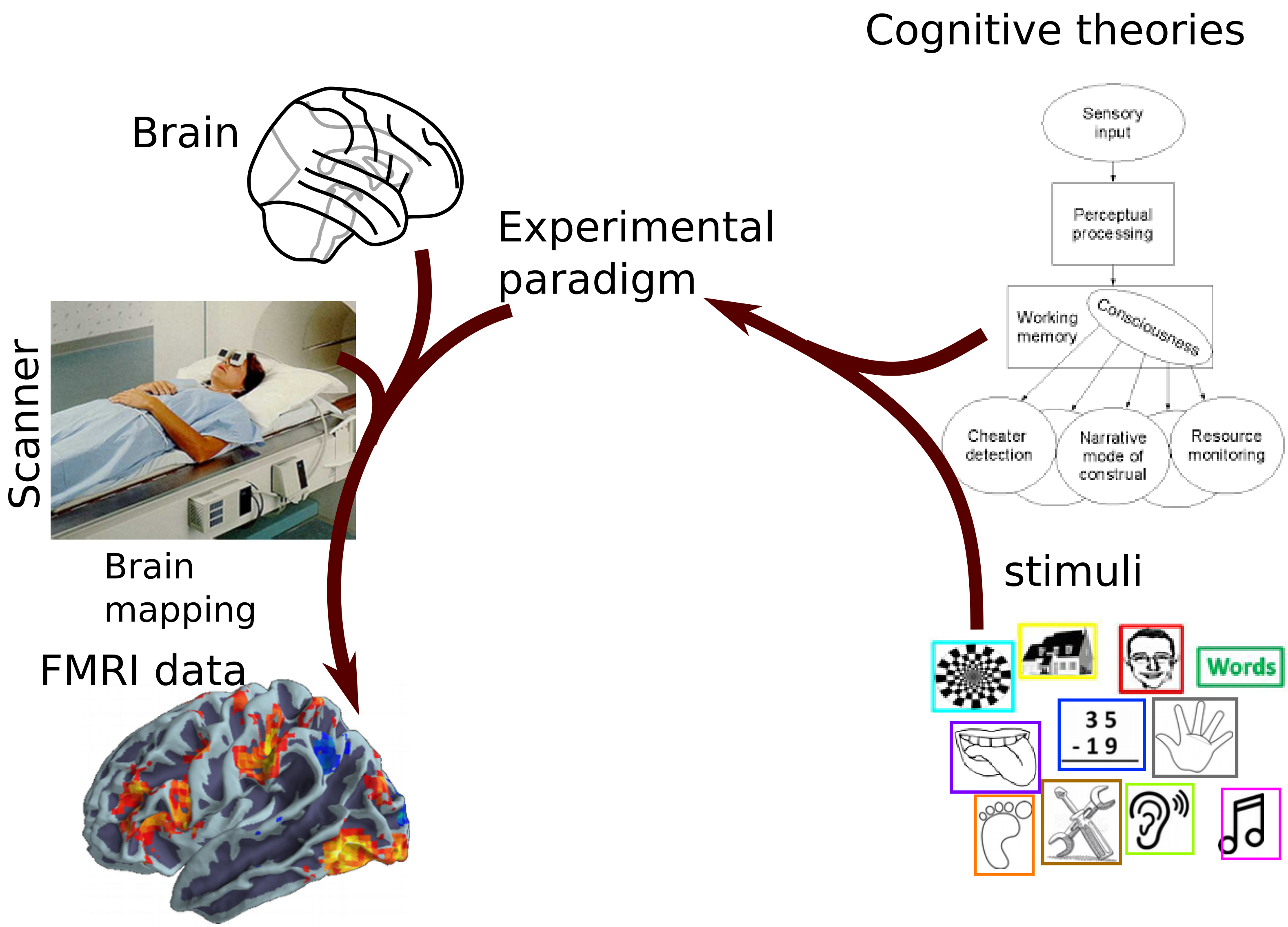
Extracting Universal Representations of Cognition from fMRI mega-analyses

Multivariate analyses of sensory representations inthe brain

Bertrand Thirion, bertrand.thirion@inria.fr

Cognitive neuroscience: Brain activity *decoding*



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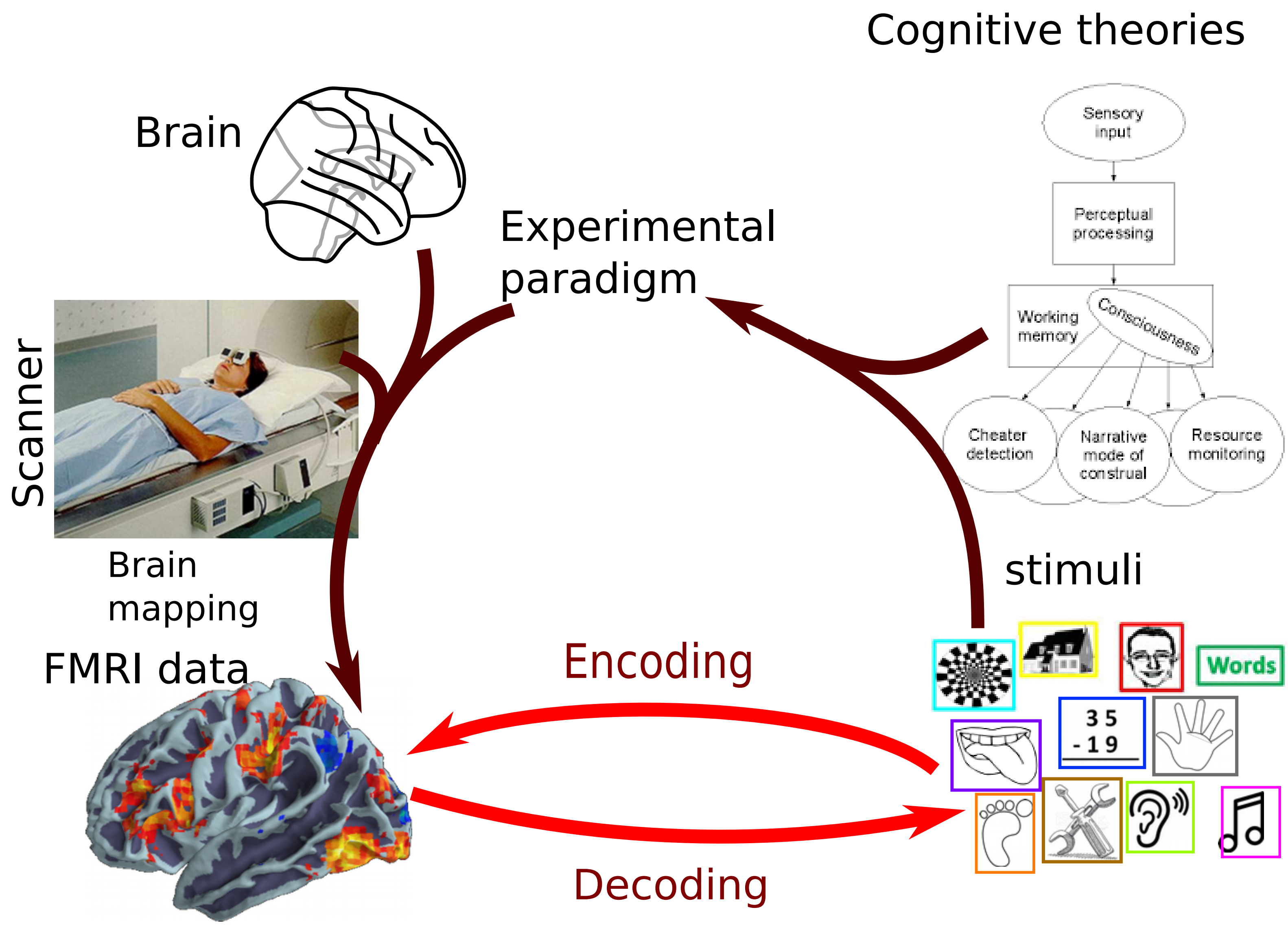

The big data revolution is ongoing – in neuroimaging also !

Nature Reviews Neuroscience | AOP, published online 10 April 2013; doi:10.1038/nrn3475

nature REVIEWS

Power failure: why small sample size undermines the reliability of neuroscience

Katherine S. Button[1,2], John P. A. Ioannidis[3], Claire Mokrysz[1], Brian A. Nosek[4], Jonathan Flint[5], Emma S. J. Robinson[6] and Marcus R. Munafò[1]

https://en.wikipedia.org/wiki/Replication_crisis

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nature REVIEWS NEUROSCIENCE

Analysis | Published: 05 January 2017

Scanning the horizon: towards transparent and reproducible neuroimaging research

Russell A. Poldrack, Chris I. Baker, Joke Durnez, Krzysztof J. Gorgolewski, Paul M. Matthews, Marcus R. Munafò, Thomas E. Nichols, Jean-Baptiste Poline, Edward Vul & Tal Yarkoni

Problem: generalization across studies

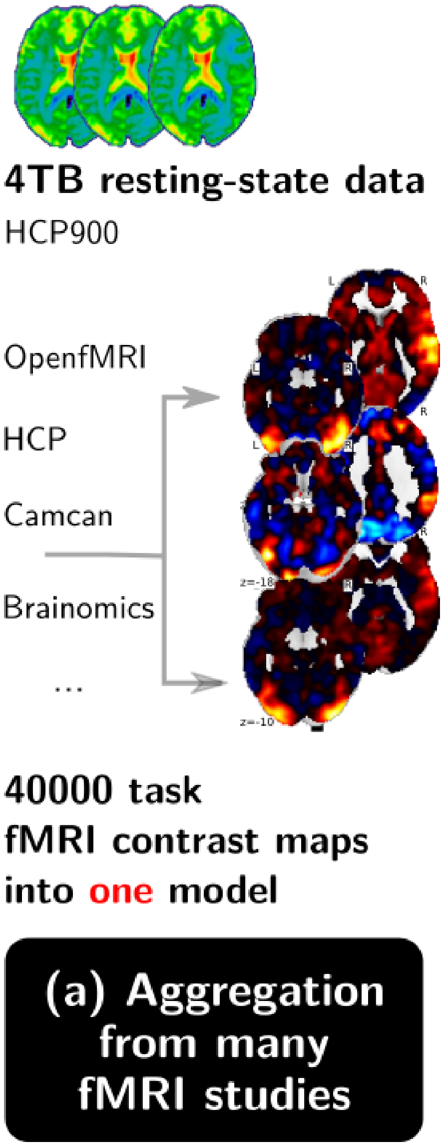
"You cannot play 20 questions with nature and win"

[Newell A. Visual information processing; 1973.]

- Joint analysis: Use large studies to inform small studies ("transfer learning")
  - Principle: co-analyse studies, leverage joint representations
- Mega-analysis: find semantic commonalities across studies
  - Difficulty: what common vocabulary across studies?

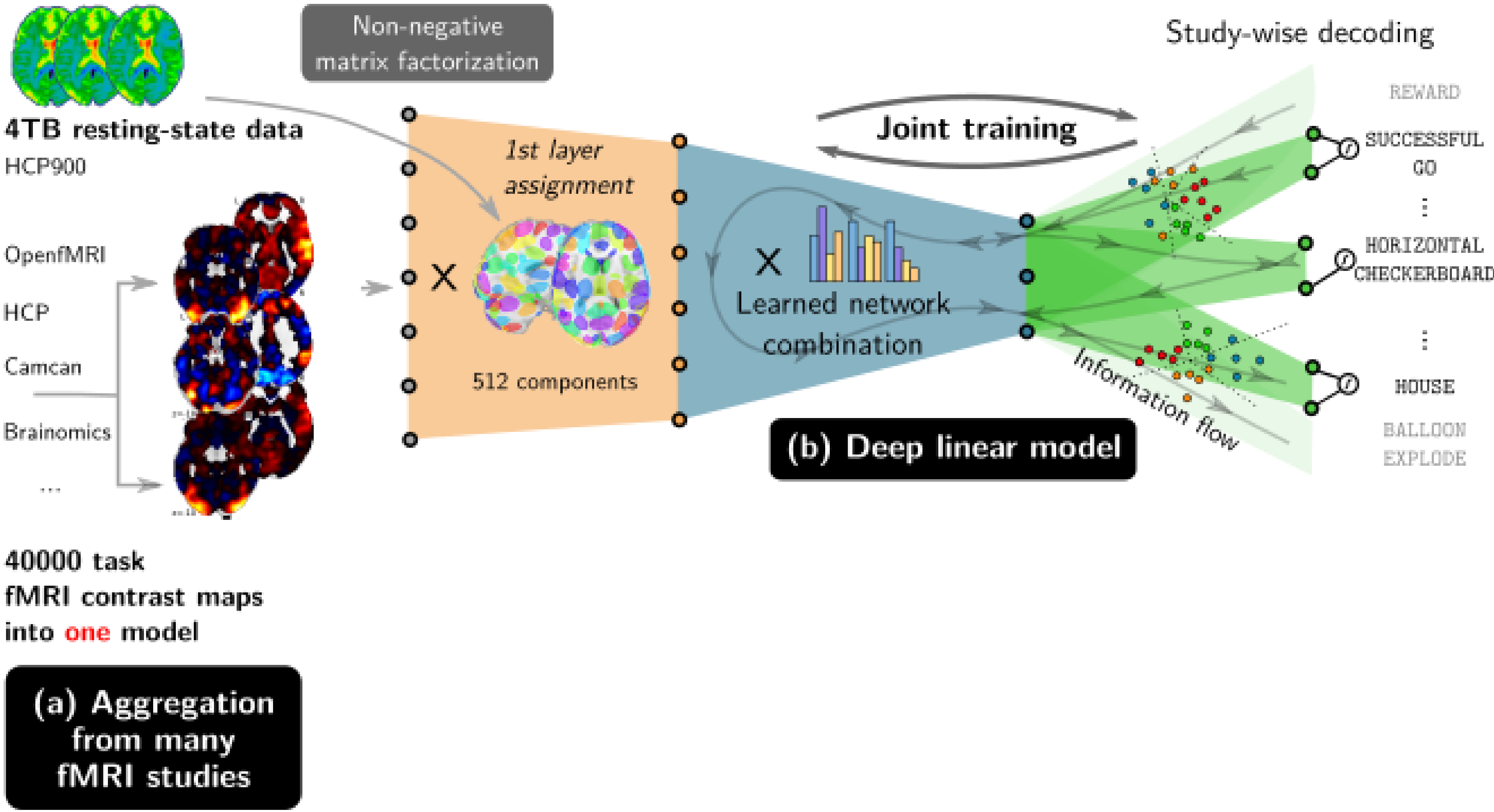
Large studies to inform analysis of small studies: *joint analysis*

