Flexible Computation in Neuronal Networks

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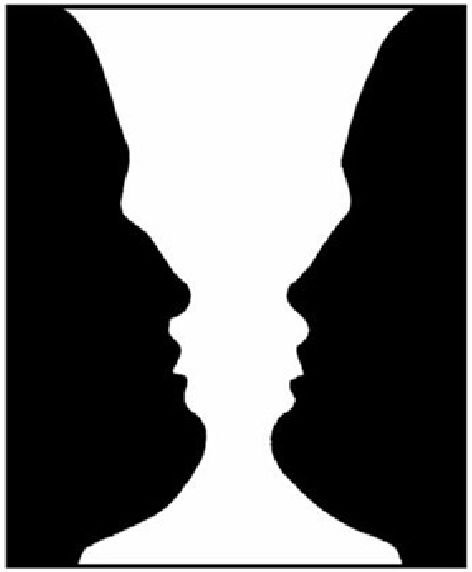
Brains dynamically route and process information

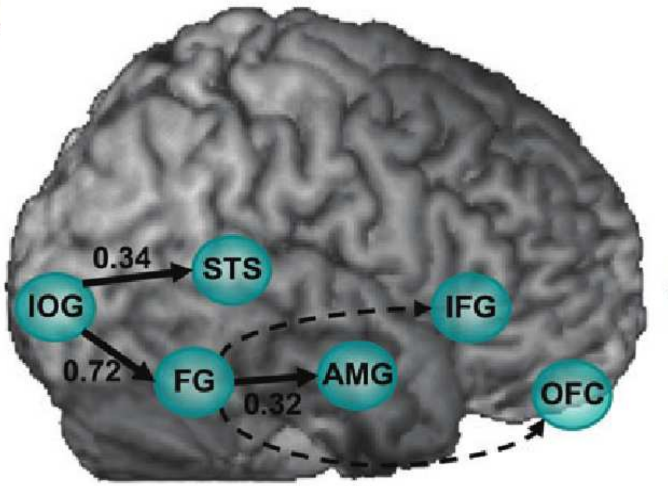


- How does the brain flexibly control information flow and processing?

- What are potential mechanisms ?

Face Recognition is a Neuronal Network Task

[Steeves et al, Neuropsychologica 2006]

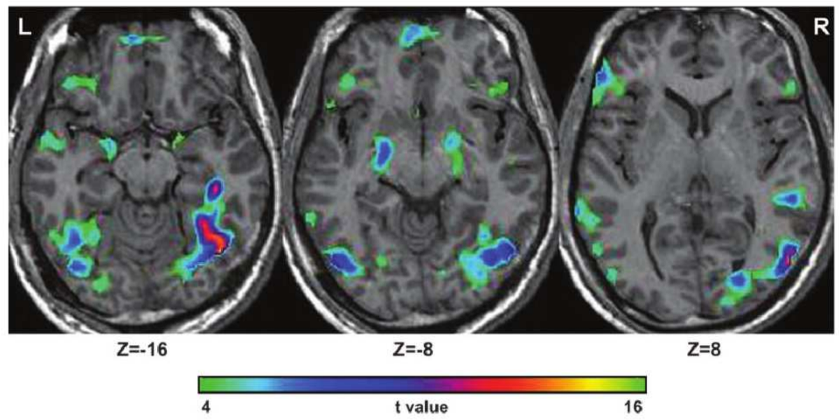


[Fairhall Ishai, Cerebral Cortex 2007]

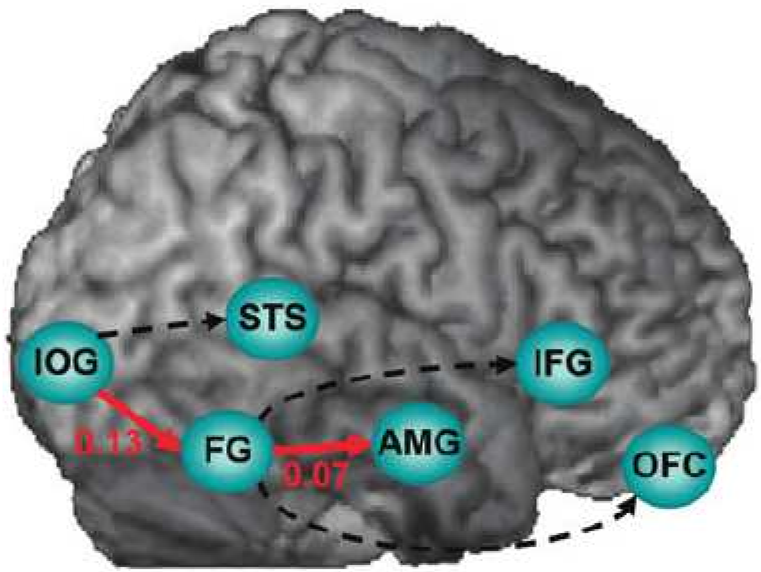
- Functional brain network necessary for higher level face recognition

The Face Recognition Network is Context Dependent

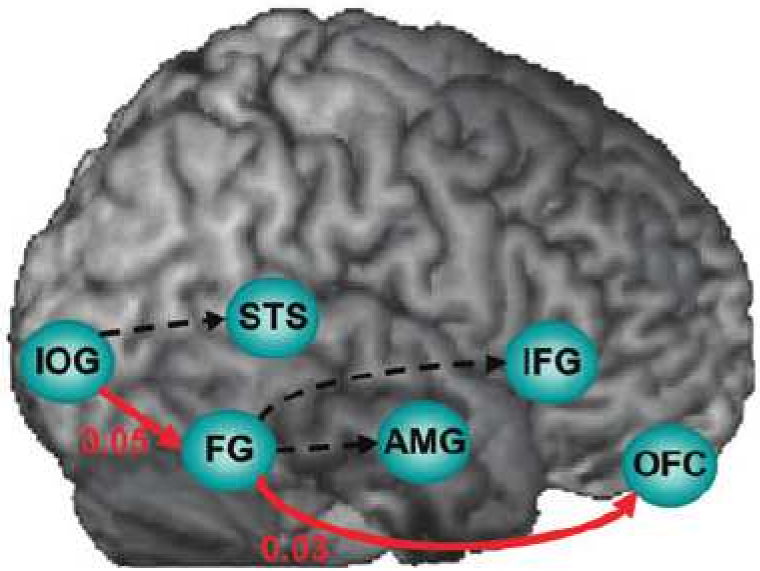
IOG: inferior occipital gyrus - core system
IFG: inferior frontal gyrus - semantic aspects
OFC: orbitofrontal cortex - facial beauty
FG: fusiform gyrus - identification of individuals
AMG: amygdala - emotions
STS: superior temporal sulcus - gaze direction



emotional faces

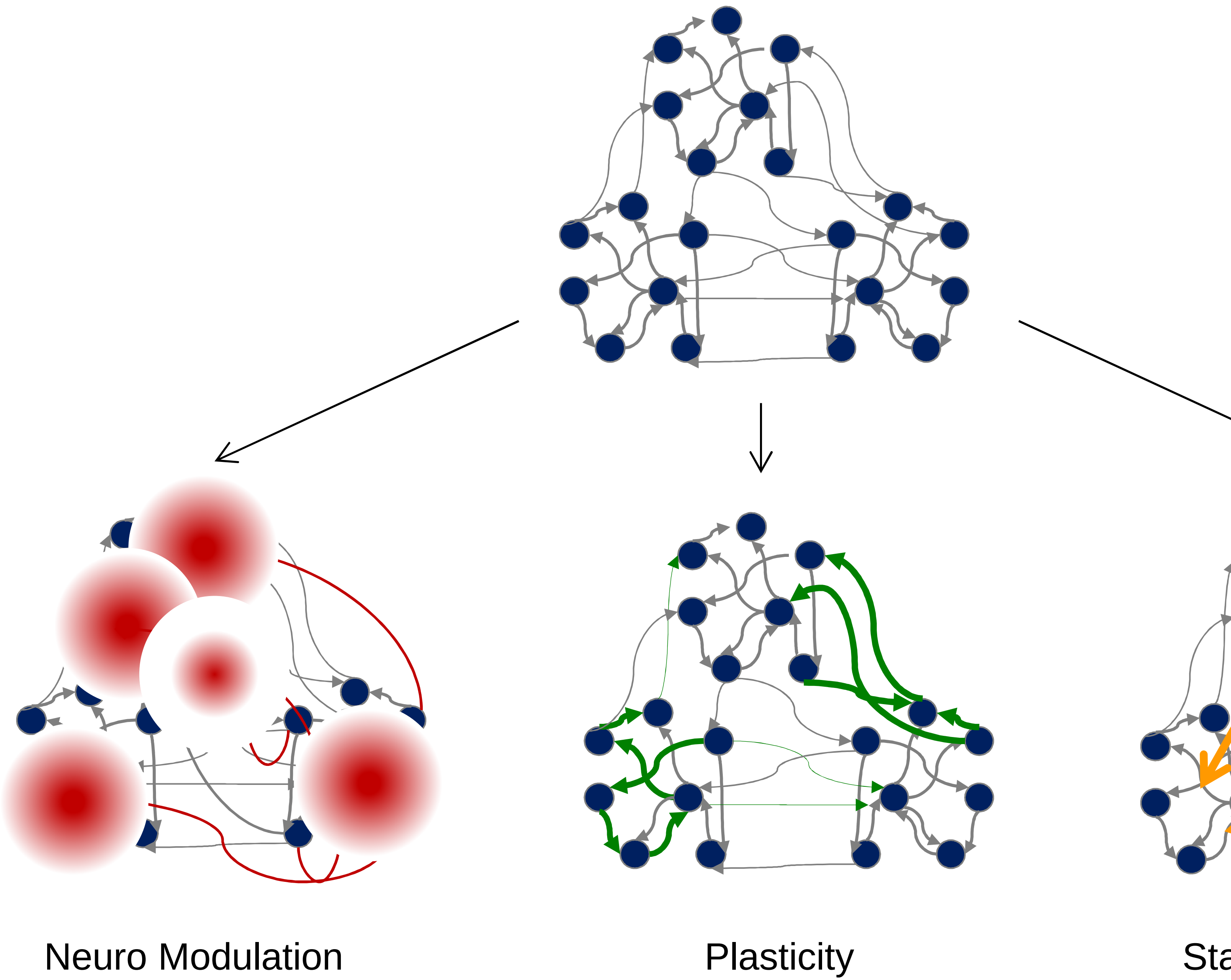


famous faces



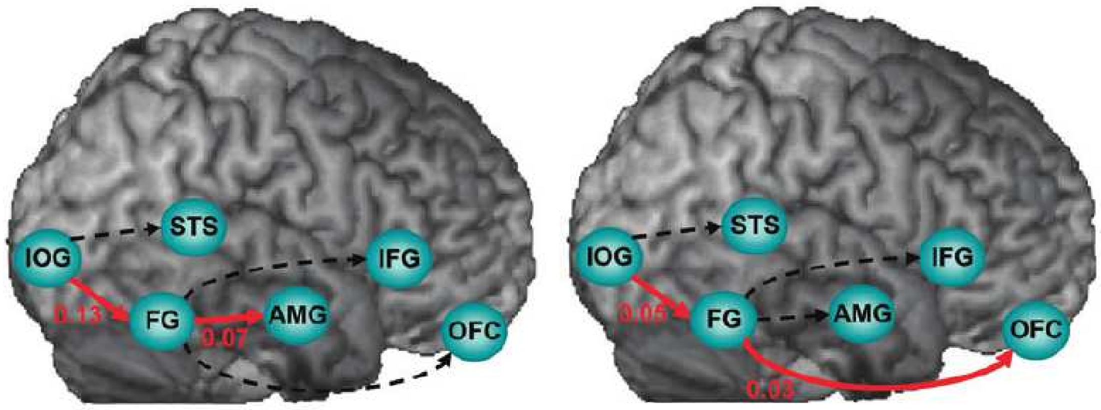
[Fairhall Ishai, Cerebral Cortex 2007]

Felxible Function of Neuronal Circuits



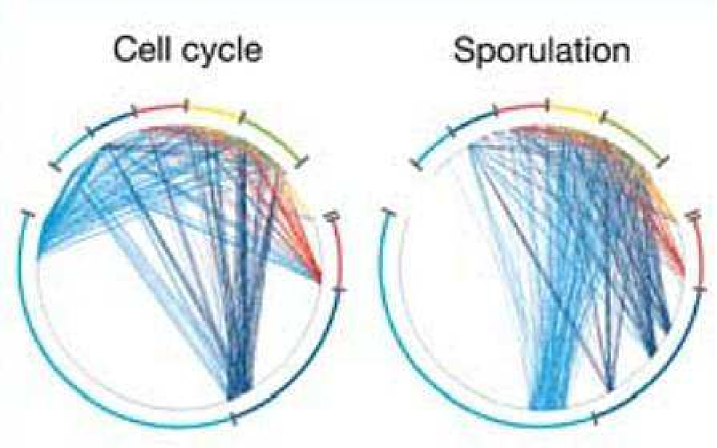
Flexible Communication in Complex Networks

- Biological Networks: Neuronal networks



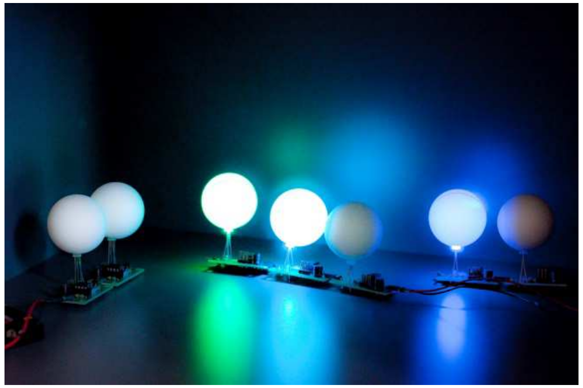
[Fairhall Ishai, Cerebral Cortex, 2007]

Gene regulatory circuits



[Luscombe, et al. Nature 2004]

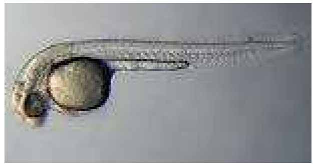
- Artificial Networks: Self-organizing distributed sensor networks

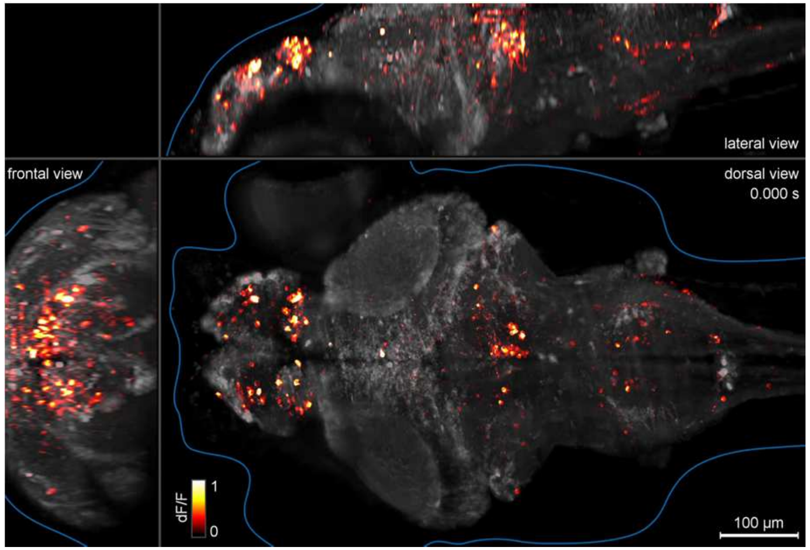


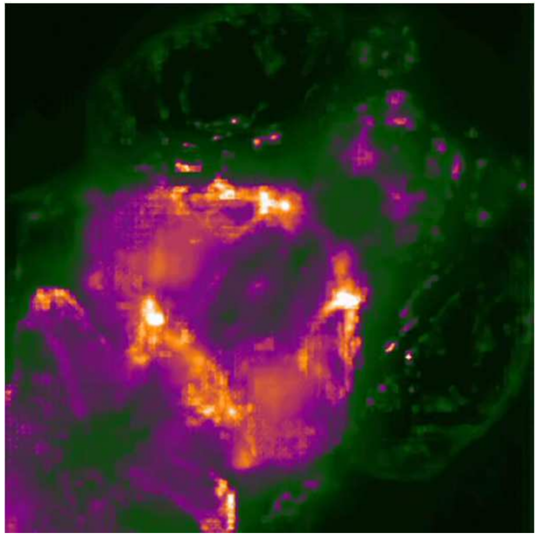
[Klinglmayr, Kirst, Timme, Bettstetter, 2012,
Klinglmayr, Bettstetter, Timme , Kirst IEEE TAC, 2016]

→ Mechanisms for flexible communication ?

Collective Dynamics in Neuronal Networks

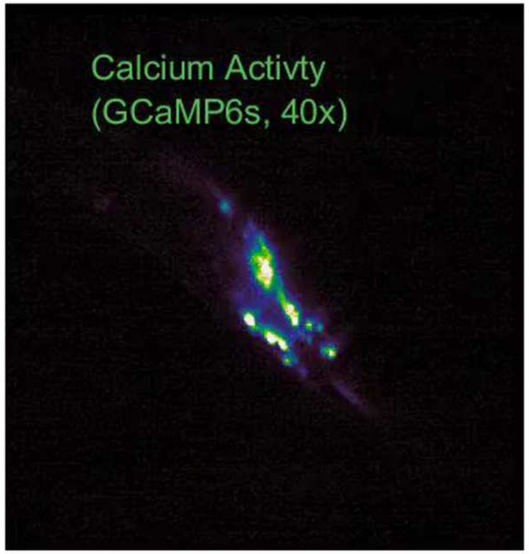


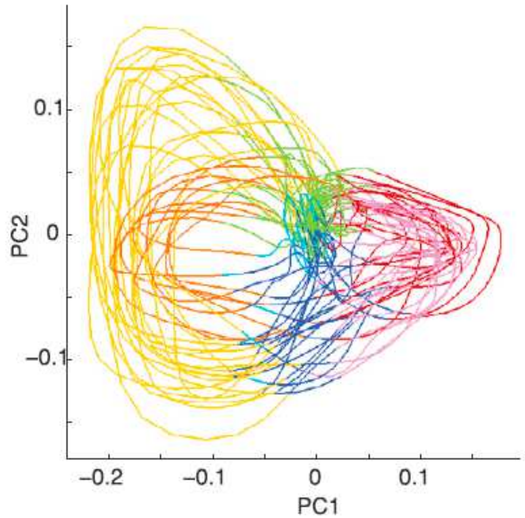




[Vladimirov, …, Ahrens, Nat Meth 2014]

[Prevendel,…,Vaziri, Nat Meth 2014]



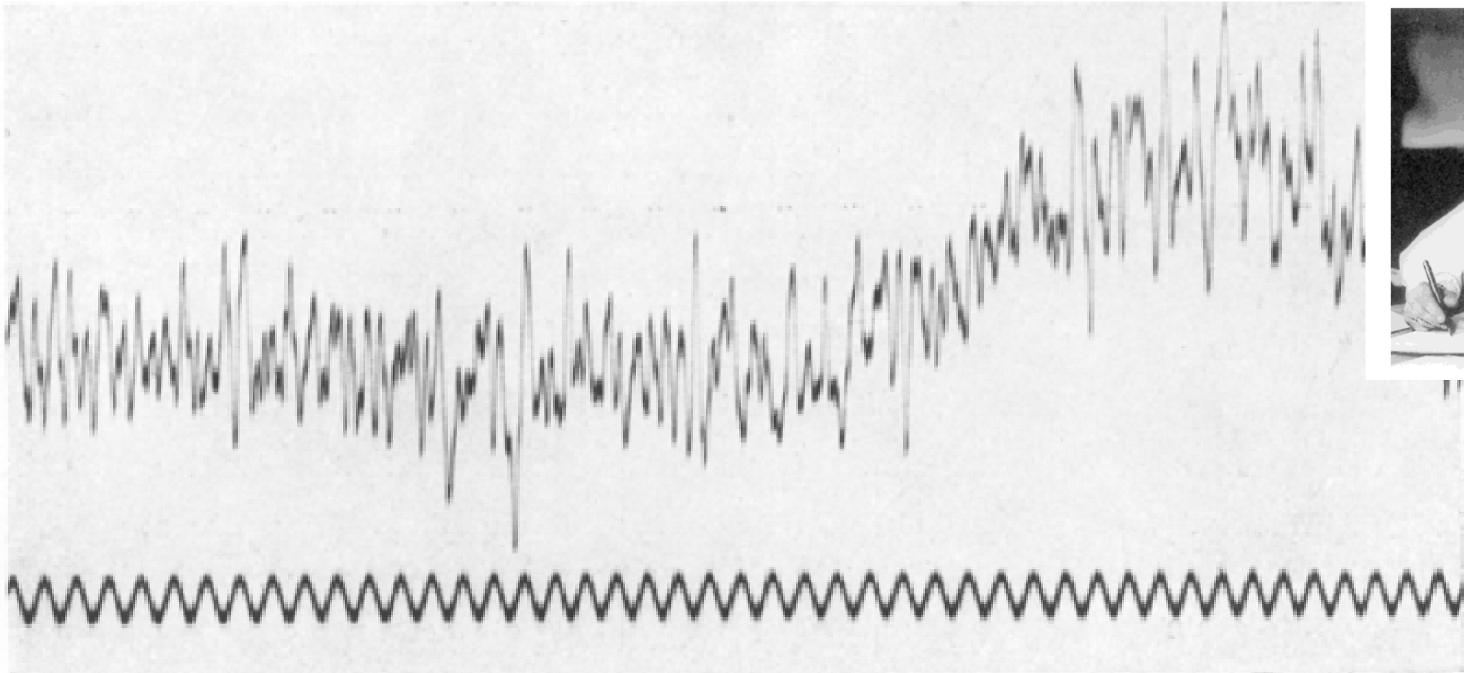


[Nguyen, …, Leifer, PNAS 2014]

[Kato et al, Cell 2015]

Collective Neuronal Oscillations

Über das Elektrenkephalogramm des Menschen.



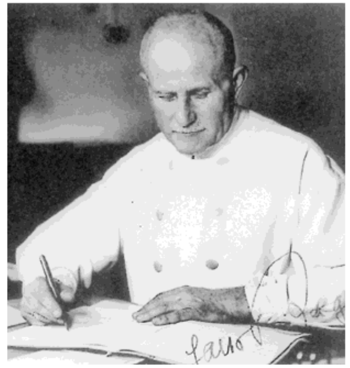


Abb. 2. W. H., 37 Jahre alt, an Dementia paralytica leidend. E.E.G. bei Nadelableitung von der Rinde des linken Stirn- und des rechten Scheitellappens. Zeit in $^1/_{10}$ Sek.

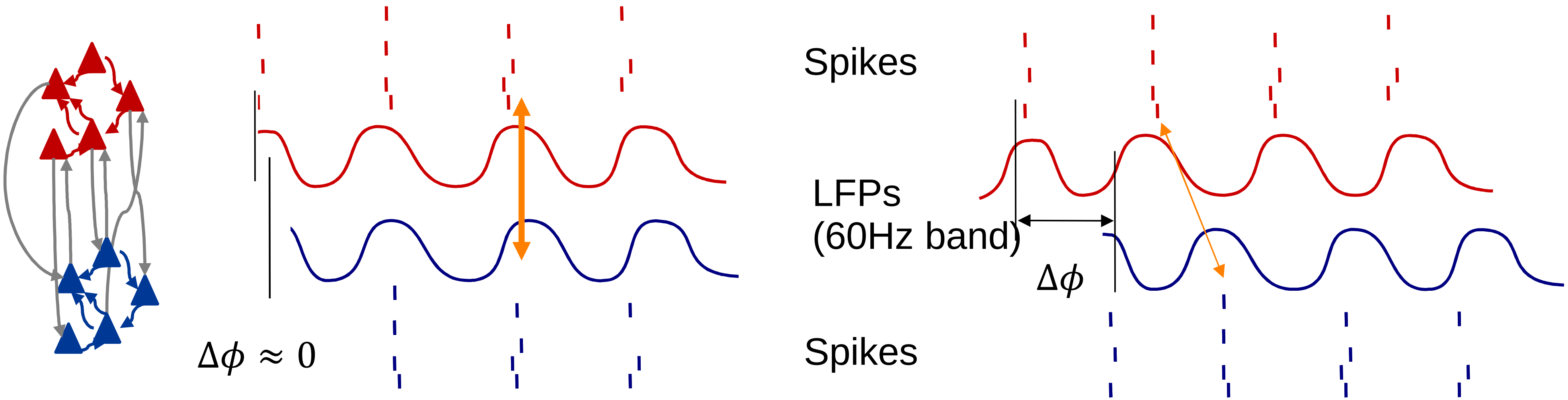
[Berger, Arch Psychiatr Nervenkr. 1929 – 1938 (14 papers + 1 book)]

→ Epi-phenomenon or functional property ?

