The ongoing activity of neuronal networks

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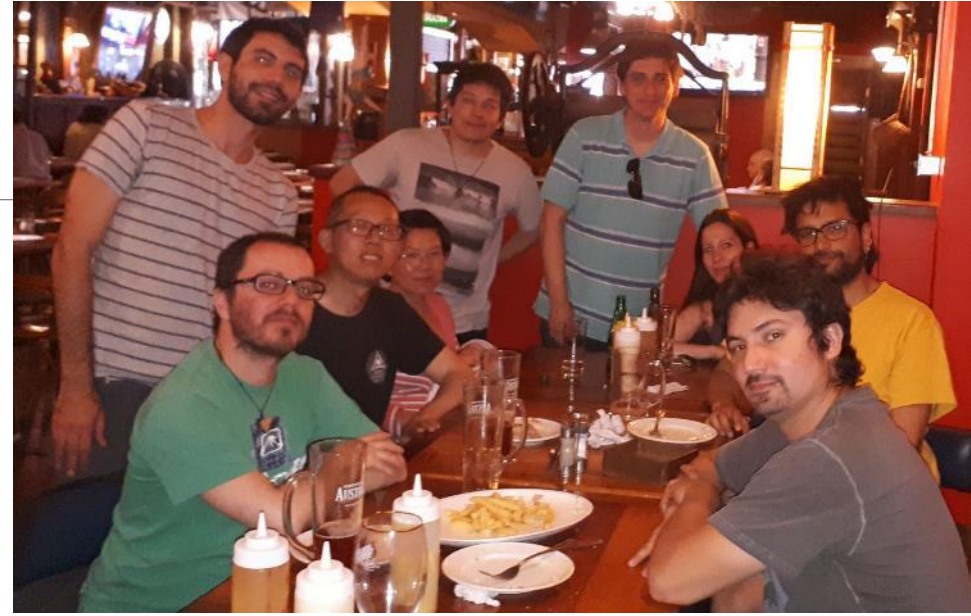
UNIVERSIDAD DE VALPARAÍSO

CRONE • 2019

VANDAL

Valparaíso Neural Dynamics Laboratory



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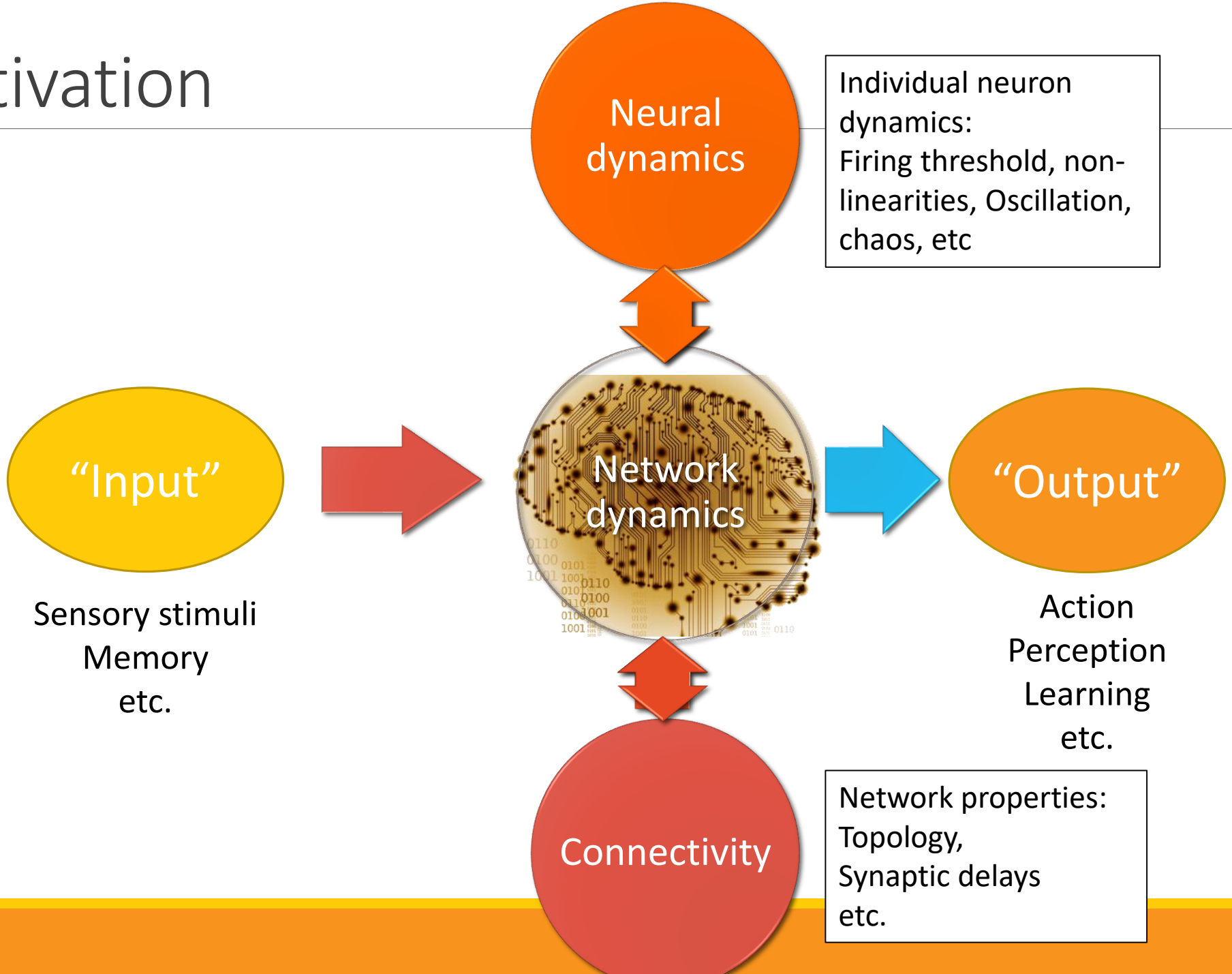
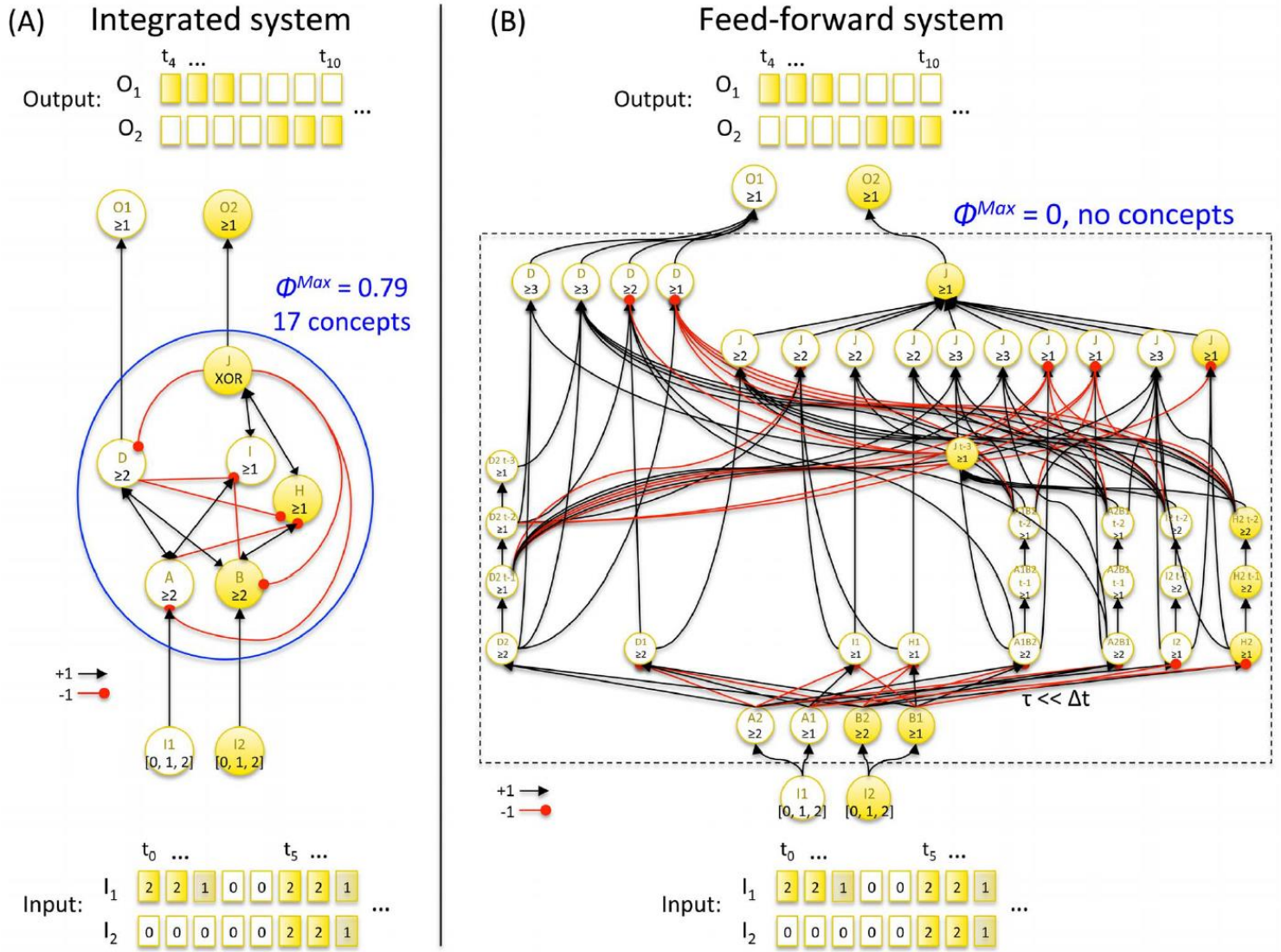
Motivation


Neural dynamics
Individual neuron dynamics:
Firing threshold, non-linearities, Oscillation, chaos, etc
"Input"
Network dynamics
"Output"
Sensory stimuli
Memory
etc.
Action
Perception
Learning
etc.
Connectivity
Network properties:
Topology,
Synaptic delays
etc.

Recurrent vs. Feed-forward



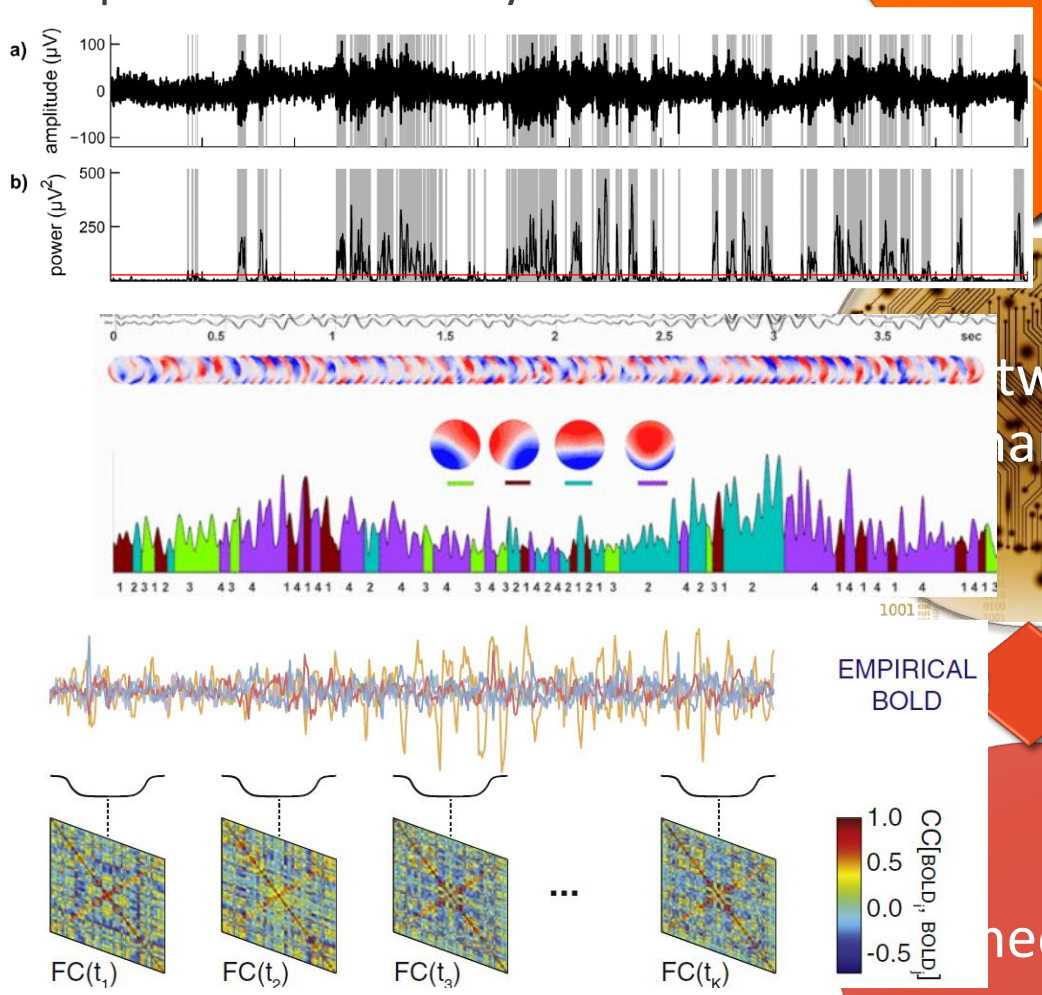
Ongoing Dynamics

a.k.a. "Resting State"
"Spontaneous activity"

