

# Why this lesson?

- Going back to the foundations of our work: how are we advancing knowledge ?
- Trying to help us stand back and think
- Most of the material is from Z. Dienes, psychology as a science
- Disclaimer 1: I am no epistemologist (but we need to think about epistemology)
- Disclaimer 2: “The philosophy of science is as useful to scientists as ornithology is to birds” (Richard Feynman)

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  - how can we best grow the scientific knowledge (ie, make fastest progress)
- Background: Reacting against logical positivism:
  - some sentences are not verifiable (eg: “free will is an illusion”)
  - 2 problems to solve:
    - verify a specific statement: “this swan is white”
    - generalization: “all swans are white”
    - induction: seeing many examples of a fact leads to trust that this fact is “true”

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- You find 12 individuals with the same destruction: their spatial navigation is very bad
  - what can you say ?
- You find an individual with the same destruction, but their spatial navigation is good
  - what do you conclude about the theory ?

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- Popper accepted all these arguments

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# Probabilistic problems

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- Leads to the creation of a severe test
  - Does this lead to classical statistical theory ?
- See arguments that “NHST” is not “Popperian” \* to be Popperian, you would need to try to falsify H1 ? - instead : we try to falsify H0 to show that we cannot falsify H1 - but what is H0 ? in many instances, a very unlikely hypothesis
  - A statistical test never entirely falsifies !

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- The concept of a “paradigm shift” : science progress with new paradigms
  - the earth rotation in the solar system
- Paradigm shifts are prompted by too many inconsistencies in the current paradigm

## But - What is a probability ?

- 3 axioms:

- Axiom 1 and 2 :  $P(\text{an event } A) \geq 0$ ;  $P(\text{all events}) = 1$
- Axiom 3: If A and B are *mutually exclusive*, then  $P(A \text{ or } B) = P(A) + P(B)$
- hence:  $P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$
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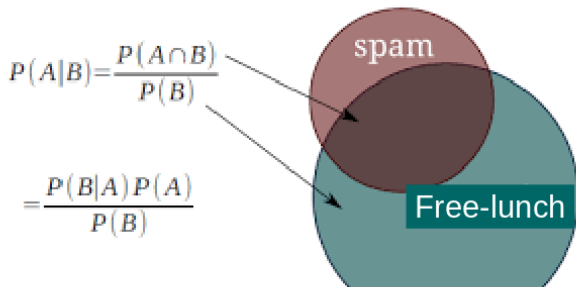
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- Frequentist interpretation: limit of the relative frequency of an event in a large number of random trials
- Objective/physical probability associated with a **collective**
  - the set of dice throws - a single event can be part of several collectives
  - prob(catch a cold) : Collective 1: people who live in cold climates.  
Collective 2: air conditioner full blast.

# Bayes and likelihood functions

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  - “as reasonable expectation representing a state of knowledge or as quantification of a personal belief”
- Subjective/Evidential probabilities should still follow the physical probability axioms



# Bayes and likelihood functions

- Derivation of Bayes theorem is easy: accept conditional probabilities

$$P(H, D) = P(H|D)P(D)$$

$$P(H, D) = P(D|H)P(H)$$

$$P(H|D) = \frac{P(D, H)}{P(D)} = \frac{P(D|H)P(H)}{P(D)}$$

$$P(H_1|D) = \frac{P(D, H_1)}{P(D)} = \frac{P(D|H_1)P(H_1)}{P(D)}$$

## Bayes and likelihood functions : can we use this to choose between theories?

- Posterior:  $P(H|D)$
- Prior:  $P(H|D)$
- Likelihood:  $P(D | H)$  : Careful: not a frequentist probability !

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- Ratio: posterior odds = Bayes-factor  $\times$  prior-odds
- $BF = \frac{P(D|H_1)}{P(D|H_0)}$
- $<1$  : supports  $H_0$ , 1-3: not worth mention , 3-10: substantial, 10-30: strong

## Back to the basics: Effect size

What is the non standardized effect ?

Imagine 2 groups (1 and 2):

$$\mu = \bar{x}_1 - \bar{x}_2$$

What is the standardized effect ? (eg Cohen's d)

$$d = \frac{\bar{x}_1 - \bar{x}_2}{\sigma} = \frac{\mu}{\sigma}$$

“Z” : Effect accounting for the sample size

$$Z = \frac{\mu}{\sigma/\sqrt{n}}$$

## Significance testing as perverse probabilistic reasoning

Consider a typical medical research study, for example designed to test the efficacy of a drug, in which a null hypothesis  $H_0$  ('no effect') is tested against an alternative hypothesis  $H_1$  ('some effect'). Suppose that the study results pass a test of statistical significance (that is  $P$ -value  $< 0.05$ ) in favor of  $H_1$ . What has been shown?