Predictive modeling across datasets



[Bzdok et al. Plos Comp Biol 2016, Mensch et al NIPS 2017]

Predictive modeling across datasets



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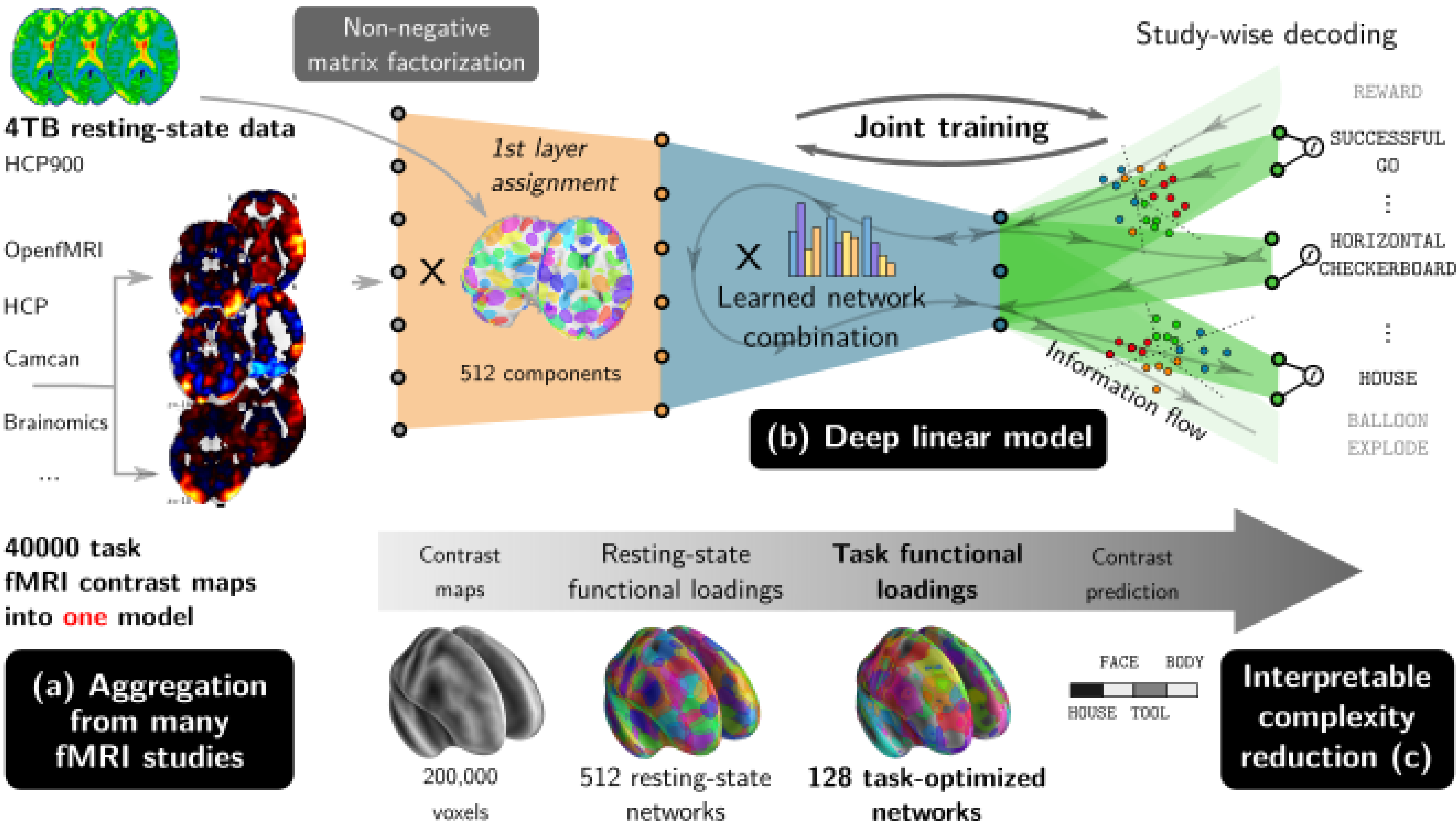

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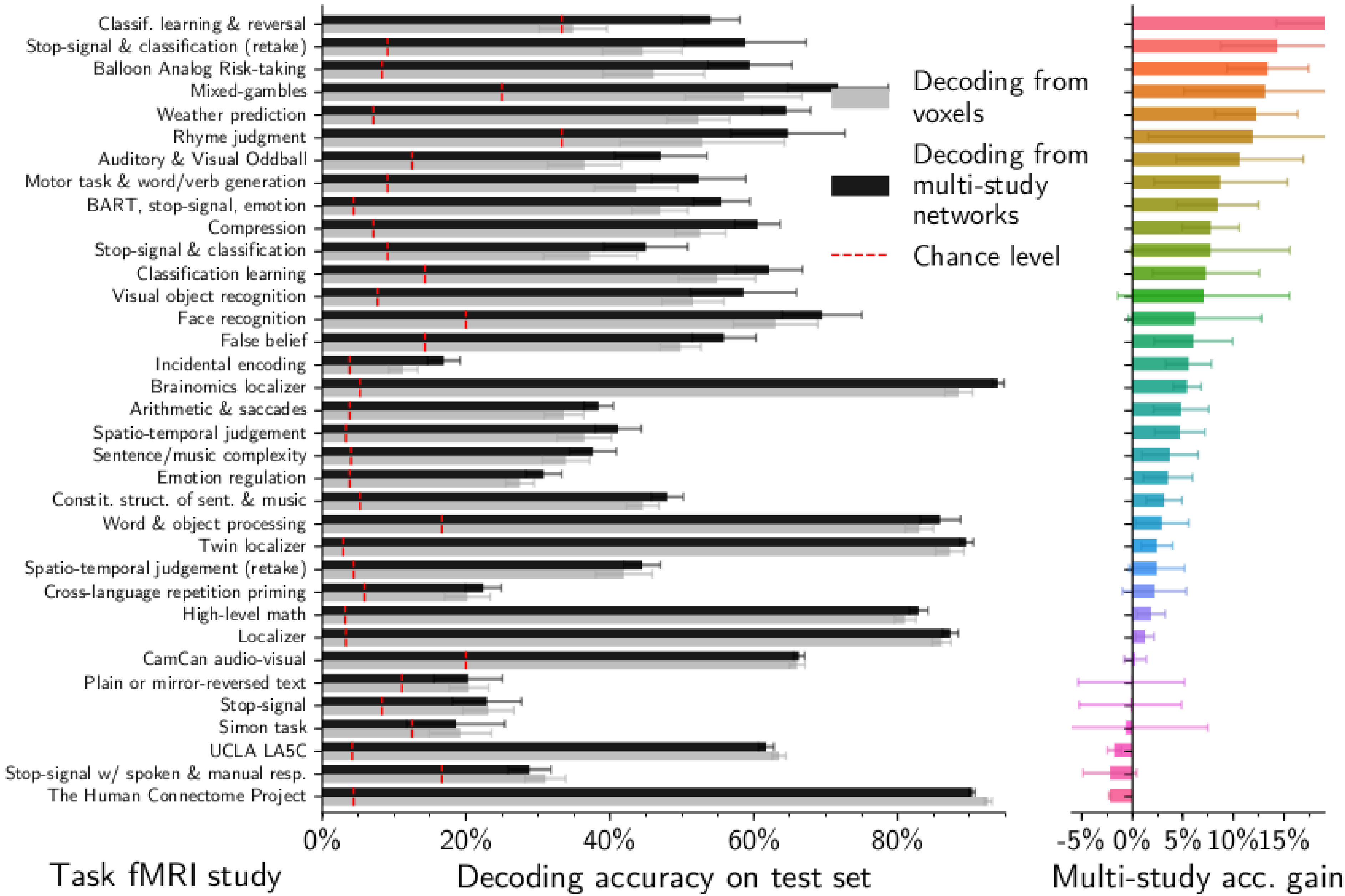
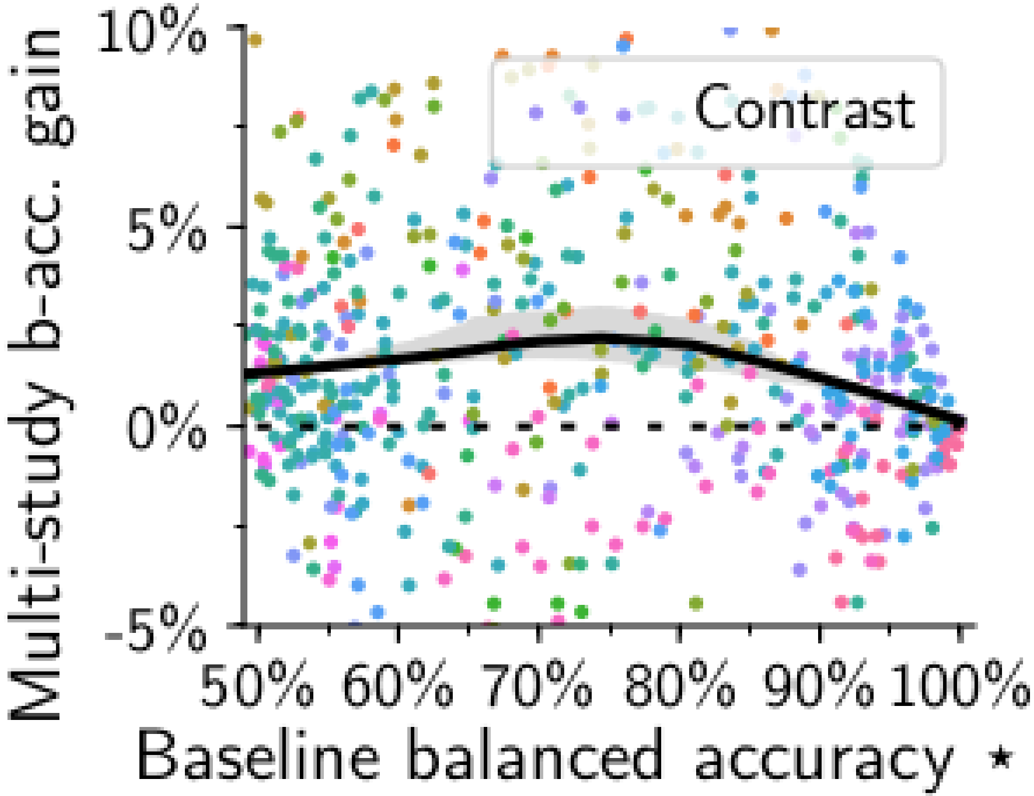
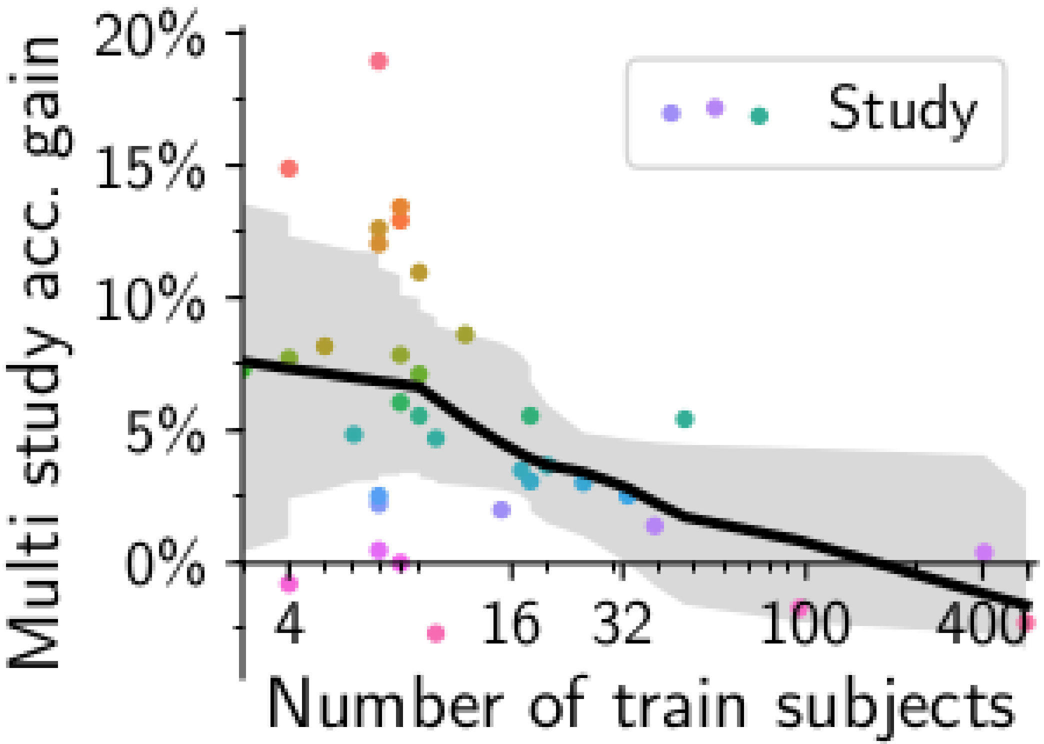
Transfer learning

