# R: A Hitchhikers Guide to Reproducible Research

- Hello

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# Reproducible or replicable

		Data			
		Same	Different		
Analysis	Same	Reproducible	Replicable		
	Different	Robust	Generalisable		

# Reproducible or replicable

		Data		
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# Reproducible or replicable

		Data			
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Analysis	Same	Replicable	Reproducible		
	Different	Robust	Generalisable		

Vol 435|9 June 2005

### COMMENTARY

### **Scientists behaving badly**

To protect the integrity of science, we must look beyond falsification, fabrication and plagiarism, to a wider range of questionable research practices, argue **Brian C. Martinson**, **Melissa S. Anderson** and **Raymond de Vries**.

Table 1   Percentage of scientists who say that they engaged in the behaviour listed within the previous three years ( $n=3,247$ )						
Top ten behaviours	All	Mid-career	Early-career			
1. Falsifying or 'cooking' research data	0.3	0.2	0.5			
2. Ignoring major aspects of human-subject requirements	0.3	0.3	0.4			
<ol> <li>Not properly disclosing involvement in firms whose products are based on one's own research</li> </ol>	0.3	0.4	0.3			
<ol> <li>Relationships with students, research subjects or clients that may be interpreted as guestionable</li> </ol>	1.4	1.3	1.4			
<ol> <li>Using another's ideas without obtaining permission or giving due credit</li> </ol>	1.4	1.7	1.0			
<ol> <li>Unauthorized use of confidential information in connection with one's own research</li> </ol>	1.7	2.4	0.8 ***			
7. Failing to present data that contradict one's own previous research	6.0	6.5	5.3			
8. Circumventing certain minor aspects of human-subject requirements	7.6	9.0	6.0 **			
<ol><li>Overlooking others' use of flawed data or questionable interpretation of data</li></ol>	12.5	12.2	12.8			
<ol> <li>Changing the design, methodology or results of a study in response to pressure from a funding source</li> </ol>	15.5	20.6	9.5***			
Other behaviours						
11. Publishing the same data or results in two or more publications	4.7	5.9	3.4**			
12. Inappropriately assigning authorship credit	10.0	12.3	7.4 ***			
13. Withholding details of methodology or results in papers or proposals	10.8	12.4	8.9 **			
14. Using inadequate or inappropriate research designs	13.5	14.6	12.2			
<ol> <li>Dropping observations or data points from analyses based on a gut feeling that they were inaccurate</li> </ol>	15.3	14.3	16.5			
16. In adequate record keeping related to research projects	27.5	27.7	27.3			

# Standing on the shoulders of giants?



Research Article

### Measuring the Prevalence of Questionable Research Practices With Incentives for Truth Telling

Psychological Science 23(5) 524–532 © The Author(s) 2012 Reprints and permission: sagepub.com/journalsPermissions.nav DOI: 10.1177/0956797611430953 http://pss.sagepub.com



### Leslie K. John<sup>1</sup>, George Loewenstein<sup>2</sup>, and Drazen Prelec<sup>3</sup>

<sup>1</sup>Marketing Unit, Harvard Business School; <sup>2</sup>Department of Social & Decision Sciences, Carnegie Mellon University; and <sup>3</sup>Sloan School of Management and Departments of Economics and Brain & Cognitive Sciences, Massachusetts Institute of Technology

#### **Abstract**

Cases of clear scientific misconduct have received significant media attention recently, but less flagrantly questionable research practices may be more prevalent and, ultimately, more damaging to the academic enterprise. Using an anonymous elicitation format supplemented by incentives for honest reporting, we surveyed over 2,000 psychologists about their involvement in questionable research practices. The impact of truth-telling incentives on self-admissions of questionable research practices was positive, and this impact was greater for practices that respondents judged to be less defensible. Combining three different estimation methods, we found that the percentage of respondents who have engaged in questionable practices was surprisingly high. This finding suggests that some questionable practices may constitute the prevailing research norm.

## 241 shades of grey



Contents lists available at SciVerse ScienceDirect

### NeuroImage

journal homepage: www.elsevier.com/locate/ynimg



**Full Length Articles** 

### The secret lives of experiments: Methods reporting in the fMRI literature

#### Joshua Carp

University of Michigan, Department of Psychology, 530 Church Street, Ann Arbor, MI, 48109, USA

#### ARTICLE INFO

Article history: Accepted 3 July 2012 Available online 10 July 2012

Keywords: fMRI Methods reporting Reproducibility Experimental design Analysis methods Statistical power

#### ABSTRACT

Replication of research findings is critical to the progress of scientific understanding. Accordingly, most scientific journals require authors to report experimental procedures in sufficient detail for independent researchers to replicate their work. To what extent do research reports in the functional neuroimaging literature live up to this standard? The present study evaluated methods reporting and methodological choices across 241 recent fMRI articles. Many studies did not report critical methodological details with regard to experimental design, data acquisition, and analysis. Further, many studies were underpowered to detect any but the largest statistical effects. Finally, data collection and analysis methods were highly flexible across studies, with nearly as many unique analysis pipelines as there were studies in the sample. Because the rate of false positive results is thought to increase with the flexibility of experimental designs, the field of functional neuroimaging may be particularly vulnerable to false positives. In sum, the present study documented significant gaps in methods reporting among fMRI studies. Improved methodological descriptions in research reports would yield significant benefits for the field.

