2023 年 4 月 5 日 强化学习 强基数学 002 吴天阳 2204210460

第四次作业 第七章

题目 1. **练习** 7.2 在 n 步方法中,价值函数需要每步都更新,所以利用 TD 误差值和代替下述公式

$$V(S_t) \leftarrow V(S_t) + \alpha [G_{t:t+n} - V(S_t)], \quad 0 \leqslant t < T$$

中的错误项的算法将会与之前不同. 这种算法是一个更好的还是更差的算法? 请设计一个小实验并编程验证这个问题.

解答. 类似 MC 算法,如果不考虑每步都进行更新,则也可表示为 TD 误差值和;在 n 步 TD 方法中,如果不考虑每步都更新,则可写为 n 个 TD 误差和

$$G_{t:t+n} - V(S_t) = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$$

$$+ \gamma (R_{t+2} + \dots + \gamma^{n-2} R_{t+n} + \gamma^{n-1} V(S_{t+n}) - V(S_{t+1}))$$

$$= \delta_t + \gamma (R_{t+2} + \gamma V(S_{t+2}) - V(S_{t+1}))$$

$$+ \gamma^2 (R_{t+3} + \dots + \gamma^{n-3} R_{t+n} + \gamma^{n-2} V(S_{t+n}) - V(S_{t+2}))$$

$$= \delta_t + \gamma \delta_{t+1} + \dots + \gamma^{n-2} \delta^{t+n-2}$$

$$+ \gamma^{n-1} (R_{t+n} + \gamma V(S_{t+n}) - V(S_{t+n-1})) + \gamma^n (V(S_{t+n}) - V(S_{t+n}))$$

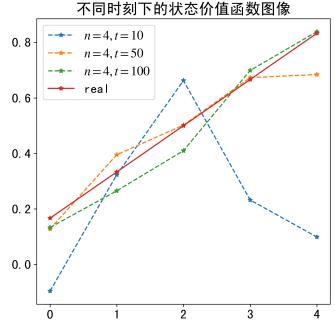
$$= \delta_t + \gamma \delta_{t+1} + \dots + \gamma^{n-1} \delta_{t+n-1} = \sum_{k=t}^{t+n-1} \gamma^{k-t} \delta_k$$

所以该题的问题就是比较 n 步 TD 算法的实时更新和非实时更新(每次一幕结束之后,更新状态价值函数)的好坏.

我使用的例子是书上**例** 6.2 **随机游走**: $A\sim E$ 的真实价值分别为 $\{\frac{1}{6},\frac{2}{6},\frac{3}{6},\frac{4}{6},\frac{5}{6}\}$,使用实时更新 4 步 TD 算法状态价值函数 (Real time n-TD) 图像如右图所示.

我绘制了实时 TD 算法(Real time)和非实时 TD 算法(non-Real time)的均方误差和幕数的变换关系图,容易看出,实时 TD 算法的均方误差一直比非实时 TD 算法要小,说明实时 TD 算法更优,因为在实时更新算法中智能体学习过程中,仍在不断更新状态价值函数,从而可以更快地收敛到真实状态价值函数.

但二者差别并不是很大,因为策略是 固定的,如果在策略迭代中,实时算法收 敛速度应该更加迅速.



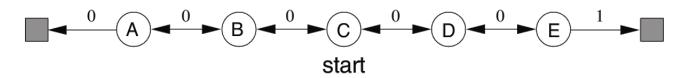
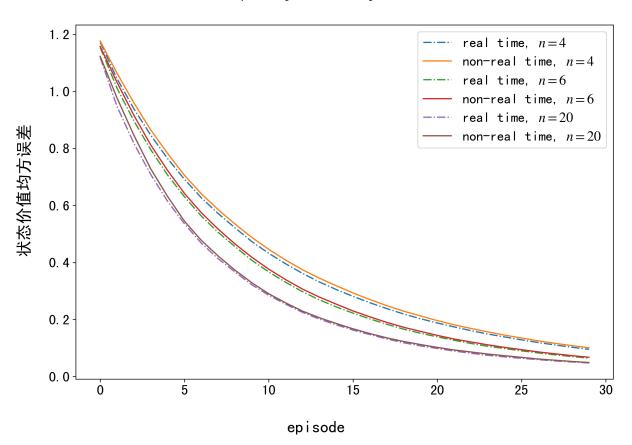


图 1: 随机游走

比较实时(real time)和非实时(non-real time)的n-TD算法状态价值均方误差变换效果 $\alpha=0.05, \gamma=1, epiode=30, epoch=1000$



