

Problem 1

Q-Learning:

Set $P=0.02$, $\gamma=0.95$, $\alpha=0.3$, $\epsilon=0.1$ implementing 10 times independent Q-Learning, 10 path from start to goal has been obtained. The plot of optimal policy, optimal path and average accumulated reward with respect to episode is as follow:

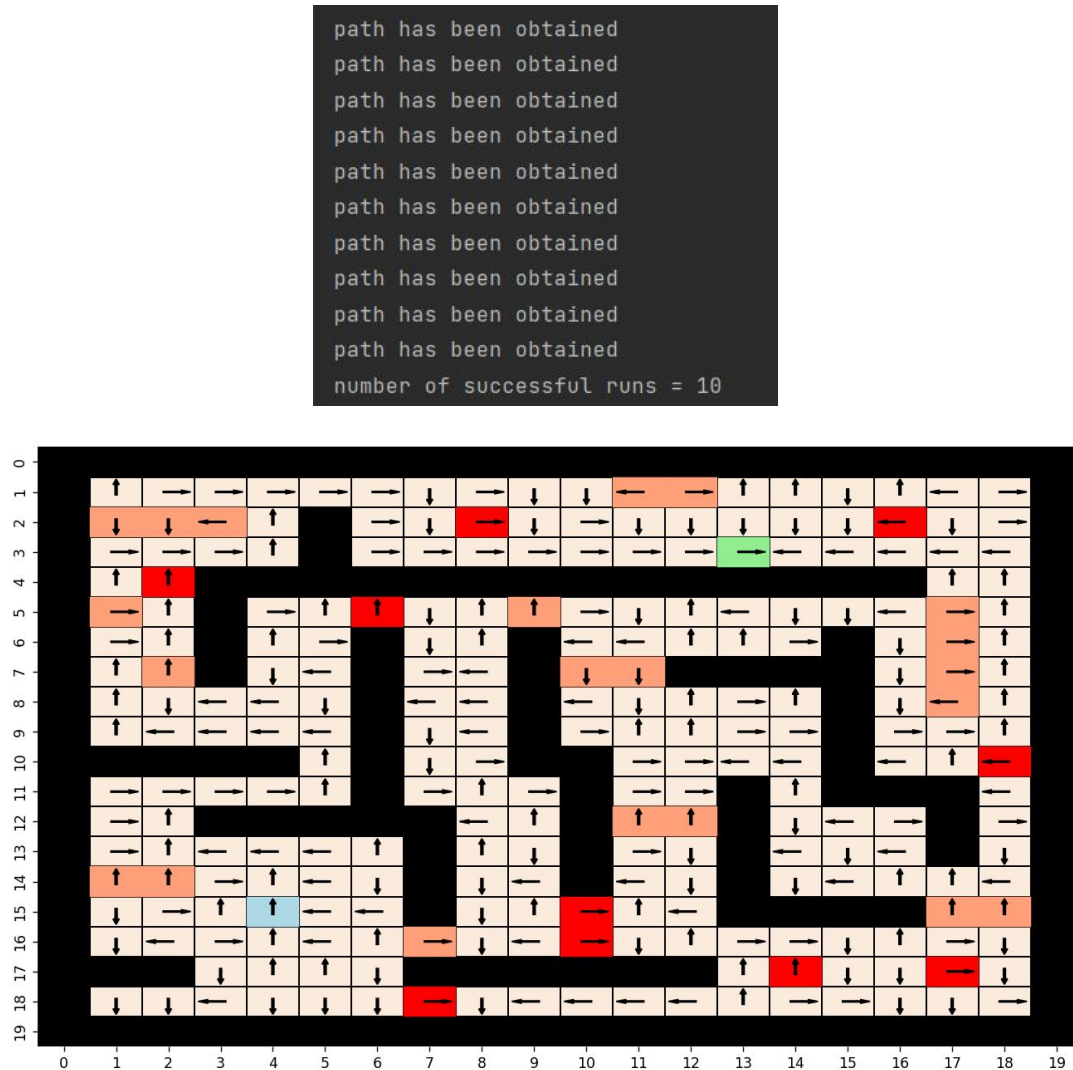


Figure 1.1 The optimal policy obtained by Q-Learning

SARSA:

Set $P=0.02$, $\gamma=0.95$, $\alpha=0.3$, $\epsilon=0.1$ implementing 10 times independent SARSA, 7 path from start to goal has been obtained. The plot of optimal policy, optimal path and average accumulated reward with respect to episode is as follow:

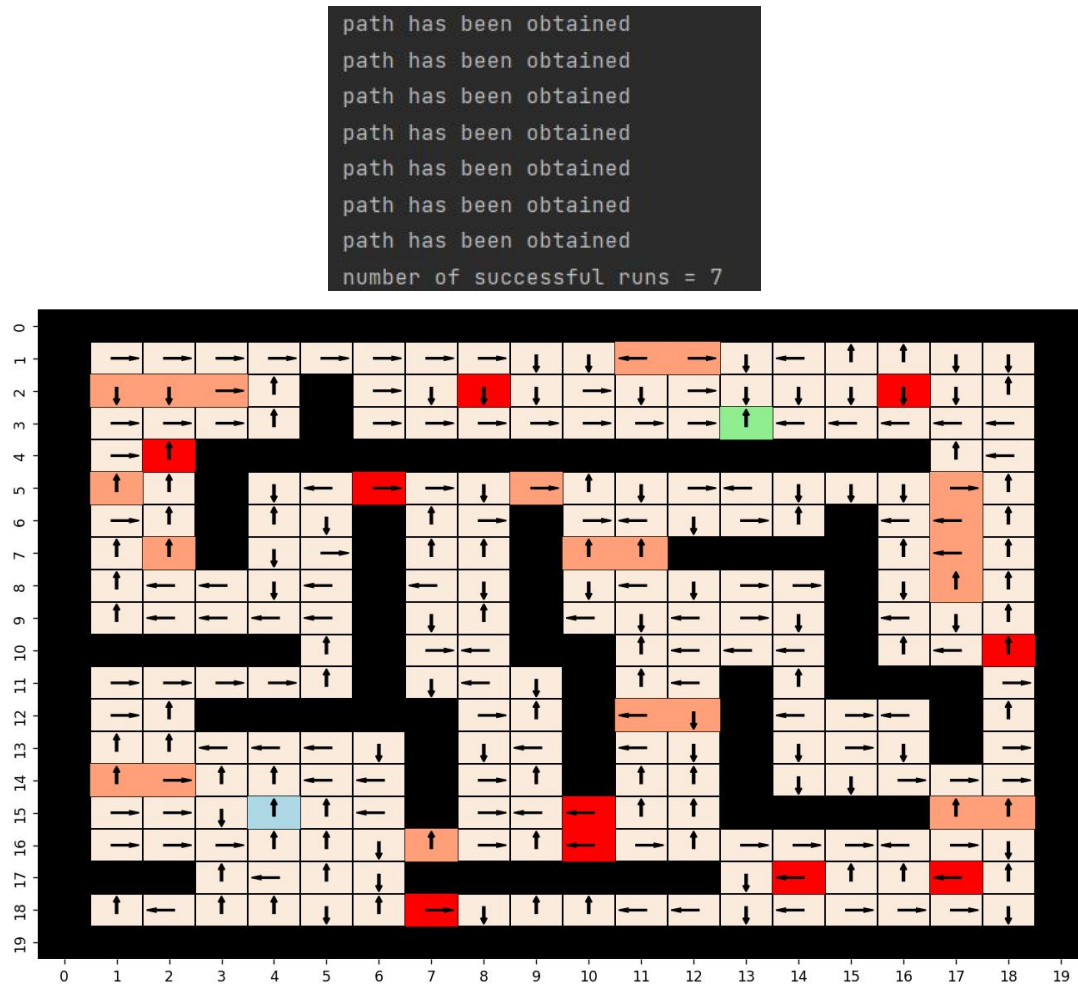


Figure 1.4 The optimal policy obtained SARSA

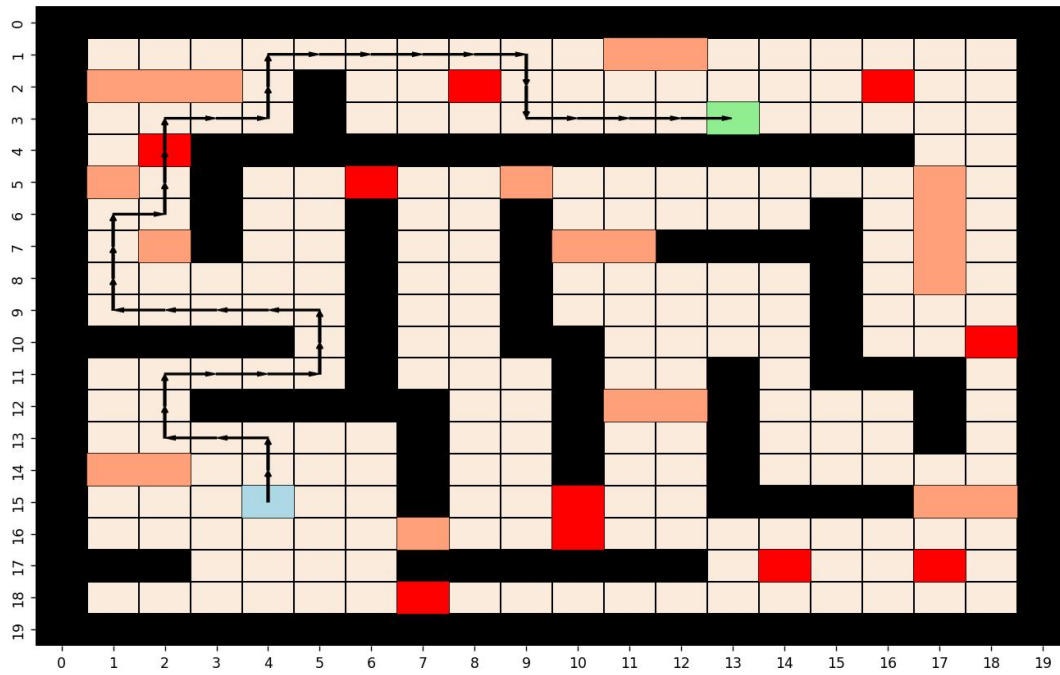


Figure 1.5 The optimal path obtained by SARSA

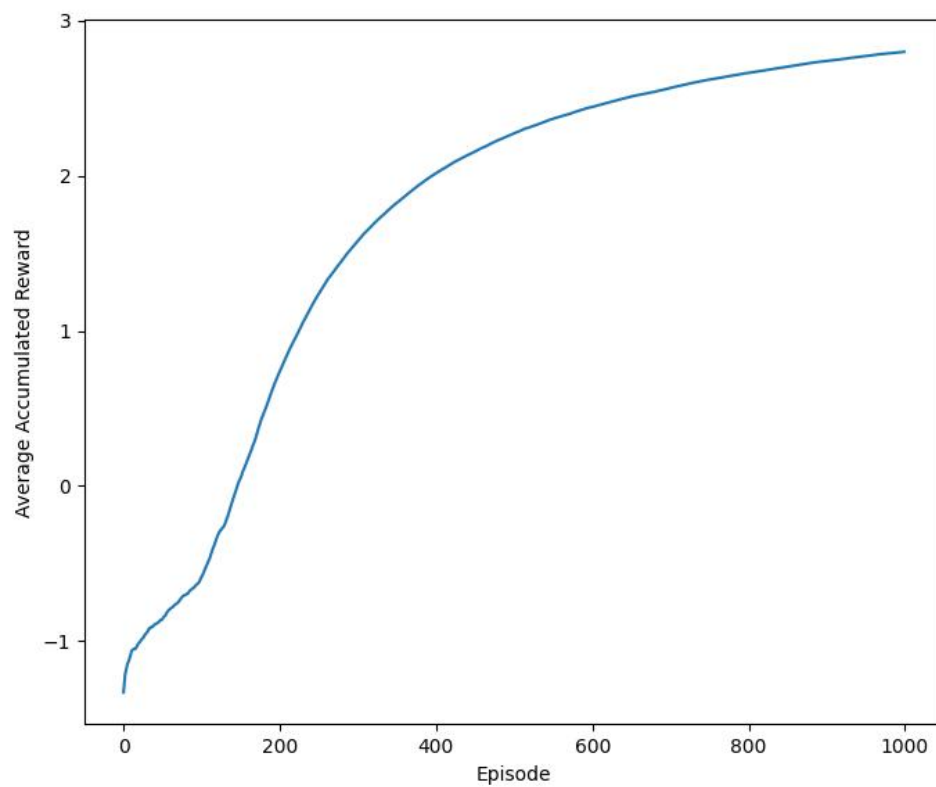


Figure 1.6 The average accumulated reward with respect to the episode obtained by SARSA

Actor-Critic:

Set $P=0.02$, $\gamma=0.95$, $\alpha=0.3$, $\beta=0.05$ implementing 10 times independent Actor - Critic.,
1 path from start to goal has been obtained. The plot of optimal policy, optimal path
and average accumulated reward with respect to episode is as follow:

