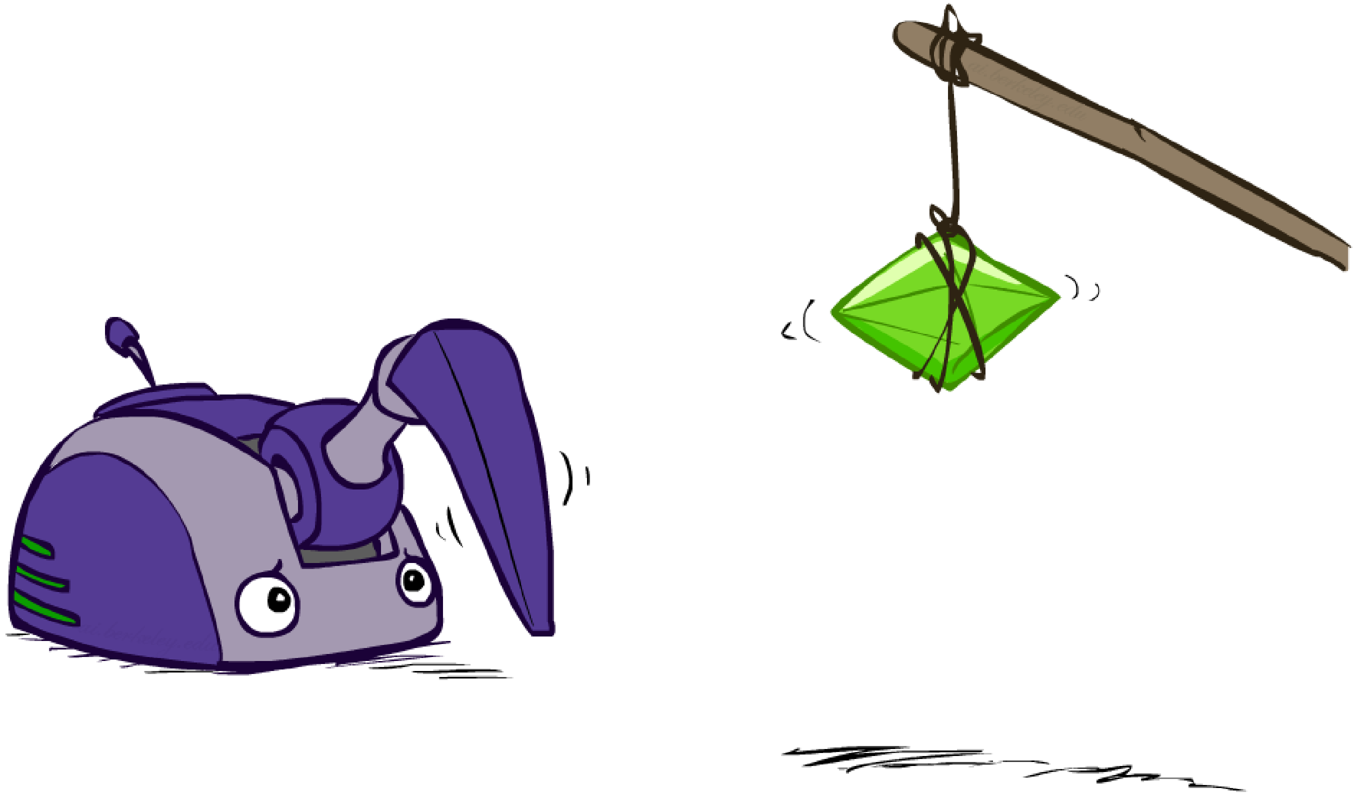
Announcements

- John Oliver "Last Week Tonight" on AI, ChatGPT, etc. (NSFW)
- Latin American and Caribbean states announce support for a treaty banning some types of autonomous weapons and regulating others
- United States, China, and many other countries announce support for a voluntary code of conduct on responsible use of autonomous weapons
- **Midterm** next Monday (March 6) 8-10pm (more details++ on ed)

CS 188: Artificial Intelligence

Reinforcement Learning I



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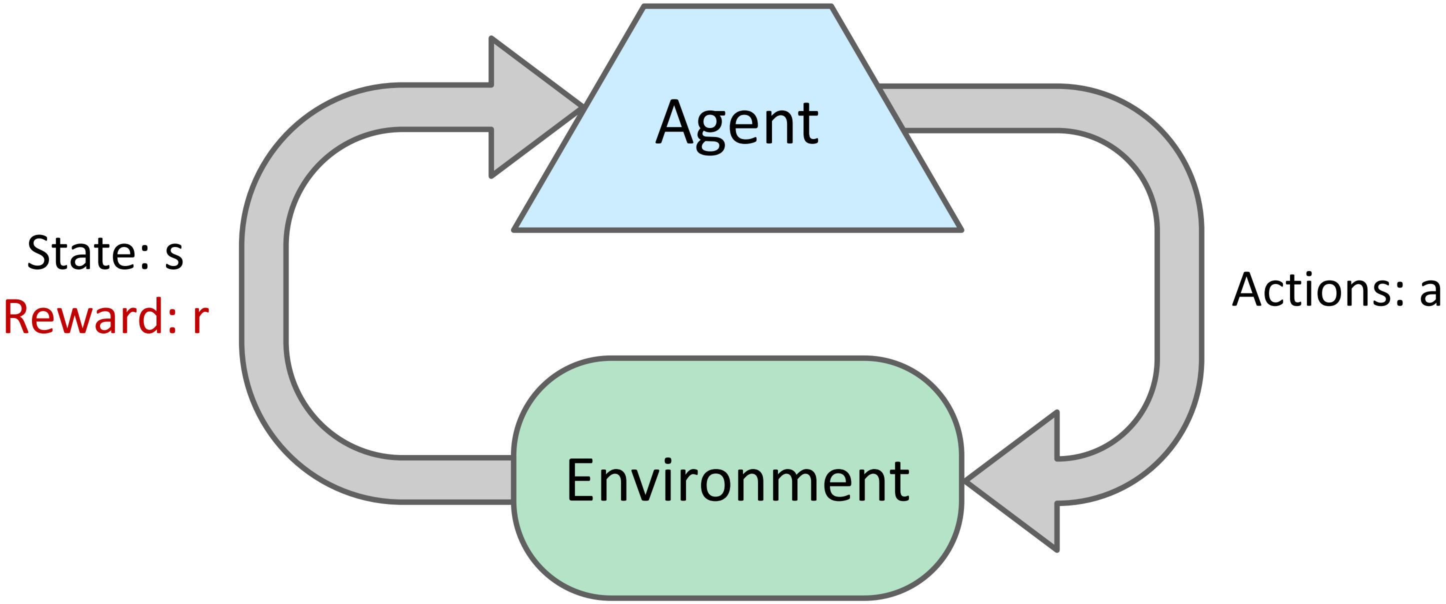
Reinforcement learning

- What if the MDP is initially unknown? Lots of things change!
  - ***Exploration***: you have to ***try unknown actions*** to get information
  - ***Exploitation***: eventually, you have to use what you know
  - ***Regret***: early on, you inevitably "make mistakes" and lose reward
  - ***Sampling***: you may need to repeat many times to get good estimates
  - ***Generalization***: what you learn in one state may apply to others too

