very

Short tutorial on deep reinforcement learning

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What is deep reinforcement learning?

Given an

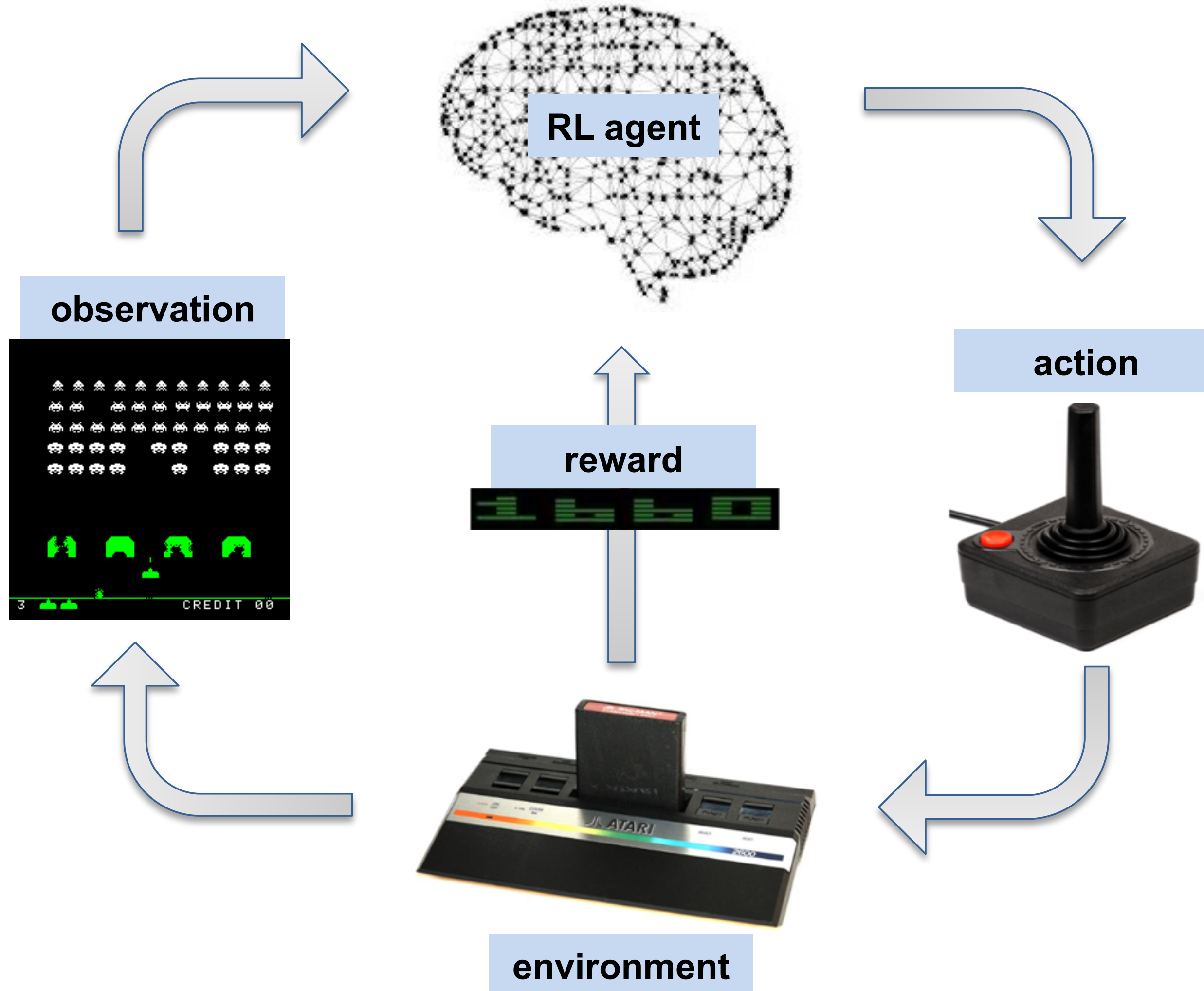
observation

choose the

action

expected to maximize the cumulative

reward



What can you do with DRL?

