

*Experimental Design and Statistical Methods*



*Workshop*

# NON-PARAMETRIC TESTS

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# Items

- Non parametric comparisons:
  - Two independent samples: Wilcoxon Sum-Rank Test
  - Two paired samples: Wilcoxon Signed-Rank Test
  - Several independent samples: Kruskal-Wallis test
  - Association/independence in proportions: Chi-square Test
- Basic commands
  - `wilcox.test`
  - `wilcox.test (paired)`
  - `kuskal.test`
  - `chisq.test`
- Libraries
  - `coin (wilcox-test)`
  - `vcd (assocstats)`

# Non-parametric procedures

In previous sessions we have analysed parametric tests for comparing means. This session is devoted to present methods to compare location parameters and also proportions through non parametric tests.

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	Parametric	Non parametric
Two independent samples	t-test	Wilcoxon Sum-Rank test
Paired data	Paired t-test	Wilcoxon Signed-Rank test
Several independent samples	ANOVA	Kruskal-Wallis test
Proportions		$\chi^2$

---

The theory and examples of this lesson are heavily based on the book from G.A. Walker, 1997.

# Comparison of two independent samples. Non parametric Wilcoxon Rank Sum test (WRST) (1)

Analogous of the two sample t-test, **based on ranks of the data**, can be used to compare location parameters (mean or median) of continuous numeric data and ordered categorical data, when the **data are not normally distributed**.

Seroxatene is an anti-depressant that would alleviate back pain, measured in a scale from – 3 to 3.

----- Seroxotene Group -----				----- Placebo Group -----				Response (y)	No. of ties (m)	Ranks	Average Rank	$c_k = m(m^2-1)$
Pat. No.	Score	Pat. No.	Score	Pat. No.	Score	Pat. No.	Score					
2	0	16	-1	1	3	15	0	-3	2	1,2	1.5	6
3	2	17	2	4	-1	18	-1	-2	3	3,4,5	4	24
5	3	20	-3	7	2	19	-3	-1	4	6,7,8,9	7.5	60
6	3	21	3	9	3	23	-2	0	4	10,11,12,13	11.5	60
8	-2	22	3	11	-2	25	1	+1	3	14,15,16	15	24
10	1	24	0	13	1	28	0	+2	4	17,18,19,20	18.5	60
12	3	26	2					+3	8	21,22,23,24,25,26,27,28	24.5	504
14	3	27	-1									
												C=738

Raw data

Conversion to ranks  
⇒ information loss

m, number of tied values in group k

## WRST (2)

$H_0$  of equal means supported by similar average ranks between the two groups, i.e.,  $R_1/n_1$  is close to  $R_2/n_2$ .

----- Seroxotene Group -----				----- Placebo Group -----			
Pat. No.	Score Rank	Pat. No.	Score Rank	Pat. No.	Score Rank	Pat. No.	Score Rank
2	11.5	16	7.5	1	24.5	15	11.5
3	18.5	17	18.5	4	7.5	18	7.5
5	24.5	20	1.5	7	18.5	19	1.5
6	24.5	21	24.5	9	24.5	23	4
8	4	22	24.5	11	4	25	15
10	15	24	11.5	13	15	28	11.5
12	24.5	26	18.5				
14	24.5	27	7.5				

We compute:

$$R_1 = 11.5 + 18.5 + 24.5 + \dots + 7.5 = 261,$$

$$R_2 = 24.5 + 7.5 + 18.5 + \dots + 11.5 = 145.$$

$R_1$  is compared to a critical value obtained from a special set of **tables** based on Wilcoxon rank-sum exact probabilities to determine the appropriate rejection region.

The requirement of special tables can be circumvented by using a **normal approximation** for larger samples, in the practice for samples larger than 8.