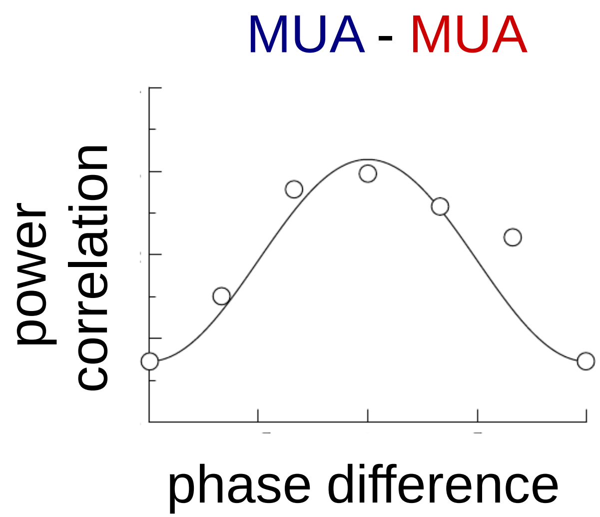
Information Flow and Neuronal Oscillations

- communication through coherence hypothesis

[Fries, TICS, 2005]



[Womelsdorf et al. Science, 2007]



Outline: Flexible Function in Neuronal Networks

- dynamic information routing in complex networks
  - structural vs. effective connectivity
  - flexible information routing in oscillator networks
  - spiking networks, transient dynamics
- flexible information processing in complex networks
  - oscillatory Hopfield networks
  - self-organized pattern recognition
- learning flexible function in neuronal networks
- connections to experiments
  - brain state identification in zebrafish
  - complete brain activity mapping in mouse
- conclusions

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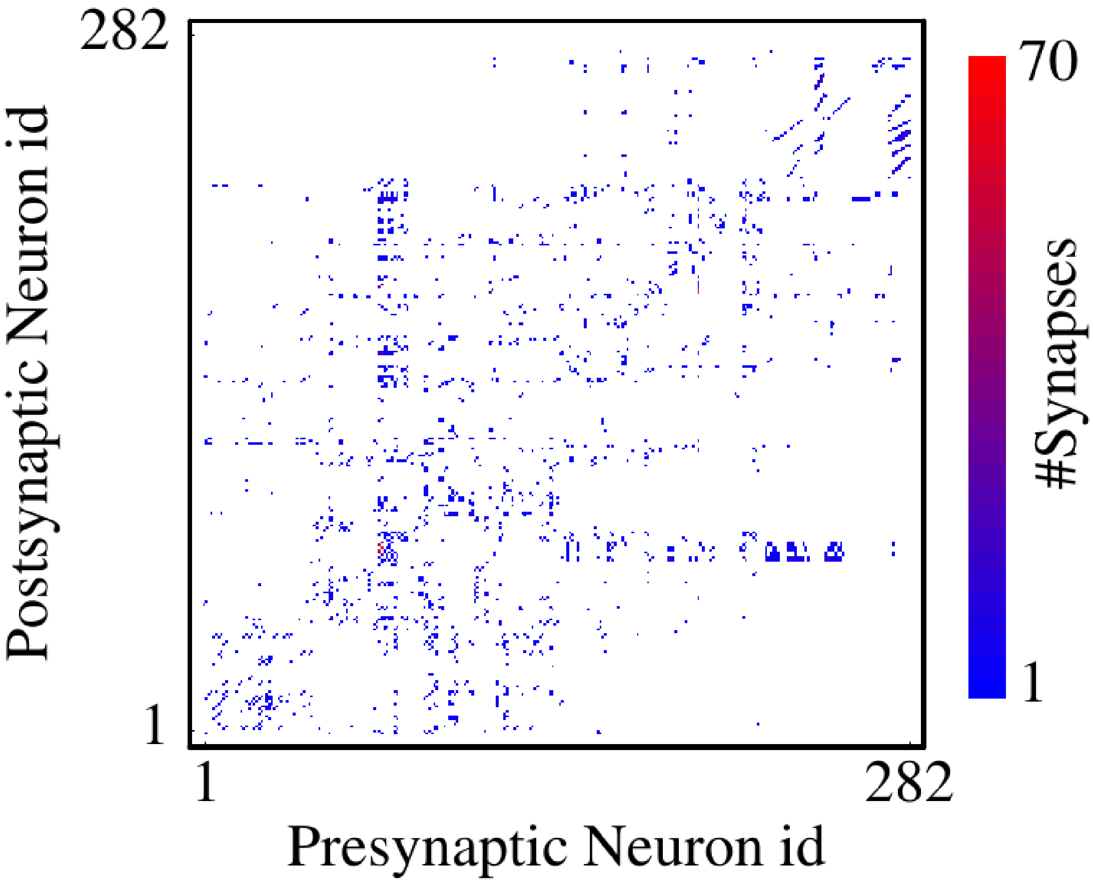
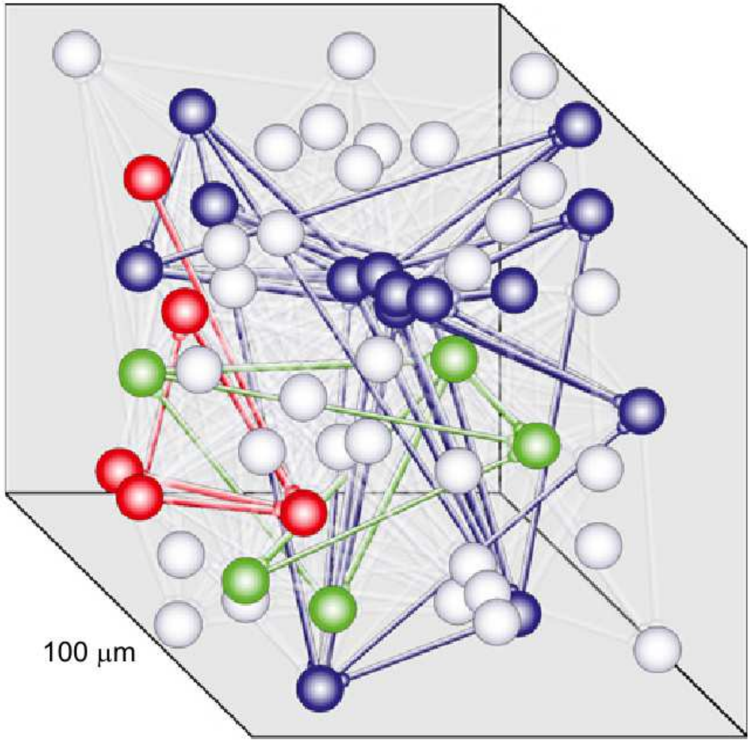
Structural Connectivity

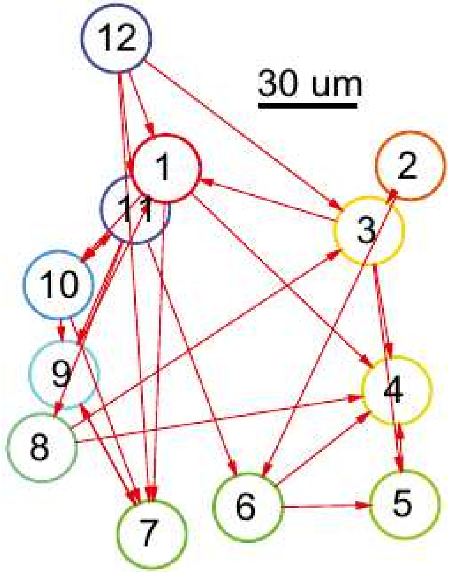
structural connectivity = physical wiring (e.g. via synapses)



[J. G. White, E. Southgate, J. N. Thomson, S. Brenner, 1986]

Clustering / Modular Network Structure





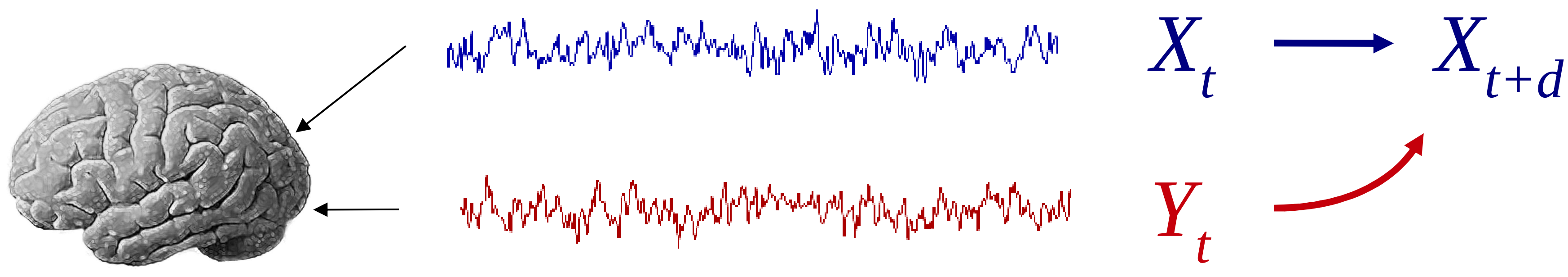
[Perin et al. PNAS 2010]

[see also: Song, .., Chklovskii, 2005]

- interlaced strongly connected groups (color) on top of a sea of weak connections (gray)

Effective connectivity

- functional connectivity as measured from dynamics
- focus on forecast: improvement of forecast of X_{t+d} by history of Y_t



"dual" view

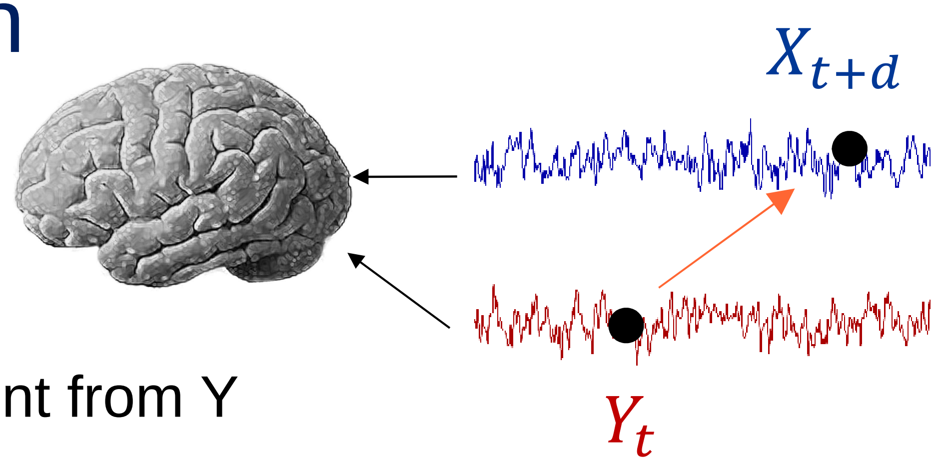
Statistical comparison of regressions

Granger Causality
Dynamic Causal Models

Model-independent information theoretical measures

Delayed Mutual Information
Transfer Entropy

Delayed mutual information



joint probability

$p(X_{t+d}, Y_t)$

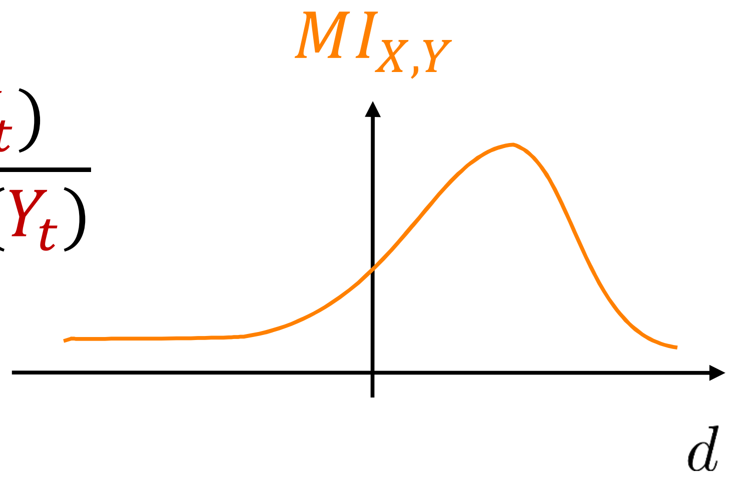
X independent from Y

$p(X_{t+d})p(Y_t)$

KL divergence

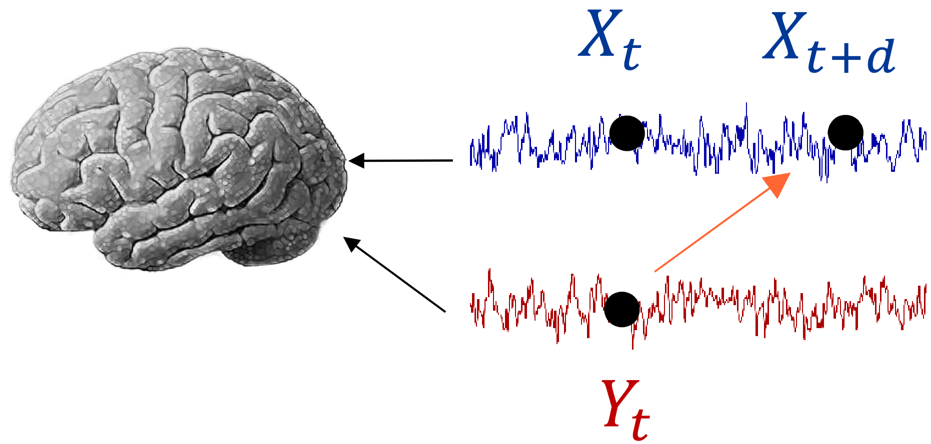
$$MI_{X,Y}(d) = \int p(X_{t+d}, Y_t)\ \log \frac{p(X_{t+d}, Y_t)}{p(X_{t+d})p(Y_t)}$$

$$= H(X_{t+d}) - H(X_{t+d}|Y_t)$$

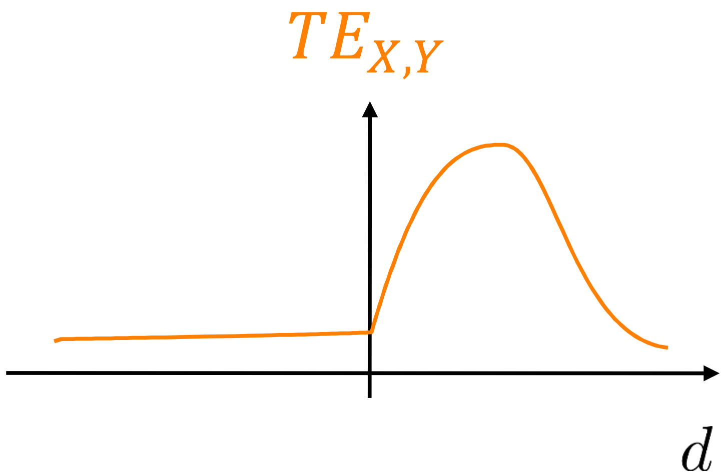


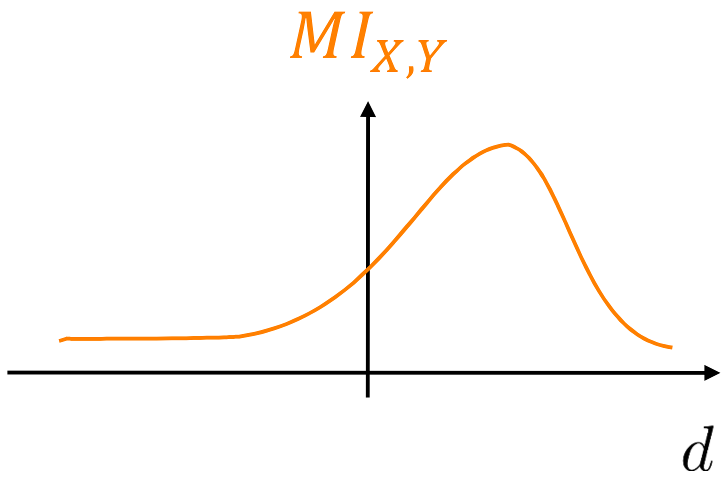
- $d > 0 \rightarrow$ ‘shared’ information from the present of Y to the future of X
- $d < 0 \rightarrow$ information ‘shared’ from X to Y
- in general non-symmetric !

Transfer Entropy



$$TE_{X,Y}(d) = H(X_{t+d}|X_t) - H(X_{t+d}|X_t, Y_t)$$

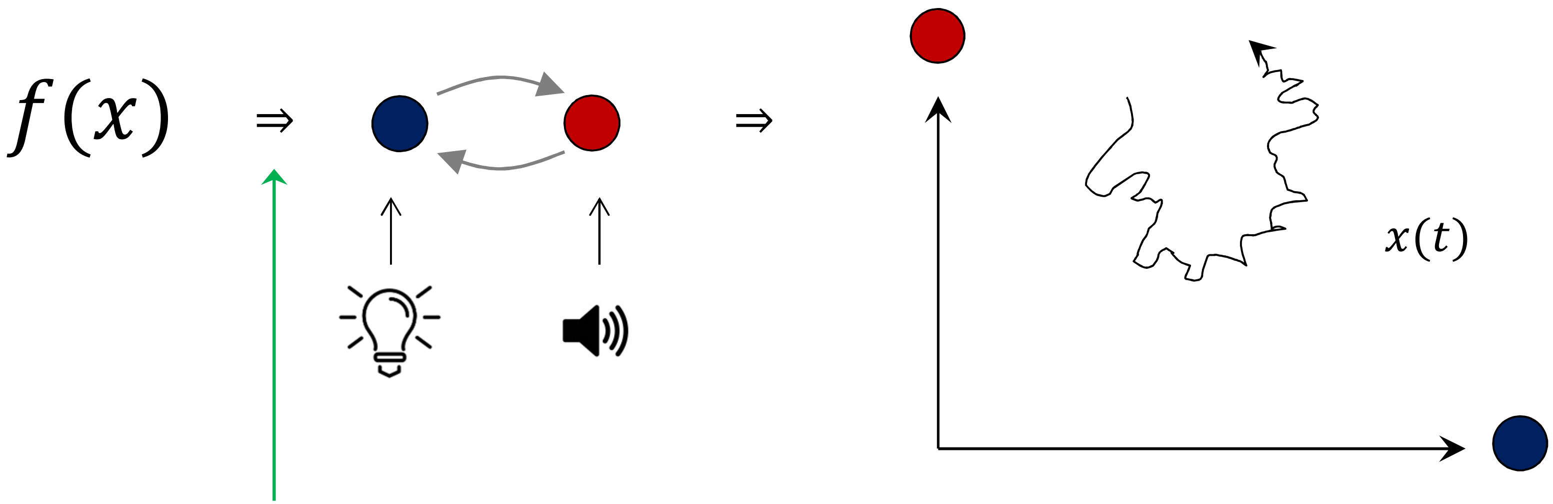




- non-symmetric by definition
- takes into account auto-correlations in time
- in general non-symmetric !

Dynamics from Function

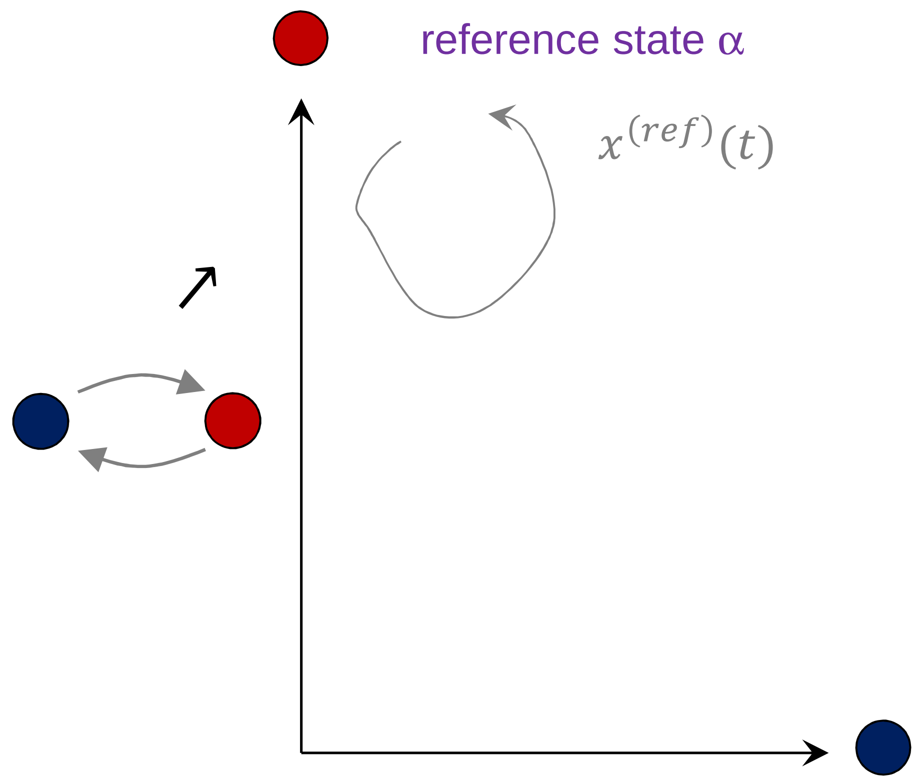
- Function ⇒ Neuronal Network ⇒ Dynamics
  - early sensory processing
  - 'direct information encoding and processing'



- artificial networks + learning [Hertz Korgh Palmer, 1991, ...]
- neuronal compiler [Eliasmith, Science 2012]
- …

Information Routed on top of Dynamical Reference States

- Function ⇒ Neuronal Network ⇒ Dynamics
  - early sensory processing
  - ‘direct information encoding and processing’
- Reference Dynamics ⇒ Effective Network ⇒ Function
  - larger scale communication / self-organized information routing
  - ‘information and processing in fluctuations around reference state’



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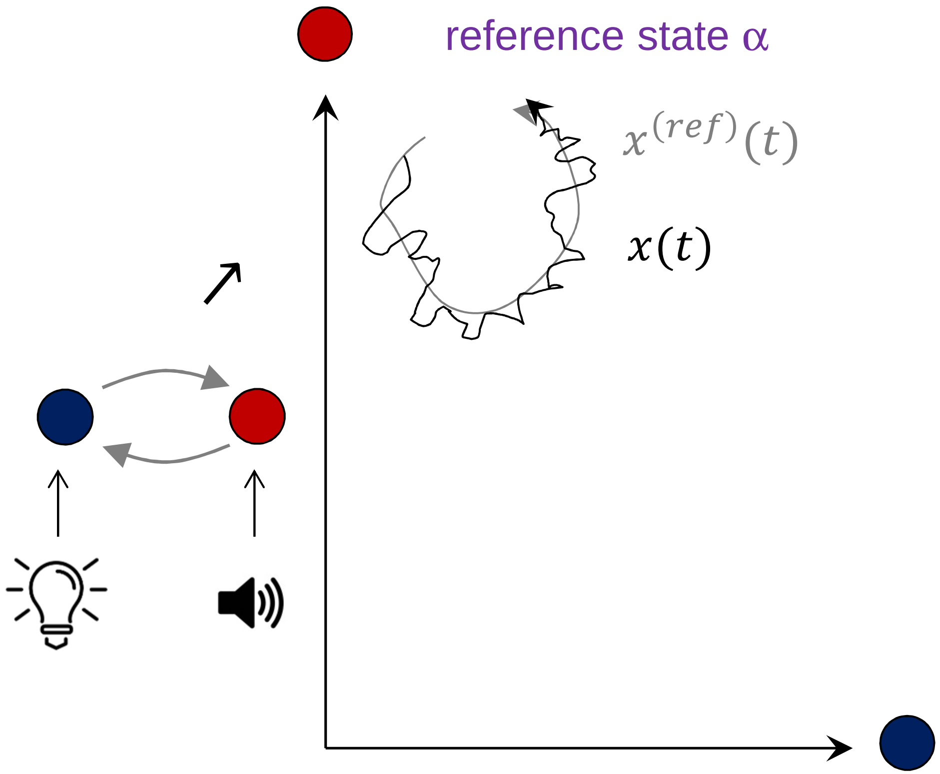

[Kirst, Time, Battaglia, Nature Communications, 2016, in press]

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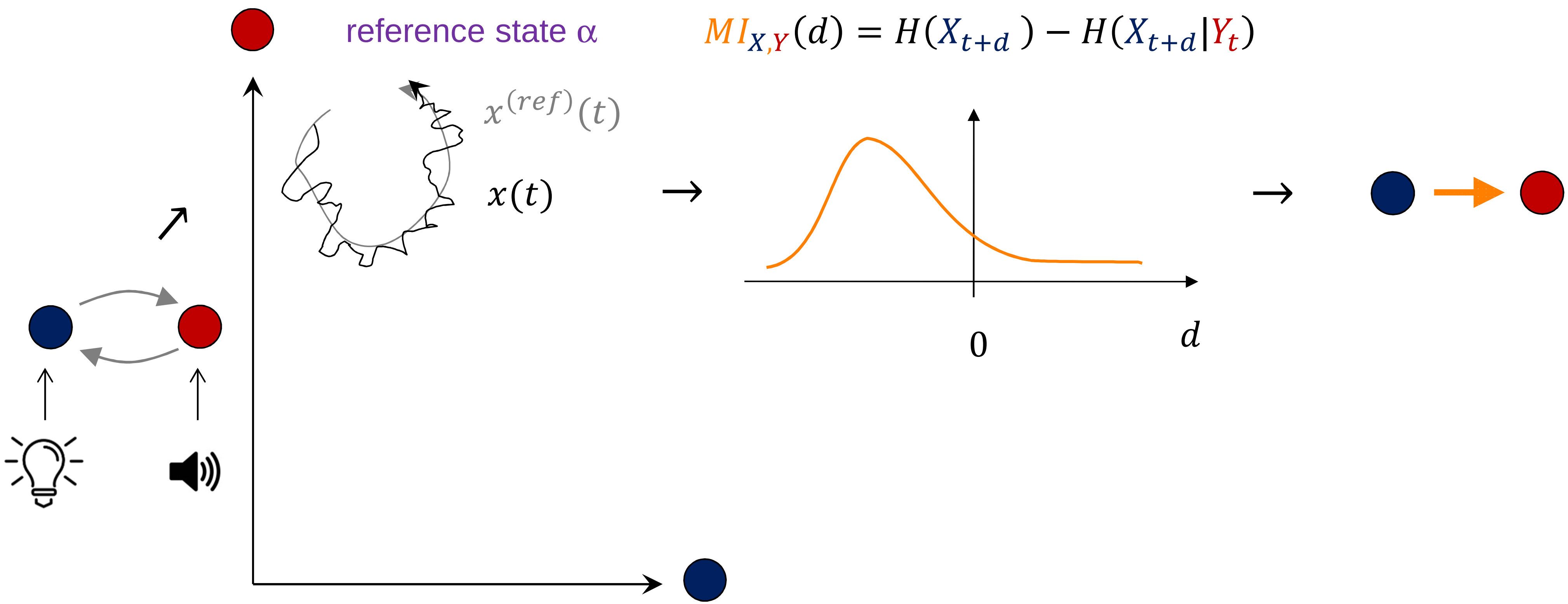

