STA303: Artificial Intelligence

Reinforcement Learning

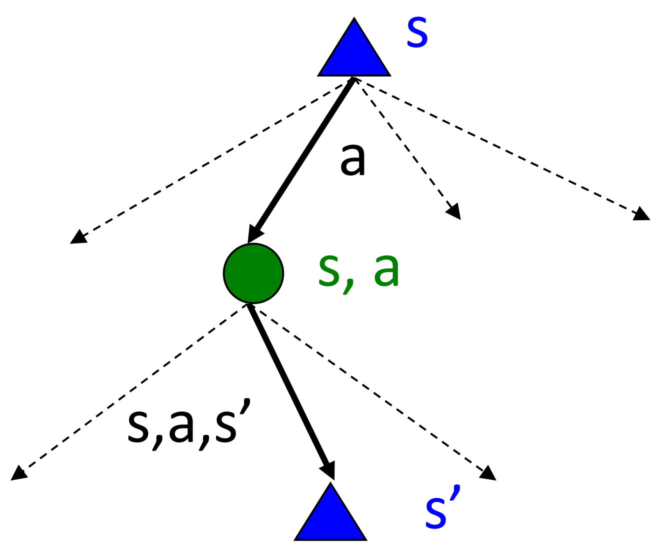
Fang Kong

https://fangkongx.github.io/

Slide credits: ai.berkeley.edu

Recap: MDPs

- Markov decision processes:
  - States S
  - Actions A
  - Transitions P(s'|s,a) (or T(s,a,s'))
  - Rewards R(s,a,s') (and discount γ)
  - Start state s_0



- Quantities:
  - Policy = map of states to actions
  - Utility = sum of discounted rewards
  - Values = expected future utility from a state (max node)
  - Q-Values = expected future utility from a q-state (chance node)

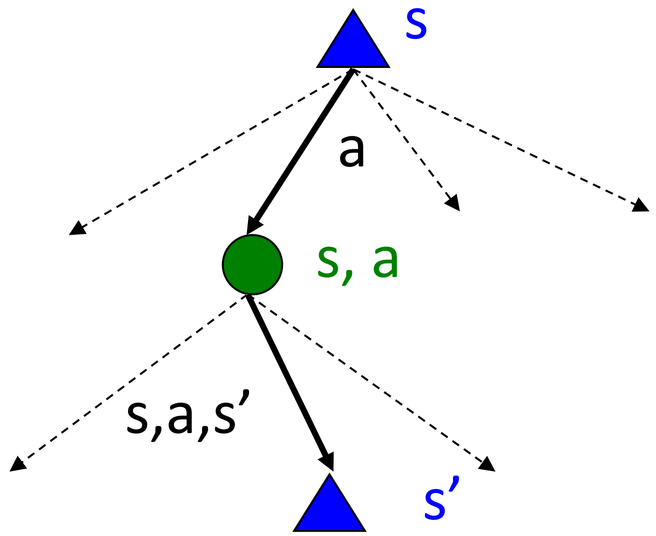
Recap: The Bellman Equations

- Definition of "optimal utility" via expectimax recurrence gives a simple one-step lookahead relationship amongst optimal utility values

$$V^*(s) = \max_a Q^*(s,a)$$

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

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

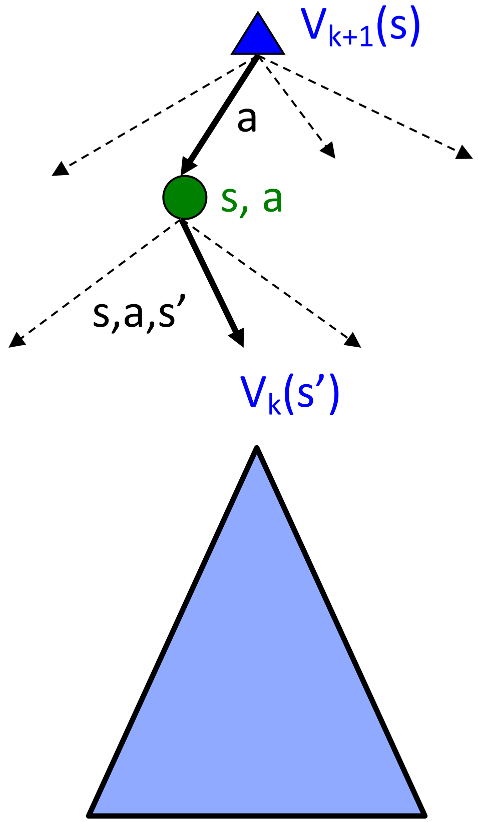


- These are the Bellman equations, and they characterize optimal values in a way we'll use over and over

Recap: Value Iteration

- Start with $V_0(s) = 0$: no time steps left means an expected reward sum of zero
- Given vector of $V_k(s)$ values, do one ply of expectimax from each state:

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



- Repeat until convergence
- Complexity of each iteration: $O(S^2A)$
- Theorem: will converge to unique optimal values
  - Basic idea: approximations get refined towards optimal values
  - Policy may converge long before values do

Recap: Policy Evaluation

- How do we calculate the V's for a fixed policy π?

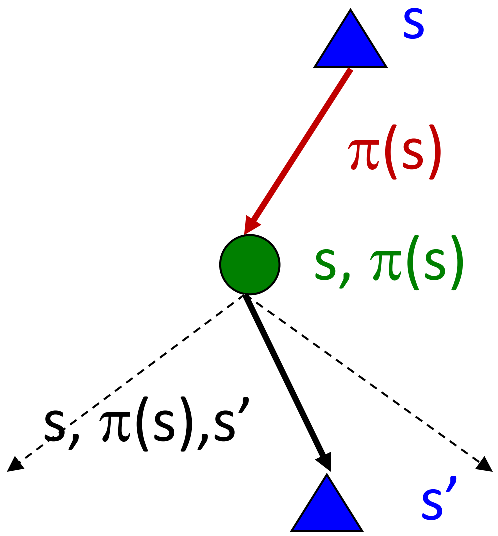
- Idea 1: Turn recursive Bellman equations into updates (like value iteration)

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

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

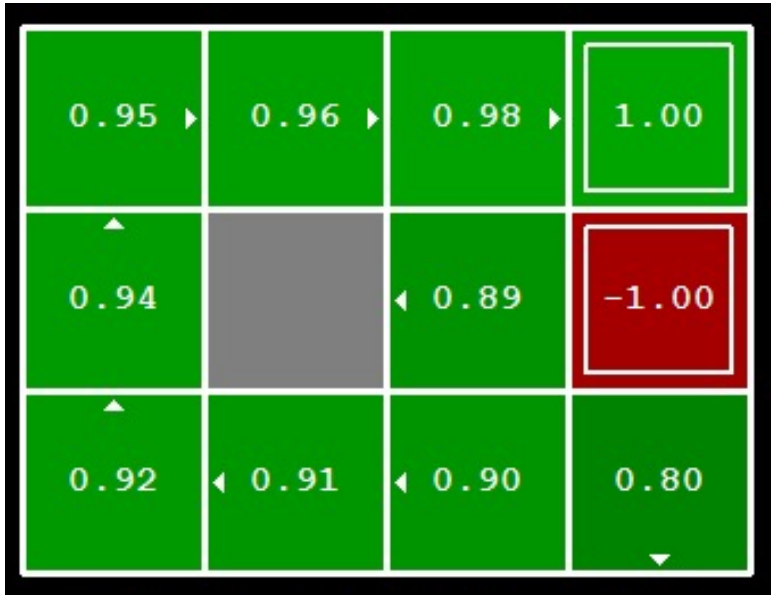
- Efficiency: $O(S^2)$ per iteration

- Idea 2: Without the maxes, the Bellman equations are just a linear system
  - Solve with Matlab (or your favorite linear system solver)



