Study of properties and dynamics in trained recurrent neural networks (RNNs)

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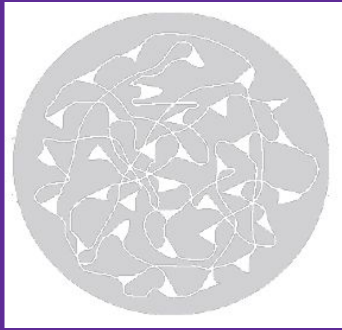


Motivation: Brain models

The neuroconnectionist research programme

(Adrien Doerig et al.)

https://doi.org/10.1038/s41583-023-00705-w

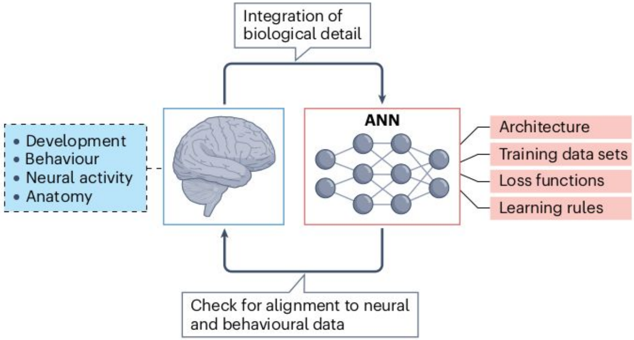
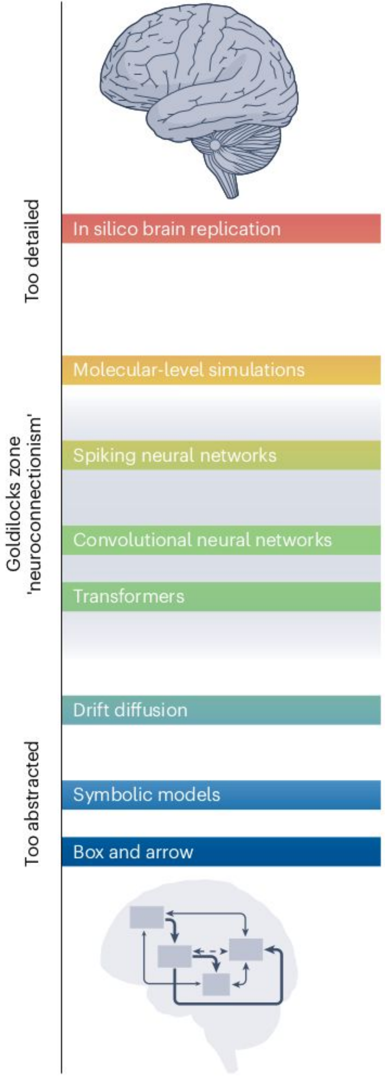


Fig. 1 | The neuroconnectionist research cycle. The integration of biological detail from neural and behavioural data across multiple scales informs the creation of new artificial neural network (ANN) models with different components, which are then tested for alignment with neural and/or behavioural data (left), leading to further cycles of model creation and model testing. Model creation involves four central ingredients: objective functions, training data sets, learning rules and architectures. Model evaluation involves hypothesis testing via tools such as representational similarity analysis, encoding models, comparisons of diagnostic readouts to human responses and in silico experimentation.



RNNs

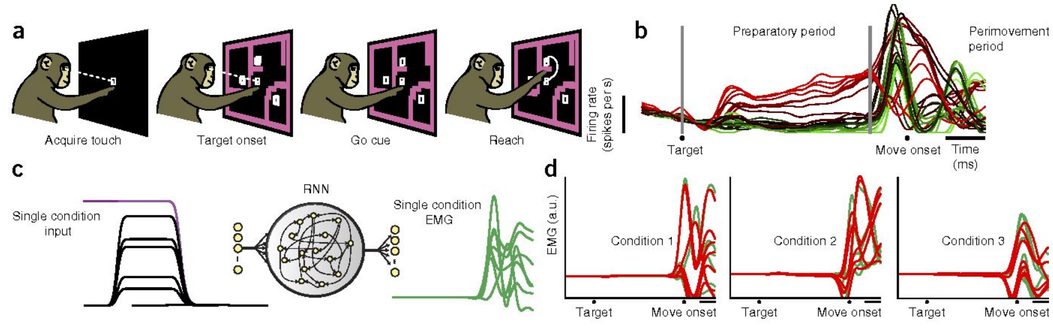
The neuroconnectionist research programme

They present neuroconnectionism as a general research programme centred around ANNs as a computational language for expressing falsifiable theories about brain computation.

Motivation

RNN constitute a versatile model in neuroscience research. They can be trained to process temporal information and perform different brain tasks :

- Stimuli selection
- Decision making
- Temporal pattern generation
- Reaching tasks [*DOI:10.1038/nn.4042*](https://doi.org/10.1038/nn.4042)



nature neuroscience

ARTICLES

https://doi.org/10.1038/s41593-018-0310-2

Task representations in neural networks trained to perform many cognitive tasks

Guangyu Robert Yang[1,2], Madhura R. Joglekar[1,6], H. Francis Song[1,7], William T. Newsome[3,4] and Xiao-Jing Wang[1,5*]

The brain has the ability to flexibly perform many tasks, but the underlying mechanism cannot be elucidated in traditional experimental and modeling studies designed for one task at a time. Here, we trained single network models to perform 20 cognitive tasks that depend on working memory, decision making, categorization, and inhibitory control. We found that after training, recurrent units can develop into clusters that are functionally specialized for different cognitive processes, and we introduce a simple yet effective measure to quantify relationships between single-unit neural representations of tasks. Learning often gives rise to compositionality of task representations, a critical feature for cognitive flexibility, whereby one task can be performed by recombining instructions for other tasks. Finally, networks developed mixed task selectivity similar to recorded prefrontal neurons after learning multiple tasks sequentially with a continual-learning technique. This work provides a computational platform to investigate neural representations of many cognitive tasks.

PLOS | COMPUTATIONAL BIOLOGY

RESEARCH ARTICLE

Coherent chaos in a recurrent neural network with structured connectivity

Itamar Daniel Landau[1]*, Haim Sompolinsky[1,2]

1 Edmond and Lily Safra Center for Brain Sciences, The Hebrew University of Jerusalem, Jerusalem, Israel, 2 Center for Brain Science, Harvard University, Cambridge, Massachusetts, United States of America

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Abstract

We present a simple model for coherent, spatially correlated chaos in a recurrent neural network. Networks of randomly connected neurons exhibit chaotic fluctuations and have been studied as a model for capturing the temporal variability of cortical activity. The dynamics generated by such networks, however, are spatially uncorrelated and do not generate coherent fluctuations, which are commonly observed across spatial scales of the neocortex. In our model we introduce a structured component of connectivity, in addition to random connections, which effectively embeds a feedforward structure via unidirectional coupling between a pair of orthogonal modes. Local fluctuations driven by the random connectivity are summed by an output mode and drive coherent activity along an input mode. The orthogonality between input and output mode preserves chaotic fluctuations by preventing feedback loops. In the regime of weak structured connectivity we apply a perturbative approach to solve the dynamic mean-field equations, showing that in this regime coherent fluctuations are driven passively by the chaos of local residual fluctuations. When we introduce a row balance constraint on the random connectivity, stronger structured connectivity puts the network in a distinct dynamical regime of self-tuned coherent chaos. In this regime the coherent component of the dynamics self-adjusts intermittently to yield periods of slow, highly coherent chaos. The dynamics display longer time-scales and switching-like activity. We show how in this regime the dynamics depend qualitatively on the particular realization of the connectivity matrix: a complex leading eigenvalue can yield coherent oscillatory chaos while a real leading eigenvalue can yield chaos with broken symmetry. The level of coherence grows with increasing strength of structured connectivity until the dynamics are almost entirely constrained to a single spatial mode. We examine the effects of network-size scaling and show that these results are not finite-size effects. Finally, we show that in the regime of weak structured connectivity, coherent chaos emerges also for a generalized structured connectivity with multiple input-output modes.

Check for updates

OPEN ACCESS

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Data Availability Statement: Data associated with this work is available at https://github.com/ilandau/Coherent-Chaos.

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William T. Newsome[3,4]

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doi:10.1038/nature12742

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Context-dependent computation by recurrent dynamics in prefrontal cortex

Valerio Mante[1]†*, David Sussillo[2]*, Krishna V. Shenoy[2,3] & William T. Newsome[1]

Prefrontal cortex is thought to have a fundamental role in flexible, context-dependent behaviour, but the exact nature of the computations underlying this role remains largely unknown. In particular, individual prefrontal neurons often generate remarkably complex responses that defy deep understanding of their contribution to behaviour. Here we study prefrontal cortex activity in macaque monkeys trained to flexibly select and integrate noisy sensory inputs towards a choice. We find that the observed complexity and functional roles of single neurons are readily understood in the framework of a dynamical process unfolding at the level of the population. The population dynamics can be reproduced by a trained recurrent neural network, which suggests a previously unknown mechanism for selection and integration of task-relevant inputs. This mechanism indicates that selection and integration are two aspects of a single dynamical process unfolding within the same prefrontal circuits, and potentially provides a novel, general framework for understanding context-dependent computations.

