MVA - Homework 1 - Reinforcement Learning (2022/2023)

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Instructions

- The deadline is **November 10 at 11:59 pm (Paris time).**
- By doing this homework you agree to the late day policy, collaboration and misconduct rules reported on Piazza.
- **Mysterious or unsupported answers will not receive full credit**. A correct answer, unsupported by calculations, explanation, or algebraic work will receive no credit; an incorrect answer supported by substantially correct calculations and explanations might still receive partial credit.
- Answers should be provided in **English**.

Colab setup

```
from IPython import get_ipython

if 'google.colab' in str(get_ipython()):
  # install rlberry library
  !pip install git+https://github.com/rlberry-py/rlberry.git@mva2021#egg=rlberry[default

  # install ffmpeg-python for saving videos
  !pip install ffmpeg-python > /dev/null 2>&1

  # packages required to show video
  !pip install pyvirtualdisplay > /dev/null 2>&1
  !apt-get install -y xvfb python-opengl ffmpeg > /dev/null 2>&1

  print("Libraries installed, please restart the runtime!")
```

```
    Libraries installed, please restart the runtime!
```

```
# Create directory for saving videos
!mkdir videos > /dev/null 2>&1

# Initialize display and import function to show videos
import rlberry.colab_utils.display_setup
```

✓ 6 sn. tamamlanma zamanı: 23:01

```
# Useful libraries
import numpy as np
import matplotlib.pyplot as plt
import numpy
```

Preparation

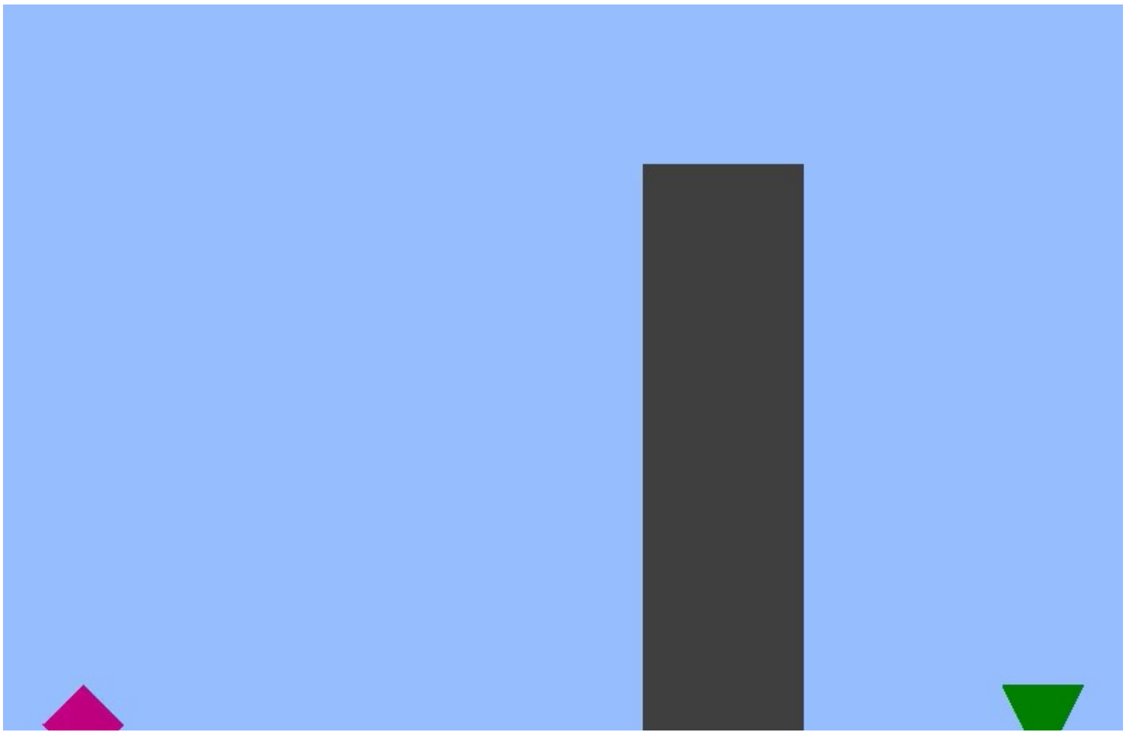
In the coding exercises, you will use a *grid-world* MDP, which is represented in Python using the interface provided by the Gym library. The cells below show how to interact with this MDP and how to visualize it.

```
from rlberry.envs import GridWorld

def get_env():
  """Creates an instance of a grid-world MDP."""
  env = GridWorld(
      nrows=5,
      ncols=7,
      reward_at = {(0, 6):1.0},
      walls=((0, 4), (1, 4), (2, 4), (3, 4)),
      success_probability=0.9,
      terminal_states=((0, 6),)
  )
  return env

def render_policy(env, policy=None, horizon=50):
  """Visualize a policy in an environment

  Args:
    env: GridWorld
        environment where to run the policy
    policy: np.array
        matrix mapping states to action (Ns).
        If None, runs random policy.
    horizon: int
        maximum number of timesteps in the environment.
  """
  env.enable_rendering()
  state = env.reset()                       # get initial state
  for timestep in range(horizon):
      if policy is None:
        action = env.action_space.sample()  # take random actions
      else:
        action = policy[state]
      next_state, reward, is_terminal, info = env.step(action)
      state = next_state
      if is_terminal:
        break
```

```
  # save video and clear buffer
  env.save_video('./videos/gw.mp4', framerate=5)
  env.clear_render_buffer()
  env.disable_rendering()
  # show video
  show_video('./videos/gw.mp4')
```

```
[INFO] OpenGL_accelerate module loaded
[INFO] Using accelerated ArrayDatatype
[INFO] Generating grammar tables from /usr/lib/python3.7/lib2to3/Grammar.txt
[INFO] Generating grammar tables from /usr/lib/python3.7/lib2to3/PatternGrammar.tx
/usr/local/lib/python3.7/dist-packages/past/types/oldstr.py:5: DeprecationWarning:
  from collections import Iterable
/usr/local/lib/python3.7/dist-packages/past/builtins/misc.py:4: DeprecationWarning
  from collections import Mapping
```

```
# Create an environment and visualize it
env = get_env()
render_policy(env)  # visualize random policy

# The reward function and transition probabilities can be accessed through
# the R and P attributes:
print(f"Shape of the reward array = (S, A) = {env.R.shape}")
print(f"Shape of the transition array = (S, A, S) = {env.P.shape}")
print(f"Reward at (s, a) = (1, 0): {env.R[1, 0]}")
print(f"Prob[s\'=2 | s=1, a=0]: {env.P[1, 0, 2]}")
print(f"Number of states and actions: {env.Ns}, {env.Na}")

# The states in the griworld correspond to (row, col) coordinates.
# The environment provides a mapping between (row, col) and the index of
# each state:
print(f"Index of state (1, 0): {env.coord2index[(1, 0)]}")
print(f"Coordinates of state 5: {env.index2coord[5]}")
```



```
Shape of the reward array = (S, A) = (31, 4)
Shape of the transition array = (S, A, S) = (31, 4, 31)
Reward at (s, a) = (1, 0): 0.0
Prob[s'=2 | s=1, a=0]: 0.04999999999999999
Number of states and actions: 31, 4
Index of state (1, 0): 6
Coordinates of state 5: (0, 6)
```

