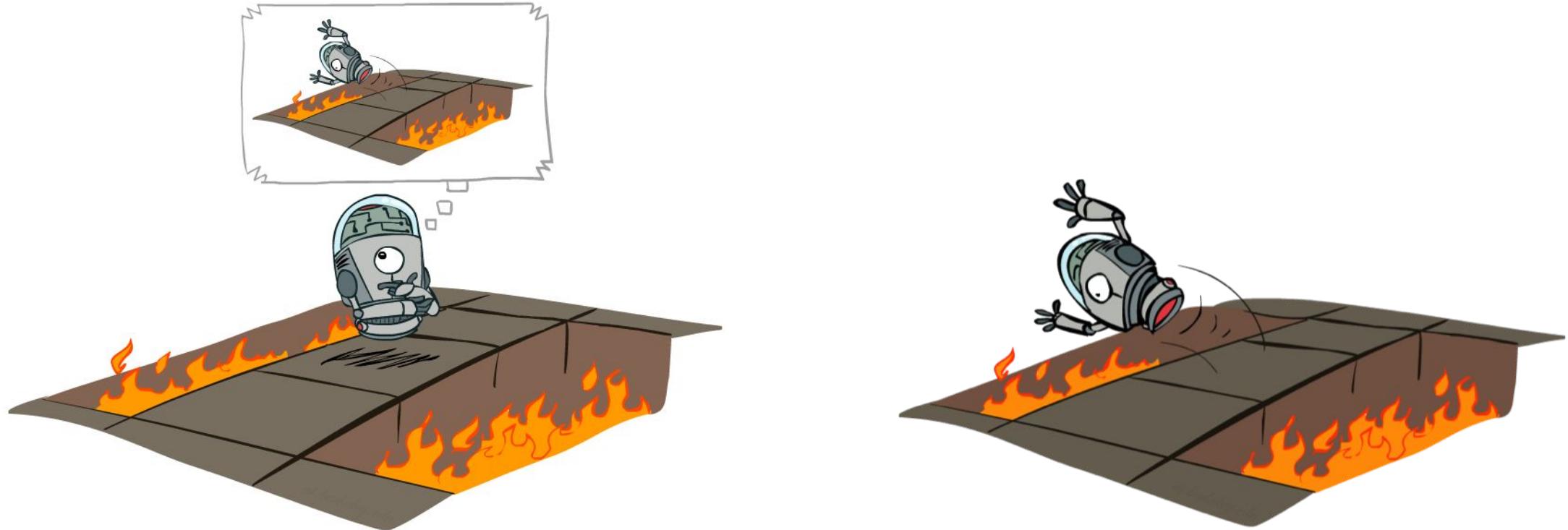


# Reinforcement Learning

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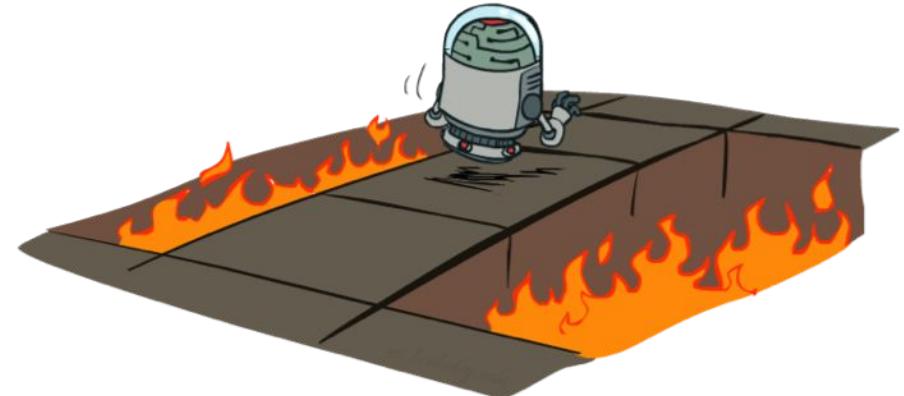
Slides courtesy of Dan Klein and Pieter Abbeel

University of California, Berkeley

[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at <http://ai.berkeley.edu>.]

