# Zhengpu Zhao CS285 HW1 Report

### **TLDR:**

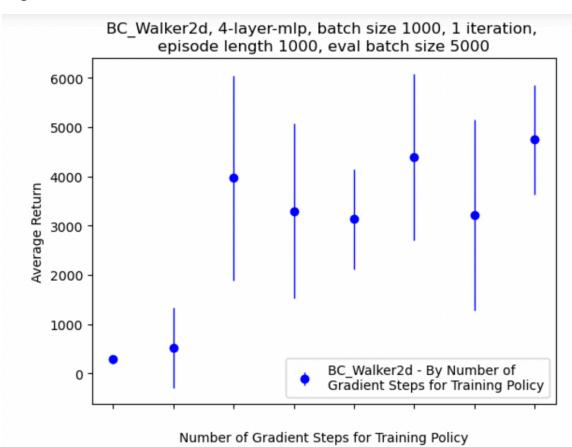
Submitting the PDF. Make a PDF report containing: Table 1 for a table of results from Question 1.2, Figure 1 for Question 1.3. and Figure 2 with results from question 2.2.

#### Table 1 for a table of results from Question 1.2:

	bc_ant	expert_ant	bc_walker2d	expert_walker2d
Average Return	4669.265625	4713.6533203125	289.3726501464844	5566.845703125
Standard Deviation	81.988525390625	12.196533203125	86.68399810791016	9.237548828125
Min Return	4585.6728515625	4701.45654296875	6.183746337890625	5557.6083984375
Max Return	4798.67333984375	4725.849609375	440.492919921875	5576.08349609375

BC\_Ant Achievement as percentage of Expert\_Ant: 99%
BC\_Walker2d Achievement as percentage of Expert\_Walker2d: 5.2%

Figure 1 for Question 1.3:

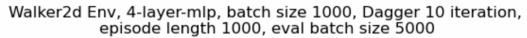


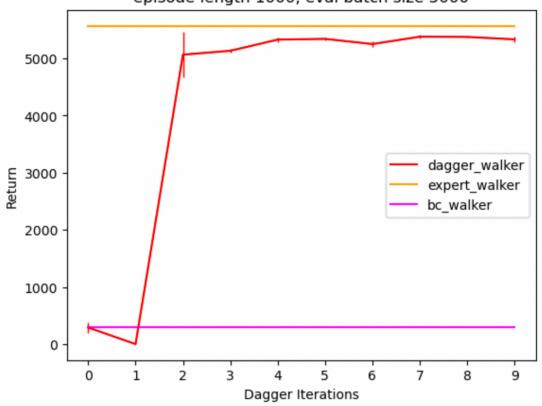
Here I choose - Number of Gradient Steps for Training Policy - to be tuned. The MLP worked fine for the Ant evnvironment leading me to believe that the model itself should be sufficient since the environments aren't too different.

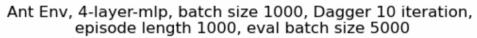
The reason for imitation learning to not work well in the begining could be due to divergence of training track too fast into the training. Thus, by providing more training data and more gradient steps to be performed on the agent we are likely to get closer trajectories to the training trajectory and hence better, longer, and more training down the line.

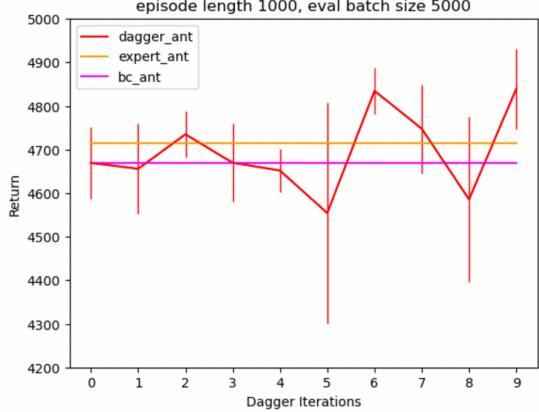
It seems the hyperparameter tuning is working well as average return is going up and eventually approached close performance to expert level.

