CPSC 340:
Machine Learning and Data Mining

Introduction to Reinforcement Learning -- Bonus Lecture

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(slides adapted from Daniele Reda)
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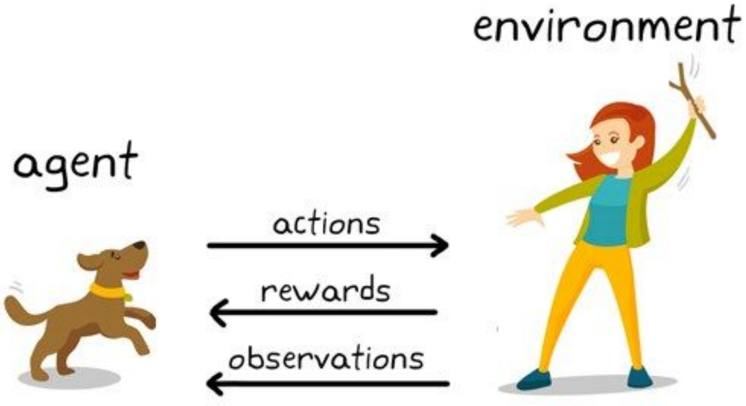
Today's Plan:

- What is RL
- Funny videos
- Q-learning, DQN
- Self-driving car



Law of Effect

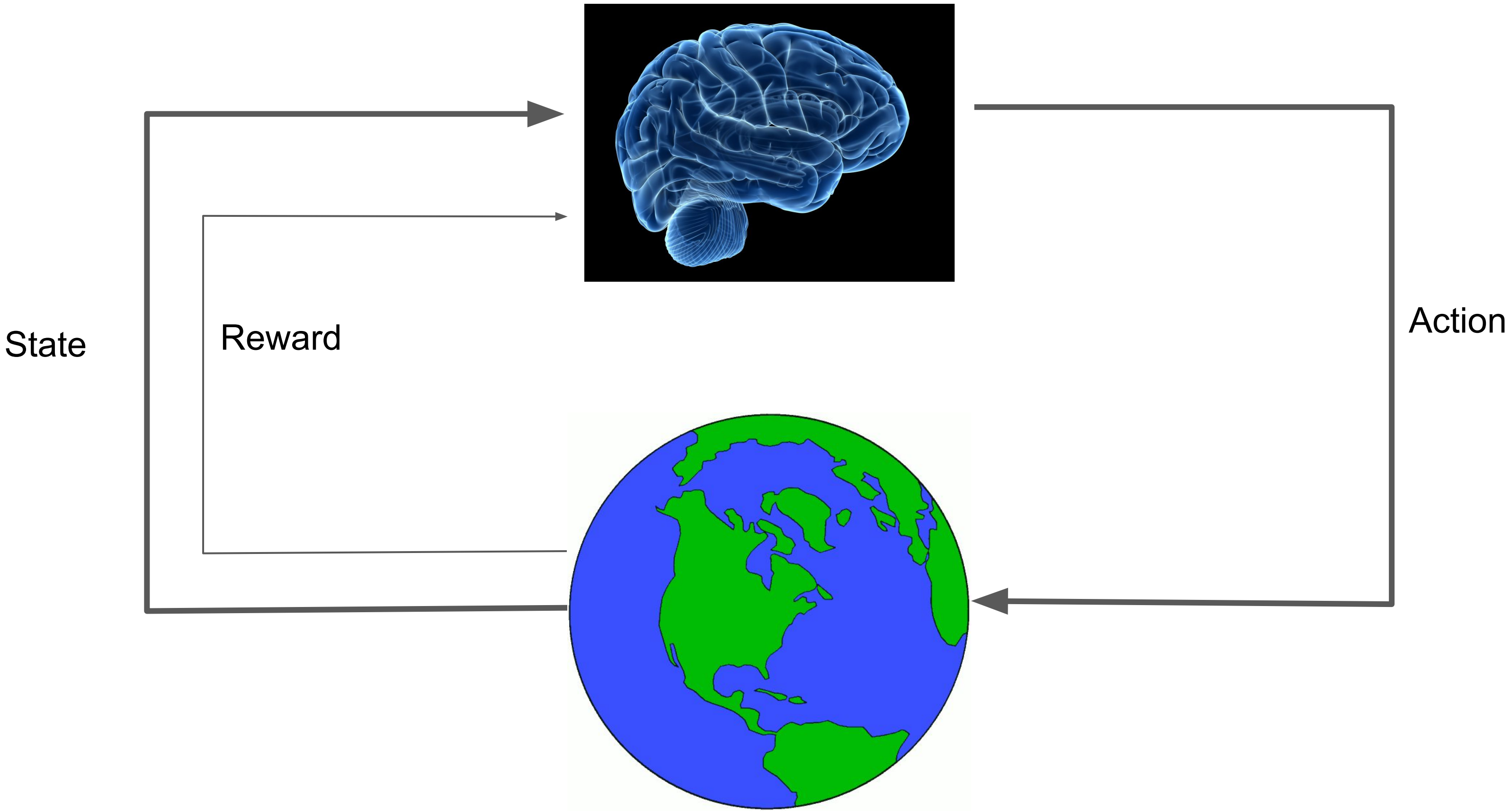
"responses that produce a satisfying effect in a particular situation become more likely to occur again in that situation, and responses that produce a discomforting effect become less likely to occur again in that situation."

