COGS 303

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UBC

Nov 3, 2023

Presentations

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Component	Criteria	Points
Content	-Clear -Well-organized -Informative	7
Speech	-Correct length (8-10 minutes) -Polished -Flows well	4
Slides	-Relevant -Interesting -Aids the presentation	4

Quick recap from last week

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- So, what needs to change in order to improve the situation?

Sources of the problem

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    - Outright fraud

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- Bias toward innovation rather than rigorously testing current ideas
  - This suggests overconfidence in our current theories
  - Innovation is exciting, but empirical testing is how we tell if our theories are likely

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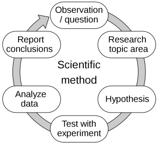

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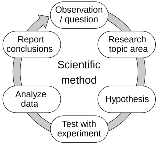
- 

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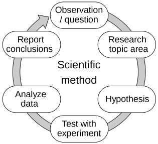
- 

- Isn't all hypothesizing done after (at least some) results are known?
- The issue with HARKing is when the HARKed hypothesis is presented as if it has been tested and confirmed rather than merely suggested by the result of the test

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  - This removes the incentive/need to have some ground-breaking innovation to get published
  - It also means you can't revision the purpose of the test (as happens in HARKing)
  - If your test has a surprising result that suggests a new hypothesis, you can present that as a candidate for future testing in your conclusion (but not as having been confirmed by the test)

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- Some suggest that frequentist/classical statistical methods should be replaced by Bayesian methods

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- These different understandings of the meaning of probability lead to different methodologies with using statistical information in scientific reasoning
- Frequentists favour the objective interpretation
- Bayesians favour the subjective interpretation
- Let's illustrate with an example

Suppose I'm about to flip a coin

- What's the probability of the toss resulting in heads?
  - Bayesian–0.5
  - Frequentist–0.5

Now suppose I have already flipped the coin, but haven't revealed the result to you...what's the probability of heads?

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- This question doesn't make sense to the frequentist
- It is what it is. The result is fixed

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- Where the Frequentist focusses on the result of repeating a type of exercise, the Bayesian focusses on the uncertainty involved in the exercise

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- Let's consider these in turn

Example–mean height of a population

Suppose we are interested in figuring out the mean height of a population. As Howson and Urbach mention, Bayesians and Frequentists go about this differently:

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- To answer this, frequentists point to the "confidence interval"

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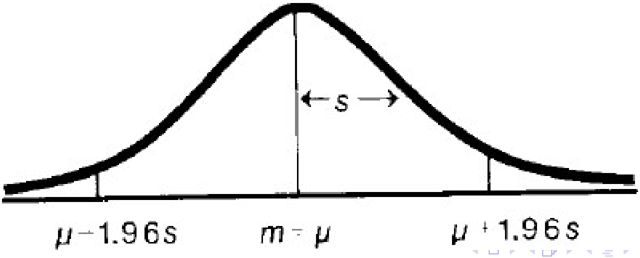
- 

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- Howson & Urbach note that this depends on the (often private) intentions of the experimenter
- So, there's some obstacles to understanding confidence intervals as purely objective

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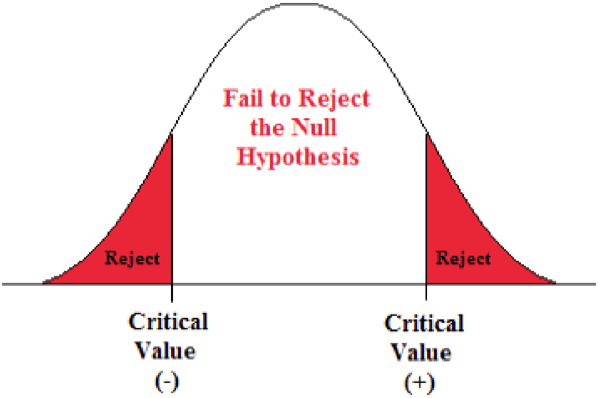
- As data comes in, they update that distribution according to Bayes' rule
- As the sample size increases, the effect of the prior distribution is minimized
- That means that as evidence accumulates, two researchers with very different prior distributions will come to the same posterior distribution


