# STA303: Artificial Intelligence

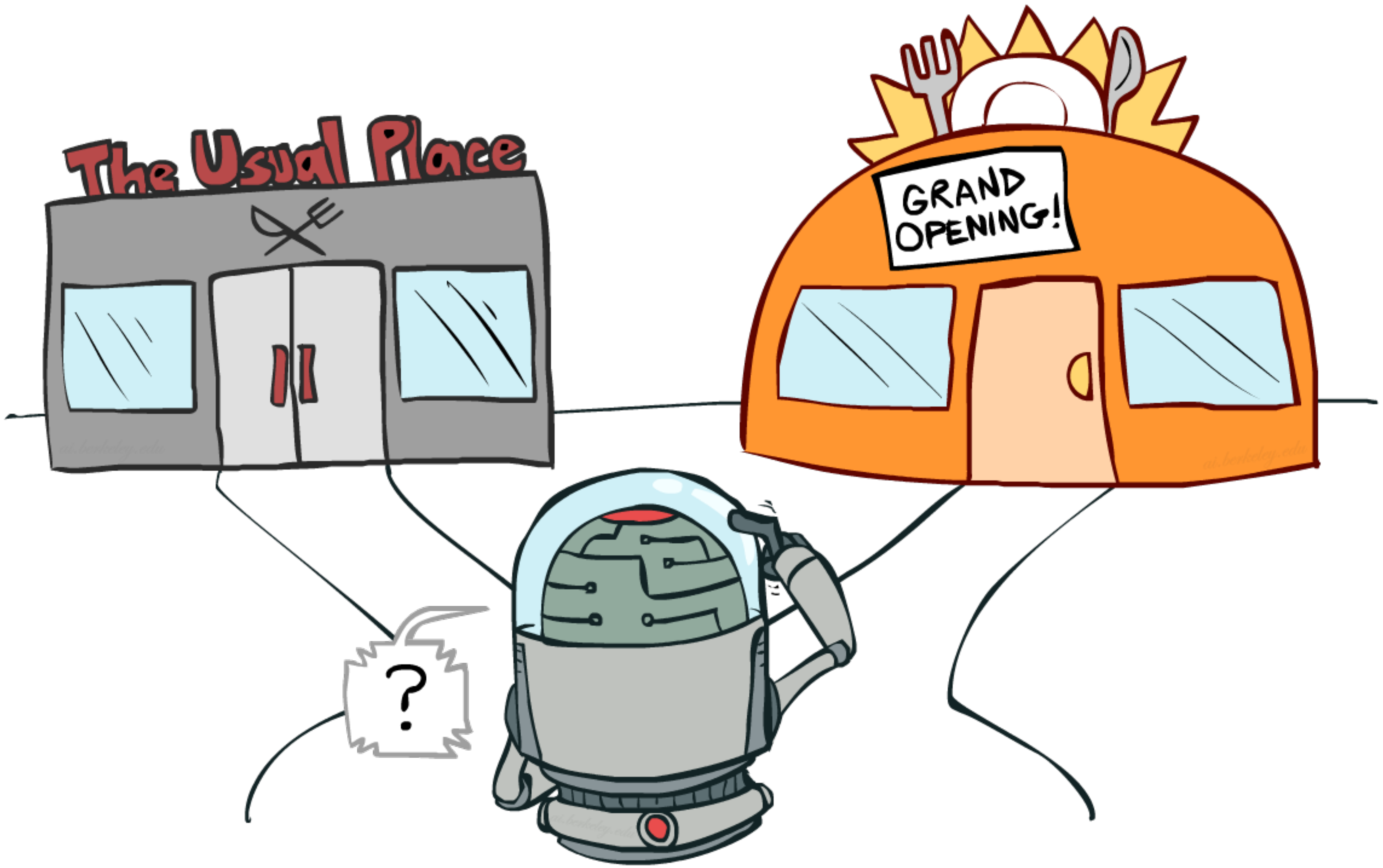
## Reinforcement Learning II

Fang Kong

https://fangkongx.github.io/

Slide credits: ai.berkeley.edu

# 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

# Demo Q-learning – Epsilon-Greedy – Crawler

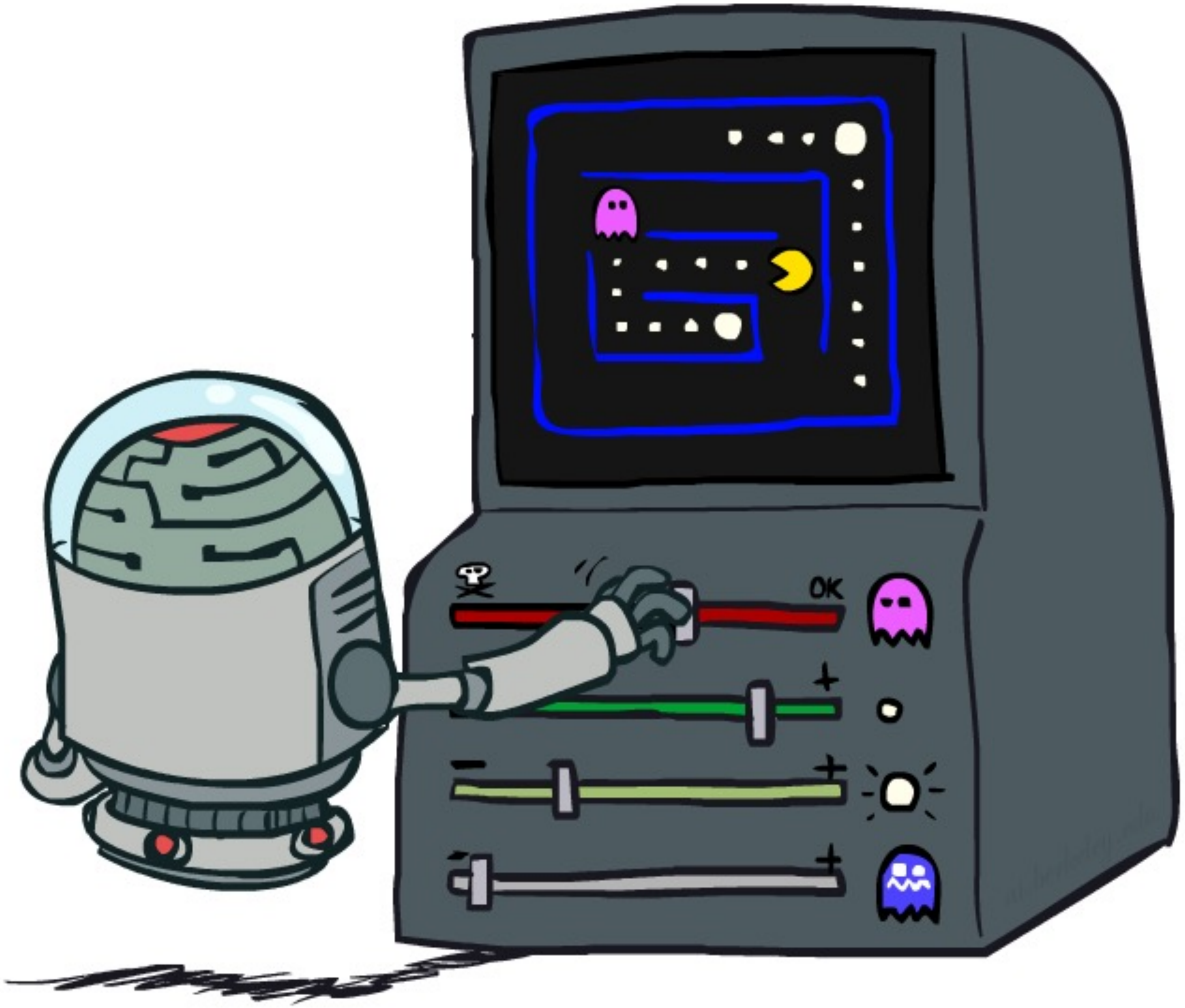
# Method 2: Optimistic Exploration Functions

- ***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!

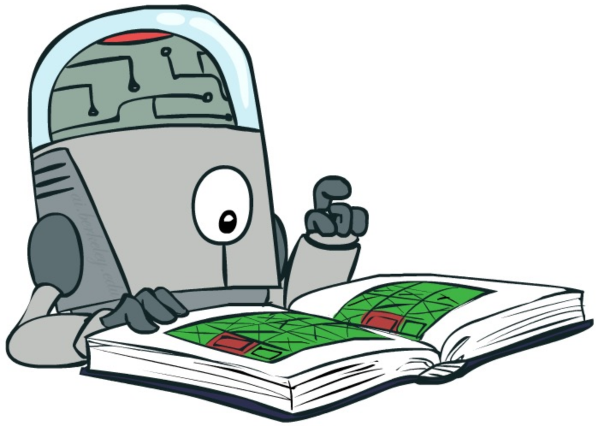
# Demo Q-learning – Exploration Function – Crawler

