## 5-Load-in-NEST

December 31, 2019

## 0.1 Load-in-NEST

In this notebook we load some of the pretrained networks in NEST.

Experiment List: 1. DQN-Training (How to train a conventional DQN and a spiking DQN using Surrogate Gradients (DSQN).) 2. Load-DQN (How to load a previously saved D(S)QN and how to save a replay dataset.) 3. Train-Classifier (How to train a spiking or non-spiking classifier on the saved replay data set.) 4. SNN-Conversion (How to convert a DQN and a Classifier to a SNN.) 5. Load in NEST (How to load a converted or directly trained spiking network in NEST.) 6. Conversion in pyNN with NEST or SpyNNaker (How to load spiking network in pyNN using NEST or SpyNNaker as backend.)

```
[1]: import torch
   import os
   import sys
   import random
   import matplotlib.pyplot as plt
    # hack to perform relative imports
   sys.path.append('../../')
   from Code import Nestwork, load_agent, FullyConnected, SQN
    # set seeds
   torch.manual_seed(1)
   random.seed(1)
   gym_seed = 1
    # device: automatically runs on GPU, if a GPU is detected, else uses CPU
   device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    # switch to the Result Directory
   os.chdir('./../../Results/')
```

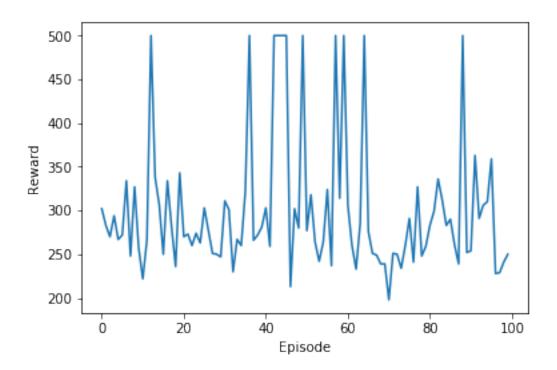
Detected PyNN version 0.9.5 and Neo version 0.6.1

To begin with, we load a network obtained by conversion from a classifier which was obtained in the previous tutorial (SNN-Conversion).

```
[2]: # specify the file, where the network is saved file = './CartPole-A/Classifier-Converted/model.pt'
```

```
# set hyperparameters of NEST:
# encoding/decoding methods are limited to constant input currents and potential_
\rightarrow outputs.
# set correct architecture
architecture = [4,16,16,2]
# set simulation time in ms, changing the resolution is not supported in our code
simulation_time = 100
# the neuron type can be set to 'iaf_psc_delta' or 'pp_psc_delta' and determinesu
→ the neuron type in the hidden layers
# this also fixes the reset method to reset-to-zero and to reset-by-subtraction
\rightarrowrespectively
# for converted DQNs the type pp_psc_delta should be chosen, for classifier it_{\sqcup}
→ makes not much difference.
neuron_type = 'iaf_psc_delta'
# set up network in NEST
nestwork = Nestwork(architecture,file,simulation_time,neuron_type=neuron_type)
```

The NEST agent can be loaded equivalently to all other agents using the function load\_agent (see tutorial 2: Load-DQN) as it implements the method 'forward'. We compare it to the original Classifier by setting compare\_against to the original classifier agent.

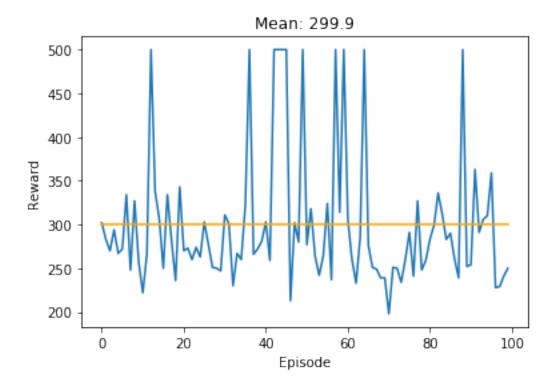


Similarity (Conversion Accuracy) after 29990 iterations: 88.62620873624542%

Complete
Mean: 299.9

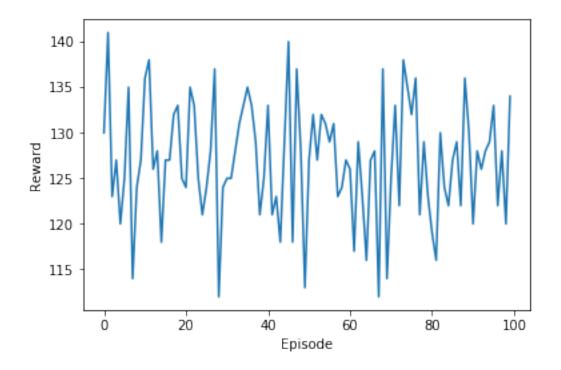
Std: 77.74531068388198

Similarity (Conversion Accuracy) after 29990 iterations: 88.62620873624542%



Likewise, we can convert the DQN directly. Next, we also run a directly trained DSQN in NEST.

```
[2]: # specify the file, where the network is saved
    file = './CartPole-A/DSQN-Surrogate-Gradients/trained/model.pt'
    # set hyperparameters of NEST:
    # encoding/decoding methods are limited to constant input currents and potential_
     \rightarrow outputs.
    # set correct architecture
    architecture = [4,17,17,2]
    # set simulation time in ms, changing the resolution is not supported in our code
    simulation_time = 100
    # this time both neuron types work similarly bad, we use pp_psc_delta
    neuron_type = 'pp_psc_delta'
    # set up network in NEST, as we load a SpyTorch trained network we have to add_{\mathsf{L}}
     → the bias to each observation
    # additionally we have to specify that the network has no biases, as this is a_{\!\scriptscriptstyle lack L}
     ⇒special case when initializing Nestwork
    nestwork = Nestwork(architecture,file,simulation_time,neuron_type=neuron_type,_
     →add_bias_as_observation=True,
                        has_biases=False)
    # Load the original DSQN to compare against
```



Similarity (Conversion Accuracy) after 12693 iterations: 65.83156070274954%

Complete

Mean: 126.93

Std: 6.440489033442957

Similarity (Conversion Accuracy) after 12693 iterations: 65.83156070274954%

