

Lab 4: Q-learning (table) exploit&exploration and discounted future reward

Exploit VS Exploration: decaying E-greedy

```
for i in range(num_episodes):
    e = 0.1 / (i+1)
    if random(1) < e:
        a = random
    else:
        a = argmax(Q(s, a))</pre>
for i in range(num_episodes):
    e = 1. / ((i / 100)+1) # Python2

# The Q-Table learning algorithm
while not done:
    # Choose an action by e greedy
    if np.random.rand(1) < e:
        action = env.action_space.sample()
    else:
        action = np.argmax(Q[state, :])</pre>
```

Exploit VS Exploration: add random noise











0.5

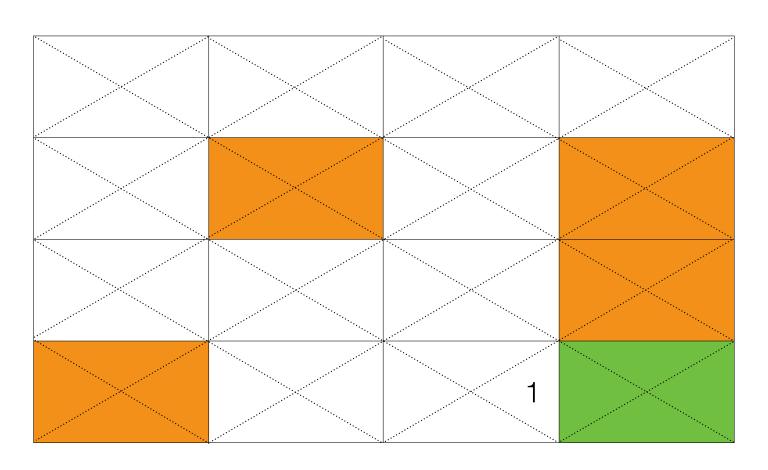
0.6

0.3

0.2

0.5

Discounted reward $\gamma = 0.9$)



Q-learning algorithm

For each s, a initialize table entry $\hat{Q}(s, a) \leftarrow 0$

Observe current state s

Do forever:

- Select an action a and execute it
- \bullet Receive immediate reward r
- Observe the new state s'
- Update the table entry for $\hat{Q}(s, a)$ as follows:

$$\hat{Q}(s, a) \leftarrow r + \gamma \max_{a'} \hat{Q}(s', a')$$

• $s \leftarrow s'$ # Discount factor dis = .99

Update Q-Table with new knowledge using decay rate
Q[state,action] = reward + dis * np.max(Q[new_state,:])

Code: setup

```
import gym
   import numpy as np
   import matplotlib.pyplot as plt
  from gym.envs.registration import register
   register(
       id='FrozenLake-v3',
       entry_point='gym.envs.toy_text:FrozenLakeEnv',
      kwargs={'map_name': '4x4',
            'is slippery': False}
v = gym.make('FrozenLake-v3')
  # Initialize table with all zeros
V Q = np.zeros([env.observation_space.n,env.action_space.n])
  # Discount factor
 Vdis = .99
   num episodes = 2000
  # create lists to contain total rewards and steps per episode
   rList = []
```

https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-0-q-learning-with-tables-and-neural-networks-d195264329d0#.pjz9g59ap

Code: Q learning

```
for i in range(num episodes):
   # Reset environment and get first new observation
    state = env.reset()
    done = False
    # The Q-Table learning algorithm
  while not done:
        # Choose an action by greedily (with noise) picking from Q table
        action = np.argmax(Q[state, :] + np.random.randn(1, env.action_space.n) / (i + 1))
        # Get new state and reward from environment
        new_state, reward, done,_ = env.step(action)
        # Update Q-Table with new knowledge using decay rate
        Q[state,action] = reward + dis * np.max(Q[new state,:])
        rAll += reward
        state = new_state
    rList.append(rAll)
```

https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-0-g-learning-with-tables-and-neural-networks-d195264329d0#.pjz9g59ap

Code: results

```
print("Success rate: " + str(sum(rList)/num_episodes))
print("Final Q-Table Values")
print(Q)
plt.bar(range(len(rList)), rList, color="blue")
plt.show()
                 Success rate: 0.9635
                 Final Q-Table Values
                 [[ 0.
                                         0.95099005
                              0.
                                         0.96059601
                              0.970299
                                                    0.
                              0.9801
                                         0.970299
                              0.9801
                                                    0.
                              0.99
                                                    0.
                                         0.
                                                    0.
                                         0.99
                                                    0.
                   0.
                                         1.
                                                    0.
                   0.
```

Code: e-greedy

Code: e-greedy results

```
Success rate: 0.828
Final O-Table Values
[[ 0.94148015  0.95099005
                           0.95099005 0.94148015]
 0.94148015
                           0.96059601 0.95099005]
 [ 0.95099005
              0.970299
                                        0.96059601]
                           0.
 [ 0.96059601
              0.96059601
 [ 0.95099005
                                        0.941480151
  0.
               0.
                                        0.
               0.9801
                                        0.960596011
                           0.
                           0.970299
 0.96059601
                                        0.950990051
 0.96059601
               0.9801
                           0.9801
 0.970299
               0.99
                                        0.970299
                           0.
 [ 0.
                           0.
               0.
                                        0.
                           0.
                                        0.
               0.
 [ 0.
               0.9801
                           0.99
                                        0.970299
 [ 0.9801
               0.99
                                        0.9801
                            1.
 [ 0.
               0.
                            0.
                                        0.
```

Next Nondeterministic Nondeterministic Stochastic worlds