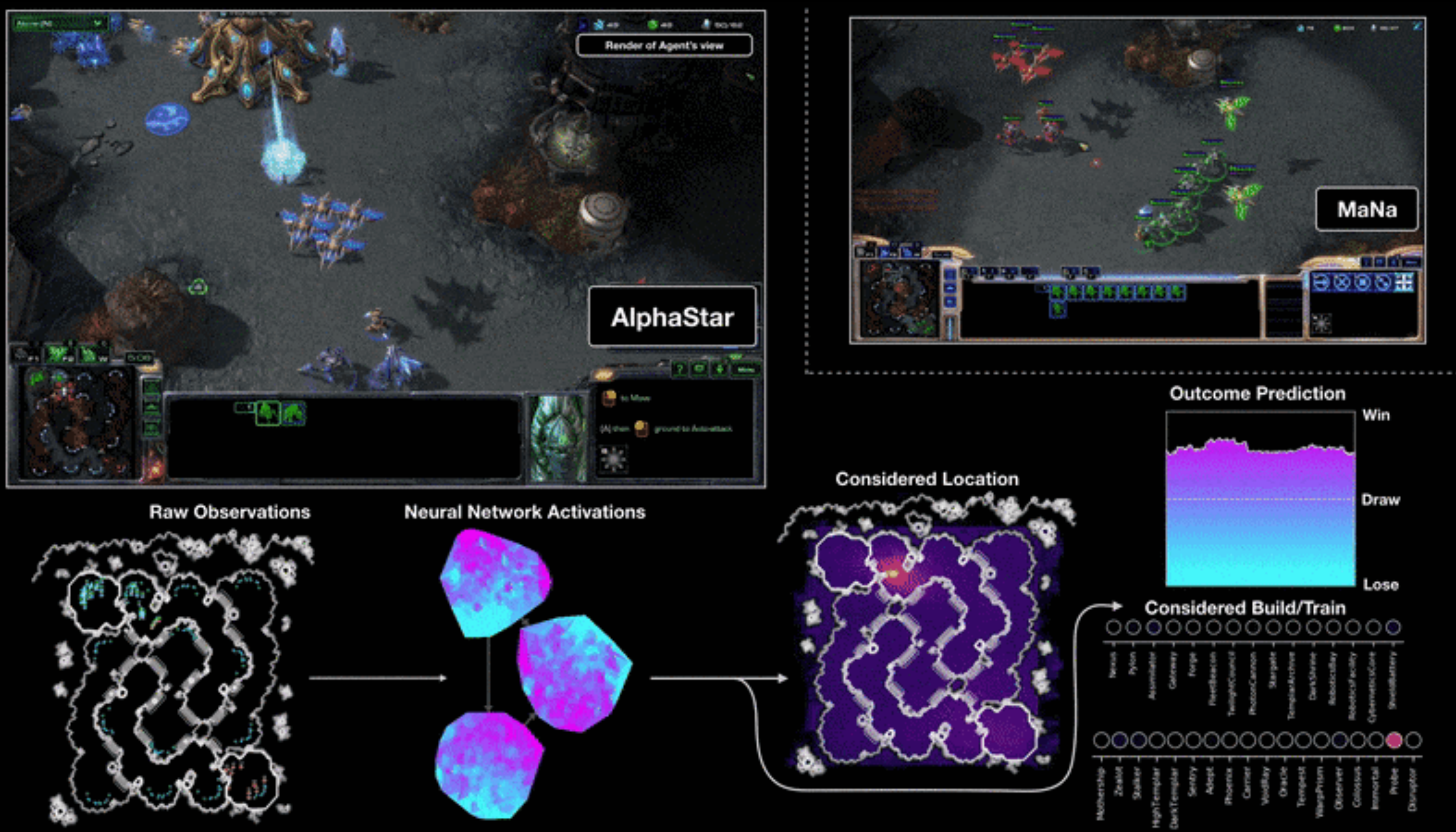
- Play video games better than a human

Observations
Pixels

Actions
{9 directions} x {Fire}

Reward
Game score


GET READY
STAGE 1
COLLECT 50 COOL POINTS!
HIGH SCORE
Day 1
TERRAPORT
5:00



Render of Agent's view
AlphaStar
MaNa
Outcome Prediction
Win
Draw
Lose
Considered Location
Raw Observations
Neural Network Activations
Considered Build/Train

