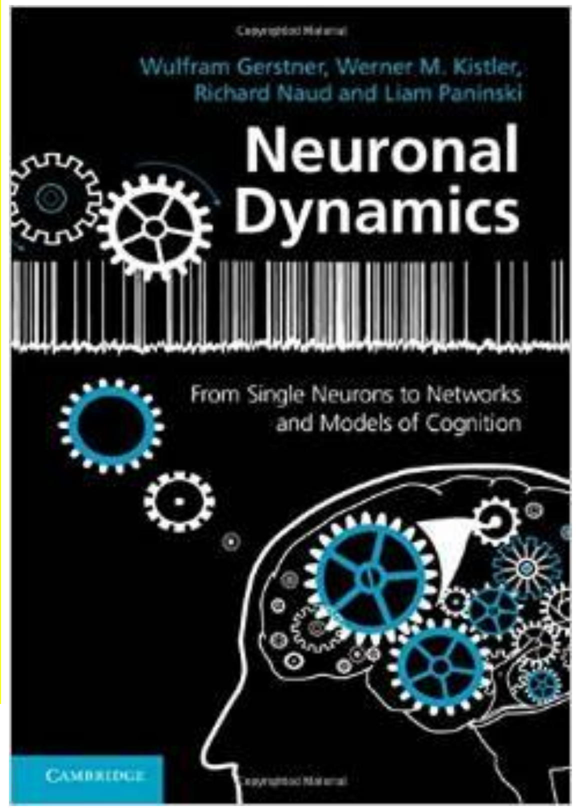
Reading for this Lecture:
NEURONAL DYNAMICS
Ch. 13.1-13.4

Cambridge Univ. Press



N. Brunel (2000) *Dynamics of sparsely connected networks of excitatory and inhibitory neurons.* J. Computational Neuroscience 8, pp. 183–208

D. Nykamp and D. Tranchina (2000) *A population density approach that facilitates large-scale modeling of neural networks: analysis and application to orientation tuning*. J. Computational Neuroscience 8, pp. 19–50

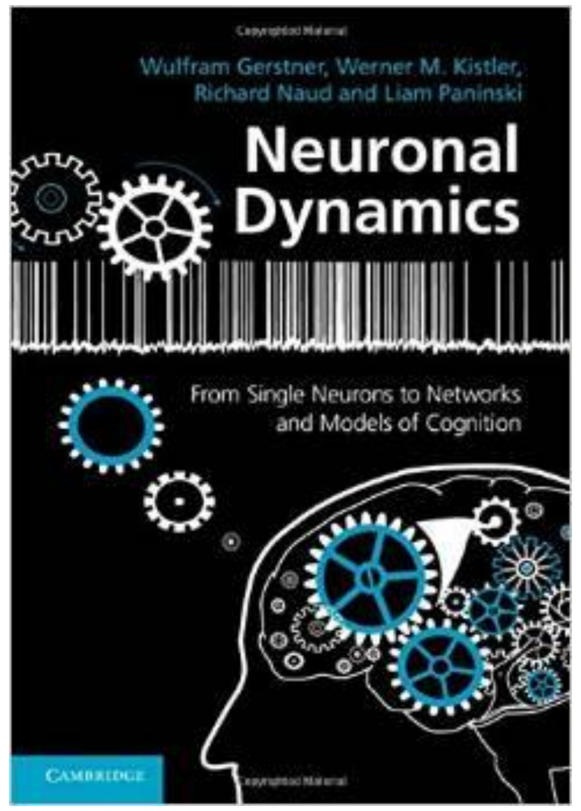
EPFL

week 14 –Neural Manifolds and Low-dimensional dynamics

Wulfram Gerstner

EPFL, Lausanne, Switzerland

Cambridge Univ. Press



1. What are Neural Manifolds?
- experimental observations

2. Two views of Neural Activity
- computing (Hopfield model)
- neural circuits (field model)

3. Low-dimensional dynamics
- formalism and assumption
- dynamics

4. Examples of low-dim dynamics
- context-dependent decision making

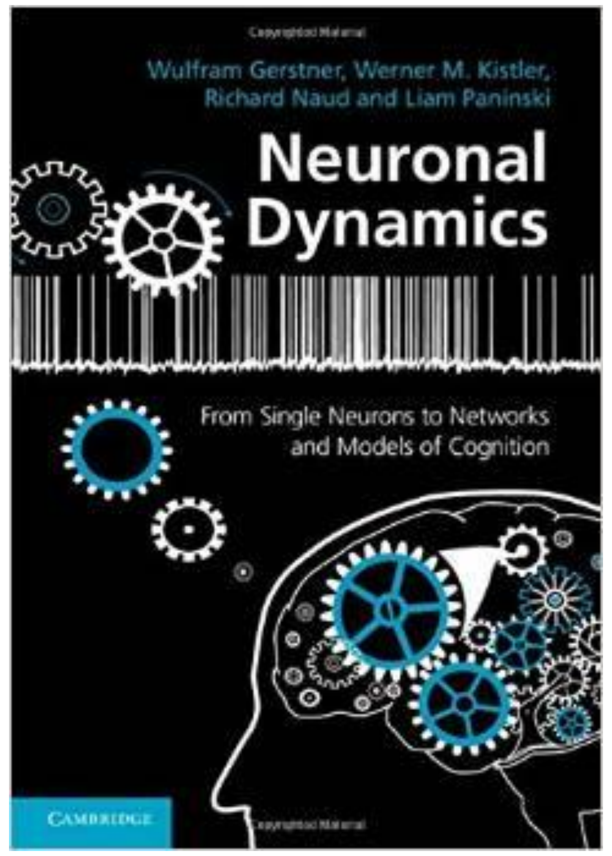
Lecture 15 of video series

https://lcnwww.epfl.ch/gerstner/NeuronalDynamics-MOOCall.html

Computational Neuroscience: Neuronal Dynamics

Written Exam (70%)
+ miniproject (30%)
→ 5 credits

- Select 1 Miniproject,
  (out of a list of 2)
- Perform task in teams of 2



Textbook:

http://neuronaldynamics.epfl.ch/

Video:

https://lcnwww.epfl.ch/gerstner/NeuronalDynamics-MOOCall.html

Miniproject in 2025: two variations of Hopfield model

Computational Neuroscience: Neuronal Dynamics

Written Exam (70%)

You can bring 1 sheet A5 (double-sided) of **handwritten** notes.
(no calculator, no textbook, no phone)

Exam is orthogonal to miniproject.
- Look at written exercises
- Look at exams from previous years

LEARNING OUTCOMES

- Solve linear **one-dimensional differential equations**
- Analyze two-dimensional models in the **phase plane**
- Develop a simplified model by **separation of time scales**
- Analyze connected networks in the mean-field limit
- Formulate stochastic models of biological phenomena
- Formalize biological facts into mathematical models
- Prove **stability** and **convergence**
- Apply model concepts in simulations
- Predict outcome of dynamics
- Describe neuronal phenomena

Transversal skills

- Plan and carry out activities in a way which makes optimal use of available time and other resources.
- Collect data.
- Write a scientific or technical report.

LEARNING OUTCOMES

- Solve linear one-dimensional differential equations
- Analyze two-dimensional models in the phase plane
- Develop a simplified model by separation of time scales
- Analyze connected networks in the mean-field limit
- **Formulate stochastic models of biological phenomena**
- Formalize biological facts into mathematical models
- Prove stability and convergence
- Apply model concepts in simulations
- Predict outcome of dynamics
- Describe neuronal phenomena

-Poisson process
-renewal process
-Ornstein-Uhlenbeck process
-escape noise
-membrane pot. density
-Focker-Planck eq.

Transversal skills

- Plan and carry out activities in a way which makes optimal use of available time and other resources.
- Collect data.
- Write a scientific or technical report.

LEARNING OUTCOMES

- Solve linear one-dimensional differential equations
- Analyze two-dimensional models in the phase plane
- Develop a simplified model by separation of time scales
- **Analyze connected networks in the mean-field limit**
- Formulate stochastic models of biological phenomena
- Formalize biological facts into mathematical models
- Prove stability and convergence
- Apply model concepts in simulations
- Predict outcome of dynamics
- Describe neuronal phenomena

-averaging
-coupled networks
-Focker-Planck eq.
-low-rank networks
-overlaps
-macroscopic
network dynamics
-competitive dynamics

Transversal skills

- Plan and carry out activities in a way which makes optimal use of available time and other resources.
- Collect data.
- Write a scientific or technical report.

EPFL

Neural Manifolds and Low-dimensional dynamics: What are Neural Manifolds?

1. What are Neural Manifolds?
   - experimental observations

2. Two views of Neural Activity
   - computing (Hopfield model)
   - neural circuits (field model)

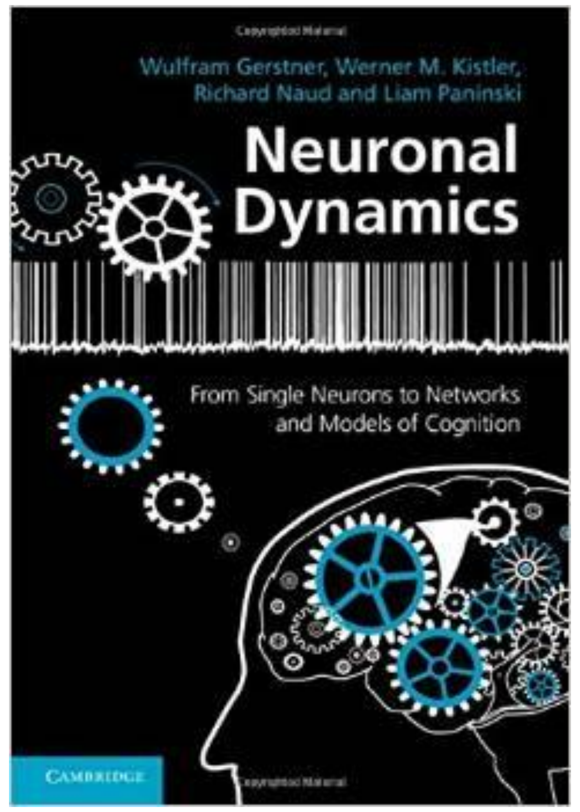
3. Low-dimensional dynamics
   - formalism and assumption
   - dynamics

