UNIVERSITY OF MARYLAND

Rhythmic Sharing

An Astrocyte-Inspired Algorithm for Robust Learning of Evolving Dynamical Systems with Applications in Anomaly Detection

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Overview

Summary – Neuromorphic Algorithms

Why do we look to the brain when developing algorithms?

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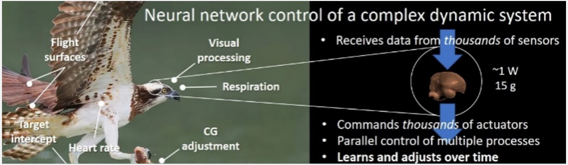

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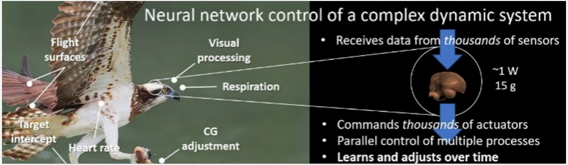

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The brain outperforms machine learning in several tasks, including:

- learning and extrapolating from limited data with different modalities, and,
- anticipating, detecting, and adapting to concept drift

Summary – Our Lab

Losert Lab works on the intersection of neuroscience research and computation. We're interested in:

- astrocytes as conductors of neuronal cognition
- hybrid systems that combine neuronal cultures and digital computers
- Neuromorphic algorithms that unify theories of neural cognition and computation

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One of these algorithms is rhythmic sharing, today's topic

This Presentation

Today, I'll discuss:

1. the astrocytic inspiration of our rhythmic sharing algorithm,
2. the rhythmic sharing algorithm,
3. how our algorithm enhances drift in a dataset, and the result of combining rhythmic sharing with concept drift detectors, and,
4. how a single rhythmic sharing instance can learn and extrapolate to different dynamics, while ESNs cannot.

Biological Inspiration

The Brain: Not Just Neurons

Most neuromorphic machine learning algorithms are inspired by neurons or compute via spiking.

The Brain: Not Just Neurons

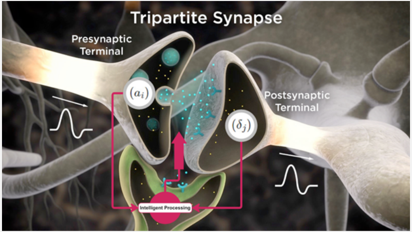
Most neuromorphic machine learning algorithms are inspired by neurons or compute via spiking.

However, **neurons are not the only cells** in the brain and **not all cells communicate through spiking!**

Other cells in the brain play an essential and understudied role in cognition.

Astrocytes and Glial Cells

Astrocytes are glial cells involved in cognition through the tripartite synapse [1].



Astrocytes and Glial Cells

Through the tripartite synapse, astrocytes are essential to cognition:

- Each astrocyte is connected to between 270,000 and 2 million synapses, coordinating and monitoring them [2]
- An astrocyte can be incredibly long, connecting to spatially-distant neurons
- The astrocytes respond to the body's state and to external stimulation [3]

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One way they potentially control neurons is through **rhythmic, physical forces** on the synapses [4]. This inspired the rhythmic sharing algorithm.

Rhythmic Sharing

RS Algorithm

The rhythmic sharing algorithm was originally proposed in Kang and Losert [5].

We proposed two hypotheses about learning in neurons after observing astrocytes' rhythmic activity:

- Learning involves rhythmic variations in link strength, and,
- Learning occurs via coordination of the phases of these rhythmic variations.

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We implement these in a reservoir computing model

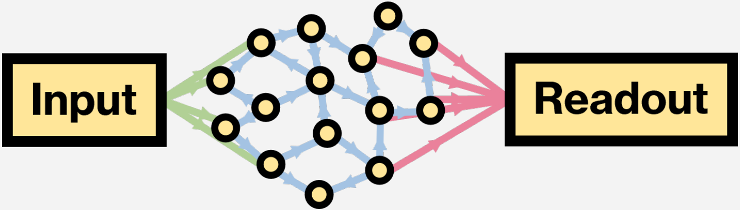
RS Algorithm – Reservoir Computing

Reservoir computing is intricately linked to neuroscience, where it was first developed as models of sensorimotor processes [6].

This makes them a natural fit for our model of the interactions between astrocytes and neurons.

