Reinforcement Learning- Final Course Project

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1 Introduction

Reinforcement learning is a sub-field of machine learning, which deals with training a machine to make a sequence of decisions in order to solve a given task. More specifically, in RL we try to teach an agent to achieve a goal in an uncertain environment, by negative or positive feedback he receives from the environment based on the actions he takes. Those feedback are called rewards and the agent is asked to maximize the total cumulative future rewards. In this project, we would explore a variety of algorithms that we learned during the course, with the goal of training agents to complete two types of games: Sokoban and Lunar Lander (LL). We will start with one of the biggest breakthroughs of this field, Deep Q-Networks, developed by DeepMind team on 2015 [1]. We will use the DQN as a baseline test of the effect of the Replay Memory, which was also addressed by DeepMind, the effect that hand-crafted features may have, and the importance of exploration during the learning stage. Then, we will try to improve our results using algorithms that followed DQN, such as Dueling DQN, also developed by DeepMind [2] and Soft Actor-Critic [3]. By the end of this project, we hope to be able to land a ship on the moon and to arrange boxes in the right place.

1.1 Related Works

Sokoban is a kind of a logic puzzle, with seemingly simple rules, but still constitutes difficulties for both humans and computers in solving the game. It can be considered as an NP-Hard search problem [4][5][6], for which the difficulty of the problem varies with the map's size, the number of boxes, and the restrictions given to players – such as the ability to pull. A variety of methods such as brute-force, BFS, DFS, hashing tables, FEEs and etc. [4] seems to solve only a subset of the puzzles but are constrained by time and computational complexity. The learning process of reinforcement algorithms may results in an enormous number of times that the agents fail to complete the task, which in real life can cause high development costs, therefore video games are a great controlled environment for RL. DeepMind's team amazed the world of RL with the DQN [1], which was the first method to allow non-task-specific learning of games based on high-level features, and not hand-crafted features or labels.

They used deep neural networks combined with Q-learning to approximate the value-action function. They also integrated the experience replay (by Lin [7]), a technique to allow batch updates from sampled transitions and dealing with the problem of correlated states that interfere with the generalization of the model. Another work by DeepMind's team is the Dueling-DQN [2], an improvement of the DQN. They show that as with other Q-learning algorithms, the DQN also tends to overestimate the value-action, which can fail the agent. They tackle the problem by separating the function into two different functions one for the state value function and one for the state-dependent action advantage function. By doing so, they achieves improvement both in results and in the training process, with faster convergence and training stability [8]. Another RL method is the Actor-Critic that introduces us to a policy gradient normalization by subtracting the mean baseline [8]. Berkeley's team suggested Soft Actor-Critic an algorithm for continuous action space (our LL environment), which adds entropy regularization, that should help the model learn while keeping exploration high. And also incorporate improved architecture for dealing with overestimations [9]. In our work, we will use the methods described above to try and solve the Sokoban and LL.

2 Solution

2.1 General approach

Both Sokoban and Lunar Lander (LL) hold the Markov Property and therefore justify the use of RL. Sokoban has an enormous number of states which vary in the different versions [4], so value iteration methods are not an option and LL has infinity states. Sokoban's model transition is known because each action will lead to a deterministic state. The game on one hand is episodic, but the algorithms rarely reach a terminal state, so algorithms based on Temporal Difference (TD) are preferred. We will start by examining Q-Learning algorithms which are off-policy, iteratively update learners. Due to the number of states in each game, we will use neural networks to approximate the action-value function instead of the tabular method. We will use DQN as our starting algorithm. DQN meets our needs. It is easy to implement, it is based on Bellman-Equation and TD logic, and it's robust to different games, it is also model-free, which means we don't need to have any transition model (even though we know it) [1]. On the DQN it will be easy to adjust and experiment the effect of hyperparameters on the results, the effect of the experience memory, which can advantage us due to the off-policy nature of the DQN [8], and the effect of changing the rewards based on hand-crafted features.

2.2 Design

All of our solutions are written with Python 3.8.10 using PyTorch library and the game's environments based on the Gym toolkit created by OpenAI. Run both on PyCharm (2021.2) and Google Colab.