Part 1 - Dynamic Programming

Question 1.1

Consider a general MDP with a discount factor of $\gamma < 1$. Assume that the horizon is infinite (so there is no termination). A policy π in this MDP induces a value function V^π. Suppose an affine transformation is applied to the reward, what is the new value function? Is the optimal policy preserved?

Answer

[your answer here]

Question 1.2

Consider an infinite-horizon γ-discounted MDP. We denote by Q^* the Q-function of the optimal policy π^*. Prove that, for any function $Q(s,a)$ (which is **not** necessarily the value function of a policy), the following inequality holds for any state s:

$$V^{\pi_Q}(s) \geq V^*(s) - \frac{2}{1-\gamma}||Q^* - Q||_\infty,$$

where $||Q^* - Q||_\infty = \max_{s,a} |Q^*(s,a) - Q(s,a)|$ and $\pi_Q(s) \in \arg\max_a Q(s,a)$. Can you use this result to show that any policy π such that $\pi(s) \in \arg\max_a Q^*(s,a)$ is optimal?

Answer

[your answer here]

Question 1.3

In this question, you will implement and compare the policy and value iteration algorithms for

In this question, you will implement and compare the policy and value iteration algorithms for a finite MDP.

Complete the functions `policy_evaluation`, `policy_iteration` and `value_iteration` below.

Compare value iteration and policy iteration. Highlight pros and cons of each method.