4. Examples of low-dim dynamics
   - context-dependent decision making

Wulfram Gerstner

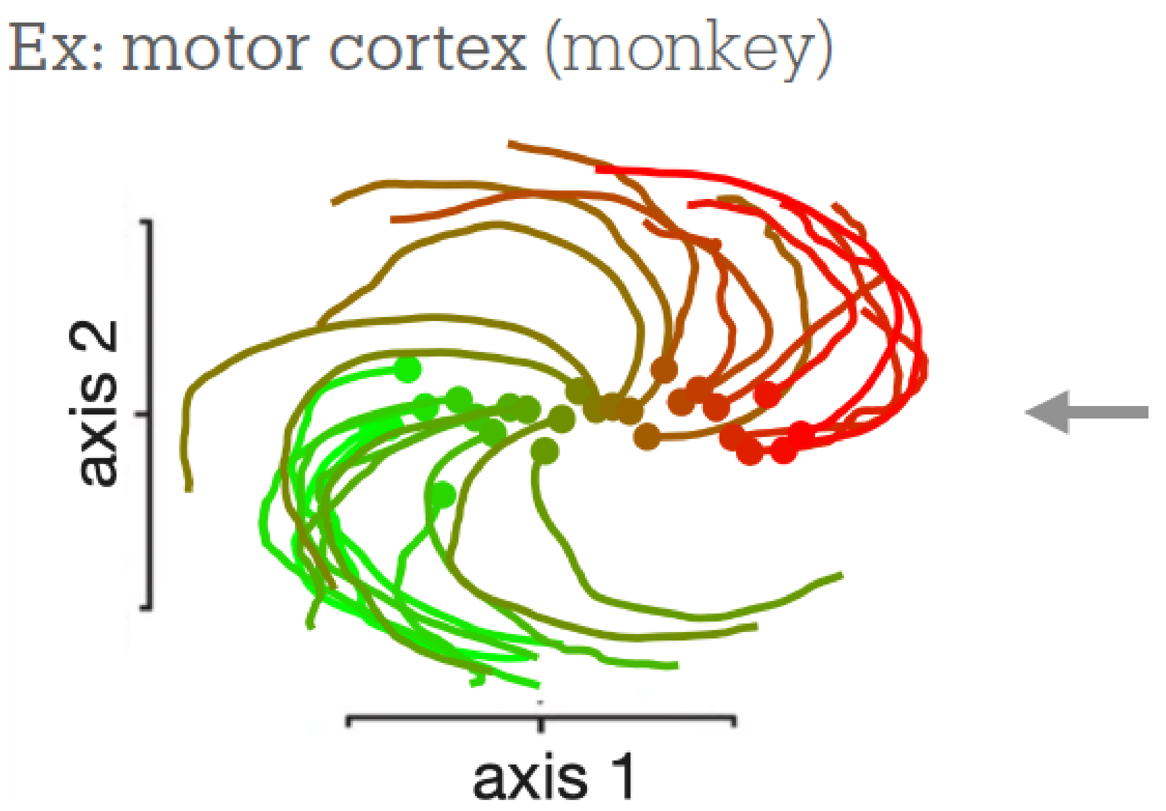
EPFL, Lausanne, Switzerland

Cambridge Univ. Press

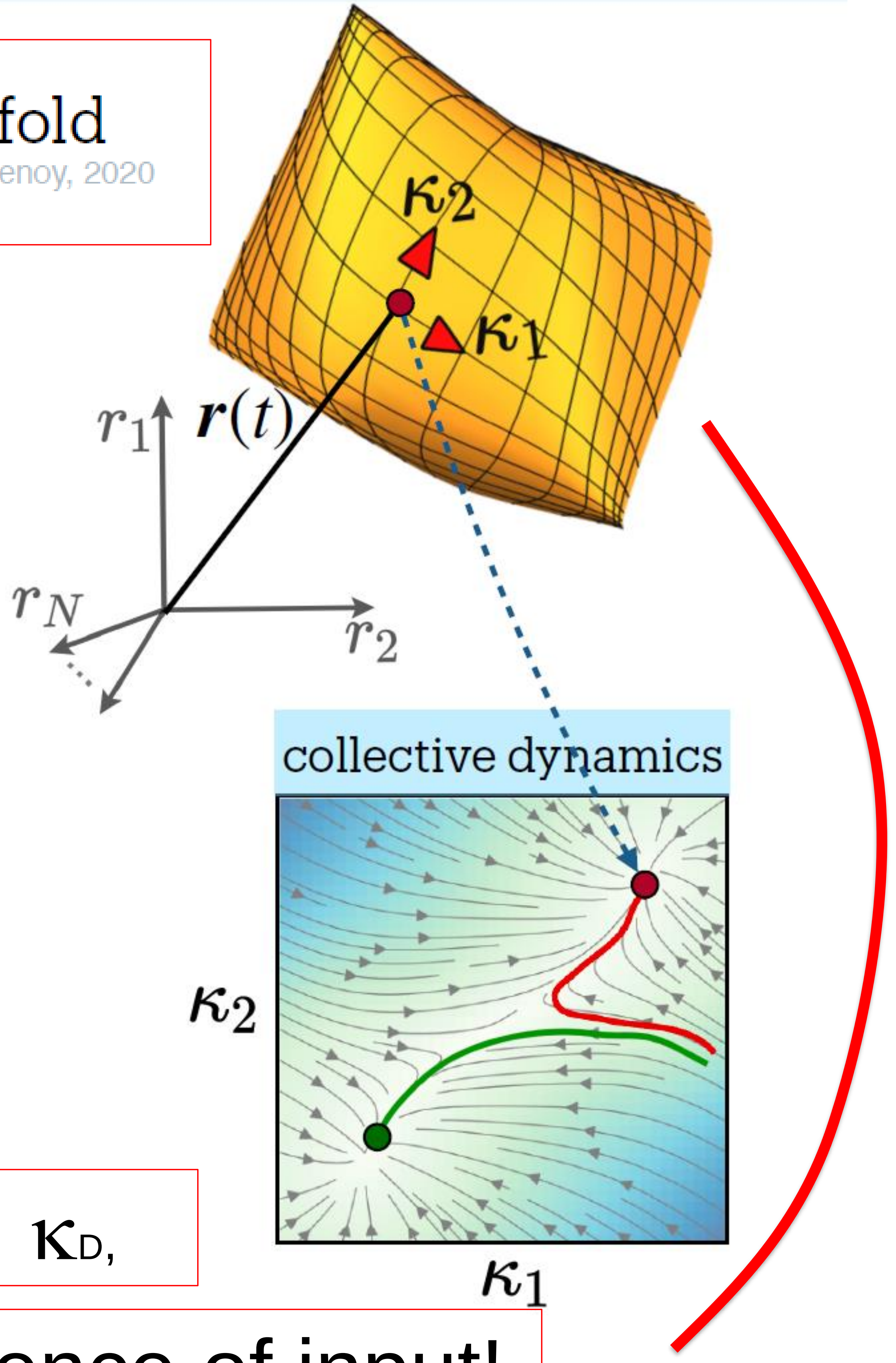


Introduction: low-dimensional dynamics

computations are described by **collective dynamics** in the manifold
Vyas, S., Golub, M.D., Sussillo, D., Shenoy, 2020



adapted from Churchland,…,Shenoy. 2012



Flow described by small number of variables κ_1, … κ_D,

Low-dimensional dynamics even during sleep/absence of input!

Chaudhuri et al, 2019

Image: Pezon et al. 2024

Summary 1:
There are **two different perspectives** on how to interpret neuronal activity:

- The classic view since Hubel and Wiesel was to start with **receptive fields.** We can then define **functional similarity** between neurons as neurons with similar receptive fields. On the theory side, this view has led to **field models** where neurons are organized along one or several abstract axis. Functionally similar neurons have typically stronger (more positive) connections to each other than to functionally different neurons. Hence **wiring** reflects functional similarity.

- The modern view is that neurons perform computational and that these computations can be described by a **flow or dynamics in low-dimensional manifolds**: Even though modern experiment probe the activity of hundreds of neurons simultaneously, we do not need 100 variables to describe the activity but only a few. On the theory this is similar to mean-field models or the Hopfield model. In the Hopfield model, we have encountered **effective variables** (‘overlap’) that describe the **collective dynamics.**

The question of today is how the two views are connected to each other and to topics that we have seen in this class.

EPFL

week 14 –Neural Manifolds and Low-dimensional dynamics

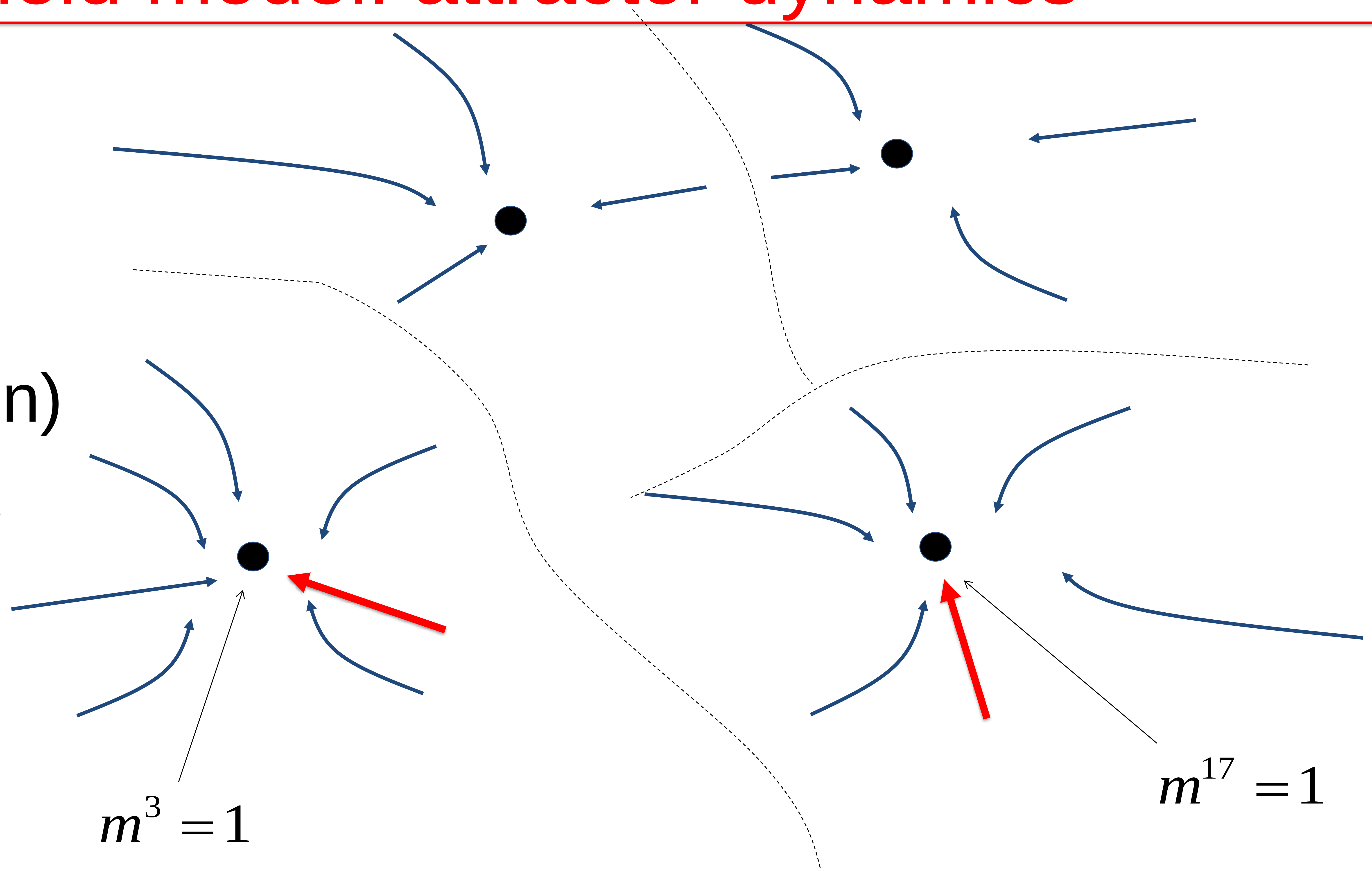
1. What are Neural Manifolds?
- experimental observations