2.2.1 Estimated action-value evaluation

This metric was suggested by DeepMind [1]. It keeps a random set of observations and then calculates the square of the mean of the expected estimated rewards for this set according to the trained agent. This metric is allegedly more stable, and we hope it might assist us to understand whether the agent learns the Sokoban environment despite the low score caused by the sparse rewards.

2.2.2 DQN and Dueling DQN

DQN and Dueling DQN architecture are similar, as shown in Figure 1. Both networks have the same input and feature extraction module. In Sokoban, we used CNN while on LL we used fully-connected architecture with a state's tuple ($s \in R^8$) as the input. The outputs are state-action values. The difference is that the DQN has a single sequence network and it directly produces Q-values estimation and the dueling network uses two sequences (streams) networks to estimate state values and action advantages, and then combines them to indirectly generate the Q-values with the following equation:

$$Q\left(s,a;\theta\right) = V\left(s;\theta\right) + \left(A\left(s,a;\theta\right) - \frac{1}{|A|}\sum_{a\prime} A\left(s,a\prime;\theta\right)\right) \tag{1}$$

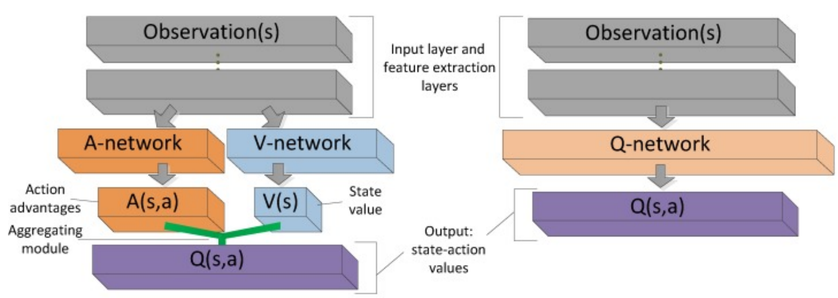


Figure 1: Dueling DQN (left) and DQN (right). [9]

Our LL is continuous, then when we tried to fetch a simple DQN we faced a problem with the output of the network. Hence a simple solution is to perform quantization and mapping on the input. We'll explain the process using an example. Our action space is $[x, y], x, y \in R^2$ where $-1 \leq x, y \leq 1$, then perform a quantization, in section 3 we'll see different results for different quantization sizes. For this example assume our size is 5. Therefore from continuous value, we transform to $[-1, -0.5, 0, 0.5, 1]$ values (we are choosing the one that is the closest to the real value). With mapping, we map each of the possible actions into a single integer, in this case, $5^2 = 25$ possible actions. To achieve a legit action from the network to our lunar we just need to perform a simple reverse mapping of the mapping we mentioned above. When it comes to Loss functions we chose to work with SmoothL1Loss [10] in PyTorch library which is similar to Huber Loss [11], it is less sensitive to outliers than the famous MSE and can prevent exploding gradients. For optimizers we tried SGD, RMSProp and Adam for training Sokoban, but due to the sparsity of the rewards, the results were unclear so we decided to go with Adam because it has the properties of RMSprop [12].

2.2.3 Soft Actor-Critic

In the previous architectures, we had to manipulate the action space because those architectures can handle only discrete action space, this is where Soft Actor-Critic (SAC) comes in. SAC can handle continuous action space. The biggest advantage of SAC over the other algorithms we have tested is that is not only seeking to maximize the future rewards, SAC seeking to also maximize the entropy of the policy. Entropy is measuring how random is a random variable is. In entropy-regularized RL, the agent gets a bonus reward at each step proportional to the entropy of the policy that can affect exploration exploitation trade-off, SAC is learning a policy π_θ and two differents Q-functions, Q_{ϕ_1}, Q_{ϕ_2}.

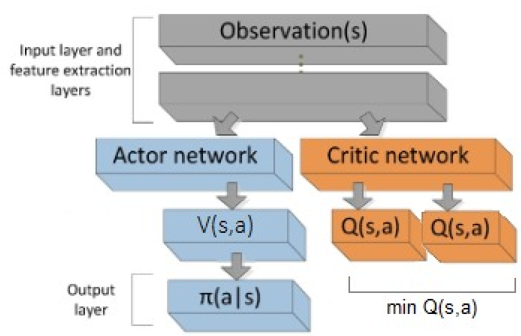


Figure 2: Soft Actor-Critic Architecture (based on [9]).