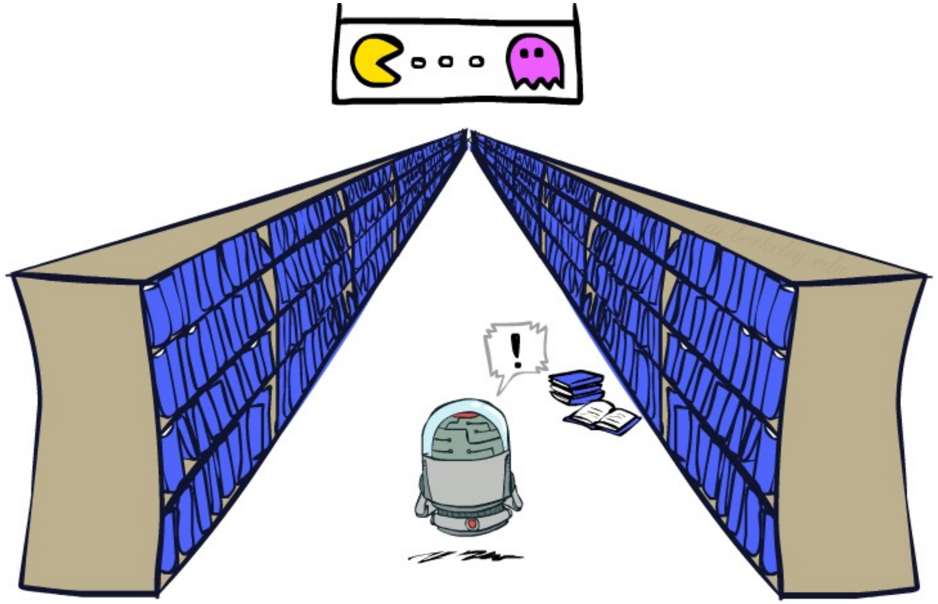
# Approximate Q-Learning



# 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?

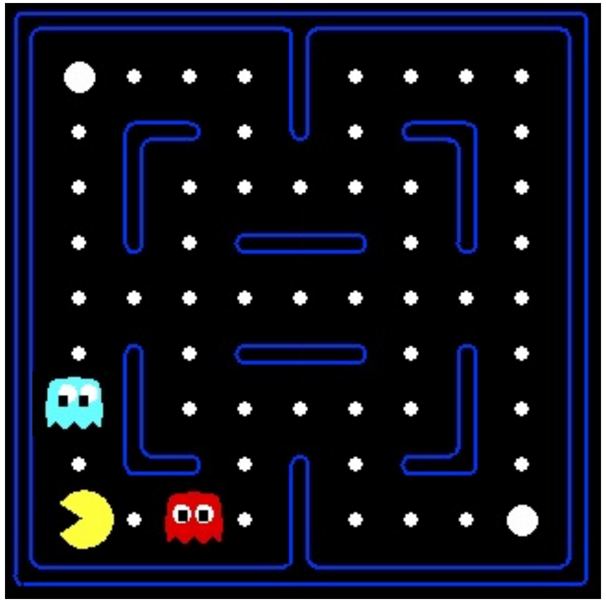




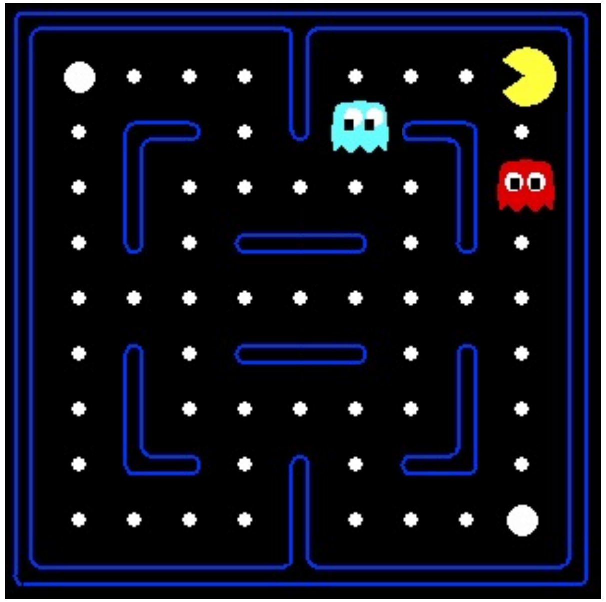

[demo – RL pacman]

# Example: Pacman

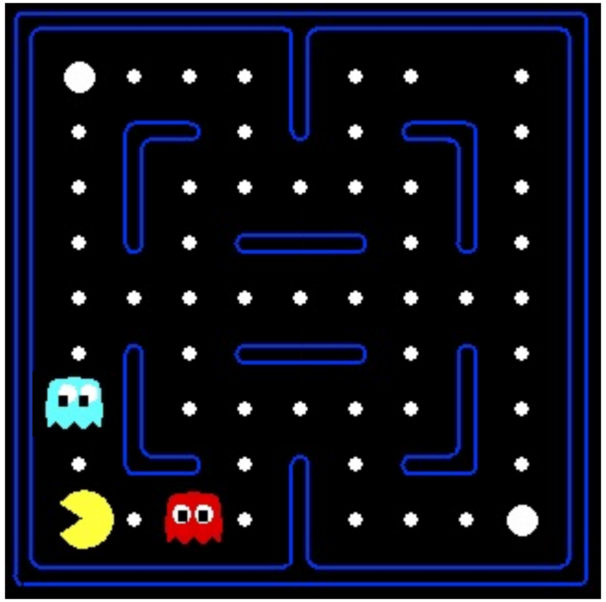
Let’s say we discover through experience that this state is bad:



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



Or even this one!



