Berekeley CS 294-112: Deep Reinforcement Learning Homework 1

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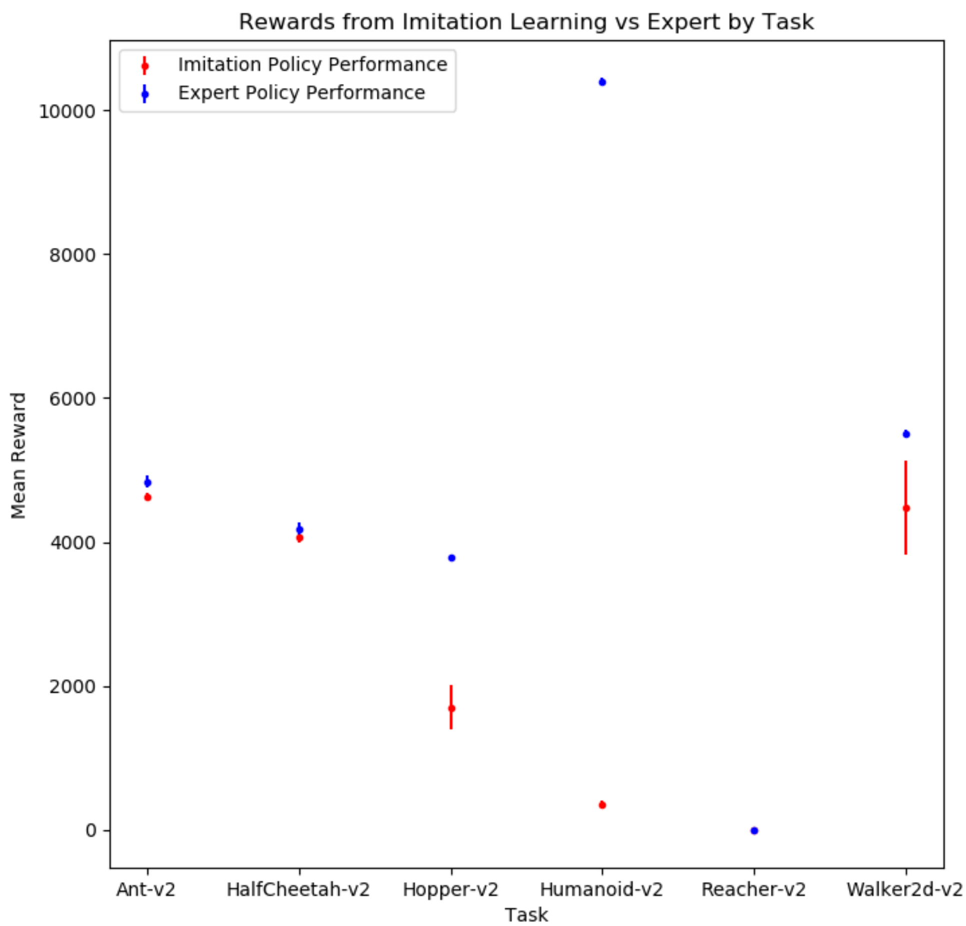
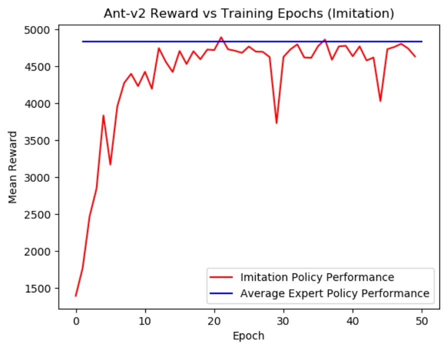
1 Behavioral Cloning (Imitation Learning)

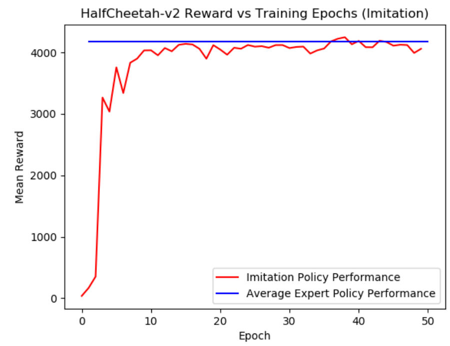
Imitation learning was implemented using a vanilla feed-forward neural network with 4 hidden layers with 512,256,128, and 64 hidden units respetively and ReLU activations for all layers except output. The network takes observations as vectors and outputs actions. The dimensions of the input and output vectors are determined by the task. During training the network received a dataset of 10 rollouts for each task and was training for 50 epochs with a batch size of 128 observations. The policy was evaluated on 5 newly sampled episodes following each training epoch. Imitation learning performed well for tasks including Ant-v2 and HalfCheetah-v2 and performed poorly for the Humanoid-v2 task where performance from the learned policy was much worse than the expert.