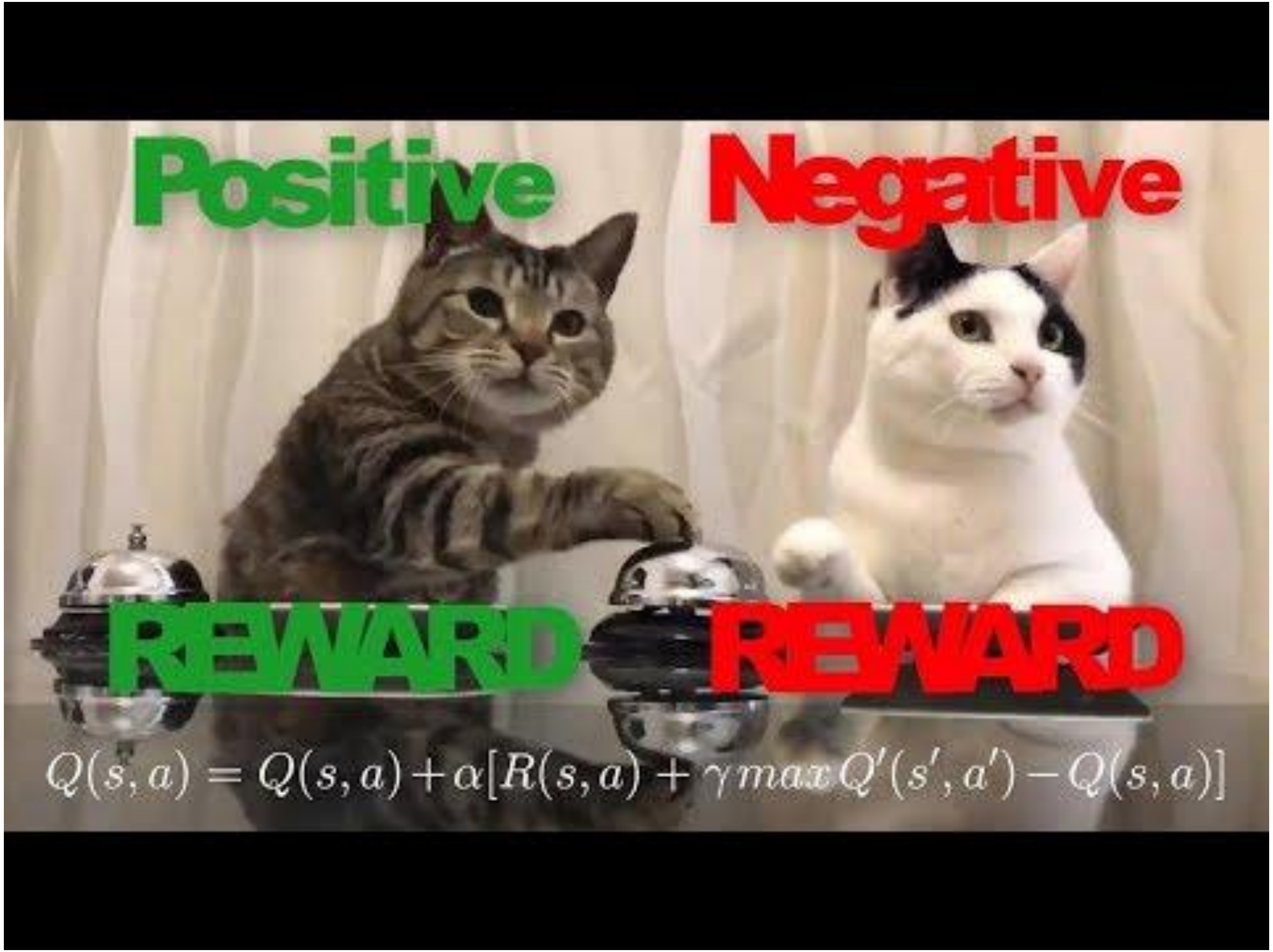
Edward Thorndike

What is Reinforcement Learning?

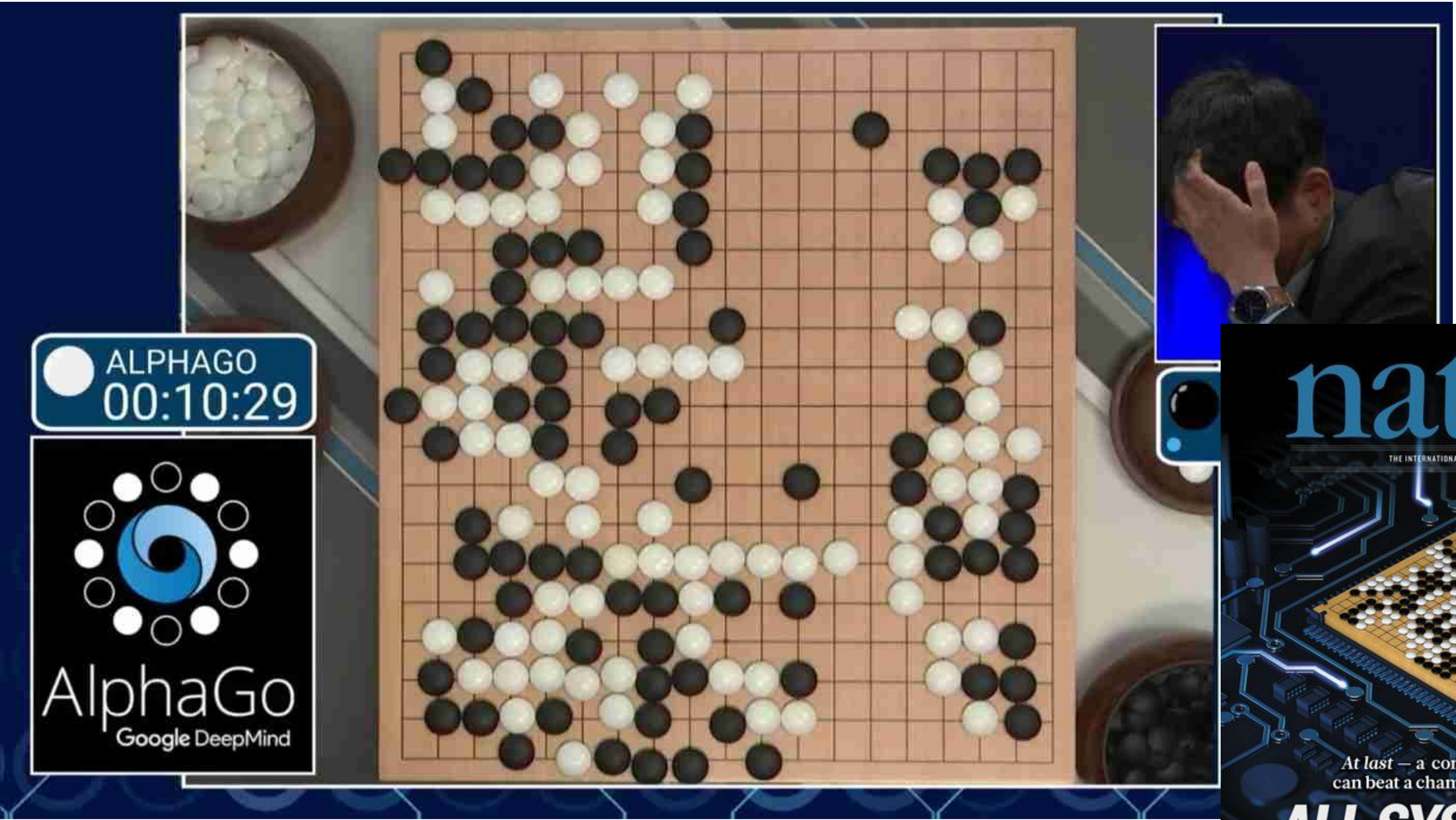
- learning by trial and error
- learning by interacting with environment

