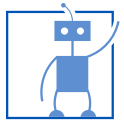


Robotics, Artificial Intelligence
and Embedded Systems

Women in Data Science

Regensburg 2022

Biologically Inspired Neuromorphic Algorithms Trained without Supervision

Negin Karimi

Technical University of Munich

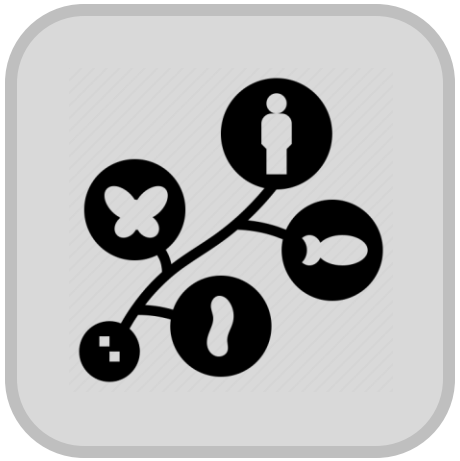
Department of Informatics

Principal Investigator: Prof. Dr.-Ing. habil. Alois Knoll

05.07.2022

Agenda

Introduction



Evolutionary Optimization

Liquid State Machines

My Background

Academic:

- Bachelor in Electrical Engineering
- Master in Robotics, Cognition, Intelligence
- PhD student since April 2021

Research:

- Project KI-ASIC: neuromorphic techniques for processing automotive radar data
- Biologically inspired Spiking Neural Network (SNN) algorithms
- Unsupervised Learning for SNNs

Neuromorphic Computing

Parallel, sparse, bio-inspired computing

- Distributed, parallel computing units
- Sparse communication between computing units
- Inspired by biological neurons
- Many global companies & research institutes involved

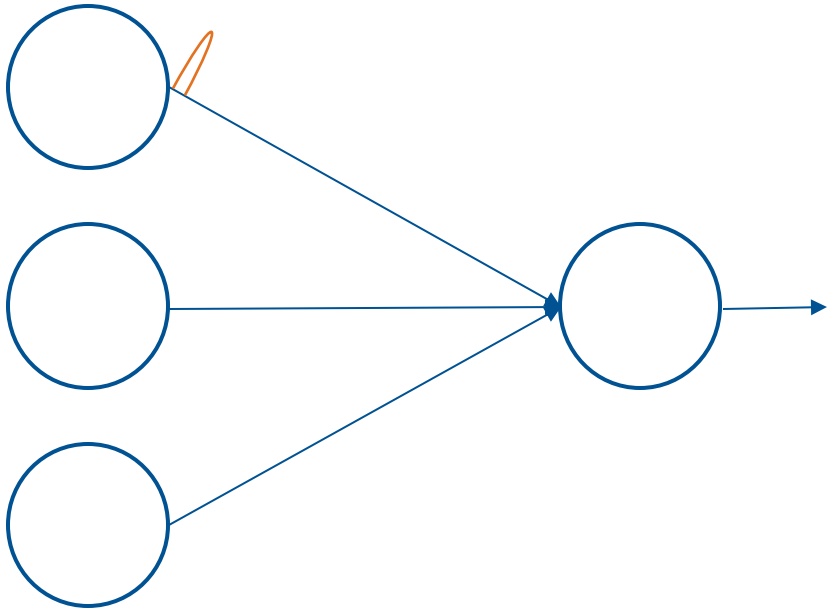
[1]

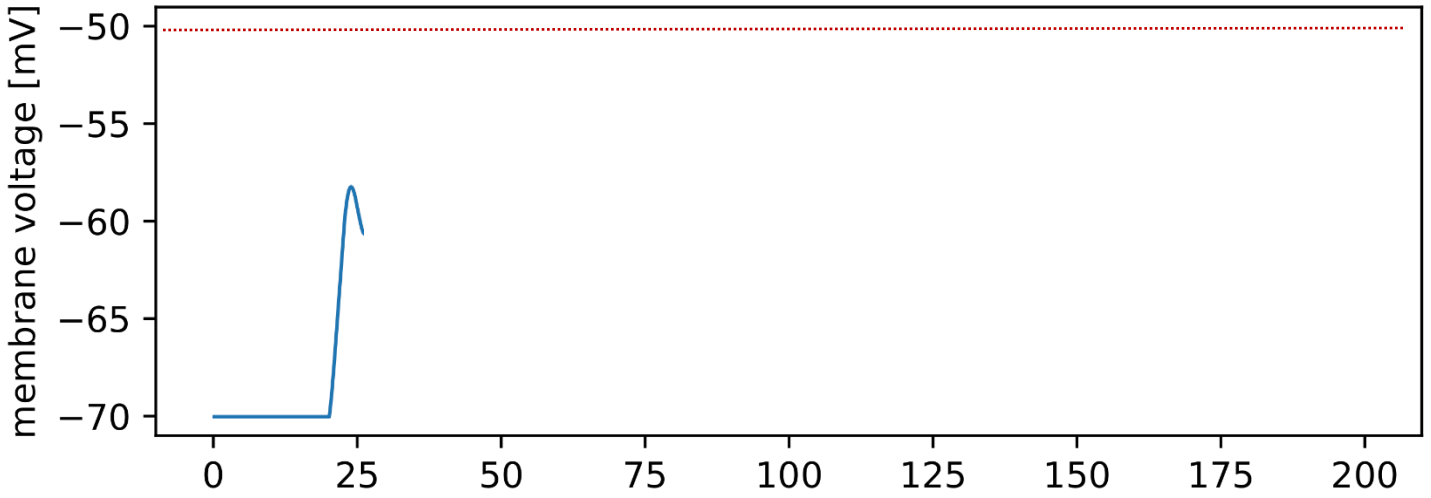
[2]

Neuromorphic Computing

Spiking neural networks (SNNs) for Neuromorphic Computing

- The “third generation” of artificial neural networks (ANNs)
- Modeled more closely after biological neurons compared to ANNs





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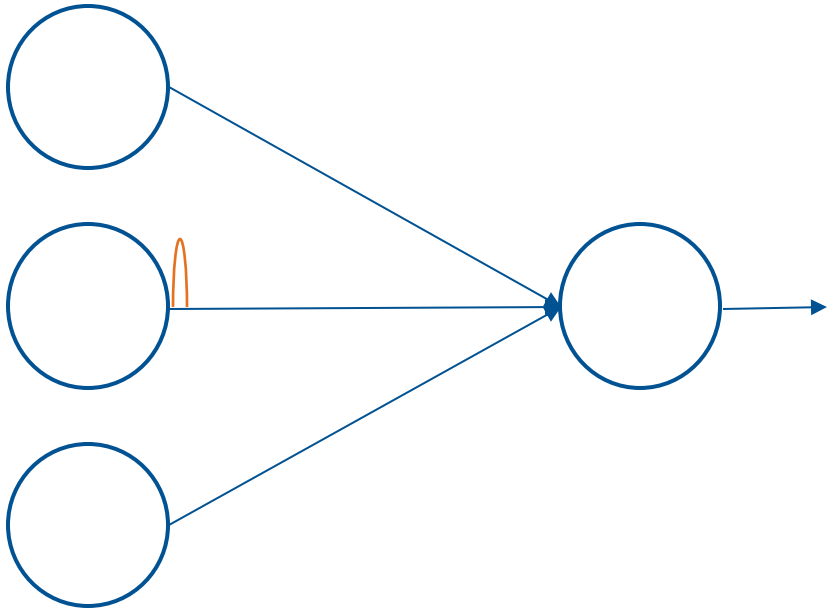