EEG α-power fluctuations

EEG microstates

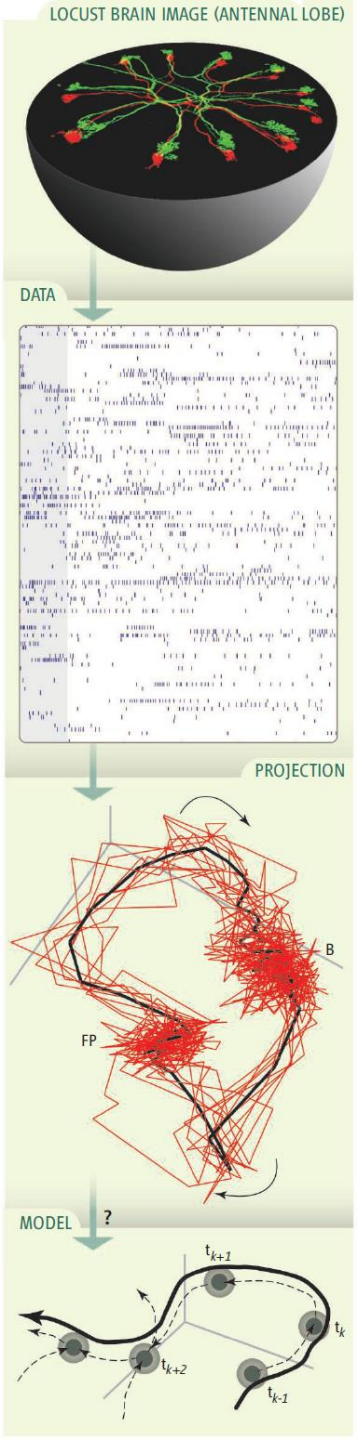
fMRI Functional connectivity dynamics (FCD)



Neural dynamics

twork
namics

nectivity

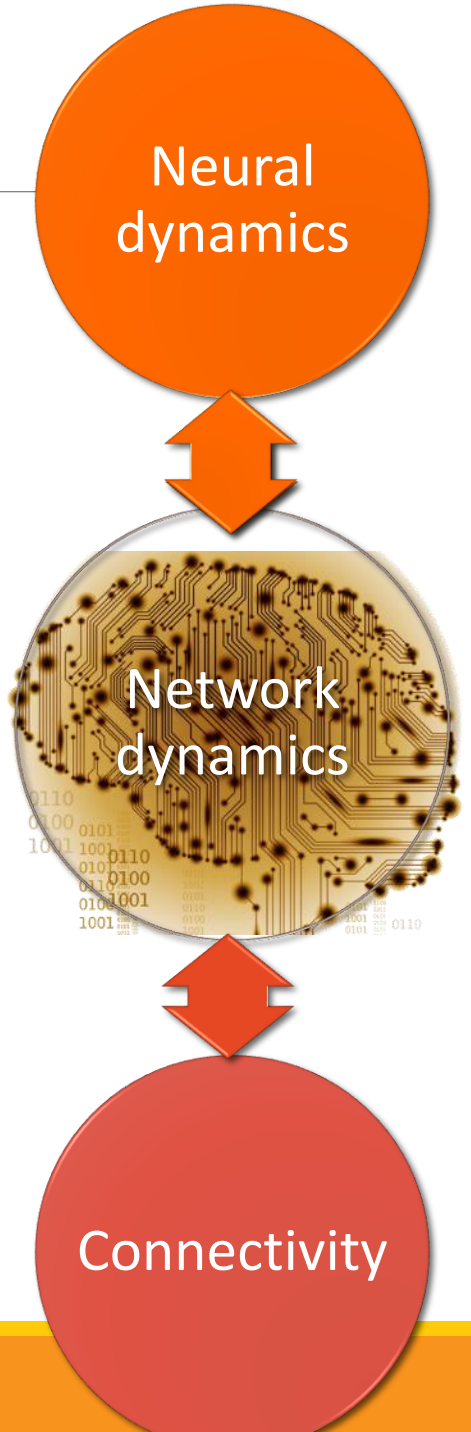


Mazor&Laurent (2005) Neuron; Rabinovich (2008) Science

Ongoing Dynamics

- Continuously evolving pattern of correlations between different brain areas.
  - Different subnetworks transiently engaging with phase synchrony in one or more oscillatory bandwidths.
- Multi-stability would allow the system to explore a large number of state configurations
  - Efficient coding of the ever-changing surrounding environment
  - Dealing with sensory novelty.

(Skarda and Freeman, 1987; Nara, 2003; Rabinovich et al., 2008; Breakspear, 2017, Deco et al., 2011; Deco and Jirsa, 2012; Tognoli and Kelso, 2014; Preti et al., 2017, Friston et al., 2012; Heitmann et al., 2012; Palmigiano et al., 2017)



Mechanisms for Multistability

Multistability has been associated to:

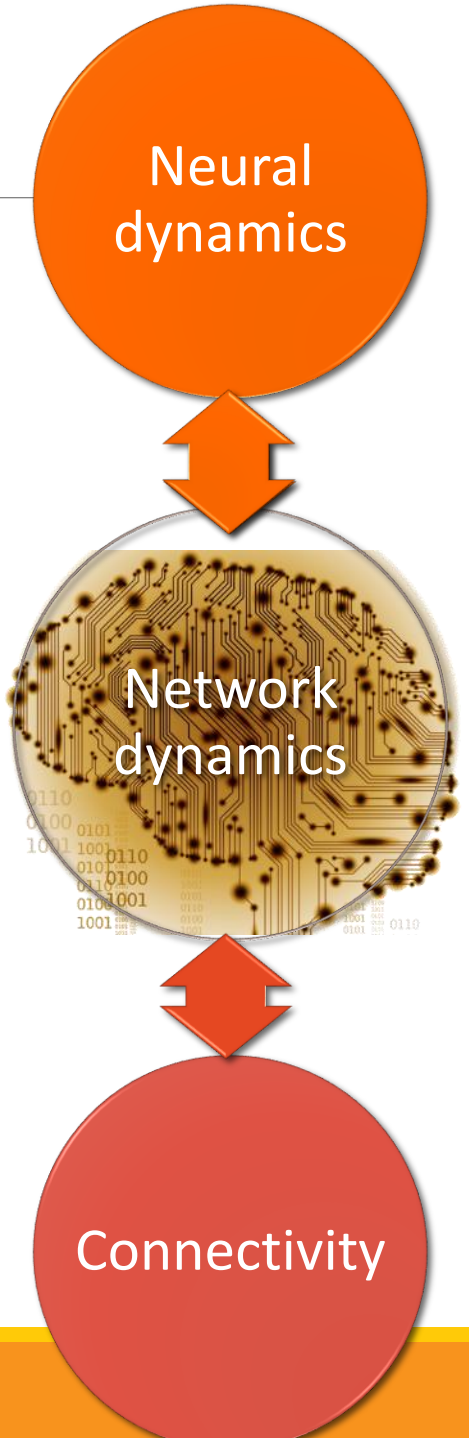
- delays in synaptic communication (Ghosh et al., 2008; Deco et al., 2009; Cabral et al., 2014; Lea-Carnall et al., 2016)

- multiple attractors can be found only within a certain range of the global coupling strength (Deco et al., 2009; Deco and Jirsa, 2012).

- network topology: multi-stability is lost when the connections are randomized (Cabral et al., 2014) and role of the 'rich club' nodes (Gollo et al., 2015).

- Network properties

- Internal node dynamics: Chaos *vs.* Noise

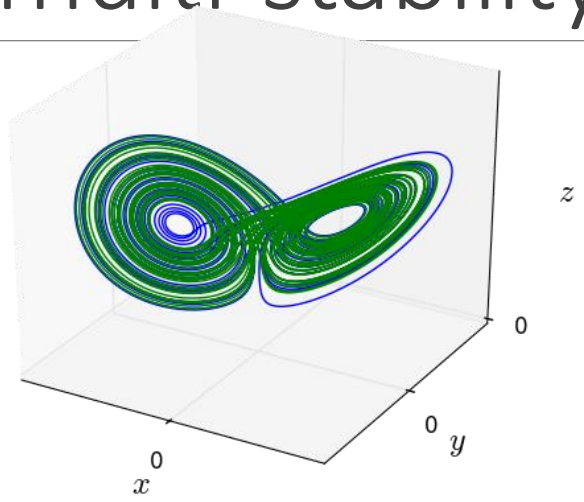


Node dynamics and Multistability

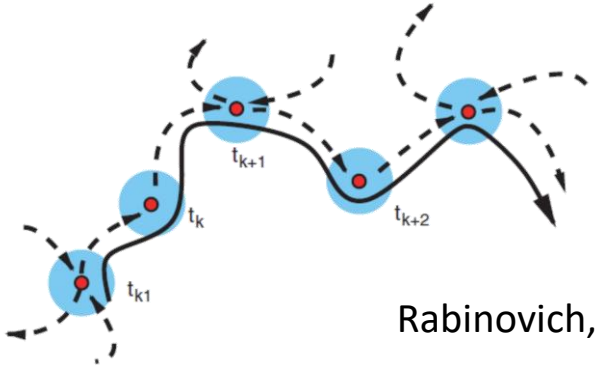
Posible origins of multi-stability

Deterministic

- Chaotic Itinerancy



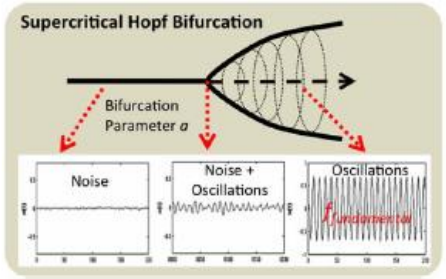
- Heteroclinic cycling

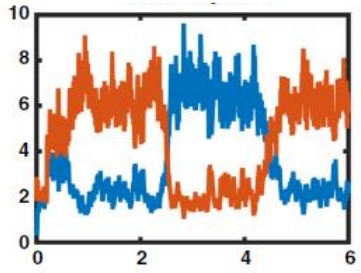


Rabinovich, 2008

Stochastic

- Switching



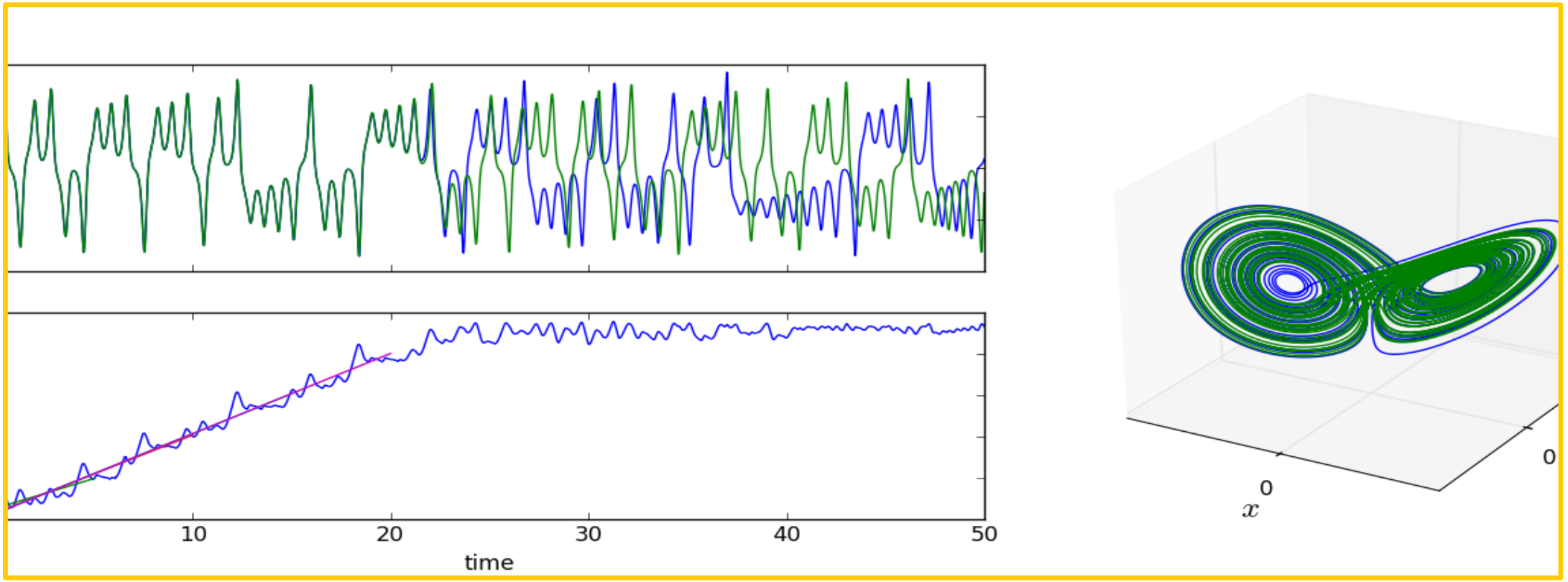


Hansen, 2015
Miller, 2016
Deco, 2017

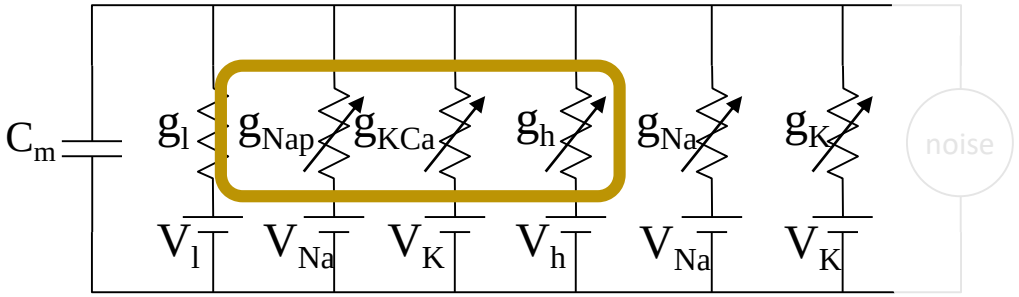
Friston, Breakspear & Deco (2012); Miller (2016)