Reinforcement Learning

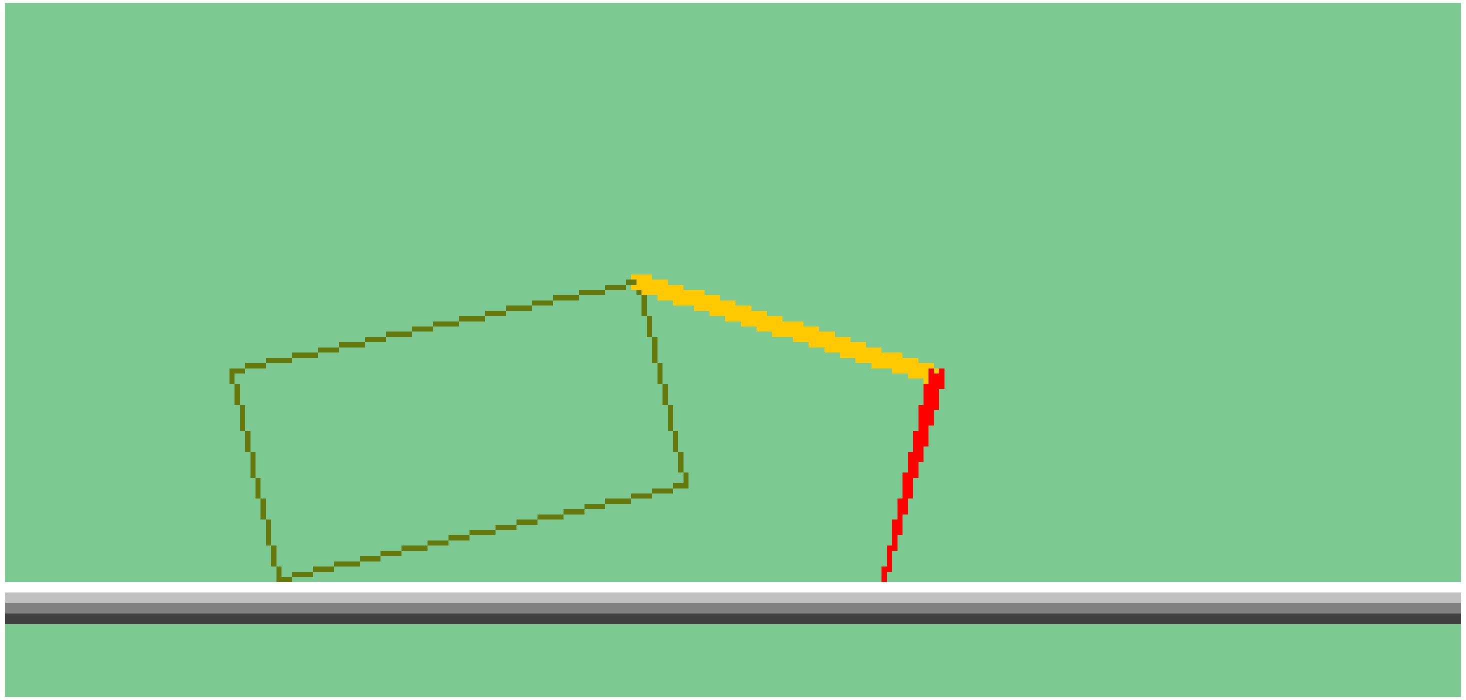


- Basic idea:
  - Learn how to ***maximize expected rewards*** based on observed samples of transitions
  - Not unlike the basic problem faced by all living things

Example: Samuel's checker player (1956-67)

Example: AlphaGo (2016)

The Crawler!



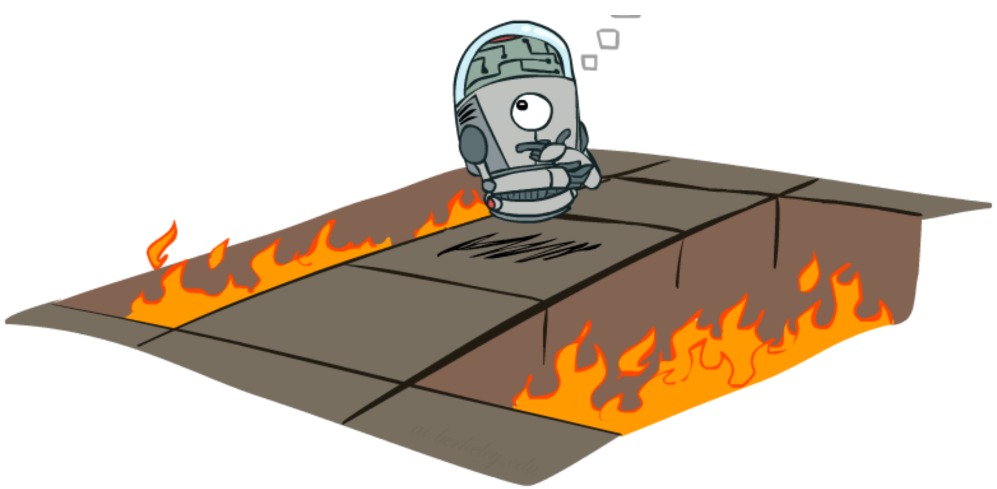
[Demo: Crawler Bot (L10D1)] [You, in Project 3]

Reinforcement Learning

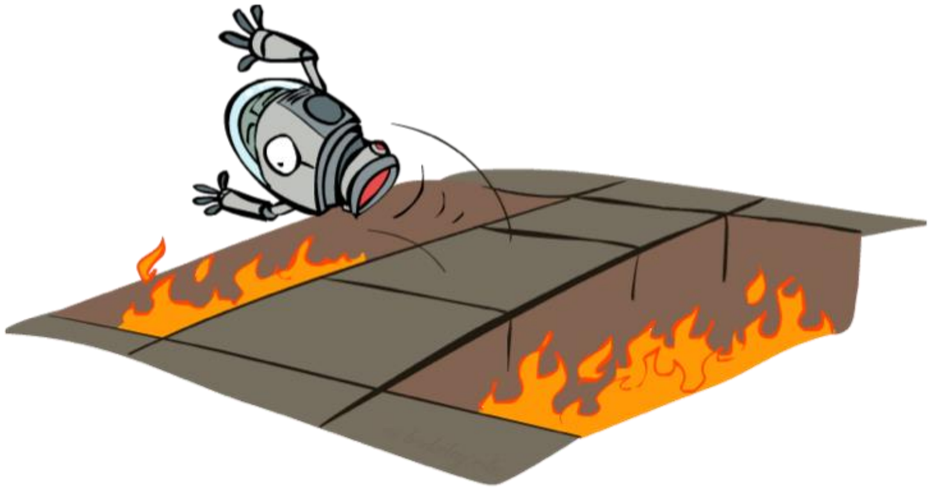
- Still assume a Markov decision process (MDP):
  - A set of states $s \in S$
  - A set of actions (per state) $A(s)$
  - A transition model $T(s,a,s')$
  - A reward function $R(s,a,s')$
- Still looking for a policy $\pi(s)$

- New twist: don't know T or R
  - I.e. we don't know which states are good or what the actions do
  - Must explore new states and actions -- to boldly go where no Pacman has gone before

Offline (MDPs) vs. Online (RL)