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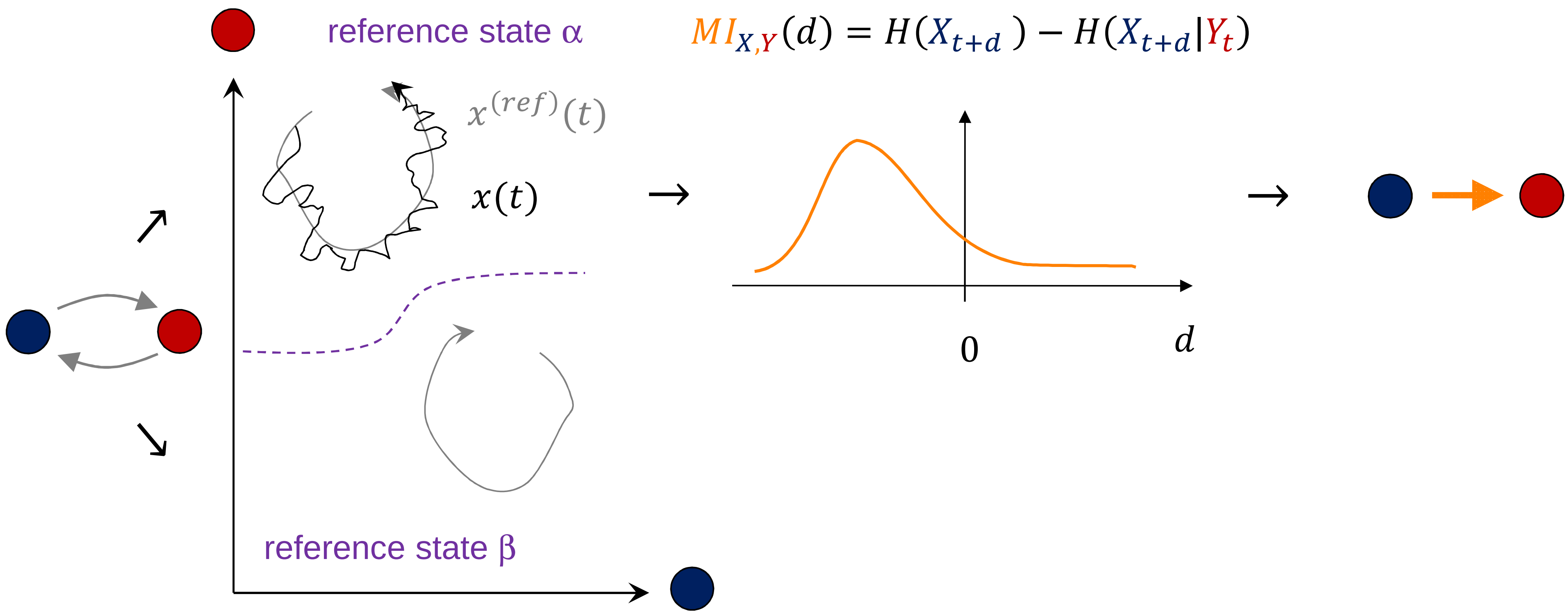

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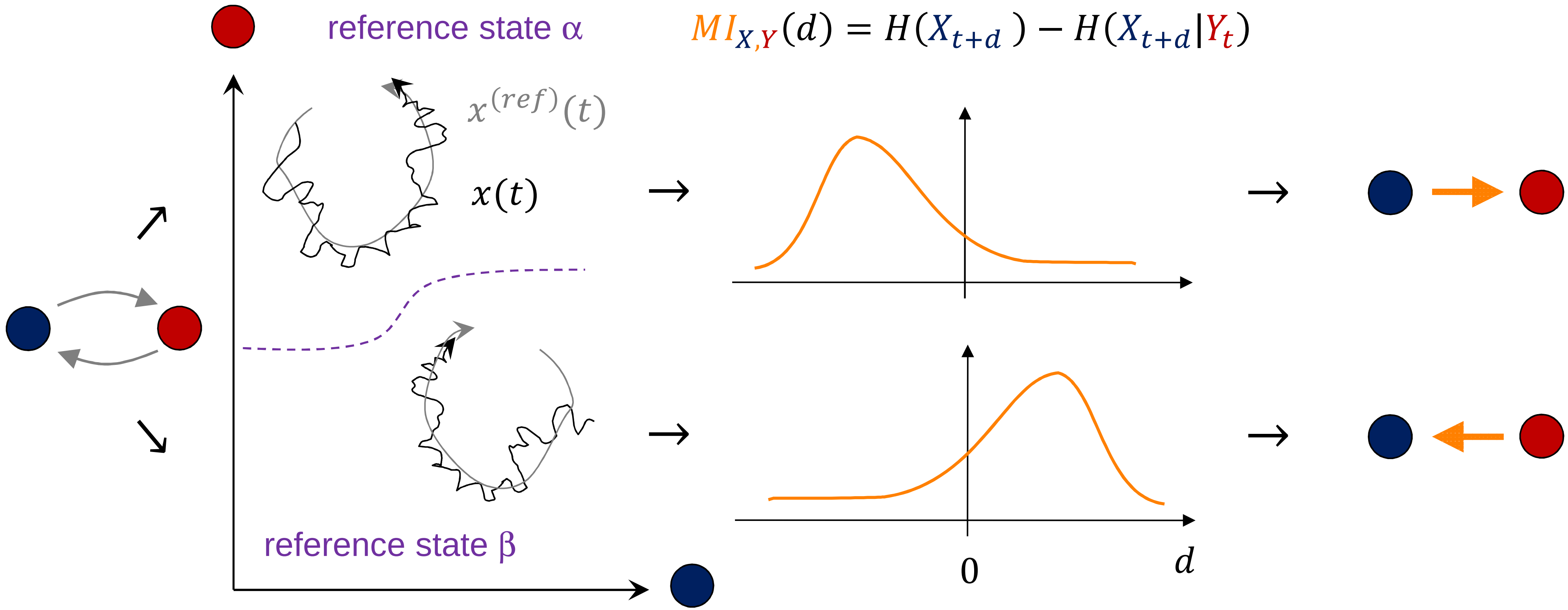

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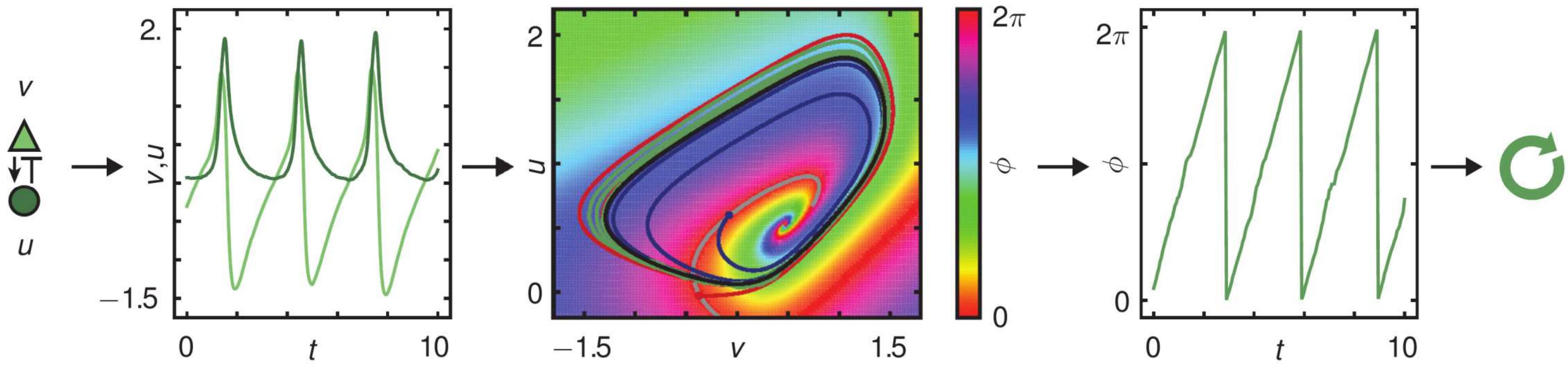
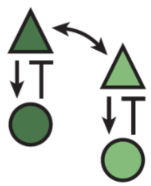
Phase Reduction and Kuramoto Oscillators

Phase reduction:



Phase dynamics (of weakly coupled oscillators):

[Kuramoto, Springer 1984]
[Acebron et al. 2005]



$$\frac{d}{dt}\phi_i = \omega_i + \sum_j \gamma_{ij}\left(\phi_i - \phi_j\right) + \zeta_i$$

- 'standard model' for synchronization
- 'phase part' of discrete Ginzburg -Landau / multiple Hopf bifurcation
- common dynamics: phase locking

Information Routing Measures in Kuramoto Networks

- $\frac{d}{dt}\phi_i = \omega_i + \sum_j \gamma_{ij}(\phi_i - \phi_j) + \zeta_i$

- joint probability distribution: $p(\phi_t, \phi_{t+d}) = p(\phi_t)\, p(\phi_{t+d}|\phi_t)$

  - no noise $\zeta_i = 0$ stable phase-locked state: $\Omega = \omega_i + \sum_j \gamma_{ij}(\Delta\phi_{ij})$

  - small noise expansion around phase locked state $\phi_i = \psi_i + \sigma\varphi_i + \ldots$

    $\Rightarrow \quad p(\phi_{t+d}|\phi_t)$

  - phase rotation symmetry / phase variables live on circle

    $\Rightarrow \quad p(\phi_t)$

- integration to marginals

$\longrightarrow$ **Theorem**

delayed mutual information $\mathrm{MI}_{ij}(d)$ and transfer entropy $\mathrm{TE}_{i\to j}(d)$

as function of *network structure* and *dynamical reference state*

[Kirst et al, Nat Comm, 2016]

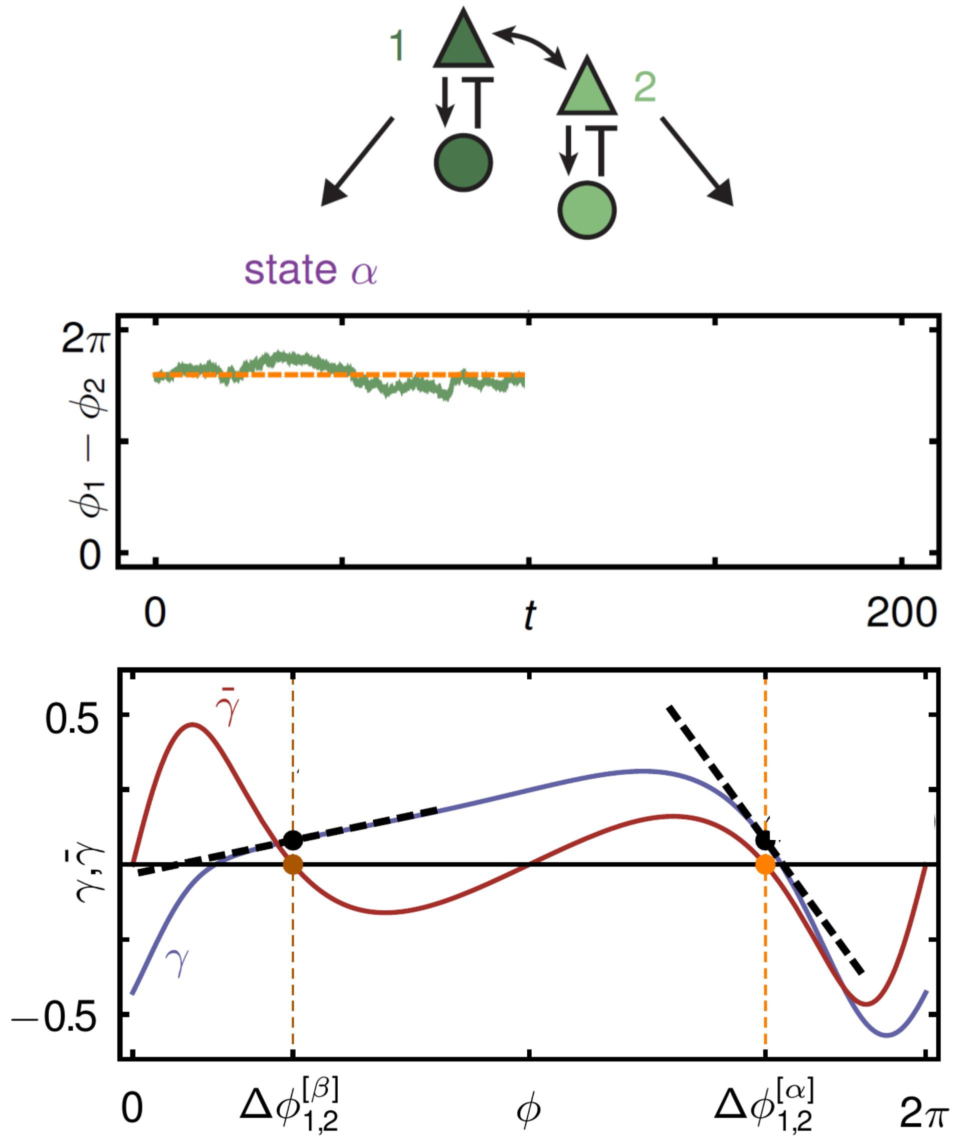
Dynamic Information Routing

- phase dynamics:

$$\dot{\phi}_i = \omega + \gamma\left(\phi_i - \phi_j\right) + \sigma\zeta_i\left(t\right)$$

- phase locking: $\sigma = 0$

$$\dot{\Delta\phi} = \gamma\left(\Delta\phi\right) - \gamma\left(-\Delta\phi\right) = \bar{\gamma}\left(\Delta\phi\right)$$



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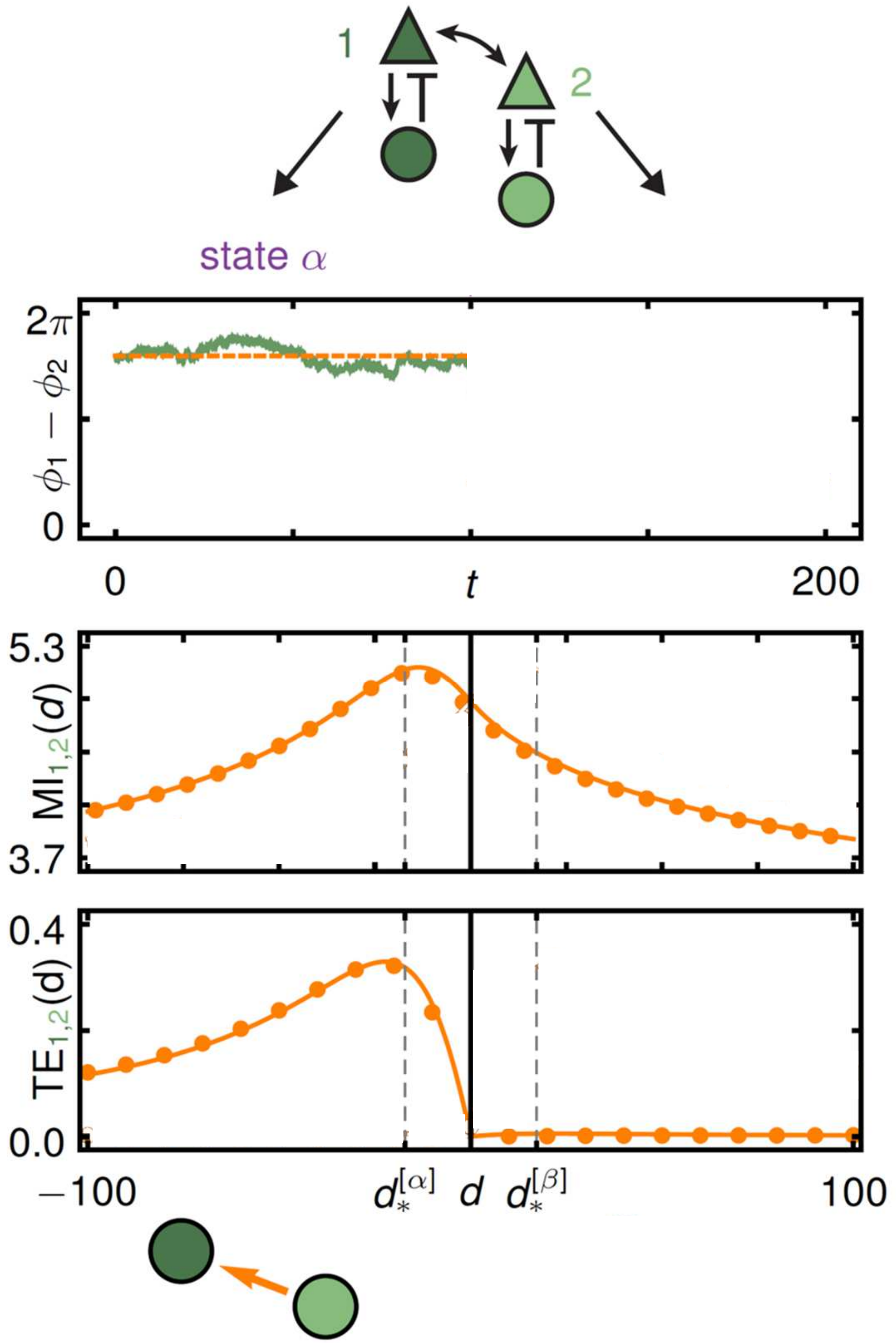

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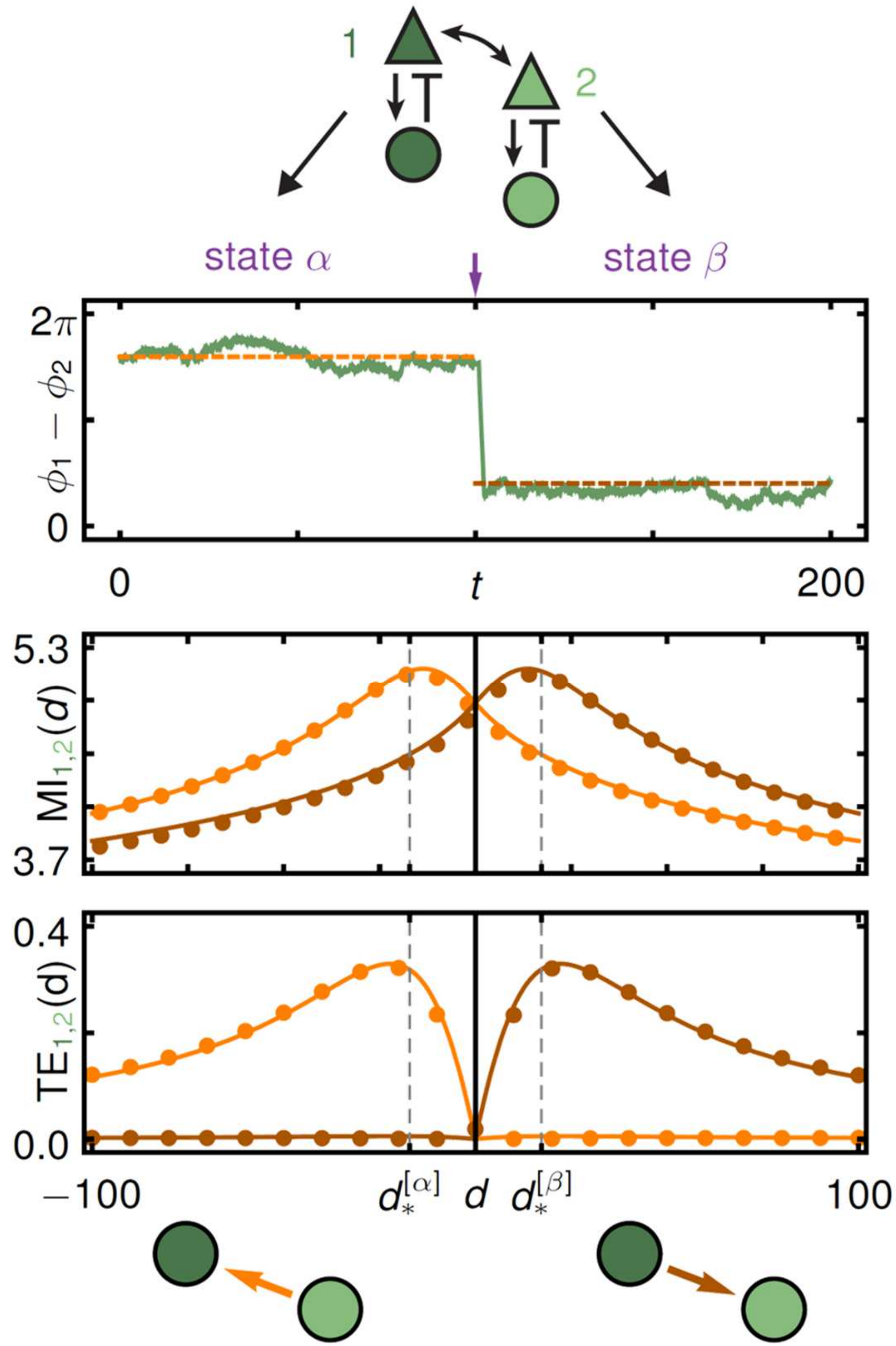

$\longrightarrow$ switching reference states switches network communication function

[Kirst et al, Nat Comm, 2016]

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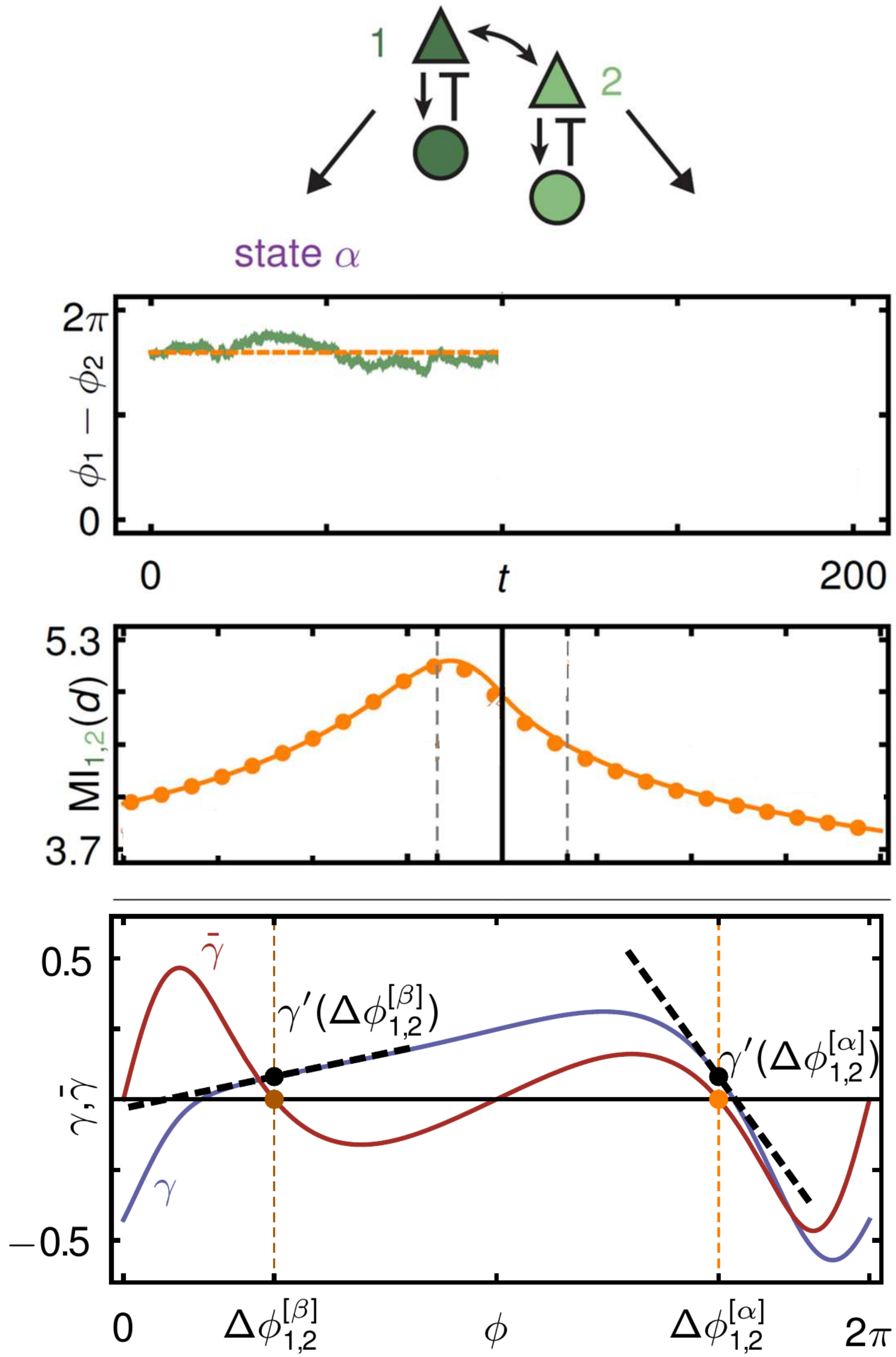
- small noise expansion:

$$\phi_i = \psi_i + \sigma\varphi_i + \ldots$$

$$\dot{\psi}_i = \omega + \gamma\left(\Delta\phi_0\right) = \Omega$$

$$\dot{\varphi}_1 = \gamma'\left(\Delta\phi_0\right)\left(\varphi_1 - \varphi_2\right) + \zeta_1$$

$$\dot{\varphi}_2 = \gamma'\left(-\Delta\phi_0\right)\left(\varphi_2 - \varphi_1\right) + \zeta_2$$



