

CSCE 790-002: Deep Reinforcement Learning and Search  
Homework 1  
Due: 09/09/2020

## Installation

We will be using the same `conda` environment as in Homework 1.

## 1 Policy Iteration

### 1.1 Policy Iteration Implementation (30 pts)

Implement `policy_evaluation_step` (shown in Algorithm 2) in `assignments_code/assignment2.py`.

**Key building blocks:**

- `env.state_action_dynamics(state, action)`: returns, in this order, the expected return  $r(s, a)$ , all possible next states given the current state and action, their probabilities. Keep in mind, this only returns states that have a non-zero state-transition probability.
- `env.get_actions()` function that returns a list of all possible actions
- `policy`: you can obtain  $\pi(a|s)$  with `policy[state][action]`

Switches:

- `--discount`, to change the discount (default=1.0)
- `--rand_right`, to change the probability that the wind blows you to the right (default=0.0)
- `--wait`, the number of seconds to wait after every iteration of policy *iteration* so that you can visualize your algorithm (default=0.0)
- `--wait_eval`, the number of seconds to wait after every iteration of policy *evaluation* so that you can visualize your algorithm (default=0.0)

**Running the code:**

```
python run_policy_evaluation.py --map maps/map1.txt --wait 1.0
```

Policy iteration can be used to find, or approximate, the optimal value function. Policy iteration starts with a given value and policy function and iterates between policy evaluation and policy improvement until the policy function stops changing. In this exercise, we will be finding the optimal value function, exactly, using policy iteration.

We will start with a uniform random policy and a value function that is zero at all states. The policy improvement step has already been implemented using the `get_action` function that you implemented in Homework 1. Feel free to use your current implementation or the solution provided to you.

Therefore, you only have to implement `policy_evaluation_step`.

Vary the environment dynamics by making the environment stochastic `--rand_right` to 0.1 and 0.5. Compare your results to the solution videos provided in Blackboard under Course Content - Homework -

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**Algorithm 1** Policy Evaluation

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```

1: procedure POLICY_EVALUATION( $\mathcal{S}, V, \theta, \gamma$ )
2:    $\Delta \leftarrow \text{inf}$ 
3:   while  $\Delta > \theta$  do
4:      $\Delta, V = \text{Policy\_Evaluation\_Step}(\mathcal{S}, V)$ 
5:   end while
6:   return  $V$  ▷ Approximation of  $v_*$ 
7: end procedure

```

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**Algorithm 2** Policy Evaluation Step

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```

1: procedure POLICY_EVALUATION_STEP( $\mathcal{S}, V, a, \gamma$ )
2:    $\Delta \leftarrow 0$ 
3:   for  $s \in \mathcal{S}$  do
4:      $v \leftarrow V(s)$ 
5:      $V(s) \leftarrow \sum_a \pi(a|s)(r(s, a) + \gamma \sum_{s'} p(s'|s, a)V(s'))$ 
6:      $\Delta \leftarrow \max(\Delta, |v - V(s)|)$ 
7:   end for
8:   return  $\Delta, V$ 
9: end procedure

```

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## 1.2 Policy Iteration Concept (20 pts)

For policy evaluation, we started with a uniform random policy, a discount of  $\gamma = 1$ , and stopped policy evaluation only when  $\Delta = 0$ . If we started, instead, with a policy that gave the same action in every state (i.e. in every state, go left) we would never converge to  $\Delta = 0$ . Why is this? If we reduce  $\gamma$ , we would converge to  $\Delta = 0$ . Why is this?

## 2 Q-learning (50 pts)

Implement `q_learning_step` (shown in Algorithm 4) in `assignments_code/assignment2.py`.

### Key building blocks:

- `env.sample_transition(state, action)`: returns, in this order, the next state and reward
- `env.get_actions()` function that returns a list of all possible actions
- `action_vals`: you can obtain  $Q(s, a)$  with `action_vals[state][action]`

### Switches:

- `--discount`, to change the discount (default=1.0)
- `--rand_right`, to change the probability that the wind blows you to the right (default=0.0)
- `--wait_greedy`, Your learned greedy policy is visualized every 100 episodes for 40 steps. This is the number of seconds to wait after each step (default=0.1)

- `--wait_step`, the number of seconds to wait after every step of Q-learning so that you can visualize your algorithm (default=0.0)

### Running the code:

```
python run_q_learning.py --map maps/map1.txt --wait_greedy 0.1
```

Q-learning is a model-free, off-policy, temporal difference algorithm. Q-learning follows an  $\epsilon$ -greedy behavior policy but evaluates a greedy policy. In this setting, we will be running Q-learning with a learning rate  $\alpha = 0.5$  and  $\epsilon = 0.1$ . Each episode ends when the agent reaches the goal. For more information about  $\epsilon$ -greedy policies, please refer to the lecture slides or Chapters 5 and 6 of Sutton and Barto.

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#### Algorithm 3 Q-learning

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```

1: procedure Q-LEARNING( $Q, \gamma, \epsilon, \alpha$ )
2:   for  $i \in 1 \dots N$  do
3:     Initialize  $S$ 
4:     while  $S$  is not terminal do
5:        $S, Q = \text{Q\_Learning\_Step}(S, Q, \epsilon, \alpha, \gamma)$ 
6:     end while
7:     return  $Q$  ▷ Approximation of  $q_*$ 
8:   end for
9: end procedure

```

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#### Algorithm 4 Q-learning Step

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```

1: procedure Q-LEARNING-STEP( $S, Q, \epsilon, \alpha, \gamma$ )
2:   Sample an action  $A$  from  $\epsilon$ -greedy policy derived from  $Q$ 
3:    $S', R = \text{env.sample\_transition}(S, A)$ 
4:    $Q(S, A) = Q(S, A) + \alpha(R + \gamma \max_a Q(S', a) - Q(S, A))$ 
5:   return  $S', Q$ 
6: end procedure

```

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Vary the environment dynamics by making the environment stochastic with `--rand_right` to 0.1 and 0.5. Compare your results to the solution videos provided in Blackboard under Course Content - Homework - Homework 2.

## What to Turn In

Turn in your implementation of `assignments_code/assignment2.py` and a PDF of your answer to question part 1.2.