Offline Solution

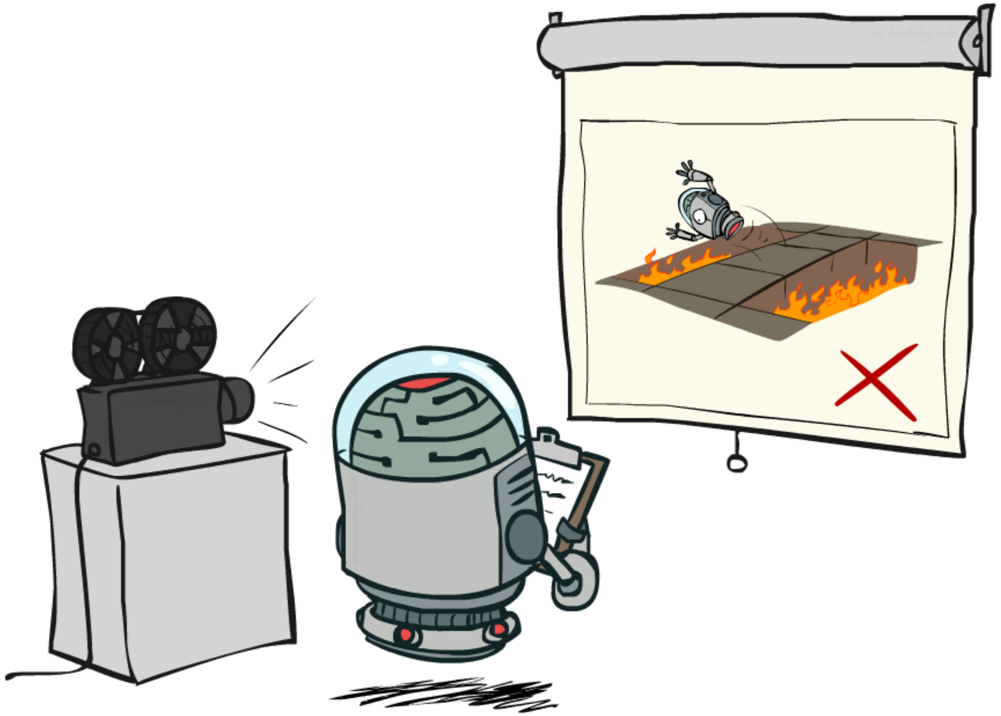


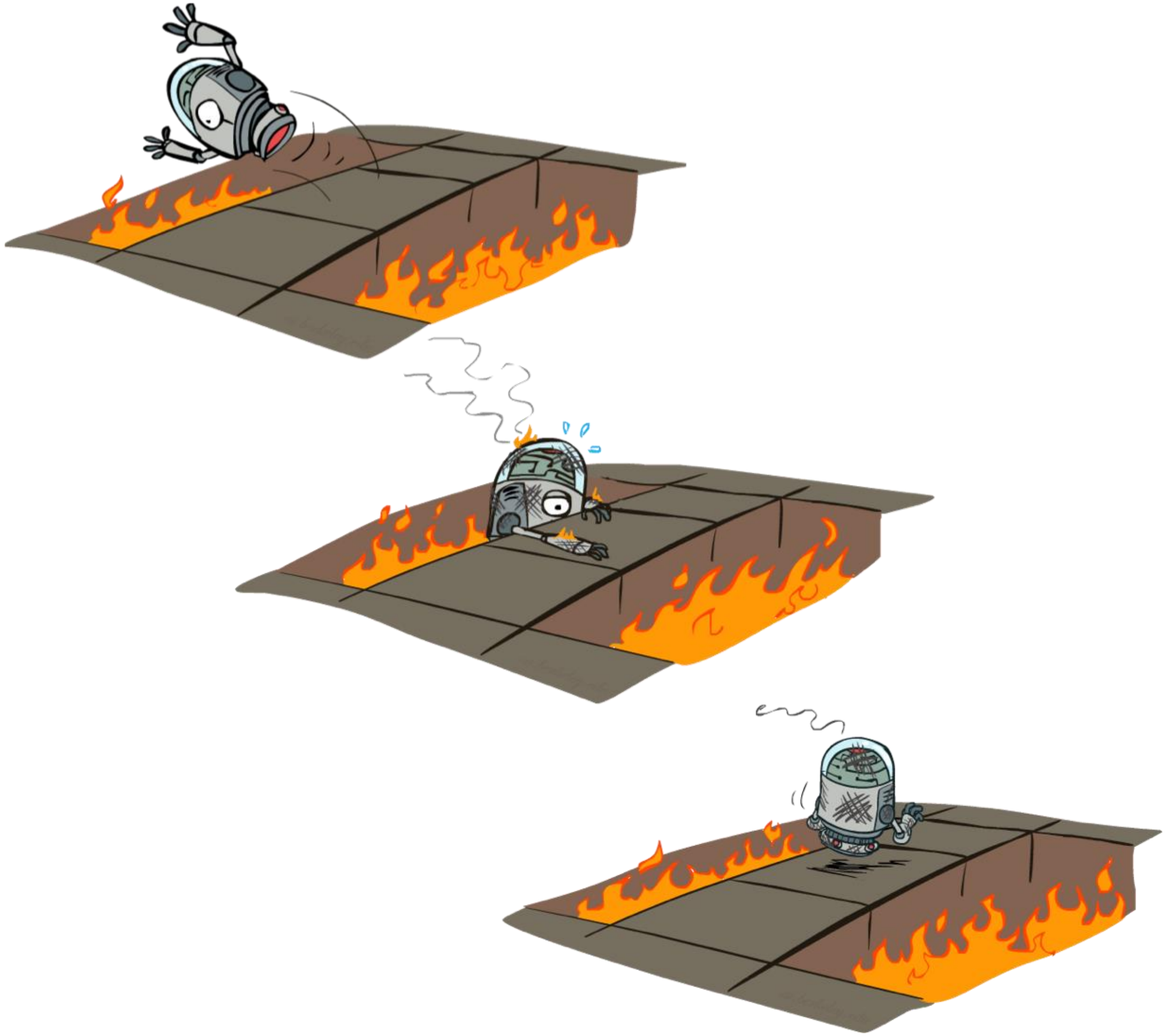
Online Learning

Approaches to reinforcement learning

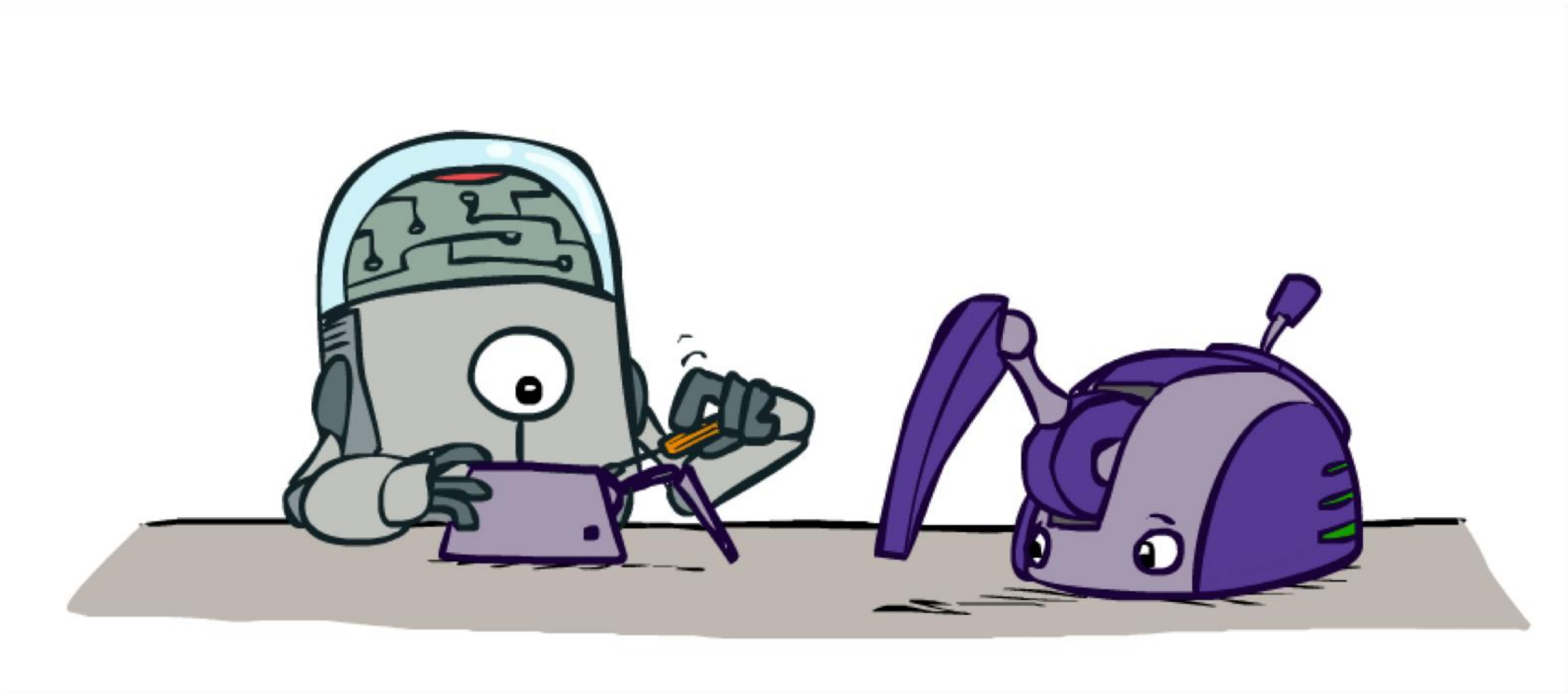
1. Model-based: Learn the model, solve it, execute the solution
2. Learn values from experiences, use to make decisions
   a. Direct evaluation
   b. Temporal difference learning
   c. Q-learning
3. Learn policies directly (see AIMA4e Section 22.5)

Passive vs Active Reinforcement Learning





Model-Based RL



Model-Based Learning

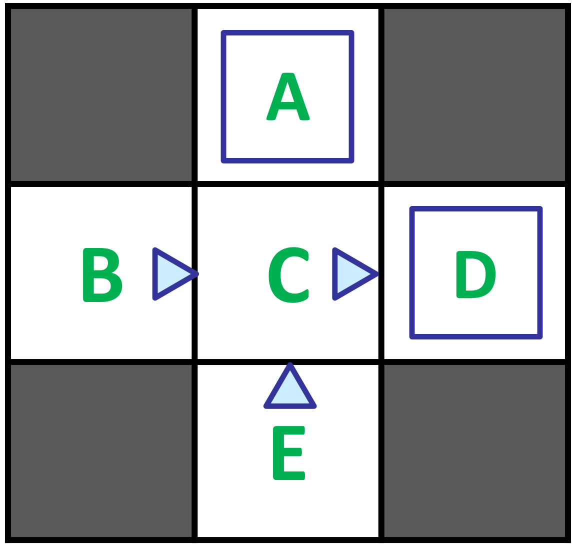
- Model-Based Idea:
  - Learn an approximate model based on experiences
  - Solve for values as if the learned model were correct

- Step 1: Learn empirical MDP model
  - Count outcomes *s'* for each *s*, *a*
  - Directly estimate each entry in $T(s,a,s')$ from counts
  - Discover each $R(s,a,s')$ when we experience the transition

- Step 2: Solve the learned MDP
