Deep Spiking Q Networks

Masterthesis - Midterm Presentation

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October 23, 2019

Outline

1. Theoretical Background
2. Motivation
3. Methods
4. State of the Art
5. Experiments and Preliminary Results
6. Outlook

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1. **Theoretical Background**
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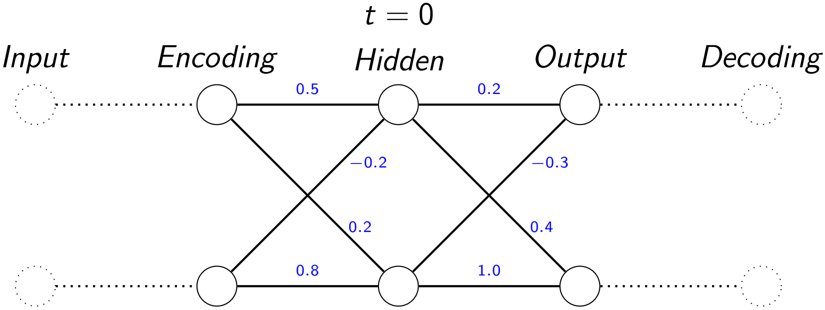
Reinforcement Learning

- An **agent** learns by moving through an **environment** and receiving **rewards**.
- **Deep Q-Learning**[1]: A neural network (**DQN**) is trained which approximates the **value function** $Q(s, a)$.
- **Policy Gradient**[2]: An agent learns to estimate (with a NN) a **stochastic policy directly** by using gradient ascent.
- More advanced RL algorithms: **Actor-Critic** methods

Spiking Neural Networks

- Inspired by neurons in the brain
- **Binary Outputs** (spike or no spike)
- Simulation over a **time period** (discrete or continuous)



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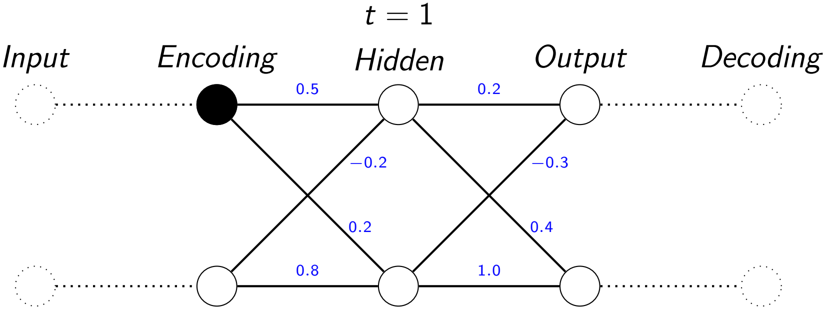

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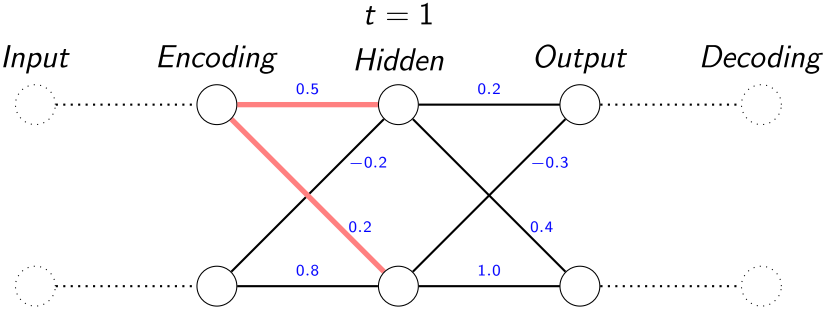

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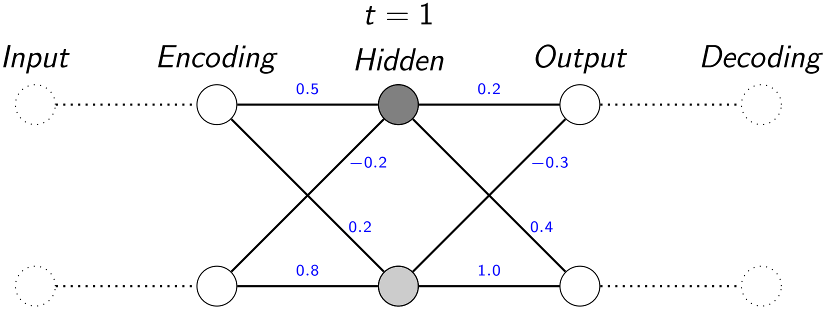

