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HOMEWORK 3 — Report

1 Questions

1.1 Agent:

Agent corresponds to the entity that interacts with the environment. It is responsible for taking actions, observing the environment, and receiving rewards. The agent is the entity that learns the optimal policy to maximize the cumulative reward. When compared to supervised learning, the agent is not provided with the correct output, but it learns the optimal policy through trial and error. That is concept of error is not exactly available in reinforcement setting.

1.2 Environment:

Environment means the world that the agent interacts with. It is the entity that the agent observes and takes actions. The environment is responsible for providing the agent with the current state, reward, and possible actions. The environment is also responsible for updating the state of the agent based on the action taken by the agent. When compared to supervised learning, the environment corresponds to the both dataset and loss function that the system trained and run on.

1.3 Reward:

Reward is the feedback that the agent receives from the environment. It is the scalar value that the agent receives after taking an action. The reward is used to evaluate the action taken by the agent. The agent aims to maximize the cumulative reward by learning the optimal policy. When compared to supervised learning, the reward corresponds to the loss function that the system tries to minimize.

1.4 Policy:

Policy is the strategy that the agent uses to take actions. It is the mapping from the state to the action. If we compare with supervised learning, the policy corresponds to the model that the system uses to predict the output.

1.5 Exploration:

The exploration corresponds to the process of trying different actions to learn the optimal policy. The agent explores the environment by taking different actions and observing the reward. The exploration is necessary to learn the optimal policy. When we try to map exploration to supervised learning step we may encounter more than one phenomena. For example, we can say that exploration corresponds to the training process of the model. On the other hand we can say the exploration corresponds to the data augmentation process or other randomization steps taken during training.

1.6 Exploitation:

Exploitation corresponds to the process of taking the best action based on the learned policy. The agent exploits the environment by taking the action that maximizes the reward. The exploitation is necessary to maximize the cumulative reward. When we try to map exploitation to supervised learning step, we can say that exploitation corresponds to the inference process of the model.

2 Experimental Work

The proper implementation for maze, temporal difference learning and Q-learning are implemented and provided in appendix.
The experimental work section is divided into four main part where each part has TD learning and Q learning related experiments seperately. First the default parameter outputs are presented. Then the effect of alpha parameter is investigated. After that the effect of gamma parameter is investigated. Lastly the effect of epsilon parameter is investigated.

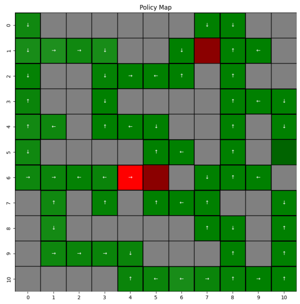
2.1 Temporal Difference Learning Default Parameters

The default parameters for the temporal difference learning are set as follows:

- Alpha: 0.1
- Gamma: 0.95
- Epsilon: 0.2
- Episodes: 10000

According to these settings the training is done. The policy maps are provided in Figure 1. The value function plots are provided in Figure 2. The convergence plots are provided in Figure 3.

Basically we can say that the agent learns the optimal policy and value function.



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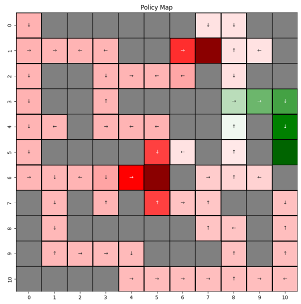

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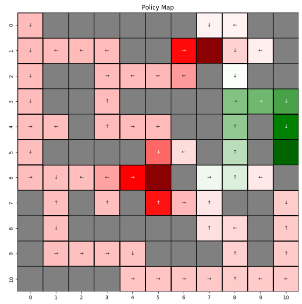

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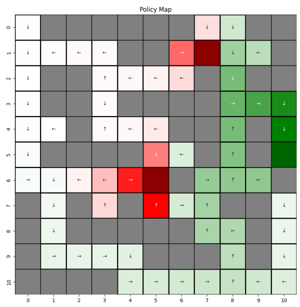

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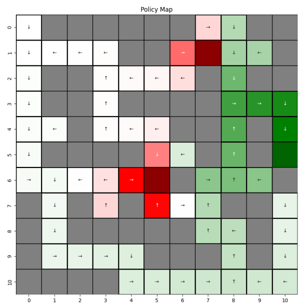

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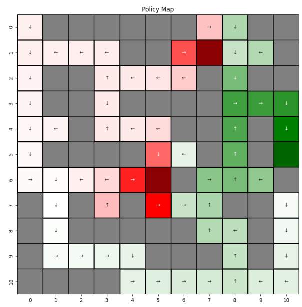
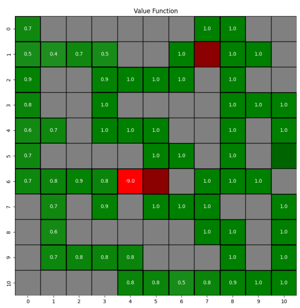


(f) Episode 10000

Figure 1: Evolution of policy maps throughout episodes.



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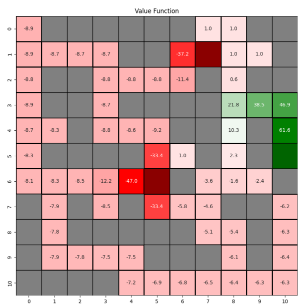

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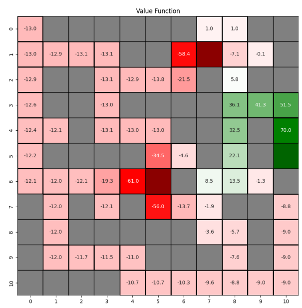

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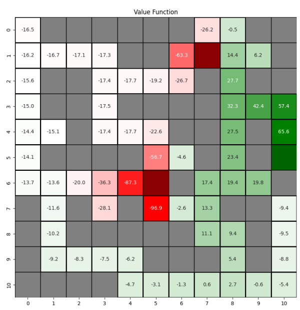

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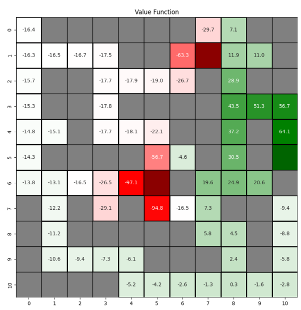

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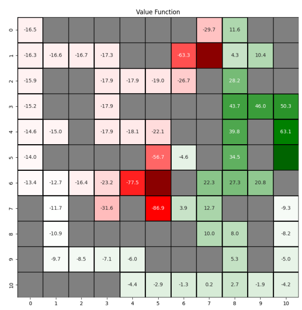
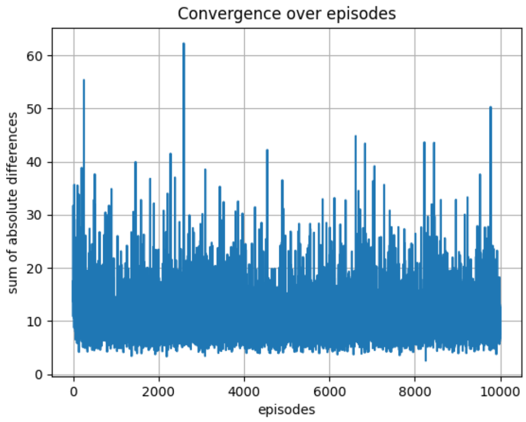
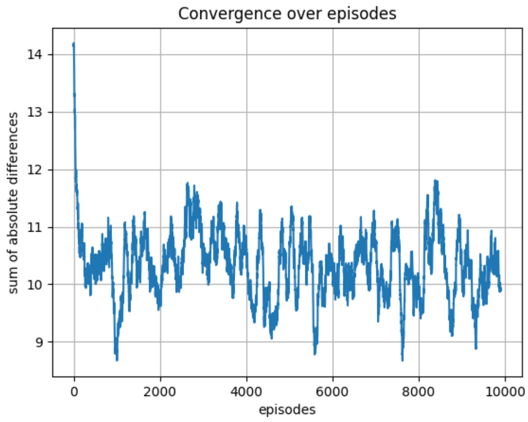


(f) Episode 10000

Figure 2: Evolution of value function throughout episodes.



(a) Converge raw.



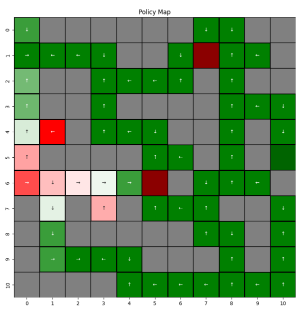
(b) Smoothed convergence.

Figure 3: Converge of value function.

2.2 Q-Learning Default Parameters

As same as the temporal difference learning, the default parameters for the Q-learning are set. Then the training is done. The policy maps are provided in Figure 4. The value function plots are provided in Figure 5. The convergence plots are provided in Figure 6.

So, again we can say that the agent learns the optimal policy and value function at the end.



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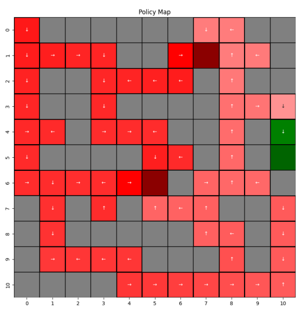

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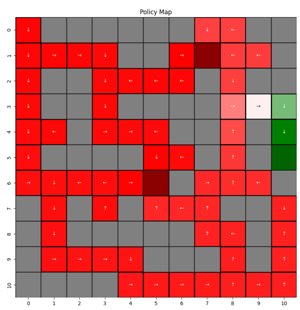

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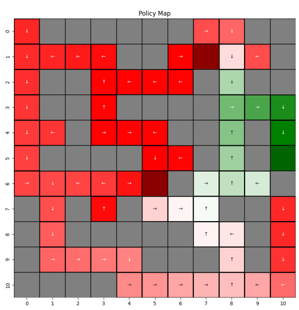

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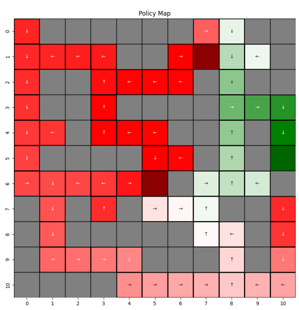

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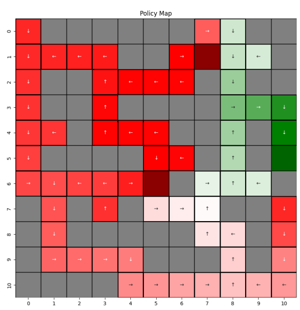
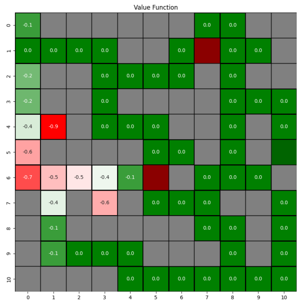
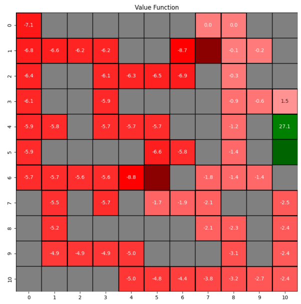


(f) Episode 10000

Figure 4: Evolution of policy maps throughout episodes.



(a) Episode 1.



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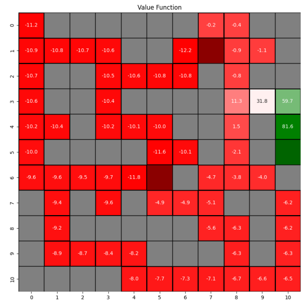

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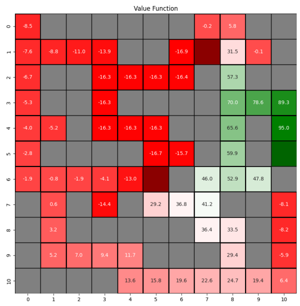

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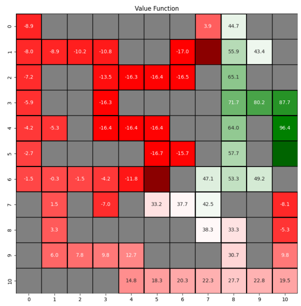

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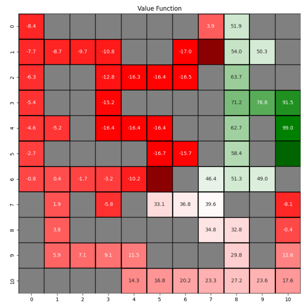
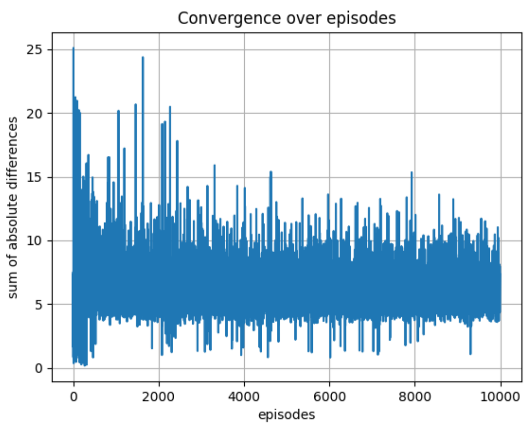
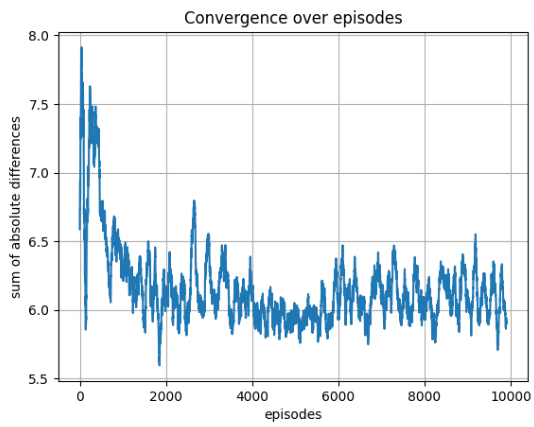


(f) Episode 10000

Figure 5: Evolution of value function throughout episodes.



(a) Converge raw.



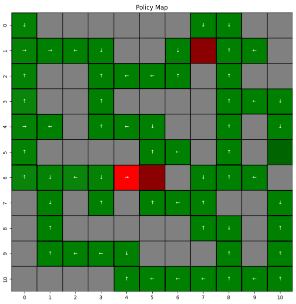
(b) Smoothed convergence.

Figure 6: Converge of value function.

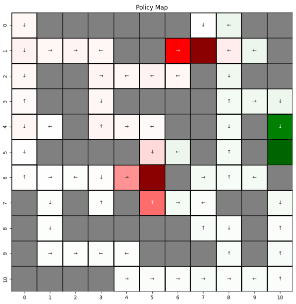
2.3 Effect of Alpha in Temporal Difference Learning

Let us first provide the necessary output for each alpha parameter and then discuss the results at the end of this section.

Figure 7 provides the policy maps for the alpha parameter set to 0.001. Figure 8 provides the value function plots for the alpha parameter set to 0.001. Figure 9 provides the convergence plots for the alpha parameter set to 0.001.



(a) Episode 1.



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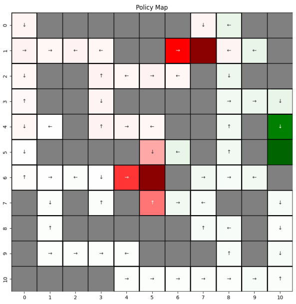

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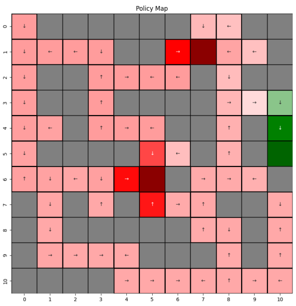

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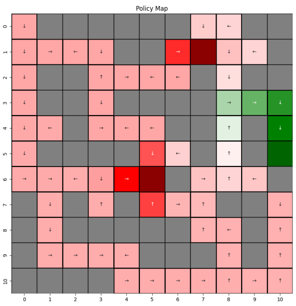

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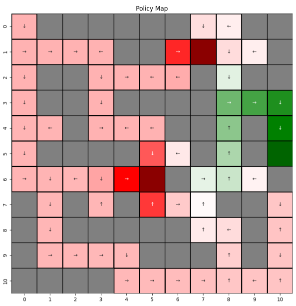
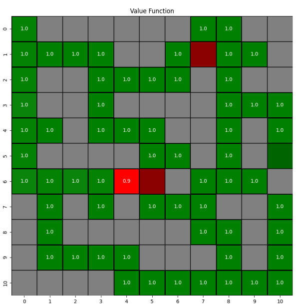
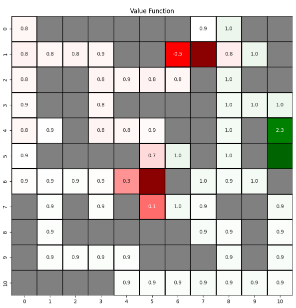


(f) Episode 10000

Figure 7: Evolution of policy maps throughout episodes.



(a) Episode 1.



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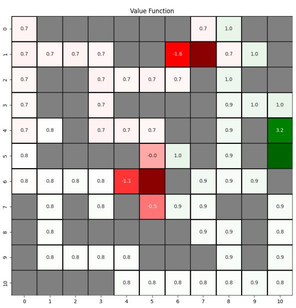

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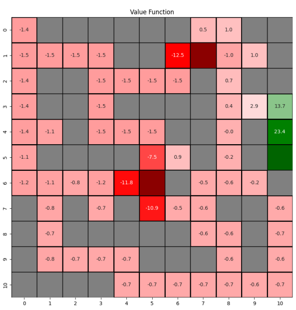

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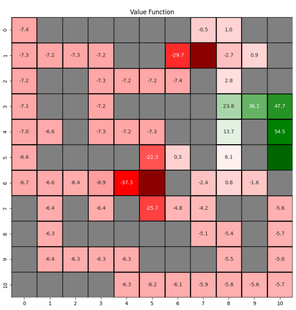

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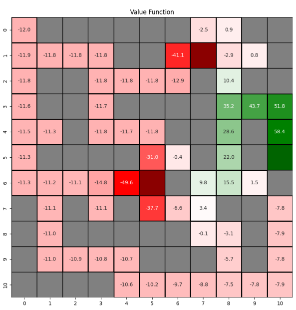
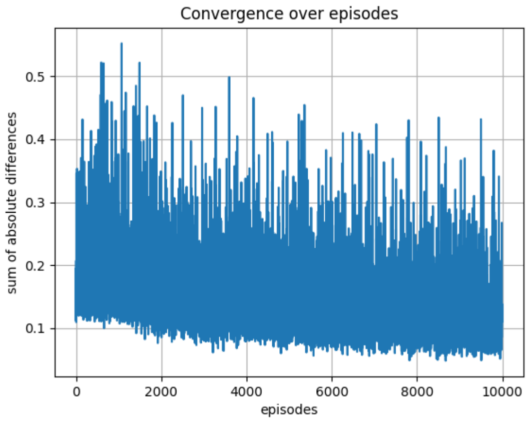
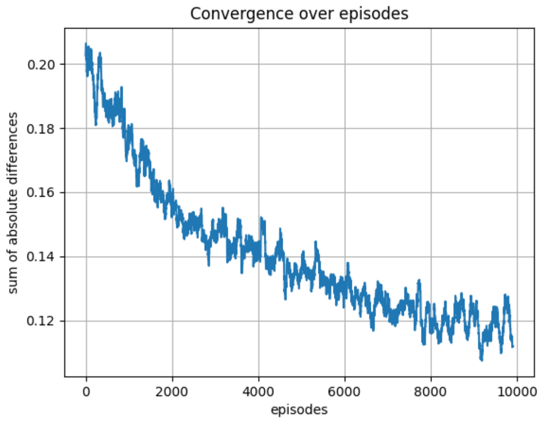


(f) Episode 10000

Figure 8: Evolution of value function throughout episodes.



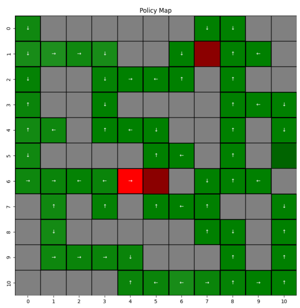
(a) Converge raw.



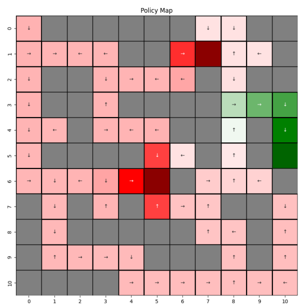
(b) Smoothed convergence.