  - Use, e.g., value or policy iteration, as before

Example: Model-Based Learning

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

$T(s,a,s')$

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

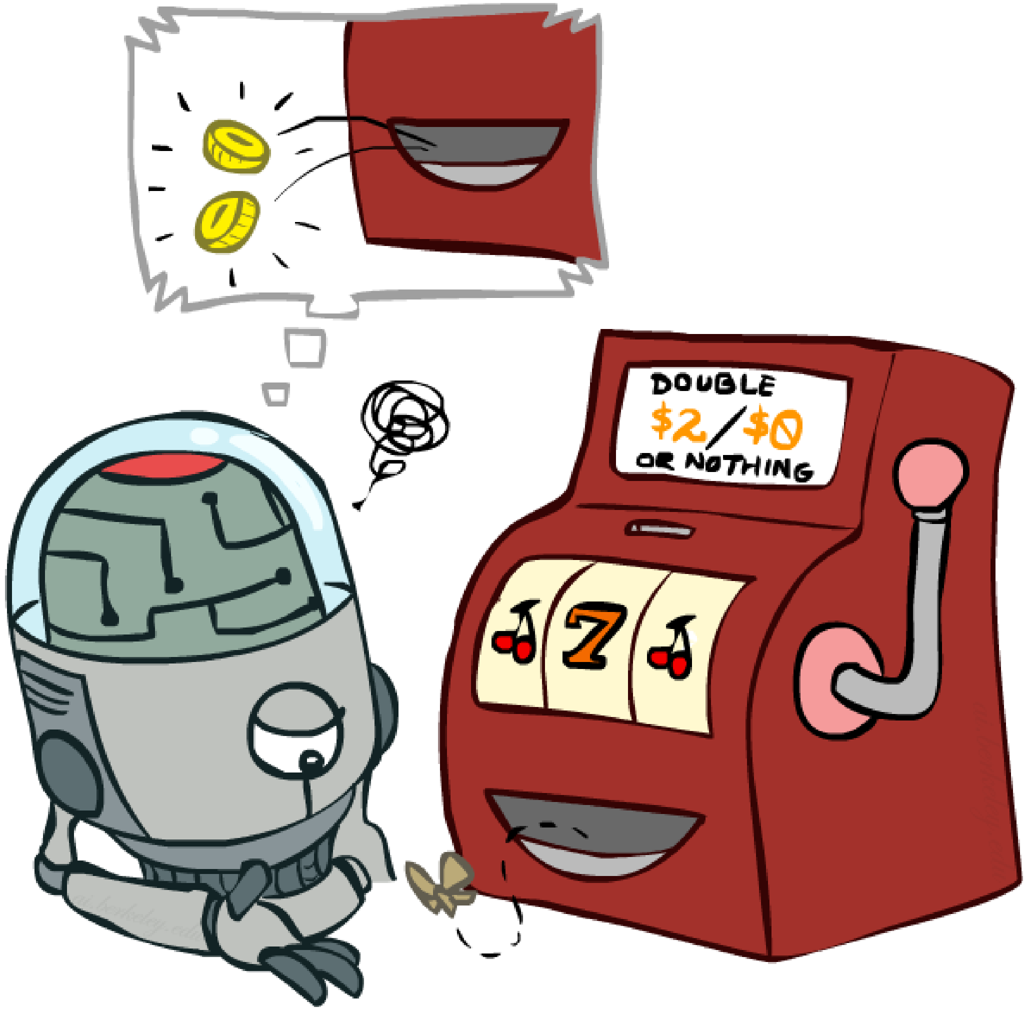
$R(s,a,s')$

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

Pros and cons

- Pro:
  - Makes efficient use of experiences (low ***sample complexity***)
- Con:
  - May not scale to large state spaces
    - Learns model one state-action pair at a time (but this is fixable)
    - Cannot solve MDP for very large $|S|$ (also somewhat fixable)
  - Much harder when the environment is partially observable

Model-Free Learning



Basic idea of model-free methods

- To approximate expectations with respect to a distribution, you can either
  - Estimate the distribution from samples, compute an expectation
  - Or, bypass the distribution and estimate the expectation from samples directly