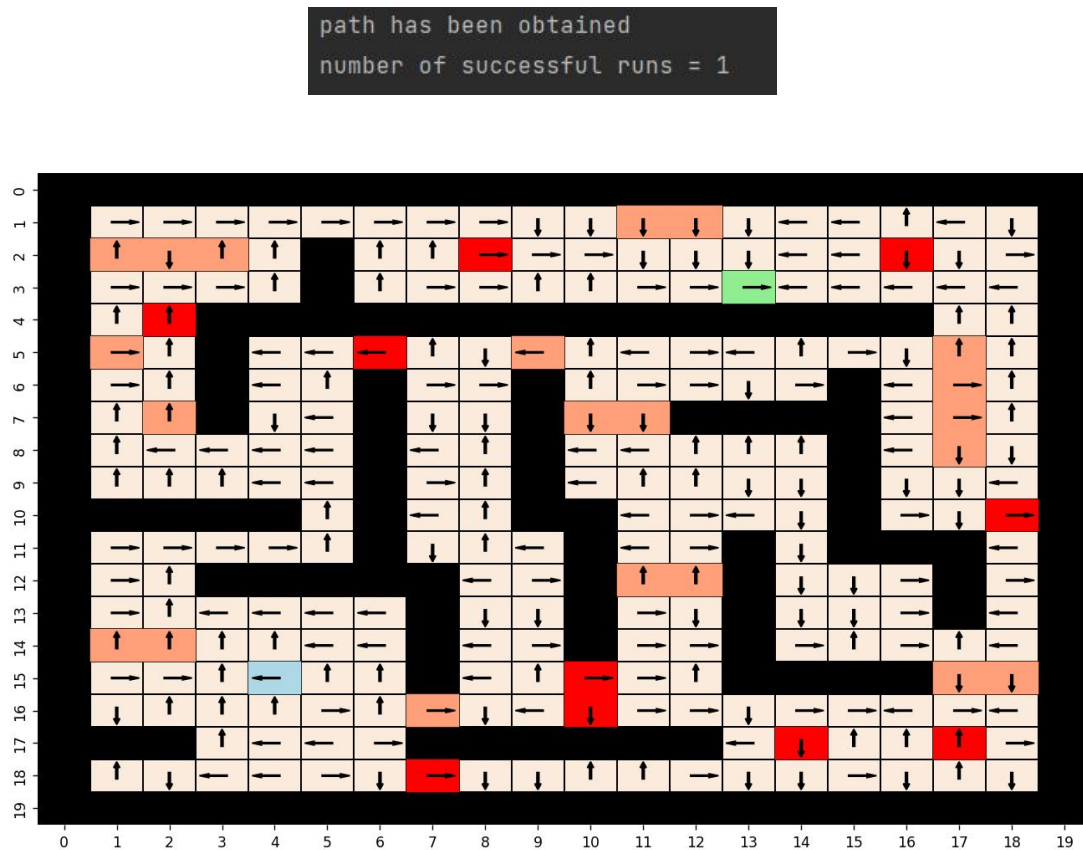
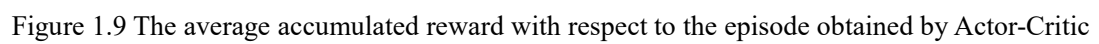
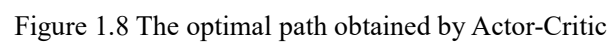


Figure 1.7 The optimal policy obtained Actor-Critic



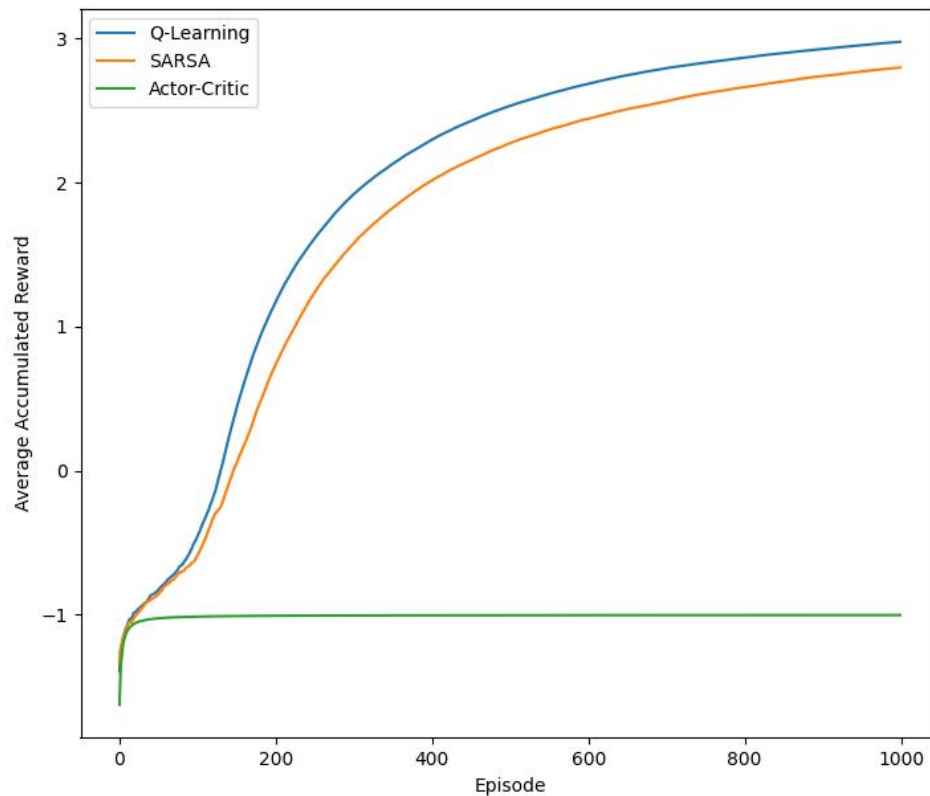


Figure 1.10 The average accumulated reward with respect to the episode obtained by Q-Learning , SARSA, Actor - Critic

According to the figure 1.10 we can conclude that because Q-learning is off-policy learning mechanism, which allows it to update its Q-values based on a policy that may be different from the one currently being followed, and Q-learning will always maximum the next state's q value which allows the Q-learning is expected to achieve a higher average accumulated reward than SARSA and Actor-Critic. Due to SARSA follows on-policy learning meaning that it updates its Q-values based on the policy it is currently following, so it will gain low accumulated reward and converge slowly than Q-Learning. Actor-Critic improve the policy and the value function simultaneously, so it converge faster than Q-Learning.