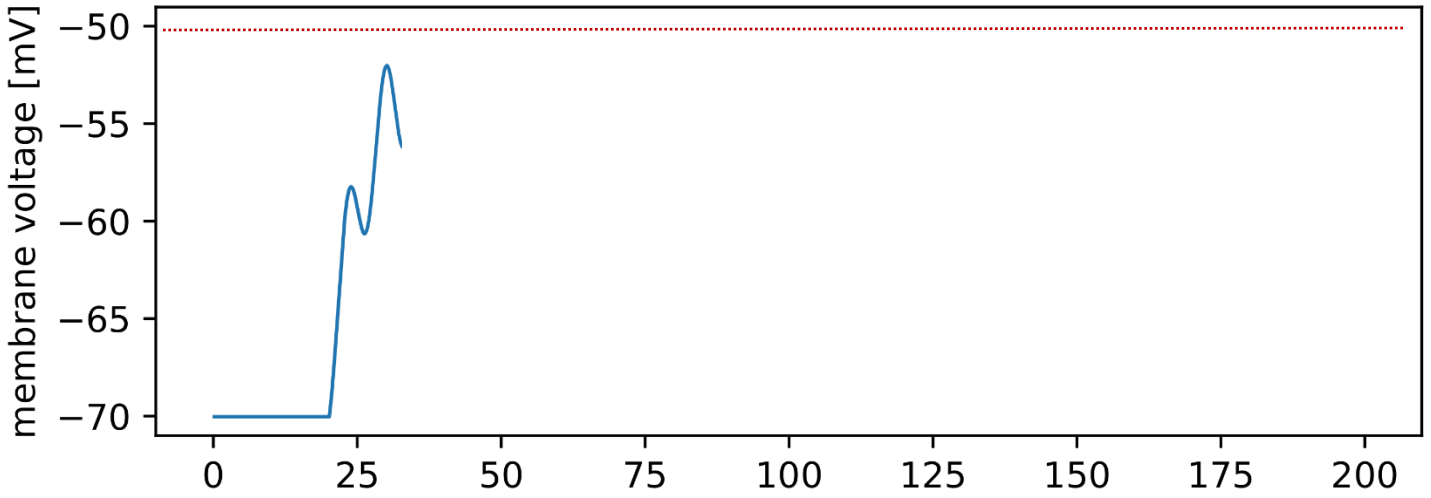

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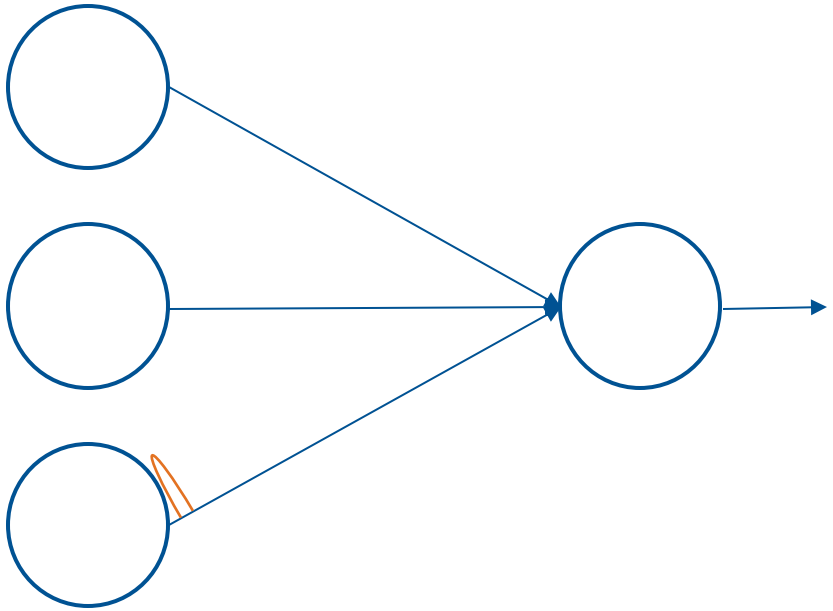

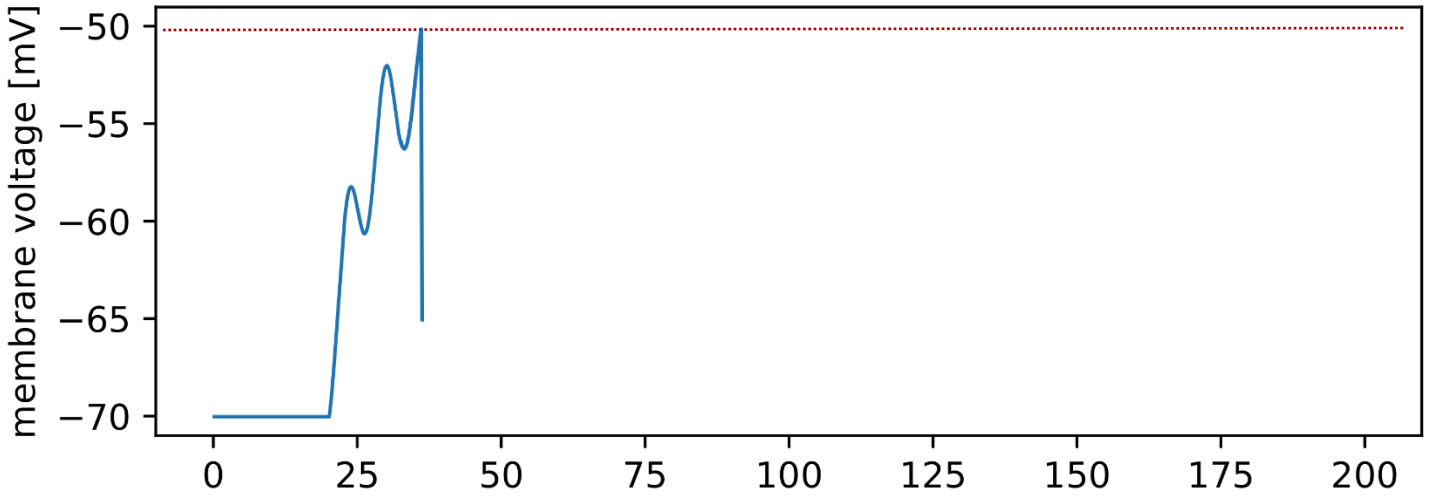

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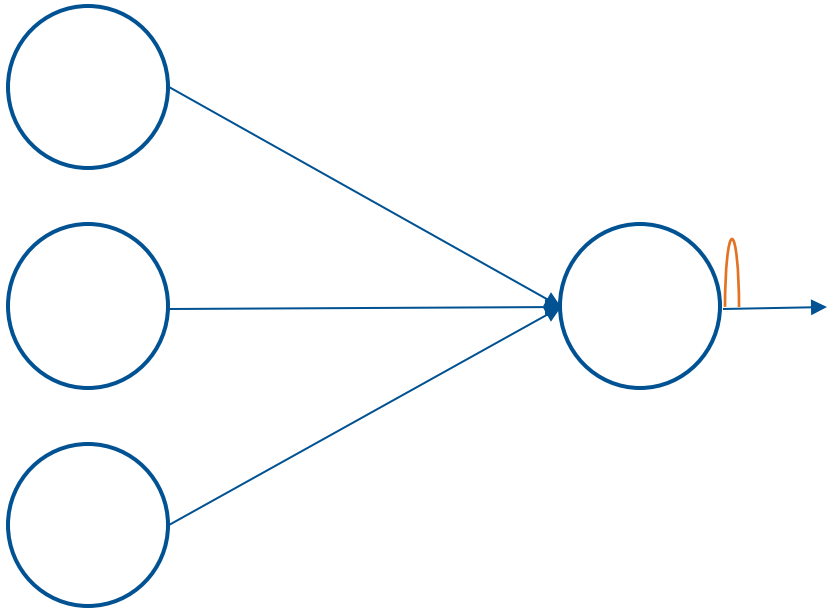

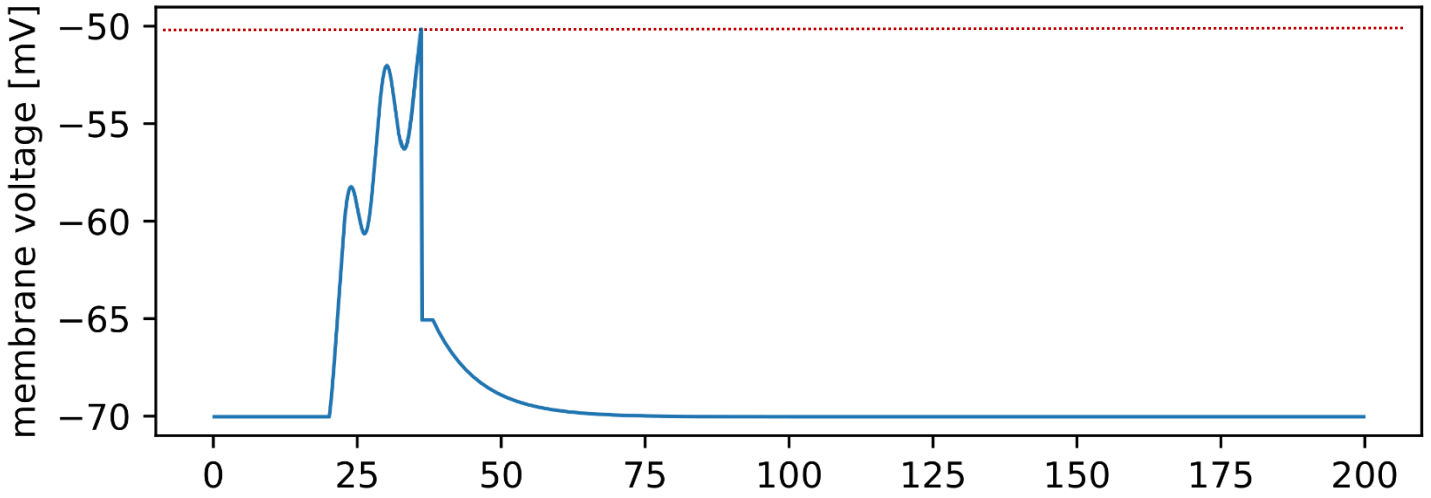

Why Spiking Neural Networks?

