

# Hypothesis testing (in R)

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## Recall: hypothesis testing

Often, the aim of the analysis is not only **estimation**.

For example,

- ▶ *Is the treatment effective?*
- ▶ *Is a gene differentially expressed?*
- ▶ *Is there an association between genotype and phenotype?*



These questions can be translated as **hypothesis testing** problems

Comic taken from Significance Magazine, December 2008.

# Outline for the course

- ▶ **Introduction to statistics**
- ▶ **Hypothesis testing (in R)**
  - ▶ Test for categorical variables
  - ▶ Tests for continuous variables
    - ▶ Parametric
    - ▶ Non-parametric
- ▶ **Linear regression (in R)**
- ▶ **Multiple testing (in R)**

# Hypothesis testing

## Basic setup

Formulate the ‘null’ and alternative hypothesis



Calculate a “test statistic” from the data



Decision rule

This afternoon:

## Hypothesis testing in R

In particular,

- ▶ Test vs data type
- ▶ Hypothesis formulation
- ▶ Assumptions

## Tests for categorical variables

## Tests for categorical variables: an example

A trial was designed to assess the effectiveness of a new treatment versus a placebo in reducing tumour size (ovarian cancer patients)

The data contains the following information

- ▶ Patient group: treatment / placebo
- ▶ Tumour shrinkage: yes / no

How would you summarise the data?

## Tests for categorical variables: an example

In the example, the data is as follows

Patient group	Tumour shrinkage	
	Yes	No
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Next steps:

1. Formulate the hypothesis
2. Calculate a “test statistic” (evidence)
3. Decision rule

## Pearson's $\chi^2$ test for independence

1. Formulate the hypothesis

Pearson's  $\chi^2$  test for **independence** is designed to contrast the following hypothesis

$$H_0 : \text{Independence} \quad \text{vs} \quad H_1 : \text{Not independence}$$

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$$H_0 : \text{Independence} \quad \text{vs} \quad H_1 : \text{Not independence}$$

In the example,

$$H_0 : \text{no association between treatment and tumour shrinkage}$$

$$H_1 : \text{treatment and tumour shrinkage are associated}$$

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*What is the probability of observing {head, head}?*

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This is used to compute **expected frequencies** under independence

# Pearson's $\chi^2$ test for independence: an example

## 2. Calculate a “test statistic”

### 2.1. Calculate expected frequencies under independence

Patient group	Tumour shrinkage	
	Yes	No
Treatment	44 (46.1)	40 (37.9)
Placebo	24 (21.9)	16 (18.1)

In this example:

$$46.1 = 124 \times \frac{(44 + 40)}{124} \times \frac{(44 + 24)}{124}$$

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$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

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The test statistic to be computed is

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

If  $H_0$  is true, it is known that

$$\chi^2 \sim \chi^2_{(r-1) \times (c-1)},$$

for a  $r \times c$  contingency table.

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$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

$$\chi^2_{(r-1) \times (c-1)} = \sum \frac{(O - E)^2}{E} = \frac{(44 - 46.1)^2}{46.1} + \frac{(40 - 37.9)^2}{37.9} + \frac{(24 - 21.9)^2}{21.9} + \frac{(16 - 18.1)^2}{18.1} = 0.64$$

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In the example, we have

$$\chi^2 = 0.64, r = 2 \text{ and } c = 2$$

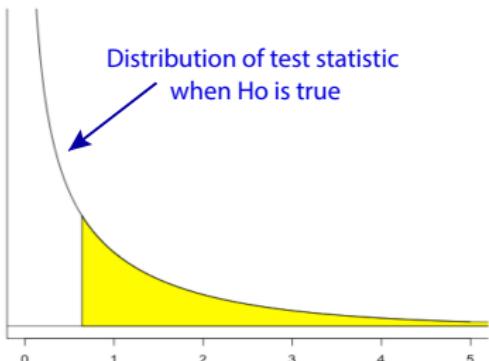
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Hence, we can calculate that  
the **p-value** is equal to 0.43