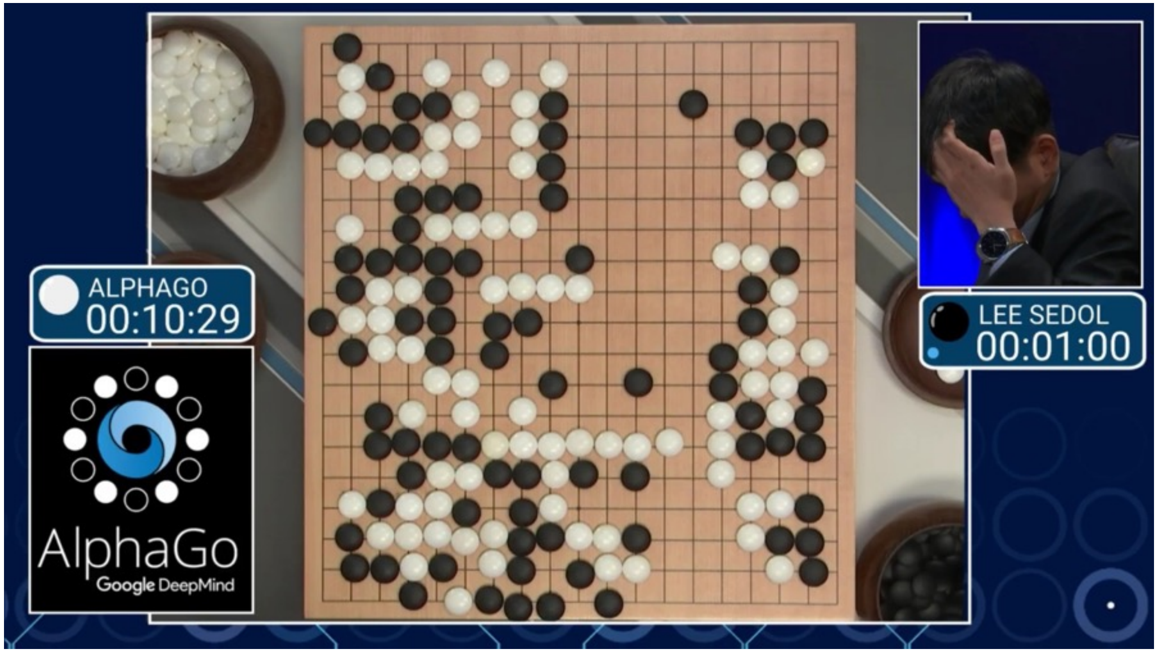
What can you do with DRL?

- Play board games better than a human

Observations
{19 x 19 grid} x
{B, W, Empty}

Actions
{19 x 19 grid}

Reward
1 (win)
0 (otherwise)



What can you do with DRL?

dance??