**See next slide**

## WRST (3)


For the normal approximation, the expected value of  $R_1$  under  $H_0$  is:

$$\mu_{R_1} = \left( \frac{n_1}{N} \right) \left( \frac{N(N+1)}{2} \right) = \frac{n_1(N+1)}{2} = \dots = 232$$

And the variance of  $R_1$

$$\sigma_{R_1}^2 = \frac{n_1 n_2}{12} \left( N+1 - \frac{C}{N(N-1)} \right) = \dots = 448.38$$

Test statistic with a 0.5 continuity correction


$$Z = \frac{|R_1 - \mu_{R_1}|}{\sigma_{R_1}} = \frac{(261 - 232) - 0.5}{\sqrt{448.38}} = 1.346$$

$$N = n_1 + n_2$$

$$N(N+1)/2 = R_1 + R_2$$

= Sum of the ranks

$$n_1/N = \text{Proportion}$$

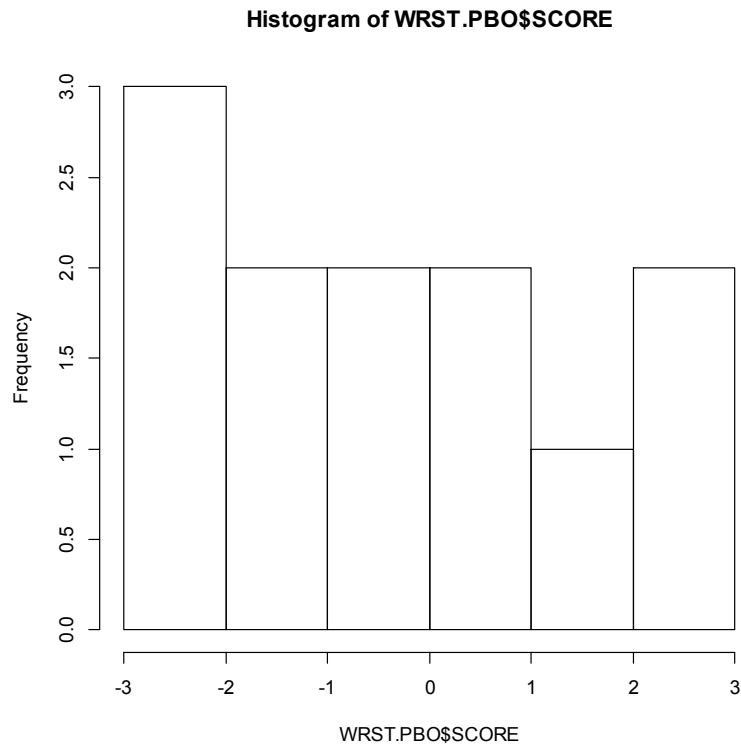
of the above sum  
from group 1

C as before

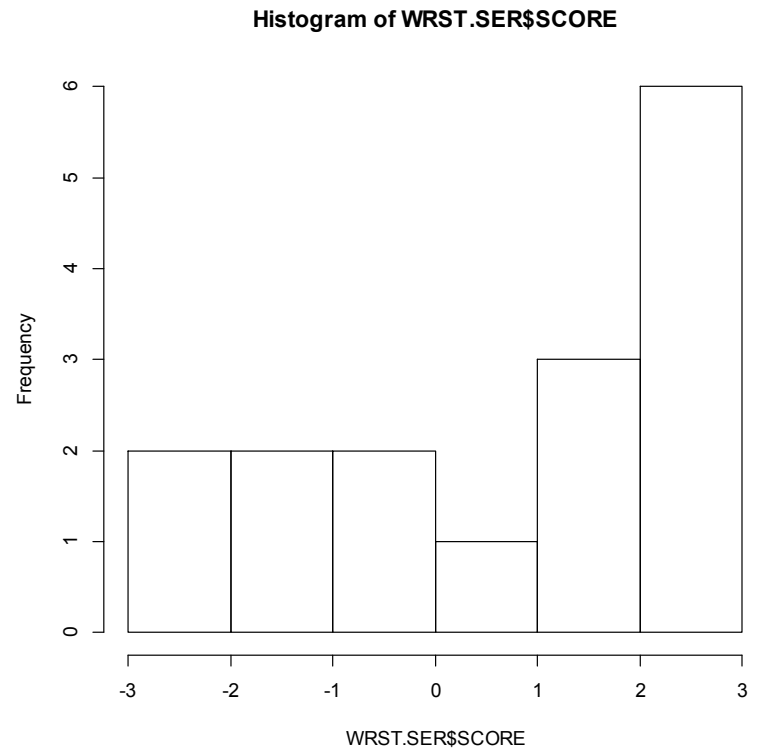
**Decision rule:** reject  $H_0$  if  $|z| > 1.96$ ; so  $H_0$  is not rejected in our example.