# 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

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- **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

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

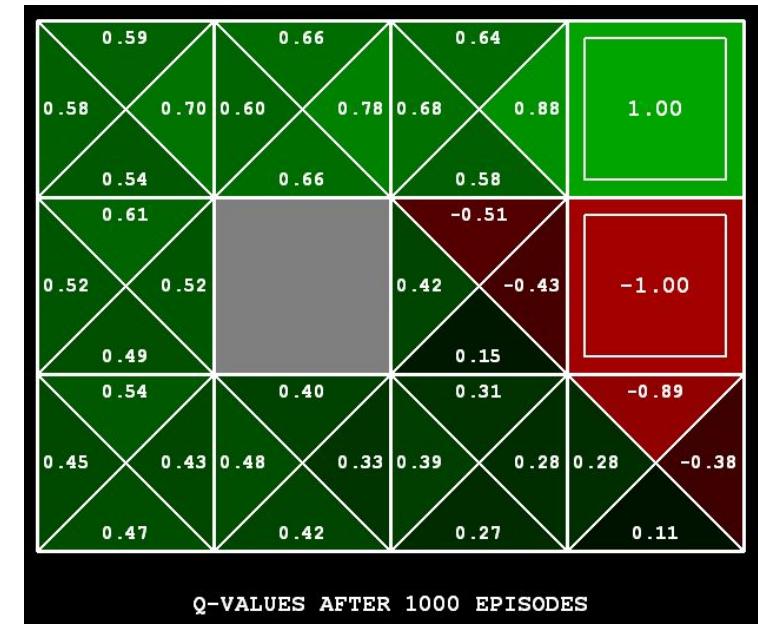
- Learn  $Q(s,a)$  values as you go

- 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:

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



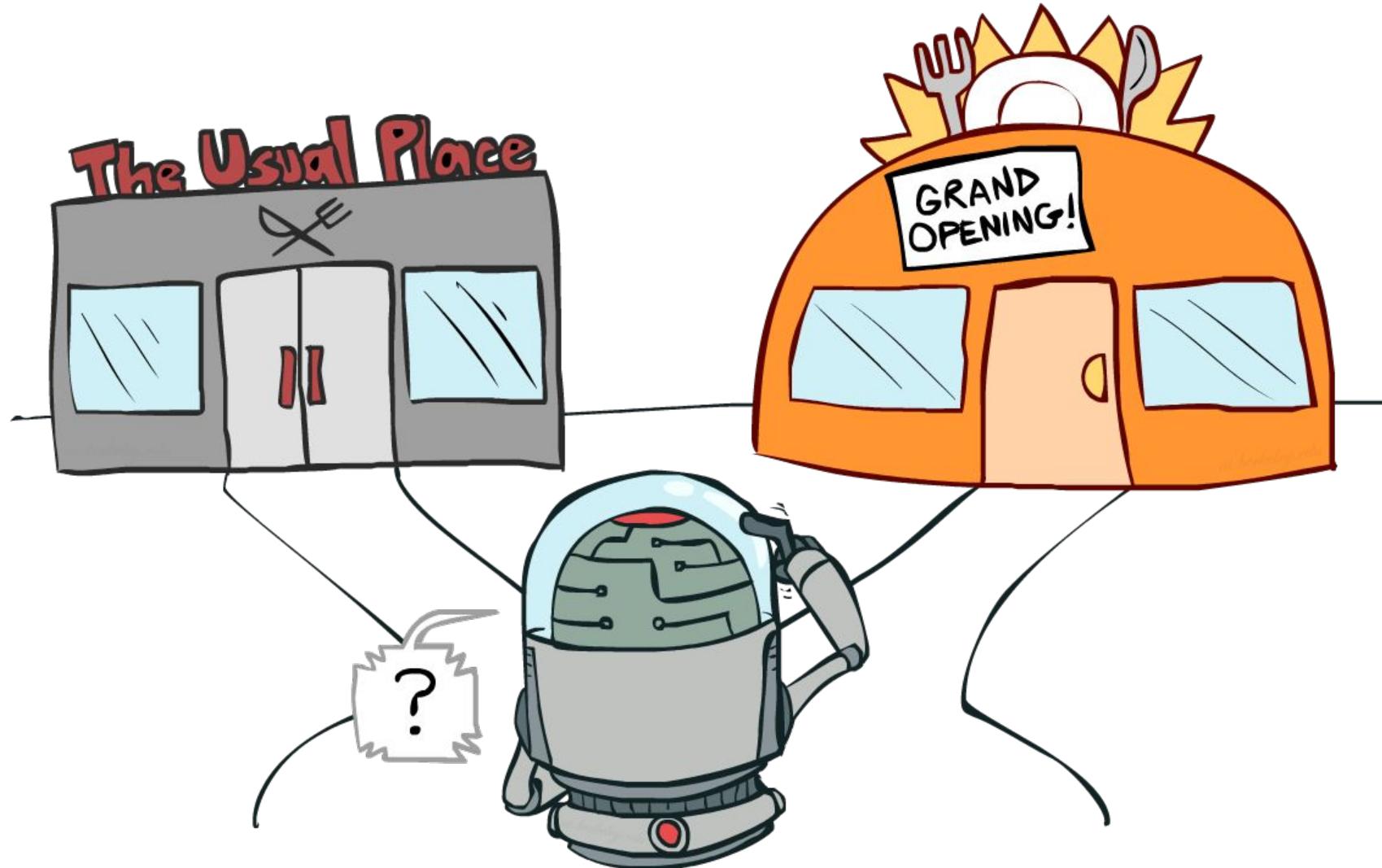
# Q-Learning Properties

- 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 (!)



# Exploration vs. Exploitation

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# How to Explore?

- Several schemes for forcing exploration
  - Simplest: random actions ( $\epsilon$ -greedy)
    - Every time step, flip a coin
    - With (small) probability  $\epsilon$ , act randomly
    - With (large) probability  $1-\epsilon$ , act on current policy



# How to Explore?

- Several schemes for forcing exploration
  - Simplest: random actions ( $\epsilon$ -greedy)
    - Every time step, flip a coin
    - With (small) probability  $\epsilon$ , act randomly
    - With (large) probability  $1-\epsilon$ , 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  $\epsilon$  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:  $Q(s, a) \leftarrow_{\alpha} R(s, a, s') + \gamma \max_{a'} Q(s', a')$

