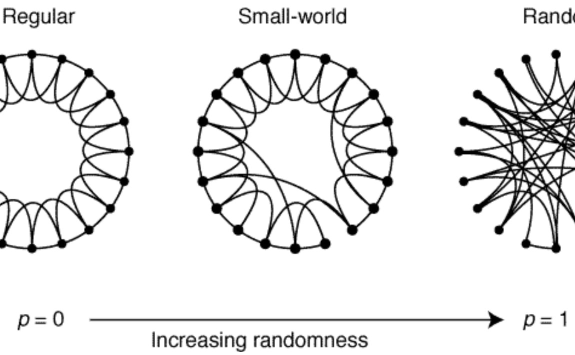
Part 4

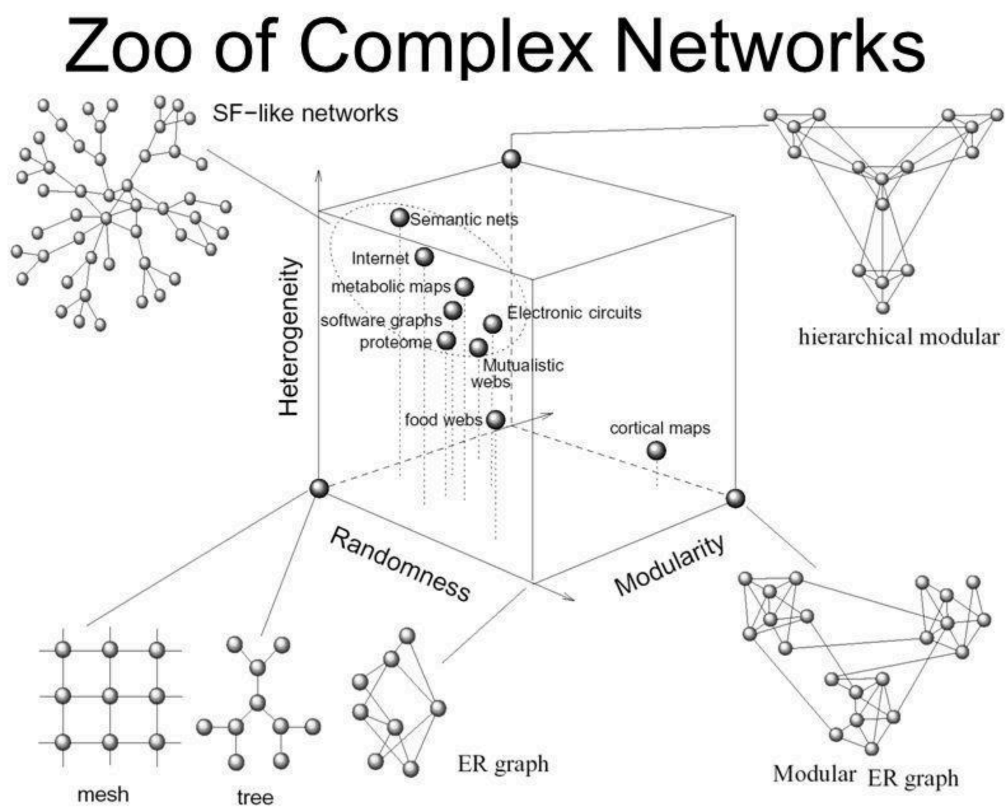
Network Architecture

Types of architecture

- Artificial
- Biologically inspired (data-driven)

