Learning 2048 with Deep Reinforcement Learning

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Ref. 1

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Outline

- Motivation
- Reinforcement Learning
- Q-Learning
- Six (Unofficial) Stages of Deep Q-Learning
- 2048-unlimited
- Implementation Overview
- Research and Results
- Demonstration and Interactive Results
- Future Work
- Conclusion
- References

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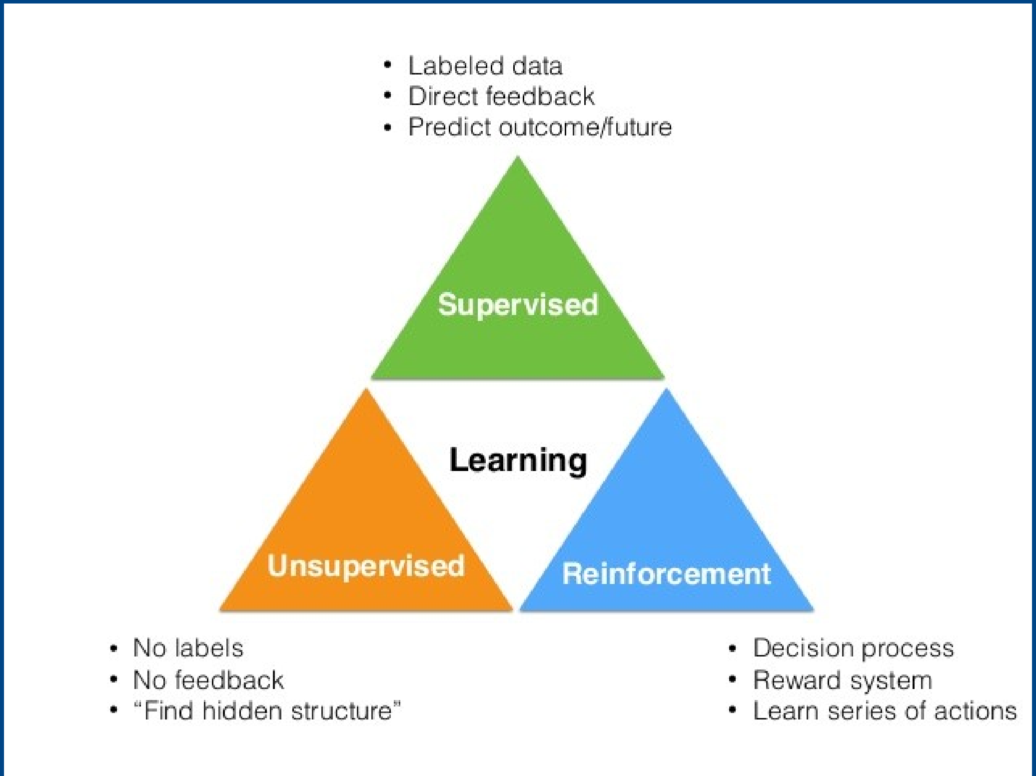
Motivation

- Applications of Deep Reinforcement Learning
  - Games
  - Self Driving Cars
  - Manufacturing
  - Robotics
  - Natural Language Processing
  - Computer Vision
  - Etc...

Reinforcement Learning

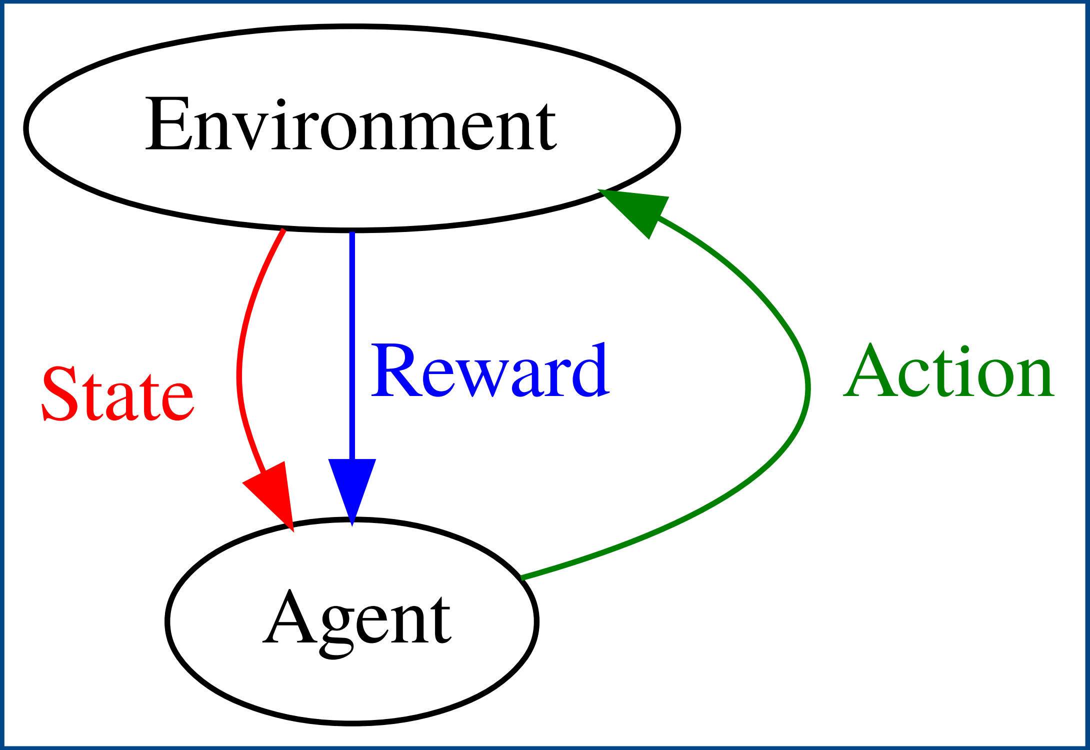
- How is it different?