Answer

[pros/cons of each method + implementation below]

```
from numpy.matrixlib.defmatrix import N

def policy_evaluation(P, R, policy, gamma=0.9, tol=1e-2):
    """
    Args:
        P: np.array
            transition matrix (NsxNaxNs)
        R: np.array
            reward matrix (NsxNa)
        policy: np.array
            matrix mapping states to action (Ns)
        gamma: float
            discount factor
        tol: float
            precision of the solution
    Return:
        value_function: np.array
            The value function of the given policy
    """
    Ns, Na = R.shape #state length, action length
    V = np.zeros(Ns) #we initialize value functions for each state
    while True:
      delta = 0
      #for each state, performing a "full backup"
      for s in range(Ns):
        v=0
        #Look for possible next actions from policy
        for a,a_prob in enumerate(policy[s]):
          #for each action, look at possible nex states
          for next_state in range(Ns):
            v+=a_prob*P[s,a,next_state]*(R[s,a]+gamma*V[next_state])
        #how much value function changed
        delta = max(delta, np.abs(v-V[s]))
        V[s]=v
      if delta<tol:
        break
    return np.array(V)

Ns,Na=env.R.shape
policy_evaluation(env.P,env.R,np.ones([Ns,Na])/Na)
```

```
array([3.40798035e-03, 4.08578575e-03, 5.12920622e-03, 5.99341260e-03,
```

```
       5.46035208e+00, 9.91272036e+00, 4.58392315e-03, 5.80688989e-03,
       7.88333856e-03, 9.83330944e-03, 3.46496072e+00, 4.52616652e+00,
       6.86950933e-03, 9.48408153e-03, 1.45341564e-02, 2.02879948e-02,
       1.96309467e+00, 2.22179801e+00, 9.95748880e-03, 1.52462061e-02,
       2.73317560e-02, 4.59822249e-02, 1.08472809e+00, 1.16965617e+00,
       1.26236906e-02, 2.13923468e-02, 4.63016432e-02, 1.11588008e-01,
       2.93676893e-01, 6.10101215e-01, 7.26572317e-01])
```

```
from ast import Name
from numpy.core.fromnumeric import argmax
from scipy.optimize import minimize
import numpy as np
def policy_iteration(P,R, gamma=0.9,tol=1e-3):

    Ns,Na=R.shape

#supportive function to look one step ahead
    def one_step_lookahead(state, V):

        A = np.zeros(Na)
        for a in range(Na):
            for next_state in range(Ns):
                A[a] += P[state,a,next_state] * (R[state,a] + gamma * V[next_state])
        return A

    # Start with a random policy
    policy = np.ones([Ns,Na])/Na

    while True:
        # Evaluate the current policy
        V = policy_evaluation(P,R,policy,gamma)

        # Will be set to false if we make any changes to the policy
        policy_stable = True

        # For each state
        for s in range(Ns):
            # The best action we would take under the current policy
            chosen_a = np.argmax(policy[s])

            # Find the best action by one-step lookahead
            action_values = one_step_lookahead(s, V)
            best_a = np.argmax(action_values)

            # Greedily update the policy
            if chosen_a != best_a:
                policy_stable = False
            policy[s] = best_a

        # If the policy is stable return it
        if policy_stable:
            return policy, V
```

```
def value_iteration(P,R,gamma=0.9,tol=1e-3):
    """
    Args:
        P: np.array
            transition matrix (NsxNaxNs)
        R: np.array
            reward matrix (NsxNa)
        gamma: float
            discount factor
        tol: float
            precision of the solution
    Return:
        Q: final Q-function (at iteration n)
        greedy_policy: greedy policy wrt Qn
        Qfs: all Q-functions generated by the algorithm (for visualization)
    """

    Ns, Na = R.shape
    Q = np.zeros((Ns, Na))
    Qfs = [Q]

    converged=False
    while not converged:
      delta = 0
      for s in range(int(Ns)):
        for a in range(int(Na)):
          tmp = Q[s,a]
          Q[s,a] = 0
          for n_s in range(int(Ns)):
            Q[s,a] += P[s,a,n_s] * (R[s,a] + gamma * np.max(Q[n_s]))
          delta = np.maximum(delta, np.abs(tmp - Q[s,a]))
      Qfs.append(Q)
      converged = True if delta < tol else False

    greedy_policy = np.argmax(Q,axis=1)
    #

    return Q, greedy_policy, Qfs
```