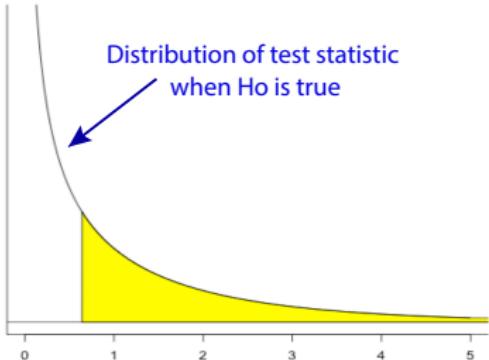
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**Do not reject  $H_0$ :** there is no evidence of an association between treatment group and tumour shrinkage (with 95% significance)

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In general, a chi-square test is appropriate when:

- ▶ Observations are **independent**, randomly sampled from a population
- ▶ None of the cells have an **expected** frequency less than 1
- ▶ Approximately at least 80% of the cells have an **expected** frequency of 5 or greater

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If the last 2 conditions aren't met, **Fisher's exact test** should be used

Questions + practical

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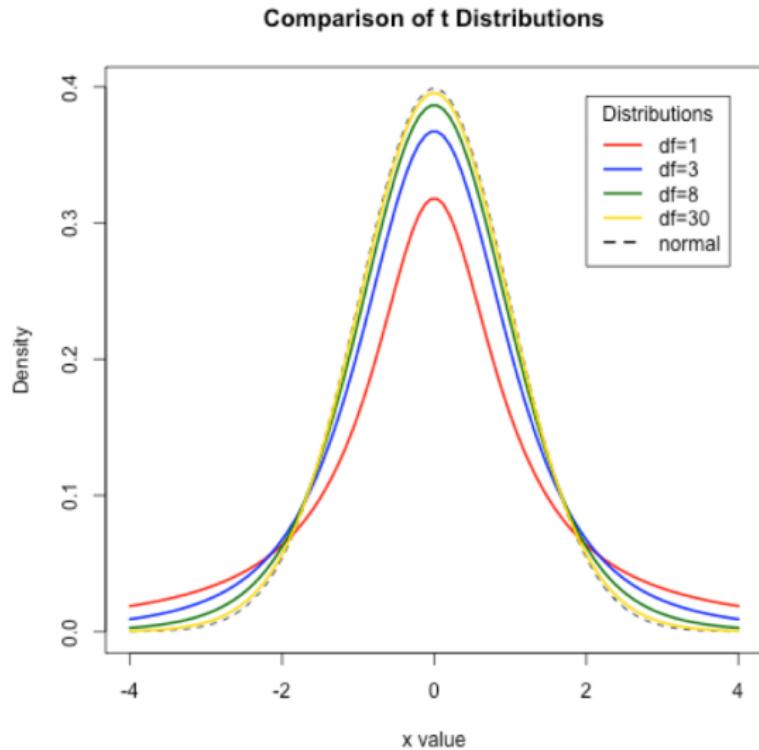
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This is no longer possible when dealing with **continuous variables**

Instead, tests for continuous variables focus on global features:

- ▶ Parametric tests
- ▶ Non-parametric tests

## Before we continue: Student's $t$ distribution



## Parametric tests

## Tests for continuous variables: an example

Published data suggests that the microarray failure rate for a particular supplier is 2.1%.

*Genomics Core want to know if this holds true?*



Next steps:

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## One-sample $t$ -test

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The one-sample  $t$ -test is designed to test hypothesis about the **mean** of a distribution. For example,

$$H_0 : \mu = \mu_0 \text{ vs } H_1 : \mu \neq \mu_0$$

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In the example:

$H_0$ : Mean failure rate = 2.1% vs  $H_1$ : Mean failure rate  $\neq$  2.1%

## One-sample $t$ -test

### 2. Calculate a “test statistic” (evidence)

- ▶ Idea: how far is  $\bar{x} = (\sum_{i=1}^n x_i)/n$  from  $\mu_0$ ?
- ▶ To quantify this, the following test statistic is defined:

$$t = \frac{\bar{x} - \mu_0}{se(\bar{x})}$$

Recall:  $se(\bar{x}) = sd(x)/\sqrt{n}$

If  $H_0$  is true, it is known that  $t \sim t_{n-1}$ .