Figure 9: Converge of value function.

Figure 10 provides the policy maps for the alpha parameter set to 0.1. Figure 11 provides the value function plots for the alpha parameter set to 0.1. Figure 12 provides the convergence plots for the alpha parameter set to 0.1.



(a) Episode 1.



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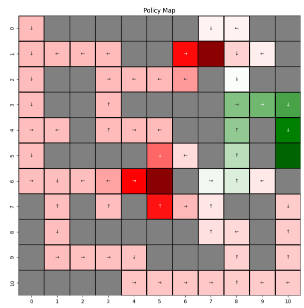

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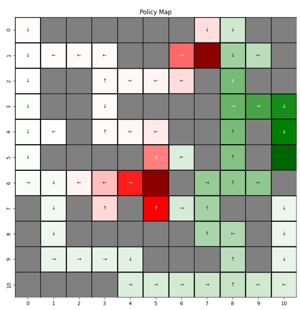

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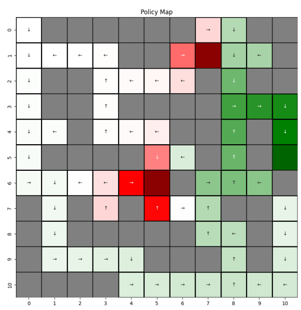

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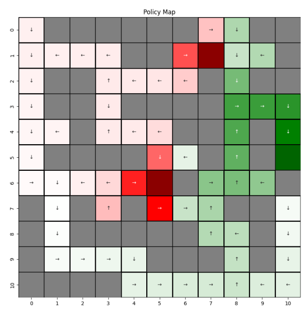
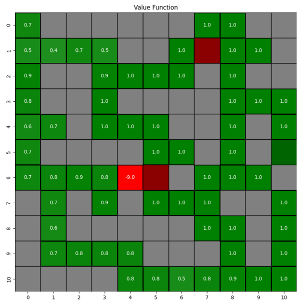
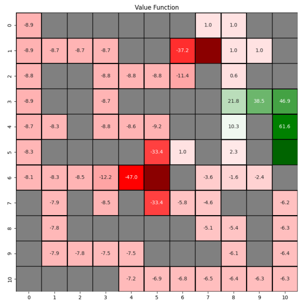


(f) Episode 10000

Figure 10: Evolution of policy maps throughout episodes.



(a) Episode 1.



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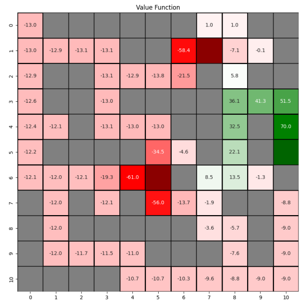

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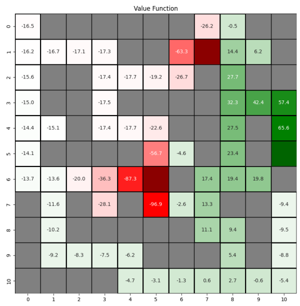

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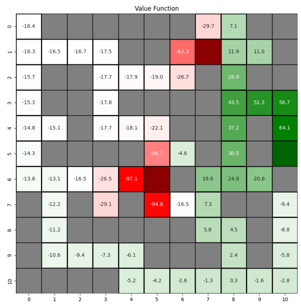

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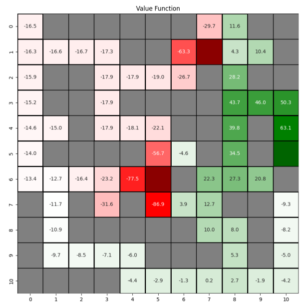
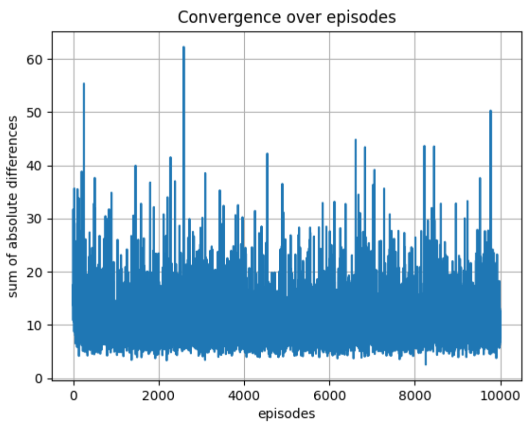
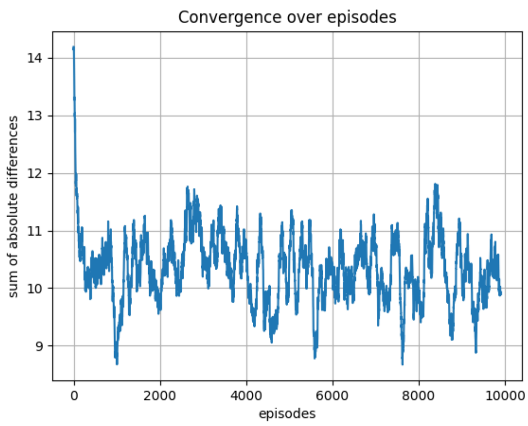


(f) Episode 10000

Figure 11: Evolution of value function throughout episodes.



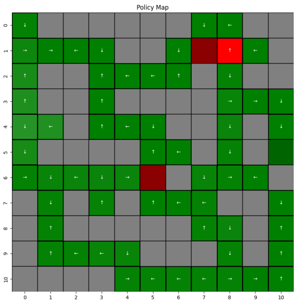
(a) Converge raw.



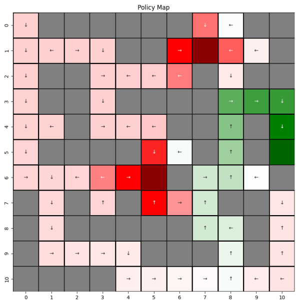
(b) Smoothed convergence.

Figure 12: Converge of value function.

Figure 13 shows the policy maps for the alpha parameter set to 0.5. Figure 14 illustrates the value function plots for the alpha parameter set to 0.5. Figure 15 provides the convergence plots for the alpha parameter set to 0.5.



(a) Episode 1.



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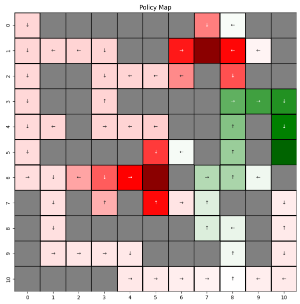

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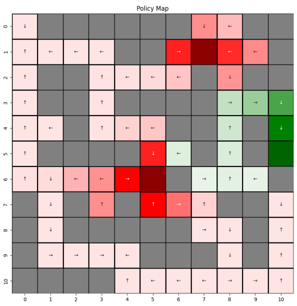

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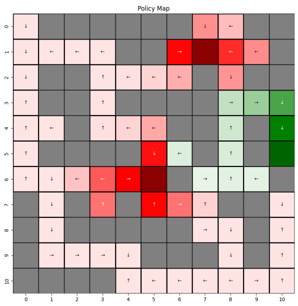
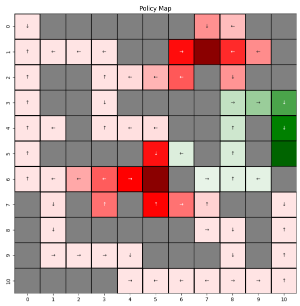
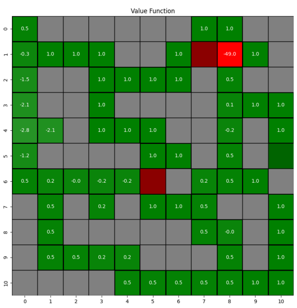


(e) Episode 5000

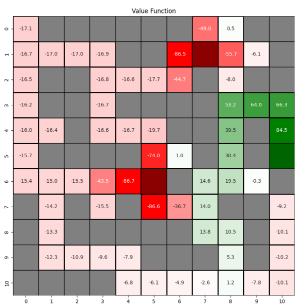


(f) Episode 10000

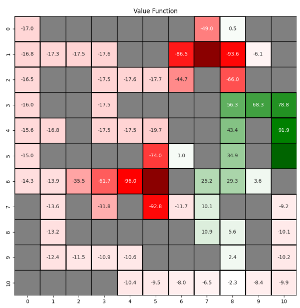
Figure 13: Evolution of policy maps throughout episodes.



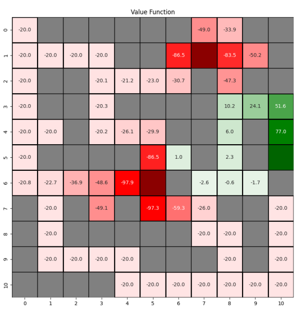
(a) Episode 1.



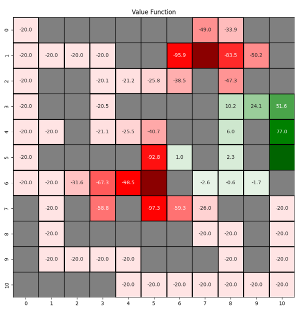
(b) Episode 50



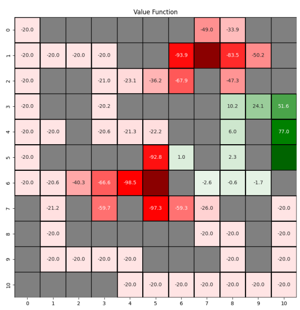
(c) Episode 100



(d) Episode 1000.

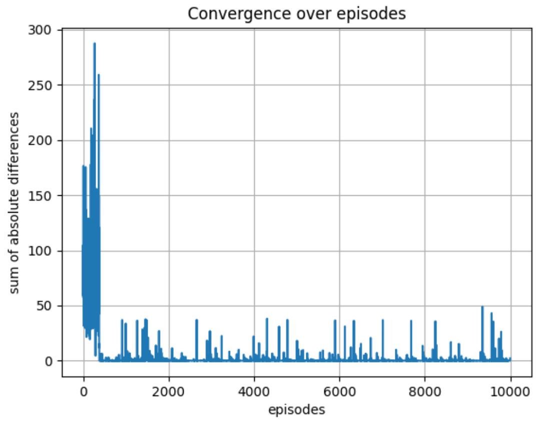


(e) Episode 5000

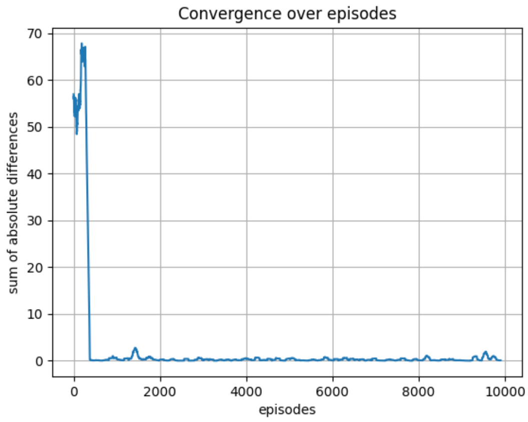


(f) Episode 10000

Figure 14: Evolution of value function throughout episodes.



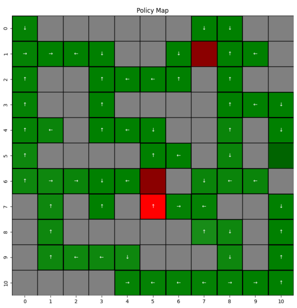
(a) Converge raw.



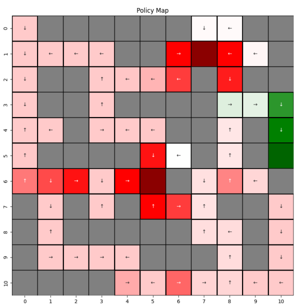
(b) Smoothed convergence.

Figure 15: Converge of value function.

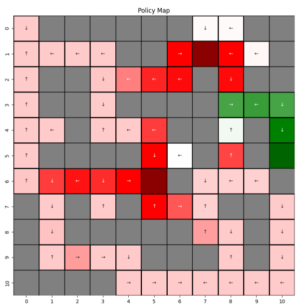
Lastly, Figure 16 shows the policy maps for the alpha parameter set to 1. Figure 17 illustrates the value function plots for the alpha parameter set to 1. Figure 18 provides the convergence plots for the alpha parameter set to 1.



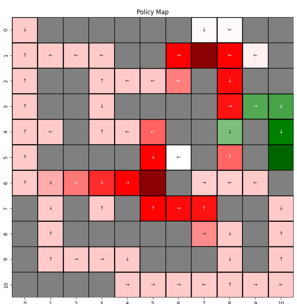
(a) Episode 1.



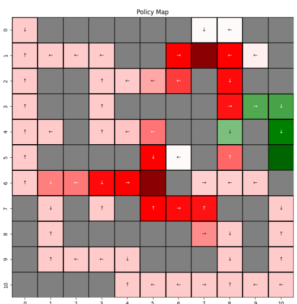
(b) Episode 50



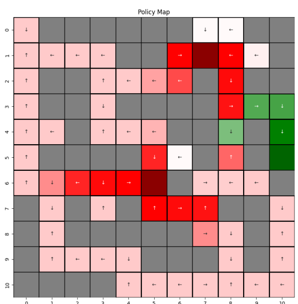
(c) Episode 100



(d) Episode 1000.

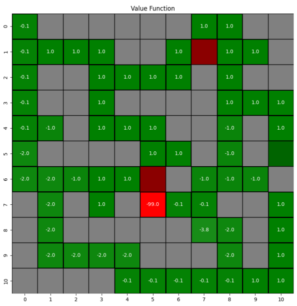


(e) Episode 5000

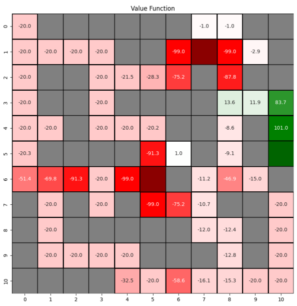


(f) Episode 10000

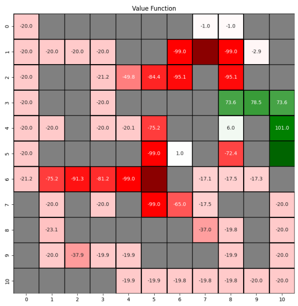
Figure 16: Evolution of policy maps throughout episodes.



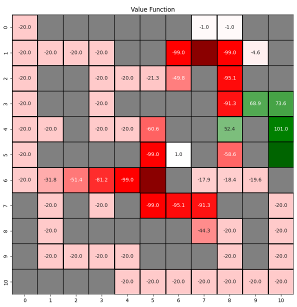
(a) Episode 1.



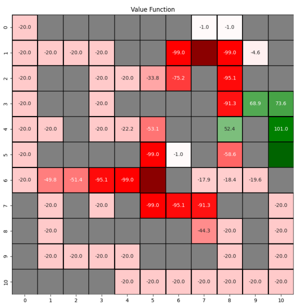
(b) Episode 50



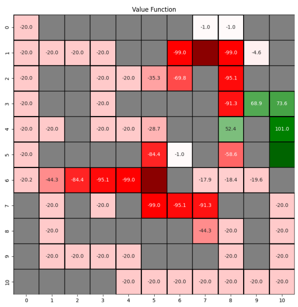
(c) Episode 100



(d) Episode 1000.

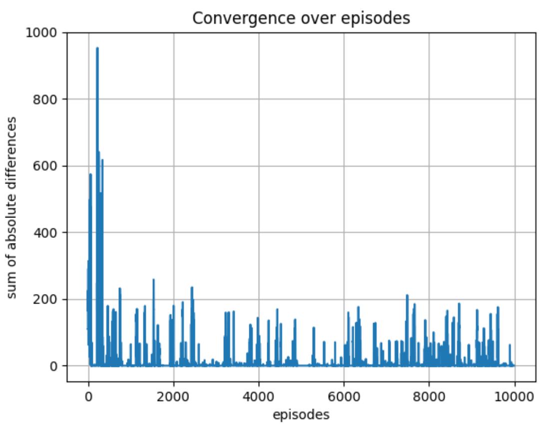


(e) Episode 5000

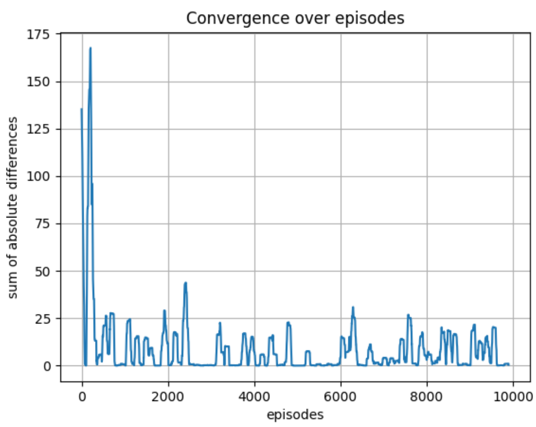


(f) Episode 10000

Figure 17: Evolution of value function throughout episodes.



(a) Converge raw.



(b) Smoothed convergence.

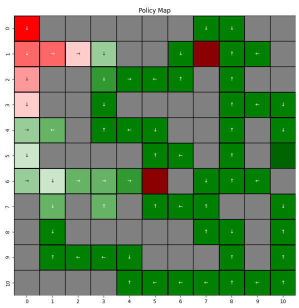
Figure 18: Converge of value function.

What we can interpret from the sweep of alpha value in temporal difference learning as follows. When the alpha value is set to 0.001, the agent try learns the optimal policy and value function as expected. However, the convergence is slower compared to the other alpha values and proper convergence is not observed. When the alpha value set to 0.01 convergence observed to optimal policy. When the alpha value is set to 0.5, the agent learns the optimal policy and value function as expected. The convergence is faster compared to the alpha value set to 0.01. Lastly, when the alpha value is set to 1, the agent can not learn the optimal policy and value function since the learning rate overshoots. The convergence is faster compared to the alpha value set to 0.5 but it is hard to say this is a stable convergence. The reason is, the convergence is not as smooth as the alpha value set to 0.5. So the defaul value and 0.5 are better choices for the alpha parameter in temporal difference learning.

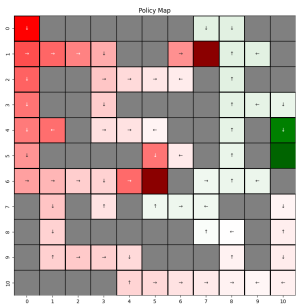
2.4 Effect of Alpha in Q-Learning

Similarly, we can analyze the effect of alpha parameter in Q-learning. The results are provided below.

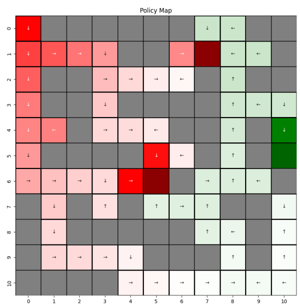
Figure 19 shows the policy maps for the alpha parameter set to 0.001. Figure 20 illustrates the value function plots for the alpha parameter set to 0.001. Figure 21 presents the convergence plots for the alpha parameter set to 0.001.



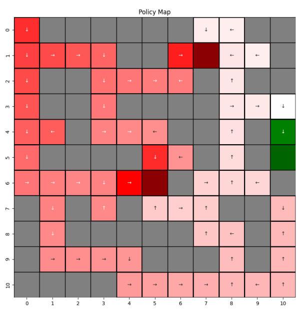
(a) Episode 1.



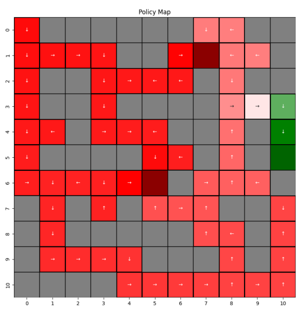
(b) Episode 50



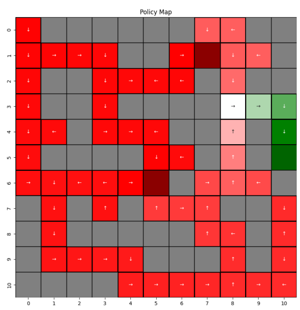
(c) Episode 100



(d) Episode 1000.

