You can download the sources of this presentation here:

github.com/severin-lemaignan/lecture-hri-data-analysis

Data Analysis for HRI

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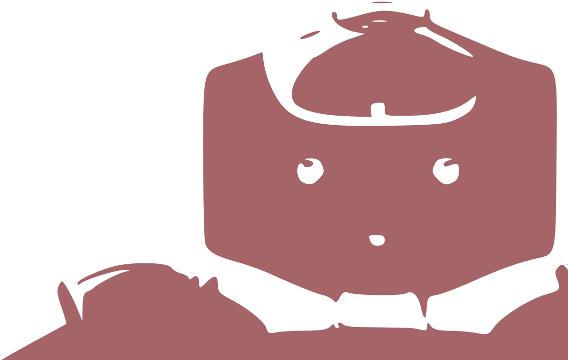
Bristol Robotics Lab
University of the West of England



IN THIS LECTURE

- Two questions to answer:

IN THIS LECTURE

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  Are my groups different?

IN THIS LECTURE

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  - Are my groups different?
  - Does a specific variable explain the difference?

IN THIS LECTURE

- Two questions to answer:

  Are my groups different?
  Does a specific variable explain the difference?

- Hands-on data analysis with Python!

ARE MY TWO GROUPS DIFFERENT?

A DATASET

pptID	age	condition	score	heartrate
1	22	control	643	76
2	26	cdt1	234	72
3	24	control	356	73
4	24	cdt1	587	75
5	29	cdt1	561	75
6	31	control	544	75
7	20	control	470	74
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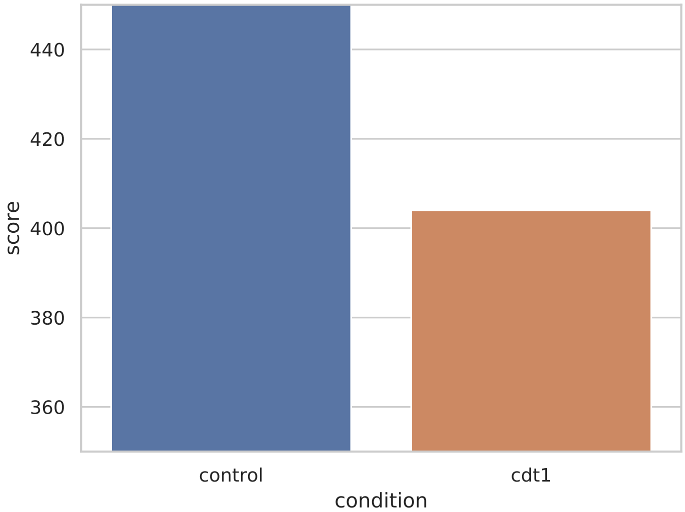
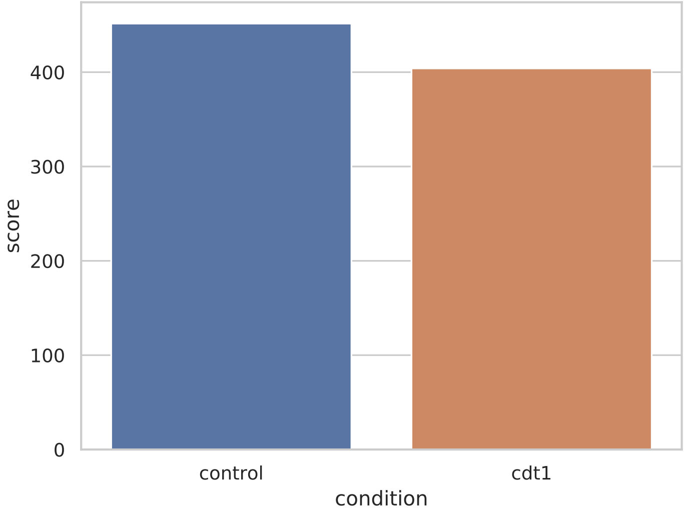
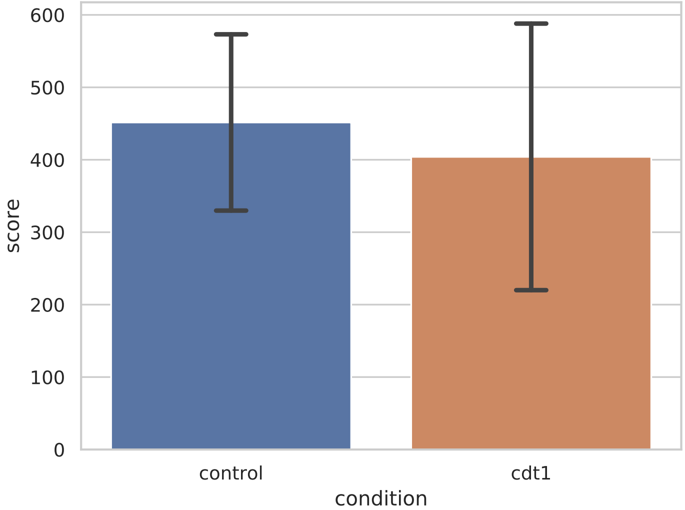


