q3

December 8, 2020

0.1 OpenAI Gym Warm-Up

[297]:
```
# Import Environment class and Libraries
from frozen_lake import FrozenLakeEnv
import numpy as np
import sys
import matplotlib.pyplot as plt
import time


# Create Environment Object
env = FrozenLakeEnv(map_name ="4x4", is_slippery=False)


# Access the number of states:
nS = env.observation_space
print("State space of the Env: ", nS)

# or you could even use
nS = env.nS
print("State space of the Env by accessing env.nS: ", nS)


# Action space of the agent:
nA = env.nA
print("Action space of the Env: ", nA)
```

```
State space of the Env:  16
State space of the Env by accessing env.nS:  16
Action space of the Env:  4
```

[298]:
```
"""
For policy iteration, you would need to access
State(s), Action(a), Next State(ns), Reward(r), episode ended? (is_done) tuples.

Note that in this environment, the orientation of the agent does not matter.
```

```
No matter what direction the agent is facing, if, say a left action is␣
 ↪performed,
the agent moves to the left of the crrent state.
"""

# For actions, this is the corresponding dictionary:
action_names = {0:'L', 1:'D', 2:"R", 3:"U"}

"""
Here,
'L' means left
'D' means down
'R' means right
'U' means up



You can access these tuples by simply env.P[s][a].
where 's' is state, and 'a' is action. For example, let's say we are at state␣
 ↪'4',
and we take an action '1' or "Down". The next state (ns) would be 8, the␣
 ↪episode would not have ended (is_done),
the reward (r) is 0 and the transition probabilty (prob) is 1 because this is a␣
 ↪deterministic setting.
"""

prob, ns, r, is_done = env.P[4][1][0]

print("Transition Probabilty: ", prob)
print("Next State: ", ns)
print("Reward: ", r)
print("Episode ended? : ", is_done)
# Note that we need to add a [0] after env.P[s][a] because it returns a list␣
 ↪containing the tuple
```

```
Transition Probabilty:  1.0
Next State:  8
Reward:  0.0
Episode ended? :  False
```

0.2 Policy Iteration

- Follow the pseudo-code given in the handout for this section

[317]:
```
action_names = {0:'L', 1:'D', 2:"R", 3:"U"}
print(action_names[1])
```

```python
# policy = np.random.randint(0, 4, size=env.nS)
# print(enumerate(policy))


# # pi = np.zeros(env.nS, dtype=int)
# # print(pi)
# print(pi.reshape([4,-1]))
# pi = np.array([1,2,1,0,1,0,1,0,2,1,1,0,0,2,2,0])
# print(pi.reshape([4,-1]))
# states = 16
# policy_print = np.array([action_names[x] for x in pi])
# print(np.array(policy_print).reshape([-1,4]))

def print_policy(policy, action_names, states):
    """Print the policy in human-readable format.
    If you've implemented this correctly, the output (for 4x4 map) should be:

    D R D L
    D L D L
    R D D L
    L R R L

    Parameters
    ----------
    policy: np.ndarray
        Array of state to action number mappings
    action_names: dict
        Mapping of action numbers to characters representing the action.
    num_states: int
        Number of states in the FrozenLakeEnvironment (16 or 64 for 4x4 or 8x8␣
 ↪maps respectively)
    """
    # WRITE YOUR CODE HERE:
    fig, ax = plt.subplots()
    ax.matshow(policy.reshape([-1,4]), cmap='YlGnBu')
    for (i,j), z in np.ndenumerate(policy.reshape([-1,4])):
        ax.text(j, i, action_names[z], ha='center',va='center')
    plt.show()
#     pi_read = np.array([action_names[x] for x in policy])
#     print(np.array(pi_read).reshape([-1,4]))
#     pass
```

D

[300]:
```python
def one_step_lookahead(env, state, value_func, gamma):
    """
```