Artificial architectures

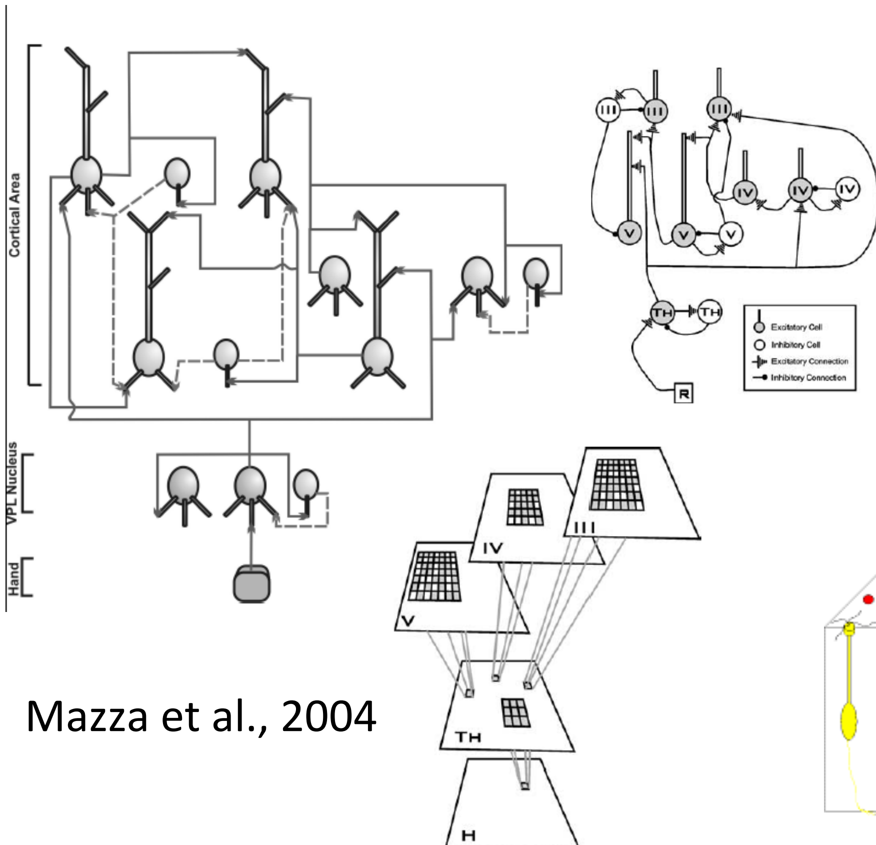




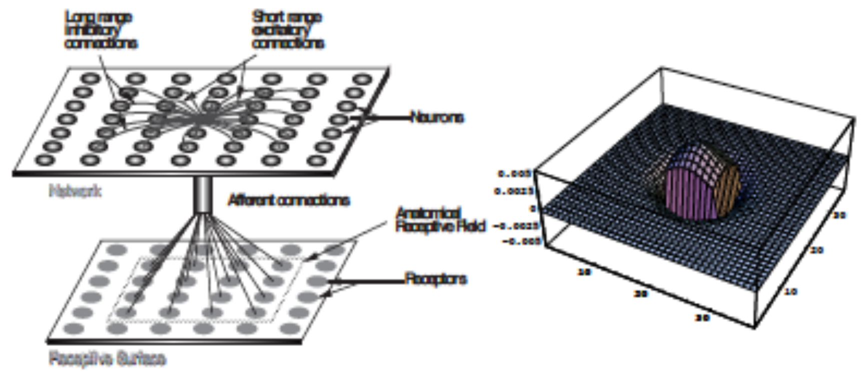
Solé & Valverde, 2004

Biologically inspired architectures

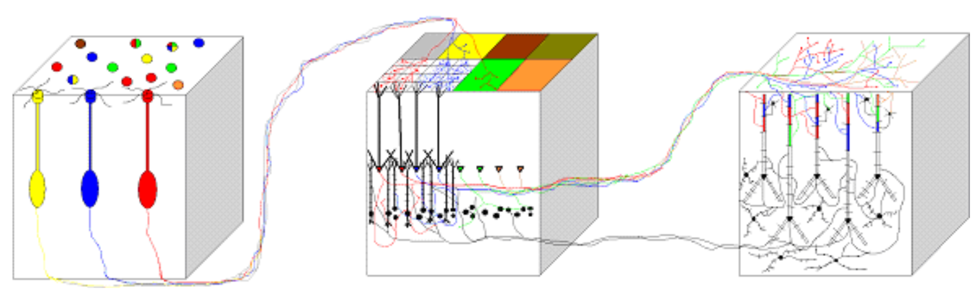
- Incorporate elements and quantitative information of real network architectures



Mazza et al., 2004



Sirosh & Miikkulainen, 1994 2004

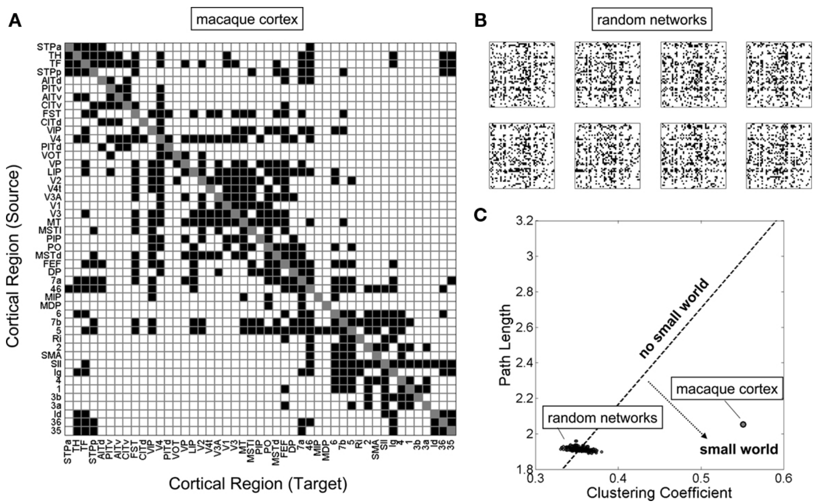


Olfactory Epithelium
Olfactory Bulb
Olfactory cortex

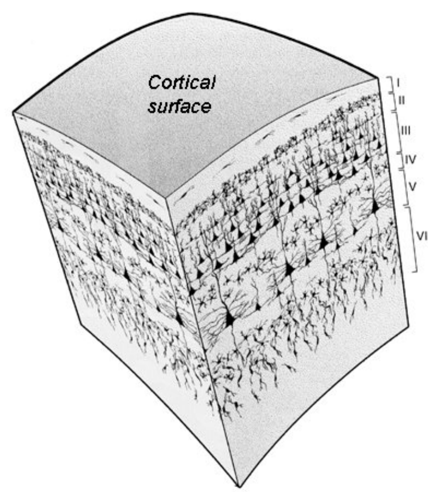
Simões-de-Souza & Roque, 2004

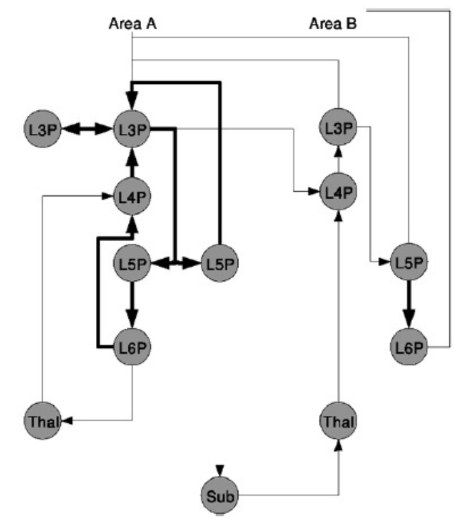
Spatial scale: macro or microscopic

Global: connectivity among cortical areas

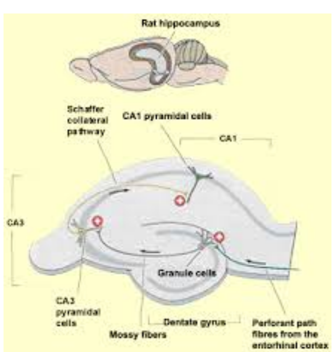


Local: connectivity among neurons in cortical layers/ columns





Connectivity among neurons in non-cortical structures (e.g. hippocampus dentate gyrus)



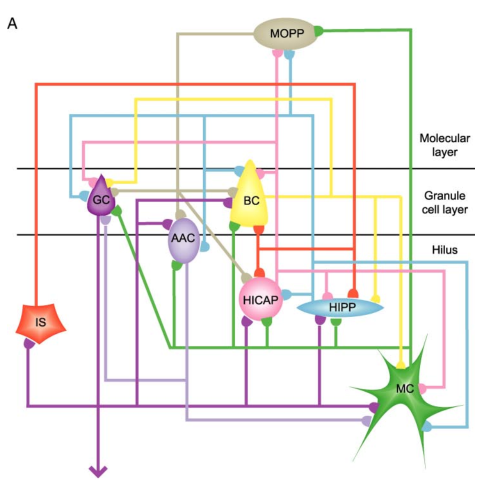
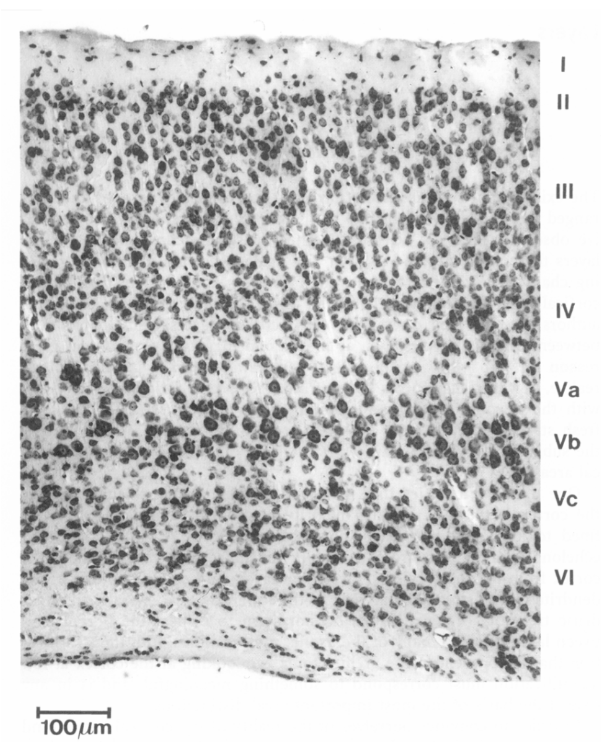


