EECS 498: Reinforcement Learning Homework 3 Responses

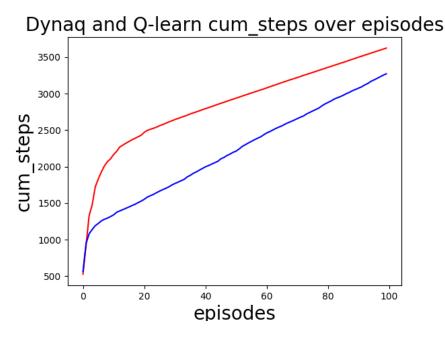
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This document includes my responses to Homework 3 questions. Responses that involved the use of coding will provide references to specific lines of code to provide a better overview of how the problem was approached. The code can either be referenced in the Appendix or in the accompanied python script submitted with this assignment.

Question 1

(a) The dynaq algorithm was implemented following the pseudocode shown on page 164 of the textbook. In the below plot, the red curve corresponds to the use the Q-learning algorithm and the blue curve represents the use of dynaq algorithm. As can be seen by the images, there curve for dynaq appears to apprach a constant slope earlier than the curve for Q-learning, indicating a faster approach towards an optimal policy with the optimal number of steps required in an episode to reach the terminal state.

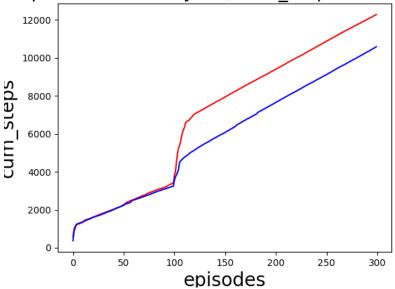


(b) In the case where the environment switches from "Taxi-v4" to "Taxi-v5" after the initial 100 episodes, the length of each episode drastically increased as the algorithm needed more iterations to adjust the

model and action-values to the new environment. As the algorithm was able to iterate and better learn the new environment, the length of each episode begins to converge to a constant as represented by a straight line. In order to better account for the change in the environment, I have modified the use of the algorithm to use a lower discount rate (γ) . In my case, I used a discout factor of 0.5, which would help in a faster adjustment to the new environment by reducing the weight placed on already learned Q values. As a result, the algorithm is affected less by future expected returns and more by the immediate rewards, which greatly boosts immediate learning to a changing environment. Note that a similar change can be seen by decreasing alpha, the learning rate, as well as a combination of both.

The plot below displays this difference with the two curves. The red curve is the original algorithm prom part (a) reacting to the change in the environment. The blue curve represents the modified algorithm as described above.





Question 2

Appendix: Relevant Code - tjha.py

```
1 # Tejas Jha
2 # 5 November 2018
3 # EECS 498 — Reinforcement Learning HW 3
4 #
5 #
```