[Kirst et al, Nat Comm, 2016]

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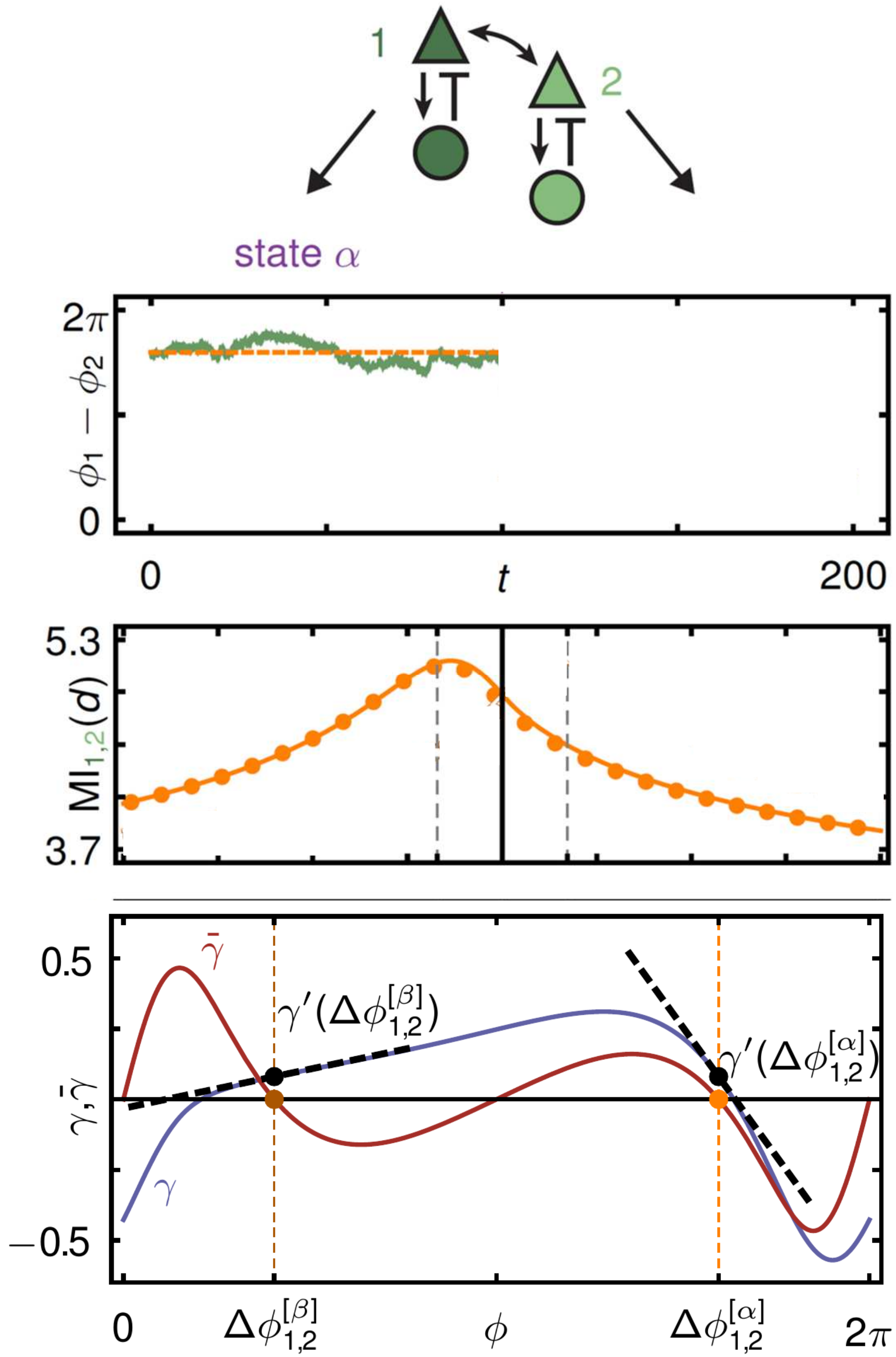
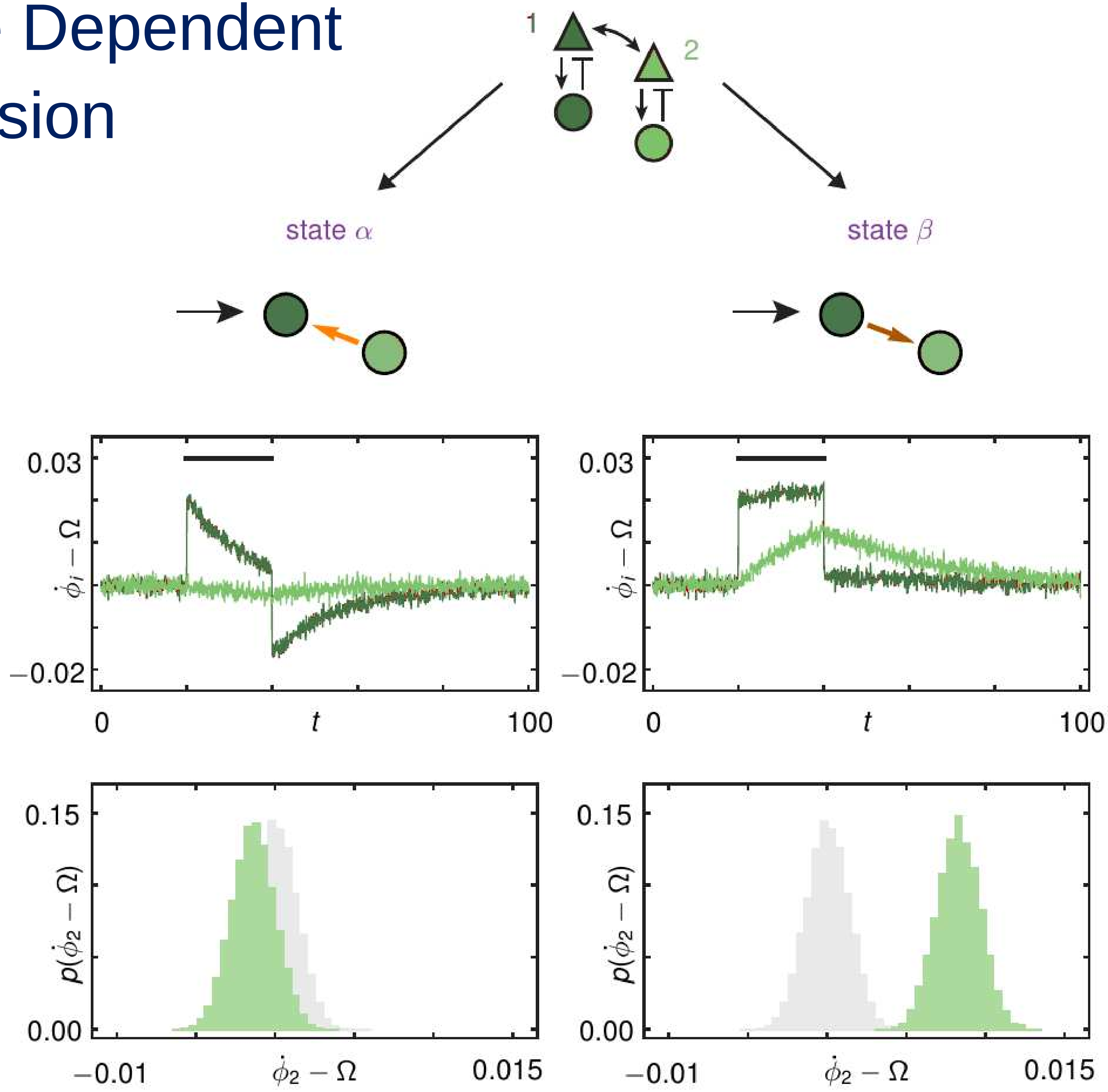


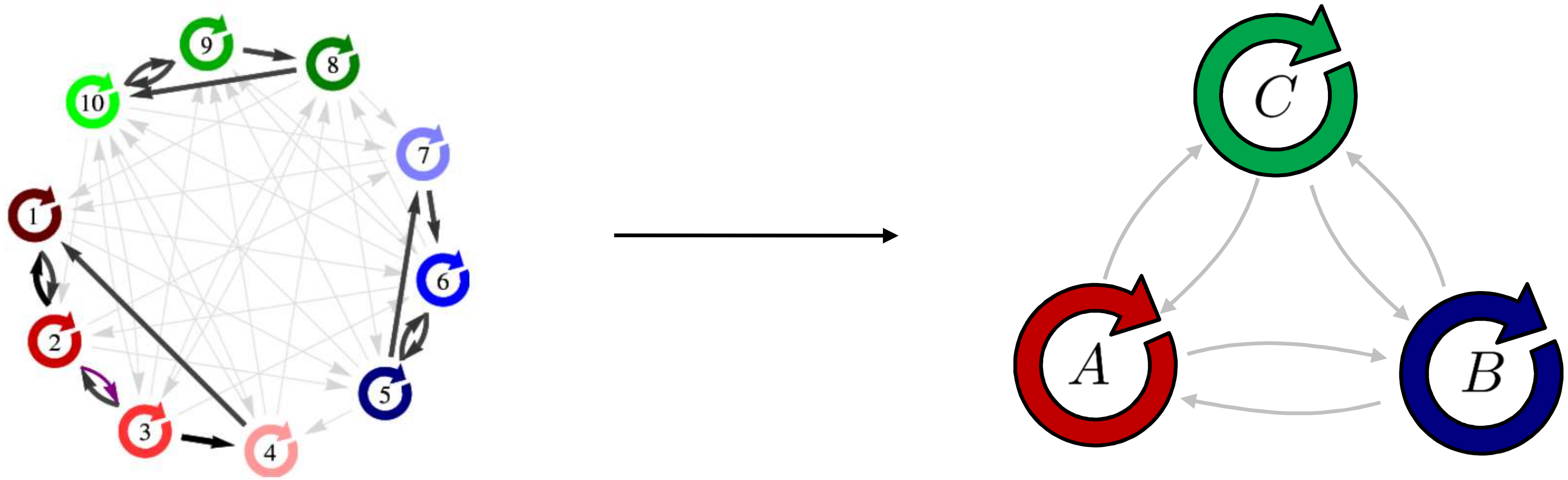
[Kirst et al, Nat Comm, 2016]

Dynamical State Dependent Signal Transmission



[Kirst et al, Nat Comm, 2016]

Information Routing in Modular Networks



- $\dot{\phi}_i = \omega_i + \sum_j \gamma_{ij} \left(\phi_i - \phi_j\right) + \zeta_i$

  $\Rightarrow$ Analytic expression
  for delayed mutual information
  $\mathrm{MI}_{ij}(d)$
  as function of
  - dynamical state and
  - network parameters

- second phase reduction step on clusters

$$\dot{\Phi}_X = \Omega_X + \sum_Y Z_X(\Phi_X) G_{XY}(\Phi_X, \Phi_Y) + \xi_X$$

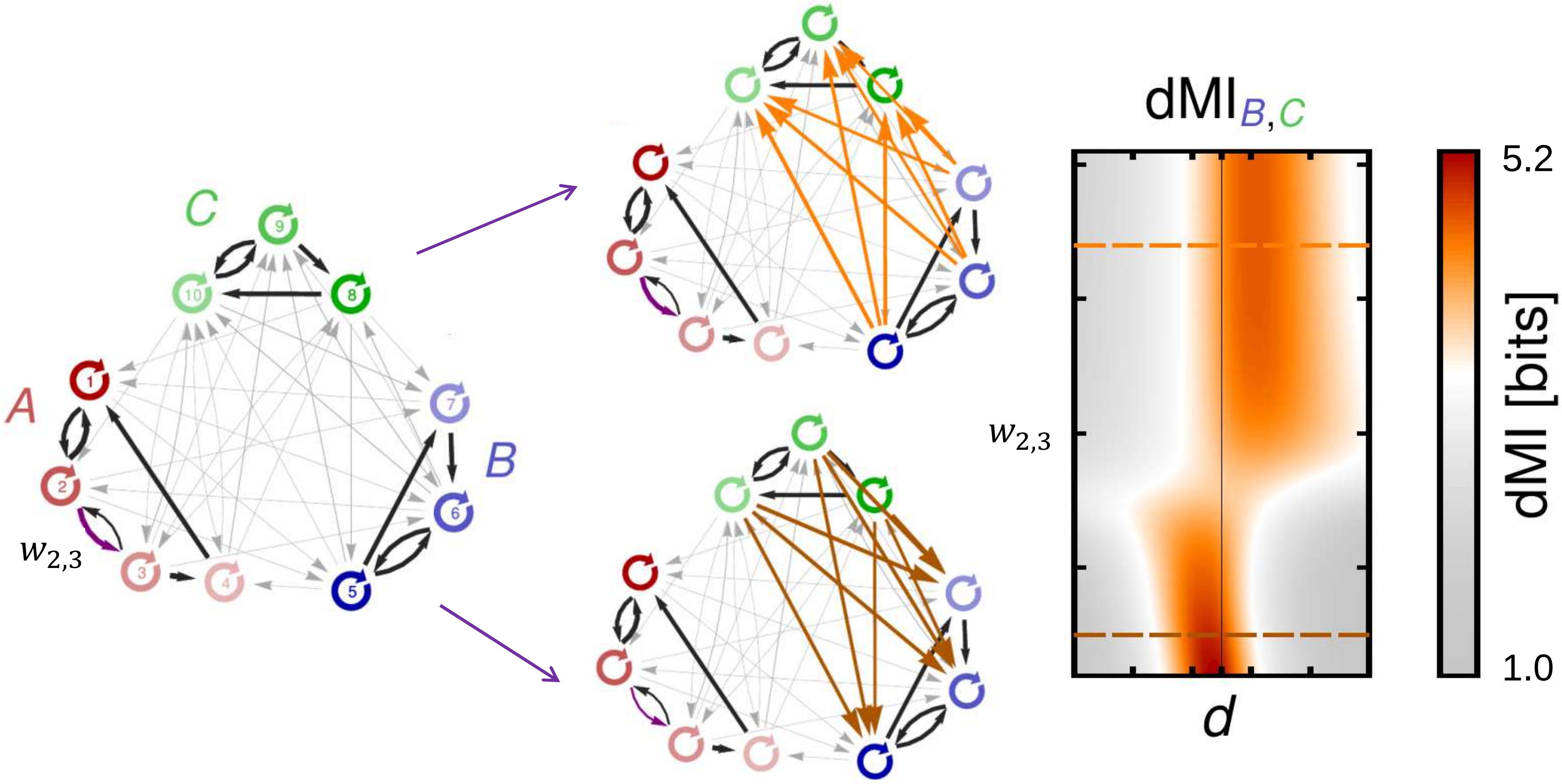
- stochastic averaging

$$\dot{\Phi}_X = \Omega_X + \sum_Y \Gamma_{XY}(\Phi_X - \Phi_Y) + \Xi_X$$

$\Rightarrow$ cluster phase response Z_X and thus Γ_{XY}
and delayed mutual information
depend on local clusters properties

[Kirst et al, Nat Comm, 2016]

Hierarchical Networks: Action at a Distance



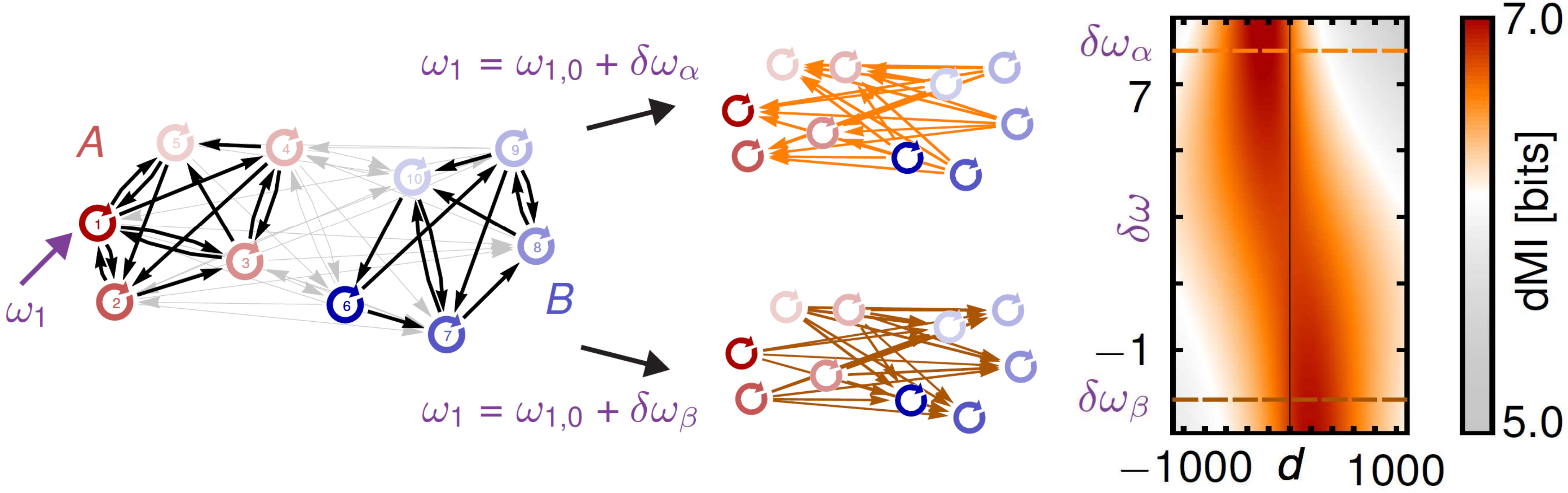
- local control of non-local functional connectivity motifs

[Kirst et al, Nat Comm, 2016]

Local Control of Non-Local Information Routing

- Reference Dynamics ⇒ Effective Network ⇒ Function
- action at a distance: local control of non-local communication

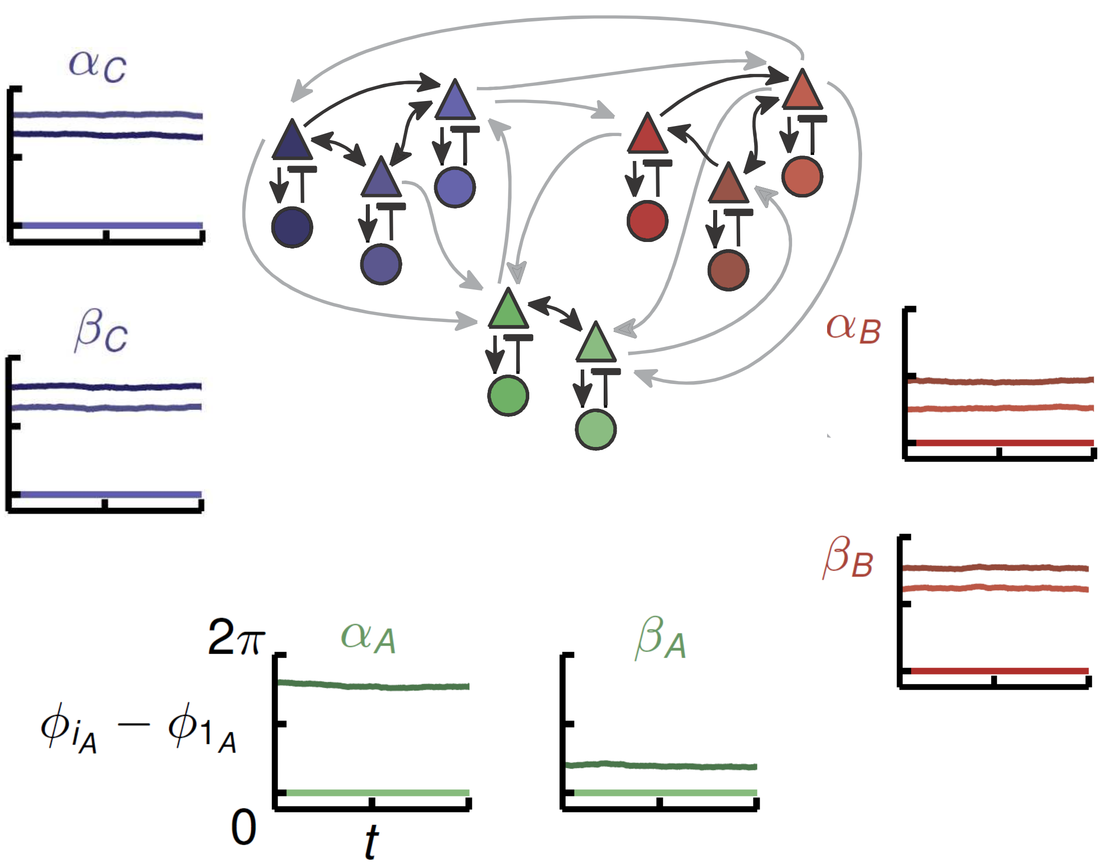
$$dMI_{X,Y}(d) = H(Y_{t+d}) - H(Y_{t+d}|X_t)$$

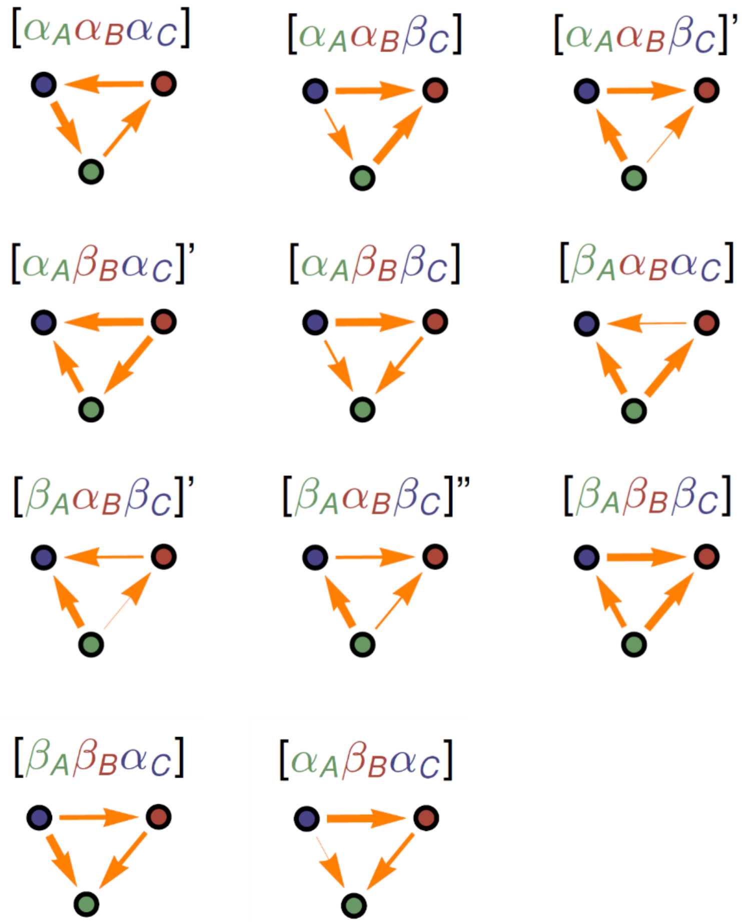


[Kirst et al, Nat Comm, 2016]

Combinatorial Information Routing

- multi-stable local dynamical states

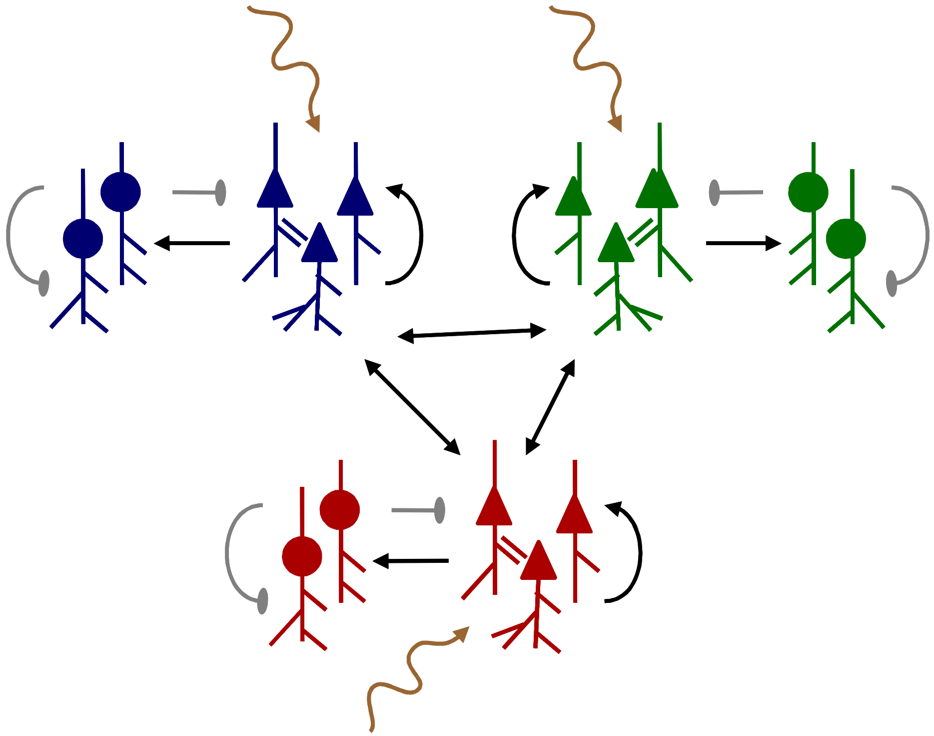




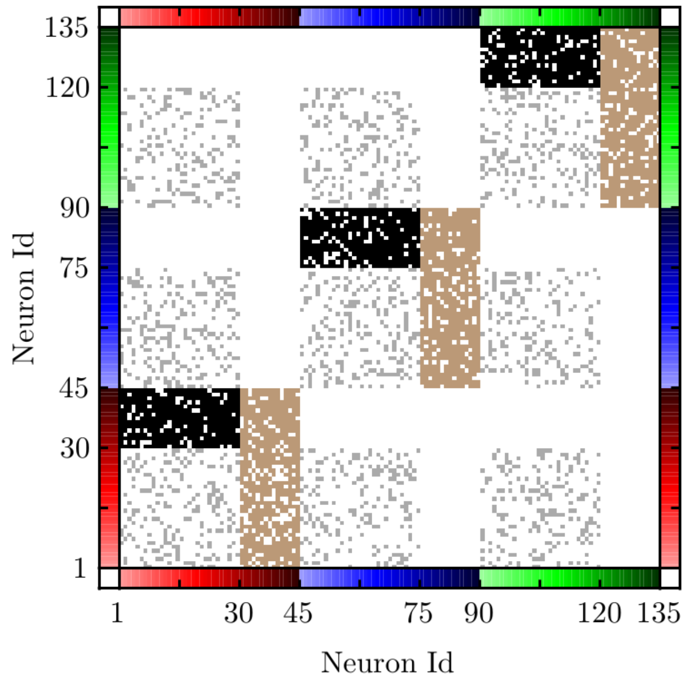
$\longrightarrow$ combination of local dynamical states determines non-local information flow pattern

