Evaluation of Reinforcement Learning Methods for a Self-learning System

David Bechtold, Alexander Wendt, and Axel Jantsch
TU Wien, Institute of Computer Technology, Gusshausstrasse 27-29, A-1040 Vienna, Austria

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Abstract: In recent years, interest in self-learning methods has increased significantly. A challenge is to learn to survive in a real or simulated world by solving tasks with as little prior knowledge about itself, the task, and the environment. In this paper, the state of the art methods of reinforcement learning, in particular, Q-learning, are analyzed regarding applicability to such a problem. The Q-learning algorithm is completed with replay memories and exploration functions. Several small improvements are proposed. The methods are then evaluated in two simulated environments: a discrete bit-flip and a continuous pendulum environment. The result is a lookup table of the best suitable algorithms for each type of problem.

1 INTRODUCTION

The interest in machine learning research has exploded in recent years. Nowadays, it helps us to accomplish tasks that could not be implemented from scratch because of the immense state space. These methods learn from experiences just as humans do, but compared to us, much more additional data is necessary. Human beings immediately recognize which impact their actions have on the environment. Machines lack that understanding. Due to the large state space, the function to be learned is usually approximated.

In a project, a self-learning agent shall be developed that learns from scratch what its sensors and actuators are doing and how to use them to reach a certain goal. The overall purpose is to develop one software that can adapt to an application, where the interfaces to the environment are unknown at design time.

A good approach to handle large state spaces is to let the system learn to solve the task completely independent. For scalability, the task should not be tied to any assumptions about the environment. Therefore, the agent should start with little prior knowledge about the task, the environment, and the meaning of the in- or outputs. In order for a new task to be learned, only a reward function has to be designed, which rewards the agent for performed actions. With that in mind, a robot-like application is appealing. For this, the following constraints should be considered:

- Continuous state space, because sensory outputs are continuous
- Work only with a partial part of the environment perceived
- Deal with sparse rewards since real numbers are uncountable
- Have as little knowledge about itself, the task and the environment as possible

The agent has to predict which action to perform next to receive a high amount of reward. Deep Q-learning (DQN) performed well on several Atari 2600 games. DQN outperformed a linear learning function in 43 out of 49 games and human game tester in 29 out of 49 games (Minh, 2013). Therefore, algorithms from the area of reinforcement learning algorithms are selected.

To prepare for a self-learning agent, the main research objective of this paper is to address the question: which combination of reinforcement learning algorithms is most suitable for discrete and continuous state spaces and action spaces.

The focus of this paper is to analyze, improve and compare different Q-learning algorithms, replay memories, and exploration functions to determine which combination of algorithms to choose for each task setting. The algorithms are being evaluated in two simulation environments: a discrete bit-flip

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environment (Andrychowicz, 2017) and a continuous pendulum environment[1].

2 AVAILABLE ALGORITHMS

Reinforcement Learning does not use labels for datasets in the same way as supervised learning does. There is no ground truth present. Instead, the agent receives a reward or punishment signal through exploration of an environment. It is attempted to maximize this reward signal in the long-term because the amount of reward describes how good or bad the agent performed. Learning is described as finding actions that result in a higher reward. Therefore, the reward signal is transferred to an expected reward for each state (Sutton, 1998).

There are two groups of methods: *model-free* or *not model-free*. Not model-free methods require prior knowledge about the environment in the form of state transition probabilities. As this agent shall start from scratch, only model-free methods are of interest.

A policy is a function, which maps states to actions. The agent perceives a state. The policy determines which action it will perform. In most cases, the policy aims to maximize the cumulative reward. *On-Policy* methods are based on known policies. *Off-Policy* methods are based on learned content.

Immediate rewards are given directly after an action and no future rewards need to be considered. To maximize the reward, only the selected action and the current state of the agent are essential. *Delayed rewards* mean that an action can generate immediate rewards, but the future must be considered, at least the next state of the environment. These problems are more challenging to solve because the agent has to choose actions that pay off in the future. *Pure-delayed rewards* are the same for all states except the last state of an environment. Playing chess, for example, could be such a problem because the environment only gives the agent a reward for winning or losing the game.

Finally, the reward function can be designed to be shaped or non-shaped. *Non-shaped reward* functions usually provide only a positive reward for the main goal of the task. *Shaped reward* functions are typically designed to guide the learner towards the main goal by providing rewards for getting closer to the goal.

Reinforcement learning techniques try to solve finite *Markov Decision Processes* (MDP). MDPs describe the agent's interaction with the environment and vice versa. At each time step, the agent is located in a state and performs an action selected by a policy that leads to a successor state and receives a reward.

The goal is to optimize the total discounted rewards over time. It requires a scalar number that estimates how good it is to be in a specific state, or which action should be performed next to receive a high amount of reward. It can be achieved with the help of the so-called state-value function and the action-value function. The *state-value function* provides the expected cumulative discounted reward (expected return) for a state of a policy. The *action-value function* provides the expected return for a state executing the action of a policy.

2.1 Q-learning

Q-learning calculates Q-values, i.e. the expected reward, which shows how much reward to expect by performing a particular action from a certain state. Deep Q-learning means that a neural net is used as a function approximation for predicting the Q-values.

