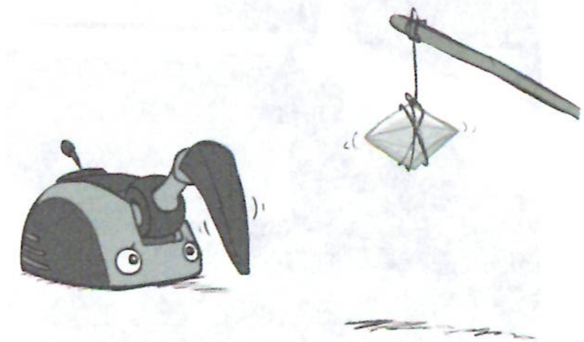
CS 188: Artificial Intelligence

Reinforcement Learning

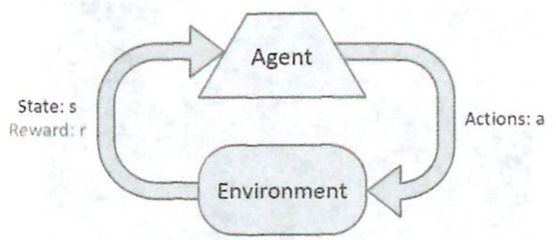
Instructors: Dan Klein and Pieter Abbeel

University of California, Berkeley

Reinforcement Learning



Reinforcement Learning



- Basic idea:
  - Receive feedback in the form of rewards
  - Agent's utility is defined by the reward function
  - Must (learn to) act so as to maximize expected rewards
  - All learning is based on observed samples of outcomes!

Example: Learning to Walk

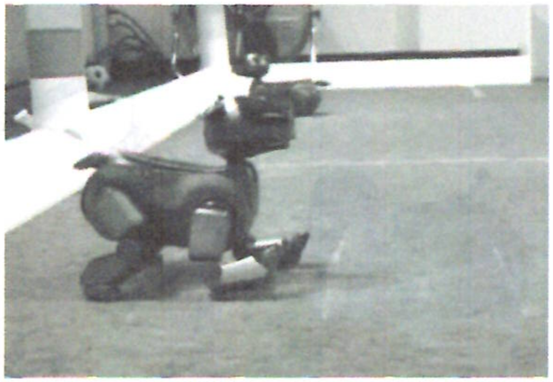
Initial

A Learning Trial

After Learning [1K Trials]

[Kohl and Stone, ICRA 2004]

Example: Learning to Walk



Initial

[Kohl and Stone, ICRA 2004]

[Video: AIBO WALK – initial]

Example: Learning to Walk

Training

[Kohl and Stone, ICRA 2004]

[Video: AIBO WALK – training]

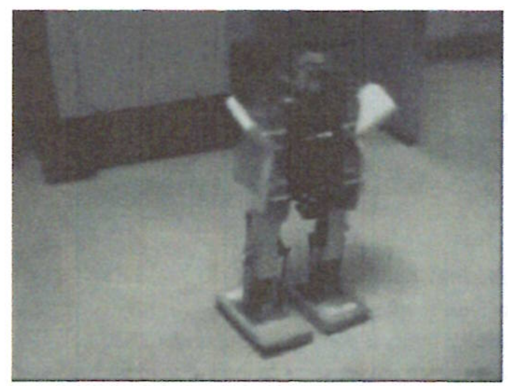
Example: Learning to Walk

Finished

[Kohl and Stone, ICRA 2004]

[Video: AIBO WALK – finished]

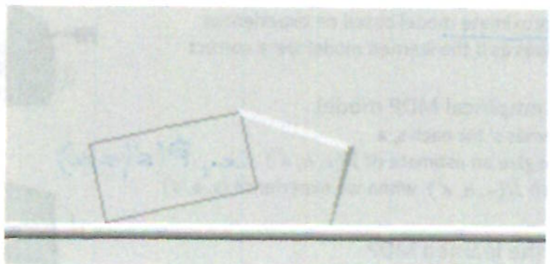
Example: Toddler Robot



[Tedrake, Zhang and Seung, 2005]

[Video: TODDLER – 40s]

The Crawler!



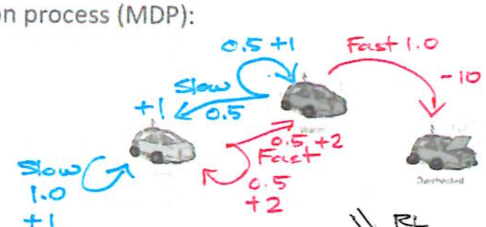
• has to figure out not only moving forward but also resetting arm (leg?)