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Valerio Mante[1]†*, David S

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Neuron

Article

Linking Connectivity, Dynamics, and Computations in Low-Rank Recurrent Neural Networks

Highlights

- We study network models characterized by minimal connectivity structures
- For such models, low-dimensional dynamics can be directly inferred from connectivity
- Computations emerge from distributed and mixed representations
- Implementing specific tasks yields predictions linking connectivity and computations

Authors

Francesca Mastrogiuseppe,
Srdjan Ostojic

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In Brief

Neural recordings show that cortical computations rely on low-dimensional dynamics over distributed representations. How are these generated by the underlying connectivity? Mastrogiuseppe et al. use a theoretical approach to infer low-dimensional dynamics and computations from connectivity and produce predictions linking connectivity and functional properties of neurons.

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Article

Neuron

Linking Connectivity, Dynamics, and Computations in Low-Rank Recurrent Neural Networks

Highlights

- We study network models characterized by minimal

Authors

Francesca Mastrogiuseppe,

Neuron

Perspective

Neural Manifolds for the Control of Movement

Juan A. Gallego,[1,2] Matthew G. Perich,[3] Lee E. Miller,[1,3,4] and Sara A. Solla[1,5,*]
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[2]Neural and Cognitive Engineering Group, Centre for Robotics and Automation CSIC-UPM, Arganda del Rey 28500, Spain
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*Correspondence: solla@northwestern.edu
http://dx.doi.org/10.1016/j.neuron.2017.05.025

The analysis of neural dynamics in several brain cortices has consistently uncovered low-dimensional manifolds that capture a significant fraction of neural variability. These neural manifolds are spanned by specific patterns of correlated neural activity, the "neural modes." We discuss a model for neural control of movement in which the time-dependent activation of these neural modes is the generator of motor behavior. This manifold-based view of motor cortex may lead to a better understanding of how the brain controls movement.

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Linking Connectivity, Dynamics, and Computations

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nature COMMUNICATIONS

ARTICLE

DOI: 10.1038/s41467-018-07161-6 OPEN

A model of temporal scaling correctly predicts that motor timing improves with speed

Nicholas F. Hardy[1,2], Vishwa Goudar[2], Juan L. Romero-Sosa[2] & Dean V. Buonomano[1,2,3]

Timing is fundamental to complex motor behaviors: from tying a knot to playing the piano. A general feature of motor timing is temporal scaling: the ability to produce motor patterns at different speeds. One theory of temporal processing proposes that the brain encodes time in dynamic patterns of neural activity (population clocks), here we first examine whether recurrent neural network (RNN) models can account for temporal scaling. Appropriately trained RNNs exhibit temporal scaling over a range similar to that of humans and capture a signature of motor timing, Weber's law, but predict that temporal precision improves at faster speeds. Human psychophysics experiments confirm this prediction: the variability of responses in absolute time are lower at faster speeds. These results establish that RNNs can account for temporal scaling and suggest a novel psychophysical principle: the Weber-Speed effect.

Summary:

- Decision-making and temporal tasks inspired by Boolean functions are analyzed.
- We will explore connectivity patterns, dynamics, and biological constraints of recurrent neural networks (RNNs) after training.
- Focus is Computational Neuroscience with the aim to describe brain regions such as the cortex and prefrontal cortex and their recurrent connections related with different cognitive tasks.
- Understanding the dynamics behind these models is crucial for building hypotheses about brain function and explaining experimental results.
- Dynamics is analyzed through numerical simulations.

NOT

x	F
0	1
1	0

AND

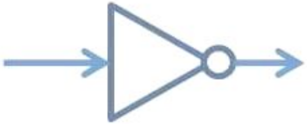
x	y	F
0	0	0
0	1	0
1	0	0
1	1	1

OR

x	y	F
0	0	0
0	1	1
1	0	1
1	1	1

XOR

x	y	F
0	0	0
0	1	1
1	0	1
1	1	0



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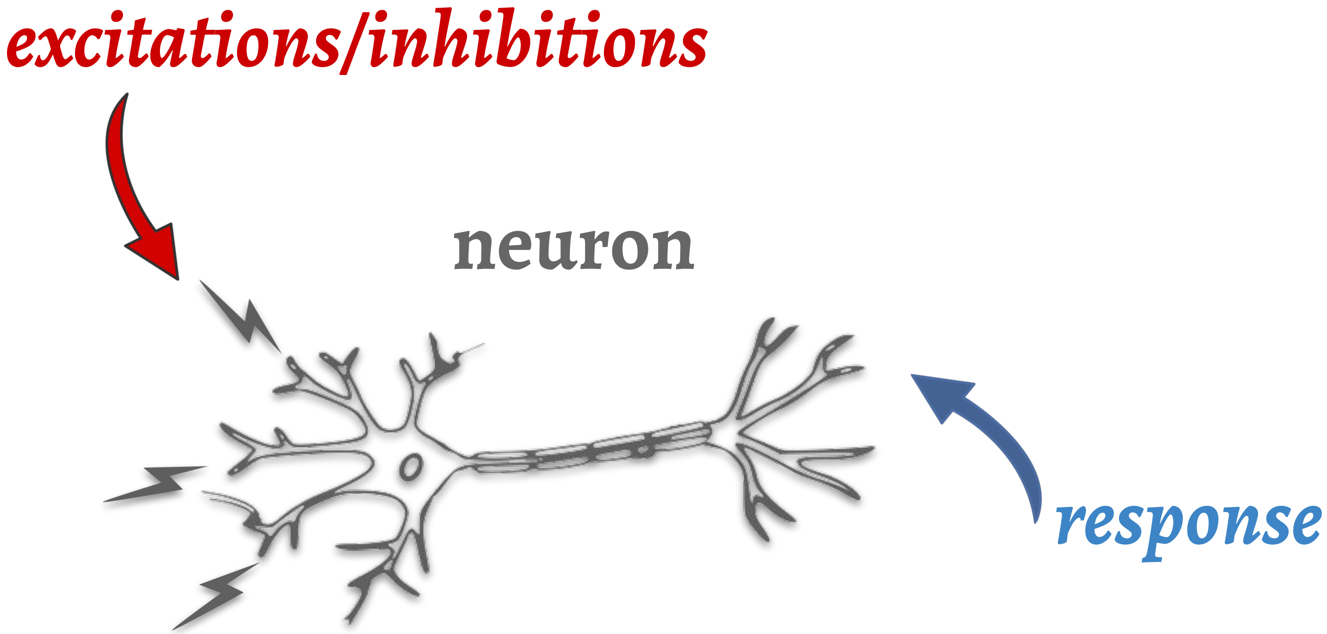
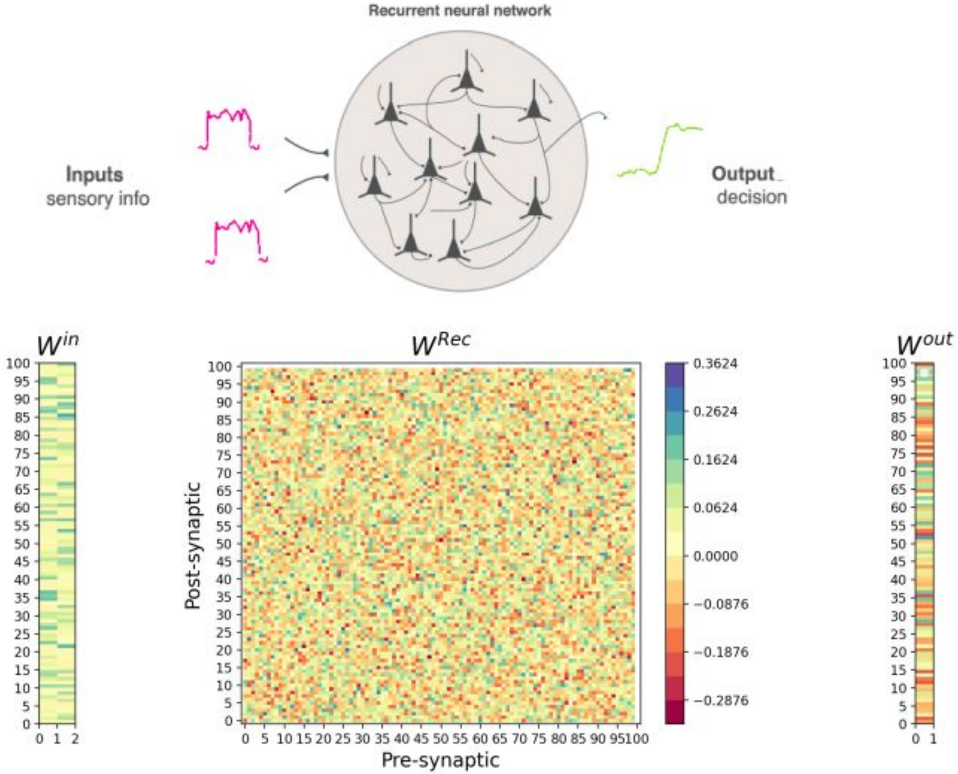
Very basic model of each "neuron"



