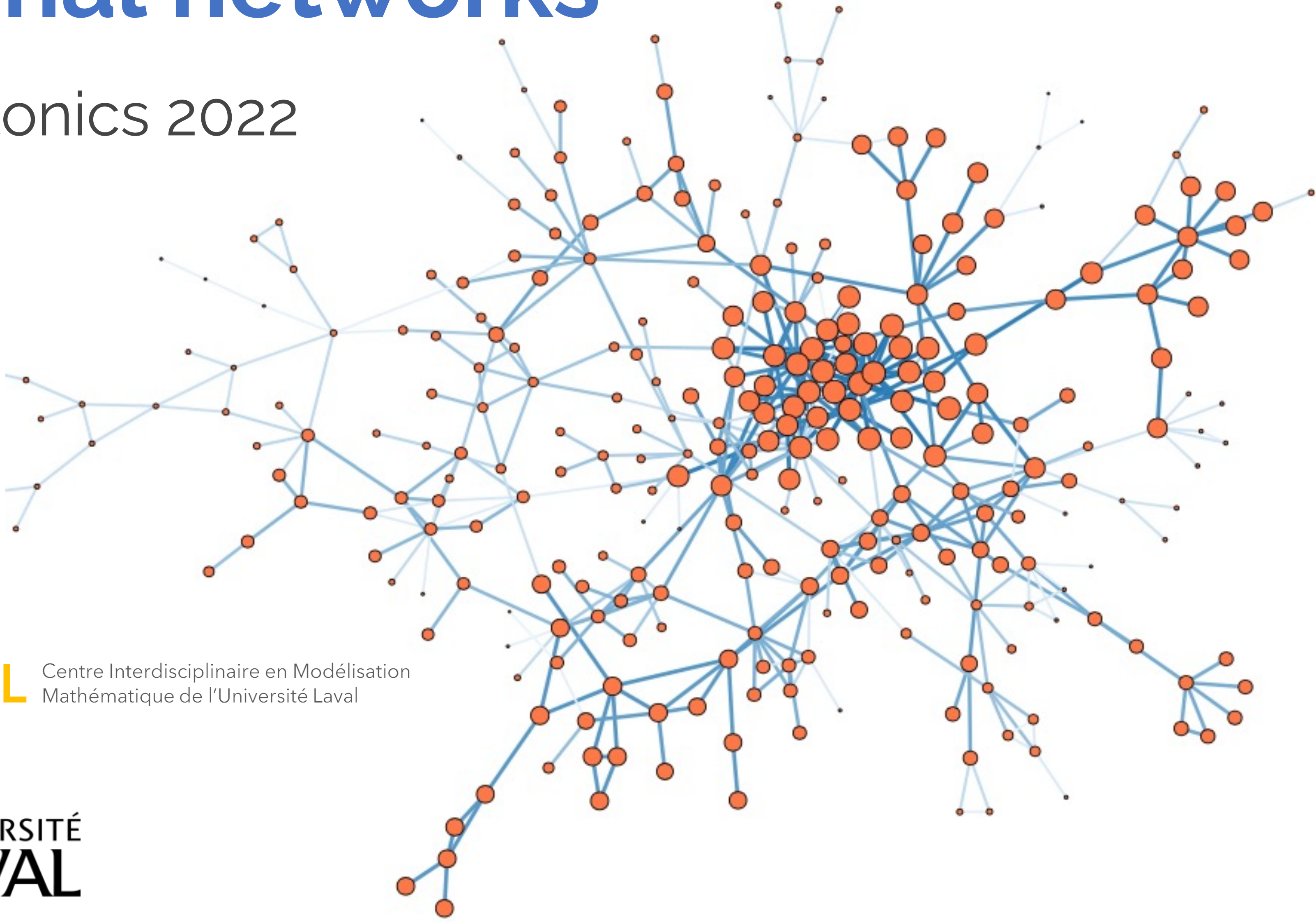
The hidden low-dimensional dynamics of large neuronal networks



Frontiers in Neurophotonics 2022

Patrick Desrosiers

Dynamica

CIMMUL Centre Interdisciplinaire en Modélisation Mathématique de l'Université Laval

