Deep Spiking Q Networks

Masterthesis - Endterm Presentation

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January 29, 2020

Outline

1. Recap Midterm
   - Research Goal
   - Motivation
   - Theoretical Background
   - State-of-the-Art
2. Experiments
3. Results
4. Future Work
5. Conclusion

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Research Goal

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

Motivation

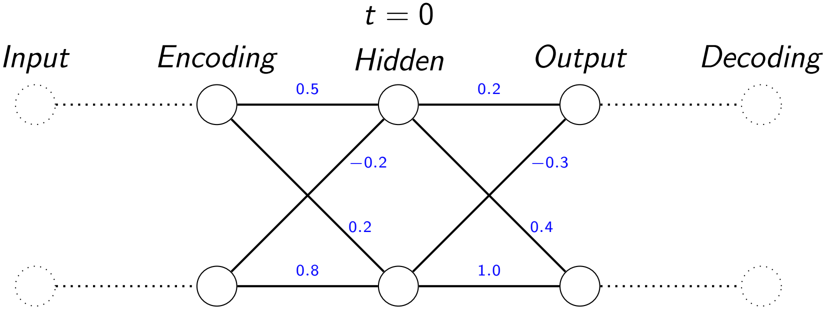
- \+ **Energy-Efficiency** and **fast inference** on dedicated hardware (**neuromorphic hardware**)[1]
- \+ **Brain-like** computation
- ? Exploit inherent **temporal** mechanics
- ? Naturally suited for **event-based inputs**

Theoretical Background: Reinforcement Learning

- An **agent** learns by moving through an **environment** and receiving **rewards**.
- **Deep Q-Learning**[2]: A neural network (**DQN**) is trained which approximates the **value function** $Q(s, a)$.
- **Policy Gradient**[3]: An agent learns to estimate (with a NN) a **stochastic policy directly** by using gradient ascent.

Theoretical Background: Spiking Neural Networks (SNNs)

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



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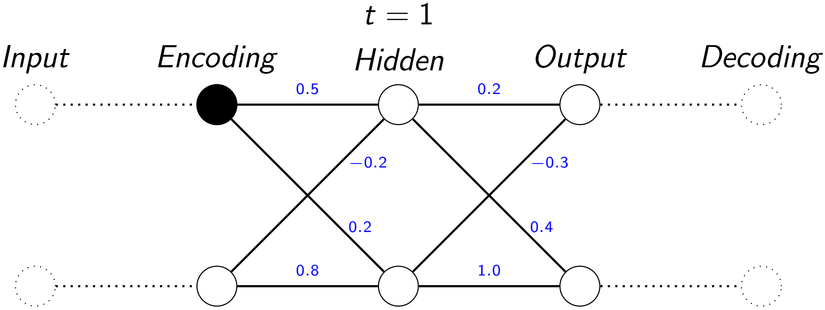

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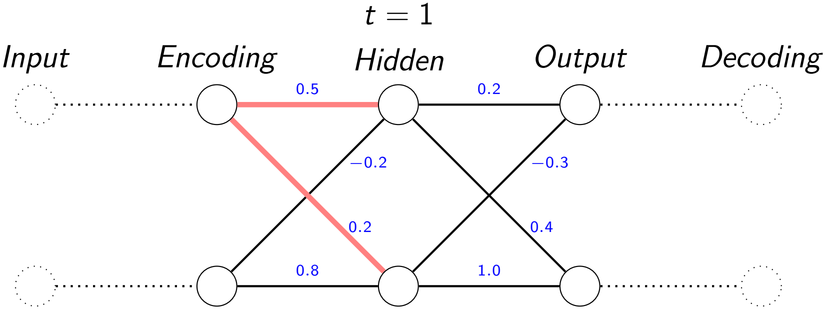

