Lab4 neural networks

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Q1. Define the V- and Q-function given an optimal policy. Use equations and describe what they represent. (See lectures/classes)

V-Function: $\hat{V}(S_k) = (1-\eta)\ \hat{V}(S_k)+\eta\ (\mathrm{r}_k+\gamma\hat{V}(S_{k+1}))$

Q-Function: $\mathrm{Q}(\mathrm{S}_k, a_j) = r(S_k, a_j)+\gamma\ \hat{V}(S_{k+1})$

η = Learning Rate
γ = Discount Factor
$\mathrm{r}_k = PotentialReward$
$S_k = CurrentState$
$S_{k+1} = NextState$
$r(S_k, a_j) = Reward\ in\ State\ S_k\ for\ performing\ action\ a_j$
$\hat{V}(S_{k+1}) = Optimal\ Policy\ value\ from\ next\ state$

Q2. Define a learning rule (equation) for the Q-function and describe how it works. (Theory, see lectures/classes)
Q-Function: $\hat{Q}(S_k, a_j) = (1-\eta)\ \hat{Q}(S_k, a_j)+\eta\ (\mathrm{r}_k+\gamma\ \max_a(\hat{Q}(S_{k+1}, a))$

The Q function is an instrument for exploration around the best policies during learning. Q function updates the values obtained from above equation when the agent performs any action. Because of this functionality we could view the values for different actions and can choose to explore actions that could lead to high rewards in the future.

Now, let us consider that the Q table is initialized with zeros. In an episode we initialize the state (S_k) of the agent. In that state agent performs an action (a_j). By performing that action the agent receives some reward (r_k) from the environment. While updating the Q table, we also consider the optimal policy of its next state ($max_a\hat{Q}(S_{k+1}, a)$)

Q3. Briefly describe your implementation, especially how you hinder the robot from exiting through the borders of a world.

To hinder the robot from leaving the borders of the world, we have set the value to $-\infty$ along the border positions in the Q table. Whenever agent tries to move towards the border, the environment will return invalid state indication along with the very high negative reward. Finally, we break the loop at that state and start a fresh episode.

Q4. Describe World 1. What is the goal of the reinforcement learning in this world? What parameters did you use to solve this world? Plot the policy and the V-function.

In the world 1 we see that the agent starts at random position every time, and there is a blue wall in between in the map. So the agent has to move towards the goal surpassing the wall. Sometimes the agent gets deployed on the goal itself.

Parameter Setting:
1. Number of Episodes: 5000
2. learning rate (η): 0.5
3. discount factor (γ): 0.9

We tested our agent for 5000 episodes out of which all 5000 times it could reach goal successfully.

Figure 1 are the plots for Policy and V-function for world 1.

(a) Policy for World 1

(b) V-function for World 1

Figure 1: Policy And V-function: World 1

Q5. Describe World 2. What is the goal of the reinforcement learning in this world? This world has a hidden trick. Describe the trick and why this can be solved with reinforcement learning. What parameters did you use to solve this world? Plot the policy and the V-function.

In world-2 the hidden trick is that the environment will be changed at random instances, there will be a wall in the environment for some episodes and in some episodes the agent wont find any wall.
The agent will be in the exploration phase during initial episodes, even with

the changing environment the agent learns about the obstacles and chooses the best policy based on the rewards it receives from the environment. Since there is total uncertainty in the environment itself the model has to have some sort of a ad-hoc feedback system to achieve the objective. Therefore the reinforcement learning (RL) can solve this problem.
Parameter Setting:
1. Number of Episodes: 5000
2. learning rate (η): 0.5
3. discount factor (γ): 0.9
We tested our agent for 5000 episodes out of which all 5000 times it could reach goal successfully.

Figure 2 are the plots for Policy and V-function for world 2.

(a) Policy for World 2 (b) V-function for World 2

Figure 2: Policy And V-function: World 2

Q6. Describe World 3. What is the goal of the reinforcement learning in this world? Is it possible to get a good policy from every state in this world, and if so how? What parameters did you use to solve this world? Plot the policy and the V-function.

The goal of the reinforcement is to reach the goal without touching the invalid borders of the world. In world 3 it's not uncommon of the agent to spawn directly on the goal. It's possible to achieve a good policy from every step if the learning rate is high enough, for the agent to not

In that the algorithm will terminate if the current step is a terminal step. For world 3

Parameter Setting:
1. Number of Episodes: 5000
2. learning rate (η): 0.75
3. discount factor (γ): 0.9

We tested our agent for 5000 episodes out of which all 5000 times it could reach goal successfully.