- Sparse and time-delayed labels

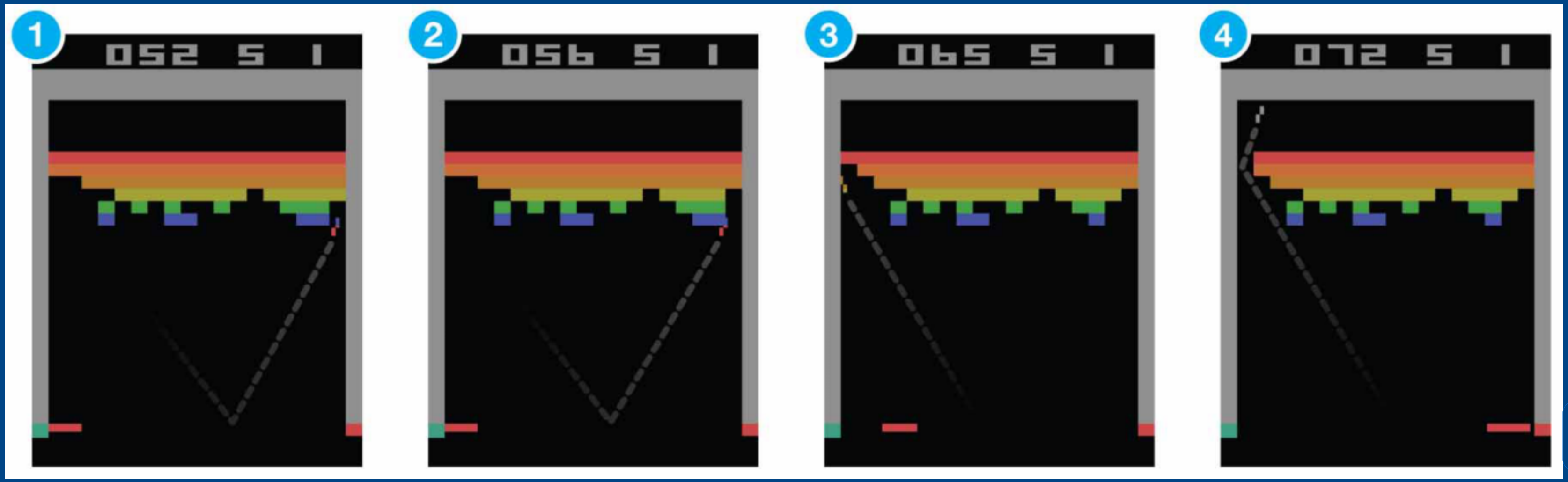
Ref. 10

Reinforcement Learning



Reinforcement Learning

- Sparse and time-delayed labels
- Credit Assignment Problem
- Explore-Exploit Dilemma: Action Selection
  - Greedy Approach
  - Random Approach
  - Epsilon-Greedy Approach



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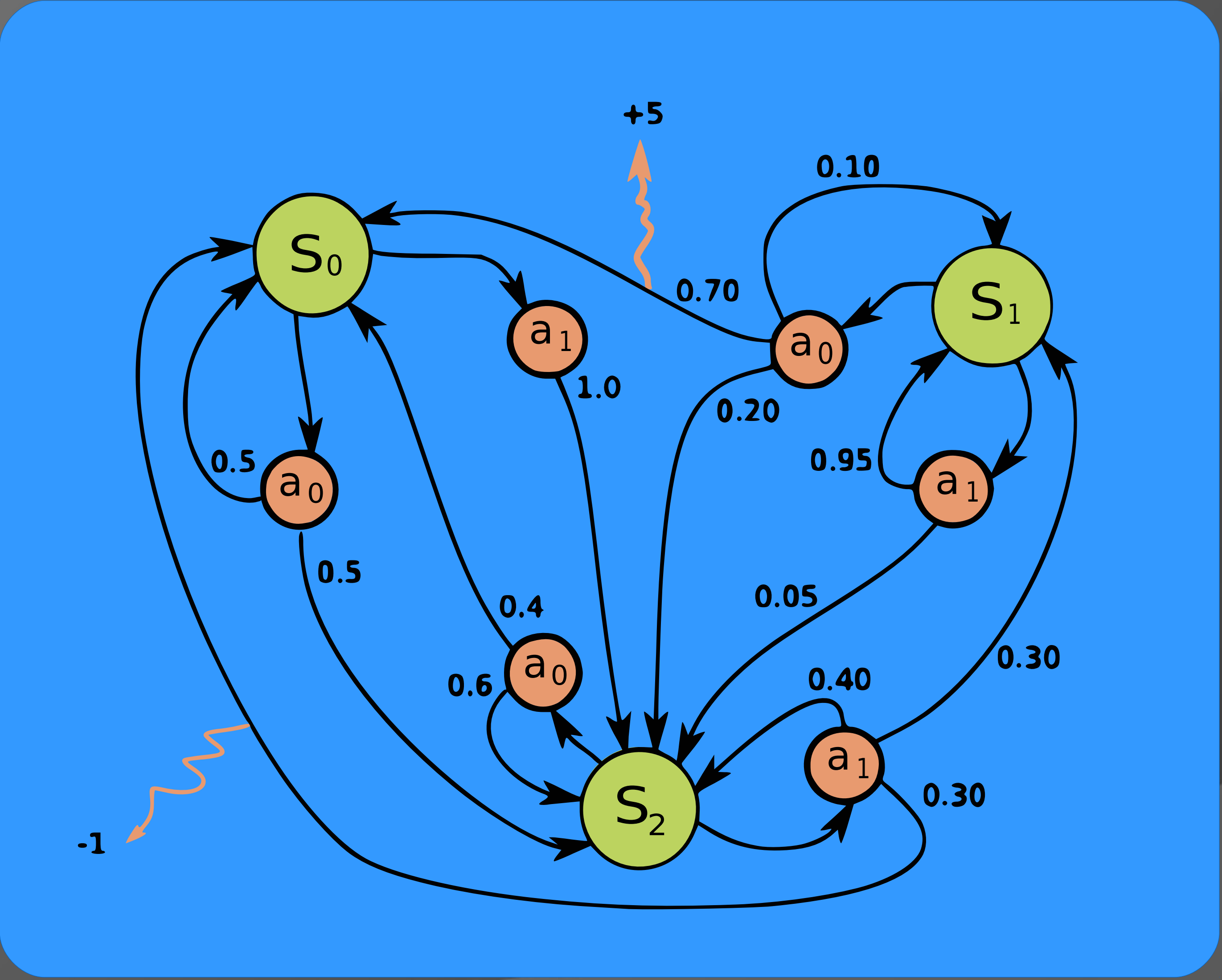
Markov Decision Process



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Markov Decision Process

- Most common way to formalize a reinforcement learning problem
- An episode of a Markov decision process is a finite sequence of states, actions, and rewards:

$$s_0, a_0, r_1, s_1, a_1, r_2, s_2, \ldots, s_{n-1}, a_{n-1}, r_n, s_n$$

- An experience or transition is defined as:

$$\langle s, a, r, s' \rangle$$

- "A Markov decision process relies on the Markov assumption, that the probability of the next state s_{i+1} depends only on current state s_i and performed action a_i, but not on preceding states or actions." (3)

