Enhancing functional neuroimaging with meta-analytic approaches

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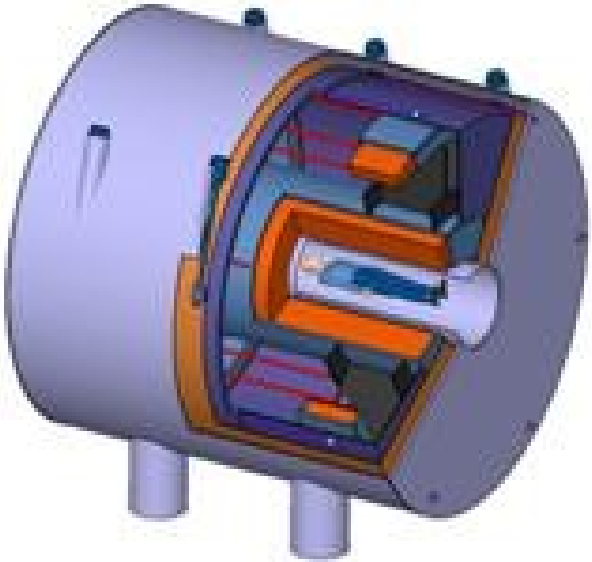
PARIETAL

Neurospin, Saclay, France

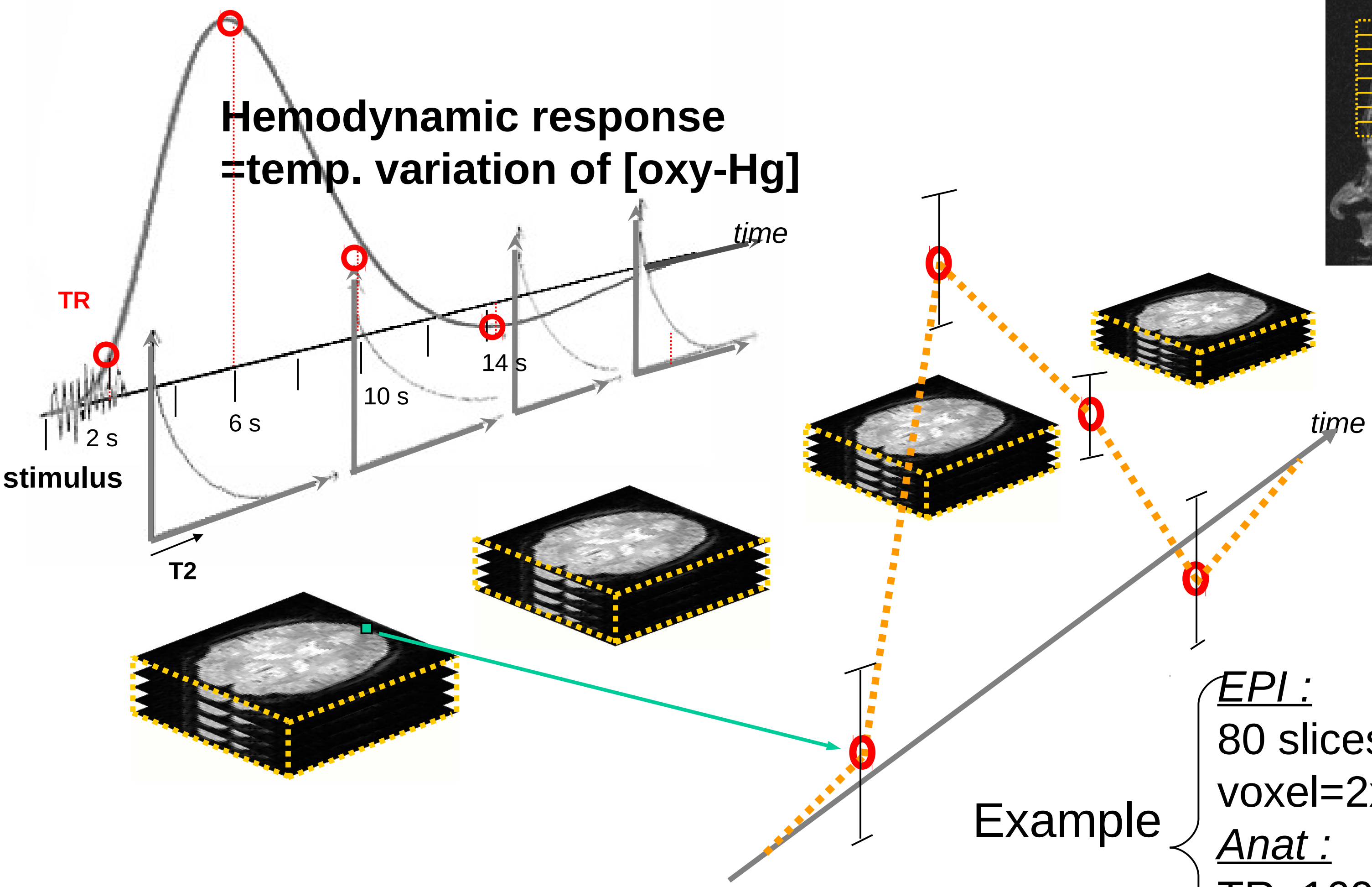
MEG

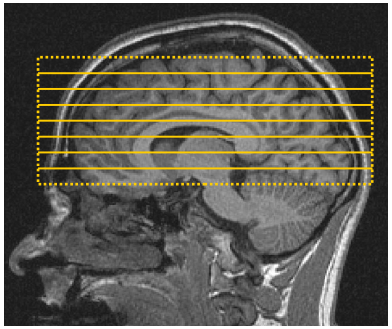
7T MRI



11.7T MRI (2014)