The network considered is input-driven



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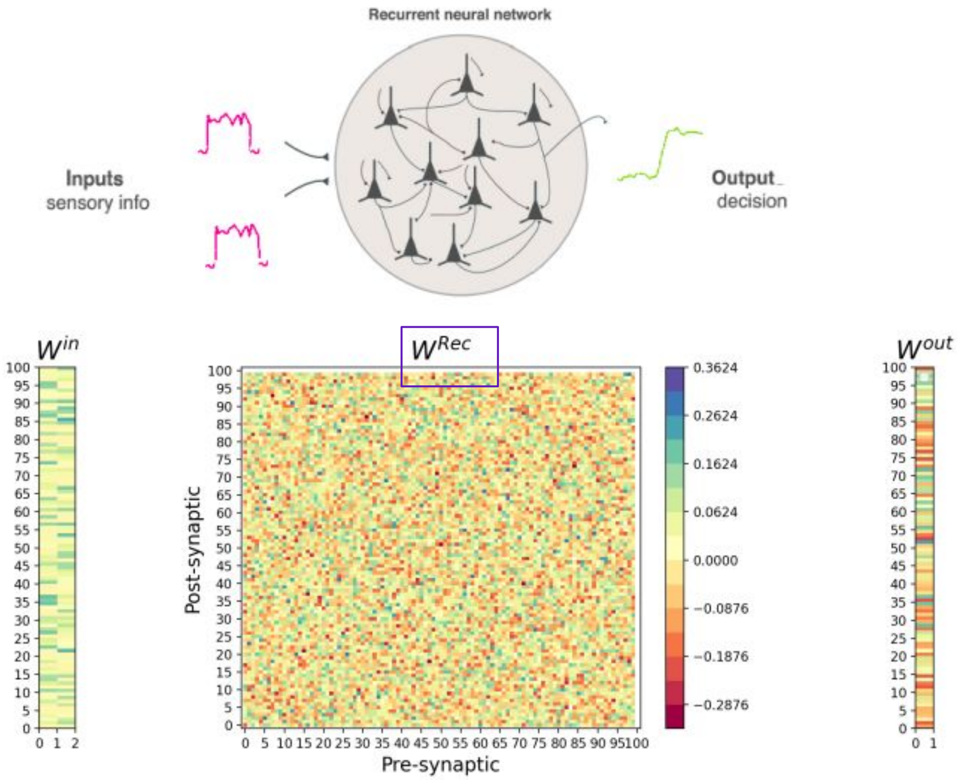

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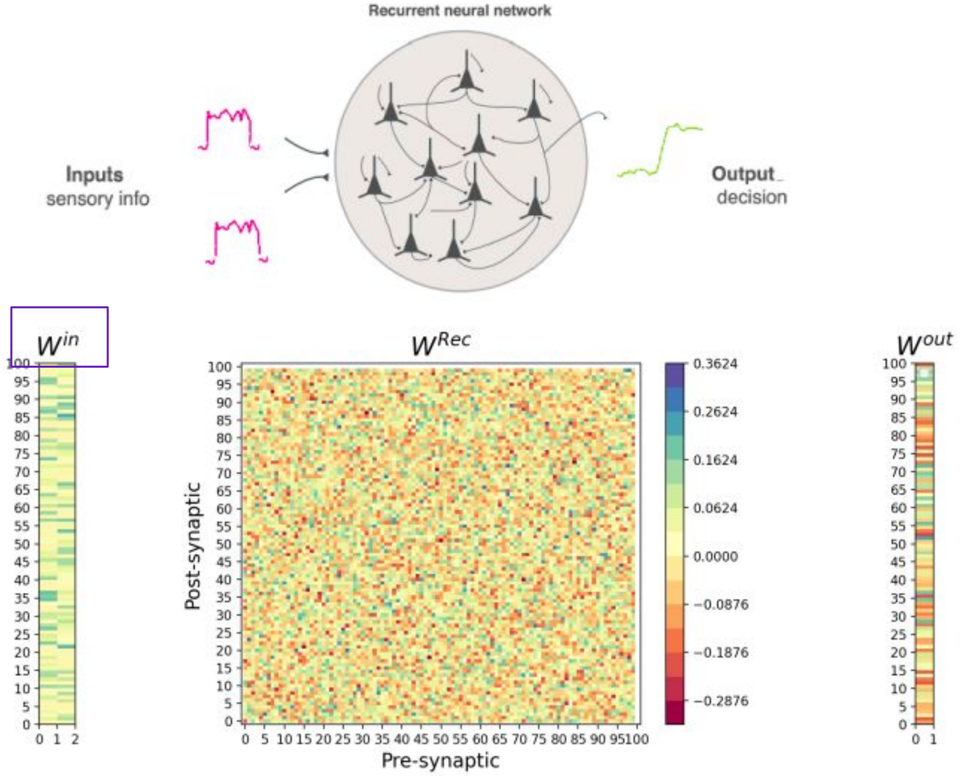

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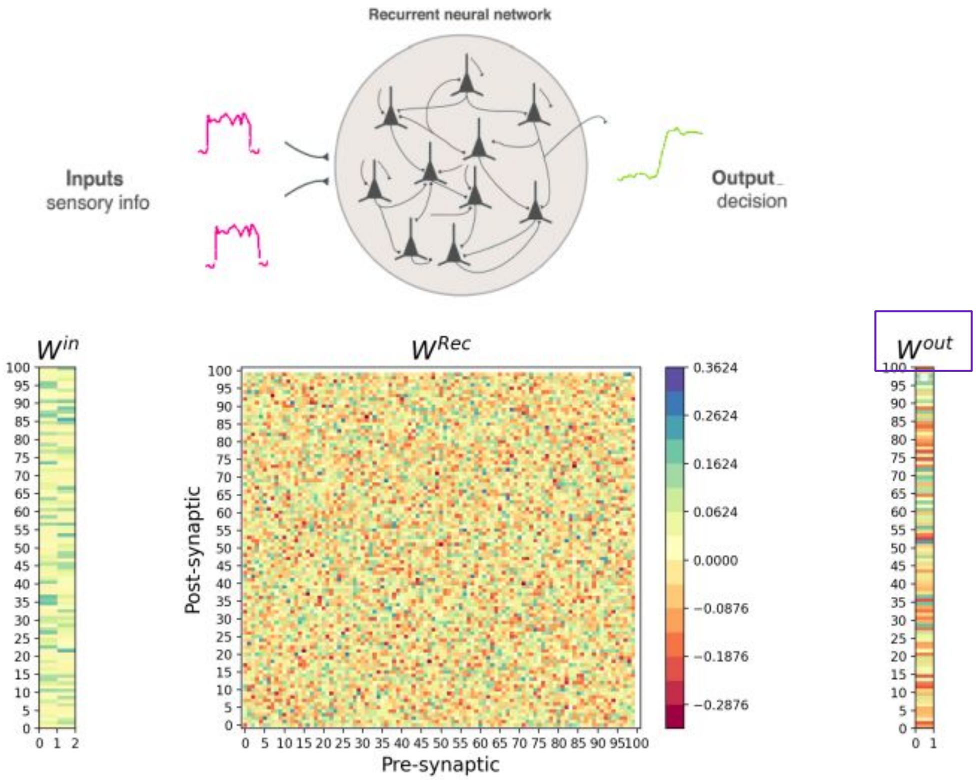


- Equation rules the dynamics of the interconnected n units in analog neural networks, where $i = 1, 2..., n$.
- Originally Equation was used to model the state of the potential membrane.
- Has been used in numerous works with different variants since Hopfield.
- $h_i(t)$ can be viewed as the activity of a biological neuron (i.e. firing rate). The continuous variable σ is a saturating nonlinear function of $h_i(t)$

$$\frac{dh_i(t)}{dt} = -\frac{h_i(t)}{\tau} + \sigma\left(\sum_{j=1}^{N} W_{ij}^{\texttt{rec}} h_j(t) + \sum_{k=1}^{M} W_{ik}^{\texttt{in}} x_k(t) + b_i\right) \tag{1}$$

- τ is time constant of the system.
- σ is the activation function.
- x_j are the components of the vector X of the input signal.
- The matrix elements w_{ij}^{Rec} are the synaptic connection strengths of the matrix $\mathrm{W}^{\mathrm{Rec}}$
- w_{ij}^{in} the matrix elements of W^{in} from the input units.