RS Algorithm – Reservoir Computing

The base of rhythmic sharing is an echo-state network with sparse connectivity



RS Algorithm – Node Update

For each timestep, the value of the nodes is set, based on the values of the nodes and inputs they are connected to.

$$n(t + \Delta t) = \alpha n(t) + (1 - \alpha)\, tanh(A^{\sim} n(t) + W_{in} u(t))$$

$W_{in} \in \mathbb{R}^{N \times C}$ is the input weight matrix (scaled by an input weight hyper-parameter) and $u(t) \in \mathbb{R}^{C}$ is the input to the system.

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This is identical to an echo state network, **with the exception of the modulated adjacency matrix $A^{\sim} \in \mathbb{R}^{N \times N}$:**

$$A^{\sim}(t) = A \circ \left(1 - \frac{m}{2}\,(1 + sin[\Phi(t)])\right)$$

RS Algorithm – Oscillations

The modulated adjacency matrix $A^{\sim} \in \mathbb{R}^{N\times N}$ function shows how the phases, Φ, control the strength of the nodes' connections.

A Kuramoto-inspired model controls synchronization of subgroups of phases based on the input [7].

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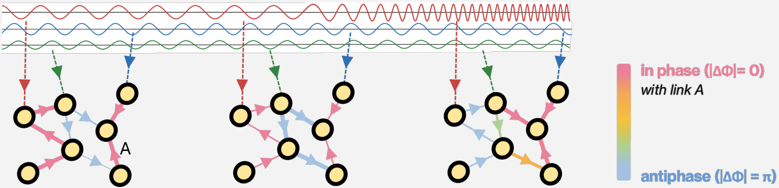

RS Algorithm – Oscillations

This is the Kuramoto model function that controls the phases of the links.

$$\frac{d\Phi}{dt} = \omega_0 + \left(\epsilon_1 + \epsilon_2 \hat{Q}^T n^*\right) \circ sin\left(\Psi - \Phi + \gamma\right)$$

ω_0 is the natural frequency of the nodes, Ψ is the local mean field, $\hat{Q}$ is the incidence matrix, ϵ_1 and ϵ_2 are coupling hyperparameters, and $\circ$ denotes element-wise multiplication.

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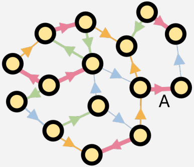
The phases are updated each timestep: $\Phi(t + \Delta t) = \Phi(t) + \Delta t * \frac{d\Phi}{dt}$

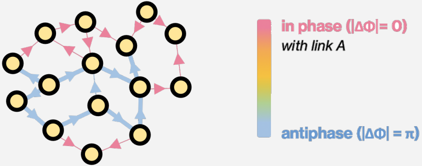
RS Algorithm – Synchrony

As proposed, the model learns as groups of links become synchronized.

This provides a path for the information to flow through the model. We measure it with the order parameter R: $R(t)e^{i\langle\Phi\rangle(t)} = \frac{1}{N_l}\sum_{k=1}^{N_l} e^{i\Phi_k(t)}$



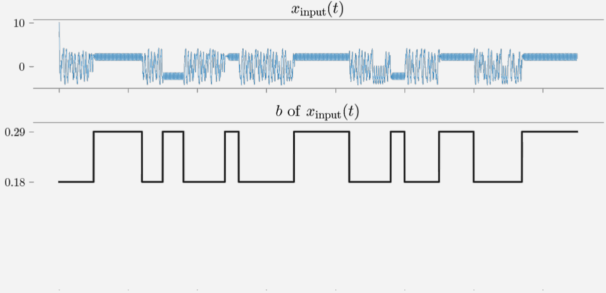
Initial, random phases, R=0.20



Learned phases, R=0.75

RS Algorithm – Reaction to Changing Dynamics

When the input dynamics change, the model adjusts which nodes are synchronized to match.



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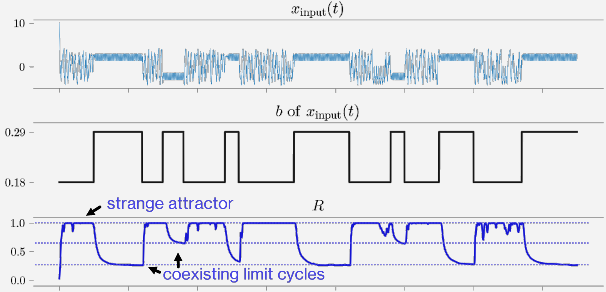

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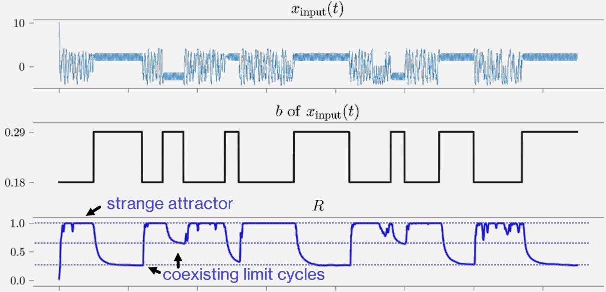

This inspired us to analyze the algorithm's applicability to anomaly and concept drift detection.

