

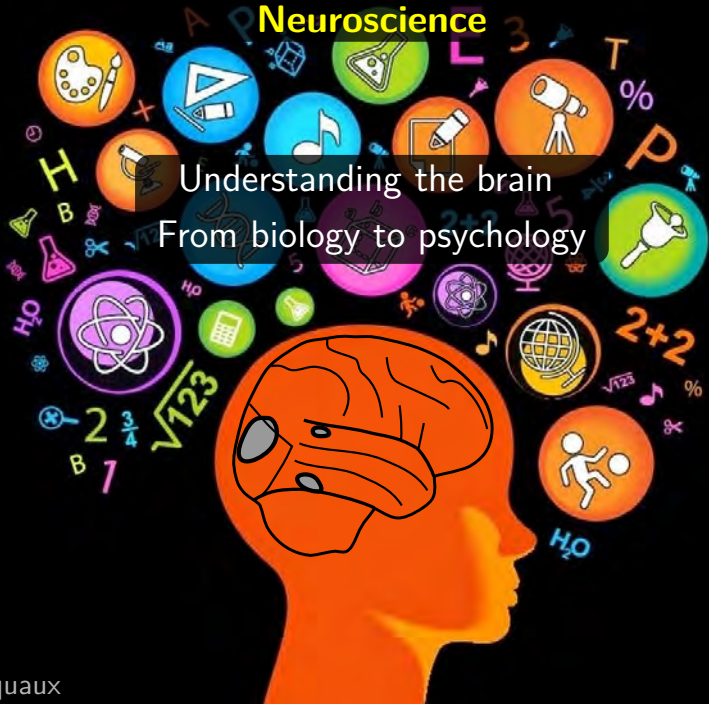
Gaël Varoquaux

NeurSpin



Neuroscience

Understanding the brain
From biology to psychology



Science

**The process of discovering
knowledge and mechanisms**

Science is above all a method

Science



**The process of discovering
knowledge and mechanisms**

Science is above all a method

“Science is not a political construct or a belief system. Scientific progress depends on openness, transparency, and the free flow of ideas and people.”

— Dr. Rush Holt, CEO of AAAS,
testimony to the House Committee on Science, Space, and Technology, Feb 8, 2017

Science

The process of discovering
knowledge and mechanisms

Science helps shaping society

- Autism and vaccines:

forged study: [Wakefield *et al*, *Lancet* 1998]

⇒ Drop in vaccination, measles outbreak

Loss of trust in science is very costly

Science in the age of data:

good process = reproducibility
better: generalization & reuse

1 Statistical reproducibility

2 Computational reproducibility

1 Statistical reproducibility



Brain theories will just emerge from data



Brain theories will just emerge from data



Biology, neuroscience, psychology...
rely on working hypotheses



☐ YES

☐ NO

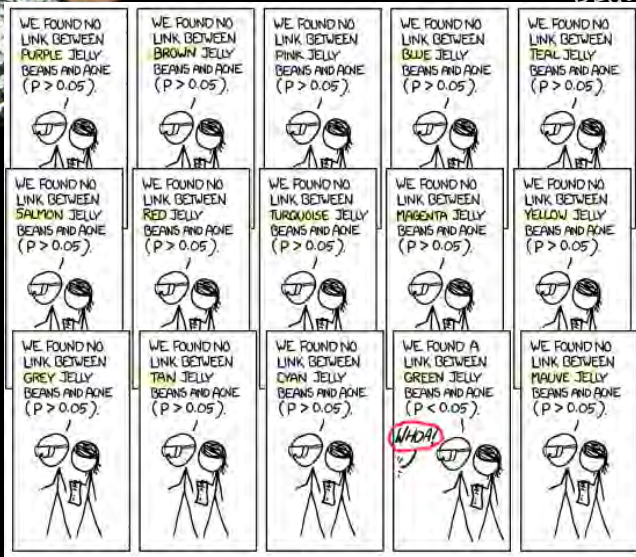
Why the tyranny of the *Working hypothesis*?

Reductionist



Why the tyranny of the *Working hypothesis*?