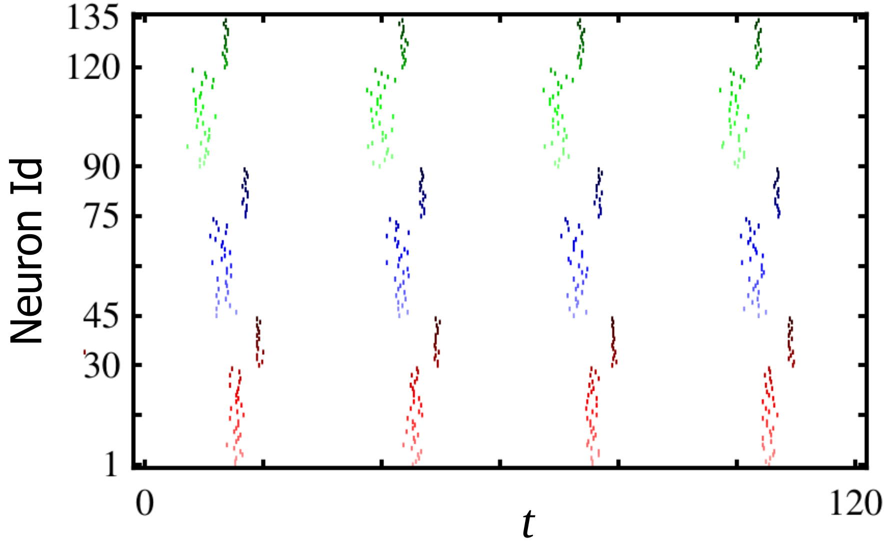
[Kirst et al, Nat Comm, 2016]

Networks of PING Clusters



coupling matrix

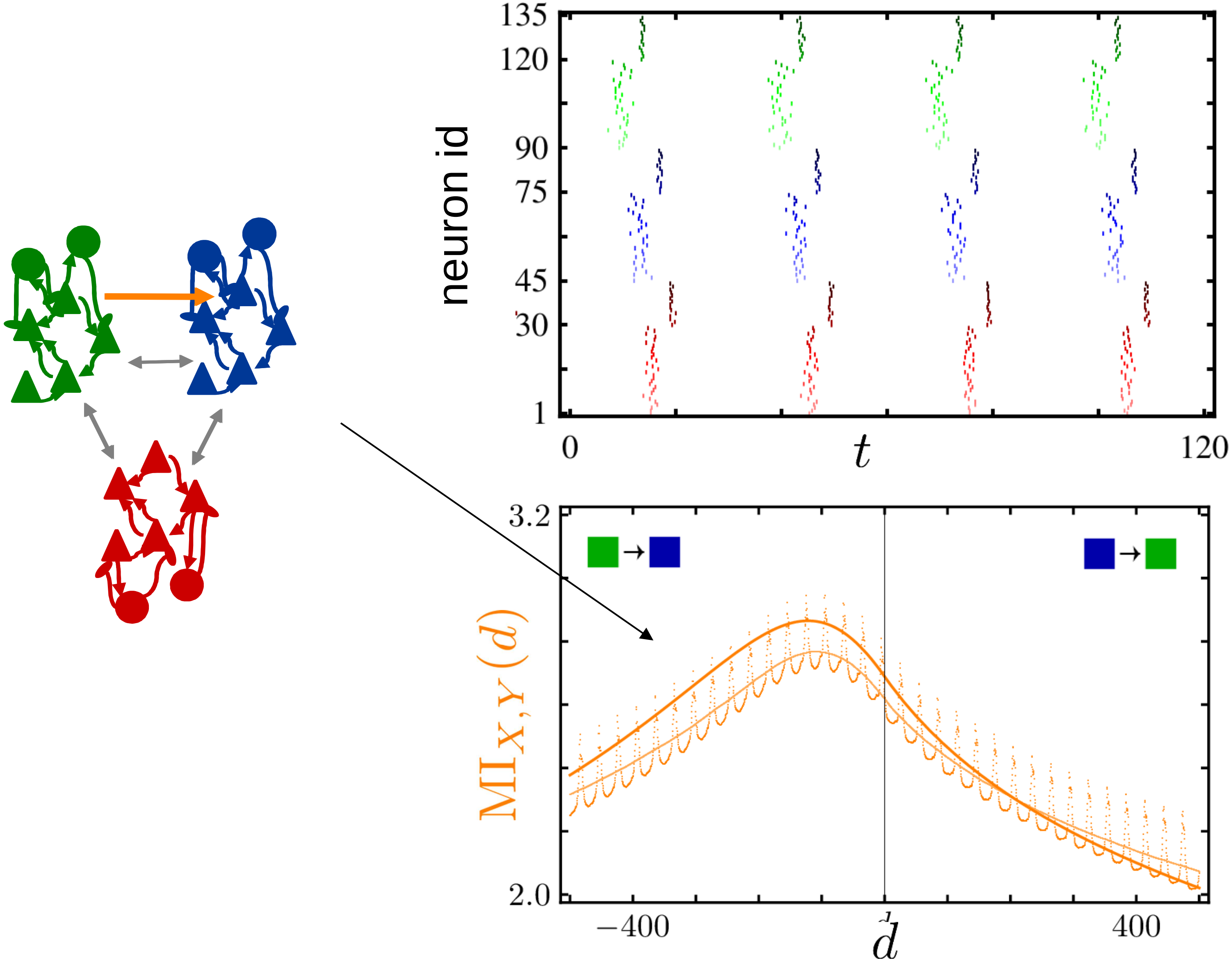




phase locking between PING clusters

Local Control of Non-Local Functional Connectivity

- clusters of **P**yramidal **I**nter-**N**euron **G**amma networks [Börgers & Kopell, 2005]



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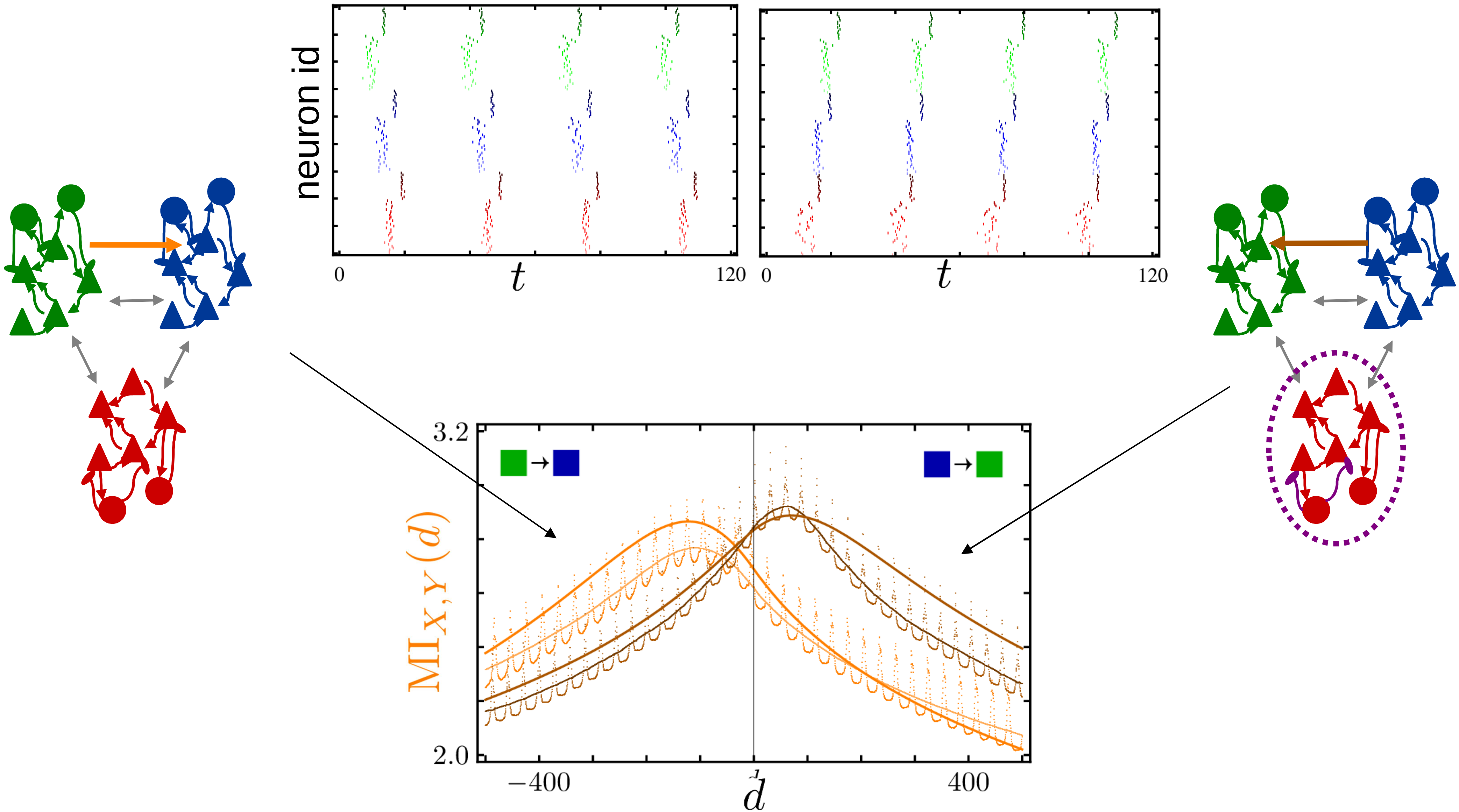


Information Flow in Spike Patterns

- phase channel:

  $\rightarrow$ limitations on precise readout / max capacity

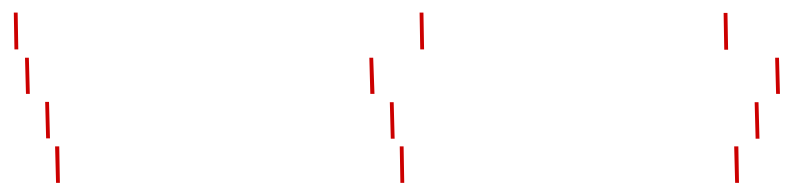
- amplitude channel / spike patterns:

  $\rightarrow$ limited by cluster size only

  $\rightarrow$ PING: spike-to-spike oscillation

  $\rightarrow$ clocked sequence of codewords (ordering of spikes)

  $\pi \in S_N$



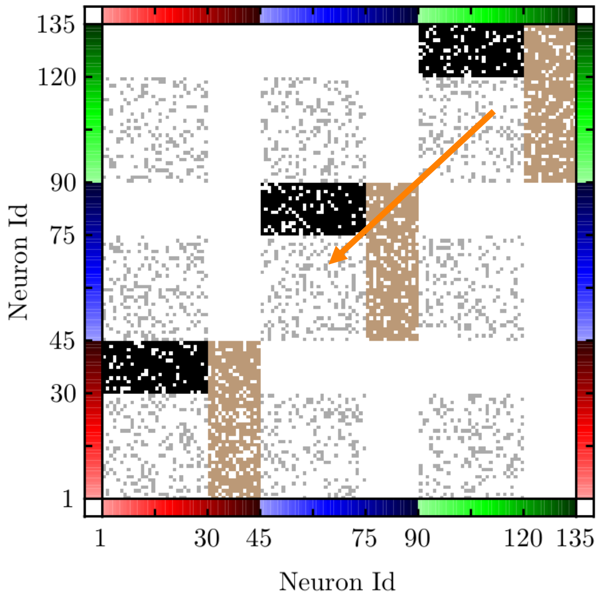
$$\{1,2,3,4\} \qquad \{2,3,4,1\} \qquad \{2,4,3,1\}$$

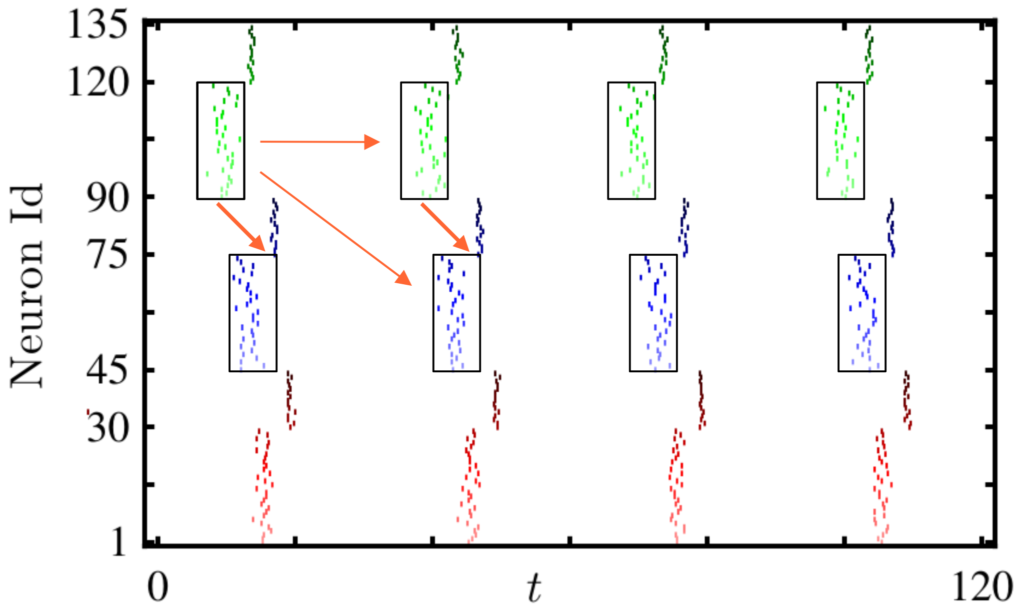
$$\pi_X(t) \qquad \pi_X(t+1) \qquad \pi_X(t+2)$$

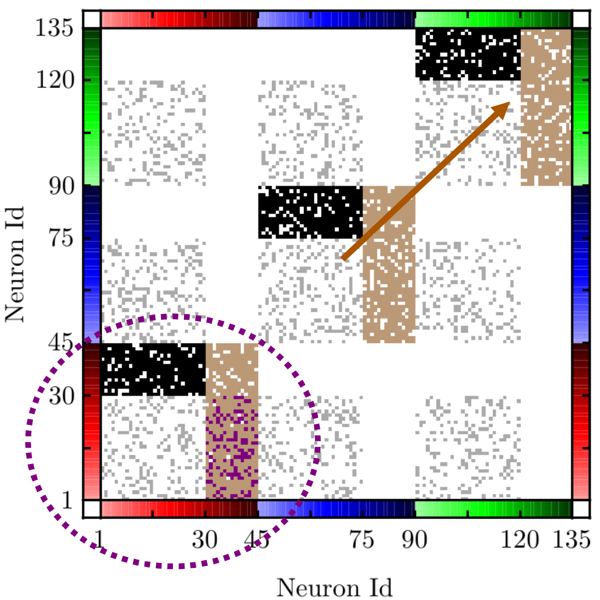
  $\rightarrow$ delayed mutual information

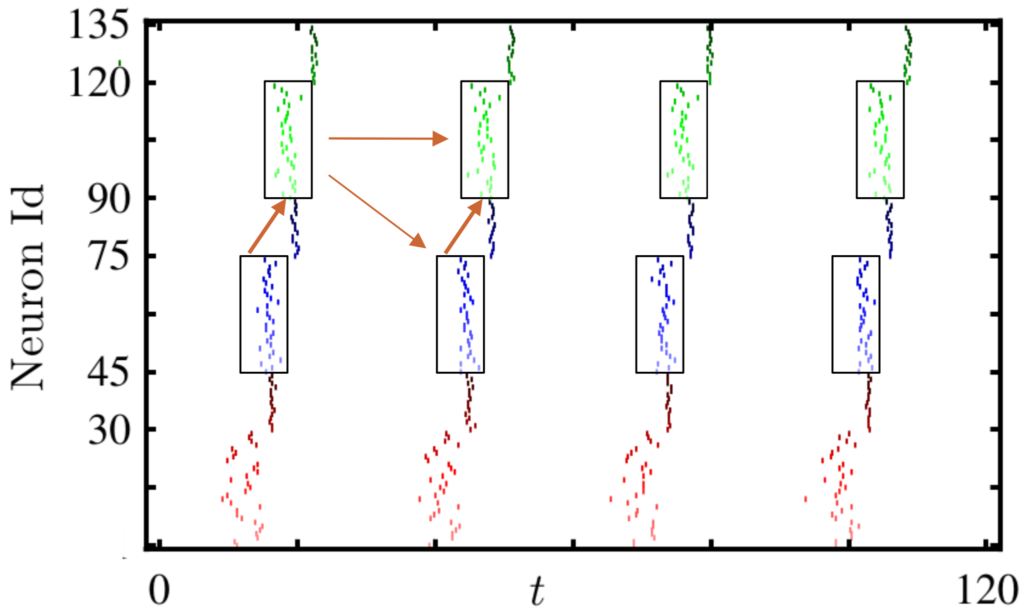
  $\mathrm{MI}^{\pi}_{XY}(d)$

Local Control of Non-Local Info Flow









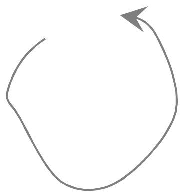
Outline: Flexible Function in Neuronal Networks

- dynamic information routing in complex networks
  - structural vs. effective connectivity
  - flexible information routing in oscillator networks
  - spiking networks, transient dynamics
- flexible information processing in complex networks
  - oscillatory Hopfield networks
  - self-organized pattern recognition
- learning flexible function in neuronal networks
- connections to experiments
  - brain state identification in zebrafish
  - complete brain activity mapping in mouse
- conclusions

Self-Reprograming Neuronal Networks via Dynamics

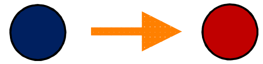
- Closing the loop from functional dynamics to dynamic function:

effective communication



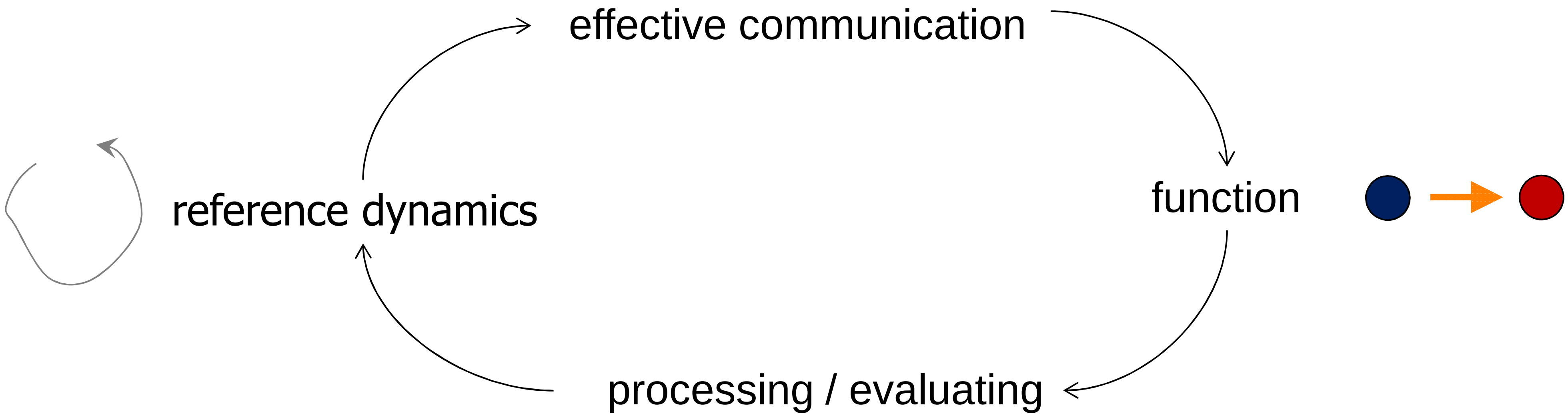
reference dynamics

function



Self-Reprograming of Neuronal Networks via Dynamics

- Closing the loop from functional dynamics to dynamic function:



Self-Reprograming of Neuronal Networks via Dynamics

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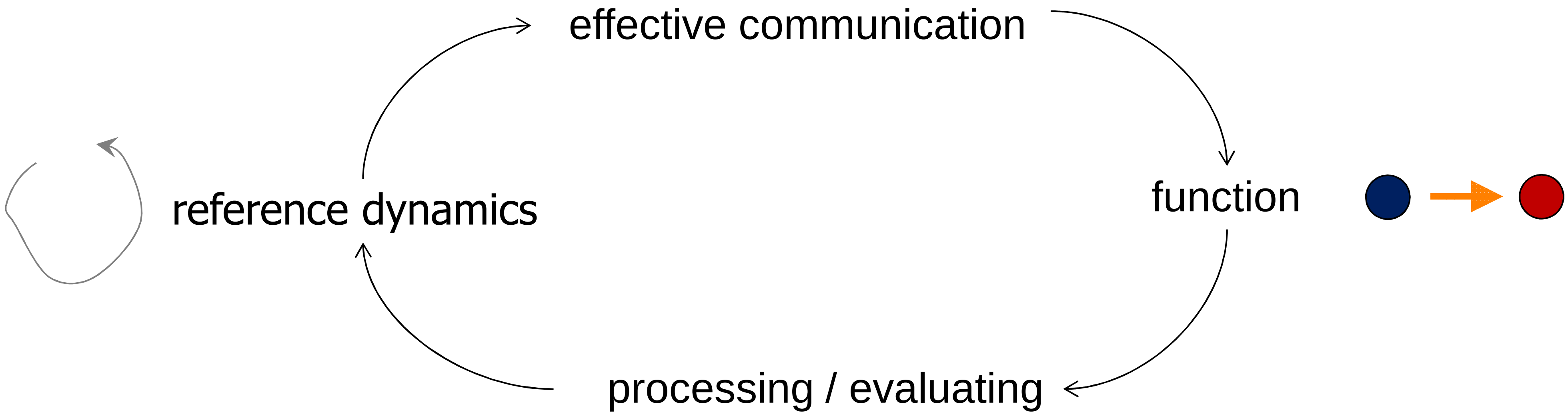
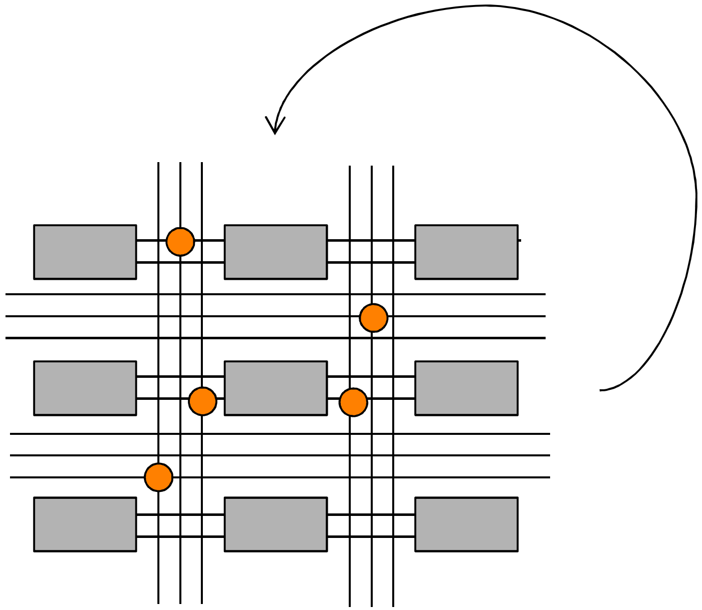
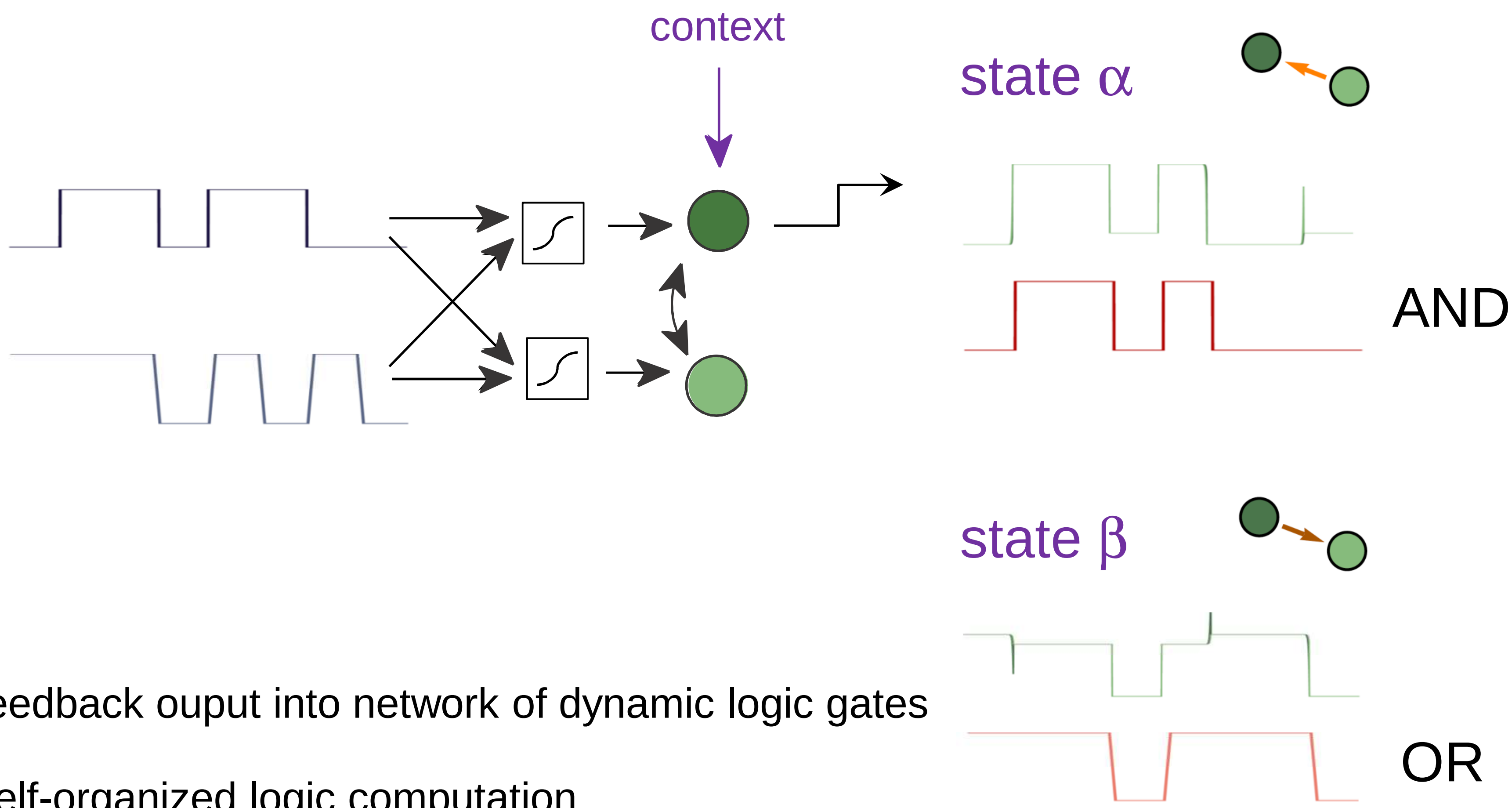