440
420
400
380
360
score
control
cdt1
condition


400
300
200
100
0
score
control
cdt1
condition

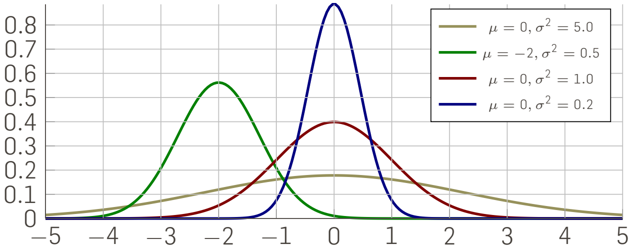

600
500
400
300
200
100
0
score
control
cdt1
condition

Is there a difference?

- Are the distributions the same?
- How big the difference?
- Could chance explain that difference?

IS THE DISTRIBUTION THE SAME?

Data often (but not always!) follows a normal (or Gaussian) distribution. Two parameters: **mean μ and variance σ^2**.



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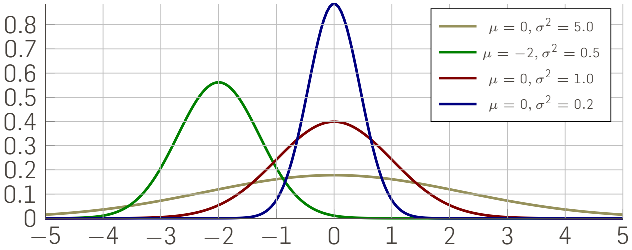
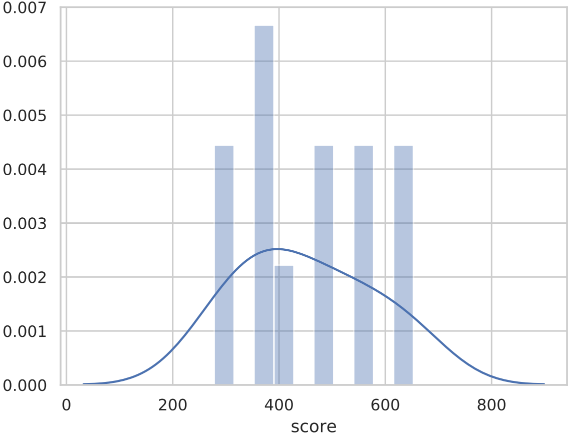


Many statistical tests only work if the underlying data follows a normal distribution – so-called **parametric tests**.