In our SAC we have 3 networks. One is the Actor-network which takes in the current state and outputs the best action to take. The second and third networks are Critic networks, which they are taking in a state and an action and output a state-action value. In contrast to Dueling DQN and DQN, we used ReLU as the activation function as described in the original paper [3], Adam as an Optimizer and, MSE as Loss function. Despite the computational power, the learning is much better, that's means that the algorithm generalizes the problem better than the other algorithms we have tested.

3 Experimental results

3.1 Lunar Lander

First, we want to show a short video of our best results. In the following video, we show a SAC model before training (randomized weights), after 120 episodes of training, after 240 episodes (environment solved), and after 360 episodes. Link, `https://youtu.be/Pn760rYQvmc`

3.1.1 DQN

We started LL experiments with DQN. We performed 6 different quantizations {25, 49, 81, 121, 169, 225} (chose to display only subset), to check the affect it has on speed of convergence. We also, tested on varianet of network depths. The full results can be found in the GitHub repository [13].

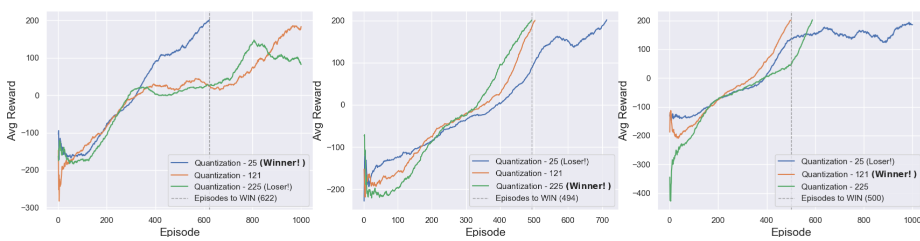


Figure 3: From left to right, (a) 2-layers depth. (b) 3-layers depth (c) 4-layers depth.

From Fig. 3, we can see interesting phenomenon, where in (a) the lowest quantization is the only one to finish, but the results alternated when we added layers. We conclude that with only 2 layers it is harder for the algorithm to generalize on large number of actions. We suggest that more layers are needed for generalization. We performed another test to check this statement, by running thousand episodes with each of the trained models.

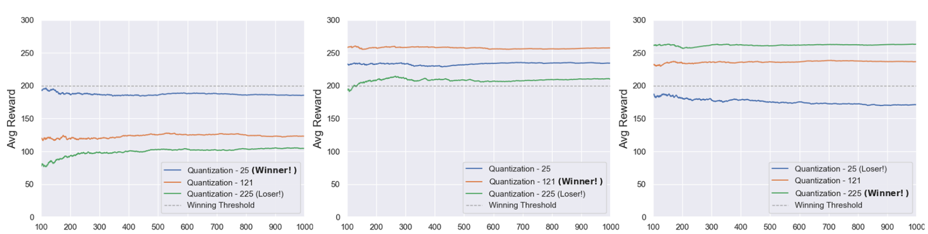


Figure 4: From left to right, (a) 2-layers depth (b) 3-layers depth (c) 4-layers depth.

We can see at Fig 4 (a) that the algorithm is indeed failed to generalized and all quantization are below 200 average reward. In (b) 3 layers with 121 actions gets the best fit and achieve more than 250 average scores over 1000 episodes.

Another interesting experiment we did is to check how important is the use of exploration. In our experiments we used epsilon-greedy with epsilon decay and we wanted to test what happens if we use only exploitation (Figure 5).

We can see the impact of the exploration. It almost seems to learn the game faster, but we notice that it got stuck in some point and oscillates around the value of 150 average score. When using exploration, the process of learning seems a bit slower, but the curve improves monotonically and surpassing the non-exploration process. Nice to see that this experiment confirm what we learned during the course about the importance of exploration.