As a model-free algorithm is required, at least two policies are usually used: one for exploring the environment, e.g. a random policy, which updates the Markov Decision Process of the agent. With this knowledge, the second policy is used after training to exploit the environment. When the state visits reach towards infinity, the trained policy converges to the optimal policy. At this point, the agent can stop performing random actions and start to act according to the trained policy.

An agent using the Q-learning approach updates the corresponding Q-value after each observed transition. A transition is a 4-tuple $(s_t, a_t, r_{t+1}, s_{t+1})$ that consists of the current state s_t, the performed action a_t, the resulting state s_{t+1} and the earned reward r_{t+1}.

A method of updating the Q-values is the Temporal Differences (TD) method (Dayan, 1992). A problem with *Temporal Difference Q-learning* is that Q-values must be stored in a lookup Q-table. For a large continuous state space, it suffers from the *Curse of Dimensionality* (Kober, 2012) and cannot be used here. The team of Google DeepMind (Minh, 2015) overcame this issue by using a neural network to approximate the action-value function. Instead of using a state and an action to update the Q-table with

[1] Open AI Gym; Pendulum, 2019. https://gym.openai.com/envs/Pendulum-v0/

a Q-value, they only feed the Q-network with a state and obtain a Q-value prediction for each action. The highest Q-value represents the best action that can be performed from a particular state. The *Deep Q-learning network* (DQN) is trained with a loss function that determines the error and allows the weights to be changed. Further, a replay memory is used to store the last n states, which are used as a mini-batch for training.

A problem with DQN is that small changes in the Q-values can lead to fast policy changes and thus, the policy can begin to oscillate. It leads to an unstable of the Q-values, which harms the task solving performance. To prevent this particular case, the *Double DQN* (DDQN) (van Hasselt, 2015) uses two Q-networks: The first Q-network that is used for action selection only and the second Q-network that evaluates actions. It is attempted to keep the Q-network as stable as possible over several transitions by slowly updating its weights.

For robotic control, it is essential to consider continuous action spaces. The predicted Q-values only determine which action leads to the highest amount of reward, but not with how much force this action should be performed. (Lillicrap, 2015) introduced the *Deep Deterministic Policy Gradient* (DDPG), which introduces an *actor-critic* (AC) algorithm to deal with continuous action spaces. DDPG uses two Q-networks, of which one learns to act (actor), while the other learns to criticize the taken action (critic).

2.2 Replay Memories

All Deep Q-learning algorithms need to store transitions in a replay memory. If this were not the case, the Q-network would have to be trained by successive transitions. It is like learning based only on immediate experiences, without considering the past. Experiences have to be considered to enable a successful learning approach. It is done by saving transitions in a so-called replay memory. However, successive transitions are very inefficient due to the strong correlation between them.

To break up these correlations, the transitions are usually sampled randomly. Further, as the memory gets full, the oldest transitions are deleted (Minh, 2013). The collaboration of the environment, Q-learning method, and replay memory can be observed in Figure 1.

An issue with this type of memory is catastrophic forgetting (Kirkpatrick, 2017). Either it means that the Q-network has learned a task correctly but forgets about it by simply being trained with many useless transitions, or it was not trained with transitions that solve the task at all, i.e. in a sparse rewarding environment.

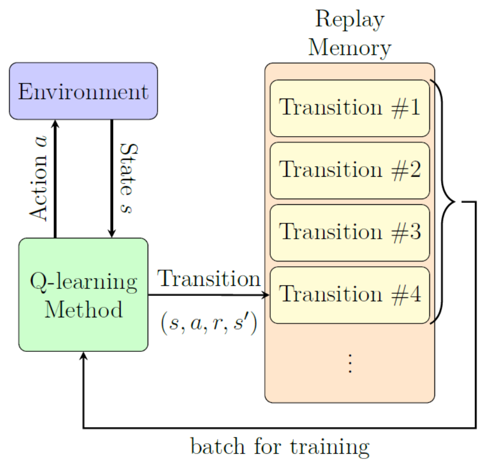


Figure 1: Collaboration of the replay memory with the Q-learning method and environment.

Experience Replay (EXPR) (Minh, 2013) is the simplest and most widely used one. Transitions are stored one after another in a memory of size N. The most recent transitions experienced are always stored at the end of the memory. Mini-batches are sampled randomly distributed from the whole memory. As the memory grows full, the oldest transitions, which are the transitions at the beginning of the memory, are deleted. Intuitively, this memory is the most susceptible to catastrophic forgetting.

Prioritized Experience Replay (PEXPR) (Schaul, 2015) takes advantage of the fact that the temporal difference (TD) error of transitions can easily be calculated. The TD error shows how surprising or unexpected a transition is, i.e. the higher the TD error of a transition, the more the agent can learn from these transitions. Sampling only transitions with high TD error can make a system prone to overfitting, due to the lack of diversity. Therefore, the TD error is converted to a priority. To guarantee that even transitions with low priorities are sampled with a non-zero probability from the memory, multiple methods are used. One method is to set the priority of a transition to the maximum for the first insert. It ensures that these transitions are sampled for sure in the upcoming mini-batch. Two types of prioritizations are available: rank-based (PRANK) and proportional-based (PPROP).

