ITCS 6156/8156 Fall 2024
Machine Learning

Reinforcement Learning

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Class Meeting: 4:00 PM – 5:15 PM, WWH 130

UNIVERSITY OF NORTH CAROLINA CHARLOTTE

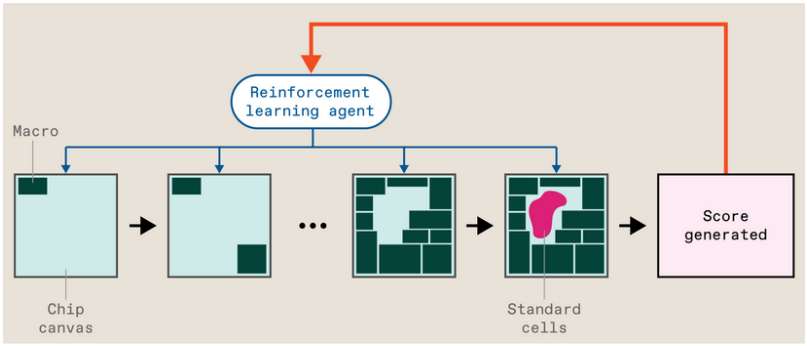
Some content in the slides is based on Dr. Raquel Urtasun's lecture

Mid-term Exam Information

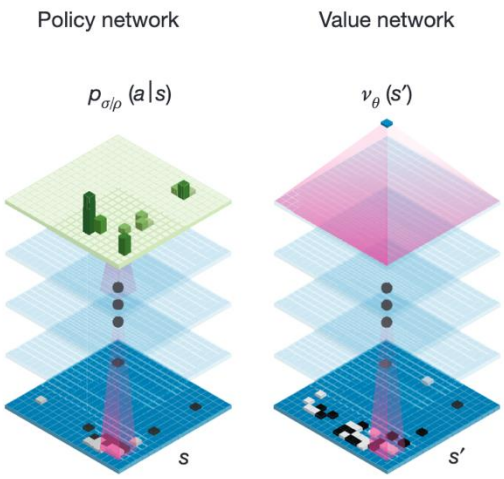
- Date: Oct. 08, Mon. (Next Tuesday)
- Duration: 75 minutes (4:00 – 5:15 PM)
- Location: This classroom (WWH 130)
- Content Scope: all lecture material presented to date (Lecture 1 - 14)
- Multi-choice question only.
- **Close-Book Exam**
  - But you can bring **1 piece of A4-sized cheat sheet**.
  - Bring your **calculator**!
- Accommodation: Send you request to DS Test Center