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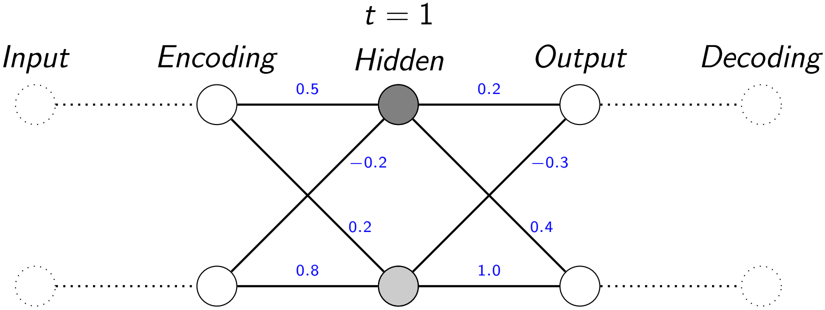

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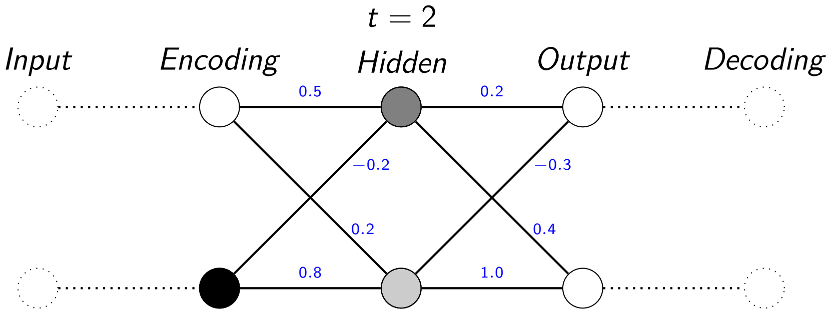

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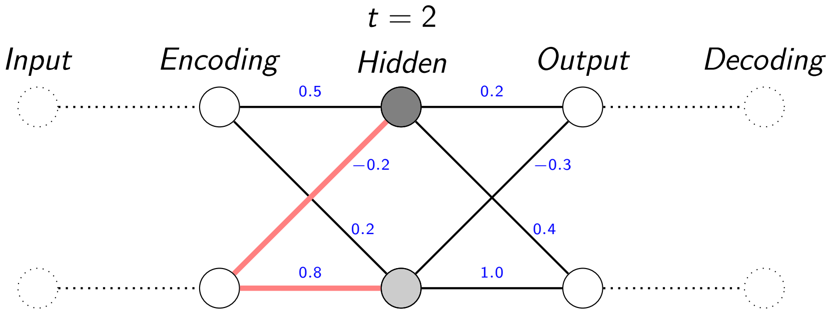

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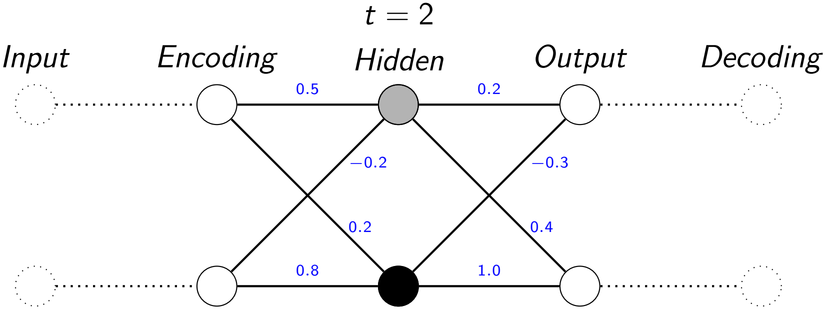

