Science: Set the Default to Open

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Séance de réflexion of the Swiss National Research Council on
“2050: A Science Odyssey”
November 16, 2016
Digitization → Openness

1. Open Access
2. Open Data
3. Reproducibility
4. Open Code and Openly Executable Methods
5. What Do Research and Publication Look Like in this World?
Open Access

• Traditional publications, without a paywall,

• Goal: “clickable” reading of research articles by everyone,

• Applies to all articles, divorced from discussions around computational research,

• An ongoing discussion.. long history, back to early 1990’s..
Open Data

- Data as a first class scholarly object, analogy to a publication,

- Ideas from open genome data movement (Bermuda Principles 1996),

- Many key policy steps toward Open Data: OSTP Executive Memorandum (2013) and Executive Order (2013).
A Credibility Crisis: Reproducibility

Researchers are rewarded for flashy findings, not for double-checking accuracy. So many scientists looking for cures to diseases have been building on ideas that aren’t even true.

By Michael Hiltzik
October 27, 2013

In today’s scientific climate, one paper published in the Journal of the American Medical Association says the fruit fly Drosophila melanogaster will live longer if you make its DNA more random. Another, published in the Journal of the American College of Cardiology, says the sugar beet does it.

The findings are, respectively, fugitive and unproven. Science has lost its way, at a big cost to humanity.

NIH Tackles Irreproducibility

The federal agency speaks out about how to improve the quality of scientific research.

By Jef Akst | January 28, 2014

Science advances on a foundation of trusted discoveries. Reproducing an experiment is one important approach that scientists use to gain confidence in their conclusions. Recently, the scientific community was shaken by reports that a troubling proportion of peer-reviewed preclinical studies are not reproducible. Because confidence in results is of paramount importance to the broad scientific community, we are announcing new initiatives to increase confidence in the studies published in Science. For preclinical studies (one of the targets of recent concern), we will be adopting recommendations of the U.S. National Institute of Neurological Disorders and Stroke (NINDS) for increasing transparency. Authors will indicate whether there was a pre-experimental plan for data handling (such as how to deal with outliers), whether they conducted a sample size estimation to ensure a sufficient signal-to-noise ratio, whether samples were treated randomly, and whether the experimenter was blind to the conduct of the experiment. These criteria will be included in our author

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Setting the Default to Reproducible

Reproducibility in Computational and Experimental Mathematics

Developed collaboratively by the ICERM workshop participants

Compiled and edited by the Organizers

V. Stodden, D. H. Bailey, J. Borwein, R. J. LeVeque, W. Rider, and W. Stein

Abstract

Science is built upon foundations of theory and experiment validated and improved through open, transparent communication. With the increasingly central role of computation in scientific discovery this means communicating all details of the computations needed for others to replicate the experiment, i.e., making available to others the associated data and code. The "reproducible research and publication practices now fall short of the production of computational science — scientists who employ them, journals and dissemination mechanisms, support reproducible research.

Set the Default to "Open"

Reproducible Science in the Computer Age. Conventional wisdom sees computing as the "third leg" of science, complementing theory and experiment. That metaphor is outdated. Computing now pervades all of science. Massive computation is often required to reduce and analyze data; simulations are employed in fields as diverse as climate modeling and astrophysics. Unfortunately, scientific computing culture has not kept pace. Experimental researchers are taught early to keep notebooks or computer logs of every work detail: design, procedures, equipment, raw results, processing techniques, statistical methods of analysis, etc. In contrast, few computational experiments are performed with such care. Typically, there is no record of workflow, computer hardware and software configuration, or parameter settings. Often source code is lost. While crippling reproducibility of results, these practices ultimately impede the researcher's own productivity.

