脑影像智能计算
及其若干应用研究进展

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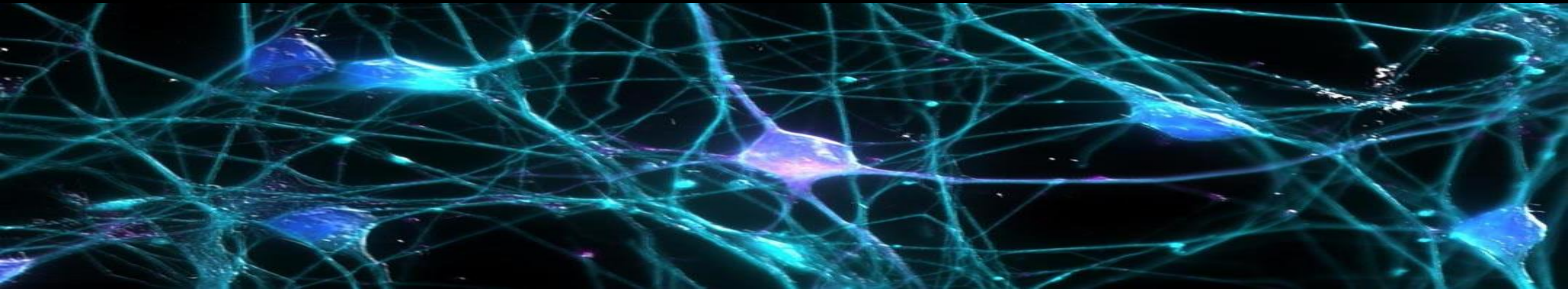
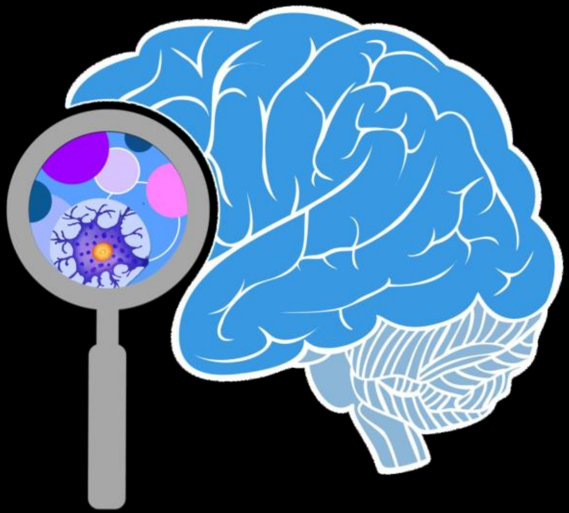


Why Study The Brain?

- The human brain is the most complicated organ in the body – probably the most complicated, calculated machine that we know of.

Dr. Story Landis (Emeritus Scientist, NIH), December 2016



The BRAIN INITIATIVE Mission

- The BRAIN Initiative seeks to deepen understanding of the inner workings of the human mind and to improve how we treat, prevent, and cure disorders of the brain.

The China Brain Project

Neuron
NeuroView

CellPress

China Brain Project: Basic Neuroscience, Brain Diseases, and Brain-Inspired Computing

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http://dx.doi.org/10.1016/j.neuron.2016.10.050

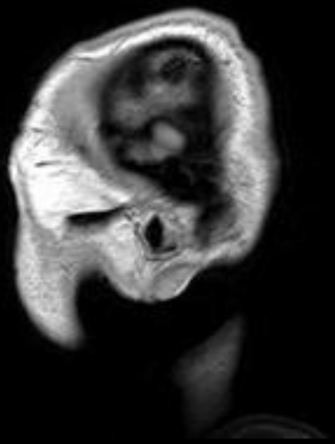
Brain Imaging (Neuroimaging)

- Neuroimaging includes the use of various techniques to either directly or indirectly image the structure or function of the brain

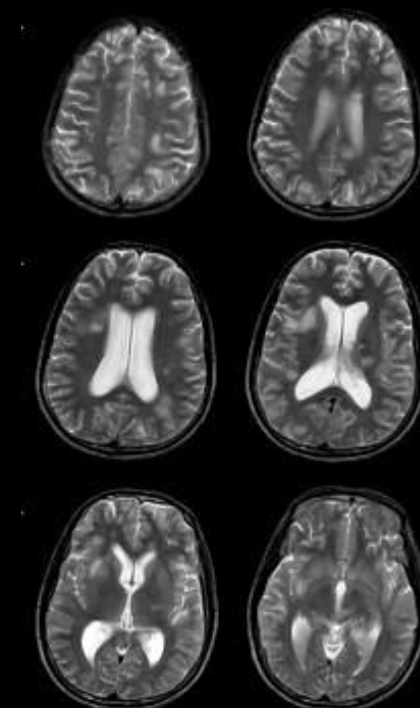
- Two broad categories

  Structural neuroimaging deal with the structure of th brain

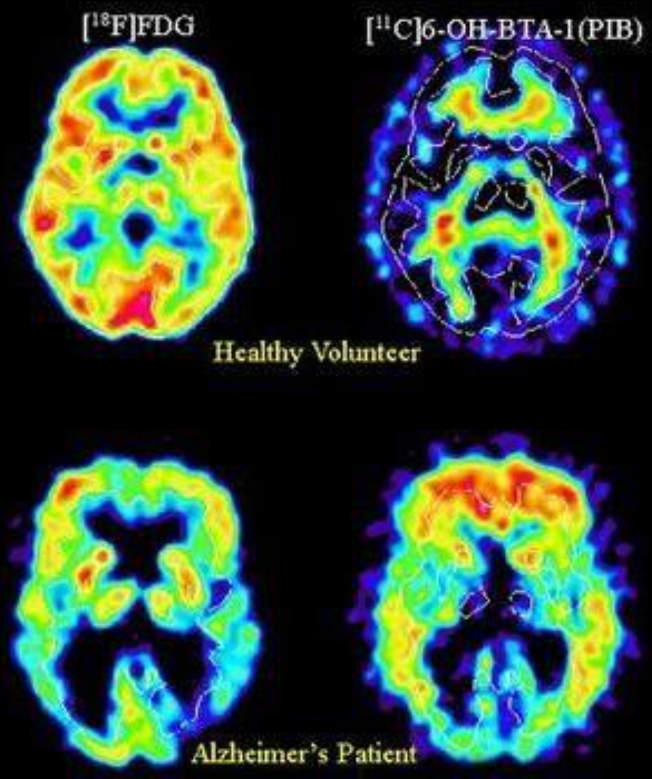
  Functional neuroimaging is used to indirectly measur brain functions



Magnetic Resonance Imaging (MRI)



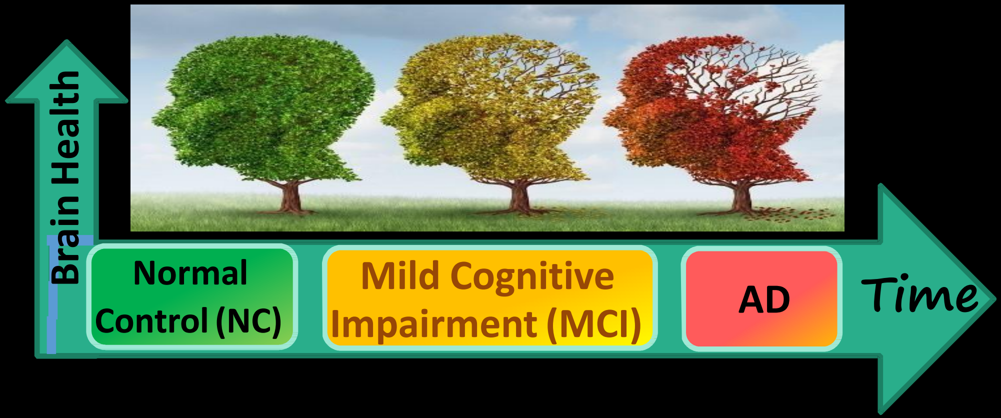
Positron Emission Tomography (PET)



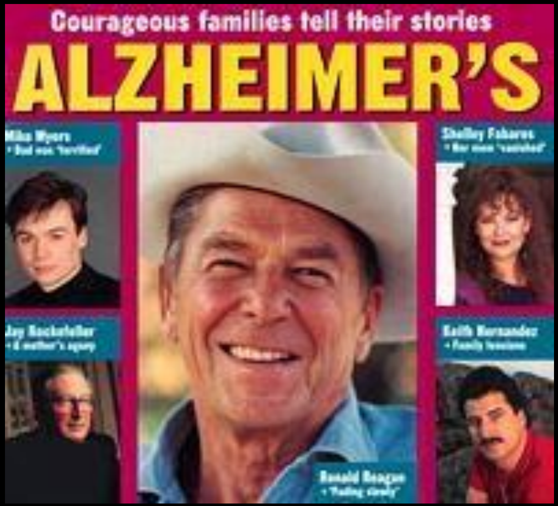
Brain Disease

Alzheimer's Disease (AD)

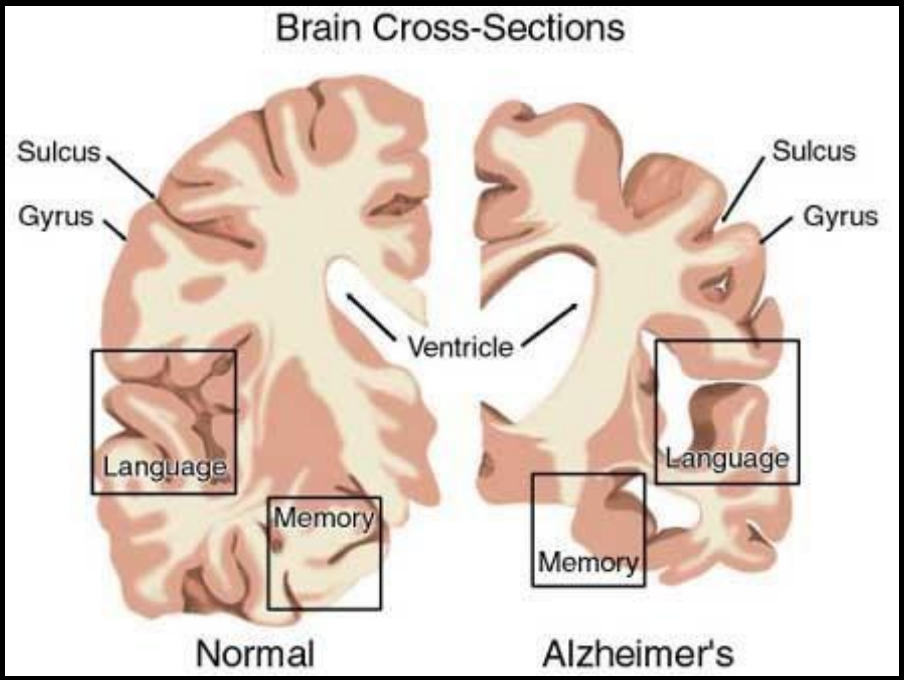
- ★ most common form of dementia
- ★ no cure, worsens as it progresses, leads to death
- ★ most often, diagnosed in people over 65 years of age
- ★ over 40 million sufferers worldwide, predicted to affect 1 in 85 people globally by 2050