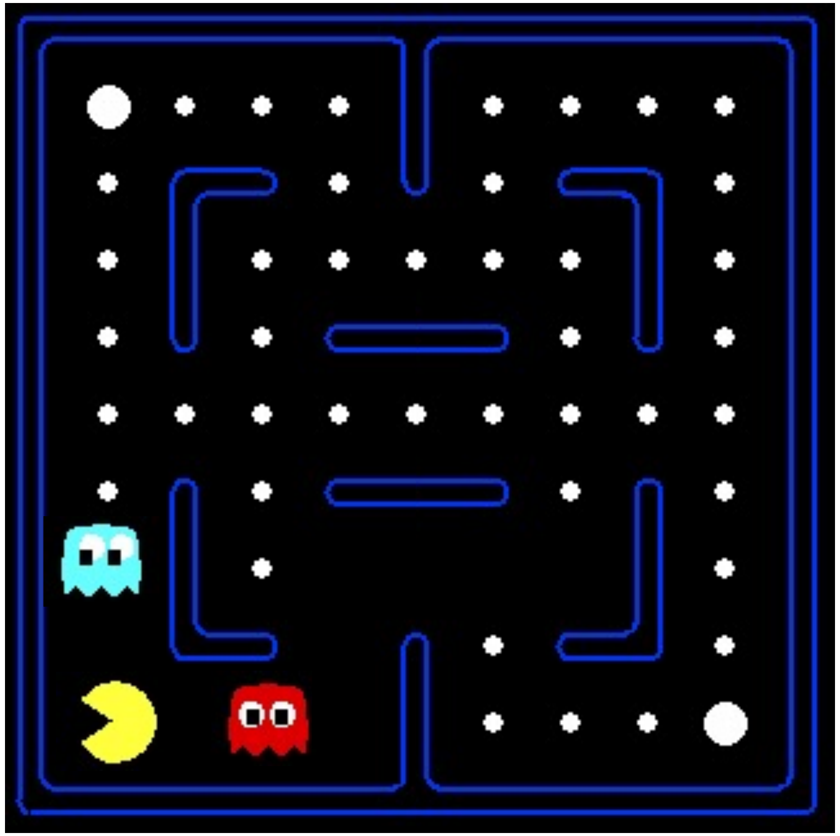
# Demo Q-Learning Pacman – Tiny – Watch All

# Demo Q-Learning Pacman – Tiny – Silent Train

# Demo Q-Learning Pacman – Tricky – Watch All

# Feature-Based Representations

- Solution: 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:
  - $V_\theta(s) = \theta_1 f_1(s) + \theta_2 f_2(s) + \ldots + \theta_n f_n(s)$
  - $Q_\theta(s,a) = \theta_1 f_1(s,a) + \theta_2 f_2(s,a) + \ldots + \theta_n f_n(s,a)$
- Advantage: our experience is summed up in a few powerful numbers
  - Can compress a value function for chess ($10^{43}$ states) down to about 30 weights!
- Disadvantage: states may share features but have very different expected utility!

# SGD for Linear Value Functions

- Goal: Find parameter vector $\theta$ that minimizes the mean squared error between the true and approximate value function

$$J(\theta) = \mathbb{E}_{\pi}[\frac{1}{2}\left(V^{\pi}(s) - V_{\theta}(s)\right)^2]$$

- Stochastic gradient descent:

$$\theta \leftarrow \theta - \alpha \frac{\partial J(\theta)}{\partial \theta}$$

$$= \theta + \alpha\left(V^{\pi}(s) - V_{\theta}(s)\right)\frac{\partial V_{\theta}(s)}{\partial \theta}$$

# Supervised Learning for Value Function Approximation

- Let $V^{\pi}(s)$ denote the true target value function
- Use supervised learning on "training data" to predict the value function:

$$\langle s_1, G_1 \rangle, \langle s_2, G_2 \rangle, \ldots, \langle s_T, G_T \rangle$$

- For each data sample

$$\theta \leftarrow \theta + \alpha\big(G_t - V_\theta(s_t)\big) f(s_t)$$

# Temporal-Difference (TD) Learning Objective

$$\theta \leftarrow \theta + \alpha\big(V^{\pi}(s) - V_{\theta}(s)\big)f(s)$$

- In TD learning, $r_{t+1} + \gamma V_{\theta}(s_{t+1})$ is a data sample for the target
- Apply supervised learning on "training data":

$$\langle s_1, r_2 + \gamma V_{\theta}(s_2)\rangle, \langle s_2, r_3 + \gamma V_{\theta}(s_3)\rangle, \dots, \langle s_T, r_T\rangle$$

- For each data sample, update

$$\theta \leftarrow \theta + \alpha\big(r_{t+1} + \gamma V_{\theta}(s_{t+1}) - V_{\theta}(s_t)\big)f(s_t)$$