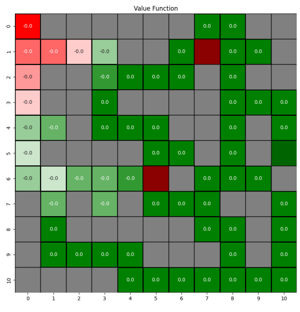


(e) Episode 5000

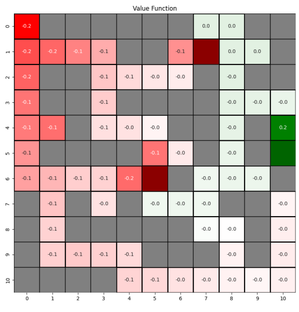


(f) Episode 10000

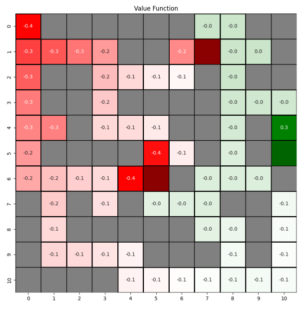
Figure 19: Evolution of policy maps throughout episodes.



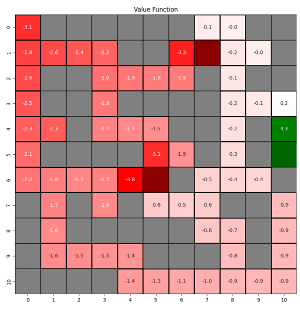
(a) Episode 1.



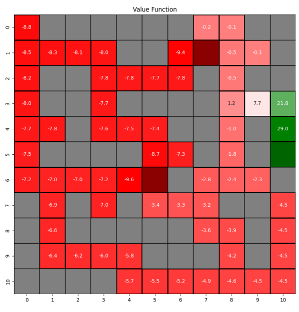
(b) Episode 50



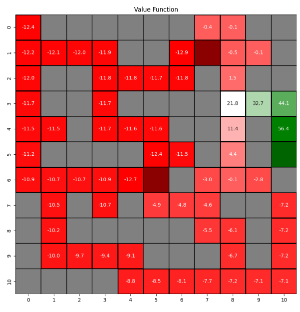
(c) Episode 100



(d) Episode 1000.

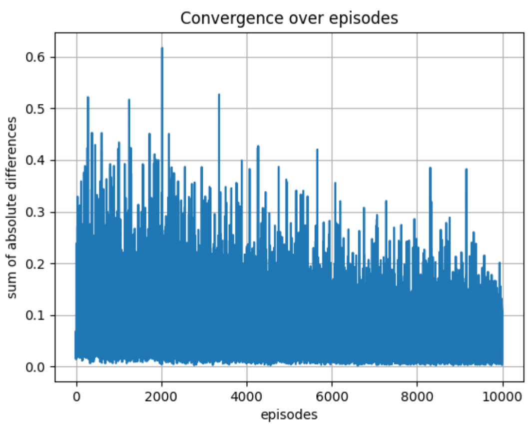


(e) Episode 5000

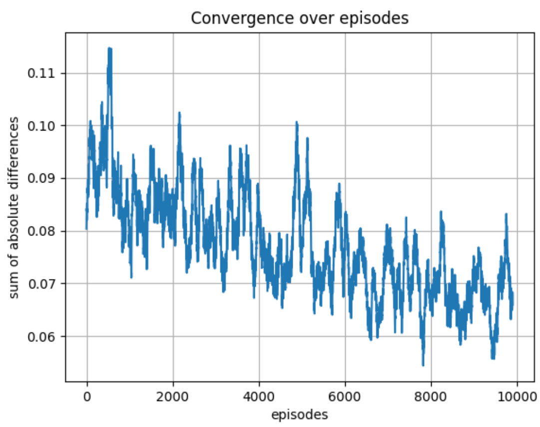


(f) Episode 10000

Figure 20: Evolution of value function throughout episodes.



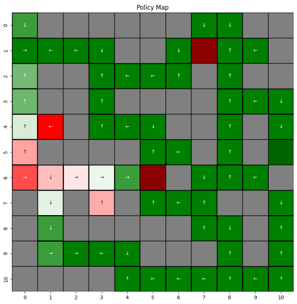
(a) Converge raw.



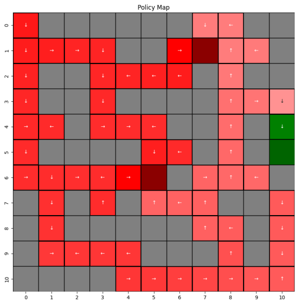
(b) Smoothed convergence.

Figure 21: Converge of value function.

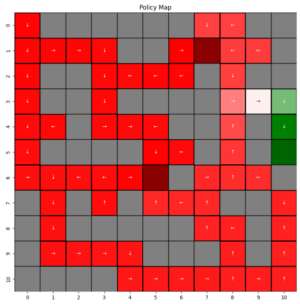
Figure 22 shows the policy maps for the alpha parameter set to 0.1. Figure 23 illustrates the value function plots for the alpha parameter set to 0.1. Figure 24 provides the convergence plots for the alpha parameter set to 0.1.



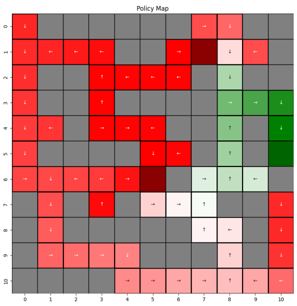
(a) Episode 1.



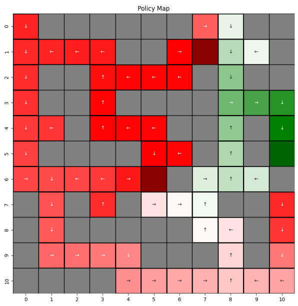
(b) Episode 50



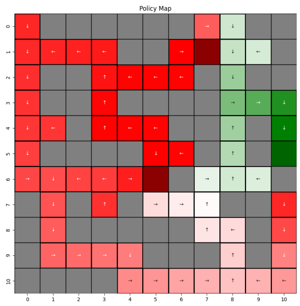
(c) Episode 100



(d) Episode 1000.

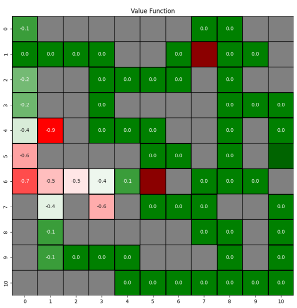


(e) Episode 5000

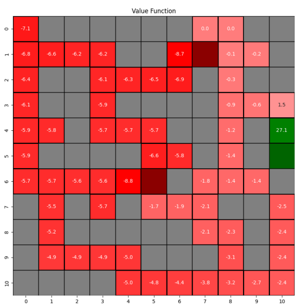


(f) Episode 10000

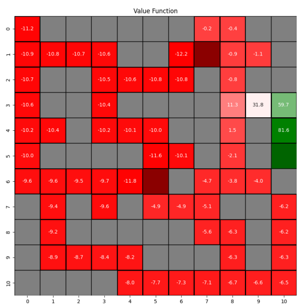
Figure 22: Evolution of policy maps throughout episodes.



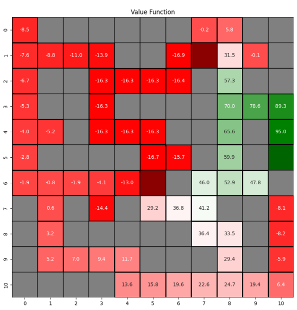
(a) Episode 1.



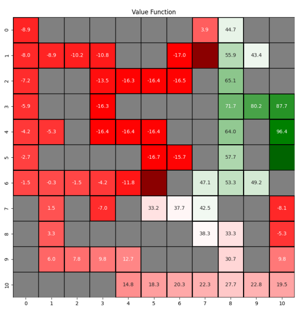
(b) Episode 50



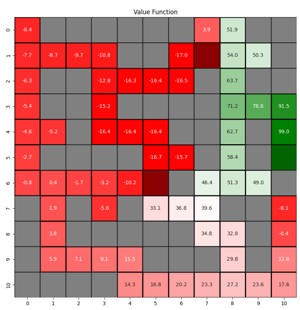
(c) Episode 100



(d) Episode 1000.

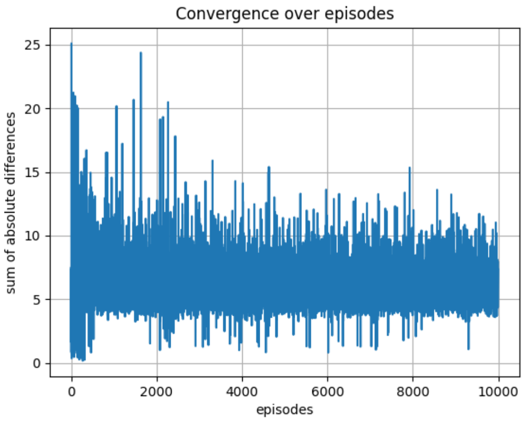


(e) Episode 5000

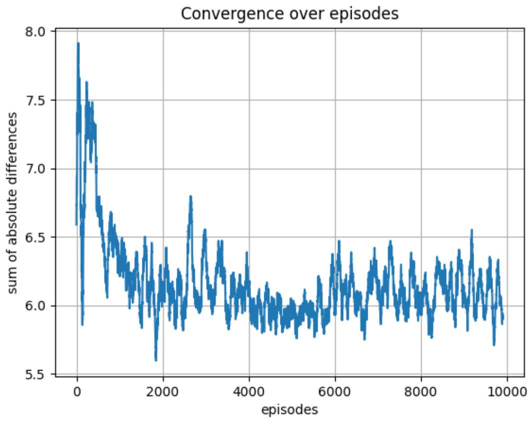


(f) Episode 10000

Figure 23: Evolution of value function throughout episodes.



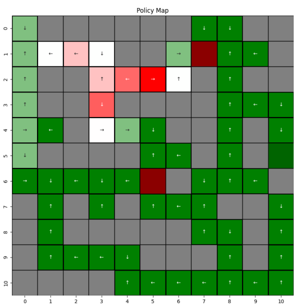
(a) Converge raw.



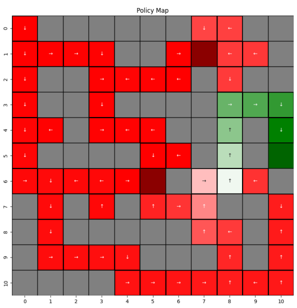
(b) Smoothed convergence.

Figure 24: Converge of value function.

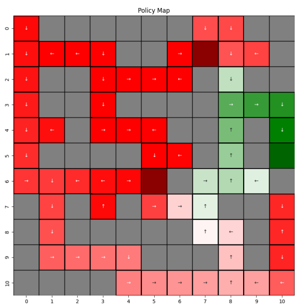
Figure 25 shows the policy maps for the alpha parameter set to 0.5. Figure 26 illustrates the value function plots for the alpha parameter set to 0.5. Figure 27 provides the convergence plots for the alpha parameter set to 0.5.



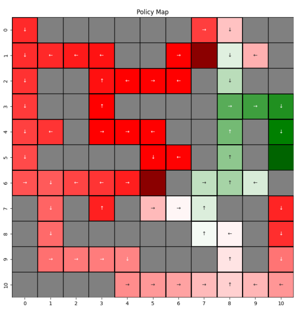
(a) Episode 1.



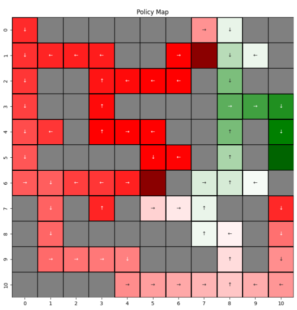
(b) Episode 50



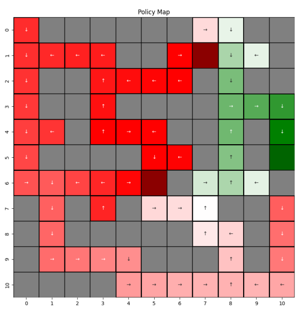
(c) Episode 100



(d) Episode 1000.

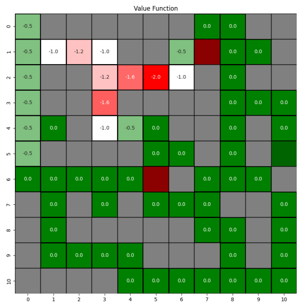


(e) Episode 5000

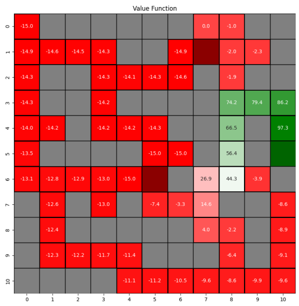


(f) Episode 10000

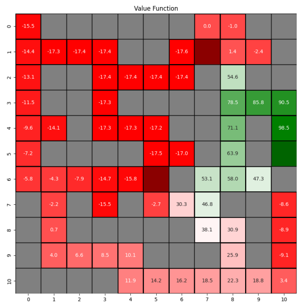
Figure 25: Evolution of policy maps throughout episodes.



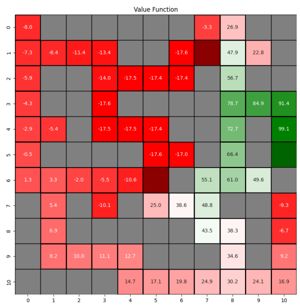
(a) Episode 1.



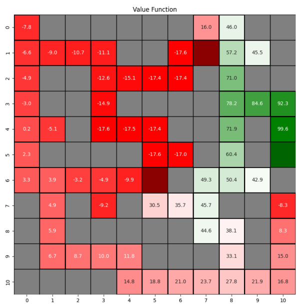
(b) Episode 50



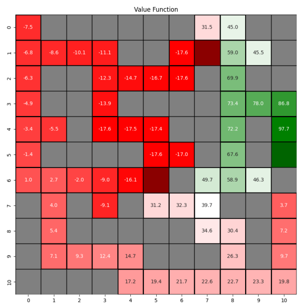
(c) Episode 100



(d) Episode 1000.

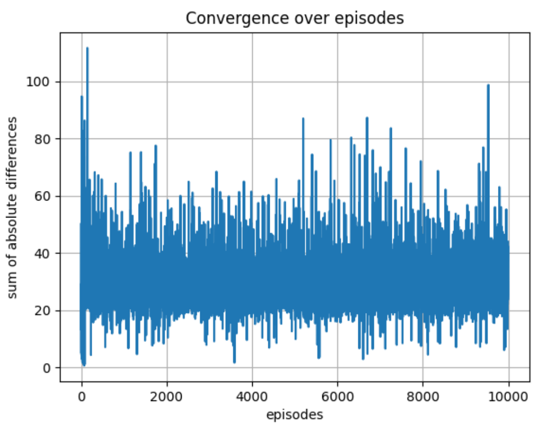


(e) Episode 5000

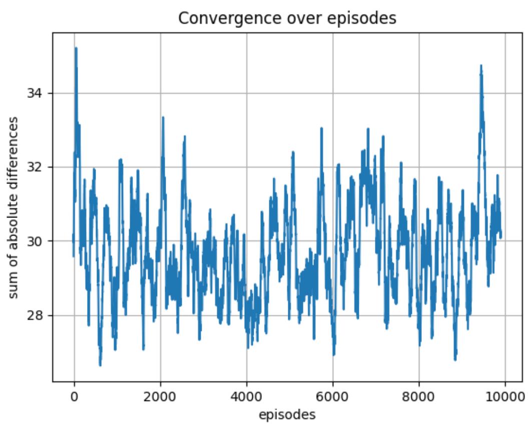


(f) Episode 10000

Figure 26: Evolution of value function throughout episodes.



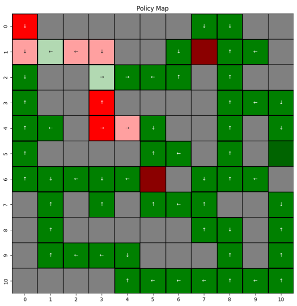
(a) Converge raw.



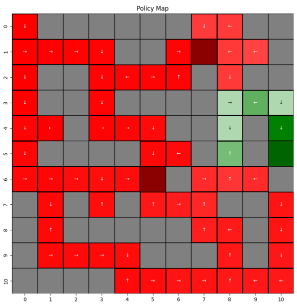
(b) Smoothed convergence.

Figure 27: Converge of value function.

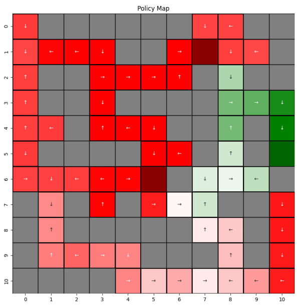
Figure 28 shows the policy maps for the alpha parameter set to 1. Figure 29 illustrates the value function plots for the alpha parameter set to 1. Figure 30 provides the convergence plots for the alpha parameter set to 1.



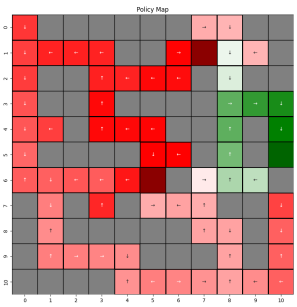
(a) Episode 1.



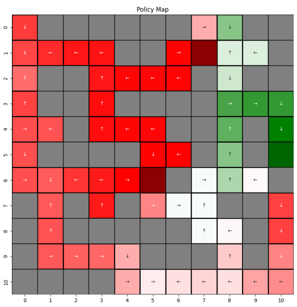
(b) Episode 50



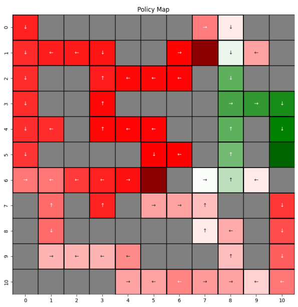
(c) Episode 100



(d) Episode 1000.

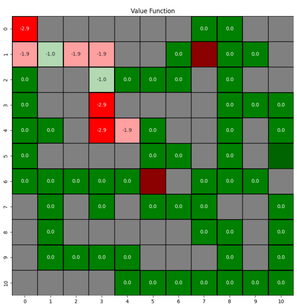


(e) Episode 5000

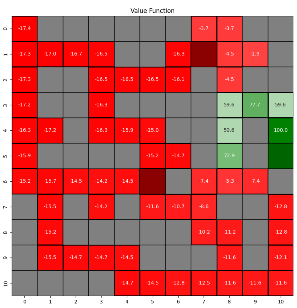


(f) Episode 10000

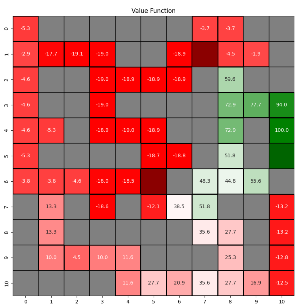
Figure 28: Evolution of policy maps throughout episodes.



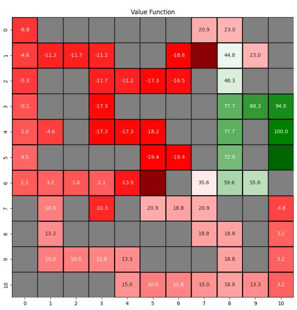
(a) Episode 1.



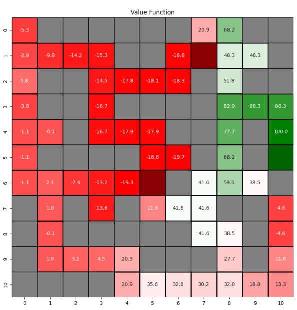
(b) Episode 50



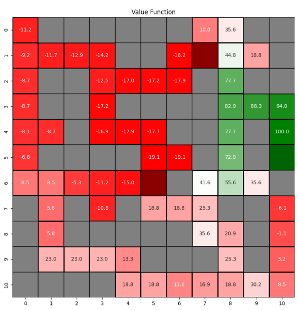
(c) Episode 100



(d) Episode 1000.