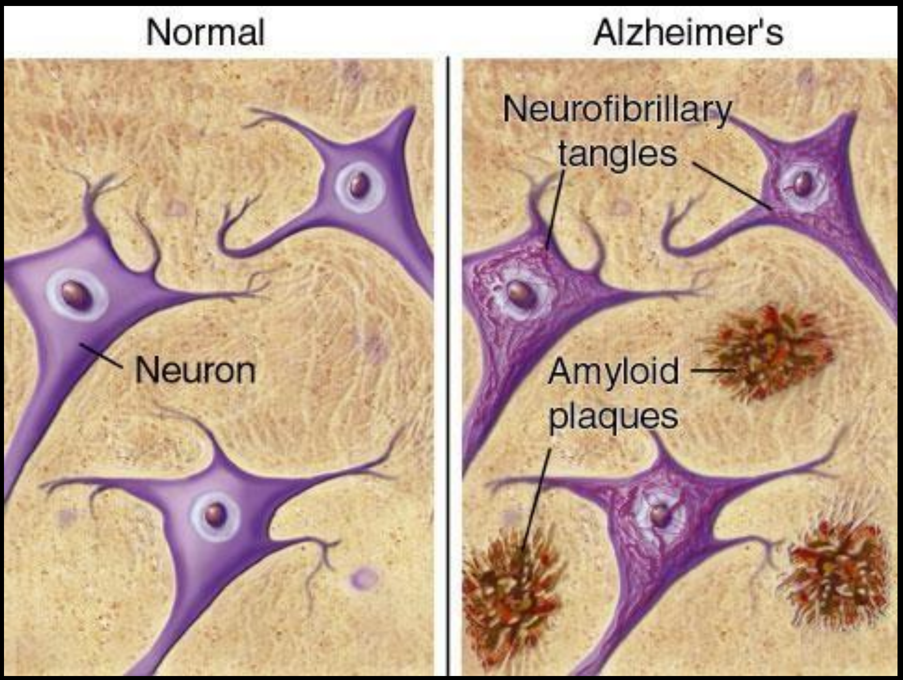


Celebrities with AD



Normal Brain vs. AD Brain





AD Self-Portrait

1967（Early year）

1996（2nd year of AD）

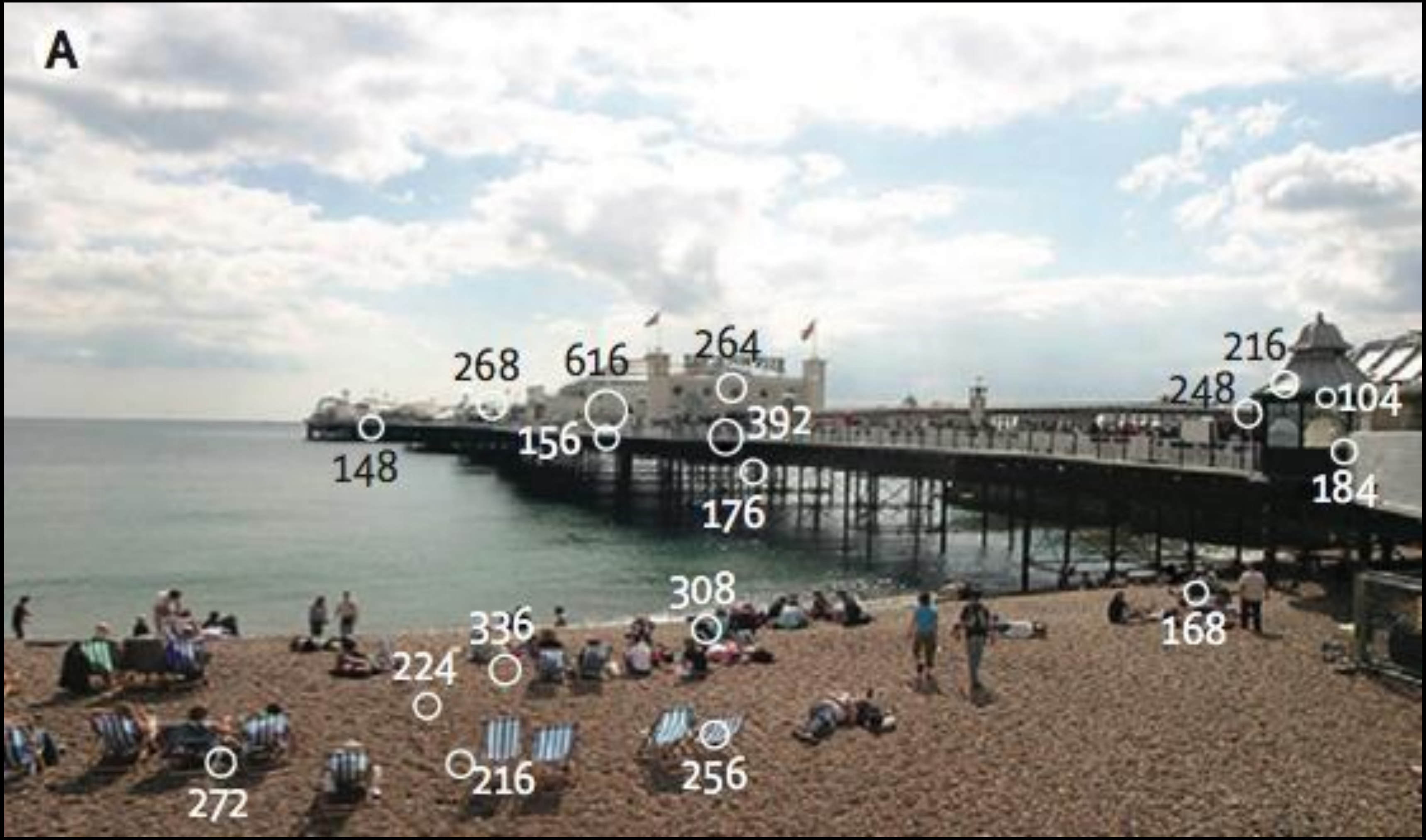
1997（3rd year of AD）

1998

1999

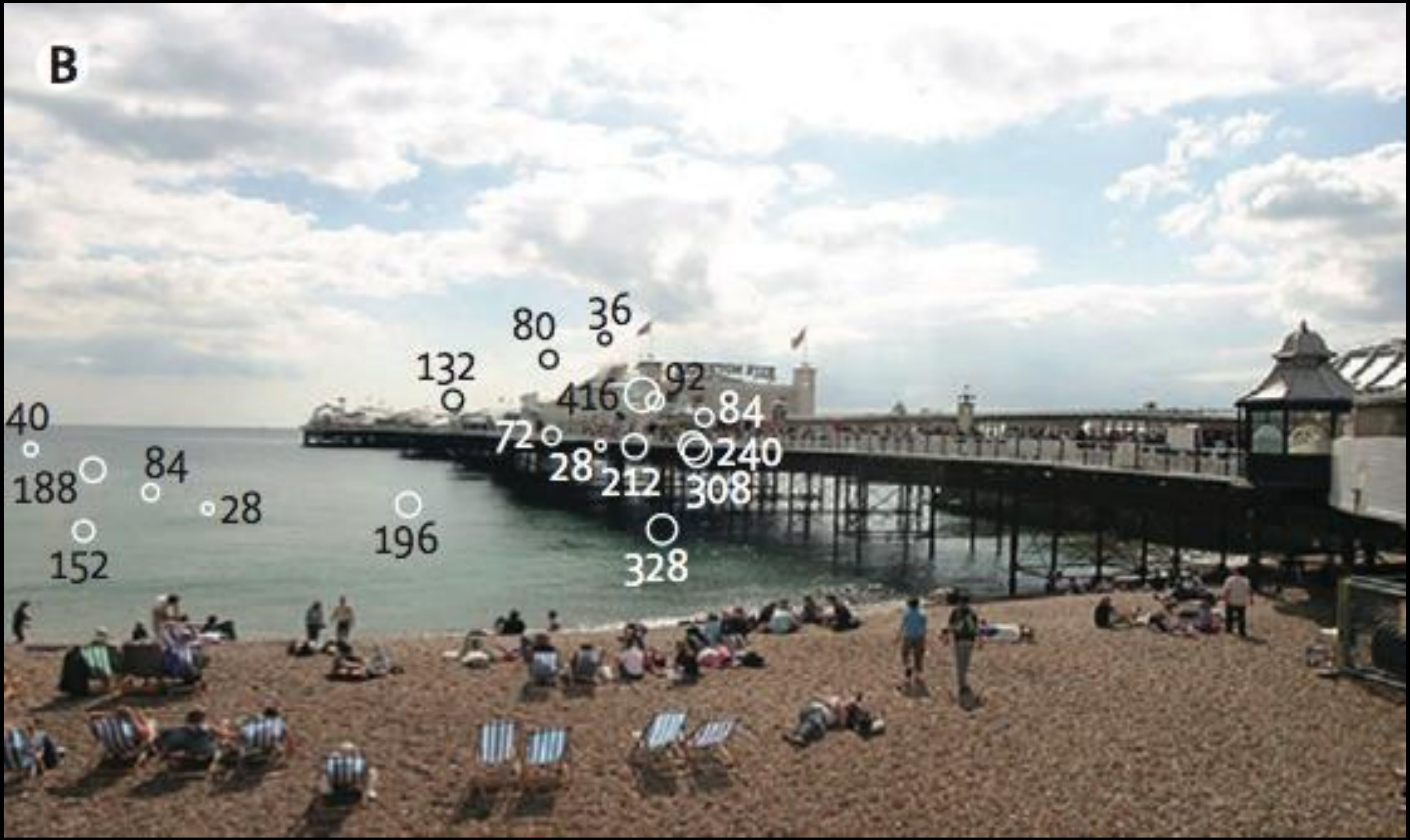
2000

Normal or diseased?



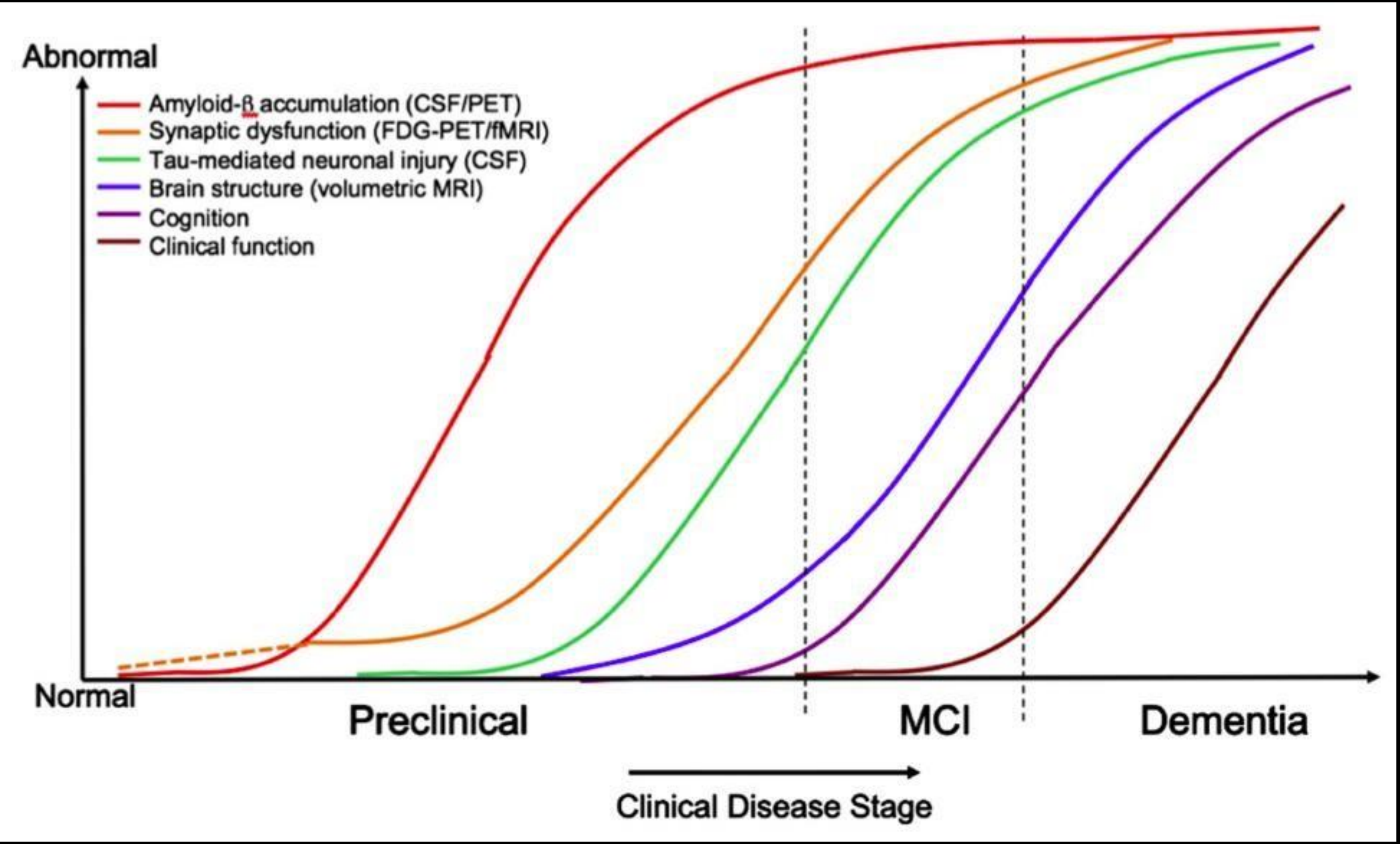
S. Crutch,et al., Lancet Neurology, 2012

Normal or diseased?



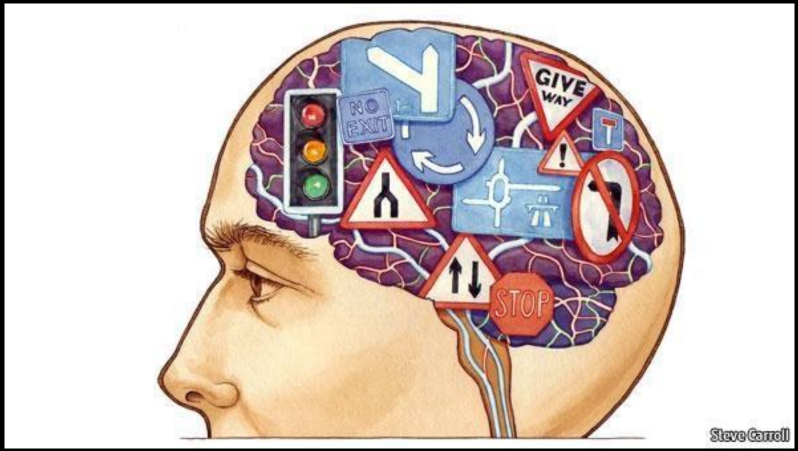
S. Crutch,et al., Lancet Neurology, 2012