Problem Setting




Positive
Negative
REWARD
REWARD
$Q(s,a) = Q(s,a) + \alpha[R(s,a) + \gamma max Q'(s',a') - Q(s,a)]$

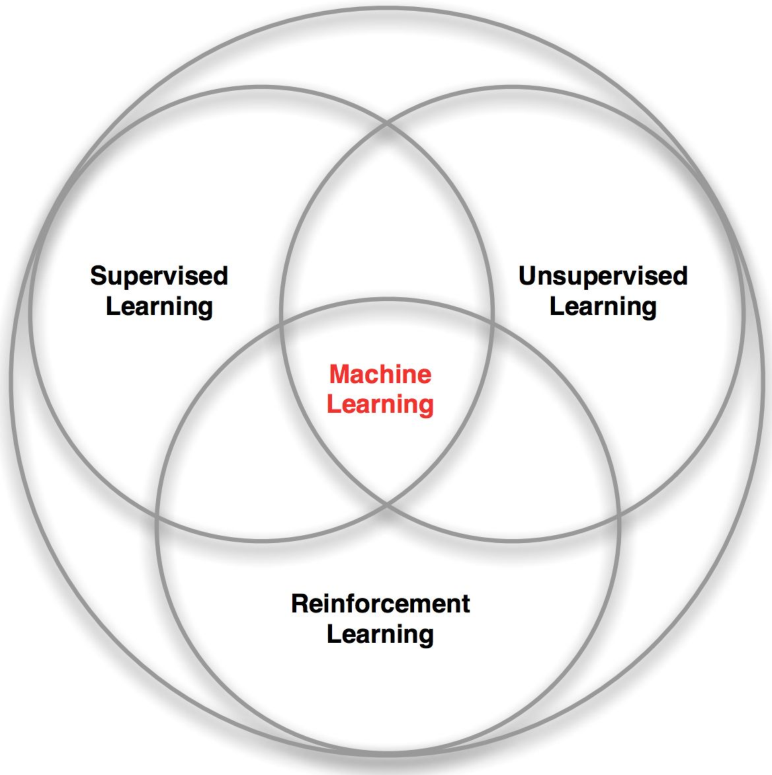
Alpha Go



Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search."