Reductionist

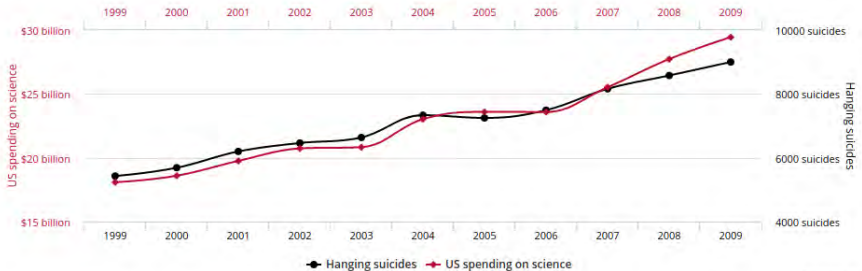


Why the tyranny of the *Working hypothesis*?

Reductionist

US spending on science, space, and technology correlates with Suicides by hanging, strangulation and suffocation

Correlation: 99.79% ($r=0.99789126$)



Data sourced: U.S. Statistical Management and Design and Centers for Disease Control & Prevention

tylervigen.com

<http://www.tylervigen.com/spurious-correlations>

The failure of the working hypothesis

Reductionist approach: \Rightarrow fragmentation



Collapse of statistical control

- Analytic variability \Rightarrow uncontrolled variance
- Publication incentives \Rightarrow selection bias

[Ioannidis 2008]

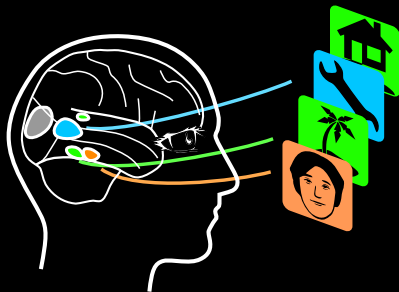
1 Generalization as a solution

Generalization

can build broader theories

[Varoquaux and Poldrack 2019]

Paradigm 1: Seen



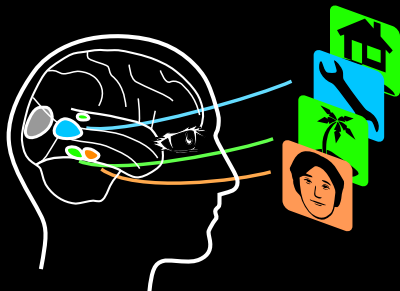
1 Generalization as a solution

Generalization

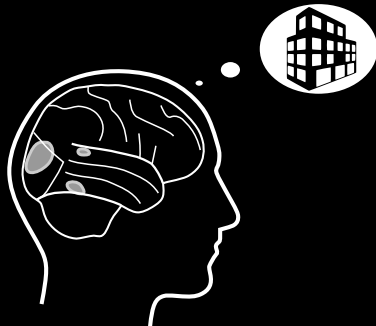
can build broader theories

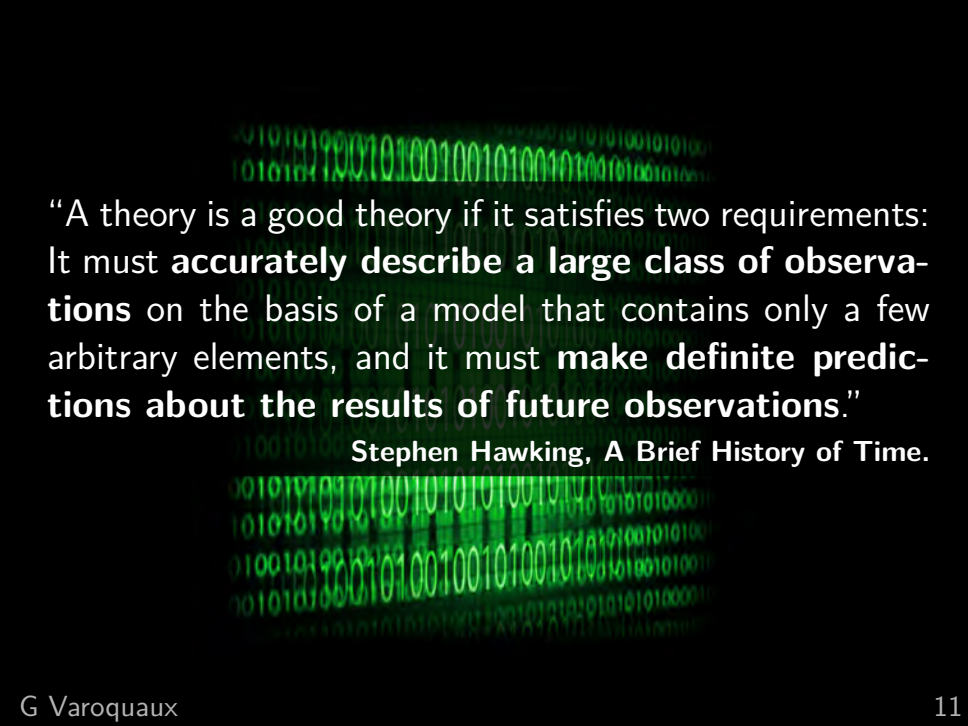
[Varoquaux and Poldrack 2019]