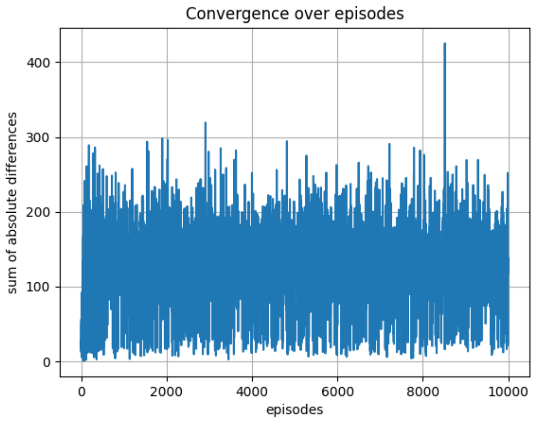


(e) Episode 5000

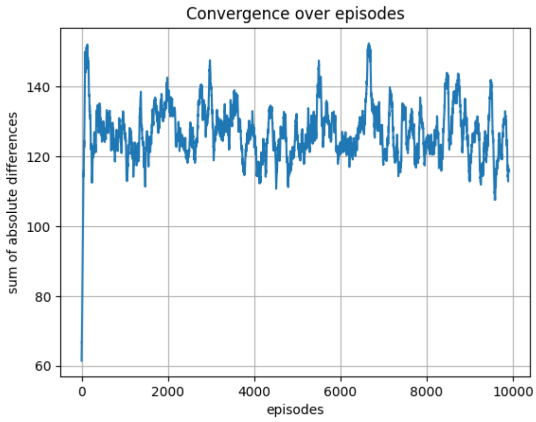


(f) Episode 10000

Figure 29: Evolution of value function throughout episodes.



(a) Converge raw.



(b) Smoothed convergence.

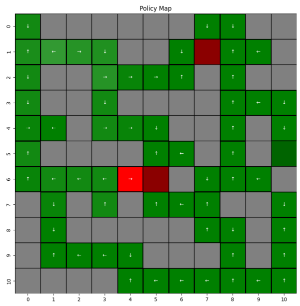
Figure 30: Converge of value function.

As a result we can say that the for small alpha values Q learning is an effective strategy as we see convergence is possible. However, for the alpha value set to 1, the agent can not learn the optimal policy and value function since the learning rate is too much again. For these values the trend of fast convergence is observed from 0.001 to 0.5. However, the convergence is not stable for the alpha value set to 1. So the values up to 0.5 are better choices for the alpha parameter in Q learning.

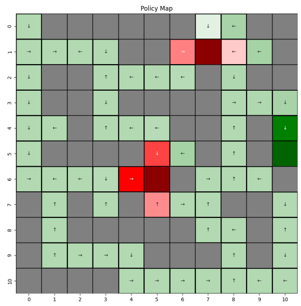
2.5 Effect of Gamma in Temporal Difference Learning

Here, we will have a look at the effect of gamma parameter in temporal difference learning. The results are provided below. The parameter set used for this experiment is as follows: $\alpha = 0.1$, $\epsilon = 0.2$, and the number of episodes is set to 10000. The gamma parameter is varied from 0.1 to 0.95.

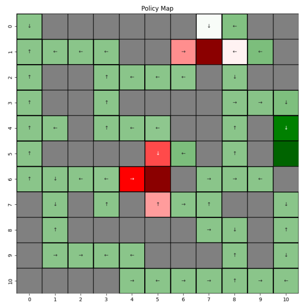
Figure 31 shows the policy maps for the gamma parameter set to 0.1. Figure 32 illustrates the value function plots for the gamma parameter set to 0.1. Figure 33 provides the convergence plots for the gamma parameter set to 0.1.



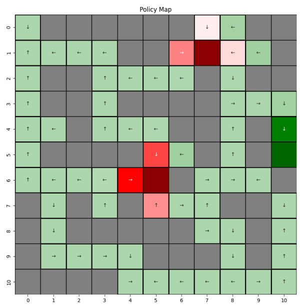
(a) Episode 1.



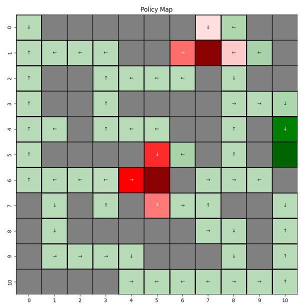
(b) Episode 50



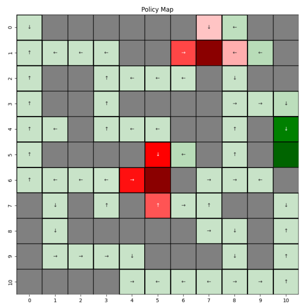
(c) Episode 100



(d) Episode 1000.

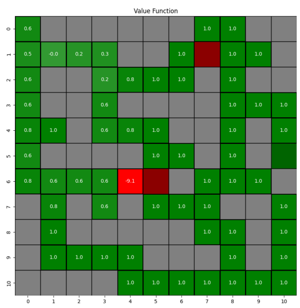


(e) Episode 5000

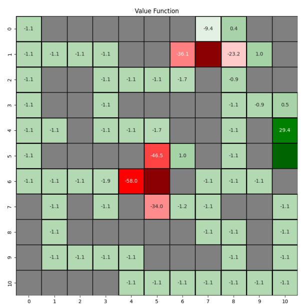


(f) Episode 10000

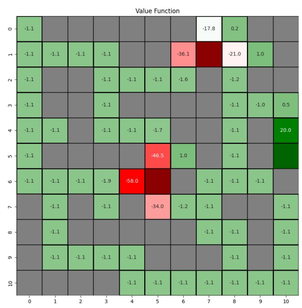
Figure 31: Evolution of policy maps throughout episodes.



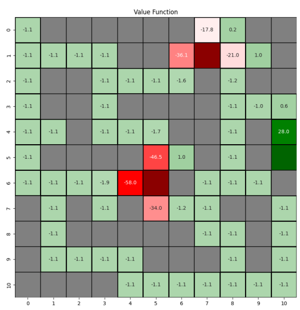
(a) Episode 1.



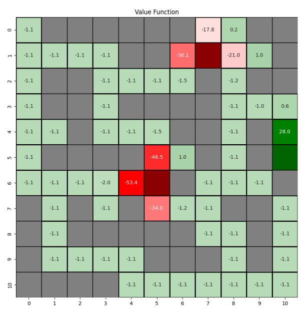
(b) Episode 50



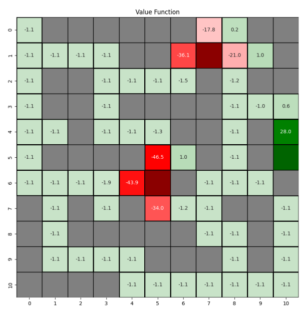
(c) Episode 100



(d) Episode 1000.

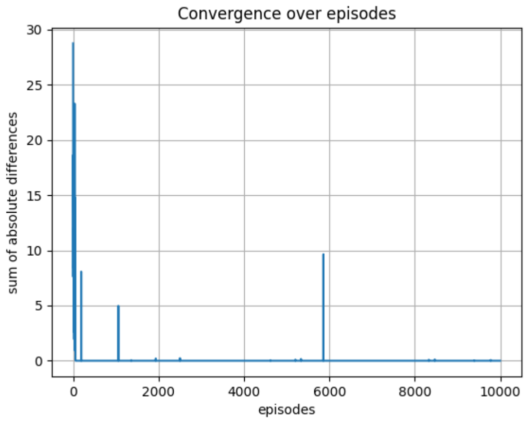


(e) Episode 5000

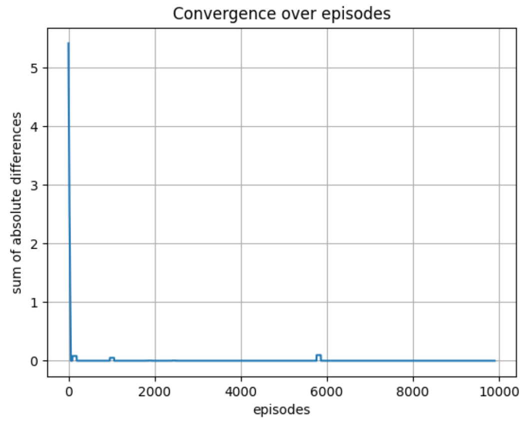


(f) Episode 10000

Figure 32: Evolution of value function throughout episodes.



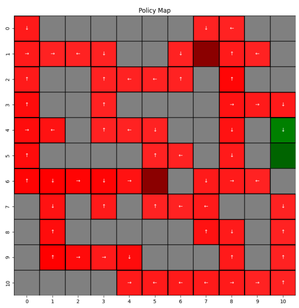
(a) Converge raw.



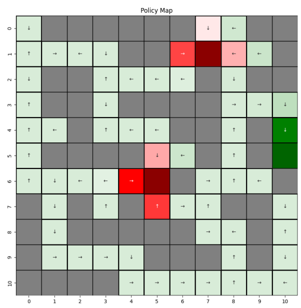
(b) Smoothed convergence.

Figure 33: Converge of value function.

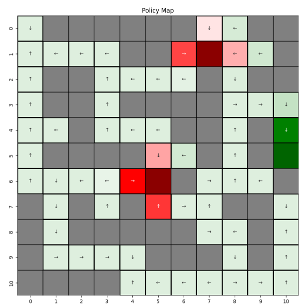
Figure 34 is provided as the policy maps for the gamma parameter set to 0.25. Figure 35 shows the value function plots for the gamma parameter set to 0.25. Figure 36 presents the convergence plots for the gamma parameter set to 0.25.



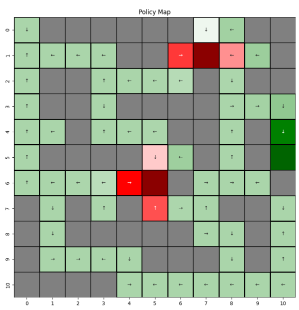
(a) Episode 1.



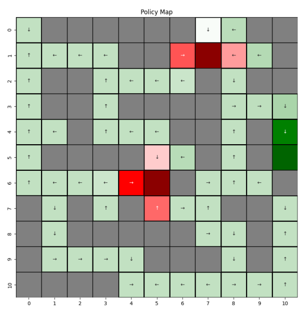
(b) Episode 50



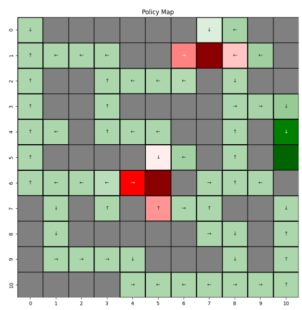
(c) Episode 100



(d) Episode 1000.

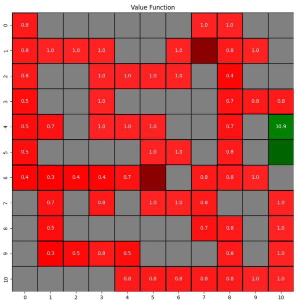


(e) Episode 5000

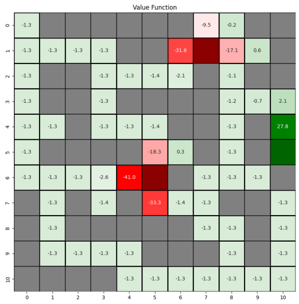


(f) Episode 10000

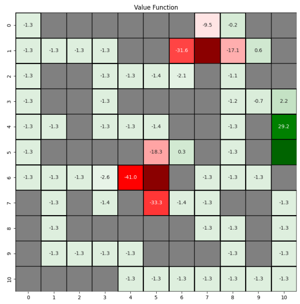
Figure 34: Evolution of policy maps throughout episodes.



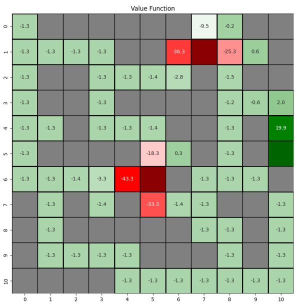
(a) Episode 1.



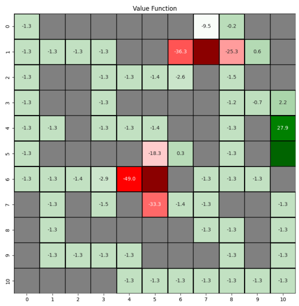
(b) Episode 50



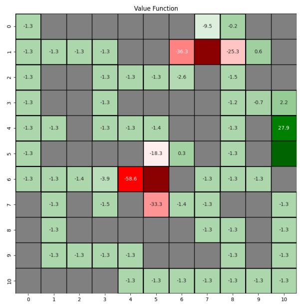
(c) Episode 100



(d) Episode 1000.

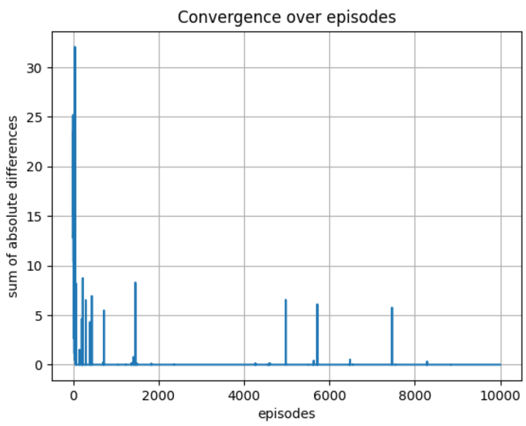


(e) Episode 5000

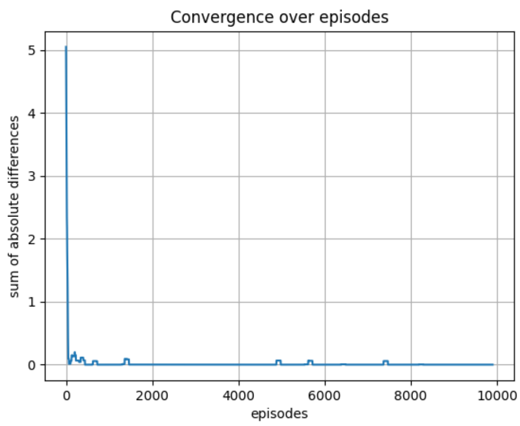


(f) Episode 10000

Figure 35: Evolution of value function throughout episodes.

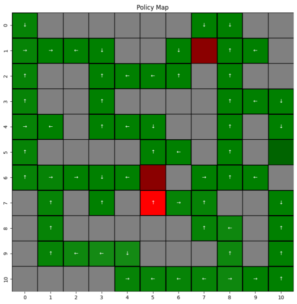


(a) Converge raw.

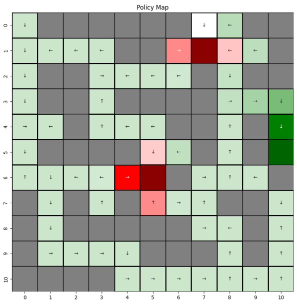


(b) Smoothed convergence.

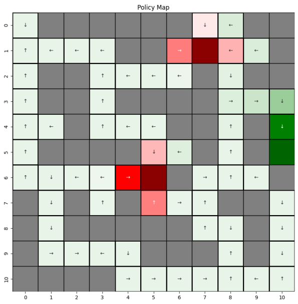
Figure 36: Converge of value function.



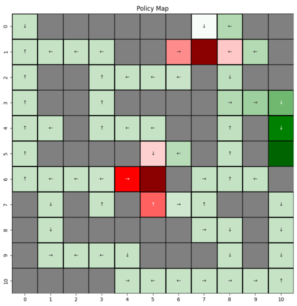
(a) Episode 1.



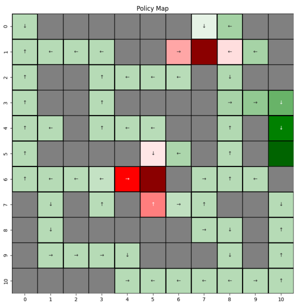
(b) Episode 50



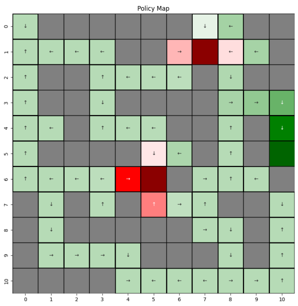
(c) Episode 100



(d) Episode 1000.

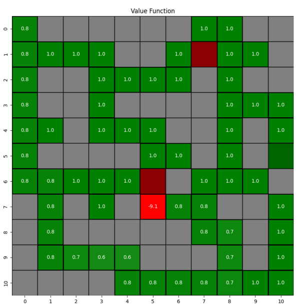


(e) Episode 5000

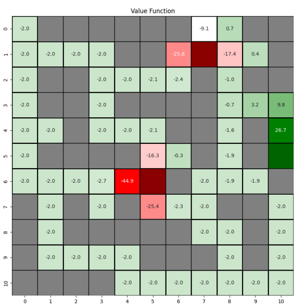


(f) Episode 10000

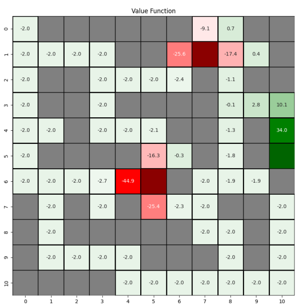
Figure 37: Evolution of policy maps throughout episodes.



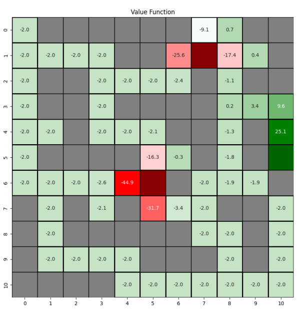
(a) Episode 1.



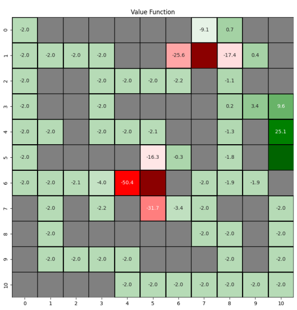
(b) Episode 50



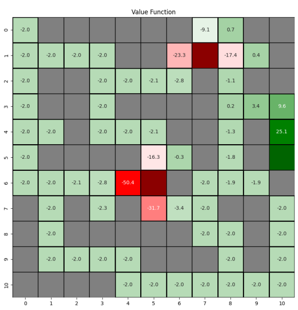
(c) Episode 100



(d) Episode 1000.

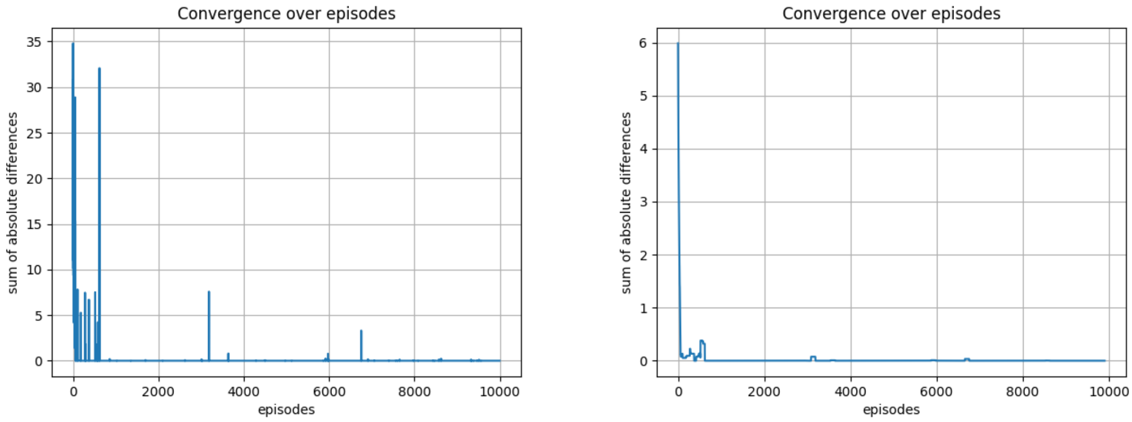


(e) Episode 5000



(f) Episode 10000

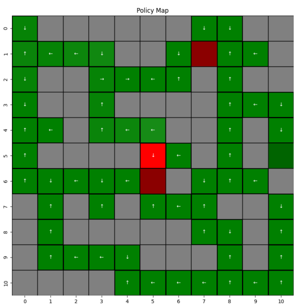
Figure 38: Evolution of value function throughout episodes.



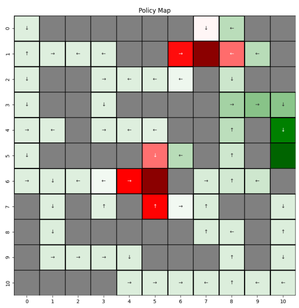
(a) Converge raw. (b) Smoothed convergence.

Figure 39: Converge of value function.

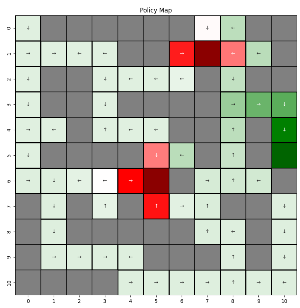
Figure 40 shows the policy maps for the gamma parameter set to 0.75. Figure 41 illustrates the value function plots for the gamma parameter set to 0.75. Figure 42 provides the convergence plots for the gamma parameter set to 0.75.