Fail to Reject the Null Hypothesis
Reject
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Critical Value (-)
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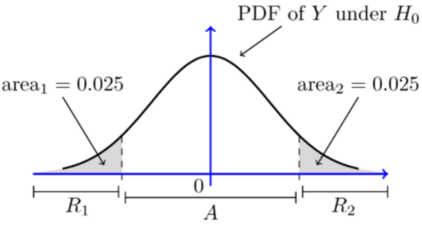
- The result of the test is a probability of the result given the "null hypothesis" (H_0)
- The null hypothesis is the hypothesis that the study will not demonstrate an effect
- It contrasts with the "alternative hypothesis" (H_a) which is the hypothesis we are actually interested in

Fisher



$$A = \text{Acceptance Region}$$
$$R = R_1 \cup R_2 = \text{Rejection Region}$$
$$\alpha = \text{P(type I error)} = \text{area}_1 + \text{area}_2 = 0.05$$

Source: Probability Course (see syllabus for link)

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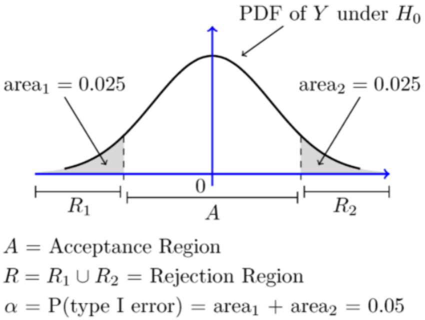

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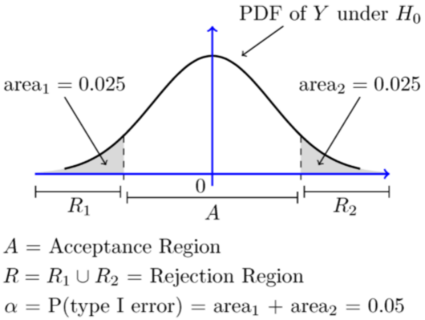

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- The curve represents the probability density function for test results given H_0
- The tail ends of the curve represent test values that are significant (ie. mathematically unlikely if H_0 were true)

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- While it uses probabilities, the logic is deductive

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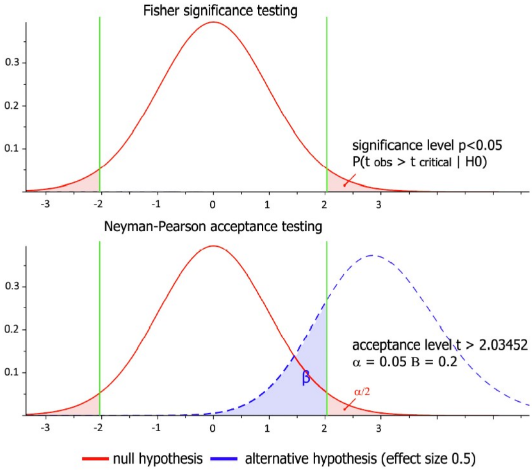
- But it does not confirm H_a! (Nothing does, because this framework is Popperian)

Fisher vs Neyman-Pearson



Source: Cyril Pernet

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- Note, Travers makes this mistake! When describing what $p = 0.26$ means: "In other words...there is a 26 percent probability that the null hypothesis is true given these results" (p.214)

