

Msc thesis
Mathematical Modelling and Computation

The dynamics of adaptive neuronal networks: influence of topology on synchronisation

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Supervisors

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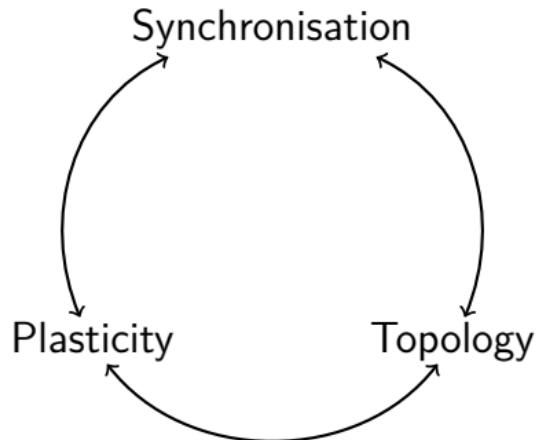
DTU Compute

Department of Applied Mathematics and Computer Science



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Holistic approach



Introduction

Neuron dynamics

How do neurons communicate?

- Neurons receive neurotransmitters
- Action potential = explosion of electrical activity
- Synapse releases the neurons' neurotransmitter

How can we capture this behaviour?

- Human brain consists of ~ 100 billion neurons
- The *MFR* yields the average dynamics of the network

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Synaptic plasticity

How do neurons learn?

- Hebbian learning: *Fire and wire*
- Correlation of neuronal activity
- Change response to incoming and outgoing signals
- Average response intensity = *synaptic strength*

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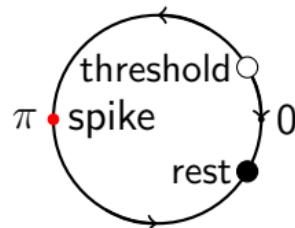
The Theta Neuron Model

Model Description

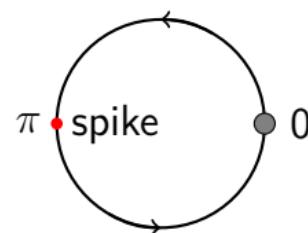
- Formulation

$$\dot{\theta} = (1 - \cos \theta) + (1 + \cos \theta) \cdot I \quad \theta \in \mathbb{T}$$

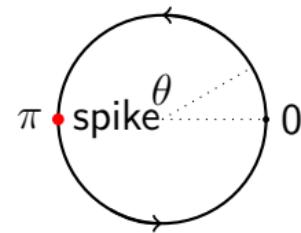
- Normal form of SNIC bifurcation



Excitable regime: $I < 0$



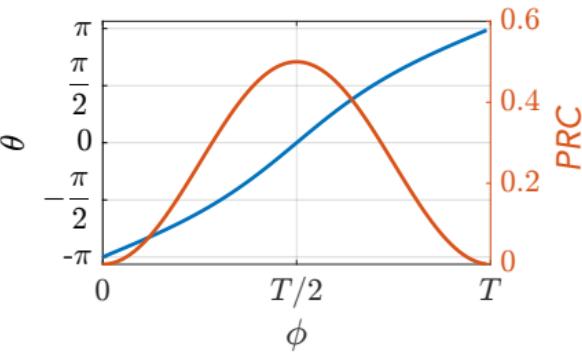
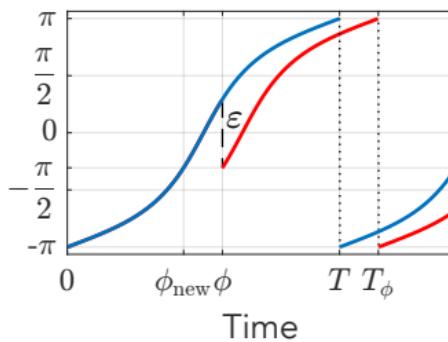
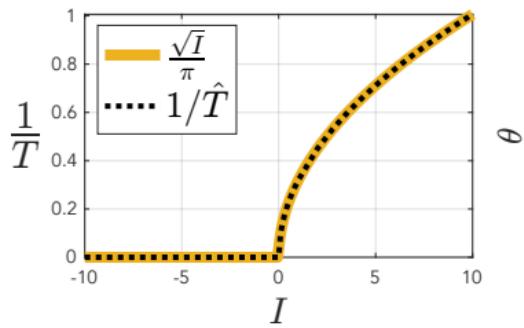
Bifurcation: $I = 0$



