Announcements

- **Midterm** next Monday (March 6) 8-10pm (more details++ on ed)

FINANCIAL TIMES

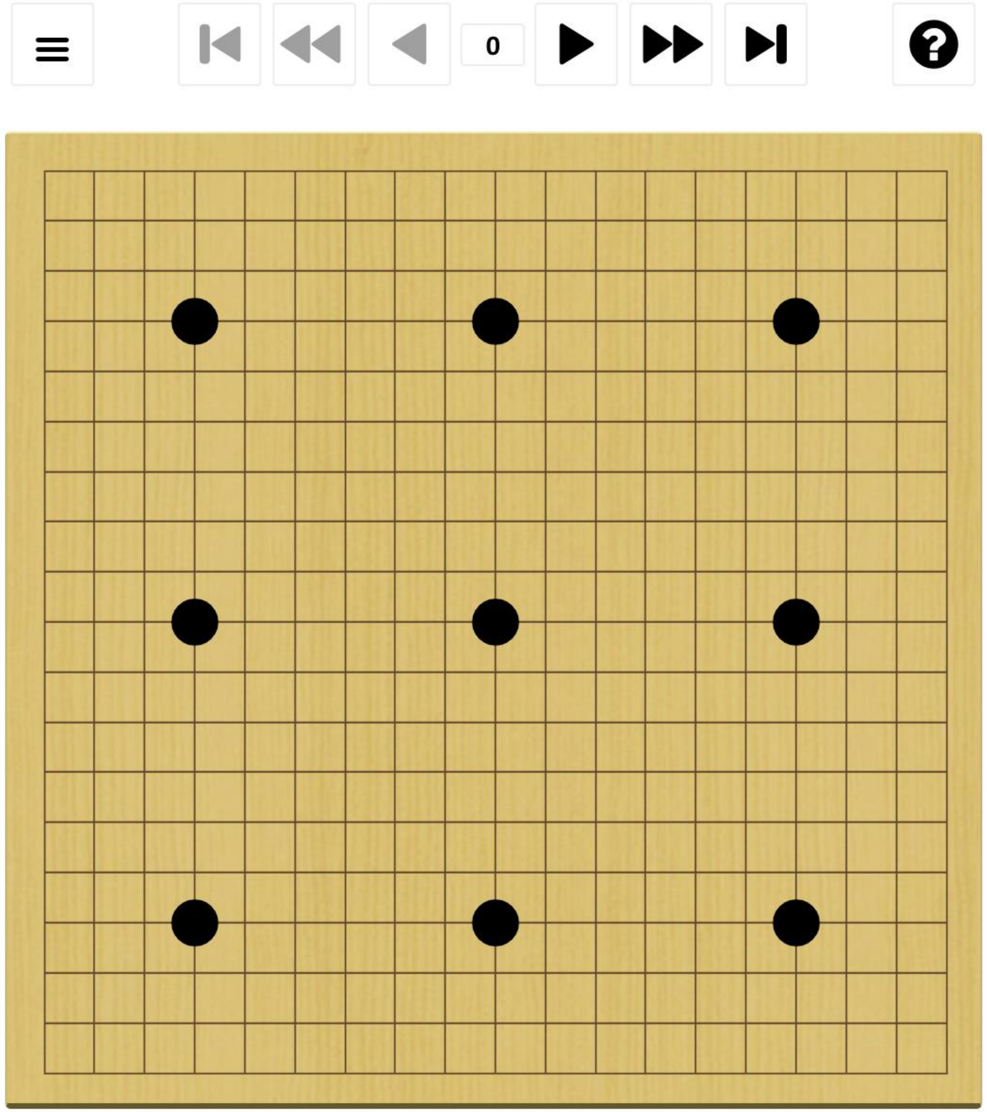
US COMPANIES TECH MARKETS CLIMATE OPINION WORK & CAREERS LIFE & ARTS HTSI Workspace Portfolio Settings

Artificial intelligence + Add to myFT

Man beats machine at Go in human victory over AI

Amateur Kellin Pelrine exploited weakness in systems that have otherwise dominated board game's grandmasters

How to beat a superhuman Go program



White: Kellin Pelrine (~2300)

Black: JBXKata005 (~5200)

9-stone handicap

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
    $V(s) = \max_a Q^*(s,a)$ and $\pi^*(s) = \text{argmax}_a Q^*(s,a)$
- 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)

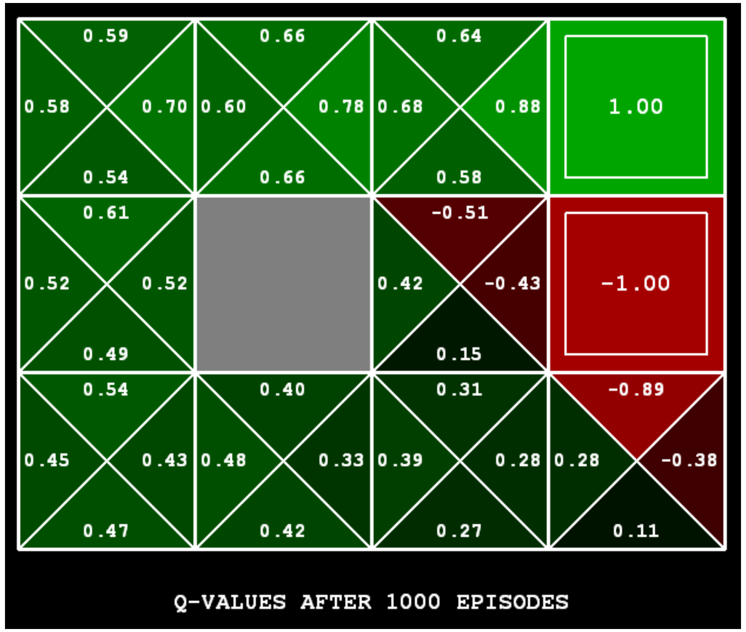
Q-Learning

- 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:

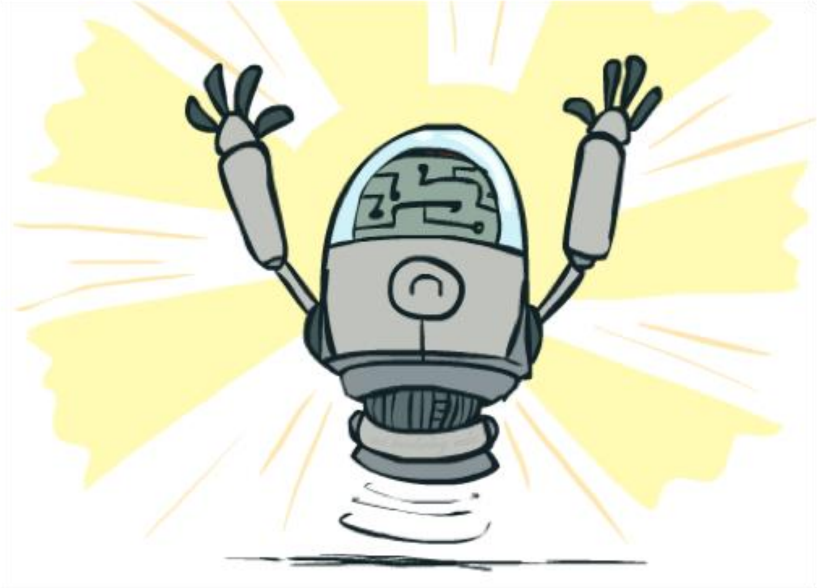
    $Q(s,a) \leftarrow (1-\alpha)\, Q(s,a) + \alpha \cdot [sample]$