Figure 2 with results from question 2.2:









```
In [1]:
         1 import os
          2 import numpy as np
         3 import pandas as pd
          5 from collections import defaultdict
          6 | from tensorboard.backend.event_processing.event_accumulator import EventAccumulator
In [2]:
            def tabulate_events(dpath):
          2
                summary_iterators = [EventAccumulator(os.path.join(dpath, dname)).Reload() for dname in os.listd
          3
          4
                tags = summary_iterators[0].Tags()['scalars']
          5
          6
                for it in summary_iterators:
          7
                    assert it.Tags()['scalars'] == tags
         8
         9
                out = defaultdict(list)
         10
                steps = []
         11
         12
                for tag in tags:
         13
                    steps = [e.step for e in summary_iterators[0].Scalars(tag)]
         14
         15
                    for events in zip(*[acc.Scalars(tag) for acc in summary_iterators]):
         16
                         assert len(set(e.step for e in events)) == 1
         17
                        out[tag].append([e.value for e in events])
         18
         19
         20
                return out, steps
         21
         22
         23
            def to_df(dpath):
         24
                dirs = os.listdir(dpath)
         25
                d, steps = tabulate_events(dpath)
         26
         27
                tags, values = zip(*d.items())
         28
                np_values = np.array(values)
         29
         30
                whole_df = pd.DataFrame()
         31
         32
                for index, tag in enumerate(tags):
         33
                    values_col = np_values[index]
         34
                    sq_val = values_col.squeeze()
```

### Use:

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if sq\_val.shape == ():

 $a_{col} = sq_{val}$ 

whole\_df[tag] = a\_col

else:

return whole\_df

def get\_file\_path(dpath, tag):

a\_col = sq\_val.reshape((1,))

file\_name = tag.replace("/", "\_") + '.csv'

return os.path.join(folder\_path, file\_name)

folder\_path = os.path.join(dpath, 'csv')

if not os.path.exists(folder\_path):

