Eric-Jan Wagenmakers

The Case for Radical Transparency in Statistical Reporting







- What researchers want
- What the field gets
- How to uncover hidden uncertainty



The Main Dilemma

- Dr. X has a favorite theory that she has worked on and published about previously.
- Dr. X designs an experiment to test a prediction from her theory.
- Dr. X collects the data, a painstaking and costly process. Part of her career and those of her students ride on the outcome.



The Main Dilemma

- Now the data need to be analyzed.
- If p < .05, the experiment is deemed a success; if p > .05, it is deemed a failure.

Who is, without a shadow of a doubt, the most biased analyst in the entire galaxy, past, present, and future?

Who is, without a shadow of a doubt, the most biased analyst in the entire galaxy, past, present, and future?





Richard Feynman

"The first principle is that you must not fool yourself---and you are the easiest person to fool"





The Main Dilemma

- So the world's most biased analyst, Dr. X, the easiest person to fool, proceeds to analyze the data.
- Dr. X can do this alone, without any oversight whatsoever. In most cases, the data and analysis code never leave the lab.



A Perfect Storm

- Data are analyzed with no accountability, by the person who is easiest to fool, often with limited statistical training, who has every incentive imaginable to produce p < .05.
- When p < .05, the result is declared "significant" and any further doubt is frowned upon, as it violates an implicit social contract [at least in psychology].



John Tukey

[Statistical procedures should not be used] "...for sanctification, for the preservation of conclusions from all criticism, for the granting of an *imprimatur*."





What Researchers Want

- To discover the truth, but also:
 - To present compelling data that leave no room for doubt or dissent
 - To develop a coherent theoretical framework
 - To publish papers that make interesting claims



Researchers Abhor Uncertainty







- What researchers want
- <u>What the field gets</u>
- How to uncover hidden uncertainty

Fruits of Perverse Incentives and Uncertainty-Allergy

- Publication bias
- Fudging
- HARKing



Artwork by Viktor Beekman • instagram.com/viktordepictor



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VARIABLES, TRANSFORMATIONS, ANALYSIS PIPELINES

$y_1 \quad y_2 \quad y_3 \quad \cdots \quad y_{\mathcal{K}}$

 \mathcal{H}_{1}

 $\mathcal{H}_{\mathcal{M}}$

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DATA

IYPOTHESES

Consequence: Overconfident Claims and Spurious Results That do Not Replicate





- What researchers want
- What the field gets
- How to uncover hidden uncertainty



Method 1: Preregistration of Analysis Plans

- Separates what was post-hoc from what was pre-planned
- Prevents researchers from fooling themselves and others
- Does not rule out exploratory expeditions; just labels them as such



Method 2: Outcome-Independent Publication

- Judge work based on quality of execution, not on whether p <. 05
- Best if combined with preregistration, as advocated by Chris Chambers



Method 3: Sensitivity Analyses

- Examine sensitivity to modeling choices: data, likelihood, and prior. For instance:
 - -Multiverse analysis
 - -Crowd sourcing
- Ideally, this is done by independent labs

Increasing Transparency Through a Multiverse Analysis

Sara Steegen¹, Francis Tuerlinckx¹, Andrew Gelman², and Wolf Vanpaemel¹

¹KU Leuven, University of Leuven and ²Columbia University

Fiscal political attitudes





Many analysts, one dataset: Making transparent how variations in analytical choices affect results

Authors

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27 Poisson regression 2.93	21	Tobit regression	2.88
	27	Poisson regression	2.93





Method 4: Share the Data

- Facilitates re-analysis
- In review process, allows reviewers to propose and carry out informative alternative analyses



Method 5: Plot the Data







Method 6: Adopt an Inclusive Inferential Approach

- A classical analysis may be reported as r(13)
 = .58, p < .05 (sometimes even without showing the data)
- This does not stimulate statistical curiosity; it is meant to suppress it



Method 6: Inclusive Analyses

• Consider a paper published this year in the Lancet:

Relation between resting amygdalar activity and cardiovascular events: a longitudinal and cohort study

Ahmed Tawakol*, Amorina Ishai*, Richard AP Takx, Amparo L Figueroa, Abdelrahman Ali, Yannick Kaiser, Quynh A Truong, Chloe JE Solomon, Claudia Calcagno, Venkatesh Mani, Cheuk Y Tang, Willem JM Mulder, James W Murrough, Udo Hoffmann, Matthias Nahrendorf, Lisa M Shin, Zahi A Fayad†, Roger K Pitman†





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File Common		=
Descriptives	ANOVA Regression Frequencies	
pp AlcBeerFirst ConfidenceRating AlcRating NonAlcRating	Correctidentify OK	CorrectIdentify - 1 Prior and Posterior BF ₁₀ = 112.646 BF ₀₁ = 0.009 data H1 median = 0.731 95% CI: [0.610, 0.833]
Test value: 0.5 Hypothesis * Test value > Test value < Test value Bayes Factor BF ₁₀ BF ₁₀ Log(BF ₁₀)	Plots Plot Additional info Sequential analysis Prior Beta prior: parameter a Beta prior: parameter b 1	$ \begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \begin{array}{c} \end{array}\\ \end{array}\\ \end{array}\\ \end{array}\\ \begin{array}{c} \end{array}\\ \end{array}\\ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array}\\ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array}\\ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array}$ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array} \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array} \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array} \begin{array}{c} \end{array}\\ \begin{array}{c} \end{array}\\ \end{array} \begin{array}{c} \end{array} \end{array} \begin{array}{c} \end{array} \begin{array}{c} \end{array} \end{array} \begin{array}{c} \end{array} \end{array} \begin{array}{c} \end{array} \end{array} \begin{array}{c} \end{array} \end{array} \end{array} $ \begin{array}{c} \end{array}$ } \end{array} $ \begin{array}{c} \end{array}$ } \end{array} $ \begin{array}{c} \end{array}$ } \end{array} } $ \begin{array}{c} \end{array}$ } $ \begin{array}{c} \end{array}$ } $ \begin{array}{c} \end{array}$ } $ \end{array}$ } $ \begin{array}{c} \end{array}$ } $ \end{array}$
		Déll logistic regression, & more

jasp-stats.org







Concluding Comments I

- More transparency is *sorely* needed
- Transparency means mental hygiene: the scientific equivalent of brushing your teeth, or washing your hands after visiting the restroom
- This requires a change in culture



Concluding Comments II

- Journals and funders can start <u>demanding</u> mental hygiene
- Mental hygiene can also be <u>rewarded</u>. For instance, journals could prefer papers that conduct multiverse analyses etc.



Concluding Comments III

 Journals could publish reviewers' reports when these contain useful re-analyses, promoting a crowd sourcing approach and rewarding reviewers for their efforts

Thanks for Your Attention

