

Meta-analysis and reproducibility

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Historical perspective: Before the *reproducibility crisis*™, we were interested in consensus across studies

Limitations of neuroimaging studies

Small Samples

Compared to other fields of cognitive and social science, particularly to clinical research

Indirect Measure of Neuronal Activity

Reliability is limited by biological, technical, and methodological confounds

Publication of Isolated Findings

Due to logistics and expense, additional experiments for confirmation and extension are rare

Generalization of Context-Specific Findings

Inference on brain function and pathomechanisms is based on a specific observed difference between two conditions

Coordinate-Based Meta-Analysis

Where do the foci converge?

Community Standards:

Spatial normalization to standard templates
Results reported as 3D coordinates (peaks)

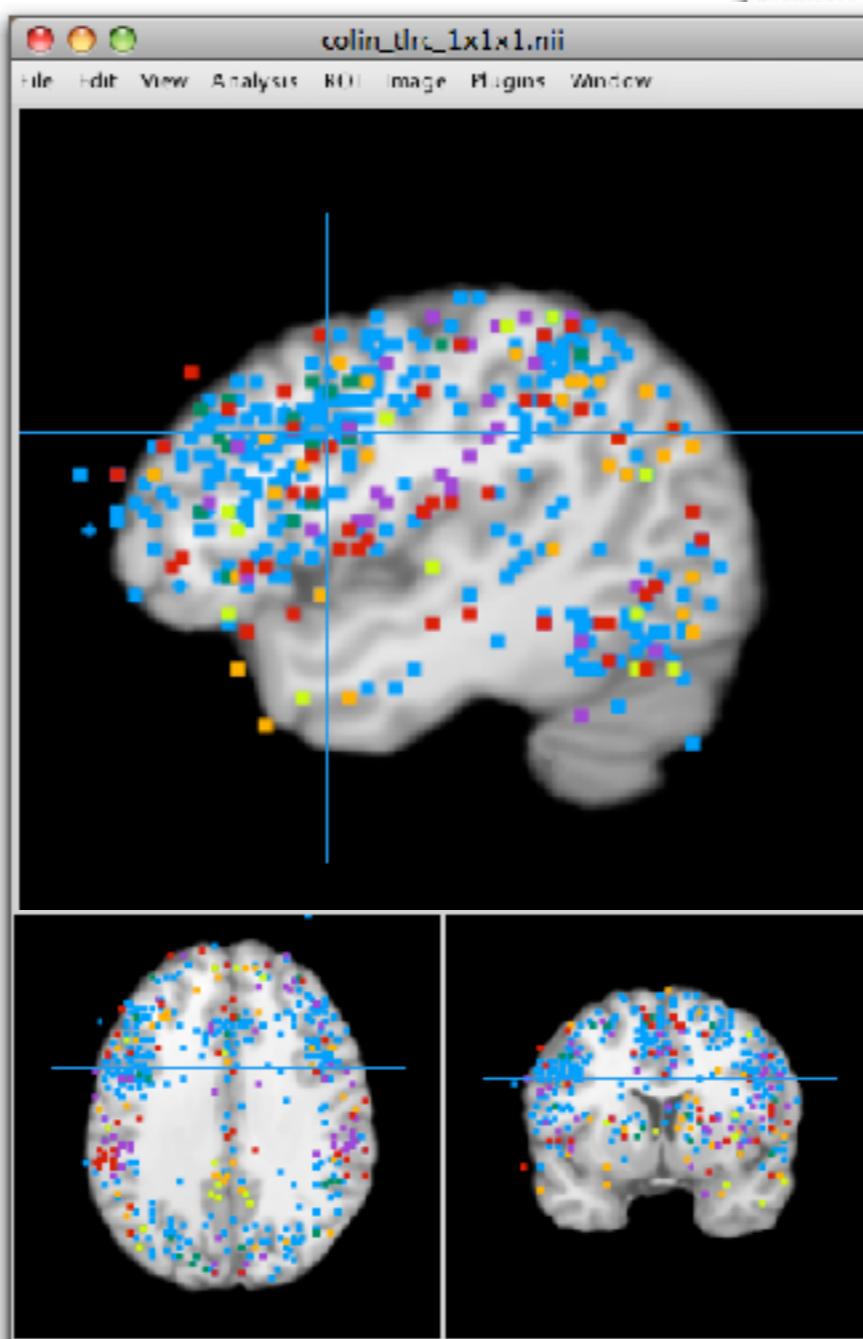
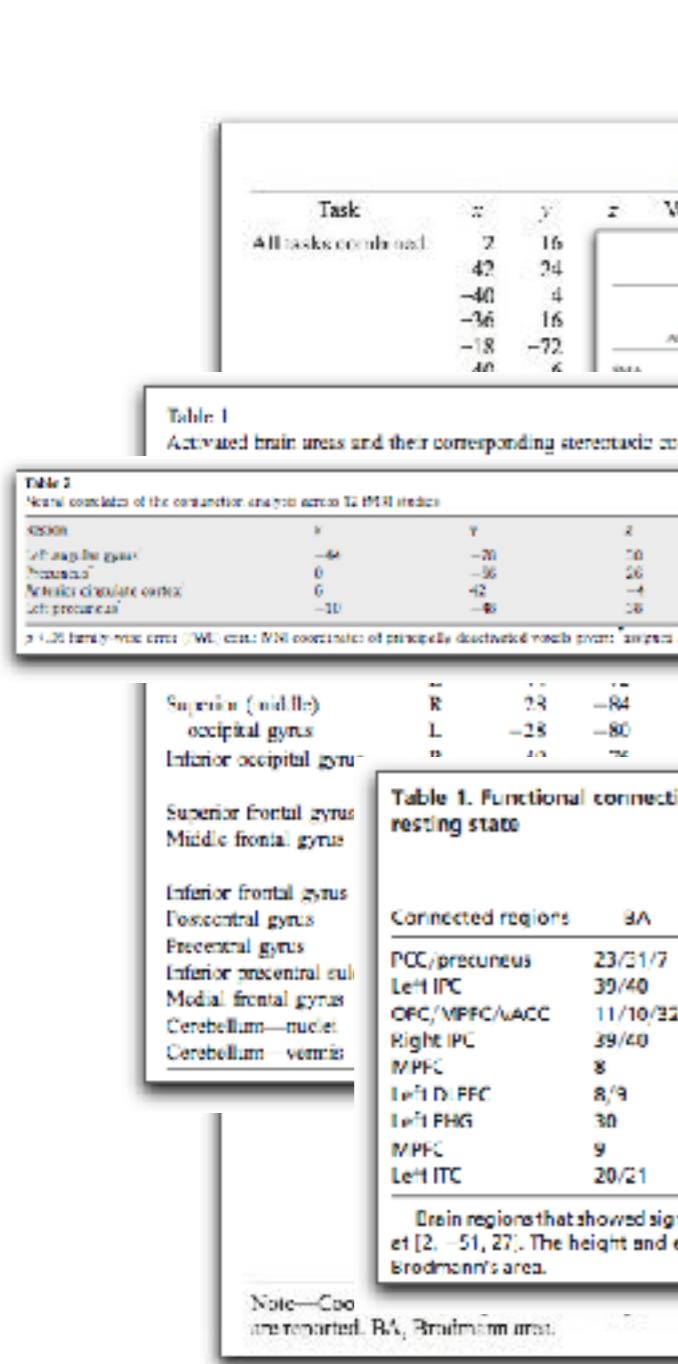


Table 1 Parametric analysis of task-dependent DCLD effects						
Main effect Coordinates Z (x y z)	Linear effect Coordinates Z (x y z)		Polynomial Z Coordinates Z (x y z)			
	Z	(x y z)	Z	(x y z)	Z	(x y z)
-12	-2	4.03	28	-6	0	na
-6	-1	4.29	16	-2	-2	na
-16	3	3.41	16	-14	15	na

Table 1 Parametric analysis of task-dependent DCLD effects				
Z coordinates or cerebral blood flow				
x	y	z	T-value	Ref
41	74	3	5.9	1
35	-75	11	6.1	2
22	5	12	6.2	3
25	18	12	5.9	4
45	41	47	5.4	5
43	5	14	5.3	6
5	-9	30	5.5	7
21	61	6	5.4	8
		15	5.2	9
		36	5.2	10
		71	5.1	11
		4	4.8	12
		37	4.4	13

x	y	z	T	Z score of peak activation	Mean flow increase (%)
-68	46	8.39			
-60	64	6.58			
-40	40	5.26			
-64	-15	5.55			
-68	-3	6.11			
-34	75	6.10			
-56	0	5.62		4.26	1.8
-56	-16	5.52		6.24	2.1
-92	-4	5.52		4.71	2.5
-84	0	5.50		7.18	5.4
-8	61	7.38		4.23	2.1
-8	60	5.56		5.85	3.1
-8	60	5.28		5.41	2.6
-8	60	5.56		6.63	3.7
26	22	8.1		4.42	2.0
12	76	5.51		3.43	2.9
4	74	4.96		6.26	2.9
-16	53	6.91		6.43	3.7
				5.65	3.9
-24	24	5.49		7.98	4.0
-4	44	4.36			
0	46	10.76			
-60	-15	6.55			
-60	-40	5.06			
-68	-28	5.43			

x	y	z	T	Z score of peak activation	Mean flow increase (%)
28	22	1	-3	18	4.8
48	1	-54	-27	5.43	
3	1	-33	-36	6.3	5.29
	1	-15	12	-6	4.95

reported if $P < 0.05$ corrected on the single voxel level.

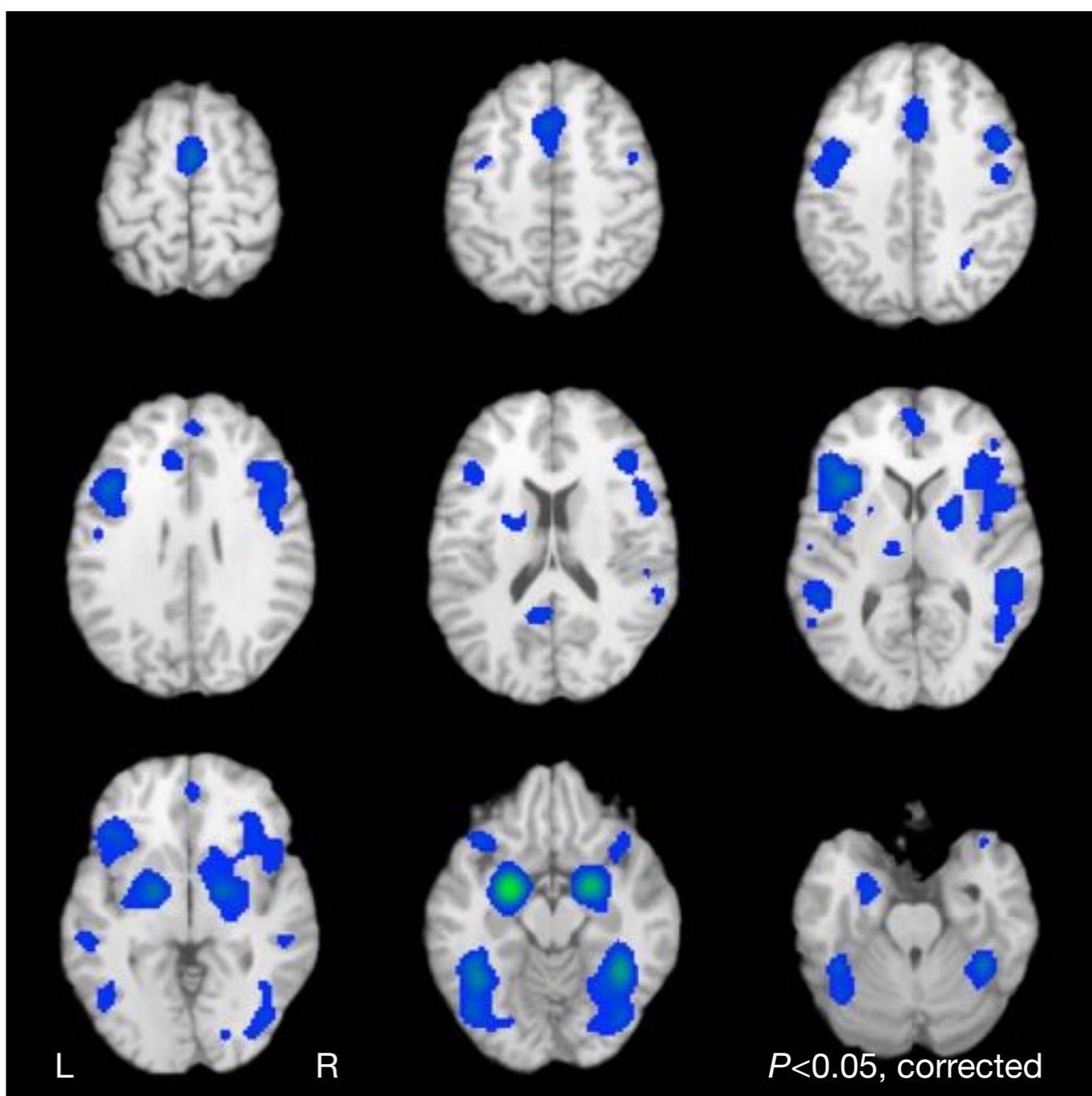
a standard stereotactic space (Talairach space, where x is the lateral displacement from the anterior commissure (— posterior to this); y is the medial-lateral displacement (the standard distance between the anterior and posterior commissures); z is the vertical displacement from the plane of maximal anterior-posterior commissure distance; CMAJ = dorsal cingulate major

Coordinate-Based Meta-Analysis

Where do the foci converge?

- Convolve foci with spatial kernel to produce study-specific modeled activation maps
- Combine those MA maps into a sample-wise map
- Compare to null distribution to determine voxel-wise statistical significance

Activation Likelihood Estimation (ALE)



Coordinate-Based Meta-Analysis

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Activation Likelihood Estimation (ALE)

Kernel Density Analysis (KDA)

Multilevel Kernel Density Analysis (MKDA)

Specific Coactivation Likelihood Estimation (SCALE)

Seed-Based d-Mapping

MKDA Chi2 Extension

Described in detail by
Samartsidis et al., Stat Sci, 2017

Image-Based Meta-Analysis

Where do the images converge?

