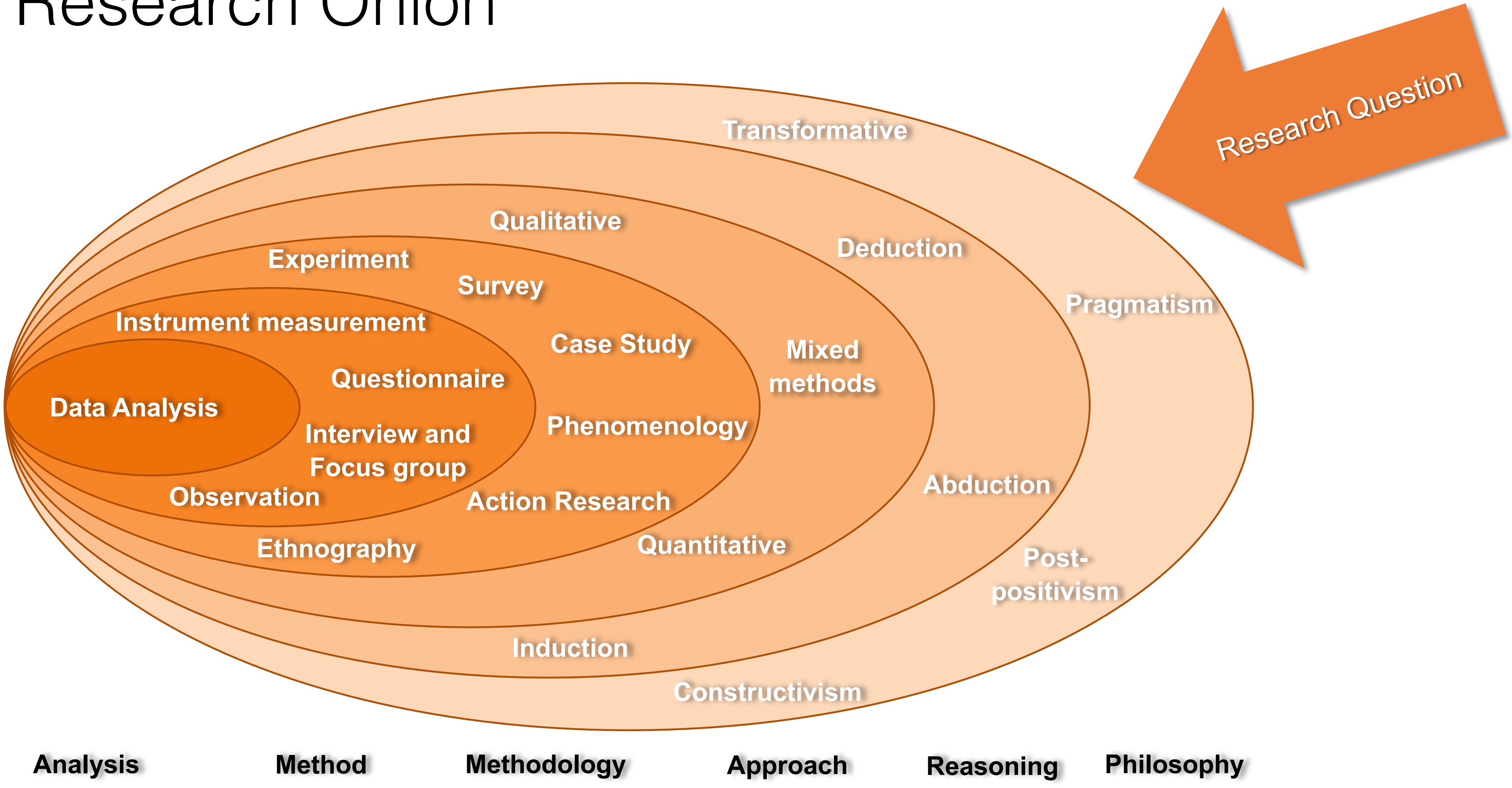
"If you don't reveal some insights soon, I'm going to be forced to slice, dice, and drill!"

Lecture 10
"Making sense of the mess."
Data analysis for HRI

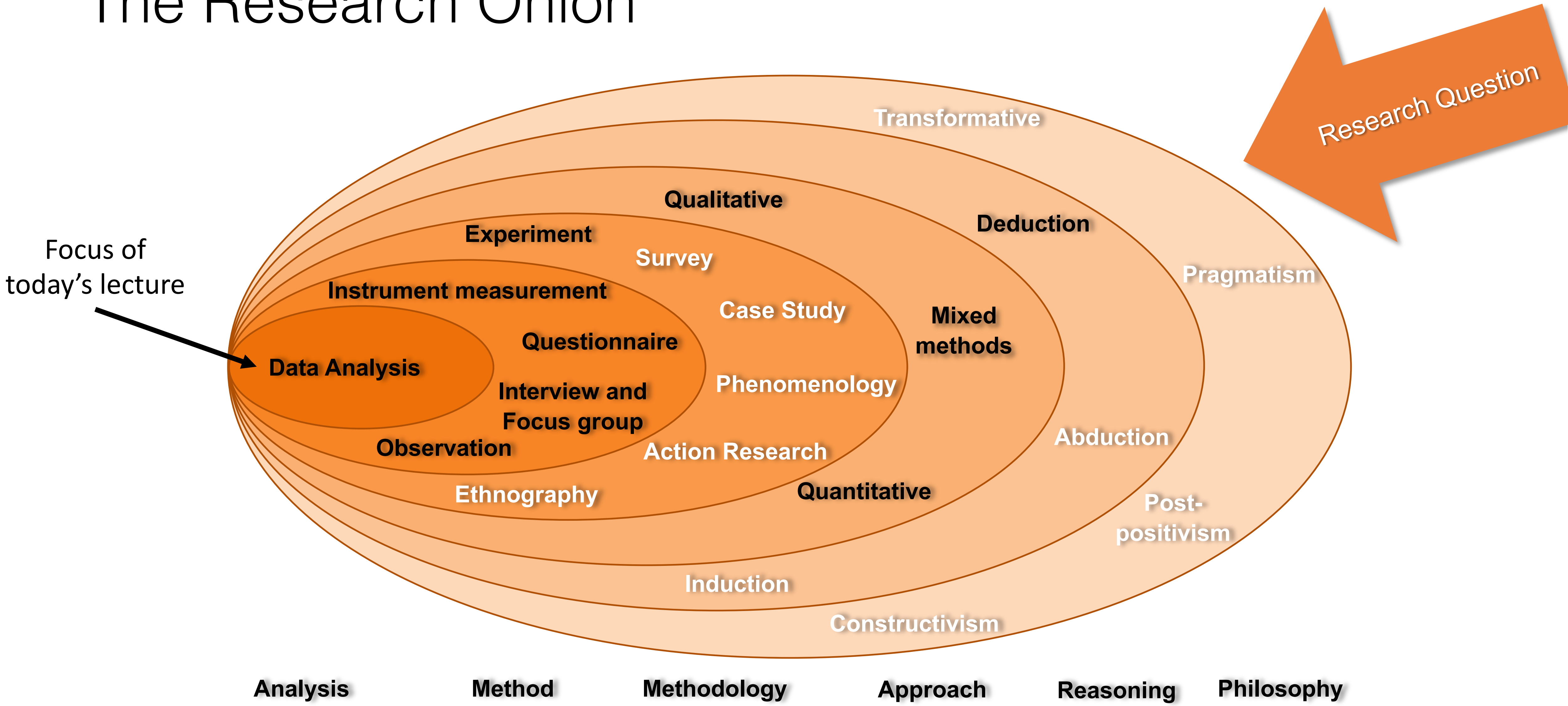
Kim Baraka
Assistant Professor
Social AI group

The Research Onion



The Research Onion, extended from Saunders, Lewis, & Thornhill (2012)

The Research Onion



The Research Onion, extended from Saunders, Lewis, & Thornhill (2012)

Learning goals

- Able to explain and apply basic tools for quantitative data analysis, namely:
  - Being able to determine whether experimental groups are different
  - Being able to determine if a specific variable explains the difference?
- Get acquainted with computational tools for quantitative data analysis
- Able to explain basic qualitative analysis tools, namely a thematic analysis pipeline and coding for observational data

Go to **www.menti.com** and use the code **7035 6269**

Examples of quantitative data?

Go to **www.menti.com** and use the code **7035 6269**

Examples of qualitative data?

https://www.mentimeter.com/s/8f4e6f61aaaf8569202a8d7710f6ac56/d8669183b18d/edit

Outline

- Quantitative analysis
  - Are my groups different?
  - Does a specific variable explain the difference?
  - Tools for quantitative data analysis
- Qualitative analysis
  - Thematic analysis
  - Analyzing observational data (e.g., videos)

Outline

- Quantitative analysis
  - Are my groups different?
  - Does a specific variable explain the difference?
  - Tools for quantitative data analysis

