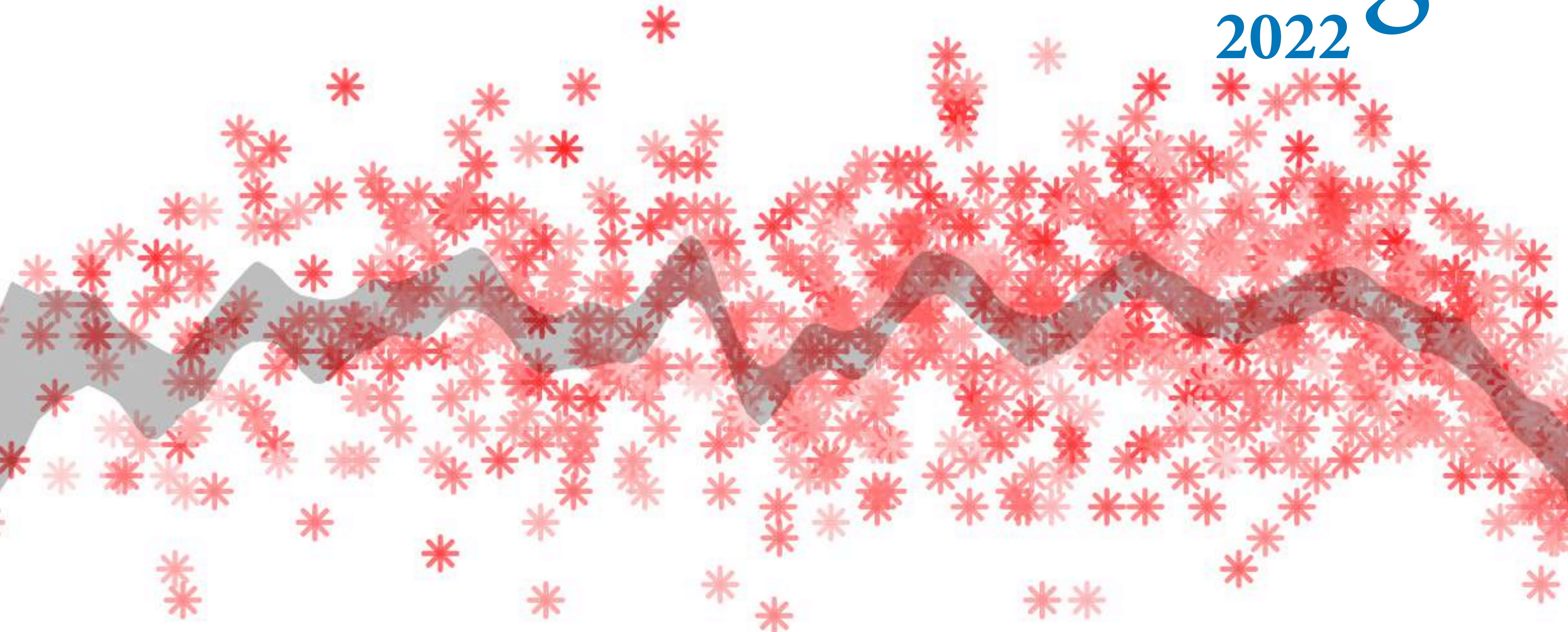


# Statistical Rethinking

2022



## 20: Horoscopes

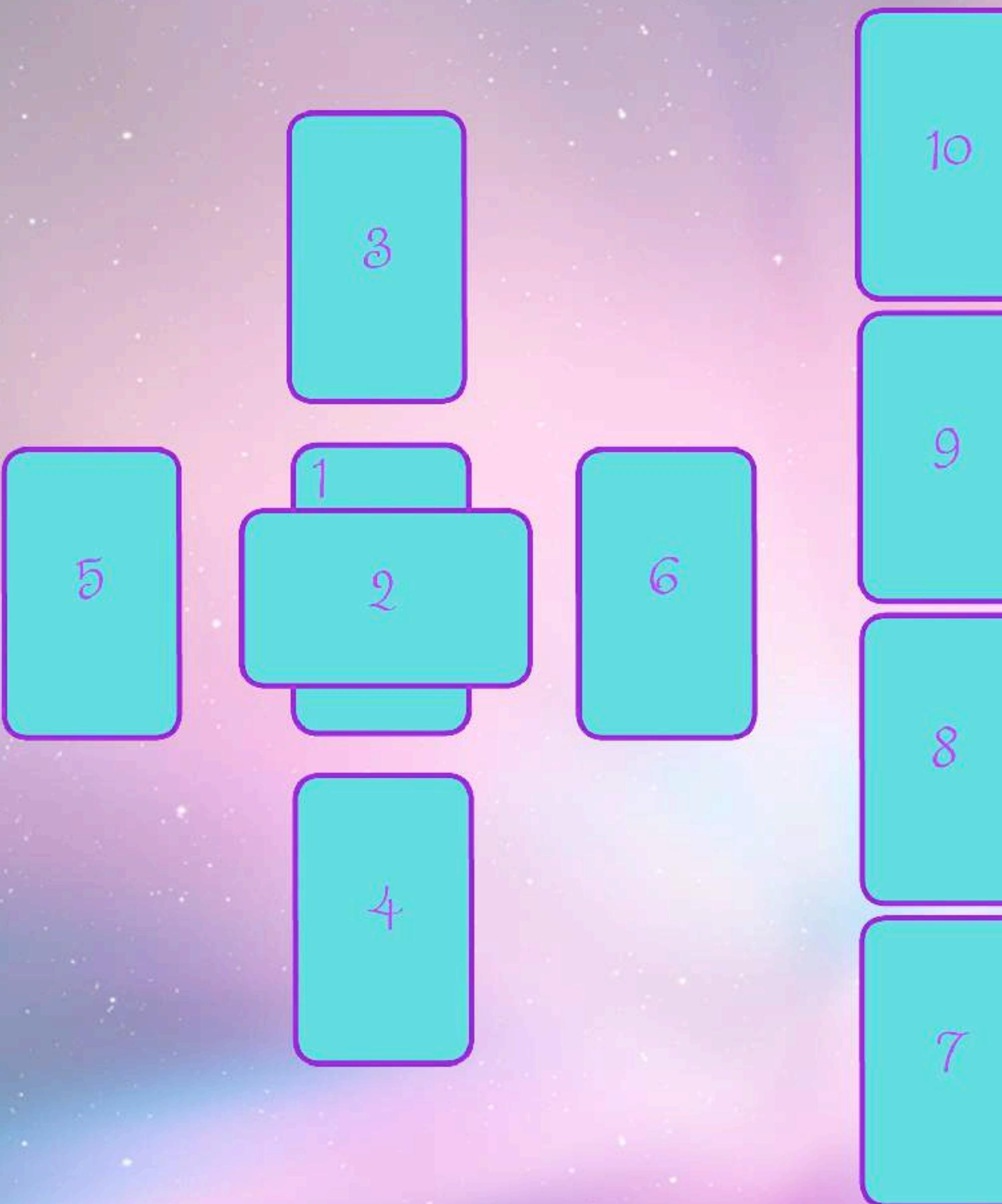


# Horoscope of Prince Iskandar, grandson of Tamerlane





# The Celtic Cross



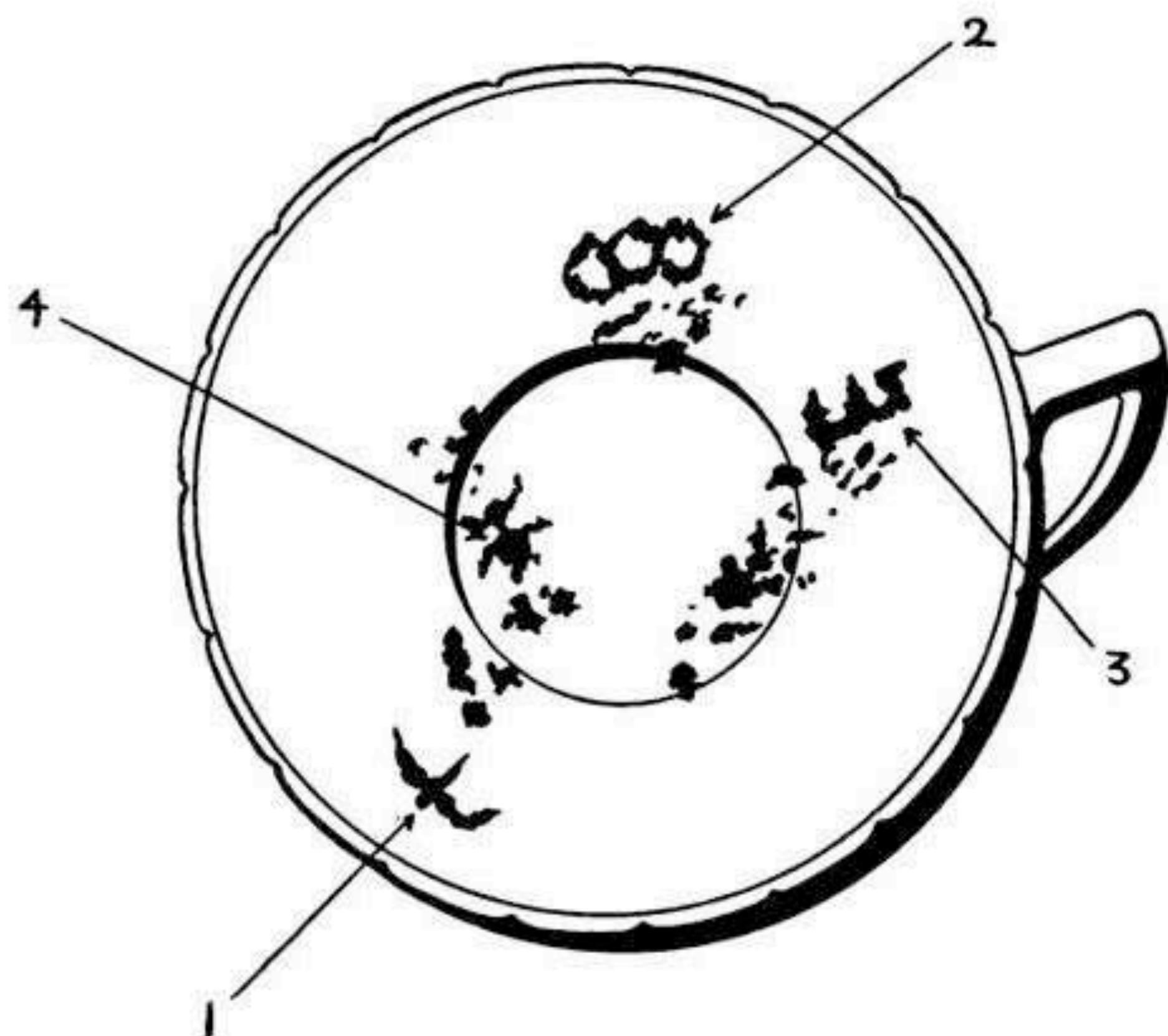
1. Situation
2. Challenge
3. Beliefs
4. Root of the Issue/  
Distant Past
5. Near Past
6. Near Future
7. Self-Perception
8. Outside Influences/  
How Others  
Perceive You
9. Action Advice
10. Likely Outcome



# TASSEOMANCY



After reading the foregoing, test your skill in fortune telling by covering up the explanation on the following pages and studying the cups. Make your prognostications from the tea-leaves distributed therein and then compare your reading with that set down.

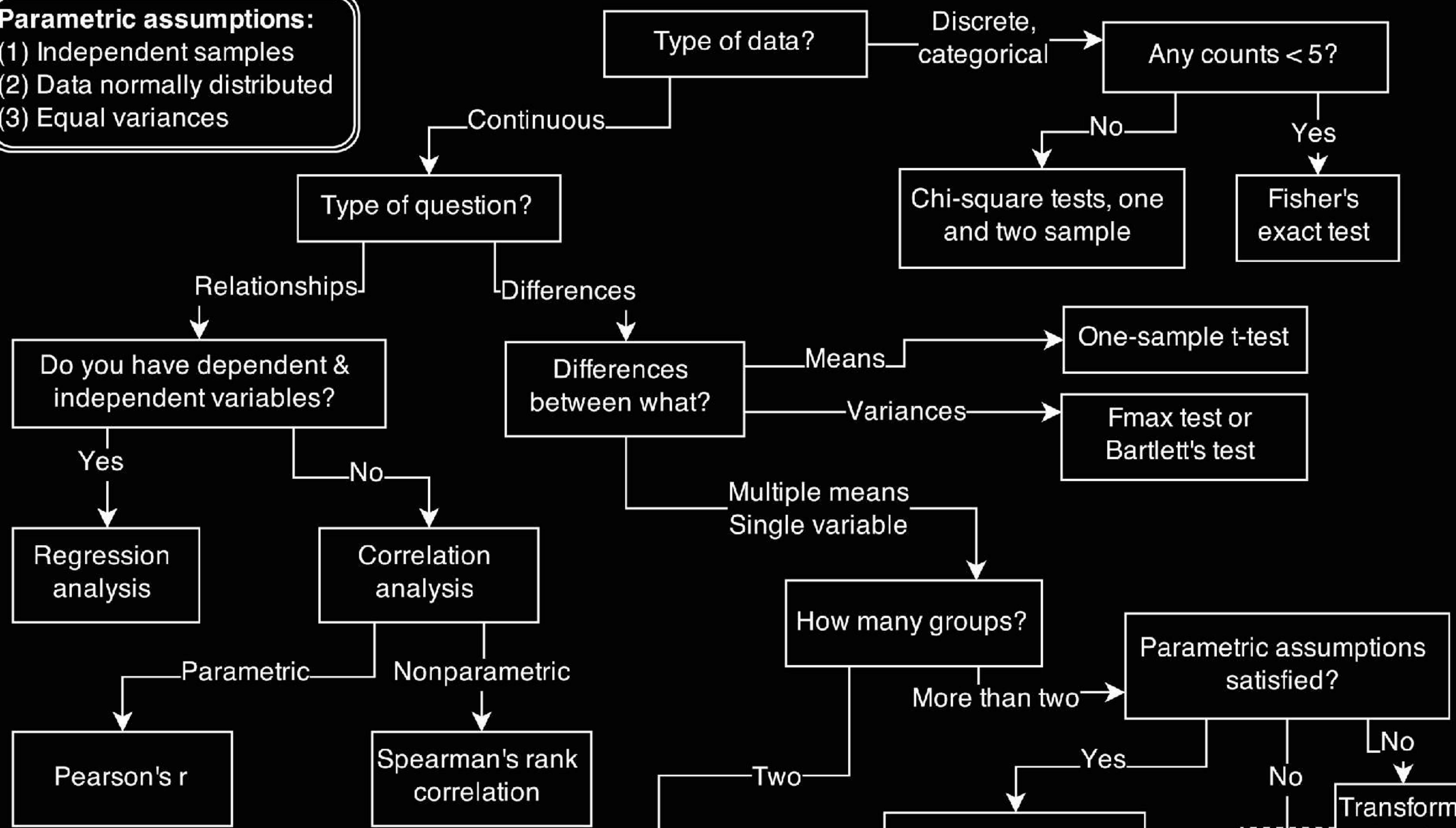


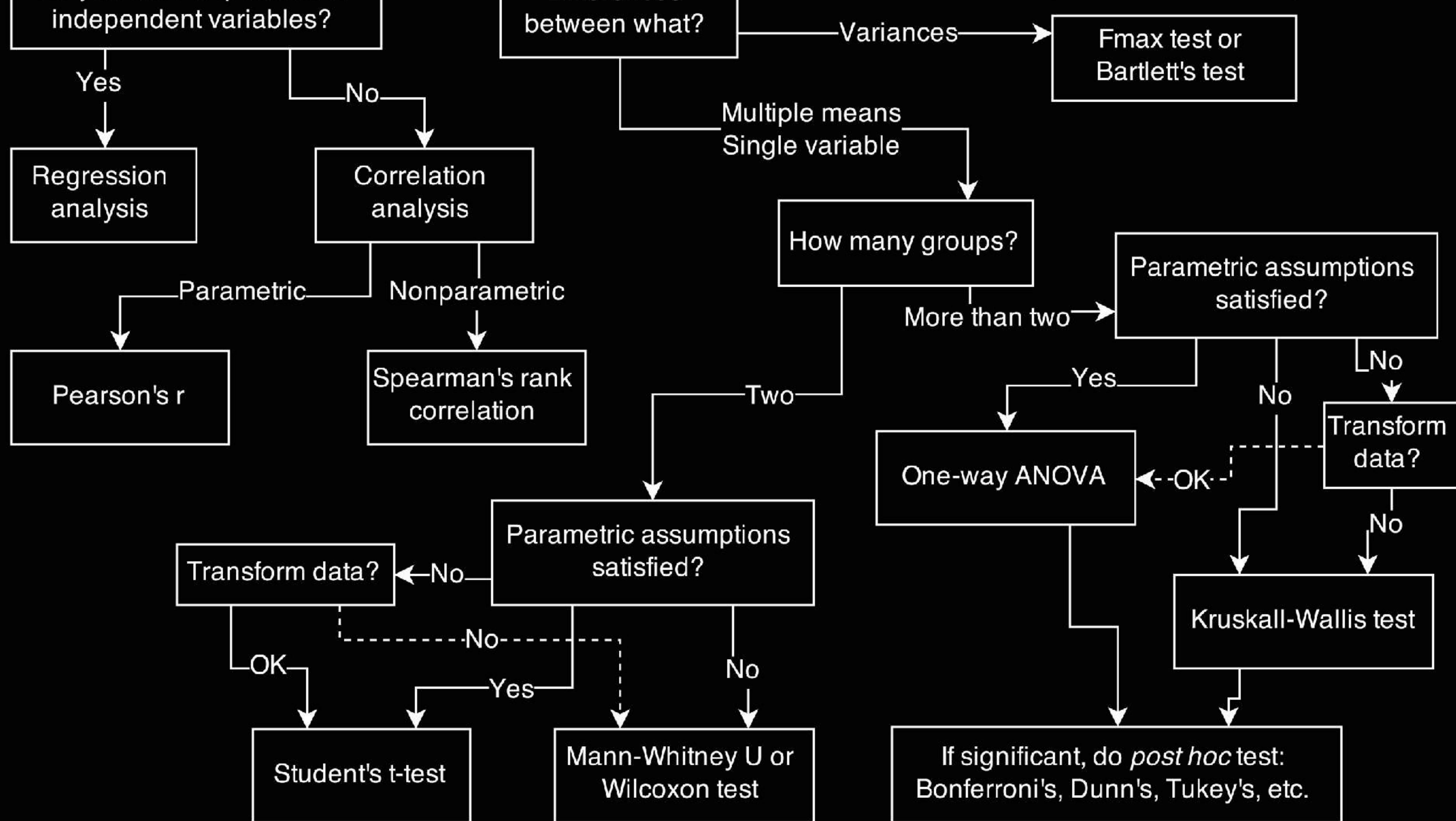
- (1) BIRD
- (2) CHAIN
- (3) "E"
- (4) SPIDER

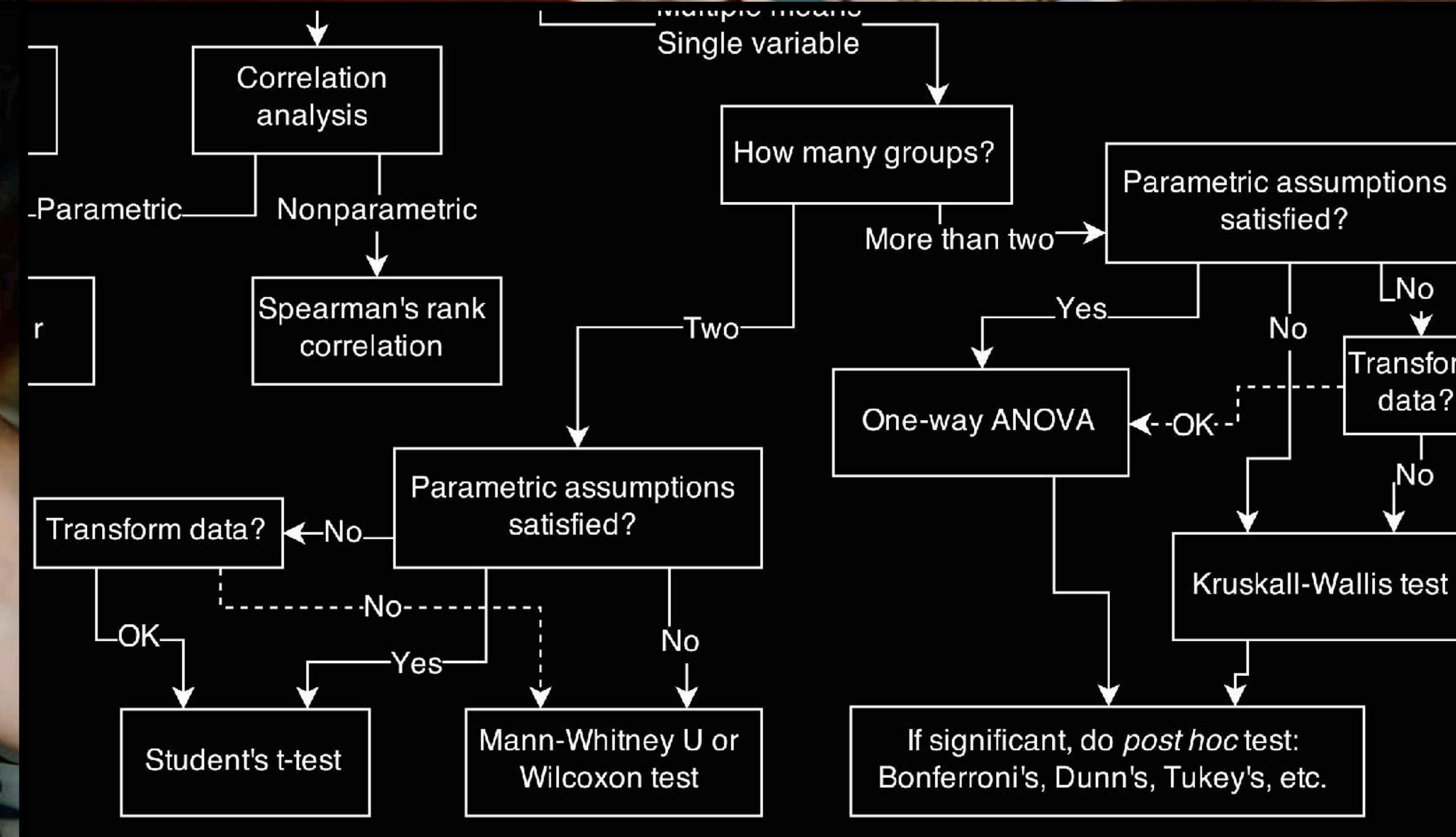
"This is a lucky tea-cup. I see good news (1) coming from the North or North-East in the very near future. It is either news of an early marriage (2) or of an unexpected legacy (4). Watch for a message from one whose first initial is 'E' (3)."

## Parametric assumptions:

- (1) Independent samples
- (2) Data normally distributed
- (3) Equal variances







# Stargazing

\*\*\*  
 $p < 0.001$

Fortune telling frameworks:

\*\*  
 $p < 0.01$

\*  
 $p < 0.05$

(1) From vague facts, vague advice

(2) Exaggerated importance

Applies to astrologers and statisticians

Valid vague advice exists, not sufficient



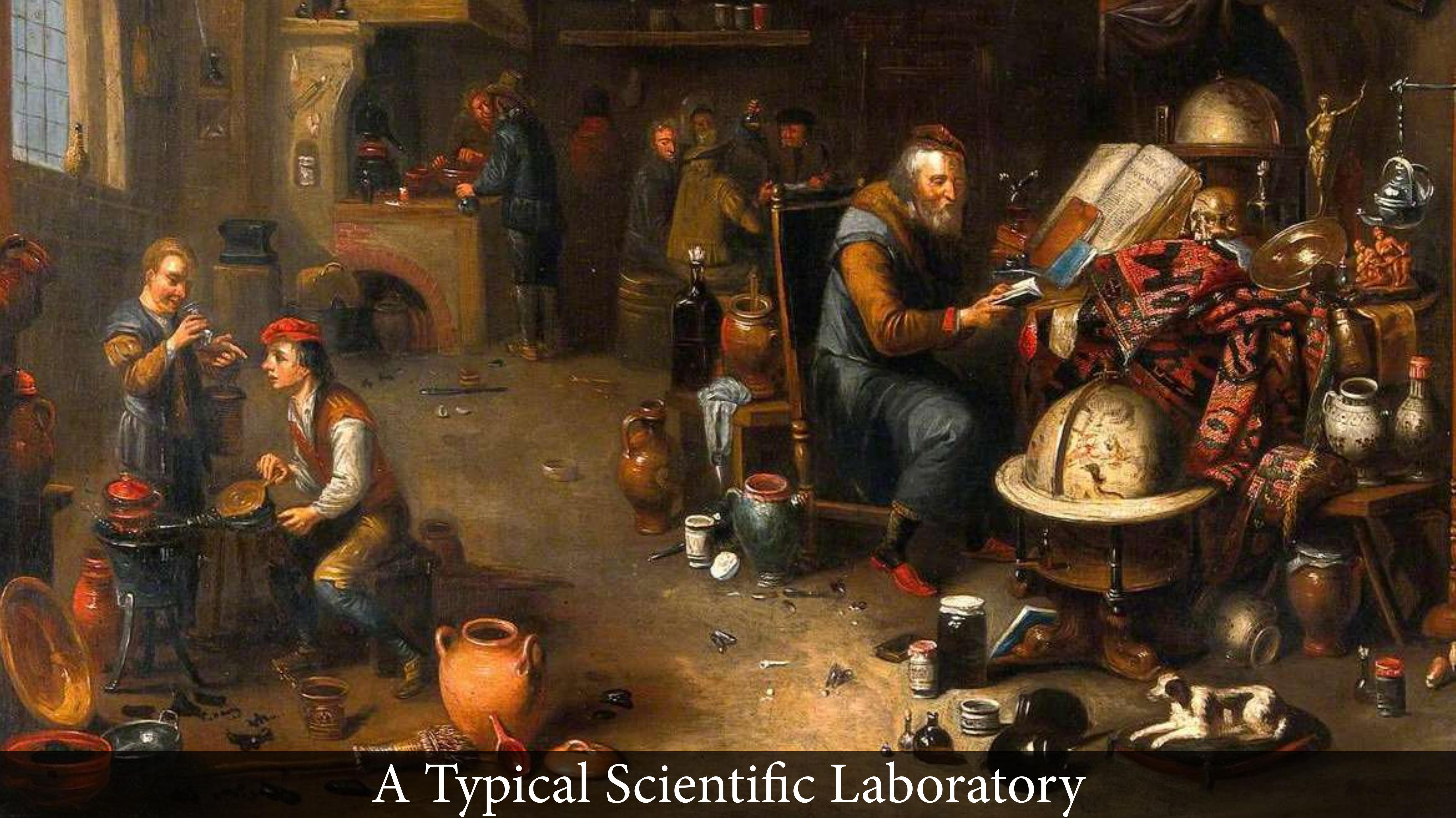
# Stargazing

Statistical procedures acquire meaning from scientific models

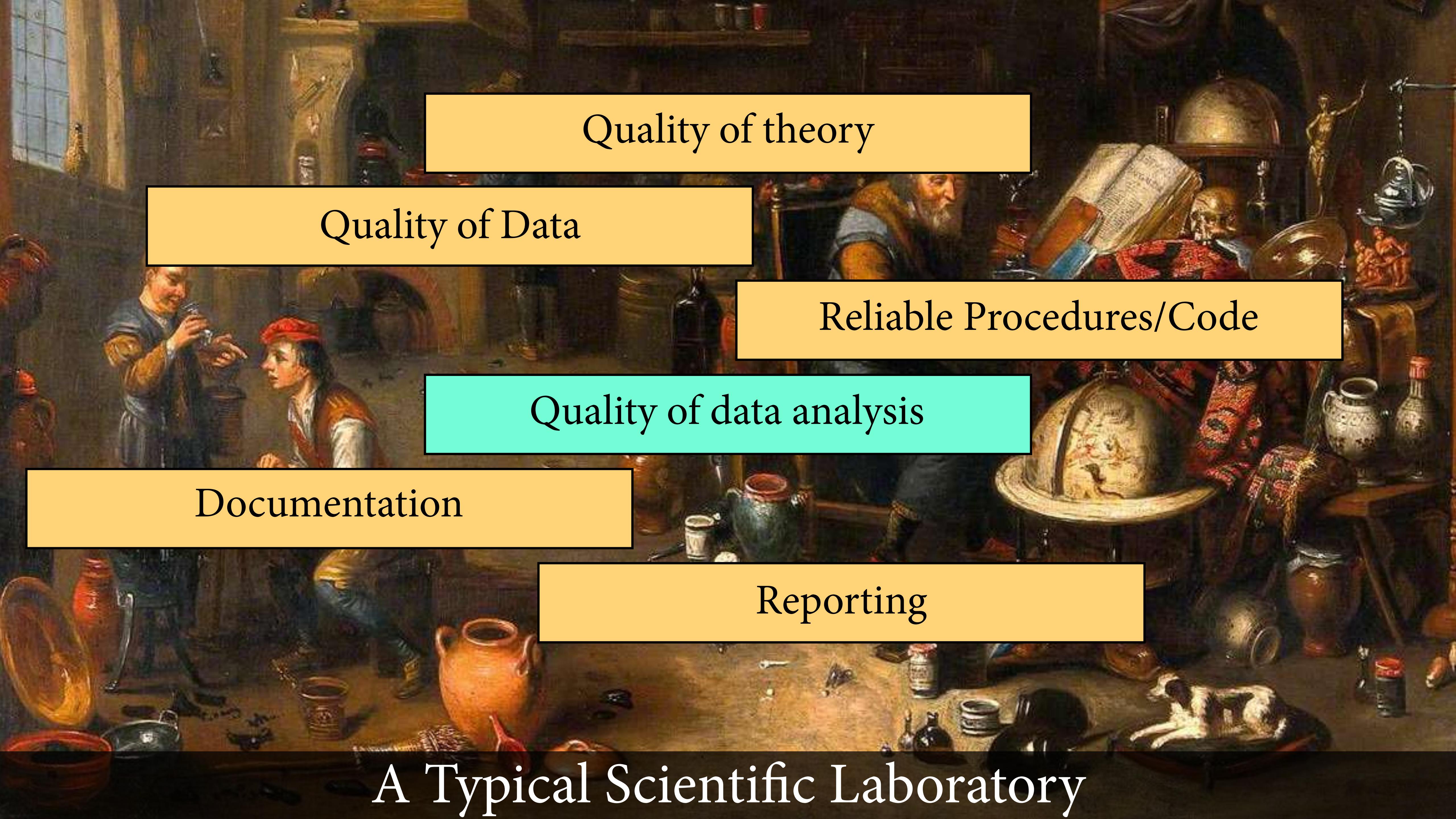
Cannot offload **subjective** responsibility to an **objective** procedure

Many subjective responsibilities





A Typical Scientific Laboratory



A historical painting depicting a scientific laboratory or alchemical workshop. Two men are shown: one in the foreground pouring liquid from a small vessel into a larger container, and another in the background looking through a telescope-like instrument. The room is filled with various pieces of scientific equipment, including a large globe on a stand, a balance scale, glassware, and books. The lighting is dramatic, with strong highlights and shadows.