Hindsight Experience Replay (HER) is suitable in a sparse reward environment. Rewards are only given if a goal is reached (pure-delayed rewards). Usually, multiple entire episodes are stored in the memory without any positive rewards (Andrychowicz, 2017).

From episodes without positive rewards, the Q-learning approach only learns which actions should not be performed. It is not useless knowledge, but in the end, it does not help to solve the task. Therefore, Q-learning learns little or even nothing from such episodes. However, these episodes contain some useful information, such as how non-goal states can be reached. This knowledge is useful and can help the agent to solve the task better and faster. If this state must be visited in order to solve the task, the knowledge about how to reach it can be considered as relevant. To enable learning, the algorithm defines a state as a virtual goal, rewards it with zero, and adds it to the memory. As Hindsight Experience Replay only instructs how virtual goals are generated and not how to save them, it is compatible with all other replay memory methods, like Experience Replay. To decide which goal the Q-network should follow, the state of the virtual or main goals is additionally provided as an input. It makes it necessary to double the size of the Q-network. Providing the main goals as an input for the Q-network is, in the authors' opinion, not suitable for self-learning. The Q-network simply learns that it must reach the state, which is equal to the goal input. Another issue is that HER performs poorly in combination with shaped reward functions (Andrychowicz, 2017).

2.3 Exploration

To learn policies in an optimal way, an agent must make two far-reaching decisions: how long should the environment be explored and when should it be exploited? Exploration means that an agent performs actions to gather more information about the task and the environment. Exploitation means that an agent only executes the best action possible from a certain state. Finding out when to explore and when to exploit is a key challenge, known as the exploration-exploitation dilemma (Sutton, 1998).

Exploration methods can be divided into two groups: directed and undirected (Thrun, 1992). Directed *exploration* uses information about the task and/or the environment. One requirement mentioned in the introduction is that the agent should know as little as possible about the task and the environment at the start. Therefore, only undirected exploration is considered here.

ε-greedy (EG) is a non-greedy exploratory method in which the agent chooses a random action with a probability of $0 \leq \varepsilon \leq 1$ at each time step instead of performing the action with the highest Q-value. To avoid the exploration-exploitation dilemma, ε is decreased at each timestep by a fixed scalar number. The main challenge is to find the right exploration decline.

For a physical environment with momentum, an Ornstein-Uhlenbeck process (OU) is usually used as additive noise to enable exploration. This process models the velocity of a Brownian particle with friction (Lillicrap, 2015). Especially in the case of robot control, such a process is used, due to the drifting behavior of the output values. The parameters can be set to produce only small drift-like values. In general, the Ornstein-Uhlenbeck process is a stochastic process with medium-reversing properties as in equation 1.

$$\pi(s) = dX_t = \theta \cdot (\mu - X_t)dt + \sigma dW_t \qquad (1)$$

where $X_0 = a$. θ means how fast the variable reverts towards the mean. σ is the degree of the process volatility and μ represents the equilibrium or mean value and a is the start value of the process, which are usually set to zero. The Ornstein-Uhlenbeck process can be considered as a noise process. It generates temporarily correlated noise. The noise $N(a, \theta, \sigma, \mu)$ is added to the action to enable exploration.

3 RELATED WORK

Although reinforcement learning is a hot topic, finding articles, which use real physical robots that learn to solve problems on their own is rare. Dozens of articles and simulation environments exist. For example, the OpenAI Gym[2] offers more than sixty environments in which learning algorithms can be evaluated and compared to the results of other competitors. However, not many articles deal with few sensors and a reduced perception of the environmental state.

Since robotic tasks are often associated with complex robot motion models, poor environmental state resolution and sparse rewards play an important role. (Vecerik, 2017) introduces a new methodology called Deep Deterministic Policy Gradient from Demonstrations (DDPGfD) that should help to solve those issues. The idea is to store a defined number of task solving demonstrations in the replay memory and keep them forever.

In to a 2D aerial combat simulation environment with near continuous state spaces (Leuenberger, 2018), the Continuous Actor-Critic Learning Automaton (CACLA) is applied. They replaced

[2] https://gym.openai.com/envs/

Gaussian noise by an Ornstein-Uhlenbeck process as an exploration function and introduced a modified version the Monte Carlo CACLA, which helped to improve performance.

In (Shi, 2018), an adaptive strategy selection method with reinforcement learning for robotic soccer games was introduced. The researchers used Q-learning to learn which strategy small robots should follow in certain situations to successfully play football. Each team consisted of four robots and the game state was observed with a camera filming the entire football field. The main issue addressed by this work was that a very dynamic environment, such as soccer with multiple teammates, requires timely and precise decision-making.

In (Hwangbo, 2017), a reinforced learning method was introduced for the control of a quadrotor. The 18-dimensional state vector of the quadrotor included a rotation matrix, the position, the linear velocity, and the angular velocity. The policy was optimized with three methods: *Trust Region Policy Optimization* (TRPO) (Schulman, 2015), DDPG (Lillicrap, 2015), and a new optimization algorithm developed by the authors. While TRPO and DDPG performed poorly, the algorithm of the authors performed well. However, the authors used a model-based learning approach, which is not applicable here.

