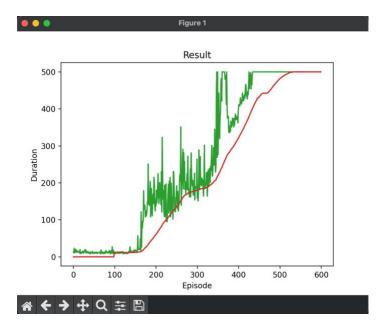
Deep Q-Network for Cartpole Report

The initial neural network (used in trials 1-7) is comprised of 3 layers, with 4 nodes on the input layer, 100 on the second, and 2 on the output. I tested with differing node amounts for the inner layer ranging from 50-150. In the end I decided on the following network architecture:

After iterative updating, I settled on the following hyperparameters:

I further tested different activation functions including sigmoid, leaky_relu, and relu. I ultimately went with the relu function as it had the highest accuracy out of the set. I do wonder how each would perform under optimized hyperparameters for the given activation function. This however would take lots and lots of testing/time.

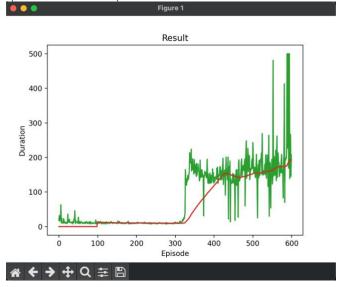
Under the specified parameters and architecture, here is how the DQN agent performed:



The agent took a little over 500 episodes to finish training, however once it did, it experienced no variance in future iterations. The agent was able to learn perform near perfect, with a consistent score of 475 (the max reward for cartpole game).

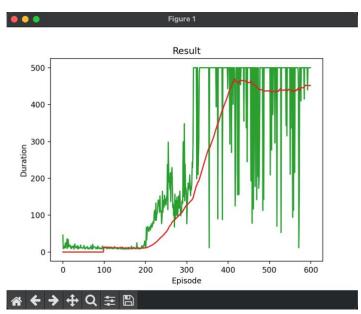
Hyperparameter Tests

Trial 1: BATCH_SIZE = 150 | GAMMA = 0.9 | EPS_START = 0.9 | EPS_END = 0.05 | EPS_DECAY = 1000 | TAU = 0.005 | LR = 0.001

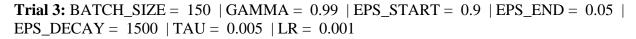


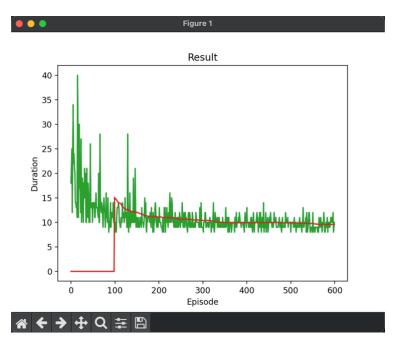
Increased the gamma to allow for greedier learning. Hopefully incentivizing the agent to perform actions which favor long-term rewards (and thus staying upwards for longer)

Trial 2: BATCH_SIZE = 150 | GAMMA = 0.99 | EPS_START = 0.9 | EPS_END = 0.05 | EPS_DECAY = 1000 | TAU = 0.005 | LR = 0.001



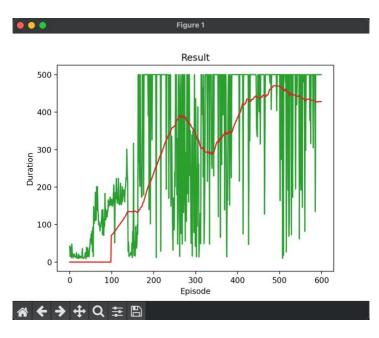
Changes to gamma worked, however now there seems to be high variance and still no convergence. Increase epsilon decay to reduce exploration/variance at the later episodes.



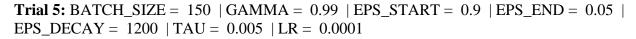


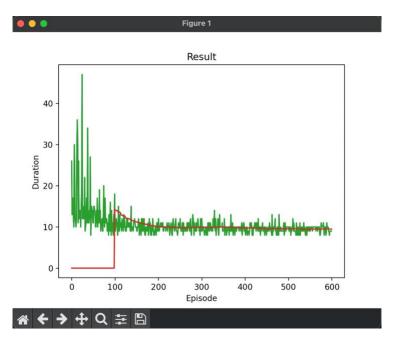
Agent was unable to converge accurately, however variance was reduced slightly. Will update epsilon decay to midway between 1000 and 1500.

Trial 4: BATCH_SIZE = $150 \mid GAMMA = 0.99 \mid EPS_START = 0.9 \mid EPS_END = 0.05 \mid EPS_DECAY = <math>1200 \mid TAU = 0.005 \mid LR = 0.001$



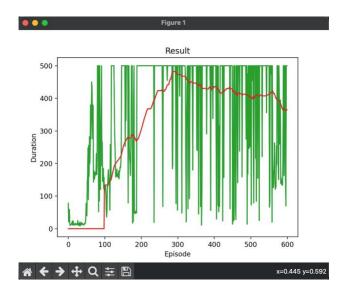
Agent seems more able to learn however still struggles with chaos in variance, will decrease learning rate to see effects.





