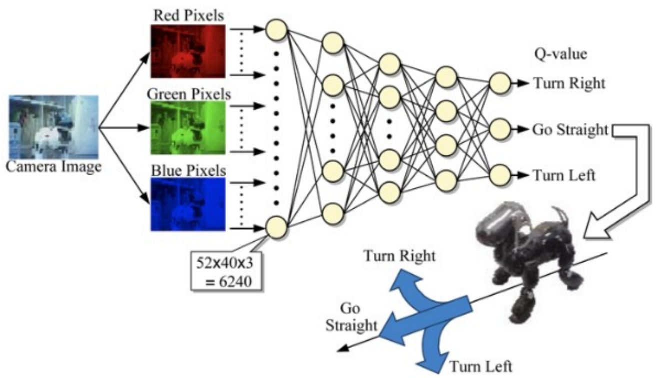
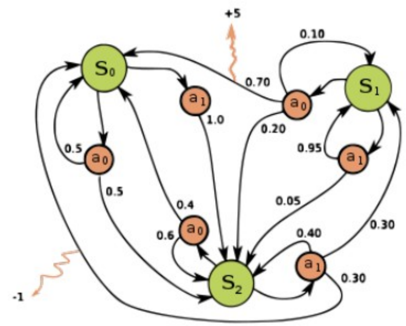
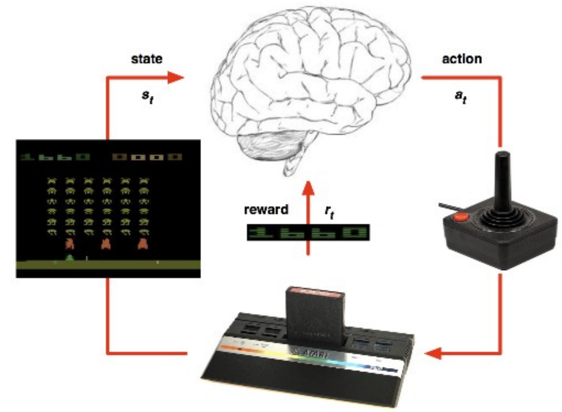
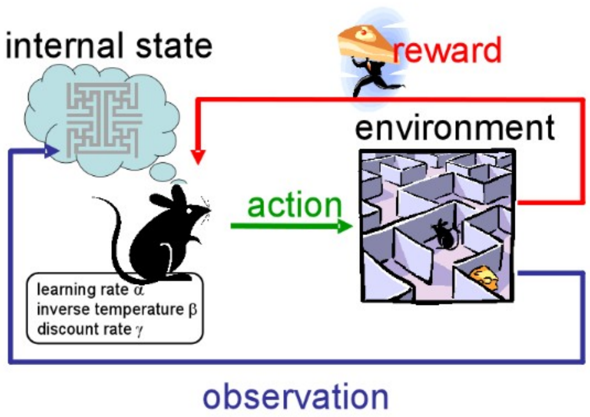
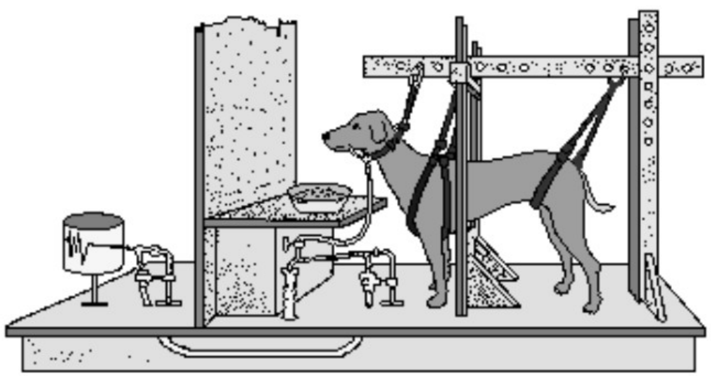
COMP 138: Reinforcement Learning











Instructor: Jivko Sinapov

Announcements

Reading Assignment

- Chapter 7 of Sutton and Barto

Research Article Topics

- Transfer learning
- Learning with human demonstrations and/or advice
- Approximating q-functions with neural networks

Research Paper

- Griffith, S., Subramanian, K., Scholz, J., Isbell, C. L., & Thomaz, A. L. (2013). **Policy shaping: Integrating human feedback with reinforcement learning**. In Advances in neural information processing systems (pp. 2625-2633).
- Responses should discuss both readings
- You get extra credit for answering others' questions!

Monte Carlo Methods

Overview of Monte Carlo ES

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:
- $Q(s, a) \leftarrow$ arbitrary
- $\pi(s) \leftarrow$ arbitrary
- $Returns(s, a) \leftarrow$ empty list

Repeat forever:
- Choose $S_0 \in \mathcal{S}$ and $A_0 \in \mathcal{A}(S_0)$ s.t. all pairs have probability > 0
- Generate an episode starting from S_0, A_0, following π
- For each pair s, a appearing in the episode:
  - $G \leftarrow$ the return that follows the first occurrence of s, a
  - Append G to $Returns(s, a)$
  - $Q(s, a) \leftarrow \text{average}(Returns(s, a))$
- For each s in the episode:
  - $\pi(s) \leftarrow \arg\max_a Q(s, a)$

On- vs. Off-policy Methods

- On-policy methods attempt to improve a policy that is used for gathering data
- Off-policy methods attempt to improve a different policy from the one used for gathering data