- Qualitative analysis
  - Thematic analysis
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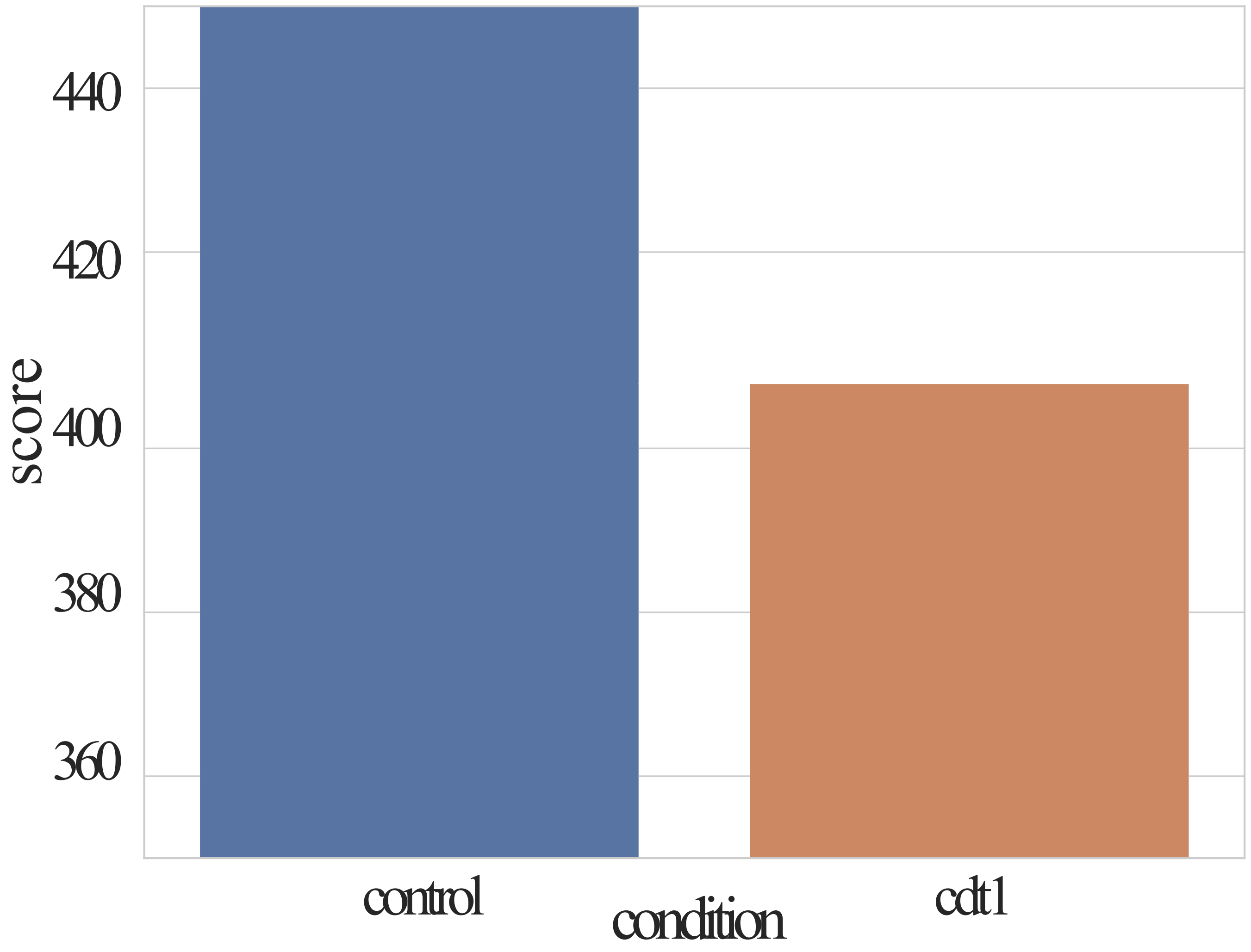
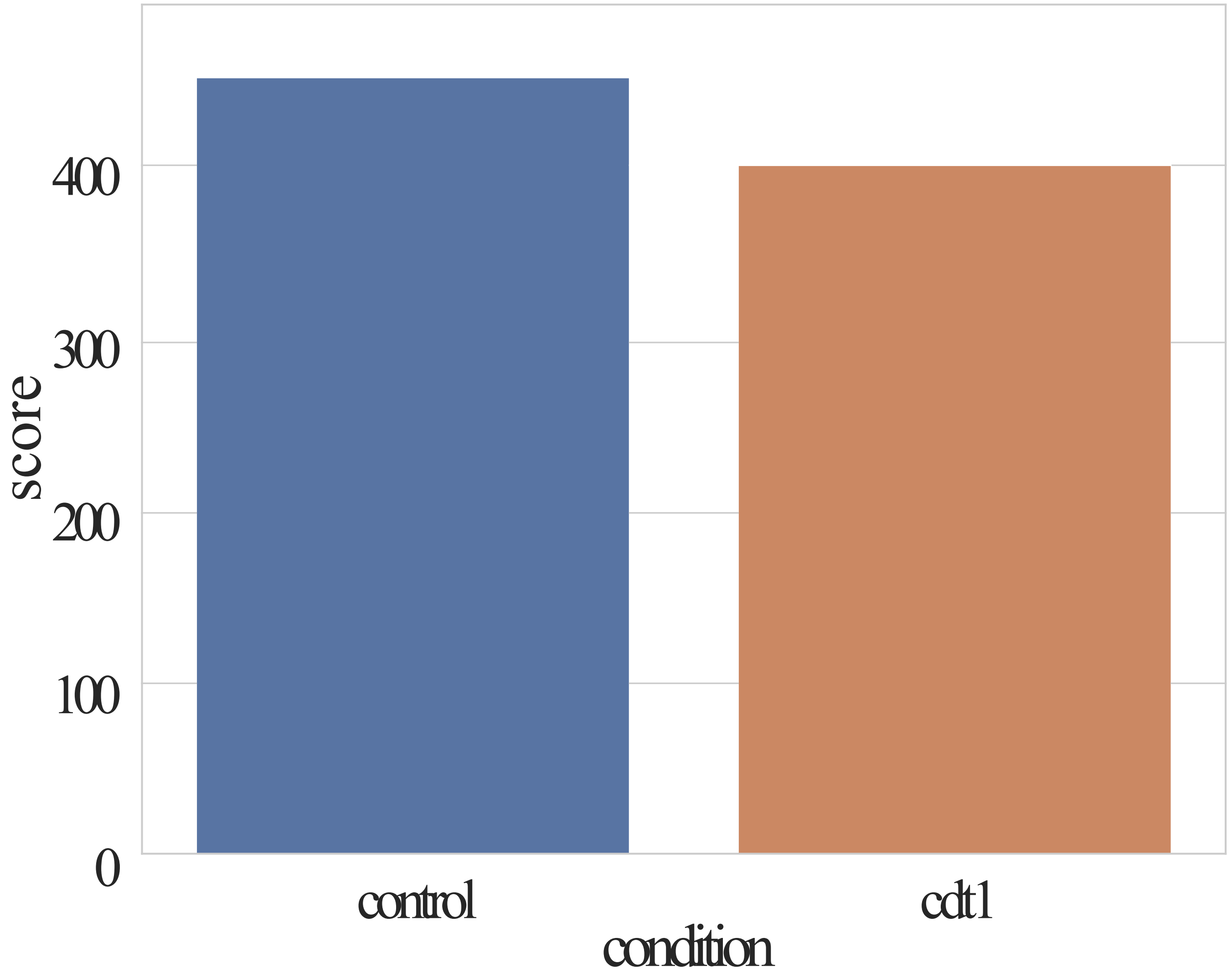
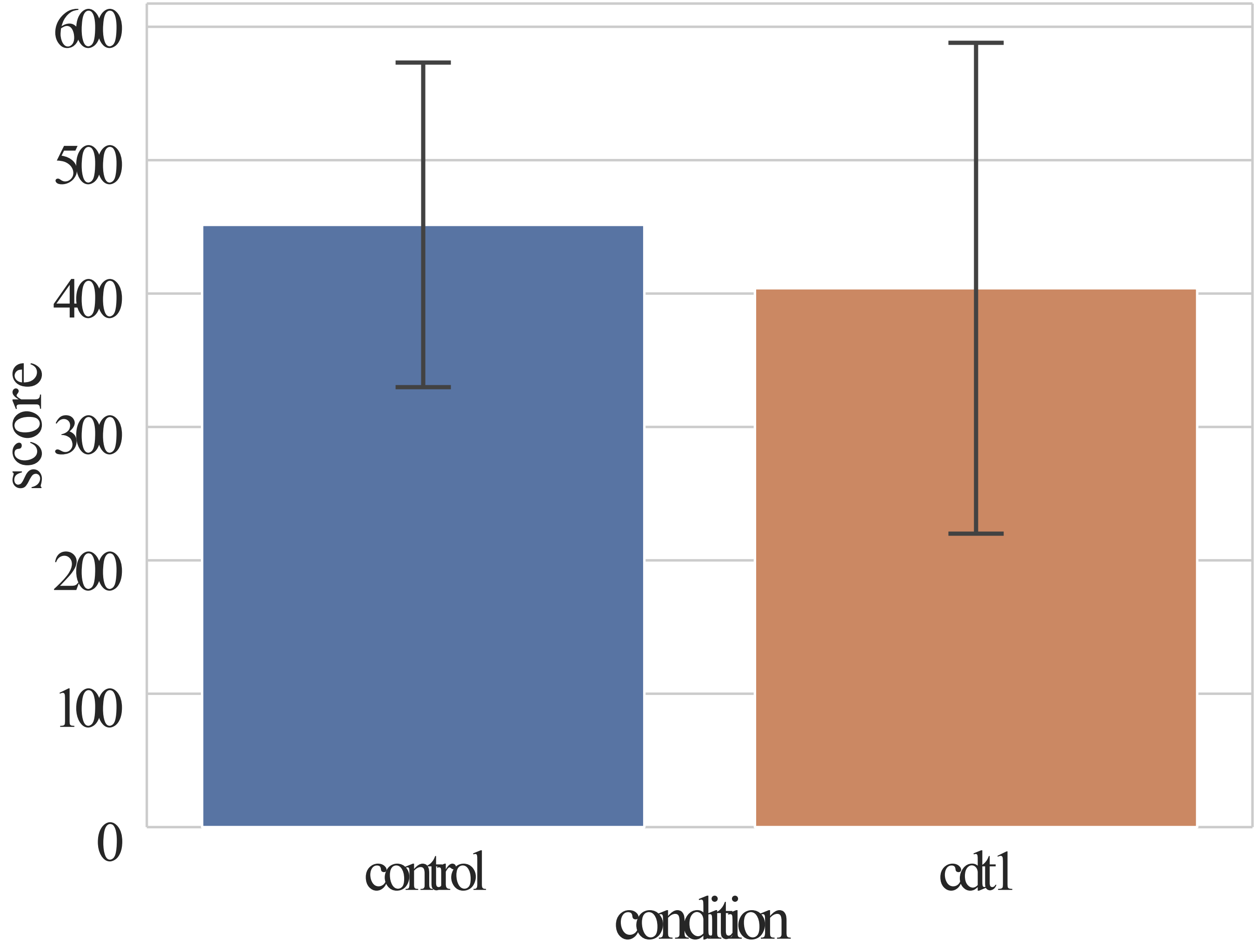
A DATASET

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
8	23	cdt1	212	72
9	23	control	388	73
10	22	cdt1	201	72
11	28	control	278	72
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


score
440
420
400
380
360
control
cdt1
condition


score
400
300
200
100
0
control
cdt1
condition

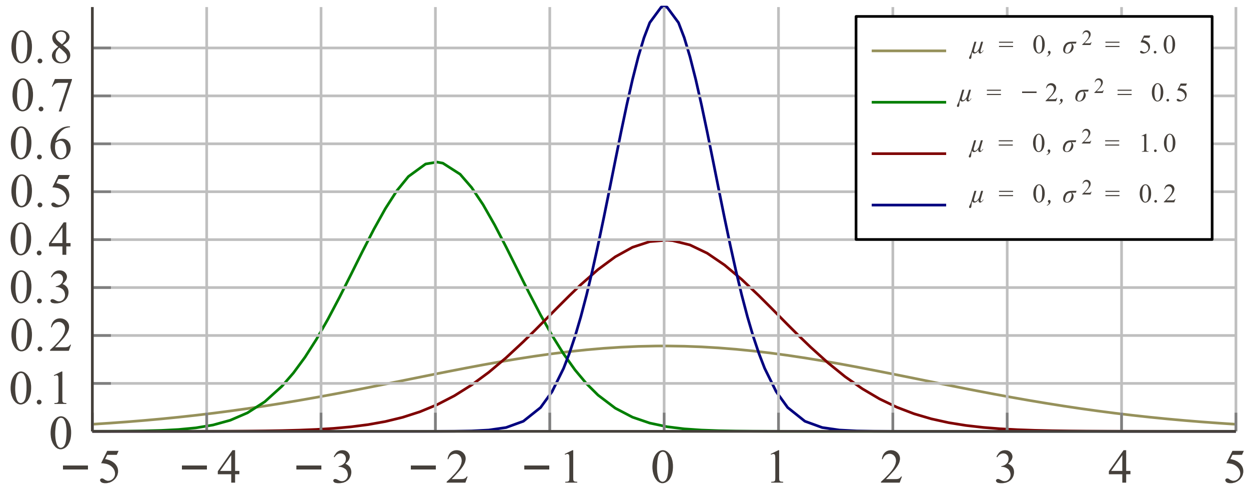

600
500
400
300
200
100
0
score
control
cdt1
condition

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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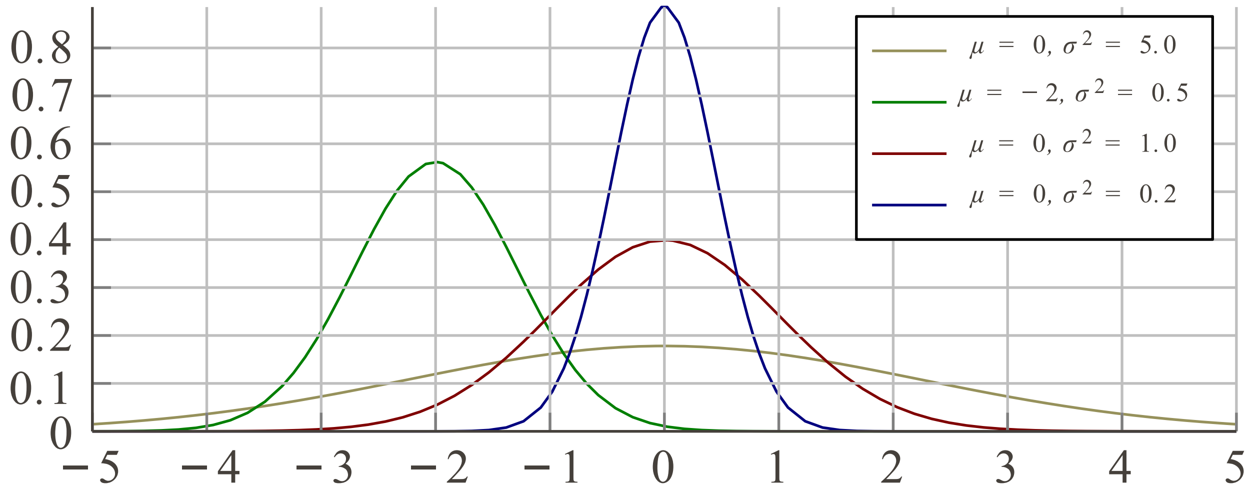
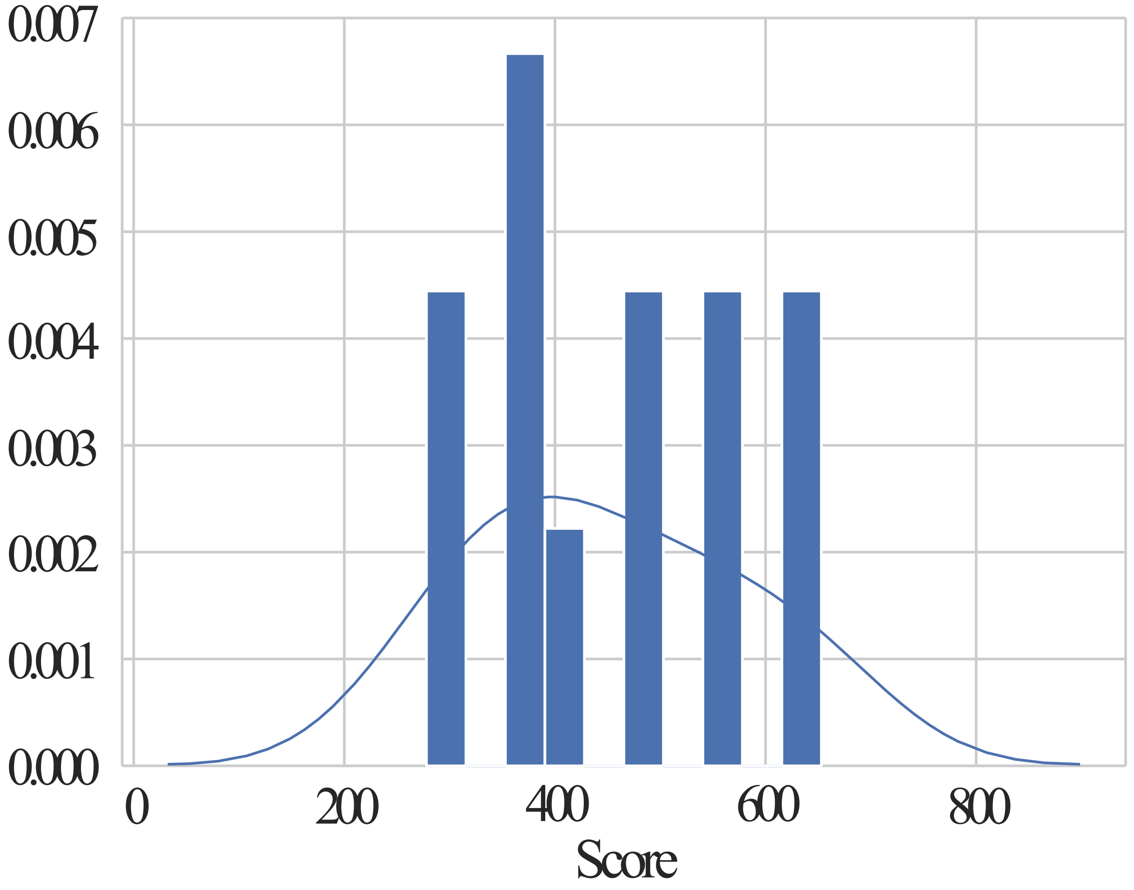


Many statistical tests only work if the underlying data follows a normal distribution – so-called parametric tests.

