Reward over Time Plots for td3_continuous from CleanRL

Eric Bae

Preliminary Thoughts

the parts i will need

- reward over time plots
- different architectures and action modeling strategies
  - compare to generic log-prob minimization
- include a chart with method name, parameter used, and final reward

steps

- first i think im going to open the files and make sure i can process them
- i want to set up a pipeline that i can modify to try different architecutres and action models
  - for pipeline, just setup basic training on generic log-prob minimization
- then research into these different methods

Preliminary Findings

Loaded up both pytorch files for data and actor weights

- dict_keys(['mean_reward', 'std_reward', 'observations', 'actions'])
- odict_keys(['action_scale', 'action_bias', 'fc1.weight', 'fc1.bias', 'fc2.weight', 'fc2.bias', 'fc_mean.weight', 'fc_mean.bias', 'fc_logstd.weight', 'fc_logstd.bias'])
- noticed 2400000 observations/actions pairs in data
- action_scale is the action space of half cheetah
- not really sure what action_bias is
- 256 fc1/fc2 weight and biases

Setting up pipeline

First, I wanted to create the training loop, evaluation function, and plotting function. I decided to start with baseline (-log prob minimization)

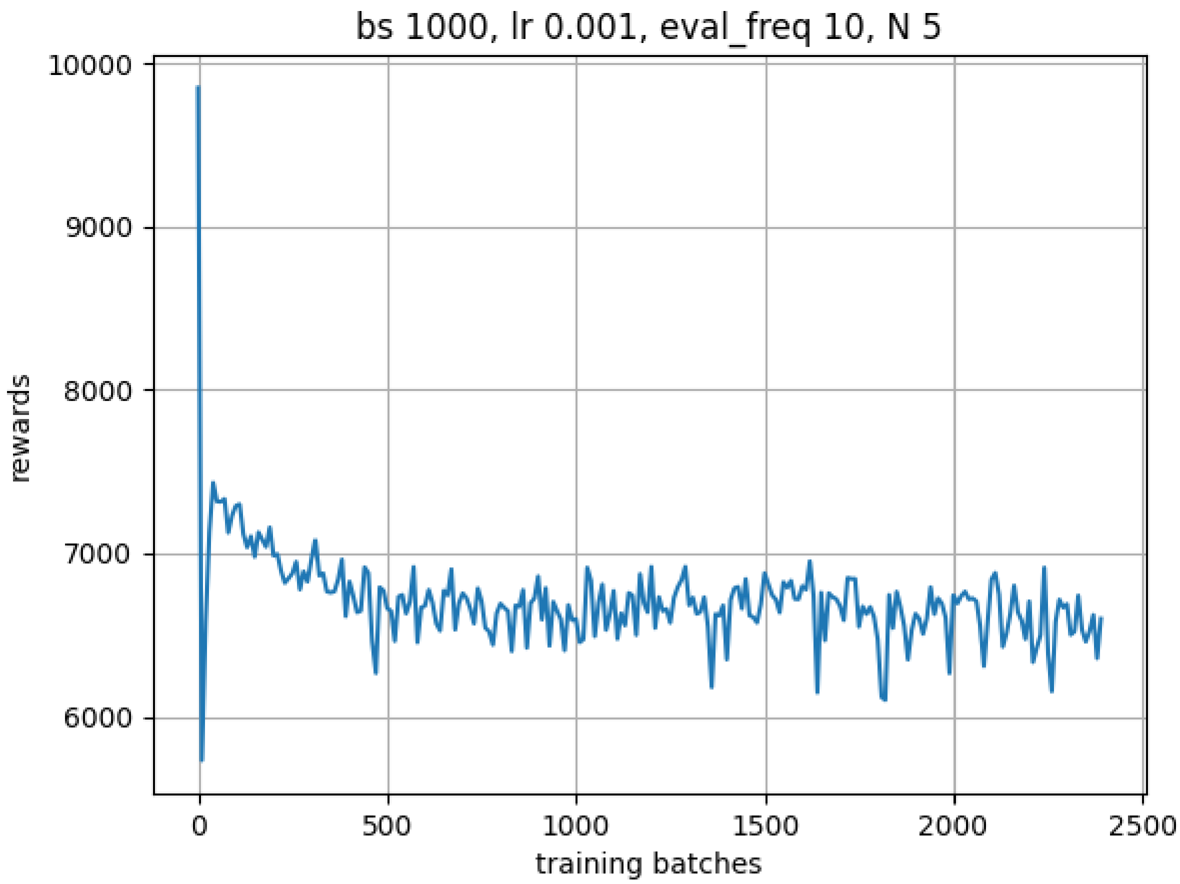
For the training loop:

- decided to start with mini-batch gradient descent
  - not sure if full batch or stochastic would be better so just went with the mini batch
- decided 1000 per batch instead of 1024 to guarantee an even num of elements per split. might adjust this number later

- intuitively, my training loop code is very similar to my checkpoint code

First try:

- in my first initial run, I decided to define a few hyperparameters: `batch_size=1000`, `lr=1e-3`, `eval_freq=10`, and `N=5`
- `eval_freq` is how often I call the eval function in between iterations
- `N` defines how many episodes to run in the eval function
- my main goal for this first run was to have a proof of concept working that I can work off on. Because of this, all hparams were somewhat arbitrary
- I decided to just try a Normal distribution with the log_prob to see what would happen



- with current hparams, there are 240 points on the graph and rewards are ~6500

Different Methodologies Tried

- different hparam searching
    - learning rate: 1e-3, 1e-4
    - batch sizes: 1000, 2000
    - N: 5, 10
    - I ran experiments trying different combinations of these hparams and found the best one was:
        - `lr=1e-4`, `batch_size=2000`, `N=10`
    - because of this, most of my hparams for the rest of the different models kept these hparams
- DAgger (Dataset Aggregation)

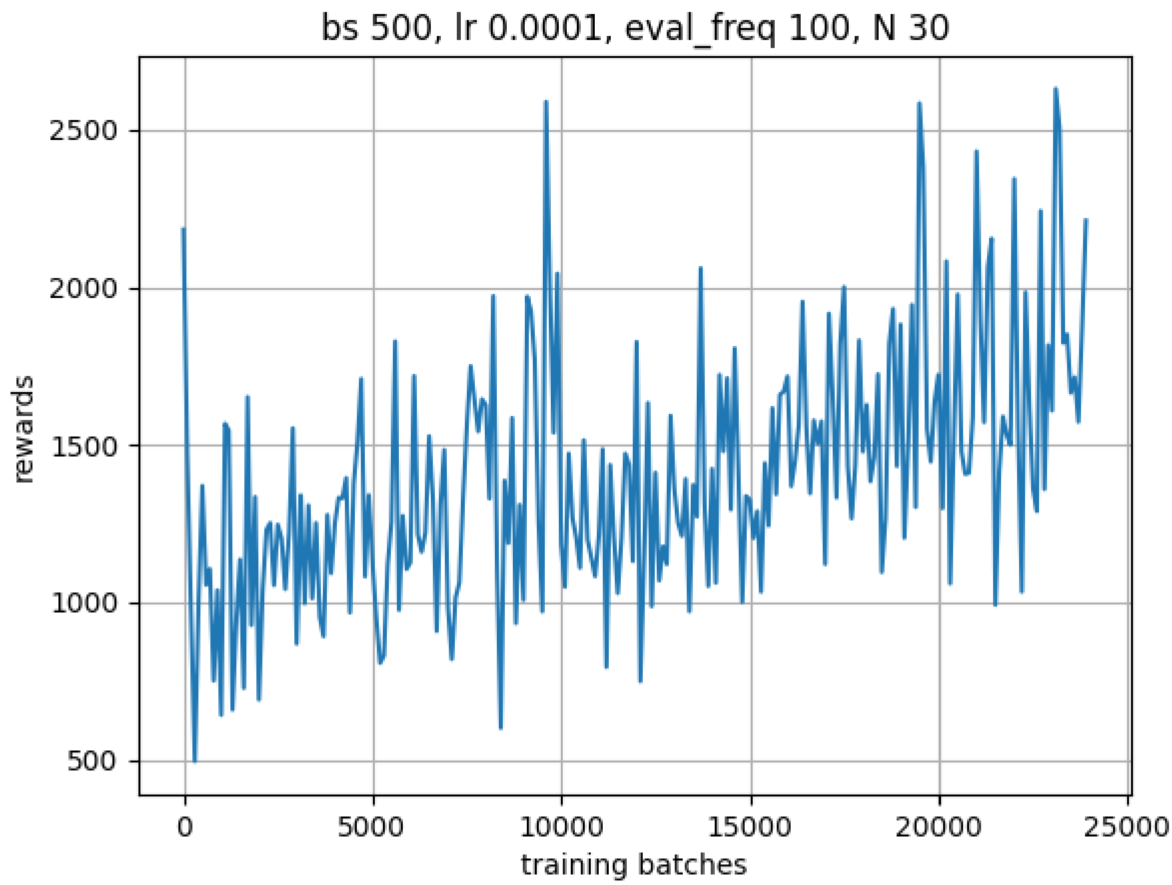
    - from what I read, this seems like a method to boost performance for models using obs-action pairs
    - it would be a modification of my training loop but it would keep my basic architecture intact so I kept it
    - "DAgger improves on behavioral cloning by training on a dataset that better resembles the observations the trained policy is likely to encounter, but it requires querying the expert online." - Source
    - on the first try, I was getting about ~6500 by the final eval, worse than my baseline so I changed a couple things on the next try
        - shuffled the data in the dataset around so old and newly added data would be mixed
        - made it retrain for 3 epochs instead of just once every time train was called but it only increased to ~7000
        - still not as good as the baseline so decided to get back to the drawing board
- Gaussian Mixture k=5
    - my first attempt at it is getting around ~6500
        - to try to increase it, I decided to run another hparam grid search
