Neural.Swarms and Neural.Orb

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Deep Quality Networks

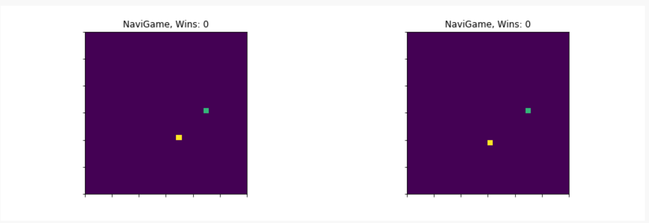
- Deep-Q Networks apply reinforcement learning to neural networks.
- The network predicts Q-values for each action the network is allowed.
- A Q-value represents quality of a state, or the expected sum of rewards as we play the game from that state.
- Our agents (almost) always select the max Q-value we predict.
- DQN's were deployed to great effect by DeepMind, most recently in their Go-playing AI, AlphaGo.

Objectives

- Simulation: demonstrate DQNs
- Navigation: utilize DQNs in a physical space
- Coordination: train multiple DQN-based agents to cooperate

Simulation

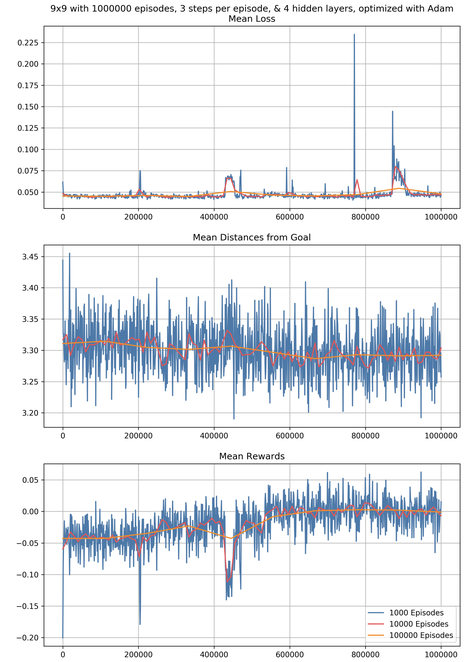
I developed the Neural.Swarms simulation engine in which I can implement either supervised or reinforcement learning.



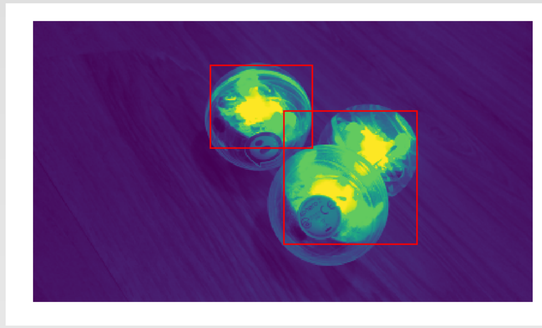
Measures

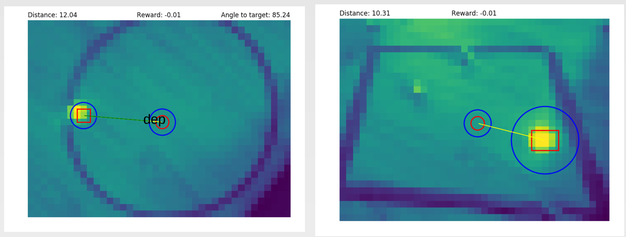
Measuring the DQN's learning was difficult, as they require a massive amount of training episodes (similar to epochs in supervised learning). I used three different measures of network learning

- Loss: mean squared error, commonly used for many machine learning algorithms
- Mean distance to target: measured over one or more game episodes, this provides feedback on actual performance in game
- Mean reward: measured in the same intervals as mean distance, mean reward tells us the same basic information as mean distance, and their inverse relationships confirm that the scoring system works.



Computer Vision





Deploying to Sphero

- Deploying a DQN to Sphero required a computer vision interface, and controlled training environment. SciKit-Image provides excellent filters and segmentation modules, and pygame.camera allows access to webcams.
- Bluetooth instability frequently interrupted training runs, and at one point the host machine overheated and crashed
- The Sphero DQN couldn't utilize the experience replay technique, which has been shown to accelerate learning
- Each game step took 4-5 seconds, meaning performing the million steps required for good performance would take roughly 10 days of continuous training.

Conclusion

While I can't live my fantasy of terrorizing friend's dogs with swarms of robot balls, I can control one, albeit inaccurately, with a neural network. The training program works, but simply doesn't run fast enough for me to have produced a viable model in the allotted time frame. However, a viable model is possible given a few improvements:

- Implementation of experience replay for the physical model (required too much disk space)
- A simulation engine similar enough to the physical problem that we could pre-train the model virtually, then deploy to the physical space
- Utilize all data from the Sphero's onboard sensors- I was only able to poll data from the locator which provides (x, y) coordinates but not acceleration or angle.

References

1. *Andrej Karpathy*
2. *Eder Santana*
3. *Charles Isbell, Michael Littman, and Chris Pryboy via Udacity*
4. *Tambet Matiisen*