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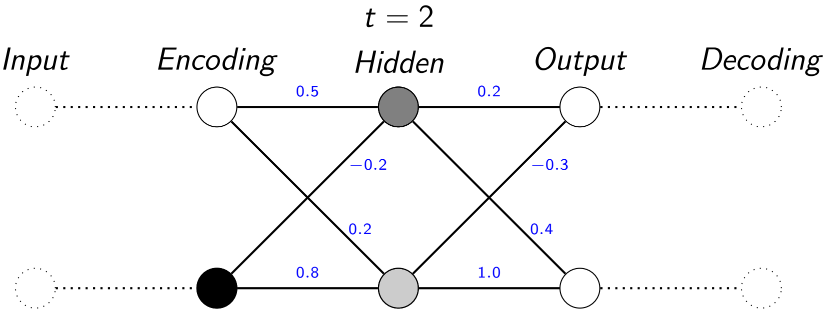

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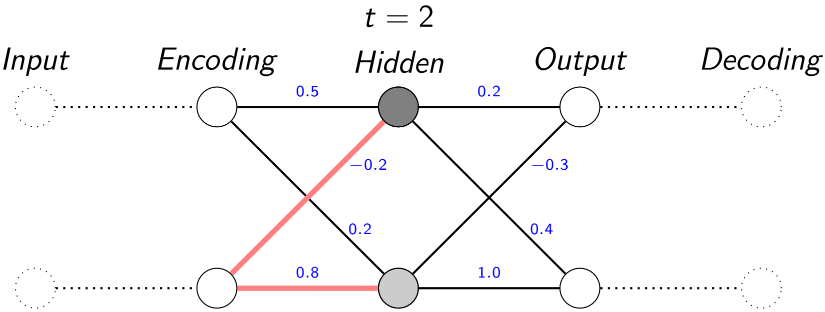

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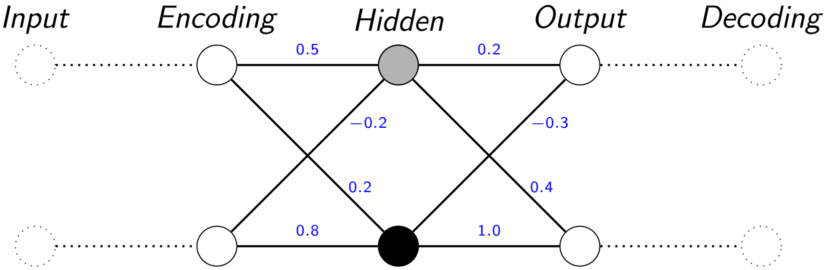

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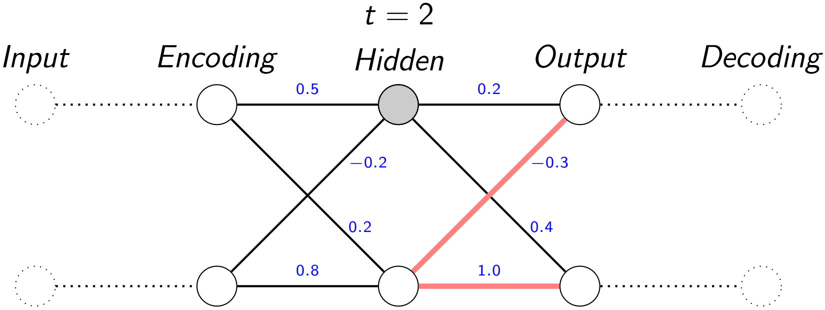