            - batch_size = [500, 1000, 2000, 4000]
            - lr = [1e-3, 1e-4, 5e-4]
            - eval_freq = 10
            - N = 10
            - epochs = 1
        - the best hyperparameters I've found is batch_size=500 and lr=1e-3
        - even with hyperparameter training, I'm getting around baseline at most
- MSE
    - in the next attempt, I widened the current linear layer up to 512 and added a 3rd Linear layer
    - also changed the loss calculation to just MSE
    - I kept the hparams similar to those from my findings while implementing MoG except for:
        - N=30, epochs=3, and weight_decay=1e-6
        - wanted more consistent results, in my first try, it was fluctuating significantly
- Diffusion T=25
    - to get a better understanding, I read this paper by Columbia University, Toyota Research Institute, MIT
    - I had the most difficulty with implementing this one properly, my rewards were absurdly low
    - I decided to try to set up a pretraining loop before diffusion as currently, my diffusion loop was starting from scratch and wasn't considering the checkpoint's weights

Chart of all methods

Method	Hparams	Final Reward Return	Notes
Baseline log-prob min	batch_size=1000, lr=1e-3, eval_freq=10, and N=5	~6500	First baseline
Baseline log-prob min	batch_size=2000, lr=1e-4, eval_freq=10, N=10	~7250	Using Best Hparams
DAgger	batch_size=2000, lr=1e-4, eval_freq=10, N=10	~7000	Trying to improve baseline
Gaussian Mixture	k=5, batch_size=500, lr=1e-3, eval_freq=10, N=10	~6500	k is number of mixtures
MoG + MSE	batch_size=500, lr=1e-3, eval_freq=10, N=30 epochs=3 weight_decay=1e-6	~9500	This one is after increasing the size of the model and finding optimal hparams
Diffusion + MSE	batch_size=500 lr=1e-4 eval_freq=100 N=30 pretrain_lr=5e-5 pretrain_epochs=20 epochs=5 weight_decay=1e-6 T=25	~2000	Added pretrain loop for weights then used diffusion policy

Diffusion

- Ran multiple different attempts on trying to make diffusion work well
- wanted to warm up the model with the checkpoint's weights so I made a pretrain loop
- increased epochs and lowered lr in attempt to increase reward output
- had the most struggle trying to have the actor learn
- this was my best I could do it right now at about ~2000 rewards



Best One Found

- With Mixture of Gaussian with MSE Loss I was able to get a reward of ~9500.