(Tallec, 2019) analyzes how various parameters in DDPG can be tuned to improve the performance in near continuous time spaces. These are discretized environments with small time steps. Through a continuous-time analysis, where the time step is considered, such as discount factor, reward, learning rate and exploration parameters.

4 IMPROVEMENTS

For the particular problem of learning from scratch, three improvements of the analyzed algorithms are proposed. The aim is to achieve better results overall.

4.1 Hindsight Experience Replay with Goal Discovery

The idea behind Hindsight Experience Replay with Goal Discovery (HERGD) is that the main goal of the agent has to be discovered first and only after its discovery, it is provided to the Q-network. This approach offers more flexibility than the standard Hindsight Experience Replay, in which the main goal has to be provided to the Q-network from the beginning. Virtual goals are inserted as defined in the standard Hindsight Experience Replay algorithm.

In environments where it is unlikely that the target will be reached with random exploration methods, HERGD will struggle in the same way as the ε-greedy and Ornstein-Uhlenbeck process. Although, once the goal is found, this approach can get to the optimal policy faster.

4.2 ε-greedy Continuous

Since ε-greedy is only applicable to integer actions, ε-greedy Continuous (EGC) extends the idea of standard ε-greedy to support continuous action spaces as well. The key idea behind this approach is that every action from the action space has its own action range $[a_{lower}, a_{upper}]$. For each action a, a random uniform value λ is drawn, for which $a_{lower} \leq \lambda \leq a_{upper}$ is valid. The policy equation (2) tells when to use a random action or a policy action.

$$\pi(s) = \begin{cases} apply\ \lambda\ to\ action\ a\ \in A(s), if\ \varsigma \leq\ \varepsilon \\ use\ action\ from\ \pi(s),\ \ otherwise \end{cases} \tag{2}$$

$\pi(s)$ is the policy, $A(s)$ is the action space and ε is the threshold of exploration that is lowered with each time step.

4.3 Ornstein-Uhlenbeck Annealed

An issue concerning the standard Ornstein-Uhlenbeck process is that switching from exploring to exploiting is done immediately. This means the process is outputting noise until the exploration stops and the exploitation begins. It can harm the learning process because actions, that are already optimally learned, can be overwritten by the outputted noise. On the other hand, limiting the outputted noise by adjusting θ or σ leads to under-exploration. Therefore, the idea behind Ornstein-Uhlenbeck Annealed (OUA) is to reduce the generated noise after every time step by a function similar to ε-greedy continuous as shown in equation 3

$$\pi(s) := \pi(s) + N(a, \theta, \sigma, \mu) \cdot f(t) \tag{3}$$

For this evaluation, the function $f(t)$ is selected to reduce the noise linearly after every timestep.

5 EVALUATION

The algorithms are being tested for suitability and being compared in different environments.

5.1 Experiment Environments

A discrete and continuous state environment is provided to evaluate the algorithms. For both environments shaped and non-shaped rewards are analyzed.

5.1.1 Discrete Bit-flip Environment

The basic idea of this environment is based on the bit-flip environment (Andrychowicz, 2017). The goal is to flip the bits in a bit vector BV_n of length n in the same way that it matches a target bit vector BVT_n within n tries. The state $S = \{BV_{n_0} \dots BV_{n_{n-1}}\}$ is the bit vector $BV_n = S$. The action a is the number of the bit to flip and it can be chosen from the action space $A = \{0, 1, \dots, n-1\}$. For instance, an action $a = 2$ means that the bit BV_{n_1} in bit vector BV_n is flipped. To make the algorithms and methods comparable, bit vector BV_n is always reset to zero and the target bit vector BVT_n is taken from a look-up table.

Minor adjustments had to be made to use this environment for this application. Since DDPG outputs continuous values and the bit to be flipped must be an integer number, a conversion from real to natural numbers has to be made. Therefore, the output of DDPG is divided into n equal sections, each representing one bit in the bit vector.

Because this is a discrete process, the Q-learning method DDPG does not use an OU process for exploration. Thus, only continuous ε-greedy exploration is used.

In the non-shaped reward function, the reward for reaching the goal is set to 1, and all other rewards are set to -1. It simulates a delayed and sparse rewards problem, since the probability of finding the target bit vector BVT_n is drastically decreasing with the bit vector length n.

The shaped reward function simply counts the equal bits of a bit vector BV_n and target bit vector BVT_n. Then, the counted number is divided by n-1.

5.1.2 Continuous Pendulum Environment

To be able to evaluate the RL methods within a continuous action and state-space environment the pendulum environment from open AI Gym was chosen. The goal is to swing a frictionless pendulum upright, so that it stays vertical, pointing upwards.

Figure 2 shows the pendulum near the maximum reward position. The perceived state of this environment is a three tuple $S \in (cos(\phi), \sin(\phi), \dot{v})$. This state is generated by the pendulum angle ϕ and vertical velocity v of the pendulum. To its state, a torque $-2 \le \tau \le 2$ can be provided as an action a. However, to make this environment more difficult to solve, the torque is limited to $-1 \le \tau \le 1$ here. Therefore, the pendulum must gain velocity through swinging to reach a rewarding position. After a reset, the pendulum starts in a random position and with a random torque.