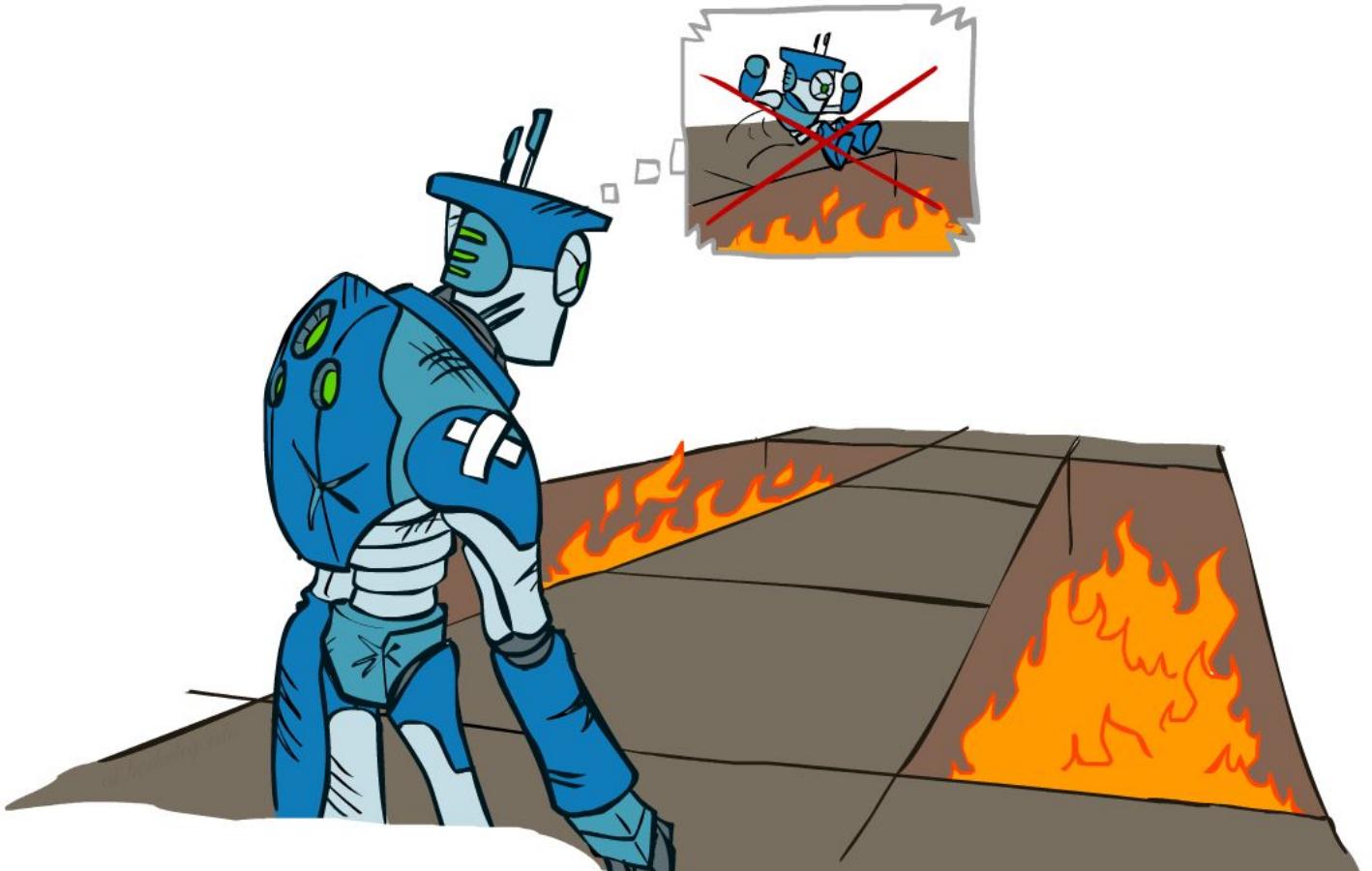
Modified Q-Update:  $Q(s, a) \leftarrow_{\alpha} R(s, a, s') + \gamma \max_{a'} f(Q(s', a'), N(s', a'))$



