Understanding brain function with machine learning on large-scale data repositories

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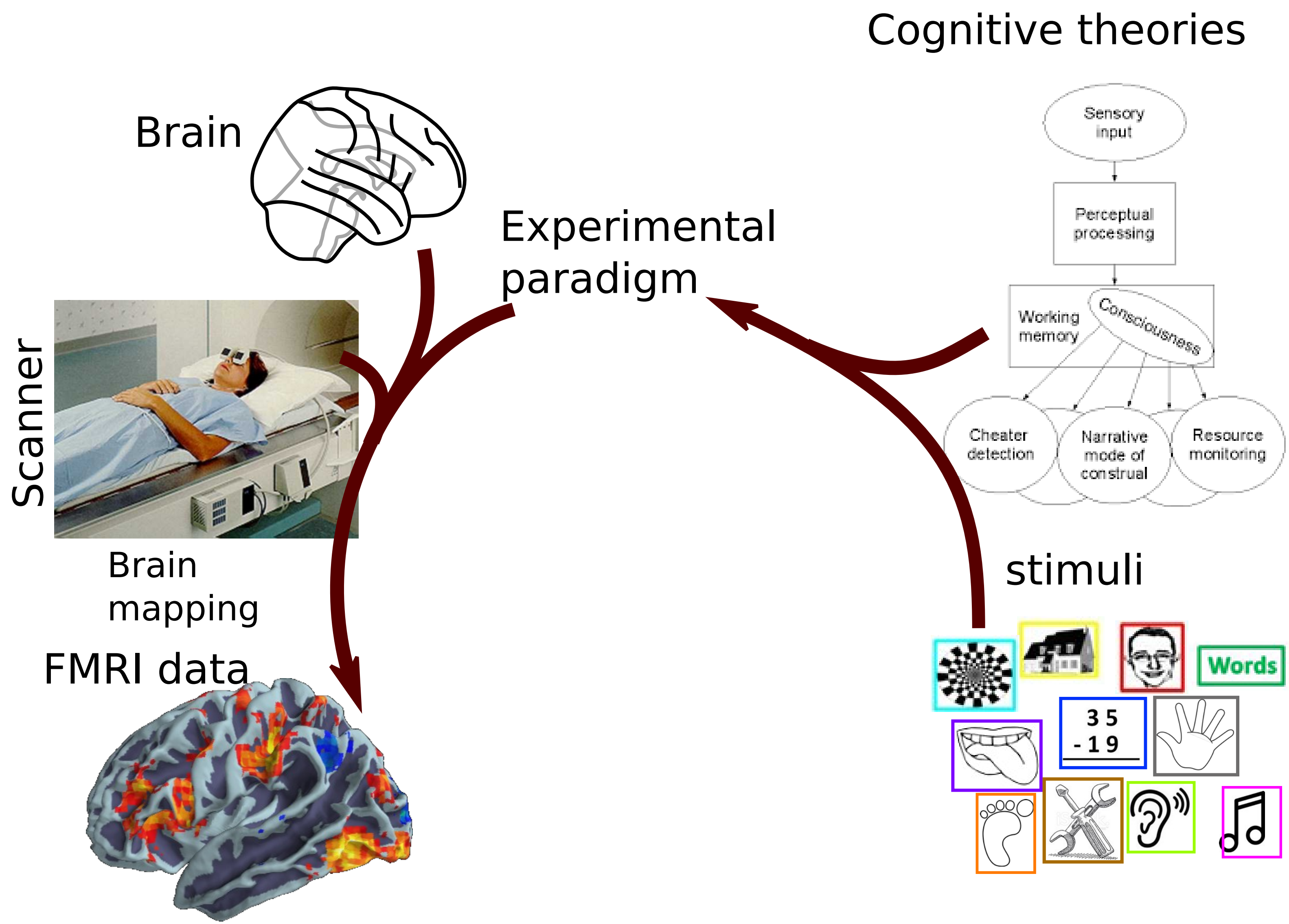
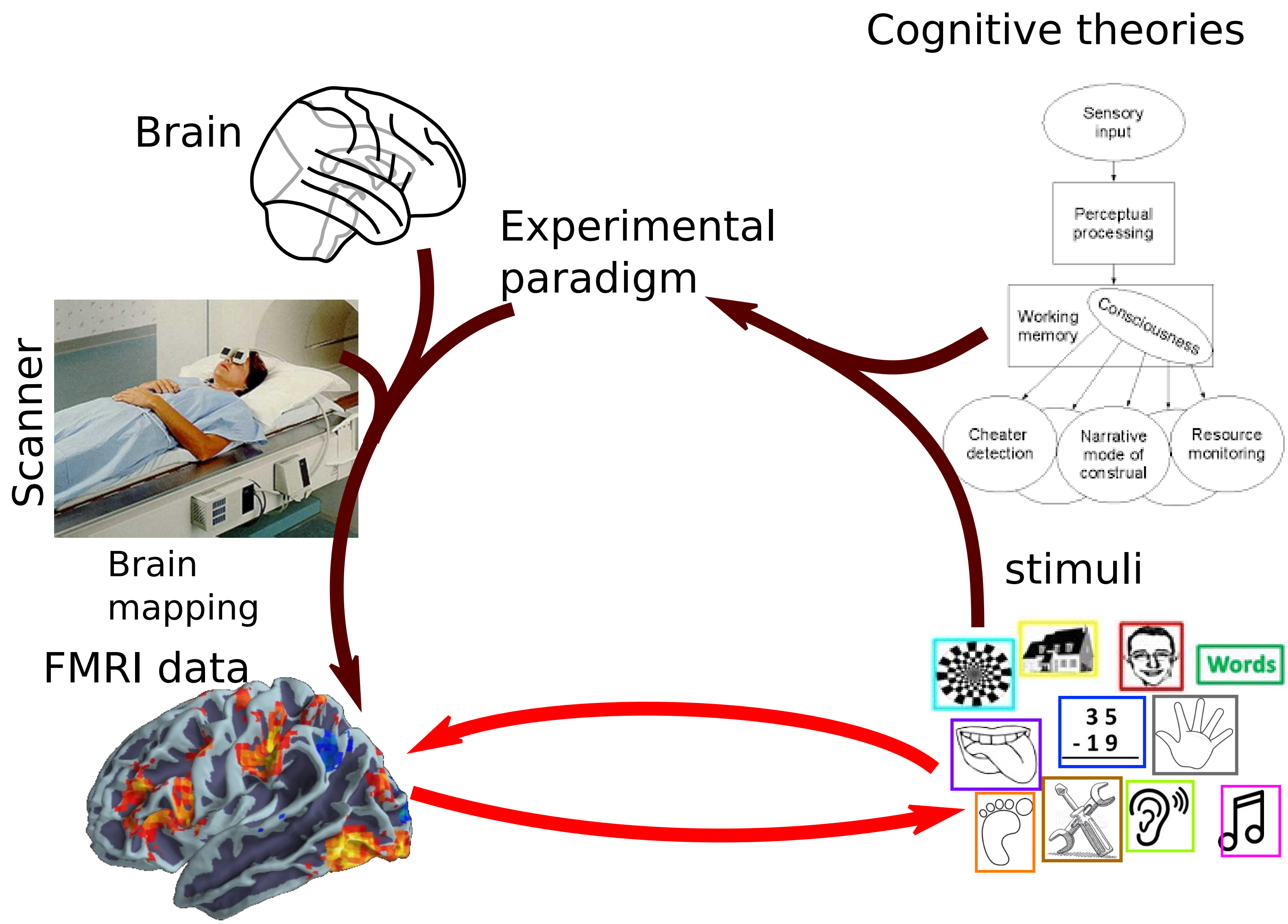
Cognitive neuroscience

How are cognitive activities affected or controlled by neural circuits in the brain ?

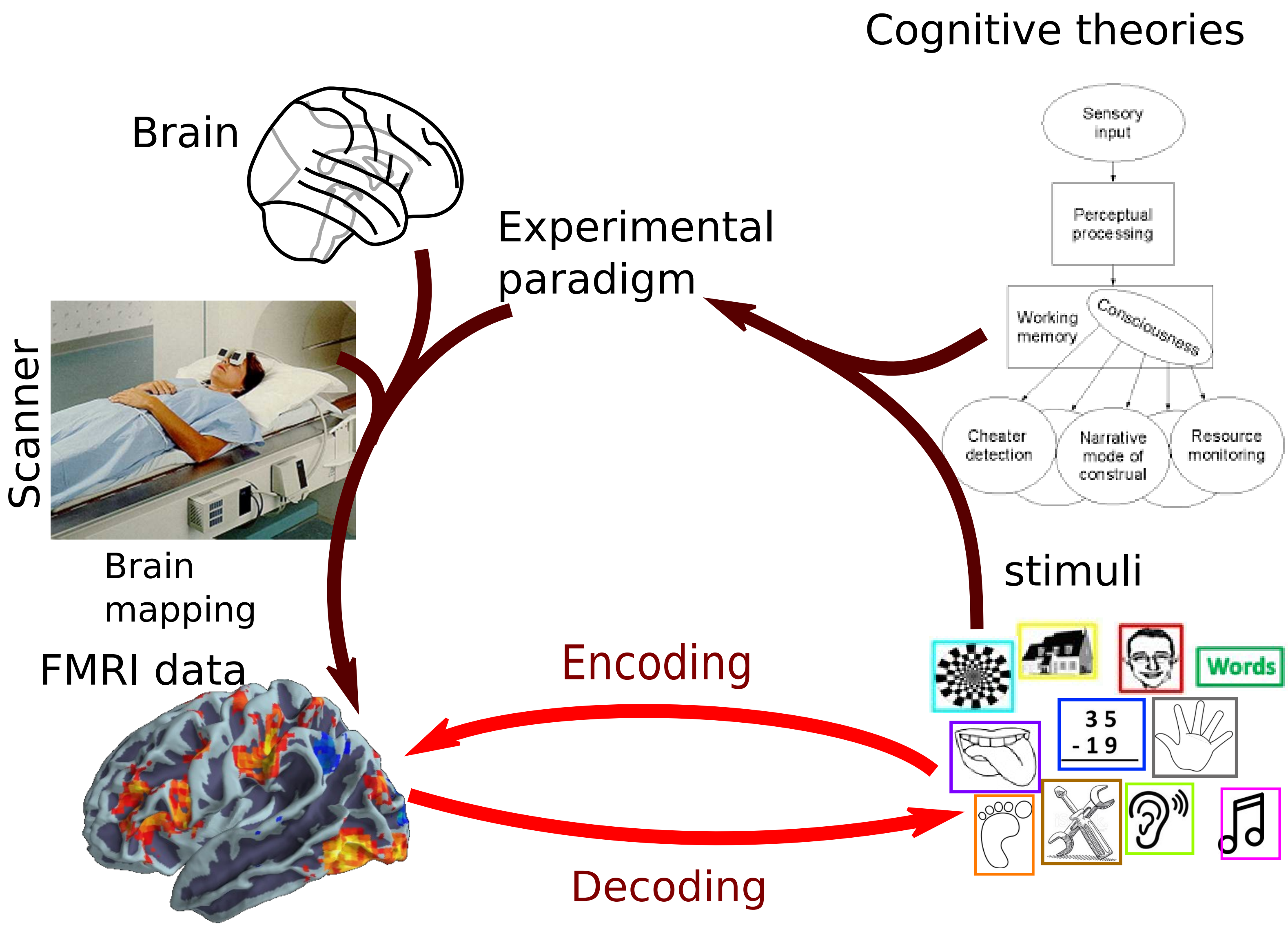
Cognitive neuroscience: From cognitive questions to data



Cognitive neuroscience: From cognitive questions to data



Cognitive neuroscience: Brain activity *decoding*



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]

[Poldrack & Yarkoni, Annu Rev Psycho 2016]

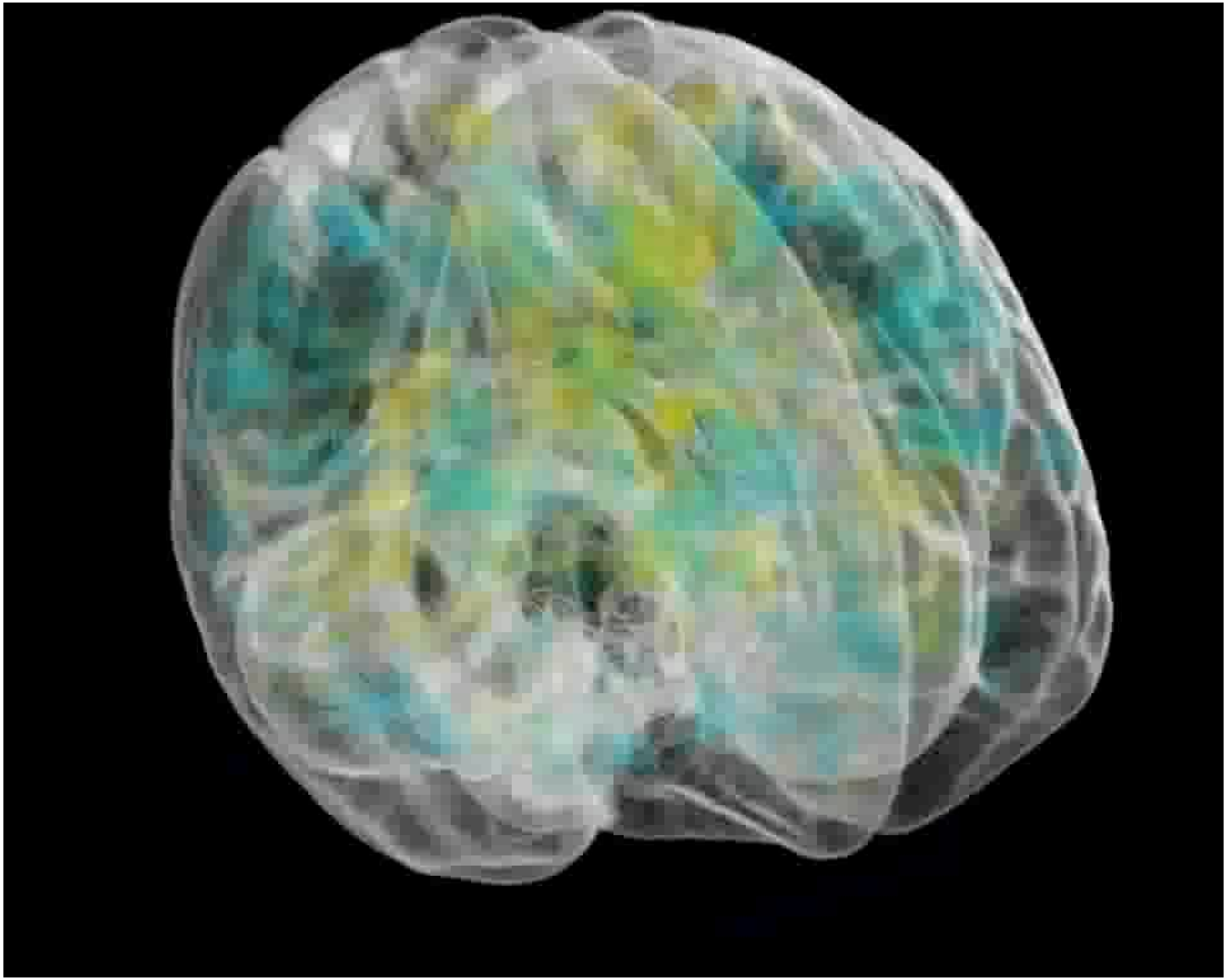
- Joint analysis: Use large studies to inform small studies (*transfer learning)*
  - Principle: leverage joint representations across datasets
- Mega-analysis: find *semantic* commonalities across studies
  - Difficulty: what common vocabulary across studies?

