Network-based pattern recognition models for neuroimaging

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Outline

- Introduction
- Pattern recognition
- Network-based pattern recognition
- Network models
- Examples
- Discussion

Introduction

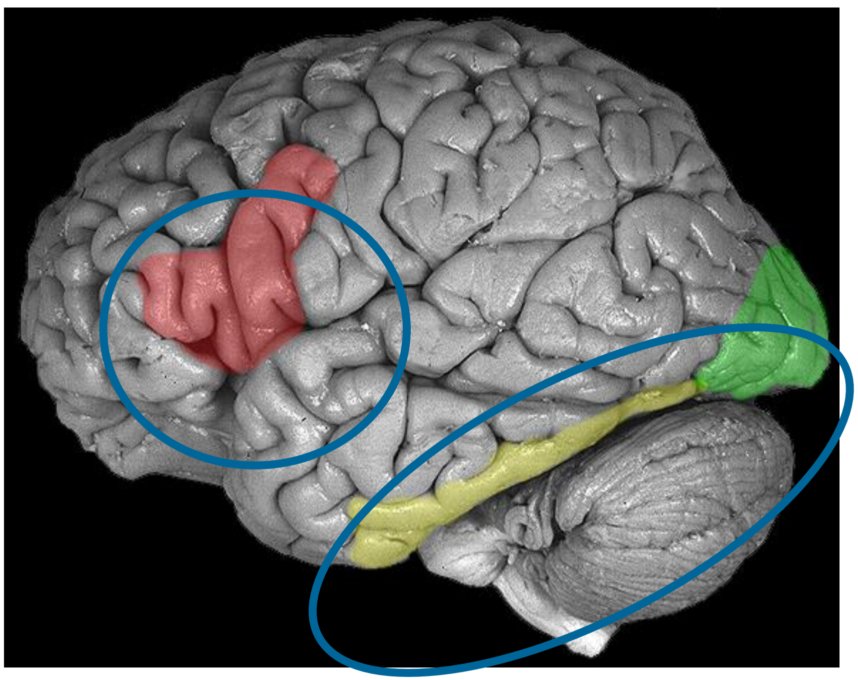
Functional specialisation:

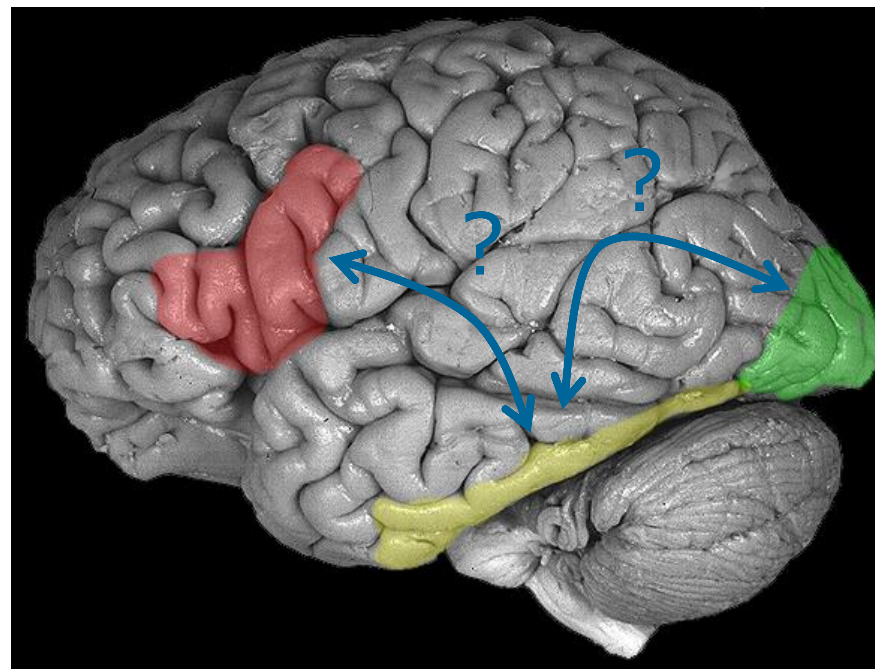
What regions respond to a particular experimental input?

Functional integration:

How do regions influence each other?