Chaos

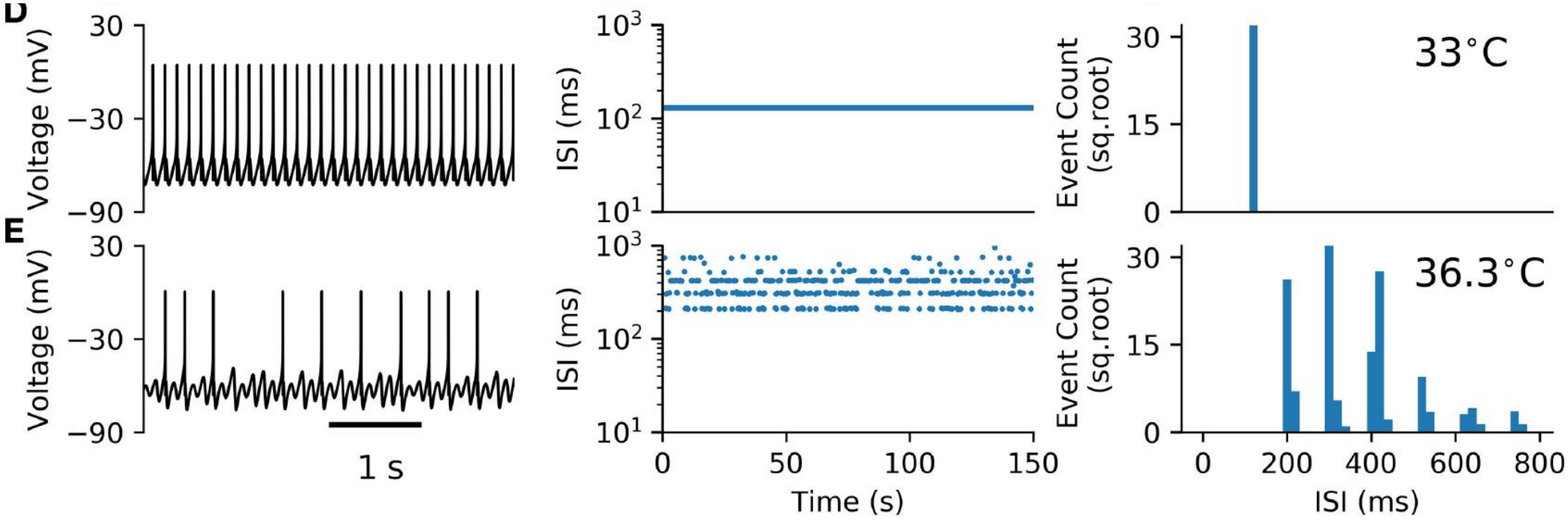
- **Aperiodic** behavior arising from a **deterministic** system.
- Exponential divergence of trajectories with close initial condition



Huber-Braun + Ih model



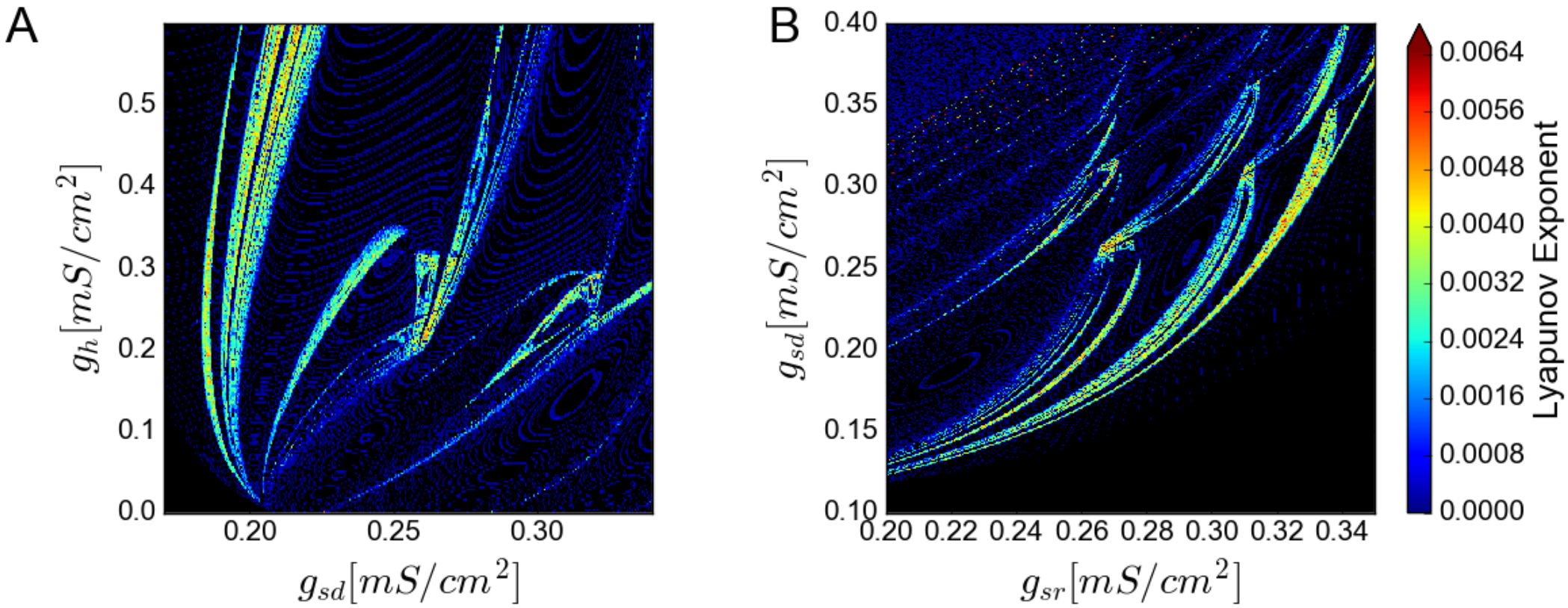
$Na_p + K_{ca} + I_h$



Orio et al., *J Neurophys* 2012; Xu et al., *Front Comp Neurosci* 2017

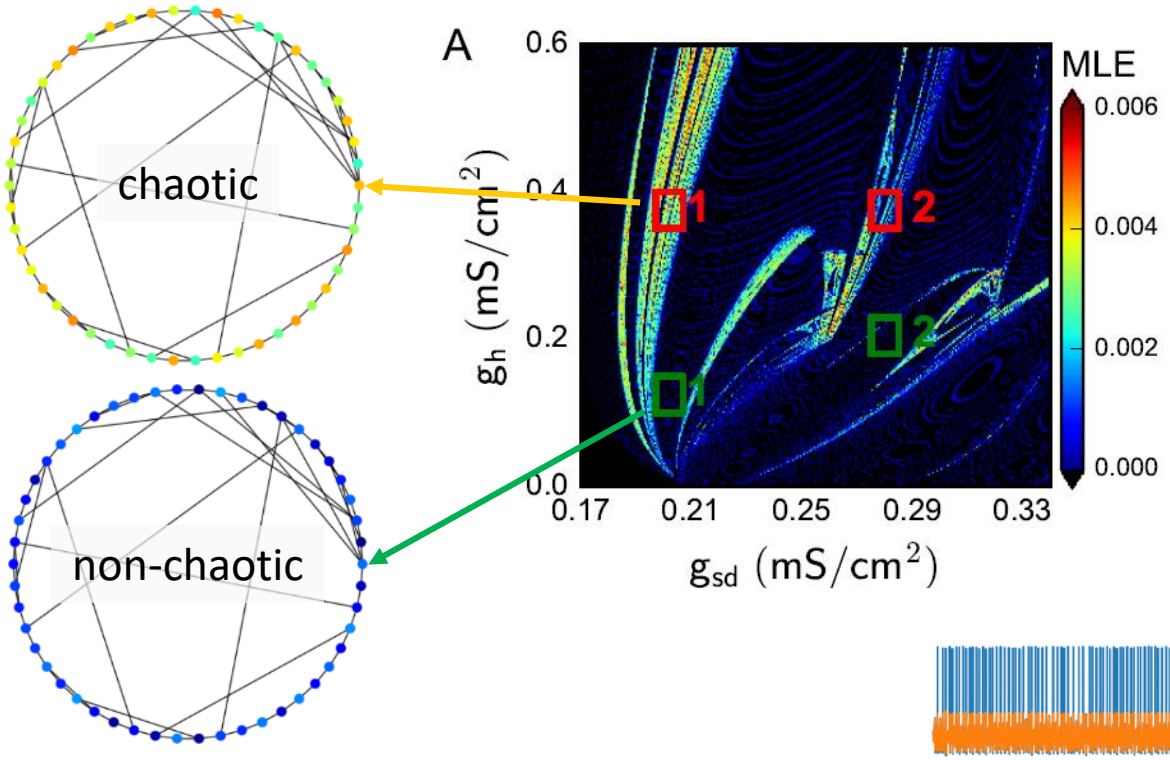
Defining chaotic parameter regions

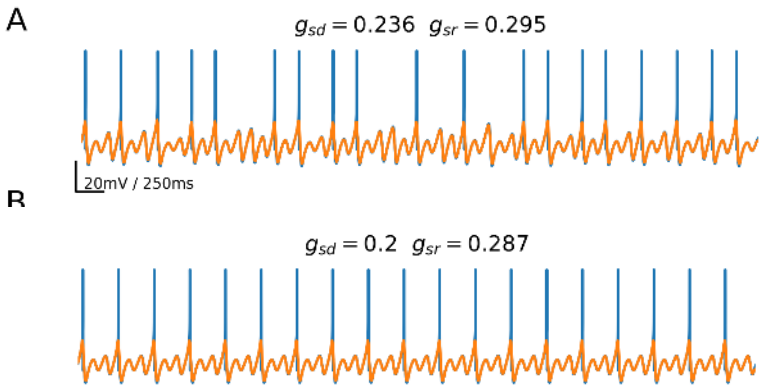
MLE from full ODE system



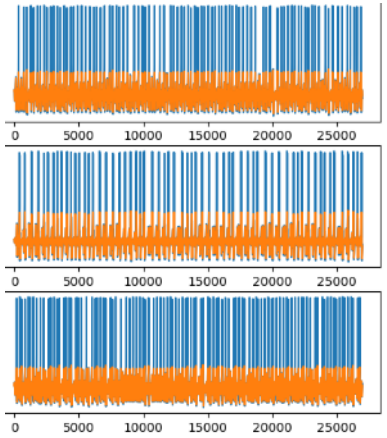
Xu et al., *Front Comp Neurosci* (2017)