- Field-Programmable Gate Arrays (FPGAs)



Dynamic Logic Gates

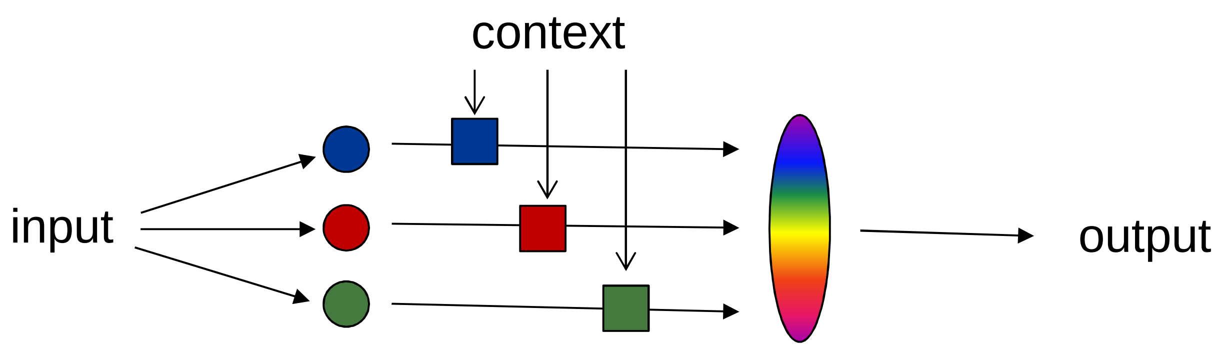


- feedback ouput into network of dynamic logic gates
- self-organized logic computation
- thermalization of logic computation

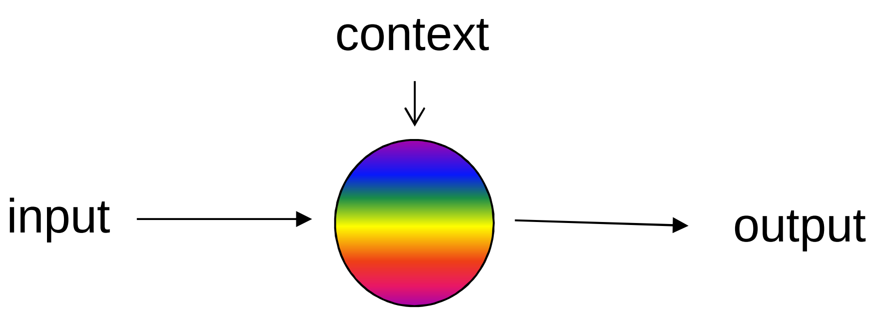
[Kirst & Modes, in prep]

Innate Dynamic Functionality

- Dynamic functionality via appropriate gating of multiple pre-computed functions



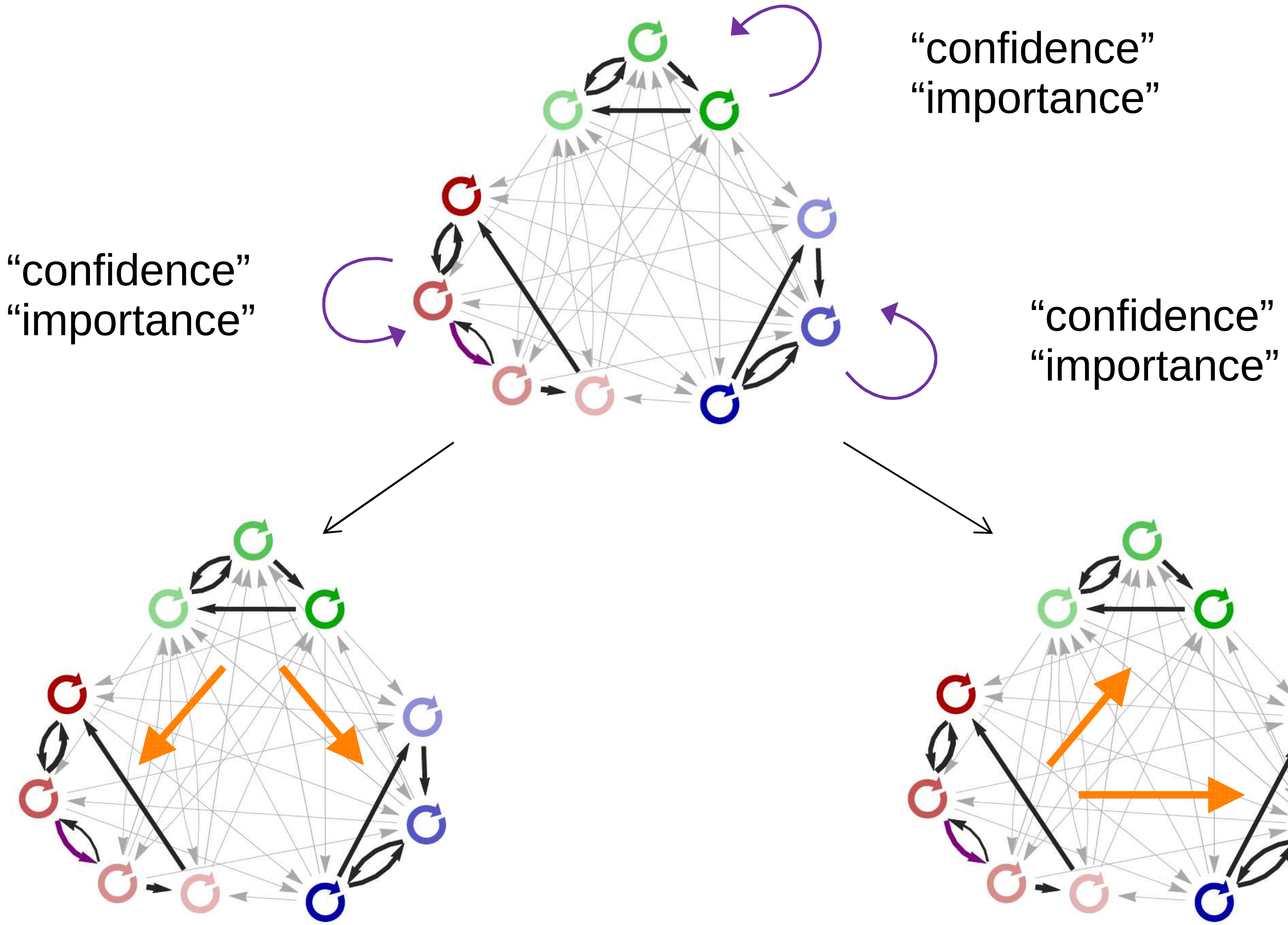
- Can we achieve direct flexible functionality ?



- oscillatory Hopfield networks
- learning innate flexible function in firing rate models

Self-Organized Information Processing

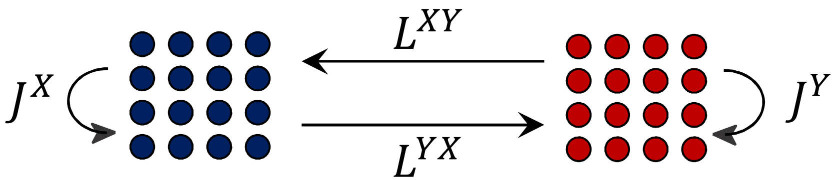
- Oscillatory drive from local importance/confidence signals



- Dynamics self-organize distribution of context information / propagate believe

Self-Organized Contextual Pattern Recognition

- hierarchical Hopfield network



- memory patterns J^X, J^Y

Self-Organized Contextual Pattern Recognition

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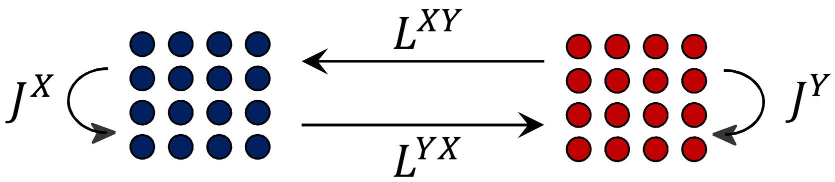
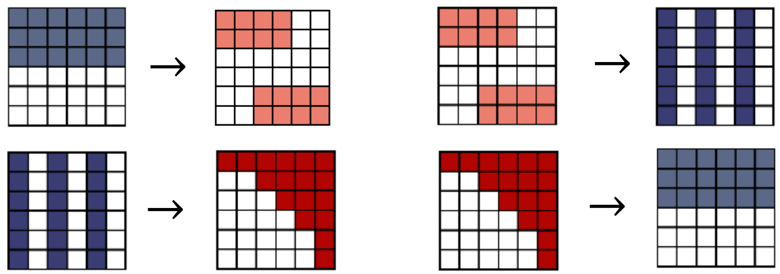


- memory patterns + context rules L^{XY}, L^{YX}



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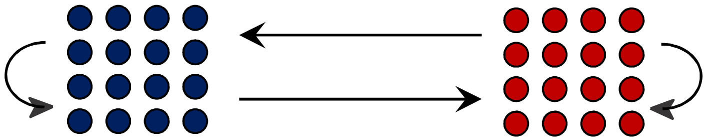

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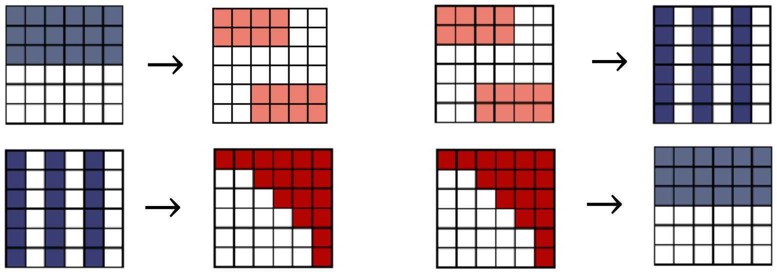
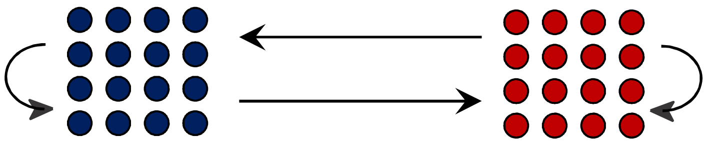


- confidence = K – min(distance to memory patterns) = η

Self-Organized Contextual Pattern Recognition

- hierarchical Hopfield network



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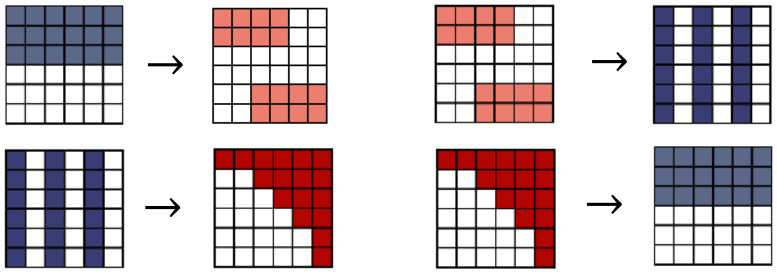
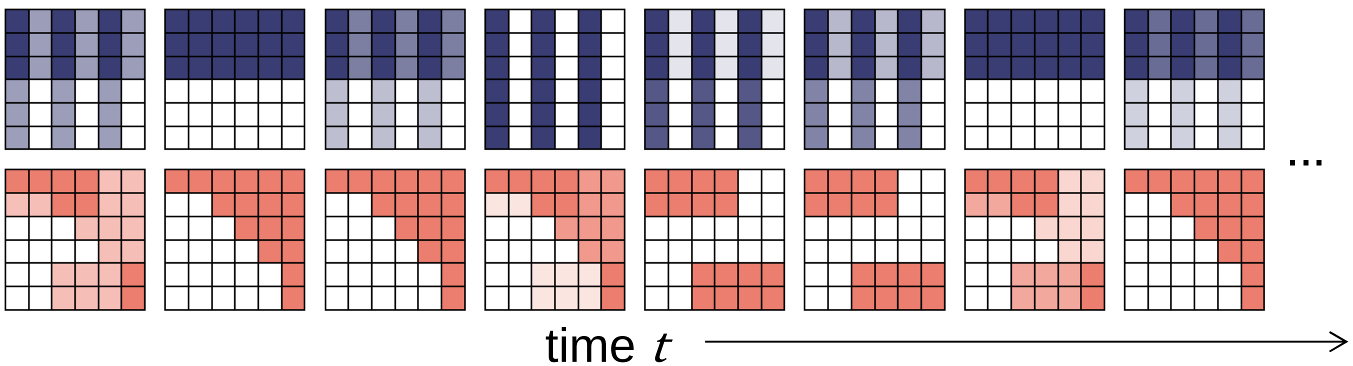
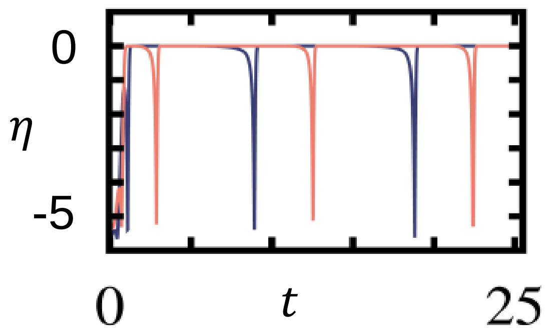


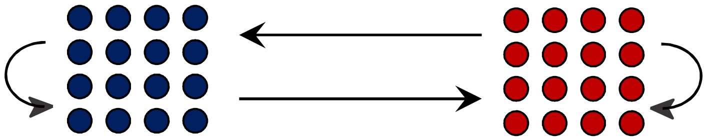
- confidence = K – min(distance to memory patterns) = η
- classical network (context rules permanently active):



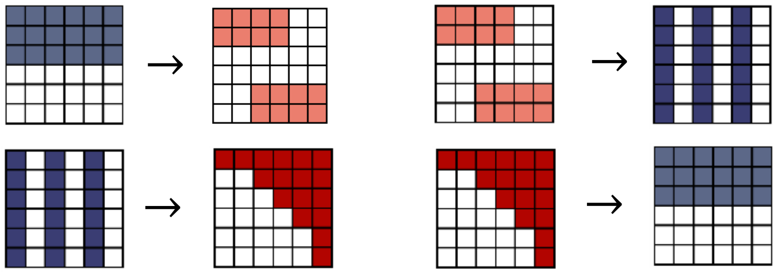


Self-Organized Contextual Pattern Recognition

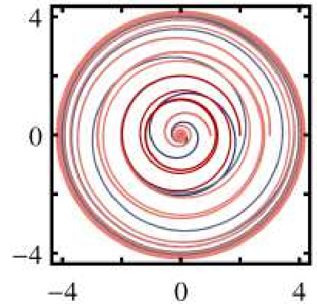
- hierarchical oscillatory Hopfield network



- memory patterns + context rules

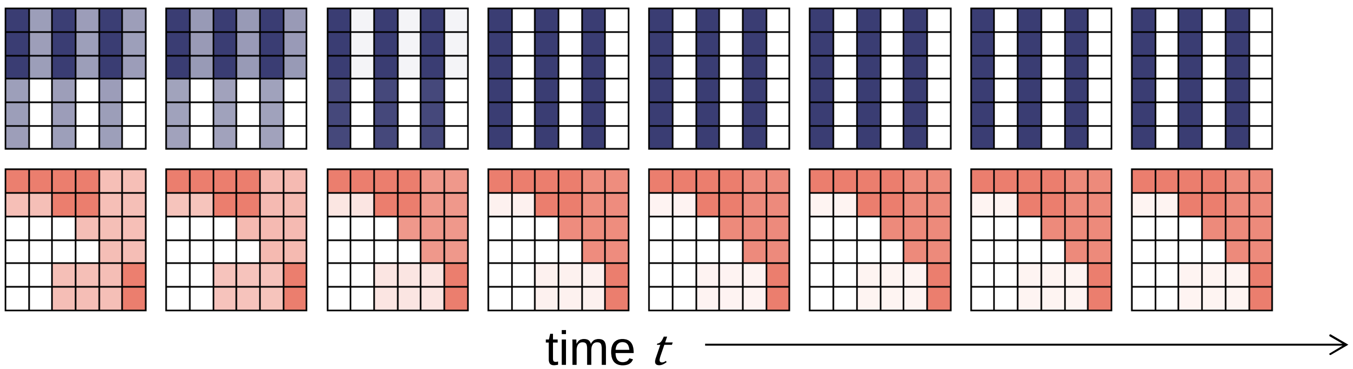


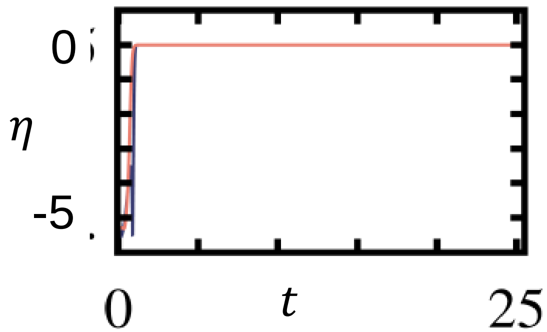
- oscillatory dynamics



- confidence = K – min(distance to memory patterns) = η

- self-organized context distribution





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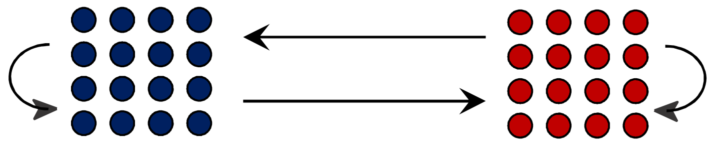
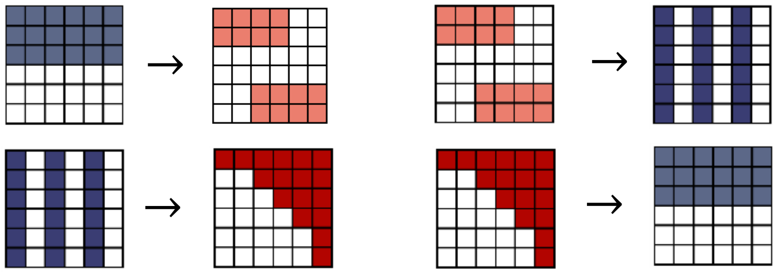


- memory patterns + context rules



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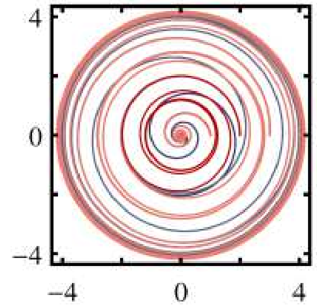
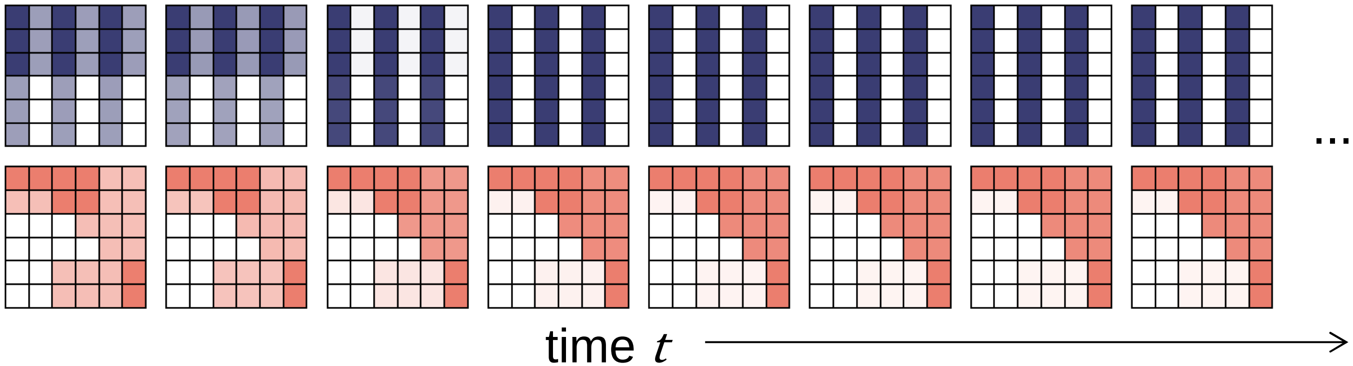
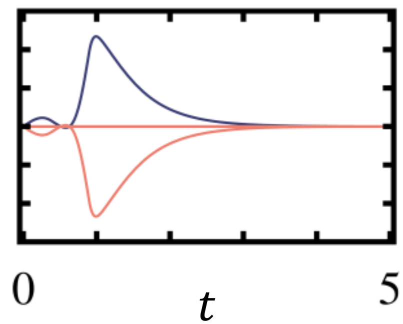


- confidence = K – min(distance to memory patterns) = η

- self-organized context distribution



effective coupling



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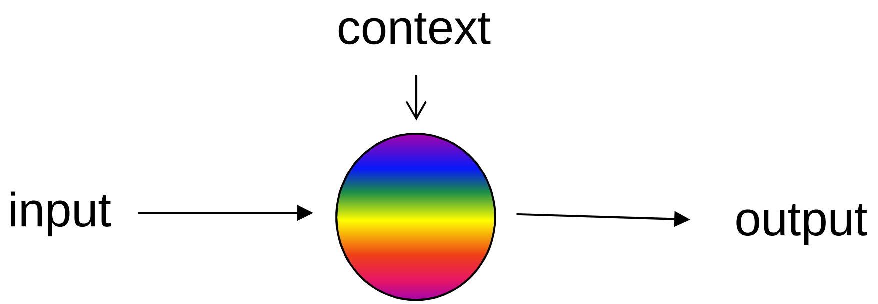
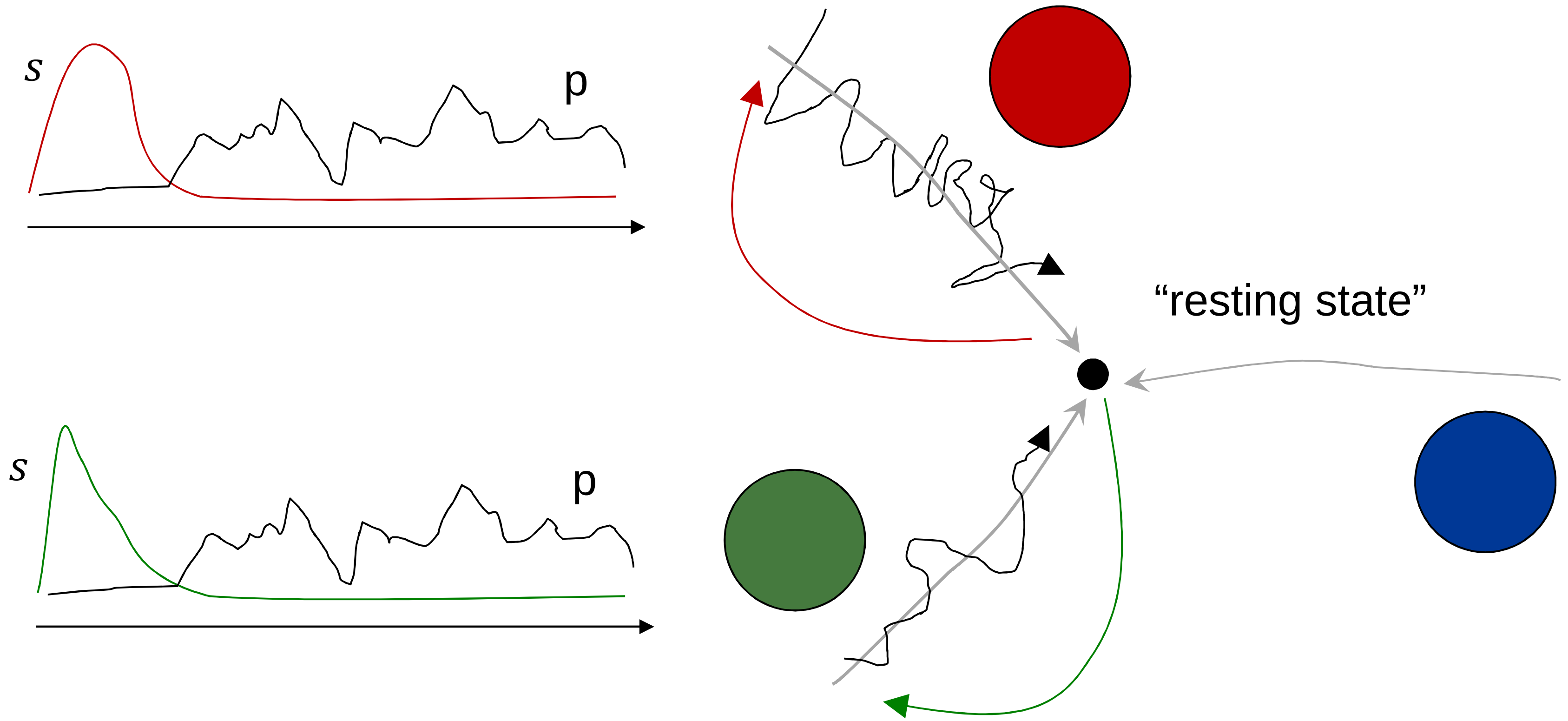
Innate Dynamic Functionality using Transients

- Can we achieve direct flexible functionality ?