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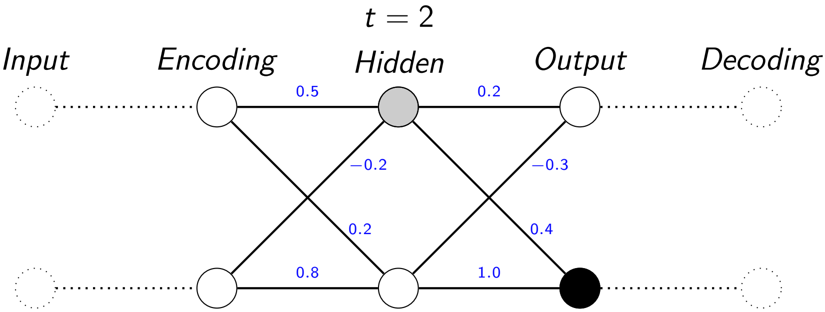

Neuron models

- Differ in complexity and biological plausibility
- **Leaky Integrate-and-Fire neurons**[3]
- (Non-Leaky) **Integrate-and-Fire** neurons
- Different reset mechanisms: Reset-by-Subtraction, Reset-to-Zero[4]

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Motivation

- **Energy-Efficiency** and **fast inference** on dedicated hardware (**neuromorphic hardware**)[5]
- **Brain-like** computation
- ? Exploit inherent **temporal** mechanics
- ? Naturally suited for **event-based inputs**

Research Goal

Research goal: **Explore** different methods to obtain a **spiking neural network** that can solve complex **reinforcement learning** tasks and **compare** these methods.

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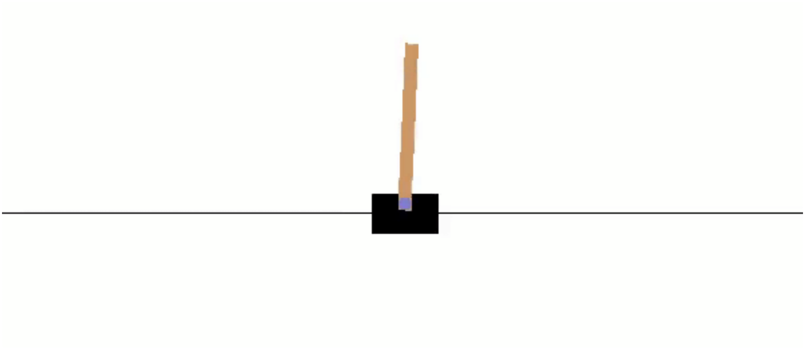
Open AI Gym[6]

- Framework for reinforcement learning algorithms
- Defines goal for "solving" an environment
- **Comparison metrics**: Environment solved?, Best 100 episode average, training time, convergence



Training Methods: Overview

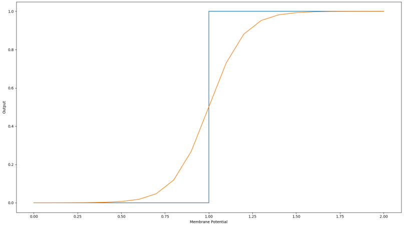
- **Conversion**
- **Surrogate Gradients**
- Local Learning
  - Spike Timing Dependent Plasticity (**STDP**)
  - event-based Random Backpropagation (**eRBP**)

Training Methods: Conversion[7] [4]

- Train a **conventional Neural Network** with certain constraints: ReLu activation in hidden layers
- **Rate-based Encoding**
- **Weight conversion** based on data
- **Rate-based Decoding**

Training Methods: Surrogate Gradients

- SNN is trained on conventional hardware using **Backpropagation**
- **Gradients** of binary function are **replaced** with a steep sigmoid function[8]
- **SpyTorch** Framework[3]



Training Methods: STDP

- **Unsupervised** local learning
- Based on relative spike timings[9]
- Reward-modulated STDP (**R-STDP**): An external reward stimulates the neurons to perform STDP or anti-STDP[10]

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- **Problem** with STDP: Unclear how to propagate errors backward => Only output layer can be trained with R-STDP, **hidden layers have to be trained unsupervised**

Training Methods: eRBP[11]

- Ideas of eRBP:
  - Use **random feedback weights** instead of symmetric weights
  - **Error neurons** that accumulate the error and emit a **spike** backward once they cross their threshold
  - **Two compartment neurons**, one for the forward pass, one for the backward pass that trigger a weight update when their threshold is crossed

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- **Problem** of eRBP in Q-Learning: Approach needs to be adapted that it **remains local**

