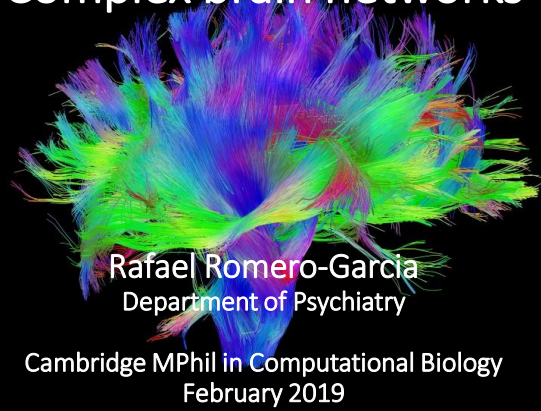


Complex brain networks

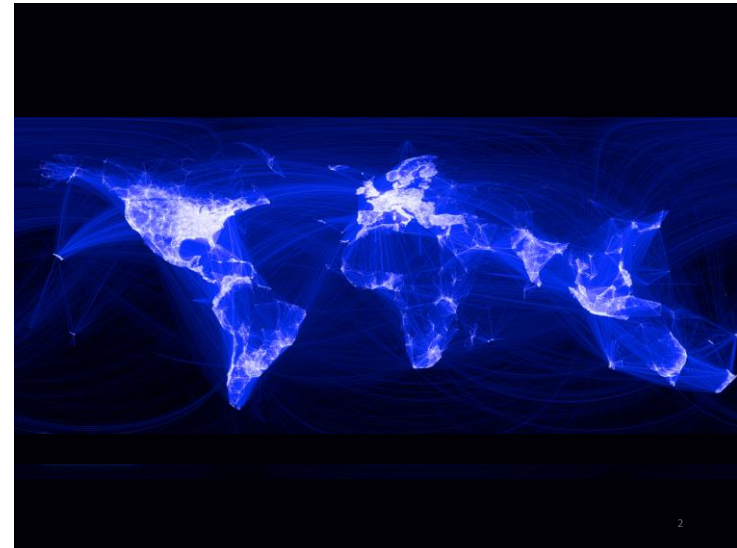


Rafael Romero-Garcia
Department of Psychiatry

Cambridge MPhil in Computational Biology
February 2019

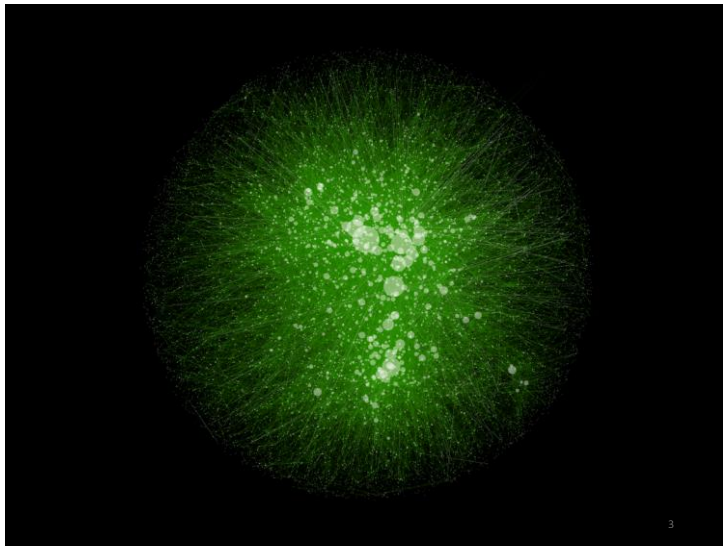
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1



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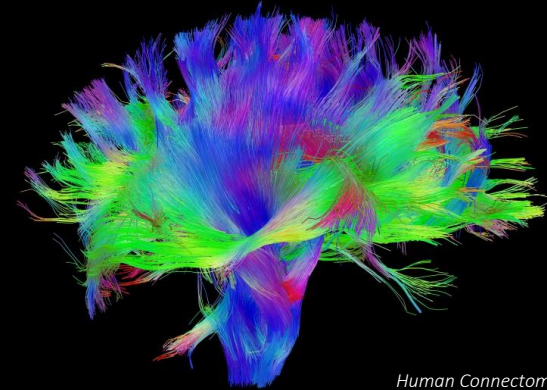
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3

3

The brain is the most
complex of networks



Human Connectome Project.

4

Review

The Human Connectome: A Structural Description of the Human Brain

Olaf Sporns*, Giulio Tononi, Rolf Kötter

To understand the functioning of a network, one must know its elements and their interconnections. The purpose of this article is to discuss research strategies aimed at a comprehensive structural description of the network of elements and connections forming the human brain. We propose to call this dataset the human “connectome,” and we argue that it is fundamentally important in cognitive neuroscience and neuropsychology. The connectome will

Sporns et al.; 2005.

5

MOTIVATION FOR COMPLEX BRAIN NETWORKS

7

7

Motivation for complex brain networks

Types of complex brain networks

Construction of complex brain networks

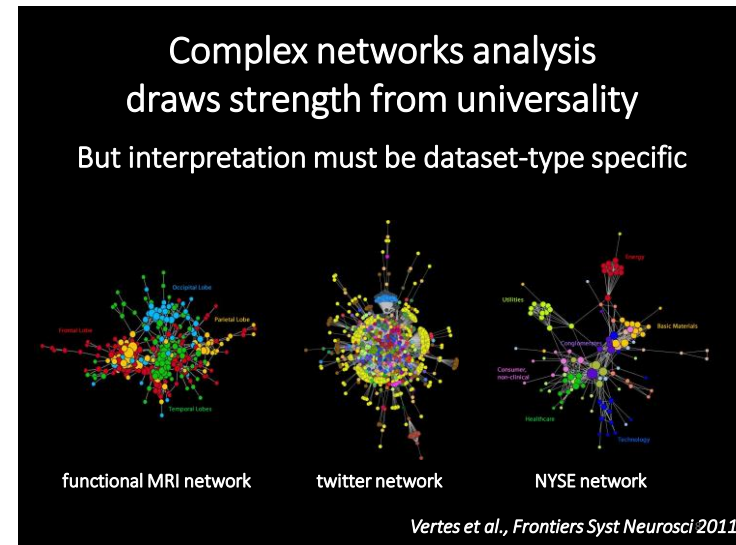
Analysis of complex brain networks

Brain network modules and hubs

Limitations

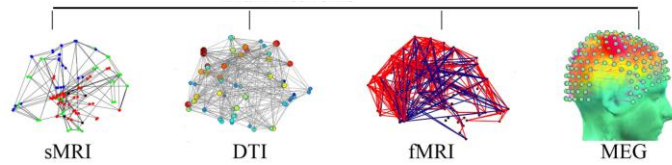
6

6



8

Complex networks are a universal framework for representation of multimodal brain connectivity

