

Announcements

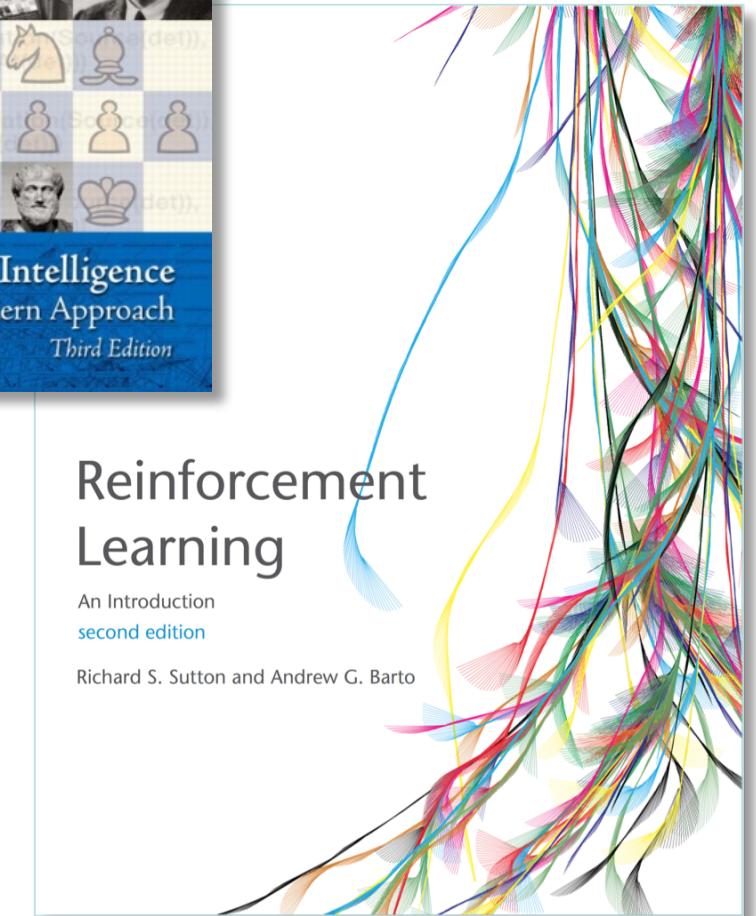
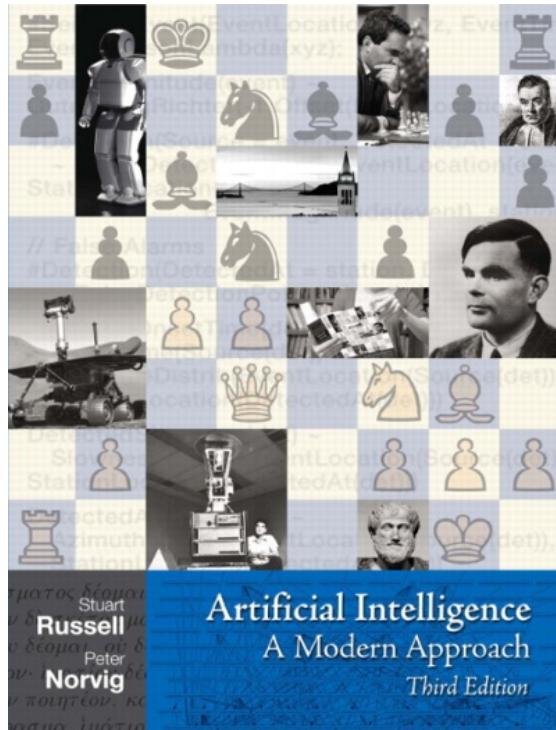
- No class on Thursday. Please use the time to read Chapter 13 of the textbook. This will be on the next midterm, but won't be covered in lecture.
- Upcoming:
 - HW5 – Markov Decision Processes – is due October Oct 22
 - Extra Credit assignment 2 has been released, it is due on Thursday October 24
 - Midterm 2 will be in class on Thursday October 31.
- My office hours are today from 3-4pm in 3401 Walnut room 463C. I won't have OH on Thursday.
- Thanks to Hanbang, I think we have a viable solution to programming R2D2s on Linux and Windows!
 - Would you like an extension on EC HW1?
- You can checkout a robot from my office tomorrow from 10am-4pm.



Reinforcement Learning 2

Sutton and Barto, Chapter 6.1, 6.2, 6.5
AIMA Chapter 21

Slides courtesy of Dan Klein and Pieter Abbeel
University of California, Berkeley

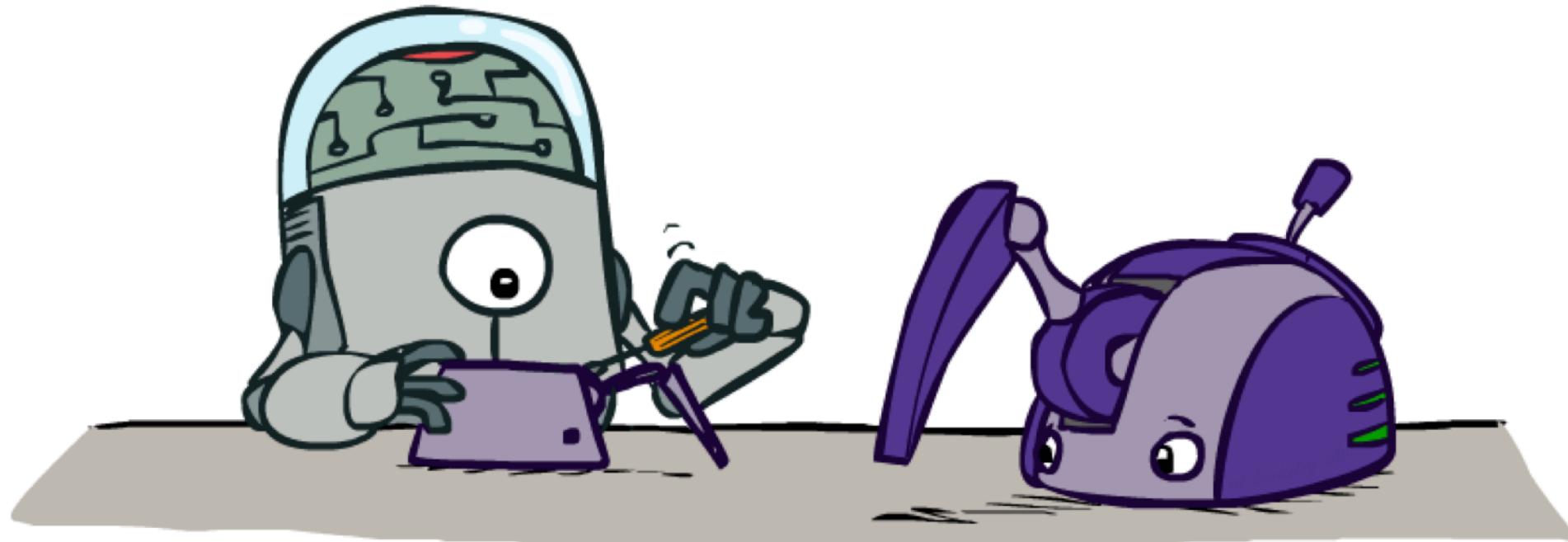


Review: Reinforcement Learning

- We still assume an 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 , so must try out actions
- Big idea: Compute all averages over T using sample outcomes

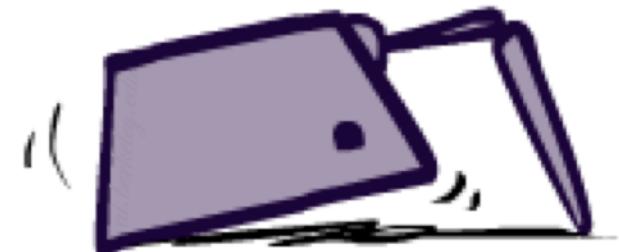


Review: Model-Based Learning



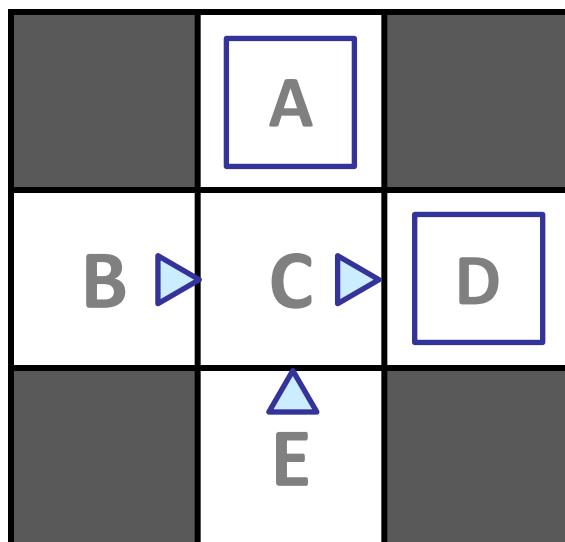
Review: Model-Based Learning

- 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 $\hat{T}(s, a, s')$
 - 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



Review: 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

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

$$\begin{aligned} T(B, \text{east}, C) &= 1.00 \\ T(C, \text{east}, D) &= 0.75 \\ T(C, \text{east}, A) &= 0.25 \\ \dots \end{aligned}$$

