

## Reproducibility in cancer research

<https://github.com/mdozmorov/presentations>

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## Overview

- What is reproducible research?
- Why do we care?
- Why reproducibility questions arise?
- The cost of reproducibility
- Reproducibility and statistics
- Current status of reproducibility
- What can we do?

## WHAT IS REPRODUCIBLE RESEARCH?



Image credit: <http://blogs.11000research.com/2014/04/04/reproducibility-science-101/>

## Reproducible research in science

- Science is the systematic enterprise of gathering knowledge about the universe and organizing and condensing that knowledge into testable laws and theories
- The success and credibility of science are anchored in the willingness of scientists to **expose their ideas and results to independent testing and replication by other scientists.**

[http://www.aps.org/policy/statements/09\\_6.cfm](http://www.aps.org/policy/statements/09_6.cfm)

## What is reproducible research?

- Reproducibility
- Replicability
- Repeatability
- Reliability
- Robustness
- Generalizability

TRANSCIENCE  
**TRUTH**  
OPEN SCIENCE

Steve Goodman, Stanford, March 18, 2015

## What is reproducible research?

Reproducible research is the ultimate standard for strengthening scientific evidence by independent:

- Investigators
- Data
- Analytical methods
- Laboratories
- Instruments

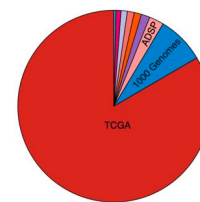


Image source: Glenn B. et al. "Validation must be first part for reproducibility" Nature 2015

## WHY DO WE CARE?

## More data = more chance for errors

- High-throughput biology generates volumes of data
- Data-generating technologies are increasingly used to make clinical recommendations and treatment decisions
- A problem may be overlooked .. Published .. Get in clinical trials



TCGA	- 2300 TB
1000 Genomes*	- 222 TB
ADSP	- 68 TB
NHGRI LSSP*	- 40 TB
GTEx	- 34 TB
NHLBI ESP	- 32 TB
HMP*	- 29 TB
ARRA Autism	- 24 TB
ENCODE*	- 9 TB

Image credit: Mut et al., "The Data Flood of Genomics," Genome Biol. 2016

## Poor medical tests getting to patients

**OvaSure diagnostic test for ovarian cancer**

### MISSING THE MARK

Why is it so hard to find a test to predict cancer?

BY LIZZIE BUCHEN

**O**n 3 March, two studies appeared online that offered 10 pages of gloomy reading for anyone interested in cancer. They focused on biological molecules, or biomarkers, the presence of which in the blood might be used to detect the earliest glimmers of

women — to ask whether these seemingly breakthrough biomarkers were better at identifying women with early ovarian cancer than the one flawed biomarker that had been in use for almost 30 years, CA-125. None of them was. CA-125 remains the “best of a bad

contrast, detected 63%.) Men’s quest already had a tortured history. A primary research paper behind it had been criticized by other scientists for allegedly using inappropriate statistical calculations and for optimistically concluding that the test would help women

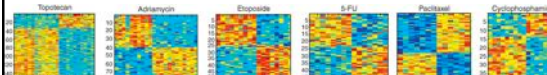
Buchen, “Cancer: Missing the mark,” Nature 2011

## Clinical trials based on flawed and fraudulent data

Genomic signatures to guide the use of chemotherapeutics

Anil Potti<sup>1,2</sup>, Holly K Dressman<sup>1,3</sup>, Andrea Bild<sup>1,3</sup>, Richard F Riedel<sup>1,3</sup>, Gina Chan<sup>4</sup>, Robyn Sayer<sup>4</sup>, Janiel Cragun<sup>4</sup>, Hope Cottrell<sup>1</sup>, Michael J Kelley<sup>1</sup>, Rebecca Petersen<sup>1</sup>, David Harpole<sup>5</sup>, Jeffrey Marks<sup>5</sup>, Andrew Berchuck<sup>1,6</sup>, Geoffrey S Ginsburg<sup>1,2</sup>, Phillip Febbo<sup>1,3</sup>, Johnathan Lancaster<sup>4</sup> & Joseph R Nevins<sup>1-3</sup>