Mixed-Effects GLM (gold standard)

Fixed-Effects GLM

Fisher's IBMA

Stouffer's IBMA

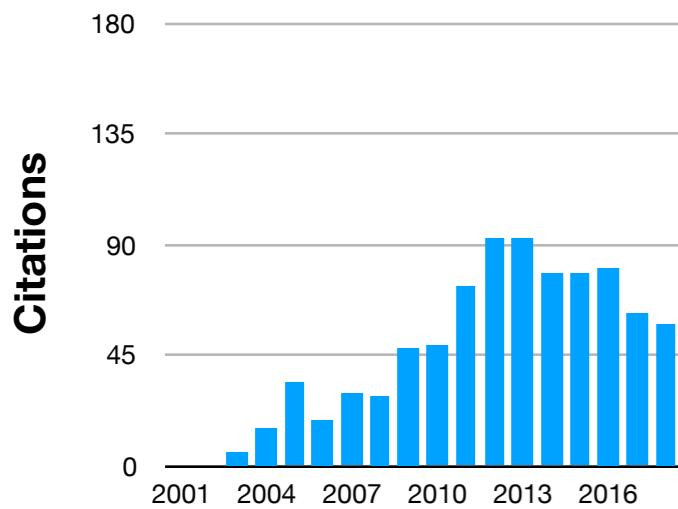
z permutation

Described in detail by Maumet and Nichols, 2016
[doi: https://doi.org/10.1101/048249](https://doi.org/10.1101/048249)

Please upload
your maps!

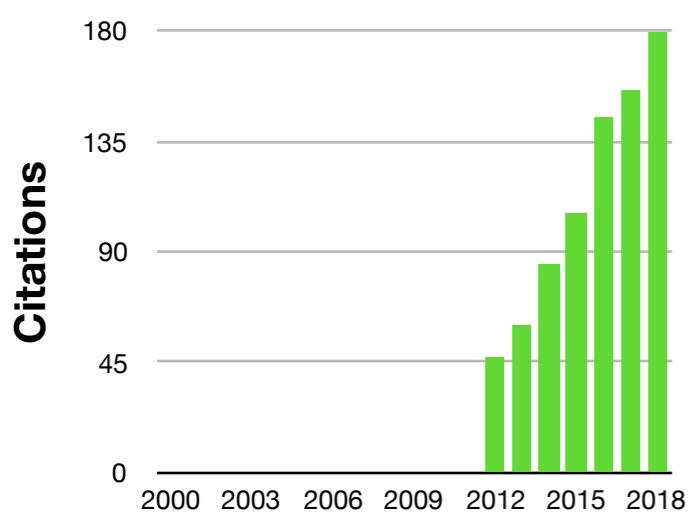
The Rising Popularity of Meta-Analyses

Introduction of ALE Approach



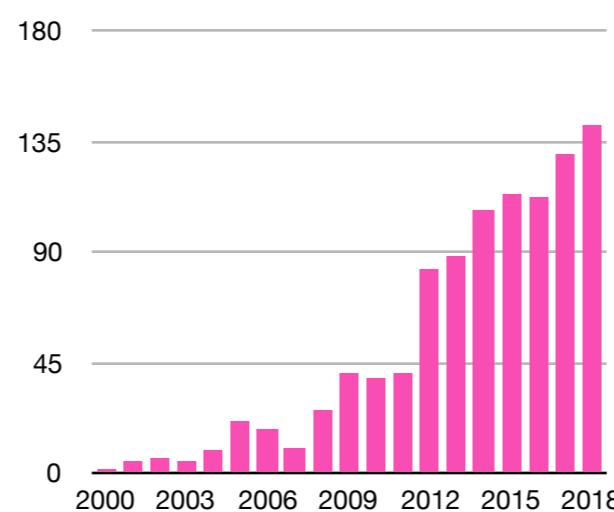
Turkeltaub et al., Neuroimage, 2002

Introduction of Neurosynth



Yarkoni et al., Nat Methods, 2011

fMRI + Meta-Analysis



What Can Meta-Analysis Do For You?

Identifying consensus (or the lack thereof) is always a good thing

I am starting a new project:

1. Great introduction to a new topic

I am mentoring an undergrad and
don't know what to assign them:

2. Feasible project for your novice trainees

I am an experienced researcher:

**3. Systematic analysis of variability (e.g., participants,
tasks) can resolve conflict in a given community**

4. Validate a new task or data acquisition approach

5. ROI selection

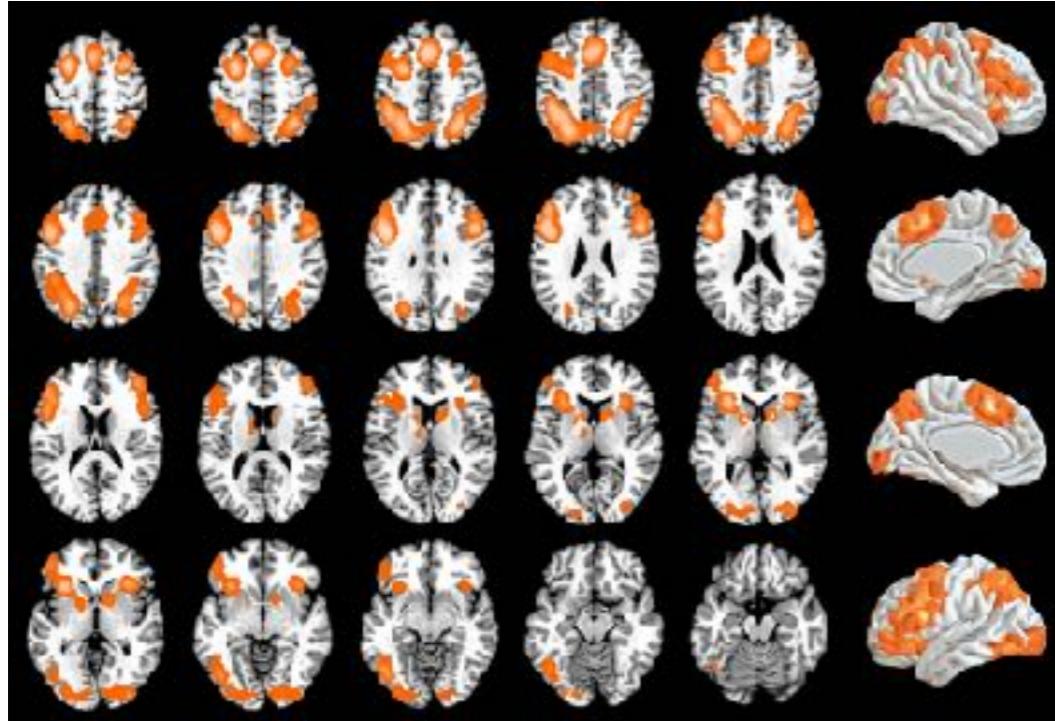
6. Functional decoding

7. Data-driven approach to validate cognitive models

Example

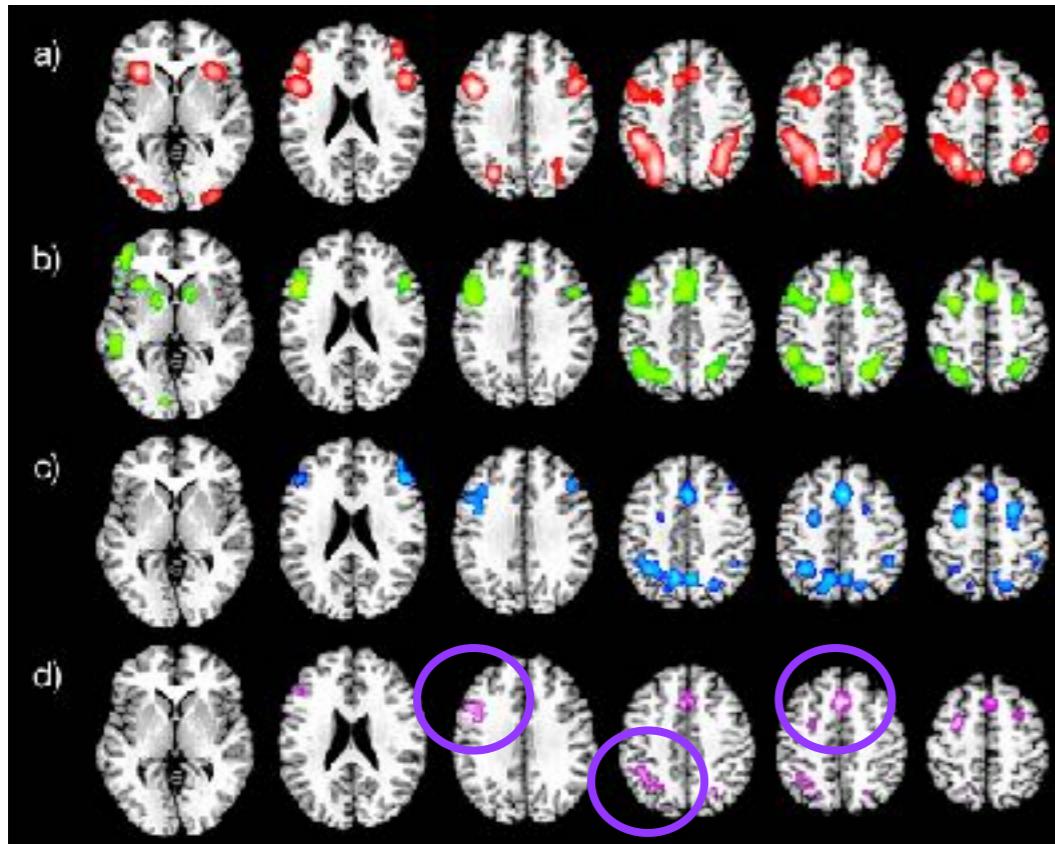
ROI Selection

Meta-Analysis of Problem Solving



Bartley et al., Neurosci Biobehv Rev, 2018

Math
Verbal
Visuospatial
Conj



Force Concept Inventory (FCI)

a) FCI Paradigm

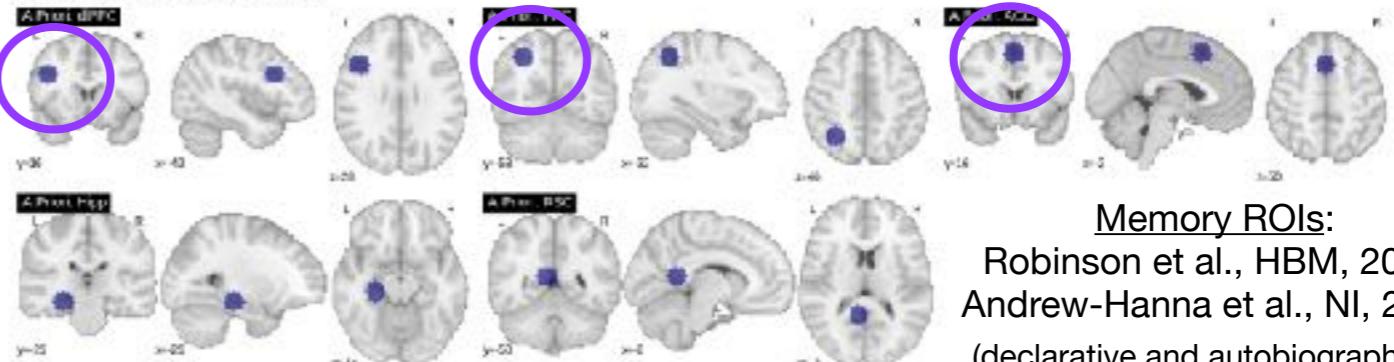
A heavy ball falls from an airplane as it flies along in a horizontal direction. Air resistance is small and can be ignored.

A heavy ball falls from an airplane as it flies along in a horizontal direction. Air resistance is small and can be ignored.
Which path would the ball take after leaving the airplane?

- (A) The ball would move along path A.
(B) The ball would move along path B.
(C) The ball would move along path C.
(D) The ball would move along path D.

H: accuracy, difficulty, strategy associated with problem solving and memory

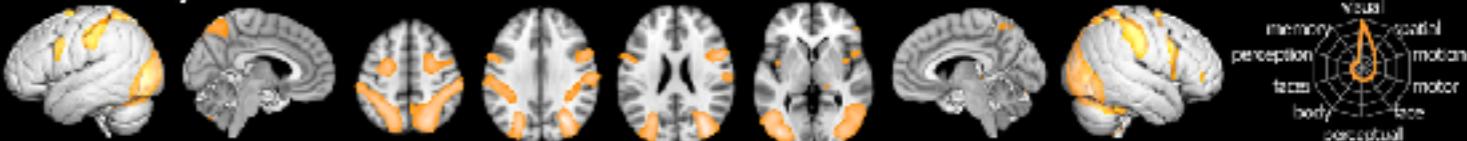
a) Parametric Modulation ROCs



Memory ROIs:

Robinson et al., HBM, 2015
Andrew-Hanna et al., NI, 2014
(declarative and autobiographical)

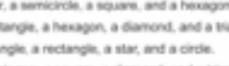
Difficulty



- We found that difficulty, but not accuracy or strategy, modulate brain activity during physics problem solving.
- Problem solving network engaged regardless of whether a correct answer was achieved and does not reflect students' perception of their reasoning strategy.
- Mental states associated with visualization, spatial/motion perception and memory engaged when difficulty



107 undergraduate physics students



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Functional Decoding

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Can cognitive processes be inferred from neuroimaging data?

Russell A. Poldrack

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There is much interest currently in using functional neuroimaging techniques to understand better the nature of cognition. One particular practice that has become common is "reverse inference", in which the engagement of a particular cognitive process is inferred from the activation of a particular brain region. Such inferences are not deductively valid, because they still provide some information. Using a Bayesian analysis of the BrainVoyager neuroimaging database, I characterize the amount of additional evidence in favor of the engagement of a cognitive process that can be offered by a reverse inference. Its usefulness is particularly limited by the selectivity of activation in the region of interest. I argue that cognitive neuroscientists should be more transparent in the use of reverse inference, particularly when selectivity of the region in question cannot be substantiated or is known to be weak.

