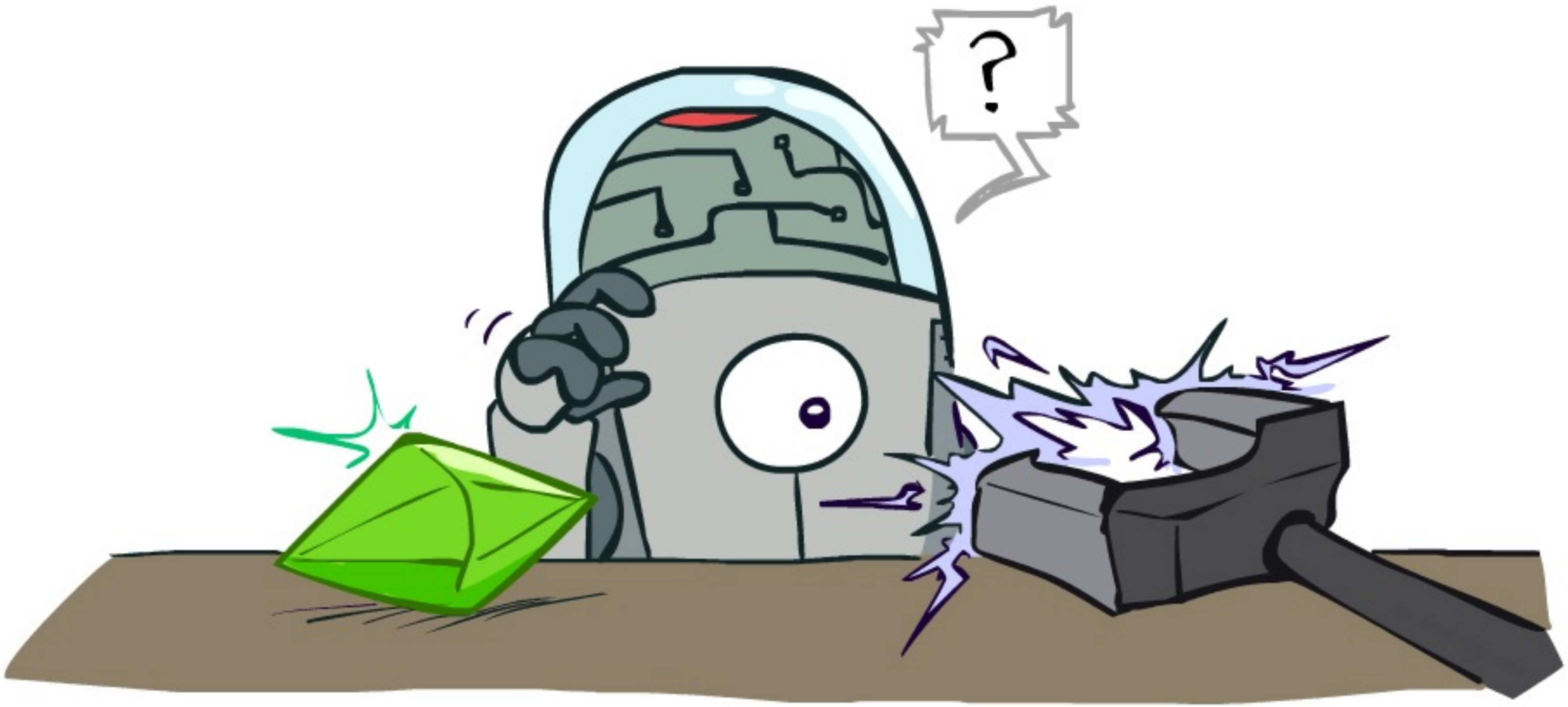
CS 188: Artificial Intelligence

Reinforcement Learning

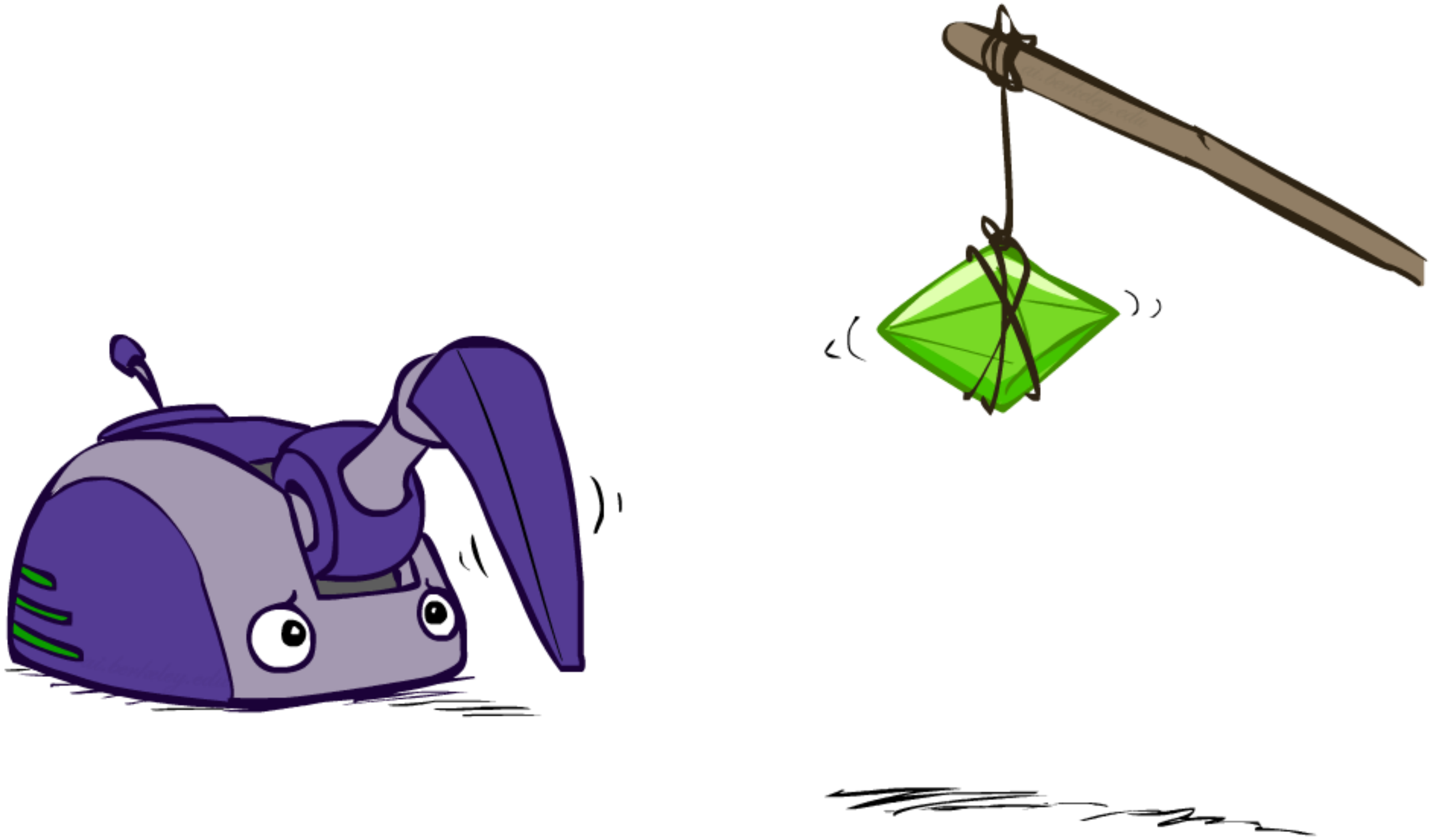


Instructors: Angela Liu and Yanlai Yang

University of California, Berkeley

(Slides adapted from Pieter Abbeel, Dan Klein, Anca Dragan, Stuart Russell and Dawn Song)