[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) $\alpha(t) = K/(K+t)$

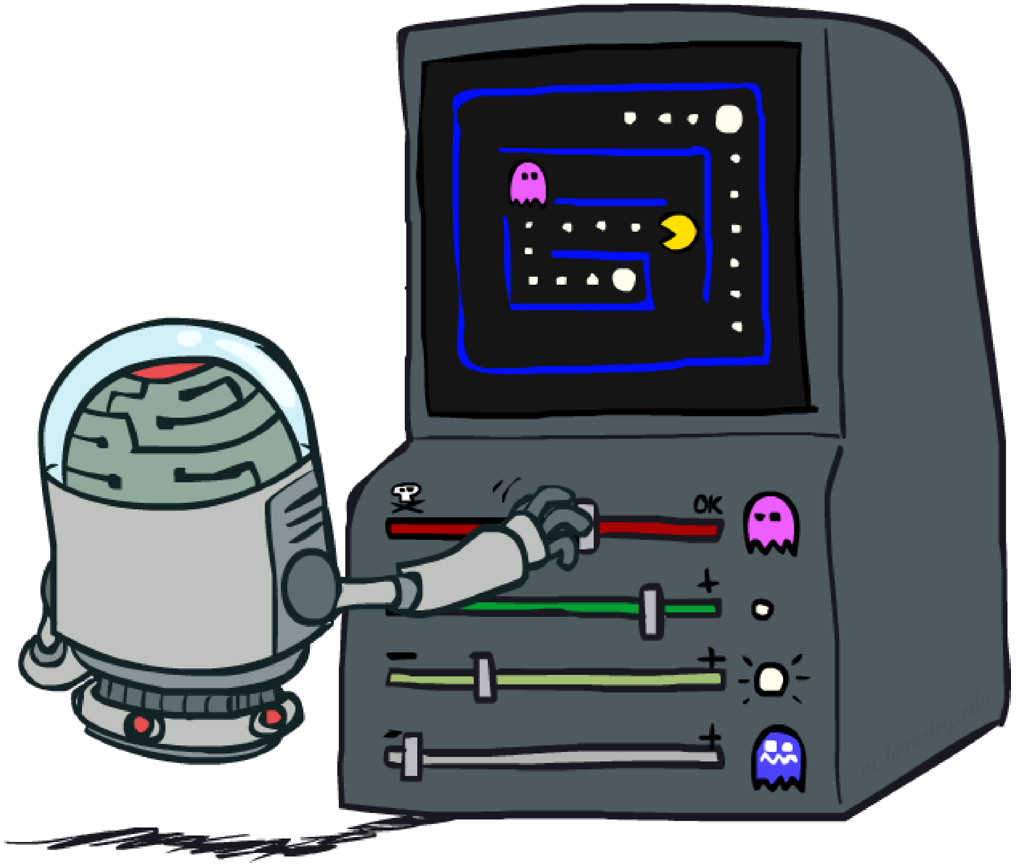


Summary

- 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 ($|A|=10^{26}$)?

CS 188: Artificial Intelligence

Reinforcement Learning II



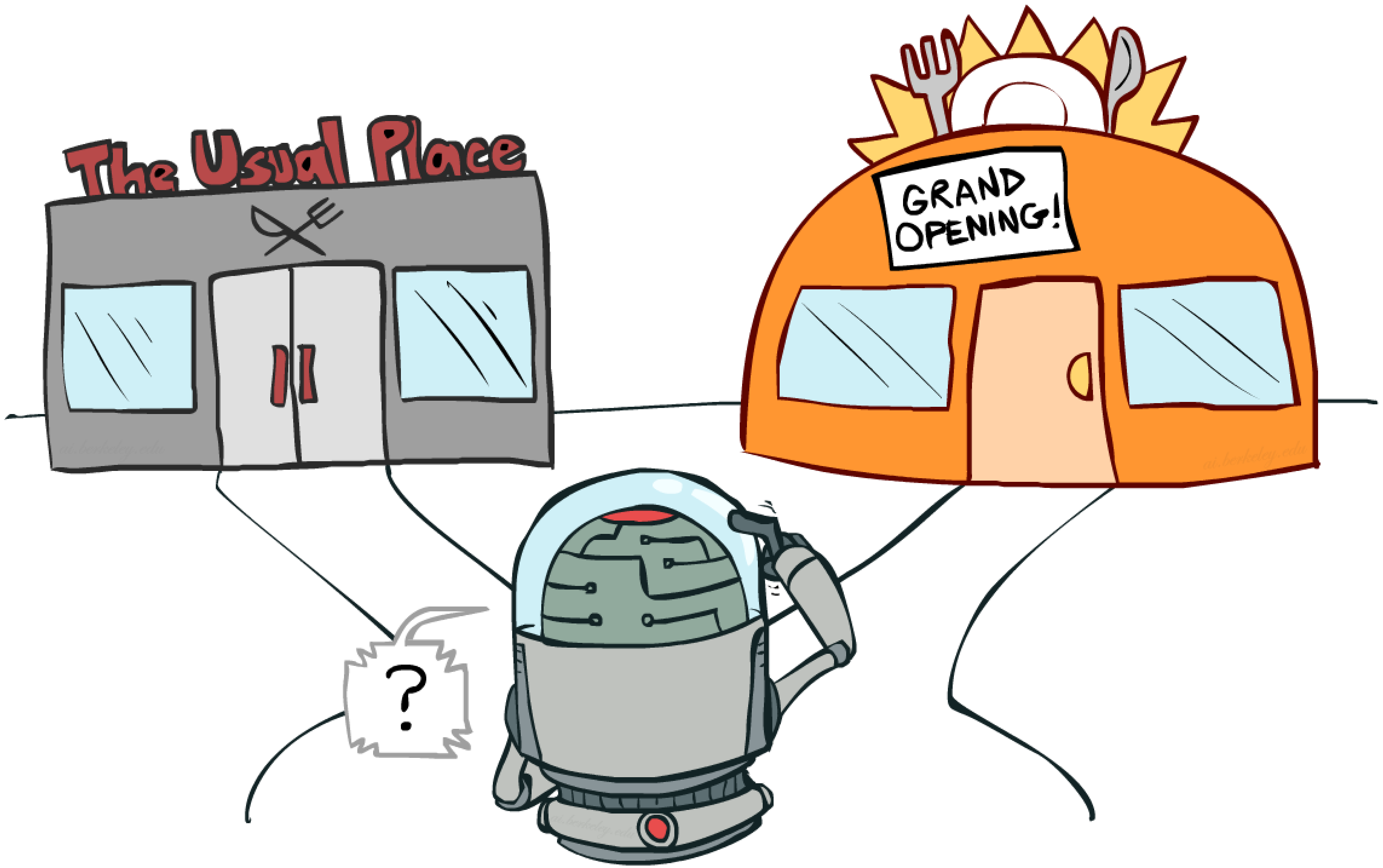
Instructors: Stuart Russell and Peyrin Kao

University of California, Berkeley

Reminder: Reinforcement Learning

- 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 ($|A|=10^{26}$)?