Testing your code

```
from matplotlib import pyplot as plt

# Parameters
tol = 1e-5
gamma = 0.99

# Environment
env = get_env()
```

```
# run value iteration to obtain Q-values
VI_Q, VI_greedypol, all_qfunctions = value_iteration(env.P, env.R, gamma=gamma, tol=tol)

print(VI_greedypol)
# render the policy
print("[VI]Greedy policy: ")
render_policy(env, VI_greedypol)

# compute the value function of the greedy policy using matrix inversion
# ====================================================
# YOUR IMPLEMENTATION HERE
# compute value function of the greedy policy

#V_greedy = policy_evaluation(env.P,env.R,VI_greedypol)

#

# ====================================================

# show the error between the computed V-functions and the final V-function
# (that should be the optimal one, if correctly implemented)
# as a function of time
final_V = all_qfunctions[-1].max(axis=1)
norms = [ np.linalg.norm(q.max(axis=1) - final_V) for q in all_qfunctions]
plt.plot(norms)
plt.xlabel('Iteration')
plt.ylabel('Error')
plt.title("Value iteration: convergence")

#### POLICY ITERATION ####
PI_policy, PI_V = policy_iteration(env.P, env.R, gamma=gamma, tol=tol)
print("\n[PI]final policy: ")
render_policy(env, PI_policy)

## Uncomment below to check that everything is correct
#assert np.allclose(PI_policy, VI_greedypol),\
#"You should check the code, the greedy policy computed by VI is not equal to the soluti
#np.allclose(PI_V, greedy_V),\
#     "Since the policies are equal, even the value function should be"

plt.show()
```

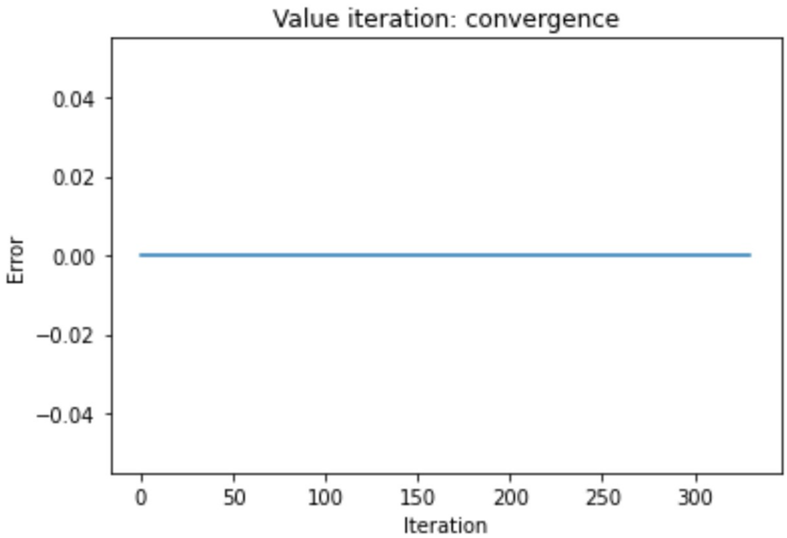
```
[3 1 3 3 1 3 3 3 3 3 2 2 3 3 3 3 2 2 1 1 3 3 2 2 1 1 1 1 1 2 2]
[VI]Greedy policy:
```

```
[PI]final policy:
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-8-ae25be51f672> in <module>
     40 PI_policy, PI_V = policy_iteration(env.P, env.R, gamma=gamma, tol=tol)
     41 print("\n[PI]final policy: ")
---> 42 render_policy(env, PI_policy)
     43 
     44 ## Uncomment below to check that everything is correct
```

1 frames

```
/usr/local/lib/python3.7/dist-packages/rlberry/envs/finite/gridworld.py in
step(self, action)
    280 
    281     def step(self, action):
--> 282         assert self.action_space.contains(action), "Invalid action!"
    283 
    284         # save state for rendering

AssertionError: Invalid action!
```

SEARCH STACK OVERFLOW



Part 2 - Tabular RL

Question 2.1

The code below collects two datasets of transitions (containing states, actions, rewards and next states) for a discrete MDP.

For each of the datasets:

1. Estimate the transitions and rewards, $\hat{P}$ and $\hat{R}$.
2. Compute the optimal value function and the optimal policy with respect to the estimated MDP (defined by $\hat{P}$ and $\hat{R}$), which we denote by $\hat{\pi}$ and $\hat{V}$.
3. Numerically compare the performance of $\hat{\pi}$ and $\pi^\star$ (the true optimal policy), and the error between $\hat{V}$ and V^* (the true optimal value function).

Which of the two data collection methods do you think is better? Why?

