CS285 - HW4

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November 1, 2022

1 Problem 1

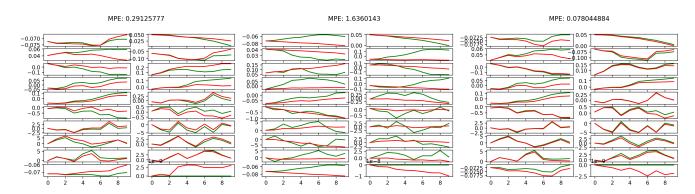


Figure 1: Left to right: n500_arch1x32, n5_arch2x250, n500_arch2x250. Best model is the last one with the most number of training steps and the most expressive architecture.

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\begin{array}{c} \text{python } \text{cs}285/\text{scripts/rum\_hw4\_mb.py} & -\text{exp\_name } \text{q1\_cheetah\_n500\_arch1x32} \\ -\text{env\_name } \text{cheetah-cs}285-\text{v0} & -\text{add\_sl\_noise} & -\text{n\_iter } 1 & -\text{batch\_size\_initial } 20000 \\ -\text{num\_agent\_train\_steps\_per\_iter } 500 & -\text{n\_layers } 1 & -\text{size } 32 & -\text{scalar\_log\_freq } -1 \\ -\text{video\_log\_freq } -1 & -\text{mpc\_action\_sampling\_strategy 'random'} \\ \\ \text{python } \text{cs}285/\text{scripts/rum\_hw4\_mb.py} & -\text{exp\_name } \text{q1\_cheetah\_n5\_arch2x250} \\ -\text{env\_name } \text{cheetah-cs}285-\text{v0} & -\text{add\_sl\_noise} & -\text{n\_iter } 1 & -\text{batch\_size\_initial } 20000 \\ -\text{num\_agent\_train\_steps\_per\_iter } 5 & -\text{n\_layers } 2 & -\text{size } 250 & -\text{scalar\_log\_freq } -1 \\ -\text{video\_log\_freq } -1 & -\text{mpc\_action\_sampling\_strategy 'random'} \\ \\ \text{python } \text{cs}285/\text{scripts/rum\_hw4\_mb.py} & -\text{exp\_name } \text{q1\_cheetah\_n500\_arch2x250} \\ -\text{env\_name } \text{cheetah-cs}285-\text{v0} & -\text{add\_sl\_noise} & -\text{n\_iter } 1 & -\text{batch\_size\_initial } 20000 \\ -\text{num\_agent\_train\_steps\_per\_iter } 500 & -\text{n\_layers } 2 & -\text{size } 250 & -\text{scalar\_log\_freq } -1 \\ -\text{video\_log\_freq } -1 & -\text{mpc\_action\_sampling\_strategy 'random'} \\ \end{aligned}
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2 Problem 2

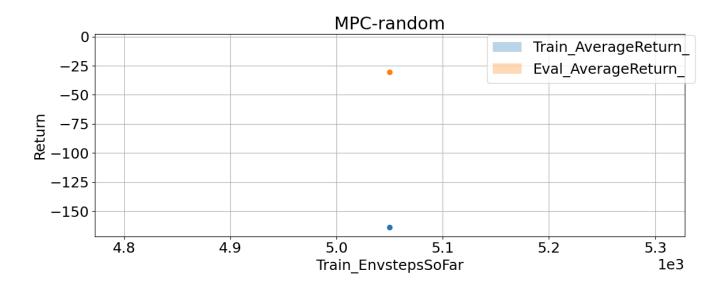


Figure 2

Commands

3 Hyperparameters - DQN

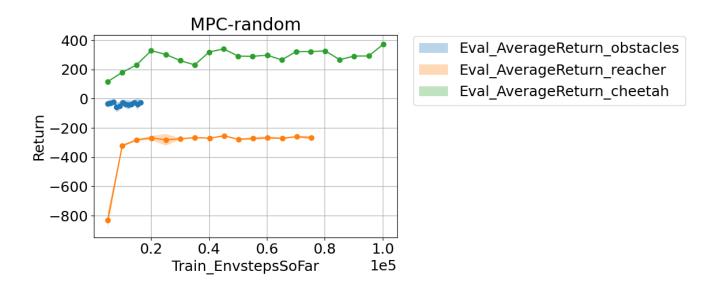


Figure 3

Commands

python cs285/scripts/run_hw4_mb.py —exp_name q3_obstacles —env_name obstacles-cs285-v0 —add_sl_noise —num_agent_train_steps_per_iter 20 —batch_size_initial 5000 —batch_size 1000 —mpc horizon 10 —n iter 12 —video log freq -1 —mpc action sampling strategy 'random'

python cs285/scripts/run_hw4_mb.py —exp_name q3_reacher —env_name reacher-cs285-v0 —add_sl_noise —mpc_horizon 10 —num_agent_train_steps_per_iter 1000 —batch_size_initial 5000 —batch_size 5000 —n iter 15 —video log freq -1 —mpc_action_sampling_strategy_'random'

