Novel Neuromorphic Deep Learning Architectures From Empirical Dynamical Modeling of the Zebrafish Brain

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&
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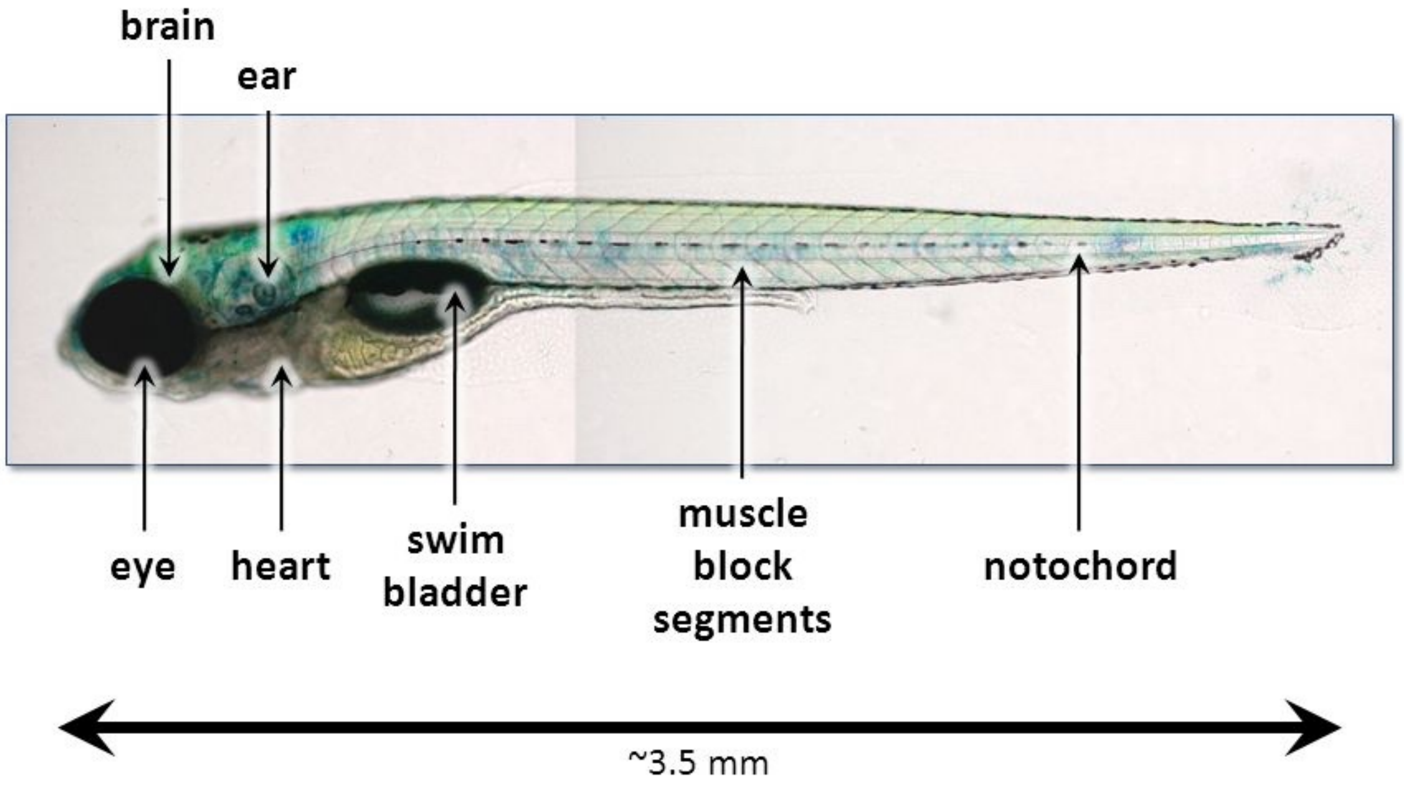
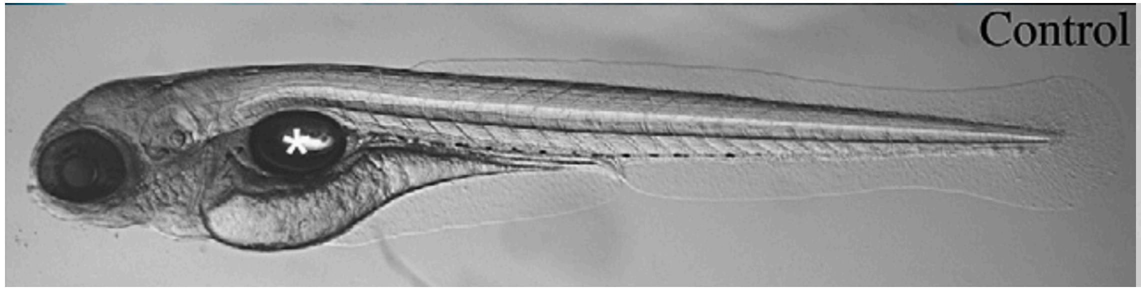
Laboratory of Genetics

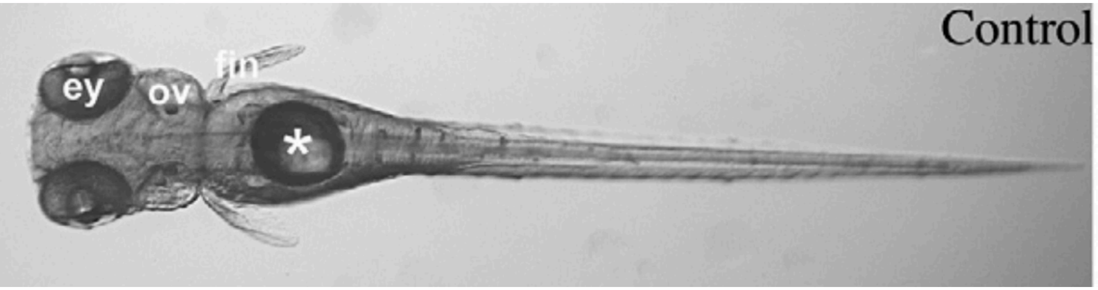
Using the Fish brain to test if brain activity can be transferred into deep learning architectures

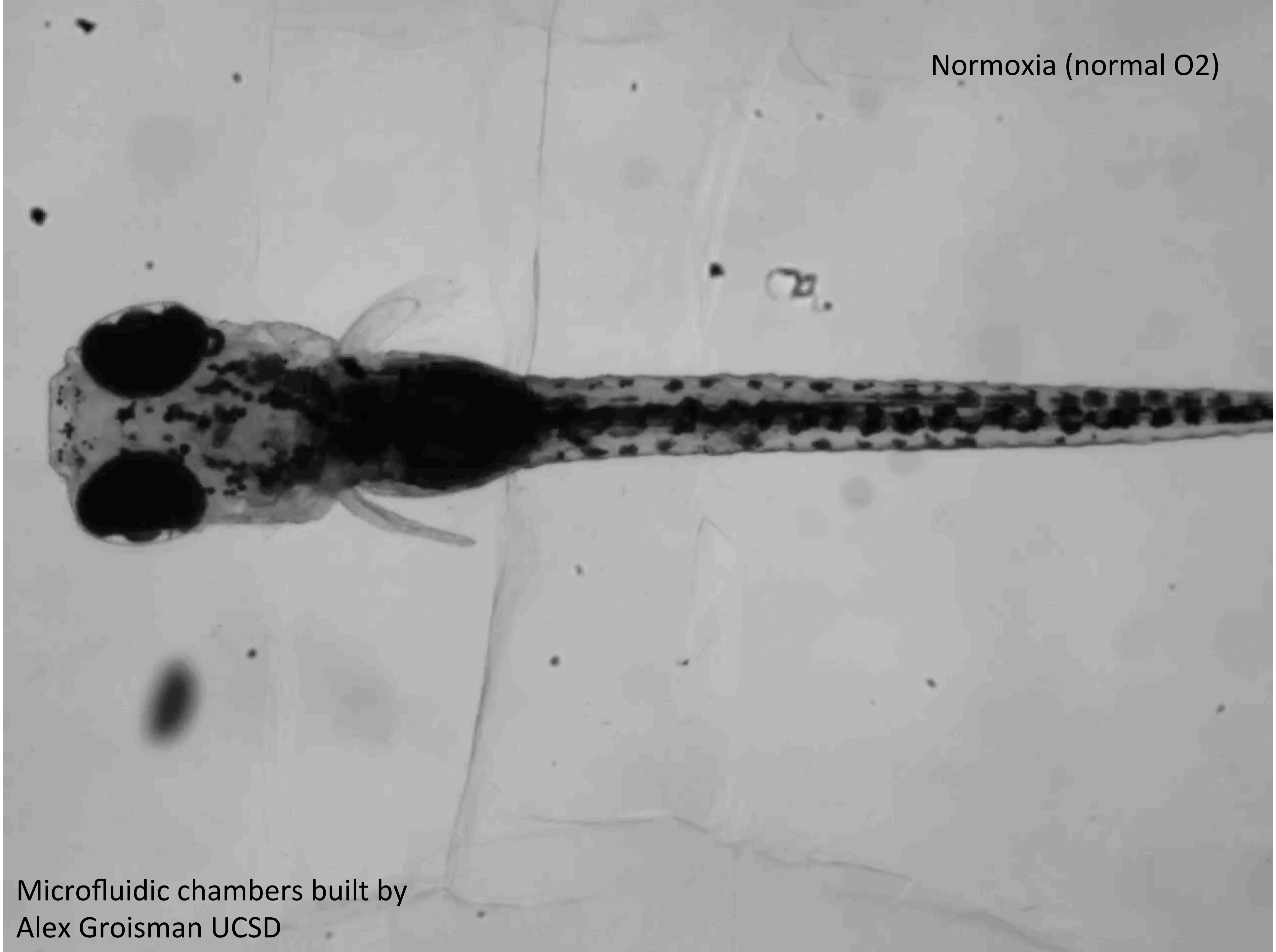
- Obtain whole brain neural activity at single cell resolution
- Extract relationship between real neurons
- Convert Relationships into something that can be transferred into a computational framework
- Adjust natural neural network to hardware/software
- Test performance in Biosimilar robots