1.  $H_0$  is false.
2.  $H_1$  is true.
3.  $H_0$  is probably false.
4.  $H_1$  is probably true.
5. Both (1) and (2).
6. Both (3) and (4).
7. None of the above.

Figure 2: Westover, 2014

# Significance testing as perverse probabilistic reasoning

**Table 1 Quiz answer profile**

Answer	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number	8	0	58	37	6	69	12
Percent	4.2	0	30.5	19.5	3.2	36.3	6.3

Figure 3: Westover, 2014

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- definition of a p-value
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  - a statistics = a function of the data:  $s = f(\text{Data})$
  - define with common sense : eg difference between the means
  - but: what if there are different choices ? What if several could be biologically relevant?
  - can I observe several statistics ? Is that a problem ?
  - test can be “more or less powerful”

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- Probability of observing a statistic **equal to the one seen in the data, or one that is more “extreme”**, when the null hypothesis is true
  - concept of repeating the same study in the same way an infinite number of times !
  - same study design
  - same sampling scheme

## Back to statistics: p-values and power ?

- Probability of observing a statistic equal to the one seen in the data, or one that is more “extreme”, **when the null hypothesis is true**
  - a statistics = a function of the data:  $s = f(\text{Data})$
  - How do we define the null ?
  - Is the null plausible ? or at least possible ?

## p-values: Illustration with a normal null

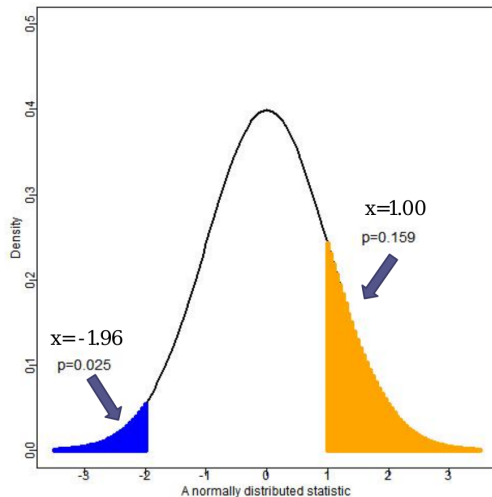


Figure 4: Illustration of p-value

## p-values: Illustration with a Gamma null

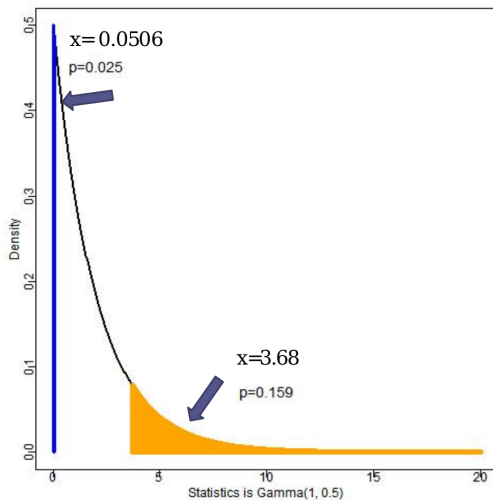


Figure 5: Illustration of p-value

## p-values: Illustration with a uniform null

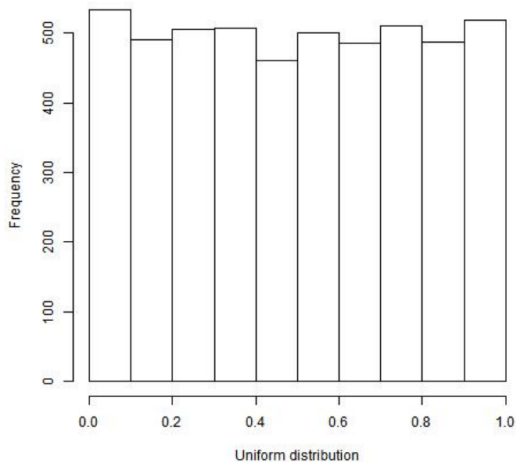


Figure 6: Illustration of p-value

## Back to statistics: p-values and power

Decision/H	H0 True	H1 True
reject	$\alpha$ (type I)	$1 - \beta$ (Power)
not reject	$1 - \alpha$	$\beta$ (type II)