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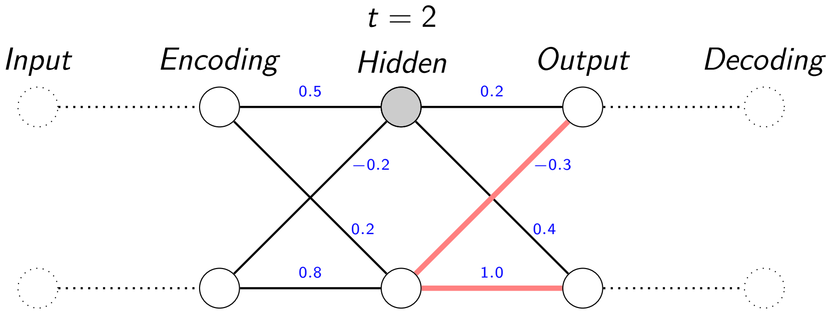

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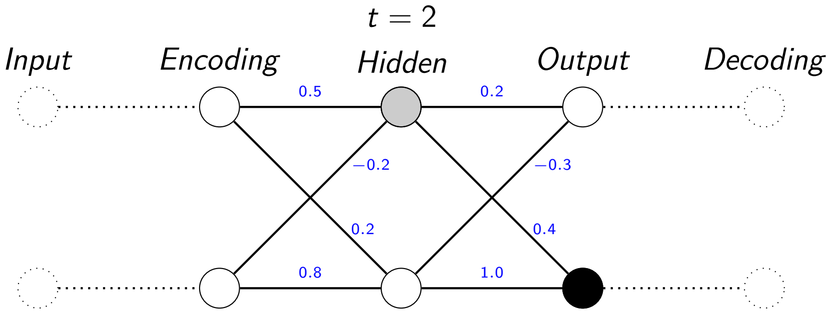
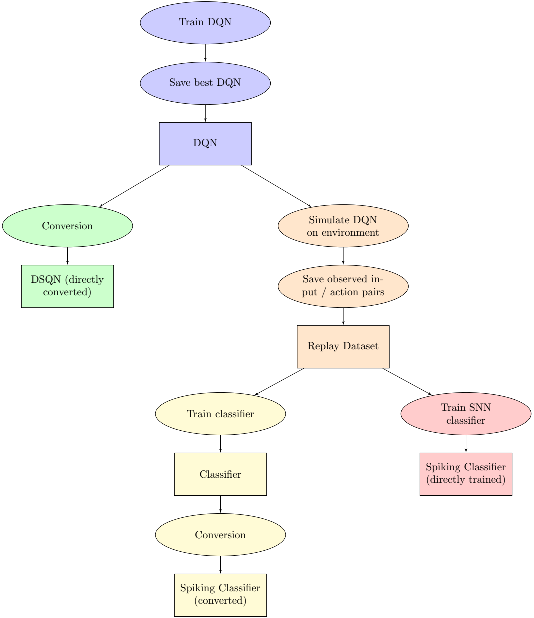


Theoretical Background: Spiking Neural Networks (SNNs)

- Inspired by neurons in the brain
- **Binary outputs** (spike or no spike)
- Simulation over a **time period** (discrete or continuous)
- Neuron model:
  - **Non-Leaky Integrate-and-Fire**
  - Reset mechanisms: **Reset-to-Zero**, **Reset-by-Subtraction**

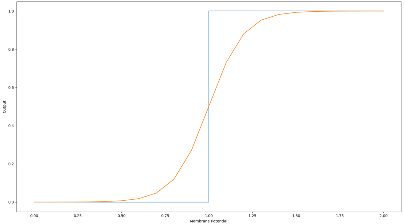
Theoretical Background: Conversion

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


Train DQN
Save best DQN
DQN
Conversion
DSQN (directly converted)
Simulate DQN on environment
Save observed input / action pairs
Replay Dataset
Train classifier
Classifier
Conversion
Spiking Classifier (converted)
Train SNN classifier
Spiking Classifier (directly trained)

Theoretical Background: Backpropagation with Surrogate Gradients

- SNN is trained on conventional hardware using **Backpropagation**
- **Gradients** of binary function are **replaced** with a steep sigmoid function[4]
- **SpyTorch** Framework[5]