Outline

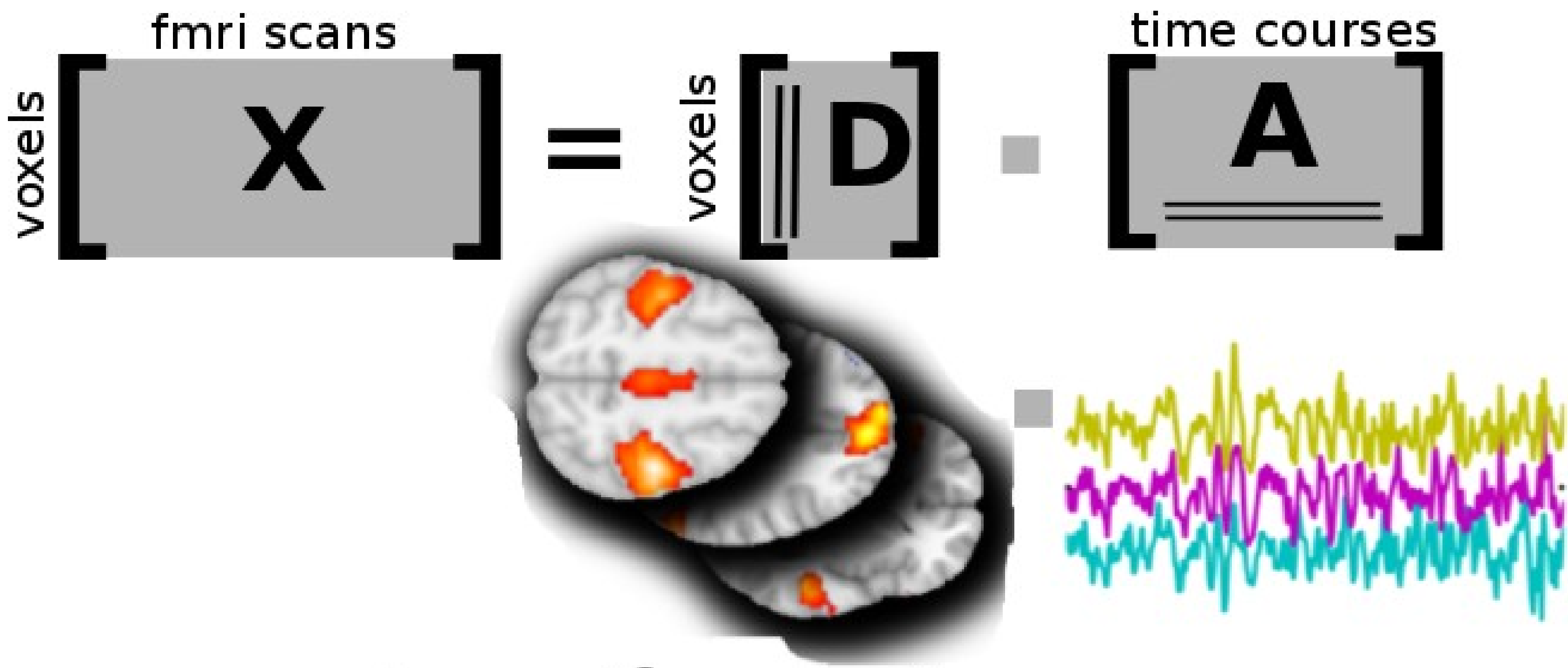
- Learning good representations for brain images: unsupervised approach
- Learning good representations for brain images: supervised approach
- *In the wild* brain activity decoding
- Dealing with semantics and data labelling issues

Learning good representations for brain images: unsupervised approach

Discovering structure in fMRI data



Discovering structure in fMRI



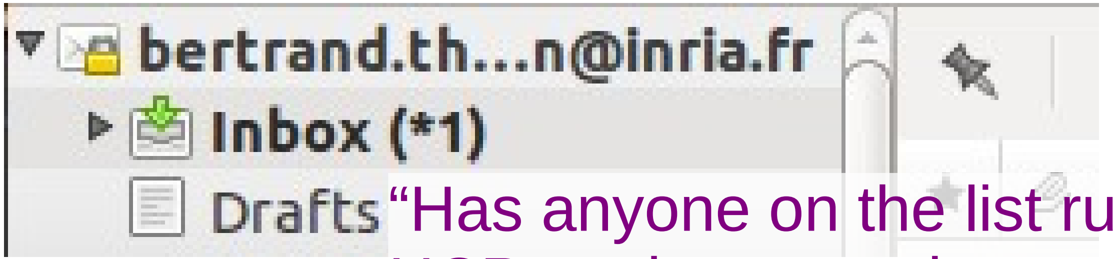
$$\underset{A,\,D}{\operatorname{argmin}} \|X-DA\|^2 + \lambda \|D\|_1$$

Can be captured by dictionary learning / sparse coding [Olshausen Nature 1996]

→ Use of sparse PCA

High-dimensional fMRI

- n = number of samples, 10^2 to 10^6
- p = number of voxels, 10^5-10^6



“Has anyone on the list run group-wise analysis on the HCP resting state data, and if so what tools did you use?

I **am having memory issues when running more than 10 subjects** and I was wondering if anyone has a way of getting around the large memory requirements when concatenating in time.”

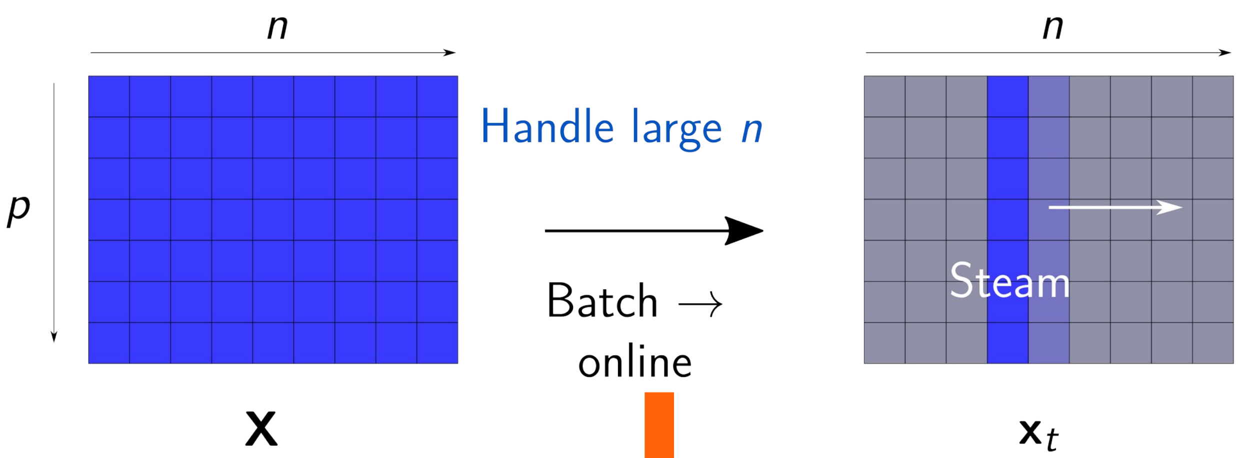
Factorizing high-dimensional data

- Human Connectome project $n=4.10^6$, $p=2.10^5$, 4**TB** of data
- Online dictionary learning [Mairal et al. ICML 2009]
- How to go faster ?
  - Work on batches of images **and** voxels
    - Online method in both samples and feature dimensions

[Mensch et al. ICML 2016, IEEE TSP 2018]

Stochastic gradient approaches

http://amensch.fr/research/2016/06/10/modl.html



$$\boldsymbol{\alpha}_t(\mathbf{D}) = \mathrm{argmin}_{\mathbf{A}\in\mathbb{R}^{k\times n}} \|\mathbf{x}_t - \mathbf{D}_{t-1}\boldsymbol{\alpha}_t\|_F^2 + \lambda\Omega(\boldsymbol{\alpha}_t)$$

$$\mathbf{D}_t = \mathrm{argmin}_{\mathbf{D}\in\mathcal{C}} \sum_{i=1}^{t} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_F^2$$

Stochastic gradient approaches

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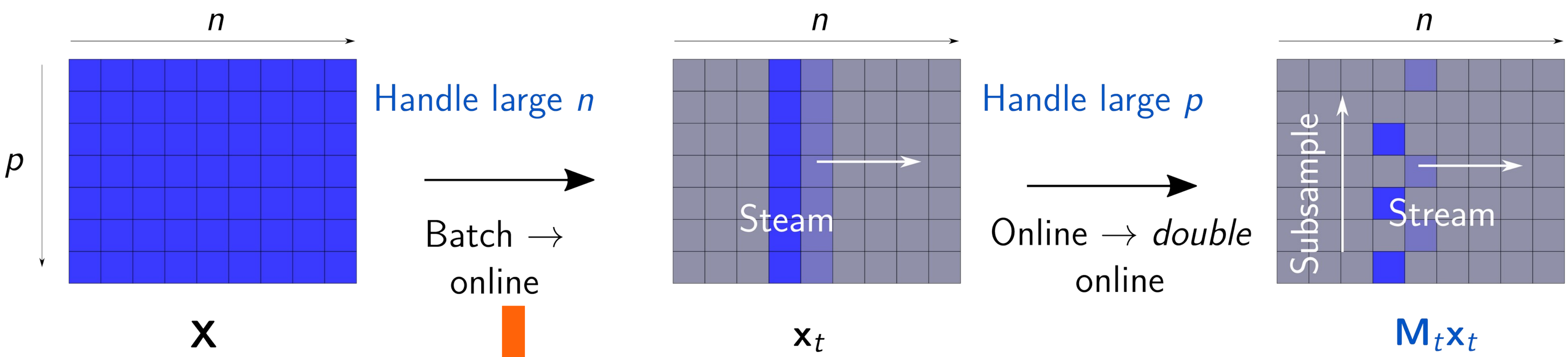

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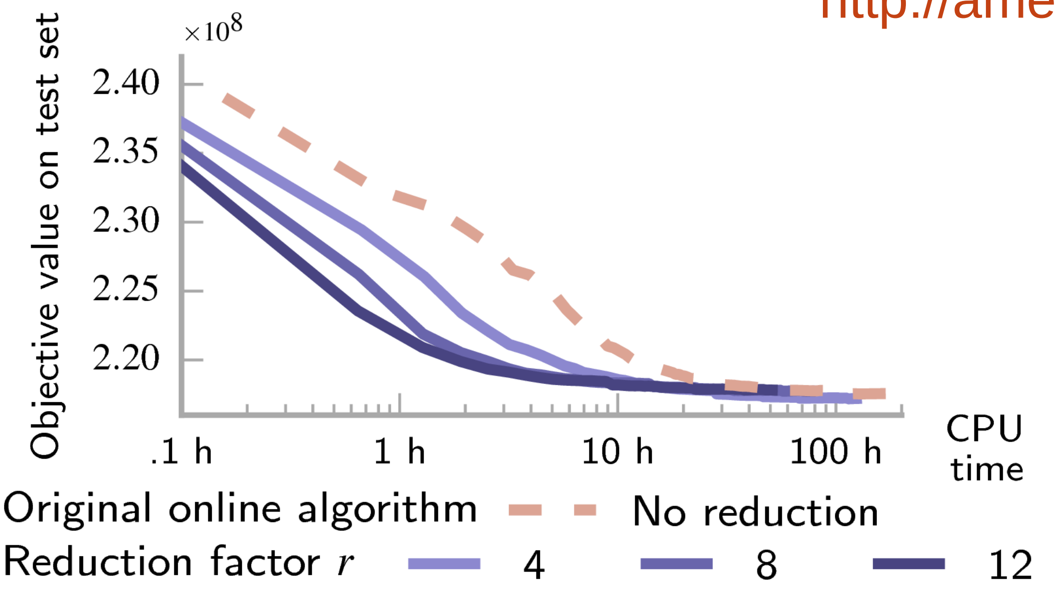
$$\boldsymbol{\alpha}_t(\mathbf{D}) = \operatorname{argmin}_{\mathbf{A}\in\mathbb{R}^{k\times n}} \|\mathbf{M}_t(\mathbf{x}_t - \mathbf{D}_{t-1}\boldsymbol{\alpha}_t)\|_F^2 + \lambda\frac{s}{p}\Omega(\boldsymbol{\alpha})$$