Sampling the BOLD response with functional MRI

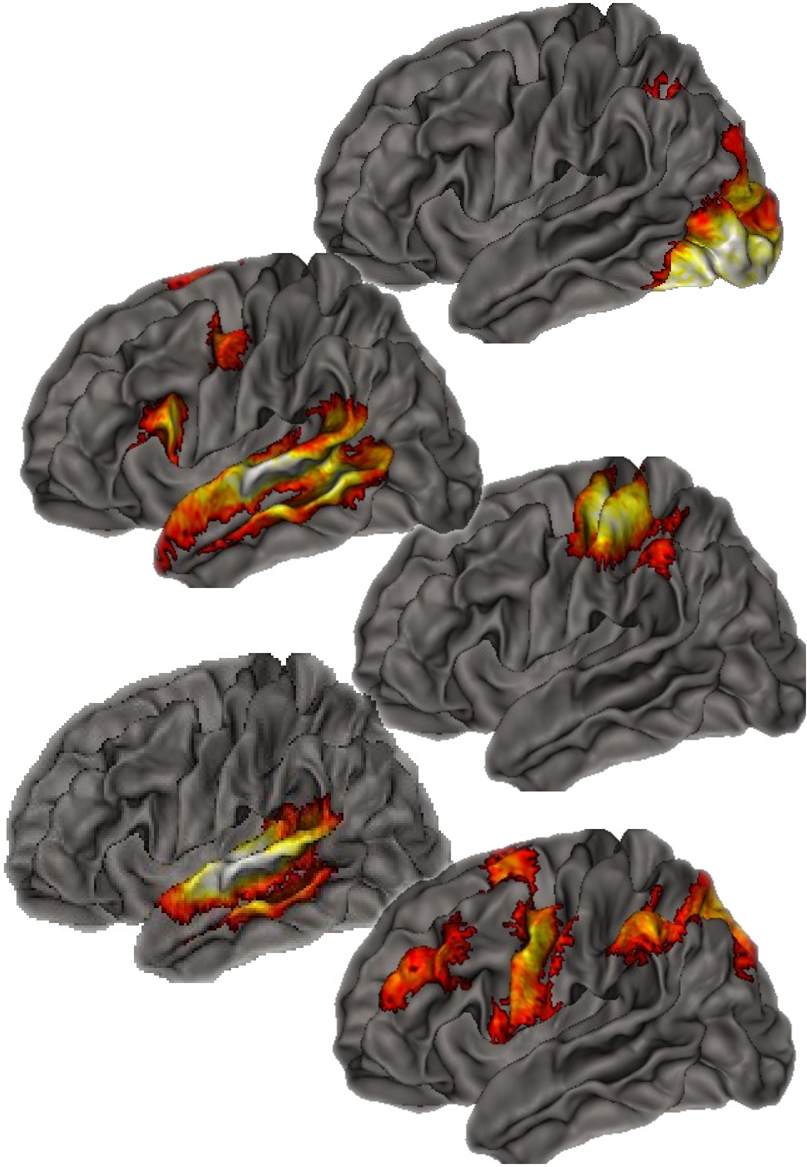




Example

EPI :
80 slices, TR=2000 ms, TE=30ms, voxel=2x2x2mm
Anat :
TR=1600ms, FOV=256x256mm2, voxel=1x1x1mm, 192 slices
Slice thickness 1mm

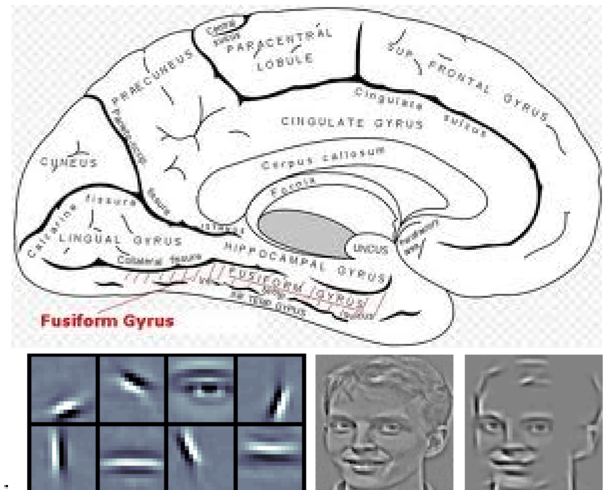
BOLD Imaging in humans



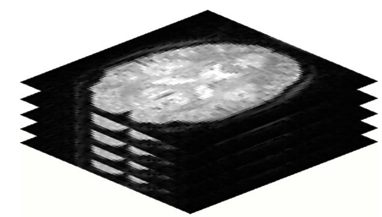
- BOLD fMRI has been used intensively to map cognitive functions in the human brain.
  - Segregation principle

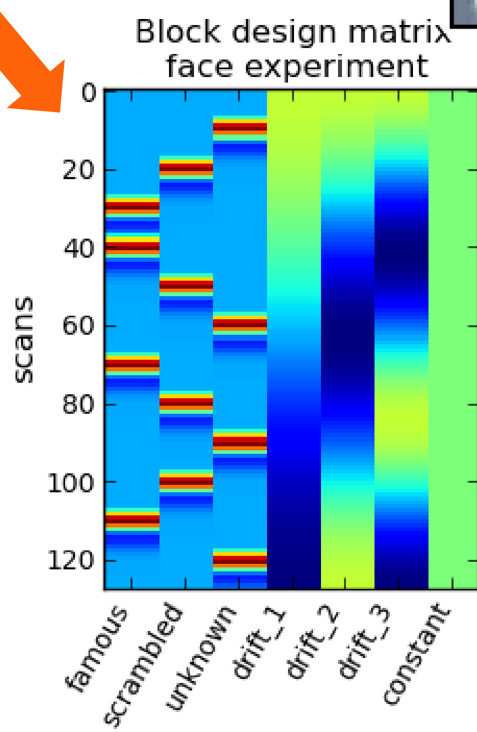
Even while the brain is “resting”

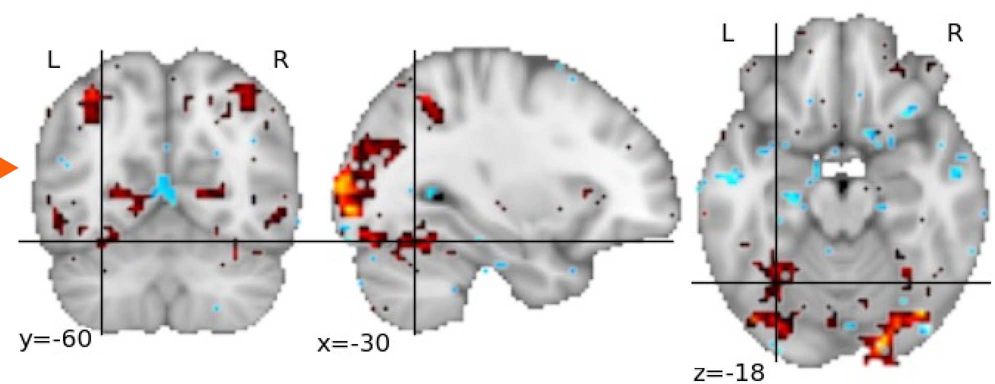
fMRI data from acquisition to analysis



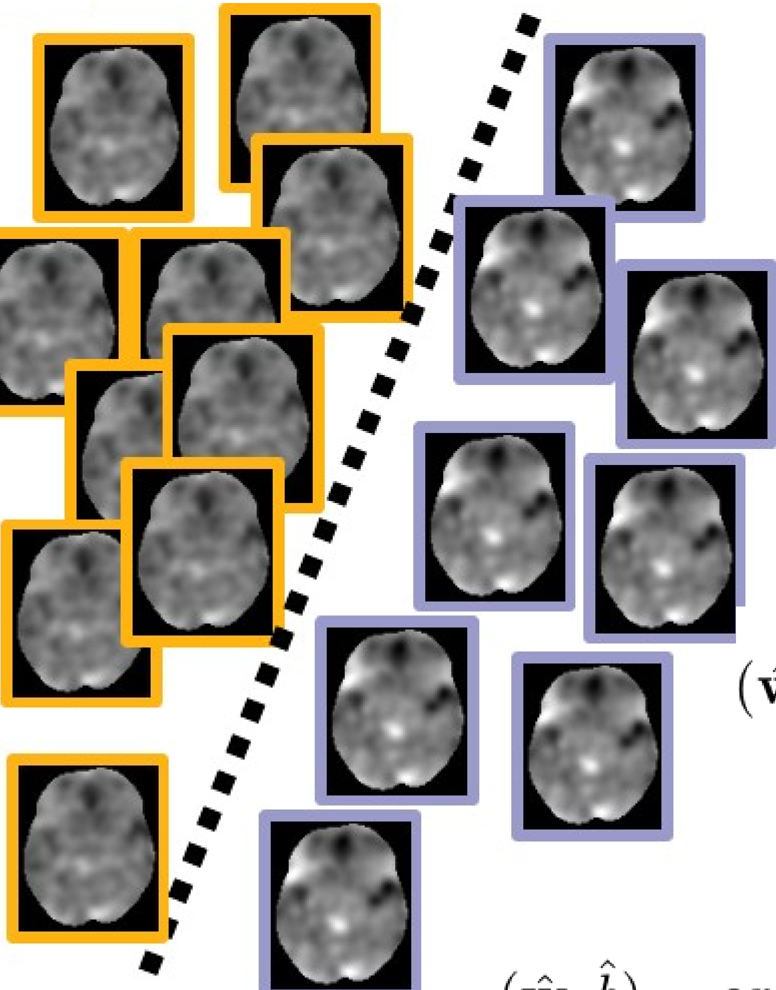
Complex metabolic pathway







FMRI data classification



- Given x in R^p, (fMRI volume with p voxels), predict a label y in {-1, 1} i.e. or

  or better the class probability Proba(y = 1|x)

