

# **Hypothesis Testing. Quantitative Variables**

Curs d'Estadística Bàsica per a la Recerca Biomèdica

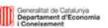
UEB – VHIR

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## Syllabus



- 1. INTRODUCTION
- 2. TYPE OF TEST
- 3. NORMALITY TEST
- 4.ONE GROUP COMPARISON
- **5.TWO GROUPS** COMPARISON IN INDEPENDENT SAMPLES
- **6.TWO GROUPS** COMPARISON IN DEPENDENT SAMPLES
- 7.MORE THAN TWO GROUPS COMPARISON IN INDEPENDENT SAMPLES
- 8. MULTIPLE COMPARISONS AND MULTIPLE TESTING







- A study was designed to compare two distinct hypertension control programs.
- 60 individuals with HTA were randomly assigned to either one or the other group (30 per group)
- Blood pressure was measured each month during a year

Α	В	С	D	E	F	G	Н	
numero	sexo	grupo	tas1	tad1	tas2	tad2	tas3	tad3
1	VARON	В	150	100	150	90	170	
2	MUJER	В	160	90	170	90	160	
3	MUJER	В	150	90	110	90	115	
4	VARON	Α	120	80	140	90	140	
5	MUJER	Α	150	85	145	85	160	
6	MUJER	В	140	75	160	70	135	
7	MUJER	A	150	100	140	90	130	
8	VARON	Α	160	90	170	90	170	
9	MUJER	Α	145	105	170	95	140	
10	MUJER	Α	210	110				
11	MUJER	Α	170	100	170	90	170	
12	MUJER	В	140	90	140	90	100	





### Questions to solve

- Are samples "comparable" at baseline?
- Has there been a change in BP between month 1 (first measure) and month 12?



# Syllabus



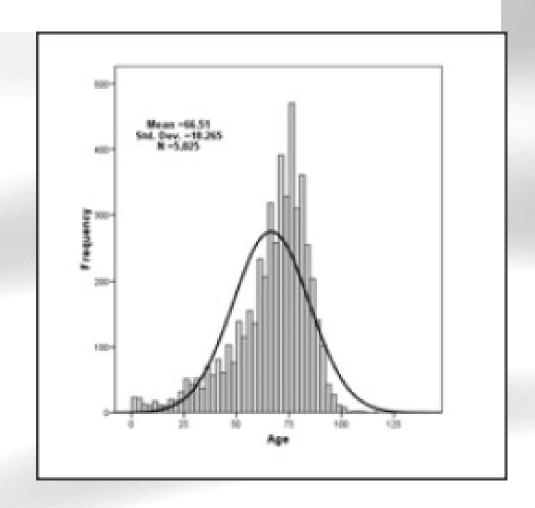
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# Normality test

- Some parametrical test assume data come from a normal population
- How can we check this assumption?
- What can we do if assumption is false?



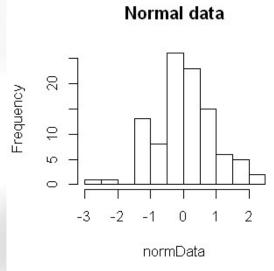


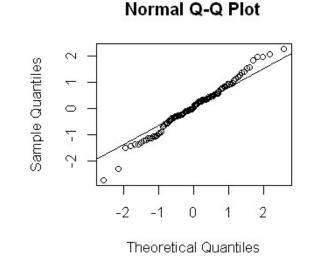


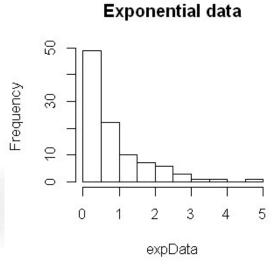
# Testing normality

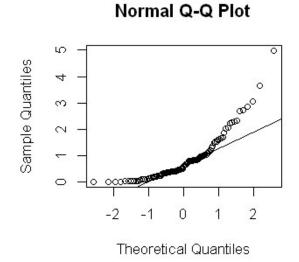
- We can use graphical methods or hypothesis tests
- Graphs
  - Check if it is a symmetric distribution
  - Probaility graphs (QQ-plots)
- Hypothesis test (Normality)
  - Kolmogorov-Smirnov test
  - Kolmogorov-Liliefors test
  - Shapiro-Wilks test