2. Two views of Neural Activity
- computing (Hopfield model)
- neural circuits (field model)

3. Low-dimensional dynamics
- formalism and assumption
- dynamics

4. Examples of low-dim dynamics
- context-dependent decision making

Review: Hopfield model: attractor dynamics



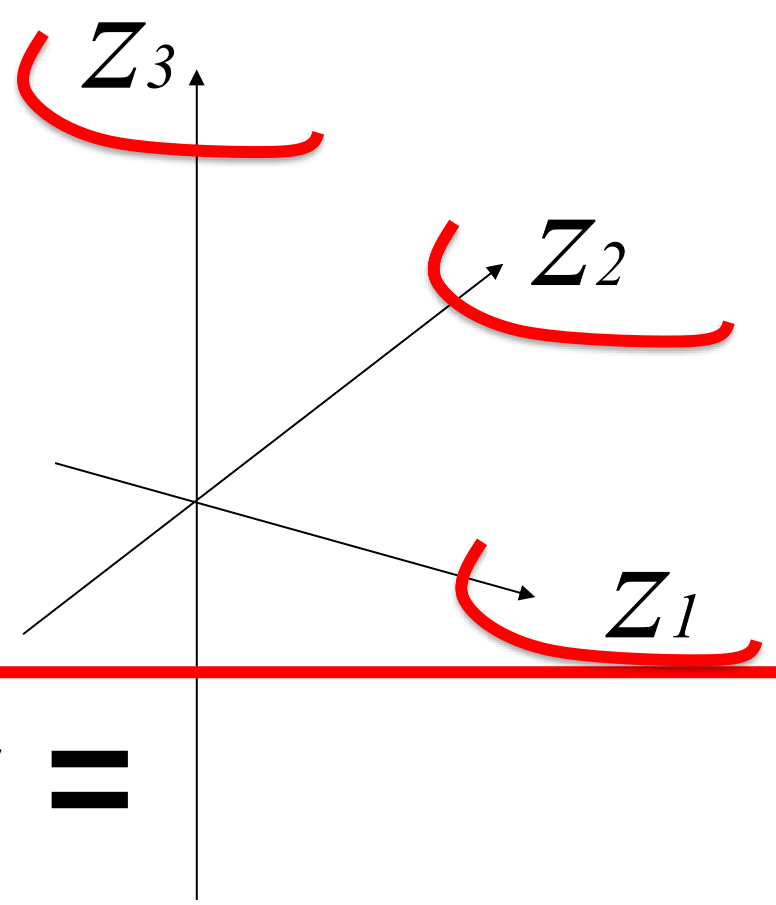
Overlap (definition)

$$m^3(t+1) = \sum_j p_j^3 S_j$$

Attractor Dynamics: *https://www.youtube.com/watch?v=9LjFqc2JRk4*

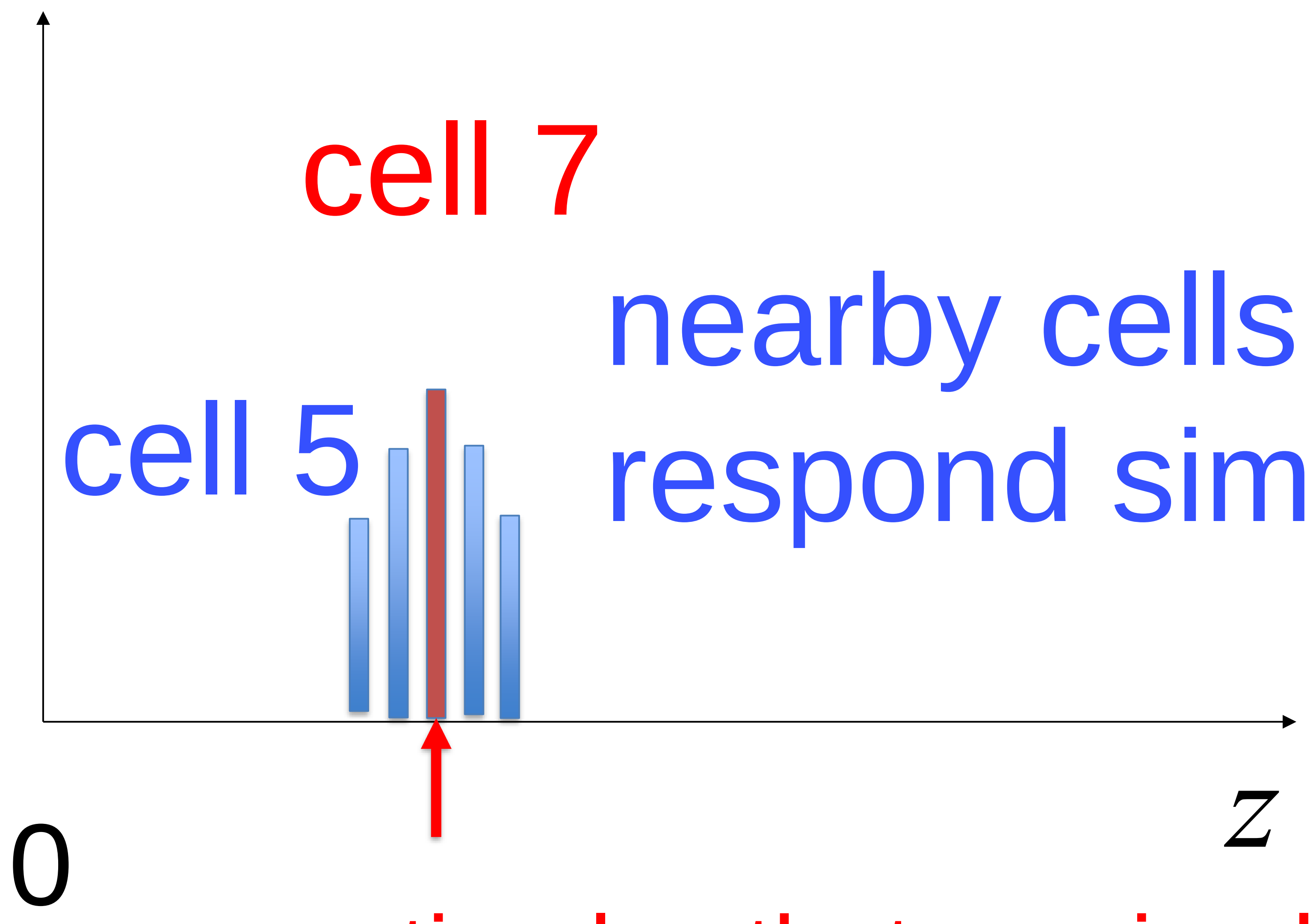
Review: functional similarity of neurons

functional characterization of neuron:
- orientation of rec. field: z_1
- horizontal placement of rec. field: z_2
- vertical placement of rec. field: z_3



functional similarity = neighborhood in abstract space

rate (response to a stimulus)



nearby cells (along abstract axis) respond similarly

abstract axis: - a feature of receptive field

a stimulus that maximally excites cell 7

Summary/review: Field equation

A population rate model in continuous space is sometimes called a field equation.

$$\tau \frac{d}{dt} h(x,t) = -h(x,t) + RI^{ext}(x,t) + d \int w(x-x') \, F(h(x',t)) dx'$$

Here the variable x can be interpreted as an **abstract quantity**, such as the **orientiation and location** of the preferred visual stimulus: **Functional similarity**

In this case we may think of x as a three-dimensional vector

In the general model w(x,x') could be an arbitrary function; but in most field equations it is taken as a distance-dependent function w(x-x'). **Therefore connectivity is stronger between cells with similar 'functional role'.**

A classic choice is the Mexican-Hat function with long-range inhibition and short-range excitation. Note that in real neural networks, inhibition involves a separated class of neurons.

Summary: How can we interpret neural activity?

How can we understand principles of neuronal activity?

D. Barack and J. Krakauer, 2021
C. Langdon and T. Engel, 2023

Two different perspectives

- **low dimensional dynamics** → Hopfield model
  (e.g., flow towards fixed point/attractor dynamics)

→ continuum model

- **neurons and functional similarity**
  (functional similarity reflected in wiring,
  wiring causes dynamics)

→Relation between the two views? Relation to known models?

week 14 –Neural Manifolds and Low-dimensional dynamics

1. What are Neural Manifolds?
   - experimental observations

2. Two views of Neural Activity
   - computing (Hopfield model)
   - neural circuits (field model)

3. Low-dimensional dynamics
   - formalism and assumption
   - dynamics

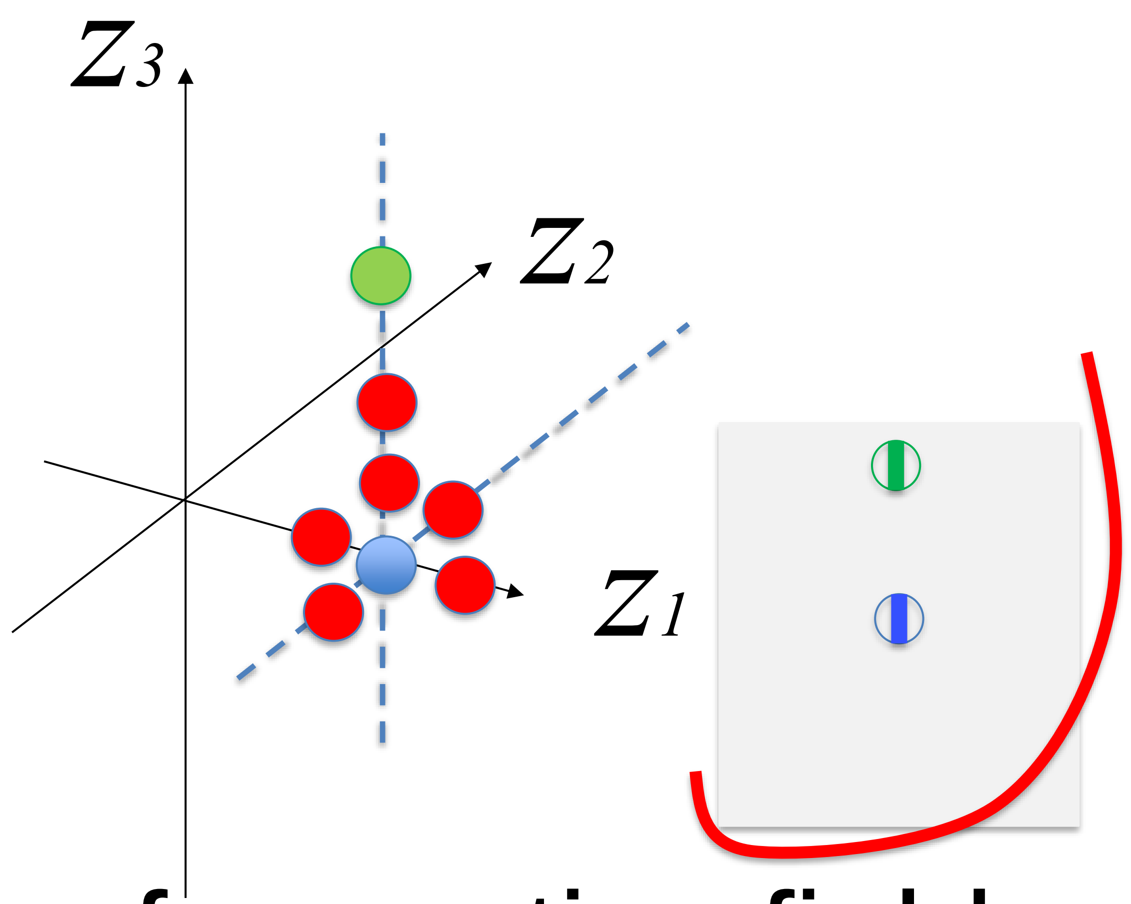
4. Examples of low-dim dynamics
   - context-dependent decision making

