Deep Reinforcement Learning with Spiking Neural Network for Robot Navigation and Continuous Control

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2021 Intel INRC Winter Workshop

Loihi-run robot applications at ComBra Lab

Neuromorphic SLAM

Artificial Intelligence

Automatic Driving

Disaster Rescue

Computer V

ogical Intelligence

(1D SLAM, IROS 2019)

(2D Mapping, NICE 2020)

Spiking Locomotion Control

(Spiking CPG, ICONS 2020)

(Oculomotor, BioRob 2020)*

Pros:

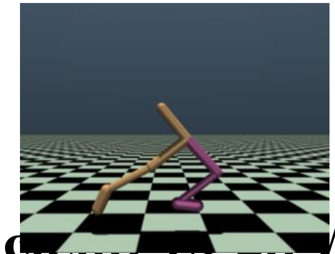
1. Fast IO and computation.
2. Consistent in repetitive and specialized tasks.

Cons:

1. **Costs a lot of energy.**
2. Lacks robustness and versatility.

Spiking Reinforcement Learning

(Navigation, IROS 2020)



(Cont. Control, CoRL 2020)

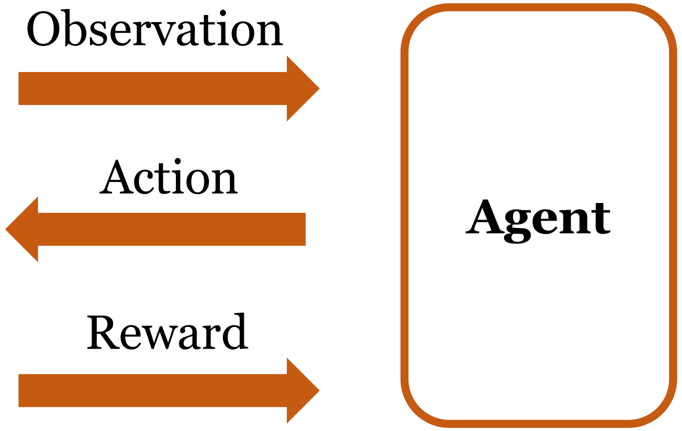
s:

1. **Energy effic Watts)**
2. Robust and versatile.

** Loihi version to be published*

Robot Planning and Control with Reinforcement Learning

Robot Interacting With Environment



Maximize Cumulative Reward

Observation: LiDAR, Point Clouds, IMU, Tactile ...

Action: Wheel Velocity, Joint Force, Decision ...

Reward: Goal Reaching, Collision, Moving Speed, ...

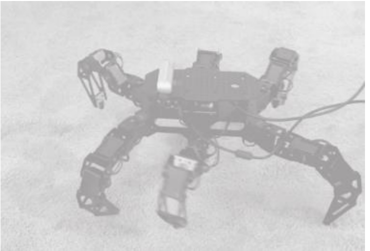
Loihi-run robot applications at ComBra Lab

Neuromorphic SLAM

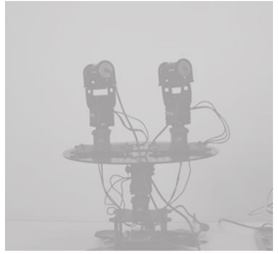
(1D SLAM, IROS 2019)

(2D Mapping, NICE 2020)

Spiking Locomotion Control



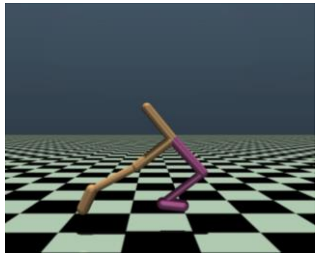
(Spiking CPG, ICONS 2020)



(Oculomotor, BioRob 2020)*

Spiking Reinforcement Learning

(Navigation, IROS 2020)



(Cont. Control, CoRL 2020)

** Loihi version to be published*

Reinforcement co-Learning for Mapless Navigation

Hybrid Training with SDDPG

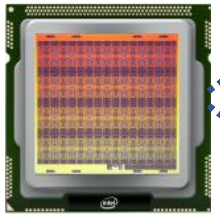
Deep Critic Network ⇄ Spiking Actor Network

- DNN and SNN are trained jointly using gradient descent
- Hybrid training allows DNN and SNN to overcome each other's limitations through a shared representation learning

Energy-Efficient Mapless Navigation

Observations

In



Intel's Loihi

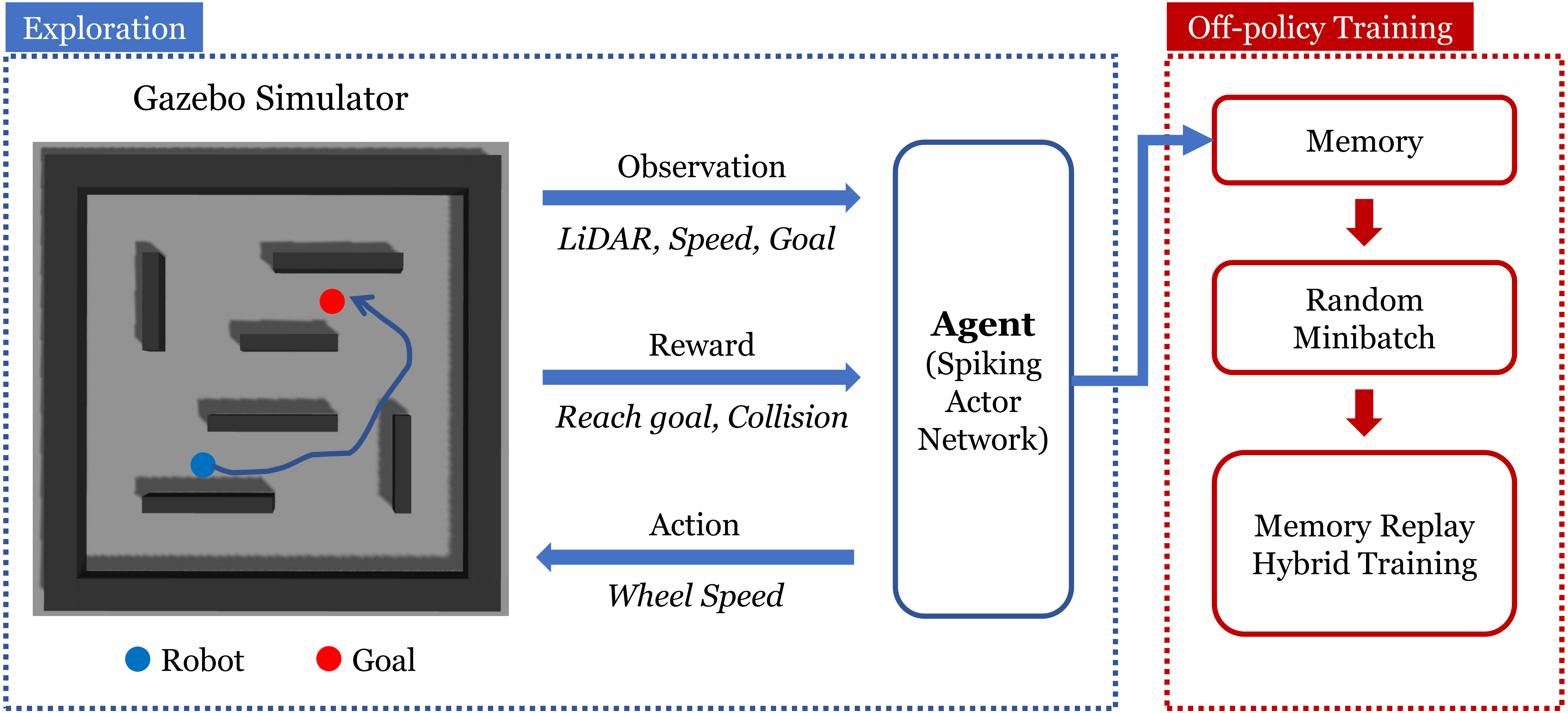
Out

Differential Wheel Speed

Control robot toward goals with obstacle avoidance

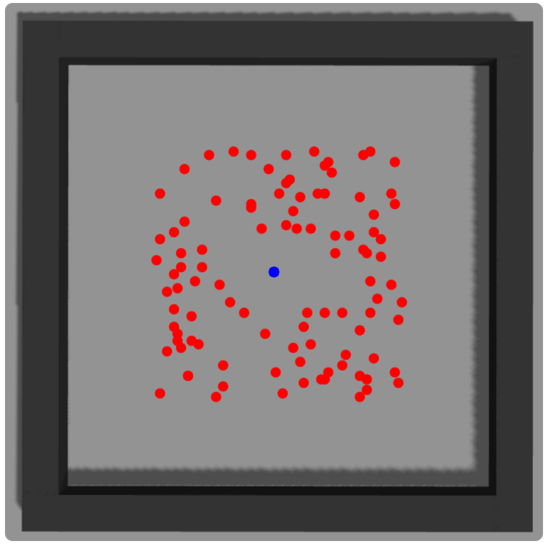
Guangzhi Tang, et al. "Reinforcement co-Learning of Deep and Spiking Neural Networks for Energy-Efficient Mapless Navigation with Neuromorphic Hardware." IROS 2020

Overview of Mapless Navigation Training

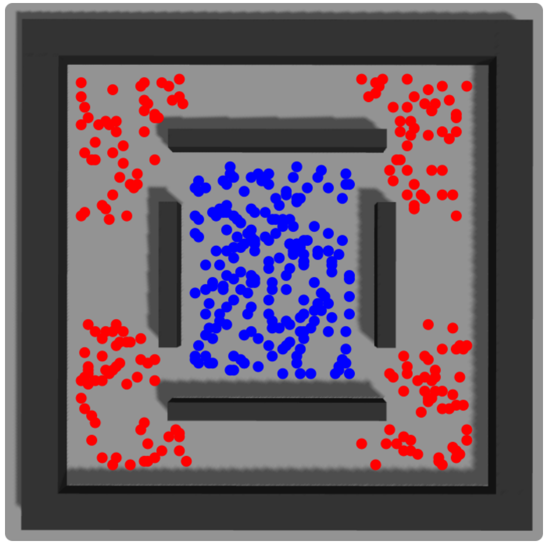


Curriculum Learning: Train from easy to hard

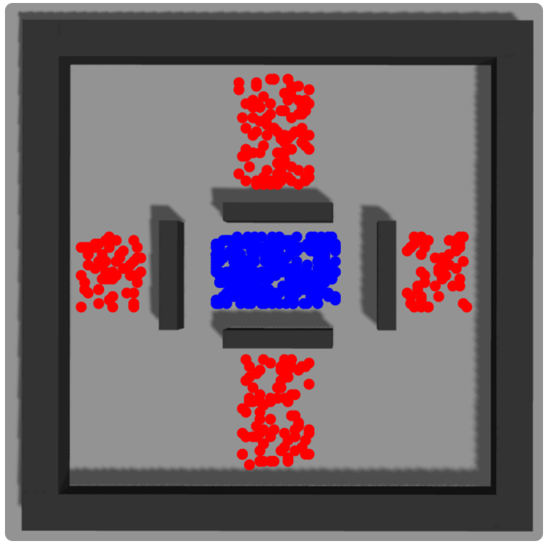
(Easy) Train Sequentially with Random Start-Goal Pairs (Hard)