# WRST - Histograms

```
> WRST.PBO <- WRST[TRT=="PBO",]  
> hist(WRST.PBO$SCORE)
```



```
> WRST.SER <- WRST[TRT=="SER",]  
> hist(WRST.SER$SCORE)
```



# WRST - Boxplots and normality tests

```
> boxplot(SCORE~TRT)
```

```
> shapiro.test(WRST.PBO$SCORE)
```

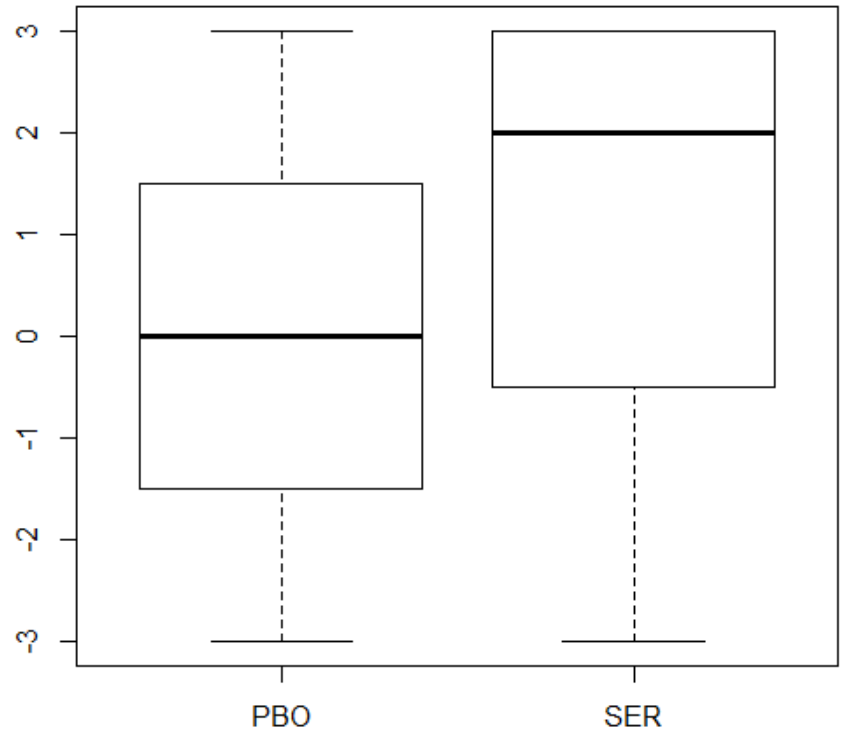
Shapiro-Wilk normality test

data: WRST.PBO\$SCORE  
W = 0.9509, p-value = 0.6501

```
> shapiro.test(WRST.SER$SCORE)
```

Shapiro-Wilk normality test

data: WRST.SER\$SCORE  
W = 0.8531, p-value = 0.01514





# Wilcoxon Rank-Sum test in R (1)

```
> wilcox.test(SCORE~TRT)
```

Wilcoxon rank sum test with continuity correction

data: SCORE by TRT

W = 67, p-value = 0.1783

←  $H_0$  is not rejected

alternative hypothesis: true location shift is not equal to 0

Mensajes de aviso perdidos

In wilcox.test.default(x = c(3L, -1L, 2L, 3L, -2L, 1L, 0L, -1L, :  
cannot compute exact p-value with ties

The test statistic  $W$  is the sum of ranks in the first group minus its theoretical minimum (i.e., it is zero if all the smallest values fall in the first group).