Introduction

Functional neuroimaging techniques such as functional magnetic resonance imaging (fMRI) provide a measure of local brain activity in response to cognitive tasks undertaken during scanning. These data allow the cognitive neuroscientist to infer something about the role of particular brain regions in cognitive function. However, there is increasing use of neuroimaging data to make the opposite inference; that is, to infer the engagement of particular cognitive functions based on activation in particular brain regions. My goal here is to analyze this practice, known as "reverse inference", and to characterize some limitations on the effectiveness of this strategy. The companion paper in this issue by Aguirre [3] describes a complementary strategy for using neuroimaging to distinguish competing cognitive theories.

The goal of cognitive psychology is to understand the underlying mental architecture that supports cognitive functions. To this end, cognitive psychologists examine the effects of task manipulations or behavioral variables, such as response time or accuracy, and use these data to test models of cognitive function. However, it is often not possible to determine on the basis of behavior alone whether a particular cognitive process is engaged. For example, there are well-known theoretical indecidability issues

neuroimaging was able to provide information regarding what cognitive processes were engaged in performance of a particular task, cognitive psychologists would have gained a powerful new tool. Researchers outside cognitive psychology are also sometimes interested in using neuroimaging to determine the engagement of particular cognitive processes. For example, philosophers might wish to know the degree to which emotion versus deliberative reasoning plays a role in moral judgments [3].

Inference in neuroimaging

The main kind of inference that is drawn from neuroimaging data is of the form "cognitive process X is engaged, then brain area Z is active". Periods of the discussion sections of a few fMRI articles will quickly reveal, however, an ecosystem of reasoning taking the following form:

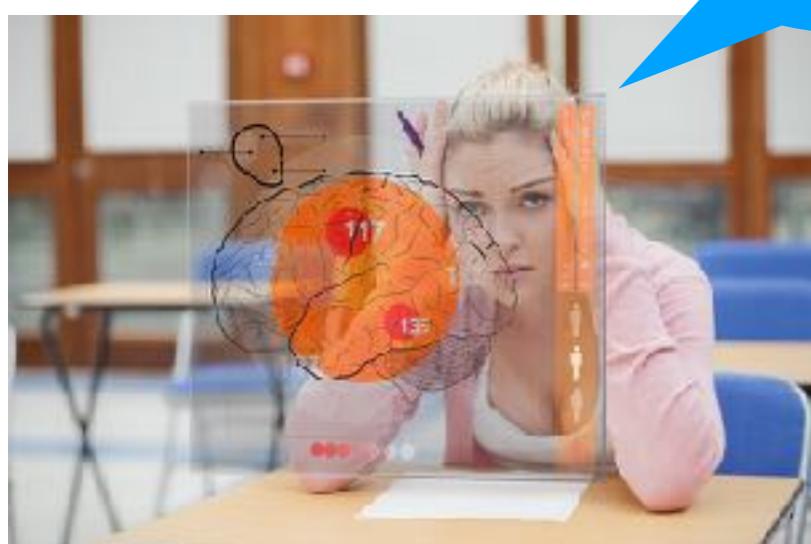
- (1) In the present study, when task comparison A was presented, brain area Z was active.
- (2) In other studies, when cognitive process X was positively engaged, then brain area Z was active.
- (3) Thus, the activity of area Z in the present study demonstrates engagement of cognitive process X by task comparison A.

This is a "reverse inference", in that it reasons backwards from the presence of brain activation to the engagement of a particular cognitive function.

In many cases the use of reverse inference is informal; the presence of expected activation in a particular region is explained by reference to other studies that found activation in the same region. However, in some studies the reverse inference is a central feature. In one study [4], subjects were asked to solve a TETRIS puzzle while performing a memory exchange task in which they had the chance to punish those who selected Activation was observed in the dorsal striatum when participants subjected defectors to electric shock. In this case, the activation was believed to reflect the "punishment" condition, and the authors used this activation to support their theory of punishment.

Such a strategy is often used in neuroimaging, along with other approaches to reverse inference. For example, one approach to reverse inference is to compare the pattern of activation in a particular region across different conditions. If the pattern of activation is similar across conditions, then the activation is considered to reflect a common cognitive process. For example, in one study [5], subjects were asked to perform a memory task while viewing faces. The activation in the amygdala was compared across conditions (neutral vs. fearful faces). The authors concluded that the activation reflected the processing of emotional faces.

Discussion: interpret findings, what does this region do?



Neuron Perspective

Infering Mental States from Neuroimaging Data: From Reverse Inference to Large-Scale Decoding

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DOI:10.1101/neuron.2011.09.017

A common goal of neuroimaging research is to use imaging data to identify the mental processes that are engaged when a subject performs a mental task. The use of reasoning from activation to mental functions, known as "reverse inference", has been previously criticized on the basis that it does not take into account how selectively the area is activated by the mental process in question. In this Perspective, I outline the critique of informal reverse inference and describe a number of new developments that provide the ability to more formally test the predictive power of neuroimaging data.

Understanding the relationship between psychological processes and brain function, the ultimate goal of cognitive neuroscience, is made particularly difficult by the fact that psychological processes are poorly defined and not directly observable, and human brain function can only be measured through the highly blurred and distorted lens of neuroimaging techniques. However, the development of functional magnetic resonance imaging (fMRI) 20 years ago afforded a new and much more powerful way to address this question in comparison to previous methods, and the fruits of this technology are apparent in the increasing number of publications using fMRI in recent years.

This strategy, employed by neuroimaging researchers (and neuroscientists), by Petersen, Posner, Fox, and Raichle in their early work using positron emission tomography (Petersen et al., 1988; Petersen et al., 1989) has been to manipulate a specific psychological function and then to calculate indices of that manipulation in brain activity. This has been referred to as "forward inference" (Poldrack, 2006) and is the focus in a large body of literature that has been derived from neuroimaging research. However, since the very days of neuroimaging, there has also been a desire to reason backwards from patterns of activation to infer the engaged specific mental processes. This has been called "reverse inference" (Poldrack, 2006; Aguirre, 2009) and often forms much of the reasoning observed in the discussion section of neuroimaging papers (under the guise of "interpreting the results"). In some cases, reverse inference underlies the central conclusion of a paper. For example, Sachdev et al. (2009) examined the neural correlates of the experience of envy and schadenfreude. They found that envy was associated with activation in the anterior cingulate cortex, in which they note: "Cognitive conflict or social pain are associated" (p. 638), whereas schadenfreude was associated with activation in the mesial striatum. A central finding means "envy activates the amygdala." A central finding means "envy activates the amygdala."

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Forward Inference: given performance of task X, brain activity was observed in region Y

Reverse Inference: given brain activity in region X, therefore mental function Y was engaged

fear task activates the amygdala

the amygdala was activated, thus fear was engaged

*There are certainly papers that have shaped my worldview, and I think that's true for everyone. We are not machines after all - we can't read *all* the papers.*

Example

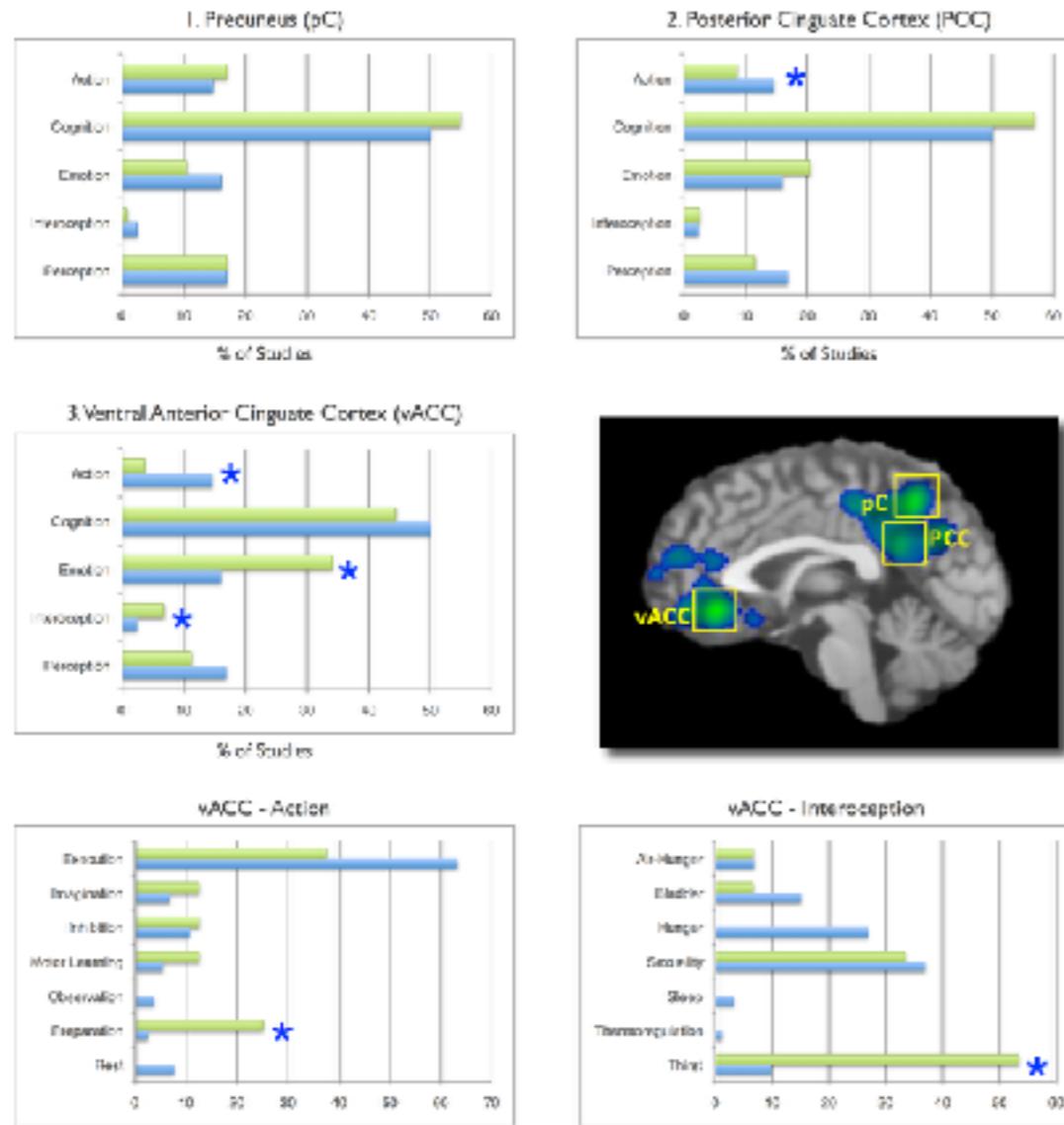
Functional Decoding

"recent developments in statistical analysis and informatics have provided new and more powerful ways to infer mental states from neuroimaging data" [BrainMap and Neurosynth databases](#)

"reverse inference can be a very useful strategy, especially if it is based on real data (such as the meta-analytic maps of from Yarkoni et al., 2011) rather than on an informal reading of the literature"

Poldrack, Neuron, 2011

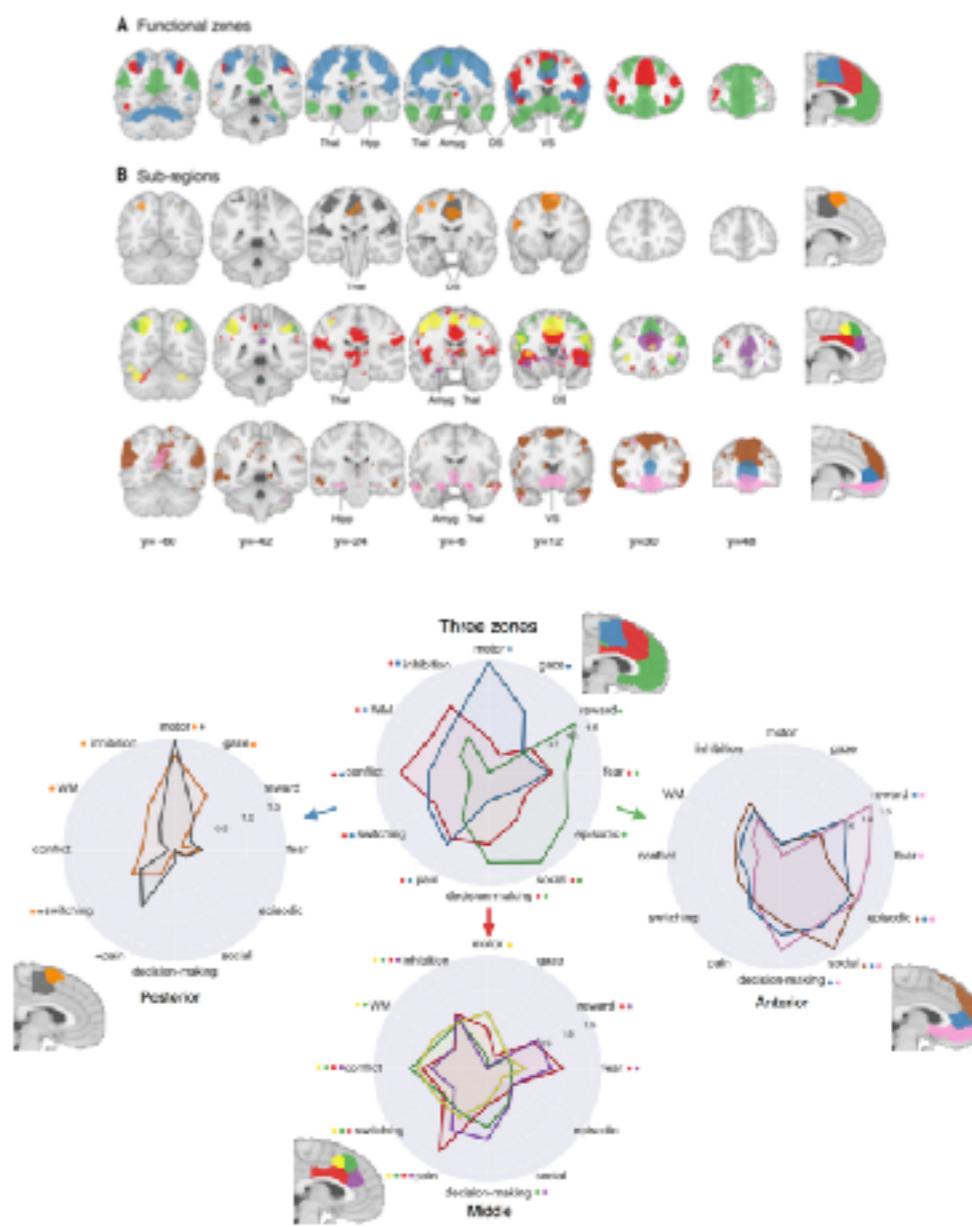
Investigating the heterogeneity of the default mode network using coordinate-based meta-analytic modeling



■ DMN ROI ■ Brain Map * Significant Domain

Laird et al., J Neurosci, 2009

Large-scale meta-analysis of human medial frontal cortex reveals tripartite functional organization



de la Vega et al., J Neurosci, 2016

Example

Functional Decoding

“recent developments in statistical analysis and informatics have provided new and more powerful ways to infer mental states from neuroimaging data” [BrainMap](#) and [Neurosynth](#) databases

“reverse inference can be a very useful strategy, especially if it is based on real data (such as the meta-analytic maps of from Yarkoni et al., 2011) rather than on an informal reading of the literature”

Poldrack, Neuron, 2011

- Large-scale meta-analytic databases consolidate results from many studies and annotate them to make them searchable
- Integrated algorithms make performing meta-analyses easier
- BrainMap and Neurosynth have complementary strengths and weaknesses

	BrainMap	Neurosynth
Created in	1994	2011
Annotation method	Manual	Automated
Annotation unit	Experiment	Paper
Size	3,010	11,406

**Both offer tools/
methods for
meta-analysis
and decoding**



Slide courtesy of Taylor Salo

What Can Meta-Analysis Do For You?