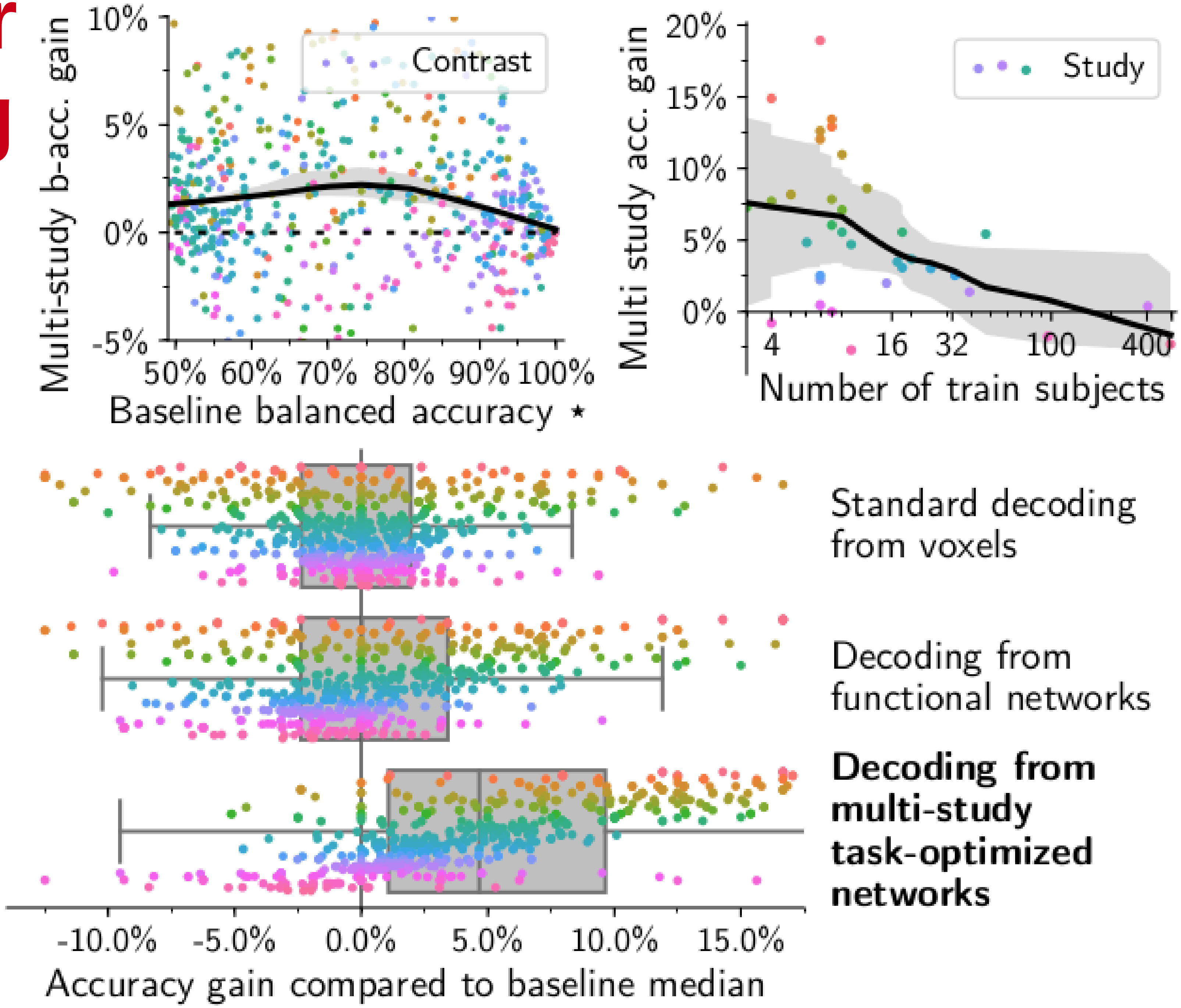


Transfer learning

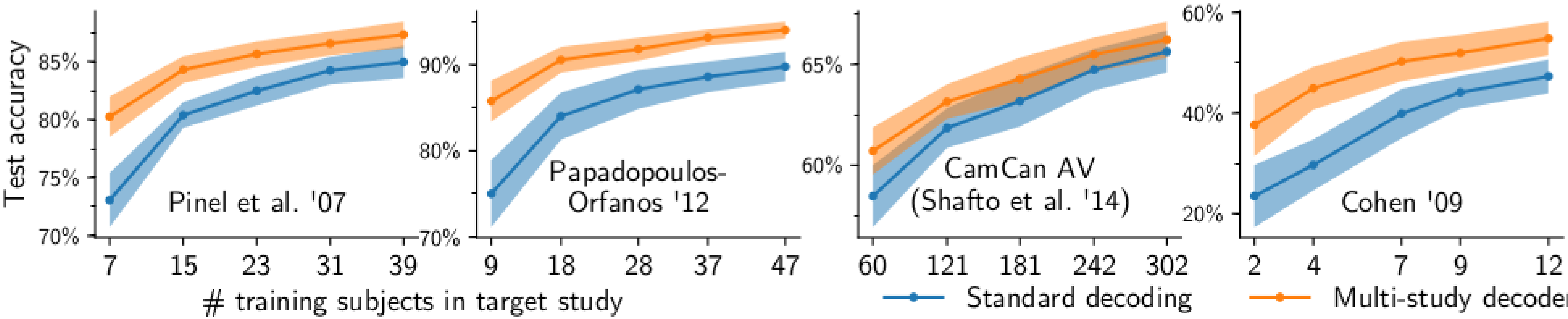




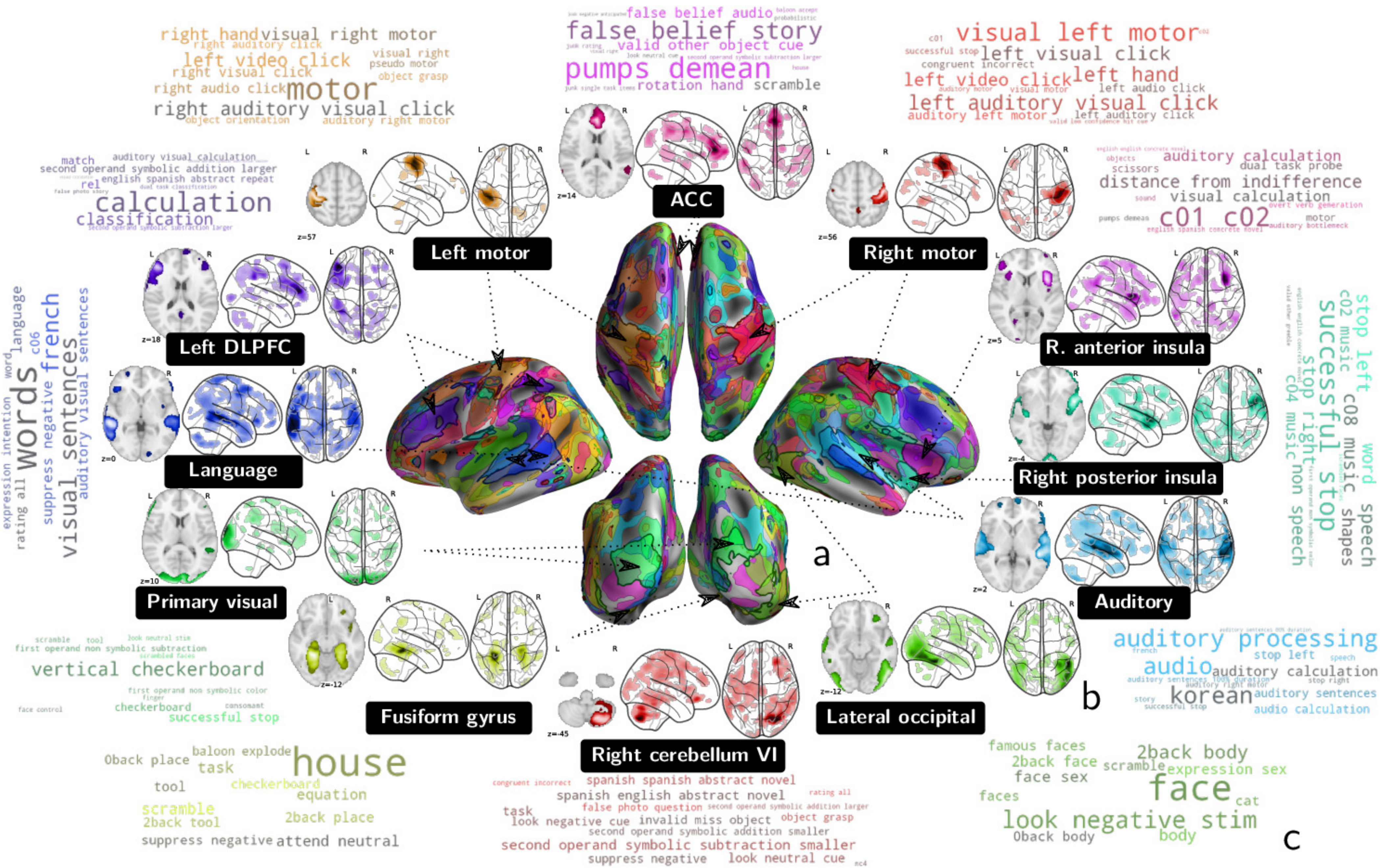
Transfer learning



Small studies benefit more than large studies



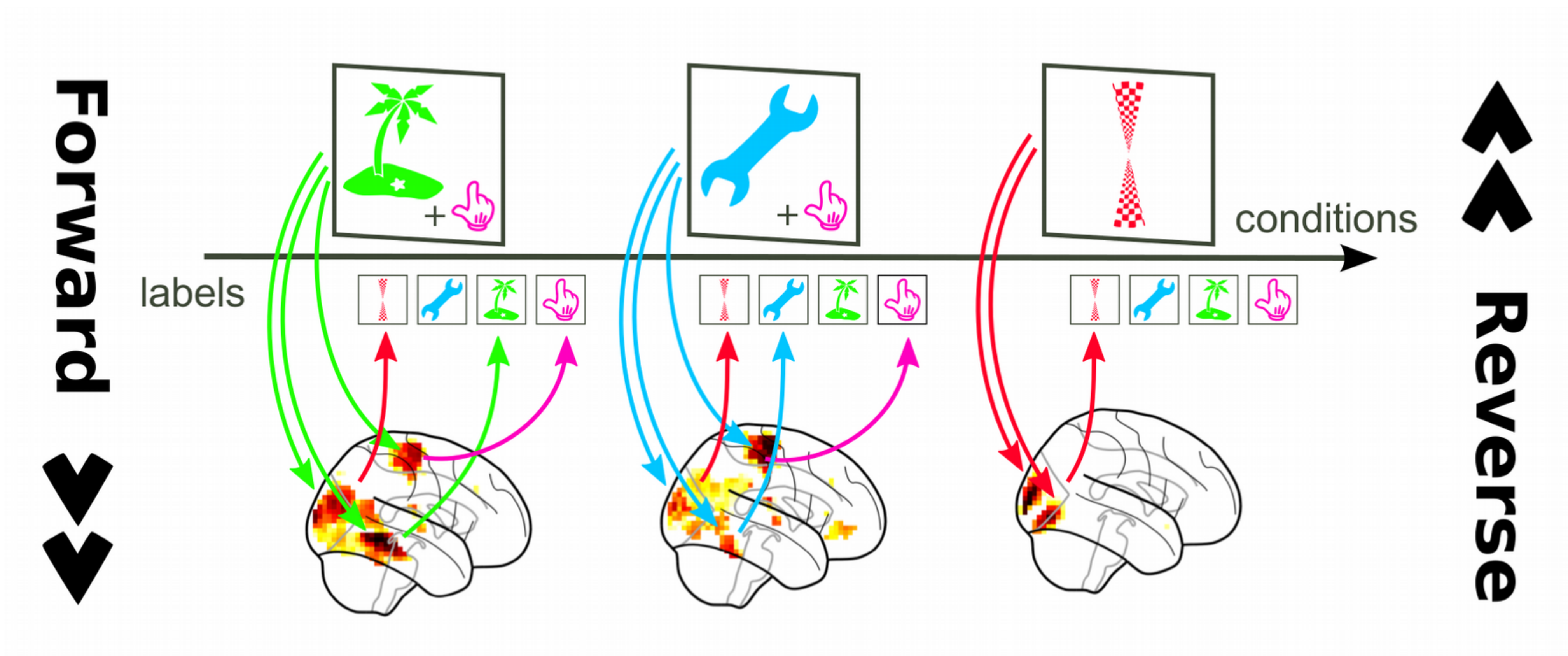
Resulting atlas



Mega-analyses

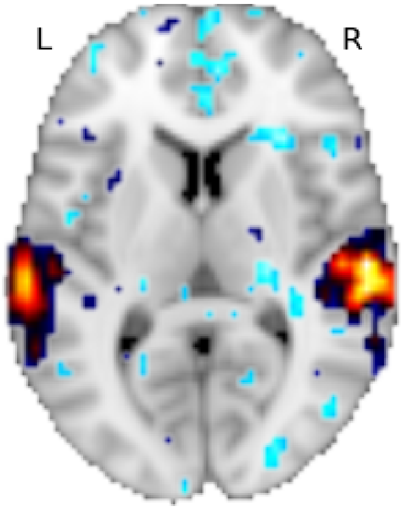
[Costafreda et al. Front. Neuroinf. 2009]

Indentifying cognitive tasks in brain activity



In the wild brain activity decoding

?

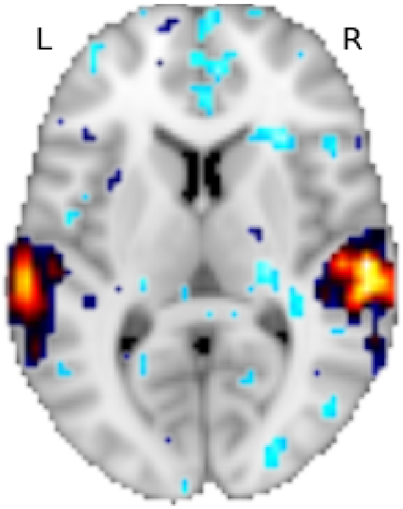


What is this brain doing?

Which regions are predictive of tasks containing a given term?

In the wild brain activity decoding

?