RS Algorithm – Per-Input Synchrony

Initially, we believed that this changing synchrony was enough to detect concept drift. However, **it only captured large dynamical shifts,** not subtle changes.

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Therefore, we introduced per-input synchrony, which only measures the synchrony of links connected to each inputs' nodes:

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We show that **per-input synchrony generates rich features that amplify drifts,** improving performance of detection algorithms.

Concept Drift Detection

Concept Drift

The concept drift detection task focuses on detecting when the distribution that an input is drawn from changes.

It is an important problem in machine learning since most models are brittle to it, and even minor drifts result in worse performance.

We utilize the ability of our model to highlight drifts to improve the performance of different algorithms on three datasets.

Concept Drift – Detectors

We test the performance of our model applied to generic concept drift detection algorithms, including:

- Autoencoder reconstruction models [8]
- Clustering algorithms
- Maximum mean discrepancy [9]

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Additionally, we test SOTA, dataset-tuned detectors

- Neural System Identification and Bayesian Filtering (NSIBF) [10]
- Bidirectional Dynamic Model (BDM) [11]

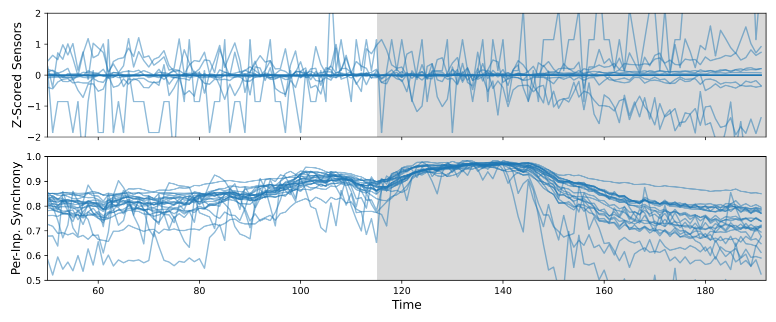
NASA C-MAPSS Dataset – Overview

The NASA C-MAPSS dataset includes recordings from sensors on a set of simulated turbofan engines as they catastrophically degrade.

Following prior work, we consider the last 40% of each recording anomalous [12, 13].

NASA C-MAPSS Dataset – Per-Input Synchrony

Per-input synchrony begins **emphasizing the drifts before the 60% cutoff**



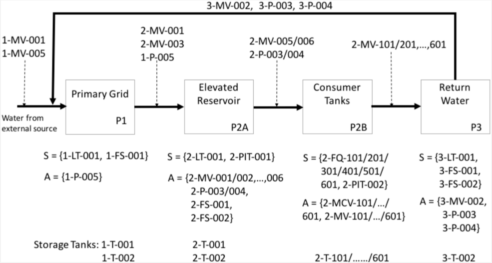
NASA C-MAPSS Dataset – Detector Performance

Per-input synchrony **elevates the performance of the generic models.**

Method	Prec.	Rec.	F1	Del.
AE	0.561	0.629	0.593	16.58
with RS	0.463	0.941	0.621	0.58
MMD	0.441	0.991	0.610	**0.00**
with RS	0.657	**0.822**	0.730	19.50
Clustering	0.413	1.000	0.585	**0.00**
with RS	**0.860**	0.804	**0.831**	0.58

WaDI and SWAT Datasets – Overview

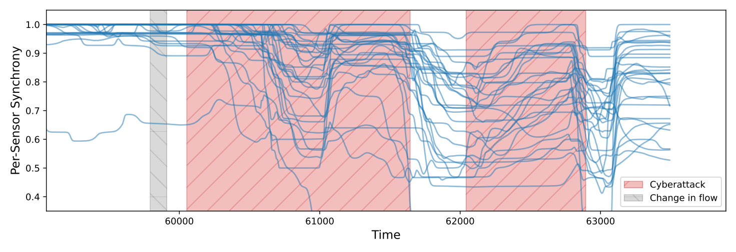
The highlights of our results are on the Secure Water Treatment testbed (SWaT) dataset and water distribution testbed (WADI) dataset [14, 15]



These are complicated datasets of real sensors and actuators treating water

WaDI and SWAT Datasets – Per-Input Synchrony

Per-input synchrony reacts to both real cyberattacks and normal drifts, showing its usefulness but potentially posing a problem for detectors.