Paradigm 1: Seen



Paradigm 2: Imagined



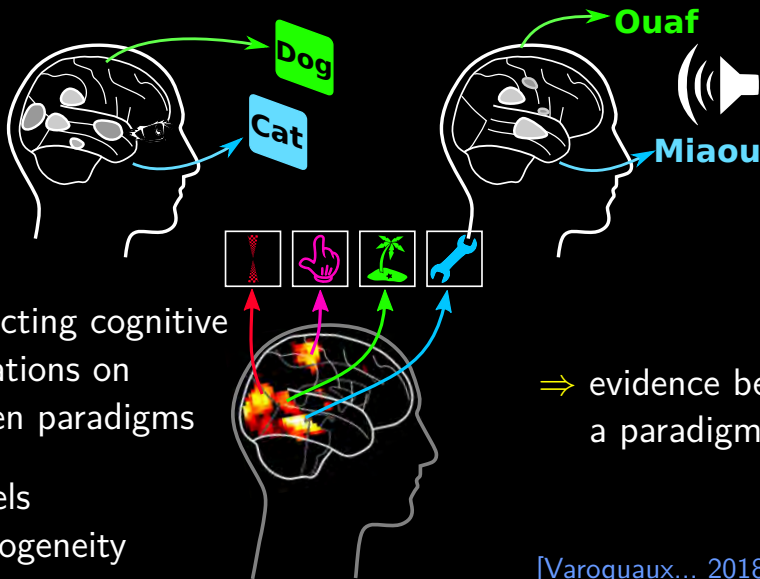


“A theory is a good theory if it satisfies two requirements: It must **accurately describe a large class of observations** on the basis of a model that contains only a few arbitrary elements, and it must **make definite predictions about the results of future observations.**”

Stephen Hawking, *A Brief History of Time*.

1 Generalization as a solution

Across tasks: atlasing cognition



Predicting cognitive
operations on
unseen paradigms

⇒ evidence beyond
a paradigm

Models
heterogeneity

G Varoquaux

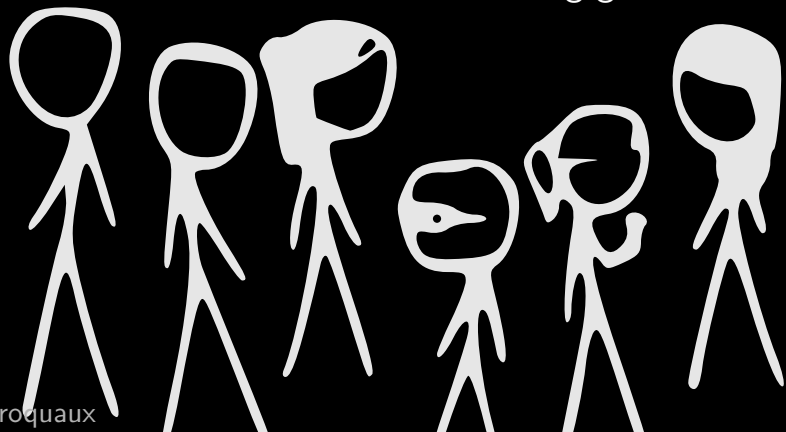
[Varoquaux... 2018]