CENTRE DE RECHERCHE CERVO BRAIN RESEARCH CENTRE

UNIVERSITÉ LAVAL

CENTRE DE RECHERCHE CERVO BRAIN RESEARCH CENTRE

NEUROPHOTONICS CENTRE

Daniel Côté

Paul De Koninck

Benoit Labonté

Pierre Marquet

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NEUROPHOTONICS CENTRE

Daniel Côté

Paul De Koninck

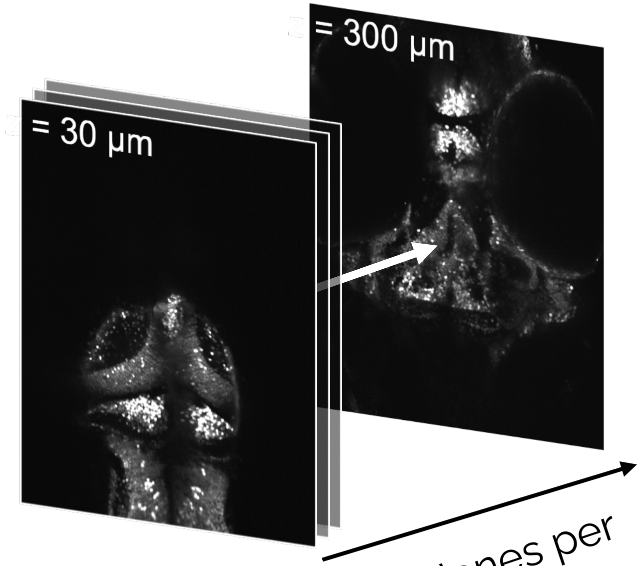
Benoit Labonté

Pierre Marquet

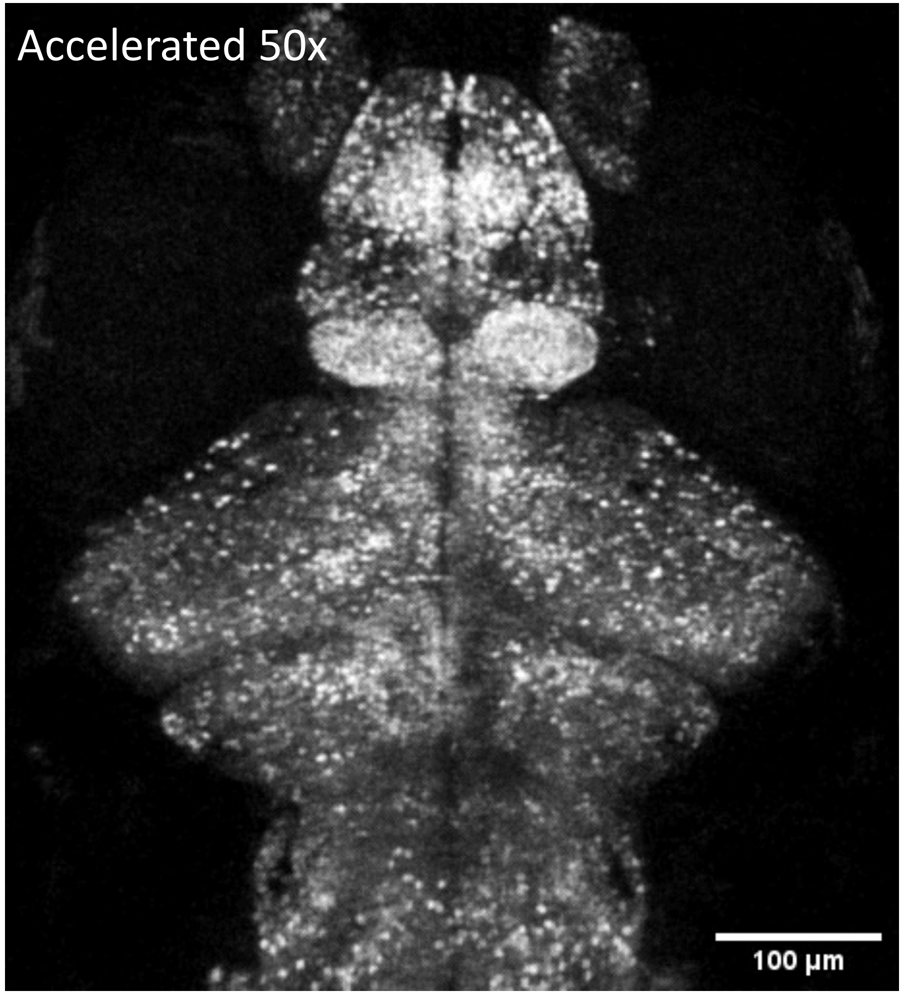
Neuronal activity in zebrafish brain

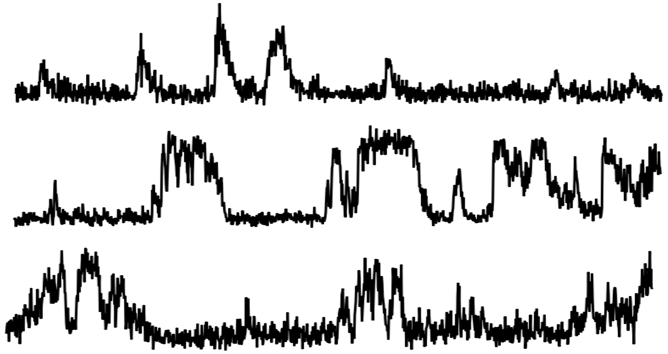
Antoine Légaré

Larval zebrafish



29 planes per second

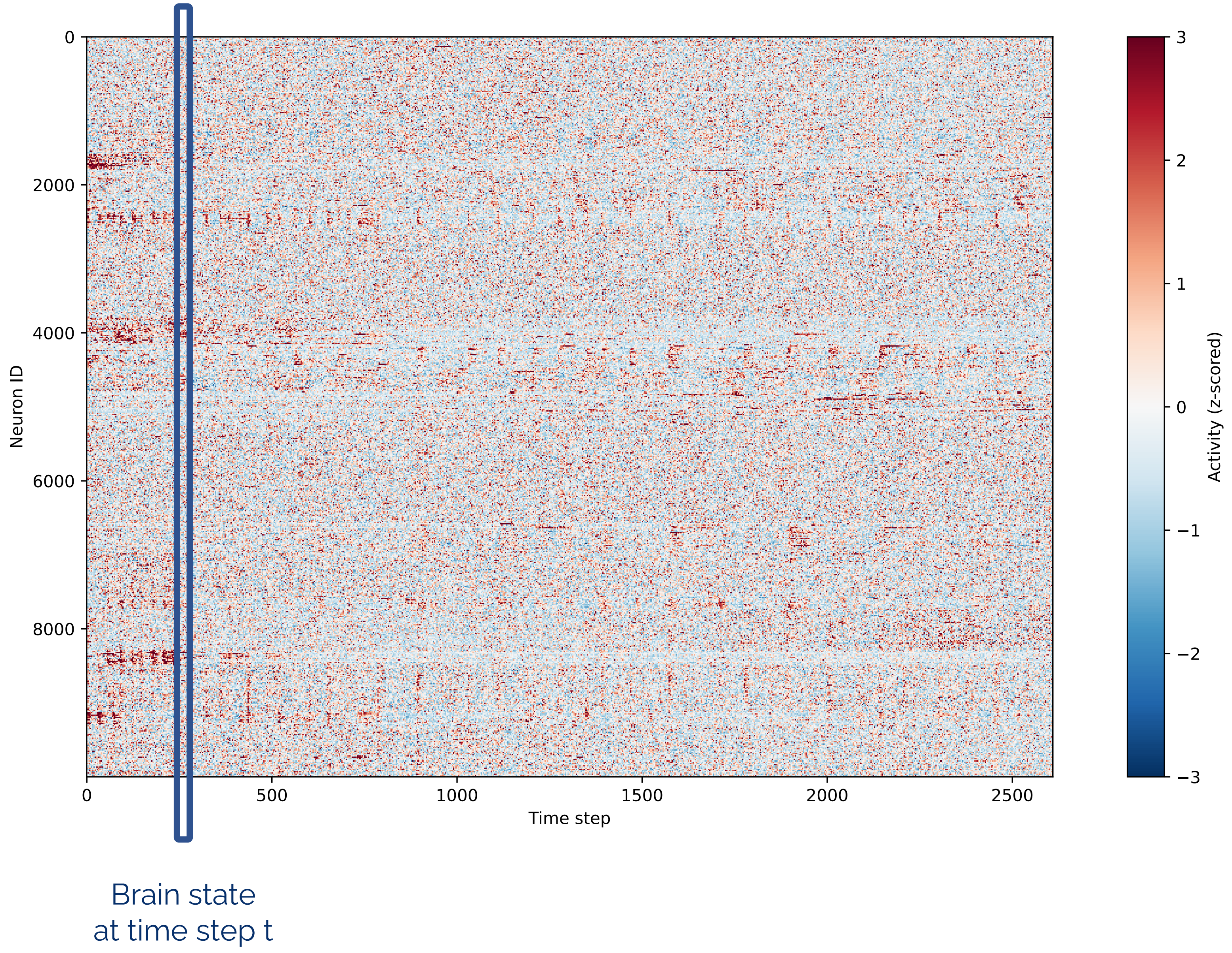




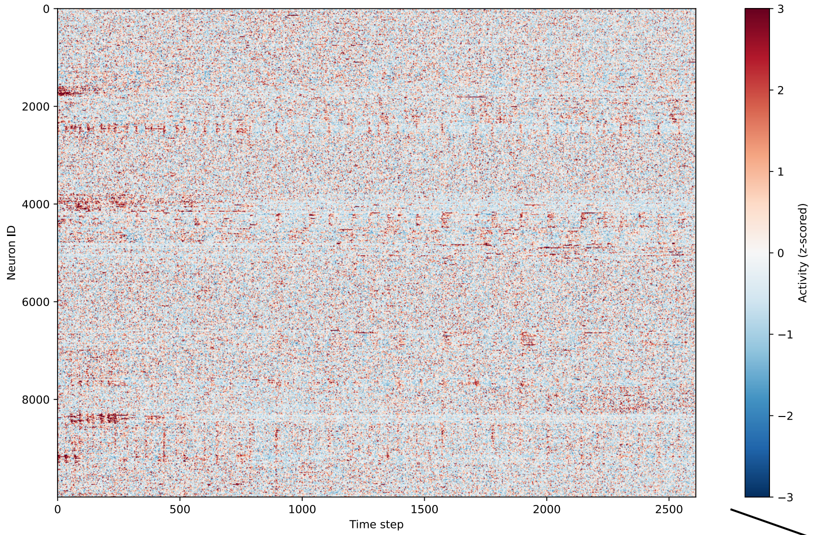
61500 neurons on average

Source: Paul De Koninck' Lab at CERVO

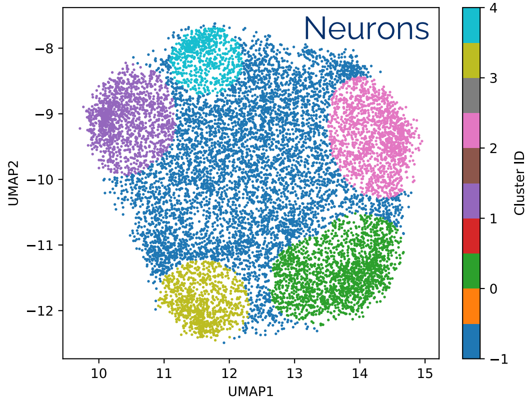
Neuronal activity in zebrafish brain: data



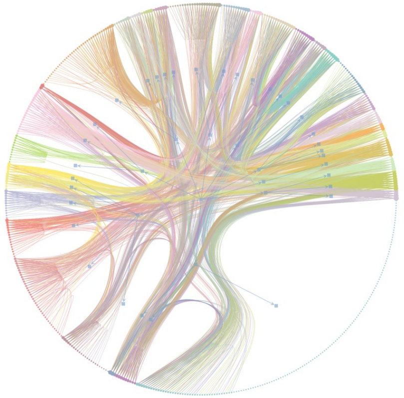
Neuronal activity in zebrafish brain: possible analyses



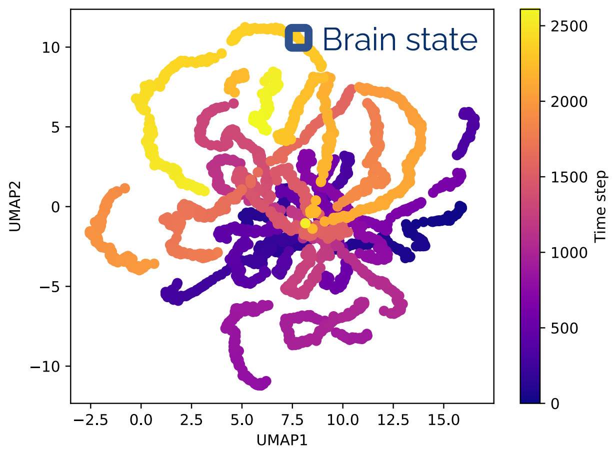
Dimensionality reduction:
PCA, Isomap, t-SNE, UMAP



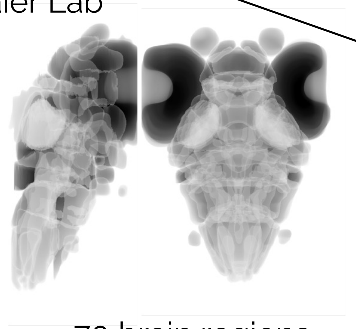
Functional connectivity:
Pearson correlation, Granger causality, Transfer entropy



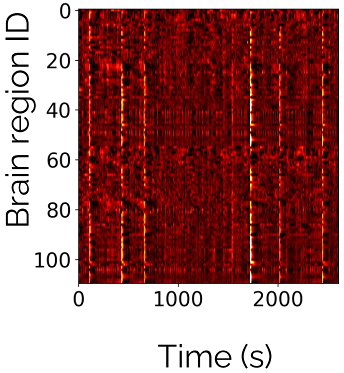
Dimensionality reduction:
PCA, Isomap, t-SNE, UMAP



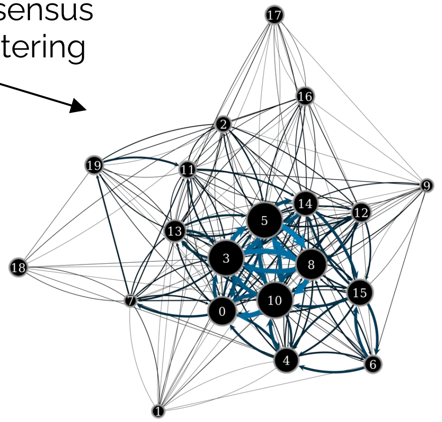
Mapzebrain,
Herwig Baier Lab



70 brain regions

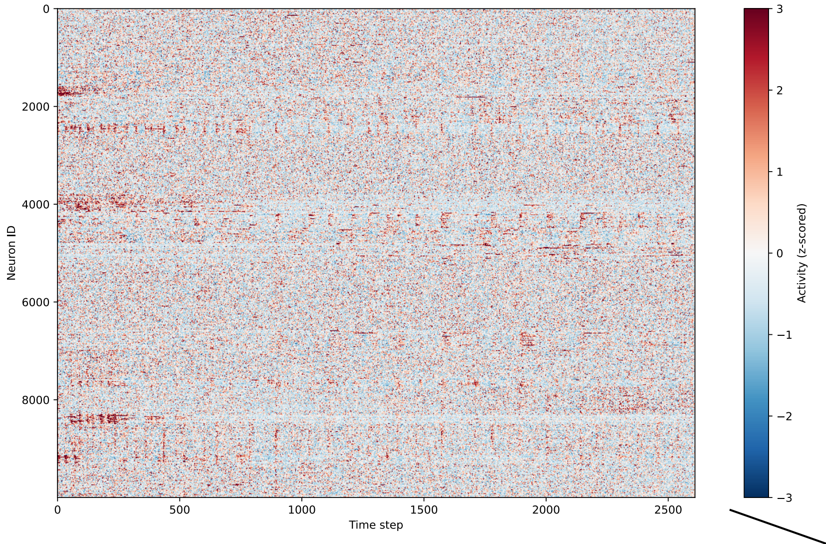


Consensus
clustering



State network

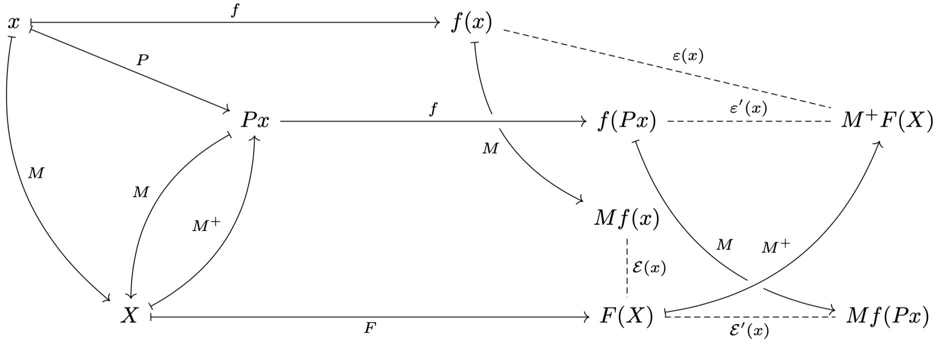
Neuronal activity in zebrafish brain: possible analyses



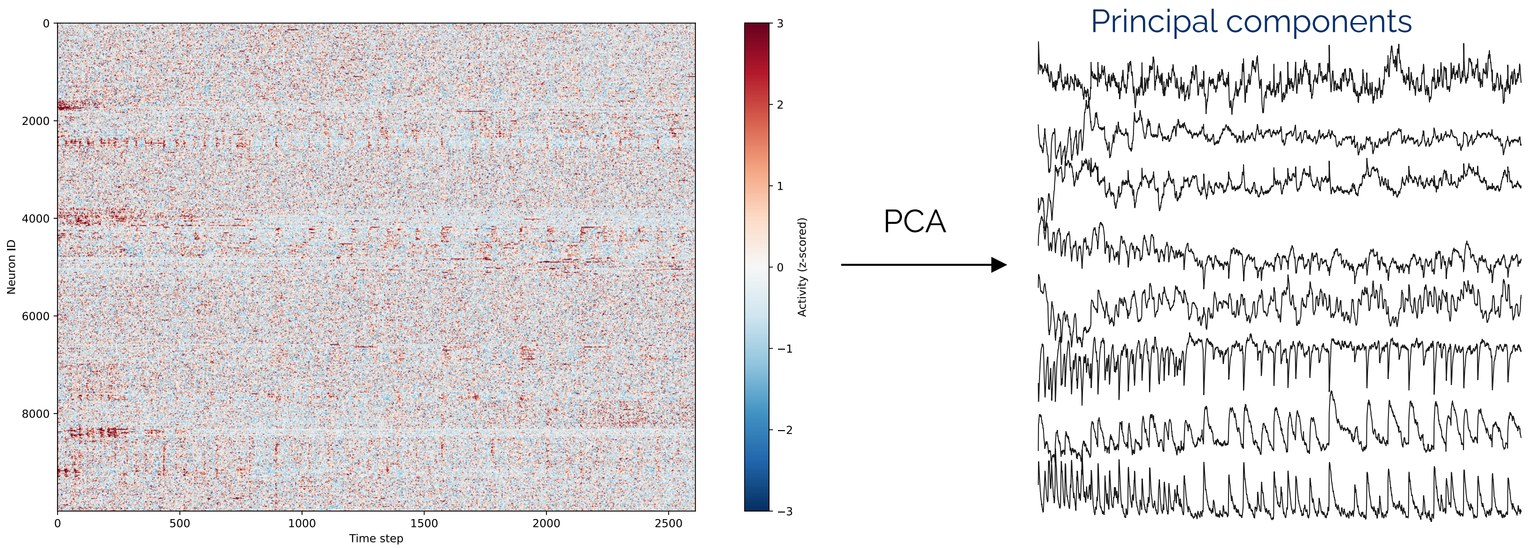
Mathematical modeling of the whole dynamics ?

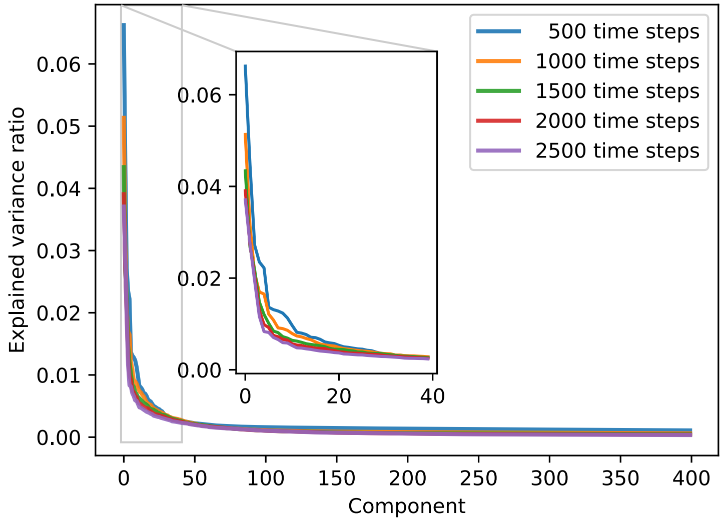
$$\dot{X} = \frac{\mathrm{d}(R \circ x)}{\mathrm{d}t} = \mathcal{U}[R] \circ x = J_R \circ f \circ x = F \circ R \circ x = F \circ X.$$

$$\dot{X} = \mathcal{U}[R] \circ x = J_R \circ f \circ x.$$

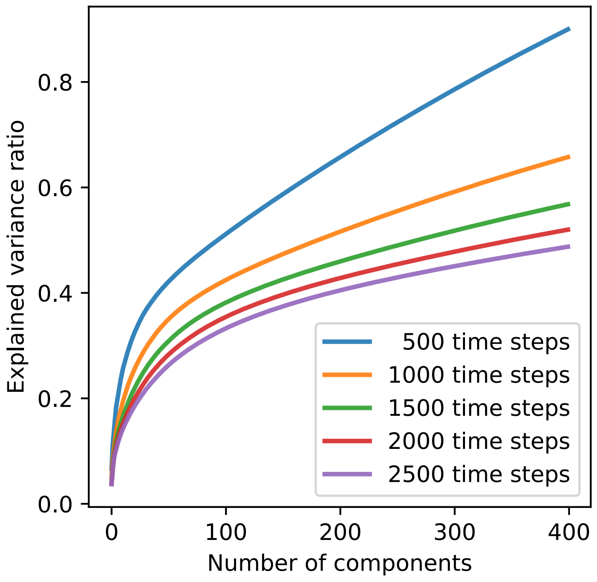


PCA and low-dimensionality





- Each neuron is approximately equal to a linear combination of a few principal components.
- Suggests that the dimensionality of the whole brain is much smaller than the number of neurons.