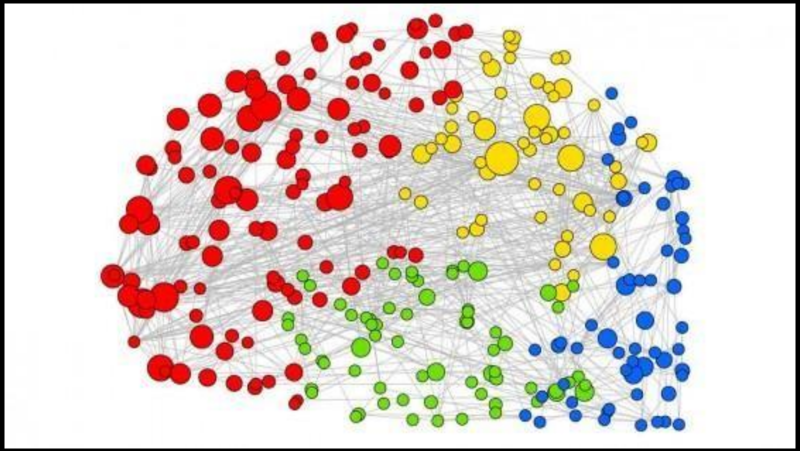
AD Biomarkers



Brain Connectomics

- Studies the interaction of brain functional regions at systems level



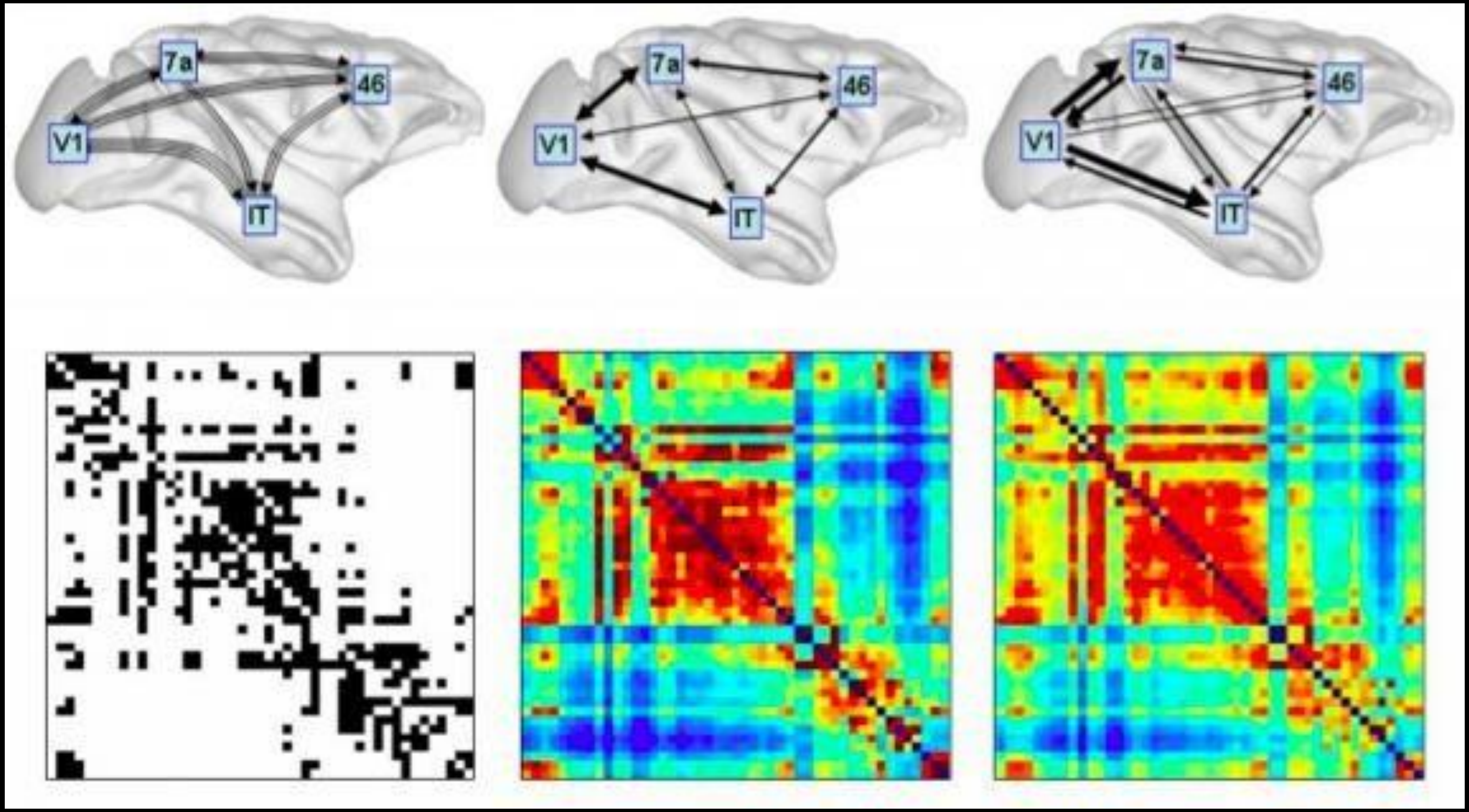


- Mapping the human brain is one of the great scientific challenges of the 21st century