os.makedirs(folder\_path)

```
path = "Path"
to_csv(path)
```

#### Q1.2

python cs285/scripts/run\_hw1.py

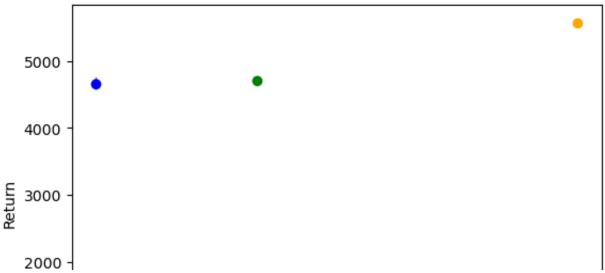
--expert\_policy\_file cs285/policies/experts/Ant.pkl --env\_name Ant-v4 --exp\_name bc\_ant --n\_iter 1

```
--expert_data cs285/expert_data/expert_data_Ant-v4.pkl
         --video_log_freq -1 --eval_batch_size 5000
         --ep_len 1000
         python cs285/scripts/run_hw1.py
         --expert_policy_file cs285/policies/experts/Walker2d.pkl
         --env_name Walker2d-v4 --exp_name bc_walker2d --n_iter 1
         --expert_data cs285/expert_data/expert_data_Walker2d-v4.pkl
         --video_log_freq -1 --eval_batch_size 5000
         --ep_len 1000
         BC_Ant
         q1_bc_ant_Ant-v4_12-09-2022_00-35-43
          1 bc_ant_exp_path = "q1_bc_ant_Ant-v4_12-09-2022_00-35-43"
In [3]:
          2 | bc_ant_exp_df = to_df(bc_ant_exp_path)
          3 # ignore error
         ImportError
                                                       Traceback (most recent call last)
         File /opt/anaconda3/envs/cs285/lib/python3.8/site-packages/tensorboard/compat/__init__.py:42, in tf()
           --> 42
                      from tensorboard.compat import notf # noqa: F401
              43 except ImportError:
         ImportError: cannot import name 'notf' from 'tensorboard.compat' (/opt/anaconda3/envs/cs285/lib/python3
         .8/site-packages/tensorboard/compat/__init__.py)
         During handling of the above exception, another exception occurred:
         RuntimeError
                                                       Traceback (most recent call last)
         RuntimeError: module compiled against API version 0xf but this version of numpy is 0xe
In [4]:
          1 bc_ant_exp_df.head()
Out [4]:
            Eval_AverageReturn Eval_StdReturn Eval_MaxReturn Eval_MinReturn Eval_AverageEpLen Train_AverageReturn Train_StdReturn Train_Max
         0
                  4669.265625
                                 81.988525
                                              4798.67334
                                                          4585.672852
                                                                               1000.0
                                                                                            4713.65332
                                                                                                                       4725
                                                                                                           12.196533
          1 | bc_ant_exp_Eval_AverageReturn = bc_ant_exp_df["Eval_AverageReturn"][0]
In [5]:
          2 bc_ant_exp_Train_AverageReturn = bc_ant_exp_df["Train_AverageReturn"][0]
          3 | achieve_percentage = bc_ant_exp_Eval_AverageReturn / bc_ant_exp_Train_AverageReturn
          4 | print("{} %".format(achieve_percentage*100))
         99.05831650534797 %
         BC_Walker2d
         q1_bc_walker2d_Walker2d-v4_12-09-2022_00-36-44
          1 | bc_walker2d_exp_path = "q1_bc_walker2d_Walker2d-v4_12-09-2022_00-36-44"
In [6]:
           2 bc_walker2d_exp_df = to_df(bc_walker2d_exp_path)
          3 bc walker2d exp df.head()
Out[6]:
            Eval_AverageReturn Eval_StdReturn Eval_MaxReturn Eval_MinReturn Eval_AverageEpLen Train_AverageReturn Train_StdReturn Train_Max
                                                                                                            9.237549
         0
                    289.37265
                                 86.683998
                                               440.49292
                                                             6.183746
                                                                           126.650002
                                                                                           5566.845703
                                                                                                                       5576
In [7]:
             bc_walker2d_exp_Eval_AverageReturn = bc_walker2d_exp_df["Eval_AverageReturn"][0]
             bc_walker2d_exp_Train_AverageReturn = bc_walker2d_exp_df["Train_AverageReturn"][0]
          3 | achieve_percentage = bc_walker2d_exp_Eval_AverageReturn / bc_walker2d_exp_Train_AverageReturn
```

T- [0].

5.198143896534484 %

print("{} %".format(achieve\_percentage\*100))





	bc_ant	expert_ant	bc_walker2d	expert_walker2d
Average Return	4669.265625	4713.6533203125	289.3726501464844	5566.845703125
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# Plotting BA\_Ant and BC\_Walker2d Achievements