PCA and low-dimensionality

Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in **Neurobiology**

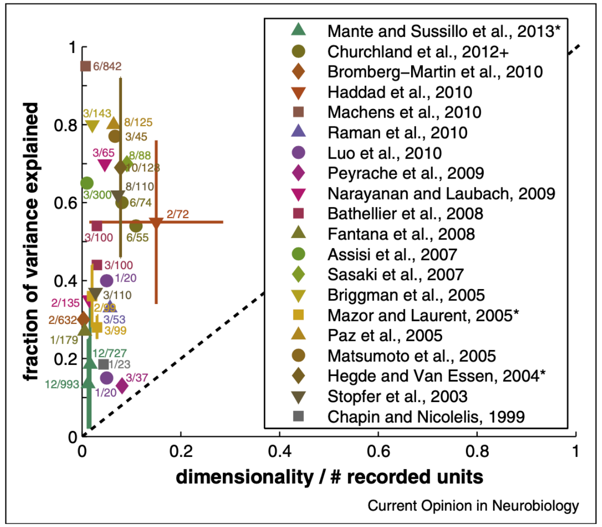
ELSEVIER

On simplicity and complexity in the brave new world of large-scale neuroscience

Peiran Gao[1] and Surya Ganguli[2]

CrossMark

Current Opinion in Neurobiology 2015, **32**:148–155



In many experiments (e.g. in insect [20,23–26] olfactory systems, mammalian olfactory [26,27], prefrontal [21,22•,28–30], motor and premotor,[31,32], somatosensory [33], visual [34,35], hippocampal [36], and brain stem [37] systems) a *much* smaller number of dimensions than the number of recorded neurons captures a large amount of variance in neural firing rates.

Why should we expect low dimensionality for large neuronal networks ?

Neuronal activity: resurgence of the dynamical system approach

Cell

Volume 177, Issue 4, 2 May 2019, Pages 970-985.e20

Article

Neuronal Dynamics Regulating Brain and Behavioral State Transitions

Aaron S. Andalman [1, 2, 12], Vanessa M. Burns [3, 12], Matthew Lovett-Barron [1, 2], Michael Broxton [4], Ben Poole [4], Samuel J. Yang [5], Logan Grosenick [1, 6], Talia N. Lerner [1], Ritchie Chen [1], Tyler Benster [6], Philippe Mourrain [7, 8, 9], Marc Levoy [4], Kanaka Rajan [10], Karl Deisseroth [1, 2, 8, 11, 13]

Computation Through Neural Population Dynamics

Annual Review of Neuroscience
Vol. 43:249-275 (Volume publication date July 2020)
https://doi.org/10.1146/annurev-neuro-092619-094115

Saurabh Vyas,[1,3] Matthew D. Golub,[2,3] David Sussillo,[2,3,4] and Krishna V. Shenoy[1,2,3,5]

ELSEVIER

Current Opinion in Neurobiology
Volume 70, October 2021, Pages 163-170

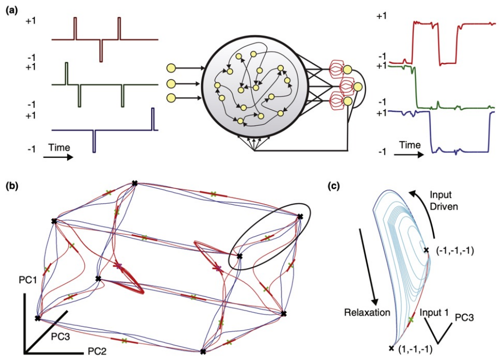
Dynamics on the manifold: Identifying computational dynamical activity from neural population recordings

Lea Duncker [1, 2], Maneesh Sahani [1]

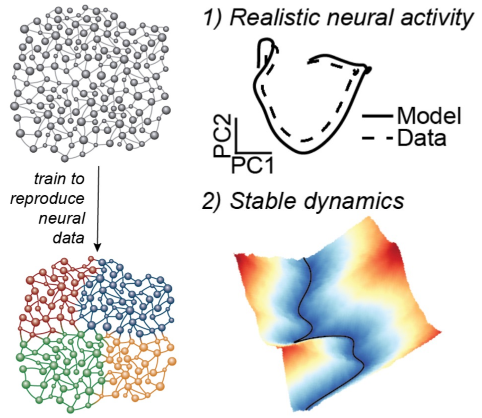
The role of population structure in computations through neural dynamics

Alexis Dubreuil, Adrian Valente, Manuel Beiran, Francesca Mastrogiuseppe & Srdjan Ostojic

Nature Neuroscience **25**, 783–794 (2022) | Cite this article



D. Sussillo 2014



M. G. Perich et al. 2020

Firing rate model for recurrent neural networks

Grossberg, Amari, Wilson–Cowan, Hopfield, …

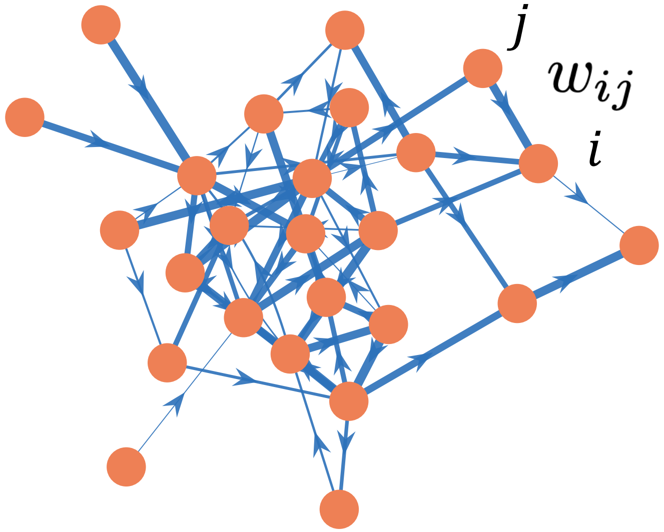
$$\frac{dx_i}{dt} = -x_i + \sigma\left(\sum_j w_{ij} x_j - \mu_i\right)$$

$x_i(t)$ = activity of neuron i at time t

μ_i = activation threshold of neuron i

w_{ij} = weight of the connection from neuron j to neuron i

$$i, j \in \{1, 2, \ldots, N\}$$

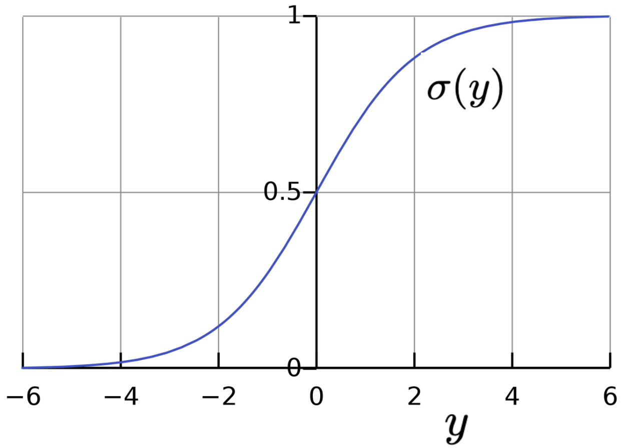


NEURAL NETWORK DYNAMICS

Annual Review of Neuroscience

Vol. 28:357-376 (Volume publication date 21 July 2005)
First published online as a Review in Advance on March 22, 2005
https://doi.org/10.1146/annurev.neuro.28.061604.135637

Tim P. Vogels, Kanaka Rajan, and L.F. Abbott



Firing rate model for recurrent neural networks

Grossberg, Amari, Wilson–Cowan, Hopfield, …

$$\frac{dx_i}{dt} = -x_i + \sigma\Big(\sum_j w_{ij}x_j - \mu_i\Big)$$

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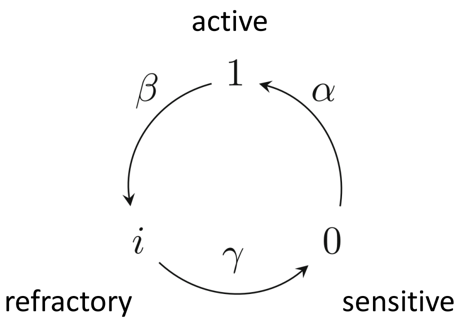
$$i, j \in \{1, 2, \ldots, N\}$$

Original Article | Open Access | Published: 05 September 2022

Beyond Wilson–Cowan dynamics: oscillations and chaos without inhibition

Vincent Painchaud, Nicolas Doyon & Patrick Desrosiers

Biological Cybernetics (2022) | Cite this article



Firing rate model for recurrent neural networks

Grossberg, Amari, Wilson–Cowan, Hopfield, …

$$\frac{d\boldsymbol{x}}{dt} = -\boldsymbol{x} + \boldsymbol{\sigma}(W\boldsymbol{x} - \boldsymbol{\mu})$$

$\boldsymbol{x} = N \times 1$ network state vector at time t

$\boldsymbol{\mu} = N \times 1$ vector of thresholds

$W = N \times N$ weight matrix

Original Article | Open Access | Published: 05 September 2022

Beyond Wilson–Cowan dynamics: oscillations and chaos without inhibition

Vincent Painchaud, Nicolas Doyon & Patrick Desrosiers

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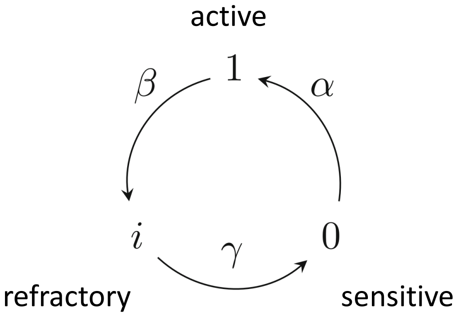


Recurrent neural networks can be trained to fit the data

Unknown parameters

$$\frac{dx}{dt} = -x + \sigma(Wx - \mu)$$

PLOS ONE

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

full-FORCE: A target-based method for training recurrent networks

Brian DePasquale, Christopher J. Cueva, Kanaka Rajan, G. Sean Escola, L. F. Abbott

Published: February 7, 2018 • https://doi.org/10.1371/journal.pone.0191527

LEARNING INTERNAL REPRESENTATIONS BY ERROR PROPAGATION

David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams

September 1985

ICS Report 8506

eLife Home Magazine Community About

Research Article

Neuroscience

Local online learning in recurrent networks with random feedback

James M Murray

Columbia University, United States

May 24, 2019 · https://doi.org/10.7554/eLife.43299

Neuron CellPress

Volume 63, Issue 4, 27 August 2009, Pages 544-557

Article

Generating Coherent Patterns of Activity from Chaotic Neural Networks

David Sussillo[1], L.F. Abbott[1]

Neuron CellPress

Volume 107, Issue 6, 23 September 2020, Pages 1048-1070

Primer

Artificial Neural Networks for Neuroscientists: A Primer

Guangyu Robert Yang[1], Xiao-Jing Wang[2]

Recurrent neural networks can be trained to fit the data

Jérémie Gince

Anthony Drouin

Simon Hardy

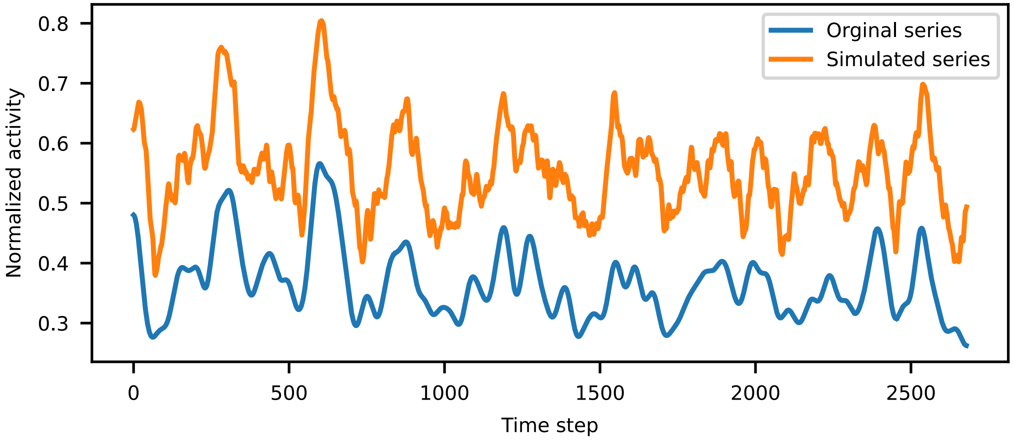
Daniel Côté

https://github.com/NeuroTorch/NeuroTorch

Current Version (v0.0.1-alpha)

- Image classification with spiking networks.
- Classification of spiking time series with spiking networks.
- Time series classification with spiking or Wilson-Cowan.
- Reconstruction/Prediction of time series with Wilson-Cowan.
- Reconstruction/Prediction of continuous time series with spiking networks.
- Backpropagation Through Time.

Antoine Légaré



Worst solution
RMSE=0.19

Recurrent neural networks can be trained to fit the data


Jérémie Gince


Anthony Drouin


Simon Hardy


Daniel Côté

NeuroTorch

https://github.com/NeuroTorch/NeuroTorch

Current Version (v0.0.1-alpha)

- Image classification with spiking networks.
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- Reconstruction/Prediction of time series with Wilson-Cowan.
- Reconstruction/Prediction of continuous time series with spiking networks.
- Backpropagation Through Time.