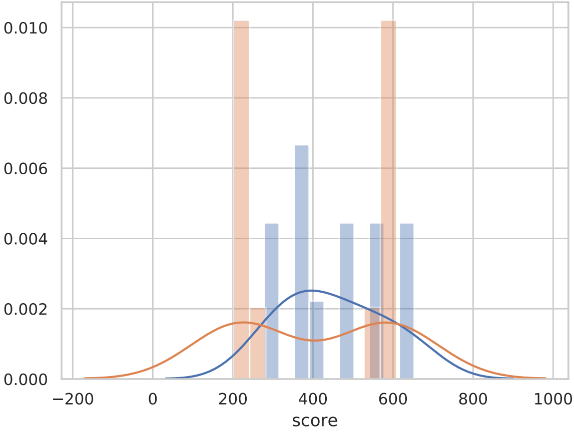
You need to check that your data is normally distributed first! (for instance, by plotting it)

COMPARE DISTRIBUTIONS (HISTOGRAMS, DENSITY)

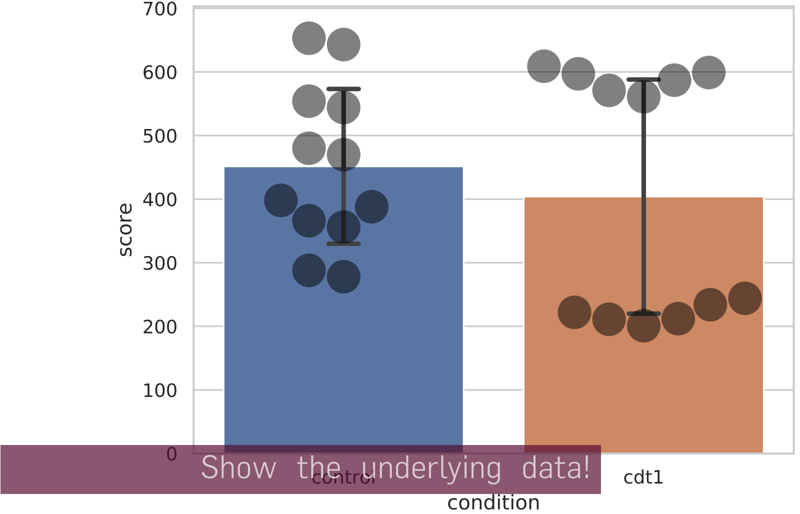


Control group

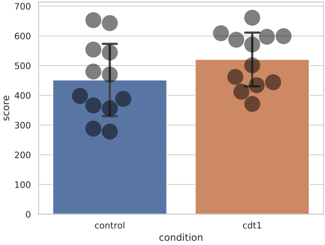
COMPARE DISTRIBUTIONS (HISTOGRAMS, DENSITY)

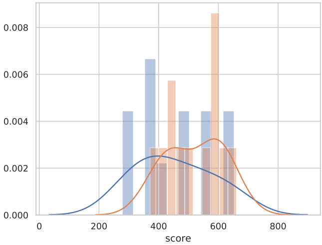


Control + condition group → beware the bimodal distribution!


700
600
500
400
300
200
100
0
score
control
cdt1
condition
Show the underlying data!

TWO ADDITIONAL DATASETS





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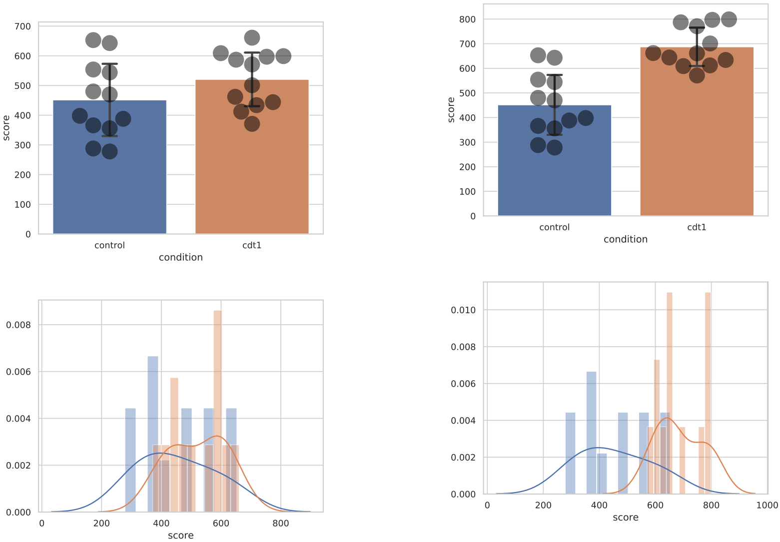
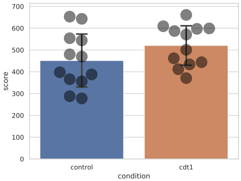