Quality of theory

Quality of Data

Reliable Procedures/Code

Quality of data analysis

Documentation

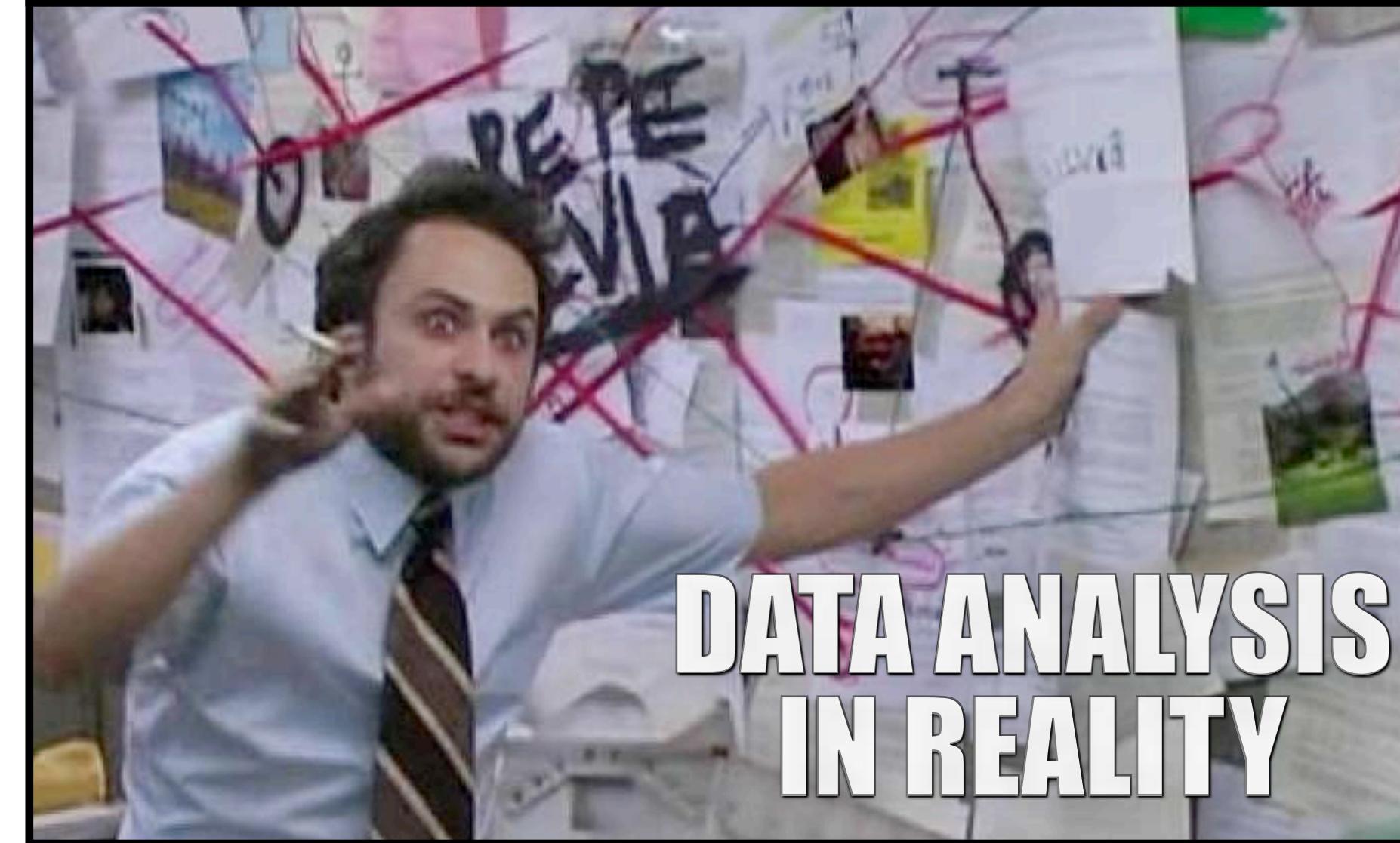
Reporting

A Typical Scientific Laboratory

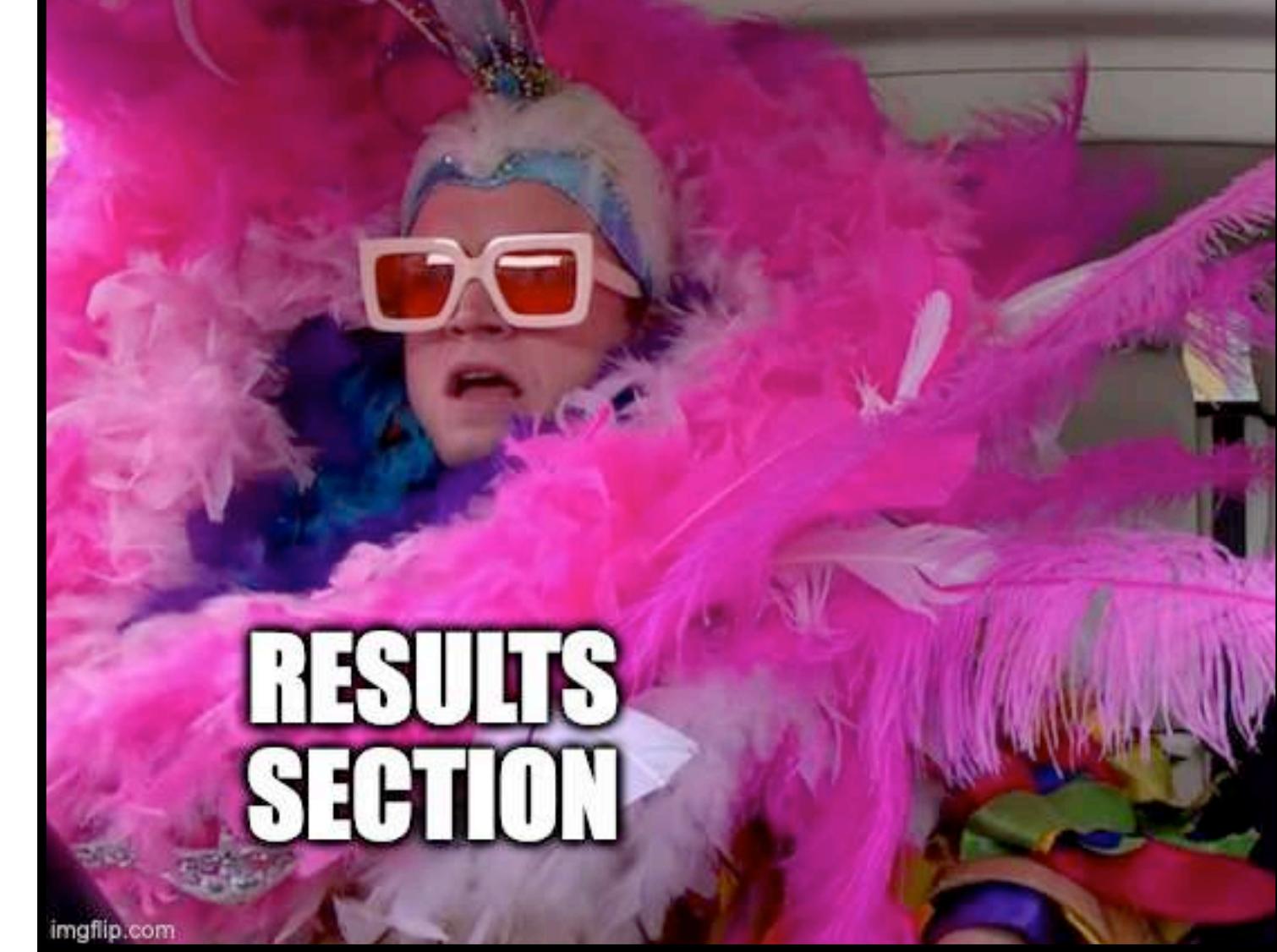
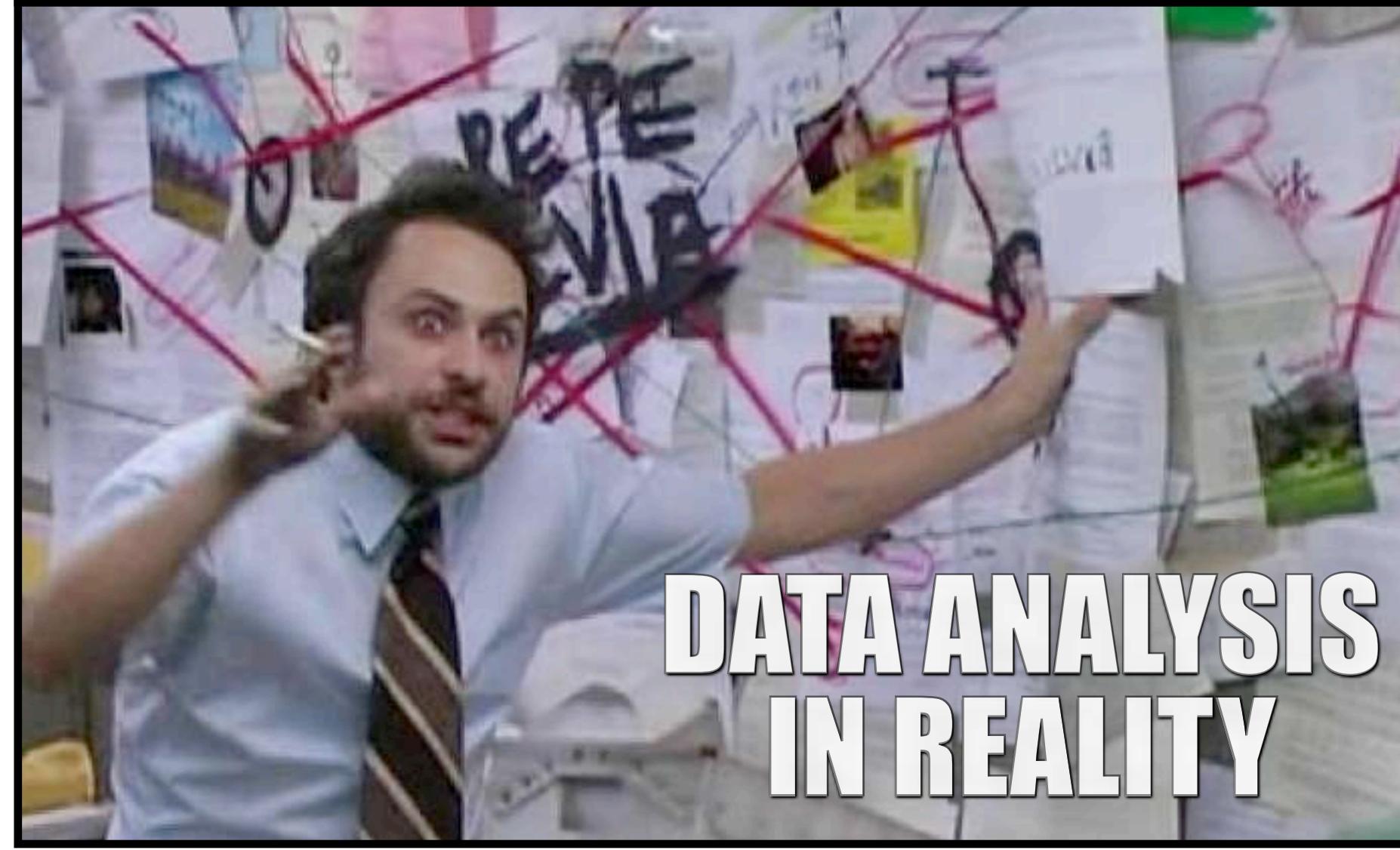
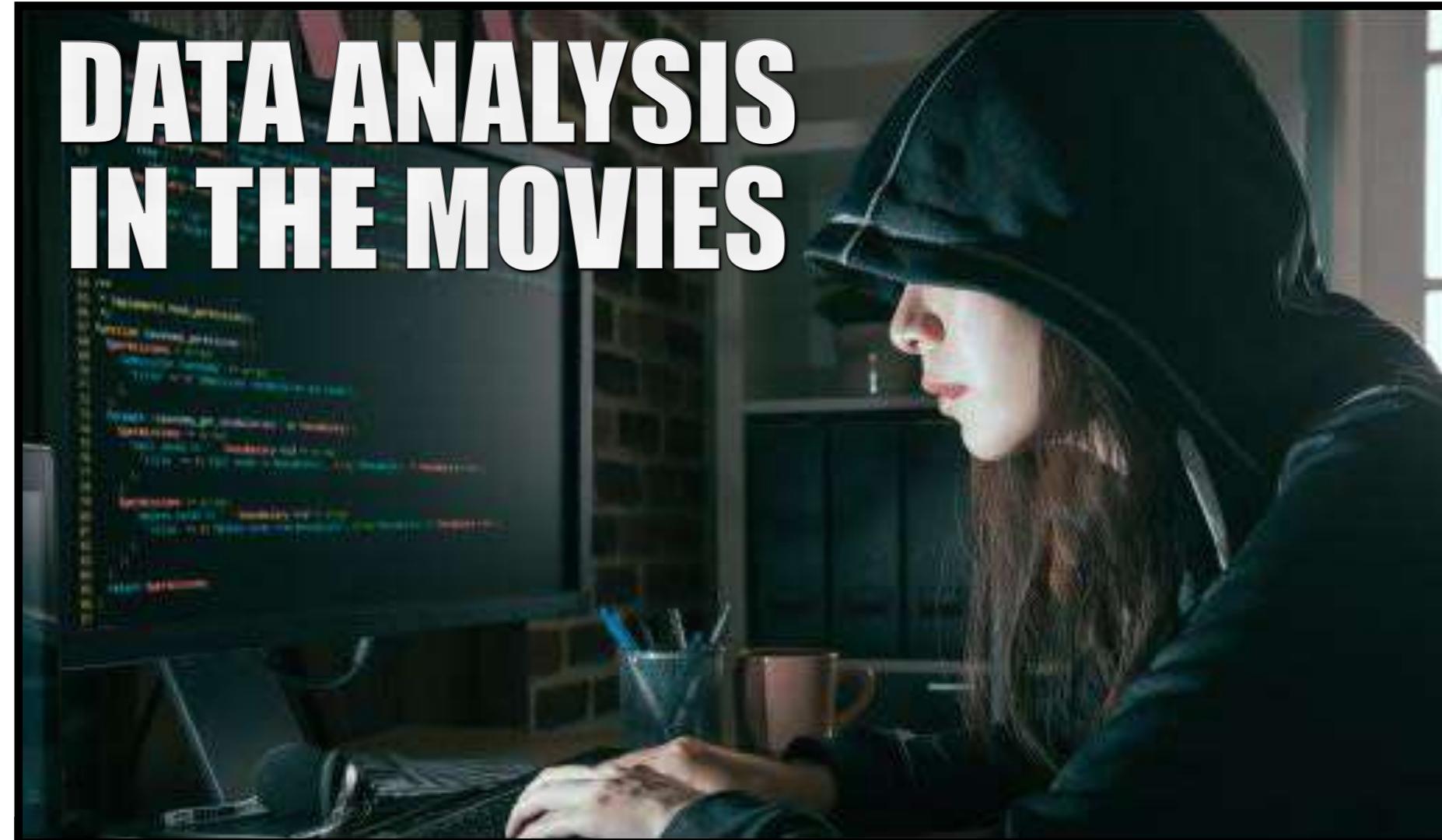
# Planning



# Planning Working



# Planning Working Reporting



# Planning

Goal setting

Theory building

Justified sampling plan

Justified analysis plan

Documentation

Open software & data formats



@StuartJRitchie

JAKE-CLARK.TUMBLR

# Planning

Goal setting – What for? Estimands

Theory building

Justified sampling plan

Justified analysis plan

Documentation

Open software & data formats



ESTIMATOR	
<b>Ingredients</b>	<b>Directions</b>
150g unsalted butter	1. Heat oven to 160C.
150g chocolate pieces	Grease 1 liter glass
150g all-purpose flour	baking pan. Line a 450g
1/2 tsp baking powder	loaf tin with baking paper.
1/2 tsp baking soda	2. Melt butter and
200g brown sugar	chocolate in a saucepan
2 large eggs	over low heat.



# Planning

Goal setting – What for? Estimands

Theory building – Which assumptions?

Justified sampling plan

Justified analysis plan

Documentation

Open software & data formats



ESTIMATOR	
<b>Ingredients</b>	<b>Directions</b>
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# Theory Building

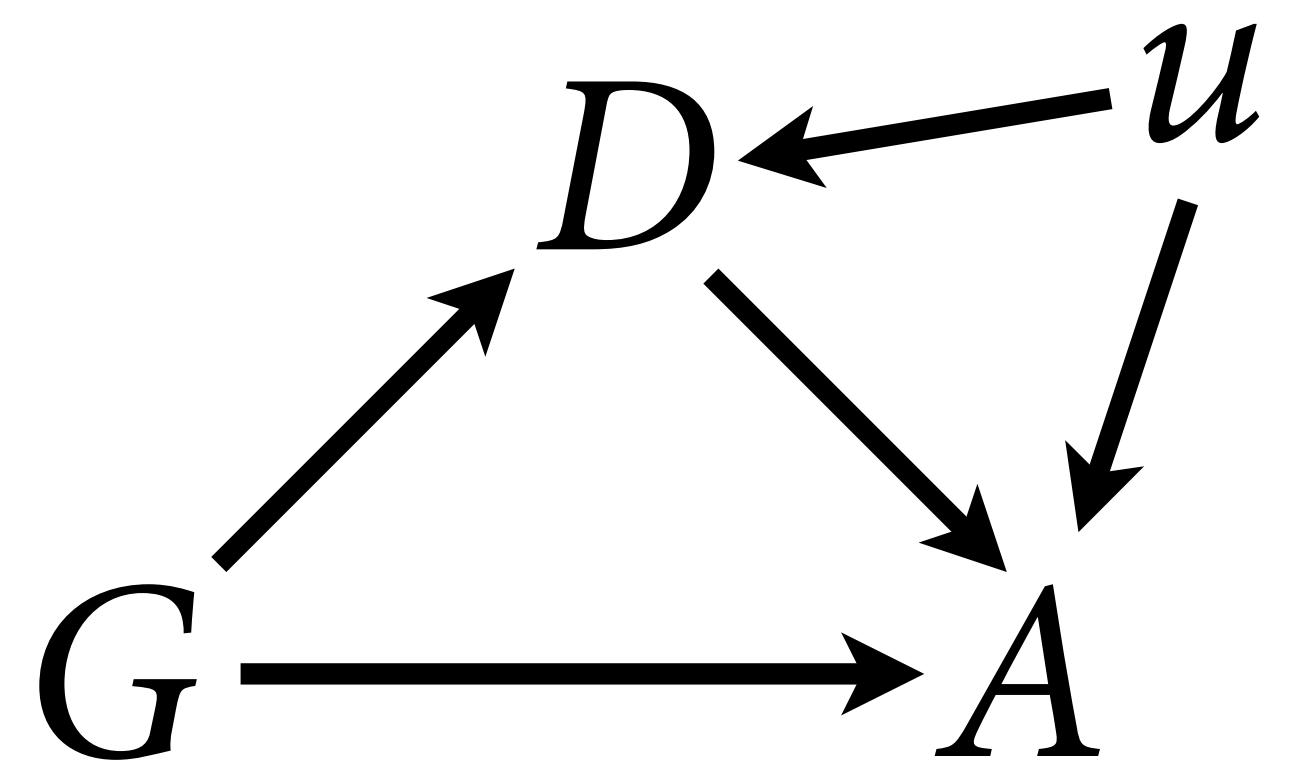
Levels of theory building

(1) Heuristic causal models (DAGs)

(2) Structural causal models

(3) Dynamic models

(4) Agent-based models



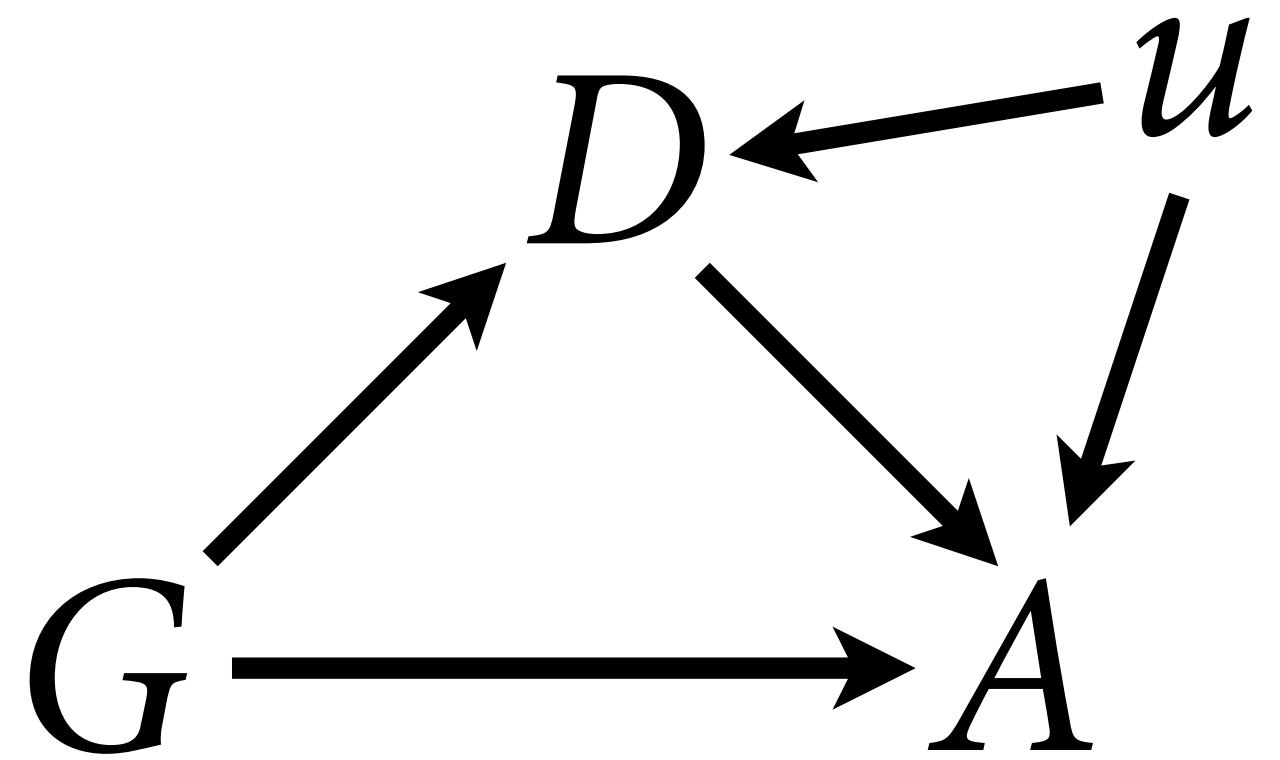
$$\frac{dH}{dt} = H_t b_H - H_t(L_t m_H)$$

$$\frac{dL}{dt} = L_t(H_t b_L) - L_t m_L$$

# Theory Building

Heuristic causal models (DAGs)

- (1) Treatment and outcome
- (2) Other causes
- (3) Other effects
- (4) Unobserved causes



# Theory Building

Heuristic causal models (DAGs)

(1) Treatment and outcome

(2) Other causes

(3) Other effects

(4) Unobserved causes

$$G \longrightarrow A$$

# Theory Building

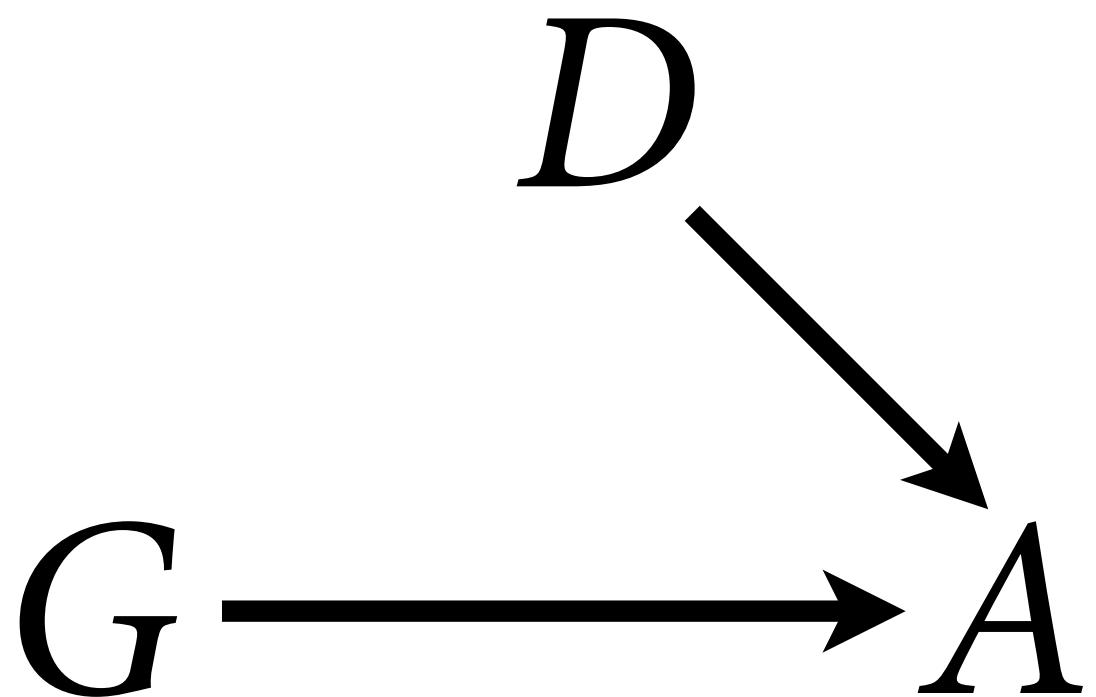
Heuristic causal models (DAGs)