Alpha Go

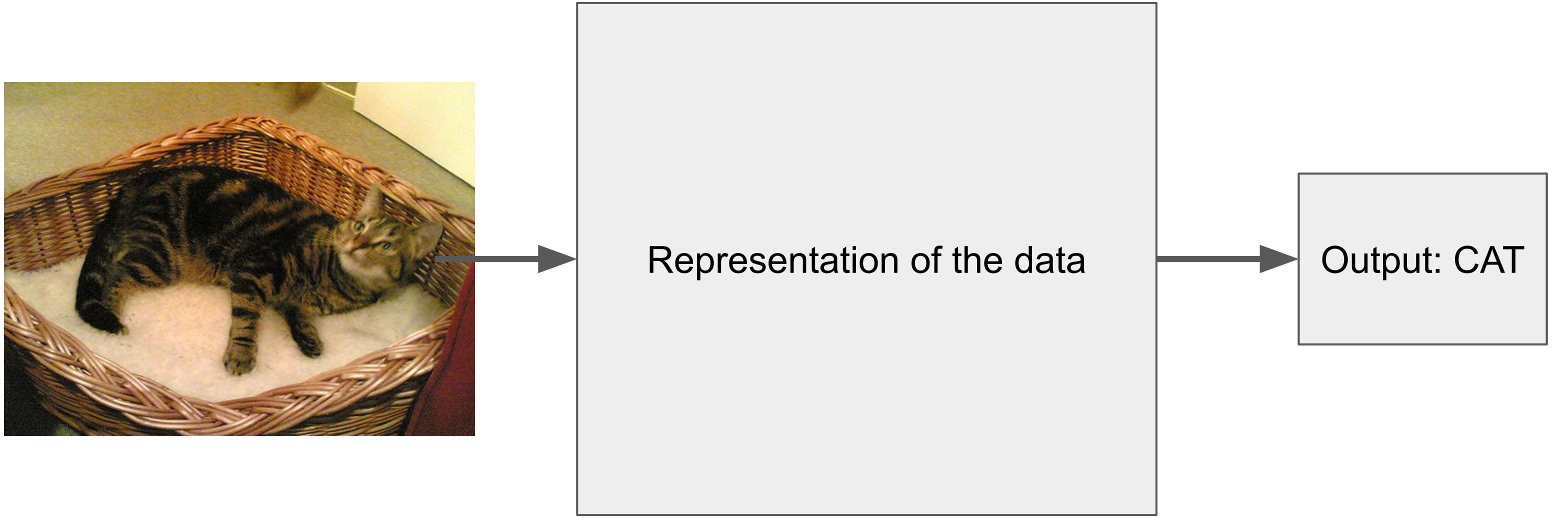
Branches of Machine Learning



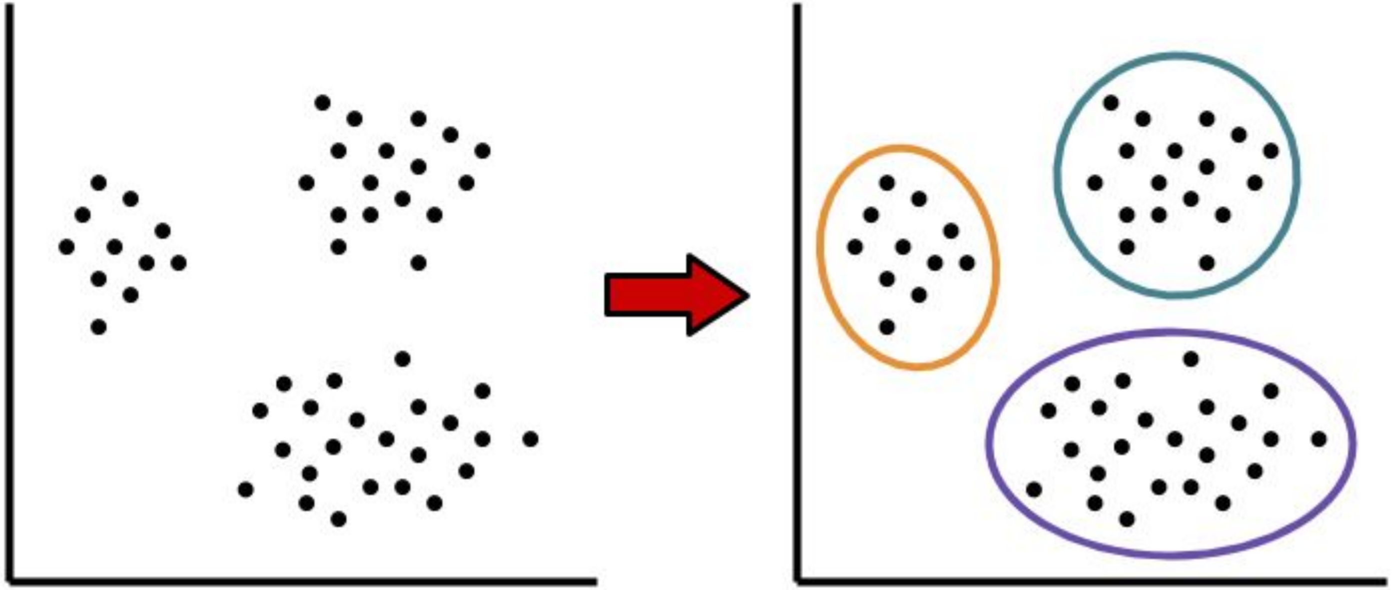
Supervised Learning

Data	Label
X1	Y1
X2	Y2
X3	Y3
...	...