## One-sample *t*-test: an example

2. Calculate a “test statistic” (evidence)

Genomics Core recorded the following data

Month	Monthly failure rate
January	2.90
February	2.99
March	2.48
April	1.48
May	2.71
June	4.17
July	3.74
August	3.04
September	1.23
October	2.72
November	3.23
December	3.40

$$\text{Mean} = (2.90 + \dots + 3.40)/12 = 2.84$$

$$\text{Standard deviation} = 0.84$$

Therefore,

$$t = \frac{2.84 - 2.10}{0.84/\sqrt{12}} = 3.07$$

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### 3. Decision rule

*Reject  $H_0$  if  $\bar{x}$  is far from  $\mu_0$ : if  $t$  is too large or too small*

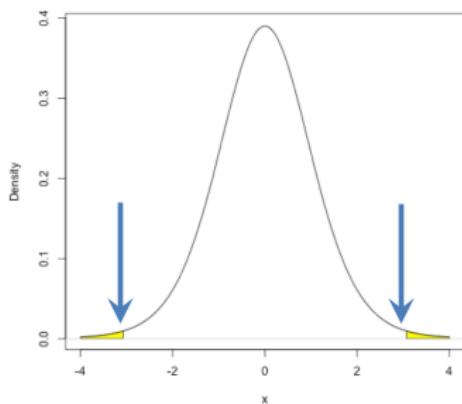
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In the example,  $t = 3.07$

The **p-value** is equal to 0.01



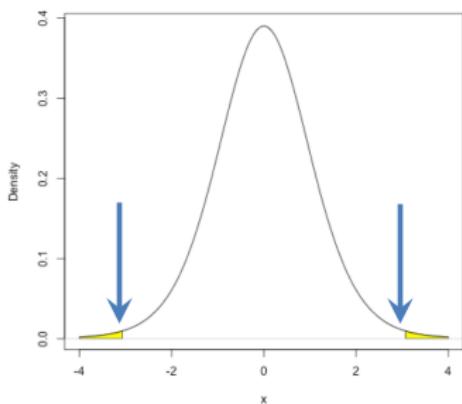
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**Reject  $H_0$ :** the Genomics Core data suggest that the supplier's claim is not true (95% significance)

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In the example,

*Is the microarray failure rate **lower** than 2.1%?*

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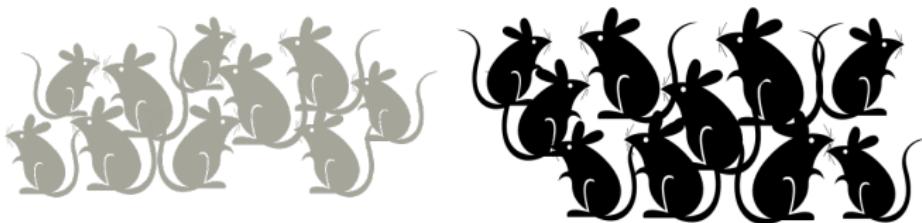
What can we do if the data is not normally distributed?

- ▶ If  $n$  is large, Central Limit Theorem allows us to use the test (rule of thumb:  $n > 30$ )
- ▶ We can transform the data (e.g.  $\log(X)$ )
- ▶ We can use a **non-parametric** test

## Tests for continuous variables: an example

The weight of 40 male mice (20 of breed A and 20 of breed B) was recorded at 4 weeks old.

*Does the weight of 4 week old male mice depend on breed?*



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In the example:

$H_0$ : Mean weight breed A = Mean weight breed B

$H_1$ : Mean weight breed A  $\neq$  Mean weight breed B

## Two-sample $t$ -test

### 2. Calculate a “test statistic”

- ▶ Idea: how far are the observed means?
- ▶ To quantify this, the following test statistic is defined:

$$t = \frac{\bar{x}_A - \bar{x}_B}{se(\bar{x}_A - \bar{x}_B)},$$

where

- ▶  $\bar{x}_A, \bar{x}_B$  are the observed means for each group
- ▶  $se(\bar{x}_A - \bar{x}_B)$  is the observed standard error for  $\bar{x}_A - \bar{x}_B$

**Important:** to calculate  $se(\bar{x}_A - \bar{x}_B)$  and to derive the distribution of  $t$  (under  $H_0$ ), we need to consider whether the groups have:

- ▶ Equal or unequal variances

# One-sample *t*-test: an example

## 2. Calculate a “test statistic” (evidence)

The following data was recorded

Breed A		Breed B	
Subject	Weight at 4 weeks (g)	Subject	Weight at 4 weeks (g)
1	20.77	21	15.51
2	9.08	22	12.93
3	9.80	23	11.50
4	8.13	24	16.07
5	16.54	25	15.51
6	11.36	26	17.66
7	11.47	27	11.25
8	12.10	28	13.65
9	14.04	29	14.28
10	16.82	30	13.21
11	6.32	31	10.28
12	17.51	32	12.41
13	9.87	33	9.63
14	12.41	34	14.75
15	7.39	35	9.81
16	9.23	36	13.02
17	4.06	37	12.33
18	8.26	38	11.90
19	10.24	39	8.98
20	14.64	40	11.29
Mean	11.50	Mean	12.80
Standard deviation	4.18	Standard deviation	2.33

Assuming **unequal variances** we obtain  $t = 1.21$

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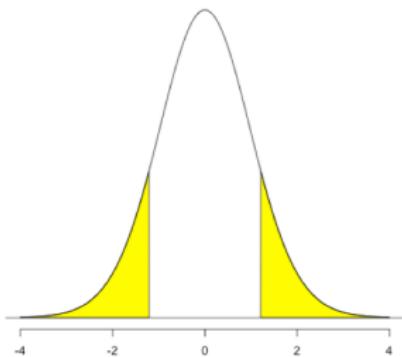
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The **p-value** is equal to 0.24

(Assumes unequal variances)



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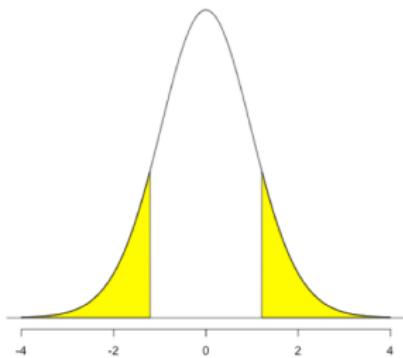
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**Do not reject  $H_0$ :** there is no evidence to believe that the mean weight of breed A differs from the mean weight of breed B (95% significance)

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- ▶ Observations are independent **between** the groups
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## Two-sample $t$ -test

What can we do if there is no independence between groups?

- We should used a **paired** two sample  $t$ -test

**Assumption:** pairs of samples are randomly drawn from a population

Examples where a paired test should be used:

- Before / after measures
- Twin studies

Questions + practical

## Non-parametric tests

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The tests for continuous variables described earlier formulate hypothesis in terms of **parameters** (e.g. the mean  $\mu$ )

Typically, **parametric** tests assume the data follows a particular distribution (e.g. normal) or rely on asymptotic results (e.g.  $\bar{x}$  is normally distributed for large  $n$ )

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**Non-parametric** tests provide an alternative for situations where these assumptions do not hold

## One-sample sign test

The **one-sample sign test** can be interpreted as a non-parametric version of the **one-sample *t*-test**

It defines hypothesis in terms of the **median** of a distribution

$H_0$ : median is equal to  $\theta_0$

$H_1$ : median is not equal to  $\theta_0$

As in the one-sample *t*-test, this assumes **independent** observations

## One-sample sign test

The test statistic is calculated by comparing the observations to  $\theta_0$ :

- ▶ + : if bigger
- ▶ - : if smaller
- ▶ = : if equal

Count the number of +'s and -'s, and calculate:

- ▶  $S^+$  = the number of +'s
- ▶  $S^-$  = the number of -'s
- ▶  $n$  = the number of non-ties

If  $H_0$  is true,  $S^+, S^- \sim \text{Binomial}(n, 0.5)$

## One-sample sign test: one example

4
1
19
8
12
15
26
4
23
19
12
1
9
25
3

15 people were asked how many times they went to the cinema during the last year

A survey from two years ago indicated that a typical person goes to the cinema 5 times per year.  
Is this still true?

## One-sample sign test: one example

4
1
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8
12
15
26
4
23
19
12
1
9
25
3

15 people were asked how many times they went to the cinema during the last year

A survey from two years ago indicated that a typical person goes to the cinema 5 times per year. Is this still true?

