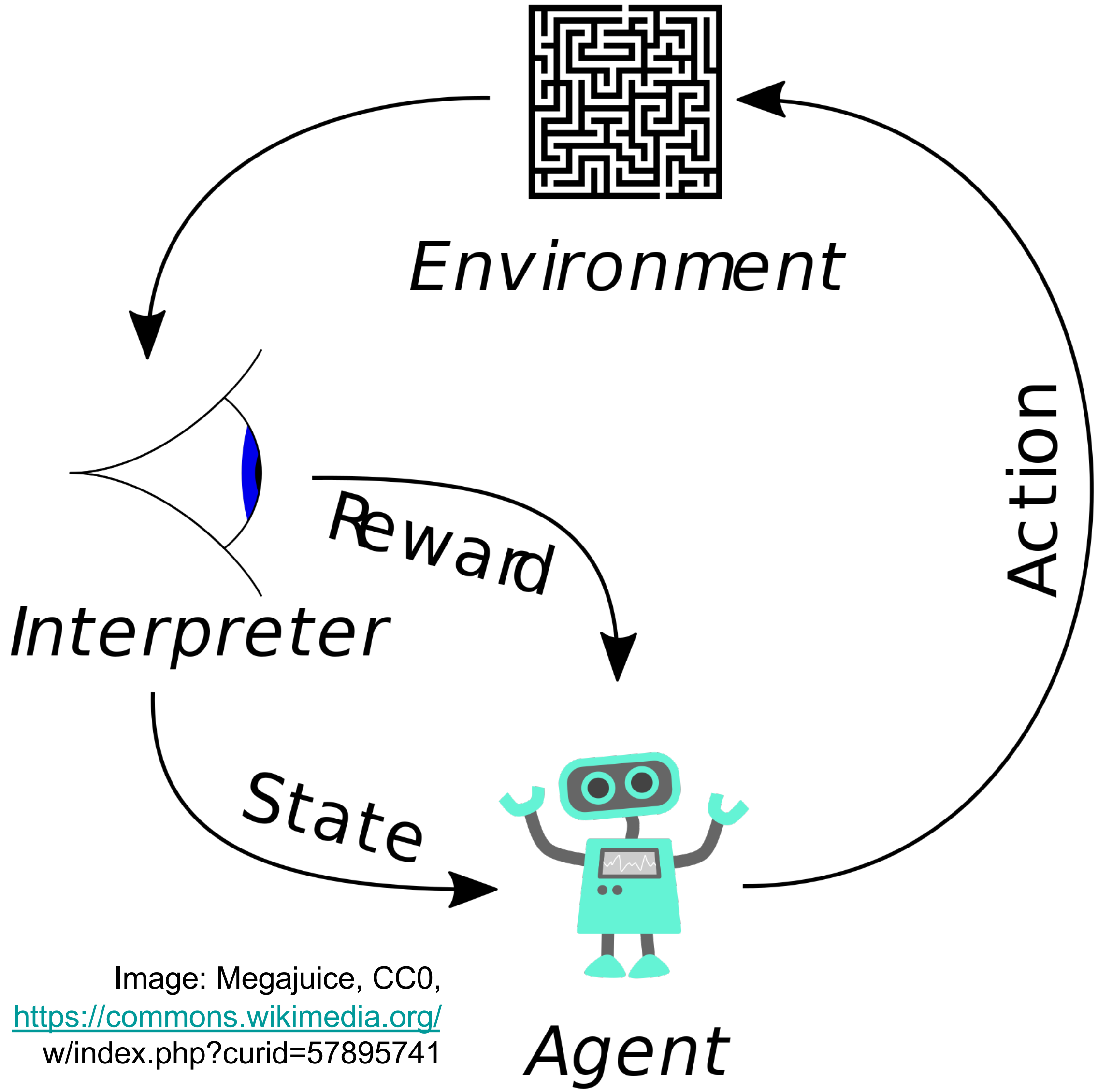
# Deep Reinforcement Learning

# CS440/ECE448 Lecture 35

Mark Hasegawa-Johnson, 4/2022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# Review: Reinforcement Learning

- Markov Decision Process (MDP): Given P(s'|s,a) and R(s), you can solve for $\pi^*(s)$, the optimal policy, by finding U(s), the value of each state, using either value iteration or policy iteration.
- Model-Based Reinforcement Learning: If P(s'|s,a) and R(s) are unknown, you can find for $\pi(s)$ by using the observation-model-policy loop.
- Model-Free Reinforcement Learning: Instead of learning P(s'|s,a) and then calculating $\pi(s)$, we can directly find the optimum action by learning Q(s,a).