Periodic regime: $I > 0$

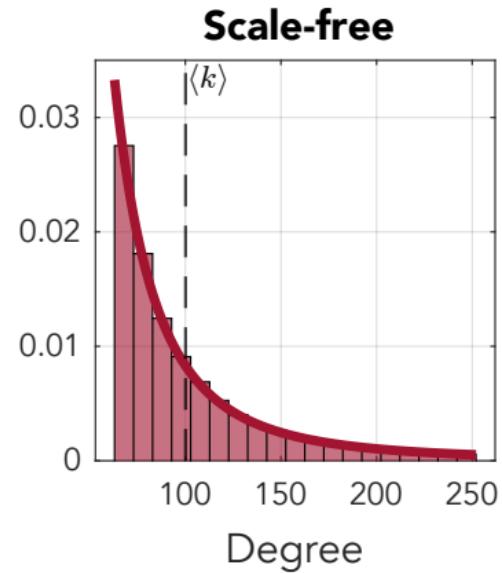
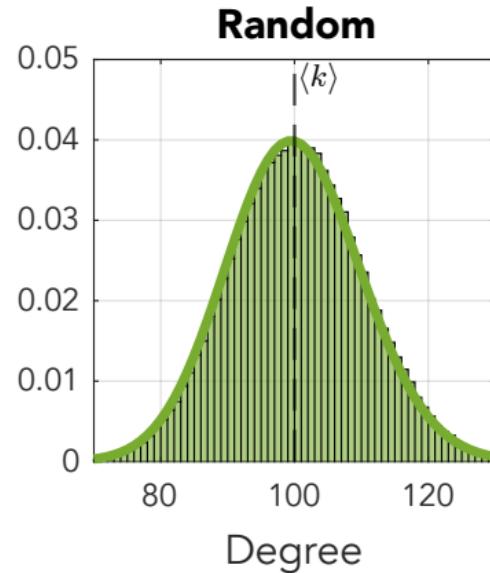
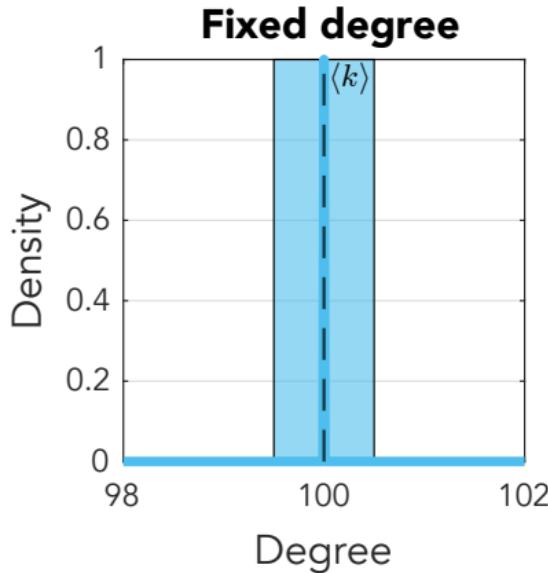
The Theta Neuron Model Response

- Formulate bifurcations in terms of spiking frequency or phase angle



Network Topologies

Three basic networks



Networks of Theta neurons

- For an arbitrary network topology:

$$\dot{\theta}_i = (1 - \cos \theta_i) + (1 + \cos \theta_i) \cdot [\eta_i + I_i(t)] \quad \theta_i \in \mathbb{T}^N$$

$$I_i(t) = \frac{\kappa}{\langle k \rangle} \sum_{j=1}^N A_{ij} \cdot \mathcal{P}_n(\theta_j)$$

- Capture average/mean synchronisation

$$Z(t) = \frac{1}{N} \sum_{j=1}^N e^{i\theta_j} \quad Z \in \mathbb{C}_o$$

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Mean Field Reductions

Predict synchronisation dynamics

The *MFR* yields a solution for $Z(t)$

- N neurons in the network
- $M_k \ll N$ unique node degrees

Then rewrite $Z(t)$ per degree $z(\mathbf{k}, t)$!