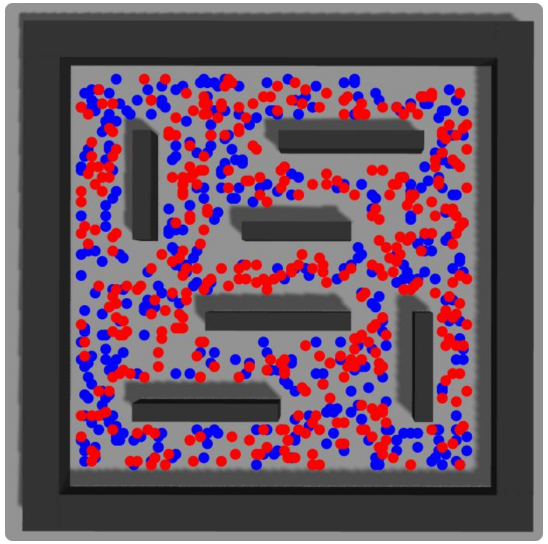
Free Path



Partially Block Path

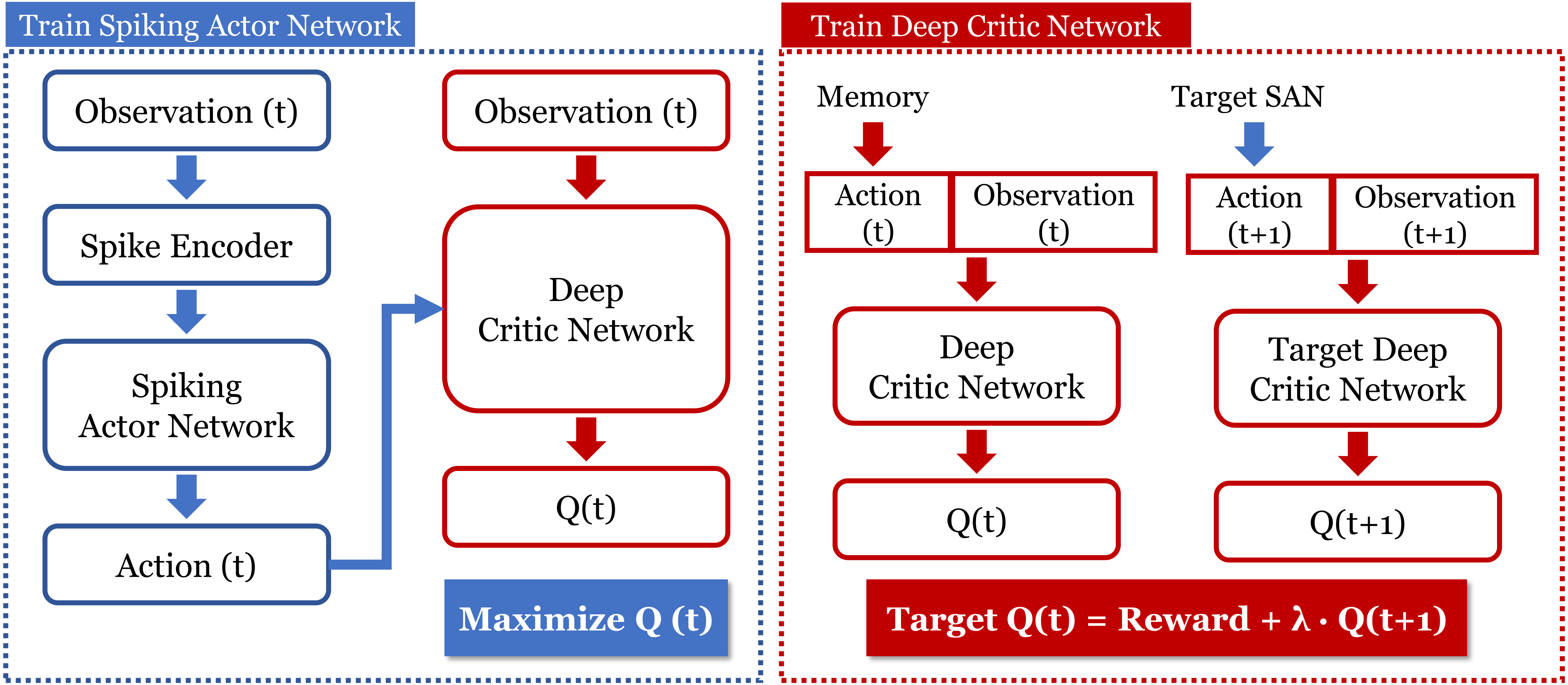


Fully Block Path

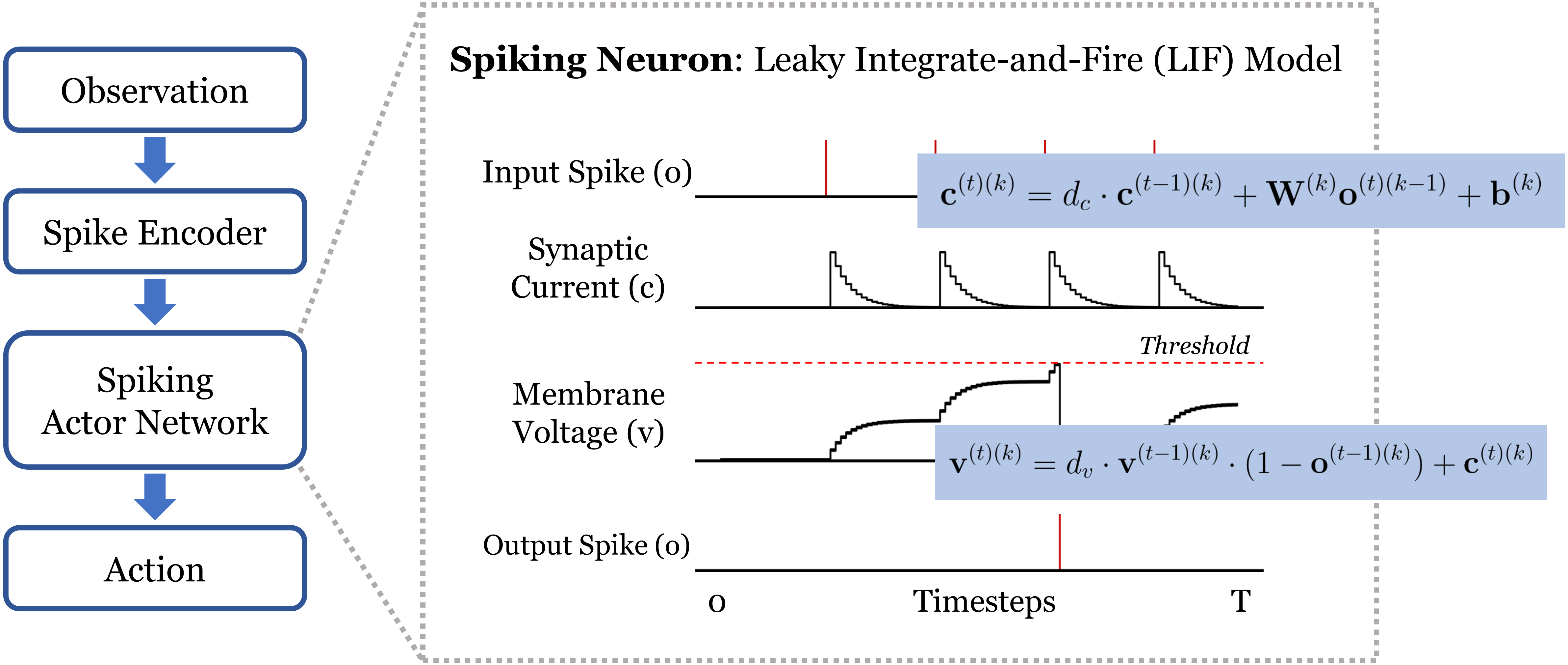


Everything Combined

SDDPG: Spiking Deep Deterministic Policy Gradient

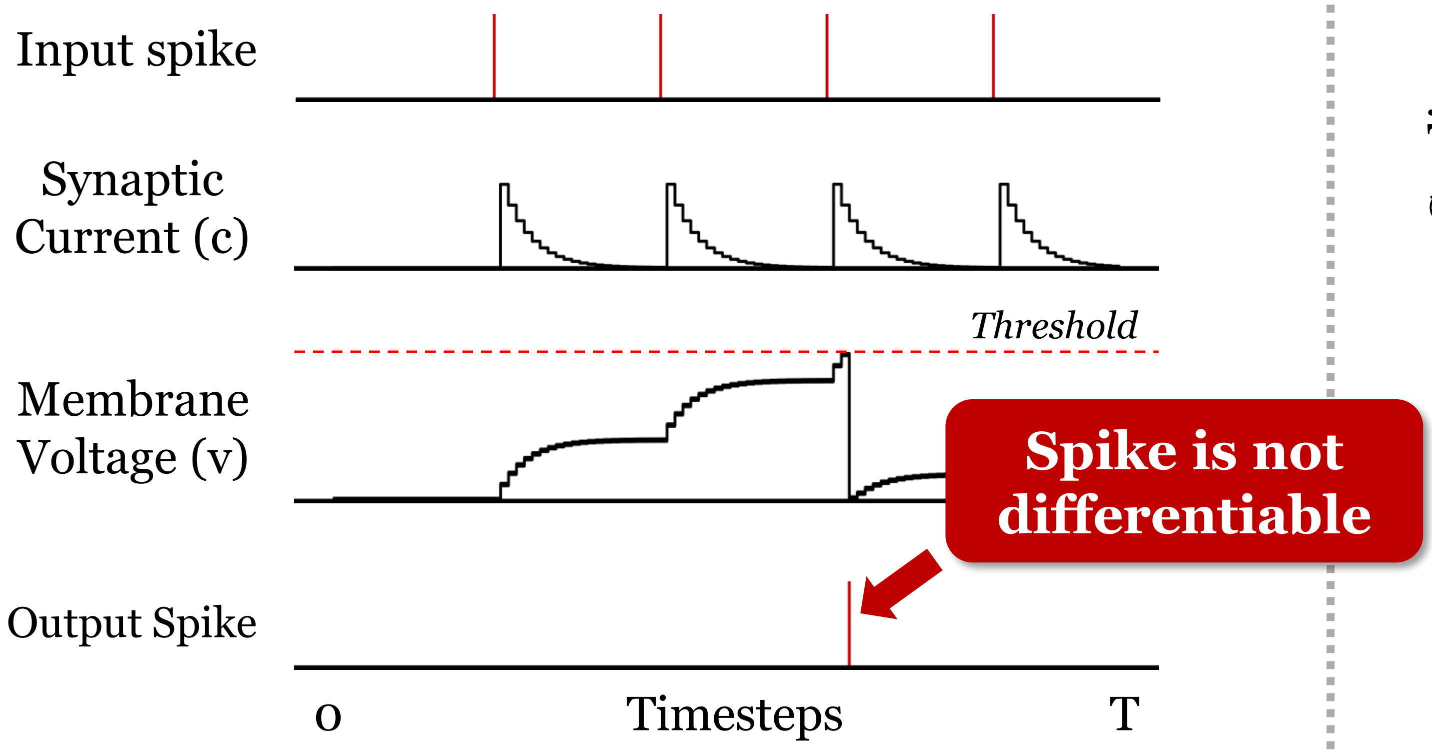


Spiking Actor Network: Forward Propagation

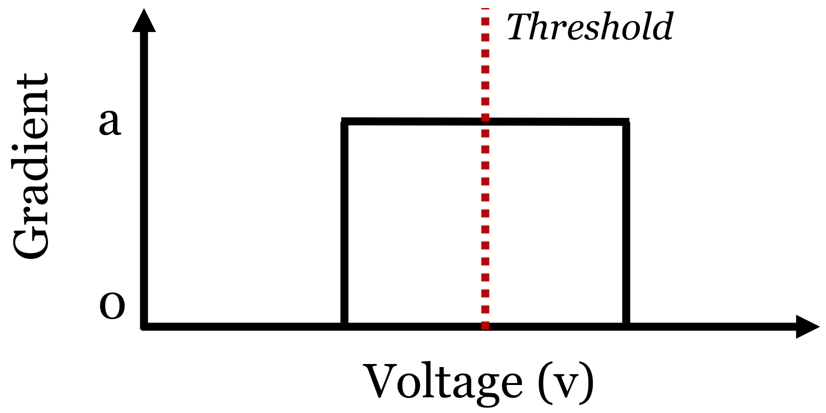


Spiking Actor Network: Backward Propagation

Spiking Neuron: Leaky Integrate-and-Fire (LIF) Model



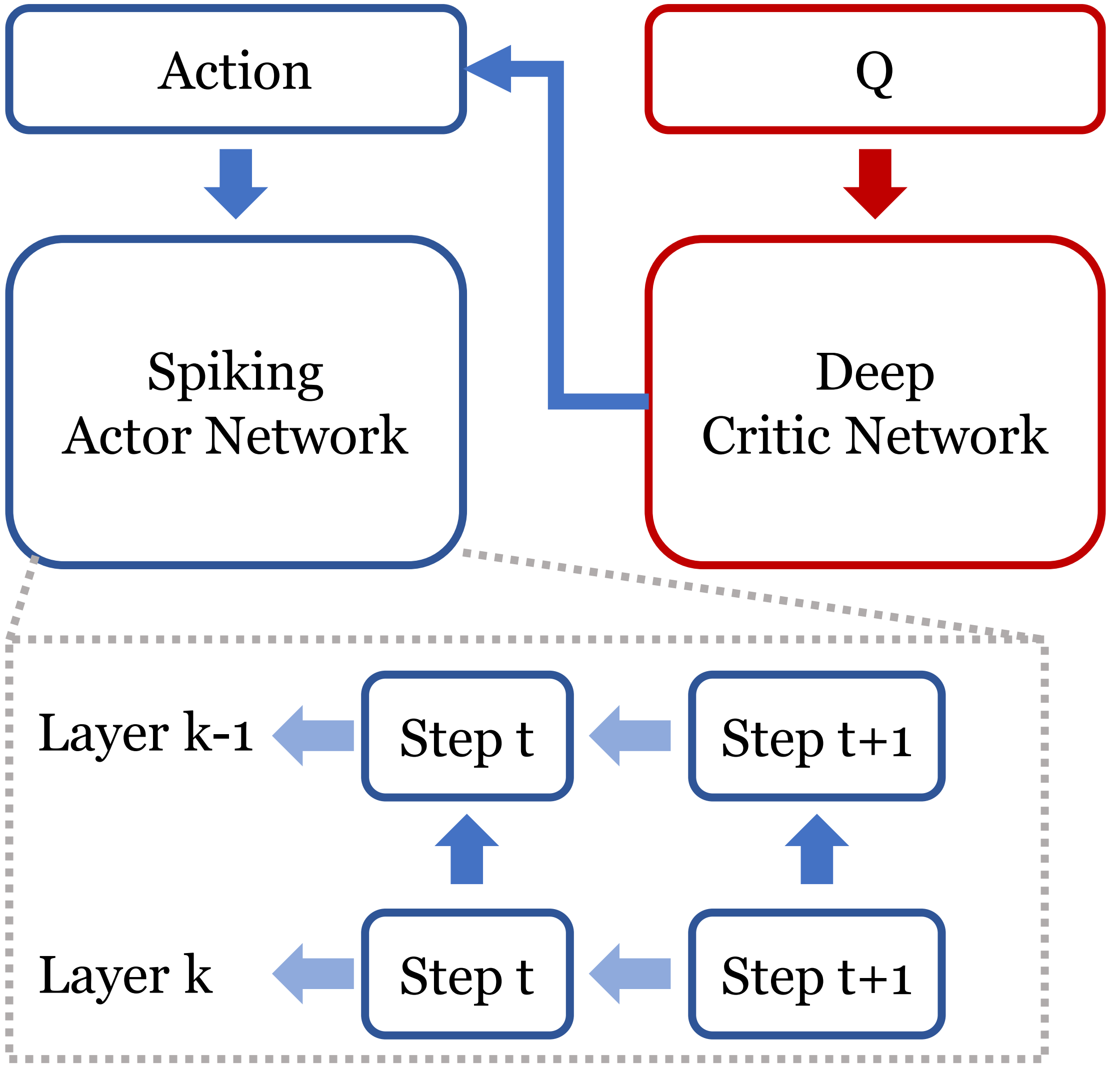
Approximate the gradient of a spike



Rectangular function

$z\left(\mathbf{v}^{(t)(k)}\right)$

Spiking Actor Network: Backward Propagation



Maximize action value Q with loss function:

$$L = -Q$$

Gradient propagates through critic network:

$$\nabla_{\mathbf{Action}} L = \mathbf{W}_c^{(n+1)'} \cdot \nabla_{a^{(n+1)}} L$$

Spatial and temporal gradients of spiking neurons:

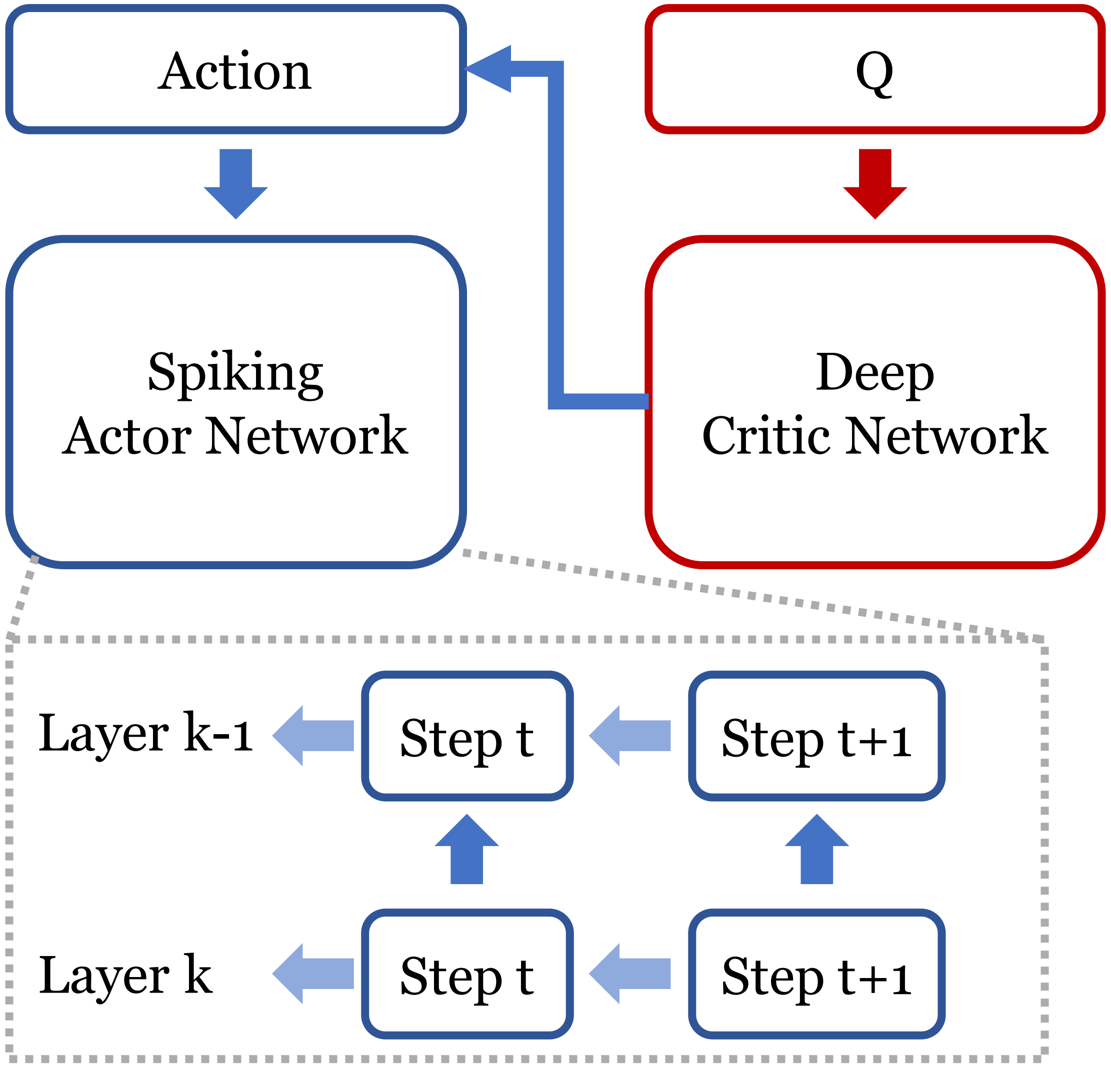