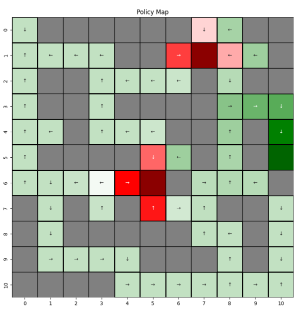
(a) Episode 1.



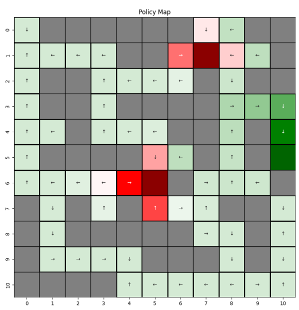
(b) Episode 50



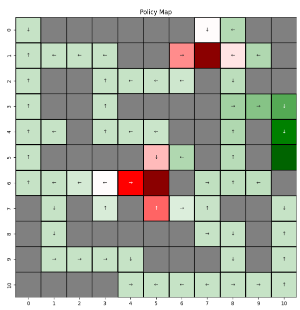
(c) Episode 100



(d) Episode 1000.

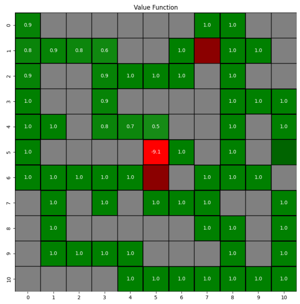


(e) Episode 5000

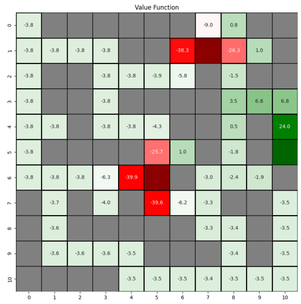


(f) Episode 10000

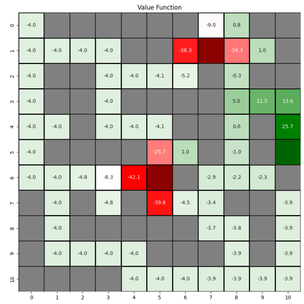
Figure 40: Evolution of policy maps throughout episodes.



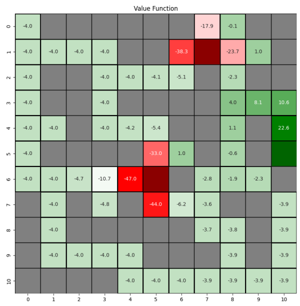
(a) Episode 1.



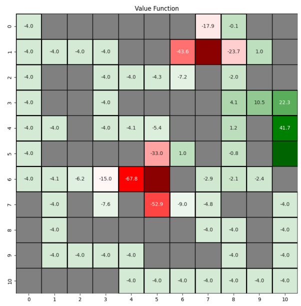
(b) Episode 50



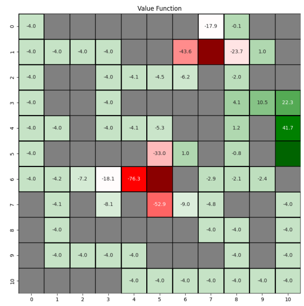
(c) Episode 100



(d) Episode 1000.

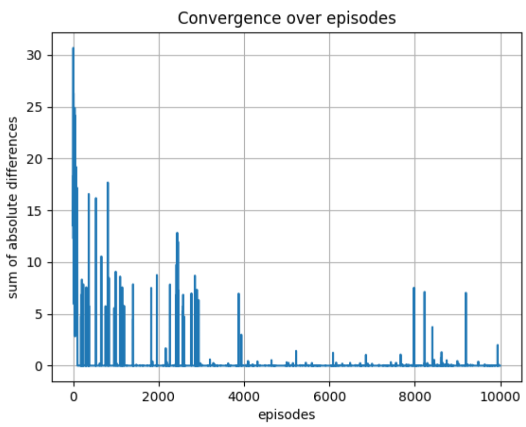


(e) Episode 5000

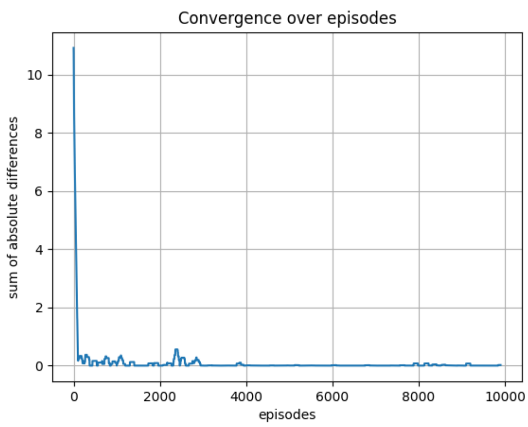


(f) Episode 10000

Figure 41: Evolution of value function throughout episodes.



(a) Converge raw.



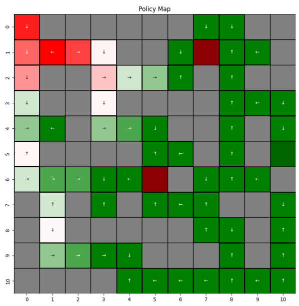
(b) Smoothed convergence.

Figure 42: Converge of value function.

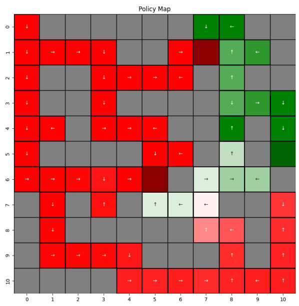
What we can interpret from the results is that the gamma parameter has a significant effect on the convergence of the value function. As we can see from the results, the gamma values up to 0.95 are not feasible choices since the agent rarely changes its policy. Also, since the agents can get stuck at exploitation we see quite long training process where having small discount factor does not help. In order to prevent too much computation time a certain limit is set for maximum number of steps. We can say that the gamma value set to default is the best choice for the gamma parameter amongst the others in temporal difference learning.

2.6 Effect of Gamma in Q-Learning

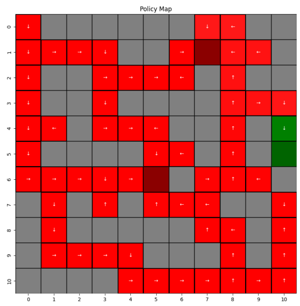
The results for the effect of gamma parameter in Q learning are provided below. The parameter set used for this experiment is as follows: $\alpha = 0.1$, $\epsilon = 0.2$, and the number of episodes is set to 10000. The gamma parameter is varied from 0.1 to 0.95. Figure 43 shows the policy maps for the gamma parameter set to 0.1. Figure 44 illustrates the value function plots for the gamma parameter set to 0.1. Figure 45 provides the convergence plots for the gamma parameter set to 0.1.



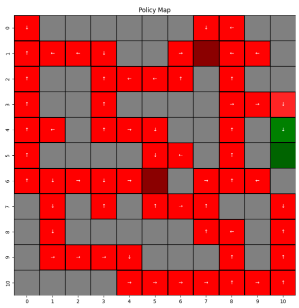
(a) Episode 1.



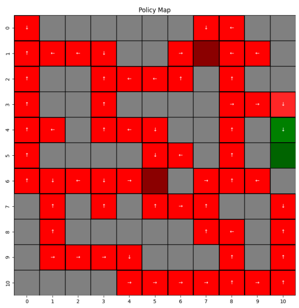
(b) Episode 50



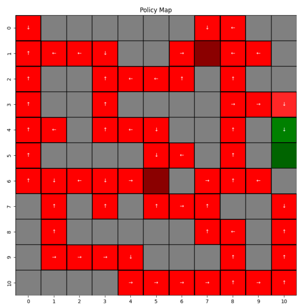
(c) Episode 100



(d) Episode 1000.

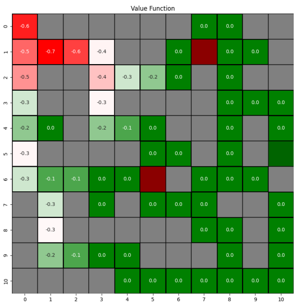


(e) Episode 5000

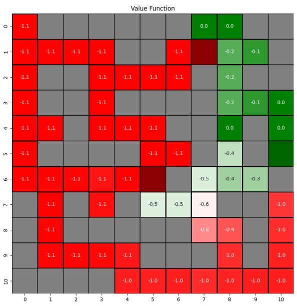


(f) Episode 10000

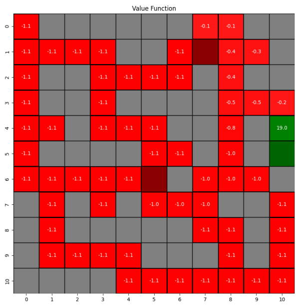
Figure 43: Evolution of policy maps throughout episodes.



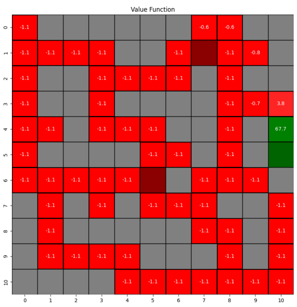
(a) Episode 1.



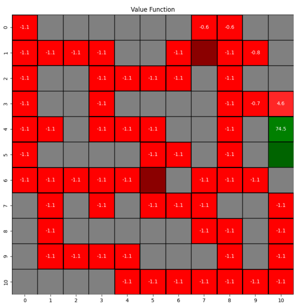
(b) Episode 50



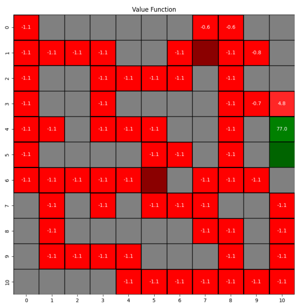
(c) Episode 100



(d) Episode 1000.

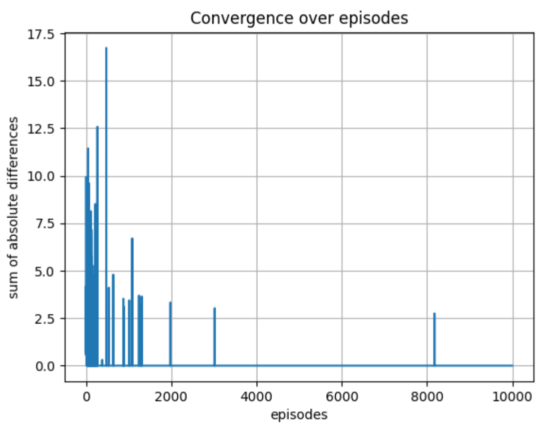


(e) Episode 5000

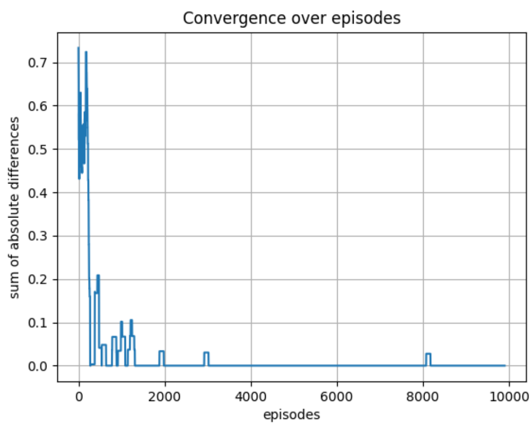


(f) Episode 10000

Figure 44: Evolution of value function throughout episodes.



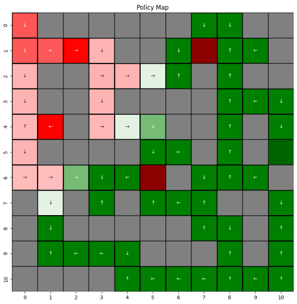
(a) Converge raw.



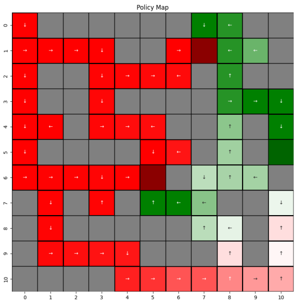
(b) Smoothed convergence.

Figure 45: Converge of value function.

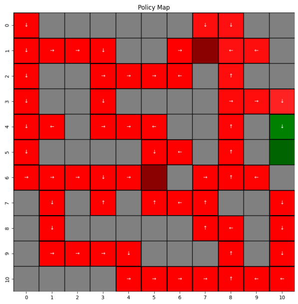
Figure 46 is provided as the policy maps for the gamma parameter set to 0.25. Figure 47 shows the value function plots for the gamma parameter set to 0.25. Figure 48 presents the convergence plots for the gamma parameter set to 0.25.



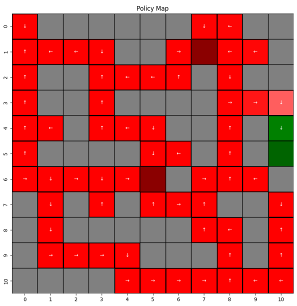
(a) Episode 1.



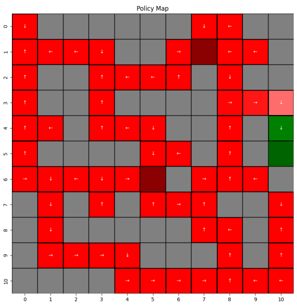
(b) Episode 50



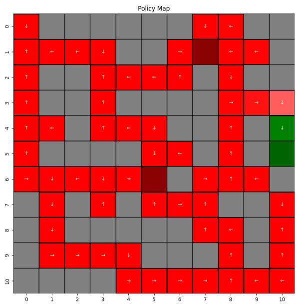
(c) Episode 100



(d) Episode 1000.

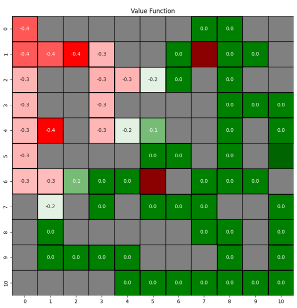


(e) Episode 5000

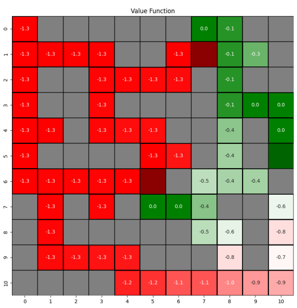


(f) Episode 10000

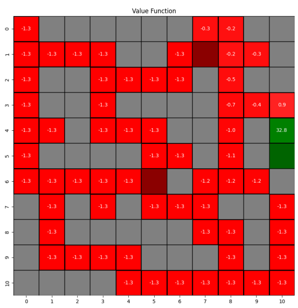
Figure 46: Evolution of policy maps throughout episodes.



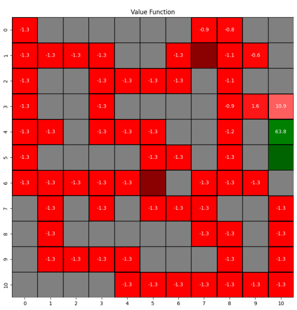
(a) Episode 1.



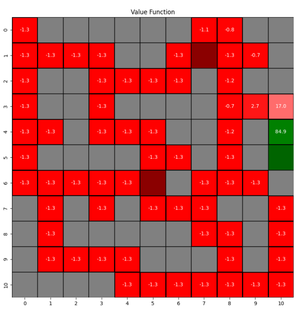
(b) Episode 50



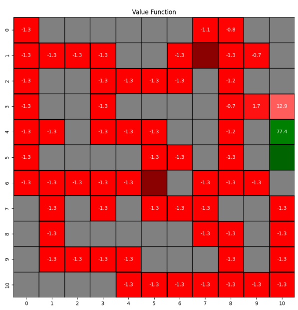
(c) Episode 100



(d) Episode 1000.

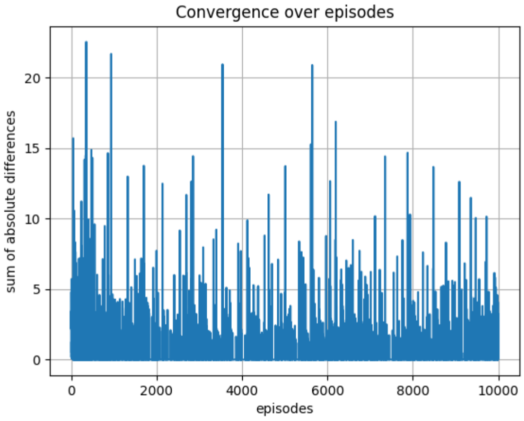


(e) Episode 5000

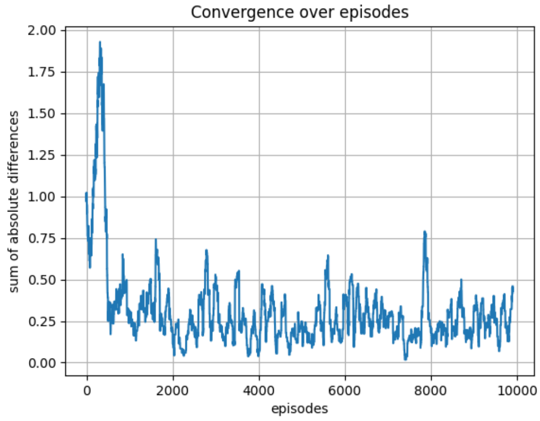


(f) Episode 10000

Figure 47: Evolution of value function throughout episodes.



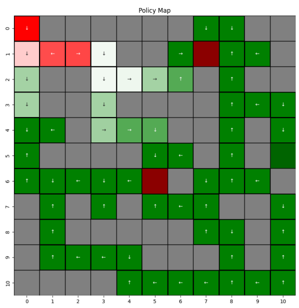
(a) Converge raw.



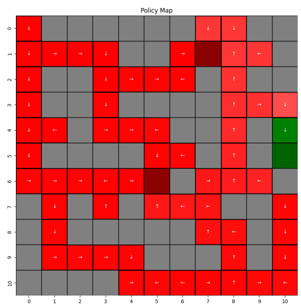
(b) Smoothed convergence.

Figure 48: Converge of value function.

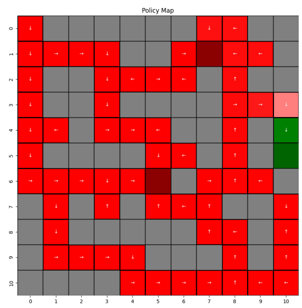
Figure 49 shows the policy maps for the gamma parameter set to 0.5. Figure 50 illustrates the value function plots for the gamma parameter set to 0.5. Figure 51 provides the convergence plots for the gamma parameter set to 0.5.



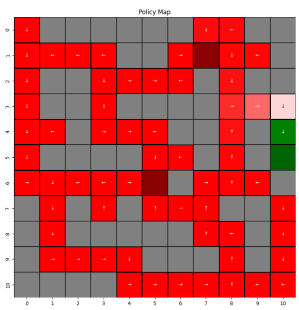
(a) Episode 1.



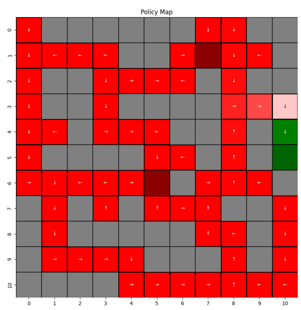
(b) Episode 50



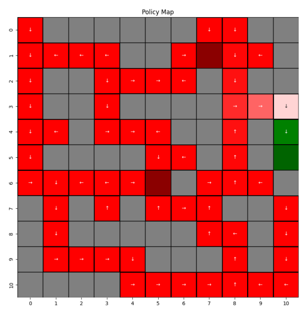
(c) Episode 100



(d) Episode 1000.

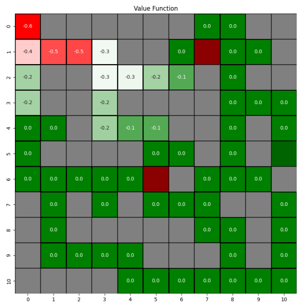


(e) Episode 5000

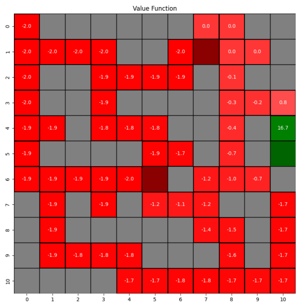


(f) Episode 10000

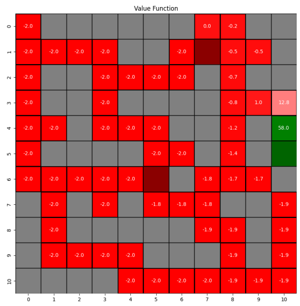
Figure 49: Evolution of policy maps throughout episodes.