(1) Treatment and outcome

(2) Other causes

(3) Other effects

(4) Unobserved causes



# Theory Building

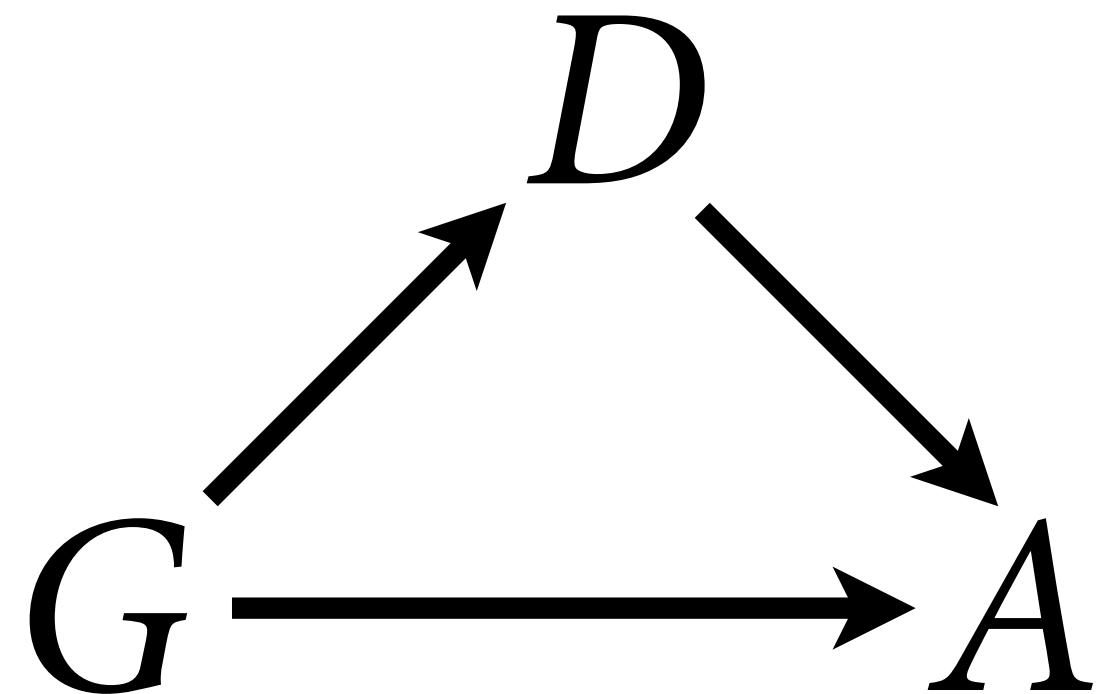
Heuristic causal models (DAGs)

(1) Treatment and outcome

(2) Other causes

(3) Other effects

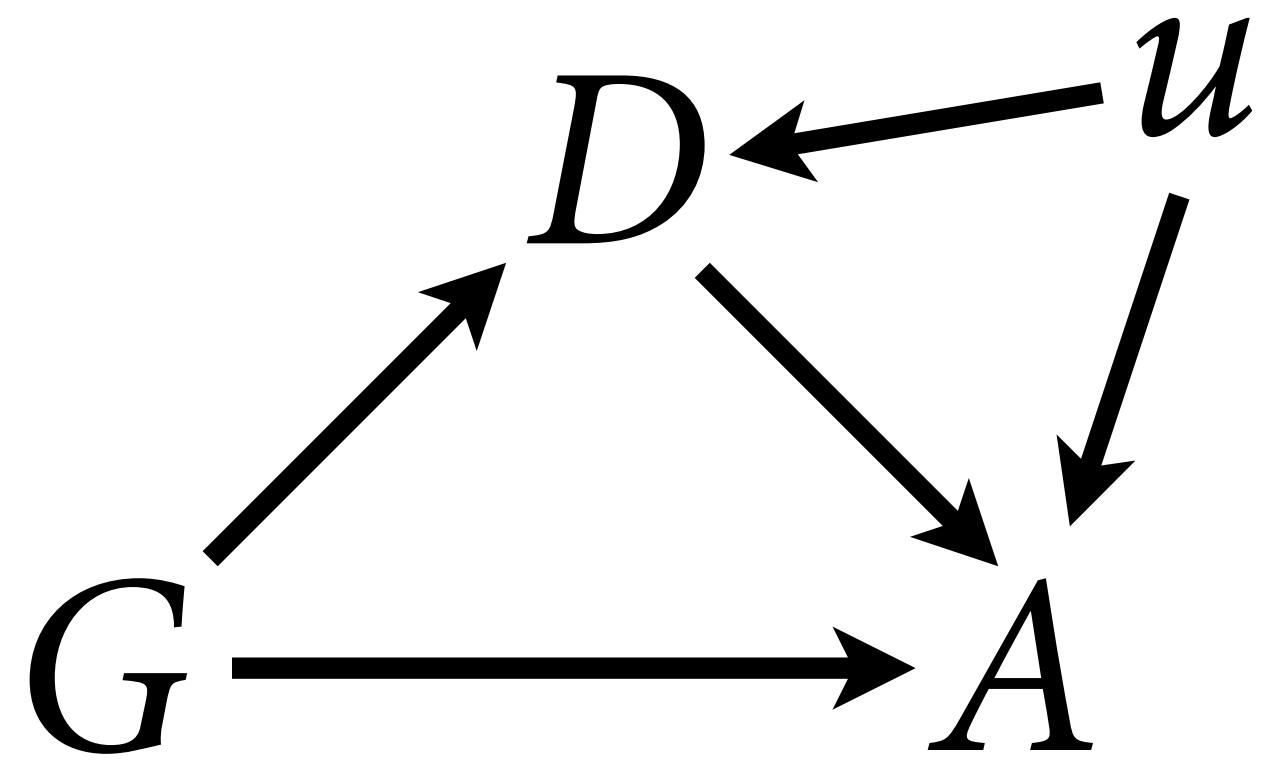
(4) Unobserved causes



# Theory Building

Heuristic causal models (DAGs)

- (1) Treatment and outcome
- (2) Other causes
- (3) Other effects
- (4) Unobserved causes



# Planning

Goal setting – What for? Estimands

Theory building – Which assumptions?

Justified sampling plan – Which data?

Justified analysis plan

Documentation

Open software & data formats



<b>ESTIMAND</b>	<b>ESTIMATOR</b>	<b>Directions</b>
	<b>Ingredients</b> 150g unsalted butter 150g chocolate pieces 150g all-purpose flour 1/2 tsp baking powder 1/2 tsp baking soda 200g brown sugar 2 large eggs	<ol style="list-style-type: none"><li>Heat oven to 160C. Grease 1 liter glass baking pan. Line a 450g loaf tin with baking paper.</li><li>Melt butter and chocolate in a saucepan over low heat.</li></ol>



# Planning

Goal setting – What for? Estimands

Theory building – Which assumptions?

Justified sampling plan – Which data?

Justified analysis plan – Which golems?

Documentation

Open software & data formats



ESTIMATOR	
<b>Ingredients</b>	<b>Directions</b>
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# Planning

Goal setting – What for? Estimands

Theory building – Which assumptions?

Justified sampling plan – Which data?

Justified analysis plan – Which golems?

Documentation – How did it happen?

Open software & data formats



ESTIMATOR	
<b>Ingredients</b>	<b>Directions</b>
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# Planning

Goal setting – What for? Estimands

Theory building – Which assumptions?

Justified sampling plan – Which data?

Justified analysis plan – Which golems?

Documentation – How did it happen?

Open software & data formats



# Pre-Registration

*Pre-registration*: Prior public documentation of research design and analysis plan

Goal: Make transparent which decisions are sample-dependent

Does little to **improve** data analysis

Lots of pre-registered causal salad



@StuartJRitchie

JAKE-CLARK.TUMBLR



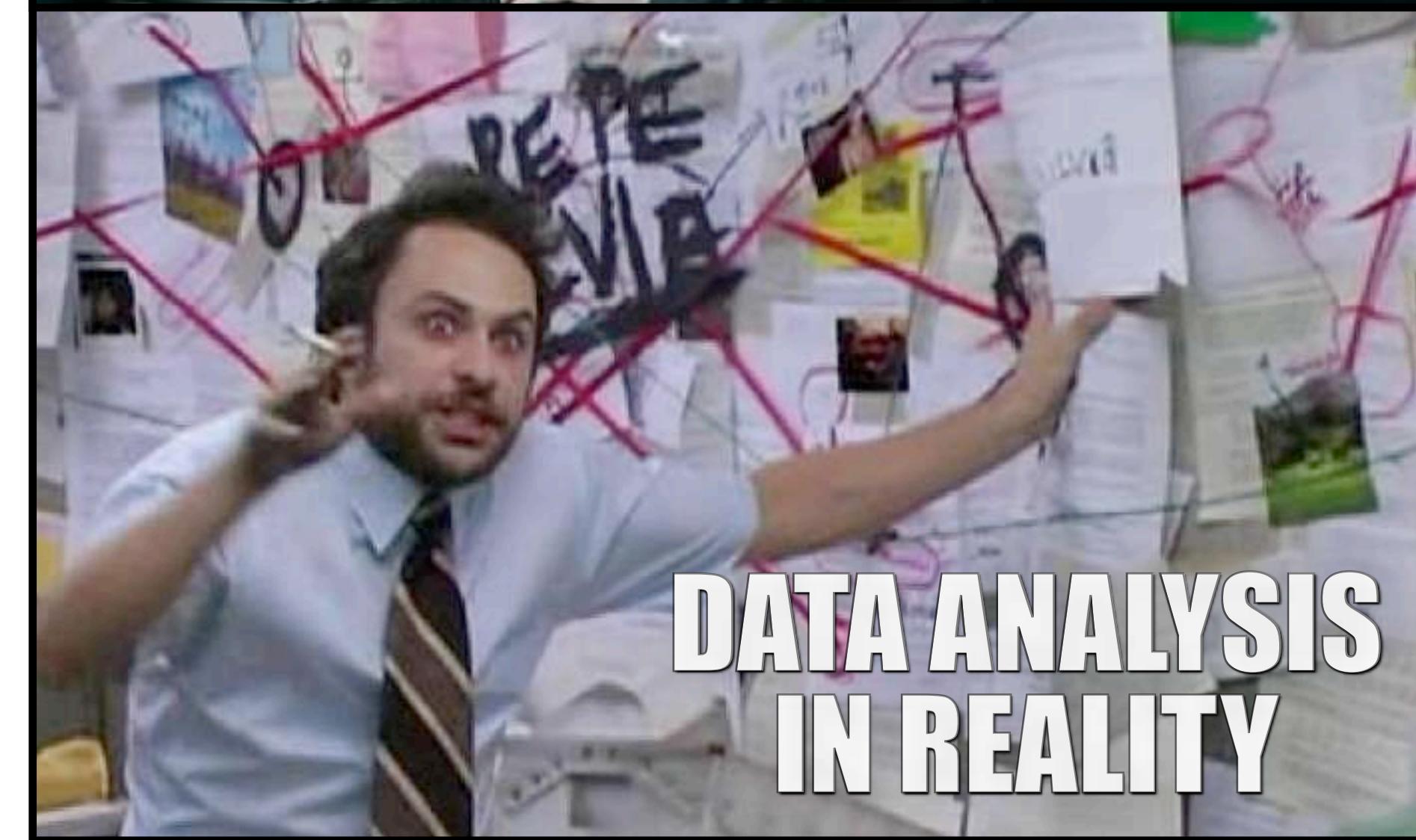
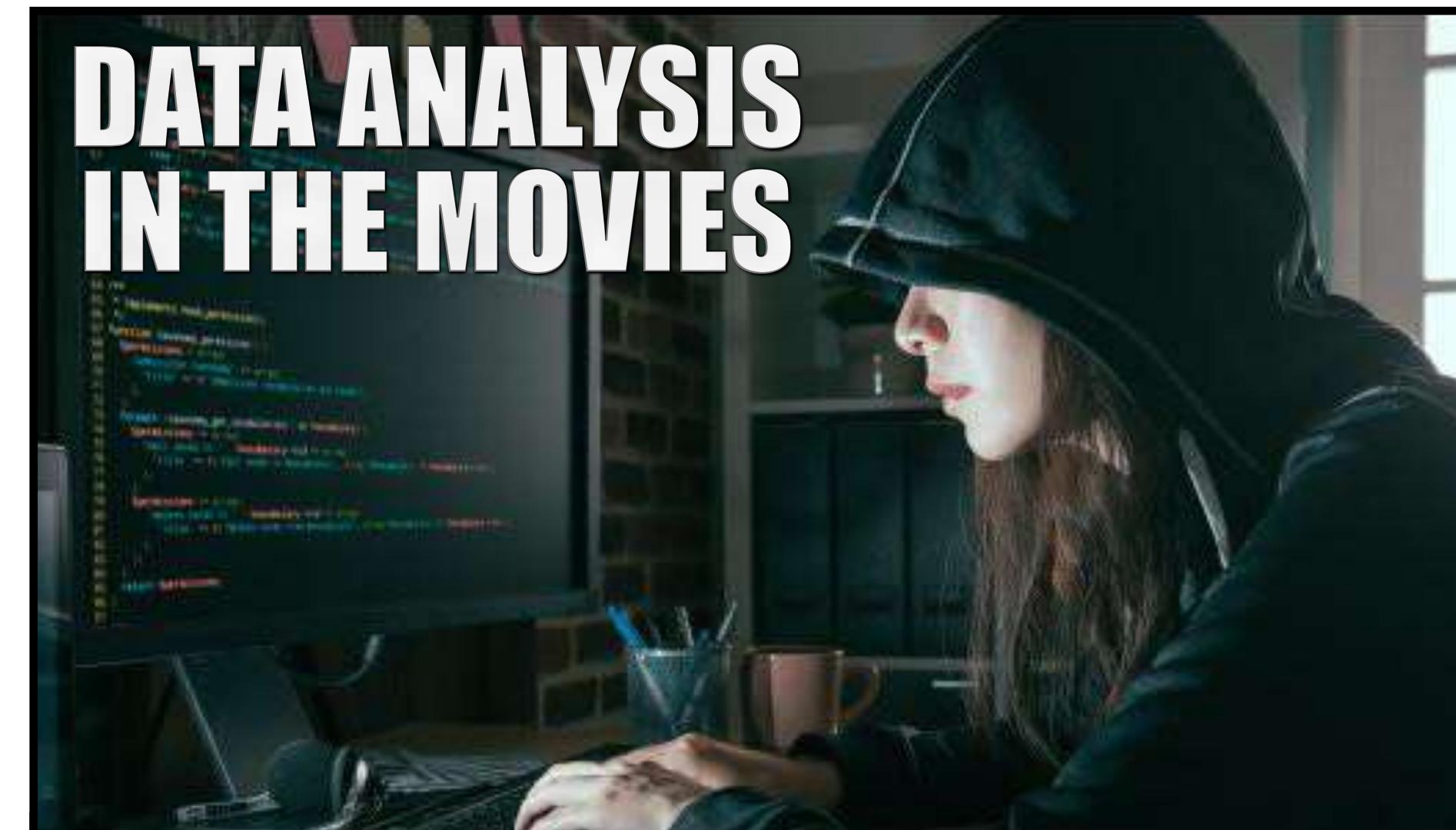
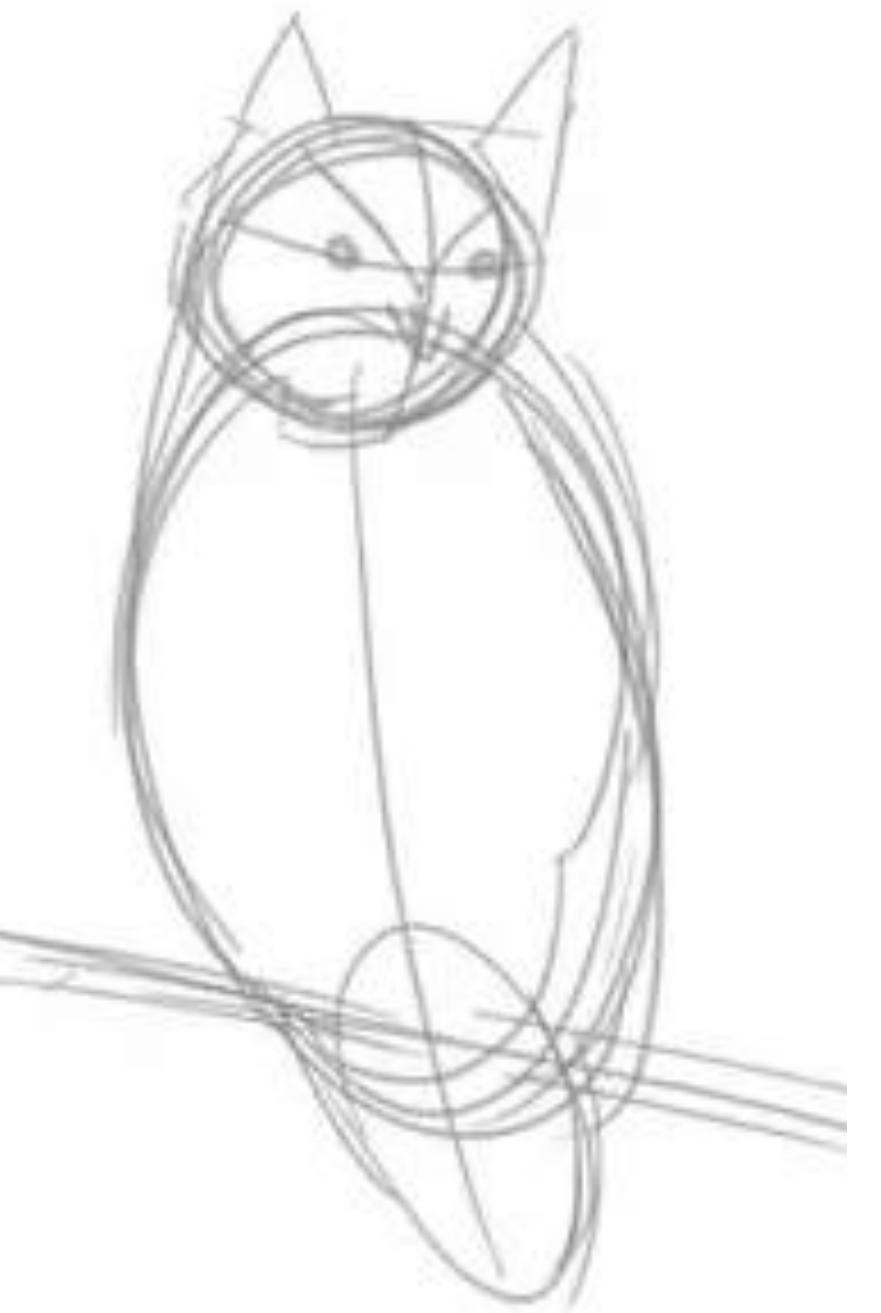
# Working

Control

Incremental testing

Documentation

Review



**DATA ANALYSIS  
IN REALITY**

1

Express theory as  
probabilistic program

2

Prove planned analysis  
could work  
(conditionally)

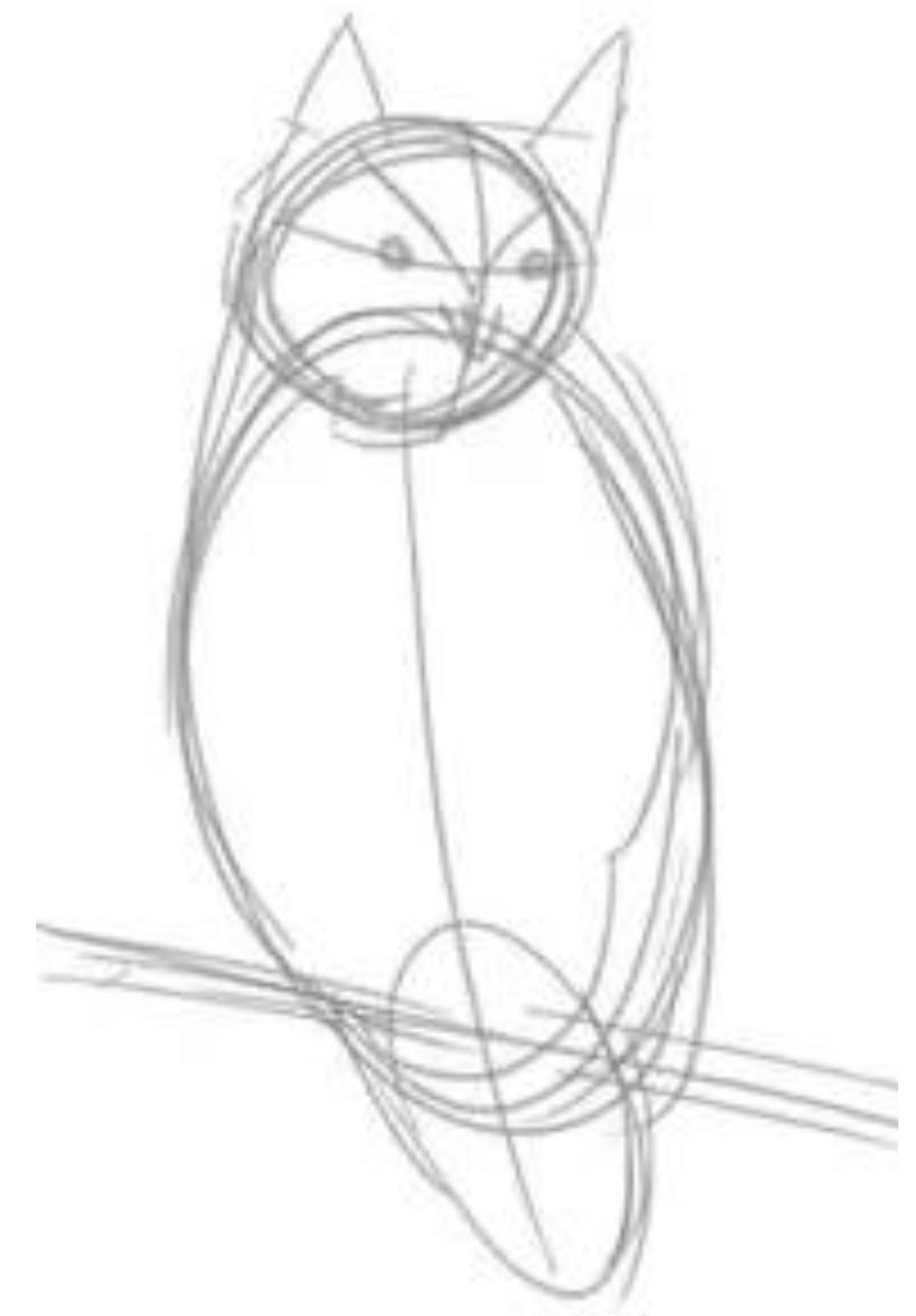
3

Test pipeline on  
synthetic data

4

Run pipeline on  
empirical data

entire history open



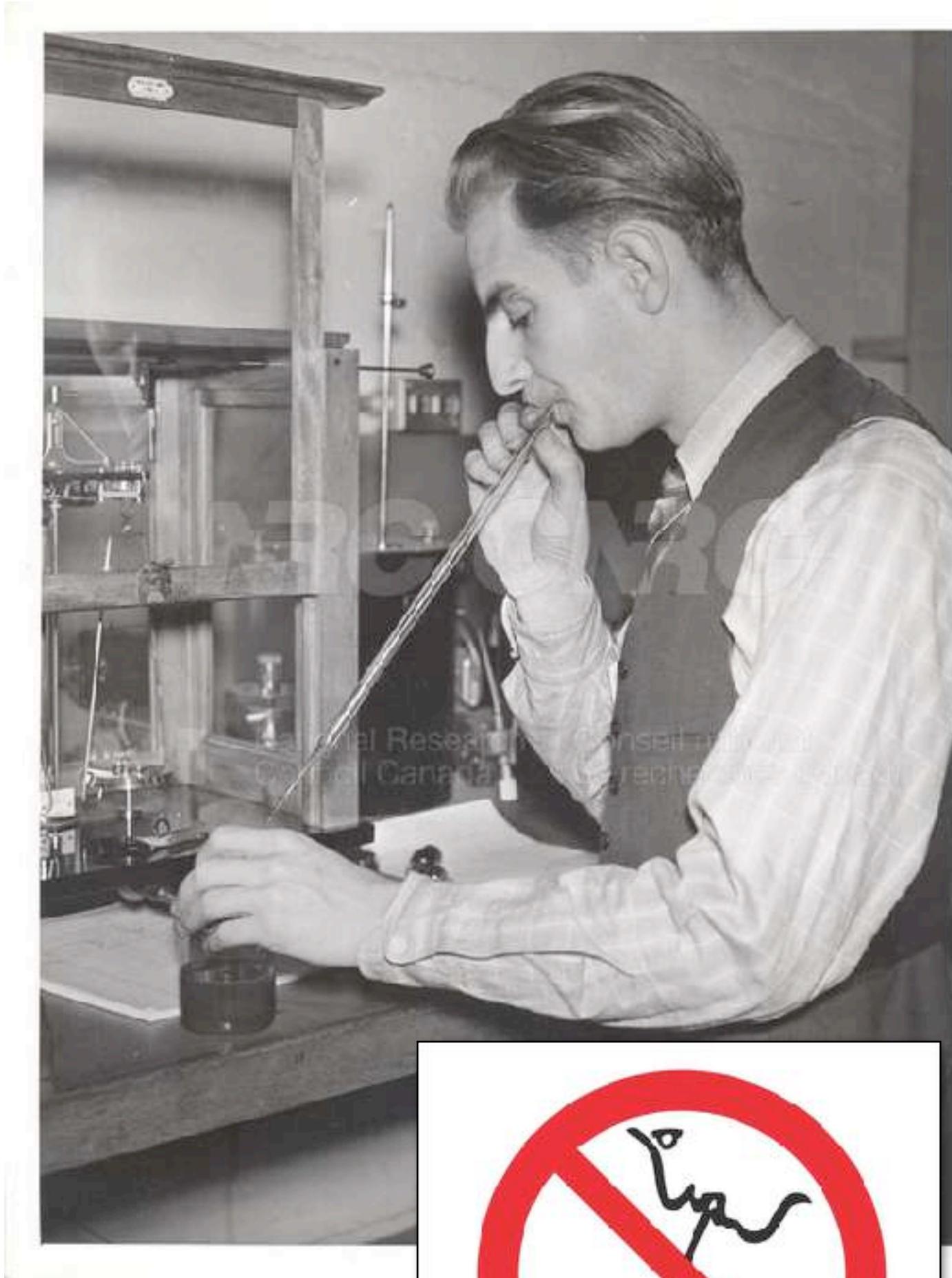
# Professional Norms

Dangerous lack of professional norms in scientific computing

Often impossible to figure out what was done

Often impossible to know if code works as intended

Like pipetting by mouth



No mouth  
pipetting

# Research Engineering

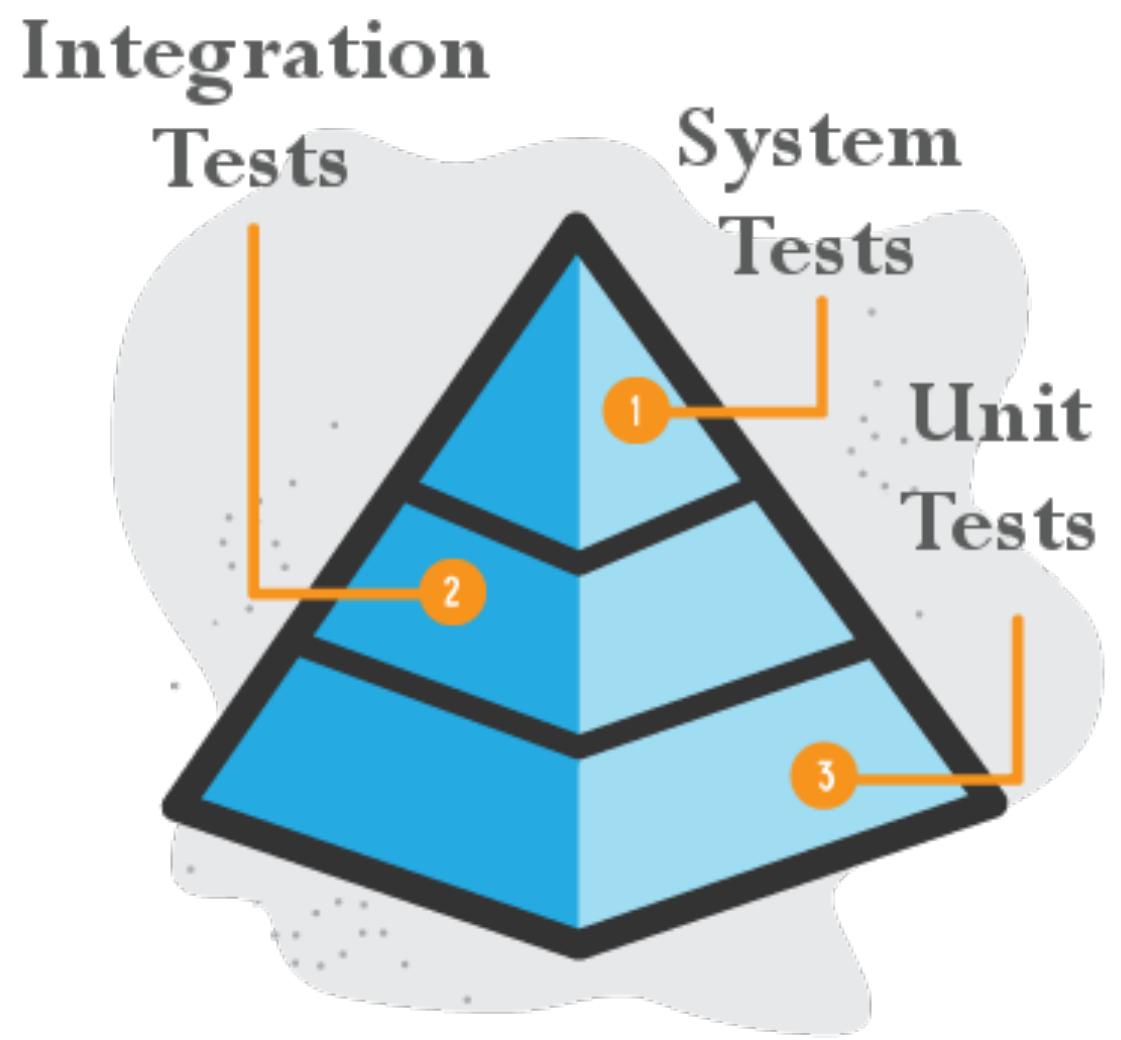


Control: Versioning, back-up, accountability

Incremental testing: Piece by piece

Documentation: Comment everything

Review: 4 eyes on code and materials



What is a LIMS?