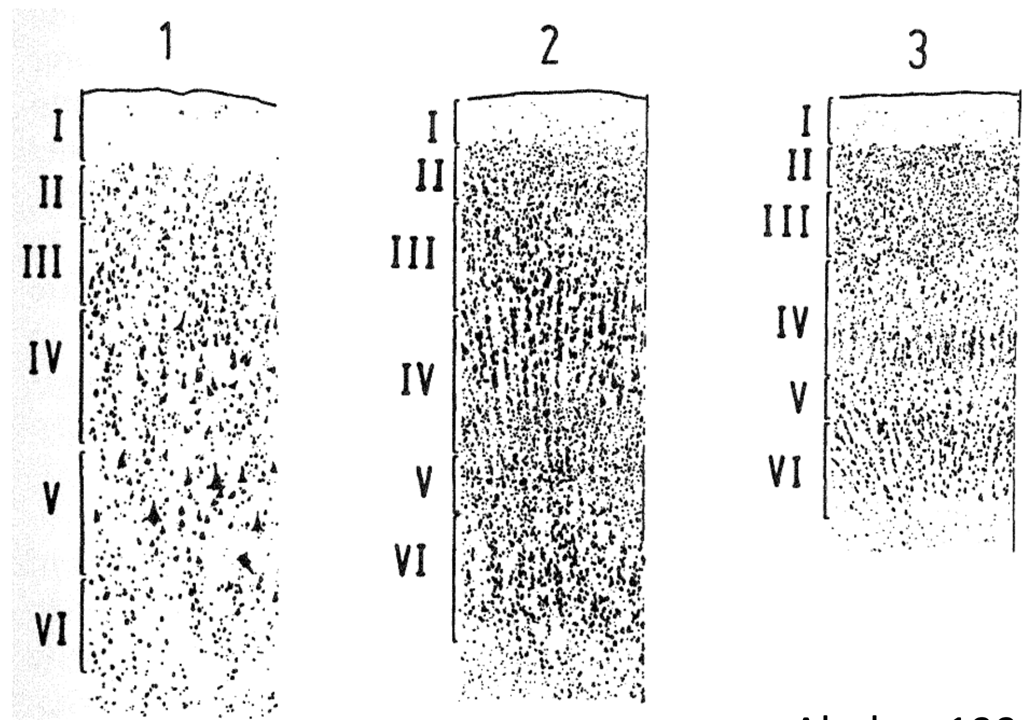
TABLE 1. *Connectivity matrix for the neuronal network of the control dentate gyrus*

	Granule Cells	Mossy Cells	Basket Cells	Axo-axonic Cells	MOPP Cells	HIPP Cells	HICAP Cells	IS Cells
Granule cells (1,000,000) ref. [1–5]	**X** X ref. [6]	**9.5** 7–12 ref. [7]	**15** 10–20 ref. [6–9]	**3** 1–5 ref. [6,7,9]	**X** X ref. [6]	**110** 100–120 ref. [4,10,11]	**40** 30–50 ref. [4,7,10,11]	**20** 10–30 ref. [7]
Mossy cells (30,000) ref. [11]	**32,500** 30,000–35,000 ref. [4,11–13]	**350** 200–500 ref. [12,13]	**7.5** 5–10 ref. [13]	**7.5** 5–10 ref. [13]	**5** 5 ref. [14]	**600** 600 ref. [12,13]	**200** 200 ref. [12,13]	**X** X ref. [15]
Basket cells (10,000) ref. [16,17]	**1,250** 1,000–1,500 ref. [4,16–19]	**75** 50–100 ref. [11,16,17,19]	**35** 20–50 ref. [16,17,20,21]	**X** X ref. [18]	**X** X ref. [18]	**0.5** 0–1 ref. [18]	**X** X ref. [18]	**X** X ref. [10,20]
Axo-axonic cells (2,000) ref. [4,22]	**3,000** 2,000–4,000 ref. [4,18,22]	**150** 100–200 ref. [4,5,11,14,23]	**X** X ref. [5,18]	**X** X ref. [5,18]	**X** X ref. [5,18]	**X** X ref. [5,18]	**X** X ref. [5,18]	**X** X ref. [5,18,19]
MOPP cells (4,000) ref. [11,14]	**7,500** 5,000–10,000 ref. [14]	**X** X ref. [14,24]	**40** 30–50 ref. [14,25]	**1.5** 1–2 ref. [14,26]	**7.5** 5–10 ref. [14,25]	**X** X ref. [14,20,25]	**7.5** 5–10 ref. [14,25]	**X** X ref. [14,15]
HIPP cells (12,000) ref. [11]	**1,550** 1,500–1,600 ref. [4,11,20]	**35** 20–50 ref. [4,11,12,27,28]	**450** 400–500 ref. [4,11,20]	**30** 20–40 ref. [20,25]	**15** 10–20 ref. [25]	**X** X ref. [14,20,25]	**15** 10–20 ref. [25]	**X** X ref. [15,20]
HICAP cells (3,000) ref. [5,29,30]	**700** 700 ref. [4,11,20]	**35** 30–40 ref. [20]	**175** 150–200 ref. [4,11,20]	**X** X ref. [20]	**15** 10–20 ref. [14,20]	**50** 50 ref. [20]	**50** 50 ref. [20]	**X** X
IS cells (3,000) ref. [15,29,30]	**X** X ref. [15]	**X** X ref. [15]	**7.5** 5–10 ref. [15,19]	**X** X ref. [15]	**X** X	**7.5** 5–10 ref. [19]	**7.5** 5–10 ref. [19]	**450** 100–800 ref. [15]

Microscopic architecture (cortex)

- The neocortex can be subdived into 6 layers
- Layers differ in terms of densities and types of cells