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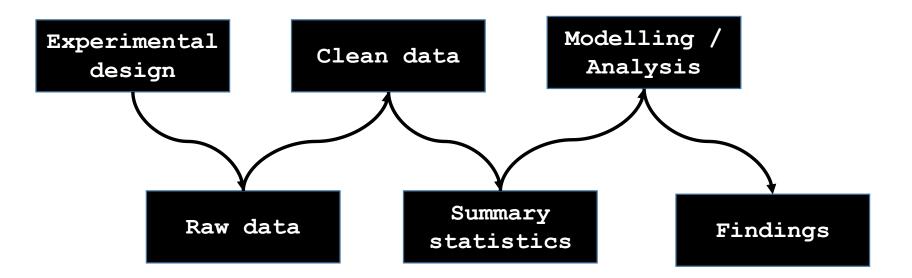
## p-values should not define a study

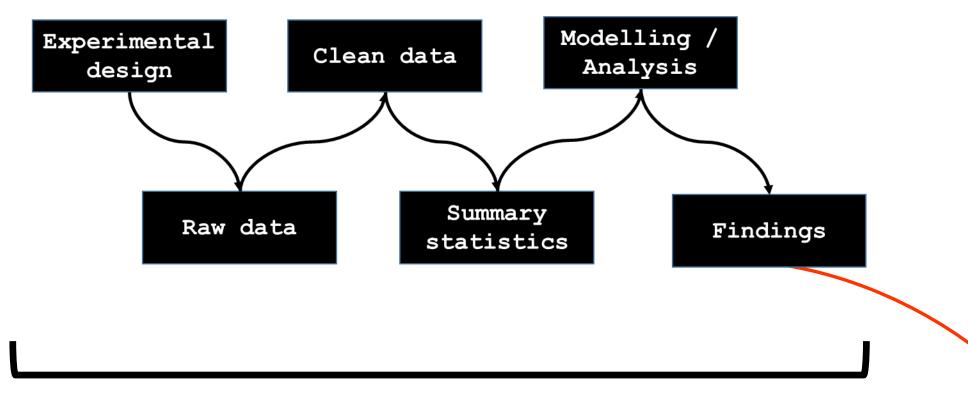


Statistics: P values are just the tip of the iceberg

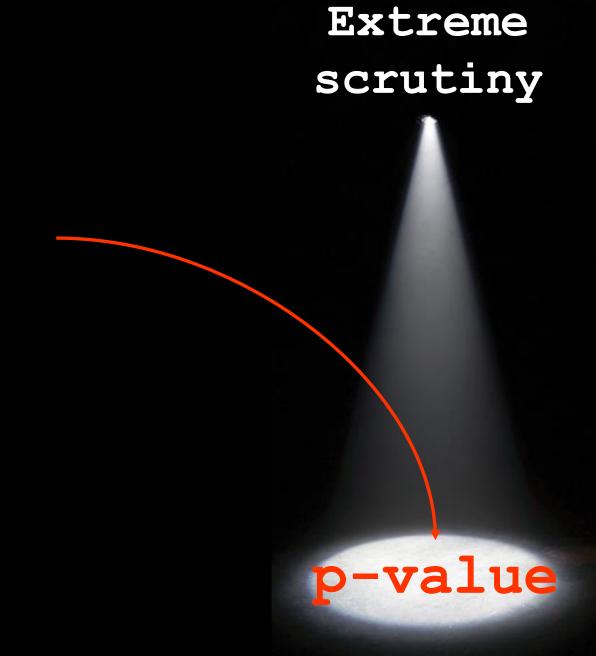
Jeffrey T. Leek & Roger D. Peng

28 April 2015

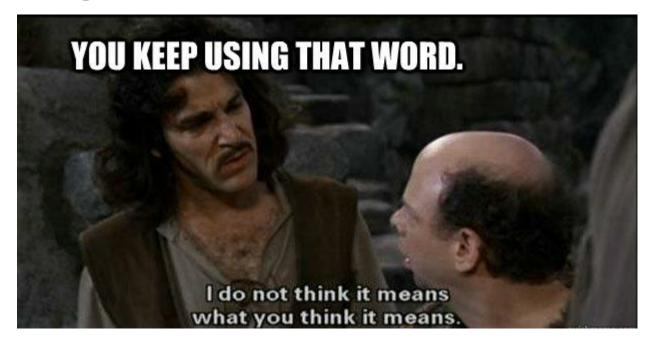


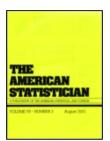


Little debate



## Significant





The American Statistician

ISSN: 0003-1305 (Print) 1537-2731 (Online) Journal homepage: http://amstat.tandfonline.com/loi/utas20

The ASA's Statement on *p*-Values: Context, Process, and Purpose

Ronald L. Wasserstein & Nicole A. Lazar

Eur J Epidemiol (2016) 31:337-350 DOI 10.1007/s10654-016-0149-3



#### ESSAY

### Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations

Sander Greenland<sup>1</sup> · Stephen J. Senn<sup>2</sup> · Kenneth J. Rothman<sup>3</sup> · John B. Carlin<sup>4</sup> · Charles Poole<sup>5</sup> · Steven N. Goodman<sup>6</sup> · Douglas G. Altman<sup>7</sup>

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The Author(s) 2016. This article is published with open access at Springerlink.com.