- Use of logistic regression: learn the weight w and bias b such that

$$(\hat{\mathbf{w}}, \hat{b}) = \operatorname{argmin}_{\mathbf{w},b} \sum_{i=1}^{n} \log\left(1 + \exp\left(-\phi(x_i)(y_i \mathbf{w} + b)\right)\right)$$

- With regularization

$$(\hat{\mathbf{w}}, \hat{b}) = \operatorname{argmin}_{\mathbf{w},b} \sum_{i=1}^{n} \log\left(1 + \exp\left(-\phi(x_i)(y_i \mathbf{w} + b)\right)\right) + \lambda \|\mathbf{w}\|_2^2$$

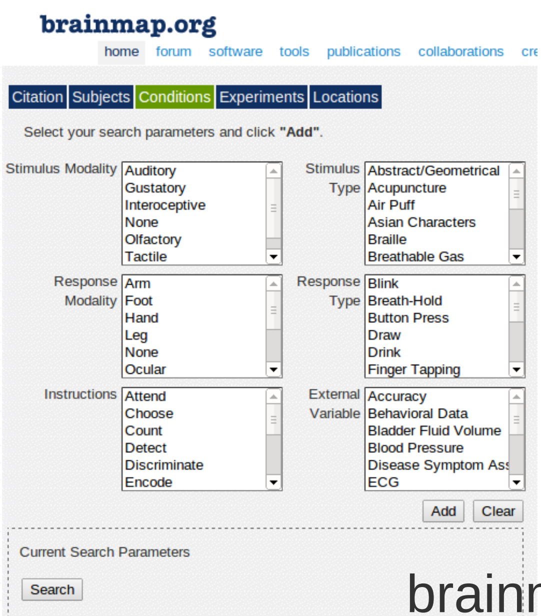
Decoding visual categories

Visual categories very well discriminated indivudally

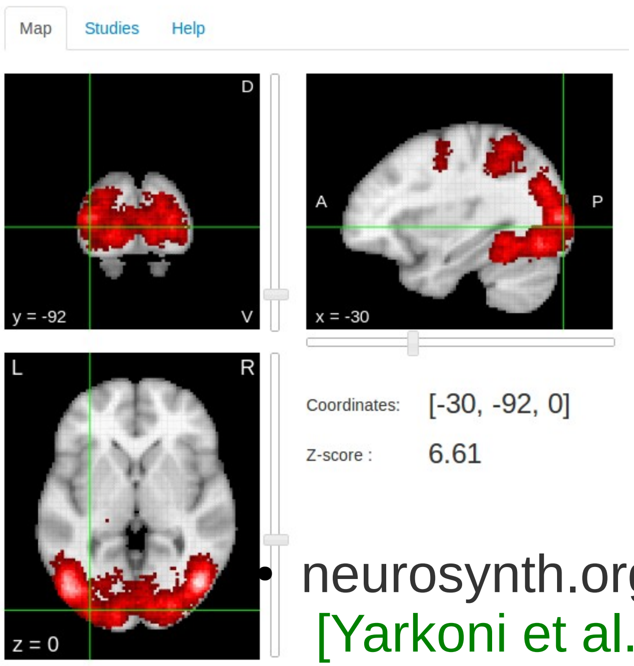
[Haxby et al. Science 2001]

fMRI meta-analyses

- Coordinate based meta-analyses
  - Activation peaks coordinates summarizing studies
  - **More functional specificity, less spatial information per study**



brainmap.org
[Laird et al., 2005]



- neurosynth.org
  [Yarkoni et al., 2011]

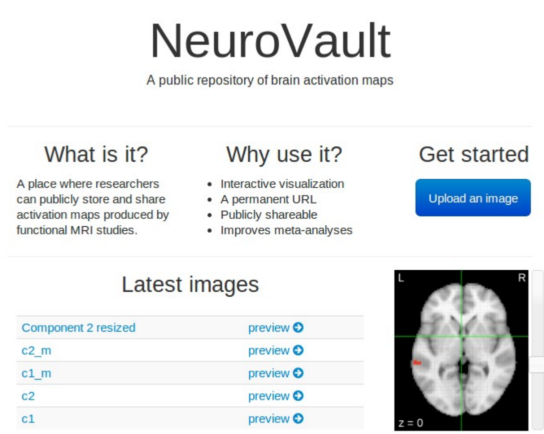
fMRI meta-analyses

- Image based meta-analyses
  - Use the actual statistical images
    - **More spatial information per study**
  - Less datasets
    - **Less functional specificity**

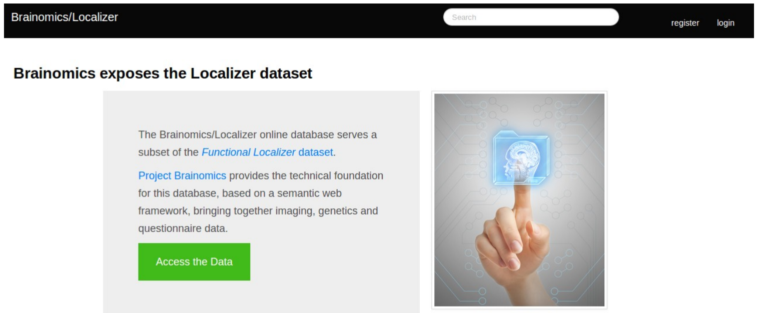
[Salimi-Khorshidi et al., 2009]

OpenfMRI

https://openfmri.org/



http://neurovault.org/



http://brainomics.cea.fr/localizer

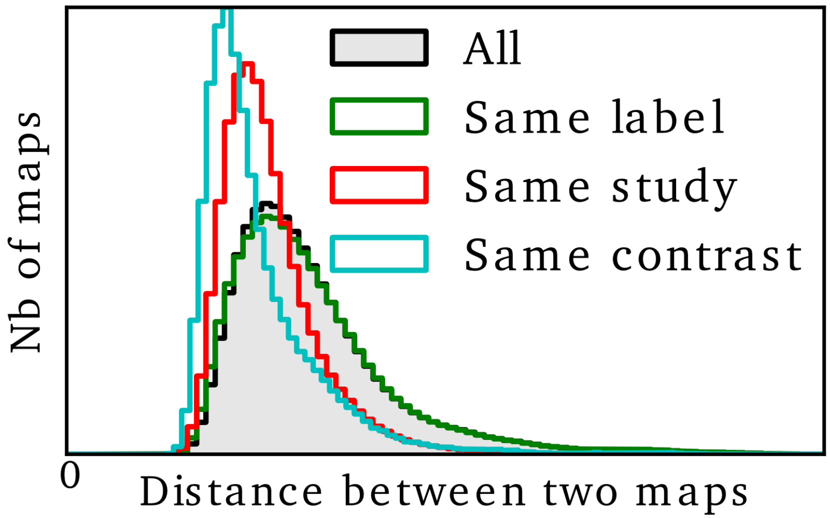
Image database

- Datasets
  - OpenfMRI (18 studies)
  - Neurospin (10 studies)
    - Functional localizers, Language & music structure Arithmetic & saccades Language temporal bottleneck
  - HCP

34 **studies**

700 **subjects**

15k **images**



Forward inference

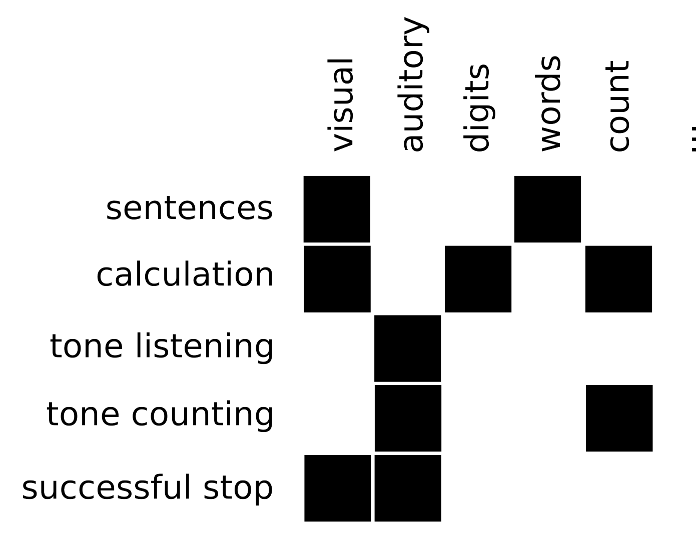
What is the brain response common to these stimuli?

