Hypotheses tests with continuous variables

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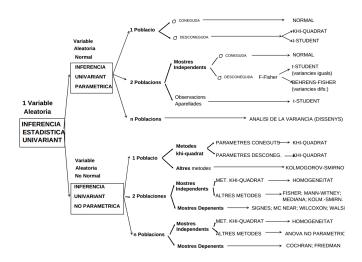
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Introduction

- Once the concept of hypothesis testing is established,
- Researchers face the problem of which test should be applied at every possible situation.
- Best solution:
 - understand the problem and the questions addressed
 - know available tests for each problem
 - be aware of applicability assumptions of each test and how to check them.
- Easier to say than to do.
 - Sometimes cheatsheets may be helpful, but be warned against a blind use, that is understand and be critic with the steps.

Which test is appropriate for which problem



Example situation

- 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

```
hta <- read_excel("datasets/hta.xls")
print(head(hta[,1:7]))</pre>
```

```
## # A tibble: 6 x 7
##
     numero sexo grupo tas1
                               tad1
                                     tas2
                                           tad2
##
      <dbl> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1
           VARON B
                          150
                                100
                                      150
                                             90
##
          2 MUJER B
                          160
                                 90
                                      170
                                             90
          3 MUJER B
                          150
                                 90
                                      110
                                             90
## 3
##
          4 VARON A
                          120
                                 80
                                      140
                                             90
## 5
          5 MUJER A
                          150
                                 85
                                      145
                                             85
## 6
          6 MUJER B
                          140
                                 75
                                      160
                                             70
```

Always start looking at the data

```
oldpar<-par(mfrow=c(1,1)) # Guarda los parámetros para el dibgujo
par(mfrow=c(2,2)) # Dibuja cuatro gráficos por grafico
with(hta, boxplot(tas1, main="Box-plot"))
with(hta, hist(tas1))
with(hta, qqnorm(tas1, main="Normal QQplot"));with(hta, qqline(tas1))
par(oldpar) # Vuelve a los parámetros de dibujo originales
```

Normality Test

```
with(hta,shapiro.test(tad1) ) # Shapiro Wilk test

##
## Shapiro-Wilk normality test
##
## data: tad1
## W = 0.96622, p-value = 0.09512
```

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
```

Homogeneity variance Test

```
library(car)
hta%>%
 group_by(sexo) %>%
 summarise(var = sd(tas1))
## # A tibble: 2 x 2
## sexo
            var
## <chr> <dbl>
## 1 MUJER 17.6
## 2 VARON 22.1
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(tas1~factor(sexo),var.equal=TRUE ))
##
##
   Two Sample t-test
##
## data: tas1 by factor(sexo)
## t = -0.2471, df = 58, p-value = 0.8057
## alternative hypothesis: true difference in means between grou
## 95 percent confidence interval:
## -11.603461 9.053519
## sample estimates:
## mean in group MUJER mean in group VARON
##
              149.5946
                                  150.8696
```

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

T test when variances are unequal

```
with(hta,t.test(tas1~factor(sexo),var.equal=FALSE ))
##
##
   Welch Two Sample t-test
##
## data: tas1 by factor(sexo)
## t = -0.23436, df = 39.098, p-value = 0.8159
## alternative hypothesis: true difference in means between grou
## 95 percent confidence interval:
## -12.277927 9.727986
## sample estimates:
## mean in group MUJER mean in group VARON
              149.5946
                                  150.8696
##
```

- Same conclusions as before
- Test is also known as Welch test

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 0
hta%>%
  group_by(sexo) %>%
  summarise(median = median(tad1))
## # A tibble: 2 x 2
## sexo median
## <chr> <dbl>
## 1 MUJER
               90
## 2 VARON
              90
```

Null Hypothesis cannot be rejected

Paired T-test

```
with(hta,t.test(tas1,tas12,paired=TRUE))
##
##
   Paired t-test
##
## data: tas1 and tas12
## t = 6.0672, df = 51, p-value = 1.609e-07
## alternative hypothesis: true mean difference is not equal to
## 95 percent confidence interval:
## 8.518285 16.943253
## sample estimates:
## mean difference
         12.73077
##
summary(hta$tas1)
##
     Min. 1st Qu. Median Mean 3rd Qu. Max.
```

```
##
    100.0 140.0 145.0 150.1 160.0 210.0
summary(hta$tas12)
```

Paired Sign-Rank Wilcoxon Test

Read diabetes data

```
library(readx1)
library(dplyr)
library(magrittr)
diabetes <- read_excel("datasets/diabetes.xls")</pre>
sapply(diabetes, class)
##
     numpacie
                     mort tempsviu
                                             edat.
                                                          bmi
                                                                 edatdiag
   "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
   <chr> <int> <dhl> <dhl> <dhl>
## 1 Anormal 11 64.9 6.76
## 2 Frontera 27 53.8 11.4
## 3 Normal 111 50.5 11.5
```

ANOVA

anova <- aov (edat~ecg, data=diabetes_factor)

Multicomparison

```
library(multcomp)
tuk <- glht(anova, linfct = mcp(ecg = "Tukey"))</pre>
 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 0.016446 *
## Normal - Anormal == 0 -14.405 3.543 -4.065 0.000222 ***
## Normal - Frontera == 0 -3.310 2.405 -1.376.0.345709
## ---
## Signif. codes: 0 '***' 0.001 '**' 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 = 2.3458
## 95% family-wise confidence level
##
##
## Linear Hypotheses:
##
                           Estimate lwr
                                             upr
## Frontera - Anormal == 0 -11.0943 -20.5002 -1.6883
## Normal - Anormal == 0 -14.4046 -22.7167 -6.0925
```

Normal - Frontera == 0 -3.3103 -8.9530 2.3324

Multicomparison plot

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-I
## Row Mean | Anormal Frontera
## Frontera | 2.721182
##
                0.0098*
##
##
    Normal |
              4.075469 1.467464
##
                0.0001*
                            0.2134
##
```