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

$$\begin{aligned} R(B, \text{east}, C) &= -1 \\ R(C, \text{east}, D) &= -1 \\ R(D, \text{exit}, x) &= +10 \\ \dots \end{aligned}$$

Review: Example: Expected Age

Goal: Compute expected age of CIS 421/521 students

Known $P(A)$

$$E[A] = \sum_a P(a) \cdot a = 0.01 \times 42 + \dots$$

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

Unknown $P(A)$: “Model Based”

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

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

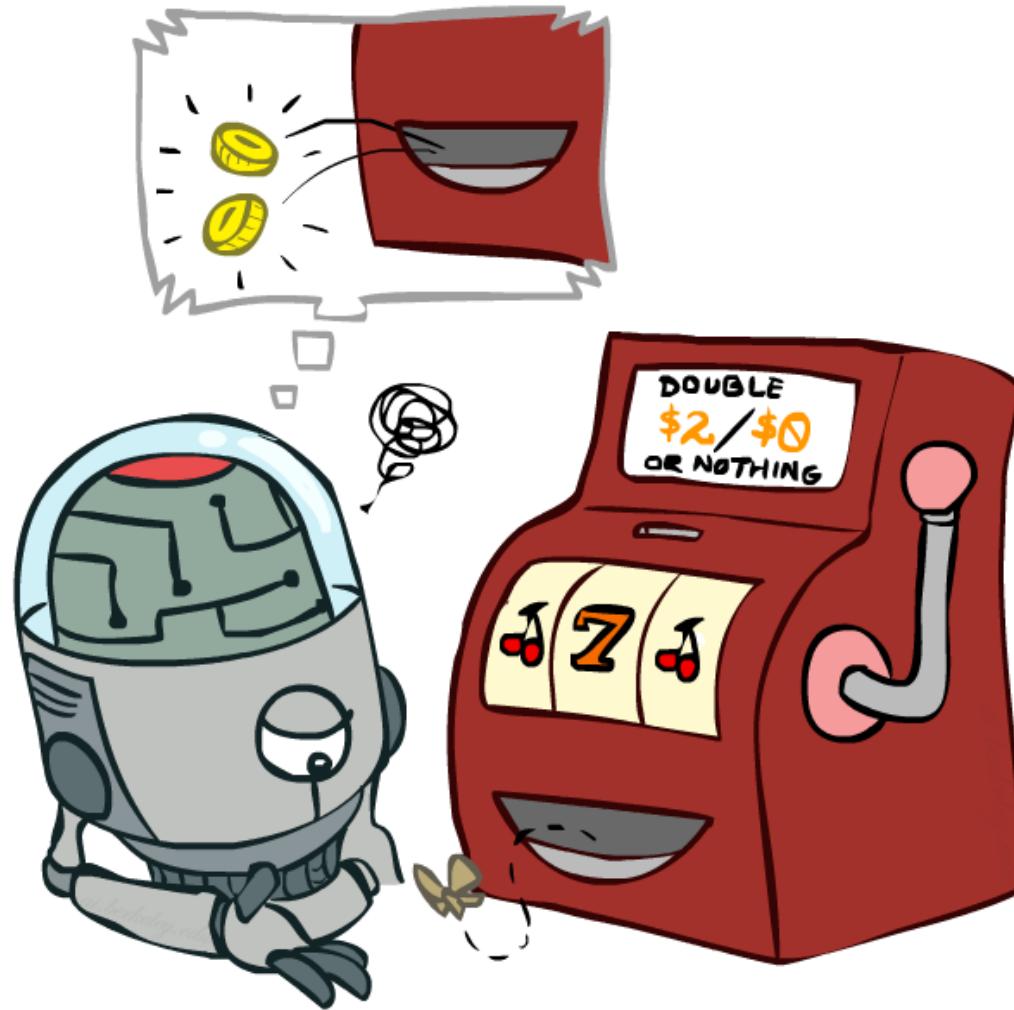
$$E[A] \approx \sum_a \hat{P}(a) \cdot a$$

Unknown $P(A)$: “Model Free”