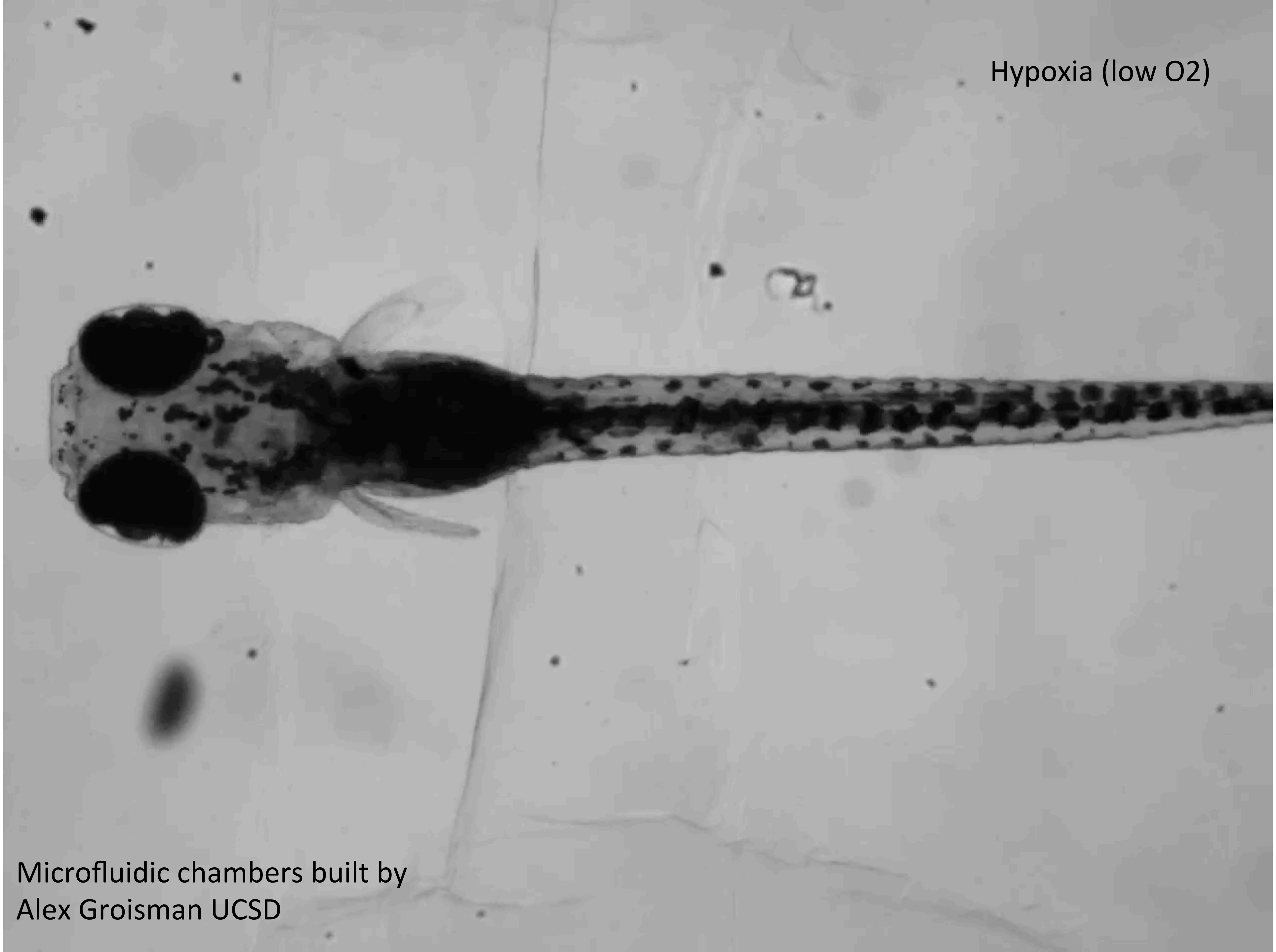
The zebrafish embryo



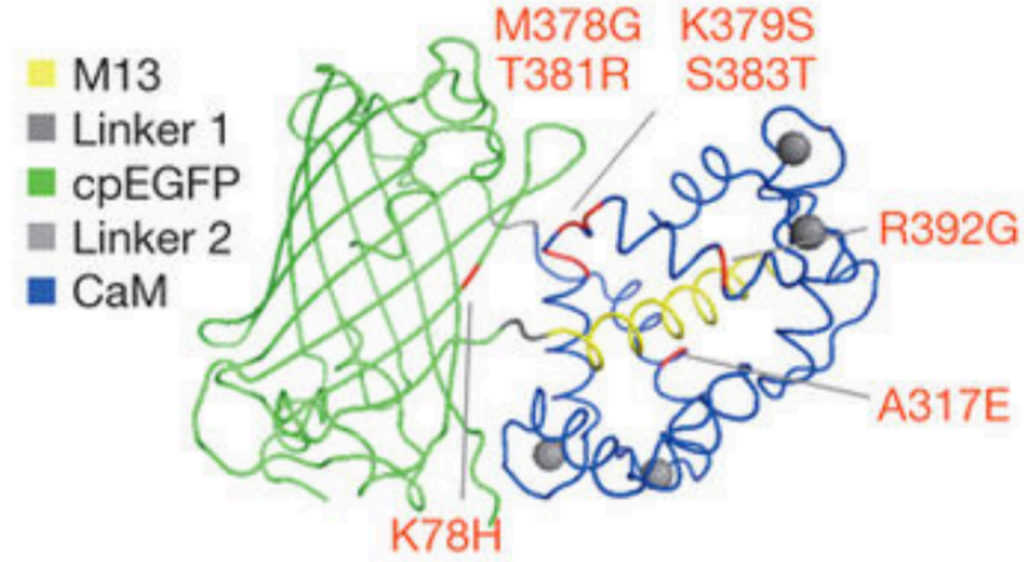





Normoxia (normal O2)
Microfluidic chambers built by
Alex Groisman UCSD

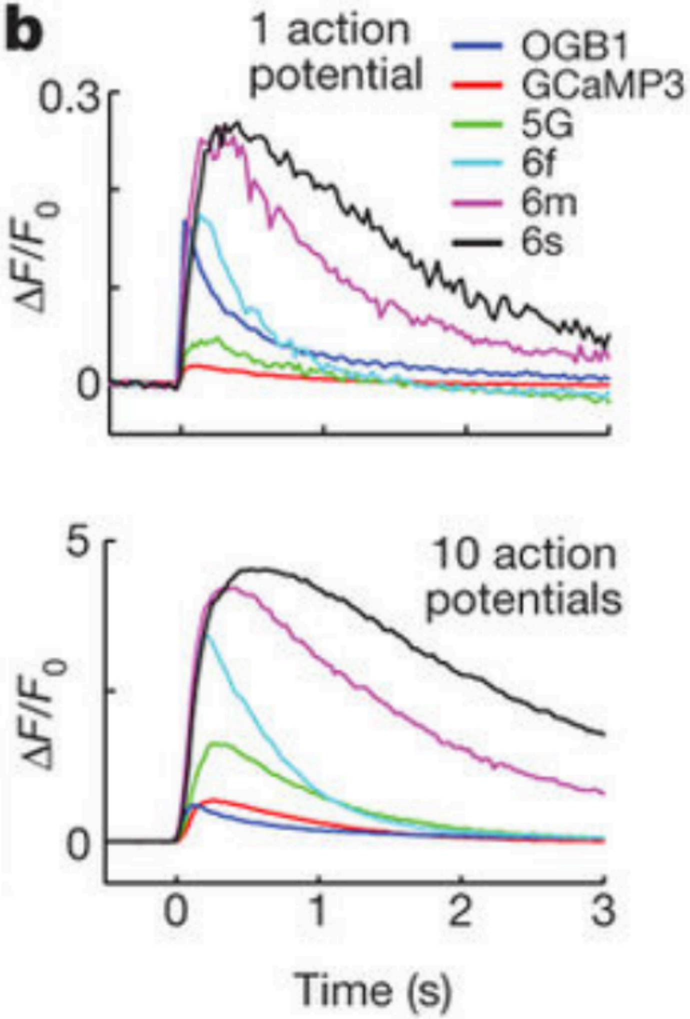

Hypoxia (low O2)
Microfluidic chambers built by
Alex Groisman UCSD

a

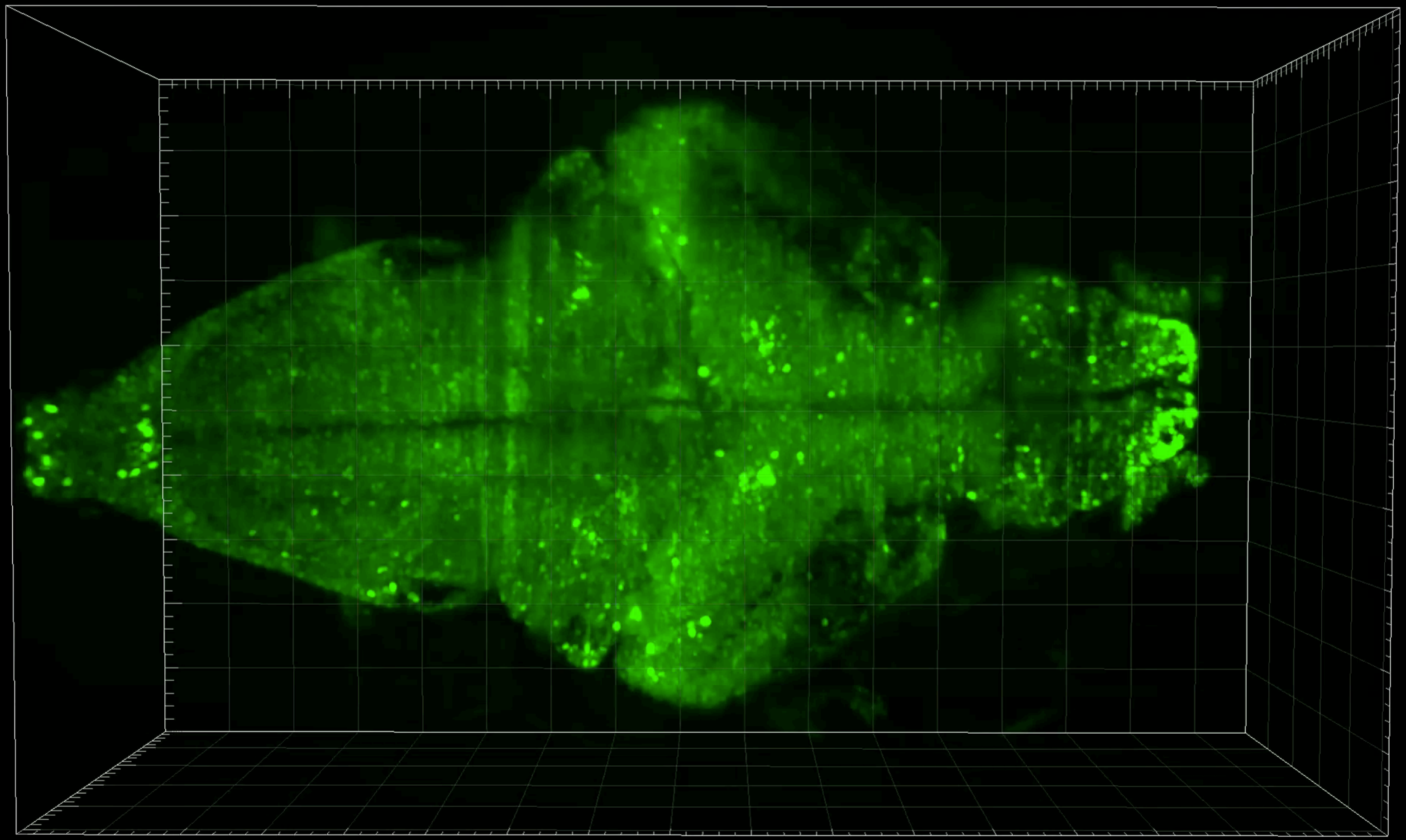


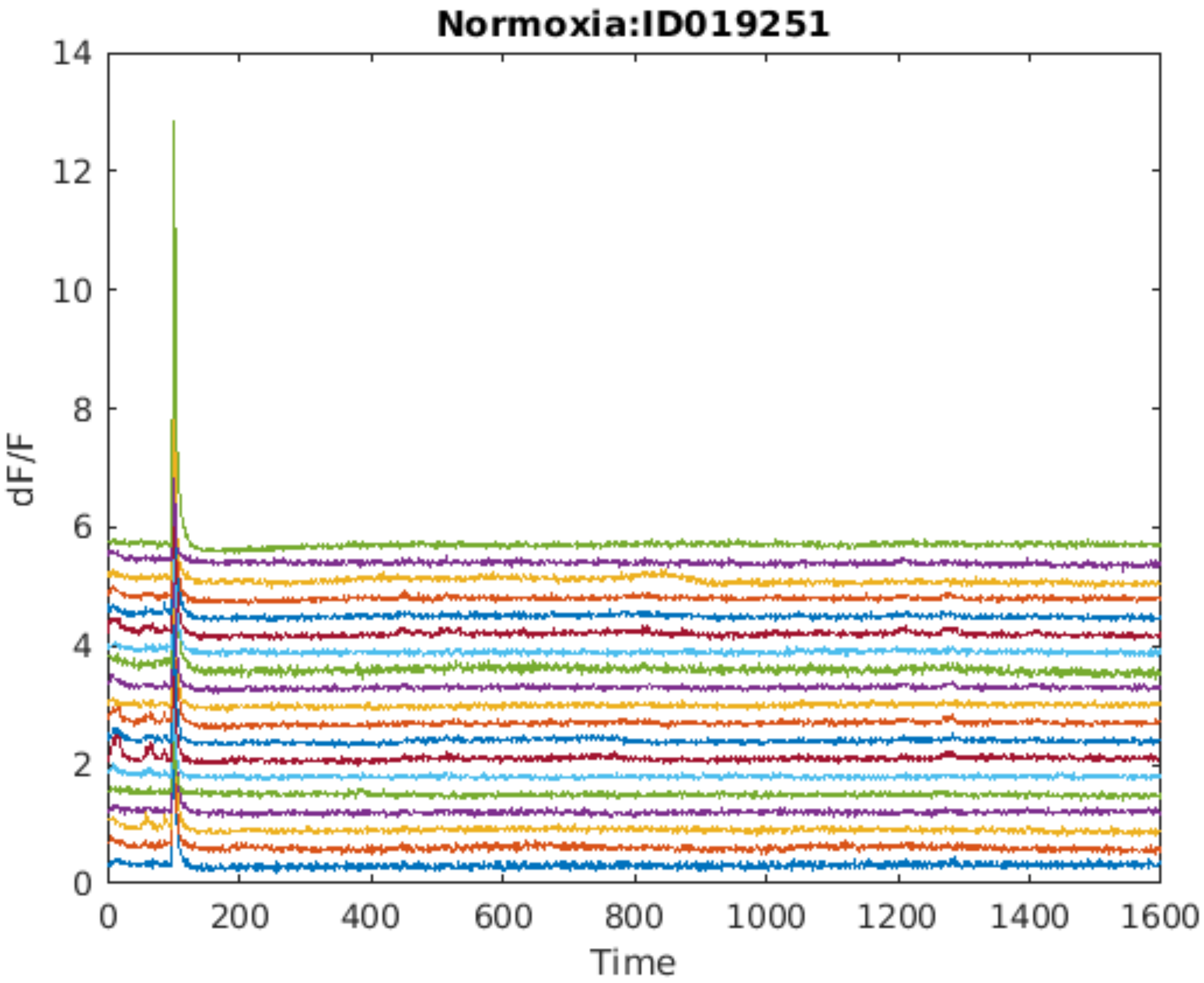
	cpEGFP	CaM					
GCaMP5G	K78	A317	M378	K379	T381	S383	R392
GCaMP6s	K78H				T381R	S383T	R392G
GCaMP6m			M378G	K379S	T381R	S383T	R392G
GCaMP6f		A317E			T381R	S383T	R392G

b



Live Calcium imaging of whole Brain Neuronal Activity of the Zebrafish embryo with Light Sheet Microscopy

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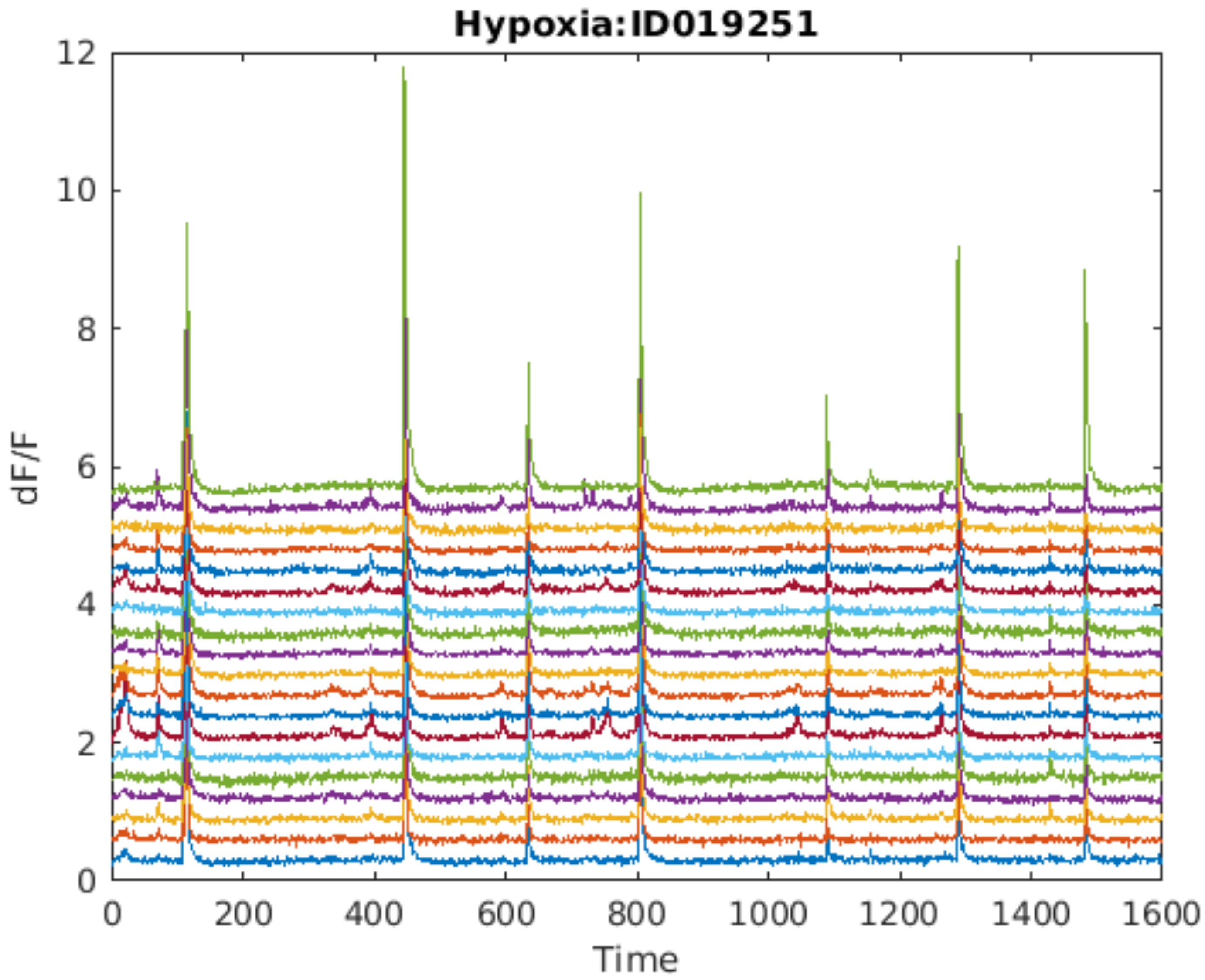
1200
1400
1600


Hypoxia:ID019251
dF/F
Time
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2
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400
600
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1000
1200
1400
1600

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RESEARCH ARTICLE

Detecting Causality in Complex Ecosystems

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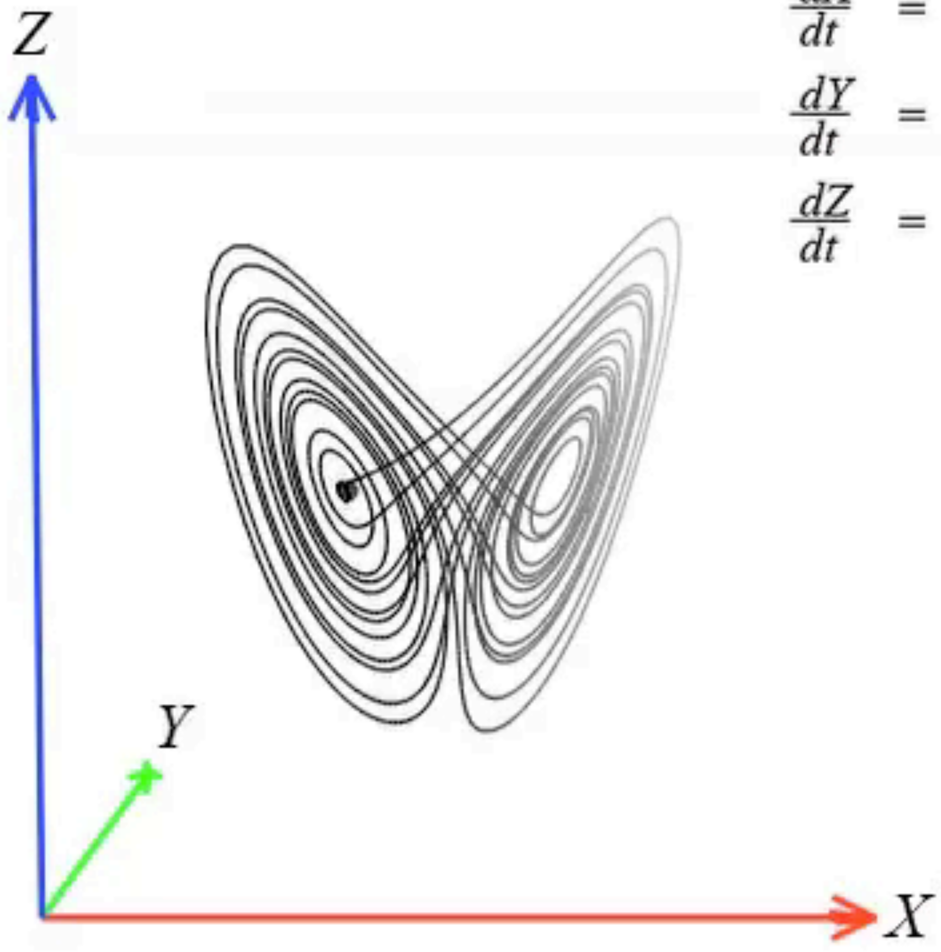
ABSTRACT

Identifying causal networks is important for effective policy and management recommendations on climate, epidemiology, financial regulation, and much else. We introduce a method, based on nonlinear state space reconstruction, that can distinguish causality from correlation. It extends to nonseparable weakly connected dynamic systems (cases not covered by the current Granger causality paradigm). The approach is illustrated both by simple models (where, in contrast to the real world, we know the underlying equations/relations and so can check the validity of our method) and by application to real ecological systems, including the controversial sardine-anchovy-temperature problem.