Answer

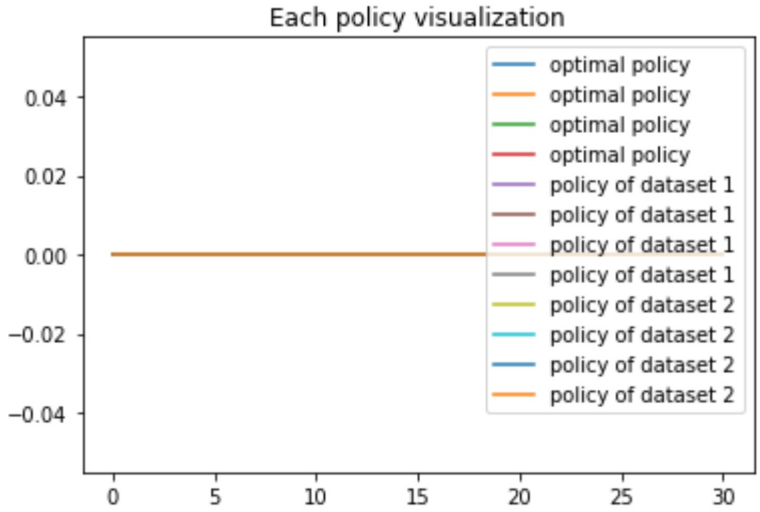
[answer last question + implementation below]

```
def get_random_policy_dataset(env, n_samples):
  """Get a dataset following a random policy to collect data."""
  states = []
  actions = []
  rewards = []
  next_states = []

  state = env.reset()
  for _ in range(n_samples):
    action = env.action_space.sample()
    next_state, reward, is_terminal, info = env.step(action)
    states.append(state)
    actions.append(action)
    rewards.append(reward)
    next_states.append(next_state)
    # update state
    state = next_state
    if is_terminal:
      state = env.reset()

  dataset = (states, actions, rewards, next_states)
  return dataset

def get_uniform_dataset(env, n_samples):
  """Get a dataset by uniformly sampling states and actions."""
  states = []
  actions = []
  rewards = []
  next_states = []
  for _ in range(n_samples):
    state = env.observation_space.sample()
```

```
    action = env.action_space.sample()
    next_state, reward, is_terminal, info = env.sample(state, action)
    states.append(state)
    actions.append(action)
    rewards.append(reward)
    next_states.append(next_state)

  dataset = (states, actions, rewards, next_states)
  return dataset


# Collect two different datasets
num_samples = 500
env = get_env()
dataset_1 = get_random_policy_dataset(env, num_samples)
dataset_2 = get_uniform_dataset(env, num_samples)


# Item 3: Estimate the MDP with the two datasets; compare the optimal value
# functions in the true and in the estimated MDPs

# ...

def estimate_p_r(env,dataset):
  Ns,Na = env.R.shape
  P = np.zeros([Ns,Na,Ns])
  R = np.zeros([Ns,Na])

  for (state,action,reward,nextState) in np.array(dataset).T:
    P[int(state),int(action),int(nextState)]+=1
    R[int(state),int(action)] += reward

  for state in range(Ns):
    for a in range(Na):
      N = max(1.,np.sum(P[int(state),int(action)])) #to divide the number of samples P a
      R[int(state),int(action)] /= N
      P[int(state),int(action)] /= N
  return P,R

P_data1, R_data1 = estimate_p_r(env,dataset_1)

P_data2, R_data2 = estimate_p_r(env,dataset_2)

optimalPolicy,optimalValueFunction=policy_iteration(env.P,env.R)
dataset_1Policy, dataset_1ValueFunction = policy_iteration(P_data1,R_data1)

dataset_2Policy, dataset_2ValueFunction = policy_iteration(P_data2,R_data2)

error_data1 = np.linalg.norm(optimalValueFunction - dataset_1ValueFunction, ord=np.inf)
error_data2 = np.linalg.norm(optimalValueFunction - dataset_2ValueFunction, ord=np.inf)

print("Error of data set 1 is:", error_data1)
print("Error of data set 2 is:", error_data2)
```

```
Ns = range(env.R.shape[0])
plt.title("Each policy visualization")
plt.plot(Ns, optimalPolicy, label="optimal policy")
plt.plot(Ns, dataset_1Policy, label="policy of dataset 1")
plt.plot(Ns, dataset_2Policy, label="policy of dataset 2")
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:31: RuntimeWarning: o
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:31: RuntimeWarning: i
Error of data set 1 is: 0.0
Error of data set 2 is: nan
```



Question 2.2

Suppose that $\hat{P}$ and $\hat{R}$ are estimated from a dataset of exactly N i.i.d. samples from **each** state-action pair. This means that, for each (s,a), we have N samples $\{(s'_1, r_1, \ldots, s'_N, r_N\}$, where $s'_i \sim P(\cdot|s,a)$ and $r_i \sim R(s,a)$ for $i = 1, \ldots, N$, and

$$\hat{P}(s'|s,a) = \frac{1}{N}\sum_{i=1}^{N} 1(s'_i = s'),$$

$$\hat{R}(s,a) = \frac{1}{N}\sum_{i=1}^{N} r_i.$$

Suppose that R is a distribution with support in $[0,1]$. Let $\hat{V}$ be the optimal value function computed in the empirical MDP (i.e., the one with transitions $\hat{P}$ and rewards $\hat{R}$). For any $\delta \in (0,1)$, derive an upper bound to the error

$$\|\hat{V} - V^*\|_\infty$$

which holds with probability at least $1-\delta$.

