UNIVERSITY OF VIRGINIA

CS 6501-012: LEARNING IN ROBOTICS

HOMEWORK 4

DUE: 05/07/25 TUE BY 11.59 PM

Instructions

Read the following instructions carefully before beginning to work on the homework.

- All the files required for this homework (starter code, reference PDFs etc.) are available in the following directory: **Canvas » Files » hw4**.
- You will submit solutions typeset in LaTeX on Gradescope. You can use hw_template.tex from the course website (under assignments).
- Please start a new problem on a fresh page and mark all the pages corresponding to each problem. Failure to do so may result in your work not graded completely.
- Clearly indicate the name and UVA email ID of all your collaborators on your submitted solutions.
- **For each problem in the homework, you should mention the total amount of time you spent on it. This helps us gauge the perceived difficulty of the problems.**
- You can be informal while typesetting the solutions, e.g., if you want to draw a picture feel free to draw it on paper clearly, click a picture and include it in your solution. Do not spend undue time on typesetting solutions.
- You will see an entry of the form "HW 4 PDF" where you will upload the PDF of your solutions. You will also see entries like "HW 4 Problem X Code" where you will upload your solution for the respective problems. **For each programming problem, you should create a fresh Python file**. This file should contain all the code to reproduce the results of the problem and you will upload the .py file to Gradescope. If we have installed Autograder for a particular problem, you will use the Autograder. Name your file to be the same filename as stated in the respective problem statement.
- **You should include all the relevant plots in the PDF, without doing so you will not get full credit.** You can, for instance, export your Jupyter notebook as a PDF (you can also use text cells to write your solutions) and export the same notebook as a Python file to upload your code.

- **Your PDF solutions should be completely self-contained. We will run the Python file to check if your solution reproduces the results in the PDF.**

Credit The points for the problems add up to 100. You only need to solve for 100 points to get full credit, i.e., your final score will be min(your total points, 100).

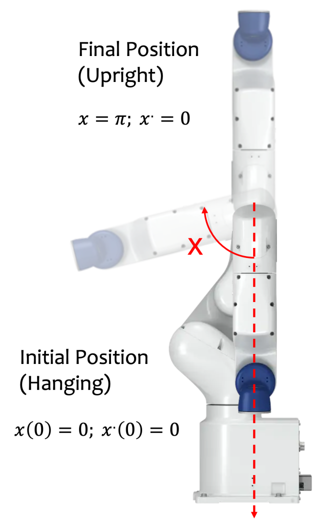
Problem 1 (Robotic Arm Stabilization, 50 points). You will develop and train a controller to balance a robotic arm, modeled similarly to a damped pendulum, to maintain an upright position. The arm has a single joint, akin to a human elbow, and must be controlled to stabilize against gravity and other disturbances.

Rather than using a complex robotic arm simulator, we will employ the following simplified dynamics to simulate the arm's behavior (think of the equation below as our simulator for this problem):

$$ml^2\ddot{x} + b\dot{x} + mgl\sin(x) = u$$

where:

- x is the angle of the arm relative to the hanging downward position (in radians), measured from the downward vertical line.
- $\ddot{x}$ and $\dot{x}$ are the angular acceleration and velocity,
- u is the torque applied at the joint,
- $g = 9.8$ m/s^2 (acceleration due to gravity),
- $m = 1$ kg (mass of the arm),
- $l = 1$ meter (length of the arm from the joint to the center of mass),
- $b = 0.1$ Nm/s (damping coefficient representing joint friction).



The robotic arm starts from a downwards hanging position with $x(0) = \dot{x}(0) = 0$ and the task is to move it to and maintain it in the upright position where $x = \pi$ and $\dot{x} = 0$. The control input u is constrained such that:

$$|u| \leq 1.$$

Implement this controller using policy gradients and a neural network. The reward at a state x and control u is

$$r(x, \dot{x}, u) = -\frac{1}{2}\left[(\pi - x)^2 + \dot{x}^2 + \frac{1}{100}u^2\right].$$

We have provided you some example code on Canvas (p1.py); feel free to modify this code as you wish. But read the comments inside the code carefully before beginning to write your solution.

(a) **(10 points)** How is the stochastic controller $u_\theta(\cdot \mid x)$ implemented in the code ? What is the probability distribution, how is the log-likelihood $\log u_\theta(u|x)$ computed ? How is the constraint $|u| \leq 1$ enforced in the implementation ?

(b) **(30 points)** Implement code to train the policy using policy gradient. In the PDF, explain in detail:

- **[5]** How many trajectories you collected per iteration and the total number of iterations you trained for. Include code snippets showing the sampling loop.
- **[10]** How did you compute the policy gradient ? Include a code snippet that clearly shows and breaks down how you computed the log-likelihoods, multiplied by the returns.
- **[10]** What form of baseline did you use and how did you implement it ?
- **[5]** How gradient ascent was performed ? What optimizer did you use? What learning rate? What did you try, and what worked ?