## Wilcoxon Rank-Sum test in R (2)

```
> library(coin)
> wilcox_test(SCORE~TRT)
```

Asymptotic Wilcoxon Mann-Whitney Rank Sum Test

```
data:  SCORE by TRT (PBO, SER)
Z = -1.3695, p-value = 0.1708
alternative hypothesis: true mu is not equal to 0
```

$H_0$  is not rejected

```
> 2*pnorm(-1.3695)
[1] 0.170843
```

# Comparison of paired data. Wilcoxon Signed-Rank test (WSRT) (1)

Used to compare responses between correlated and **paired data**, without requiring the assumption of **normality**.

Given a sample of  $n$  non-zero differences (zero's are ignored) we have to compute  $r_i$ , the rank of  $|y_i|$  (lowest to highest).

$R^{(+)}$  and  $R^{(-)}$  represent the sums of the ranks associated with positive and negative values of the  $y_i$ 's

The test statistic is based on the smaller of  $R^{(+)}$  and  $R^{(-)}$ .

$$S = (R^{(+)} - R^{(-)})/2$$

$$V = [n(n+1)(2n+1)]/24$$

**Test statistic** (approximated)

$$T = \frac{S\sqrt{n-1}}{\sqrt{nV - S^2}}$$

**Decision rule**

Reject  $H_0$  if  $|T| > t_{\frac{\alpha}{2}, n-1}$

## WSRT (2)

Let see an example on a new ocular wetting agent in patients of *keratitis sicca*.

Pat No.	Differ- ence	Rank	Pat No.	Differ- ence	Rank
1	7	14.5	13	-2	3
2	7	14.5	14	8	18.5
3	-1	1.5	15	7	14.5
4	-8	18.5	16	6	11
5	8	18.5	17	5	7.5
6	3	4.5	18	-5	7.5
7	-7	14.5	19	6	11
8	-3	4.5	20	0	--
9	-5	7.5	21	8	18.5
10	9	21	22	1	1.5
11	-5	7.5	23	6	11
12	10	22	24	0	--