Stochastic gradient approaches

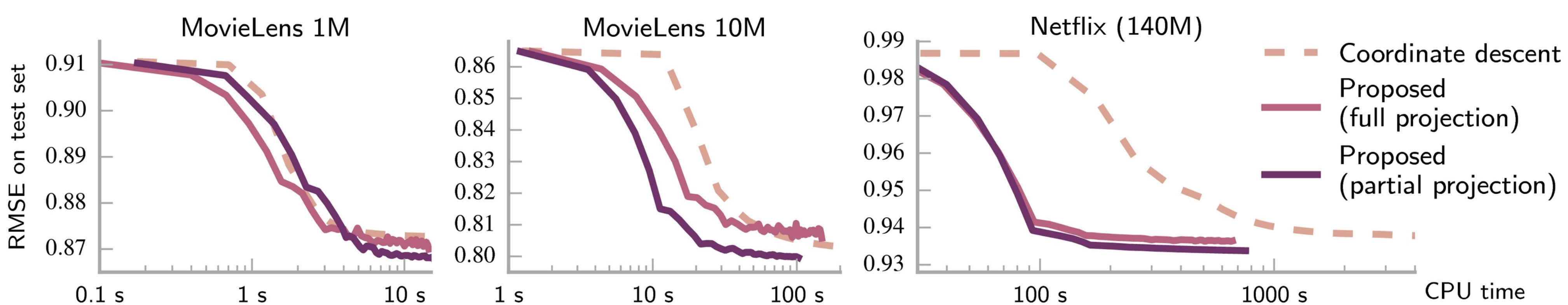
http://amensch.fr/research/2016/06/10/modl.html



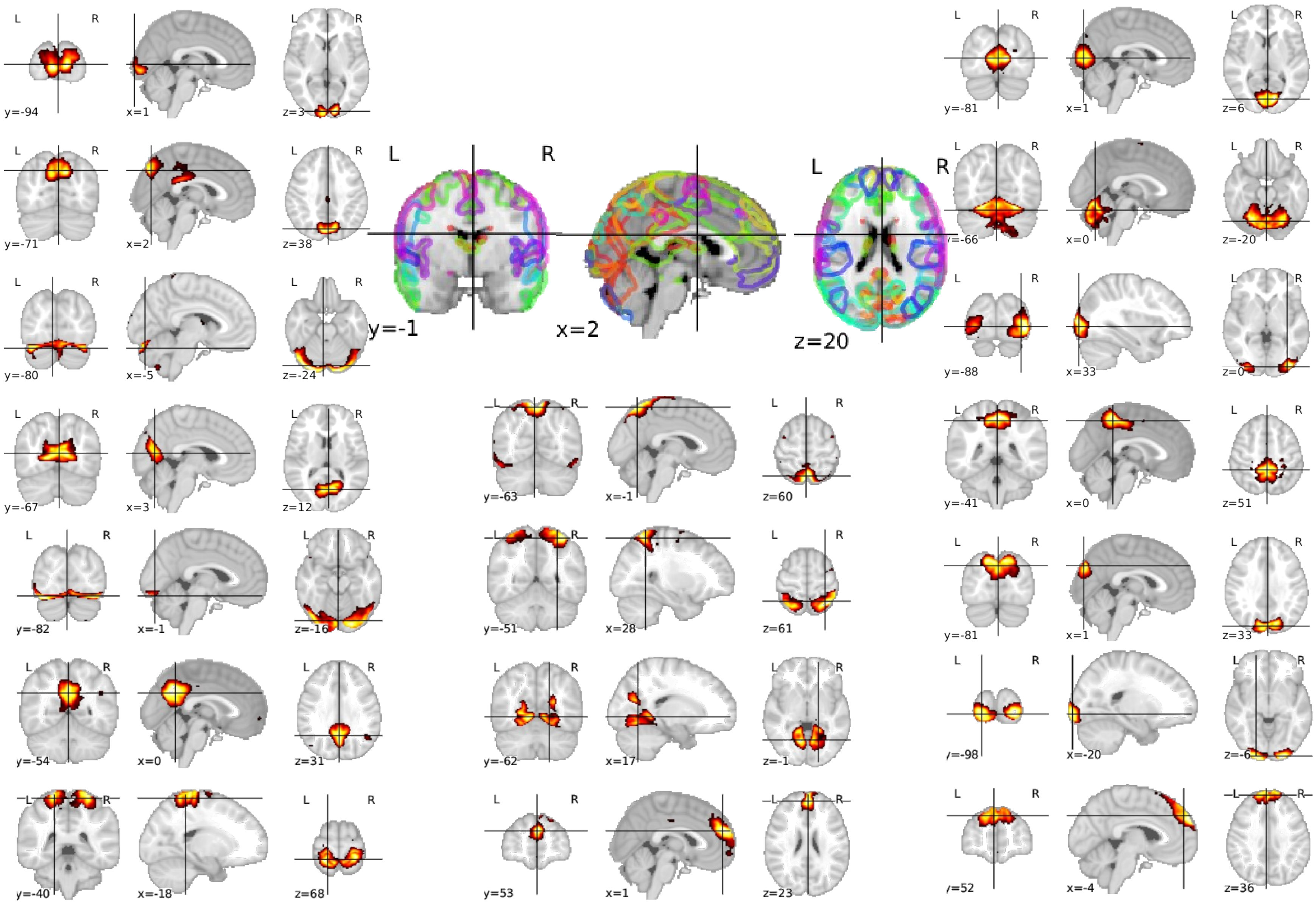
10-fold gain in CPU time without loss in accuracy

[Mensch et al. ICML 2016, IEEE TSP 2018]

Can be used for recommender systems



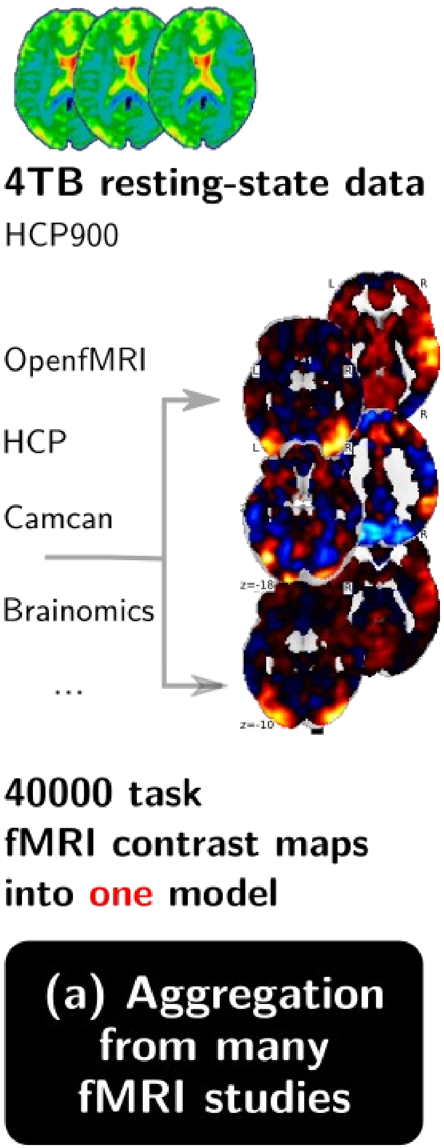
Brain atlases



[Mensch et al. ICML 2016 IEEE TSP 2018, Dadi et al. Nimg 2020]

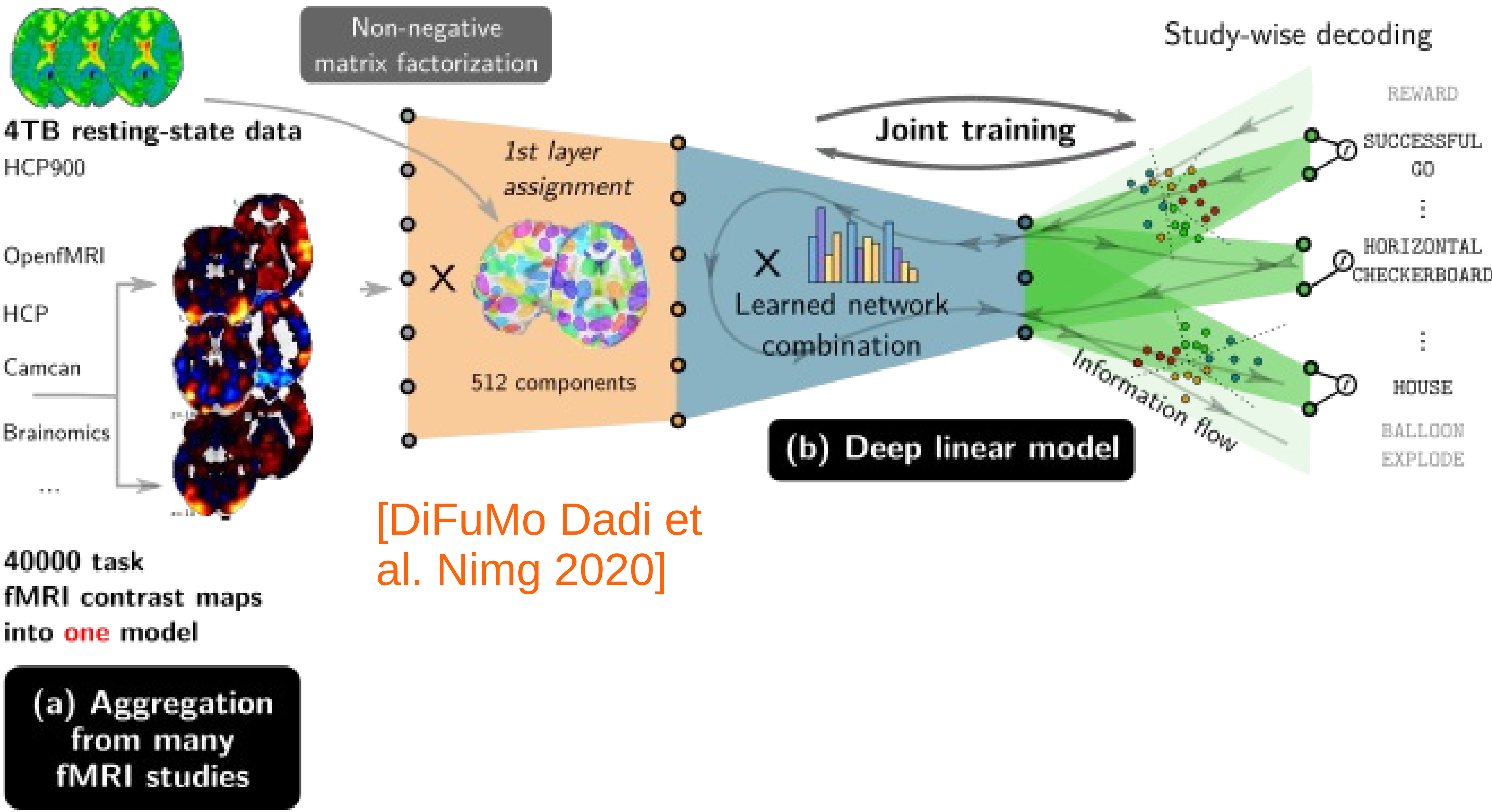
Learning good representations for brain images: supervised approach

Predictive modeling across datasets



[Bzdok et al. Plos Comp Biol 2016, Mensch et al NIPS 2017, PCB 2021]

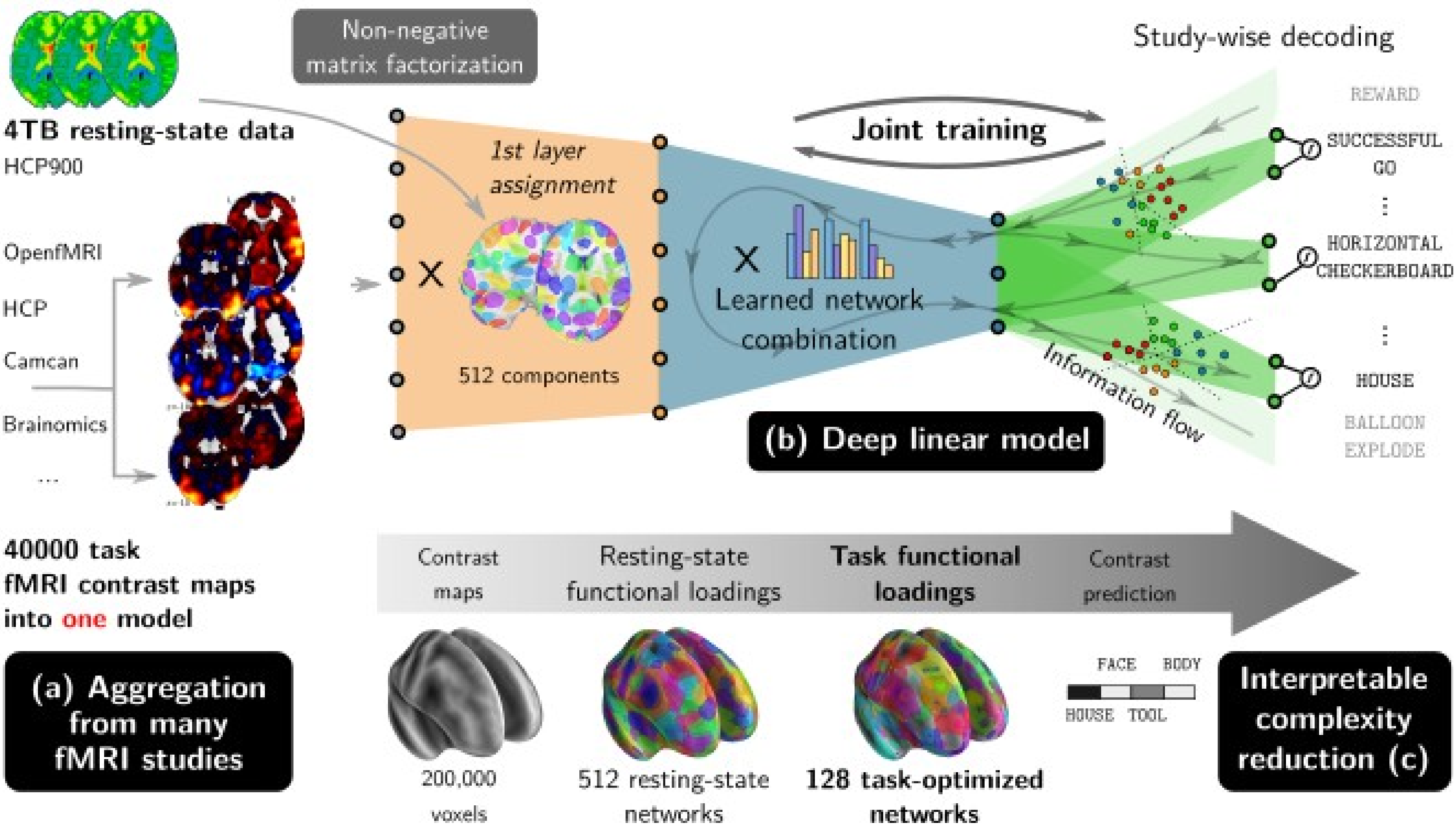
Predictive modeling across datasets



[DiFuMo Dadi et al. Nimg 2020]