Attractor reconstruction from Time Series



$$
\begin{aligned}
\frac{dX}{dt} &= -\sigma Y + \sigma X \\
\frac{dY}{dt} &= -XZ + \rho X - Y \\
\frac{dZ}{dt} &= XY - \beta Z
\end{aligned}
$$

Takens 1981

Let M be a compact manifold of dimension m, F a smooth (c^2) vector field, and h a smooth function on M. It is a generic property that

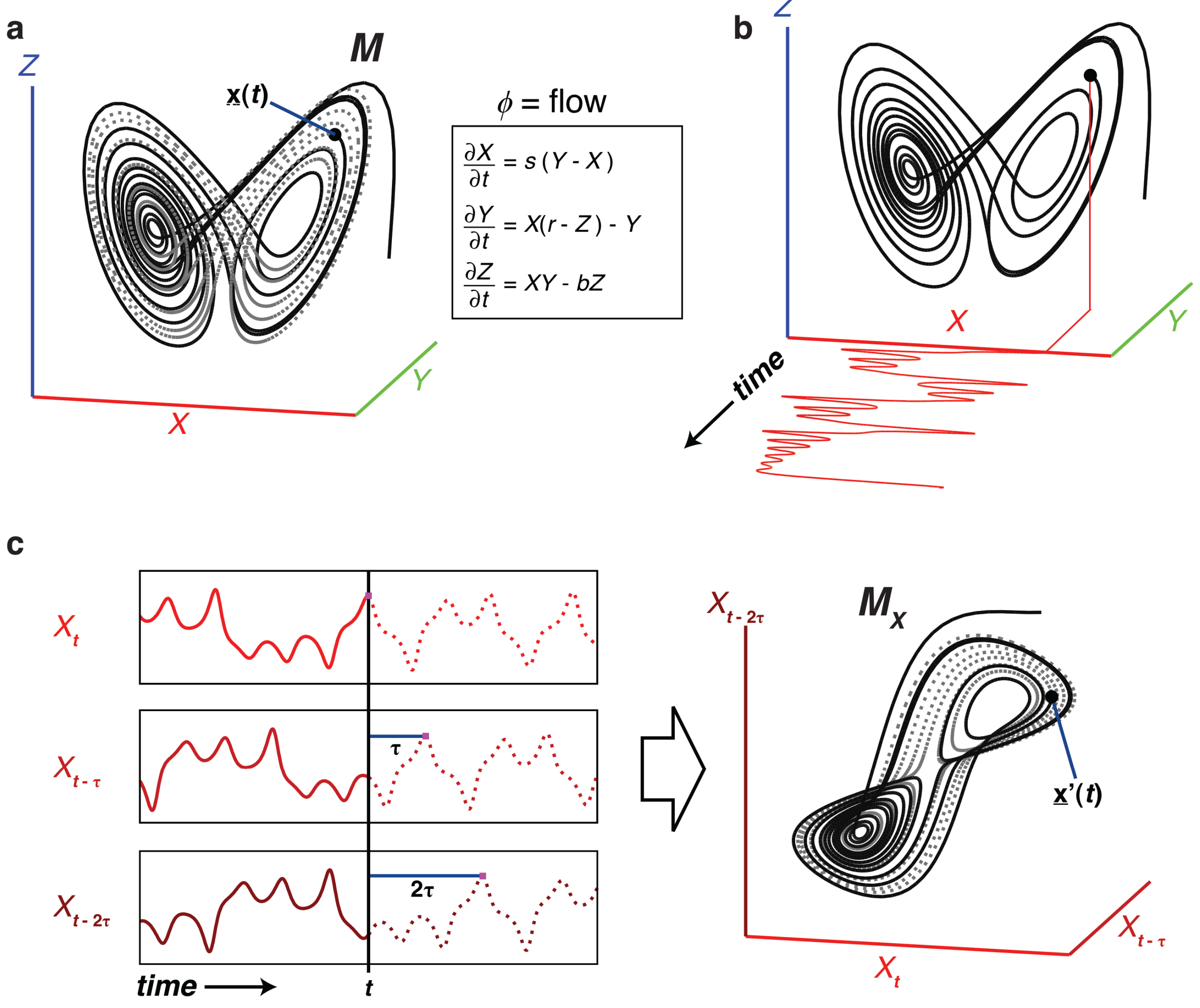
$$\Phi_{F,h}(m): \quad M \Rightarrow R^{2m+1}$$

Is an embedding, where f^t is the flow of F on M and

$$\Phi_{F,h}(m) = (h(f(m)),\ h(f'(m)),\ h(f^2(m)),\ \ldots,\ h(f^{2m}(m))$$

An Illustration of Taken's Theorem

Box 1 Figure



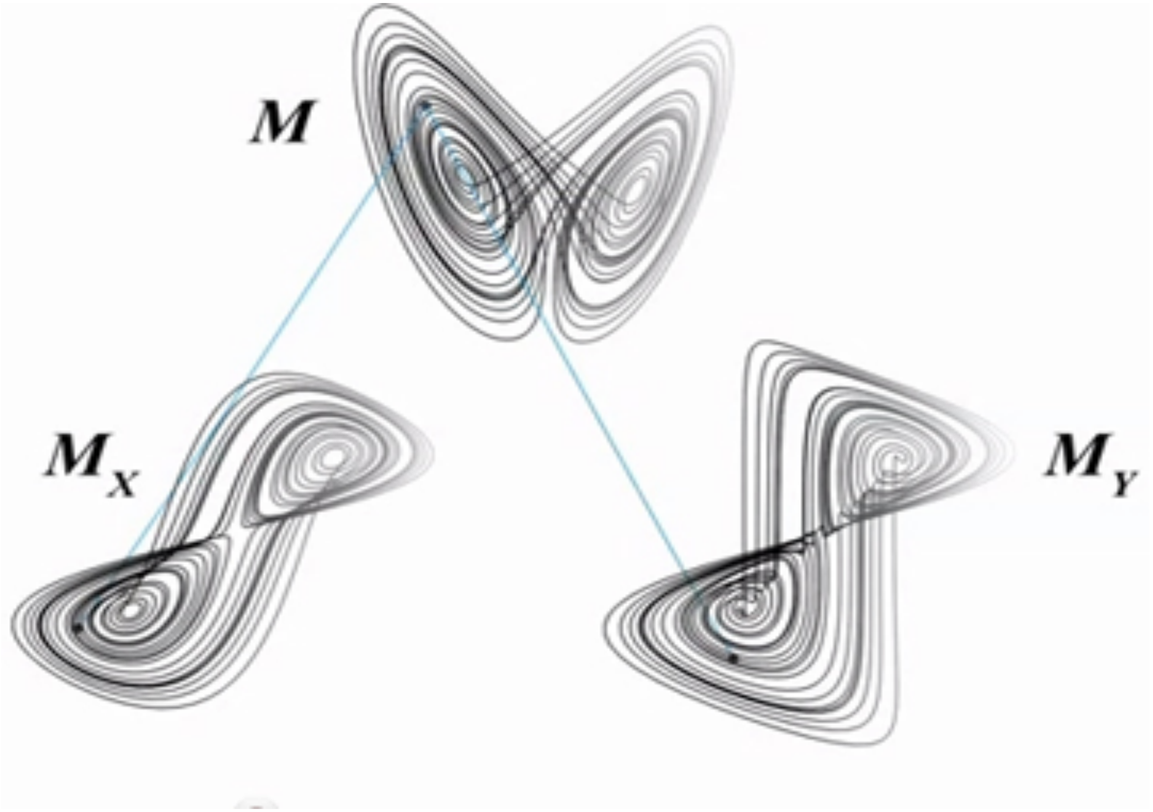
State Space Reconstruction: Convergent Cross Mapping

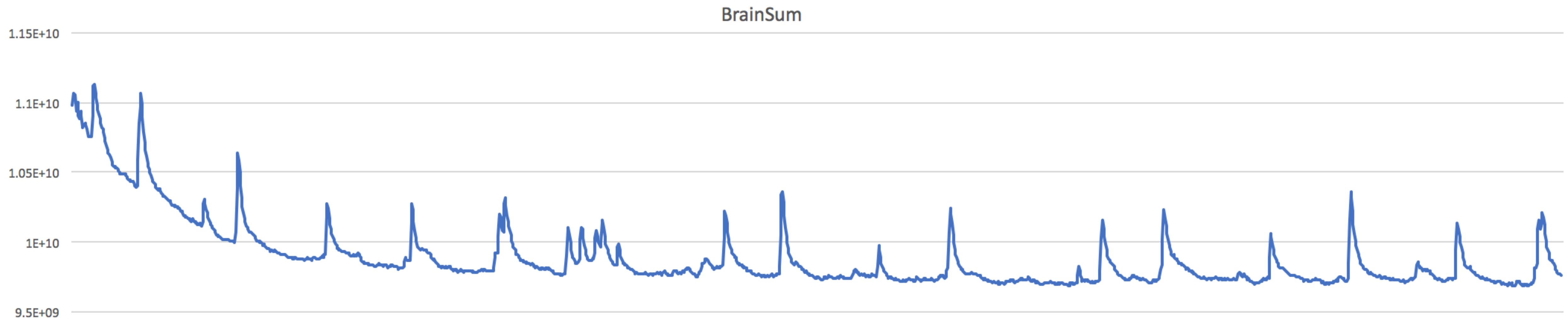
A supplemental simulation and animation for "Detecting Causality in Complex Ecosystems"

George Sugihara, Robert May, Hao Ye, Chih-hao Hsieh, Ethan Deyle, Mike Fogarty, and Stephan Munch

animation by: Peter Sugihara, Hao Ye, and George Sugihara

Convergent Cross Mapping tests the predictability across reconstructed shadow manifolds to infer causality.

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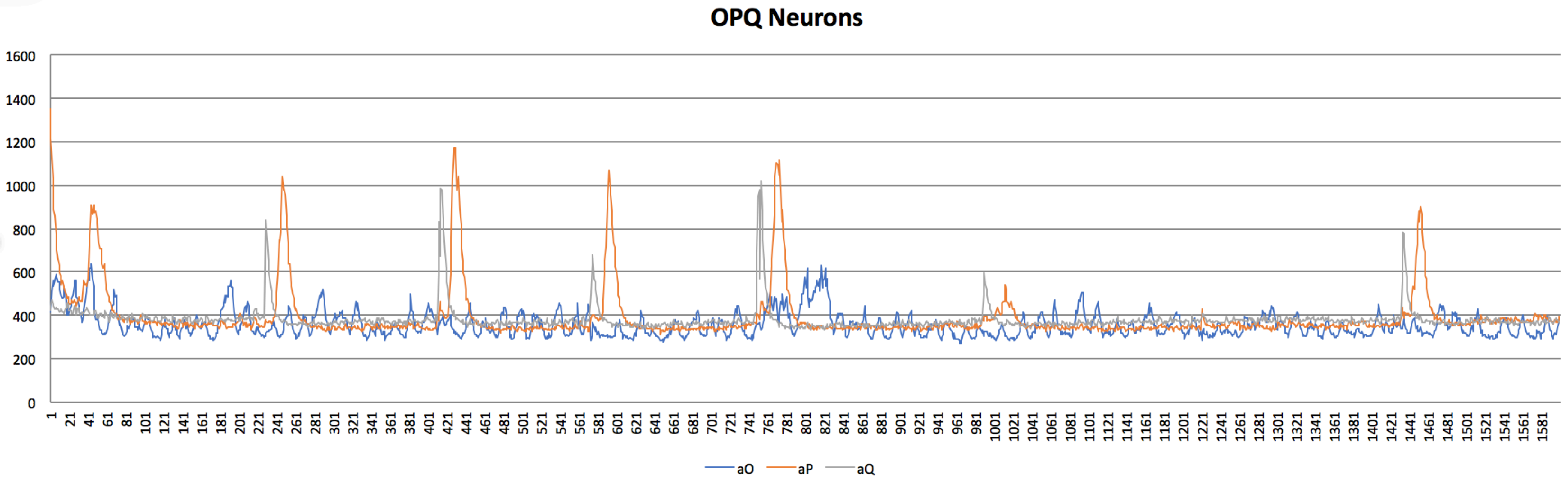
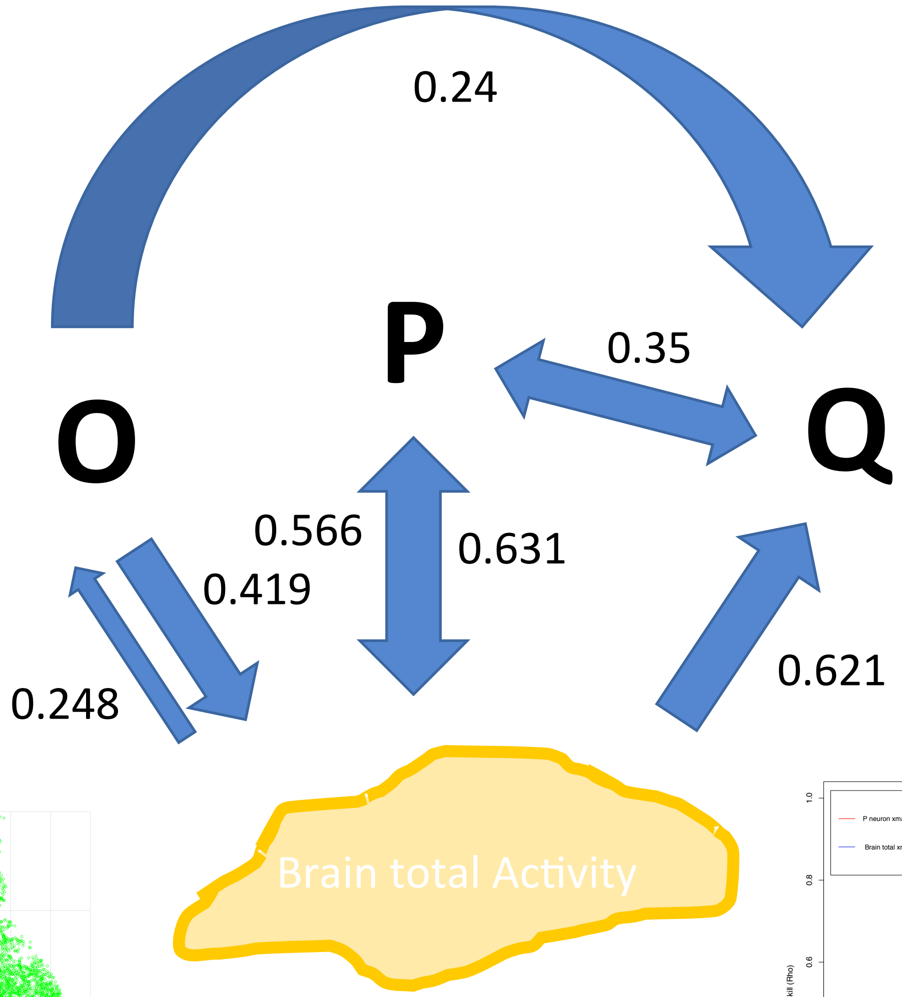
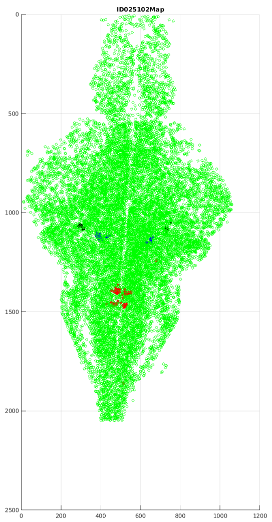
1.15E+10
1.1E+10
1.05E+10
1E+10
9.5E+09


