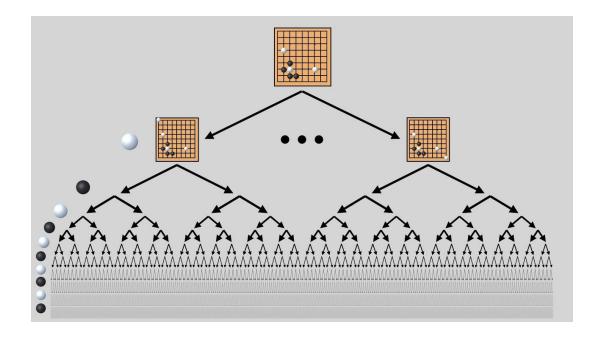
Reinforcement Learning: Function Approximation

AI/ML Teaching

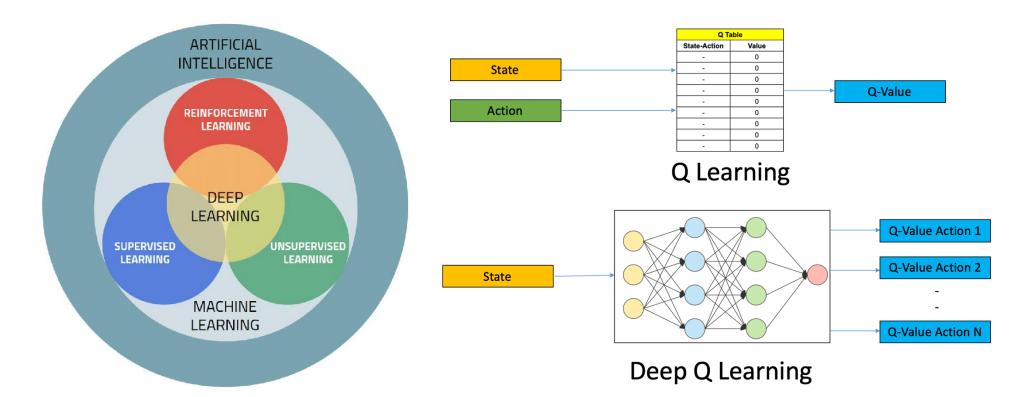
Motivation

- There are too many states and/or actions to store in memory
- It is too slow to learn the value of each state individually

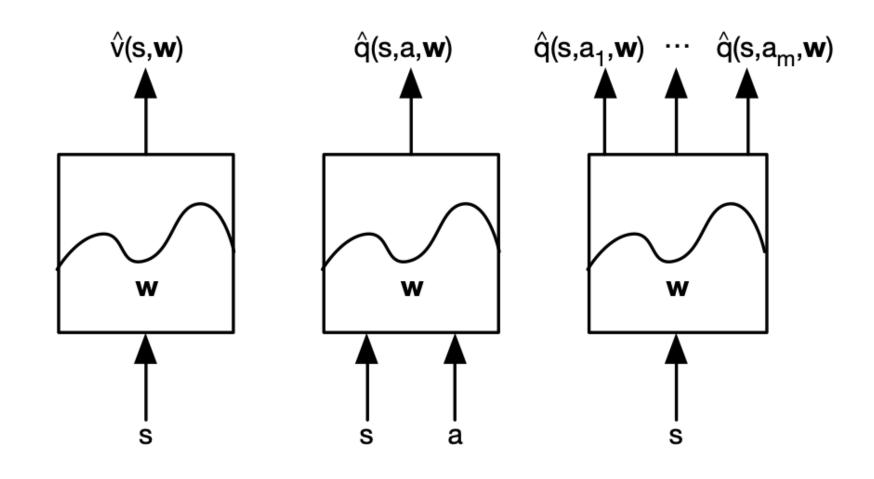


Deep learning & Reinforcement Learning

- Estimate value function with function approximation
 - $\hat{v}(s, \mathbf{w}) \approx v_{\pi}(s) / \hat{q}(s, a, \mathbf{w}) \approx q_{\pi}(s, a)$
 - Generalize from seen states to unseen states
 - Neural network as a universal function approximator

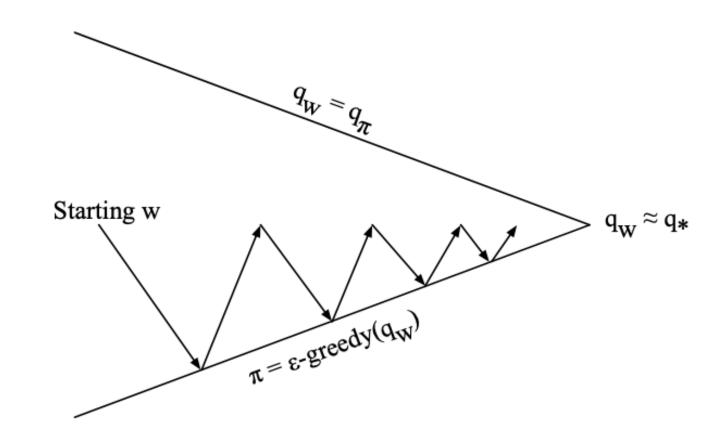


Types of Value Function Approximation



Policy Iteration with approximate evaluation

- Policy evaluation: approximate policy evaluation
- Policy improvement: ϵ -greedy



Batch methods to RL (like supervised learning)

- Given value function approximation $\hat{v}(s, \mathbf{w}) \approx v_{\pi}(s)$
- Experience $\mathcal{D} = \{\langle s_1, v_1^{\pi} \rangle, \langle s_2, v_2^{\pi} \rangle, \dots, \langle s_T, v_T^{\pi} \rangle\}$
- Repeat:
 - Sample state, value from experience

$$\langle s_1, v_1^\pi \rangle \sim \mathcal{D}$$

- Apply stochastic gradient descent update $\Delta \mathbf{w} = \alpha (v^{\pi} \hat{v}(s, \mathbf{w})) \nabla_{\mathbf{w}} \hat{v}(s, \mathbf{w})$
- $\mathbf{w}^{\pi} = \arg\min LS(\mathbf{w})$
- DQN uses experience replay and fixed Q-targets

Reference

- David Silver, COMPM050/COMPGI13 Lecture Notes
- Richard S. Sutton and Andrew G. Barto, "Reinforcement Learning: An Introduction," 2nd Ed.