Which regions are recruited by tasks containing a given term?

- General Linear Model (GLM) for terms effects

$$x = Y\beta + \varepsilon$$

x	Conditions images
Y	Design matrix
β	Terms effect
ε	Error

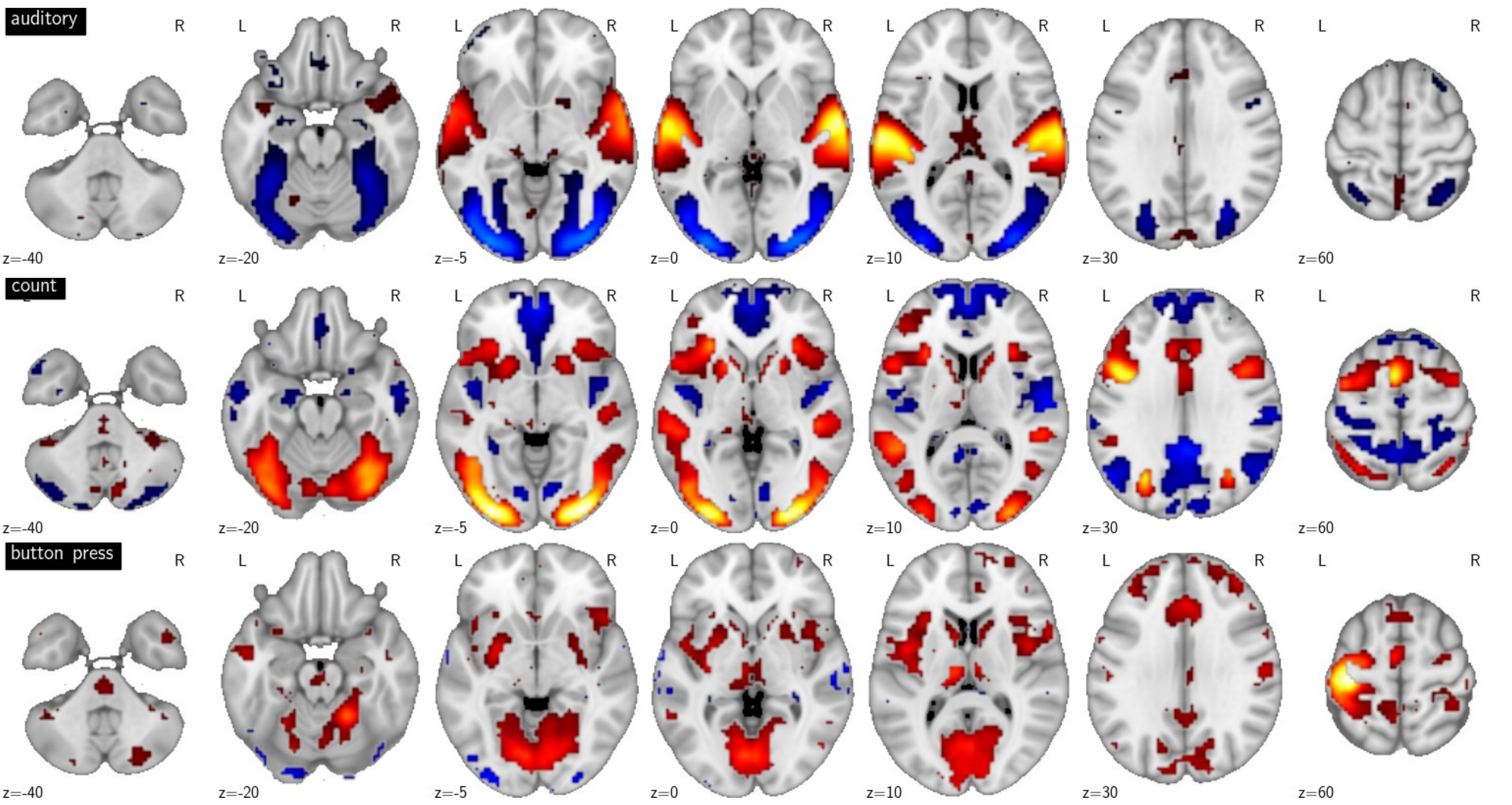


Forward inference

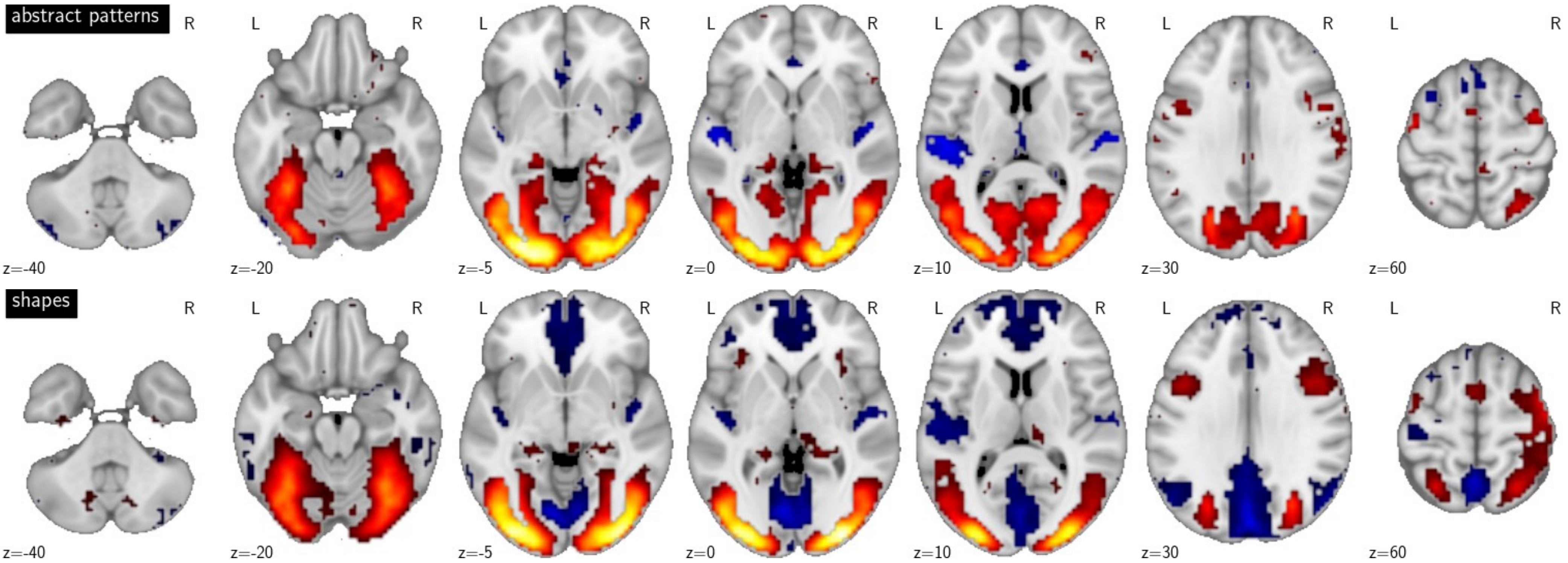
	visual	auditory	digits	face	patterns	scramble	saccades	none	button press	count	inhibit	discriminate	read	move	track	sounds	shapes	attend	words
visual	+1.0	-0.9	+0.0	+0.1	+0.1	+0.1	+0.1	-0.1	+0.1	-0.1	-0.0	+0.2	+0.4	-0.2	+0.1	-0.3	+0.2	-0.3	-0.1
auditory	-0.9	+1.0	-0.0	-0.1	-0.2	-0.1	-0.1	+0.1	-0.2	+0.0	+0.2	-0.3	-0.2	+0.2	-0.1	+0.4	-0.2	+0.3	+0.2
digits	+0.0	-0.0	+1.0	-0.1	-0.1	-0.1	-0.1	+0.3	-0.3	+0.8	-0.1	-0.2	-0.1	-0.2	-0.1	-0.1	-0.1	-0.2	-0.4
face	+0.1	-0.1	-0.1	+1.0	-0.1	-0.0	-0.0	+0.1	-0.1	-0.0	-0.0	-0.0	-0.1	-0.1	-0.0	-0.0	-0.0	+0.2	-0.1
patterns	+0.1	-0.2	-0.1	-0.1	+1.0	-0.1	-0.1	-0.0	+0.1	-0.1	+0.1	+0.3	-0.2	-0.2	-0.1	+0.0	-0.1	+0.1	-0.4
scramble	+0.1	-0.1	-0.1	-0.0	-0.1	+1.0	-0.0	-0.0	+0.0	-0.1	-0.0	+0.1	-0.1	-0.1	-0.0	-0.1	-0.1	+0.1	-0.2
saccades	+0.1	-0.1	-0.1	-0.0	-0.1	-0.0	+1.0	-0.2	-0.1	-0.1	-0.0	-0.1	-0.1	-0.1	+0.9	-0.1	+0.5	-0.1	-0.2
none	-0.1	+0.1	+0.3	+0.1	-0.0	-0.0	-0.2	+1.0	-0.9	+0.2	-0.0	-0.5	+0.1	-0.5	-0.2	+0.1	-0.1	+0.6	-0.2
button press	+0.1	-0.2	-0.3	-0.1	+0.1	+0.0	-0.1	-0.9	+1.0	-0.2	-0.1	+0.6	-0.1	+0.5	-0.1	-0.2	+0.0	-0.5	+0.2
count	-0.1	+0.0	+0.8	-0.0	-0.1	-0.1	-0.1	+0.2	-0.2	+1.0	-0.1	-0.1	-0.2	-0.1	-0.1	+0.0	-0.1	-0.2	-0.4