HOW BIG IS THE DIFFERENCE?



	mean	std
cdt1	516.5	85.3
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$\mu_1 - \mu_2$	69.2	

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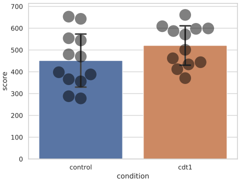
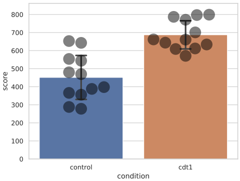
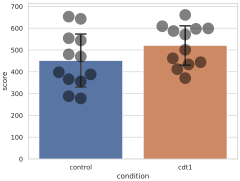


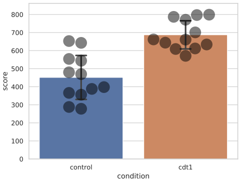


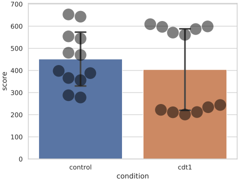
	mean	std
cdt1	516.5	85.3
control	451.5	127.1
$\mu_1 - \mu_2$	69.2	

	mean	std
cdt1	687.3	81.5
control	451.5	127.1
$\mu_1 - \mu_2$	235.8	

HOW BIG IS THE DIFFERENCE?







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	mean	std
cdt1	404.0	192.2
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$\mu_1 - \mu_2$	47.5	

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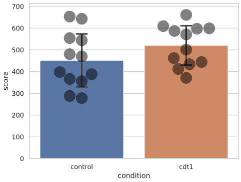

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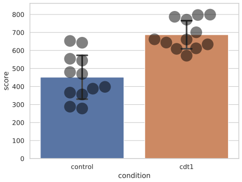

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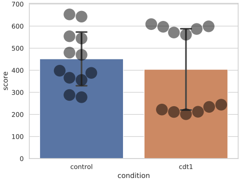
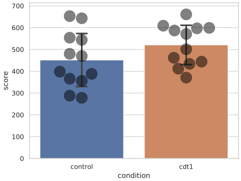
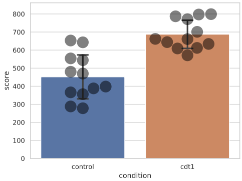


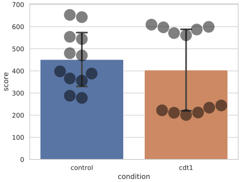
	mean	std
cdt1	404.0	192.2
control	451.5	127.1
$\mu_1 - \mu_2$	47.5	

does not account for the variance in the dataset

HOW BIG IS THE DIFFERENCE?







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cdt1	516.5	85.3
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$\mu_1 - \mu_2$	69.2	
$\frac{\mu_1 - \mu_2}{\sigma}$	0.62	

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cdt1	687.3	81.5
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$\mu_1 - \mu_2$	235.8	
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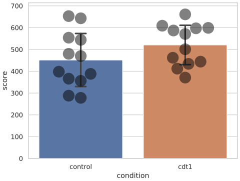

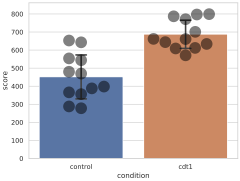

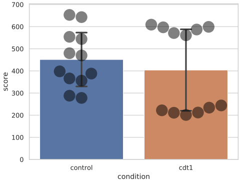

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A common measure of effect size: **Cohen's** ***d*** $= \frac{\mu_1-\mu_2}{\sigma}$

$\rightarrow$ Interactive visualisation and interpretation of Cohen's ***d***

DIFFERENCE DUE TO CHANCE?

A statistical hypothesis test makes an assumption about the outcome, called the **null hypothesis**.