~~skip~~

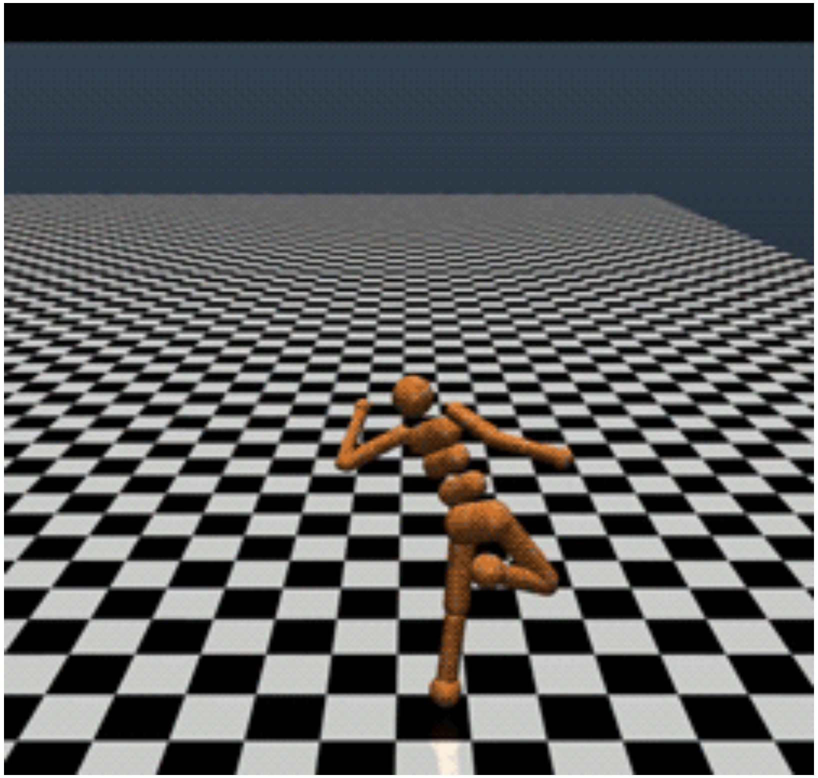
~~hop~~

- Teach a simulated robot how to ~~walk~~

Observations
Joint positions, angles, and velocities

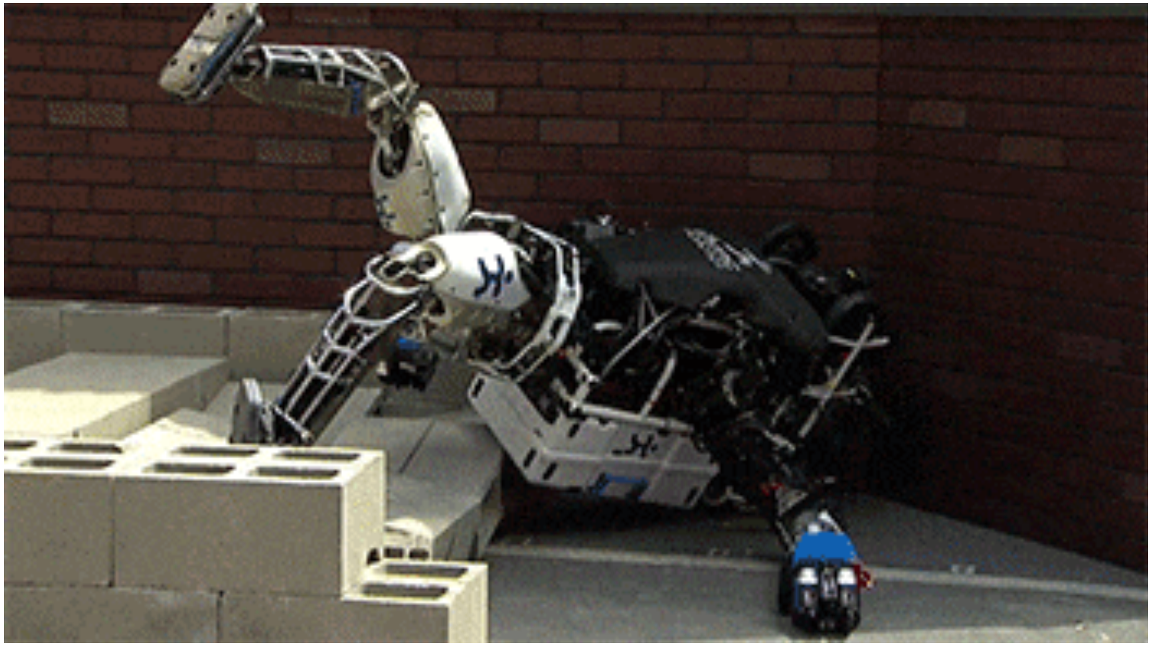
Actions
Joint torques

Reward
Distance travelled



What can you do with DRL?

- Teach a real robot how to walk
  - or perhaps not…



Formulating an RL problem

- An RL problem is formulated as a Markov decision process (MDP)

$$(\mathcal{S}, \mathcal{A}, \mathcal{E}, r, \gamma)$$

Observation space

Action space

State transition function or *environment*:
$\mathcal{E} = P_a(s, s') = \Pr(s'|s, a)$
This is often **unknown**.

Scalar reward signal
$r(s, a, s') \in \mathbb{R}$

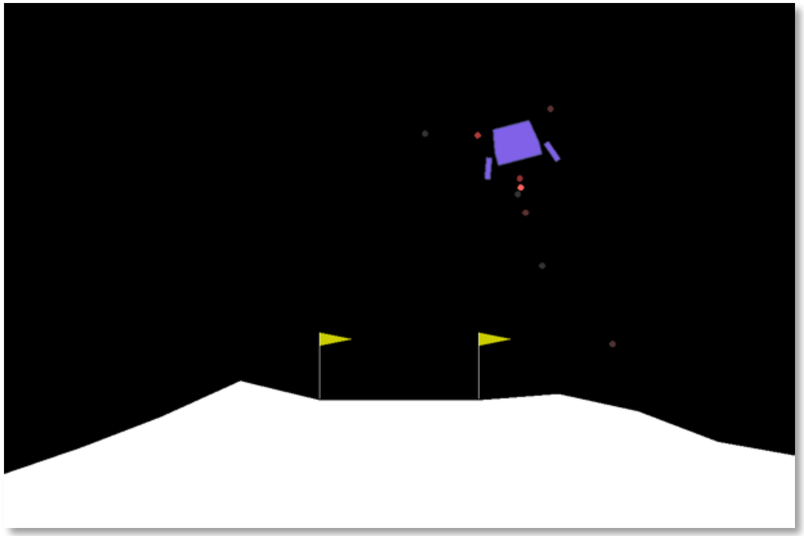
Discount factor
$\gamma \in (0,1]$

- MDPs satisfy the Markov property:

$$\Pr(s_{t+1}|s_0, a_0, s_1, a_1, \ldots, s_t, a_t) = \Pr(s_{t+1}|s_t, a_t)$$

Demo – LunarLander

- Goal: Get to the landing pad without crashing
- Observation space:
  - x, y coordinate
  - x, y velocity
  - Angle w.r.t. horizontal
  - Angular velocity
  - Left/right ground contact
- Action space:
  - Main thrusters (up): [0, 1]
  - Side thrusters (left/right): [-1, 1]
- Reward:
  - +100 for landing safely
  - –100 for crashing
  - Small penalty for fuel consumed
  - Bonus/penalty for moving closer to/further from goal



