README.md

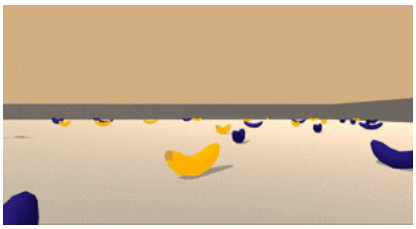
Udacity Deep Reinforcement Learning Nanodegree

Project 1: Navigation

Collecting Bananas with DQN

Introduction

The project teaches a DQN in a banana-collecting environment. The agent navigates in an environment to collect yellow bananas while avoiding black ones. A trained agent may act like this example:



A reward of +1 is provided for collecting a yellow banana, and a reward of -1 is provided for collecting a blue banana. Thus, the goal of your agent is to collect as many yellow bananas as possible while avoiding blue bananas.

The state space has 37 dimensions and contains the agent's velocity, along with ray-based perception of objects around agent's forward direction. Given this information, the agent has to learn how to best select actions. Four discrete actions are available, corresponding to:

- `0` - move forward.
- `1` - move backward.
- `2` - turn left.
- `3` - turn right.

The task is episodic, and in order to solve the environment, the agent must get an average score of +13 over 100 consecutive episodes.

Getting Started

1. Download the environment from one of the links below. You need only select the environment that matches your operating system:
    - Linux: click here
    - Mac OSX: click here
    - Windows (32-bit): click here
    - Windows (64-bit): click here
2. Extract the files into the root folder. If used in non-linux 64 bit environment, change the path in the navigation*.py files in the following line:

```
env = UnityEnvironment(file_name="Banana_Linux/Banana.x86_64")
```

3a. Use Anaconda to install the 'pytorch' environment

```
conda env create -f environment.yml
conda activate pytorch
```

3b. alternatively, use the requirements.txt to install via pip in your favorite python distribution

```
pip install -r requirements.txt (Python 2),
pip3 install -r requirements.txt (Python 3)
```

4. Train or watch the pretrained agent with the arguments in the file dqn/arguments.py by executing in folder dqn

```
python train.py
python watch.py
```

Concept of Reinforcement learning:

Reinforcement learning means an agent learns to interact with an environment. At each time step, the agent bases an action on an perceived state of the environment. The environment provides a reward. The agent thus tries to maximize the expected reward. This expected reward is discounted, because awards in the future are less valuable and certain. The function mapping a state to an action is the policy. It can be either deterministic or stochastic. A stochastic policy computes probabilities from which the actions will be sampled. Value-based methods use a value function to map the value of each state. Alternatively, action-value functions map the value of each value-action pair. By using the action with the highest value, the agent obtains a policy which maximizes the expected reward. A value function can be learned using monte carlo methods. A monte carlo methods samples many trajectories and uses the received rewards to learn the value of each state and the actions. A TD-method does not wait for an entire episode to be completed. The current q-value table is used to estimate the next value after each action. This means, the value iteration is quicker, but also that rough estimated value tables lead to error propagation. A Monte Carlo Iteration is therefore not biased,whereas a TD-Method can learn faster. Both methods can use random actions or a greedy strategy to obtain new episodes. Mostly, a epsilon greedy approach is used, in which greedy reward-maximizing actions are mixed with random actions for exploration.
Both methods are originally optimized for small state-action spaces, because they are built around q-tables storing each state value in a table. Continous state-spaces therefore need discretization methods. These discretization methods introduce a lot of human expert knowledge, and it is kind of obvious that they can be optimized with automated approaches. Machine learning inherently provides methods to automatically divide continous spaces (for example CNN layers), therefore deep-q-learning substitutes the q-table with a neural network. The q-learning algorithm is based on the q-table algorithm sarsamax. In Sarsamax, the value of executing an action in a specific state is estimated by looking into the q-table of the next state. The question now is: how to derive the value of the next state? In Monte Carlo Method, this value is derived by analyzing the entire episode at once, therefore the "true" value is used to train. In TD-Learning, the next value is estimated by estimating the value with the same q-table that is trained. Therefore, the target value of the state, action pair is estimated as follows.

```
q_target(state, action) = discount * (reward + value(next_state, greedy_action))
```

The locally stored value in the q-table is corrected with the experienced state-action-reward-state tuple and a learning rate alpha:

```
q_local = q_table(state, action)
q_table(state, action) = q_local + alpha * (q_target - q_local)
```

The value is iterated with itself. This is inherently instable and biased. Contrary to that, in monte-carlo estimation, the rewards are collected in total and then the episode is analyzed in it's entirety.