Fancy Applications of RL

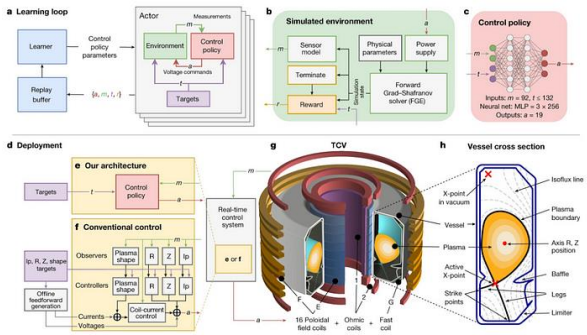
Play Dota



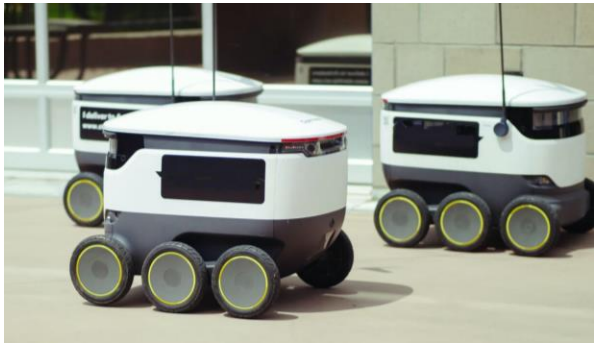
Chip Design



AlphaGo



Nuclear Fusion



AWS Deep Racer

Playing Games: Atari

From YouTube: https://www.youtube.com/watch?v=V1eYniJ0Rnk

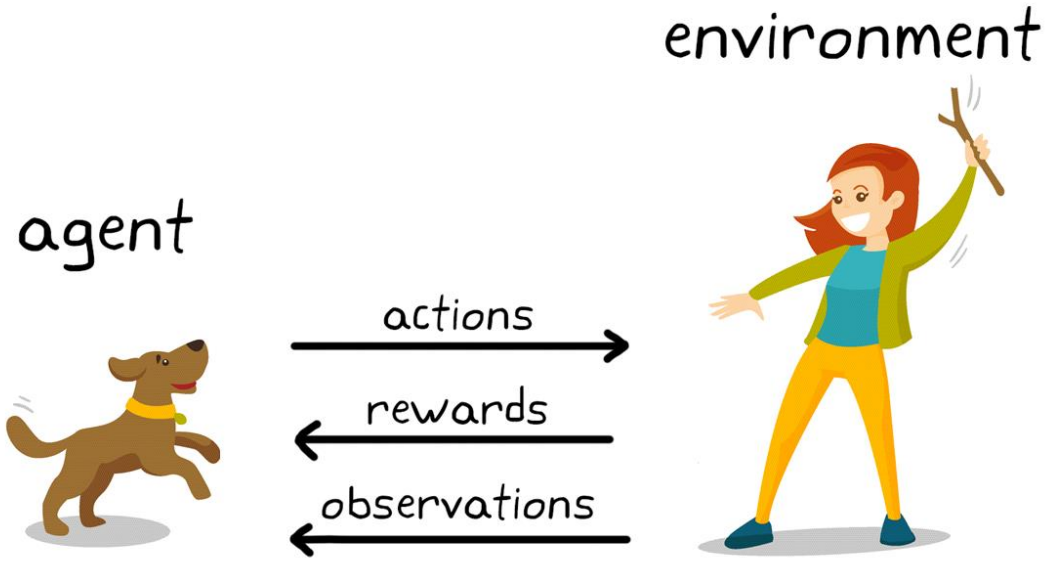
Playing Games: Hide and Seek

From YouTube: https://www.youtube.com/watch?v=Lu56xVlZ40M

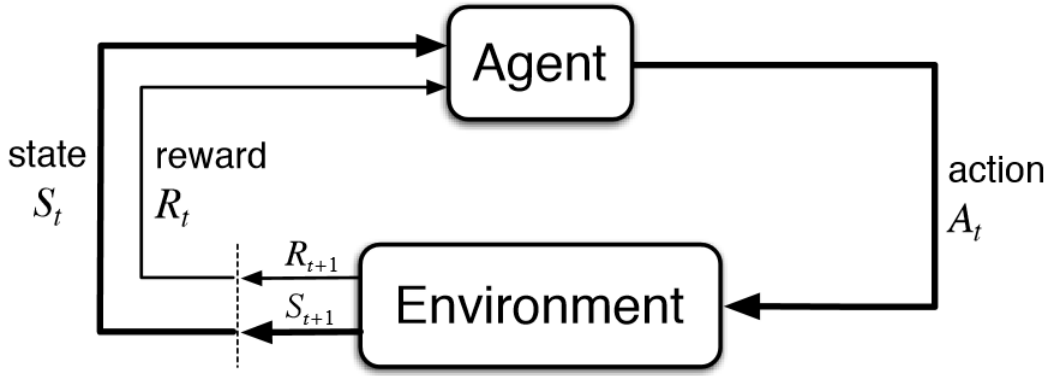
Reinforcement Learning

- Learning algorithms differ in the information available to learner
  - Supervised: correct outputs
  - Unsupervised: no feedback, must construct measure of good output
  - Reinforcement learning
- More realistic learning scenario:
  - Continuous stream of input information, and actions
  - Effects of action depend on state of the world
  - Obtain reward that depends on world state and actions
    - not correct response, just some feedback