# Outline

- Imitation learning: learn the optimal policy by imitating a human
- Deep Q learning: compute Q(s,a) using a neural network

# Policy Learning

Why can’t we just learn a model (neural net, or even a table lookup) that does this:

$$s \longrightarrow \boxed{\text{Model}} \longrightarrow a = \pi(s)$$

# Probabilistic Policy

If we have $|A|$ possible, actions, $1 \leq a \leq |A|$, we could train the network to learn a hidden layer $h(s)$ so that:

$$\pi_a(s) = \frac{\exp(w_a^T h(s))}{\sum_{k=1}^{|A|} \exp(w_k^T h(s))} = P(A = a | S = s)$$

Meaning "the probability that the best action is a."

# How do we train it?

- Training data only give us $(s_i, a_i, s_i', R_i)$.
- BAD IDEA: train the network to choose $\mathrm{A} = a_i$ that maximizes the immediate reward, $R_i$, and just ignore future rewards.
- GOOD IDEA: Train the network to maximize $U(s_i') =$ sum of all future rewards.
- PROBLEM: we don't know $U(s_i')$.

$$(s_1, a_1, s_1', R_1)$$
$$(s_2, a_2, s_2', R_2)$$
$$(s_3, a_3, s_3', R_3)$$
$$(s_4, a_4, s_4', R_4)$$
$$(s_5, a_5, s_5', R_5)$$
$$\vdots$$

# How to make Policy Learning trainable

1. Actor-Critic RL. We’ll come back to this next time.
2. Imitation learning.

# Imitation learning

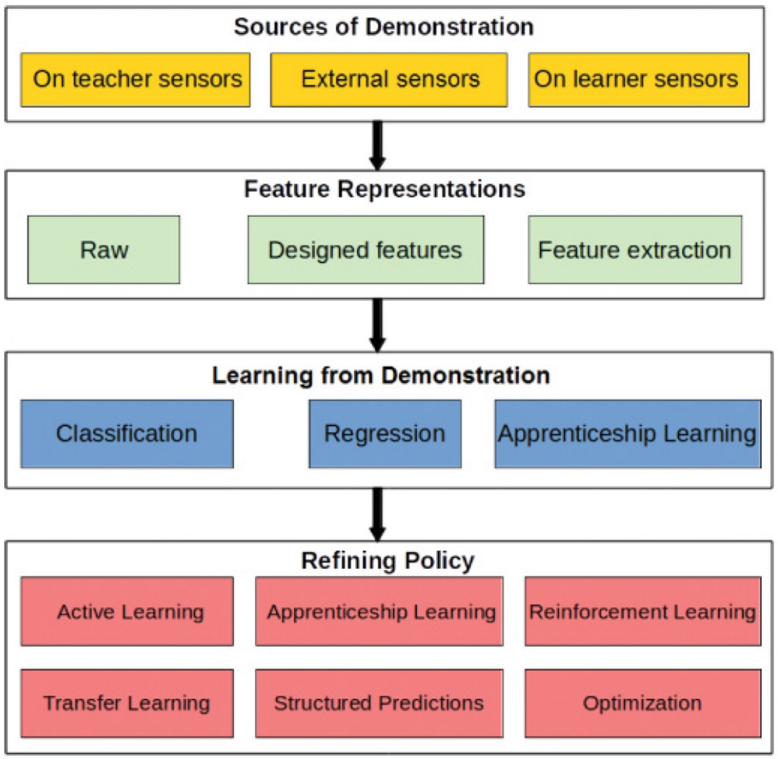
- In some applications, you cannot bootstrap yourself from random policies
  - High-dimensional state and action spaces where most random trajectories fail miserably
  - Expensive to evaluate policies in the physical world, especially in cases of failure
- **Solution:** learn to imitate sample trajectories or demonstrations
  - This is also helpful when there is no natural reward formulation

# Imitation learning

- $\vec{s}_t$ = a representation of the state of the environment at time t (can be a real-valued vector)
- $a_t$= the action that a human actor performed in response to this state (must be discrete)
- $f_k(\vec{s}_t)$ = $k^{th}$ element in the softmax output of a neural network, given $\vec{s}_t$ as the input
- Training criterion: train the neural network in order to minimize