✓ Flexible computation on top of transients:



Innate Dynamic Functionality using Transients

- network dynamics:

  $$\dot{x}(t) = f(x(t)) + s(t) + p(t)$$

  x: state
  s: contextual / steering input
  p: input to process

- reference transient $x_0(t)$:

  $$s = s^{(0)}, p = 0:$$

  $$\dot{x}_0(t) = f(x_0(t)) + s^{(0)}(t)$$

- processing along transient ($p \ll 1$):

  $$\dot{x}(t) = f(x(t)) + s^{(0)}(t) + p(t)$$

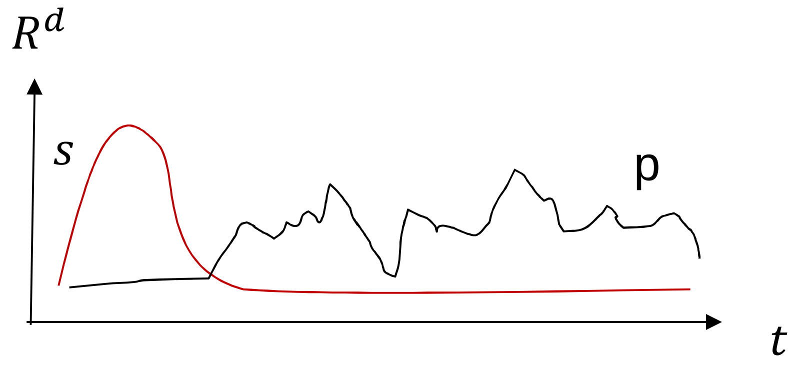
  $$x(t) = x^{(0)}(t) + \delta x(t)$$

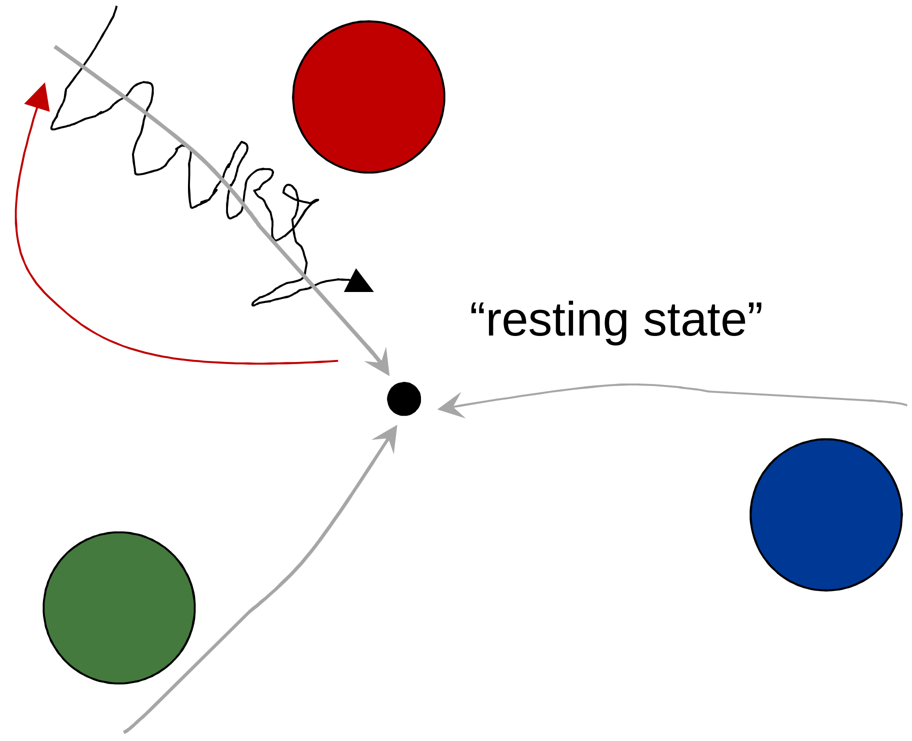
  $$\dot{\delta x}(t) \approx Df\left(x^{(0)}(t)\right)\delta x + p(t)$$

  $\longrightarrow$ linear time varying system:

  $$\delta x(t) = \int_0^t \Phi^{(0)}(t,\tau)p(\tau)d\tau$$

  $x^{(0)}$ dependent





Taming Chaos in Neuronal Networks

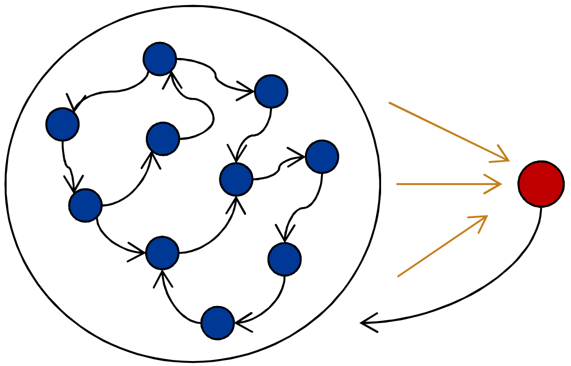
- firing rate network:

$$\dot{x}_i = -x_i + g \sum_j w_{ij} r(x_i)$$

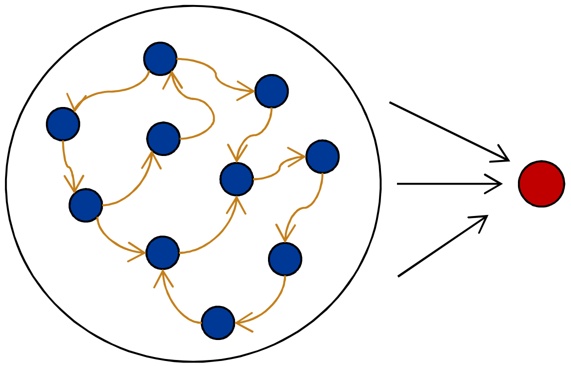
- network transitions to chaos when gain g is increased

[Sompolinsky, Crisanti, Sommers, PRL 1988]

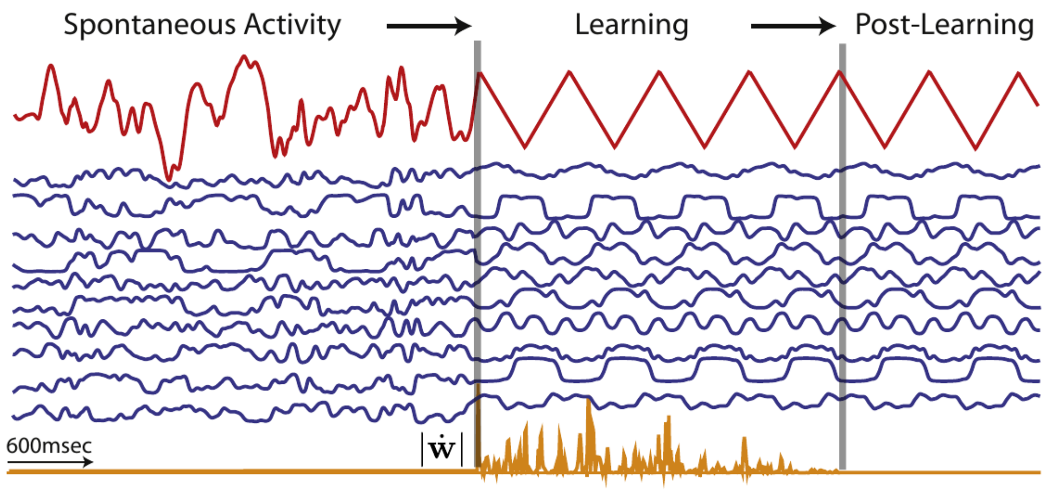
- learning output or recurrent weights to stabilize transients (FORCE learning)



or



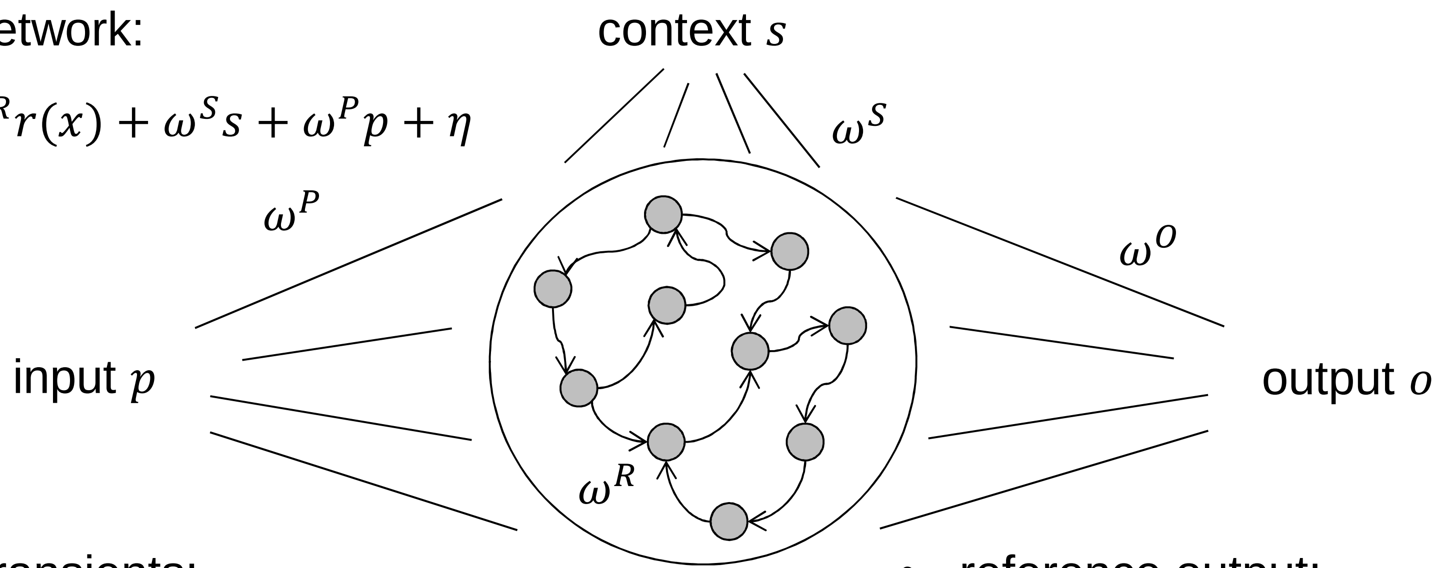
[Sussilo, Abbott, Neuron 2009]
[Laje, Buonomano, Nat Neuro, 2013]



Flexible Network Function Along Stabilized Transients

- firing rate network:

$$\dot{x} = -x + \omega^R r(x) + \omega^S s + \omega^P p + \eta$$



- reference transients:

$$\dot{x}^{(0)} = -x^{(0)} + \omega^R r(x^{(0)}) + \omega^S s^{(0)}$$

trained to stabilize transients

- reference output:

$$o(t) = \omega^O r(x) = o^{(0)} = const$$

trained to stabilize output

- small inputs:

$$\delta\dot{x}(t) = \omega^R DR\left(x^{(0)}(t)\right)\delta x(t) + \omega^P p$$

$$\delta o(t) = \omega^O DR\left(x^{(0)}(t)\right)\delta x(t)$$

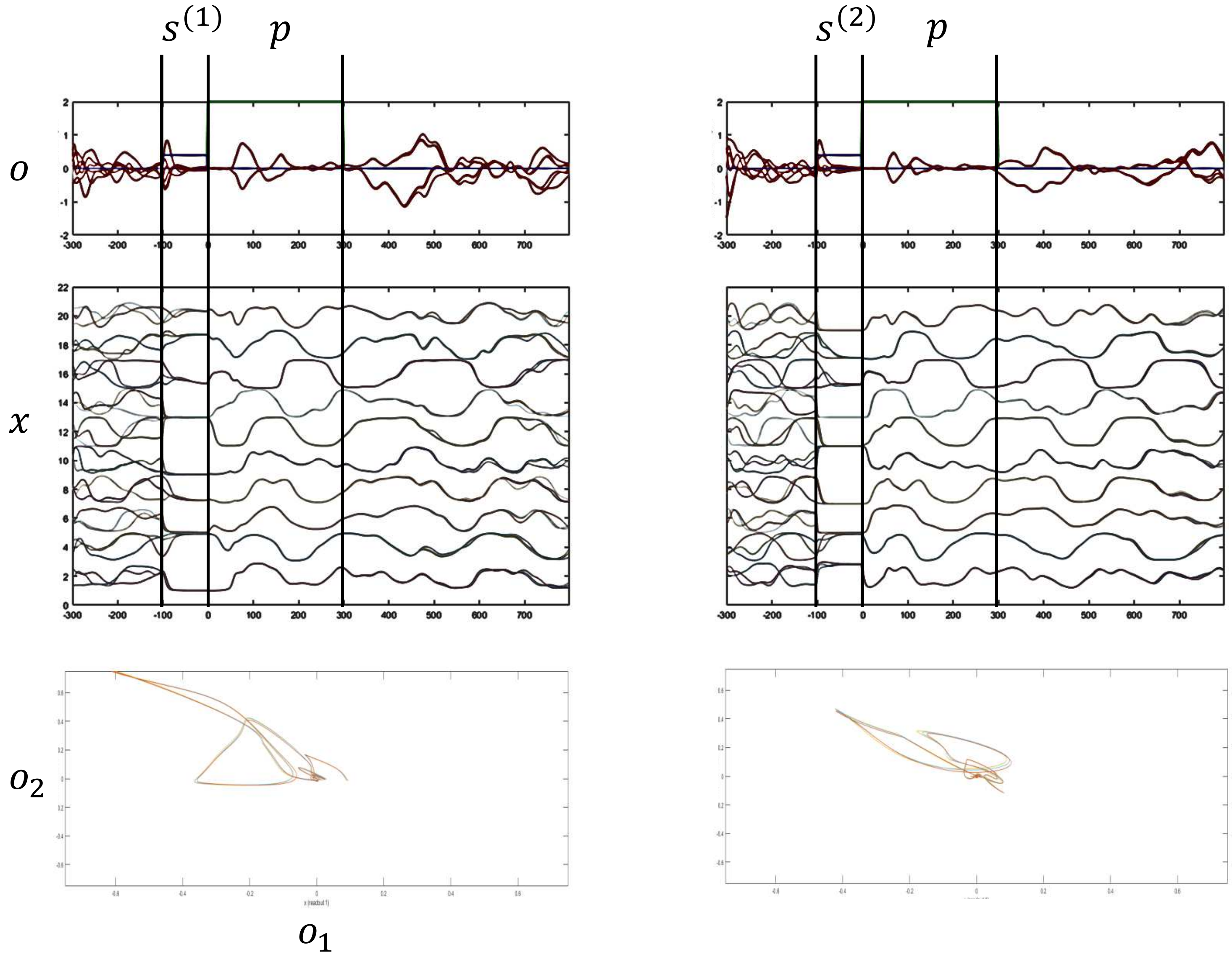
- reference state dependent filtering:

$$\delta o = \omega^O DR(x^{(0)}(t)) \int_0^t \Phi^{(0)}(t,\tau)\omega^P p(\tau) d\tau$$

train to achieve specific function

Flexible Network Function Along Stabilized Transients

- example:
  - reference transient 1
  - reference transient 2



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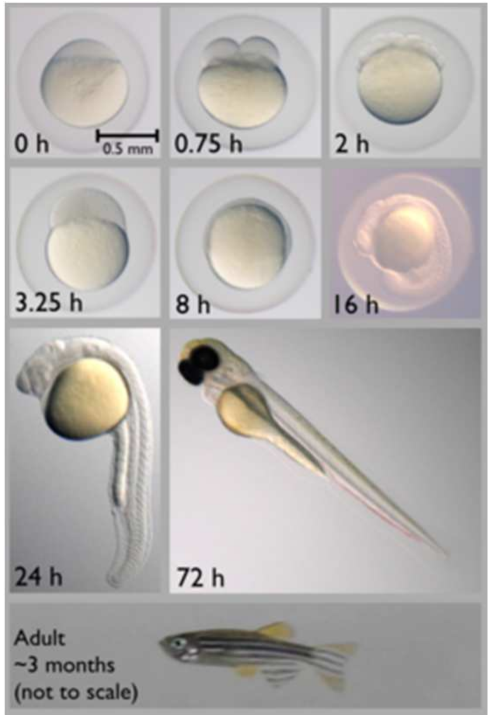
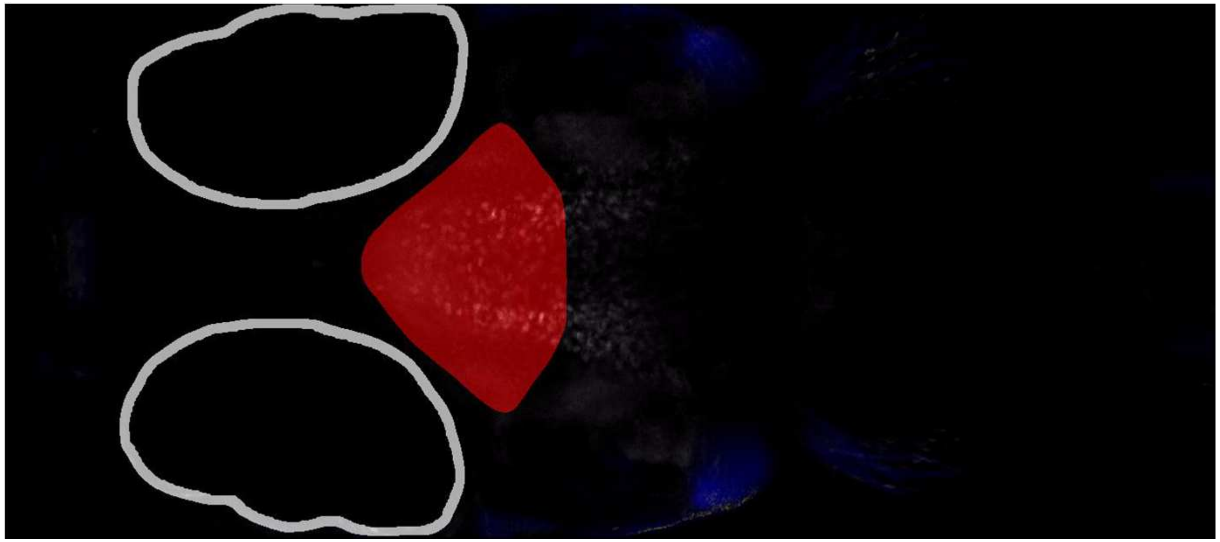
The Zebrafish Larvae Brain



Zebrafish:

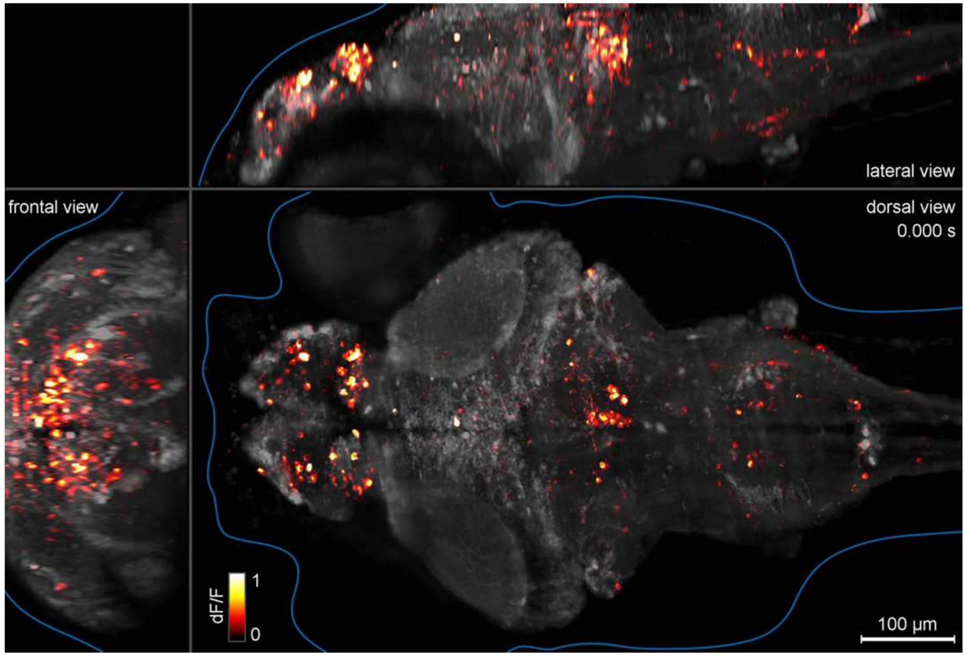
- tropical fish from Ganges River in East India and Burma
- used to study development (clear eggs, vertebrate)
- transparent larvae – imaging 'easy'
- Z-brain: zebrafish brain atlas

[Randlett, et al, Nature Methods 2015]