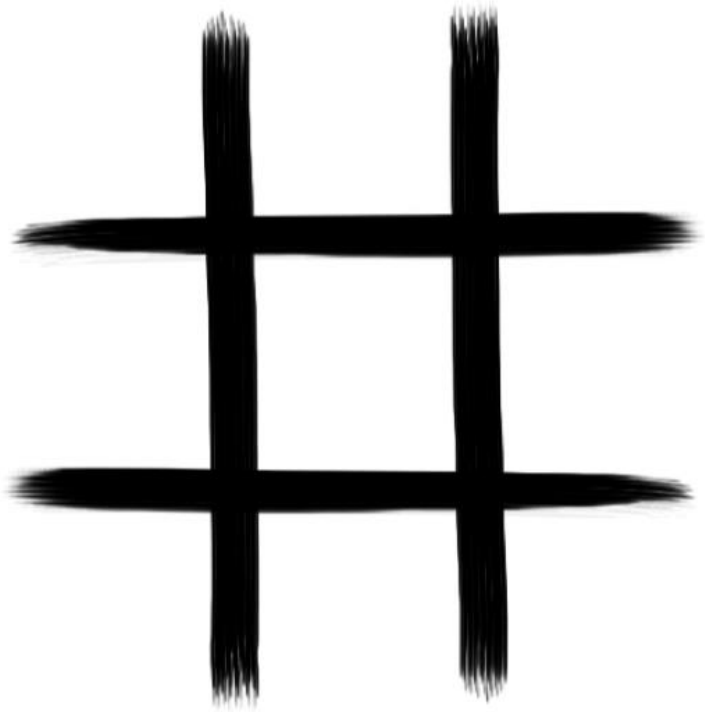
Reinforcement Learning



Reinforcement Learning in Dog Training

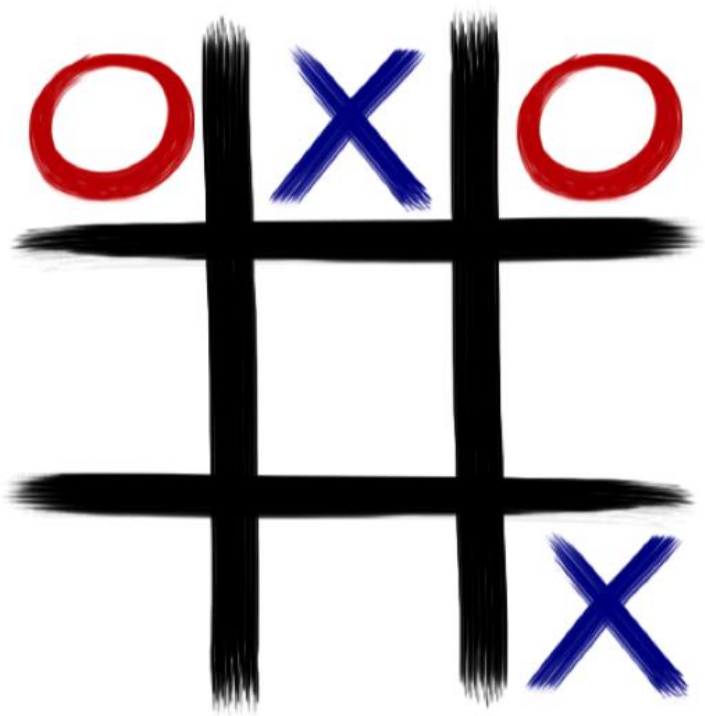


Example: Tic Tac Toe, Notation



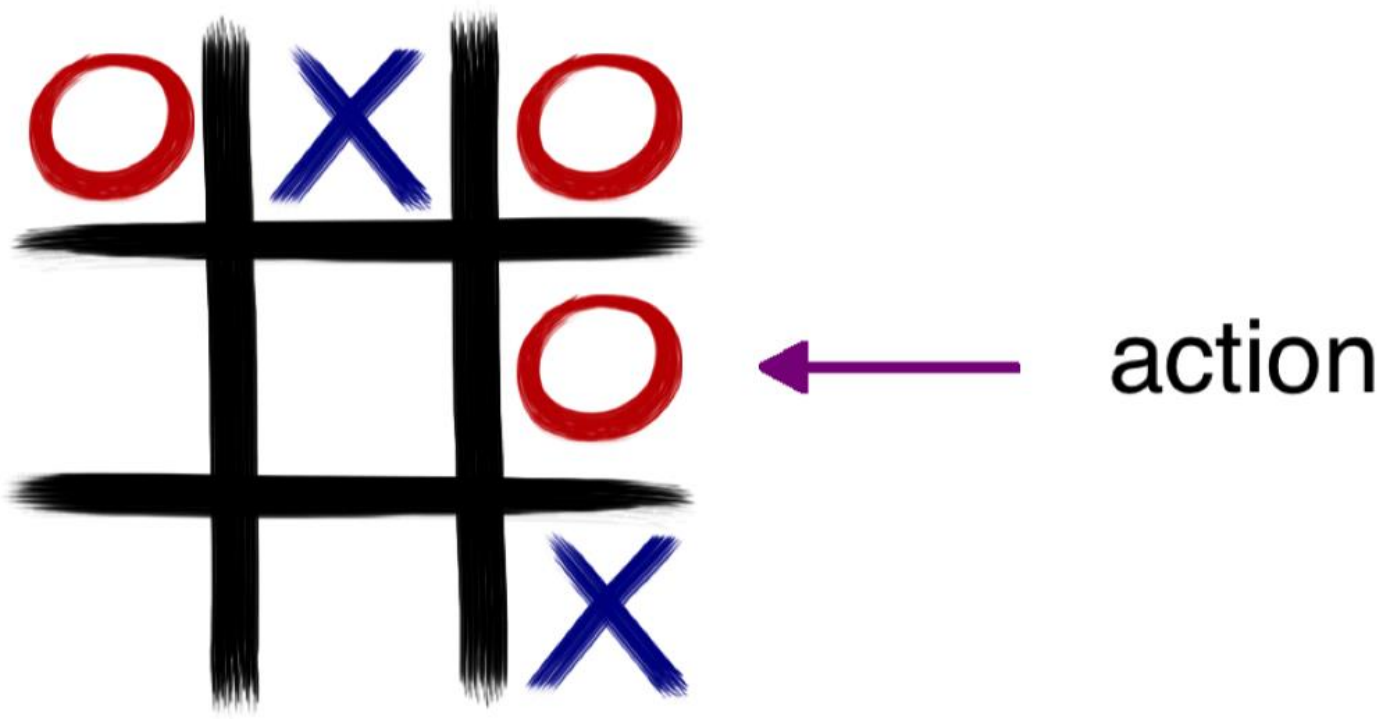
environment

Example: Tic Tac Toe, Notation

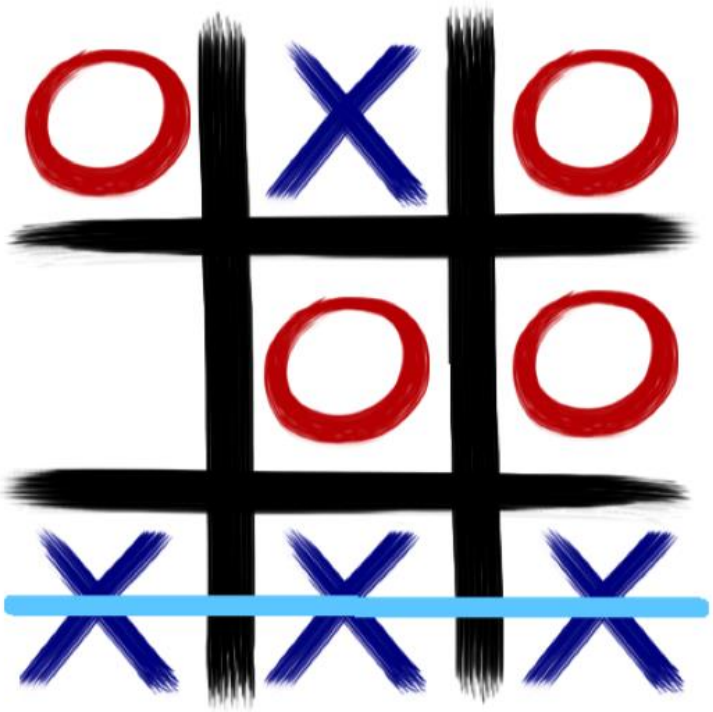


(current)