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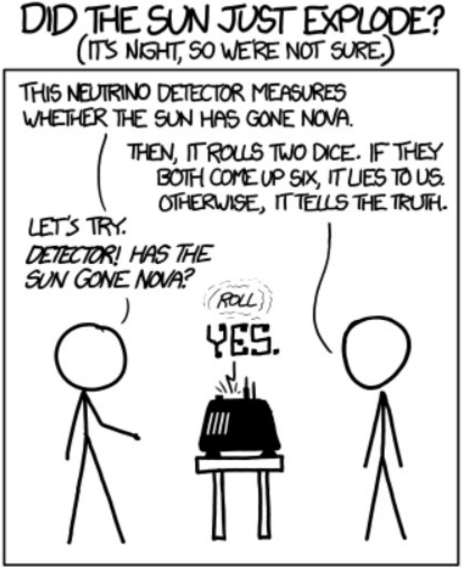
- That the result would be unlikely if H_0 were true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THEN, IT ROLLS TWO DICE. IF THEY BOTH COME UP SIX, IT LIES TO US. OTHERWISE, IT TELLS THE TRUTH.
LET'S TRY.
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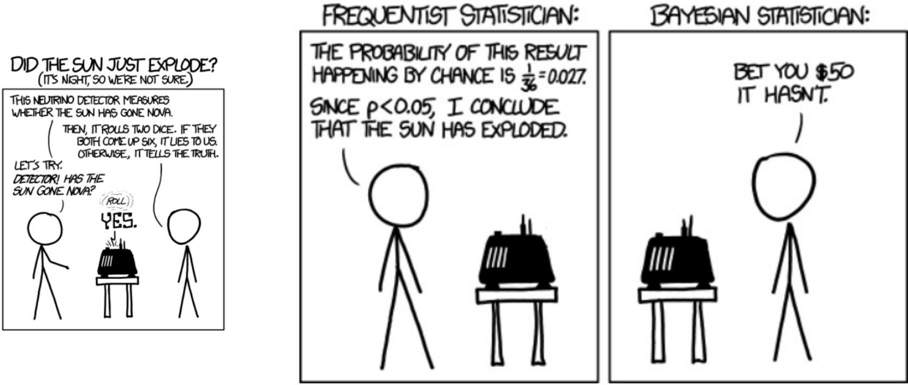
ROLL
YES.



Source: xkcd.com

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- Statistically insignificant findings can also be of interest. For example, a famous study out of Denmark in 2003 found no significant correlation between thimerasol exposure (in vaccines) and autism diagnoses. (In fact, they were slightly negatively correlated–as thimerasol use went down, the rate of autism diagnoses went up.)

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  - It is tempting to see significance as a pass/fail measure of whether the test was successful. But that's overly simplistic

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- What do you think?

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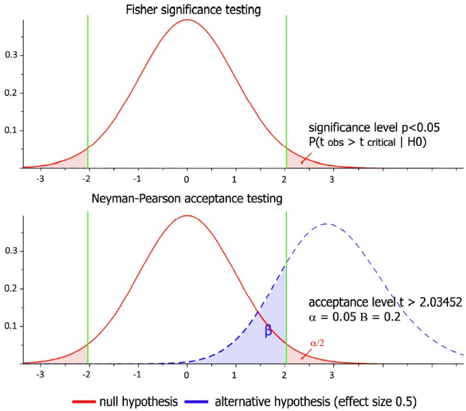
- By convention: "Inconclusive" is when $\frac{1}{3} < BF < 3$

Inconclusive Evidence

Where we would see $\frac{1}{3} < BF < 3$ on either of these graphs?



Source: Cyril Pernet

Can Bayesian analysis help replication?

Romero & Sprenger: There is less of a "file-drawer" effect with Bayesian analysis

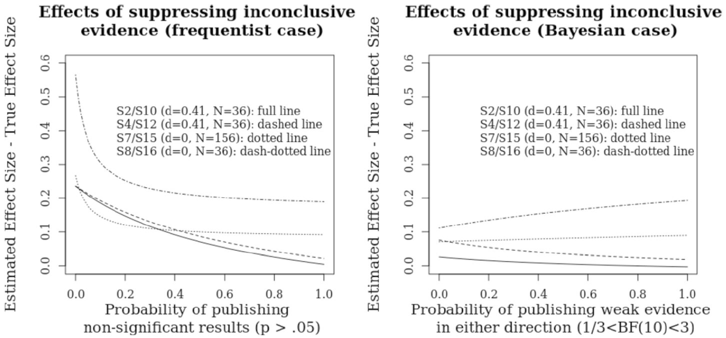


Fig. 4 Difference between estimated and true effect size as a function of the probability of suppressing inconclusive evidence, that is, the prevalence of the file drawer effect. Left graph = frequentist analysis, right graph = Bayesian analysis

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    - Misapplication of it (through suppression of inconclusive results) does contribute
    - A switch to Bayesian analysis *might* help improve that problem
    - But other changes like publishing data sets (facilitating meta-analysis) and pre-accepting studies for publication (to avoid suppressing valuable data) should also be encouraged

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Readings for next week

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  - Dentith and Keeley "The Applied Epistemology of Conspiracy Theories: an Overview"
  - Grimes "On the Viability of Conspiratorial Beliefs"
  - O'Connor and Weatherall "The Social Network"