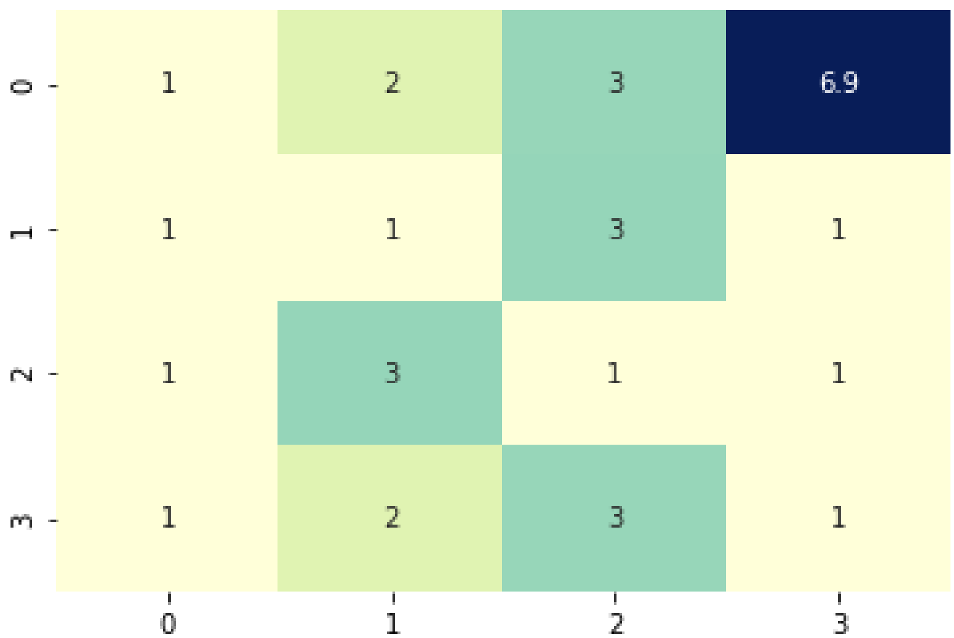
```python
    Helps calculate the value for all action in a given state.

    Parameters
    ----------
    env: Frozen Lake Environment
      The environment to comput value iteration for.
    state: int
      The state to consider.
    value_func: np.array
      The value function to use as an estimator.
    gamma: float
      Discount factor, must be in range [0, 1)

    Returns
    -------
    A: np.array
      A vector of length env.nA containing the expected value of
      each iteration
    """
#     A = np.zeros(env.nA)
#     val = 0
#     for a in range(env.nA):
#         for prob, next_state, reward, done in env.model[state][a]:
#             val += prob *(reward + gamma*value_func[next_state])
#         A[a] = val
    action_values = []
    state_value = 0
    for action in range(env.nA):
        for i in range(len(env.P[state][action])):
            prob, next_state, reward, done = env.P[state][action][i]
            state_action_value = prob * reward + (gamma*value_func[next_state])
            state_value += state_action_value
        action_values.append(state_value)

    return np.asarray(action_values)

def q_value(env, s, value_func, gamma):
    q = np.zeros(env.nA)
    for a in range(env.nA):
        for prob, next_state, reward, done in env.P[s][a]:
            q[a] += prob*(reward + gamma * value_func[next_state])
    return q

# Q = np.zeros([env.nA, env.sA])
# for s in range(env.nS):
#     Q[s] = q_value(env, V, s)
# print(Q)
```