Off-policy exploration in humans

https://www.youtube.com/watch?v=8vNxjwt2AqY

[illegible] first-visit MC control (for ε-soft policies), estimates $\pi \approx \pi_*$

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:

  $Q(s, a) \leftarrow$ arbitrary

  $Returns(s, a) \leftarrow$ empty list

  $\pi(a|s) \leftarrow$ an arbitrary ε-soft policy

Repeat forever:

  (a) Generate an episode using π

  (b) For each pair s, a appearing in the episode:

    $G \leftarrow$ the return that follows the first occurrence of s, a

    Append G to $Returns(s, a)$

    $Q(s, a) \leftarrow \text{average}(Returns(s, a))$

  (c) For each s in the episode:

    $A^* \leftarrow \arg\max_a Q(s, a)$ (with ties broken arbitrarily)

    For all $a \in \mathcal{A}(s)$:

$$\pi(a|s) \leftarrow \begin{cases} 1 - \varepsilon + \varepsilon/|\mathcal{A}(s)| & \text{if } a = A^* \\ \varepsilon/|\mathcal{A}(s)| & \text{if } a \neq A^* \end{cases}$$

Is this on- or off-policy learning?

Does this algorithm learn the optimal policy?

Does it estimate the true Q function?

[redacted] first-visit MC control (

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:
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- $Returns(s,a) \leftarrow$ empty list
- $\pi(a|s) \leftarrow$ an arbitrary ε-soft policy

Repeat forever:
- (a) Generate an episode using π
- (b) For each pair s, a appearing in the episode:
  - $G \leftarrow$ the return that follows the first occurrence of s, a
  - Append G to $Returns(s,a)$
  - $Q(s,a) \leftarrow \text{average}(Returns(s,a))$
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  - For all $a \in \mathcal{A}(s)$:

$$\pi(a|s) \leftarrow \begin{cases} 1 - \varepsilon + \varepsilon/|\mathcal{A}(s)| & \text{if } a = A^* \\ \varepsilon/|\mathcal{A}(s)| & \text{if } a \neq A^* \end{cases}$$

Programming Assignment #2

On-policy MC

How can we implement this algorithm efficiently?

On-policy first-visit MC control (

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:
$Q(s,a) \leftarrow$ arbitrary
$Returns(s,a) \leftarrow$ empty list
$\pi(a|s) \leftarrow$ an arbitrary ε-soft policy

Repeat forever:
(a) Generate an episode using π
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Off-policy learning and importance sampling

- The prediction problem: given data generated using policy *b*, what is the value function for policy *π?*
- Off-policy prediction and control

Temporal Difference Learning

- Overview of Section 6.1

Learning in a Grid World

https://www.youtube.com/watch?v=tovrpoUkzYU

Q-Learning and Sarsa

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

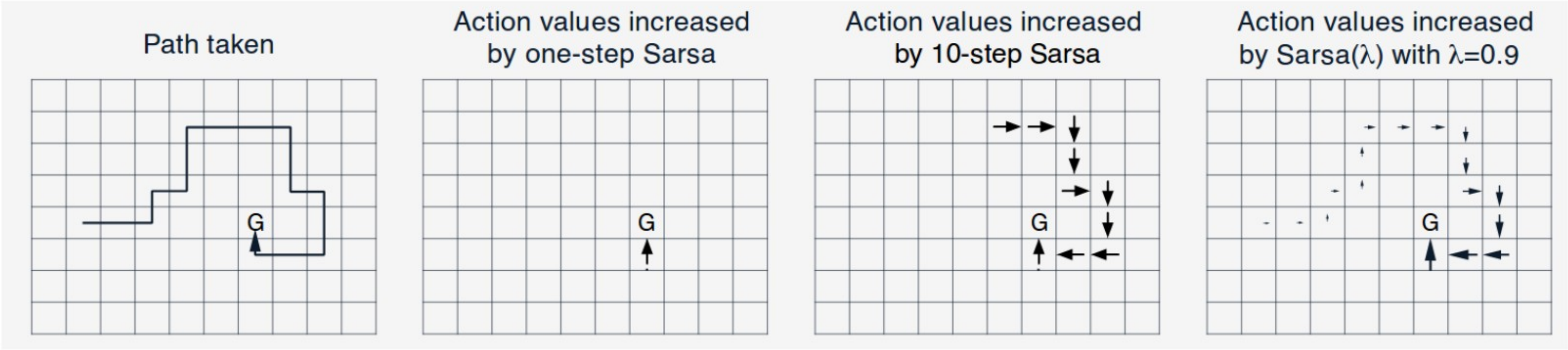
Initialize $Q(s, a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize S
  Repeat (for each step of episode):
    Choose A from S using policy derived from Q (e.g., ϵ-greedy)
    Take action A, observe R, S'
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
    $S \leftarrow S'$
  until S is terminal

Sarsa (on-policy TD control) for estimating $Q \approx q_*$

Initialize $Q(s, a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize S
  Choose A from S using policy derived from Q (e.g., ϵ-greedy)
  Repeat (for each step of episode):
    Take action A, observe R, S'
    Choose A' from S' using policy derived from Q (e.g., ϵ-greedy)
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma Q(S', A') - Q(S, A)\big]$
    $S \leftarrow S'$; $A \leftarrow A'$;
  until S is terminal

Cliff-walking example

Beyond 1-step updates



Moderated Discussion

THE END