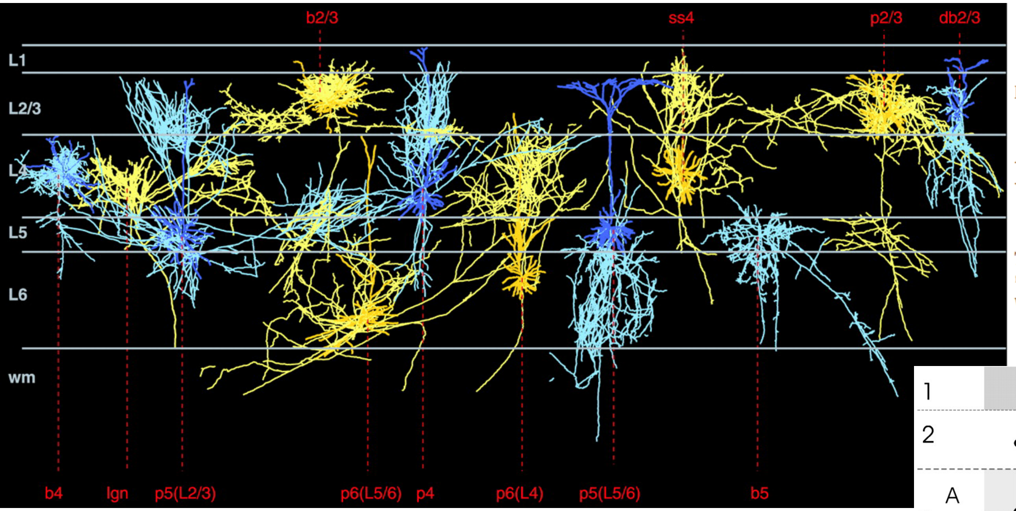


Abeles, 1991

The anatomical details of neuronal connections in the mammalian cerebral cortex are still being determined, but recently there have been published comprehensive schemes involving excitatory and inhibitory cells in various layers along with external thalamic inputs (Douglas and Martin, 2004). Cortical circuits involve excitatory (spiny cells) and smooth inhibitory neurons with numbers in the ratio of about 4 to 1. Inhibitory cells are usually fast spiking inter-neurons, with only local connections, which may be pre-dominantly vertical or horizontal. These cells and their subtypes have quite different anatomical and physiological properties and have different concentrations in the various layers (McCormick et al., 1985). Excitatory cells send their output through both local and long range connections to other parts of cortex or other structures (Binzegger et al., 2005).

Tuckwell (2006)

Microscopic architecture (cortex)

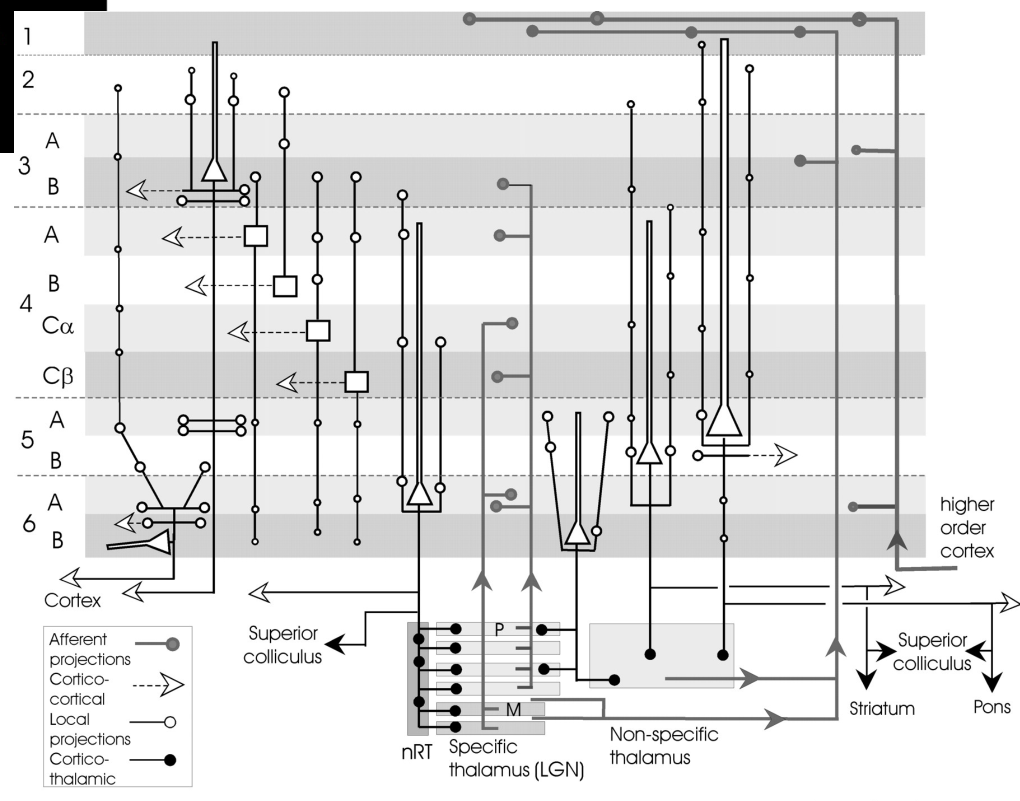


The Journal of Neuroscience, September 29, 2004 • 24(39):8441–8453 • 8441

Behavioral/Systems/Cognitive

A Quantitative Map of the Circuit of Cat Primary Visual Cortex

Tom Binzegger,[1,2] **Rodney J. Douglas,**[1] **and Kevan A. C. Martin**[1]
[1]Institute of Neuroinformatics, University of Zürich, and Eidgenössische Technische Hochschule Zürich, CH-8057 Zürich, Switzerland, and [2]Henry Wellcome Building for Neuroecology, University of Newcastle upon Tyne, Newcastle upon Tyne NE2 4HH, United Kingdom



Synaptic Connections and Small Circuits Involving Excitatory and Inhibitory Neurons in Layers 2–5 of Adult Rat and Cat Neocortex: Triple Intracellular Recordings and Biocytin Labelling *In Vitro*

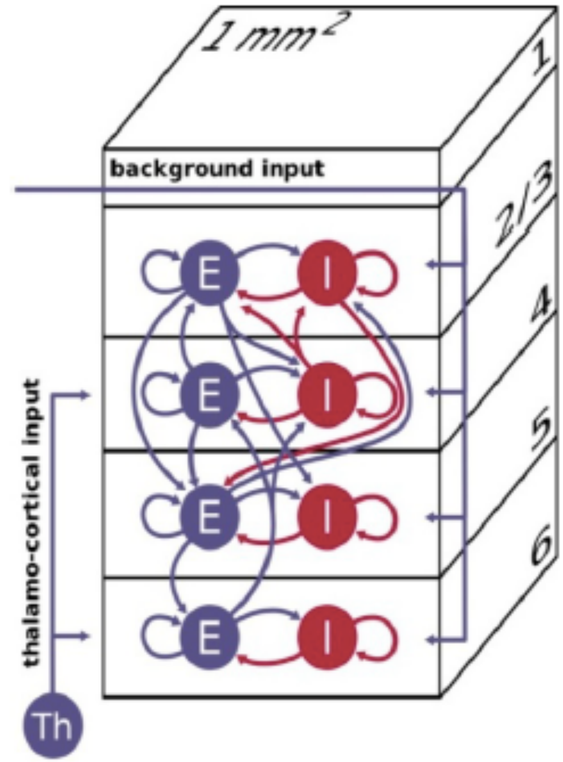
Alex M. Thomson, David C. West, Yun Wang[1] and A. Peter Bannister

Department of Physiology, Royal Free and University College Medical School, Rowland Hill Street, London NW3 2PF, UK
[1]Present address: Lilly Research Centre, Eli Lilly & Co. Ltd, Windlesham, Surrey GU20 6PH, UK