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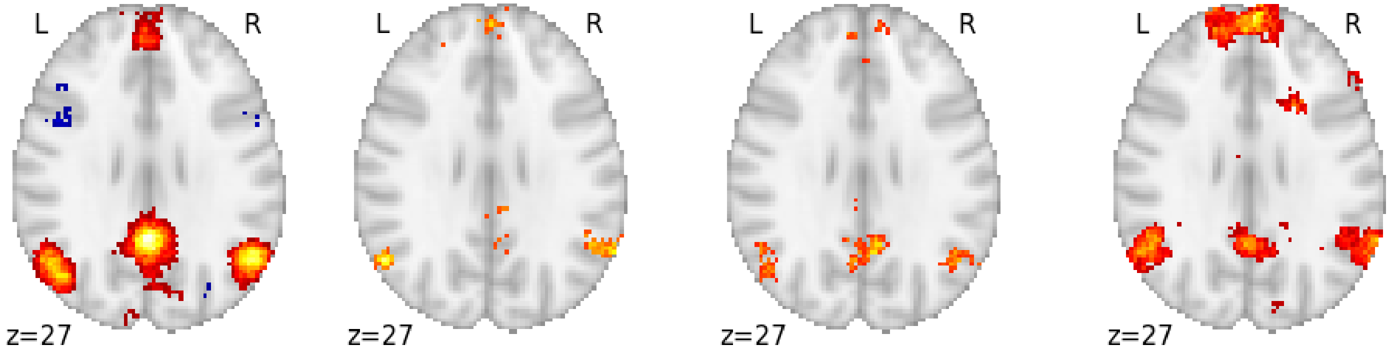


Default mode moral self-referential Theory of mind

An image database

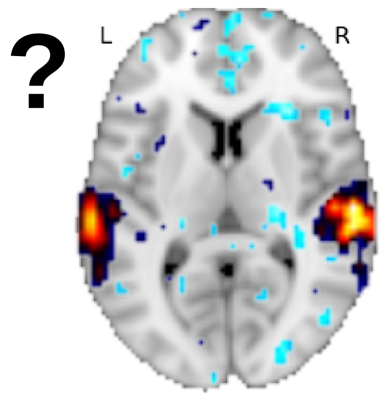
Task fMRI repository
[Gorgolewski et al. 2015]

Currently 48k independent usable fMRIs

[Poldrack 2011], knowledge-base

- *concepts*: cognitive activity/state (e.g. working memory)
- *tasks*: standard experiment to probe it (e.g. n-back task)

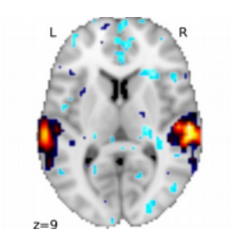
Open-ended brain decoding



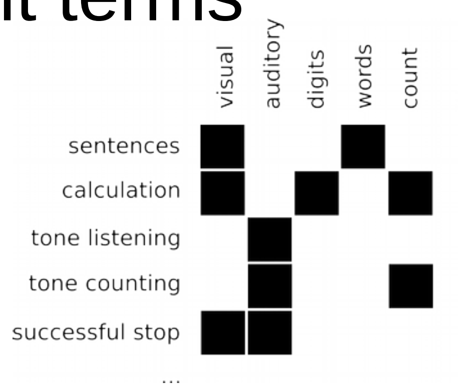
What is
this brain doing?

Which regions are predictive of tasks containing a given term?

- **Multilabel** classification problem
  - more than one class may be associated with each sample
- Predict occurrence of frequent terms

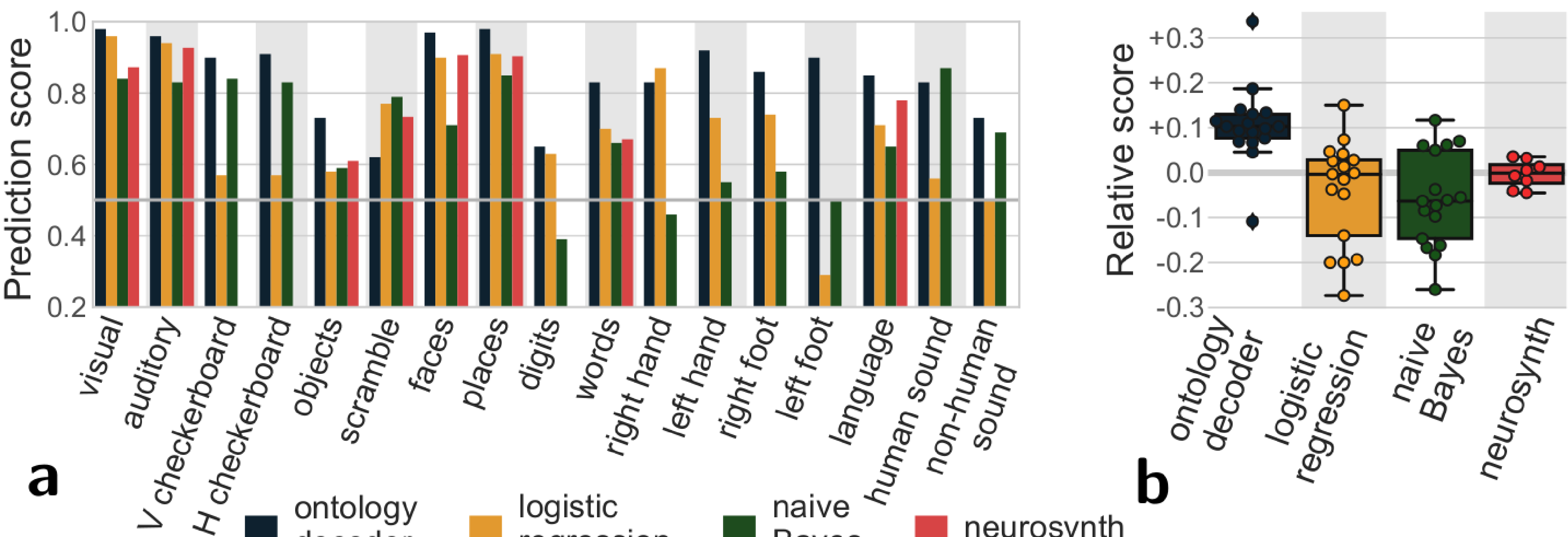


Data: experimental condition images



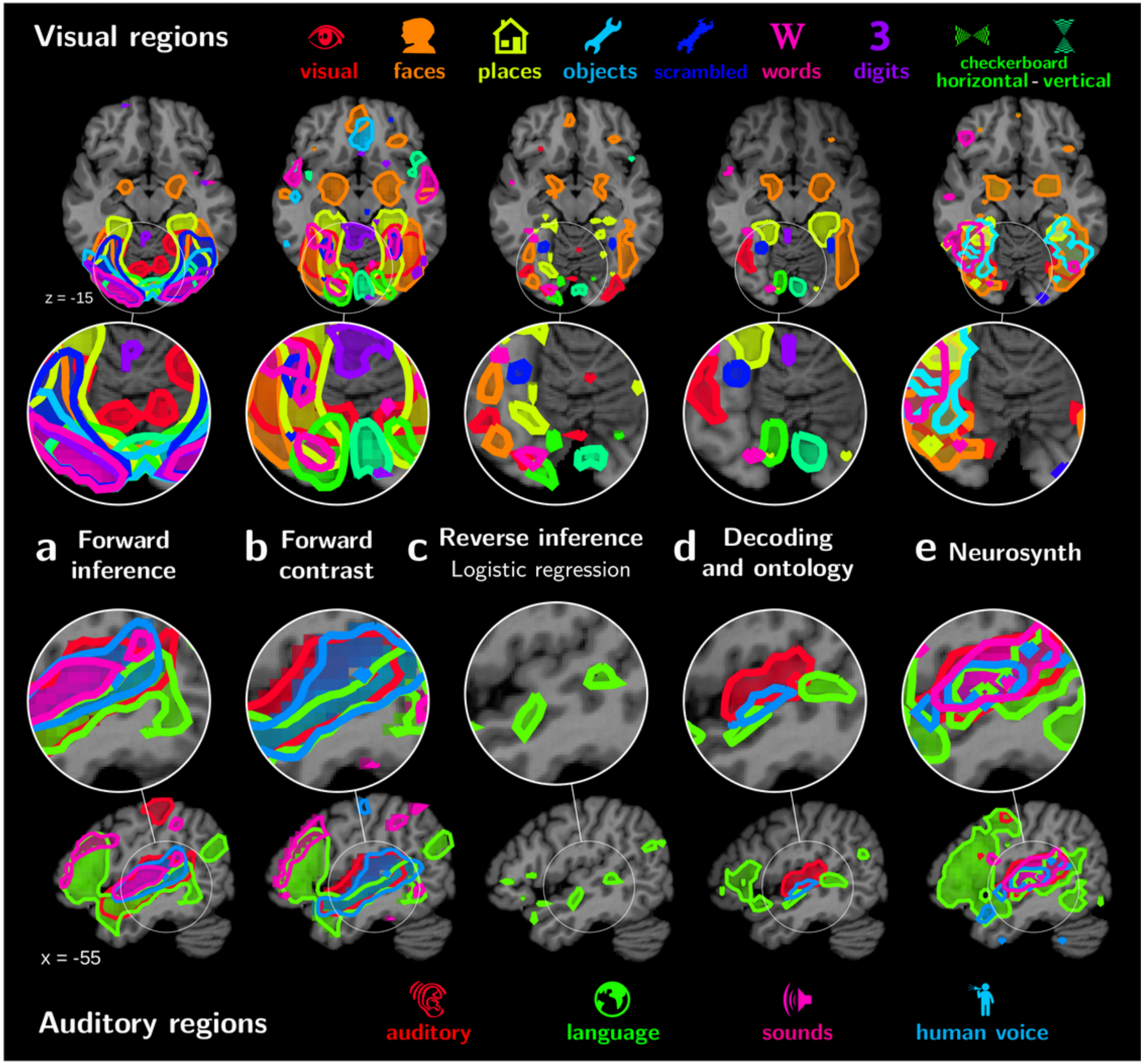
Target

Classification results

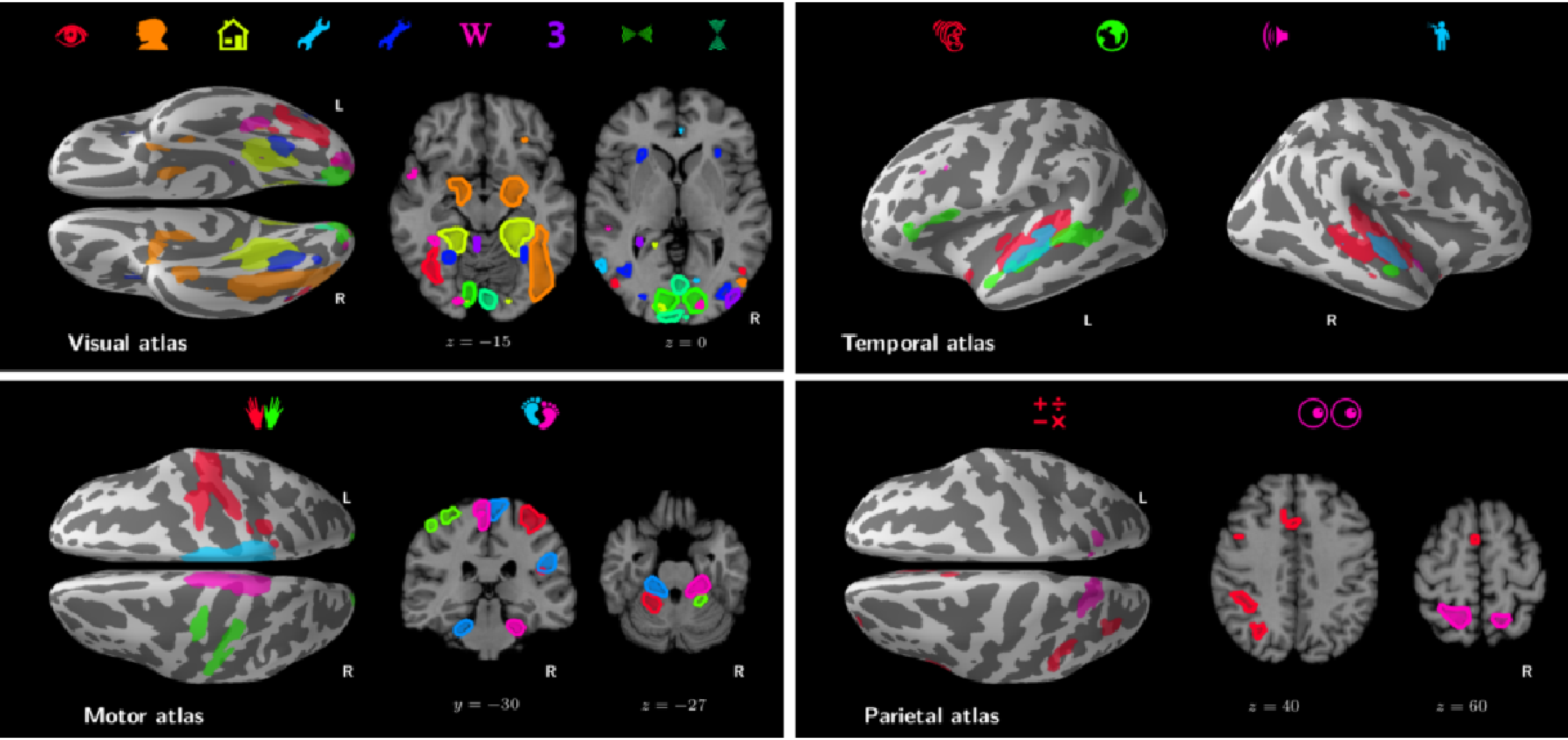


[Schwartz et al. NIPS 2013, Varoquaux et al. PCB 2018]