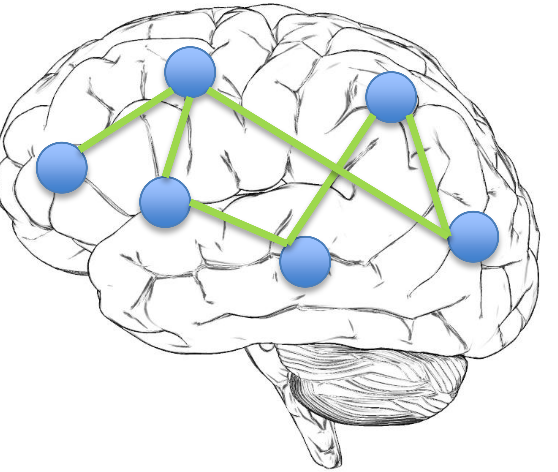
→ Brain Connectivity





Introduction

- Functional integration explains most of high level brain function

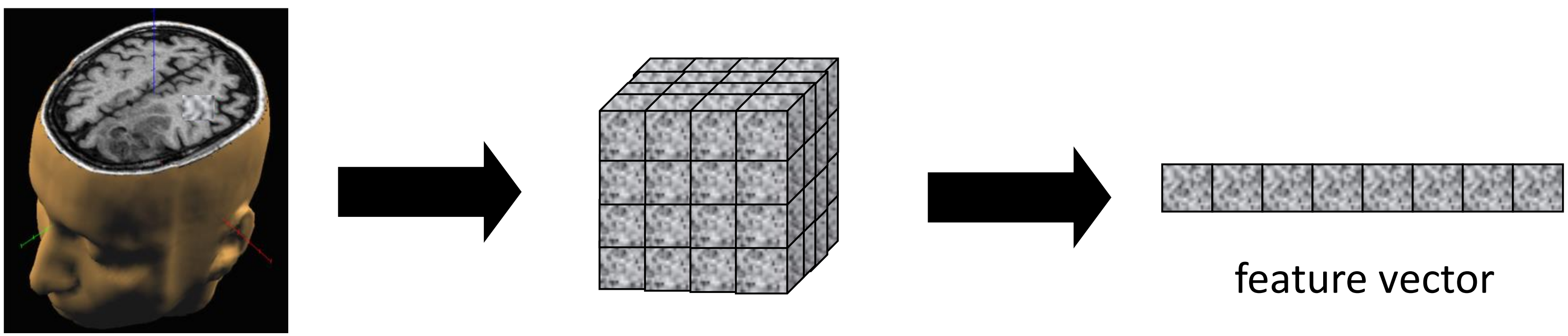


- Natural fluctuations can capture brain interactions
- Abnormal brain function (e.g. psychiatric disorders) can also be expressed by modified brain connections

Why use connectivity models with pattern recognition?

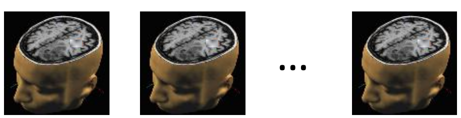
- Increased sensitivity to connectivity patterns
- Make individual predictions (biomarkers)

Pattern recognition (PR)

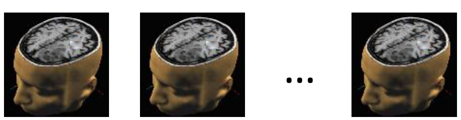


feature vector

Input



Volumes from task 1



Volumes from task 2

New example 

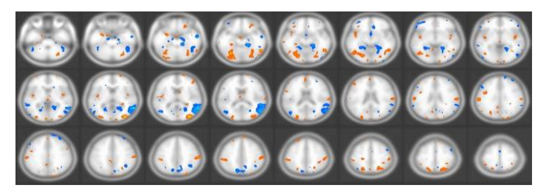
Training Phase

Test Phase

Output

Prediction function, f(**X**)

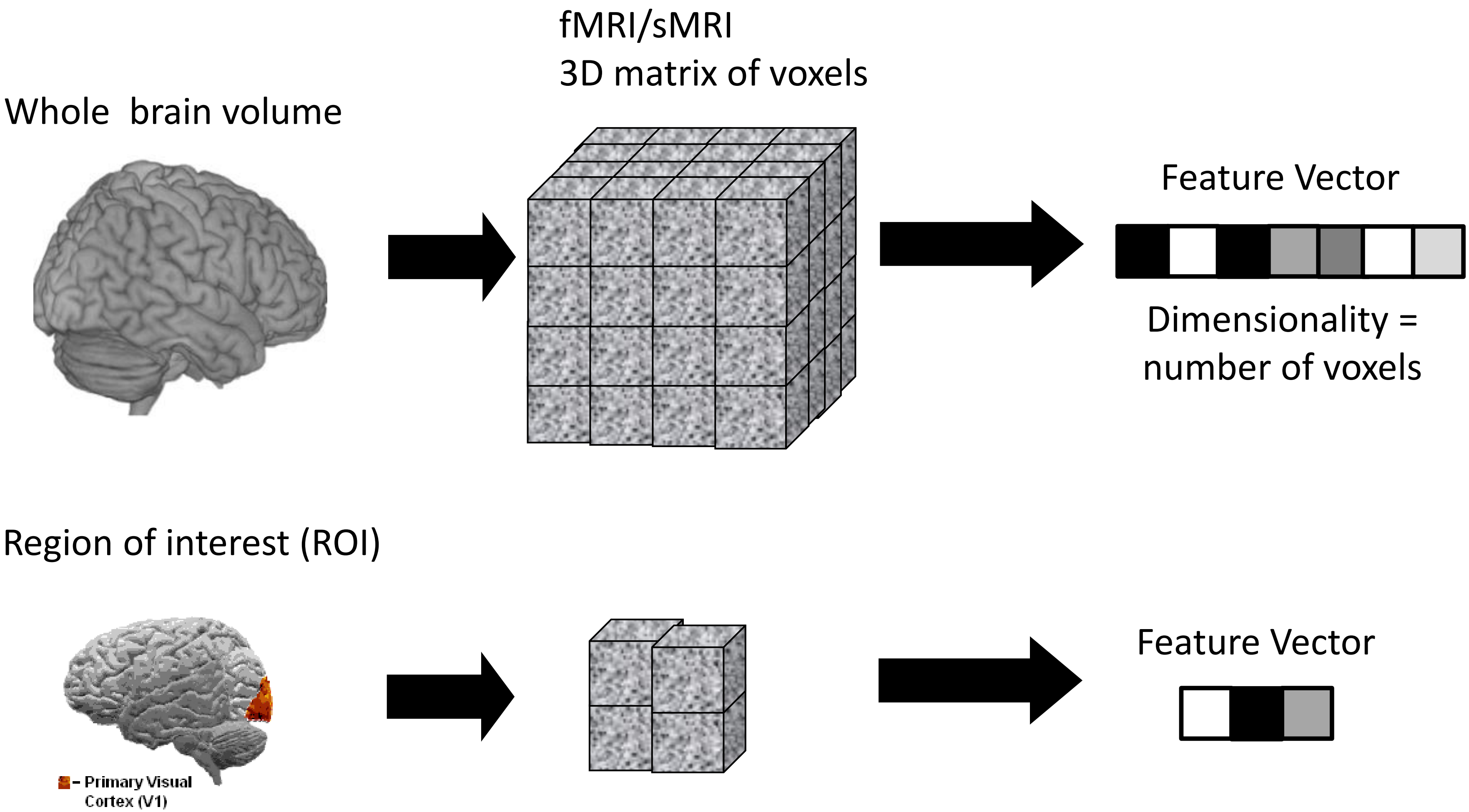
Decision boundary



Prediction:

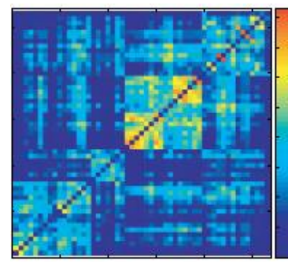
task 1 or task 2

Pattern recognition (PR)

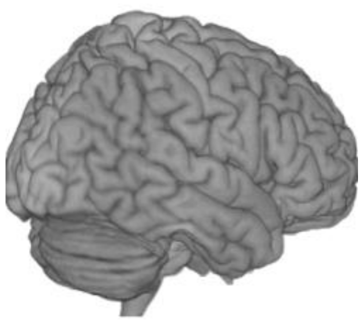


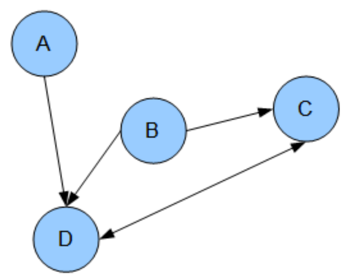
Network-based PR

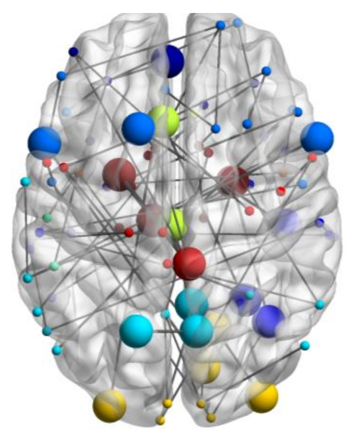
Connectivity measures



Whole brain volume



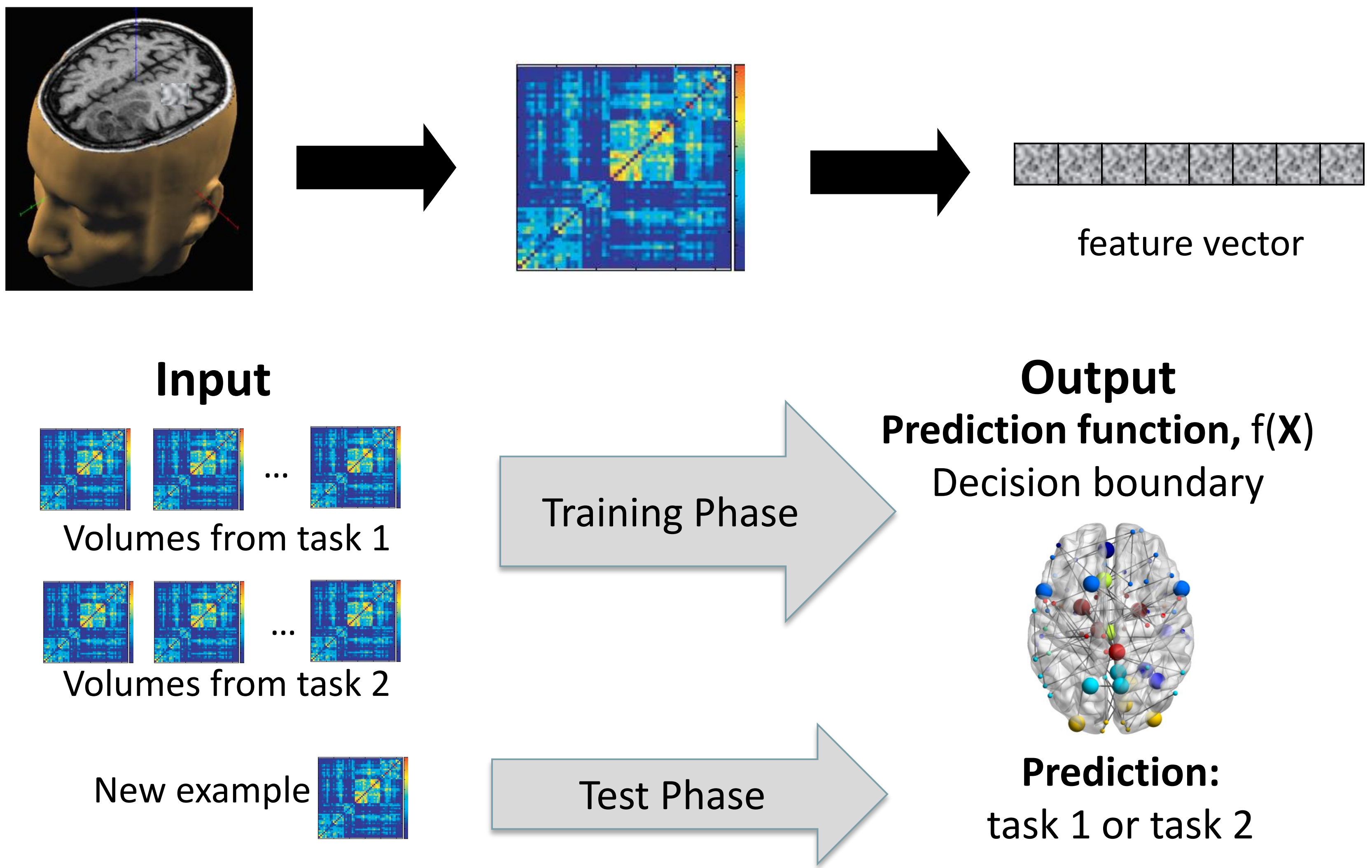




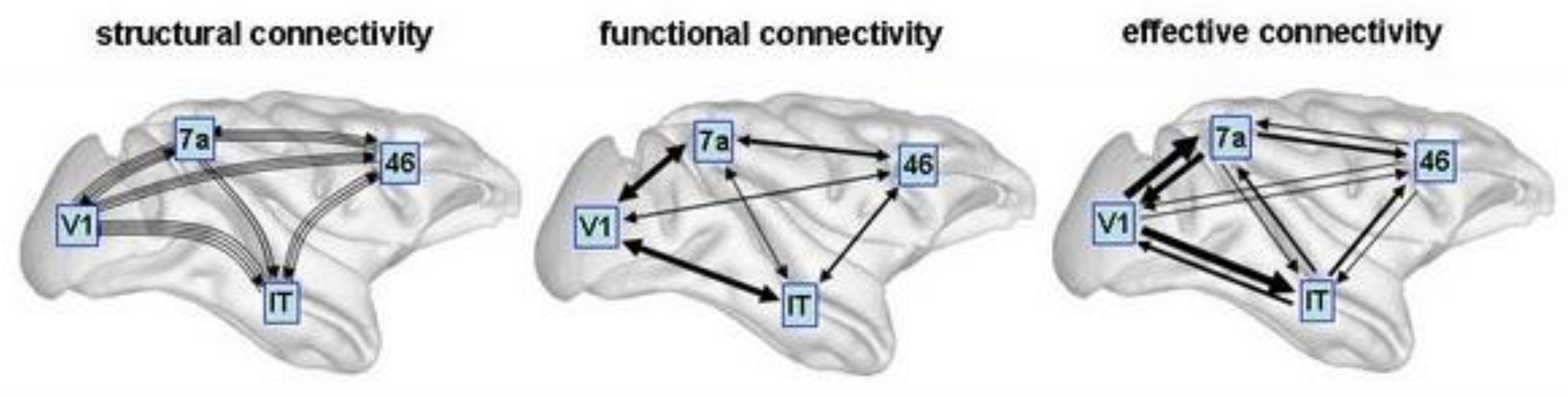
Feature Vector

Dimensionality =
number of voxels

Network-based PR



Network models



(Sporns, *Scholarpedia,* 2007)

- **anatomical/structural connectivity**
  = presence of axonal connections