Supervised Learning



Unsupervised Learning

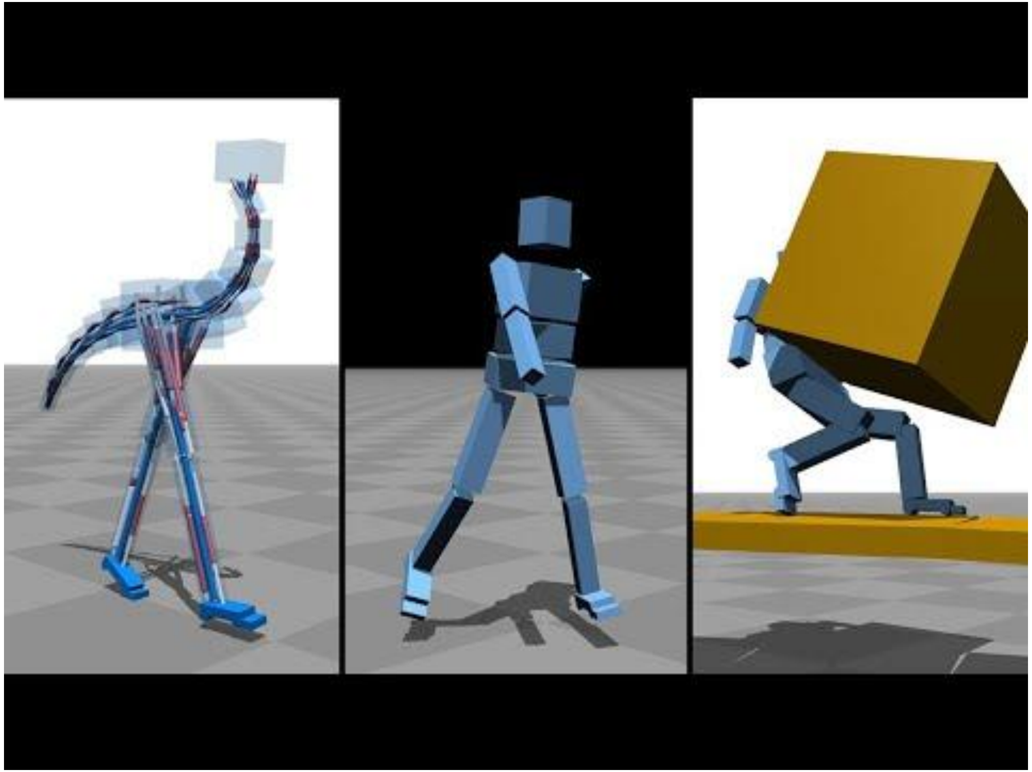


Characteristics

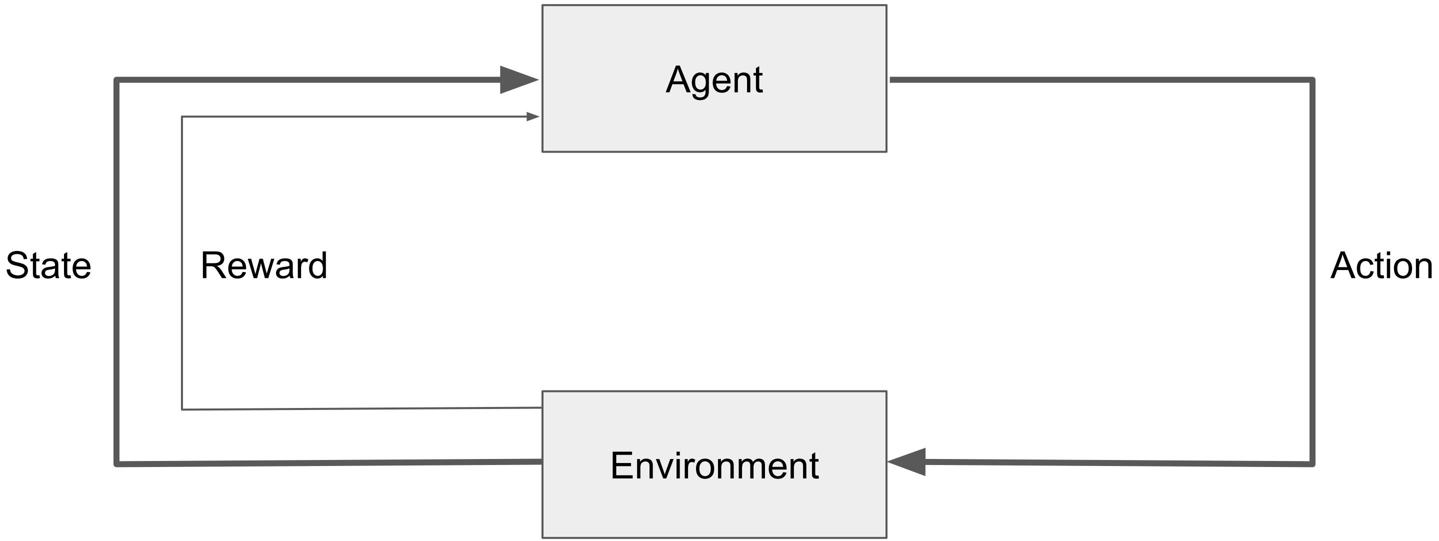
- no supervisor, only a reward signal
- feedback is delayed, not instantaneous
- process is iterative (time matters)
- agent’s actions affect subsequent data it receives

Flipping pancakes

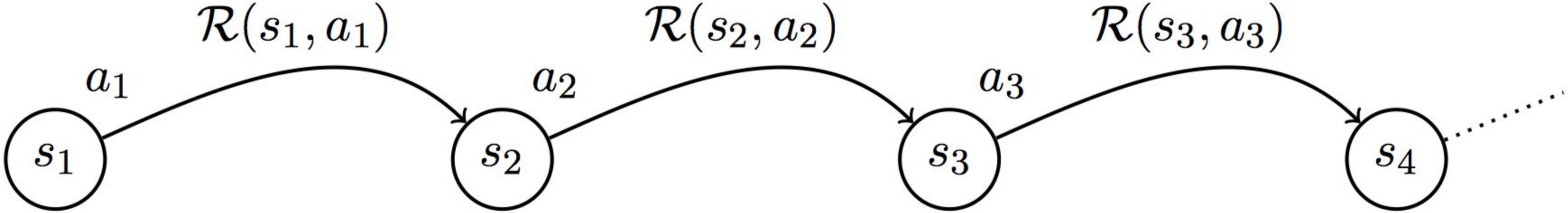
Walking simulation



Problem Setting



Representation of the system



Goal

- maximize total reward

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots + \gamma^{T-t-1} r_T$$

- T to infinity
- Why discount factor?
    - convergence
    - sooner rewards are usually more useful than later ones

Value Function

$$V^\star(S) = max_a \left[R(s,a) + \gamma \sum_{s'} p(s'|s,a) V^\star(s')\right]$$

- Tells you what is the best value you could get out of the current state
- But not which action to take

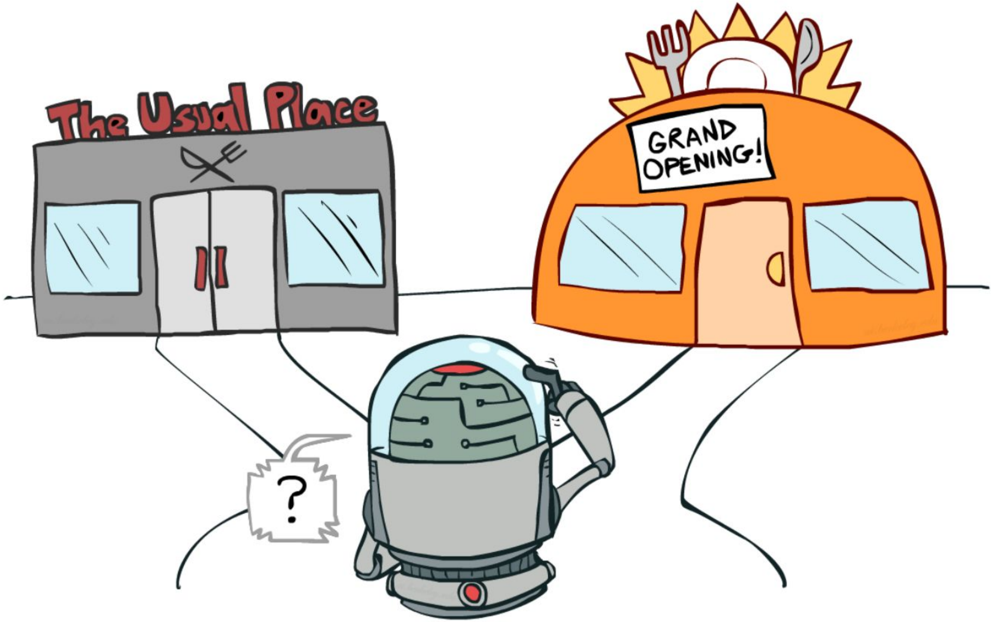
Q-Value Function

$$Q^{\star}(s, a) = R(s, a) + \gamma \sum\nolimits_{s'} p(s' \mid s, a) \max_{\alpha} \left(Q^{\star}(s', \alpha)\right)$$

A very simple algorithm: Q-learning

		Actions					
		0	1	2	3	4	5
States	0	-1	-1	-1	-1	0	-1
	1	-1	-1	-1	0	1	100
	2	-1	-1	-1	0	-1	-1
	3	-1	0	0	-1	0	-1
	4	0	-1	-1	0	-1	100
	5	-1	0	-1	-1	0	100

Exploration vs Exploitation



One strategy: ε-greedy

Q-learning

Initialize Q-table with random values.