## What is power ?

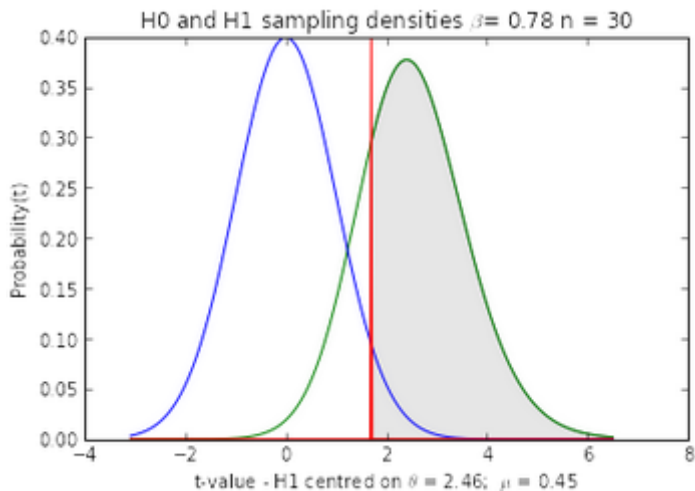


Figure 7: Illustration of Power

## Power: experimentally

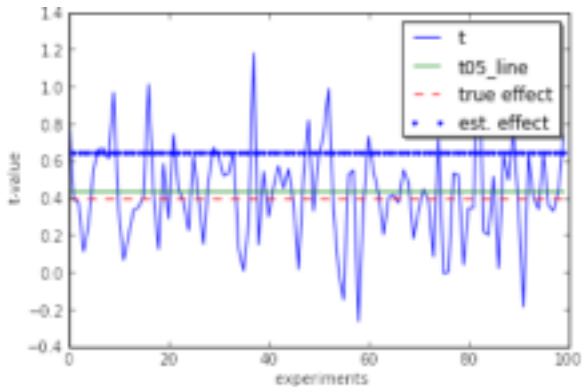


Figure 8: Illustration of Power

## recall the definition

- Power will depend on **5** things:
  - The non standardized effect :  $\mu$
  - The standard deviation of the data :  $\sigma$
  - The number of subjects :  $n$
  - The type I risk of error :  $\alpha$
- And on the distribution of the statistic under the alternative hypothesis.

## Computing power in a simple case:

- We estimate the effect  $\hat{\mu}$  under normal noise. Our statistic is:

$$t_{obs} = \frac{\hat{\mu}}{\hat{\sigma}_{\mu}} = \frac{\hat{\mu}}{SE_{\mu}}$$

- Power is  $P(t_{obs} > t_{.05})$ , with  $t_{.05}$  the t for  $\alpha = 0.05$  **under the null**.
- We easily compute  $t_{.05}$  because we know the null, but need to compute  $P(t_{obs} > t_{.05})$ .
- We therefore need the distribution of  $t_{obs}$  - and therefore we need to **know the signal / effect size** !
- Let's assume we know this and call it  $t_{nc}$ , and  $F_{nc}$  for the cumulative distribution (nc for non central).
- Power =  $1 - \beta = P(t_{obs} > t_{.05}) = 1 - F_{nc}(t_{.05})$

## We need a theoretical result

- With normal data, the  $t = \frac{\hat{\mu}}{SE_{\mu}}$  statistic follows a *non central t distribution* with non centrality parameter:

$$\theta = \mu\sqrt{n}/\sigma$$

and  $n - 1$  degrees of freedom.

- We are done ! **assuming we know all these things ... ;)**

## Some python code:

Inputs: sample\_size (n), mu, sigma, alpha

Returns: power

```
"""
```

```
import scipy.stats as sst
```

```
# define H1
```

```
df = n-1
```

```
theta = np.sqrt(n)*mu/sigma
```

```
ncrv = sst.nct(df, theta)
```

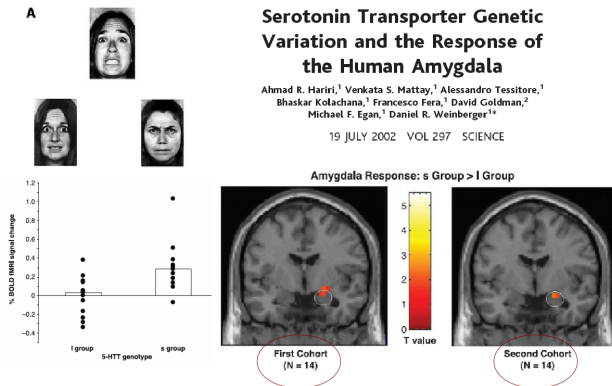
```
# find the threshold value
```

```
t_alph_null = sst.t.isf(alpha, df)
```

```
power = 1 - ncrv.cdf(t_alph_null)
```

```
return power
```

# Some first studies: small Ns



- Authors report  $m_1 = .28$ ,  $m_2 = .03$ ,  $\text{SDM}_1 = 0.08$ ,  $\text{SDM}_2 = 0.05$ ,  $N_1 = N_2 = 14$
- How do we compute the effect size ?