Key concepts & terminology

- The **return** is the cumulative discounted reward

$$R = \sum_{t=0}^{T} \gamma^t r_t$$

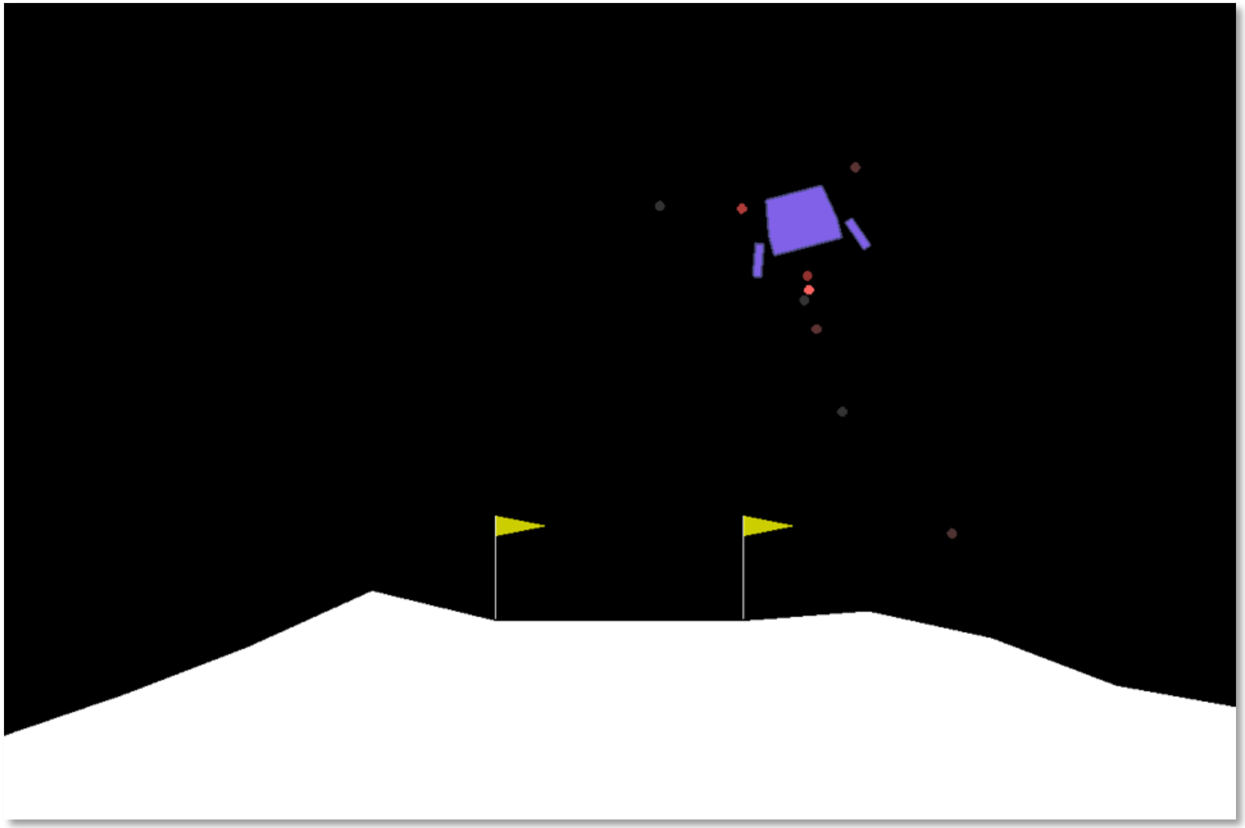
- A **policy** defines a mapping from state to action

$$\pi : \mathcal{S} \mapsto \mathcal{A}$$

- A **value function** estimates “how good it is” to be in a certain state

$$V_\pi(s) = \mathbb{E}\left[R | s, \pi\right]$$
$$Q_\pi(s, a) = \mathbb{E}\left[R | s, a, \pi\right]$$

How’s our LunarLander doing?



How do you learn an optimal policy?

