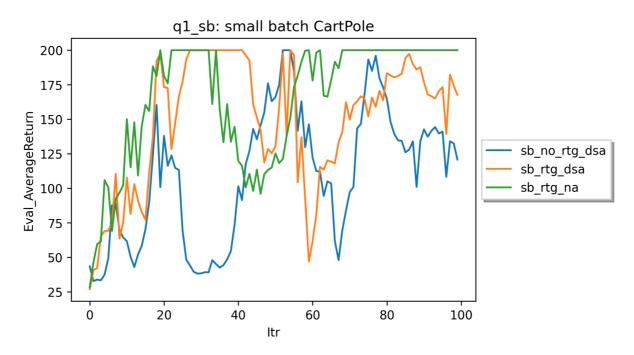
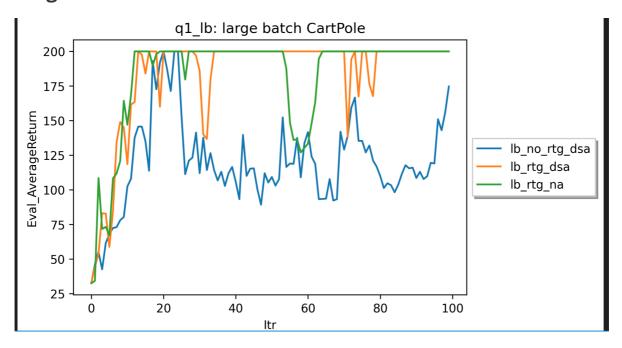
# **HW2 Policy Gradient**

# **Experiment 1**

#### **Small batch**



## Large batch



-Which better? rtg or trajectory centric?

Reward to go.

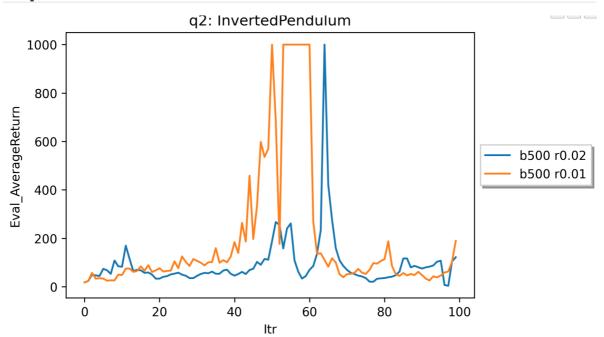
### -Did advantage standardization help?

In small batch, it did increase the performance. In large batch, it didn't help a lot.

#### -Did batch size make an impact?

Yes. Large batch size increases the stability of the performance, and takes fewer iterations to reach 200.

# **Experiment 2**

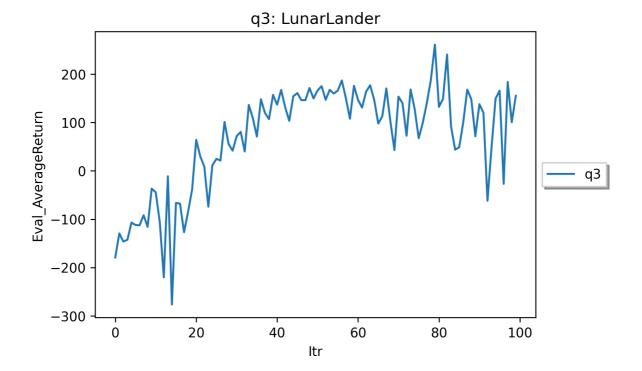


The smallest batch size for reaching 1000 is 500 with largest learning rate 0.02. The performance is not very stable.

#### **Command:**

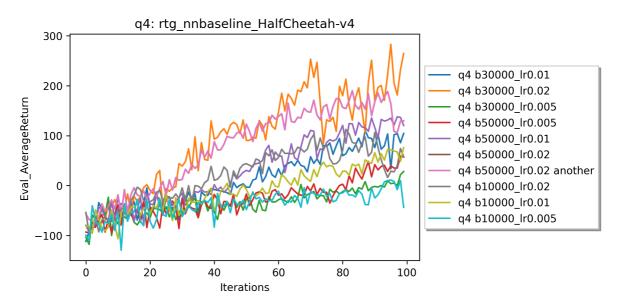
```
`python cs285/scripts/run_hw2.py --env_name InvertedPendulum-v4 \
--ep_len 1000 --discount 0.9 -n 100 -l 2 -s 64 -b 500 -lr 0.02 -rtg \
--exp_name q2_b500_r0.02`
```

## **Experiment 3**



# **Experiment 4**

(a)

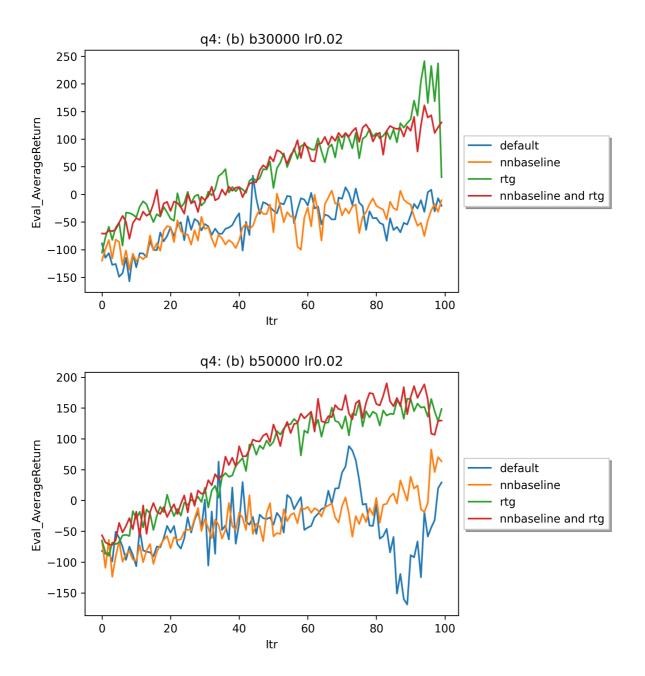


The one with batch\_size = 30000 and learning\_rate = 0.02 performances the best. Meanwhile, the one with batch\_size = 50000 and learning\_rate = 0.02 also behaves well.

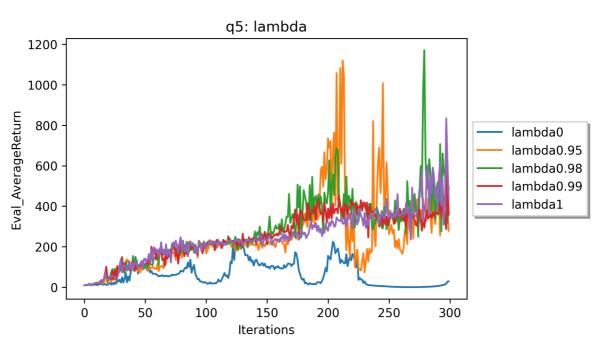
Large learning rate increases the speed of convergence. Large batch size increases the stability of performance.

#### (b)

Since experiments with batch size of 30000 and 50000 both behave well, I applied both of them in this problem.



# **Experiment 5**



 $\lambda=0.98$ , the performance achieves its best.