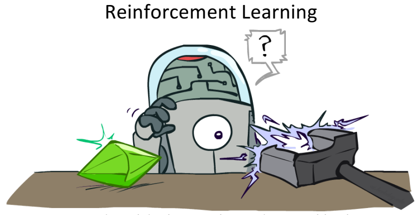
CSE 473: Introduction to Artificial Intelligence

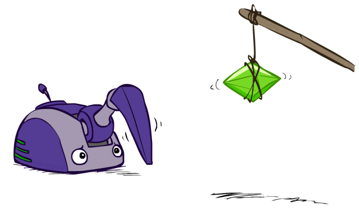
Reinforcement Learning



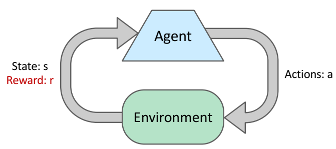
Based on Slides by Dan Klein and Pieter Abbeel

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!

The "Credit Assignment" Problem

I'm in state 43, reward = 0, action = 2

The "Credit Assignment" Problem

I'm in state 43, reward = 0, action = 2
" " " 39, " = 0, " = 4

The "Credit Assignment" Problem

I'm in state 43, reward = 0, action = 2
" " " 39, " = 0, " = 4
" " " 22, " = 0, " = 1

The “Credit Assignment” Problem

I’m in state 43,	reward = 0,	action = 2
“ “ “ 39,	“ = 0,	“ = 4
“ “ “ 22,	“ = 0,	“ = 1
“ “ “ 21,	“ = 0,	“ = 1

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“ “ “ 22,	“ = 0,	“ = 1
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“ “ “ 13,	“ = 0,	“ = 2
“ “ “ 54,	“ = 0,	“ = 2

The “Credit Assignment” Problem

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“ “ “ 22,	“ = 0,	“ = 1
“ “ “ 21,	“ = 0,	“ = 1
“ “ “ 21,	“ = 0,	“ = 1
“ “ “ 13,	“ = 0,	“ = 2
“ “ “ 54,	“ = 0,	“ = 2
“ “ “ 26,	“ = **100**,	

Yippee! I got to a state with a big reward!
But which of my actions along the way
actually helped me get there??
This is the Credit Assignment problem.

The “Credit Assignment” Problem

I’m in state 43,	reward = 0,	action = 2
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“ “ “ 21,	“ = 0,	“ = 1
“ “ “ 13,	“ = 0,	“ = 2
“ “ “ 54,	“ = 0,	“ = 2
“ “ “ 95,	“ = **-10**,	

Yippee! I got to a state with a big reward!
But which of my actions along the way
actually helped me get there??
This is the Credit Assignment problem.

Exploration-Exploitation tradeoff

- You have visited part of the state space and found a reward of 100
  - is this the best you can hope for???
- **Exploitation**: should I stick with what I know and find a good policy w.r.t. this knowledge?
  - at risk of missing out on a better reward somewhere
- **Exploration**: should I look for states w/ more reward?
  - at risk of wasting time & getting some negative reward

Example: Learning to Walk


Initial


A Learning Trial


After Learning [1K Trials]

[Kohl and Stone, ICRA 2004]

Example: Learning to Walk


Initial

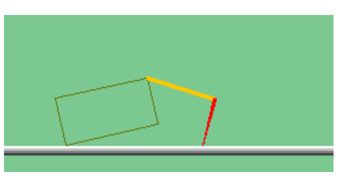
[Kohl and Stone, ICRA 2004]

Example: Learning to Walk


Finished

[Kohl and Stone, ICRA 2004]

The Crawler!