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$\Rightarrow$ **Meaning of a low *p*-value?**

To interpret ***p***, you need to choose a ***significance level*** α.
For instance, 10% (0.1), 5% (0.05), 2% (0.02)...

$p = 0.05$

'There's only 5% of chance of observing these distributions if my null hypothesis is true (ie, no difference between my groups).'

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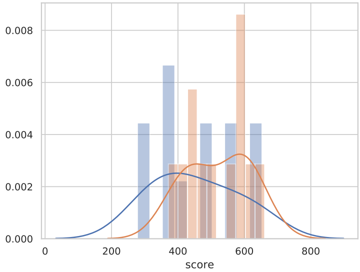

t statistic	-1.51
p	0.155

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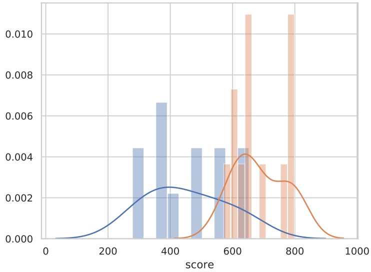

t statistic	-5.41
p	< 0.001

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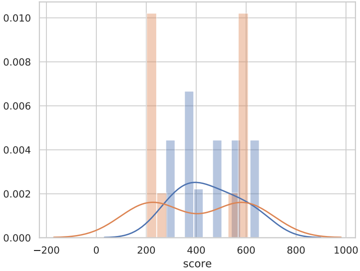

t statistic	0.71
p	0.48

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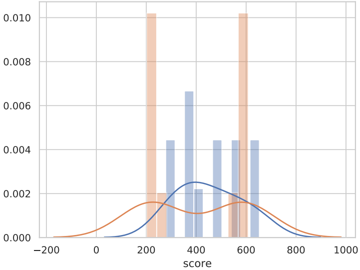

U statistic	46.0
p	0.07

See Wikipedia page for examples and interpreation of *U*

IMPACT OF *N*?

What is the impact of the sample size n on p?

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$$\nearrow n \Rightarrow \searrow p$$

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BE CAREFUL WITH "STATISTICALLY SIGNIFICANT"!

gender	iq
male	76.51
male	76.53
female	76.66
female	76.65
female	76.64
female	76.63
male	76.54
female	76.64
male	76.51
female	76.60
female	76.63
male	76.52
female	76.64
male	76.51
female	76.60
female	76.63

BE CAREFUL WITH "STATISTICALLY SIGNIFICANT"!

t statistic	12.52
p	< 0.001
Mean female	76.64
Mean male	76.54

$$M_{female} > M_{male}, p < 0.001$$

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Cohen's d

$d = \frac{\mu_1 - \mu_2}{\sigma} = 4.12 \Rightarrow$ high, because σ very low

STATISTICAL POWER ANALYSIS

Statistical power

The statistical power of a hypothesis test is the probability of detecting an effect, if there is a true effect present to detect.

or:

Statistical power

The statistical power of the test is the probability that the test correctly rejects a ***false*** null hypothesis.

STATISTICAL POWER ANALYSIS

Types of errors

- **Type I error**: Reject the null hypothesis when there is in fact no significant effect ***(too optimistic!)***
- **Type II error**: Not reject the null hypothesis when there is a significant effect ***(too pessimistic!)***

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Power = 1 - Type II Error

STATISTICAL POWER ANALYSIS

A puzzle with four pieces:

- **Effect size**
- **Sample size**
- **Significance** (chance of Type I error – found inexistant effect)
- **Statistical power** (1 - chance of Type II error – missed the effect)

EXAMPLE: POWER ANALYSIS OF STUDENT'S *T*-TEST

- **Effect size**: Cohen's *d* > 0.8
- **Significance**: 5%
- **Statistical power**: 80%
- **Sample size?**

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A good read on statistical power analysis:

A Gentle Introduction to Statistical Power and Power Analysis in Python

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Keep a close eye on your data distributions (**plot them**)

DOES ONE VARIABLE EXPLAIN THE DIFFERENCE?