- Only M_k equations
- Weighed by $P(\mathbf{k})$

$$\bar{Z}(t) = \frac{1}{N} \sum_{\mathbf{k}} P(\mathbf{k}) z(\mathbf{k}, t) \quad \bar{Z} \in \mathbb{C}.$$

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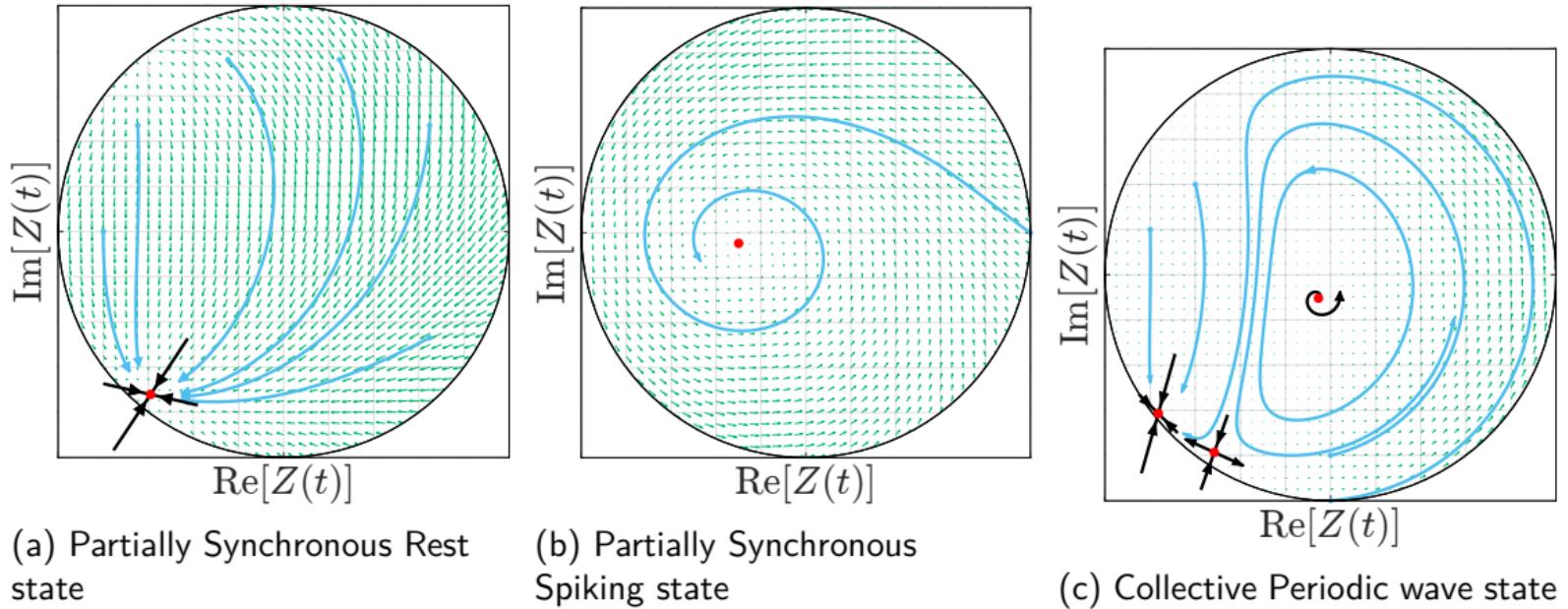
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Mean Field Reductions Fixed-degree networks



(a) Partially Synchronous Rest state

(b) Partially Synchronous Spiking state

(c) Collective Periodic wave state

Investigation: Mean Field Reductions for undirected graphs

Goals

$Z(t)$ can be measured and predicted: are they the same?