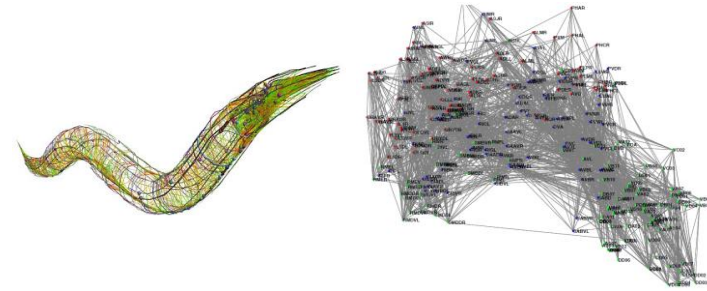


Bassett and Bullmore, *Curr Opin Neurol* 2009

9

Complex networks intuitively represents connectivity at multiple spatial scales

The *C. elegans* connectome



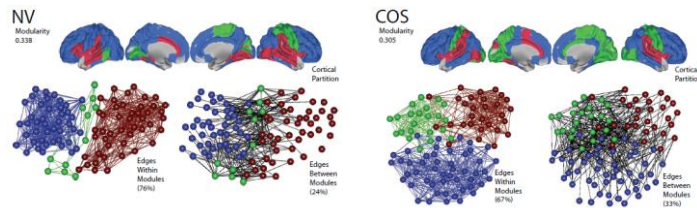
The Open Worm Project

Chen et al., *PNAS* 2006

10

10

Dysconnectivity in neuropsychiatric disorders is likely to be complex



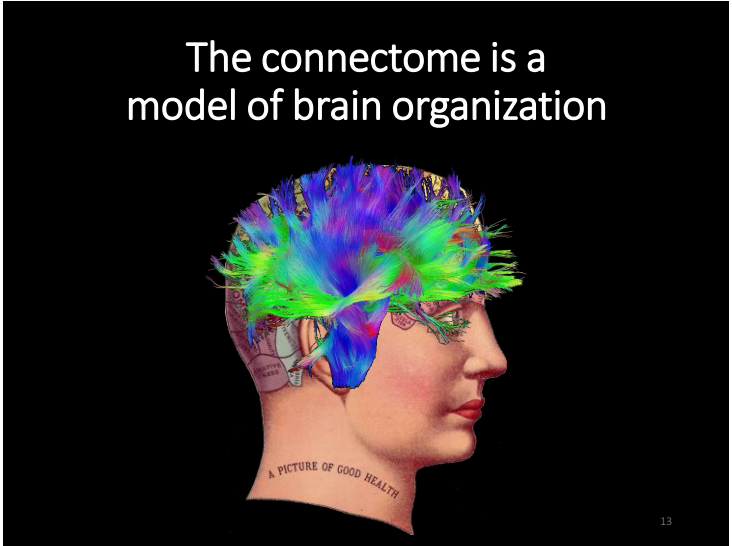
Alexander-Bloch et al., *Frontiers Syst Neurosci* 2011

11

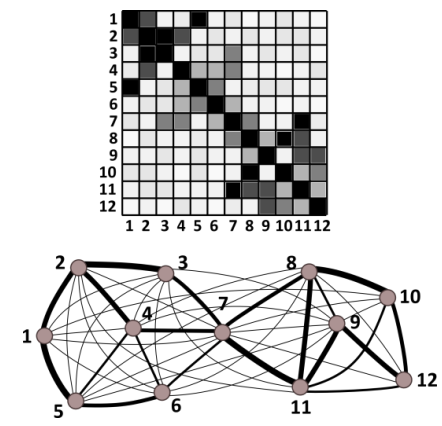
TYPES OF COMPLEX BRAIN NETWORKS

12

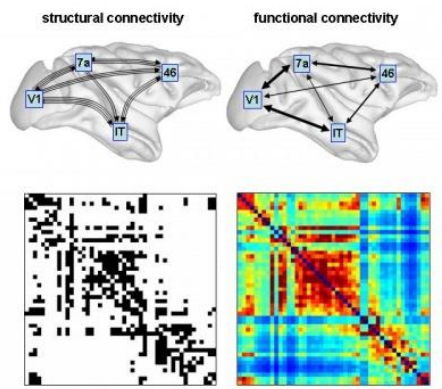
12



Connectivity matrix represents a graph



Types of brain connectivity



Sporns, Scholarpedia 2012

Structural Connectivity	Functional connectivity
Anatomical links	Correlational links
Electron or light microscopy MRI	Multielectrode array recordings, MRI, EEG/MEG
Manual or automated reconstruction	Correlation, synchronization
Positively weighted connections	Positive and negatively weighted connections

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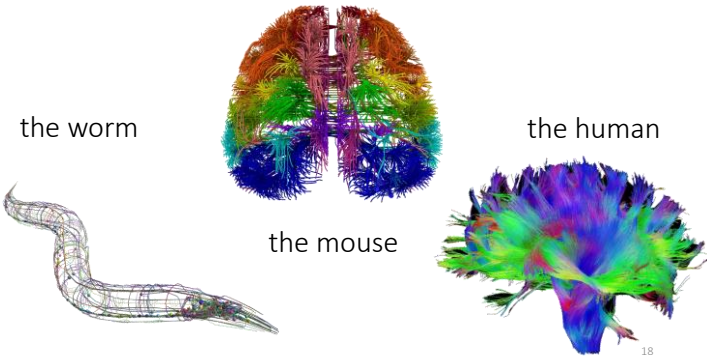
STRUCTURAL BRAIN NETWORKS

17

Mapping Methods	Electron Microscopy	Light Microscopy	Magnetic Resonance Imaging
Resolution	nm	μm	mm
Density	dense	sparse	sparse
Connectivity	synaptic	directed	undirected
Feasibility	roundworm fruit fly <i>ex vivo</i>	small mammals <i>ex vivo</i>	large mammals <i>in vivo</i>

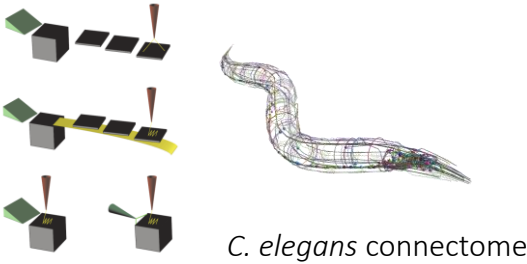
19

There is a data quality vs organism complexity trade-off



18

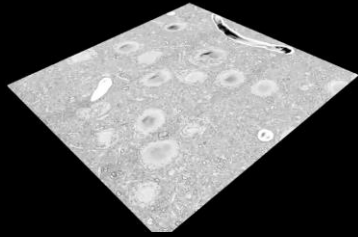
Electron-microscopy allows dense synaptic maps of neuronal circuits



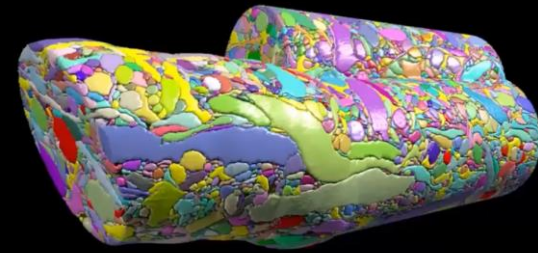
Helmstaedter, 2013; Open Worm project.