OPQ Neurons
1600
1400
1200
1000
800
600
400
200
0
aO
aP
aQ



0.24
P
0.35
O
Q
0.566
0.631
0.419
0.621
0.248
Brain total Activity



ID025102Map
0
500
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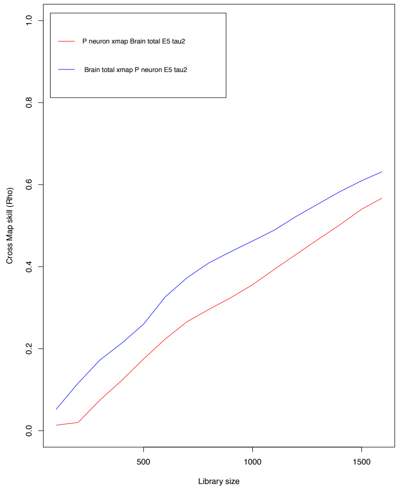
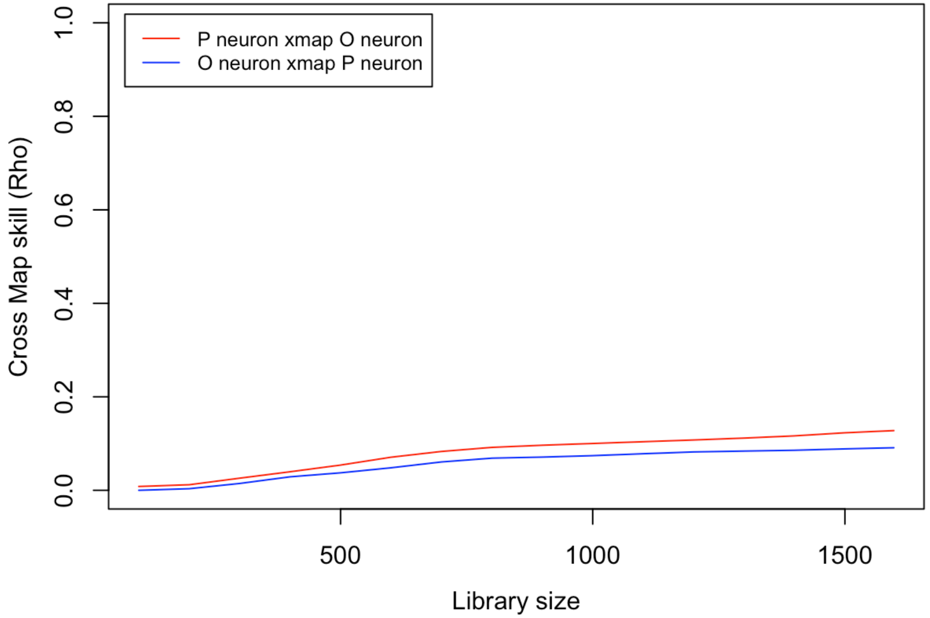
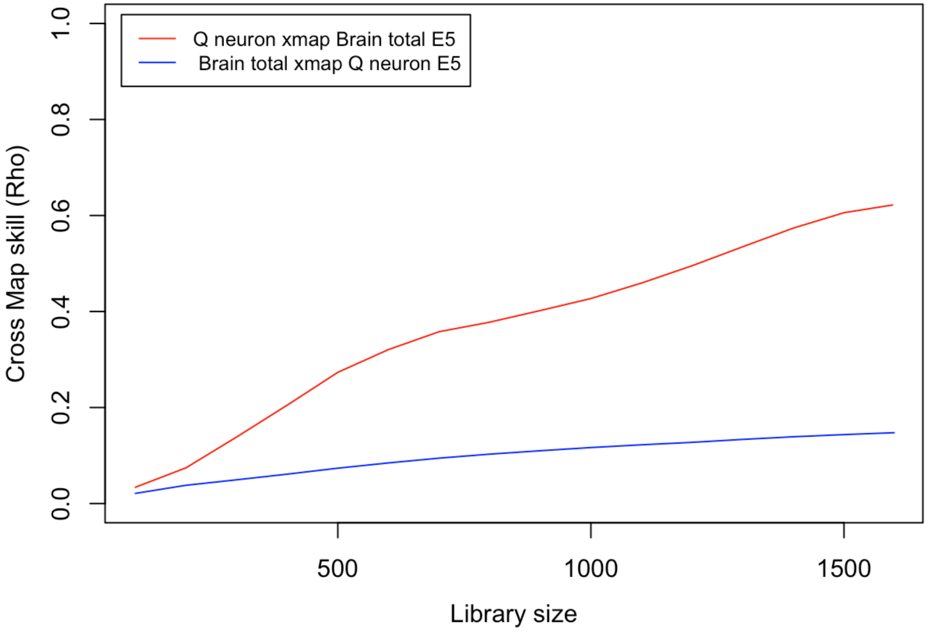
1500
2000
2500
0
200
400
600
800
1000
1200



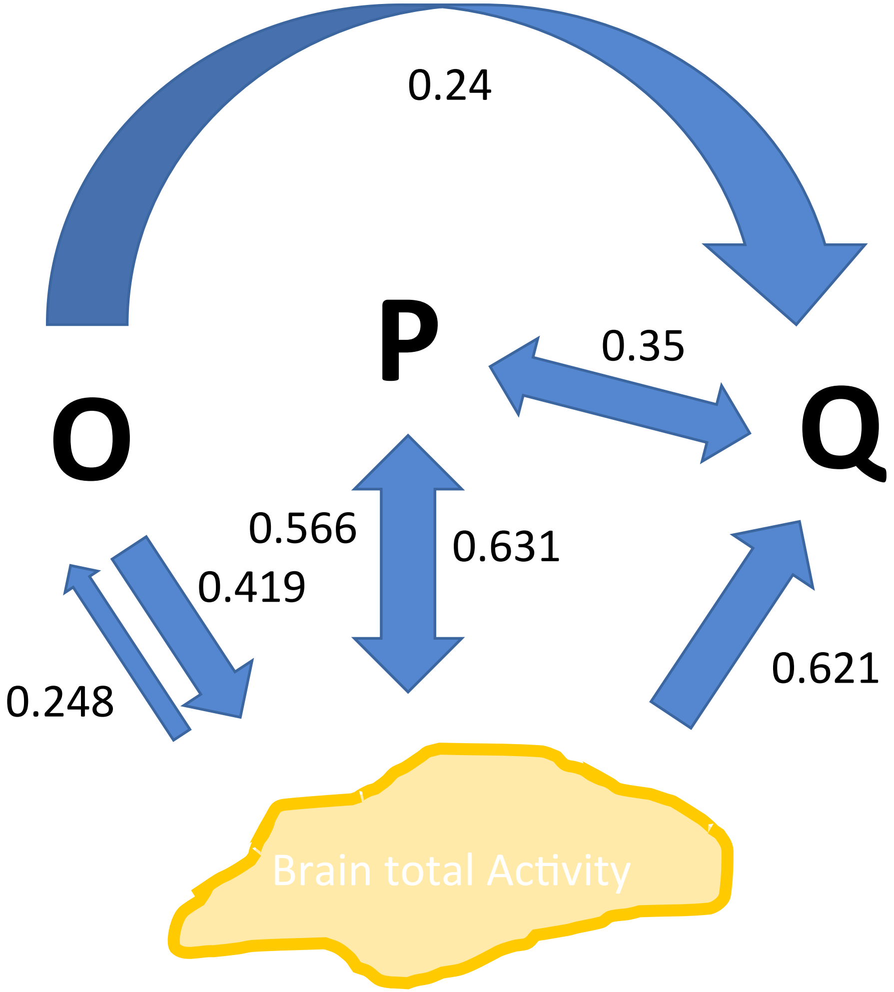
P neuron xmap Brain total E5 tau2
Brain total xmap P neuron E5 tau2
Cross Map skill (Rho)
0.0
0.2
0.4
0.6
0.8
1.0
500
1000
1500
Library size

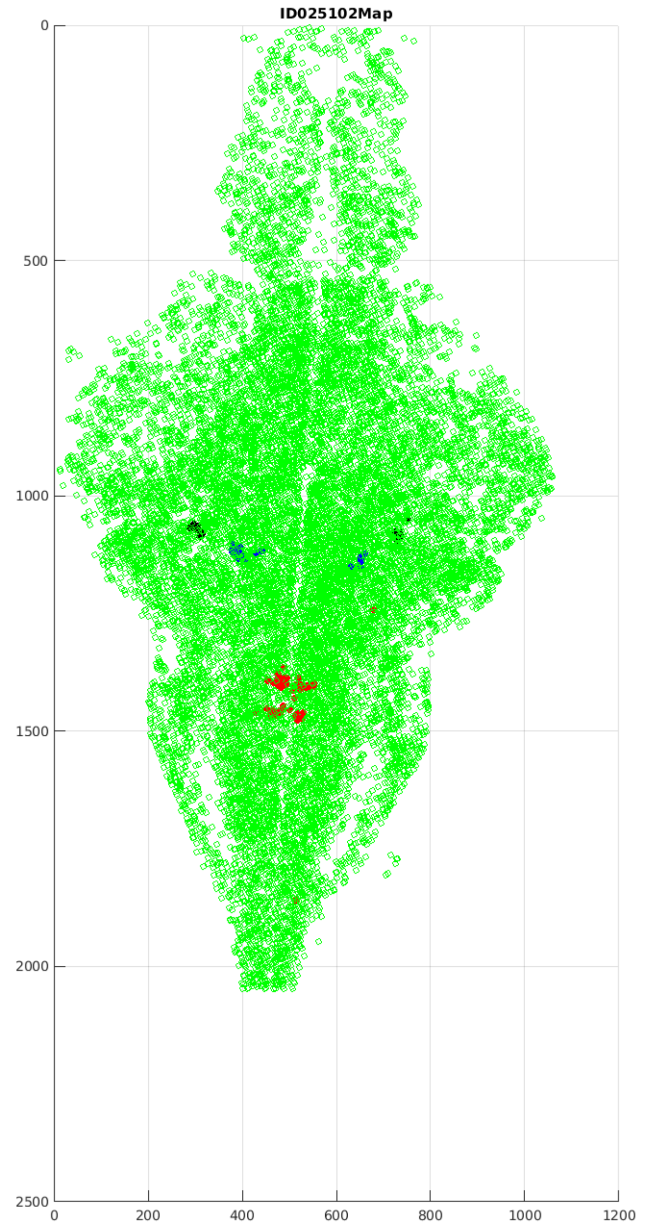


P neuron xmap O neuron
O neuron xmap P neuron
Cross Map skill (Rho)
0.0
0.2
0.4
0.6
0.8
1.0
500
1000
1500
Library size



Q neuron xmap Brain total E5
Brain total xmap Q neuron E5
Cross Map skill (Rho)
0.0
0.2
0.4
0.6
0.8
1.0
500
1000
1500
Library size


0.24
P
0.35
O
Q
0.566
0.631
0.419
0.248
0.621
Brain total Activity


ID025102Map
0
500
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2500
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600
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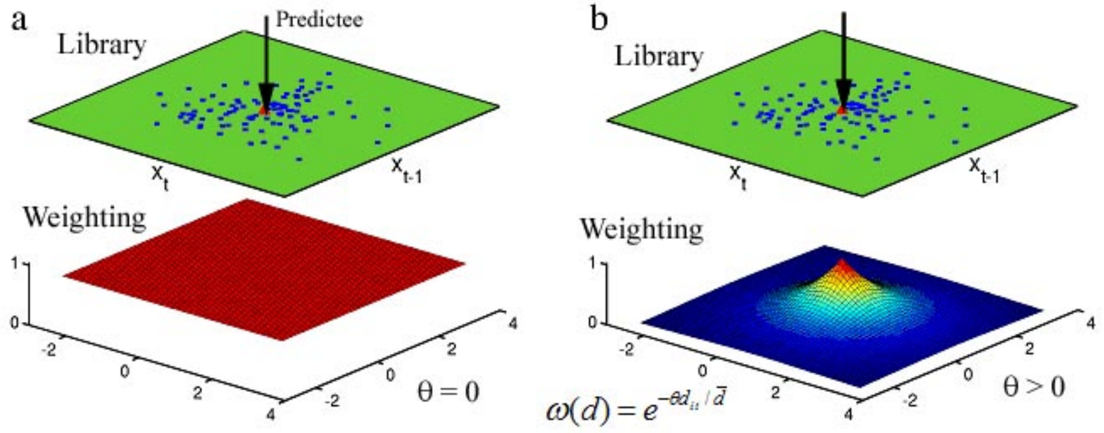
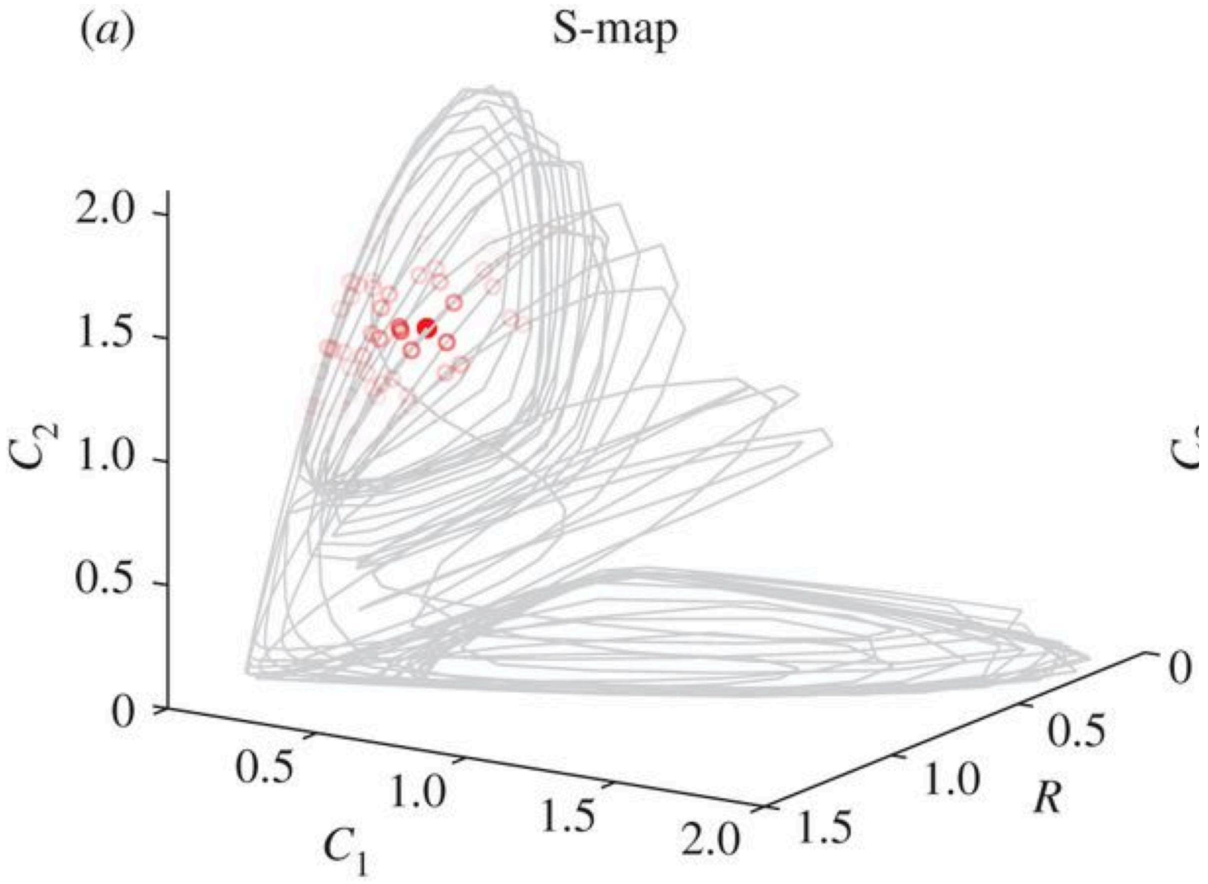
1200

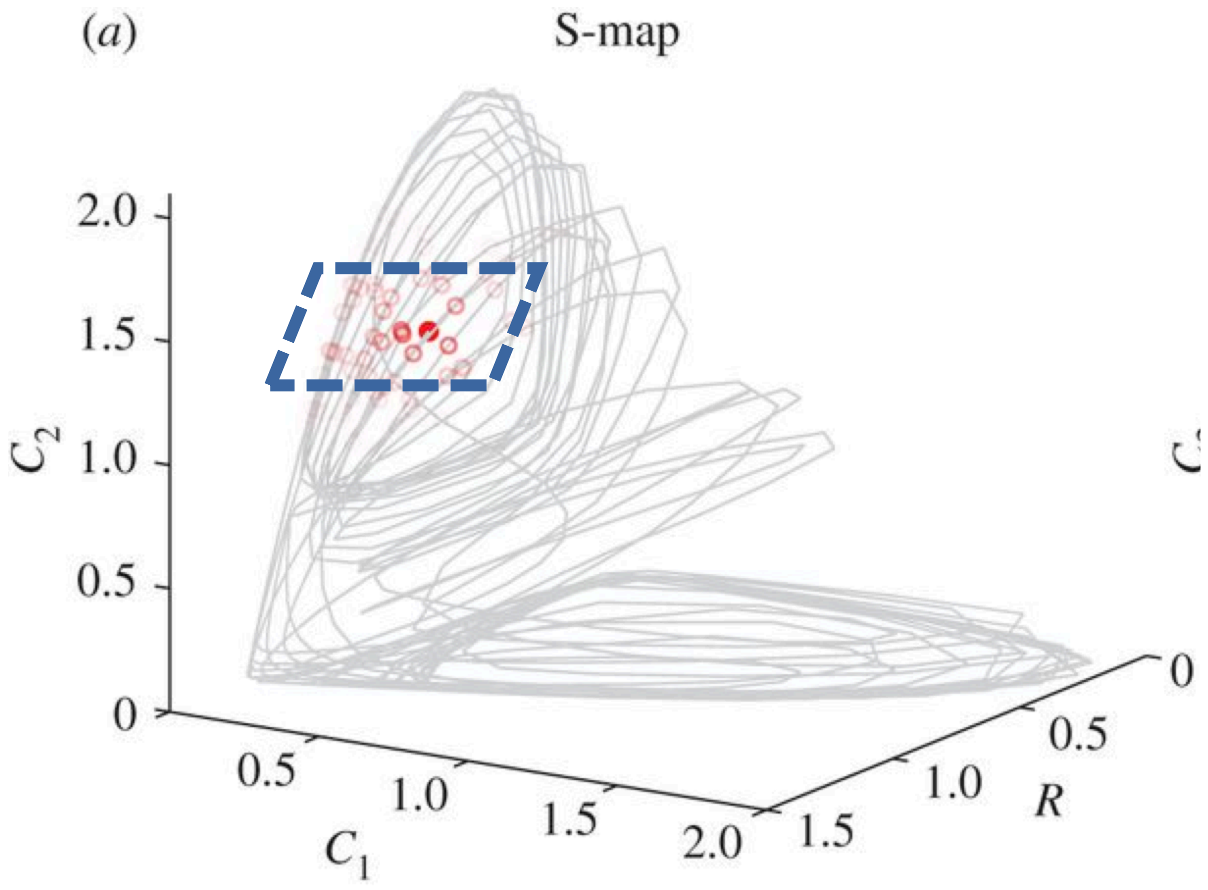
S-MAP
Sequential locally weighted global linear maps

