Large-scale analyses in functional brain Imaging

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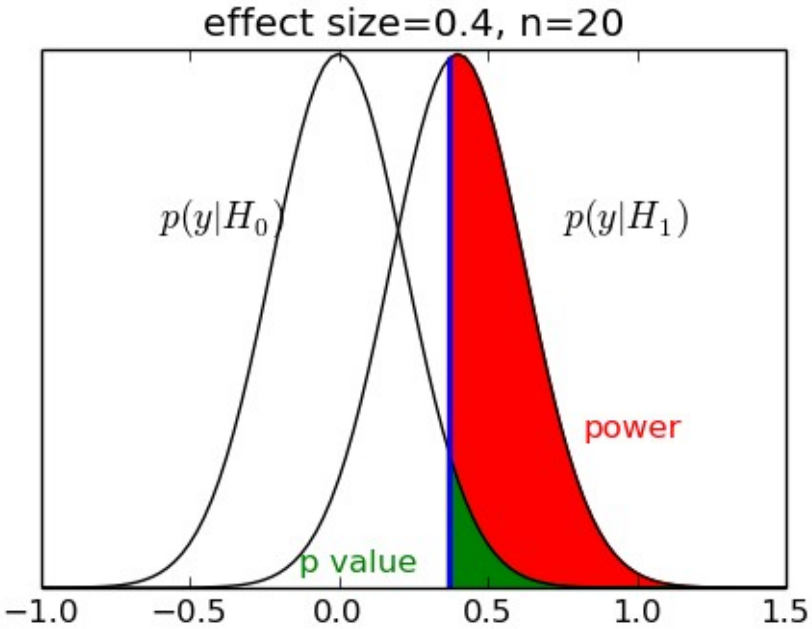
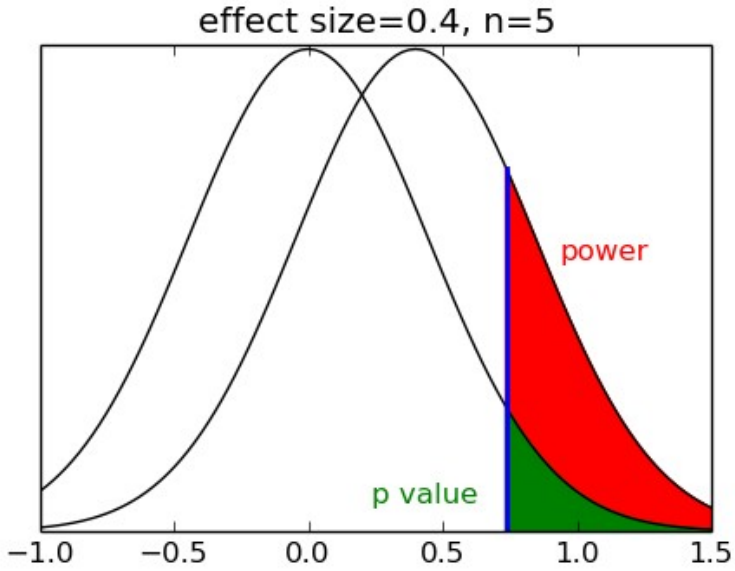
Outline

- The importance of using large(r) datasets in medical imaging
- Combining modalities to increase power
- Identify ensuing computational bottlenecks and algorithmic solutions

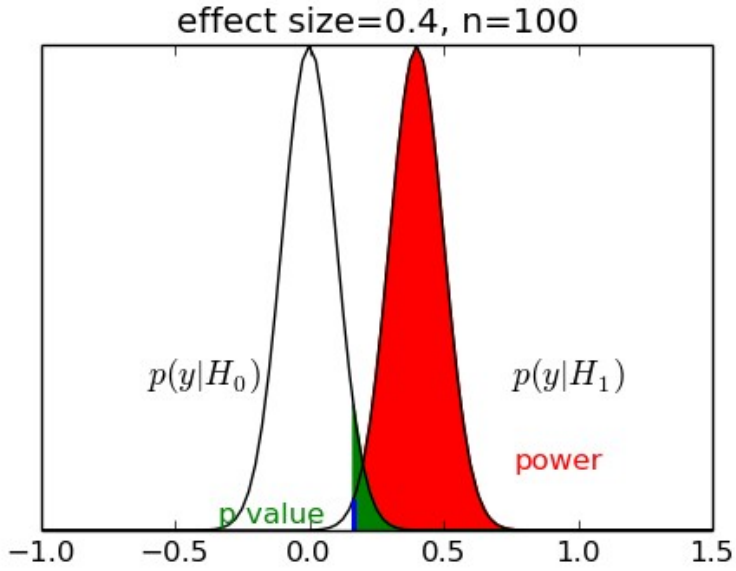
Increasing the number of samples: power



Less subjects

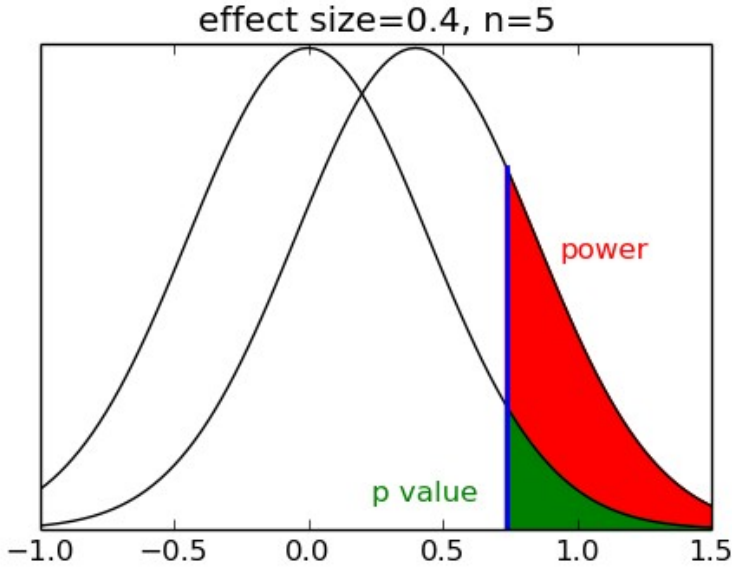


more subjects

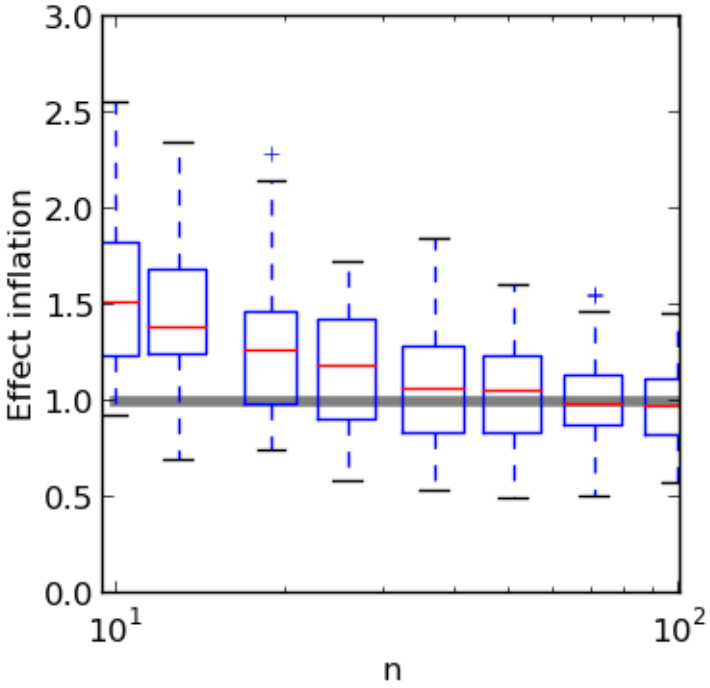


Imaging in the low power regime

Low power → unreliable findings



Low positive predictive value: low likelihood that a statistically significant finding is actually true



Exaggerated estimate of the magnitude of discovered effects "*winner's curse*"

Medical imaging in the big data era ?

- Neuroscientists reluctant to using big data : this is a burden
- Common belief : you should only focus on large effects
  → small datasets are good enough
- But...