- **functional connectivity**
  = statistical dependencies between regional time series

- **effective connectivity**
  = causal (directed) influences between neurons or neuronal populations

Network models

Data preprocessing

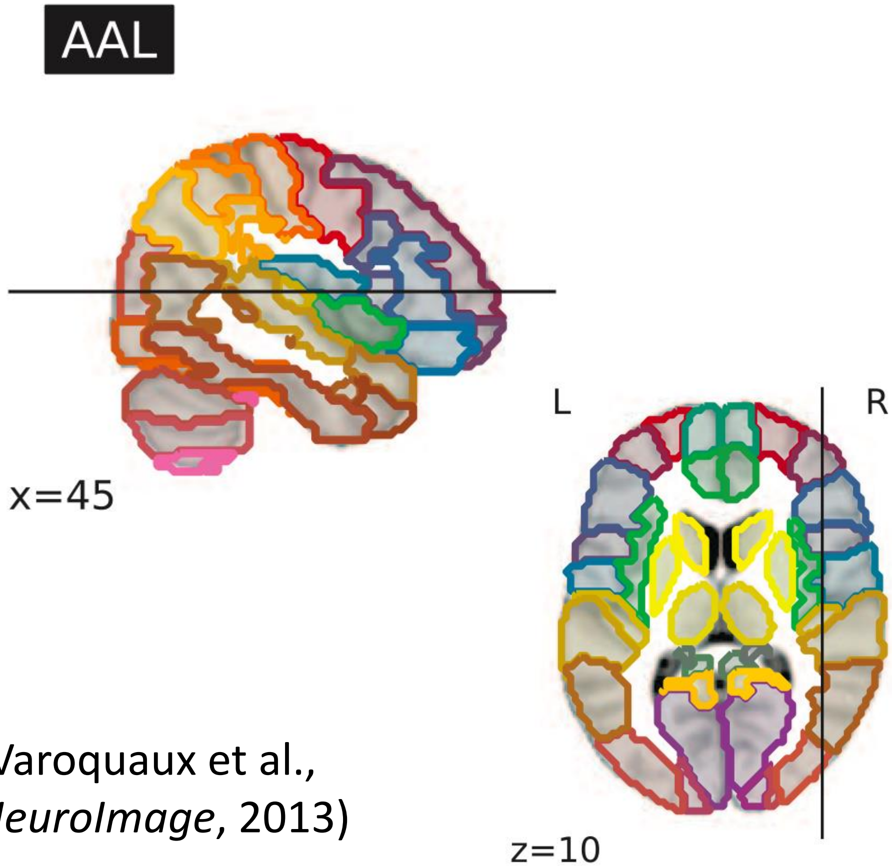
- Standard preprocessing in general

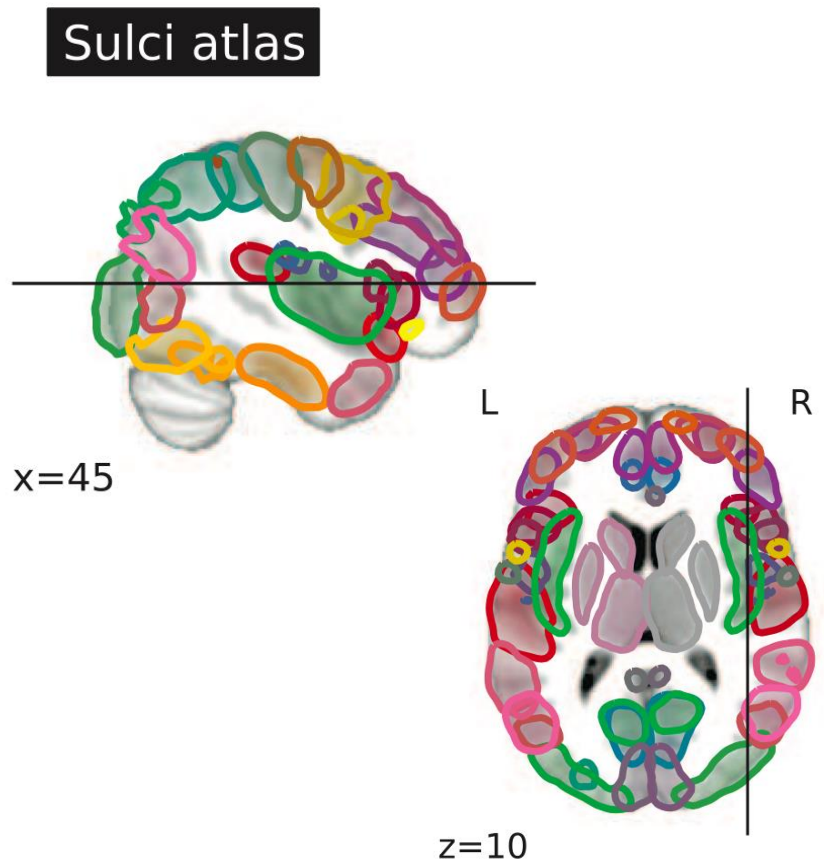
- Remove extra confounds from time-series:
  - White-matter and cerebrospinal fluid
  - Noise-related principal components (CompCor)
  - Regress out movement parameters
  - Linear trend
  - Filtering (<0.1Hz for resting state)