Exploration vs. Exploitation



Exploration vs exploitation

- ***Exploration***: try new things
- ***Exploitation***: do what's best given what you've learned so far
- Key point: pure exploitation often gets ***stuck in a rut*** and never finds an optimal policy!

Exploration method 1: ε-greedy

- ε-greedy exploration
  - Every time step, flip a biased coin
  - With (small) probability ε, act randomly
  - With (large) probability 1-ε, act on current policy

- Properties of ε-greedy exploration
  - Every s,a pair is tried infinitely often
  - Does a lot of stupid things
    - Jumping off a cliff *lots of times* to make sure it hurts
  - Keeps doing stupid things for ever
    - Decay ε towards 0

Sensible exploration: Bandits

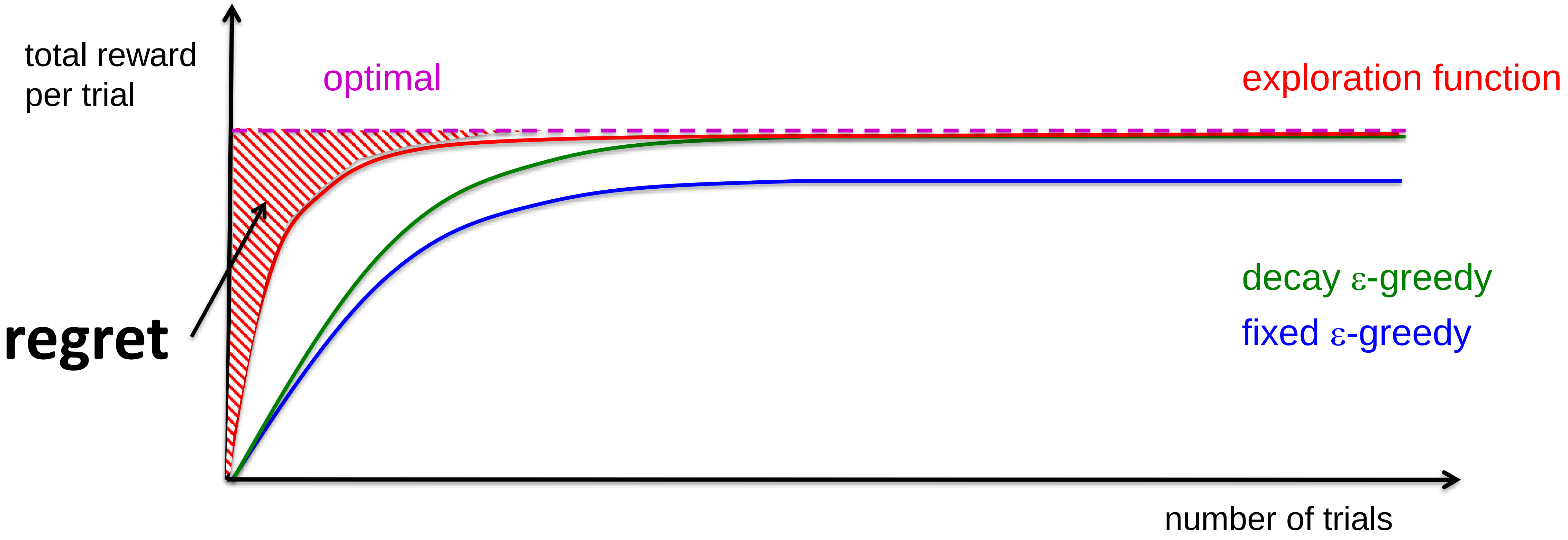
A	Tries:	1000
	Winnings:	900
B	Tries:	100
	Winnings:	90
C	Tries:	5
	Winnings:	4
D	Tries:	100
	Winnings:	0

- Which one-armed bandit to try next?
- Most people would choose C > B > A > D
- Basic intuition: higher mean is better; more uncertainty is better
- Gittins (1979): rank arms by an index that depends only on the arm itself

Exploration Functions

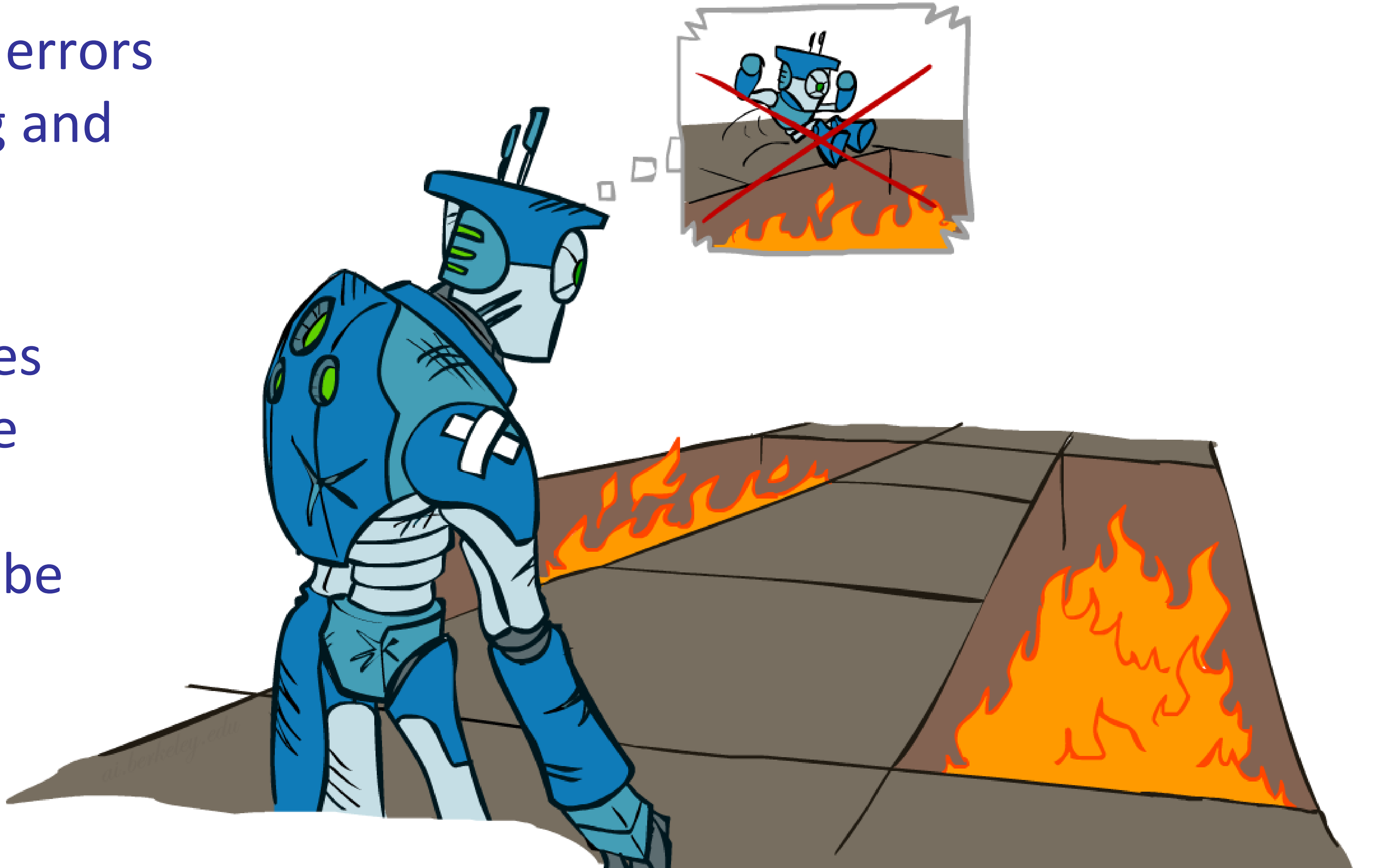
- ***Exploration functions*** implement this tradeoff
  - Takes a value estimate u and a visit count n, and returns an optimistic utility, e.g., $f(u,n) = u + k/\sqrt{n}$
- Regular Q-update:
  - $Q(s,a) \leftarrow (1-\alpha) \cdot Q(s,a) + \alpha \cdot [R(s,a,s') + \gamma \max_a Q(s',a)]$
- Modified Q-update:
  - $Q(s,a) \leftarrow (1-\alpha) \cdot Q(s,a) + \alpha \cdot [R(s,a,s') + \gamma \max_a f(Q(s',a),n(s',a'))]$
- Note: this propagates the “bonus” back to states that lead to unknown states as well!