In Deep-Q-Learning, this inherent instability is mitigated with the following main concepts:

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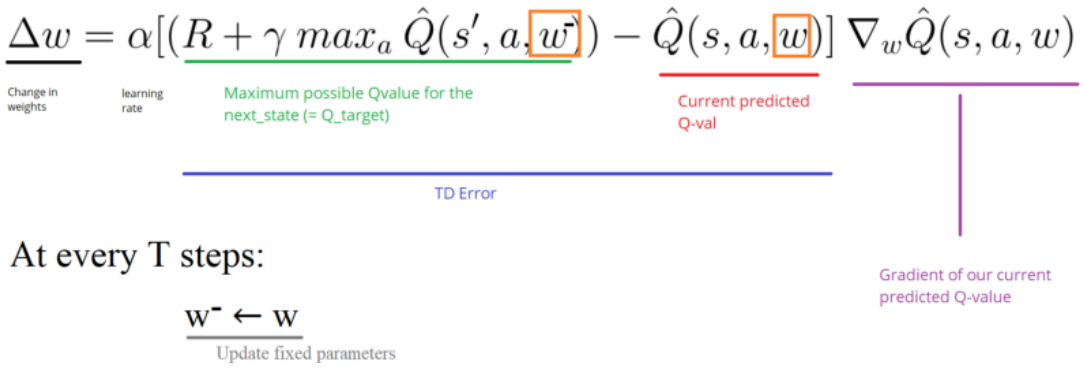
Experience Replay: Vanilla Online TD-Learning is temporally correlated. Each step results in immediate learning. Instead, the state, action, reward, next_state events are saved in memory and the training happens later (at k steps). The experience buffer stores and reuses the tuples and many tuples are used to learn in batches, which is very efficient using matrices instead of single operations. Each learning step uses randomly sampled occasions so learning is temporally decoupled and the batch shows increased representativeness of the underlying MDP.

- Fixed Q targets. The local network is learning values that a different target network has estimated. Therefore, the formula above is decoupled into the following:

```
q_target(state, action, target_network) = discount * (reward + value(next_state, target_network))
q_local = q_table(state, action)
q_table(state, action) = q_local + alpha * (q_target - q_local)
```

The Bellman equations for this are as follows:




```
Riedmiller, Martin. "Neural fitted Q iteration–first experiences with a data efficient neural reinforcement learning
method." European Conference on Machine Learning. Springer, Berlin, Heidelberg, 2005.
http://ml.informatik.uni-freiburg.de/former/_media/publications/rieecml05.pdf

Mnih, Volodymyr, et al. "Human-level control through deep reinforcement learning." Nature518.7540 (2015): 529.
http://www.davidqiu.com:8888/research/nature14236.pdf
```


With the two core concepts, deep-q-learning is able to play atari-games and solve this banana collection task!

Main improvement concepts of the vanilla dqn algorithm

Double DQN

The value estimation of the next state can be overestimated. This happens, because only the maximum q-value of each noisy action is used. The idea of Double Q-learning is to reduce overestimations by decomposing the max operation in the target into action selection and action evaluation. Although not fully decoupled, the target network in the DQN architecture provides a natural candidate for the second value function, without having to introduce additional networks. It is therefore proposed to evaluate the greedy policy according to the online network, but using the target network to estimate its value.

Prioritized experience replay

Prioritized experience replay gives priority to experiences with a big loss. These high-loss experiences get sampled for new learning more often. This introduced bias needs to be mitigated especially in the late stages of training. Therefore the paper suggests to compensate the bias by learning less fast from these high-loss samples. At the end of learning, this bias needs high or full compensation.

Dueling DQN (DDQN)

The core idea is to estimate state-value functions v(s) and the advantage of each action seperately and combine them into an output. The beauty of this algorithm is that it only changes the network architecture and can be combined neatly into the dqn architecture with addons.