20

Neural circuit reconstruction

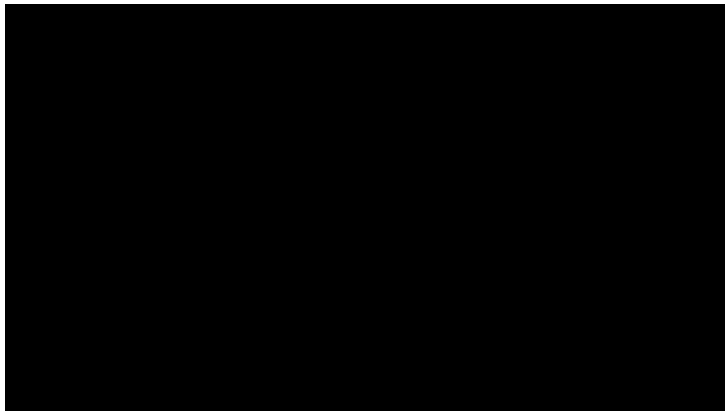


21

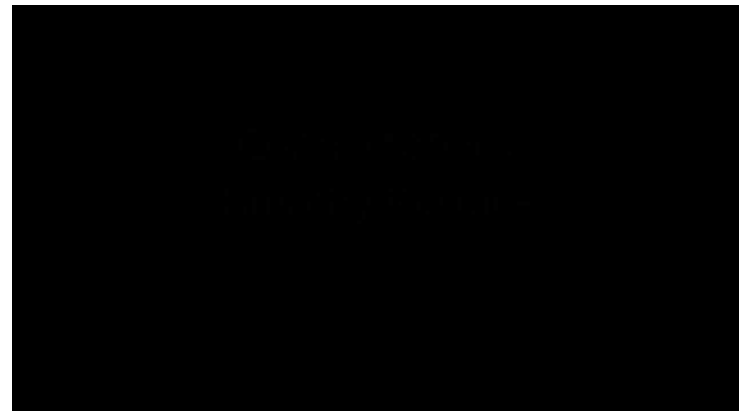
*Bobby Kasthuri, Boston University*

22

C. elegans



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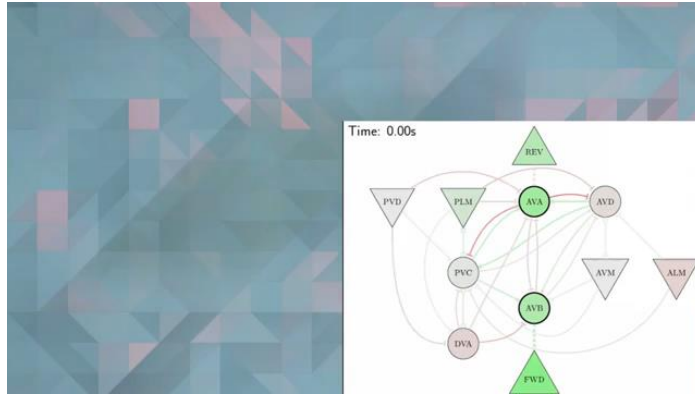


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2018-02-06 [Florian Aigner | Press Release 10/2018]

Worm Uploaded to a Computer and Trained to Balance a Pole

Is it a computer program or a living being? At TU Wien (Vienna), the boundaries become blurred. The neural system of a nematode was translated into computer code – and then the virtual worm was taught amazing tricks.



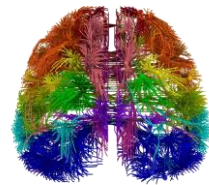
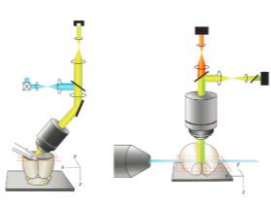
25

GoPiGo (Dexter Industries) Robot
running a C elegans connectome
simulation using Python 2.7 on a Raspberry Pi B+

Timothy Busbice
<http://www.connectomeengine.com>
@interintel
(c) 2015

26

Light-microscopy allows sparse
directed maps of mammalian brains



mouse connectome

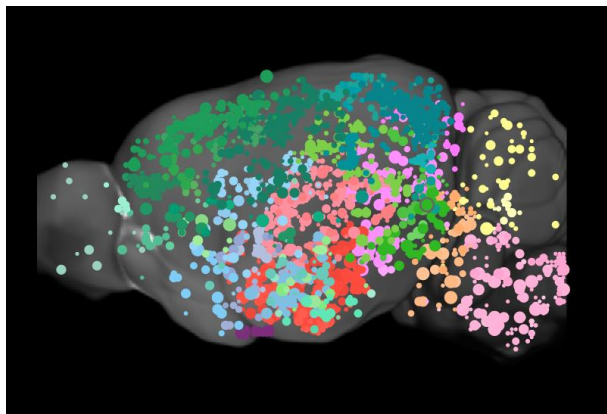
Osten and Margrie, 2013; Oh et al.; 2014.

27



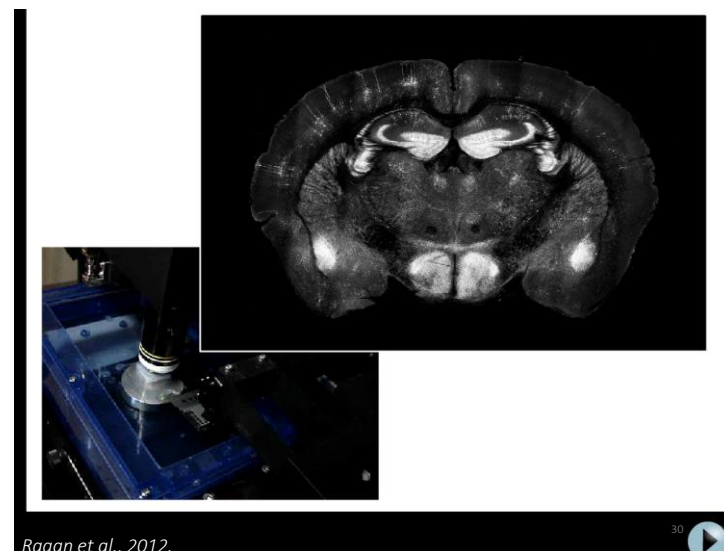
Mouse Connectome Project, University of Southern California

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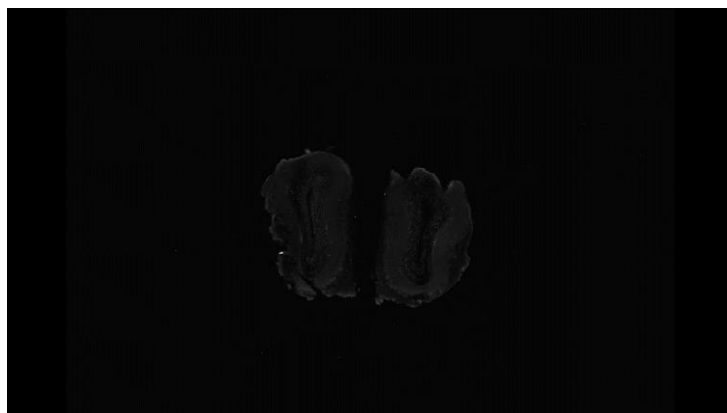
29



Ragan et al., 2012.