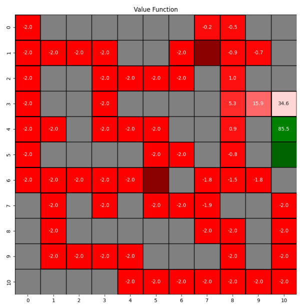
(a) Episode 1.



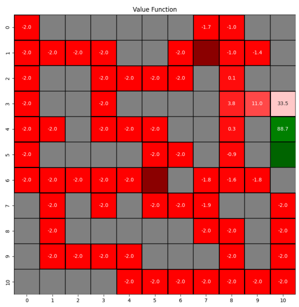
(b) Episode 50



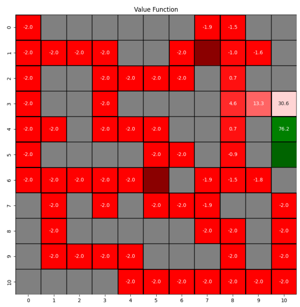
(c) Episode 100



(d) Episode 1000.

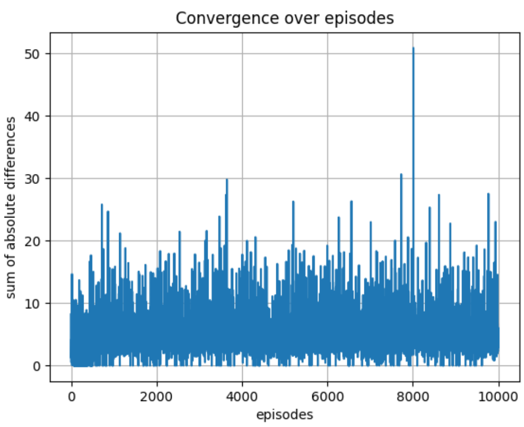


(e) Episode 5000

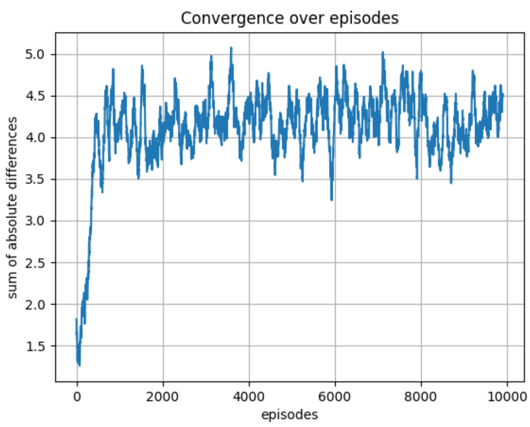


(f) Episode 10000

Figure 50: Evolution of value function throughout episodes.



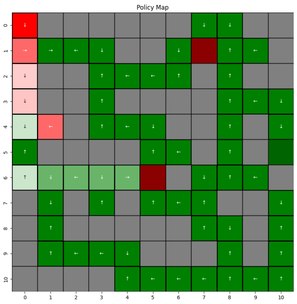
(a) Converge raw.



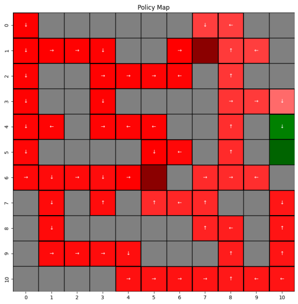
(b) Smoothed convergence.

Figure 51: Converge of value function.

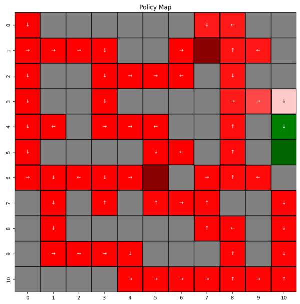
Figure 52 shows the policy maps for the gamma parameter set to 0.75. Figure 53 illustrates the value function plots for the gamma parameter set to 0.75. Figure 54 provides the convergence plots for the gamma parameter set to 0.75.



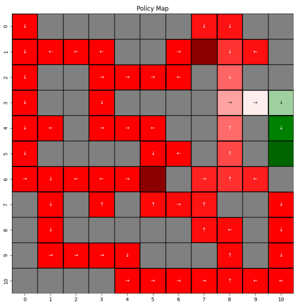
(a) Episode 1.



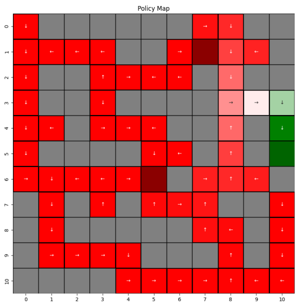
(b) Episode 50



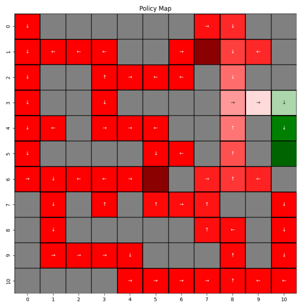
(c) Episode 100



(d) Episode 1000.

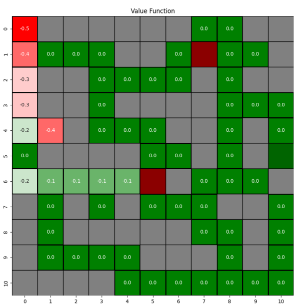


(e) Episode 5000

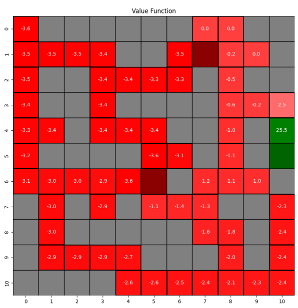


(f) Episode 10000

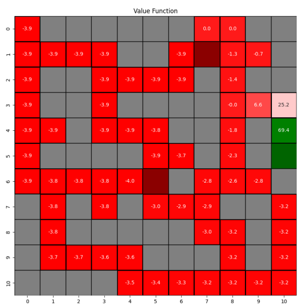
Figure 52: Evolution of policy maps throughout episodes.



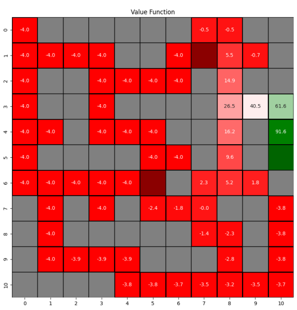
(a) Episode 1.



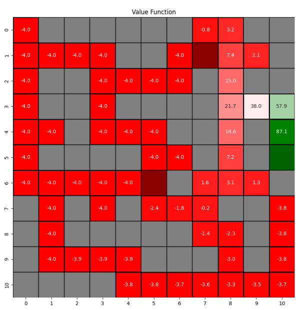
(b) Episode 50



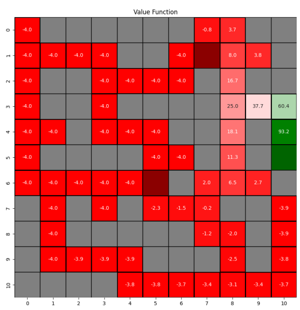
(c) Episode 100



(d) Episode 1000.

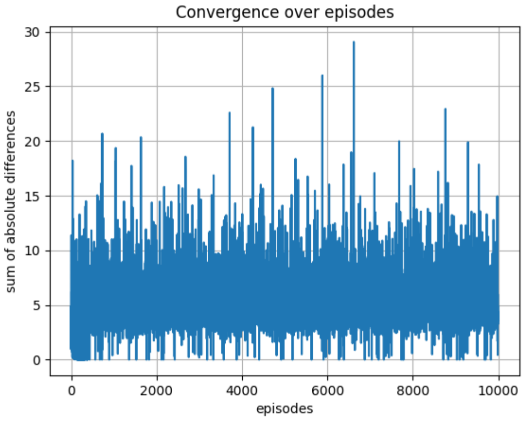


(e) Episode 5000

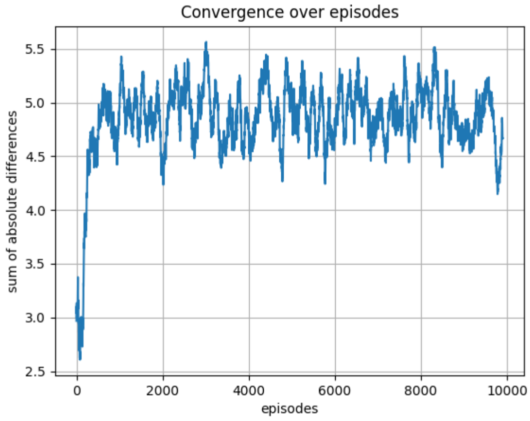


(f) Episode 10000

Figure 53: Evolution of value function throughout episodes.



(a) Converge raw.



(b) Smoothed convergence.

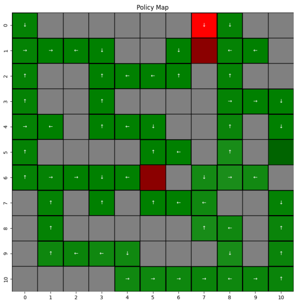
Figure 54: Converge of value function.

Contrary to temporal difference learning, we can say that smaller gamma values can yield to optimal policy for Q learning. From the results, we can see that the gamma value set to above 0.5 can be choosen, otherwise the agent can get stuck at exploitation.

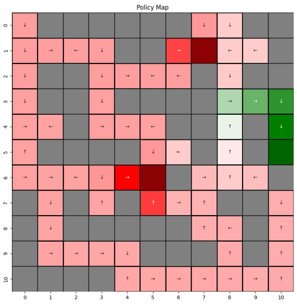
2.7 Effect of Epsilon in Temporal Difference Learning

Here the sweep of epsilon resuls are presented. The parameters used for these experiments are as follows: $\alpha = 0.1$, $\gamma = 0.95$, and the number of episodes is set to 10000. The epsilon parameter is varied from 0.0 to 1.0.

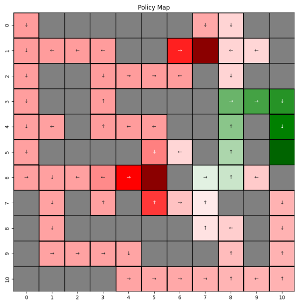
Figure 55 shows the policy maps for the epsilon parameter set to 0.0. Figure 56 illustrates the value function plots for the epsilon parameter set to 0.0. Figure 57 provides the convergence plots for the epsilon parameter set to 0.0.



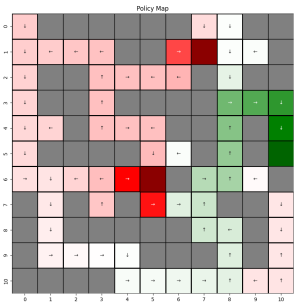
(a) Episode 1.



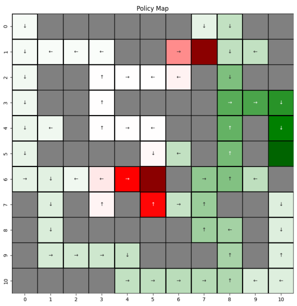
(b) Episode 50



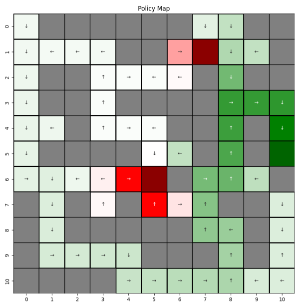
(c) Episode 100



(d) Episode 1000.

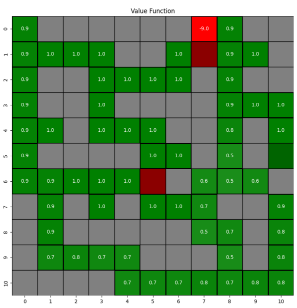


(e) Episode 5000

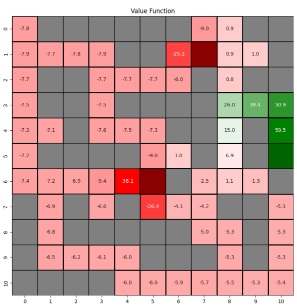


(f) Episode 10000

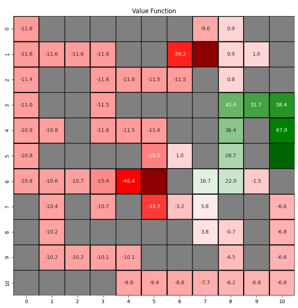
Figure 55: Evolution of policy maps throughout episodes.



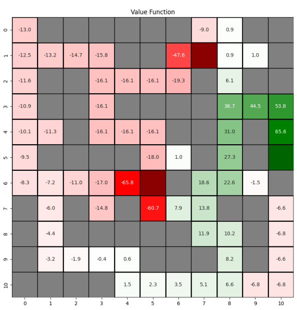
(a) Episode 1.



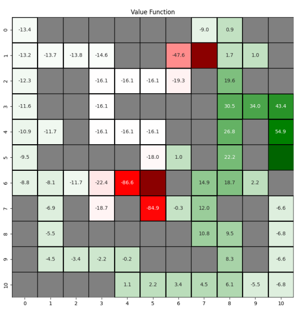
(b) Episode 50



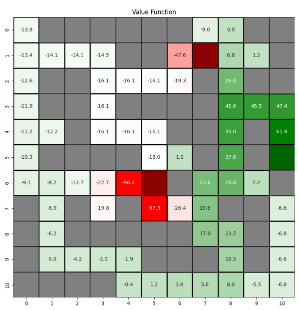
(c) Episode 100



(d) Episode 1000.

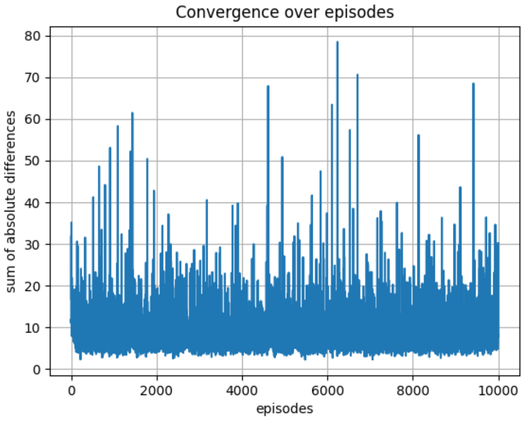


(e) Episode 5000

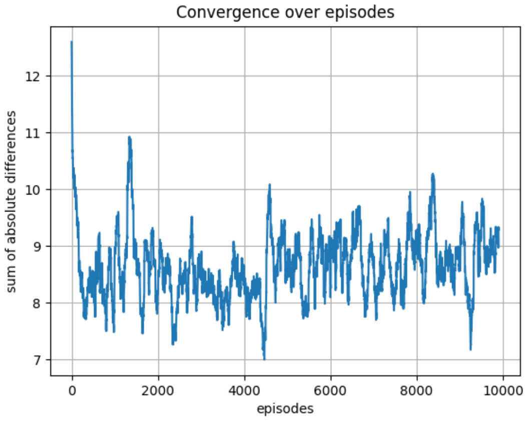


(f) Episode 10000

Figure 56: Evolution of value function throughout episodes.



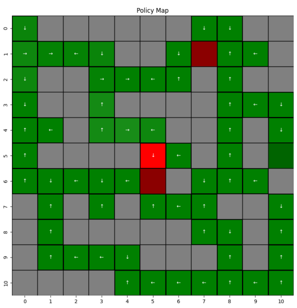
(a) Converge raw.



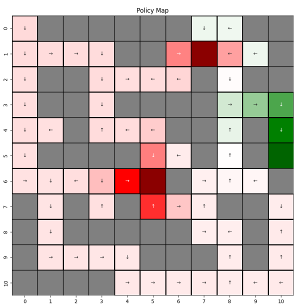
(b) Smoothed convergence.

Figure 57: Converge of value function.

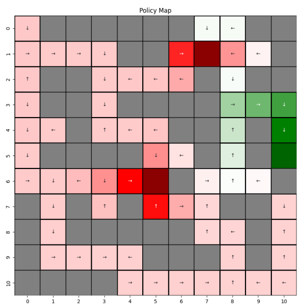
Figure 58 shows the policy maps for the epsilon parameter set to 0.5. Figure 59 illustrates the value function plots for the epsilon parameter set to 0.5. Figure 60 provides the convergence plots for the epsilon parameter set to 0.5.



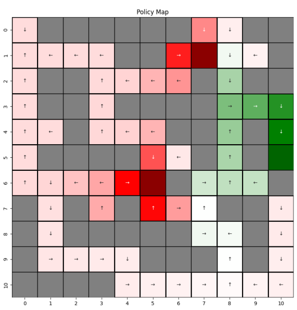
(a) Episode 1.



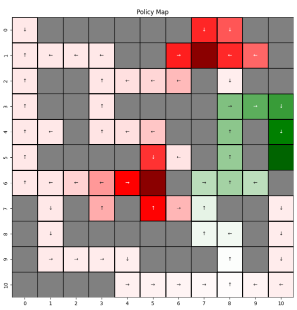
(b) Episode 50



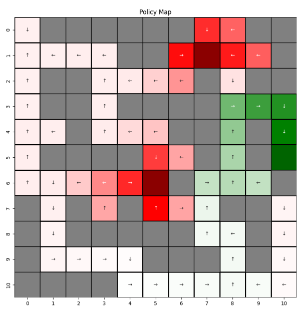
(c) Episode 100



(d) Episode 1000.

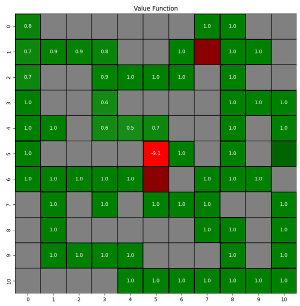


(e) Episode 5000

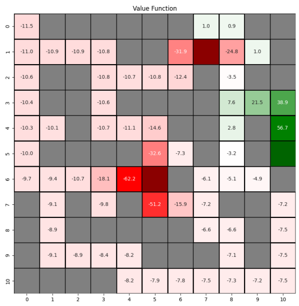


(f) Episode 10000

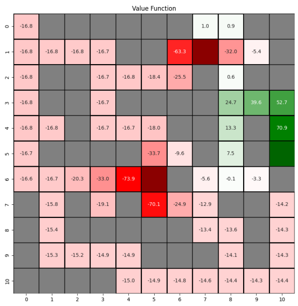
Figure 58: Evolution of policy maps throughout episodes.



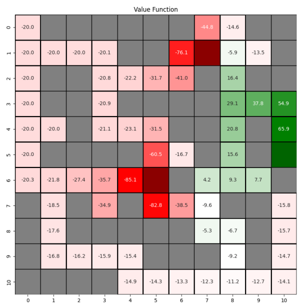
(a) Episode 1.



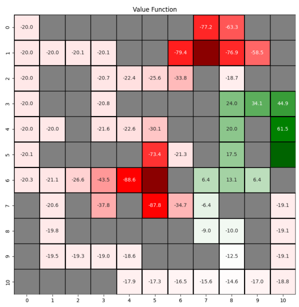
(b) Episode 50



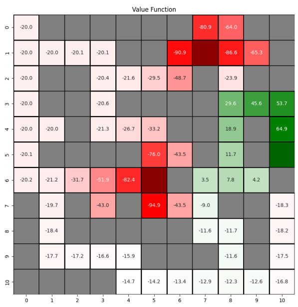
(c) Episode 100



(d) Episode 1000.

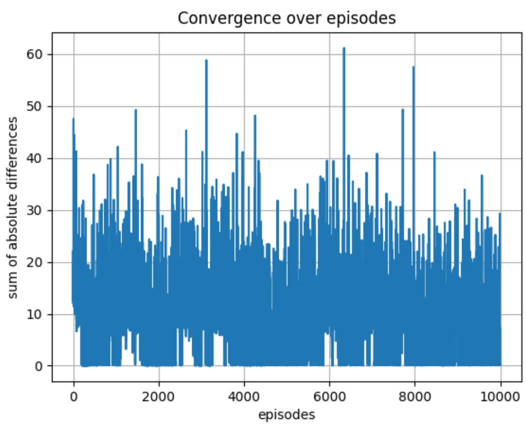


(e) Episode 5000

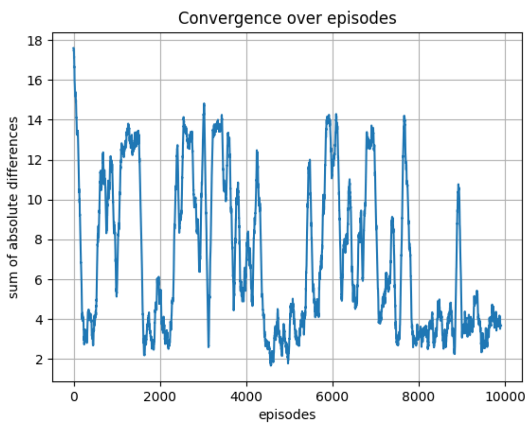


(f) Episode 10000

Figure 59: Evolution of value function throughout episodes.