$$\mathcal{L} = -\log f_{a_t}(\vec{s}_t)$$

# Overview of imitation learning methods

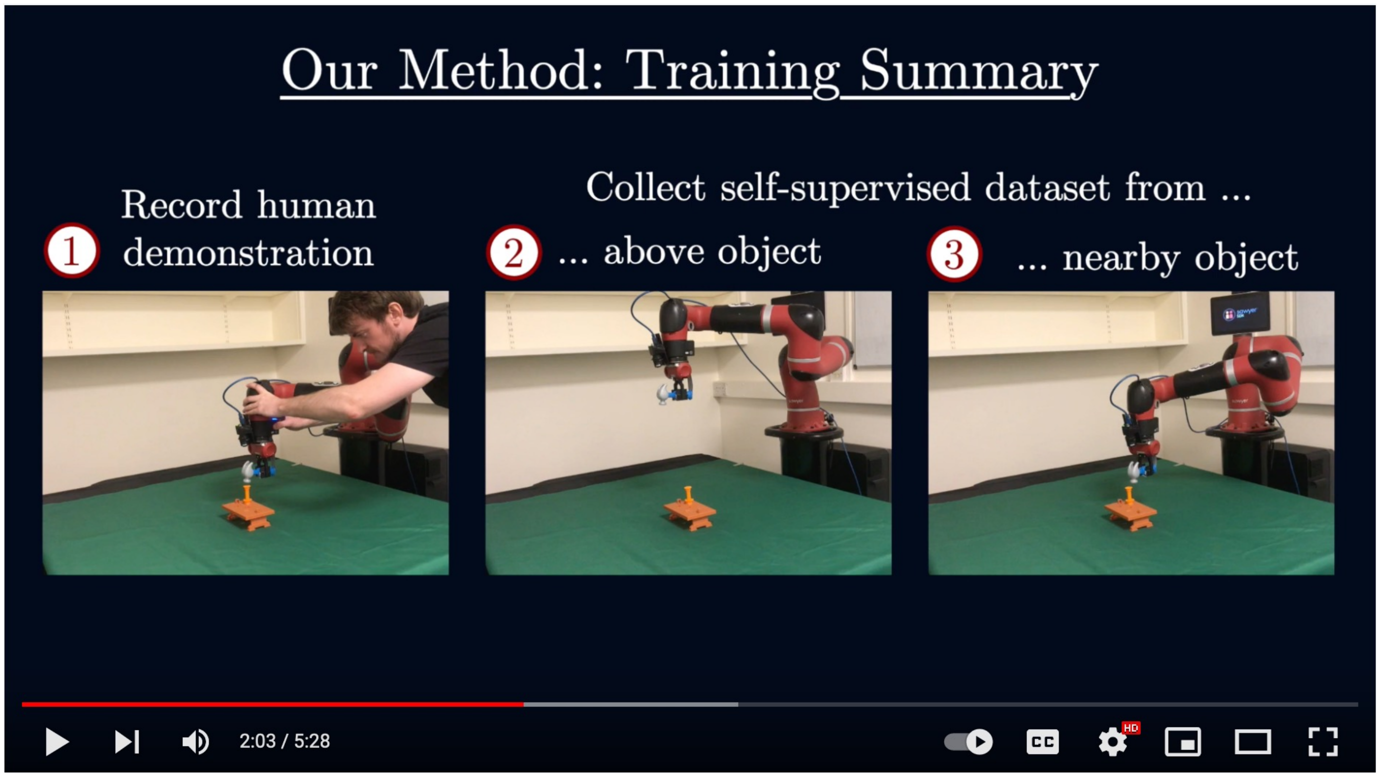



Methods differ in:

- Feature representation: raw pixels/joint angles, or have you already used some other method to learn a deep feature representation?
- Training criterion: classification (discrete actions), or regression (continuous actions)?

Hussein et al. [Imitation Learning: A Survey of Learning Methods](), 2018.

# Example: Coarse-to-Fine Imitation Learning




Edward Johns, [Coarse-to-Fine Imitation Learning: Robot Manipulation from a Single Demonstration](), 2021.

# Outline

- Imitation learning: learn the optimal policy by imitating a human
- Deep Q learning: compute Q(s,a) using a neural network

# Review: Q-Learning

- Q(s,a) – the “quality” of an action

$$Q(s,a) = R(s) + \gamma \sum_{s'} P(s'|s,a)U(s')$$
$$U(s) = \max_{a \in A(s)} Q(s,a)$$

- Q-learning
- Off-policy learning: TD

$$Q_{local}(s_t, a_t) = R_t(s_t) + \gamma \max_{a' \in A(s_{t+1})} Q_t(s_{t+1}, a')$$
$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha\big(Q_{local}(s_t, a_t) - Q_t(s_t, a_t)\big)$$

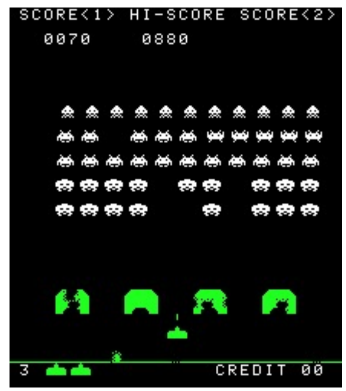
- On-policy learning: SARSA

$$a_{t+1} = \pi_t(s_{t+1})$$
$$Q_{local}(s_t, a_t) = R_t(s_t) + \gamma Q_t(s_{t+1}, a_{t+1})$$