- Histogram
  - It should be symmetric with gaussian shape.
- QQ-plot
  - Dots should be over the diagonal line
- Non normal data deviate from normal patterns.
- Difficult to quantify if there are few data









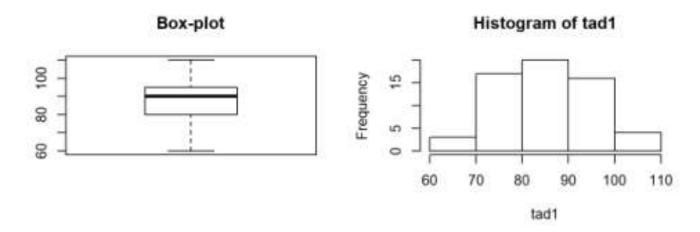
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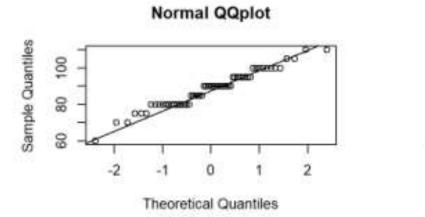
```
oldpar<-par(mfrow=c(1,1)) # Guarda los parametros para el dibgujo
par(mfrow=c(2,2)) # Dibuja cuatro gráficos por grafico
with(hta, boxplot(tad1, main="Box-plot"))

with(hta, hist(tad1))

with(hta, qqnorm(tad1, main="Normal QQplot"))
;with(hta, qqline(tad1))

par(oldpar) # Vuelve a los parametros de dibujo originales
```







# Normality test



- Statistical normality test are more precise than graphs. It is possible to calculate a p-value.
- The most used tests are Kolmogorov-Smirnov and Shapiro-Wilks test.
- The hypothesis to test are:
  - H<sub>0</sub>: Data follow a normal distribution
  - H₁: Data do not follow a normal distribution





# **Normality Test**

```
with(hta, shapiro.test(tas1)) # Shapiro Wilk test
```

```
##
## Shapiro-Wilk normality test
##
##
## data: tas1
## W = 0.91869, p-value = 0.0006796
```







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# One sample t-test

- We do not use it very often.
- Very similar to estimation questions. It can be solved calculalting a confidence itnerval
- Idea: We want to verify form a sample a previous hypothesis about the mean in a population
- Can it be accepted that the initial TAD is 90 in Hipertensive patients?





#### One sample Test

```
with(hta,t.test(tad1,mu=90)) # One sample T.test
##
   One Sample t-test
##
##
## data: tad1
## t = -1.2137, df = 59, p-value = 0.2297
## alternative hypothesis: true mean is not equal to 90
## 95 percent confidence interval:
## 85.80626 91.02707
## sample estimates:
## mean of x
## 88.41667
```







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## Questions to answer

- Are samples comparable at baseline time
- Is blood pressure comparable between first and 12th measures



# Boxplot TAD, by group

```
#Plot the data
  bp \leftarrow ggplot(hta, aes(x = grupo, y = tasl)) +
     geom boxplot(fill = "#ffd3b9", color = "darkred")
  bp
    210 -
     180 -
150 -
    120 -
                                                                      В
                                                grupo
```



#### Compare a Quantitative variable in two groups

# Null Hypothesis: There is not difference of the variable in two population or groups

## Samples have been generated



#### INDEPENDENT

Selected individuals in a group have nothing to do with selected individuals in the other group.