Reinforcement Learning

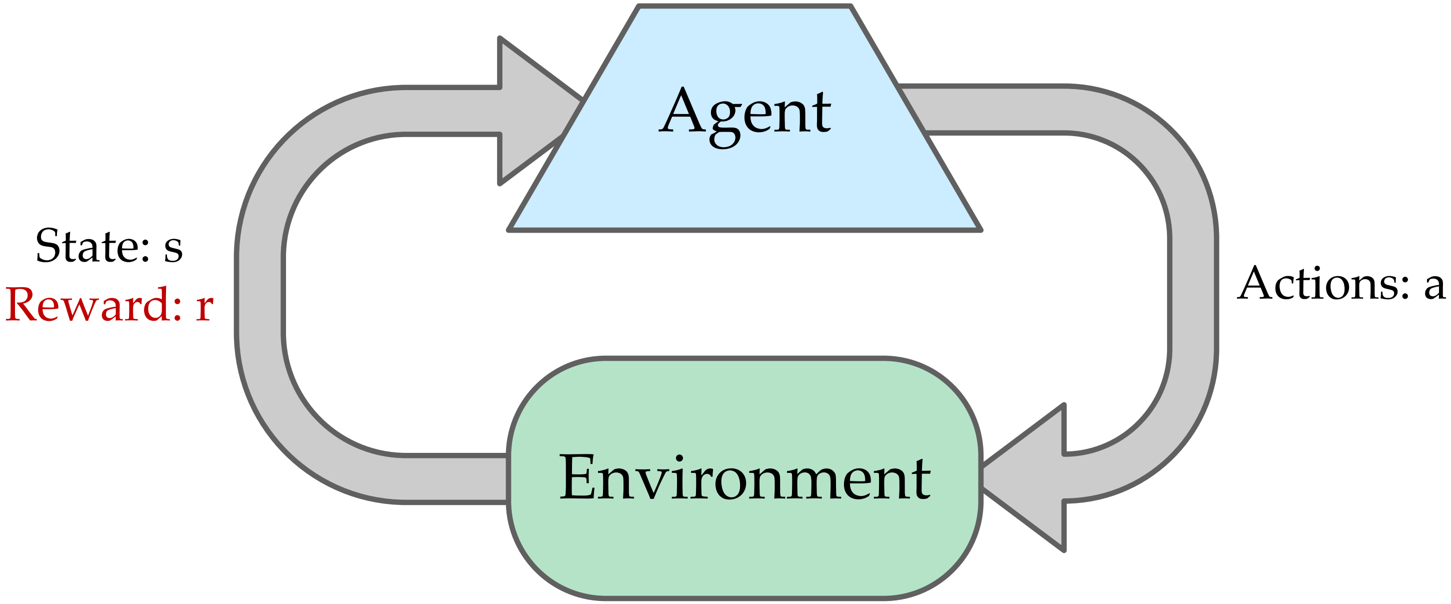


Reinforcement Learning

- Still assume a Markov decision process (MDP):
  - A set of states $s \in S$
  - 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 $\pi(s)$

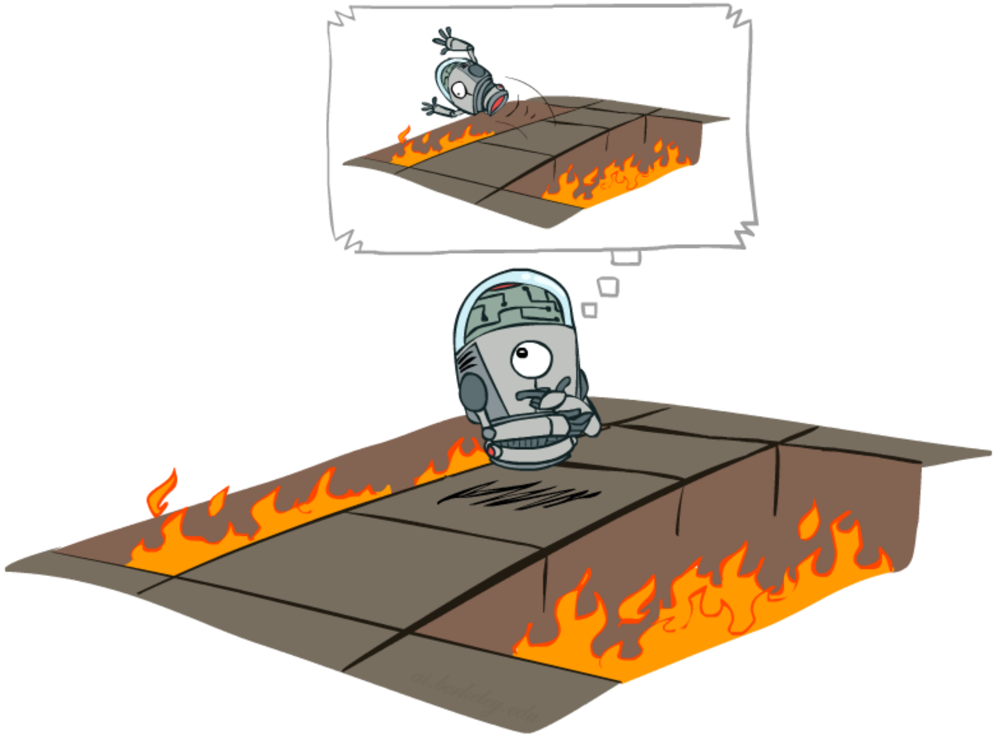
- New twist: don't know T or R
  - I.e. we don't know which states are good or what the actions do
  - Must actually try actions and states out to learn

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!

Offline (MDPs) vs. Online (RL)



Offline Solution

Online Learning

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

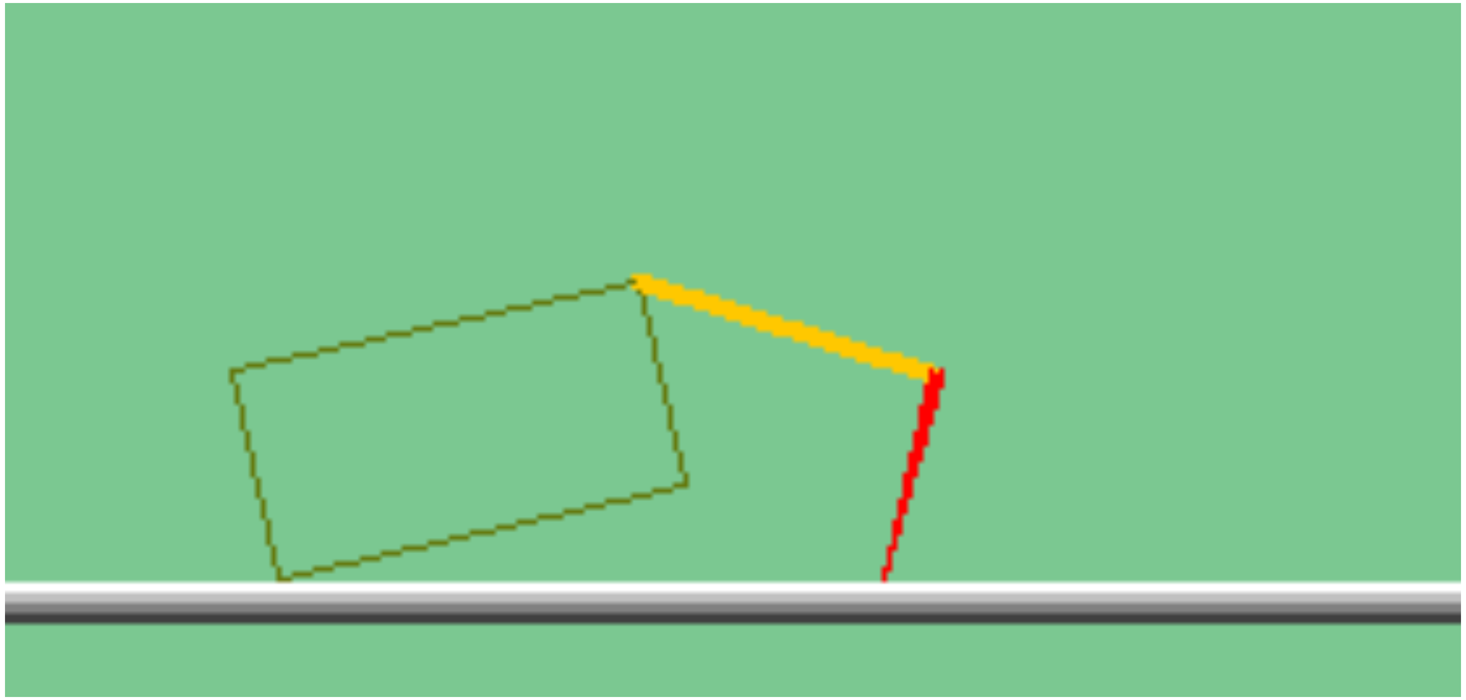
Finished

[Kohl and Stone, ICRA 2004]

[Video: AIBO WALK – finished]

DeepMind Atari (©Two Minute Lectures)

The Crawler!