Abstract Misinterpretation and abuse of statistical tests, confidence intervals, and statistical power have been decried for decades, yet remain rampant. A key problem is that there are no interpretations of these concepts that are at once simple, intuitive, correct, and foolproof. Instead, correct use and interpretation of these statistics requires an attention to detail which seems to tax the patience of working scientists. This high cognitive demand has led to an epidemic of shortcut definitions and interpretations that are simply wrong, sometimes disastrously so—and yet these misinterpretations dominate much of the scientific

Editor's note This article has been published online as supplementary material with an article of Wasserstein RL, Lazar NA. The ASA's statement on p-values: context, process and purpose. The American Statistician 2016.

Albert Hofman, Editor-in-Chief EJE.

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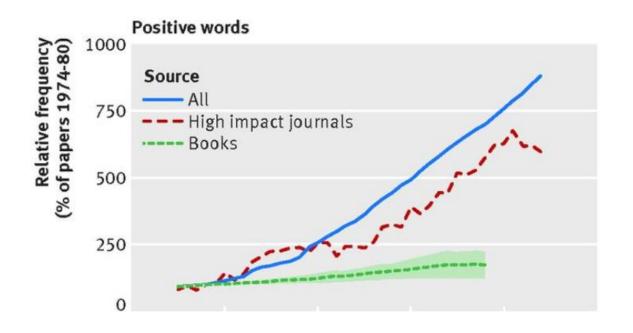
literature. In light of this problem, we provide definitions and a discussion of basic statistics that are more general and critical than typically found in traditional introductory expositions. Our goal is to provide a resource for instructors, researchers, and consumers of statistics whose knowledge of statistical theory and technique may be limited but who wish to avoid and spot misinterpretations. We emphasize how violation of often unstated analysis protocols (such as selecting analyses for presentation based on the P values they produce) can lead to small P values even if the declared test hypothesis is correct, and can lead to large P values even if that hypothesis is incorrect. We then provide an explanatory list of 25 misinterpretations of P values, confidence intervals, and power. We conclude with guidelines for improving statistical interpretation and reporting.

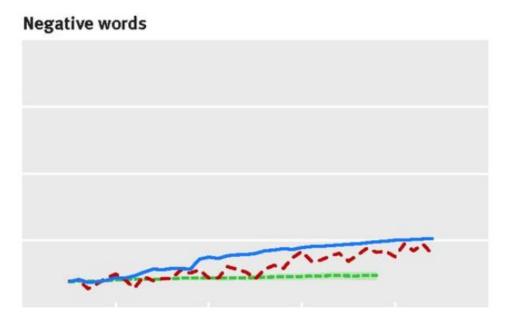
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- <sup>7</sup> Centre for Statistics in Medicine, Nuffield Department of Orthopaedics, Rheumatology and Musculoskeletal Sciences, University of Oxford, Oxford, UK