[Demo: Crawler Bot (L10D1)] [You, in Project 3]

Video of Demo Crawler Bot

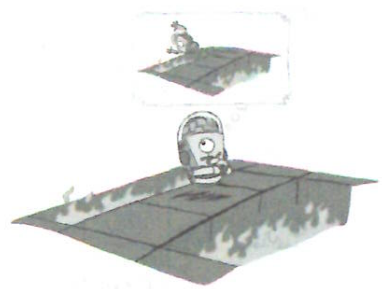
Reinforcement Learning

- Still assume a Markov decision process (MDP):
  - A set of states s ∈ S
  - A set of actions (per state) A
  - A model T(s,a,s')
  - A reward function R(s,a,s')
- Still looking for a policy π(s)
- New twist: don't know T or R
  - I.e. we don't know which states are good or what the actions do
  - Must actually try actions and states out to learn

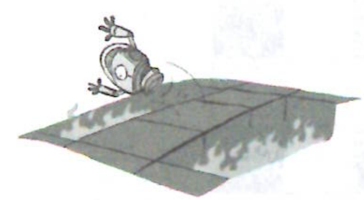


RL
only-know
Warm
Cool
OH
+ actions for each state

Offline (MDPs) vs. Online (RL)



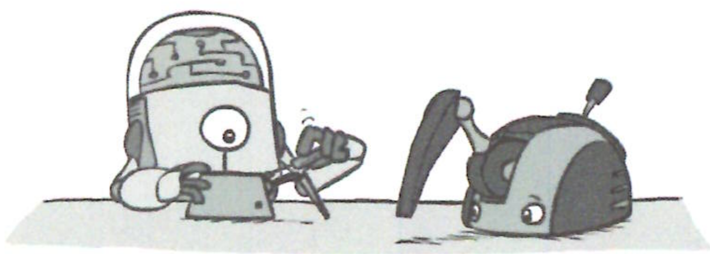
Offline Solution



Online Learning

• have to jump into pit to learn it is bad

Model-Based Learning



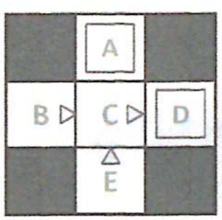
• reduce the RL problem to MDP

Model-Based Learning

- Model-Based Idea:
  - Learn an approximate model based on experiences
  - Solve for values as if the learned model were correct
- Step 1: Learn empirical MDP model
  - Count outcomes s' for each s, a
  - Normalize to give an estimate of $\hat{T}(s,a,s')$ i.e., $\hat{P}(s'|s,a)$
  - Discover each $\hat{R}(s,a,s')$ when we experience (s, a, s')
- Step 2: Solve the learned MDP
  - For example, use value iteration, as before

Example: Model-Based Learning

Input Policy π



Assume: γ = 1

Observed Episodes (Training)

Episode 1
B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2
B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 3
E, north, C, -1
C, east, D, -1
D, exit, x, +10

Episode 4
E, north, C, -1
C, east, A, -1
A, exit, x, -10

Learned Model

$\hat{T}(s,a,s')$
T(B, east, C) = 1.00
T(C, east, D) = 0.75
T(C, east, A) = 0.25
...

$\hat{R}(s,a,s')$
R(B, east, C) = -1
R(C, east, D) = -1
R(D, exit, x) = +10
...

Example: Expected Age

Goal: Compute expected age of cs188 students

Known P(A)

$$E[A] = \sum_a P(a) \cdot a \quad = 0.35 \times 20 + \ldots$$

Without P(A), instead collect samples [a_1, a_2, ... a_N]

Unknown P(A): "Model Based"

$$\hat{P}(a) = \frac{\text{num}(a)}{N}$$

$$E[A] \approx \sum_a \hat{P}(a) \cdot a$$

• i.e., reduced to MDP

Why does this work? Because eventually you learn the right model.