## Q1.3

for i in 2000 3000 4000 5000 6000 7000 8000 do

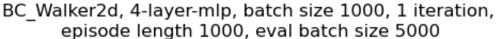
python cs285/scripts/run\_hw1.py

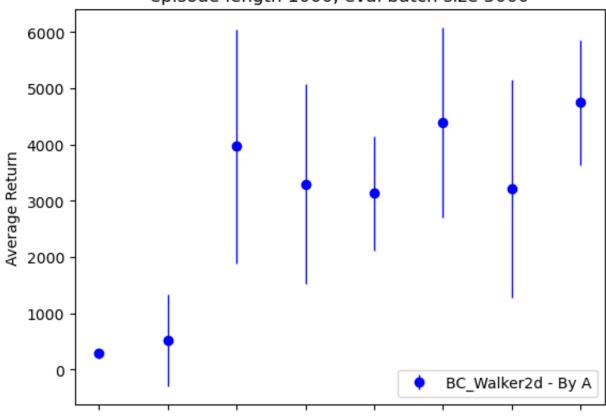
- --expert\_policy\_file cs285/policies/experts/Walker2d.pkl
- --env\_name Walker2d-v4 --exp\_name bc\_walker2d --n\_iter 1
- --expert\_data cs285/expert\_data/expert\_data\_Walker2d-v4.pkl
- --video\_log\_freq -1 --eval\_batch\_size 5000
- --ep\_len 1000 --num\_agent\_train\_steps\_per\_iter \$i done
- q1\_bc\_walker2d\_Walker2d-v4\_12-09-2022\_00-51-27
- q1\_bc\_walker2d\_Walker2d-v4\_12-09-2022\_00-51-29
- q1\_bc\_walker2d\_Walker2d-v4\_12-09-2022\_00-51-32
- q1\_bc\_walker2d\_Walker2d-v4\_12-09-2022\_00-51-34
- q1\_bc\_walker2d\_Walker2d-v4\_12-09-2022\_00-51-37
- q1\_bc\_walker2d\_Walker2d-v4\_12-09-2022\_00-51-39

```
In [9]:
          1 q_1_3_list_of_df = []
          2 dir_name_prefix = 'q1_bc_walker2d_Walker2d-v4_12-09-2022_00-51-'
         3 for i in [27,29,30,32,34,37,39]:
                dir_name = dir_name_prefix + '{}'.format(i)
          5
                exp_df = to_df(dir_name)
                q_1_3_list_of_df.append(exp_df)
          6
         8 means = [bc_walker2d_exp_Eval_AverageReturn]
         9 stds = [bc_walker2d_exp_df["Eval_StdReturn"][0]]
        10 for df in q_1_3_list_of_df:
                Eval_AverageReturn = df["Eval_AverageReturn"][0]
        11
        12
                Eval_StdReturn = df["Eval_StdReturn"][0]
        13
                means.append(Eval_AverageReturn)
        14
                stds.append(Eval_StdReturn)
        15
        16 plt.errorbar(np.array([1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000]),
                         np.array(means), np.array(stds), color='blue', fmt='ok', lw=1)
        17
        18
        19 plt.legend(['BC Walker2d - By A'],loc='lower right')
        20 plt.xlabel("Number of Gradient Steps for Training Policy")
        21 plt.ylabel("Average Return")
        22 plt.xticks(color='w')
        23 plt.title("BC_Walker2d, 4-layer-mlp, batch size 1000, 1 iteration, \nepisode length 1000, eval batch
        24 plt.show()
        25
```

/var/folders/80/mq\_tqq2929b94txcm70\_rbyr0000gn/T/ipykernel\_93228/3643757393.py:16: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "ok" (-> color='k'). The keyword argument will take precedence.

plt.errorbar(np.array([1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000]),





Number of Gradient Steps for Training Policy

Here I choose - Number of Gradient Steps for Training Policy - to be tuned. The MLP worked fine for the Ant evnvironment leading me to believe that the model itself should be sufficient since the environments aren't too different.

The reason for imitation learning to not work well in the begining could be due to divergence of training track too fast into the training. Thus, by providing more training data and more gradient steps to be performed on the agent we are likely to get closer trajectories to the training trajectory and hence better, longer, and more training down the line.

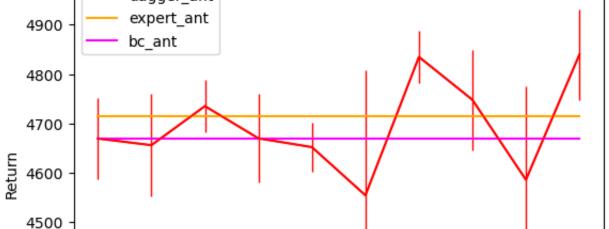
It seems the hyperparameter tuning is working well as average return is going up and eventually approached close performance to expert level.