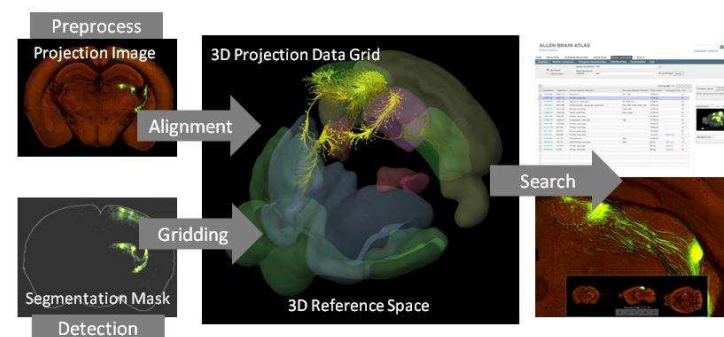
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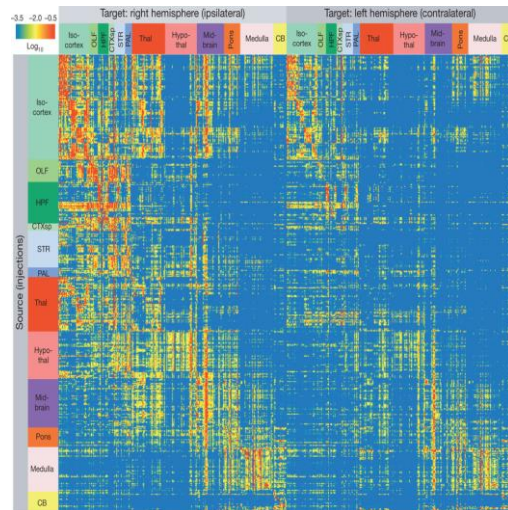
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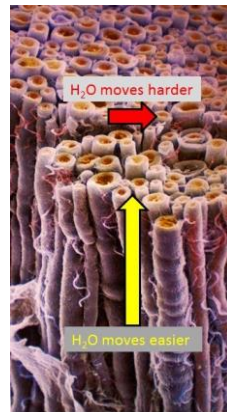
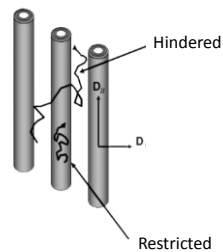
32



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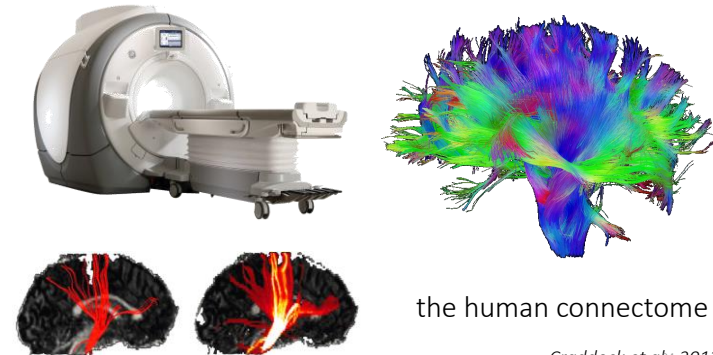
Diffusion MRI/tractography methods detect white-matter fibers from patterns of anisotropic water diffusion (I)

- Gradients are applied in different directions and attenuation is measured
 - Mobility is higher in white-matter fiber direction



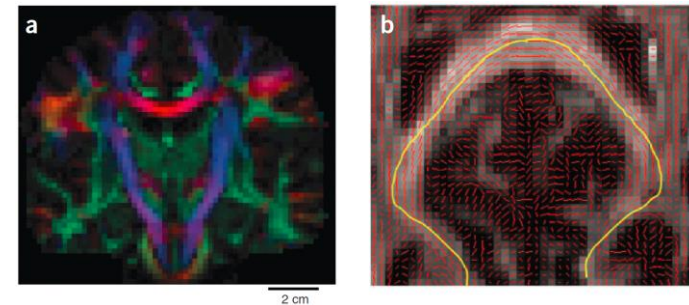
35

Magnetic resonance imaging allows whole-brain maps of living humans



34

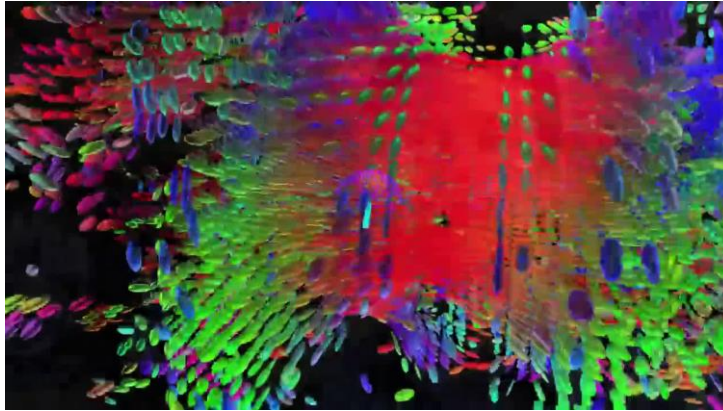
Diffusion MRI/tractography methods detect white-matter fibers from patterns of anisotropic water diffusion (II)



36

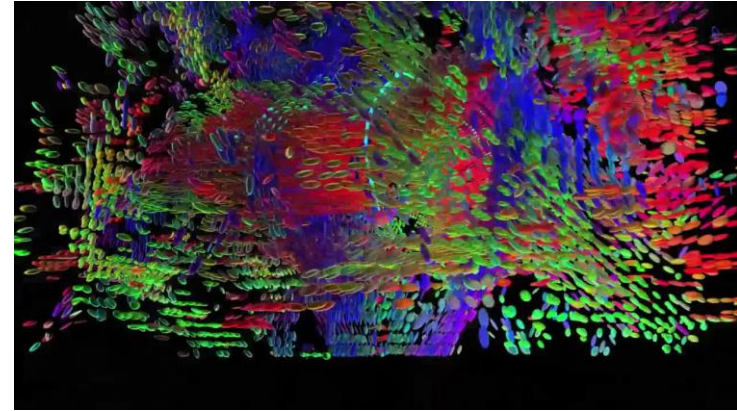
Craddock et al., 2013.

Diffusion MRI/tractography methods detect white-matter fibers from patterns of anisotropic water diffusion



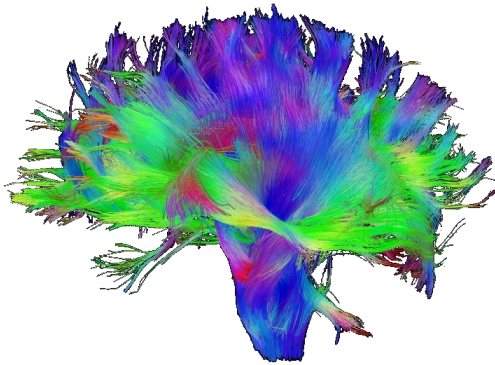
37

Diffusion MRI/tractography methods detect white-matter fibers from patterns of anisotropic water diffusion



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Diffusion MRI/tractography methods detect white-matter fibers from patterns of anisotropic water diffusion (III)



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Interactive real-time
orientation-dependent opacity rendering

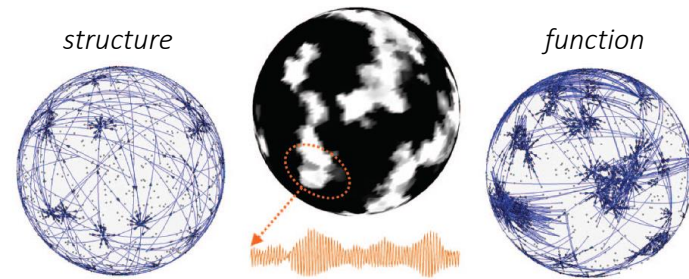
40

FUNCTIONAL BRAIN NETWORKS

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Complex brain function
emerges on and is constrained by
neuroanatomical network connectivity

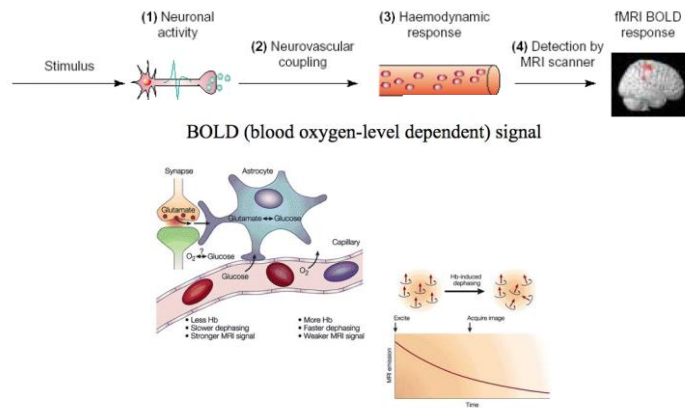
dynamics



Sporns and Honey, 2006.