- Described drug response “gene signatures” in NC160 cell lines
- Demonstrated these “signatures” correspond to patient-specific signatures and can be used to predict patient response to the drugs

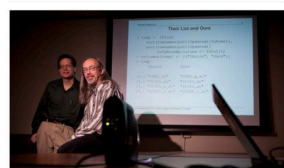


Retraction Watch “The Importance of Being Reproducible: Keith Baggey tells the Anil Potti story” 2011

## Bioinformatics statisticians spot errors

How Bright Promise in Cancer Testing Fell Apart

By GINA KOLATA JULY 3, 2011



Keith Baggey, left, and Maria Gordin, researcher at M.D. Anderson Cancer Center, present research on tumors. Michael Brennan for The New York Times

When Juliet Jacobs found out she had lung cancer, she was terrified, but realized that her hope lay in getting the best treatment medicine could offer. So she got a second opinion, then a third. In February of 2010, she ended up at Dana-Farber, where she entered a research study whose premise seemed stunning.

New York Times “How Bright Promise in Cancer Testing Fell Apart” 2011

## “Off-by-one” error

**Published**

**Replicated**

...

[3,]

1881\_at

1882\_g\_at

[4,]

31321\_at

31322\_at

[5,]

31725\_s\_at

31726\_at

[6,]

32307\_r\_at

32308\_r\_at

...

## New signatures continue to be published

Pharmacogenomic Strategies Provide a Rational Approach to the Treatment of Cisplatin-Resistant Patients With Advanced Cancer

David S. Hsu, Bala S. Balakumaran, Chaitanya R. Acharya, Vanja Vlahovic, Kelli S. Walters, Katherine Garman, Carey Anders, Richard F. Riedel, Johnathan Lancaster, David Harpole, Holly K. Dressman, Joseph R. Nevins, Phillip G. Febbo, and Anil Potti

Validation of gene signatures that predict the response of breast cancer to neoadjuvant chemotherapy: a substudy of the EORTC 10994/BIG 00-01 clinical trial

Harold Bonnefide, Anil Potti, Mauro Delorenzi, Louis Mauriac, Maria Campos, Michelle Tubiana-Hulin, Thierry Petit, Philippe Rouanet, Jack Janssen, Emmanuel Blet, Veronique Belette, Pierre Farmer, Sylvie André, Chaitanya R. Acharya, Sayan Mukherjee, David Cameron, Jonas Bengt, Joseph R. Nevins, Richard D. Iggo

## More data added

Sample ID	Response		
1 GSM44303	RES	11 GSM9694	RES
2 GSM44304	RES	12 GSM9695	RES
3 GSM9653	RES	13 GSM9696	RES
4 GSM9653	RES	14 GSM9698	RES
5 GSM9654	RES	15 GSM9699	SEN
6 GSM9655	RES	16 GSM9701	RES
7 GSM9656	RES	17 GSM9708	RES
8 GSM9657	RES	18 GSM9708	SEN
9 GSM9658	SEN	19 GSM9709	RES
10 GSM9658	SEN	20 GSM9711	RES

RES/SEN – resistant/sensitive

## Summary of the Duke case

- A total of 162 co-authors
- 40 papers
- Two-thirds are partially or completely retracted

### THE CANCER LETTER

Inside information on cancer research and drug development

publication date: 2011-05-04

Duke University issued the following press release Nov. 19:

**Duke Accepts Potti Resignation; Retraction Process Initiated with Nature Medicine**  
 Durham, NC – Anil Potti, PhD, has voluntarily resigned from his positions as associate professor of medicine at Duke University School of Medicine and at the university's Institute for Genome Science & Policy. Dr. Potti's resignation is effective immediately.