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7. Data-driven approach to validate cognitive models

Example

Data-Driven Validation of Cognitive Models

- More resources are being deployed for the management, sharing, and meta-analysis of neuroimaging big data; this includes **knowledge representation systems** (e.g., ontologies)
- However, **cognitive data descriptors** are relatively under-developed (even a listing of the sub-types of a paradigm or mental function is challenging due to lack of consensus)
- **Why not let the data facilitate consensus?**

Overall Premise: **differences in activation patterns** across studies should be captured and leveraged as they indicate **meaningful segregations in brain function**

Tasks activating similar brain networks should be grouped as functionally similar in a cognitive schema

Tasks demonstrating differential activation patterns should be classified as functionally distinct

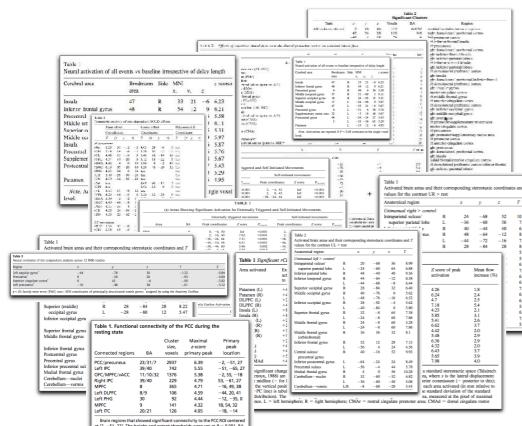
Example

Data-Driven Validation of Cognitive Models

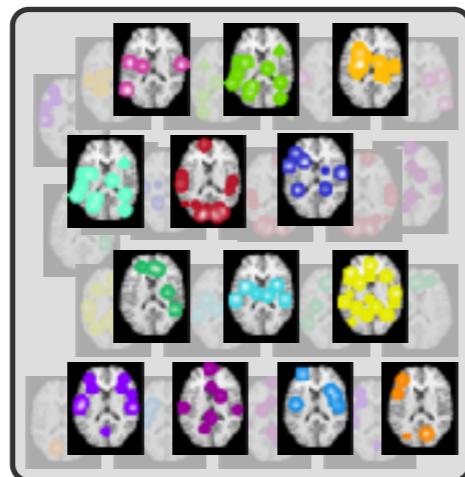
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Extract Coordinates from Literature

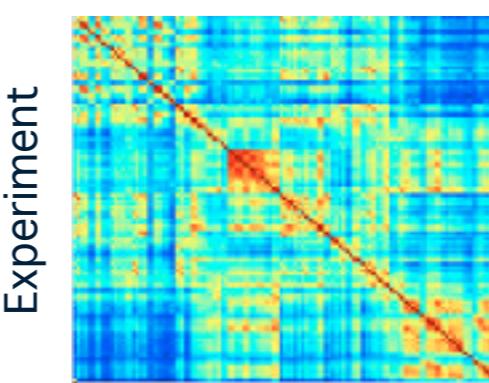


Generate Modeled Activation Maps



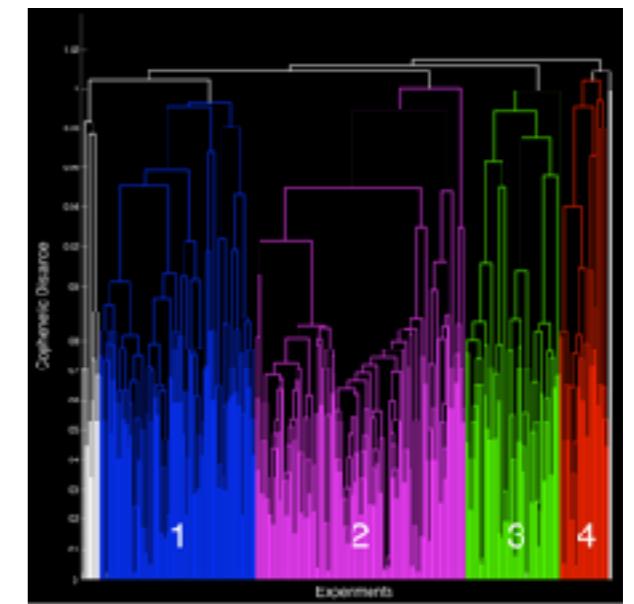
The whole brain sets of coordinates were blurred using a Gaussian distribution (FWHM defined by Eickhoff et al., 2009), filtered through a gray matter mask, and concatenated to form an experiment-by-voxel array

Generate Correlation Matrix



Correlation Matrix: correlation coefficients were computed to form an experiment-by-experiment matrix of activation patterns

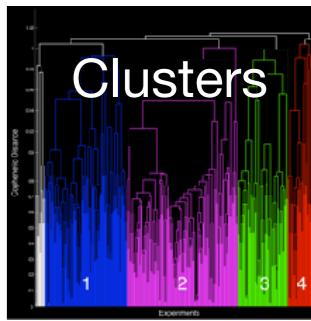
Perform Clustering of Modeled Activation Maps



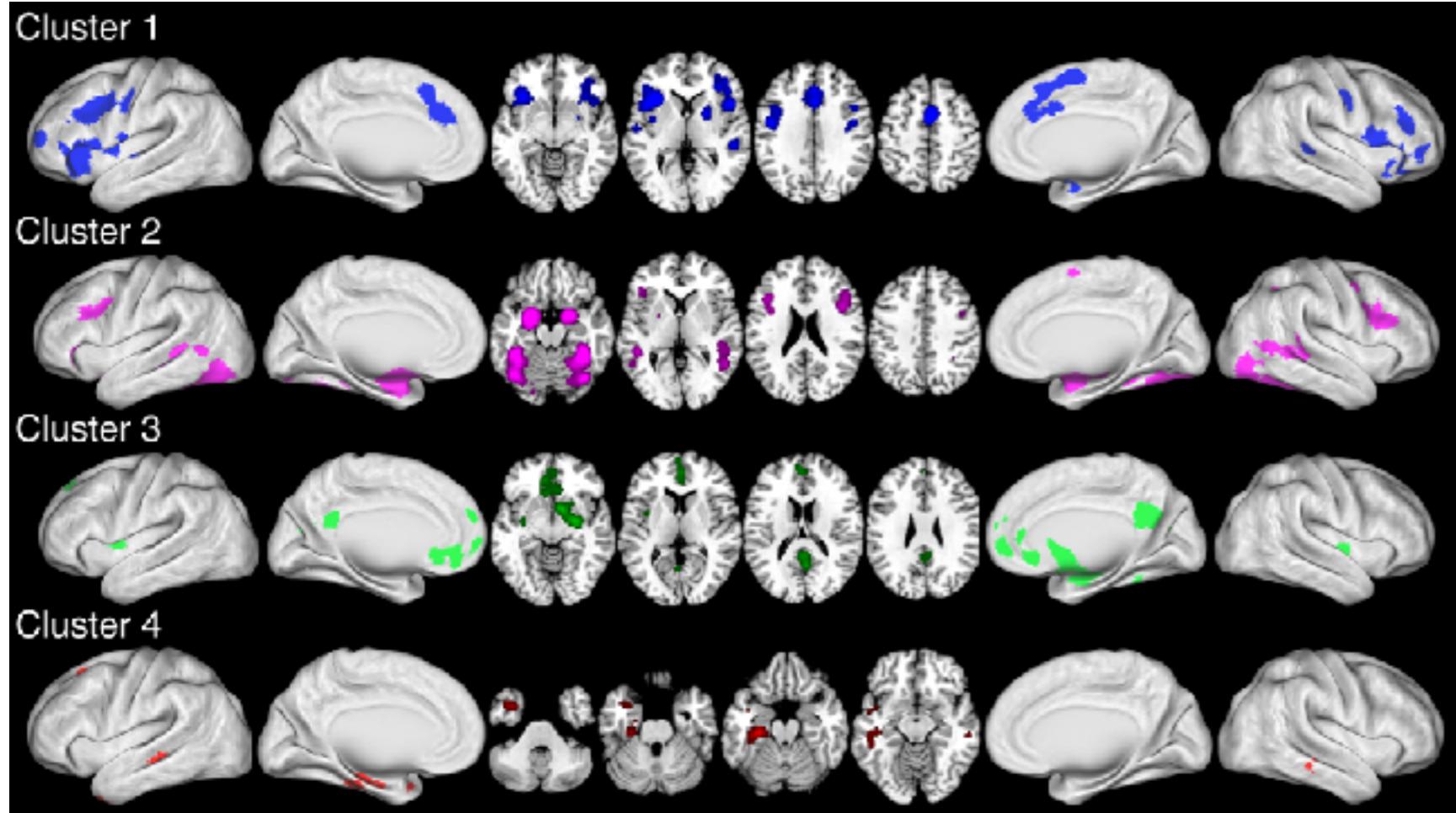
Hierarchical Clustering Analysis
applied to the correlation matrix to
identify clusters of experiments with
similar activation patterns, generate
ALE map, analyze metadata

Example

Data-Driven Validation of Cognitive Models



Face Perception Tasks



Visuospatial Attention and Visuomotor Coordination to Faces

Salience Network (bilateral insula and anterior cingulate)

Perception and Recognition of Faces

Amygdala, fusiform face area, occipito-temporal areas

Social Processing and Episodic Recall of Faces

Default Mode Network (MPFC and precuneus)

Face Naming and Lexical Retrieval

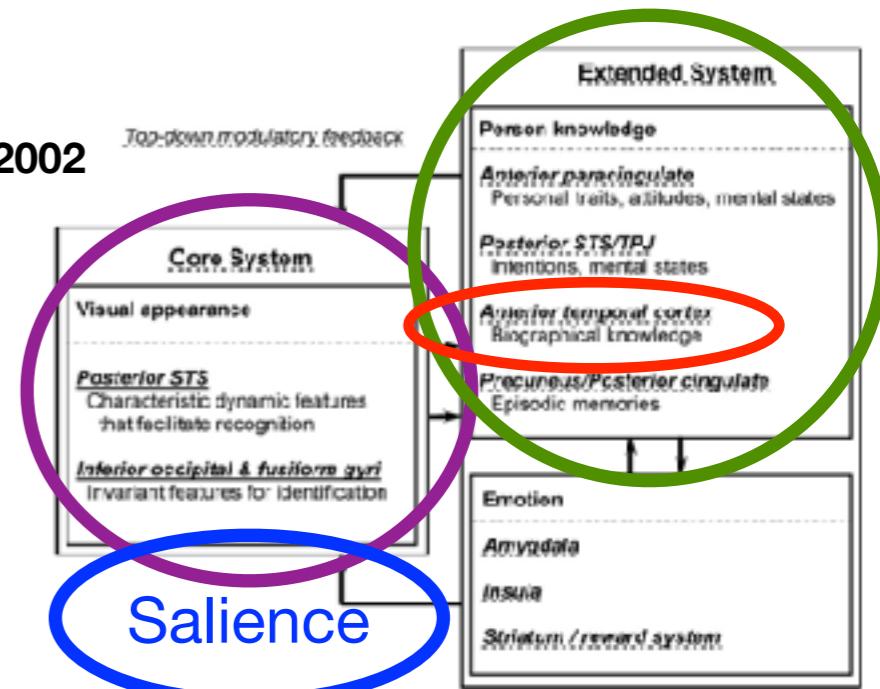
Middle temporal gyrus and inferotemporal cortex, temporal pole, parahippocampal gyrus

How well do our current results align? Gobbini and Haxby, 2002



- Confirm and extend a well-known cognitive model of face perception
- Our results demonstrate that a large-scale data mining approach can inform the evolution of cognitive models by meta-analytically probing the range of behavioral manipulations across experimental tasks