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Discounted Future Reward

- Total Reward:

$$R = r_1 + r_2 + r_3 + \ldots + r_n$$

- Total Future Reward:

$$R_t = r_t + r_{t+1} + r_{t+2} + \ldots + r_n$$

- Discounted Future Reward:

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots + \gamma^{n-t} r_n$$

- Discounted Future Reward:

$$R_t = r_t + \gamma \left(r_{t+1} + \gamma \left(r_{t+2} + \ldots \right) \right) = r_t + \gamma R_{t+1}$$

Q-Learning

- "In Q-learning we define a function Q*(s,a) representing the discounted future reward when we perform action ‘a’ in state ‘s’, and continue optimally from that point on." (3)

$$Q^*(s_t, a_t) = max_\pi R_{t+1}$$

- Rewrite as the Bellman Equation:

$$Q^*(s, a) = r + \gamma max_{a'} Q^*(s', a')$$

- If we have Q*(s, a) then:

$$\pi(s) = \pi^*(s) = \text{argmax}_a Q^*(s, a)$$

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Q-Learning

- However, we do not know Q*(s,a); therefore we must estimate it with a non-optimal function Q(s,a). This enables us to define Q*(s,a) as

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a)$$

- The whole idea behind Q-learning is that the Bellman equation can be used iteratively to improve our approximation of the optimal Q-function.

$$Q(s,a) = r + \gamma max_{a'} Q(s',a')$$

Q-Learning

Bellman Equation:

$$Q(s,a) = r + \gamma max_{a'} Q(s',a')$$

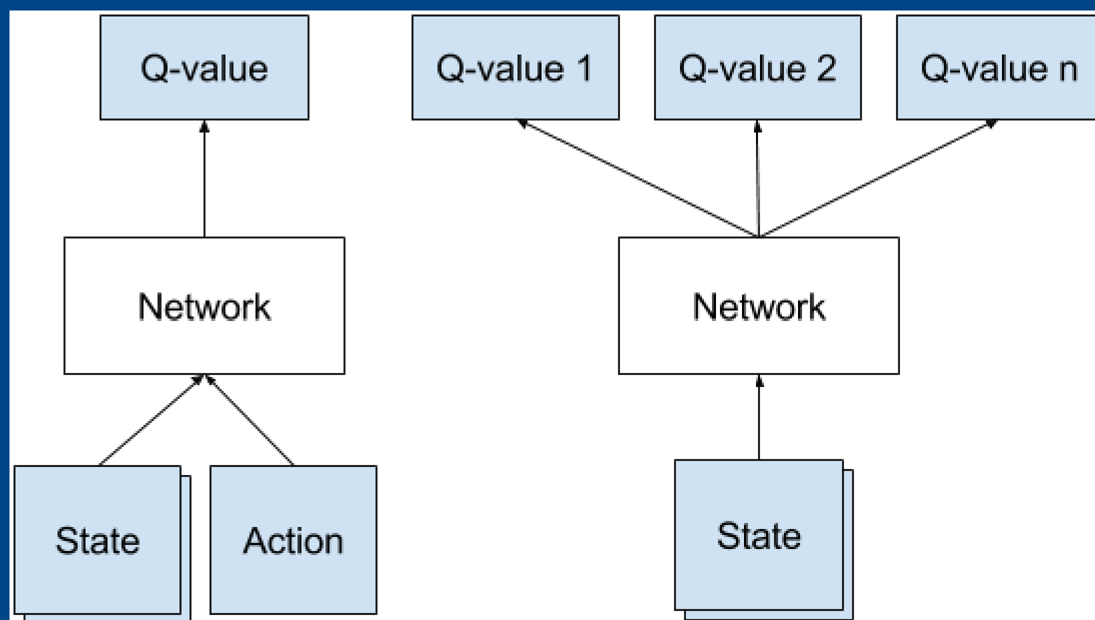
Update for simple Q-Learning:

$$Q(s,a) = Q(s,a) + \alpha \left(r + \gamma max_{a'} Q(s',a') - Q(s,a)\right)$$

	Action 0	Action 1	...	Action n-1
State 0	Q(0, 0)	Q(0, 1)	...	Q(0, n-1)
State 1	Q(1, 0)	Q(1, 1)	...	Q(1, n-1)
...	...	...	...	...
State n-1	Q(n-1, 0)	Q(n-1, 1)	...	Q(n-1, n-1)

Deep Q Network

Problem? Too many states!
Solution? Use a Neural Network to approximate it!



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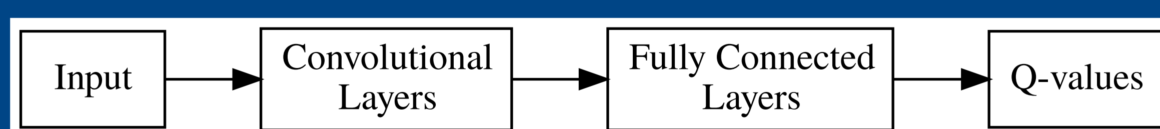

Deep Q-Learning: Stage 1

- Now that we have a DQN all we need for deep reinforcement learning is a loss function,

$$\mathcal{L} = \frac{1}{|B|} \sum_{(s,a,s',r) \ \in \ B} \mathcal{L}(\delta)$$

- where δ is temporal difference,

$$\delta = \underbrace{Q(s,a)}_{\text{prediction}} - \underbrace{\left(r + \gamma \max_a Q(s',a)\right)}_{\text{target}}$$

- L(δ) for MSE loss is,

$$\mathcal{L}(\delta) = \frac{1}{2}\delta^2$$

- and L(δ) for Huber Loss is,

$$\mathcal{L}(\delta) = \begin{cases} \frac{1}{2}\delta^2 & \text{for } |\delta| \le 1, \\ |\delta| - \frac{1}{2} & otherwise \end{cases}$$

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Deep Q-Learning: Stage 2

- Add Experience Replay
  - Store transitions and sample batches during training
  - Stabilizes learning
  - Needed because successive experiences are highly co-related

Deep Q-Learning: Stage 3

Add a separate target network

$$\delta = \underbrace{Q\left(s, a; \theta\right)}_{\text{prediction}} - \underbrace{\left(r + \gamma \max_{a'} Q\left(s', a'; \theta^{-}\right)\right)}_{\text{target}}$$

- The problem: "...the max operator uses the same values to both select and evaluate an action. This can therefore lead to overoptimistic value estimates." (7)
  - The target network is used to:
    - Determine a'
    - Evaluate state-action value of Q(s', a')

Deep Q-Learning: Stage 4

Double Deep Q-Networks

- Mitigates overoptimistic value estimates.

$$\delta = \underbrace{Q\left(s,a;\theta\right)}_{\text{prediction}} - \underbrace{\left(r + \gamma Q\left(s', \mathrm{argmax}_{a'} Q\left(s',a';\theta\right);\theta^{-}\right)\right)}_{\text{target}}$$

- Use the online network to determine a' and then use the target network as a measure of how good that action is Q(s', a').