inhibit	-0.0	+0.2	-0.1	-0.0	+0.1	-0.0	-0.0	-0.0	-0.1	-0.1	+1.0	+0.1	+0.1	-0.1	-0.0	+0.5	-0.1	-0.1	+0.0
discriminate	+0.2	-0.3	-0.2	-0.0	+0.3	+0.1	-0.1	-0.5	+0.6	-0.1	+0.1	+1.0	+0.0	-0.2	-0.1	-0.0	+0.1	-0.4	-0.1
read	+0.4	-0.2	-0.1	-0.1	-0.2	-0.1	-0.1	+0.1	-0.1	-0.2	+0.1	+0.0	+1.0	-0.2	-0.1	-0.0	-0.2	-0.4	+0.5
move	-0.2	+0.2	-0.2	-0.1	-0.2	-0.1	-0.1	-0.5	+0.5	-0.1	-0.1	-0.2	-0.2	+1.0	-0.1	-0.1	-0.1	-0.3	+0.4
track	+0.1	-0.1	-0.1	-0.0	-0.1	-0.0	+0.9	-0.2	-0.1	-0.1	-0.0	-0.1	-0.1	-0.1	+1.0	-0.1	+0.5	-0.1	-0.2
sounds	-0.3	+0.4	-0.1	-0.0	+0.0	-0.1	-0.1	+0.1	-0.2	+0.0	+0.5	-0.0	-0.0	-0.1	-0.1	+1.0	-0.1	+0.2	-0.2
shapes	+0.2	-0.2	-0.1	-0.0	-0.1	-0.1	+0.5	-0.1	+0.0	-0.1	-0.1	+0.1	-0.2	-0.1	+0.5	-0.1	+1.0	+0.0	-0.3
attend	-0.3	+0.3	-0.2	+0.2	+0.1	+0.1	-0.1	+0.6	-0.5	-0.2	-0.1	-0.4	-0.4	-0.3	-0.1	+0.2	+0.0	+1.0	-0.2
words	-0.1	+0.2	-0.4	-0.1	-0.4	-0.2	-0.2	-0.2	+0.2	-0.4	+0.0	-0.1	+0.5	+0.4	-0.2	-0.2	-0.3	-0.2	+1.0

Correlation of the design matrix: difficulties from the heavily correlated terms (database bias)

Results

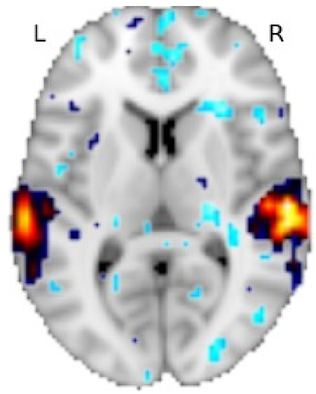


Results



Reverse inference

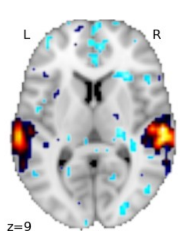
?



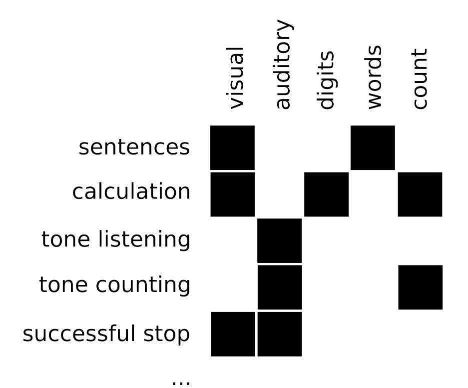
What is
this brain doing?

Which regions are predictive of tasks containing a given term?

- **Multilabel** classification problem
  - more than one class may be associated with each sample
- Predict the CogPO terms