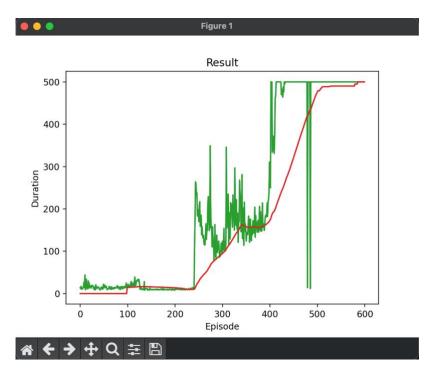
Similar issue to high variance, where agent fails to learn fast enough, will reset to eps_decay =1000 and LR =0.001, and test tweaking the batch_size. Hopefully with smaller batch sizes the agent will learn quicker before beginning to converge.

Trial 6: BATCH_SIZE = 125 | GAMMA = 0.99 | EPS_START = 0.9 | EPS_END = 0.05 | EPS_DECAY = 1000 | TAU = 0.005 | LR = 0.001



The smaller batch size worked, however agent fails to converge policy, will apply updates to learning rate and decay.

Trial 7: BATCH_SIZE = 125 | GAMMA = 0.99 | EPS_START = 0.9 | EPS_END = 0.05 | EPS_DECAY = 1000 | TAU = 0.005 | LR = 0.0001

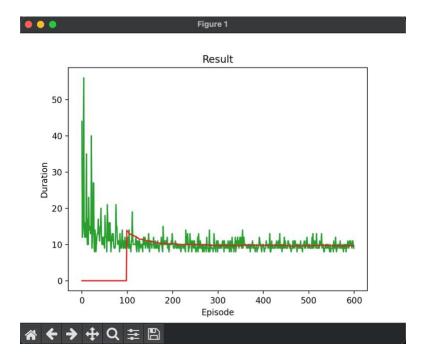


These are the hyper parameters I chose to go with, partly due to getting fed up with the iterative process (many trails not shown here), and because I wanted to work on the layer nodes. Agent seems to converge on an optimal policy with minor variance.

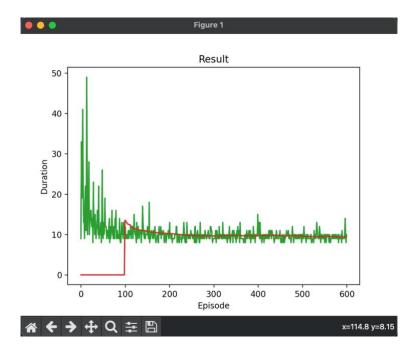
NN Architecture Tests

Hyperparameters: BATCH_SIZE = $125 \mid GAMMA = 0.99 \mid EPS_START = 0.9 \mid EPS_END = 0.05 \mid EPS_DECAY = <math>1000 \mid TAU = 0.005 \mid LR = 0.0001$

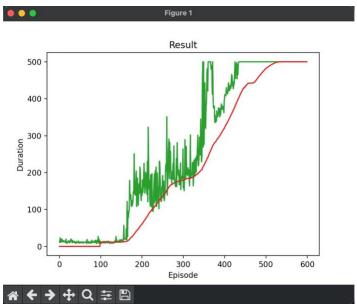
Trial 8: layer 1: (4, 50) | layer2: (50,50) | layer3: (50,2)



Trial 9: layer 1: (4, 75) | layer2: (75,75) | layer3: (75,2)

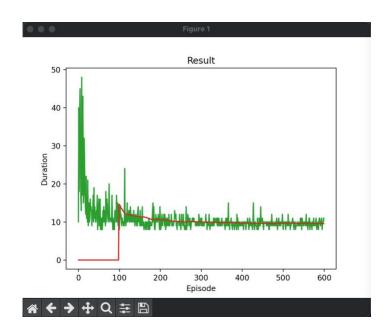


Trial 10: layer 1: (4, 125) | layer 2: (125,125) | layer 3: (125,2)



This seem to be the sweet spot

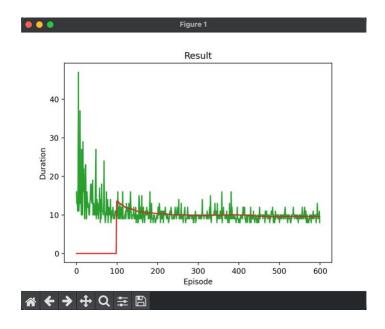
Trial 11: layer 1: (4, 150) | layer 2: (150,150) | layer 3: (150,2)



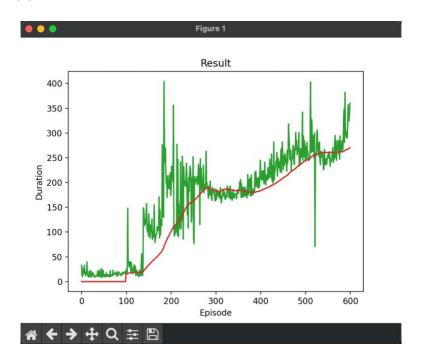
Activation Function Testing

BATCH_SIZE = 125 | GAMMA = 0.99 | EPS_START = 0.9 | EPS_END = 0.05 | EPS_DECAY = 1000 | TAU = 0.005 | LR = 0.0001 layer 1: (4, 125) | layer2: (125,125) | layer3: (125,2)

Trial 12: sigmoid



Trial 13: leaky Relu



Trial 14: Tanh