# Deep Q learning

Instead of discrete $s$, suppose $\vec{s}$ is a vector of real numbers, e.g., the image from the robot's eye camera:

$$\vec{s} = [s_1, \ldots, s_D] =$$

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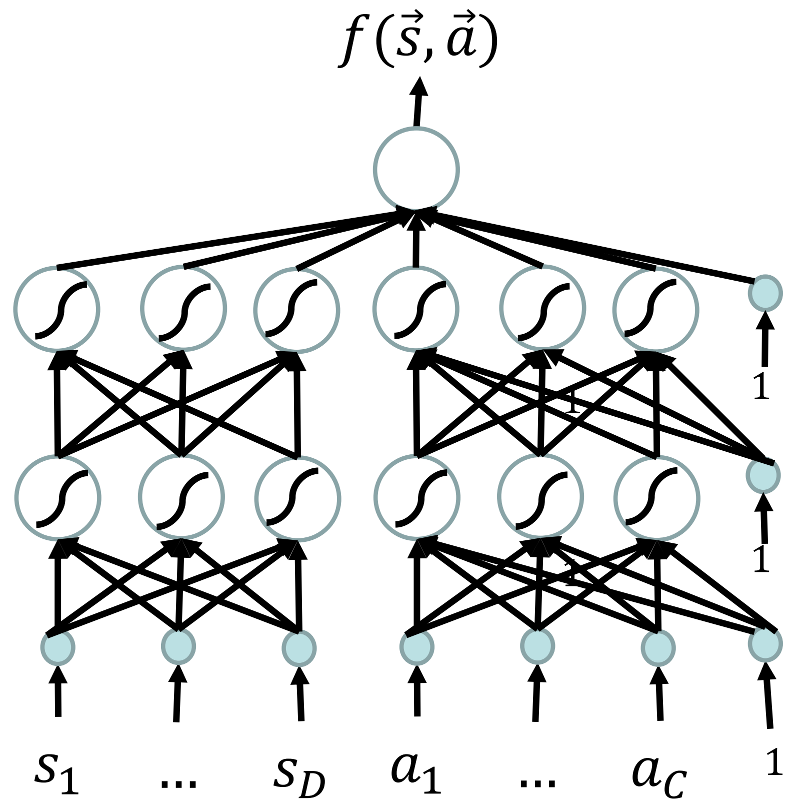
Instead of discrete $a$, suppose $\vec{a}$ is a vector, e.g., cannon angle and velocity,

$$\vec{a} = [a_1, \ldots, a_C]$$

Deep Q-learning uses a neural network to compute an estimate $f(\vec{s}, \vec{a})$ which is as close as possible to $Q(\vec{s}, \vec{a})$.



# MMSE Deep Q learning

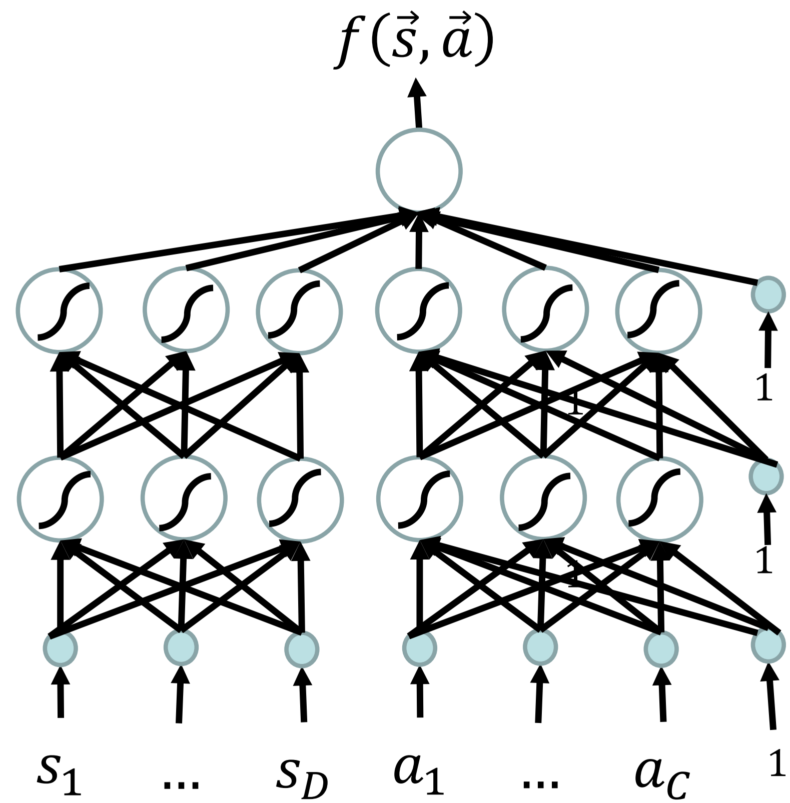
Suppose we train the neural network weights in order to minimize the mean-squared error (MMSE):