WaDI and SWAT Datasets – Simple Detectors

Our methodology improves performance on the simple, generic detectors:

Method	SWaT Dataset Precision	SWaT Dataset Recall	SWaT Dataset F1-Score	WADI Dataset Precision	WADI Dataset Recall	WADI Dataset F1-Score
AE	0.028	0.492	0.052	0.202	0.55	0.252
with RS	0.038	**1.000**	0.073	0.187	0.673	0.284
MMD	0.045	0.747	0.084	**0.225**	0.012	0.024
with RS	**0.142**	0.172	0.156	0.215	0.611	0.318
Clustering	0.039	0.998	0.075	0.154	**1.000**	0.268
with RS	0.139	0.840	**0.238**	0.192	0.962	**0.321**

WaDI and SWAT Datasets – SOTA Detectors

Finally, **our method achieves SOTA results** with the NSIBF model [10].

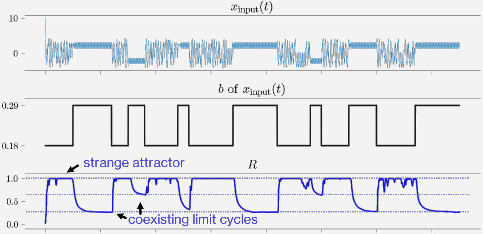
Method	SWaT Dataset Precision	SWaT Dataset Recall	SWaT Dataset F1-Score	WADI Dataset Precision	WADI Dataset Recall	WADI Dataset F1-Score
DAGMM [16]	0.957	0.643	0.769	**0.904**	0.131	0.228
USAD [17]	**0.995**	0.629	0.771	0.243	0.462	0.319
BDM [11]	0.991	0.685	0.811	0.276	0.593	0.377
with RS	0.972	0.631	0.765	0.130	0.557	0.210
NSIBF [10]	0.892	0.712	0.792	0.234	0.496	0.318
with RS	0.943	**0.810**	**0.871**	0.574	**0.876**	**0.694**

Per-input synchrony is a low-dimensional dynamical representation that matches the assumption of neural state-space models like NSIBF but not the reconstruction-based BDM.

Controlled Dynamics Using Synchrony

Controlled Dynamics – Training an RS Network

As we showed, training the rhythmic sharing network using input with multiple dynamics leads to different synchrony values



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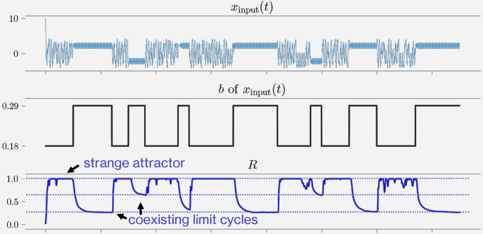
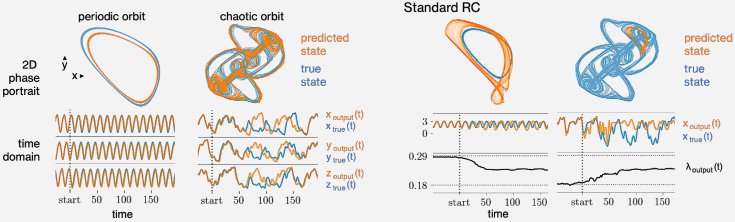


But what happens when we predict future dynamics with this network?

Controlled Dynamics – Prediction of Different Dynamics

Here, we show the results of predicting future dynamics after being trained on both dynamics:



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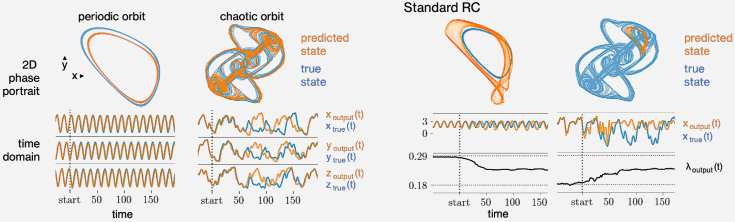

Rhythmic sharing is able to reproduce both, while a generic ESN creates a combination of the two.

Controlled Dynamics – Synchrony Freezing

Knowing this, can we control which dynamics we reproduce?

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Yes! We can freeze the synchrony and introduce a new variable, the mean phase $\langle \Phi \rangle$.

By setting the mean phase, we lock the network in a static configuration.