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State of the Art

- Conversion
  - Patel et al.[12] **convert a DQN** for BreakOut and report better results after conversion and more robustness

State of the Art

- Conversion
  - Patel et al.[12] **convert a DQN** for BreakOut and report better results after conversion and more robustness
- All methods
  - Good performance on **classification** tasks
  - Few (conversion) to no (all others) papers on deep reinforcement learning

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Experiments: Direct Conversion DQN

- DQN on CartPole: Average performance 224.11

Simulation Time	**Conversion Accuracy Original DQN**	**Average Performance after Conversion over 100 episodes**
100	64.36%	133.45
1000	84.97%	107.68
10000	94.89%	151.77

Experiments: Indirect Conversion DQN

- Train a classifier to predict the action the DQN would take in state s[13]
- Average performance of the classifier 229.06

Simulation Time	Conversion Accuracy Classifier	Average Performance after Conversion over 100 episodes
100	95.37%	197.34
1000	99.50%	220.82
10000	99.9%	takes too much time

Experiments: Conversion in NEST

- Challenge: **different Neuron models** in NEST compared to the conversion papers
- iaf_psc_delta neurons with reset-to-zero mechanism
  - **classifier** converts with $\approx$ **97%** accuracy (1000 time steps)
  - **direct conversion** does not work ($\approx$**57%**) accuracy for 10000 time steps
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  - **Policy Gradient** converts with $\approx$ **98%** (100 timesteps)
- pp_psc_delta neurons with adaptive threshold and stochastic firing
  - **classifier** converts with $\approx$**96%** accuracy (1000 time steps)
  - **direct conversion** with $\approx$ **93%** accuracy (10000 time steps)

Experiments: Surrogate Gradients DQN

- Setup: Same hyperparameters for Q-Learning, Non-Leaky Integrate-and-Fire neurons, 20 simulation time steps
- Experiment: Run DQN and DSQN for **1000 episodes 5 times each**
- Result:
  - DQN: Reached gym standard twice, best 100 episode **average** $>$ **190 for all runs**
  - DSQN: Reached gym standard once, two runs with average $>$ 190, **lowest best average 170**

Preliminary Results

- **Conversion** accuracy is **dependent** on the relative difference between the outputs

=> Conversion works better with a softmax **output function** (e.g. Classifier or Policy Gradient)

=> Conversion accuracy for DQNs depends on the specific agent and **environment**

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=> Conversion accuracy for DQNs depends on the specific agent and **environment**

- Training with **surrogate gradients works** for DSQNs, although **worse than** training a standard **DQN**
- Direct Training with **STDP** of a deep reinforcement learning algorithm is **difficult**, because only the last layer can be trained with R-STDP and therefore relies on meaningful features calculated in unsupervised STDP layers

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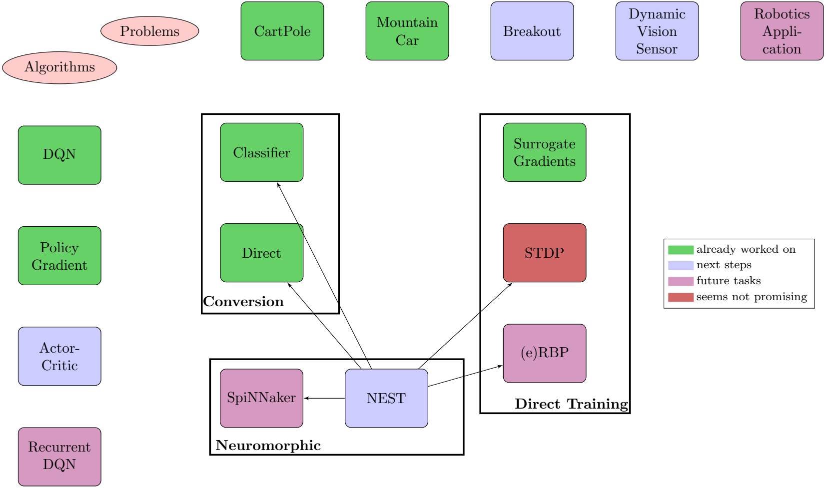