In addition, Dr. Potti's collaborator, Joseph Nevins, PhD, has initiated a process intended to lead to a retraction request regarding a paper previously published in Nature Medicine. This process has been initiated due to concerns about the reproducibility of reported predictors, and their possible effect on the overall conclusions in this paper. Other papers published based on this science are currently being reviewed for any concerns.

The three clinical trials based on this science for which new enrollment was suspended in mid-July, have been closed.

<http://retractionwatch.com/2011/05/04/the-importance-of-being-reproducible-keith-baggerly-tells-the-anil-potti-story/>

## IOM guidelines on translational omics

Report 14 PAGES Get this Report

Evolution of Translational Omics: Lessons Learned and the Path Forward

Released: March 23, 2012

REPORT AT A GLANCE

- Press Release (HTML)
- Report Brief (PDF, HTML)

Details

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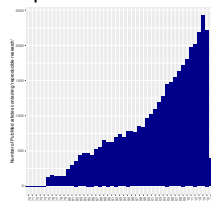
Kaiser J "Clinical medicine, Biomarker tests need closer scrutiny, IOM concludes." *Science* 2012

McShane LM et al. "Criteria for the use of omics-based predictors in clinical trials." *Nature* 2013

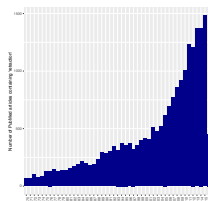
IOM report "Evolution of Translational Omics: Lessons Learned and the Path Forward" 2012

## PubMed stats on "Reproducible research" vs. "Retraction"

"Reproducible research"



"Retraction"



Number of publications per year, from 1970 through April 2016

Retraction Watch

<http://retractionwatch.com/>

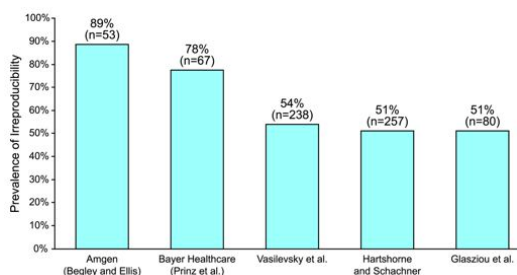
Tracking retractions as a window into the scientific process

## THE COST OF REPRODUCIBILITY



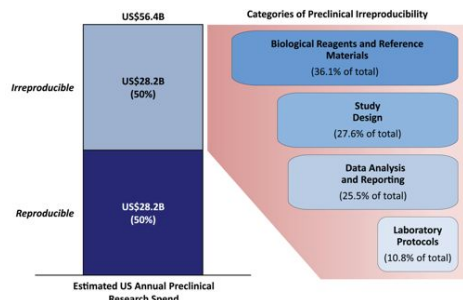
Image credit: The Cost of Living

## Irreproducibility ranges from 51% to 89%



Leonard Freedman, Iain Cockburn, and Timothy Simcoe, "The Economics of Reproducibility in Preclinical Research," PLOS Biol 2015

## Cost of irreproducibility



Leonard Freedman, Iain Cockburn, and Timothy Simcoe, "The Economics of Reproducibility in Preclinical Research," PLOS Biol 2015

## WHY REPRODUCIBILITY QUESTIONS ARISE?



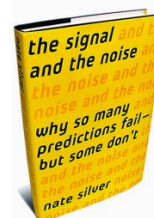
Image credit: [Demystifying the p-value](#)

## Patterns in the noise

- Humans are good at recognizing patterns

Human beings do not have very many natural defenses. We are not all that fast, and we are not all that strong. We do not have claws or fangs or body armor. We cannot spit venom. We cannot camouflage ourselves. And we cannot fly. Instead, we survive by means of our wits. Our minds are quick. **We are wired to detect patterns** and respond to opportunities and threats without much hesitation.