#### DEPENDENT

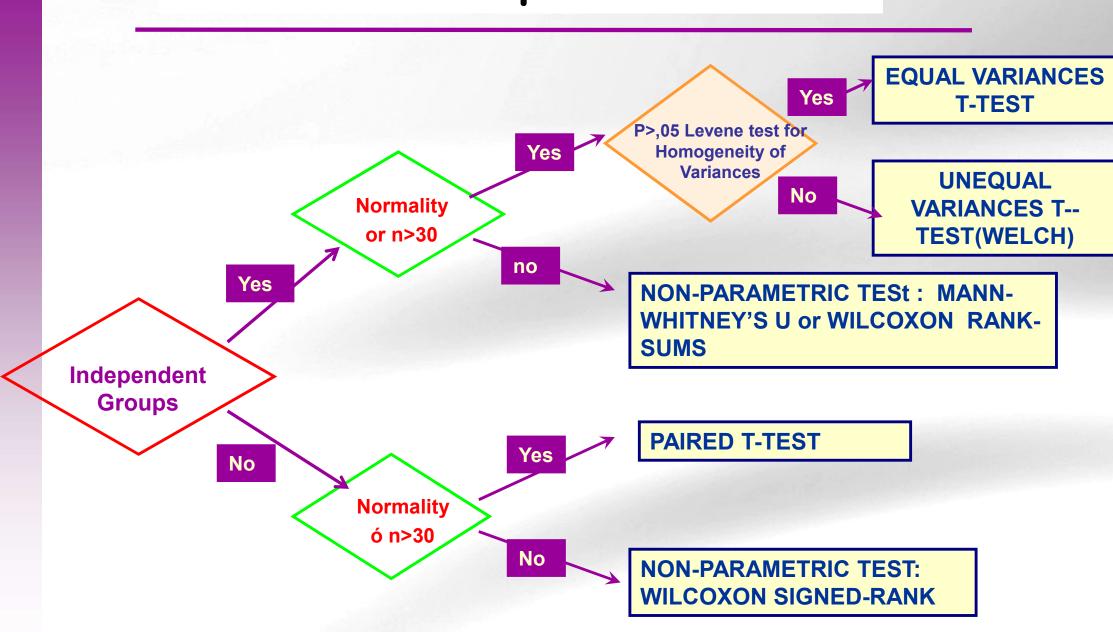
Each individual in a group has a correspondent in other group.

These are *paired data*.



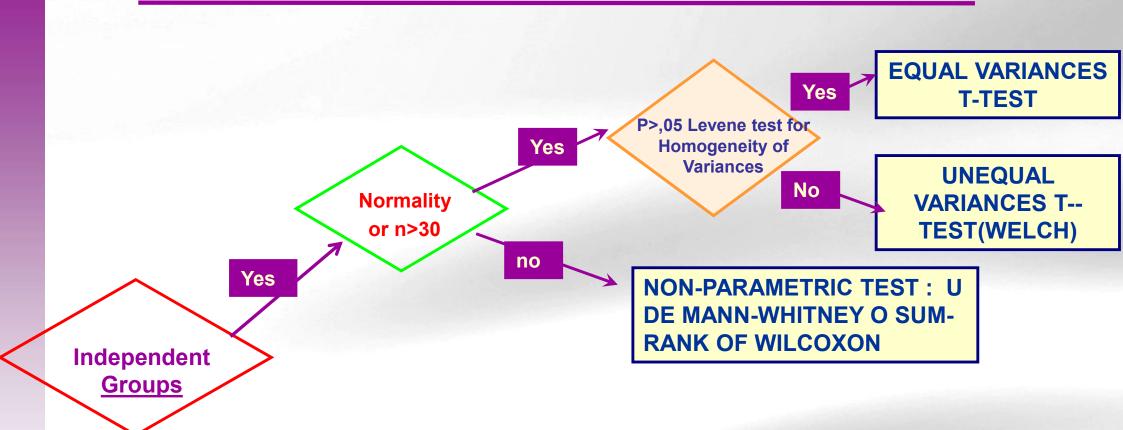
# Two sample tests







# Two sample tests (1)



- 1. Data is normal (normality test) or sample size > 30.
- 2. Mean is a good summary statistic for this problem.
- 3. Test homogeneity of variances

#### Homogeneity variance Test

```
library(car)
hta%>%
  group_by(sexo) %>%
  summarize(var = sd(tad1))
## # A tibble: 2 x 2
##
     sexo
             var
## <chr> <dbl>
## 1 MUJER 9.08
## 2 VARON 11.8
with(hta,leveneTest(tad1~factor(sexo),center="median"))
## Levene's Test for Homogeneity of Variance (center = "median")
        Df F value Pr(>F)
##
## group 1 1.3506 0.2499
         58
##
```