After training: $$\frac{d\boldsymbol{x}}{dt} = -\boldsymbol{x} + \boldsymbol{\sigma}(W\boldsymbol{x} - \boldsymbol{\mu})$$

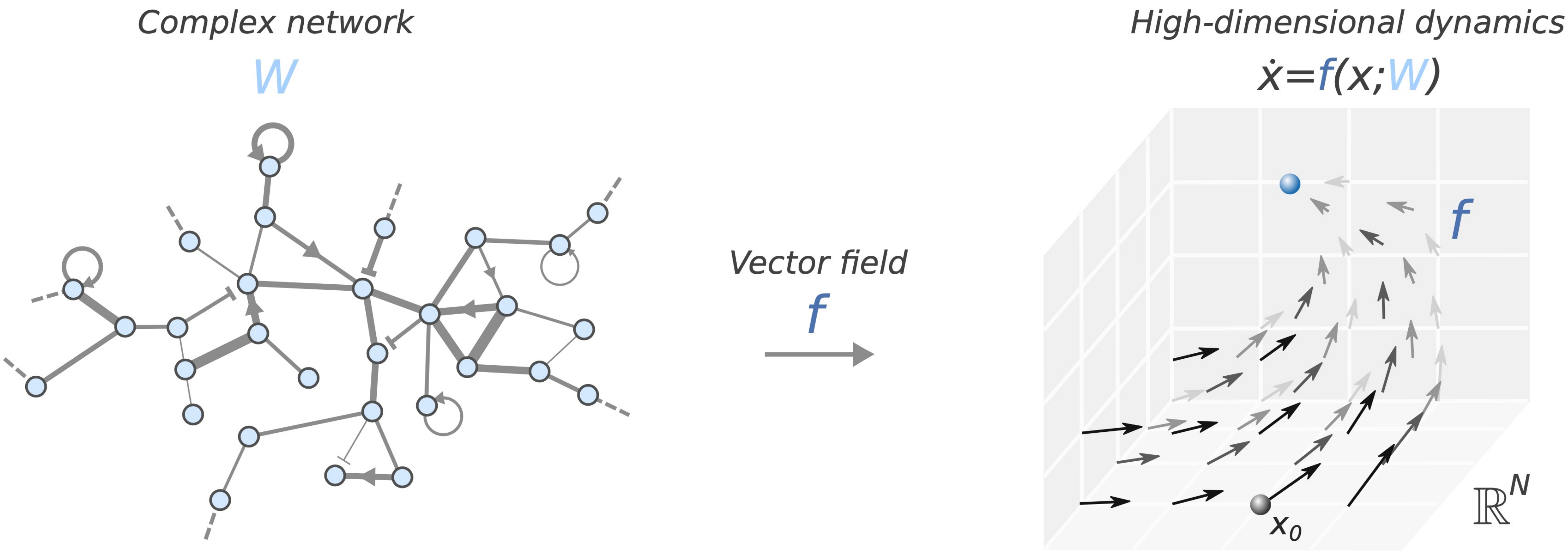
Learned parameters

High-dimensional dynamical system

How to reduce the dimensionality of large dynamical systems?

Is it justified to reduce the dimensionality?

Our point of view: complex systems theory

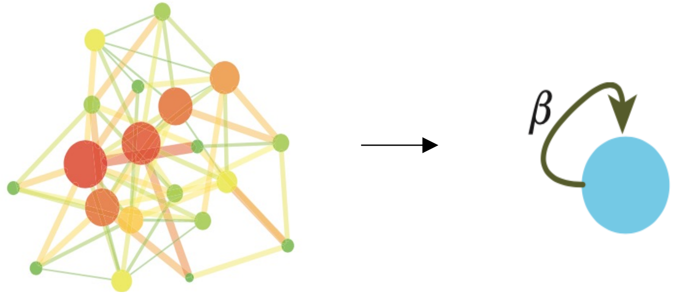


Our first inspiration:
Dimension reduction to study resilience

Universal resilience patterns in complex networks

Jianxi Gao[1]*, Baruch Barzel[2]* & Albert-László Barabási[1,3,4,5]

18 FEBRUARY 2016 | VOL 530 | NATURE | 307



Dimension reduction based on degrees:

$$\frac{dx_i}{dt} = F(x_i) + \sum_j W_{ij} G(x_i, x_j) \quad \longrightarrow \quad \frac{dx}{dt} = F(x) + \beta G(x, x)$$

where

$$x = \frac{\sum_{i,j} W_{ij} x_j}{\sum_{i,j} W_{ij}} = \text{degree-weighted average activity}$$

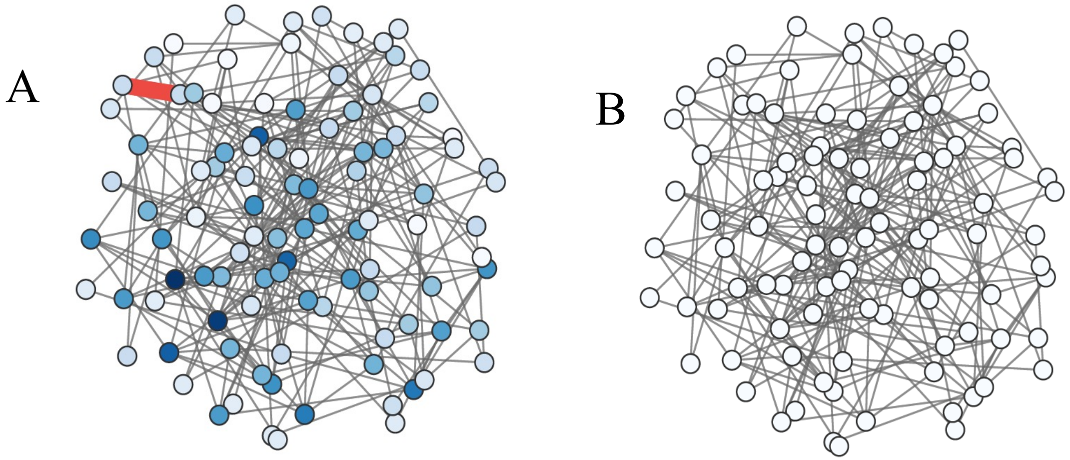
$$\beta = \frac{\sum_{i,j,k} W_{ij} W_{jk}}{\sum_{i,j} W_{ij}} = \text{degree-weighted average degree}$$

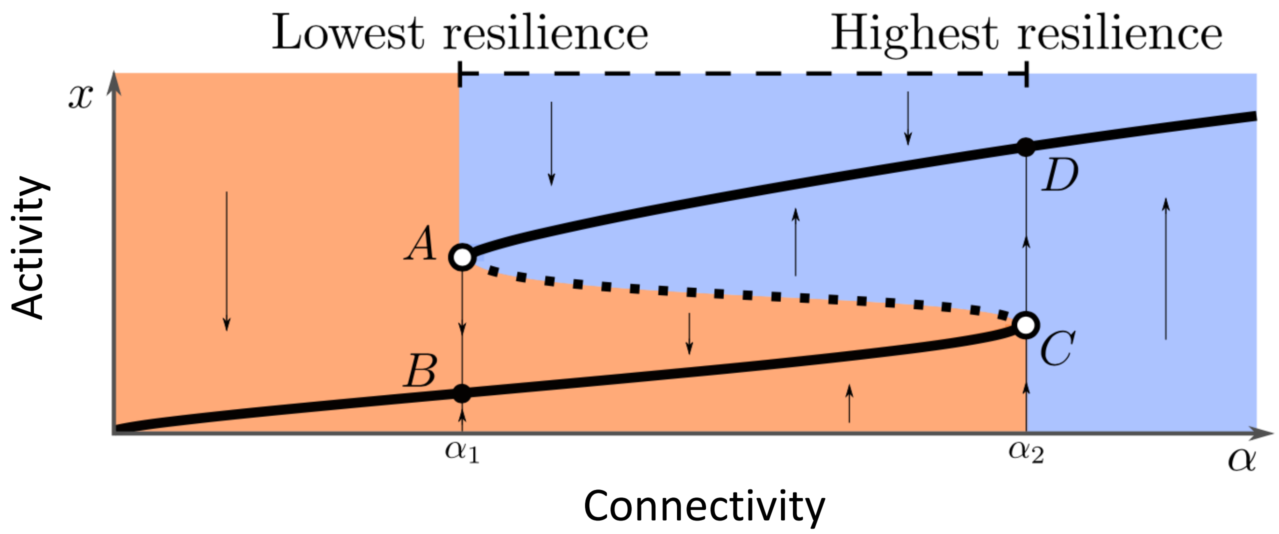
$$i, j, k \in \{1, \ldots, N\}$$

Success: The reduction allows studying resilience.

Problem: The reduction does not work well with all networks.

Resilience in complex systems





Desrosiers & Roy-Pomerleau, Nature Physics 2022

More complete solutions:

PHYSICAL REVIEW X **9,** 011042 (2019)

Spectral Dimension Reduction of Complex Dynamical Networks

Edward Laurence,[1,2] Nicolas Doyon,[2,3,4] Louis J. Dubé,[1,2] and Patrick Desrosiers[1,2,4]

PHYSICAL REVIEW RESEARCH **2**, 043215 (2020)

Threefold way to the dimension reduction of dynamics on networks: An application to synchronization

Vincent Thibeault,[1,2,*] Guillaume St-Onge,[1,2] Louis J. Dubé,[1,2] and Patrick Desrosiers[1,2,3,†]

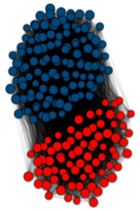
  

DART: Dynamics Approximate Reduction Technique

Complete dynamics

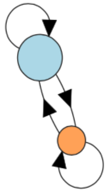
$N \gg 1$ dimensions

$$\frac{dz_j}{dt} = F(z_j) + \sum_{k=1}^{N} A_{jk} G(z_j, z_k)$$



$q \ll N$ dimensions

$$\frac{dZ_\mu}{dt} \approx F(Z_\mu) + \sum_{\nu=1}^{q} \mathcal{A}_{\mu\nu} G(Z_\mu, Z_\nu)$$



Reduced dynamics

PAPER

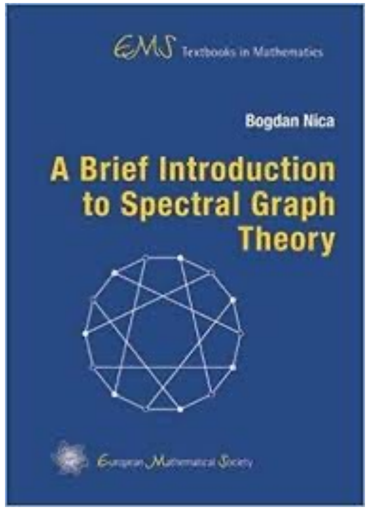
Dimension reduction of dynamics on modular and heterogeneous directed networks

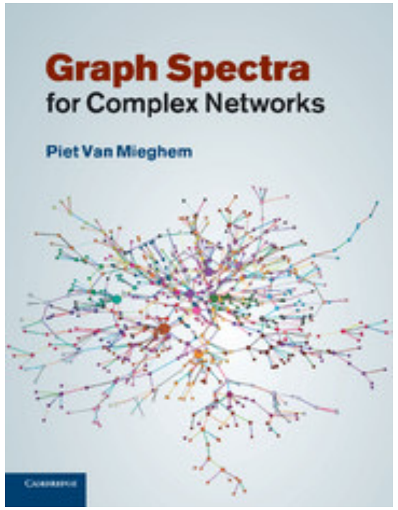
Marina Vegué,[a,b,*] Vincent Thibeault,[a,b] Patrick Desrosiers[a,b,c] and Antoine Allard[a,b]

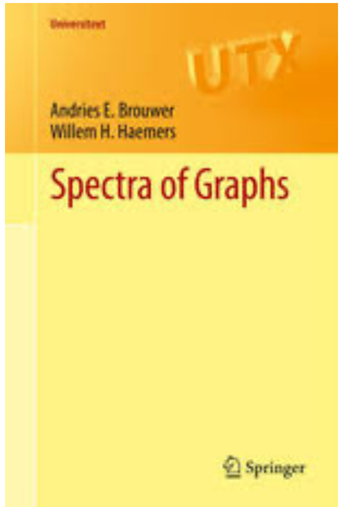
  

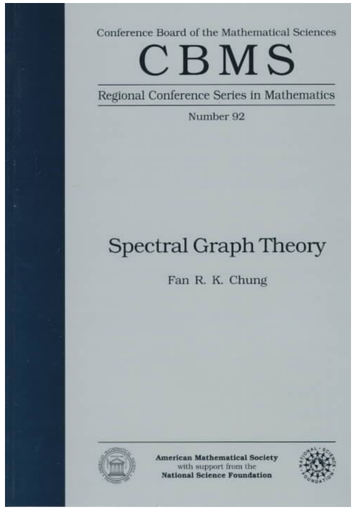
Theoretical framework:
Spectral Graph Theory and Matrix factorization

Good sources of information:









Learning the parts of objects by non-negative matrix factorization

Daniel D. Lee* & H. Sebastian Seung*†

NATURE | VOL 401 | 21 OCTOBER 1999 | www.nature.com

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 32, NO. 1, JANUARY 2010

Convex and Semi-Nonnegative Matrix Factorizations

Chris Ding, *Member*, *IEEE*, Tao Li, and Michael I. Jordan, *Fellow*, *IEEE*

Old treasure:

A GENERALIZED INVERSE FOR MATRICES

By R. PENROSE

Communicated by J. A. Todd

Received 26 July 1954

Recent treasure:

IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. 60, NO. 8, AUGUST 2014

The Optimal Hard Threshold for Singular Values is $4/\sqrt{3}$

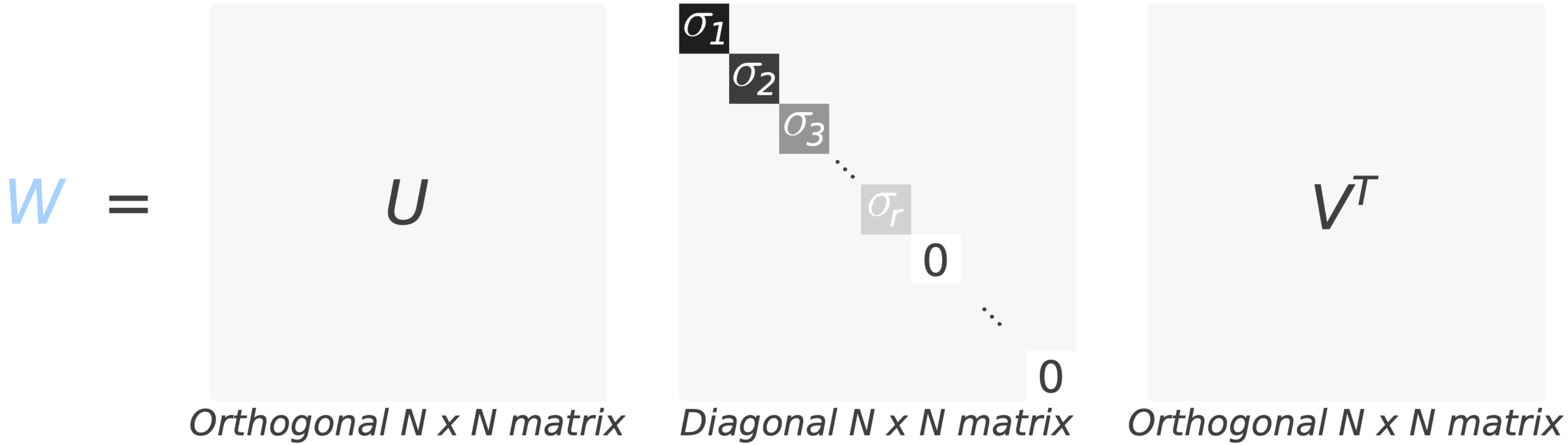
Matan Gavish, *Student Member, IEEE*, and David L. Donoho, *Member, IEEE*

Our latest approach: Singular Value Decomposition

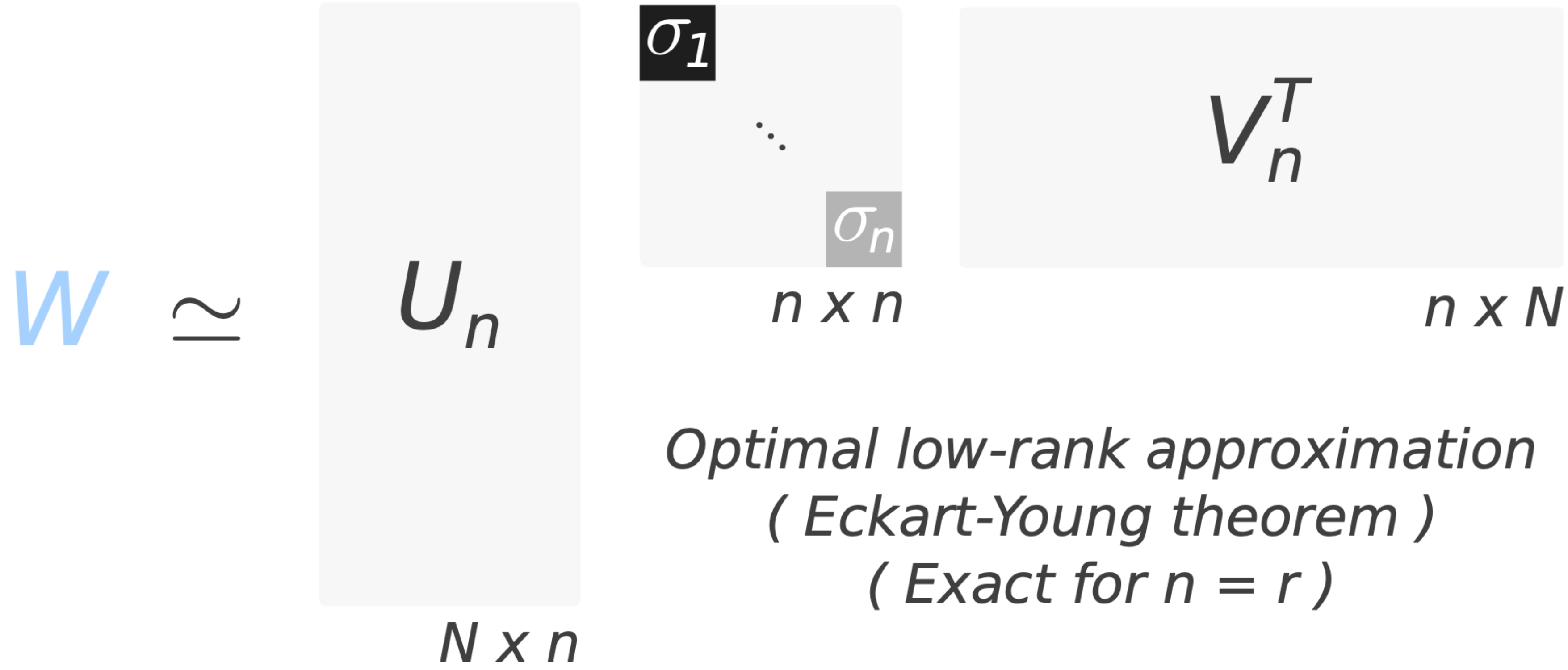
arXiv:2208.04848

**The low-rank hypothesis of complex systems:
From empirical and theoretical evidence to the emergence of higher-order interactions**

Vincent Thibeault,[1,2,*] Antoine Allard,[1,2,†] and Patrick Desrosiers[1,2,3,‡]



Rank : number of linearly independent rows/columns of a matrix



Optimal low-rank approximation
(Eckart-Young theorem)
(Exact for $n = r$)

rank 1

$$W = \sigma_1 X_1 + \sigma_2 X_2 + \ldots + \sigma_r X_r$$

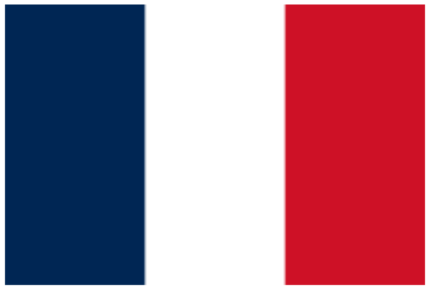
largest contribution

smallest contribution

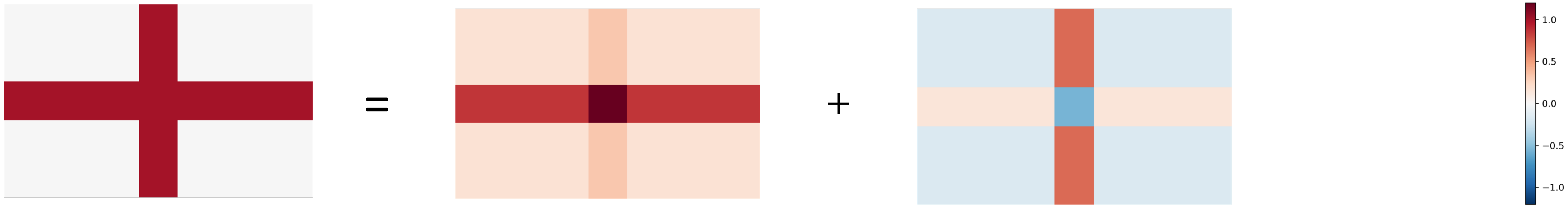
Flags have low rank

Inspired by a lecture by Alex Townsend on [Rapidly Decreasing Singular Values]

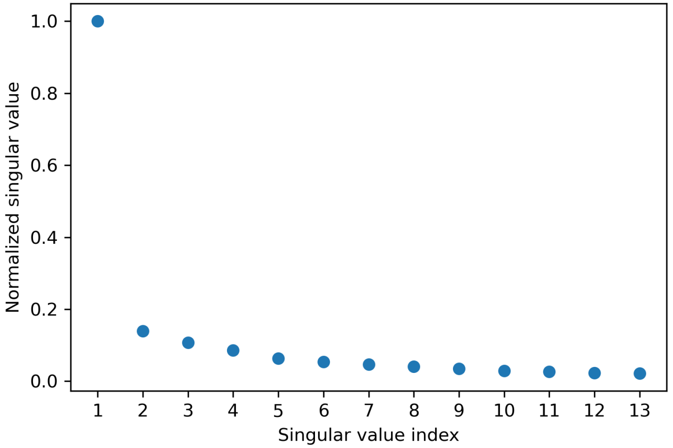
France's flag has rank 1



England's flag has rank 2

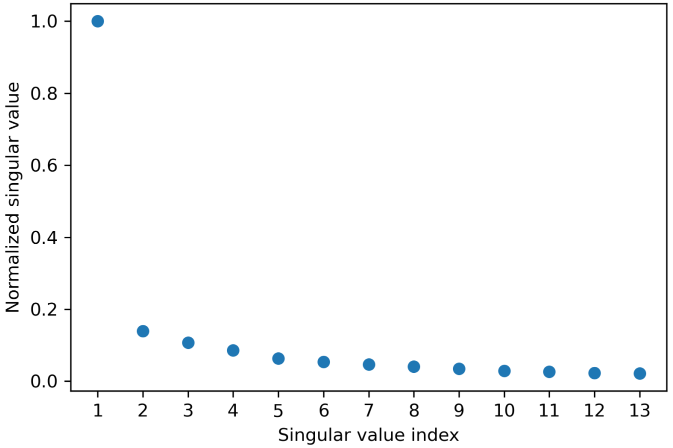


Nunavik’s flag is more complex



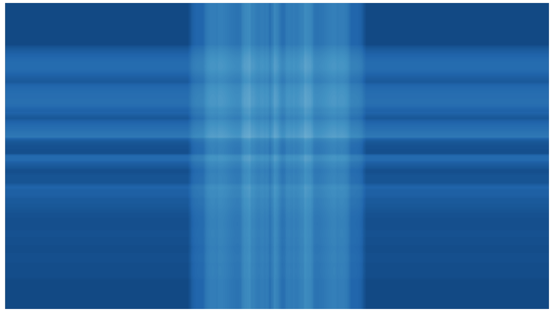
⇒ Good low-rank approximation

Nunavik’s flag is more complex

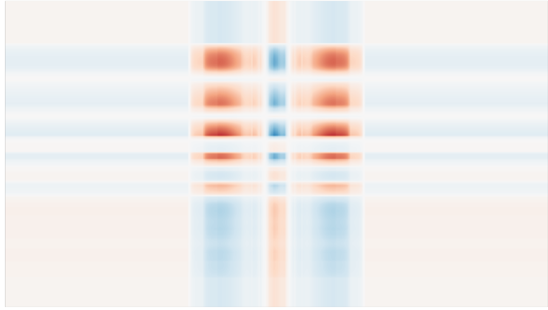


$\Rightarrow$ Good low-rank approximation

$=$



$+$



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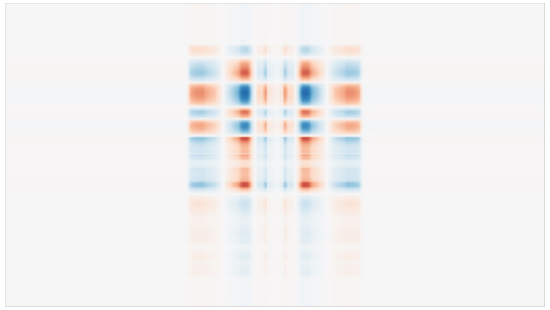