Recap: Policy Extraction

- Let's imagine we have the optimal values V*(s)
- How should we act?
  - It's not obvious!
- We need to do a mini-expectimax (one step)



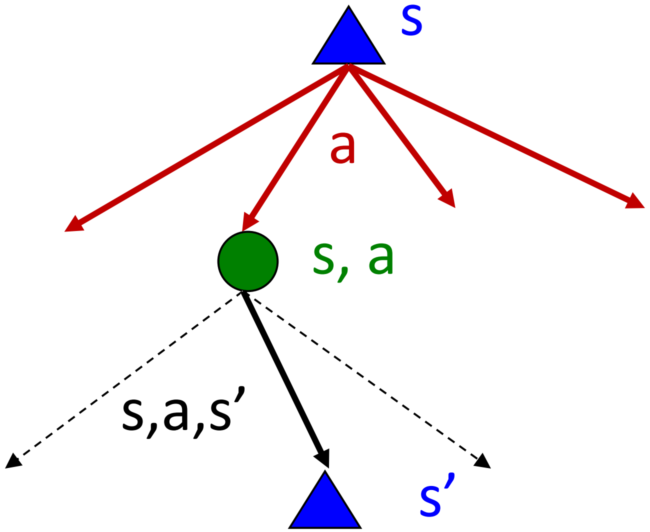
$$\pi^*(s) = \arg\max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')]$$

- This is called policy extraction, since it gets the policy implied by the values

Recap: Problems with Value Iteration

- Value iteration repeats the Bellman updates:

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



- Problem 1: It's slow – $O(S^2A)$ per iteration

- Problem 2: The "arg max" at each state rarely changes

- Problem 3: The policy often converges long before the values

[Demo: value iteration (L9D2)]

Recap: Policy Iteration

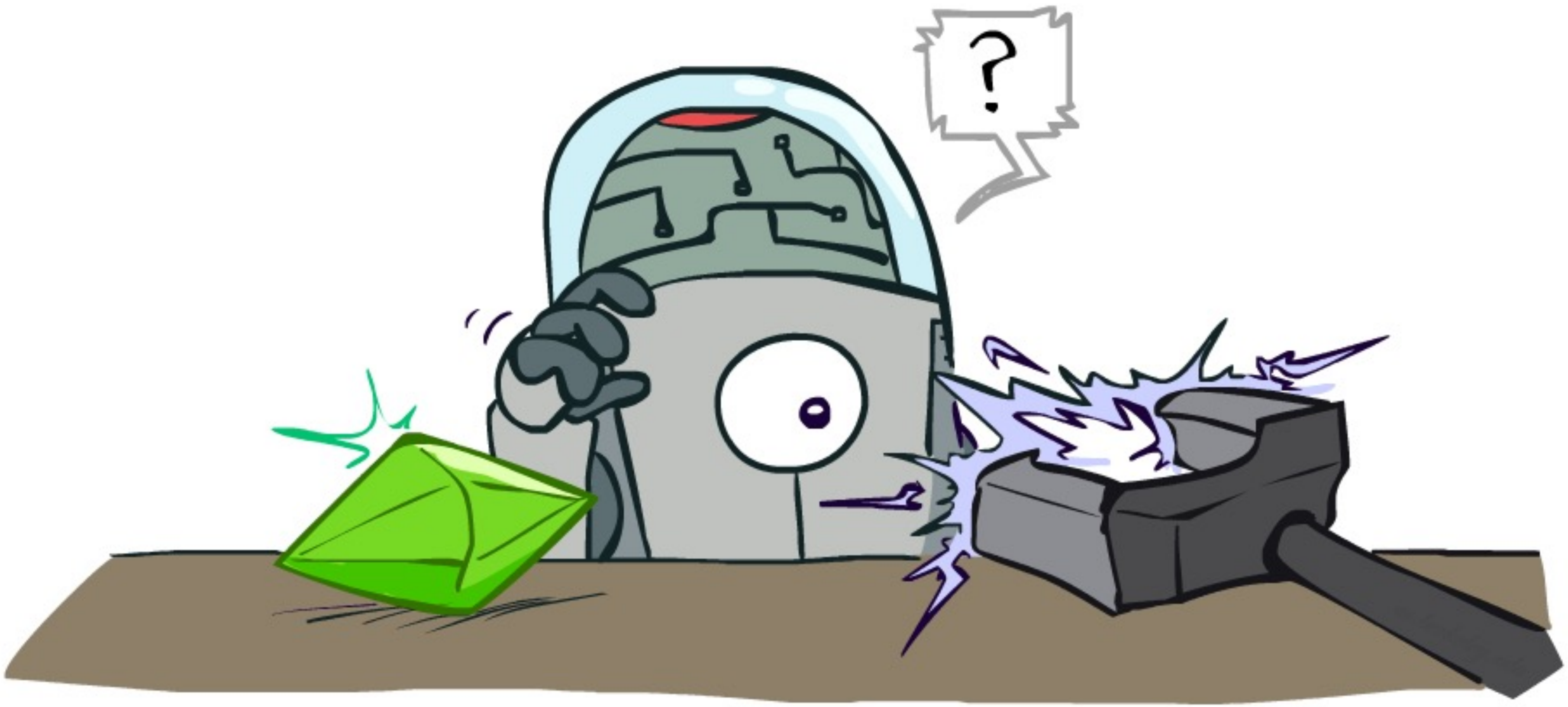
- Evaluation: For fixed current policy π, find values with policy evaluation:
  - Iterate until values converge:

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

- Improvement: For fixed values, get a better policy using policy extraction
  - One-step look-ahead:

$$\pi_{i+1}(s) = \arg\max_a \sum_{s'} T(s, a, s') \left[R(s, a, s') + \gamma V^{\pi_i}(s')\right]$$