- Nate Silver



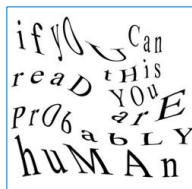
Nate Silver "The Signal and the Noise: Why So Many Predictions Fail—but Some Don't" 2015

## Patterns in the noise

- Humans are good at recognizing patterns



overlooks inquiry

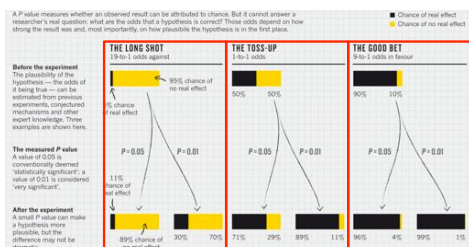


Using neural nets to recognize handwritten digits  
Spammers Use The Human Touch To Avoid CAPTCHA

## Irreproducibility in high-throughput biology

- Our intuition about patterns in high dimensional data quickly drops with the increased dimensionality of the data
- We rely on computation to uncover patterns
- P values, the 'gold standard' of statistical validity, are not as reliable as many researchers assume.

## The chance of being wrong



**The probability of irreproducibility of studies with p-values in the range 0.005 to 0.05 is roughly 0.33**

Regina Nuzzo, "Scientific Method: Statistical errors" *Nature* 2014  
Dennis Boos and Leonard Stefanski "P-value precision and reproducibility" *Am Statistician*, 2001

## The chance of being wrong

### Why Most Published Research Findings Are False

John P.A. Ioannidis

#### Summary

There is increasing concern that most current published research findings are false. The probability that a research claim is true given the research study outcome and

factors that influence this problem and some correlates thereof.

#### Modeling the Framework for False Positive Findings

Several methodologists have

is characteristic of the field and can vary a lot depending on whether the field targets highly likely relationships or searches for only one or a few true relationships among thousands and millions of hypotheses that may

1. In evaluating any study try to take into account the amount of background noise. That is, remember that the more hypotheses which are tested and the less selection which goes into choosing hypotheses the more likely it is that you are looking at noise.
2. Bigger samples are better. (But note that even big samples won't help to solve the problems of observational studies which is a whole other problem).
3. Small effects are to be distrusted.
4. Multiple sources and types of evidence are desirable.
5. Evaluate literatures not individual papers.
6. Trust empirical papers which test other people's theories more than empirical papers which test the author's theory.
7. As an editor or referee, don't reject papers that fail to reject the null.

John Ioannidis "Why Most Published Research Findings Are False" *PLOS Medicine* 2005  
Alex Tabarrok blog "Why Most Published Research Findings Are False" 2005

## Understanding the p-value



The ASA's statement on p-values: context, process, and purpose

DOI: 10.1080/00031305.2016.1154108  
Ronald L. Wasserstein & Nicole A. Lazar  
Publishing models and article dates explained  
Received: 4 Feb 2016  
Accepted: 9 Feb 2016



1. P-values can indicate how incompatible the data are with a specified statistical model.
2. P-values do not measure the probability that the studied hypothesis is true, or the probability that the data were produced by random chance alone.
3. Scientific conclusions and business or policy decisions should not be based only on whether a p-value passes a specific threshold.
4. Proper inference requires full reporting and transparency.
5. A p-value, or statistical significance, does not measure the size of an effect or the importance of a result.
6. By itself, a p-value does not provide a good measure of evidence regarding a model or hypothesis.

Ronald Wasserstein and Nicole Lazar "The ASA's statement on p-values: context, process, and purpose" *Am Stat* 2016  
Monya Baker "Statisticians issue warning over misuse of P value" *Nature* 2016

## P-value warning: consult a statistician before the experiment



To consult the statistician after an experiment is finished is often merely to ask him to conduct a post mortem examination. He can perhaps say what the experiment died of.

— Ronald Fisher —

AZ QUOTES

Image credit: azquotes.com

## CURRENT STATUS OF REPRODUCIBILITY



Image credit: [Bridges to Accelerate Open Practices](#)

## Focus on preclinical research

### Raise standards for preclinical cancer research

C. Glenn Begley and Lee M. Ellis propose how methods, publications and incentives must change if patients are to benefit.