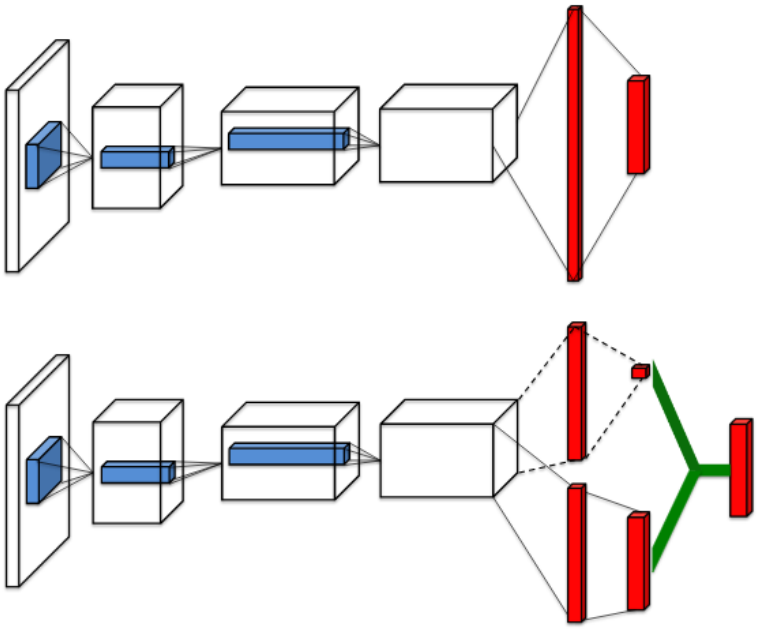


Figure 1. A popular single stream Q-network (**top**) and the dueling Q-network (**bottom**). The dueling network has two streams to separately estimate (scalar) state-value and the advantages for each action; the green output module implements equation (9) to combine them. Both networks output Q-values for each action.

Asynchronous Methods for Deep Reinforcement Learning

"We propose a conceptually simple and lightweight framework for deep reinforcement learning that uses asynchronous gradient descent for optimization of deep neural network controllers. We present asynchronous variants of four standard reinforcement learning algorithms and show that parallel actor-learners have a stabilizing effect on training allowing all four methods to successfully train neural network controllers. The best performing method, an asynchronous variant of actor-critic, surpasses the current state-of-the-art on the Atari domain while training for half the time on a single multi-core CPU instead of a GPU. Furthermore, we show that asynchronous actor-critic succeeds on a wide variety of continuous motor control problems as well as on a new task of navigating random 3D mazes using a visual input. "

A Distributional Perspective on Reinforcement Learning

In this paper we argue for the fundamental importance of the value distribution: the distribution of the random return received by a reinforcement learning agent. This is in contrast to the common approach to reinforcement learning which models the expectation of this return, or value. Although there is an established body of literature studying the value distribution, thus far it has always been used for a specific purpose such as implementing risk-aware behaviour. We begin with theoretical results in both the policy evaluation and control settings, exposing a significant distributional instability in the latter. We then use the distributional perspective to design a new algorithm which applies Bellman's equation to the learning of approximate value distributions. We evaluate our algorithm using the suite of games from the Arcade Learning Environment. We obtain both state-of-the-art results and anecdotal evidence demonstrating the importance of the value distribution in approximate reinforcement learning. Finally, we combine theoretical and empirical evidence to highlight the ways in which the value distribution impacts learning in the approximate setting.

Noisy Networks for Exploration

> "We introduce NoisyNet, a deep reinforcement learning agent with parametric noise added to its weights, and show that the induced stochasticity of the agent's policy can be used to aid efficient exploration. The parameters of the noise are learned with gradient descent along with the remaining network weights. NoisyNet is straightforward to implement and adds little computational overhead. We find that replacing the conventional exploration heuristics for A3C, DQN and dueling agents (entropy reward and ϵ-greedy respectively) with NoisyNet yields substantially higher scores for a wide range of Atari games, in some cases advancing the agent from sub to super-human performance."

Rainbow: Combining Improvements in Deep Reinforcement Learning

> "The deep reinforcement learning community has made several independent improvements to the DQN algorithm. However, it is unclear which of these extensions are complementary and can be fruitfully combined. This paper examines six extensions to the DQN algorithm and empirically studies their combination. Our experiments show that the combination provides state-of-the-art performance on the Atari 2600 benchmark, both in terms of data efficiency and final performance. We also provide results from a detailed ablation study that shows the contribution of each component to overall performance. "

The picture below shows the performance of all above algorithms.

