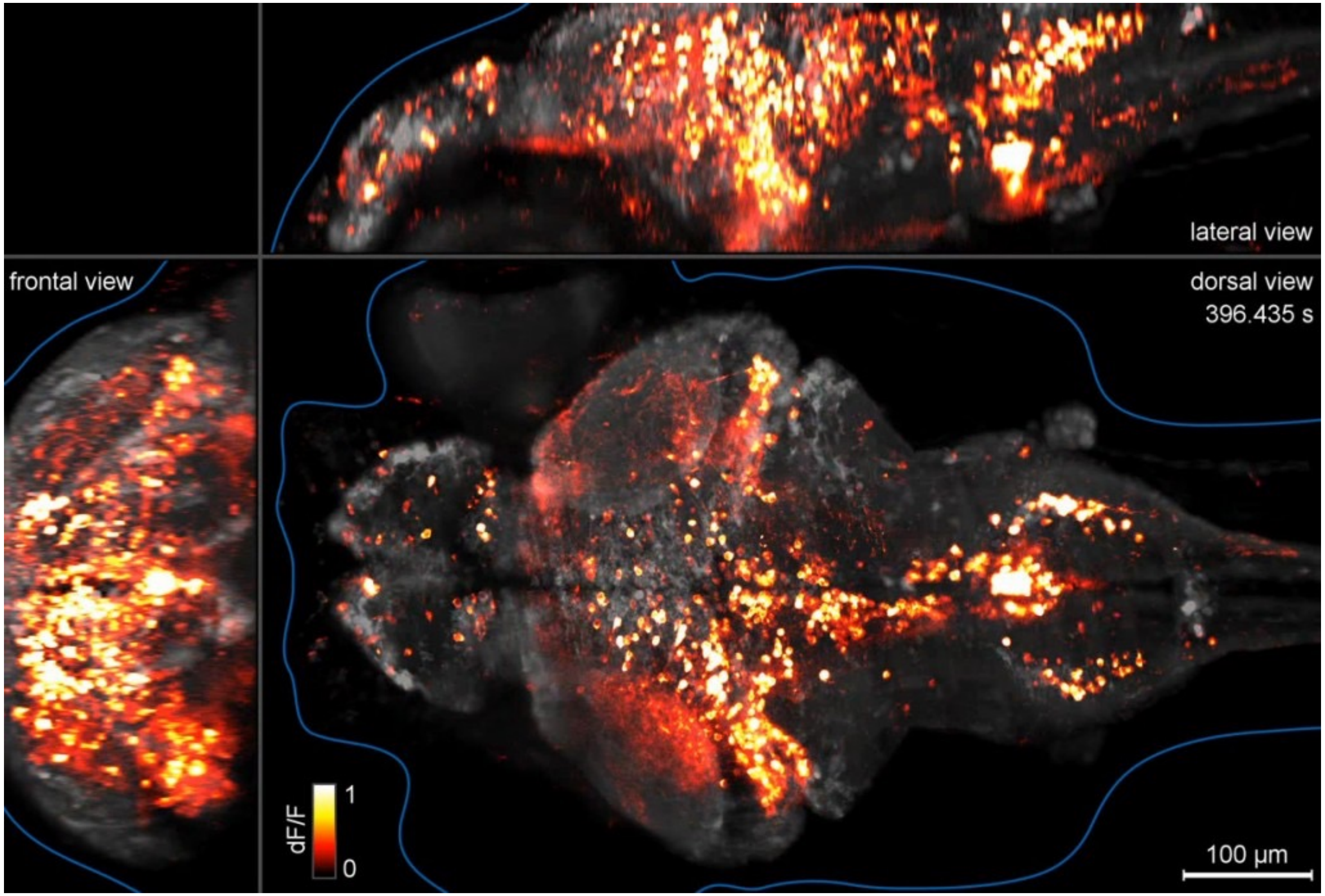
Applied Algebraic Topology 2017
August 10, Sapporo, Japan
http://www.wpi-aimr.tohoku.ac.jp/hiraoka_labo/aat2017/index.html

Characterizing and Modeling Neural Dynamic Complexity

Taro Toyoizumi
RIKEN Brain Science Institute

Characterizing neural dynamic complexity

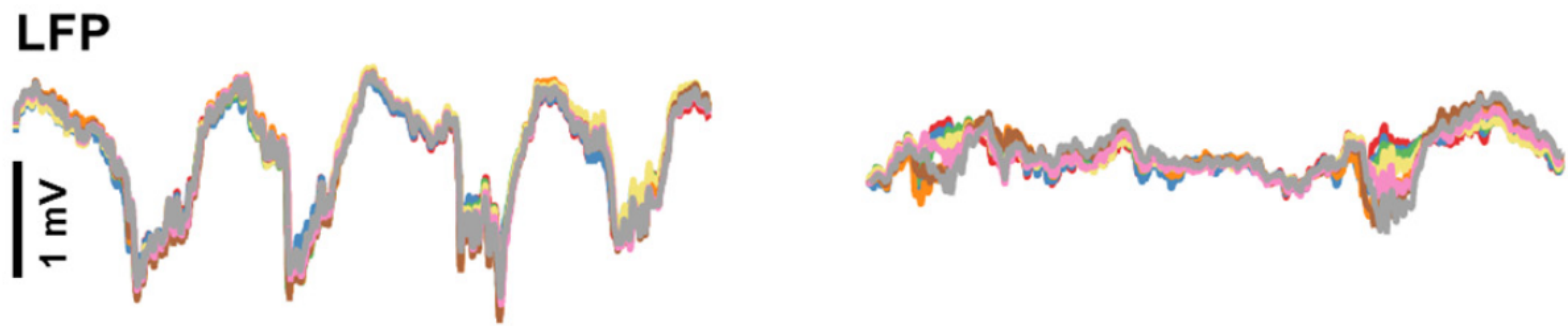
Recording technology has been advanced.



Ahrens and Keller 2013

Yet, big data challenge our understanding.

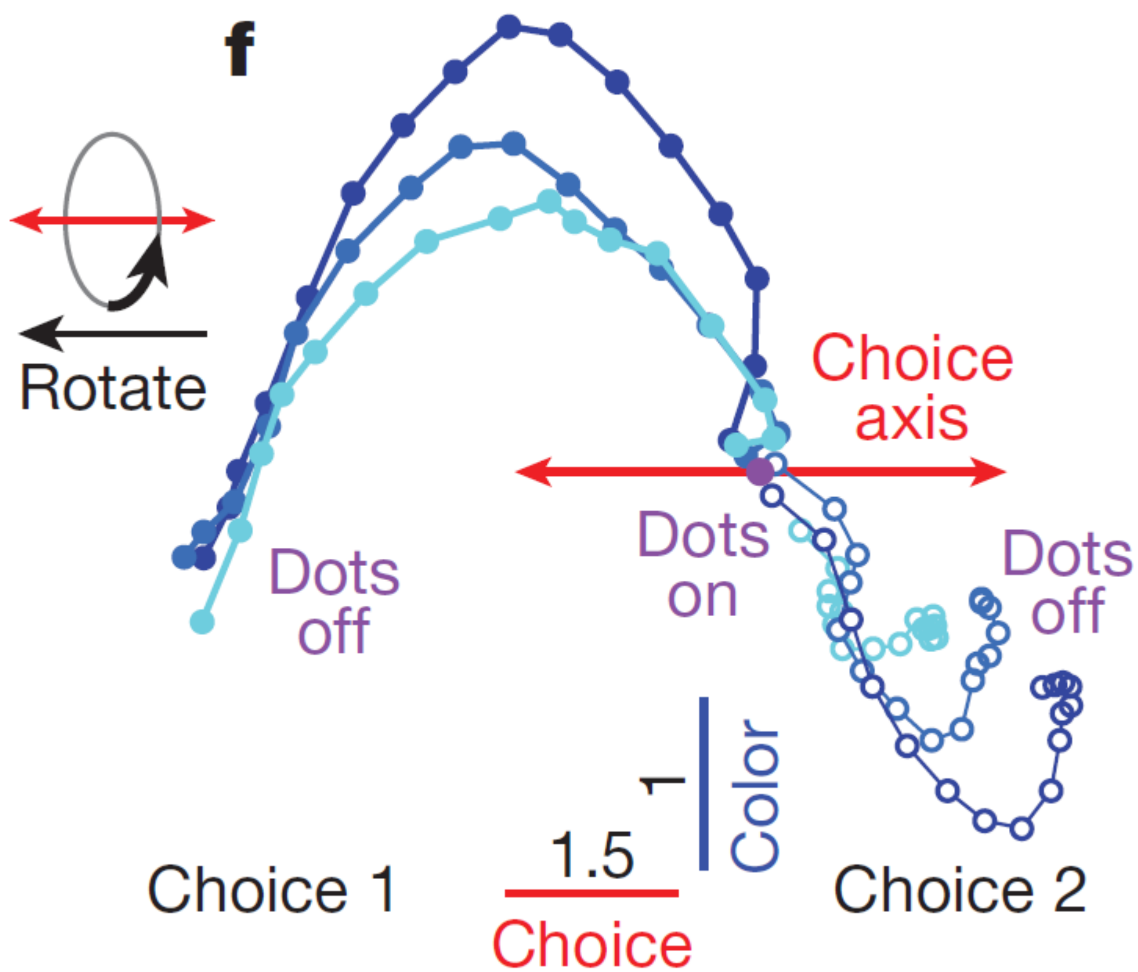
Neural activity is variable.