Elegance of Biology

[3]

Why Spiking Neural Networks?

Elegance of Biology

Low-Power

[3]

Why Spiking Neural Networks?

Elegance of Biology

Low-Power

Data, Data Everywhere

[3]

Why Spiking Neural Networks?

Elegance of Biology

Low-Power

Data, Data Everywhere

Security

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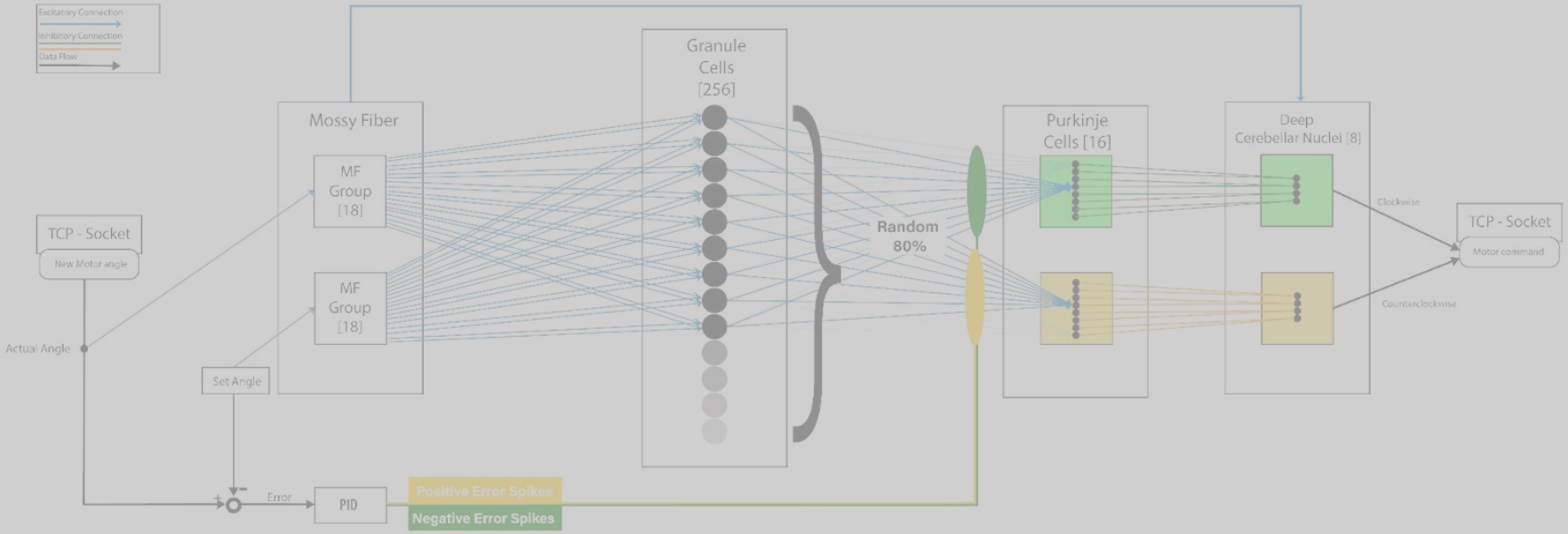
Why Unsupervised Learning?

Implementation of Cerebellar Model on Intel's Loihi



Why Unsupervised Learning?

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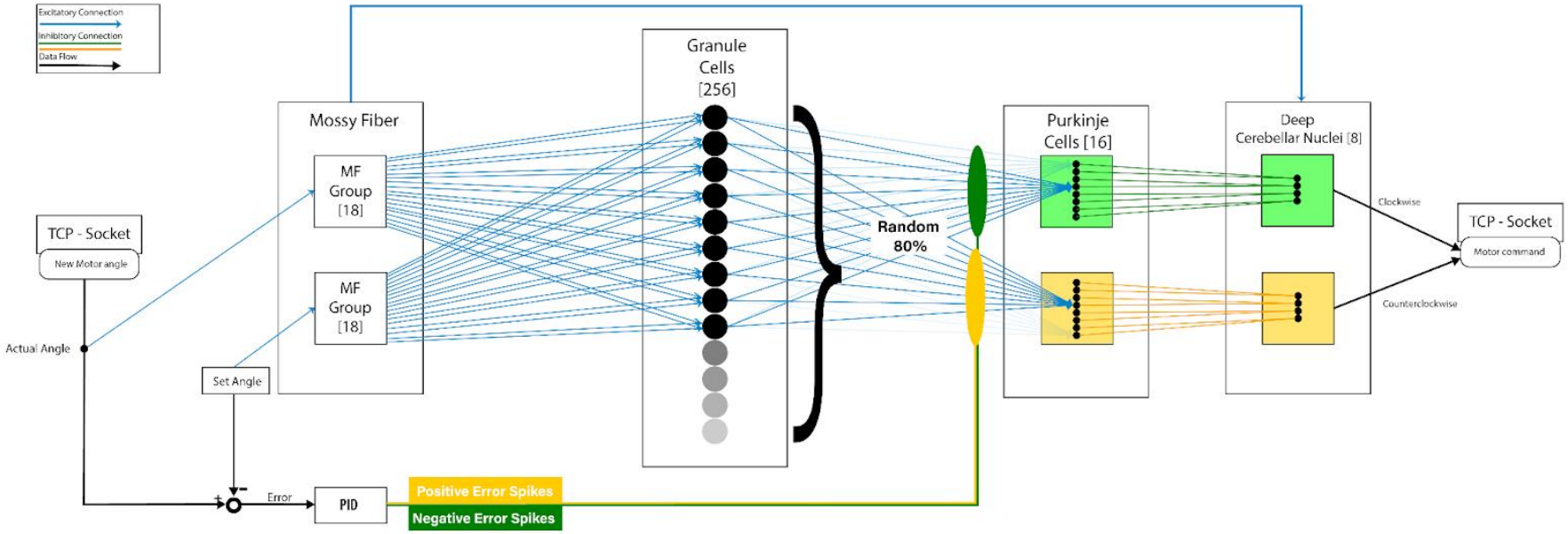
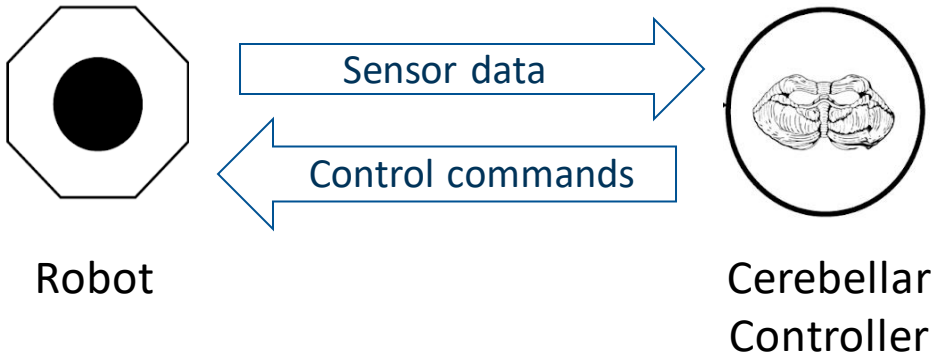