Controlled Dynamics – Mean Phase

Each static configuration predicts a different set of dynamics.

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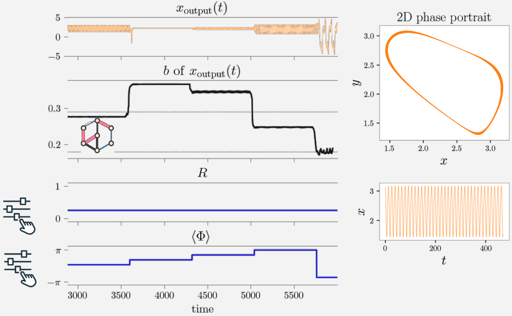

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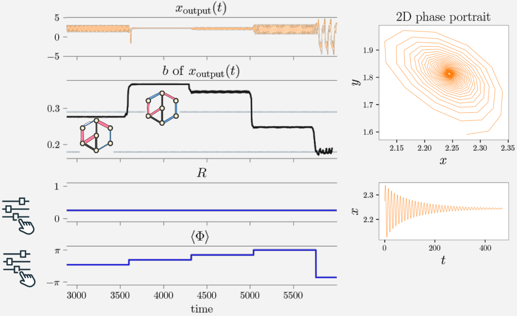

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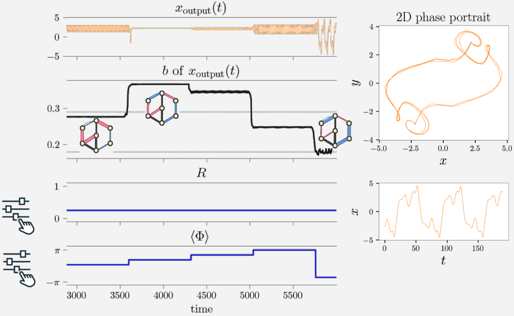

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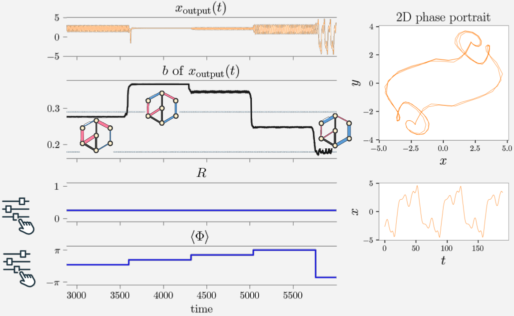

Rhythmic sharing's oscillations make it **equivalent to many different ESNs!**

Conclusions

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The algorithm implements two hypotheses of astrocytes' role in learning:

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The resulting algorithm learns despite, and detects, changes in the input data.

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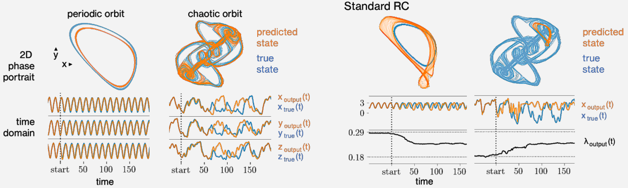
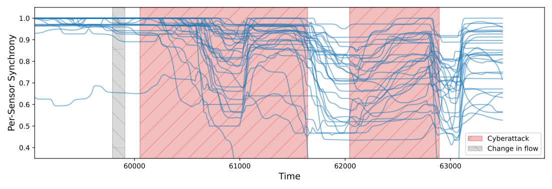
While an echo-state network breaks down if presented with two different input dynamics, **rhythmic sharing retains both** and can be controlled to extract different dynamics that it has saved.



Contributions

The resulting algorithm learns despite, and detects, changes in the input data.

As the model adjusts to a change in the data, it generates signals that amplify the change. These signals **significantly improve the ability of downstream concept drift detectors.**



Future Work – Algorithmic Development

We plan to continue working on understanding the rhythmic sharing algorithm. Specifically, we want to focus on:

- how hyperparameter selection changes performance when extrapolating or detecting drifts,
- how we can perform drift detection in more complex environments, and,
- how we can apply our ability to learn multiple sets of dynamics to real-world datasets.

Future Work – Biology Experiments

Additionally, we want to understand if the model changes how we think about the brain. Some interesting connections suggested by the algorithm are:

- the role of astrocytes during environmental or sensory change,
- if astrocyte synchronization alters neuronal computation, and,
- whether our algorithm's abilities map to in-vitro neuronal reservoir.

Acknowledgements and Questions

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Please reach out to learn more:

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Wolfgang Losert: `wlosert@umd.edu`

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