To read out the network's activity it is common to include a readout $z(t)$ in terms of the matrix elements w_{ij}^{out} from $\mathrm{W}^{\mathrm{out}}$ as:

$$z(t) = \sum_{i=1}^{N} W_i^{\mathbf{out}} h_i(t)$$

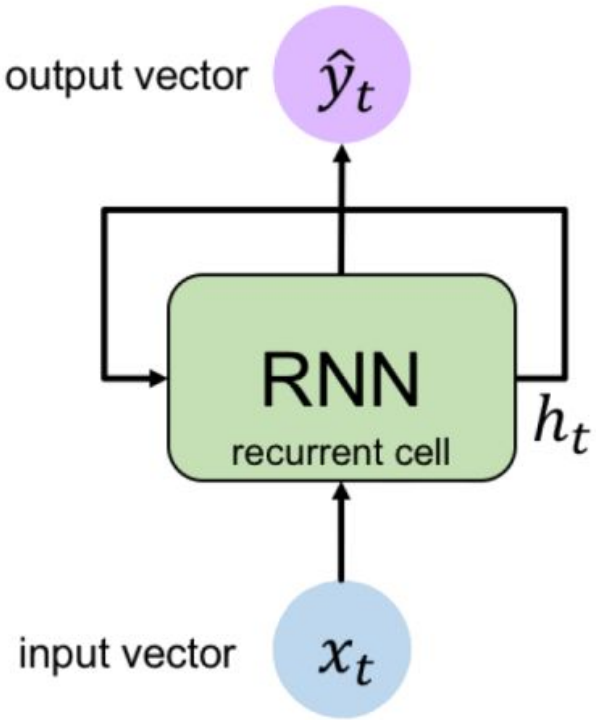
Discretization

Traditionally the system represented by Equation 1 is approximated using Euler's method. With value of the time step for the time evolution equal to 1:

$$\boldsymbol{h}(t_{s+1}) = \boldsymbol{\sigma}\Big(W^{\mathtt{rec}}\boldsymbol{h}(t_s) + \boldsymbol{b} + \boldsymbol{W}^{\mathtt{in}}\boldsymbol{x}(t_s)\Big)$$

$$z(t_s) = \boldsymbol{W}^{\mathrm{out}}\boldsymbol{h}(t_s)$$

RNNs



Output Vector

$$\hat{y}_t = \boldsymbol{W}_{\boldsymbol{hy}}^{\boldsymbol{T}} h_t$$

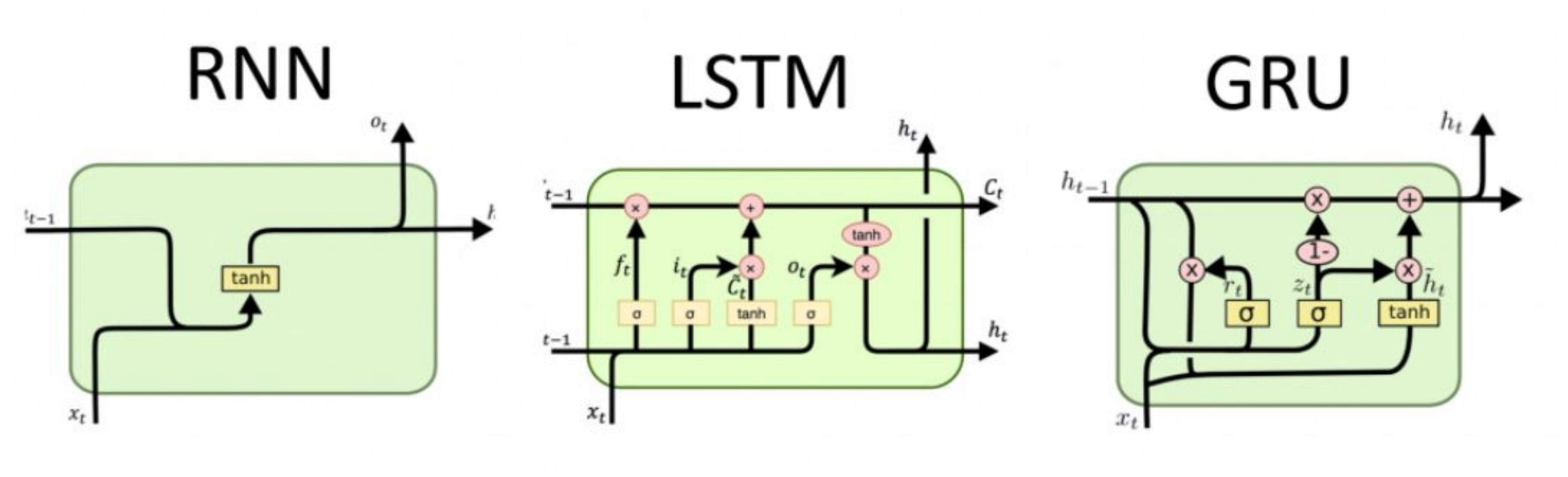
Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{\boldsymbol{hh}}^{\boldsymbol{T}} h_{t-1} + \boldsymbol{W}_{\boldsymbol{xh}}^{\boldsymbol{T}} x_t)$$

Input Vector

$$x_t$$

Other architectures



Training

-Supervised method.

-The loss function used to train the model is the mean square error between the target function and the output of the network.

$$E(w) = \frac{1}{2} \sum_{t=1} \sum_{j=1} (\mathbf{Z_j}(t) - \mathbf{Z_j^{target}}(t))^2$$

Some results in our papers

- Exploring weight initialization, diversity of solutions, and degradation in recurrent neural networks trained for temporal and decision-making tasks Acepted https://arxiv.org/abs/1906.01094
- Effect in the spectra of eigenvalues and dynamics of RNNs trained with Excitatory-Inhibitory constraint https://doi.org/10.1007/s11571-023-09956-w
- Recurrent Neural Networks as Electrical Networks, a Formalization 10.1007/978-3-031-23210-7_10
- Different eigenvalue distributions encode the same temporal tasks in recurrent neural networks 10.1007/s11571-022-09802-5
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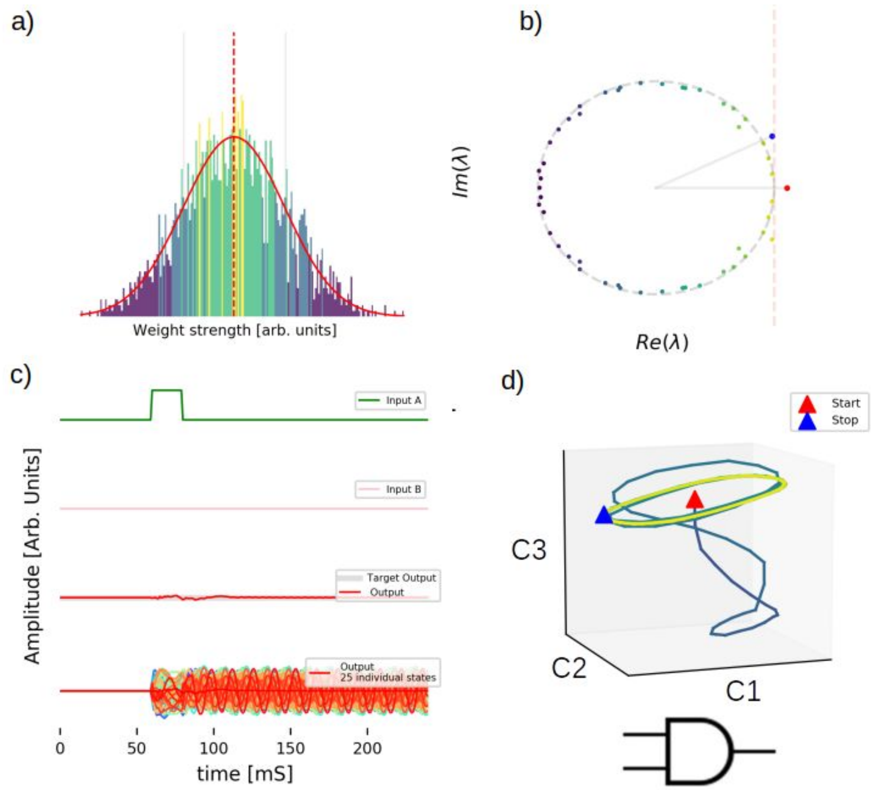
What can we study?



What can we study?