Three assumptions

Assumption 1: neurons are functionally characterized by features

functional characterization of neuron

- orientation of rec. field: z_1
- horizontal placement of rec. field: z_2
- vertical placement of rec. field: z_3



Each abstract axis: a feature of receptive field

functional similarity = neighborhood in abstract space

Functional similarities and 'wiring'

functional similarity = neighborhood in abstract space

Assumption 1:

Position of neuron i in abstract space: $\boldsymbol{z_i}=(z_1,z_2,z_3,...)(\boldsymbol{i})$

Assumption 2:

Weight of connection from j to i depends on the positions $\boldsymbol{z_i}$, $\boldsymbol{z_j}$:

$$W_{ij} = w(\boldsymbol{z_i}, \boldsymbol{z_j})$$

Assumption 3:

Specific choice of weight from *j* to *i*:

$$W_{ij} = \sum_{\mu}^{D} F_i^{\mu} G_j^{\mu} = \sum_{\mu}^{D} f_{\mu}(\boldsymbol{z_i}) g_{\mu}(\boldsymbol{z_j})$$

$$f_{\mu}(\boldsymbol{z_i}) = F_i^{\mu}$$

$$g_{\mu}(\boldsymbol{z_j}) = G_j^{\mu}$$

Field equation in functional similarity space

$$\frac{d}{dt}h_i(t) = -\frac{1}{\tau}h_i(t) + \sum_j W_{ij}\,\phi(h_j(t))$$

with neuron i at position $\boldsymbol{z_i}$

use weights:

$$W_{ij} = \sum_{\mu}^{D} f_\mu(\boldsymbol{z_i})g_\mu(\boldsymbol{z_j})$$

$$\frac{d}{dt}h(\boldsymbol{z_i},t) = -\frac{1}{\tau}h(\boldsymbol{z_i},t) + \sum_j \sum_{\mu}^{D} f_\mu(\boldsymbol{z_i})g_\mu(\boldsymbol{z_j})\,\phi(h(\boldsymbol{z_j},t))$$

$$\frac{d}{dt}h(\boldsymbol{z},t) = -\frac{1}{\tau}h(\boldsymbol{z},t) + \int d\boldsymbol{z}'\rho(\boldsymbol{z}') \sum_{\mu}^{D} f_\mu(\boldsymbol{z})g_\mu(\boldsymbol{z}')\,\phi(h(\boldsymbol{z}',t))$$

generalized field equation (large number of neurons)

Field equation and low-dimensional dynamics

$$\frac{d}{dt}h(\mathbf{z},t) = -\frac{1}{\tau}h(\mathbf{z},t) + \underbrace{\int d\mathbf{z}'\rho(\mathbf{z}')}\sum_{\mu}^{D} f_\mu(\mathbf{z})\underbrace{g_\mu(\mathbf{z}')\,\phi(h(\mathbf{z}',t))}$$

$\alpha_\mu(t)$

$$\frac{d}{dt}h(\mathbf{z},t) = -\frac{1}{\tau}h(\mathbf{z},t) + \sum_{\mu}^{D} f_\mu(\mathbf{z})\alpha_\mu(t)$$

coefficient

D ‘basis functions’

Idea: write

$$h(\mathbf{z},t) = \sum_{\mu}^{D} f_\mu(\mathbf{z})\kappa_\mu(t)$$

projection onto basis f.

Field equation and low-dimensional dynamics

Idea: write

$$h(\mathbf{z},t) = \sum_{\mu}^{D} f_\mu(\mathbf{z})\kappa_\mu(t)$$

→yields D coupled equations

$$\frac{d}{dt}\kappa_\mu(t) = -\frac{1}{\tau}\kappa_\mu(t) + \int d\mathbf{z}\rho(\mathbf{z})g_\mu(\mathbf{z})\phi(\underbrace{\sum_{\nu}^{D} f_\nu(\mathbf{z})\kappa_\nu(t)}_{\phi(h(\mathbf{z},t))}\ )$$

→ activity of all N neurons (N>>1) is described by D equations in recurrent network (without external input)

Summary 3: low-dimensional dynamics

To generate **low-dimensional dynamics** in **heterogeneous** networks of neurons, three ingredients are important:

(i) neurons characterized by abstract positions z representing functional similarity

(ii) Weight matrix depends on z and z’

(iii) Weight matrix is of low rank: outer-product of rank D

Result: - field model for N to infinity
- small number D<<N of variables describe dynamics

Exercise at 11h15

$$\frac{d}{dt}h(t,z) = -\frac{1}{\tau}h(t,z) + J\int_V \sum_{\mu=1}^{D} f_\mu(z)g_\mu(z')\phi(h(t,z'))\rho(z')dz' \tag{3}$$

As a field model, this is an infinite-dimensional dynamical system. Yet, due to the particular form of the connectivity in Eq.(2), it can be reduced to a D-dimensional description. The goal of this exercise is to derive the hidden D-dimensional dynamics.

In this exercise, we assume that the functions f_μ are orthonormal:

$$\int_V f_\mu(z)f_\nu(z)\rho(z)dz = \delta_{\mu\nu} = \{1 \text{ if } \mu=\nu, \text{ and } 0 \text{ otherwise}\} \tag{4}$$

1.1 Assume that the field $h(t,z)$ is given by a linear combination of the functions f_μ, with time-dependent coefficients $\kappa_\mu(t)$ $(\mu = 1,\dots,D)$; that is:

$$h(t,z) = \sum_{\mu=1}^{D} f_\mu(z)\kappa_\mu(t) \tag{5}$$

What is the expression of each coefficient κ_μ in terms of the field $h(t,z)$?

Hint: compute the projection of the field on the function f_μ: $\int_V f_\mu(z)h(t,z)\rho(z)dz$.

1.2 We are now interested in the fixed points of Eq.(3). Find a closed-form expression solved by the coefficients κ_μ in the steady-state.

Hint: use Eq.(5) to replace the field with the variables κ_μ.

1.3 Starting from the field dynamics of Eq.(3), derive a closed-form expression for the dynamics of the coefficients κ_μ.

Hint: use Eq.(5) to compute the time derivative of the variables $\kappa_\mu(t)$.

1.4 Consider that, at initial time $t = 0$, the field is a linear combination of the functions f_μ, *plus* an additional term:

$$h(t=0,z) = \sum_\mu f_\mu(z)\kappa_\mu(0) + \Delta h(z)$$

where $\int_V \Delta h(z) f_\mu(z)\rho(z)dz = 0$, for all μ. What are the dynamics of Δh? Why is Eq.(5) a good assumption?

1.5 Consider now that the network receives an external input, given by an additional term in Eq.(3):

$$I^{\text{ext}}(z) = \sum_{\mu=1}^{D} f_\mu(z)I_\mu(t)$$

What are the dynamics of the coefficients κ_μ now? Can the external input affect the fixed points?

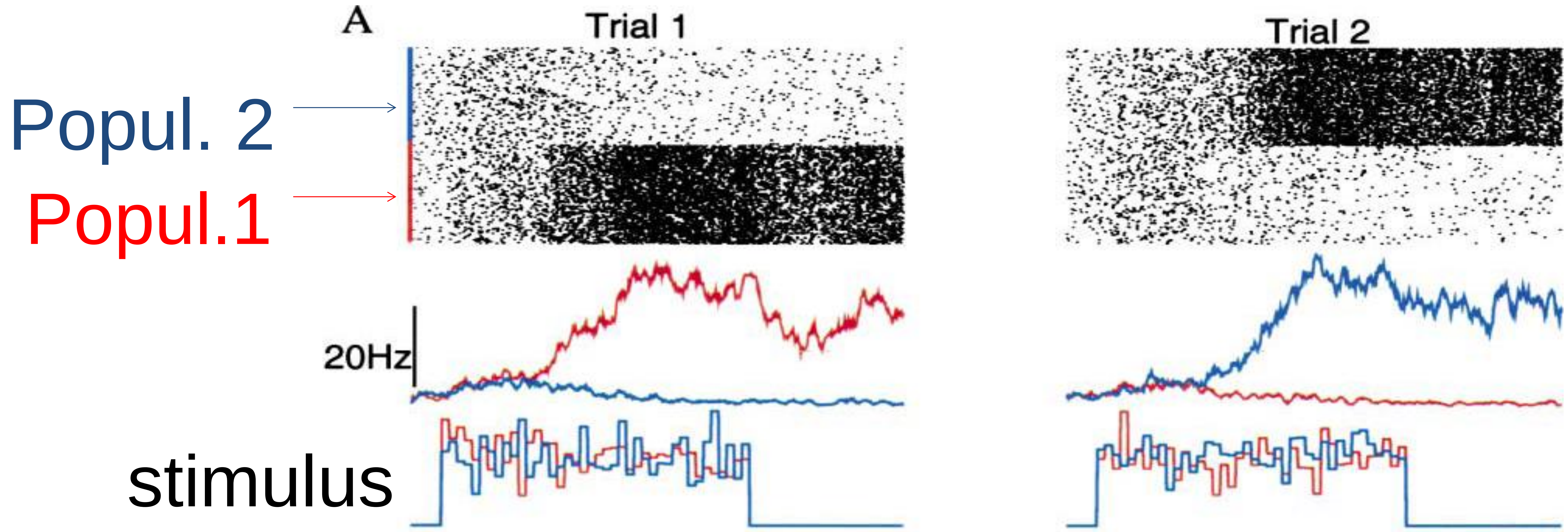
Examples of low-dimensional dynamics:

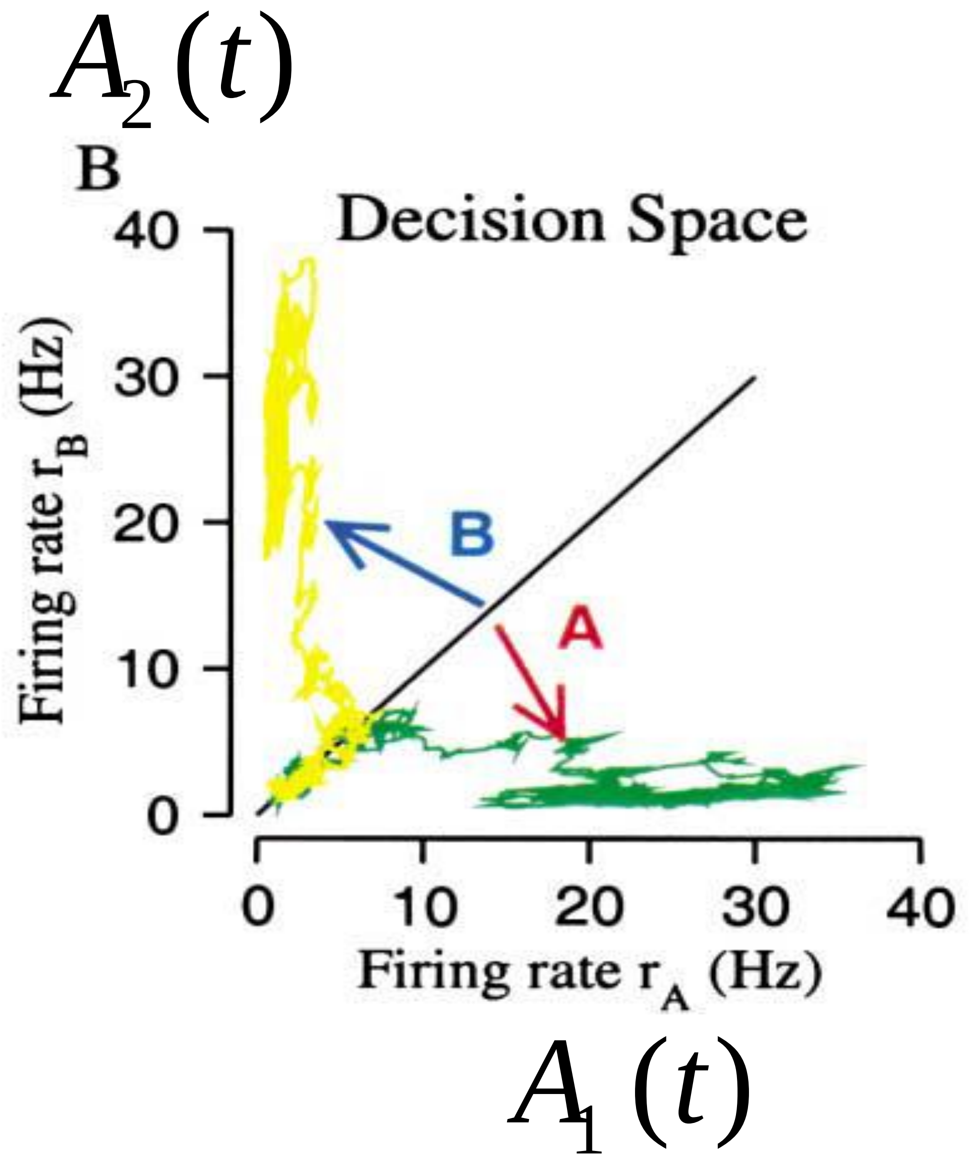
- Visual Cortex Model
- Ring model (with sinusoidal coupling)
- Hopfield model
- **Decision making**

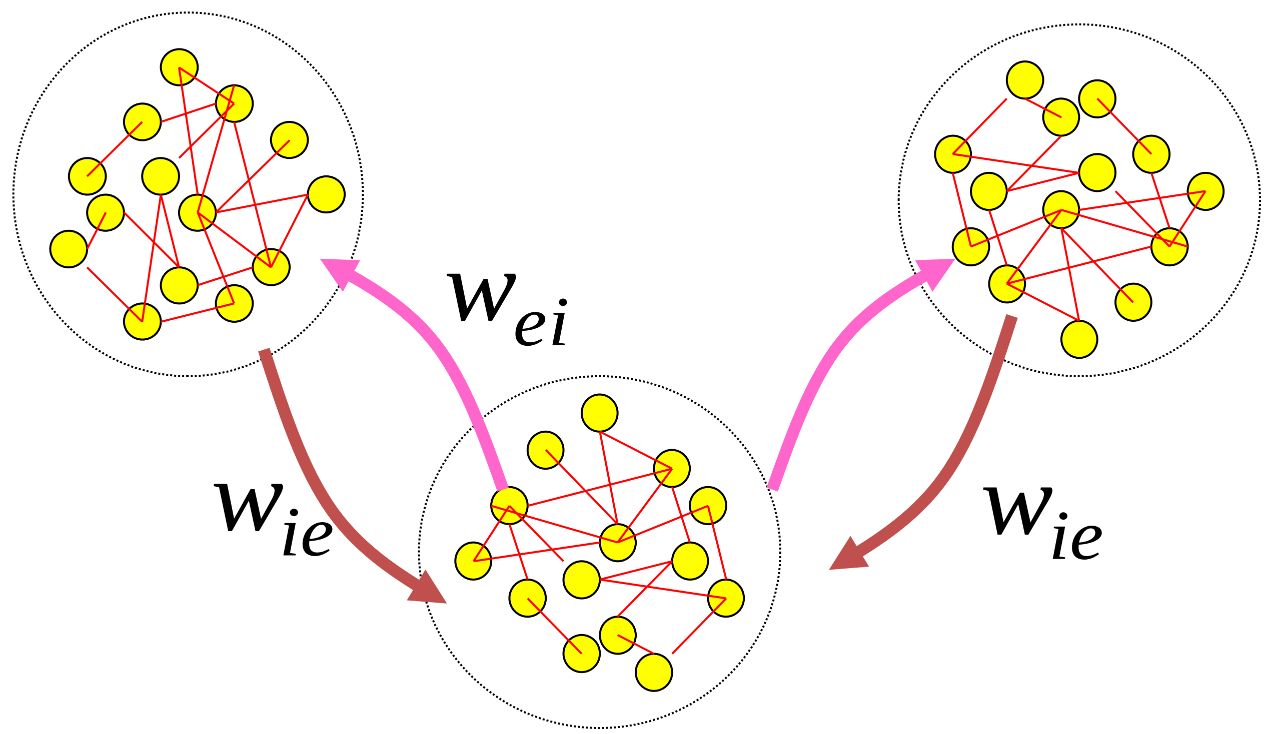
Review: Decisions in populations of neurons: simulation

Simulation of 3 populations of spiking neurons, unbiased strong input

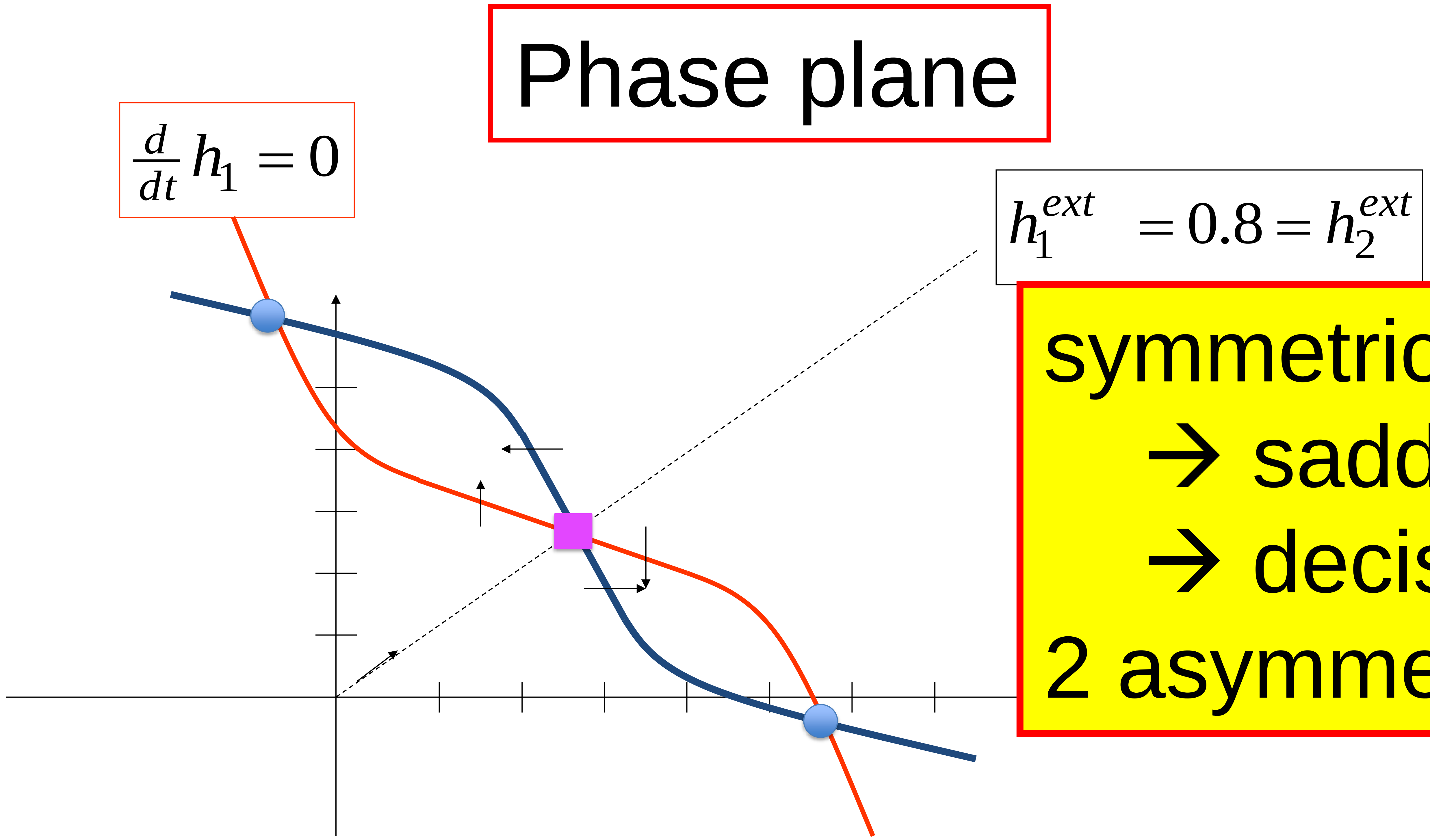
X.J. Wang, 2002 NEURON







Review. Theory of decision dynamics: unbiased strong



symmetric solution exists, but
→ saddle point
→ decision must be taken
2 asymmetric stable solutions

With unbiased input, there is a minimal input strength where the (single) stable solution turns into a saddle