- p value is over 0.05
- We can assume homogeneity of variances

# T test when variances are equal

```
with(hta,t.test(tad1~factor(sexo),var.equal=TRUE))
##
   Two Sample t-test
##
##
## data: tad1 by factor(sexo)
## t = 0.35427, df = 58, p-value = 0.7244
## alternative hypothesis: true difference in means is not equal
## 95 percent confidence interval:
## -4.453505 6.368899
## sample estimates:
## mean in group MUJER mean in group VARON
##
              88.78378
                                  87.82609
```

- Type I Error is over than 0.05
- We cannot reject mean equality

# T test when variances are unequal

```
with(hta,t.test(tad1~factor(sexo),var.equal=FALSE))
##
   Welch Two Sample t-test
##
##
## data: tad1 by factor(sexo)
## t = 0.33362, df = 38.144, p-value = 0.7405
## alternative hypothesis: true difference in means is not equal
## 95 percent confidence interval:
## -4.852834 6.768228
## sample estimates:
## mean in group MUJER mean in group VARON
```

87.82609

Same conclusions as before

##

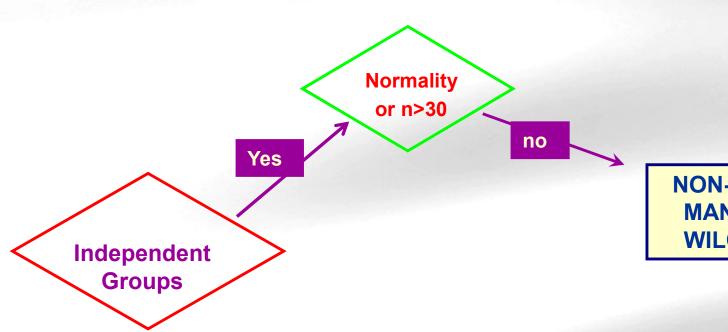
Test is also known as Welch test

88.78378



# Two groups, data non normal





NON-PARAMETRIC TEST: MANN-WHITNEY'S U O WILCOXON SUM-RANK





# Non parametric tests

- If data distribution is unknown or mean is not the best way to summarize data ...
  - Non parametric test are not based on the usual parameters from a distribution, such as  $\mu$  or  $\sigma^{2}$
  - Instead they may be based ...
    - On order statistics, such as median or percentiles
  - They take into account the whole distribution.



# Test based on ranks(Wilcoxon)



- Based on susbtituting original values by "ranks" in a joint sample
  - $-12, 5, 14, 16, 3 \rightarrow \text{ranks are: } 3, 2, 4, 5, 1$
- Ranks only depend on the position of each value in the ordered sample.
  - 120, 95, 121, 130, 3 have the same ranks as values in the first sample
- ② NP test are more robust than parametrics ones
- 1 In the ideal situation where parametric tests are valid they are considered to be preferable.



#### Will U Mann-Whitney or Sum Rank non parametric test

```
with(hta, wilcox.test(tad1-factor(sexo)
    ,alternative='two.sided',exact=TRUE, correct=FALSE))
##
    Wilcoxon rank sum test
##
##
## data: tad1 by factor(sexo)
## W = 434, p-value = 0.8955
## alternative hypothesis: true location shift is not equal to (
hta%>%
  group_by(sexo) %>%
  summarize(median = median(tad1))
## # A tibble: 2 x 2
##
     sexo median
##
   <chr> <dbl>
## 1 MUJER
               90
## 2 VARON
               90
```

Null Hypothesis cannot be rejected



#### Questions to answer



- Are samples comparable at baseline time?
- Is blood pressure comparable between first and 12th measures?