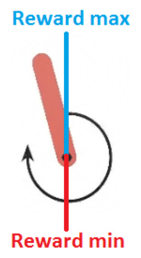


Figure 2: The pendulum environment with the pendulum position near the maximum reward position.

Non-shaped rewards are set to 1 if the pendulum points upwards and its angle is in range of $-1° \le \phi \le 1°$. If not, the reward is set to -1.

For shaped rewards, this environment uses equation 4 with $-\pi \le \phi_{norm} \le \pi$ and $-8 \le \dot{v} \le 8$. Therefore, the reward is in the range of $-16.27 \le R \le 0$.

$$R = -(\phi_{norm}^2 + 0.1 * \dot{v}^2 + 0.001 * \tau) \qquad (4)$$

Since Q-learning algorithms output discrete actions, conversion from natural numbers to real numbers is done. The output layer of DQN and DDQN are extended to 21 nodes. Each of them represents a specific torque value, starting from -1.0, with a step size of 0.1, to 1.0 including zero.

5.2 Test Setup

A Q-learning method requires the following methods to work: A Q-algorithm, an exploration method, a replay memory, and a reward function. The Q-learning algorithm can be considered as the brain. Learning and decision making is done here. DQN and DDQN use standard feed-forward multilayer neural networks. Important parameters are the number of layers and neurons, the activation functions, the optimizer, the learning rate, the discount factor, and the soft target update factor. The soft target factor is only required for DDQN and DDPG because DQN Q-networks do not include a second neural net. According to (Lillicrap, 2015), all Q-networks in this work use the Adam optimizer (Kingma, 2014).

The learning rate is multiplied by the values computed by the optimizer. Therefore, it determines how fast the Q-network learns. Since some of our evaluations have to deal with sparse rewards, which means that the past experiences are important, the discount factor is chosen to be 0.98, which is close to 1.0. The learning rate and soft target update factor are chosen to be small, i.e. 0.001, because solving sparse reward problems requires many transitions, since the rewarding state is not often experienced. All hidden layers use RELU units as activation function, as they are currently the most successful and widely used (Ramachandran, 2017).

For the replay memory, the most essential parameter is its size. It determines how many transitions can be stored. While large memory sizes can only slow down learning, too small memory sizes can drastically reduce learning success or even make it impossible. Sizes from 16 to 128 state transitions will be tested.

For the Hindsight Experience Replay, additionally, the sampling method and the quantity of new goals to sample has to be chosen. Based on (Andrychowicz, 2017), the sampling method *future* is selected because it gives the best overall results together with the best value for parameter k = 4. For PPROP, (Schaul, 2015) mentioned that a good value for the prioritization factor is 0.6.

When exploring, it is sometimes necessary to carry out already learned actions to be able to refine them further and finally to solve the task in the best way possible. For the exploration function, the most critical parameter here is the exploration rate, which determines after how many actions performed the exploration ends and the exploitation begins. It is common practice to place this value at the end of the entire learning procedure, i.e. $e = episodes * steps_{episode}$.

The evaluations are carried out with Keras[3] framework, which is programmed with Python. It is used to model neural networks and runs on top of the symbolic math library TensorFlow[4].

5.3 Results

The measurements are performed in two separate environments: a discrete bit-flip and a continuous pendulum environment

5.3.1 Discrete Bit-flip Environment

The evaluation starts with a bit vector length of n = 1. At the end of each episode, which is exactly after 200 bit flips, it is checked if the current method solves the bit vector with length n within n bit flips. If so, the current attempt t is considered as successful. An attempt t is assumed to be failed if a method fails to solve a certain bit vector within 50 episodes. After determining whether the bit vector length n has been solved successfully or the attempt has failed, the method is reset and the next attempt t = t+1 is started.

After five tries, it is checked if the current method has at least one successful attempt. If this is the case, the next bit vector of length n := n + 1 can be performed. The success rate of a reinforcement learning method can be calculated by dividing the total successful attempts by the number of attempts.

Figure 3 shows representative results of the non-shaped reward function. With raising bit vector lengths, the target bit vector BVT_n is more challenging to discover. Only HER has the advantage that the Q-network knows the goal state of the environment right from the beginning. HERGD first has the same discovery issue as PPROP and EXPR until the goal is experienced once. In general, larger batch sizes in combination with HER, HERGD or PPROP helps when dealing with sparse rewards. Between the batch size 16 and 128, only a difference of 3 bits was measured, i.e. 21% better results.

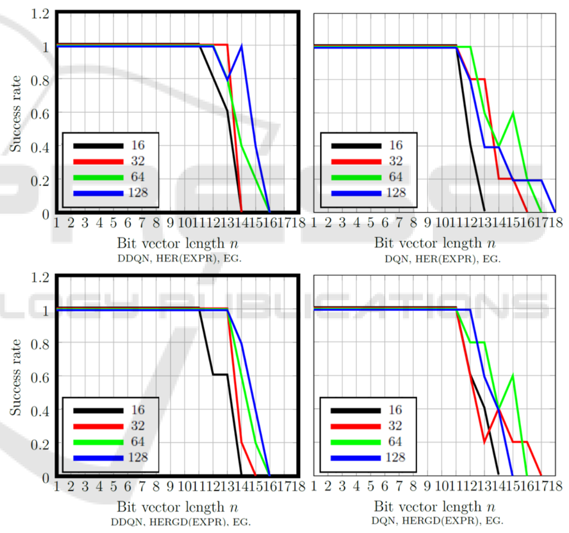


Figure 3: Bit-flip environment with non-shaped rewards for different batch sizes and combinations of Q-Learning, replay memories and exploration methods.