1. Choose action a to perform in current state s. (ε-greedy)
2. Perform a and receive reward R(s,a).
3. Observe new state S(s,a).
4. Update Q-table.

$$Q'(s,a) \leftarrow \mathcal{R}(s,a) + \gamma \max_{\alpha} \left\{ Q'(\mathcal{S}(s,a),\alpha) \right\}$$

PROBLEM:
TABLE CAN EASILY EXPLODE IN DIMENSIONS

Let’s look at an example: ATARI

State (the actual image)
84x84x4 pixels (gray-scale)

2 Actions
Left-Right

Mnih, Volodymyr, et al. "Playing atari with deep reinforcement learning.

Could we use a q-table?

Atari Breakout example:

State = raw pixels of last 4 frames (84x84) with 256 different possible values.

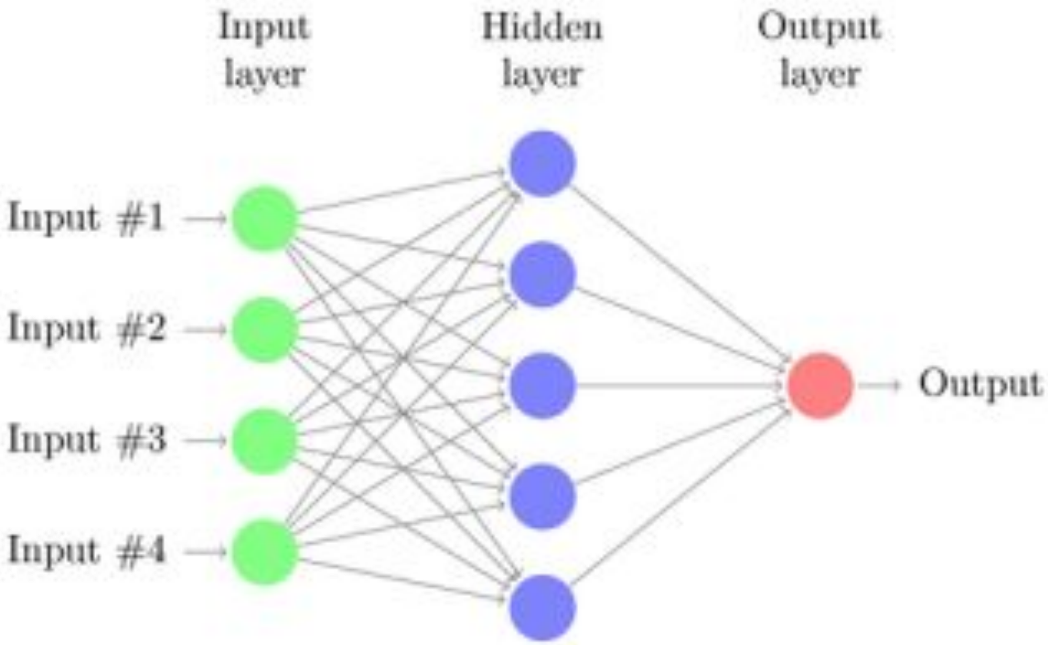
Actions = 2 actions available

(4x84x84x256)x2 = 14,450,688 different values

Solution

Neural networks!

Neural Networks



Neural Networks

$$loss = \Big(\underbrace{\overset{\text{Reward}}{\mathrm{r}} + \overset{\text{Decay Rate}}{\gamma} \max_{a`} \hat{Q}(s, a`)}_{\text{Target}} - \underbrace{Q(s, a)}_{\text{Prediction}} \Big)^2$$

$$Q'(s, a) \leftarrow \mathcal{R}(s, a) + \gamma \max_{\alpha} \left\{ Q'\left(\mathcal{S}(s, a), \alpha\right) \right\}$$