state

Example: Tic Tac Toe, Notation



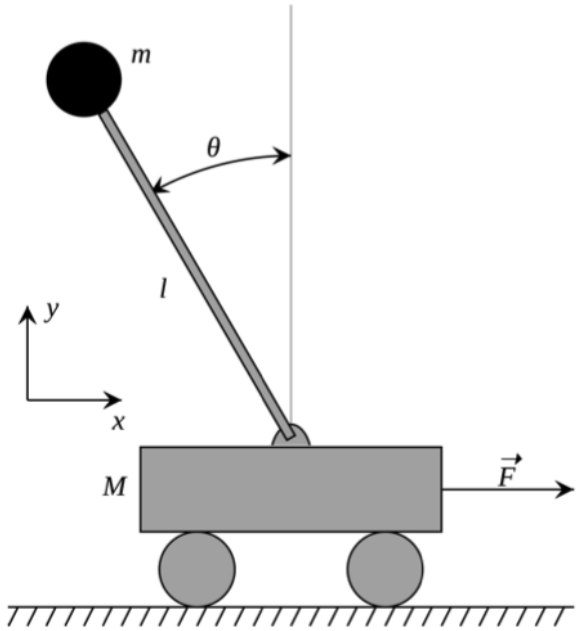
Example: Tic Tac Toe, Notation



reward

(here: -1)

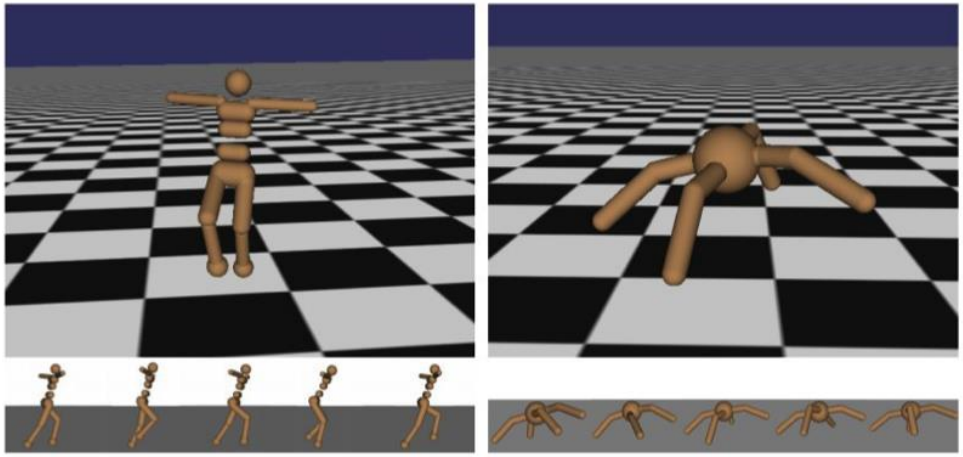
Example: Cart-Pole Problem



Objective: Balance a pole on top of a movable cart

State: angle, angular speed, position, horizontal velocity
