Report RL Self Study

Jens Hartsuiker

February 2024

1 Introduction

The aim of this project is to familiarize ourselves with reinforcement learning one slightly covered by our study programs and a field closely related to our favourite one: mathematical optimization.

We studied the field at the hand of this Huggingface tutorial [?]. From which we implemented the following algorithms from scratch ourselves: Q-learning, the Reinforce algorithm, actor critic methods and finally the PPO algorithm.

Our final goal is to apply a learning algorithm to the MsPacman Atari environment included in the gymnasium project [?].

2 Problem statement

It is when we implemented the bare PPO algorithm from said tutorial when we ran into our problem. MsPacman moved itself in a corner, to be stuck there until she got eaten by a ghost: we are stuck in a local optimum. We varied various hyperparameters: learning rate, number of model parameters, number of epochs, number of parallel learners, gamma, etc. However this was all to no avail.

3 Solution Hypothesis

At this point in time we went back to the drawing board. The bare PPO algorithm learns the average value for a state. We presumed that, especially for the MsPacman environment, this did not allow for enough expressive power within the model. Hence we constructed an algorithm that estimates the values of state actions pairs, adjusting the loss accordingly.

In pursuit of better results still, we also tried modifying the critics' loss function such that at low value estimation discrepancies the total loss does not get outweighed by the actors' loss.

Note that in our algorithms our actors'- and critics' loss share values. We tried severing this link by detaching the advantage vector, but this resulted in worse performance.

Bare algorithm

The mathematical formulas for the basic algorithm are the following:

$$Critic\,loss = (\gamma * V(s_1) - (V(s) - reward(a)))^2 \tag{1}$$

Here $V(s)$ denotes the value of state s, and $reward(a)$ denotes the reward that taking action a gives while going from state s to $s1$.

$$Advantage = \gamma * V(s_1) - (V(s) - reward(a)) \tag{2}$$

Action pair version
The mathematical formulas for the state action pair version are the following:

$$Critic\,loss = (\gamma * max_{a'} Q(s_1, a') - (Q(s, a), -rewards(a)))^2 \tag{3}$$

Here $Q(s, a)$ denotes the value of taking action a in state s, and $reward(a)$ denotes the reward that taking action a gives while going from state s to $s1$.

$$Advantage = \gamma * Q(s_1, a_1) - (Q(s, a), -rewards(a)) \tag{4}$$

Substituting the critic loss into the advantage gives us:

$$Advantage = \gamma * Q(s_1, a_1) - (\gamma * max_{a'} * Q(s_1, a') + reward(a) - reward(a)) \tag{5}$$

Which simplifies to:

$$Advantage = \gamma * (Q(s_1, a_1) - max_{a'} * Q(s_1, a')) \tag{6}$$

Action pair version - own twist
For this model we kept the advantage the same as the action pair version, however we modified to critic loss as follows:

$$\begin{split} Critic\,loss = Max(C * (\gamma * max_{a'} Q(s_1, a') - (Q(s, a), -rewards(a)))^2, \\ C * abs(\gamma * max_{a'} Q(s_1, a') - (Q(s, a), -rewards(a))) \end{split} \tag{7}$$

For C we chose a value of 1.25. We also tried values 1.01 and 2, but these did not provide better results.

3.1 Other changes

Besides the already existing features from our first trial such as parallel learning, we added new features to our new trials. Examples are kernel initialization, logarithmic subtraction instead of division of probabilities.

4 Results

Here we test these algorithms on the Lunar Lander environment, as this environment is less computationally expensive than the MsPacman environment. Thereafter we will train the MsPacman

	Average	Min	Max
Bare algorithm	65.5	-310.0	288.9
State action	91.8	-328.0	302.1
Own	-21.2	-296.6	261.1

Table 1: Reward scores after following optimal policy for 250 epochs.

environment on the best approach.

We present the training curve of the models described above. All these trials are executed with the same hyperparameters:

- Number of episodes: 1000
- Number of epochs: 5
- Number of parallel learners: 10
- Learning rate: 0.0001
- Eps: 0.2

This means that we sample 10 times, update our models and repeat a 1000 times, resulting in a total of 10000 samples.

In this plot (1), we show for each trial a plot of the minimum, average and maximum reward of the parallel learners, for each epoch. A score of 200 or higher is considered a success.
From both the learning plots in figure 1 and table 2 we see that the standard state action pair approach works better than our algorithm.

5 Conclusion

We've seen that our improvements made a significant difference and that our algorithms are capable of learning. Our idea to implement a state action pair value estimation proved more successful than a mere state estimation. Our idea to modify the critic function was to no avail however.