$$\nabla_{\mathbf{v}^{(t)(k)}} L = \overbrace{z(\mathbf{v}^{(t)(k)}) \cdot \nabla_{\mathbf{o}^{(t)(k)}} L}^{Spatial} + \overbrace{d_v(1 - \mathbf{o}^{(t)(k)}) \cdot \nabla_{\mathbf{v}^{(t+1)(k)}} L}^{Temporal}$$

$$\nabla_{\mathbf{c}^{(t)(k)}} L = \overbrace{\nabla_{\mathbf{v}^{(t+1)(k)}} L}^{Spatial} + \overbrace{d_c \nabla_{\mathbf{c}^{(t+1)(k)}} L}^{Temporal}$$

$$\nabla_{\mathbf{o}^{(t)(k-1)}} L = \mathbf{W}^{(k)'} \cdot \nabla_{\mathbf{c}^{(t)(k)}} L$$

Propagate gradient to presynaptic layer

Spiking Actor Network: Backward Propagation



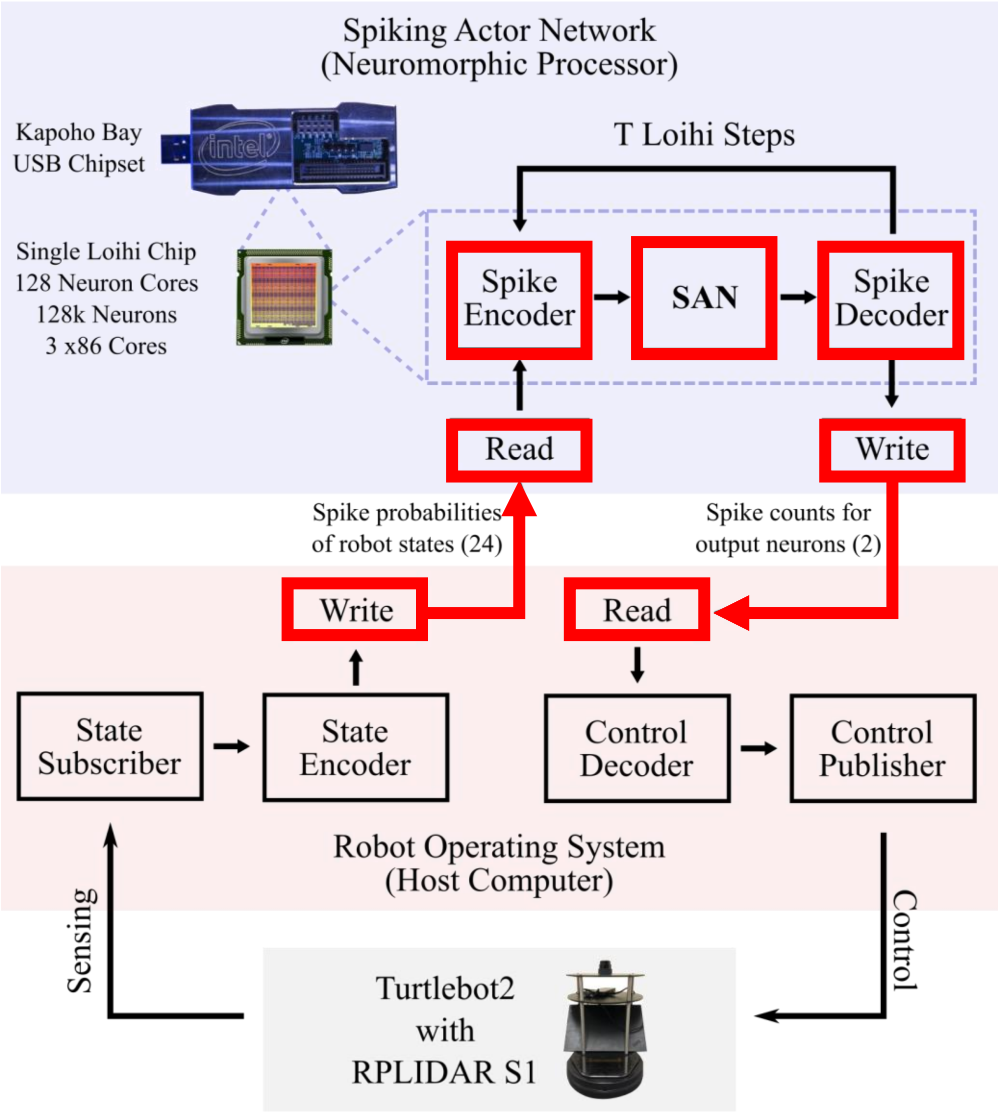
Combining gradients from all timesteps and update weights and biases:

$$\nabla_{\mathbf{W}^{(k)}} L = \sum_{t=1}^{T} \mathbf{o}^{(t)(k-1)} \cdot \nabla_{\mathbf{c}^{(t)(k)}} L$$

$$\nabla_{\mathbf{b}^{(k)}} L = \sum_{t=1}^{T} \nabla_{\mathbf{c}^{(t)(k)}} L$$

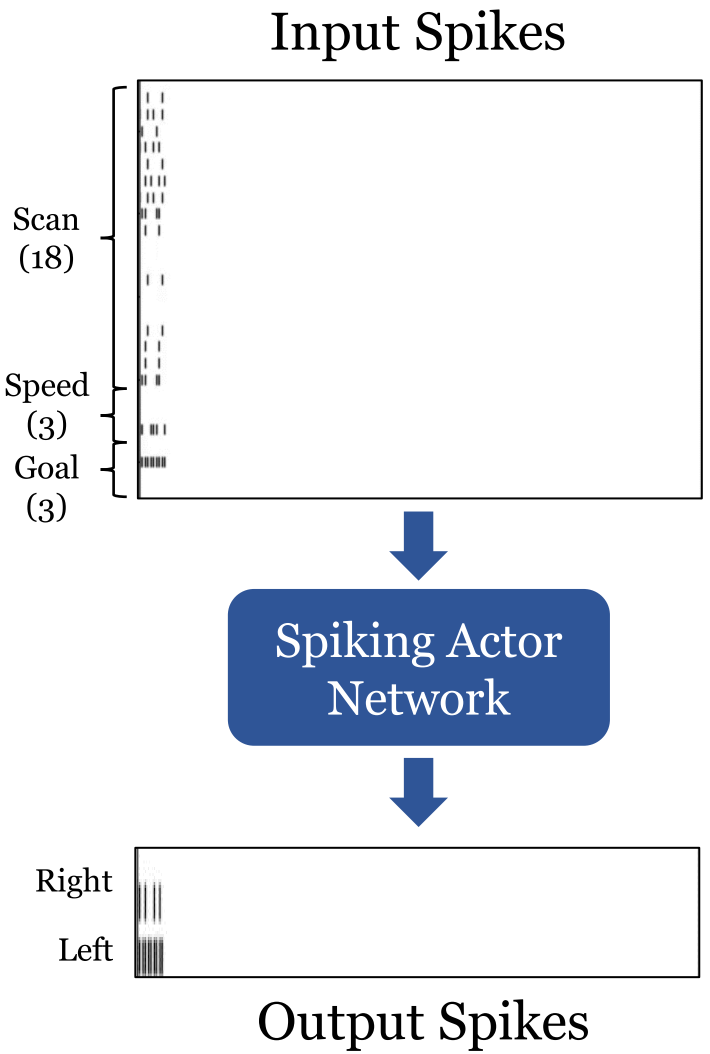
Update network parameters every T timesteps