The State of Experimental and Computational Mathematics. Experimental mathematics — application of high-performance computing technology to research questions in pure and applied mathematics, including physicists, legal scholars, journal editors, and funding agency officials representing academia, government labs, industry research, and all points in between. While
Defining Reproducibility

“Empirical Reproducibility”

“Statistical Reproducibility”

“Computational Reproducibility”

V. Stodden, IMS Bulletin (2013)
The Impact of Technology

1. Big Data / Data Driven Discovery: high dimensional data, $p >> n$,

2. Computational Power: simulation of the complete evolution of a physical system, systematically varying parameters,

3. Deep intellectual contributions now encoded only in software.

Claim 1: Virtually all published discoveries today have a computational component. (is Data Science all science?)

Claim 2: There is a mismatch between the traditional scientific process and computation, leading to reproducibility concerns.

The software contains “ideas that enable biology...”

Stories from the Supplement, 2013

“...The actual scholarship is the full software environment, code and data, that produced the result.”

Buckheit & Donoho, 1995
Modeling and Simulation: A NIST Multi-Laboratory Strategic Planning Workshop

Gaithersburg, MD
September 21, 1995

Workshop Overview

The workshop consisted of an introduction; five talks, each followed by a discussion period; and an open discussion session. Capsule versions follow immediately; more substantial summaries follow later.

Jim Blue opened the workshop with brief introductory remarks. He emphasized that the purpose of doing modeling and simulation is to gain understanding and insight. The three benefits are that modeling and simulation can be cheaper, quicker, and better than experimentation alone. It is common now to consider computation as a third branch of science, besides theory and experiment.

“It is common now to consider computation as a third branch of science, besides theory and experiment.”

“This book is about a new, fourth paradigm for science based on data-intensive computing.”
Computational Reproducibility

Traditionally two branches to the scientific method:

• Branch 1 (deductive): mathematics, formal logic,

• Branch 2 (empirical): statistical analysis of controlled experiments.

Now, new branches due to technological changes?

• Branch 3,4? (computational): large scale simulations / data driven computational science.
The Ubiquity of Error

The central motivation for the scientific method is to root out error:

- Deductive branch: the well-defined concept of the proof,
- Empirical branch: the machinery of hypothesis testing, appropriate statistical methods, structured communication of methods and protocols.

Claim: Computation and Data Science present only potential third/fourth branches of the scientific method (Donoho et al. 2009), until the development of comparable standards.
Really Reproducible Research

“Really Reproducible Research” (1992) inspired by Stanford Professor Jon Claerbout:

“The idea is: An article about computational science in a scientific publication is not the scholarship itself, it is merely advertising of the scholarship. The actual scholarship is the complete ... set of instructions [and data] which generated the figures.” David Donoho, 1998

Note the difference between: reproducing the computational steps and, replicating the experiments independently including data collection and software implementation (both needed).
Recent Advances
This workshop will consider ways to make code and modeling information more readily available, and include a variety of stakeholders.

The computational steps that produce scientific findings are increasingly considered a crucial part of the scholarly record, permitting transparency, reproducibility, and re-use. Important information about data preparation and model implementation, such as parameter settings or the treatment of outliers and missing values, is often expressed only in code. Such decisions can have substantial impacts on research outcomes, yet such details are rarely available with scientific findings.

http://www.aaas.org/event/iii-arnold-workshop-modeling-and-code
Feb 16-17, 2016
Workshop Recommendations: “Reproducibility Enhancement Principles”

RECOMMENDATION 1: To facilitate reproducibility, share the data, software, workflows, and details of the computational environment in open repositories.

RECOMMENDATION 2: To enable discoverability, persistent links should appear in the published article and include a permanent identifier for data, code, and digital artifacts upon which the results depend.

RECOMMENDATION 3: To enable credit for shared digital scholarly objects, citation should be standard practice.

RECOMMENDATION 4: To facilitate reuse, adequately document digital scholarly artifacts.
Workshop Recommendations: “Reproducibility Enhancement Principles”

RECOMMENDATION 5: Journals should conduct a Reproducibility Check as part of the publication process and enact the TOP Standards at level 2 or 3.

RECOMMENDATION 6: Use Open Licensing when publishing digital scholarly objects.