4 Problem 4

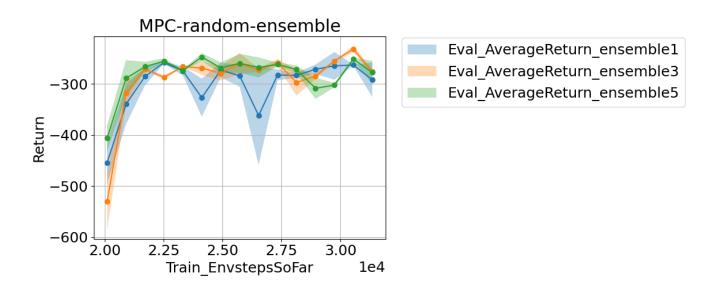


Figure 4: No significant difference

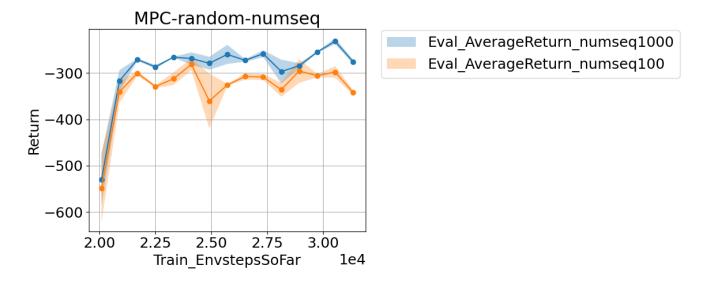


Figure 5: Larger number of candidate action sequences is better

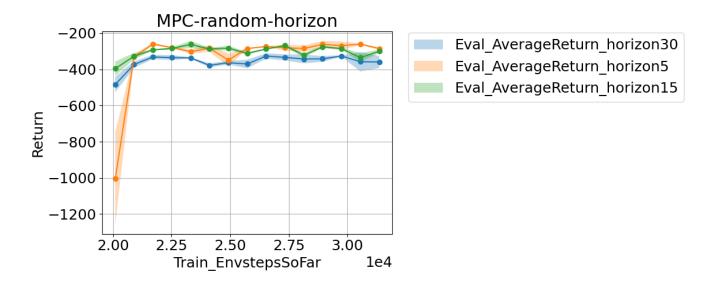


Figure 6: No significant difference

```
python cs285/scripts/run hw4 mb.py —exp name q4 reacher horizon5
—env_name reacher-cs285-v0 —add sl noise —mpc horizon 5
—mpc action sampling strategy 'random' —num agent train steps per iter 1000
—batch size 800 —n iter 15 —video log freq -1 —mpc action sampling strategy 'random'
python cs285/scripts/run hw4 mb.py —exp name q4 reacher horizon15
—env name reacher-cs285-v0 —add sl noise —mpc horizon 15
—num agent train steps per iter 1000 —batch size 800 —n iter 15
—video log freq -1 —mpc action sampling strategy 'random'
python cs285/scripts/run hw4 mb.py —exp name q4 reacher horizon30
—env name reacher-cs285-v0 —add sl noise —mpc horizon 30
—num agent train steps per iter 1000 —batch size 800 —n iter 15
—video log freq -1 —mpc action sampling strategy 'random'
python cs285/scripts/run hw4 mb.py —exp name q4 reacher numseq100
—env name reacher-cs285-v0 —add sl noise —mpc horizon 10
—num agent train steps per iter 1000 —batch size 800 —n iter 15
—mpc num action sequences 100 —mpc action sampling strategy 'random'
python cs285/scripts/run_hw4_mb.py —exp_name q4_reacher_numseq1000
—env name reacher-cs285-v0 —add sl noise —mpc horizon 10
—num agent train steps per iter 1000 —batch size 800
—n iter 15 —video log freq -1 —mpc num action sequences 1000
—mpc action sampling strategy 'random'
python cs285/scripts/run hw4 mb.py —exp name q4 reacher ensemble1
—env name reacher—cs285—v0 —ensemble size 1 —add sl noise —mpc horizon 10
—num agent train steps per iter 1000 —batch size 800 —n iter 15
—video log freq -1 —mpc action sampling strategy 'random'
python cs285/scripts/run hw4 mb.py —exp name q4 reacher ensemble3
—env name reacher-cs285-v0 —ensemble size 3 —add sl noise —mpc horizon 10
—num_agent_train_steps_per iter 1000 —batch size 800 —n iter 15
-video_log_freq -1 -mpc action sampling strategy 'random'
python cs285/scripts/run hw4 mb.py —exp name q4 reacher ensemble5
—env name reacher-cs285-v0 —ensemble size 5 —add sl noise —mpc horizon 10
```

```
—num_agent_train_steps_per_iter 1000 —batch_size 800 —n_iter 15 —video_log_freq -1 —mpc_action_sampling_strategy 'random'
```