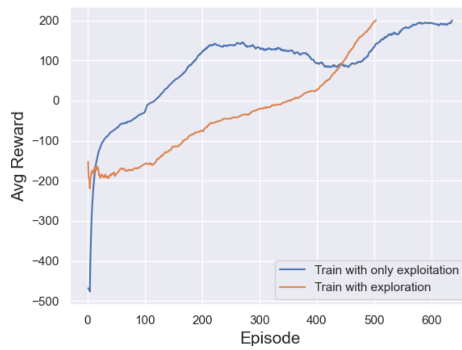
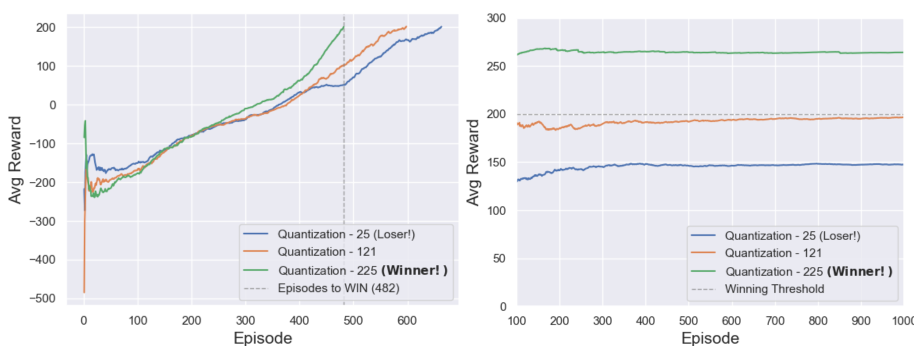


Figure 5: Exploitation and Exploration in DQN.

3.1.2 Dueling DQN

The results of Dueling DQN experiments are pretty similar to what we saw in DQN above. Hence we will show only the results with 3 layers.



(a) Training with Dueling DQN.

(b) Testing with Dueling DQN.

Hyperparameter	Value	Hyperparameter	Value
Episodes	1000	Max Steps	500
Gamma	0.99	Learning Rate	0.0005
Epsilon Start	1	Epsilon End	0.05

Table 1: Important Hyperparameters.

We can see in Table 1 the important hyperparameters that we found, the full list of hyperparameters can be found in the GitHub repository [13].

3.1.3 Soft Actor-Critic

The results of the experiments were different from the experiments in Dueling DQN and DQN, not only by the results but also in the way that the algorithm learns this game. The best result we have seen is as Fig. 7 but a lot of time with the same setting the algorithm solved this game with 450-500 episodes which is a big difference. Another big disadvantage for this algorithm is the time of training that can be range from 30 minutes to an hour. Most of our experiments focus on the temperature parameter α that controls the exploration-exploitation trade-off, we found that the best fit α is 0.2. The other hyperparameters were like in the original paper [3].

Figure 7: Training a SAC model.

3.2 Sokoban

During the experiments, we notice that the rewards are sparse and for 500 episodes, solving the episode is almost random. We needed metrics to gain some information from the grid search. At first, we thought about taking the top 5 episodes, but the game rarely finishes so, this is still random. We decided to go with the average of the last 100 episodes.

3.2.1 Optimizer choosing

As part of our grid search effort, we tried to test most of the hyperparameters with each of the three optimizers: SGD, RMSProp, and Adam. As we explained, results are close to random, and therefore impossible to tell the impact. We decided to continue our experiments using Adam.

Optimizer	LR*	MC**	Batch Size	Filters	TU***	AVG Score
SGD	0.0001	1	1	[16, 32]	5	0.130
RMSProp	0.0001	1	1	[16, 32]	5	0.876
Adam	0.0001	1	1	[16, 32]	5	0.314
SGD	0.001	100	20	[16, 32]	5	0.070
RMSProp	0.001	100	20	[16, 32]	5	0.430
Adam	0.001	100	20	[16, 32]	5	0.757

Table 2: *Learning Rate, **Memory Capacity, ***Target Update

3.2.2 Hyperparameters Grid Search

For each of the hyperparameters, we tried three different values. We tested: learning rate, memory capacity, batch size, number of filters for each layer, and number of episodes until the update of the target network. Unfortunately, we weren't able to draw any conclusions from the results which seems random. Probably a lot more episodes are needed to better understand if we're in the right direction.