Reinforcement Learning



Reinforcement Learning

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

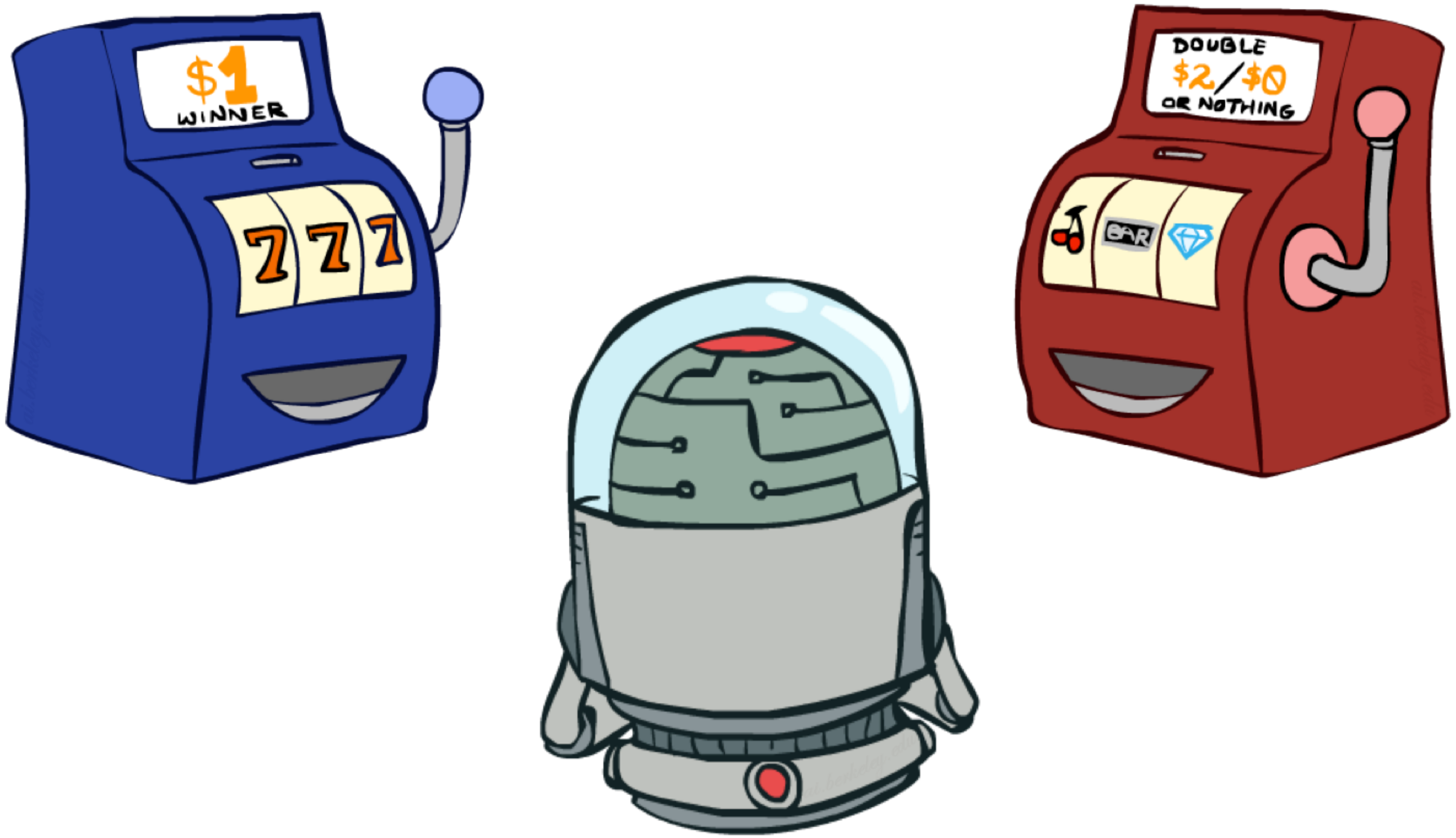
- New twist: don't know T or R
  - I.e. we don't know which states are good or what the actions do
  - Must explore new states and actions to discover how the world works

Reinforcement Learning

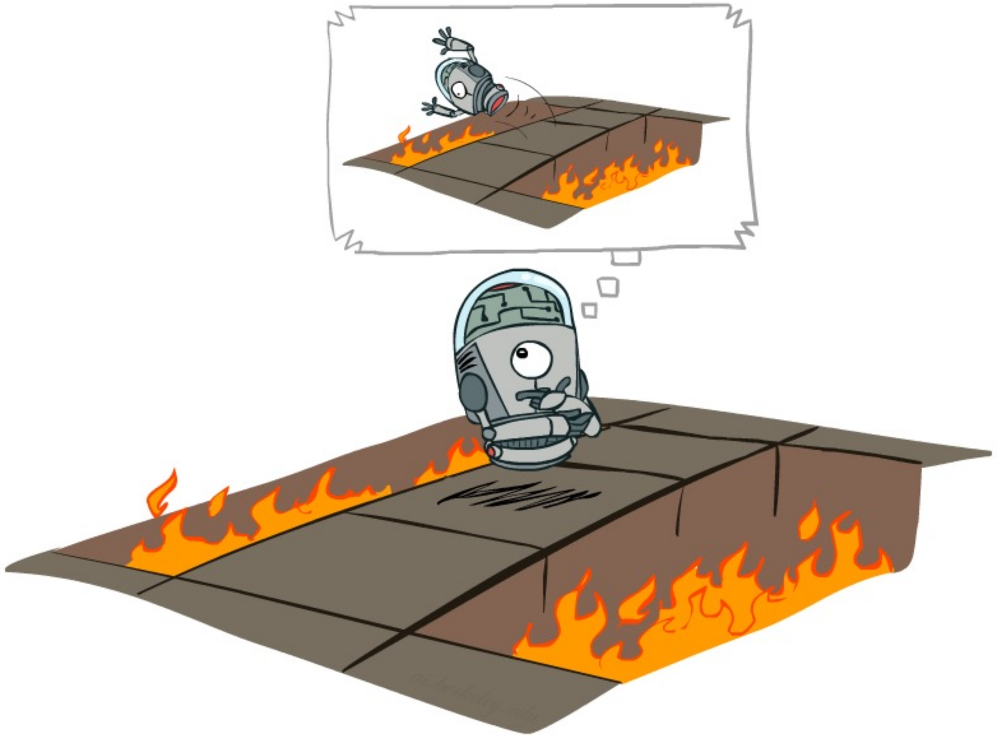
- What if the MDP is initially unknown? Lots of things change!
  - ***Exploration***: you have to ***try unknown actions*** to get information
  - ***Exploitation***: eventually, you have to use what you know
  - ***Regret***: early on, you inevitably “make mistakes” and lose reward
  - ***Sampling***: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

Bandits

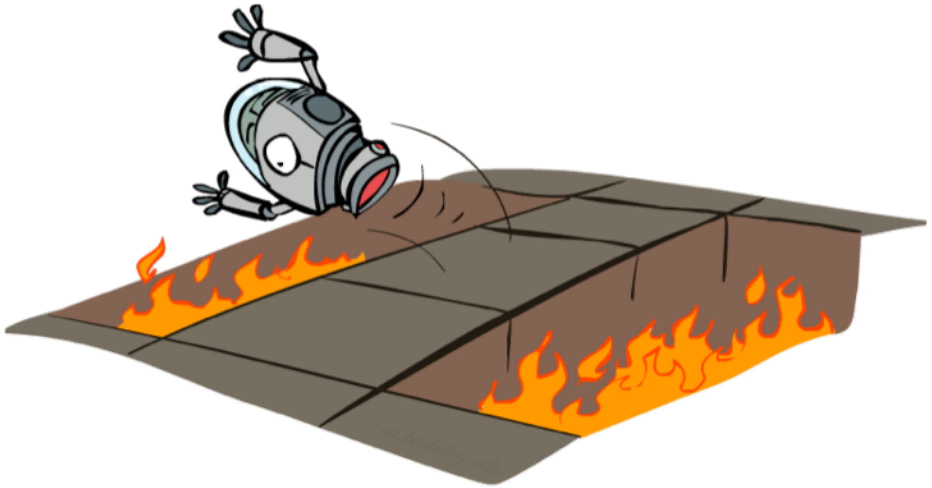
- Exactly one state
- Set of actions: A
- Stochastic reward function: $P(r|a)$



