Ex8 CS5180 Hongyan Yang

1. Nonlinear Function Approximation with Neural Networks

(e) Written:

My learned model is very accurate to fit the training dataset while performs poorly to fit the testing set with out of sample data.

Within the range of [-10, 10], it has a loss function measured by MSE at around 0.01, which is really accurate. While out of the range, as infered by the plot, it cannot fit the true label well.

I have noticed the difference between models with different layer dimensions. With 16-dim hidden layer, the model fits the out of sample better than that with 8-dim hidden layer. However, increase the dimension of the hidden layer to 64 and 128 causes worse performance because of over-fitting to the in-sample data and resulting in low bias and high variance. It's also worth noting that this effect is not symmetric at range [-30, 10] and [10, 30].

2(e) After plotting the learning curve of the Double DQN and comparing with the vanilla one. I found that the learning curve of the double DQN converges more stable and a little faster than the vanilla DQN. However, the double DQN shows higher volatility in terms of its training loss wrt training steps. It is because double DQN is essentially unaffected by the maximization bias. Thus it converges more stable and a little faster.

3(c) I found that a network architecture of 4 dense fully connected layers work for CartPole and a gradully decayed epsilon value works for CartPole.

I found that a network architecture of 3 dense fully connected layers with relu activation, and a gradully decayed epsilon value from 1.0 to 0.001 works for LunarLander.

(d) At early stages. The CartPole seems to be always moving left constantly to balance the pole. The corresponding value function has a much larger value for moving left no matter what state it is.

At early stages of LunarLander. It can not land at correct location and cannot even adjust itself towards the correct direction after landing. The corresponding value function has similar value for actions given different states.