Action: horizontal force applied on the cart
Reward: 1 at each time step if the pole is upright

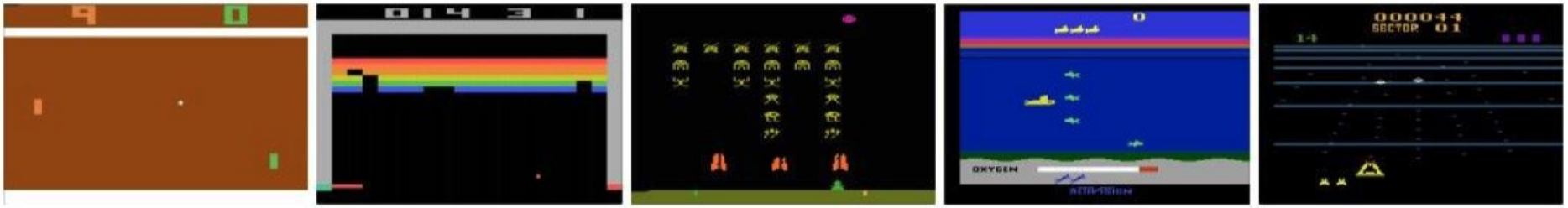
Example: Robot Locomotion



Objective: Make the robot move forward

State: Angle and position of the joints
Action: Torques applied on joints
Reward: 1 at each time step upright + forward movement