RECOMMENDATION 7: To better enable reproducibility across the scientific enterprise, funding agencies should instigate new research programs and pilot studies.
### Summary of the eight standards and three levels of the TOP guidelines

Levels 1 to 3 are increasingly stringent for each standard. Level 0 offers a comparison that does not meet the standard.

<table>
<thead>
<tr>
<th>Standards</th>
<th>Level 0</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
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<tbody>
<tr>
<td><strong>Citation standards</strong></td>
<td>Journal encourages citation of data, code, and materials—or says nothing.</td>
<td>Journal describes citation of data in guidelines to authors with clear rules and examples.</td>
<td>Article provides appropriate citation for data and materials used, consistent with journal’s author guidelines.</td>
<td>Article is not published until appropriate citation for data and materials is provided that follows journal’s author guidelines.</td>
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<tr>
<td><strong>Data transparency</strong></td>
<td>Journal encourages data sharing—or says nothing.</td>
<td>Article states whether data are available and, if so, where to access them.</td>
<td>Data must be posted to a trusted repository. Exceptions must be identified at article submission.</td>
<td>Data must be posted to a trusted repository, and reported analyses will be reproduced independently before publication.</td>
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<tr>
<td><strong>Analytic methods (code) transparency</strong></td>
<td>Journal encourages code sharing—or says nothing.</td>
<td>Article states whether code is available and, if so, where to access them.</td>
<td>Code must be posted to a trusted repository. Exceptions must be identified at article submission.</td>
<td>Code must be posted to a trusted repository, and reported analyses will be reproduced independently before publication.</td>
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<tr>
<td><strong>Research materials transparency</strong></td>
<td>Journal encourages materials sharing—or says nothing</td>
<td>Article states whether materials are available and, if so, where to access them.</td>
<td>Materials must be posted to a trusted repository. Exceptions must be identified at article submission.</td>
<td>Materials must be posted to a trusted repository, and reported analyses will be reproduced independently before publication.</td>
</tr>
<tr>
<td><strong>Design and analysis transparency</strong></td>
<td>Journal encourages design and analysis transparency or says nothing.</td>
<td>Journal articulates design transparency standards.</td>
<td>Journal requires adherence to design transparency standards for review and publication.</td>
<td>Journal requires and enforces adherence to design transparency standards for review and publication.</td>
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<td><strong>Preregistration of studies</strong></td>
<td>Journal says nothing.</td>
<td>Journal encourages preregistration of studies and provides link in article to preregistration if it exists.</td>
<td>Journal encourages preregistration of studies and provides link in article and certification of meeting preregistration requirements.</td>
<td>Journal requires preregistration of studies and provides link and badge in article to meeting requirements.</td>
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<td><strong>Preregistration of analysis plans</strong></td>
<td>Journal says nothing.</td>
<td>Journal encourages preanalysis plans and provides link in article to registered analysis plan if it exists.</td>
<td>Journal encourages preanalysis plans and provides link in article and certification of meeting registered analysis plan badge requirements.</td>
<td>Journal requires preregistration of studies with analysis plans and provides link and badge in article to meeting requirements.</td>
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<td><strong>Replication</strong></td>
<td>Journal discourages submission of replication studies—or says nothing.</td>
<td>Journal encourages submission of replication studies.</td>
<td>Journal encourages submission of replication studies and conducts blind review of results.</td>
<td>Journal uses Registered Reports as a submission option for replication studies with peer review before observing the study outcomes.</td>
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Result and Artifact Review and Badging

An experimental result is not fully established unless it can be independently reproduced. A variety of recent studies, primarily in the biomedical field, have revealed that an uncomfortably large number of research results found in the literature fail this test, because of sloppy experimental methods, flawed
**Terminology.**

A variety of research communities have embraced the goal of reproducibility in experimental science. Unfortunately, the terminology in use has not been uniform. Because of this we find it necessary to define our terms. The following are inspired by the International Vocabulary for Metrology (VIM); see the Appendix for details.