Optimality and exploration

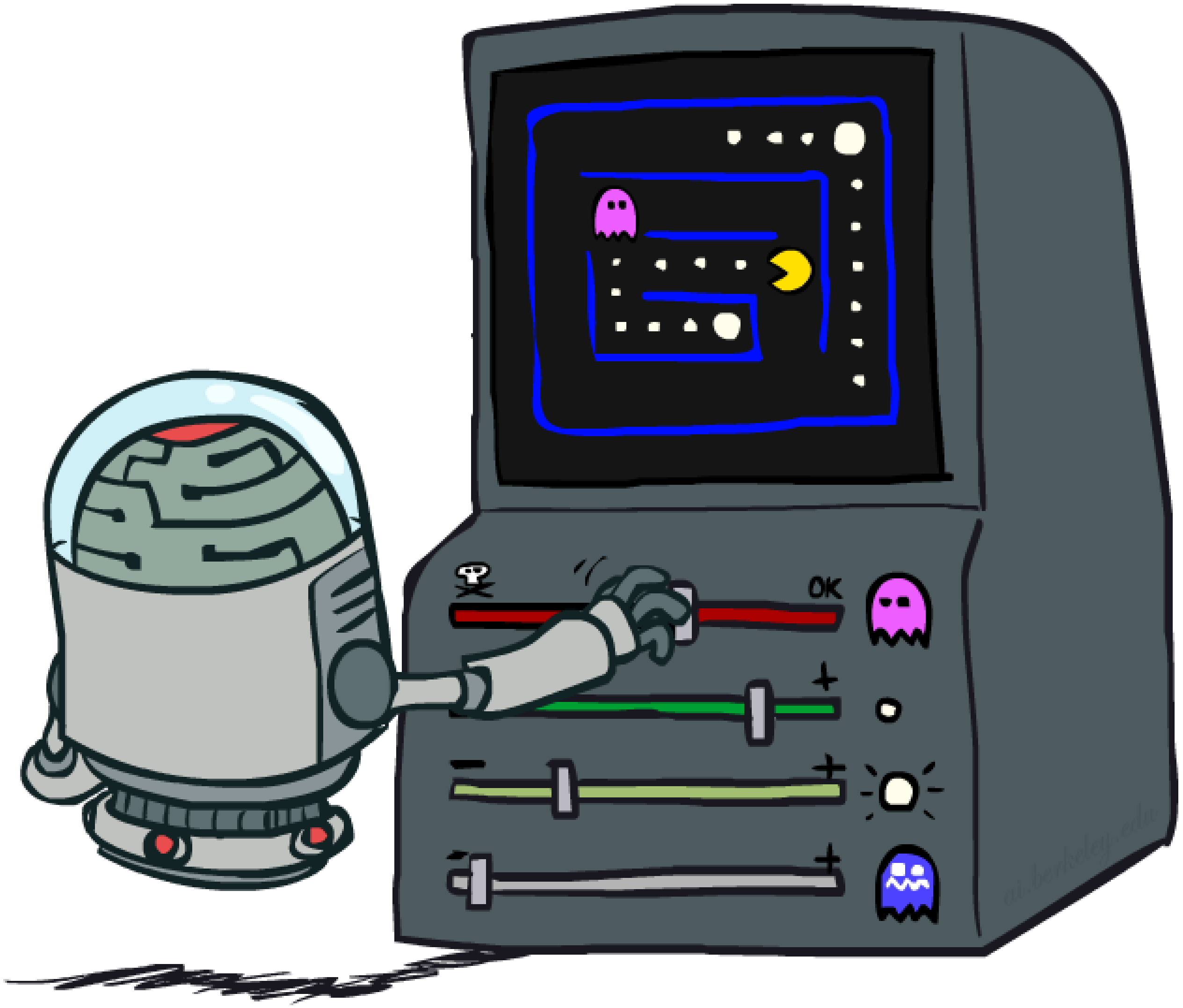


Regret

- ***Regret*** measures the total cost of your youthful errors made while exploring and learning instead of behaving optimally
- Minimizing regret goes beyond learning to be optimal – it requires optimally learning to be optimal



