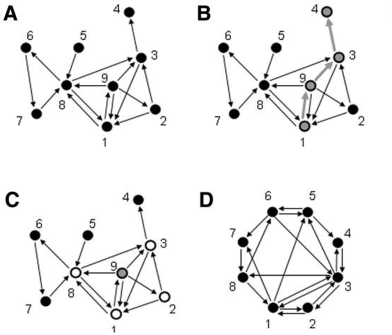
CS 4884: Small World of Brain Networks



T. M. Murali

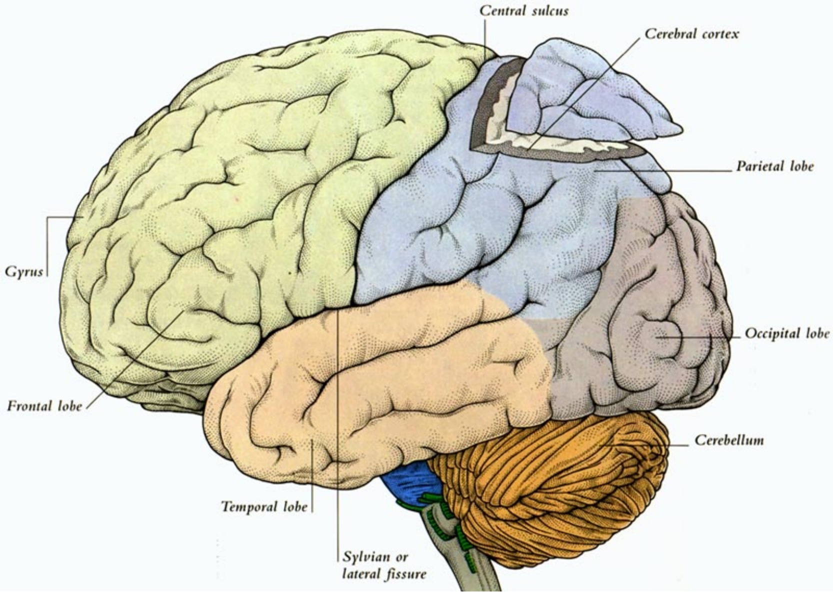
February 13, 2020

Motivation

- The Watts-Strogatz paper set off a storm of research.
- It has 41,500 citations. Even in 2004, it had more than 2,100 citations.
- The *C. elegans* neuronal network is small-world.

Do mammalian brain networks have the small world property?

Visual and Cerebral Cortices



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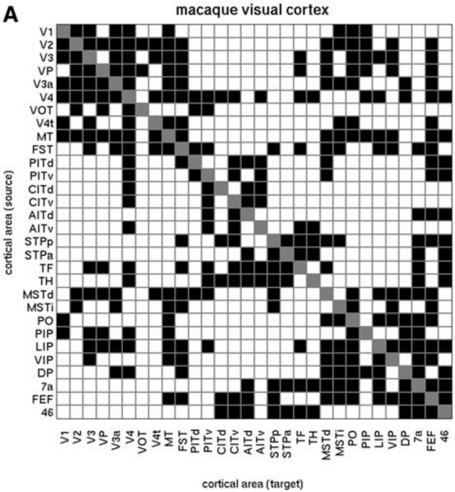
Datasets: Macaque Visual Cortex



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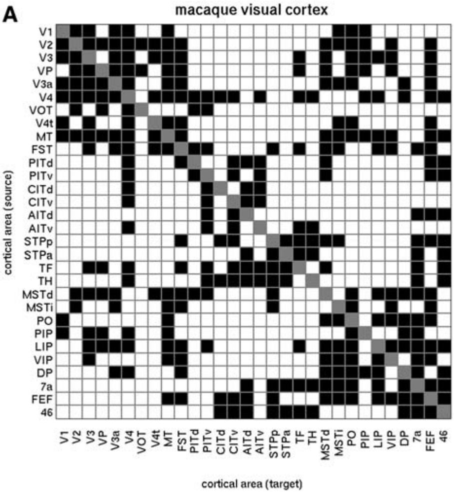