Decoding maps

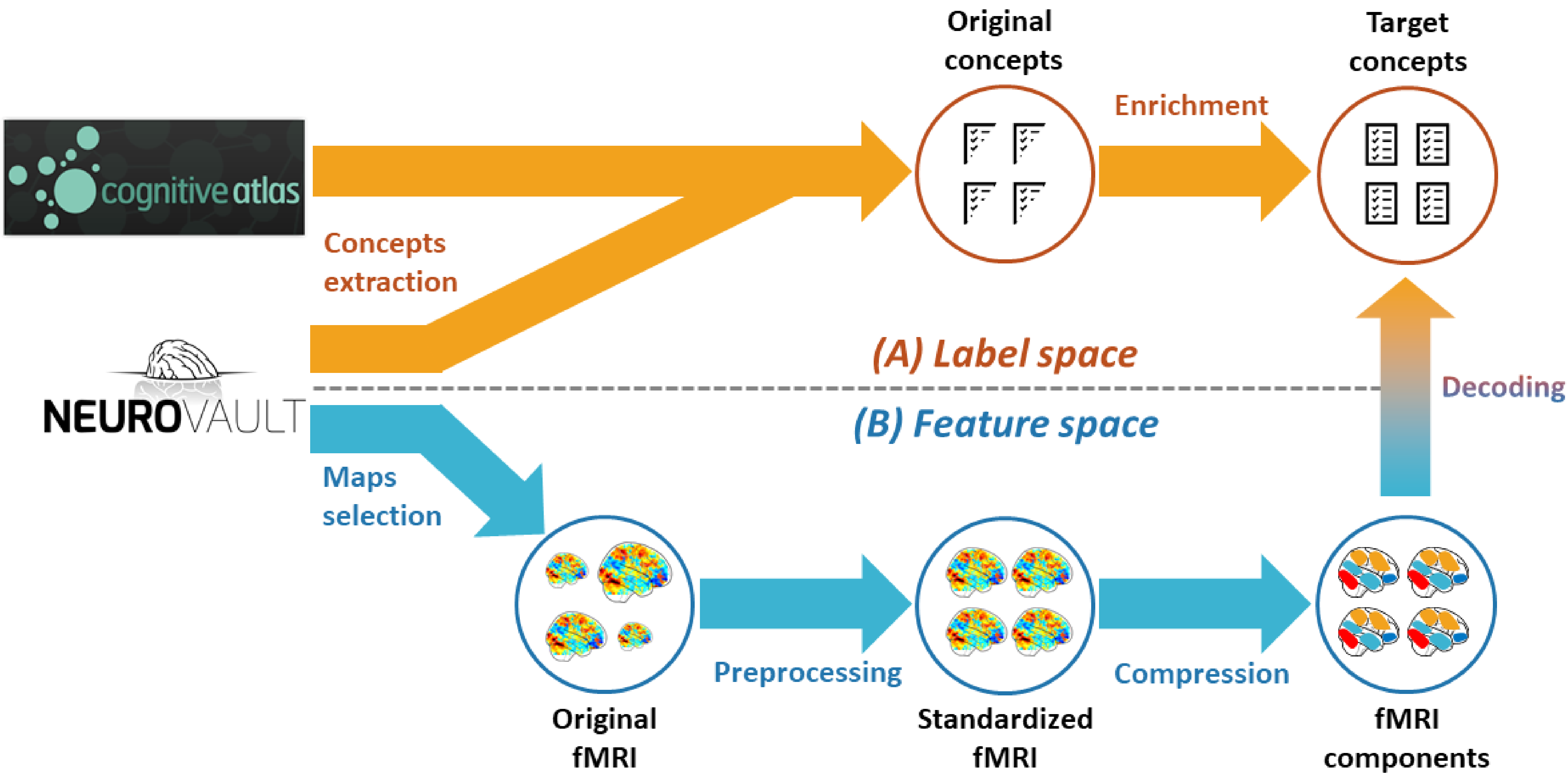


Discriminative patterns

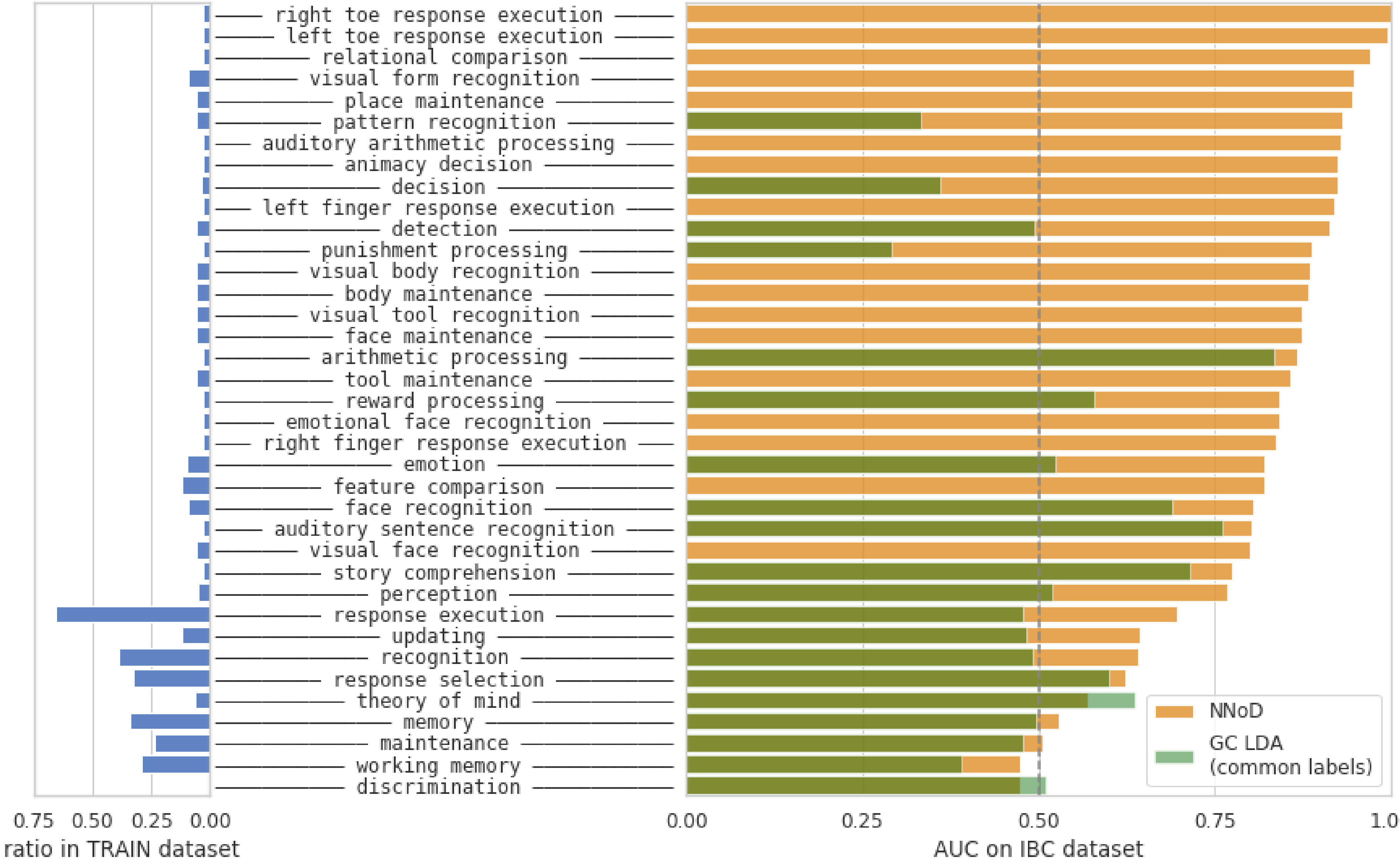


[Schwartz et al. NIPS 2013, Varoquaux et al. PCB 2018.]

Our pipeline



Results (naive approach)

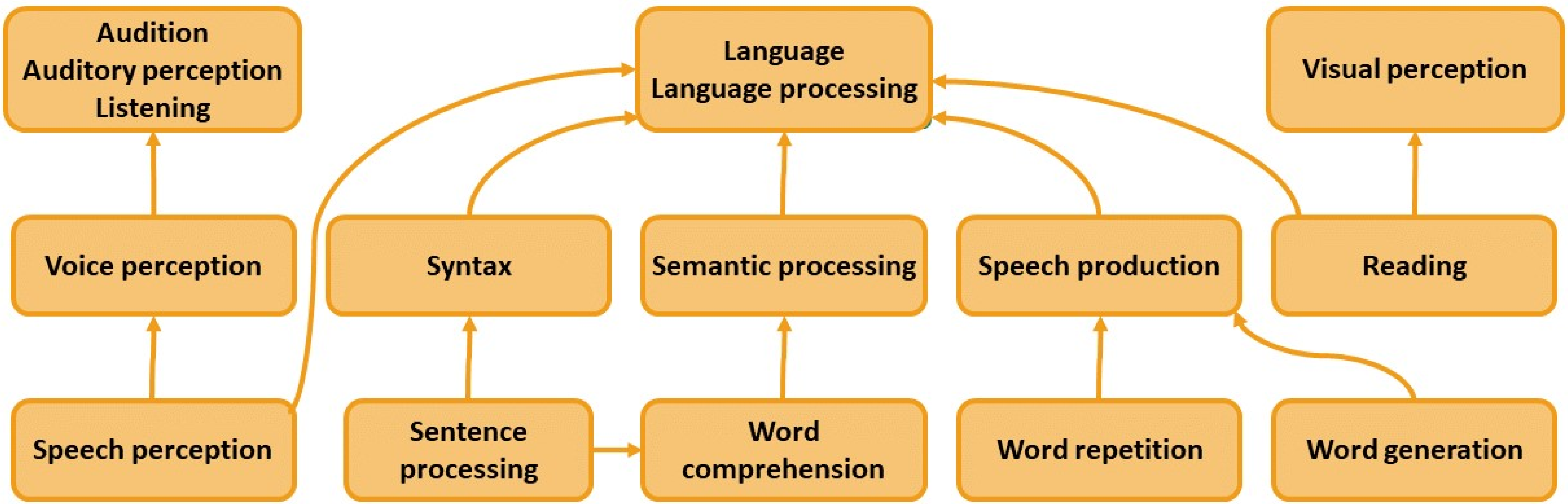


Fixing labels

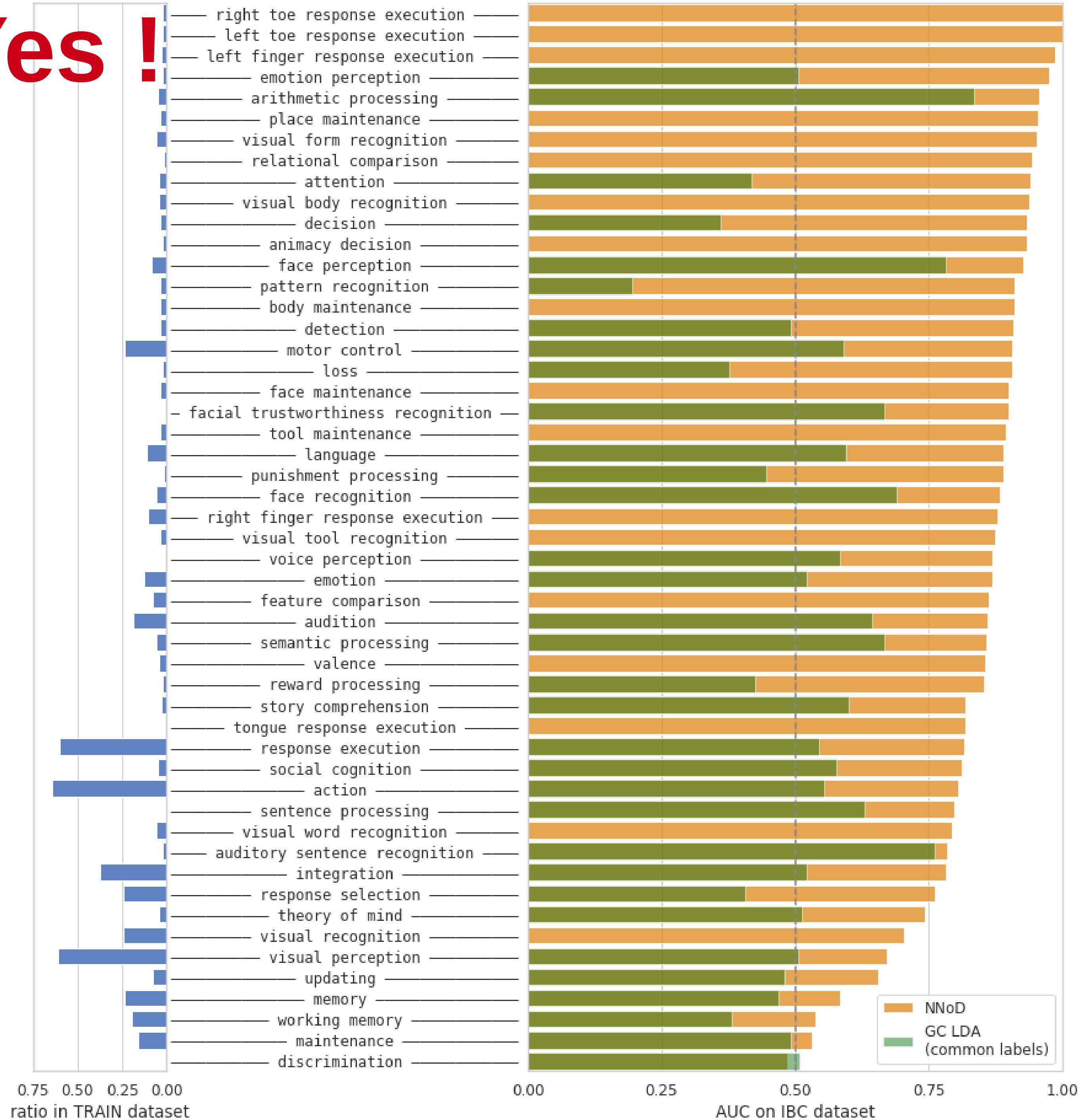
Problem:

synonims, false negatives (missing annotations)

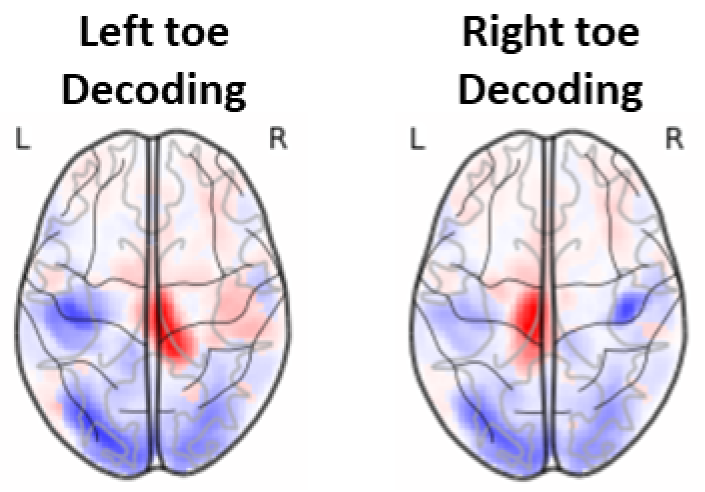
→ **Simple rules to impute labels:**



Results (2): Yes !