$$\mathcal{L} = \frac{1}{2} E[(f(\vec{s}, \vec{a}) - Q(\vec{s}, \vec{a})\ )^2]$$

(where I'm using $E[\cdot]$ as a lazy way to write "average over all training runs of the game").

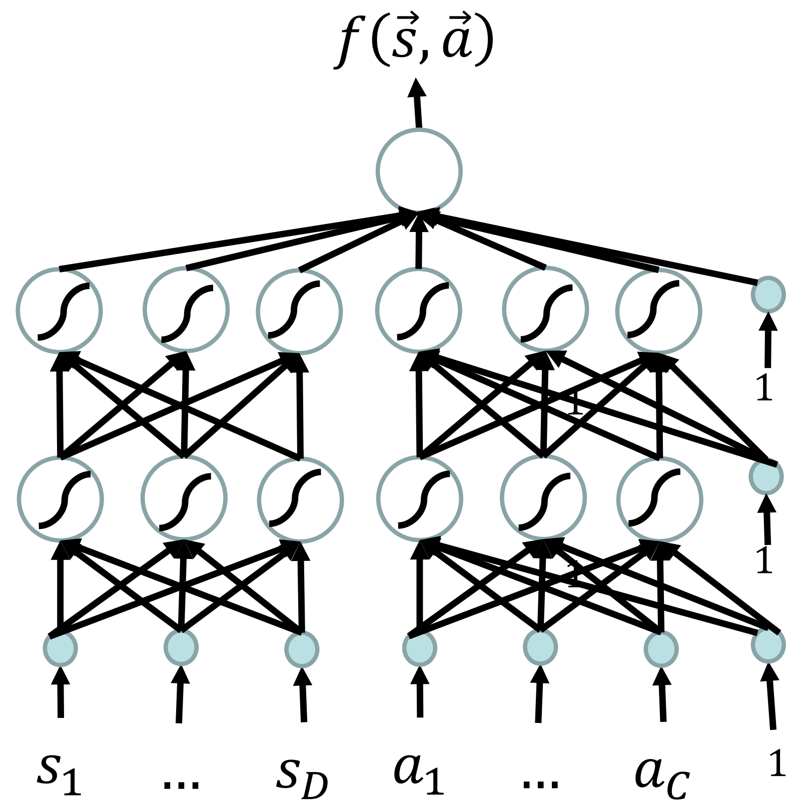
Then, for each weight $w$, we update as

$$w \leftarrow w - \eta \frac{d\mathcal{L}}{dw}$$



# What makes deep Q learning harder than normal neural network training

- We don't know the true value of $Q(\vec{s},\vec{a})$ for ***<u>any</u>*** of the training runs!
- $Q(\vec{s},\vec{a})$ is defined to be the expected value of performing action $\vec{a}$. We never know its true expected value: all we know is whether we won or lost that particular game.
- So we can't compute $\mathcal{L}$, and we can't compute $\frac{d\mathcal{L}}{dw}$, and we can't update $w$!