Petra E. Vértes, et al., PNAS, 2012

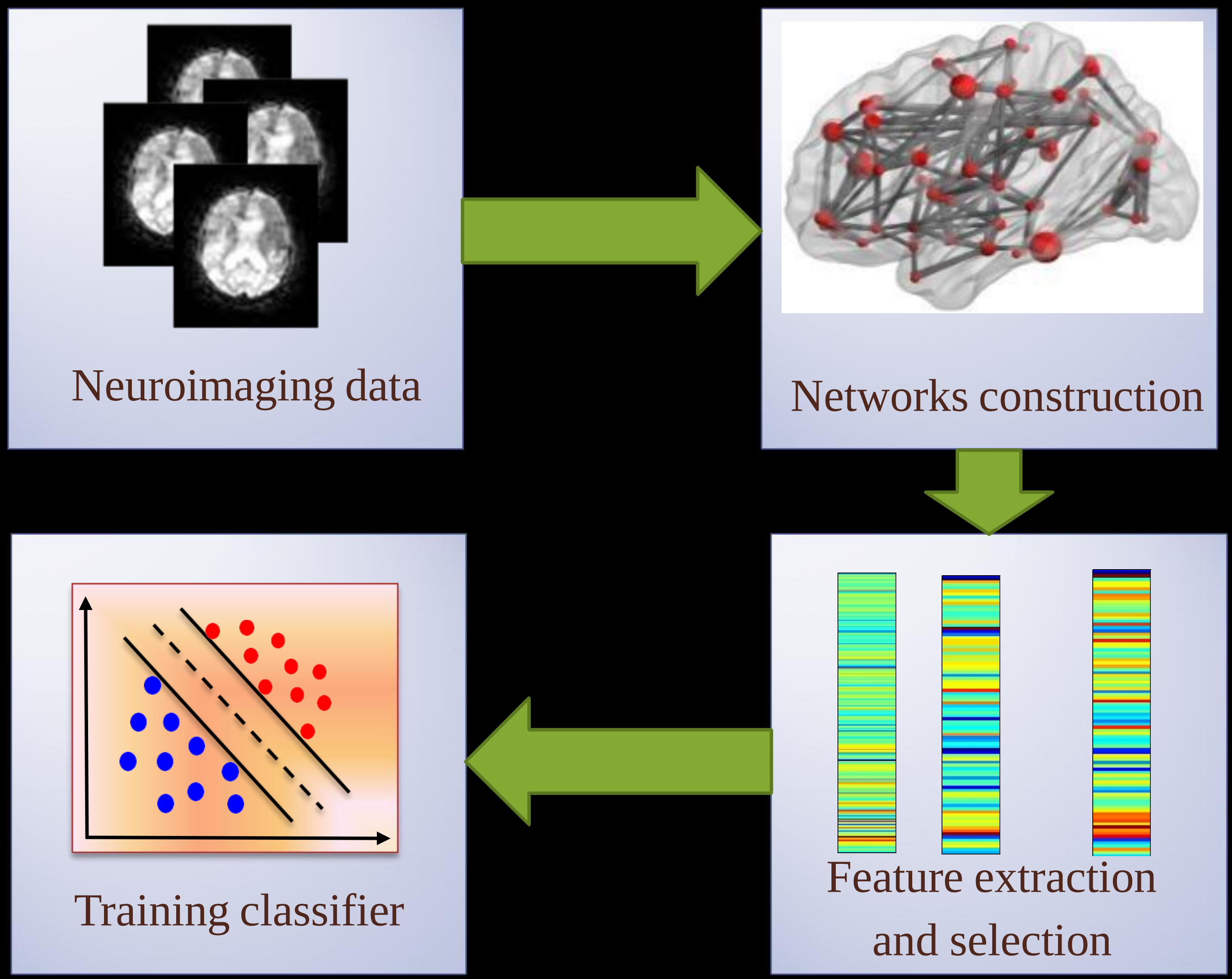
Connectivity Types

structural connectivity   functional connectivity   effective connectivity

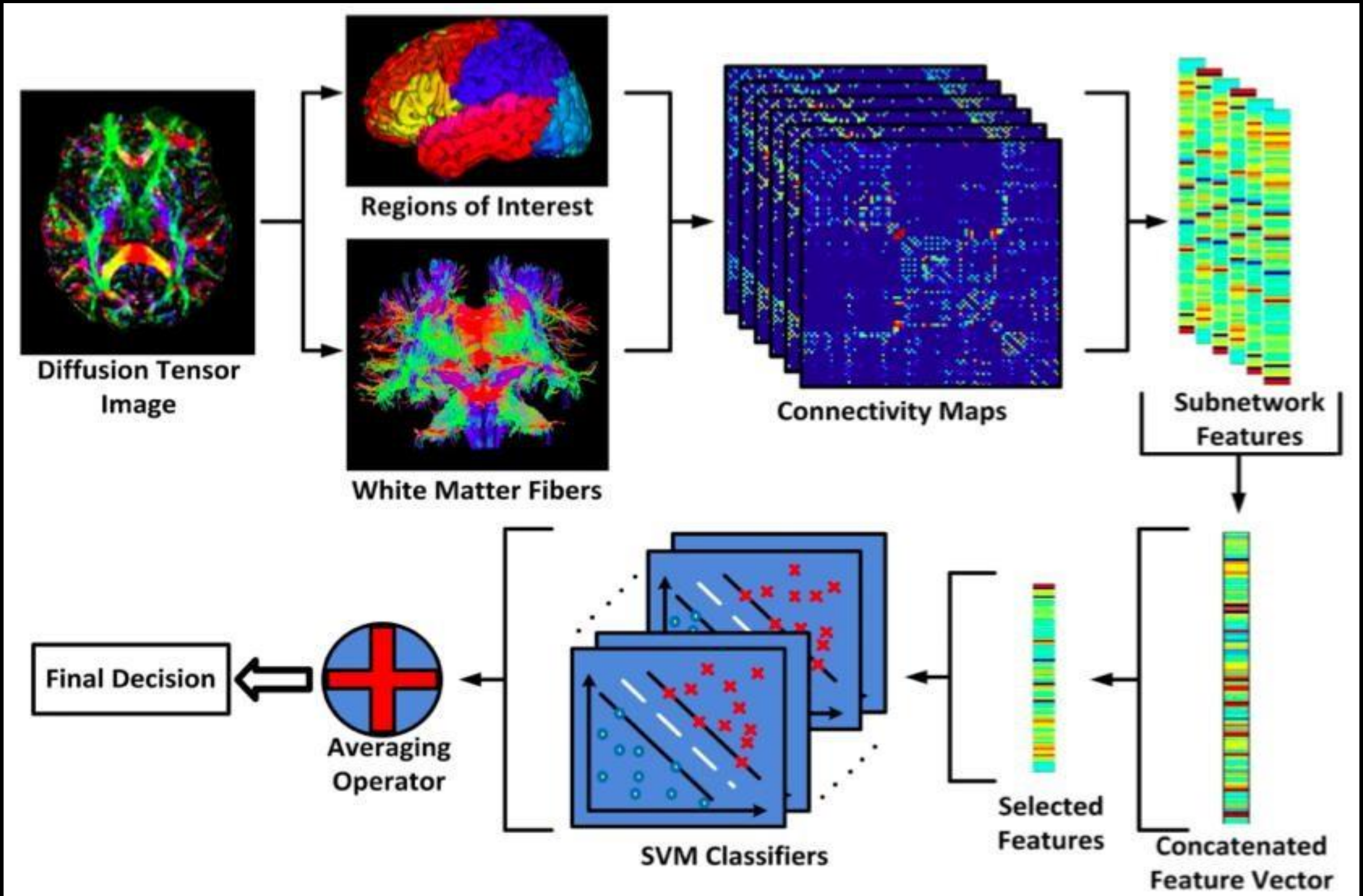


Honey et al., PNAS, 2007

Network-based Classification

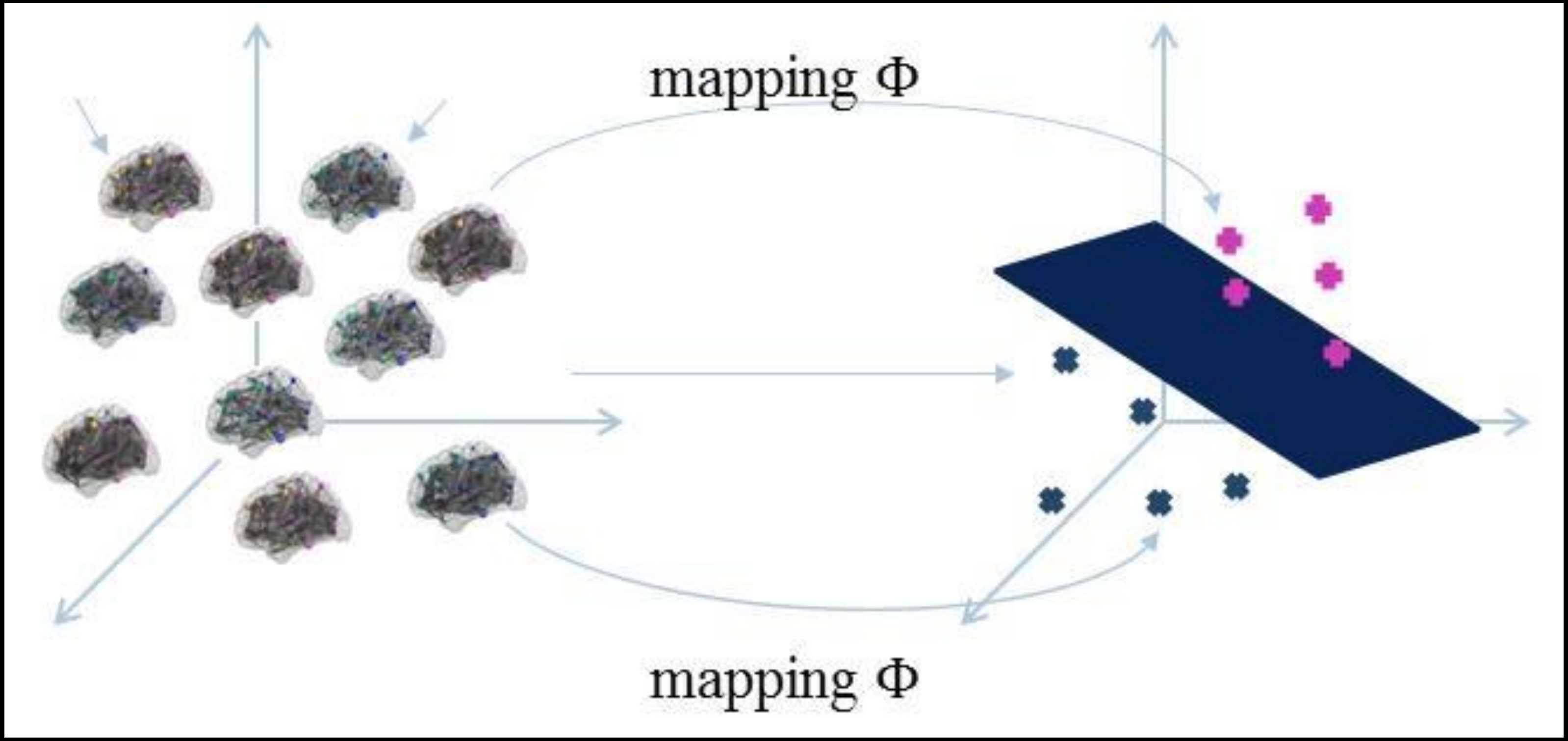


Local Measures of Network



C.Y Wee, et al. Neuroimage, 2011

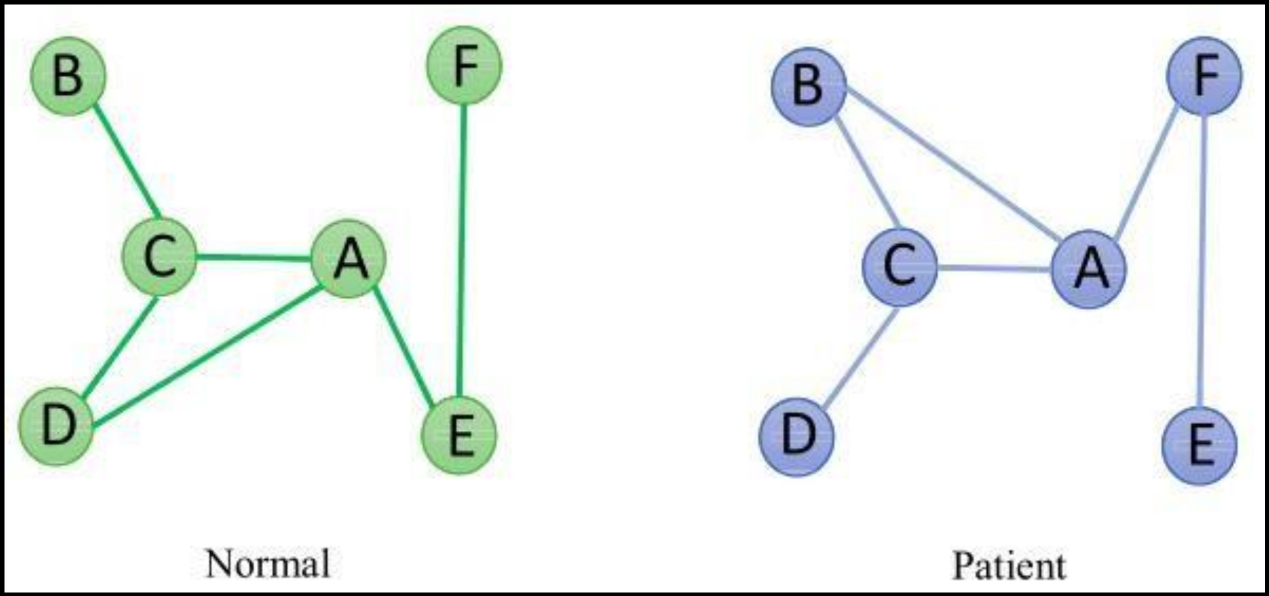
Topological Graph Kernel



B. Jie, et al., Human Brain Mapping, 2014

Limitations of Existing Graph Kernels

- ignoring the uniqueness of each node in brain networks

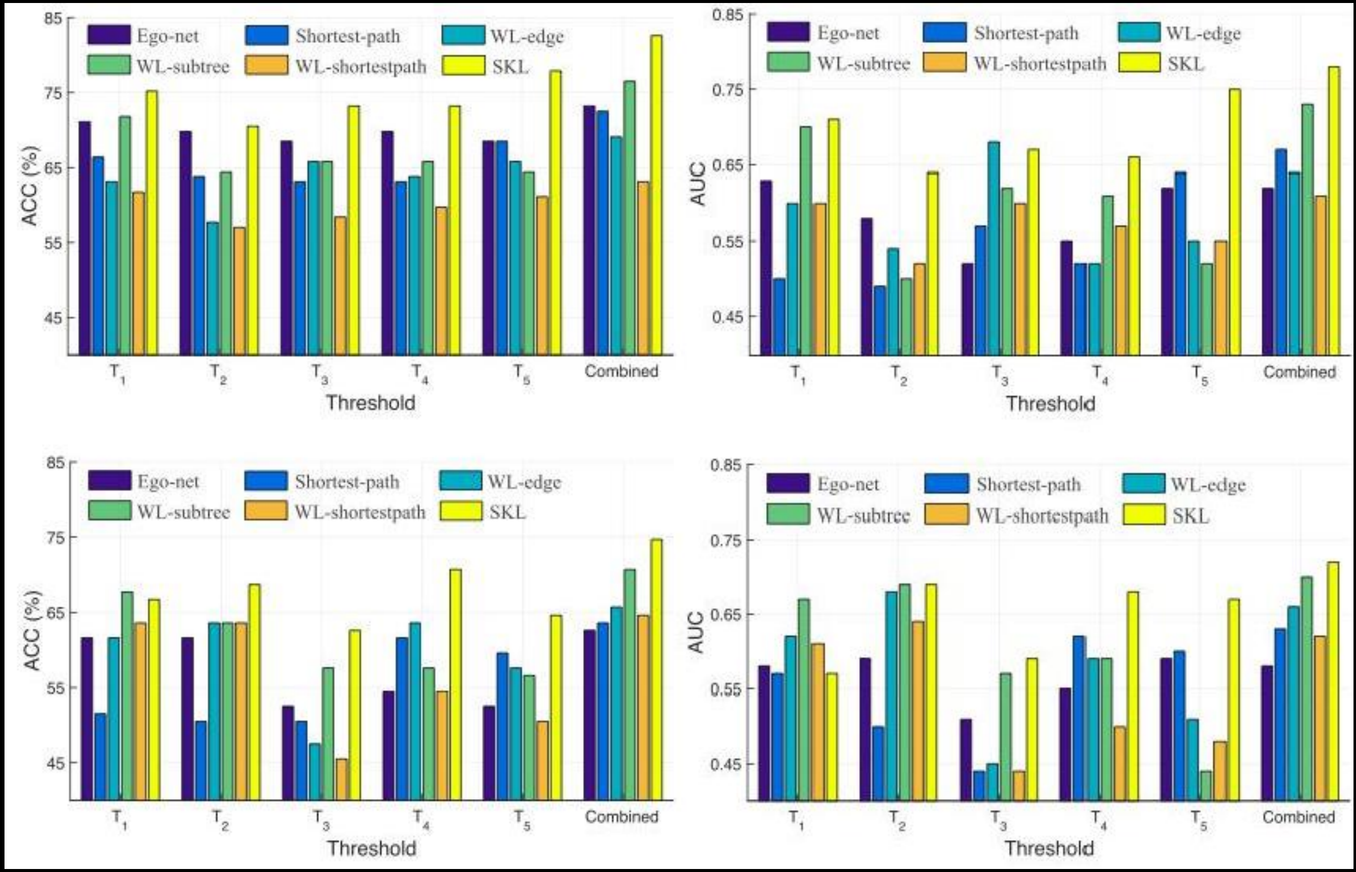


B. Jie, et al., IEEE TIP, 2018

Classification Results

MCI vs. NC classification

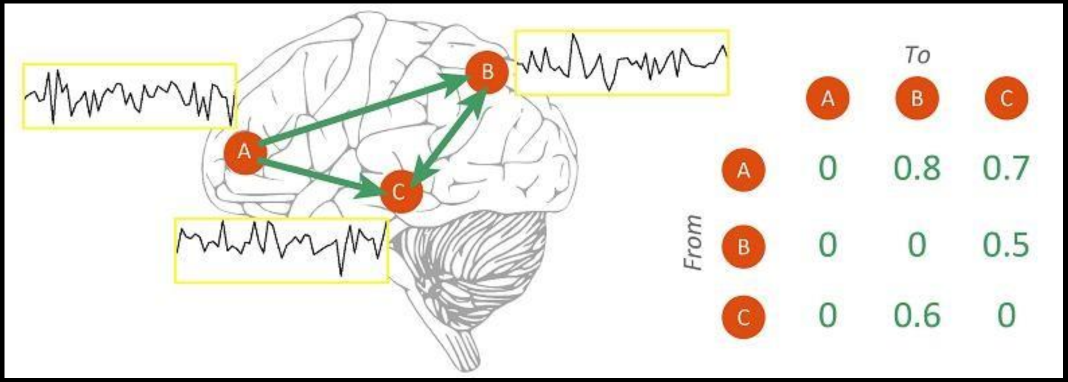
EMCI vs. LMCI classification



B. Jie, et al., IEEE TIP, 2018

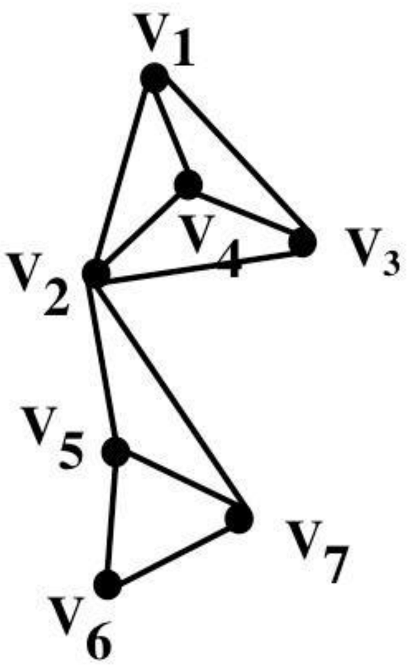
Brain Hyper-network

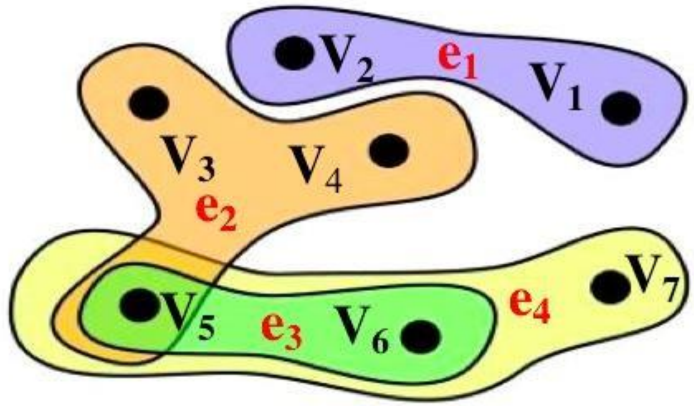
- Conventional network is usually constructed based on the pairwise correlation among brain regions
- Cannot reflect the useful higher-order relationship among brain regions



- Question: how to character the higher-order relationship among brain regions?

Solution: Hyper-graph





$$\mathcal{G} = (\mathcal{V}, \mathcal{E})$$

$$\mathcal{V} = \{v_1, v_2, \dots, v_7\}, \quad \mathcal{E} = \{e_1, e_2, e_3, e_4\}$$

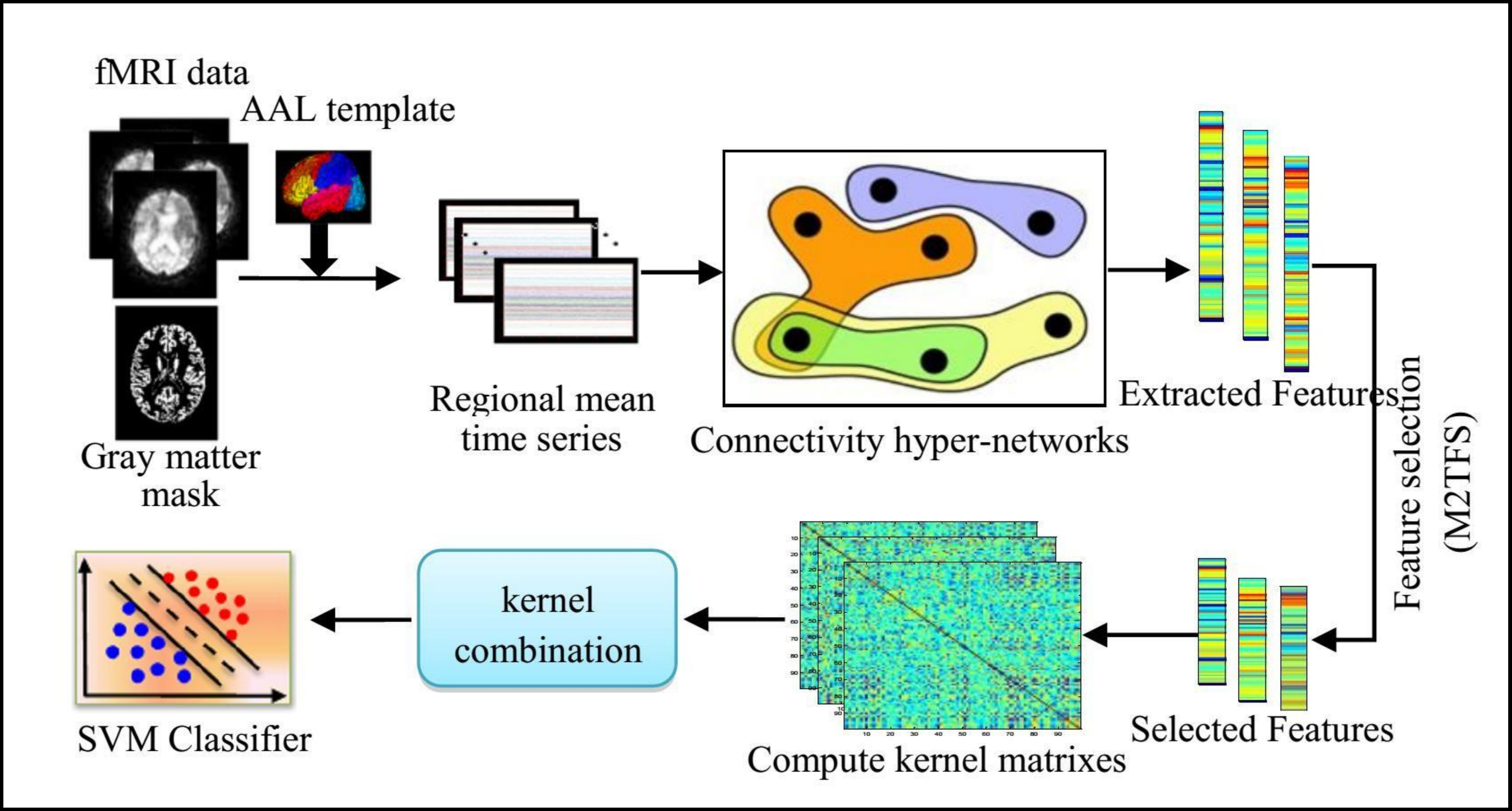
$$e_1 = \{v_1, v_2\}, \quad e_2 = \{v_3, v_4, v_5\}$$