Problems
Algorithms
CartPole
Mountain Car
Breakout
Dynamic Vision Sensor
Robotics Appli-cation
DQN
Policy Gradient
Actor-Critic
Recurrent DQN
Classifier
Direct
Conversion
Surrogate Gradients
STDP
(e)RBP
Direct Training
SpiNNaker
NEST
Neuromorphic
already worked on
next steps
future tasks
seems not promising

Discussion

- Feedback (Presentation, Experiments, Results, ...)
- ? Which direction to go into
- ? How to compare reinforcement learning algorithms

Backup

Reinforcement Learning

- An **agent** learns by moving through an **environment** and receiving **rewards**.
- **Deep Q-Learning**[1]: A neural network (**DQN**) is trained which approximates the **value function** $Q(s, a)$.
- Loss function for DQN:

$$L = ((r_t + \gamma max_a Q(s_{t+1}, a)) - Q_{old}(s_t, a_t))^2$$

Reinforcement Learning

- **Policy Gradient**[2]: An agent learns to estimate (with a NN) a **stochastic policy directly** by using gradient ascent.
- More advanced RL algorithms: **Actor-Critic** methods

Neuron models

- Differ in complexity and biological plausibility
- **Leaky Integrate-and-Fire neurons**[3]

$$I_i[n+1] = \alpha I_i[n] + \sum_j W_{ij}[n] S_j[n]$$
$$U_i[n+1] = \beta U_i[n] + I_i[n] - S_i[n]$$

- (Non-Leaky) **Integrate-and-Fire** neurons: $\alpha = 0, \beta = 1$
- Reset-by-Subtraction, Reset-to-Zero[4]

Input Encoding/Output Decoding

- **Rate-based** methods
  - Encoding: Poisson spike trains[14], Equidistant spikes, Constant Input Currents[4]
  - Decoding: Number of spikes, Potential of output neurons[4]

Input Encoding/Output Decoding

- **Rate-based** methods
  - Encoding: Poisson spike trains [14], Equidistant spikes, Constant Input Currents [4]
  - Decoding: Number of spikes, Potential of output neurons [4]
  - + Straightforward, **easy to apply** for conversion methods [5]
  - – **No temporal information processing**, lots of spikes needed for good precision [5]

Input Encoding/Output Decoding

- **Temporal** methods
  - Encoding: Rank-based[15], Latency[10]
  - Decoding: Time to first spike[10]

Input Encoding/Output Decoding

- **Temporal** methods
  - Encoding: Rank-based[15], Latency[10]
  - Decoding: Time to first spike[10]
  - \+ Sparse spikes => **Energy efficiency and fast inference**[5]
  - − **Difficult to apply**

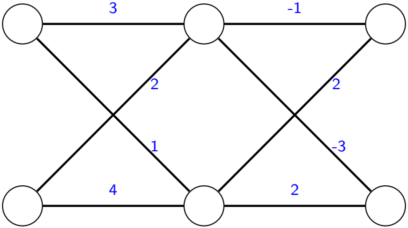
Training Methods: Overview

- Conversion methods
  - Generic conversion
  - Training of a constraint network
- Backpropagation based methods
  - Surrogate Gradients
  - Shadow network for training
  - Binary ANNs
- Local Learning
  - Spike Timing Dependent Plasticity (STDP)
  - event-based Random Backpropagation (eRBP)

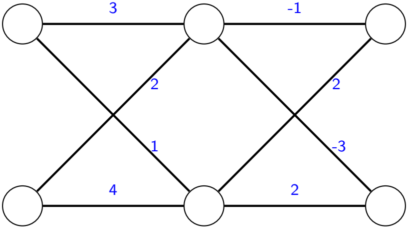
Training Methods: Conversion[7] [4]

- Train a **conventional Neural Network** with certain constraints: ReLu activation in hidden layers
- **Encoding** methods: Poisson, Equidistant Spikes, Constant Input current
- **Weight conversion**/normalization: Data-based, Model-based, Robust, Parameter search
- Output **Decoding**: Function of Potentials or Spikes

