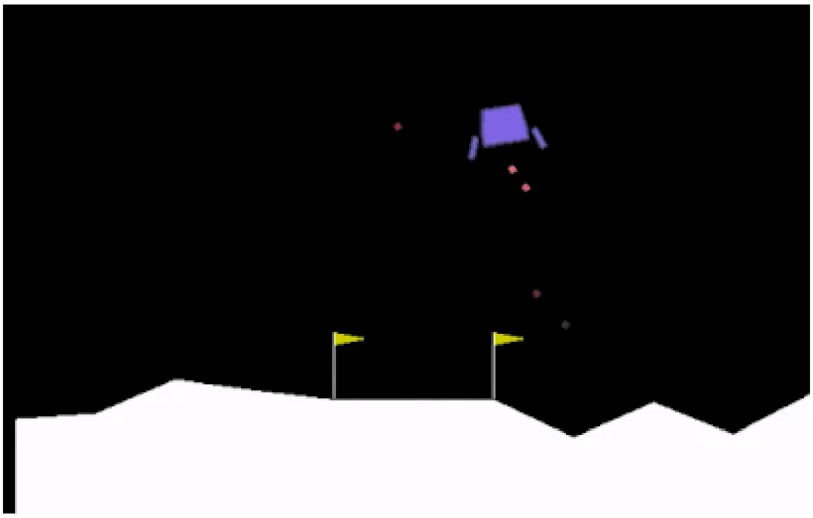
Probabilistic Artificial Intelligence Task 4: Reinforcement Learning

1 Task Description

Your task is to control a lunar lander in a smooth descent to the ground. It must land in-between two flags, quickly, using minimal fuel, and without damaging the lander. Implement a reinforcement learning algorithm that, by practicing on a simulator, learns a control policy for the lander.

This '.pdf' gives task-specific information. For logistics on submission and setup, see the description on the task webpage. In this document, we will first explain the task environment and scoring. Second, we will outline the minimal changes ('TODO's) needed to pass the baseline, before giving some ideas for extensions. Finally, we will provide some supplementary material on policy gradients to help you get started on the necessary 'TODO's.

2 Environment and Scoring Details



At each discrete time step, the controller can maneuver the lander by taking one of four actions: doing nothing, firing the left engine, firing the right engine, or firing the main engine. The goal is to accumulate as much reward as possible in 300 timesteps. In evaluation, after 300 timesteps the episode ends. Positive reward is obtained for landing between the flags and landing on the lander's legs. Negative reward is obtained for firing the main engine or side engines (more negative for the main engine) or for crashing the lander. Note that the lander only obtains positive reward for landing on its legs: if you land so fast that the legs hit the ground followed by the main lander body, it is counted as only crashing. Since the focus of this task is the implementation of reinforcement learning algorithms, it is not necessary to have a detailed understanding of the mechanics of the lunar lander environment beyond the observation and action space sizes (given in the train function of 'solution.py').

When you run 'solution.py', your algorithm will have access to the standard lunar lander environment that is commonly used in evaluating RL algorithms. To run 'solution.py' you will need to install the packages listed in 'requirements.txt'. You are encouraged to run 'solution.py' for testing.

In a single run of 'runner.sh', you will be able to query up to 150000 transitions (single timepoints) in order to learn a policy for the modified lunar lander environment. Each individual episode can contain up to 300 transitions. The score is then based upon the average performance of the learned policy over 100 episodes after the training episodes. The final score will be

$$\frac{1}{100}\sum_{i=1}^{100}\sum_{t=1}^{T} R_t^i.$$

where R_t^i is the reward achieved at time step t, episode i on the modified version of the environment, when using your final policy. In other words, the final score is an estimate of the expected cumulative reward of your final policy over an episode. Your goal is to maximize this final score.

The maximum possible score is around 200.

3 Solution Details

We give you skeleton code that provides most of the infrastructure for policy gradient algorithms. The 'TODO's in the code will guide you through implementing vanilla policy gradients with Generalized Advantage Estimation. Implementing only the 'TODO's as intended is sufficient to pass this task.

The skeleton provides you with the implementation of neural networks for computing the policy and the value function estimate. It is possible to pass the baseline by correctly implementing policy gradients with the suggested modifications and not changing the given network architectures.

We suggest working through the 'TODO's in three stages. The way the skeleton is written, after each stage you will have a working algorithm that you can test. To find the first TODO, search solution.py for 'TODO1'.

First, you will implement vanilla policy gradients or REINFORCE. The policy gradients computed in this approach have very high variance, which leads to poor sample complexity.

1. Implement the 'step' function in the 'MLPActorCritic' class. Given an observation, this function samples an action from the policy, computes its log-likelihood, and computes the value function estimate of the observation. The value function is not necessary in vanilla policy gradients, but you will need it for later steps in this walk-through.
2. Use the optimizers and architectures already given to you in order to update the policy neural networks at the end of each epoch.
3. Implement 'get_action' which is used by your agent to control the lander at evaluation time. It should take in an observation and return an action.

Second, you will implement rewards-to-go on top of policy gradients. This modifies the policy gradient to only consider information that happened **after** the taken action. It reduces variance by ignoring noisy rewards from the past which were not a consequence of the action under consideration.

4. Implement the computation of rewards-to-go in the ret_buf. For more information on what this means see the next section. Now your policy gradients update should use the rewards-to-go instead of full episode return.

