Experiment 1

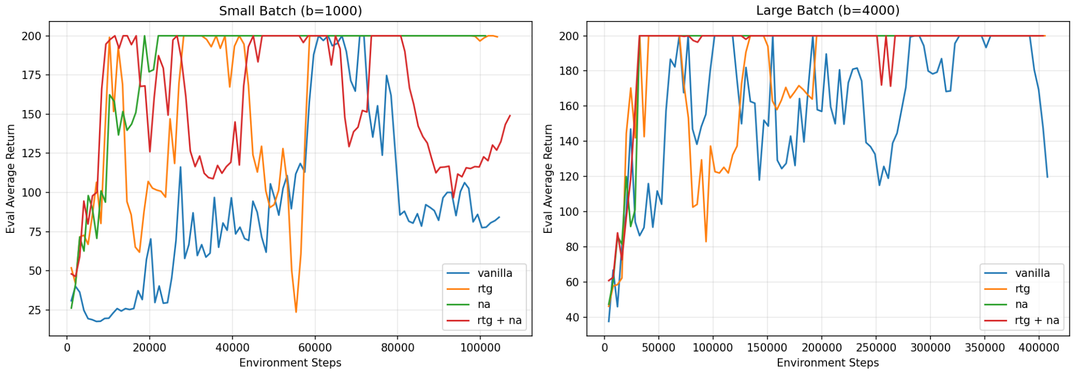


Figure 1: **Eval Return** vs. **Env Steps**

1. Without **advantage normalization**, the **reward-to-go** value estimator performs better than the **trajectory-centric** one.

2. **advantage normalization** helps the policy to achieve the same performance in **fewer environment step**.

3. In fact, the training with a **larger batch size** achieves the same performance in **more environment steps** but **fewer training iteration steps**.

4. The command line configuration i use is totally the same as the one given in homework document.

Experiment 2

1.

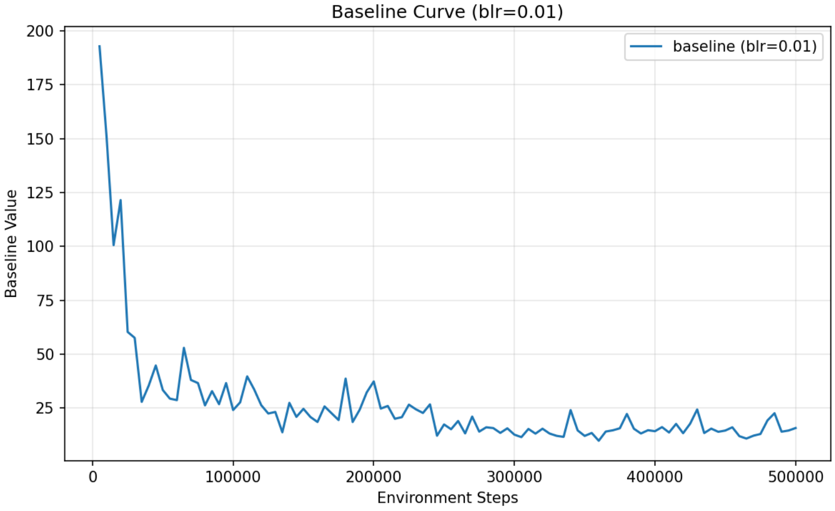


Figure 2: **Baseline Loss** vs. **Env Steps** with baseline learning rate=0.01

2.