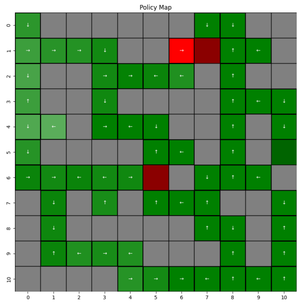
(a) Converge raw.



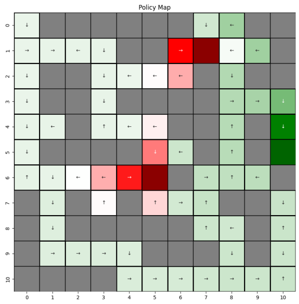
(b) Smoothed convergence.

Figure 60: Converge of value function.

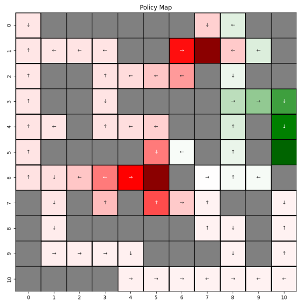
Figure 61 shows the policy maps for the epsilon parameter set to 0.8. Figure 62 illustrates the value function plots for the epsilon parameter set to 0.8. Figure 63 provides the convergence plots for the epsilon parameter set to 0.8.



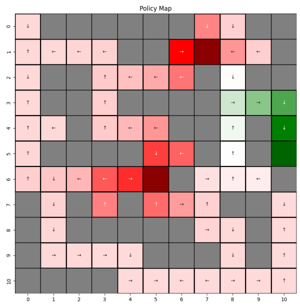
(a) Episode 1.



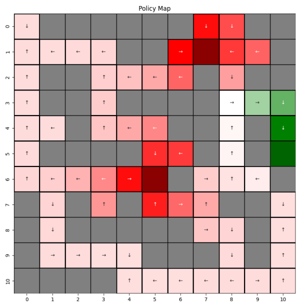
(b) Episode 50



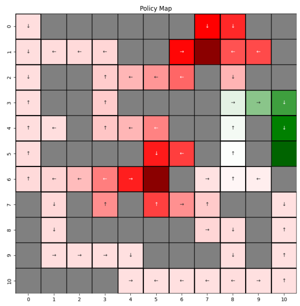
(c) Episode 100



(d) Episode 1000.

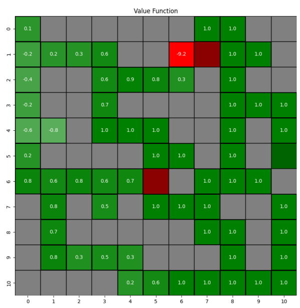


(e) Episode 5000

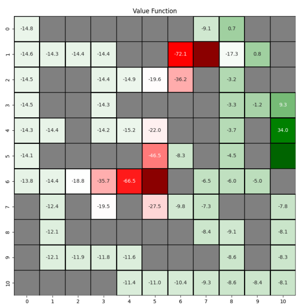


(f) Episode 10000

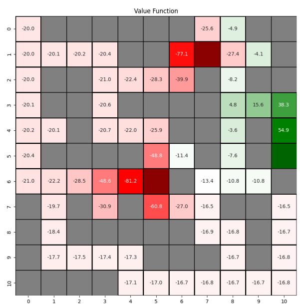
Figure 61: Evolution of policy maps throughout episodes.



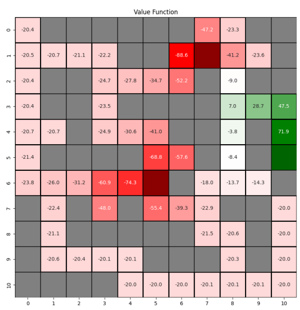
(a) Episode 1.



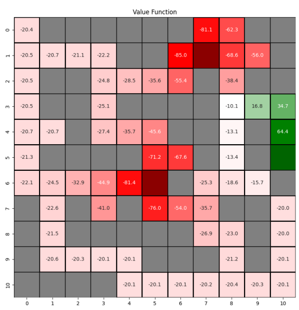
(b) Episode 50



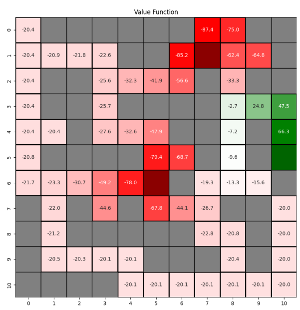
(c) Episode 100



(d) Episode 1000.

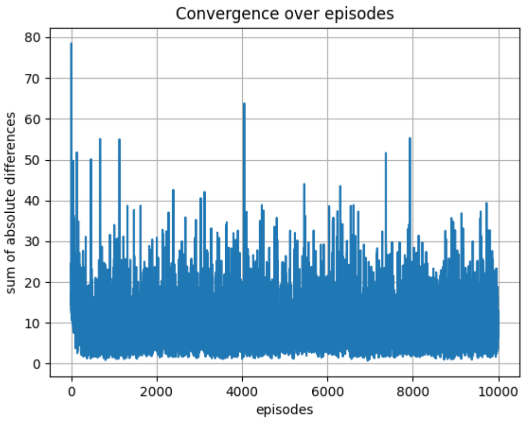


(e) Episode 5000

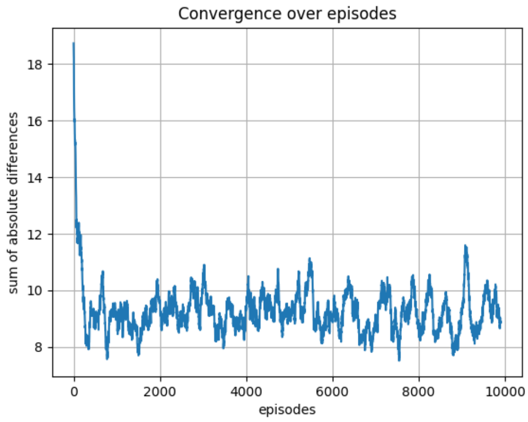


(f) Episode 10000

Figure 62: Evolution of value function throughout episodes.



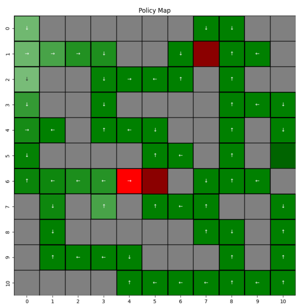
(a) Converge raw.



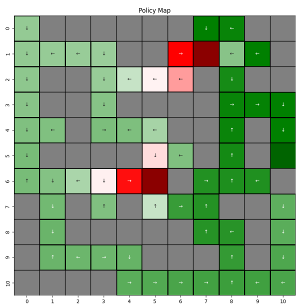
(b) Smoothed convergence.

Figure 63: Converge of value function.

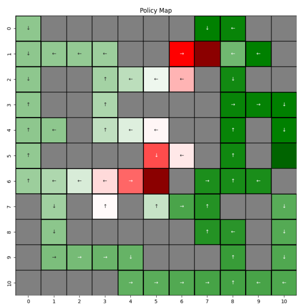
Figure 64 shows the policy maps for the epsilon parameter set to 1.0. Figure 65 illustrates the value function plots for the epsilon parameter set to 1.0. Figure 66 provides the convergence plots for the epsilon parameter set to 1.0.



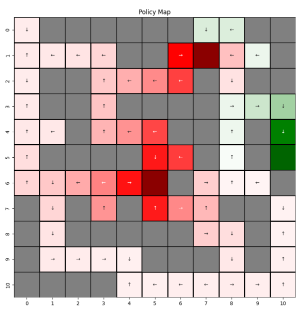
(a) Episode 1.



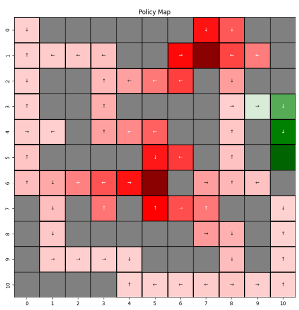
(b) Episode 50



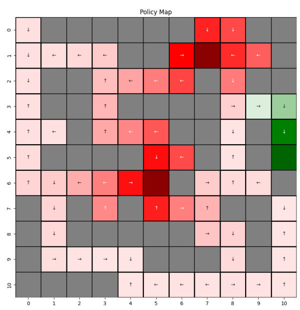
(c) Episode 100



(d) Episode 1000.

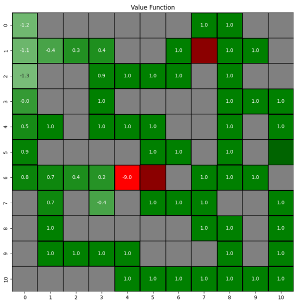


(e) Episode 5000

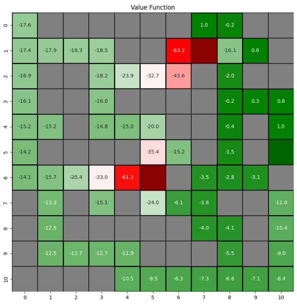


(f) Episode 10000

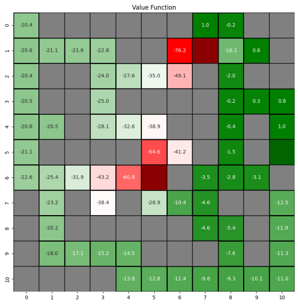
Figure 64: Evolution of policy maps throughout episodes.



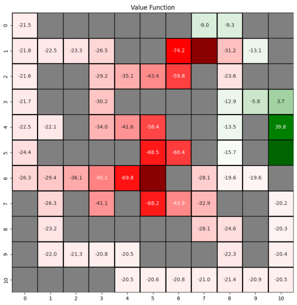
(a) Episode 1.



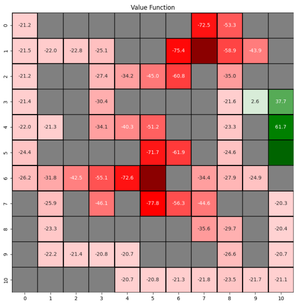
(b) Episode 50



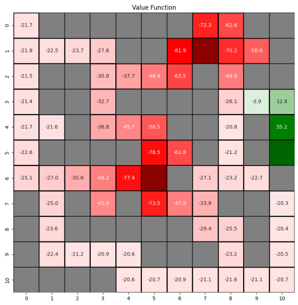
(c) Episode 100



(d) Episode 1000.

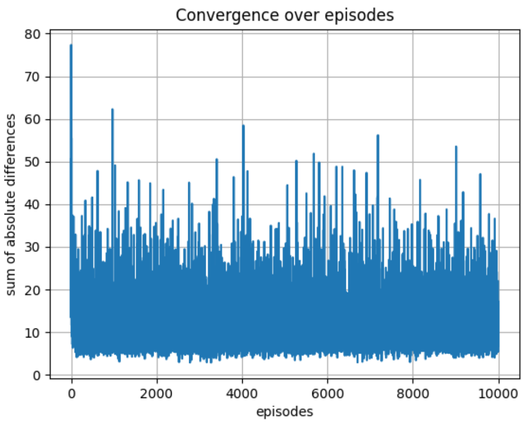


(e) Episode 5000

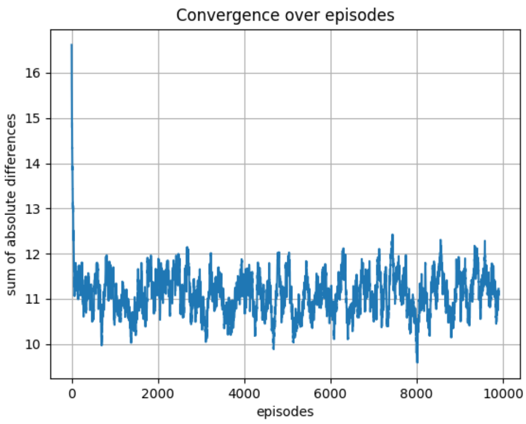


(f) Episode 10000

Figure 65: Evolution of value function throughout episodes.



(a) Converge raw.



(b) Smoothed convergence.

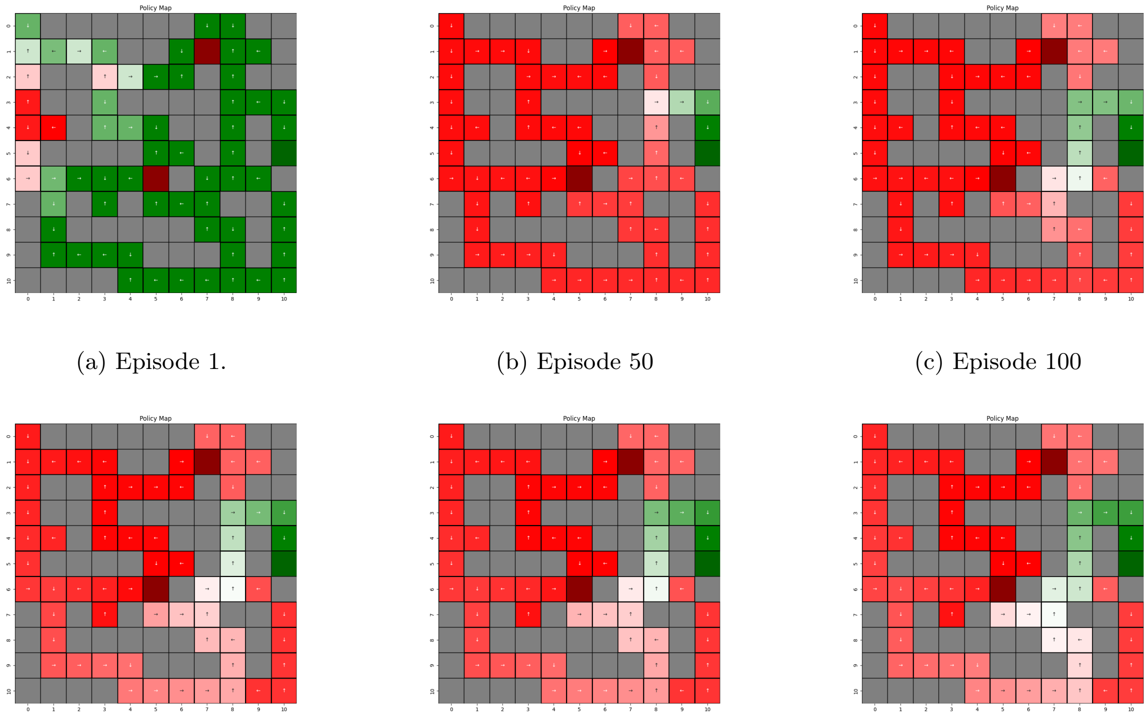
Figure 66: Converge of value function.

What we have observed from the results is that the epsilon parameter is another crucial one for the convergence of the value function. The epsilon parameter set to 0.0 can lead to the optimal policy than the other epsilon values. Even though the epsilon greater that the 0.2 can lead to a converged value function, the optimal policy can not be achieved since exploration-exploitation balance is exceedingly towards exploration.

2.8 Effect of Epsilon in Q-Learning

Using same set of parameters, we have conducted the experiments for Q learning. The epsilon parameter is varied from 0.0 to 1.0.

Figure 67 shows the policy maps for the epsilon parameter set to 0.0. Figure 68 illustrates the value function plots for the epsilon parameter set to 0.0. Figure 69 provides the convergence plots for the epsilon parameter set to 0.0.



(a) Episode 1.

(b) Episode 50

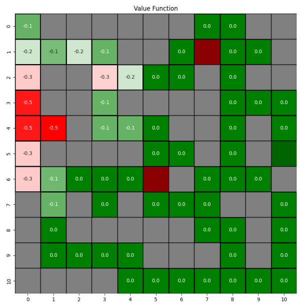
(c) Episode 100

(d) Episode 1000.

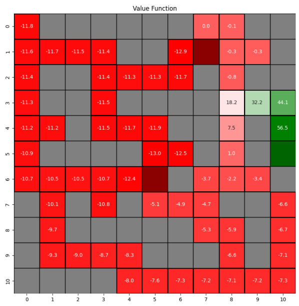
(e) Episode 5000

(f) Episode 10000

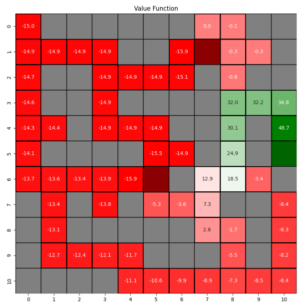
Figure 67: Evolution of policy maps throughout episodes.



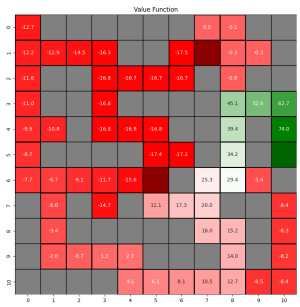
(a) Episode 1.



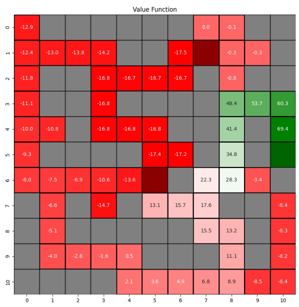
(b) Episode 50



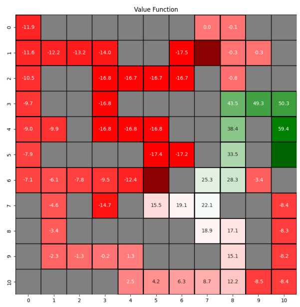
(c) Episode 100



(d) Episode 1000.

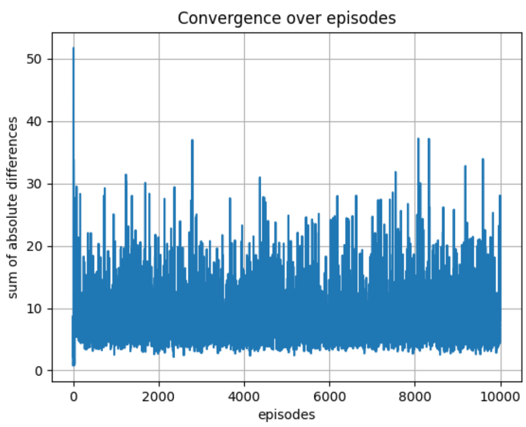


(e) Episode 5000

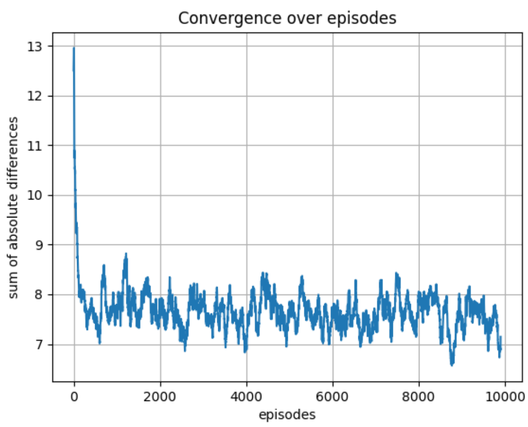


(f) Episode 10000

Figure 68: Evolution of value function throughout episodes.



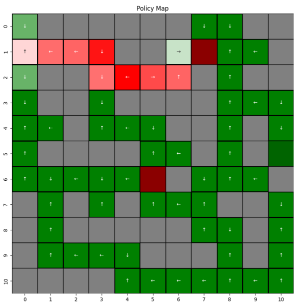
(a) Converge raw.



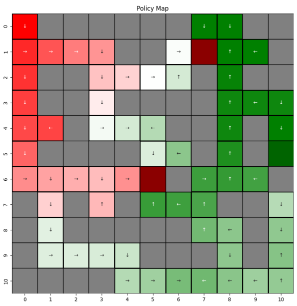
(b) Smoothed convergence.

Figure 69: Converge of value function.