Third, you will implement generalized advantage estimation as a baseline in policy gradients. See the next section for more detail on this. The policy gradient variance is further reduced by using a value function to pool information across noisy episodes and then updating actions based upon their relative **advantage** compared to the behavior of the current policy.

5. Use the optimizers and architectures already given to you in order to update the value function neural networks at the end of each epoch.

6. Implement the estimation of the advantage at each timestep (called phi in the code). For more information on what this means see the next section.

7. In a separate 'TODO' later in the code, you should also normalize the advantage values (to mean 0 standard deviation 1). This is an empirical trick which stabilizes gradient updates by ensuring that in each batch of updates, the distribution of the advantages is the same.

8. Change the update rule for the policy to make use of the advantage function as a baseline.

We follow the pattern of the evaluation environment and terminate episodes after 300 timesteps. If an epoch has ended before the episode is complete, we use the value function estimate to estimate the remaining return of that episode.

Our recommendation is to read the section below on rewards-to-go and the use of a baseline; read the original paper introducing Generalized Advantage Estimation; read the skeleton code carefully; and then implement the TODOS, testing after each one. You can pass the baseline without modifying anything outside of the TODOs. The skeleton code makes use of Pytorch, but since a lot of the structure is given to you, experience with Pytorch should not be necessary in order to implement what is required to pass the baseline. After passing the baseline, to score higher on the leaderboard and learn more about reinforcement learning you are encouraged to implement additional improvements. For example

- Use a different baseline in your policy gradients implementation. See the options after equation 1 in Generalized Advantage Estimation.
- Try different neural network architectures and hyperparameter choices.
- Other variants of policy gradients such as Proximal Policy Optimization.
- Other types of reinforcement learning algorithms such as Q-learning or model-based approaches.

4 Policy Gradients

Recall the policy gradients algorithm seen in class. Notation: superscript is episode number and subscript is timepoint in the episode. So s_t^i is the state at the tth timepoint of the ith episode. We write a generic episode generated by the current policy and environment as τ and the ith episode in our dataset as τ^i. $\tau^i = (s_0^i, a_0^i, r_0^i, s_1^i, a_1^i, r_1^i, \dots)$ and for a generic episode $\tau = (s_0, a_0, r_0, \dots)$.

Expectations are always being taken over the distribution from which a single episode τ is sampled. Therefore the sources of noise are the stochasticity of the policy and the environment.

Result: Optimized policy π_θ
Input: Randomly initialized parameters θ, environment E, stepsize α

while *training* **do**
    generate data $\mathcal{D} = [\tau^0, \tau^1 \dots]$ by interacting with E using π_θ for T timesteps
    $\forall i$ compute $G(\tau^i) = \sum_{t=0} \gamma^t r_t^i$, the discounted cumulative rewards of the ith episode
    $\theta \leftarrow \theta + \alpha \nabla_\theta J(\pi(\theta))$
end

Algorithm 1: The policy gradients algorithm

$\nabla_\theta J(\pi_\theta)$ is the policy gradient and is given by $\nabla_\theta \mathbb{E}[G(\tau)] = \mathbb{E}[\sum_t G(\tau) \nabla_\theta \log \pi_\theta(a_t \mid s_t)]$ (the proof of this equality is not given here). Since the policy gradient is just an expectation over episodes we can estimate it unbiasedly on a finite dataset by computing $\frac{1}{\mathcal{D}} \sum_{i,t} G(\tau^i) \nabla_\theta \log \pi_\theta(a_t^i \mid s_t^i)$.

The above estimate of the policy gradient has high variance for small sample sizes, and obtaining episodes can be time-intensive. Therefore we seek still unbiased but lower variance estimates of the policy gradient. We give two ways of doing this below: rewards-to-go and the use of a baseline via the advantage function. More mathematical details can be found in blog post 1, blog post 2 and

Generalized Advantage Estimation. Here we just present a summary and the intuition of the two ideas.

Rewards-to-go is a modification based upon the observation that the policy gradient naively increases the probability of action a_t at state s_t depending upon the total reward accumulated in the episode. However, this includes rewards accumulated before the action was taken, which are not a consequence of the action and hence are just adding noise to our policy gradient. It can be shown that the policy gradient can also be written by only considering rewards obtained after the action was taken

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}[\sum_t R_{t:}(\tau) \nabla_\theta \log \pi_\theta(a_t \mid s_t)]$$

where $R_{t:}(\tau)$ is the discounted sum of rewards obtained in an episode after and including time-point t. Our new estimate will have lower variance since we have removed some reward terms that were just contributing noise and no signal (unrelated to whether we chose this action or not).

Whilst the basic policy gradient method optimizes the policy directly, one can reduce the variance of gradient updates by maintaining an estimate of the value function. In Generalized Advantage Estimation it's shown that one can actually write the policy gradient as

$$\mathbb{E}[\sum_t \phi_t(\tau) \nabla_\theta \log \pi_\theta(a_t \mid s_t)]$$

where ϕ_t can take numerous possible values and still be equivalent to the policy gradient given above. Examples include $\phi_t = R_{t:}$ as above. Generalized Advantage Estimation gives several other alternatives for ϕ_t. Most of these make some use of a value function, which reduces variance by pooling information across trajectories. Please see the paper for more details on the suggested use of ϕ for this task, the advantage function, and how to estimate it. For estimating the advantage function, note the use of two different discount factors in the paper. Implementing the 'TODO's and using $\gamma = 0.99$ and $\lambda = 0.97$ should beat the baseline for passing the task.