Closed Loop Cerebellar Control of a Robot



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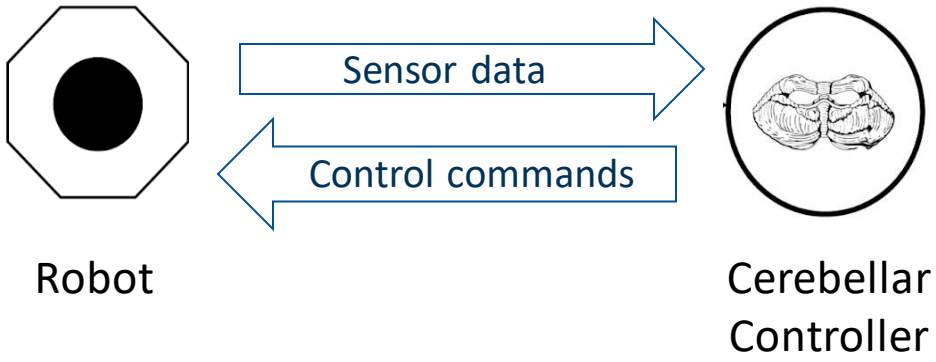
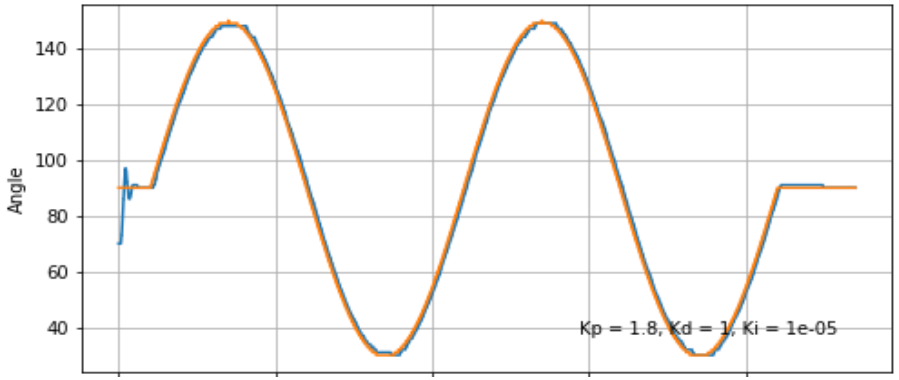
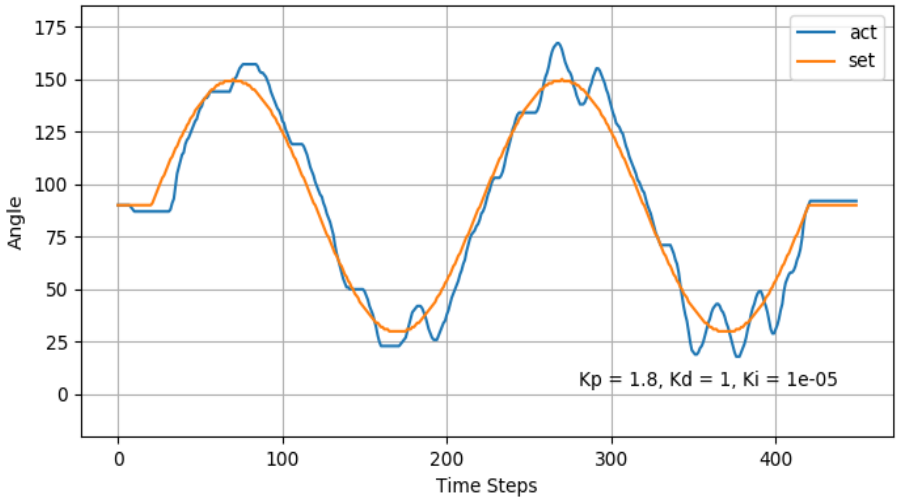


PID

Actual angle and Set motor angle



Cerebellum



Agenda

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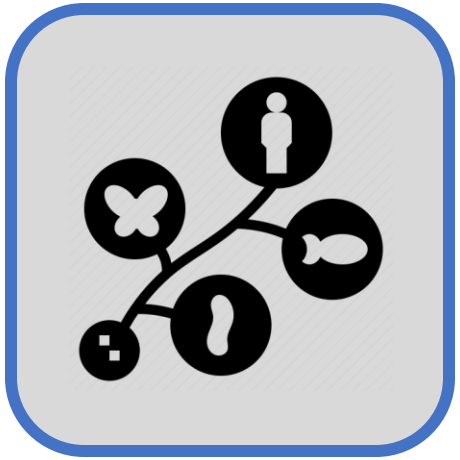


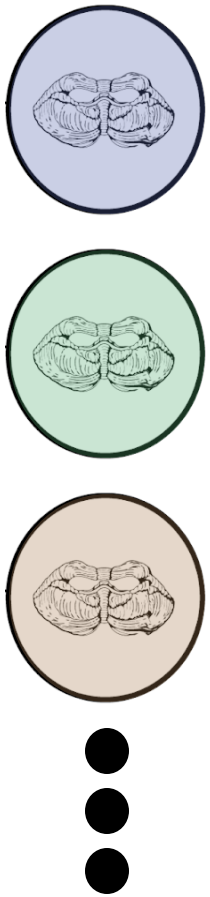
Evolutionary Optimization

Liquid State Machines

Evolutionary Optimization for SNNs

Evolutionary Optimization for SNNs

Random Initialization



Evolutionary Optimization for SNNs

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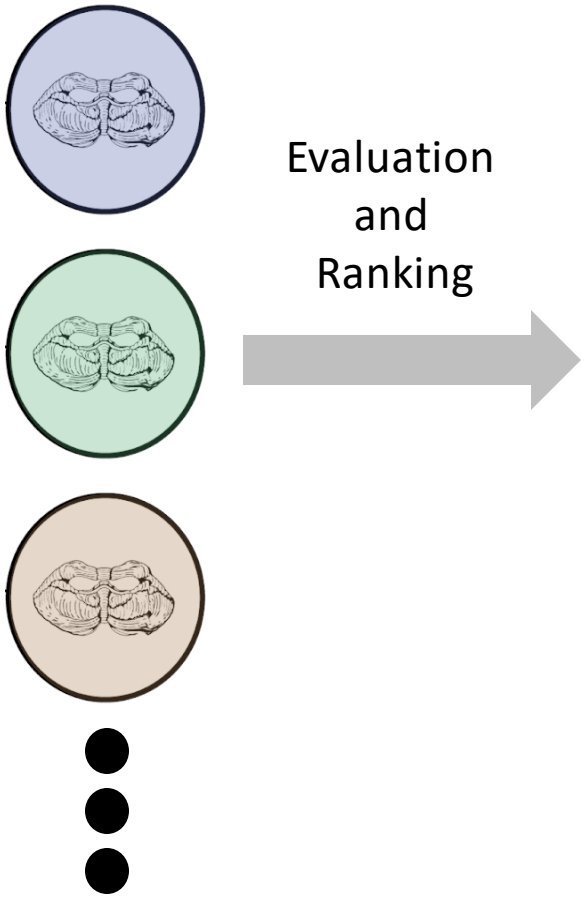
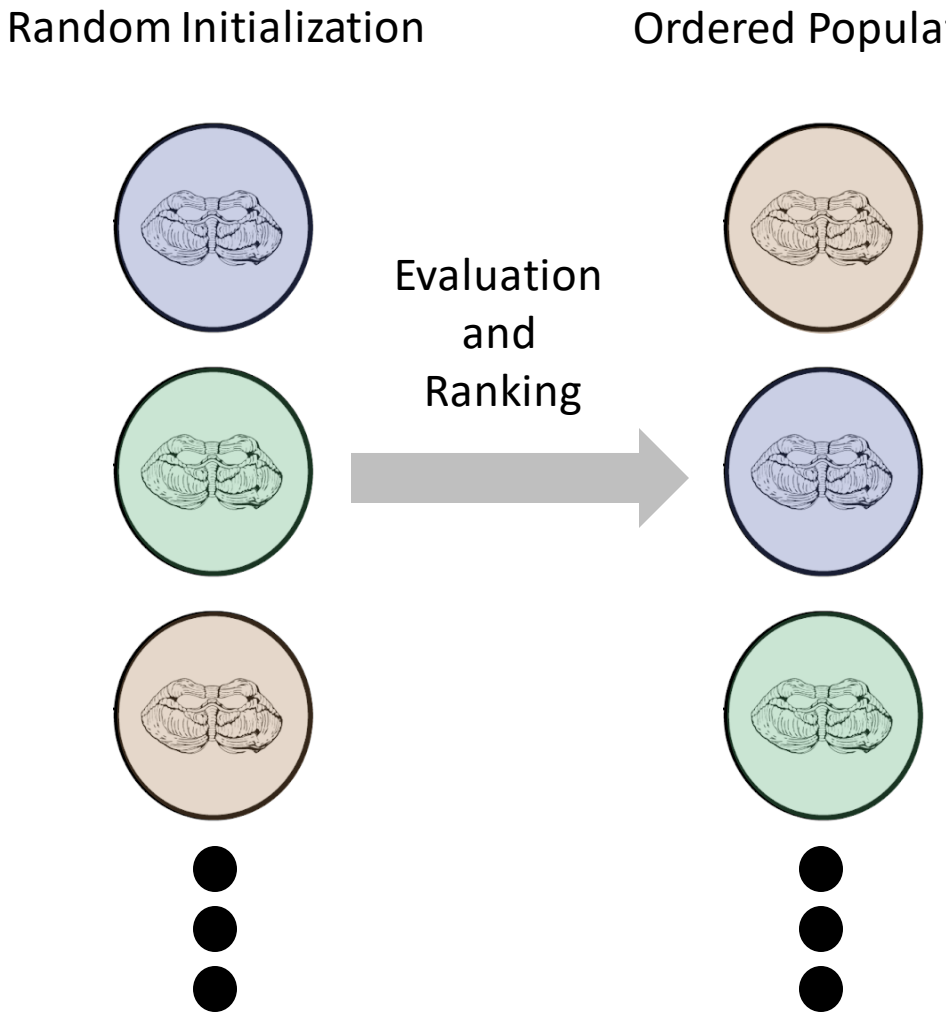