$$e_3 = \{v_5, v_6\}, \quad e_4 = \{v_5, v_6, v_7\}$$

	e_1	e_2	e_3	e_4
V_1	1	0	0	0
V_2	1	0	0	0
V_3	0	1	0	0
V_4	0	1	0	0
V_5	0	1	1	1
V_6	0	0	1	1
V_7	0	0	0	1

simple graph hyper-graph incidence matrix

Hyper-connectivity Network for Brain Disease Diagnosis



B. Jie, et al., Medical Image Analysis, 2016

Classification Results

Table 2
Classification performances of compared methods.

Method	Accuracy(%)	BAC(%)	Sensitivity(%)	Specificity(%)	AUC
CN-CC (*)	62.2	56.9	41.7	72.0	0.54
HN_HCC[1] (*)	75.7	66.9	41.7	92.0	0.75
HN_HCC[2]	81.1	79.5	75.0	84.0	0.80
HN_HCC[3]	89.2	87.7	83.3	92.0	0.93
CONCAT	91.9	91.8	91.7	92.0	0.94
Proposed	**94.6**	**93.9**	**91.7**	**96.0**	0.96

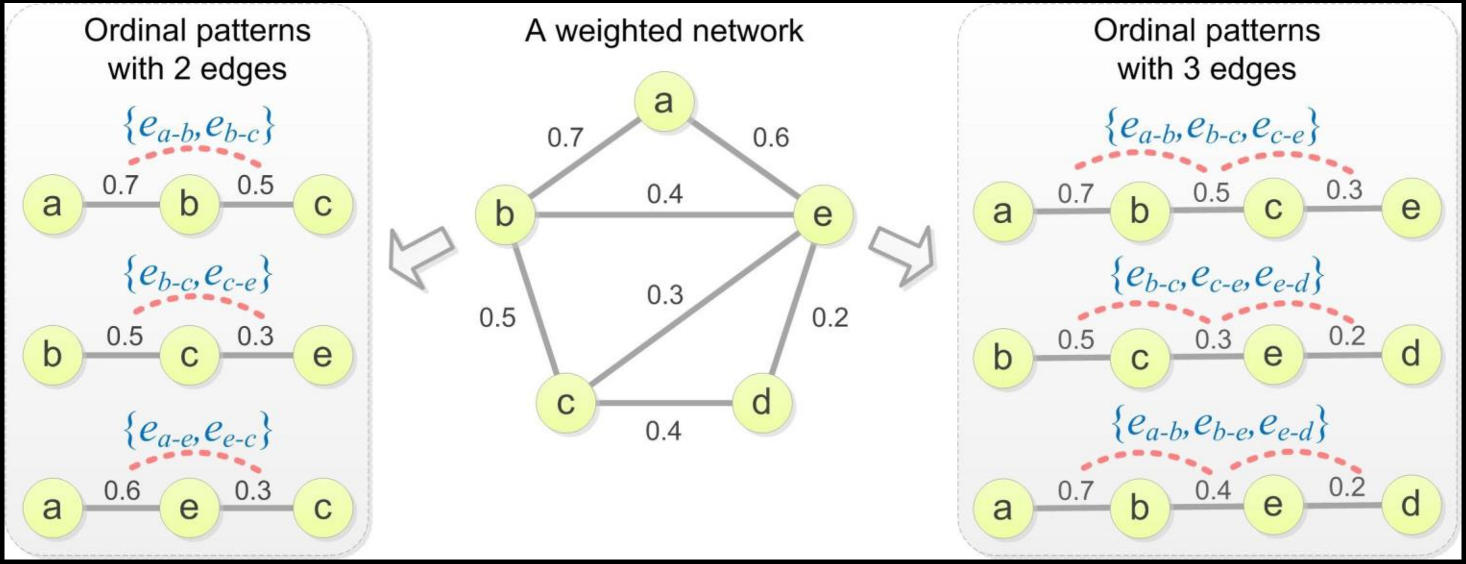
* indicates significant (i.e., p-value < 0.05) difference in terms of classification accuracy compared to the proposed method based on McNemar's test. BAC: balanced accuracy; AUC: area under receiver operating characteristic (ROC) curve.

B. Jie, et al., Medical Image Analysis, 2016

Weighted Nework Mining

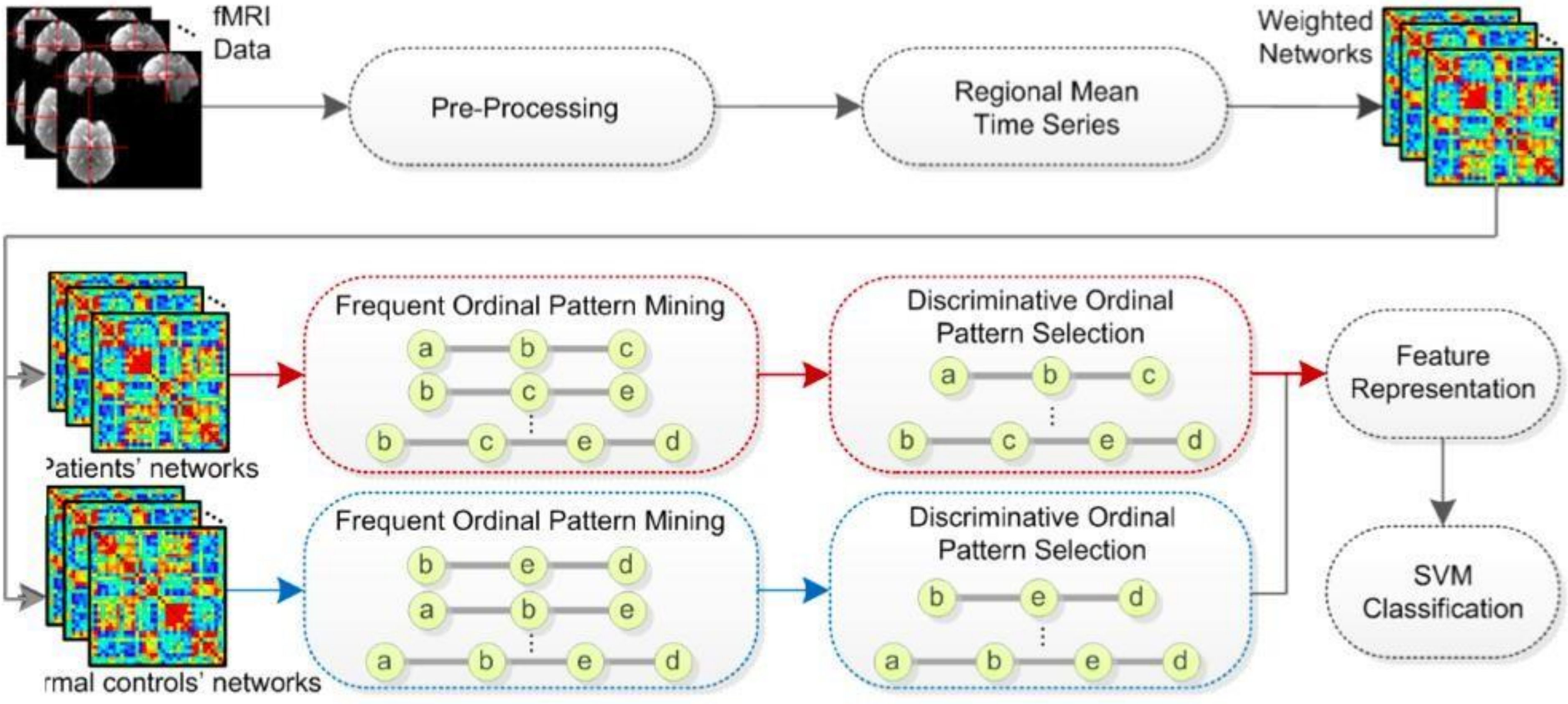
- Conventional network descriptors are usually designed on un-weighted brain networks
- Qestion: how to directly mine novel network descriptors on weighted brain networks?

Solution: Frequent ordinal pattern mining



D. Zhang, et al., IEEE TMI, 2018

Ordinal Pattern for Brain Network Classification



D. Zhang, et al., IEEE TMI, 2018

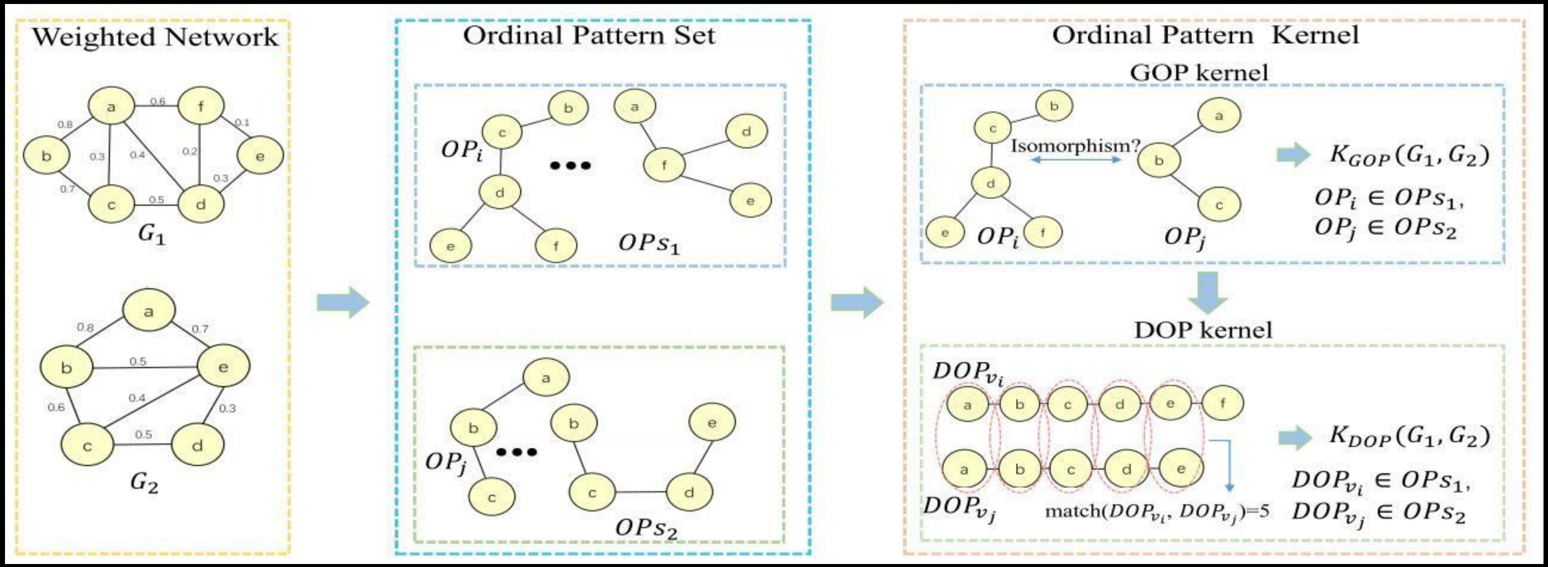
Classification Results

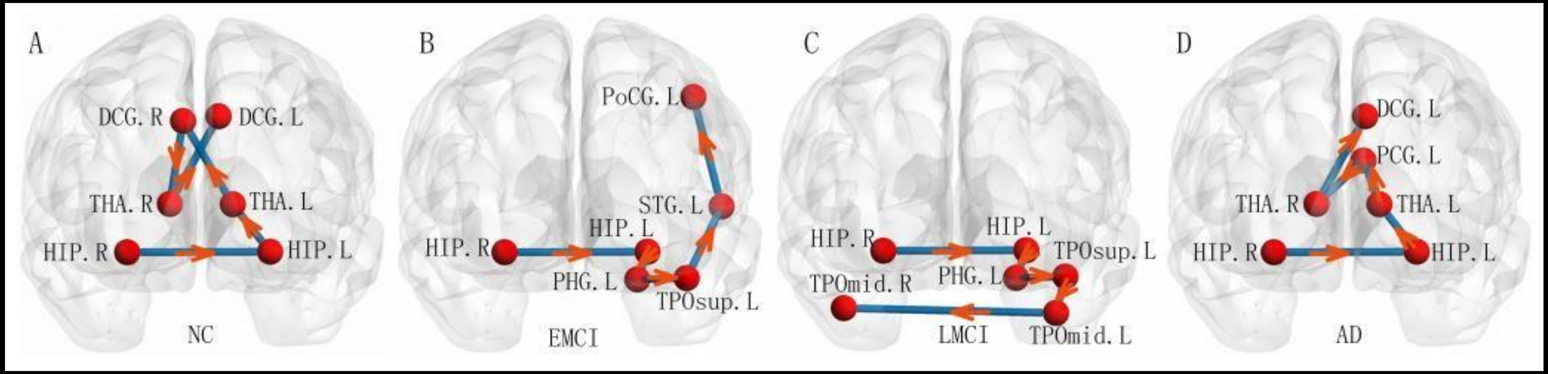
Comparison of different methods in 3 classification tasks