Building a network

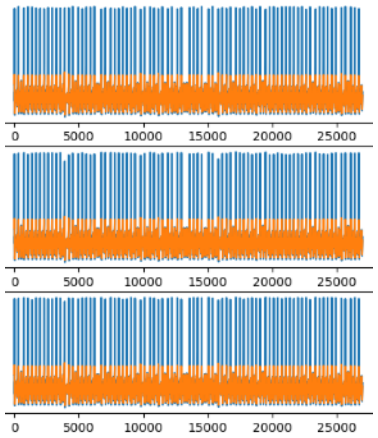




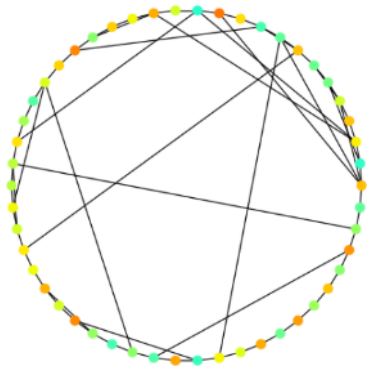
Uncoupled asynchronous

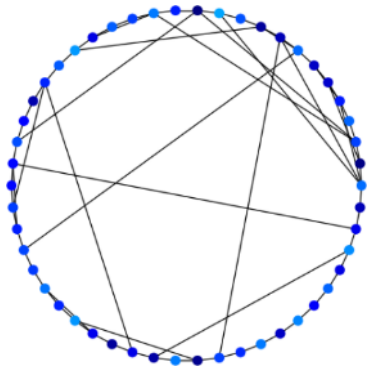


Increase coupling G



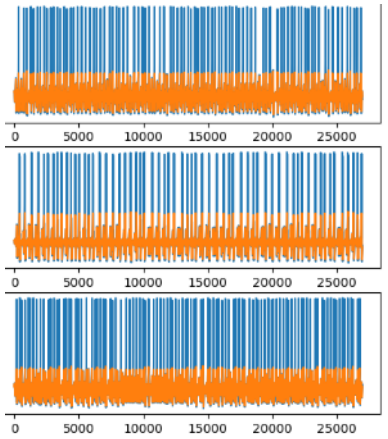
synchronous



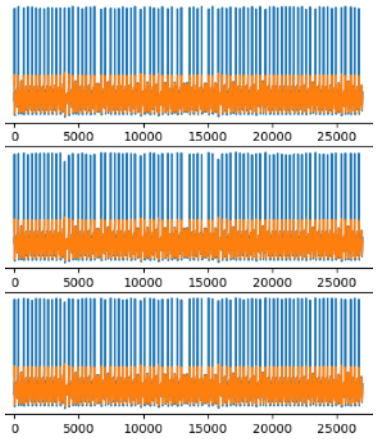


Small-world network
250 nodes
Mean degree 10
Reconnection prob 0.05

Uncoupled
asynchronous

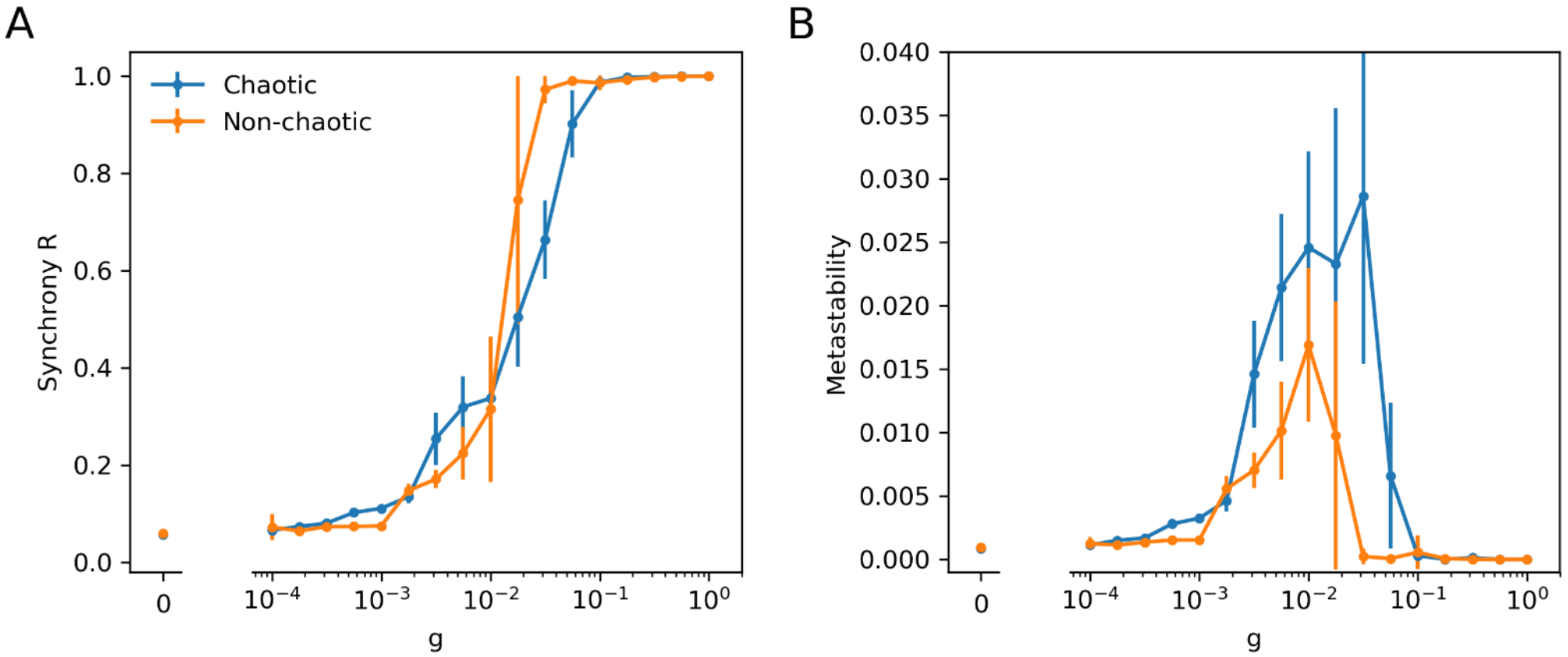


Increase
coupling G



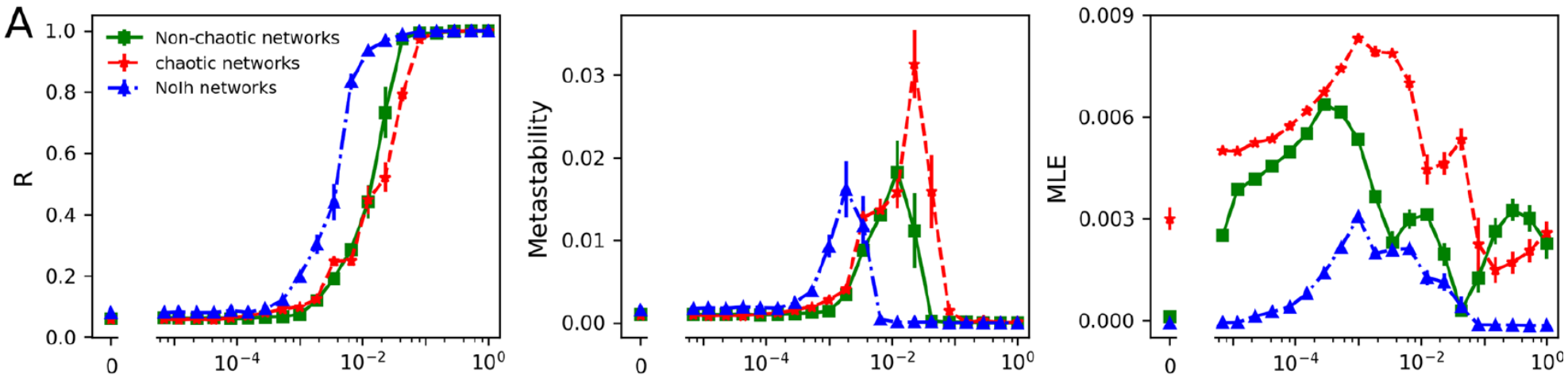
synchronous

Synchronization behavior

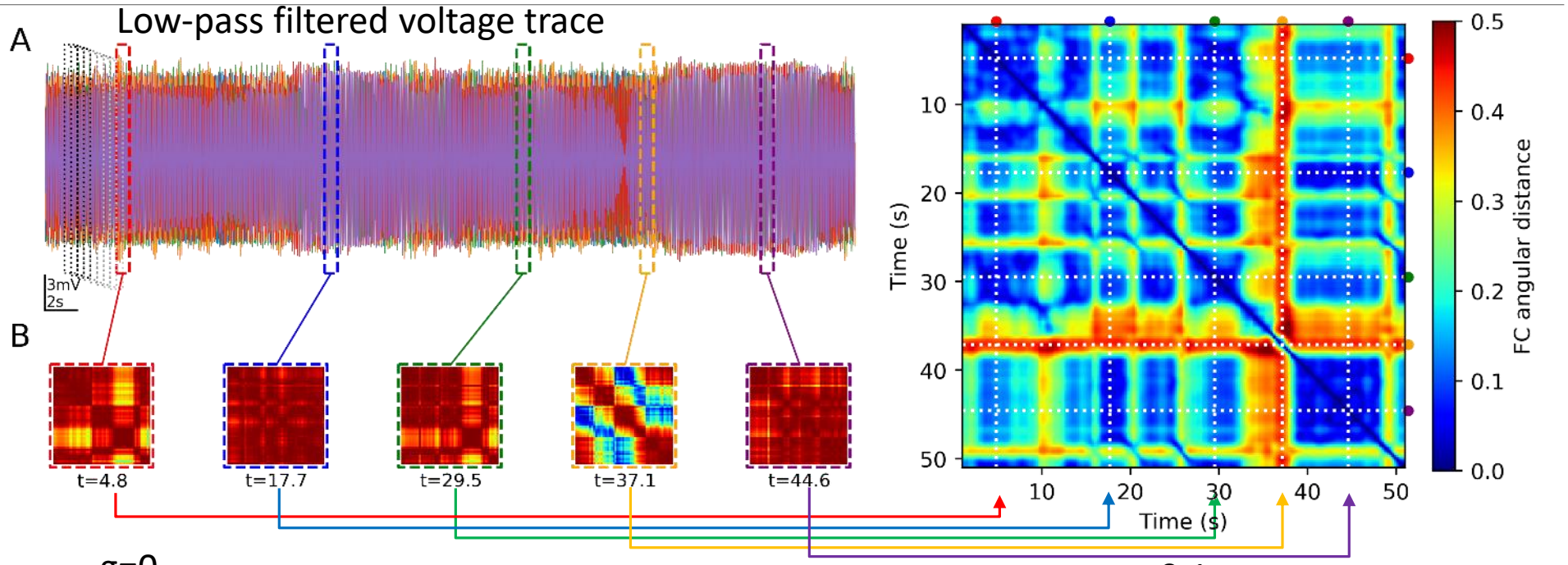


Xu et al., *Sci Reports* 2018; Orio et al., *Chaos* 2018

Networks of nonchaotic neurons are chaotic



Functional connectivity dynamics



g=0

g>=0.1

$$FC_{k,l} = R_{k,l} = \left| \frac{1}{T} \int \left(e^{i\varphi_k(t)} + e^{i\varphi_l(t)} \right) \right|$$

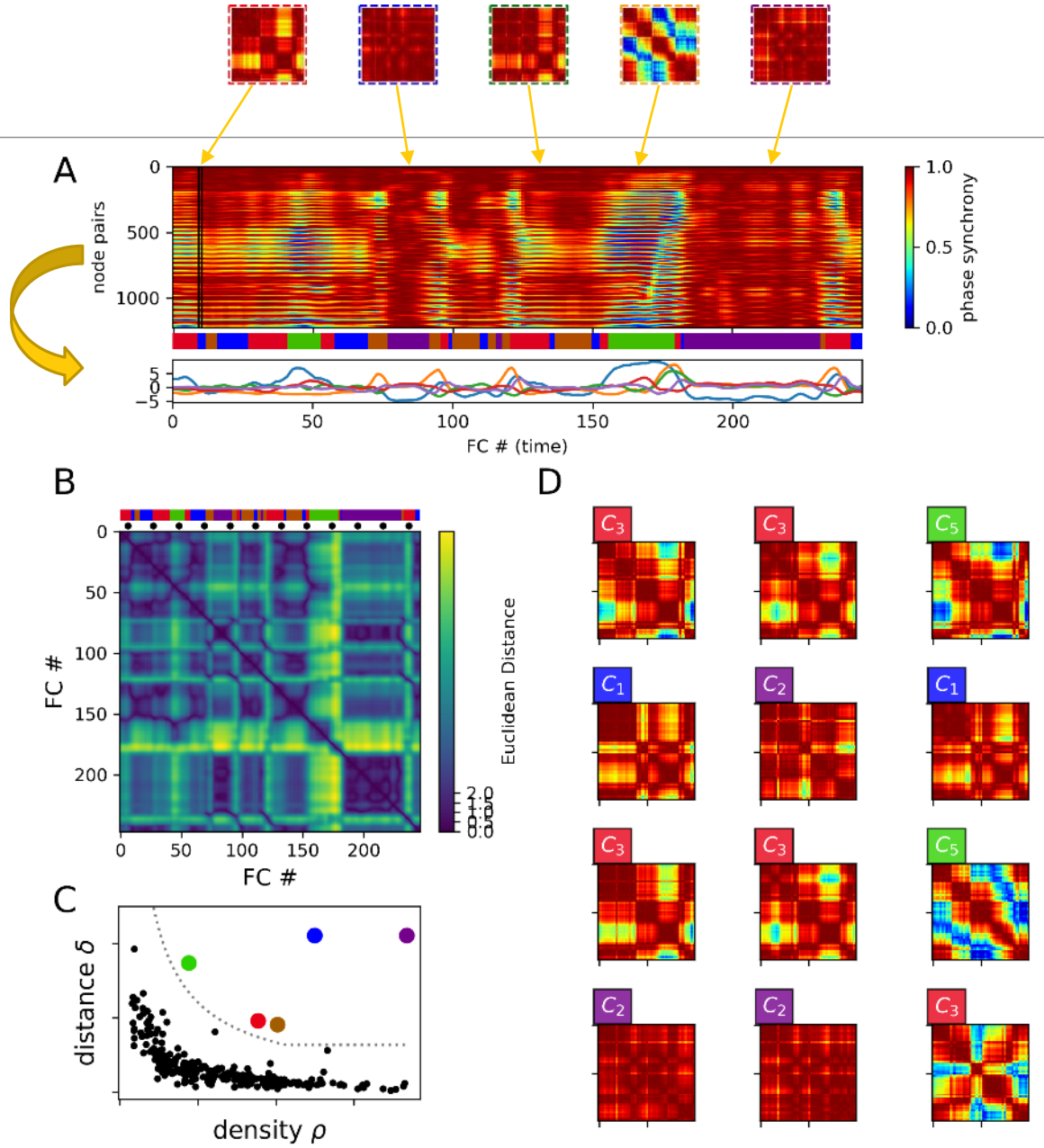
Kuramoto order parameter
(Phase synchrony)