Figure 3 are the plots for Policy and V-function for world 3.

(a) Policy for World 3

(b) V-function for World 3

Figure 3: Policy And V-function: World 3

Q7. Describe World 4. What is the goal of the reinforcement learning in this world? This world has a hidden trick. How is it different from world 3, and why can this be solved using reinforcement learning? What parameters did you use to solve this world? Plot the policy and the V-function.

The difference from world 3 to 4 is that the agent will not spawn on the on the goal frequently. It also is spawned more frequently on the opposite side of the blue invalid borders. It can be solved using by RL because which ever position the agent is spawned one it will learn from previous information in which direction to go.

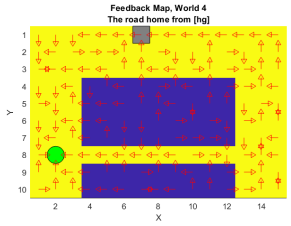
Parameter Setting:
1. Number of Episodes: 5000
2. learning rate (η): 0.75
3. discount factor (γ): 0.9

We tested our agent for 5000 episodes out of which all 89 times it could reach goal successfully.

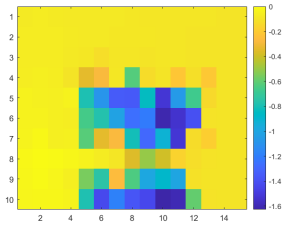
Figure 4 are the plots for Policy and V-function for world 4.

Q8. Explain how the learning rate a influences the policy and V-function. Use figures to make your point.

Learning rate impacts the rate of which information is stored in the algorithm. The learning rate can take values for $0 \leq \eta \leq 1$. If the value is close to zero it means that the algorithm will not take into account the current information to the same extent. Increasing the η will increase the impact of each iteration to the previous.

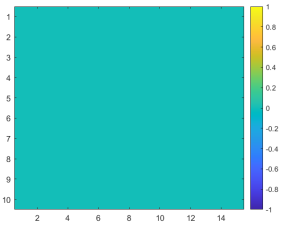


(a) Policy for World 4

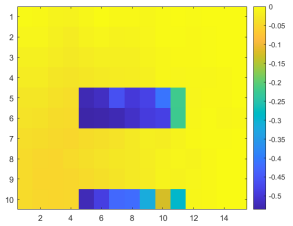


(b) V-function for World 4

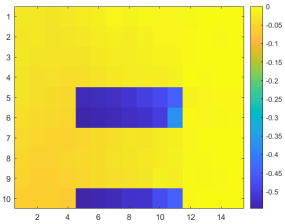
Figure 4: Policy And V-function: World 4



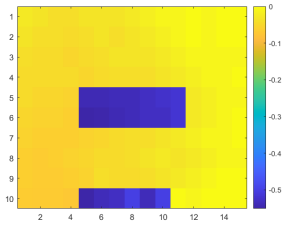
(a) V-Function of World 3 When $\eta = 0$



(b) V-Function of World 3 When $\eta = 0.25$



(c) V-Function for World 3 When $\eta = 0.5$



(d) V-Function of World 3 When $\eta = 1$

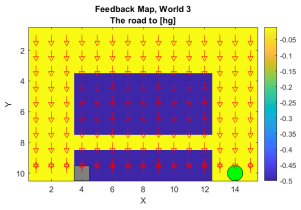
Figure 5: V-Function of World 3 for different Learning Rate η

Q9. Explain how the discount factor g influences the policy and V-function. Use figures to make your point.

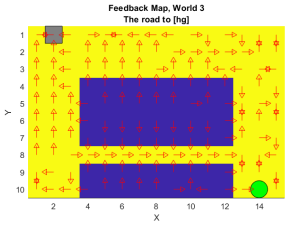
The discount factor γ takes on values between $0 < \gamma < 1$ where a lower value will maximize the short term rewards for learning and a higher value will focus more on the long term rewards in the system.

Q10. Explain how the exploration rate e influences the policy and V-function. Use figures to make your point. Did you use any strategy for changing e during training?