Laird et al., Neuroimage, 2015

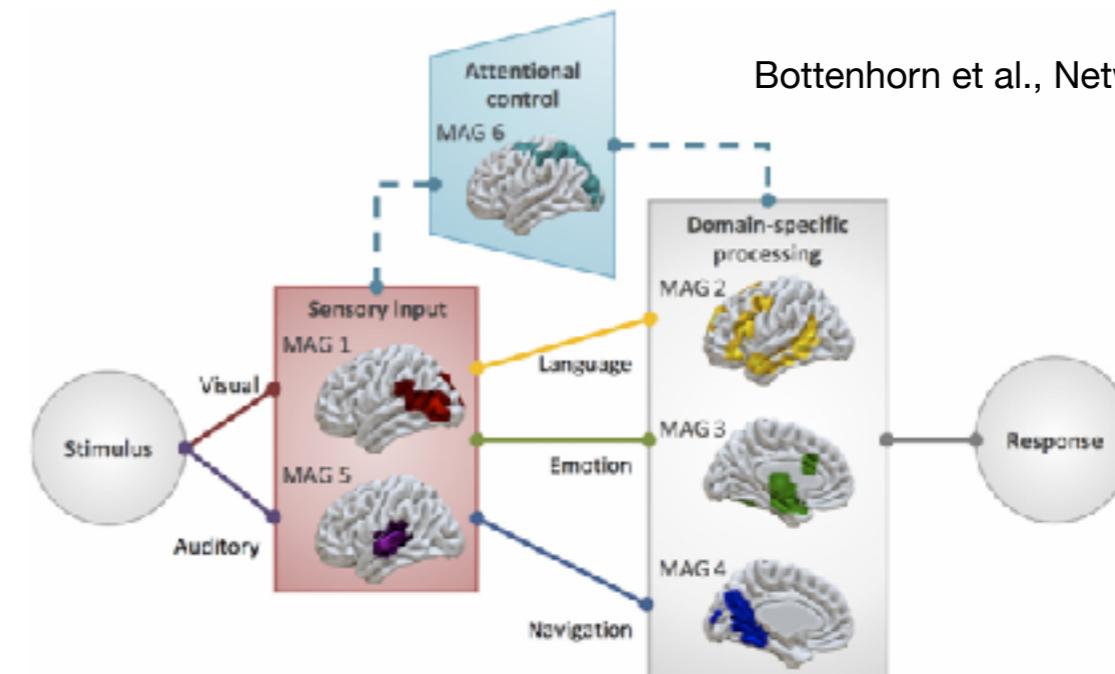
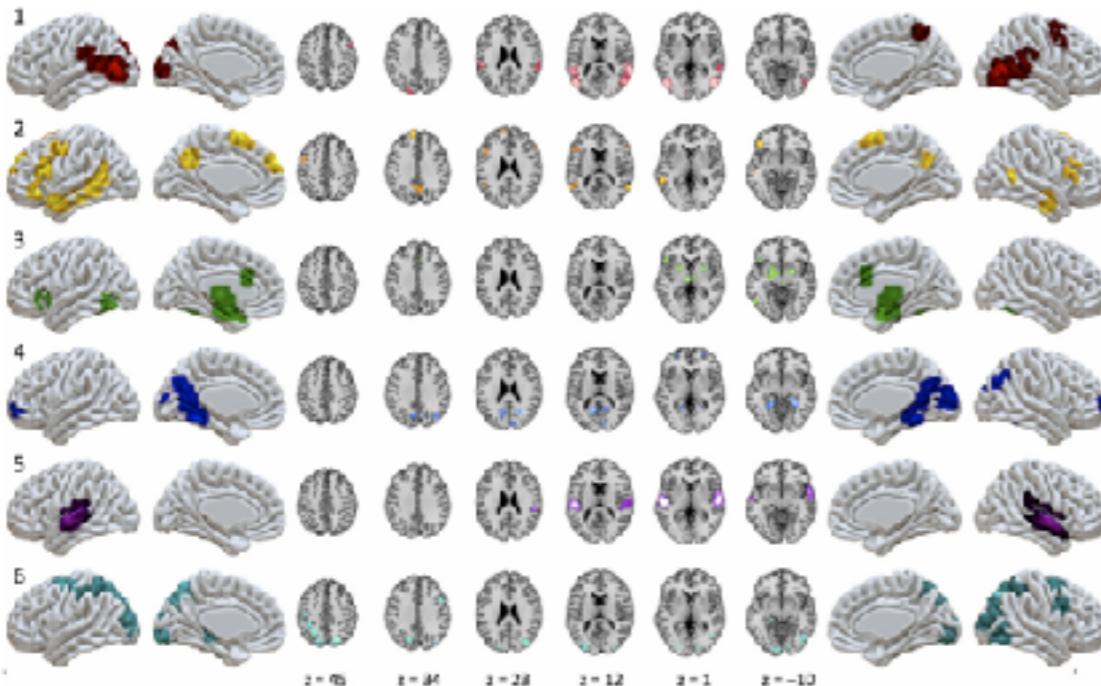


Example

Data-Driven Validation of Cognitive Models

Naturalistic Tasks

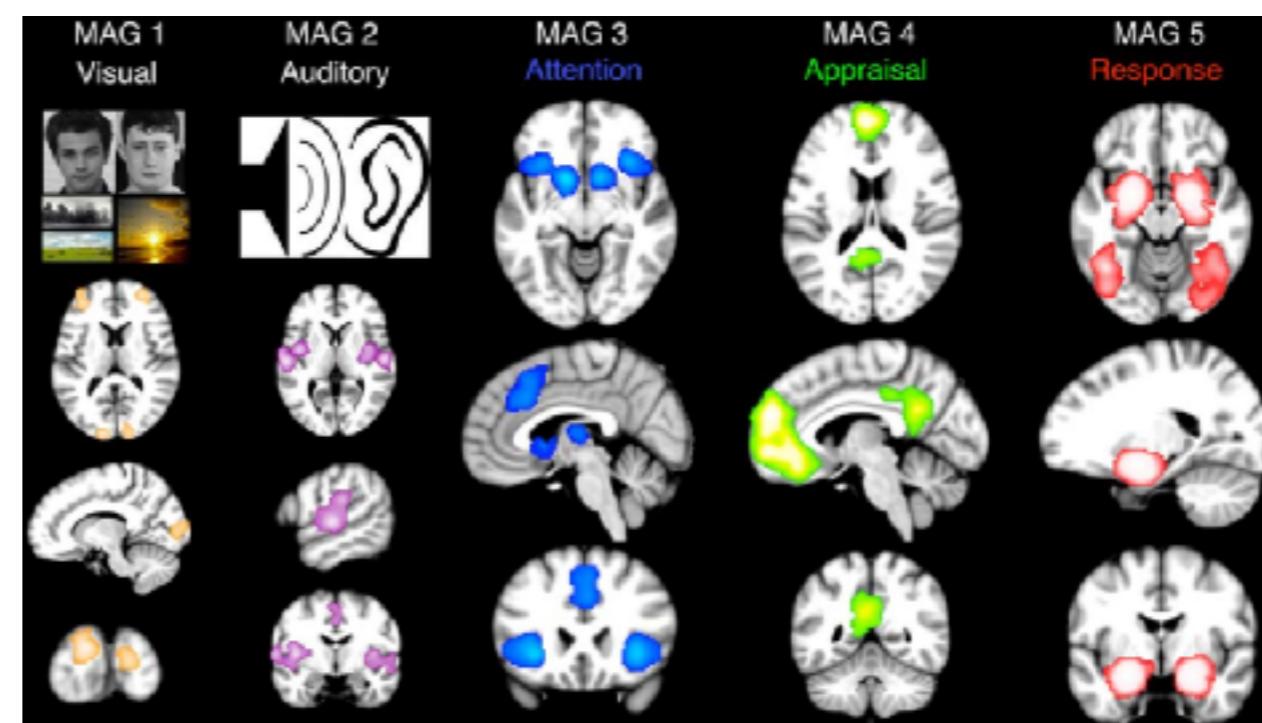
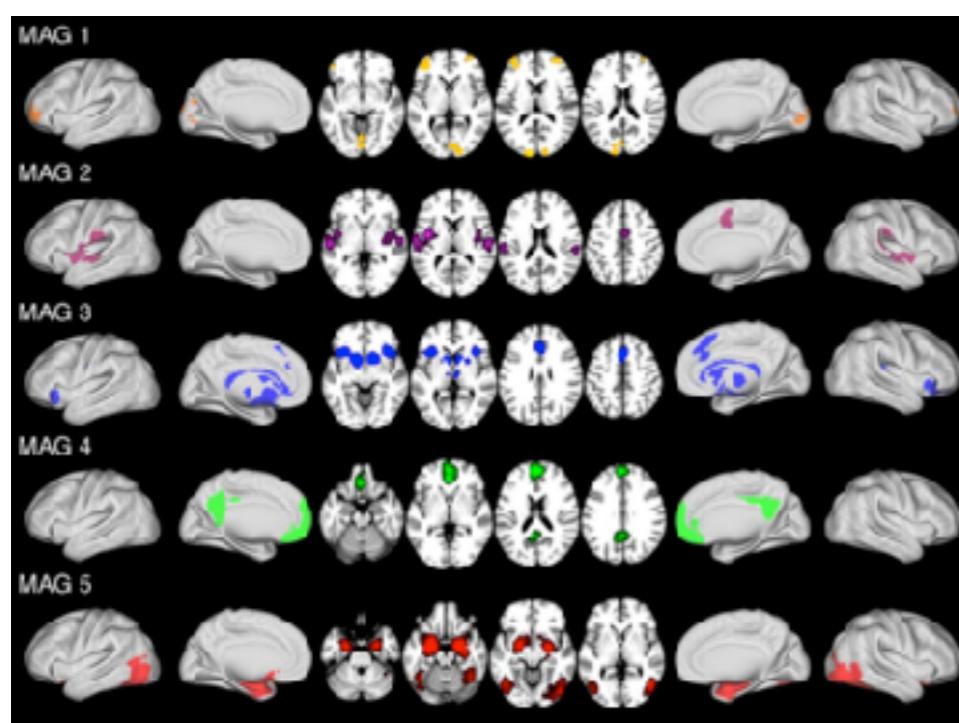
Cooperating yet distinct brain networks engaged during naturalistic paradigms



Emotional Tasks

Dissociable meta-analytic brain networks contribute to coordinated emotional processing

Riedel et al., HBM, 2018



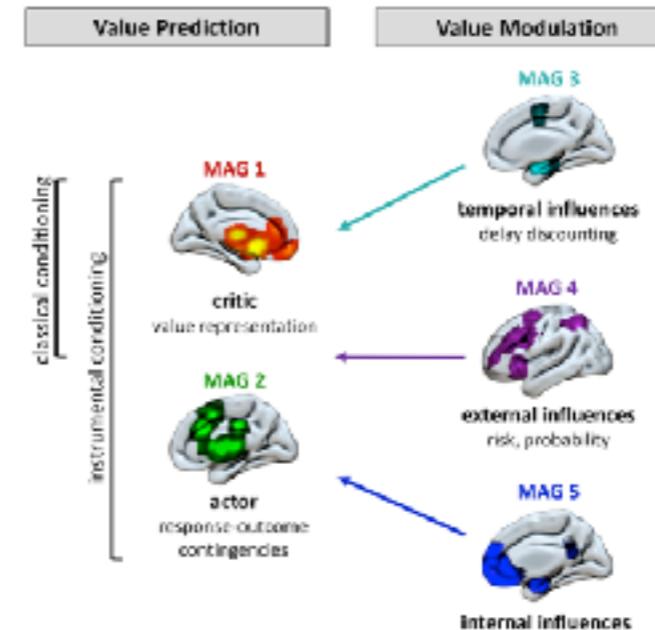
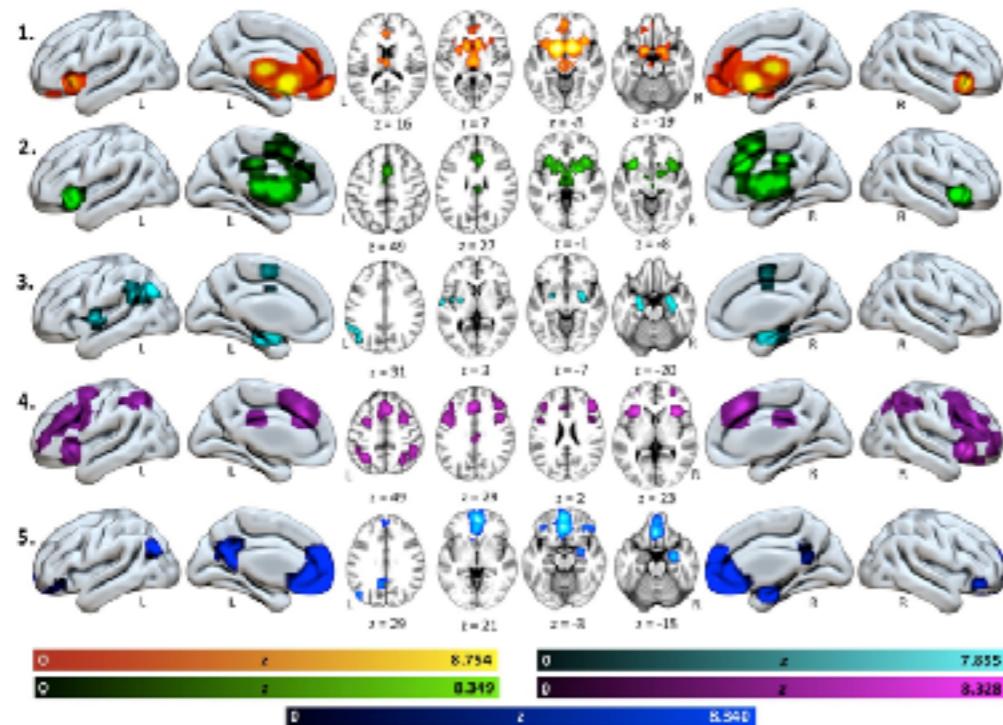
MAG = meta-analytic grouping

Example

Data-Driven Validation of Cognitive Models

Reward Tasks

Meta-analytic clustering dissociates brain activity and behavior profiles across reward processing paradigms