# Research Engineering

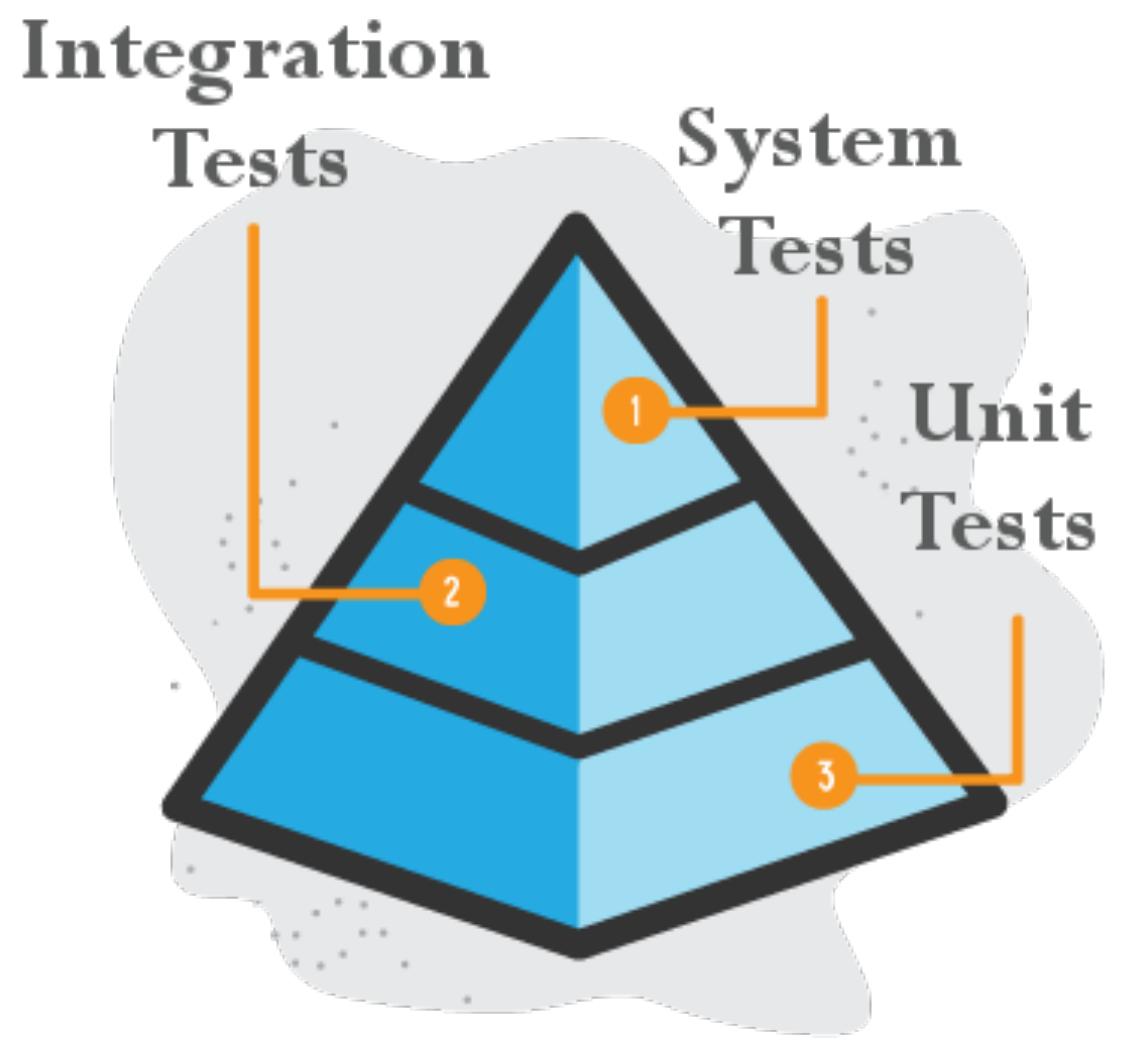


Control: Versioning, back-up, accountability

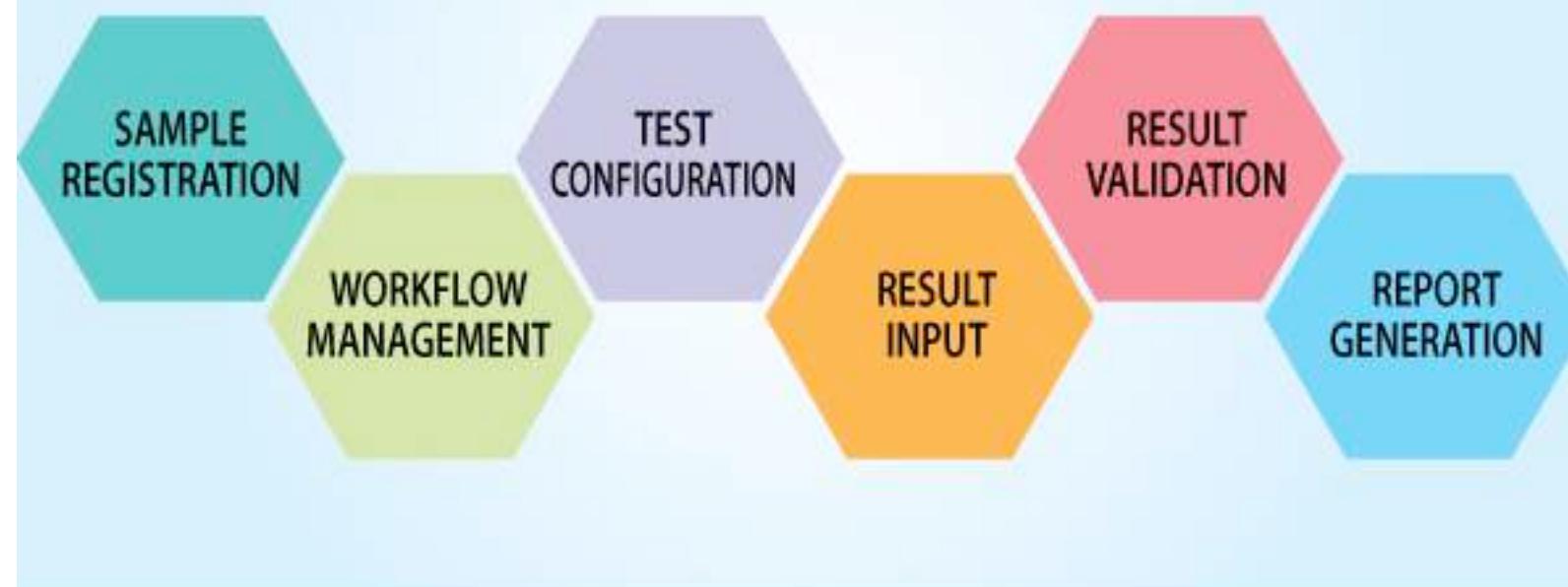
Incremental testing: Piece by piece

Documentation: Comment everything

Review: 4 eyes on code and materials



What is a LIMS?

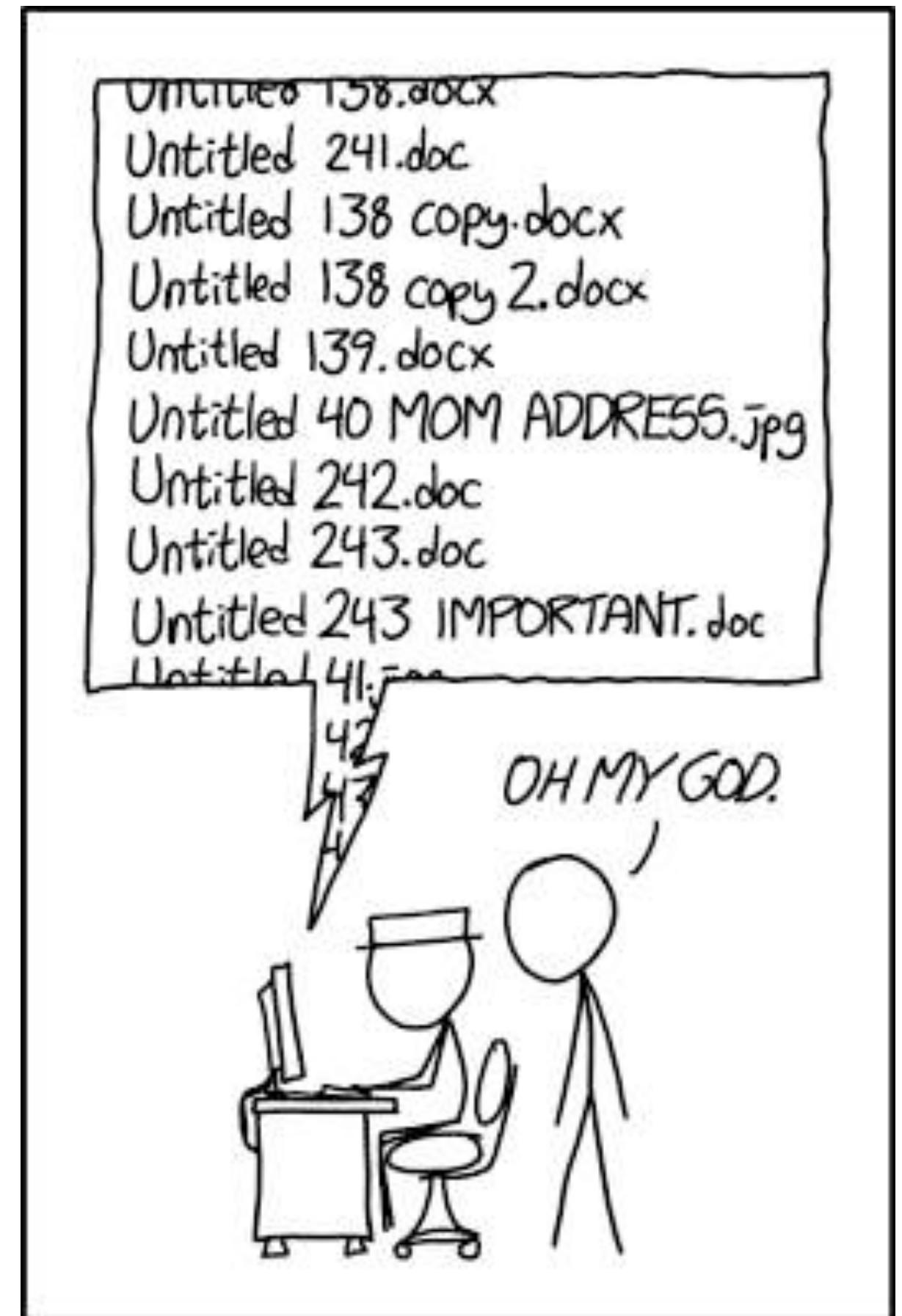


# Versioning and Testing



**Version control:** Database of changes to project files, managed history

**Testing:** Incremental milestones, test each before moving to next



PROTIP: NEVER LOOK IN SOMEONE ELSE'S DOCUMENTS FOLDER.

[Code](#)[Issues 4](#)[Pull requests 1](#)[Actions](#)[Projects](#)[Wiki](#)[Security](#)[Insights](#)[...](#)[main](#)

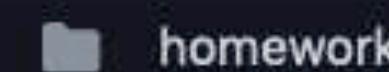
1 branch

0 tags

[Go to file](#)[Add file](#)[Code](#)

rmcelreath week 9 solutions

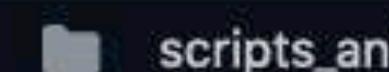
49baa56 3 days ago 64 commits



homework

week 9 solutions

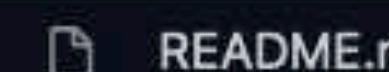
3 days ago



scripts\_animation

lecture 10 script

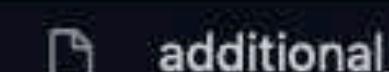
7 days ago



README.md

lecture 19 links

7 days ago



additional\_reading.md

poststrat link

22 days ago

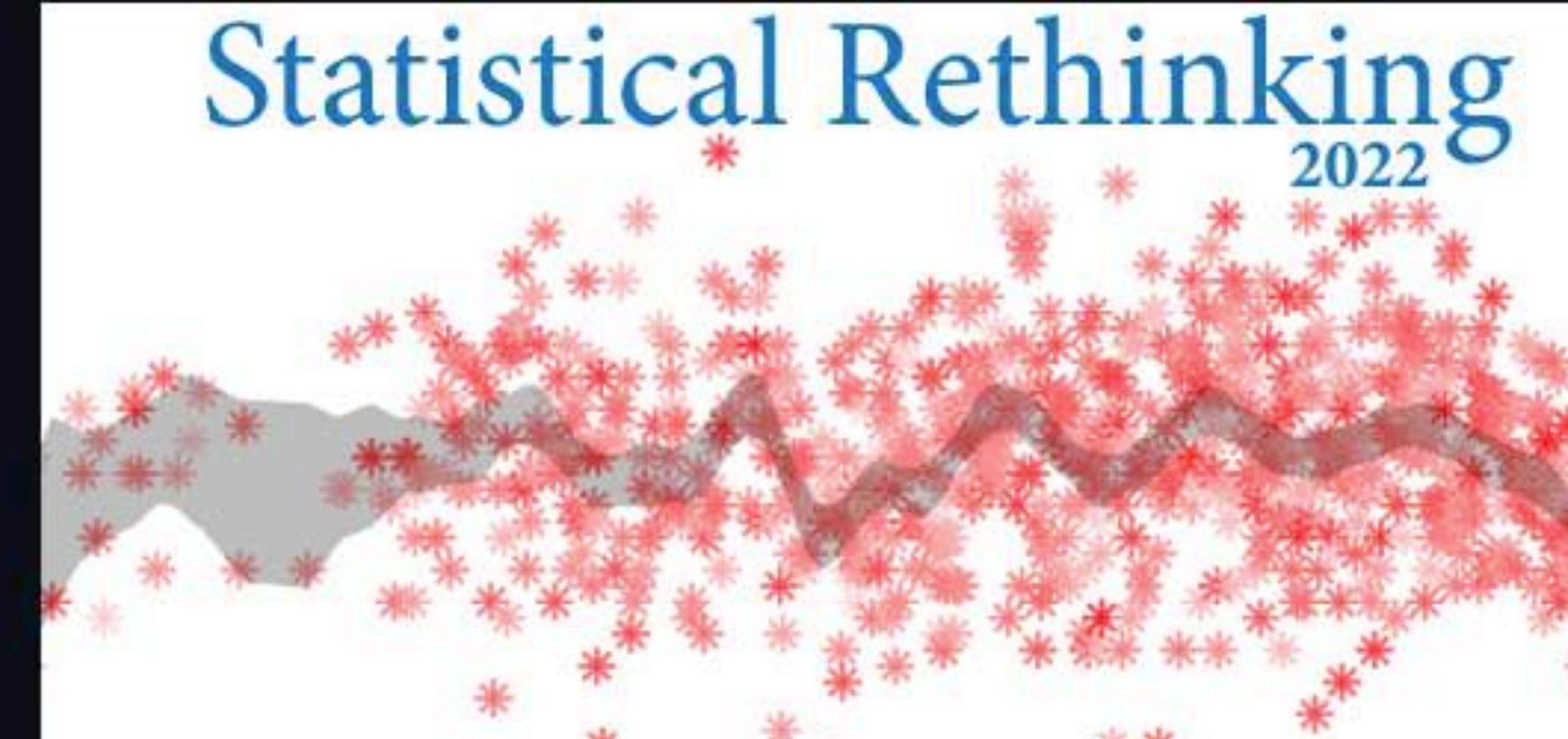


title.gif

README update

4 months ago

README.md



## About

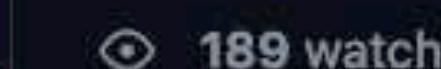
Statistical Rethinking course winter  
2022



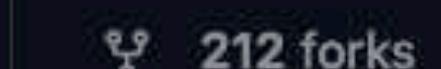
Readme



2.8k stars



189 watching



212 forks

## Releases

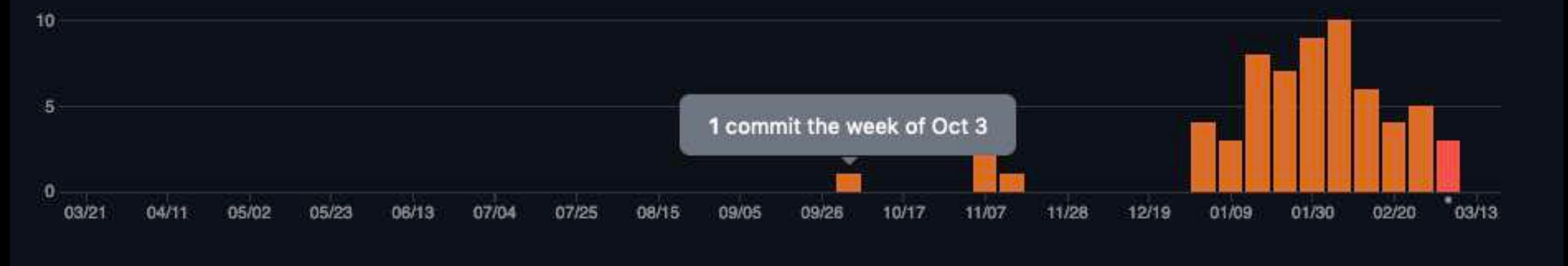
No releases published  
[Create a new release](#)

## Packages

No packages published  
[Publish your first package](#)

## Languages





```
@@ -40,7 +40,7 @@ Lecture playlist on Youtube: <[Statistical Rethinking 2022]>(https://www.youtube.com/watch?v=n2aJYtuGu54&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=13) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-13) <br> [14] <[Correlated varying effects]>(https://www.youtube.com/watch?v=XDoAglqd7ss&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=14) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-14)>
```

```
40 40 | Week 07 | 18 February | Chapters 13 and 14 | [13] <[Multi-Multilevel Models]>(https://www.youtube.com/watch?v=n2aJYtuGu54&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=13) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-13) <br> [14] <[Correlated varying effects]>(https://www.youtube.com/watch?v=XDoAglqd7ss&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=14) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-14)>
```

```
41 41 | Week 08 | 25 February | Chapter 14 | [15] <[Social Networks]>(https://www.youtube.com/watch?v=L_QumFUv7C8&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=15) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-15) <br> [16] <[Gaussian Processes]>(https://www.youtube.com/watch?v=PIuqxOBJqLU&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=16) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-16)>
```

```
42 42 | Week 09 | 04 March | Chapter 15 | [17] <[Measurement Error]>(https://www.youtube.com/watch?v=lTFAB6QmwHM&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=17) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-17) <br> [18] <[Missing Data]>(https://www.youtube.com/watch?v=oMiSb8GKR0o&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=18) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-18)>
```

```
43 - | Week 10 | 11 March | Chapters 16 and 17 | [19] Beyond GLMs: State-space Models, ODEs <br> [20] Horoscopes
```

```
43 + | Week 10 | 11 March | Chapters 16 and 17 | [19] <[Beyond GLMs]>(https://www.youtube.com/watch?v=Doaod09YitA&list=PLDcUM9US4XdMR0Z57-0IRtIK0a0ynbgZN&index=19) <[(Slides)]>(https://speakerdeck.com/rmcelreath/statistical-rethinking-2022-lecture-19) <br> [20] Horoscopes
```

```
44 44
```

```
45 45
```

```
46 46 # Coding
```

# Versioning and Testing



Most researchers don't need all git's features

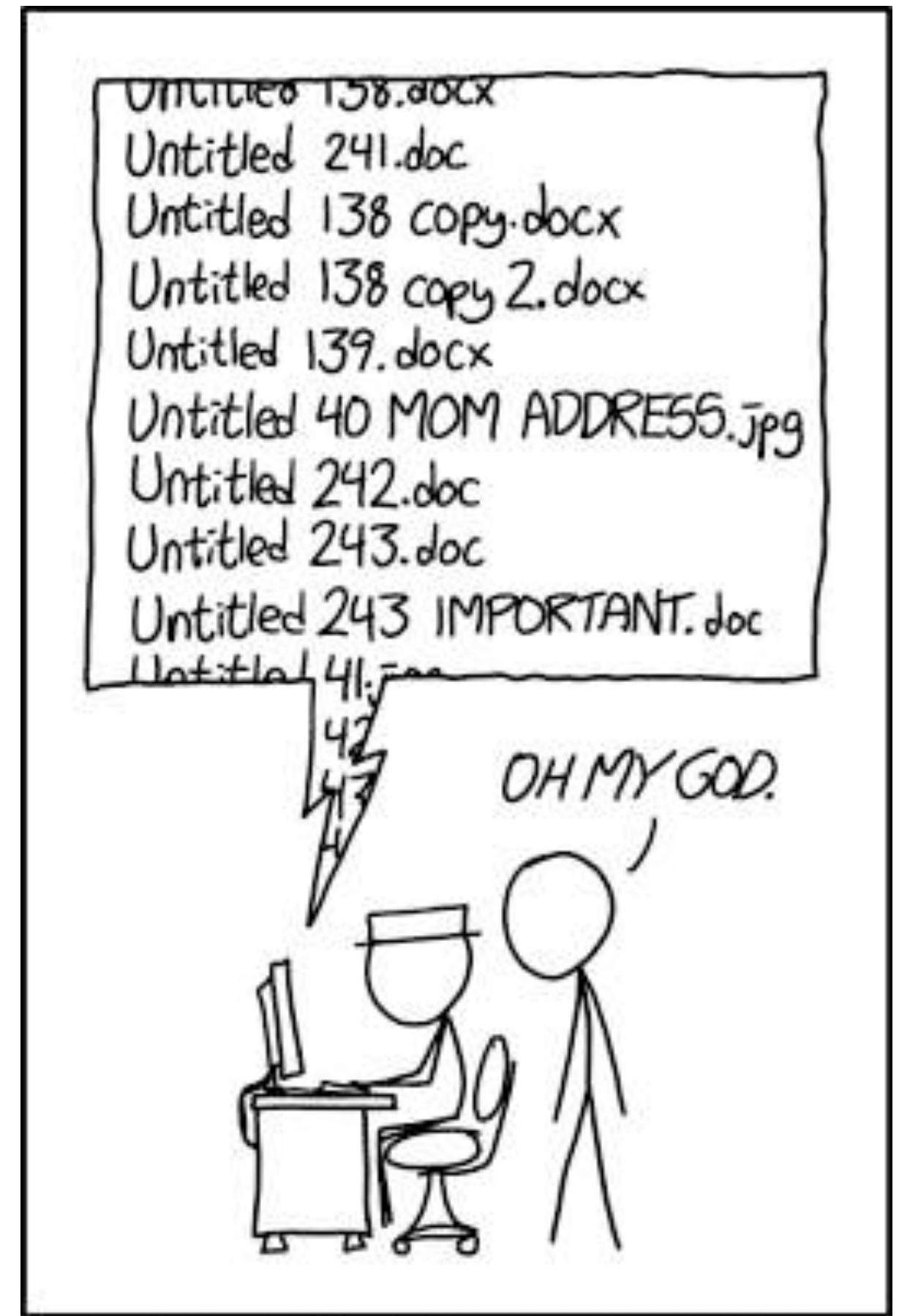
But do:

Commit changes after each milestone

Maintain test code in project

Do not:

Replace raw data with processed data



PROTIP: NEVER LOOK IN SOMEONE  
ELSE'S DOCUMENTS FOLDER.

# More on Testing

Complex analyses must be built in steps

Test each step

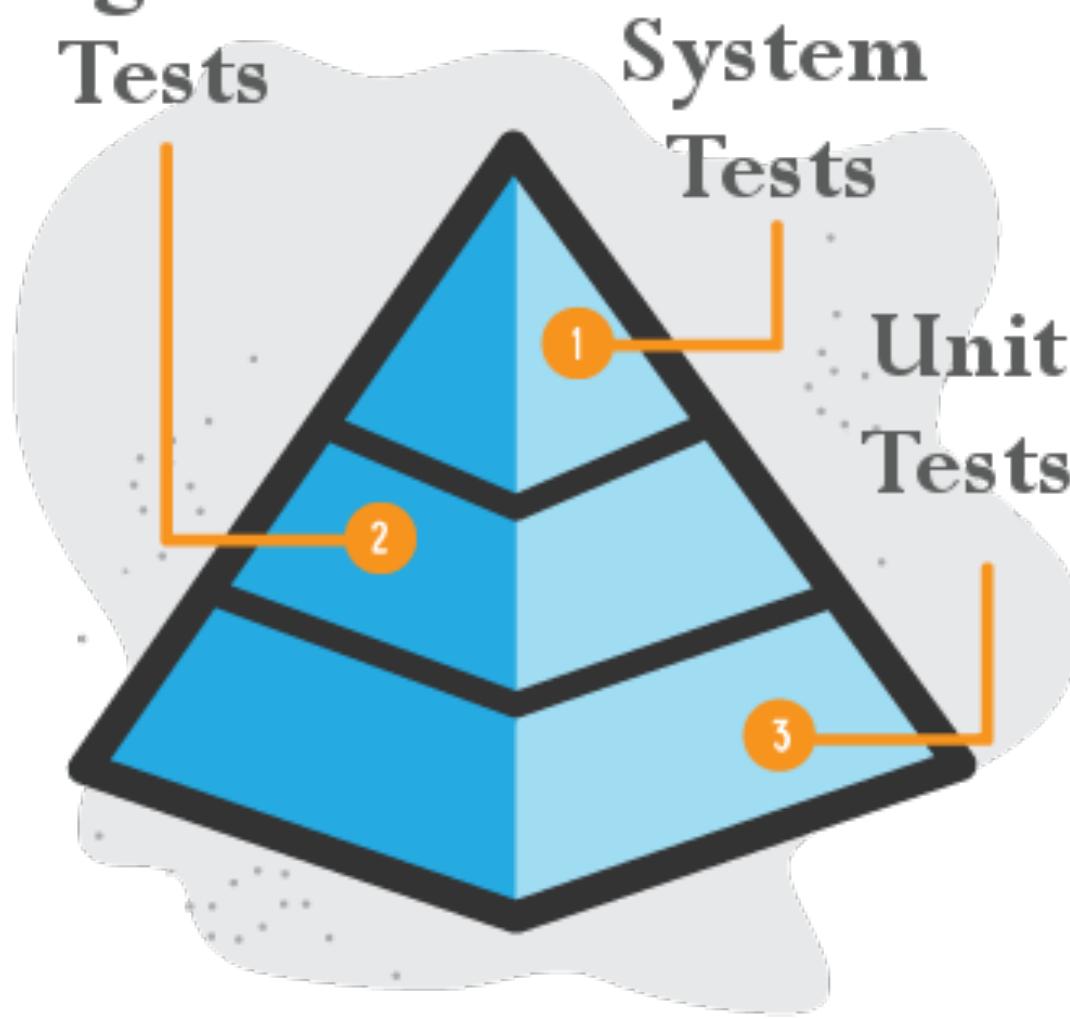
Social networks lecture (#15) as example

Milestones:

- (1) Synthetic data simulation
- (2) Dyadic reciprocity model
- (3) Add generalized giving/receiving
- (4) Add wealth, association index



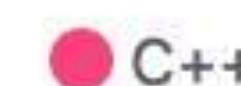
## Integration



## math

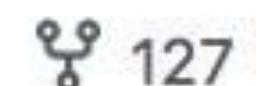
The Stan Math Library is a C++ template library for automatic differentiation of any order using forward, reverse, and mixed modes. It includes a range of built-in functions for probabilistic modeling, linear algebra, and equation solving.