differences of 0 are ignored

$$R^{(+)} = (14.5 + 14.5 + 18.5 + 4.5 + 21 + 22 + 18.5 + 14.5 + 11 + 7.5 + 11 + 18.5 + 1.5 + 11) = 188.5,$$

$$R^{(-)} = (1.5 + 18.5 + 14.5 + 4.5 + 7.5 + 7.5 + 3 + 7.5) = 64.5$$

$$S = (188.5 - 64.5)/2 = 62$$

After correcting for ties

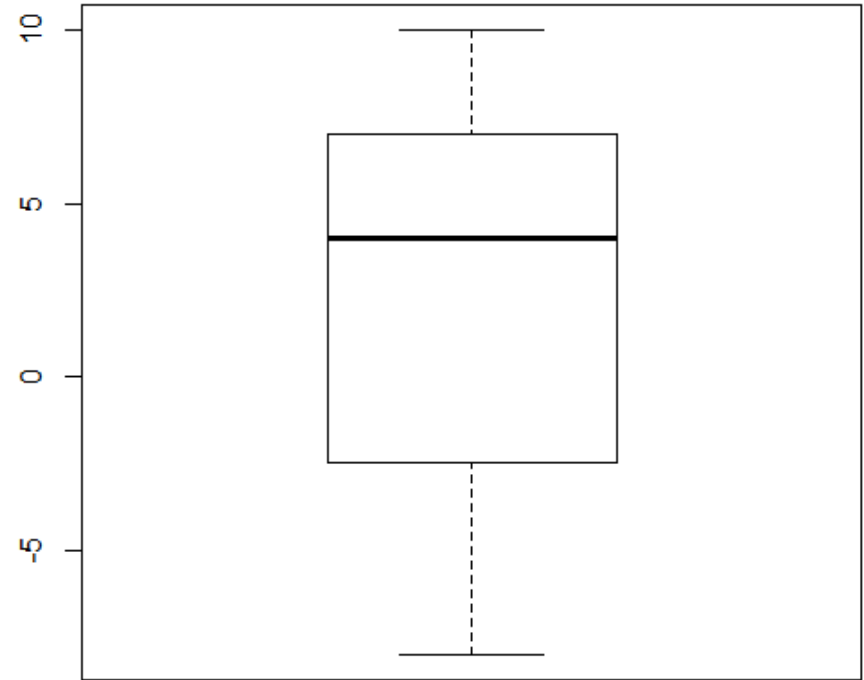
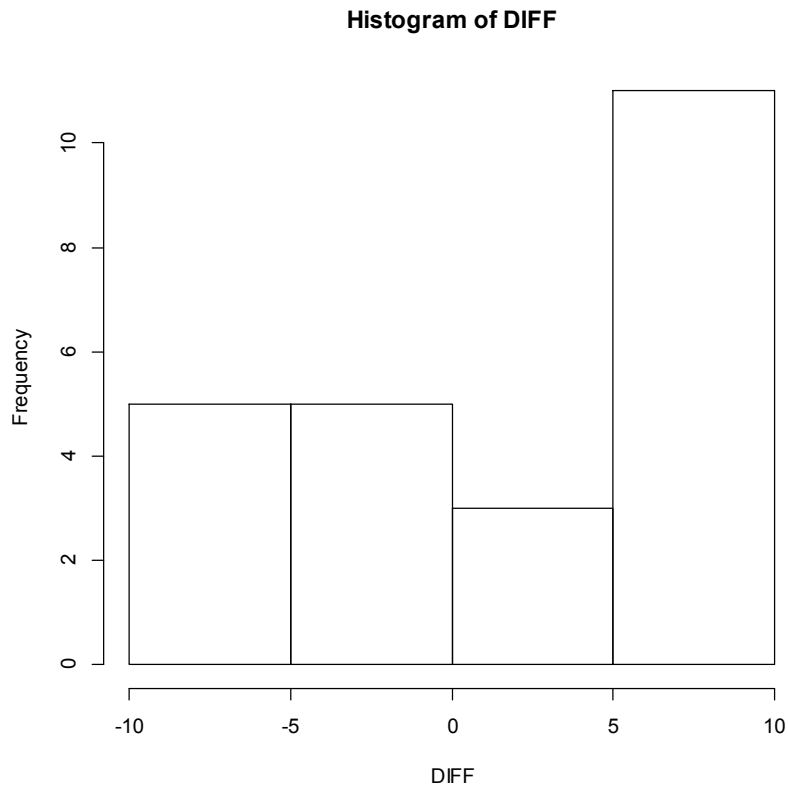
$$V = 944.25$$

$$T = 2.184 > t_{0.025, 21} = 2.080$$

$H_0$  (no difference) is rejected

# WSRT – Histogram and boxplot

```
> DIFF <- (HYPO-OKER)  
> hist(DIFF) ; boxplot(DIFF)
```



```
> shapiro.test(DIFF)  
Shapiro-Wilk normality test  
data: DIFF  
W = 0.9082, p-value = 0.03223
```

# Wilcoxon Signed-Rank test in R

```
> wilcox.test(HYPO, OKER, paired=T)
```

Wilcoxon signed rank test with continuity correction

data: HYPO and OKER

V = 188.5, p-value = 0.04535

←  $H_0$  is rejected

alternative hypothesis: true location shift is not equal to 0

Mensajes de aviso perdidos

1: In wilcox.test.default(HYPO, OKER, paired = T) :  
cannot compute exact p-value with ties

2: In wilcox.test.default(HYPO, OKER, paired = T) :  
cannot compute exact p-value with zeroes

## Kruskal-Wallis test – intro -

Non-parametric test **analogue of One-Way ANOVA**. This is an extension of the Wilcoxon Rank-Sum Test, used to compare population location parameters (mean, median, etc.) among two or more groups including independent samples. It is based on the **ranks** of the data.