- Formulate directed networks
- Construct adjacency matrix from degree distribution
- Initial conditions
- Results

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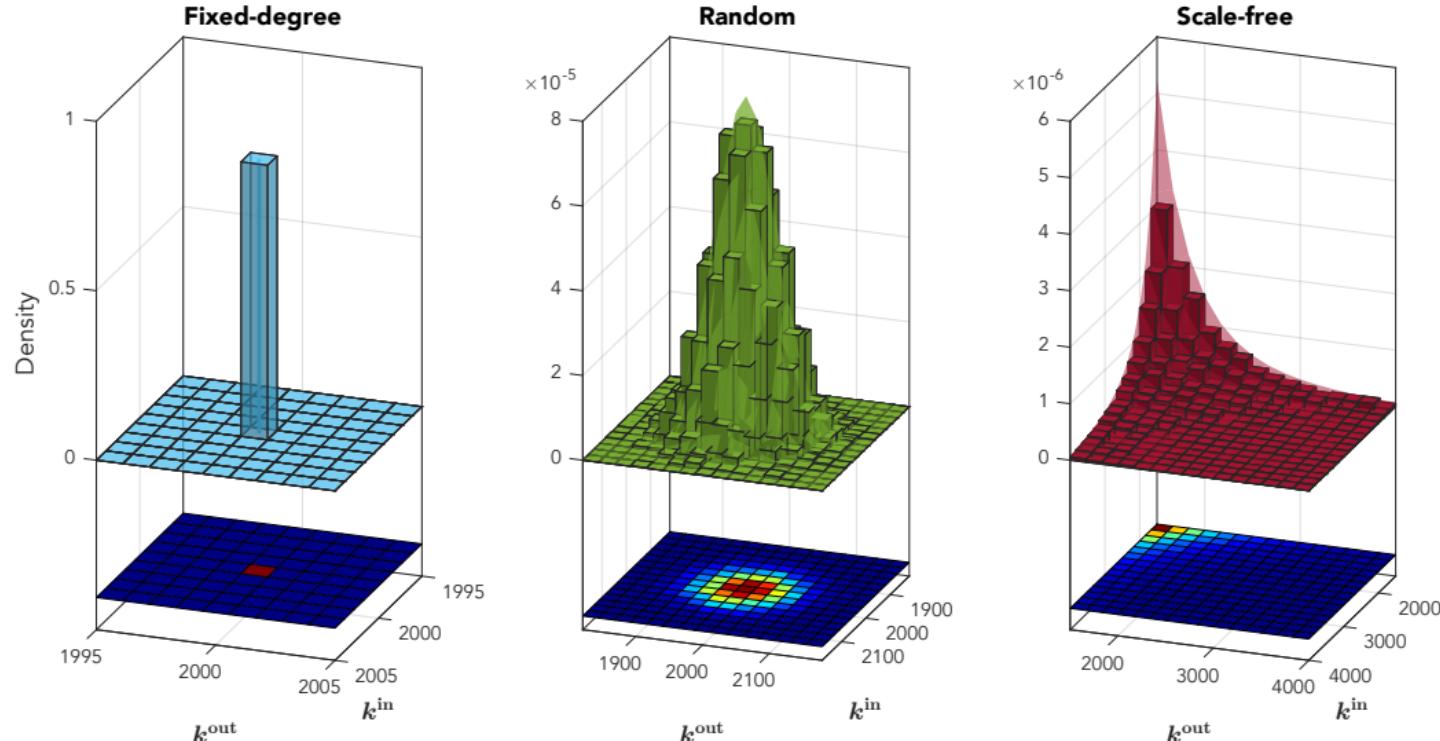
Directed networks

Use a bivariate degree distribution

- Use identical and independant distributions
- In- and outdegrees are found as a permutation