- 6 # The code below implements a modified version of "Tabular Dyna-Q" as well as
- 7 # implementation modifications to adapt to changes in the environemnt faster.

```
8 # This file also contains the code used to implement n-step semi-
       gradient TD estimation
9 #
10 # The functions below expand on the starter code provided that help
      generate the
11 # states, actions, and rewards using Taxi-v4 and Taxi-v5 on openAi gym
12 #
13
14 import numpy as np
15 import gym
16 import copy
17 import mytaxi
18 import math
19 import matplotlib.pyplot as plt
20
21 # Environment for Taxi-v4
22 ENV4 = gym.make('Taxi-v4').unwrapped
23 # Einvironment for Taxi-v5
24 \text{ ENV5} = \text{gym.make}('Taxi-v5').unwrapped
25 # Possible actions that can be taken
26 ACTIONS = [0,1,2,3,4,5]
27
28 # Helpers to choose best action given probability distributions
29 \operatorname{def}_{-\operatorname{greedy}}(Q, s):
30
       qmax = np.max(Q[s])
31
        actions = []
32
       for i,q in enumerate(Q[s]):
33
            if q == qmax:
34
                actions.append(i)
35
       return actions
36
37
   def greedy (Q, s):
38
       return np.random.choice(_greedy(Q,s))
39
40
   def ep_greedy (Q, s, ep):
        if np.random.rand() < ep:</pre>
41
42
            return np.random.choice(len(Q[s]))
43
        else:
44
            return greedy (Q, s)
45
46 \# Part(a) - Tabular Dyna-Q:
   # Function implementation of dynaq to handle the stochastic nature of
      the environment
48 # returns Q and cum_steps – list of the cumulatative number of steps
       counted from the
49 # first episode to the end of each episode.
```

```
50
   def dynaq (env, n=10, gamma=1, alpha=1, epsilon=0.1, runs=1, episodes=100):
51
        for run in range(runs):
            # Update kept on cumulative number of steps
52
53
            cum_steps = np.zeros(episodes)
            Q = np.zeros((env.nS,env.nA))
54
            # Using deterministic model
55
56
            Model = \{\}
57
            for s in range(env.nS):
58
                Model[s] = \{\}
59
                for a in range (env.nA):
                     Model[s][a] = (-1, s)
60
            # Loop over episodes
61
            for idx in range(episodes):
62
                 visited_states = []
63
64
                taken_actions = \{\}
                s = env.reset()
65
                 visited_states.append(s)
66
67
                done = False
                counter = 0
68
                while not done:
69
                     a = ep_greedy(Q, s, epsilon)
70
                     if s in taken_actions:
71
72
                         if a not in taken_actions[s]:
73
                              taken_actions[s].append(a)
74
                     else:
75
                         taken_actions[s] = []
76
                         taken_actions[s].append(a)
77
                     ss, r, done, = env.step(a)
78
                     Q[s,a] = Q[s,a] + alpha * (r + gamma * np.max(Q[ss]) -
                        Q[s,a]
                     Model[s][a] = (r, ss)
79
80
                     s = ss
81
                     for i in range(n):
82
                         rand_s = np.random.choice(visited_states, size=1)
83
                         rand_s = rand_s[0]
                         rand_a = np.random.choice(taken_actions[rand_s],
84
                             size = 1
85
                         rand_a = rand_a[0]
86
                         tup = Model[rand_s][rand_a]
                         Q[rand_s, rand_a] = Q[rand_s, rand_a] + alpha * (tup)
87
                             [0] + \text{gamma} * \text{np.} \max(Q[\text{tup}[1]]) - Q[\text{rand}_s],
                             rand_a 1
88
                     counter += 1
89
                     visited_states.append(s)
90
                if idx == 0:
91
                     cum_steps[idx] = counter
92
                else:
93
                     cum_steps[idx] = counter + cum_steps[idx - 1]
```

```
94
        return Q, cum_steps
95
96 # Part (a) - adaptation of glearn from hw2 to compare with Tabular Dyna
97 # Key difference is 100 episodes instead of 500 by default
98 # Also, steps are now everaged through multiple callings of function
    \mathbf{def} qlearn (env, gamma=1, alpha=0.9, ep=0.05, runs=1, episodes=100):
100
        #np.random.seed(3)
        \#env.seed(5)
101
        nS = env.nS
102
103
        nA = env.nA
104
        rew_alloc = []
        for run in range(runs):
105
            Q = np.zeros((nS,nA))
106
             rew_list = np.zeros(episodes)
107
108
             cum_steps = np.zeros(episodes)
109
             for idx in range(episodes):
                 s = env.reset()
110
111