Method	AD vs. NC			MCI vs. NC			ADHD vs. NC		
	ACC	SEN	AUC	ACC	SEN	AUC	ACC	SEN	AUC
CC	72.62	73.53	70.94	71.14	72.73	68.69	71.29	72.03	70.51
CCMT	80.95	82.35	76.35	74.50	75.76	74.79	74.53	75.43	77.64
DS	76.19	76.47	75.59	77.18	78.79	74.89	81.01	81.36	80.82
DSMT	85.71	85.29	87.59	79.19	80.81	76.99	83.79	84.74	84.63
Proposed	**94.05**	**96.77**	**96.35**	**88.59**	**87.27**	**84.57**	**87.50**	**88.89**	**87.37**

D. Zhang, et al., IEEE TMI, 2018

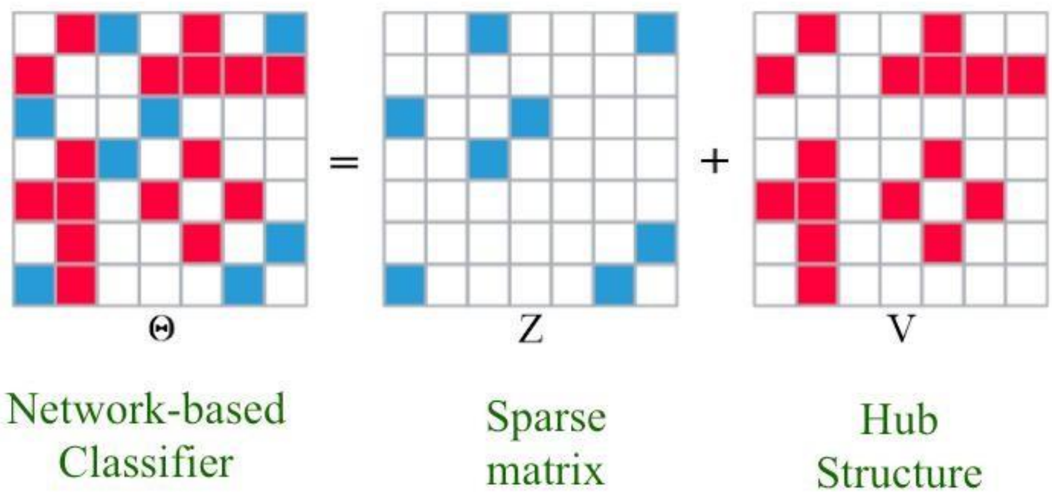
Ordinal Pattern Kernel for Brain Network Classification



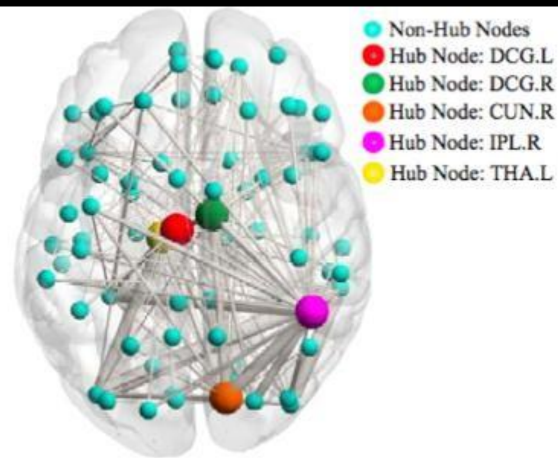


K. Ma, et al., IEEE TNSRE, 2022; MICCAI 2022

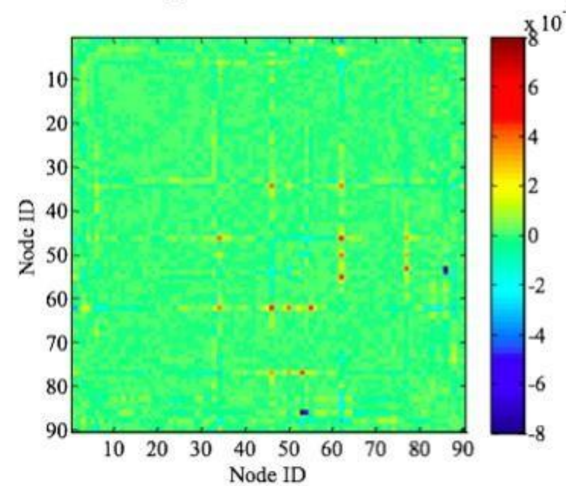
Brain Network Hub Detection



$$
\begin{aligned}
\arg \min_{\Theta, b, \mathbf{Z}, \mathbf{V}} \quad & \frac{1}{N} \sum_{n=1}^{N} \log(1 + \exp(-Y_n(tr(\Theta^T \mathbf{A}^{(n)}) + b))) \\
& + \lambda \|\mathbf{Z}\|_1 + \beta \|\mathbf{V}\|_1 + \gamma \|\mathbf{V}\|_{2,1} \\
\text{s.t.} \quad & \Theta = \mathbf{Z} + \mathbf{V}, \mathbf{Z} = \mathbf{Z}^T, \mathbf{V} = \mathbf{V}^T, \\
& diag(\Theta) = \mathbf{0}
\end{aligned}
$$

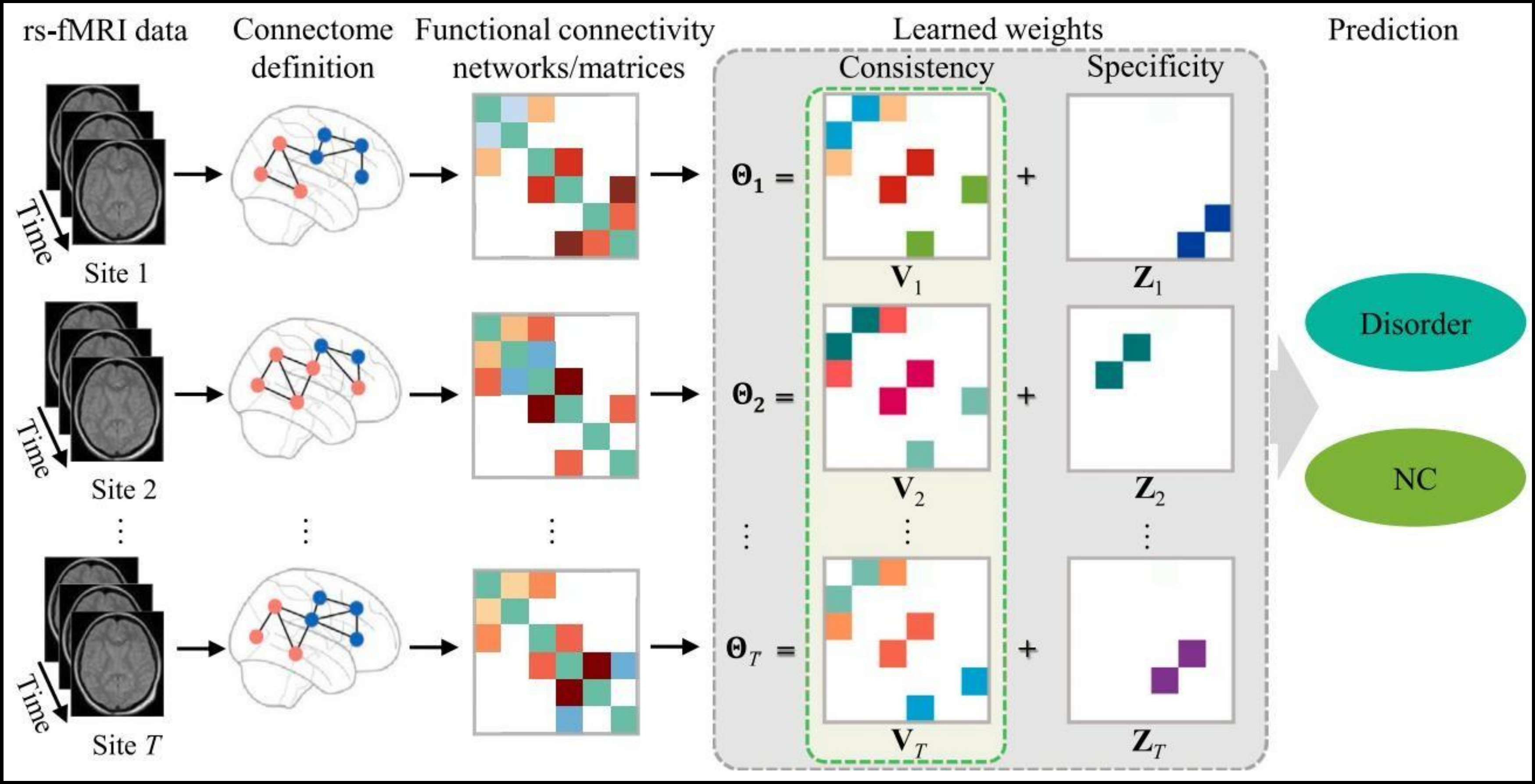


(a) NBH



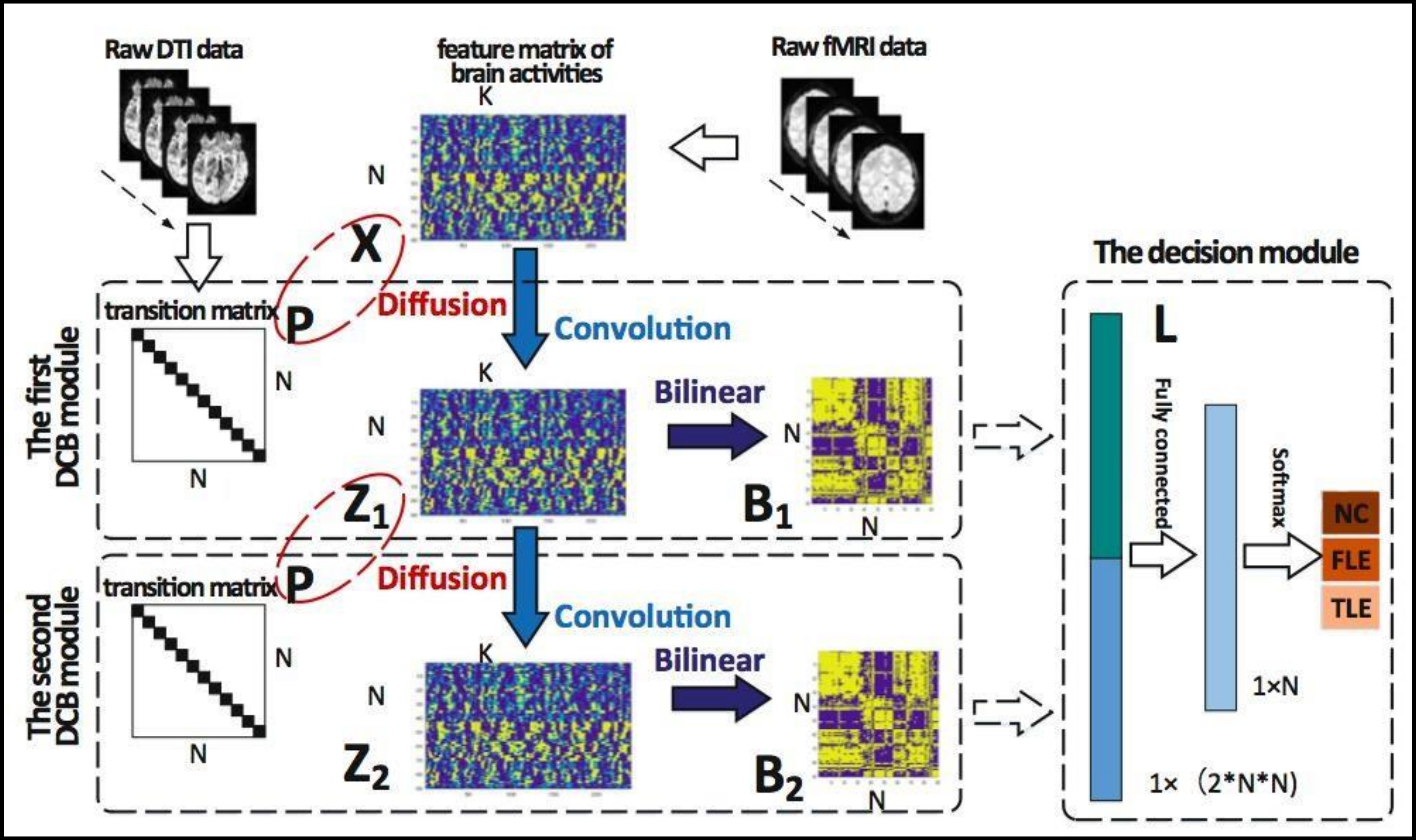
M. Wang, et al., AAAI 2019; IEEE TBME 2020