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

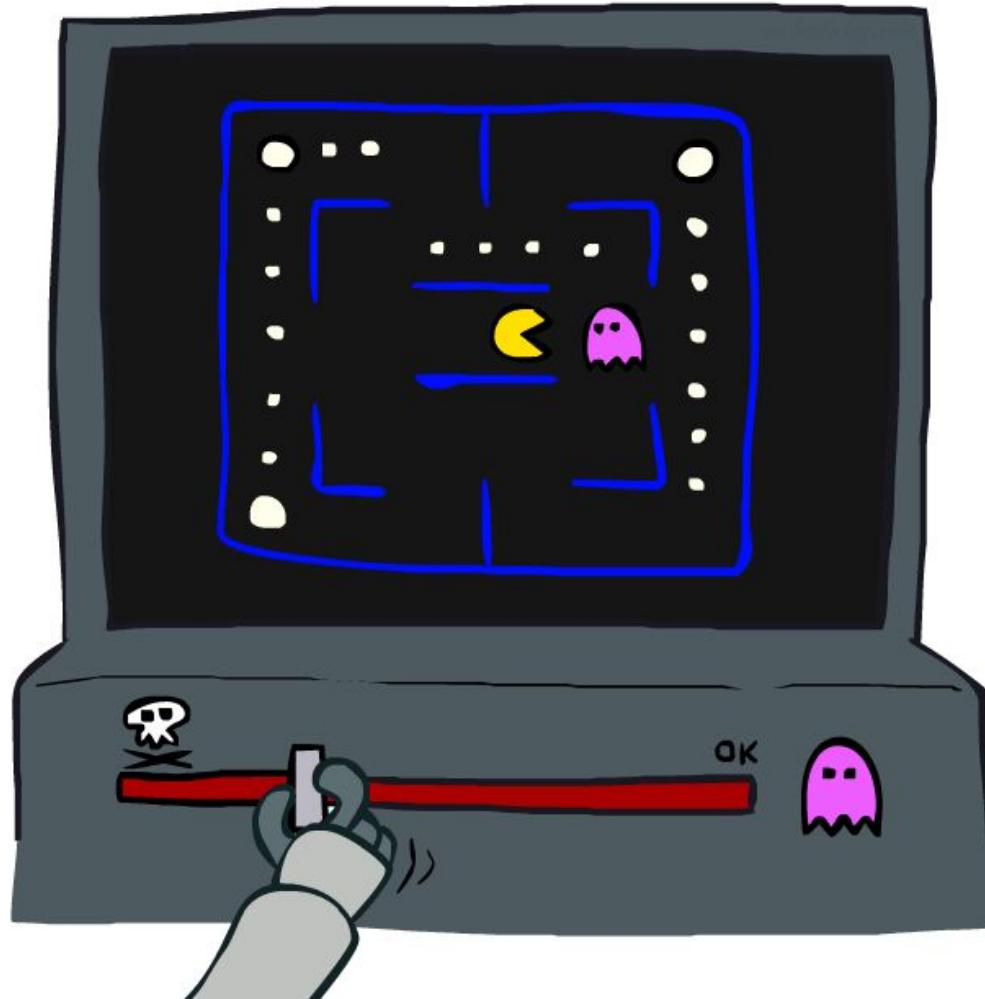
# Regret

- 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



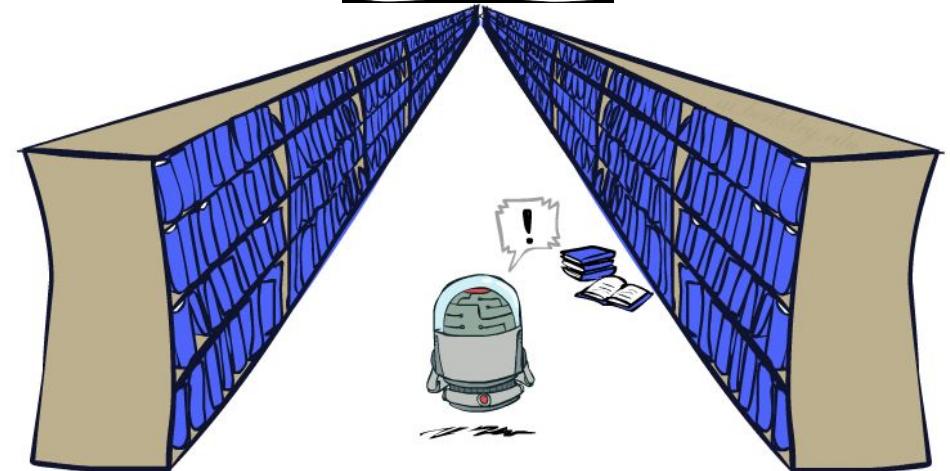
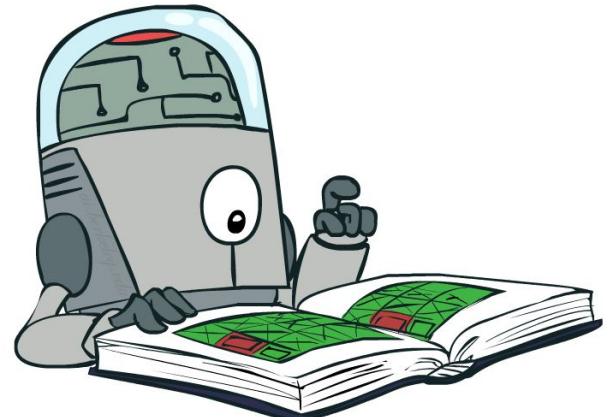
# Approximate Q-Learning

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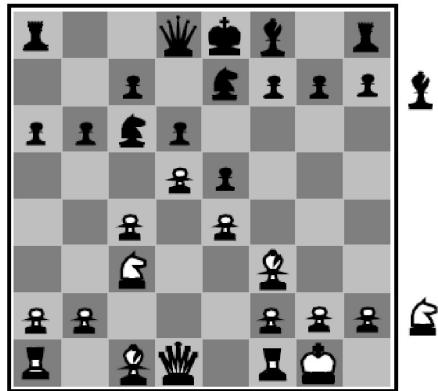
# Generalizing Across States