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

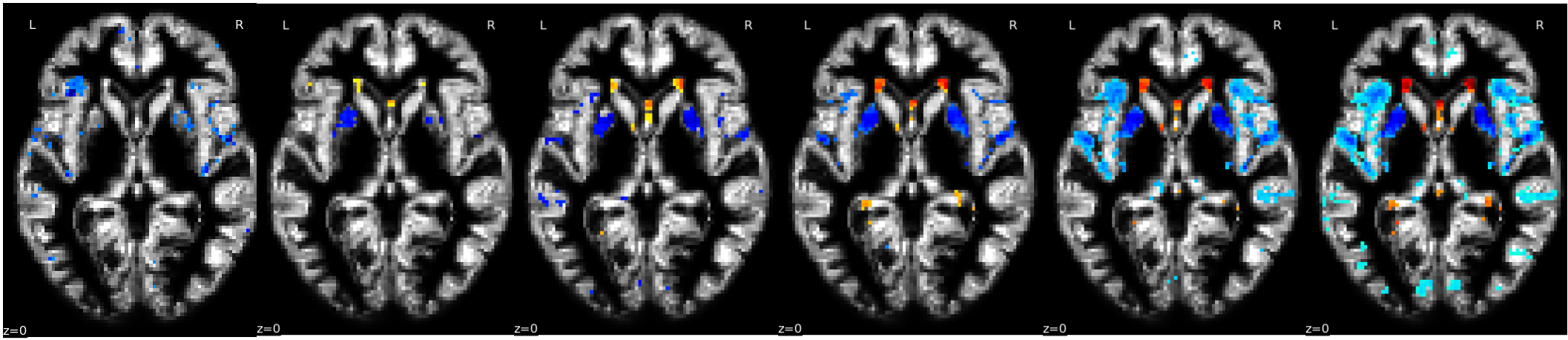
nature REVIEWS

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]

Example

OASIS dataset, effet of age on gray matter density

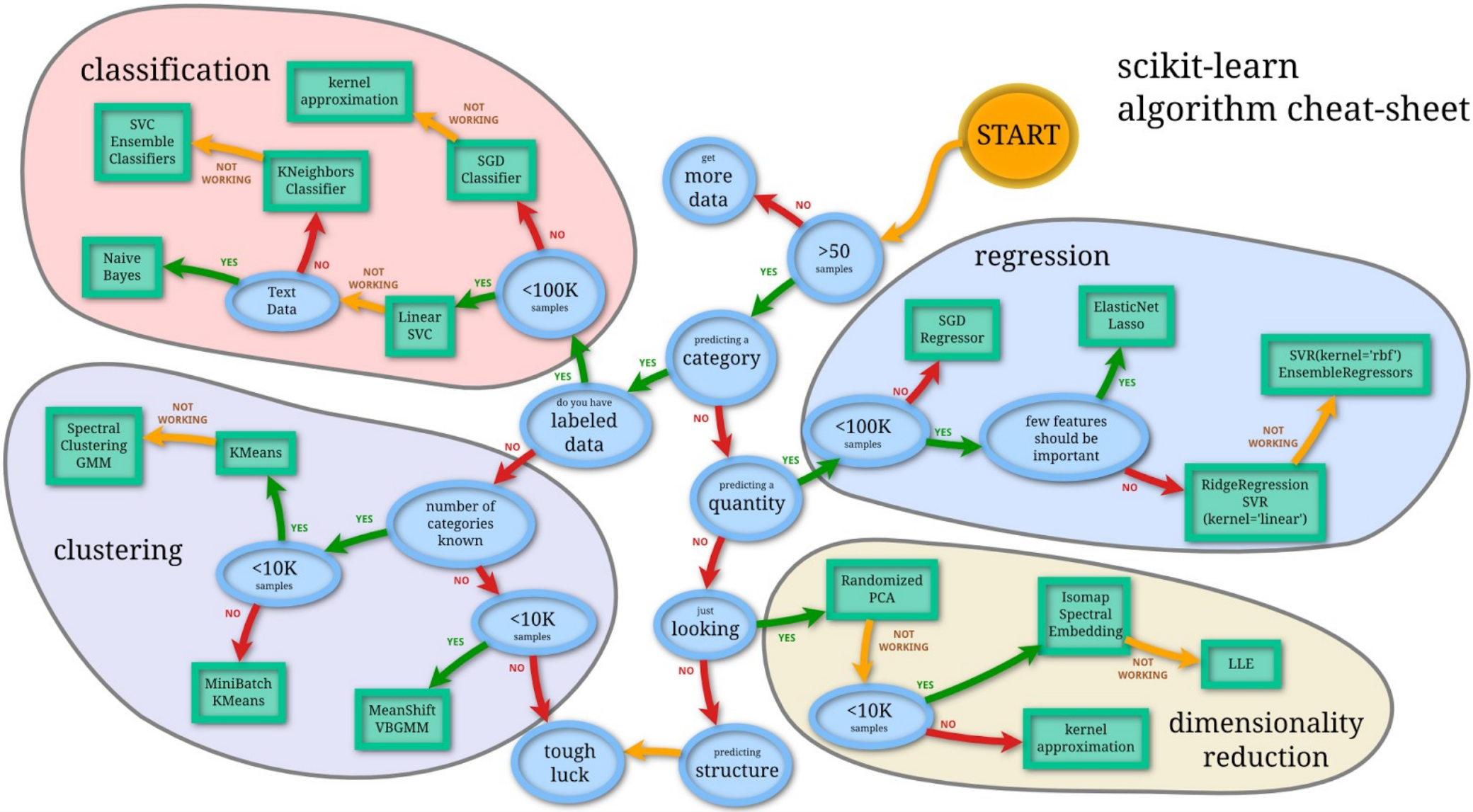


n=10 **n=20** **n=30** **n=50** **n=70** **n=100**

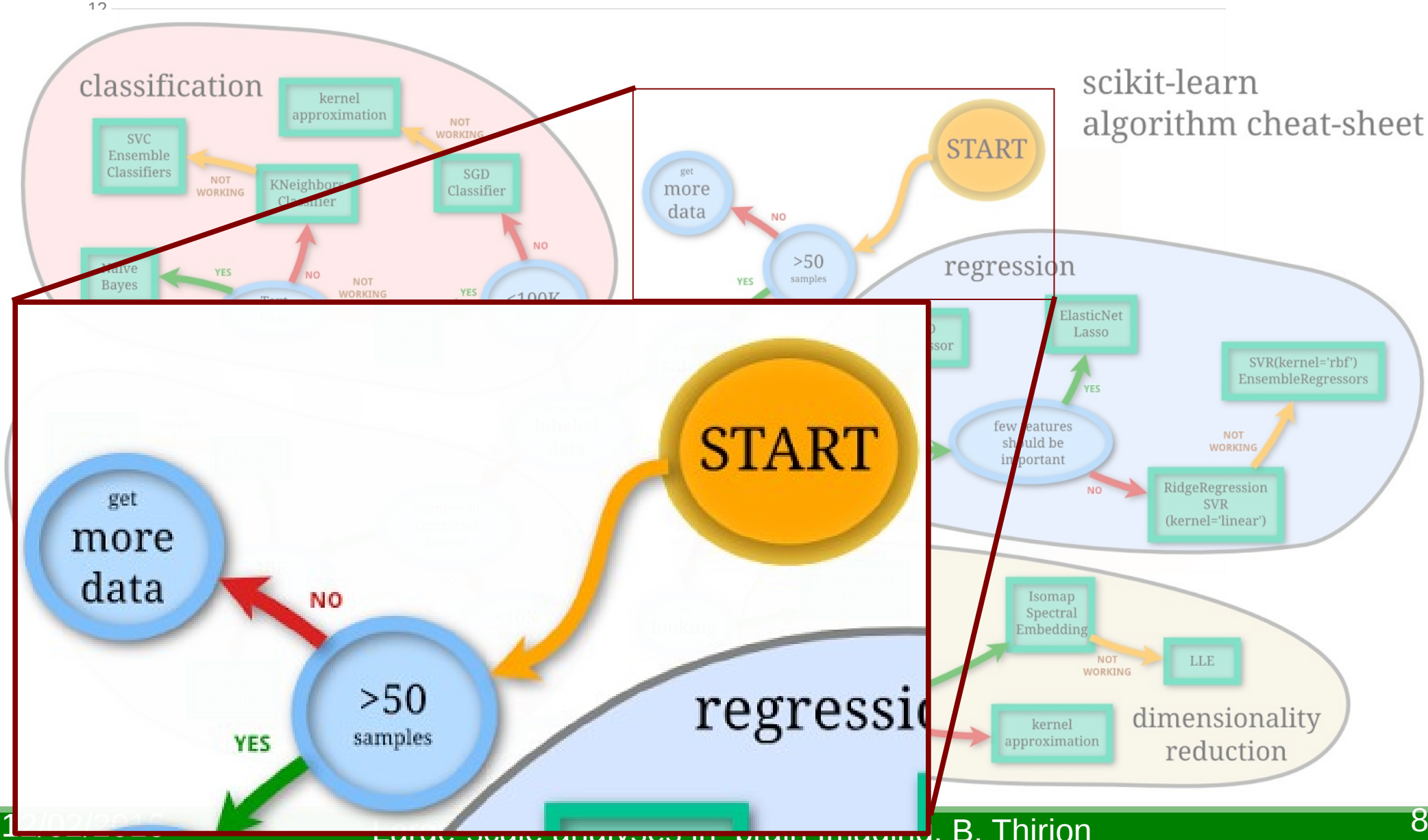
Reproducibility by bootstrap:

7% 19% 32% 53% 66% 75%

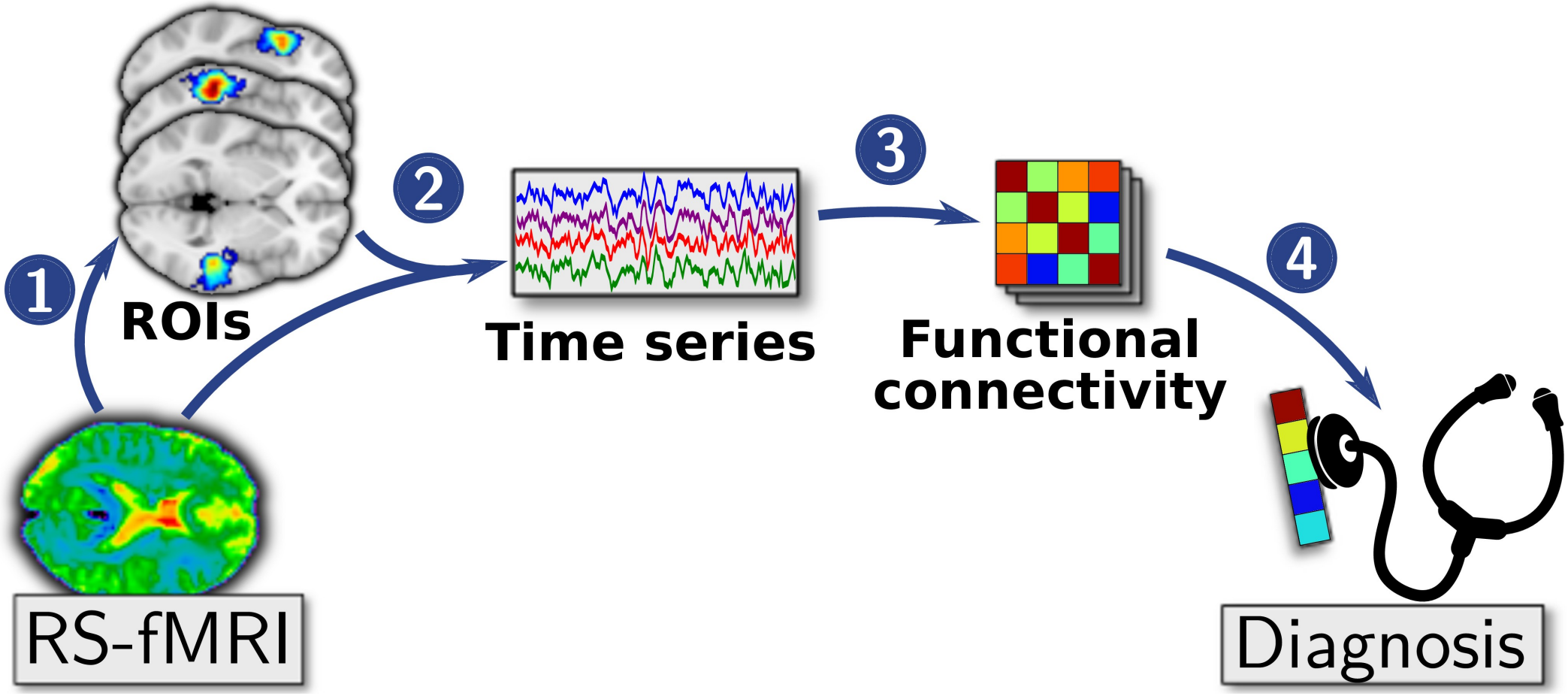
Multivariate analysis



Multivariate_analysis



Large-scale connectome analysis for disease prediction



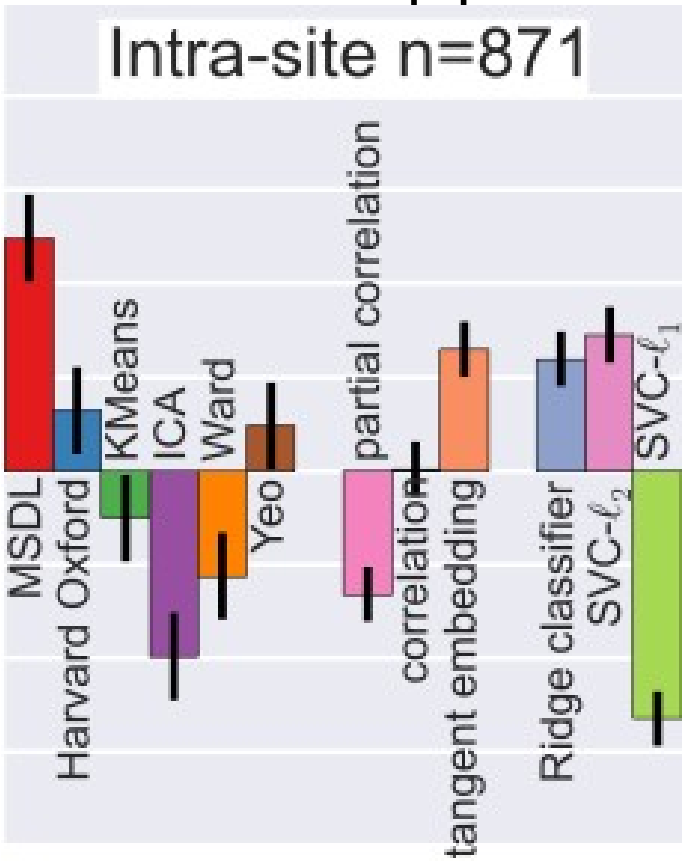
871 subjects, 300-400GB of data

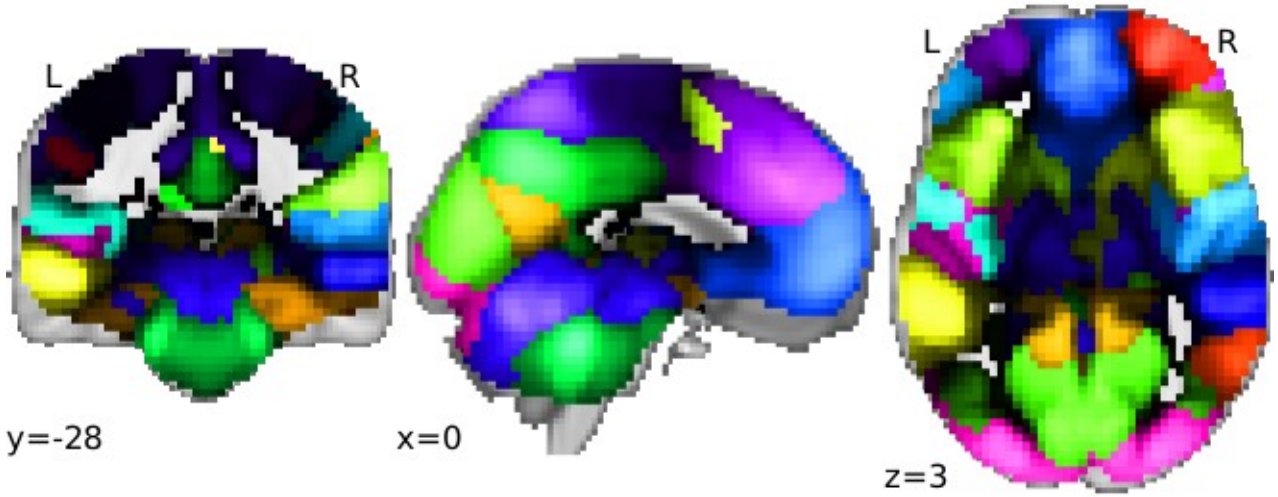
Large scale connectome analysis for disease prediction

- Classification of ASD patients
  - Public ABIDE dataset [Di Martino et al. Mol. Psych. 2014]
  - Large heterogeneity: multi-centric study
  - Functional connectivity: weakly sensitive marker
- 68% correct classification (65% when generalizing across sites)

Large scale connectome analysis for disease prediction

What are the most important factors of the pipeline ?