Deep Q-Learning: Stage 5

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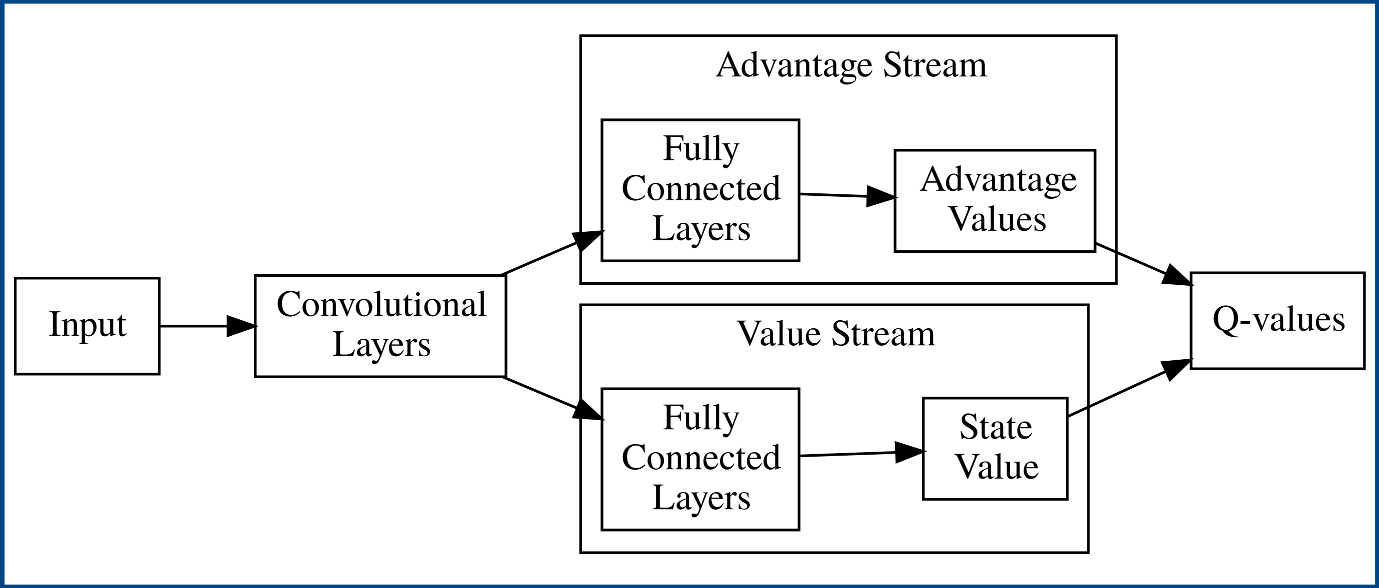
Dueling Double Deep Q-Networks

$$Q^{\pi}(s,a) = \mathbb{E}[R_{t+1} | s_t = s, a_t = a, \pi]$$

$$V^{\pi}(s) = \mathbb{E}_{a \sim \pi(s)}[Q^{\pi}(s,a)] \qquad A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$



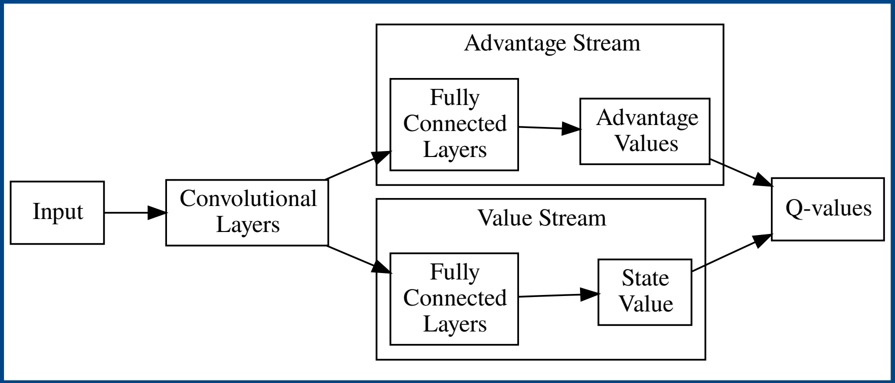
Deep Q-Learning: Stage 5

Now we must combine the approximate value and advantage functions to form an approximate state-action value function.

$$Q(s, a; \theta, \alpha, \beta) = V(s; \theta, \beta) + A(s, a; \theta, \alpha)$$

$$Q(s, a; \theta, \alpha, \beta) = V(s; \theta, \beta) + \left(A(s, a; \theta, \alpha) - \max_{a' \in |\mathcal{A}|} A(s, a'; \theta, \alpha) \right)$$

$$Q(s, a; \theta, \alpha, \beta) = V(s; \theta, \beta) + \left(A(s, a; \theta, \alpha) - \frac{1}{|\mathcal{A}|} \sum_{a'} A(s, a'; \theta, \alpha) \right)$$



Deep Q-Learning: Stage 6

- Stage for further extensions such as:
  - Prioritized Replay
  - Continuous Action Domain
  - Continuous target network updates

$$\theta^{-} \leftarrow \tau\theta + (1-\tau)\,\theta^{-}$$

2048-Unlimited

- What is 2048?
  - Demo
- State space: realistically ~15^{16}, theoretically more.
- Action Space = {0, 1, 2, 3} or {<up>, <right>, <down>, <left>}

Implementation Overview

- Show a config file
- Huber Loss & MSE Loss & batch updates
- Gradient Clipping
- Double DQN
- Dueling DQN
  - Average Advantage
  - Max Advantage
- Target Network syncing
- Slow tracking
- Update frequency
- Adaptive Learning Rate
- Replay memory
- Epsilon decay mode = {linear, exponential, sinusoidal}
- Epsilon annealing duration
- Epsilon Explorer
- Agent knows best & unsticking agent
- Various activation functions: ReLU, ELU, SreLU
- Various Networks: Convolutional, Fully Connected, Self Normalizing Fully Connected