Unknown P(A): "Model Free"

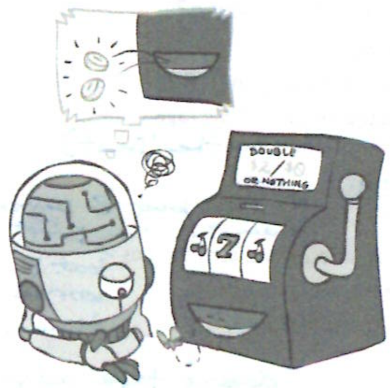
$$E[A] \approx \frac{1}{N} \sum_i a_i$$

unweighted b/c

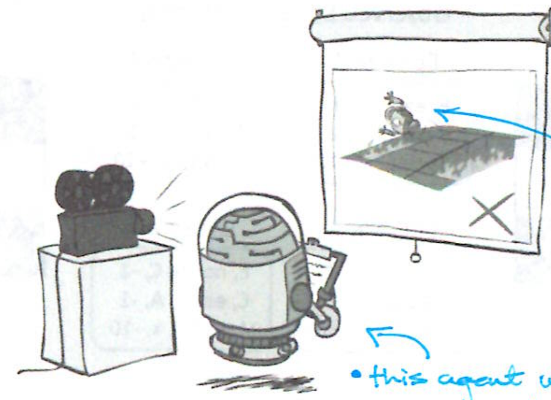
Why does this work? Because samples appear with the right frequencies.

• Model free case: often much simpler

Model-Free Learning



Passive Reinforcement Learning



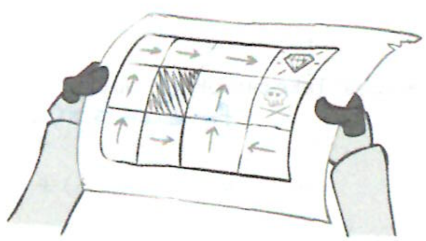
• this agent watches another agent act + learns

i.e., passive RL has a fixed policy π + just executes π + learns state values from exp.

• no choice on which actions to take

Passive Reinforcement Learning

- Simplified task: policy evaluation
  - Input: a fixed policy $\pi(s)$
  - You don't know the transitions $T(s,a,s')$
  - You don't know the rewards $R(s,a,s')$
  - Goal: learn the state values
- In this case:
  - Learner is "along for the ride"
  - No choice about what actions to take
  - Just execute the policy and learn from experience
  - This is NOT offline planning! You actually take actions in the world.

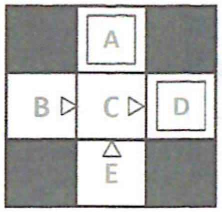


Direct Evaluation

- Goal: Compute values for each state under π
- Idea: Average together observed sample values
  - Act according to π
  - For each ~~Every~~ time you visit a state, write down what the sum of discounted rewards ~~turned out to be~~ eventually turns out to be
  - Average those samples per state
- This is called direct evaluation

Example: Direct Evaluation

Input Policy π



Assume: γ = 1

Observed Episodes (Training)

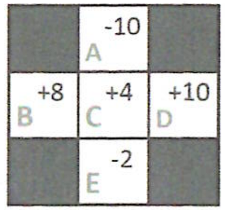
Episode 1
B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2
B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 3
E, north, C, -1
C, east, D, -1
D, exit, x, +10

Episode 4
E, north, C, -1
C, east, A, -1
A, exit, x, -10

Output Values



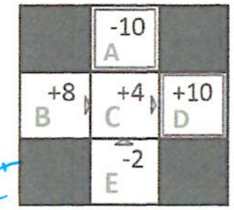
Problems with Direct Evaluation

- What's good about direct evaluation?
  - It's easy to understand
  - It doesn't require any knowledge of T, R
  - It eventually computes the correct average values, using just sample transitions (in the limit)
- What bad about it?
  - It wastes information about state connections
  - Each state must be learned separately
  - So, it takes a long time to learn

e.g., $B \xrightarrow{100\%} C$ but B better than C. $E \xrightarrow{100\%} C$ but E worse than C

doesn't take advantage of info like a good state → another state w/ high prob. implies 2^{nd} state is also good.

Output Values



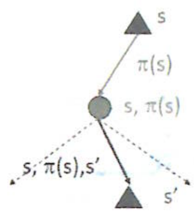
If B and E both go to C under this policy, how can their values be different?

Why Not Use Policy Evaluation?

- Simplified Bellman updates calculate V for a fixed policy:
  - Each round, replace V with a one-step-look-ahead layer over V

$$V_0^\pi(s) = 0$$

$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s,\pi(s),s')[R(s,\pi(s),s') + \gamma V_k^\pi(s')]$$



  - This approach fully exploited the connections between the states
  - Unfortunately, we need T and R to do it!
- Key question: how can we do this update to V without knowing T and R?
  - In other words, how to we take a weighted average without knowing the weights?

• By sampling + ~~add~~ averaging w/ equal weight

Sample-Based Policy Evaluation?