$$FCD_{i,j} = 1 - \frac{FC_i \cdot FC_j}{\|FC_i\| \|FC_j\|}$$

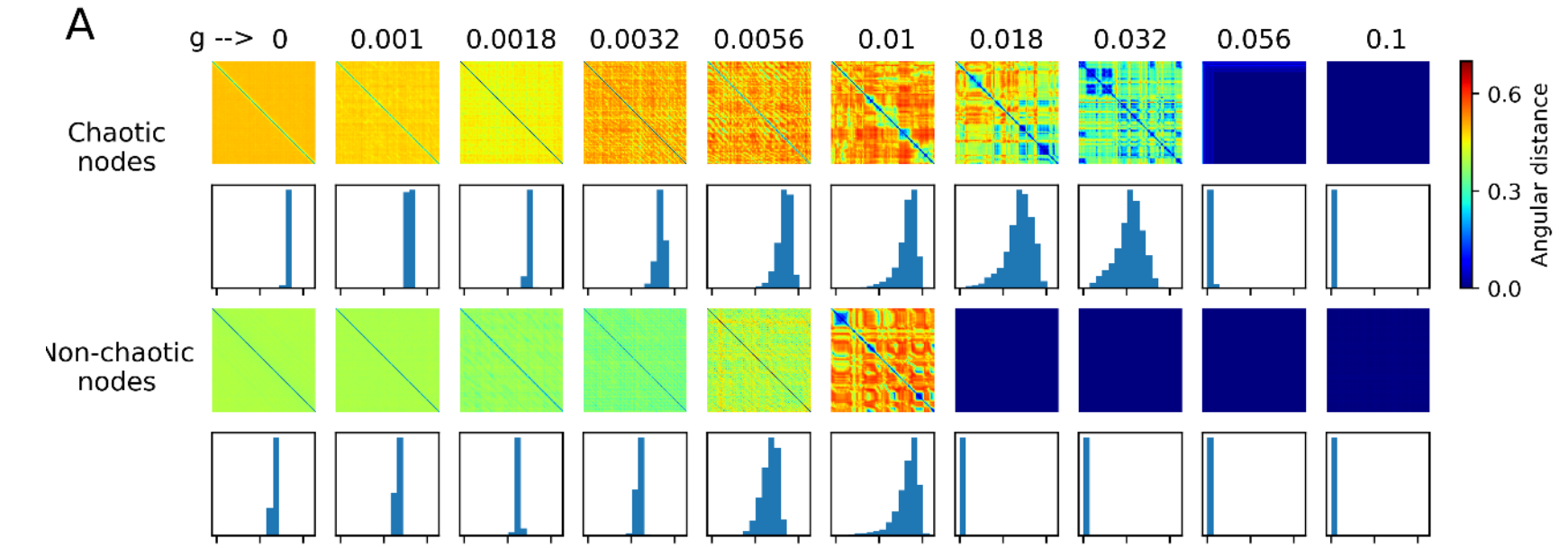
Identifying ‘states’

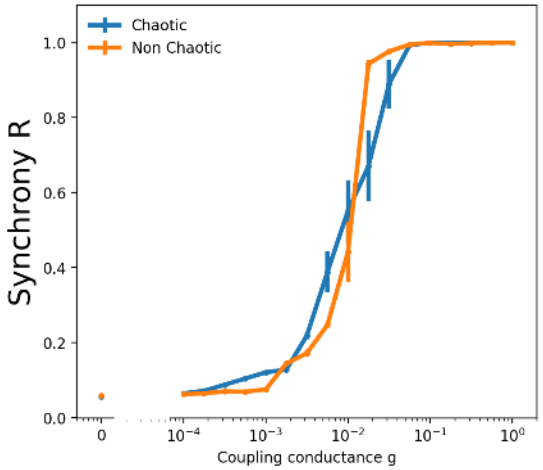
PCA to reduce dimensionality

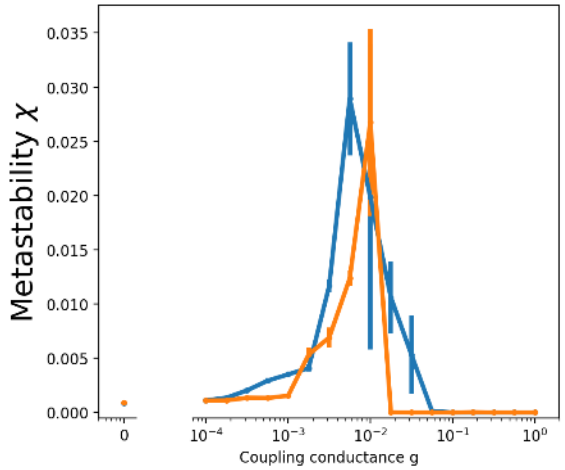
Density-based clustering.
No need to specify number of clusters

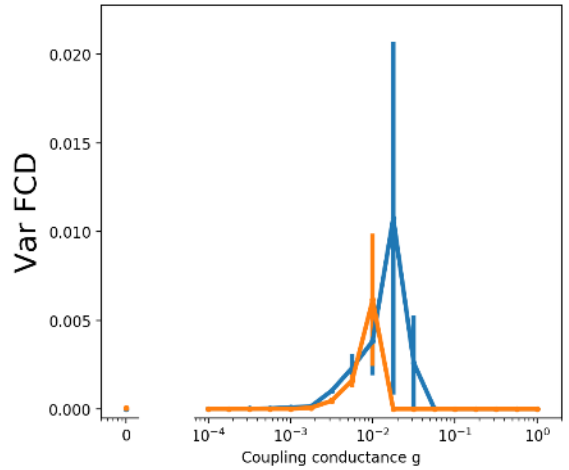


FCD in deterministic simulations





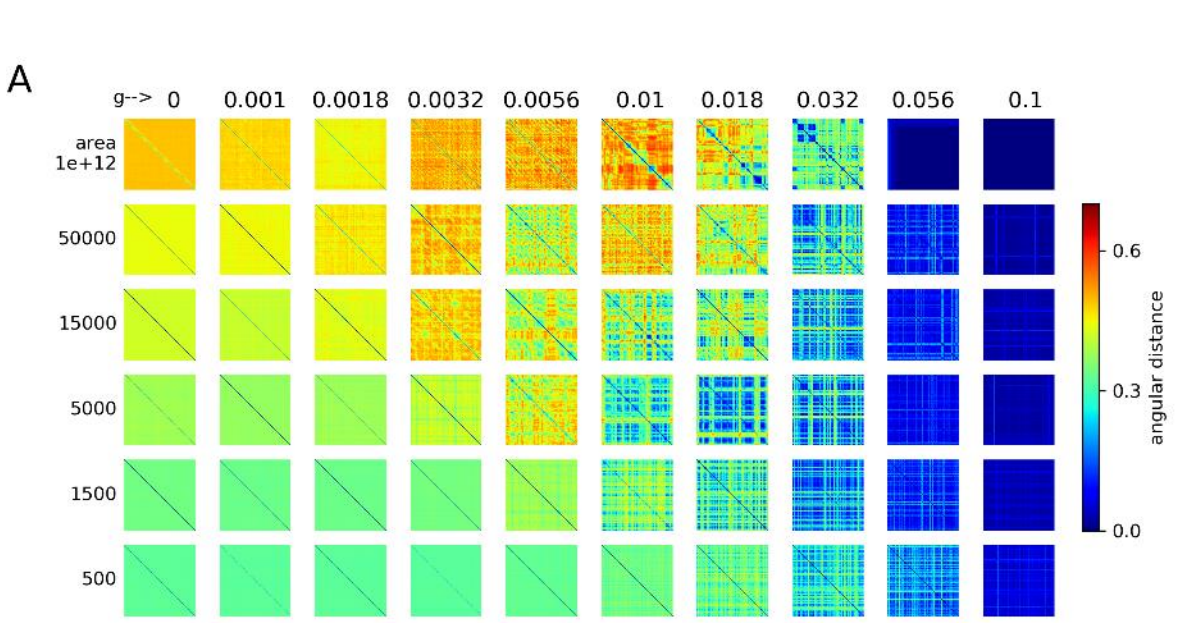


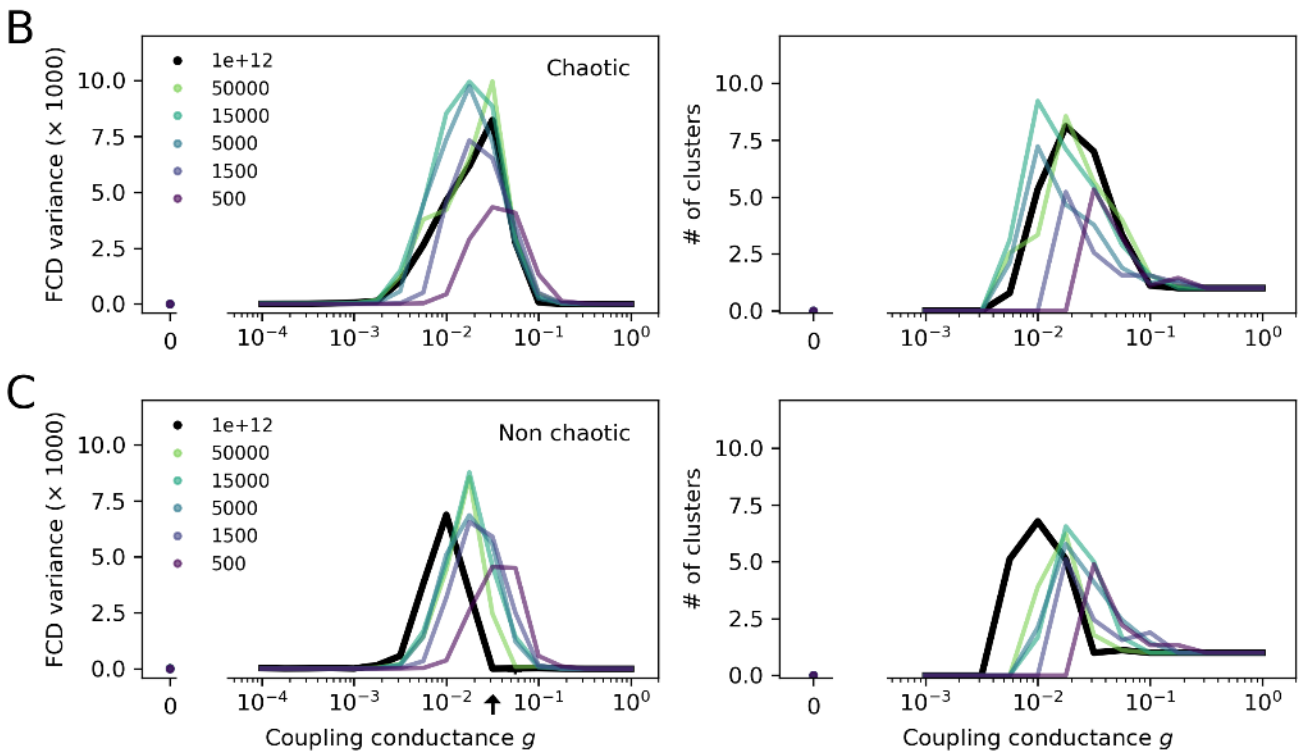


Chaotic dynamics at the node level enhances multistable behavior, even though at the network level the dynamics is always chaotic

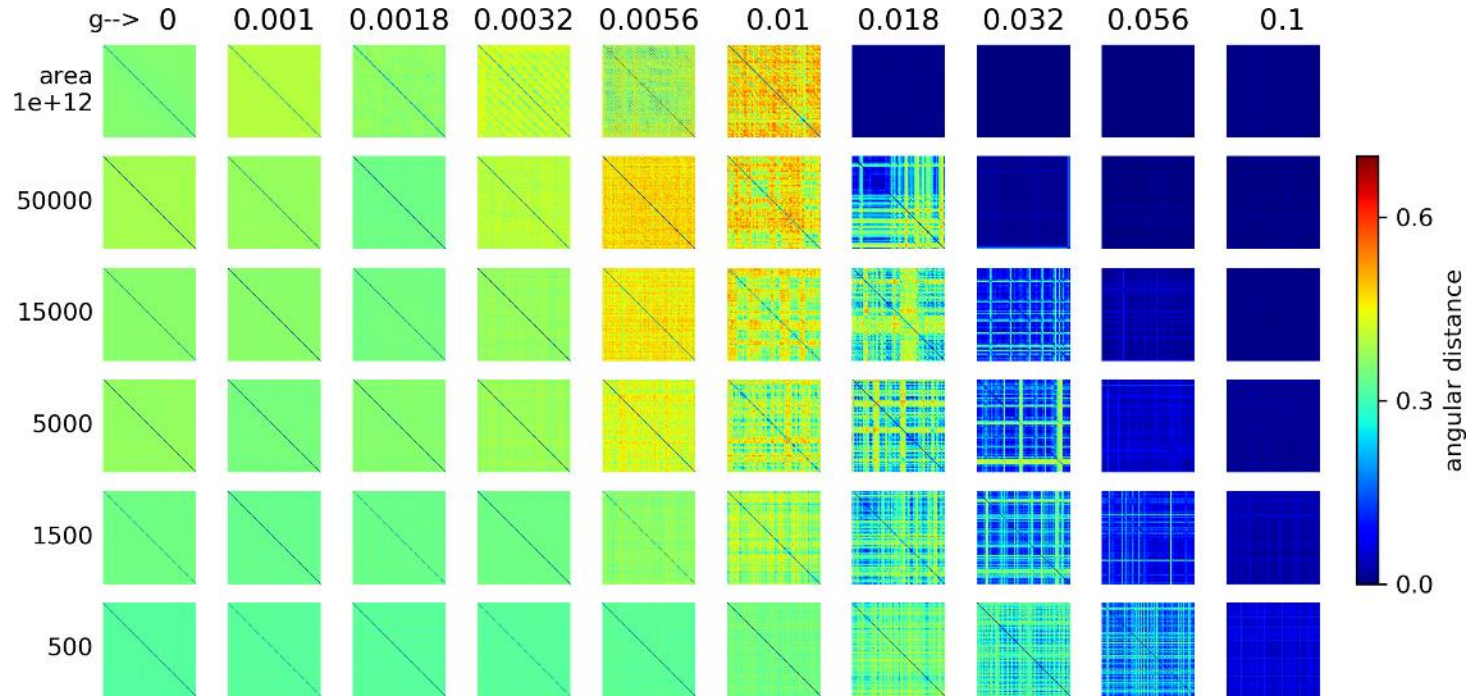
Orio P, Gatica M, Herzog R, Maidana JP, Castro S, Xu K (2018) *Chaos*