Problem 2

Q-Learning:

Set $P=0.02$, $\gamma=0.95$, $\alpha=0.2$, $\epsilon=0.1$ implementing 10 times independent Q-Learning. The optimal policy and average accumulated reward with respect to episode is as follow:

```
optimal policy for all 10 independent runs when implementing Q-Learning
['a2', 'a4', 'a2', 'a1', 'a2', 'a3', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a1', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a1', 'a2', 'a1', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2']
['a2', 'a4', 'a2', 'a1', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a3', 'a2', 'a3', 'a2', 'a4', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a4', 'a2', 'a1', 'a2', 'a2', 'a2', 'a4', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a4', 'a2', 'a2', 'a2', 'a3', 'a2', 'a1', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a4', 'a2', 'a4', 'a2', 'a4', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a4', 'a2', 'a1', 'a2', 'a4', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a4', 'a2', 'a3', 'a2', 'a2', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
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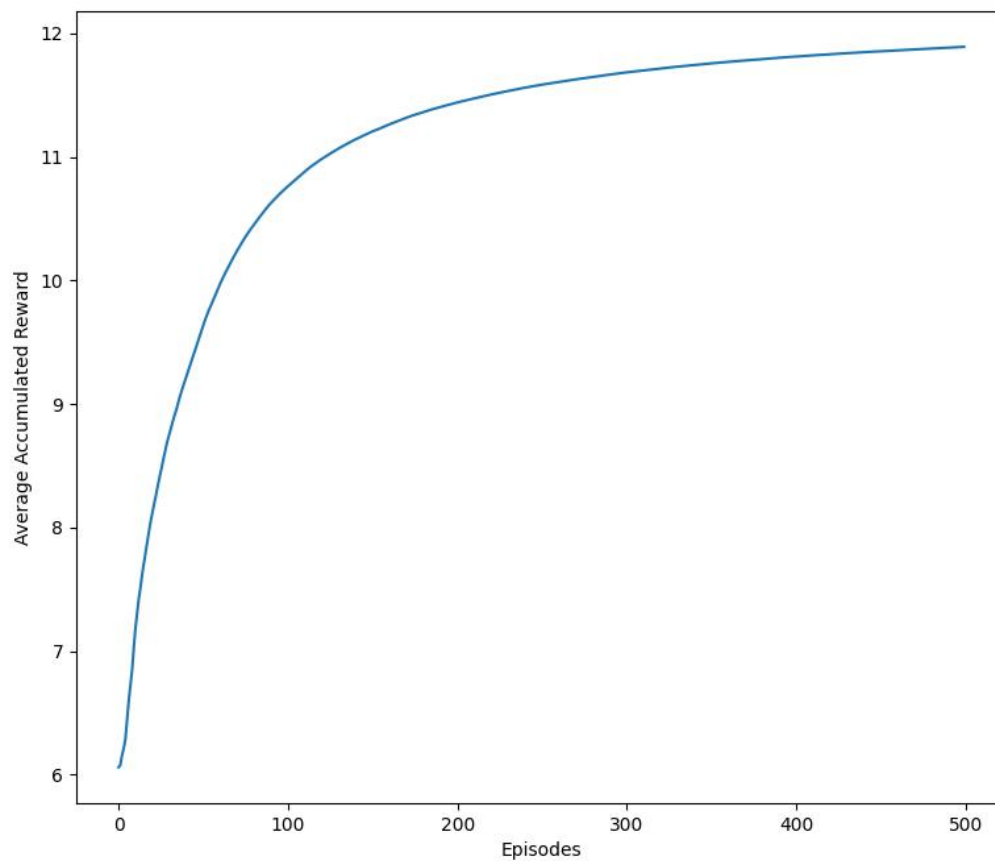


Figure 2.1 The average accumulated reward with respect to the episodes obtained by Q-Learning ,

SARSA:

Set $P=0.05$, $\gamma=0.95$, $\alpha=0.2$, $\epsilon=0.1$ implementing 10 times independent SARSA. The optimal policy and average accumulated reward with respect to episode is as follow:

```
optimal policy for all 10 independent runs when implementing SARSA
['a3', 'a4', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a4', 'a2', 'a2', 'a2', 'a3', 'a2', 'a3', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2']
['a2', 'a2', 'a2', 'a4', 'a2', 'a4', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a3', 'a4', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a2', 'a2', 'a1', 'a2', 'a2', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a1', 'a2', 'a1', 'a2', 'a3', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a4', 'a2', 'a3', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a1', 'a2', 'a1', 'a2', 'a2', 'a3', 'a4', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a2', 'a2', 'a4', 'a2', 'a1', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a4', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2']
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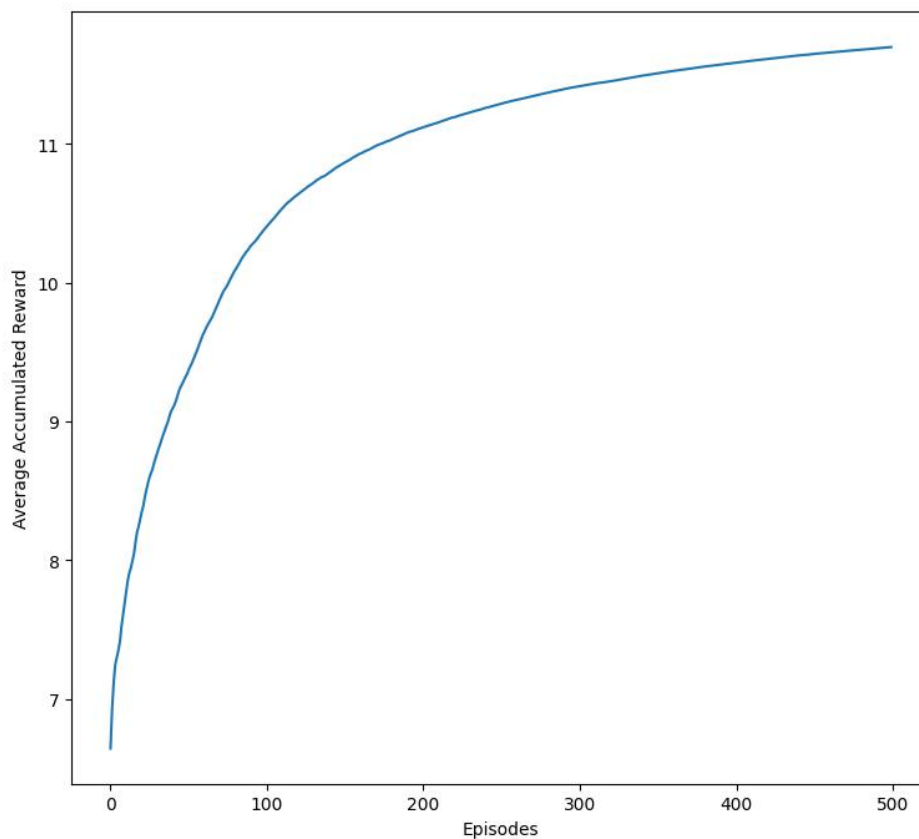


Figure 2.2 The average accumulated reward with respect to the episodes obtained by SARSA

SARSA- λ :