Evaluation and Ranking

Evolutionary Optimization for SNNs



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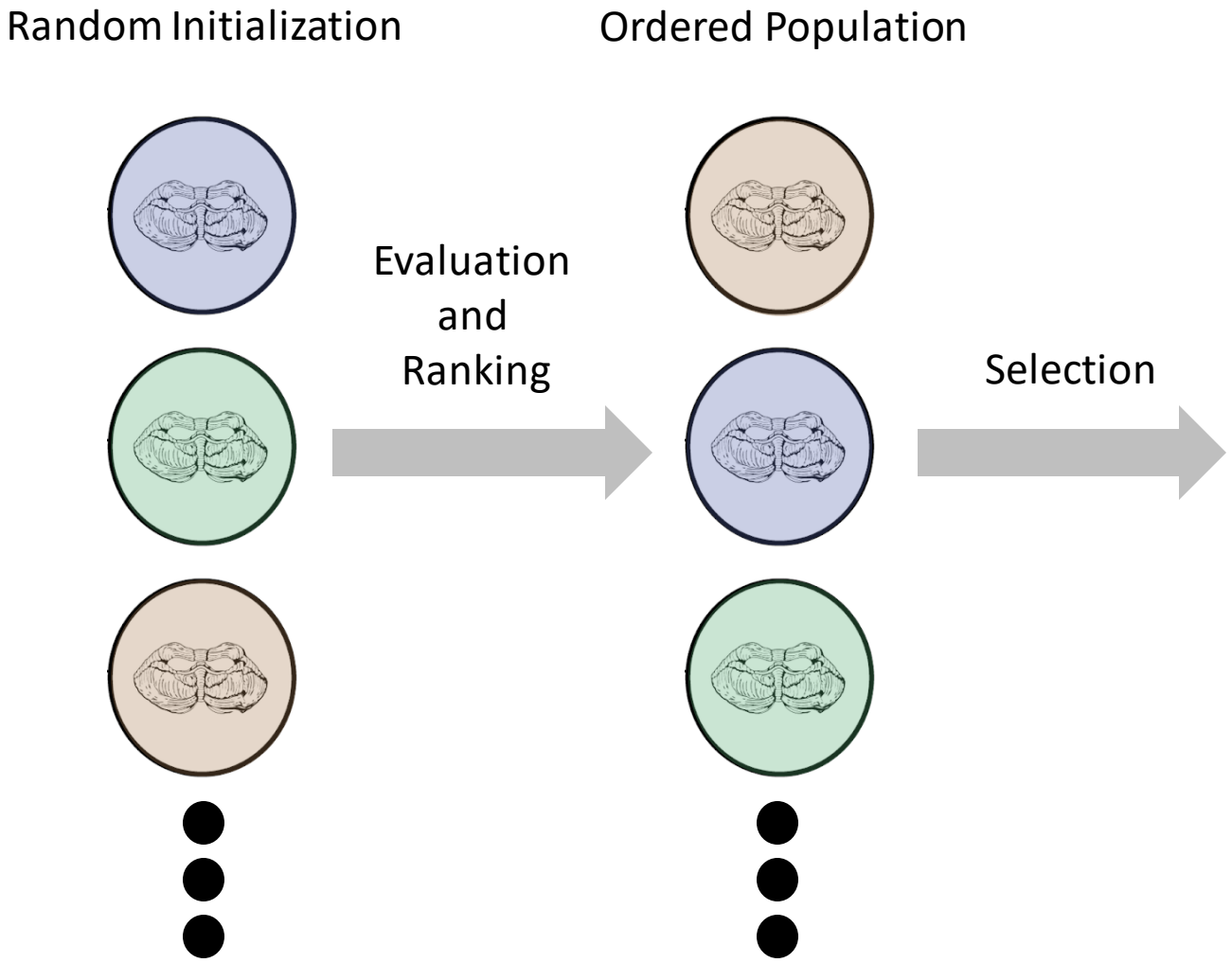

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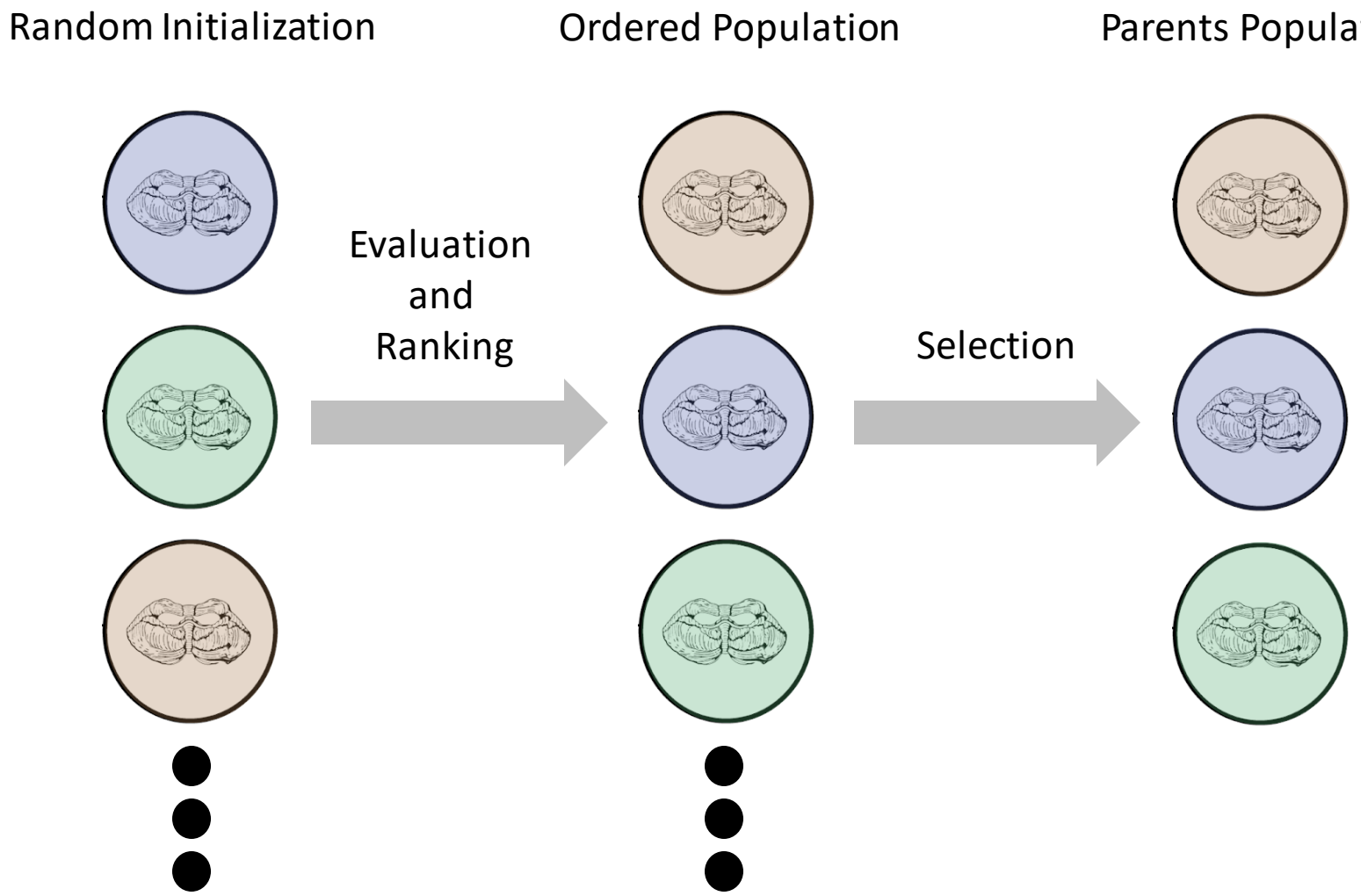