Network models

Defining regions

- Define regions from literature (e.g. meta-analysis).
- Atlas-based approach:



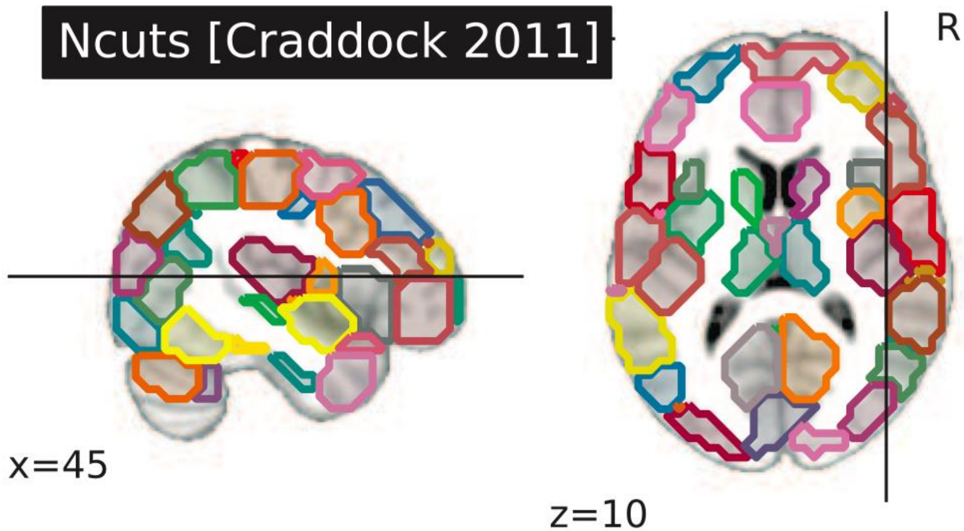


(Varoquaux et al., *NeuroImage*, 2013)

Network models

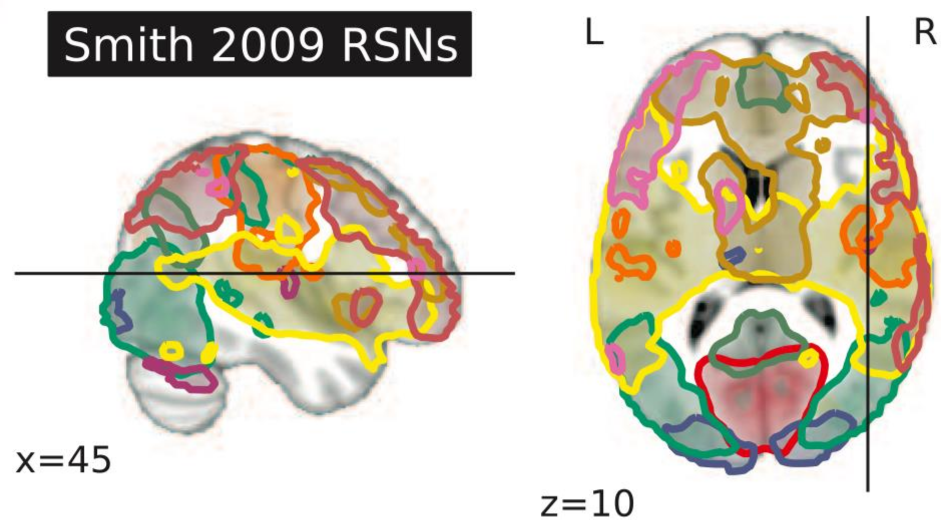
Defining regions

- fMRI-based approaches: clustering and decomposition:



Clustering

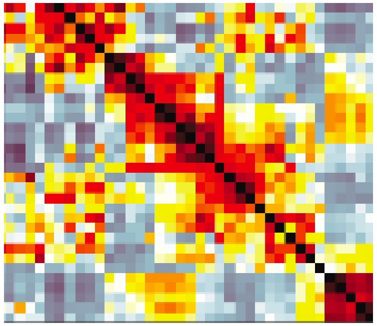
ICA-based

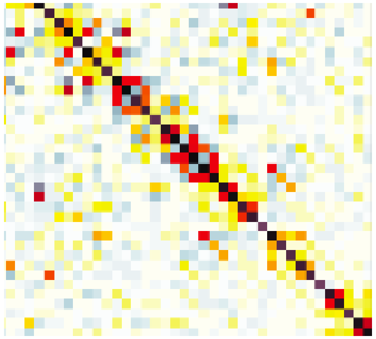


(Varoquaux et al.,
NeuroImage, 2013)

Network models

Estimating connectivity





(Varoquaux et al., *NeuroImage*, 2013)

Signal extraction:

- Averaging time-series
- First eigenvector

Connectivity measures:

- Pearson's correlation

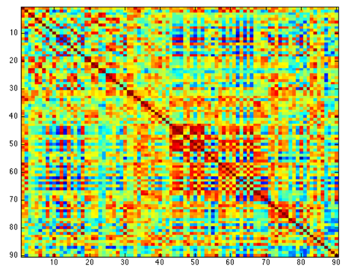
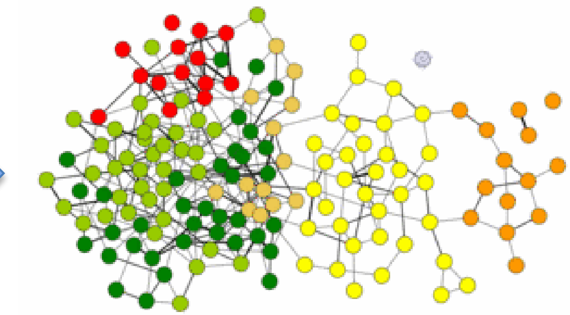
  Better estimates:

  - Ledoit-Wolf shrinkage estimate
  - Regularized inverse covariance

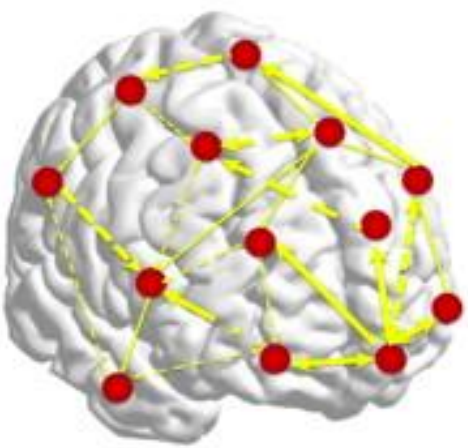
  (conditional independence) – partial correlations
- Coherence, frequency depended measures, etc.
- Graph measures

Network models

Graph analysis (Fornito et al., *NeuroImage*, 2013)