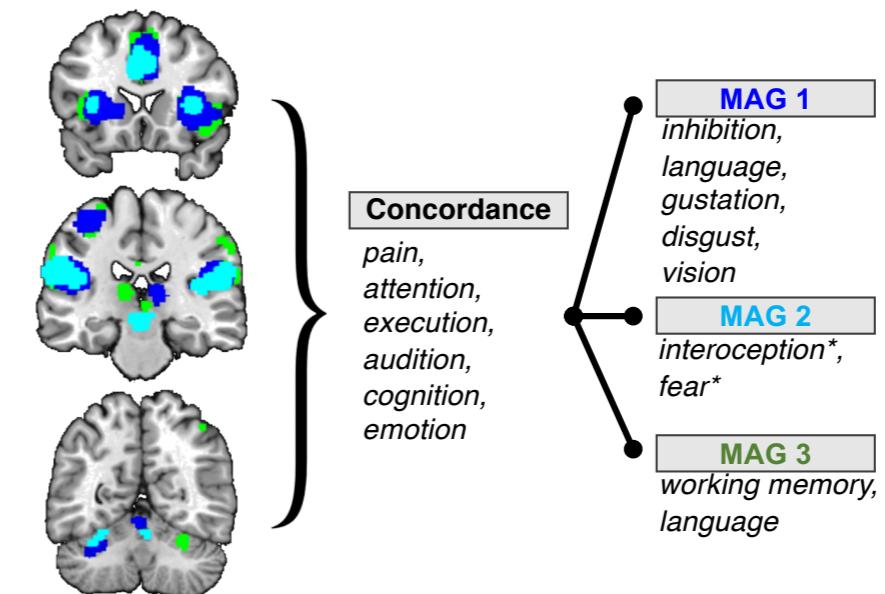
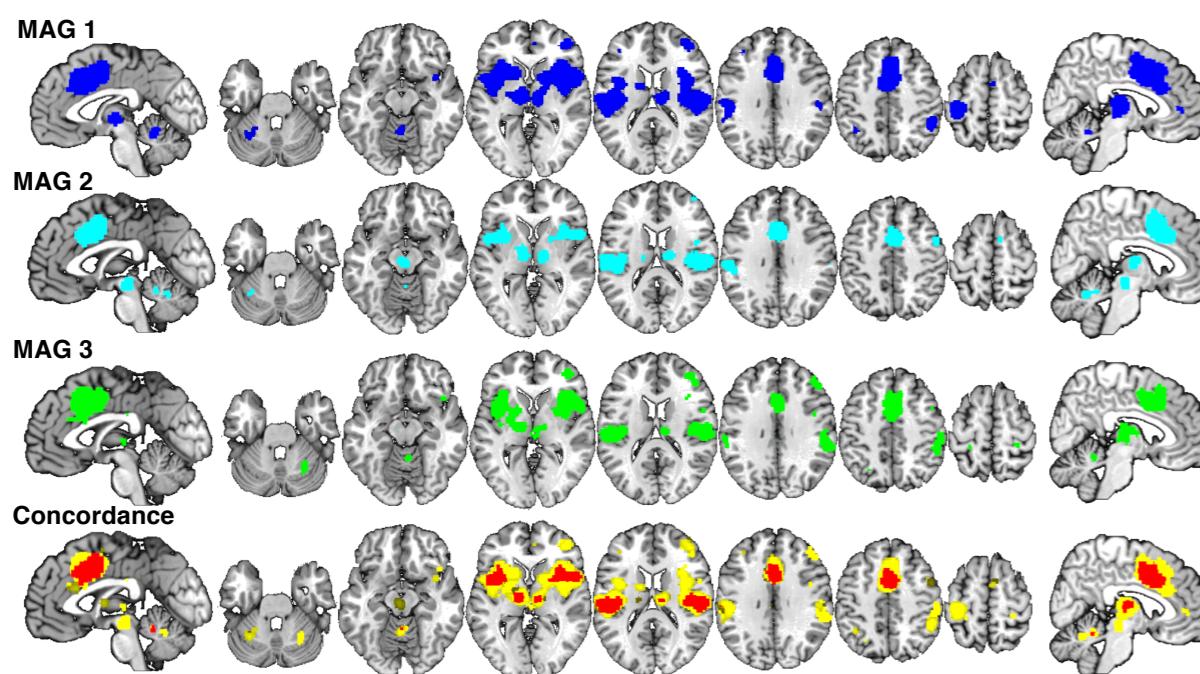
Flannery et al., In Revision



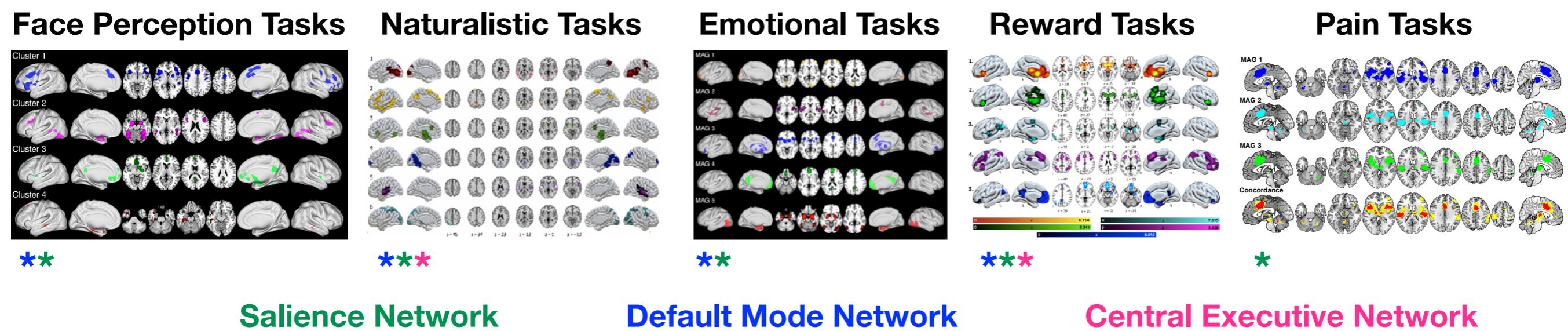
Pain Tasks

Data mining reveals discrete neurobiological systems that contribute to pain processing

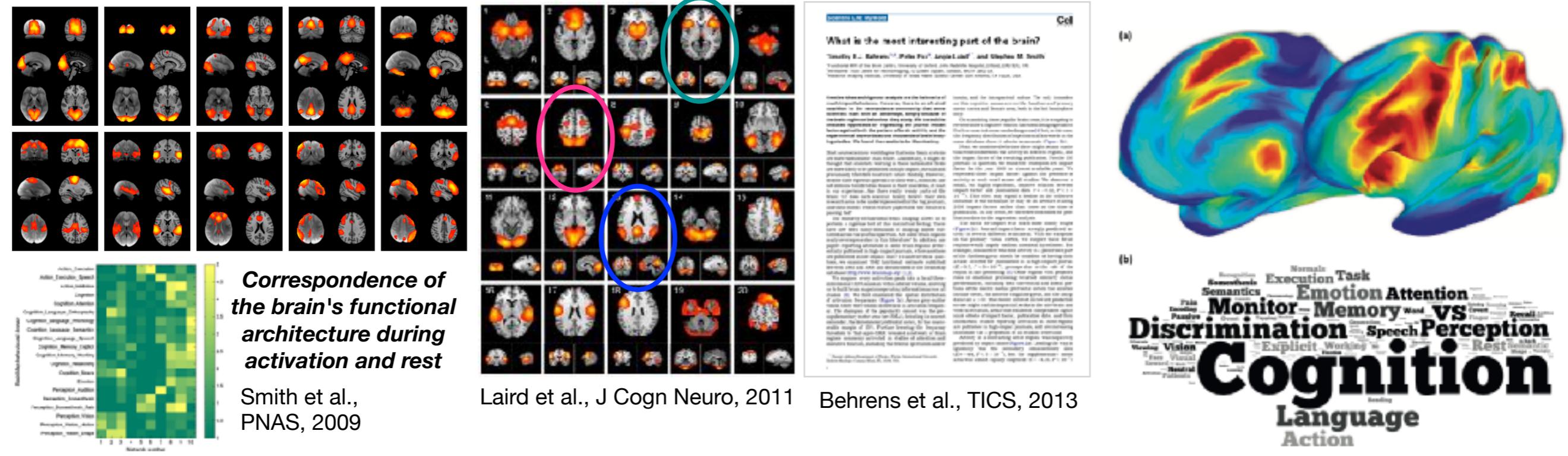
Yanes et al., In Preparation



Personal perspective: Starting at so many meta-analytic images for 15+ years reframes how you think about brain networks



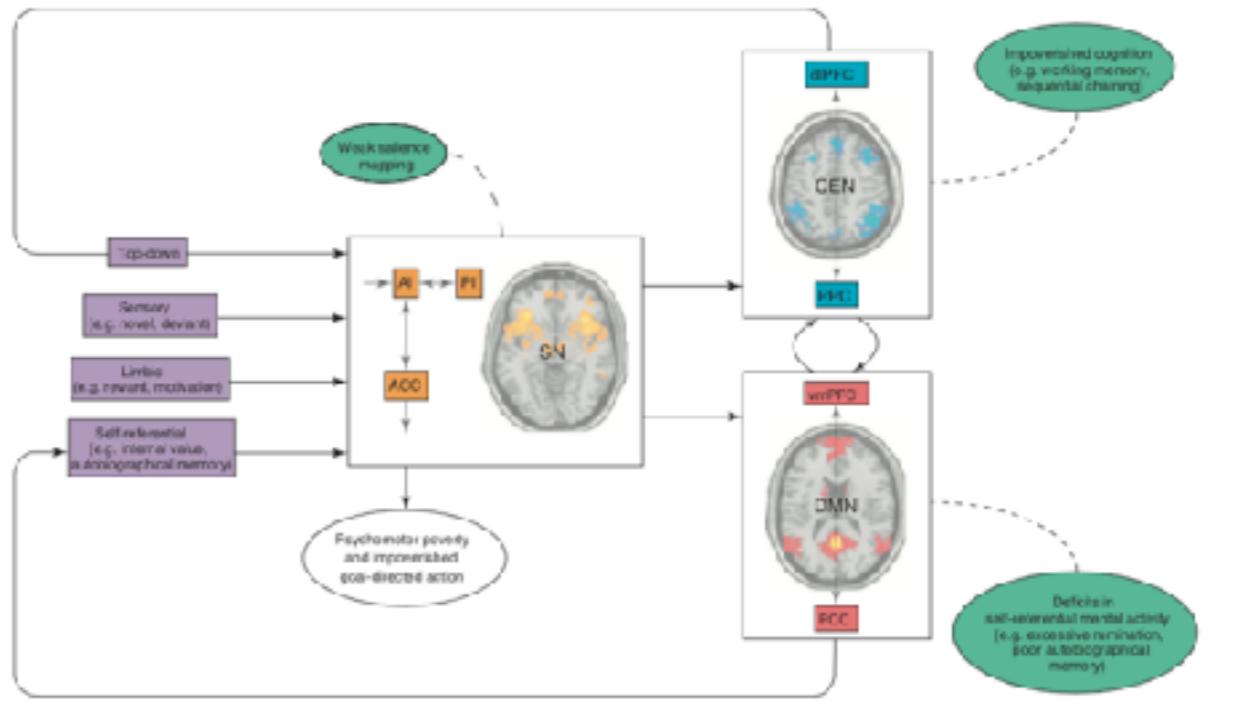
Large-Scale Meta-Analytic Data Mining



Large-Scale Brain Networks

- Psychopathological processes, especially those found in mood disorders, are commonly associated with **aberrant connectivity within and between**:
 - the salience network (**SN**),
 - the default mode network (**DMN**),
 - and the central executive network (**CEN**)
- The interaction of these three, core networks underlies a unifying **triple network model** that characterizes the maladaptive network organization and function in psychiatric disorders
 - Dysfunctional connectivity in these networks can lead to diminished cognitive ability, and diminished control over self-referential processes such as rumination

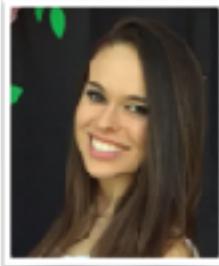
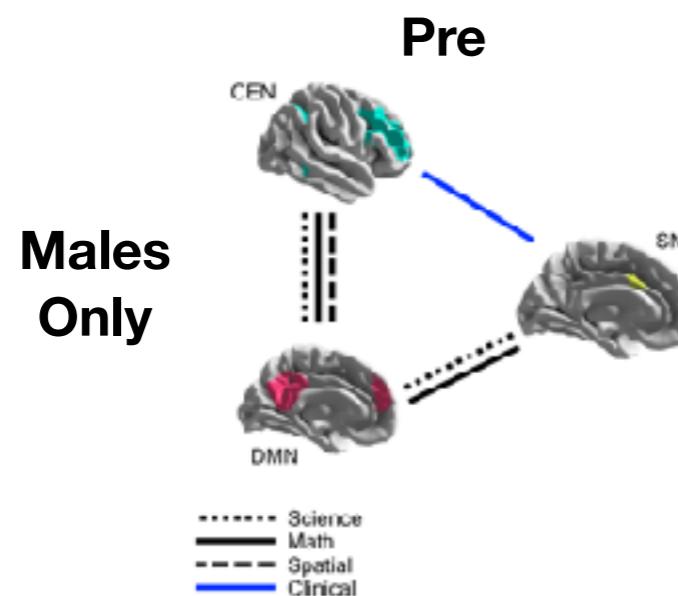
Aberrant interconnectivity of the SN, CEN, and DMN is characteristic of **many psychiatric disorders**



TRENDS in Cognitive Sciences

Menon, TICS, 2011

Sex differences in brain correlates of STEM anxiety

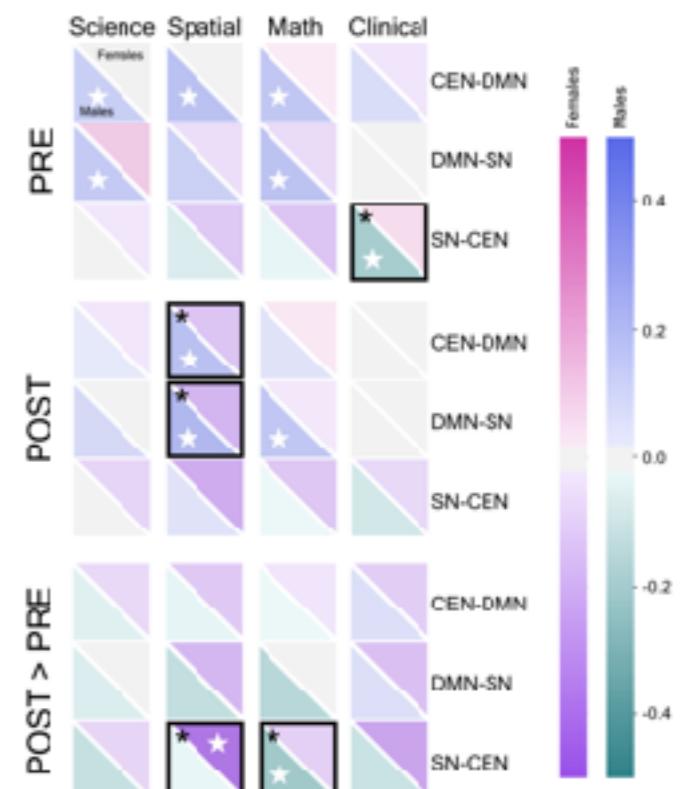


Gonzalez et al., In Revision

PREPRINT: <https://doi.org/10.1101/528075>

- For male students,
- Separate brain connections for STEM and clinical anxiety
 - Fewer correlations at post

Between-Network Correlates of Anxiety



What Can Meta-Analysis Do For You?

