

Reinforcement Learning Project Report

Unsupervised and Reinforcement Learning in Neural Networks

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1 Introduction

In this project we implemented a reinforcement learning experiment with continuous state space and a neural network model. Unlike the discrete state learning experiments, in a continuous state space we can't enumerate over all possible states, that makes the classic Q-learning algorithm not applicable here. Instead, with the help of a neural network model taught in the course, we are able to code the state space by a finite number of input neurons, namely the place cells. On the other side, we have the action cells, each represents an possible action of the agent in the experiment. Given this set up, the expected reward for a particular point in the state space is just the dot product of the point's activation of all place cells and the weight vector of a place-action pair. So essentially we use the classic SARSA algorithm's framework, but what we update is the weight vector, and the Q-values are computed dynamically for choosing an action.

For the implementation, we adapt it from the given python code in the exercise session.

2 Learning curve

Right after the implementation according to the project set-up, we begin our experiment by conducting 10 independent runs with 50 trials each. Figure 1 is the resulting learning curve.

For this very first experiment, we set the epsilon parameter to 0.5, which means half of agent's moves are random. The leaning curve makes perfect sense : the first several runs are nearly random walks, which take over 5000 steps thanks to the randomness and the yet not very effective W-values. However, after several tastes of the goal, due to the effect of the eligibility trace, this information is quickly propagated throughout the weight vectors between the input space cells and the action neurons. As a result, half of the time the agent chooses the right direction that leads it to the goal area and avoids the wall hitting, the steps needed are decreasing drastically. We can observe that within 10 trials, this number goes down from 8000 to a stable value of approximately 100. Note that because of the randomness, there is some fluctuation on the curve.

As for the average reward, showed in red curve in the figure, it has generally the same trend as the latency curve. For example in the first several trials, the agent is essentially exploring the state space, so it hits often the wall and that causes a very low overall reward. As the agent's knowledge of the state space grows, its reward per trial converges to 10, which means it pursues directly the goal area without hitting too much the wall.

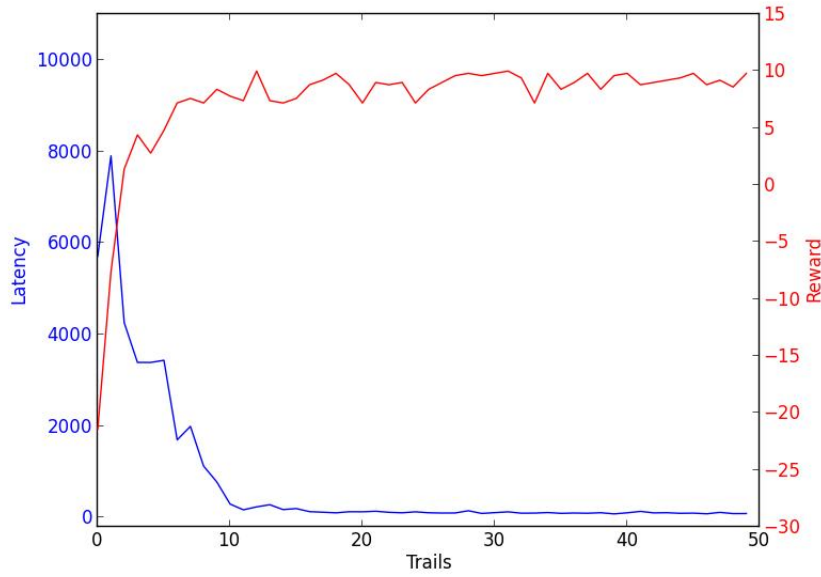


FIGURE 1 – Learning curve of a complete experiment

3 Exploration & Exploitation

The parameter ϵ controls the balance between exploration and exploitation. When ϵ is big, the agent has more possibilities to take a random step in order to explore more place in the environment, while small ϵ makes the agent more likely to take a step according to the ϵ -greedy policy. The implementation of the SARSA algorithm depends on the choice of the ϵ , we have to make a tradeoff. If the ϵ is too big, the agent will seldom take a step with the greedy policy, the whole learning process is more stochastic, so the learning result is not significant. However, if ϵ is too small, the agent will be more likely to exploit the state around where it is, because the weights are not largely updated, the agent sometimes will travel around several same states, sometimes even not get to the goal within a given time step limit.