# The solution: $Q_{local}$

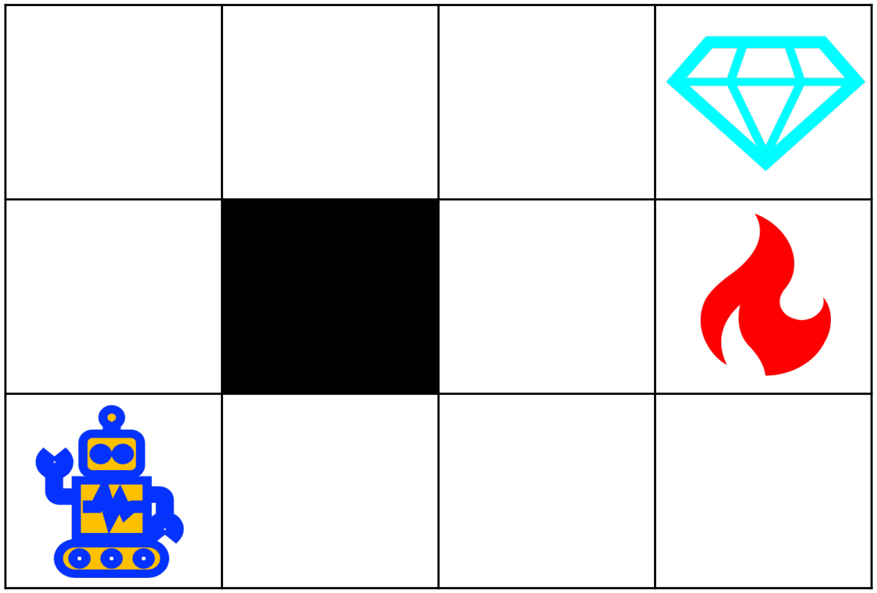
Remember that Q learning was defined as

$$Q_{t+1}(s_t, a_t) \\ = Q_t(s_t, a_t) + \alpha\big(Q_{local}(s_t, a_t) - Q_t(s_t, a_t)\big)$$

where $Q_{local}(s_t, a_t)$ is defined, e.g., in TD as

$$Q_{local}(s_t, a_t) = R_t(s_t) + \gamma \max_{a'} Q_t(s_{t+1}, a')$$

…for $s_{t+1}$ equal to the next state we reach after action $a_t$ on **<u>this particular game</u>**.



# The solution: $Q_{local}$

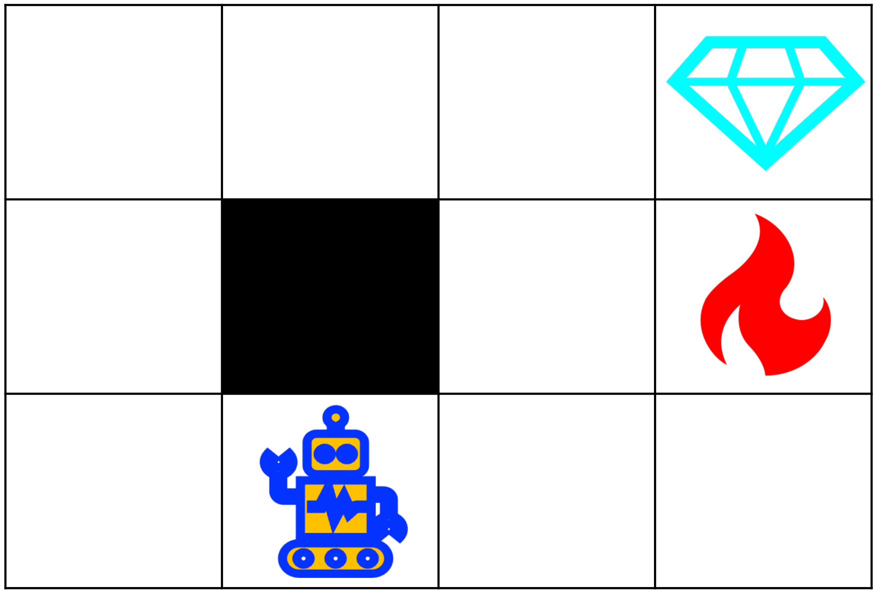
Let's define deep Q learning using the same $Q_{local}$:

$$\mathcal{L} = \frac{1}{2} E[(f(\vec{s}_t, \vec{a}_t) - Q_{local}(\vec{s}_t, \vec{a}_t)\ )^2]$$

where $Q_{local}(\vec{s}_t, \vec{a}_t)$ is:

$$Q_{local}(\vec{s}_t, \vec{a}_t) = R_t(\vec{s}_t) + \gamma \max_{\vec{a}'} f(\vec{s}_{t+1}, \vec{a}')$$

Now we have an L that depends only on things we know ($f(\vec{s}_t, \vec{a}_t)$, $R_t(\vec{s}_t)$, and $f(\vec{s}_{t+1}, \vec{a}')$), so it can be calculated, differentiated, and used to update the neural network.



# Dealing with training instability

- Challenges
  - Target values are not fixed
  - Successive experiences are correlated and dependent on the policy
  - Policy may change rapidly with slight changes to parameters, leading to drastic change in data distribution
- Solutions
  - Freeze target Q network
  - Use *experience replay*

# Experience replay

- At each time step:
  - Take action $\vec{a}_t$ according to epsilon-greedy policy
  - Store experience $(\vec{s}_t, \vec{a}_t, r_{t+1}, \vec{s}_{t+1})$ in *replay memory buffer*