1. Great introduction to a new topic
2. Feasible project for your novice trainees
3. Systematic analysis of variability (e.g., participants, tasks) can resolve conflict in a given community
4. Validate a new task or data acquisition approach
5. ROI selection ✓
6. Functional decoding ✓
7. Data-driven approach to validate cognitive models ✓

Meta-Analysis Methods*

Coordinate-Based Meta-Analysis

Activation Likelihood Estimation (ALE)

Kernel Density Analysis (KDA)

Multilevel Kernel Density Analysis (MKDA)

Specific Coactivation Likelihood Estimation (SCALE)

Seed-Based d-Mapping

MKDA Chi2 Extension

Where do the foci converge?

Image-Based Meta-Analysis

Mixed-Effects GLM (gold standard)

Fixed-Effects GLM

Fisher's IBMA

Stouffer's IBMA

z permutation

Where do the images converge?

*Currently, these methods are spread out across programming languages and user interfaces

Okay, I've convinced you... what do you do next?

Library of meta-analytic images



Browse for ideas and examples

Database and software for meta-analyses



Detailed manual, paradigm-based meta-analysis

- ALE method
- Structured taxonomy terms



Automated and fast meta-analysis and decoding

- MKDA method
- Rich set of author terms

<http://anima.fz-juelich.de/query>

<http://brainmap.org>

<http://neurosynth.org>

NiMARE: A Neuroimaging Meta-Analysis Research Environment

NiMARE: A Neuroimaging Meta-Analysis Research Environment



Motivation

- Meta-analysis is crucial for neuroimaging, which suffers from low power, sample sizes, and signal-to-noise.
- Meta-analyser and derivative analyses may use databases, algorithms, annotation modes, and decoding models.
- No common interface across several meta-analysis packages that perform similar tasks.
- Available tools are often closed source, GUI-based, and/or written in languages unfamiliar to most neuroimagers.
- No available implementations for many algorithms or workflows.

Features

- NiMARE** is a Python package for performing meta-analysis and related analyses of the neuroimaging literature.
- Provides a standard syntax for a variety of analyses and to interact with coordinate and image databases from fMRI studies (e.g., Neurosynth, Brainspell, and NeuroVault).
- Joins the burgeoning Python neuroimaging ecosystem including nipype, nistats, and nilearn.
- Is open source, collaboratively developed, and built for simplicity.

Want to get involved?

Visit

<https://github.com/neurostuff/NiMARE>

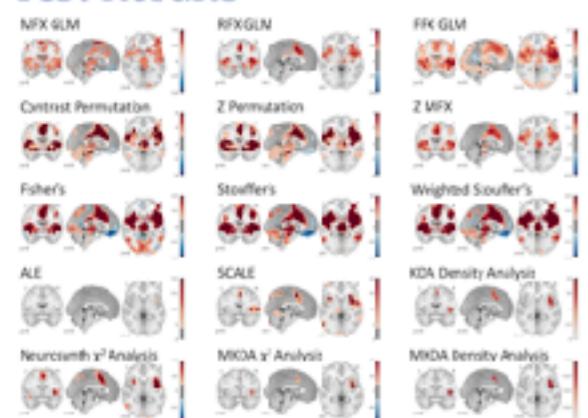


or scan this QR code:
Check out our contributing guidelines
and open Issue!

Test Methods

- NIDM Results packs for 21 pain studies from NeuroVault collection 1425.
- Convert ICA json for NiMARE
- Apoly meta-analytic algorithms to all datasets
- Code available at <https://github.com/neurostuff/NiMARE/blob/2018>

Test Results



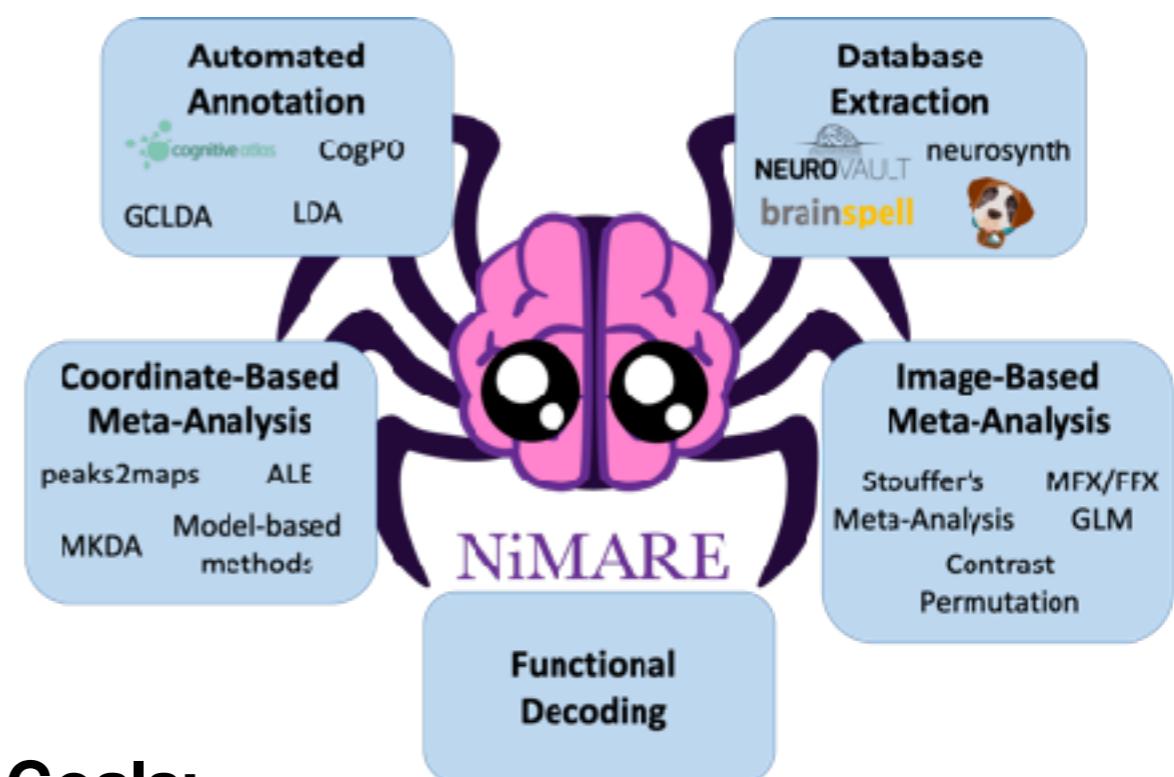
This work was supported by awards from the National Science Foundation (NSF) 1651325
and the National Institutes of Health (NIH) U24 DA039832 & NIH R01 DA041363

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Goals:

- Implement a common interface across different meta-analysis packages that perform similar tasks
- Facilitate open source community development
- Provide a standard syntax for a variety of different analyses that interact with coordinate and image-based databases (e.g., Neurosynth, Brainspell, NeuroVault)
- Joins the Python neuroimaging ecosystem (along with nipype, nistats, and nilearn)

<https://github.com/neurostuff/NiMARE>

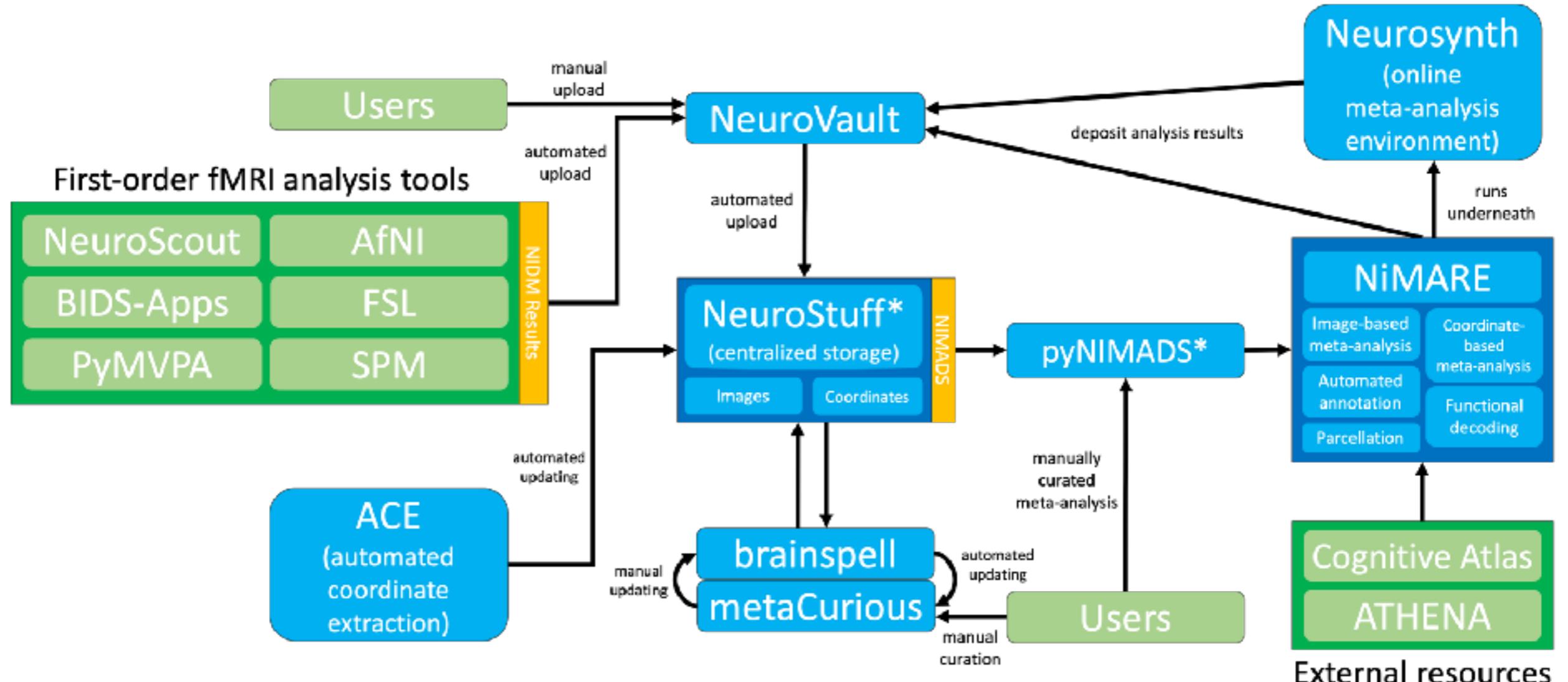
Please contribute!



Slide courtesy of Taylor Salo

NiMARE: A Neuroimaging Meta-Analysis Research Environment

What role does NiMARE play in the broader Python ecosystem?



- NiMARE aims to fill a gap in a burgeoning meta-analytic ecosystem.
- The goal of NiMARE is to collect a wide range of meta-analytic tools in one Python library.
- Currently, those methods are spread out across a range of programming languages and user interfaces, or are never even translated from the original papers into useable tools.
- NiMARE operates on NIMADS-format datasets, which users will be able to compile by searching the NeuroStuff database with the pyNIMADS library.
- A number of other services in the ecosystem will then use NiMARE functions to perform meta-analyses, including Neurosynth 2.0, NeuroVault, and metaCurious.

<https://nimare.readthedocs.io/en/latest/about.html>

Please contribute!



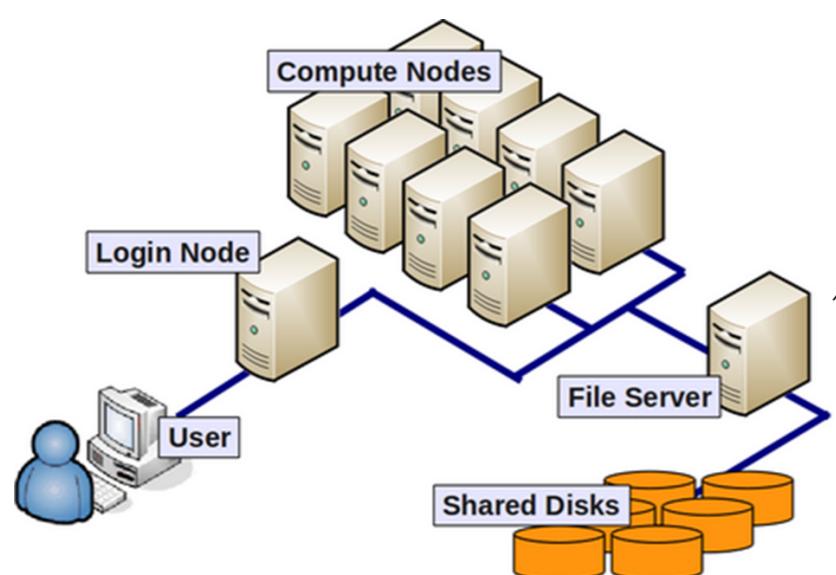
Slide courtesy of Taylor Salo

Our lab's best practices for Open Science and Reproducible Neuroimaging

Data Acquisition



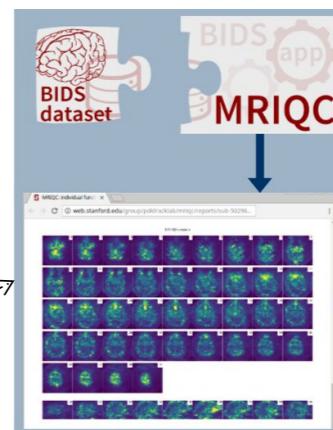
Data Processing



* * * * command to execute
| | | |
| | | L day of week (0 - 7)
| | | month (1 - 12)
| | | day of month (1 - 31)
| | | hour (0 - 23)
| | | min (0 - 59)

cron

bids.neuroimaging.io



fMRIPrep a robust preprocessing pipeline for task-based and resting-state fMRI data 