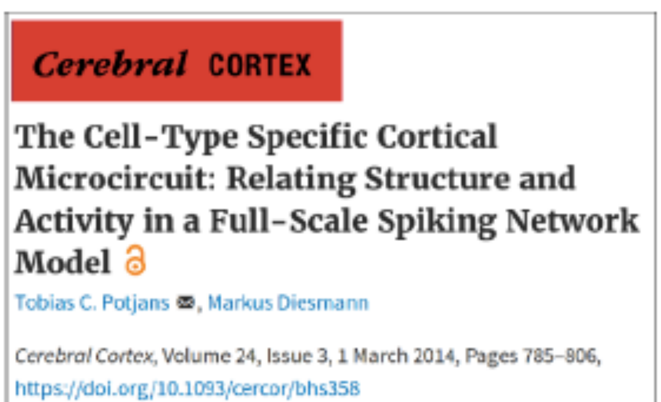
Cerebral Cortex Sep 2002;12:936–953; 1047–3211/02/$4.00

Minimal layered cortical network model

- Local cortical microcircuit model
- 1 mm^2 cortical surface
- Integrates knowledge from over 50 experimental papers
- Excitatory (E) and inhibitory (I) populations of point neurons in each layer
- Layer and type-specific connection probabilities
- Replicates well the layer-specific distribution of spike rates



10^5 neurons
(80% excit. 20% inhibit.)
10^9 synapses


Cerebral CORTEX

The Cell-Type Specific Cortical Microcircuit: Relating Structure and Activity in a Full-Scale Spiking Network Model

Tobias C. Potjans, Markus Diesmann

Cerebral Cortex, Volume 24, Issue 3, 1 March 2014, Pages 785–806,
https://doi.org/10.1093/cercor/bhs358

Macroscopic architecture (cortex)

- Brain regions as network nodes
- Nodes can be linked via axonal tracing or diffusion tensor imaging (DTI)

Macroscopic architecture (cortex)

- Hierarchical and modular structure
- Rich club structure

Connectome

C. Elegans Connectome

- Small Nervous System ~ **302** neurons
- Genome mapped (1998)
- Somatic connectome mapped: White et al. **1986 (~35 years)**
  - **279** neurons;
  - ~**8000** connections: (Gap, Glutamatergic, Cholinergic, GABA)
  - Constantly being **updated** (e.g. Varshney et al 2011, Haspel et al 2012, Cook et al 2019)
  - Additional **extra synaptic currents** mapped (monoamines, neuropeptides)
  - **Evolutionary** Information is available
  - Central resource combine the data: **Wormatlas**

+ more

Wormatlas.org

Fruit Fly

FlyEM is making the data – and all the tools necessary to use it – available for free.

bioRxiv paper published on January 21, 2020.

They are currently on track to complete a connectome of the entire fly nervous system by 2022

https://www.janelia.org/project-team/flyem

Zebra Fish

Olfactory bulb

Adrian A. Wanner & Rainer W. Friedrich, Nature Neuroscience 23:433-442, 2020

Mouse

Allen Brain Atlas – connectivity.brain-map.org

Macaque Macro Connectivity

http://cocomac.g-node.org/main/index.php?

Human Brain Project

https://www.humanbrainproject.eu/en/explore-the-brain/

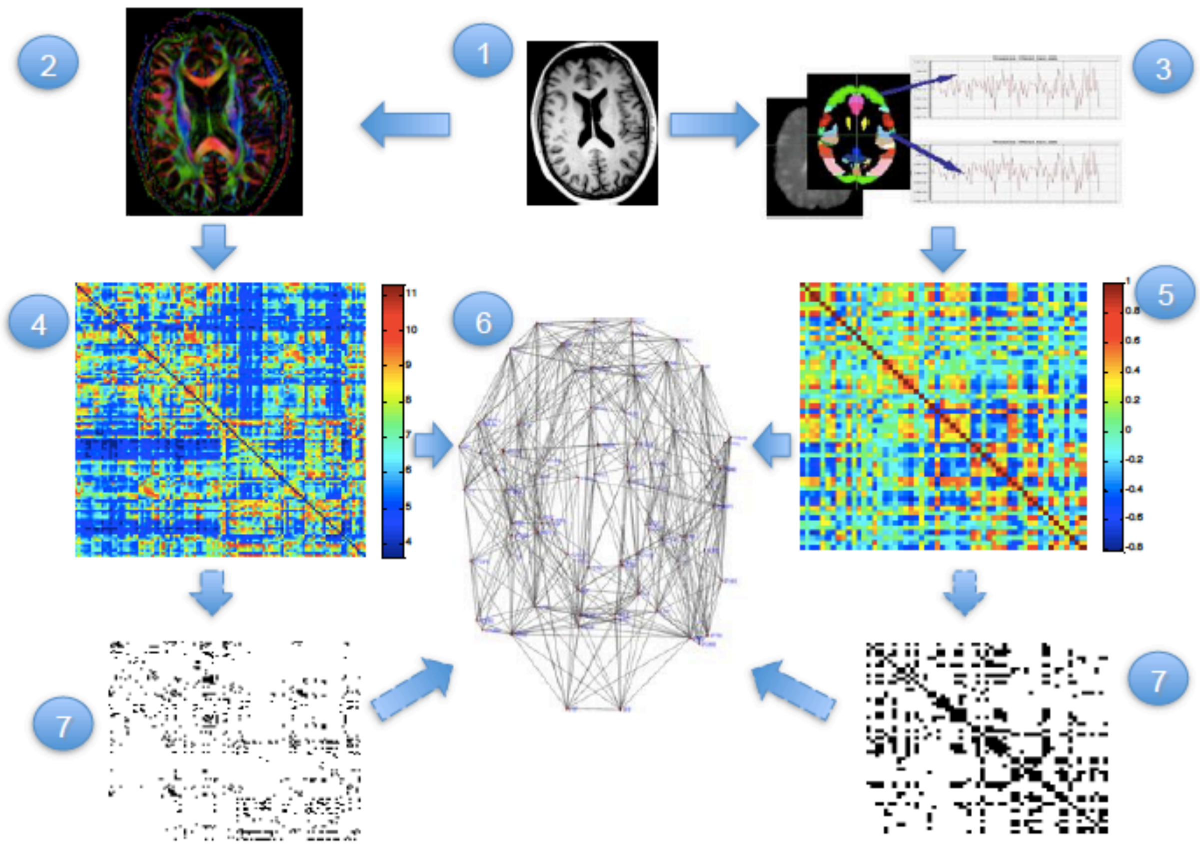
The connectome is not enough

- The connectome gives a view of the static graph of nodes and edges that comprise the cortex: structural connectome
- To go beyond we need to capture somehow statistical interdependencies among the activities displayed by the network nodes: functional connectome

Structural and functional connectivity

Structural Connectivity

Usually based on axonal tracing or water diffusion measures



Functional Connectivity

Usually based on correlation measures

Fig. 2. Workflow for structural and functional connectivity analysis. High-resolution anatomical MRI scans of each subject are used as references for further measurements (1). For establishing functional connectivity, a time series of brain activity in different voxels or regions can be derived (3). The correlation between the time series of different voxels or, using aggregated measures, brain regions can be detected and represented as a correlation matrix (5). This matrix can either directly be interpreted as a weighted network (6) or it can be binarized in that only values above a threshold lead to a network connection (7). For establishing structural connectivity, diffusion tensor imaging or diffusion spectrum imaging can be applied (2). Using deterministic tracking, for example, the number of streamlines between brain regions can be represented in a matrix (4). This weighted matrix can either be analyzed directly (6) or be tresholded so that connections are only formed if a minimum number of streamlines has been reached (7).