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FUNCTIONAL MAGNETIC RESONANCE IMAGING (FMRI)



Arthurs & Boniface, 2002

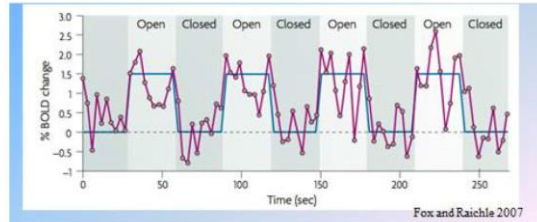
43



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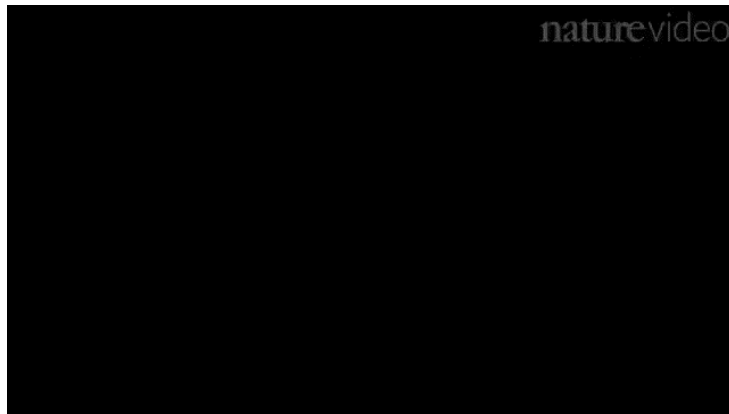
fMRI: Functional Magnetic Resonance Imaging

- There is blood in the brain at all times so a good *experimental paradigm* will contrast two brain states to see which areas are *more active* in one than the other



45

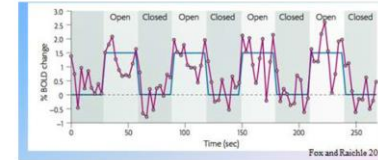
Natural speech reveals the semantic maps that tile human cerebral cortex



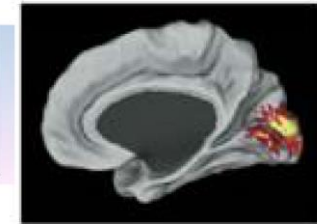
47

fMRI: Functional Magnetic Resonance Imaging

- For example occipital cortex is more active when eyes are open than when eyes are closed



- OPEN – CLOSED



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Movie reconstruction from human brain activity

Presented clip



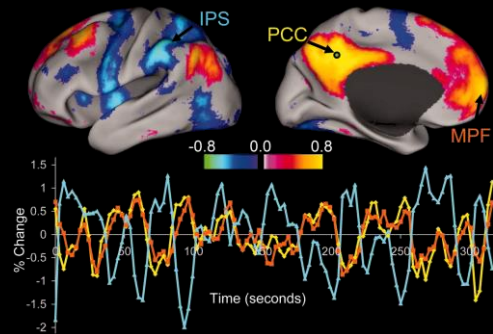
Clip reconstructed from brain activity



Nishimoto et al., 2011, Current Biology

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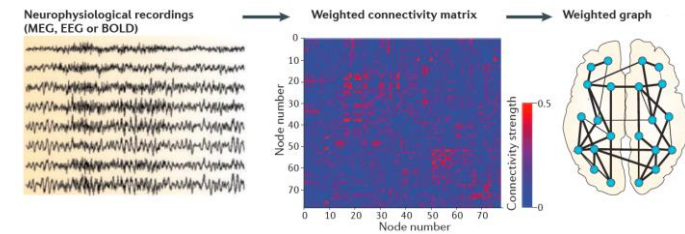
Functional MRI methods detect correlations of interregional changes in oxygenated hemoglobin



Fox et al., 2005.

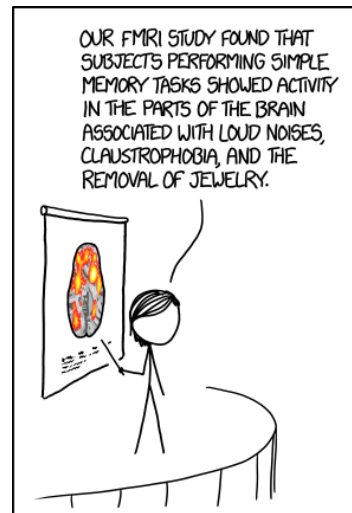
49

EEG/MEG networks detect correlations between neurophysiological signals



Stam, Nature Reviews Neurology 2014

50



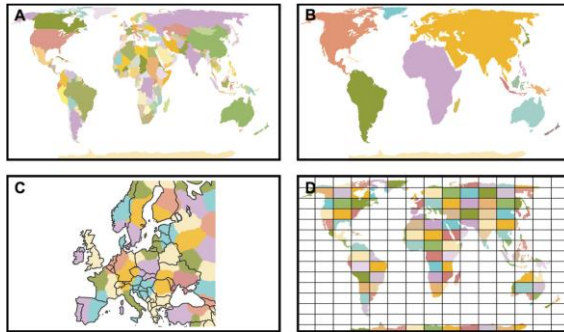
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CONSTRUCTION OF COMPLEX BRAIN NETWORKS

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The definition of brain-network nodes is an important problem



Wig et al., 2011

53

Features of a good parcellation scheme

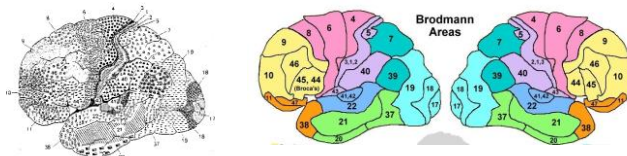
- Structural/functional homogeneity
- spatial contiguity
- whole-brain coverage
- high signal-to-noise ratio
 - clear choice for number of regions
- between-subject reproducibility

54

54

Types of parcellation approaches

- anatomical (atlases)