Learning Rate	MC*	Batch Size	Filters	TU**	AVG Score
No Experience Replay					
0.01	1	1	[32, 64]	5	0.745
0.001	1	1	[32, 64]	5	0.828
0.0001	1	1	[32, 64]	5	0.296
0.0001	1	1	[16, 32]	5	0.314
Experience Replay					
0.01	100	20	[16, 32]	5	0.495
0.001	100	20	[16, 32]	5	0.757
0.001	100	20	[32, 64]	5	0.809
0.0001	100	20	[32, 64]	5	0.431
0.01	100	80	[16, 32]	5	0.599
0.001	100	80	[16, 32]	5	0.318
0.01	2000	20	[16, 32]	5	0.276
0.001	2000	20	[16, 32]	5	0.653
0.001	2000	80	[16, 32]	5	0.338
0.0001	2000	80	[16, 32]	5	0.348
0.0001	100	20	[16, 32]	20	1.134
0.001	100	20	[32, 64]	20	0.750
0.0001	100	20	[32, 64]	20	0.610
0.01	2000	20	[16, 32]	20	0.403
0.001	2000	20	[16, 32]	20	0.259
0.0001	2000	20	[16, 32]	20	0.683
0.01	2000	80	[16, 32]	20	0.971
0.0001	2000	80	[16, 32]	20	0.645

Table 3: *Memory Capacity, *Target Update

3.2.3 Hand Crafted Features

After we tested the hyper-parameters we noticed the sparse rewards are not sufficient for the learning process. We wanted to check whether we can help the agent finish the game more often, by adjusting the rewards. We defined 3 features: reward the agent for choosing action that results in new state (movement), reward it for having a box in one of his neighbored pixels and punishment for distance between box and a target.

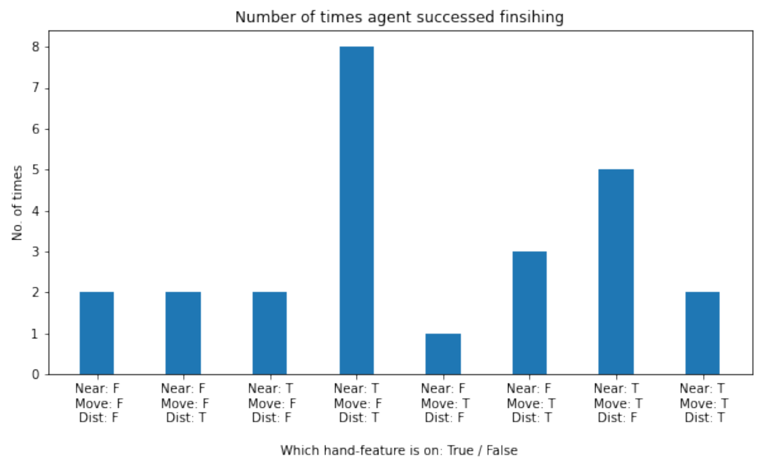


Figure 8: 8 experiments, in each one different flags are True/ False, which indicates if the feature was part of the training

As we can see, from figure 8, the solving of the puzzle is still rare. Nonetheless, based on the graph it seems that crafted features might have impact, especially the feature of being near boxes. In future work, more reruns of this experiment are needed, during which, we need to adjust the size of rewards/punishments for each option to get a better sense on the affects of reward adjusting.

3.2.4 Few words

We've implemented the Estimated action-value evaluation in the hope we will have a more stable indicator for visualizing the learning process. Though that by this metric the agent does seems to learn. In reality, finishing an episode and solving the task was still random, and it doesn't seem to really indicate the agent's understanding of the task as we can see in Figure 9.