[math](#) [automatic-differentiation](#) [stan](#) [stan-math-library](#)

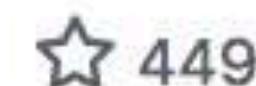


C++

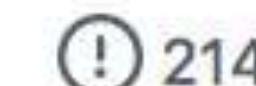
BSD-3-Clause



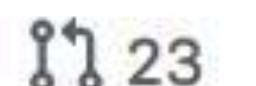
127



449



214 (20 issues need help)



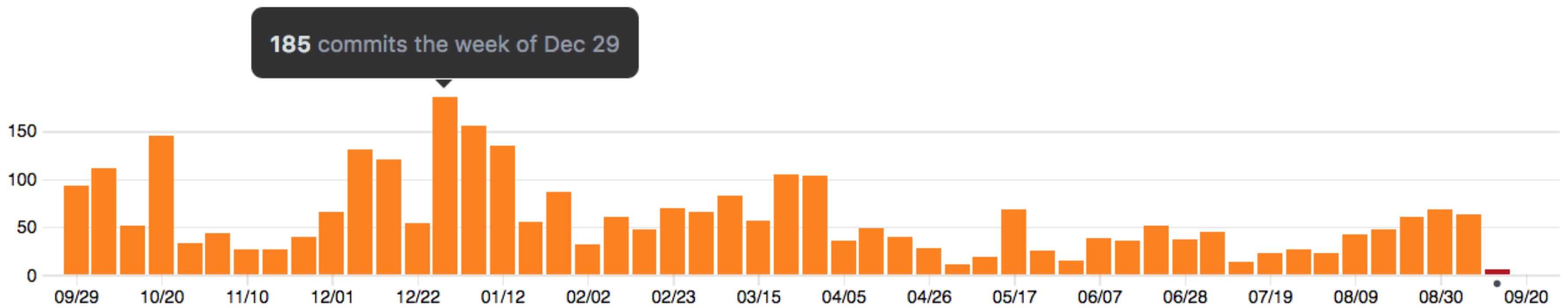
23

Updated 5 minutes ago



# 5.1 MB of library code

# 8.2 MB of test code



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Richard McElreath publish anon data

756a82f on 12 Jun 2021

3 commits

 doc	init	9 months ago
 CES_ratings1_develop.r	report stage	9 months ago
 CES_ratings2_testing.r	report stage	9 months ago
 CES_ratings3_production.r	publish anon data	9 months ago
 README.md	init	9 months ago
 dat_anon.csv	publish anon data	9 months ago
 example_data.csv	init	9 months ago
 model1.stan	init	9 months ago
 model_null.stan	init	9 months ago

[Code](#)[Issues](#)[Pull requests](#)[Actions](#)[Projects](#)[Wiki](#)[Security](#)[Insights](#)[main](#)[1 branch](#)[0 tags](#)[Go to file](#)[Add file](#)[Code](#)

Richard McElreath publish anon data

756a82f on 12 Jun 2021

3 commits



doc

**Documentation & reports**

9 months ago



CES\_ratings1\_develop.r

**Simulation code**

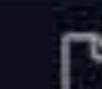
9 months ago



CES\_ratings2\_testing.r

**Validation code**

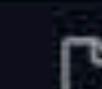
9 months ago



CES\_ratings3\_production.r

**Analysis code**

9 months ago



README.md

init

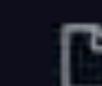
9 months ago



dat\_anon.csv

**Sharable data**

9 months ago



example\_data.csv

**Template data**

9 months ago



model1.stan

**Stan model, full**

9 months ago



model\_null.stan

**Stan model, milestone 1**

9 months ago



# DATA CARPENTRY

BUILDING COMMUNITIES TEACHING UNIVERSAL DATA LITERACY

## What is Data Carpentry?

Data Carpentry develops and teaches workshops on the fundamental data skills needed to conduct research. Our mission is to provide researchers high-quality, domain-specific training covering the full lifecycle of data-driven research.

Data Carpentry is now a lesson program within [The Carpentries](#), having merged with [Software Carpentry](#) in January, 2018. Data Carpentry's focus is on the introductory computational skills needed for data management and analysis in all domains of research. Our lessons are domain-specific, and build on the existing knowledge of learners to enable them to quickly apply skills learned to their own research. *Our initial target audience is learners who have little to no prior computational experience.* We create a friendly environment for learning to empower researchers and enable data driven discovery.

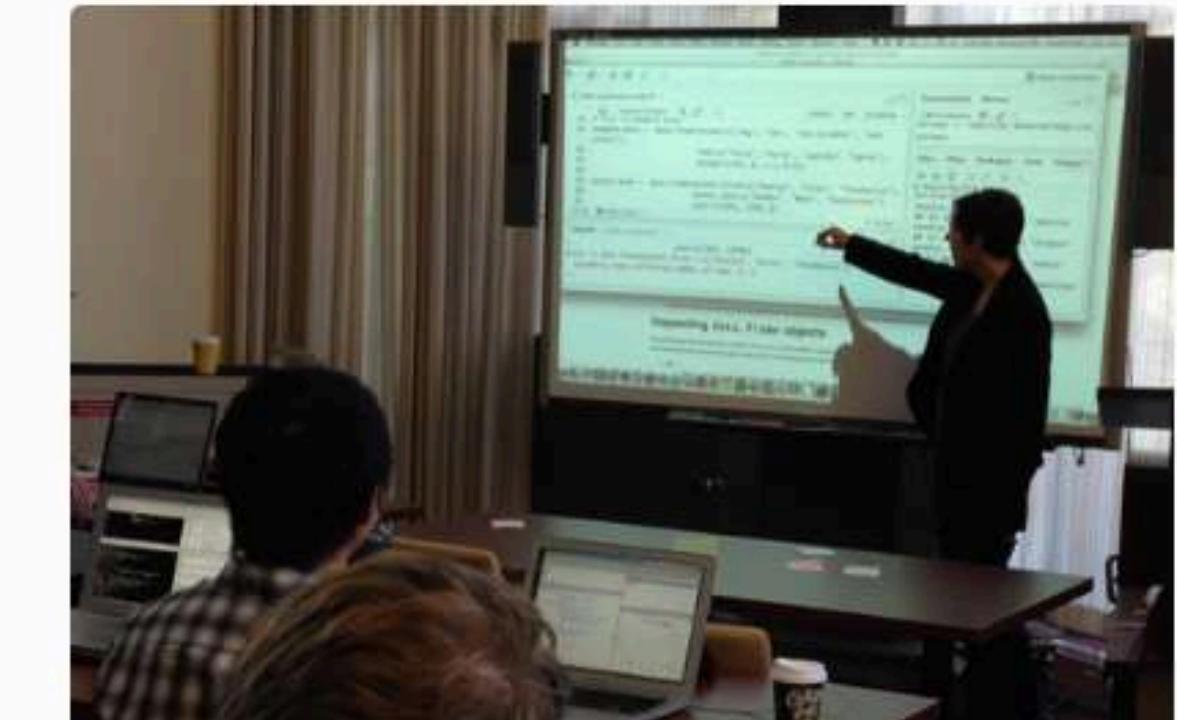
### Host a Workshop



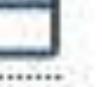
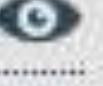
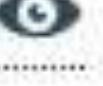
### Attend a Workshop



### Get Involved



# Lessons in English

Lesson	Site	Repository	Reference	Instructor Notes
Ecology Workshop Overview				
Data Organization in Spreadsheets for Ecologists				
Data Cleaning with OpenRefine for Ecologists				
Data Management with SQL for Ecologists				
Data Analysis and Visualization in R for Ecologists				
Data Analysis and Visualization in Python for Ecologists				

# Scientists rename human genes to stop Microsoft Excel from misreading them as dates

*Sometimes it's easier to rewrite genetics than update Excel*

By [James Vincent](#) | Aug 6, 2020, 8:44am EDT

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**STUDIES FOUND A FIFTH OF GENETIC DATA IN PAPERS WAS AFFECTED BY EXCEL ERRORS**

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**WHY DID MICROSOFT WIN IN A FIGHT AGAINST HUMAN GENETICS?**

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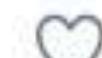
**WHY DID MICROSOFT WIN IN A FIGHT AGAINST HUMAN GENETICS?**

 **Janna Hutz**  
@jannahutz 

THRILLED by this announcement by the Human Gene Nomenclature Committee.

- Symbols that affect data handling and retrieval. For example, all symbols that autoconverted to dates in Microsoft Excel have been changed (for example, SEPT1 is now SEPTIN1; MARCH1 is now MARCHF1); tRNA synthetase symbols that were also common words have been changed (for example, WARS is now WARS1; CARS is now CARS1).

5:08 PM · Aug 4, 2020 

 1.5K  611 people are Tweeting about this



# Scientists rename human genes to stop Microsoft Excel from misreading them as dates

*Sometimes it's easier to rewrite genetics than update Excel*

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**STUDIES  
GENETIC D  
AFFECTED**

**WHY DID MICROSOFT WIN IN A  
FIGHT AGAINST HUMAN  
GENETICS?**

Careful primary data entry, okay with rules, tests

Never process data in Excel; use code

Microsoft Excel have been changed (for example, SEPT1 is now SEPTIN1; MARCH1 is now MARCHF1); tRNA synthetase symbols that were also common words have been changed (for example, WARS is now WARS1; CARS is now CARS1).

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**No mouth  
pipetting**

**PAUSE**

# Reporting

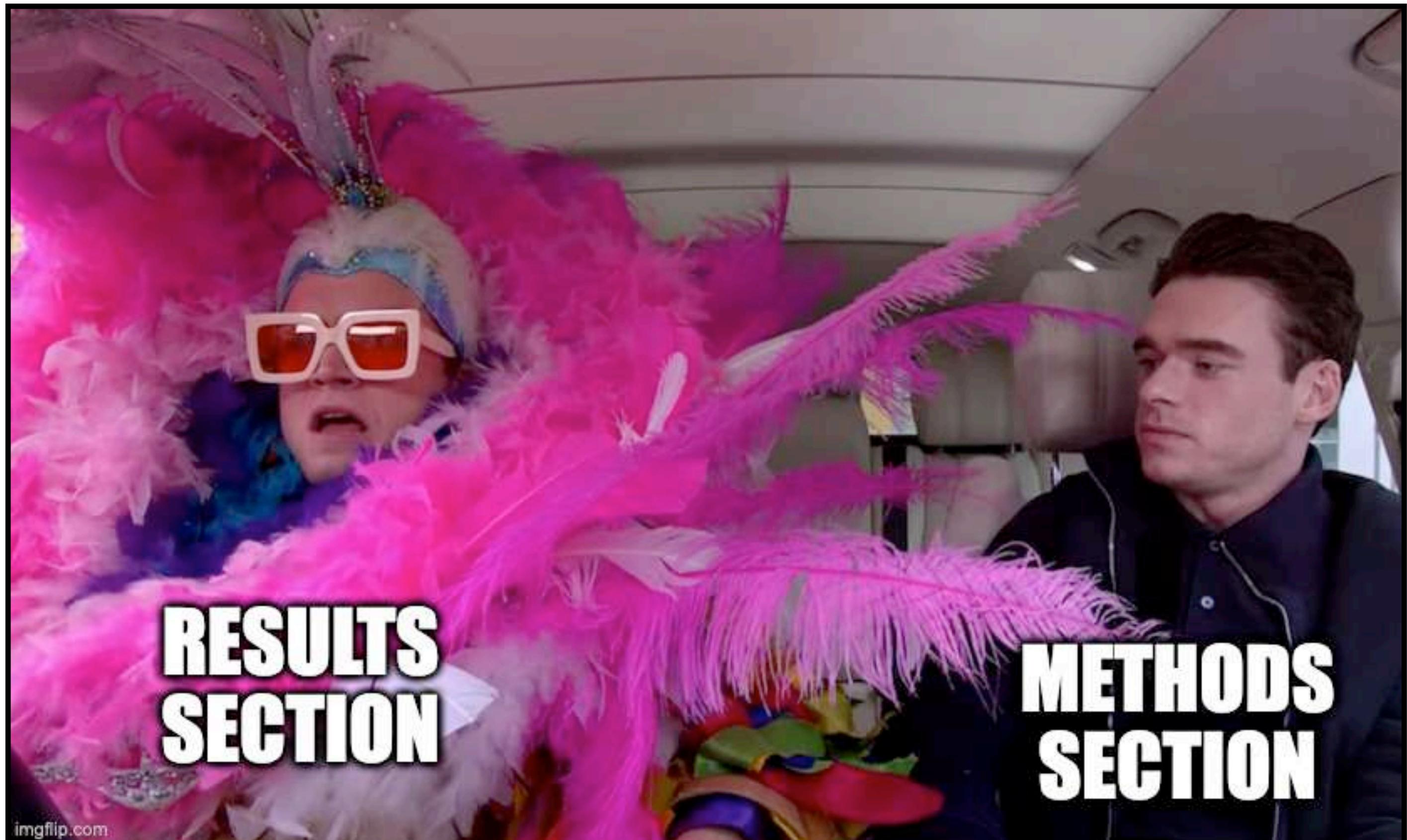
Sharing materials

Describing methods

Describing data

Describing results

Making decisions



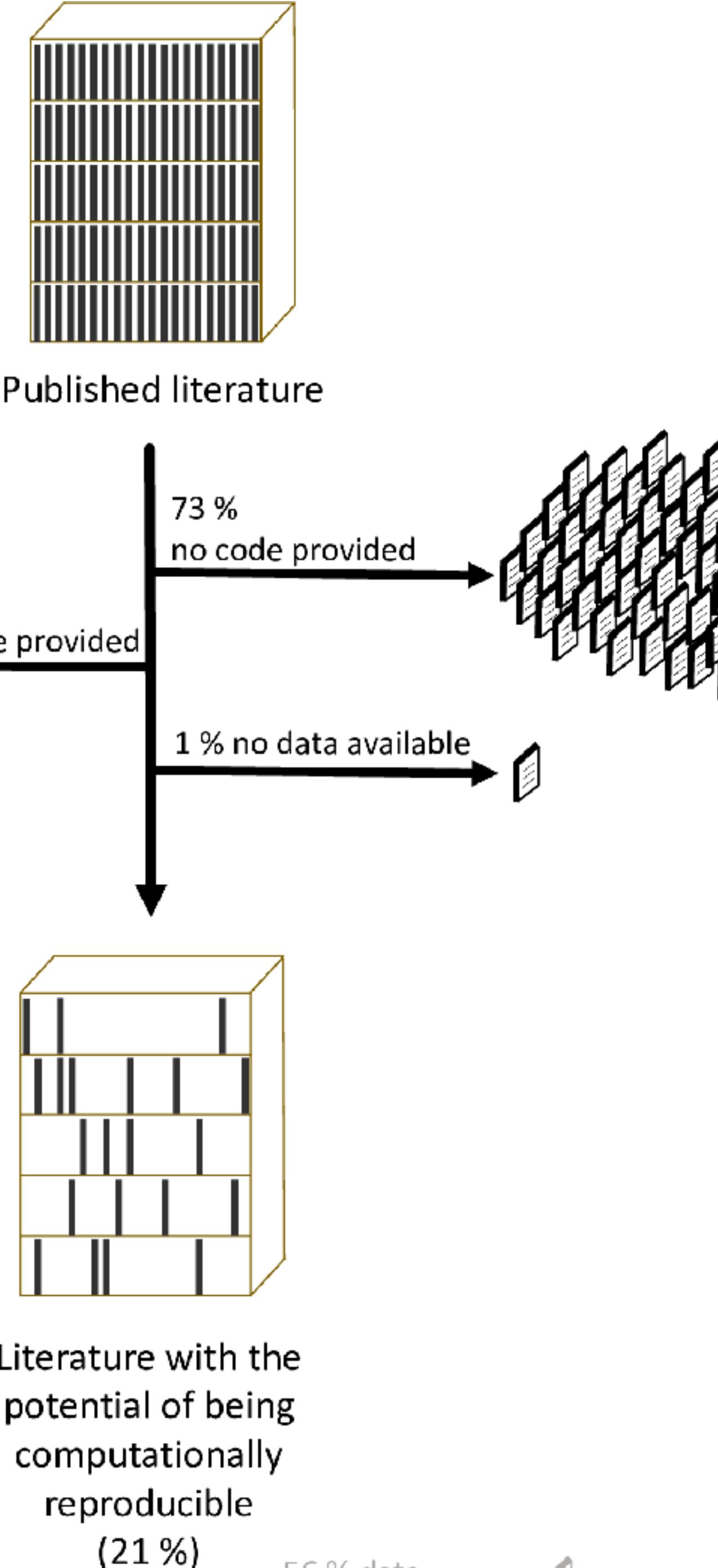
# Sharing Materials

The paper is an advertisement; the data and its analysis are the product

Make code and data available through a link, **not “by request”**

Some data not shareable; code always shareable

**Archived code & data will be required**



# Describing Methods

$$G_{AB} \sim \text{Poisson}(\lambda_{AB})$$

$$\log(\lambda_{AB}) = \alpha + T_{AB} + G_A + R_B$$

Minimal information:

$$G_{BA} \sim \text{Poisson}(\lambda_{BA})$$

$$\log(\lambda_{BA}) = \alpha + T_{BA} + G_B + R_A$$

$$\begin{pmatrix} T_{AB} \\ T_{BA} \end{pmatrix} \sim \text{MVNormal} \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix} \right)$$

$$\rho \sim \text{LKJCorr}(2)$$

$$\sigma \sim \text{Exponential}(1)$$

$$\alpha \sim \text{Normal}(0,1)$$

$$\begin{pmatrix} G_A \\ R_A \end{pmatrix} \sim \text{MVNormal} \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \mathbf{R}_{GR}, \mathbf{S}_{GR} \right)$$

$$\mathbf{R}_{GR} \sim \text{LKJCorr}(2)$$

$$\mathbf{S}_{GR} \sim \text{Exponential}(1)$$

- (1) Math-stats notation of stat model
- (2) Explanation of how (1) provides estimand
- (3) Algorithm used to produce estimate
- (4) Diagnostics, code tests
- (5) Cite software packages

To estimate the reciprocity within dyads, we model the correlation within dyads in giving, using a multilevel mixed-membership model (*textbook citation*). To control for confounding from generalized giving and receiving, as indicated by the DAG in the previous section, we stratify giving and receiving by household. The full model with priors is presented at right. We estimated the posterior distribution using Hamiltonian Monte Carlo as implemented in Stan version 2.29. We validated the model on simulated data and assessed convergence by inspection of trace plots, R-hat values, and effective sample sizes. Diagnostics are reported in Appendix B and all results can be replicated using the code available at [LINK](#).

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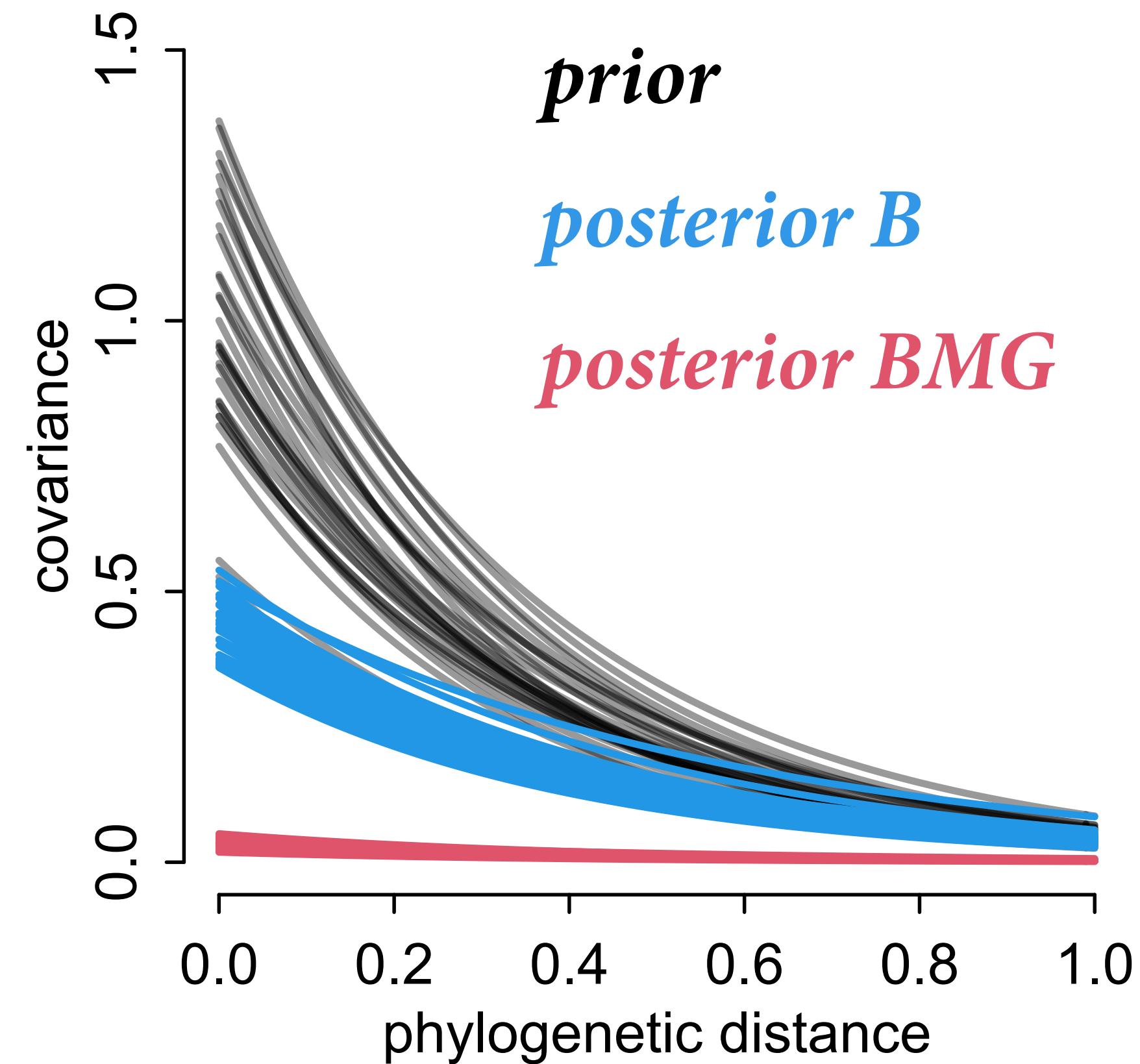
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# Justify Priors

“Priors were chosen through prior predictive simulation so that pre-data predictions span the range of scientifically plausible outcomes.

In the results, we explicitly compare the posterior distribution to the prior, so that the impact of the sample is obvious.”



# Justifying Methods

Naive reviewers: “*Good science doesn’t need complex stats*”

Causal model often requires complexity

Big data => unit heterogeneity

Ethical responsibility to do our best

Change discussion from statistics to causal models

“Pooh?” said Piglet.  
“Yes, Piglet?” said Pooh.  
“27417 parameters,” said Piglet.  
“Oh, bother,” said Pooh.



# Justifying Methods

Write for the editor, not the reviewer

Find other papers in discipline/journal  
that have used Bayesian methods or  
similar models (Bayesian or not)

Explain results in Bayesian terms, show  
densities, cite disciplinary guides

Bayes is ancient, normative, often the only  
practical way to estimate complex models

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# Describing Data

1k observations of 1 person

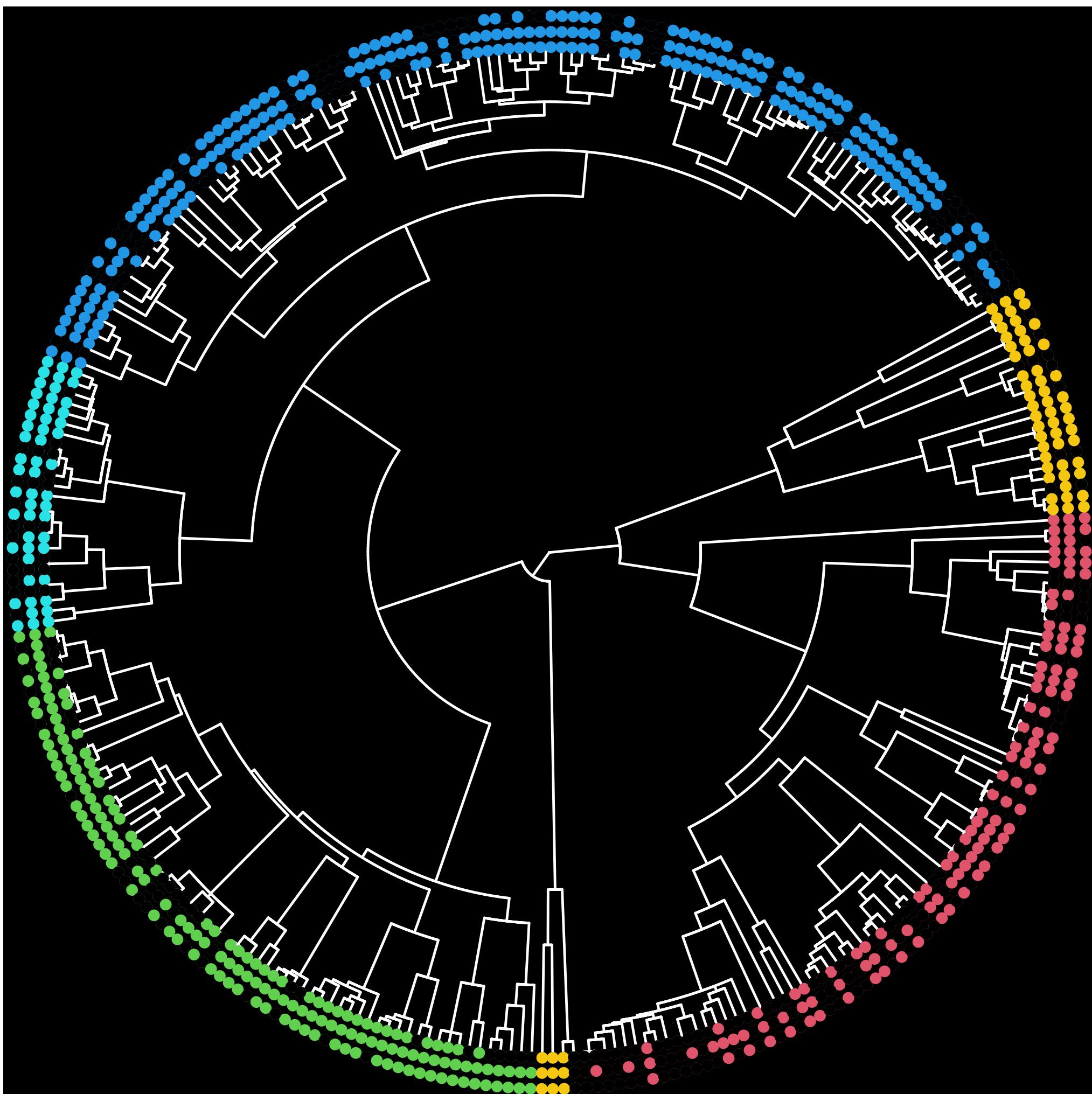
-VS-

1 observation of each of 1k people

“Effective” sample size function of estimand and hierarchical structure

Variables measured at which levels?