- Connectivity patterns (based on weight distribution)
- Activation patterns (level of activity of groups of units against different stimuli)
- Dynamical behavior
- Performance
- Effects on the parametrization of the task/network

Parameters:

Table 1 Model's parameters and criteria for the network's implementation and training

Parameter/criteria	Value
Units	50
Input weights	2×50
Recurrent weights	50×50
Output weights	50
Training algorithm	BPTT ADAM
Epochs	20
Initialization	Ran Orthogonal– Ran Normal
Regularization	None
Input Noise	10%

The tasks

Time reproduction.

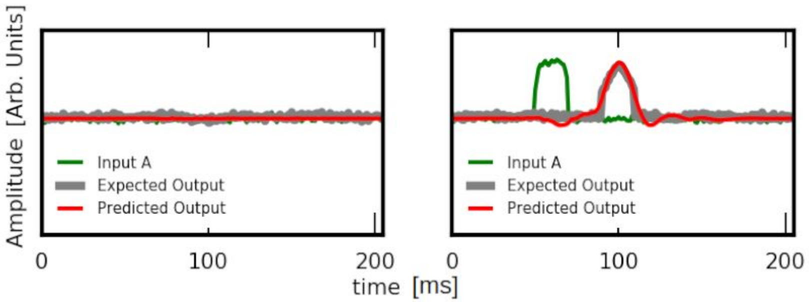
Basic logic gate operation (decision making): AND, OR, NOT, XOR.

Finite-duration oscillation.

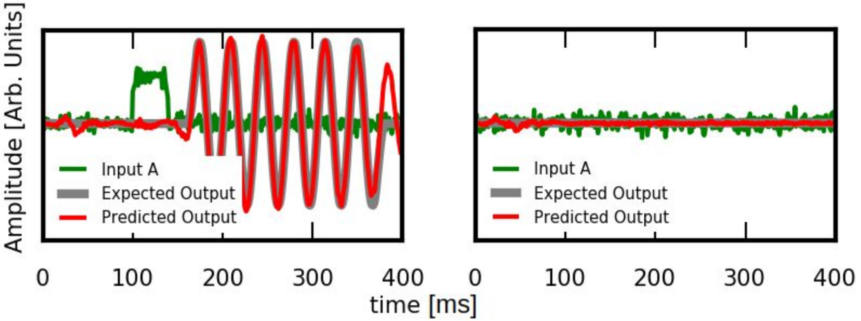
Flip-Flop (1-bit memory storage).

The tasks

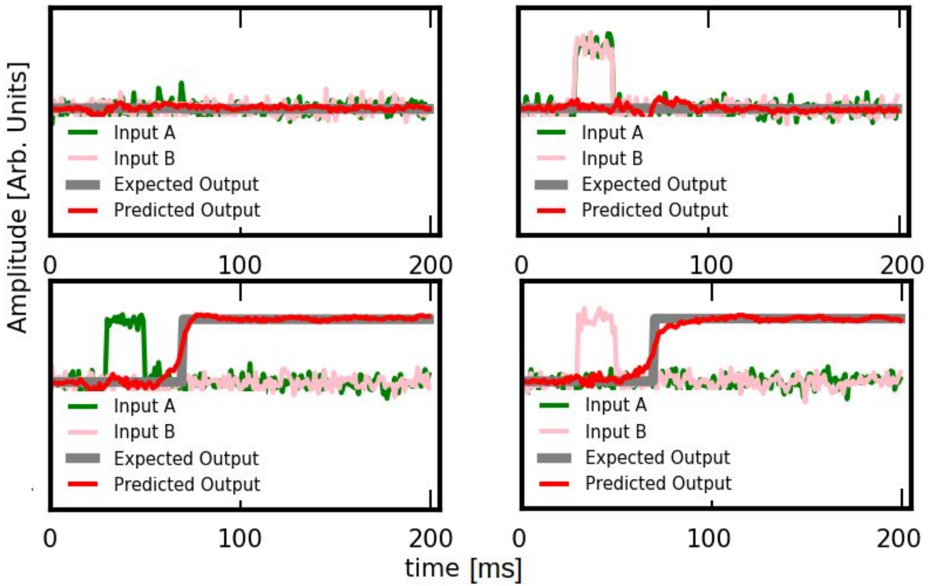
Time reproduction



Finite-duration oscillation



XOR Task



*Relevant for information processing and flow control.
*Traditionally used in previous works to model the behavior of different brain areas.

Task	Reference
Oscillatory induced by pulse	Sussillo and Barak 2013
Flip Flop	Sussillo and Barak 2013
Context Dependent DM	Mante et al., 2013
Perceptual DM	Britten et al., 1992; Roitman and Shadlen, 2002
Delay match to sample	Freedman and Assad,2006
Parametric Working Memory	Romo et al.,1999
Time reproduction of pulse	C. Jarne; R. Laje https://arxiv:org/abs/1906.01095
XOR DM	C. Jarne; R. Laje https://arxiv:org/abs/1906.01095
OR DM	C. Jarne; R. Laje https://arxiv:org/abs/1906.01095
AND DM (*example shown)	C. Jarne; R. Laje https://arxiv:org/abs/1906.01096
Not DM	C. Jarne; R. Laje https://arxiv:org/abs/1906.01095

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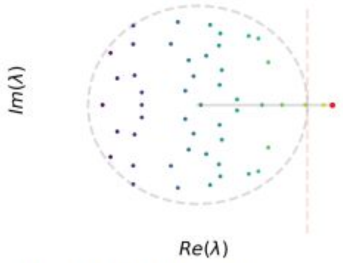
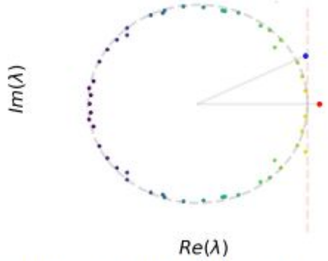
Not DM	C. Jarne; R. Laje https://arxiv:org/abs/1906.01095

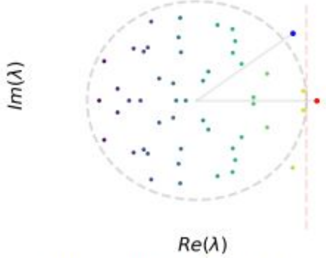
Eigenvalue Distribution of trained networks



Normal AND Gate
Sim No. 07



Orthogonal AND Gate
Sim No. 15



Normal OR Gate
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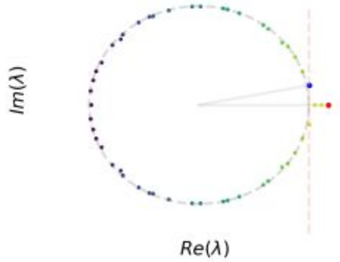

Orthogonal Flip Flop
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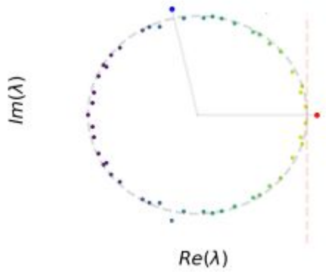
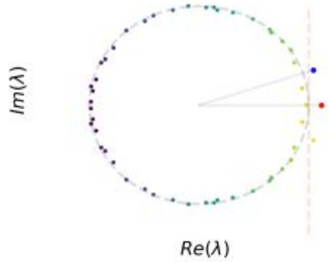


Orthogonal OR Gate
Sim No. 01



Orthogonal XOR Gate
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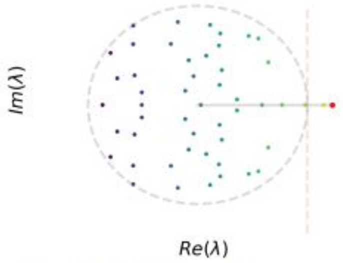
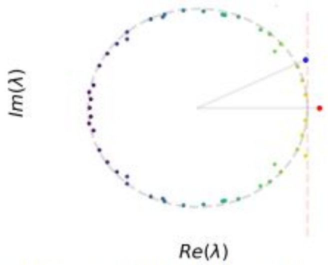
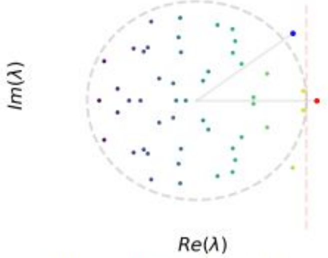
Eigenvalue Distribution of trained networks