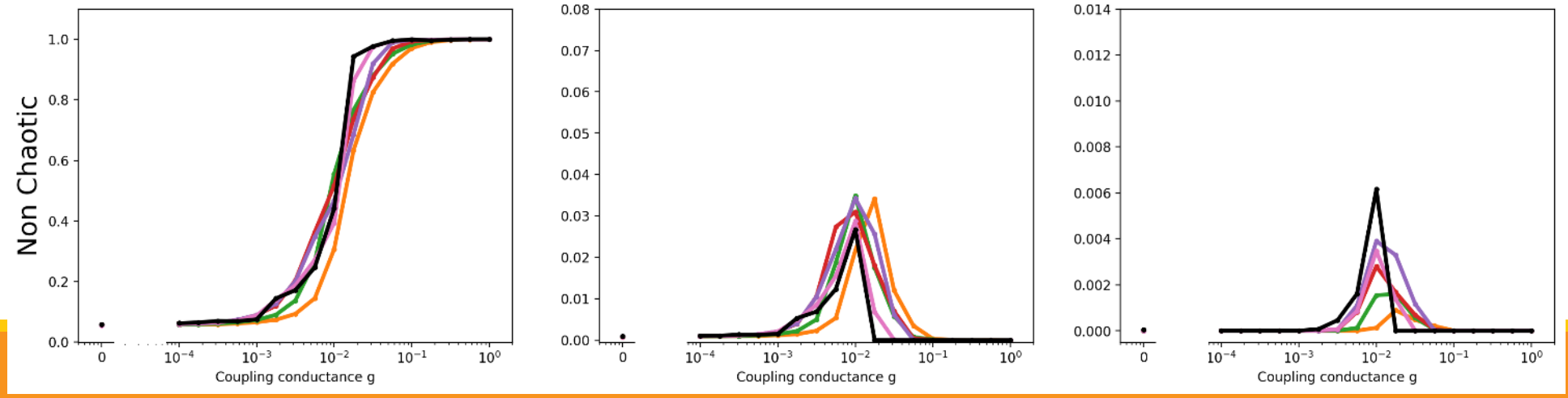
Dynamical Noise abolishes chaos-induced multi-stability





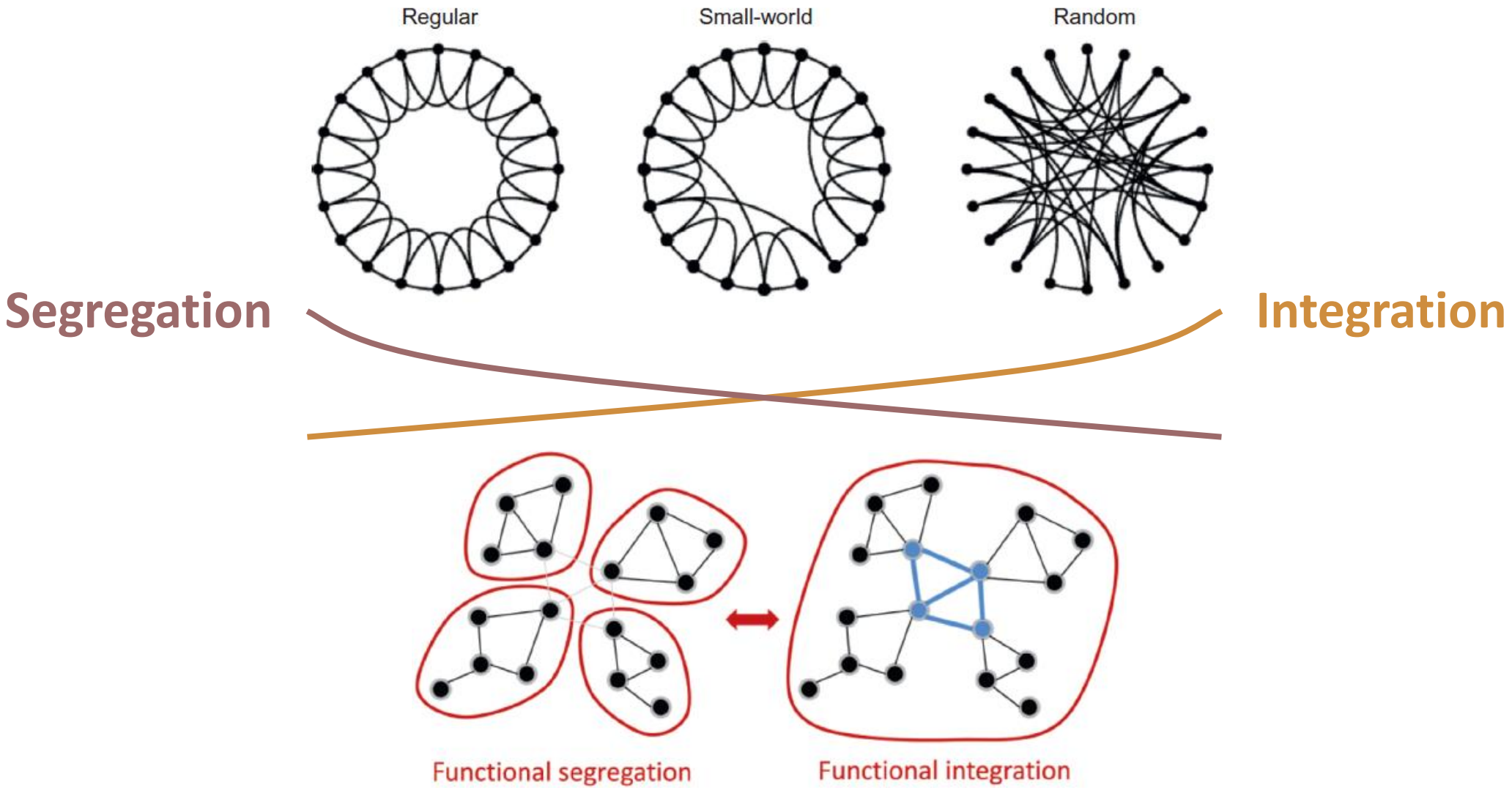
With non-chaotic nodes, noise *induces* multistability