If perform a one-sample *t*-test for

$$H_0 : \mu = 5 \text{ versus } H_1 : \mu \neq 5,$$

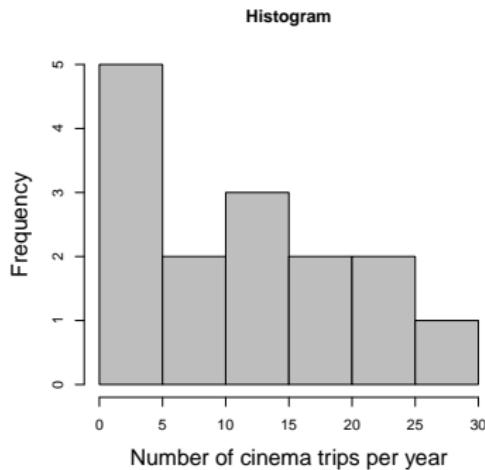
the p-value is equal to 0.007.

Therefore, the data suggests that this information is no longer true.

## One-sample sign test: one example

4
1
19
8
12
15
26
4
23
19
12
1
9
25
3

Let's look at the data again



The data does not look normal!

## One-sample sign test: one example

4
1
19
8
12
15
26
4
23
19
12
1
9
25
3

Instead, we can use a one-sample sign test

## One-sample sign test: one example

4	-
1	-
19	+
8	+
12	+
15	+
26	+
4	-
23	+
19	+
12	+
1	-
9	+
25	+
3	-

Instead, we can use a one-sample sign test

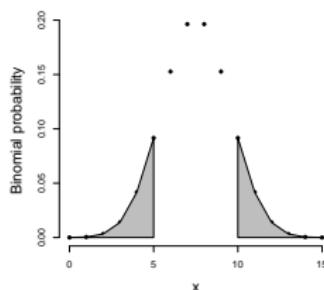
- ▶  $S^+ = 10$  (number of observations  $> 5$ )
- ▶  $S^- = 5$  (number of observations  $< 5$ )
- ▶  $n = 15$  (number of observations  $\neq 5$ )

## One-sample sign test: one example

4	-
1	-
19	+
8	+
12	+
15	+
26	+
4	-
23	+
19	+
12	+
1	-
9	+
25	+
3	-

Instead, we can use a one-sample sign test

- ▶  $S^+ = 10$  (number of observations  $> 5$ )
- ▶  $S^- = 5$  (number of observations  $< 5$ )
- ▶  $n = 15$  (number of observations  $\neq 5$ )



The p-value is equal to 0.301

Recall: t-test p-value = 0.007

There is no evidence to suggest the information is no longer true.

## Two-sample sign test

The **two-sample sign test** can be interpreted as a non-parametric version of the **two-sample paired *t*-test**

It defines hypothesis in terms of the **median** of the distributions

$H_0$ : median is equal in both groups

$H_1$ : median is not equal in both groups

As in the two-sample paired *t*-test, this assumes **independent pairs** of observations

## Two-sample sign test

The test statistic is calculated by comparing observed values between groups:

- ▶ + : if bigger in the first group
- ▶ - : if smaller in the second group
- ▶ = : if equal

Count the number of +'s and -'s, and calculate:

- ▶  $S^+$  = the number of +'s
- ▶  $S^-$  = the number of -'s
- ▶  $n$  = the number of non-ties

If  $H_0$  is true,  $S^+, S^- \sim \text{Binomial}(n, 0.5)$

## Two-sample sign test: an example

General health section of SF-36 was collected in a breast cancer study. Data includes information for two time points (same patients)

Is there a difference between the time points?

$H_0$  : medians of the two time points are the same

$H_1$  : medians of the two time points are not the same

## Two-sample sign test: an example

**GH Value 1 GH Value 2**

60	70
55	65
75	100
100	50
55	70
60	95
50	95
60	65
72	85
40	55
90	95
75	45
70	75
75	65
55	60

## Two-sample sign test: an example

GH Value 1	GH Value 2	Difference
------------	------------	------------

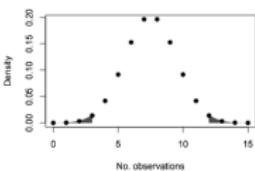
60	70	-10
55	65	-10
75	100	-25
100	50	50
55	70	-15
60	95	-35
50	95	-45
60	65	-5
72	85	-13
40	55	-15
90	95	-5
75	45	30
70	75	-5
75	65	10
55	60	-5

## Two-sample sign test: an example

GH Value 1	GH Value 2	Difference	Sign
60	70	-10	-
55	65	-10	-
75	100	-25	-
100	50	50	+
55	70	-15	-
60	95	-35	-
50	95	-45	-
60	65	-5	-
72	85	-13	-
40	55	-15	-
90	95	-5	-
75	45	30	+
70	75	-5	-
75	65	10	+
55	60	-5	-