DQN Framework

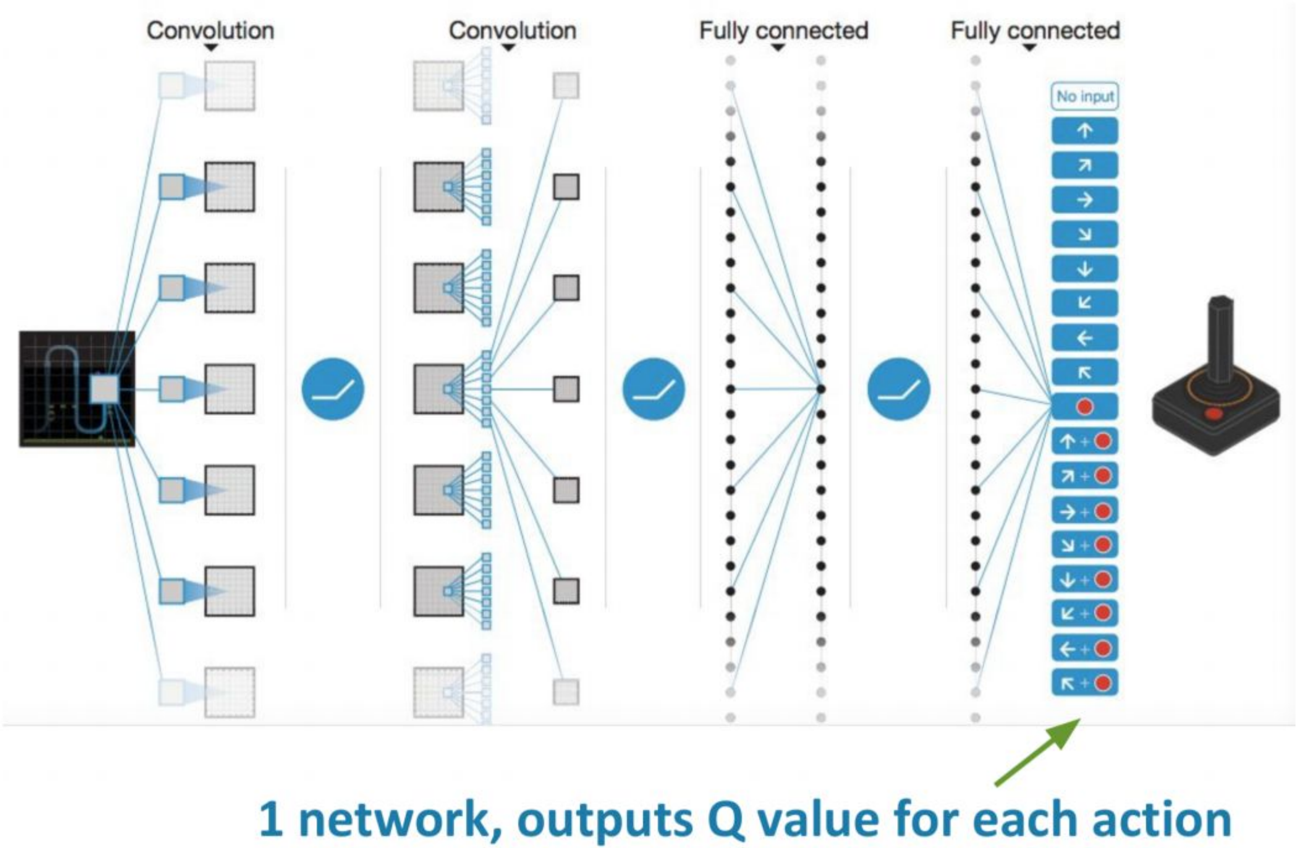


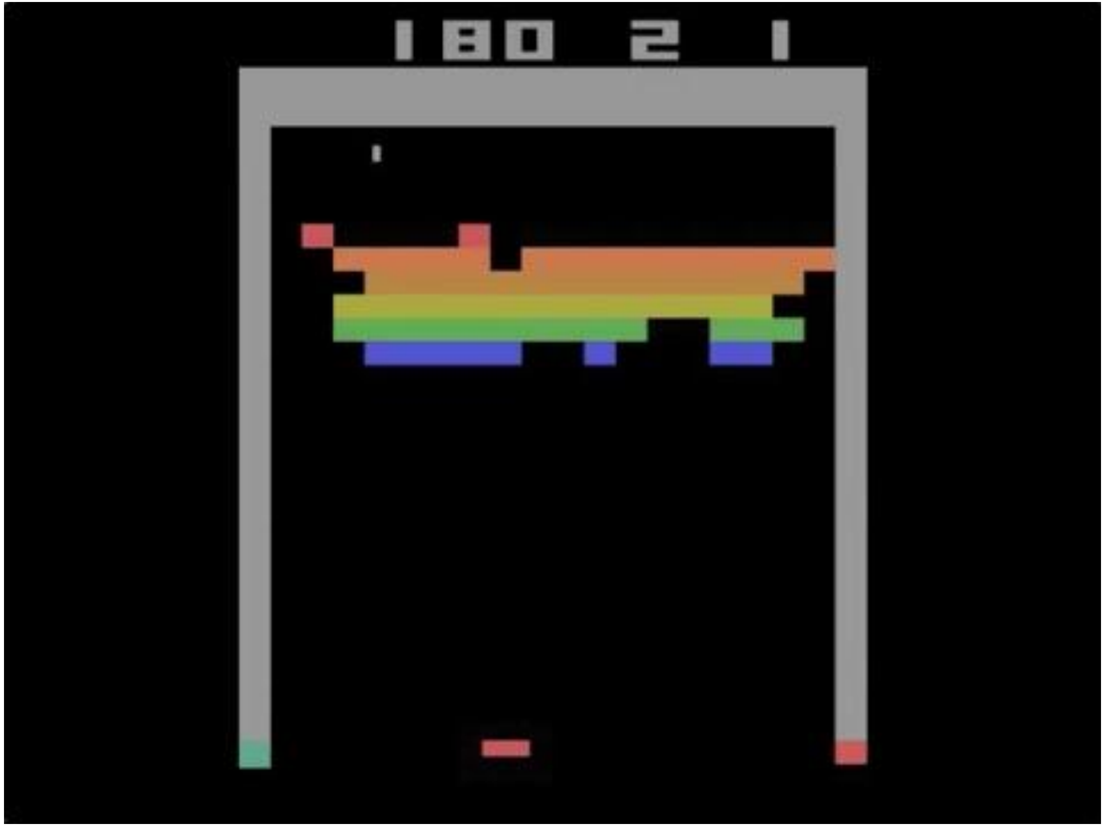
Image from Emma Brunskill's RL course CS234, Stanford

DQN Framework

Algorithm 1: DQN Pesudocode

Randomly initialize neural network NN
Get initial state s_0
$t = 0$
while *1* **do**
    `// ϵ-greedy strategy`
    r = get random value from $(0, 1)$
    if $r > \epsilon$ **then**
        $a_t = NN(s_0)$
    else
        a_t = random action between the ones available
    end
    $s_{t+1}, r_t, done = environment(a_t)$
    if $done = True$ **then**
        $y = r_t$
    else
        $y = r + \gamma * \max_{a^i} NN(s_{t+1}$
    end
    Do gradient descent on $y - NN(s_t, a_t)$ to update weights of NN
    $t = t + 1$
end