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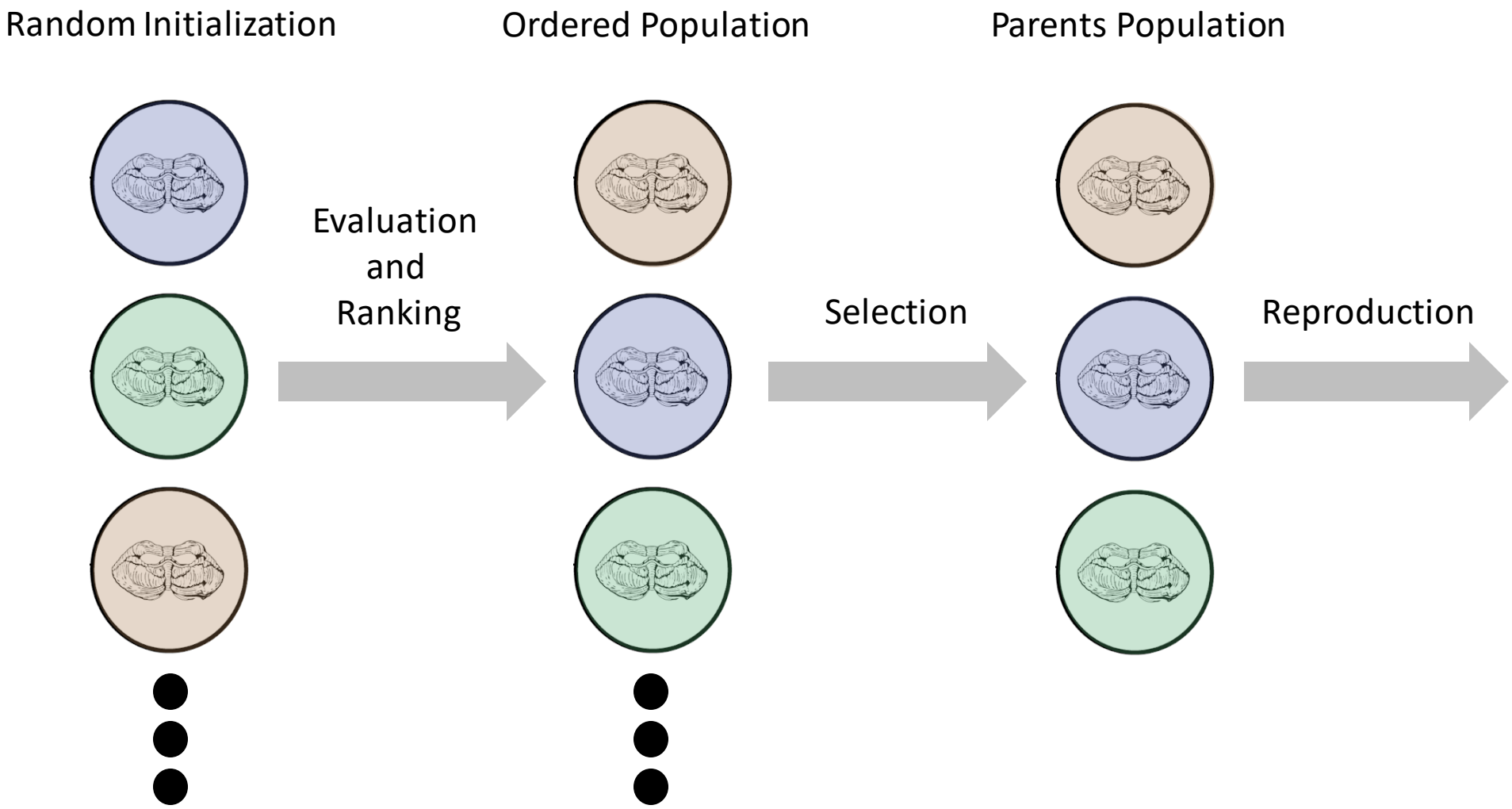

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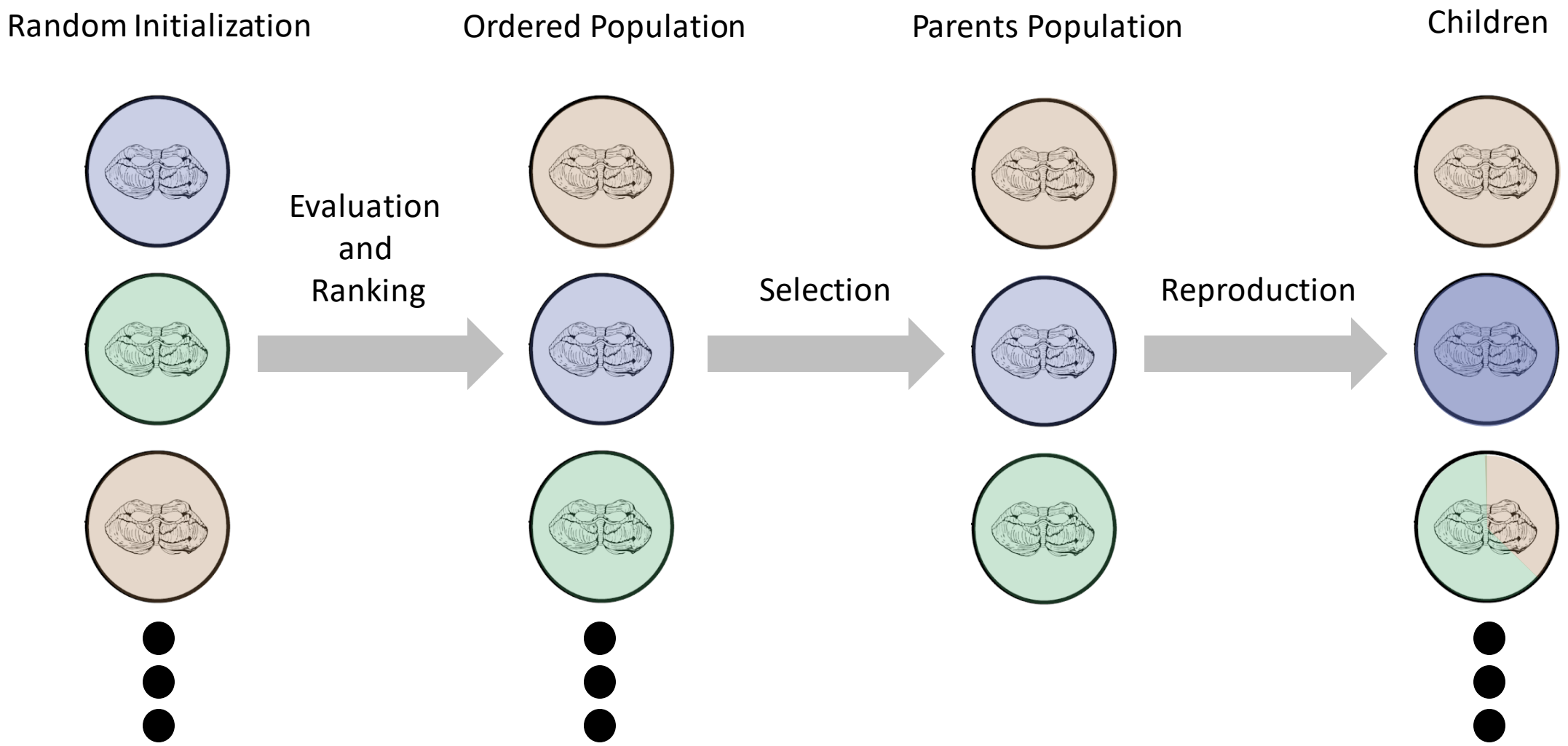