Realization on Loihi Neuromorphic Processor

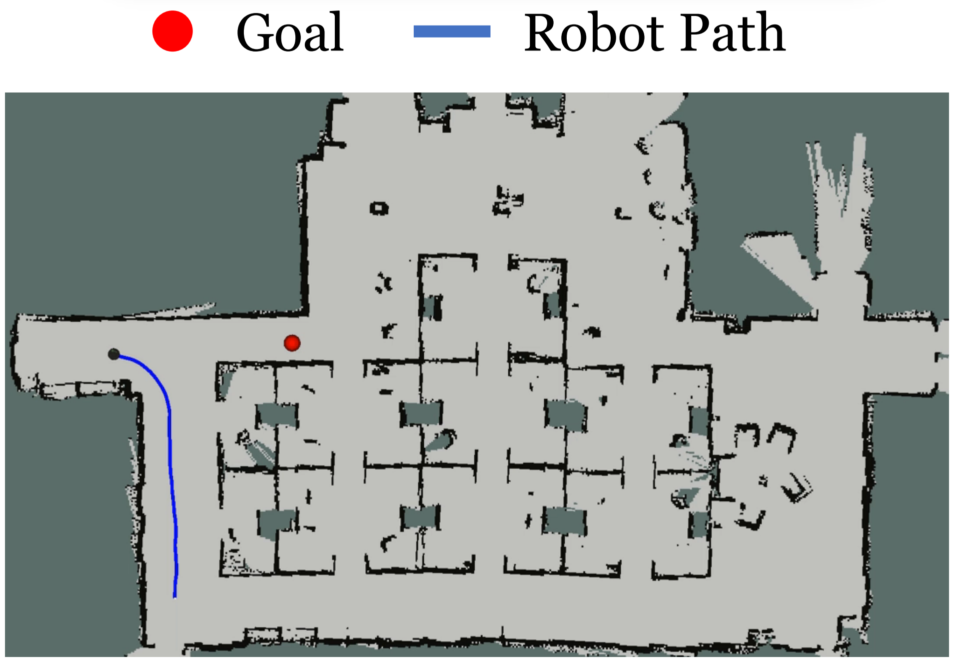


- Realize the trained SAN onto Loihi with low precision weights using layer-wise rescaling
- ROS communicates with Loihi using data channels
- Deploy encoder and decoder on Loihi's low-frequency x86 cores to reduce data transfer load
- ROS-Loihi interaction framework controls the mobile robot in real-time

Spiking Neural Network for Autonomous Navigation



Real-world evaluation for SNN on Loihi



Speed x2

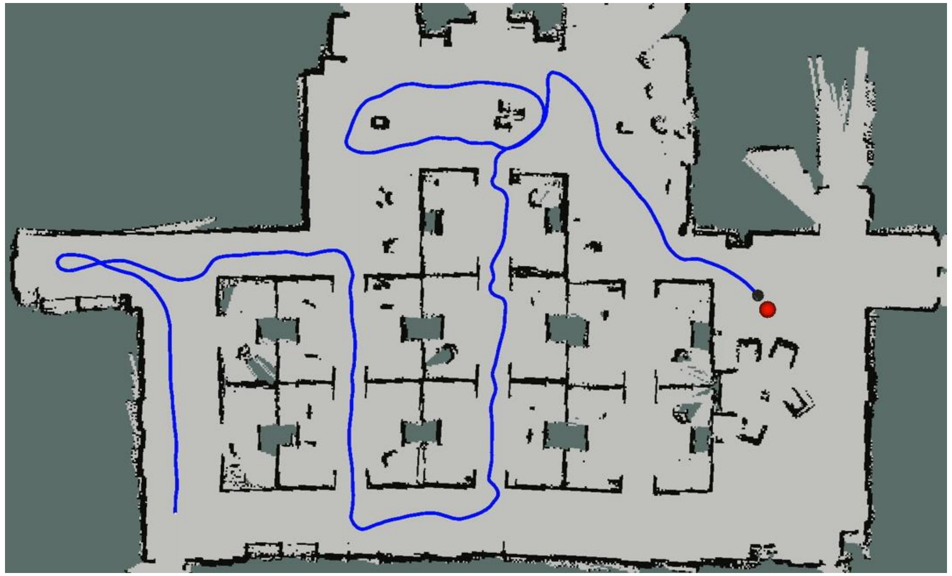
Spiking Neural Network for Autonomous Navigation

Deep Network on Jetson TX2

SNN on Loihi

SNN is **75** times more energy efficient than Deep Network

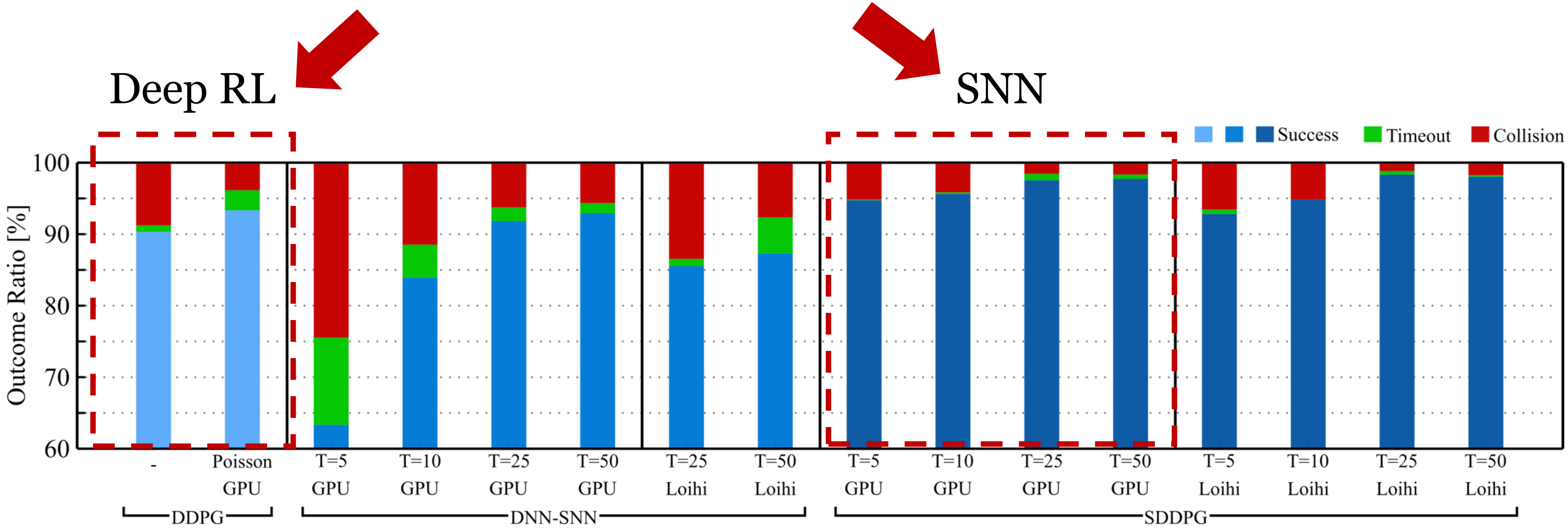
● Goal — Robot Path



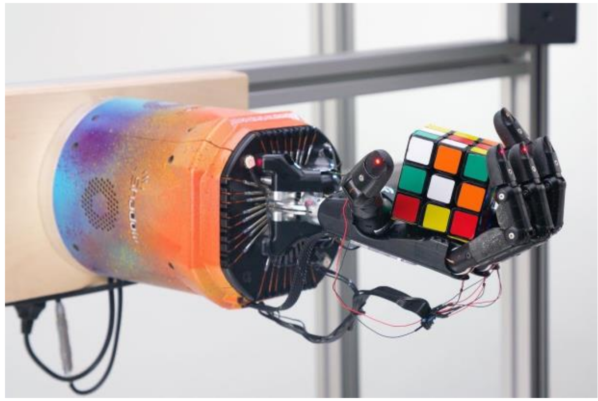
Speed x4

Spiking Neural Network for Autonomous Navigation

SNN shows higher successful rate navigating in complex environment

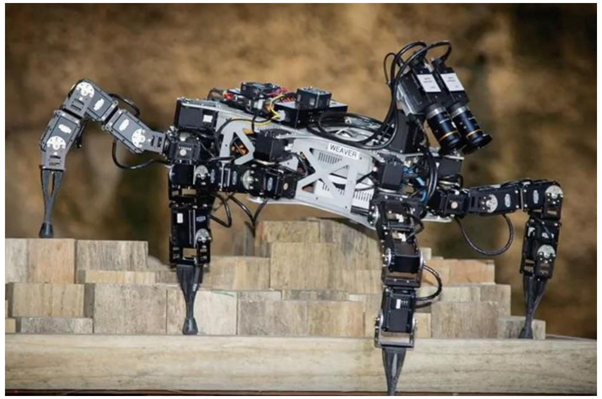


High-dimensional Continuous Control



OpenAI Robot Hand

Google Robot Arm Farm

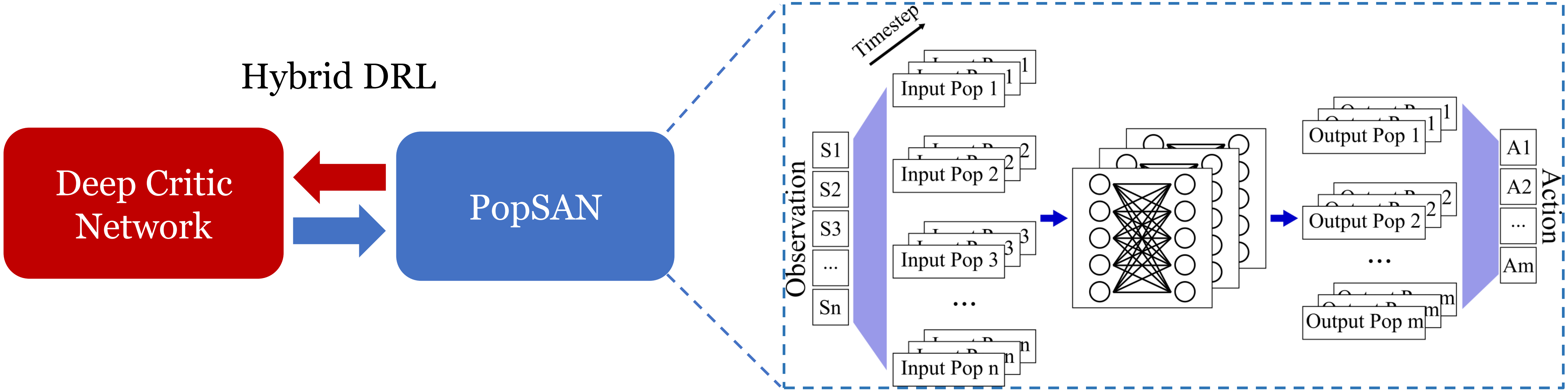


CSIRO Weaver Hexapod

Boston Dynamic Spot Robot

- Robot systems for complex applications often have high-dimensional observation and action space
- Optimality of the control policy highly depends on the encoding precision of the continuous observation and action
- Encoding precision of individual spiking neuron is limited due to event-based computation
- Especially problematic when a small inference timestep is used for better energy efficiency