Offline (MDPs) vs. Online (RL)



Offline Solution

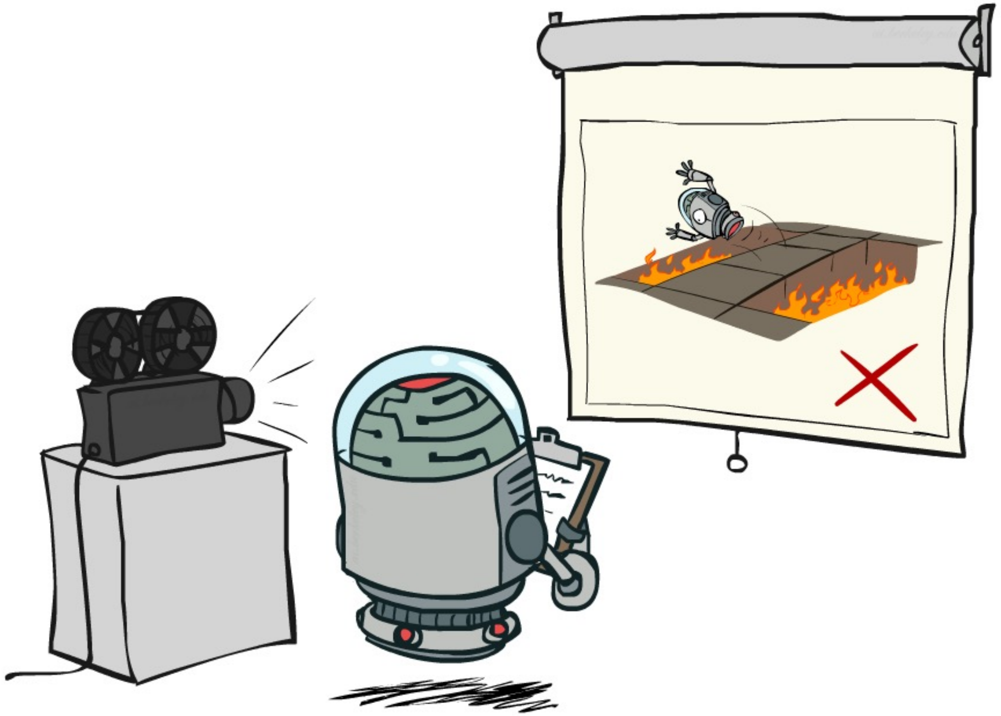


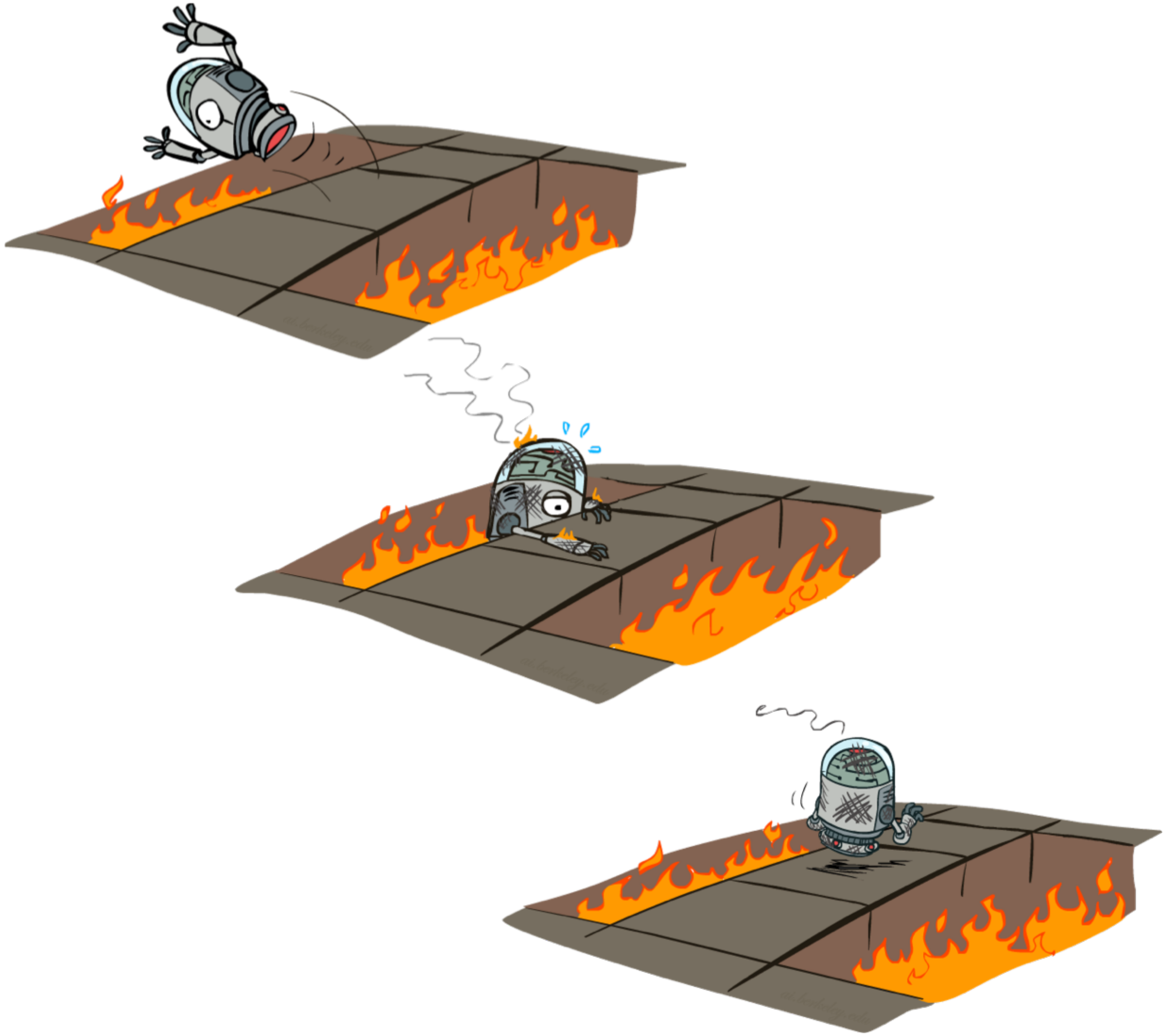
Online Learning

Approaches to reinforcement learning

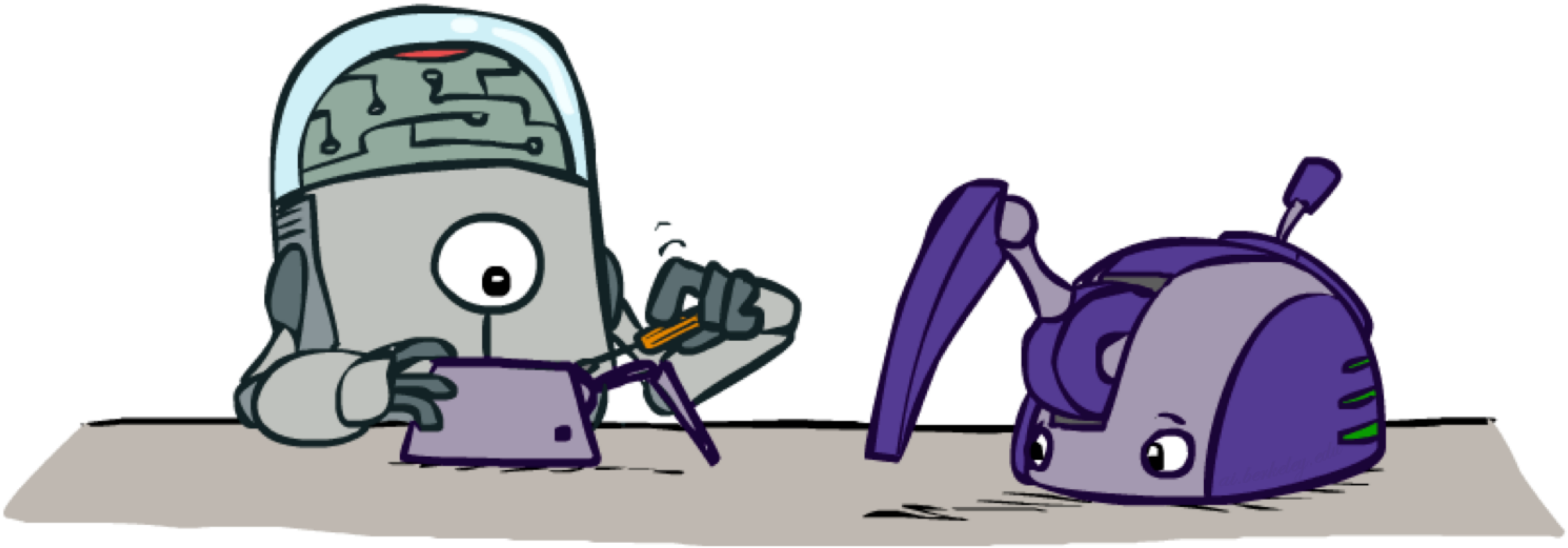
1. Model-based: Learn the model, solve it, execute the solution
2. Learn values from experiences, use to make decisions
   a. Direct evaluation
   b. Temporal difference learning
   c. Q-learning
3. Optimize the policy directly

Passive vs Active Reinforcement Learning





Model-Based RL



Model-Based Learning

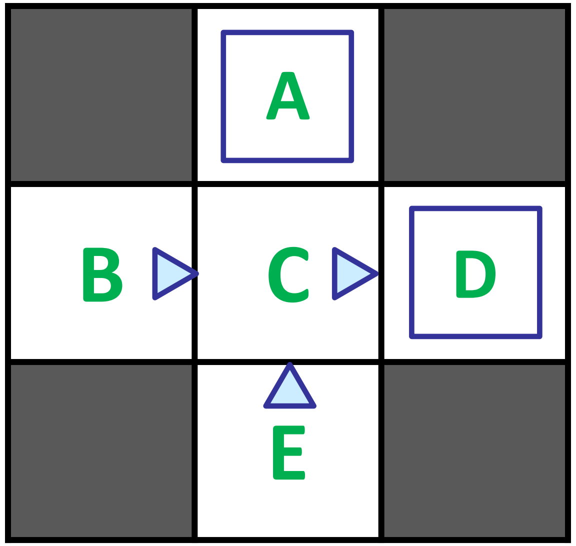
- Model-Based Idea:
  - Learn an approximate model based on experiences
  - Solve for values as if the learned model were correct

- 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
    - Solving MDP is intractable for very large $|S|$
  - RL feedback loop tends to magnify small model errors
  - Much harder when the environment is partially observable

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 MAT8034 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.