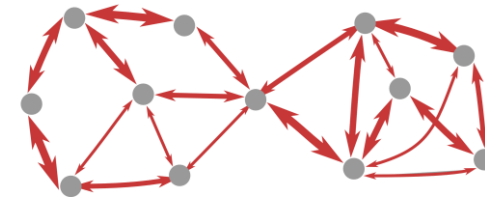
- functional



55

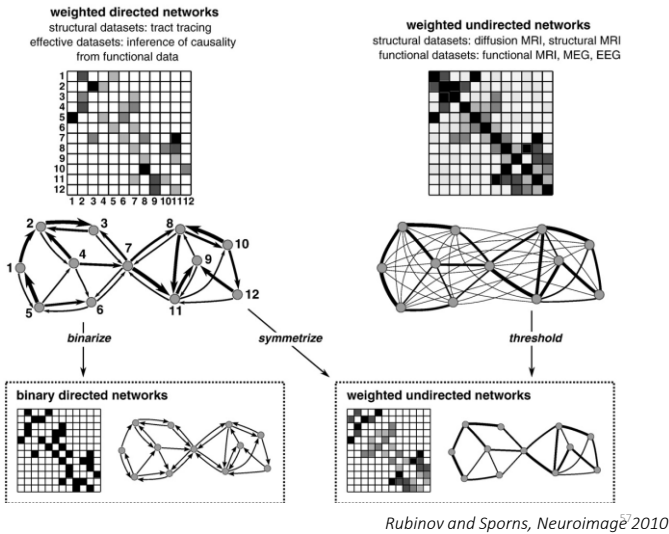
The definition of connection weights is an important problem

- structural or functional
- choice of acquisition
- choice of connection measure
- link magnitude, weight and sign



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ANALYSIS OF COMPLEX BRAIN NETWORKS

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There are many measures of functional association

- Most common measures include:
 - Pearson correlation coefficient
 - Partial correlation coefficient
 - Mutual information
 - Lag-based measures:
E.g. Granger causality and transfer entropy
 - Inference is less common (networks are too big)

58

Pre-connectome-era descriptions of neuroanatomical circuits emphasize spatial constraints and nonspecific wiring



- Ramon y Cajal's principle of wiring economy:

"All of the conformations of the neuron and its components are simply morphological adaptations governed by laws of conservation for time, space, and material"

60

Hierarchical organisation of the monkey visual cortex

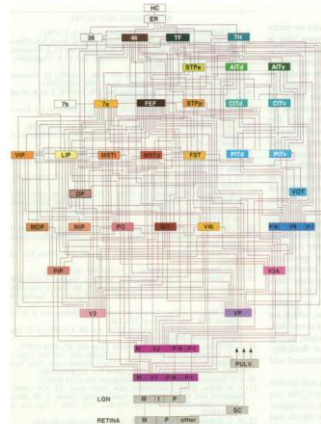
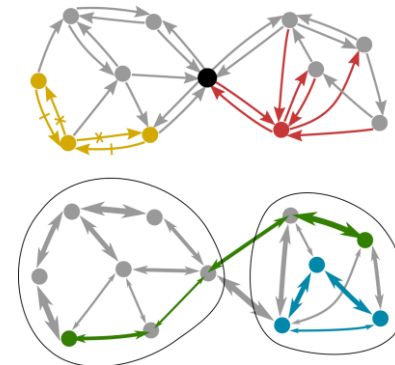


Fig. 2. A hierarchy of visual areas in the macaque, based on laminar patterns of anatomical connections. About 90% of the known pathways are consistent with the hierarchical scheme; the exceptions may reflect either inaccuracy in the reported anatomical data or genuine deviations from a rigid hierarchical scheme. [Modified, with permission, from (1), with subcortical connections based on (2)]

Van Essen et al. 1992

61

Analyses of network topology provide insights about emergent function

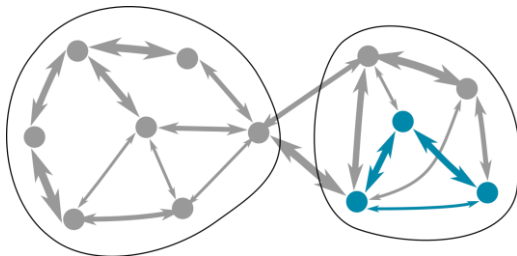


Rubinov and Sporns, 2010.

62

Measures of segregation

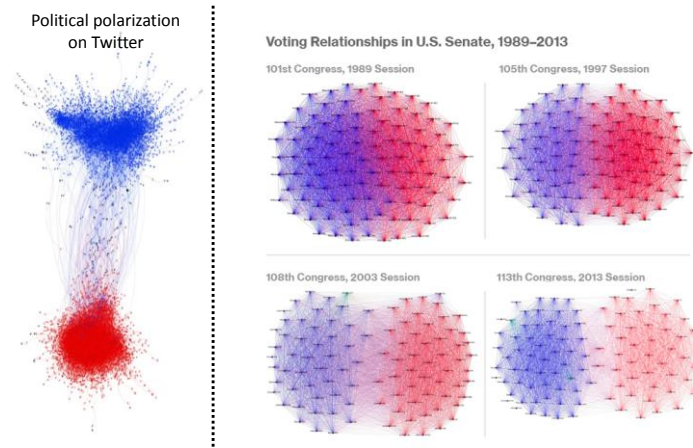
- clustering coefficients
- community structure



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Network segregation in social networks



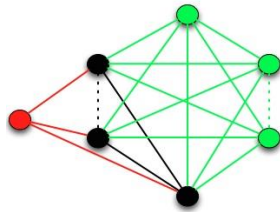
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Measures of segregation: Clustering

- clustering coefficient

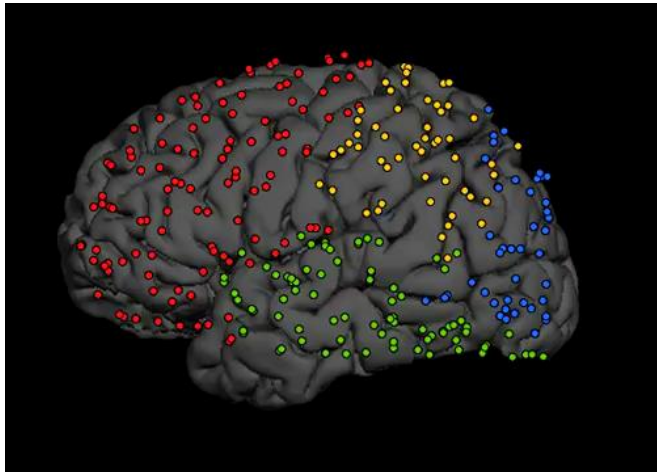
$$C_i = \frac{2 n_i}{k_i (k_i - 1)}$$

where n_i denotes the number of links connecting the k_i neighbors of node i .



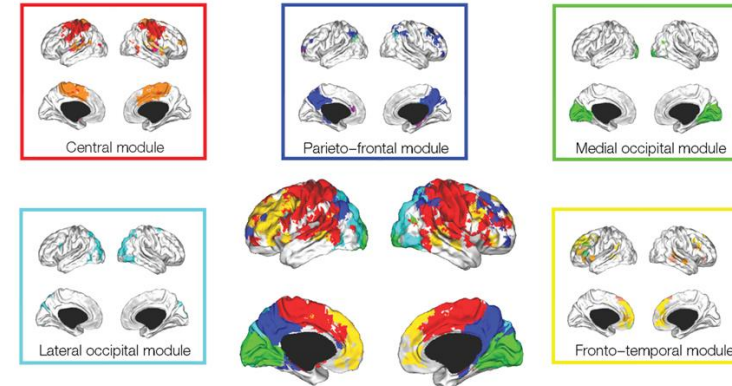
$$C_{red} = \frac{2*2}{3*(3-1)} = 0.66$$

65



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Community structure in human brain