Set $P=0.05$, $\gamma=0.95$, $\alpha=0.2$, $\epsilon=0.1$ implementing 10 times independent SARSA- λ . The optimal policy and average accumulated reward with respect to episode is as follow:

```
optimal policy for all 10 independent runs when implementing SARSA-Lambda
['a2', 'a2', 'a2', 'a4', 'a2', 'a2', 'a2', 'a1', 'a3', 'a4', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a1', 'a2', 'a2', 'a2', 'a1', 'a2', 'a4', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2']
['a2', 'a1', 'a2', 'a4', 'a2', 'a4', 'a2', 'a1', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a3', 'a2', 'a2', 'a1', 'a2', 'a3', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a1', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2', 'a3', 'a3', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2']
['a2', 'a2', 'a2', 'a1', 'a2', 'a2', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a3', 'a2', 'a3', 'a2', 'a3', 'a2', 'a1', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a2', 'a1', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
['a3', 'a4', 'a2', 'a1', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2', 'a2', 'a4', 'a2', 'a2', 'a2', 'a2']
['a2', 'a2', 'a2', 'a4', 'a2', 'a3', 'a2', 'a4', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2', 'a2']
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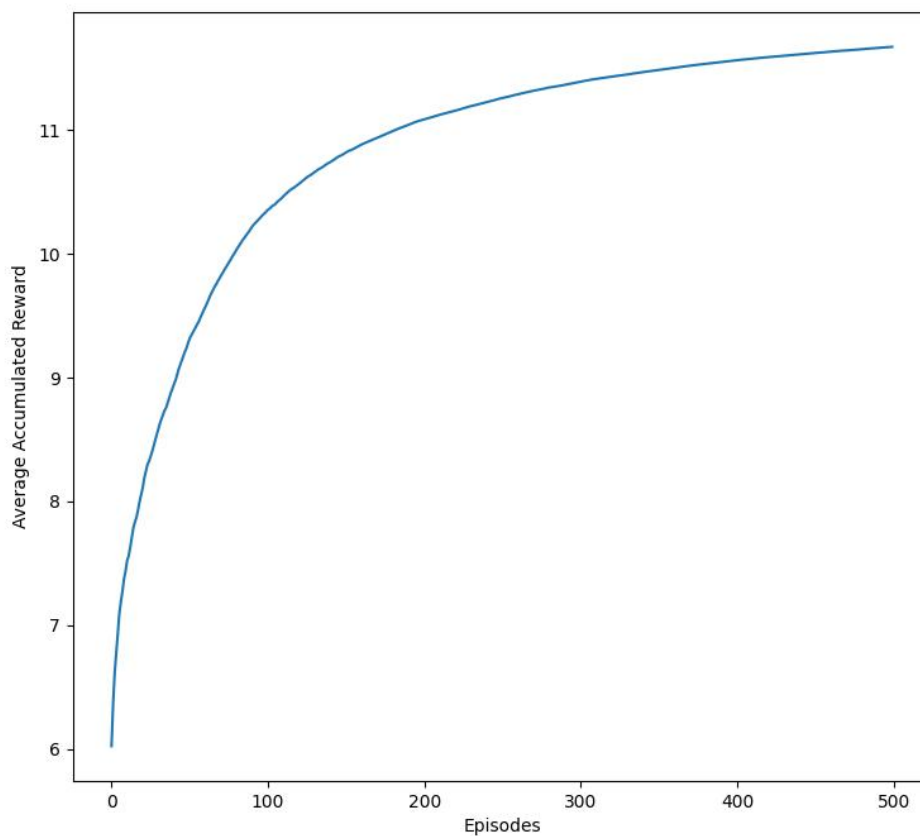


Figure 2.3 The average accumulated reward with respect to the episodes obtained by SARSA- λ

Actor-Critic:

Set $P=0.05$, $\gamma=0.95$, $\alpha=0.2$, $\beta=0.05$ implementing 10 times independent Actor-Critic. The optimal policy and average accumulated reward with respect to episode is as follow:

```
optimal policy for all 10 independent runs when implementing Actor_Critic
['a3', 'a4', 'a3', 'a4', 'a4', 'a1', 'a2', 'a2', 'a2', 'a3', 'a2', 'a1', 'a2', 'a2', 'a2', 'a2']
['a3', 'a2', 'a3', 'a3', 'a4', 'a2', 'a2', 'a2', 'a2', 'a4', 'a2', 'a2', 'a2', 'a1', 'a2', 'a2']
['a3', 'a2', 'a4', 'a2', 'a2', 'a4', 'a4', 'a1', 'a1', 'a2', 'a1', 'a3', 'a2', 'a2', 'a1', 'a2']
['a2', 'a3', 'a3', 'a4', 'a4', 'a2', 'a1', 'a4', 'a2', 'a3', 'a2', 'a3', 'a2', 'a1', 'a2', 'a1']
['a2', 'a1', 'a3', 'a4', 'a2', 'a2', 'a4', 'a2', 'a2', 'a3', 'a3', 'a3', 'a2', 'a1', 'a1', 'a1']
['a3', 'a3', 'a3', 'a3', 'a4', 'a2', 'a2', 'a2', 'a2', 'a4', 'a2', 'a3', 'a2', 'a1', 'a2', 'a2']
['a3', 'a1', 'a4', 'a2', 'a2', 'a3', 'a4', 'a2', 'a2', 'a2', 'a3', 'a2', 'a2', 'a2', 'a2', 'a2']
['a4', 'a2', 'a3', 'a4', 'a2', 'a2', 'a2', 'a2', 'a2', 'a4', 'a4', 'a4', 'a2', 'a2', 'a2', 'a2']
['a4', 'a1', 'a3', 'a3', 'a2', 'a4', 'a1', 'a1', 'a2', 'a1', 'a3', 'a3', 'a2', 'a1', 'a2', 'a1']
['a3', 'a3', 'a4', 'a3', 'a2', 'a4', 'a4', 'a1', 'a2', 'a2', 'a3', 'a3', 'a1', 'a2', 'a1', 'a1']
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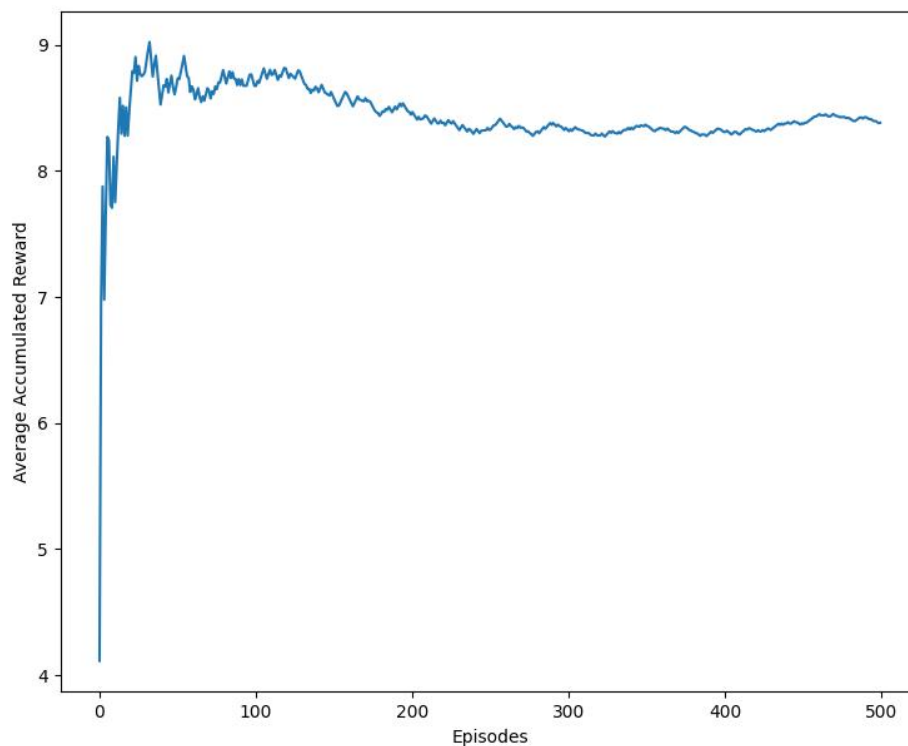