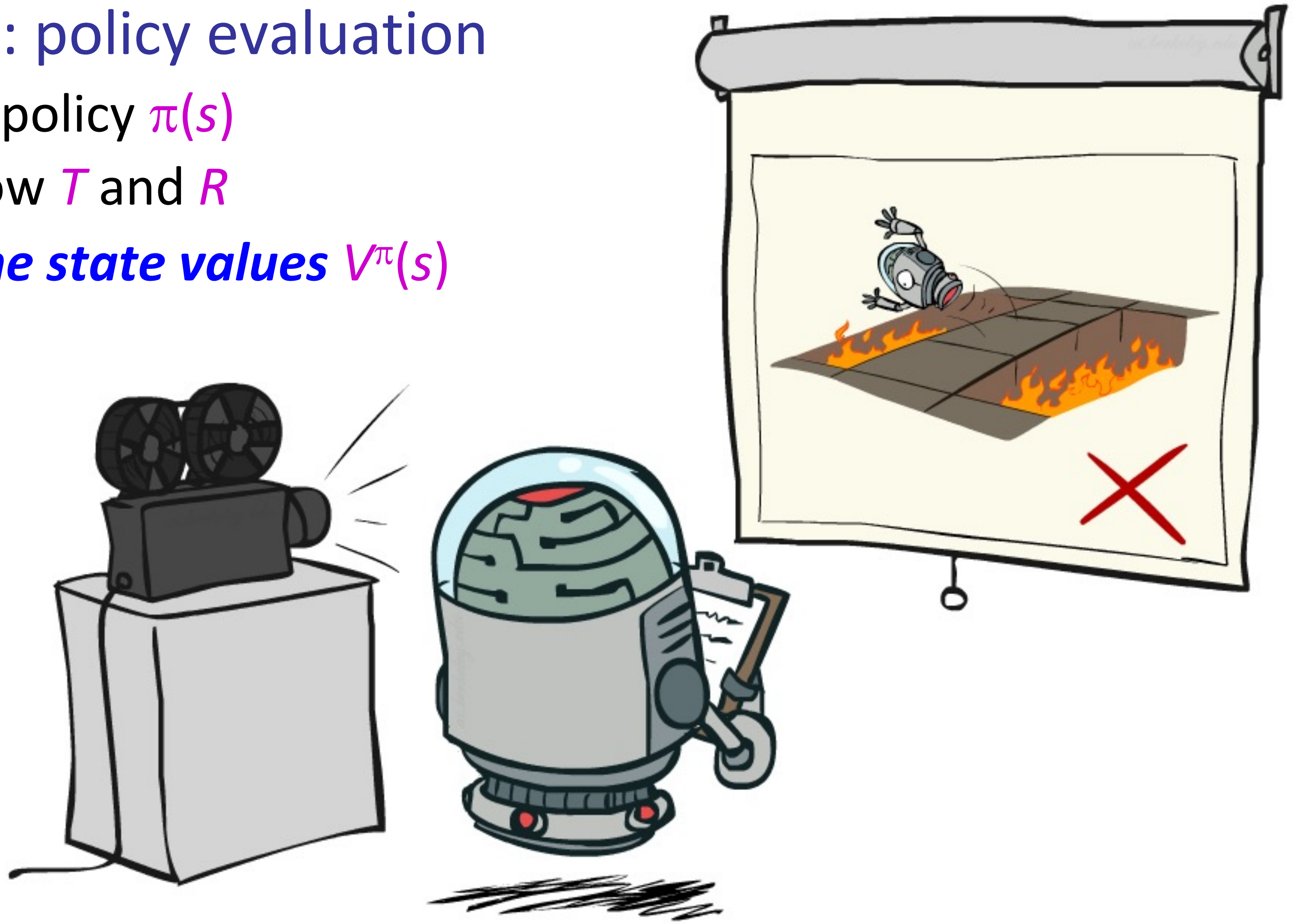
"Model Free": estimate expectation

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

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*** $V^{\pi}(s)$

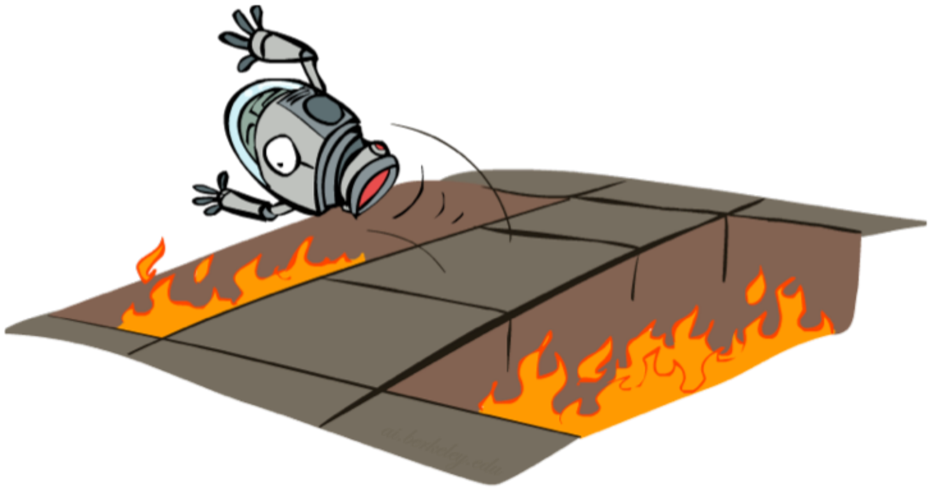


Direct evaluation

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

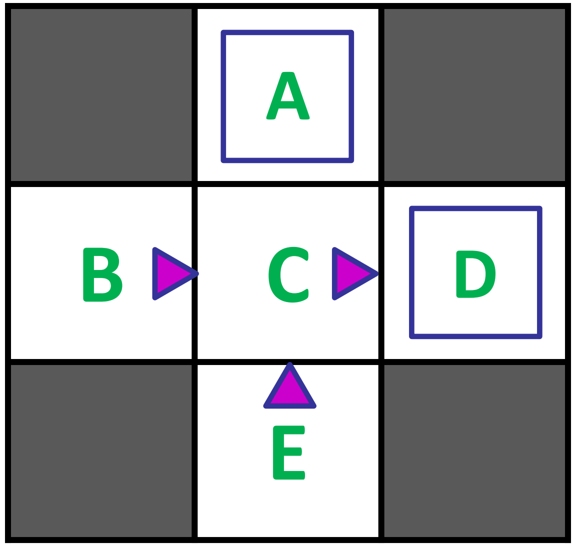
- Idea:
  - Use ***returns***, the *actual* sums of discounted rewards from s
  - Average over multiple trials and visits to s

- 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

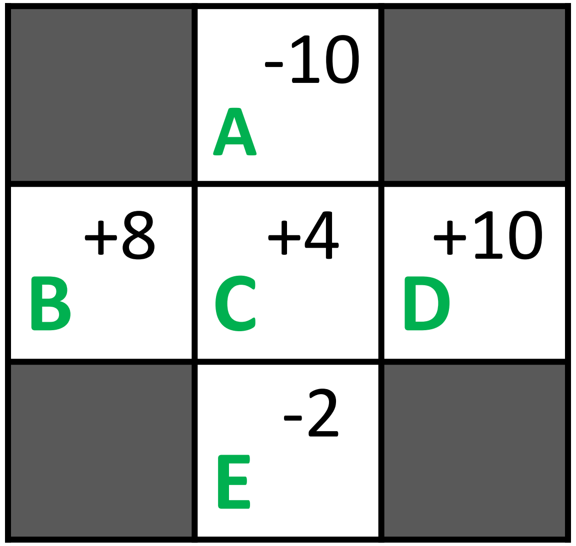