The best solution is to start with a big ϵ so as to explore the space as widely as possible. The ϵ decreases after each trails Thus, the first several trials with big ϵ will collect enough information about the weights (Q values), and the later trials with small ϵ can take a good use of these information via the greedy policy which makes the agent more likely to get into the goal area.

The learning curves and the average latency of the last 10 trails with $\epsilon=0.8, 0.6, 0.4, 0.2$ are shown in figure-2,3,4,5 :

$\epsilon = 0.8 \Rightarrow 219$ steps

$\epsilon = 0.6 \Rightarrow 113$ steps

$\epsilon = 0.4 \Rightarrow 77$ steps

$\epsilon = 0.2 \Rightarrow 79$ steps

The result is exactly what we expected. When ϵ equals to 0.8, the agent quickly finish the first trail (2000 steps average), but it takes more steps in the end. For the small ones, it takes 9000 steps to get to the goal at the begining, but the final average step is less.

If we start with a big ϵ and decrease it after each trial, we will get the learning curve as below :

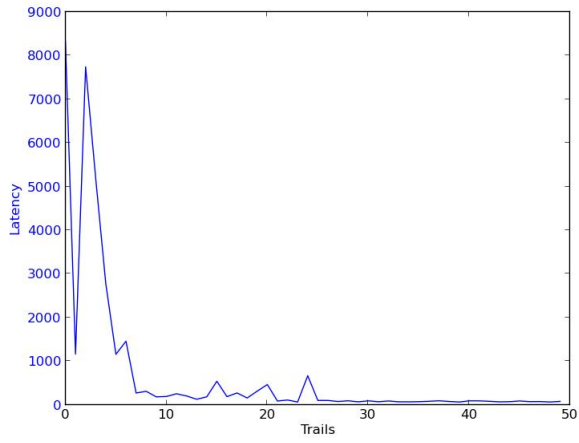


FIGURE 2 – $\epsilon = 0.2$