Approximate Q-Learning

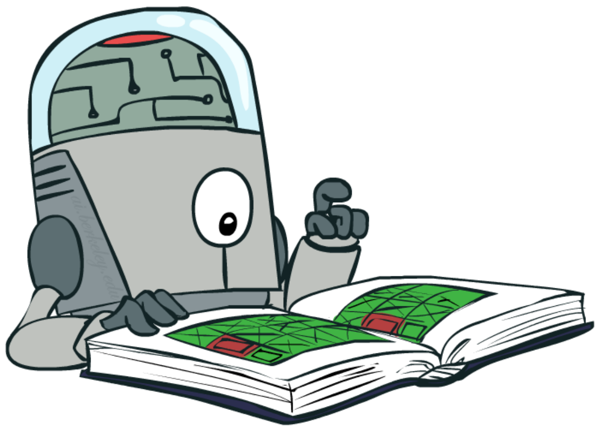


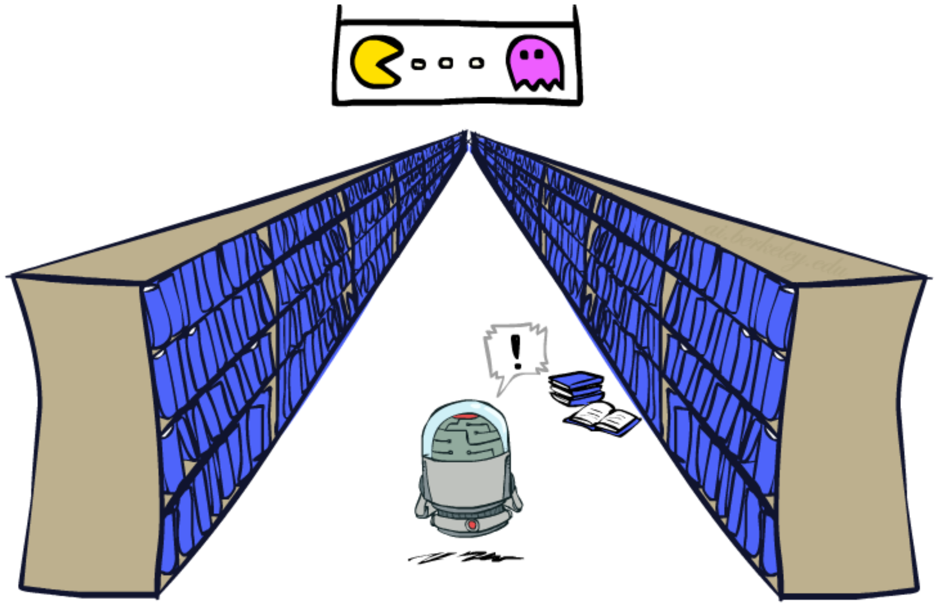
Generalizing Across States

- 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
  - Can we apply some machine learning tools to do this?

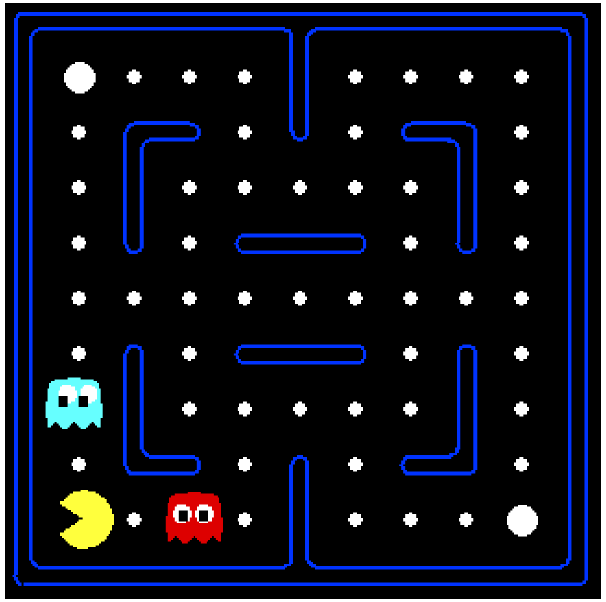




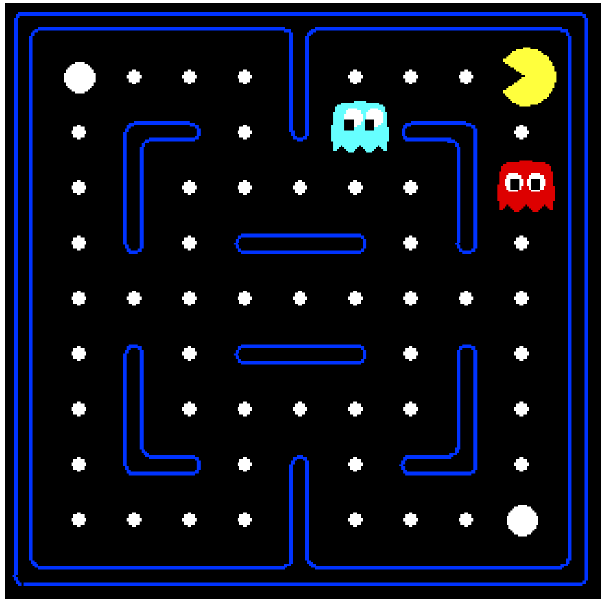
[demo – RL pacman]

Example: Pacman

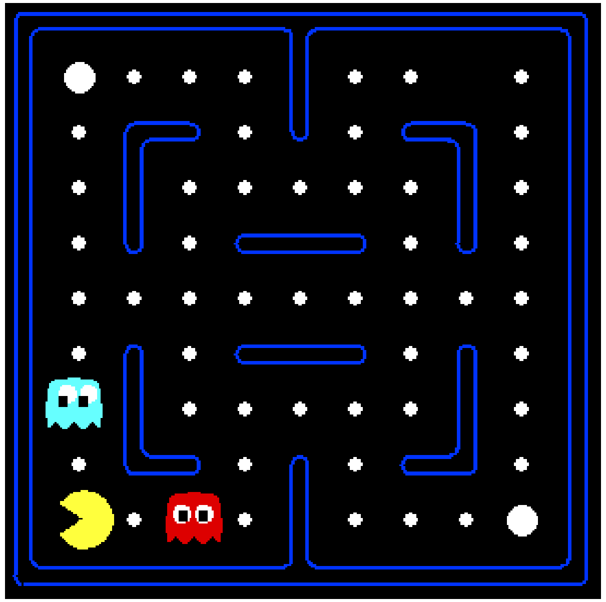
Let's say we discover through experience that this state is bad:



In naïve q-learning, we know nothing about this state:

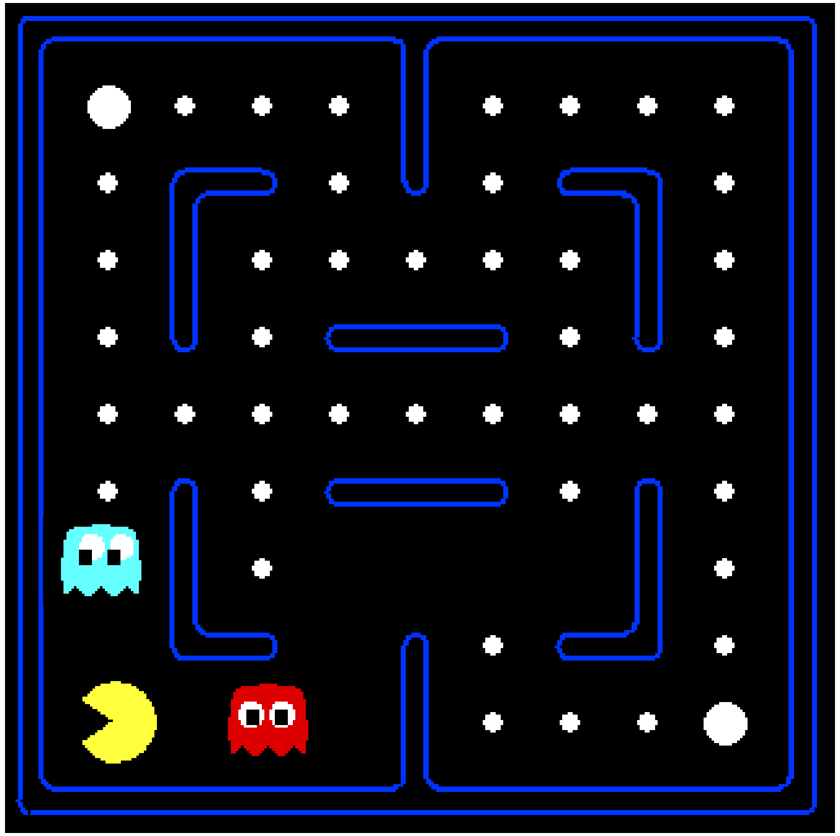


Or even this one!



Feature-Based Representations

- Describe a state using a vector of ***features***
  - Features are functions from states to real numbers (often 0/1) that capture important properties of the state
  - Example features:
    - Distance to closest ghost f_{GST}
    - Distance to closest dot
    - Number of ghosts
    - 1 / (distance to closest dot) f_{DOT}
    - Is Pacman in a tunnel? (0/1)
    - …… etc.
  - Can also describe a q-state (s, a) with features (e.g., action moves closer to food)



Linear Value Functions

- We can express V and Q (approximately) as weighted linear functions of feature values:
  - $V_{\mathbf{w}}(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s)$
  - $Q_{\mathbf{w}}(s,a) = w_1 f_1(s,a) + w_2 f_2(s,a) + \ldots + w_n f_n(s,a)$

- With the wrong features, the best possible approximation may be terrible!
- But in practice we can compress a value function for chess (10^{43} states) down to about 30 weights and get decent play!!!

Updating a linear value function

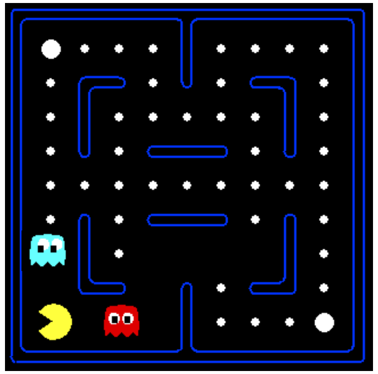
- Original Q-learning rule tries to reduce prediction error at s,a:
  - $Q(s,a) \leftarrow Q(s,a) + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)]$
- Instead, we update the weights to try to reduce the error at s,a:
  - $w_i \leftarrow w_i + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)] \, \partial Q_{\mathbf{w}}(s,a)/\partial w_i$

    $= w_i + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)] \, f_i(s,a)$
- Qualitative justification:
  - Pleasant surprise: increase weights on +ve features, decrease on –ve ones
  - Unpleasant surprise: decrease weights on +ve features, increase on –ve ones

Example: Q-Pacman

$Q(s,a) = 4.0\, f_{DOT}(s,a) - 1.0\, f_{GST}(s,a)$

s

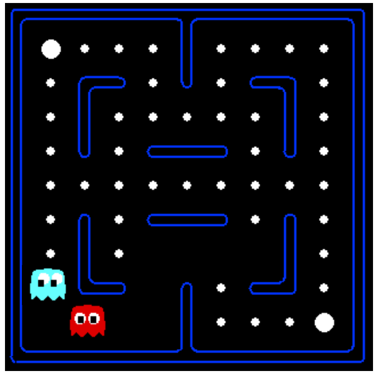


$f_{DOT}(s,\text{NORTH}) = 0.5$

$f_{GST}(s,\text{NORTH}) = 1.0$

a = NORTH
r = –500

s’