Pachitariu et al. 2015

How to characterize dynamic complexity?

PCA is often used to characterize the complexity, i.e., dimensionality of the dynamics.

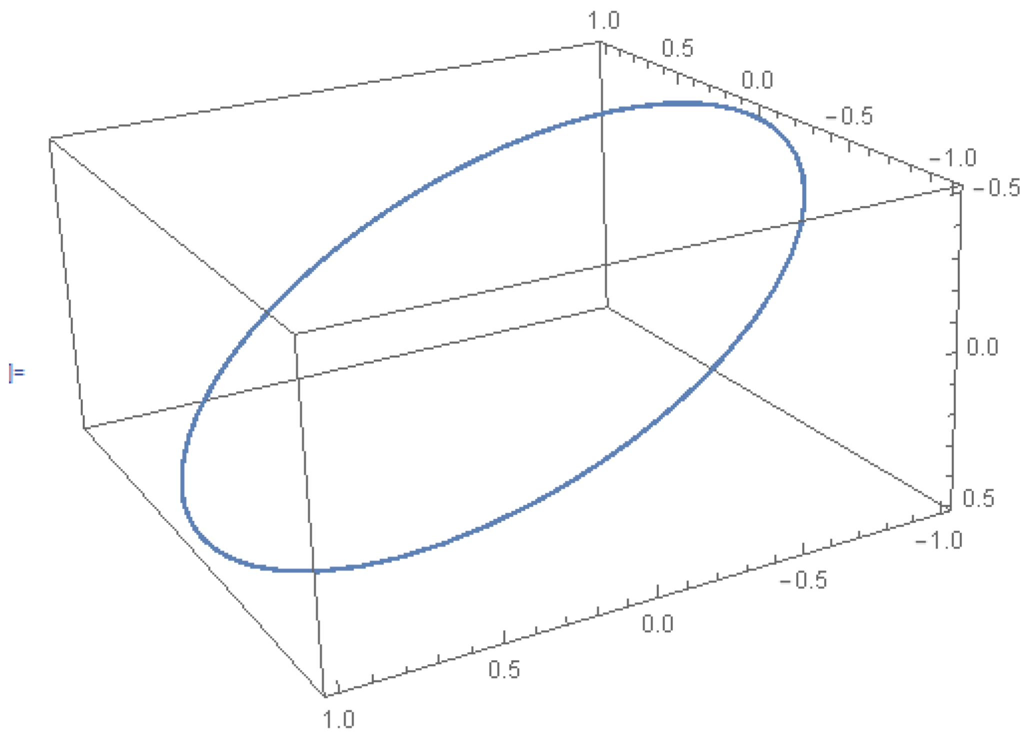


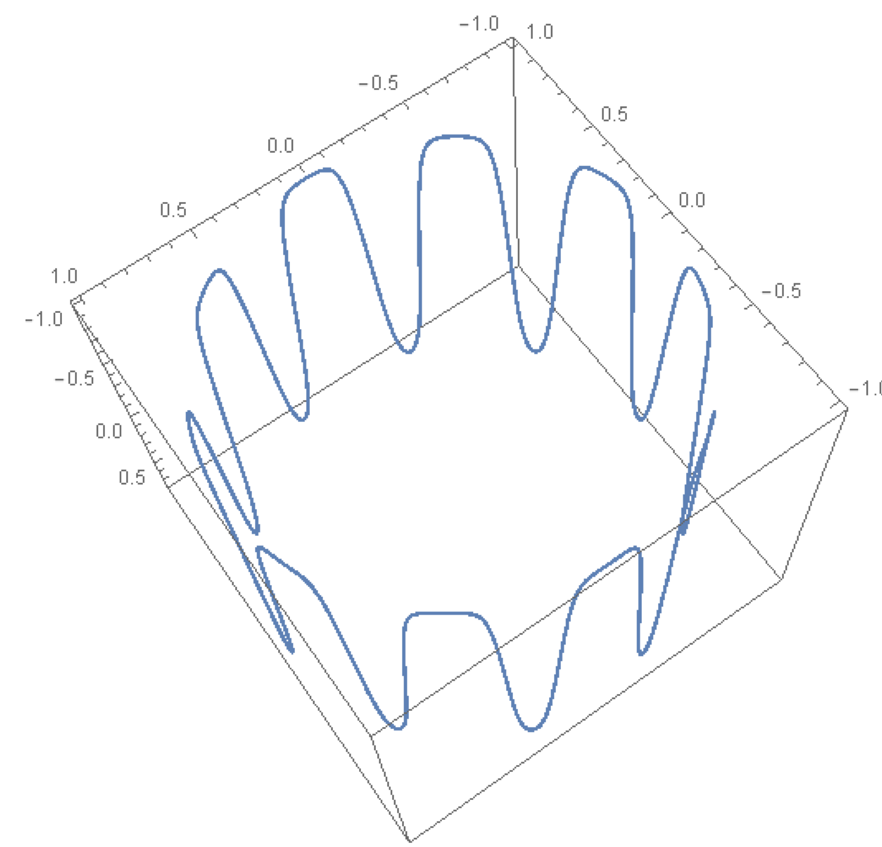
Mante et al. 2013

But the method does not capture

- How the complexity is generated by the network.
- Nonlinear properties

Nonlinearity can obscure PCA dimensions

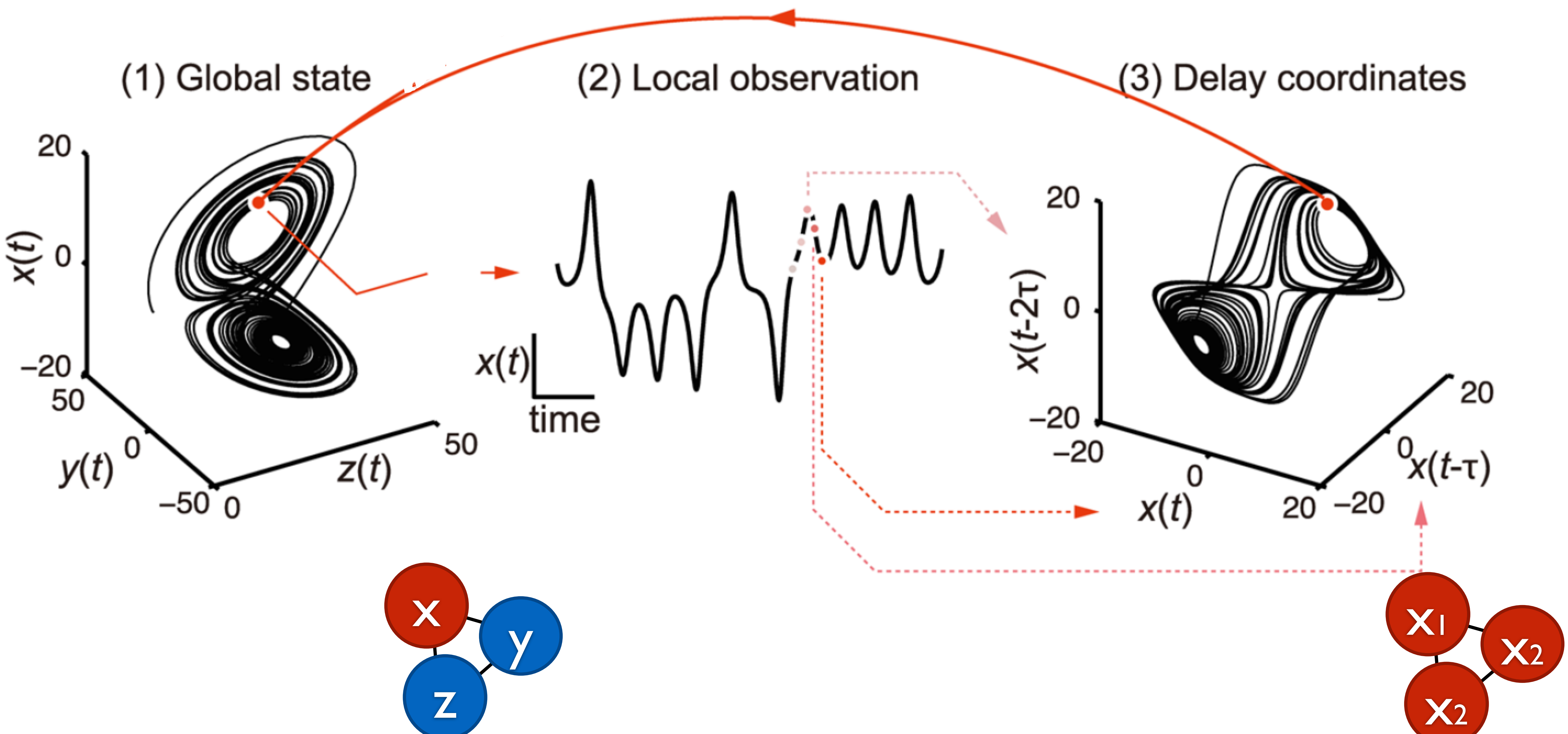




We develop a model-free, nonlinear method that can estimate fundamental **dynamical complexity** and show that it is related to **information processing hierarchy**.

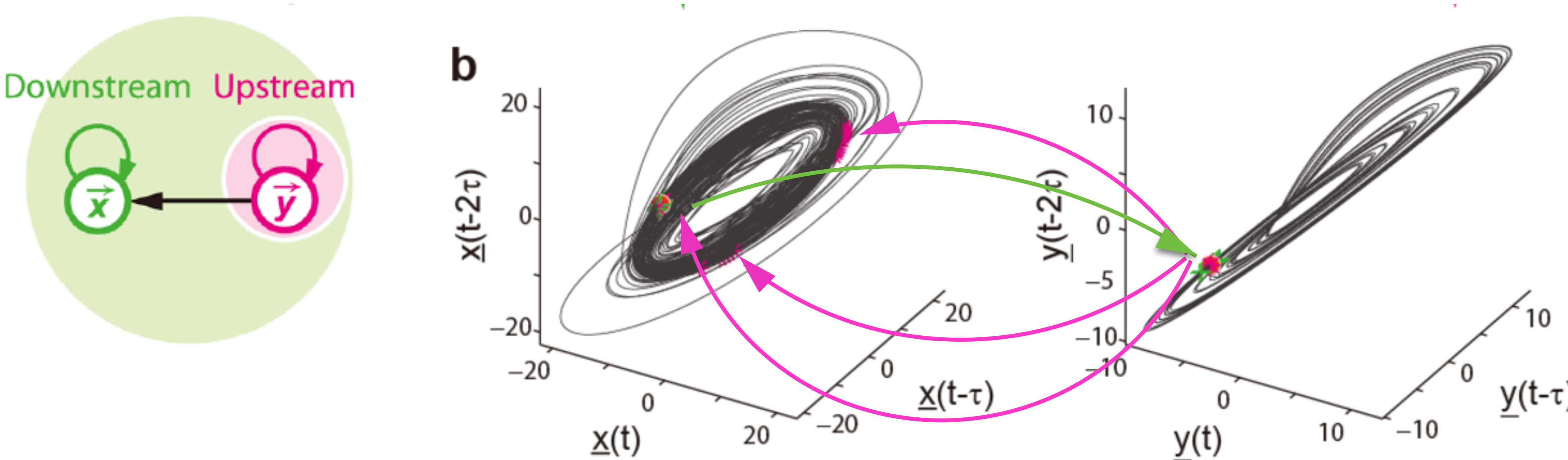
Delay embedding
