Reinforcement Learning
Exercise 6 - Solution

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1 Planning and Learning

a) Why did Dyna-Q+ perform better in both test phase Lets start with the **second phase**. For the phase of the suddenly appearing shortcut in the beginning of the wall, Dyna-Q+ is able to exploit the gained benefit faster, since it generates a higher reward since the state was not visited for a long time. On the other hand Dyna-Q remains on its fixed strategy which proofed to perform better for a longer period of time(i.e. the hole on the left of the wall) and therefore remains slow.

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Lets consider the **first phase** and the tricky question: Why doesn't it cost Dyna-Q+ to explore its environment? This can be explained by living in a grid universe and one can not exploit walking diagonal. Therefore, each path to the hole in the wall is of the same length. Dyna-Q+ performs initially better, since it tends to explore the terrain and finds the hole in the wall earlier.

b) Tabular Dyna-Q algorithm Adaptations in order to include stochastic environments could be achieved by implementing a stochastic process in the model itself. This can be done in multiple ways, I will present two approaches here. Either, probability is directly sampled by occurence

$$Model(S, A) \leftarrow R_i, S'_i \quad \text{for} i = 1, ..., N \tag{1}$$

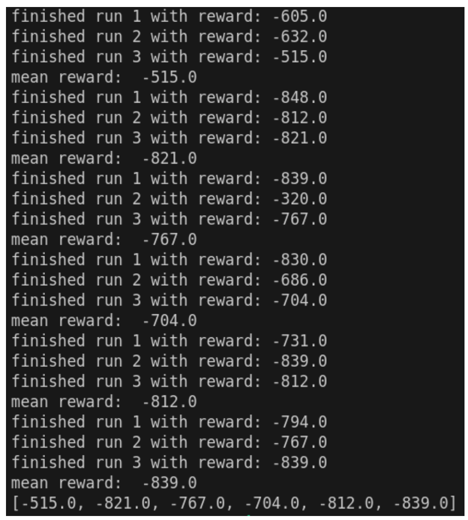
$$Model(S, A) := \begin{cases} R_1, & x < p_1 \\ & \vdots \\ R_j, & x < \sum_{i=1}^{j} p_j \\ & \vdots \\ R_n, & x < 1 \end{cases} \tag{2}$$

where $p_j = \frac{\#R_j}{N}$ and x is a random number drawn from a uniform distribution over the interval $[0, 1]$. Alternatively one can use a Kernel-interpolation, e.g.

with a gaussian Kernel from each Reward (and State if they are also continuos otherwise either do first method or floor to integer representation).

Does this still perform well on changing environments? - If not how could it? The problem is that in the planning phase the Q value for the cost of the state action, could be reduced to such an extend, that it doesn't visit the state again. This can again be solved by using a term in the reward to make state which haven't benn visited for a long time more attractive via Dyna-Q+.

2 Monte Carlo Tree Search on the Taxi environment



```
finished run 1 with reward: -605.0
finished run 2 with reward: -632.0
finished run 3 with reward: -515.0
mean reward:  -515.0
finished run 1 with reward: -848.0
finished run 2 with reward: -812.0
finished run 3 with reward: -821.0
mean reward:  -821.0
finished run 1 with reward: -839.0
finished run 2 with reward: -320.0
finished run 3 with reward: -767.0
mean reward:  -767.0
finished run 1 with reward: -830.0
finished run 2 with reward: -686.0
finished run 3 with reward: -704.0
mean reward:  -704.0
finished run 1 with reward: -731.0
finished run 2 with reward: -839.0
finished run 3 with reward: -812.0
mean reward:  -812.0
finished run 1 with reward: -794.0
finished run 2 with reward: -767.0
finished run 3 with reward: -839.0
mean reward:  -839.0
[-515.0, -821.0, -767.0, -704.0, -812.0, -839.0]
```

Figure 1: Output for Trees with `maxiter` = [10, 20, 50, 100, 200, 500]

TODO:

b -2