Investigation: Mean Field Reductions for undirected graphs

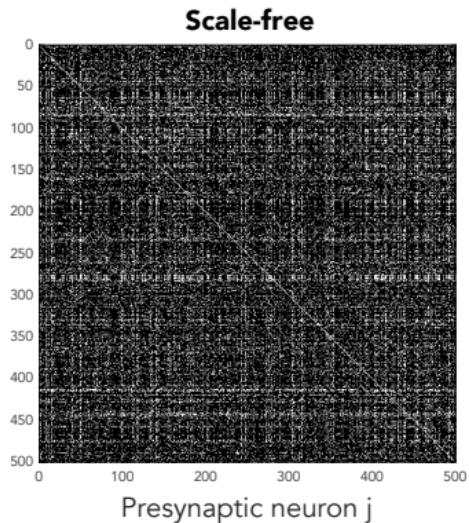
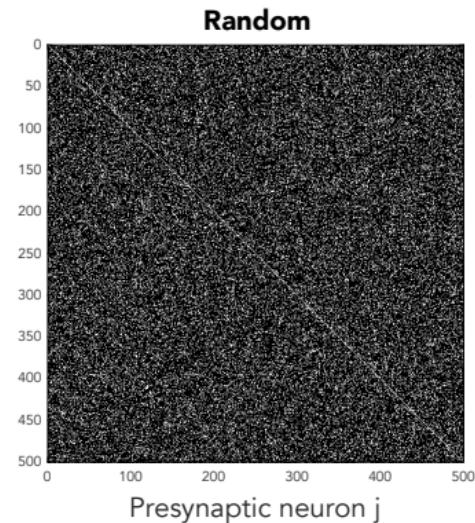
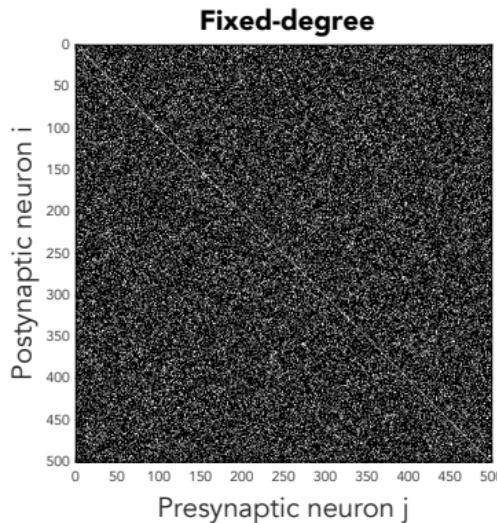
Directed networks



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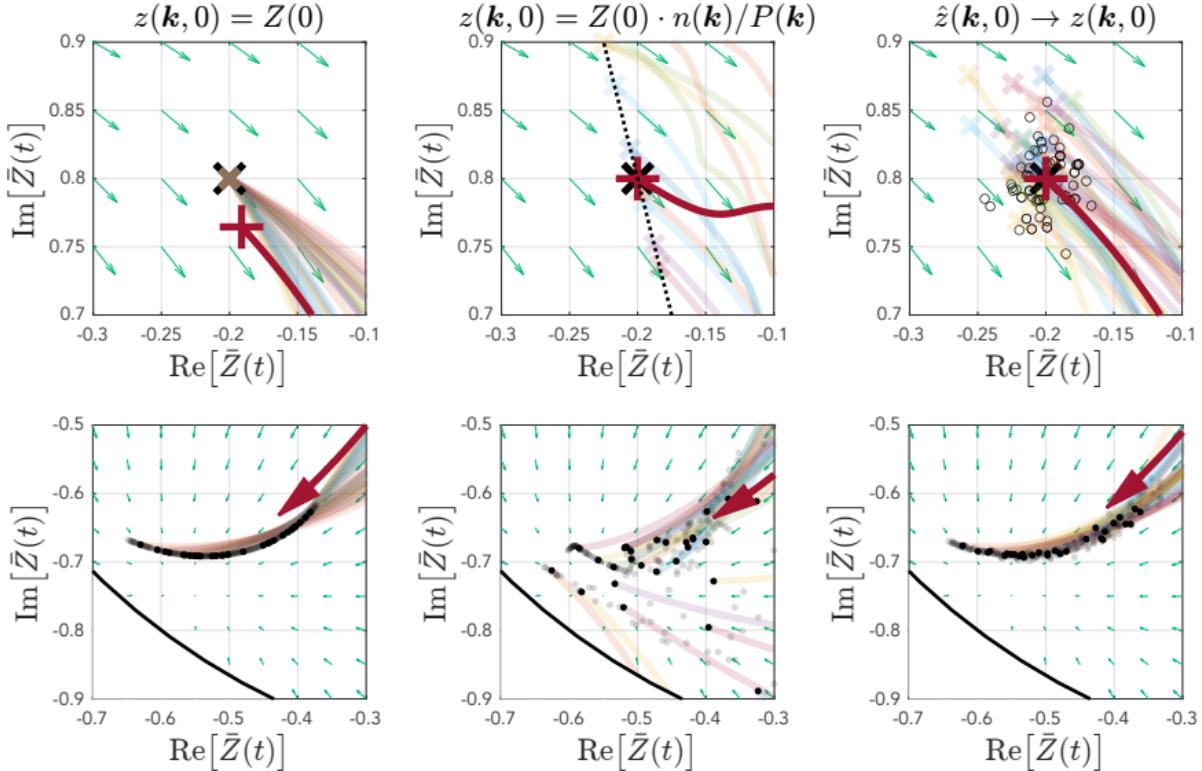
Adjacency matrix