— a principle in deterministic dynamical systems —

The Takens embedding theorem guarantees a mapping with one-to-one correspondence between a global state and a local state in delay-coordinates (with enough dimensions).



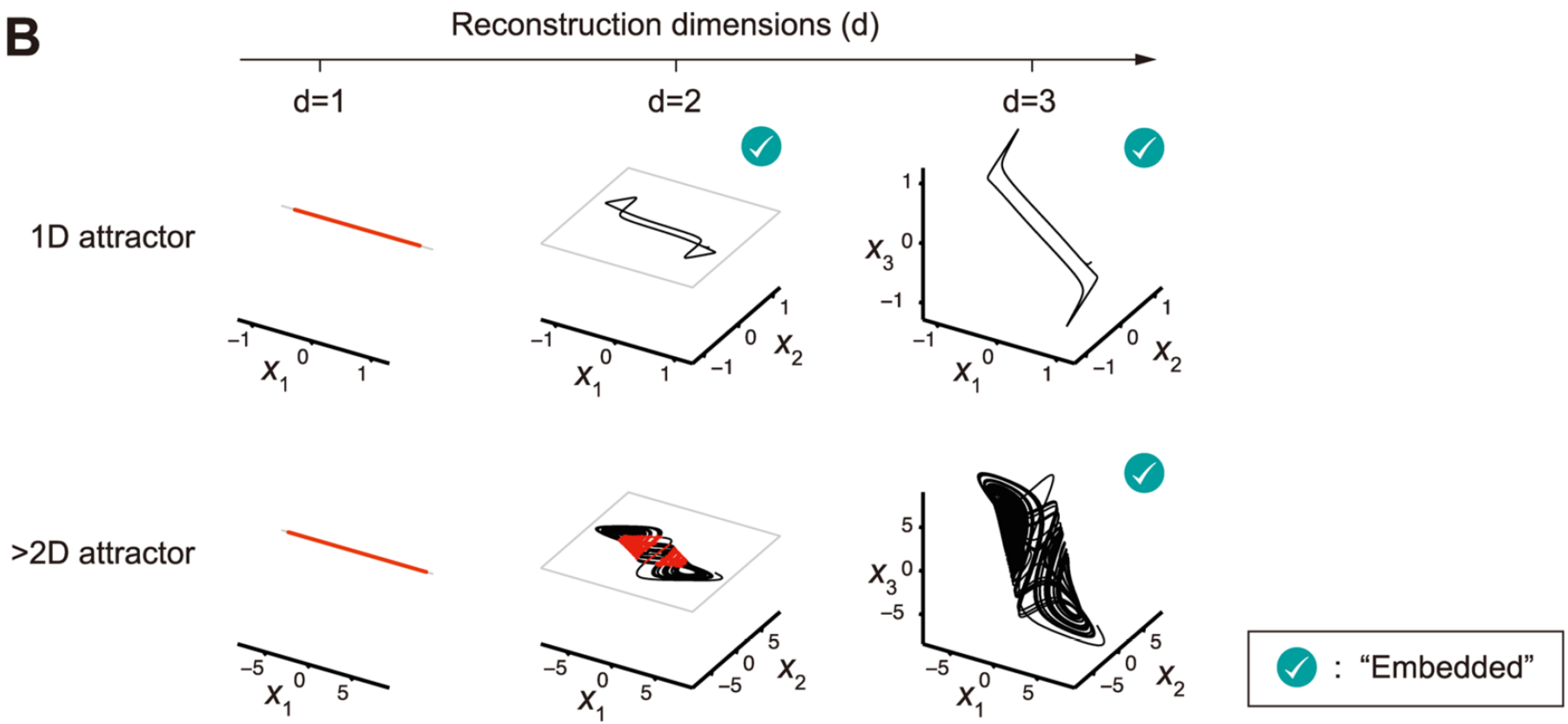
Cross-embedding reveals causal network interactions

Sugihara et al. 2012



Generically, the state of the upstream node is completely specified by the observation of the downstream node.

Embedding can be used to define the complexity: Embedding requires sufficient dimensionality



Nice principle.
In practice, the estimated dimension is sensitive to the time bin
-- the estimation is biased if observations are coherent with the dynamics.