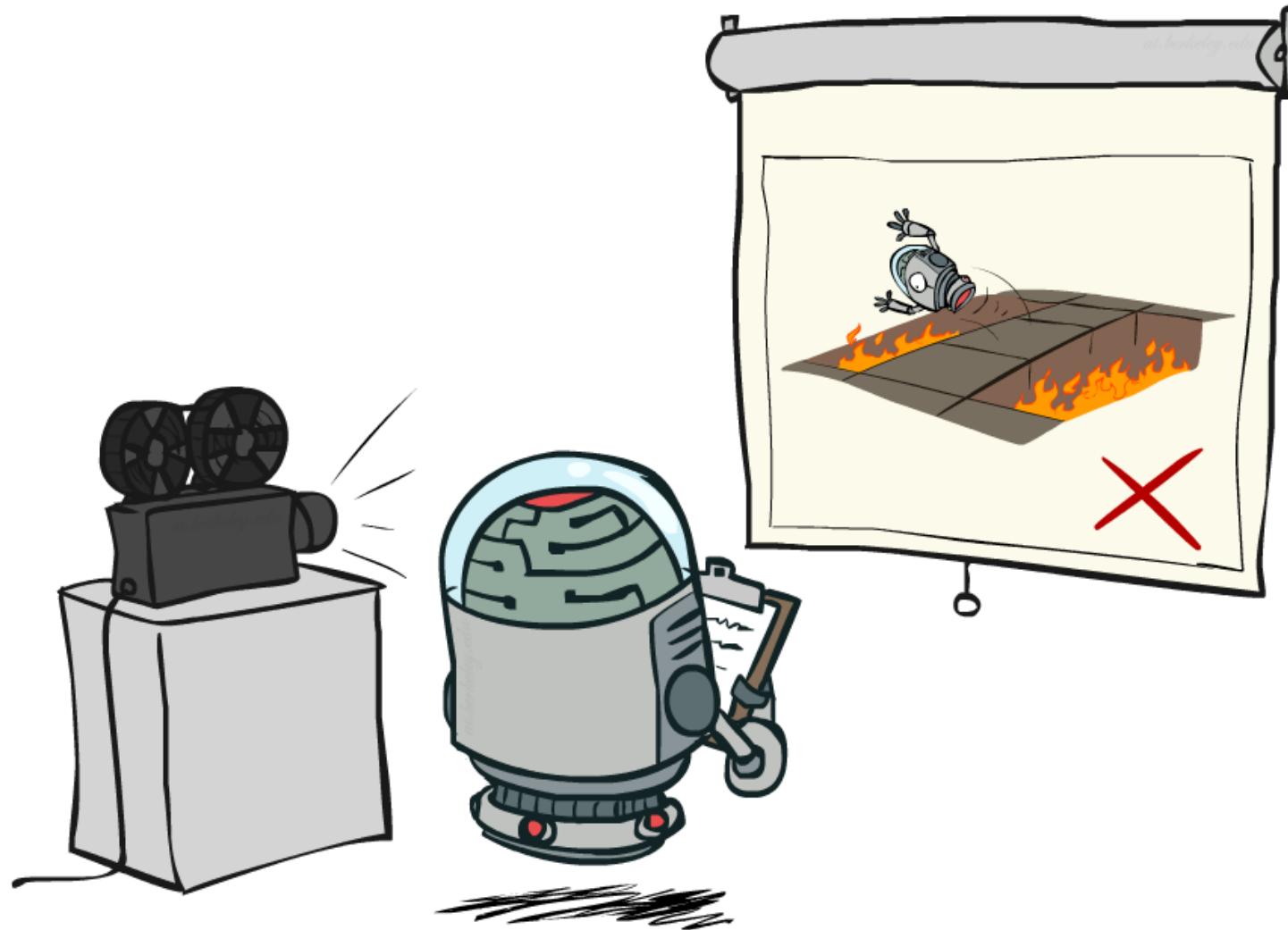
$$E[A] \approx \frac{1}{N} \sum_i a_i$$

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

Model-Free Learning



Passive Reinforcement Learning



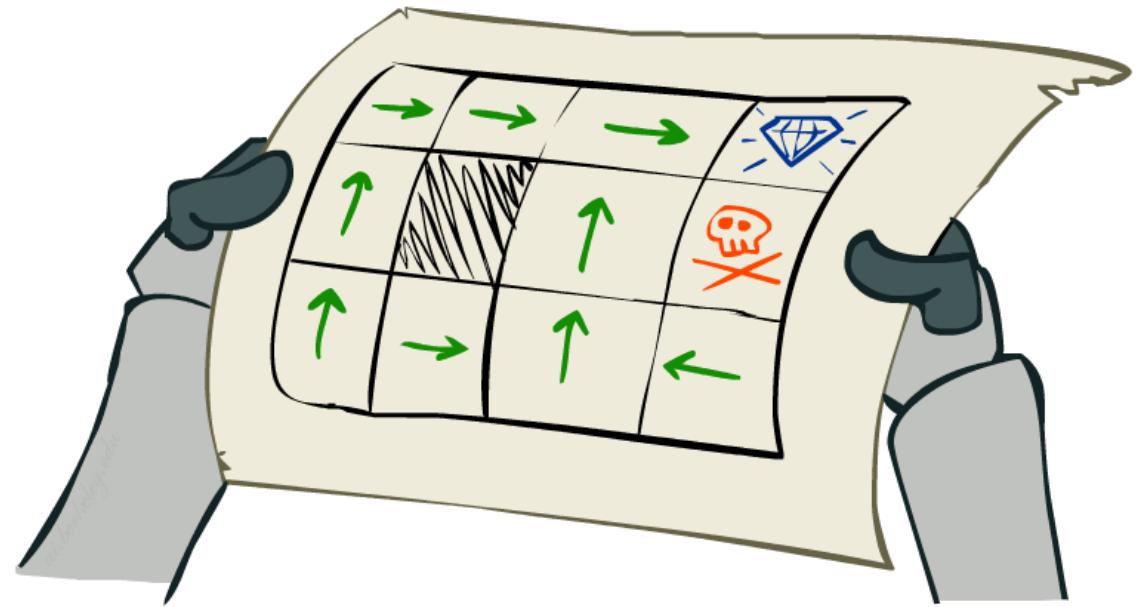
Passive Reinforcement Learning

- 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

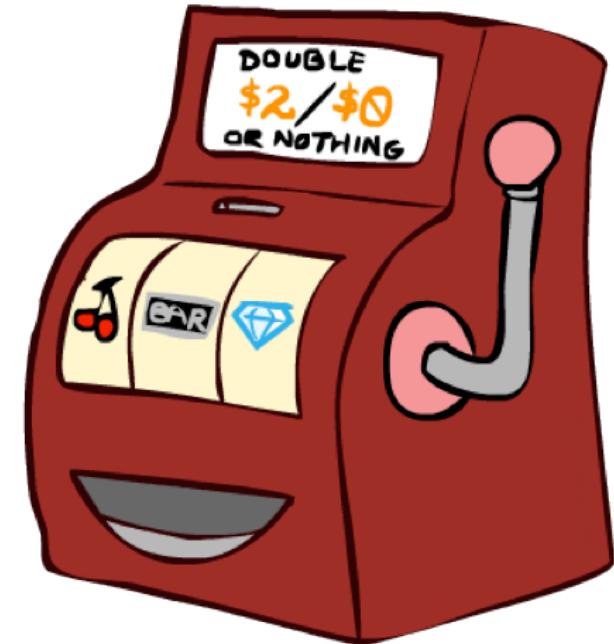
- In this case:

- 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.



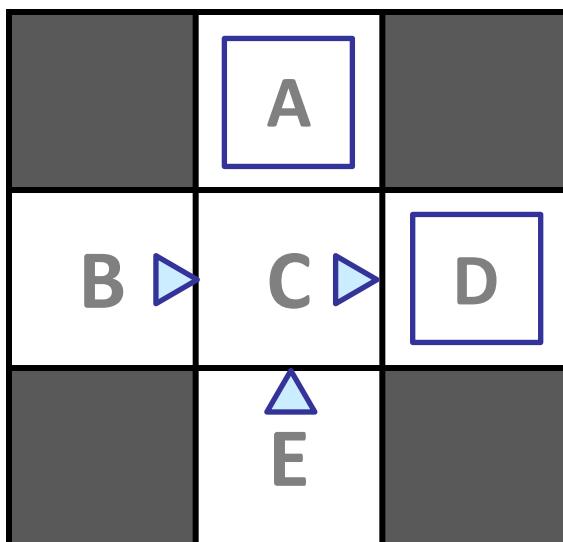
Direct Evaluation

- Goal: Compute values for each state under π
- Idea: Average together observed sample values
 - Act according to π
 - 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

	-10	
A	+4	+10
B	+8	
C		D
E	-2	

Problems with Direct Evaluation

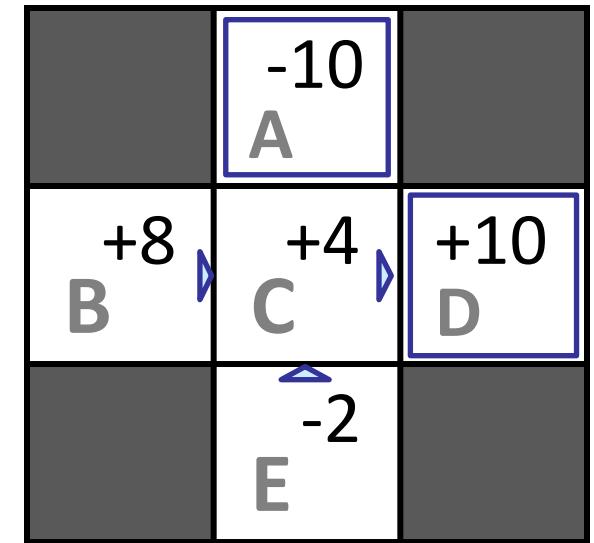
- What's good about direct evaluation?

- 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?

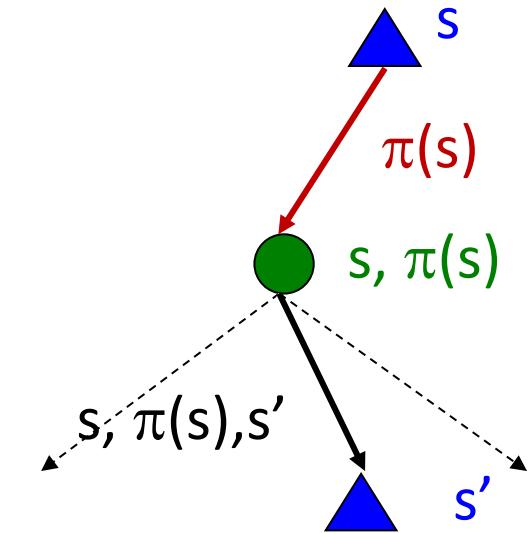
Why Not Use Policy Evaluation Instead?

- Simplified Bellman updates calculate V for a fixed policy:

- Each round, replace V with a one-step-look-ahead layer over V

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

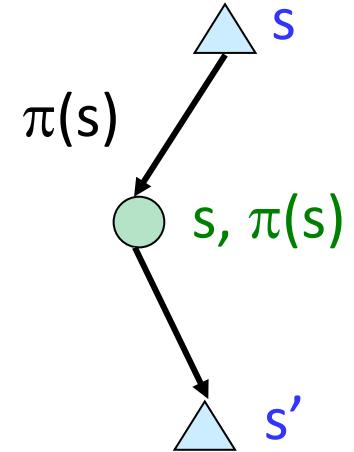
$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V_k^\pi(s')]$$



- 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?

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

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

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

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:

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

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

Example: Temporal Difference Learning

States

	A	
B	C	D
	E	

Observed Transitions

B, east, C, -2

	0	
0	0	8
	0	

C, east, D, -2

	0	
-1	0	8
	0	

	0	
-1	3	8
	0	

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

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

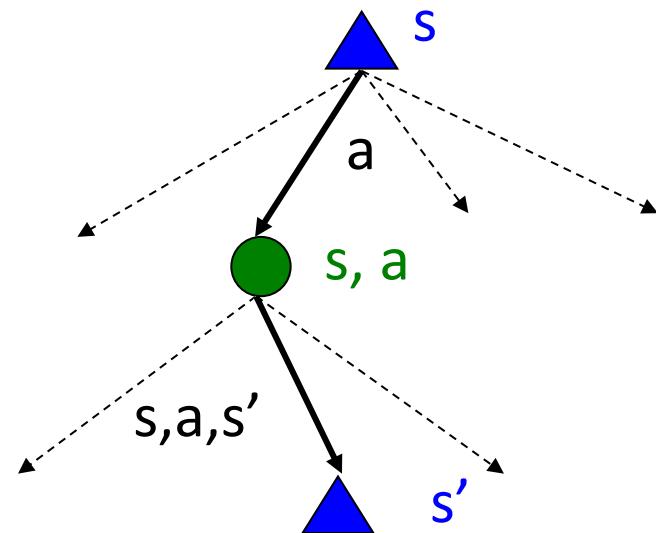
Problems with TD Value Learning

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

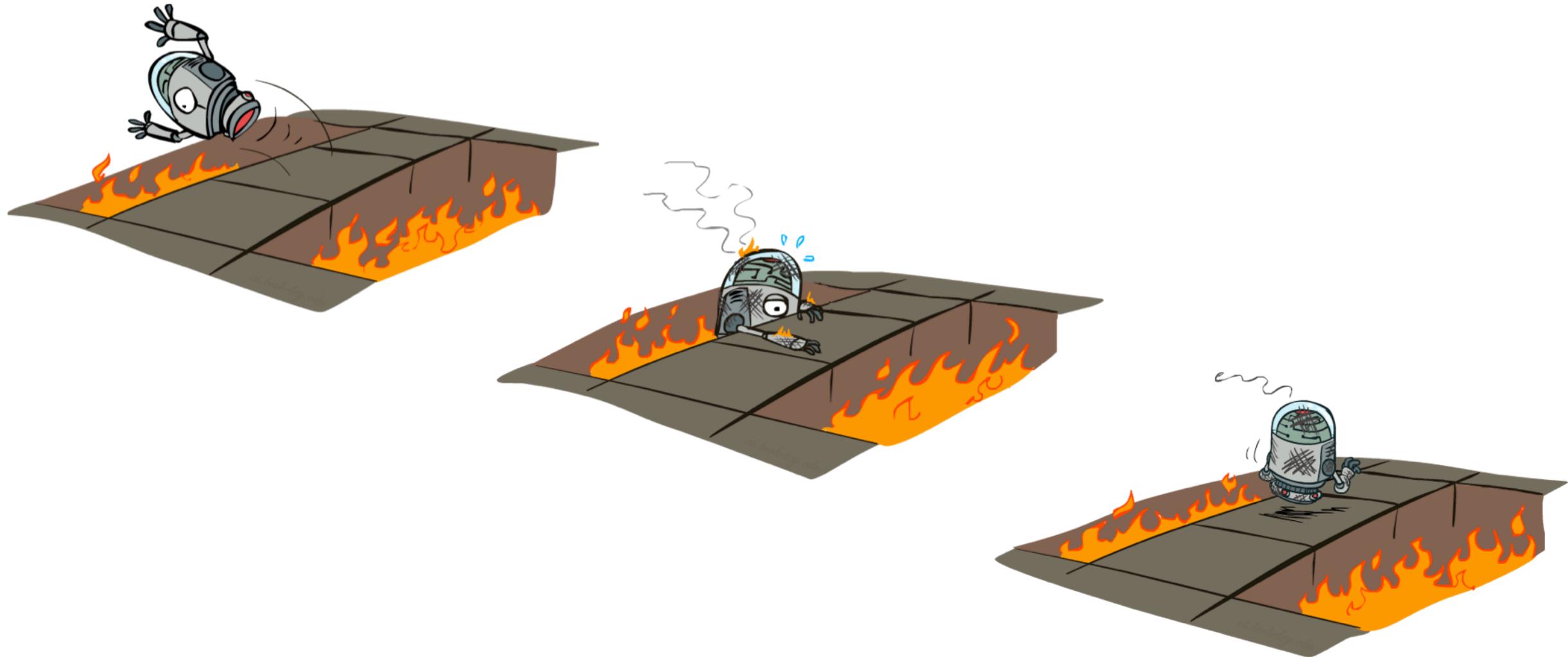
$$\pi(s) = \arg \max_a Q(s, a)$$

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

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

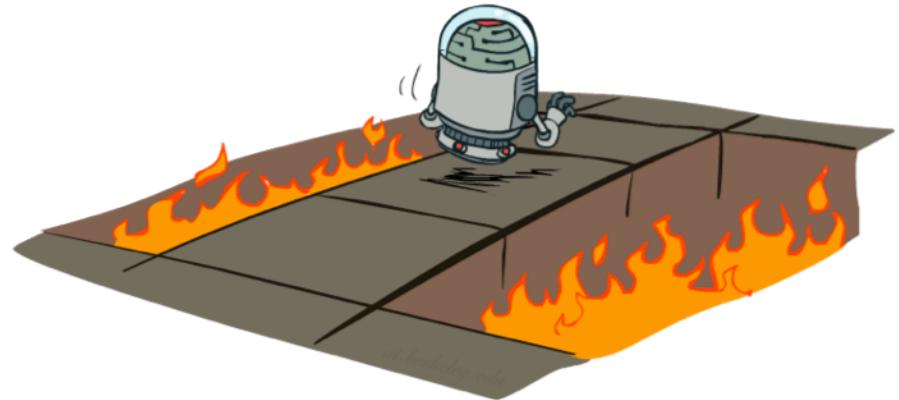


Active Reinforcement Learning



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:

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

- 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:

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

Q-Learning

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

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

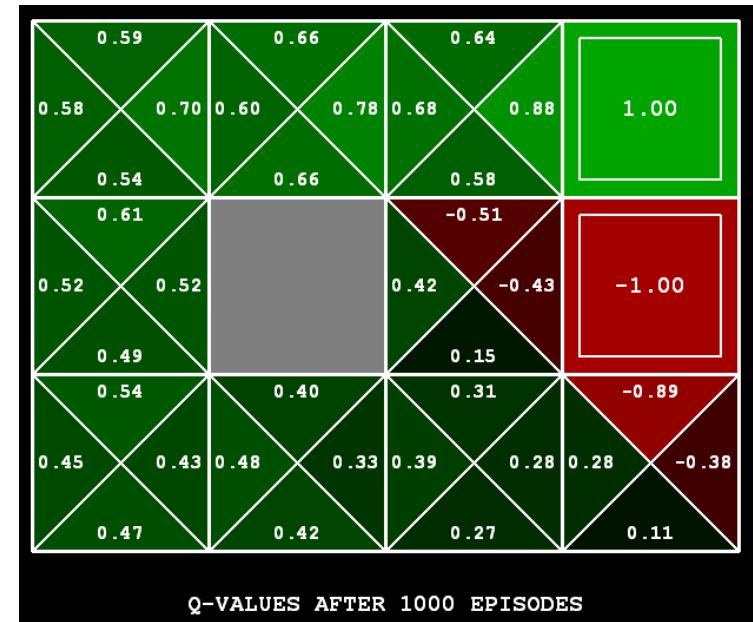
- Learn $Q(s,a)$ values as you go

- 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:

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

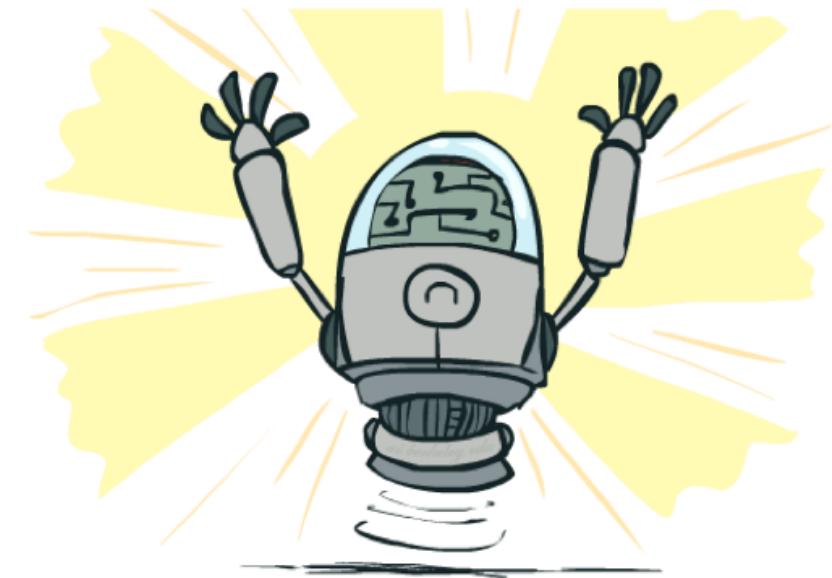


Video of Demo Q-Learning -- Gridworld



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 (!)



Review: Exponential Moving Average

- **Exponential moving average**

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- Makes recent samples more important:

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

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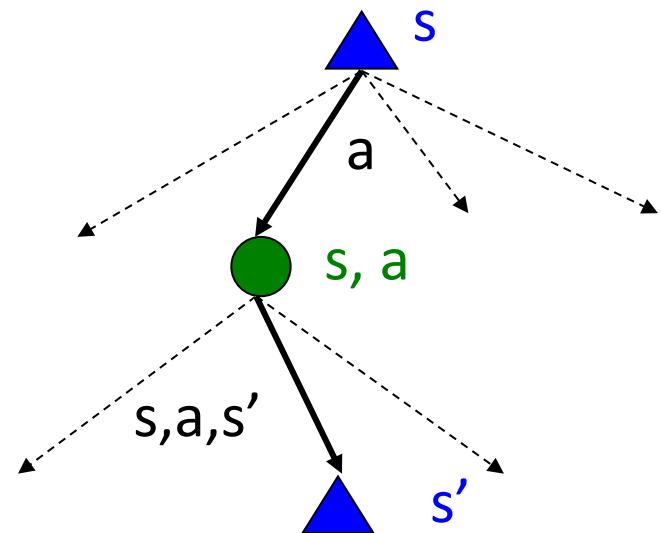
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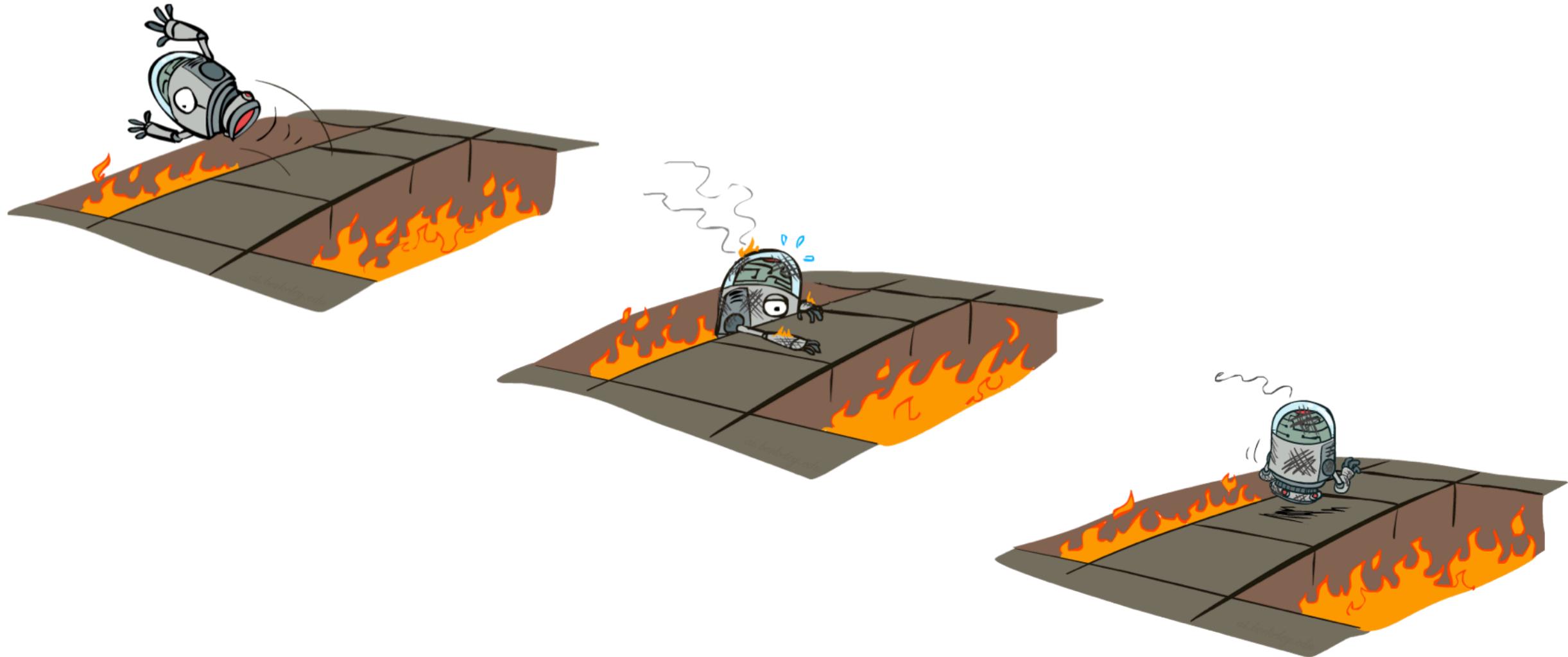
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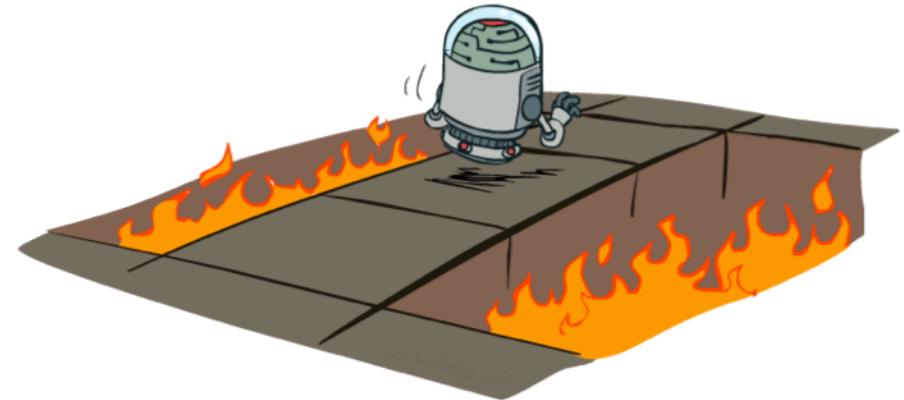


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Q-Learning

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

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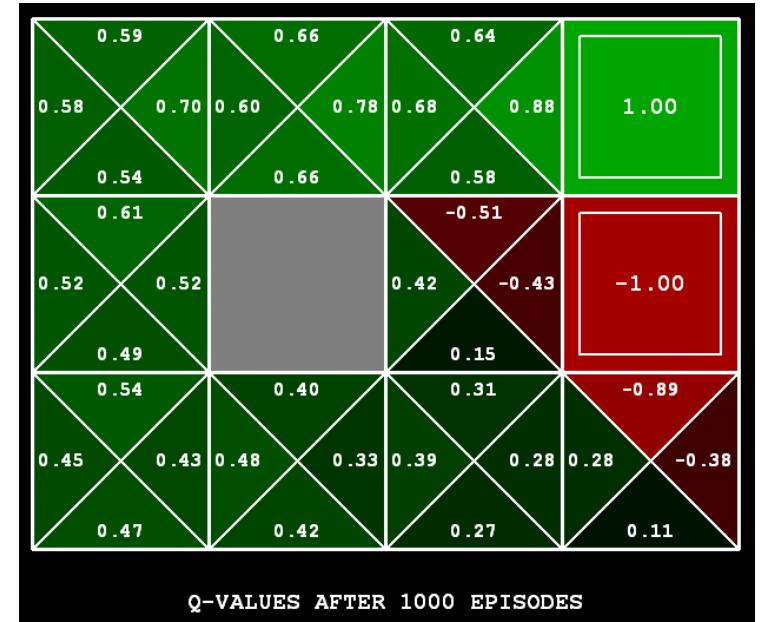
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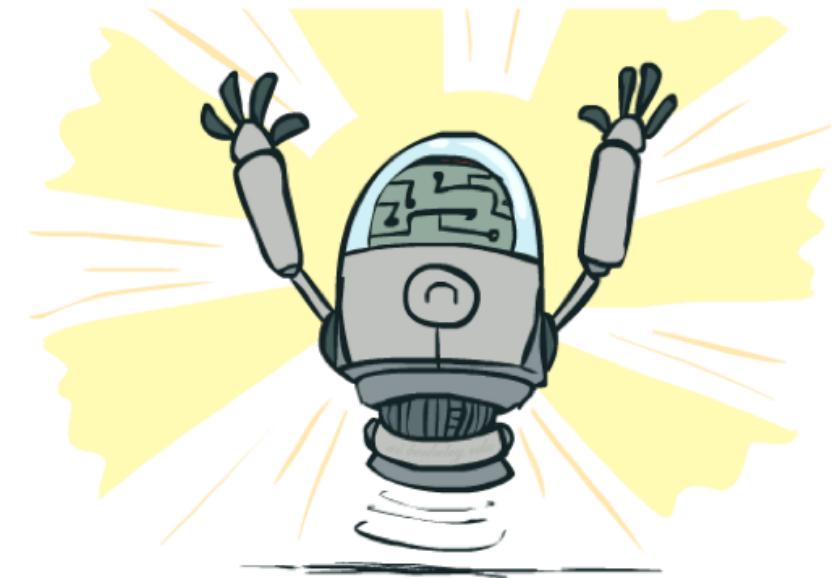
- Incorporate the new estimate into a running average:

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



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 - 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 , so must try out actions
- Big idea: Compute all averages over T using sample outcomes



The Story So Far: MDPs and RL

Known MDP: Offline Solution

Goal

Compute V^* , Q^* , π^*

Evaluate a fixed policy π

Technique

Value / policy iteration

Policy evaluation

Unknown MDP: Model-Based

Goal

Compute V^* , Q^* , π^*

Technique

VI/PI on approx. MDP

Evaluate a fixed policy π

PE on approx. MDP

Unknown MDP: Model-Free

Goal

Compute V^* , Q^* , π^*

Technique

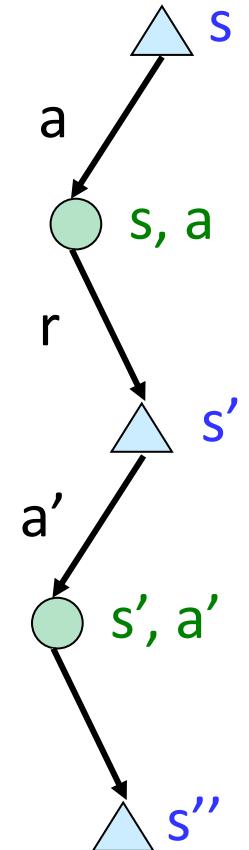
Q-learning

Evaluate a fixed policy π

Value Learning

Model-Free Learning

- Model-free (temporal difference) learning
 - Experience world through episodes
$$(s, a, r, s', a', r', s'', a'', r'', s''', \dots)$$
 - Update estimates each transition (s, a, r, s')
 - Over time, updates will mimic Bellman updates



Q-Learning

- We'd like to do Q-value updates to each Q-state:

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

- But can't compute this update without knowing T, R
- Instead, compute average as we go
 - Receive a sample transition (s, a, r, s')
 - This sample suggests

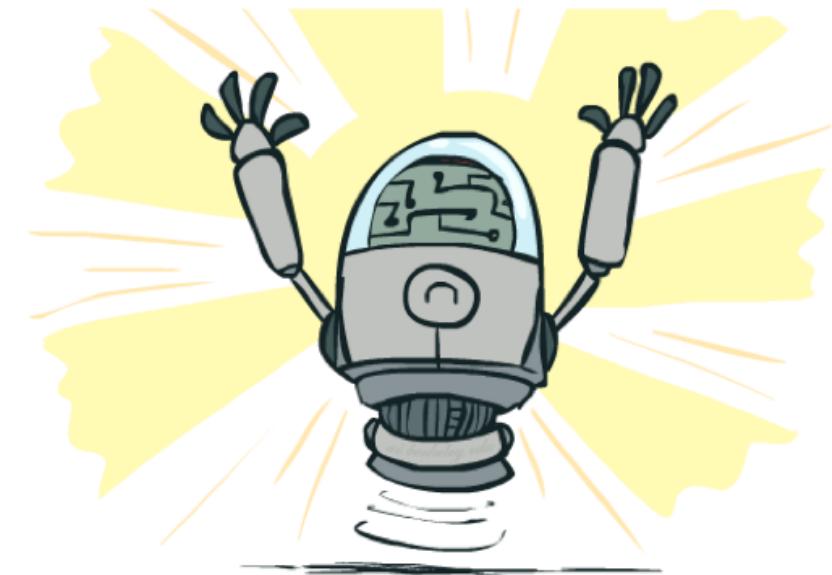
$$Q(s, a) \approx r + \gamma \max_{a'} Q(s', a')$$