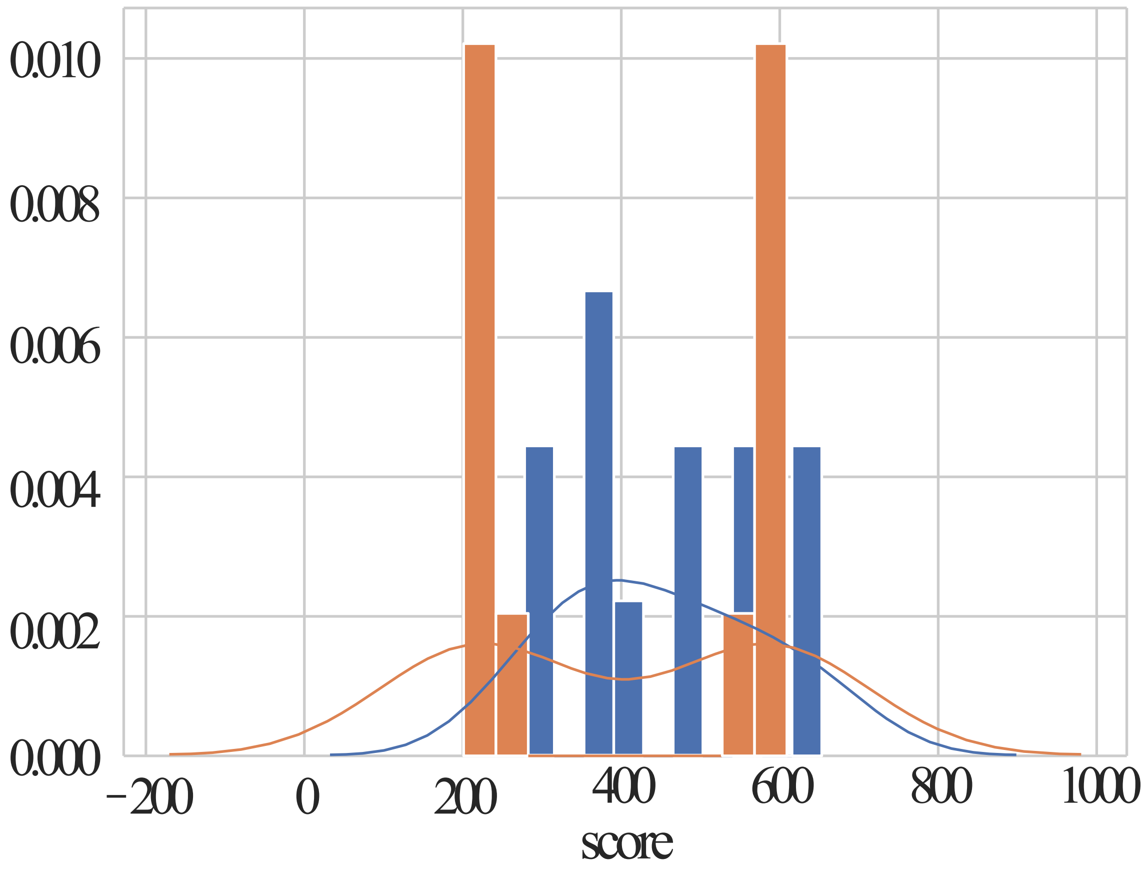
You need to check that your data is normally distributed first! (for instance, by plotting it)

COMPARE DISTRIBUTIONS (HISTOGRAMS, DENSITY)

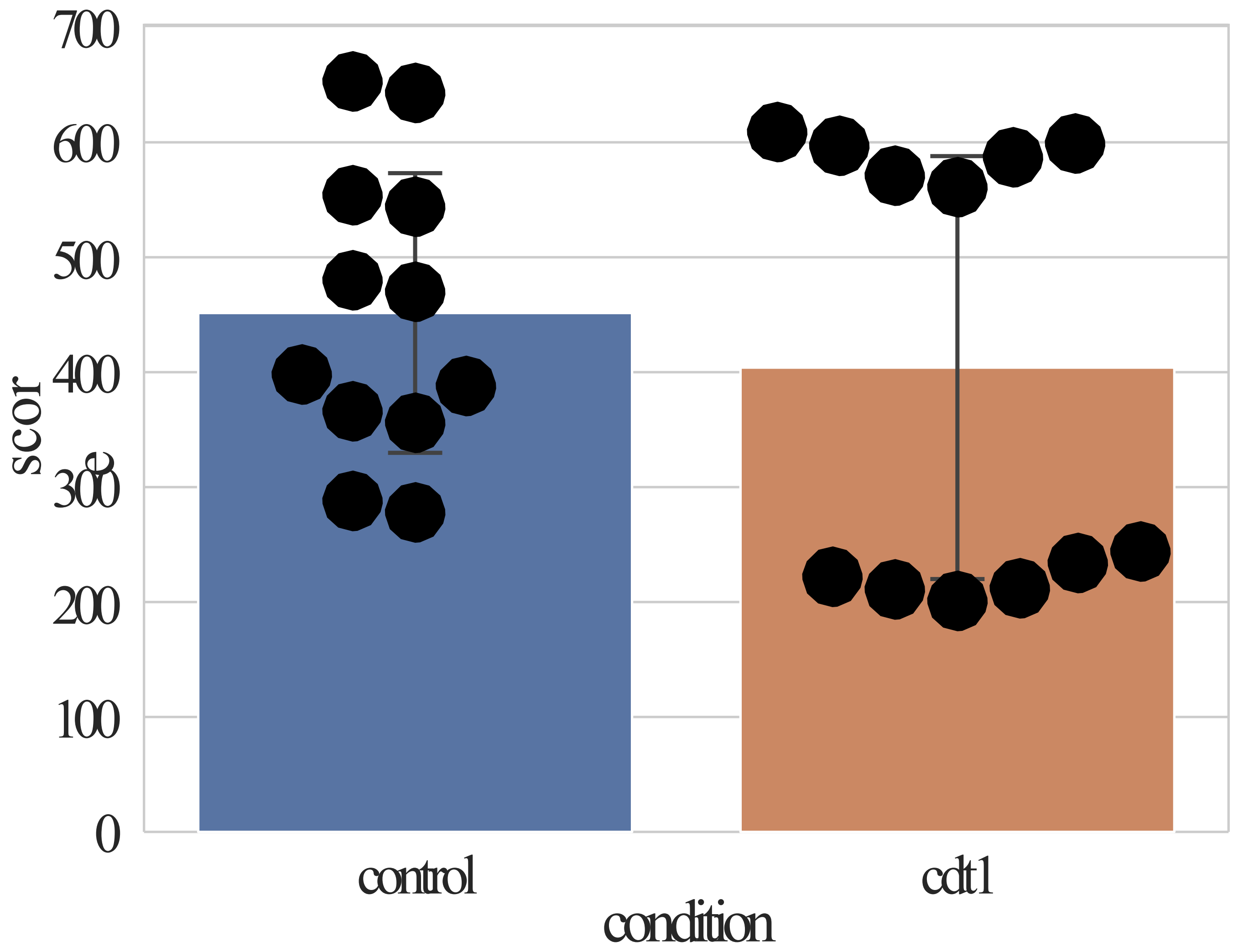


Control group

COMPARE DISTRIBUTIONS (HISTOGRAMS, DENSITY)

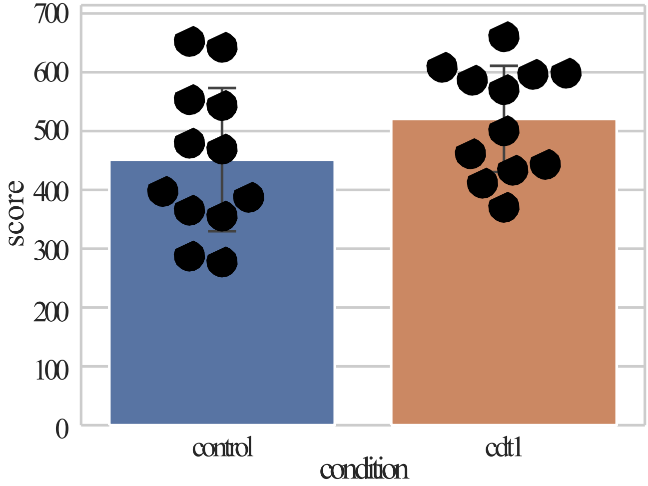


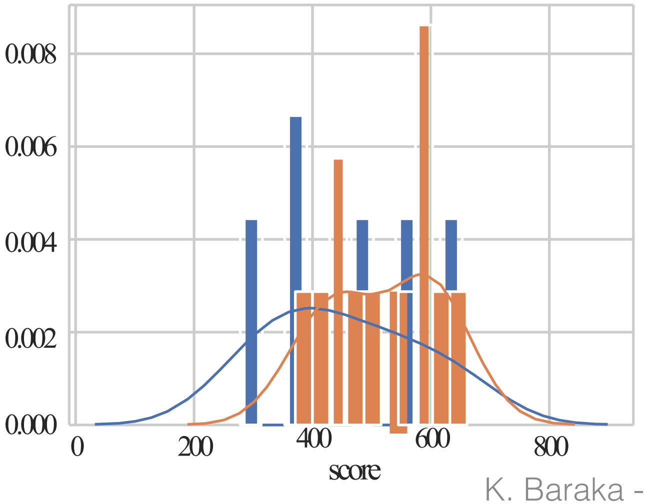
Control + condition group → beware the bimodal distribution!



Show the underlying data!

TWO ADDITIONAL DATASETS





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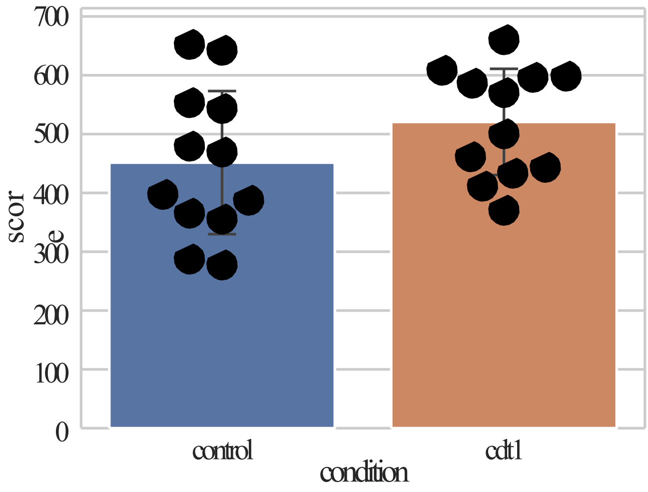
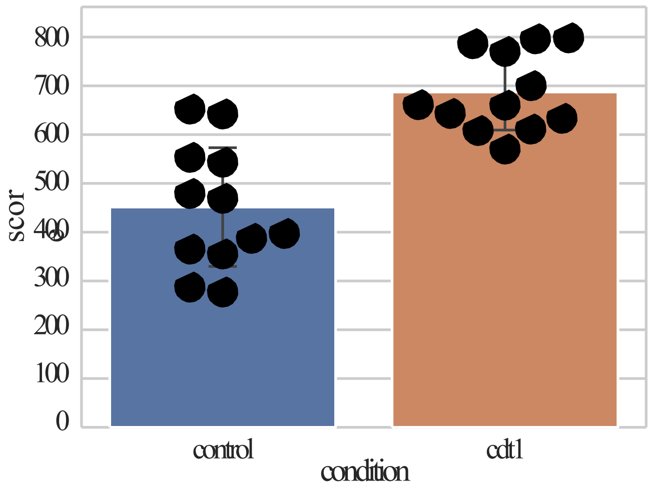
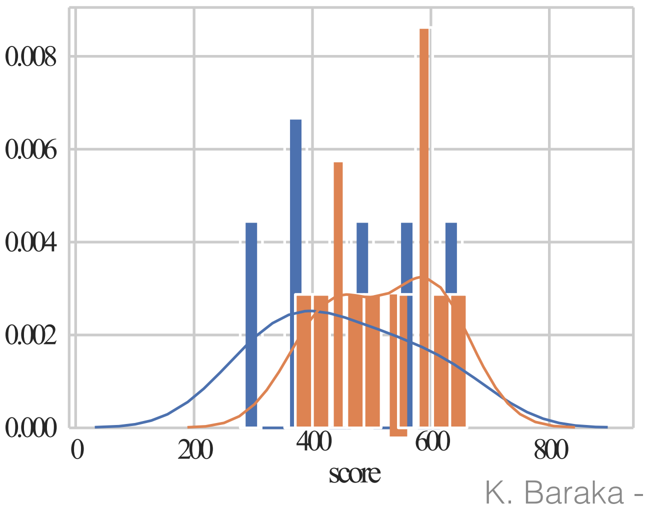
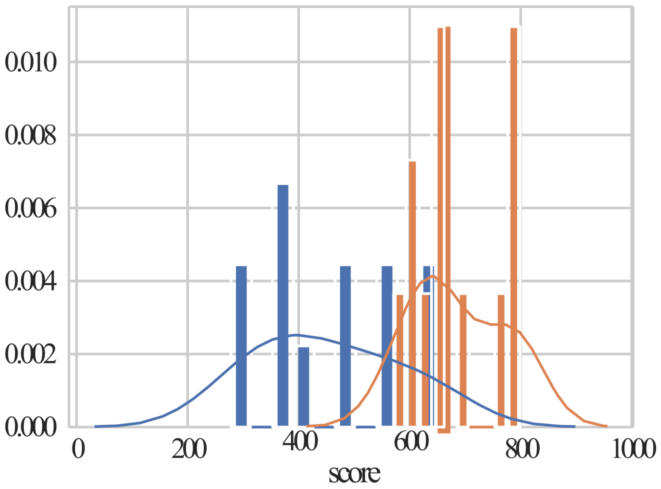
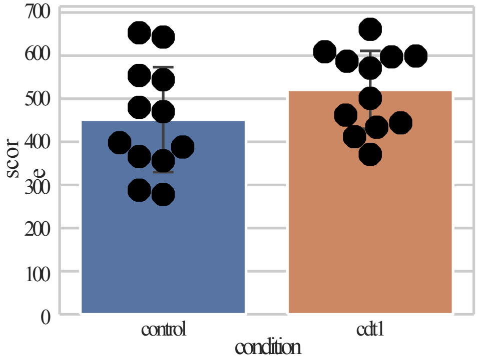






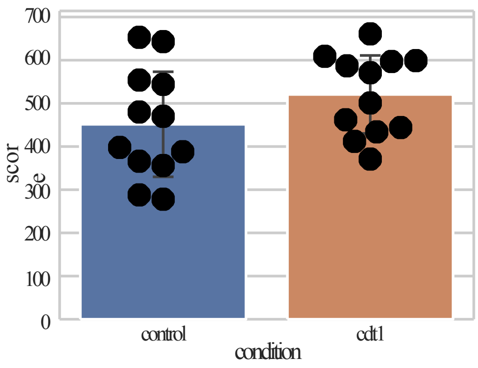


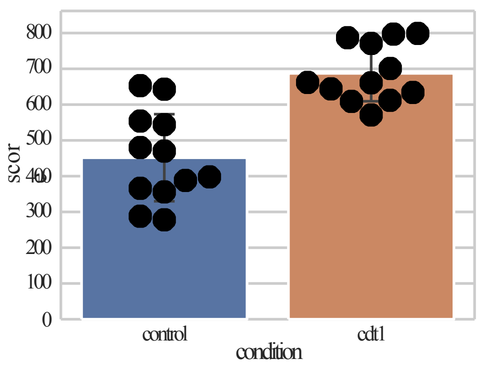
HOW BIG IS THE DIFFERENCE?