- **Repeatability** (Same team, same experimental setup)
  - The measurement can be obtained with stated precision by the same team using the same measurement procedure, the same measuring system, under the same operating conditions, in the same location on multiple trials. For computational experiments, this means that a researcher can reliably repeat her own computation.

- **Replicability** (Different team, same experimental setup)
  - The measurement can be obtained with stated precision by a different team using the same measurement procedure, the same measuring system, under the same operating conditions, in the same or a different location on multiple trials. For computational experiments, this means that an independent group can obtain the same result using the author’s own artifacts.

- **Reproducibility** (Different team, different experimental setup)
  - The measurement can be obtained with stated precision by a different team, a different measuring system, in a different location on multiple trials. For computational experiments, this means that an independent group can obtain the same result using artifacts which they develop completely independently.
## Journal Data and Code Sharing Policies

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<td>Required as condition of publication, barring exceptions</td>
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<td>Required but may not affect editorial decisions</td>
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<td>Encouraged/addressed, may be reviewed and/or hosted</td>
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Source: Stodden, Guo, Ma (2013) PLoS ONE, 8(6)
Science 2014

In January 2014 Science enacted new manuscript submission requirements:

• a “data-handling plan” i.e. how outliers will be dealt with,

• sample size estimation for effect size,

• whether samples are treated randomly,

• whether experimenter blind to the conduct of the experiment.

Also added statisticians to the Board of Reviewing Editors.
Infrastructure Responses

Tools and software to enhance reproducibility and disseminate the scholarly record:

Dissemination Platforms

- ResearchCompendia.org
- MLOSS.org
- IPOL
- Madagascar
- MLOSS.org
- thedatahub.org
- nanoHUB.org
- Open Science Framework
- RunMyCode.org

Workflow Tracking and Research Environments

- Vistrails
- Galaxy
- Kepler
- GenePattern
- CDE
- Sumatra
- Jupyter
- Taverna
- torch.ch
- DataCenterHub
- Pegasus
- Kurator

Embedded Publishing

- Verifiable Computational Research
- Collage Authoring Environment
- SHARE
- SOLE
- knitR
- Sweave
The Future
Encouraging Reproducibility While Expanding Access to Massive Computation

We see the convergence of two (ordinarily antagonistic) trends:

- Scientific projects will become massively more computing intensive,
- Scientific computing dramatically more transparent.
Converging Trends

These two trends need to be addressed simultaneously:

Better transparency will allow people to run much more ambitious computational experiments.

And better computational experiment infrastructure will allow researchers to be more transparent.
Proposition 1: Experiment Definition Systems

We imagine a major effort to develop a new infrastructure that promotes good scientific practice downstream like transparency and reproducibility.

But plan for people to use it not out of ethics or hygiene, but because this is a corollary of managing massive amounts of computational work. Enables efficiency and productivity, and discovery.

Define and create “Experiment Definition Systems” to (easily) manage the conduct of massive computational experiments and expose the resulting data for analysis and structure the subsequent data analysis.
Proposition 2: Inducing a Reproducibility Industry by Grant Set-asides

Previously, NIH required that clinical trials hire Biostatistician PhD's to design and analyze experiments.

This set-aside requirement more or less directly transformed clinical trials practice and resulted in much more good science being done. It also spawned the modern field of Biostatistics, by creating a demand for a specific set of services and trained people who could conduct them.

Why not try a similar idea for reproducibility?
We propose a set-aside that will initiate and sustain near-universal following of reproducibility and transparency practices.

The set-aside has these components:

1. Each grant contains a budget of $X$ times number of anticipated papers. (say $X=500$)

2. these funds are only to be used to pay for reproducibility certification by an accredited reproducibility certifier.

3. the certifier *both* provides a "badge" on the publication, *and* hosts digital content allowing partial or complete reproduction of results of the paper.
4. A certifier might be a traditional entity, like a journal, a society, or a library. The certifier might also be a novel institution.

5. The certifier would develop and disseminate software tools that potential certifiees would use during their research. These entities will also determine standards for research areas.

6. It is to be expected although not a requirement, that reproducibility certification would become automated, although in early days it might be humans certifying reproducibility.