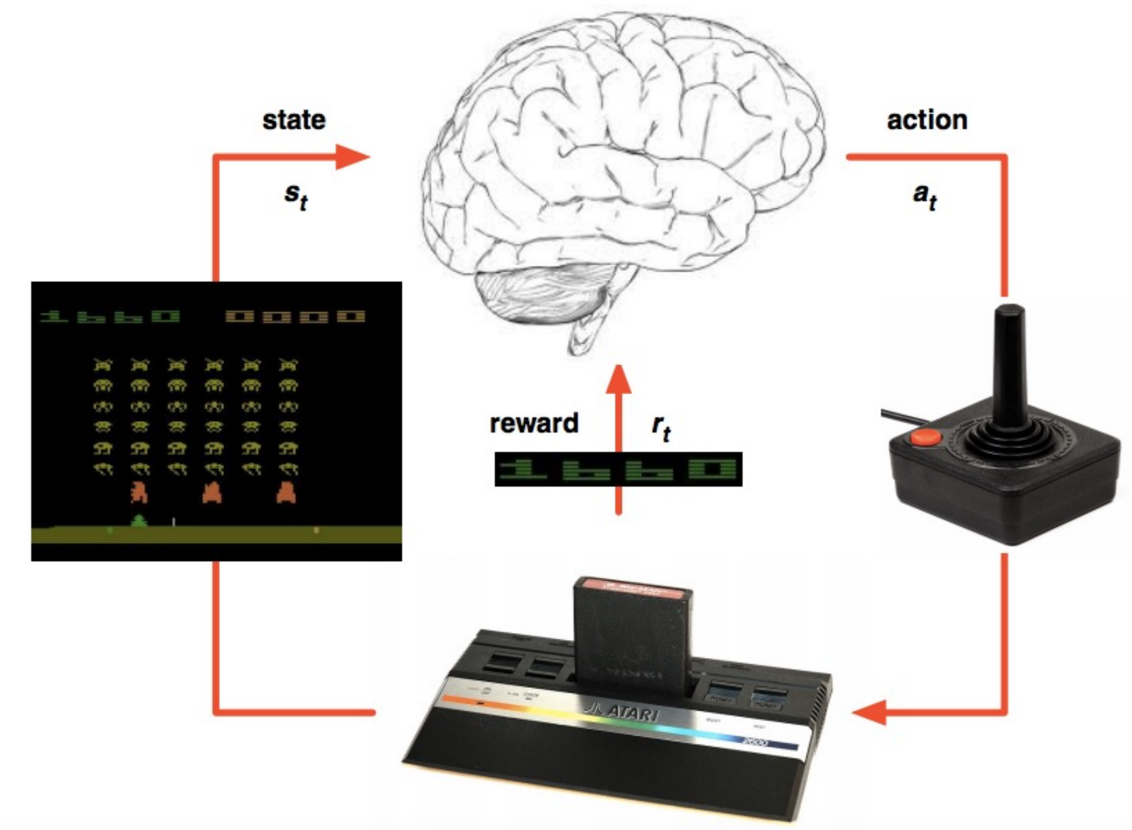
| |
|---|
| $(\vec{s}_1, \vec{a}_1, r_2, \vec{s}_2)$ |
| $(\vec{s}_2, \vec{a}_2, r_3, \vec{s}_3)$ |
| ... |
| |

$(\vec{s}_t, \vec{a}_t, r_{t+1}, \vec{s}_{t+1})$

- Learning:
  - Randomly sample a minibatch, $\mathcal{D}$, from the replay buffer.