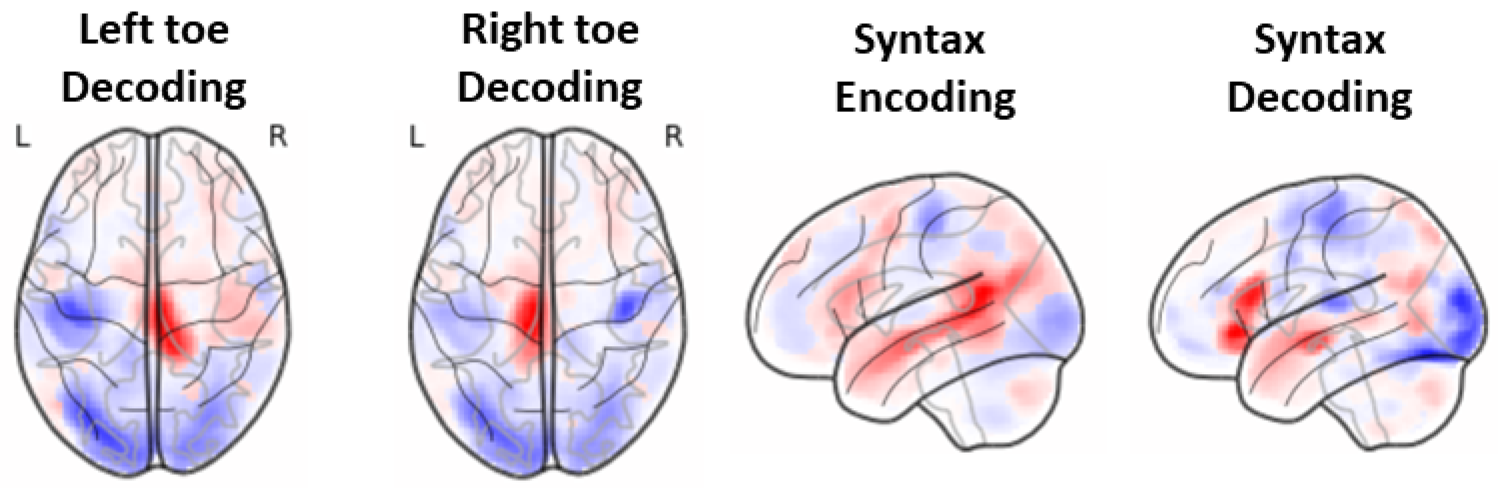


Open the box



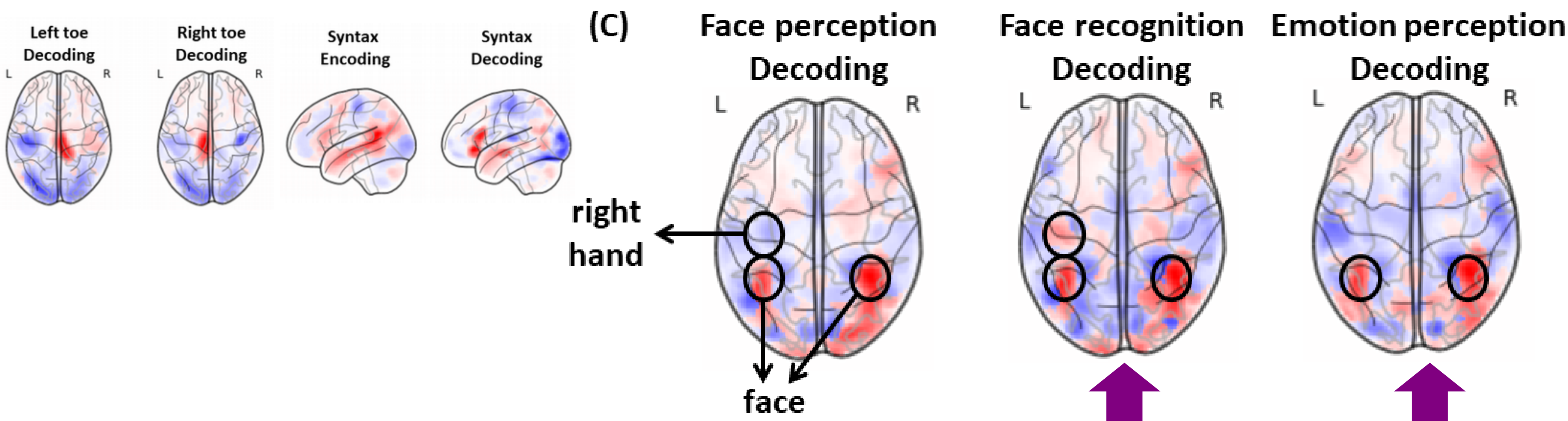
Non-controversial case

Open the box



decoding > encoding

Open the box



Experimental biases

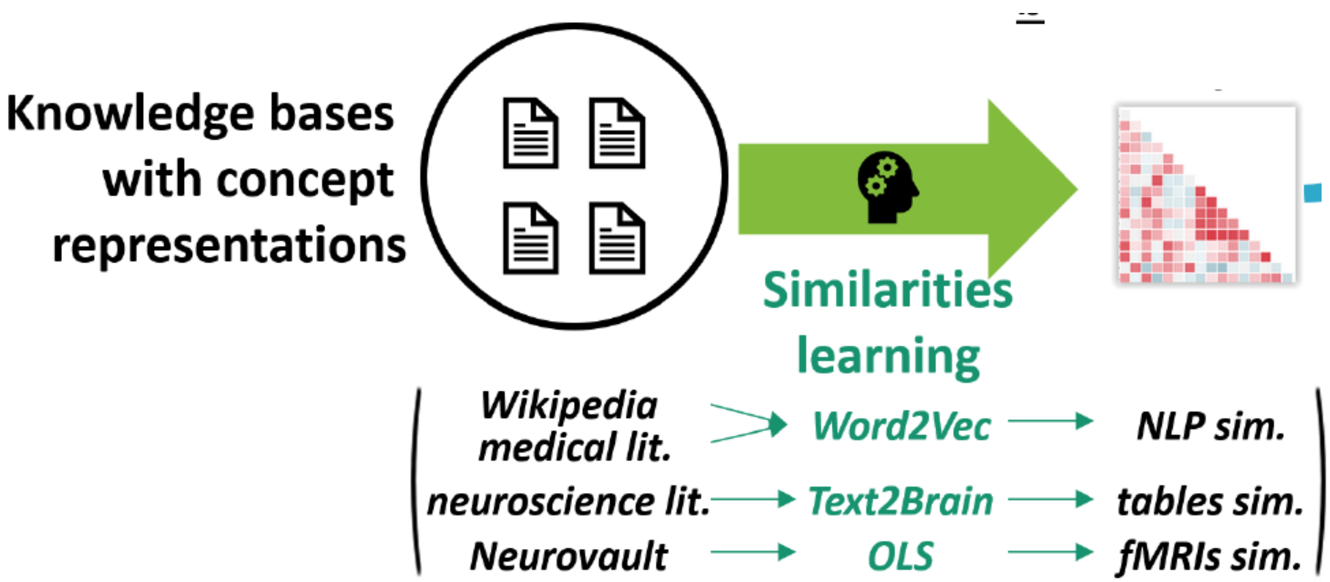
[Menuet et al. In prep]

Find good image annotations

Mining the neuroscientific literature

Need curated annotations

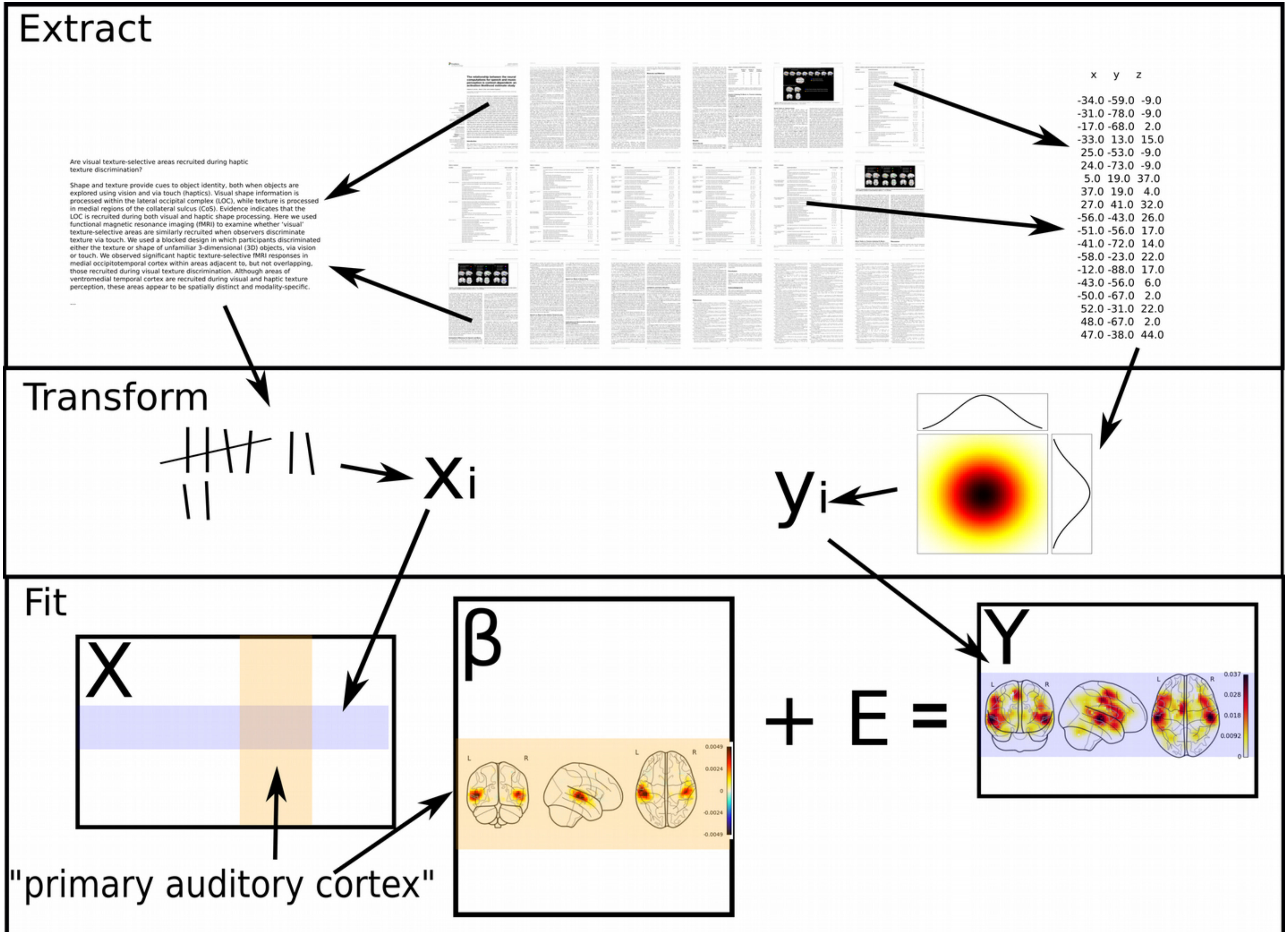
- Current ontology incomplete
- Bigger limitation = lack of consistent vocabulary
  [Poldrack & Yarkoni, Annu Rev Psycho 2016]
- How to get those ?