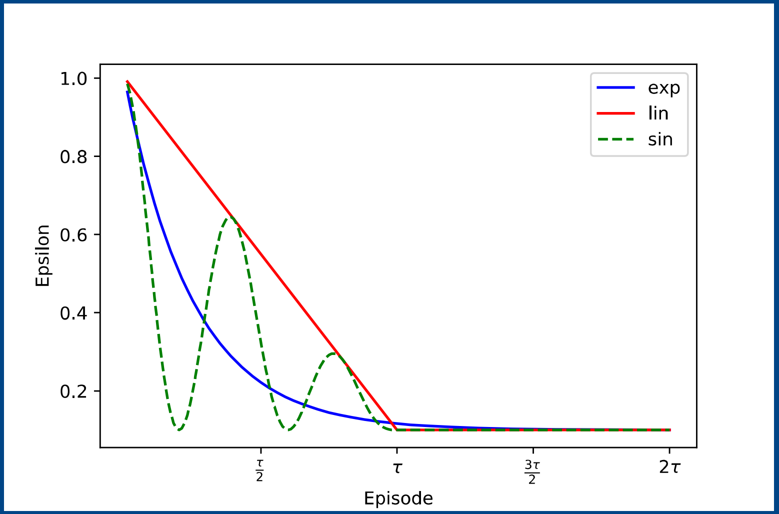
Implementation Overview

- PyTorch; my own implementation starting from DQN State 2
- Normalize states and rewards:

$$processed\_s = \frac{log_2 s}{15}$$

$$processed\_r = \frac{log_2 r}{15}$$

- Epsilon Decay Modes



Implementation Overview

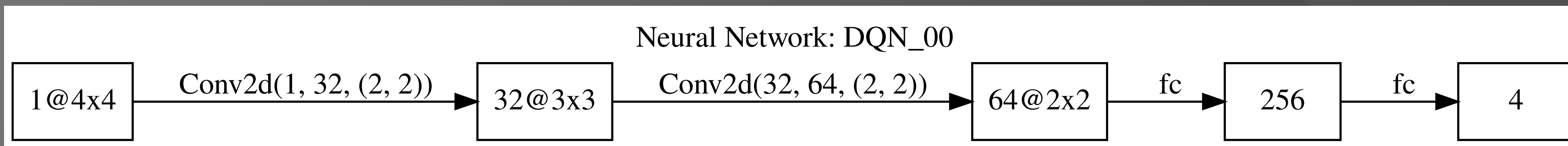
- Epsilon Explorer
  - A novel contribution: modify epsilon within an episode in addition to between episodes
  - Goal: increase exploration as you get further in the episode and reduce exploration near the beginning of the episode
  - See jupyter notebook

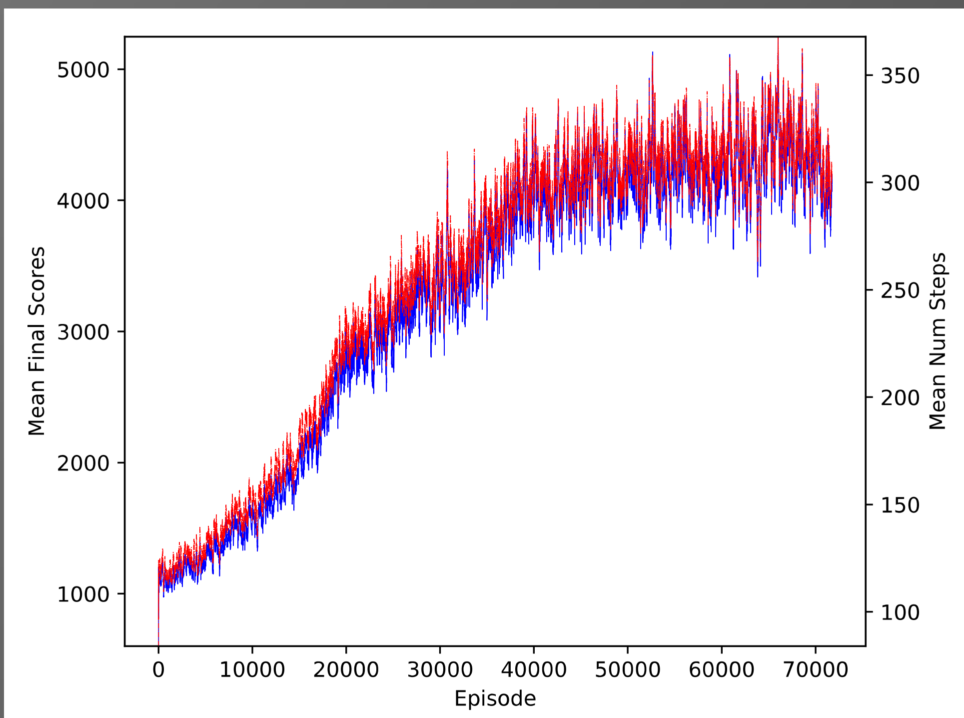
- Use smaller epsilon values
- Agent Knows Best
- Unstick Agent

Research and Results

- ~26 runs with my code
  - We will look at a very small subset
- Exploration of the hyperparameter space was limited by computational constraints
  - See config file and networks module
- Best human performance is ~100,000