Famous successes of RL: Atari Breakout



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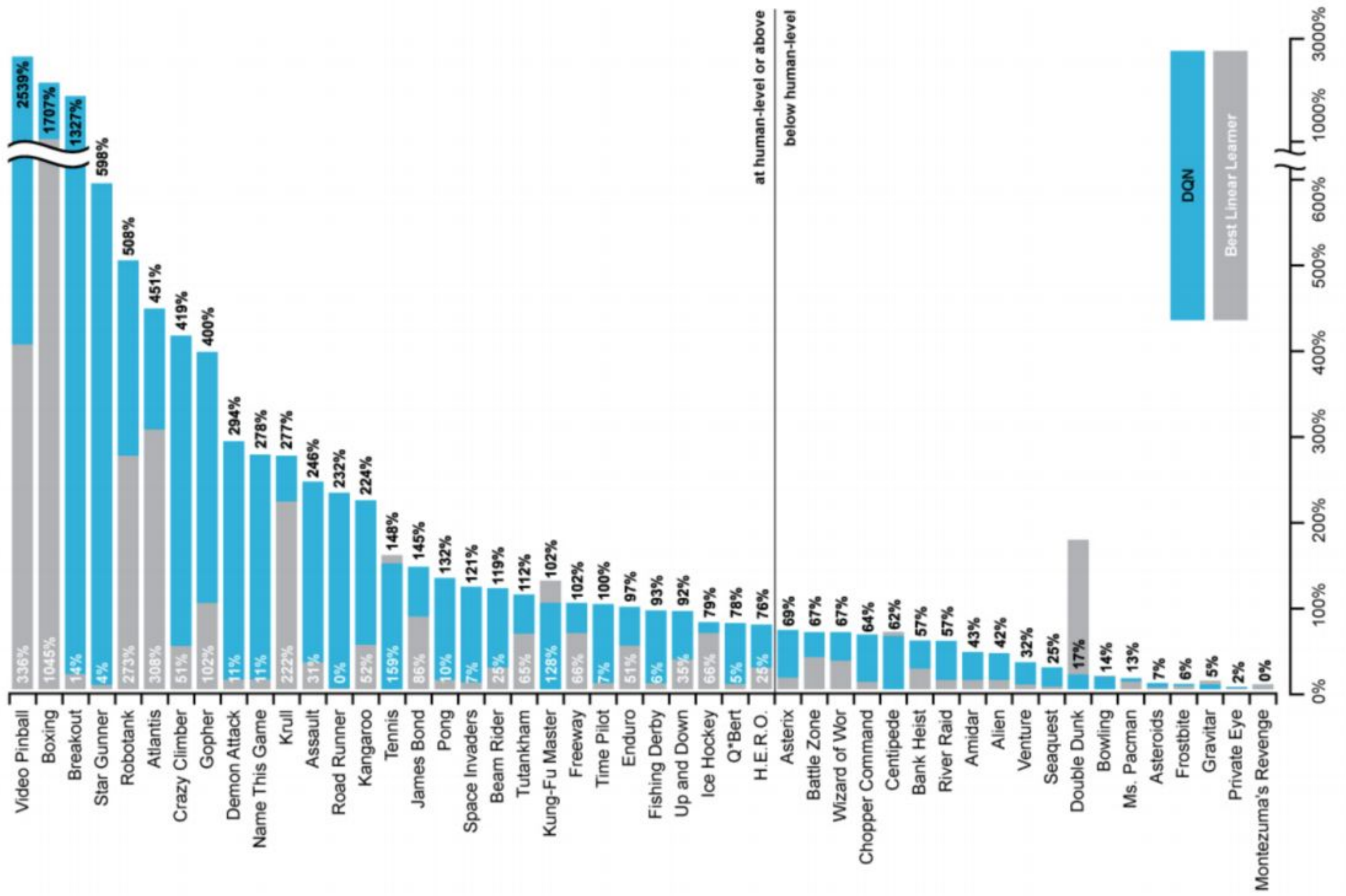
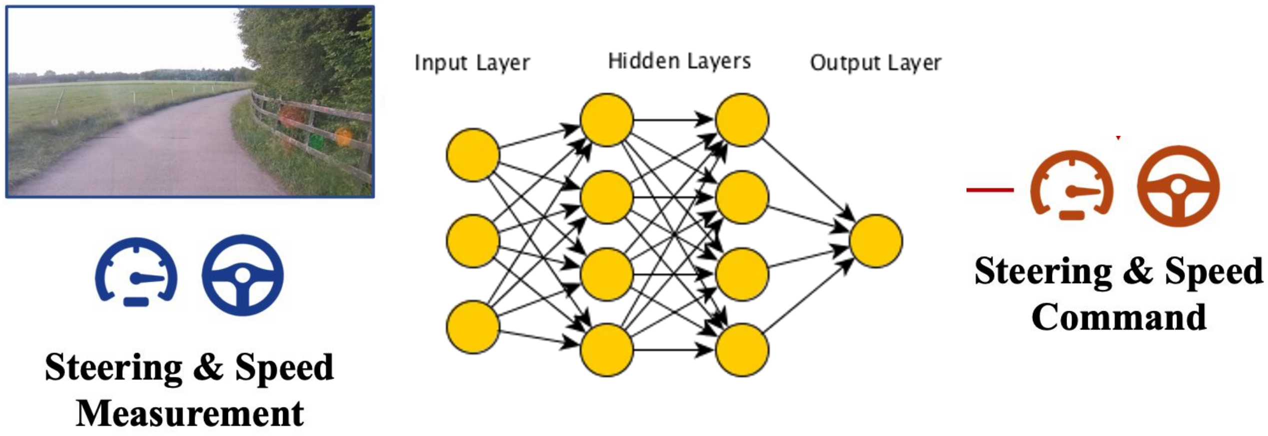


Image from Emma Brunskill’s RL course CS234, Stanford

A real world example:
Learning to drive with Reinforcement Learning

Kendall, Alex, et al. "Learning to drive in a day."

Learning to drive with RL



Reward: forward distance

Terminate when it goes out of the lane

Kendall, Alex, et al. "Learning to drive in a day."

Kendall, Alex, et al. "Learning to drive in a day."

Where to go from here?

- openAI Spinning Up RL
- Sutton book
- David Silver UCL Course