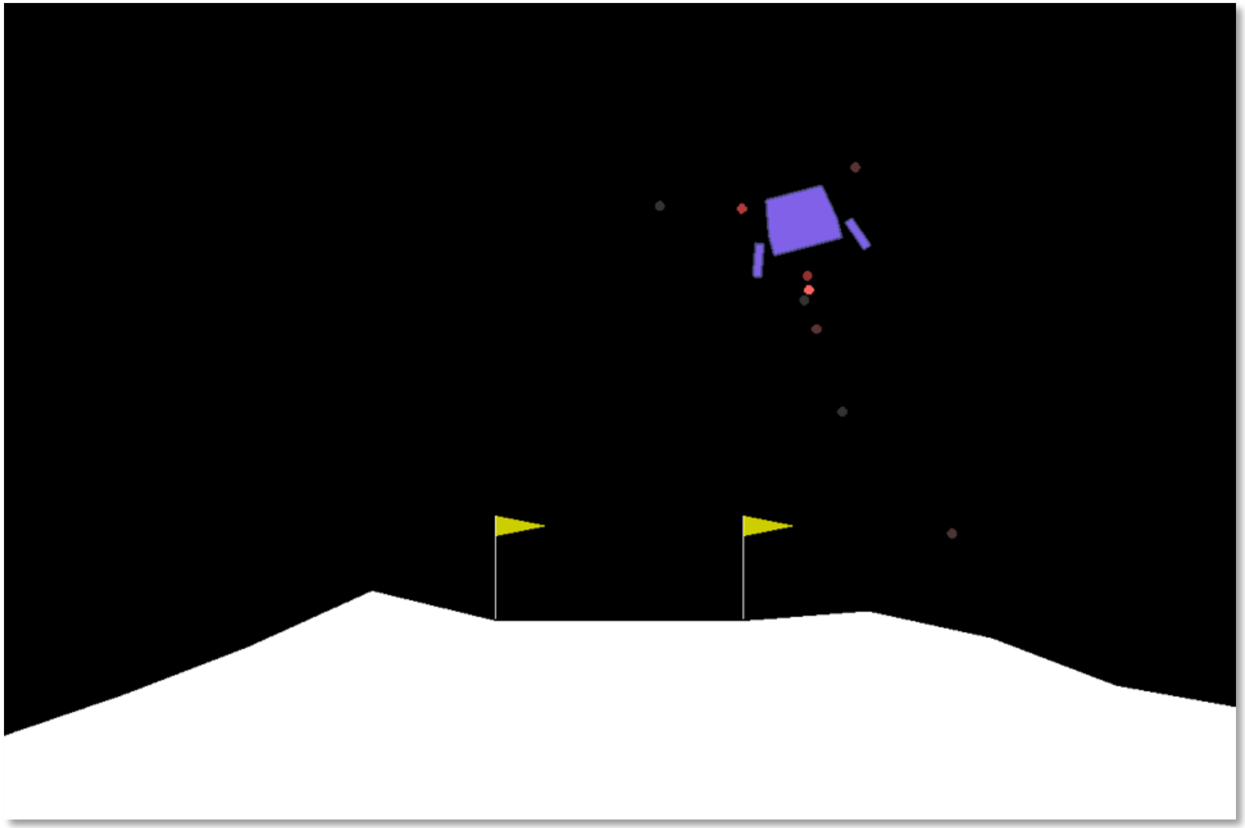
- If you can estimate the *Q* value, the optimal policy is to select the action with the largest *Q* value

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

- We can **learn** a value function by iteratively updating our current estimate based on the reward we received

$$\Delta Q \sim \underbrace{Q(s,a)}_{\text{what you thought you'd get}} - \underbrace{\left(r + \gamma \max_a Q(s',a)\right)}_{\text{what you got}}$$

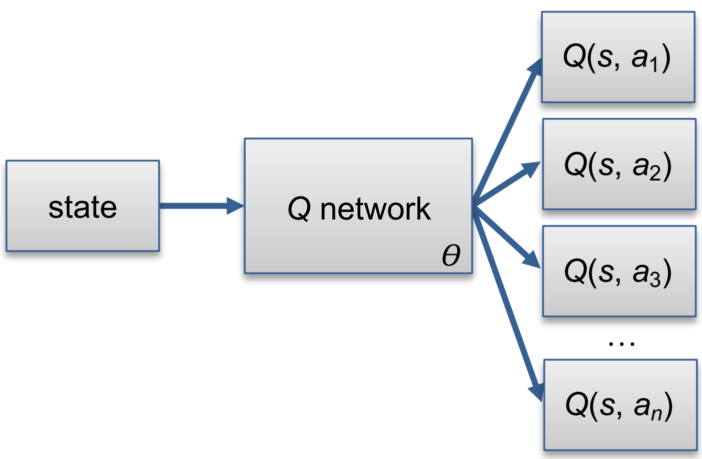
Are we landing yet??