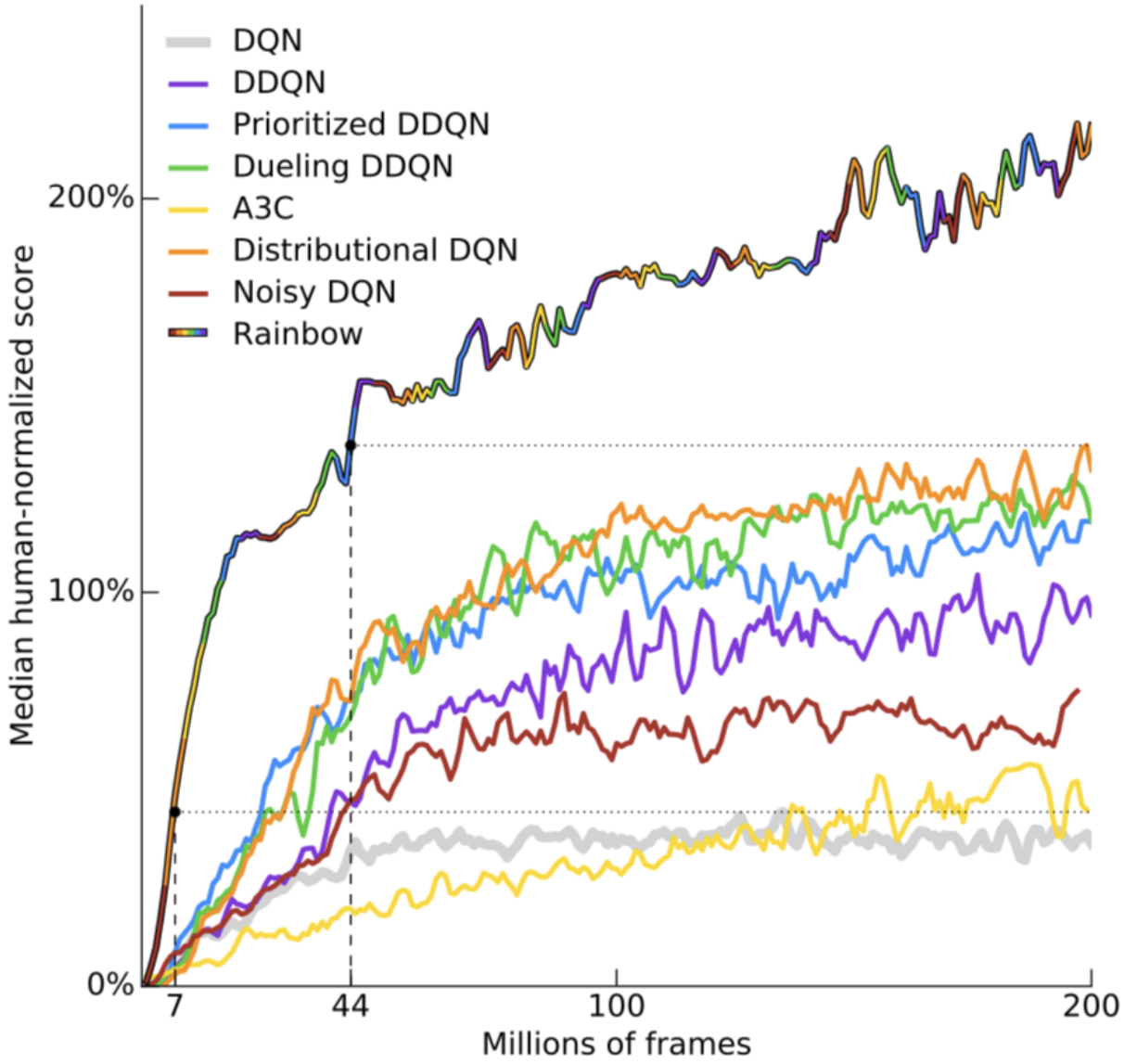


Figure 1: **Median human-normalized performance** across 57 Atari games. We compare our integrated agent (rainbow-colored) to DQN (grey) and six published baselines. Note that we match DQN's best performance after 7M frames, surpass any baseline within 44M frames, and reach substantially improved final performance. Curves are smoothed with a moving average over 5 points.