In the comparison of DQN with DDQN, it can be observed that DDQN solves a bit vector length n more consistently, even with smaller batch size like 16. One reason that DDQN behaved in this evaluation pretty much like DQN is the low number of episodes and bit flips to solve for a bit vector length n. Since the target network used by DDQN is updated slowly to avoid divergence, this method requires more training steps than DQN. For DDGP, the environment was even more challenging to solve because a

[3]https://keras.io

[4]https://www.tensorflow.org

continuous action space has to be searched, while DQN and DDQN only have to search a discrete action space.

The average training time increases with larger batch sizes. Also, methods using PPROP or DDPG require a lot more training time as depicted in Figure 4. One reason is that the DDPG Q-network architecture is more complex than the others because it consists of four neural networks. PPROP internally uses a sum-tree to store transitions, which increases training durations.

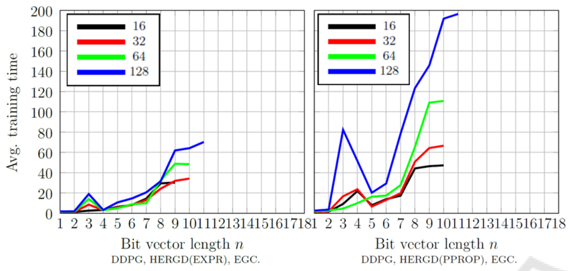


Figure 4: Training time in the bit-flip environment of PPROP with non-shaped rewards

The evaluation results of the bit-flip environment with a shaped reward function can be observed in a subset of representative results in Figure 5. It can be noticed that DQN and DDQN were able to solve a much larger number of bit vector lengths. Reward shaping drastically improved performance. Only DDPG performed worse with non-shaped rewards, which was expected as DDPG is designed for continuous spaces.

Comparing DQN with DDQN as in Figure 5, shows that DDQN solves the same bit vector length more consistently, even with smaller batch sizes, as it was the case with the non-shaped reward function. HER and HERGD performed similar but worse than the EXPR or PPROP. This is not surprising since the HER (Andrychowicz, 2017) performs badly with shaped rewards. PPROP performed a little bit better than EXPR. Average training times do not differ much from the non-shaped ones.

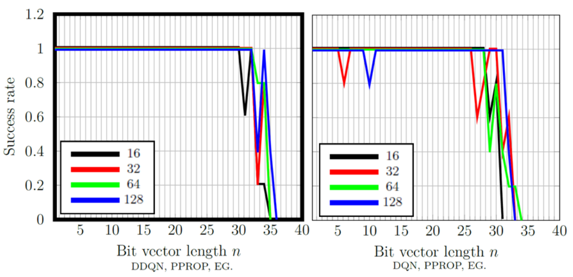


Figure 5: Success rates in the bit-flip environment of PPROP with shaped rewards.

5.3.2 Ornstein-Uhlenbeck Process Parameter Evaluation

In this section, different parameter settings for an OU and the introduced OUA process are evaluated to determine which values are useful in certain environments. All Q-networks use an output range of $-1 \leq output \leq 1$. An OU process consists of four parameters to adjust: θ, σ, μ and a. μ, the mean value and the starting value are set to 0.0. θ indicates how fast the process reverts towards the mean. σ determines the maximum volatility. The evaluation only records the noise generated by the OU or OUA process.

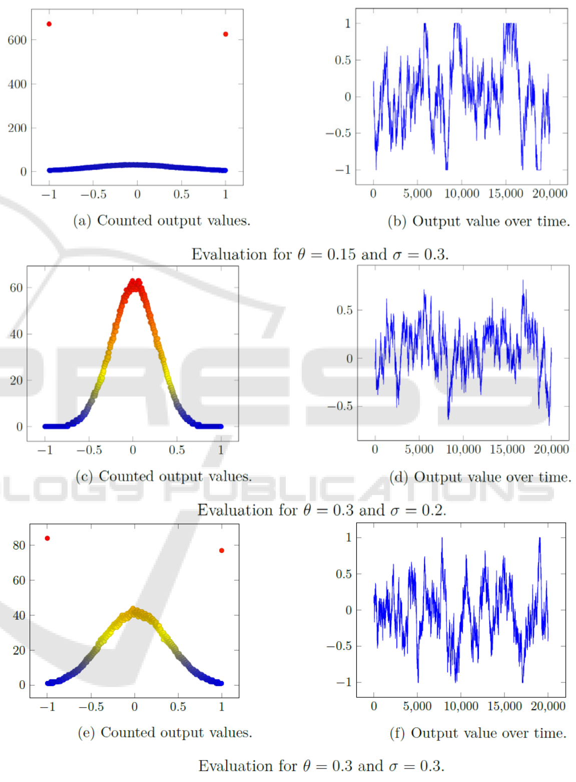
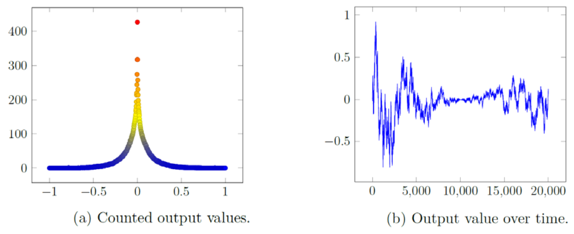


Figure 6: The Ornstein-Uhlenbeck process.