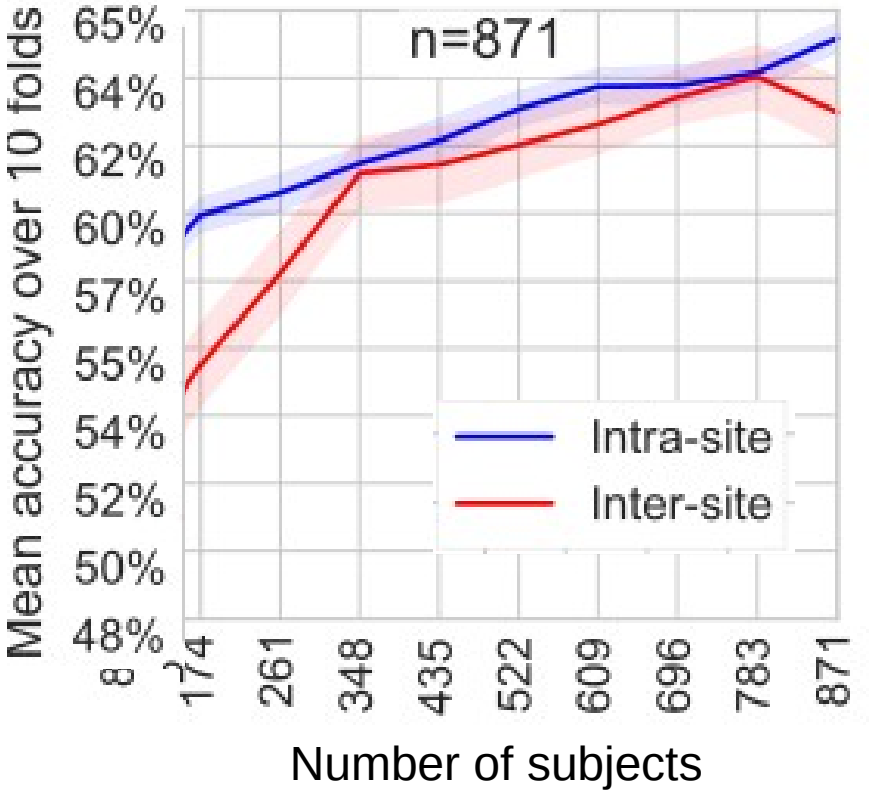
Response: the choice of the atlas.

[Abraham et al. Subm to NIMG]

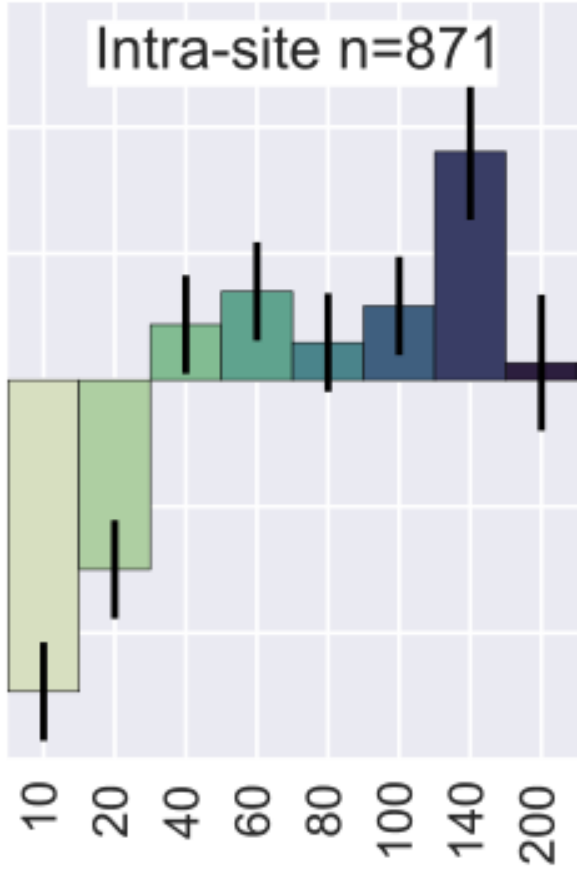
Large scale connectome analysis for disease prediction