[Bzdok et al. Plos Comp Biol 2016, Mensch et al NIPS 2017 PCB 2021]

Predictive modeling across datasets



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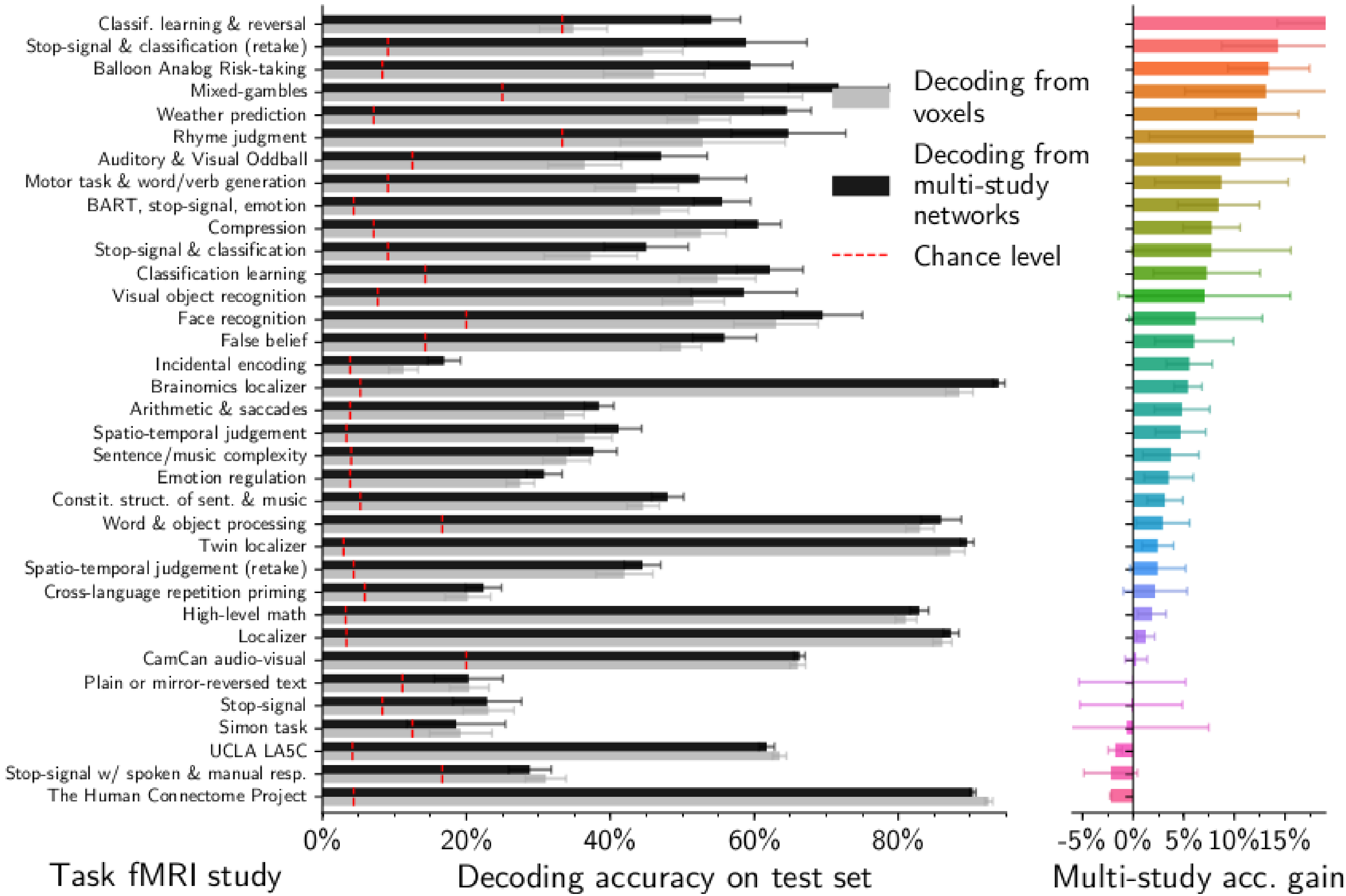
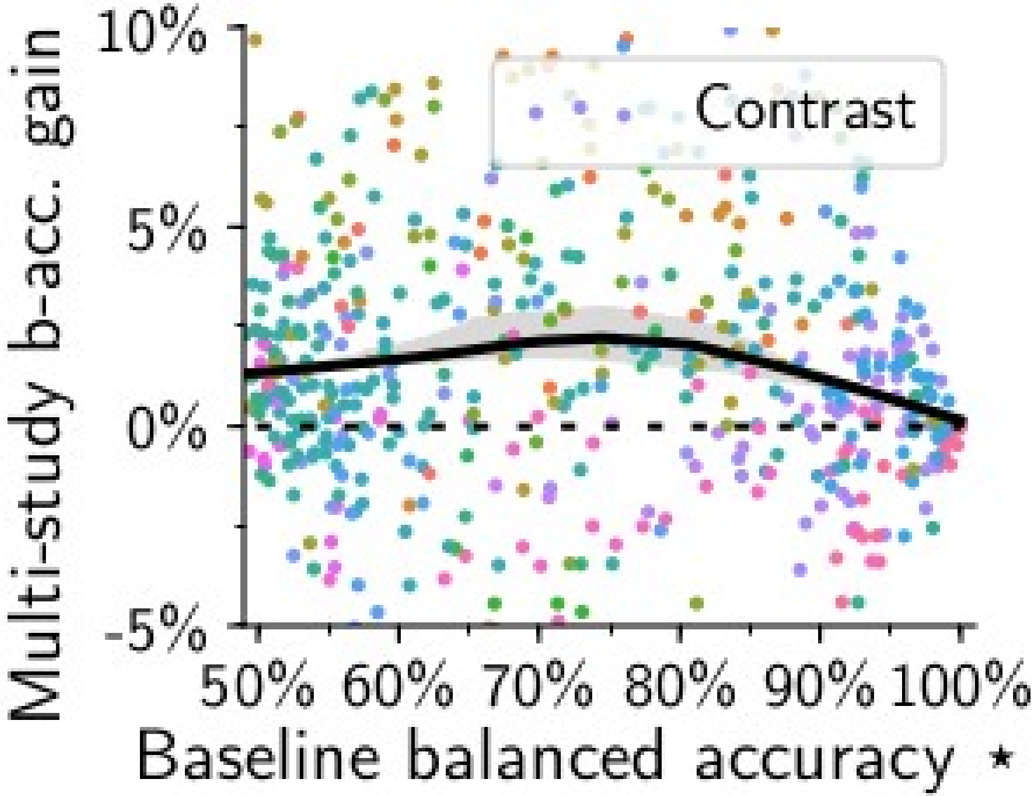
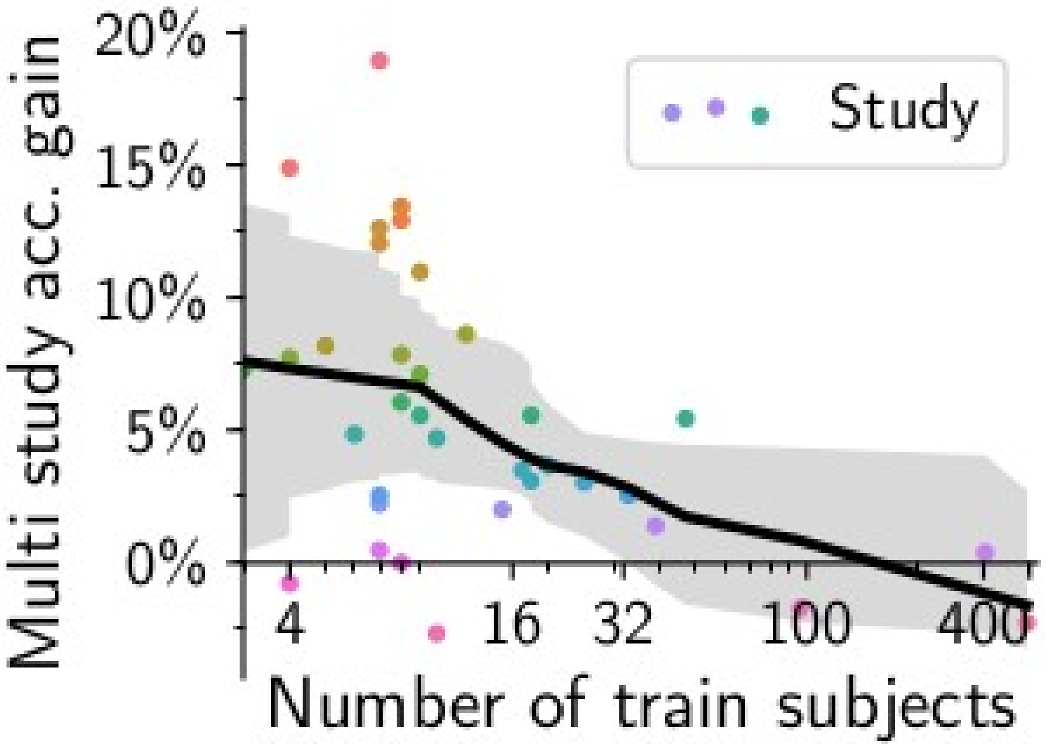
Transfer learning