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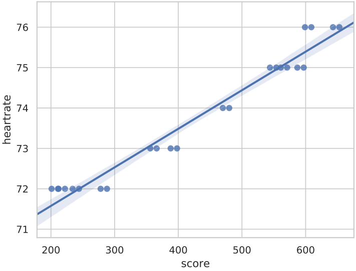
12	29	cdt1	599	76
13	27	control	366	73
14	21	cdt1	597	75
15	22	cdt1	571	75
16	30	control	554	75

ASSOCIATION

What is the degree of association between two variables?

$\rightarrow$ **main tool: correlation**

PEARSON CORRELATION



Pearson's correlation	
ρ	0.98
p	< 0.001

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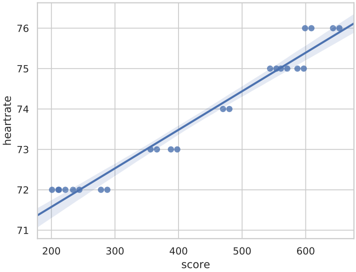

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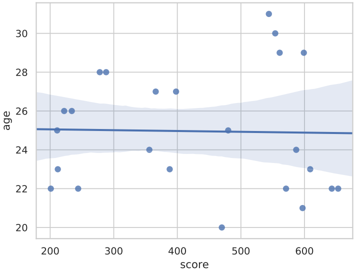
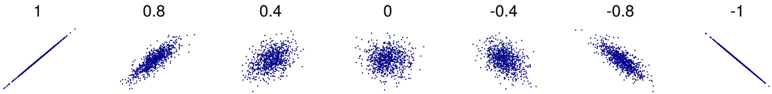
ρ	0.98
p	< 0.001



Pearson's correlation	
ρ	-0.022
p	0.92

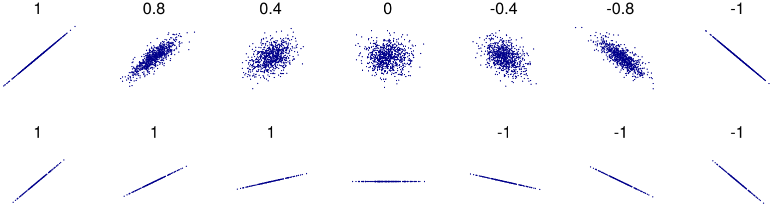
INTERPRETATION OF ρ



ρ reflects the degree of linearity and direction

Source: Wikipedia

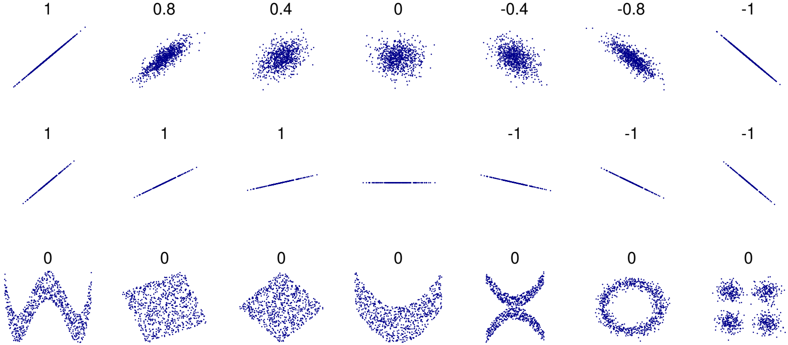
INTERPRETATION OF ρ



ρ does not reflect the slope of the regression line

Source: Wikipedia

INTERPRETATION OF ρ



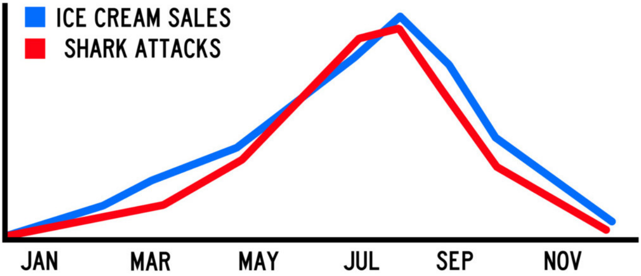
ρ does not capture non-linear interactions