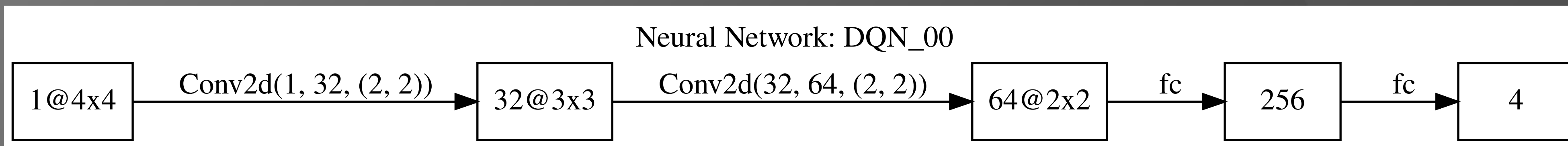
Research and Results

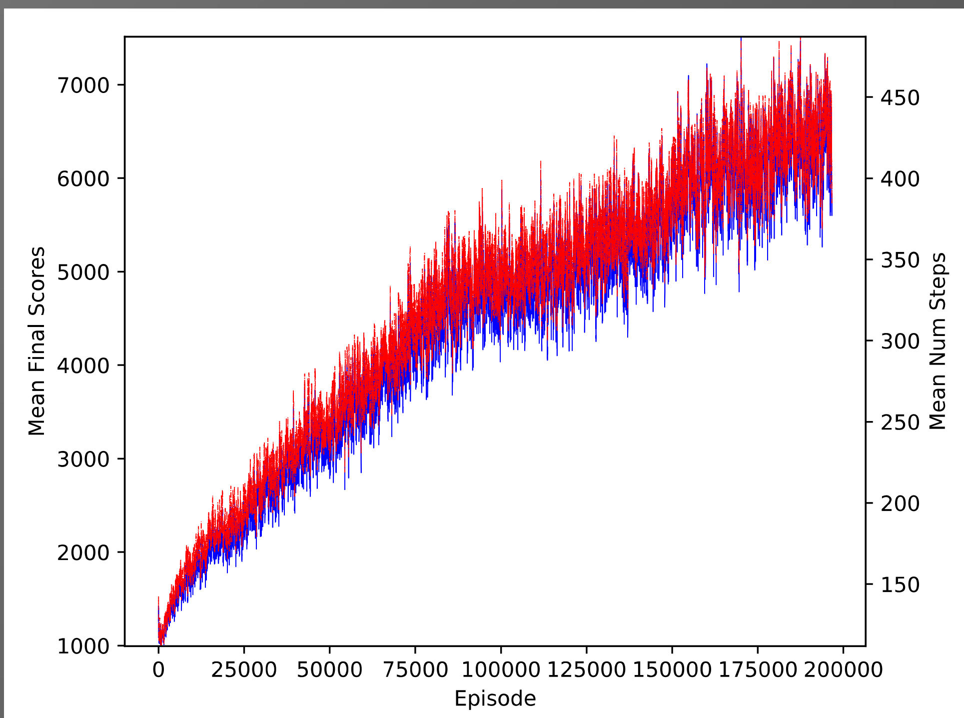




- scspc677:run20170719_01
- Parameters: 75236
- epsilon_decay_mode = linear
- epsilon_annealing_duration = 20,000
- slow_tracking = False
- epsilon_explorer = False

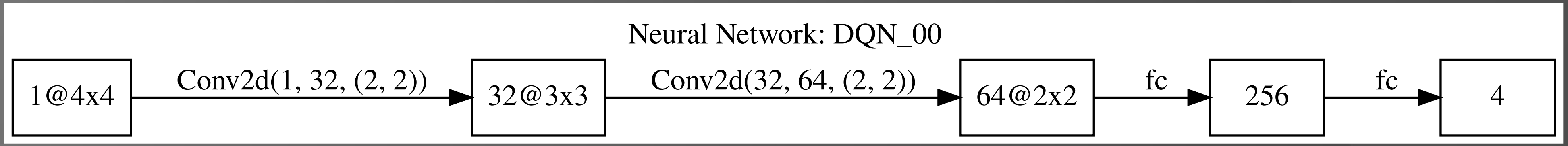
Research and Results

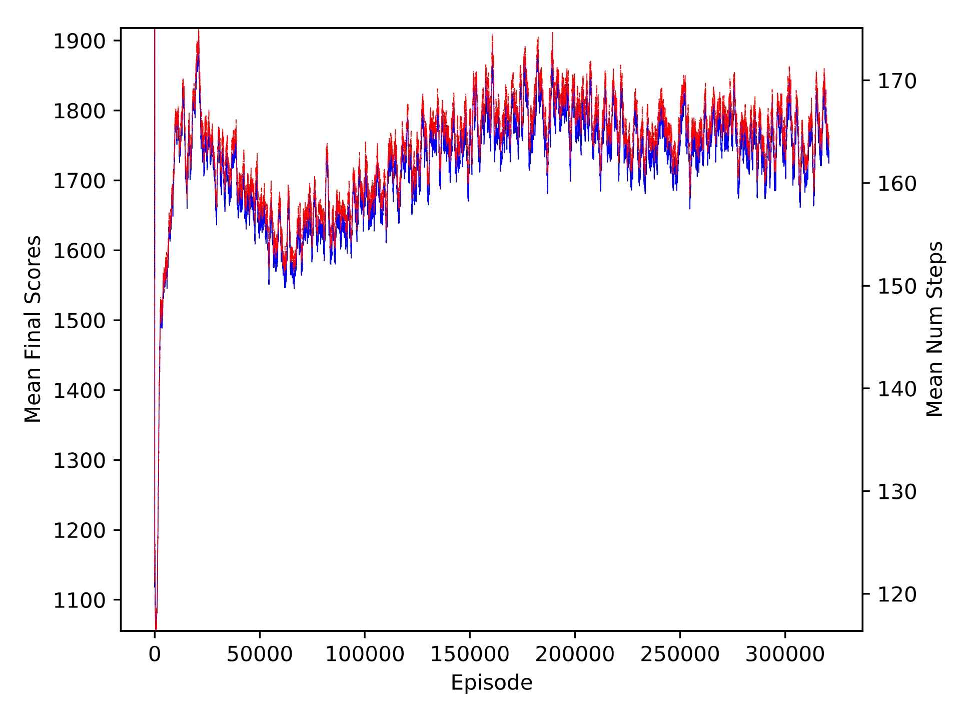




- ubuntu1404:run20170719_01
- Parameters: 75236
- Compare to scspc677:run20170719_01
- epsilon_decay_mode = exponential
- epsilon_annealing_duration = 40,000
- slow_tracking = False
- epsilon_explorer = True