Find a probable solution by sampling from the in- and outdegrees



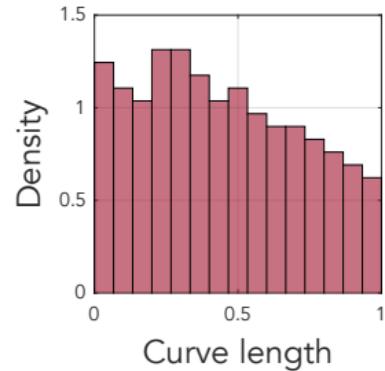
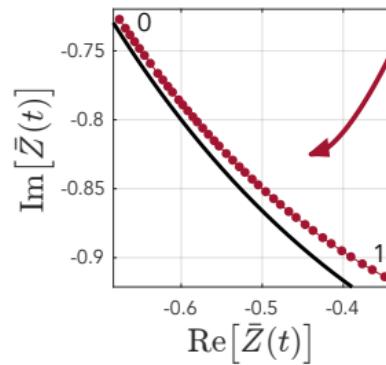
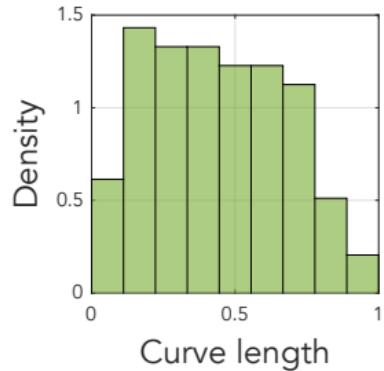
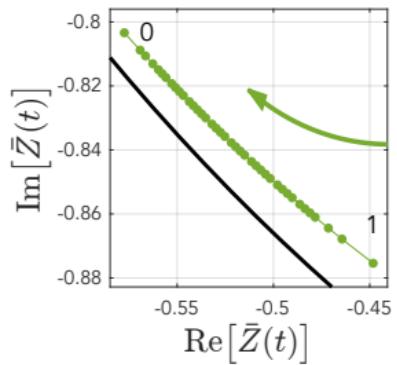
Investigation: Mean Field Reductions for undirected graphs