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

HOW BIG IS THE DIFFERENCE?





	mean	std
cdt1	516.5	85.3
control	451.5	127.1
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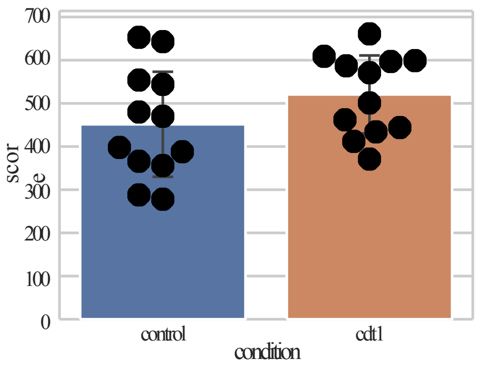
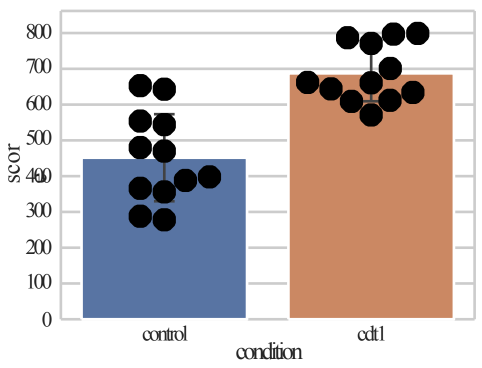
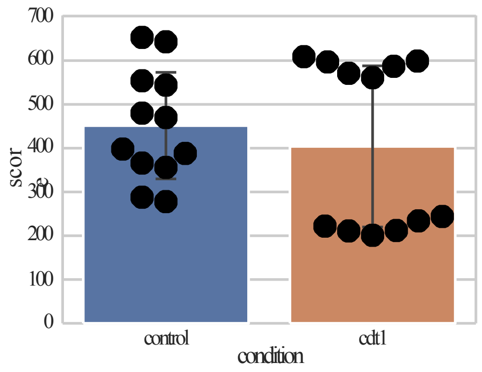
	mean
cdt1	687.3
control	451.5
$\mu_1 - \mu_2$	235.8

HOW BIG IS THE DIFFERENCE?





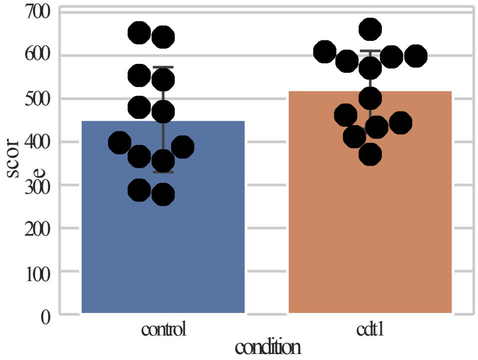


	mean	std
cdt1	516.5	85.3
control	451.5	127.1
$\mu_1 - \mu_2$	69.2	

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

	mean
cdt1	404.0
control	451.5
$\mu_1 - \mu_2$	47.5

HOW BIG IS THE DIFFERENCE?



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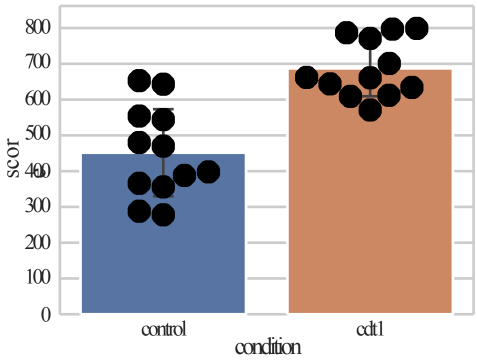

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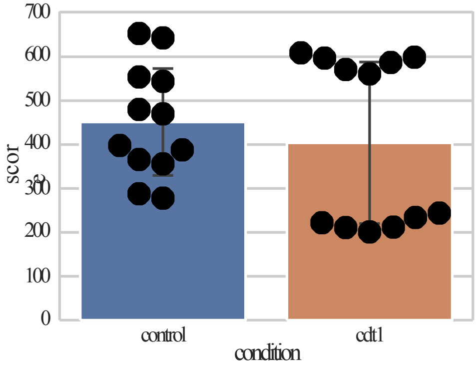
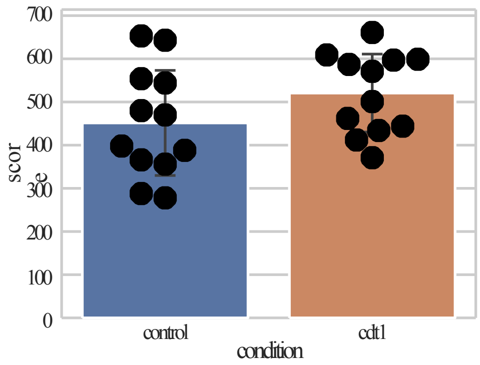


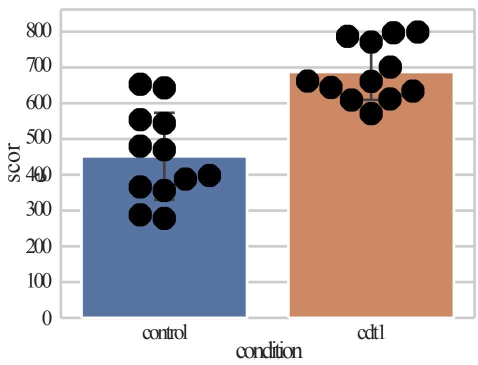
	mean
cdt1	404.0
control	451.5
$\mu_1 - \mu_2$	47.5

does not account for the variance in the dataset

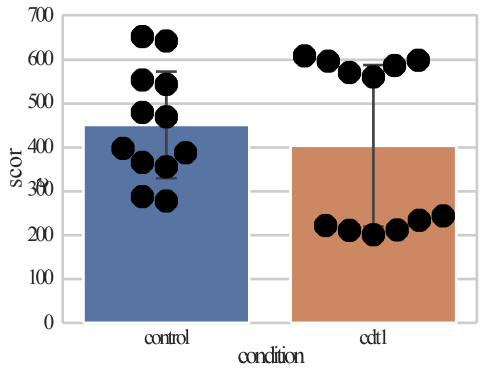
HOW BIG IS THE DIFFERENCE?



	mean	std
cdt1	516.5	85.3
control	451.5	127.1
$\mu_1 - \mu_2$	69.2	
$\frac{\mu_1 - \mu_2}{\sigma}$	0.62	



	mean	std
cdt1	687.3	81.5
control	451.5	127.1
$\mu_1 - \mu_2$	235.8	
$\frac{\mu_1 - \mu_2}{\sigma}$	2.21	



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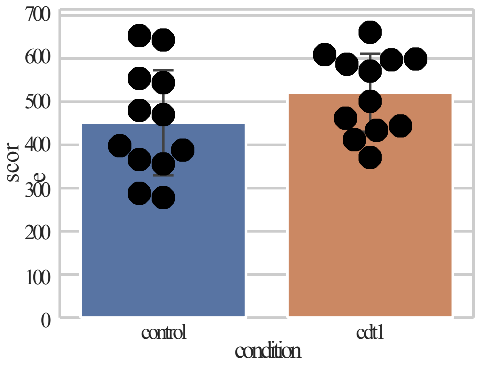

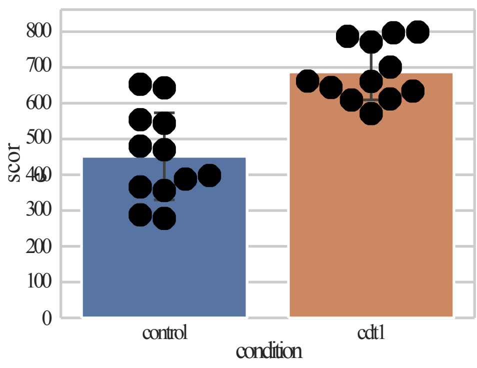

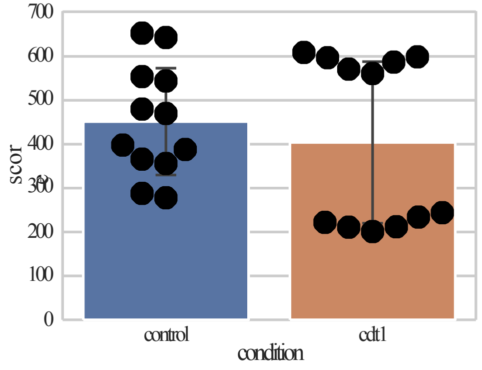

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A common measure of effect size: Cohen's $d = \frac{\mu_1 - \mu_2}{\sigma}$

→ [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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⇒ Meaning of a low p-value?

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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).'

HOW TO CALCULATE *P*?

- If parametric data, Student's *t*-test

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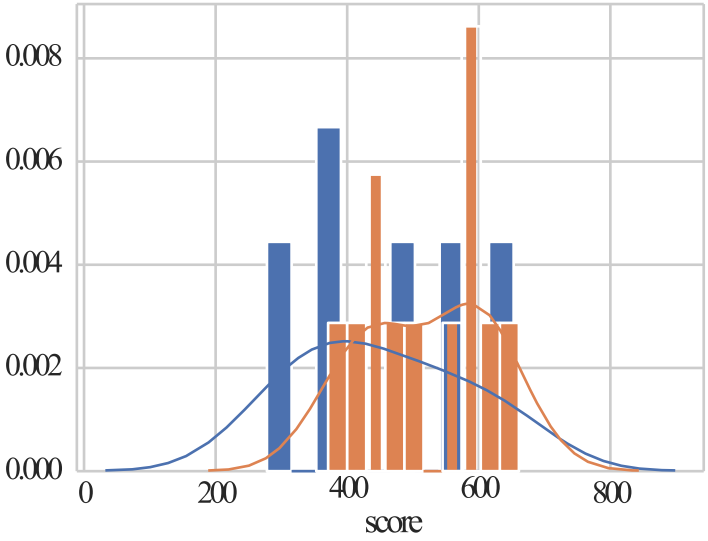

t statistic	-1.51
p	0.155

HOW TO CALCULATE *P*?

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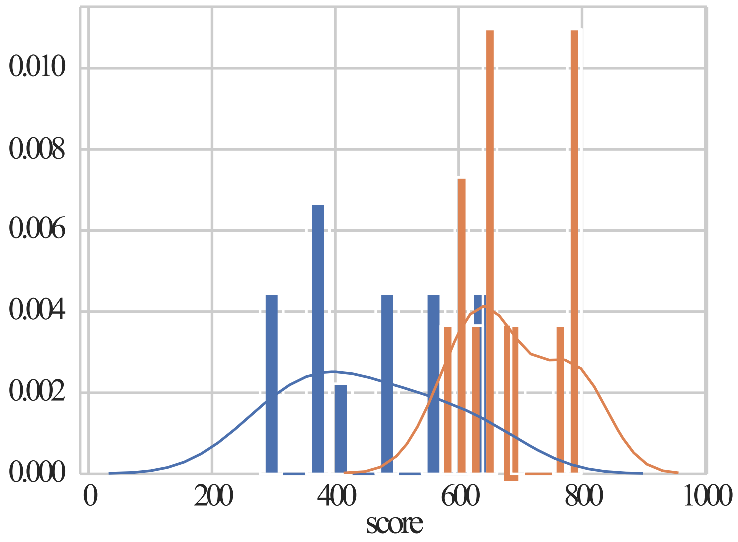

t statistic	-5.41
p	< 0.001

HOW TO CALCULATE *P*?

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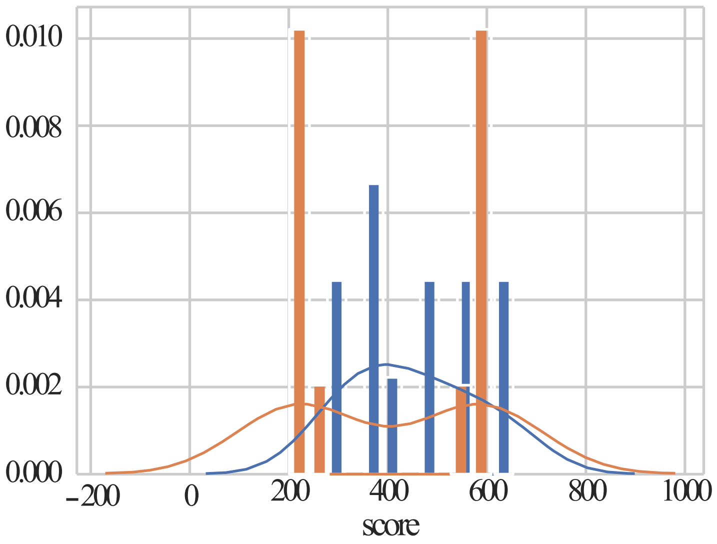

t statistic	0.71
p	0.48

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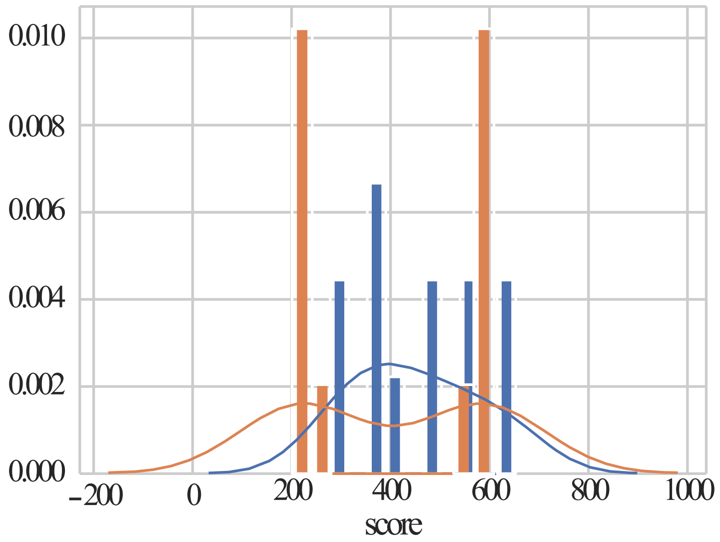

U statistic	46.0
p	0.07

See Wikipedia page for examples and interpreation of U

IMPACT OF *N*?