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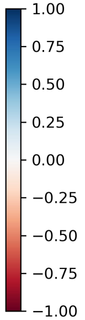
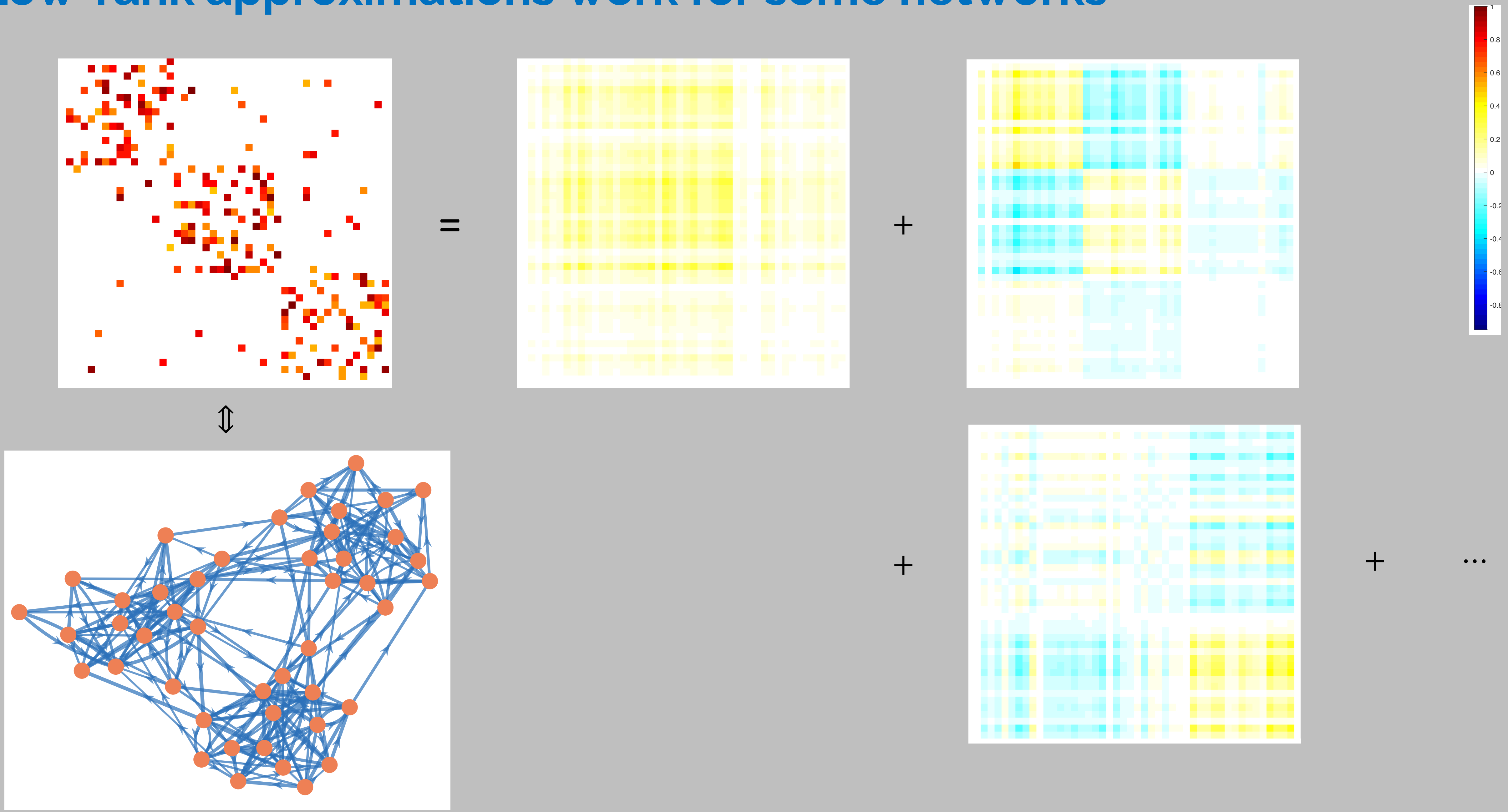


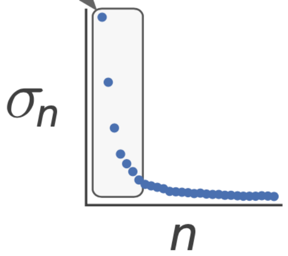
Low-rank approximations work for some networks



Fundamental notion: effective rank

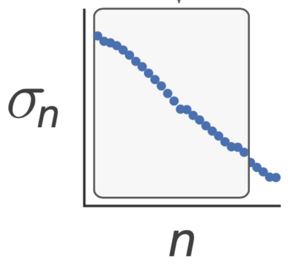
$$\text{Effective rank of } W = \text{number of significant singular values of } W$$

$$\text{Example: the stable rank defined as } \operatorname{srank}(W) = \frac{\sum_{i=1}^{N} \sigma_i^2}{\sigma_1^2}$$



Low effective rank

or

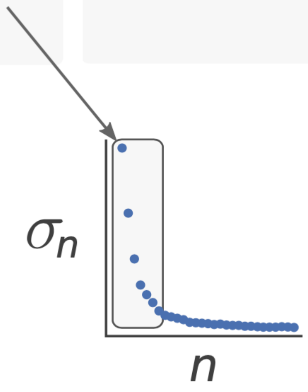


High effective rank

?

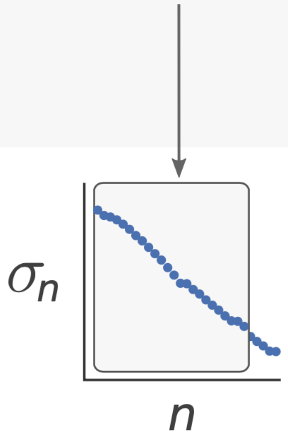
Fundamental notion: effective rank

Effective rank of W = approximate dimension of the space generated by all $W\boldsymbol{x}$



Low effective rank

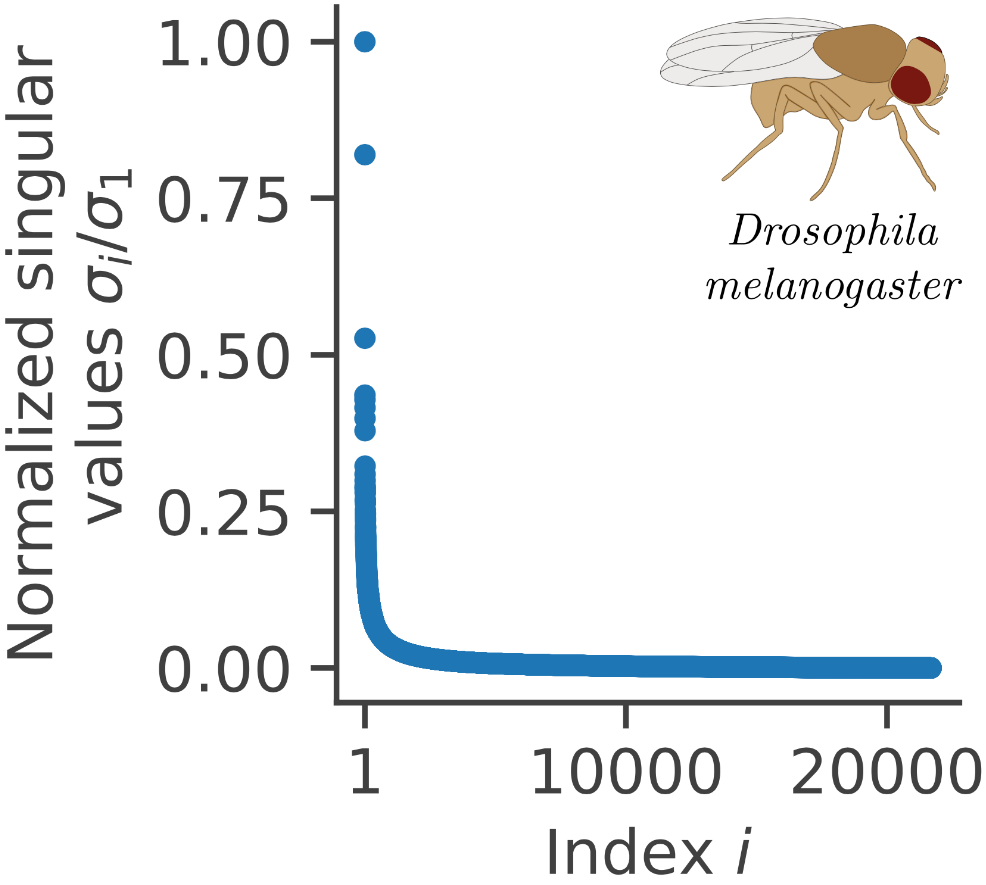
or



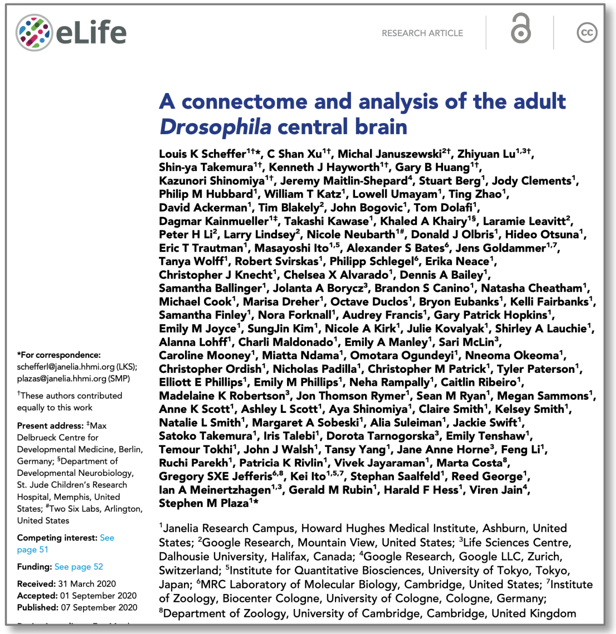
High effective rank

?

Experimental results:
Connectomes have low effective rank



Drosophila melanogaster



eLife
RESEARCH ARTICLE

A connectome and analysis of the adult *Drosophila* central brain

Louis K Scheffer[1†*], C Shan Xu[1†], Michal Januszewski[2†], Zhiyuan Lu[1,3†], Shin-ya Takemura[1†], Kenneth J Hayworth[1†], Gary B Huang[1†], Kazunori Shinomiya[1†], Jeremy Maitlin-Shepard[4], Stuart Berg[1], Jody Clements[1], Philip M Hubbard[1], William T Katz[1], Lowell Umayam[1], Ting Zhao[1], David Ackerman[1], Tim Blakely[2], John Bogovic[1], Tom Dolafi[1], Dagmar Kainmueller[1‡], Takashi Kawase[1], Khaled A Khairy[1§], Laramie Leavitt[2], Peter H Li[2], Larry Lindsey[2], Nicole Neubarth[1#], Donald J Olbris[1], Hideo Otsuna[1], Eric T Trautman[1], Masayoshi Ito[1,5], Alexander S Bates[6], Jens Goldammer[1,7], Tanya Wolff[1], Robert Svirskas[1], Philipp Schlegel[6], Erika Neace[1], Christopher J Knecht[1], Chelsea X Alvarado[1], Dennis A Bailey[1], Samantha Ballinger[1], Jolanta A Borycz[3], Brandon S Canino[1], Natasha Cheatham[1], Michael Cook[1], Marisa Dreher[1], Octave Duclos[1], Bryon Eubanks[1], Kelli Fairbanks[1], Samantha Finley[1], Nora Forknall[1], Audrey Francis[1], Gary Patrick Hopkins[1], Emily M Joyce[1], SungJin Kim[1], Nicole A Kirk[1], Julie Kovalyak[1], Shirley A Lauchie[1], Alanna Lohff[1], Charli Maldonado[1], Emily A Manley[1], Sari McLin[3], Caroline Mooney[1], Miatta Ndama[1], Omotara Ogundeyi[1], Nneoma Okeoma[1], Christopher Ordish[1], Nicholas Padilla[1], Christopher M Patrick[1], Tyler Paterson[1], Elliott E Phillips[1], Emily M Phillips[1], Neha Rampally[1], Caitlin Ribeiro[1], Madelaine K Robertson[3], Jon Thomson Rymer[1], Sean M Ryan[1], Megan Sammons[1], Anne K Scott[1], Ashley L Scott[1], Aya Shinomiya[1], Claire Smith[1], Kelsey Smith[1], Natalie L Smith[1], Margaret A Sobeski[1], Alia Suleiman[1], Jackie Swift[1], Satoko Takemura[1], Iris Talebi[1], Dorota Tarnogorska[3], Emily Tenshaw[1], Temour Tokhi[1], John J Walsh[1], Tansy Yang[1], Jane Anne Horne[3], Feng Li[1], Ruchi Parekh[1], Patricia K Rivlin[1], Vivek Jayaraman[1], Marta Costa[8], Gregory SXE Jefferis[6,8], Kei Ito[1,5,7], Stephan Saalfeld[1], Reed George[1], Ian A Meinertzhagen[1,3], Gerald M Rubin[1], Harald F Hess[1], Viren Jain[4], Stephen M Plaza[1*]

[1]Janelia Research Campus, Howard Hughes Medical Institute, Ashburn, United States; [2]Google Research, Mountain View, United States; [3]Life Sciences Centre, Dalhousie University, Halifax, Canada; [4]Google Research, Google LLC, Zurich, Switzerland; [5]Institute for Quantitative Biosciences, University of Tokyo, Tokyo, Japan; [6]MRC Laboratory of Molecular Biology, Cambridge, United States; [7]Institute of Zoology, Biocenter Cologne, University of Cologne, Cologne, Germany; [8]Department of Zoology, University of Cambridge, Cambridge, United Kingdom