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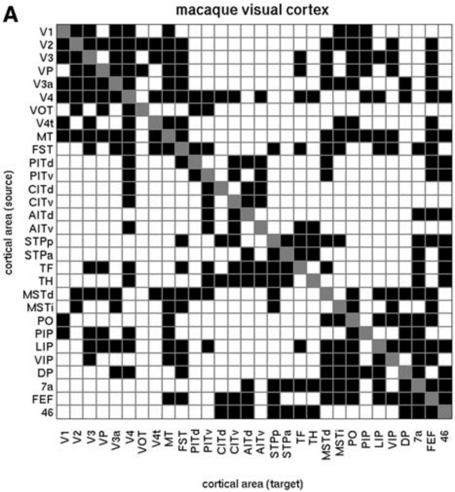

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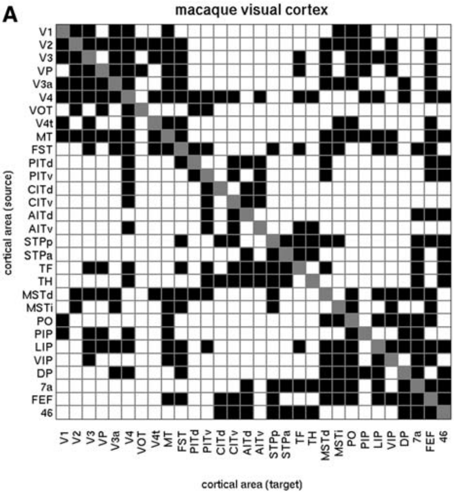

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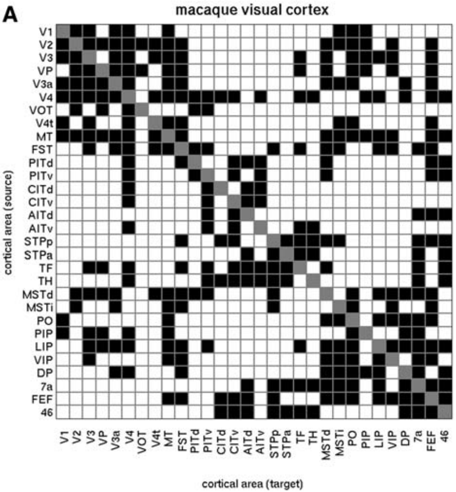

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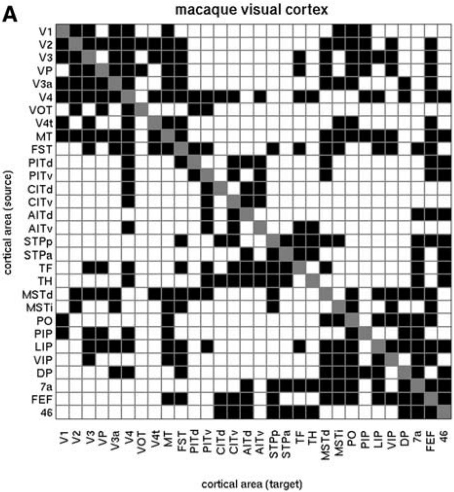

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- Matrix is asymmetric. Corresponds to an unweighted, directed graph.
- $n = 30$, $m = 311$. (The authors use N for the number of nodes and K for the number of edges.)