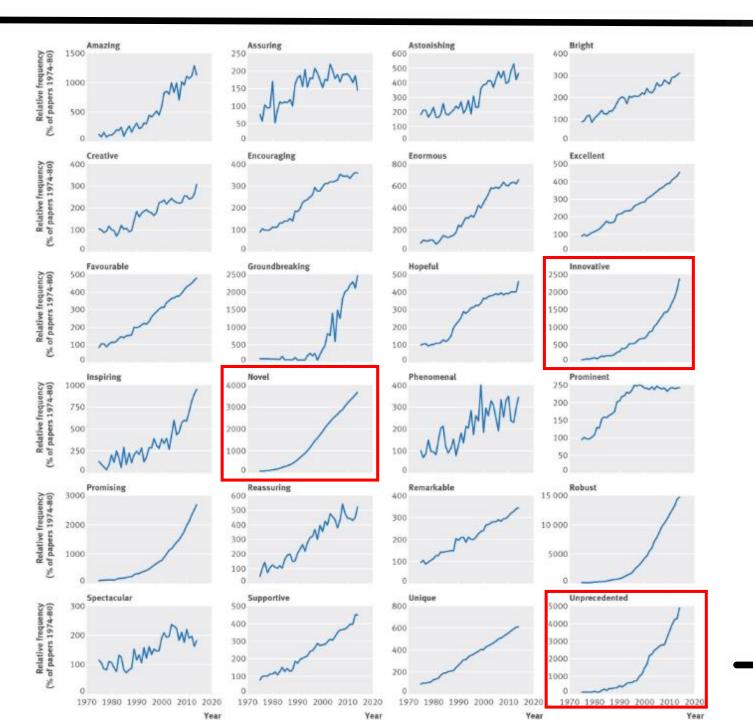


# Everything is awesome!



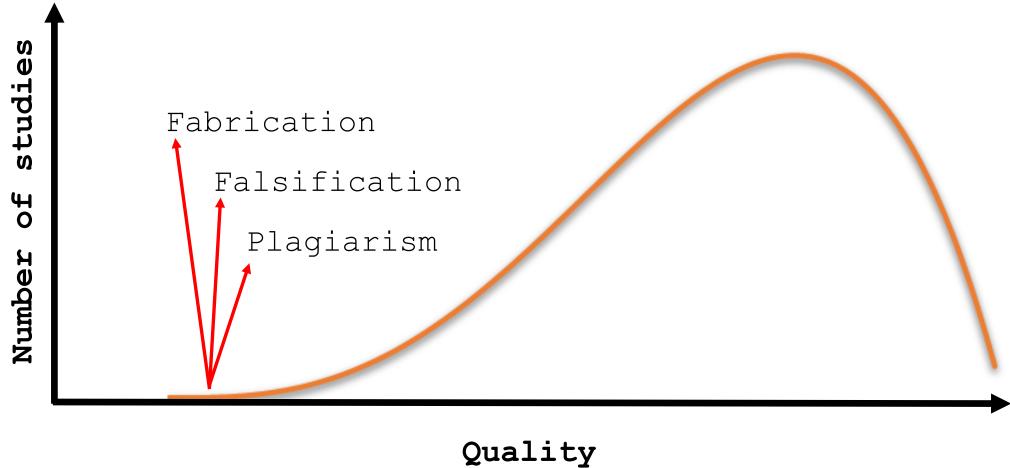






Relative frequencies of individual words as used in PubMed between 1975 and 2014

# Today



## Don't do what Donny Dont does!



"In short, peer review misses all the hard stuff, and a worrying amount of the easy stuff"

James Heathers, Northwestern University

### #datathugs



### Brian Wansink: The grad student who never said no

"Every day we would scratch our heads, ask "Why," and come up with another way to reanalyze the data with yet another set of plausible hypotheses. Eventually we started discovering solutions"

## Install the Chrome plugin PubPeer



## **Twitter**



#### UK Reproducibility Network

@ukrepro

UK Reproducibility Network: a peer-led consortium to investigate factors which contribute to robust research, provide training, and disseminate best practice.



#### **Retraction Watch**

@RetractionWatch

Tracking retractions as a window into the scientific process. Sign up for our daily newsletter: eepurl.com/bNRIUn Tips? team@retractionwatch.com



#### **Dorothy Bishop**

@deevybee

Professor of developmental neuropsychology. Blog on deevybee.blogspot.com Main focus #devlangdis, see: youtube.com/radld



#### James Heathers

@iamesheathers

Research scientist. Biosignals, metascience, error detection. Yelling has vitamins. Cohost of @hertzpodcast.



#### **Open Science MOOC**

@OpenScienceMOOC Follows you

A community designed for students and researchers to help make 'Open' the default setting for the future of research. Slack: osmooc.herokuapp.com

Everywhere



#### Malcolm Macleod #FBPE

@Maclomaclee Follows you

clinical neurologist, stroke trialist, and interested in improving the quality of laboratory research



#### Elisabeth Bik 🥏

@MicrobiomDigest

Science consultant, PhD. Harbers-Bik LLC. Microbiome, research integrity & misconduct. Ex @Stanford.
MicrobiomeDigest/Bik's Picks. Dutch/USA. My views.