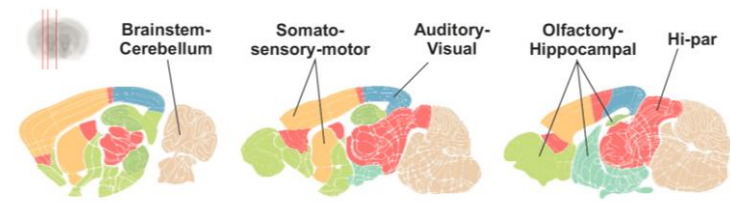


Meunier et al. , Front. Neuroinform2009

66

Network modules reflect functionally specialized brain areas and are often spatially contiguous

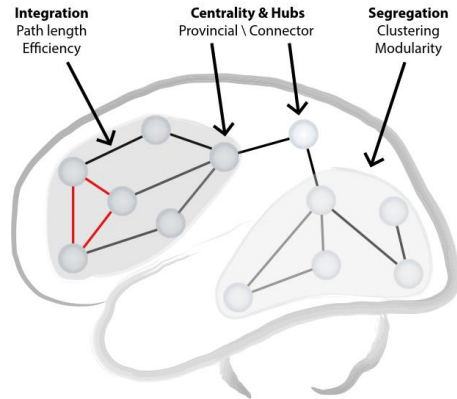
Examples include primary sensory and motor areas



Rubinov, Ypma, Watson, Bullmore, 2015.

68

Some nodes cannot be assigned to any module



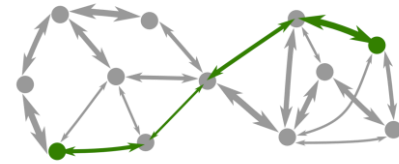
Hart, 2017

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Measures of integration

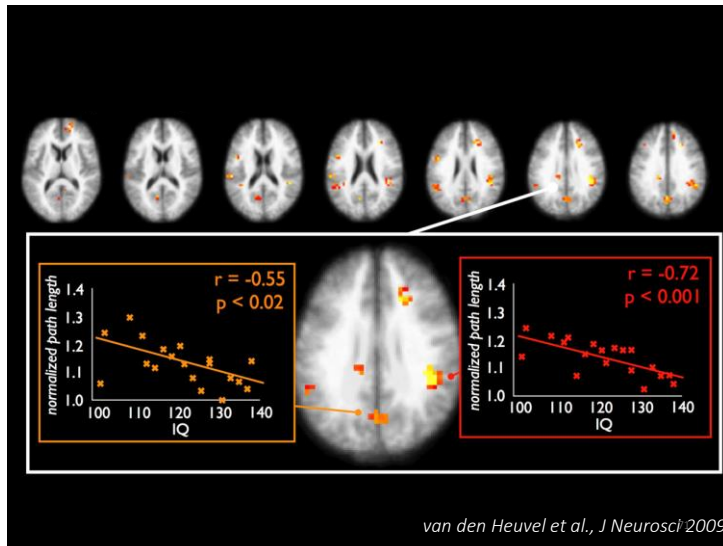
- path lengths
$$L(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \min(d_{ij})$$
- global efficiency
$$E_{glob}(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{\min(d_{ij})}$$

where N is the number of nodes and d_{ij} denotes the distance between node i and node j .



70

70

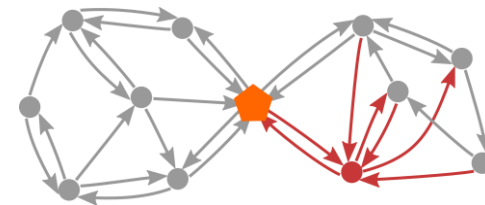


van den Heuvel et al., J Neurosci 2009

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Measures of centrality

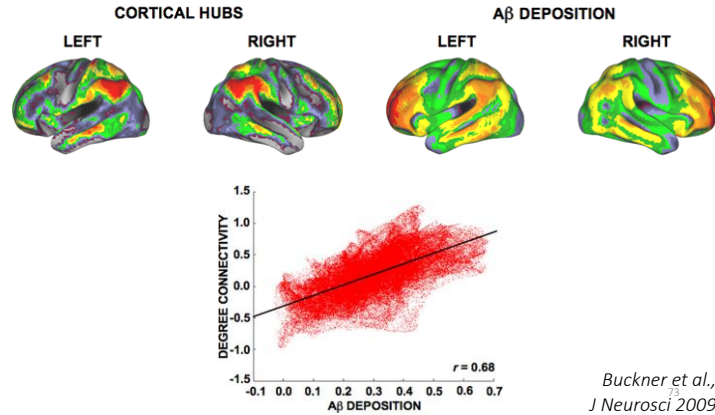
- degree centrality
- betweenness centrality
- participation coefficient



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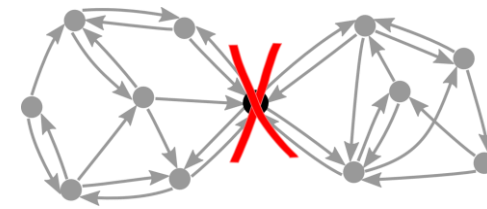
Central nodes (hubs) are more vulnerable to disease



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Measures of resilience

- indirect, e.g. presence of core structure
- direct, e.g. response to lesions

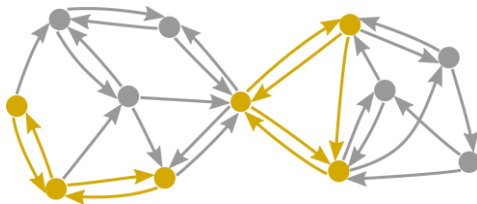


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Network motifs

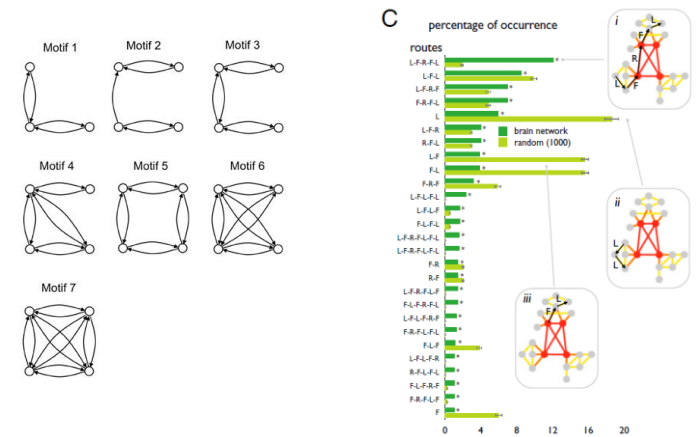
- directed motifs
- undirected motifs



75

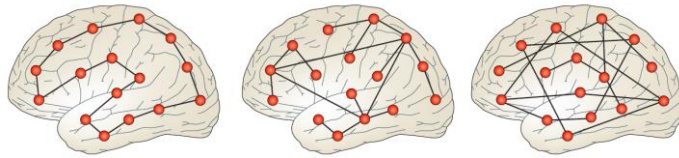
75

Motifs over-representation in brain network

*Shanahan, et al 2013**van den Heuvel and Sporns, PNAS 2012*

76

Measures of network macroscale summarize properties of the whole network in a single statistic



Bullmore and Sporns, 2012.