Efforts over the past decade to characterize the genetic alterations in human cancers have led to a better

understanding of the genetic alterations in human cancers have led to a better

understanding of the genetic alterations in human cancers have led to a better

### NIH plans to enhance reproducibility

Francis S. Collins and Lawrence A. Tabak discuss initiatives that the US National Institutes of Health is exploring to restore the self-correcting nature of preclinical research.

A growing chorus of concerns, from scientists and laypeople, contends that the complex system for ensuring

shorter terms, however, the checks and balances that once ensured scientific fidelity have been hollowed. This has compromised

investigators must reassess their approach to translating discovery research into greater clinical success and impact.

ing agencies to establish or enforce policies that insist on data access.

**PRECLINICAL PROBLEMS**  
Reproducibility is generally a problem in all scientific disciplines. However, human clinical trials seem to be less at risk because they are already governed by various regulations that stipulate rigorous design and independent oversight — including randomization, blinding, power estimates, pre registration of outcome measures in standardized, public databases such as ClinicalTrials.gov and oversight by institutional review boards and data safety monitoring boards. Furthermore, the clinical trials community has taken important steps towards adopting standard reporting formats.

Glenn Begley and Lee Ellis, "Drug Development" *Nature* 2012  
Francis Collins and Lawrence Tabak, "Policy: NIH Plans to Enhance Reproducibility" *Nature* 2014

## NIH focus on openness

NIH National Institutes of Health  
Office of Extramural Research

Grants & Funding  
NIH's Central Resource for Grants and Funding Information

Entire Site Search this Site

Home > Grants Policy > Rigor and Reproducibility

### Rigor and Reproducibility

Scientific rigor and transparency in conducting biomedical research is key to the successful application of knowledge toward improving health outcomes. The information provided on

- Public Access Policy
- Data Sharing Policies
- Genomics Data Sharing (GDS)
- Model Organism Sharing Policy
- Research Tools Policy

<https://grants.nih.gov/reproducibility/index.htm>

## NSF stance on openness

National Science Foundation  
WHERE DISCOVERIES BEGIN

Office of Budget, Finance and Award Management (BFA)

### Dissemination and Sharing of Research Results

NSF Data Sharing Policy

Investigators are expected to share with other researchers, at no more than incremental cost and within a reasonable time, the primary data, samples, physical collections and other supporting materials created or gathered in the course of work under NSF grants. Grantees are expected to encourage and facilitate such sharing. See [Appendix A Administration Guide \(AAG\)](#), Chapter VI.D.4.

NSF Data Management Plan Requirements

Proposals submitted or due on or after January 18, 2011, must include a supplementary document of no more than two pages labeled "Data Management Plan". This supplementary document should describe how the proposal will conform to NSF policy on the dissemination and sharing of research results. See [Grant Proposal Guide \(GPG\)](#), Chapter II.C.2.3 for full policy implementation.

- Responsible Conduct of Research (RCR)
- NSF Scientific Integrity Policy

<https://www.nsf.gov/bfa/dias/policy/dmp.jsp>

## Reproducibility initiatives

**nature.com**

### Enhancing reproducibility

New reporting standards for Nature Journal authors are intended to improve transparency and reproducibility.

**REPRODUCIBLE RESEARCH**  
ADDRESSING THE NEED FOR DATA AND CODE SHARING IN COMPUTATIONAL SCIENCE  
By the Yale Law School Roundtable on Data and Code Sharing

Victoria Slodden et al. "Reproducible Research" Yale Law School

**COS** CENTER FOR OPEN SCIENCE

**Open Science Framework**  
A library connects to connect the entire research cycle

<https://cos.io/>

<https://osf.io/>

## Reproducibility guidelines

- ARRIVE – Animal Research Reporting of In Vivo Experiments
- CONSORT – Consolidated Standards of Reporting Trials
- SPIRIT – Standard Protocol Items: Recommendations for Interventional Trials
- STROBE – The Strengthening the Reporting of Observational Studies in Epidemiology
- (STARD) TRIPOD – Transparent Reporting of a multivariable prediction model for Individual PROgnosis of Diagnosis
- REMARK – REporting recommendations for tumour MARKer prognostic studies

