Reinforcement Learning Lab

Lesson 8: Deep Q-Networks

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Environment Setup

The first step for the setup of the laboratory environment is to update the repository and load the miniconda environment.

- Update the repository of the lab:

```
cd RL-Lab
git stash
git pull
git stash pop
```

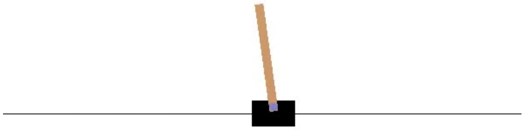
- Activate the *miniconda* environment:

```
conda activate rl-lab
```

Safe Procedure

Always back up the previous lessons' solutions before executing the repository update.

Environment: CartPole



- A pole is attached by an unactuated joint to a cart, which moves along a frictionless track. The pendulum starts upright, and the goal is to prevent it from falling over. A **reward** of $+1$ is provided for every timestep that the pole remains upright.
- The **state** of the environment is represented as a tuple of 4 values: *Cart Position*, *Cart Velocity*, *Pole Angle*, and *Pole Velocity*.
- The **actions** allowed in the environment are 2: *action 0 (push cart to left)* and *action 1 (push cart to right)*.

Today Assignment

In today's lesson, we will implement the Deep Q-Network (DQN) algorithm to solve the CartPole problem. In particular, the file to complete is:

```
RL-Lab/lessons/lesson_8_code.py
```

Inside the file, a python class and a function are partially implemented. The objective of this lesson is to complete it.

- **def training_loop()**
- **def DQNUpdate()**

Expected results can be found in:

```
RL-Lab/results/lesson_8_results.txt
```

Suggestions and Code Snippets

1. In today's lesson, the code is already partially implemented. Some functions related to Numpy and Matplotlib should not be modified. All the *entry points* for your code are marked with the keyword TODO.
2. Some methods of Gymnasium (the *new* Gym version) can be slightly different with respect to DangerousGridworld. Following are some snippets for the most important functions:

```
# Generation and Reset of the environment
env = gymnasium.make( "CartPole-v1" )
state = env.reset()[0]
# To generate a random action
action = env.action_space.sample()
# The updated 'step' function
next_state, reward, terminated, truncated, info = env.step(action)
done = terminated or truncated
```

training_loop()

```
Require: environment, neural_network, trials, expl_param, score_queue
Ensure: neural_network, score_queue
initialize the experience buffer                                   ▷ A fixed size queue
initialize the score queue                                         ▷ An infinite size queue
for i ← 0 to epochs do
    initialize s observe current state
    repeat
        Select and execute action a                                ▷ ε-greedy approach
        Observe new state s' and receive immediate reward r
        Add (s, a, s', r) to experience buffer
        DQNUpdate(neural_network, buffer)                          ▷ Call the training function
        update state s ← s'
    until s is terminal
    update score_queue

return score_queue
```

DQNUpdate()

Require: *neural_network*, *experience_buffer*(*MB*), *gamma*
Ensure: *neural_network*

Sample mini-batch MB of experiences from buffer
for $s, a, s', r \in$ MB **do** ▷ (state, action, next_state, reward)
    target ← PREDICT(*neural_network*, *s*)
    if s' is terminal **then**
        target[a] = r
    else
        max-q = max(PREDICT(*neural_network*, *s'*)) ▷ max q-value from s'
        target[a] = r + (max-q * gamma)
    mse = MSE(*state*, *target*)
    COMPUTE_GRADIENT(*mse*, *neural_network*) ▷ back-propagation
return *neural_network*

Expected Results

Seeding

Given the (particularly) high stochasticity of the method and the environment, for this lesson, we fixed a random seed equal to 2.

Expected results

The plot on the right is the expected result. Notice that it has been obtained with an ϵ-greedy strategy, starting with $\epsilon = 1$ and multiplying it by 0.999 each epoch.

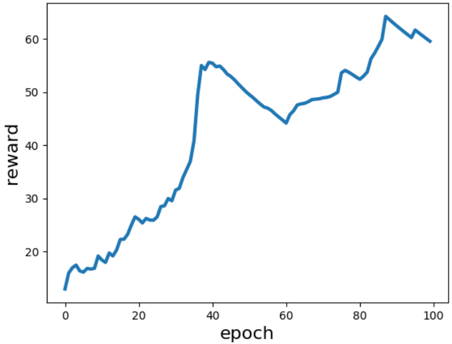


Figure: Note that obtaining this result requires time. You can stop the training after fewer iterations if one observes a growth in the reward.