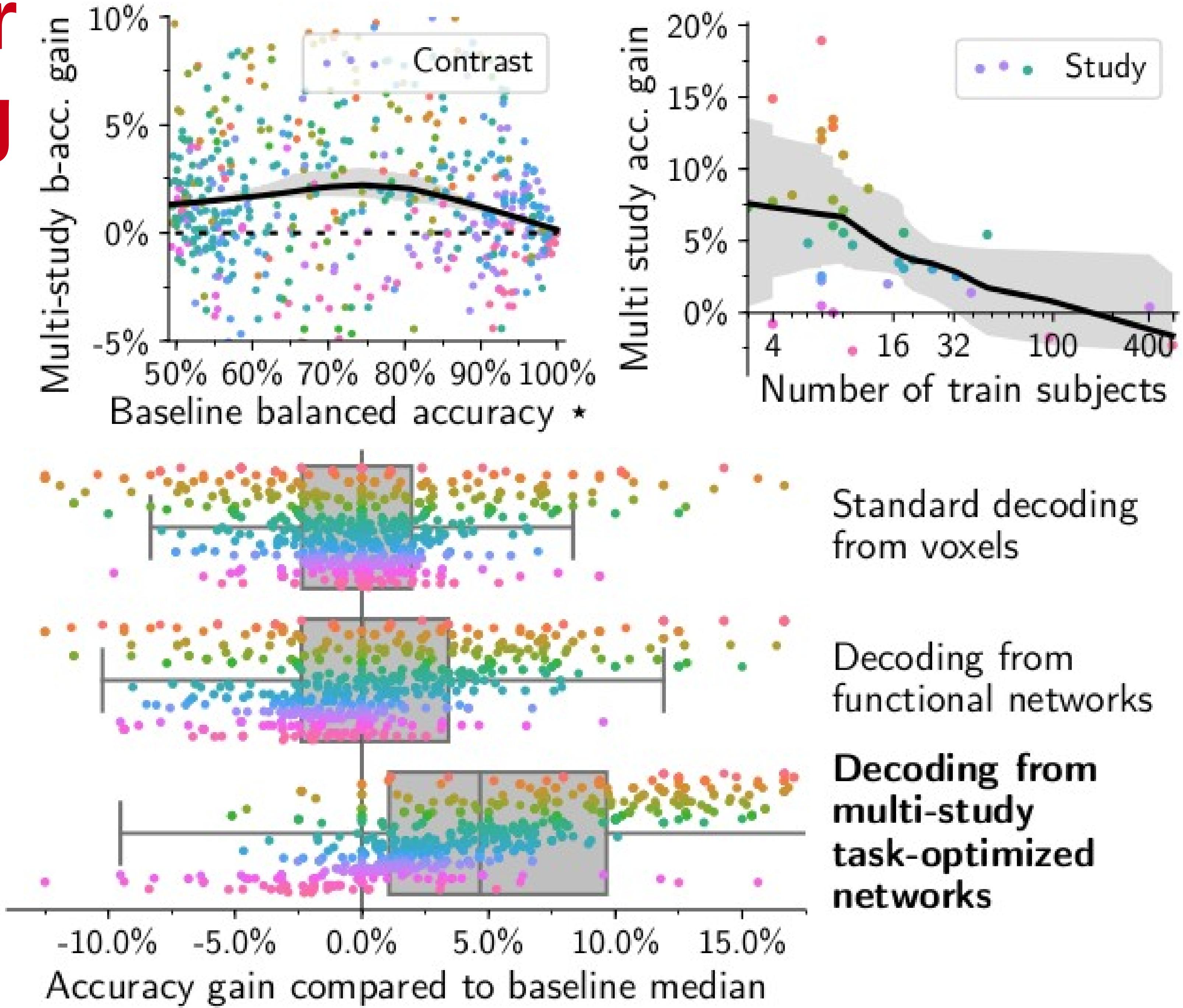


Transfer learning

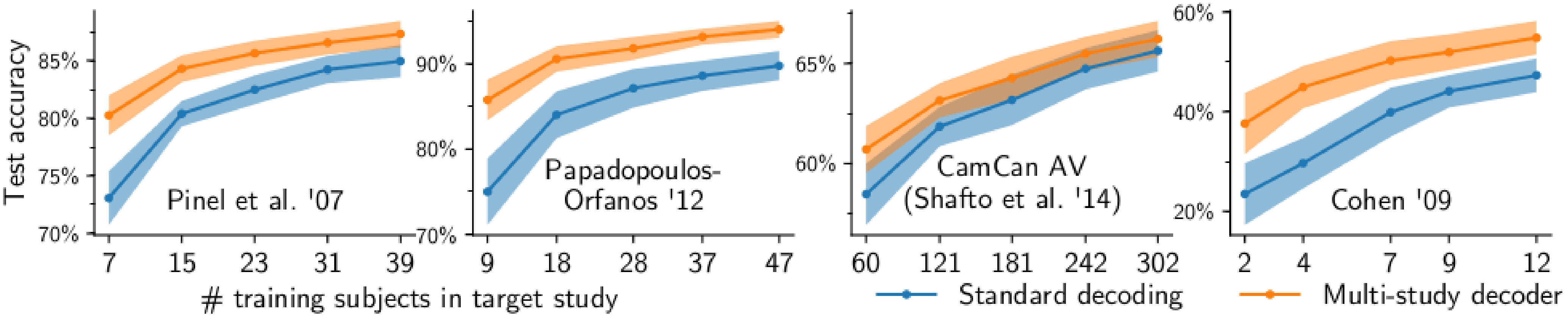




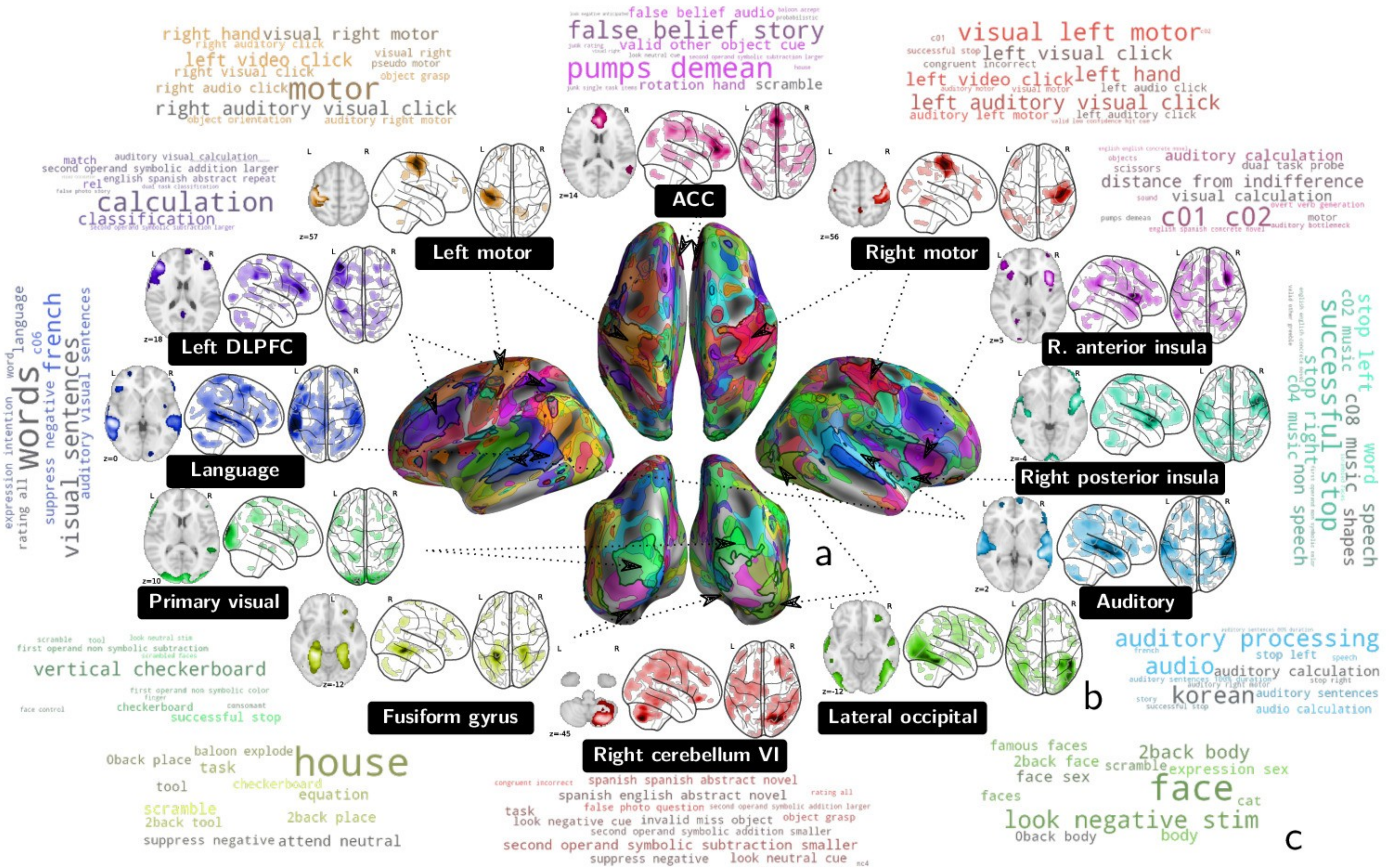
Transfer learning



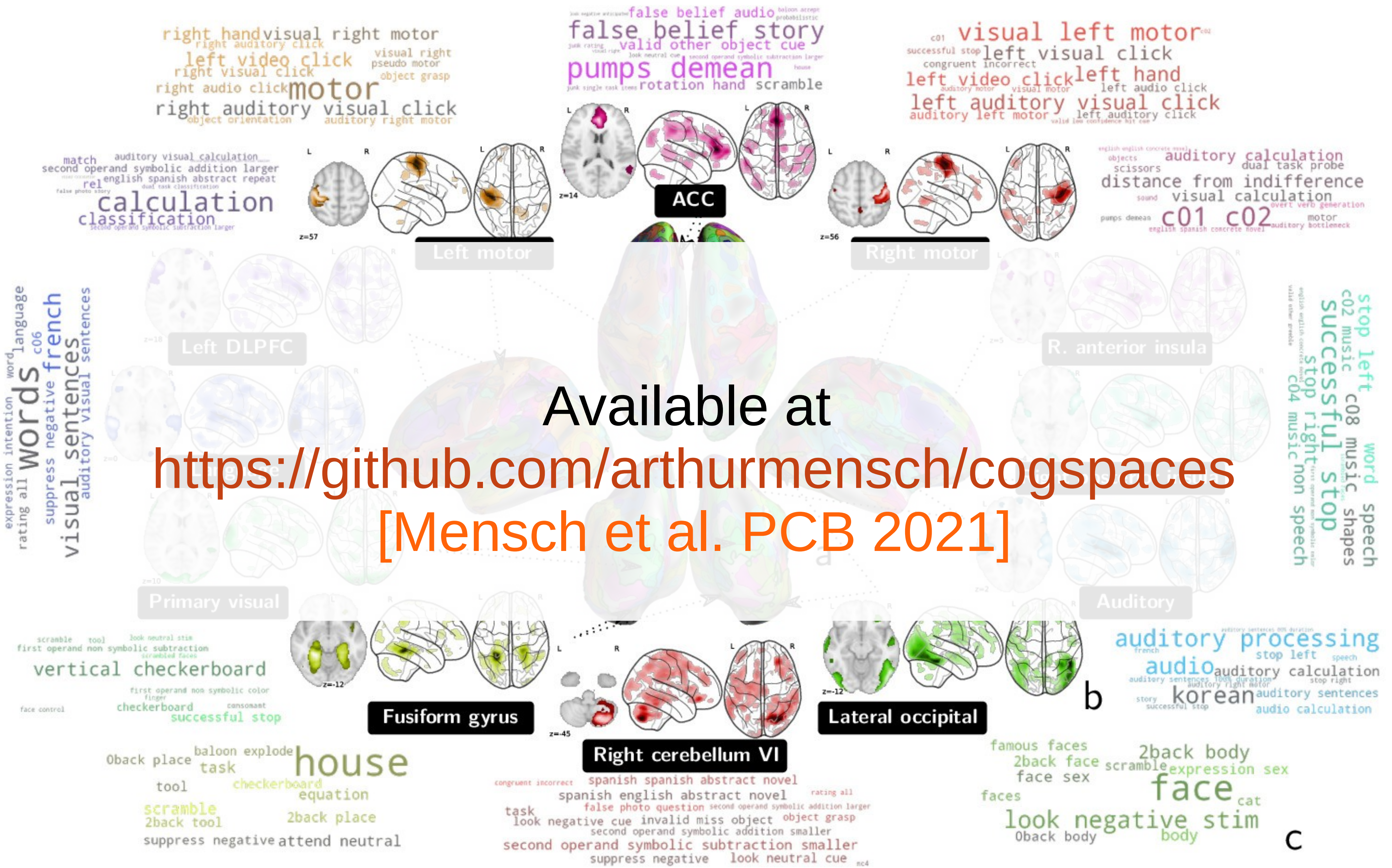
Small studies benefit more than large studies



Resulting atlas



Resulting atlas



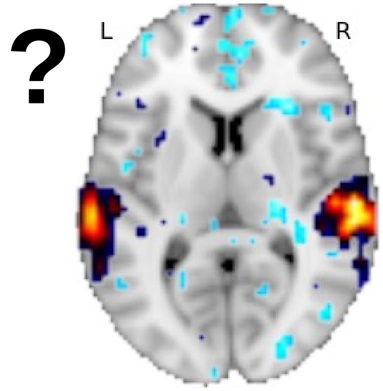
Available at

https://github.com/arthurmensch/cogspaces

[Mensch et al. PCB 2021]

In the wild brain activity decoding

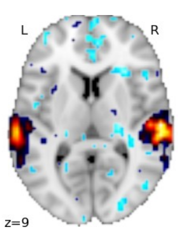
Open-ended brain decoding



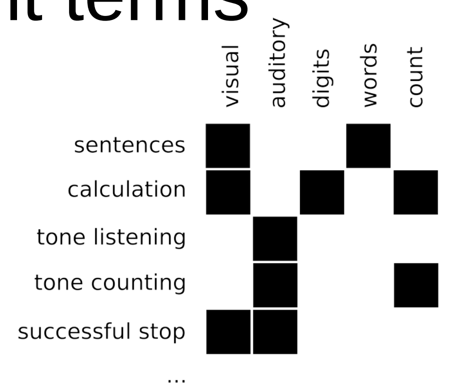
What is this brain doing?