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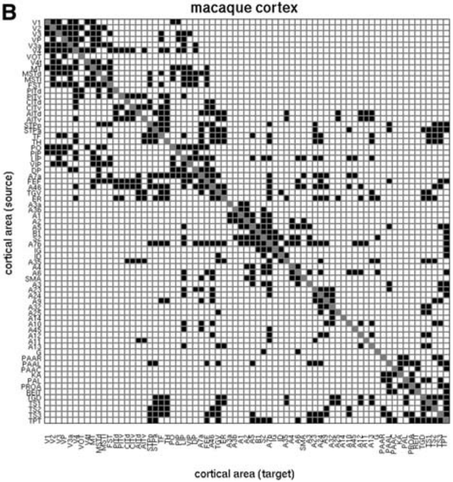

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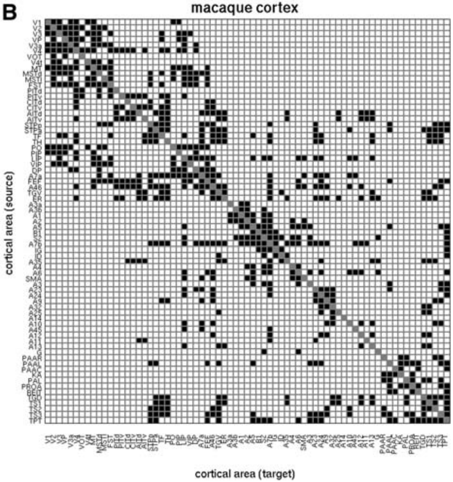

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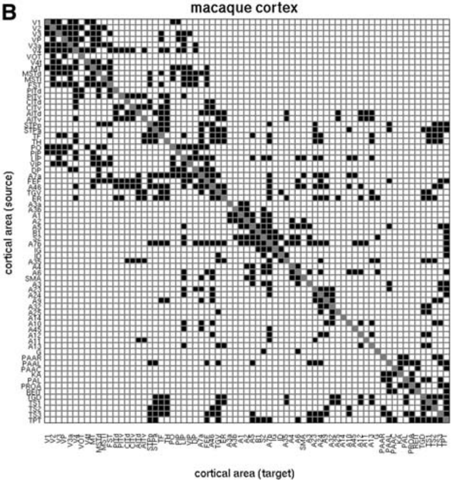

- $n = 71, m = 746$.
- What is the relation between this graph and the one for the macaque visual cortex? Most of the edges in the previous graph are in this one.

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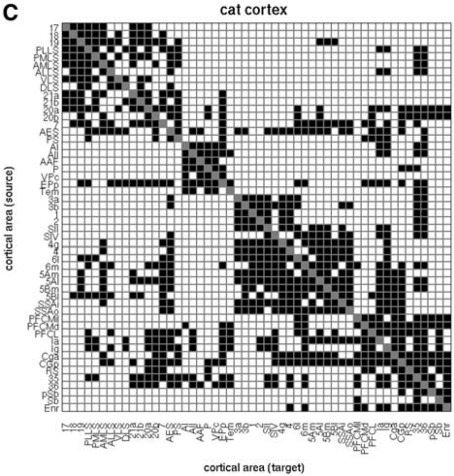

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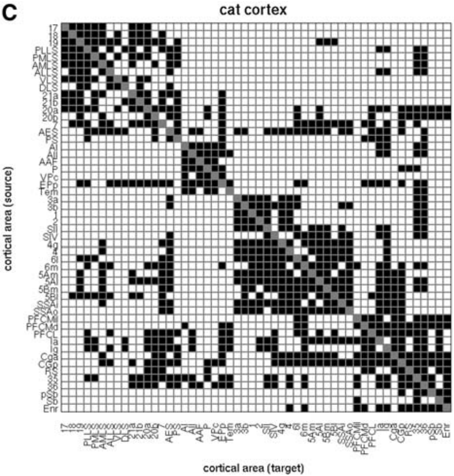

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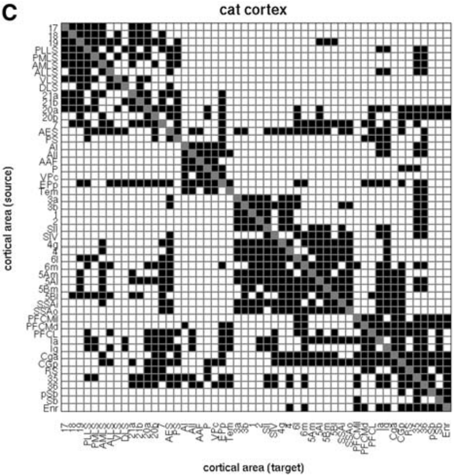

- $n = 52$, $m = 820$.
- What approximation did the authors make? Discarded density information.
- We will ignore density-based connectivity data sets.