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

IMPACT OF *N*?

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

The higher n, the more unlikely the difference is due to chance

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

BE CAREFUL WITH "STATISTICALLY SIGNIFICANT"!

Gender assigned at birth	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

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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...wait... how big is our effect?

$M_{female} - M_{male} =$ 0.1 on a scale of 100??

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Cohen's d

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

“p-hacking”

Insights from reading assignment?

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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The boy who cried wolf

- Type I error:
  "there's a wolf!" (too optimistic: there's no wolf!)
- Type II error:
  ...the villager don't respond when there really is a wolf
  (too pessimistic: there is indeed a wolf!)

STATISTICAL POWER ANALYSIS

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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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- 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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Always report an effect size (for instance, Cohen's d)

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

Statistical tests: Interactive tools (also on the course webpage under Resources)

- Choosing a statistical test https://www.graphpad.com/support/faqid/1790/
- The decision tree for statistics https://www.microsiris.com/Statistical%20Decision%20Tree/

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  - Does a specific variable explain the difference?
  - Tools for quantitative data analysis
- Qualitative analysis
  - Thematic analysis
  - Analyzing observational data (e.g., videos)

OUR DATASET

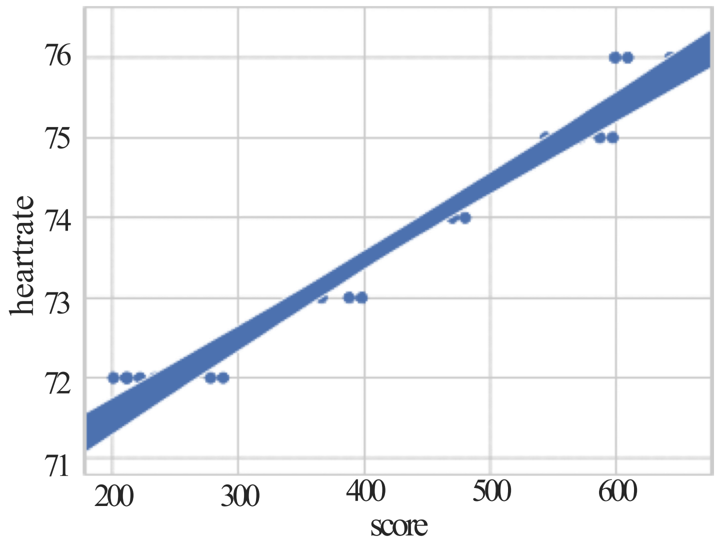
pptID	age	condition	score	heartrate
1	22	control	643	76
2	26	cdt1	234	72
3	24	control	356	73
4	24	cdt1	587	75
5	29	cdt1	561	75
6	31	control	544	75
7	20	control	470	74
8	23	cdt1	212	72
9	23	control	388	73
10	22	cdt1	201	72
11	28	control	278	72
12	29	cdt1	599	76
13	27	control	366	73
14	21	cdt1	597	75
15	22	cdt1	571	75
16	30	control	554	75

ASSOCIATION

What is the degree of association between two variables?

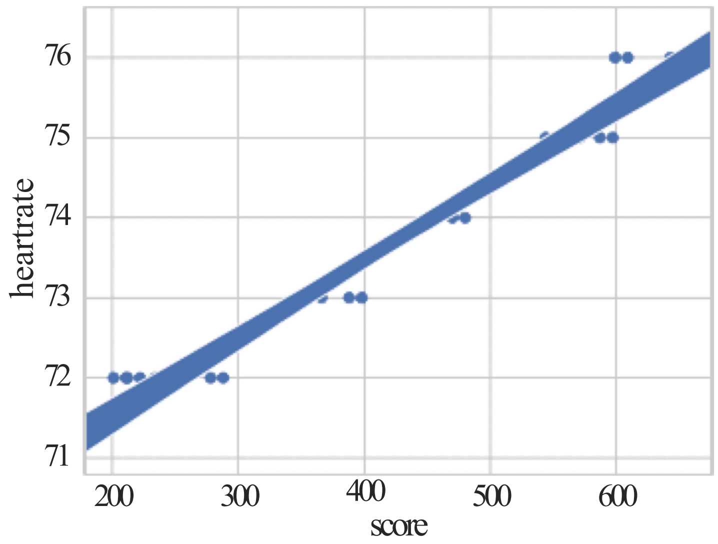
→ main tool: correlation

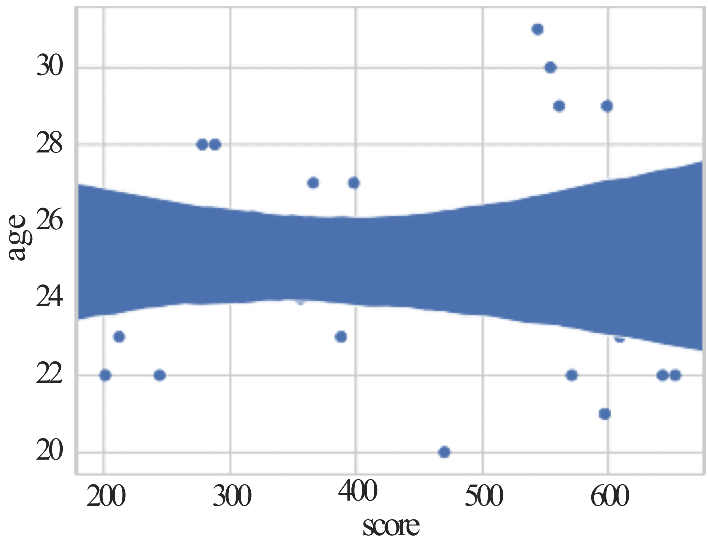
PEARSON CORRELATION



Pearson's correlation	
ρ	0.98
p	< 0.001

PEARSON CORRELATION

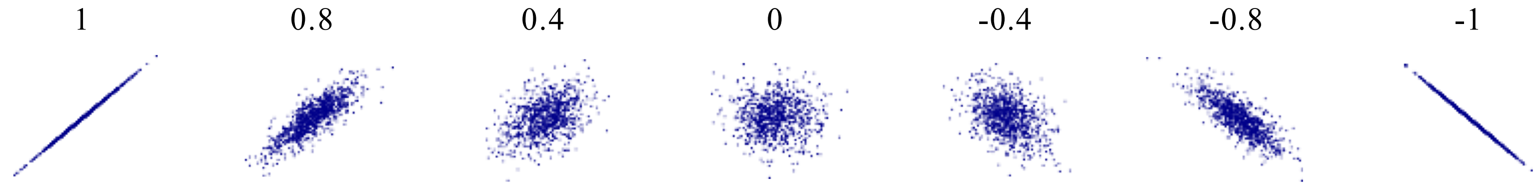




Pearson's correlation	
ρ	0.98
p	< 0.001

Pearson's correlation	
ρ	-0.022
p	0.92

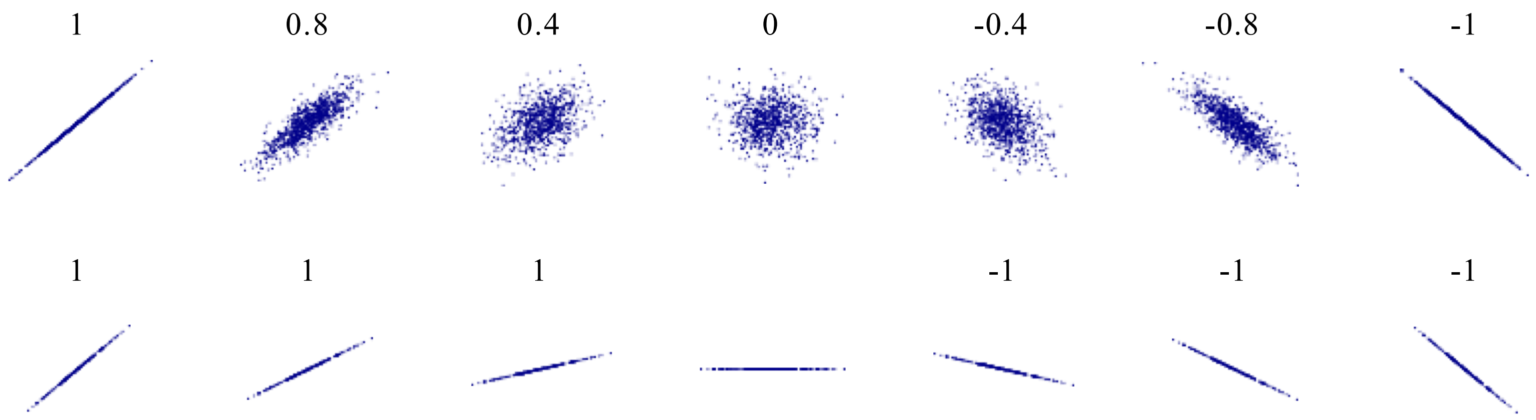
INTERPRETATION OF ρ



ρ reflects the degree of linearity and direction

Source: Wikipedia

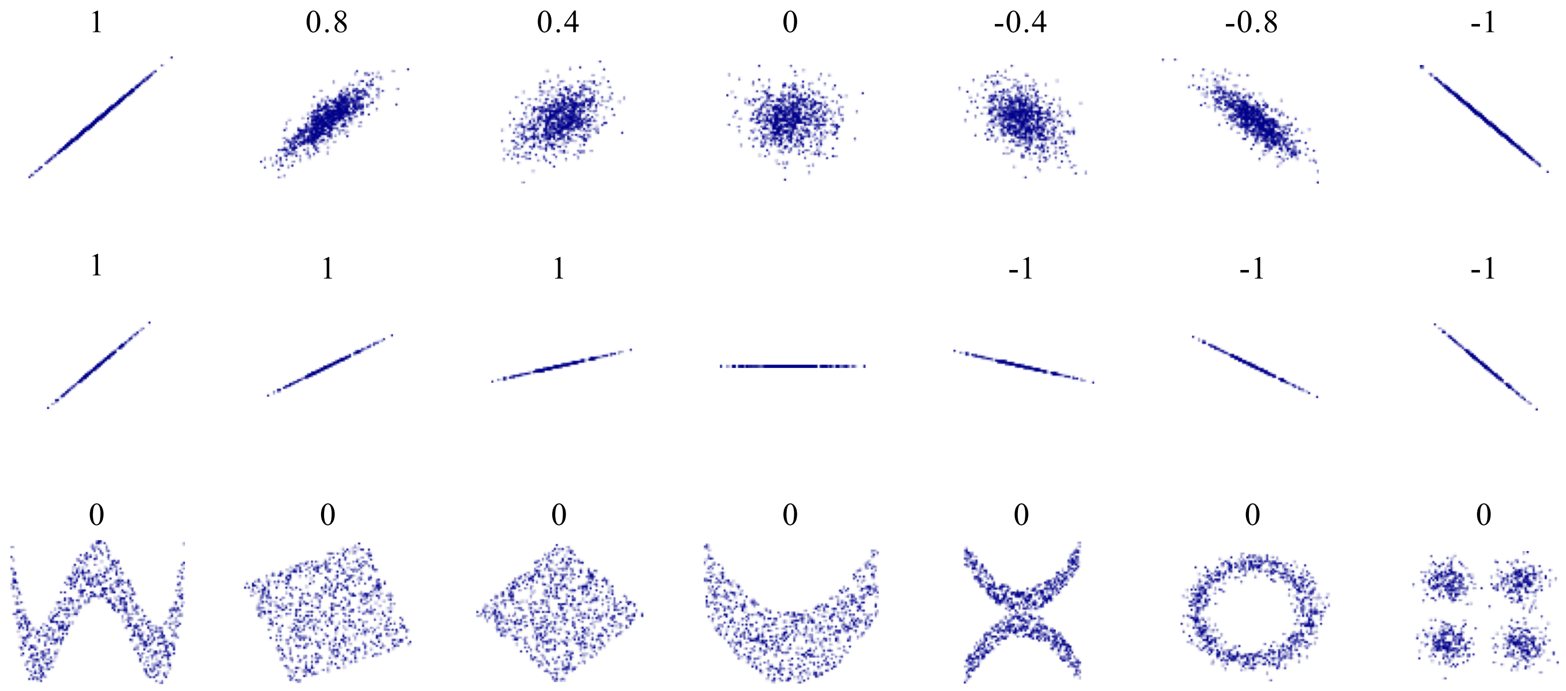
INTERPRETATION OF ρ



ρ does not reflect the slope of the regression line

Source: Wikipedia

INTERPRETATION OF ρ



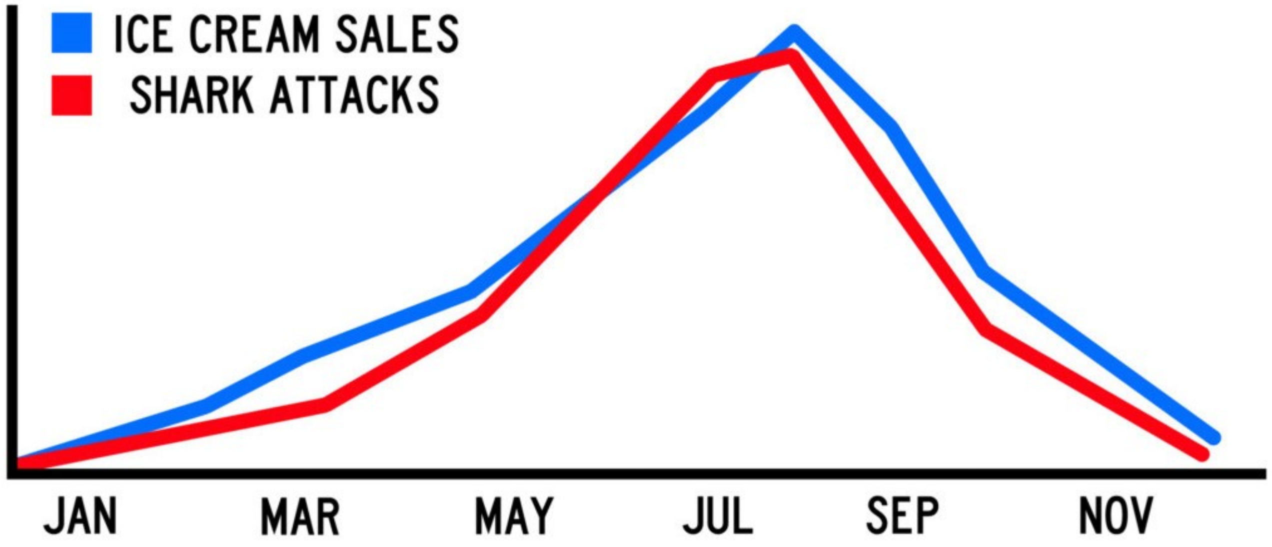
ρ does not capture non-linear interactions