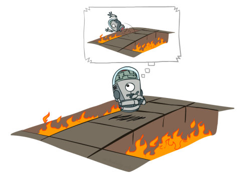


Video of Demo Crawler Bot

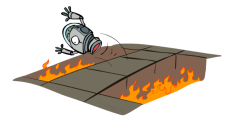
Reinforcement Learning

- Still assume a Markov decision process (MDP):
  - A set of states s in S
  - A set of actions a in A
  - A transition function 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

Offline (MDPs) vs. Online (RL)

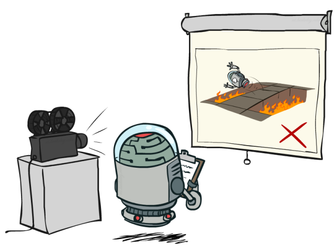


Offline Solution



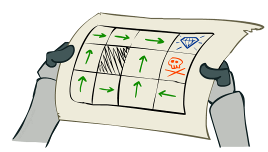
Online Learning

Passive Reinforcement Learning

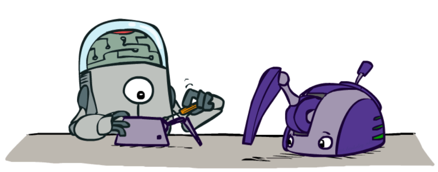


Passive Reinforcement Learning

- Simplified task: policy evaluation
  - Input: a fixed policy π(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.



Model-Based Learning

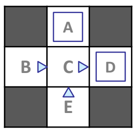


Model-Based Learning

- 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 $\widehat{T}(s,a,s')$
  - Discover each $\widehat{R}(s,a,s')$ 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

$\widehat{T}(s,a,s')$

T(B, east, C) = 1.00
T(C, east, D) = 0.75
T(C, east, A) = 0.25
…

$\widehat{R}(s,a,s')$

R(B, east, C) = -1
R(C, east, D) = -1
R(D, exit, x) = +10
…

Example: Expected Age

Goal: Compute expected age of cs473 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"

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

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

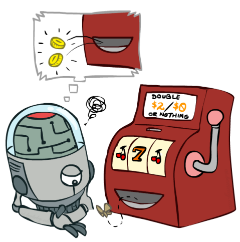
Why does this work? Because eventually you learn the right model.

Unknown P(A): "Model Free"

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

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

Model-Free Learning

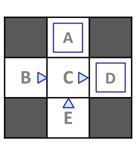


Direct Evaluation

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

Example: Direct Evaluation

Input Policy π



Assume: γ = 1

Observed Episodes (Training)

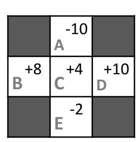
Episode 1
B, east, C, -1
C, east, D, -1
D, exit, x, +10

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

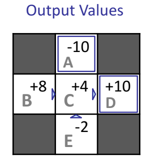
Output Values



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
- What's bad about it?
  - It wastes information about state connections
  - Each state must be learned separately
  - So, it takes a long time to learn

Output Values



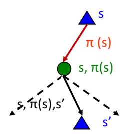
If B and E both go to C under this policy, how can their values be different?

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 do we take a weighted average without knowing the weights?

Sample-Based Policy Evaluation?

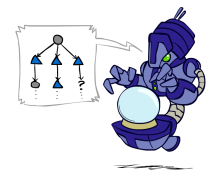
- We want to improve our estimate of V by computing these averages:

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

- Idea: Take samples of outcomes s' (by doing the action!) and average

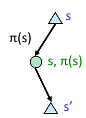
$$sample_1 = R(s,\pi(s),s_1') + \gamma V_k^\pi(s_1')$$
$$sample_2 = R(s,\pi(s),s_2') + \gamma V_k^\pi(s_2')$$
$$\ldots$$
$$sample_n = R(s,\pi(s),s_n') + \gamma V_k^\pi(s_n')$$

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



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): $sample = R(s,\pi(s),s') + \gamma V^\pi(s')$

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

Same update: $V^\pi(s) \leftarrow V^\pi(s) + \alpha(sample - V^\pi(s))$

Exponential Moving Average

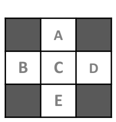
- Exponential moving average
  - The running interpolation update: $\bar{x}_n = (1-\alpha)\cdot \bar{x}_{n-1} + \alpha \cdot x_n$
  - Makes recent samples more important:

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

  - Forgets about the past (distant past values were wrong anyway)
- Decreasing learning rate (alpha) can give converging averages

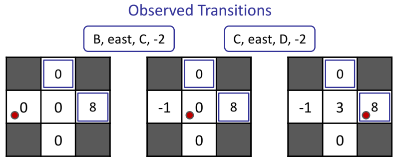
Example: Temporal Difference Learning

States



Assume: γ = 1, α = 1/2

Observed Transitions



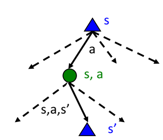
$$V^\pi(s) \leftarrow (1-\alpha)V^\pi(s) + \alpha\left[R(s,\pi(s),s') + \gamma V^\pi(s')\right]$$

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:

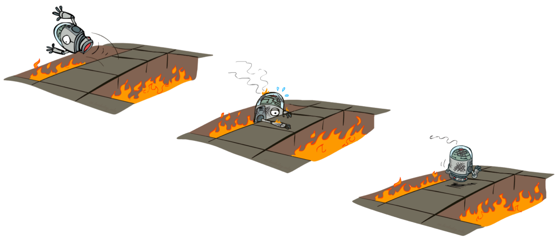
$$\pi(s) = \arg\max_a Q(s,a)$$

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



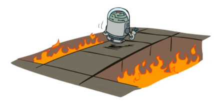
- Idea: learn Q-values, not values
- Makes action selection model-free too!

Active Reinforcement Learning



Active Reinforcement Learning

- Full reinforcement learning: optimal policies (like value iteration)
  - 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:

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

- 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:

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

Q-Learning

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

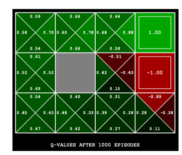
$$Q_{k+1}(s,a) \leftarrow \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma \max_{a'} Q_k(s',a')\right]$$

- Learn Q(s,a) values as you go
  - Receive a sample (s,a,s',r)
  - 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:

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



Q-Learning

- **Forall s, a**
  - **Initialize Q(s, a) = 0**
- **Repeat Forever**

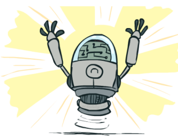
  Where are you? s
  Choose some action a
  Execute it in real world: *(s, a, r, s')*
  Do update:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + (\alpha)\left[r + \gamma \max_{a'} Q(s',a')\right]$$

Video of Demo Q-Learning -- Gridworld

Q-Learning Properties

- Amazing result: Q-learning converges to optimal policy -- even if you're acting suboptimally!
- This is called off-policy learning
- 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 (!)



Two main reinforcement learning approaches

- Model-based approaches:
  - explore environment & learn model, T=P(**s**'|**s**,**a**) and R(**s**,**a**), (almost) everywhere
  - use model to plan policy, MDP-style
  - approach leads to strongest theoretical results
  - often works well when state-space is manageable
- Model-free approach:
  - don't learn a model; learn value function or policy directly
  - weaker theoretical results
  - often works better when state space is large

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The Story So Far: MDPs and RL

Known MDP: Offline Solution

Goal	Technique
Compute V*, Q*, π*	Value / policy iteration
Evaluate a fixed policy π	Policy evaluation

Unknown MDP: Model-Based

Goal	Technique
Compute V*, Q*, π*	VI/PI on approx. MDP
Evaluate a fixed policy π	PE on approx. MDP

Unknown MDP: Model-Free

Goal	Technique
Compute V*, Q*, π*	Q-learning
Evaluate a fixed policy π	Value Learning

Two main reinforcement learning approaches

- Model-based approaches:

  Learn T + R

  $|S|^2|A| + |S||A|$ parameters (40,400)

- Model-free approach:

  Learn Q

  $|S||A|$ parameters (400)

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Video of Demo Q-Learning Auto Cliff Grid