- ▶  $S^+ = 3$  (no. pairs where diff > 0)
- ▶  $S^- = 12$  (no. pairs where diff < 0)
- ▶  $n = 15$  (no. pairs where diff  $\neq 0$ )

p-value = 0.035



The data suggests medians differ, i.e. there is a difference in general health between the two time points

## Advantages and limitations of sign tests

- ▶ Simple
  - ▶ Few assumptions thus widely applicable
- ▶ Less powerful than other tests
  - ▶ Does not consider magnitude of differences
  - ▶ May fail to reject  $H_0$  when other tests would
- ▶ Can be used for quick assessment of direction

## Wilcoxon signed rank test

The **Wilcoxon signed rank test** is an alternative to the **two-sample sign test** (uses the magnitude of the differences rather than just the sign)

In addition to the assumptions of the two-sample sign test, it also assumes:

symmetry of differences around true median difference

It's designed to contrast the hypothesis:

$H_0$ : distribution of paired differences is symmetric around zero

$H_1$ : distribution of paired differences is not symmetric around zero

## Wilcoxon signed rank test

Method:

- ▶ Calculate differences for each pair
- ▶ Rank the paired differences by (absolute) magnitude
- ▶ Split the ranks into two groups: positive and negative signed
  - ▶ Calculate sum of positive ranks:  $W^+$
  - ▶ Calculate sum of negative ranks:  $W^-$
- ▶ Compare smaller of and  $W^+$  and  $W^-$  to the critical value from the tables

# Wilcoxon signed rank test: an example

Revisiting the previous example:

GH Value 1	GH Value 2	Difference	Sign
60	70	-10	-
55	65	-10	-
75	100	-25	-
100	50	50	+
55	70	-15	-
60	95	-35	-
50	95	-45	-
60	65	-5	-
72	85	-13	-
40	55	-15	-
90	95	-5	-
75	45	30	+
70	75	-5	-
75	65	10	+
55	60	-5	-

1. Record sign of the differences

# Wilcoxon signed rank test: an example

Revisiting the previous example:

GH Value 1	GH Value 2	Difference	Sign	Abs.Diff.
60	70	-10	-	10
55	65	-10	-	10
75	100	-25	-	25
100	50	50	+	50
55	70	-15	-	15
60	95	-35	-	35
50	95	-45	-	45
60	65	-5	-	5
72	85	-13	-	13
40	55	-15	-	15
90	95	-5	-	5
75	45	30	+	30
70	75	-5	-	5
75	65	10	+	10
55	60	-5	-	5

1. Record sign of the differences
2. Record absolute differences

# Wilcoxon signed rank test: an example

Revisiting the previous example:

GH Value 1	GH Value 2	Difference	Sign	Abs.Diff.
60	65	-5	-	5
90	95	-5	-	5
70	75	-5	-	5
55	60	-5	-	5
60	70	-10	-	10
55	65	-10	-	10
75	65	10	+	10
72	85	-13	-	13
55	70	-15	-	15
40	55	-15	-	15
75	100	-25	-	25
75	45	30	+	30
60	95	-35	-	35
50	95	-45	-	45
100	50	50	+	50

1. Record sign of the differences
2. Record absolute differences
3. Order observations according to absolute difference

# Wilcoxon signed rank test: an example

Revisiting the previous example:

GH Value 1	GH Value 2	Difference	Sign	Abs.Dif.	Rank
60	65	-5	-	5	2.5
90	95	-5	-	5	2.5
70	75	-5	-	5	2.5
55	60	-5	-	5	2.5
60	70	-10	-	10	6
55	65	-10	-	10	6
75	65	10	+	10	6
72	85	-13	-	13	8
55	70	-15	-	15	9.5
40	55	-15	-	15	9.5
75	100	-25	-	25	11
75	45	30	+	30	12
60	95	-35	-	35	13
50	95	-45	-	45	14
100	50	50	+	50	15

1. Record sign of the differences
2. Record absolute differences
3. Order observations according to absolute difference
4. Calculate ranks
  - ▶ Ties → average rank

# Wilcoxon signed rank test: an example

Revisiting the previous example:

GH Value 1	GH Value 2	Difference	Sign	Abs.Dif.	Rank	Signed-Rank
60	65	-5	-	5	2.5	-2.5
90	95	-5	-	5	2.5	-2.5
70	75	-5	-	5	2.5	-2.5
55	60	-5	-	5	2.5	-2.5
60	70	-10	-	10	6	-6
55	65	-10	-	10	6	-6
75	65	10	+	10	6	6
72	85	-13	-	13	8	-8
55	70	-15	-	15	9.5	-9.5
40	55	-15	-	15	9.5	-9.5
75	100	-25	-	25	11	-11
75	45	30	+	30	12	12
60	95	-35	-	35	13	-13
50	95	-45	-	45	14	-14
100	50	50	+	50	15	15

1. Record sign of the differences
2. Record absolute differences
3. Order observations according to absolute difference
4. Calculate ranks
  - ▶ Ties → average rank
5. Calculate signed ranks

# Wilcoxon signed rank test: an example

Revisiting the previous example:

Here we obtain

GH Value 1	GH Value 2	Difference	Sign	Abs.Dif.	Rank	Signed-Rank
60	65	-5	-	5	2.5	-2.5
90	95	-5	-	5	2.5	-2.5
70	75	-5	-	5	2.5	-2.5
55	60	-5	-	5	2.5	-2.5
60	70	-10	-	10	6	-6
55	65	-10	-	10	6	-6
75	65	10	+	10	6	6
72	85	-13	-	13	8	-8
55	70	-15	-	15	9.5	-9.5
40	55	-15	-	15	9.5	-9.5
75	100	-25	-	25	11	-11
75	45	30	+	30	12	12
60	95	-35	-	35	13	-13
50	95	-45	-	45	14	-14
100	50	50	+	50	15	15

►  $W^+ = 33$

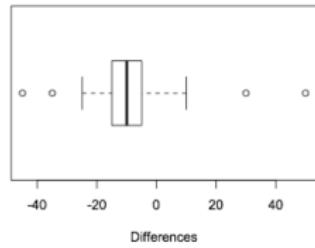
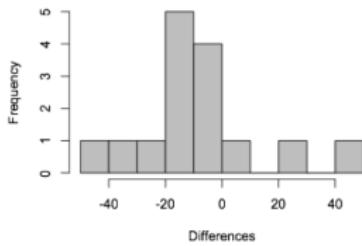
►  $W^- = 87$

$p\text{-value} = 0.12$

No evidence to conclude that there is a difference in general health between the two time points

# Wilcoxon signed rank test: an example

Validity of assumptions may affect results



## Wilcoxon signed rank test

- ▶ Easy to apply
- ▶ More powerful than the sign test
- ▶ Less powerful than the paired  $t$ -test
- ▶ Relies on the symmetry assumption

# Other popular tests

Here, we only explored a small subset of the tests that are available in standard statistical software. Here is a summary of other alternatives:

		RESPONSE		
NO OF SAMPLES		NOMINAL	ORDINAL OR NON-NORMAL	NORMALLY DISTRIBUTED
ONE SAMPLE		$\chi^2$ -test, Z-test	Kolmogorov-Smirnov Sign test	t-test
TWO SAMPLE	INDEPENDENT	$\chi^2$ -test ( $r \times c$ ), Fisher's exact test	Mann-Whitney U Median test	Unpaired t-test
	PAIRED	McNemar's test Stuart-Maxwell test	Wilcoxon signed rank Sign test	Paired t-test
MULTIPLE SAMPLES ( $K > 2$ )	INDEPENDENT	$\chi^2$ -test ( $r \times k$ ) Fisher-Freeman-Halton	Kruskal-Wallis test Median Test Jonckheere-Terpstra test	Analysis of variance (ANOVA)
	PAIRED	Cochran Q test	Friedman test Page test Quade test	Repeated measures ANOVA
ASSOCIATION BETWEEN TWO VARIABLES		Contingency coefficient Phi, $r_{\phi}$ Cramér, C	Spearman's rank Kendall's tau	Pearson product moment correlation
AGREEMENT BETWEEN TWO VARIABLES		Simple kappa	Weighted kappa	Limits of agreement

Questions + practical

## Acknowledgements

Part of the materials discussed today have been adapted from materials provided by

- ▶ Mark Dunning (CRUK-CI)