Example: Expected Age

Goal: Compute expected age of cs188 students

Known P(A)

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

Without P(A), instead collect samples $[a_1, a_2, \ldots a_N]$

"Model Based": estimate P(A):

$$\hat{P}(A=a) = N_a/N$$

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

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

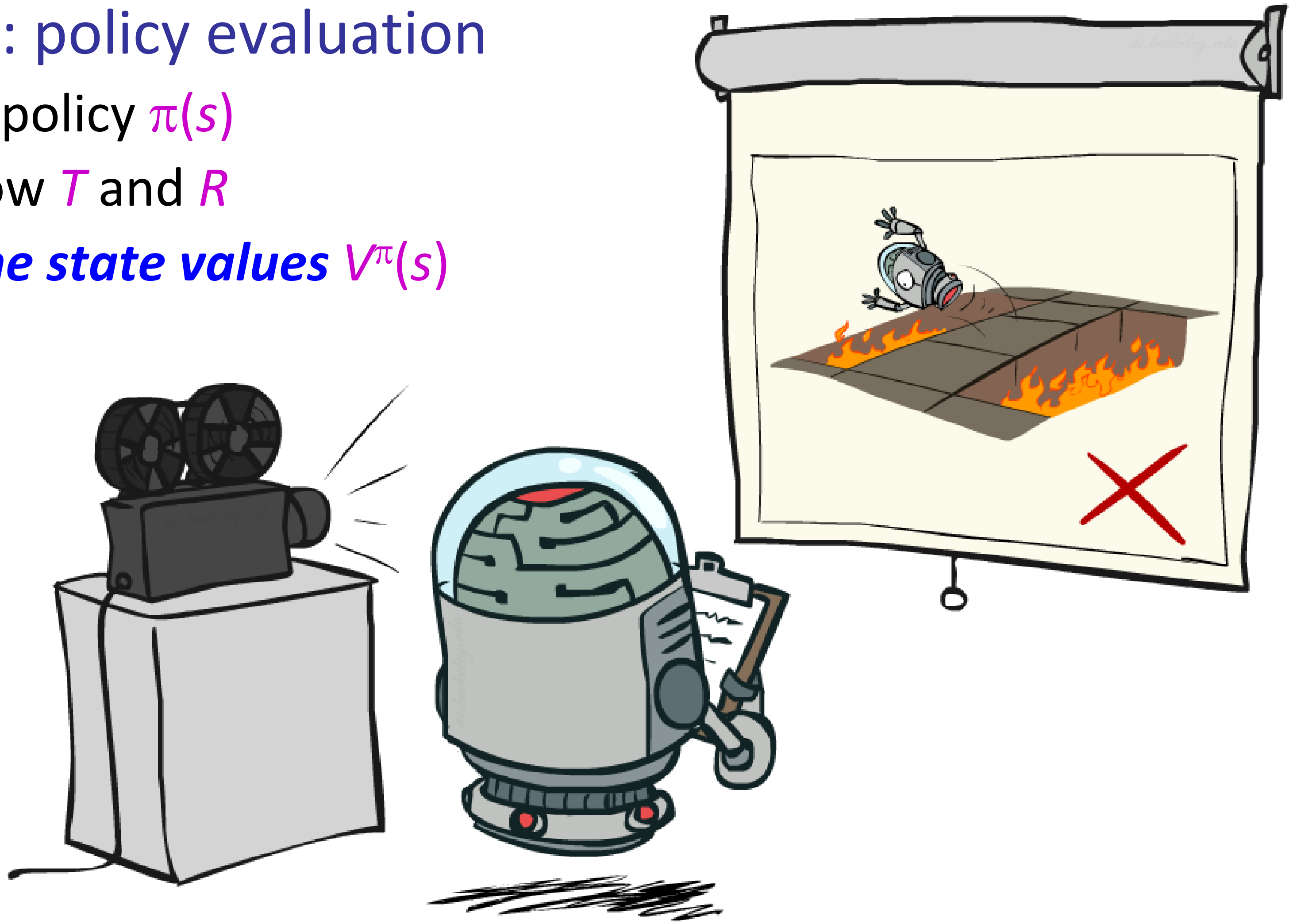
"Model Free": estimate expectation

$$E[A] \approx 1/N \sum_i a_i$$

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

Passive Reinforcement Learning

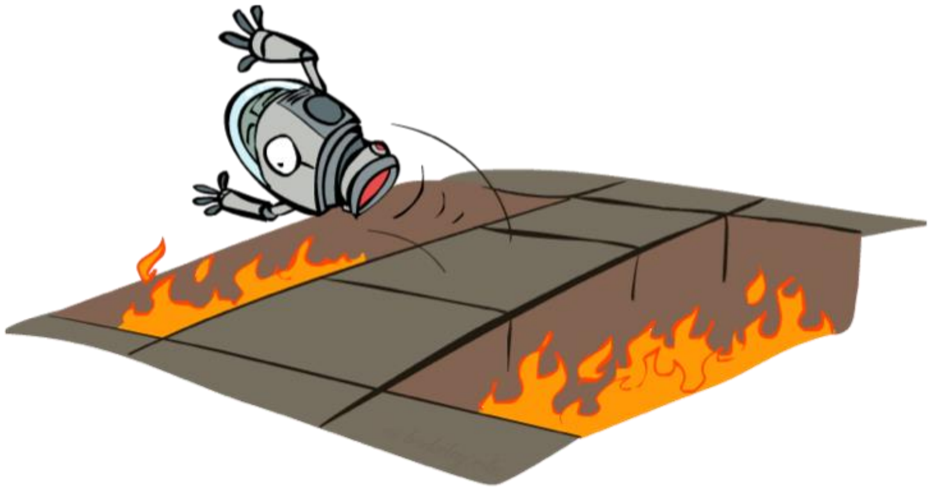
- Simplified task: policy evaluation
  - Input: a fixed policy $\pi(s)$
  - You don't know T and R
  - ***Goal: learn the state values*** $V^{\pi}(s)$



Direct evaluation

- Goal: Estimate $V^{\pi}(s)$, i.e., expected total discounted reward from s onwards

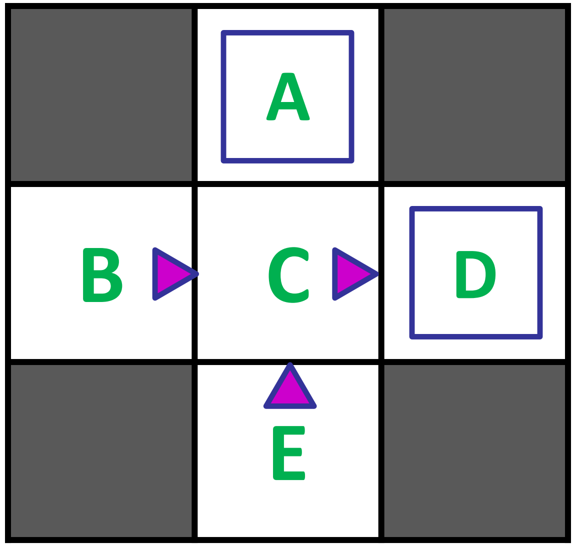
- Idea:
  - Use ***returns***, the *actual* sums of discounted rewards from s
  - Average over multiple trials and visits to s



- This is called ***direct evaluation*** (or direct utility estimation)