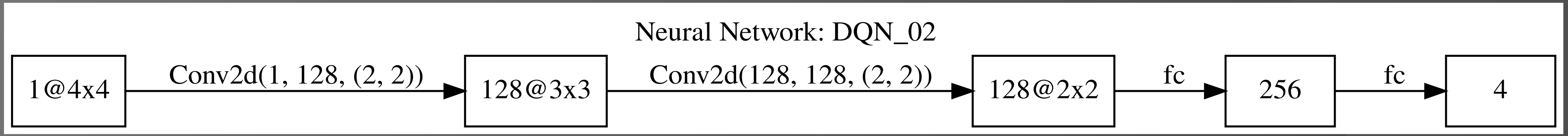
Research and Results

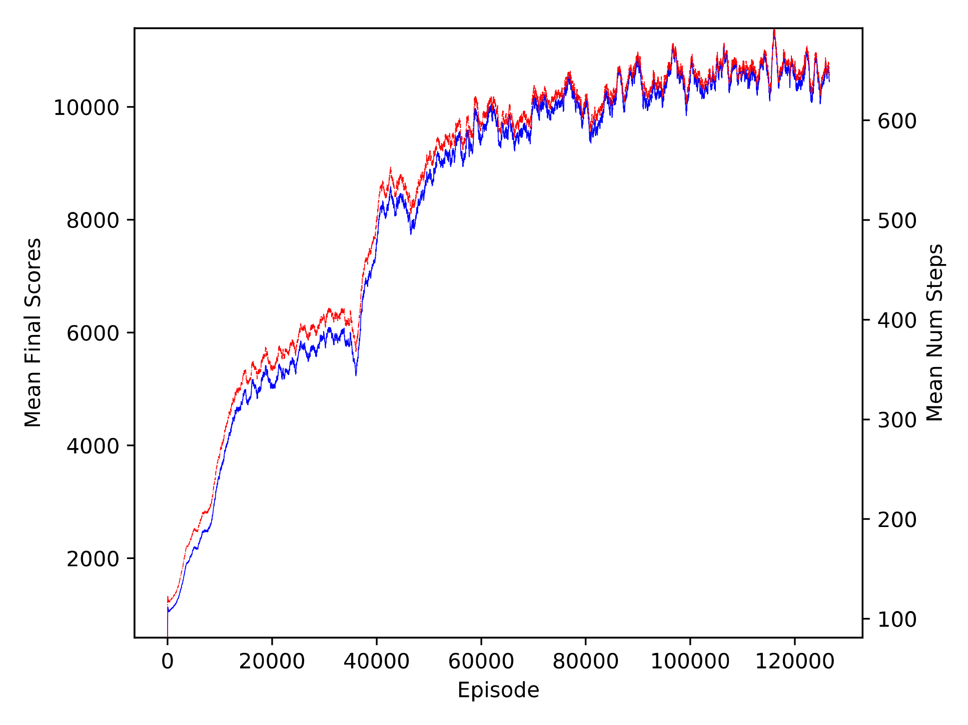




- ubuntu1404:run20170719_02
- Parameters: 75236
- Compare to scspc677:run20170719_01
- slow_tracking = True
- epsilon_explorer = False