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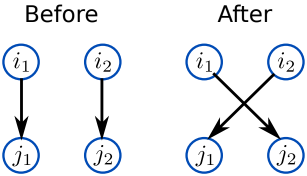

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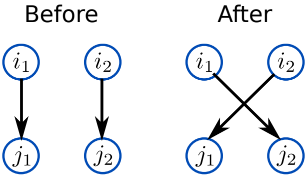

- Degree-preserving lattice matrix:

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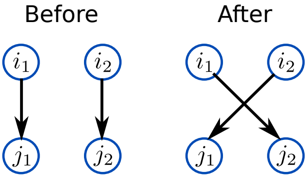

- Degree-preserving lattice matrix: Very poorly specified. Will need to read the code to understand.

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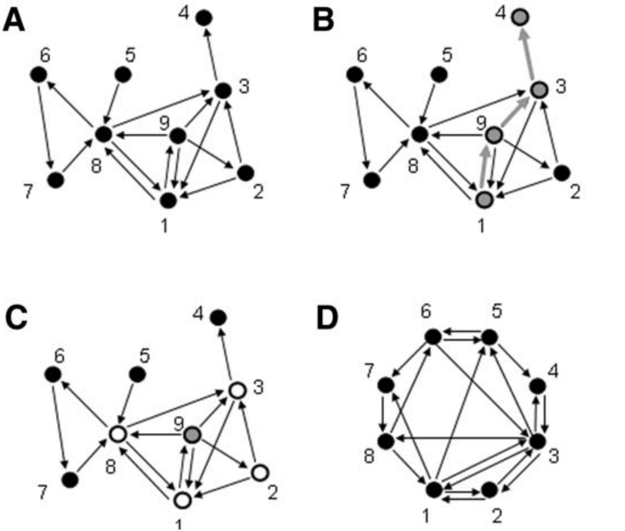
  - Clustering coefficient, $c(v)$, called "cluster index" and denoted by $\gamma(v)$ in this paper.

Computing $l(G)$ and $c(G)$ for Directed Graphs



- Appropriately generalise definitions for undirected graphs.

Scaling $l(G)$ and $c(G)$

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- What values will a small world network have for these quantities? Small $l_{\text{scl}}(G)$ and large $c_{\text{scl}}(G)$.

Results for $l(G)$ and $c(G)$

Table 1. Path Length (λ, λ_{scl}) and Cluster Index (γ, γ_{scl}) for Large-Scale Connection Matrices of Cortico-Cortical Pathways