Data: experimental condition images



Target

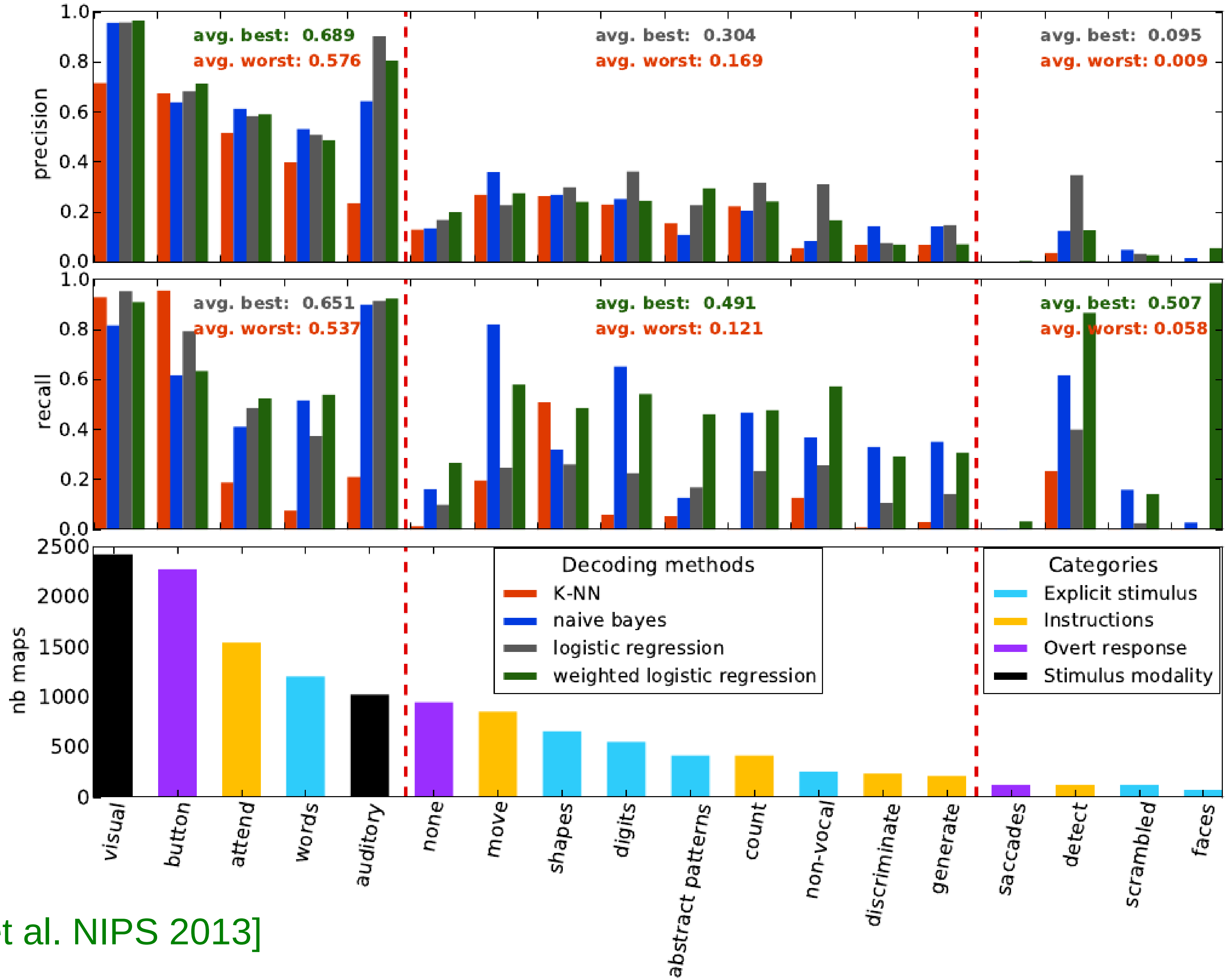
Reverse inference

Which regions are predictive of tasks containing a given term?

- Model details
  - **One-vs-all** approach with an *l2* penalized logistic regression
  - Features selection: hierarchical clustering (Ward) & ANOVA.
- Cross validation
  - **Leave-one study out, leave-one lab out**
  - Predict unseen conditions
- Problems
  - Class distribution (imbalance & covariate shift)
  - Long tailed distribution of terms

Precision: does not label as positive a sample that is negative

Recall: finds all the positive samples



[Schwartz et al. NIPS 2013]

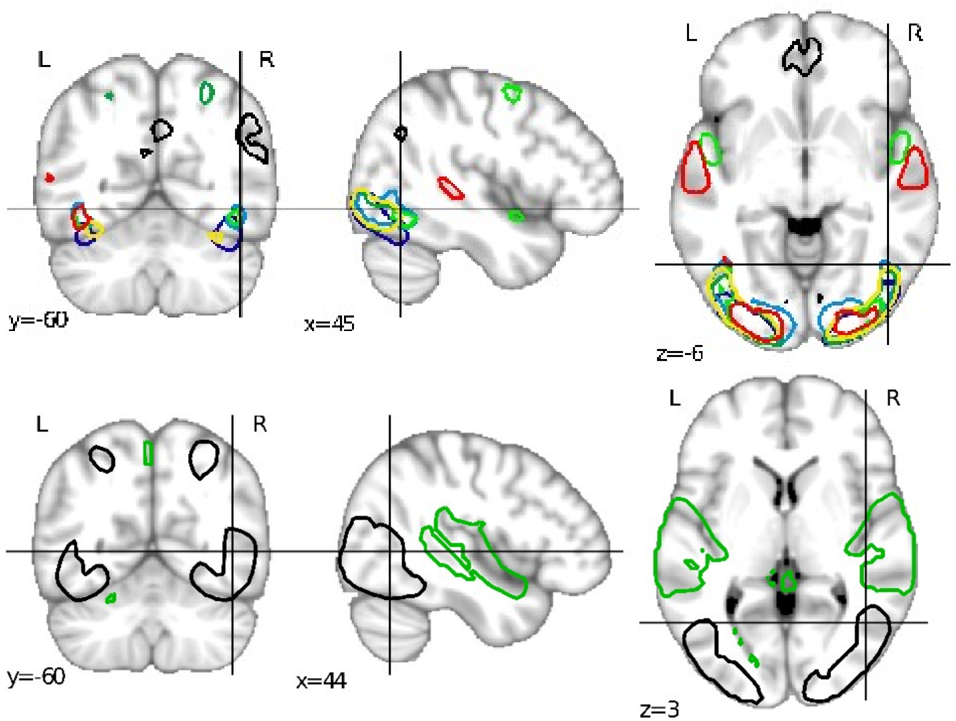
Forward vs. Reverse

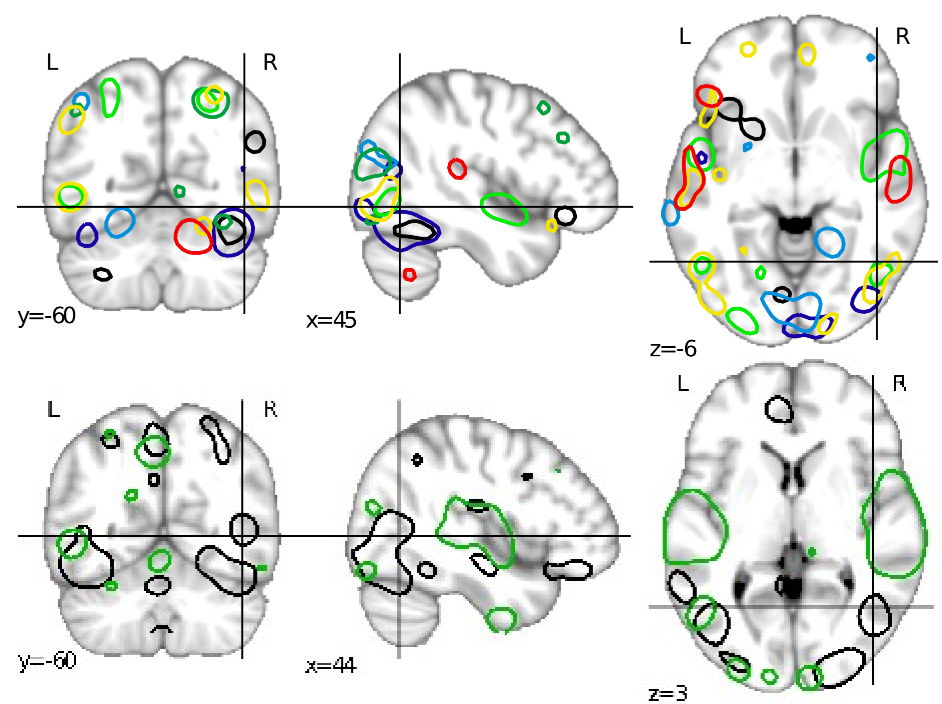
Terms
- digits
- face
- patterns
- scramble
- sounds
- shapes
- words