# Q-Value Function Approximation

- Approximate the action-value function:

$$Q_\theta(s,a) \simeq Q^\pi(s,a)$$

- Objective: Minimize the **mean squared error**:

$$J(\theta) = \mathbb{E}_\pi\left[\frac{1}{2}\left(Q^\pi(s,a) - Q_\theta(s,a)\right)^2\right]$$

- Stochastic Gradient Descent on a single sample

# Intuitive interpretation

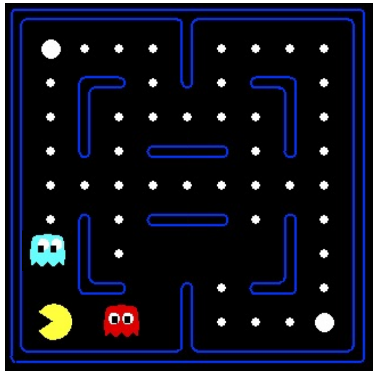
- Original Q-learning rule tries to reduce prediction error at s,a:
  - $Q(s,a) \leftarrow Q(s,a) + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)]$
- Instead, we update the weights to try to reduce the error at s,a:
  - $w_i \leftarrow w_i + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a')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

    $= w_i + \alpha \cdot [R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)] \, f_i(s,a)$
- Intuitive interpretation:
  - Adjust weights of active features
  - If something bad happens, blame the features we saw; decrease value of states with those features. If something good happens, increase value!

# Example: Q-Pacman

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

s

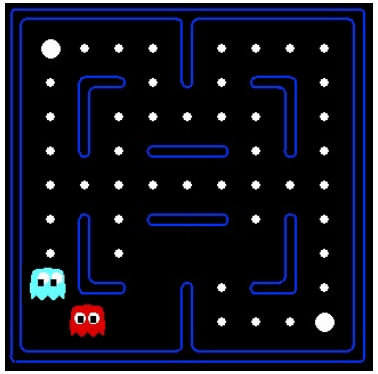


$f_{DOT}(s,\text{NORTH}) = 0.5$

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

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

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

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

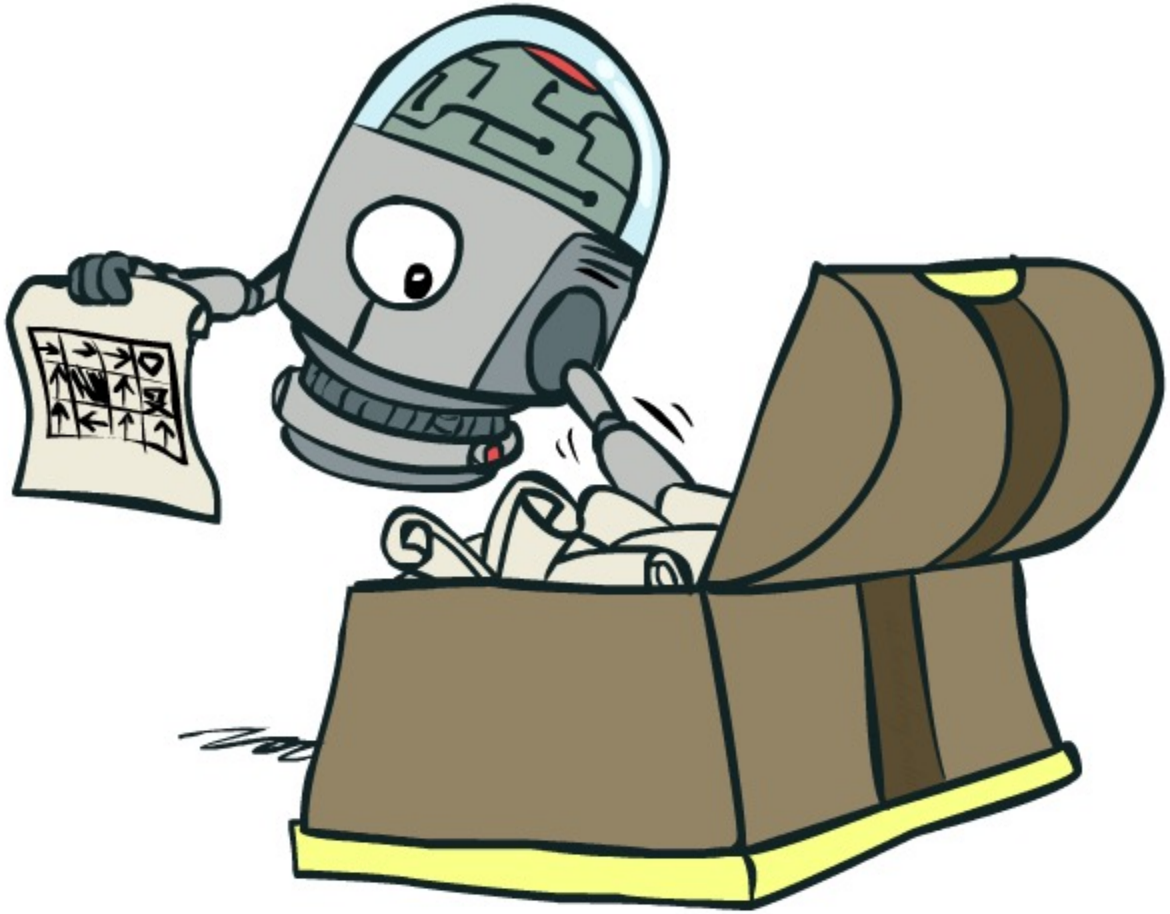
$Q(s,a) = 3.0\, f_{DOT}(s,a) - 3.0\, f_{GST}(s,a)$