Figure 6 shows the evaluation of the standard OU process with different settings for θ and σ. In the top graph ($\theta = 0.15$, $\sigma = 0.3$), it can be observed that setting $\theta < \sigma$ will cause the process to output many values near to the range boundaries. It can be useful for agents where abrupt control of the actuators is required. For instance, if a robotic arm is used to control a heavy mass object, abrupt controlling can be useful. If $\theta > \sigma$ like in the middle graph, it results in many output values being close to zero. For agents, where fine steering is necessary, this setting is useful. If $\theta = \sigma$ like in the bottom graph, the output values are concentrated close to zero and at the boundaries of the range. This setting might be useful for environments where the entire output range must be covered.



Evaluation for $\theta = 0.3$ and $\sigma = 0.3$.

Figure 7: The Ornstein-Uhlenbeck Annealed process.

Results of the introduced OUA process is shown in Figure 7. Linear decreasing can be observed. Unfortunately, since an OU process uses the previous outputted value, the output value increases over some time again. This behavior is contra-productive, since it was planned to decrease the outputted noise slowly to enable soft-switching from exploring to exploiting. Therefore, the OUA process did not improve the standard OU method.

5.3.3 Continuous Pendulum Environment

Each tested method has exactly 250 episodes to solve the pendulum environment. Each episode consists of 300 steps. At each step, an action is predicted by the Q-network and applied as torque to the pendulum. After every 10th episode, the learning success is tested. For this purpose, the learned policy is used over 20 episodes, and the received rewards are summed up. Then the mean value is calculated from the sum of rewards. Also, the standard deviation is computed and presented as a transparent background in the graph.

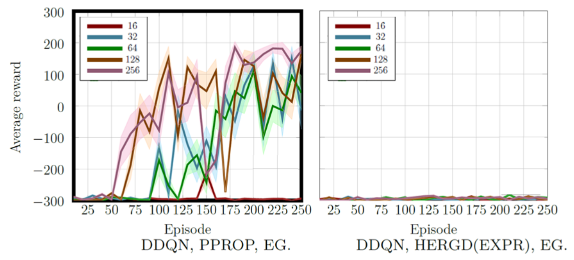


Figure 8: pendulum environment with non-shaped rewards.

The evaluation results of the non-shaped reward function can be observed in Figure 8. In general, it can be concluded that the task solving performance is quite bad. Only, DDQN and DDPG in combination with EXPR or PPROP as replay memories and EG or EGC as exploration method managed to perform acceptably. HERGD was not able to solve the environment at all. HER delivers quite the same result as HERGD. In continuous state space environments, the main goal can only be defined within a small range. In addition, since the state of the pendulum environment consists of the vertical velocity, goal discovery is very bad since the goal is discovered with a non-zero velocity. This is a limit because the goal is to keep the pendulum upright in a vertical position.

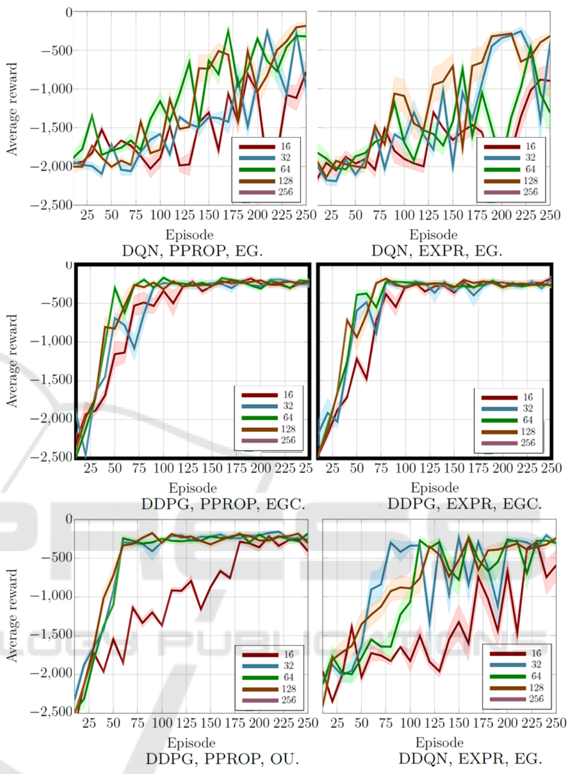


Figure 9: pendulum environment with shaped rewards.

The evaluation results for the shaped reward function can be observed in Figure 9. Since HER and HERGD in combination with shaped reward functions are documented to perform poorly with shaped rewards, these evaluations are discarded. DDPG performed well, while DQN and DDQN did very poorly in comparison.

Surprisingly, EXPR delivered a little bit better results than PPROP. Concerning the fact that the dimension of a discrete state space is countable, this is not the case for a continuous state space. PPROP prioritizes the transitions that are new or surprising. For continuous state spaces, this almost applies to every transition. Especially this affects the learning performance for small batch sizes.