More subjects → higher accuracy

Asymptote not yet reached at n=871

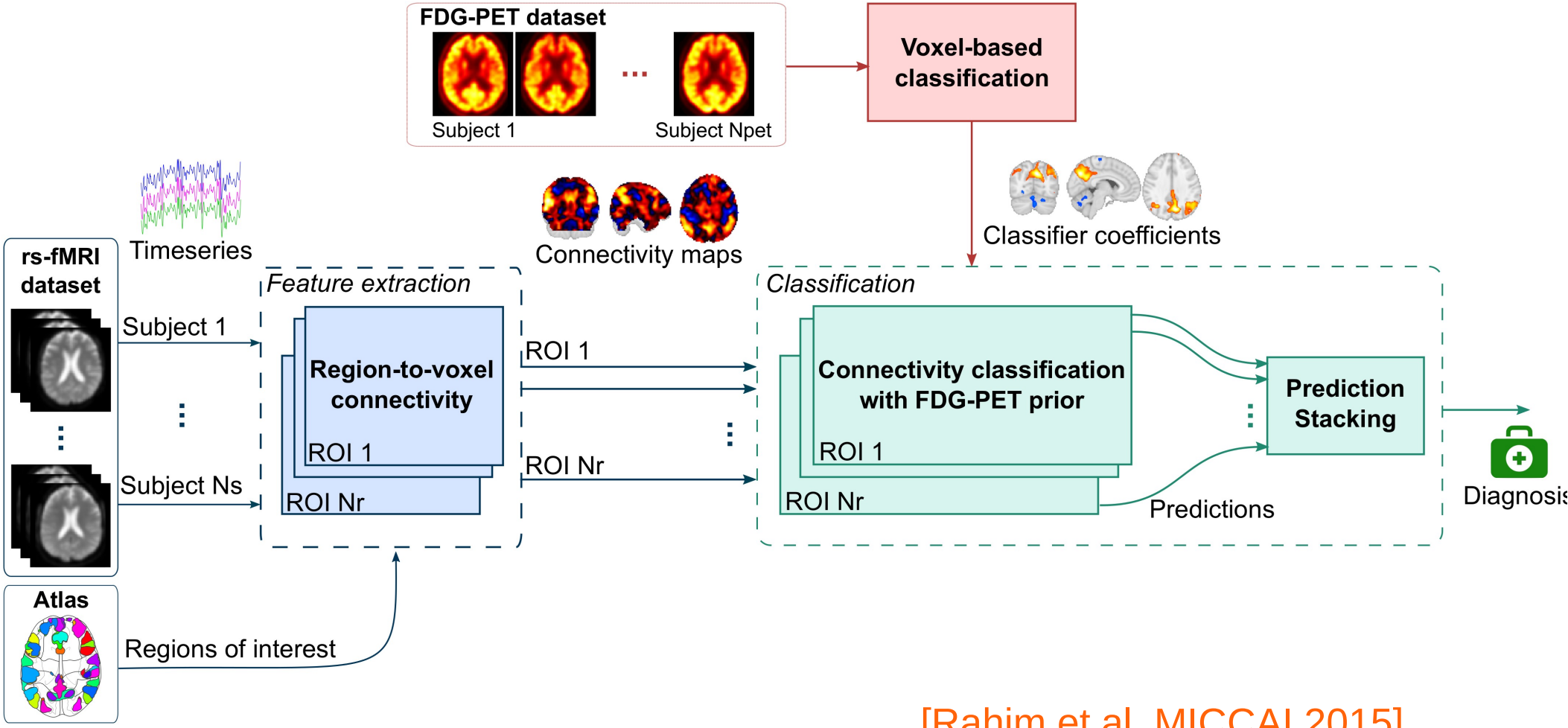


Impact of the number of regions



Leveraging multi-modal datasets

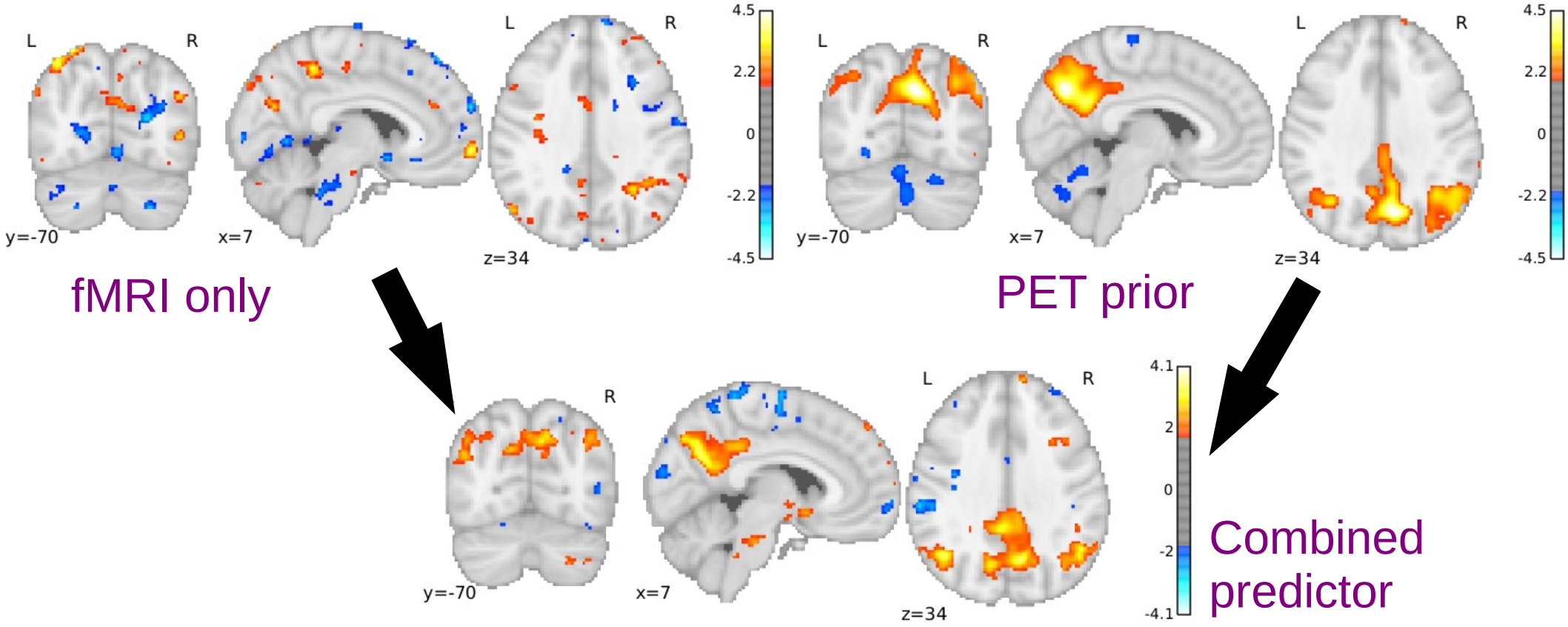
Combining images from Different modalities



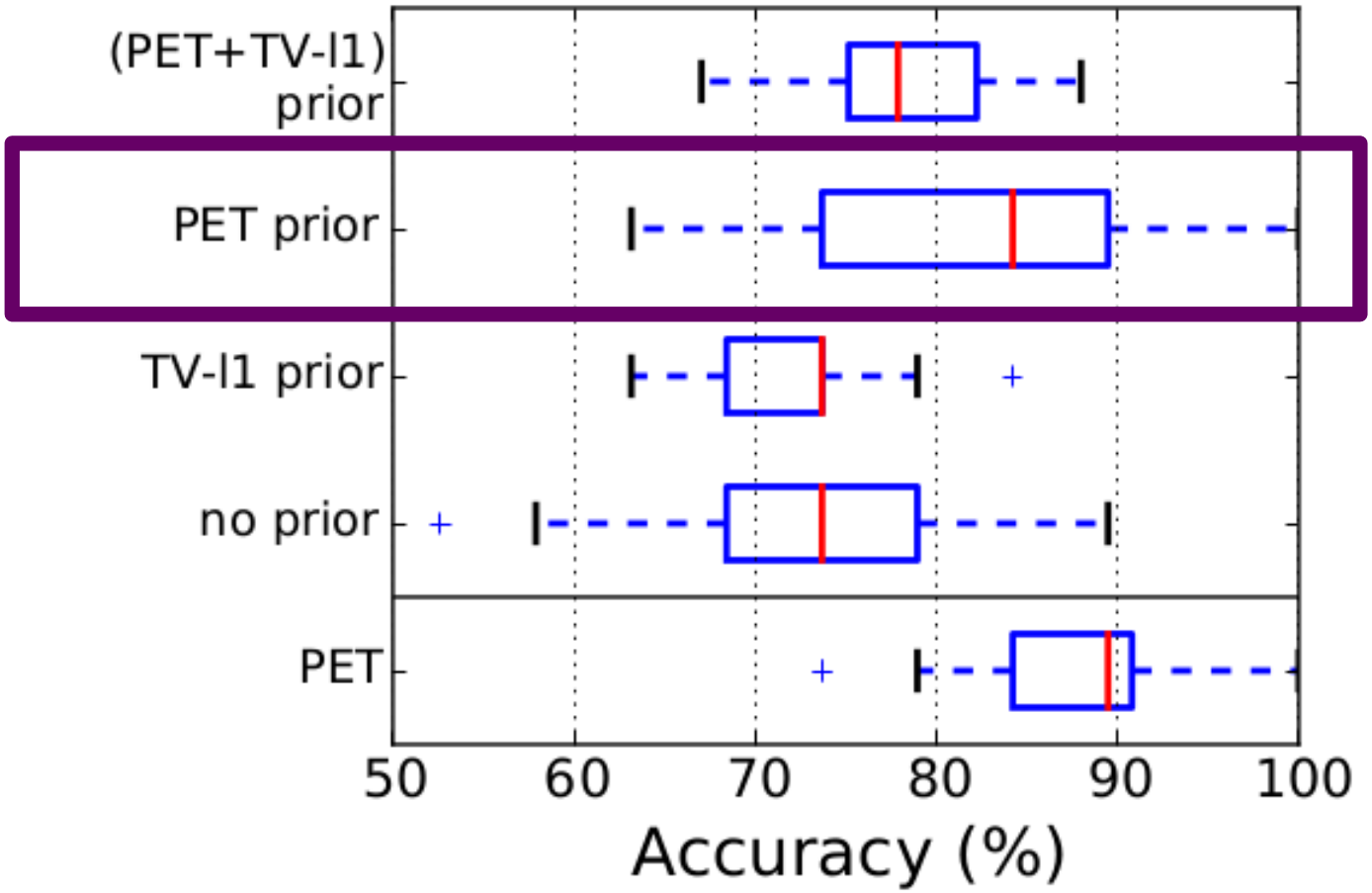
[Rahim et al. MICCAI 2015]

Trans-modal priors improve discriminative models

Diagnosis of Alzheimer disease (Alzheimer vs MCI) using resting-state fMRI and a PET prior



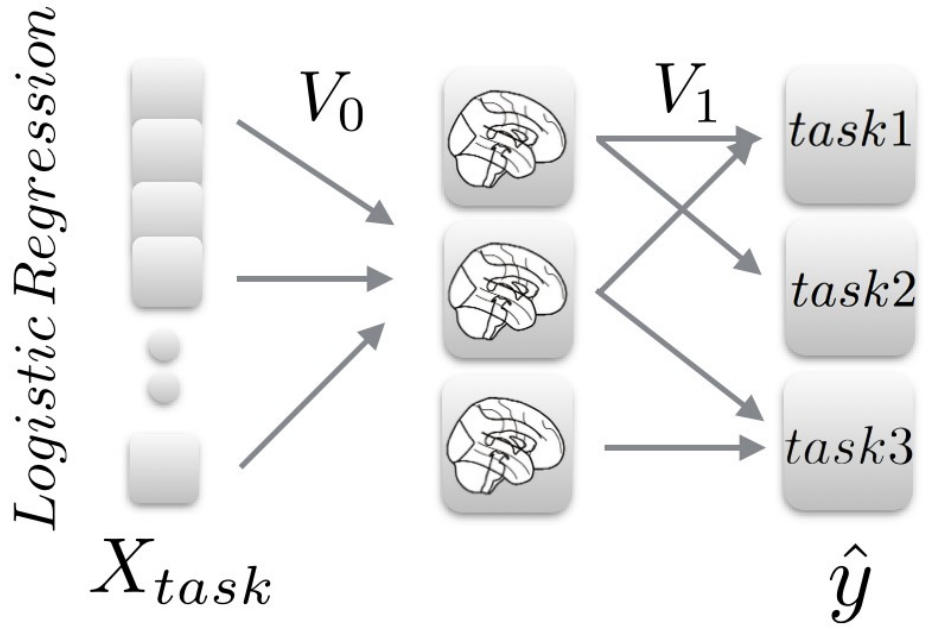
Trans-modal priors improve discriminative models