Explicit stimulus

Stimulus modality

Terms
- visual
- auditory





Forward

Less specific but more accurate

Reverse

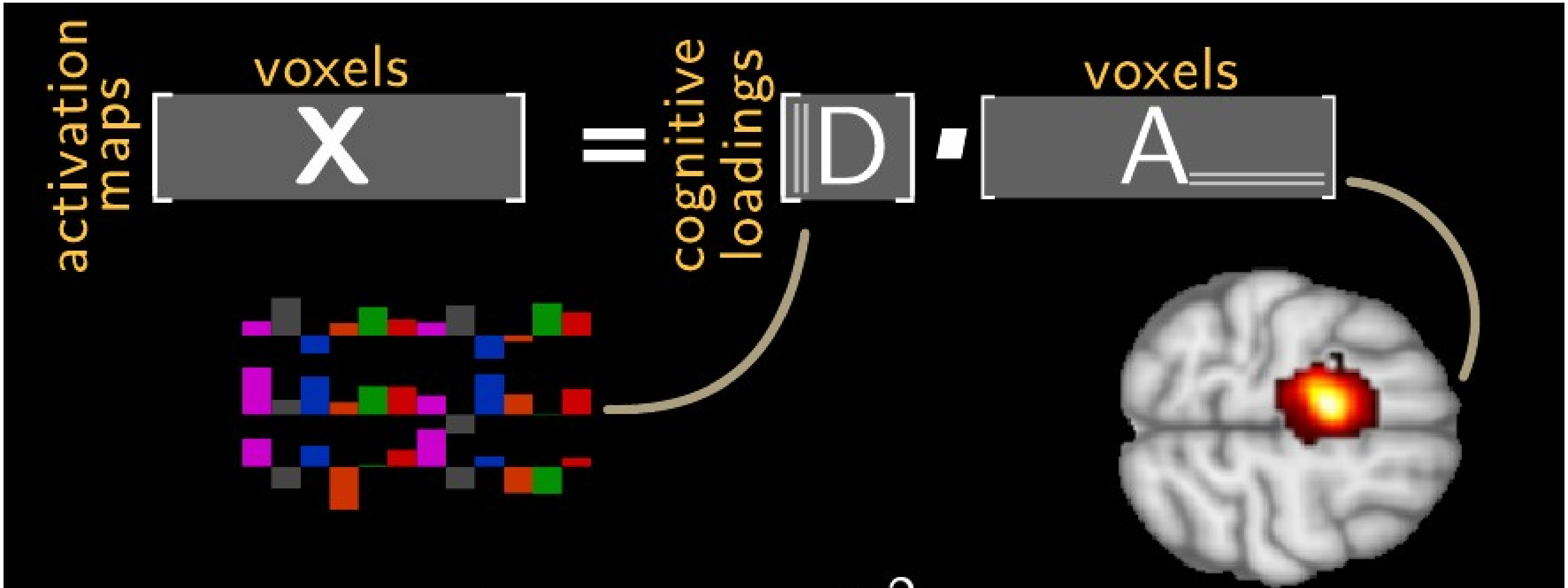
Less accurate but more specific

[Schwartz et al. NIPS 2013]

Unsupervised Setting

- Goal: build a brain atlas that represents the contrasts in a database
  - Sets of regions with given functional features
- Technical issues:
  - Inter-subject variability: both in spatial definition and functional characteristics
  - How to measure model quality ? Perform model selection ?
  - Tractability

Functional segregation = sparse coding



$$\underset{\mathbf{D},\mathbf{A},\ \Omega(\mathbf{D})\leq 1}{\operatorname{argmin}} \left\| \mathbf{X} - \mathbf{D}\,\mathbf{A}^{T} \right\|_2^2 + \lambda \left\| \mathbf{A} \right\|_1$$

Similar to learning contrasts + maps – closely related to ICA or clustering

Learning problem

Optimization

$$\hat{\boldsymbol{D}} = \underset{\boldsymbol{D},\, \Omega(\boldsymbol{D}) \leq 1}{\operatorname{argmin}} \sum_v \min_{\boldsymbol{a}_v} \left(\|\boldsymbol{x}_v - \boldsymbol{D}\boldsymbol{a}_v^{\mathsf{T}}\|_2^2 + \lambda \|\boldsymbol{a}_v\|_1 \right)$$

D is essentially a sample mean → stochastic gradient descent
On a small number of x_v : LARS to learn a_v
Projected gradient descent for D.

Structured norm: $\Omega(\bar{\mathbf{f}}_i) = \max\left(\|\bar{\mathbf{f}}_i\mathbf{C}\|_2^2, \mu\|\bar{\mathbf{f}}_i\mathbf{C}_\perp\|_2^2\right)$

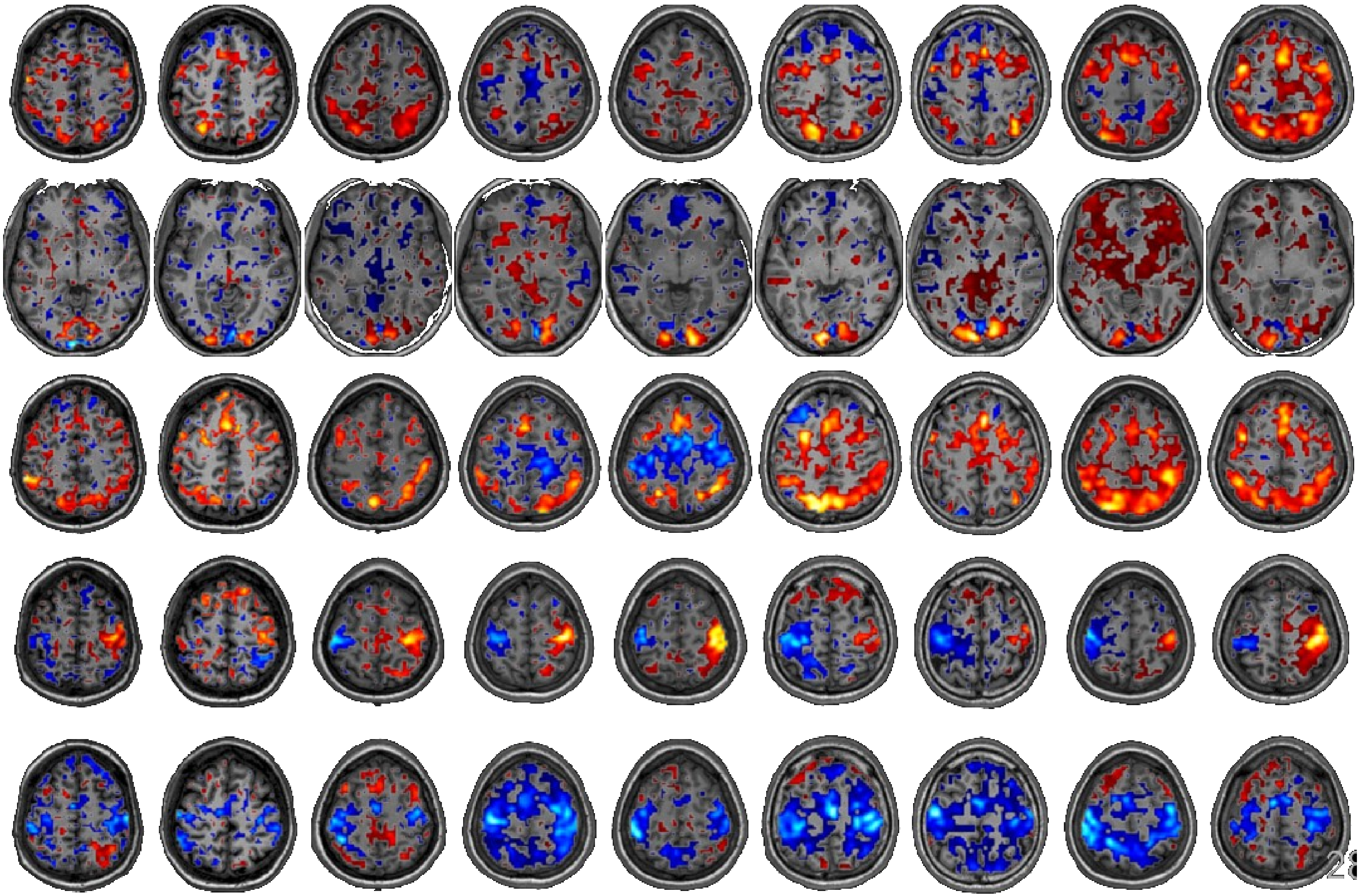
weighted $\ell_{2\infty}$ in $\{\mathbf{C}, \mathbf{C}_\perp\}$ basis