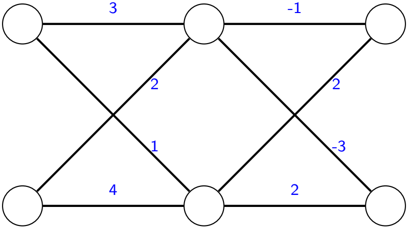
Conversion Example



Data-based normalization



Layer 1: Max-activation is 5 => Rescale by 0.2



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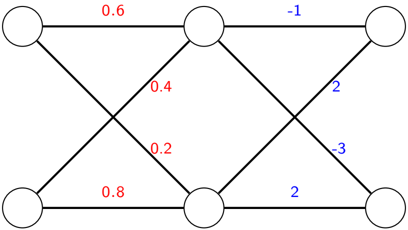
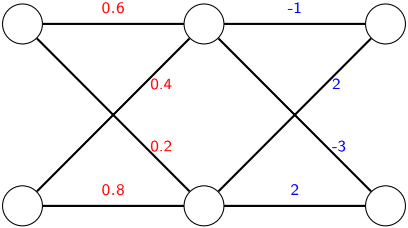


Layer 2: Max activation is 2 => Rescale by 0.5



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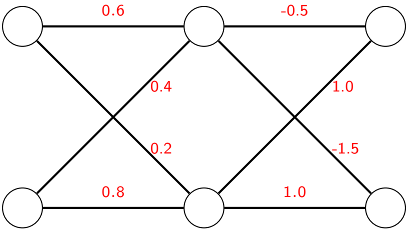
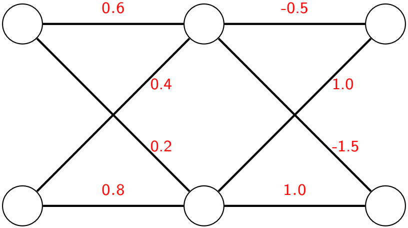


Problem: Underactivation



Training Methods: STDP

- **Unsupervised** local learning
- Connections where a pre-synaptic spike occurs just before a post-synaptic spike are strengthened
- Connections where a post-synaptic spike occurs just before a pre-synaptic spike are weakened[9]
- Reward-modulated STDP (**R-STDP**): An external reward stimulates the neurons to perform STDP or anti-STDP[10]
- **Problem** with STDP: Unclear how to propagate errors backward => Only output layer can be trained with R-STDP, **hidden layers have to be trained unsupervised**

Training Methods: eRBP[11]

- Problems of Conventional Backpropagation:
  - Keep symmetric forward and backward weights (**weight transport problem**)
  - backpropagate error signals
- Ideas of eRBP:
  - use **random feedback weights** instead of symmetric weights
  - **error neurons** that accumulate the error and emit a **spike** backward once they cross their threshold
  - **two compartment neurons**, one for the forward pass, one for the backward pass that trigger a weight update when their threshold is crossed
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State of the Art

- Conversion
  - Patel et al.[12] **convert a DQN** for BreakOut and report better results after conversion and more robustness
  - Many papers (e.g.[7,4])that **convert classification networks** with high accuracy
  - Converted SNNs perform best in terms of accuracy compared to other training methods[5]
- Surrogate Gradients
  - State-of-the-art results for **classification tasks** such as MNIST[5]

State of the Art

- STDP
  - **Deep classification networks**, where the hidden layers are trained unsupervised and the output layer is trained with R-STDP[16] [17]
  - Competitive performance in **unsupervised** networks[5]
- (e)RBP
  - Performance of RBP almost as good as of standard BP on **classification** tasks[18]
  - State-of-the-art performance for classification with eRBP on **DVS**-**gesture** data set[19]

Experiments: En-/Decoding Methods DQN

- A classifier with normalized inputs (between 0 and 1) is converted and simulated for 100 time steps per episode
- Conversion Accuracy for 1000 time steps is reported

Encoding Method \ Decoding Method	Spikes	Potential
Poisson spike train	74.1%	74.1%
Equidistant Spikes	77.6%	82.2%
Constant input currents	93.7%	92.4%

Open research questions

- **Comparison** of **conversion methods** for DQNs
- Running a DSQN on **neuromorphic hardware**
- **Influence of the environment** on DQN conversion
- Conversion and Direct Training of **more advanced Reinforcement Learning algorithms**
- Adapt **eRBP for Q-Learning**
- **Exploit temporal capabilities** of SNN for reinforcement learning tasks
- **Compare conversion and direct training** methods for reinforcement learning

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