Report

The repository contains the following algorithms with optimized parameters

- Vanilla DQN
- Double DQN
- Dueling DQN
- Prioritized experience replay Each algorithm can be switched off and on individually. To help understanding, the interested reader can search for the occurrence of these switches and learn about their effect on the overall DQN architecture.

Interestingly, the Prioritized Experience Replay did not improve on the baseline. Though PER is able to solve the environment with a score > 13 if the parameters are carefully optimized, PER diminishes the score of any tested parameter set compared to deactivated PER. Therefore, a problem with the implementation is likely, but so far has not been found.

Model

The Double DQN uses a simple network architecture exhibiting fully connected layers. This simple architecture is suitable to learn the required Q_values without a lot of data. The dqn_model_test loads the dqn network and prints the nodes.

(fc1): Linear(in_features=37, out_features=64, bias=True) (fc2): Linear(in_features=64, out_features=64, bias=True) (fc3): Linear(in_features=64, out_features=4, bias=True) (state_value): Linear(in_features=64, out_features=1, bias=True)

The activation functions are relu and as Adam Optimizer was chosen.

Parameters

The following parameters help the network to learn fast. It is interesting to note that the Epsilon decays faster and the learning rate is higher to boost fast learning of a relatively simple task.

The parameters from the Atari Papers work well. With the small network, a score of 13 is achieved in 550 episodes. The parameters from the prioritized experience replay are: Learning rate 1e-4, learn every 4 steps from 32 episodes. If the agent learns every 16 steps from 256 episodes, the steps are fewer, but the episodes are faster due to the usage of a graphics card with enough memory.
The average score is improved from 14.3 to 15 in fewer episodes.

Improved parameters

A faster training can be achieved using the following parameters:

Experience Buffer 10000

Since the learning is quick, the experience buffer is smaller, because older examples do not represent the quickly adapted policy that well.

n_episodes 700

The network overfits beyond 700, indicated by reduced scores. The useful number of episodes varies greatly among the parameters. Basically if the network does not improve or substantially (more than 2 points from max) decreases, training is futile.

Epsilon

Only a small epsilon guarantuees high scores because the random parameters are typically non-optimal actions. Technically the skill of a learned agent should be evaluated with epsilon = 0.

- eps_start=1.0
- eps_min=0.01
- eps_decay=0.99

Learning parameters

The batch size in combination with the update_every parameter shows how often experience is reused on average. In the current implementation 256 batch size does not cost a lot of extra time since the network is small. Learning at every 16 step means that the average experience is reused 8 times. The achievable score improves with bigger batches and faster learning events.

- BATCH_SIZE = 256 A large minibatch size stabilizes the learning parameters
- UPDATE_EVERY = 16 # how often to update the network
- BUFFER_SIZE = int(1e3) # replay buffer size

The discount factor gamma shows how far into the future the lookahead shows. The halftime of 0.99 is ~ 70 steps, so the agent roughly overlooks the entire episode of 300 steps weighing a step 2*70 ahead with 25 %.

- GAMMA = 0.99 The discount factor shows how much importance future expectand reward has

The soft update of the target parameters shows how far ahead the local network is from the target network. If this parameter is too big, it destabilizes learning.