- But we want to average over results from (s, a) (Why?)
- So keep a running average

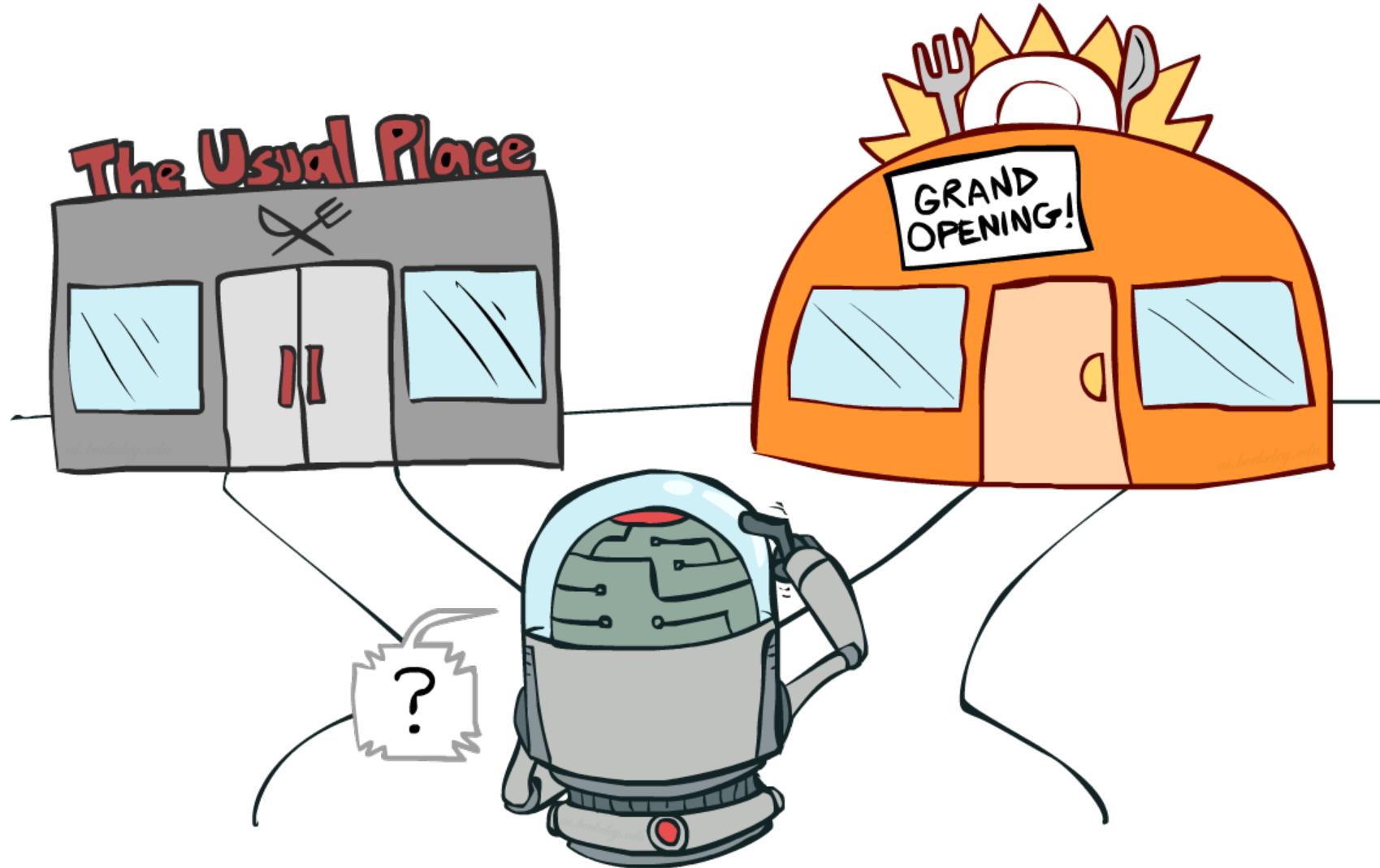
$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + (\alpha) \left[r + \gamma \max_{a'} Q(s', a') \right]$$

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Exploration vs. Exploitation



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 $1-\varepsilon$, act on current policy



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 $1-\varepsilon$, 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



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

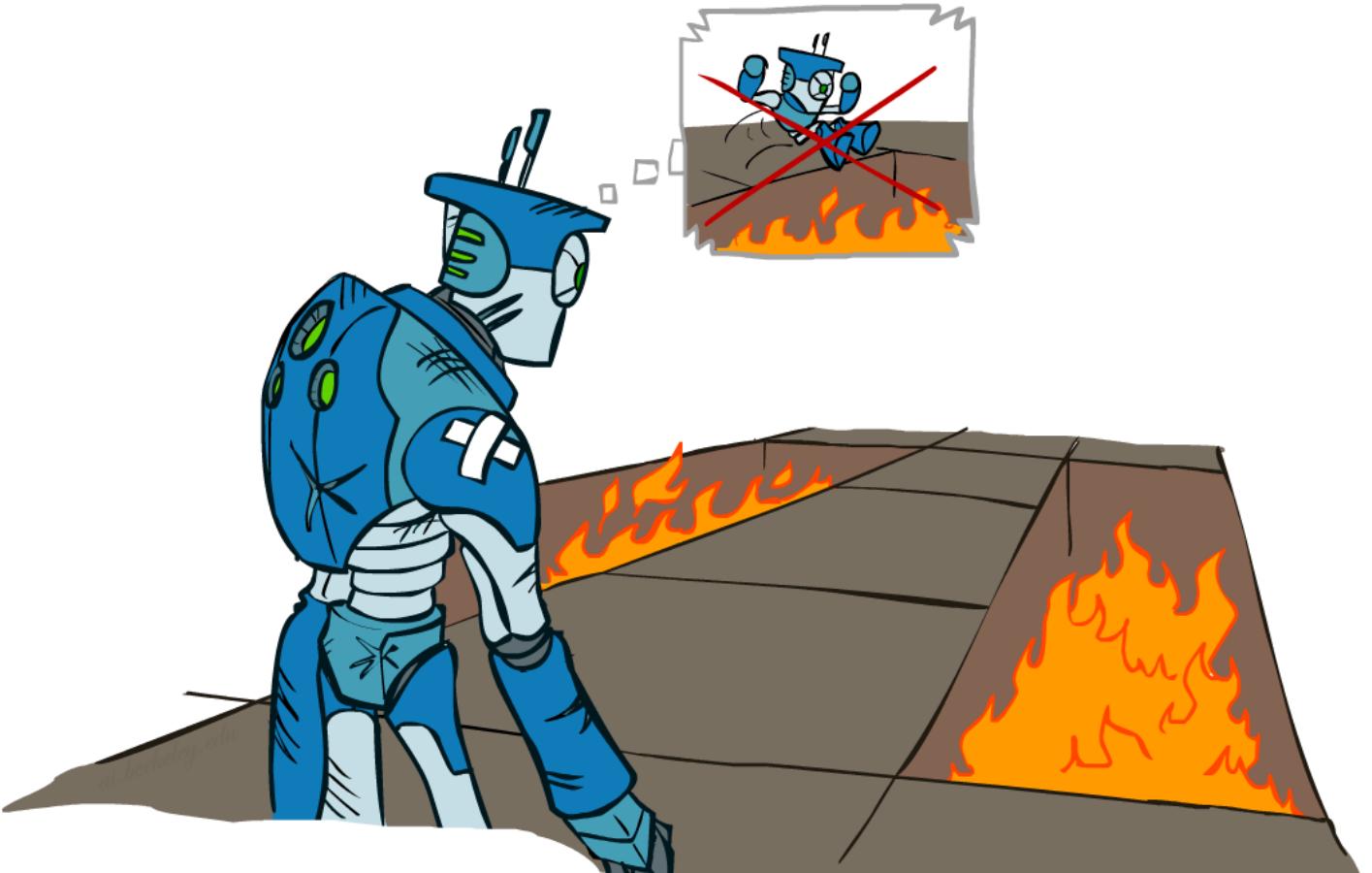
Modified Q-Update: $Q(s, a) \leftarrow_{\alpha} R(s, a, s') + \gamma \max_{a'} f(Q(s', a'), N(s', a'))$