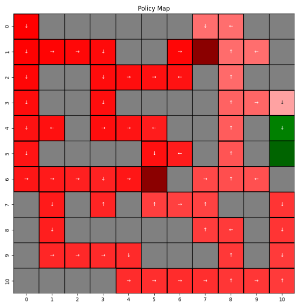
Figure 70 shows the policy maps for the epsilon parameter set to 0.5. Figure 71 illustrates the value function plots for the epsilon parameter set to 0.5. Figure 72 provides the convergence plots for the epsilon parameter set to 0.5.



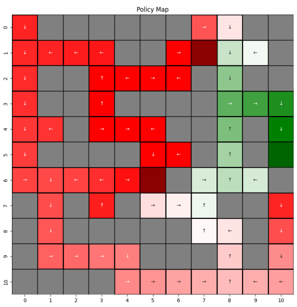
(a) Episode 1.



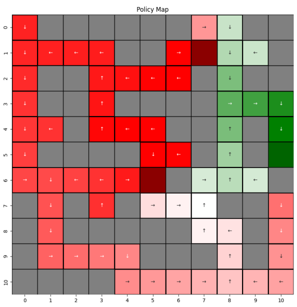
(b) Episode 50



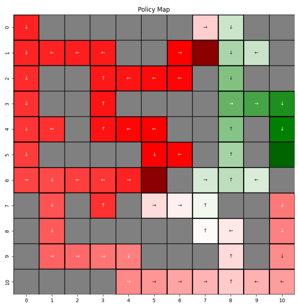
(c) Episode 100



(d) Episode 1000.

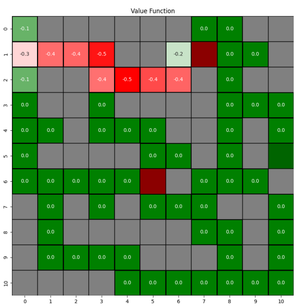


(e) Episode 5000

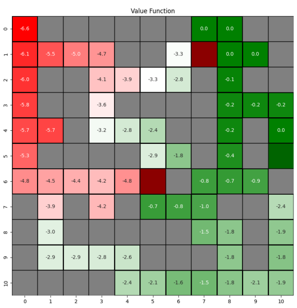


(f) Episode 10000

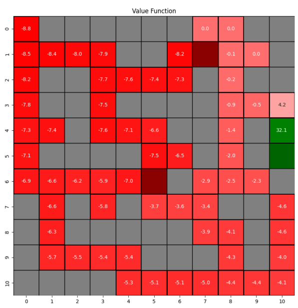
Figure 70: Evolution of policy maps throughout episodes.



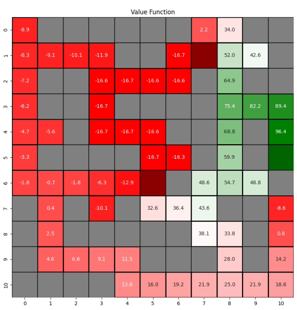
(a) Episode 1.



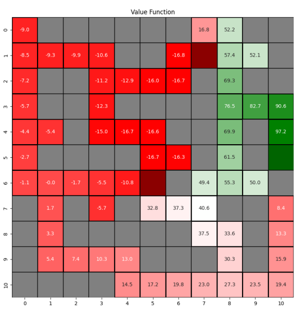
(b) Episode 50



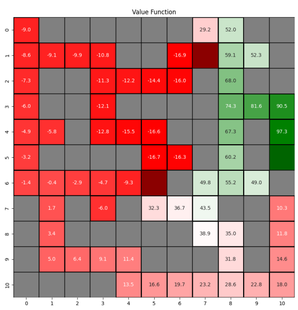
(c) Episode 100



(d) Episode 1000.

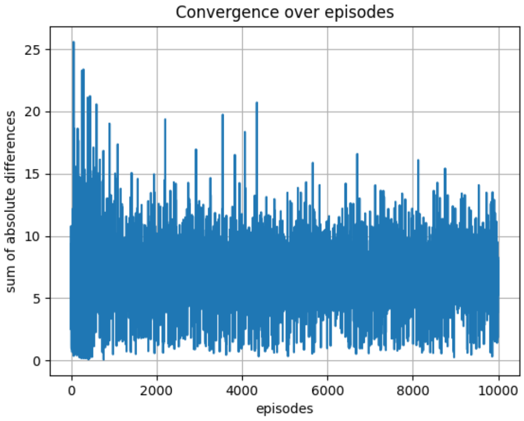


(e) Episode 5000

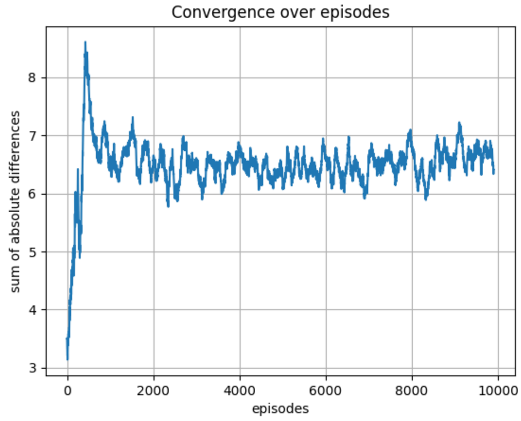


(f) Episode 10000

Figure 71: Evolution of value function throughout episodes.



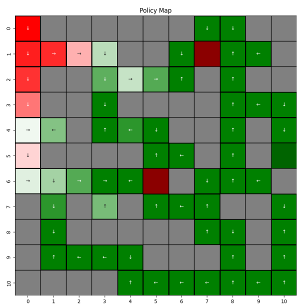
(a) Converge raw.



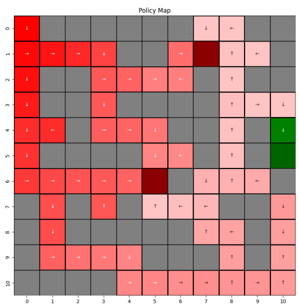
(b) Smoothed convergence.

Figure 72: Converge of value function.

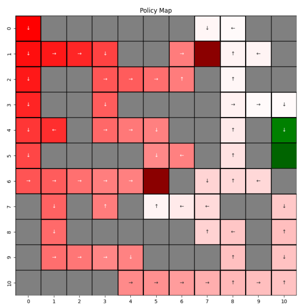
Figure 73 shows the policy maps for the epsilon parameter set to 0.8. Figure 74 illustrates the value function plots for the epsilon parameter set to 0.8. Figure 75 provides the convergence plots for the epsilon parameter set to 0.8.



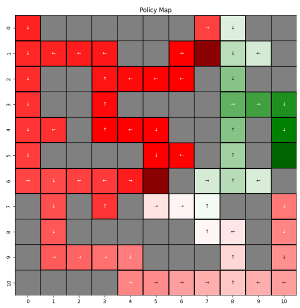
(a) Episode 1.



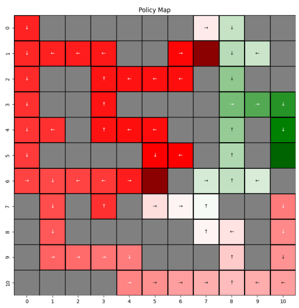
(b) Episode 50



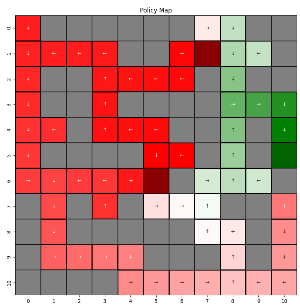
(c) Episode 100



(d) Episode 1000.

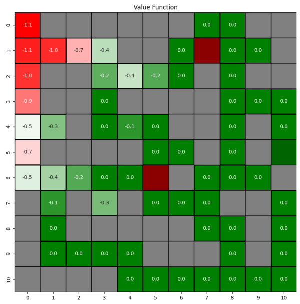


(e) Episode 5000

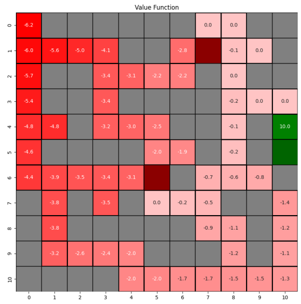


(f) Episode 10000

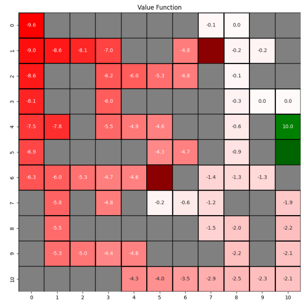
Figure 73: Evolution of policy maps throughout episodes.



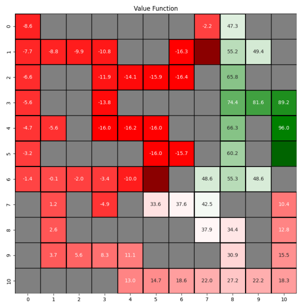
(a) Episode 1.



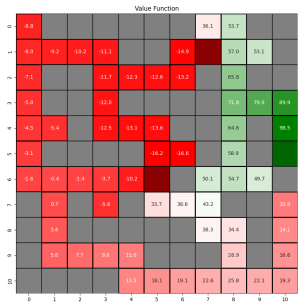
(b) Episode 50



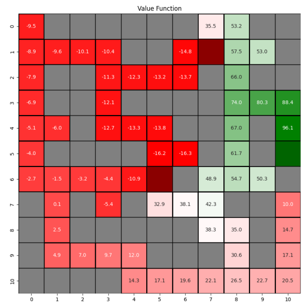
(c) Episode 100



(d) Episode 1000.

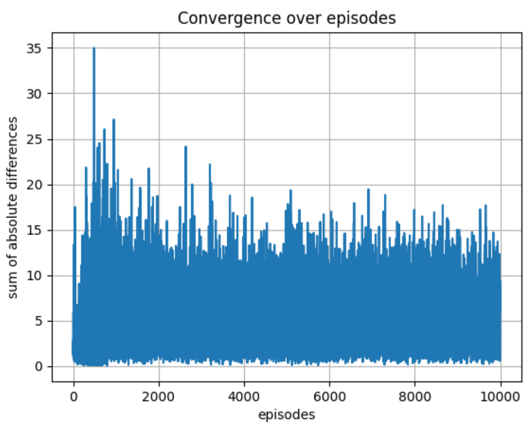


(e) Episode 5000

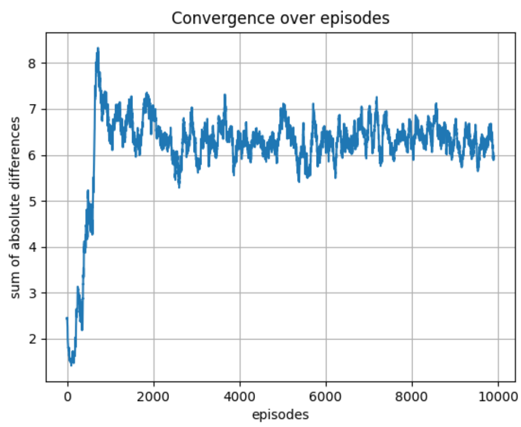


(f) Episode 10000

Figure 74: Evolution of value function throughout episodes.



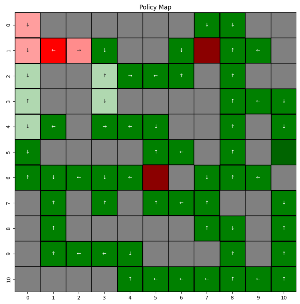
(a) Converge raw.



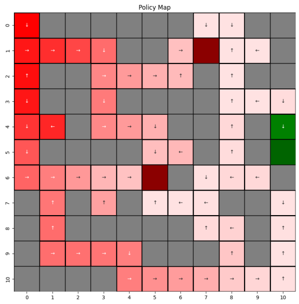
(b) Smoothed convergence.

Figure 75: Converge of value function.

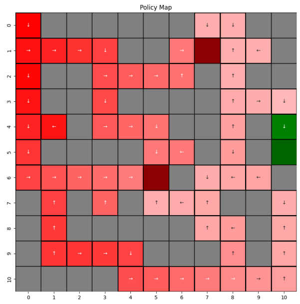
Figure 76 shows the policy maps for the epsilon parameter set to 1.0. Figure 77 illustrates the value function plots for the epsilon parameter set to 1.0. Figure 78 provides the convergence plots for the epsilon parameter set to 1.0.



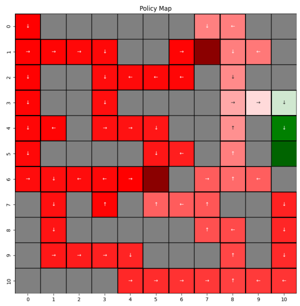
(a) Episode 1.



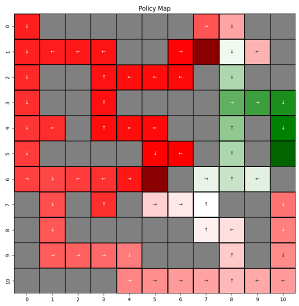
(b) Episode 50



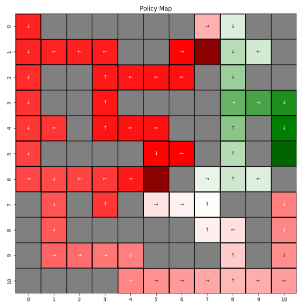
(c) Episode 100



(d) Episode 1000.

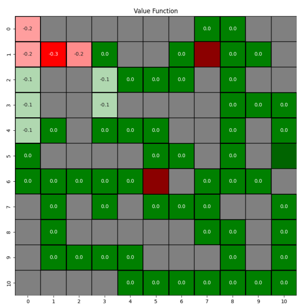


(e) Episode 5000

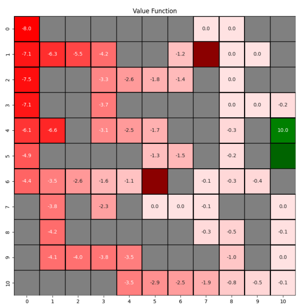


(f) Episode 10000

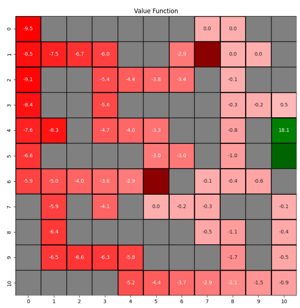
Figure 76: Evolution of policy maps throughout episodes.



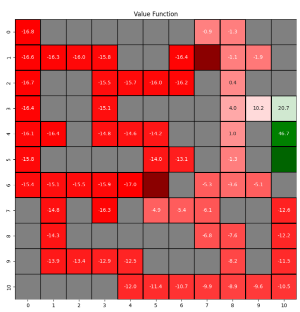
(a) Episode 1.



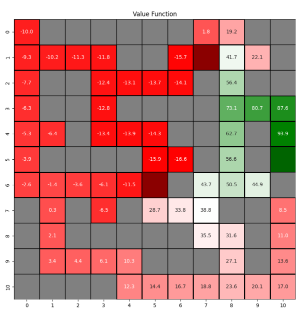
(b) Episode 50



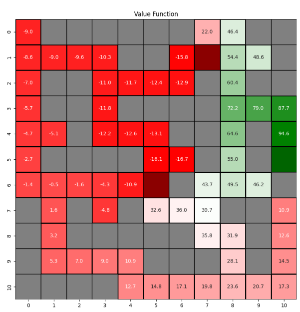
(c) Episode 100



(d) Episode 1000.

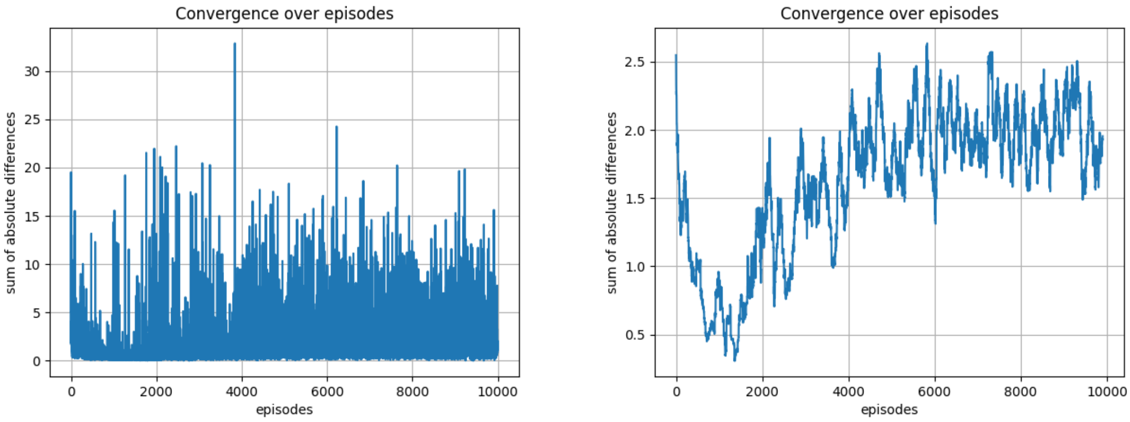


(e) Episode 5000



(f) Episode 10000

Figure 77: Evolution of value function throughout episodes.



(a) Converge raw. (b) Smoothed convergence.

Figure 78: Converge of value function.

What we observed from the Q-learning experiments that all of them have converged to the optimal policy. The epsilon parameter does not have a significant effect on the eventual convergence of the value function, where the epsilon parameter associated with the exploration side of the exploration-exploitation trade-off.

3 Discussions

3.1 Q1

The rationale behind transition probabilities and reward function can be explained as follows. The transition probabilities are the probabilities of transitioning from one state to another state given an action. The stochastic setting is used in this experiment where the choosen action may not be the action that the agent will take. This allow the agent to explore the environment and learn the optimal policy. The reward function is the function that provides the reward for the agent when it takes an action in a state. So the reward function is the feedback mechanism for the agent to learn the optimal policy.

3.2 Q2

By looking at the value maps in default settings we can describe the evolution of the vale function as follows. The value function is initialized with zeros. The value function is updated by the Bellman equation. The value function is updated by the sum of the reward and the discounted value of the next state. The value function is updated iteratively until the convergence. Here, at first iterations exploration is more dominant since most of the values are zeros. At first trials the agent hits traps and episodes proceed. Then, the agent starts o explore the regions close to the goal. When the agent hits the goal states, the values of the nearby states starts to increase and ,roughly speaking, positive reinforcement starts to propagate as the optimal path gets higher and higher values from goal to start state epiosde by episode.

3.3 Q3

Utility value function converged for TD(0) learning in cases convergence said to available. Approximately, first 1000 episodes were the time the values are more or less converged.

3.4 Q4

As explained, the TD(0) learning is sensitive to learning rate (alpha) and discount factor (gamma) parameters. As the learning rate increases, the value function converges faster. However, if the learning rate is too high, the value function may not converge. The discount factor is another crucial parameter for the convergence of the value function. The discount factor is the factor that determines the importance of the future rewards. If the discount factor is too high, the value function may not converge. If the discount factor is too low, the value function may converge to the suboptimal policy.

3.5 Q5

There were two points that I encountered while implementing TD(0) learning. First, the borders of the map needed to be handled properly like the invalid states. I set additional layer of invalid states, making the map (12, 12) which makes the map borders shared (like torus shaped periodicty). This allowed us to have equally generic algorithm every state. Second, utility values invalid states were intially set to same value as others. This caused the agent to stuck in the invalid states while exploiation is dominant. I set the utility values of invalid states to quite negative value so this way the policy maps are also not detoriated.

3.6 Q6

We can see from the experiments that the Q-learning stabilizes much faster than temporal difference learning algorithm. The reason is that the Q-learning algorithm is an off-policy algorithm, which means that the Q-learning algorithm learns the optimal policy while following another policy. The TD (0) only evaluaes one possible action where the Q-learning evaluates all possible actions.

3.7 Q7

The epsilon parameter (exploration rate) allow us to set a balance between exploration and exploitation. If the epsilon parameter is set to 0.0, the agent will always exploit the environment. If the epsilon parameter is set to 1.0, the agent will always explore the environment. Here, we see also from the experiments that if we select the exploration rate too high, the agent will not be able to learn the optimal policy. However it is important to note that the epsilon parameter is ineffective for the Q-learning algorithm. The reason is that the Q-learning algorithm is an off-policy algorithm, which means that the Q-learning algorithm learns the optimal policy while following another policy. The TD (0) only evaluaes one possible action where the Q-learning evaluates all possible actions.

3.8 Q8

3.9 Q9

3.10 Q10

Appendix

The code set used throughout this homework is provided as follows.

Submitted by Ahmet Akman 2442366 on May 25, 2024.