4400

4300

4200

```
q2_dagger_ant_Ant-v4_12-09-2022_01-29-46
          g2 dagger walker2d Walker2d-v4 12-09-2022 01-31-24
          python cs285/scripts/run_hw1.py
          --expert_policy_file cs285/policies/experts/Ant.pkl
          --env_name Ant-v4 --exp_name dagger_ant --n_iter 10
          --do_dagger --expert_data cs285/expert_data/expert_data_Ant-v4.pkl
          --video_log_freq -1 --eval_batch_size 5000 --ep_len 1000
          python cs285/scripts/run_hw1.py
          --expert_policy_file cs285/policies/experts/Walker2d.pkl
          --env_name Walker2d-v4 --exp_name dagger_walker2d --n_iter 10
          --do_dagger --expert_data cs285/expert_data/expert_data_Walker2d-v4.pkl
          --video_log_freq -1 --eval_batch_size 5000 --ep_len 1000
In [10]:
              dagger_ant_exp_path = "q2_dagger_ant_Ant-v4_12-09-2022_01-29-46"
              dagger_ant_exp_df = to_df(dagger_ant_exp_path)
             dagger_walker2d_exp_path = "q2_dagger_walker2d_Walker2d-v4_12-09-2022 01-31-24"
             dagger_walker2d_exp_df = to_df(dagger_walker2d_exp_path)
In [11]:
              dagger_ant_Eval_AverageReturn = dagger_ant_exp_df["Eval_AverageReturn"]
           2 dagger_ant_Eval_StdReturn = dagger_ant_exp_df["Eval_StdReturn"]
           3 dagger_ant_eval = dagger_ant_Eval_AverageReturn
           4 expert_ant = np.ones(len(dagger_ant_Eval_AverageReturn)) * dagger_ant_exp_df["Train_AverageReturn"][
           5 | bc_ant = np.ones(len(dagger_ant_Eval_AverageReturn)) * bc_ant_exp_Eval_AverageReturn
           6 plt.errorbar(np.array([0,1,2,3,4,5,6,7,8,9]), np.array(dagger_ant_Eval_AverageReturn),
                            np.array(dagger_ant_Eval_StdReturn), color='red', lw=1)
           8
              plt.plot(dagger_ant_eval, color = 'r')
          10 | plt.plot(expert_ant, color = 'orange')
          11 | plt.plot(bc_ant, color = 'magenta')
          12 plt.ylim([4200,5000])
          13 plt.xticks([0,1,2,3,4,5,6,7,8,9])
          14 | plt.legend(['dagger_ant','expert_ant','bc_ant'])
          15 plt.xlabel("Dagger Iterations")
          16 plt.ylabel("Return")
          17 plt.title("Ant Env, 4-layer-mlp, batch size 1000, Dagger 10 iteration, \nepisode length 1000, eval b
          18 plt.show()
                   Ant Env, 4-layer-mlp, batch size 1000, Dagger 10 iteration,
                            episode length 1000, eval batch size 5000
              5000
                          dagger ant
```



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3

Dagger Iterations

7

```
In [12]:
          dagger_walker_Eval_AverageReturn = dagger_walker2d_exp_df["Eval_AverageReturn"]
          dagger_walker_Eval_StdReturn = dagger_walker2d_exp_df["Eval_StdReturn"]
          dagger_walker_eval = dagger_walker_Eval_AverageReturn
          expert_walker = np.ones(len(dagger_walker_Eval_AverageReturn)) * dagger_walker2d_exp_df["Train_Average
          bc_walker = np.ones(len(dagger_ant_Eval_AverageReturn)) * bc_walker2d_exp_Eval_AverageReturn
          flt.errorbar(np.array([0,1,2,3,4,5,6,7,8,9]), np.array(dagger_walker_Eval_AverageReturn),
                       np.array(dagger_walker_Eval_StdReturn), color='red', lw=1)
          8
          plt.plot(dagger_walker_eval, color = 'r')
         10lt.plot(expert_walker, color = 'orange')
         1plt.plot(bc_walker, color = 'magenta')
         1#plt.ylim([3000,5000])
         16lt.xticks([0,1,2,3,4,5,6,7,8,9])
         1plt.legend(['dagger_walker','expert_walker', 'bc_walker'])
         15lt.xlabel("Dagger Iterations")
         16lt.ylabel("Return")
         1plt.title("Walker2d Env, 4-layer-mlp, batch size 1000, Dagger 10 iteration, \nepisode length 1000, eva
         16lt.show()
```

Walker2d Env, 4-layer-mlp, batch size 1000, Dagger 10 iteration, episode length 1000, eval batch size 5000