Source: Wikipedia

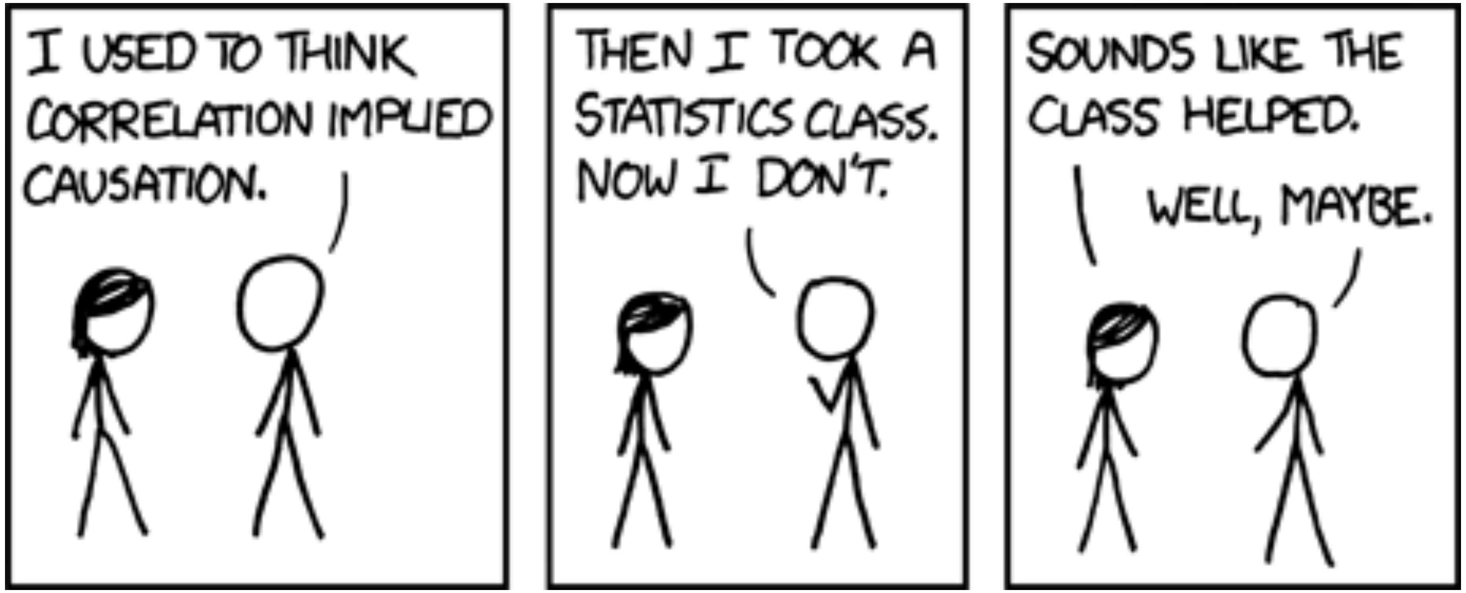
OTHER MEASURES OF ASSOCIATION

- 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



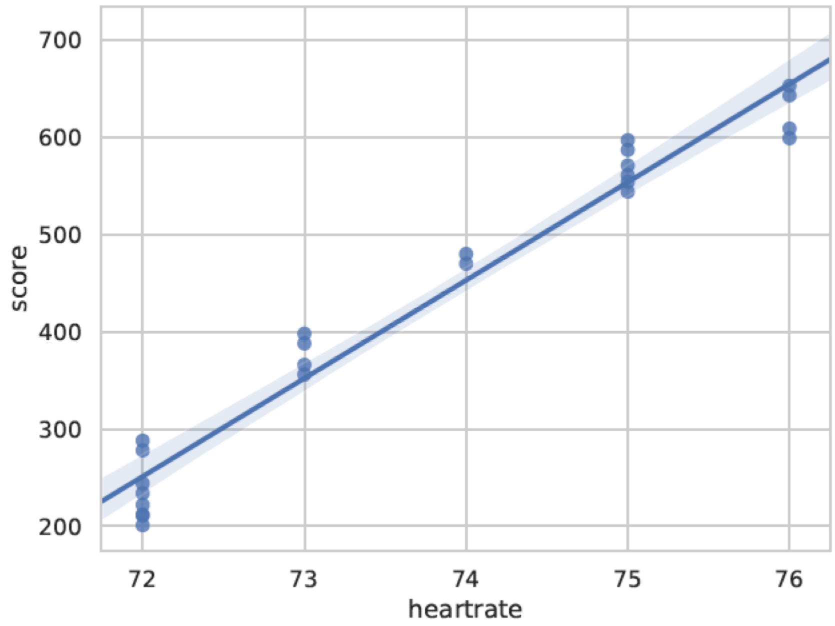
CORRELATION IS NOT CAUSATION



Source: XKCD

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"

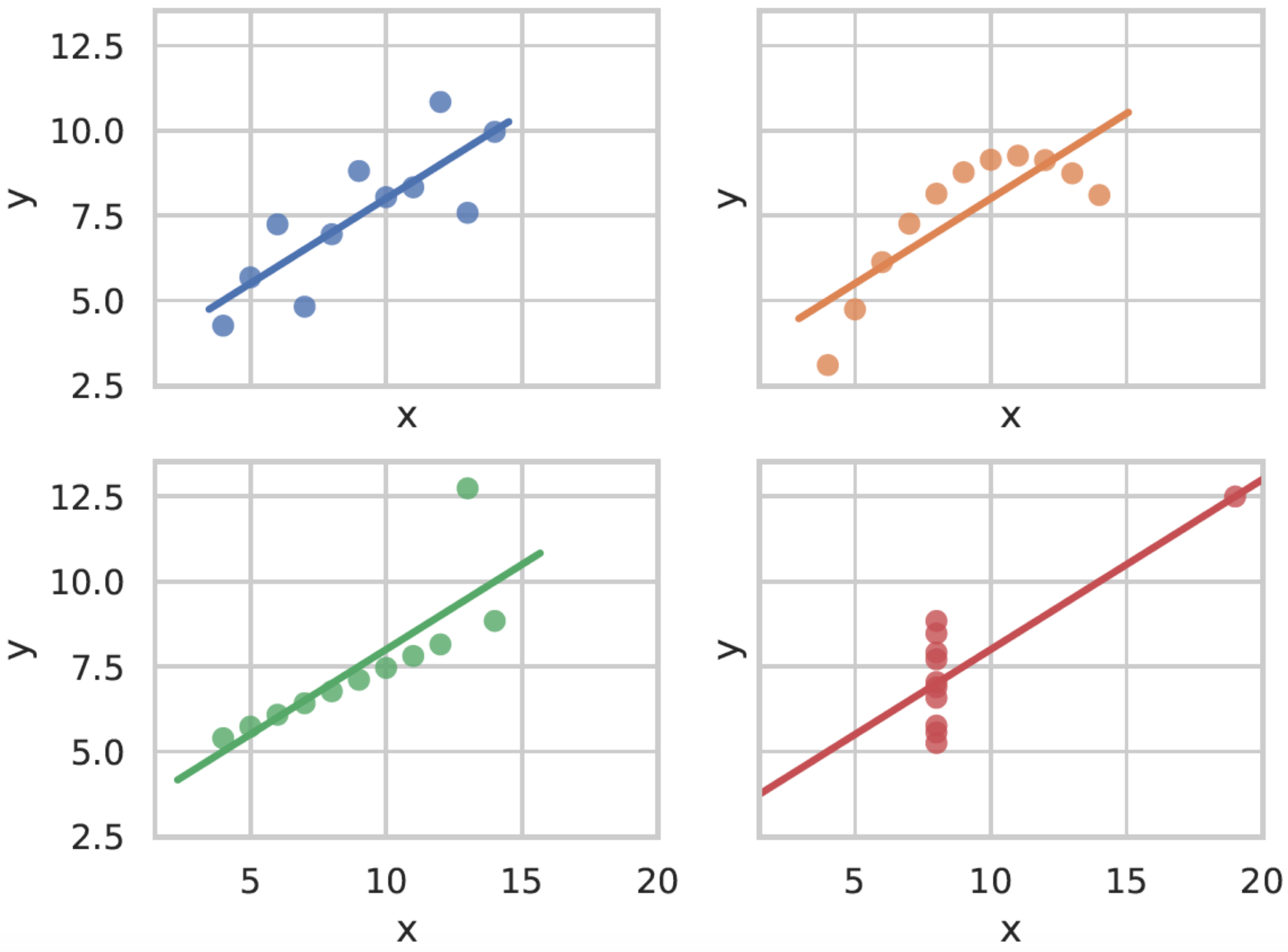
TO CONCLUDE: ANSCOMBE'S QUARTET

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



Outline

- Quantitative analysis
  - Are my groups different?
  - Does a specific variable explain the difference?
  - Tools for quantitative data analysis
- Qualitative analysis
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THE TOOLS

Data analysis tools:

- R: www.r-project.org
- Python's Pandas: pandas.pydata.org

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- R: www.r-project.org
- Python's Pandas: pandas.pydata.org

Jupyter notebooks are a great way of creating an interactive, easy-to-follow, data analysis.

(SIDE NOTE ON PYTHON FOR DATA ANALYSIS)

Python is the leading language in data analysis/data mining/machine learning. Learn it!

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

Outline

- Quantitative analysis
  - Are my groups different?
  - Does a specific variable explain the difference?
  - Tools for quantitative data analysis

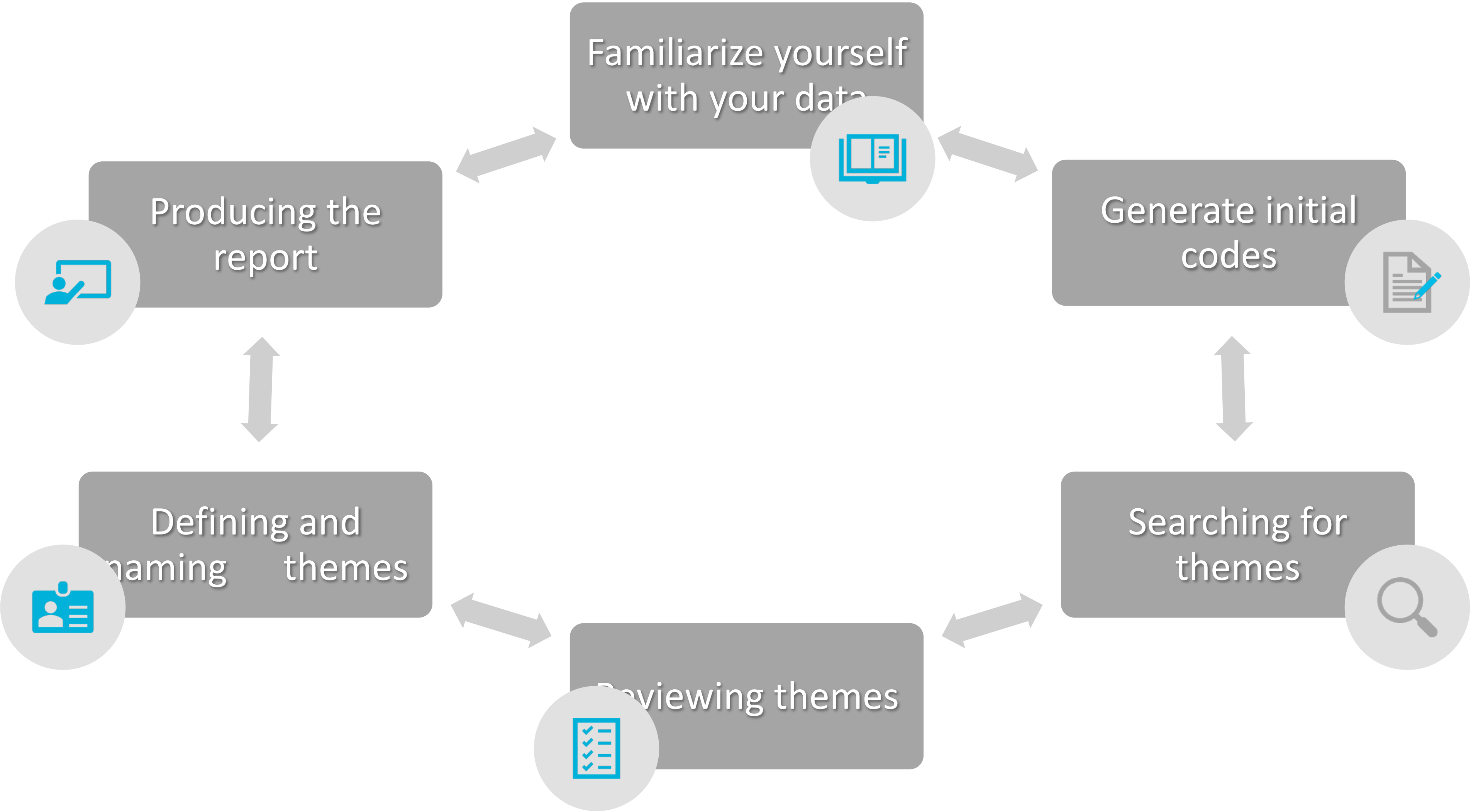
- Qualitative analysis
  - Thematic analysis
  - Analyzing observational data (e.g., videos)

Thematic Analysis

- '... method for identifying, analyzing and reporting patterns (themes) within data.'
  - Systematic method for data analysis
- Flexible & Foundational
  - Range of data
  - Large and small datasets alike
  - Applied to various methodological frameworks
  - Multiple approaches to align with theoretical assumptions
- Great for beginners!