完整代码:

```
# -*- coding: utf-8 -*-
1
   1.1.1
2
  @File
3
           : main.py
   @Time
            : 2023/03/21 19:43:45
4
  @Author : wty-yy
  @Version: 1.0
   @Blog
           : https://wty-yy.space/
7
           :《强化学习》中文书第 141 页练习 7.2, 比较 n-TD 算法的两种实现方法
   @Desc
           1. 实时更新与书上写法一致。
9
           2. 进行完一回合之后更新一次。
10
           两种算法均对状态价值函数进行估计,选的例子是第 123 页的"随机游走",
11
           随机游走例子中每个节点的真实状态价值函数都是已知的,
12
           通过绘制"步数-价值函数的均方误差"的图像来比较两种算法。
13
   111
14
15
16
   import numpy as np
   import matplotlib.pyplot as plt
17
   from tqdm import tqdm
18
  from template.reinforcement import Environment, Agent
19
  from pathlib import Path
20
   PATH FIGURES = Path( file ).parent
21
22
   class RandomWalk(Environment):
23
       avail points = 5
24
       def __init__(self, avail_points=5) -> None:
25
           super().__init__()
26
           self.avail_points = avail_points
27
           self.rewards = [0 for _ in range(self.avail_points + 1)]
28
           self.rewards.append(1)
29
           self.true_state_value = [0, *[(i+1)/(1+self.avail_points) for i in
30

¬ range(self.avail_points)], 0]

31
       def reset(self):
32
           self.state = self.avail points // 2 + 1
33
           return self.state
35
       def step(self, action):
36
           self.state += action
37
           reward = self.rewards[self.state]
38
           terminal = 0 if self.state != 0 and self.state != self.avail_points + 1
39
           → else 1
           return reward, self.state, terminal
40
41
   class n_TD_Agent(Agent):
42
       def __init__(self, n_TD=6, alpha=0.05, epsilon=0, gamma=1, seed=42,
43
       → episode=30, epoch=1000) -> None:
           super().__init__(alpha, epsilon, gamma, seed, episode, epoch)
44
           self.n_TD = n_TD
45
46
       def start(self):
47
           for real time in [True, False]:
48
```

```
# for real time in [True]:
49
                self.history = np.zeros(self.episode)
50
                for in tqdm(range(self.epoch)):
51
                    self.history += (self.train(real_time) - self.history) / (1 + _)
                self.plot_MSE(label=f"{'' if real_time else 'non-'}real time,
53

    $n={self.n TD}$", ls='-.' if real time else '-')

54
       def train(self, real_time=True, verbose=False, **kargs):
55
56
            def choose_action():
                return 1 if np.random.rand(1)[0] > 0.5 else -1
57
58
           history = []
           n = self.n TD
60
            state value = np.random.normal(size=RandomWalk.avail points + 2)
61
            state value[0] = state value[-1] = 0
62
           for _ in range(self.episode):
64
                env = RandomWalk()
65
                state = env.reset()
66
                t, T = 0, np.inf
67
                # rewards, states = ([0 for _ in range(n + 1)] for _ in range(2))
68
                # states[0] = state
69
                rewards, states = [0], []
70
                states.append(state)
71
72
                def update_state_value():
73
                    if tau >= 0:
74
                        target = 0
75
                        for i in range(tau + 1, min(tau + n, T) + 1):
76
                             # target += np.power(self.gamma, i - tau - 1) * rewards[i
77
                             → % (n+1)]
                            target += np.power(self.gamma, i - tau - 1) * rewards[i]
78
                        if tau + n < T:
79
                             # target += np.power(self.gamma, n) *
80

    state_value[states[(tau+n) % (n+1)]]

                            target += np.power(self.gamma, n) *
81

    state_value[states[tau+n]]

                        # delta = target - state_value[states[tau % (n+1)]]
82
                        delta = target - state_value[states[tau]]
83
                        # state_value[states[tau % (n+1)]] += self.alpha * delta
84
                        state_value[states[tau]] += self.alpha * delta
85
86
                while True:
87
                    if t < T:
88
                        action = choose action()
                        reward, state, terminal = env.step(action)
90
                        rewards.append(reward)
91
                        states.append(state)
92
                        \# rewards[(t+1) % (n+1)] = reward
93
                        # states[(t+1) % (n+1)] = state
                        if terminal:
95
                            T = t + 1
96
                    tau = t - n + 1
97
```

```
if real_time:
98
                         update state value()
99
                    if tau == T - 1:
100
                        break
101
                    t += 1
102
                if not real time:
103
                    for tau in range(T):
104
                         update_state_value()
105
106
                mse = np.sum(np.power(state_value - env.true_state_value, 2)) /
107
                 history.append(mse)
                if verbose and (_+1) in kargs['verbose_time']:
109
                    plt.plot(state_value[1:-1], '--*', label=f"$n={n}, t={_+1}$")
110
            if verbose:
111
                plt.plot(env.true_state_value[1:-1], '-*', label="real")
113
            return np.array(history)
114
115
        def plot MSE(self, label, ls):
116
            plt.plot(self.history, label=label, ls=ls)
117
118
    if name == ' main 1':
119
        plt.title("不同时刻下的状态价值函数图像")
120
        agent = n_TD_Agent(n_TD=4, alpha=0.05, episode=100)
121
        agent.train(real_time=True, verbose=True, verbose_time=[10, 50, 100])
122
        plt.legend()
123
        plt.tight layout()
124
        plt.savefig(PATH_FIGURES.joinpath("state value function in diff time.png"),
125
        \rightarrow dpi=300)
        plt.show()
126
127
    if __name__ == "__main__":
128
        fig = plt.figure(figsize=(10, 8))
129
        for subid, n in enumerate([4, 6, 20]):
130
            agent = n_TD_Agent(n_TD=n)
131
            agent.start()
132
            plt.legend()
133
        fig.suptitle(" 比较实时 (real time) 和非实时 (non-real time) 的 n-TD 算法\n状态
134
         → 价值均方误差变换效果\n"
135
                      +f"$\\alpha={agent.alpha},\\gamma={agent.gamma},epiode={agent.episode}
        fig.supylabel("状态价值均方误差")
136
        fig.supxlabel("episode")
137
138
        plt.tight_layout()
139
        plt.savefig(PATH_FIGURES.joinpath("compare (non)real time n-TD.png"),
140
        \rightarrow dpi=300)
        plt.show()
141
```