Contrast with Reproducibility Editors being used by some journals.
Reproducible Research in JASA

1 July 2016  910 Views  3 Comments

Montse Fuentes, Coordinating Editor of JASA and Editor of JASA ACS

Societal impact through scientific advances is predicated on discovery and new knowledge that is reliable and robust and provides a solid foundation on which further advances can be built. Unfortunately, there is evidence many published scientific results will not stand the test of time, in part due to the lack of good scientific practices for reproducibility.

Our statistical profession has a responsibility to establish publication standards that improve the transparency and robustness of what we publish and to promote awareness within the scientific community of the need for rigor in our statistical research to ensure reproducibility of our scientific results. JASA is committed to helping lead the effort by presenting solutions that can help improve research quality and reproducibility.

Starting September 1, JASA ACS will require code and data as a minimum standard for reproducibility of statistical scientific research. New infrastructure is being established to support this initiative. Each manuscript will go through the current review process managed by an associate editor (AE), who will assign to one of the reviewers the broad evaluation of the code. A new editorial role—associate editor for reproducibility (AER)—will be added to ensure we meet a standard of reproducibility.

Reproducibility of scientific research is our ultimate goal, and the code and data requirement is a first step in that direction.
Querying the Scholarly Record

- Show a table of effect sizes and p-values in all phase-3 clinical trials for Melanoma published after 1994;

- Name all of the image denoising algorithms ever used to remove white noise from the famous “Barbara” image, with citations;

- List all of the classifiers applied to the famous acute lymphoblastic leukemia dataset, along with their type-1 and type-2 error rates;

- Create a unified dataset containing all published whole-genome sequences identified with mutation in the gene BRCA1;

- Randomly reassign treatment and control labels to cases in published clinical trial X and calculate effect size. Repeat many times and create a histogram of the effect sizes. Perform this for every clinical trial published in the year 2003 and list the trial name and histogram side by side.

Courtesy of Donoho and Gavish 2012
Conclusion

Reproducibility issues of some sort travel will all computational research.

Cyberinfrastructure is underdeveloped and can help resolve irreproducibility.

Grant set-asides could foment a “Reproducibility Industry”

**Principle: Access / Verification**
Legal Issues in Software

Intellectual property is associated with software (and all digital scholarly objects) via the Constitution and subsequent Acts:

“To promote the Progress of Science and useful Arts, by securing for limited Times to Authors and Inventors the exclusive Right to their respective Writings and Discoveries.” (U.S. Const. art. I, §8, cl. 8)

**Argument**: both types of intellectual property are an imperfect fit with scholarly norms, and require action from the research community to enable re-use, verification, reproducibility, and support the acceleration of scientific discovery.
Copyright

- Original expression of ideas falls under copyright by default (papers, code, figures, tables..)

- Copyright secures exclusive rights vested in the author to:
  - reproduce the work
  - prepare derivative works based upon the original

- limited time: generally life of the author +70 years

- Exceptions and Limitations: e.g. Fair Use.
Patents

Patentable subject matter: “new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof” (35 U.S.C. §101) that is

1. Novel, in at least one aspect,

2. Non-obvious,

3. Useful.

USPTO Final Computer Related Examination Guidelines (1996) “A practical application of a computer-related invention is statutory subject matter. This requirement can be discerned from the variously phrased prohibitions against the patenting of abstract ideas, laws of nature or natural phenomena” (see e.g. Bilski v. Kappos, 561 U.S. 593 (2010)).
Bayh-Dole Act (1980)

- Promote the transfer of academic discoveries for commercial development, via licensing of patents (i.e. Technology Transfer Offices), and harmonize federal funding agency grant intellectual property regs.

- Bayh-Dole gave federal agency grantees and contractors title to government-funded inventions and charged them with using the patent system to aid disclosure and commercialization of the inventions.