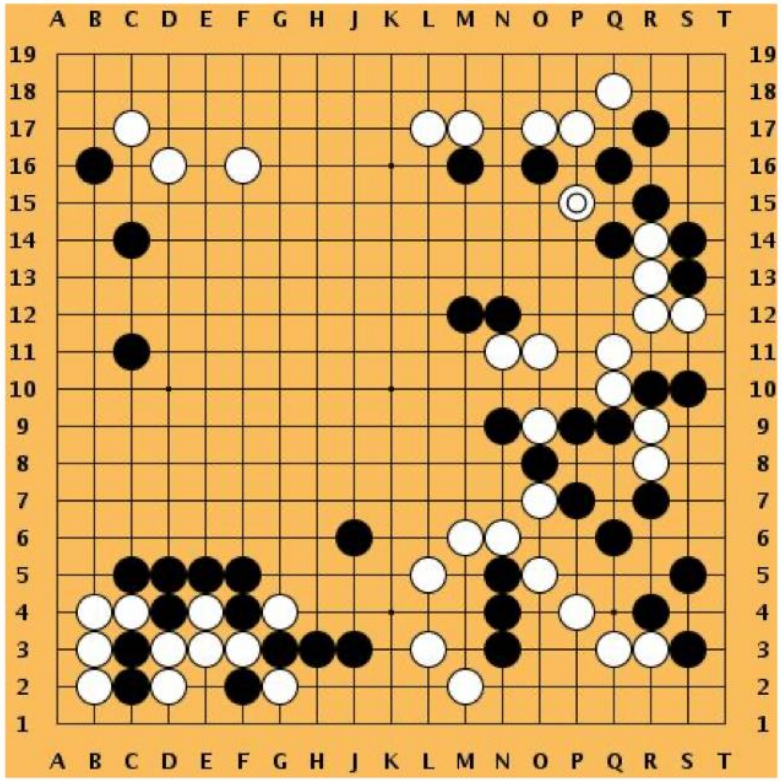
Example: Atari Games



Objective: Complete the game with the highest score

State: Raw pixel inputs of the game state
Action: Game controls e.g. Left, Right, Up, Down
Reward: Score increase/decrease at each time step

Example: Go



Objective: Win the game!

State: Position of all pieces
Action: Where to put the next piece down
Reward: 1 if win at the end of the game, 0 otherwise

Rewards

- A **reward** R_t is a scalar feedback signal
- Indicates how well agent is doing at step t — defines the goal
- The agent's job is to maximize cumulative reward

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \ldots$$

- We call this the **return**

Reinforcement learning is based on the **reward hypothesis**:

Any goal can be formalized as the outcome of maximizing a cumulative reward

Values

- We call the expected cumulative reward, from a state s, the **value**

$$\begin{aligned} v(s) &= \mathbb{E}\left[G_t \mid S_t = s\right] \\ &= \mathbb{E}\left[R_{t+1} + R_{t+2} + R_{t+3} + \ldots \mid S_t = s\right] \end{aligned}$$

- The value depends on the actions the agent takes
- Goal is to **maximize value**, by picking suitable actions
- Rewards and values define **utility** of states and action (no supervised feedback)
- Returns and values can be defined recursively

$$\begin{aligned} G_t &= R_{t+1} + G_{t+1} \\ v(s) &= \mathbb{E}\left[R_{t+1} + v(S_{t+1}) \mid S_t = s\right] \end{aligned}$$

Maximizing Value by Taking Actions

- Goal: **select actions to maximise value**
- Actions may have long term consequences
- Reward may be delayed
- It may be better to sacrifice immediate reward to gain more long-term reward
- Examples:
  - Refueling a helicopter (might prevent a crash in several hours)
  - Defensive moves in a game (may help chances of winning later)
  - Learning a new skill (can be costly & time-consuming at first)
- A mapping from states to actions is called a **policy**