Note Your bound should only depend on deterministic quantities like N, γ, δ, S, A. It should *not* dependent on the actual random samples.

Hint The following two inequalities may be helpful.

1. **A (simplified) lemma**. For any state s,

$$|\hat{V}(\bar{s}) - V^*(\bar{s})| \leq \frac{1}{1-\gamma} \max_{s,a} \left| R(s,a) - \hat{R}(s,a) + \gamma \sum_{s'} (P(s'|s,a) - \hat{P}(s'|s,a)) V \right.$$

2. **Hoeffding's inequality**. Let $X_1, \ldots X_N$ be N i.i.d. random variables bounded in the interval $[0, b]$ for some $b > 0$. Let $\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i$ be the empirical mean. Then, for any $\epsilon > 0$,

$$\mathbb{P}(|\bar{X} - \mathbb{E}[\bar{X}]| > \epsilon) \leq 2e^{-\frac{2N\epsilon^2}{b^2}}.$$

Answer

[your derivation here]

Question 2.3

Suppose once again that we are given a dataset of N samples in the form of tuples (s_i, a_i, s_i', r_i). We know that each tuple contains a valid transition from the true MDP, i.e., $s_i' \sim P(\cdot|s_i, a_i)$ and $r_i \sim R(s_i, a_i)$, while the state-action pairs (s_i, a_i) from which the transition started can be arbitrary.

Suppose we want to apply Q-learning to this MDP. Can you think of a way to leverage this offline data to improve the sample-efficiency of the algorithm? What if we were using SARSA instead?

Answer

[your answer here]

Part 3 - RL with Function Approximation

Question 3.1

Given a datset (s_i, a_i, r_i, s_i') of (states, actions, rewards, next states), the Fitted Q-Iteration (FQI) algorithm proceeds as follows:

- We start from a Q function $Q_0 \in \mathcal{F}$, where $\mathcal{F}$ is a function space;
- At every iteration k, we compute Q_{k+1} as:

$$Q_{k+1} \in \arg\min \frac{1}{2} \sum^{N} \left(f(s_i, a_i) - y_i^k\right)^2 + \lambda\Omega(f)$$

$$f \in \mathcal{F} \quad 2 \sum_{i=1}$$

where $y_i^k = r_i + \gamma \max_{a'} Q_k(s_i', a')$, $\Omega(f)$ is a regularization term and $\lambda > 0$ is the regularization coefficient.

Consider FQI with *linear* function approximation. That is, for a given feature map $\phi : S \to \mathbb{R}^d$, we consider a parametric family of Q functions $Q_\theta(s, a) = \phi(s)^T \theta_a$ for $\theta_a \in \mathbb{R}^d$. Suppose we are applying FQI on a given dataset of N tuples of the form (s_i, a_i, r_i, s_i') and we are at the k-th iteration. Let $\theta_k \in \mathbb{R}^{d \times A}$ be our current parameter. Derive the *closed-form* update to find θ_{k+1}, using $\frac{1}{2} \sum_a ||\theta_a||_2^2$ as regularization.

Answer

[your derivation here]

Question 3.2

The code below creates a larger gridworld (with more states than the one used in the previous questions), and defines a feature map. Implement linear FQI to this environment (in the function `linear_fqi()` below), and compare the approximated Q function to the optimal Q function computed with value iteration.

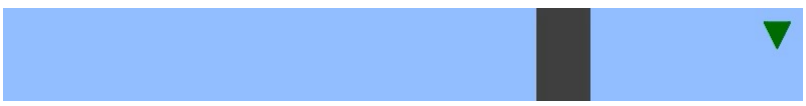
Can you improve the feature map in order to reduce the approximation error?