77

Measures of network macroscale

- small-worldness

$$\sigma(G) = \frac{C(G)}{L(G)}$$

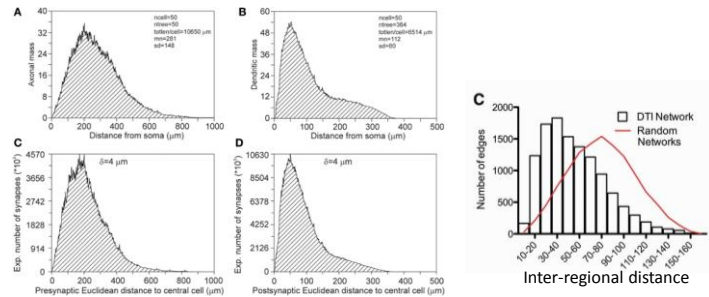


Small world brain functional networks

Achard et al., J Neurosci 2006

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The effect of space
Brain network topology is highly determined by spatial constraints



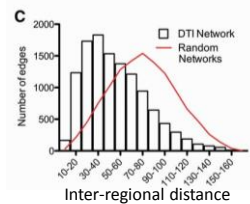
Pelt and van Ooyen 2013

Crossley et al. 2014

79

79

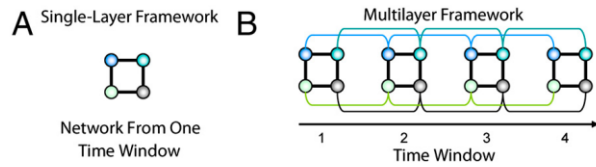
Limitations



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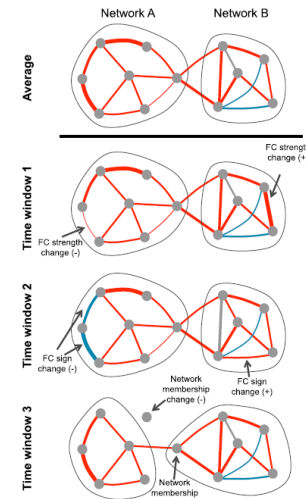
The effect of time

Studies are beginning to capture network states with temporally local measures



Bassett et al., PNAS[©] 2011

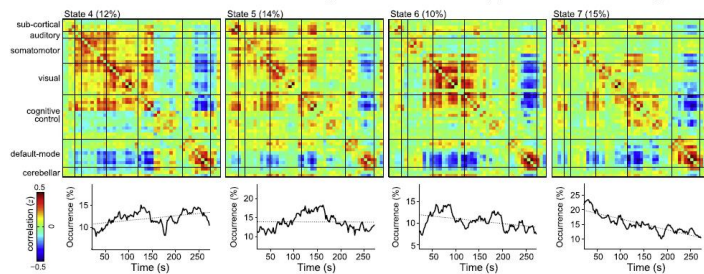
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Hutchison et al.,[©] 2013

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Temporally local measures can capture distinct network states

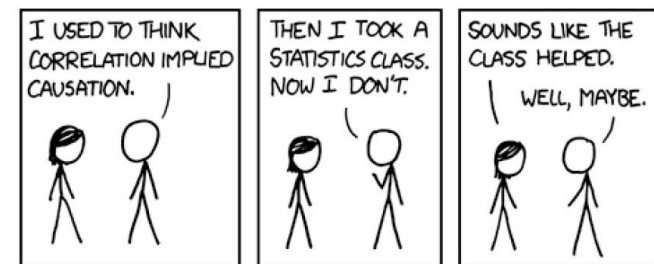


Hutchison et al.,[©] 2013

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Interpretability can be hard

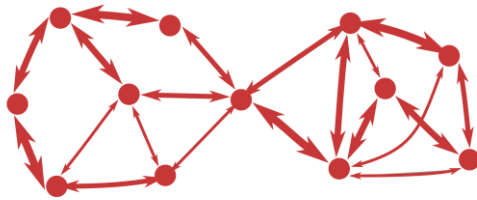
Functional connectivity is a statistical measure that does not necessarily describe causal interactions or information flow.



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Measures of network macroscale are often too general to be useful

- small-worldness

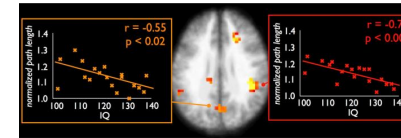


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Replicability crisis

Efficiency of Functional Brain Networks and Intellectual Performance



van den Heuvel et al., *J Neurosci* 2009

General, crystallized and fluid intelligence are not associated with functional global network efficiency: a replication study with the human connectome project 1200 data set.

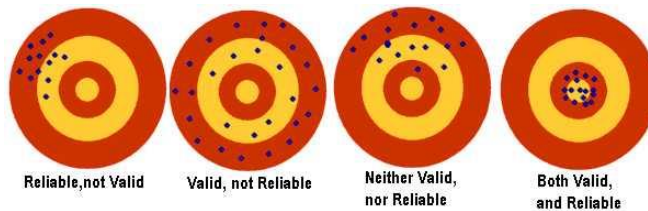
J.D. Kruschwitz *^{1,2}, L. Waller *¹, L.S. Daedelow¹, H. Walter *¹, I.M. Veer *¹

Kruschwitz et al., *Neuroimage* 2018

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Methodological considerations

- Common problems:
 - Results change depending on the processing pipeline
 - Findings are specific of each modality
 - Healthy brains are as different as pathological brains
 - Low Replicability
 - Small sample size



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UK Biobank



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Some take home thoughts

- Complex brain networks are an intuitive and powerful representation of brain systems.
- There is a data quality vs organism complexity trade-off in connectomes. Model organisms should be chosen carefully if possible (humans aren't necessarily "optimal").

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Complex-networks software

- igraph (C-based, multiple wrappers)
<http://igraph.sourceforge.net/>
- networkX (python library)
<https://networkx.github.io>
- Visualization
 - Pajek: <http://pajek.imfm.si/doku.php>
 - Brainnet: <https://www.nitrc.org/projects/bnv/>

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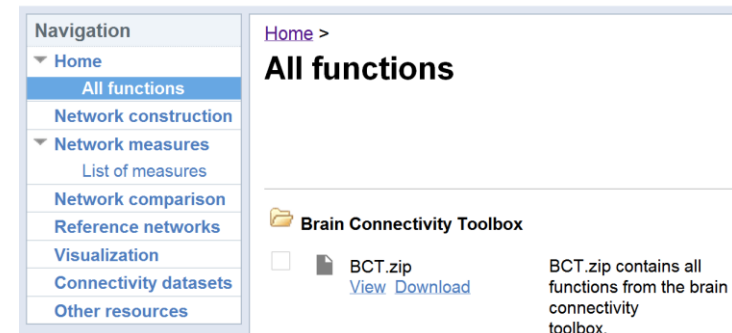
Some take home thoughts

- The definition of nodes and edges is fundamental to network analysis.
- Analysis may be generic but interpretation needs to be organism and modality specific.
- Network specificity is important for translation and mechanistic relevance.

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Brain Connectivity Toolbox



<http://www.brain-connectivity-toolbox.net>

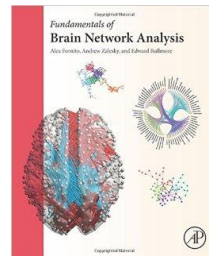
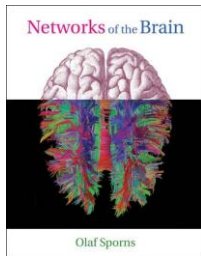
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Any questions: rr480@cam.ac.uk

Further reading

Literature: see recent (2013-2019) special issues on connectomics and mapping the brain in Nature Methods, Science, Neuron, Trends in Cognitive Science, etc.



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