## Computing Effect size: practice

- First, compute the standard deviation of the data from the SDM
  - get  $\sigma$  from SDM :  $\sigma = \sqrt{14-1} \times \text{SDM}$
  - Combine the  $\sigma$  to have one estimation across the groups
    - formula easy to recompute or find
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  - Write the estimated model:  $Y = [1 \dots 1]^t [m_1 - m_2] + \text{residual}$
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- Compute the total sum of square  $Y^t Y$ , then the proportion:
  - $V_e = \frac{(n_1 + n_2)(m_1 - m_2)^2}{n_1 s_1^2 + n_2 s_2^2 + (n_1 + n_2)(m_1 - m_2)^2} > 40\%$

## Power in practice:

- Harvard Medical School researchers show that broccoli reduces Parkinson patients symptoms X. 20 participants in each of 2 groups.
- The difference in the measure of symptom A is significant with a t-test  $p=0.02$
- You decide to replicate the study at the MNI. How many subjects should you test ?

## What happens if ... $p$ is “significant” but study power is low ?

- Study in Button et al, 2013, more than half of the studies published have less than 30% power
- Low Positive Predictive Value  $P(H_A \text{ true} \mid \text{test significant})$
- Inflated effect size
- Depends on the prior probability of  $H_A$  and  $H_0$

# PPV

- Define :  $P_1 = P(H_1)$  and  $P_0 = P(H_0)$

$$PPV = \frac{(1 - \beta)P_1}{(1 - \beta)P_1 + \alpha P_0}$$

- With  $R = P_1/P_0$  and  $W = 1 - \beta$  :

$$PPV = \frac{WR}{WR + \alpha}$$

- Wikipedia (ML):  $PPV = \text{number-of-true-positive} / (\text{number-of-true-positive} + \text{number-of-false-positive})$

Low PPV  $P(H_A \text{ is true} \mid \text{test signif.})$  with low power

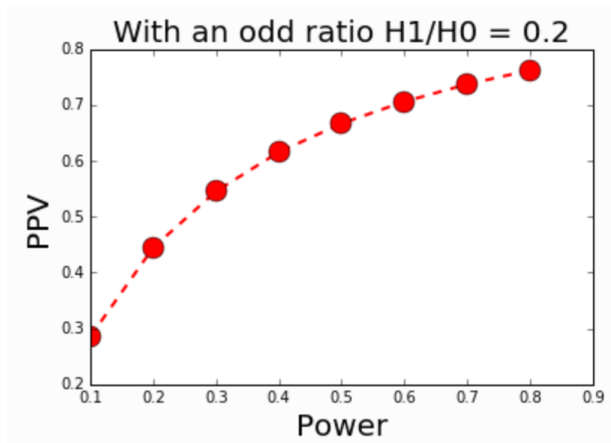


Figure 9:  $PPV = f(\text{power})$ ,  $\alpha=0.05$

Low PPV with high alpha :  $P(H_A \text{ is true} \mid \text{test signif.})$

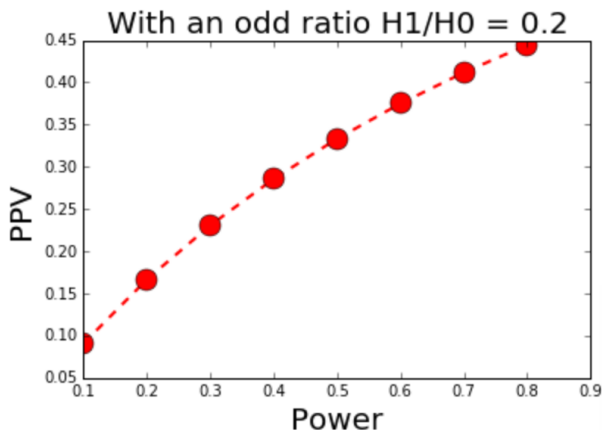


Figure 10:  $PPV = f(\text{power})$ ,  $\alpha=0.2$

# Credits and References

- Zoltan Dienes: understanding psychology as a science
- Celia Greenwood for some slides
- Many others

# Questions

- Questions

# Acknowledgements

- Elizabeth Dupré (co-organizer)
- Jake Vogel (co-organizer)
- Andrew Doyle
- Félix-Antoine Fortin
- Peer Herholz
- Greg Kiar
- Liza Levitis
- Bratislav Misic
- Manjari Narayan
- Estefany Suarez
- Joe Viviano