Example: Direct Estimation

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

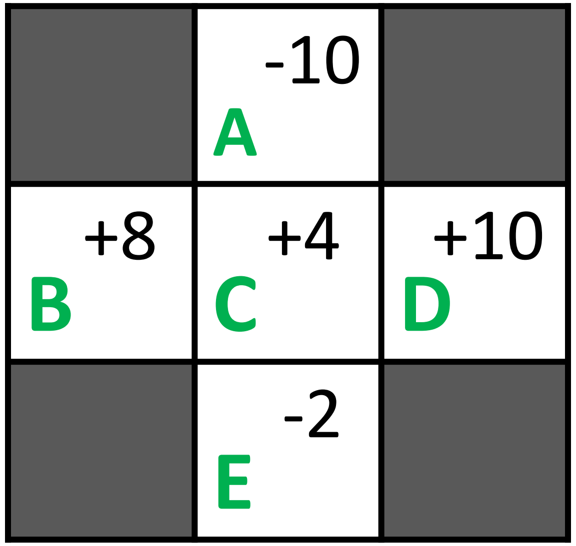
Episode 3

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

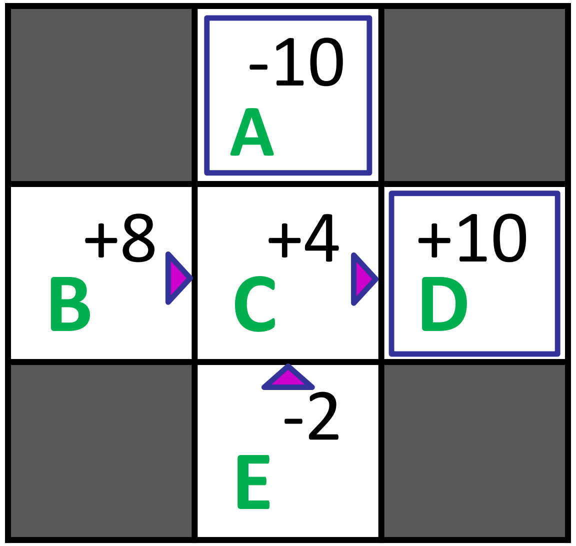


Problems with Direct Estimation

- What's good about direct estimation?
  - It's easy to understand
  - It doesn't require any knowledge of *T* and *R*
  - It converges to the right answer in the limit

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

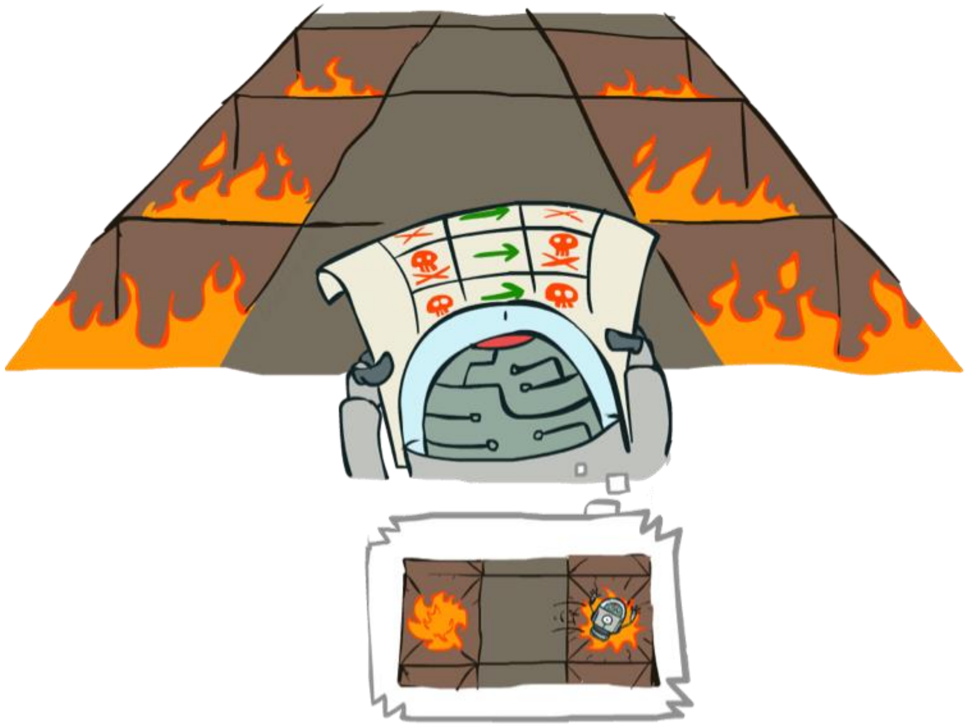
Output Values

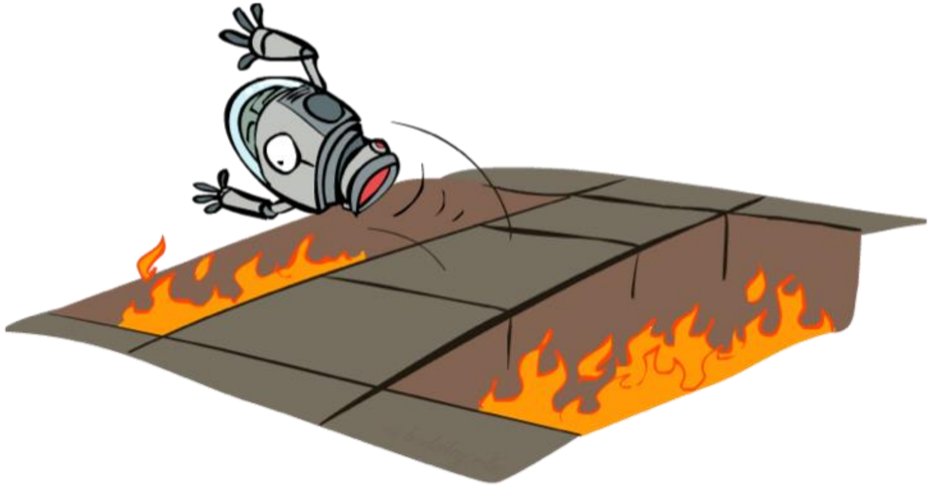


If B and E both go to C under this policy, how can their values be different?