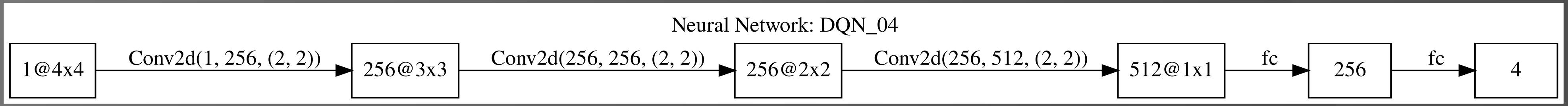
Research and Results

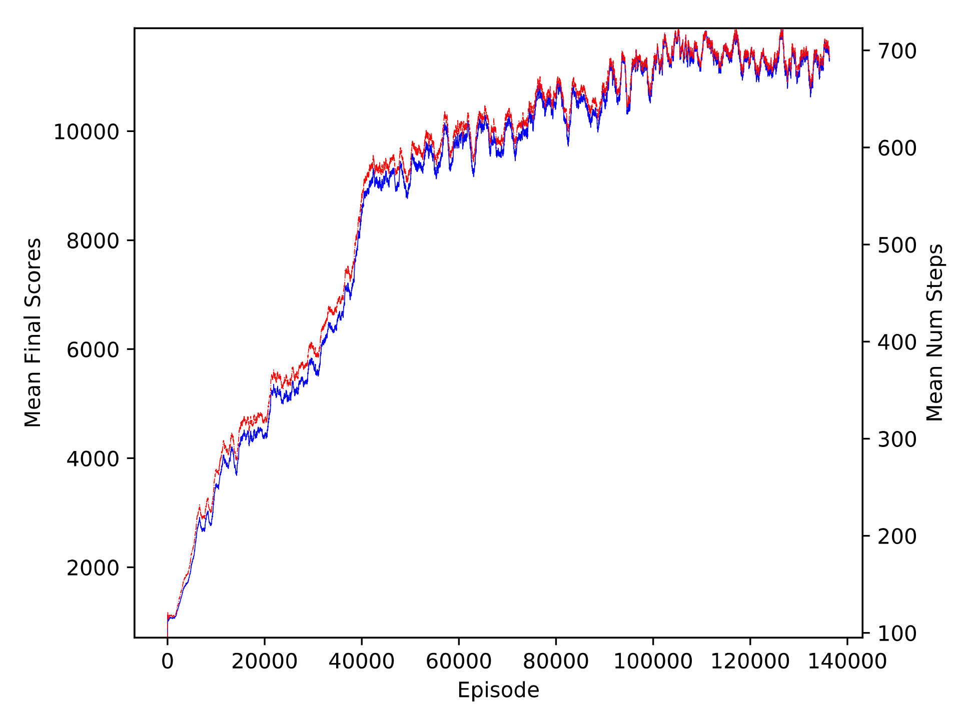




- scspc675.cs:run20170720_03
- Parameters: 198660

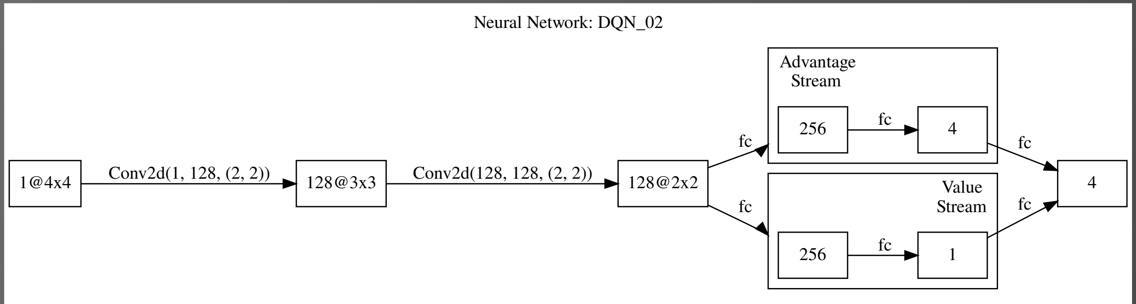
Research and Results

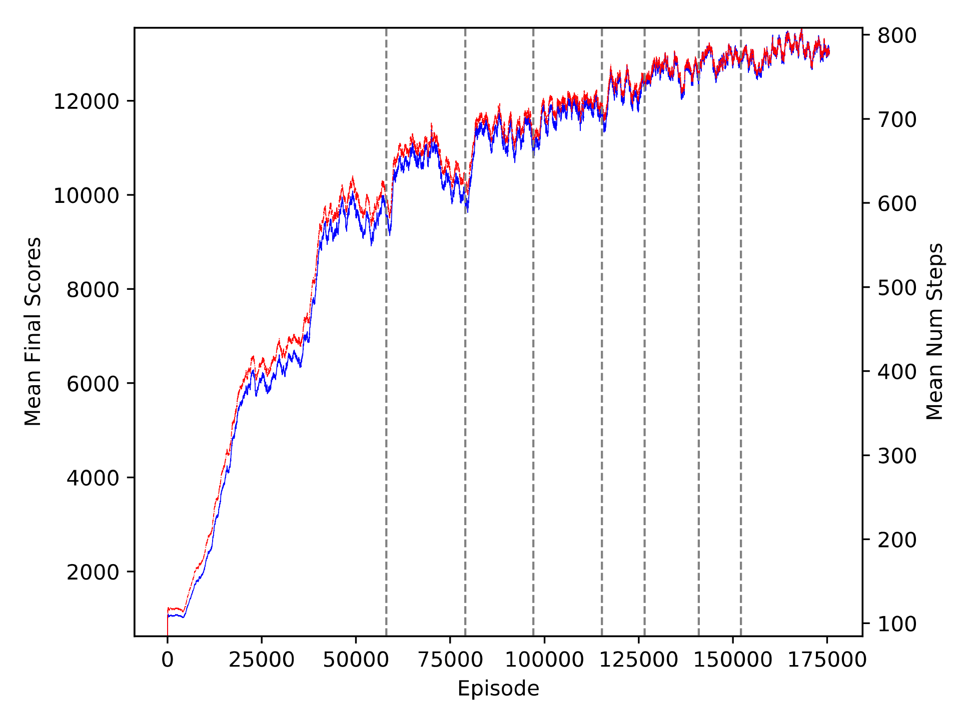




- scspc665:run20170721_01
- Parameters: 920836
- This is the same run as scspc675:run20170720_03 except:
  - Network 4 instead of network 2

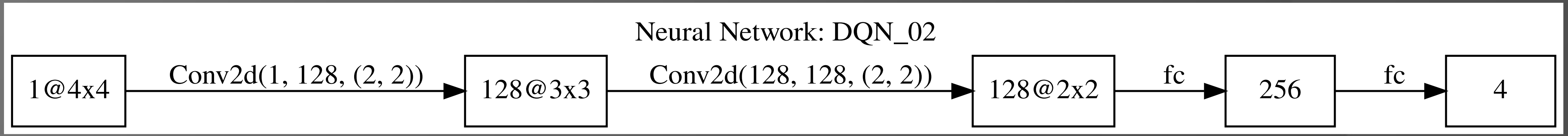
Research and Results

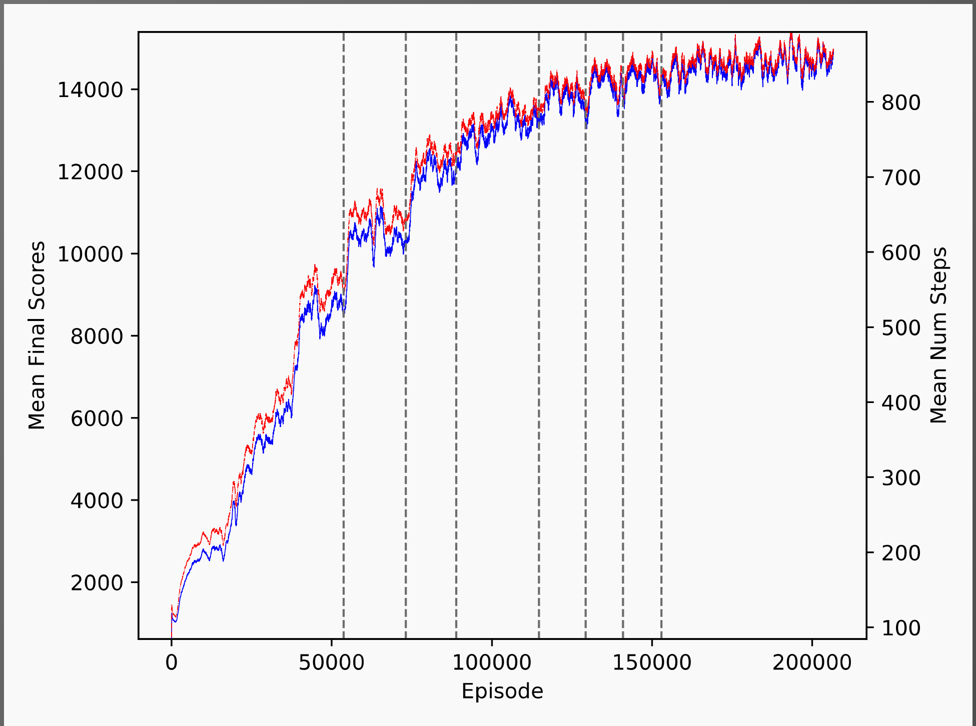




- scspc675:run20170723_01
- Parameters: 330245
- This is the same run as scspc675:run20170720_03 except:
  - dueling_dqn = True instead of False
  - plateau length changed from annealing_duration to annealing_duration/4

Research and Results





- scspc675:run20170723_02
- Parameters: 198660
- This is the same run as scspc675:run20170720_03 except:
  - no penalty for a reward of 0
  - plateau length changed from annealing_duration to annealing_duration/4

Research and Results

- Best results so far:
  - Largest Tile = 4096
  - Longest Episode Duration = 3127
  - Highest Score = 67988
  - Largest Mean Total Rewards = 15390
  - Largest Mean Duration = 893
  - My personal highest Tile = 2048
  - My personal highest Score = 27556

Demonstration and Interactive Results

- Show the demo and interactive results

Future Work

- We would like to experiment with ways that may increase the speed the model learns while avoiding longer training, longer annealing times, and larger models such as:
  - Prioritized Experience Replay
  - Epsilon Explorer
- We would like to experiment more (in general):
  - Larger networks
  - Longer training/annealing
  - Different Networks
  - Wider variety of activation funcitons

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Conclusion

- To the best of our knowledge, this is the first successful application of Deep Q-Learning to 2048
- My Deep Learning Model can play better than I can on average
- The model is not yet at superhuman performance
- Agent Knows Best is benificial
- We hypothesize that performance can be increased by:
  - Longer training times
  - Longer annealing times
  - Larger models
  - Prioritized Experience Replay
  - Epsilon Explorer

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