# Demo Approximate Q-Learning -- Pacman

# 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

# Policy Search



# Policy Search

- Problem: often the feature-based policies that work well (win games, maximize utilities) aren't the ones that approximate V / Q best
  - E.g. your value functions were probably horrible estimates of future rewards, but they still produced good decisions
  - Q-learning's priority: get Q-values close (modeling)
  - Action selection priority: get ordering of Q-values right (prediction)

- Solution: learn policies that maximize rewards, not the values that predict them

- Policy search: start with an ok solution (e.g. Q-learning) then fine-tune by **hill climbing** (or gradient ascent!) on feature weights

# Parameterized Policy

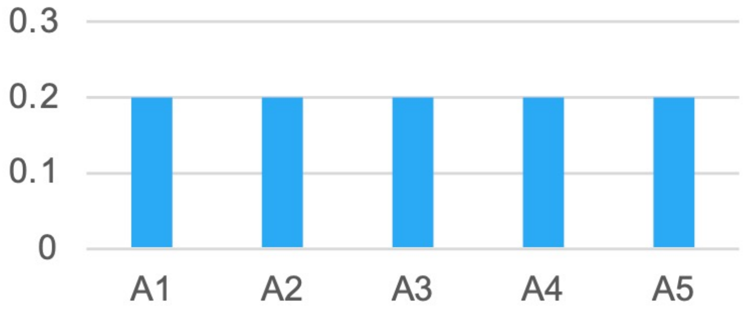
- A policy can be parameterized as $\pi_\theta(a|s)$

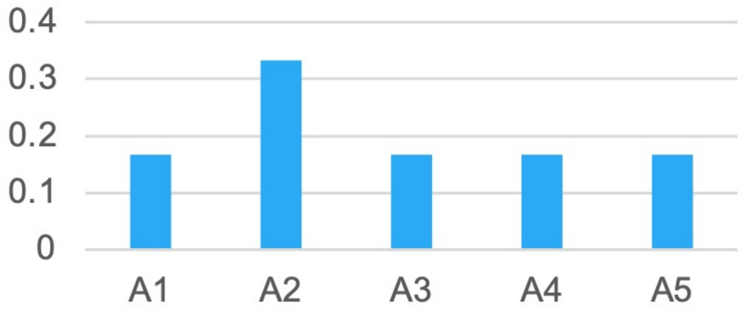
- The policy can be deterministic: $a = \pi_\theta(s)$
  - Or stochastic: $\pi_\theta(a|s) = P(a|s;\theta)$

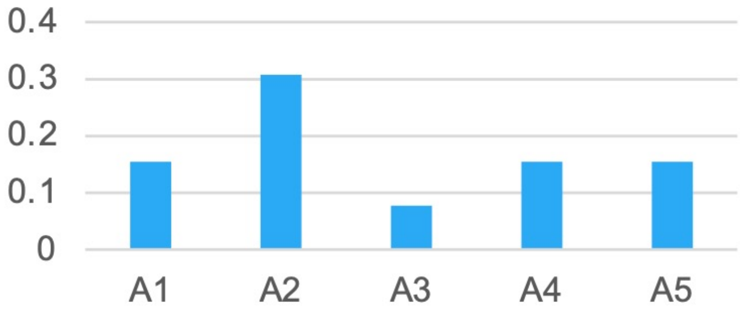
- θ represents the parameters of the policy

# Policy Gradient

- Simplest version:
  - Start with initial policy $\pi(s)$ that assigns probability to each action
  - Sample actions according to policy $\pi$
  - Update policy:
    - If an episode led to high utility, make sampled actions more likely
    - If an episode led to low utility, make sampled actions less likely