**Unlike ANOVA, the assumption of normally distributed responses is not necessary**

We will present an example a low dose (0.1%) compared to a high dose (0.2%) of a non-steroidal anti-psoriasis medication, using placebo as a control. The response was measured as degree of psoriatic lesion reduction, rated in an ordinal scale (see next slide).

# Kruskal-Wallis test – data -

0.1% Solution		0.2% Solution		Placebo	
Pat No.	Category Code	Pat No.	Category Code	Pat No.	Category Code
1	5	3	5	2	5
6	4	5	8	4	3
9	1	7	2	8	7
12	7	10	8	11	1
15	4	14	7	13	2
19	3	18	4	16	4
20	6	22	5	17	2
23	7	26	4	21	1
27	8	28	6	24	4
32	7	31	4	25	5
				29	4
				30	5

Data are ranked, from lowest to highest over the combined samples

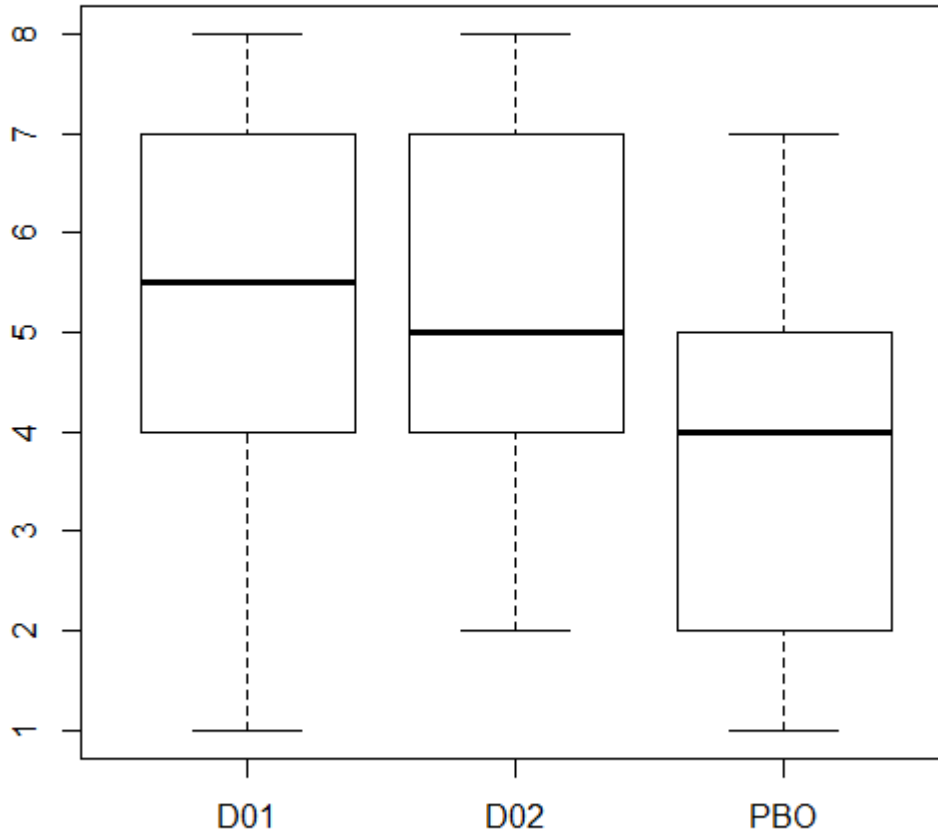
Response Category	Code	--- Frequencies ---			Ranks	Ave. Rank	Total Frequency (m)	c = $m(m^2-1)$
		0.1%	0.2%	Pbo				
<0%	1	1	0	2	1-3	2	3	24
0%	2	0	1	2	4-6	5	3	24
1-10%	3	1	0	1	7-8	7.5	2	6
11-25%	4	2	3	3	9-16	12.5	8	504
26-50%	5	1	2	3	17-22	19.5	6	210
51-75%	6	1	1	0	23-24	23.5	2	6
76-99%	7	3	1	1	25-29	27	5	120
100%	8	1	2	0	30-32	31	3	24
		10	10	12			32	C = 918

Since the code 1-8 is arbitrary, K-W test is appropriate because the results do not depend on the magnitude of the coded values, but in their ranks.