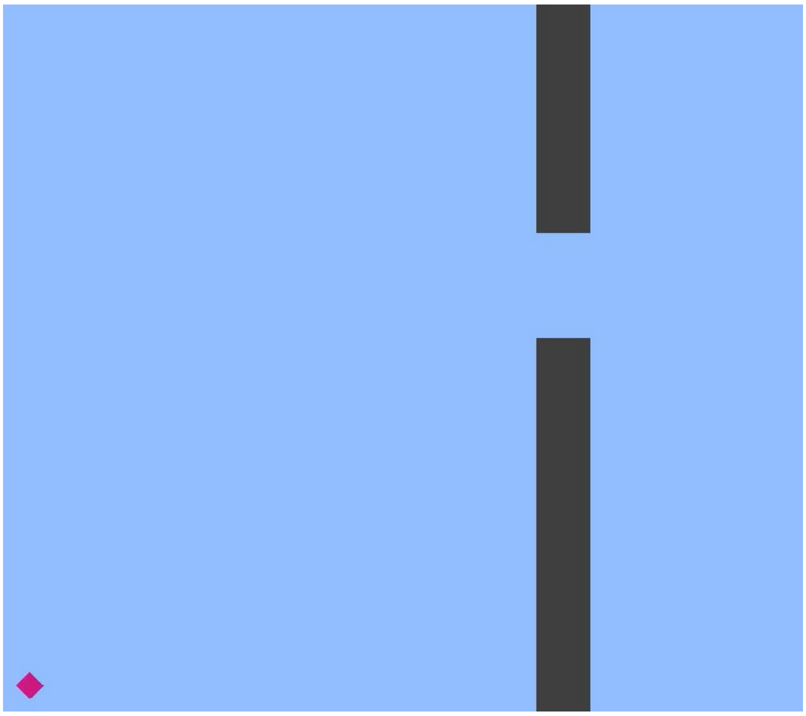
Answer

[explanation about how you tried to reduce the approximation error + FQI implementation below]

```
def get_large_gridworld():
  """Creates an instance of a grid-world MDP with more states."""
  walls = [(ii, 10) for ii in range(15) if (ii != 7 and ii != 8)]
  env = GridWorld(
      nrows=15,
      ncols=15,
      reward_at = {(14, 14):1.0},
      walls=tuple(walls),
      success_probability=0.9,
      terminal_states=((14, 14),)
  )
  return env


class GridWorldFeatureMap:
  """Create features for state-action pairs

  Args:
```

```
    dim: int
      Feature dimension
    sigma: float
      RBF kernel bandwidth
  """
  def __init__(self, env, dim=15, sigma=0.25):
    self.index2coord = env.index2coord
    self.n_states = env.Ns
    self.n_actions = env.Na
    self.dim = dim
    self.sigma = sigma

    n_rows = env.nrows
    n_cols = env.ncols

    # build similarity matrix
    sim_matrix = np.zeros((self.n_states, self.n_states))
    for ii in range(self.n_states):
        row_ii, col_ii = self.index2coord[ii]
        x_ii = row_ii / n_rows
        y_ii = col_ii / n_cols
        for jj in range(self.n_states):
            row_jj, col_jj = self.index2coord[jj]
            x_jj = row_jj / n_rows
            y_jj = col_jj / n_cols
            dist = np.sqrt((x_jj - x_ii) ** 2.0 + (y_jj - y_ii) ** 2.0)
            sim_matrix[ii, jj] = np.exp(-(dist / sigma) ** 2.0)

    # factorize similarity matrix to obtain features
    uu, ss, vh = np.linalg.svd(sim_matrix, hermitian=True)
    self.feats = vh[:dim, :]

  def map(self, observation):
    feat = self.feats[:, observation].copy()
    return feat


env = get_large_gridworld()
feat_map = GridWorldFeatureMap(env)

# Visualize large gridworld
render_policy(env)

# The features have dimension (feature_dim).
feature_example = feat_map.map(1) # feature representation of s=1
print(feature_example)

# Initial vector theta representing the Q function
theta = np.zeros((feat_map.dim, env.action_space.n))
print(theta.shape)
print(feature_example @ theta) # approximation of Q(s=1, a)
```