Missing values!



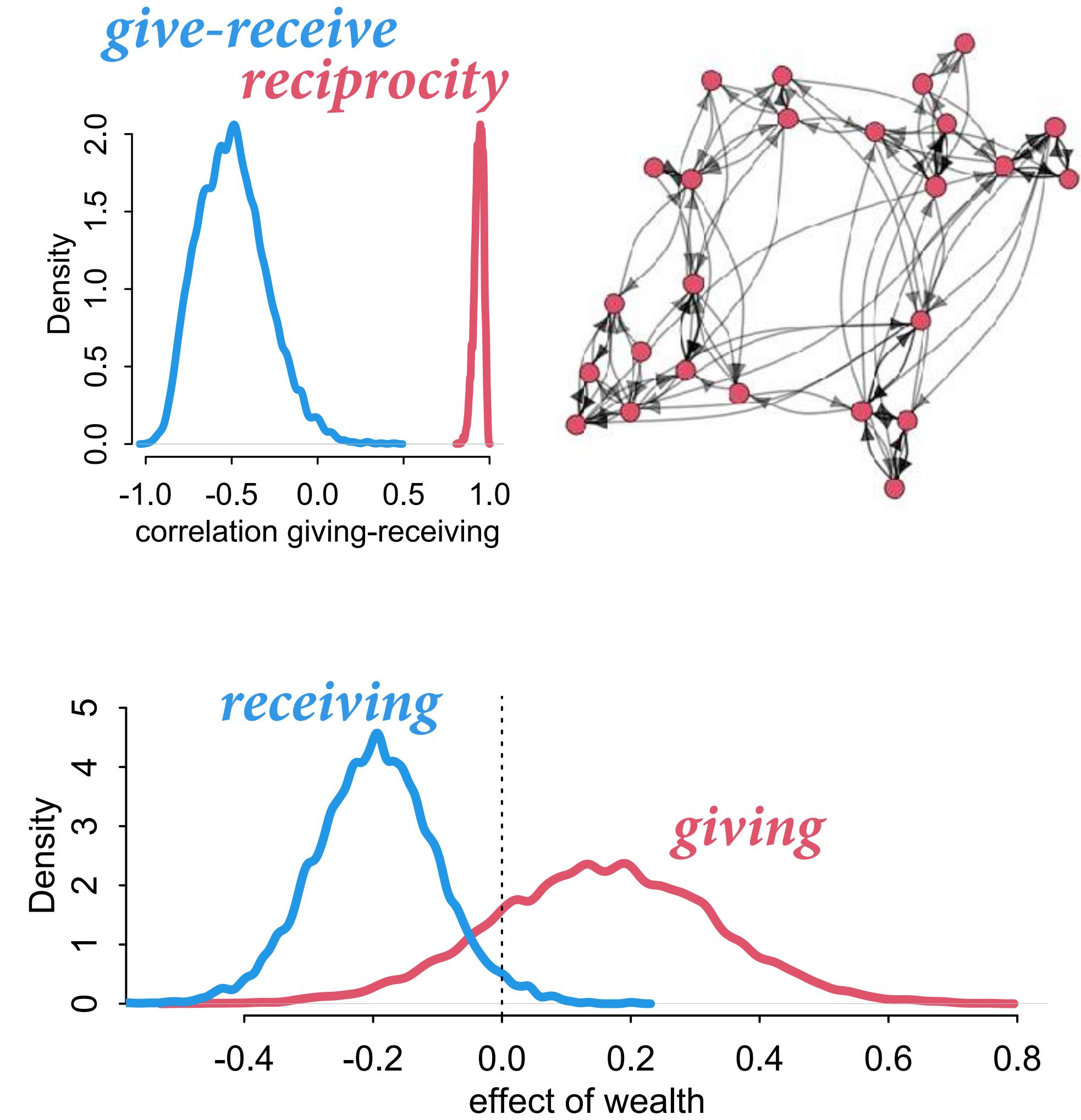
# Describing Results

Estimands, marginal causal effects

Warn against causal interpretation of control variables (Table 2 fallacy)

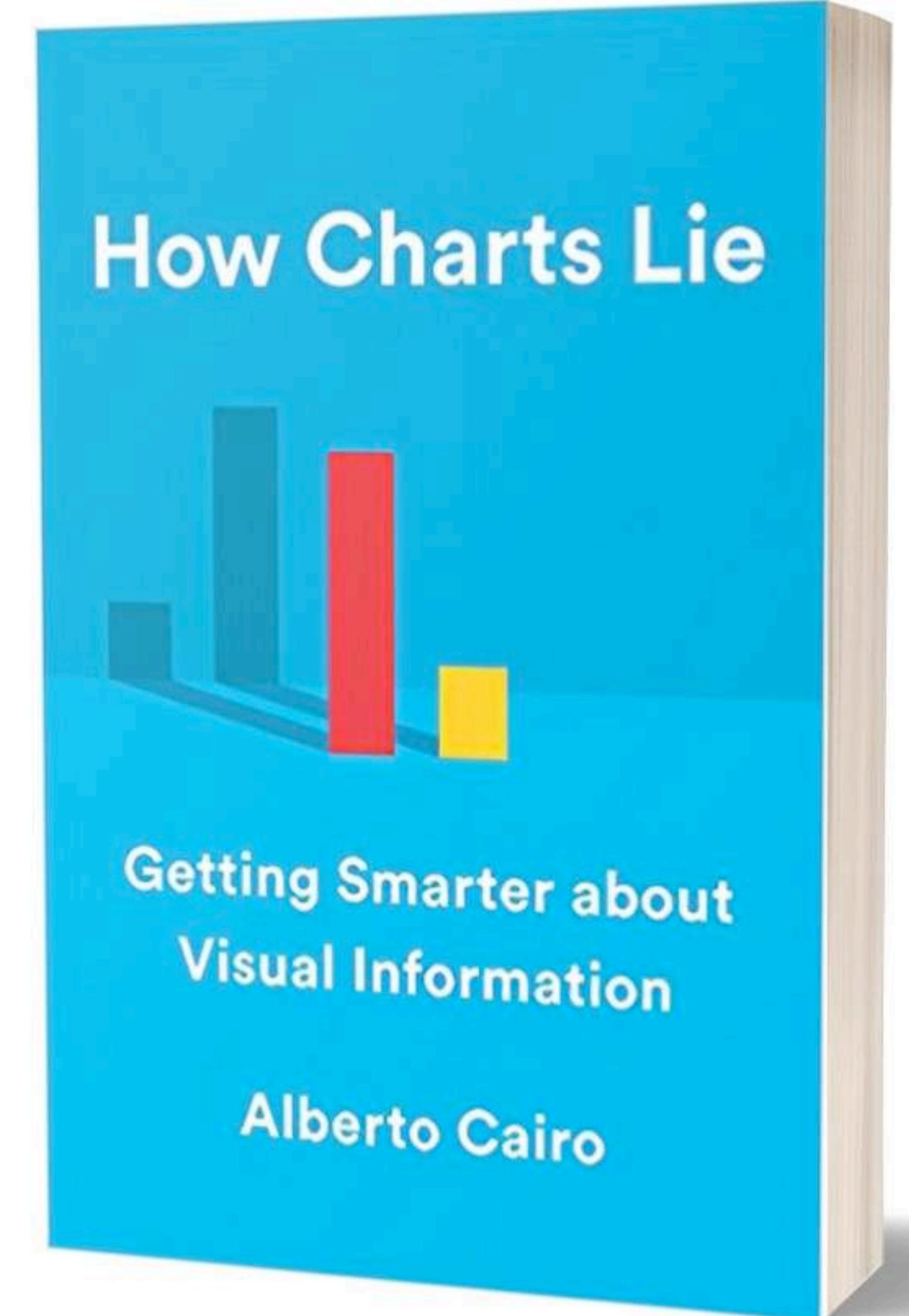
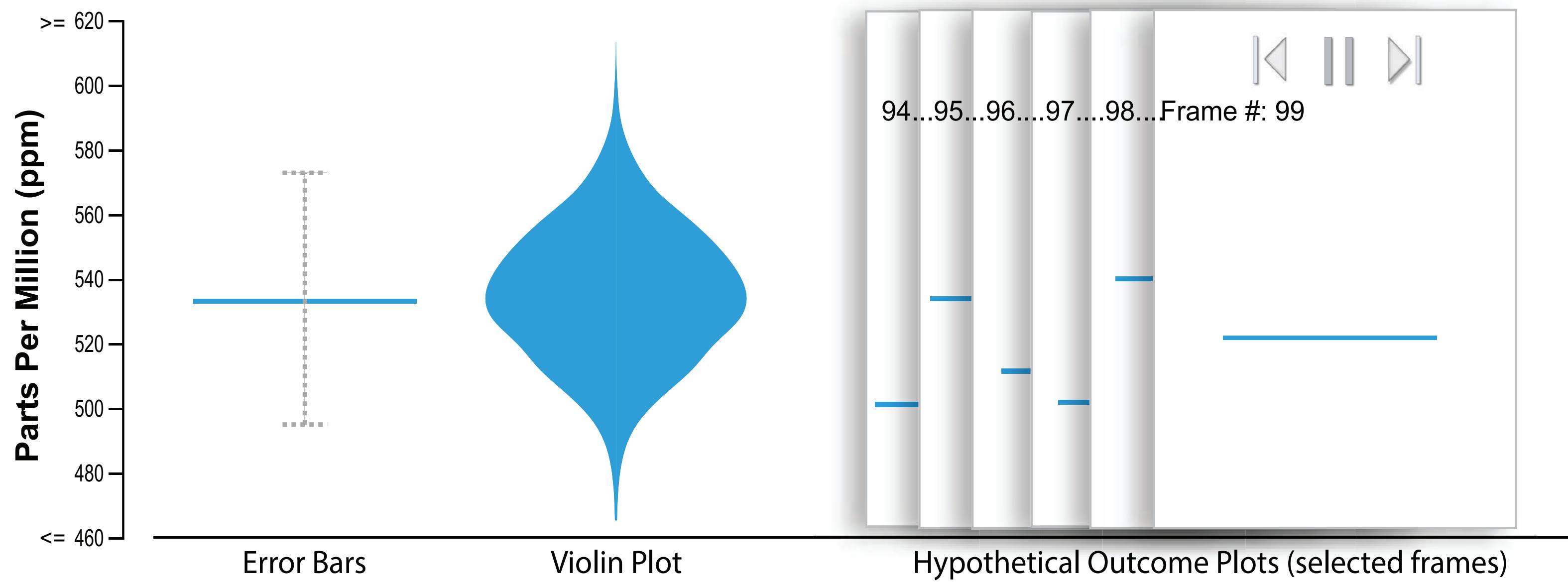
Densities better than intervals; Sample realizations often better than densities

Figures assist comparisons



# Hypothetical Outcome Plots Outperform Error Bars and Violin Plots for Inferences About Reliability of Variable Ordering

Jessica Hullman<sup>1,\*</sup>, Paul Resnick<sup>2</sup>, Eytan Adar<sup>2</sup>,



# Making Decisions

Academic research: **Communicate uncertainty**, conditional on sample & models

Industry research: **What should we do**, given the uncertainty, conditional on sample & models?

Also: “Does my boss have any idea what ‘uncertainty’ means, or does he think that’s the refuge of cowards?”



**POSTERIOR DOGE**



**DECISION DOGE**

# Making Decisions

Bayesian decision theory:

- (1) State costs & benefits of outcomes
- (2) Compute posterior benefits of hypothetical policy choices

Simple example in Chapter 3

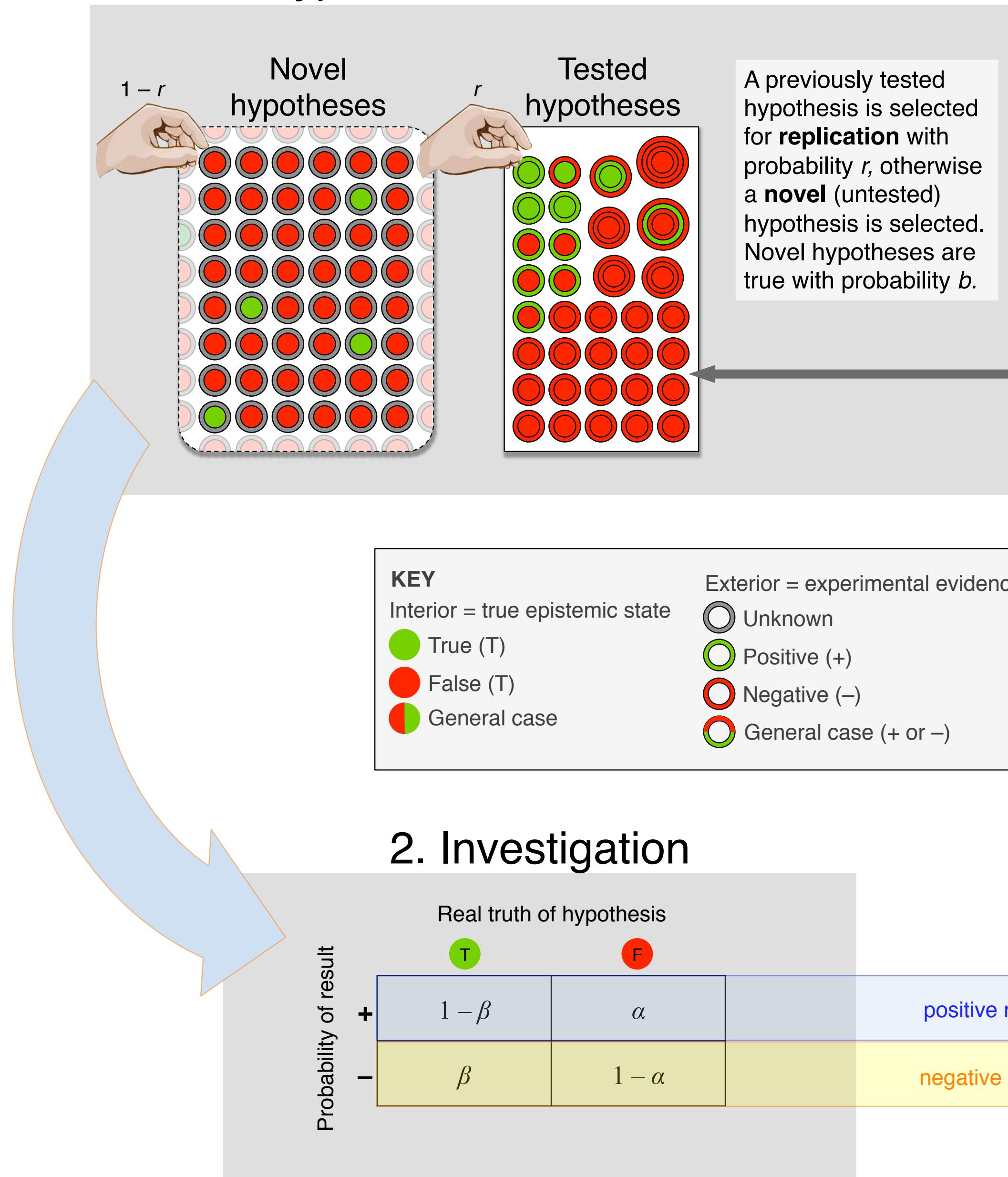
Can be integrated with dynamic optimization



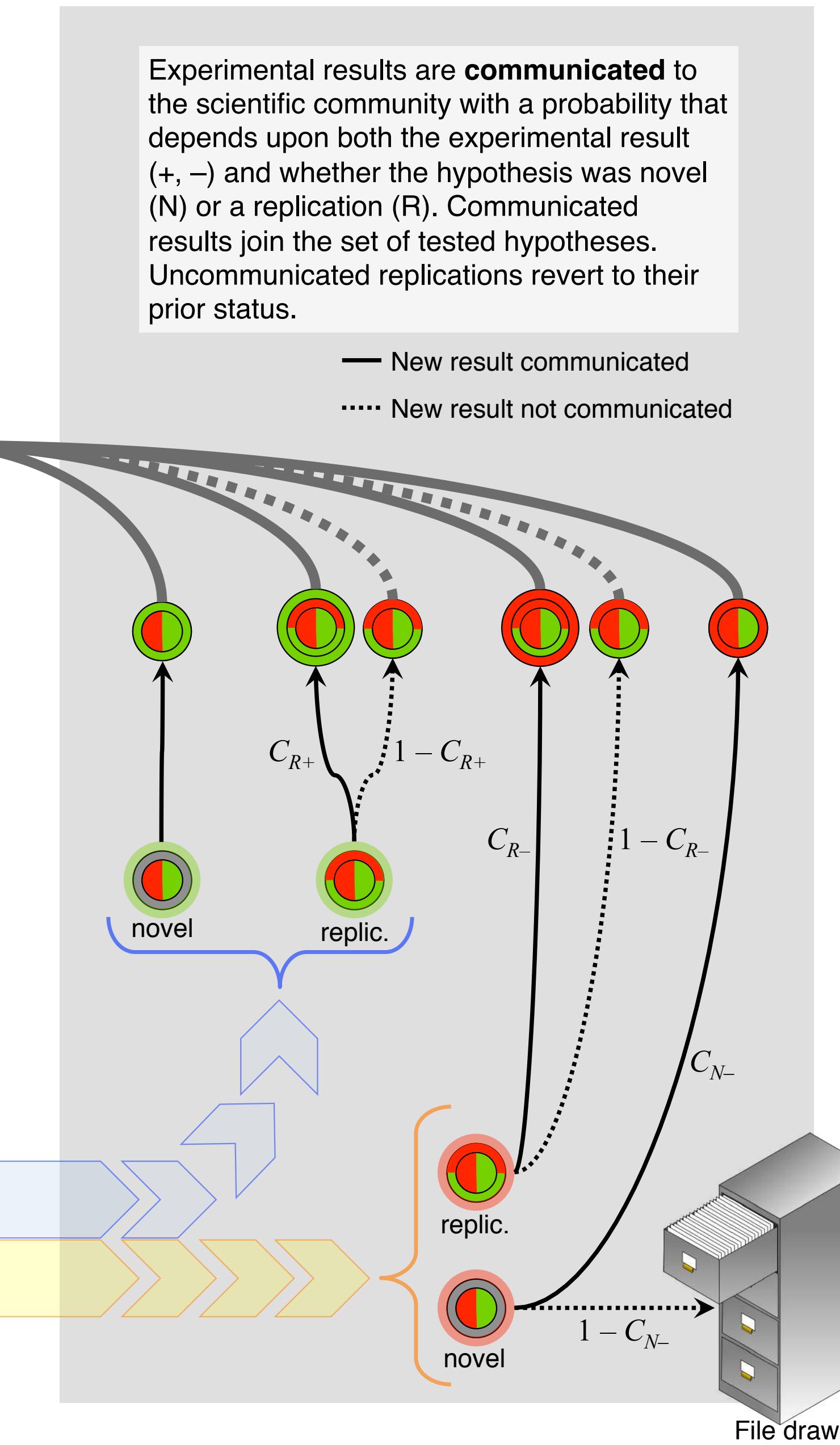
**ME DISCUSSING  
SCIENCE REFORM**

**SCIENCE**

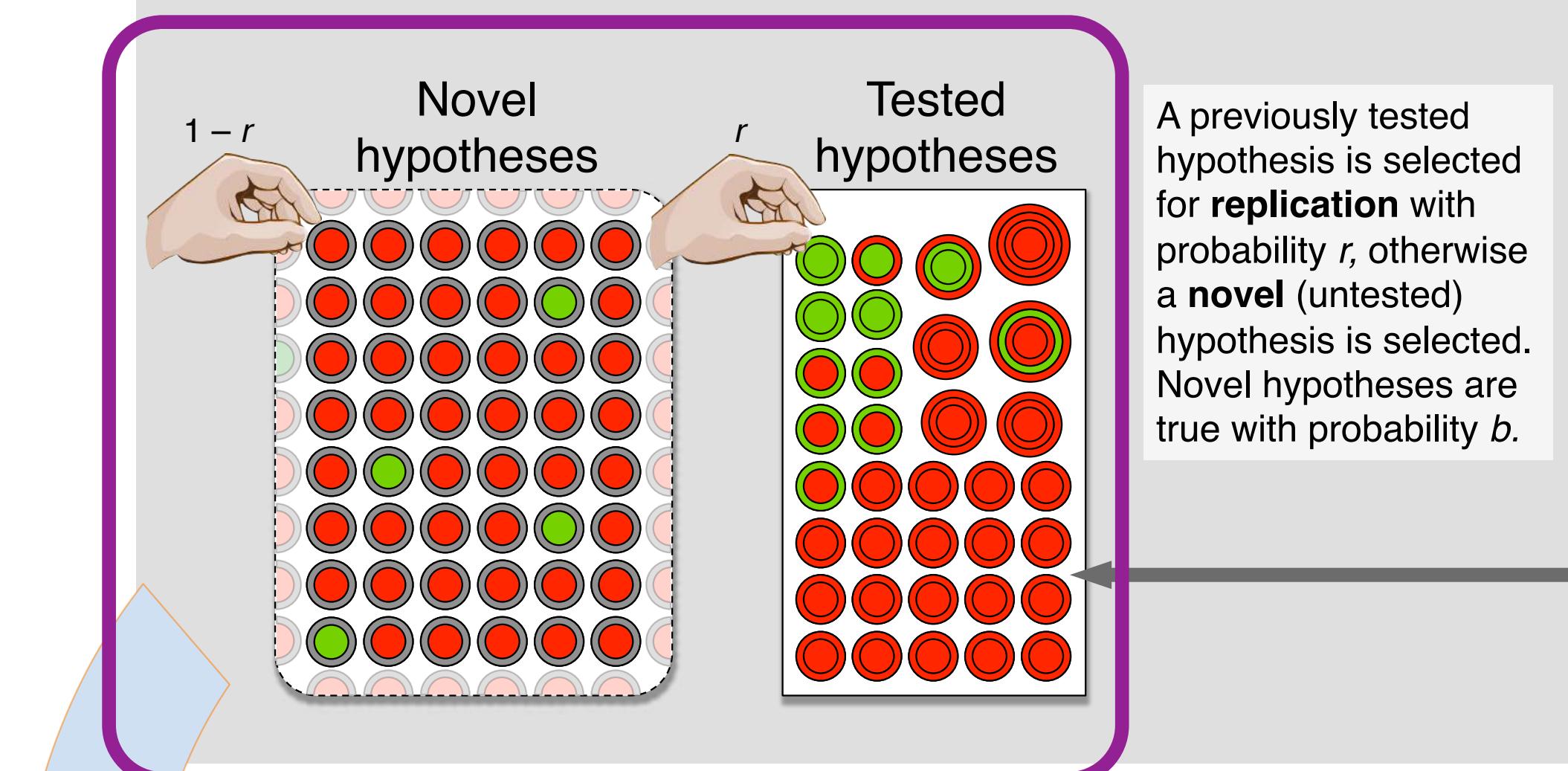
# 1. Hypothesis Selection



# 3. Communication

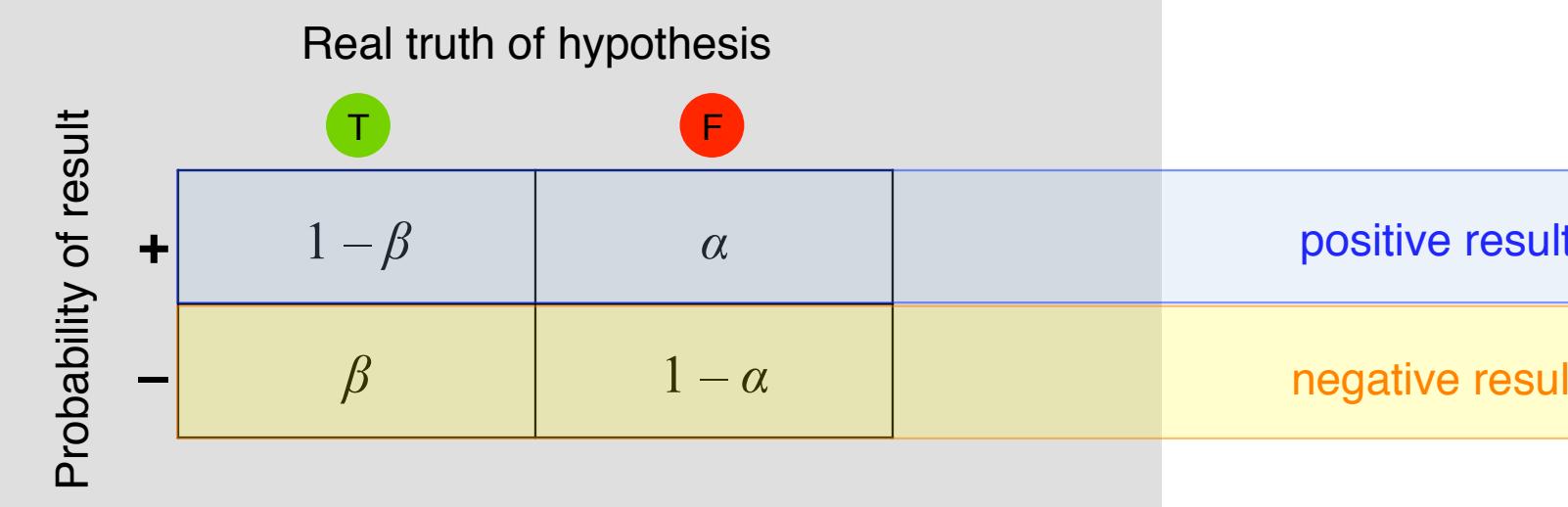


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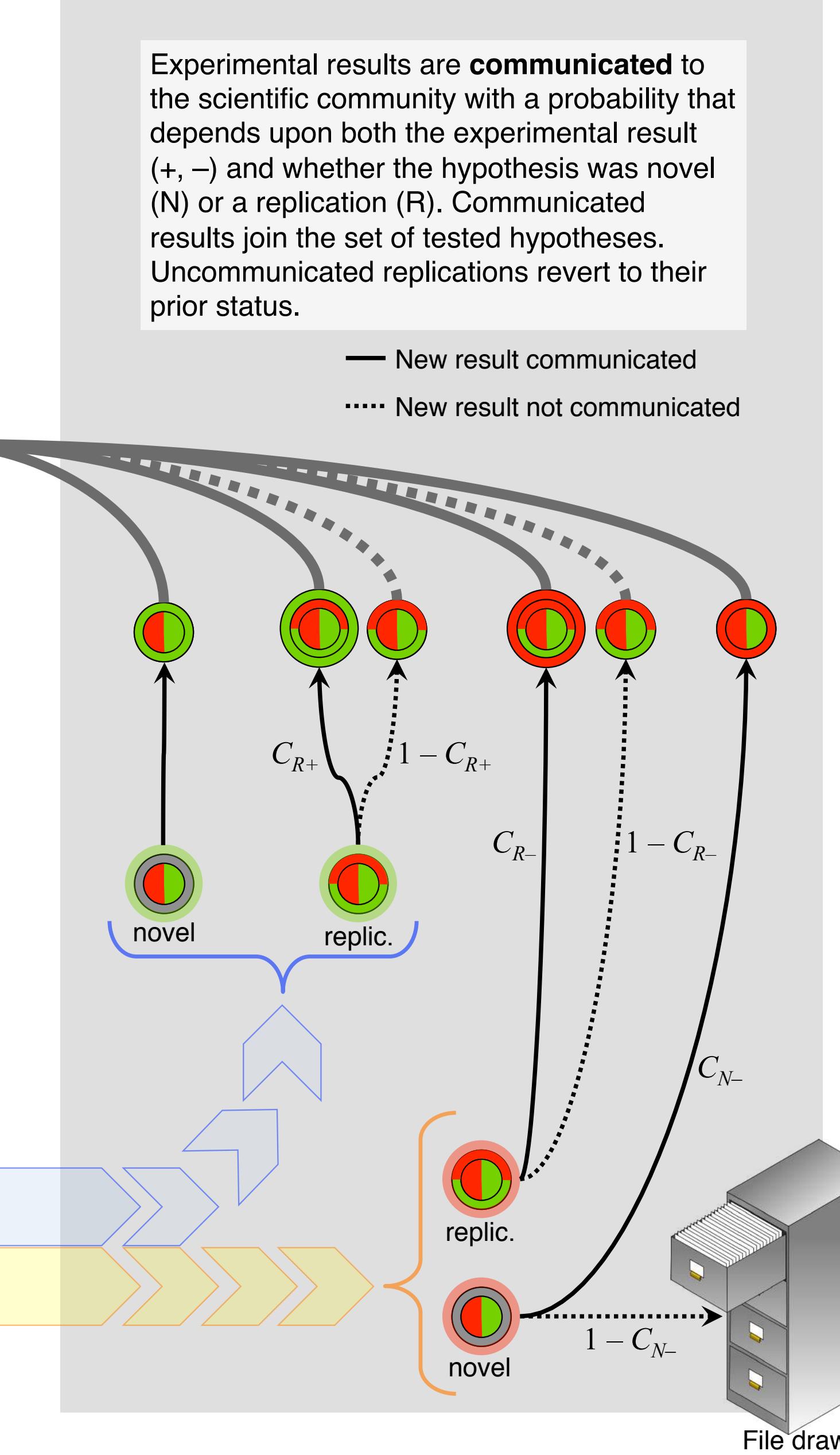