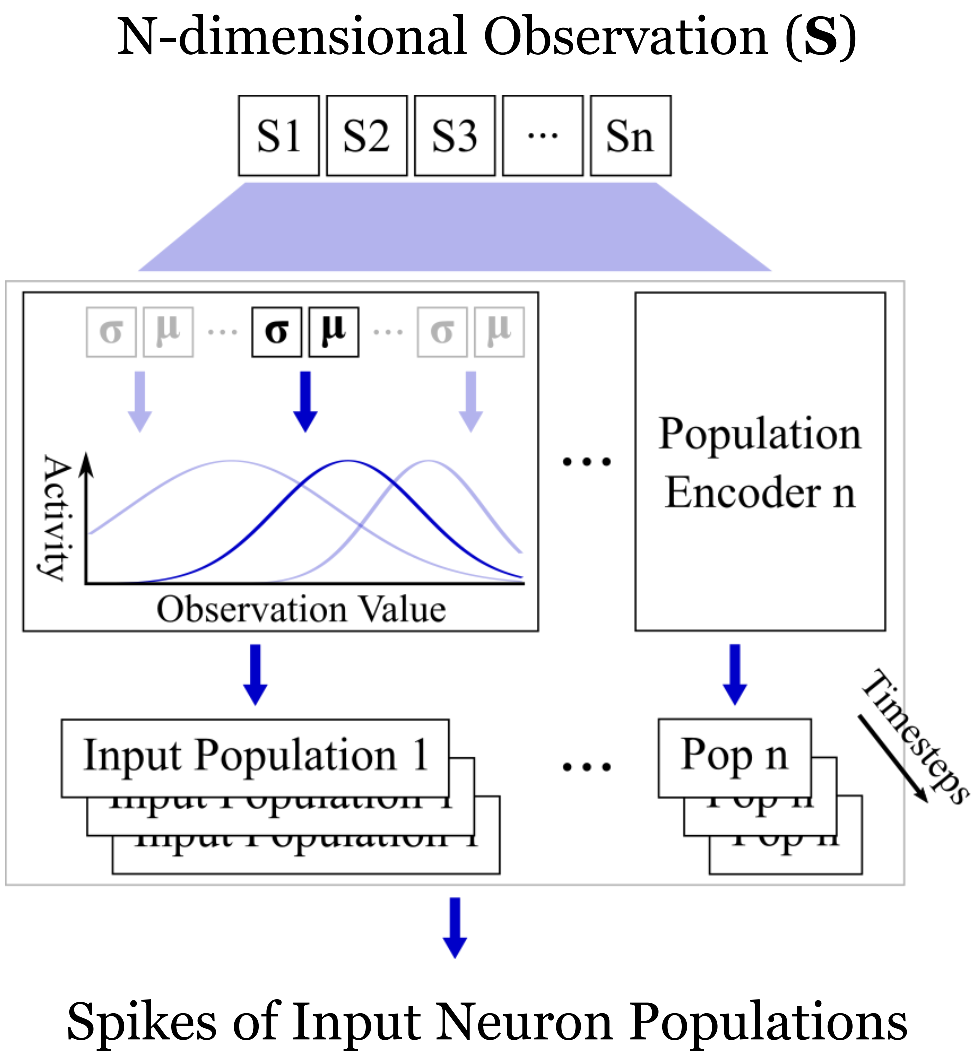
Population-coded Spiking Actor Network (PopSAN)



- Encodes each dimension of the observation and action spaces in individual neuron populations with learnable receptive fields
- Supports a wide spectrum of DRL algorithms (DDPG, TD3, SAC, and PPO) to learn energy-efficient solutions for continuous control problems

Guangzhi Tang, et al. "Deep Reinforcement Learning with Population-coded Spiking Neural Network for Continuous Control." CoRL 2020

Input Neuron Populations in PopSAN

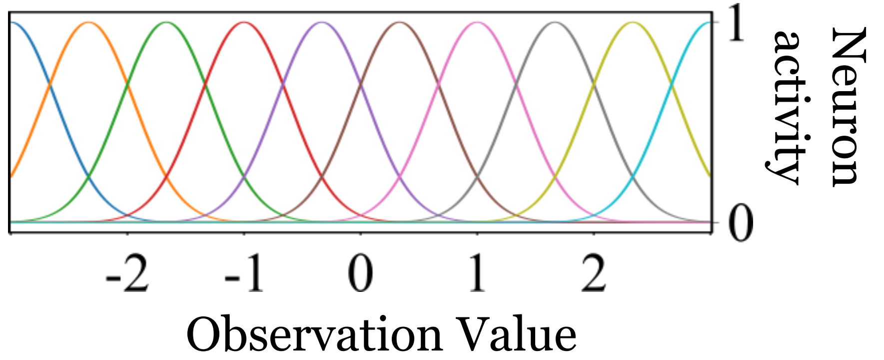


Each dimension of **S** is encoded by a population of neurons with neuron activity defined by:

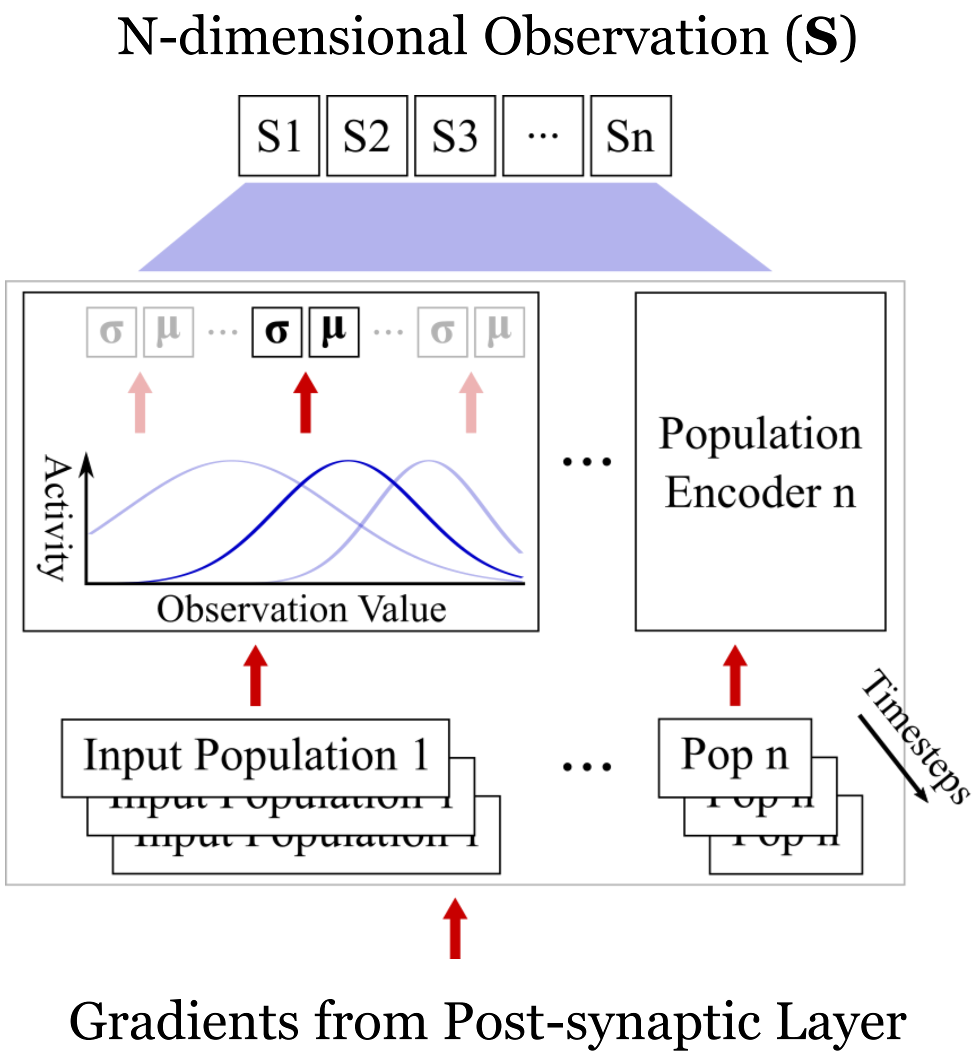
$$A_E = exp(-1/2 \cdot ((S_i - \mu)/\sigma)^2)$$

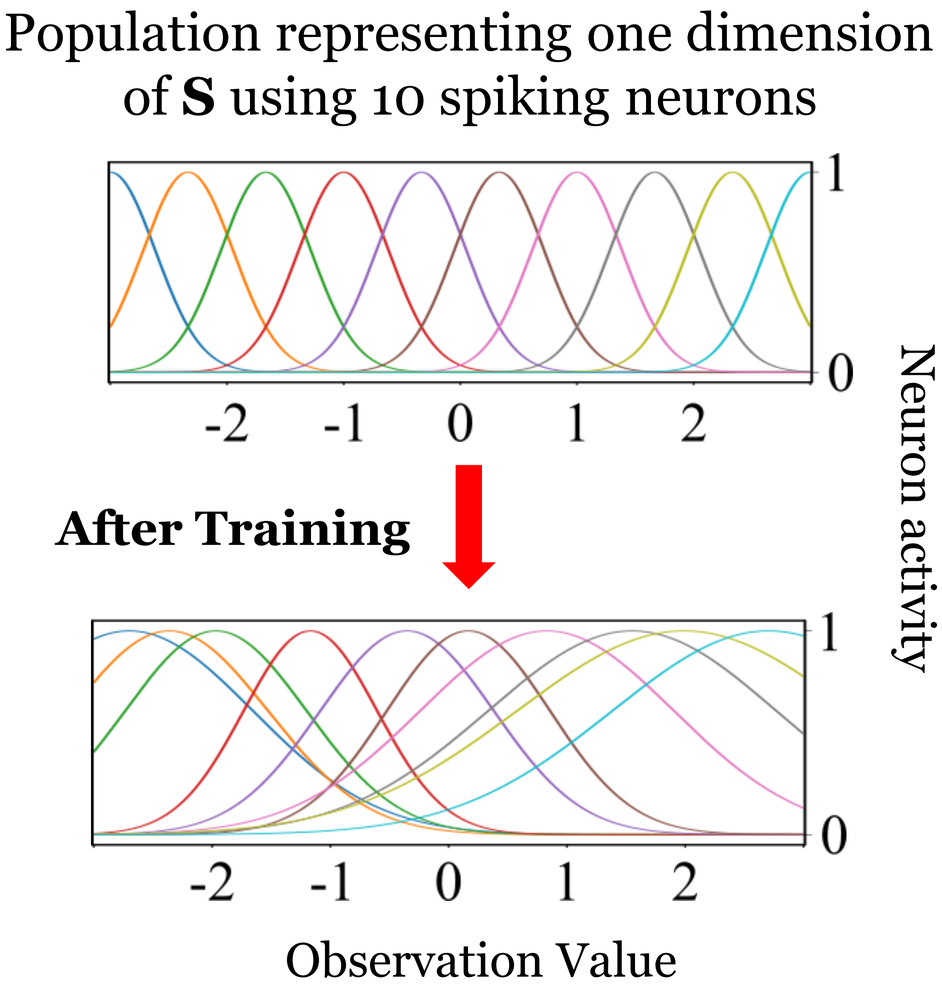
Neuron receptive field is defined by (**μ**, **σ**), which are trainable