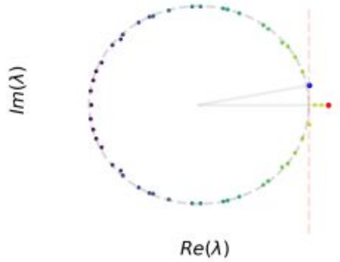
Normal AND Gate
Sim No. 07



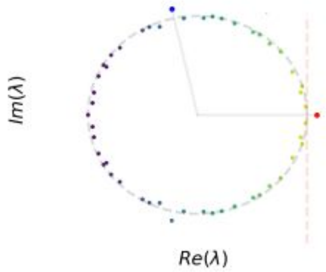
Orthogonal AND Gate
Sim No. 15



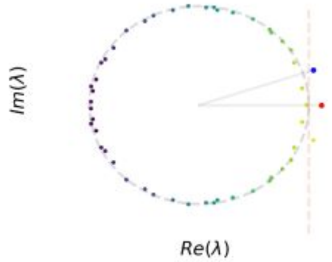
Normal OR Gate
Sim No. 01



Orthogonal Flip Flop
Sim No. 18

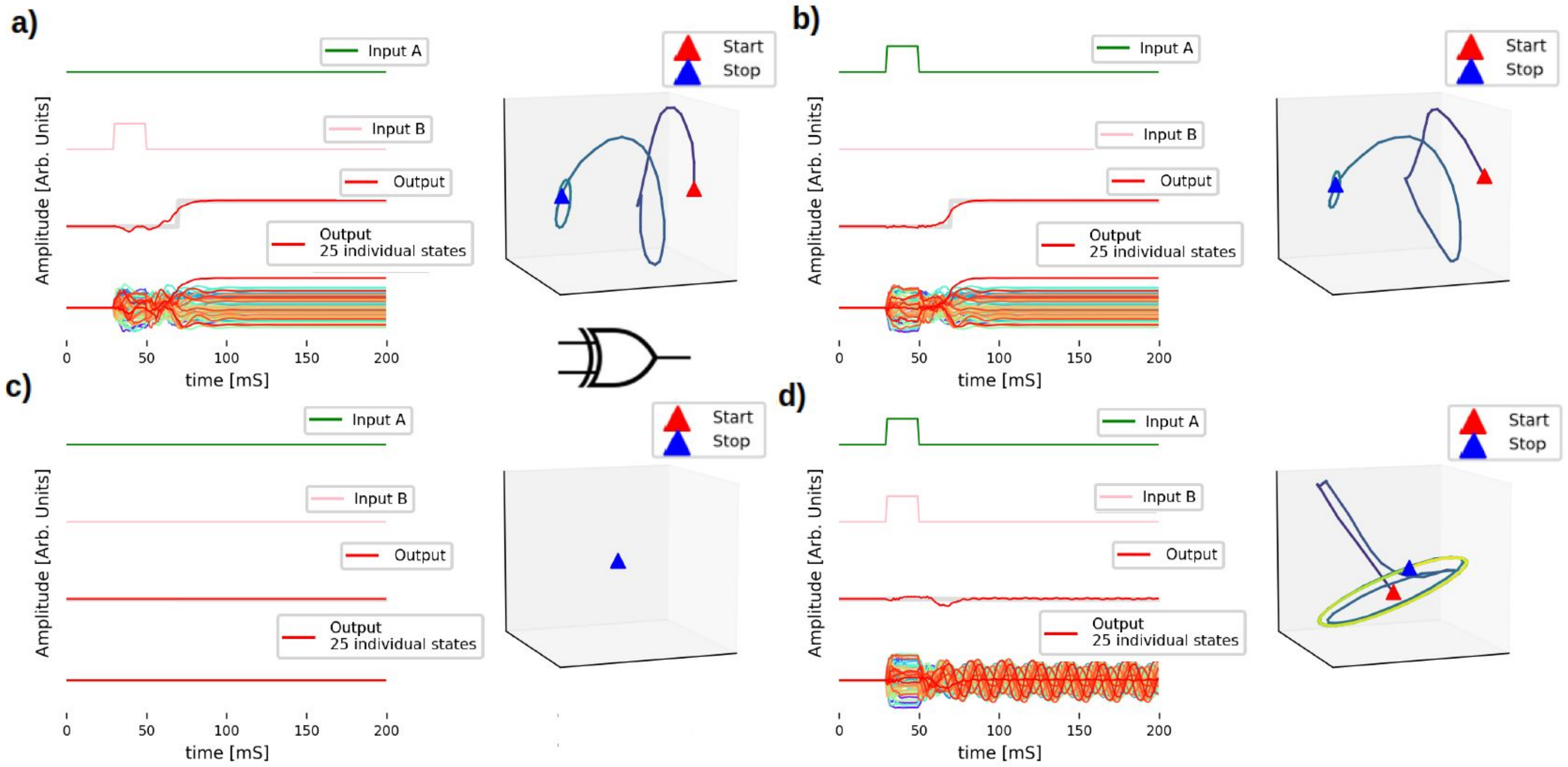


Orthogonal OR Gate
Sim No. 01



Orthogonal XOR Gate
Sim No. 10

Activity of the trained network



Long term dynamics

$$\frac{dh_i(t)}{dt} = -h_i(t) + \sum_{j=1}^{N} w_{ij}^{Rec} h_j(t) + \mathbf{I}(\mathbf{t}) \cdot w_{0,i}$$

$$\mathrm{h} = \mathrm{V}\bar{\mathrm{h}}$$

$$\mathbf{W}^{\mathbf{Rec}} \to \Lambda = \mathbf{V}^{-1}\mathbf{W}^{\mathbf{Rec}}\mathbf{V}$$

$$\frac{d\tilde{h_i}(t)}{dt} = -\tilde{h_i}(t) + \lambda_i \tilde{h_i} + \delta(t).\tilde{w}_{0,i}$$

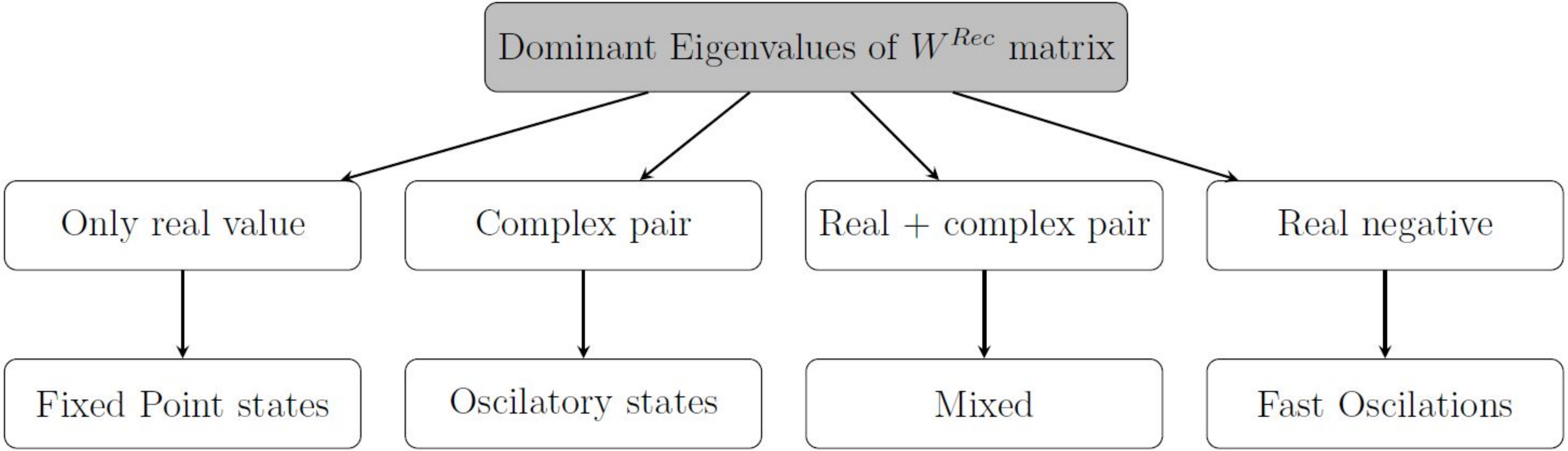
$$\mathbf{h}(t) = \sum_{i=1}^{N} \tilde{h_i}(t)\mathbf{v_i}$$

$$\tilde{h_i}(t) = e^{t(\lambda_i - 1)}$$

$$f = \frac{1}{2\pi}\frac{Im(\lambda_{max})}{Re(\lambda_{max})}$$

Thus, the long-term dynamics is governed by the eigenmodes with the eigenvalue (or eigenvalues) with the largest real part. Linearization performed in this section has some limitations to interpret the results of trained networks. In particular, when eigenvalues satisfy that $Re(\lambda) > 1$

Solutions



Dominant Eigenvalues of W^{Rec} matrix
Only real value
Complex pair
Real + complex pair
Real negative
Fixed Point states
Oscilatory states
Mixed
Fast Oscilations

Conclusions

Networks trained for these four tasks (AND, XOR, OR, and Flip Flop) have consistent patterns, and they are not stable systems, in the sense described in Bondanelli and Ostojic (2020), meaning that the trajectory asymptotically decays to the equilibrium state.

Different realizations for the same task were obtained with different dynamical behaviours.

The obtained dynamics was not created on purpose. The dynamics of the system arises as a result of requesting the system to learn the task, with the considered initial conditions.