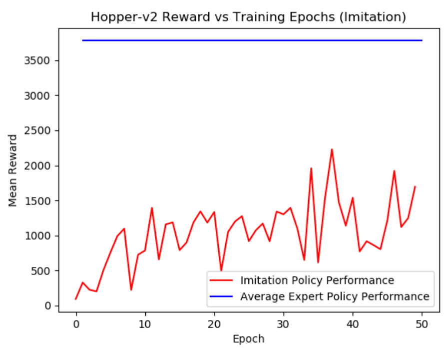
Imitation, and Expert Policy Reward Comparison				
	Imitation		**Expert**	
	Mean	**STD**	**Mean**	**STD**
Ant-v2	4633.421	56.376	4838.639	89.365
HalfCheetah-v2	4058.767	66.907	4177.480	97.426
Hopper-v2	1694.749	308.172	3779.356	2.931
Humanoid-v2	346.837	52.922	10403.923	53.300
Reacher-v2	-6.1001	2.428	-4.470	1.591
Walker2d-v2	4481.929	656.555	5512.973	48.089

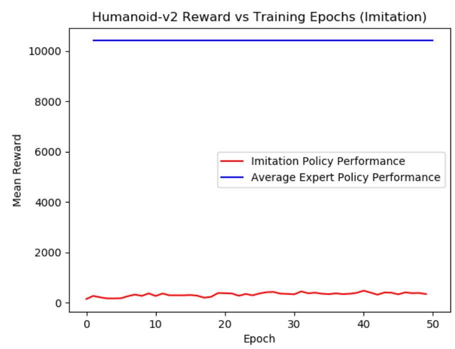


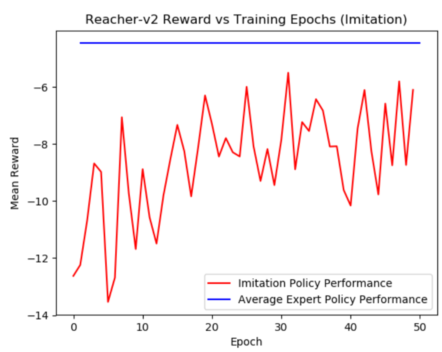
As the number of training epochs increases, average reward achieved by the policy increases, as expected in a traditional supervised learning setting. On tasks where imitation learning performs comparibly to the expert, performance increases rapidly with epochs and plateaus at expert performace. For other tasks, improvement is slower as shown in the learning curves below.

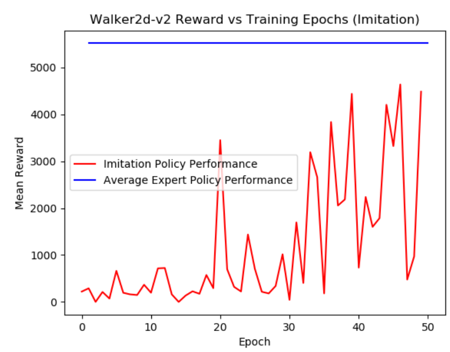

Ant-v2 Reward vs Training Epochs (Imitation)
Mean Reward
Epoch
Imitation Policy Performance
Average Expert Policy Performance


HalfCheetah-v2 Reward vs Training Epochs (Imitation)
Mean Reward
Epoch
Imitation Policy Performance
Average Expert Policy Performance


Hopper-v2 Reward vs Training Epochs (Imitation)
Mean Reward
Epoch
Imitation Policy Performance
Average Expert Policy Performance


Humanoid-v2 Reward vs Training Epochs (Imitation)
Mean Reward
Epoch
Imitation Policy Performance
Average Expert Policy Performance


Reacher-v2 Reward vs Training Epochs (Imitation)
Mean Reward
Epoch
Imitation Policy Performance
Average Expert Policy Performance


Walker2d-v2 Reward vs Training Epochs (Imitation)
Mean Reward
Epoch
Imitation Policy Performance
Average Expert Policy Performance

2 Dataset Aggregation (Dagger)

Dagger was implemented using the same neural network architecture mentioned above for imitation learning. The same imitation learning procedure detailed above for imitation is performed before 20 dagger loops for each task. Within each dagger loop, 5 new rollouts are performed using the learned policy and labeled by the expert for aggregation with the original dataset. As expected, using Dagger allows for learning of a policy significantly closer in performance to that of the expert policy in all tasks. For Humanoid-v2, Dagger achieves comparable performance to the expert, where imitation learning did not. Dagger achieves performance improvement over pure imitation learning on all tasks including those where imitation learning was already comparable to the expert policy performance.

Imitation, Dagger, and Expert Policy Reward Comparison						
	Imitation		**Dagger**		**Expert**	
	Mean	**STD**	**Mean**	**STD**	**Mean**	**STD**
Ant-v2	4633.421	56.376	4771.465	127.483	4838.639	89.365
HalfCheetah-v2	4058.767	66.907	4189.402	40.374	4177.480	97.426
Hopper-v2	1694.749	308.172	3778.243	2.105	3779.356	2.931
Humanoid-v2	346.837	52.922	8313.896	3884.014	10403.923	53.300
Reacher-v2	-6.1001	2.428	-3.138	1.701	-4.470	1.591
Walker2d-v2	4481.929	656.555	5507.156	71.321	5512.973	48.089

Dagger performance increases with the number of Dagger loops. Performance improves until reaching expert level performance, where the learning curve begins to plateau.

3 Scripts Used

To reproduce these results run the following commands from the hw2 directory.

```
python dagger.py
python plotPerformance.py
```