***For correspondence:** schefferl@janelia.hhmi.org (LKS); plazas@janelia.hhmi.org (SMP)

[†]These authors contributed equally to this work

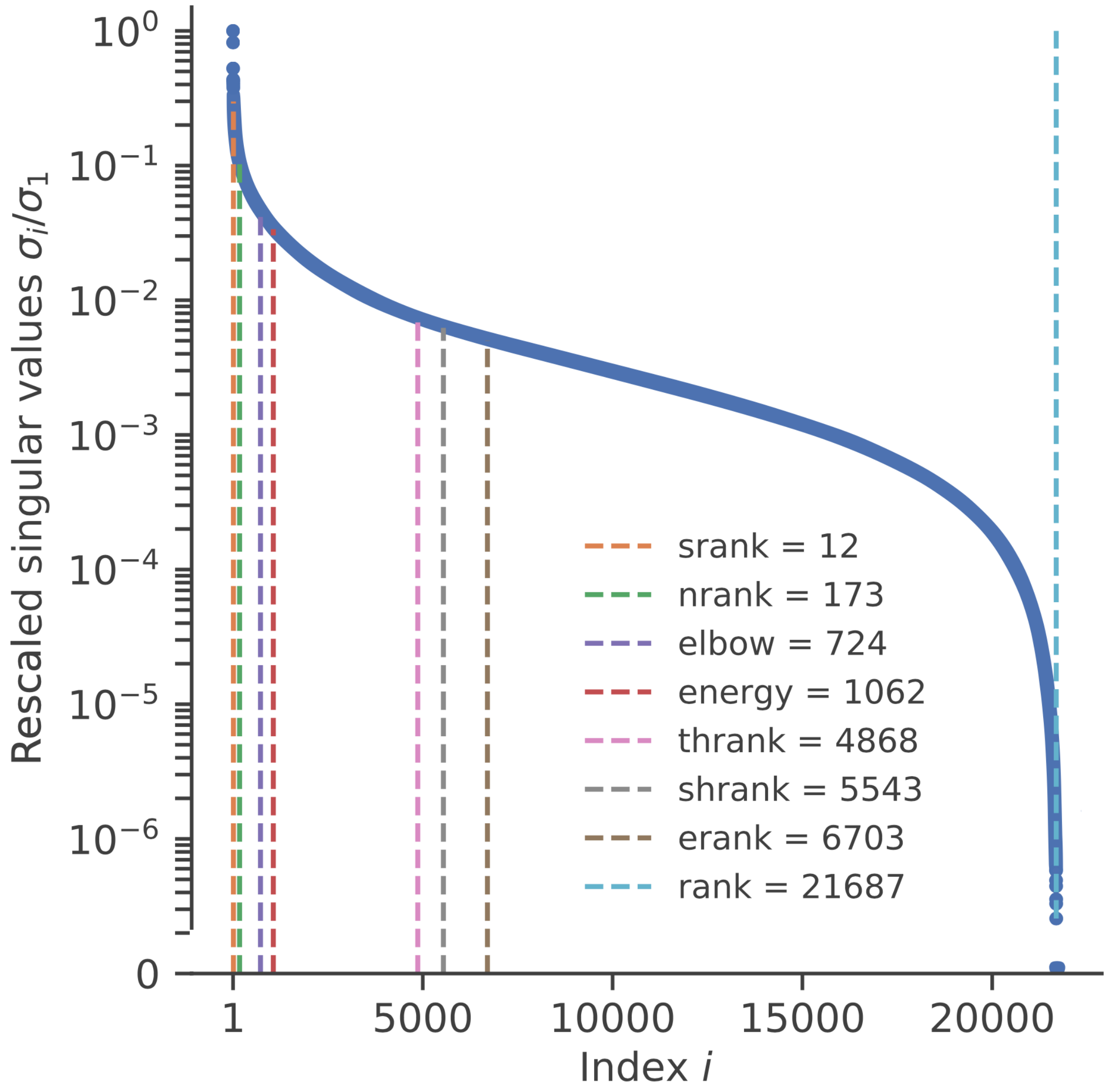
Present address: [‡]Max Delbrueck Centre for Developmental Medicine, Berlin, Germany; [§]Department of Developmental Neurobiology, St. Jude Children's Research Hospital, Memphis, United States; [#]Two Six Labs, Arlington, United States

Competing interest: See page 51

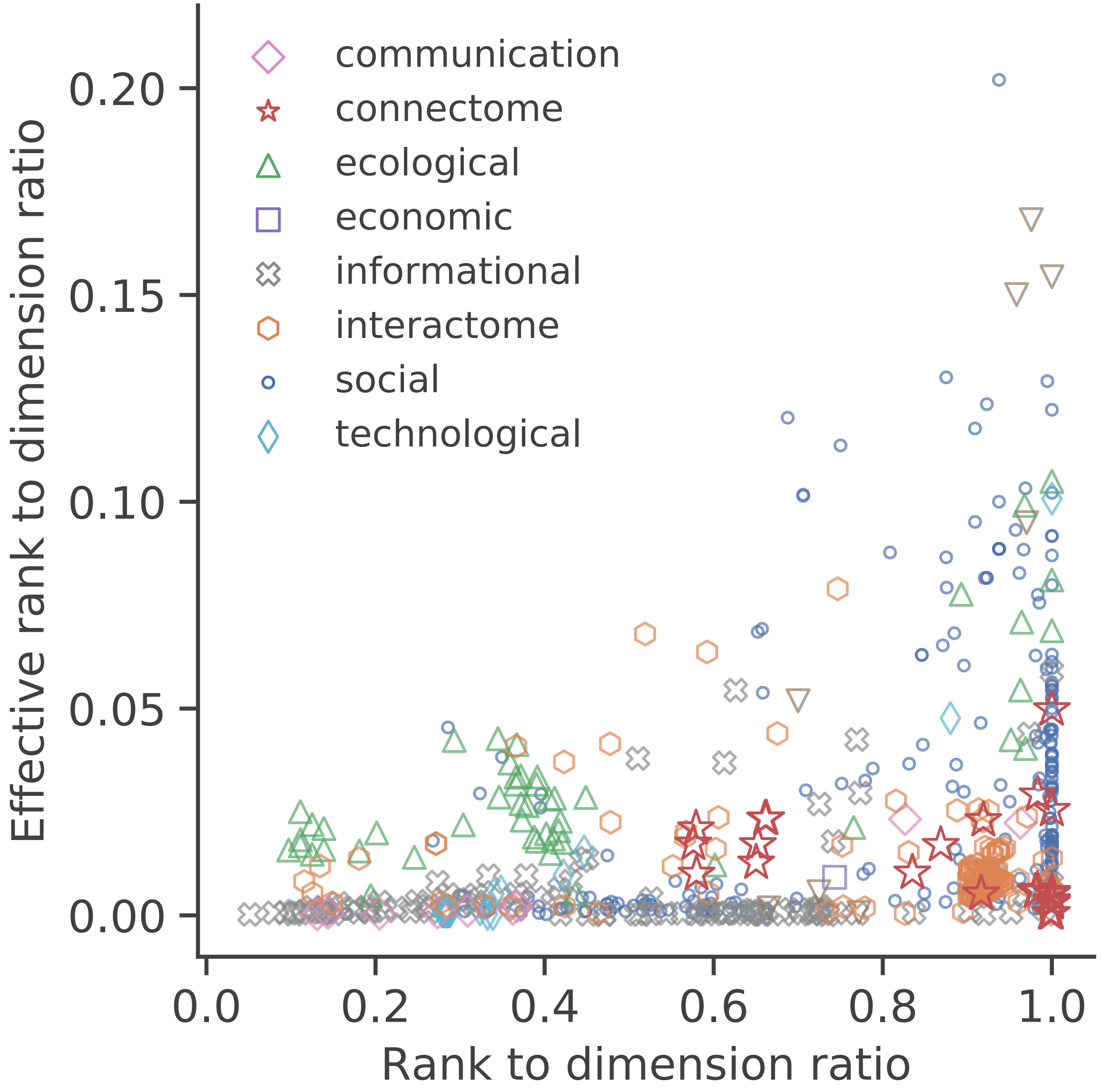
Funding: See page 52

Received: 31 March 2020
Accepted: 01 September 2020
Published: 07 September 2020

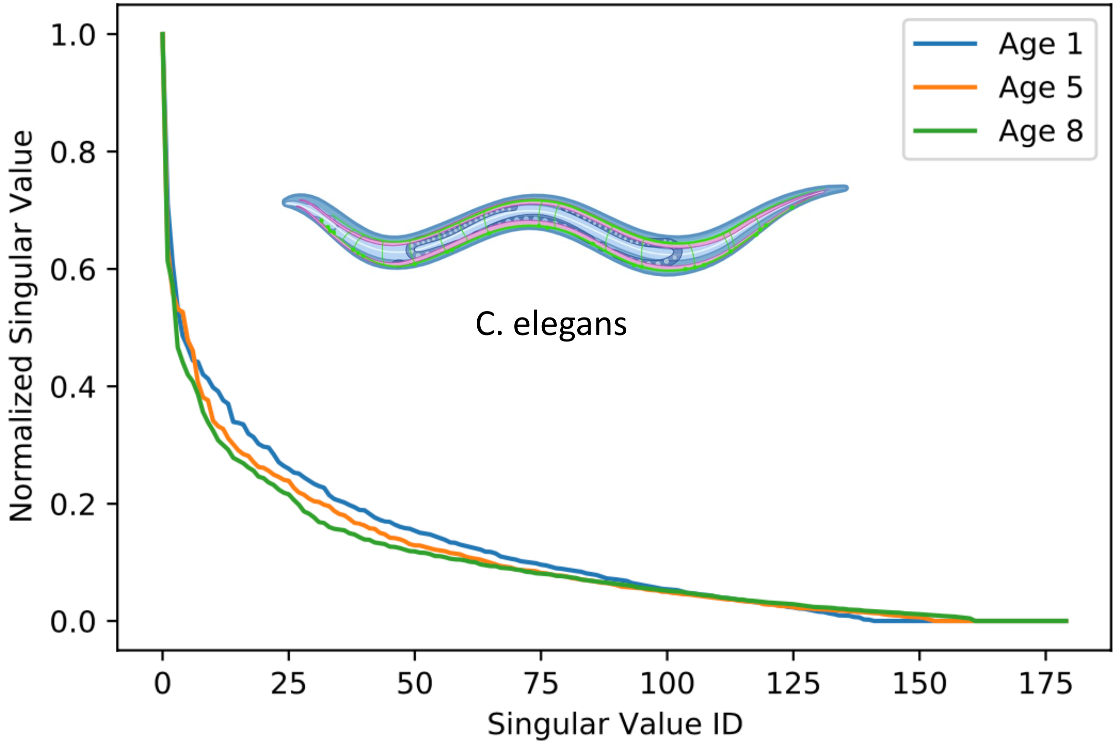
Experimental results:
Connectomes have low effective rank



Experimental results:
real complex networks have low effective rank

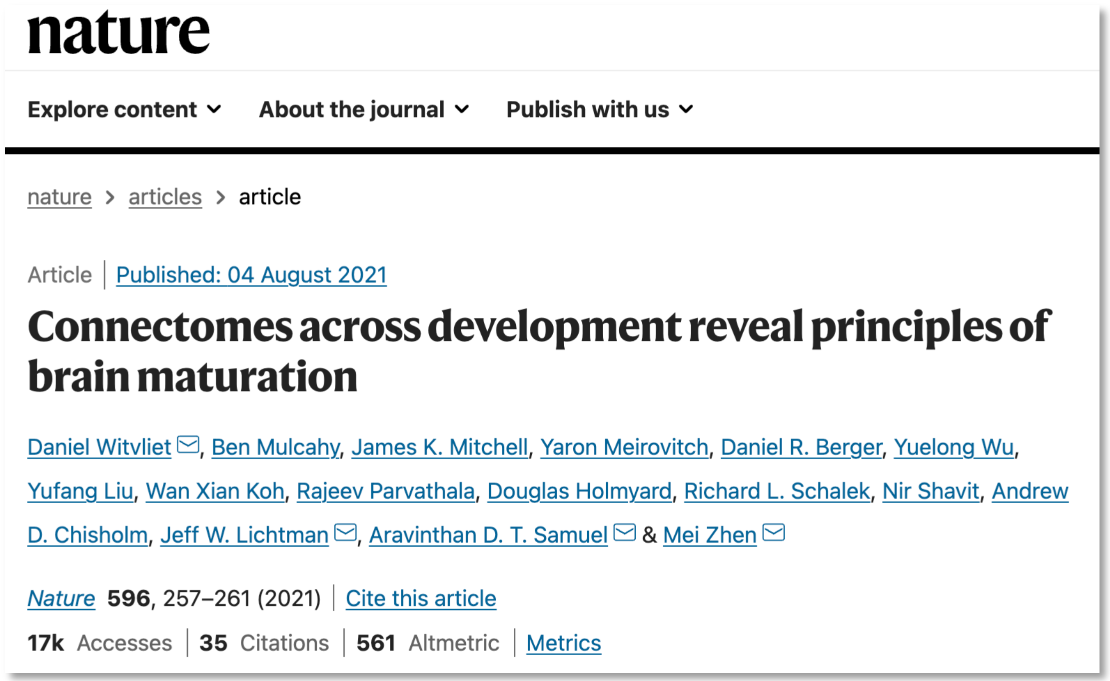


Observation:
Maturation seems to reduce effective rank



Singular values of the matrices describing the connectivity of the C. elegans brain at different maturation stages. The stable ranks are 21.6 (age 1), 19.7 (age 5), 18.5 (age 8).