1 Generalization as a solution

Across subjects: biomarkers

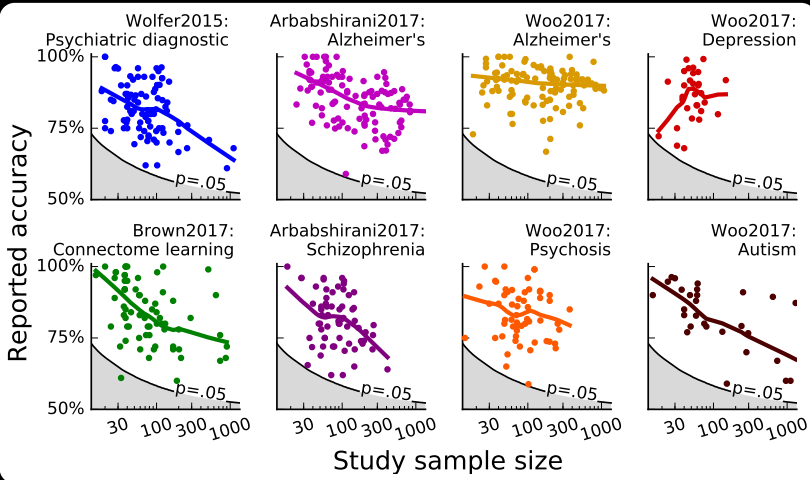
Predicting autism status to new sites [Abraham... 2017]

Many samples overcome heterogeneity
strong generalization



1 Cross-validation failure: not enough data

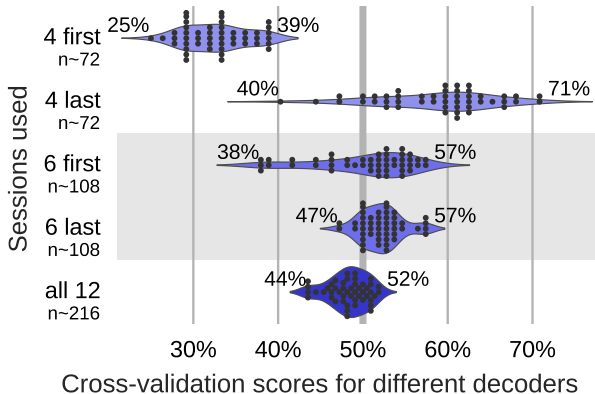
In the literature, effect sizes decrease with sample sizes



[Varoquaux 2017]

1 Cross-validation failure: not enough data

Analytic variability strikes back



[Varoquaux 2017]

2 Computational reproducibility



2 Trust and productivity: reproducible research

“if it’s not open and verifiable by others, it’s not science, or engineering, or whatever it is you call what we do”

— V. Stodden, *The scientific method in practice*



Computational reproducibility:

- Automate everything
- Control the environment

2 Libraries enable reproducible science

Reproducibility

Rerun and come to the same conclusion

An argument for copying all scripts

for each paper

Better: a tag in git

2 Libraries enable reproducible science

Reproducibility

Rerun and come to the same conclusion

An argument for copying all scripts

for each paper

Better: a tag in git

Copying scripts scales very poorly:

- Accumulation of half-dead code \Rightarrow cognitive overload
- No consolidation across studies
- Each study has different variants of different bugs

Garden of forking code

2 Libraries enable reproducible science

Reproducibility

Rerun and come to the same conclusion

An argument for copying all scripts
for each paper

Better: a tag in git

		Data	
		Same	Different
Code	Same	Reproducible	Replicable
	Different	Robust	Generalisable

2 Libraries enable reproducible science

Reproducibility

Rerun and come to the same conclusion

An argument for copying all scripts
for each paper



Frozen food

Reusability

Apply the approach to a new problem

Being able to understand, modify,
run in new settings



Generalization is the true scientific test

Reusable computational science = **libraries**

2 Building foundations of neuroimaging with computers

scikit-learn



Make research in machine-learning models and algorithm useable to people who do not understand them



nilearn

Make it easy to answer neuroimaging problems with them



2 Building foundations of neuroimaging with computers

scikit-learn



Make research in machine-learning models and algorithm useable to people who do not understand them

Challenges:

- Variety of that space
- Statistical concepts \gg coding concepts



nilearn

Make it easy to answer neuroimaging problems with them

Challenges:

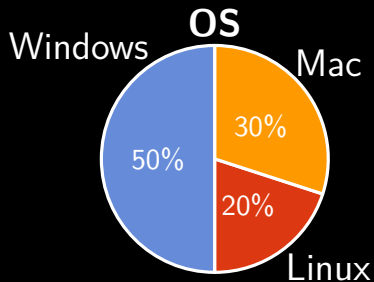
- Onboarding technology-adverse users

2 Building foundations of neuroimaging with computers

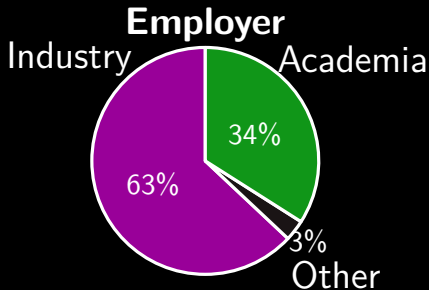
Scikit-learn, an impact



$\frac{1}{2}$ million returning users



12 000 citations



2 Research code \neq software library

Factor 10 in time investment

- Corner cases in algorithm (numerical stability)
- Multiple platforms and library versions
- Documentation
- Making it simpler (and get less educated users)
- User and developer support (\sim 100 mails/day)

An impact on science and society

2 Research code \neq software library

Factor 10 in time investment

Technical + scientific tradeoffs

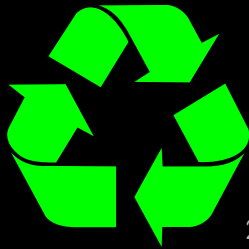
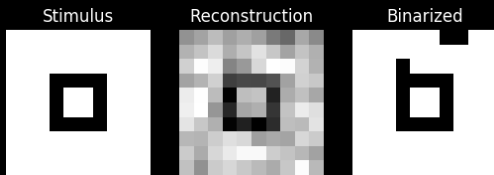
- Ease of install/ease of use rather than speed
 - Focus on “old science”
-
- Software good practice mandatory:
 - Automated testing
 - Version control
-
- Open source to grow a community

2 Reusable science

scikit-learn is the new machine-learning textbook
nilearn is the new neuroimaging review article

Experiments reproduced
at each commit
eg: brain reading

nilearn.github.io/auto_examples/02_decoding/plot_miyawaki_reconstruction.html

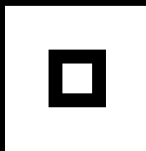


2 Reusable science

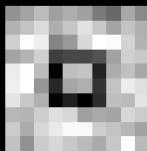
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Stimulus



Reconstruction



Binarized



nilearn.github.io/auto_examples/02_decoding/plot_miyawaki_reconstruction.html

Resource intensive Continuous integration:

- Data \Rightarrow Fight for good open data
 - Computation \Rightarrow Find good algorithms and tradeoffs
- Forces us to distill the literature (as a review)

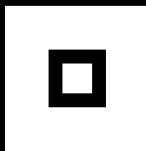
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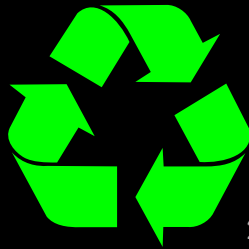
Reconstruction



Binarized



**Package development consolidates
science and moves it outside the lab**



2 Reusable science

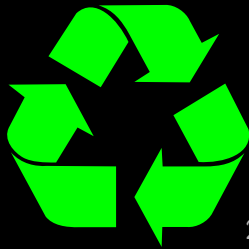
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ni **scipy-lectures: living book for Python in science**

Package development consolidates
science and moves it outside the lab



Statistical and computational reproducibility

Statistical

- Variability in question & methods makes control hard
- Aim for **generalization**:

Broader theories in the face of heterogeneity

[Varoquaux and Poldrack 2019]

Computational

- Libraries enable reproducibility
- Aim for **reusability**

Easy of reuse and reproducibility fosters innovation

References I

- A. Abraham, M. P. Milham, A. Di Martino, R. C. Craddock, D. Samaras, B. Thirion, and G. Varoquaux. Deriving reproducible biomarkers from multi-site resting-state data: An autism-based example. *NeuroImage*, 147:736–745, 2017.
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