跨站点脑网络共性Hub结构检测



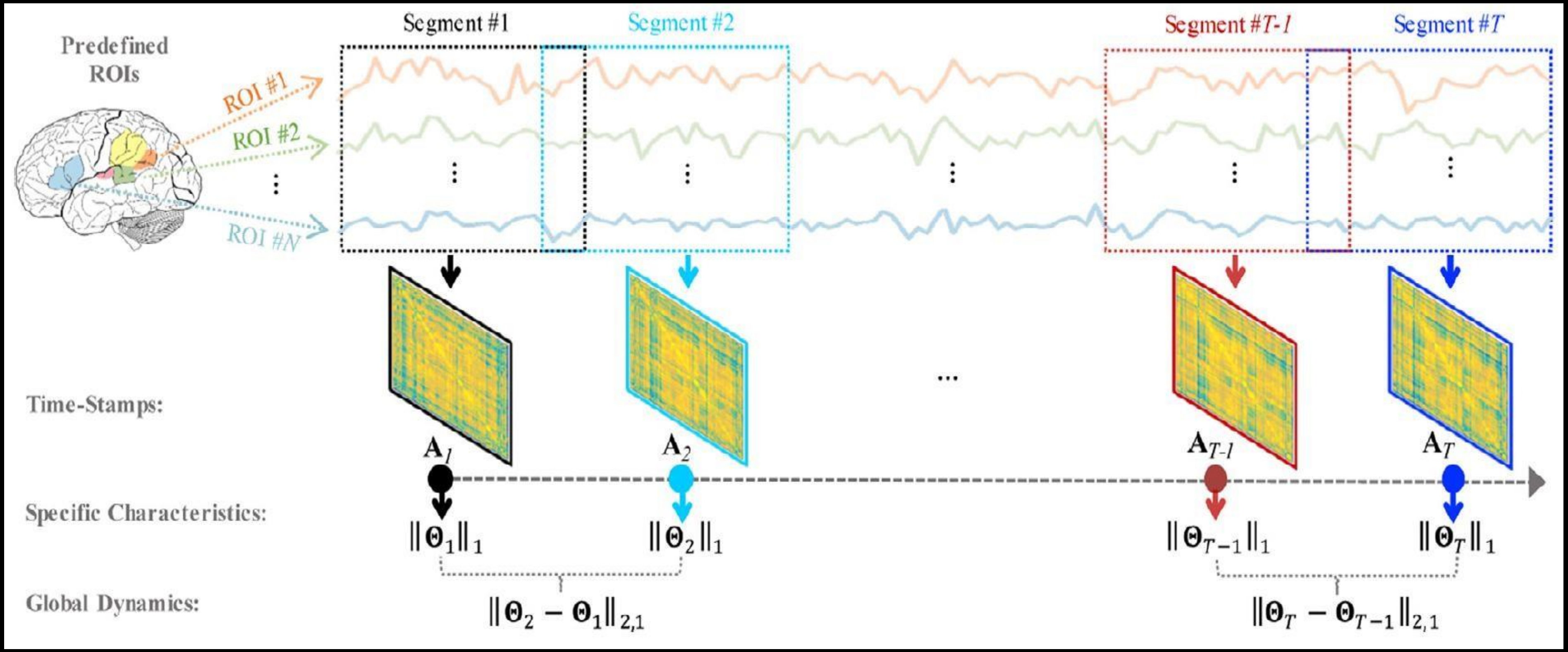
M. Wang, et al., Medical Image Analysis, 2022

Integrating Functional and Structural Connectivities



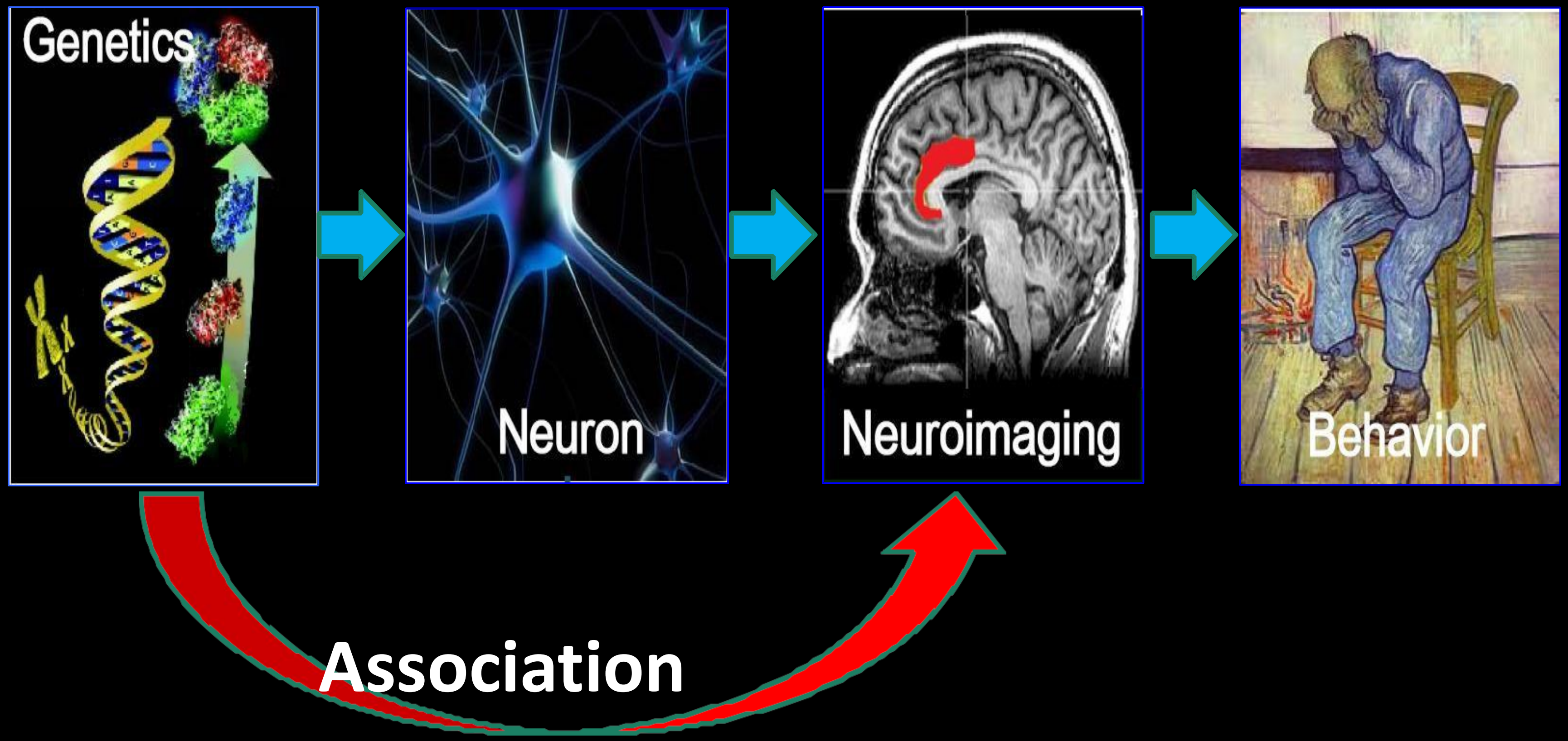
J. Huang, et al., MICCAI 2019; IEEE TMI, 2020

Temporal Dynamics Learning for Functional Brain Networks



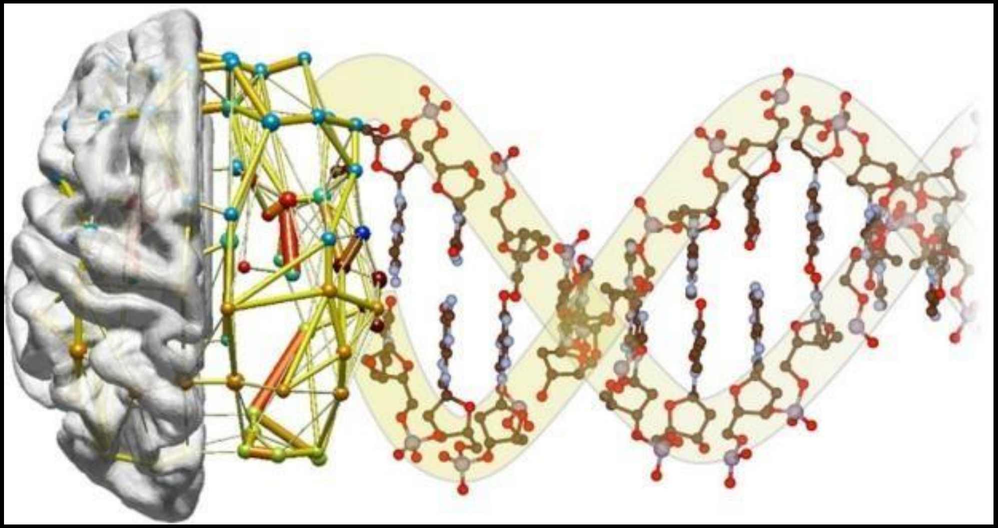
M. Wang, et al., Medical Image Analysis, 2021

Imaging Genetics

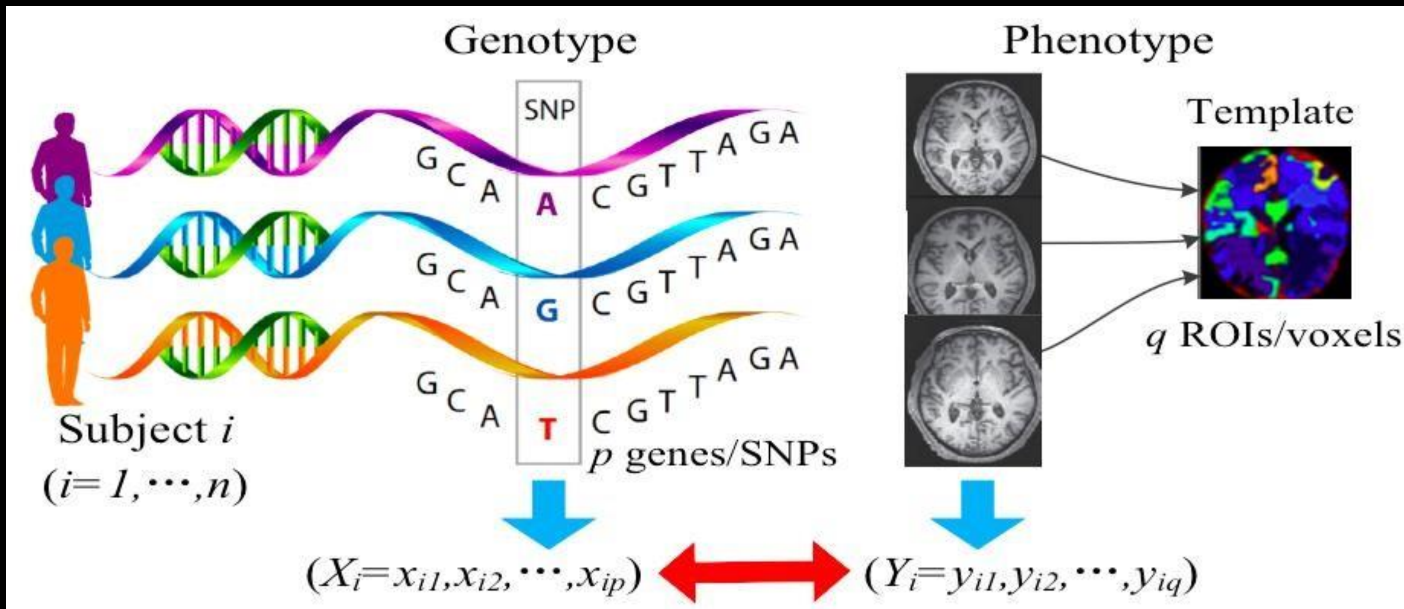


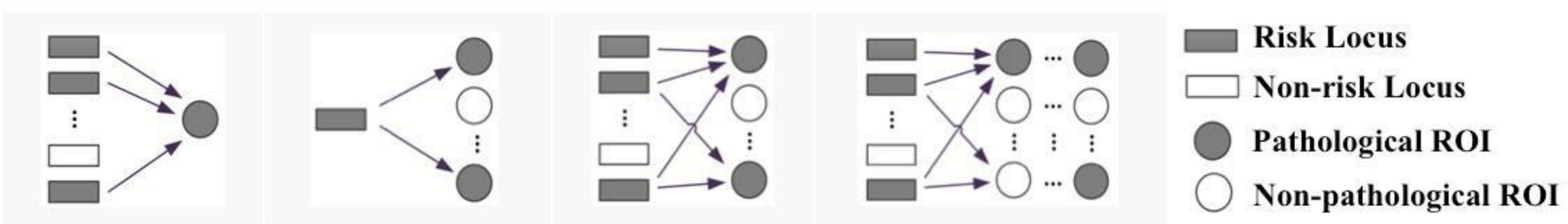
Imaging Genetics

- To establish important physiological links between functional genetic polymorphisms and robust differences in information processing within distinct brain regions and circuits that have been linked to the manifestation of various disease states