Mining neuroimaging literature

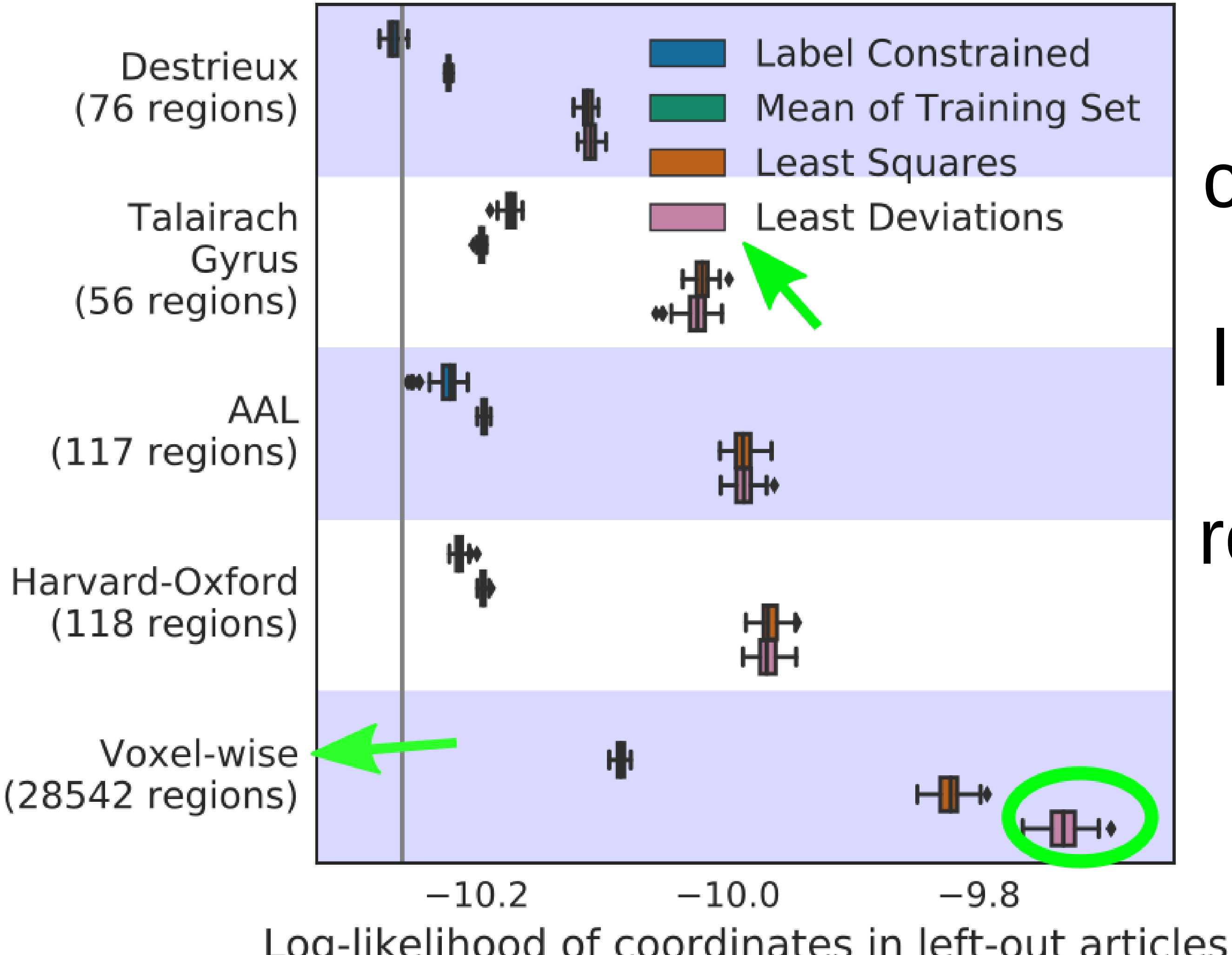
- Neuroimaging observations often stored in text.
- e.g “[...] in the anterolateral temporal cortex, especially the temporal pole and inferior and middle temporal gyri”
- Objectives:
  - transform neuroimaging publications into brain maps
  - meta-analysis of text-only corpora

“Text2brain”



Extract
Are visual texture-selective areas recruited during haptic texture discrimination?
Shape and texture provide cues to object identity, both when objects are explored using vision and via touch (haptics). Visual shape information is processed within the lateral occipital complex (LOC), while texture is processed in medial regions of the collateral sulcus (CoS). Evidence indicates that the LOC is recruited during both visual and haptic shape processing. Here we used functional magnetic resonance imaging (fMRI) to examine whether 'visual' texture-selective areas are similarly recruited when observers discriminate texture via touch. We used a blocked design in which participants discriminated either the texture or shape of unfamiliar 3-dimensional (3D) objects, via vision or touch. We observed significant haptic texture-selective fMRI responses in medial occipitotemporal cortex within areas adjacent to, but not overlapping, those recruited during visual texture discrimination. Although areas of ventromedial temporal cortex are recruited during visual and haptic texture perception, these areas appear to be spatially distinct and modality-specific.
...
x y z
-34.0 -59.0 -9.0
-31.0 -78.0 -9.0
-17.0 -68.0 2.0
-33.0 13.0 15.0
25.0 -53.0 -9.0
24.0 -73.0 -9.0
5.0 19.0 37.0
37.0 19.0 4.0
27.0 41.0 32.0
-56.0 -43.0 26.0
-51.0 -56.0 17.0
-41.0 -72.0 14.0
-58.0 -23.0 22.0
-12.0 -88.0 17.0
-43.0 -56.0 6.0
-50.0 -67.0 2.0
52.0 -31.0 22.0
48.0 -67.0 2.0
47.0 -38.0 44.0
Transform
xi
yi
Fit
X
β
+ E =
Y
"primary auditory cortex"

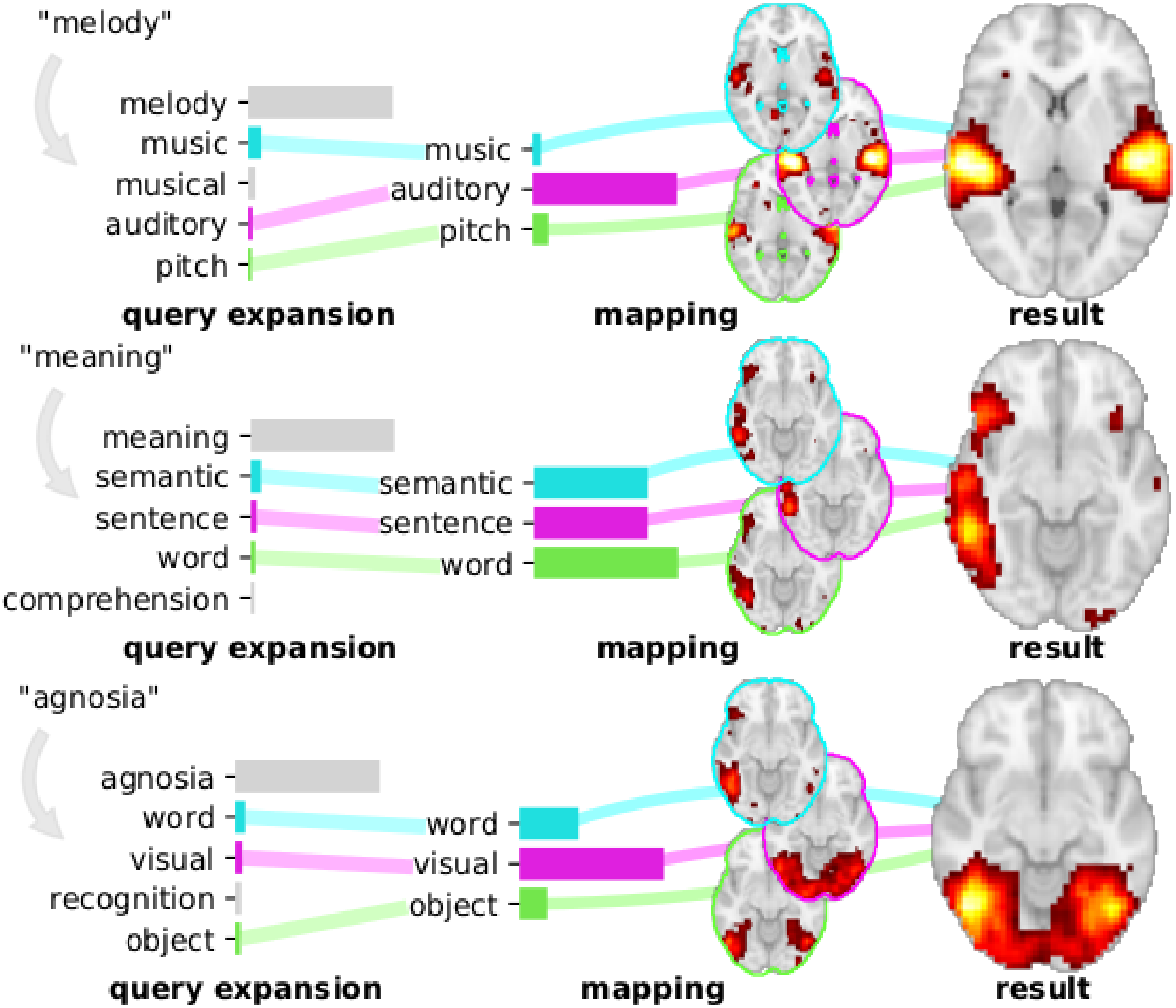
Text2brain



Learning statistical correspondences across the literature is more effective than relying on atlases !

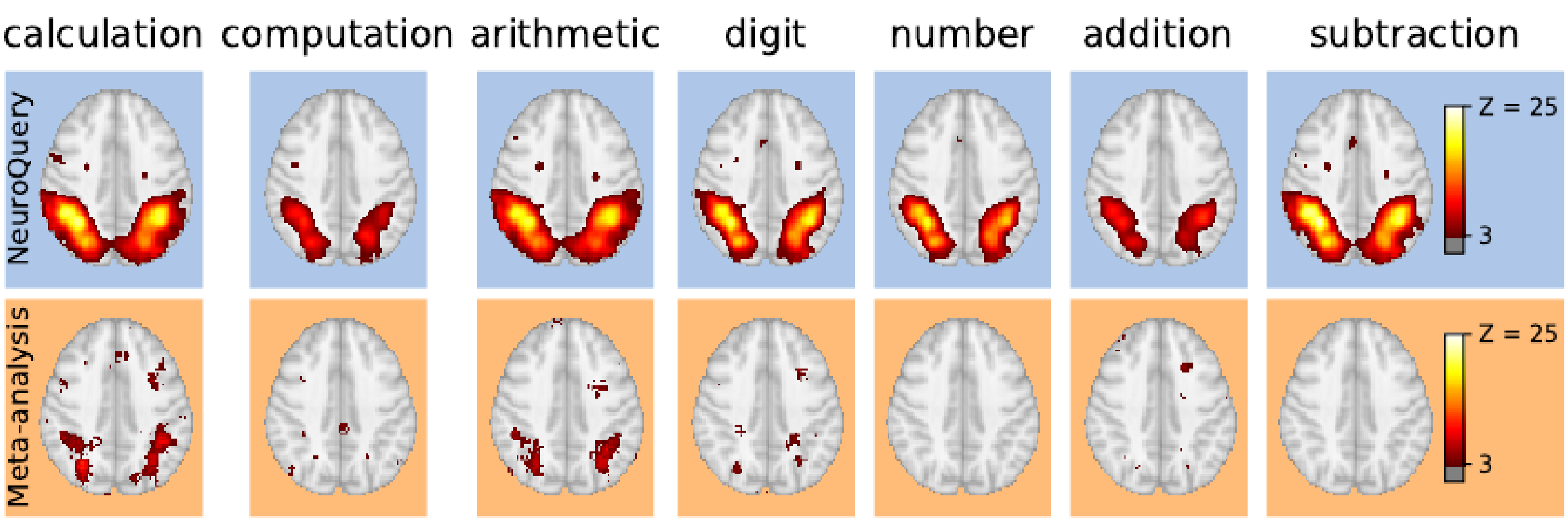
[Dockès et al. MICCAI 2018]

Leveraging semantics for better encoding



Semantic structure
→ map concepts with few/no data

Neuroquery

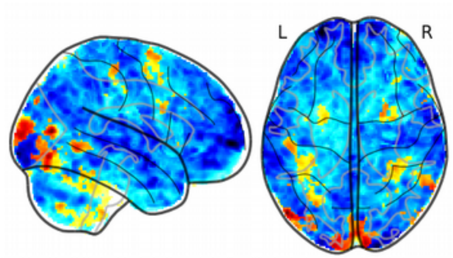


https://neuroquery.saclay.inria.fr

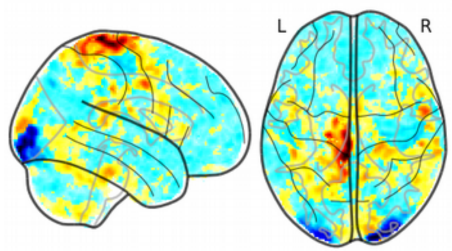
[Dockès et al. Subm to Elife]

Get more good public images !

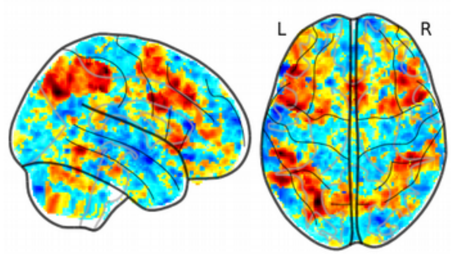
Importance of annotations



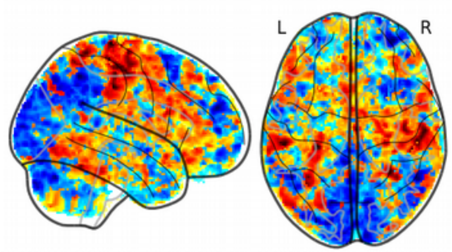
response execution, working memory, updating, body maintenance, visual body recognition,



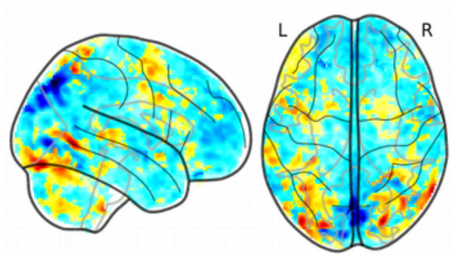
response execution, right toe response execution,



visual arithmetic processing, sentence processing,



response selection, response execution, right finger response execution, visual tool recognition, grasping,