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

Video of Demo Crawler Bot

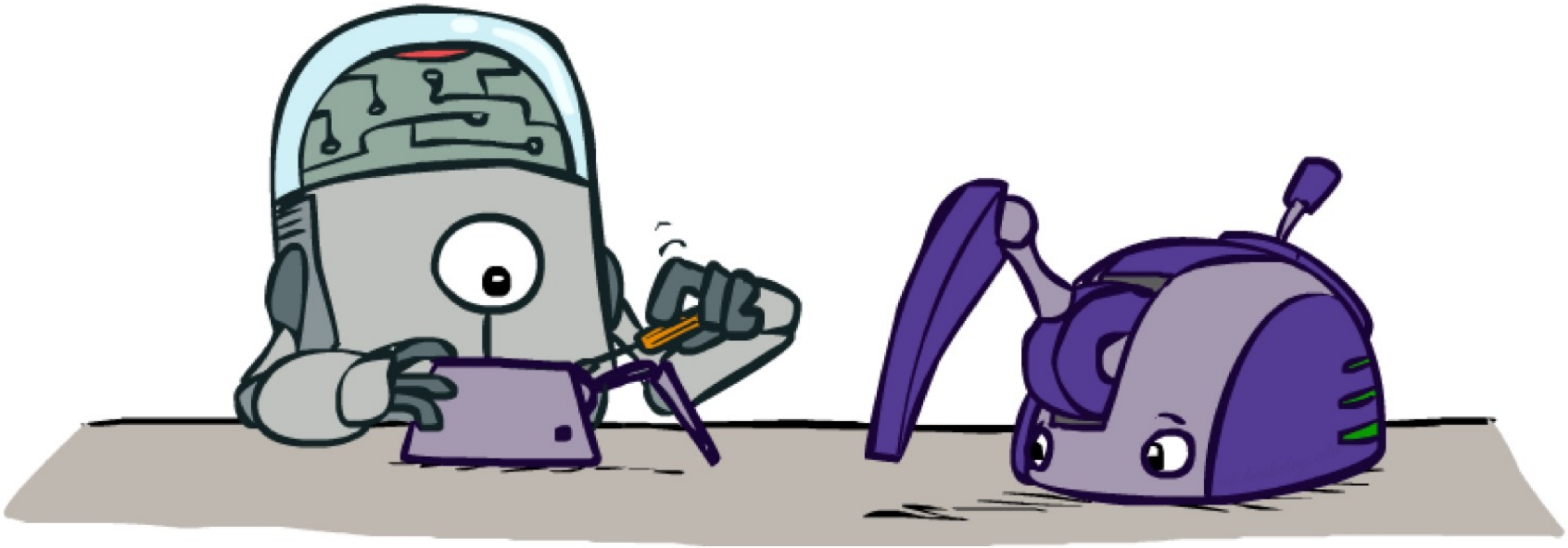
Reinforcement Learning -- Overview

- Passive Reinforcement Learning (= how to learn from experiences)
  - Model-based Passive RL
    - Learn the MDP model from experiences, then solve the MDP
  - Model-free Passive RL
    - Forego learning the MDP model, directly learn V or Q:
      - Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning
      - Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)
- Active Reinforcement Learning (= agent also needs to decide how to collect experiences)
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning

Reinforcement Learning -- Overview

- **Passive Reinforcement Learning (= how to learn from experiences)**
  - **Model-based Passive RL**
    - Learn the MDP model from experiences, then solve the MDP
  - Model-free Passive RL
    - Forego learning the MDP model, directly learn V or Q:
      - Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning
      - Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)
- Active Reinforcement Learning (= agent also needs to decide how to collect experiences)
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning

Model-Based Reinforcement Learning



Model-Based Reinforcement Learning

- Model-Based Idea:
  - Learn an approximate model based on experiences
  - Solve for values as if the learned model were correct

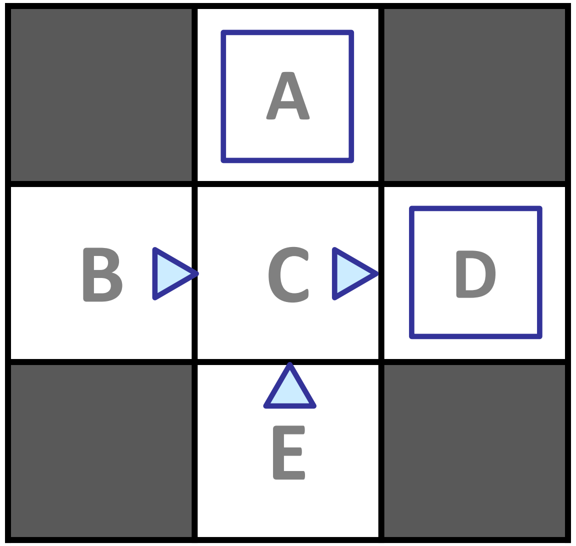
- Step 1: Learn empirical MDP model
  - Count outcomes s′ for each s, a
  - Normalize to give an estimate $\widehat{T}(s,a,s')$
  - Discover each $\widehat{R}(s,a,s')$ when we experience (s, a, s′)

- Step 2: Solve the learned MDP
  - For example, use value iteration, as before

(and repeat as needed)