[Rahim et al. MICCAI 2015]

Using rest data to better model task data

- A wealth of “resting-state” data available
- Little cognitive data with proper annotations
- Idea: use unlabelled data to improve the learning of discriminative models



[Bzdok et al. NIPS 2015]

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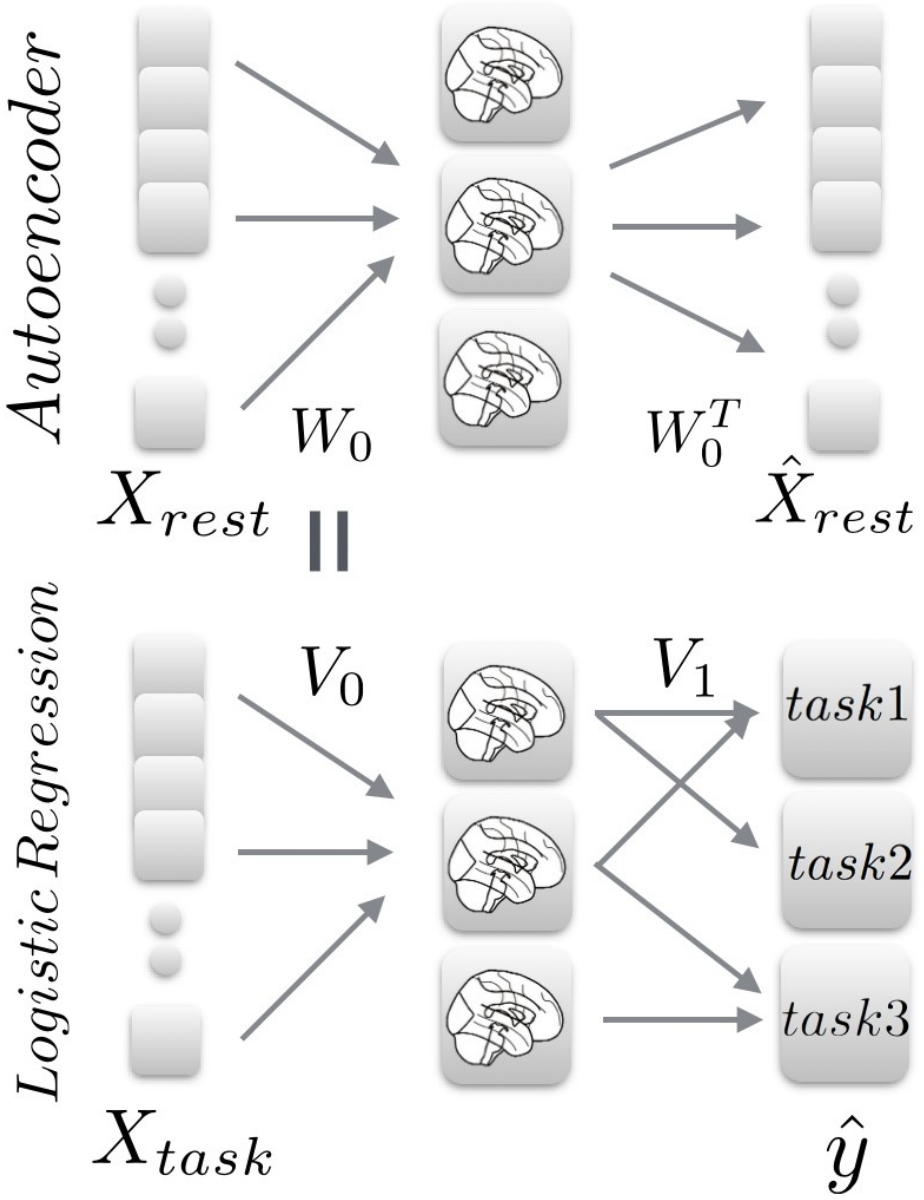
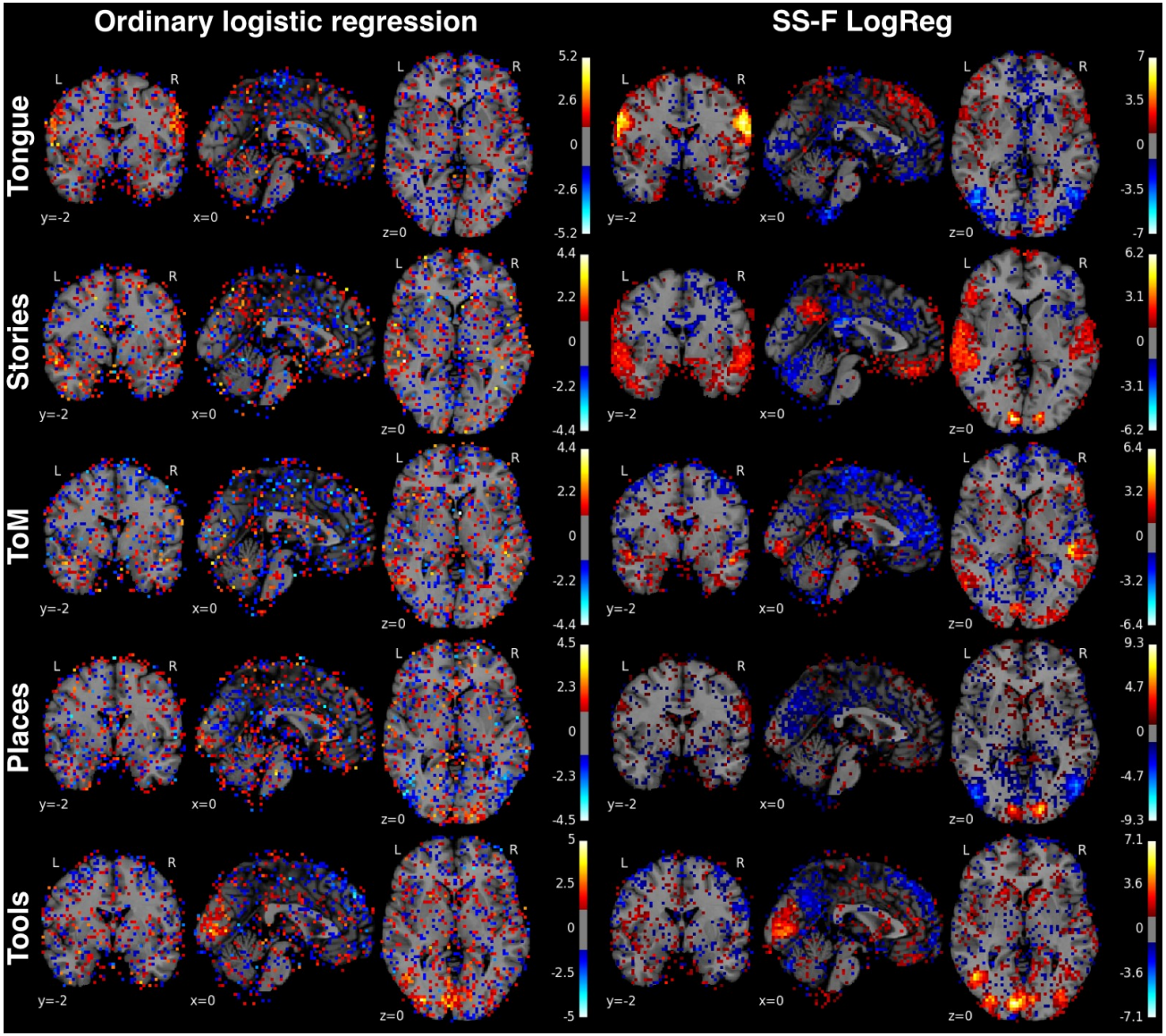


[Bzdok et al. NIPS 2015]

Using rest data to better model task data

- The discriminative patterns for many task data is much cleaner thanks to the composite objective



[Bzdok et al. NIPS 2015]

Technical aspects of big data analysis

Big data in medical imaging ?