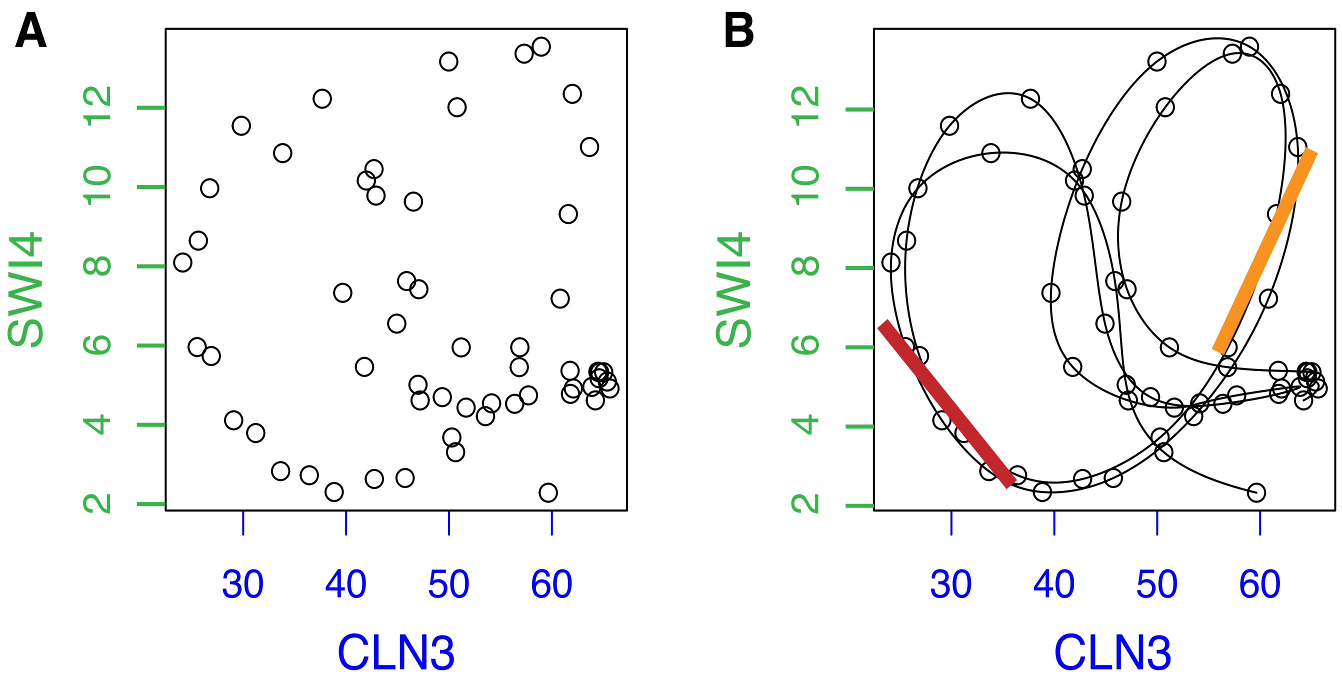


S-MAP locally weighted local linear map



S-MAP locally weighted local linear map




A
B
SWI4
CLN3
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10
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30
40
50
60

Using S-map to track changing interactions in real time

PROCEEDINGS B

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Research

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http://dx.doi.org/10.1098/rspb.2015.2258

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Tracking and forecasting ecosystem interactions in real time

Ethan R. Deyle[1], Robert M. May[2], Stephan B. Munch[3] and George Sugihara[1]

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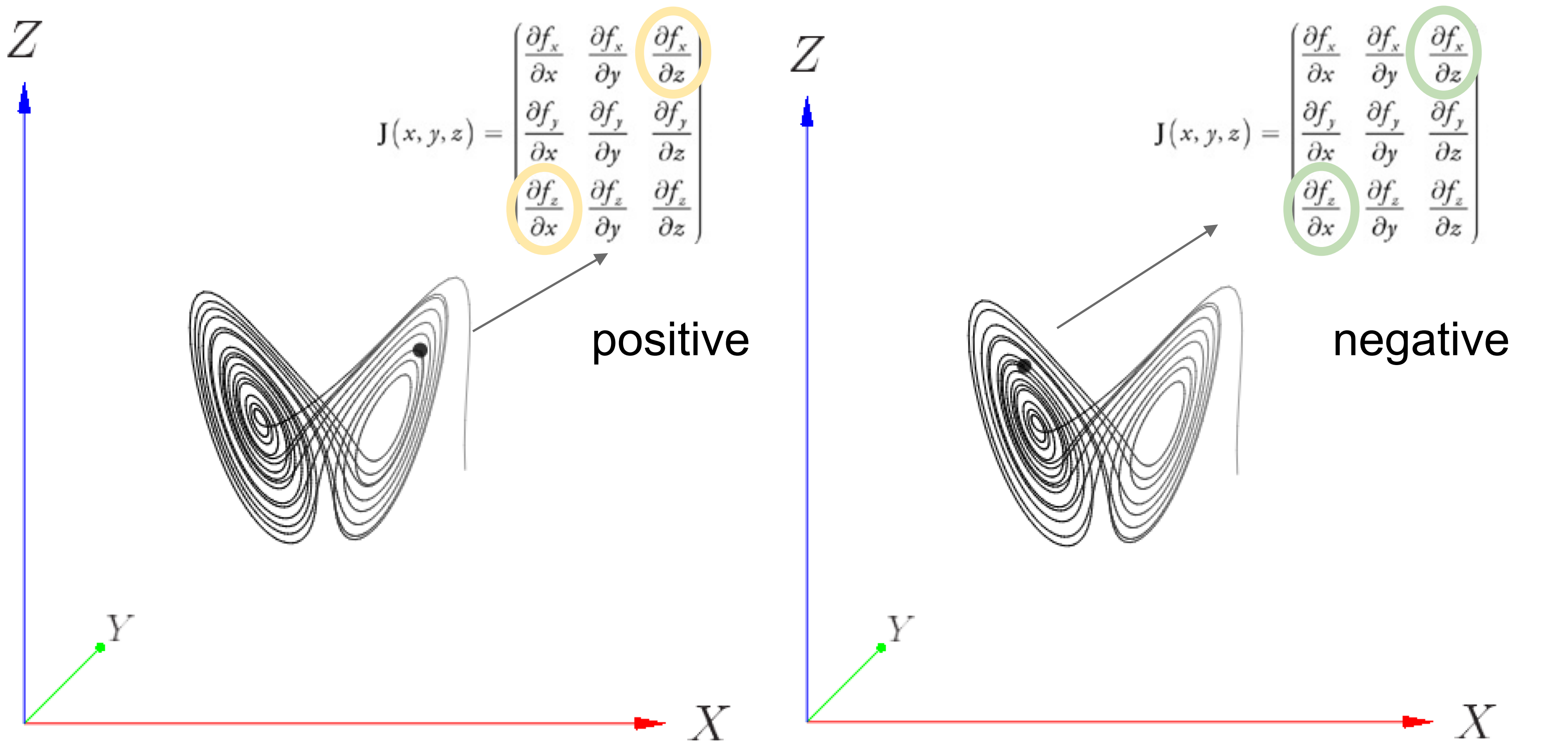
[2]Department of Zoology, University of Oxford, Oxford OX1 3PS, UK
[3]National Marine Fisheries Service, Southwest Fisheries Science Center, Santa Cruz, CA, USA

Evidence shows that species interactions are not constant but change as the ecosystem shifts to new states. Although controlled experiments and model investigations demonstrate how nonlinear interactions can arise in principle, empirical tools to track and predict them in nature are lacking. Here we present a practical method, using available time-series data, to measure and forecast changing interactions in real systems, and identify the underlying mechanisms. The method is illustrated with model data from a marine mesocosm experiment and limnologic field data from Sparkling Lake, WI, USA. From simple to complex, these examples demonstrate the feasibility of quantifying, predicting and understanding state-dependent, nonlinear interactions as they occur *in situ* and in real time—a requirement for managing resources in a nonlinear, non-equilibrium world.

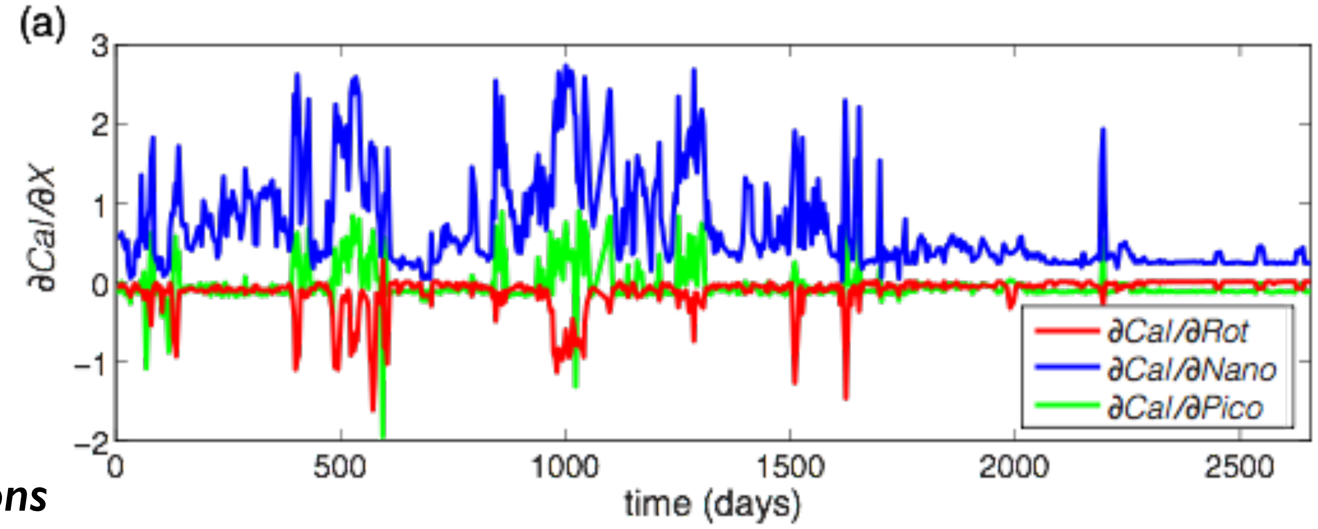
Tracking Changing Interactions with S-map



The jacobian coefficients (partial derivatives) vary depending on location on the attractor

Variable (state dependent) Interaction Strength in a Marine Mesocosm (extracted with S-maps)

Competition between the two main grazers (shown in red), calanoid copepods (Cal) and rotifers (Rot), waxes and wanes



Impressions

- Interactions vary considerably in time
- As expected, competition (dCal/dRot) is always negative
- Competition occurs only occasionally

Is this State Dependent?

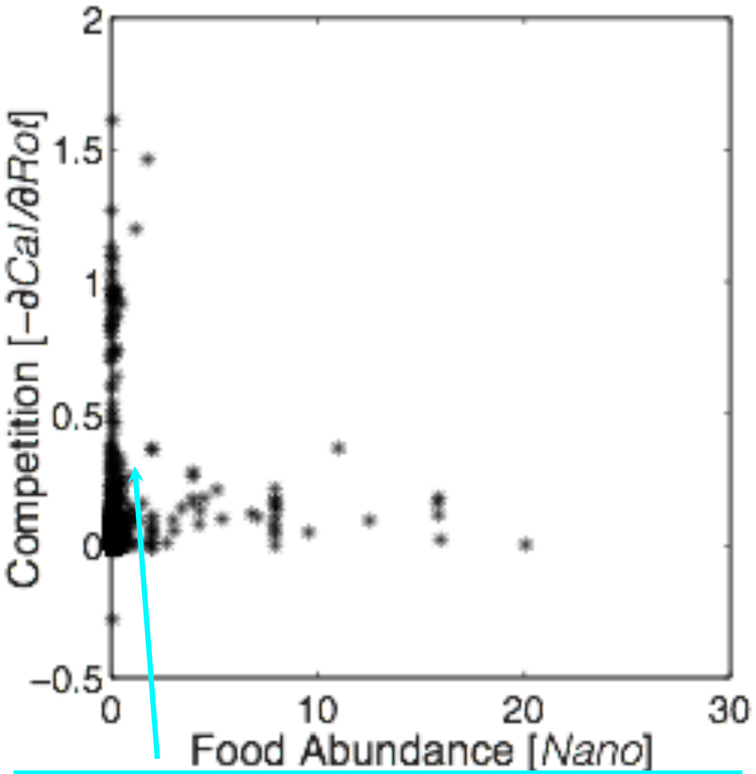
What is characteristic of system state during these intervals?

Data from Huisman et al 2011

Competition is State Dependent

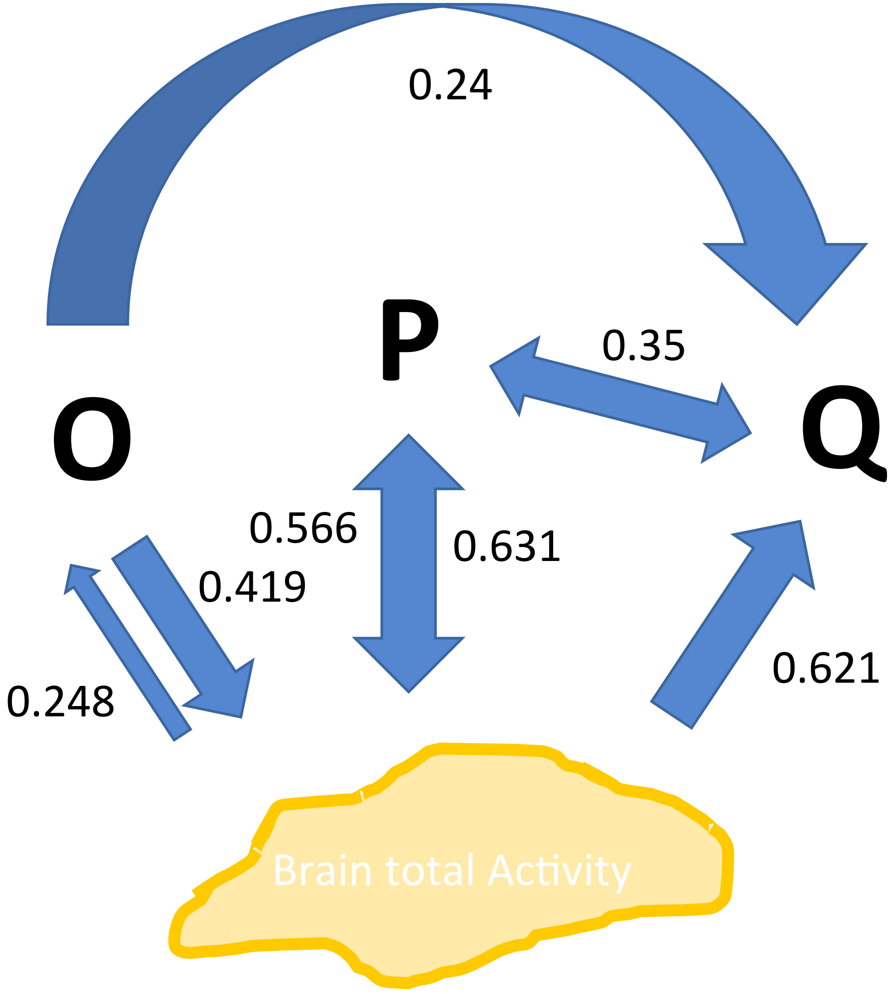
Consequence of saturating feeding responses:

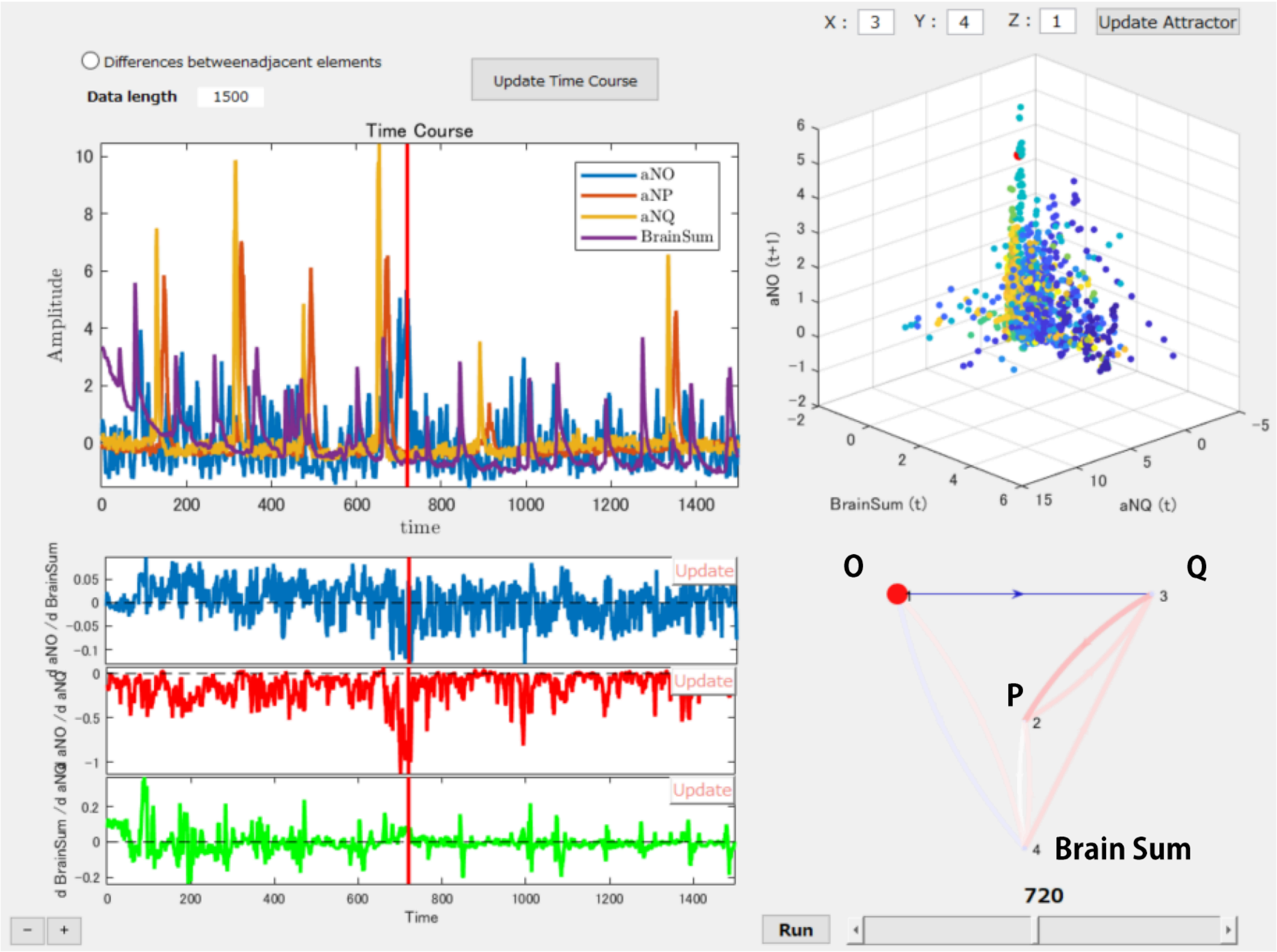
when there is ample food, there should be very little competition



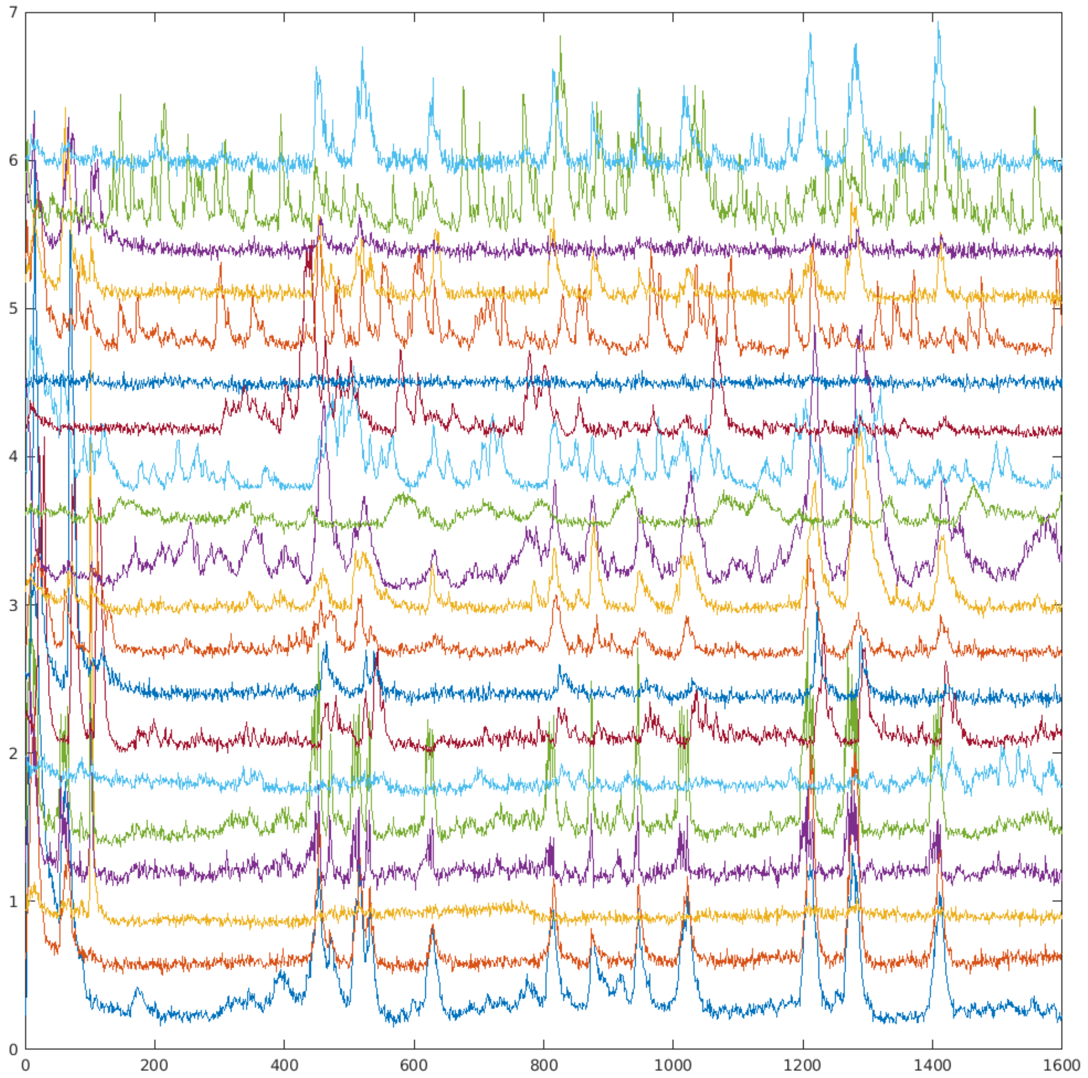
Only get competition when main prey item is scarce

The Oscillator helps terminate spike trains during bursting

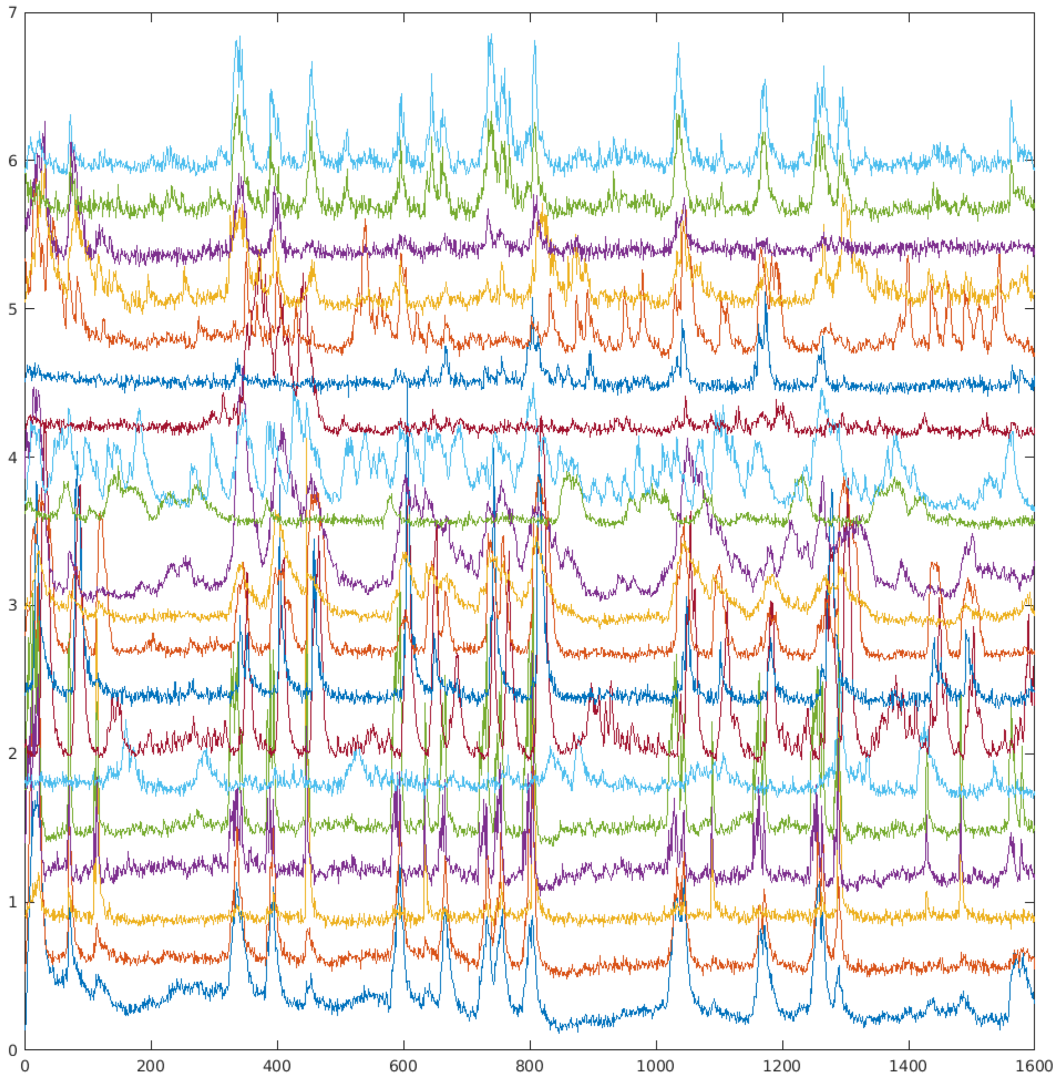




A large variety of responses to low Oxygen

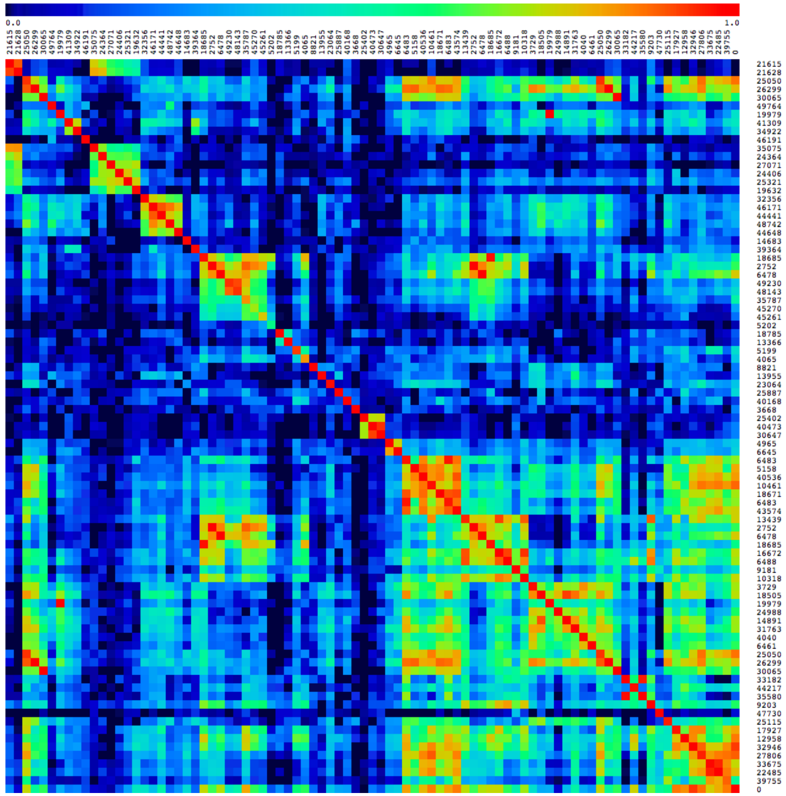


Normal O2

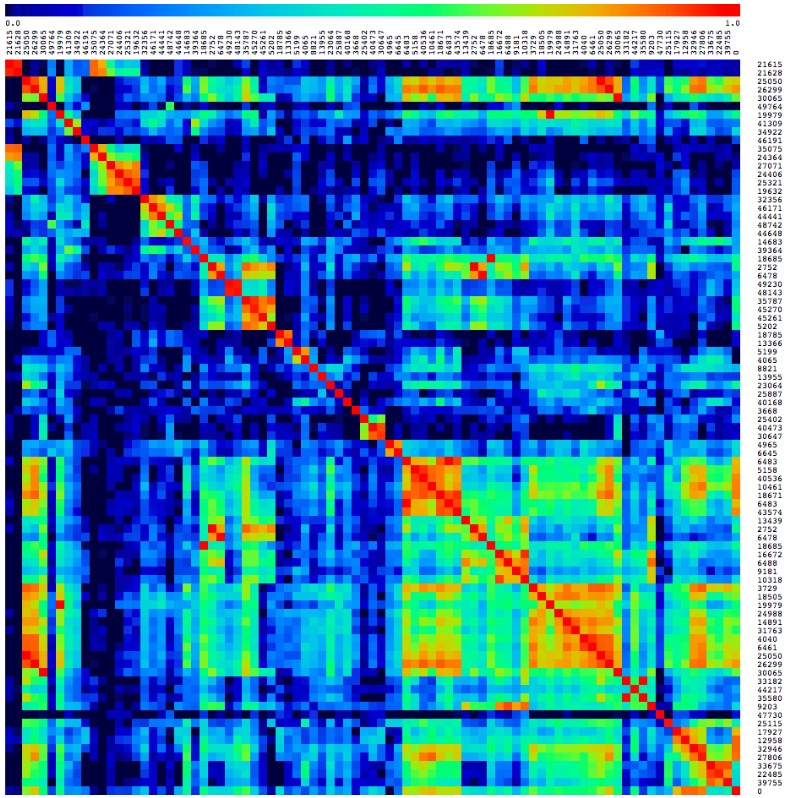


Low O2

CCM causal network inference across 86 classes of neuron dynamical behaviors



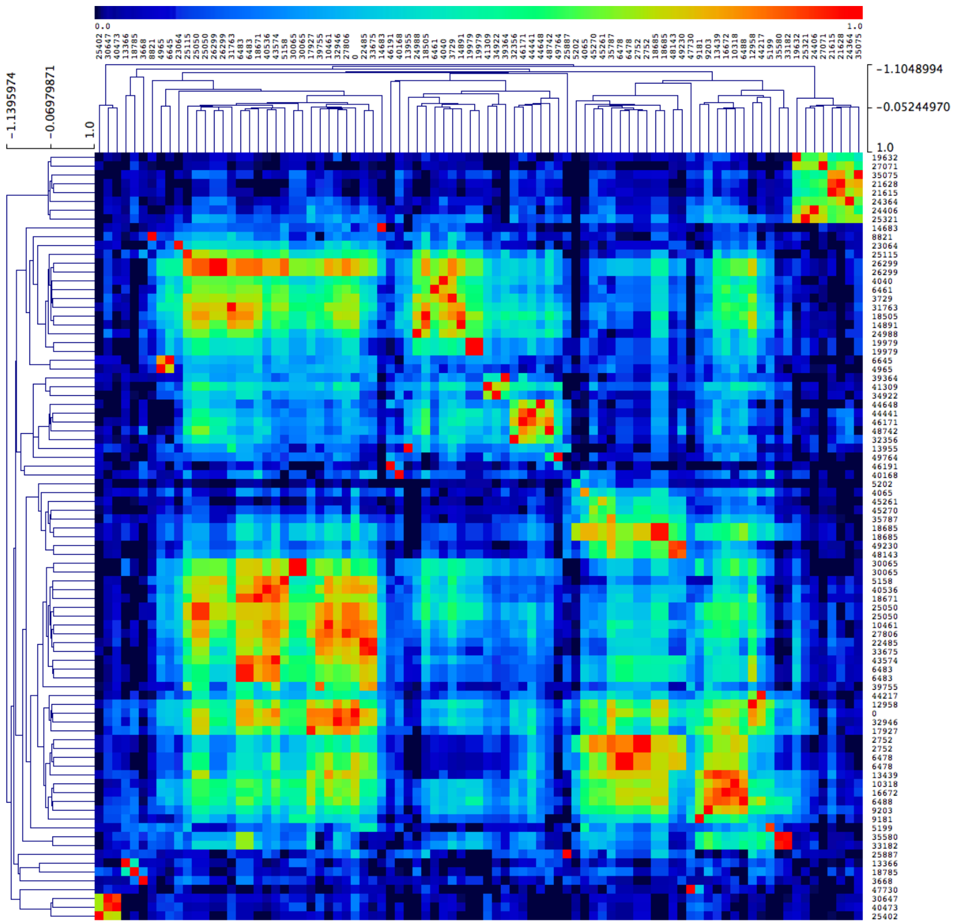
Normoxia (normal O2)