Figure 2.4 The average accumulated reward with respect to the episode obtained by Actor - Critic

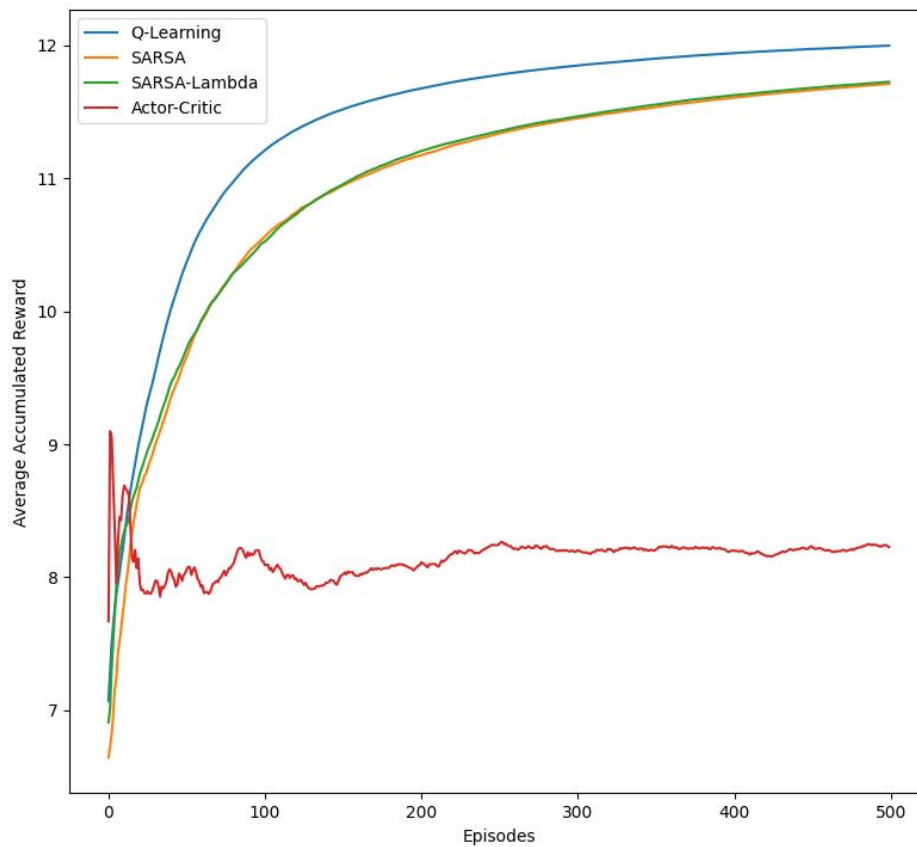


Figure 2.5 The average accumulated reward with respect to the episode obtained by Q-Learning , SARSA, SARSA- λ , Actor - Critic

Based on figure 2.5, Actor-Critic converge faster than other learning algorithms because it can balance exploration and exploitation more effectively but we can also see it also brings lower accumulated reward. Q-learning can explore suboptimal policies during training, leading to better exploration and a higher probability of finding the optimal policy. So Moreover, Q-learning is less prone to being stuck in a suboptimal policy compared to SARSA, SARSA- λ , Actor-Critic. SARSA- λ is a more sophisticated algorithm than SARSA that can provide faster convergence and a better bias-variance trade-off. However, it also has additional hyperparameters to tune so it may be more sensitive to their values.