- 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

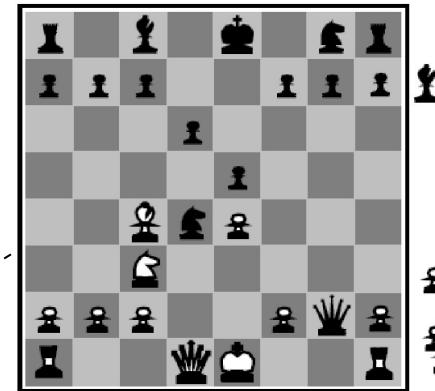
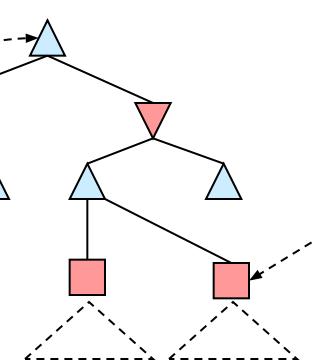


# Flashback: Evaluation Functions

- 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

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

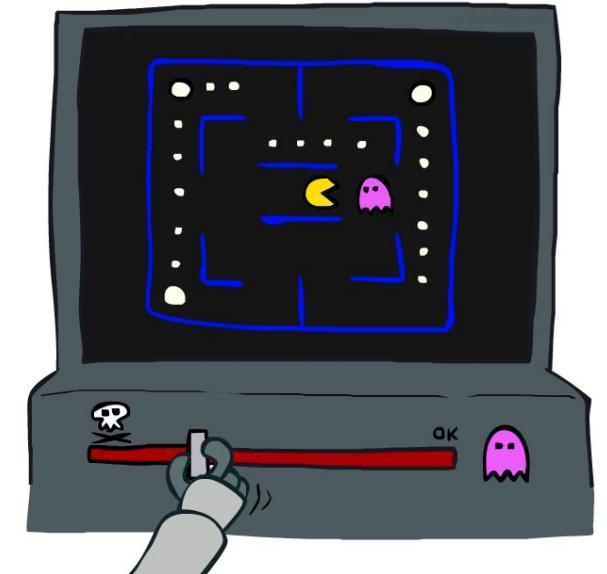
$Q(s, a) \leftarrow Q(s, a) + \alpha \text{ [difference]}$       Exact Q's

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

- Intuitive interpretation:

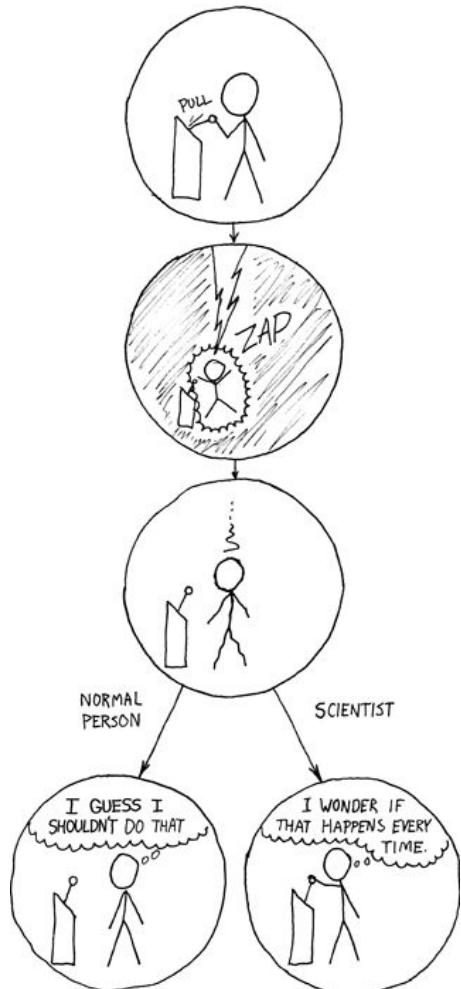
- Adjust weights of active features
- E.g., if something unexpectedly bad happens, blame the features that were on: disprefer all states with that state's features