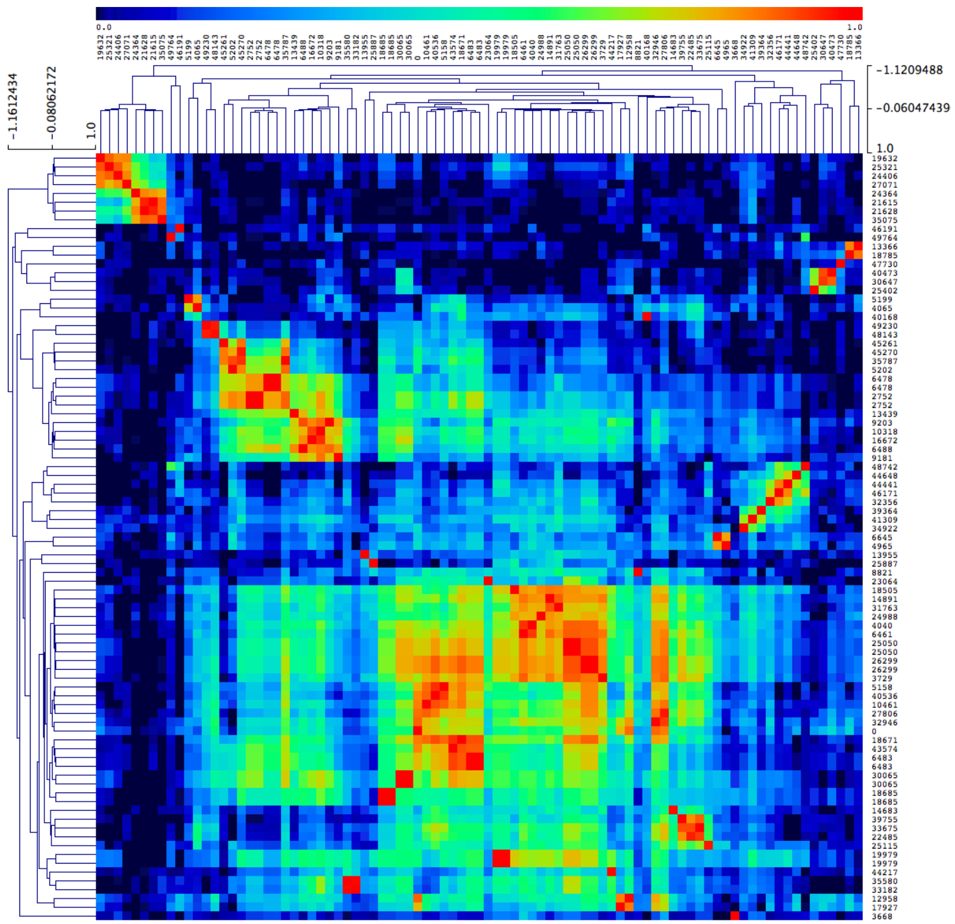
Hypoxia (low O2)

Increased local interaction and decreased global interactions during low O2 response

CCM causal network inference across 86 classes of neuron dynamical behaviors



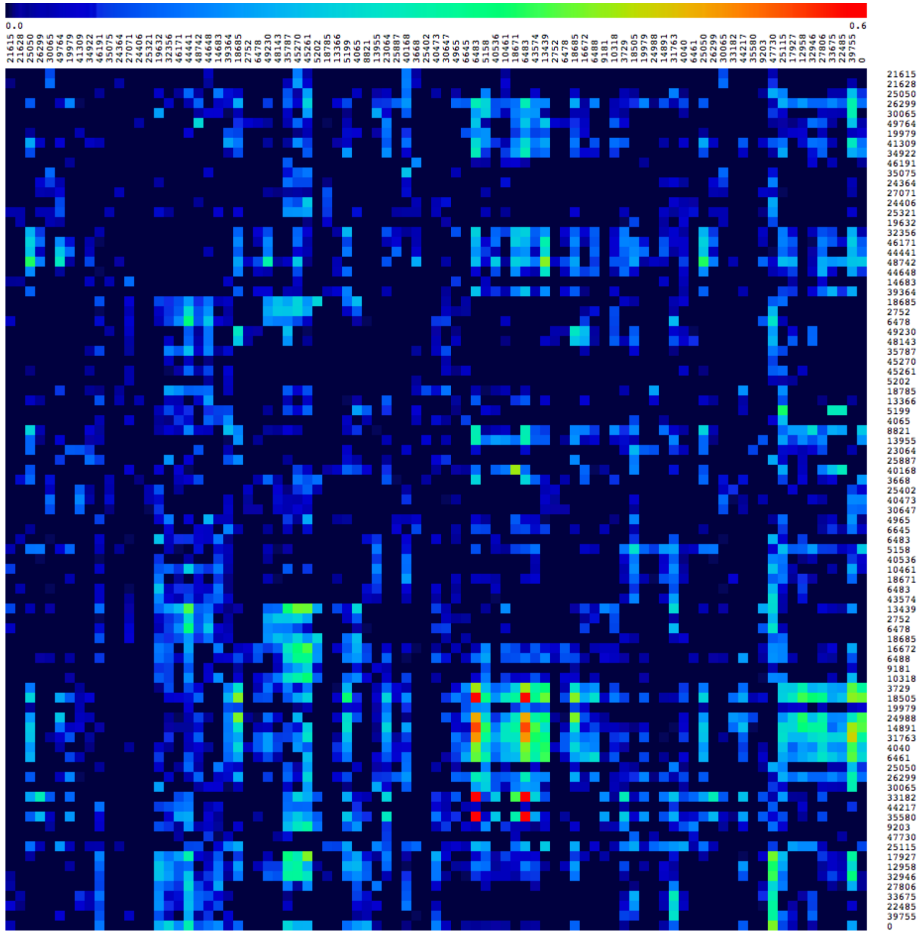
Normoxia (normal O2)



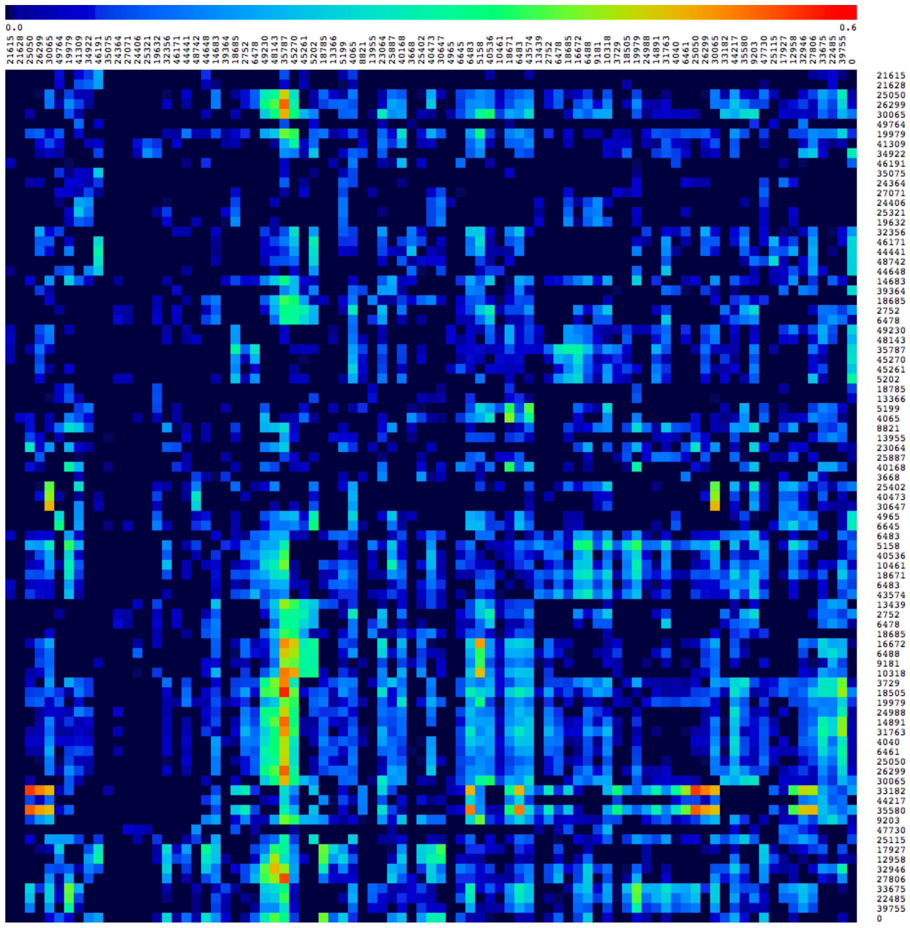
Hypoxia (low O2)

Increased local interaction and decreased global interactions during low O2 response

High Nonlinear/Linear predictability identifies high state dependence i.e. Signal integration



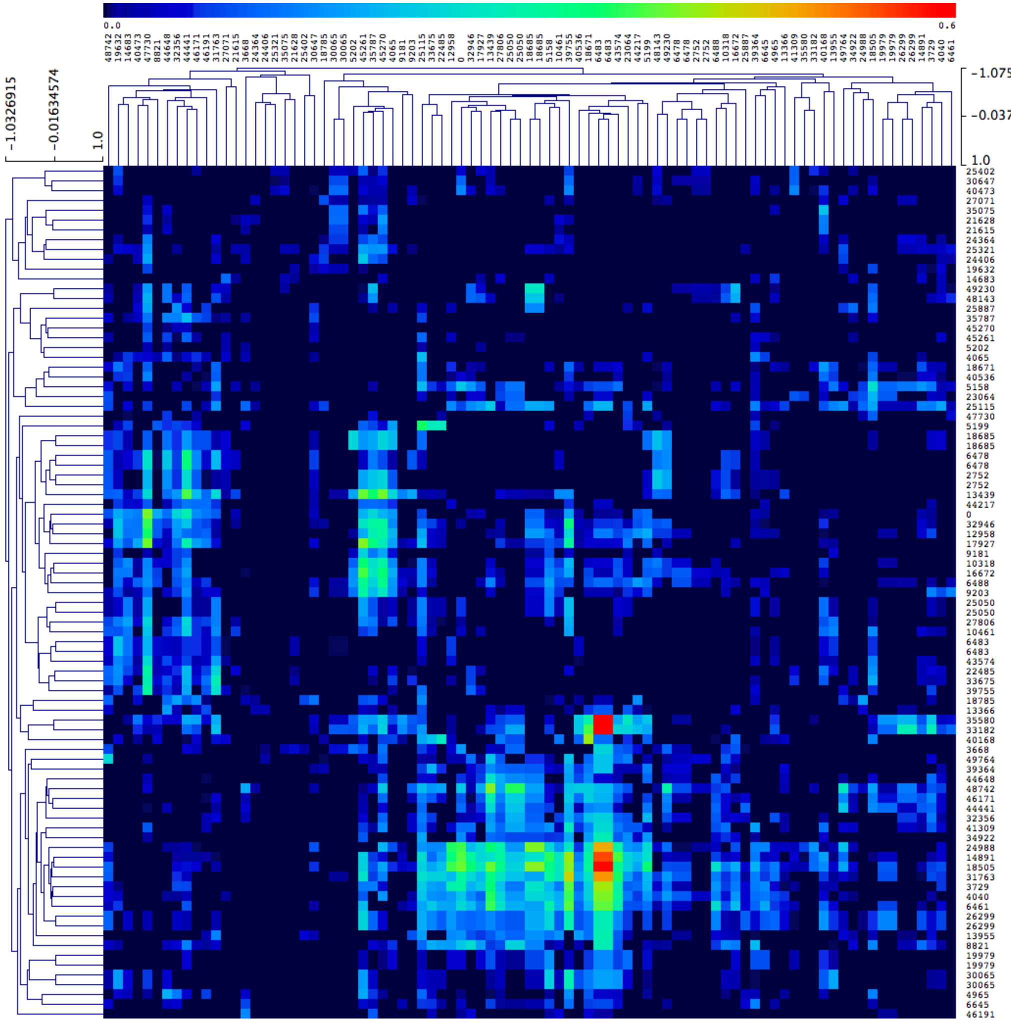
Normoxia (normal O2)



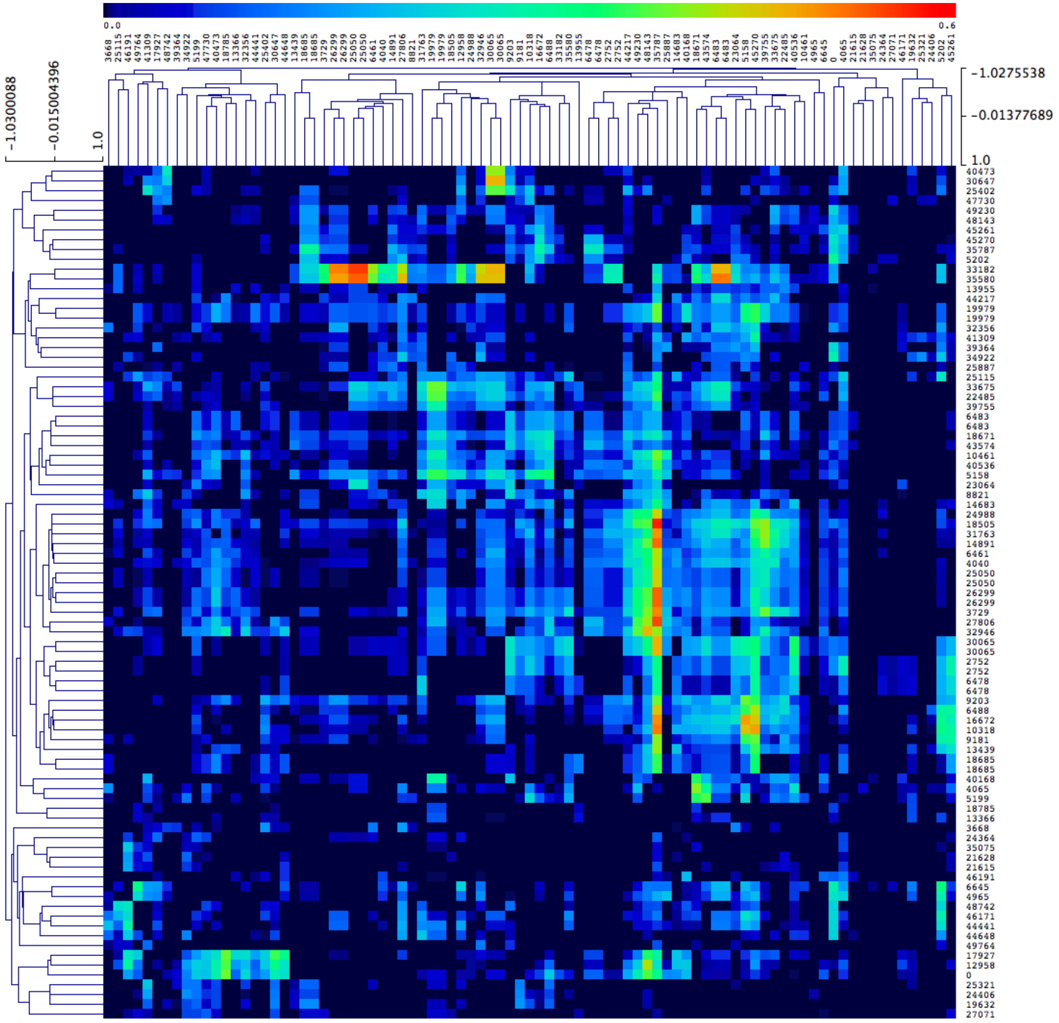
Hypoxia (low O2)

