value    Pr(>F)
## (Intercept) 57526  1 607.6778 5.614e-11 ***
## in_weight     5319  1  56.1840 1.207e-05 ***
## trt          1051  2   5.5499   0.02155 *
## Residuals    1041 11
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Multiple comparisons

```
TukeyHSD(fm, "trt")          # Tukey test for multiple comparisons

## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = gain ~ in_weight + trt, data = gain)
##
## $trt
##      diff      lwr      upr   p adj
## B-A -18.273292 -34.89314 -1.653444 0.0315687
## C-A -14.102484 -30.72233  2.517363 0.0991696
## C-B   4.170807 -12.44904 20.790655 0.7808618
plot(TukeyHSD(fm, "trt"))    # Plot for tukey test
```

95% family-wise confidence level



```
aggregate(gain$gain, by=list(gain$trt), FUN = mean) # Means by group

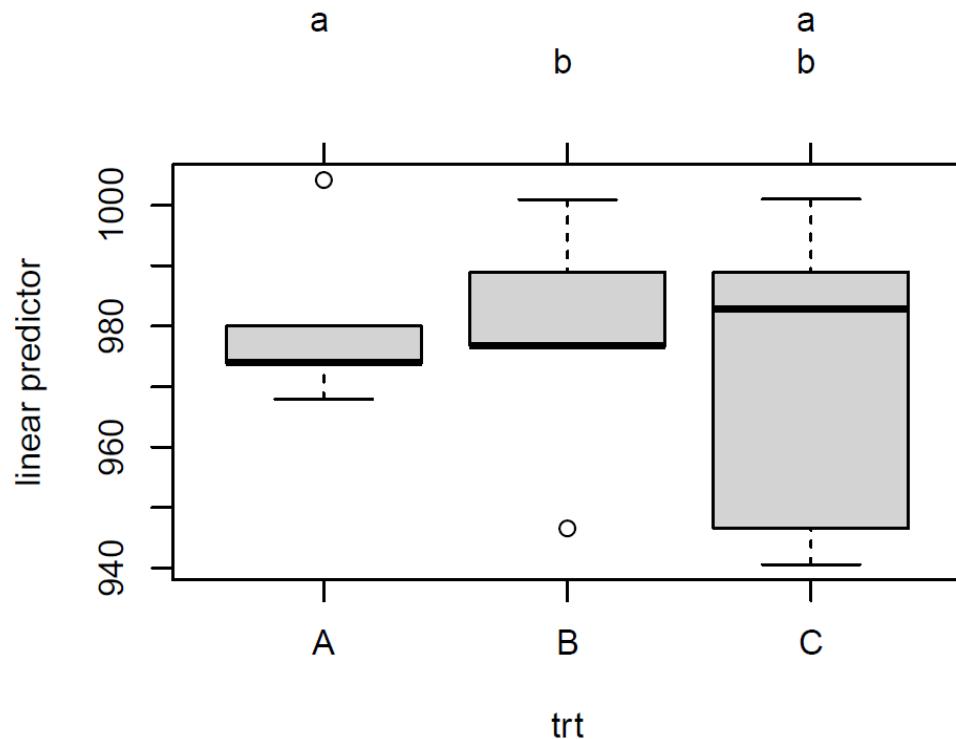
##  Group.1   x
## 1      A 980
## 2      B 978
## 3      C 972

lsmeans::lsmeans(tm, "trt")           #LSM for treatment

##  trt  lsmean      SE df lower.CL upper.CL
##  A  988.8645 4.509065 11 978.9401 998.7889
##  B  967.5238 4.570173 11 957.4649 977.5827
##  C  973.6117 4.356524 11 964.0231 983.2004
##
## Confidence level used: 0.95
```

Plot for differences

```
library(multcomp)
par(mar=c(4,4,6,2)) # Change parameters for the plot margins
tuk <- multcomp::glht(fm, linfct=multcomp::mcp(trt="Tukey")) # Fit the general Linear Hypotheses
plot(multcomp::cld(tuk, level=0.05), col="lightgrey") # Plot the mean differences
```



Questions?