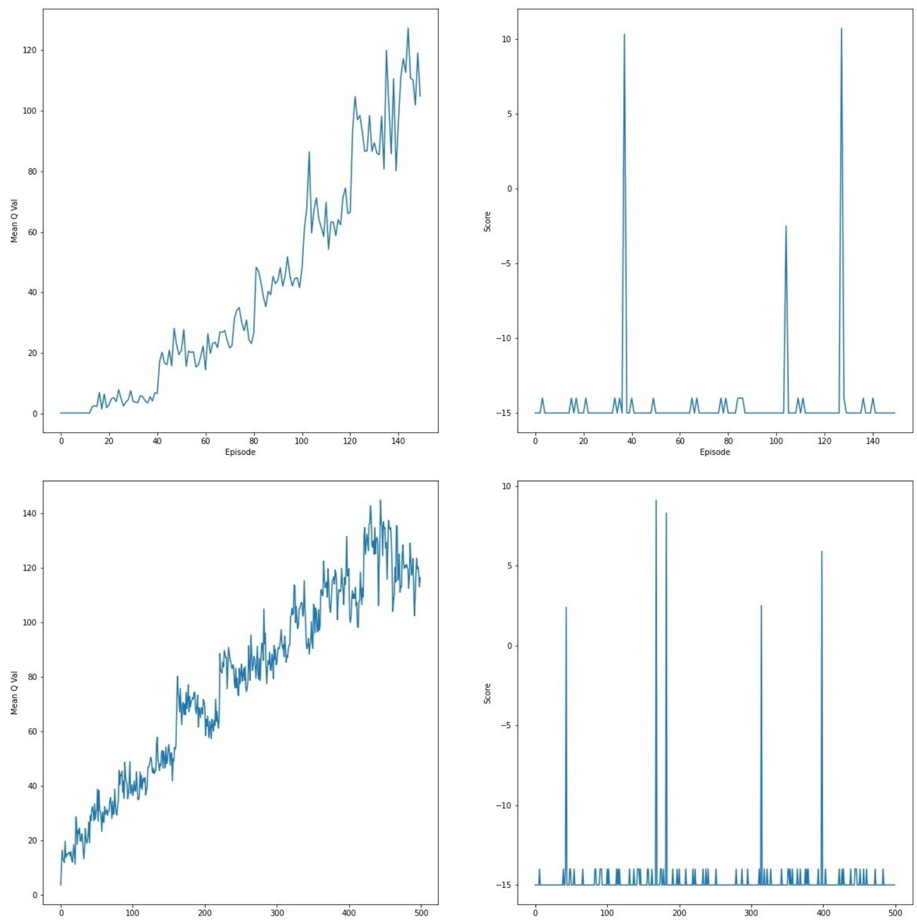


Figure 9: Left: The mean Action-Value metric, Right: Score per episode.

4 Discussion

When we started this project, the task was to solve a more complex version of Sokoban. Our research went in two paths. The first was a review of more recent RL updates and the second was specific to Sokoban and how to solve it. We were naive and thought DQN would be enough to solve it, but very fast we understood that more complex algorithms are needed. We tried Dulleing DQN and A2C (Actor-Critic with advantages) that failed. So we started to come up with more creative ideas such as adjusting rewards and even thought about solving Sokoban with BFS and injecting steps discovered by it, to the experience memory buffer. It was only after a very extensive grid-search and upsetting results, that we realized that based on the two metrics we use (Mean Action-Value and average score) it is hard to tell whether the training of Sokoban makes any progress. So we decided to move on to LL and to try and use the knowledge we gained on the sokoban. Armed with this knowledge we were able to solve LL much easier with 3 different architectures. We tested assumptions we learned during the course about the exploration-exploitation and quantization of continues game's input and even solve it with architecture suitable for continuous inputs (SAC) for comparison.

4.1 Conclusions and Future Work

In the making of the summary paper, we tried to show most of the stages we've been to, with the logic that lead us in each of them. We tried and tackle different methods we learn such as experience memory, discount factor, eps-greedy, quantization and Q-learning algorithms. That gave us some sense of feeling on how complex is the task of teaching computers to solve and conduct tasks. The gap between what we see as obvious and our ability to translate it into instructions that might be beneficial for the agent's learning process. We also learned how to make use of GYM environments, and how to implement PyTorch based RL algorithms. Reflecting the work, it might was a smarter choice to start with the LL and not the Sokoban because it is clearer whether the agent learns or not, the run time of the environment is much faster and the rewards are way less sparse. We got caught in the challenge of the Sokban for a bit to long. If we had more time and computational power, we would like to test the new method by DeepMind - Imagination-Augmentation[14], which seems to be able to solve the 2-boxes Sokoban by adding a ability of imagination to the agent which give him the ability to test future trajectories before deciding on a move.

5 Code

`https://github.com/stav95/CourseReinforcementLearning`

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