**equator** NETWORK  
Enhancing the QUALITY and Transparency Of health Research

Library for health research reporting

Reporting guidelines for main study types

Study Type	Reporting Guideline	Checkmark
Interventional study	CONSORT	Yes
Observational study	STROBE	Yes
Diagnostic study	STARD	Yes
Prognostic study	TRIPOD	Yes
Systematic review	PRISMA	Yes
Health economics study	HEALTHY	Yes
Health services research	SRIS	Yes
Healthcare delivery research	SRIS	Yes
Healthcare evaluation research	SRIS	Yes
Healthcare implementation research	SRIS	Yes
Healthcare management research	SRIS	Yes
Healthcare policy research	SRIS	Yes
Healthcare practice research	SRIS	Yes
Healthcare system research	SRIS	Yes
Healthcare workforce research	SRIS	Yes
Healthcare quality research	SRIS	Yes
Healthcare equity research	SRIS	Yes
Healthcare access research	SRIS	Yes
Healthcare cost research	SRIS	Yes
Healthcare value research	SRIS	Yes
Healthcare innovation research	SRIS	Yes
Healthcare leadership research	SRIS	Yes
Healthcare culture research	SRIS	Yes
Healthcare change research	SRIS	Yes
Healthcare improvement research	SRIS	Yes
Healthcare research	SRIS	Yes

<http://www.equator-network.org/> - over 300 reporting guidelines

## WHAT CAN WE DO TO ENHANCE REPRODUCIBILITY?



Image credit: [JPL & Materials Online Foundation](#)

## Flavors of reproducibility

- Empirical reproducibility
- Computational reproducibility
- Statistical reproducibility




## Steps in reproducible research

The most important is the mindset, when starting, that the end product will be reproducible.

– Keith Baggerly

- Experimental design
- Data generation
- Data analysis
- Results interpretation
- Dissemination of results

## Poor experimental design

Related Commentary, page 26  Research article

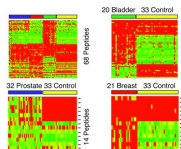
**Differential exoprotease activities confer tumor-specific serum peptidome patterns**

Josep Villanueva, David R. Shaffer, John Philip, Carlos A. Chaparro, Hediye Erdjument-Bromage, Adam B. Olshen, Martin Fleischer, Hans Lijss, Ed Brogi, Jeff Boyd, Maria Sanchez-Carbayo, Eric C. Holland, Carlos Cordon-Cardo, Howard I. Scher, and Paul Tempst

Memorial Sloan-Kettering Cancer Center, New York, New York, USA.

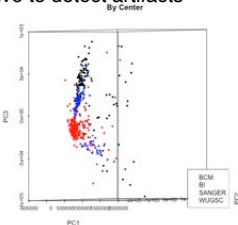
Villanueva J et al. "Differential exoprotease activities confer tumor-specific serum peptidome patterns." *J Clin Invest*. 2006

- 100% sensitive and specific for prostate cancer
- Patient characteristics
  - Cancer patients: Age: mean 67 years, Sex: 100% male
  - Healthy controls: Age: mean 35 years, Sex: 58% women



## Considerations for data generations

- Assay artifacts and batch effects
  - 'Omics' technologies are extremely well suited to detect biological features
  - They are exquisitely sensitive to detect artifacts
- Note everything:
  - changes in procedures
  - reagents
  - equipment
  - technician
  - date of experiment



## Basics of reproducible research

- Lab notebook
  - Complete record of procedures, reagents, data, and thoughts to share with other researchers
  - Explanation of why experiments were initiated, how they were performed, what are the results
  - Legal document to prove your experiments against irreproducibility

## Common approach: write report around results

### Point and click approach

- Use MS Excel for data entry/cleaning/preparation, and possibly statistical analysis