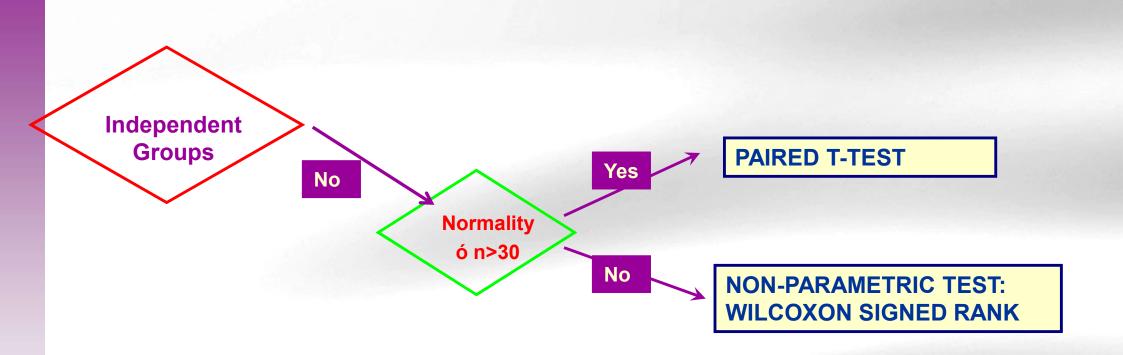


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# Two dependent groups









#### Paired T-test

```
with(hta,t.test(tad1,tad12,paired=TRUE))
##
##
   Paired t-test
##
## data: tad1 and tad12
## t = 1.8507, df = 51, p-value = 0.07001
## alternative hypothesis: true difference in means is not equal
## 95 percent confidence interval:
## -0.2364274 5.8133505
## sample estimates:
## mean of the differences
                  2.788462
##
```

P value is over 0.05

## Paired Sign-Rank Wilcoxon Test

```
with(hta, wilcox.test(tad1, tad12,
     exact=TRUE, paired=TRUE))
##
    Wilcoxon signed rank test with continuity correction
##
##
## data: tad1 and tad12
## V = 478.5, p-value = 0.05333
## alternative hypothesis: true location shift is not equal to 0
```