E.g., B=at home, study hard
E=at library, study hard
C=know material, go to exam

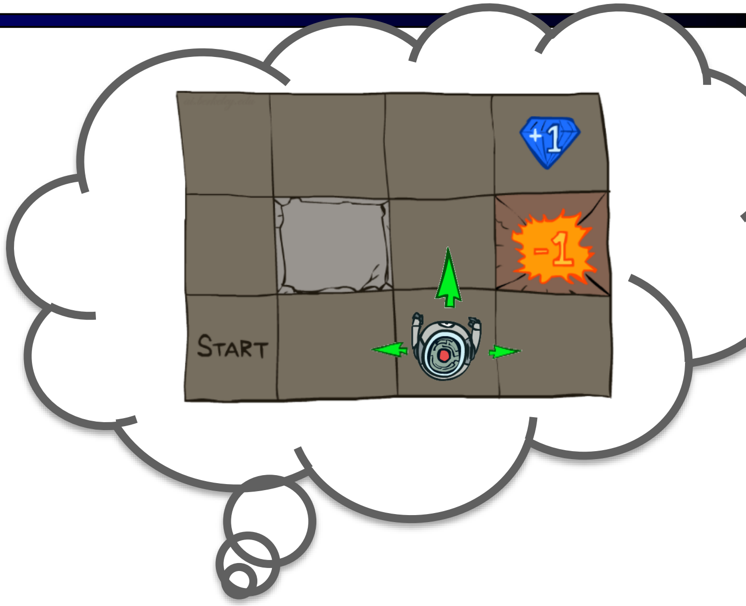
Temporal difference (TD) learning



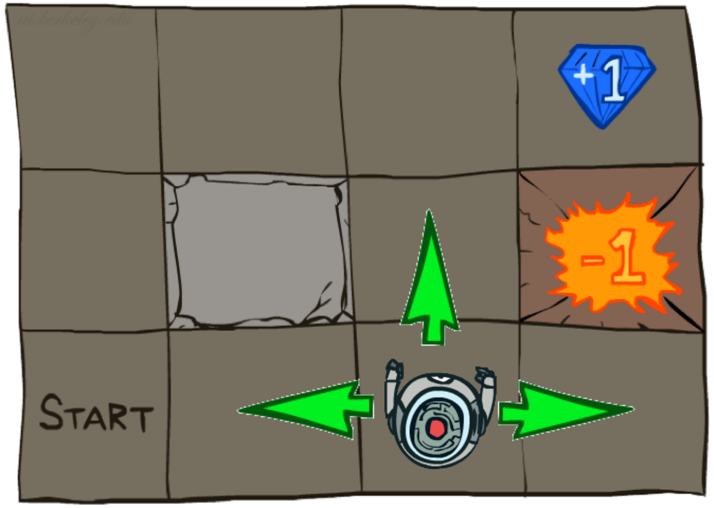


TD as approximate Bellman update

- Given a fixed policy, the value of a state is an expectation over next-state values:
  - $V^{\pi}(s) = \sum_{s'} T(s,\pi(s),s') [R(s,\pi(s),s') + \gamma V^{\pi}(s')]$



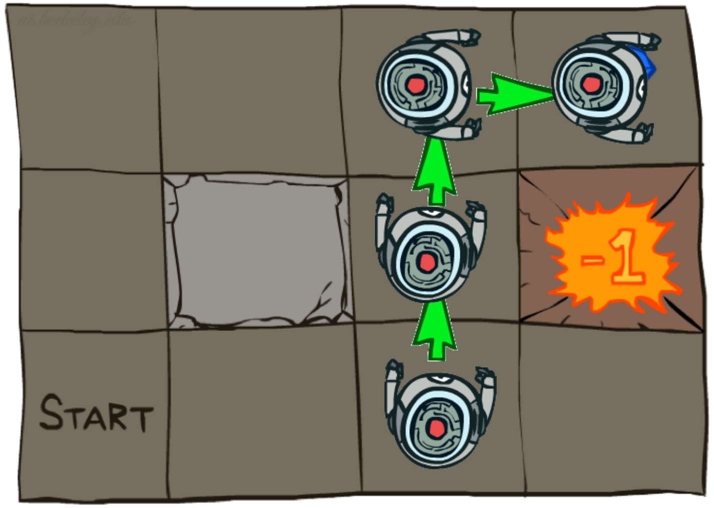
- Idea 1: Use actual samples to estimate the expectation:
  - $sample_1 = R(s,\pi(s),s_1') + \gamma V^{\pi}(s_1')$
  - $sample_2 = R(s,\pi(s),s_2') + \gamma V^{\pi}(s_2')$
  - …
  - $sample_N = R(s,\pi(s),s_N') + \gamma V^{\pi}(s_N')$
  - $V^{\pi}(s) \leftarrow 1/N \sum_i sample_i$



TD as approximate Bellman update

- Idea 2: Update value of s after each transition s,a,s',r :

- Update $V^{\pi}([3,1])$ based on $R([3,1],up,[3,2])$ and $\gamma V^{\pi}([3,2])$
- Update $V^{\pi}([3,2])$ based on $R([3,2],up,[3,3])$ and $\gamma V^{\pi}([3,3])$
- Update $V^{\pi}([3,3])$ based on $R([3,3],right,[4,3])$ and $\gamma V^{\pi}([4,3])$



TD as approximate Bellman update

- Idea 3: Update values by maintaining a ***running average***

Running averages

- How do you compute the average of 1, 4, 7?
- Method 1: add them up and divide by N
  - 1+4+7 = 12
  - average = 12/N = 12/3 = 4
- Method 2: keep a running average μ_n and a running count n
  - $n=0 \quad \mu_0=0$
  - $n=1 \quad \mu_1 = (0 \cdot \mu_0 + x_1)/1 = (0 \cdot 0 + 1)/1 = 1$
  - $n=2 \quad \mu_2 = (1 \cdot \mu_1 + x_2)/2 = (1 \cdot 1 + 4)/2 = 2.5$
  - $n=3 \quad \mu_3 = (2 \cdot \mu_2 + x_3)/3 = (2 \cdot 2.5 + 7)/3 = 4$
  - General formula: $\mu_n = ((n-1) \cdot \mu_{n-1} + x_n)/n$
  - $= [(n-1)/n]\, \mu_{n-1} + [1/n]\, x_n$ (weighted average of old mean, new sample)

Running averages contd.

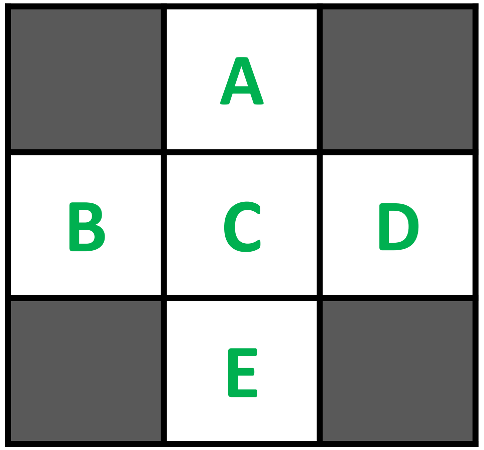
- What if we use a weighted average with a fixed weight?
  - $\mu_n = (1-\alpha)\,\mu_{n-1} + \alpha\, x_n$
  - n=1 $\quad \mu_1 = x_1$
  - n=2 $\quad \mu_2 = (1-\alpha) \cdot \mu_1 + \alpha x_2 = (1-\alpha) \cdot x_1 + \alpha x_2$
  - n=3 $\quad \mu_3 = (1-\alpha) \cdot \mu_2 + \alpha x_3 = (1-\alpha)^2 \cdot x_1 + \alpha(1-\alpha)x_2 + \alpha x_3$
  - n=4 $\quad \mu_4 = (1-\alpha) \cdot \mu_3 + \alpha x_4 = (1-\alpha)^3 \cdot x_1 + \alpha(1-\alpha)^2 x_2 + \alpha(1-\alpha)x_3 + \alpha x_4$
- I.e., ***exponential forgetting*** of old values
- μ_n is a convex combination of sample values (weights sum to 1)
- $E[\mu_n]$ is a convex combination of $E[X_i]$ values, hence unbiased

TD as approximate Bellman update

- Idea 3: Update values by maintaining a ***running average***
- sample = $R(s,\pi(s),s') + \gamma V^{\pi}(s')$
- $V^{\pi}(s) \leftarrow (1-\alpha) \cdot V^{\pi}(s) + \alpha \cdot \text{sample}$
- $V^{\pi}(s) \leftarrow V^{\pi}(s) + \alpha \cdot [\text{sample} - V^{\pi}(s)]$
- This is the ***temporal difference learning rule***
- $[\text{sample} - V^{\pi}(s)]$ is the "TD error"
- α is the ***learning rate***
- I.e., observe a sample, move $V^{\pi}(s)$ a little bit to make it more consistent with its neighbor $V^{\pi}(s')$