$Q(s,\text{NORTH}) = +1$

$r + \gamma \max_{a'} Q(s',a') = -500 + 0$

$Q(s',\cdot) = 0$

difference = –501

$w_{DOT} \leftarrow 4.0 + \alpha[-501]0.5$

$w_{GST} \leftarrow -1.0 + \alpha[-501]1.0$

$Q(s,a) = 3.0\, f_{DOT}(s,a) - 3.0\, f_{GST}(s,a)$

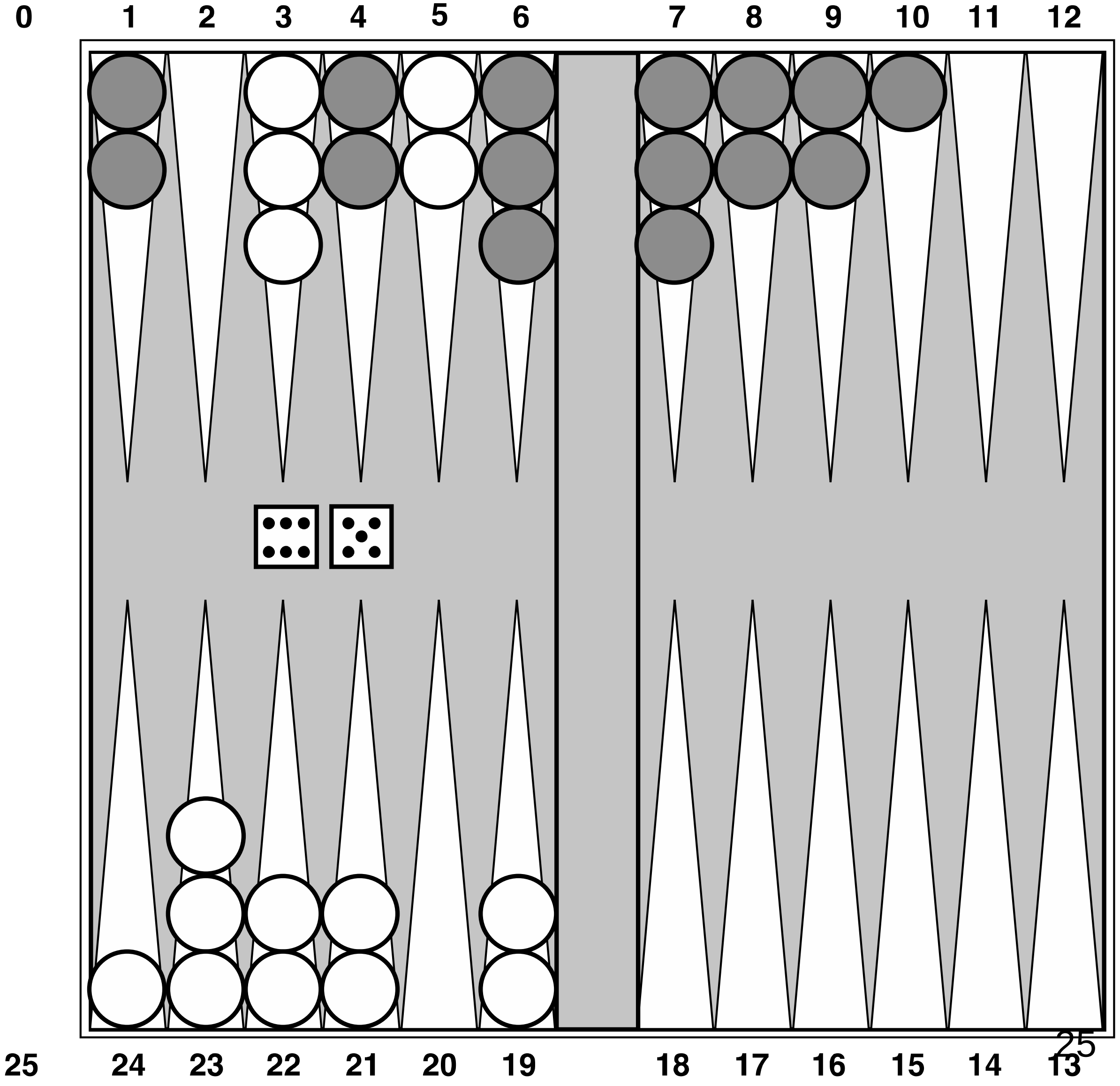
Convergence*

- Let V^L be the closest linear approximation to V^*.
- TD learning with a linear function approximator converges to some V that is pretty close to V^L
- Q-learning with a linear function approximator may diverge
- With much more complicated update rules, stronger convergence results can be proved – even for nonlinear function approximators such as neural nets

Nonlinear function approximators

- We can still use the gradient-based update for ***any*** Q_w:
  - $w_i \leftarrow w_i + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)] \, \partial Q_w(s,a)/\partial w_i$
- Neural network error back-propagation already does this!
- Maybe we can get much better V or Q approximators using a complicated neural net instead of a linear function