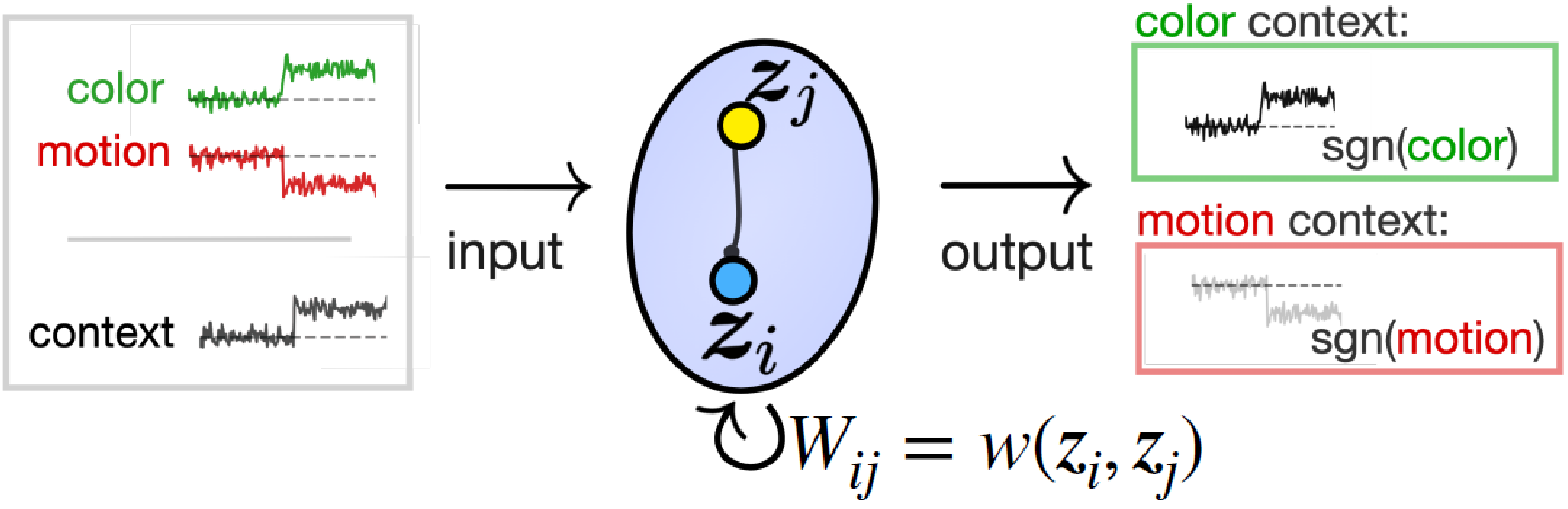
Example : low-dimensional dynamics in decision making

Context-dependent decision making

Task setup:

- 2 sensory inputs (color & motion)
- binary context input
- the network must output the sign of the specified sensory feature

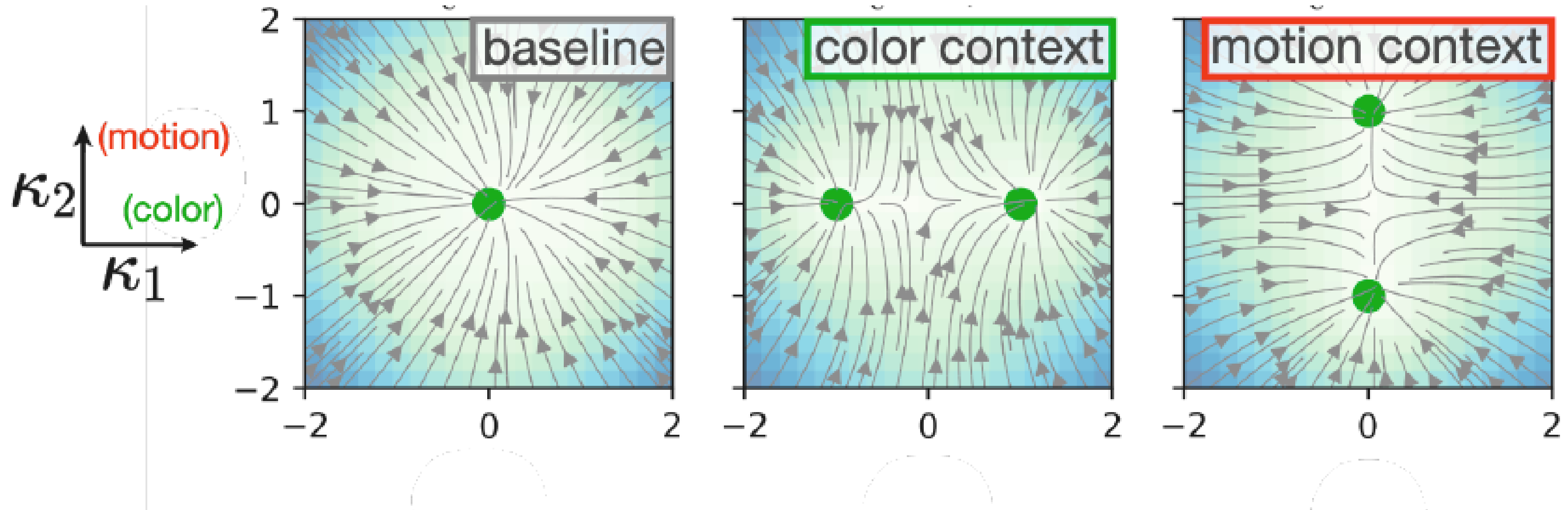
Mante,...,Newsome. 2014



Task: Mante, … Newsome 2014

... solved by 2-dimensional collective dynamics.

Mastrogiuseppe, Ostojic. 2018
Mante,...,Newsome. 2014



Model of 2-dim dynamics

- Mante, … Newsome 2014

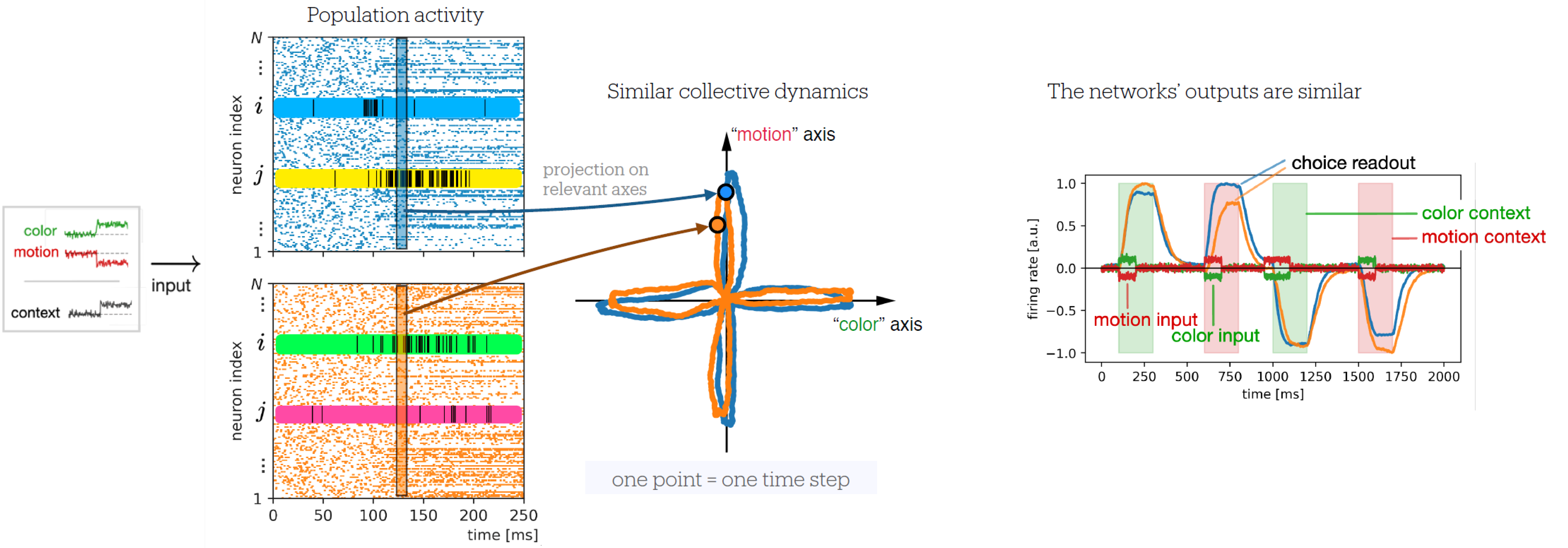
- Mastrogiuseppe, Ostojic, 2018

Idea: - design fixed-point structure in D-dim. decision space
- embedded in N-dimensional neuronal space

Example: low-dimensional dynamics in decision making

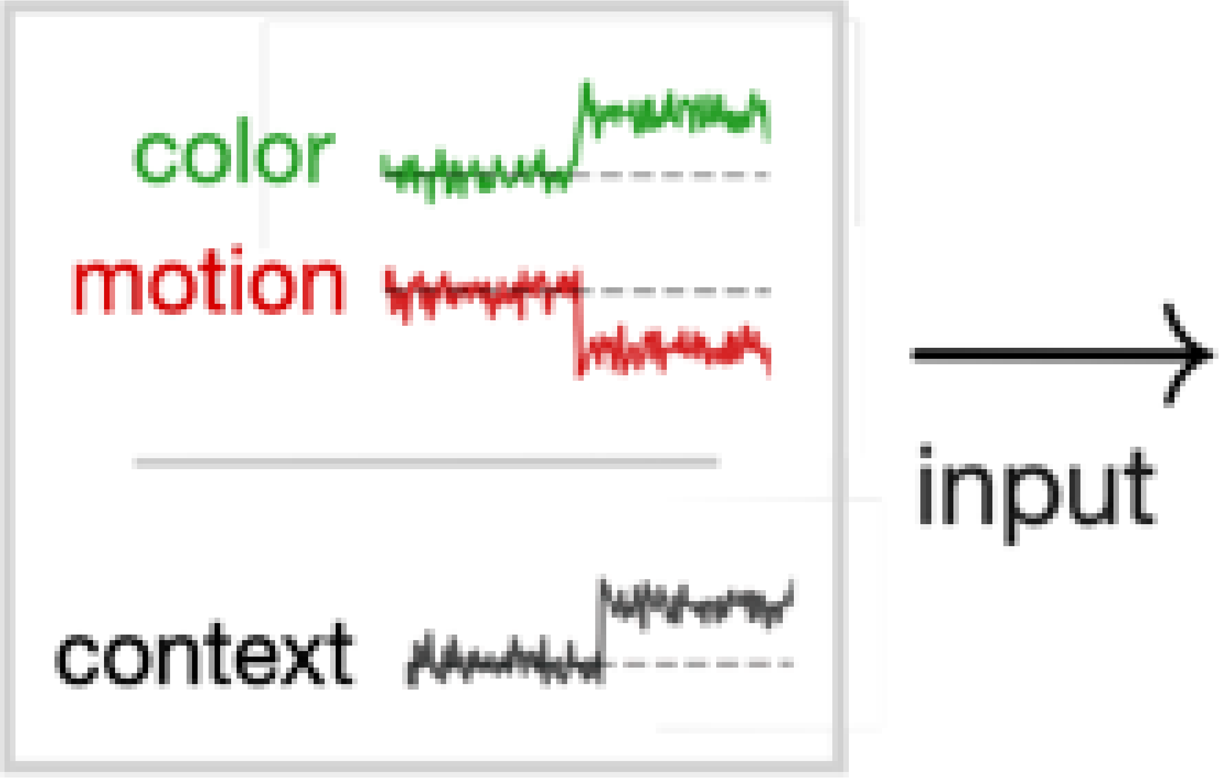
Two different spiking neuron models, similar dynamics