Example: Temporal Difference Learning

States

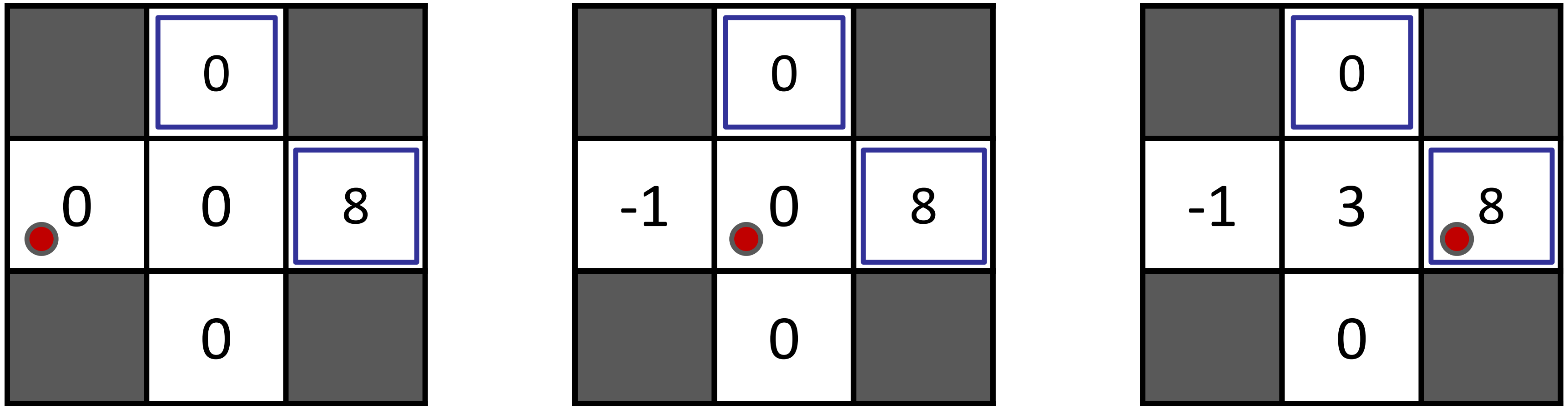


Assume: $\gamma = 1$, $\alpha = 1/2$

Observed Transitions

B, east, C, -2

C, east, D, -2



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

Problems with TD Value Learning

- TD value learning is a model-free way to do policy evaluation, mimicking Bellman updates with running sample averages
- But we can’t use the value function, or improve the policy, without a transition model to do one-step greedy expectimax!
- (Will see later how to use it with a known model in large state spaces)

Q-learning as approximate Q-iteration

- Recall the definition of Q values:
  - $Q^*(s,a)$ = expected return from doing a in s and then behaving optimally thereafter; and $\pi^*(s) = \max_a Q^*(s,a)$
- Bellman equation for Q values:
  - $Q^*(s,a) = \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma \max_{a'} Q^*(s',a')]$
- Approximate Bellman update for Q values:
  - $Q(s,a) \leftarrow (1-\alpha) \cdot Q(s,a) + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a')]$
- We obtain a policy from learned Q(s,a), with no model!
  - (No free lunch: Q(s,a) table is |A| times bigger than V(s) table)

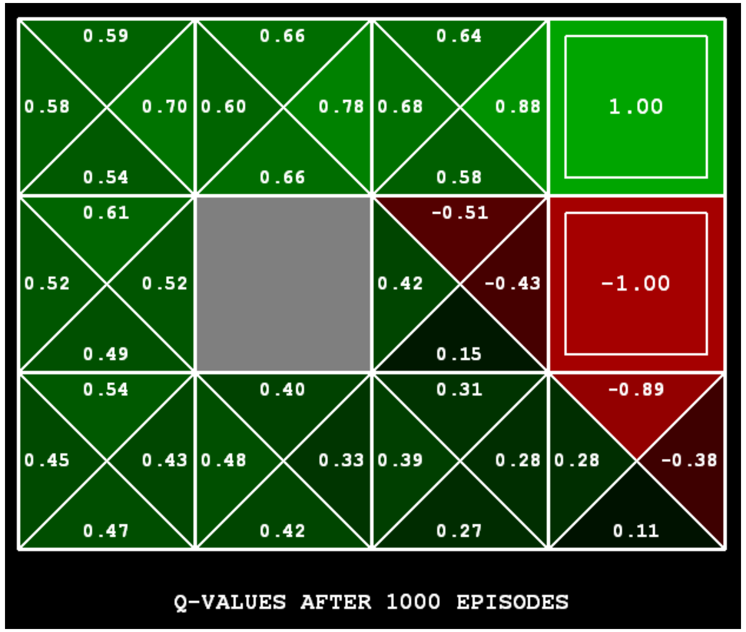
Q-Learning

- 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:

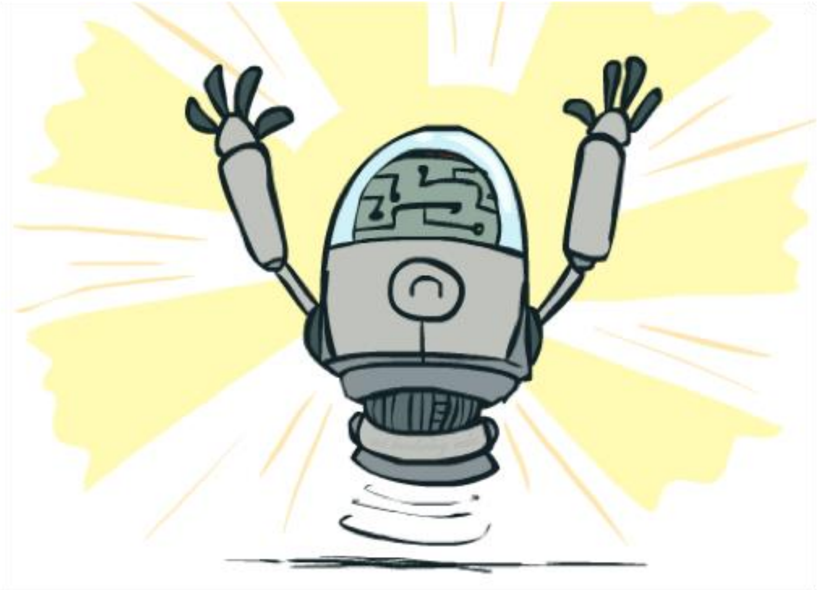
    $Q(s,a) \leftarrow (1-\alpha)\, Q(s,a) + \alpha \cdot [sample]$



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

Q-Learning Properties

- Amazing result: Q-learning converges to optimal policy -- even if samples are generated from a suboptimal policy!
- This is called ***off-policy learning***
- Caveats:
  - You have to explore enough (eventually try every state/action pair infinitely often)
  - You have to decrease the learning rate appropriately
    - Technical requirements: $\sum_t \alpha(t) = \infty$, $\sum_t \alpha^2(t) < \infty$
    - Satisfied by: $\alpha(t) = 1/t$ or (better) $\alpha(t) = K/(K+t)$



Summary

- RL solves MDPs via direct experience of transitions and rewards
- There are several schemes:
  - Learn the MDP model and solve it
  - Learn V directly from sums of rewards, or by TD local adjustments
    - Still need a model to make decisions by lookahead
  - Learn Q by local Q-learning adjustments, use it directly to pick actions
  - (and about 100 other variations)
- Big missing pieces:
  - How to explore without too much regret?
  - How to scale this up to Tetris (10^{60}), Go (10^{172}), StarCraft ($|A|=10^{26}$)?