Statistical-learning Methods for Imaging Genetics



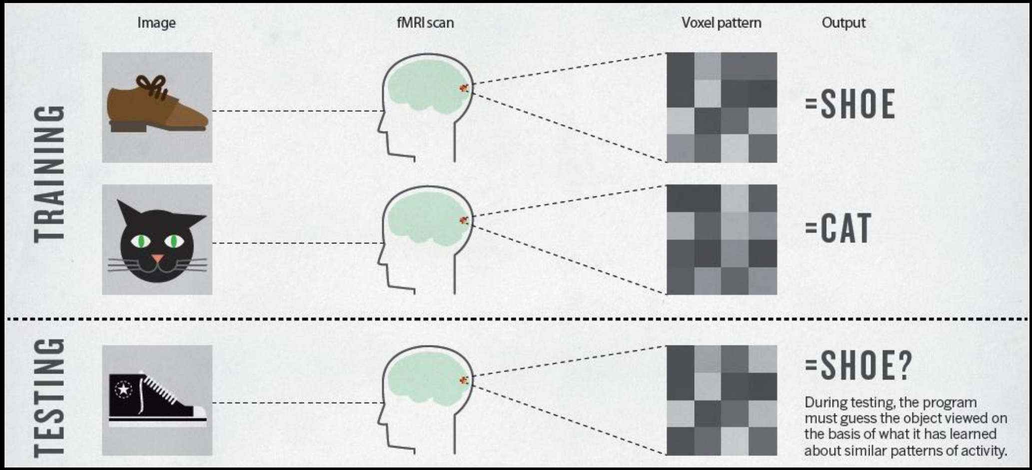


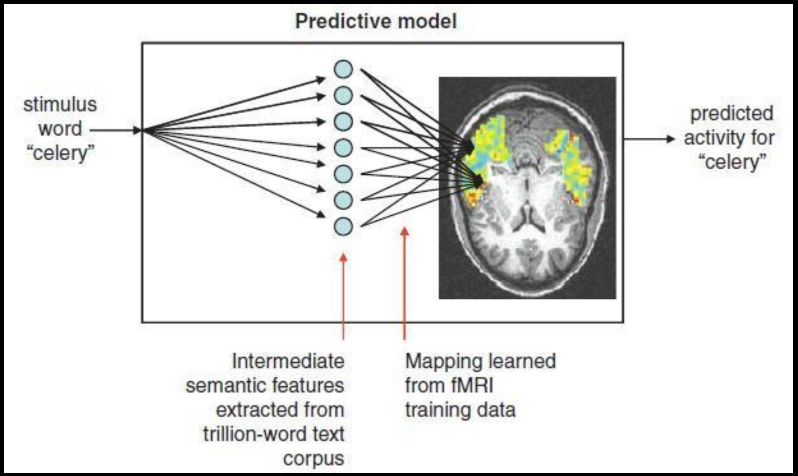
(1) Multivariate-Univariate (2) Univariate-Multivariate (3) Multivariate-Multivariate (4) Static Multivariate-Dynamic Multivariate

郝小可, et al.,基于统计学习的影像遗传学方法综述. 自动化学报, 2018

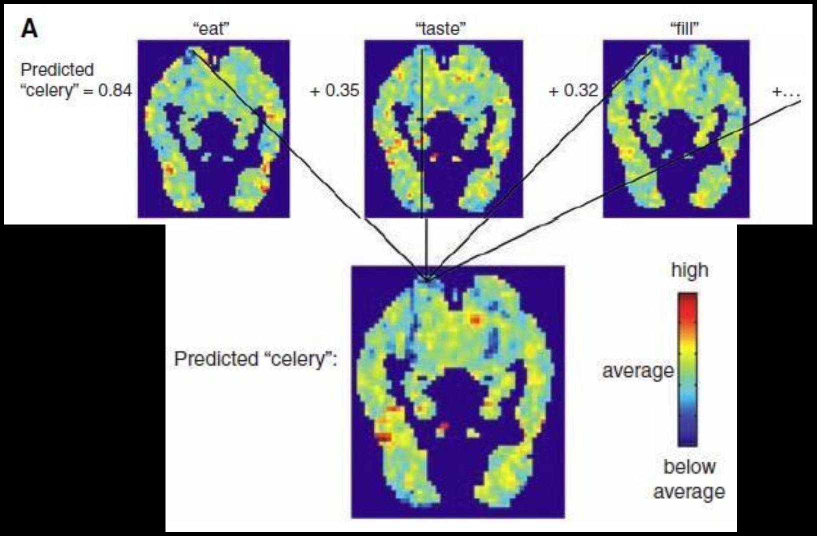
Human Brain Decoding

(Smith et al., Nature, 2013)

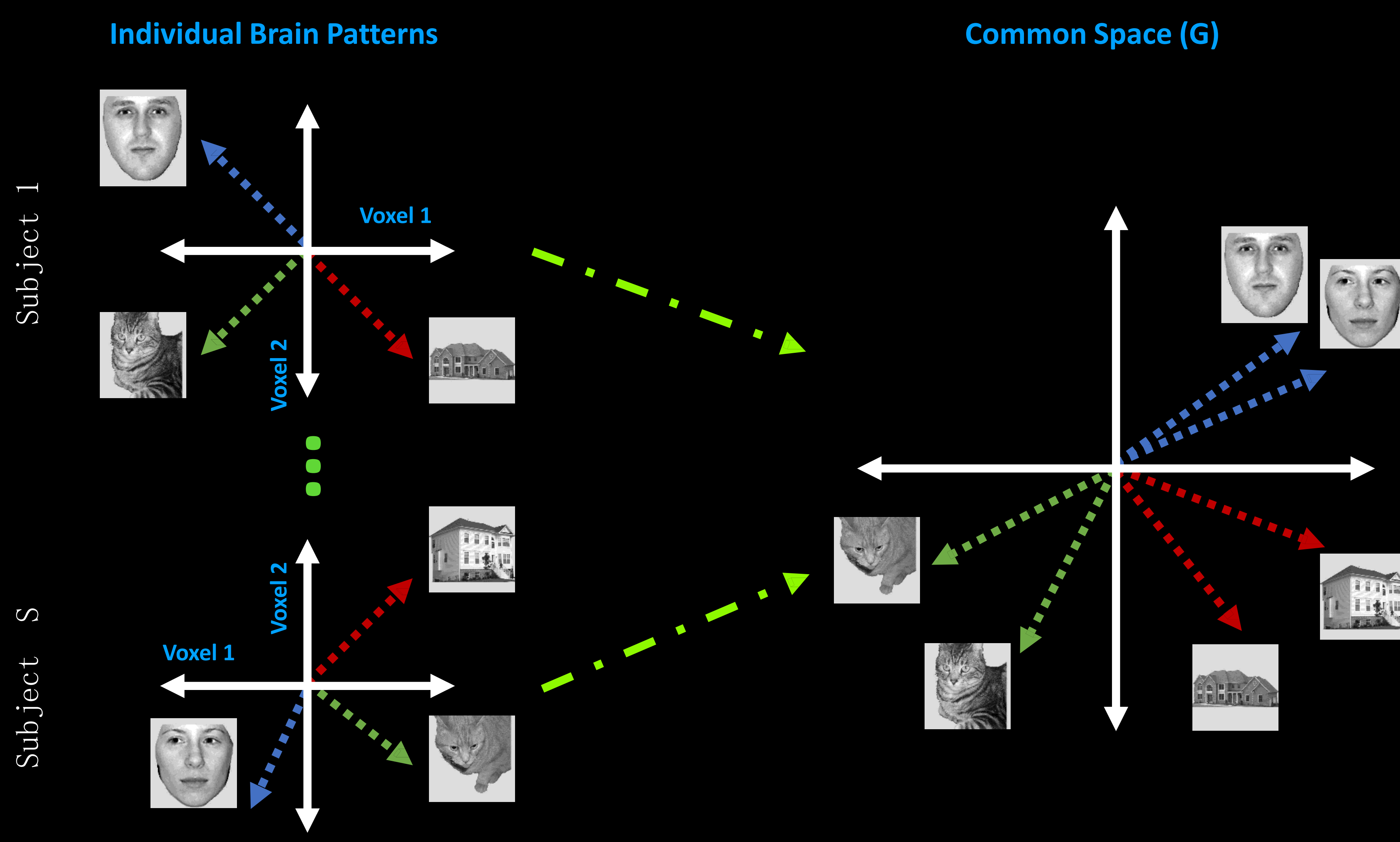




(Mitchell et al., Science, 2008)



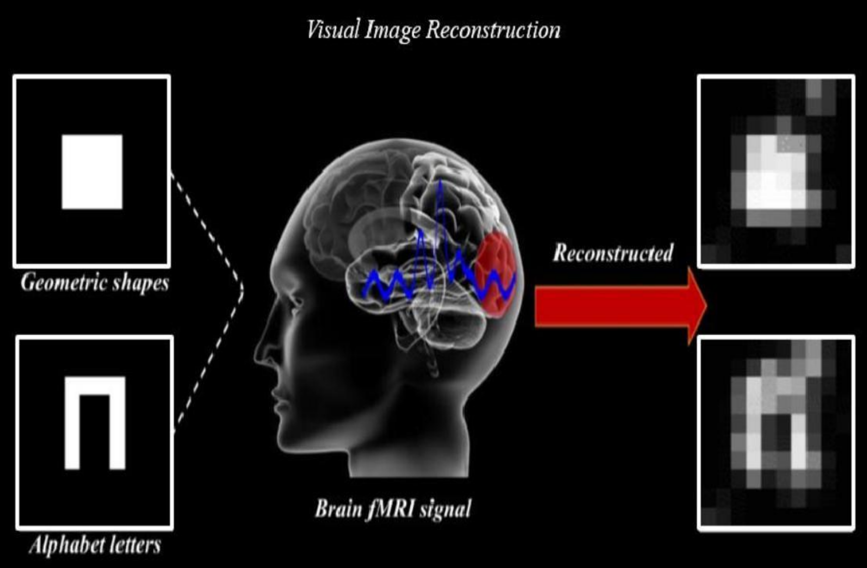
Hyperalignment



More Works

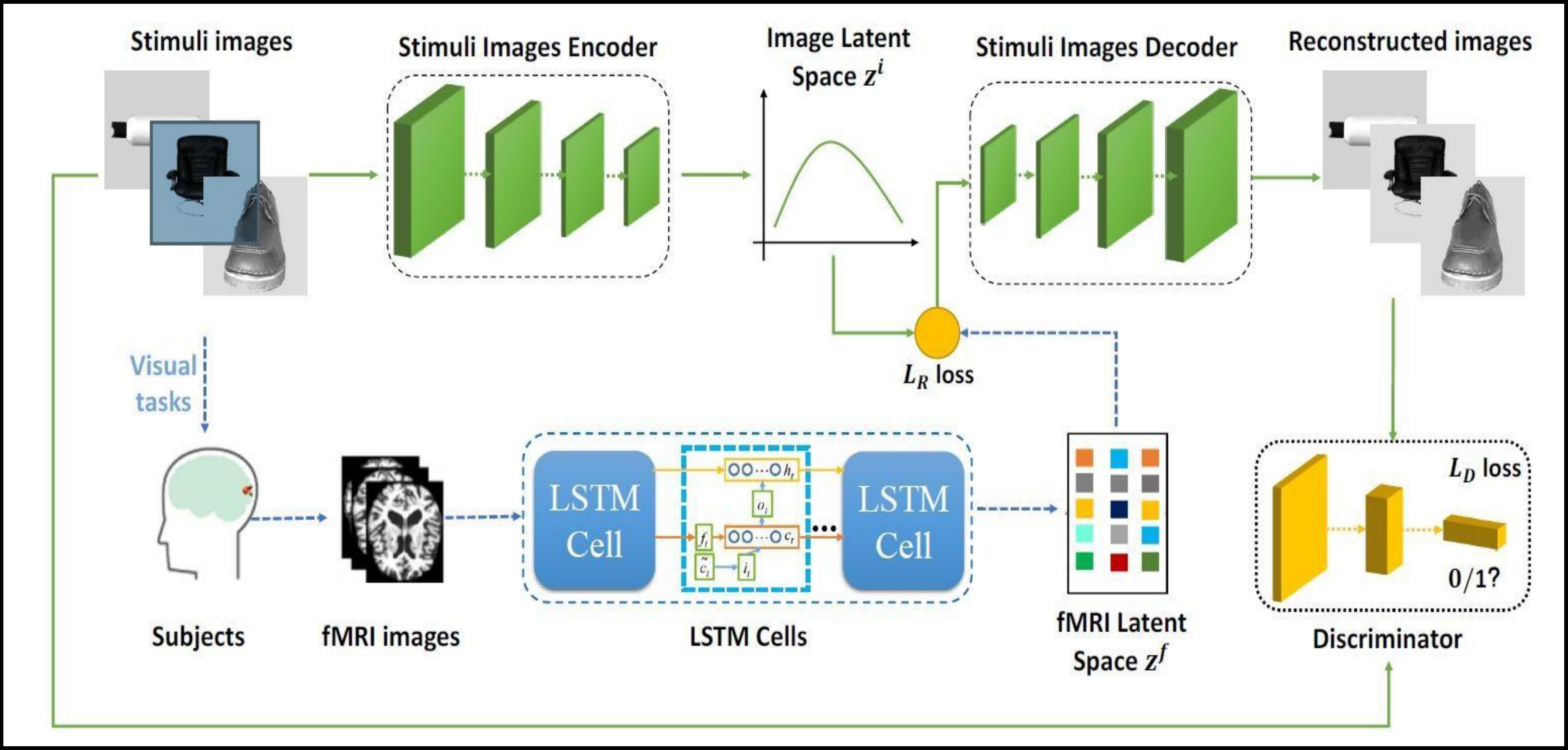
1. Supervised Hyperalignment for multi-subject fMRI data alignment. IEEE Trans. on Cognitive and Developmental Systems, 2021
2. Deep Representational Similarity Learning for analyzing neural signatures in task-based fMRI dataset. Neuroinformatics, 2021
3. Shared Space Transfer Learning for analyzing multi-site fMRI data. NeurIPS, 2020
4. Graph-Based Decoding Model for Functional Alignment of Unaligned fMRI Data. AAAI, 2020
5. Multi-Objective Cognitive Model: a Supervised Approach for Multi-subject fMRI Analysis. Neuroinformatics, 2019
6. Local Discriminant Hyperalignment for Multi-Subject fMRI Data Alignment. AAAI, 2017
7. Multi-Region Neural Representation: A novel model for decoding visual stimuli in human brains. SDM, 2017

Visual Image Reconstruction



Huang et al., IEEE TCDS, 2022

Deep Learning Based Image Reconstruction



Brain Imaging

Thanks for Your Attention!