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

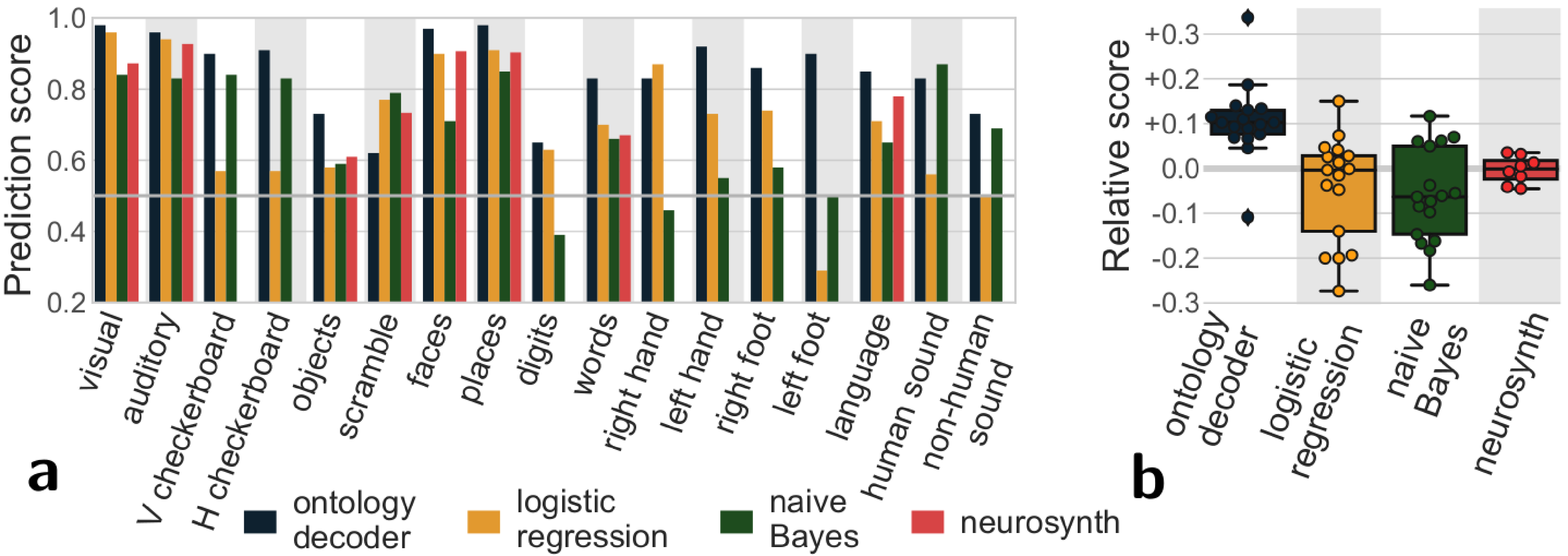


Data: experimental condition images



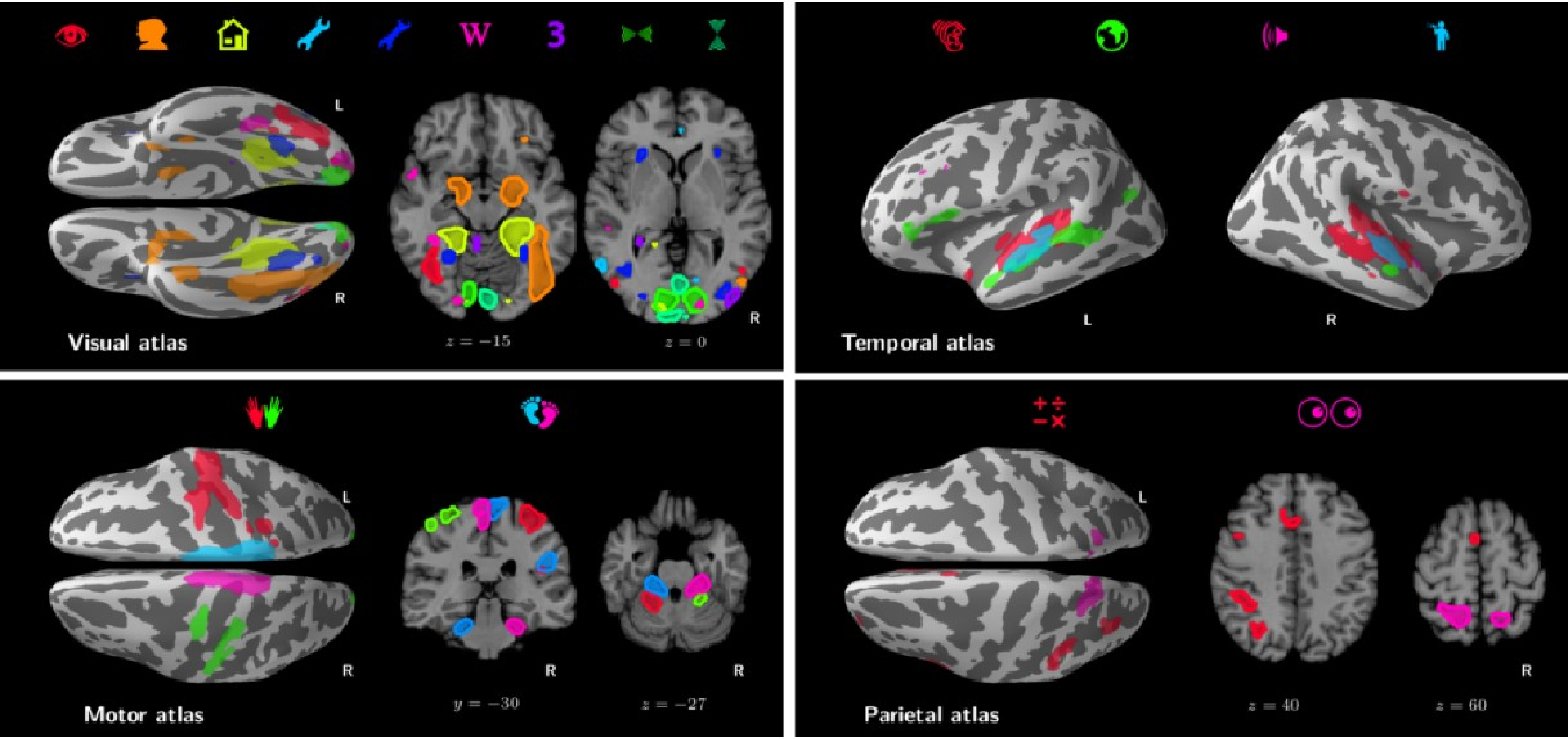
Target

Classification results



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

Discriminative patterns



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

An image database

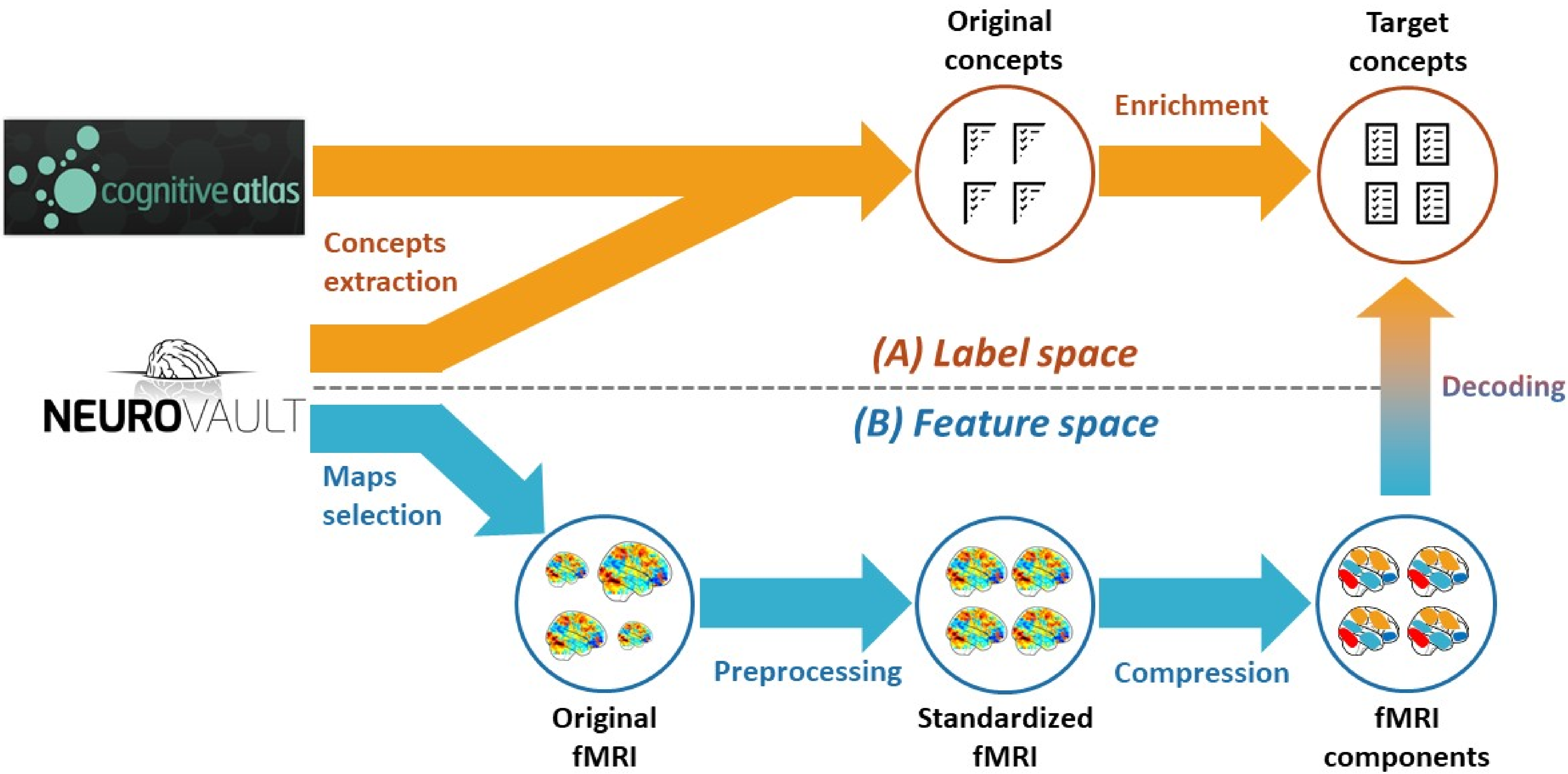
Task fMRI repository
[Gorgolewski et al. 2015]

Currently 48k independent usable fMRIs

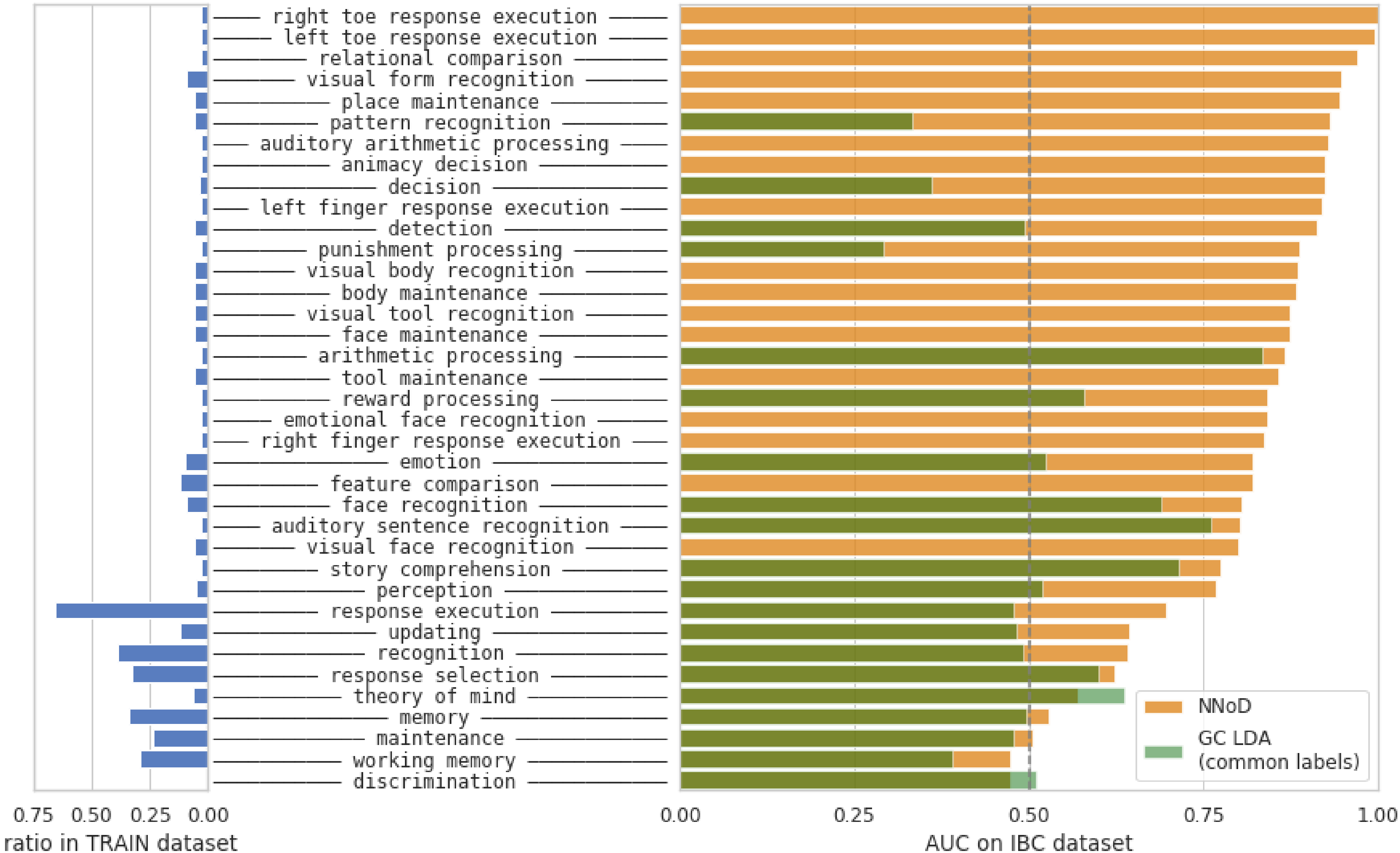
[Poldrack 2011], knowledge-base

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

From multi-study to universal decoder

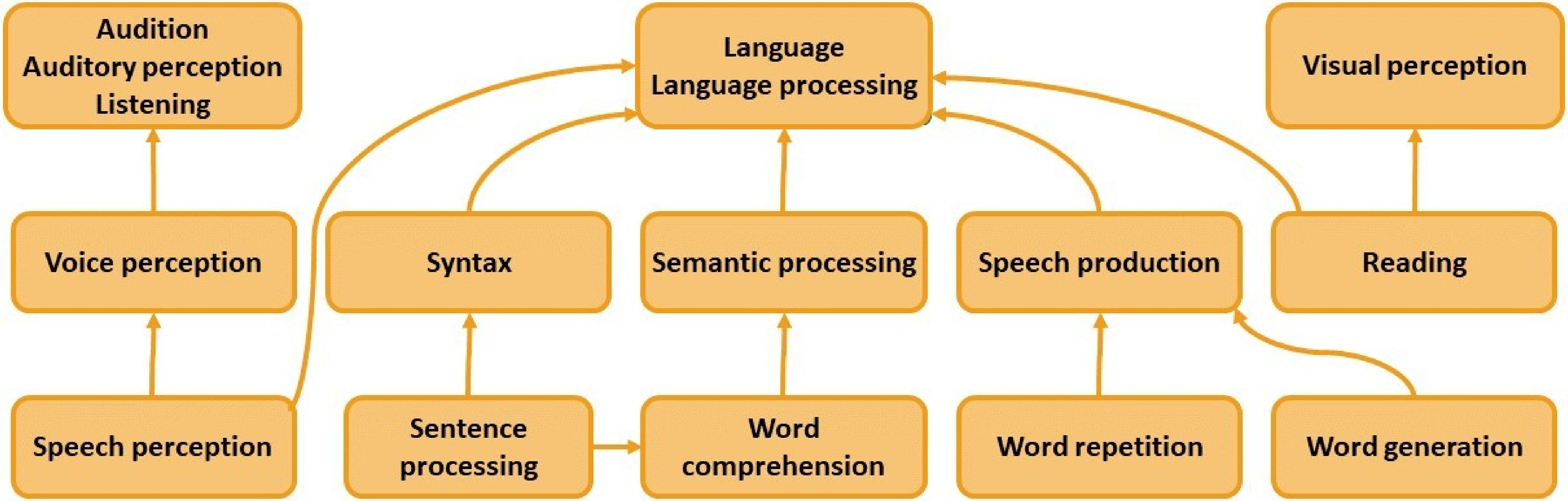


Results (naive approach)