Example: Model-Based RL

Input Policy π



Assume: $\gamma = 1$

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
…

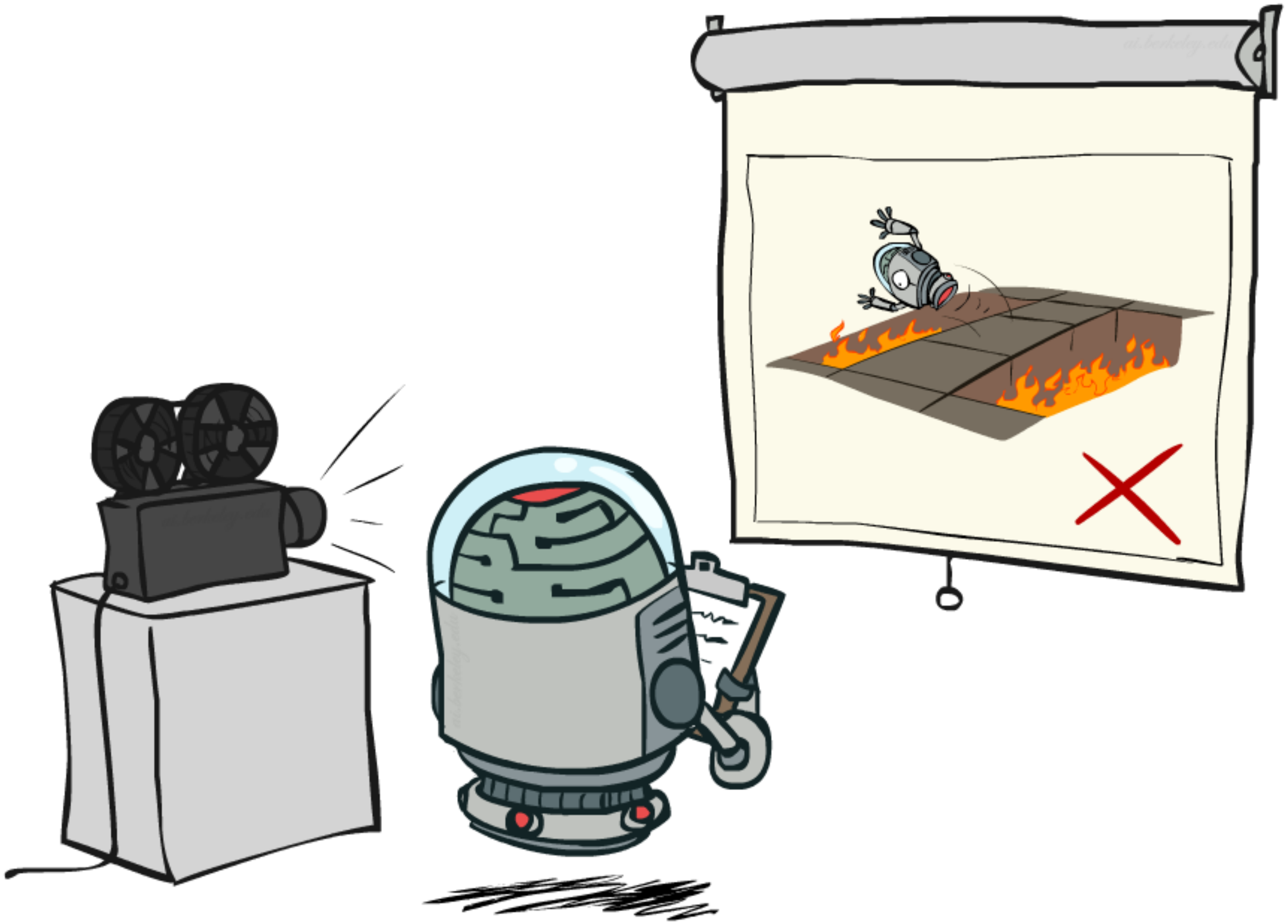
$$\hat{R}(s, a, s')$$

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

Reinforcement Learning -- Overview

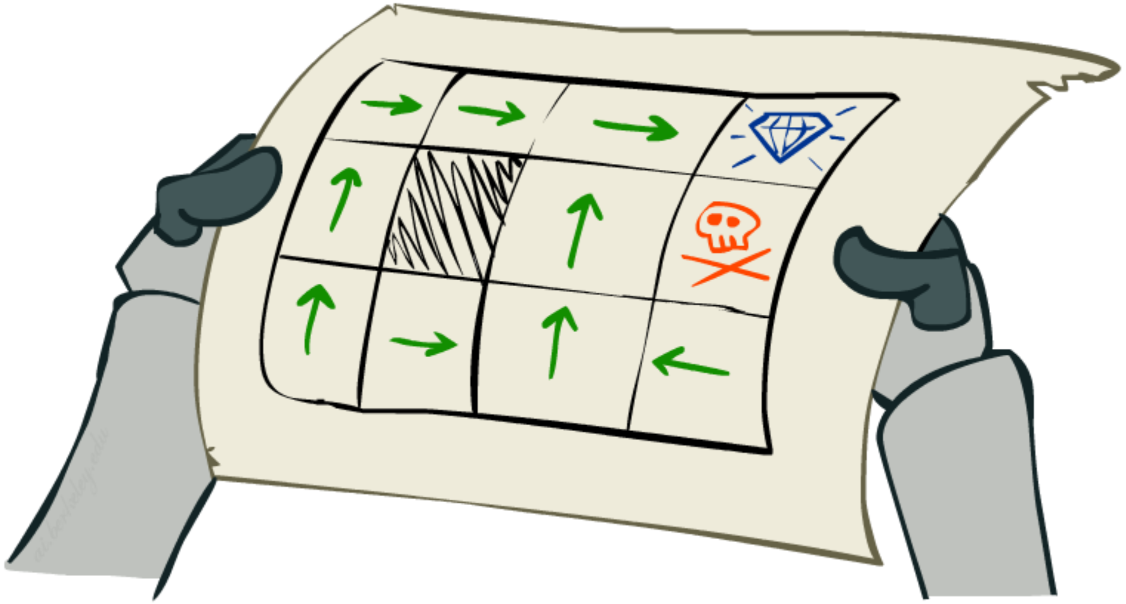
- Passive Reinforcement Learning (= how to learn from experiences)
  - Model-based Passive RL
    - Learn the MDP model from experiences, then solve the MDP
  - **Model-free Passive RL**
    - **Forego learning the MDP model, directly learn V or Q:**
      - **Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning**
      - Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)
- Active Reinforcement Learning (= agent also needs to decide how to collect experiences)
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning

Passive Model-Free Reinforcement Learning



Passive Model-Free 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.

Analogy: Expected Age

Goal: Compute expected age of cs188 students

Known P(A)

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

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"

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

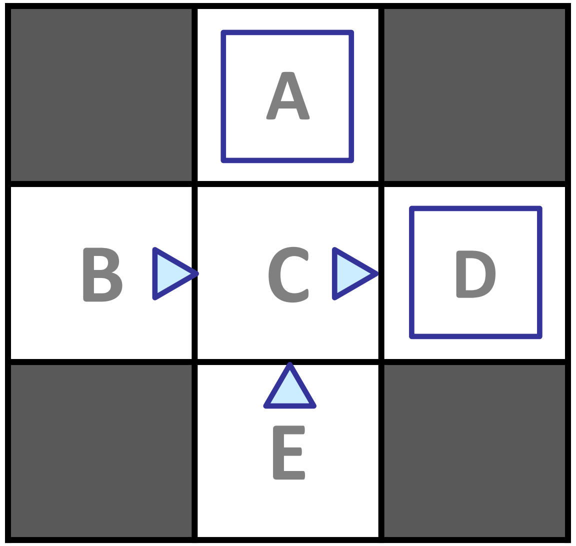
Why does this work? Because samples appear with the right frequencies.

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: $\gamma = 1$

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

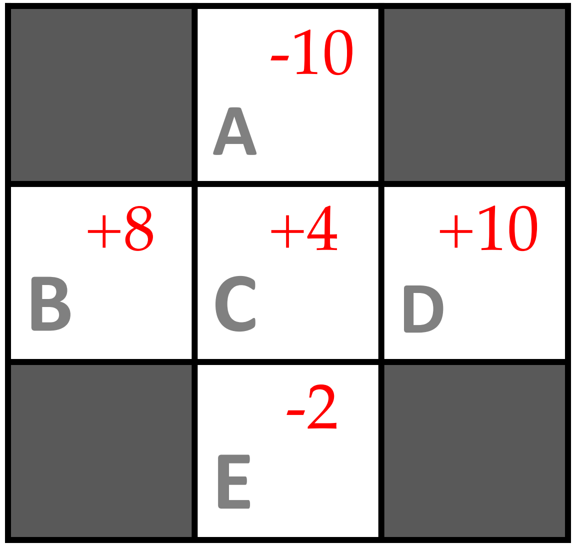
Episode 3

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



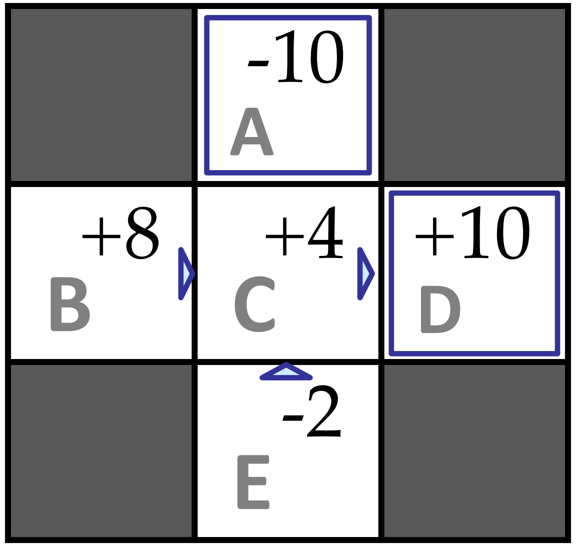
If B and E both go to C under this policy, how can their values be different?