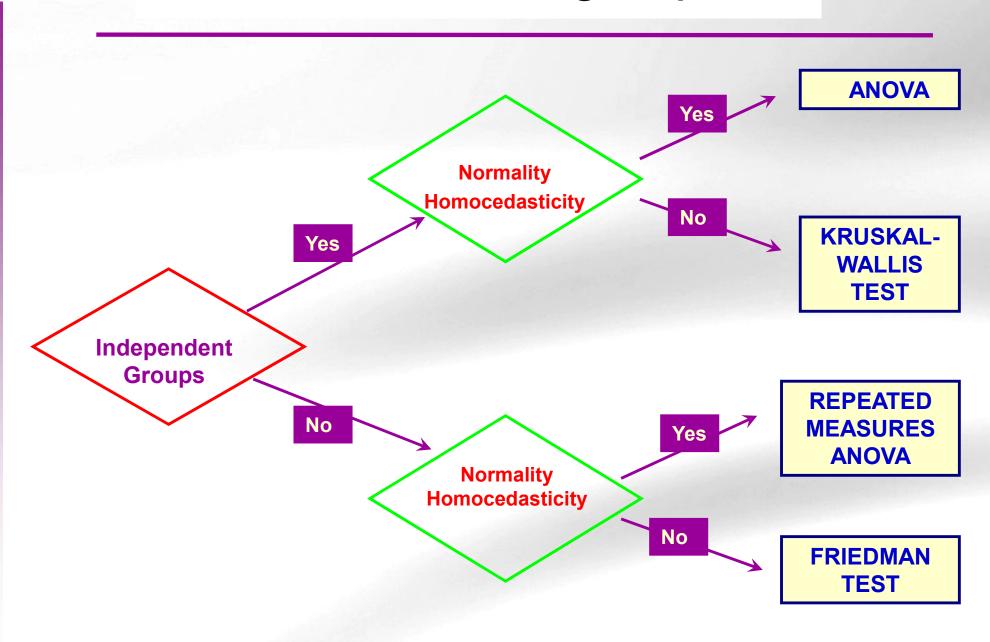


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# Three or more groups

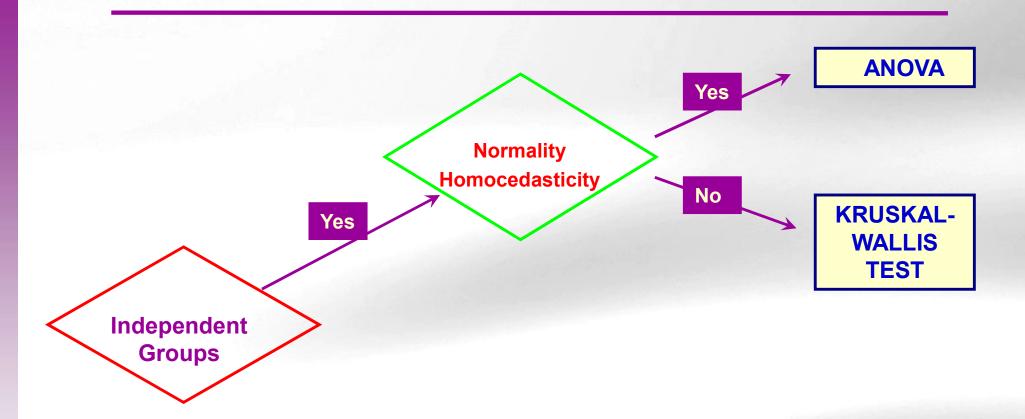






# Three or more groups







# Analysis of the variance

#### Null Hypothesis

The means of all population are equal

$$H_0 \quad \mu_1 = \mu_2 = \dots = \mu_k$$

#### Alternative Hypothesis

Not all the means are equal. At least there are two different means

$$H_a = \exists i,j \; \mu_i \neq \mu_j$$





## Could we use Student's t test? We will see with and example:

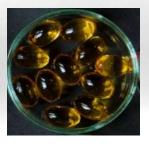
A pharmaceutical laboratory wants to test which of three drugs are better:







drug 2



drug 3

To know which of the drugs is the best one, one could think to perform the following comparison using a t test:





## Could we use Student's t test? We will see with and example:

Comparisons with separate t test would be:

#### Chance of Type I error Chance of Accept H0



<u>vs</u>



$$\alpha$$
 = 5%

$$1-\alpha = 95\%$$



<u>vs</u>



$$\alpha$$
 = 5%

$$1-\alpha = 95\%$$



<u>vs</u>



$$\alpha = 5\%$$

$$1-\alpha = 95\%$$





## Could we use Student's t test? We will see with and example:

Comparisons with t test would be:

#### Chance of Type I error

#### Chance of Accept H0



<u>vs</u>



$$\alpha = 5\%$$

$$1-\alpha = 95\%$$



<u>vs</u>



$$1-\alpha = 95\%*95\%$$



<u>vs</u>



$$1-\alpha = 95\%*95\%*95\%$$





## Could we use Student's t test? We will see with and example:

Comparisons with t test would be:

#### Chance of Type I error

#### Chance of Accept H0



<u>vs</u>



$$\alpha = 5\%$$

$$1-\alpha = 95\%$$



<u>vs</u>



$$1-\alpha = 95\%*95\%$$



<u>vs</u>



$$1-\alpha = 95\%*95\%*95\%$$

Would be easier not reject the null hypothesis when it was wrong (more false positives)

## 4. Introduction to ANOVA



# Could we use Student's t test? We will see with and example:

## Comparisons with t test would be:

#### Chance of Type I error



<u>vs</u>





$$\alpha = 5\%$$



<u>vs</u>





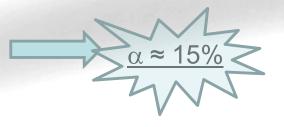
<u>α</u> ≈ 10%

Would be easier to accept the null hypothesis when it was wrong (more false positives)



<u>vs</u>







## Read diabetes data

111 50.5 11.5

## 3 Normal

```
library(readxl)
library(dplyr)
library(magrittr)
diabetes <- read_excel("datasets/diabetes.xls")
sapply(diabetes, class)
##
      numpacie
                              tempsviu
                                               edat
                                                            bmi
                                                                    edatdiag
                      mort
     "numeric" "character"
                              "numeric"
                                          "numeric"
##
                                                      "numeric"
                                                                   "numeric"
##
         tabac
                       sbp
                                   dbp
                                                ecg
                                                            chd
                             "numeric" "character" "character"
## "character"
                 "numeric"
diabetes_factor <- diabetes %>%
  mutate_if(sapply(diabetes, is.character), as.factor) %>%
  select (-numpacie)
diabetes%>%
  group_by(ecg) %>%
  summarise( n=n(),
    mean = mean(edat),
            sd=sd(edat))
## # A tibble: 3 x 4
     ecg
                  n mean
                             sd
              <int> <dbl> <dbl>
    <chr>>
## 1 Anormal
                 11 64.9 6.76
                 27 53.8 11.4
## 2 Frontera
```