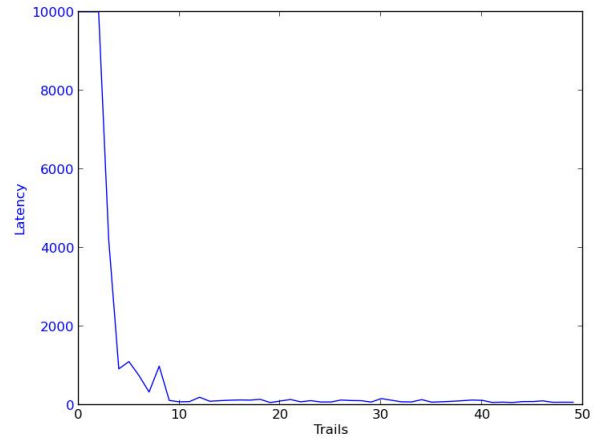


FIGURE 3 – $\epsilon = 0.4$

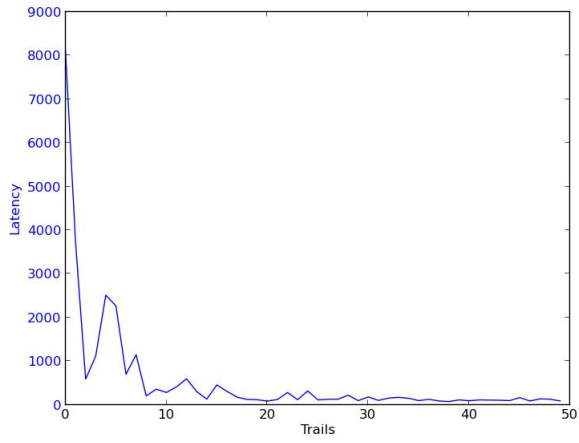


FIGURE 4 – $\epsilon = 0.6$

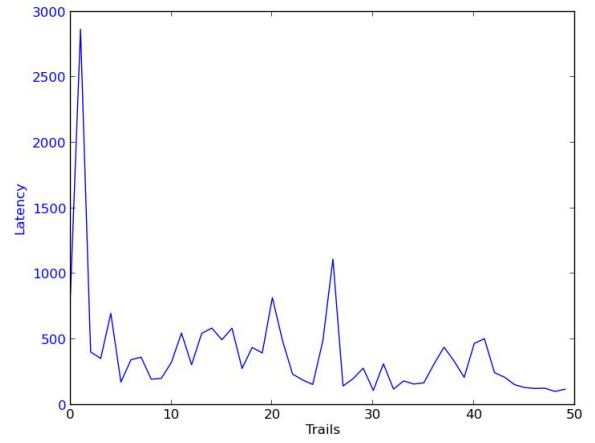


FIGURE 5 – $\epsilon = 0.8$

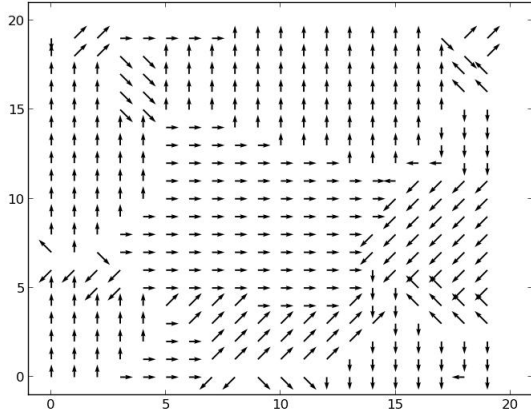


FIGURE 6 – Navigation map after 10 steps

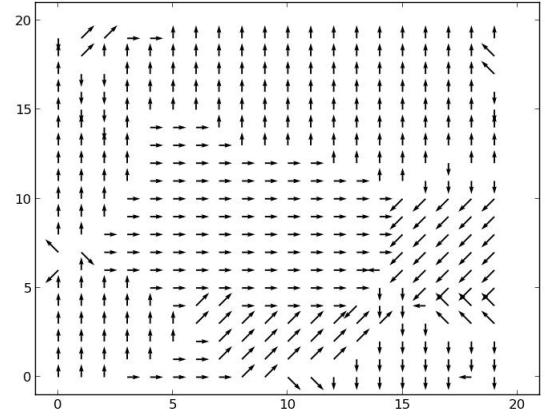


FIGURE 7 – Navigation map after 30 steps

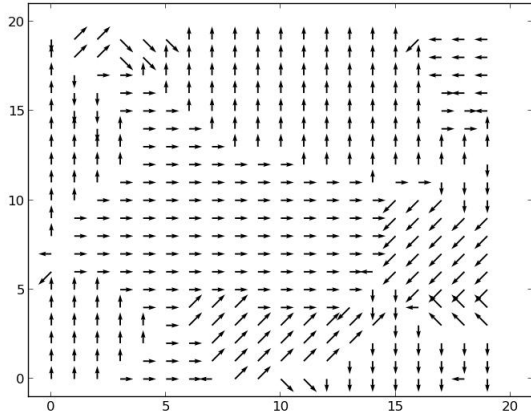


FIGURE 8 – Navigation map after 50 steps

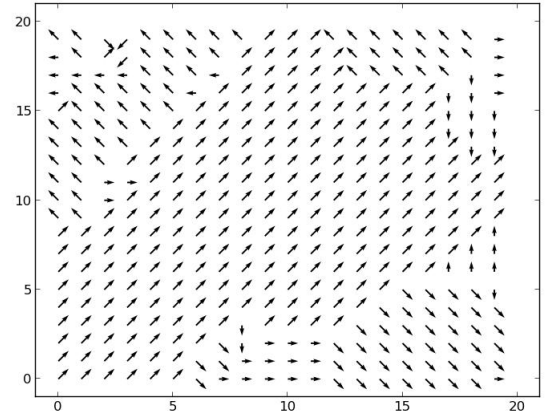


FIGURE 9 – Best navigation map

figure

It takes 1800 steps to finish the first trial, and the last 10 average steps is about 50. So, this approach makes the learning more efficient and the result more significant.

4 Navigation Map

The navigation maps for different stages of learning are shown as below, where the arrows mean the preferred direction (with the highest Q value) at each place field center.

Figure 7,8,9 shows the progress of the navigation during the training. And the figure 10 is the ideal navigation map which is also one of our training result with the decrease ϵ approach.