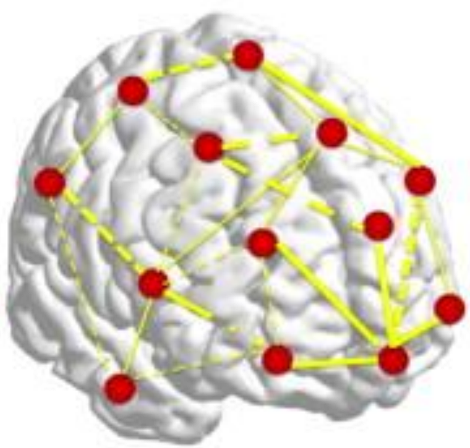



Directed, weighted, heterogeneous edges



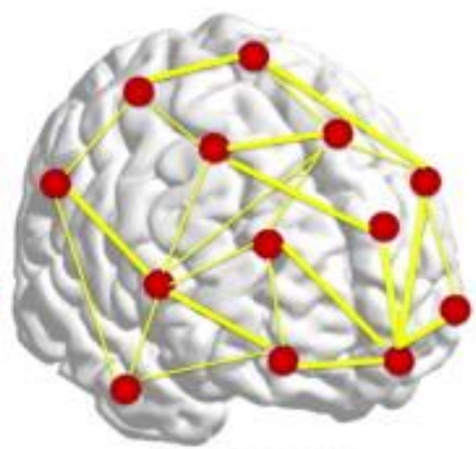
Some fMRI

Undirected, weighted, heterogeneous edges



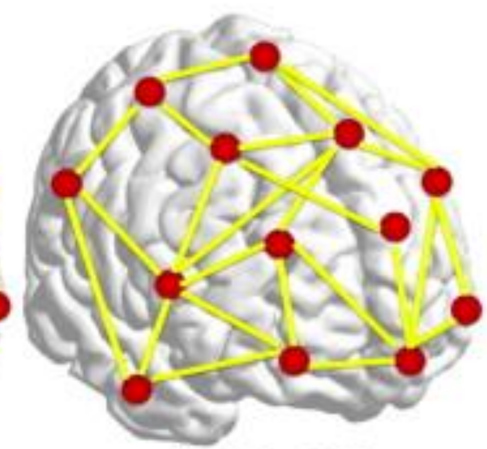
Some fMRI

Undirected, weighted



fMRI & DWI

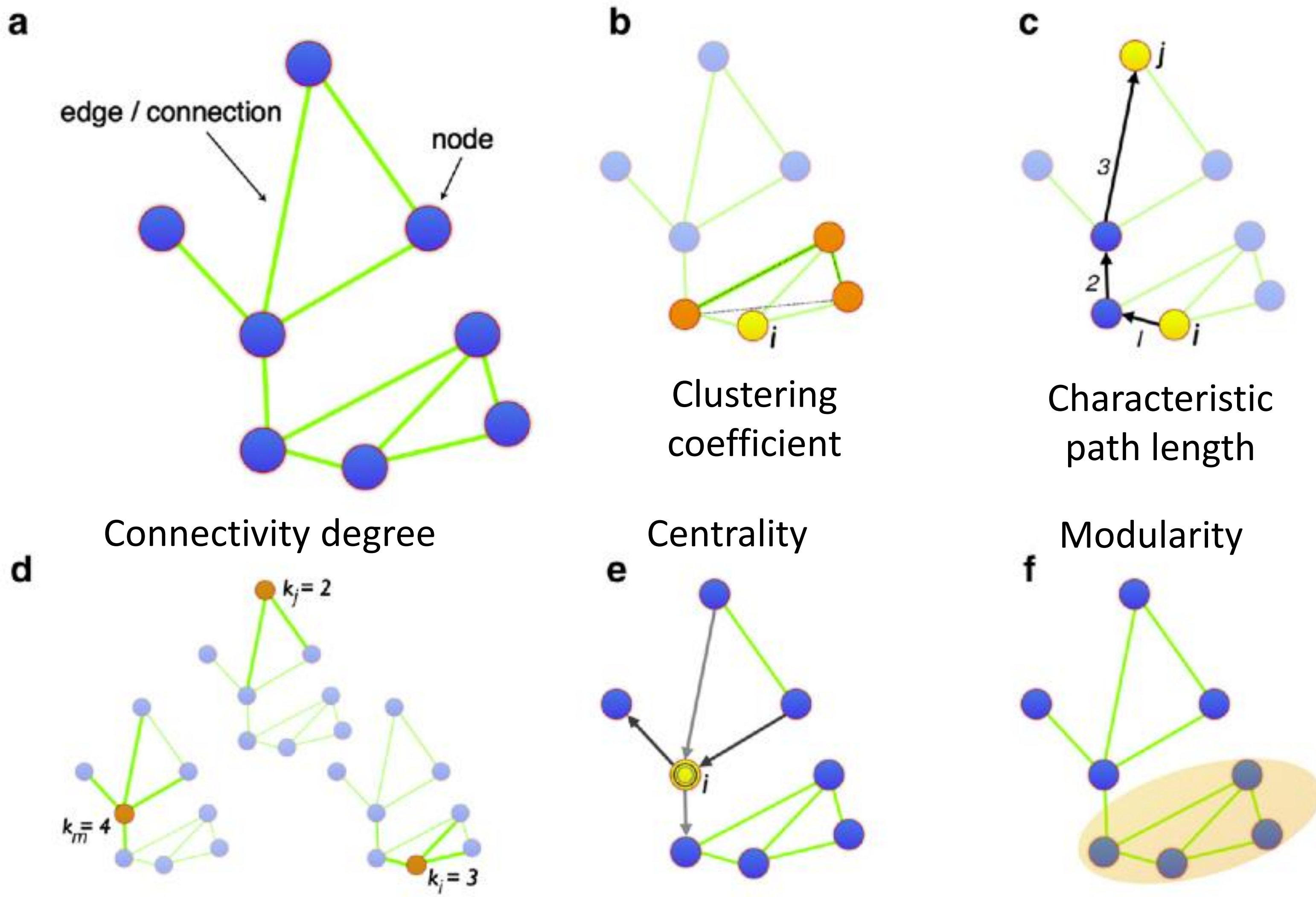
Undirected, binary edges



fMRI & DWI

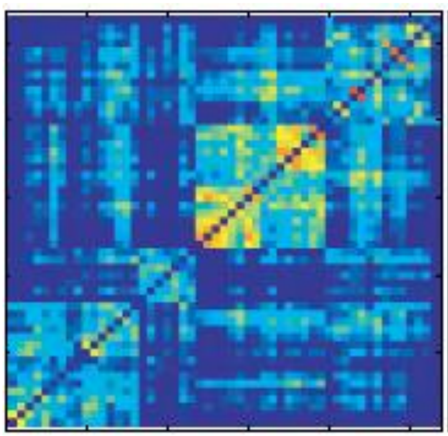
Network models

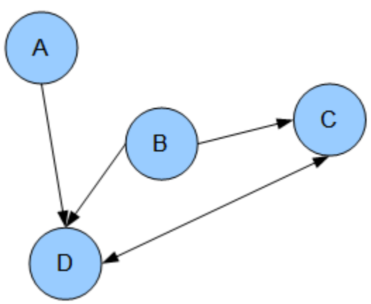
Topological measures (van den Heuvel, *Euro. NeuroPsy.*, 2010)