Linearization was a useful mechanism to understand the behaviour of the system in the first order. Thus the decomposition into eigenvalues of the matrix of recurrent weights is linked with the activity for these tasks.

The results obtained support the hypothesis that trained network represents the information of the tasks in a low dimensional dynamics implemented in a high dimensional network or structure (Barak 2017) as also reported in Kuroki and Isomura (2018).

Knowing the details of the model's dynamics is important to understand the observed experimental results with greater precision.

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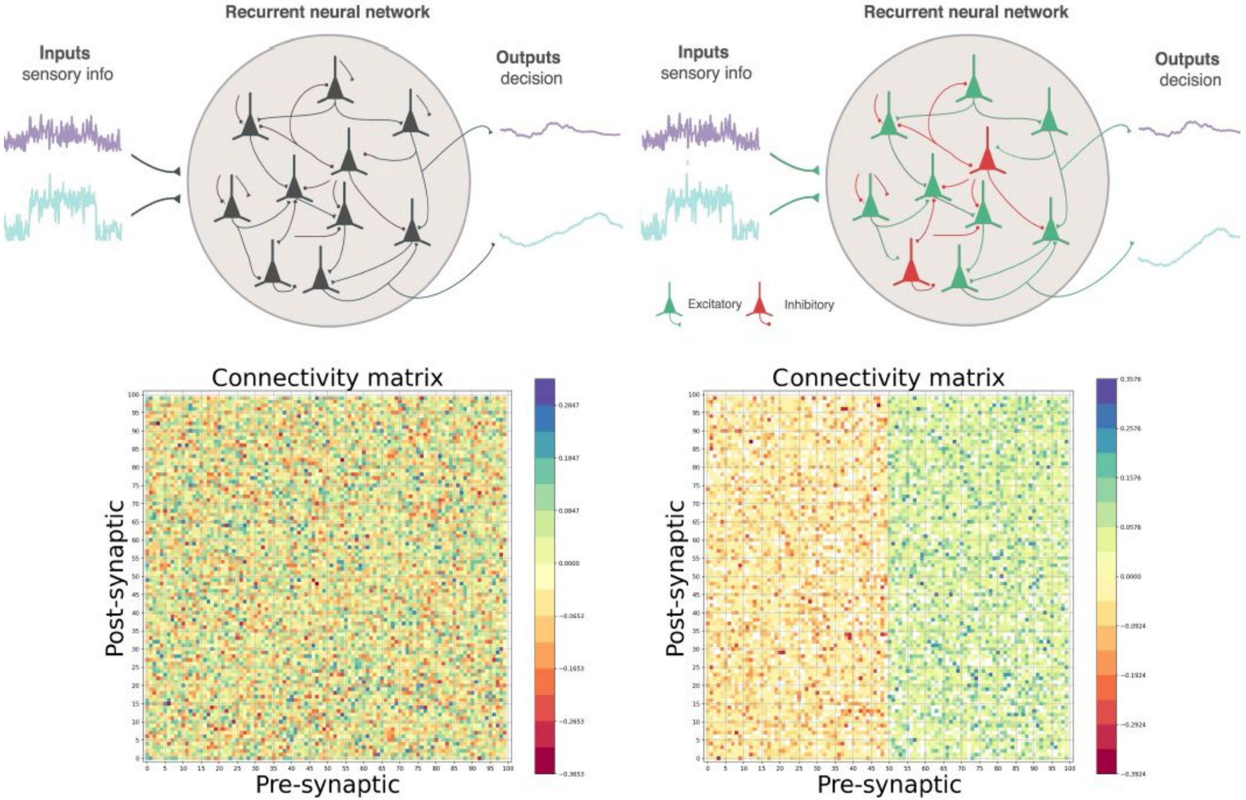
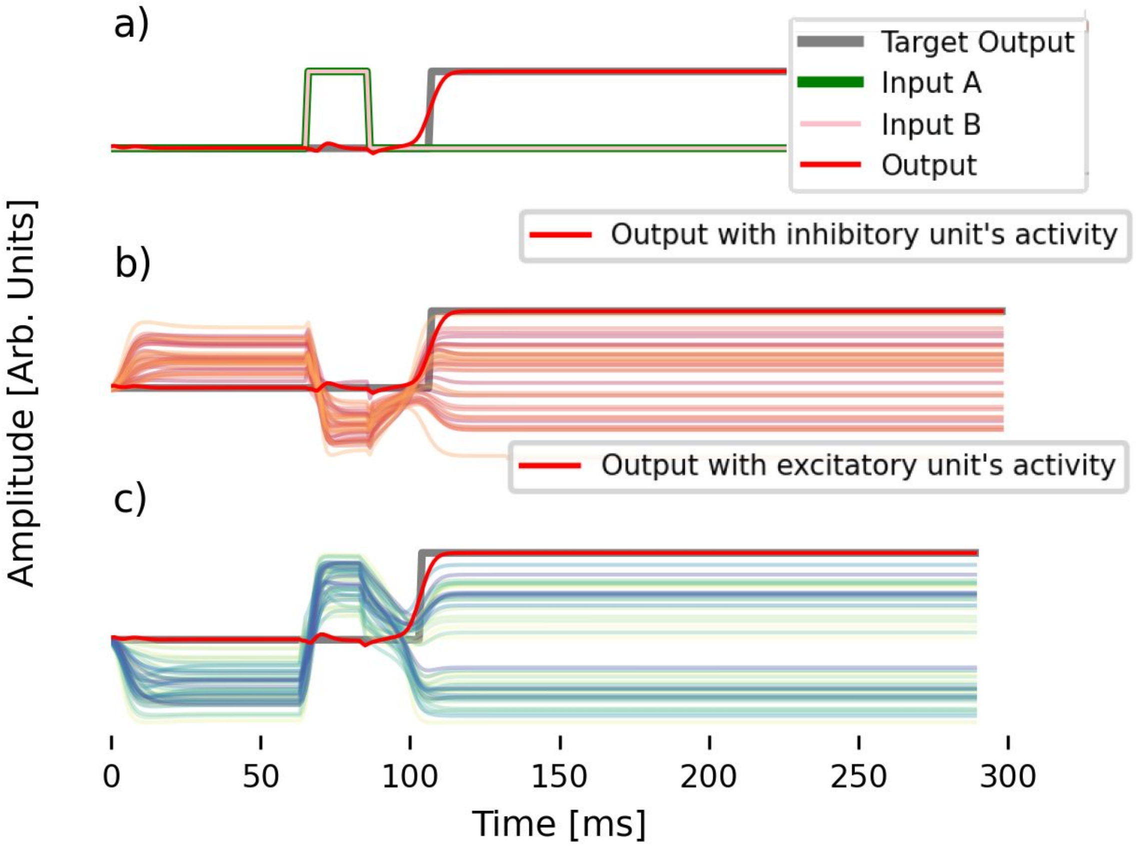
Do we have more time?

Excitatory and Inhibitory units:

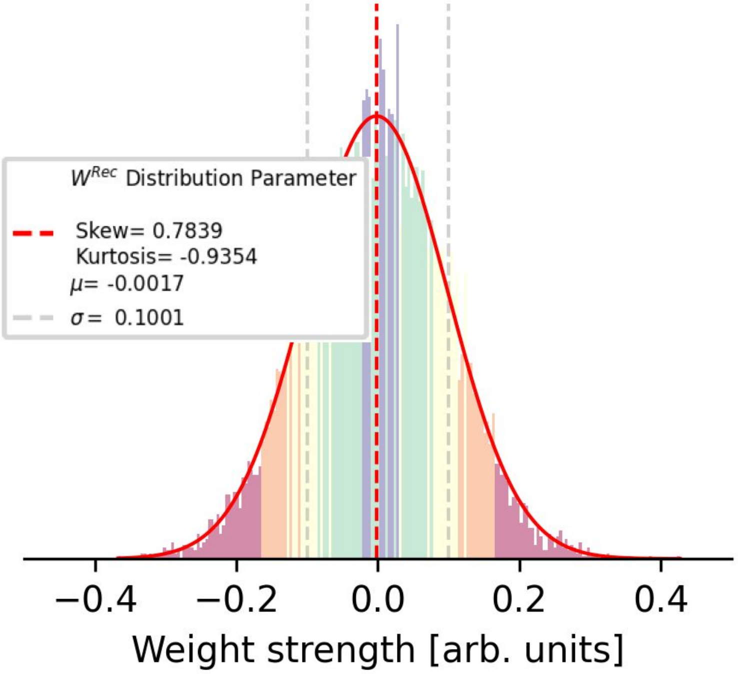


Activity:

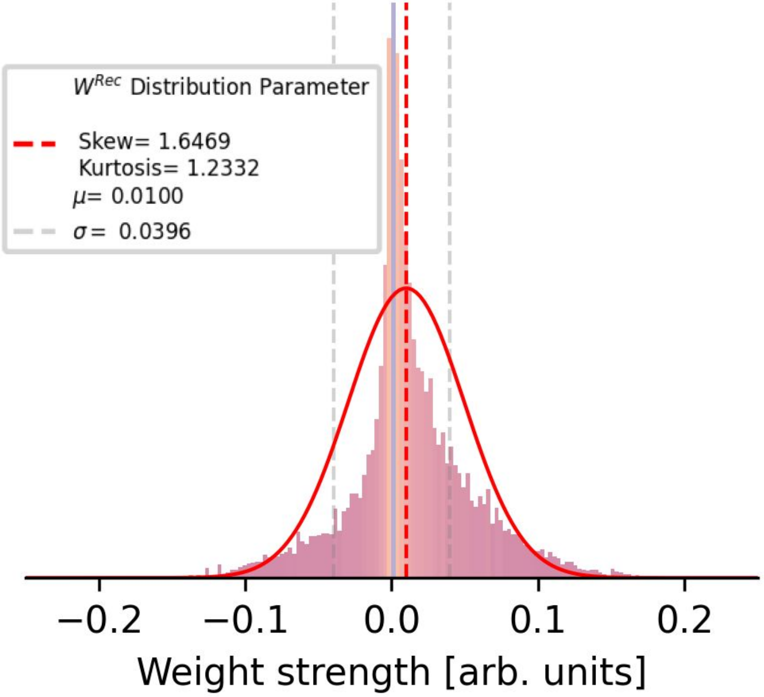


a)
Target Output
Input A
Input B
Output
b)
Output with inhibitory unit's activity
c)
Output with excitatory unit's activity
Amplitude [Arb. Units]
0
50
100
150
200
250
300
Time [ms]

Weights

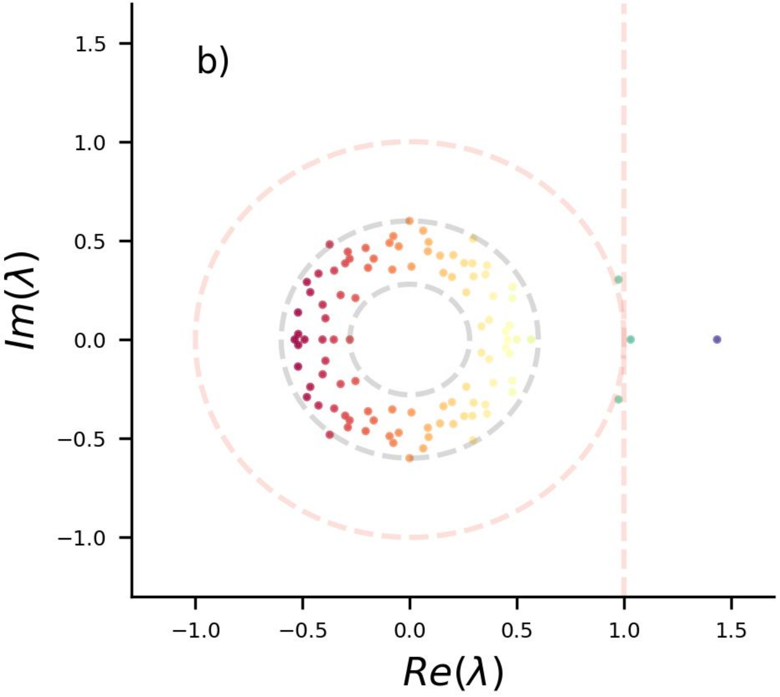


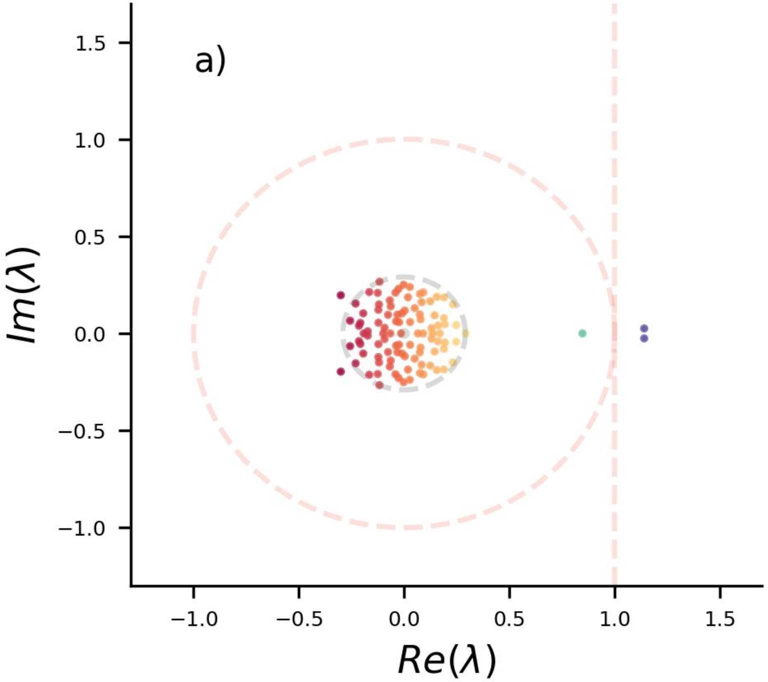
W^{Rec} Distribution Parameter
Skew= 0.7839
Kurtosis= -0.9354
μ= -0.0017
σ= 0.1001
−0.4
−0.2
0.0
0.2
0.4
Weight strength [arb. units]



W^{Rec} Distribution Parameter
Skew= 1.6469
Kurtosis= 1.2332
μ= 0.0100
σ= 0.0396
−0.2
−0.1
0.0
0.1
0.2
Weight strength [arb. units]

Eigenvalue Distribution of trained networks



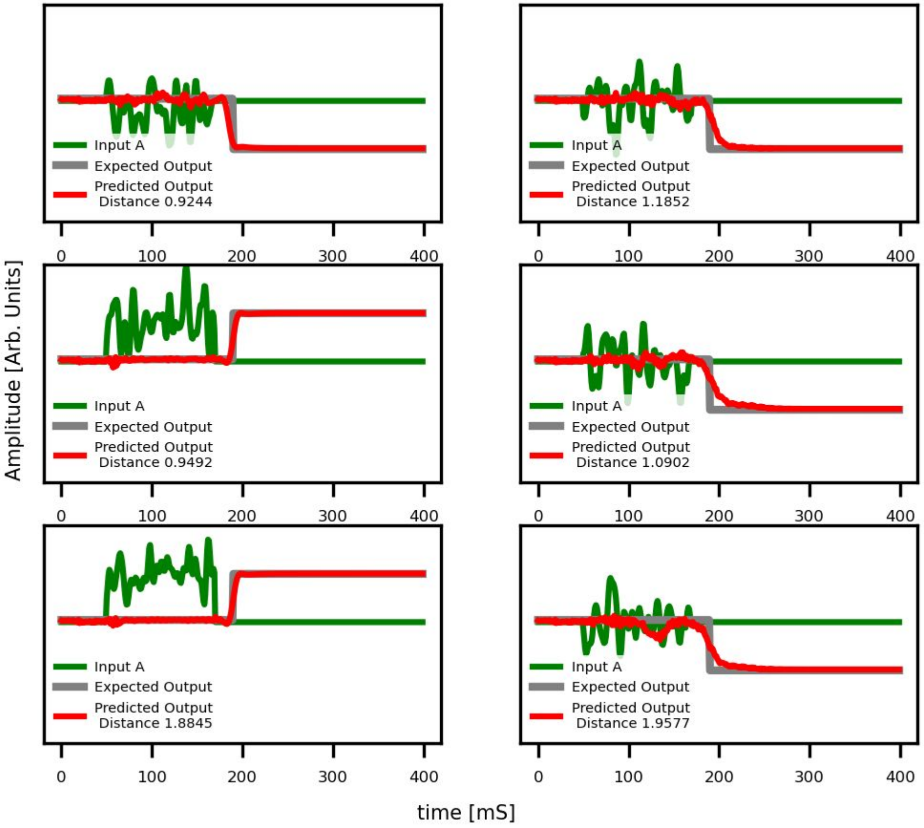


Conclusions

- Non-dominant eigenvalues of the recurrent weight matrix are distributed in a circle with radius less than 1 for those whose initial condition prior to training was random normal and in a ring for those whose initial condition was random orthogonal.
- In both the radius does not depend on the fraction of excitatory and inhibitory units nor on the size of the network.
- Diminution in the radius of the non-dominant eigenvalues, compared to networks trained without the constraint, has implications for unit activity attenuating the expected oscillations which have been explained in mathematical terms.
- Our computer simulations offer a framework for investigating the stimulus-driven dynamics of biological neural networks and further inspire theoretical research.

Perceptual DM

Task from the notebook



Thanks for listening!

Lets train and analyse some networks