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 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

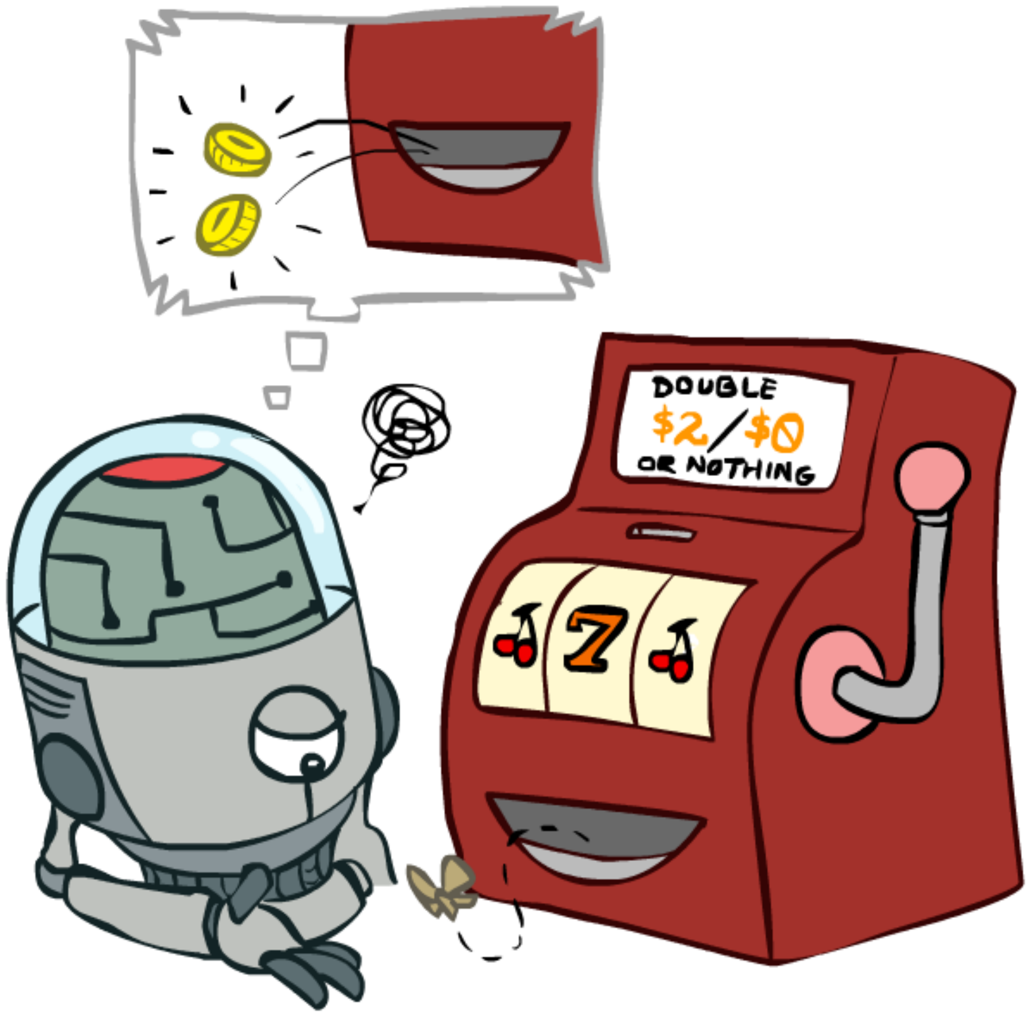


If B and E both go to C under this policy, how can their values be different?

Reinforcement Learning -- Overview

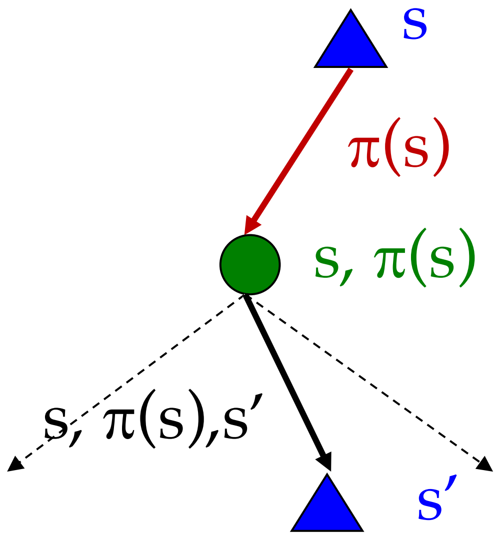
- Passive Reinforcement Learning (= how to learn from experiences)
  - Model-based Passive RL
    - Learn the MDP model from experiences, then solve the MDP
  - **Model-free Passive RL**
    - **Forego learning the MDP model, directly learn V or Q:**
      - **Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning**
      - Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)
- Active Reinforcement Learning (= agent also needs to decide how to collect experiences)
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning

Temporal Difference Value Learning



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?

Sample-Based Policy Evaluation?

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

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

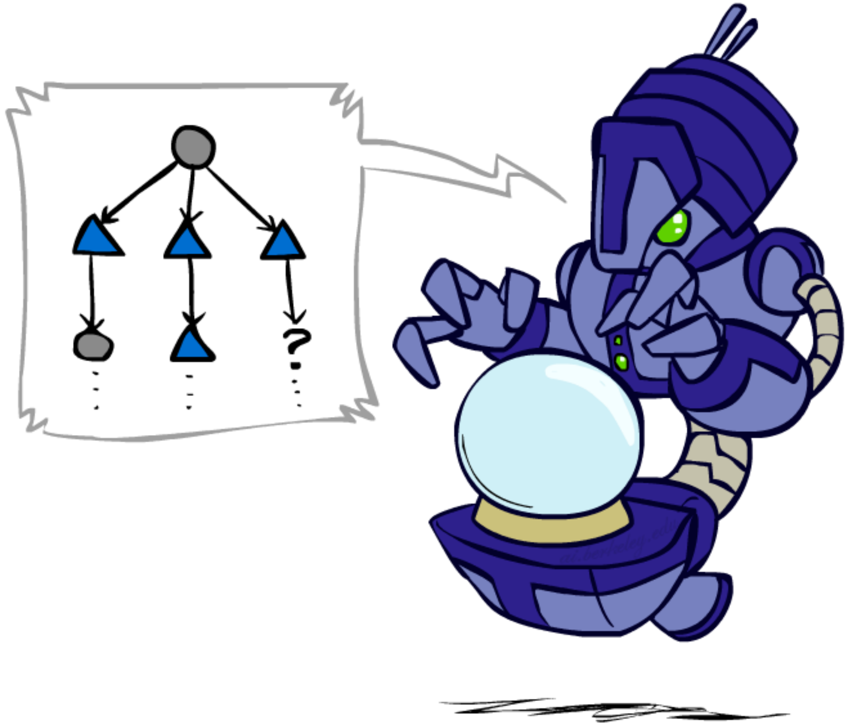
- Idea: Take samples of outcomes s′ (by doing the action!) and average

$$sample_1 = R(s,\pi(s),s'_1) + \gamma V^{\pi}_{k}(s'_1)$$

$$sample_2 = R(s,\pi(s),s'_2) + \gamma V^{\pi}_{k}(s'_2)$$

$$\dots$$

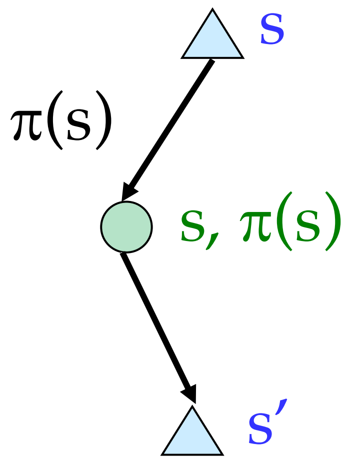
$$sample_n = R(s,\pi(s),s'_n) + \gamma V^{\pi}_{k}(s'_n)$$



$$V^{\pi}_{k+1}(s) \leftarrow \frac{1}{n}\sum_{i} sample_i$$

Temporal Difference Value 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): $V^{\pi}(s) \leftarrow (1-\alpha)V^{\pi}(s) + (\alpha)sample$