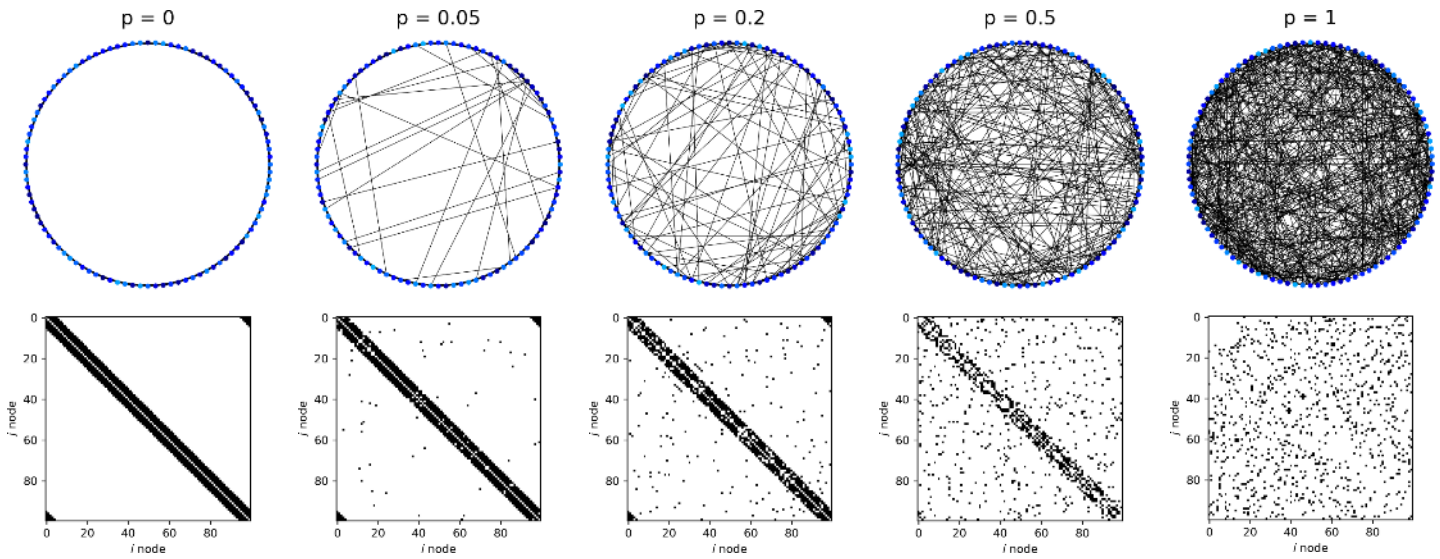


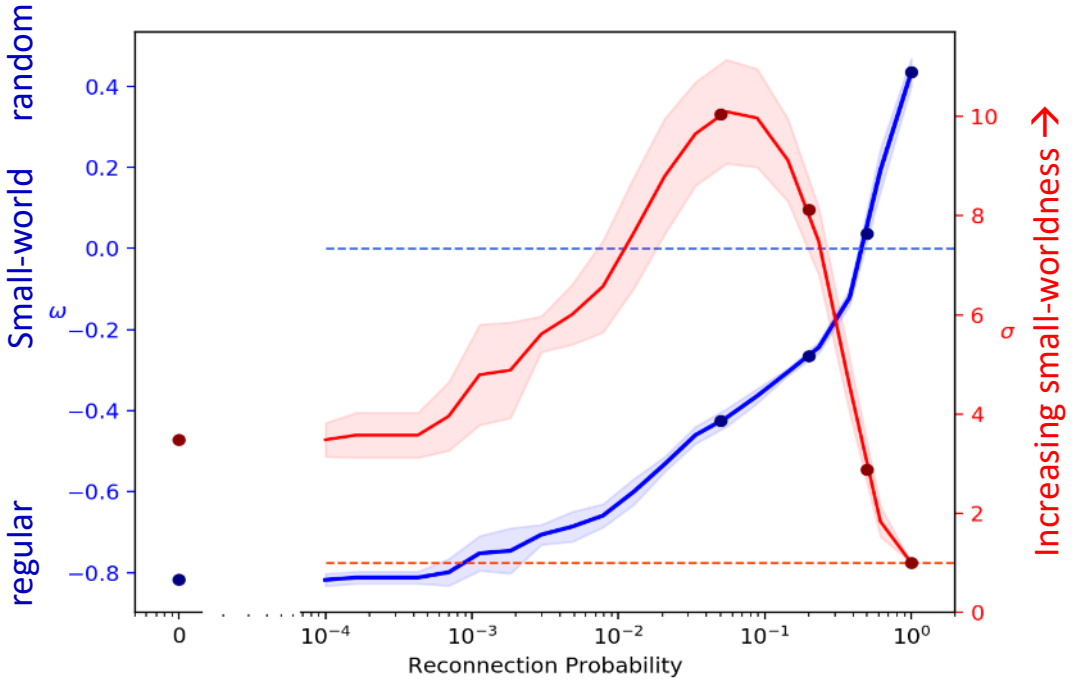
Network topology

Small-world networks



From regular to random



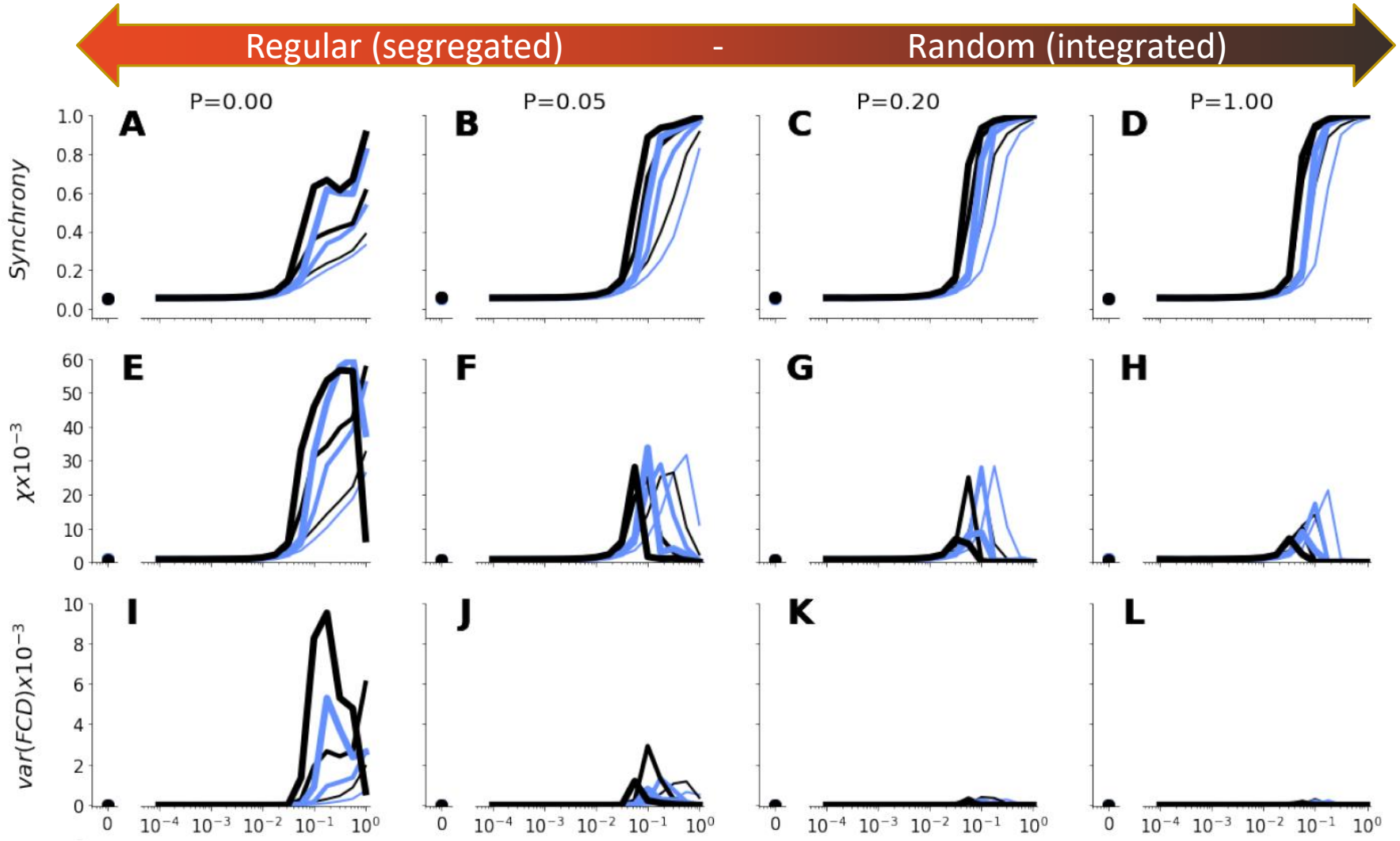


Small world indices:

σ (Humphries) and ω (Telesford):

$$\sigma = \frac{C/C_r}{L/L_r} \qquad \omega = \frac{L_r}{L} - \frac{C}{C_0}$$

Higher modularity (segregation?) → more dFC



Conclusions

- Networks of chaotic oscillators show dynamical Functional Connectivity in a wider range of global coupling strength.
- Noise reduces the dFC induced by chaos, regularizing the network dynamics
  - However, noise can induce dFC in some circumstances.
    - Moderate noise → More variability, more states.
- Network topology plays a role in shaping dFC
  - *With our model*, dFC is enhanced with modularity. *i.e.,* when global synchrony is disfavored

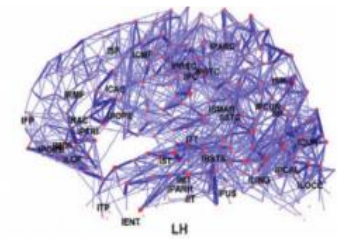
Future (ongoing) work

- Contrast to empirical data
  - Empirical connectomes, fMRI data
- Explore multistability (FCD) in networks of Neural Mass Models.

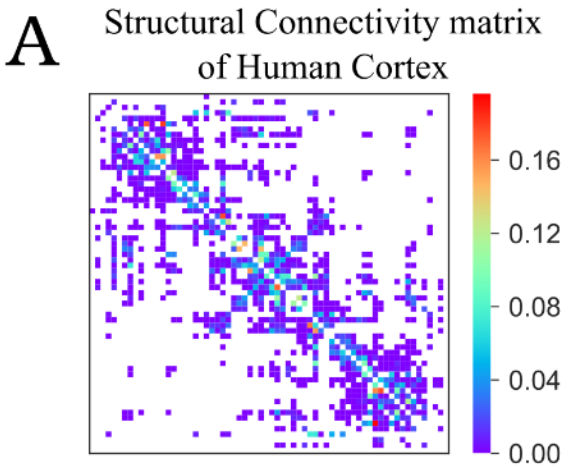
Connectome motifs and Multistability

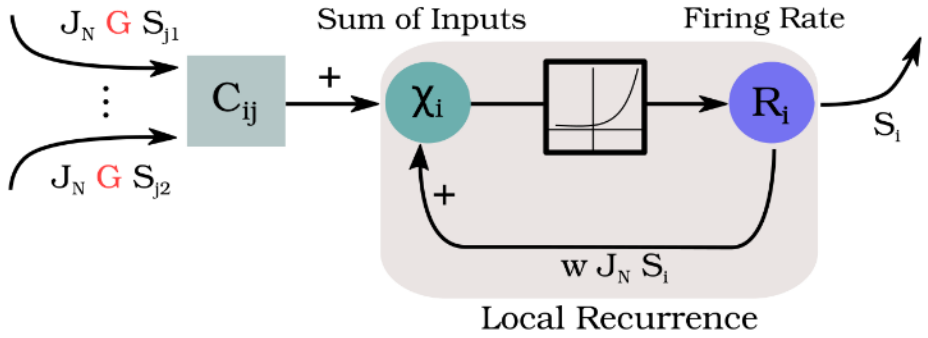
Human connectome + dynamical model

= bistability

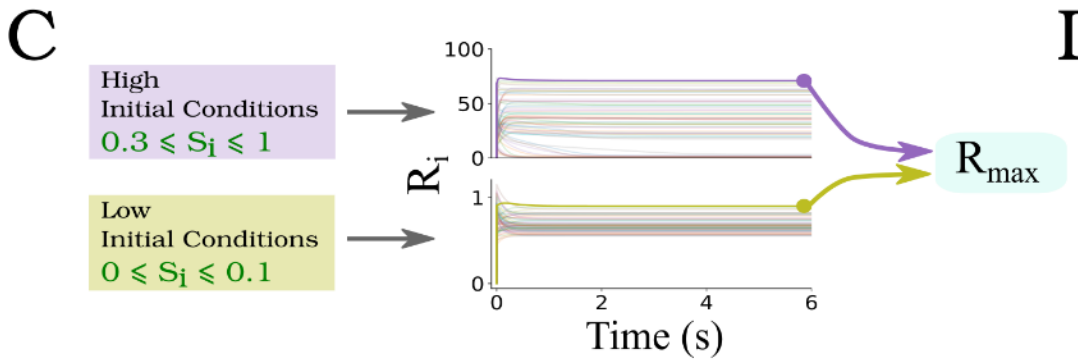


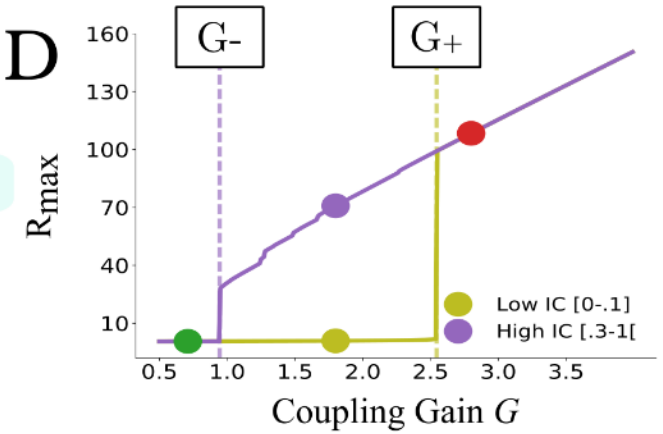
Hagmann *et al.*, *PLoS Biol* (2008)





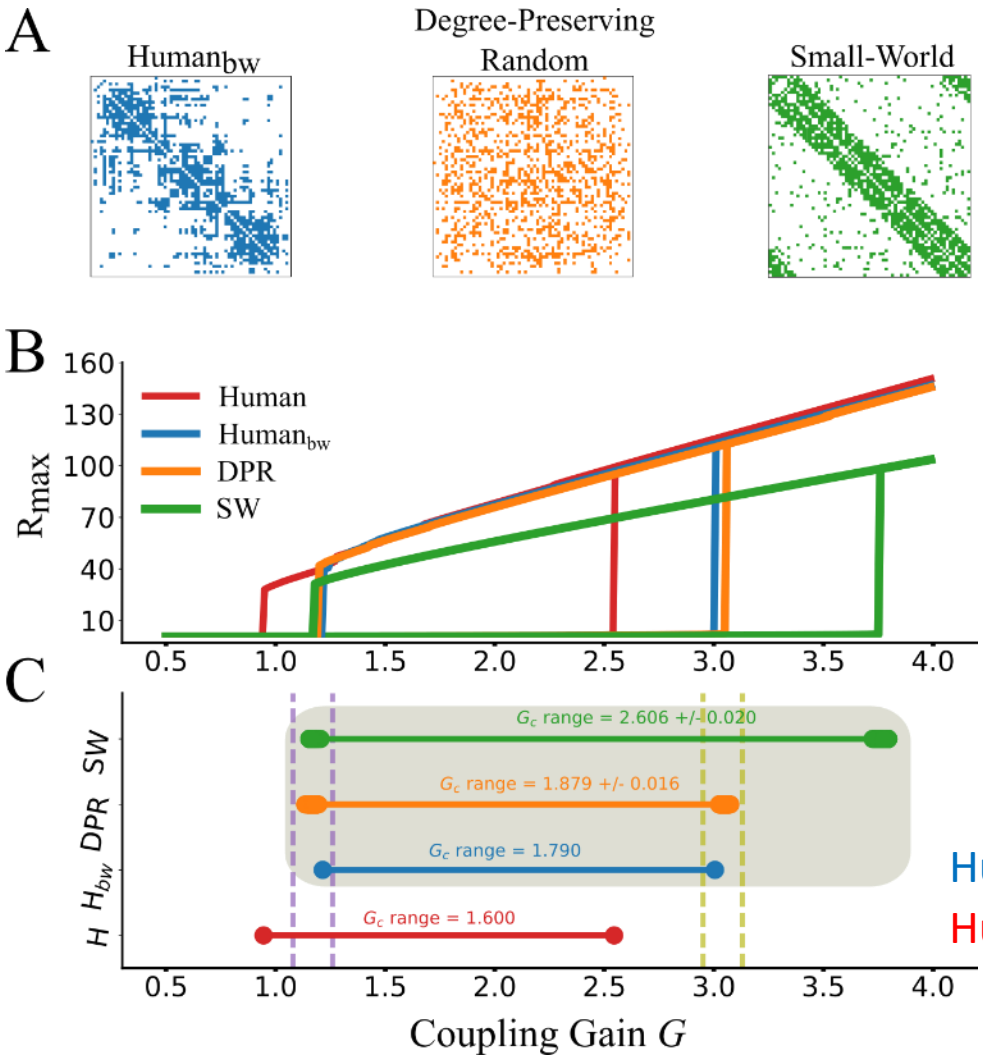
Hansen *et al.*, *Neuroimage* (2015)

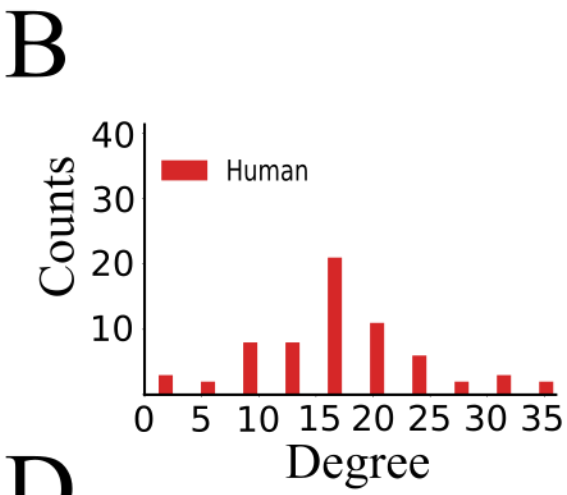


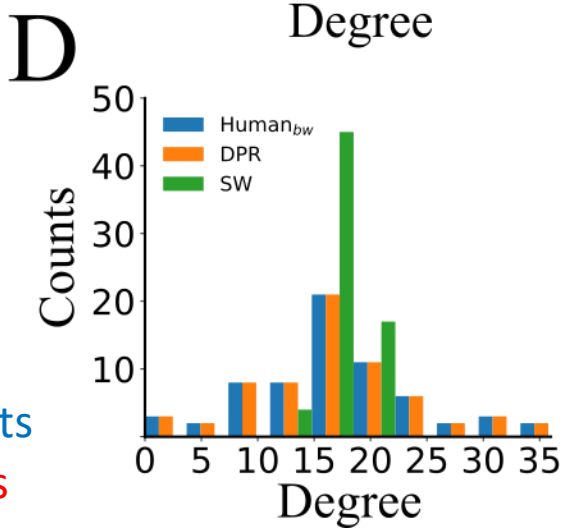


Samy Castro, submitted.