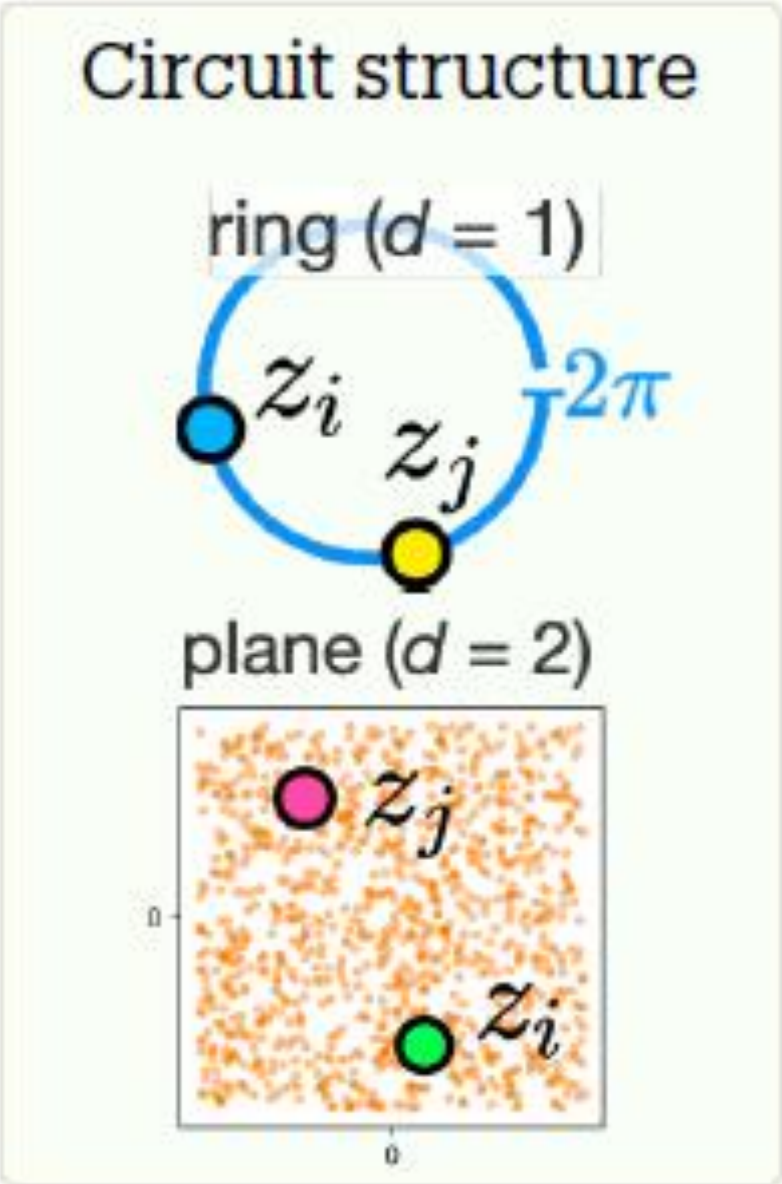
model of context-dependent decision-making



Example 2: low-dimensional dynamics in decision making

Two different spiking neuron models, similar dynamics

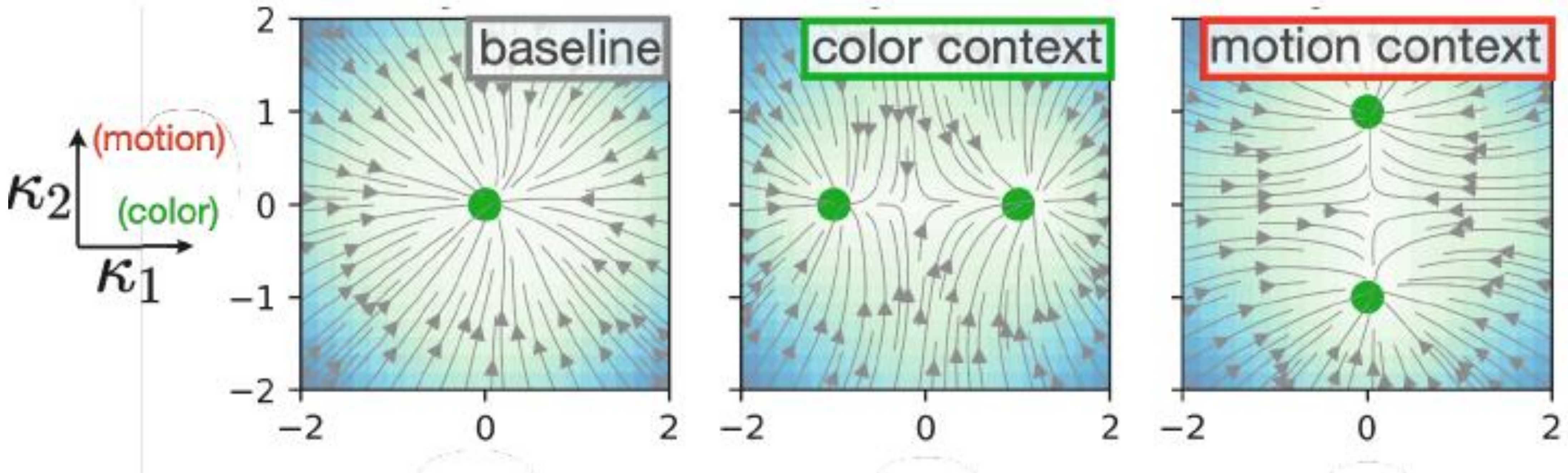




uniform in 1d, ring

uniform in 2d, square

Flow in 2 dimensions:
1st axis: color
2nd axis: motion
Flow pattern depends
on context input



Summary 4: **Task of context-dependent decision making (Mante et al.)**
Patterns of dots move on a screen. Dots have two characteristic features, i.e. color (green or magenta) and motion (movement up or down). A monkey watches the dot pattern. An additional context input tells the monkey which of the two features he should consider, color or motion.

After a go-cue, the monkey has to respond positively if the majority of the dots move upwards (for motion context) or if the majority of dots is green (color context).

Simulations of a model with thousands of neurons can reproduce this behavior. A theoretical model implements a low-dimensional manifold as follows.

(i) If no context cue is given, then there is a single fixed point. The monkey does not move.
(ii) If color context is given, then there are two fixed points at two different horizontal positions. The one to the left corresponds to color=green.
(iii) If motion context is given, then there are two fixed points at two different vertical positions. The one on top corresponds to motion=upward.

The model can be implemented with the formalism of outer-product matrix as described starting from two different layouts of functional similarity in the z-space: either a one-dimensional ring model (blue model), or a two-dimensional square (orange model). Both models generate the same trajectories in the manifold and both lead to a valid choice readout.

Summary 4, Mante task, continued.
To extract the similarity space (embeddings of neurons in the z-space), one can use the fact that functionally similar neurons generate very similar time-dependent signals r(t).
Therefore the similarity becomes visible if we plot the time-series r(t) of each neuron (= one row of the experimental data matrix) in some high-dimensional space: similar neurons will be neighbors.

The simplest way of doing this would be to cut the time series in K distinct intervals, and plot neurons as point in K-dimensional space. However, any other preprocessing tool that takes the time series and transforms it into K values can be used as well.

Hence:
if you plot the columns (rate vector) of the data matrix in the N-dimension space as a function of time , you can extract the low-dimensional manifold.

If you plot the rows (time series for each neuron) in the K-dimensional space as a function of neurons (1 neuron = 1 point), then you can extract the similarity of neurons in the z-space.

Importantly, different implementations in z-space can give rise to qualitatively identical low-dimension trajectories in the manifold: trajectory (κ_1(t),κ_2(t)|context)

Barack, D.L., Krakauer, J.W.: Two views on the cognitive brain. Nature Reviews Neuroscience 22(6), 359–371 (2021)

Langdon, C., Genkin, M., Engel, T.A.: A unifying perspective on neural manifolds and circuits for cognition. Nature Reviews Neuroscience 24(6), 363–377 (2023)

DePasquale, B., Sussillo, D., Abbott, L.F., Churchland, M.M.: The centrality of population-level factors to network computation is demonstrated by a versatile approach for training spiking networks. Neuron 111(5), 631–64910 (2023)

Mastrogiuseppe, F., Ostojic, S.: Linking connectivity, dynamics, and computations in low-rank recurrent neural networks. Neuron 99(3), 609–62329 (2018)

Taube, J., Muller, R., JB Ranck, J.: Head-direction cells recorded from the postsubiculum in freely moving rats. 1. description and quantitative analysis. Journal of Neuroscience 10(2), 420–435 (1990)

Bonhoeffer, T., Grinvald, A.: Iso-orientation domains in cat visual cortex are arranged in pinwheel-like patterns. Nature 353, 429–431 (1991)

Chaudhuri, R., Ger cek, B., Pandey, B., Peyrache, A., Fiete, I.: The intrinsic attractor manifold and population dynamics of a canonical cognitive circuit across waking and sleep. Nature Neuroscience 22(9), 1512–1520 (2019)

Churchland, M.M., Cunningham, J.P., Kaufman, M.T., Foster, J.D., Nuyujukian, P., Ryu, S.I., Shenoy, K.V.: Neural population dynamics during reaching. Nature 487(7405), 51–56 (2012)

Vyas, S., Golub, M.D., Sussillo, D., Shenoy, K.V.: Computation through neural population dynamics. Annual Review of Neuroscience 43(1), 249–275 (2020)

Mante, V., Sussillo, D., Shenoy, K.V., Newsome, W.T.: Context-dependent computation by recurrent dynamics in prefrontal cortex. Nature 503(7474), 78–84 (2013)

Shenoy, K.V., Sahani, M., Churchland, M.M.: Cortical control of arm movements: A dynamical systems perspective. Annual Review of Neuroscience 36(1), 337–359 (2013) https://doi.org/10.1146/annurev-neuro-062111-150509 . PMID: 23725001