## Kruskal-Wallis test – Normality -

```
> boxplot(SCORE~DOSE)
```



The student is invited to contrast whether or not the distributions deviate from normality

# Kruskal-Wallis test – table of ranks and calculus -

0.1% Solution		0.2% Solution		Placebo	
Pat No.	Category Rank	Pat No.	Category Rank	Pat No.	Category Rank
1	19.5	3	19.5	2	19.5
6	12.5	5	31	4	7.5
9	2	7	5	8	27
12	27	10	31	11	2
15	12.5	14	27	13	5
19	7.5	18	12.5	16	12.5
20	23.5	22	19.5	17	5
23	27	26	12.5	21	2
27	31	28	23.5	24	12.5
32	27	31	12.5	25	19.5
				29	12.5
				30	19.5
$R_1 = 189.5$ ( $n_1=10$ )		$R_2 = 194.0$ ( $n_2=10$ )		$R_3 = 144.5$ ( $n_3=12$ )	

When  $H_0$  is true (means do not differ), the average rank for each group should be close to the overall average rank. The Kruskal-Wallis test is

$$h^* = \frac{12}{N(N+1)} \left[ \sum_{i=1}^k \frac{R_i^2}{n_i} \right] - 3(N+1)$$

$$= \frac{12}{32(33)} \left[ \frac{189.5^2}{10} + \frac{194.0^2}{10} + \frac{144.5^2}{12} \right] - 3(33)$$

$$= 4.348$$

and correcting for ties,

$$h = \frac{4.348}{\left[ 1 - \frac{918}{32(32^2 - 1)} \right]} = \frac{4.348}{0.972} = 4.473$$

$H_0$  is not rejected, because

$$h < \chi^2_{2(0.05)} (=5.991)$$

$$R_i = \sum_{j=1}^{n_i} r_{ij}; \quad \bar{R}_i = R_i / n_i; \quad \bar{R} = (N+1)/2; \quad N = \sum_i n_i$$

## Kruskal-Wallis test – R program and results -

```
> kruskal.test(SCORE~DOSE)
```

Kruskal-Wallis rank sum test

data: SCORE by DOSE  
Kruskal-Wallis chi-squared =  $4.4737$ ,  
df = 2, p-value =  $0.1068$  → Not significant

$h$  corrected for ties  
↑

When the K-W test is significant, pair-wise comparisons can be carried out with the Wilcoxon Rank Sum Test for each pair of groups.

# Some comments on non-parametric comparisons

1. The  $t$ -test is a more powerful test in detecting true differences when data are normally distributed. Since normality occurs often in nature, the  $t$ -test is the method of choice for a wide range of applications.
2. The WRST does assume the two population distributions have the same shape and differ only by a possible shift in location. Thus we assume the same dispersion, which is analogous to the variance homogeneity required in two sample  $t$ -tests.
3. The Mann-Whitney U-test is mathematically equivalent to the WRST.
4. The WSRT does require the assumption of symmetrical underlying distribution. When the data are highly skewed or non symmetrical, the Sign test can be used.
5. One-sample  $t$ -test can be used for larger samples ( $n > 30$ ) regardless the distribution of data. But, the  $t$ -test should be used only if the mean is the appropriate measure of central tendency for the population being studied.
6. When you perform a WRST to compare each pair of means after a K-W test, the problem of overall error rate alteration must be considered for larger values of  $k$  (number of comparisons).

## $\chi^2$ test – association / independence -

The general layout is a r-by-c **contingence table**, with a total of  $r \times c$  cells. A contingency table express the possibility that something happens or not.

The **null hypothesis** is that of **random distributions** among the levels of the two factors, or more generally, independence of row and column factors.

The  $\chi^2$  test is based on the tests statistic

$$\chi^2 = \sum_{i=1}^{kg} \frac{(O_i - E_i)^2}{E_i}$$

where  $O_i$  and  $E_i$  represent the observed and expected values, respectively, in the i-th cell.