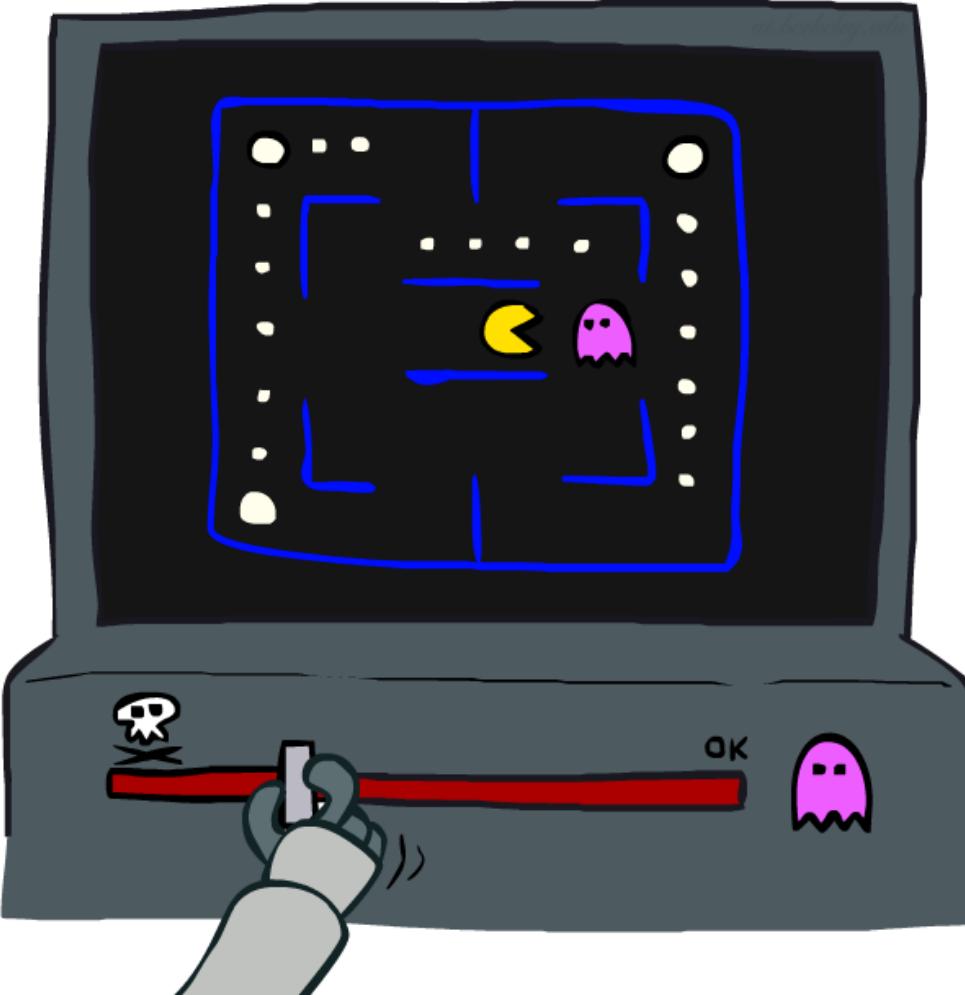
- Note: this propagates the “bonus” back to states that lead to unknown states as well!

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

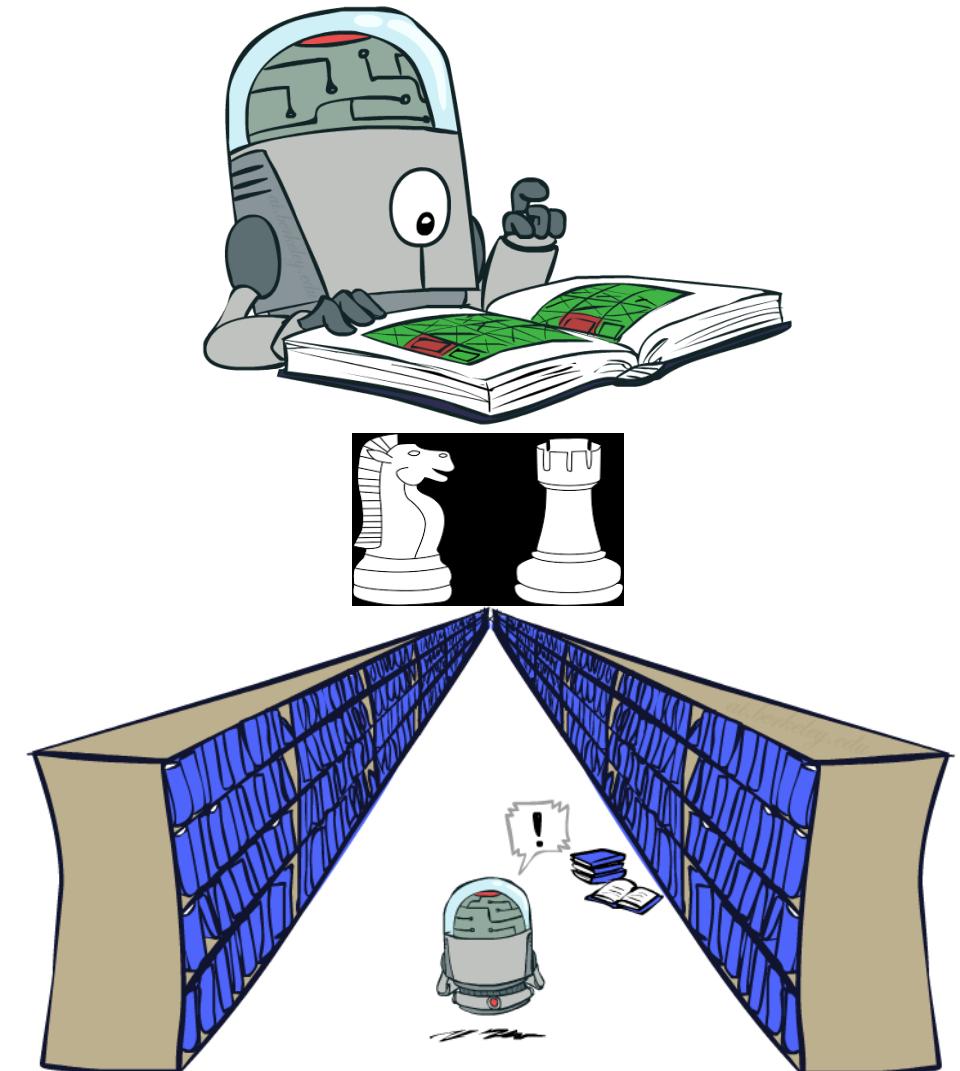


Approximate Q-Learning



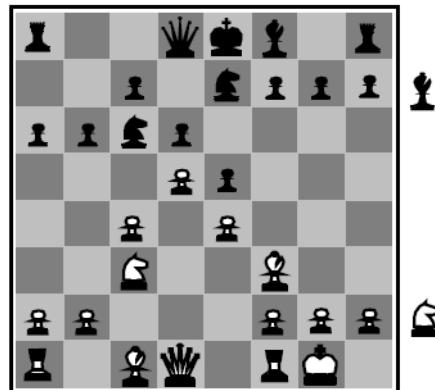
Generalizing Across States

- Basic Q-Learning keeps a table of all q-values
- In realistic situations, we cannot possibly learn about every single state!
 - Too many states to visit them all in training
 - Too many states to hold the q-tables in memory
- Instead, we want to generalize:
 - Learn about some small number of training states from experience
 - Generalize that experience to new, similar situations
 - This is a fundamental idea in machine learning, and we'll see it over and over again

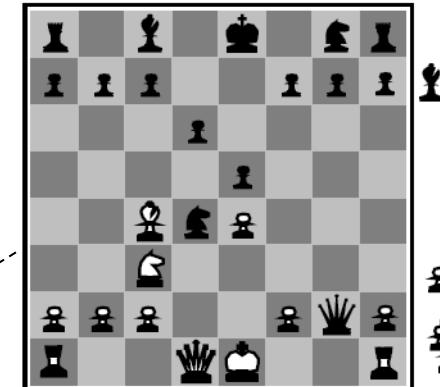
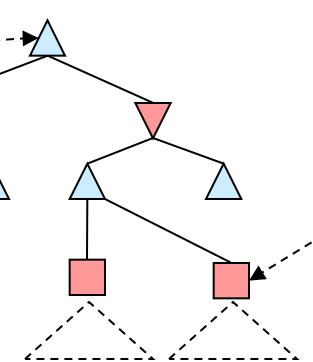


Flashback: Evaluation Functions

- Evaluation functions score non-terminals in depth-limited search



Black to move
White slightly better



White to move
Black winning

- Ideal function: returns the actual minimax value of the position
- In practice: typically weighted linear sum of features:

$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \dots + w_n f_n(s)$$

- e.g. $f_1(s) = (\text{num white queens} - \text{num black queens})$, etc.

Linear Value Functions

- Using a feature representation, we can write a q function (or value function) for any state using a few weights:

$$V(s) = w_1 f_1(s) + w_2 f_2(s) + \dots + w_n f_n(s)$$

$$Q(s, a) = w_1 f_1(s, a) + w_2 f_2(s, a) + \dots + w_n f_n(s, a)$$

- Advantage: our experience is summed up in a few powerful numbers
- Disadvantage: states may share features but actually be very different in value!