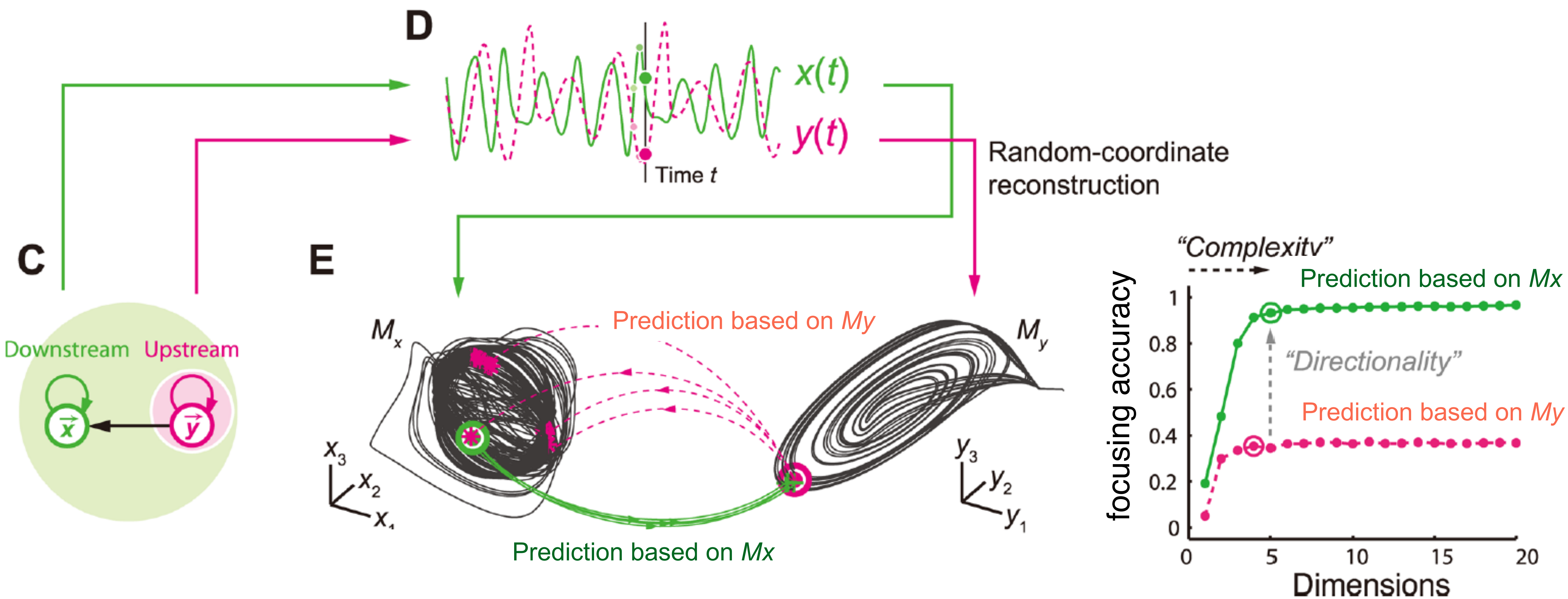
We propose a simple extension:
embedding timeseries in **randomized** delay coordinates.

This allows us to reliably and simultaneously estimate

the **complexity** of each node
and
information flow between pairs of nodes.

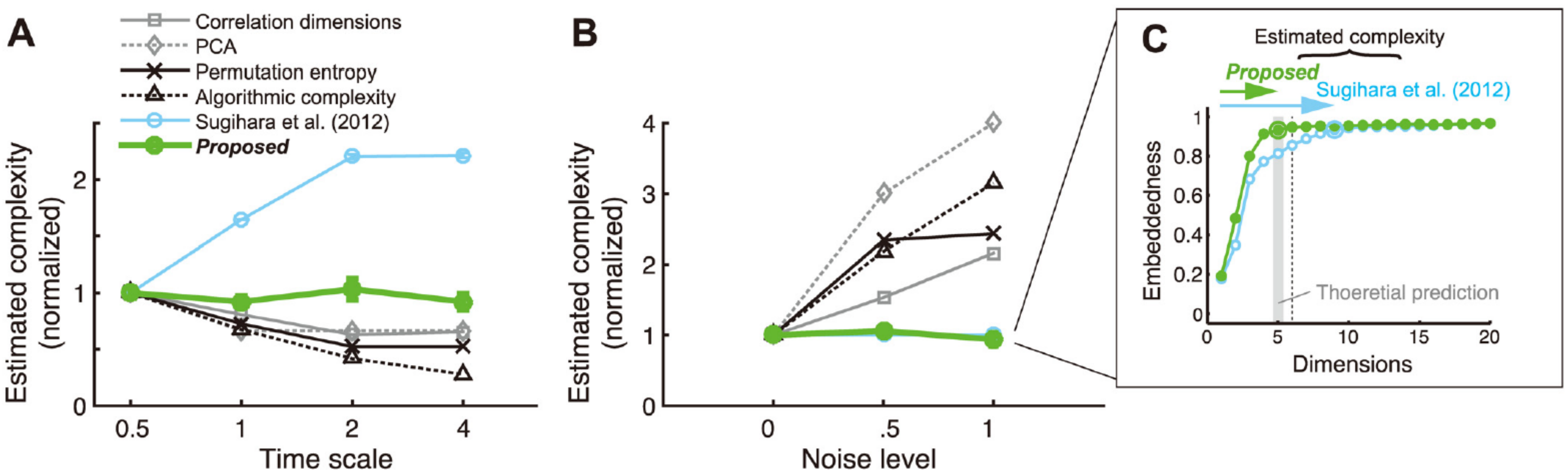
Cross-embedding in randomized delay-coordinates for accurate dimensionality estimation

Tajima et al. 2015



The downstream attractor must have higher dimensions than the upstream attractor.

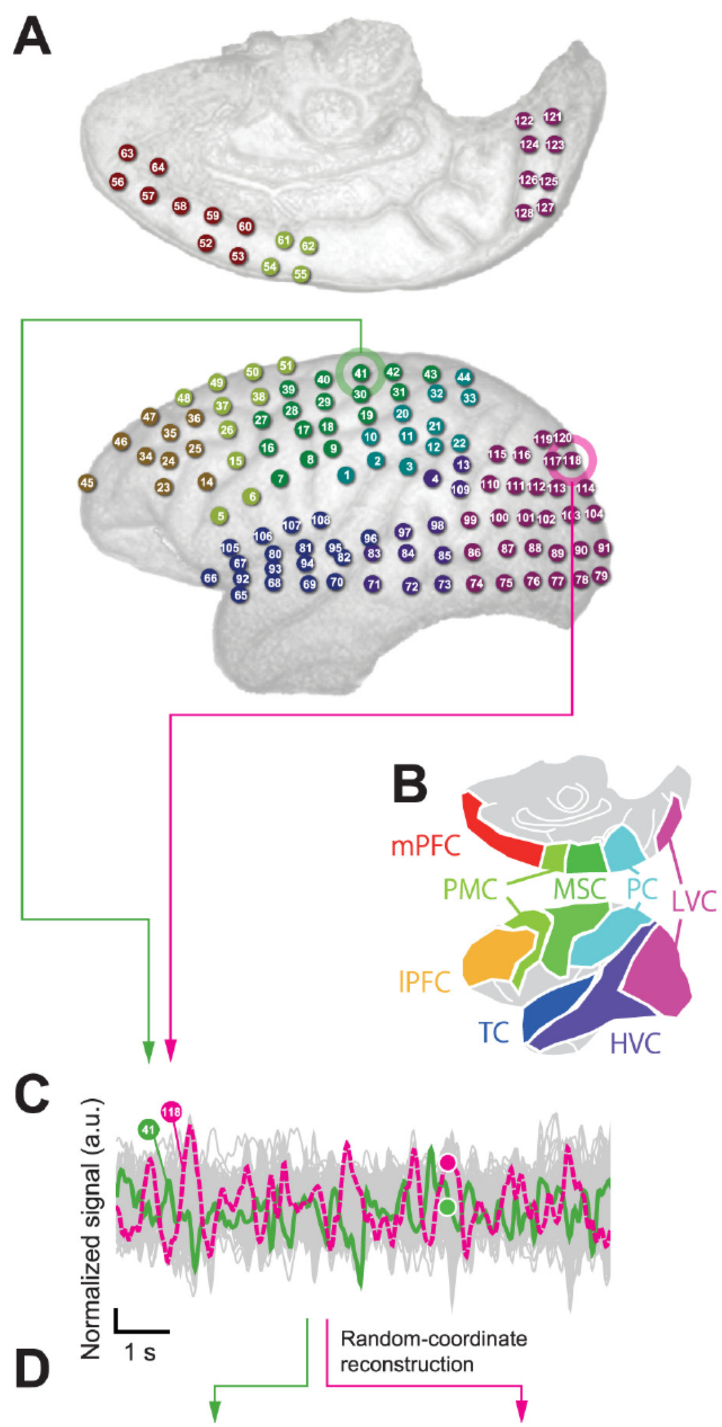
Randomized delay-coordinates enable robust estimation of dynamical complexity.