State-of-the-Art: Training of SNNs

Conversion

- Strong performance on **classification** tasks
- Patel et al.[6] **convert a DQN directly** for BreakOut and report similar performance after conversion with better robustness
- Meschede[7] **converts a DQN indirectly** for a lane following task

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Other methods (Surrogate gradients, STDP, eRBP)

- Strong performance on **classification** tasks
- Few (STDP) to no (all others) papers on deep reinforcement learning
- Fremaux et al.[8] propose **STDP based actor-critic** framework which relies on **smart preprocessing** and **network layout**

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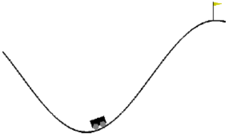

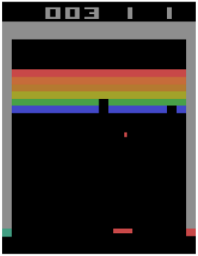

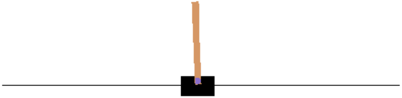

Experiments

- Experiments on three different **Open AI Gym**[9] environments: **CartPole**, **MountainCar**, **Breakout**
- Compare **conversion methods**
- Compare conventional DQN training and DSQN training using **surrogate gradients**
- Run networks in **NEST**[10] and on **SpiNNaker** hardware[11]

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Reproducibility

Problems:

- Results are **difficult to reproduce**
- Reported **metrics vary greatly**[12]

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Approaches in this thesis:

- Report **hyperparameters**, **software versions**, **seeds**
- **Average performance** of single agent + **standard deviation**
- **Conversion Accuracy**/Similarity as additional metric
- **Multiple training runs** to compare Backpropagation with and without surrogate gradients

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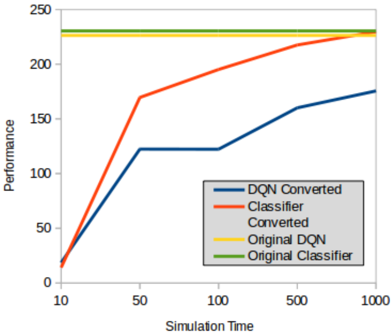
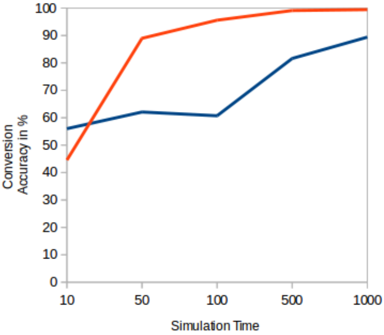
Further improvements:

- **Average performance of multiple trained agents** and **confidence intervals** (see Henderson et al.[12])

