



What can Universities do to Foster Responsible Research Practices?

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Concentrate on

Questionable Research Practices

(QRPs)

and

Responsible Research Practices

(RRPs)

Not on

Fabrication, Falsification, Plagiarism (FFP)

Fabrication: Making up data, producing artificial data, no empirical data

Falsification: Manipulating real data, changing scores to obtain the desired effect

Plagiarism: Steal text and ideas from fellow researchers without reference

Steneck (2006):

RRPs – QRPs – FFP

RRPs = Responsible Research Practices

Textbook Behavior,

Perfect

QRPs = Questionable Research Practices

Real-World Behavior,

Fallible

~~FFP = Fabrication, Falsification, Plagiarism~~

~~Real-World Behavior,~~

Misconduct

We know textbooks, what are QRPs?

Examples of QRPs (John, Loewenstein, & Prelec, 2012; $N \approx 2,000$):

- 1 Not reporting all measurements (63%)
- 2 **If test** is non-significant, collect more data, and repeat (56%)
- 3 Not reporting all experimental conditions (28%)
- 4 Report intermediate result as if it were the final result (16%)
- 5 Favorable rounding of p -values ($p = .058$ reported as .05) (22%)
- 6 **Report** only results favoring ones hypothesis (46%)
- 7 Delete cases if that produces better results (38%)
- 8 **Present** unexpected result as if it were expected (27%)
- 9 Deny relation with demographic variables when uncertain (3%)
- 10 Falsify data, etc—**FFP** (0.6%); do not discuss here

Three topics:

- Most likely ***causes of errors*** researchers make when designing research, analyzing data, and interpreting results from data analysis
- Why research ***policy*** helps more effectively to encourage **RRPs** than improved methodological and statistical methods
- How Tilburg University ***implements policy*** to encourage **RRPs** and ***prevent QRPs***

Causes of Errors

Where do errors in use of statistics come from?

- Researchers ***need to use*** methodology and statistics, but M&S are ***not*** their ***profession***; they practice M&S ***on the side***
- Statistics is difficult and results are counter-intuitive; one is constantly ***misled***
- Add this to ***climate*** of performance pressure, and a ***toxic mixture*** called Questionable Research Practices (QRPs) is unavoidable

Why is statistics difficult?

Tversky & Kahneman (1970s) explained this:

Statistical reasoning requires ***rational and conscious reasoning***, costs a lot of effort, ***people do not do this***; first inclination is to follow their ***intuition*** and jump to conclusions

Intuition works two ways:

- Based on **experience**; makes one do approximately the right things, *before* one has started thinking about a well-founded answer
- Based on **heuristics**; makes one respond using cognitive *automatisms* that replace the difficult but correct question (impossible to answer) with an easier but incorrect one (answerable); puts researcher on wrong track

Third reaction is cognitively demanding: Try to solve problem **rationally**; this is **not** what we do first, we rather react intuitively

Example difficult question

Fold Saturday's edition of the newspaper (1 cm thick), then once more, again, and again; when is the pack of paper thick enough to reach from here to the moon?

Intuitive, *experienced* response: Something's going on, be careful!

Puts one on guard: *Don't answer right away, take your time!*

Intuitive, *heuristic* response: Replace Q with easier Q that looks like it:

“What's the distance to the moon?” A: Huge, folding takes forever

Rational, demanding response: Solve the problem; no one does this

Here is the solution:

Folding **35** times is too little, but **36** times is too much

Notice:

You ***experience*** an impossible task, and intuitively move to a wrong answer

You do not have a clue what is going on, even if you know the answer

Policy instead of Statistics

Lessons learned:

Because they use *intuition by heuristics*, people do not understand

- *Exponential growth*; Increase of # Covid-19 contaminations, governed by the *R*-number, can speed up and slow down, et cetera

- Further:

Probabilities (e.g., group vs subgroup; event over time)

Chance (e.g., lotteries, casino's)

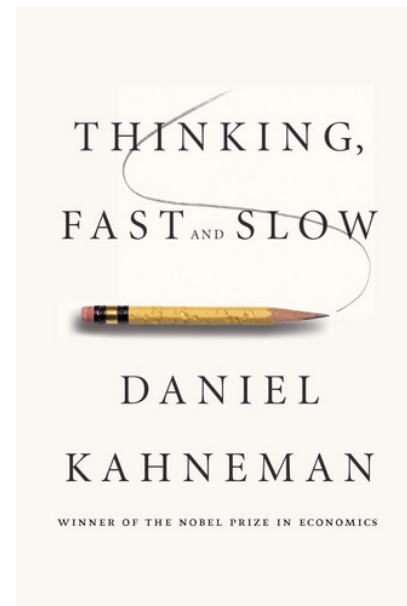
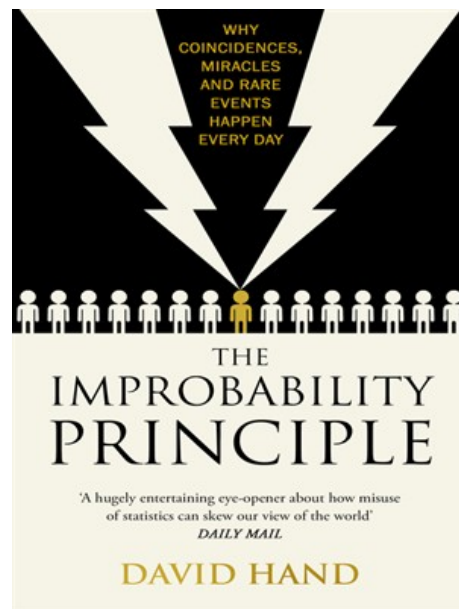
(Large) numbers (how much is a million?)