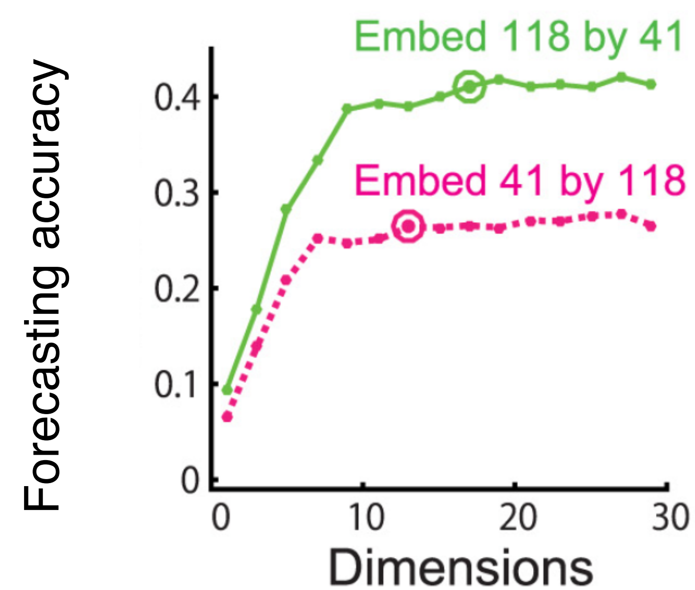


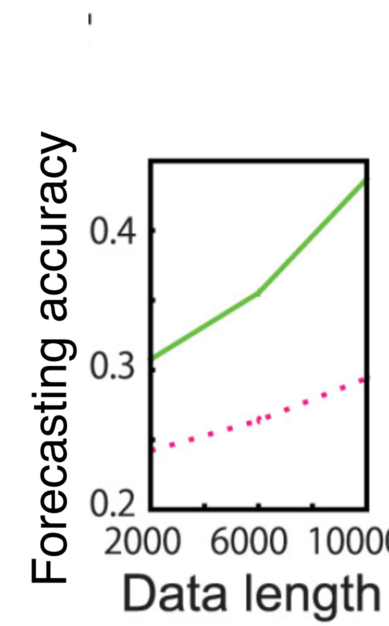
An application to neural activity data

Large-scale ECoG recording from monkeys

Yanagawa et al. 2013

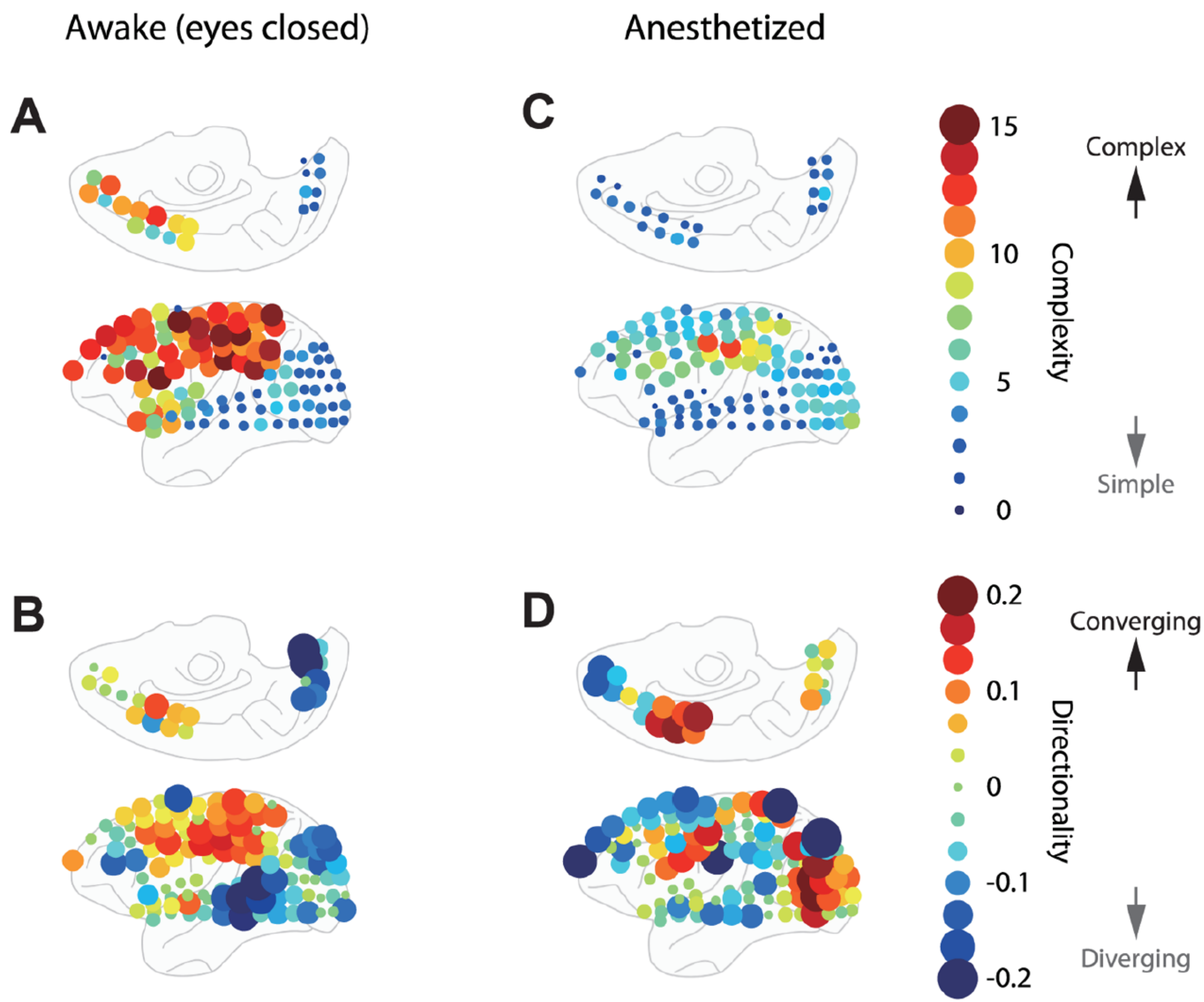






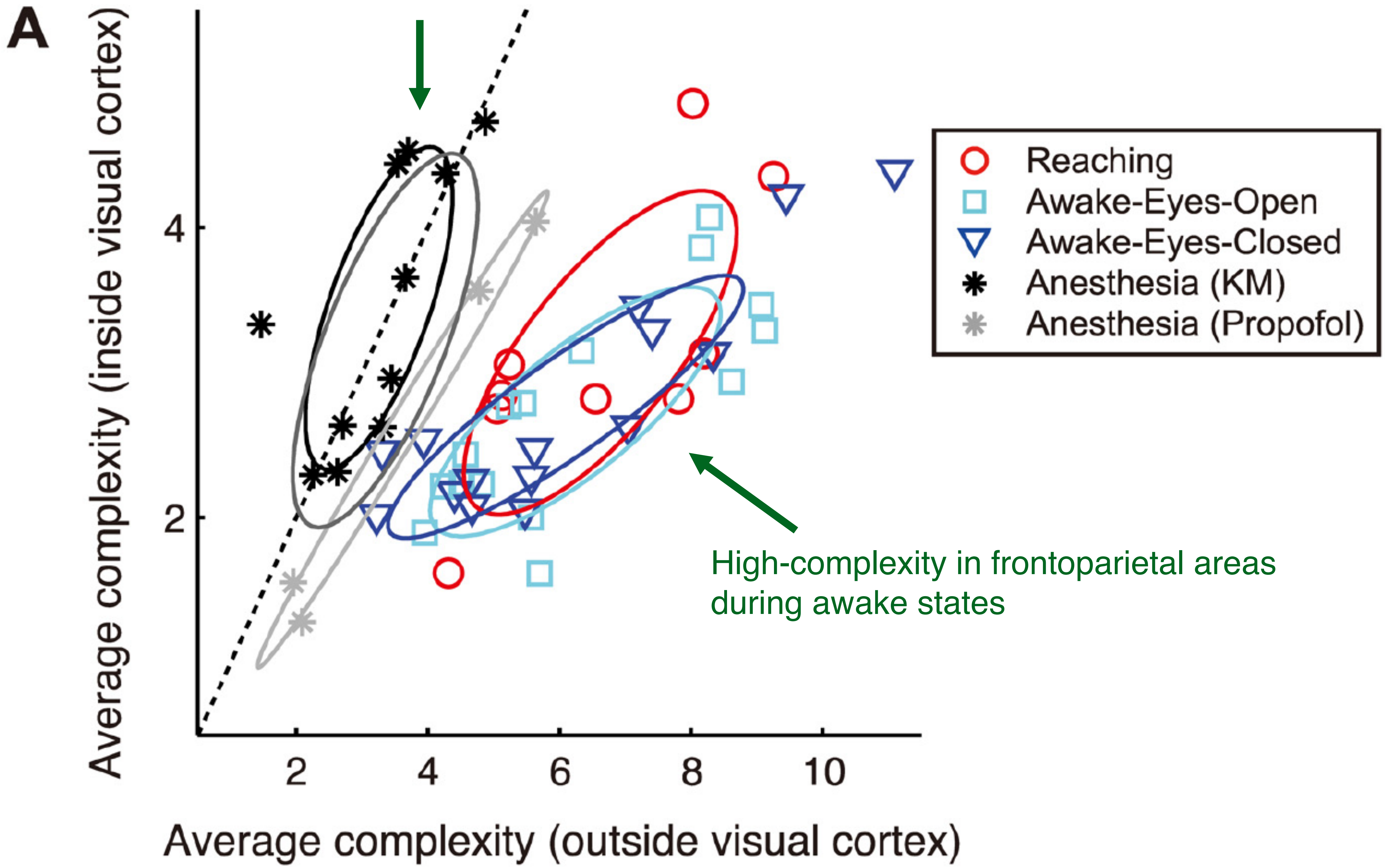
Information flows from 118 to 41.
The complexity of 118 is 13 dimensions.
The complexity of 41 is 17 dimensions.