For the exploration methods, EGC performed better than OU, because the behavior of OU is drift-like. In the pendulum environment, it is better to switch the torque repeatedly from positive to negative values. This behavior increases the speed and allows the pendulum to move to a vertical position. Finally, it results show that PPROP increases the training times drastically.

5.3.4 Discussion

Based on the evaluations done with the bit-flip environment and pendulum environment, the best combinations of the reinforced learning methods are summarized in Table 1.

For discrete action spaces, it is recommended to use the Double Deep Q-learning network (DDQN), as it works better in such environments than the Deep Q-learning network (DQN) and Deep Deterministic Policy Gradient (DDPG). On the other side, DDPG works best for continuous action spaces.

If continuous state spaces are considered, it is recommended to use Experience Replay (EXPR) as replay memory, because it performs quite the same as Proportional Based Prioritized Experience Replay (PPROP) and HERGD, but requires less training time. On the other hand, for discrete state space environments, where a non-shaped reward function is used, it is recommended to use Hindsight Experience Replay With Goal Discovery (HERGD) in combination with PPROP. This will help to successfully solve sparse reward environments. Regarding the batch size, it is recommended to choose a larger value depending on how sparse the rewards are. The selection of the exploration method has to be tuned based on the environment. In all cases, a shaped reward function should be used, since it drastically improves learning performance.

In a real world, robotic environment where the agent is a robotic arm, standard OU process is recommended. In environments, such as the pendulum environment, where drift-like behavior of the output values is not good, the introduced EGC performed the best. With the aid of these evaluations, it is possible to determine which methods should be used for a robot in continuous action and state space.

5.3.5 Future Improvements

Some issues can be addressed that emerged during this work. One problem with sparse reward tasks is that a transition with a positive reward has to be sampled from replay memory and has to be propagated back by repeatedly sampling the predecessor states. The Q-network slowly learns which actions to perform from certain states in order to reach the rewarding state. If the rewarding state is perceived only a few times, this process is disturbed. Considering catastrophic forgetting, successful learning of the task becomes unlikely. To accelerate the back propagating of Q-values, the Q-function could be applied to the transitions before saving an episode to the replay memory.

In that case, a positive reward is present throughout an entire episode. Sampling a transition with positive reward would become more likely. A disadvantage is that the algorithm would convert more slowly to the ideal policy. This approach can be combined with the n-step loss mentioned in (Vecerik, 2017), which should help to propagate the Q-values along the trajectories.

A great influence on the learning time and the learning success would be the improvement of the exploration methods. Only random exploration methods are possible because the agent should know as little as possible about the environment. If there is a memory limitation like in embedded systems, count-based exploration methods are not applicable. Count-based methods that store a counter, how many times a state has been visited, and what actions are taken to exit the state (Tang, 2016). Instead of applying noise only to the output neurons, it could be applied to the entire Q-network (Plappert, 2017).

Table 1: Summary of the best reinforced learning method combinations based on reward function.

	Reward function	
	Non shaped	**shaped**
cont. action space cont. state space	DDPG, EXPR	DDPG, EXPR
dis. action space cont. state space	DDQN, EXPR	DDQN, EXPR
cont. action space dis. state space	DDPG, HERGD(PPROP)	DDPG, EXPR
dis. action space dis. state space	DDQN, HERGD(PPROP)	DDQN, PPROP

Another approach is to let the decision maker adaptively learn the exploration policy in DDPG (Xu, 2018). The advantage is that this approach is scalable and yields to a better global exploration. The disadvantage is that this approach consumes more memory than OU or EGC.

Finally, deep reinforcement learning in continuous state and time spaces is still not robust to small environmental changes and hyper parameter optimization. For DDPG, the effect of every individual action vanishes if the discretization timestep becomes infinitesimal (Tallec, 2019). For the pendulum environment, algorithm parameters could be tuned to generate better performance through a continuous-time analysis.

6 CONCLUSION

The main objective of this paper was to analyze which combinations of reinforcement learning algorithms, exploration methods and replay memories are most suitable for discrete and continuous state spaces as well as action spaces. Tests were performed in a simulated discrete bit-flip and continuous pendulum environment.

This research introduced new techniques to the state-of-the-art methods, such as Hindsight Experience Replay with Goal Discovery (HERGD), ε-greedy Continuous (EGC), and Ornstein-Uhlenbeck Annealed (OUA). While Ornstein-Uhlenbeck Annealed did not improve performance, Hindsight Experience Replay with Goal Discovery, ε-greedy Continuous proved to perform well.

Equipped with a suitable combination of algorithms, the next step is to transfer it into a self-learning robot, which is based on embedded hardware. The robot is supposed to start without knowing anything about its sensors, actuators and environment and gradually learn to survive. In embedded hardware resource constraints will be an important challenge to handle.

Enabling robots to learn complex tasks through experience allows us to take a big step into the future. The applications for such self-learning robots are limitless. Writing complex algorithms to control these robots is eliminated because they learn to control themselves. In addition, through repetition, they are able to optimize their behavior. Changes in the environment do not affect them because they can adapt to them automatically.

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