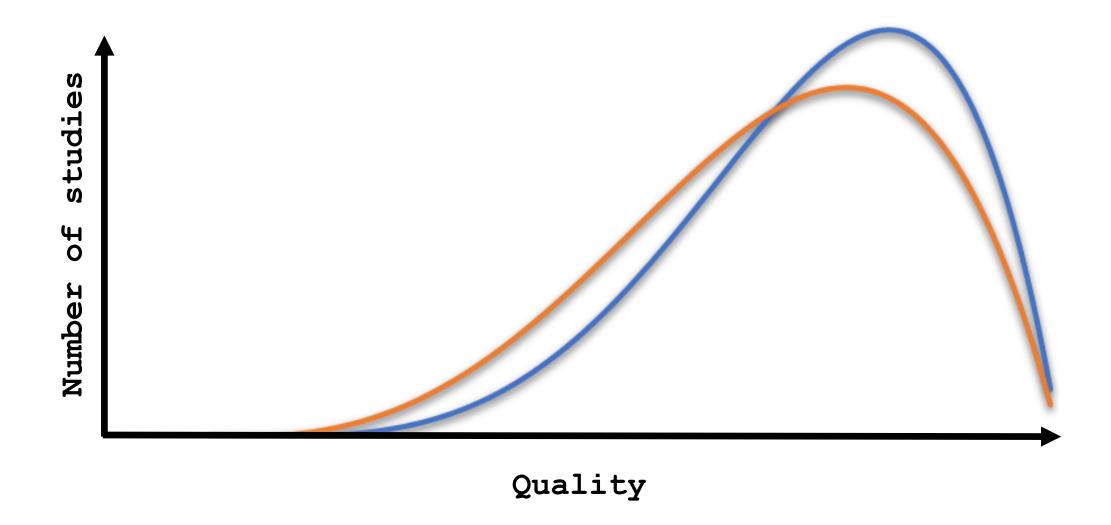


#### **Brian Nosek**

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# Tomorrow



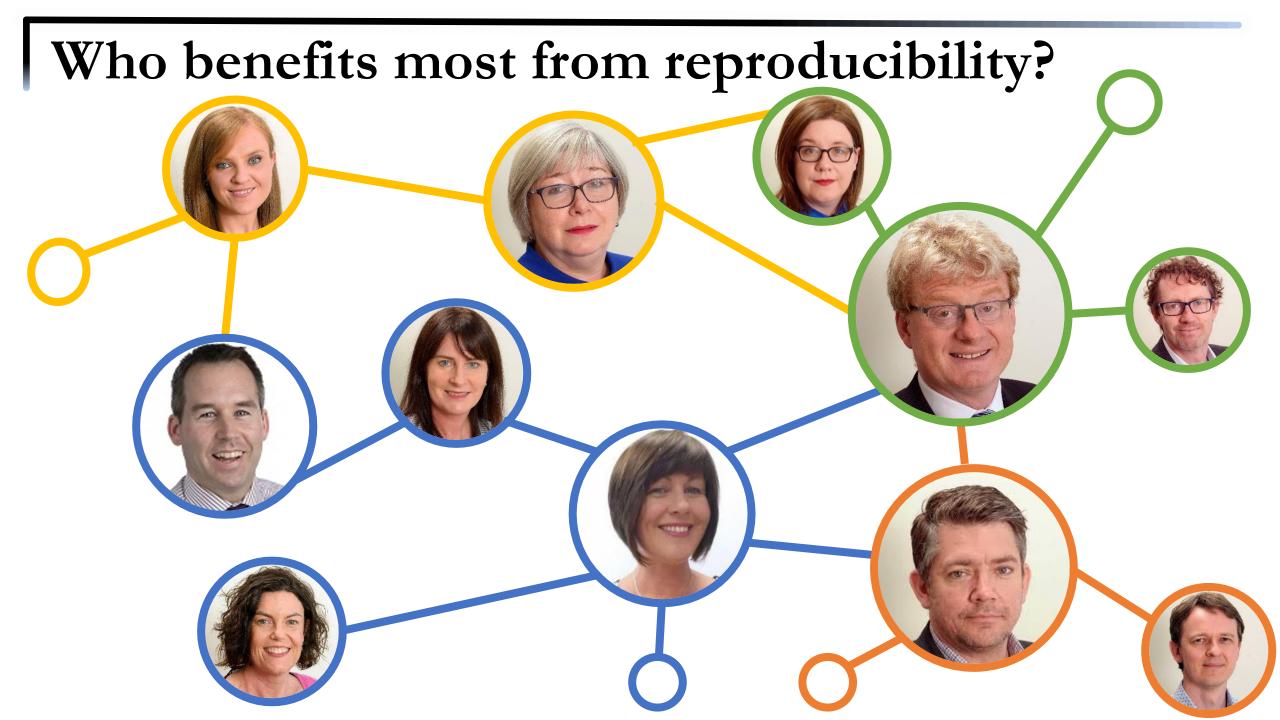
# Who benefits most from reproducibility?



Reproducibility is important because the you of 3 months ago is terrible at answering email! - @tracykteal at #2016dssummit

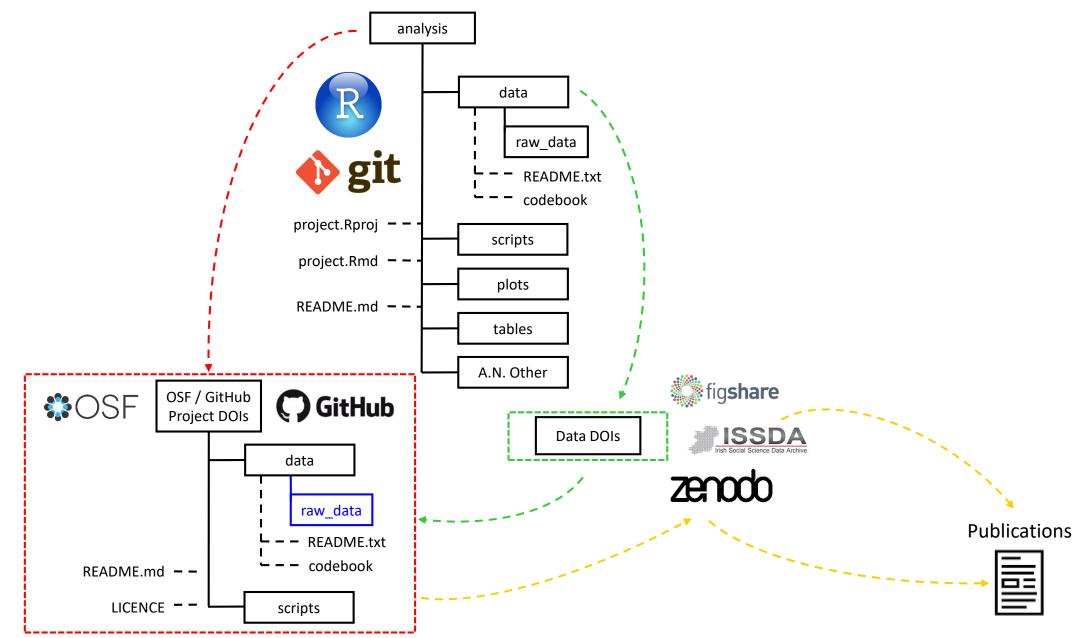
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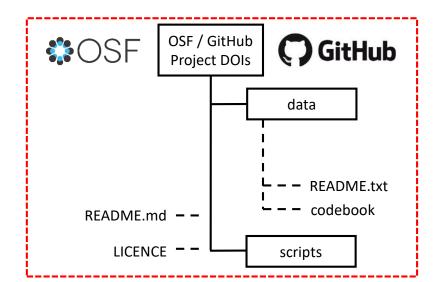