Signatures of the awake brain dynamics



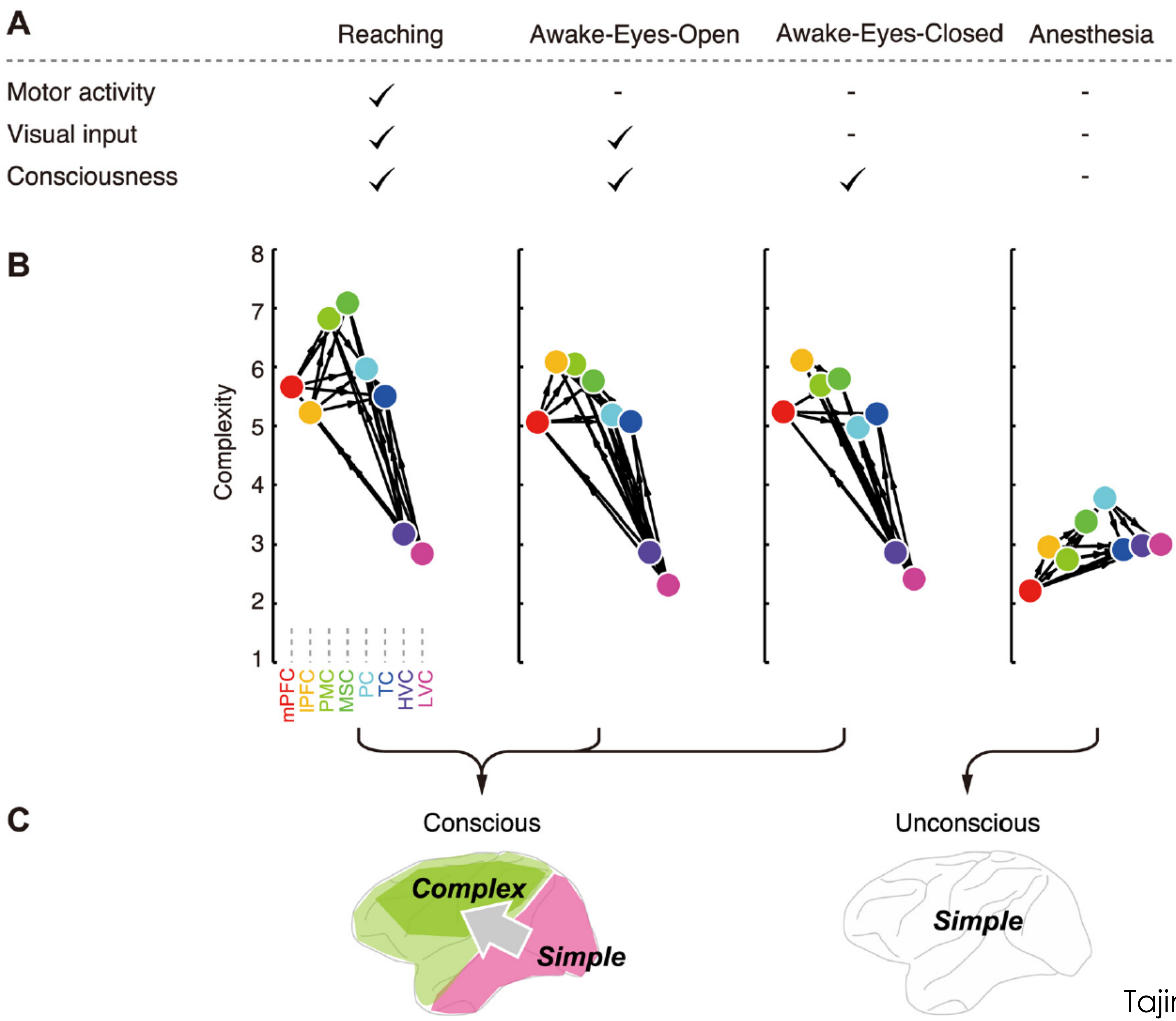
Consistency across conditions

Overall low-complexity during anesthesia.



High-complexity in frontoparietal areas during awake states

A hierarchy of cortical dynamics: The complexity increases along cross-areal information flow



Tajima et al. 2015

Summary 1

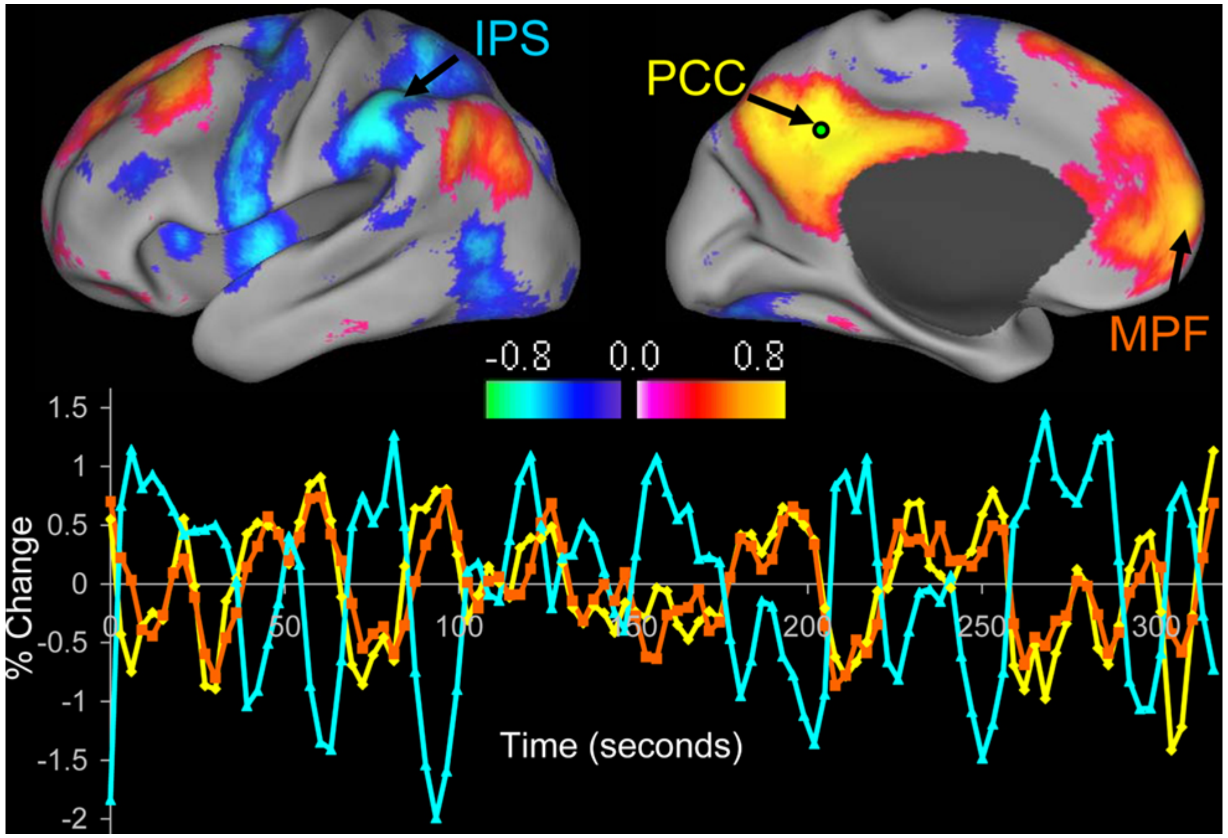
- We extended the embedding method for a model-free nonlinear characterization of neural dynamics.
- By randomized embedding coordinates, our method robustly extracts both dynamic complexity and information flow across brain regions.
- The approach reveals a new hierarchical organization of brain areas based on dynamical complexity.
- The approach is readily applicable for general large-scale network dynamics.