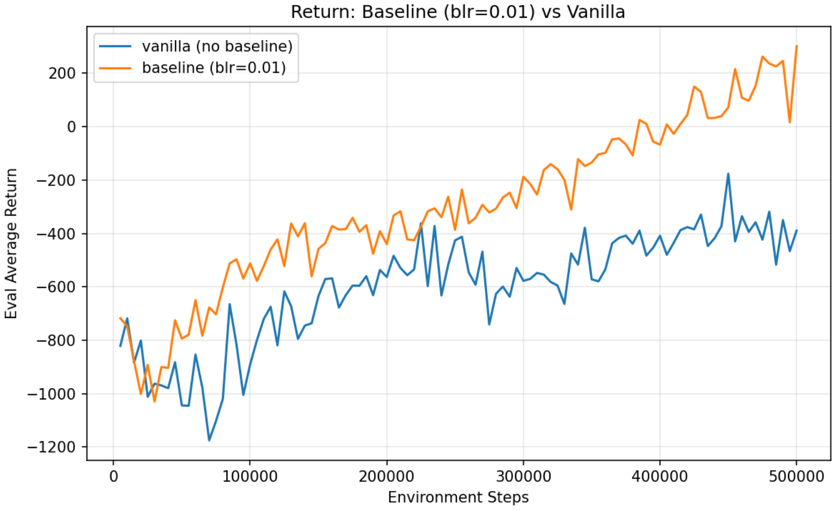
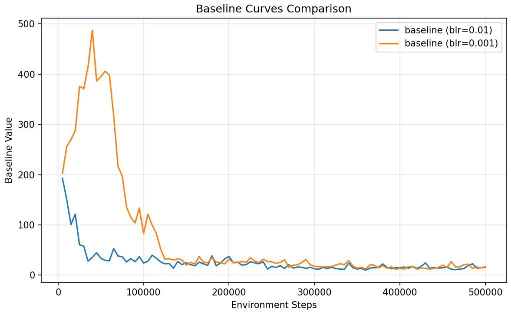
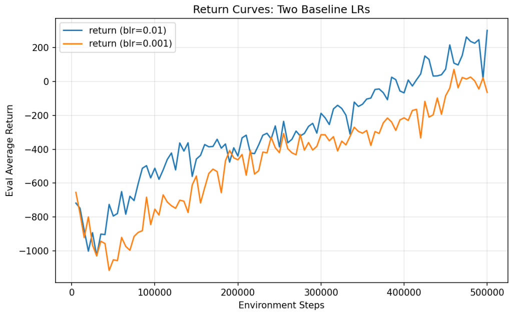


Figure 3: **Average Return** vs. **Env Steps** with baseline learning rate=0.01

3.



(a) Baseline Loss with different baseline learning rate



(b) Baseline Return with different baseline learning rate

Compared to **baseline learning rate = 0.01**, training with **baseline learning rate 0.001** causes slower **baseline loss convergence** and a slower increase in **average return**.

Experiment 3

1.

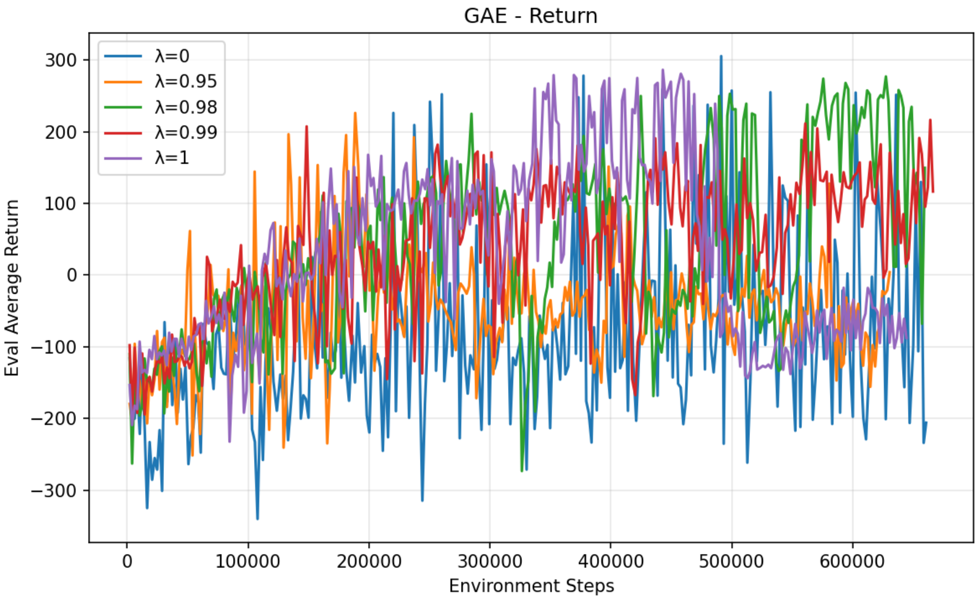


Figure 5: **Average Return** vs. **Env Steps** with different GAE lambda

While increasing λ generally improves policy performance, an excessively large λ leads to instabilities in the later stages of training.