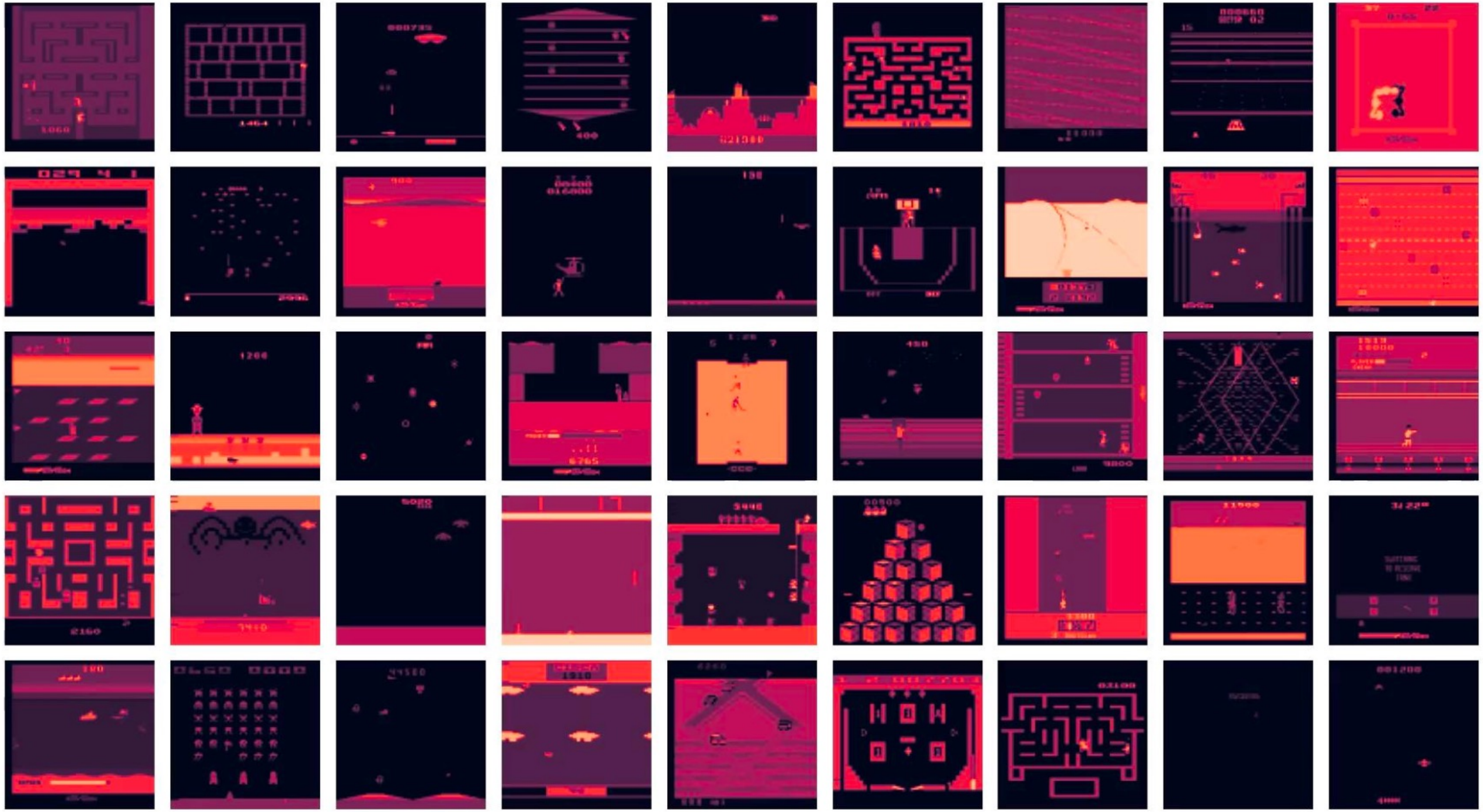




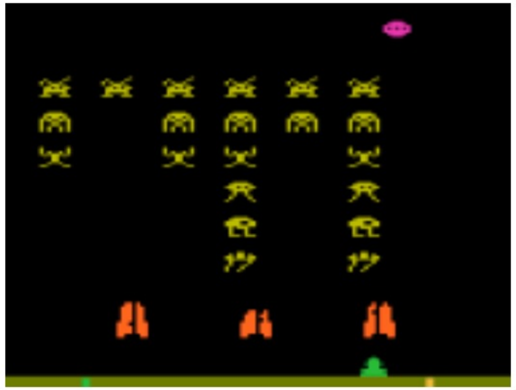
# Case Studies of Reinforcement Learning!