$\mathcal{D}$ =randomly sampled set of tuples

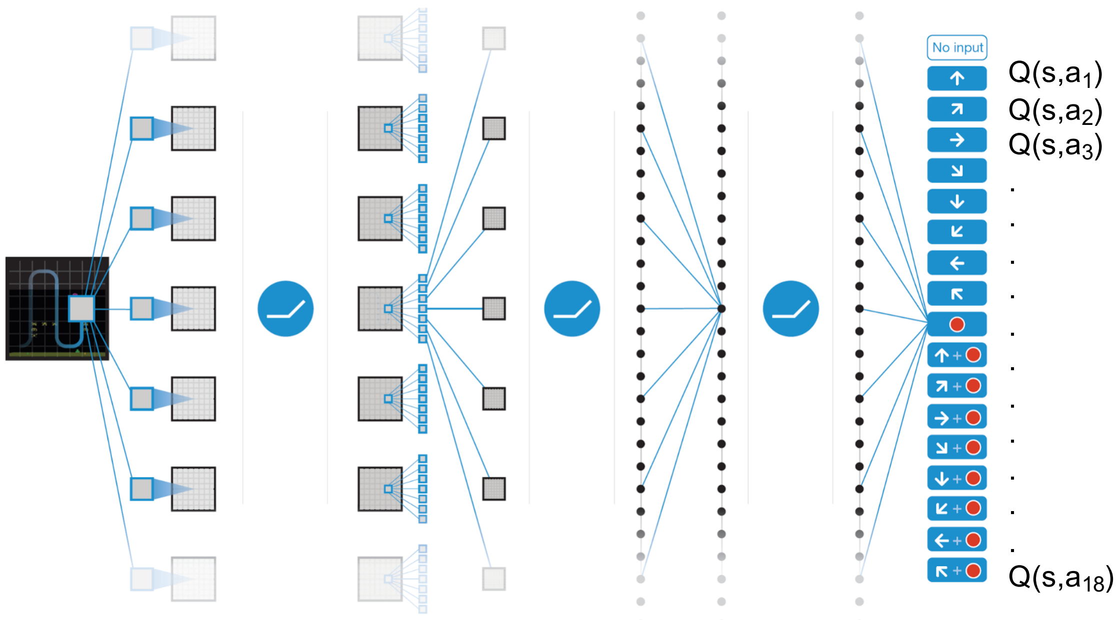
# Deep Q learning in Atari




Mnih et al. [Human-level control through deep reinforcement learning](), *Nature* 2015

# Deep Q learning in Atari

- End-to-end learning of Q(s,a) from pixels s
- Output is Q(s,a) for 18 joystick/button configurations
- Reward is change in score for that step

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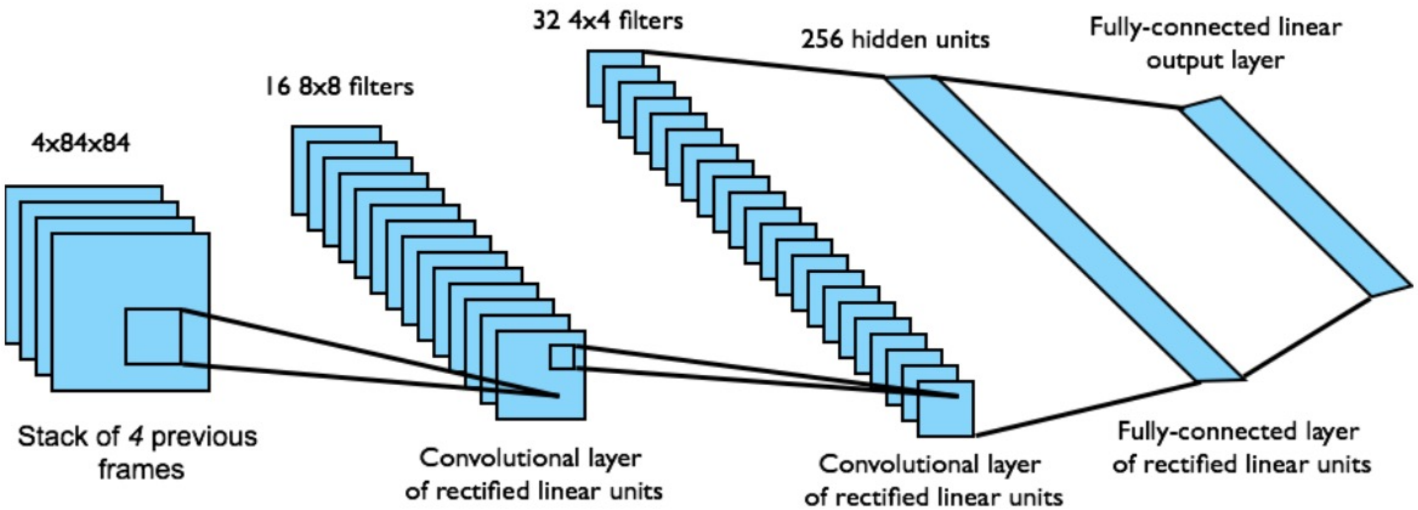
# Deep Q learning in Atari

- Input state s is stack of raw pixels from last 4 frames
- Network architecture and hyperparameters fixed for all games




Mnih et al. [Human-level control through deep reinforcement learning](), *Nature* 2015

# Deep Q learning in Atari


Deep Q-Learning Playing Atari Breakout

# Summary: Deep RL, Part 1

- Imitation learning: learn the optimal policy by imitating a human

$$\mathcal{L} = -\log f_{a_t}(\vec{s}_t)$$

- Deep Q learning: compute Q(s,a) using a neural network

$$\mathcal{L} = \frac{1}{2} E[(f(\vec{s}_t, \vec{a}_t) - Q_{local}(\vec{s}_t, \vec{a}_t)\ )^2]$$

$$Q_{local}(\vec{s}_t, \vec{a}_t) = R_t(\vec{s}_t) + \gamma \max_{\vec{a}'} f(\vec{s}_{t+1}, \vec{a}')$$