[306]:
```
def evaluate_policy_sync(env, gamma, policy, value_func,␣
↪max_iterations=int(1e3), tol=1e-3):
    """Performs policy evaluation.

    Evaluates the value of a given policy.

    Parameters
    ----------
    env: Frozen Lake Environment
      The environment to compute value iteration for.
    gamma: float
      Discount factor, must be in range [0, 1)
    policy: np.array
      The policy to evaluate. Maps states to actions.
    value_func: np.array
      Array of scalar values for each state
    max_iterations: int
      The maximum number of iterations to run before stopping.
    tol: float
      Determines when value function has converged.

    Returns
    -------
    np.ndarray, int
      The value for the given policy and the number of iterations till
      the value function converged.
    """
    val_iter=0
    new_value_func = np.zeros(env.nS)
    for val_iter in range(max_iterations):
        delta = 0
        # For each state, perform a "full backup"
        for s in range(env.nS):
            Vs = 1
            for a, action_prob in enumerate([policy[s]]):
                for prob, next_state, reward, done in env.P[s][a]:
                    if next_state == s:
                        Vs += reward
                    else:
                        Vs += action_prob * prob * (reward + gamma *␣
↪value_func[next_state])
            delta = max(delta, np.abs(value_func[s] - Vs))
            value_func[s] = Vs
        if delta < tol:
            break
    return value_func, val_iter
```

```
#     val_iter=0
#     new_value_func = np.zeros(env.nS)
#     for val_iter in range(max_iterations):
#         delta = 0
#         # For each state, perform a "full backup"
#         for s in range(env.nS):
#             old_value = value_func
#             a = policy[s]
#             for prob, next_state, reward, done in env.P[s][a]:
#                 if next_state == s:
#                     new_value_func[s] = reward
#                 else:
#                     new_value_func[s] = action_prob * prob * (reward + gamma␣
↪* value_func[next_state])
#             delta = np.abs(old_value - new_value_func)
#         if np.all(delta < tol):
#             break
#     return new_value_func, val_iter

env = FrozenLakeEnv(map_name ="4x4", is_slippery=False)
env.reset()
action = 1
(observation, reward, done, prob) = env.step(action)
env.render()
action = 1
(observation, reward, done, prob) = env.step(action)
env.render()
action = 1
(observation, reward, done, prob) = env.step(action)
env.render()


# Checking #
policy = np.random.randint(0, 4, size=env.nS)
value_func = np.zeros(env.nS)
gamma = 0.99
V, val_iter = evaluate_policy_sync(env, gamma, policy, value_func)
print(V)
import seaborn as sns
plt.figure()
sns.heatmap(V.reshape(4,4), cmap='YlGnBu', annot=True, cbar=False)
S_n = env.observation_space
A_n = env.action_space
print(S_n)
```

```
  (Down)
SFFF
```

```
FHFH
FFFH
HFFG
  (Down)
SFFF
FHFH
FFFH
HFFG
  (Down)
SFFF
FHFH
FFFH
HFFG
[1.        1.99      2.9701    6.880798 1.        1.        2.98      1.
 1.        2.98      1.        1.        1.        1.99      2.9701    1.        ]
16
```



[302]:

```python
def improve_policy(env, gamma, value_func, policy):
    """Performs policy improvement.

    Given a policy and value function, improves the policy.

    Parameters
    ----------
    env: Frozen Lake Environment
      The environment to compute value iteration for.
```

```
    gamma: float
      Discount factor, must be in range [0, 1)
    value_func: np.ndarray
      Value function for the given policy.
    policy: dict or np.array
      The policy to improve. Maps states to actions.

    Returns
    -------
    bool, np.ndarray
      Returns the new imporved policy.
    """
    for s in range(env.nS):
        old_action = policy[s]
        action_values = q_value(env, s, value_func, gamma)
        policy[s] = np.argmax(action_values)

    return policy

#     return new_policy
```

[303]:

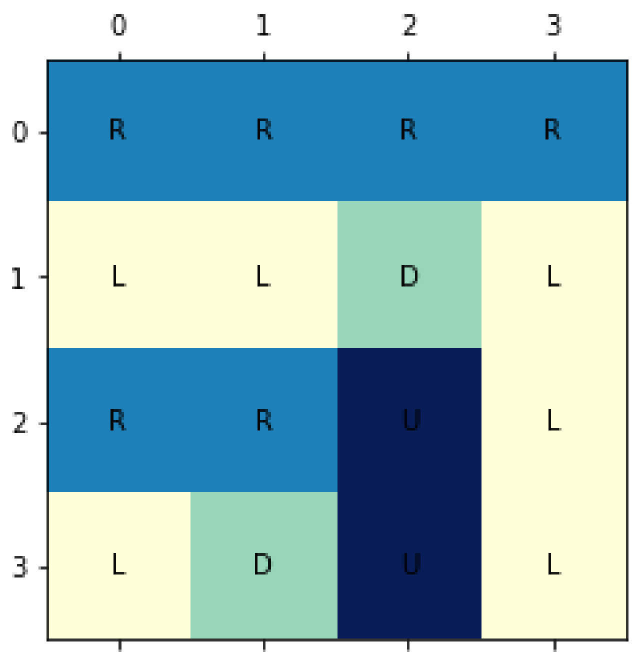
```
import copy
def policy_iteration_sync(env, gamma, max_iterations=int(1e3), tol=1e-3):
    """Runs policy iteration.

    See page 85 of the Sutton & Barto Second Edition book.

    You should call the improve_policy() and evaluate_policy_sync() methods to
    implement this method.

    If you've implemented this correctly, it should take much less than 1␣
 ↪second.

    Parameters
    ----------
    env: Frozen Lake Environment
      The environment to compute value iteration for.
    gamma: float
      Discount factor, must be in range [0, 1)
    max_iterations: int
      The maximum number of iterations to run before stopping.
    tol: float
      Determines when value function has converged.

    Returns
    -------
    (np.ndarray, np.ndarray, int, int)
```

```
        Returns optimal policy, value function, number of policy
        improvement iterations, and number of value iterations.
    """

    policy = np.random.randint(0, 4, size=env.nS)   #Define random policy
    value_func = np.zeros(env.nS)     # Define initial value function
    num_pol_iter = 0
    num_val_iter = 0
    value_iter_list = []
    for i in range(max_iterations):
        value_func, val_iter = evaluate_policy_sync(env, gamma, policy,␣
↪value_func)
        num_val_iter += val_iter
        value_iter_list.append(value_func)
        new_policy = improve_policy(env, gamma, value_func, policy)
        num_pol_iter +=1
        policy=new_policy.copy()
        delta = policy-new_policy
        if delta.all() < tol:
            break



    return policy, value_func, num_pol_iter, num_val_iter, value_iter_list
```