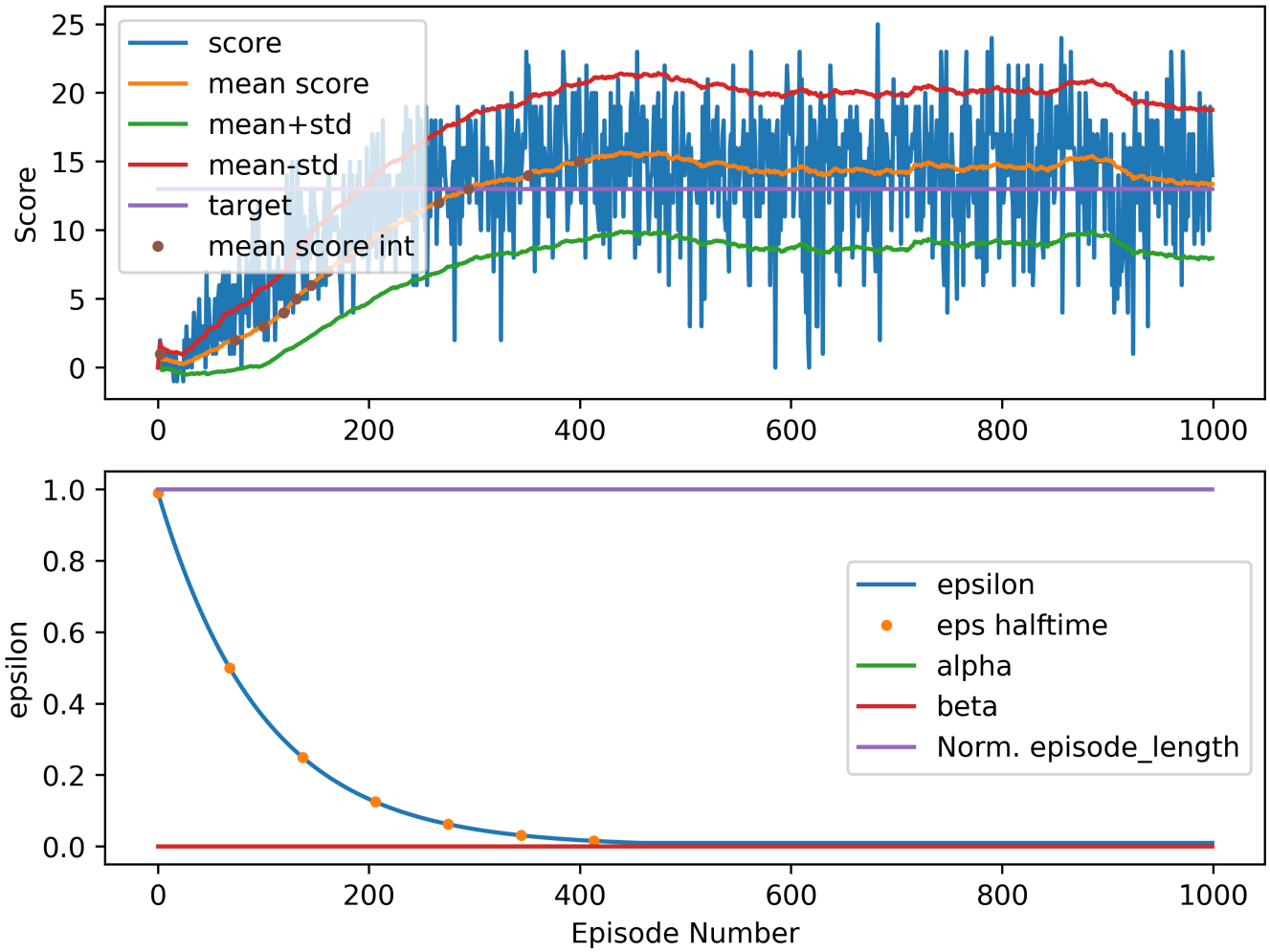
- TAU = 1e-2 # for soft update of target parameters

Using double-dqn, a learning rate of 1e-3 is better, for prioritized experience replay 1e-4 is showing better results.