5 Problem 5 - CEM

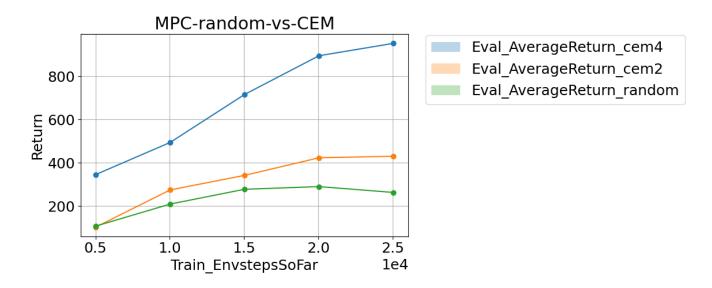


Figure 7: CEM is more effective: blue (4 iterations) is better than orange (2 iterations)

```
python cs285/scripts/rum_hw4_mb.py —exp_name q5_cheetah_random
—env_name cheetah—cs285-v0 —mpc_horizon 15 —add_sl_noise
—num_agent_train_steps_per_iter 1500 —batch_size_initial 5000 —batch_size 5000
—n_iter 5 —video_log_freq -1 —mpc_action_sampling_strategy random

python cs285/scripts/rum_hw4_mb.py —exp_name q5_cheetah_cem_2
—env_name 'cheetah—cs285-v0' —mpc_horizon 15 —add_sl_noise
—num_agent_train_steps_per_iter 1500 —batch_size_initial 5000 —batch_size 5000
—n_iter 5 —video_log_freq -1 —mpc_action_sampling_strategy 'cem' —cem_iterations 2

python cs285/scripts/rum_hw4_mb.py —exp_name q5_cheetah_cem_4
—env_name 'cheetah—cs285-v0' —mpc_horizon 15 —add_sl_noise
—num_agent_train_steps_per_iter 1500 —batch_size_initial 5000 —batch_size 5000
—n_iter 5 —video_log_freq -1 —mpc_action_sampling_strategy 'cem' —cem_iterations 4
```

6 SAC using learned model

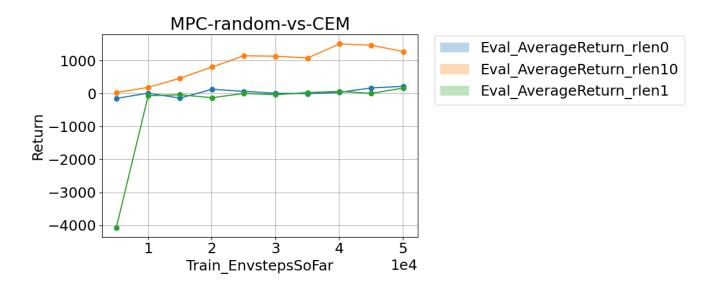


Figure 8: More rollouts from model increase the performance dramatically

```
python cs285/scripts/rum_hw4_mbpo.py —exp_name q6_cheetah_rlen0
—env_name 'cheetah—cs285-v0' —add_sl_noise —num_agent_train_steps_per_iter 1500
—batch_size_initial 5000 —batch_size 5000 —n_iter 10 —video_log_freq -1 —sac_discount 0.99
—sac_n_layers 2 —sac_size 256 —sac_batch_size 1500 —sac_learning_rate 0.0003
—sac_init_temperature 0.1 —sac_n_iter 1000 —mbpo_rollout_length 0

python cs285/scripts/rum_hw4_mbpo.py —exp_name q6_cheetah_rlen1
—env_name 'cheetah—cs285-v0' —add_sl_noise —num_agent_train_steps_per_iter 1500
—batch_size_initial 5000 —batch_size 5000 —n_iter 10 —video_log_freq -1 —sac_discount 0.99
—sac_n_layers 2 —sac_size 256 —sac_batch_size 1500 —sac_learning_rate 0.0003
—sac_init_temperature 0.1 —sac_n_iter 5000 —mbpo_rollout_length 1

python cs285/scripts/rum_hw4_mbpo.py —exp_name q6_cheetah_rlen10
—env_name 'cheetah—cs285-v0' —add_sl_noise —num_agent_train_steps_per_iter 1500
—batch_size_initial 5000 —batch_size 5000 —n_iter 10 —video_log_freq -1 —sac_discount 0.99
—sac_n_layers 2 —sac_size 256 —sac_batch_size 1500 —sac_learning_rate 0.0003
—sac_init_temperature 0.1 —sac n iter 5000 —mbpo_rollout_length 10
```