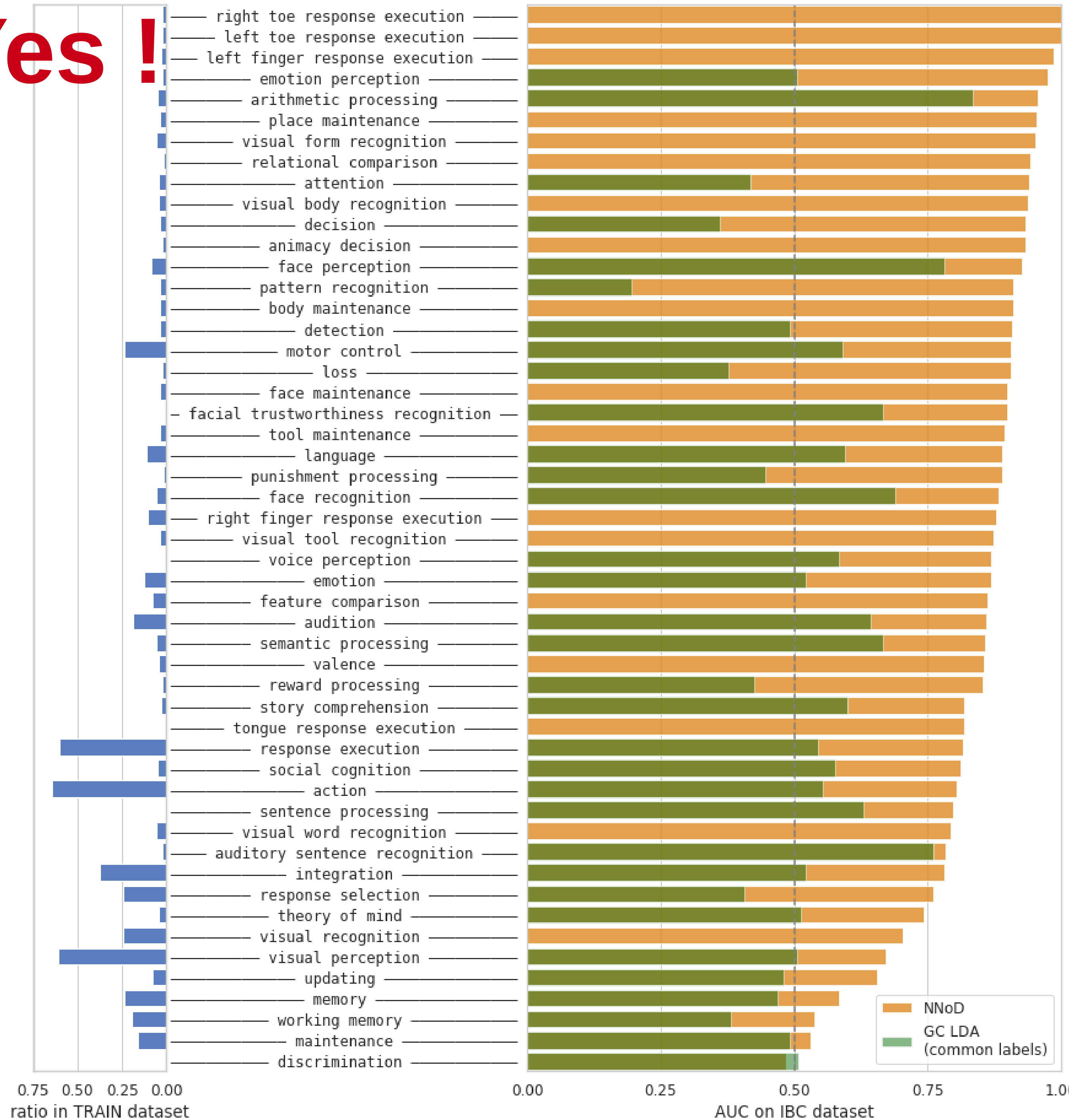


Fixing labels

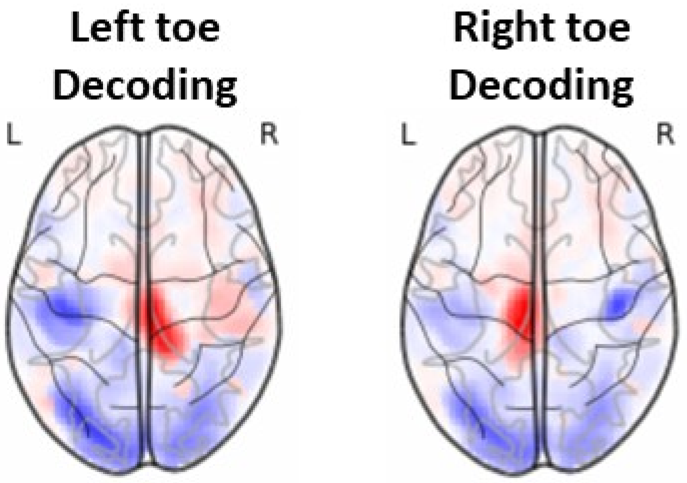
Problem:
synonyms, false negatives (missing annotations)
→ **Simple rules to impute labels:**



Results (2): Yes !

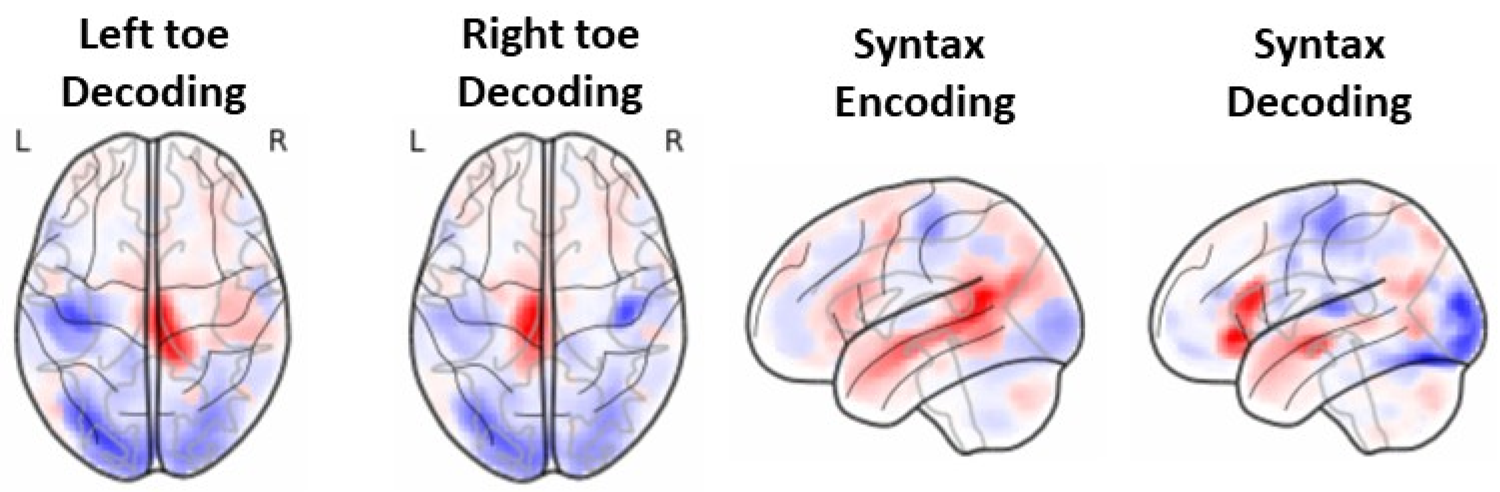


Open the box



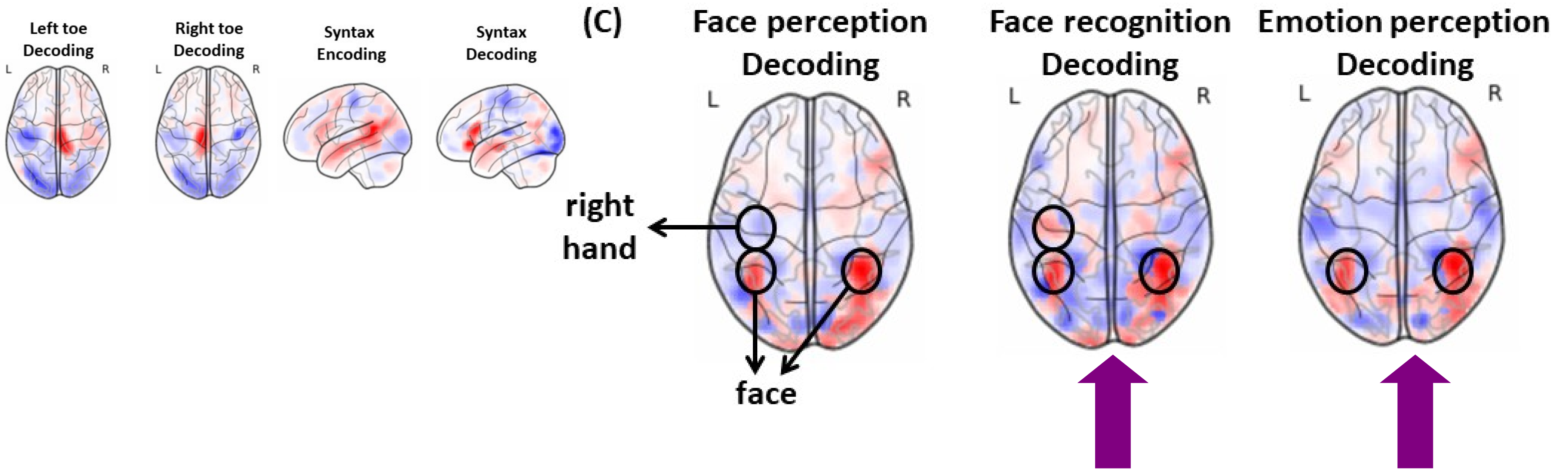
Non-controversial case

Open the box



decoding > encoding

Open the box



Experimental biases

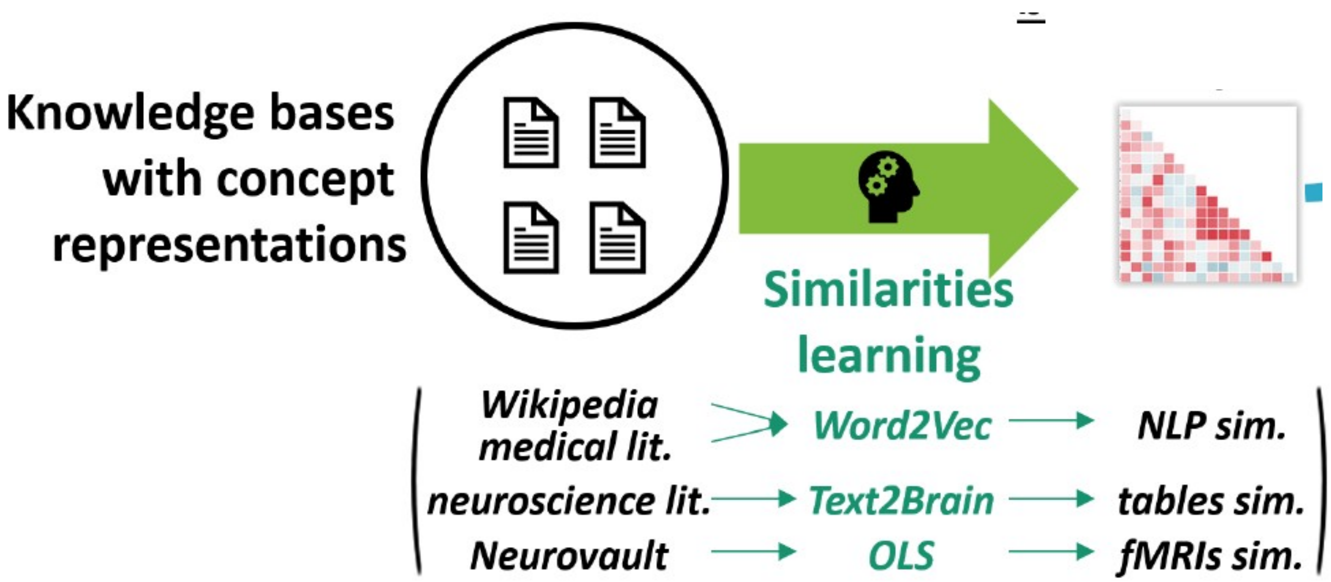
[Menuet et al. Scientific Reports 2022]

Dealing with semantics and data labelling issues

… by mining the neuroscientific literature

Need curated annotations

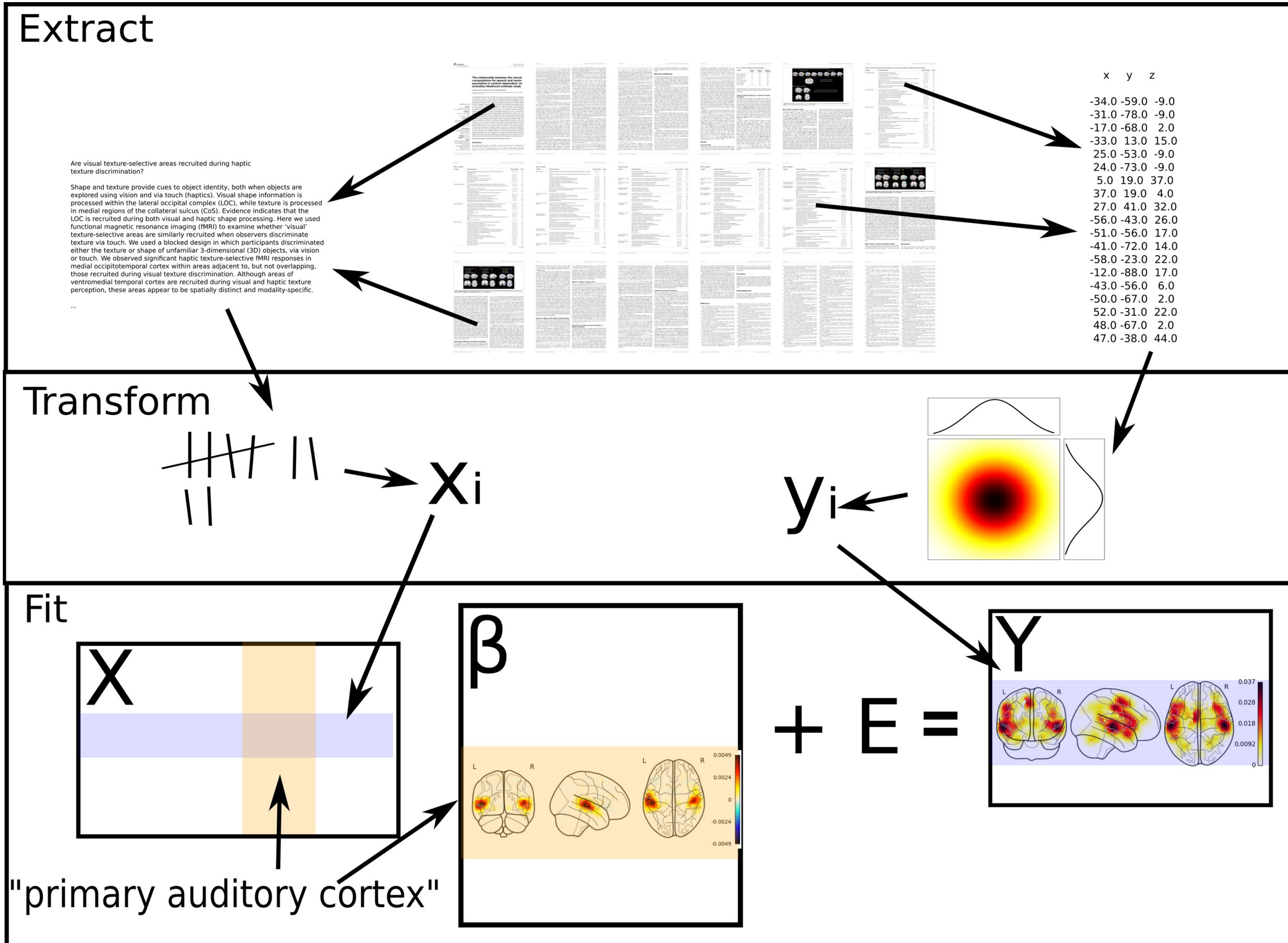
- Current ontology incomplete
- Bigger limitation = lack of consistent vocabulary
  [Poldrack & Yarkoni, Annu Rev Psycho 2016]
- How to get those ?