Approximate Q-Learning

$$Q(s, a) = w_1 f_1(s, a) + w_2 f_2(s, a) + \dots + w_n f_n(s, a)$$

- Q-learning with linear Q-functions:

transition $= (s, a, r, s')$

difference $= [r + \gamma \max_{a'} Q(s', a')] - Q(s, a)$

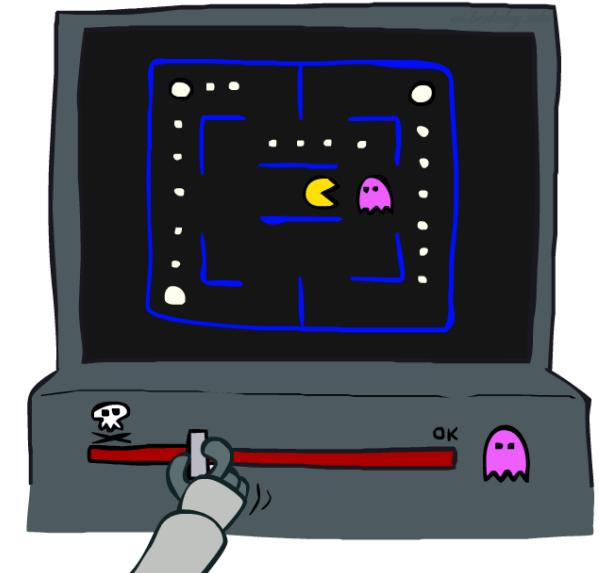
$Q(s, a) \leftarrow Q(s, a) + \alpha \text{ [difference]}$ Exact Q's

$w_i \leftarrow w_i + \alpha \text{ [difference]} f_i(s, a)$ Approximate Q's

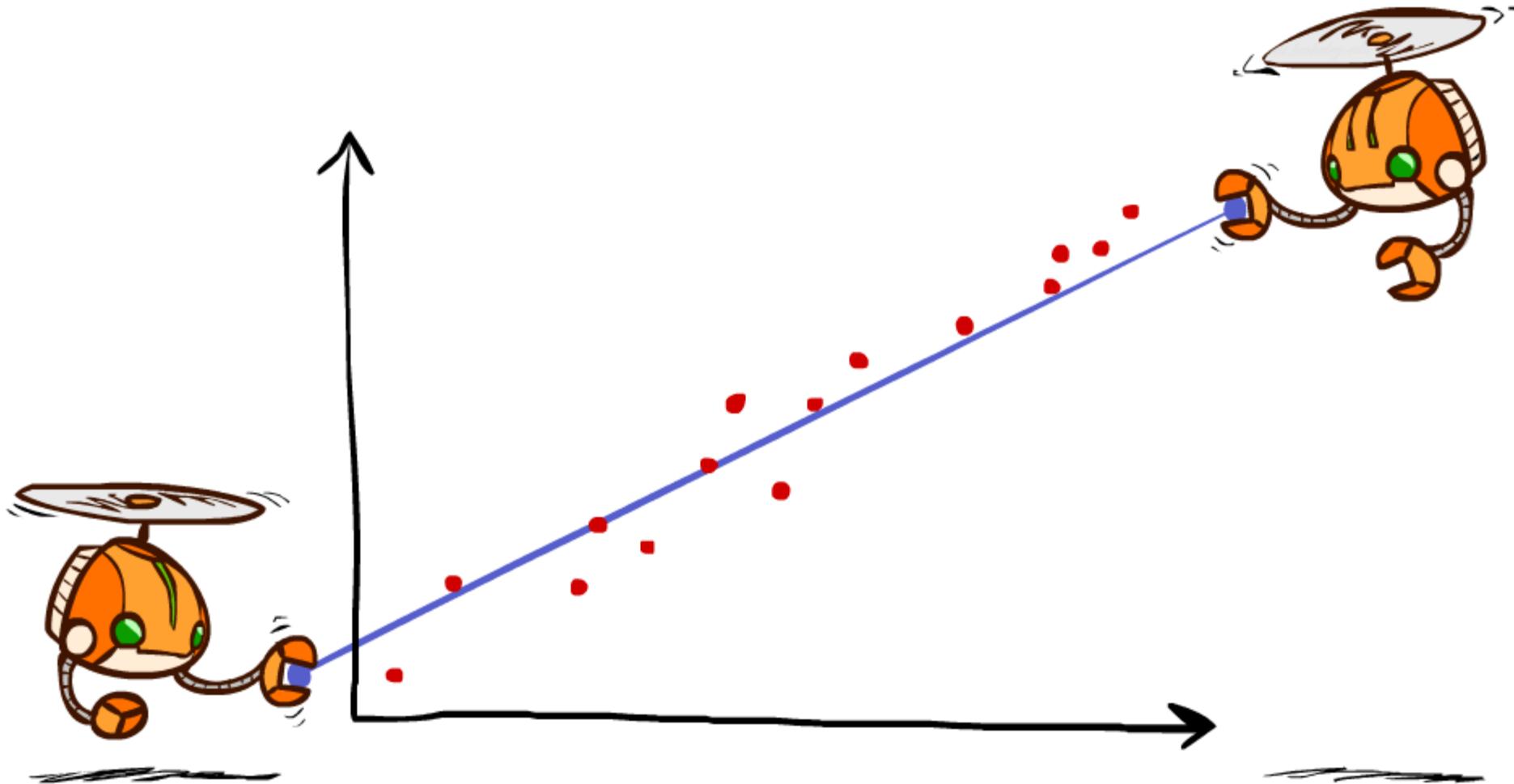
- Intuitive interpretation:

- Adjust weights of active features
- E.g., if something unexpectedly bad happens, blame the features that were on:
disprefer all states with that state's features

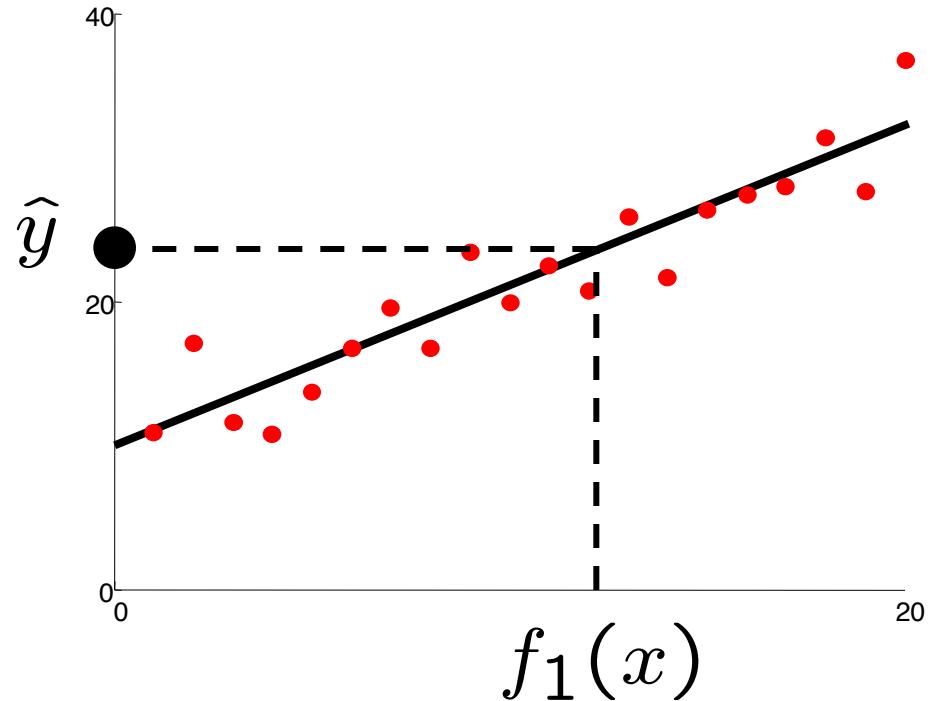
- Formal justification: online least squares



Q-Learning and Least Squares

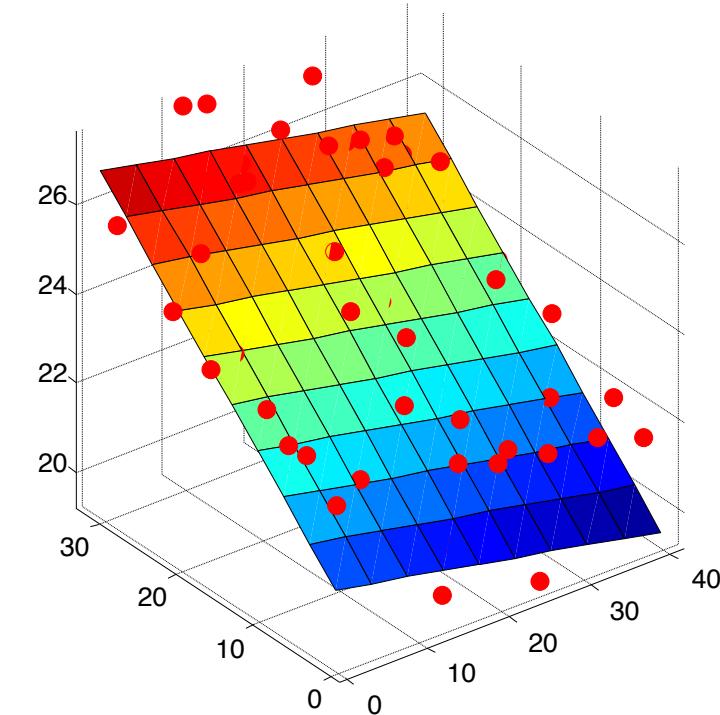


Linear Approximation: Regression*



Prediction:

$$\hat{y} = w_0 + w_1 f_1(x)$$



Prediction:

$$\hat{y}_i = w_0 + w_1 f_1(x) + w_2 f_2(x)$$

Optimization: Least Squares*

$$\text{total error} = \sum_i (y_i - \hat{y}_i)^2 = \sum_i \left(y_i - \sum_k w_k f_k(x_i) \right)^2$$