KEY	
Interior = true epistemic state	Exterior = experimental evidence
True (T)	Unknown
False (F)	Positive (+)
General case	Negative (-)
	General case (+ or -)

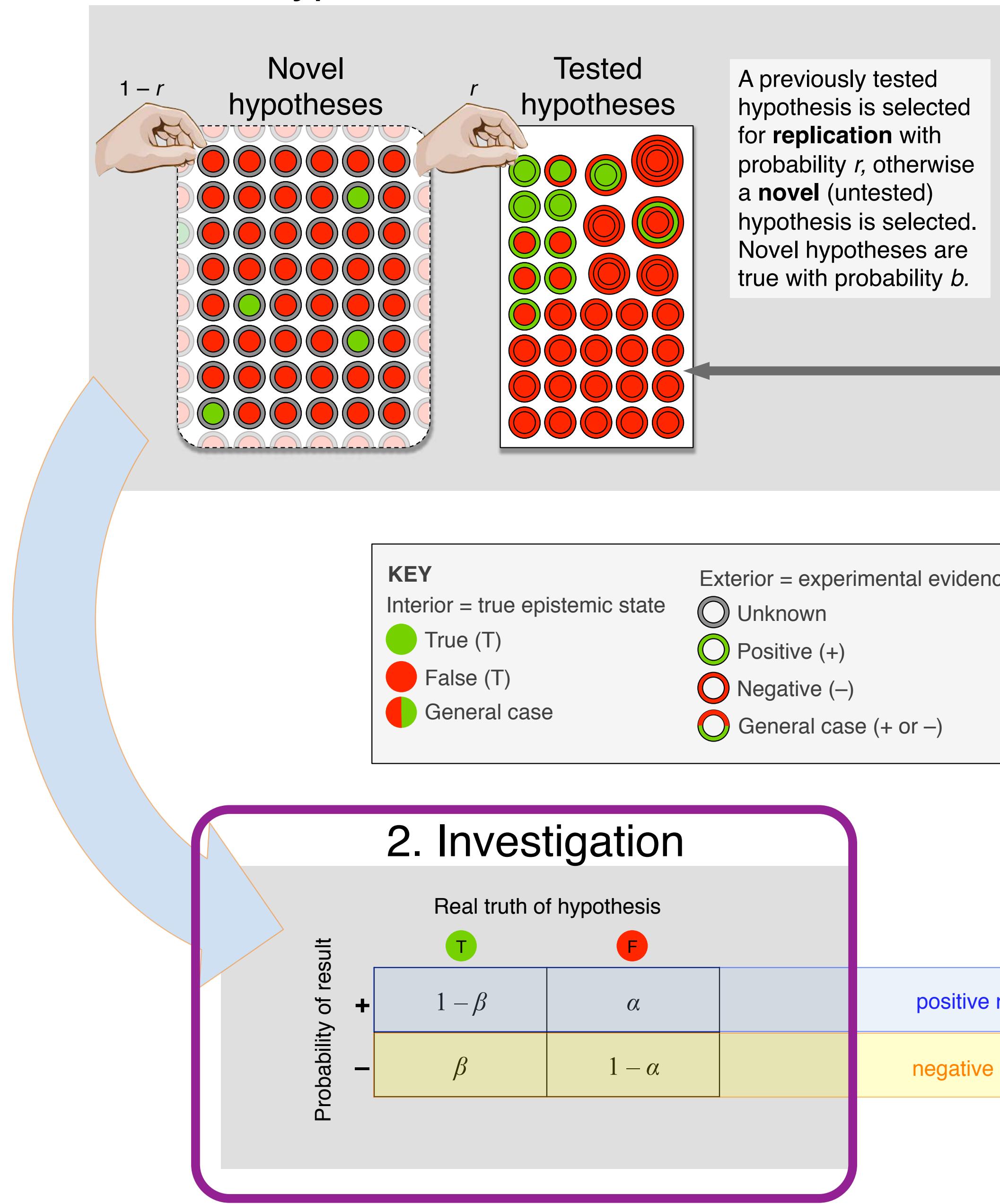
# 2. Investigation



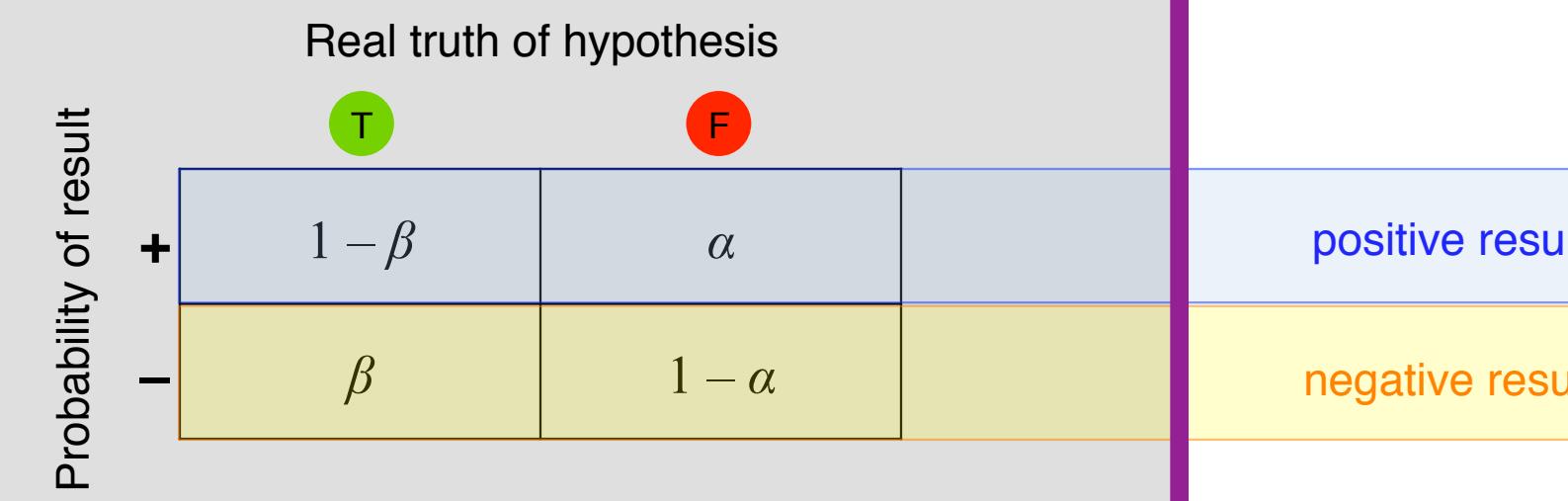
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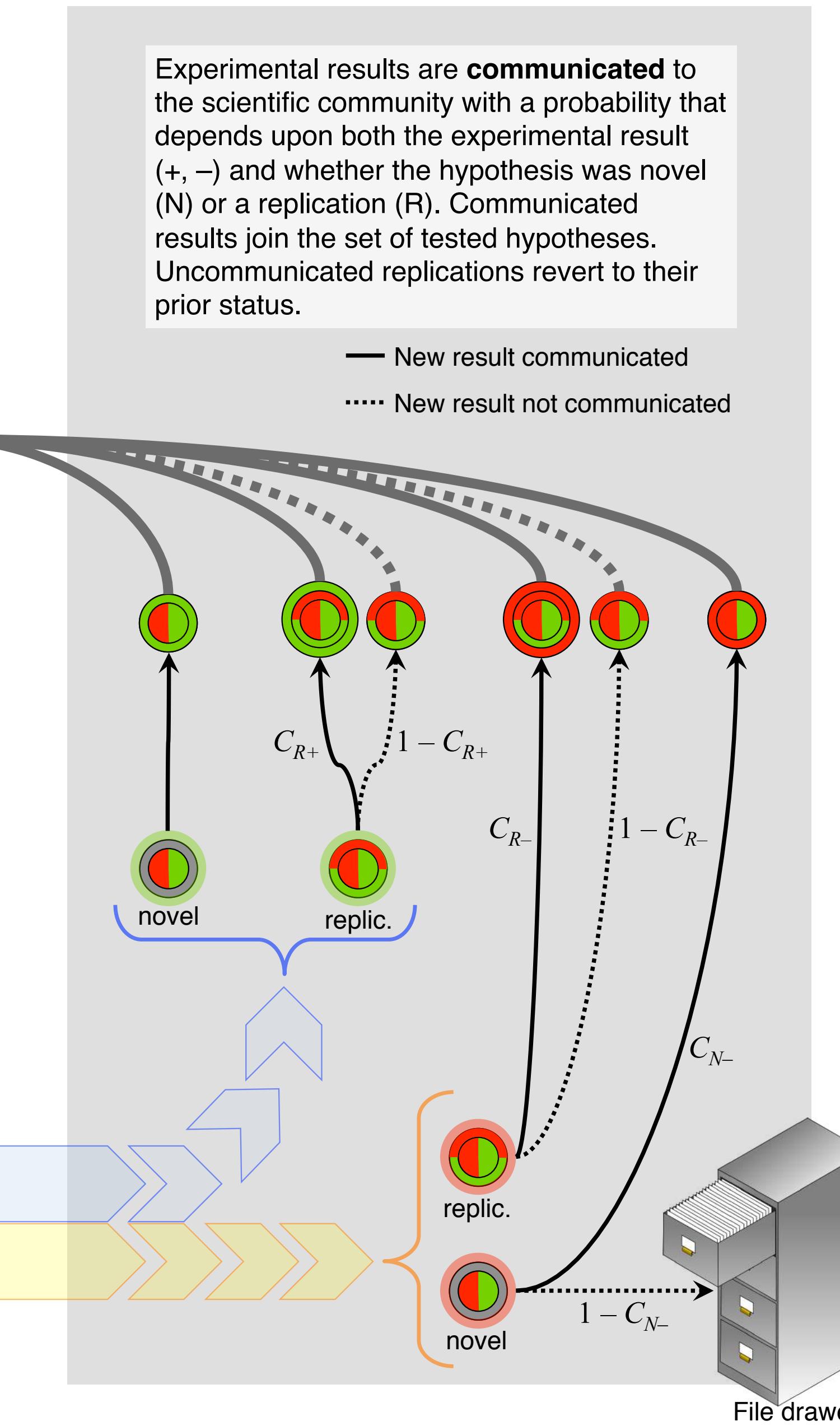
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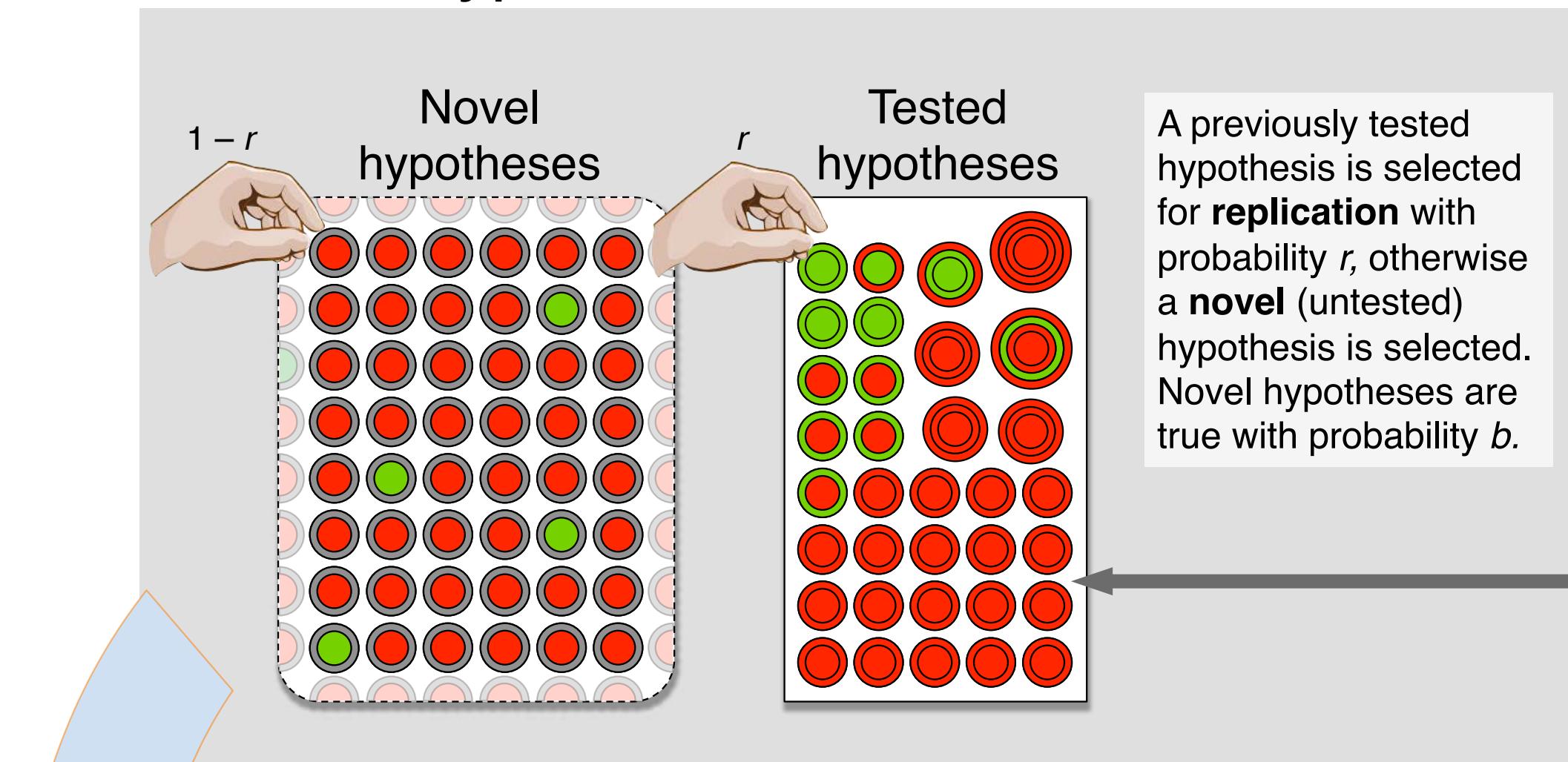
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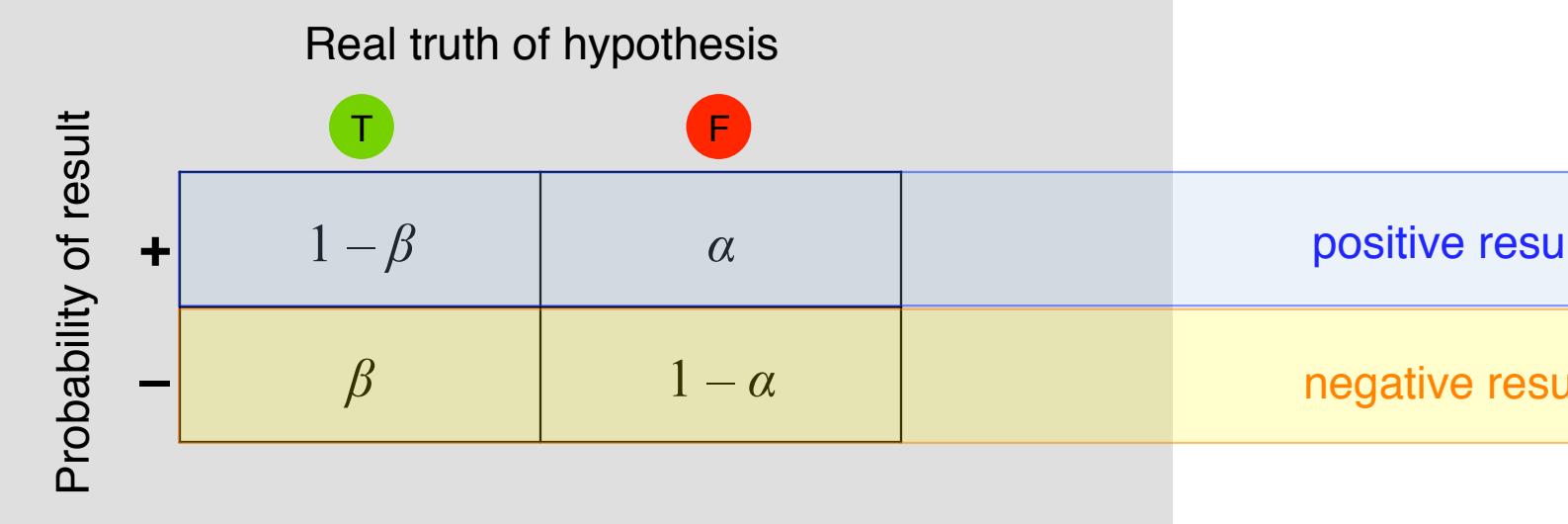
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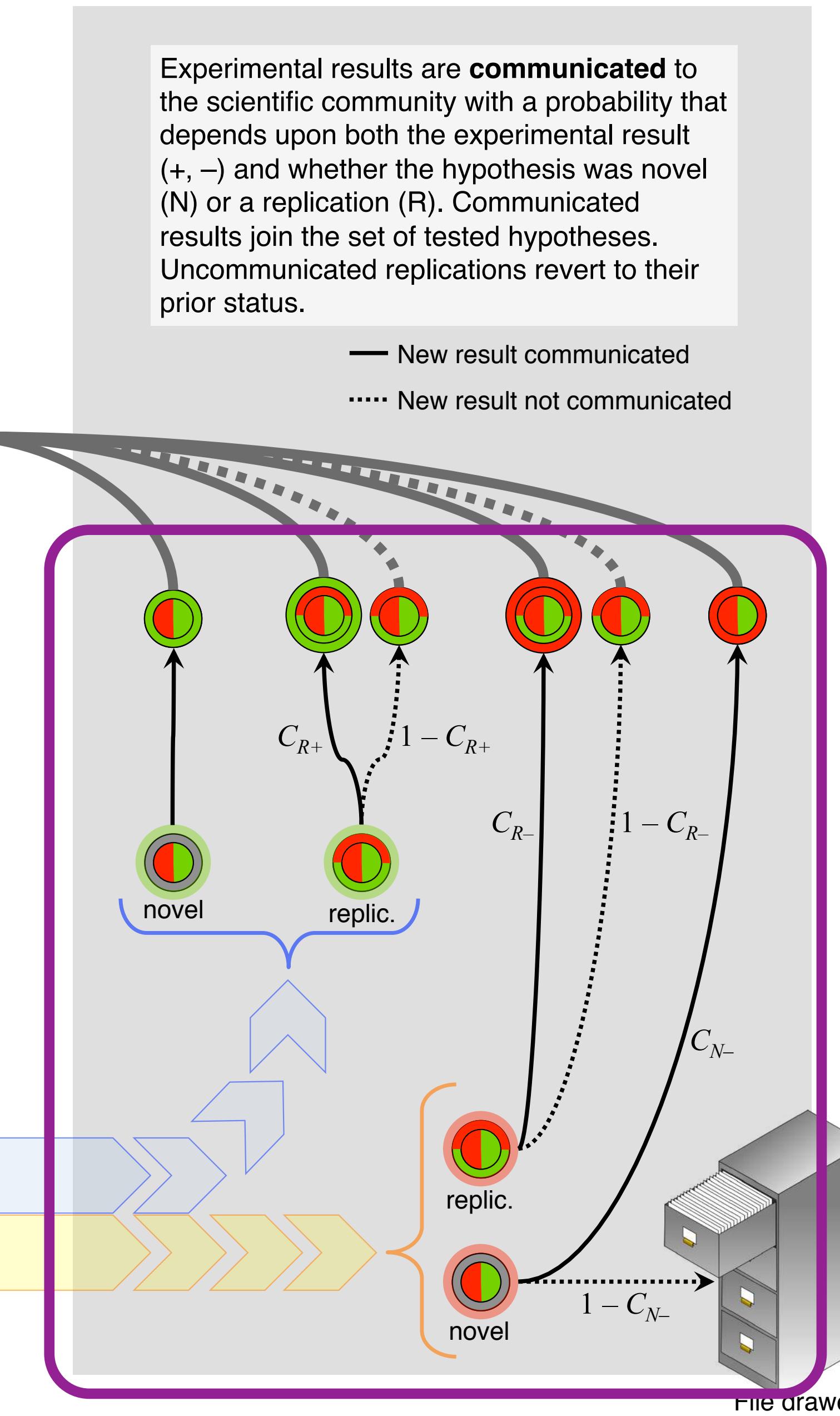
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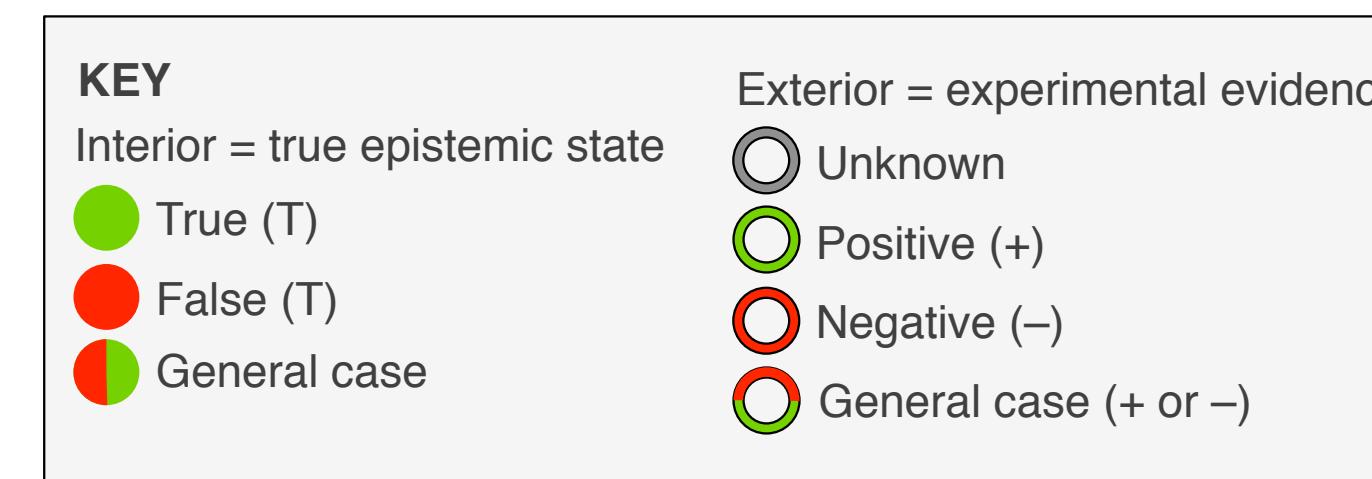
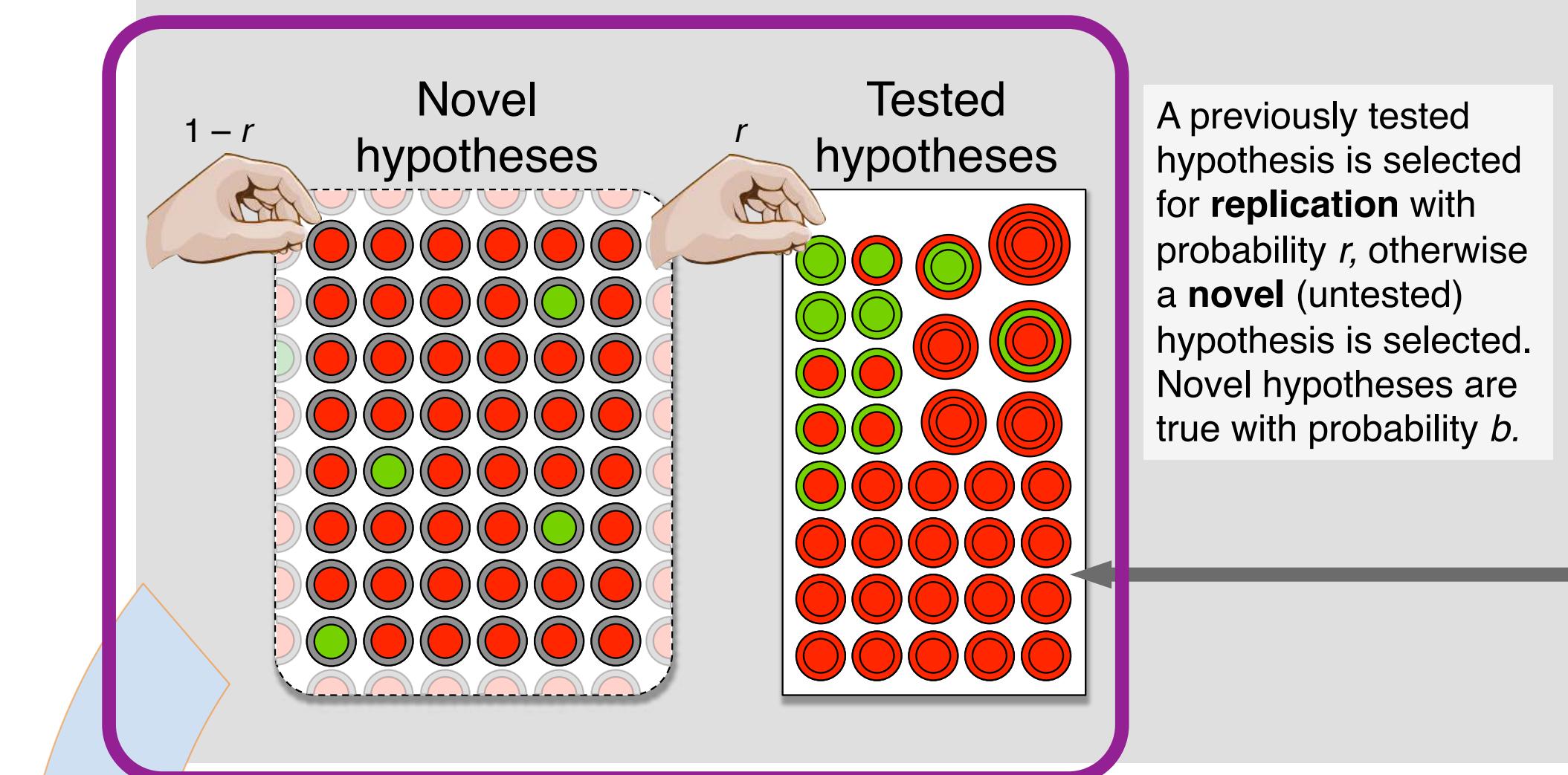
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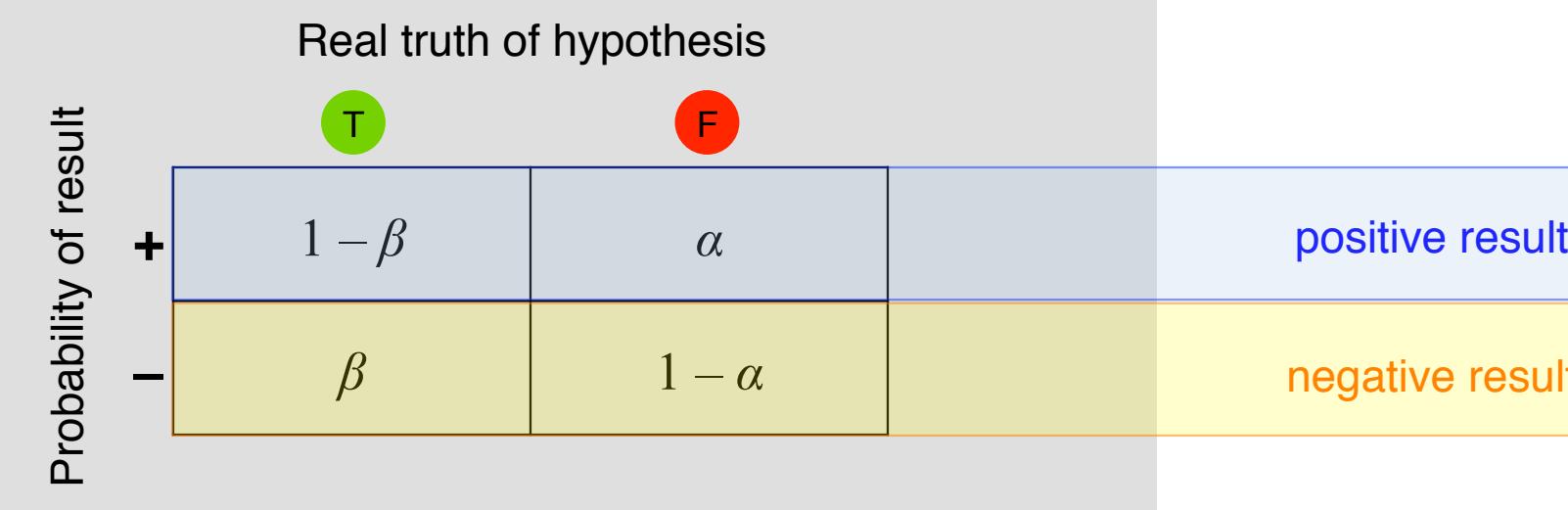
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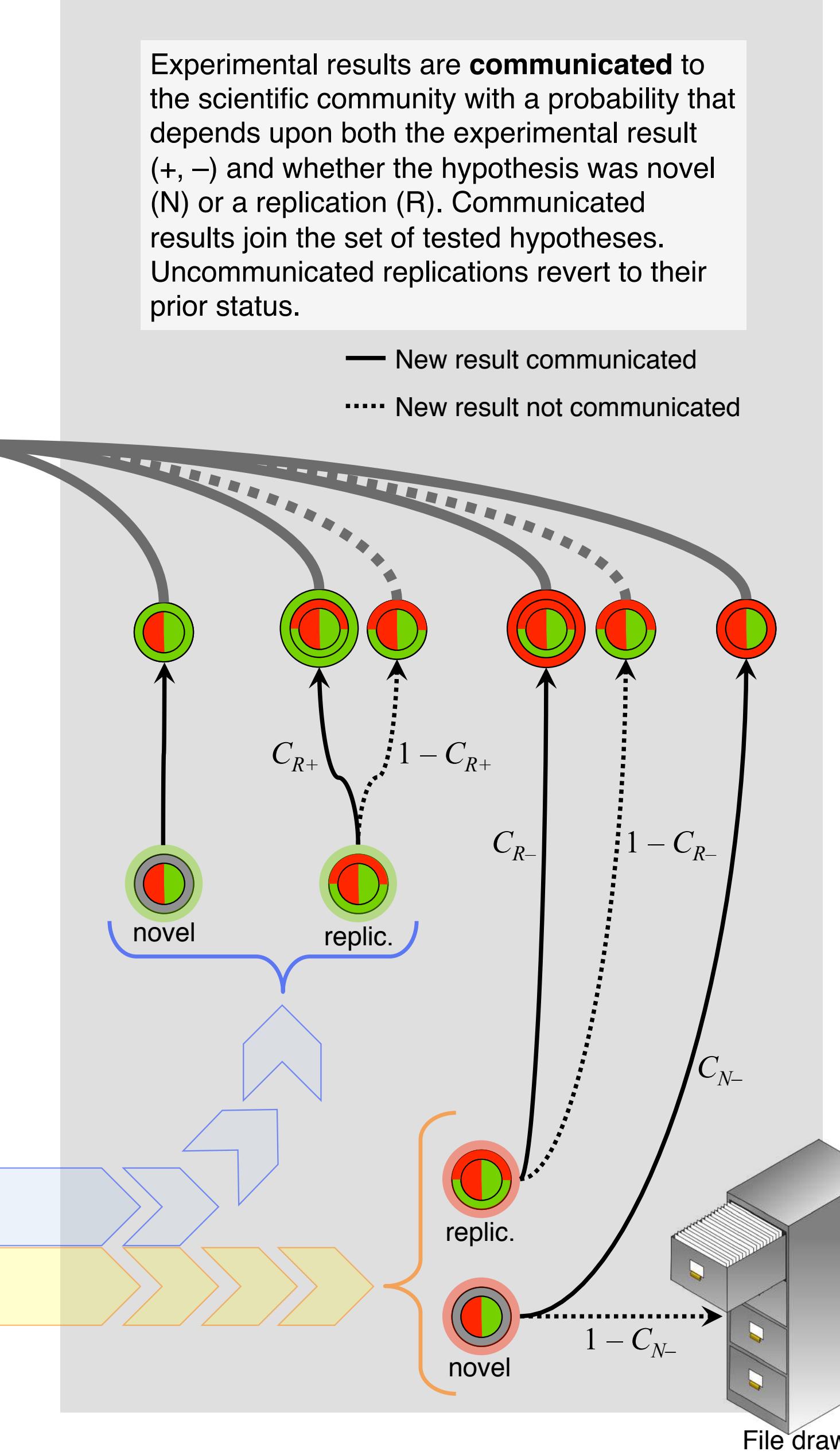
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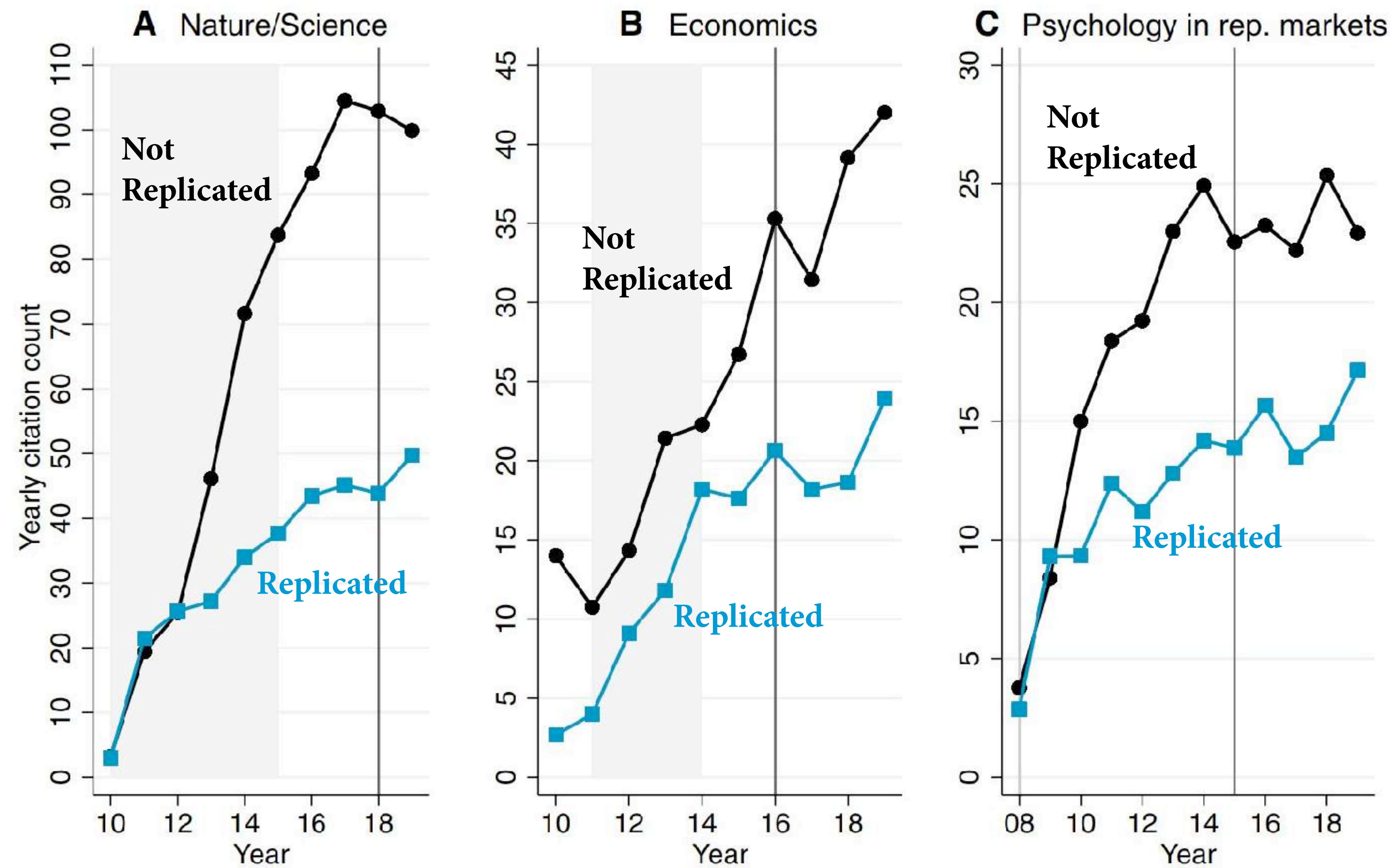