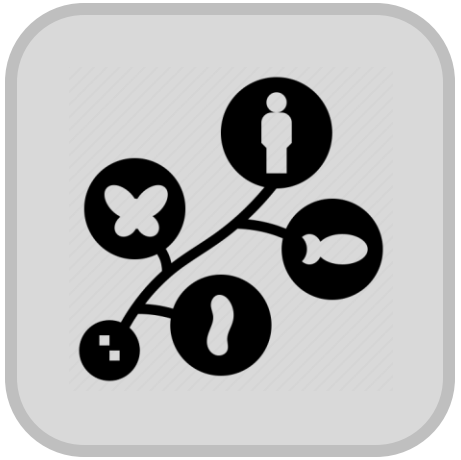
Evolutionary Optimization for SNNs

The underlying aspirations:

- Learning learning rules
- Dealing with hardware constraints
- Enhacing resilience
- Applicability to various tasks

Agenda

Introduction

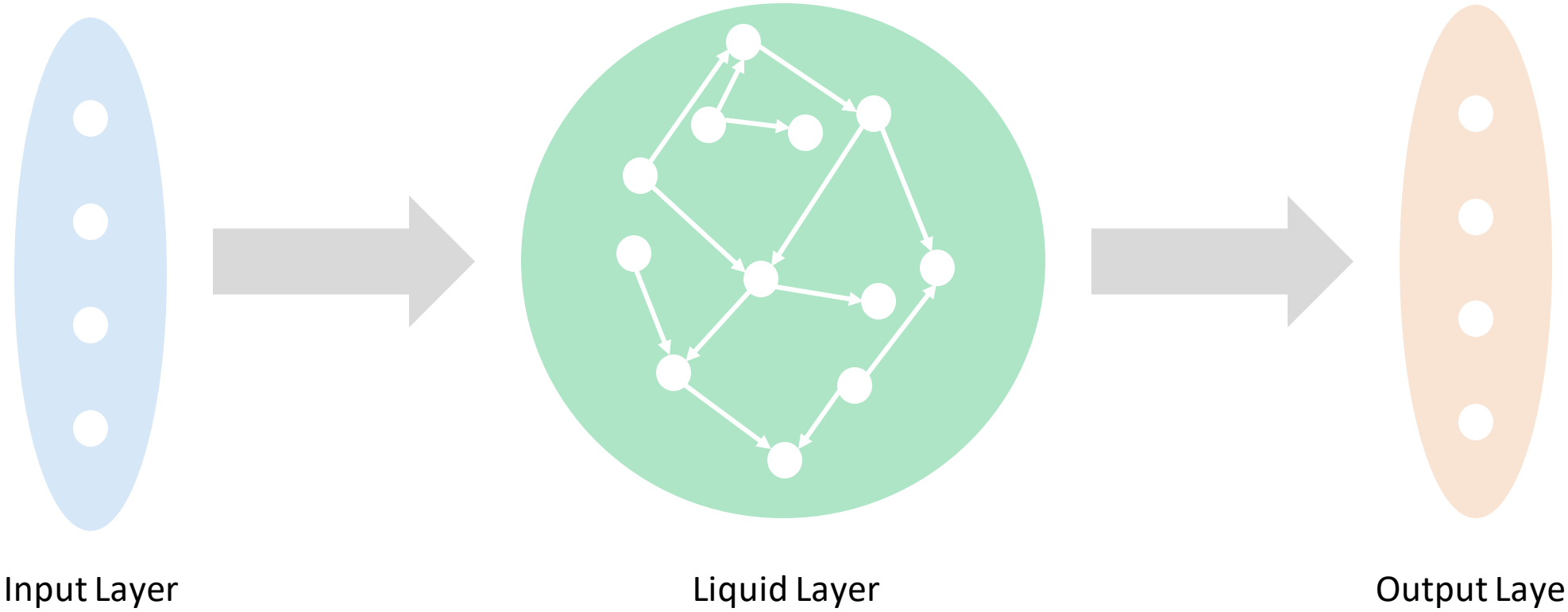


Evolutionary Optimization

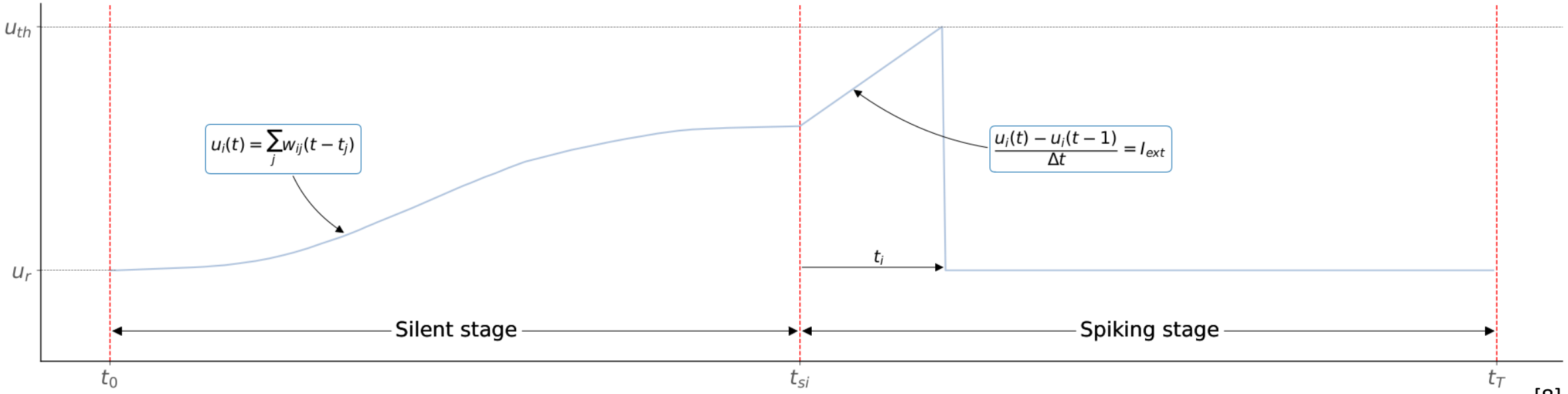
Liquid State Machines

Liquid State Machines

Reservoir Computing for SNNs



Time-to-first-spike Neuron



[8]