                 done = False
112
                 counter = 0
                 cum_rew = 0
113
                 while not done:
114
                     a = ep_greedy(Q, s, ep)
115
116
                     ss, r, done, = env.step(a)
117
                     Q[s,a] = Q[s,a] + alpha * (r + gamma * np.max(Q[ss]) -
                        O[s,a]
118
                     s = ss
119
                     cum_rew += gamma**counter * r
120
                     counter += 1.
121
                 rew_list[idx] = cum_rew
122
                 if idx == 0:
123
                     cum_steps[idx] = counter
124
                 else:
125
                     cum_steps[idx] = counter + cum_steps[idx - 1]
126
             rew_alloc.append(rew_list)
        rew_list = np.mean(np.array(rew_alloc), axis=0)
127
        return Q, cum_steps
128
129
130
    # Modified versions of the algorithms above for usage in random change
       to v5 environment after 100 episodes
    \mathbf{def} original_dynaq (env1, env2, n=10,gamma=1,alpha=1,epsilon=0.1,runs=1,
131
       episodes = 300):
        for run in range(runs):
132
             # Update kept on cumulative number of steps
133
             cum_steps = np.zeros(episodes)
134
135
            Q = np.zeros((env1.nS,env1.nA))
             # Using deterministic model
136
137
             Model = \{\}
```

```
138
             for s in range(env1.nS):
139
                 Model[s] = \{\}
                 for a in range(env1.nA):
140
141
                     Model[s][a] = (-1, s)
142
             env = env1
             # Loop over episodes
143
144
             for idx in range(episodes):
                 if idx == 100:
145
146
                     env = env2
147
                 visited_states = []
148
                 taken_actions = \{\}
                 s = env.reset()
149
                 visited_states.append(s)
150
                 done = False
151
152
                 counter = 0
                 while not done:
153
154
                     a = ep_greedy(Q, s, epsilon)
155
                     if s in taken_actions:
156
                          if a not in taken_actions[s]:
157
                              taken_actions[s].append(a)
158
                     else:
159
                          taken_actions[s] = []
160
                          taken_actions[s].append(a)
161
                     ss, r, done, = env.step(a)
162
                     Q[s,a] = Q[s,a] + alpha * (r + gamma * np.max(Q[ss]) -
                        O[s,a]
163
                     Model[s][a] = (r, ss)
164
                     s = ss
165
                     for i in range(n):
166
                          rand_s = np.random.choice(visited_states, size=1)
                          rand_s = rand_s[0]
167
168
                          rand_a = np.random.choice(taken_actions[rand_s],
                             size = 1)
169
                          rand_a = rand_a[0]
170
                          tup = Model[rand_s][rand_a]
                         Q[rand_s, rand_a] = Q[rand_s, rand_a] + alpha * (tup)
171
                             [0] + gamma * np.max(Q[tup[1]]) - Q[rand_s],
                             rand_a])
172
                     counter += 1
173
                     visited_states.append(s)
174
                 if idx == 0:
175
                     cum_steps[idx] = counter
176
                     cum_steps[idx] = counter + cum_steps[idx - 1]
177
178
        return Q, cum_steps
179
180
    # Modified improvement for dynag to account for environment change
    def modified_dynaq (env1, env2, n=10, gamma=0.5, alpha=0.5, epsilon=0.1,
181
```

```
runs=1, episodes=300):
182
         for run in range(runs):
             # Update kept on cumulative number of steps
183
184
             cum_steps = np.zeros(episodes)
             Q = np.zeros((env1.nS,env1.nA))
185
             # Using deterministic model
186
187
             Model = \{\}
             for s in range(env1.nS):
188
189
                  Model[s] = \{\}
190
                  for a in range(env1.nA):
191
                       Model[s][a] = (-1, s)
192
             env = env1
             # Loop over episodes
193
             for idx in range(episodes):
194
                  if idx == 100:
195
196
                      env = env2
197
                  visited_states = []
198
                  taken\_actions = \{\}
199
                  s = env.reset()
200
                  visited_states.append(s)
201
                  done = False
                  counter = 0
202
203
                  while not done:
204
                       a = ep_greedy(Q, s, epsilon)
205
                       if s in taken_actions:
                           if a not in taken_actions[s]:
206
207
                                taken_actions[s].append(a)
208
                       else:
209
                           taken_actions[s] = []
210
                           taken_actions[s].append(a)
211
                       ss, r, done, = env.step(a)
212
                      Q[s,a] = Q[s,a] + alpha * (r + gamma * np.max(Q[ss]) -
                          Q[s,a]
213
                      Model[s][a] = (r, ss)
214
                       s = ss
215
                       for i in range(n):
                           rand_s = np.random.choice(visited_states, size=1)
216
217
                           rand_s = rand_s[0]
                           rand_a = np.random.choice(taken_actions[rand_s],
218
                               size = 1)
219
                           rand_a = rand_a[0]
220
                           tup = Model[rand_s][rand_a]
221
                           Q[rand_s, rand_a] = Q[rand_s, rand_a] + alpha * (tup)
                               [0] + \operatorname{gamma} * \operatorname{np.} \operatorname{max}(Q[\operatorname{tup}[1]]) - Q[\operatorname{rand}_s],
                               rand_a
222
                       counter += 1
223
                       visited_states.append(s)
224
                  if idx == 0:
```

```
225
                     cum_steps[idx] = counter
226
                 else:
227
                     cum_steps[idx] = counter + cum_steps[idx - 1]
228
        return Q, cum_steps
229
230
    if __name__ == '__main__':
231
232
        # Part (a)
        print ("Training _using _Tabular _Dyna-Q_for _100 _episodes _using _Taxi-v4
233
234
        # Average results over 20 runs
235
        \#dynaq_Q_avg = 0
236
        \#qlearn_O_avg = 0
237
238
        \# dynaq\_cum\_steps\_avg = np.zeros(shape=(100,))
239
        \# q learn\_cum\_steps\_avg = np. zeros(shape=(100,))
240
241
        # for i in range (20):
242
               print("Performing run:" + str(i + 1))
243
        #
               # Randomize seeds so runs are independent
244
        #
               np.random.seed(i)
               ENV4. seed(i)
245
        #
246
        #
               _{-}, dynaq_{cum\_steps} = dynaq(ENV4)
247
        #
               _{-}, qlearn_{cum\_steps} = qlearn(ENV4)
248
        #
               # Update averages
249
        #
               \#dynaq_Q_avg += dynaq_Q / 20.0
250
               \#qlearn_Q_avg += qlearn_Q / 20.0
        #
251
        #
               dynaq\_cum\_steps\_avg += np. divide(dynaq\_cum\_steps, 20.0)
               qlearn_cum_steps_avg += np.divide(qlearn_cum_steps, 20.0)
252
253
254
        # # Compare results with Q learning implementation used in hw2 in
            plot
255
        # # Generate plots for Question 1 Part(a)
256
        # episodes = np.arange(len(qlearn_cum_steps_avg))
        # plt.plot(episodes, glearn_cum_steps_avg, 'r')
257
258
        # plt.plot(episodes, dynaq_cum_steps_avg, 'b')
        # plt.xlabel("episodes", fontdict={'fontname':'DejaVu Sans', 'size
259
            ': '20 '})
260
        # plt.ylabel("cum_steps", fontdict={'fontname':'DejaVu Sans', 'size
            ': '20 '})
        # plt.title("Dynag and Q-learn cum_steps over episodes", fontdict
261
            ={ 'fontname ': 'DejaVu Sans', 'size': '20'})
262
        # plt. savefig("Figure1")
263
264
265
        dynaq_cum_steps_avg1 = np.zeros(shape=(300,))
        dynaq_cum_steps_avg2 = np.zeros(shape=(300,))
266
267
        for i in range (5):
```

```
268
            print("Performing_run:_" + str(i + 1))
269
            # Randomize seeds so runs are independent
270
            np.random.seed(i)
271
            ENV4. seed(i)
272
            ENV5. seed(i)
273
            _, dynaq_cum_steps1 = original_dynaq(ENV4, ENV5)
            _, dynaq_cum_steps2 = modified_dynaq(ENV4, ENV5)
274
            # Update averages
275
            \#dynaq_Qavg += dynaq_Q / 20.0
276
            \#qlearn_Q_avg += qlearn_Q / 20.0
277
            dynaq_cum_steps_avg1 += np.divide(dynaq_cum_steps1, 5.0)
278
279
            dynaq_cum_steps_avg2 += np.divide(dynaq_cum_steps2, 5.0)
280
281
        episodes = np.arange(len(dynaq_cum_steps_avg1))
        plt.plot(episodes, dynaq_cum_steps_avg1, 'r')
282
        plt.plot(episodes, dynaq_cum_steps_avg2, 'b')
283
284
        plt.xlabel("episodes", fontdict={'fontname':'DejaVu_Sans', 'size':'
           20'})
285
        plt.ylabel("cum_steps", fontdict={'fontname': 'DejaVu_Sans', 'size':
           '20'})
286
        plt.title("Dynaq_and_Modified_DynaQ_cum_steps_over_episodes",
           fontdict={'fontname': 'DejaVu_Sans', 'size': '20'})
        plt.savefig("Figure4")
287
```