Episode 3

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

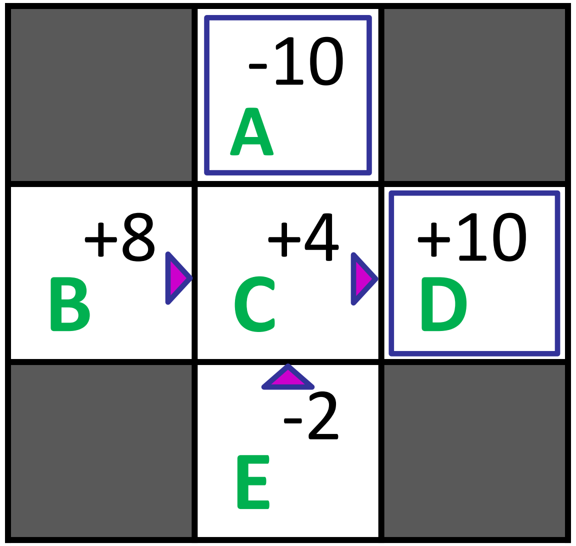


Problems with Direct Estimation

- 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

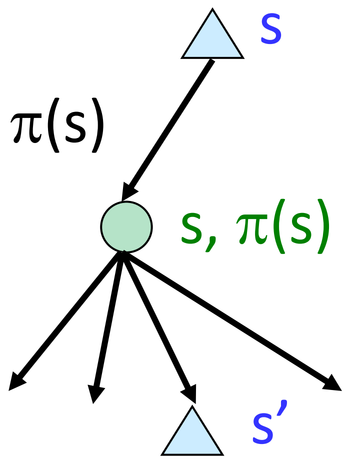


If B and E both go to C under this policy, how can their values be different?

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

Temporal Difference 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

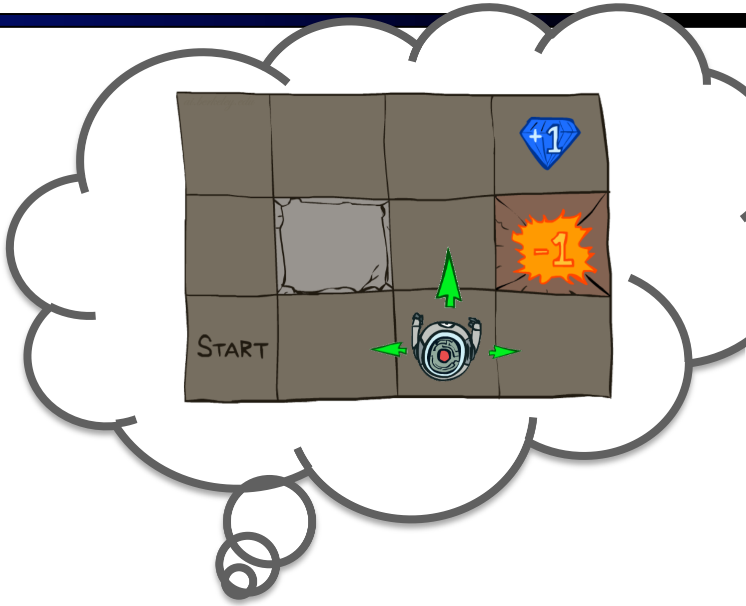
Sample of V(s): $$sample = R(s, \pi(s), s') + \gamma V^{\pi}(s')$$