# Where to begin...

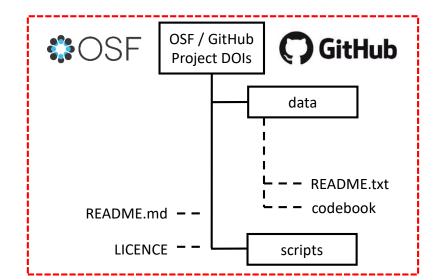






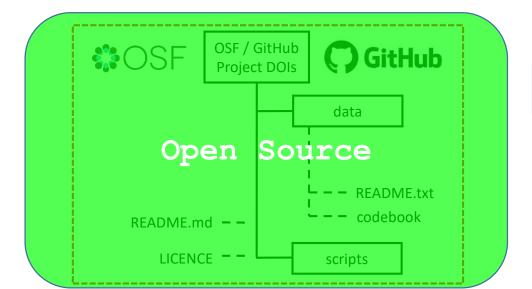
Data DOIs





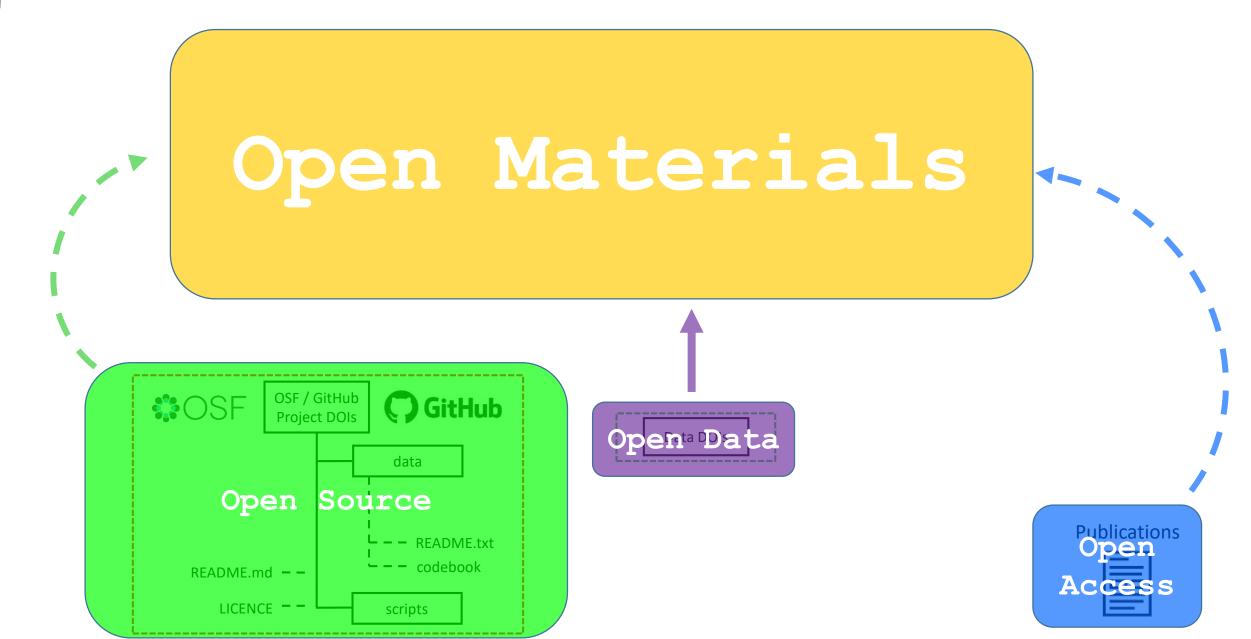












## The butterfly has started flapping its wings



Why Plan S 10 Principles Funders & support Implementation About Contact

"After 1 January 2020 scientific publications on the results from research funded by public grants provided by national and European research councils and funding bodies, must be published in compliant Open Access Journals or on compliant Open Access Platforms."