Backgammon

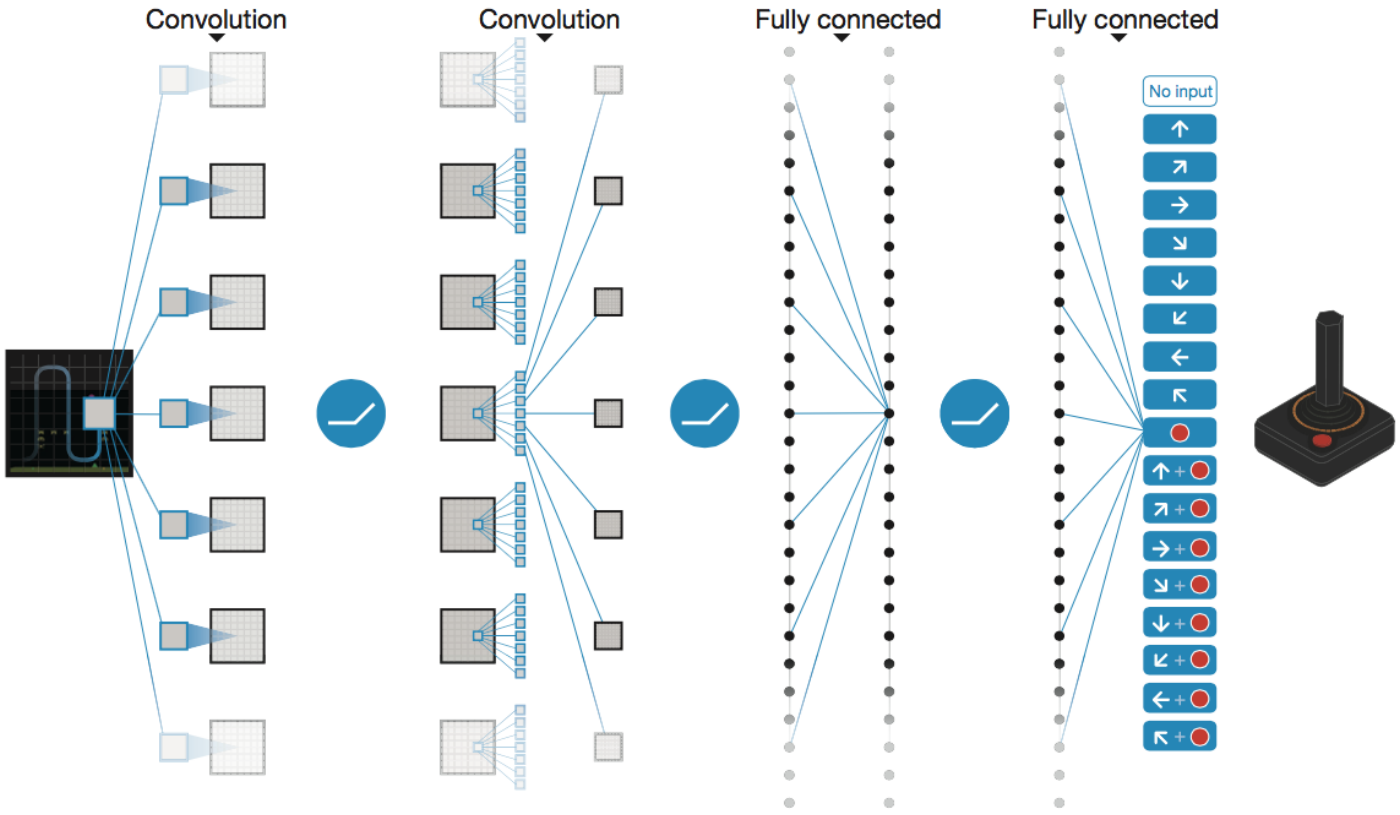


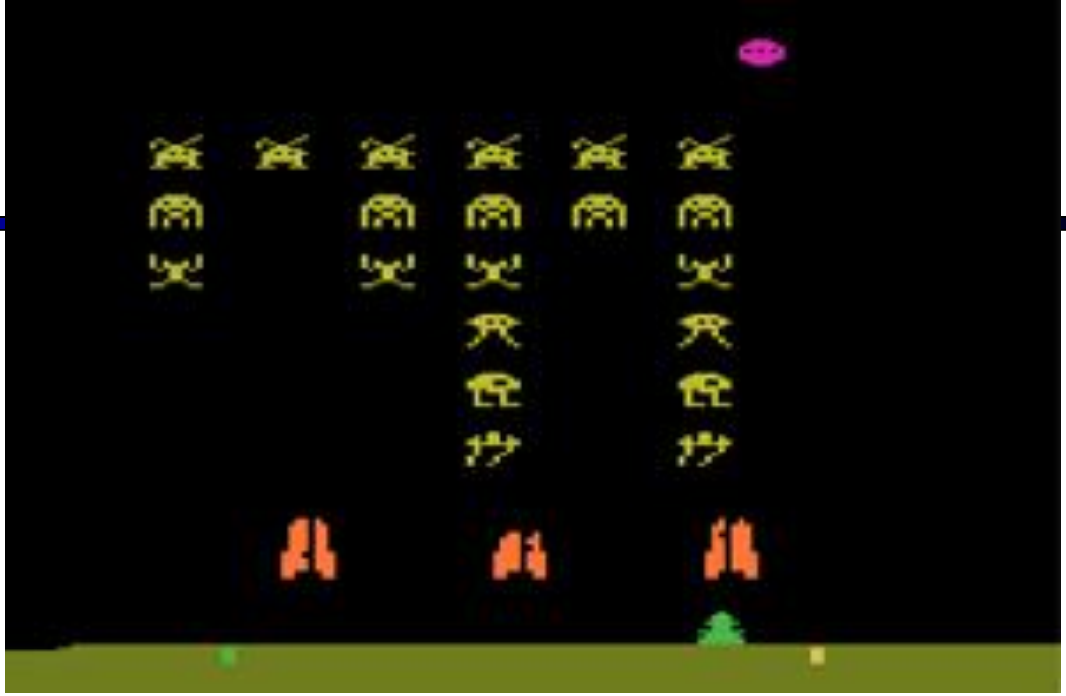
TDGammon

- 4-ply lookahead using V(s) trained from 1,500,000 games of self-play
- 3 hidden layers, ~100 units each
- Input: contents of each location ***plus several handcrafted features***
- Experimental results:
  - Plays approximately at parity with world champion
  - Led to radical changes in the way humans play backgammon

DeepMind DQN

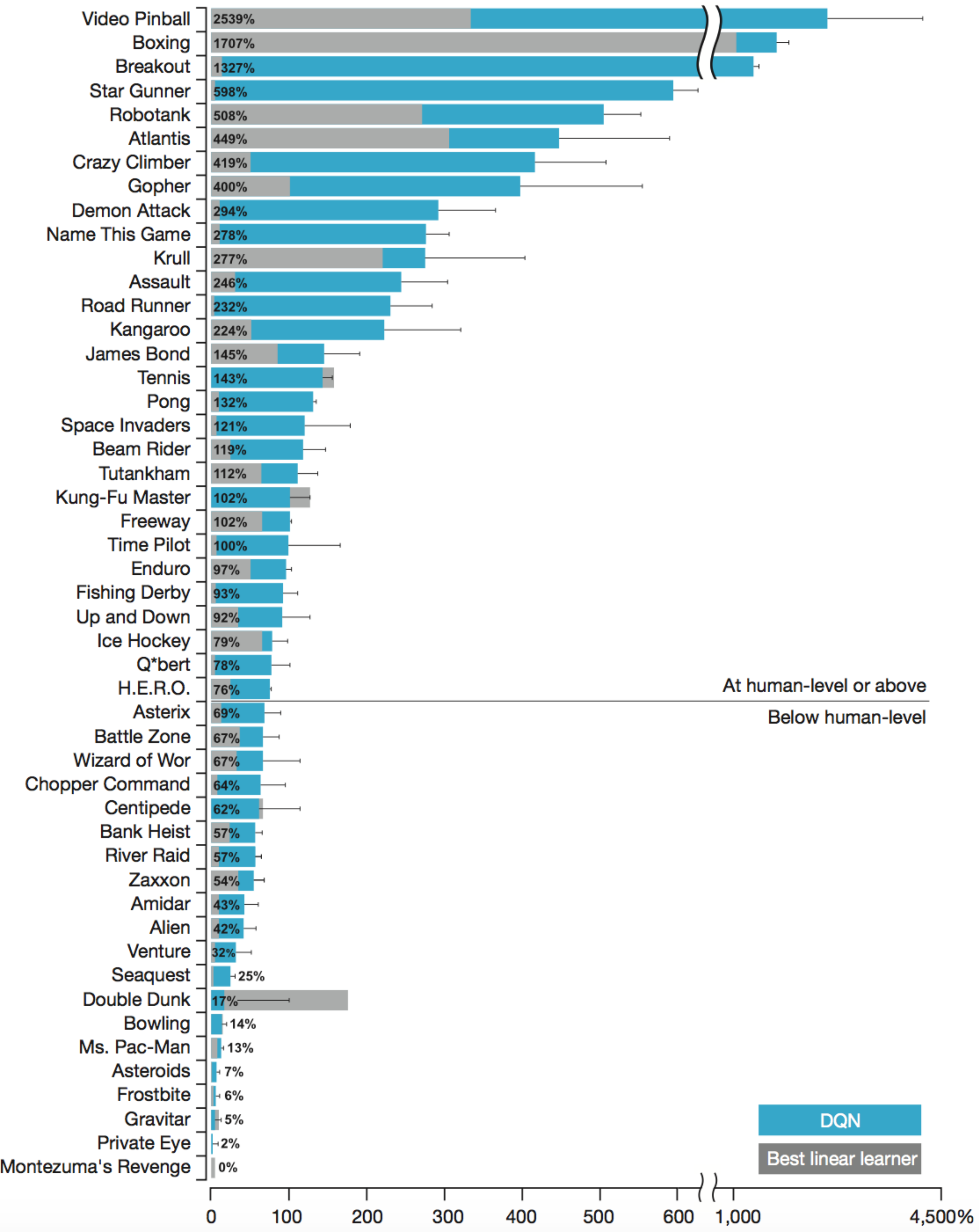
- Used a deep learning network to represent Q:
  - Input is last 4 images (84x84 pixel values) plus score
- 49 Atari games, incl. Breakout, Space Invaders, Seaquest, Enduro






0
OXYGEN
ACTIVISION


0000025
01
142KM/H



Video Pinball 2539%
Boxing 1707%
Breakout 1327%
Star Gunner 598%
Robotank 508%
Atlantis 449%
Crazy Climber 419%
Gopher 400%
Demon Attack 294%
Name This Game 278%
Krull 277%
Assault 246%
Road Runner 232%
Kangaroo 224%
James Bond 145%
Tennis 143%
Pong 132%
Space Invaders 121%
Beam Rider 119%
Tutankham 112%
Kung-Fu Master 102%
Freeway 102%
Time Pilot 100%
Enduro 97%
Fishing Derby 93%
Up and Down 92%
Ice Hockey 79%
Q*bert 78%
H.E.R.O. 76%
At human-level or above
Below human-level
Asterix 69%
Battle Zone 67%
Wizard of Wor 67%
Chopper Command 64%
Centipede 62%
Bank Heist 57%
River Raid 57%
Zaxxon 54%
Amidar 43%
Alien 42%
Venture 32%
Seaquest 25%
Double Dunk 17%
Bowling 14%
Ms. Pac-Man 13%
Asteroids 7%
Frostbite 6%
Gravitar 5%
Private Eye 2%
Montezuma's Revenge 0%
DQN
Best linear learner
0
100
200
300
400
500
600
1,000
4,500%

Summary

- Exploration vs. exploitation
  - Exploration guided by unfamiliarity and potential
  - Appropriately designed bonuses tend to minimize regret
- Generalization allows RL to scale up to real problems
  - Represent V or Q with parameterized functions
  - Adjust parameters to reduce sample prediction error