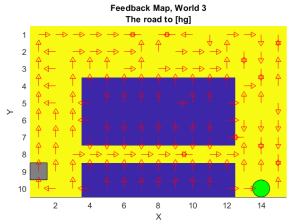
For deciding the exploration rate the following formula were used:



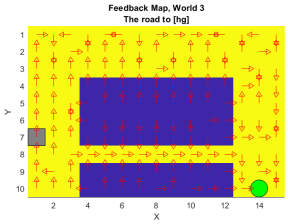
(a) Policy of World 3 When $\eta = 0$



(b) Policy of World 3 When $\eta = 0.25$



(c) Policy for World 3 When $\eta = 0.5$



(d) Policy of World 3 When $\eta = 1$

Figure 6: Policy of World 3 for different Learning Rate η

$$\epsilon = \frac{maxiteration - currentiteration}{maxiteration}$$

Where in the beginning the algorithm will explore more and as for each iteration the probability for a random walk is reduced until it becomes 0 in the last iteration

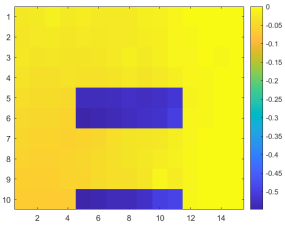
Figure 7 and 8 depicts the V-function and Best policy of World 3 for different Exploration Rates.

Q11. What would happen if we instead of reinforcement learning were to use Dijkstra's cheapest path finding algorithm in the "Suddenly irritating blob" world? What about in the static "Irritating blob" world?

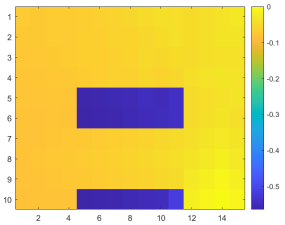
In the static irritating blob world it would have to calculate the shortest path for every every different starting position on the map. As for each new starting position there would be a new shortest path. For the suddenly irritating blob world it would have to do more than twice the amount of calculations as now it could start within the invalid regions. Which could quickly become very computationally expensive for more complex cases.

Q12. Can you think of any application where reinforcement learning could be of practical use? A hint is to use the Internet.

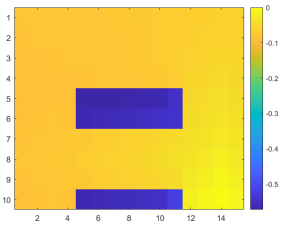
Application areas for RL could be for example to autonomously for robots to



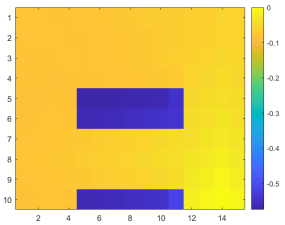
(a) V-Function of World 3 When $\epsilon = 0.9$



(b) V-Function of World 3 When $\epsilon = 0.7$

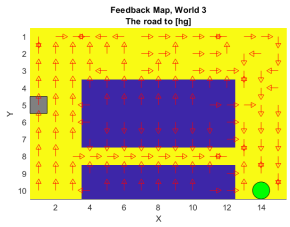


(c) Policy for World 3 When $\epsilon = 0.5$

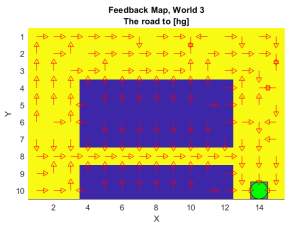


(d) V-Function of World 3 When $\epsilon = 0.2$

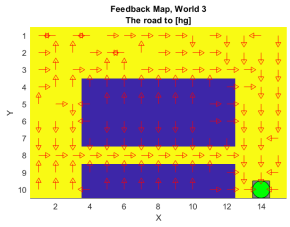
Figure 7: V-Function of World 3 for different Exploration Rate ϵ



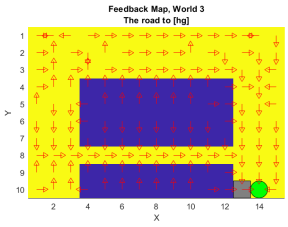
(a) Policy of World 3 When $\epsilon = 0.9$



(b) Policy of World 3 When $\epsilon = 0.7$



(c) Policy of World 3 When $\epsilon = 0.5$



(d) Policy of World 3 When $\epsilon = 0.2$

Figure 8: Policy of World 3 for different Exploration Rate ϵ

learn different actions, in the lecture a video of a robot flipping a pancake was presented. In more real world applications it could be a robot arm used in

manufacturing to improve it's gripping performance.

RL could be used for implementation of autonomus driving vehicles, from using sensors to describe the world around it. It can then define a Q-learning function to keep the car on the road and between lanes.