Characterizing dynamic complexity

Modeling dynamic complexity

The brain is active even at rest.

resting BOLD signal

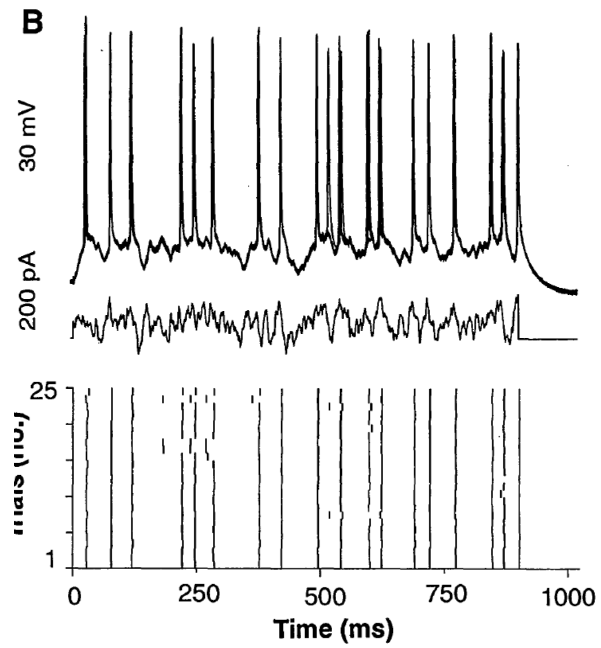


Fox and Greicius 2010

How to model neural variability?

Hypothesis:
variability due to “high-dimensional chaos”

- Dynamical behavior of a neuron is reliable in isolation.



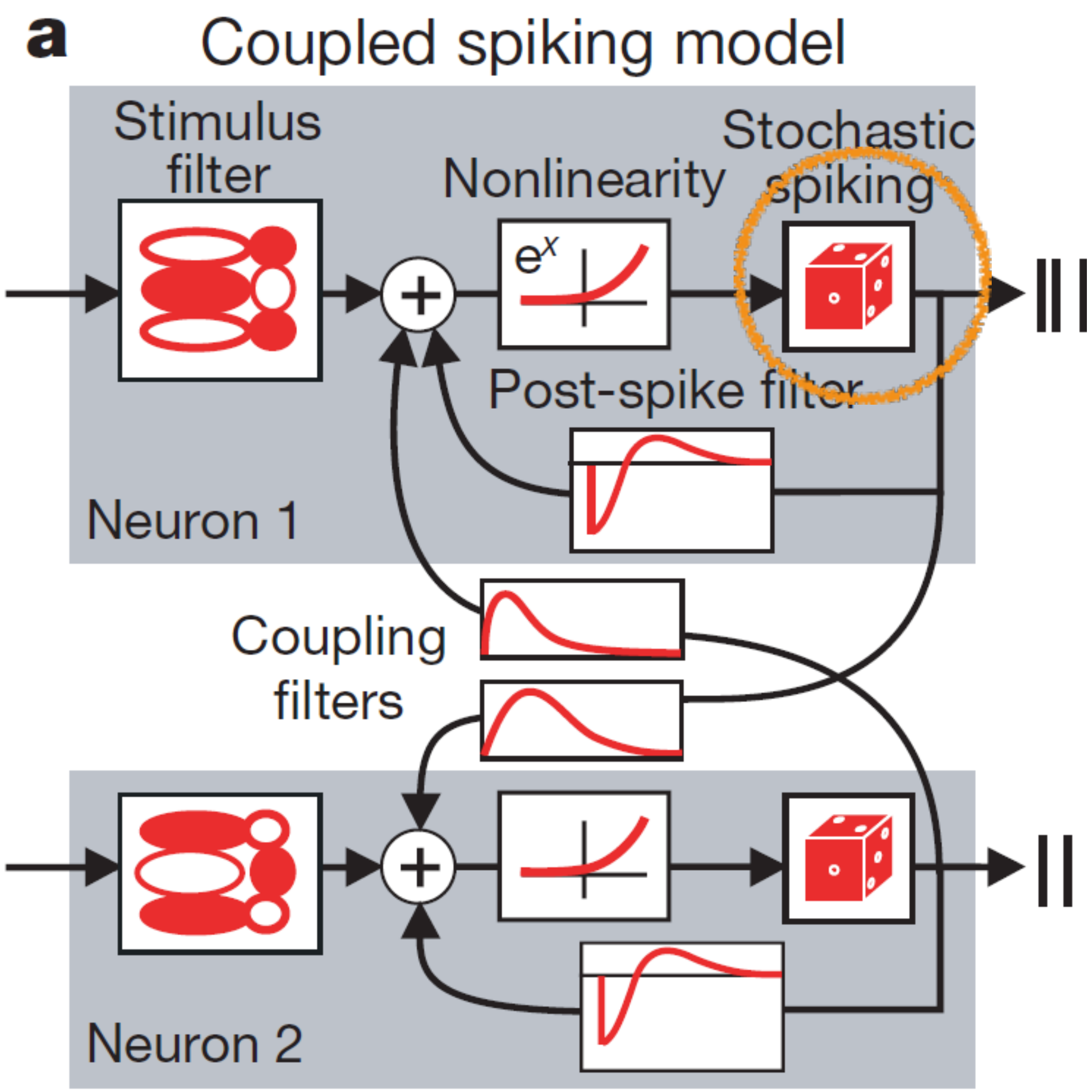
Mainen and Sejnowski 1995

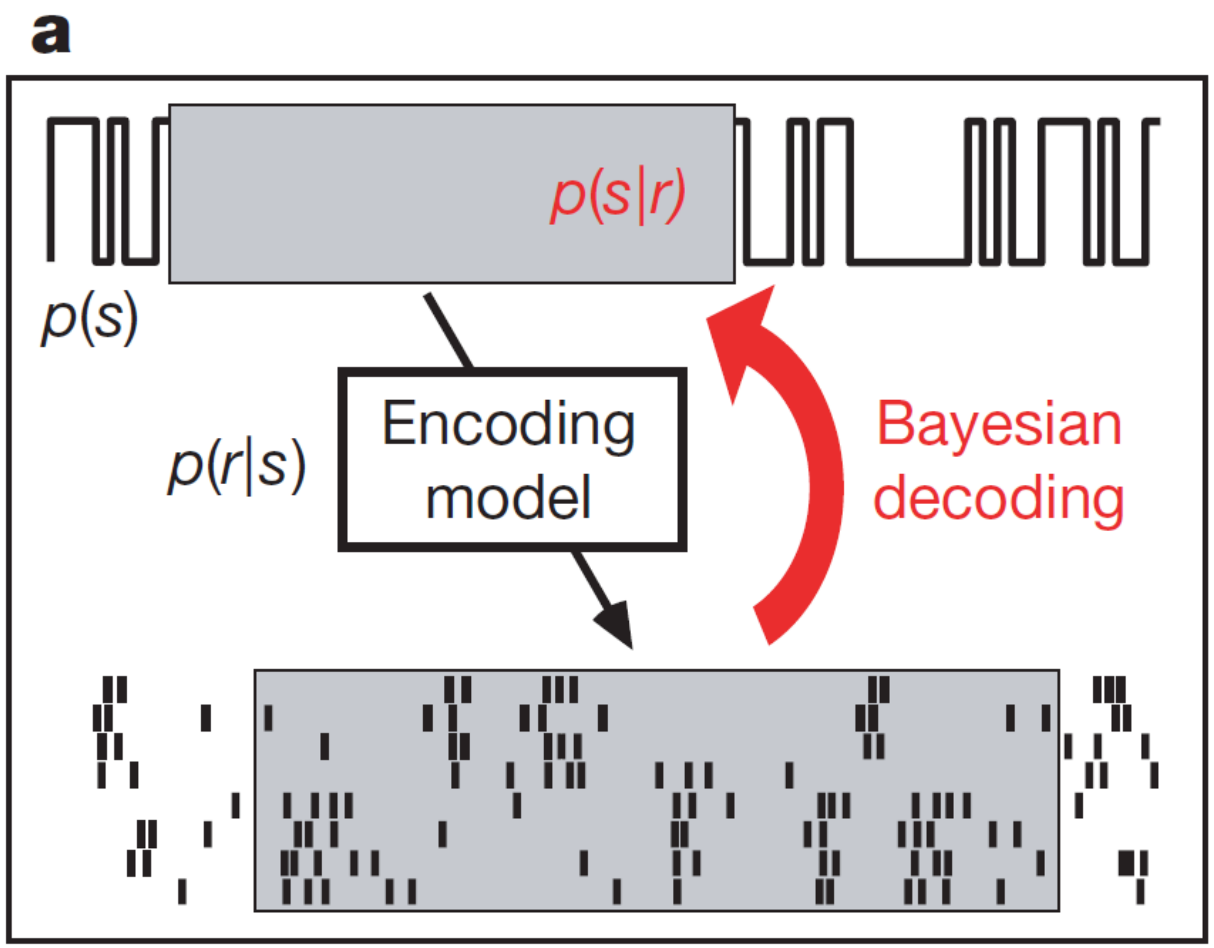
- One hypothesis is that the chaotic activity of a network of neurons produces the stochastic nature of background activity seen in vivo (van Vreeswijik and Sompolinsky 1996).