References

[1]	https://en.wikichip.org/w/images/thumb/8/88/loihi_kapoho_bay.png/400px-loihi_kapoho_bay.png
[2]	https://www.researchgate.net/profile/Cameron-Patterson-4/publication/262493829/figure/fig1/AS:216473378267140@1428622683327/A-48-chip-SpiNNaker-board-228-233-mm-the-building-block-from-which-larger-systems.png
[3]	https://commons.wikimedia.org/wiki/File:Bee-apis.jpg; https://blog.westerndigital.com/wp-content/uploads/2019/12/top_iot_use_cases_featured.jpg; https://www.scinexx.de/wp-content/uploads/t/u/turbolerng.jpg; https://cdn.pixabay.com/photo/2018/05/14/16/25/cyber-security-3400657_1280.jpg
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[5]	J. López-Randulfe et al., "Spiking Neural Network for Fourier Transform and Object Detection for Automotive Radar," Frontiers in Neurorobotics, vol. 15, 2021, Accessed: Apr. 22, 2022
[6]	D. Floreano, P. Dürr, and C. Mattiussi. 2008. Neuroevolution: from architectures to learning. Evolutionary intelligence 1, 47–62.
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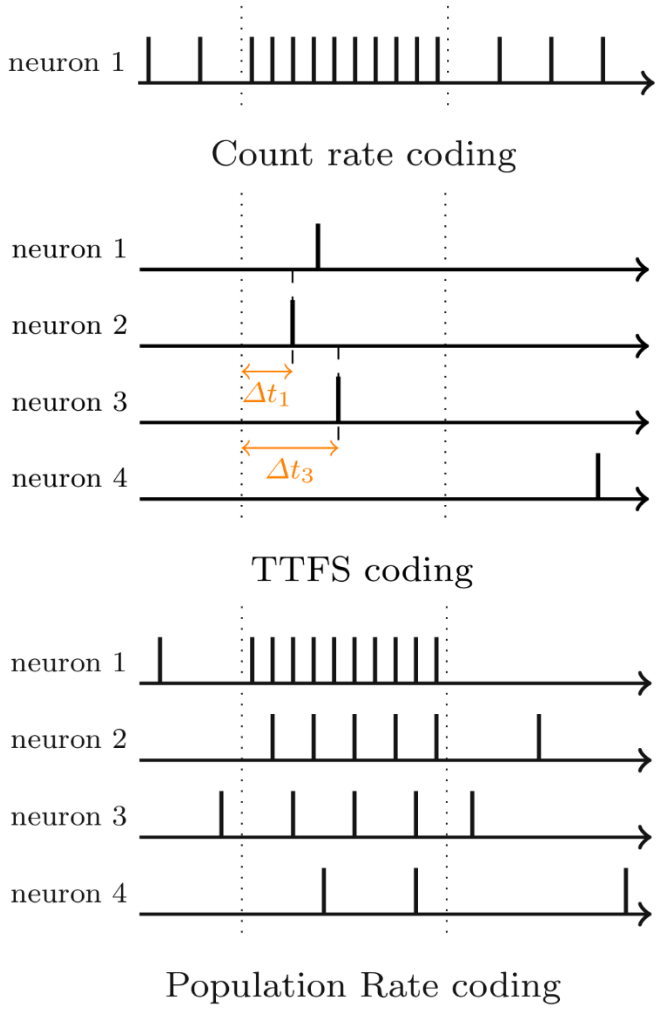
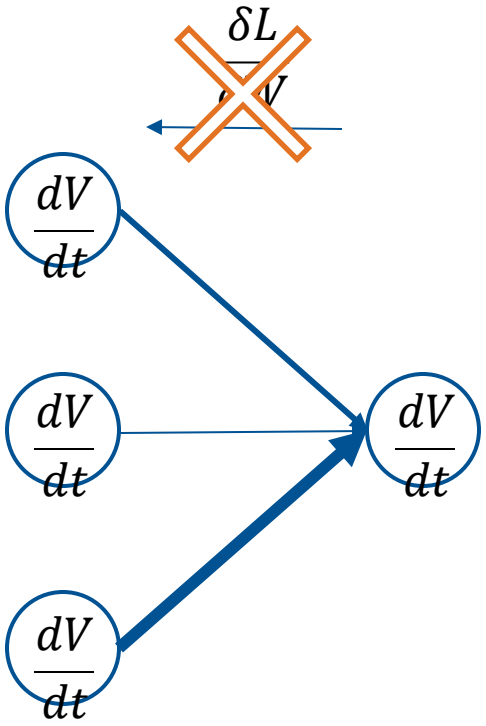
Neuromorphic Computing – Next Gen. AI

Modeling principles of SNNs

1. Encoding/decoding of the data
   - ➢ Rate, temporal and population code
   - ➢ Accuracy ↔ energy efficiency
2. Neuron model
   - ➢ Differential equation for voltage
3. Synaptic model
   - ➢ Weights, delays
4. Training algorithm
   - ➢ Classic backpropagation does not work
   - ➢ Bio. Inspired Hebbian learning, conversion of ANNs, surrogate gradients





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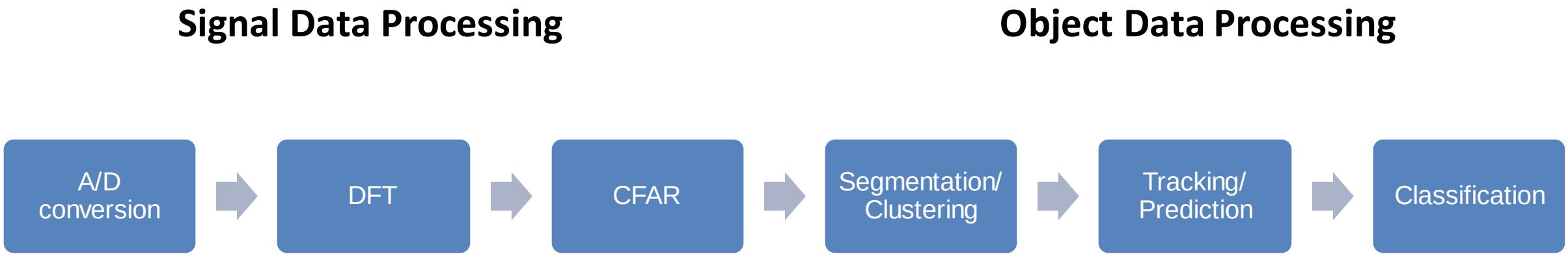
The KI-ASIC Project

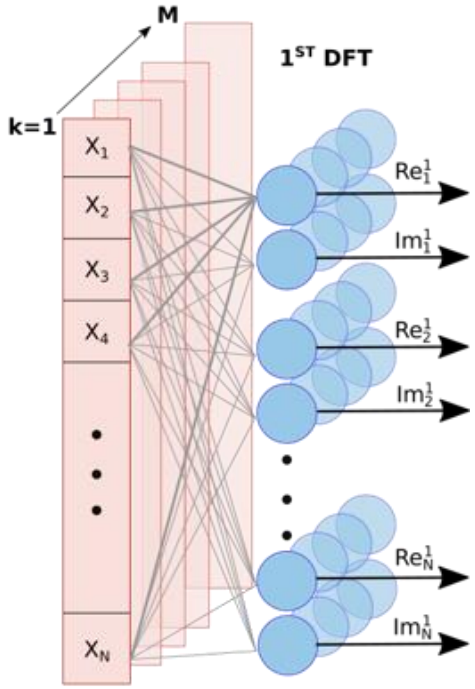
- Funded by the German Ministry of Education and Research (BMBF)
- Implementation and evaluation of a full neuromorphic RADAR processing chain
- One of the first real-world implementations of SNNs on neuromorphic hardware

RADAR Processing Chain



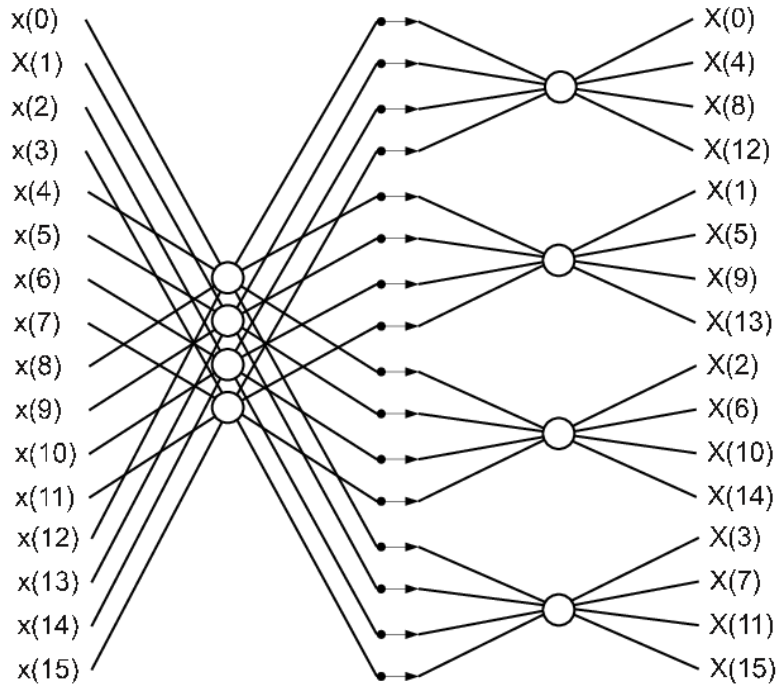
Spiking FT architecture

DFT



- All-to-all connections
- One layer

Radix-4 FFT



- 8 connections per neuron
- Multiple layers

Spiking FT architecture