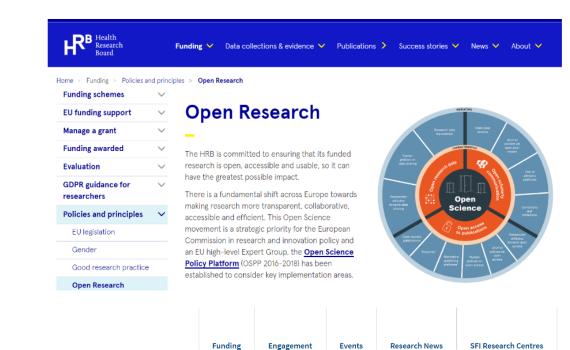
**EUROPEAN COMMISSION** Directorate-General for Research & Innovation H2020 Programme

Guidelines on

FAIR Data Management in Horizon 2020



- Data Management Plan 2 pages max.
  - · Applicants should address the following issues:
    - o What standards will be applied?
    - o How will data be exploited and/or shared/made accessible for verification and reuse? If data cannot be made available, why?
    - o How data will be curated & preserved?
    - If applicable, how does the applicant plan to make the research data FAIR (findable, accessible, interoperable and reusable).



### Science Foundation Ireland joins DORA

14th February 2019, Dublin - Science Foundation Ireland has become a signatory to the San Francisco Declaration of Research Assessment (DORA), making a formal commitment to assessing the quality and impact of research through means other than journal impact factors.

### The movement towards FAIR data























**Findable** 

**Accessible** 

**Interoperable** 

Reusable

(Replicable, Reproducible)