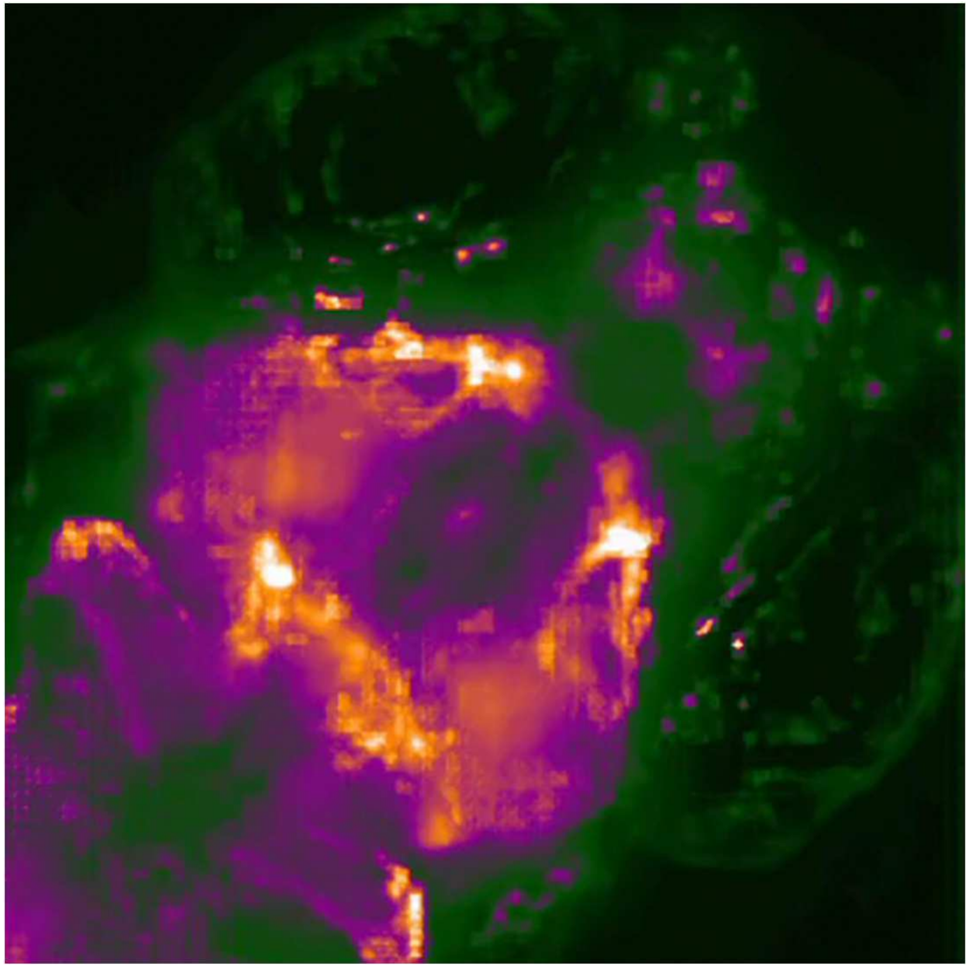
Zebrafish Whole Brain Imaging

- light sheet imaging



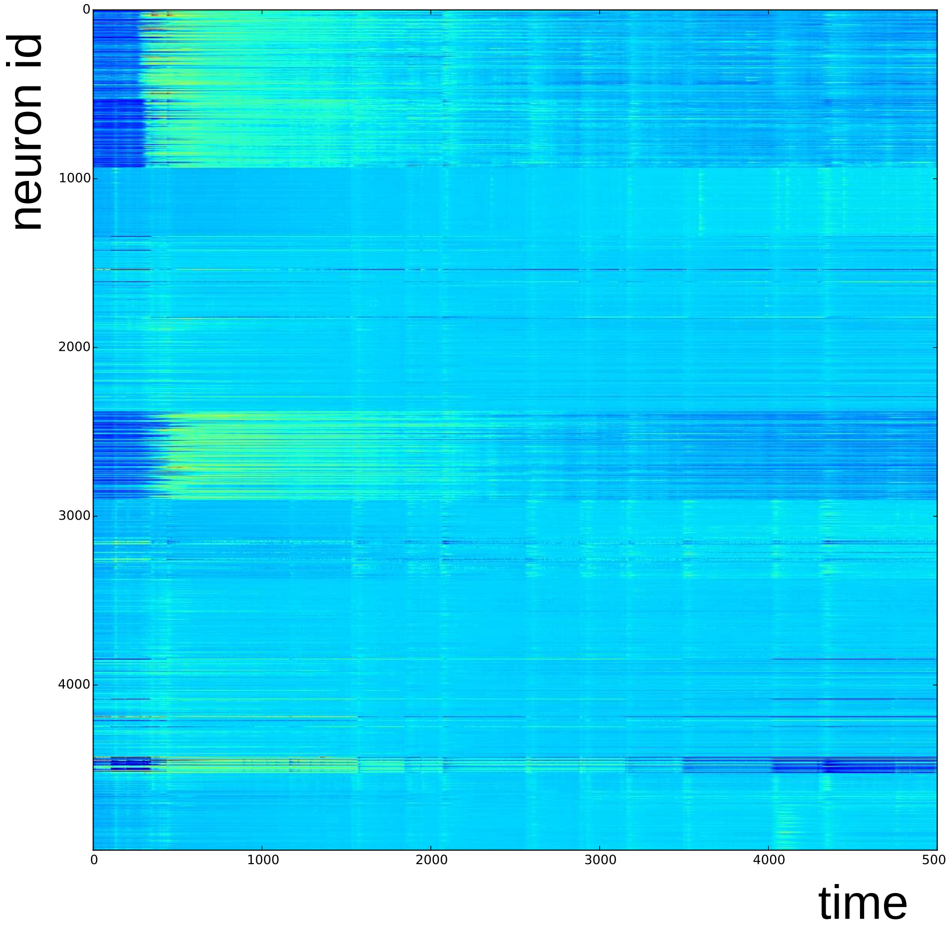
[Vladimirov, …, Ahrens, Nature Methods 2014]

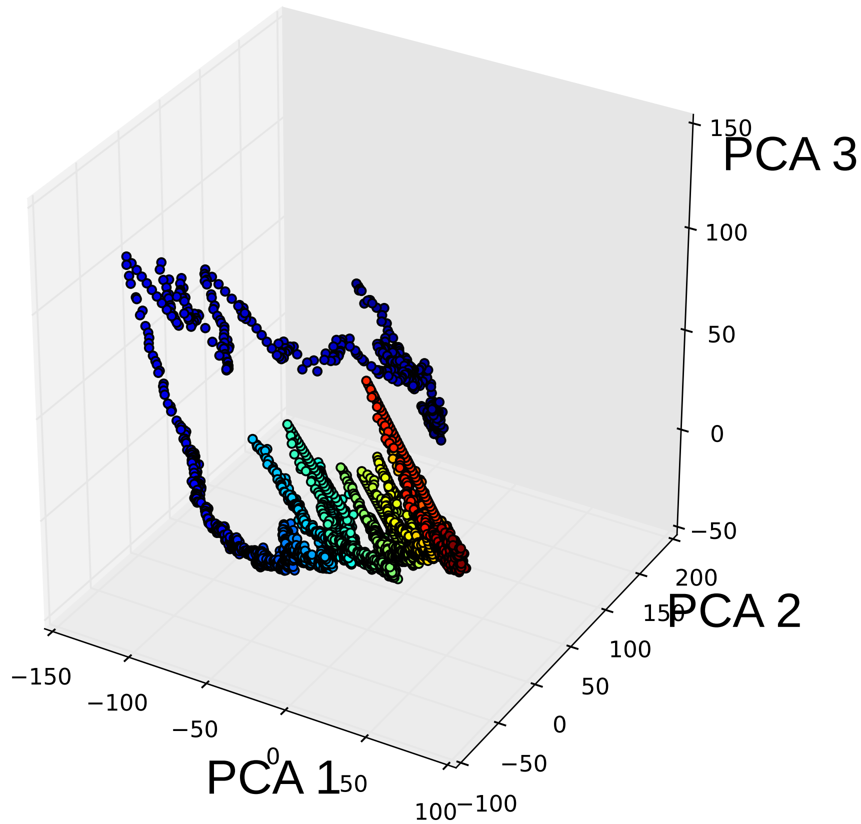
- light field deconvolution imaging



[Prevendel,…,Vaziri et al, Nature Methods 2014]

Zebrafish Whole Brain Dynamics - PCA



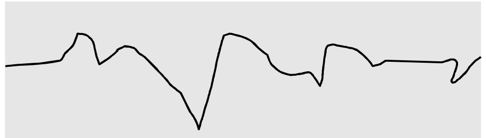


Data: [Prevendel,…,Vaziri et al, Nature Methods 2014]

Dynamical Sate Identification

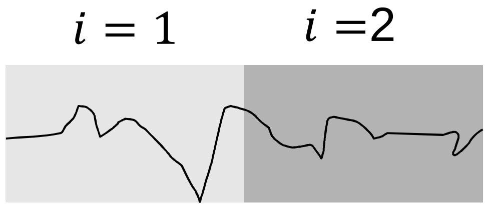
- single auto-regressive (AR) processes $\boldsymbol{M}_1$

$$x_t = a_0 + a_1 x_{t-1} + a_2 x_{t-2} + \cdots + a_K x_{t-K} + \varepsilon_t$$



  - log likelihood: $l_1 = -\frac{N}{2}(1 + \log(2\pi)) - \frac{1}{2} N \log(\hat{\sigma})^2$
  - #parameter: $k_1 = K + 1$

- multiple AR processes for non-stationary time series $\boldsymbol{M}_2$



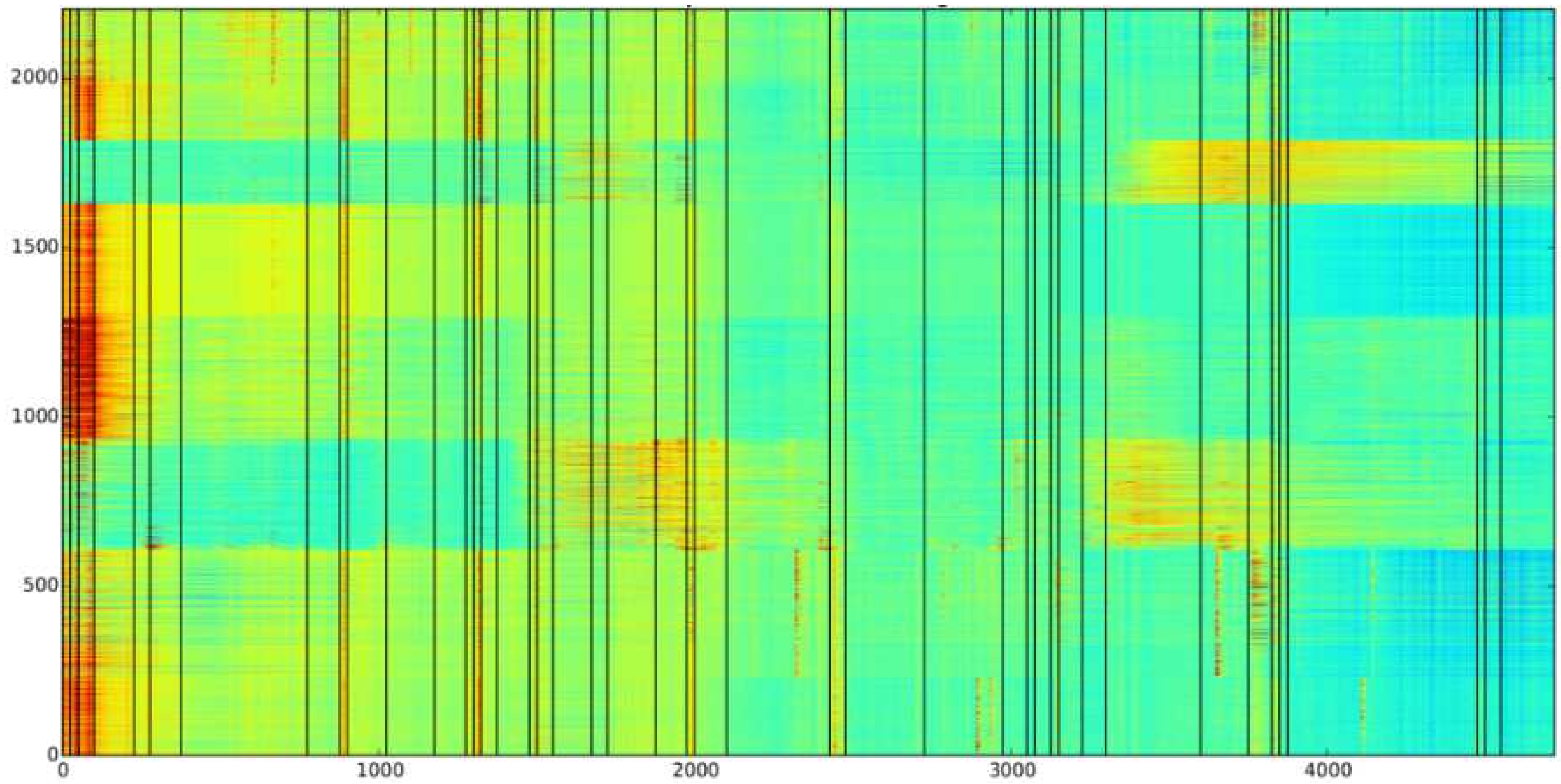
$$x_t = a_{0,i} + \sum_m a_{m,i} x_{t-m} + \varepsilon_{i,t} \qquad \begin{array}{l} 0 \le t < t_1, i = 1 \\ \mathrm{t}_1 \le t < t_2, i = 2 \end{array}$$

  - log likelihood: $l_2 = -\frac{N}{2}(1 + \log(2\pi)) - \frac{1}{2} \sum N_i \log(\hat{\sigma}_i)^2$
  - #parameter: $k_2 = 2K + 2$

- max AIC to select if a switch has occurred:

$$\mathrm{AIC}_j = l_j - k_j$$

Dynamical Sate Identification in Whole Brain Zebrafish Recordings

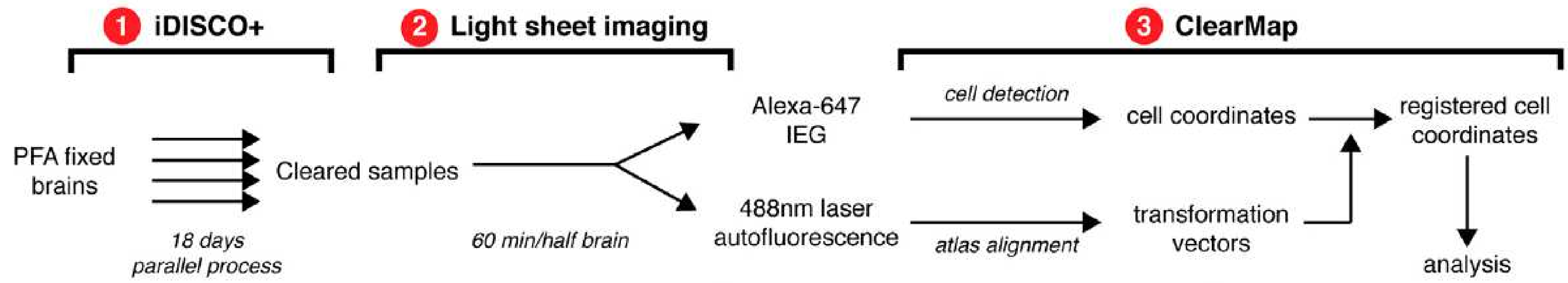


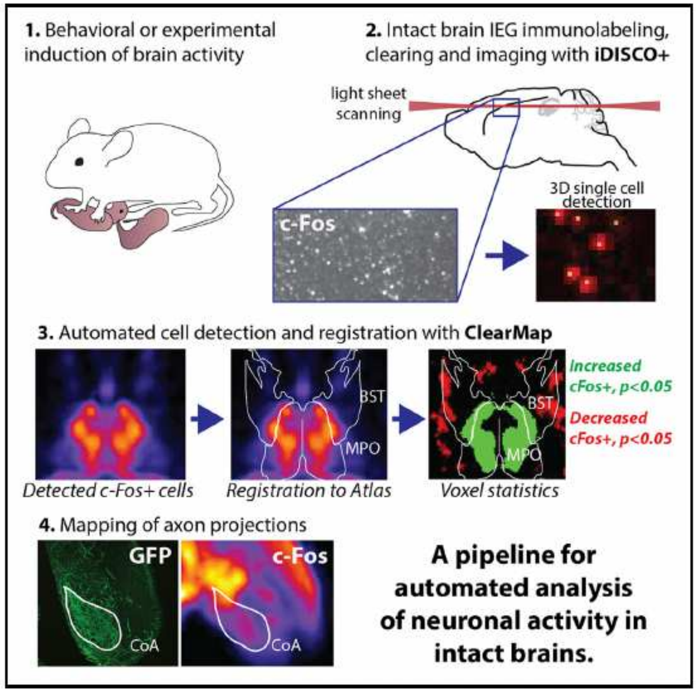
- fast
- takes into account all neurons equally
- extensions to groups of neurons (multi-dimensional ARs)

Outline: Flexible Function in Neuronal Networks

- dynamic information routing in complex networks
  - structural vs. effective connectivity
  - flexible information routing in oscillator networks
  - spiking networks, transient dynamics
- flexible information processing in complex networks
  - oscillatory Hopfield networks
  - self-organized pattern recognition
- learning flexible function in neuronal networks
- connections to experiments
  - brain state identification in zebrafish
  - complete brain activity mapping in mouse
- conclusions

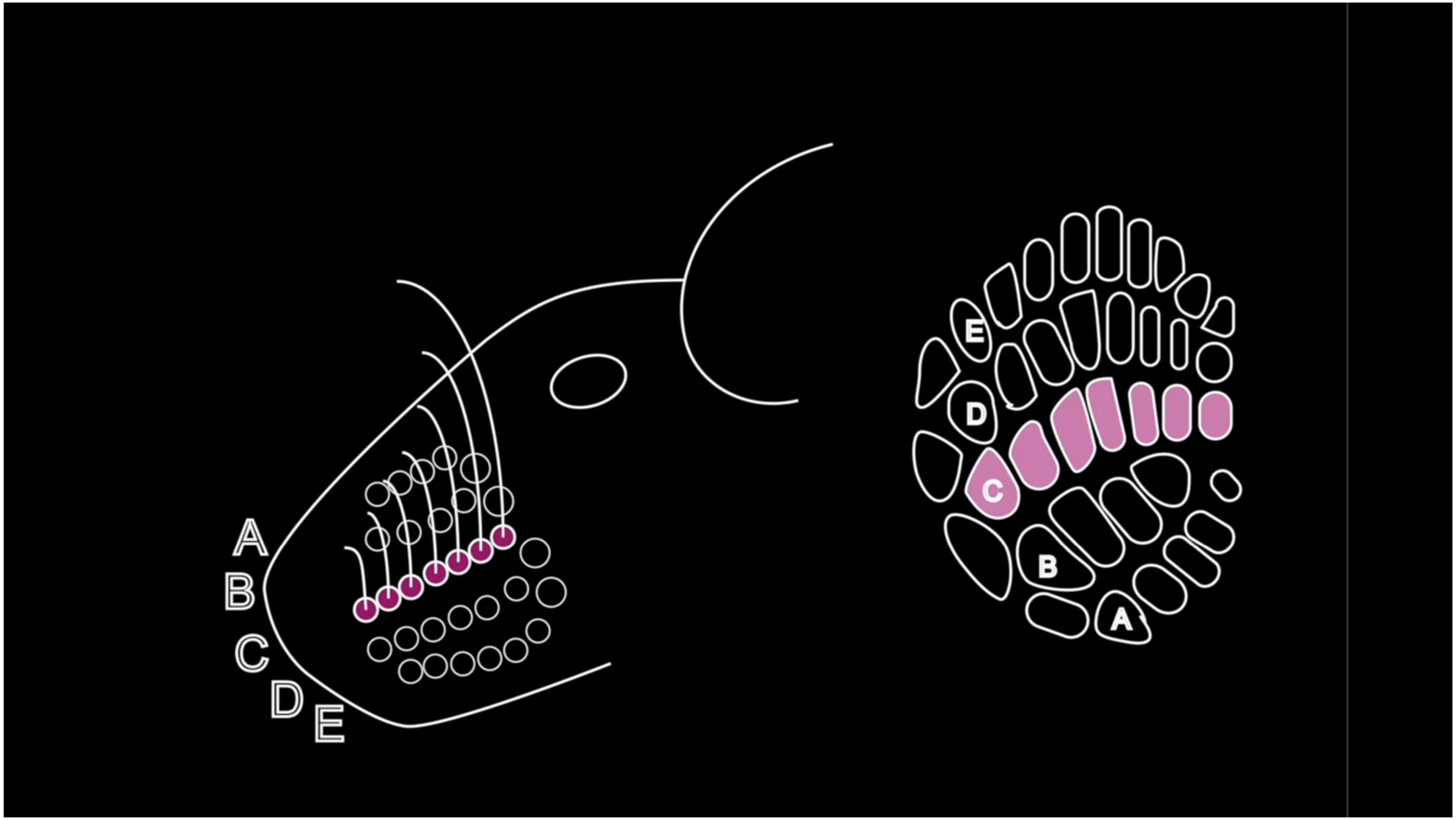
Complete mapping of cellular brain activity by automated volume analysis of immediate early genes



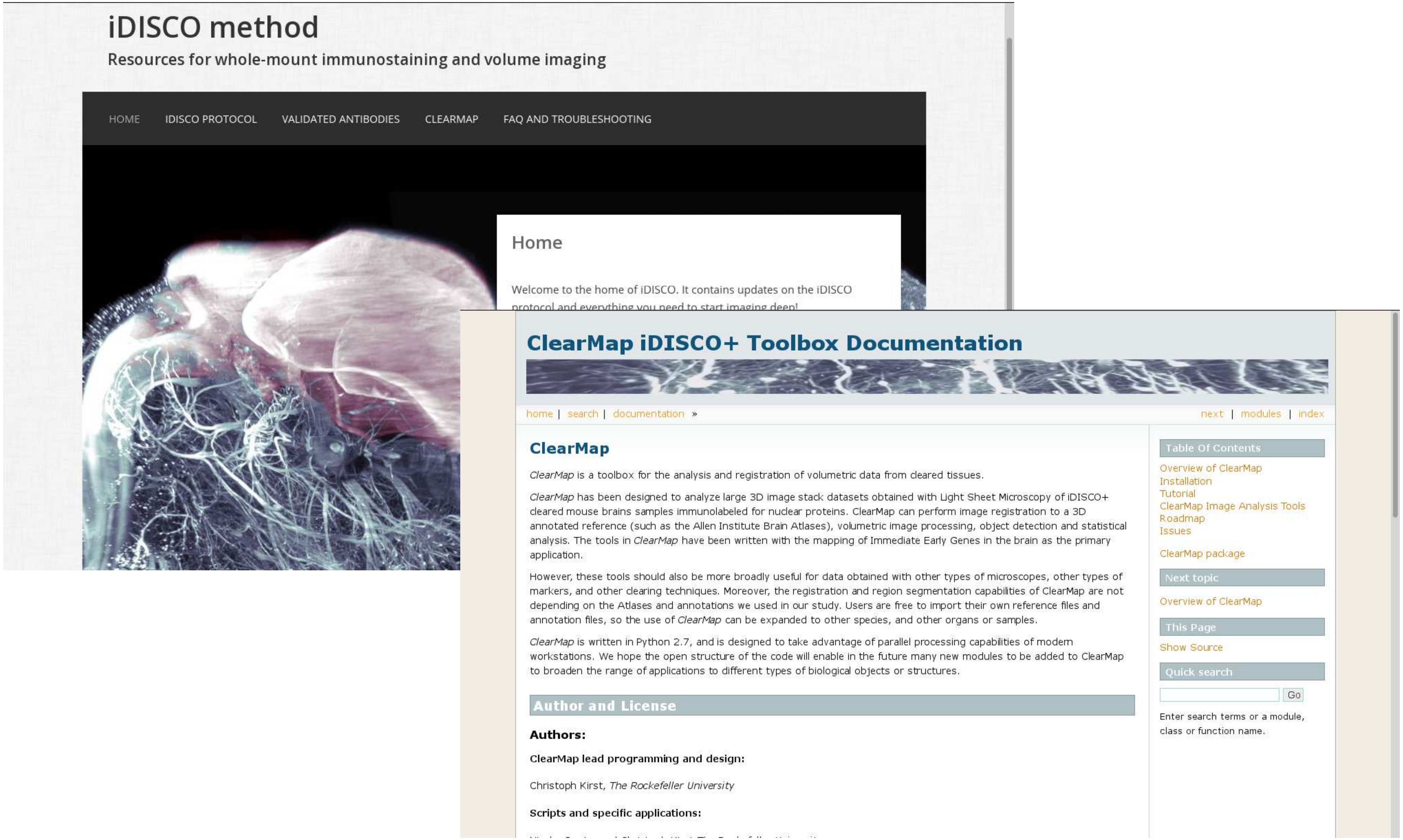


[Renier*,. Adams*, Kirst*, Wu*,...,
Dulac, Osten, Tessier-Lavigne, Cell 2016]

Complete mapping of cellular brain activity by automated volume analysis of immediate early genes



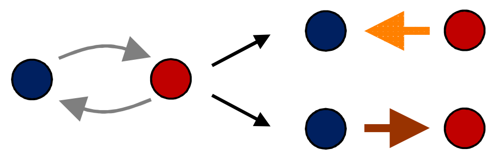
[Renier*,. Adams*, Kirst*, Wu*,..., Dulac, Osten, Tessier-Lavigne, Cell 2016] https://idisco.info/



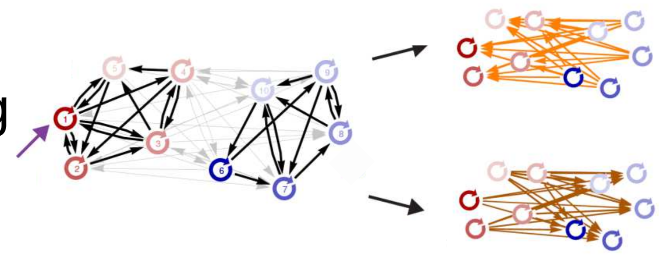
[Renier*,. Adams*, Kirst*, Wu* ..., Dulac, Osten, Tessier-Lavigne, Cell 2016]

https://github.com/ChristophKirst/ClearMap

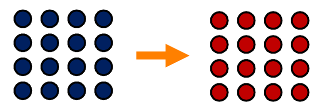
Conclusion



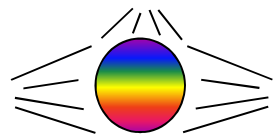
- reference dynamics ⇒ effective network ⇒ function
- theory for information routing in phase oscillator networks
- flexible dynamic information routing on top of dynamics:
  - multi-stable dynamical states
    → fast and self-organized information re-routing
  - hierarchical networks
    → action at a distance, combinatorial IRPs



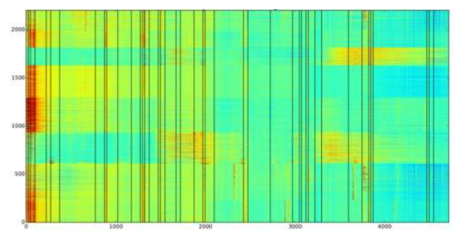
- self-organized information processing by closing the loop
  - contextual pattern recognition in oscillatory Hopfield nets



- learning flexible function on top of dynamical reference states



- novel approaches to the analysis of large scale neural activity



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You for your Attention !