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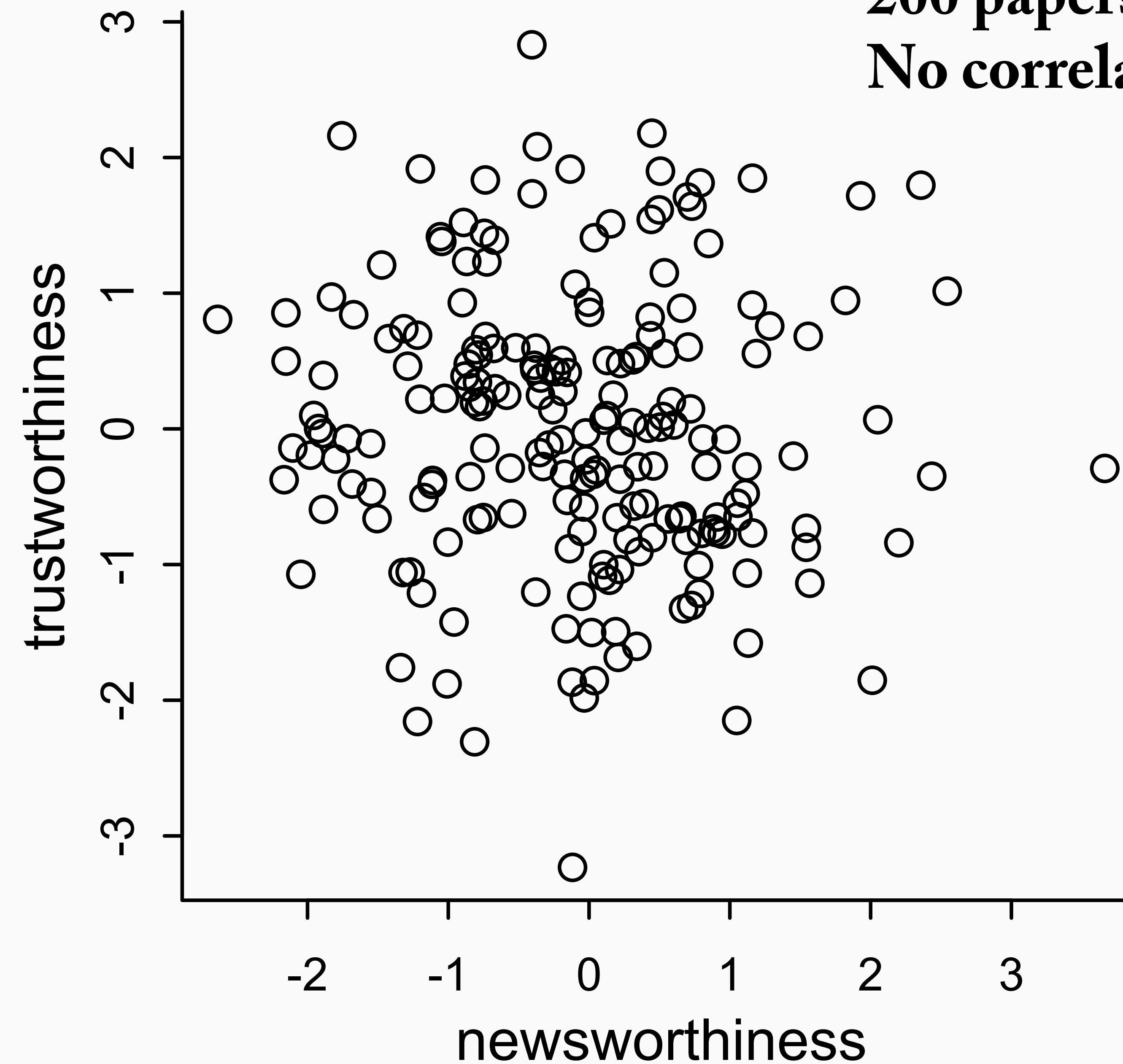
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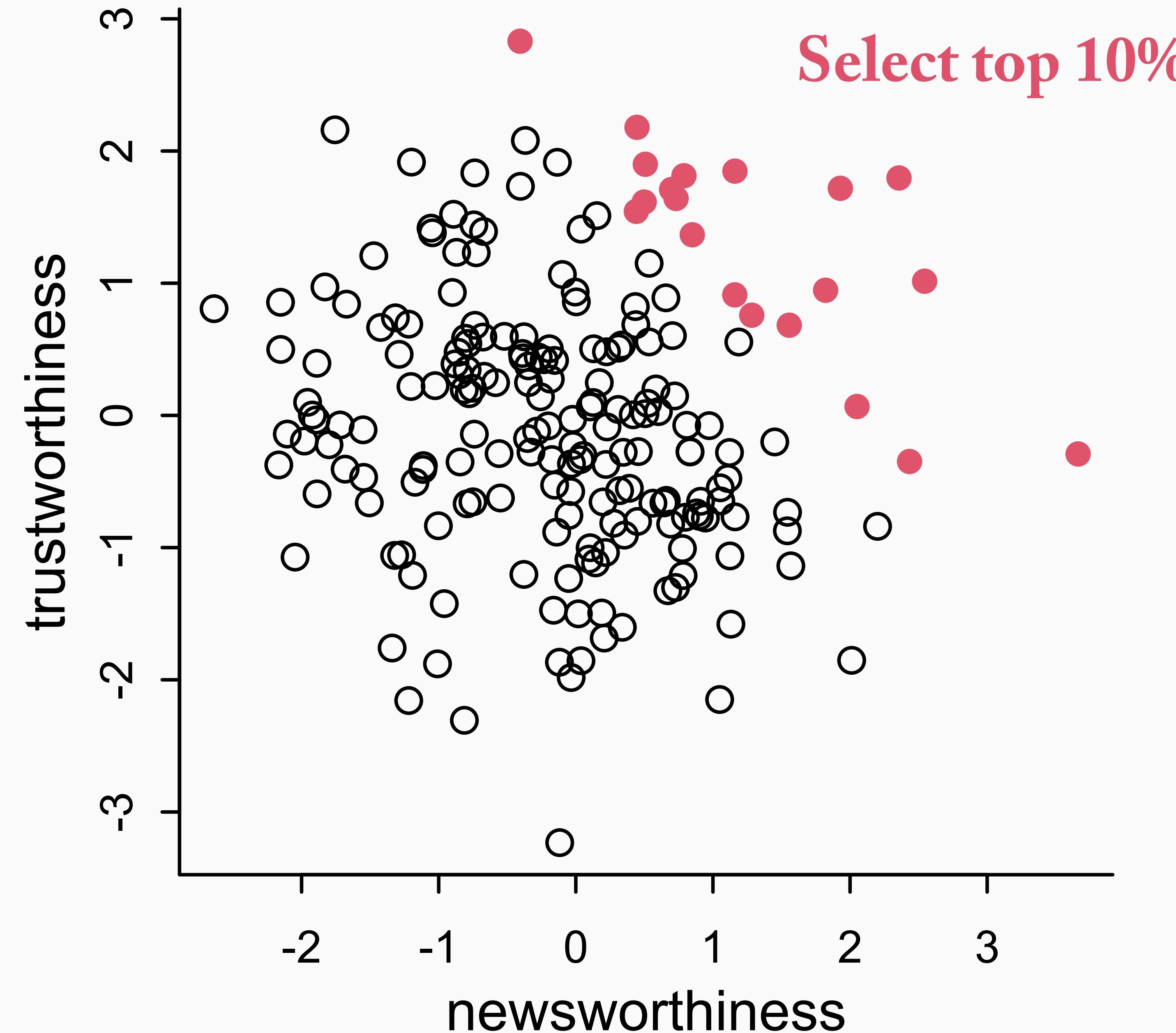


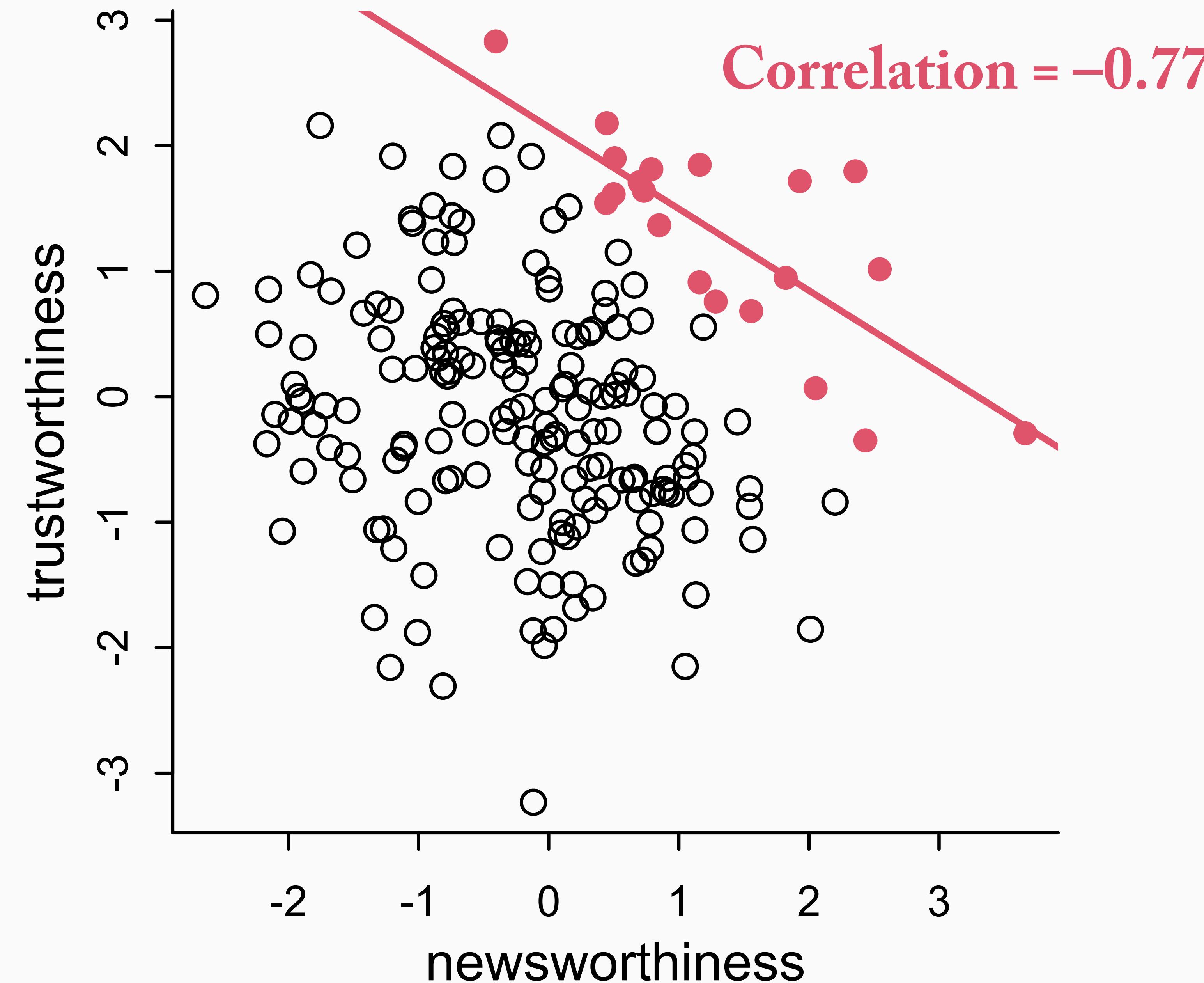


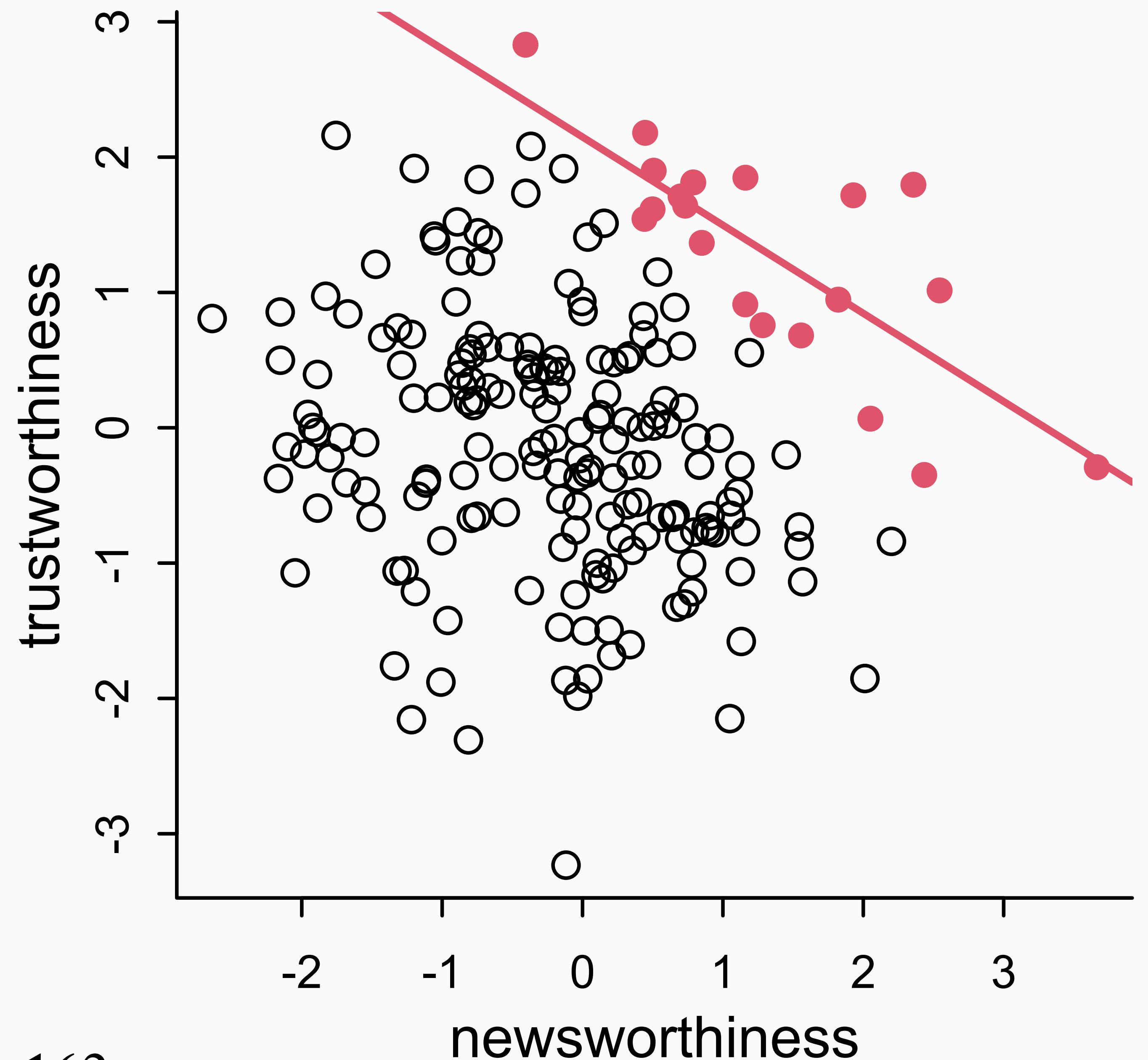
Serra-Garcia & Gneezy 2021 Nonreplicable publications are cited more than replicable ones

**200 papers/proposals  
No correlation**









*published*  
 $P$   
 $N$  *newsworthy*  
 $T$  *trustworthy*

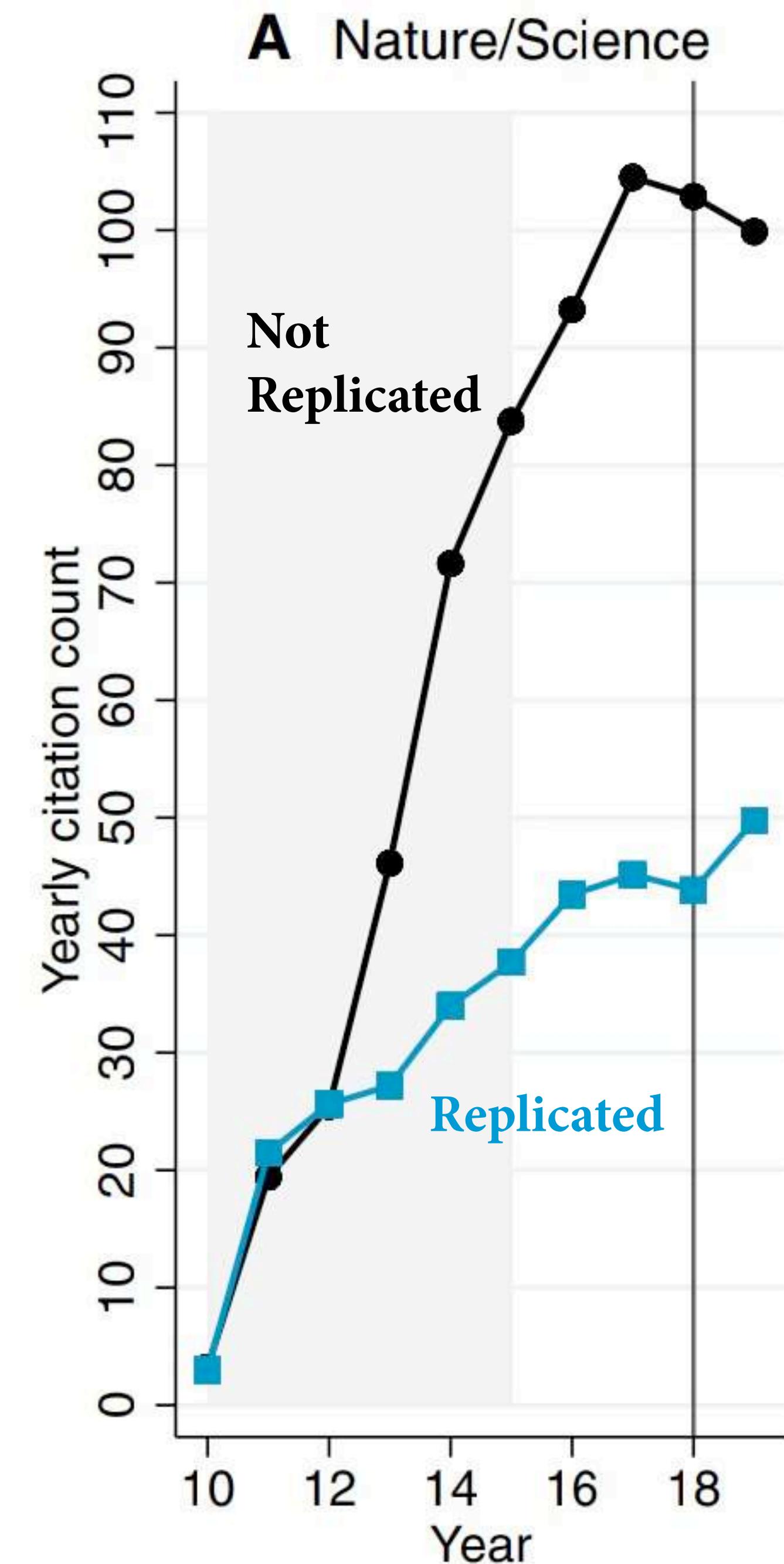
# Horoscopes for Research

No one knows how research works

But many easy fixes at hand

- (1) No stats without associated causal model
- (2) Prove that your code works (in principle)
- (3) Share as much as possible
- (4) Beware proxies of research quality

Many things you dislike about academia were once well-intentioned reforms



**END**