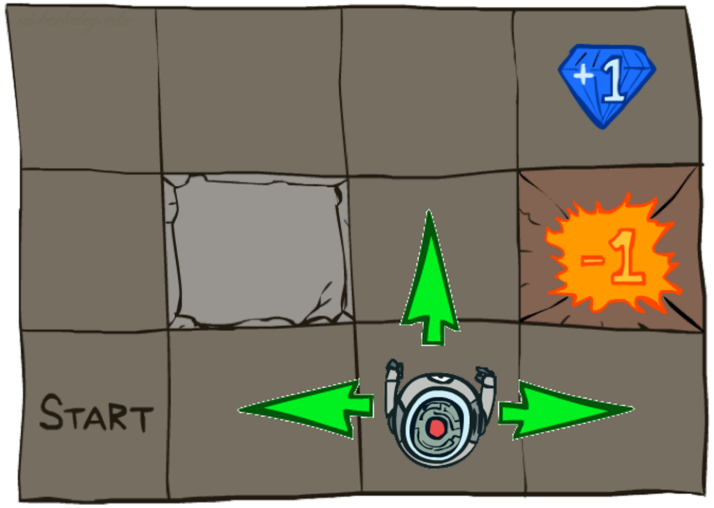
Update to V(s): $$V^{\pi}(s) \leftarrow (1-\alpha)V^{\pi}(s) + (\alpha)sample$$

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

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:
  - $\text{sample}_1 = R(s,\pi(s),s_1') + \gamma V^\pi(s_1')$
  - $\text{sample}_2 = R(s,\pi(s),s_2') + \gamma V^\pi(s_2')$
  - …
  - $\text{sample}_N = R(s,\pi(s),s_N') + \gamma V^\pi(s_N')$
  - $V^\pi(s) \leftarrow 1/N \sum_i \text{sample}_i$

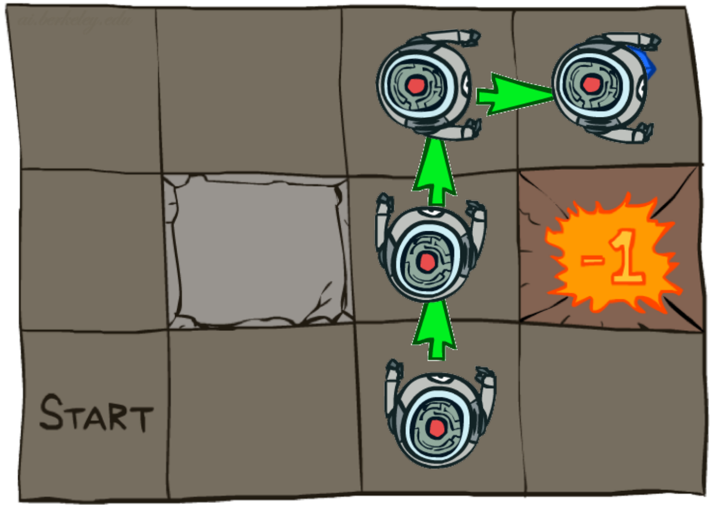




TD as approximate Bellman update

- 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.

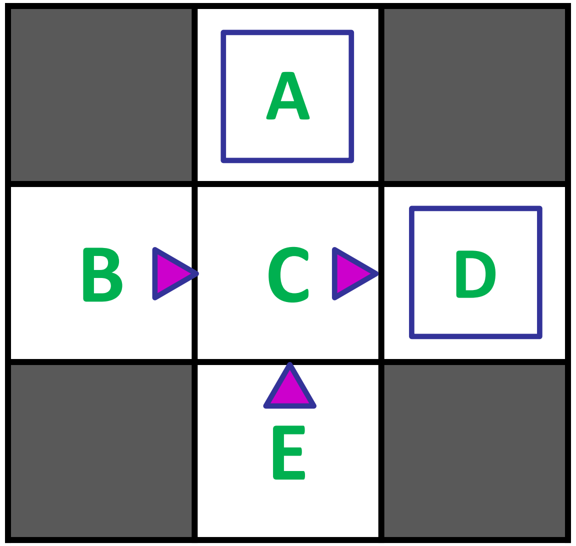
- What if we use a weighted average with a fixed weight?
  - $\mu_n = (1-\alpha)\, \mu_{n-1} + \alpha\, x_n$
  - n=1 $\mu_1 = x_1$
  - n=2 $\mu_2 = (1-\alpha) \cdot \mu_1 + \alpha x_2 = (1-\alpha) \cdot x_1 + \alpha x_2$
  - n=3 $\mu_3 = (1-\alpha) \cdot \mu_2 + \alpha x_3 = (1-\alpha)^2 \cdot x_1 + \alpha(1-\alpha) x_2 + \alpha x_3$
  - n=4 $\mu_4 = (1-\alpha) \cdot \mu_3 + \alpha x_4 = (1-\alpha)^3 \cdot x_1 + \alpha(1-\alpha)^2 x_2 + \alpha(1-\alpha) x_3 + \alpha x_4$
- I.e., ***exponential forgetting*** of old values
- μ_n is a convex combination of sample values (weights sum to 1)
- $\mathbb{E}[\mu_n]$ is a convex combination of $\mathbb{E}[x_i]$, 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***
- Observe a sample, move $V^{\pi}(s)$ a little bit to make it more consistent with its neighbor $V^{\pi}(s')$

Example: TD Value 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

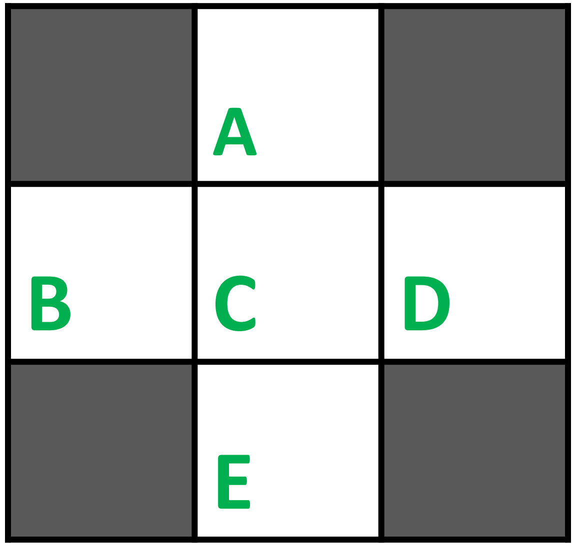
Episode 3

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



Example: TD Value Estimation

- Experience transition *i:* (s_i, a_i, s_i', r_i).
- Compute sampled value "target": $r_i + \gamma V^\pi(s_i')$.
- Compute "TD error": $\delta_i = \left(r_i + \gamma V^\pi(s_i')\right) - V^\pi(s_i)$.
- Update: $V^\pi(s_i)$ += $\alpha_i \cdot \delta_i$.

s	***V(s)***
A	
B	
C	
D	
E	

i	***s***	***a***	***s'***	***r***	$r + \gamma V^\pi(s')$	$V^\pi(s)$	δ
1							
2							
3							
4							
5							
6							
7							