- We want to improve our estimate of V by computing these averages: (RHS es)

$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s,\pi(s),s')[R(s,\pi(s),s') + \gamma V_k^\pi(s')]$$

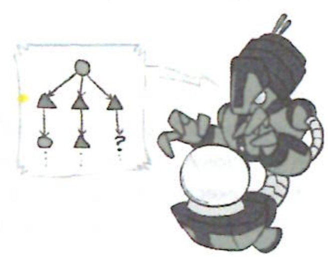
- Idea: Take samples of outcomes s' for each $(s,\pi(s))$ (by doing the action!) and average

$$sample_1 = R(s,\pi(s),s_1') + \gamma V_k^\pi(s_1')$$

$$sample_2 = R(s,\pi(s),s_2') + \gamma V_k^\pi(s_2')$$

$$\ldots$$

$$sample_n = R(s,\pi(s),s_n') + \gamma V_k^\pi(s_n')$$

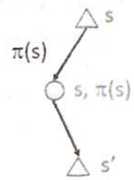


$$V_{k+1}^\pi(s) \leftarrow \frac{1}{n}\sum_i sample_i$$

• Issue is that we have no idea when we'll return to state s (if ever) after 1^{st} sample.

Temporal Difference Learning

- Big idea: learn from every experience!
  - Update V(s) each time we experience a transition (s, a, s', r)
  - Likely outcomes s' will contribute updates more often
- Temporal difference learning of values
  - Policy still fixed, still doing evaluation!
  - Move values toward value of whatever successor occurs: running average



Sample of V(s): $sample = R(s,\pi(s),s') + \gamma \underbrace{V^\pi(s')}_{\text{old estimate}}$

Update to V(s): $V^\pi(s) \leftarrow (1-\alpha)V^\pi(s) + (\alpha) sample$

Same update: $V^\pi(s) \leftarrow V^\pi(s) + \alpha\overbrace{(\underbrace{sample - V^\pi(s)}_{\text{"error"}})}^{}$ add in direction of error.

- Values of states are influenced by connections, unlike for direct evaluation

Exponential Moving Average

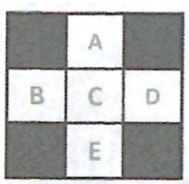
- Exponential moving average
  - The running interpolation update: $\bar{x}_n = (1-\alpha)\cdot \bar{x}_{n-1} + \alpha \cdot x_n$
  - Makes recent samples more important:

$$\bar{x}_n = \frac{x_n + (1-\alpha)\cdot x_{n-1} + (1-\alpha)^2 \cdot x_{n-2} + \dots}{1 + (1-\alpha) + (1-\alpha)^2 + \dots}$$

  - Forgets about the past (distant past values were wrong anyway)
- Decreasing learning rate (alpha) can give converging averages
- Bellman updates are not exponentially moving averages

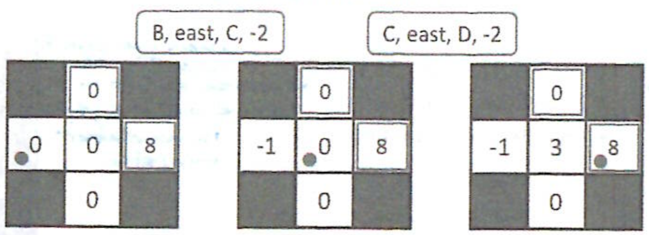
Example: Temporal Difference Learning

States



Assume: $\gamma = 1$, $\alpha = 1/2$

Observed Transitions



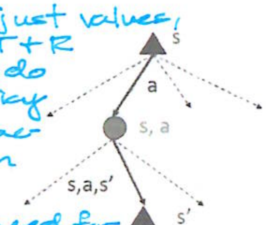
$$V^\pi(s) \leftarrow (1-\alpha)V^\pi(s) + \alpha\left[R(s,\pi(s),s') + \gamma V^\pi(s')\right]$$

Problems with TD Value Learning

- TD value leaning is a model-free way to do policy evaluation, mimicking Bellman updates with running sample averages
- However, if we want to turn values into a (new) policy, we're sunk:

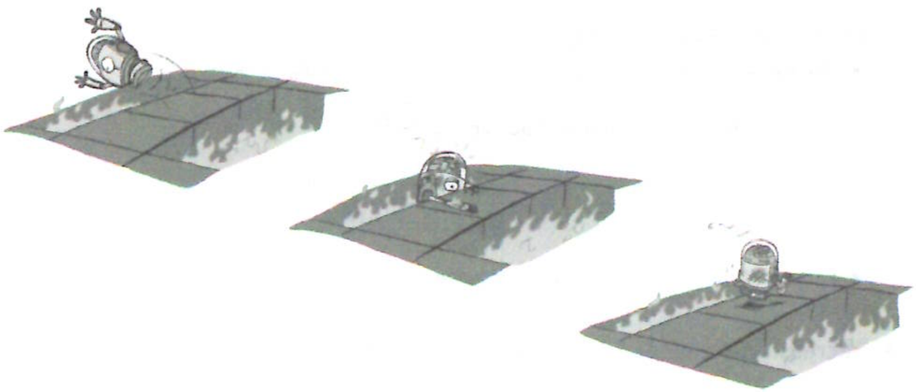
$$\pi(s) = \arg\max_a Q(s,a)$$ — if we have just values, we need T+R to do policy extraction

$$Q(s,a) = \sum_{s'} T(s,a,s')\left[R(s,a,s') + \gamma V(s')\right]$$



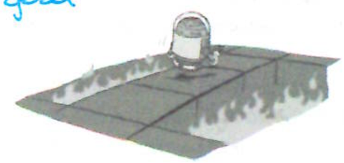
- Idea: learn Q-values, not values
- Makes action selection model-free too! — no need for T+R: just look at Q-values and choose best.
- Q-values are critical for choosing actions in RL

Active Reinforcement Learning



Active Reinforcement Learning

- Full reinforcement learning: optimal policies (like value iteration) goal
  - You don't know the transitions T(s,a,s')
  - You don't know the rewards R(s,a,s')
  - You choose the actions now *
  - Goal: learn the optimal policy / values



- In this case:
  - Learner makes choices!
  - Fundamental tradeoff: exploration vs. exploitation
  - This is NOT offline planning! You actually take actions in the world and find out what happens…

Detour: Q-Value Iteration

- Value iteration: find successive (depth-limited) values
  - Start with $V_0(s) = 0$, which we know is right
  - Given V_k, calculate the depth k+1 values for all states:

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V_k(s') \right]$$

• doesnt work w/ samples bc we can only avg w samples; we dont know how to maximize w/ samples

- But Q-values are more useful, so compute them instead
  - Start with $Q_0(s,a) = 0$, which we know is right
  - Given Q_k, calculate the depth k+1 q-values for all q-states:

$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma \underbrace{\max_{a'} Q_k(s',a')}_{= V_k(s')} \right]$$

• avg, so can use samples to update Q-values

Q-Learning

- Q-Learning: sample-based Q-value iteration

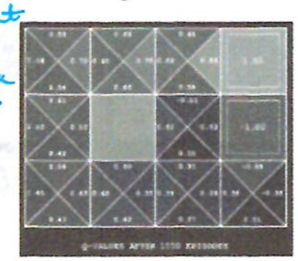
$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma \max_{a'} Q_k(s',a') \right]$$ — if we had T+R

- Learn Q(s,a) values as you go — when we dont have T+R
  - Receive a sample (s,a,s',r) • choose action (somehow) • s'|s,a is nondeterministic
  - Consider your old estimate: $Q(s,a)$
  - Consider your new sample estimate:

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

  - Incorporate the new estimate into a running average:

$$Q(s,a) \leftarrow (1-\alpha) Q(s,a) + (\alpha) \left[sample \right]$$



[Demo: Q-learning – gridworld (L10D2)]
[Demo: Q-learning – crawler (L10D3)]

Video of Demo Q-Learning -- Gridworld

- ~~sample looks at only~~
- ~~Sample estimat~~
- The only Q-value the sample estimate looks at is max over all a' in Q(s',a'), so ~~tour~~ suboptimal Q(s',a'), over a', dont affect Q(s,a) value over iterations

Video of Demo Q-Learning -- Crawler

Q-Learning Properties

- Amazing result: Q-learning converges to optimal policy -- even if you're acting suboptimally!

  bc it updates Q-values based on the next state s' and the greedy action a'. ~~instead of the action of the current policy~~

- This is called off-policy learning

  Q-Learning estimates $\gamma V(s')$ ~~assumes~~ assuming a greedy policy, even though the policy is not greedy.

- Caveats:
  - You have to explore enough
  - You have to eventually make the learning rate small enough
  - ... but not decrease it too quickly
  - Basically, in the limit, it doesn't matter how you select actions (!)
    - guessing this means convergence i.p.