Population representing one dimension of **S** using 10 spiking neurons

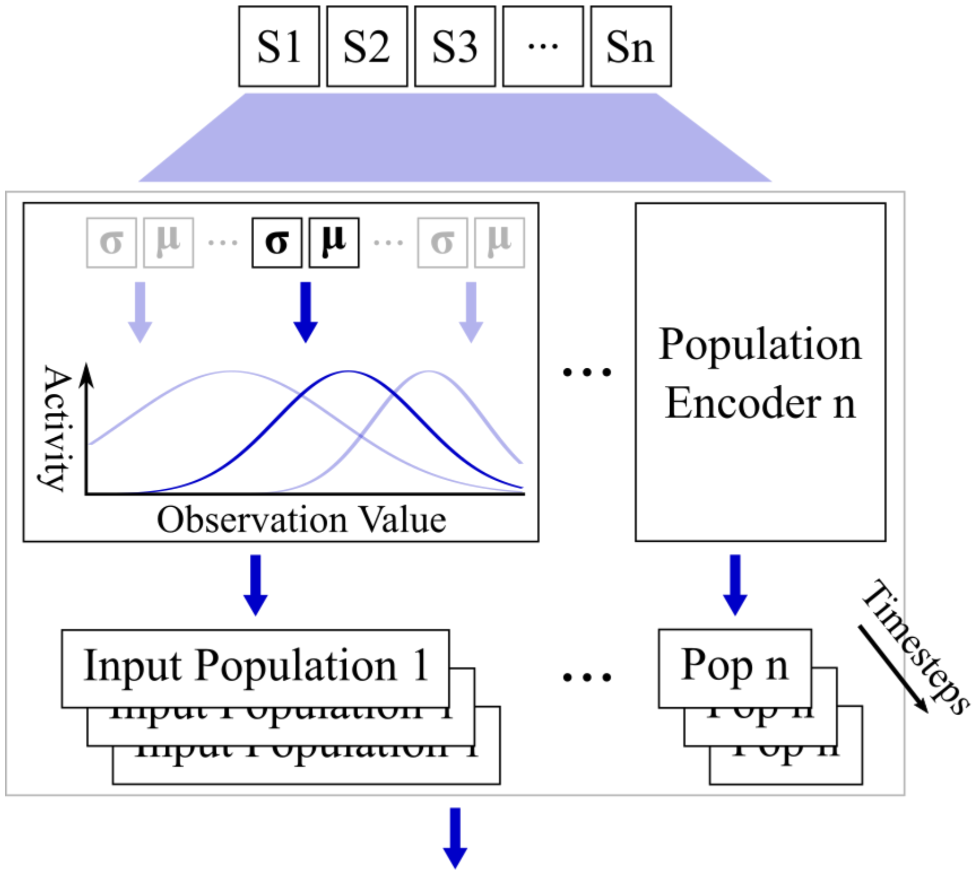


Input Neuron Populations in PopSAN

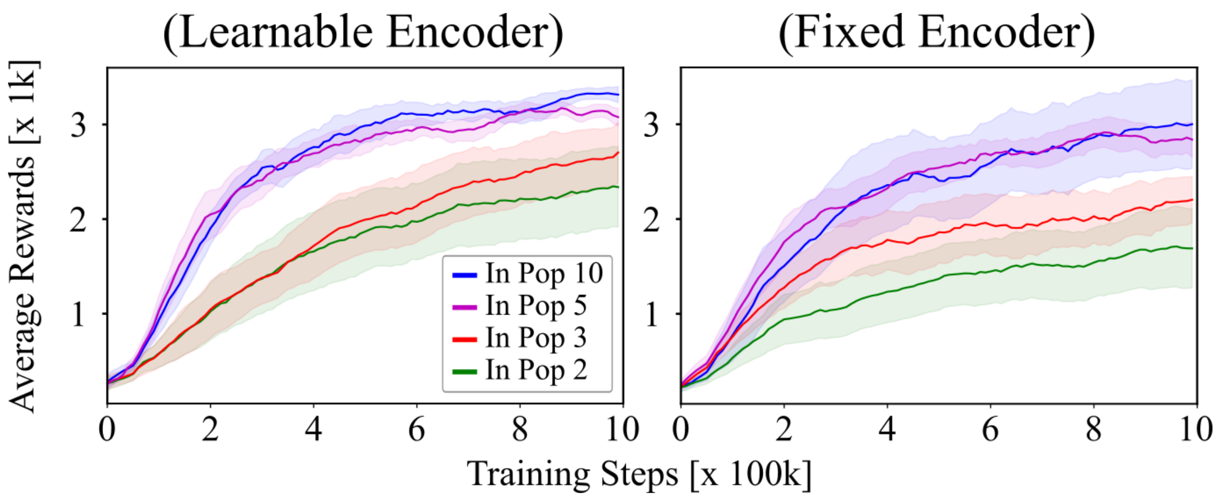




Input Neuron Populations in PopSAN

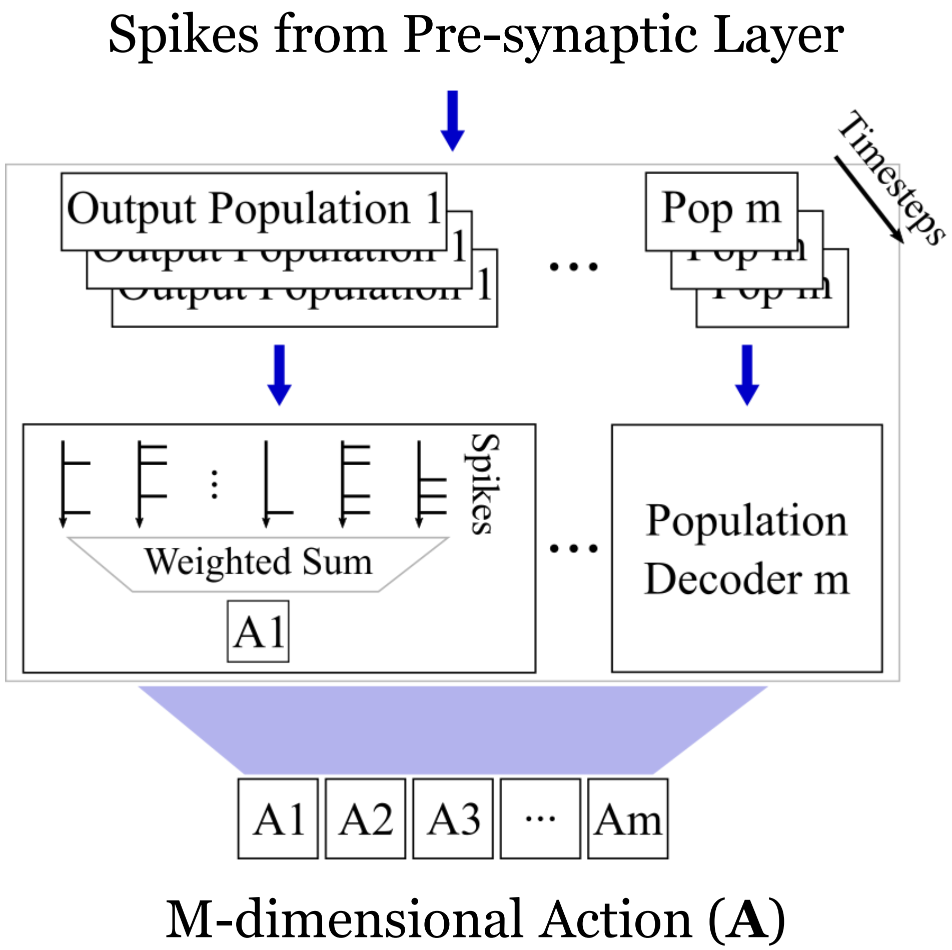


PopSAN trained using TD3 for Hopper-v3



- Learnable encoder performs better than fixed encoder
- Decrease of population size hurts the performance of PopSAN

Output Neuron Populations in PopSAN



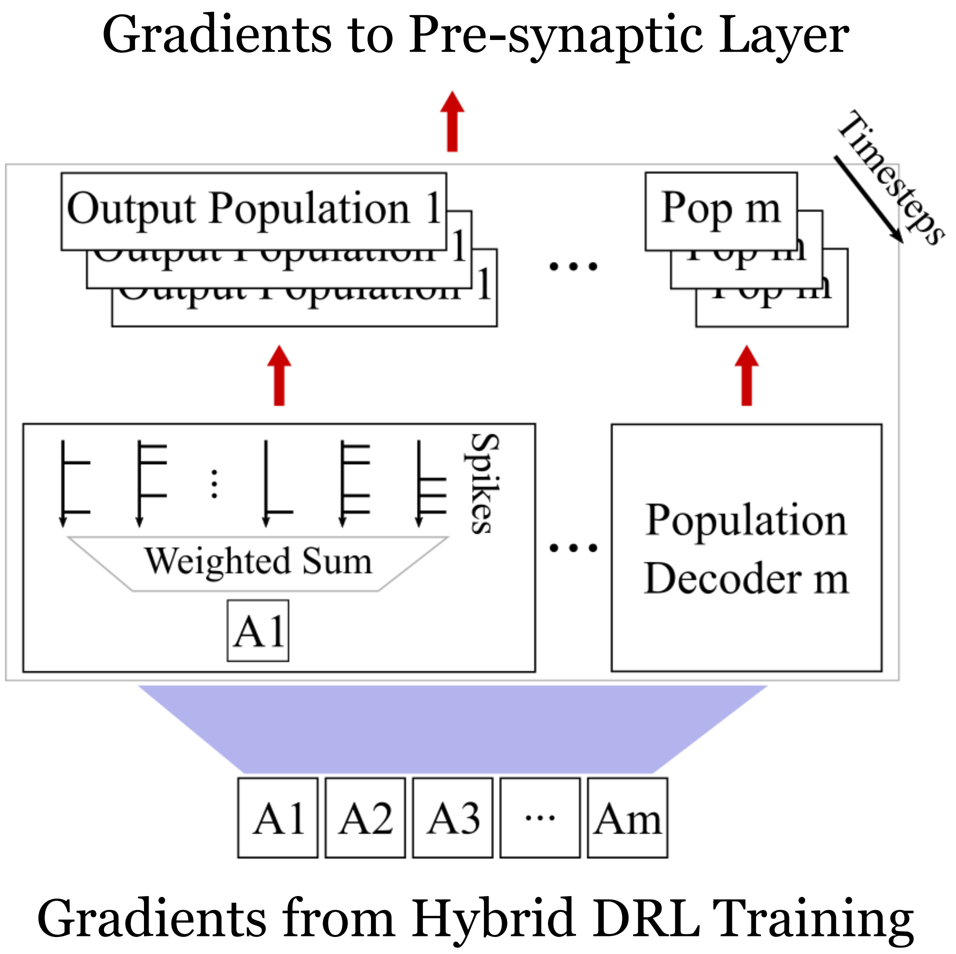
Output populations are fully connected to the last hidden layer of PopSAN.

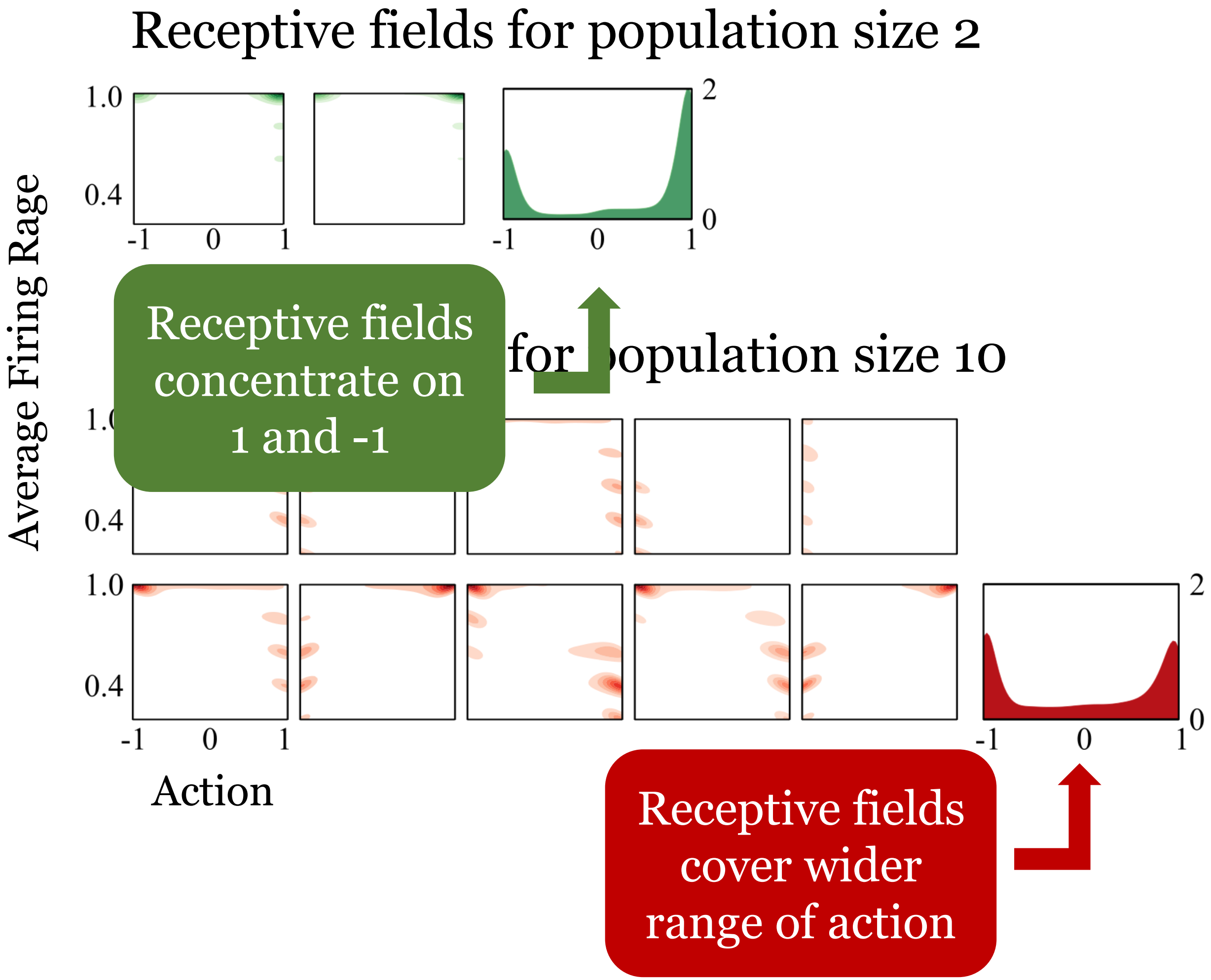
Each dimension of A is decoded by the weighted sum of neuron activities in the population:

$$A_i = \frac{1}{T}\sum_{t=1}^{T} W_i O_i(t)$$

Neuron receptive field is defined by W, which are trainable

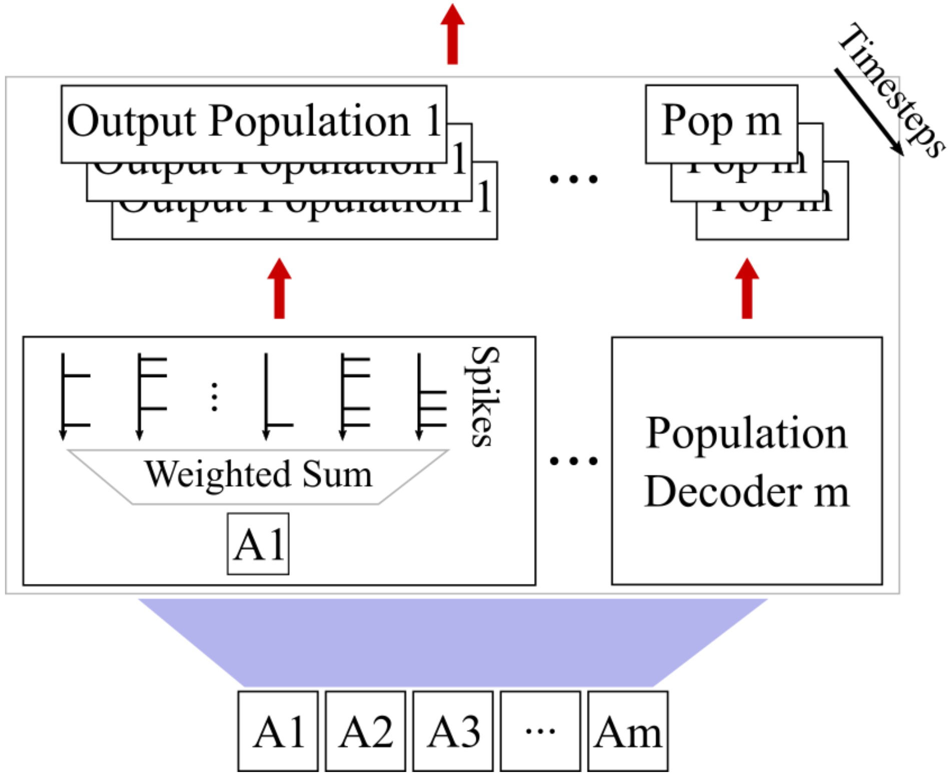
Output Neuron Populations in PopSAN



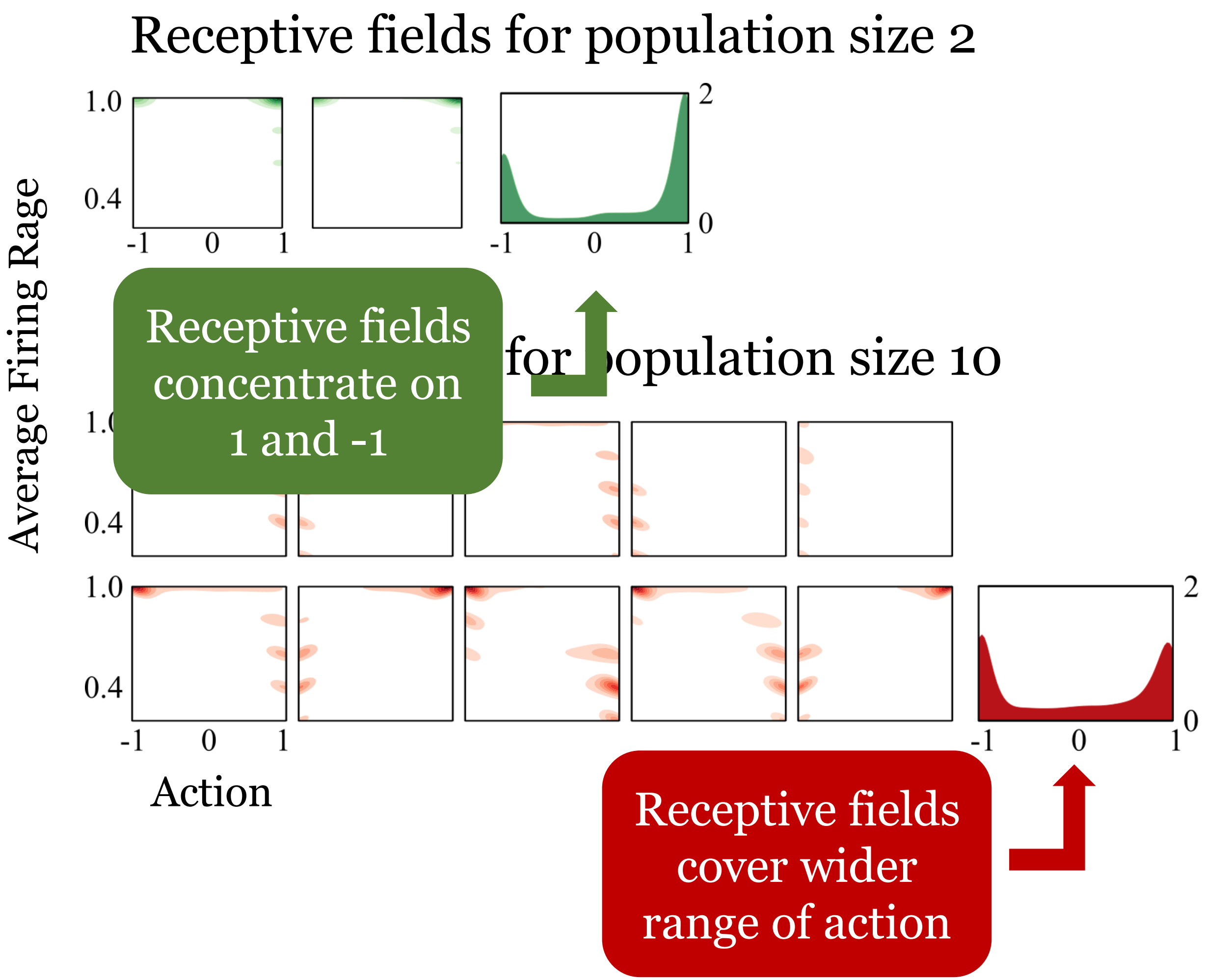


Output Neuron Populations in PopSAN

Gradients to Pre-synaptic Layer

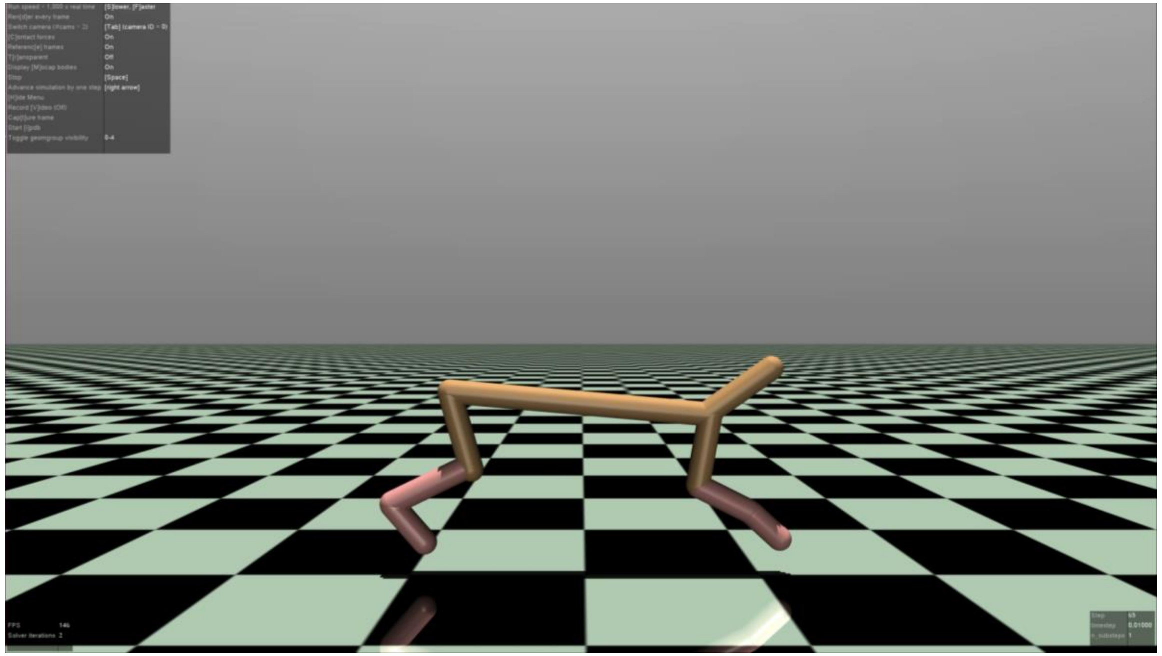


Gradients from Hybrid DRL Training

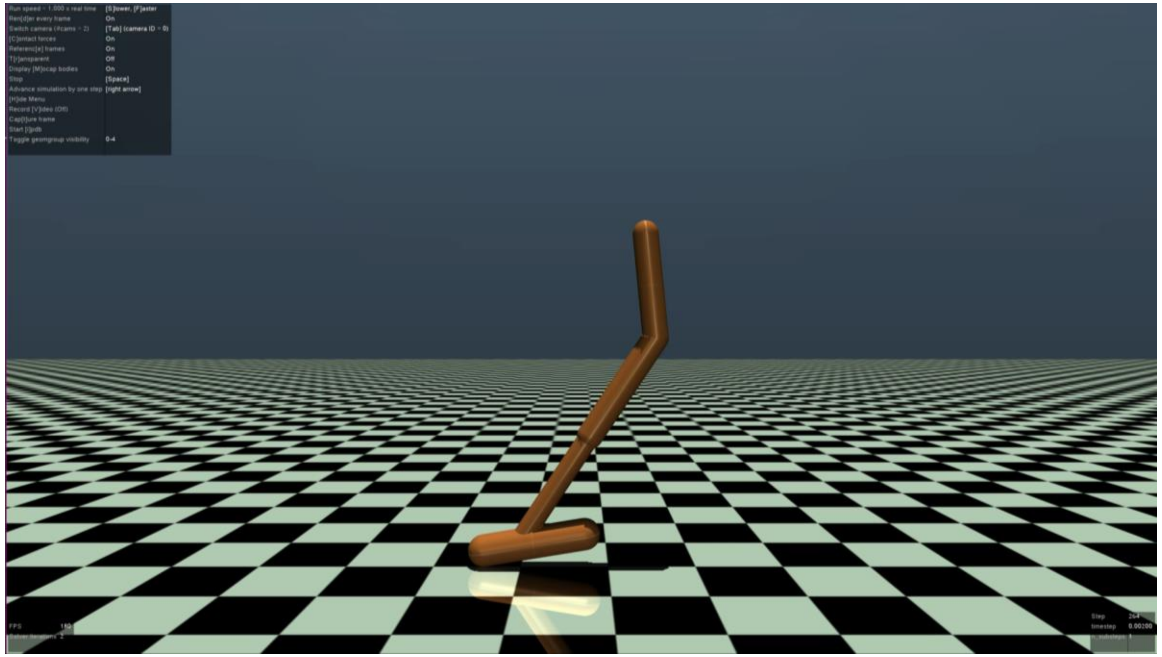


Real-time Loihi Control with PopSAN

HalfCheetah



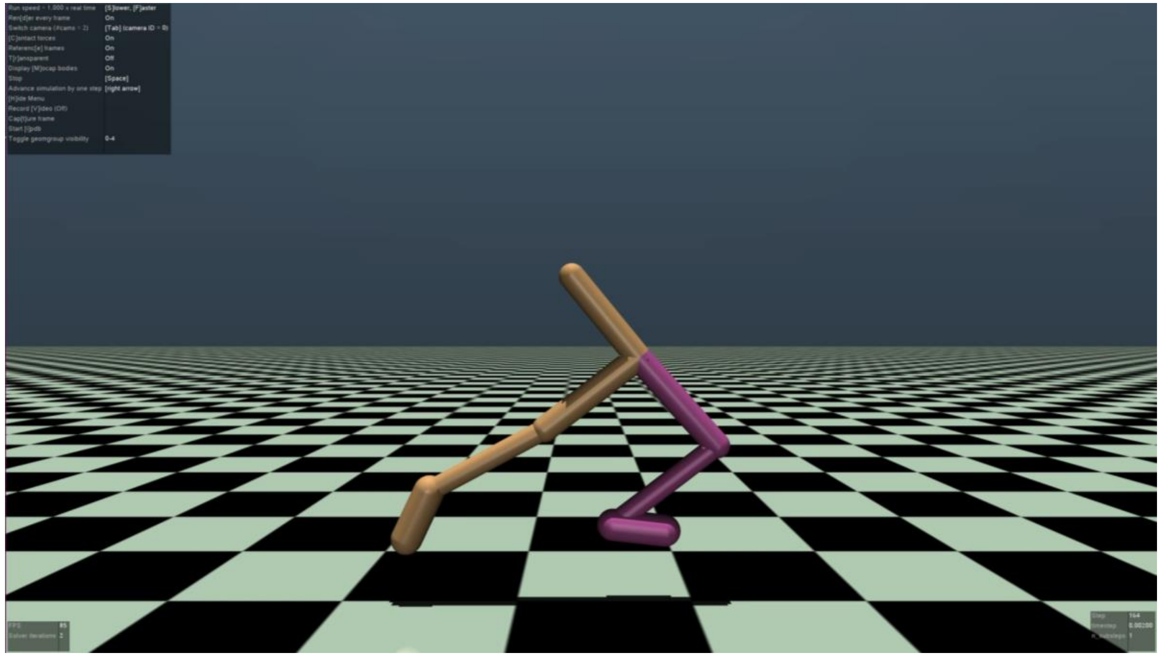
Hopper



(Trained using TD3 algorithm)

