**CSE 6369 – Special Topics in Advance Artificial Intelligence**

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**Introduction:**

This report briefly describes about the implementation of the *Policy Gradient (PG)* algorithm and its variations. The implemented PG algorithm is applied in two experiments *CartPole* and *LunarLander,* and the implemented variants are compared with each other in terms of learning curves and variance.

**Implementation:**

The loss function is derived as the negative mean of sum of the product of log-probabilities sum and reward sum.

Text

Description automatically generated

The reward is calculated in 3 different ways, as shown below, and one among three will be used in calculating the loss function based on the user-given flag.

* **Return**

This is equivalent to the sum of all the rewards obtained in a trajectory. The implementation is given below:

Text

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* **Reward-to-go:**

Here, the reward-to-go of a trajectory for an action at is calculated as the sum of rewards from that time t to the end of the trajectory. Its implementation is given below:

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* **Reward Discount:**

In this method, a discounting factor γ will be multiplied to the reward adding more weight on near-future rewards compared to the far-future rewards. This helps sum-of-reward to converge better to a lesser-variance distribution. The implementation is given below:

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Description automatically generated

**Experiment 1 (CartPole):**

In this experiment by gymnasium, a pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The pendulum is placed upright on the cart, and the goal is to balance the pole by applying forces in the left and right direction on the cart. The above-implemented policy is trained in this environment and the action determined by the policy is applied to the state in the environment and a reward is received. The agent updates the policy based on the rewards it received by the above-implemented methods.

The below three trials are executed with the agent on the CartPole-v1 environment,

* **T0: python main hw1.py -e CartPole-v1 -nr 100 -ntr 10 -hdim 64 -lr 3e-3 -xn CartPole v1 t0**
* **T1: python main hw1.py -e CartPole-v1 -rtg -nr 100 -ntr 10 -hdim 64 -lr 3e-3 -xn CartPole v1 t1**
* **T2: python main hw1.py -e CartPole-v1 -rd -nr 100 -ntr 10 -hdim 64 -lr 3e-3 -xn CartPole v1 t2**

A graph is plotted to compare the learning curves from the three trials,

**T0 – Total Return**

**T1 – Reward-to-go**

**T2 – Reward Discount**

Chart, line chart

Description automatically generated

From the above graph, it is clear that **T1 and T2** performs better compared to **T0**. But in this particular experiment ,the learning rate of both T1 and T2 are so close and mostly similar. But as we observe, the increase in reward achieved quick in **T2** compared to **T1**. So, according to this graph, it can be asserted that **discounted-reward-based is slightly better than reward-to-go.**

**BONUS:**

In order to compare the variance among three implementations T0 (Total Return), T1 (Reward-to-go), T2(Discounted Reward), I have ran each trial with 5 different seeds and combined all the average trajectory rewards of each trial (i.e. 100\*5 = 500 avg trajectpry rewards per trial). The three lists of average trajectory rewards are compared to check the variance below,

Chart, box and whisker chart

Description automatically generated

As we can see from the above graph, **T0** has lower variance compared to the other two.

**Experiment 2 (LunarLander):**

In this experiment by the gymnasium, the environment is a classic rocket trajectory optimization problem. After every step a reward is granted. The total reward of an episode is the sum of the rewards for all the steps within that episode.

The above-implemented policy is trained in this environment and the action determined by the policy is applied to the state in the environment and a reward is received. The agent updates the policy based on the rewards it received by the above-implemented methods.

The below three trials are executed with the agent on the LunarLander-v2 environment,

* **T0: python main hw1.py -e LunarLander-v2 -rd -nr 125 -ntr 5 -hdim 128 -lr 3e-3 -xn LunarLand v2 t0**
* **T1: python main hw1.py -e LunarLander-v2 -rd -nr 125 -ntr 20 -hdim 128 -lr 3e-3 -xn LunarLand v2 t1**
* **T3: python main hw1.py -e LunarLander-v2 -rd -nr 125 -ntr 60 -hdim 128 -lr 3e-3 -xn LunarLand v2 t2**

A graph is plotted to compare the learning curves from the three trials,

**T0 – 5 trajectories per rollout**

**T1 – 20 trajectories per rollout**

**T2 – 60 trajectories per rollout**

Chart, scatter chart

Description automatically generated

As we can see from the above graph, **the higher the number-of-trajectories-per-rollout is, higher the learning rate will be**. Since T2 has 60 trajectories per rollout, its learning is better compared to others.

**Git Repository:**

<https://github.com/PavanTejaa/cse6369_assignment1.git>

**References:**

<https://gymnasium.farama.org/environments/classic_control/cart_pole/#cart-pole>

<https://gymnasium.farama.org/environments/box2d/lunar_lander/>  
<https://pytorch.org/docs/stable/distributions.html>

<https://gymnasium.farama.org/api/env/#gymnasium.Env.step>

<https://pytorch.org/docs/stable/generated/torch.tensor.html>