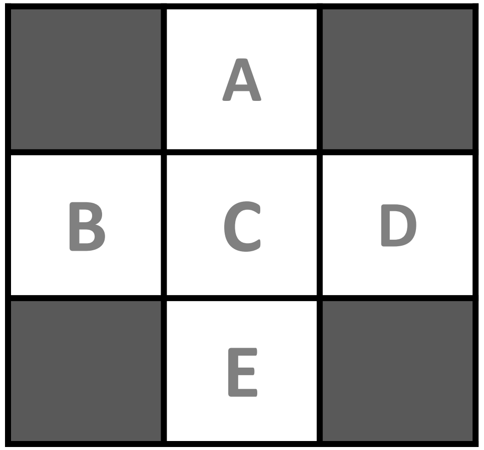
Same update: $V^{\pi}(s) \leftarrow V^{\pi}(s) + \alpha(sample - V^{\pi}(s))$

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

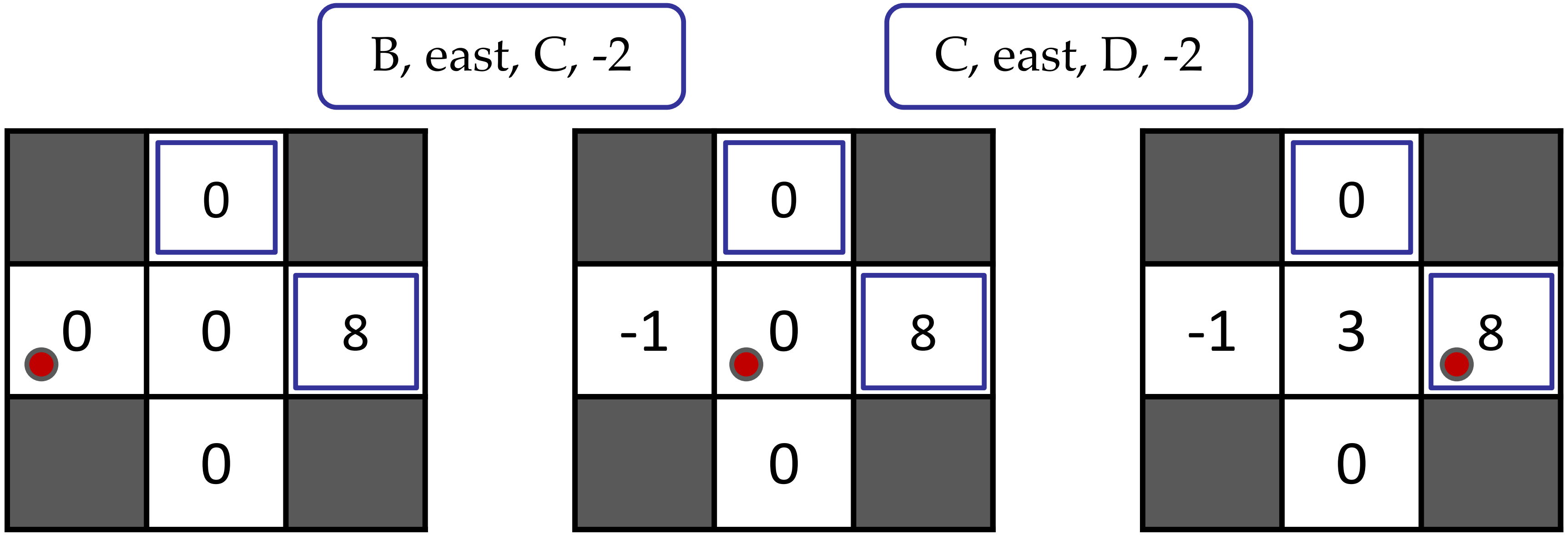
Example: Temporal Difference Value Learning

States



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

Observed Transitions



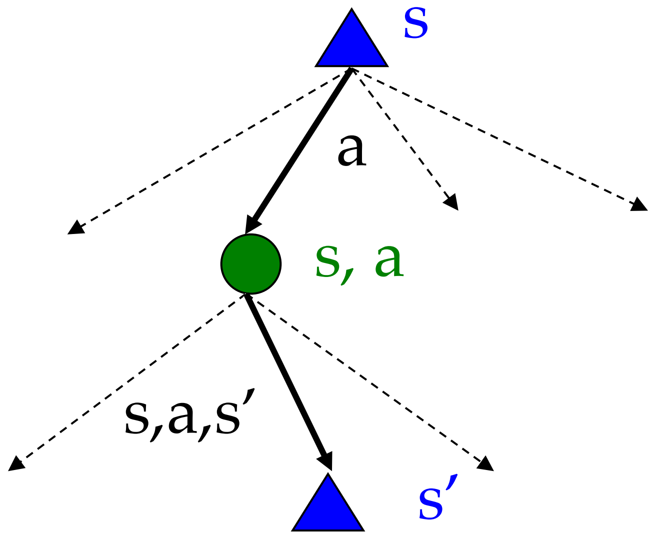
$$V^{\pi}(s) \leftarrow (1-\alpha)V^{\pi}(s) + \alpha\left[R(s,\pi(s),s') + \gamma V^{\pi}(s')\right]$$

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:

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

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



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

Reinforcement Learning -- Overview

- Passive Reinforcement Learning (= how to learn from experiences)
  - Model-based Passive RL
    - Learn the MDP model from experiences, then solve the MDP
  - **Model-free Passive RL**
    - Forego learning the MDP model, directly learn V or Q:
      - Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning
      - **Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)**
- Active Reinforcement Learning (= agent also needs to decide how to collect experiences)
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning

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

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

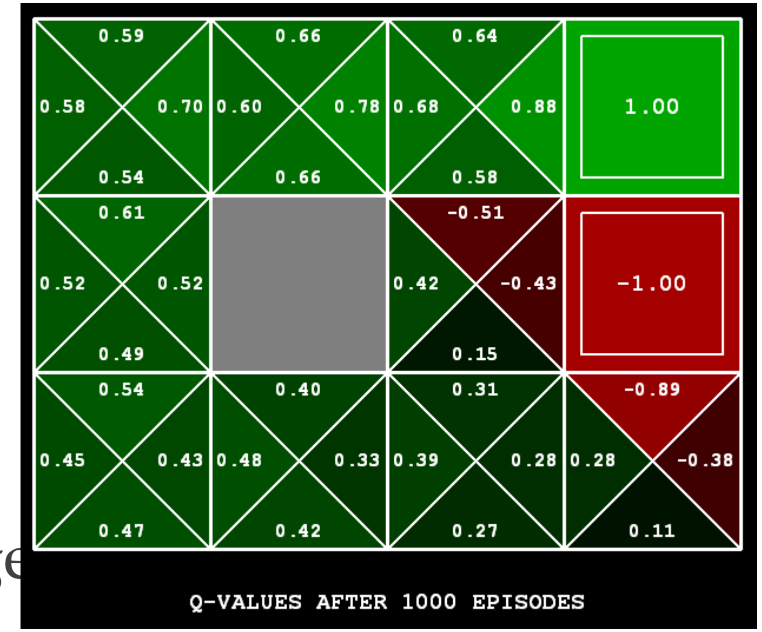
- Learn Q(s,a) values as you go
  - Receive a sample (s,a,s',r)
  - Consider your old estimate: $Q(s,a)$
  - Consider your new sample estimate:

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

no longer policy evaluation!

  - Incorporate the new estimate into a running average

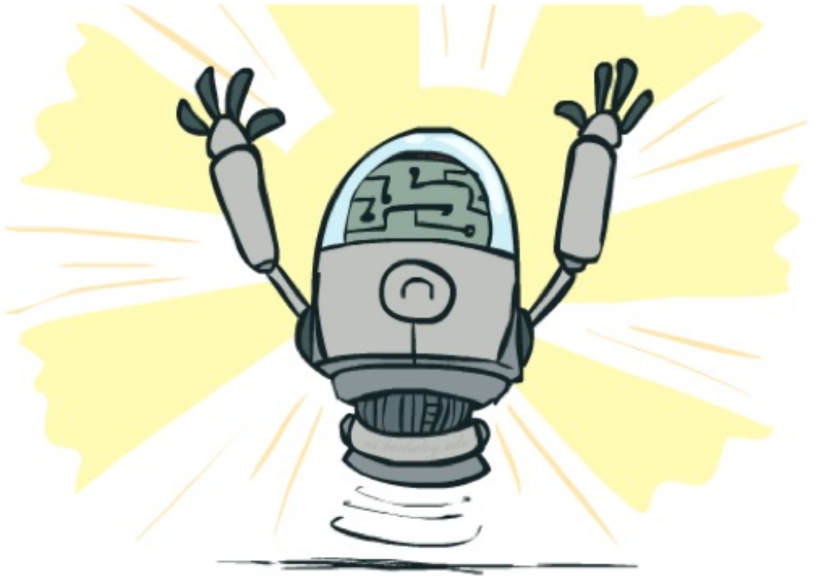
$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + (\alpha)\left[sample\right]$$



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

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 (!)