- Hence, institutions such as universities charged with utilizing the patent system for technology transfer.
Legal Issues in Data

• In the US raw facts are not copyrightable, but the original “selection and arrangement” of these facts is copyrightable. (Feist Publns Inc. v. Rural Tel. Serv. Co., 499 U.S. 340 (1991)).

• Copyright adheres to raw facts in Europe.

• the possibility of a residual copyright in data (attribution licensing or public domain certification).

• Legal mismatch: What constitutes a “raw” fact anyway?
Privacy and Data

• HIPAA, FERPA, IRB mandates create legally binding restrictions on the sharing human subjects data (see e.g. http://www.dataprivacybook.org/)

• Potential privacy implications for industry generated data.

• Solutions: access restrictions, technological e.g. encryption, restricted querying, simulation..
Ownership: What Defines Contribution?

- Issue for producers: credit and citation.
- What is the role of peer-review?
- Repositories adding meta-data and discoverability make a contribution.
- Data repositories may be inadequate: velocity of contributions
- Future coders may contribute in part to new software, other software components may already be in the scholarly record. Attribution vs sharealike.
  - (at least) 2 aspects: legal ownership vs scholarly credit.
- Redefining plagiarism for software contributions.
Licensing in Research

Background: Open Source Software

Innovation: Open Licensing

- Software with licenses that communicate alternative terms of use to code developers, rather than the copyright default.

Hundreds of open source software licenses:

- GNU Public License (GPL)
- (Modified) BSD License
- MIT License
- Apache 2.0 License
- ... see http://www.opensource.org/licenses/alphabetical
The Reproducible Research Standard

The Reproducible Research Standard (RRS) (Stodden, 2009)

A suite of license recommendations for computational science:

• Release media components (text, figures) under CC BY,

• Release code components under MIT License or similar,

• Release data to public domain (CC0) or attach attribution license.

➡ Remove copyright’s barrier to reproducible research and,

➡ Realign the IP framework with longstanding scientific norms.
Computational Barriers

Barriers to Replication in Computational Science:

• rerunning same code, same parameter settings, same system can produce different results (?),

• same code (Reprozip, containerization/Docker), but updated libraries, compiler, operating system..

• software customization to underlying architectures; portability, modularity, re-usability,

• numerical stability of the underlying software architecture,

• unique hardware, scarce allocations, long runtimes..
Encouraging Reproducibility While Expanding Access to Massive Computation

We are at the convergence of two (ordinarily antagonistic) trends:

1. Scientific projects will become massively more computing intensive,

2. Scientific computing dramatically more transparent.

These two trends can reinforce each other: better transparency will allow people to run much more ambitious computational experiments. And better computational experiment infrastructure will allow researchers to be more transparent.
Merging Science and Cyberinfrastructure Pathways: The Whole Tale

Encouraging reproducibility while expanding access to massive computation: leverage & contribute to existing cyberinfrastructure and tools to support the whole discovery story (= run-to-pub-cycle).

Organization through Working Groups. Examples needed..

CC*DNI DIBBS:
- 5 Institutions, 5 Years ($5M total).
- Cooperative Agreement.
Remember Google Flu Trends?

In 2008 Google Flu Trends claimed it can tell you whether “the number of influenza cases is increasing in areas around the U.S., earlier than many existing methods”

In 2013 Google Flu Trends was predicting more than double the proportion of doctor visits for flu than the CDC.

Today:

Google Flu Trends and Google Dengue Trends are no longer publishing current estimates of Flu and Dengue fever based on search patterns. The historic estimates produced by Google Flu Trends and Google Dengue Trends are available below. It is still early days for nowcasting and similar tools for understanding the spread of diseases like flu and dengue – we’re excited to see what comes next. Academic research groups interested in working with us should fill out this form.

Sincerely,
The Google Flu and Dengue Trends Team.
What Happened?

- How did Google Flu Trends work? What was the data collection process? What was the algorithm?
- Why should we believe Google Flu Trends output? Many people did in 2008..