Topology	λ	γ	λ_{scl}	γ_{scl}
MVC	1.7256	0.5313	0.2188	0.5645
$R_{30,311}$	1.6680 (0.0038)*	0.3616 (0.0048) *		
$L_{30,311}$	1.9313 (0.0018)*	0.6622 (0.0000) *		
$Rio_{30,311}$	1.6880 (0.0033)*	0.4305 (0.0059) *		
$Lio_{30,311}$	1.8190 (0.0391)	0.6214 (0.0243)		
MC	2.3769	0.4614	0.1927	0.6117
$R_{71,746}$	2.0310 (0.0051)*	0.1497 (0.0030) *		
$L_{71,746}$	3.8262 (0.0099)*	0.6593 (0.0002) *		
$Rio_{71,746}$	2.1159 (0.0133)*	0.2409 (0.0047) *		
$Lio_{71,746}$	2.8901 (0.1173)*	0.8992 (0.0211) *		
CC	1.8114	0.5514	0.2498	0.6292
$R_{52,820}$	1.7014 (0.0013)*	0.3103 (0.0026) *		
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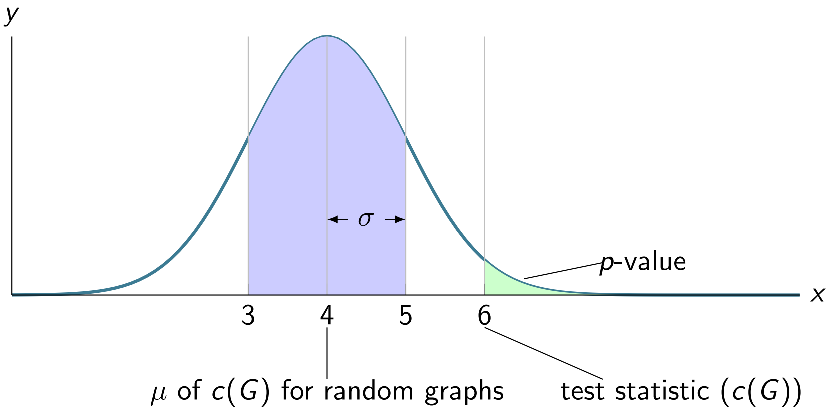
Measures for reference cases represent means and standard deviations (in brackets) for 10 exemplars. Topologies: MVC = macaque visual cortex (Fig. 1A), MC = macaque cortex (Fig. 1B), CC = cat cortex (Fig. 1C), $R_{N,K}$ = random, $L_{N,K}$ = lattice, $Rio_{N,K}$, $Lio_{N,K}$ = random, lattice matrices with in-degree and out-degree distribution preserved. Statistical significance for all comparisons between cortical matrices and random, lattice, Rio, or Lio matrices marked by "*" are p<0.001, the remaining comparisons are p<0.05.

Statistical Significance



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$R_{52,820}$	1.7014 (0.0013)*	0.3103 (0.0026) *	< 0.5	> 0.5
$L_{52,820}$	2.1418 (0.0024)*	0.6933 (0.0000) *		
$Rio_{52,820}$	1.7217 (0.0037)*	0.4023 (0.0030) *		
$Lio_{52,820}$	1.8570 (0.0283)	0.5893 (0.0172)		

Measures for reference cases represent means and standard deviations (in brackets) for 10 exemplars. Topologies: MVC = macaque visual cortex (Fig. 1A), MC = macaque cortex (Fig. 1B), CC = cat cortex (Fig. 1C), $R_{N,K}$ = random, $L_{N,K}$ = lattice, $Rio_{N,K}$, $Lio_{N,K}$ = random, lattice matrices with in-degree and out-degree distribution preserved. Statistical significance for all comparisons between cortical matrices and random, lattice, Rio, or Lio matrices marked by "*" are p<0.001, the remaining comparisons are p<0.05.

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- Values of $l(G)$ and $c(G)$ for connectomes are higher than for random networks with the same number of nodes and edges; difference is statistically significant.
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- Caveats:
  - p-values are likely to be underestimated. They should be estimated from empirical distributions built from many more random samples.
  - No indication of correction for testing multiple hypotheses.
  - No p-value associated with the scaled values of $l(G)$ and $c(G)$.

Computing Small-Worldness

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Is Small-Worldness Universal in Connectomes?


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connectome, *n.*

Text size: A A

View as: Outline | Full entry

Quotations: Show all | Hide all Keywords: On | Off

Pronunciation: Brit. /kəˈnɛktəʊm/, U.S. /kəˈnɛkˌtoʊm/

Origin: Formed within English, by compounding. **Etymons:** CONNECT *v.*, -OME *comb. form.*

Etymology: < CONNECT *v.* + -OME *comb. form.*

The network of nerve cells and their connections found in the brain or other part of the nervous system; a description or map of such a network.

Thesaurus »
Categories »

2005 O. SPORNS et al. in *PLoS Computational Biol.* (e-journal, accessed 31 July 2018) 1 0245/1 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’.

2008 *Science* 11 July 181/3 The ‘connectome’ of the human cortex has been produced by an international team of brain scientists and imagers.