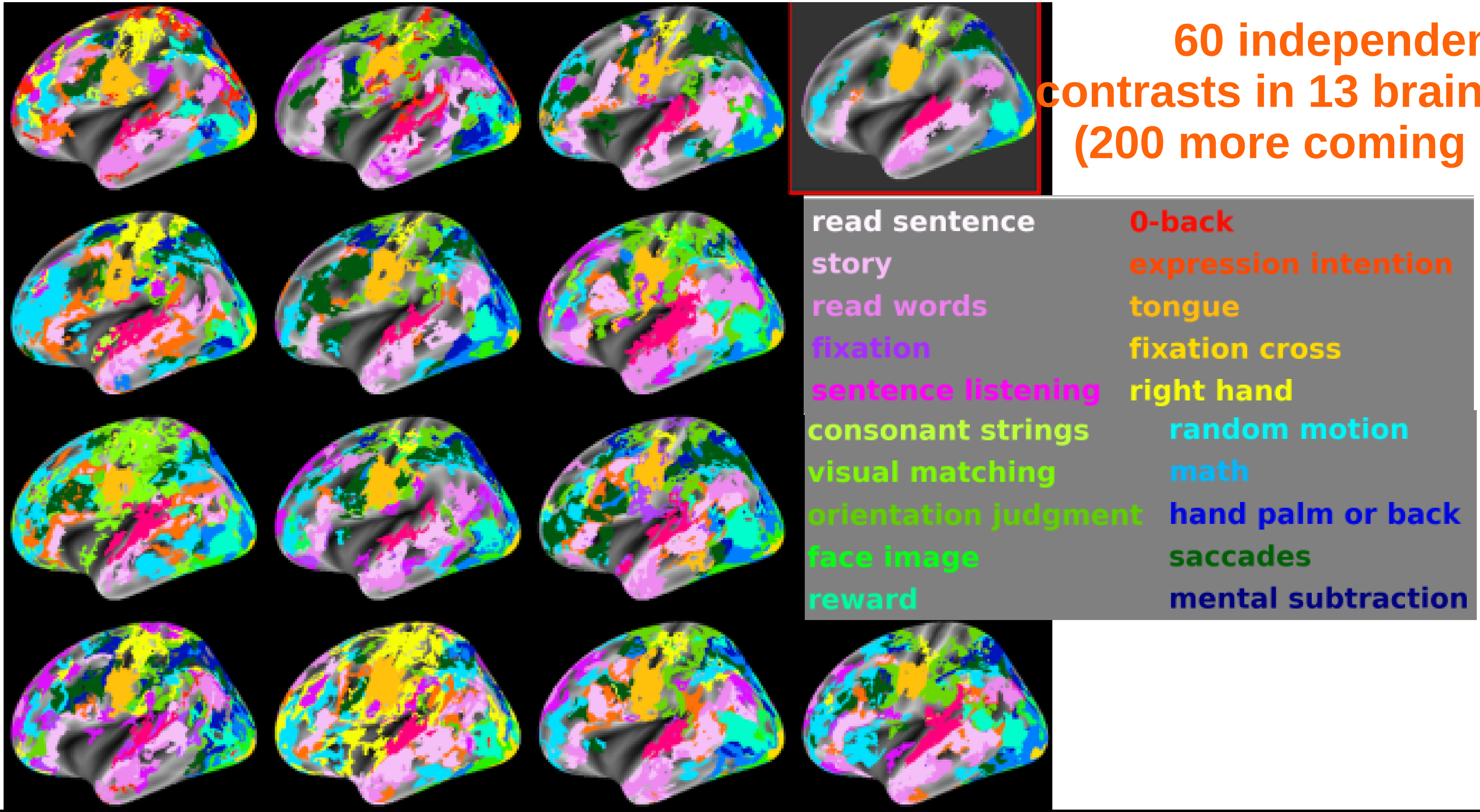
working memory, visual word recognition, word maintenance, sentence processing, syntactic parsing,

IBC in a nutshell

- 13 subjects
- About 30 acquisitions completed per subject
- Mostly fMRI, plus diffusion, relaxometry, high resolution anat
- 1.5mm isotropic resolution for fMRI
- Retinotopy, HCP/archi/Lyon/stanford batteries, free movie watching/story listening, language, social/pain/self localizer, valuation system, self, numerosity, mental time travel, tonotopy

Please share your protocols !

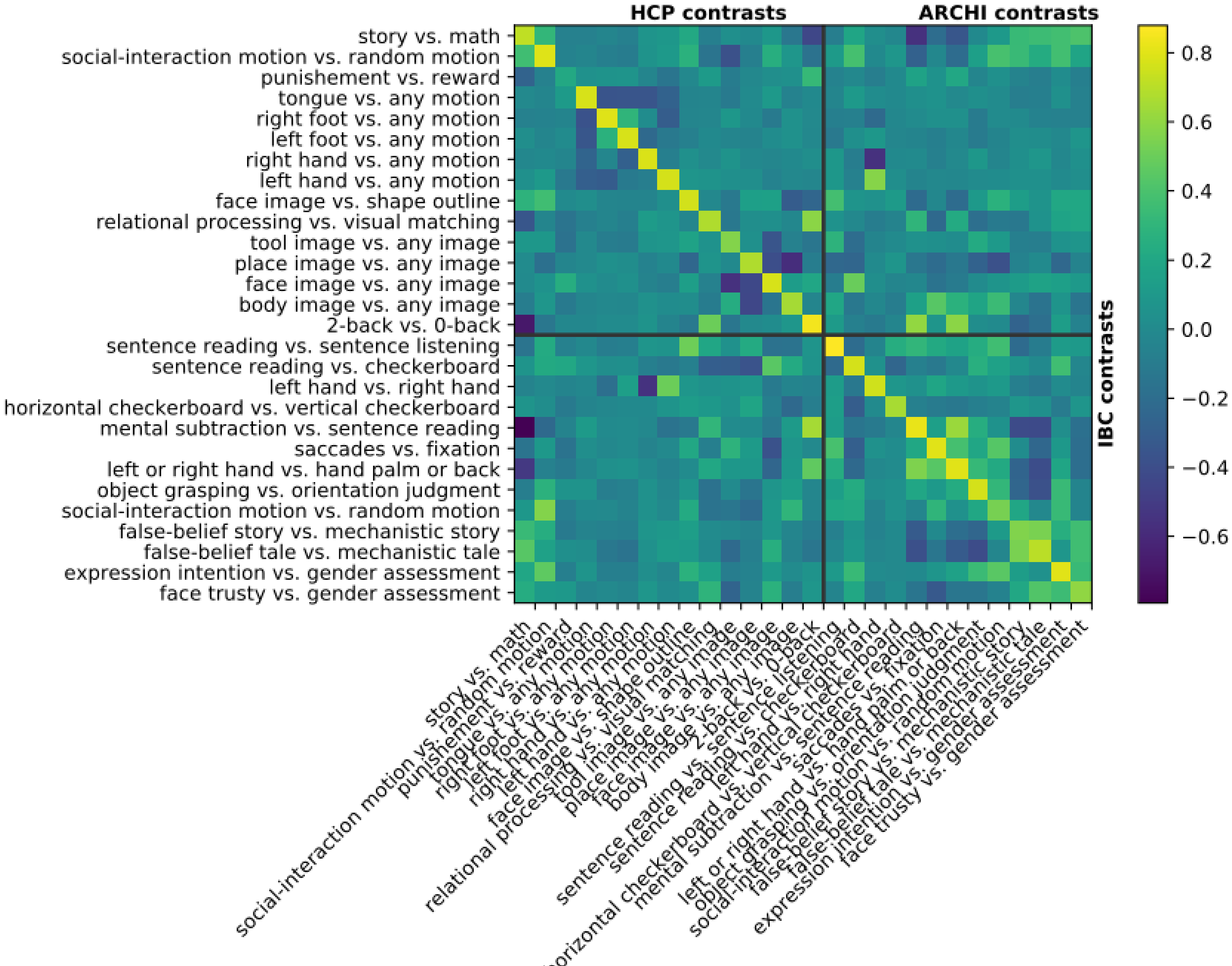
IBC: deeper phenotyping



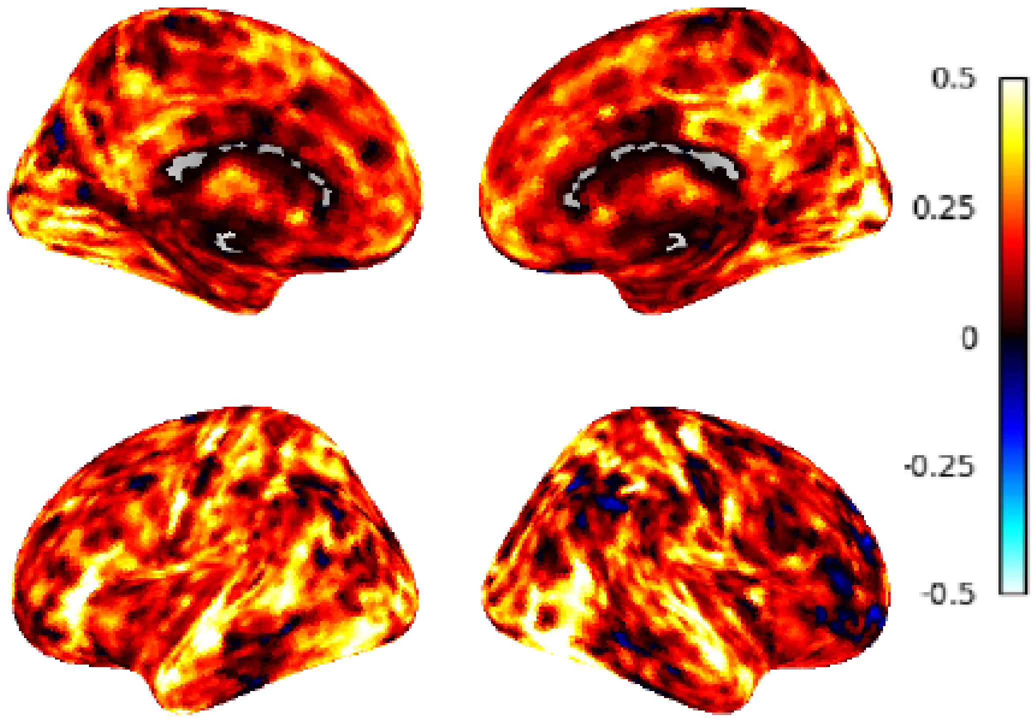
60 independent contrasts in 13 brains (200 more coming !)

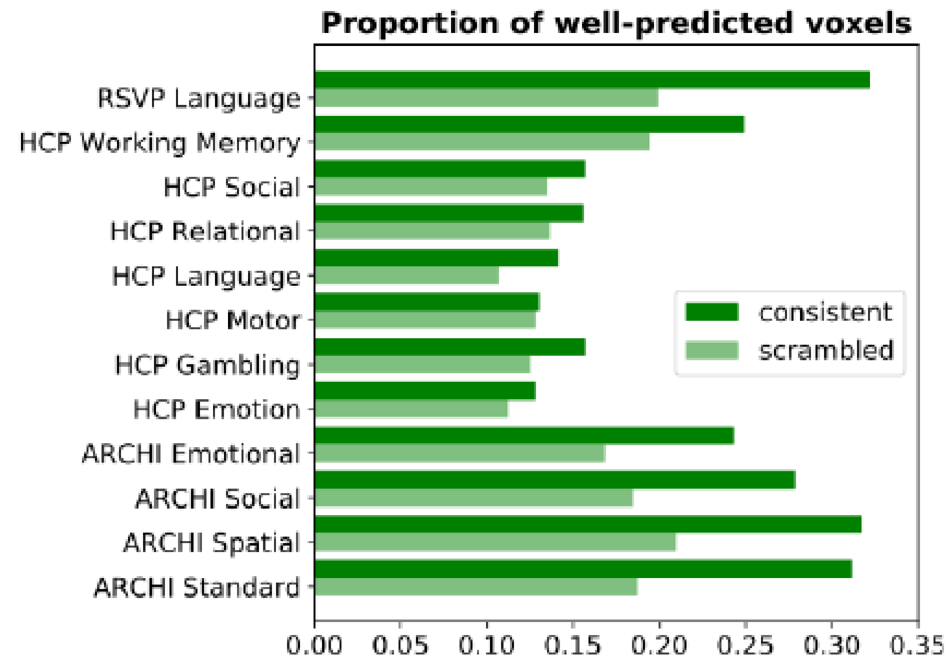
https://neurovault.org/collections/4438/ https://openneuro.org/datasets/ds000244

Reproduce previous experiments



Structure underlying contrast maps





Prediction of the response for an unseen contrast, given other contrasts

Prediction per prtocol and subject dependence

Highly subject-specific response and contrast between primary and associative areas

Conclusion

- Joint decoding/encoding for better functional specificity
- Finding commonalities across cognitive studies is hard
- Big data approach:
  - Extract weak signals from huge amounts of data
  - Common representation across datasets (*bottleneck*)

WIP

- Structure underlying cognitive concepts

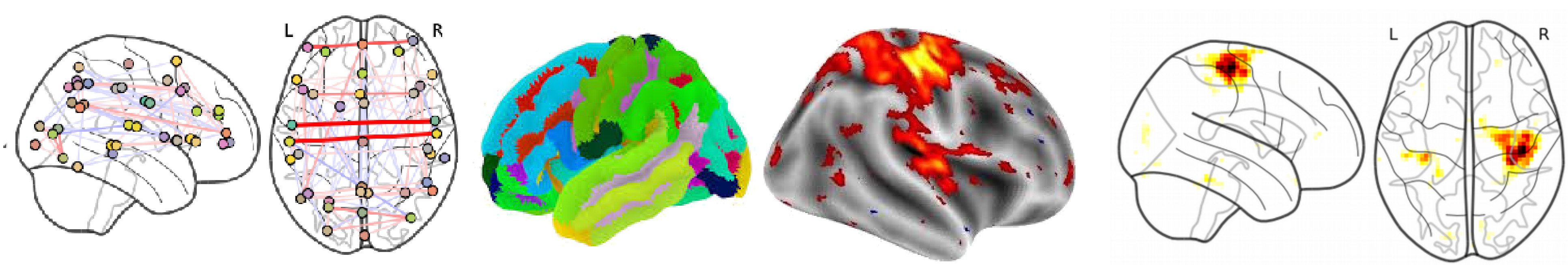
From good ideas to good practices: software

scikits learn
machine learning in Python

ni learn

MNE
MEG + EEG ANALYSIS & VISUALIZATION

- Machine learning in Python
- Machine learning for neuroimaging
  http://nilearn.github.io
- BSD, Python, OSS
  - Classification of (neuroimaging) data
  - Network analysis



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Human Brain Project

université PARIS-SACLAY

AGENCE NATIONALE DE LA RECHERCHE ANR