Kaiser, 2010

Structural Connectivity

(Anatomy,
Synaptic connections, …)

?

Macro-scale
DTI, tracing studies

Micro-scale
Detailed reconstructions

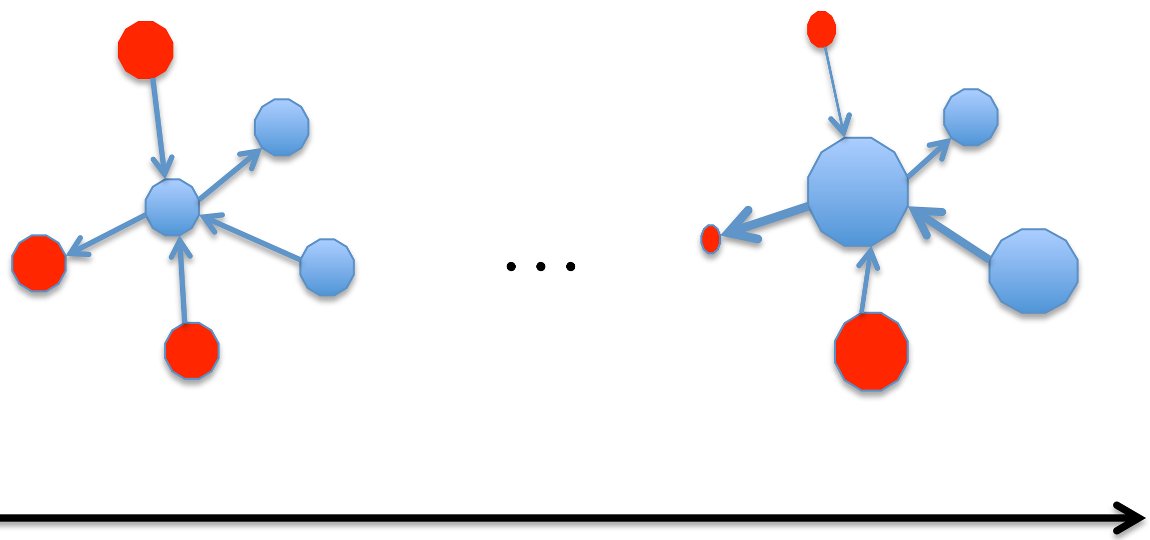
Functional Connectivity

(Correlated or anti-correlated clusters of nodes, …)

Resting-state
fMRI
fluctuations

The “dynome”

Connectome + neural and synaptic dynamics = **Dynome**



Neuron
Perspective

Beyond the Connectome: The Dynome

Nancy J. Kopell,[1,*] Howard J. Gritton,[2] Miles A. Whittington,[3] and Mark A. Kramer[1]
[1]Department of Mathematics and Statistics, Boston University, Boston, MA 02215, USA
[2]Department of Biomedical Engineering, Boston University, Boston, MA 02215, USA
[3]The Hull York Medical School, University of York, Heslington, York YO10 5DD, UK
*Correspondence: nk@math.bu.edu
http://dx.doi.org/10.1016/j.neuron.2014.08.016

Part 5

Putting it all together: neuron and synapse models in a network architecture (some models from my group and collaborators)

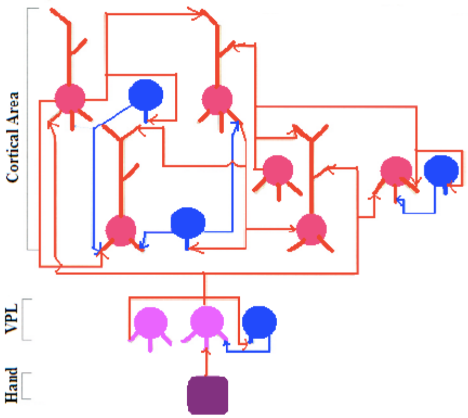
Laboratory of Neural Systems – SisNe

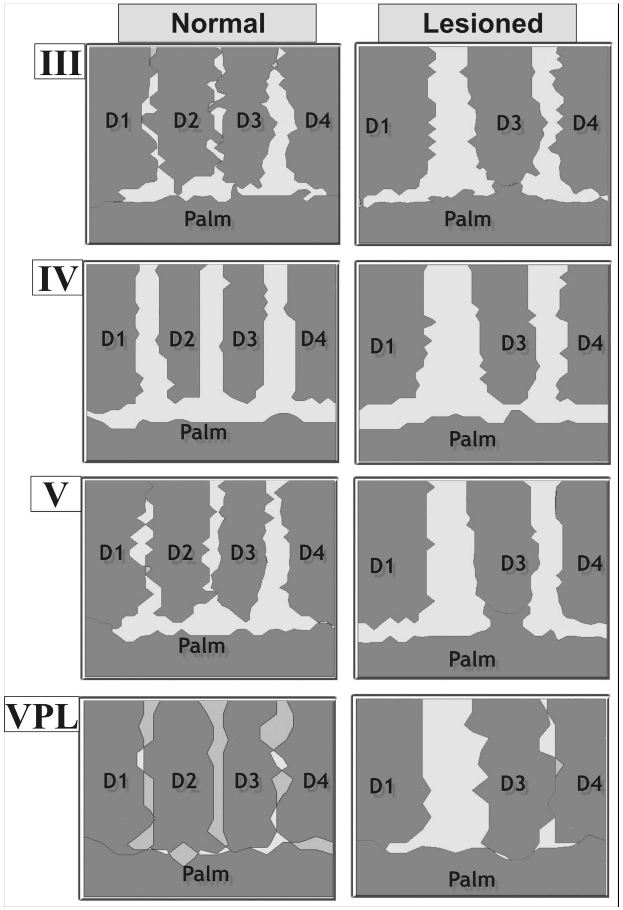
sisne.org

- Dynamic phenomena in models of neurons and neural networks
- HH-type and simplified neurons