Direct vs Indirect Conversion

CartPole Results

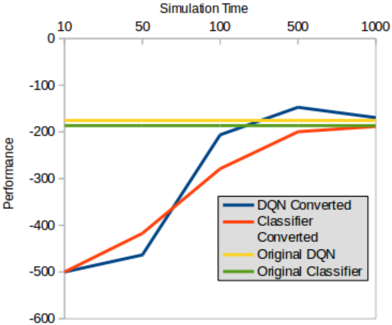


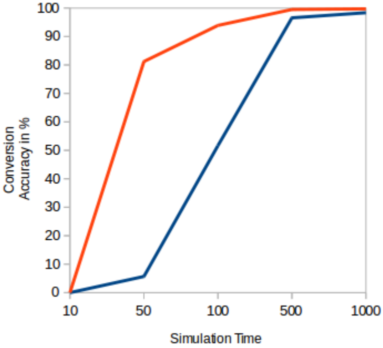


=> Classifier conversion works with smaller simulation time

Direct vs Indirect Conversion

MountainCar Results

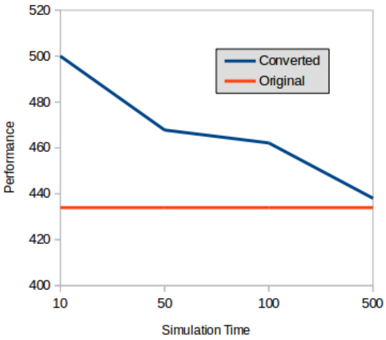


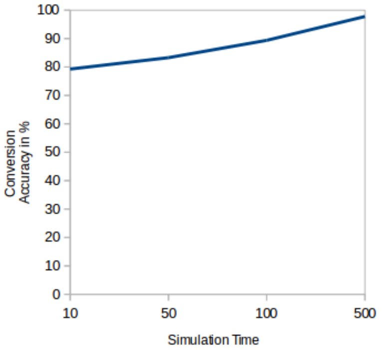


=> **Classifier can have worse performance than DQN**
Converting can improve performance

Policy Gradient Conversion

CartPole Results





=> Policy Gradient Networks convert well

Comparison of Conversion Methods

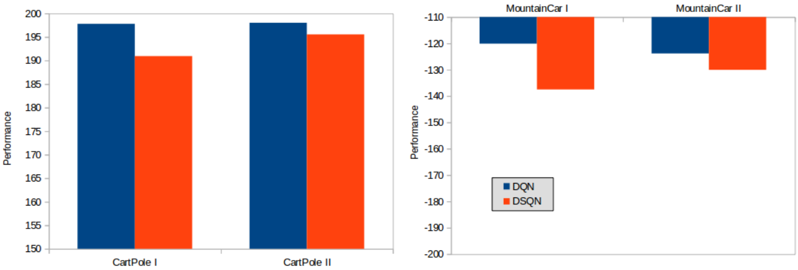
- Encoding: Poisson, Equidistant Spikes, **Constant Input Currents**
  - **Noise** from Poisson encoding can improve performance
- Decoding: Argmax of spikes, Argmax of **potentials**
- Resetting: Reset-to-Zero, **Reset-By-Subtraction**
- Weight Normalization: Model-based, Data-based, **Robust**

Backpropagation with Surrogate Gradients

Methodology

- **5 training runs** of DQN and DSQN each
- **Same hyperparameters**
- Two different learning rates

Backpropagation with Surrogate Gradients



=> **Less stable training** (of DSQN)
Longer training time (of DSQN)

Backpropagation with Surrogate Gradients

But:

Average performance when loading:

- CartPole: 454.84 (DSQN) vs 226.31 (DQN)
- MountainCar: -130.92 (DSQN) vs -175.4 (DQN)

=> **Better Performance** (of DSQN)
=> **Better Generalization**?

Surrogate Gradients vs Conversion

Conversion

+ More stable training
+ Less training time

Surrogate Gradients

+ Shorter inference time (except SNN classifier)
+ Better Generalization/Performance

NEST[10]

Challenge: Different neuron models, Simulation hyperparameters
Neuron Models: iaf_psc_delta, pp_psc_delta
Results: Classifier conversion is more robust against different neuron models

SpiNNaker[11]

Description: Neuromorphic hardware backend using PyNN[13]
Problem: Long simulation times
Results: Classifier conversion works, DQN conversion not yet

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Future Work

- More **complex environments**
- Convert **Actor-Critic** network
- Optimize algorithms for **SpiNNaker** or **NEST**
- **Event-based Random Backpropagation**[14]
- Facilitate the use of **state-of-the-art RL libraries**

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Conclusion

- **Conversion** of DQNs (direct, indirect, SNN-classifier) principally **works**
- **Direct conversion** of DQNs needs relatively **long simulation** times
- **Backpropagation with surrogate gradients** is **harder to train** (needs more time, more unstable)
- Networks trained with **surrogate gradients generalize better**
- Reproducing results is difficult
- Adapting networks to run on **NEST**, **PyNN**, or **SpiNNaker** is possible

Thank you!

Github repository:
https://github.com/vhris/Deep-Spiking-Q-Networks

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