2. $\lambda = 0$ correspond to $\hat{A}(s_t, a_t) = r(s_t, a_t) + \gamma \hat{V}(s_{t+1}) - \hat{A}(s_t)$, which means we totally use prediction from critic as the estimation of state value. At the beginning of training, the critic's predictions are **highly biased**, which leads to **suboptimal** policy performance. However, because the critic's predictions have **low variance**, the resulting training curves exhibit fewer oscillations.

$\lambda = 1$ correspond to $\hat{A}(s_t, a_t) = \sum_{t'=t}^{T} \gamma^{t'-t} r(s_{t'}, a_{t'}) - \hat{V}(s_t)$, which means we totally use the following steps' rewards from environment to estimate the advantage of a_t. This causes high variance since the estimate is based on the sum of actual rewards, it is unbiased but suffers from high variance due to the stochasticity of the environment.

In the figure 5, the blue curve($\lambda = 0$)'s *eval_return* struggles near -100 because of huge bias caused by estimating the value totally depend on critic. And other four curves obviously perform better than the blue one. However, due to the high variance from stochastic step reward from environment, sometimes the return falls down violently.

Experiment 4

1. **Hyperparameters**

Parameter	**Value**
iteration	100
batch size	500
learning rate	0.01
discount	0.99
GAE lambda	0.98
reward to go	true
use baseline	true
baseline learning rate	0.01
baseline gradient steps	5
n layers	2
layer size	64

Table 1: Hyperparameters

2. **Return Curves**

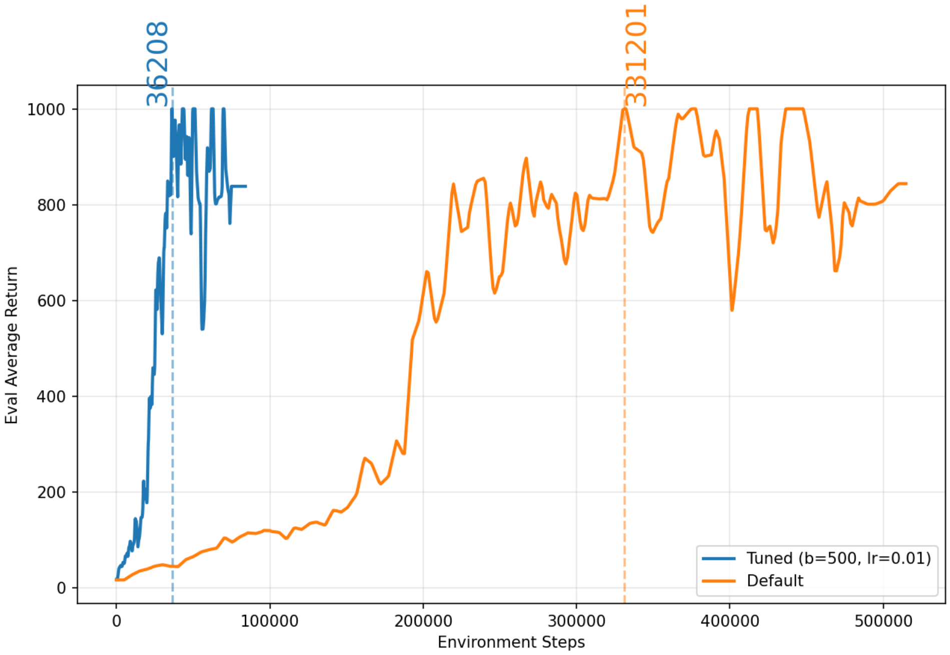


Figure 6: Eval Average Return-Env Steps(default VS. self-define)