The expected value is computed under the assumption that the null hypothesis is true, found by multiplying the marginal frequencies by the total sample size,  $N$ .

The test statistic is compared with the critical chi-square value with  $(r-1) \times (c-1)$  degrees of freedom to obtain the decision rule

Caution must be used when cell sizes are small.

## $\chi^2$ - Contingency table – data -

Data used come from a study relating eye and hair colours in men of Baden country.

	HBLACK	HBLOND	HBROWN	HRED	Total
EBLUE	189	1768	807	47	2811 (0.4134)
EBROWN	288	115	438	16	857 (0.1260)
EGREEN	746	946	1387	53	3132 (0.4606)
Total	1223 (0.1799)	2829 (0.4160)	2632 (0.3871)	116 (0.0171)	



**Marginal frequencies** expressed in absolute -1223-  
or relative terms:  $1223 / 6800 = 0.1799$

## $\chi^2$ - Contingency table – table in R -

First we define the elements of a matrix by the `c()` command. The order is the elements of each row from left to right, starting with the first row and so on. Then we define that the matrix has 3 rows and that the elements are ordered within row.

```
> BADEN.MEN <- matrix(c(189,1768,807,47,288,115  
+ ,438,16,746,946,1387,53),nrow=3, byrow=T)
```

After that we define the names of the column and row headers.

```
> colnames(BADEN.MEN) <- c("HBLACK", "HBLOND", "HBROWN", "HRED")  
> rownames(BADEN.MEN) <- c("EBLUE", "EBROWN", "EGREEN")
```

## $\chi^2$ test – results in R (1) -

```
> chisq.test(BADEN.MEN)$observed
```

	HBLACK	HBLOND	HBROWN	HRED
EBLUE	189	1768	807	47
EBROWN	288	115	438	16
EGREEN	746	946	1387	53

```
> chisq.test(BADEN.MEN)$expected
```

	HBLACK	HBLOND	HBROWN	HRED
EBLUE	505.5666	1169.4587	1088.0224	47.95235
EBROWN	154.1340	356.5372	331.7094	14.61941
EGREEN	563.2994	1303.0041	1212.2682	53.42824



The **expected value** is calculated as  
 $116/6800 * 3132/6800 * 6800 = 53.428$



## $\chi^2$ test – results in R (2) -

```
> O <- chisq.test(BADEN.MEN)$observed  
> E <- chisq.test(BADEN.MEN)$expected  
> (O-E)
```

	HBLACK	HBLOND	HBROWN	HRED
EBLUE	-316.5666	598.5413	-281.0224	-0.9523529
EBROWN	133.8660	-241.5372	106.2906	1.3805882
EGREEN	182.7006	-357.0041	174.7318	-0.4282353

```
> chisq.test(BADEN.MEN)
```

Pearson's Chi-squared test

data: BADEN.MEN

X-squared = 1073.508, df = 6, p-value < 2.2e-16

The colour of the eyes and the colour of the hair are **not independent**, i.e., not distributed at random among each other.

```
> 1-pchisq(1073.508, 6)  
[1] 0
```

## $\chi^2$ test – results in R (3) -

```
> assocstats(BADEN.MEN)
```

	X^2	df	P(> X^2)	
Likelihood Ratio	1137.6	6	0	$H_0$ of random distribution of colours of eyes and hair is rejected
Pearson	1073.5	6	0	
Phi-Coefficient	:	0.397		Measurements of the degree of association
Contingency Coeff.:	0.369			
Cramer's V	:	0.281		

The measurements of the degree of association are derived from the  $\chi^2$  estimate. These measurements are similar in concept to a correlation coefficient between variables.

For 2×2 designs (1 degree of freedom) and cells with less than 5 observations, use the Fisher Exact Test (write **fisher.test**).

## References

Walker G.A. 1997. *Common Statistical Methods for Medical Research*. SAS Institute, Cary, NC.