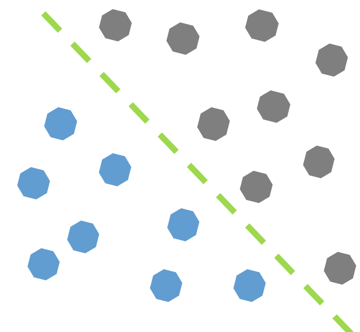


Network models

Network-based pattern recognition



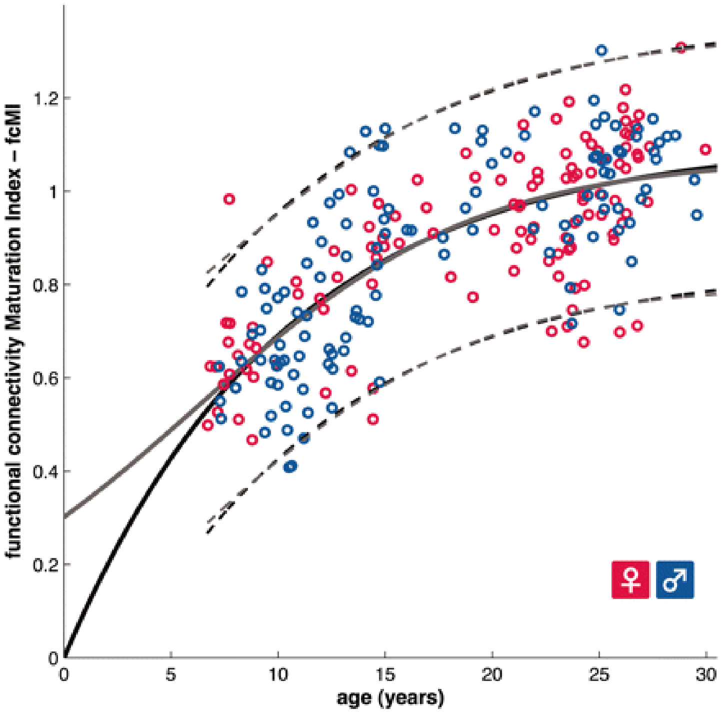


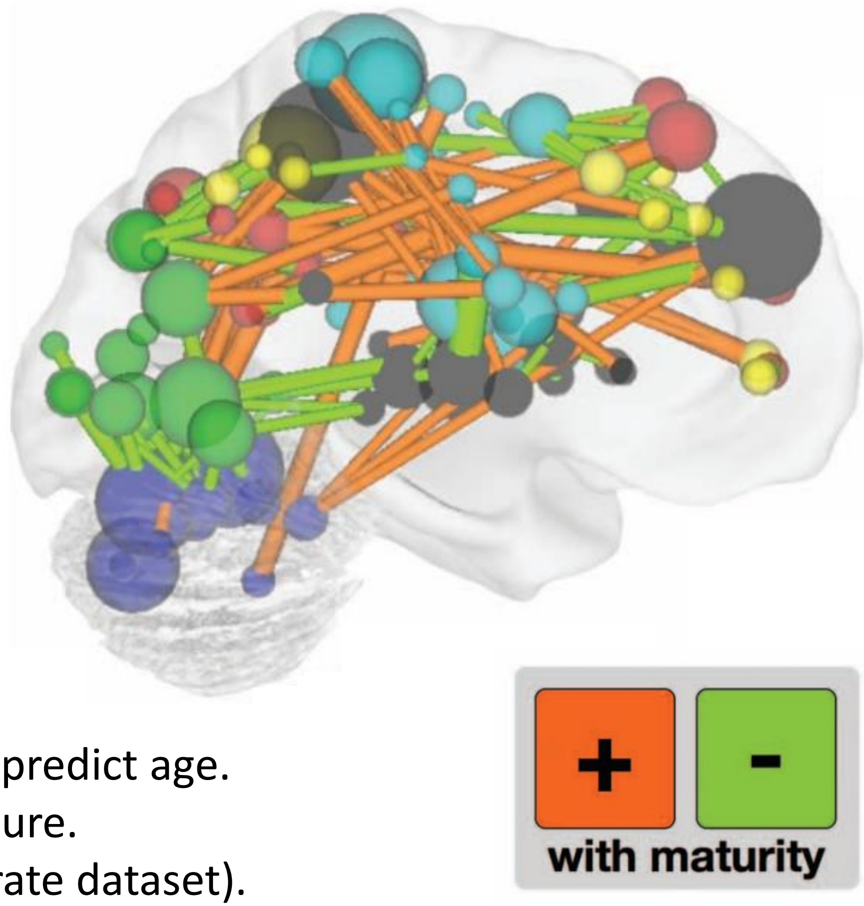


Linear embedding
Dissimilarity measures
Kernel methods:
    Non-linear kernels
    Kernels for graphs

Example 1

- Dosenbach et al., *Science*, 2010.



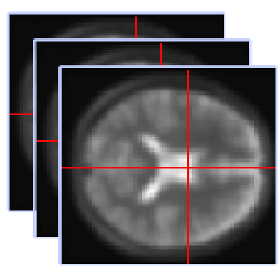


- Support vector regression used to predict age.
- 160 regions of interest from literature.
- Univariate feature selection (separate dataset).
- Radial basis function kernel.

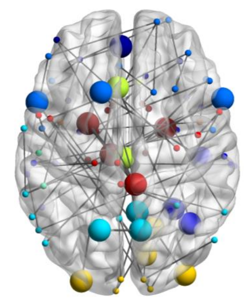
Example 2

Sparse network-based discriminative models for depression

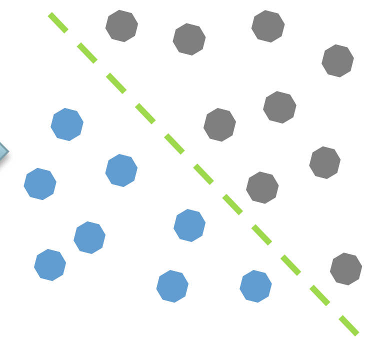
(M. J. Rosa et al., *PRNI* 2014)



fMRI time series



Sparse inverse covariance
(gLASSO)



Sparse classifier
(L1-norm SVM)

Results: 19 medication free patients with depression and 19 controls using fMRI

Atlas	Accuracy (pval)*	Sensitivity	Specificity
Sulci	**78.95 %** (<0.05)	**73.68 %**	**84.21 %**

*P-value from permutation test (1000 samples)

Most discriminative connections:

- Amygdala <-> insula
- OFC <-> motor regions
- Amygdala <-> temporal cortex
- Anterior cingulate <-> frontal cortex

Software

Human brain atlases	Software	Site
AAL	WFU PickAtlas	http://www.fmri.wfubmc.edu/cms/
Brodmann	MRICRO	http://www.cabiatl.com/mricro/
Freesurfer	Freesurfer	http://surfer.nmr.mgh.harvard.edu/
Harvard-Oxford	FSL	http://www.fmrib.ox.ac.uk/fsl/
LPBA40	LONI	http://www.loni.ucla.edu/Atlases/
Reference networks	**Laboratory**	**Site**
C. elegans (N = 131,277)	Kaiser	http://www.biological-networks.org
Macaque (N = 95)	Kaiser	http://www.biological-networks.org
Macaque (N = 71,47)	Sporns	http://www.indiana.edu/cortex/
Macaque Visual (N = 30,32)	Sporns	http://www.indiana.edu/cortex/
Cat (N = 95,52)	Sporns	http://www.indiana.edu/cortex/
Network Toolboxes	**Language**	**Site**
Matlab BGL	Matlab	
Brain Connectivity Toolbox	Matlab	http://www.indiana.edu/cortex/
Brainwaver	R	
Network visualization	**Description**	**Site**
gplot	Matlab	http://www.mathworks.com/matlabcentral/fileexchange
Pajek	Closed source	http://pajek.imfm.si/doku.php
Caret	Van Essen	http://brainvis.wustl.edu/wiki/index.php

Pattern Recognition: PRoNTo, scikit-learn, pyMVPA, R packages (kernlab; caret), …

Discussion

- Network-based pattern recognition has great potential in neuroimaging
- Connectivity-based biomarkers could aid diagnosis, prognosis and treatment of brain disorders

However, methodological/practical challenges still remain:

- **How to properly treat confounds?**
- **How to best choose brain regions?**
- **Move beyond steady-state assumption?**
- **Use more complex, mechanistic models (e.g. DCM)?**
- **Use more more informed embedding methods?**

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