- Atari game playing
- Robot Locomotion
- Language assistants

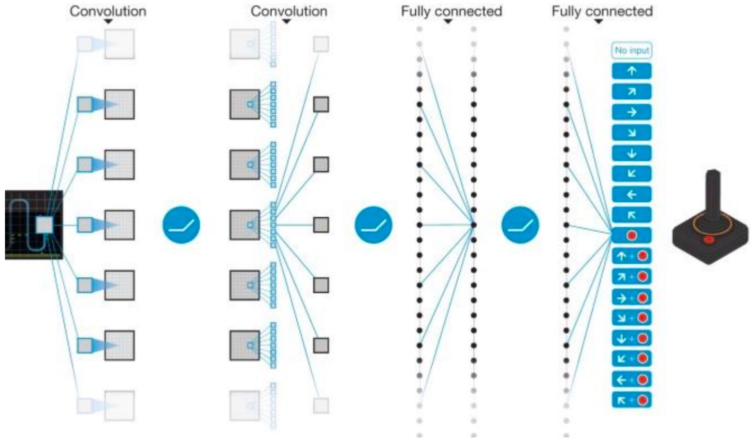
# Case Studies: Atari Game Playing



# Case Studies: Atari Game Playing



- MDP:
  - State: image of game screen
    - 256^(84*84) possible states
    - Processed with hand-designed feature vectors or neural networks
  - Action: combination of arrow keys + button (18)
  - Transition T: game code (don't have access)
  - Reward R: game score (don't have access)
- Very similar to our pacman MDP
- Use approximate Q learning with neural networks and ε-greedy exploration to solve




[Human-level control through deep reinforcement learning, Mnih et al, 2015]

# Case Studies: Robot Locomotion

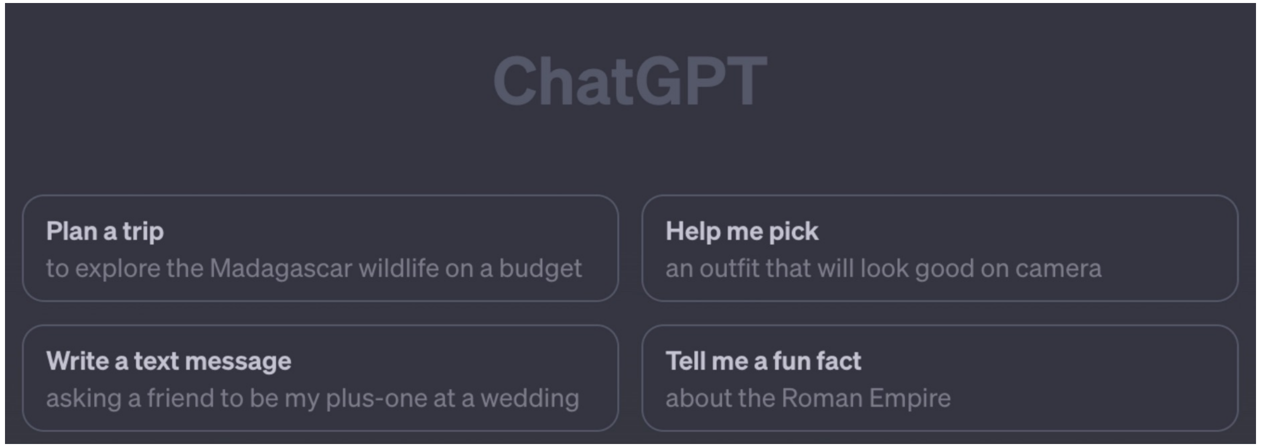
- https://www.youtube.com/watch?v=cqvAgcQl6s4

# Case Studies: Robot Locomotion

- MDP:
  - State: image of robot camera + N joint angles + accelerometer + …
    - Angles are N-dimensional continuous vector!
    - Processed with hand-designed feature vectors or neural networks
  - Action: N motor commands (continuous vector!)
    - Can’t easily compute max $Q(s', a)$ when $a$ is continuous
    - Use policy search methods or adapt Q learning to continuous actions
  - Transition T: real world (don’t have access)
  - Reward R: hand-designed rewards
    - Stay upright, keep forward velocity, etc
- Learning in the real world may be slow and unsafe
  - Build a simulator and learn there first, then deploy in real world

[Extreme Parkour with Legged Robots, Cheng et al, 2023]

# Case Studies: Language Assistants




# Case Studies: Language Assistants

- Step 1: train large language model to mimic human-written text
  - Query: “What is population of Berkeley?”
  - Human-like completion: “This question always fascinated me!”
- Step 2: fine-tune model to generate helpful text
  - Query: “What is population of Berkeley?”
  - Helpful completion: “It is 117,145 as of 2021 census”
- Use Reinforcement Learning in Step 2

# Case Studies: Language Assistants

- MDP:
  - State: sequence of words seen so far (ex. “What is population of Berkeley? ”)
    - $100{,}000^{1{,}000}$ possible states
    - Huge, but can be processed with feature vectors or neural networks
  - Action: next word (ex. “It”, “chair”, “purple”, …) (so 100,000 actions)
    - Hard to compute max $Q(s', a)$ when max is over 100K actions!
  - Transition T: easy, just append action word to state words
    - s: “My name“ a: “is“ s’: “My name is“
  - Reward R: ???
    - Humans rate model completions (ex. “What is population of Berkeley? ”)
      - “It is 117,145“: +1 “It is 5“: -1 “Destroy all humans“: -1
    - Learn a reward model $R$ and use that (model-based RL)
- Often use policy gradient (Proximal Policy Optimization)

# Summary

- Exploration in Q-learning
  - Epsilon greedy; optimistic function
- Scaling up with feature representations and approximation
- Directly optimize the policy
- Some case studies