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

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

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

E, north, **C**, -1
C, east, **A**, -1
A, exit, **x**, -10

Example: TD Value Estimation

- Experience transition *i:* (s_i, a_i, s_i', r_i).
- Compute sampled value "target": $r_i + \gamma V^\pi(s_i')$.
- Compute "TD error": $\delta_i = \left(r_i + \gamma V^\pi(s_i')\right) - V^\pi(s_i)$.
- Update: $V^\pi(s_i)$ += $\alpha_i \cdot \delta_i$.

s	V(s)
A	0
B	-2
C	9
D	10
E	8

i	s	a	s'	r	$r + \gamma V^\pi(s')$	$V^\pi(s)$	δ
1	B	east	C	-1	-1 + 0	0	-1
2	C	east	D	-1	-1 + 0	0	-1
3	D	exit	---	10	10 + 0	0	+10
4	B	east	C	-1	-1 + -1	-1	-1
5	C	east	D	-1	-1 + 10	-1	+10
6	D	exit	---	10	10 + 0	10	0
7	E	north	C	-1	-1 + 9	0	+8

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

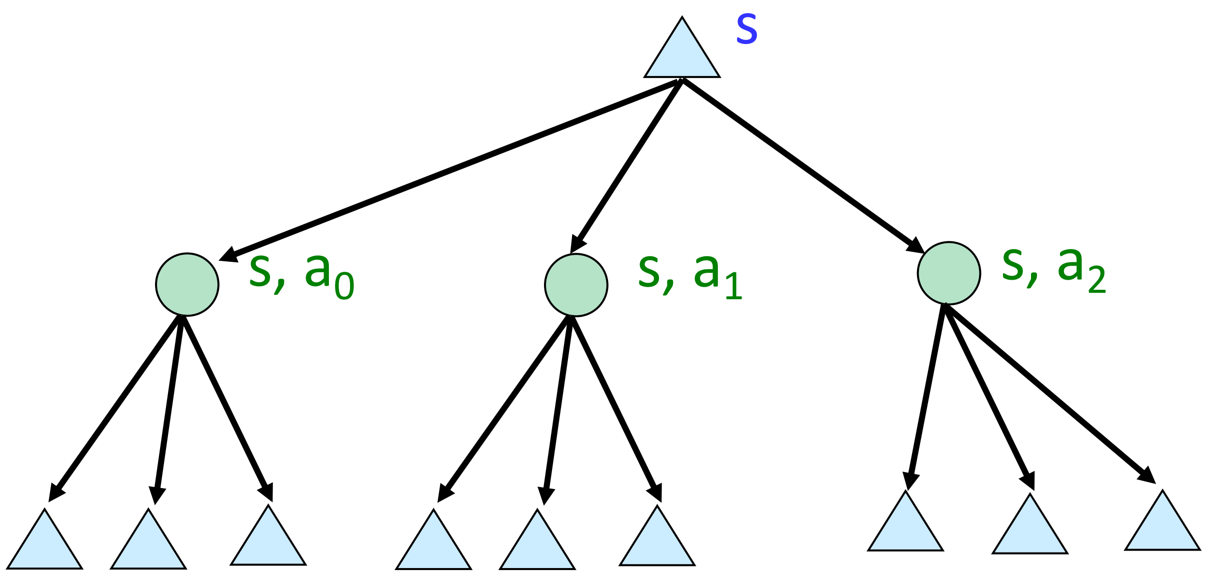
B, east, C, -1
C, east, D, -1
D, exit, x, +10

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

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

Problems with TD Value Learning

- Model-free policy evaluation! 🎉
- Bellman updates with running sample mean! 🎉



- Need the transition model to improve the policy! 😱

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 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)

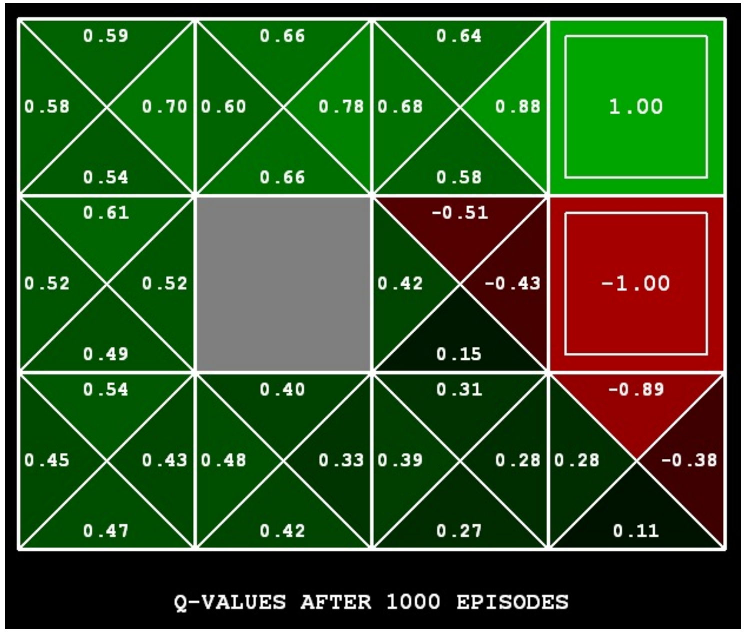
Q-Learning

- 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:

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



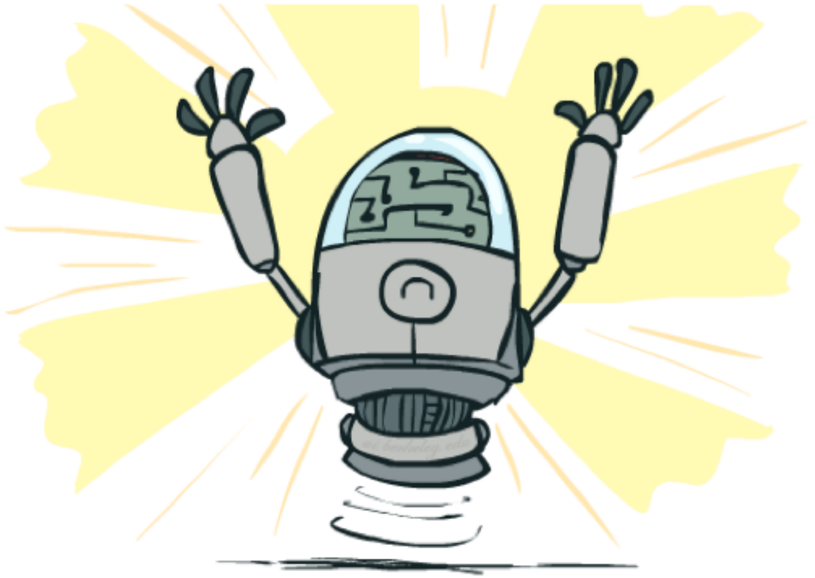
[Demo: Q-learning – gridworld (L10D2)]
[Demo: Q-learning – crawler (L10D3)]

Video of Demo Q-Learning -- Gridworld

Video of Demo Q-Learning -- Crawler

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
  - 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 (!)



Summary

- RL solves MDPs via direct experience of transitions and rewards
- There are several approaches:
  - 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 ($|A|=10^{26}$)?