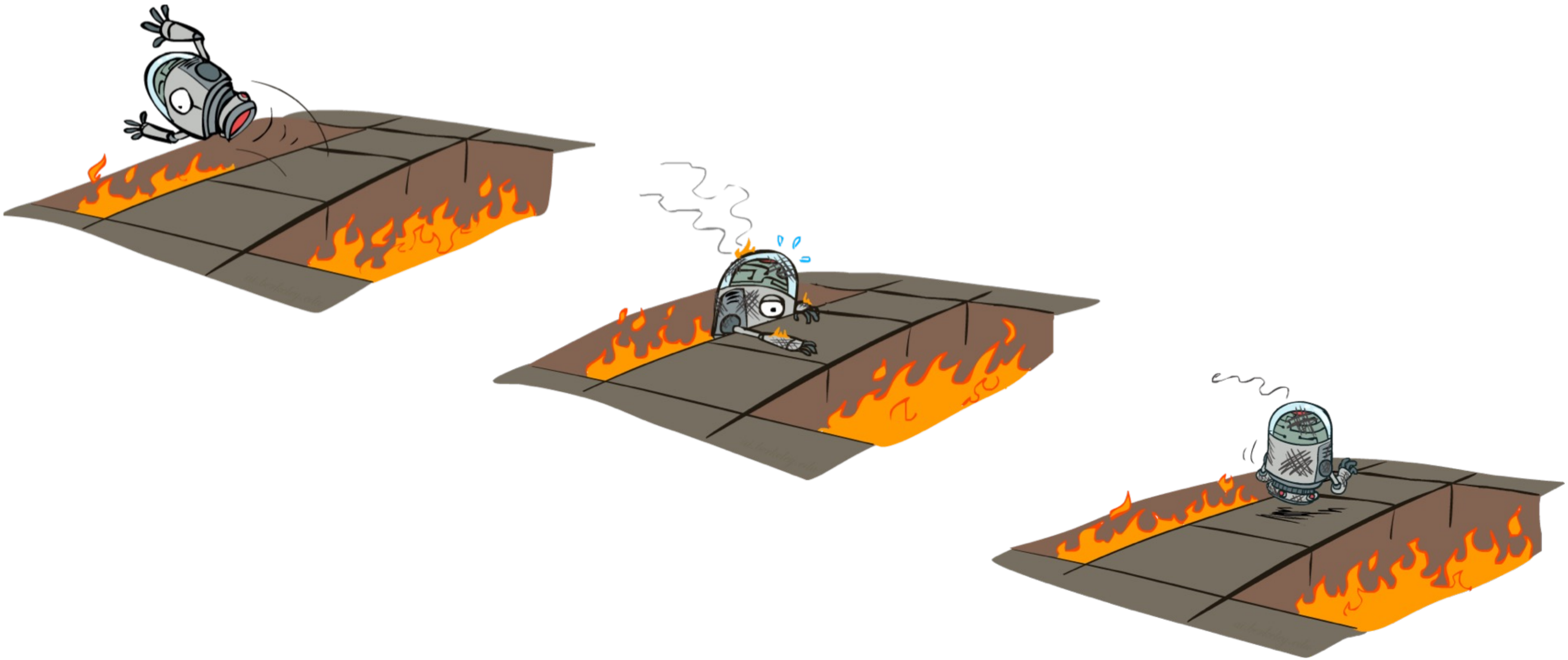
Video of Demo Q-Learning -- Gridworld

Video of Demo Q-Learning -- Crawler

Reinforcement Learning -- Overview

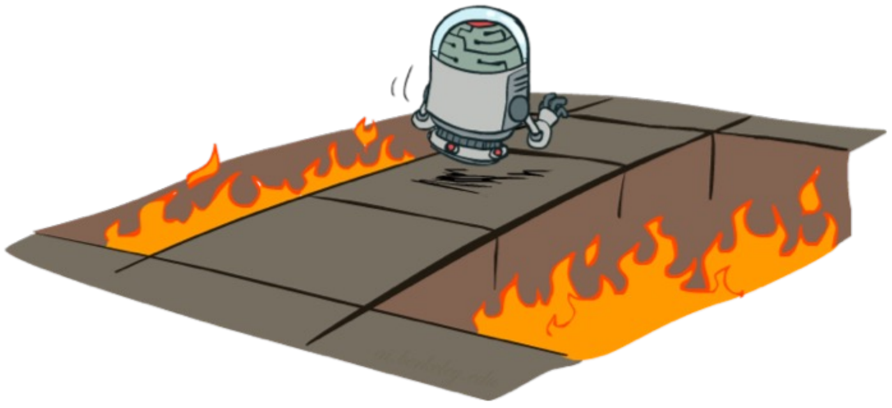
- Passive Reinforcement Learning (= how to learn from experiences)
  - Model-based Passive RL
    - Learn the MDP model from experiences, then solve the MDP
  - Model-free Passive RL
    - Forego learning the MDP model, directly learn V or Q:
      - Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning
      - Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)
- **Active Reinforcement Learning (= agent also needs to decide how to collect experiences)**
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning

Active Reinforcement Learning



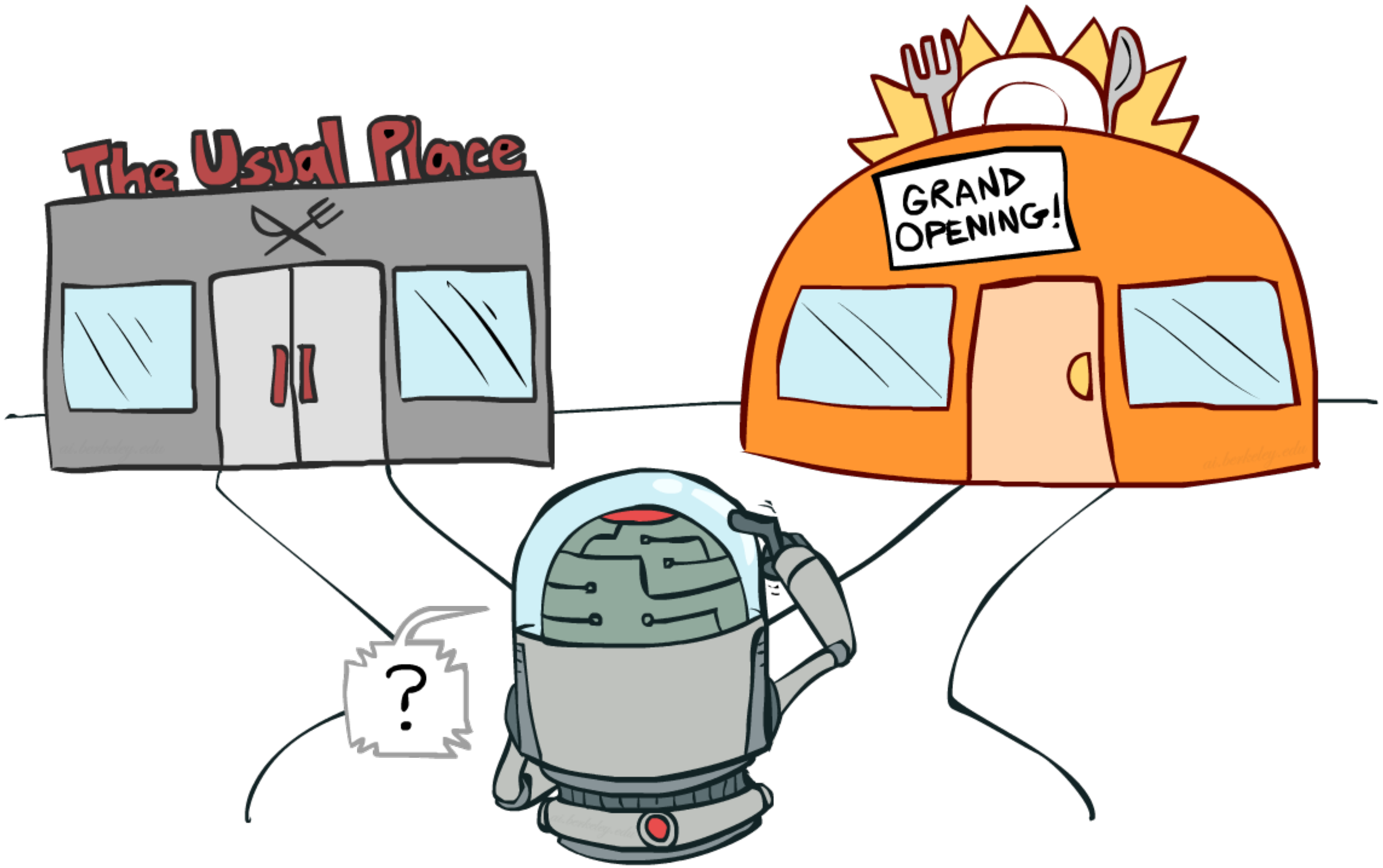
Active Reinforcement Learning

- 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…

Exploration vs. Exploitation



Video of Demo Q-learning – Manual Exploration – Bridge Grid

How to Explore?

- Several schemes for forcing exploration
  - Simplest: random actions (ε-greedy)
    - Every time step, flip a coin
    - With (small) probability ε, act randomly
    - With (large) probability 1-ε, act on current policy
  - Problems with random actions?
    - You do eventually explore the space, but keep thrashing around once learning is done
    - One solution: lower ε over time
    - Another solution: exploration functions

[Demo: Q-learning – manual exploration – bridge grid (L10D5)]
[Demo: Q-learning – epsilon-greedy -- crawler (L10D3)]

Video of Demo Q-learning – Epsilon-Greedy – Crawler

Exploration Functions

- When to explore?
  - Random actions: explore a fixed amount
  - Better idea: explore areas whose badness is not (yet) established, eventually stop exploring

- Exploration function
  - Takes a value estimate u and a visit count n, and returns an optimistic utility, e.g. $f(u, n) = u + k/n$

Regular Q-Update: $Q(s,a) \leftarrow_\alpha R(s,a,s') + \gamma \max_{a'} Q(s',a')$

Modified Q-Update: $Q(s,a) \leftarrow_\alpha R(s,a,s') + \gamma \max_{a'} f(Q(s',a'), N(s',a'))$

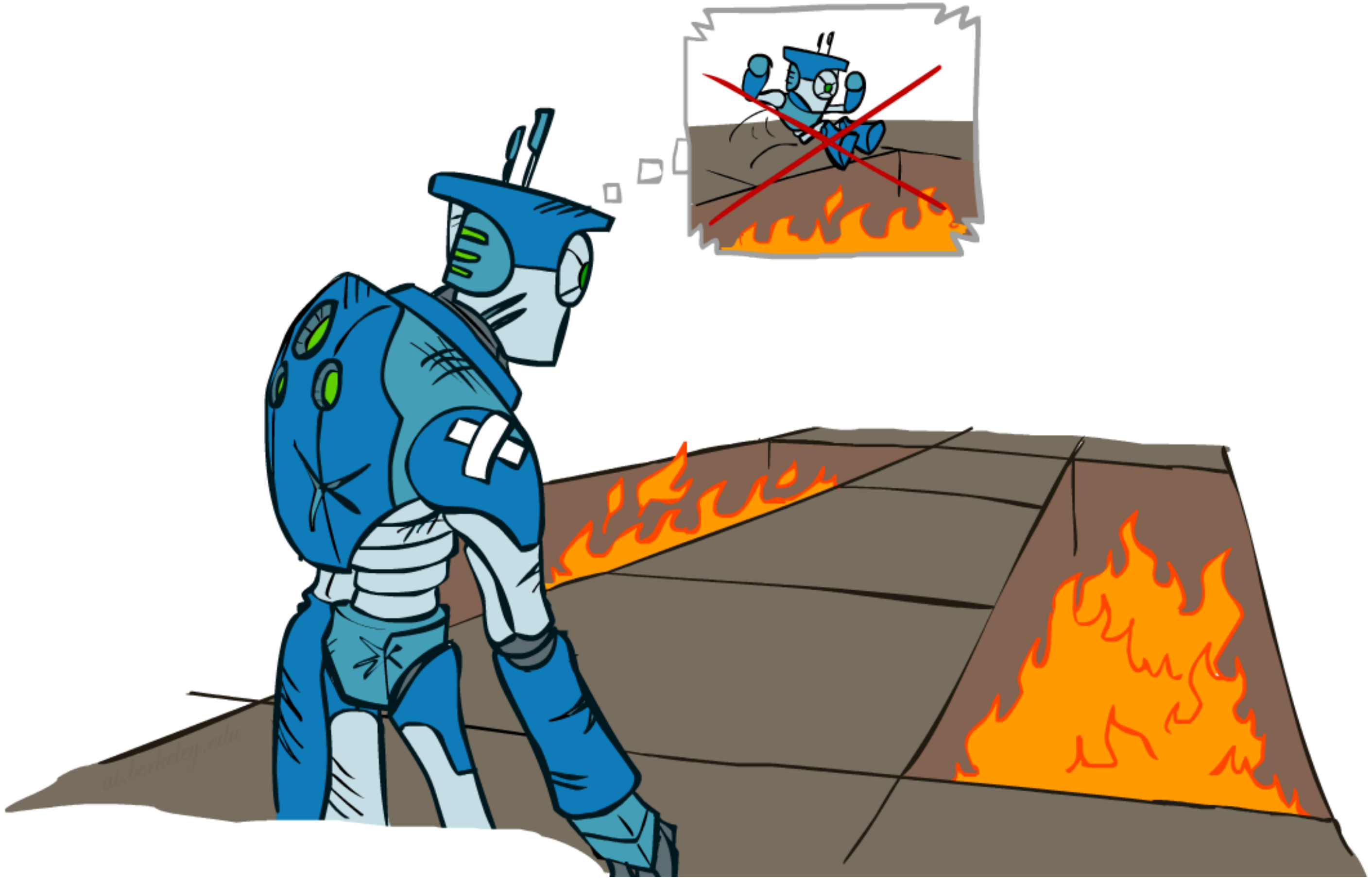
  - Note: this propagates the "bonus" back to states that lead to unknown states as well!

[Demo: exploration – Q-learning – crawler – exploration function (L10D4)]

Video of Demo Q-learning – Exploration Function – Crawler

Regret

- Even if you learn the optimal policy, you still make mistakes along the way!
- Regret is a measure of your total mistake cost: the difference between your (expected) rewards, including youthful suboptimality, and optimal (expected) rewards
- Minimizing regret goes beyond learning to be optimal – it requires optimally learning to be optimal
- Example: random exploration and exploration functions both end up optimal, but random exploration has higher regret



Reinforcement Learning -- Overview

- Passive Reinforcement Learning (= how to learn from experiences)
  - Model-based Passive RL
    - Learn the MDP model from experiences, then solve the MDP
  - Model-free Passive RL
    - Forego learning the MDP model, directly learn V or Q:
      - Value learning – learns value of a fixed policy; 2 approaches: Direct Evaluation & TD Learning
      - Q learning – learns Q values of the optimal policy (uses a Q version of TD Learning)
- Active Reinforcement Learning (= agent also needs to decide how to collect experiences)
  - Key challenges:
    - How to efficiently explore?
    - How to trade off exploration <> exploitation
  - Applies to both model-based and model-free. In CS188 we'll cover only in context of Q-learning