Mining neuroimaging literature

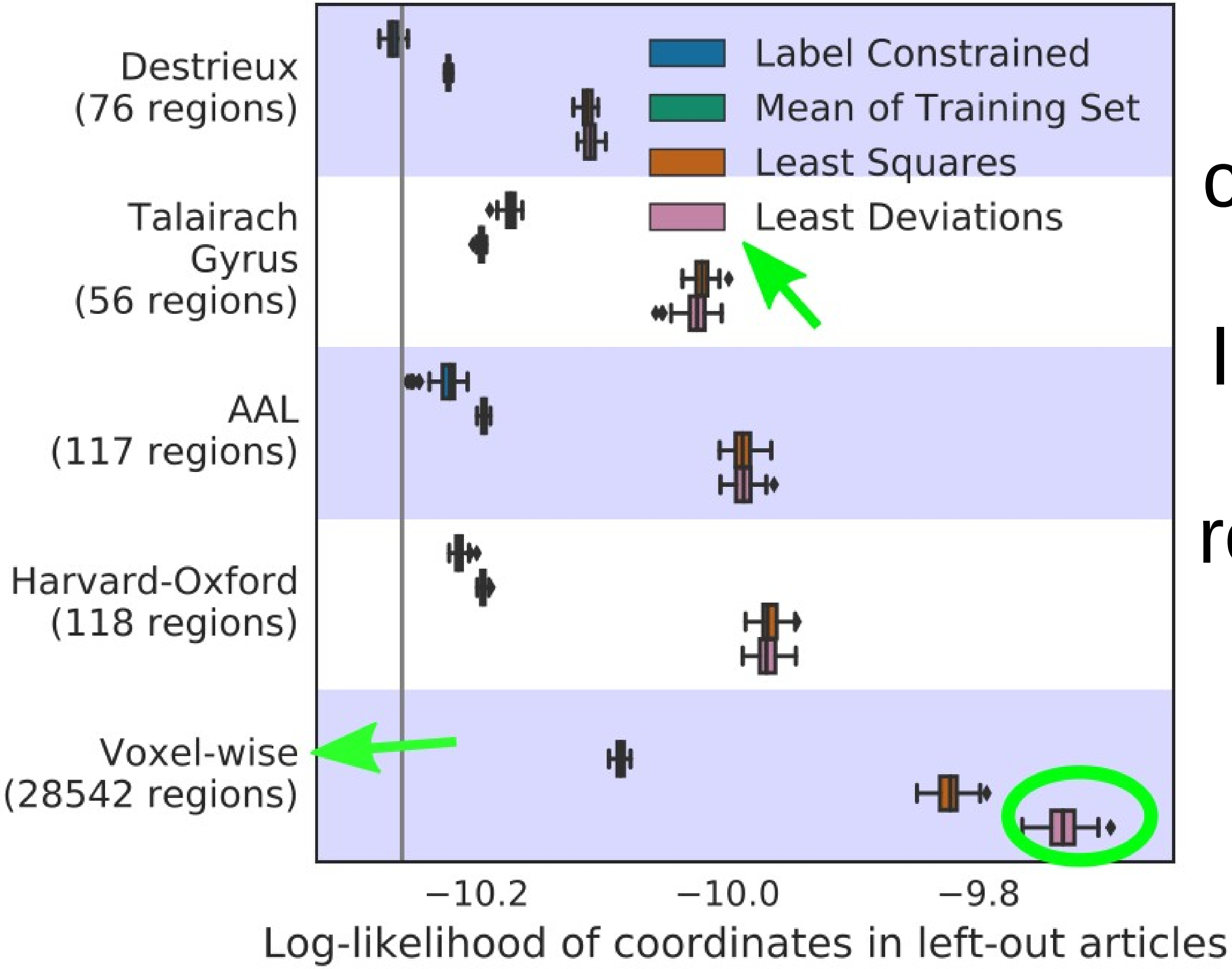
- Neuroimaging observations often stored in text.
- e.g “[...] in the anterolateral temporal cortex, especially the temporal pole and inferior and middle temporal gyri”
- Objectives:
  - transform neuroimaging publications into brain maps
  - meta-analysis of text-only corpora

Neuroquery



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
x_i
y_i
Fit
X
β
+ E =
Y
"primary auditory cortex"

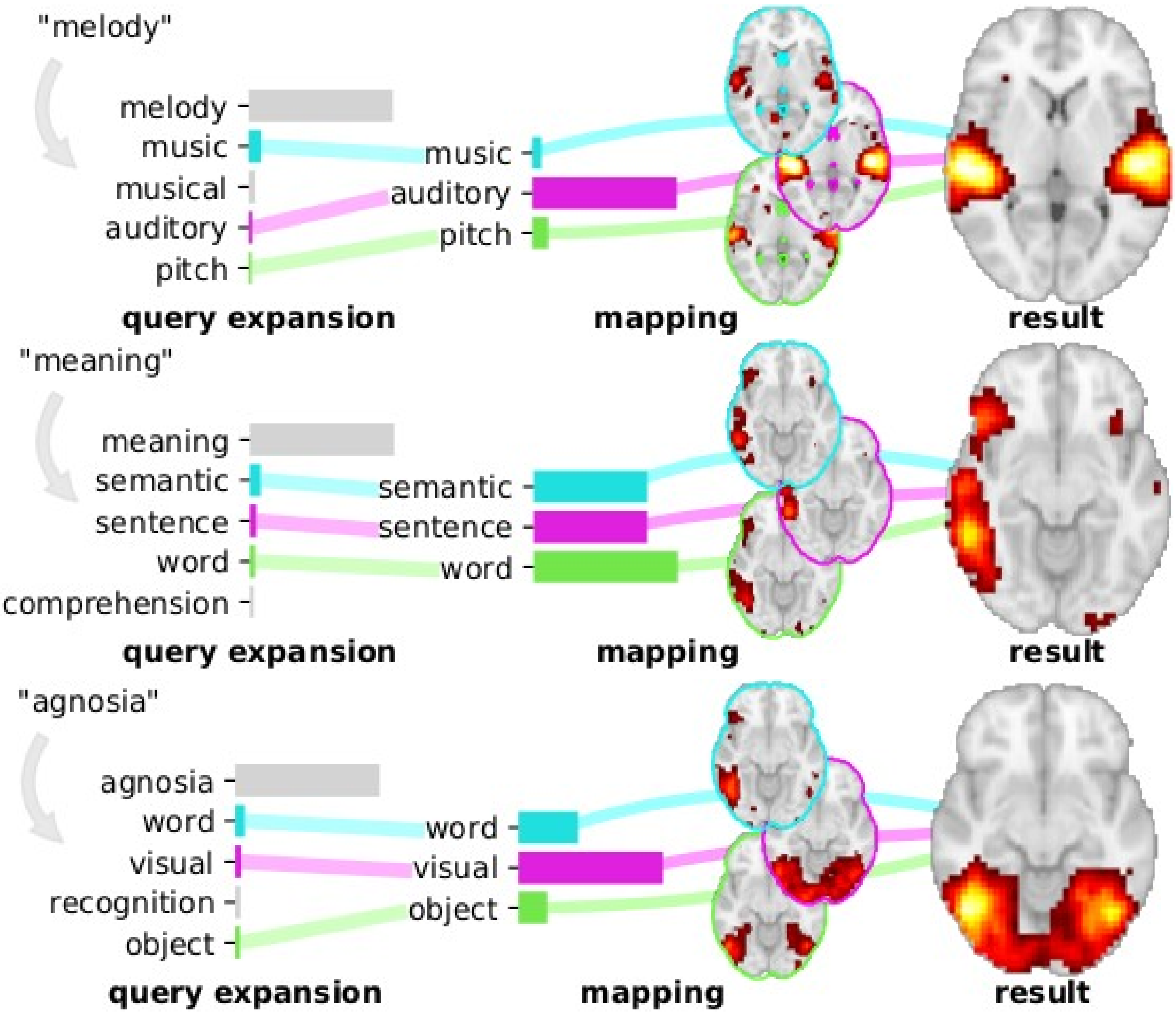
Empirical evaluation of representations



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

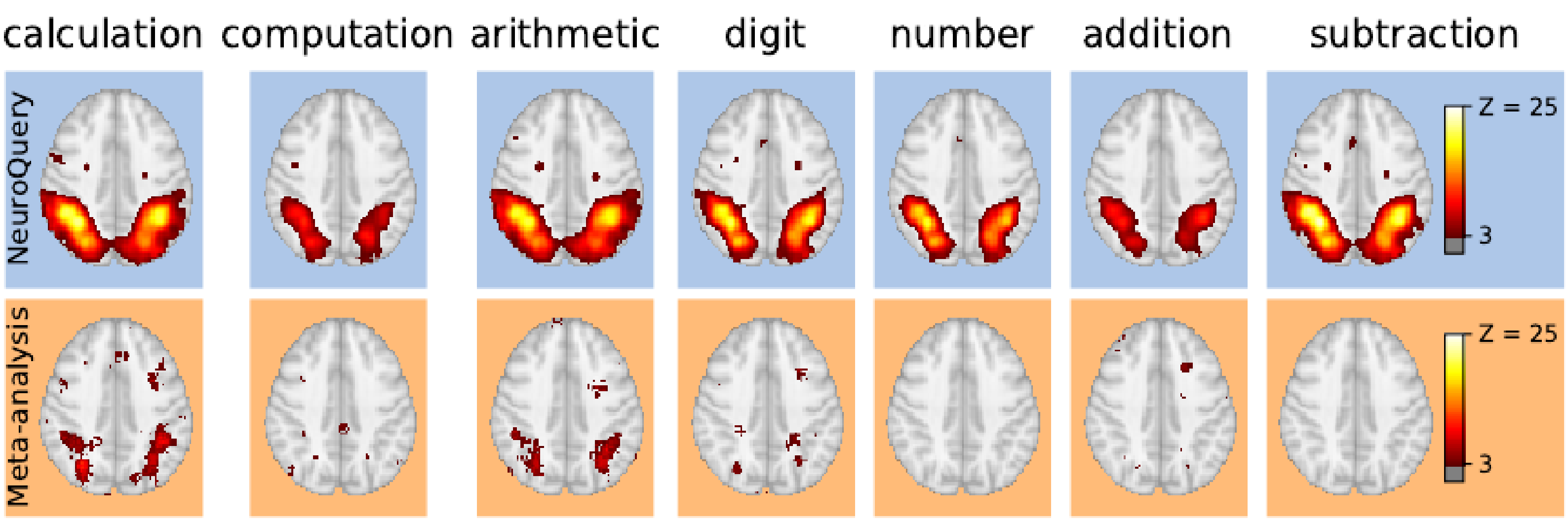
[Dockès et al. MICCAI 2018]

Leveraging semantics for better encoding



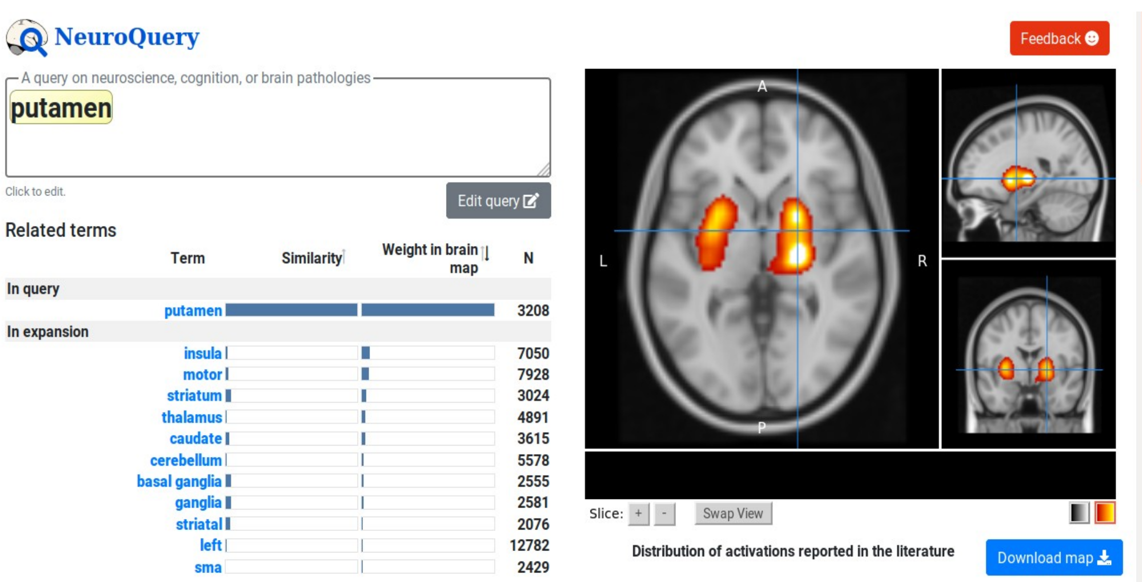
Semantic structure
→ map concepts with few/no data

Neuroquery



https://neuroquery.org

[Dockès et al. elife 2020]



Conclusion

- Large-p data bring challenges:
  - Computation cost
  - Difficulty of statistical inference
- Solutions: compression, subsampling, ensembling
- Finding commonalities across cognitive studies is hard
- Big data approach:
  - Extract weak signals from huge amounts of data
  - Common representation across datasets (*bottleneck*)

Image processing may not be the hard part !

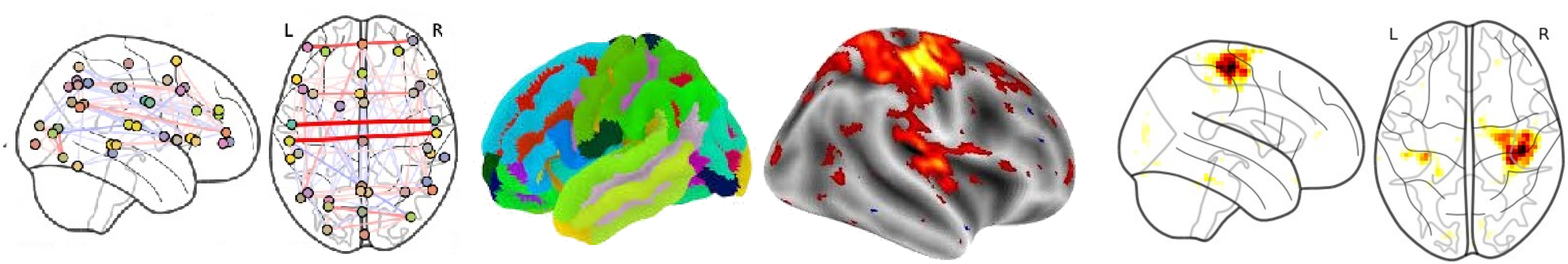
From good ideas to good practices: software

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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THEVIRTUALBRAIN.

Human Brain Project

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