HCP mailing list, Jan 19th, 2015

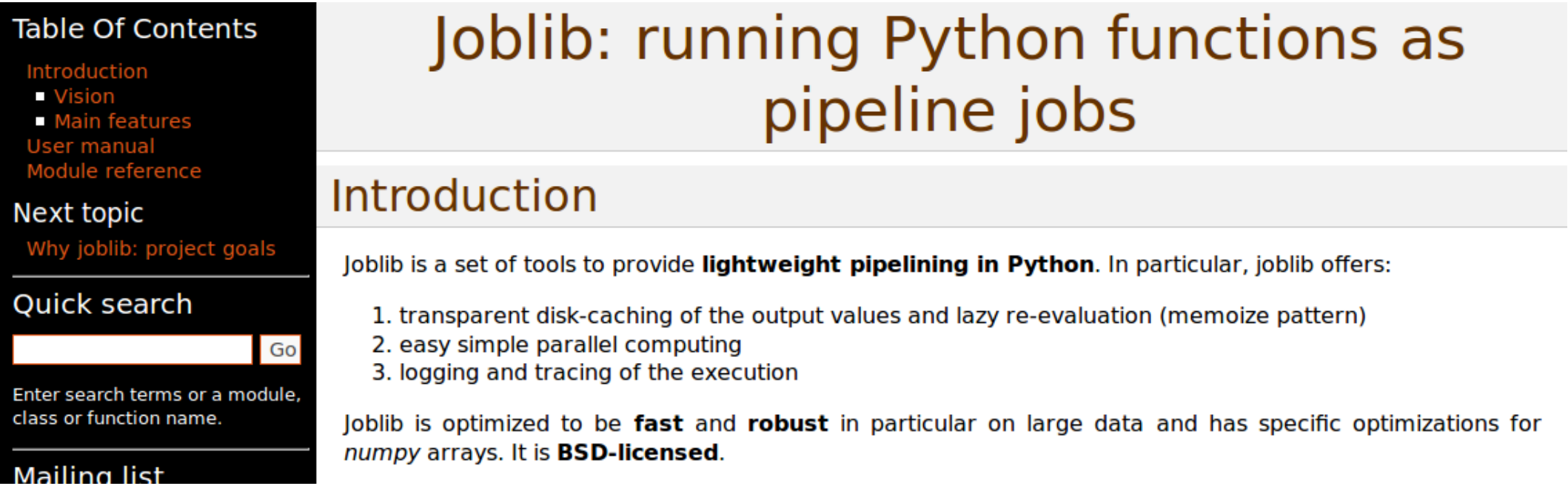
"Has anyone on the run group-wise analysis on the HCP resting state data, and if so what tools did you use?

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."

Diagnosis and strategy

- Modern, multiple, datasets: 100 GB-TBs
  - Do not fit in memory. Need online learning
  - Memory access is the main bottleneck
  - Large p, large n
  - Better file formats would help, but compatibility with existing tool stacks.
- Agile approach: readable Python code, runs on your laptop
  - Online learning, SGD algorithms
  - compression

Caching & parallel comp.: joblib



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Why joblib: project goals

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Enter search terms or a module, class or function name.

Mailing list

Joblib: running Python functions as pipeline jobs

Introduction

Joblib is a set of tools to provide **lightweight pipelining in Python**. In particular, joblib offers:

1. transparent disk-caching of the output values and lazy re-evaluation (memoize pattern)
2. easy simple parallel computing
3. logging and tracing of the execution

Joblib is optimized to be **fast** and **robust** in particular on large data and has specific optimizations for *numpy* arrays. It is **BSD-licensed**.

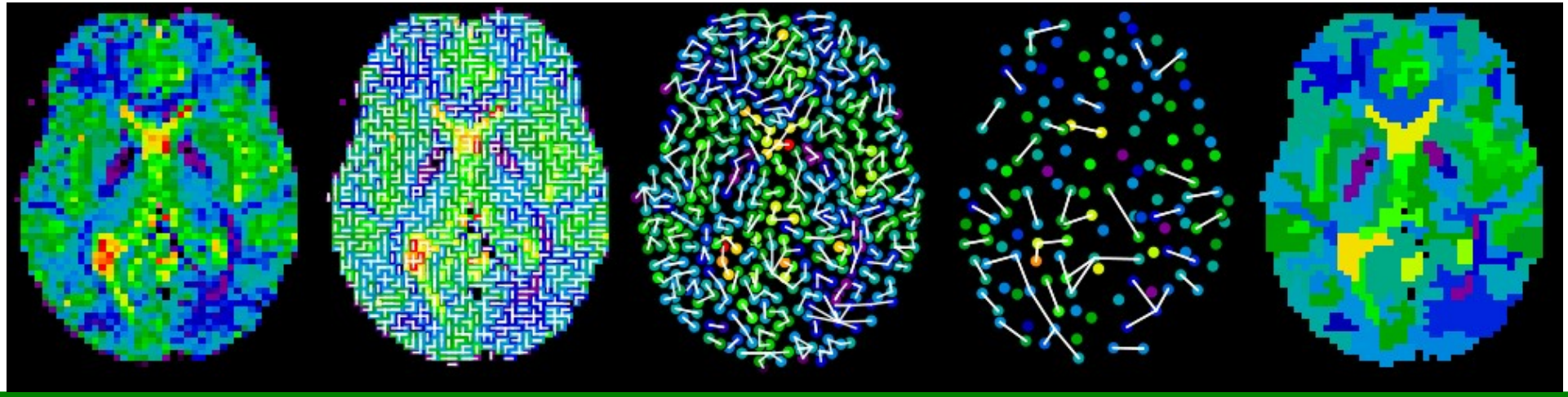
```
$ from nilearn.decomposition.dict_learning import DictLearning
$ dict_learning = DictLearning(n_components=n_components, smoothing_fwhm=6.,
                               memory="nilearn_cache", memory_level=5,
                               threshold=1., verbose=2, random_state=0,
                               n_jobs=8, n_init=1, alpha=3, n_iter=1000)
```

Fast image compression

- Cost of Logistic regression $\propto pn^2$

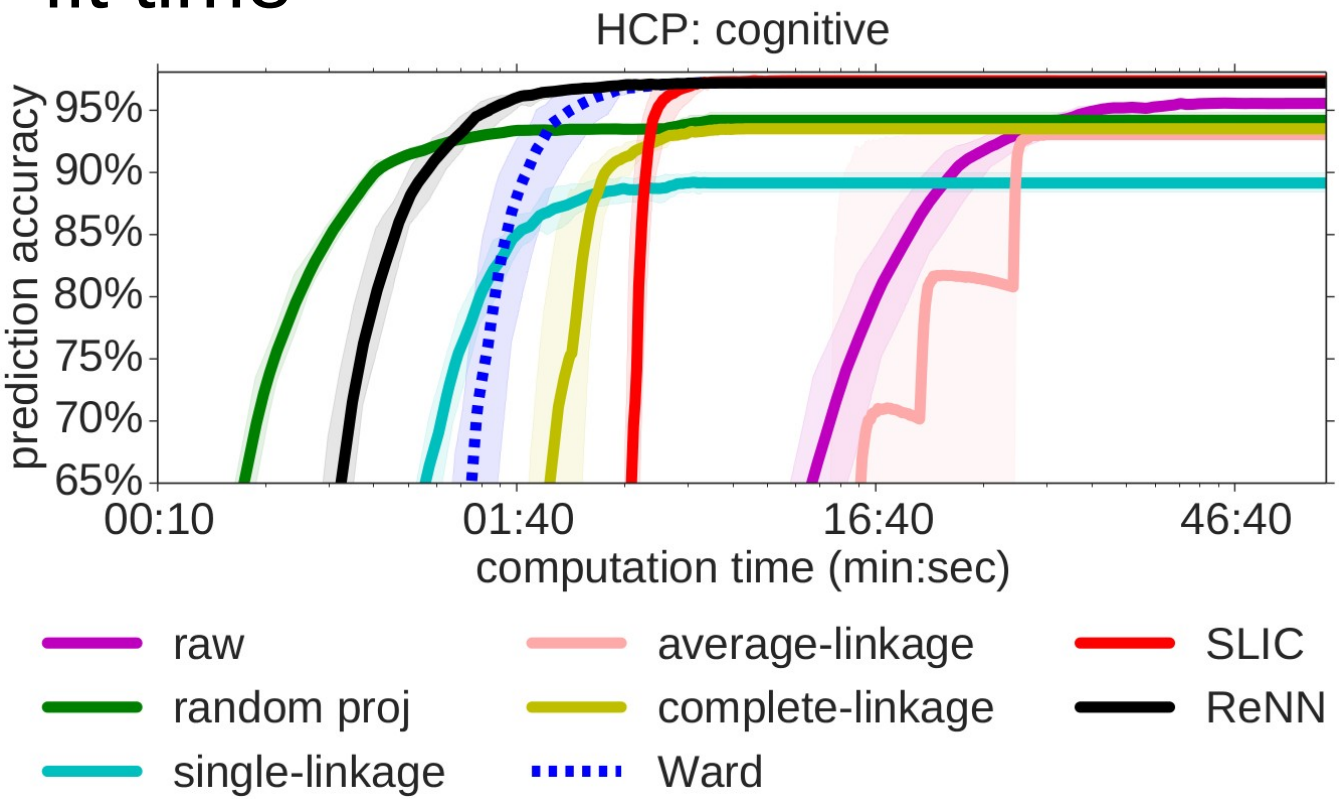
  + memory consumption $\propto pn$

- Solution: reduce p by compression
  - Random projections [Johnson, Lindenstrauss, AMS 1984]
    - Explicit control on precision
  - Clustering: informed by data [Thirion et al. Stamlins 2015]