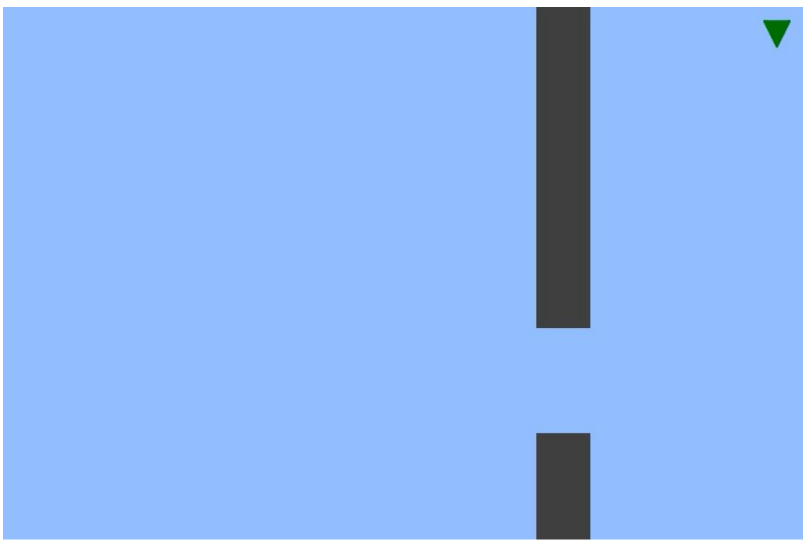


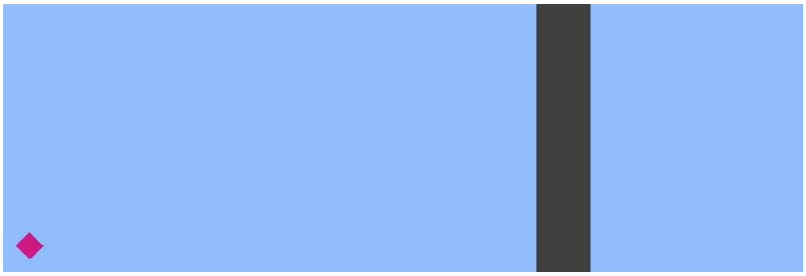
```
[-0.02850699  0.063555   -0.02169407 -0.06441918  0.04505794 -0.07537777
  0.08506473 -0.09325287  0.09644275 -0.00535101  0.11632395 -0.13074085
  0.00921342 -0.13853662  0.07118419]
(15, 4)
[0. 0. 0. 0.]
```

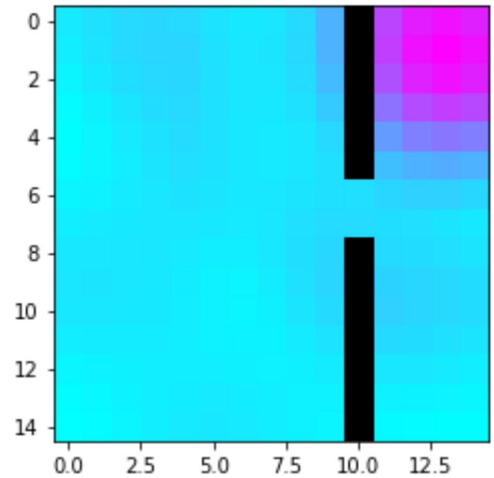
```
def linear_fqi(env, feat_map, num_iterations, lambd=0.1, gamma=0.95):
  """
  # Linear FQI implementation
  # TO BE COMPLETED
  """

  # get a dataset
  dataset = get_uniform_dataset(env, n_samples=400)
  #dataset = get_random_policy_dataset(env, n_samples=400)
  (states, actions, rewards, nextStates) = dataset

  x = 0
  while max(rewards) == 0 and x < 20  :
    dataset = get_random_policy_dataset(env, n_samples=500)
    (states, actions, rewards, nextStates) = dataset
    x +=1
  print(x)

  Rmax = max(rewards)
  theta = np.zeros((feat_map.dim, env.Na))

  for it in range(num_iterations):
    for action in range(env.Na):
      temp = np.copy(theta)
      to_inv = 0
      sum_term = 0
      for j in range(len(actions)):
        if  actions[j] == action :
          to_inv += np.outer(feat_map.map(states[j]), feat_map.map(states[j]))
```

```
     fsa = max( feat_map.map(nextStates[j]) @ temp )
     if fsa > 0 :
      fsa = min(fsa , Rmax / (1-gamma) )
     else :
      fsa = max(fsa, - Rmax/(1-gamma))

     y_i_k = rewards[j] + gamma * fsa
     sum_term += y_i_k * feat_map.map(states[j])

   to_inv += lambd * np.eye(feat_map.dim)
   theta[:,action] =  np.linalg.inv(to_inv) @ sum_term
 return theta

# ----------------------------
# Environment and feature map
# ----------------------------
env = get_large_gridworld()
# you can change the parameters of the feature map, and even try other maps!
feat_map = GridWorldFeatureMap(env, dim=15, sigma=0.25)

# -------
# Run FQI
# -------
theta = linear_fqi(env, feat_map, num_iterations=100)
# Compute and run greedy policy
Q_fqi = np.zeros((env.Ns, env.Na))
for x in range(env.Ns):
 state_feat = feat_map.map(x)
 Q_fqi[x, :] = state_feat @ theta

V_fqi = Q_fqi.max(axis=1)
policy_fqi = Q_fqi.argmax(axis=1)
render_policy(env, policy_fqi, horizon=100)

# Visualize the approximate value function in the gridworld.
img = env.get_layout_img(V_fqi)
plt.imshow(img)
plt.show()
```

```
0
```







Colab'in ücretli ürünleri - Sözleşmeleri buradan iptal edebilirsiniz