Signal Integrator neurons differ under normal and low O2 response conditions

Increase in local nonlinearity in many neurons indicates increase in local signal integration

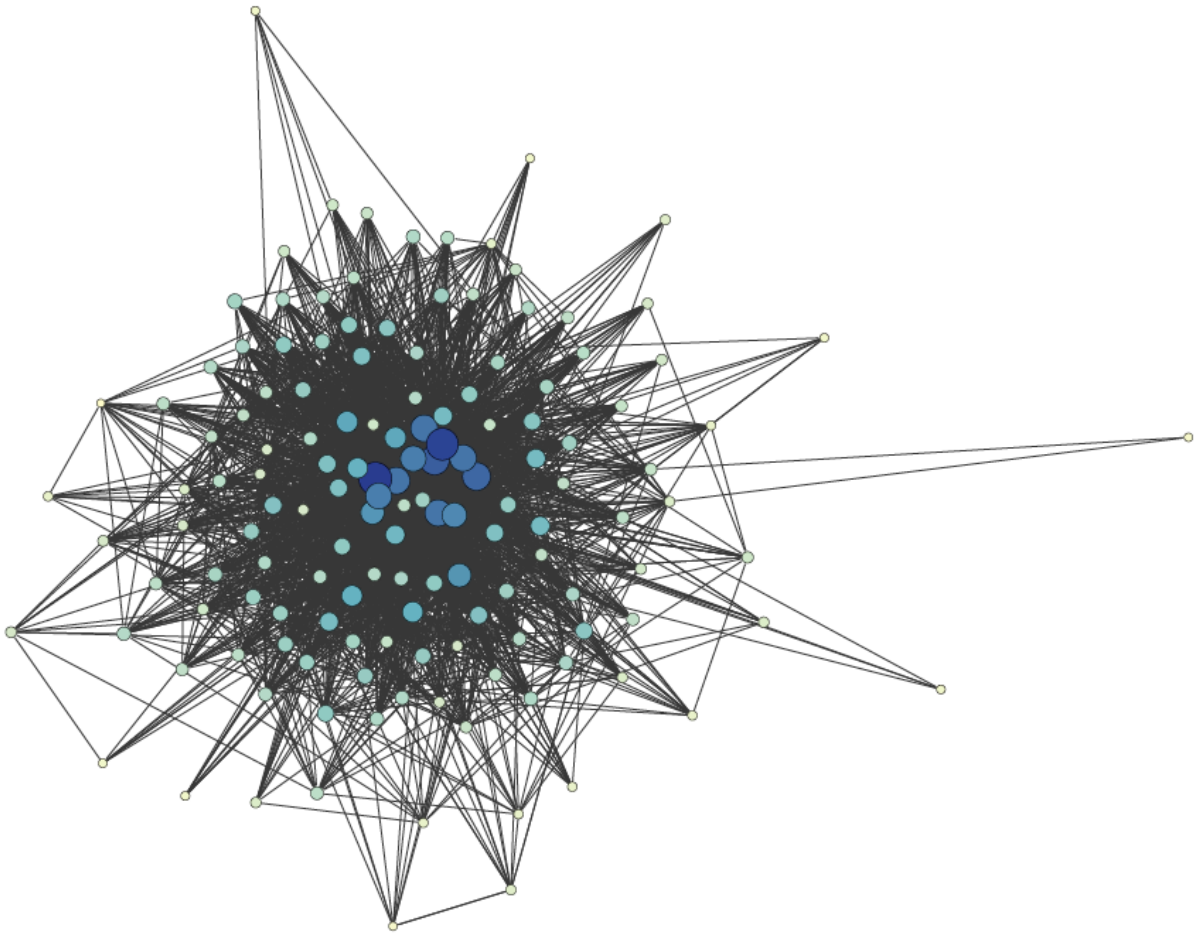


Normoxia (normal O2)

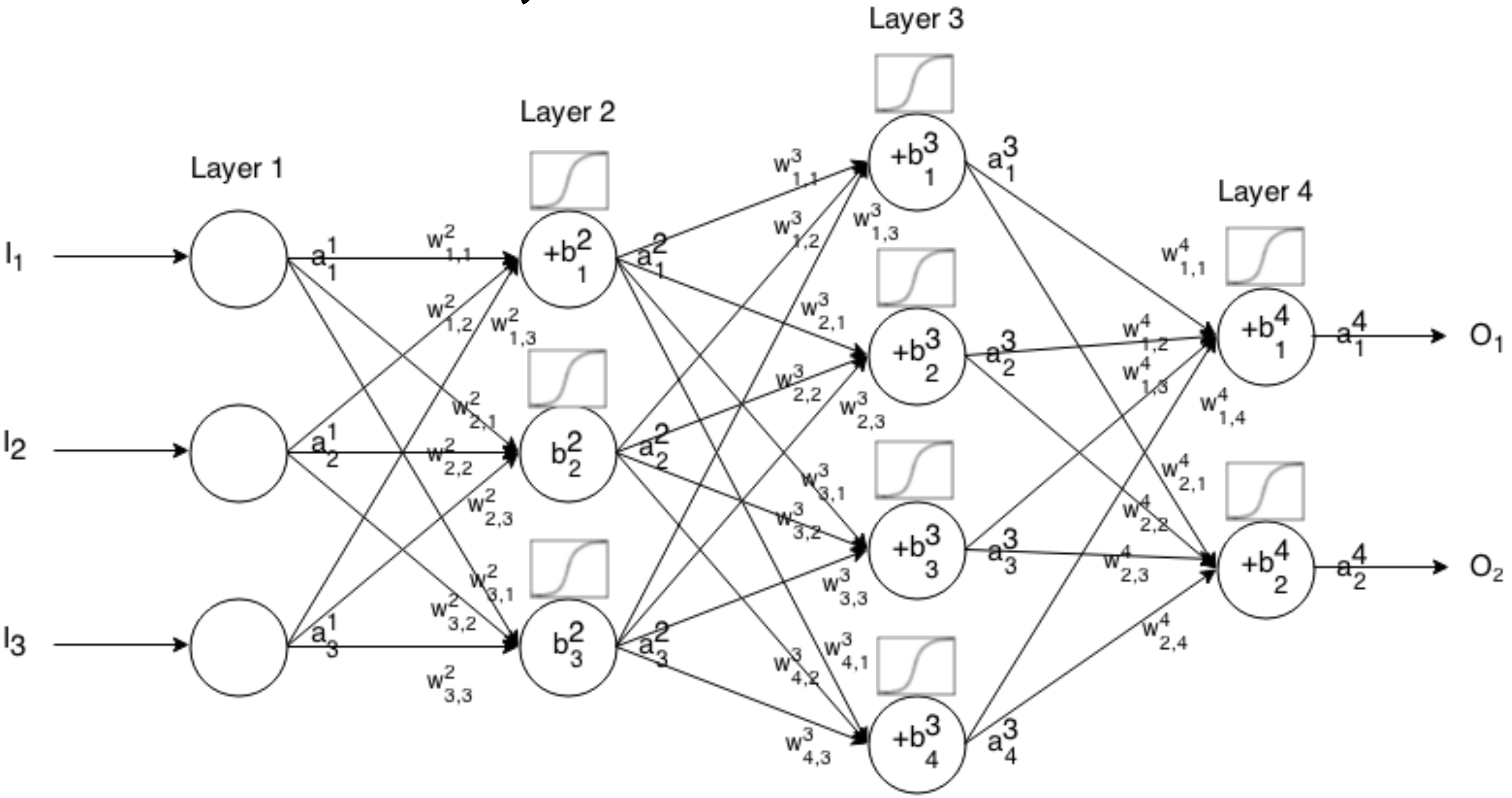


Hypoxia (low O2)

Use discovered network as starting point to train a fish neuromorphic artificial neural network to perform tasks similar to what the fish is doing



CCM Rho values will be converted into weights in a recurrent neural network and trained further to correct inaccuracies of measurement and adjustment to hardware, artificial sensor code.

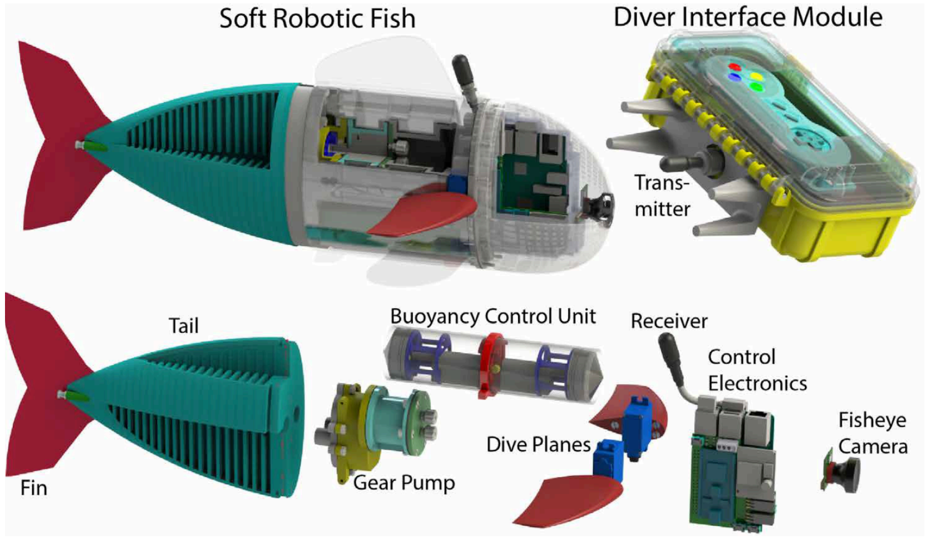


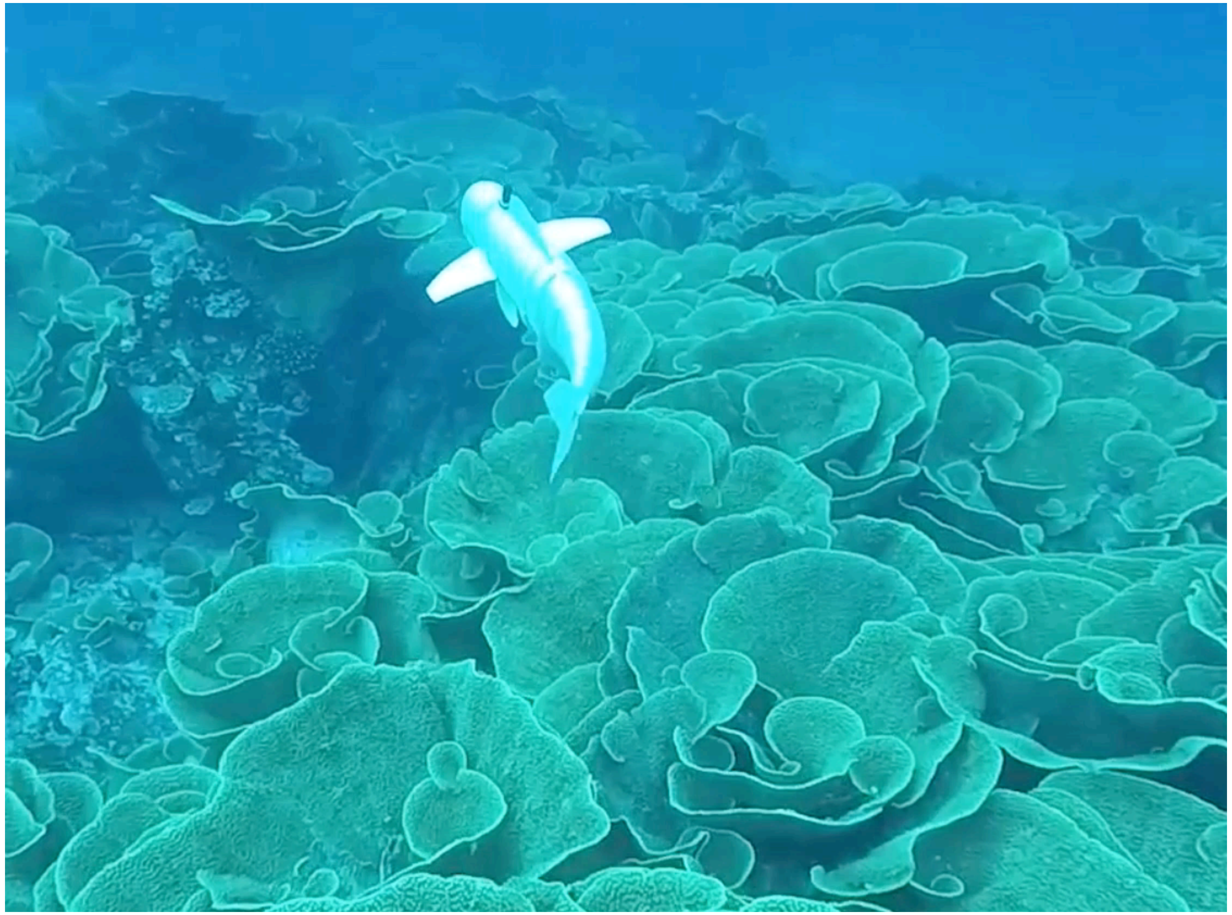
BIOMIMETICS

Exploration of underwater life with an acoustically controlled soft robotic fish

Robert K. Katzschmann,* Joseph DelPreto, Robert MacCurdy, Daniela Rus

Closeup exploration of underwater life requires new forms of interaction, using biomimetic creatures that are capable of agile swimming maneuvers, equipped with cameras, and supported by remote human operation. Current robotic prototypes do not provide adequate platforms for studying marine life in their natural habitats. This work presents the design, fabrication, control, and oceanic testing of a soft robotic fish that can swim in three dimensions to continuously record the aquatic life it is following or engaging. Using a miniaturized acoustic communication module, a diver can direct the fish by sending commands such as speed, turning angle, and dynamic vertical diving. This work builds on previous generations of robotic fish that were restricted to one plane in shallow water and lacked remote control. Experimental results gathered from tests along coral reefs in the Pacific Ocean show that the robotic fish can successfully navigate around aquatic life at depths ranging from 0 to 18 meters. Furthermore, our robotic fish exhibits a lifelike undulating tail motion enabled by a soft robotic actuator design that can potentially facilitate a more natural integration into the ocean environment. We believe that our study advances beyond what is currently achievable using traditional thruster-based and tethered autonomous underwater vehicles, demonstrating methods that can be used in the future for studying the interactions of aquatic life and ocean dynamics.





Katzschmann et al., Sci. Robot. 3, eaar3449 (2018) 21 March 2018

Nature of the Data & Pre-processing

- Larval fish:
- The brain contains 120,000 neurons. (70,000 imaged)
- Image:
- The volume is 300x800x300 microns; resolution: 0.41 microm per pixel for xy; 5 microns in z.
- Imaging frame rate: 1-2 Hz.
- The size of one sample (a fish for normoxia and 2xhypoxia recording) before any processing: 1.2 TB
- After processing: 3 TB
- The size of 1 stack (xyz): 300MB; 1600 stacks per condition
- Dataset 30TB

- Processing (Matlab):
- Imaging registration; traces extraction. Data analysis.
-
- Outcomes after processing:
- Neuron trace matrix: 70,000 x 1,600
-

Current processing times & hardware

- Time use from the computer:
- It takes **240 hours** to extract the traces (parallel computing on 8x2.6Hz cores with 250GB RAM used). Similar amount of time or even longer for registration.
- chi:
  Colfax Workstation SS8400:
      Intel S2600CW: Dual Intel Xeon E5-2697A v4 @2.60 GHz 16 Cores 512 GB RAM

  Local Storage:
      2 Micron 1100 SATA3 2TB in RAID 01 Seagate Constellation ES.4 6TB SAS3

  GPU:
      Nvidia GeForce Pascal Titan X
- Node08:
  Cisco UCS B200M4 Blade:
      Dual Intel Xeon E5-2697A v4 @2.60 GHz 16 Cores 256 GB of RAM

  Local Storage:
      2 Seagate 900GB SAS3 10K RPM Drives

CCM calculations

- CCM Causality inference 70,000 X 70,000 = 4.9 X 10^9 binary CCM runs
- On my MacBook Pro laptop a binary comparison ~2 minutes with a single core
- For 70K neurons it would take ~4,661 years to complete.
- (even a reduced simplified calculation with 4 cores would take 900 days)

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