2012 *Guardian* 8 May 10/3 The first detailed connectomes are expected to be completed, and made publicly available for scientists to work on, later this year.

2018 E. C. GOLDFIELD *Bioinspired Devices* vi. 202 The rapid increase in synaptic density, as well as the elongation of axons at around twenty-six weeks, may initiate connectome formation.

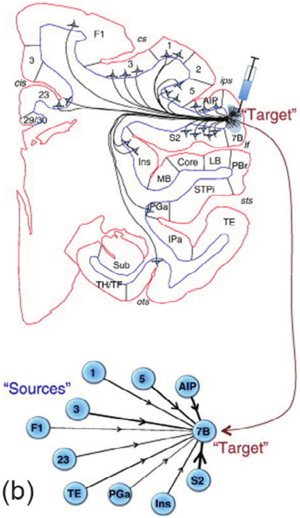
(Hide quotations)

This is a new entry (OED Third Edition, March 2019).

Entry history
Entry profile

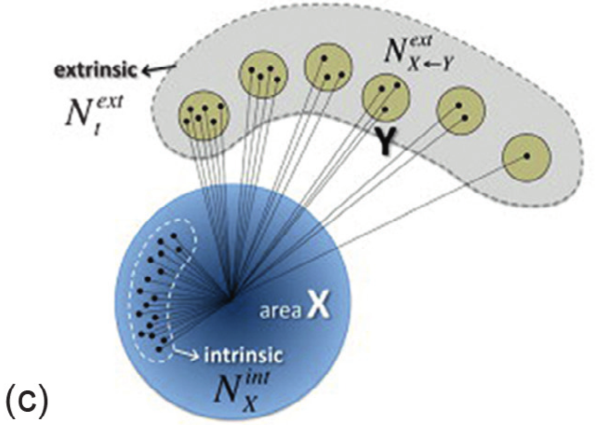
- How does small-worldness emerge in connectomes?
- Do all connectomes have the small-world property?

Structural Connectivity at the Mesoscale: Macaque



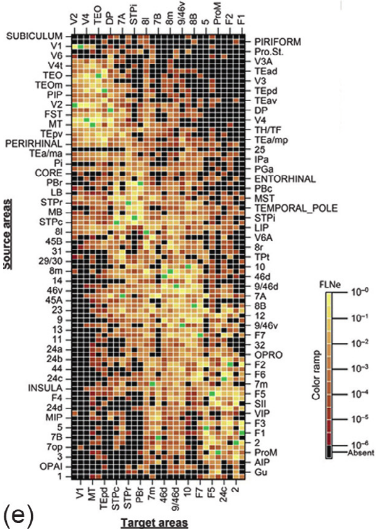
Use retrograde tract tracing. Determine edges coming into node representing area of injection from "labelled" nodes representing neurons that the tracer reaches.

Structural Connectivity at the Mesoscale: Macaque



Injection is at X: $w(Y,X) = \frac{\text{number of neurons labelled in } Y}{\text{total number of labelled neurons}}$

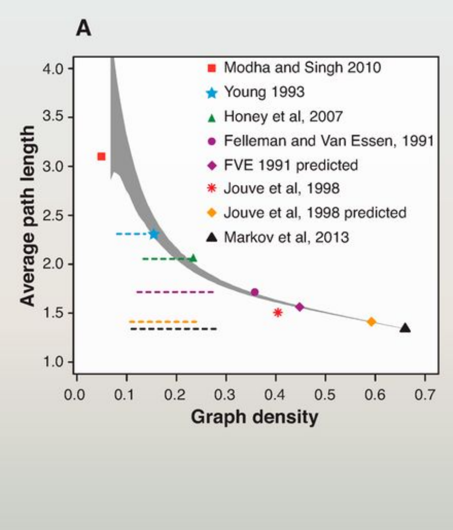
Structural Connectivity at the Mesoscale: Macaque



Example of connectivity matrix.