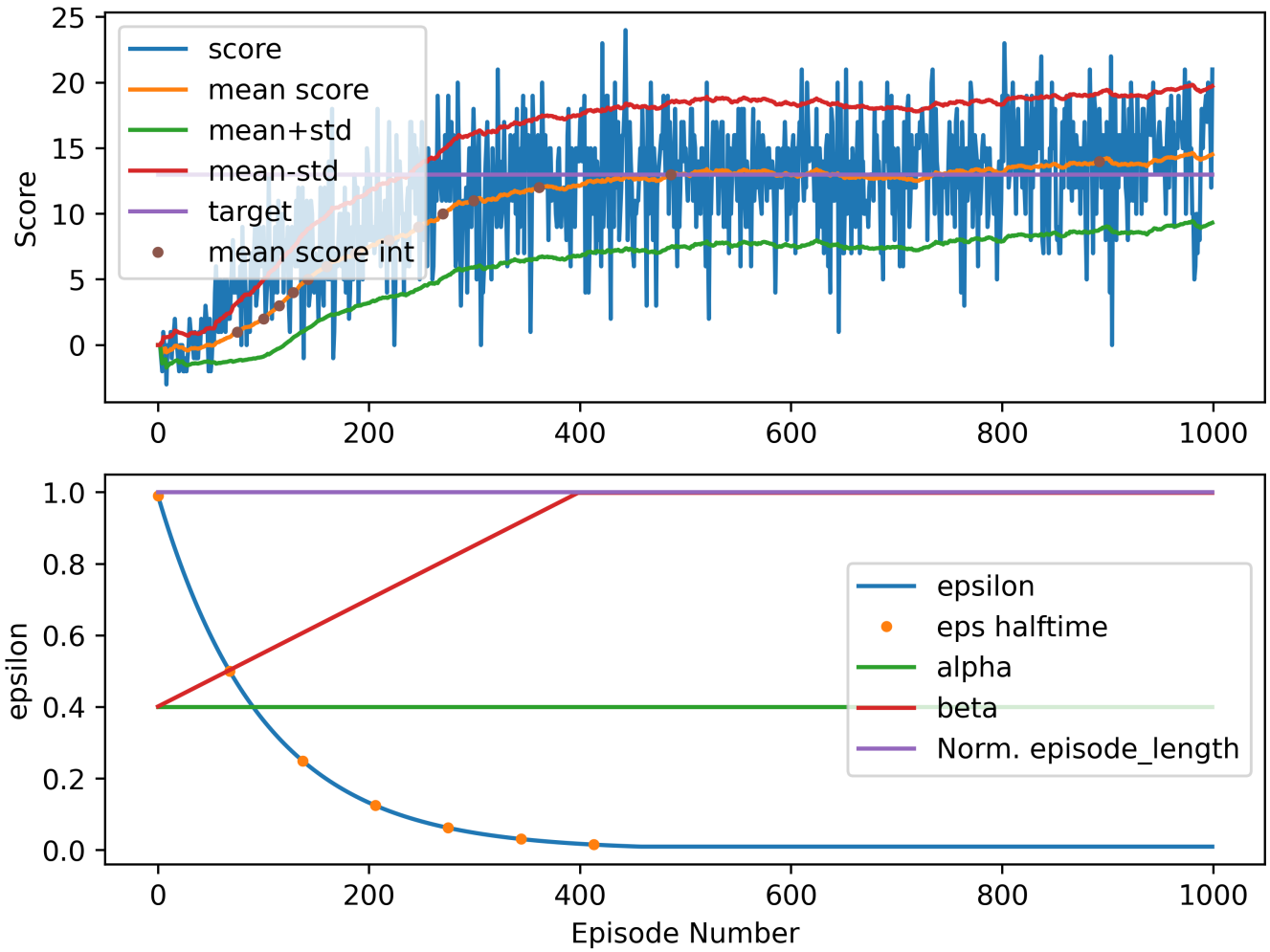
- LR = 1e-3 # learning rate.

Achieved score

The environment is solved in ~300 episodes with an average score of 100 episodes above 13. After 400 Episodes, a score of 15 is achieved. This run uses double and dueling algorithms as well as the above parameters with a small 64, 64 neural network. The watch.py file uses the weights obtained at episode 400 of this run.



The best run using Prioritized experience Replay is shown in the following diagram. The weighting factors for using PER are actually decayed in order to achieve a high score. With per activated but the weighting factor alpha and the scaling factor beta both to 0, per achieves a similar performance than using double dqn with more training examples. The learning rate is set to 1e-4 in contrast to the above implementation with 1e-3.



Potential improvements

The main improvement would be a randomized parameter-search. By giving each parameter a (discretized) interval, a random search or a small hill climber could optimize meta-parameters. That helps to identify the potential of each algorithm. With the current implementation, a practical approach is to use only double dqn and then optimize the parameters.

The implementation of prioritized experience replay are currently not working as expected and need further work. Then, it would be very interesting to use saliency maps and the visual simulator to further analyze the algorithmic performance and fallacies.

Watching the agent, a more capable neural network could improve the behavior in the environment.

Troubleshooting

```
    unityagents.exception.UnityEnvironmentException: Couldn't launch the Banana environment. Provided filename does
not match any environments.
```

means the unityenvironment is not found. The path is configured in dqn/arguments.py in line 12. Using linux, the downloaded folder should be placed in this root directory.