Some examples

Synaptic and cortical plasticity

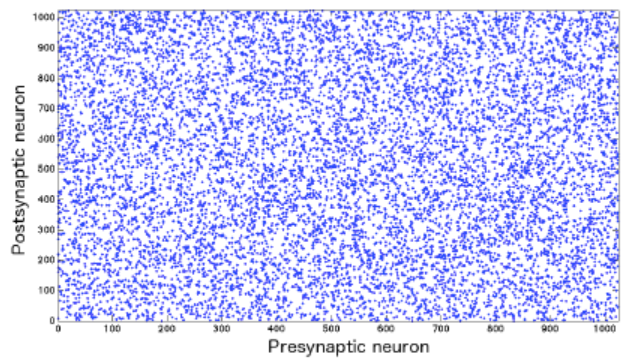




Mazza, de Pinho, Piqueira & Roque, J Comput Neurosci 16:177-201, 2004

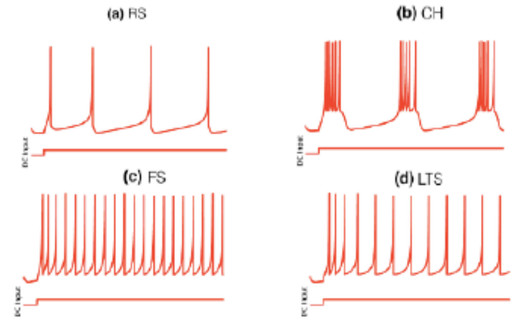
Spontaneous activity in cortical network models 1

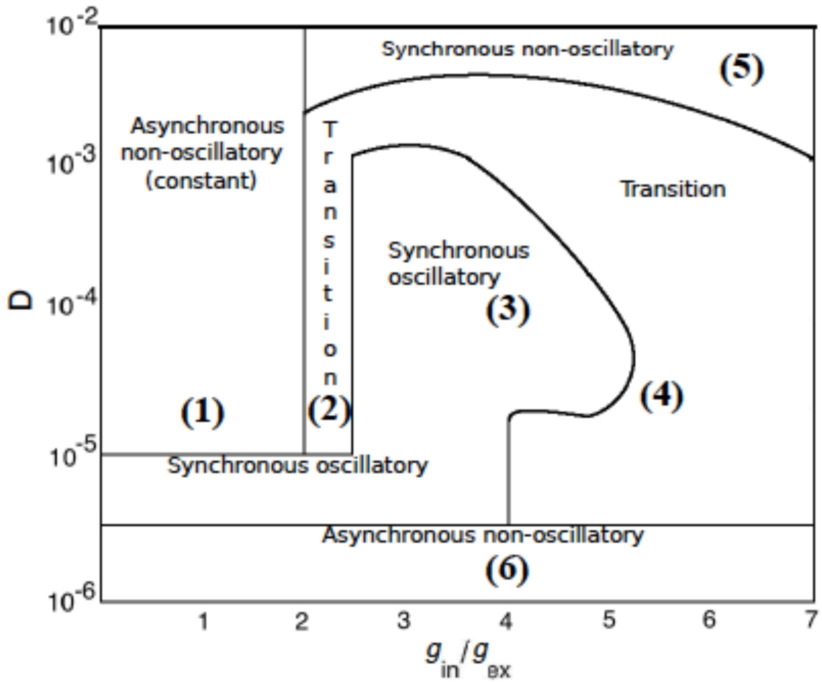
Random network

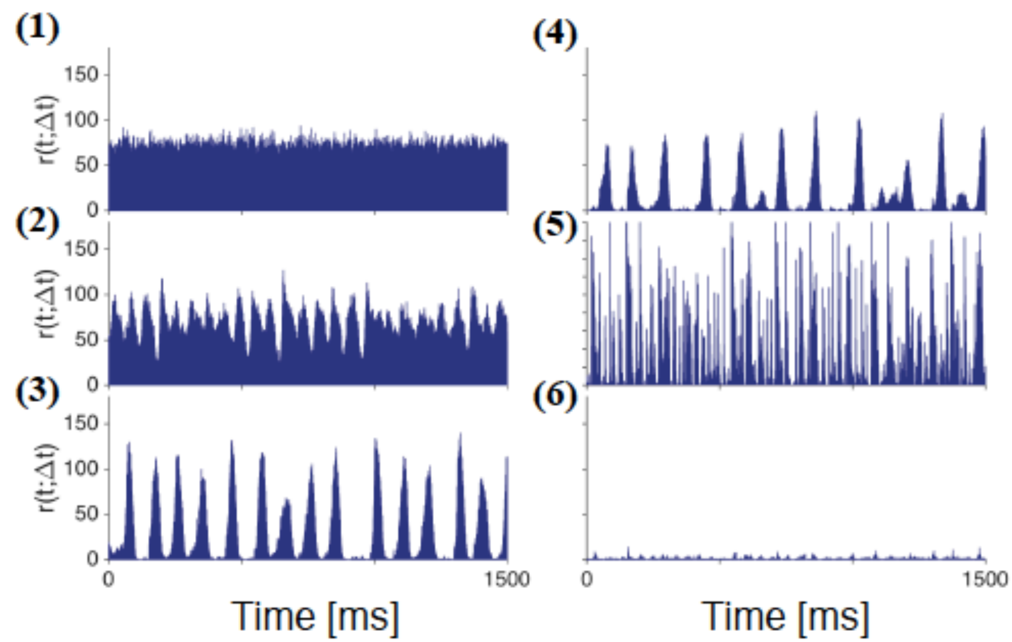


Excitatory 80%

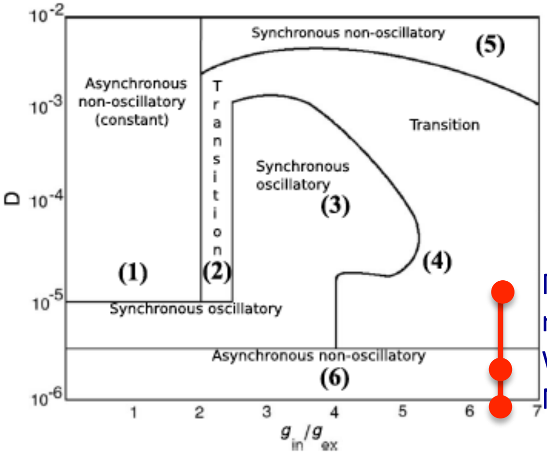
Inhibitory 20%







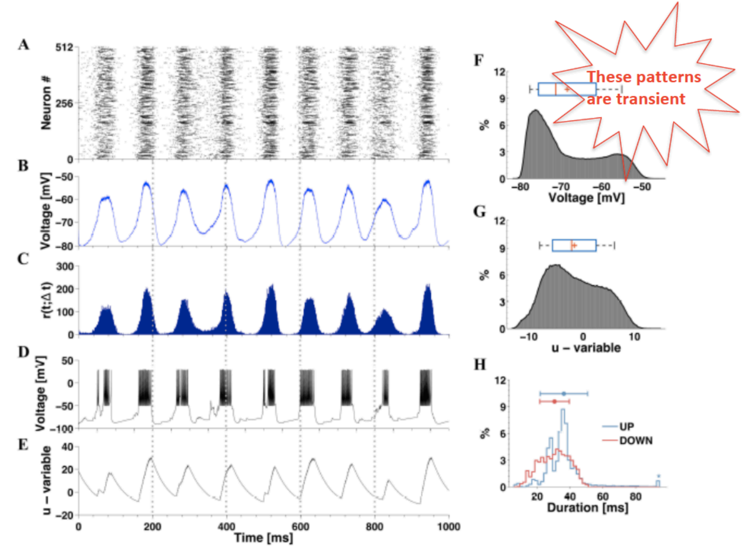
Pena, Zaks & Roque, J Comput Neurosci 45:1-28, 2018