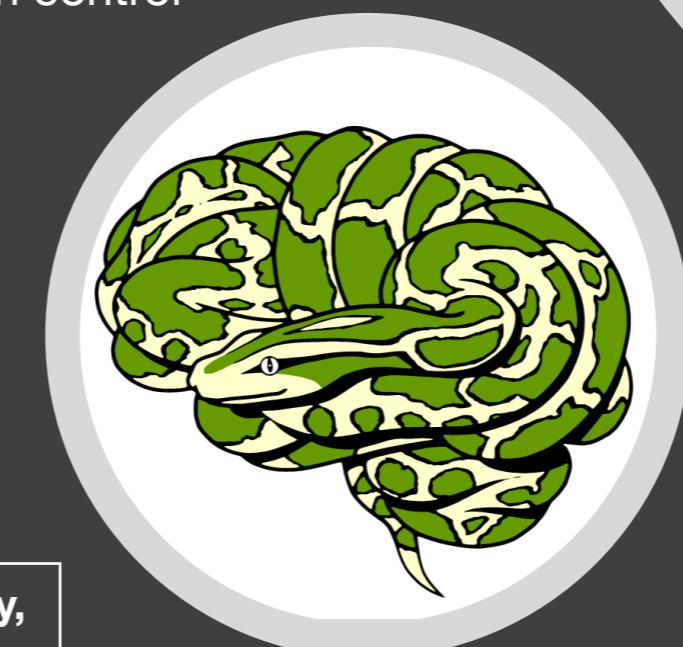


Slide courtesy of Michael Riedel

Our lab's best practices for Open Science and Reproducible Neuroimaging

Data and Software Resources

- **OpenNeuro**: hosts open-source datasets
- **Neurovault**: hosts statistical maps
- **ANIMA**: hosts meta-analysis maps
- **Neurosynth**: coordinate-based database
- **Nipy**: community of practice devoted to use of Python*
- **Github**: code hosting for collaboration and version control
- **NITRC**: software clearinghouse and repository



Community Resources

- **NeuroStars**: neuroinformatics forum run by INCF
- **Brainhack Slack**: collaborative workshops
- **Listservs & Slack**
- **ReproNim**: “*Discover, Describe, Do*”

*[nipype](#), [dipy](#), [mindboggle](#), [nibabel](#), [Scitran SDM](#), [Nipy](#), [Nitime](#), [popeye](#), [Nilearn](#), [PyMVPA](#), [MNE](#), [niwidgets](#)

- [nipype](#): provides an interface to existing software
- [nibabel](#): read/write common file formats
- [Nilearn](#): uses scikit-learn for statistical learning

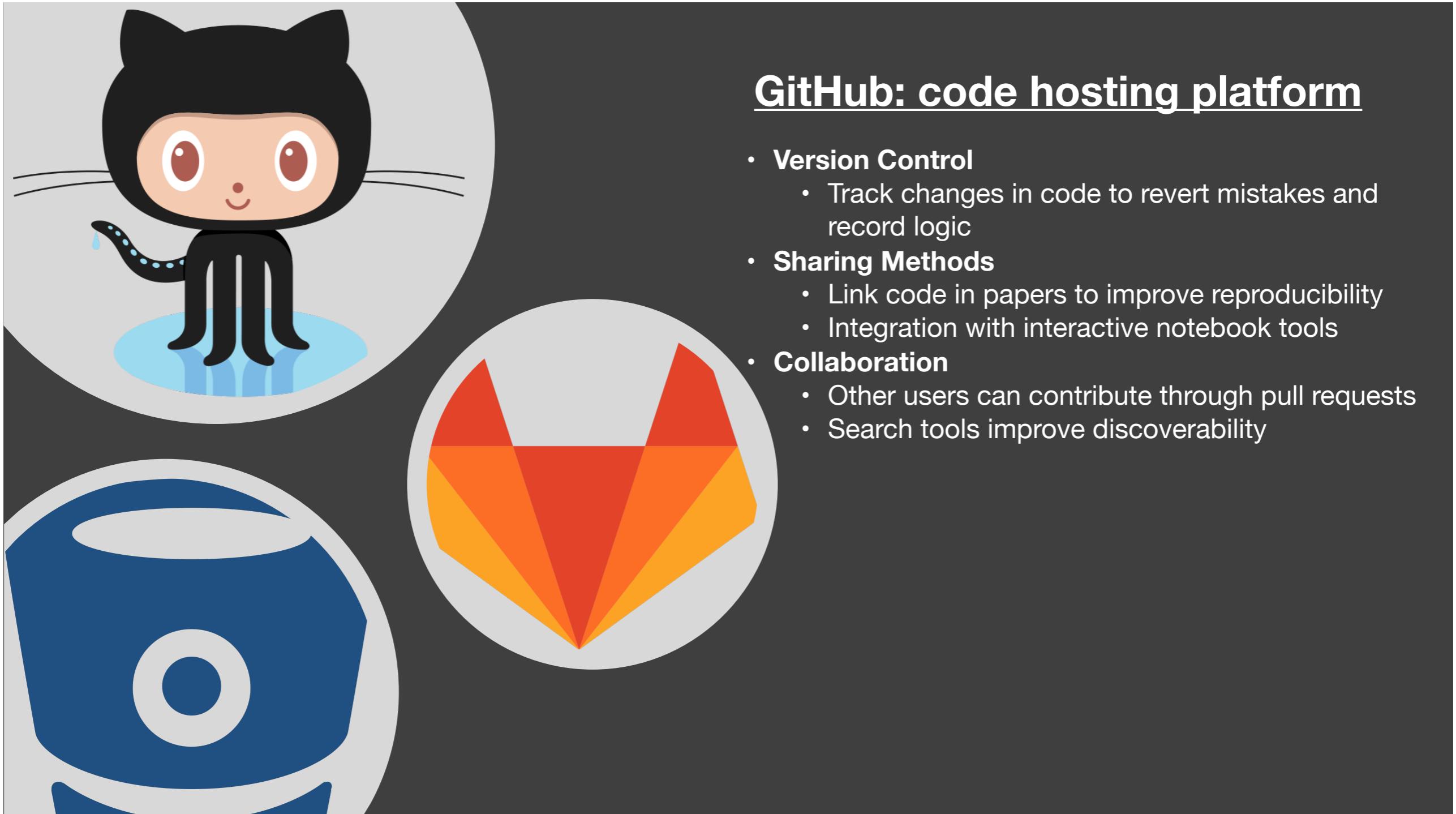


OpenNEURO



Slide courtesy of Katie Bottenhorn

Our lab's best practices for Open Science and Reproducible Neuroimaging



Slide courtesy of Taylor Salo

Our lab's best practices for Open Science and Reproducible Neuroimaging

Analyses and Sharing

1. Use open-source, BIDS-friendly tools

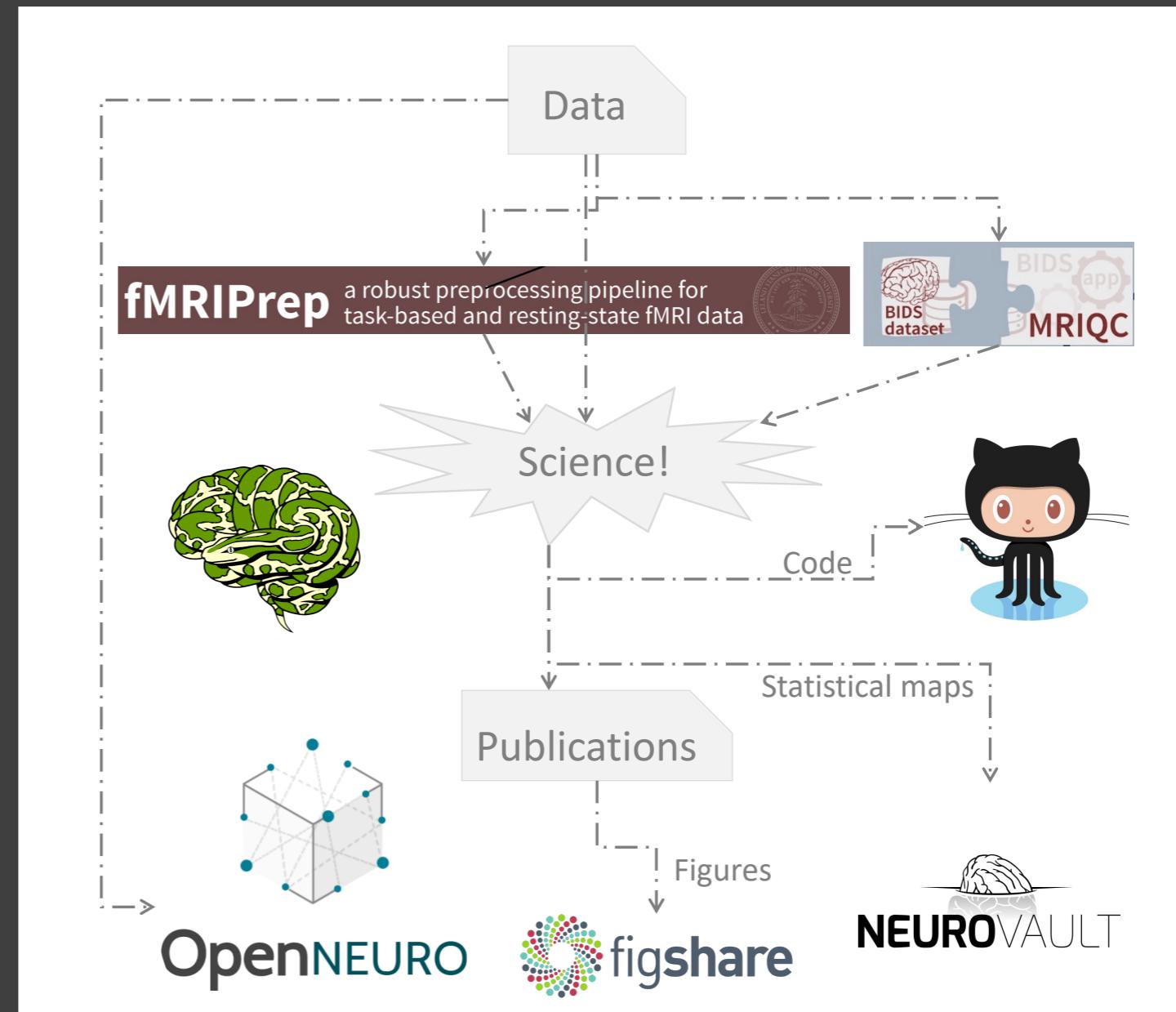
- fMRIPrep
- MRIQC
- Nipy
- Github

2. Share your code & results

- Code on GitHub
- Maps to NeuroVault
- Figures to figshare
- Reference in your paper!

3. Share your data on OpenNeuro

- Share with the community
- Citable datasets (data papers)



Slide courtesy of Katie Bottenhorn

Our lab's best practices for Open Science and Reproducible Neuroimaging

Analyses and Manuscripts

Preregistration: Design analysis plan prior to data acquisition

- Separate confirmatory and exploratory analyses
- Prevent HARKing, p-hacking, etc.



Registered Report: Submit manuscript prior to data acquisition

- Same benefits as above
- Plus peer-reviewed analysis plan



Preprint: Share manuscripts openly prior to peer review

- Crowdsourced peer review
- Early access to research findings
- Open access



aims to increase openness, integrity,
and reproducibility of research



Slide courtesy of Taylor Salo

Our lab's best practices for Open Science and Reproducible Neuroimaging

Sharing Other Study Materials

- Analysis Plans
- Figures
- Posters
- Talks
- Tasks and Stimuli

OSF includes tools for collaboration, registration, and integrations for storage tools like Figshare, GitHub, and Google Drive. OSF projects can be kept private until publication in order to prevent scooping.

figshare provides DOIs for stored objects, like figures or data (but not neuroimaging data).

Zenodo integrates with GitHub to allow you to assign citable DOIs to versioned releases of your code. DataCite is working with Zenodo to track code citations, and can be integrated with ORCID very easily.



Slide courtesy of Taylor Salo

Before we go...

**Academia is very hierarchical
And power differentials always create space for the abuse of power
This is true regardless of gender, sexual, racial/ethnic, or cultural identity**

Lots of advice is well-intentioned but pretty terrible

Tell someone. Report the abuse. Inaction. Retaliation. Career suicide.

It'll get better... I survived and so can you. Deal with it?

Find a community of support. This isn't the victims' problem to fix/cope/manage.

A toxic climate hurts everyone. What can we collectively do?



Listen. Don't interrupt. Prevent others from interrupting.

Seek out other perspectives. Twitter is a hell site, but go find the voices you can learn from. Follow LGBTQ+, Black, Latinx, Muslim scientists, scholars, and activists

Change your surroundings, situate yourself as an Other. Look at your collaborators. We naturally seek out “like-minded people” but this can create our own scientific echo chambers. Rich and innovative ideas are cultivated in a diverse and inclusive environment.

Florida International University, Miami, FL, USA

FIU is an urban, multi-campus, public research university serving its students and the diverse population of South Florida.



57,000

Students Enrolled

FOURTH

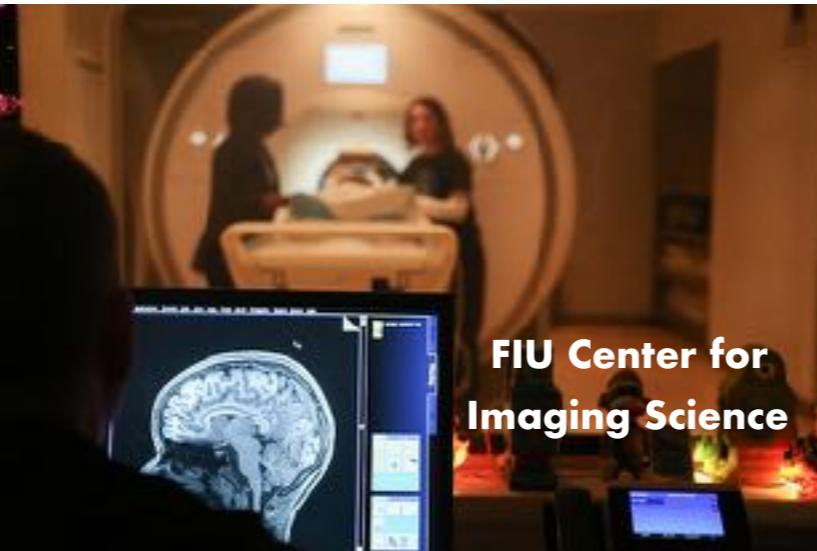
Largest University in USA

DIVERSE

61% Hispanic, 15% White Non-Hispanic, 13% Black, 4% API, 7% Other

SECOND

Highest Number of Bachelor and Master's Degrees to Latinxs in STEM



Thank You!

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<http://neurolab.fiu.edu>



<http://github.com/nbclab>