Braun & Clarke (2006, 2013)

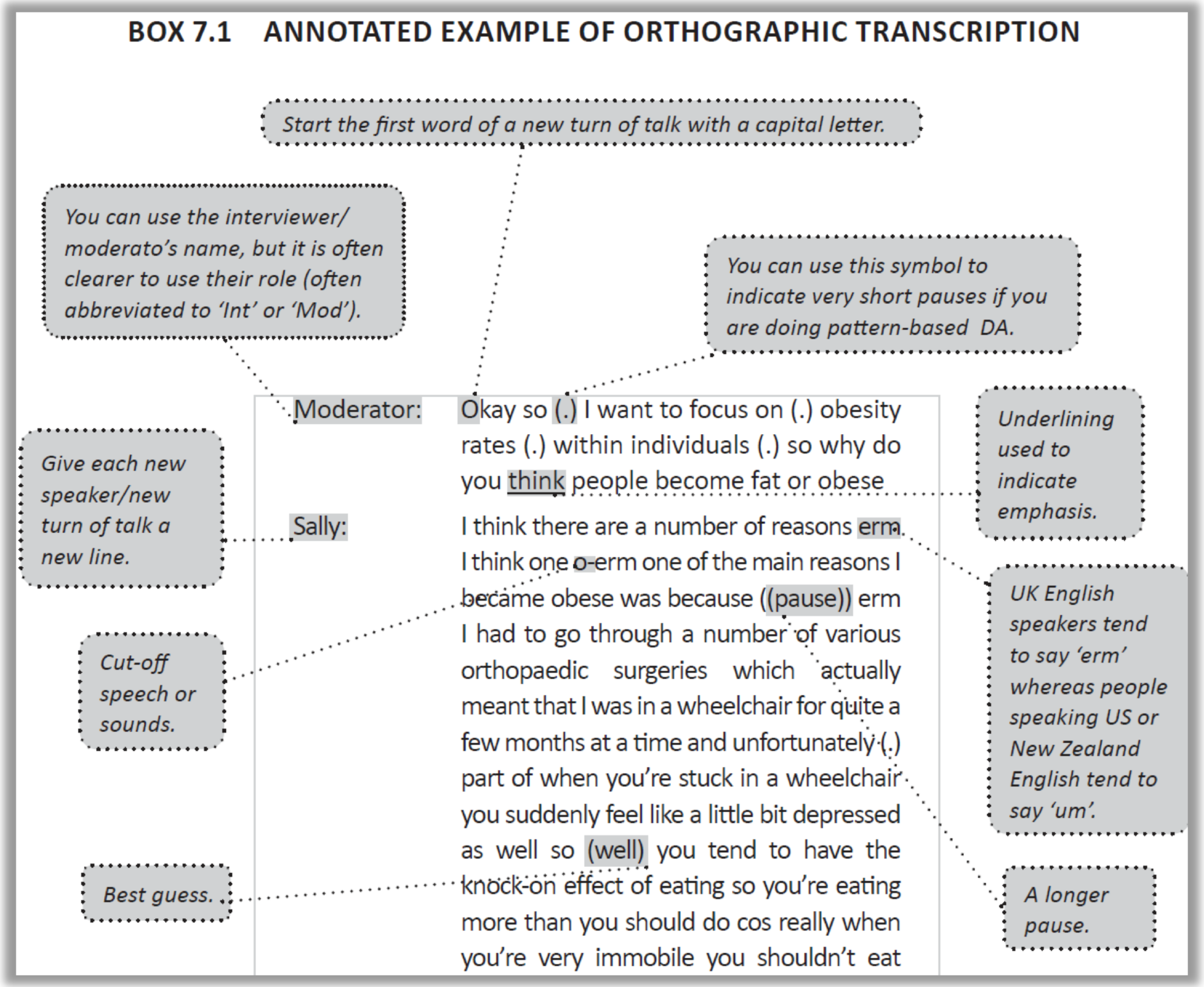
Phases of Thematic Analysis



Braun & Clarke (2006)

1. Familiarize yourself with your data

- Transcribing data
- Reading and re-reading the data
- Noting initial ideas



Braun & Clarke (2006)

2. Generate Initial Codes

- Coding relevant features across entire dataset
- Organizing data into meaningful groups
  - The most basic element of the raw data
- Data-driven or theory-driven? Entire data set or specific portion?
- Collating data relevant to each code
- Manually or in qualitative software

Braun & Clarke (2006, 2013)

2. Generate Initial Codes

Data extract	Coded for
it's too much like hard work I mean how much paper have you got to sign to change a flippin' name no I I mean no I no we we have thought about it ((inaudible)) half heartedly and thought no no I jus- I can't be bothered, it's too much like hard work. (Kate F07a)	1. Talked about with partner 2. Too much hassle to change name

Table 9.2 Coding in thematic analysis: a worked example of the early stages

Data	Codes
Moderator: What do you think about the modern lifestyle and weight and obesity? Do you think that's had a big effect?	
Sally: I think it's had a huge effect because I remember, say forty years ago, we had a lot more industry in this country, so people were actually what you might call working harder. I know we all work hard, but erm working more...	Important factor influencing obesity Modern lifestyles are sedentary Lack of physical work nowadays Hard physical work is beneficial to avoid obesity Times have changed

Braun & Clarke (2006 – Figure 1, 2013 – Table 9.2)

3. Searching for themes

- Collating codes to potential (or candidate) themes
  - units of analysis
- Start thinking about the relationship between...
  - Codes, themes, different levels of themes, and the ‘Miscellaneous’
- Gathering all data relevant to each potential theme
- Using tables, mind-maps, organize theme piles with post-its, etc.

Braun & Clarke (2006, 2013)

3. Searching for themes

Table 10.1 Candidate themes showing *selected* associated codes

2. Modern Life			
2.1. Those halcyon days of yore	**2.2. Modern life is rubbish**	**2.2.1. Technology trumps all**	**2.3. They don't get no education**
'Dadadada' – common story – a past we all recognise Different lifestyles Past – no such thing as 'exercise'; physical activity an integral part of life Times have	Cost as a bottom line that determines what you eat Time poor (money rich) 'Bad foods' associated with positive things in ads/marketing Advertising/ marketing of junk food (to children) problematic Children engage in	Children engage in sedentary 'play' Modern technology encourages/ facilitates obesity/lack of exercise Negative impacts of technology She's not responsible for	Adequate socialisation: cooking needs to be learned (taught in home or school) Children's socialisation is important (but inadequate) Irresponsible parenting: adults pander to children; don't regulate children's eating towards healthy foods; feed them unhealthy food

Braun & Clarke (2013)

4. Reviewing themes

- Check if themes work in relation to extracted codes
  - (Level 1)
- Generate a candidate thematic map
  - Illustration of the overall conceptualization of data patterns and relationships
- Check if themes work with the data set
  - (Level 2)

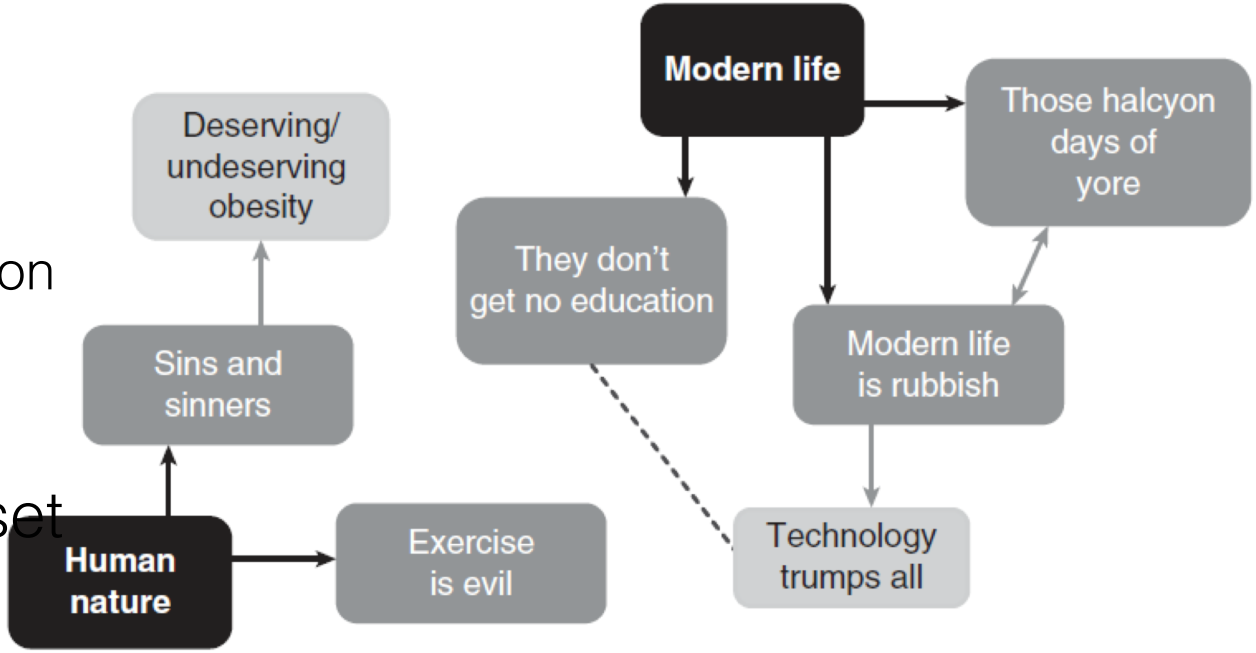


Figure 10.1 Our candidate overarching themes, themes and subthemes

Braun & Clarke (2006; 2013)

5. Defining and naming themes

- Define and refine the *essence* of what each theme is about
- Refine the story the analysis tells
  - e.g., sub-themes, overarching themes
- Generate clear definitions
  - *Can I describe the scope in a sentence or two?*
- Working titles → concise and clear names

Braun & Clarke (2006)

5. Defining and naming themes

BOX 11.1 THEME DEFINITIONS FROM OUR FG DATA

Modern life

An overarching theme which explains weight-gain and obesity as a result of the features of our contemporary society (rather than human nature, although these two intersect). Frequent references to an idealised past are discussed in the theme *those halcyon days of yore*. This mythical past was one in which people led healthier lives, and was clearly contrasted with the way the present was talked about. The theme *modern life is rubbish* captures two facets of talk about the present. First, the structural organisation and functioning of society was described as enabling (even demanding) all sorts of *unhealthy* behaviours; second, this was seen to produce 'rubbish' people who (understandably) make unhealthy choices. Within this, modern technology was situated as dominating our lives, and being an enemy of healthiness, described in the subtheme *technology trumps all*. The final theme, *they don't get no education*, highlights contemporary failures of education, both formal and informal, so that people are ignorant of ways to be healthy, and subject to the impacts of subsequent 'unhealthy' choices.

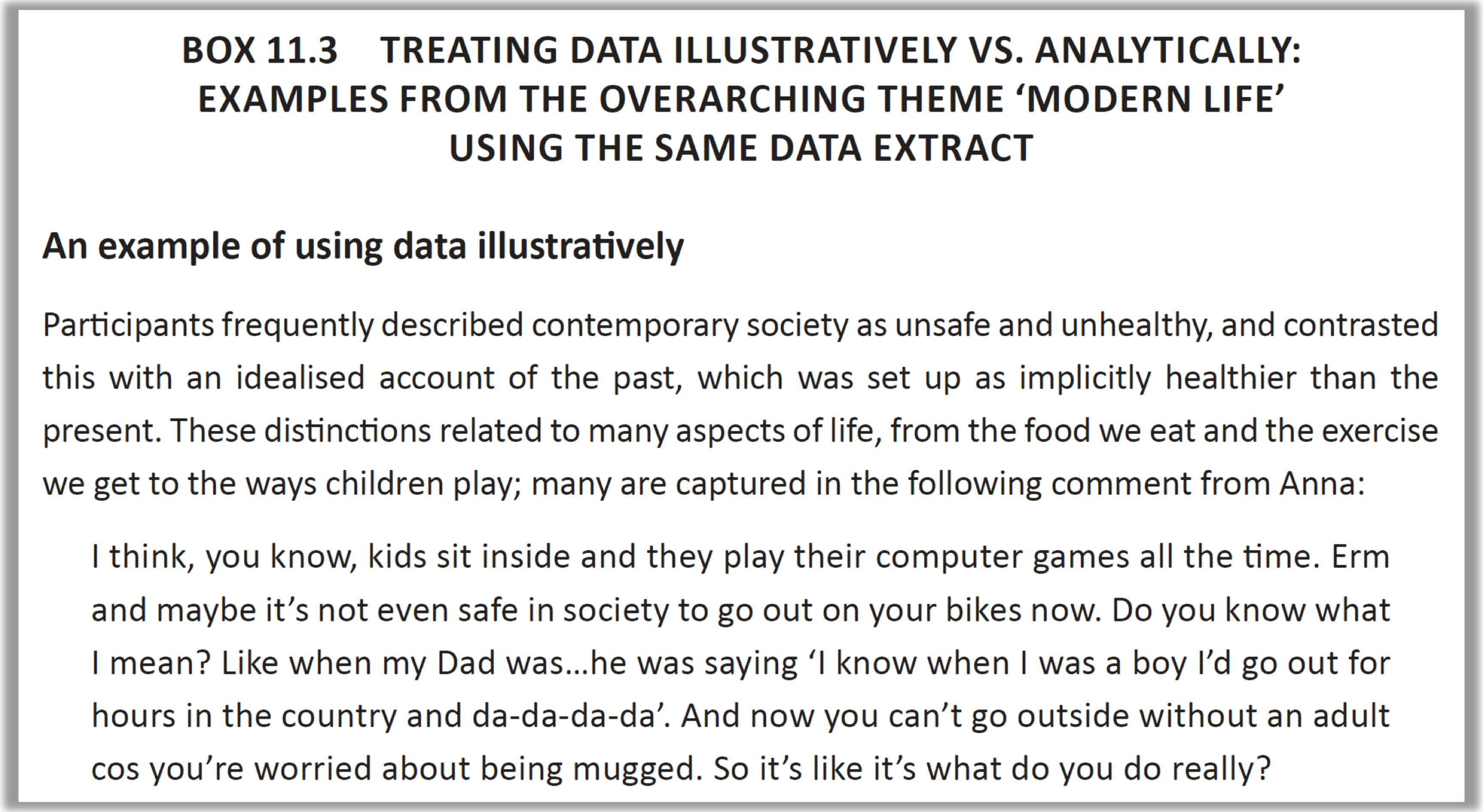
Braun & Clarke (2013)