Data from :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Article | Published: 04 August 2021

Connectomes across development reveal principles of brain maturation

Daniel Witvliet, Ben Mulcahy, James K. Mitchell, Yaron Meirovitch, Daniel R. Berger, Yuelong Wu, Yufang Liu, Wan Xian Koh, Rajeev Parvathala, Douglas Holmyard, Richard L. Schalek, Nir Shavit, Andrew D. Chisholm, Jeff W. Lichtman, Aravinthan D. T. Samuel & Mei Zhen

Nature **596**, 257–261 (2021) | Cite this article

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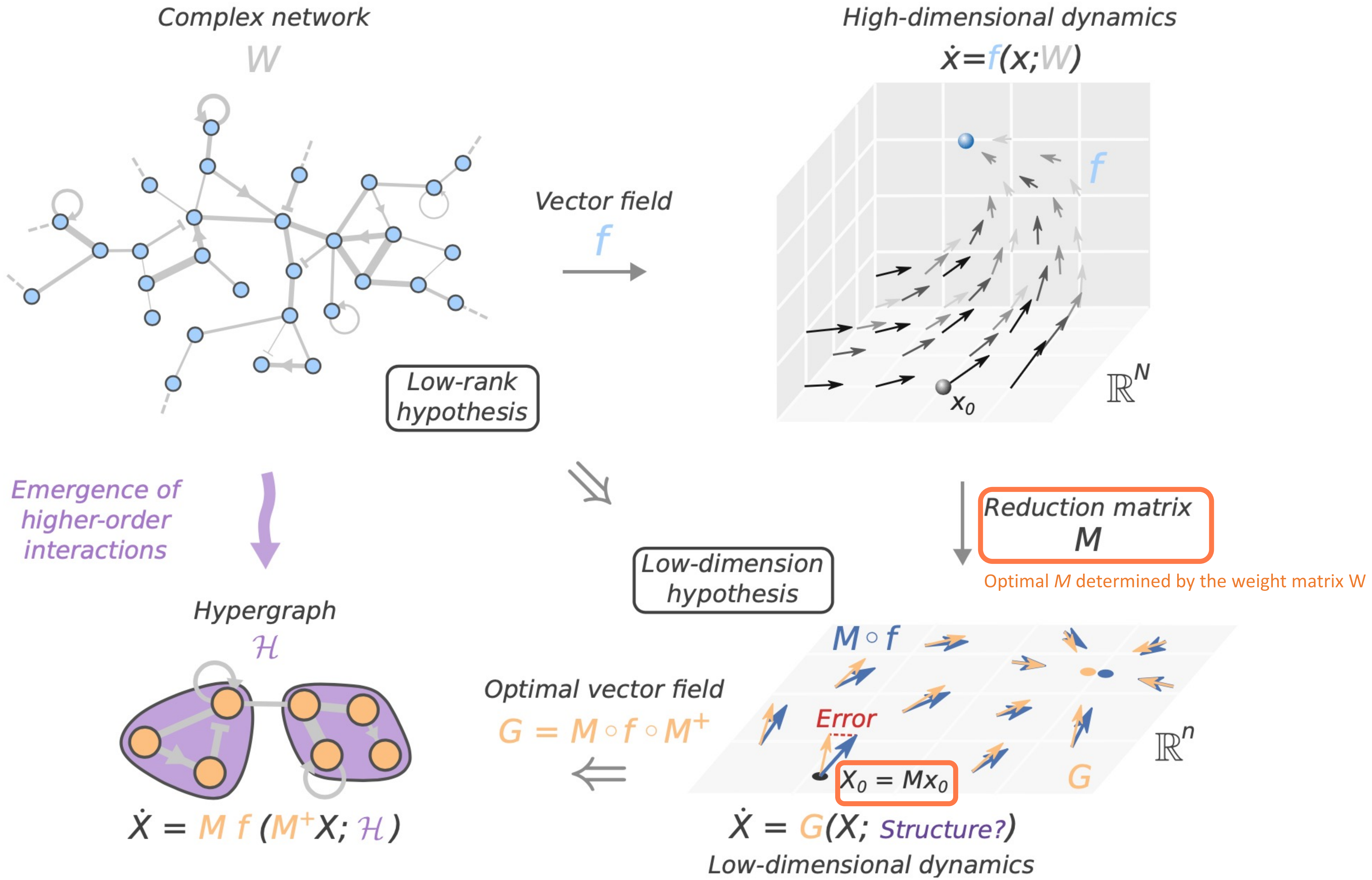
What are the dynamical consequences of low effective rank ?



Complex network
W
High-dimensional dynamics
$\dot{x}=f(x;W)$
Vector field
f
f
$\mathbb{R}^N$
x_0
Low-rank hypothesis
Emergence of higher-order interactions
Reduction matrix M
Optimal M determined by the weight matrix W
Low-dimension hypothesis
Hypergraph
$\mathcal{H}$
Optimal vector field
$G = M \circ f \circ M^+$
$M \circ f$
Error
$\mathbb{R}^n$
$X_0 = Mx_0$
G
$\dot{X} = M f(M^+X; \mathcal{H})$
$\dot{X} = G(X;$ Structure?$)$
Low-dimensional dynamics

Complete dynamics : $\dot{x} = f(x)$

Reduced dynamics : $\dot{X} = G(X)$ where $X = Mx$

Theorem (simplified)

The vector field G^* that minimizes the quadratic error between the projected dynamics $\dot{p} = f(p)$ with $p = M^+Mx$ and the reduced dynamics in $\mathbb{R}^N$ $[M^+G(X)]$ is

$$G^*(X) = Mf(M^+X).$$

Proof : Just use least-squares.

Theorem (simplified)

The alignment error $\mathcal{E}_f(x)$ *for some* $x \in \mathbb{R}^N$ *is upper-bounded by*

$$\mathcal{E}_f(x) \leq \frac{1}{\sqrt{n}} \Big[\|V_n^\top J_x(x', y')(I - V_n V_n^\top) x\| + \frac{\sigma_{n+1}}{\sigma_1} \|V_n^\top J_y(x', y')\|_2 \|x\| \Big].$$

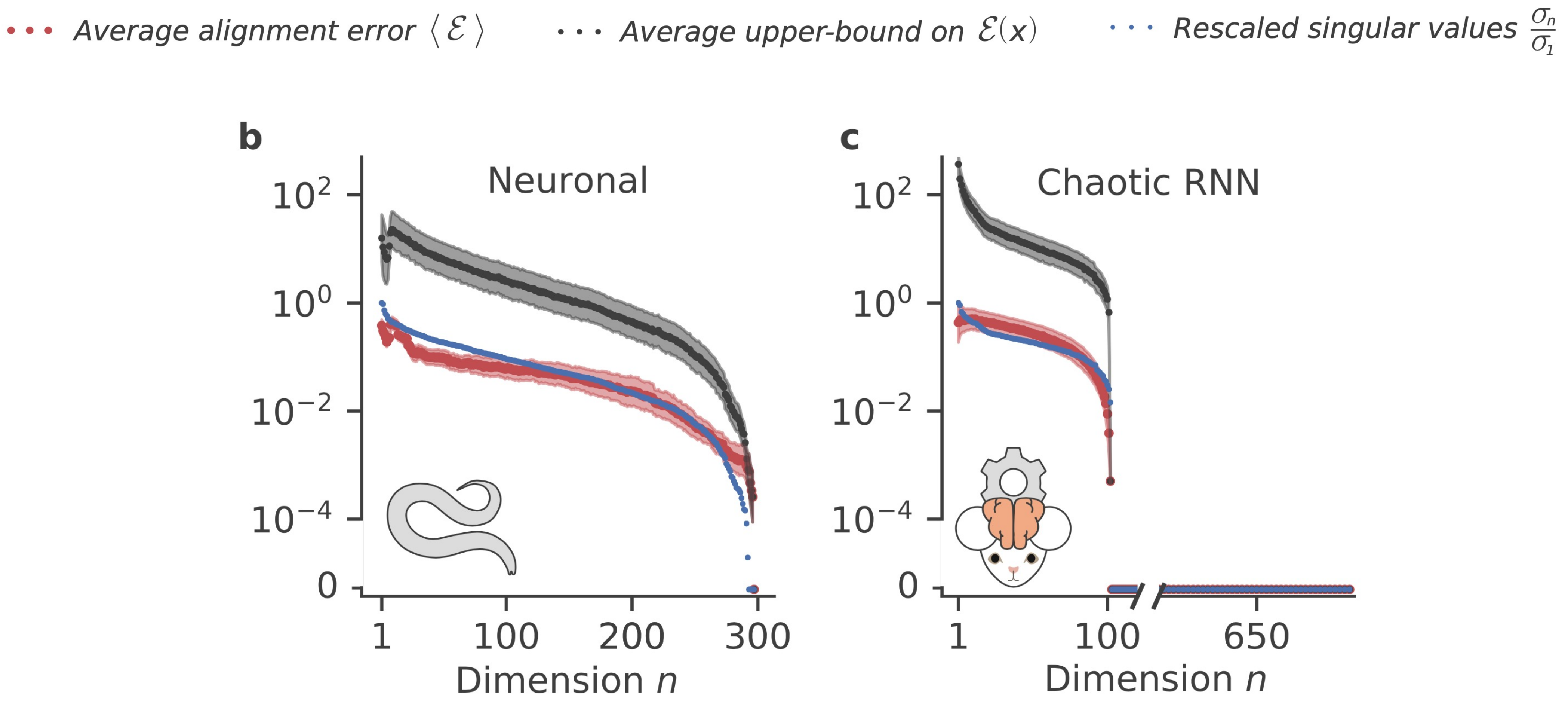
σ_i : *i-th singular values of* W

V_n : n*-truncated right singular vector matrix*

J_x, J_y : *Jacobian matrices evaluated at some point* x', y'

n : *dimension of the reduced system*

$J_x(x', y') = aI$ and $n \geq \text{rank}(W)$ $\Rightarrow$ *Exact* dimension reduction



Average alignment error ⟨ℰ⟩
Average upper-bound on ℰ(x)
Rescaled singular values σn/σ1
b
Neuronal
10^2
10^0
10^−2
10^−4
0
1
100
200
300
Dimension n
c
Chaotic RNN
10^2
10^0
10^−2
10^−4
0
1
100
650
Dimension n

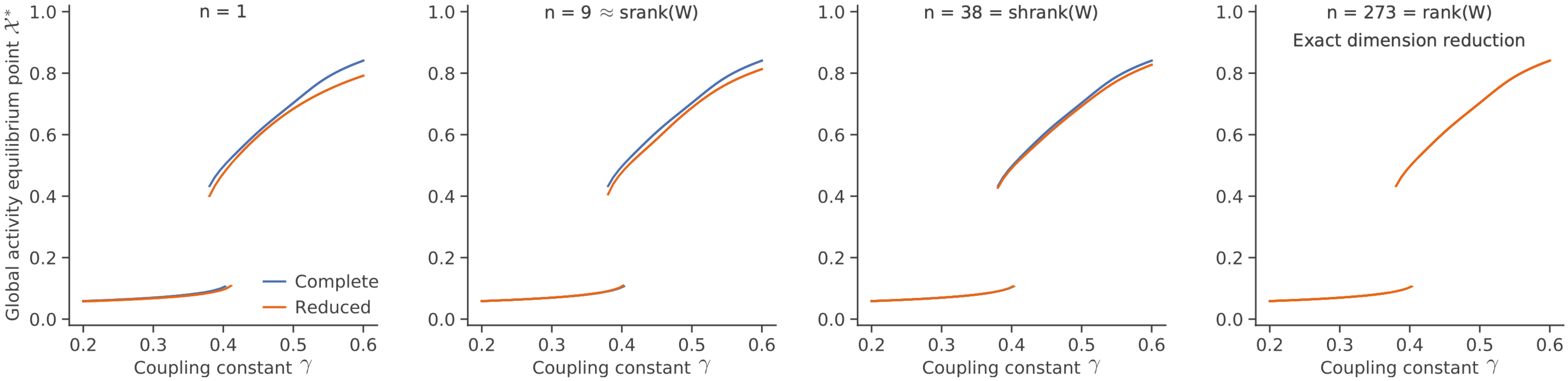


Fig. S8: Comparison between the global observable at equilibrium $\mathcal{X}^*$ of the complete (blue) and reduced (orange) Wilson-Cowan dynamics on the (unsigned) *C. elegans* connectomes ($N = 279$, $\text{rank}(W) = 273$) vs. the global coupling γ for $n \in \{1, 9, 38, 273\}$. Parameters: $d = 1$, $a = 0$, $b = 1$, $c = 3$. For the weight matrix, see the GitHub repository, module get_real_network.py, function get_connectome_weight_matrix(graph_name="celegans"). The effective ranks of this connectome with weight matrix W are $\text{srank}(W) \approx 9$, $\text{thrank}(W) = 27$, $\text{elbow}(W) = 31$, $\text{nrank}(W) \approx 36$, $\text{shrank}(W) = 38$, $\text{energy}(W) = 106$, and $\text{erank}(W) \approx 192$.

Take-home messages

1. Whole brain neuronal activity can be modeled using firing rate models, which are high dimensional.

2. Real networks, and especially ***connectomes, have low effective rank***.

3. Large neuronal networks with **firing rate dynamics possess low-dimensional dynamical systems** that approximately describe the activity at large scale.

4. Alignment errors of reduced vector fields can rapidly decrease following the singular values of complex networks.

5. Our theoretical findings support the use of Principal Component Analysis when analyzing neuronal activity.

6. Dimension reduction can lead to dynamics with *higher-order interactions.*

Still so much work to do …

Thank you! Questions?

Dynamica Research Lab

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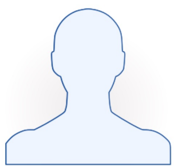
DOCTORAL STUDENTS


Antoine Légaré


Simon Lizotte


Charles Murphy


Marziyeh Pourmousavi


François Thibault


Vincent Thibeault


Zahra Yazdani

MASTER STUDENTS


Jérémie Gince


Jeson Hermans


Jérémi Lesage

INTERNS


Émile Baril


Benjamin Claveau


Anthony Drouin

GROUP LEADERS


Antoine Allard


Patrick Desrosiers

HONORARY MEMBER


Louis J. Dubé

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