[318]:
```
# from plot_utils import plot_values
def main():

    # WRITE YOUR CODE HERE:
    env = FrozenLakeEnv(map_name ="4x4", is_slippery=False)
    gamma = 0.99
    startTime = time.time()
    policy, value_func, num_pol_iter, num_val_iter, value_iter_list =␣
↪policy_iteration_sync(env, gamma)

    endTime = time.time()
    print("The running time for value iterations is ", endTime-startTime, '␣
↪seconds')
    print(num_pol_iter)
    print(num_val_iter)
    action_names = {0:'L', 1:'D', 2:"R", 3:"U"}
    print_policy(policy, action_names, env.nS)
    print(value_func.reshape([-1,4]))

    fig = plt.figure()
    ax = fig.add_subplot(111)
    plt.title('Value Function of the policy')
```

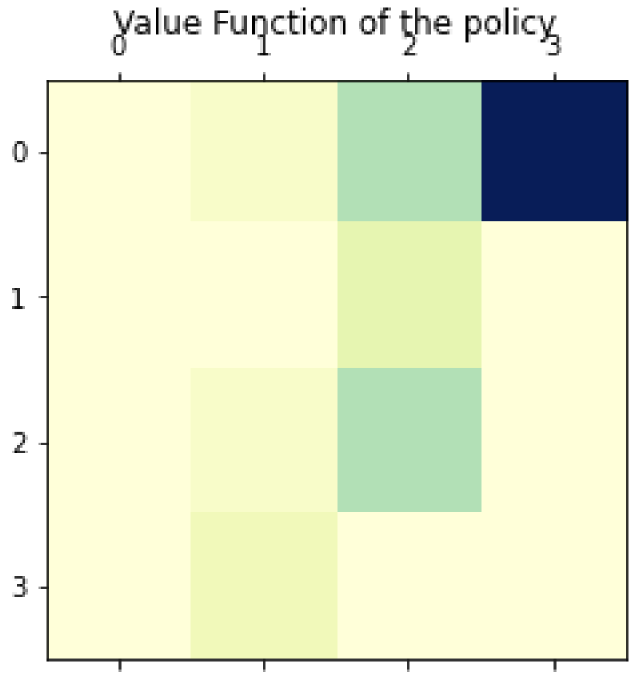
```
    ax.matshow(value_func.reshape([-1,4]), cmap='YlGnBu')

#     plot_values(value_func)

#     env.render()
#     obs, reward, done, _ = env.step(policy[env.s])
#     while done is False:
#         env.render()
#         obs, reward, done, _, env.step(policy[obs])
#     env.render()
# Plot a graph showing the value function of all states as a function of number
 ↪of policy iterations
# for 4 by 4 maps.



if __name__ == "__main__":
    main()
```

```
The running time for value iterations is  0.0008482933044433594  seconds
1
1
```




```
[[ 1.         1.99       6.9103    21.523591]
 [ 1.         1.         3.97       1.       ]
 [ 1.         1.99       6.9103     1.       ]
```

```
[ 1.          2.98       1.          1.       ]]
```

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