Real-time Loihi Control with PopSAN

Walker2d



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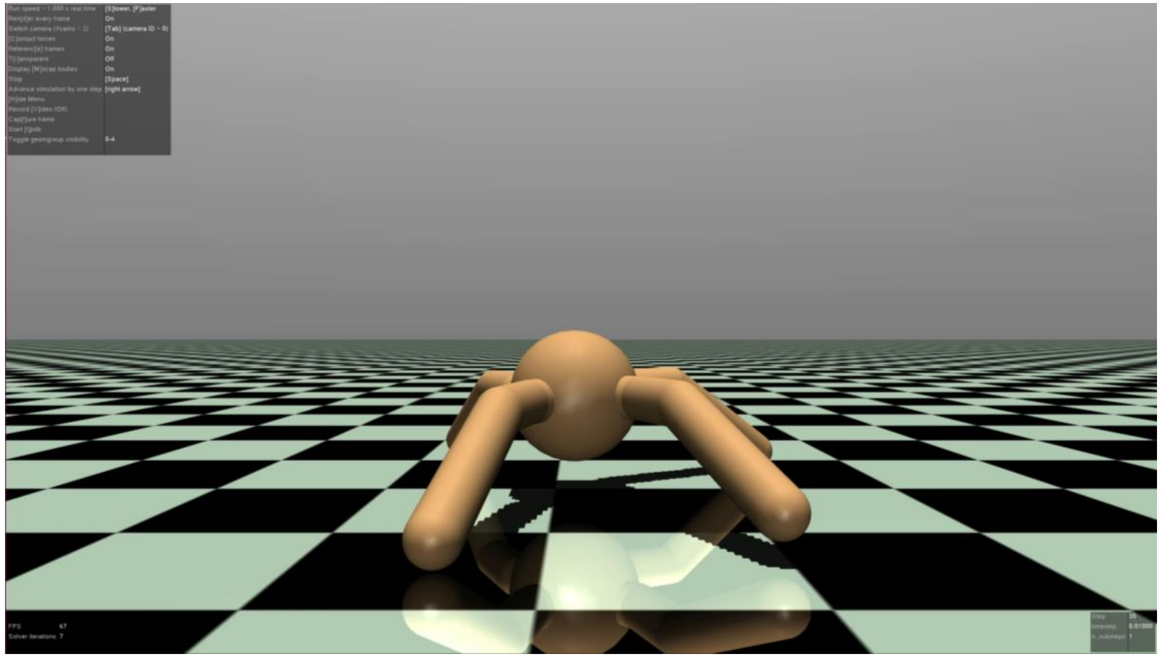
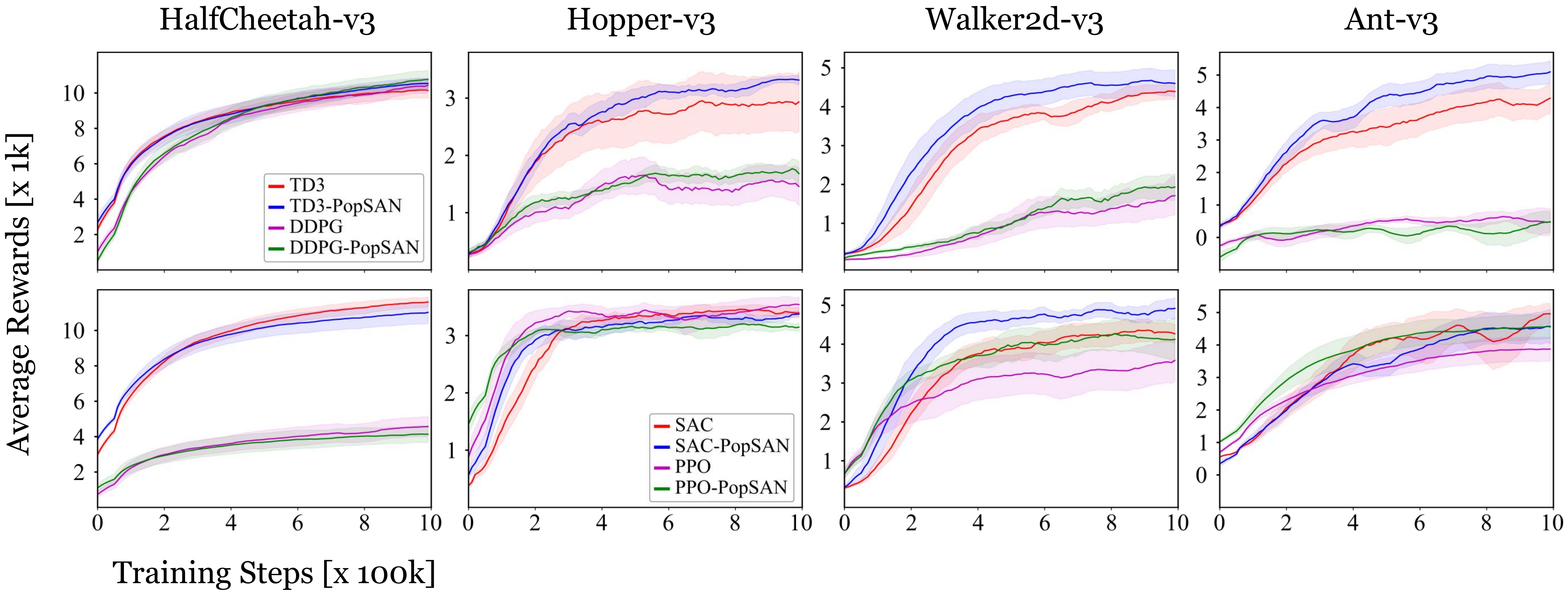


(Trained using TD3 algorithm)

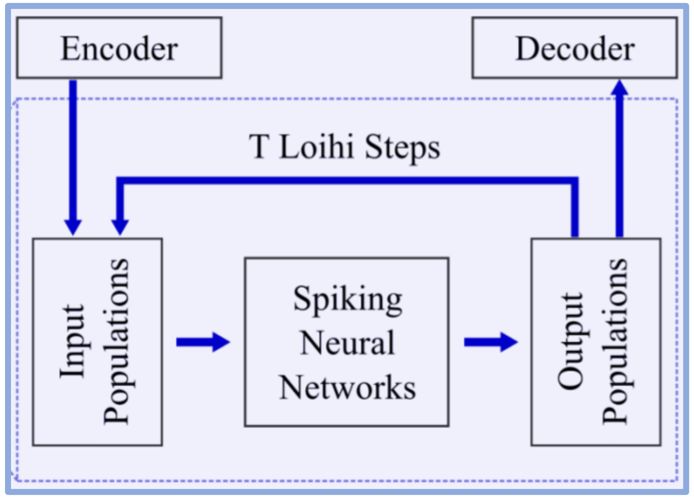
PopSAN trained using on-policy and off-policy DRL



PopSAN achieved **the same level of performance** as the Deep Actor Networks across all tasks, while **140 times more energy efficient** during inference.

Challenges for Robot Control and DRL with Loihi

Inference Control Loop on Loihi



Limited inference speed with Loihi when compared with other processors for the same control task

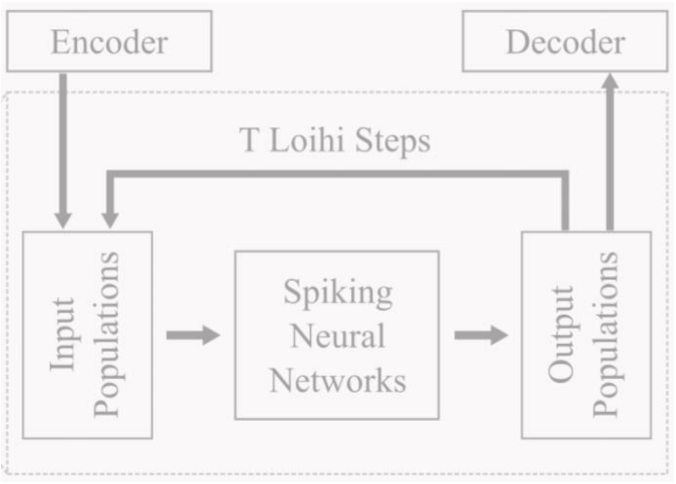
- Frame-based inference requires multiple Loihi steps to produce one control command
- Input/Output bandwidth becomes a bottleneck of Loihi for high-dimensional observation and action

Method	Device	Idle (W)	Dynamic (W)	Inf/s	[illegible]
DNN	CPU	15.51	58.93	7450	7909.86
DNN	GPU	24.68	46.04	3782	12174.46
DNN	TX2(N)	1.24	1.76	750	2346.71
DNN	TX2(Q)	[illegible]	[illegible]	[illegible]	[illegible]
PopSAN	Loihi	1.084	0.003	226	**1198**

Power performance and inference speed across hardware

Challenges for Robot Control and DRL with Loihi

Inference Control Loop on Loihi



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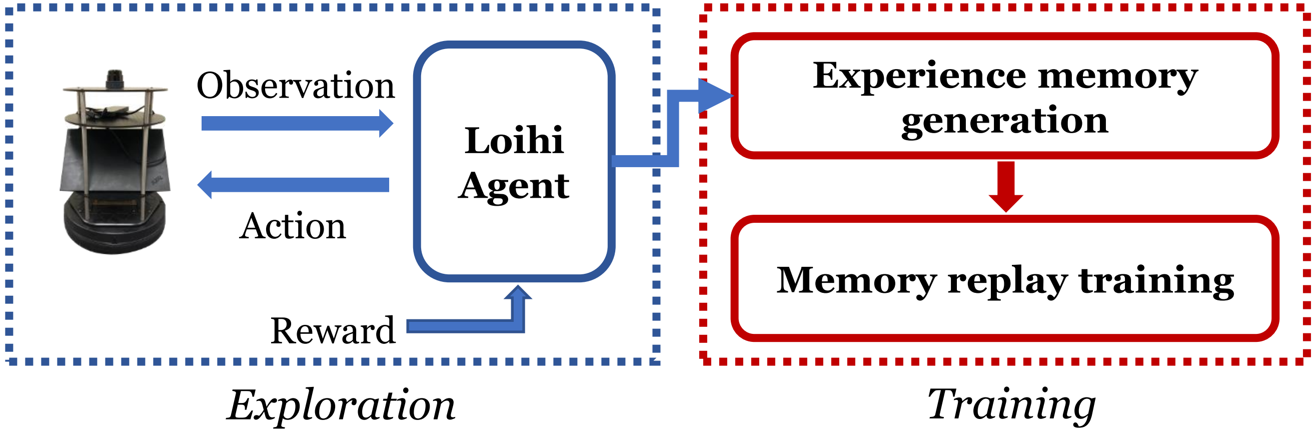
Real-world Robotic Reinforcement Learning



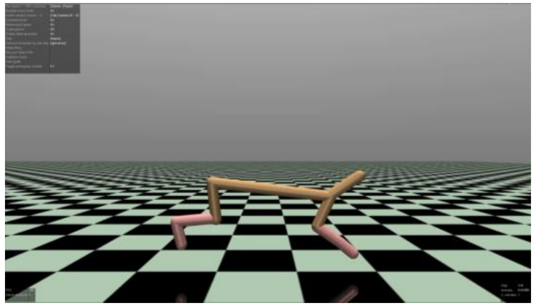
Extend our approach to a continuous and autonomous robotic learning system on Loihi for real-world applications

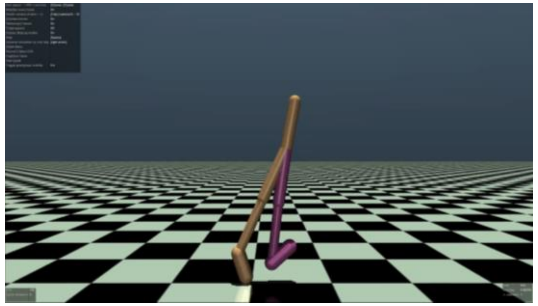
- Experience generation replacing experience storage
- Minibatch training and high-precision gradient encoding

In Conclusion:

- Towards energy-efficient and versatile robotic perception and control solutions applicable to Loihi-controlled mobile robots.

- General solution for training spiking neural network in complex real-world reinforcement learning applications.





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