Alternative hypothesis: variability due to noise

Stochastic models have played an important role in the literature.

Stochastic networks for studying information coding



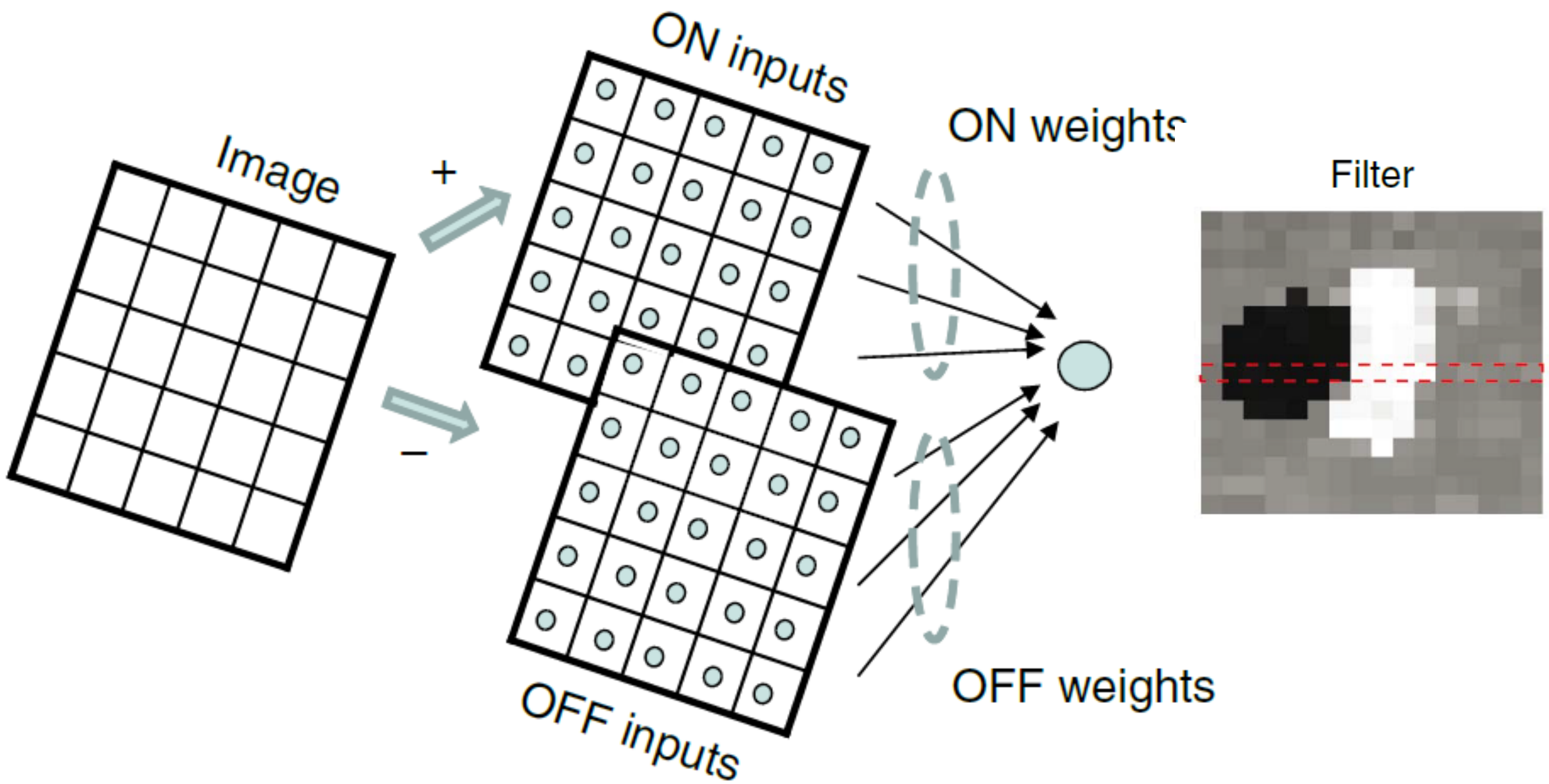


Pillow et al. 2008

Stochastic networks for studying plasticity

θ_-. The linear Poisson neuron generates spikes stochastically with stochastic firing intensity ν^{post} proportional (with parameter $1/\alpha$) to u^s, hence the probability of firing in a short time between t and $t+\Delta$ is $P_F(t;t+\Delta) = \nu^{\text{post}}(t)\Delta = u^s(t)\dfrac{\Delta}{\alpha}$.

a



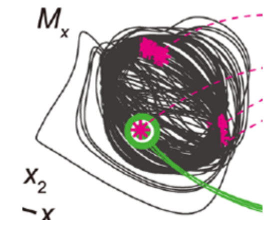
Clopath et al. 2010

How does the origin of neural variability affect neural coding and plasticity?

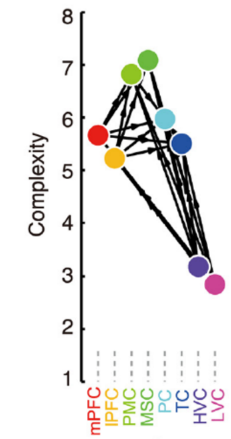
Summary 2

- We have proposed a one-parameter family of networks, interpolating between the deterministic and stochastic networks, that share the same spontaneous activity.
- The response to external stimulus monotonically increases with the coupling strengths in this family.
- The consequence of plasticity depends on the origin of variability.
- The deterministic network with chaotic dynamics can perform near optimal Monte Carlo sampling by integrating sensory cues.

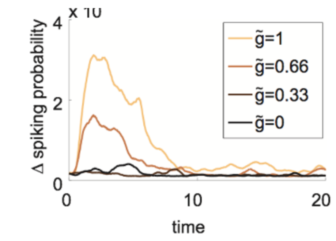
Neural attractors can represent



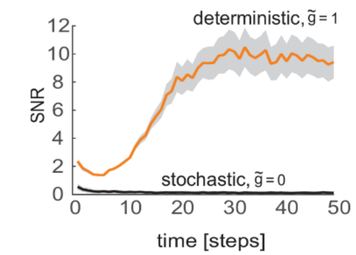
- state-dependent hierarchical information flow



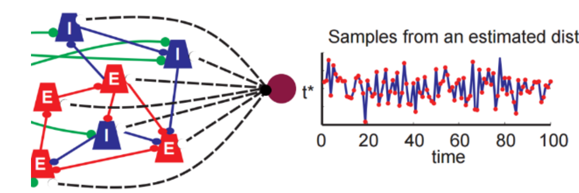
- neural sensitivity to sensory input



- efficiency of synaptic plasticity and learning



- sampling based on integrated information



Topological characterization of neural attractors would shed light on the information used in these processes…

Acknowledgement

- Collaborators

Embedding:

- Satohiro Tajima (RIKEN BSI / U. Geneva)
- Toru Yanagawa (RIKEN BSI)
- Naotaka Fujii (RIKEN BSI)

Chaotic sampling:

- Sakyashingha Dasgupta (RIKEN BSI / IBM)
- Isao Nishikawa (U Tokyo)
- Kazuyuki Aihara (U Tokyo)

- Funding

Brain/MINDS

Brain Science Institute RIKEN