From tabular to deep RL

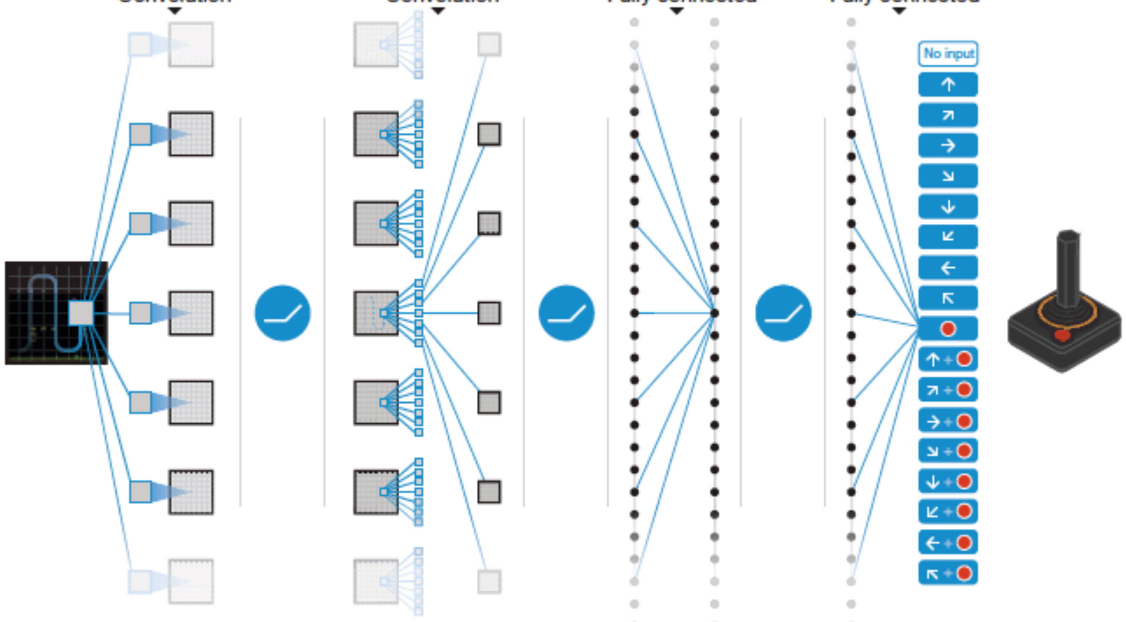
- Tabular (traditional) RL:
  - Learn the Q value separately for every state-action combination
  - Requires **discrete** states
  - Requires **discrete** actions
- Deep RL:
  - Learn a *function* that maps states to Q values
  - Works for **continuous** states
  - Requires **discrete** actions

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	…	a_m
s_1	1.21	2.23	1.42	2.42	5.32	3.14	6.37		1.30
s_2	4.56	3.33	1.43	3.16	2.67	2.53	2.22		3.16
s_3	4.46	5.66	2.16	3.45	2.53	6.35	2.64		3.56
s_4	4.77	3.16	7.77	3.54	9.01	6.46	3.26		4.26
…								⋱	
s_n	8.11	2.22	8.00	7.64	7.66	5.66	5.44		9.03



Playing Atari with DRL: Problem setup

- States = sequence of 4 images
- 18 possible actions
- *Q* function network architecture:



Space Invaders

Breakout

Frostbite

Playing Atari with DRL: Algorithm

Algorithm 1 Deep Q Networks (DQN)

Initialize replay buffer $\mathcal{D}$
Initialize Q network with random weights
for episode $= 1, M$ **do**
    for $t = 1, T$ **do**
        With probability ϵ select random action...
        ...otherwise select $a = \max_a Q(s, a; \theta)$
        Execute action a in environment; receive s', r
        Store transition (s, a, s', r) in $\mathcal{D}$
        Sample minibatch from $\mathcal{D}$
        Perform gradient step: $\nabla_\theta \frac{1}{2} \left[Q(s, a; \theta) - (r + \gamma \max_a Q(s', a; \theta))\right]^2$

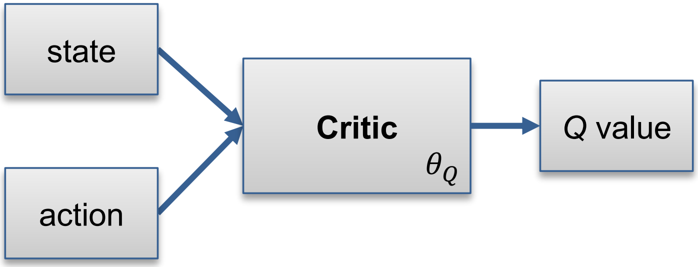
Tabular:

$$\Delta Q \sim Q(s, a) - \Big(r + \gamma \max_a Q(s', a)\Big)$$

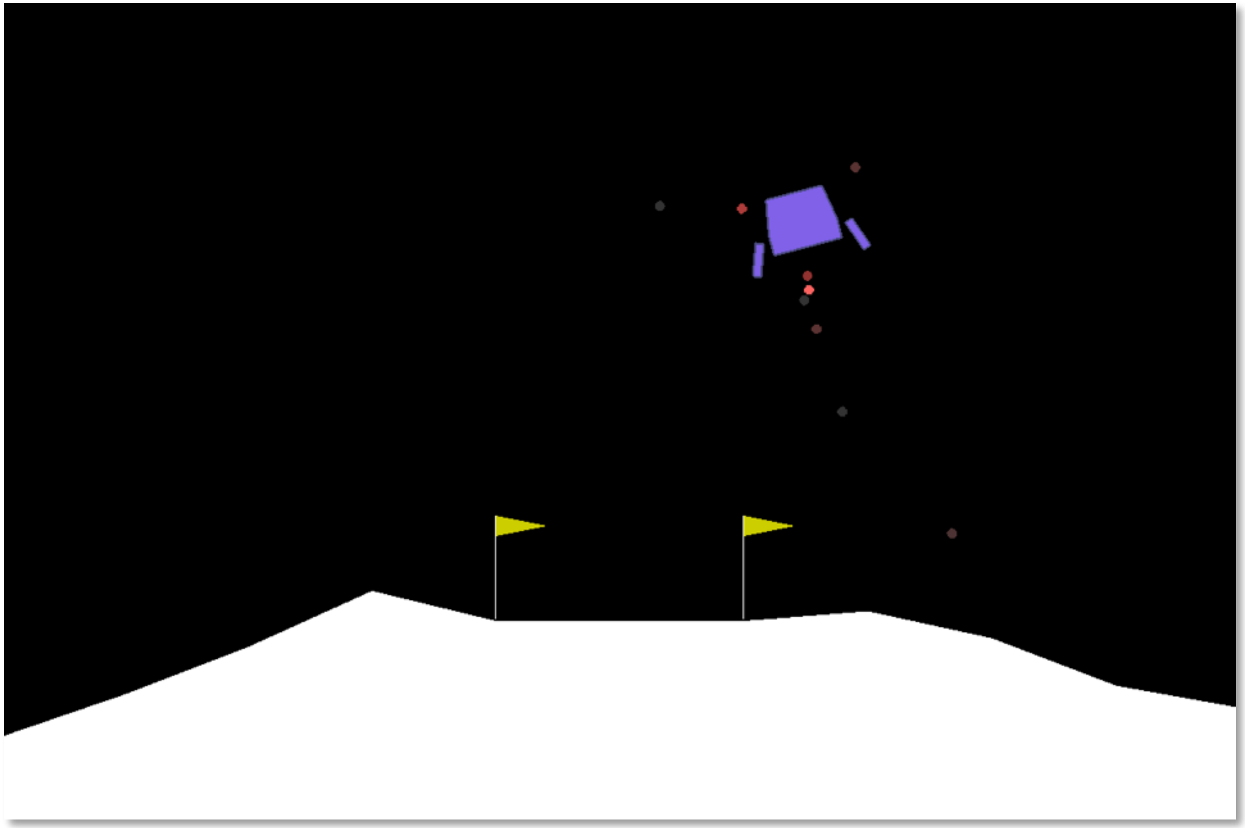
What about continuous action spaces?

- One network selects an action
  - Policy network or “actor”
  - Updated using the *policy gradient theorem*

- Another network evaluates the action
  - *Q* network or “critic”
  - Updated the same way as DQN

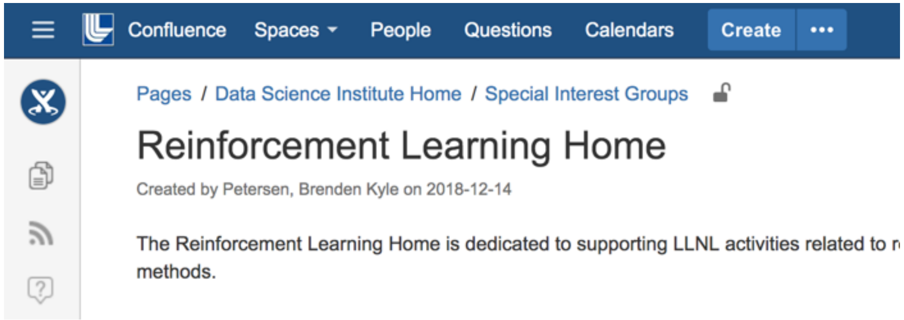


Have we converged?



Want to learn more?

- LLNL Reinforcement Learning reading group
  - Wednesdays 2 – 3
  - B170 or B155



- OpenAI Spinning Up
  - Web-based "fast-track to DRL" tutorial
  - spinningup.openai.com

- Sutton & Barto
  - Free online PDF of textbook