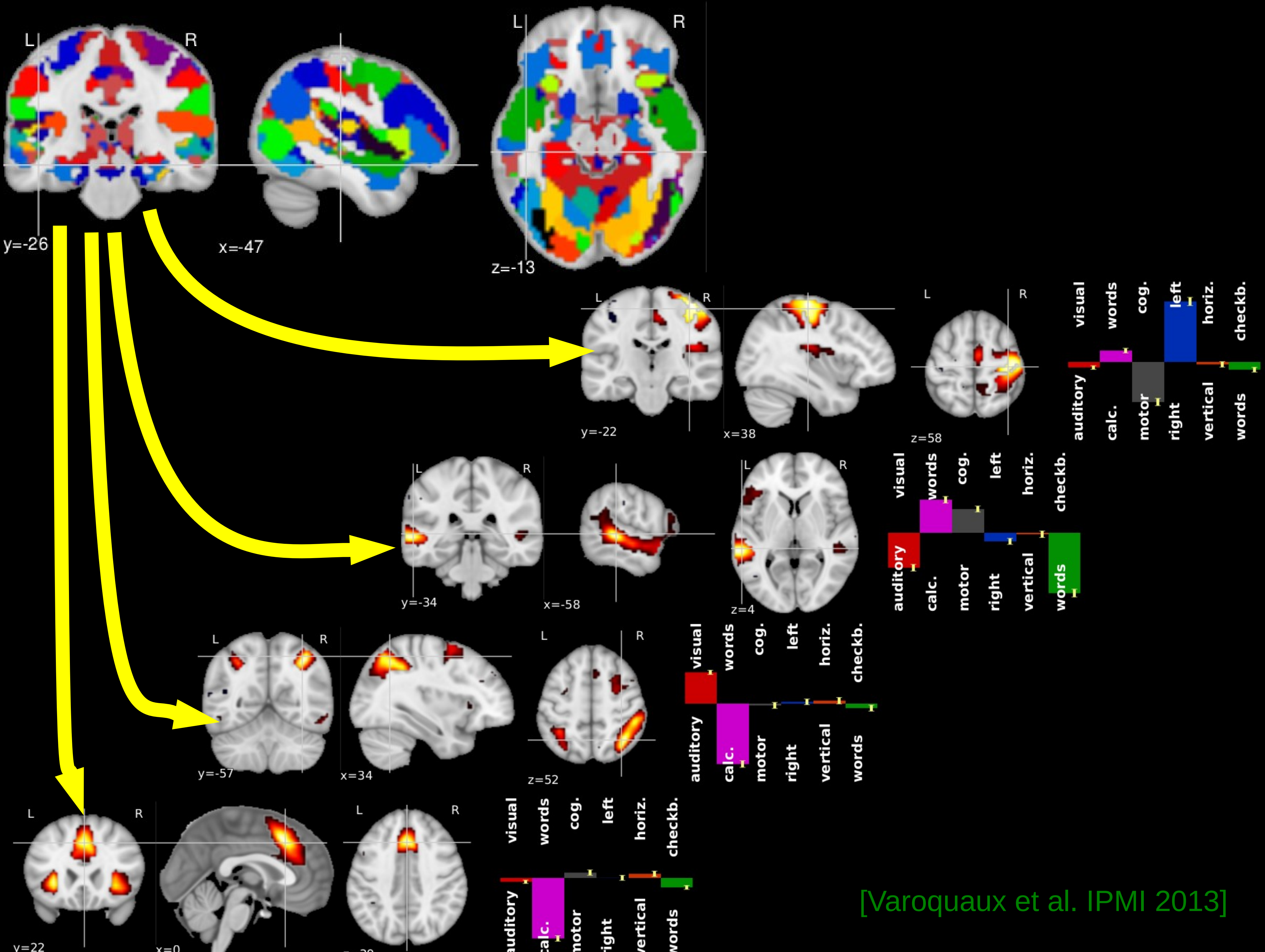
Parameter setting

$$\lambda \propto \frac{1}{\sqrt{p}} \operatorname{std} \boldsymbol{X}.$$

$$\mu = .1, K = 50$$

Dataset – and variability





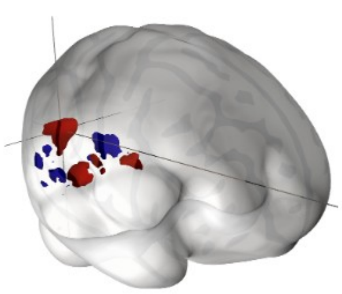
[Varoquaux et al. IPMI 2013]

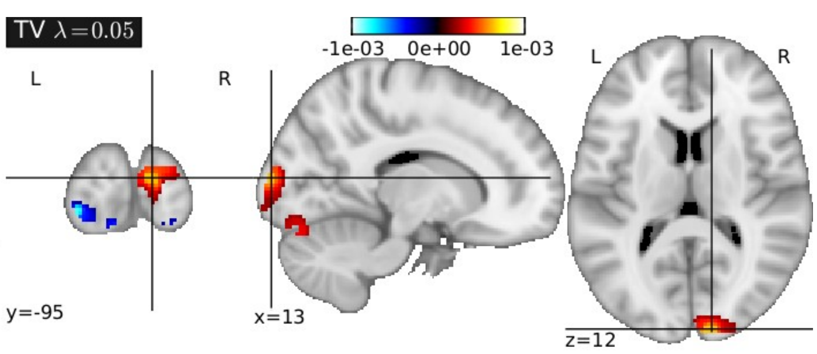
Discussion – work in progress

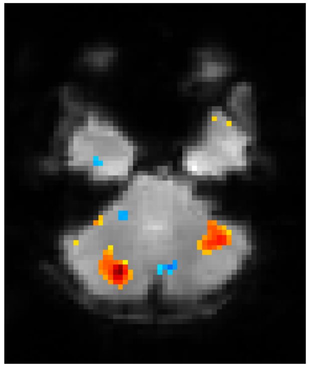
- Better penalties (smoothness, total variation)
  - Not yet compatible with online learning
- Extension to multiple datasets:
  - Use of summary statistics for speed-up
- Model selection – if doable ?

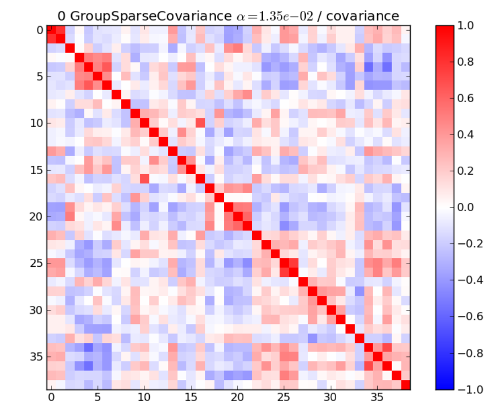
Data analysis tools

- Machine learning for neuroimaging http://nilearn.github.io
- Scikit-learn-like API
- BSD, Python, OSS
    - Classification of neuroimaging data (decoding)
    - Functional connectivity analysis









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