Source: Wikipedia

OTHER MEASURES OF ASSOCIATION

- Non-parametric ordinal data: **Spearman rank correlation**
- Association between categorical data (for instance, relationship between 'gender' and 'preferred style of cuisine'): **Pearson's Chi-Square** χ^2

CORRELATION IS NOT CAUSATION



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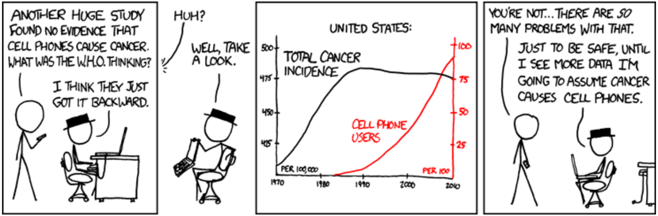

Source: XKCD

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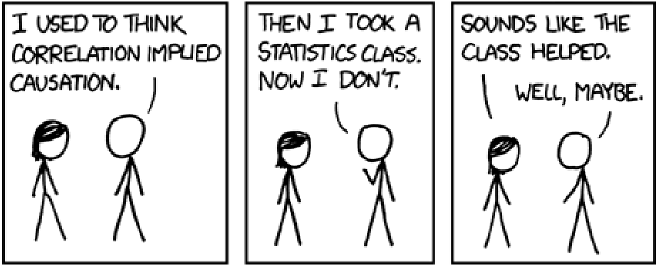

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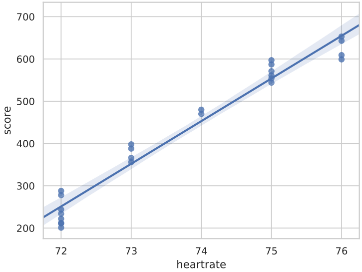
CORRELATION IS NOT CAUSATION

Be careful when tempted to write something like:



“the significant positive correlation between the heart rate and the score shows that you need to have a high heart rate to win”

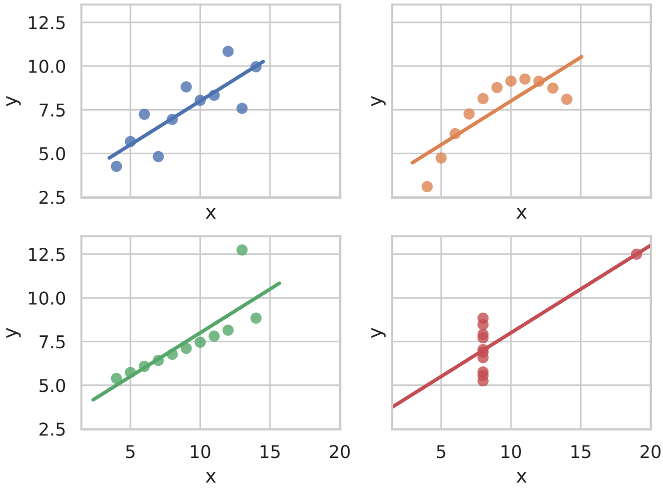
TO CONCLUDE: ANSCOMBE'S QUARTET

I		II		III		IV	
x	*y*	*x*	*y*	*x*	*y*	*x*	*y*
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

TO CONCLUDE: ANSCOMBE'S QUARTET

Property	Value
Mean of x	9
Sample variance of x	11
Mean of y	7.50
Sample variance of y	4.125
Correlation between x and y	0.816
Linear regression line	y = 3.00 + 0.500x
Coefficient of determination of the linear regression	0.67

TO CONCLUDE: ANSCOMBE'S QUARTET



IN PRACTICE

THE TOOLS

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- R: **www.r-project.org**
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Jupyter notebooks are a great way of creating an interactive, easy-to-follow, data analysis.

(SIDE NOTE ON PYTHON FOR DATA ANALYSIS)

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- `anaconda` (and a few other): Python distribution for scientific computing

Let’s give it a go!