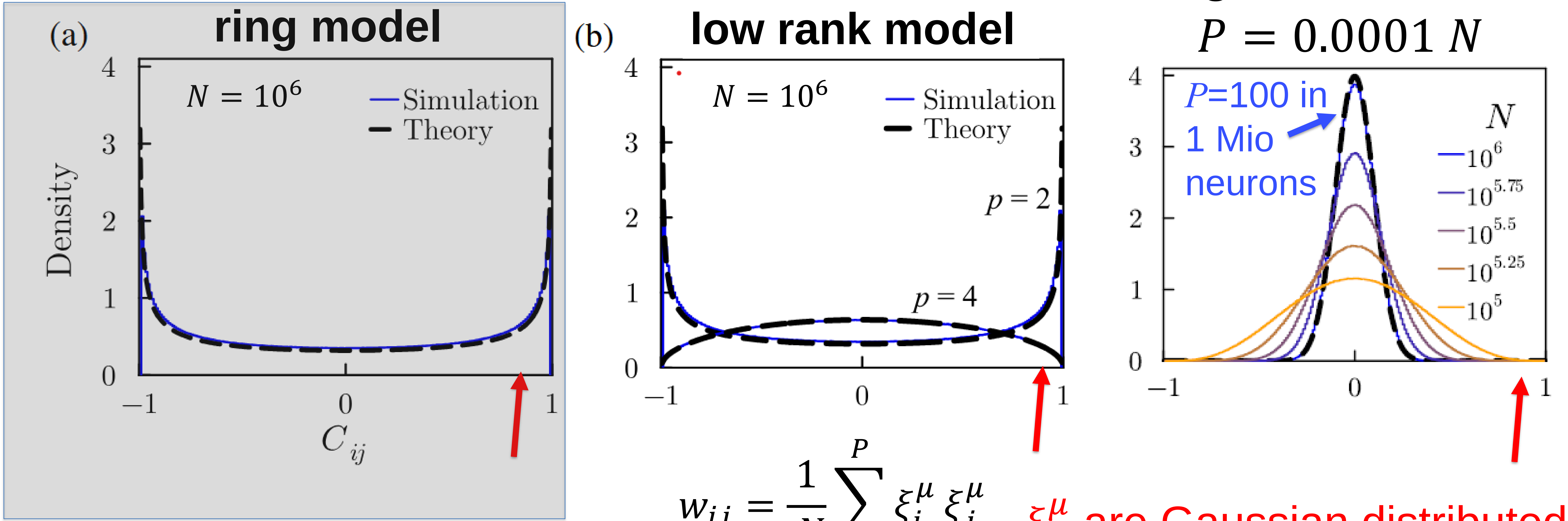
Gallego, J.A., Perich, M.G., Miller, L.E., Solla, S.A.: Neural manifolds for the control of movement. Neuron 94(5), 978–984 (2017)

THE END

Neural Manifolds and Low-dimensional dynamics:

1. What are Neural Manifolds?
   - experimental observations
2. Two views of Neural Activity
   - computing (Hopfield model)
   - neural circuits (field model)
3. Low-dimensional dynamics
   - formalism and assumption
   - dynamics
4. Examples of low-dim dynamics
   - context-dependent decision making
5. From Spikes to Rates

Correlations between two neurons: low-rank weight matrix



$$w_{ij} = \frac{1}{N}\sum_{\mu}^{P} \xi_i^\mu \, \xi_j^\mu$$

ξ_j^μ are Gaussian distributed

Neurons become uncorrelated for $P \to \infty;\ N \to \infty;\ \frac{P}{N} \to 0$

$e.g.\ P = N^{1/3}$

→ **no duplicate neurons**

V. Schmutz, J. Brea, W. Gerstner (2025) ***Emergent rate-based dynamics in duplicate-free populations of spiking neurons***
Physical Review Letters, 134:018401

Quiz: Hopfield model –
Are neurons correlated or uncorrelated for large N?

We have stored P binary patterns in a networks of N neurons using
The standard weight matrix

$$w_{ij} = \frac{1}{N}\sum_{\mu}^{P} \xi_i^{\mu}\, \xi_j^{\mu}$$

The number of neurons N is (much) larger than the number P.

[ ] There are at most P different 'types of neuron' so that if
N>P neurons can become correlated.

[ ] There are at most P^3 different 'types of neuron' so that if
$N > P^3$ neurons can become correlated.

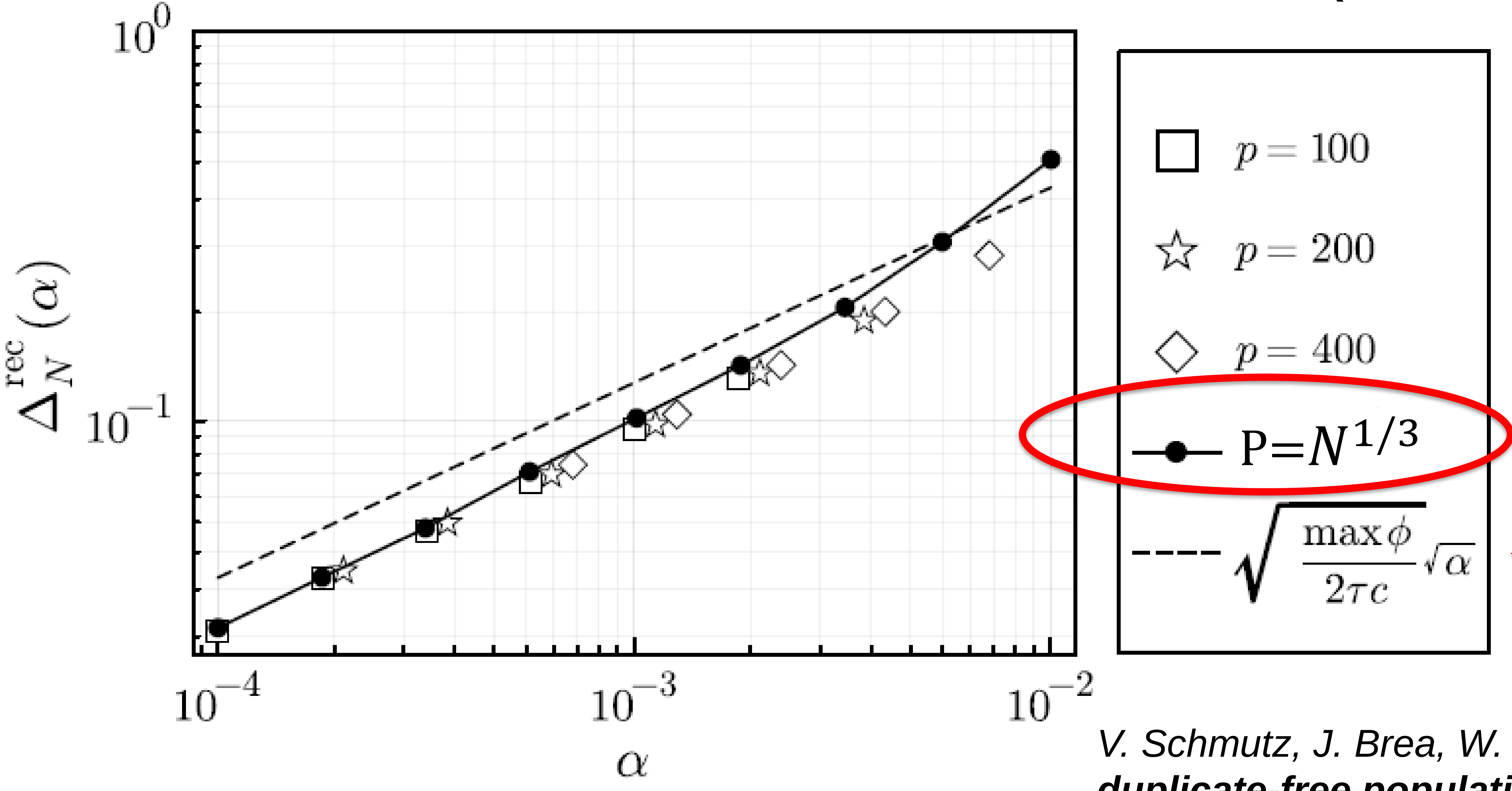
[ ] There are at most 2^P different 'types of neuron' so that if
$N > 2^P$ neurons can become correlated.

Distance between potential in SNN (spikes) and RNN (rates)

fixed P while $N \to \infty$: correlated neurons (duplicates, e.g. ring model)

$P = \alpha N$ while $N \to \infty$: uncorrelated neurons (no duplicates)

$P = N^{1/3}$ while $N \to \infty$: uncorrelated neurons (no duplicates)



$\alpha = P/N$

bound for small α

V. Schmutz, J. Brea, W. Gerstner (2025) ***Emergent rate-based dynamics in duplicate-free populations of spiking neurons*** *Phys.Rev. Lett. 134:018401*

$P = \alpha N$ while $N \to \infty$: distance $\Delta_N^{rec} \propto \sqrt{\alpha}$ finite! SNN ≠ RNN

$P = N^{1/3}$ while $N \to \infty$: distance $\Delta_N^{rec} \propto \sqrt{\alpha} = 1/N^{1/3}$ SNN → RNN

Summary Rate coding with
instantaneous time-dependent rates
is possible in network of spiking neurons even though not a single pair of neurons is correlated (**no duplicates**)

→ completely heterogeneous population
→ no spatial averaging
→ no temporal averaging

SNN → RNN

Rather: low-rank weight matrix

→ **low-dimensional** network-input to each neuron
→ neural activity lives in a $\boldsymbol{P}$**-dimensional manifold**
→ $e.g.\ P = N^{1/3}$
→ P=100-dimensional activity in 1 Mio neurons

V. Schmutz, J. Brea, W. Gerstner (2025) ***Emergent rate-based dynamics in duplicate-free populations of spiking neurons*** *Phys.Rev. Lett. 134:018401*

Conclusions

- SNN → RNN without averaging!
- rather ‘loose’ conditions
- rank *P* can be ‘relatively large’

V. Schmutz, J. Brea, W. Gerstner (2025) ***Emergent rate-based dynamics in duplicate-free populations of spiking neurons***
Phys.Rev. Lett. 134:018401

Is low-rank connectivity a strange assumption?

1) *"Neurons have receptive fields and wiring patterns: is a low-rank model realistic AT ALL?"*

Barack, D.L., Krakauer, J.W.: Two views on the cognitive brain. Nat. Rev. Neurosc. (2021)
Langdon, C., Genkin, M., Engel, T.A.: A unifying perspective on neural manifolds and circuits for cognition. Nat. Rev. Neurosci. (2023)

Answer: All standard models of cortex are dominated by a low-rank connectivity matrix

Pezon, L., Schmutz, V, Gerstner, W. (2024), Linking Neural Manifolds to Principles of Circuit Structure in Recurrent Networks bioRxiv doi: https://doi.org/10.1101/2024.02.28.582565

2) *"How are low-rank networks related to low-dim. dynamics?"*

Answer: rank *P* weight matrix (outer product matrix) **always** generate *P*-dimensional dynamics (→neural manifolds)

Mastrogiuseppe, F., Ostojic, S.: Linking connectivity, dynamics, and computations in low-rank recurrent neural networks. Neuron 99(3), 609–62329 (2018)

Computational Neuroscience: Neuronal Dynamics

Written Exam (70%)

You can bring 1 sheet A5 (double-sided) of **handwritten** notes.
(no calculator, no textbook, no phone)

Exam is orthogonal to miniproject.

- Look at written exercises
- Look at exams from previous years

I wish you Good Luck and Great Success
for the Written Examv