Machine Learning

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University of Illinois at Urbana-Champaign, 2018

L24: Q-learning

Goals of this lecture

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- Extending MDPs

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- Getting to know Q-learning

Recap so far: Known MDP

- To compute V^*, Q^*, π^*: use **policy/value iteration or exhaustive**
- To evaluate fixed policy π: use policy evaluation

But what if:

- Transition probabilities and rewards are not known
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- Run a simulator to collect experience tuples/samples (s, a, r, s')
- Approximate transition probability using samples

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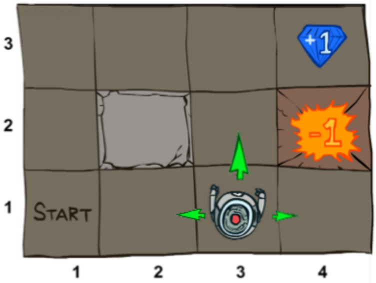
$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha y_{(s,a,r,s')}$$

Summary:

- Known MDP
  - To compute V^*, Q^*, π^*: use value/policy iteration
  - To evaluate fixed policy π: use policy evaluation

- Unknown MDP: Model free
  - To compute V^*, Q^*, π^*: use Q-learning
  - To evaluate fixed policy π: use value learning

Our current Q-learning works fine in case we have a tabular environment:



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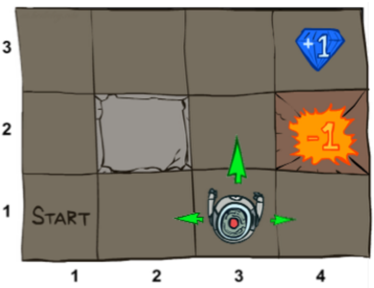

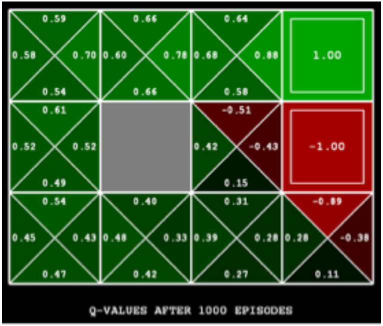

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How about $Q_\theta(s, a)$ as a neural net which takes images as input and produces a number for each of the possible actions?

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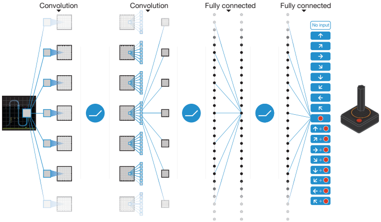

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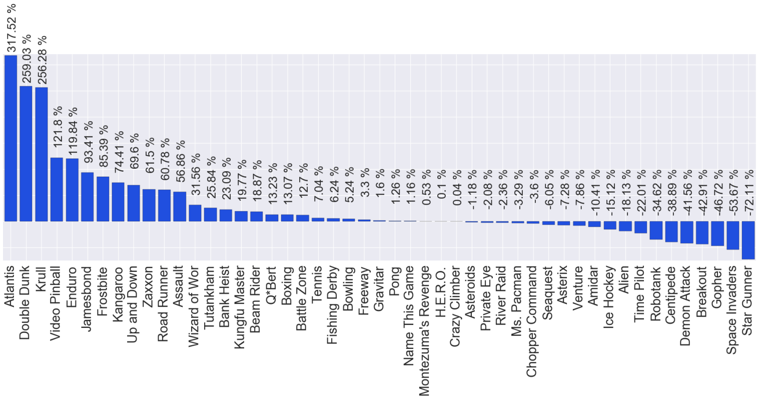
- Perform ϵ-greedy action and augment $\mathcal{D}$

Results:



317.52 %
259.03 %
256.28 %
121.8 %
119.84 %
93.41 %
85.39 %
74.41 %
69.6 %
61.5 %
60.78 %
56.86 %
31.56 %
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5.24 %
3.3 %
1.6 %
1.26 %
1.16 %
0.53 %
0.1 %
0.04 %
-1.18 %
-2.08 %
-2.36 %
-3.29 %
-3.6 %
-6.05 %
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-7.86 %
-10.41 %
-15.12 %
-18.13 %
-22.01 %
-34.62 %
-38.89 %
-41.56 %
-42.91 %
-46.72 %
-53.67 %
-72.11 %
Atlantis
Double Dunk
Krull
Video Pinball
Enduro
Jamesbond
Frostbite
Kangaroo
Up and Down
Zaxxon
Road Runner
Assault
Wizard of Wor
Tutankham
Bank Heist
Kungfu Master
Beam Rider
Q*Bert
Boxing
Battle Zone
Tennis
Fishing Derby
Bowling
Freeway
Gravitar
Pong
Name This Game
Montezuma's Revenge
H.E.R.O.
Crazy Climber
Asteroids
Private Eye
River Raid
Ms. Pacman
Chopper Command
Seaquest
Asterix
Venture
Amidar
Ice Hockey
Alien
Time Pilot
Robotank
Centipede
Demon Attack
Breakout
Gopher
Space Invaders
Star Gunner

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- What differentiates RL from supervised learning?
- What is a MDP?
- What to do if no transition probabilities are available?

Important topics of this lecture

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- Getting a feeling for reinforcement learning

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- Understanding how to use reinforcement learning

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What's next:

Policy Gradient Methods