Bistability in structural (binarized) models





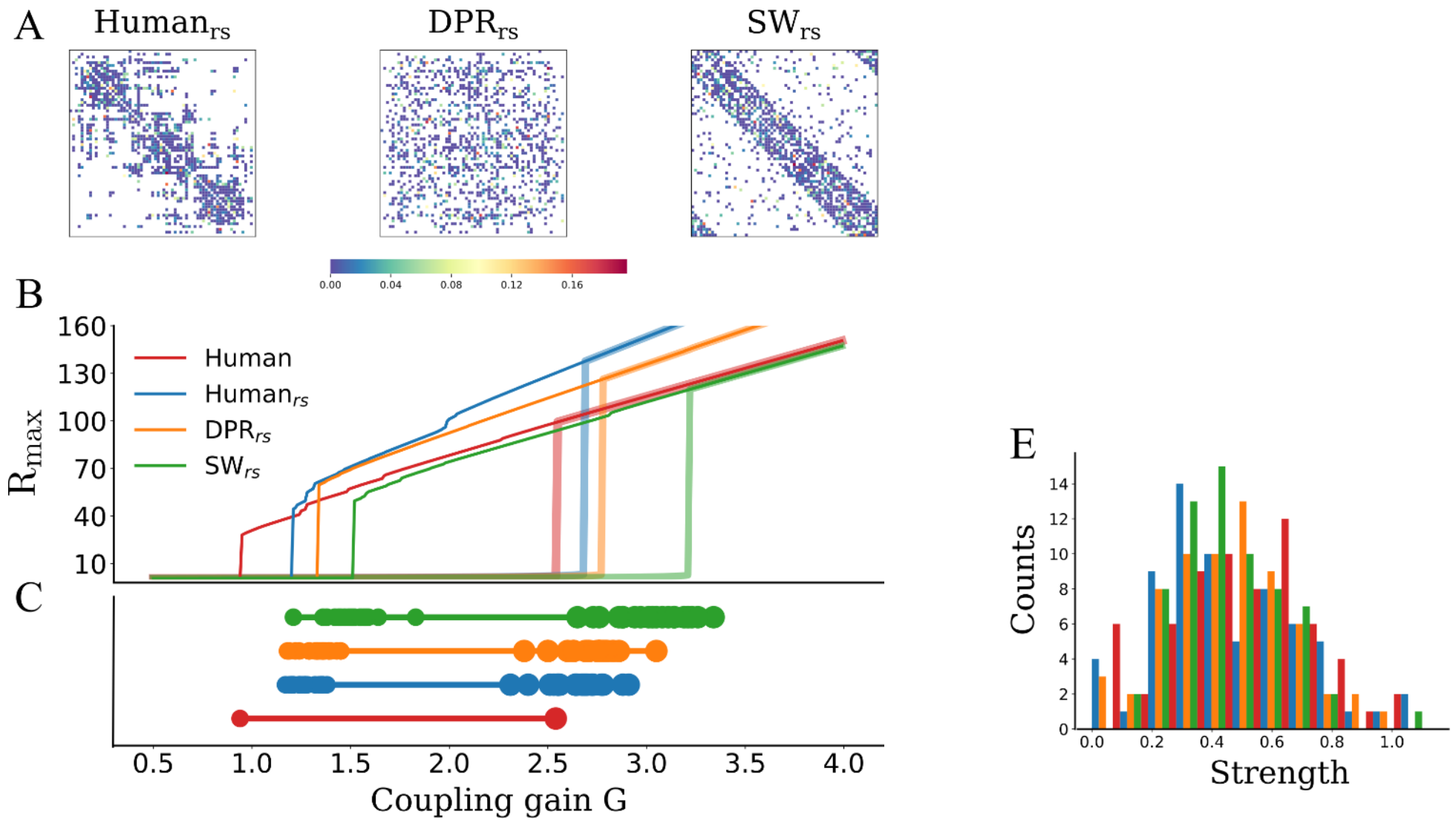


Human$_{bw}$ – homogeneous weights

Human – heterogeneous weights

Samy Castro, submitted.

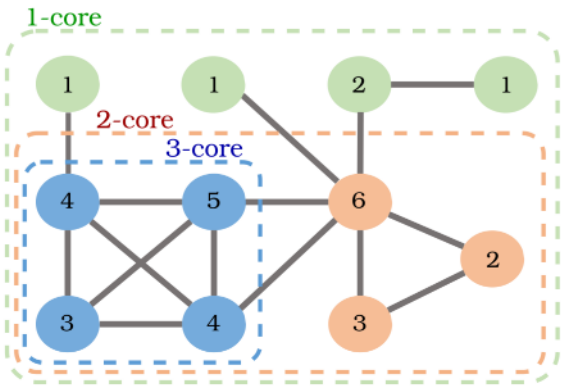
Bistability in random weigthed models



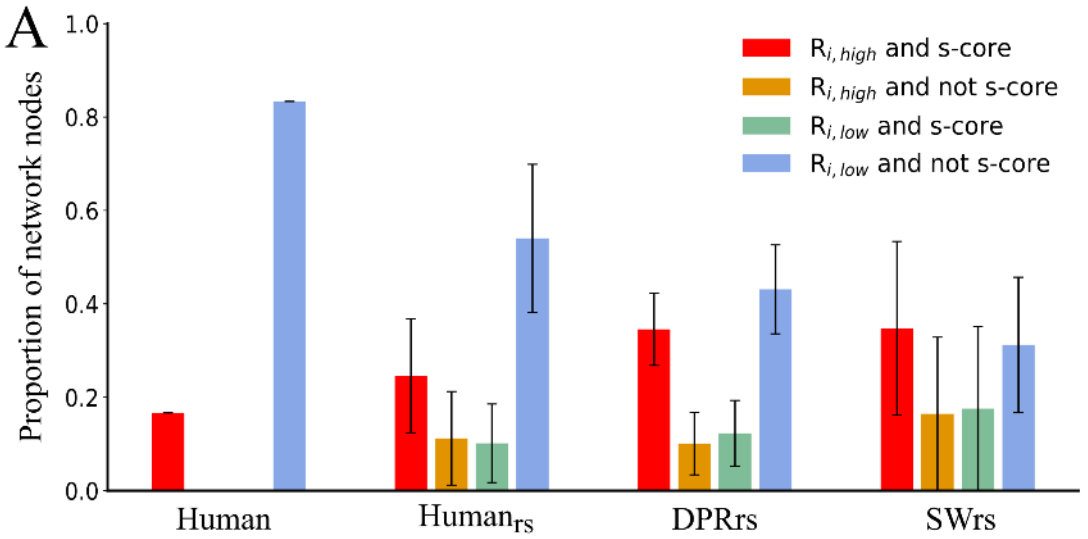
Samy Castro, submitted.

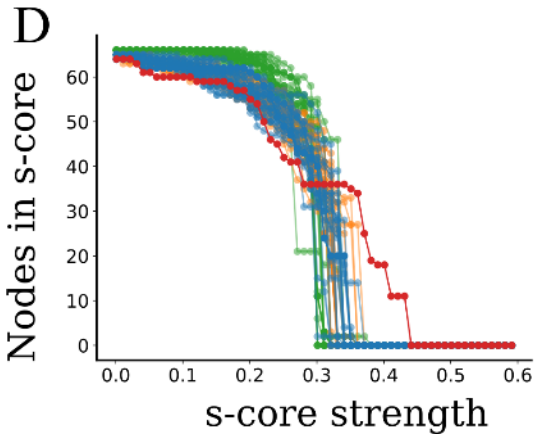
The ‘ignition core’

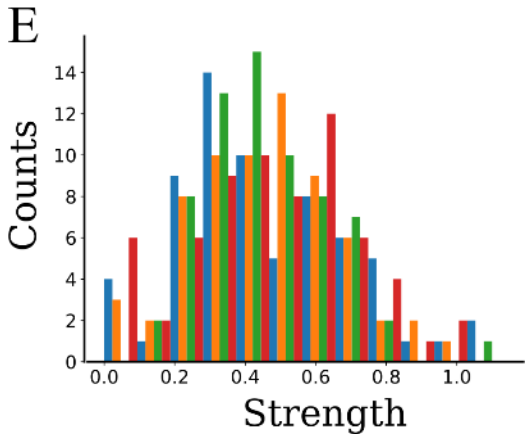
A



k-core decomposition





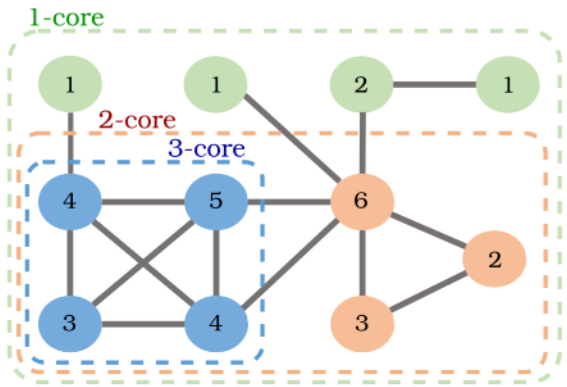


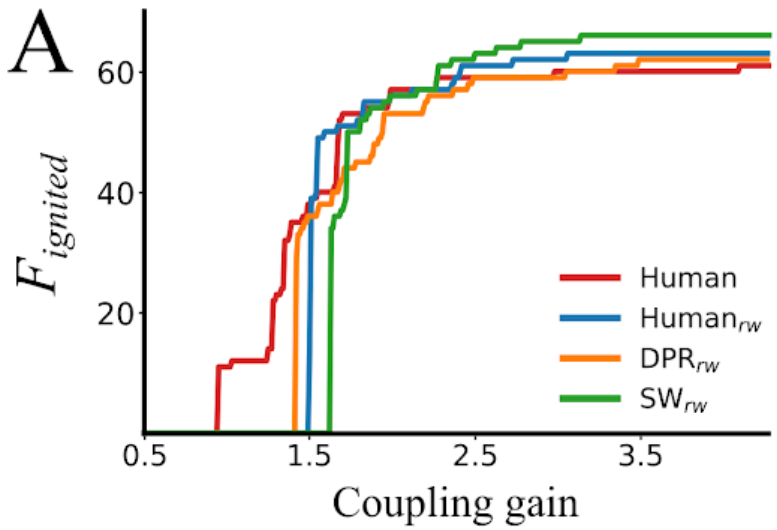
s- core

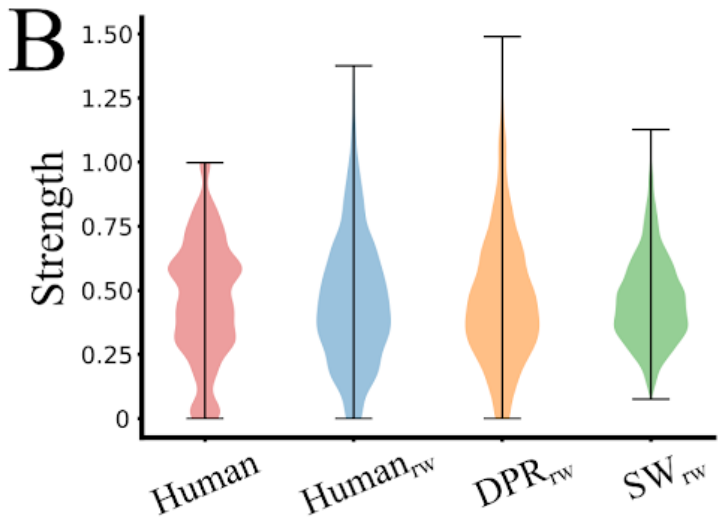
Weighted version of *k*-core

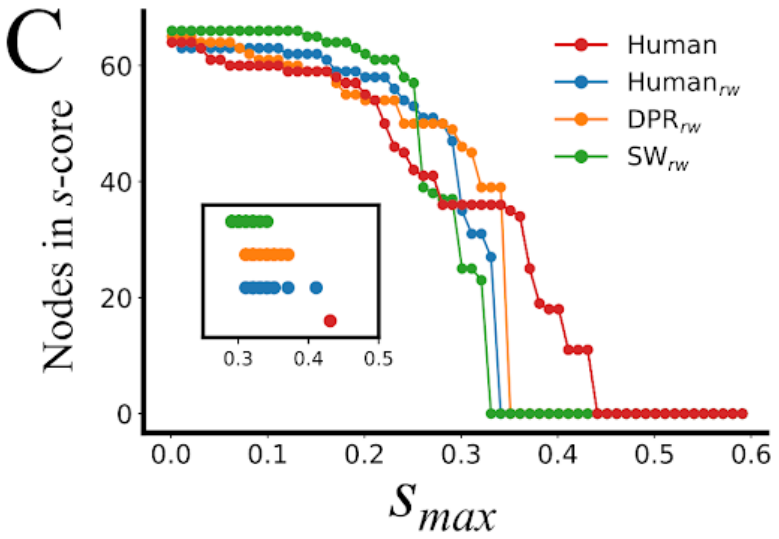
Pericalcarine Cortex (PCAL) (L-R)
Paracentral Lobule (PARC) (L)
Isthmus of the cingulate cortex (ISTC) (L-R)
Precuneus (PCUN) (L-R)
Cuneus (CUN) (L-R)
Posterior Cingulate Cortex (PC) (L-R)

Graded ignition in the human connectome









Conclusions

- Highly connected nodes and densely interconnected cores shape two cortical states and the bifurcations at which they emerge
- The *s*-core fully depicts the subset of nodes which increase their activity at the G- bifurcation (ignition core) and thus shape the high activity state of collective dynamics
- ‘Graded’ s-core organization in the Human connectome allows a graded network ignition.

23 y 24 de Marzo

neurociencia.udp.cl/conectoma

Thank you