6. Producing the report

- Selection of vivid, compelling extract examples
- Final analysis of selected extracts
- Relating the analysis back to the research question and literature
- Producing a scholarly report of the analysis

Braun & Clarke (2006)

6. Producing the report


BOX 11.3 TREATING DATA ILLUSTRATIVELY VS. ANALYTICALLY: EXAMPLES FROM THE OVERARCHING THEME 'MODERN LIFE' USING THE SAME DATA EXTRACT

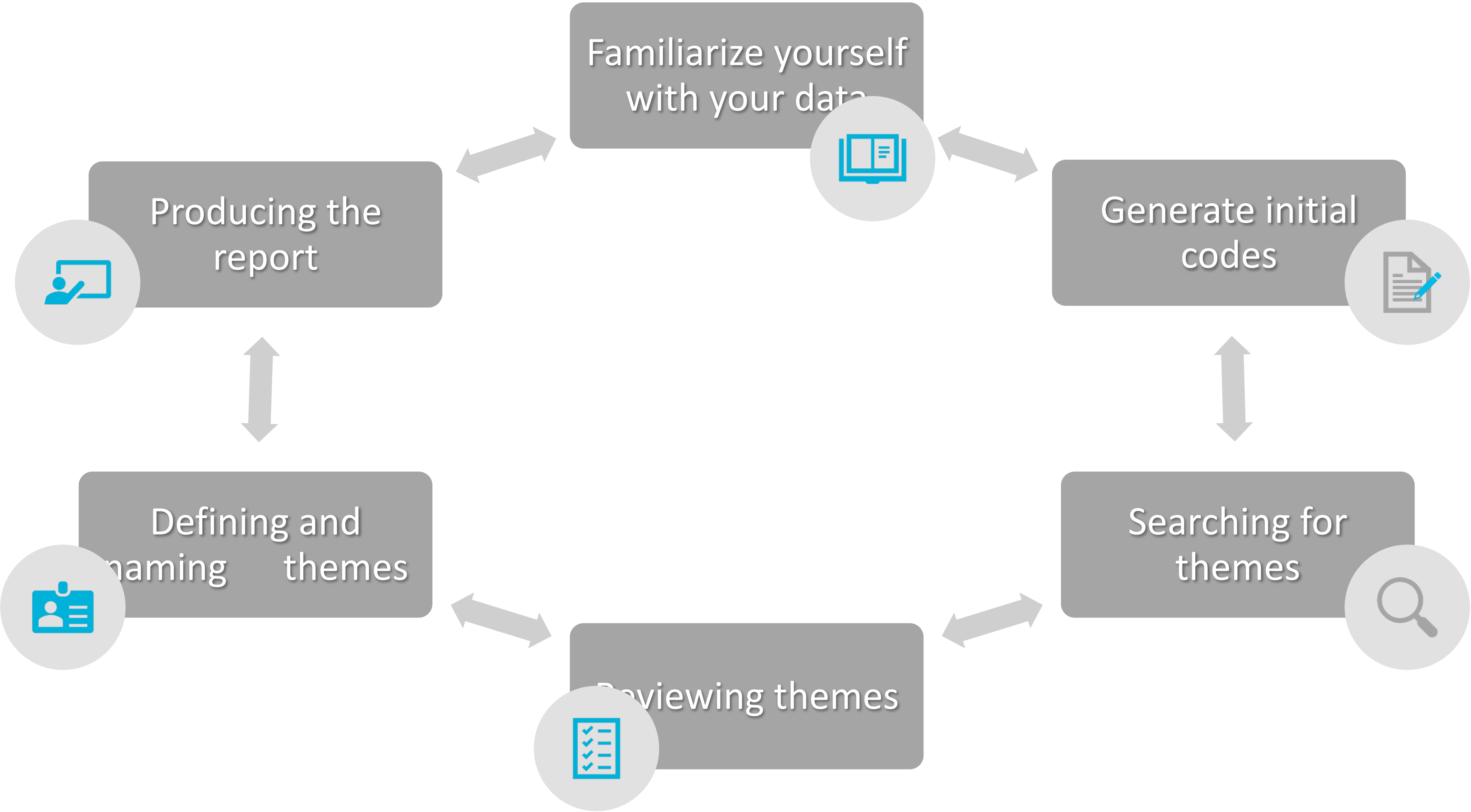
An example of using data illustratively

Participants frequently described contemporary society as unsafe and unhealthy, and contrasted this with an idealised account of the past, which was set up as implicitly healthier than the present. These distinctions related to many aspects of life, from the food we eat and the exercise we get to the ways children play; many are captured in the following comment from Anna:

> I think, you know, kids sit inside and they play their computer games all the time. Erm and maybe it's not even safe in society to go out on your bikes now. Do you know what I mean? Like when my Dad was...he was saying 'I know when I was a boy I'd go out for hours in the country and da-da-da-da'. And now you can't go outside without an adult cos you're worried about being mugged. So it's like it's what do you do really?

Braun & Clarke (2013)

Phases of Thematic Analysis



Braun & Clarke (2006)

Thematic Analysis

Strengths	Potential Pitfalls
Flexibility	'lack substance'
Relatively easy and quick to learn and to do	Weak or unconvincing analysis
A great 'starter' to qualitative analysis	Mismatch between data and analytic claims
Usefully summarize key feature of a large body of data	Mismatch between theory and analytic claims
Allows for social and psychological interpretations of data	Fails to spell out its theoretical assumptions, or clarify how it was undertaken, and for what purpose.
Results are accessible and understandable	

Braun & Clarke (2006;2013)

Computer-Assisted Qualitative Data Analysis Software (CAQDAS) e.g., NVivo

- Facilitate coding, as well as organization and retrieval of coded data
- Allow for conceptual mapping to explore relationships
- Tools to *assist* with coding and analysis
  - Interpretative process of the researcher
  - Requiring defined frameworks and approaches

- Braun & Clarke (2006): Using thematic analysis in psychology
  - Braun & Clarke (2006) Using thematic analysis in psychology, Qualitative Research in Psychology, 3:2, 77-101.
- Braun & Clarke (2013): Section 3: Successfully analysing qualitative data
  - Braun, V., & Clarke, V., (2013). *Successful Qualitative Research: A practical guide for beginners*. Great Britain: Sage.
    - See also the accompanying online resources here.
- Denscombe (2014): Ch. 16 Qualitative Data
  - Denscombe, M. (2014). The Good Research Guide: For small-scale social research projects (5th ed.). Great Britain: Open University Press/McGraw-Hill Education.
- Flick (2014): Ch. 26 Thematic Coding and Content Analysis
  - Flick, U. (2014). *An Introduction to Qualitative Research* (5th ed.). Great Britain: Sage.
- Smith, J. A., Flowers, P., & Larkin, M. (2009). *Interpretative phenomenological analysis: Theory, method and research*. London: Sage.

Qualitative Analysis

Resources

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Strategies for Observation

Structure

- Naturalistic
- Systematic

Participation

- Participant observer
- (Self-observation)

Denscombe (2014); Bell (2006)

Naturalistic observation

- Descriptive account of behavioral events in their natural settings
- Tracked chronologically over time
- Preliminary step to identify salient behaviors and environmental events
- Approaches:
    - Descriptive account
    - AEIOU
    - A-B-C Observation

Denscombe (2014); Hintze et al. (2002)

Naturalistic observation: Advantages and disadvantages

Advantages	Disadvantages
Ease of use	Inclination to over interpret
Rich description of environment	Tendency for confirmatory search
Grounding preliminary step	Limited conclusions when considered alone

Hintze et al. (2002)

Systematic observation

- Introduces an operationalized system to observe reality
- Five characteristics:
  - Specific behaviors
  - Operationally define behaviors a priori
  - Standardized procedures for observation
  - Specifically selected times and places for observation
  - Standardized procedures for scoring and summarizing of data
- *Quantifies* behavior

Denscombe (2014); Hintze et al. (2003)

Observation Schedules

- Protocol for observation
- Specifies *what* is being observed and *how* those things should be measured
- Ensures consistency in observation across researchers and events → *Inter-observer reliability*
- Collect quantitative data based on counts, amounts, and frequencies

Denscombe (2014)

Frequency

Figure 2. Example of frequency recording. Target behaviors include getting out of the seat (OS), calling out (CAL), and teacher redirection (TR).

Date: May 13

Observer: Art Van Delay

Time	OS	CAL	TR
9:00 a.m. to 10:00 a.m.	XXX	XXXXX	XXXXXXX
10:00 a.m. to 11:00 a.m.	X	XXX	XXXX
11:00 a.m. to 12:00 p.m.	XX	X	XXXXXX
Total	6	9	17
Calculate rate	6/3hr	9/3hr	17/3hr
	2 per hour	3 per hour	5.6 ~6 per hour

What can I observe?

Hintze et al. (2003)

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Duration

Figure 3. Example of duration recording for thumb sucking.

Student: Tori | Observer: C. Kramer

Behavior: Thumb sucking

Date: April 18

Time start: 10:10 Thumb sucking (separate incidents)		Time stop: 10:30 Elapsed time per episode
1		1 min 17 s
2		6 min 42 s
3		2 min 11 s
4		7 min 26 s
5		52 s
	Total:	18 min 28 s
	Average duration per episode:	3 min 42 s

What can I observe?

Hintze et al. (2003)

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Individual Attributes

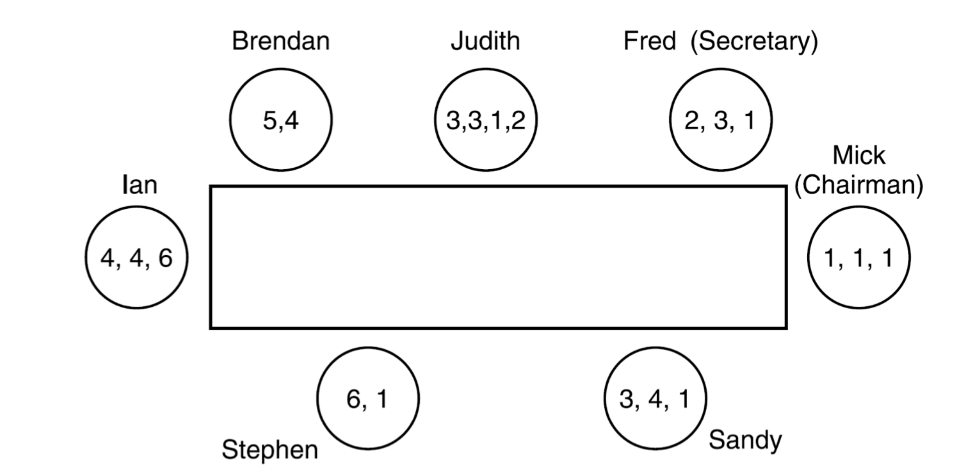

Figure 11.1 Table plan recording individual behaviour according to categories.

Participants	Categories						
	1	2	3	4	5	6	Totals
Chairman (Mick)	✓✓✓						3
Secretary (Fred)	✓	✓	✓				3
Judith	✓	✓	✓✓				4
Brendan				✓	✓		2
Ian				✓✓		✓	3
Stephen	✓					✓	2
Sandy	✓		✓	✓			3
Totals	7	2	4	4	1	2	

Figure 11.2 Chart recording total number of entries for each behaviour category.

What can I observe?

Bell (2006)

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Combination

Participants	
Mick	///=
Fred	
Judith	/≡//
Brendan	//
Ian	////=/≡
Stephen	//
Sandy	/=//
Multiple speaking	///

Figure 11.3 Example of a chart recording speaking contributions by individuals.

What can I observe?

Bell (2006)

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Research Question

Frequency

Duration

Latency

Individual Attributes

Combination

→ *Plus fieldnotes!*

What can I observe?

Denscombe (2014); Bell (2006); Hintze et al. (2003)

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Sampling and observation

- Incorporate a representative sample of the event in question
- Deliberate selection of people or events to obtain an optimal cross-section of the research population
    - Time-sampling
        - Snapshots at set intervals
    - Set instances
        - Tracking the activities of specific individuals one after another

Denscombe (2014)

Systematic observation: Advantages and disadvantages

Advantages	Disadvantages
Direct data collection	Behaviors not intentions
Systematic and rigorous	Oversimplifies
Efficient	Lack of contextual information
Pre-coded data	Naturalness of the setting
Reliability (with training)	
Quantitative data → Statistical analysis	

Denscombe (2014)

- Denscombe (2014): Ch. 13 Observation
  - Denscombe, M. (2014). The Good Research Guide: For small-scale social research projects (5th ed.). Great Britain: Open University Press/McGraw-Hill Education.
- Bell (2006): Ch. 11 Observation studies
  - Bell, J. (2006). Doing your Research Project: A guide for first-time researchers in education, health and social science (4th ed.). Maidenhead Berkshire England: Open University Press.
- Hintze, J. M., Volpe, R. J., & Shapiro, E. S. (2002). Best practices in the systematic direct observation of student behavior. *Best Practices in School Psychology*, *4*, 993-1006.
- Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology*, *54*(1), 579-616.
- Anguera, M. T., Blanco-Villaseñor, A., Jonsson, G. K., Losada, J. L., & Portell, M. (2019). Systematic observation: Engaging researchers in the study of daily life as it is lived. *Frontiers in Psychology*, *10*, 864.

Observation

Resources

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