B

# Multicomparison

```
library (multcomp)
tuk <- glht(anova, linfct = mcp(ecg = "Tukey"))
  print(summary(tuk)) # pairwise tests
##
     Simultaneous Tests for General Linear Hypotheses
##
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: aov(formula = edat - ecg, data = diabetes_factor)
## Linear Hypotheses:
                          Estimate Std. Error t value Pr(>|t|)
## Frontera - Anormal == 0 -11.094 4.010 -2.767 0.016496 *
## Normal - Anormal == 0 -14.405 3.543 -4.065 0.000217 ***
## Normal - Frontera == 0 -3.310
                                        2.405 -1.376 0.345732
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```





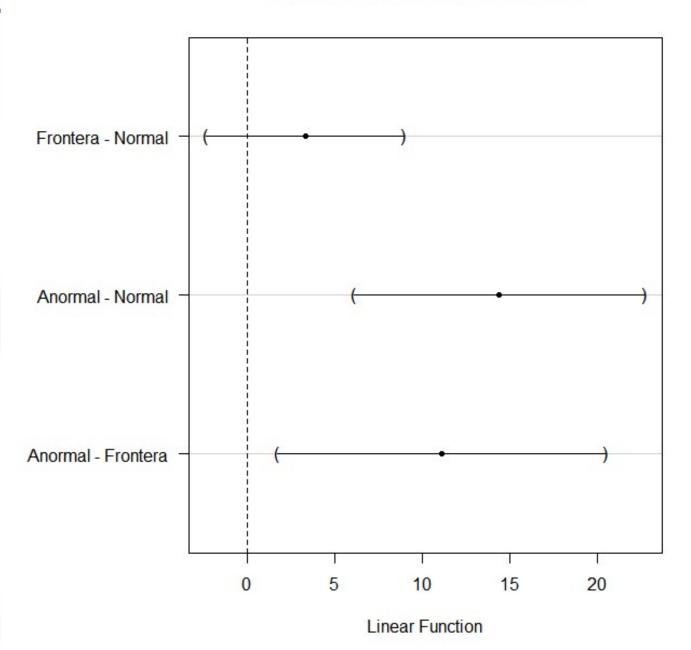
#### print(confint(tuk, level=0.95)) # confidence intervals

```
##
    Simultaneous Confidence Intervals
##
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: aov(formula = edat - ecg, data = diabetes_factor)
##
## Quantile = 2.3459
## 95% family-wise confidence level
##
##
## Linear Hypotheses:
##
                          Estimate lwr
                                         upr
## Frontera - Anormal == 0 -11.0943 -20.5009 -1.6876
## Normal - Anormal == 0 -14.4046 -22.7173 -6.0919
                          -23103 -8.9534 2.3328
## Normal - Frontera == 0
```





### 95% family-wise confidence level



plot(confint(tuk))



## Kruskal-Wallis Test

```
diabetes_factor%>%
 group_by(ecg) %>%
 summarise(median = median(edat))
## # A tibble: 3 x 2
## ecg median
## <fct> <dbl>
## 1 Anormal
                64
## 2 Frontera 53
## 3 Normal
             49
kruskal.test(edat~ecg,data=diabetes_factor)
##
   Kruskal-Wallis rank sum test
##
##
## data: edat by ecg
## Kruskal-Wallis chi-squared = 17.483, df = 2, p-value = 0.0001
```

# Dunn Test for multiple comparison

```
library(dunn.test)
with(diabetes_factor,dunn.test(edat,ecg,method="bonferroni"))
     Kruskal-Wallis rank sum test
##
##
## data: edat and ecg
## Kruskal-Wallis chi-squared = 17.4826, df = 2, p-value = 0
##
##
                              Comparison of edat by ecg
##
                                     (Bonferroni)
##
## Col Mean-
                 Anormal Frontera
## Row Mean
## Frontera |
                2.721182
                 0.0098*
##
##
     Normal
                4.075469 1.467464
##
##
                 0.0001*
                             0.2134
##
```







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