### Problems

- With point-and-click, there's no way to record/save the steps that generated the (copy/pasted) results
- Data files are kept separately from the analysis code, and from reports
- After modifications of one of the files, it becomes unclear which version corresponds exactly to the reported results
- Every time something changes, you have to regenerate the figures/results/reports by hand – very time consuming

Zeeberg BR et al. "Mistaken identifiers: gene name errors can be introduced inadvertently when using Excel in bioinformatics." *BMC Bioinformatics* 2004

## Better approach: write report that generates results

- The report is automated via code
- Data is attached to the well-documented code
- History of any changes should be preserved

**The final report should be self-sufficient and reproducible with a single command**





## Publishing with Git

### B-Cell and Monocyte Contribution to Systemic Lupus Erythematosus Identified by Cell-Type-Specific Differential Expression Analysis in RNA-Seq Data



Mikhail G. Dozmorov<sup>1</sup>, Nicolas Dominguez<sup>2</sup>, Krista Bean<sup>2</sup>, Susan R. Macwana<sup>2</sup>, Virginia Roberts<sup>2</sup>, Edmund Glass<sup>1</sup>, Judith A. James<sup>2</sup> and Joel M. Guthridge<sup>2</sup>

**Implementation and availability.** All RNA-seq data processing steps were performed in CentOS 6.6 high-performance cluster computing environment. All analyses were conducted in R/Bioconductor environment v 3.2.0.<sup>36,37</sup>

All analytical scripts are available at <https://github.com/mdozmorov/deconvolution>.

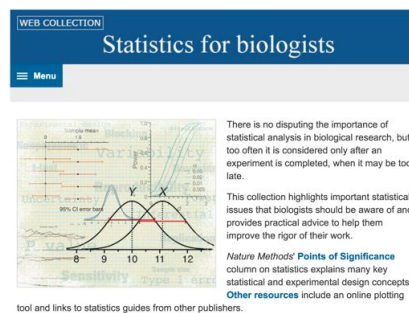
<https://www.ncbi.nlm.nih.gov/pubmed/26512198>

## Reproducibility 101

- **Reproducibility made easy**
  - Begin with the final product in mind
  - Use literate programming (self-documenting code)
  - History of changes via code versioning and sharing
- **Replication made easy**
  - Get basic statistics right
  - Set stringent cutoffs, correct p-values for multiple testing
  - Be critical, consider batch effects, visualize, do sanity checks, use random controls, cross-validation
  - Follow reporting guidelines

## LEARN MORE

## Nature “Statistics for Biologists”



<http://www.nature.com/collections/qghqhm>

## Reproducible research made simple

OPEN ACCESS Freely available online



### Editorial

### Ten Simple Rules for Reproducible Computational Research

Geir Kjetil Sandve<sup>1,2\*</sup>, Anton Nekrutenko<sup>3</sup>, James Taylor<sup>4</sup>, Eivind Hovig<sup>1,5,6</sup>

<https://www.ncbi.nlm.nih.gov/pubmed/24204232>

### Best Practices for Scientific Computing

Greg Wilson<sup>\*</sup>, D.A. Aruliah<sup>1</sup>, C. Titus Brown<sup>1</sup>, Neil P. Chue Hong<sup>3</sup>, Matt Davis<sup>4</sup>, Richard T. Guy<sup>1</sup>, Steven H.D. Haddock<sup>2\*</sup>, Katy Huff<sup>11</sup>, Ian M. Mitchell<sup>12</sup>, Mark D. Plumbley<sup>13</sup>, Ben Waugh<sup>14</sup>, Ethan P. White<sup>15</sup>, Paul Wilson<sup>11††</sup>

<https://www.ncbi.nlm.nih.gov/pubmed/24415924>

## Practical reproducibility

- BOIS 692 “Reproducible Research Tools”
- June 13-16, 2016
- <https://mdozmorov.github.io/BIOS692/>

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