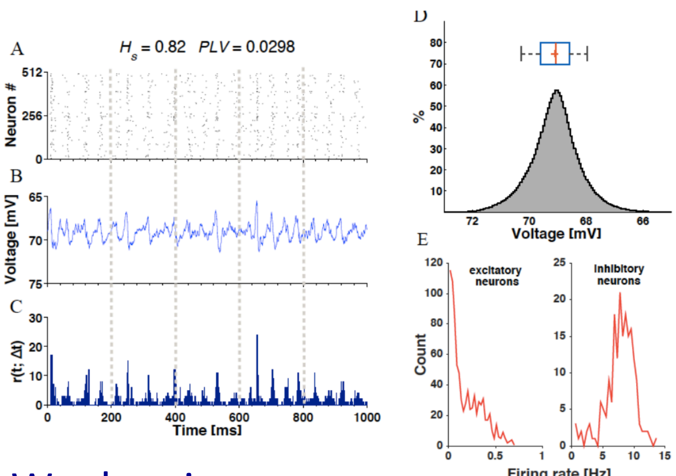
Moderate noise
Weak noise
Noiseless

Noiseless: up/down oscillations

Sample neuron

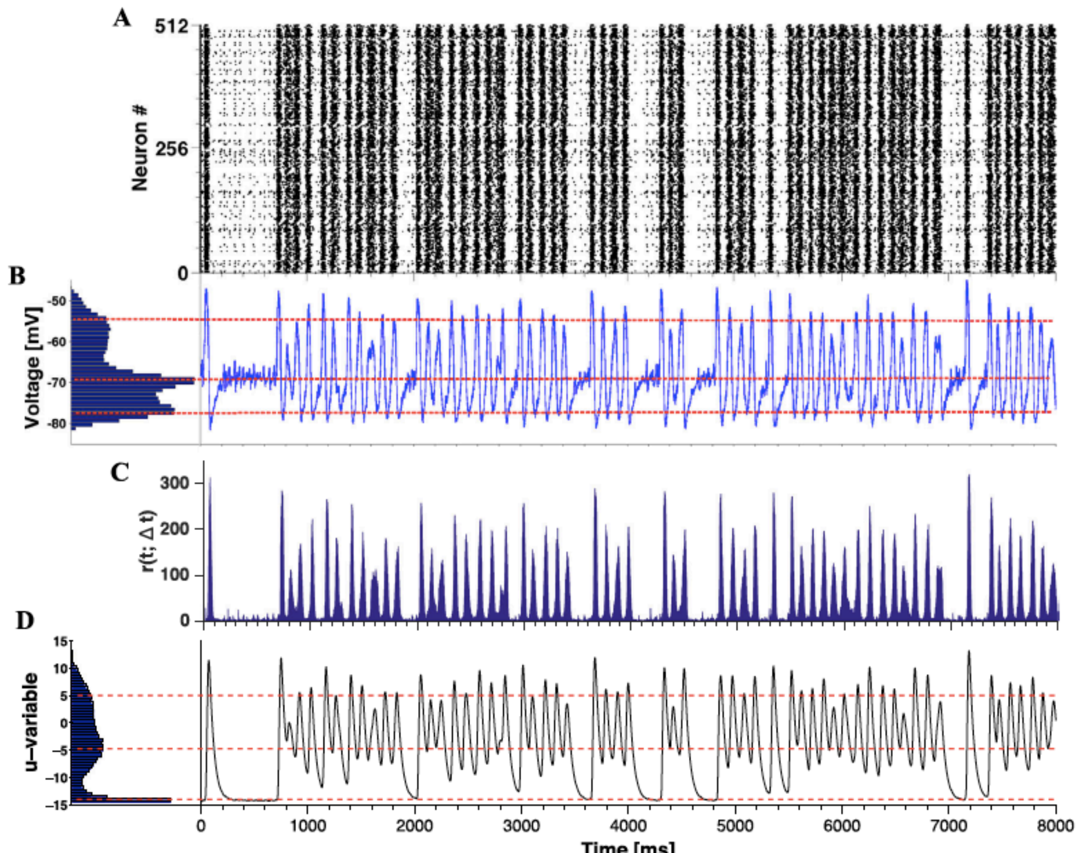


64% RS, 16% CH, 20% LTS



Weak noise: asynchronous nonoscillatory activity

Moderate noise: intermittent switches between active (u/d osc.) and quiescent (AI) states



Optimal interplay between synaptic strengths and network structure enhances activity fluctuations and information propagation in hierarchical modular networks

Rodrigo F.O. Pena, Vinicius Lima, Renan O. Shimoura, João P. Novato, Antonio C. Roque

(Submitted on 3 May 2019 (v1), last revised 6 May 2019 (this version, v2))

In network models of spiking neurons, the coupled impact of network structure and synaptic parameters on activity propagation is still an open problem. For spiking networks with hierarchical modular topology, we show that slow spike-train fluctuations emerge due to the increase of either the global synaptic strength parameter or the network hierarchical level, while the network size remains constant. Through an information-theoretical approach we show that information propagation of activity among adjacent modules is enhanced as the number of modules increases until an optimal value is reached and then decreases. This suggests that there is an optimal interplay between hierarchical level and synaptic strengths for information propagation among modules, but we also found that information transfer measured from the spike-trains differs from this one indicating that modular organization restructures information communicated in the mesoscopic level. By examining the increase of synaptic strengths and number of modules we find that the network behavior changes following different mechanisms: (1) increase of autocorrelations among individual neurons, and (2) increase of cross-correlations among pairs of neurons, respectively. The latter being better for information propagation. Our results have important implications and suggest roles that link topological features and synaptic levels to the transmission of information in cortical networks.

Comments: 27 pages, 7 figures
Subjects: **Neurons and Cognition (q-bio.NC)**; Adaptation and Self-Organizing Systems (nlin.AO)
Cite as: arXiv:1905.01181 [q-bio.NC]
(or arXiv:1905.01181v2 [q-bio.NC] for this version)

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http://neuromat.numec.prp.usp.br

FAPESP
SÃO PAULO RESEARCH FOUNDATION

USP
Universidade de São Paulo

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Thank you