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer,\textsuperscript{1,2*} Ryan Kennedy,\textsuperscript{1,3,4} Gary King,\textsuperscript{3} Alessandro Vespignani\textsuperscript{3,5,6}

Large errors in flu prediction were largely avoidable, which offers lessons for the use of big data.
Empirical Reproducibility

Sorting Out the FACS: A Devil in the Details

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The reproducibility of results is the cornerstone of science; yet, at times, reproducing the results of others can be a difficult challenge. Our two laboratories, one on the East and the other on the West Coast of the United States, decided to collaborate on a problem of mutual interest—namely, the heterogeneity of the human breast. Despite using seemingly identical methods, reagents, and specimens, our two laboratories quite reproducibly were unable to replicate each other’s fluorescence-activated cell sorting (FACS) profiles of primary breast cells. Frustration of studying cells close to their context in vivo makes the exercise even more challenging.

Paired with in situ characterizations, FACS has emerged as the technology most suitable for distinguishing diversity among different cell populations in the mammary gland. Flow instruments have evolved from being able to detect only a few parameters to those now capable of measuring up to 30 parameters per cell (Cheung and Ultsch, 2011). An exponential increase in data complexity, breast reduction mammoplasties, molecular analysis of separated fractions was to be performed in Boston (K.P. laboratory, Dana-Farber Cancer Institute, Harvard Medical School), whereas functional analysis of separated cell populations grown in 3D matrices was to take place in Berkeley (M.J.B.’s laboratory, Lawrence Berkeley National Lab, University of California, Berkeley). Both our laboratories have decades of experience and established protocols for isolating cells from primary normal breast tissues as well as the capabilities required for reproducibility issues in research with animals and animal models.

Reproducibility Issues in Research with Animals and Animal Models

The missing “PP”: Reproducibility in a Changing Research Landscape

A workshop of the Roundtable on Science and Welfare in Laboratory Animal Use

National Academy of Sciences, NAS 125
2100 C Street NW, Washington DC
June 4-5, 2014

The ability to reproduce an experiment is one important approach that scientists use to gain confidence in their conclusions. Studies that show that a number of significant peer-reviewed studies are not reproducible has alarmed the scientific community. Research that uses animals and animal models seems to be one of the most susceptible to reproducibility issues.

Evidence indicates that there are many factors that may be contributing to scientific irreproducibility, including insufficient reporting of details pertaining to study design and planning; inappropriate interpretation of results; and author, reviewer, and editor abstracted reporting, assessing, and accepting studies for publication.

In this workshop, speakers from around the world will explore the many facets of the issue and potential pathways to reducing the problems. Audience participation portions of the workshop are designed to facilitate understanding of the issue.
Statistical Reproducibility

- False discovery, p-hacking (Simonsohn 2012), file drawer problem, overuse and mis-use of p-values, lack of multiple testing adjustments,

- Low power, poor experimental design, nonrandom sampling, insufficient sample size,

- Data preparation, treatment of outliers and missing values, recombination of datasets,

- Inappropriate tests or models, model misspecification, poor parameter estimation techniques,

- Model robustness to parameter changes and data perturbations,

- ...
“Experiment Definition Systems”

• Define and create “Experiment Definition Systems” to (easily) manage the conduct of massive computational experiments and expose the resulting data for analysis and structure the subsequent data analysis.

• The two trends need to be addressed simultaneously: better transparency will allow people to run much more ambitious computational experiments. And better computational experiment infrastructure will allow researchers to be more transparent.
Proposition 1

• We propose a major effort to develop a new infrastructure that promotes good scientific practice downstream like transparency and reproducibility.

• But plan for people to use it not out of ethics or hygiene, but because this is a corollary of managing massive amounts of computational work. Enables efficiency and productivity, and discovery.
Inducing a Reproducibility Industry by Grant Set-asides

• Previously, NIH required that clinical trials hire Biostatistician PhD's to design and analyze experiments. This set-aside requirement more or less directly transformed clinical trials practice and resulted in much more good science being done. It also spawned the modern field of Biostatistics, by creating a demand for a specific set of services and trained people who could conduct them.

• Why not try a similar idea for reproducibility?