(c) **(10 points)** First report and plot the cumulative reward over 1000 time-steps as a function of parameter updates to θ for **[5]** points. Then Modify your code to change the mass to $m = 2$ and evaluate the trained policy (with $m = 1$ on this new dynamics. Report the cumulative reward and comment on generalization. Only the evaluation phase uses $m = 2$. You should freeze the weights for $m = 1$ and do not retrain. **[5]**

Problem 2 (Q-Learning, 50 points). You will write code for Q-learning with the DDQN trick in this problem for a simple environment called the CartPole https://stanford.edu/ jeffjar/cartpole.html. We have provided some example code that uses PyTorch for Q-learning. You need to fill in the functions for epsilon-greedy exploration and the optimization objective. The code is given at p2.py on Canvas; feel free to modify this code as you wish.

We will be using OpenAI Gym's version of CartPole, read the code at https://github.com/openai/gym/blob/master/gym/envs/classic_control/cartpole.py to understand the environment. The class for the q-function in the example code looks as follows. The neural network s.m is a two-layer neural network with ReLU non-linearity. Notice that we have structured the network not as $q(x, u) : X \times U \to \mathbb{R}$ but instead as $q(x) : X \to U$. This way the neural network returns the q-value for all controls u with a single call to q_t.forward. You should implement the epsilon-greedy strategy to pick a control in the function q_t.control.

```
class q_t(nn.Module):
    def __init__(s, xdim, udim, hdim=16):
        super().__init__()
        s.xdim, s.udim = xdim, udim
        s.m = nn.Sequential(
                            nn.Linear(xdim, hdim),
                            nn.ReLU(True),
                            nn.Linear(hdim, udim),
                            )
    def forward(s, x):
        return s.m(x)

    def control(s, x, eps=0):
```

```
        # 1. get q values for all controls
        q = s.m(x)

        # eps-greedy strategy to choose control input
        # note that for eps=0
        # you should return the correct control u
        return u
```

Read the rollout function carefully. It takes a q-network and runs it for T timesteps to return a trajectory. You should add this trajectory to the replay buffer.

```
def rollout(e, q, eps=0, T=1000):
    traj = []

    x = e.reset()
    for t in range(T):
        u = q.control(th.from_numpy(x).float().unsqueeze(0),
                      eps=eps)
        u = u.int().numpy().squeeze()

        xp,r,d,info = e.step(u)
        t = dict(x=x,xp=xp,r=r,u=u,d=d,info=info)
        x = xp
        traj.append(t)
        if d:
            break
    return traj
```

You will code up the Bellman error minimization objective with the Double-Q network trick. Hint: You can use the following code to create a copy of the q-network. You can also modify the class q_t to create a copy of s.m inside it directly.

```
import copy
qc = copy.deepcopy(q)
```

Read the main function. We will create an environment e using the OpenAI Gym library, then initialize the q-network and create an optimizer (in this case Adam) to update the parameters of the q-network. The power of PyTorch lies in being able to call f.backward() to compute the gradient of whatever objective that depends on the parameters of the q-function. The call optim.step() udpates the parameters of the value-function.

```
if __name__=='__main__':
    e = gym.make('CartPole-v0')

    xdim, udim =    e.observation_space.shape[0], \
                    e.action_space.n

    q = q_t(xdim, udim, 8)
    optim = th.optim.Adam(q.parameters(), lr=1e-3,
```

```
                                weight_decay=1e-4)

    # this is the replay buffer
    ds = []

    # collect few random trajectories with
    # eps=1
    for i in range(1000):
        ds.append(rollout(e, q, eps=1, T=200))

    for i in range(1000):
        q.train()
        t = rollout(e, q)
        ds.append(t)

        # perform sgd updates on the q network
        # need to call zero grad on q function
        # to clear the gradient buffer
        q.zero_grad()
        f = loss(q, ds)
        f.backward()
        optim.step()
        print('Log data to plot')
```

During training you should keep track of the average return of the network. You should also fill in this function that evaluates the learnt q-function on a new environment.

```
def evaluate(q):
    # 1. create a new environment e
    # 2. run the learned q network for 100 trajectories on
    # this new environment and report the average discounted
    # return of these 100 trajectories
    return r
```

(30 points) Correctly code up all the methods above. Plot the following

1. **(30 points)** Explain your implementation with code snippets.
2. **(10 points)** Every 1000 gradient steps, evaluate the current q-network by running the learned policy for 10 episodes on the **training** environment. Plot the average total return across these episodes over the course of training.
3. **(10 points)** Similarly, evaluate the learned policy on a separate evaluation environment every 1000 gradient steps. Plot the average total return across 10 episodes over training.

The maximum achievable average reward for this environment is 200. You can call the render() function of the environment to see your trained policy on the Cartpole in action.