Initial conditions



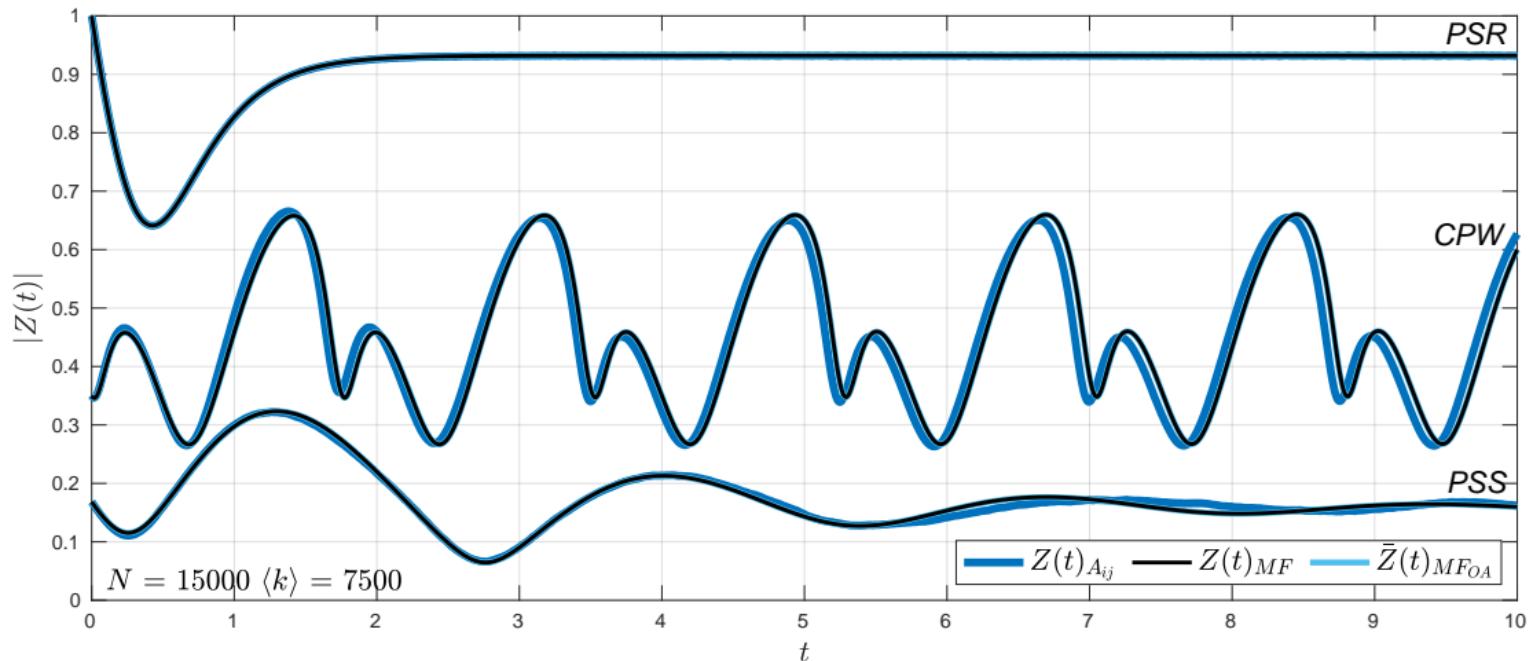
Investigation: Mean Field Reductions for undirected graphs

Final conditions



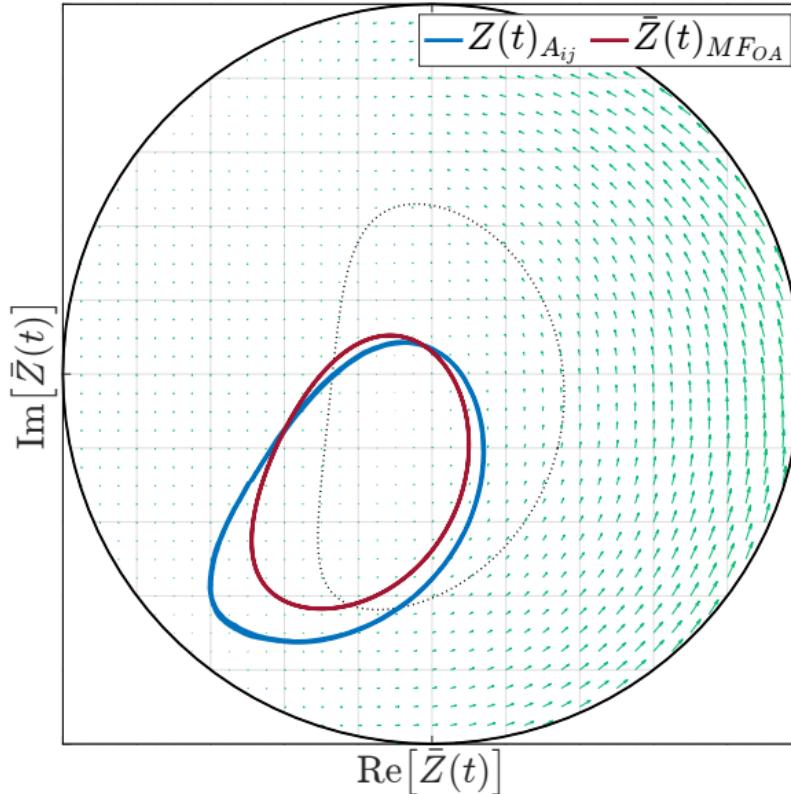
Investigation: Mean Field Reductions for undirected graphs

Results



Investigation: Mean Field Reductions for undirected graphs

Results



Hebbian Learning and Synaptic Plasticity

Hebbian Learning and Synaptic Plasticity

Investigation: Emerging Network Topologies

Investigation: Emerging Network Topologies

Conclusion and Discussion

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