Efficient discriminative models

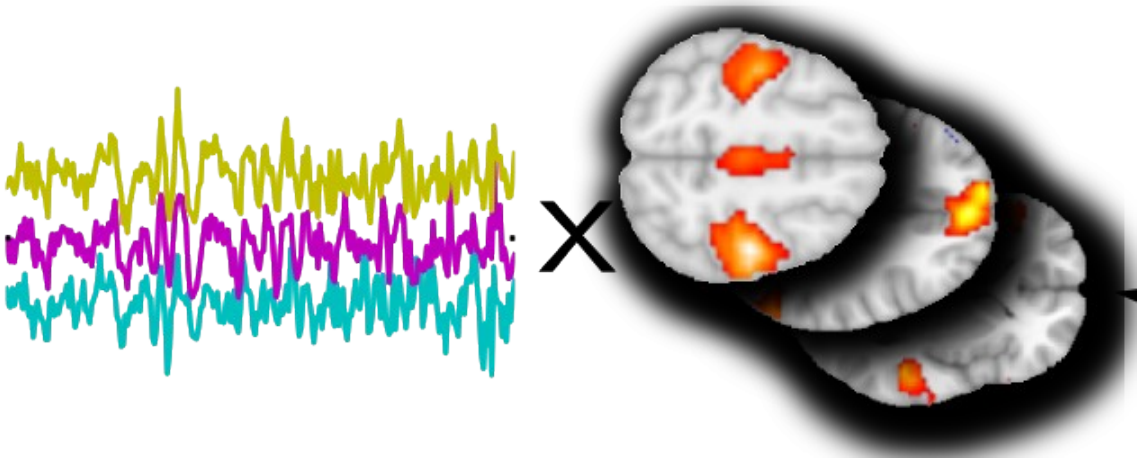
Example: HCP dataset, multi-class prediction (k=18), clustering + fit time



- Time savings are more than linear wrt data volume
- Data compression also benefits to accuracy

(Sparse) Principal Components Analysis

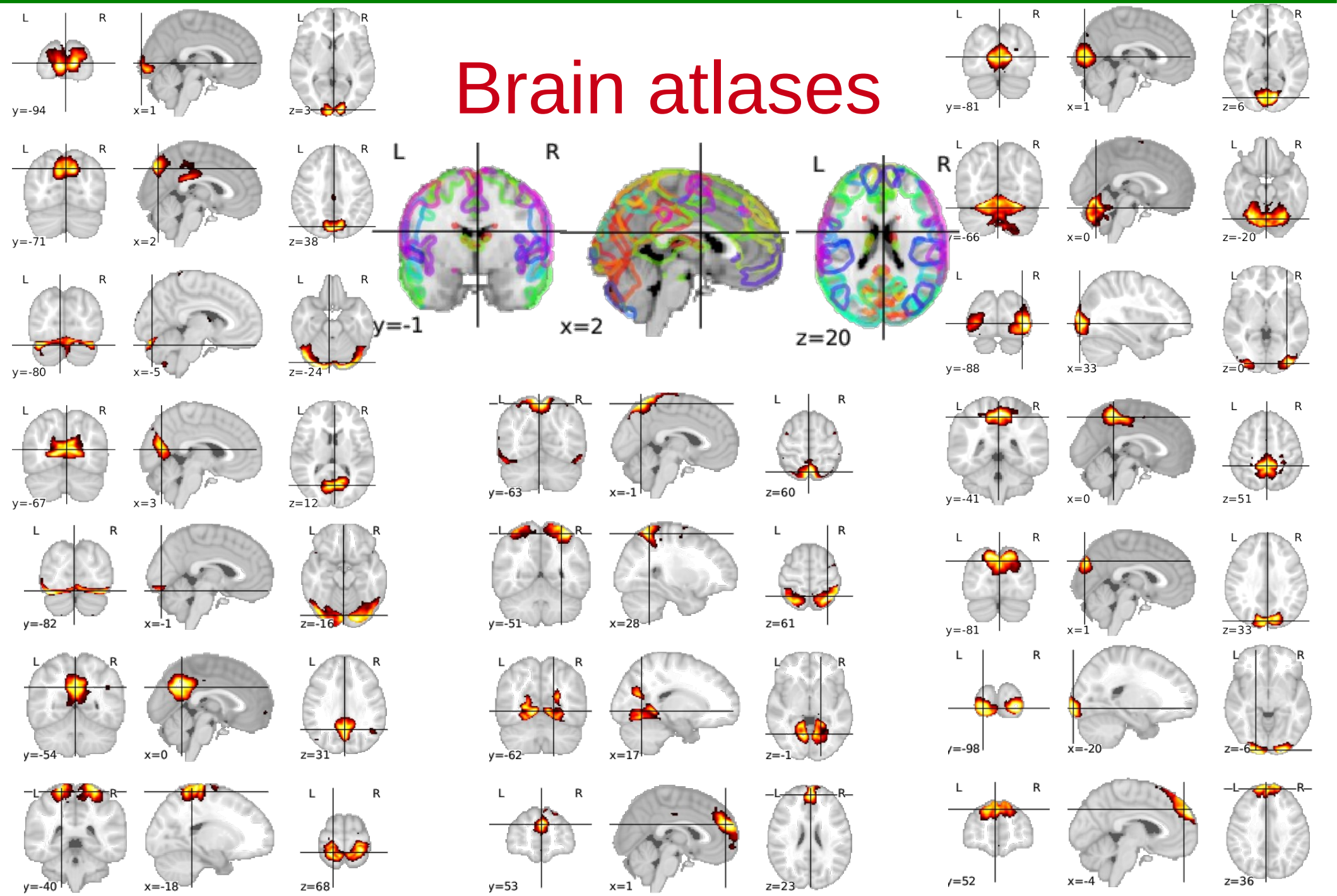
- Identify structure in data with *dictionary learning / sparse principal components analysis*



- Memory cost: n.p → scales poorly with large n (large number of subjects): 2TB of data on HCP
  - Run this on computers with 8GB of RAM
  - Possible with stochastic (online) methods !

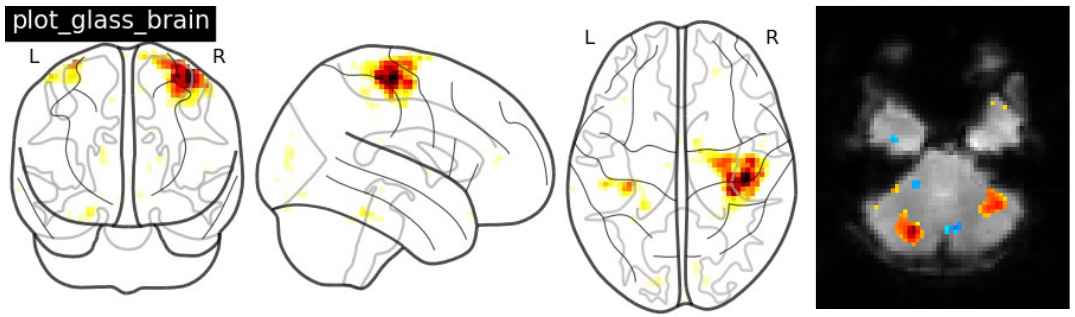
    [Mensch et al. ISBI 2016, ICML 2016]

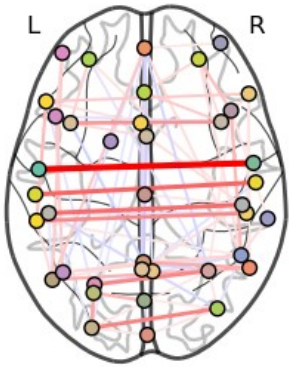
Brain atlases



Summary

- Large(r) sample sizes to make imagine findings more reliable
  - Even though less homogeneous data
- Combining multi-modal data to improve statistical analysis
- Improve software to support large data analysis
  - Reduce memory requirements: online methods
  - Leverage parallel computers





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