Edge weights range over six orders of magnitude.

Arguments Against Universality



Markov et al., Cortical high-density counterstream architectures. Science, 2013.

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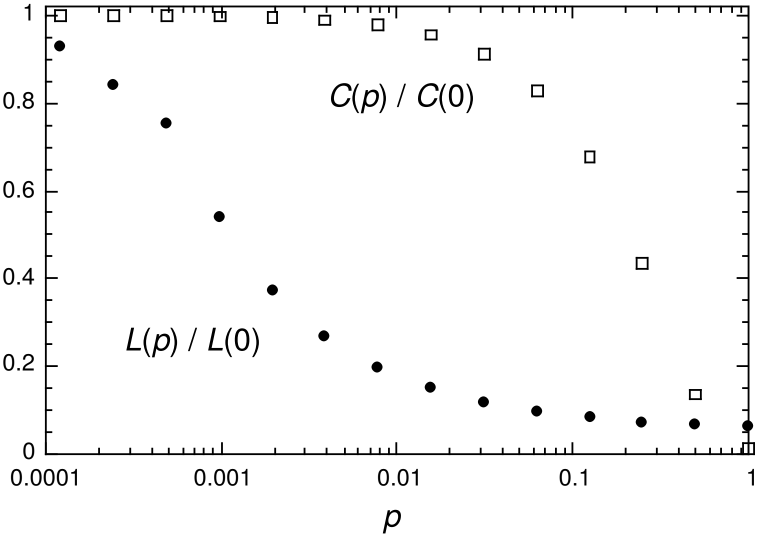

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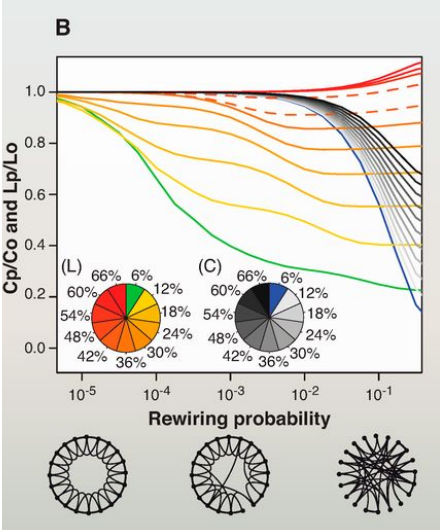

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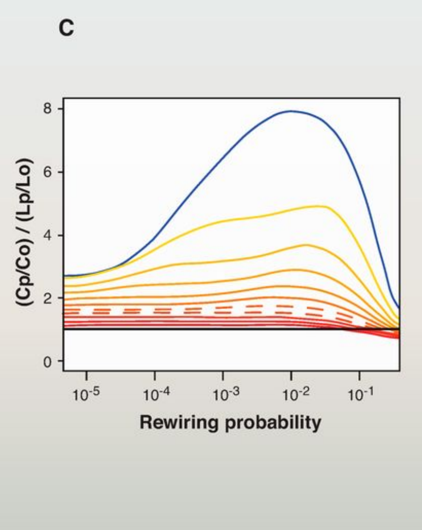

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- How do you define shortest paths?
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Table 1. Small-World Metrics.[a]

	Macaque		Mouse	
	Binary	Weighted	Binary	Weighted
Γ	1.21 ± 0.014	1.59 ± 0.007	1.31 ± 0.004	1.76 ± 0.009
Λ	1.00 ± 0.000	1.27 ± 0.057	1.00 ± 0.000	1.47 ± 0.021
σ	1.21 ± 0.014	1.25 ± 0.071	1.31 ± 0.004	1.20 ± 0.019
ϕ	N/A	0.574 ± 0.041	N/A	0.800 ± 0.002

[a]For the macaque and mouse connectomes, we show the mean and standard deviation of the normalized clustering coefficient (Γ), the normalized path length (Λ), the small-world index (σ), and the small-world propensity (ϕ) for both binary and weighted graphs.