These and other concepts are *central to statistical reasoning*

Further reading (let others convince you):

Hand, D. (2014). *The improbability principle. Why coincidences, miracles and rare events happen every day*. London, UK: Penguin Random House.

Kahneman, D. (2011). *Thinking, fast and slow*. London: Penguin Books Ltd.



If statistics is ***difficult*** for ***everybody***,

Does additional statistics ***education*** help (to prevent QRPs)?

- Statistics education shows researchers what's in the toolbox, and what you can use the tools for; necessary knowledge
- More education provides ***more methods***, no ***experience***

So, ***what can statisticians do?***

In addition to helping people to *recognize* the method that suits their problem

- Teach people to recognize situations ***in which they need help***
- *Stop* suggesting everybody can do statistics
- Be *careful* teaching “crash courses” in multilevel analysis, etc.

Policy Advice (to help encourage RCR)

I. Make Data Publicly Available

*Let other people look across your shoulder and **check** what you do*

Many researchers keep their data to themselves, also when asked to share them (Ioannides, 2016; Wicherts et al., 2006)

Make it easier for researchers to share data:

- Allow researchers first use of data until they have published
- “Owner” of data can be coauthor with others using their data
- Data sharing produces new results and develops networks

Policy Advice (to help encourage RCR)

II. Involve a Methodologist or Statistician in Data Analysis

*Hire intuition based on **experience** that you do not have yourself*

- Simmons, Nelson, & Simonsohn, 2011, *PsychScience*: Understanding and use of statistics are difficult and are the main causes of errors made in data analysis
- Tversky & Kahneman (1970s): Explanation of errors is absence of *experience*, and use of “wrong” intuition based on *heuristics*, causing researchers to fall into all the traps set by counter-intuitive statistics

By the way, statisticians do not always provide good solutions, may be too optimistic about statistics' possibilities:

- Bayesian statistics instead of frequentist statistics, Bayes factor instead of p -value; however, both approaches provide rules of thumb to researchers looking for “results”
- Alternative α -values: $\alpha = .005$ instead of $\alpha = .05$ (recent discussion in *Nature*); however, it's just another rule of thumb
- Et cetera

Implementation of Policy at TiU

Responding to the Stapel data-fraud affair in 2011, Tilburg School of *Social and Behavioral Sciences* installed the **Science Committee**

Science Committee—What is it, what does it do, and why?

- ***Audit*** committee samples 20/500 articles from School's data base; assesses ***quality of data storage*** and ***reporting of research methods***
- *Advises* researchers about data storage, completeness data sets, honoring subjects' privacy, access to data, and data availability
- Aims:
 - ✓ Encourage concerted effort to improve researchers' ***accountability*** for data handling and methods reporting
 - ✓ Create opportunity for all to ***learn***; not a witch hunt
 - ✓ Contribute to development *university's* research policy and to a *Dutch* national protocol concerning research policy

Science Committee was installed in 2012, started working as follows

- Set up rules and regulations for researchers' data handling
- Announced annual random audits (20/500 articles)
- Research groups devised their own data (storage) policy that suited their needs best; initially no general policy

Works quite well, but not perfectly:

- Some groups had their data policy better in place than others
- People tended to arrange their data storage only when they were audited
- When people left the School, they tended to loose commitment
- Remains much work to do, but creates greater awareness, stronger sense of responsibility and accountability

Tilburg University policy with respect to *research policy and data management*; state of the art

- Other TiU Schools did not (yet) install a *Science Committee*
- They did install ***Ethics Committees***: Check in advance compliance with research ethics and privacy regulations, and data management.
- Presents one counter, almost all researchers comply
- But no auditing in retrospect
- Most Schools require researchers to assemble *data package*, saved on **TiU servers** (partly consistent with VSNU Integrity Code)
- TiU provides **Data Verse** (consistent!) for safe storage meta-data, data, code, etc., easy access; researchers have ***cold feet*** so far

Questions:

- Why do researchers have cold feet?
 - “Local” storage feels better, Data Verse is not local
 - Afraid they will be “scooped”
 - Researcher may not be owner of data, not free to act
- Why differences between disciplines?
 - Exact sciences have long tradition of *team science*; data are available to all team members
 - Human sciences are *individualistic*; VSNU’s “**Room for Everyone’s Talent**” with emphasis on team science may help acceptance of open data culture

Summary

- Our brains were designed for *intuitive reasoning* based on *heuristics*; rational reasoning came later in evolution, and is *difficult*

Statisticians have *experience*: postpone acting, are cautious

- Teach people which methods are available and to recognize their weakness; that is, *no experience*, only heuristics, thus *ask for help*
- QRPs are best fought *not* through more training and novel statistical methods (although neither will hurt) but through *policy: Publish data, involve a statistician, and perhaps be audited to improve*



Thank You