- Formal justification: online least squares



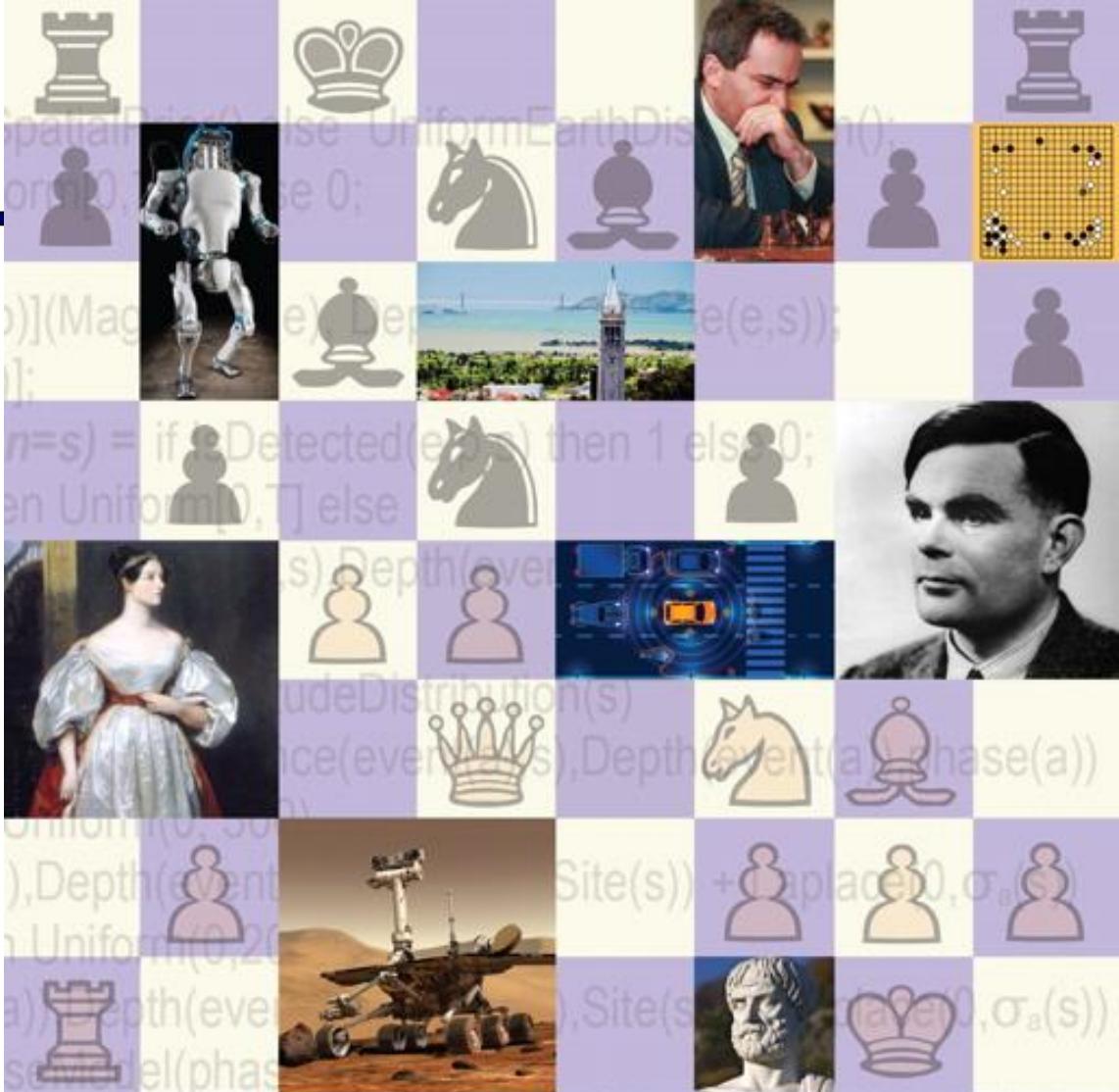
# HW6

- Homework 6: Reinforcement learning [100 points]
- 1. Q-Learning [35 Points]
- Epsilon Greedy [20 points]
- Bridge Crossing Revisited [10 points]
- Q-Learning and Pacman [10 points]
- Approximate Q-Learning [20 points]



# Reading

Chapter 22 – Reinforcement Learning  
Sections 22.1-22.5



Stuart  
**Russell**  
Peter  
**Norvig**

**Artificial Intelligence**  
A Modern Approach  
Fourth Edition