6 Extension 1: Replay

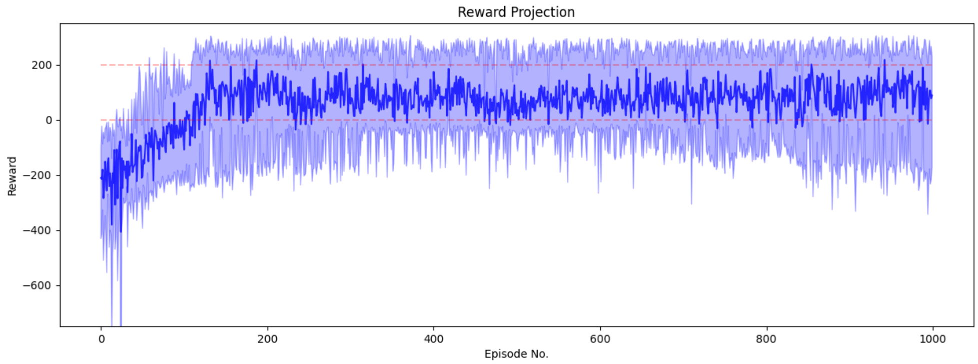
After the trials above, we added replay to our system. Meaning that in every update step, we also consider the N all time best episodes so far for the critic loss. This parameter is configurable. We ran this with our best result: the state action model (1b). The results can be seen in figure 2a. The hyperparameters for this trial are equal to the previous ones, except for the learning rate which is 0.00025. The number of replay frames is 5. As can be seen, our average reward is much higher, our learning curve is much more stable, and we have less bad performing outliers as the minima in the graphs are higher than in previous trials. This also the trial in which the average epoch score exceeds the success limit the most times.

	Average	Min	Max
Replay extension	140.9	-67.3	288.9

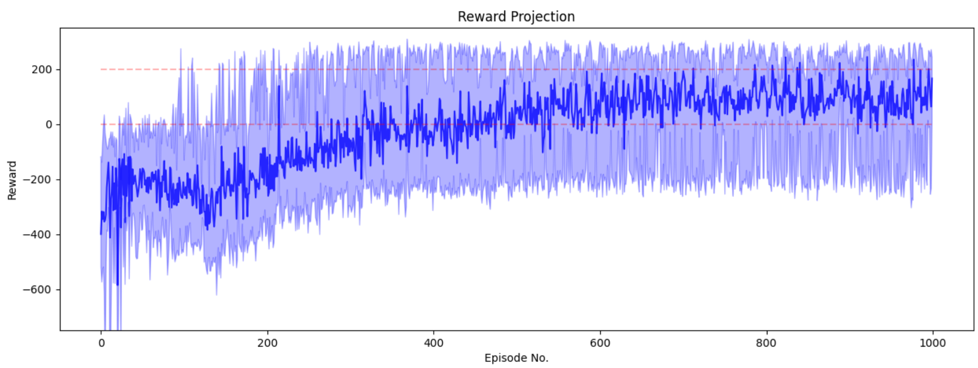
Table 2: Reward scores after following optimal policy for 250 epochs.

7 Future work

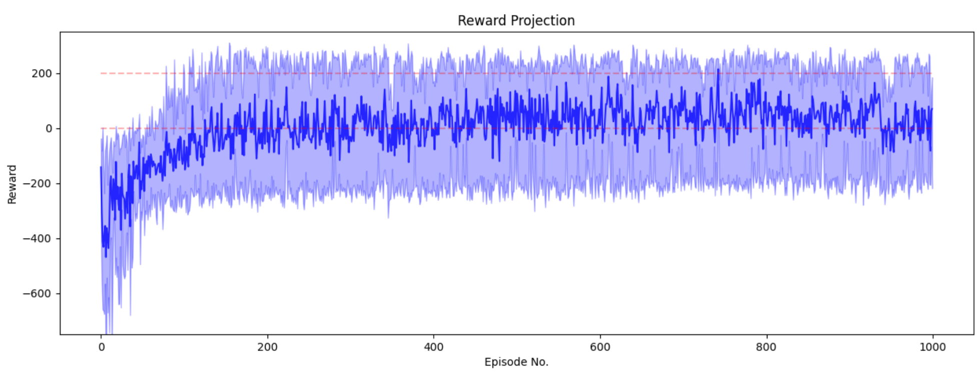
In a future work we want to try and test the effect of increasing the number of replay episodes.
We also want to incorporate ideas from the paper "World Models" by David Ha and Jürgen Schmidhuber, specifically a specific loss for the state and time representation of the environment.
We want to test the final algorithm on the MsPacman environment.



(a) The state estimation only trial

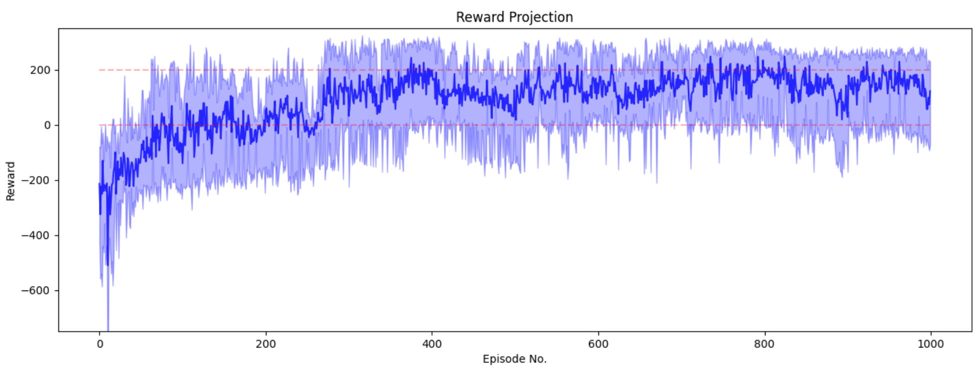


(b) The state action pair estimation trial



(c) Our modified loss trial.

Figure 1: A plot of the minimum, average and maximum reward of the parallel learners for each epoch, for each trial.



(a) The state action pair estimation with replay.