## SCIENTIFIC DATA

SUBJECT CATEGORIES

» Research data » Publication characteristics

**OPEN** Comment: The FAIR Guiding Principles for scientific data management and stewardship

Mark D. Wilkinson et al.#

## Three main take home messages

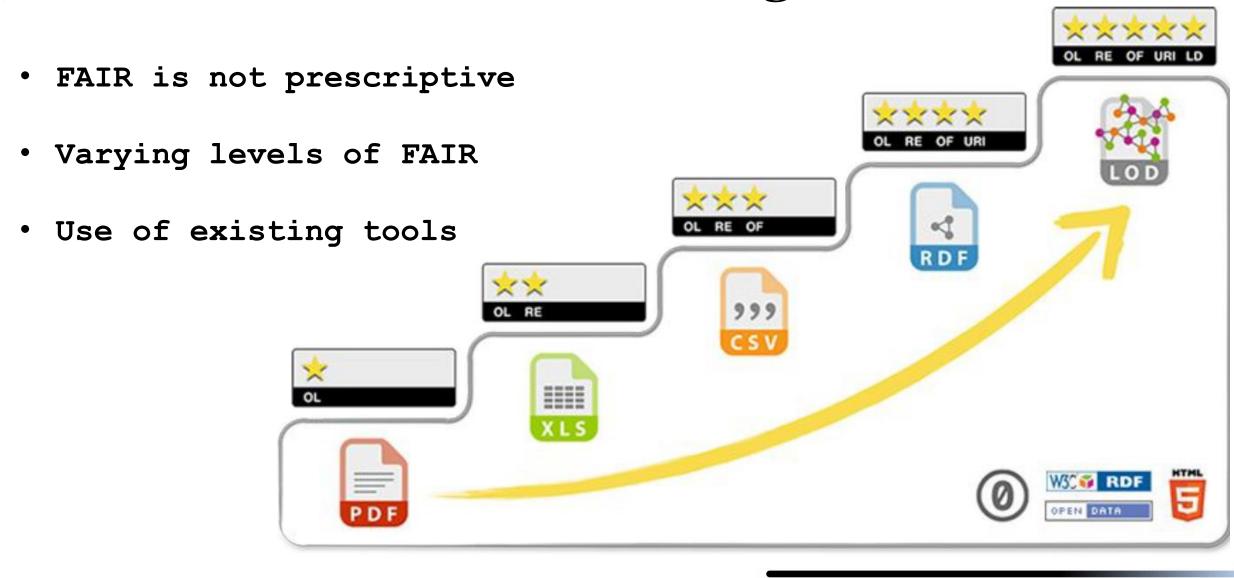


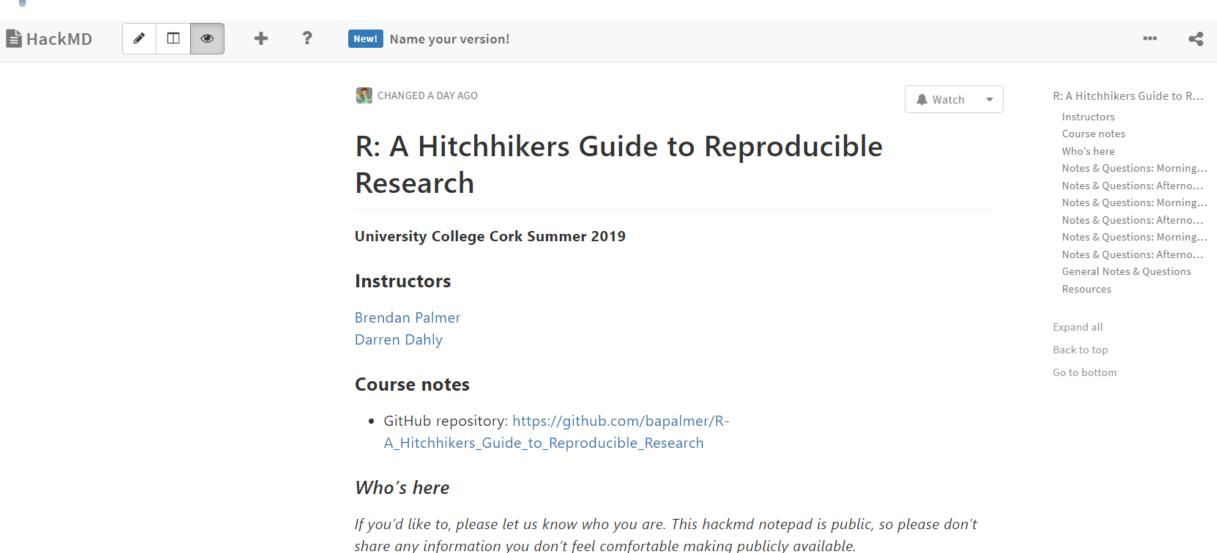
Image: 5 ★ OPEN DATA

# Ask questions



### Live feedback and resources

Name / Group / Twitter



• Brendan Palmer / CRF-C | School of Public Health / @B\_A\_Palmer

## RStudio Cloud



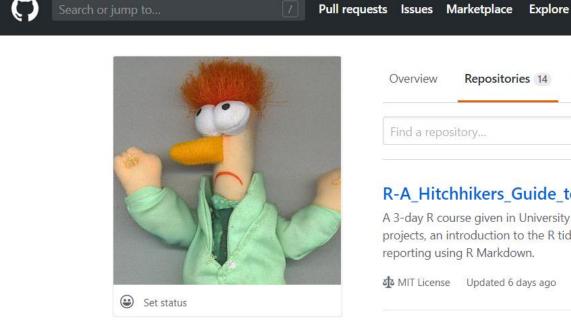
Log In Sign Up

### Welcome to RStudio Cloud alpha

Do, share, teach and learn data science with R.

Get Started

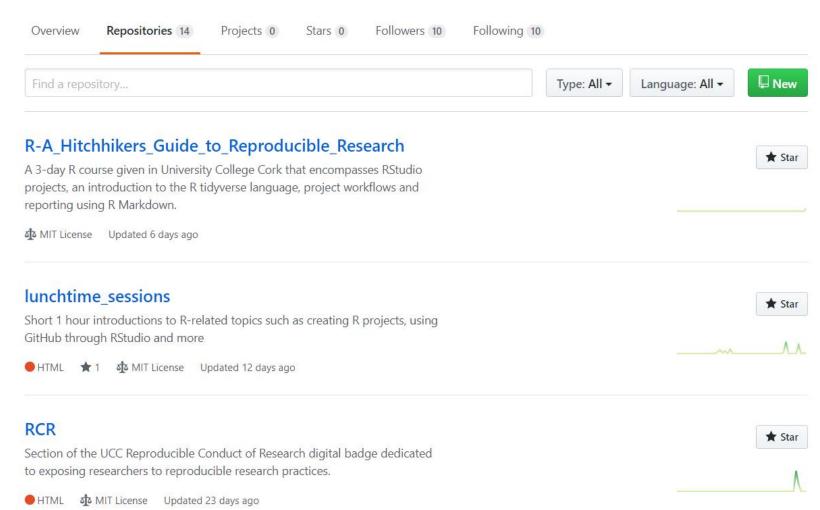
### GitHub



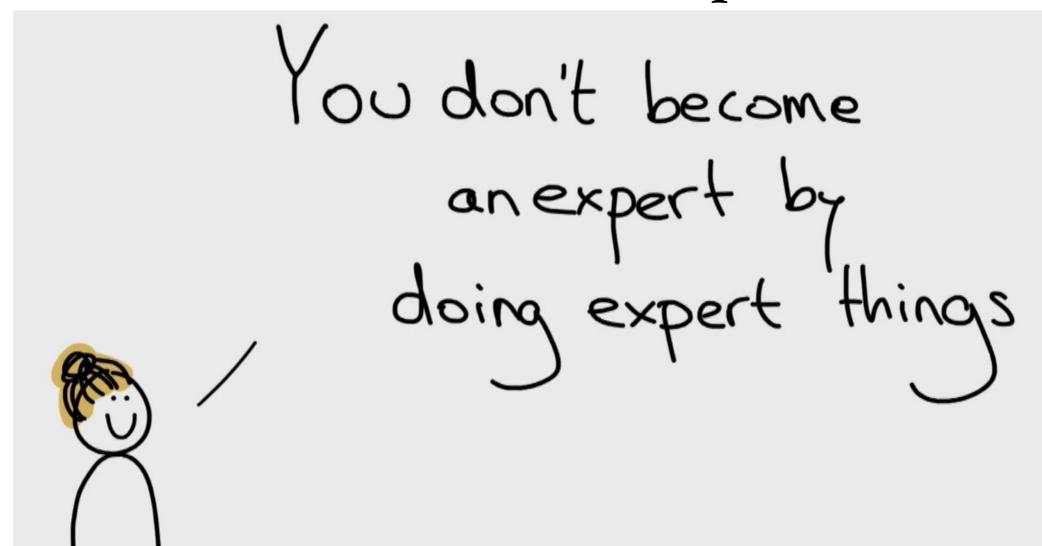
### Brendan Palmer bapalmer







## Central theme of this workshop



# Workshop content