Action Values

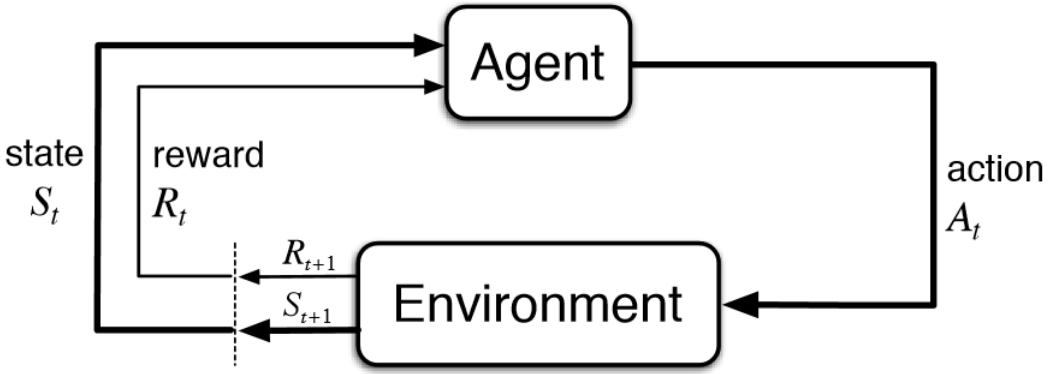
- It is also possible to condition the value on **actions**:

$$\begin{aligned} q(s,a) &= \mathbb{E}\left[G_t \mid S_t = s, A_t = a\right] \\ &= \mathbb{E}\left[R_{t+1} + R_{t+2} + R_{t+3} + \ldots \mid S_t = s, A_t = a\right] \end{aligned}$$

- We will talk in depth about state and action values later

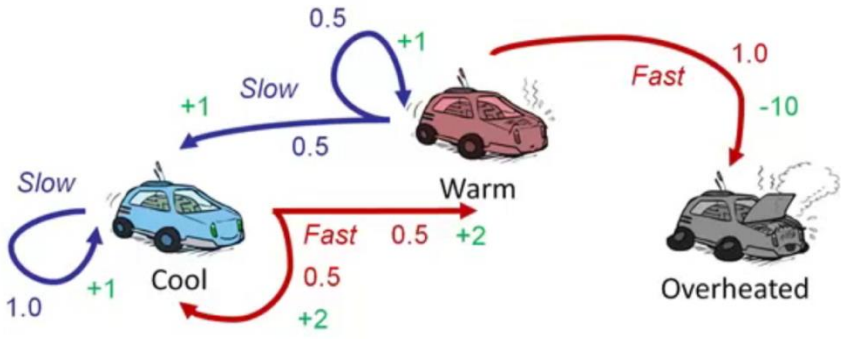
Markov Decision Process

How can we mathematically formalize the RL problem?



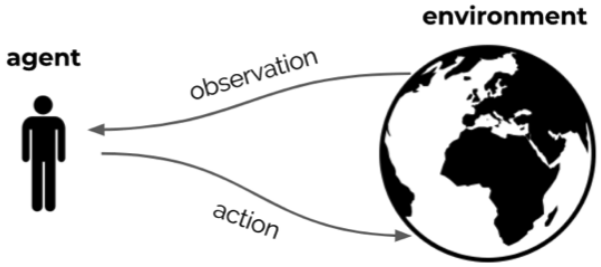
Markov Decision Process:

- Mathematical formulation of the RL problem
- **Markov property**: Current state completely characterises the state of the world : $p(r, s \mid S_t, A_t) = p(r, s \mid \mathcal{H}_t, A_t)$



- H_t is the history.
- This means that the state contains all we need to know from the history.
- Doesn't mean it contains everything, just that adding more history doesn't help. ⇒ Once the state is known, the history may be thrown away.
- Typically, the agent state S_t is some compression of H_t
- Note: we use S_t to denote the agent state, not the environment state

Fully Observable Environments



Full observability

Suppose the agent sees the full environment state

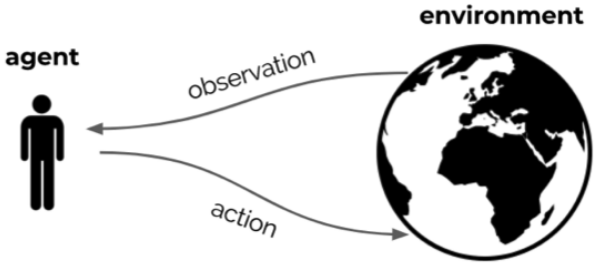
- observation = environment state
- The agent state could just be this observation:

$$S_t = O_t = \text{environment state}$$

Partially Observable Environments

- **Partial observability**: The observations are not Markovian
  - A robot with camera vision isn't told its absolute location
  - A poker playing agent only observes public cards
- Now using the observation as state would not be Markovian
- This is called a **partially observable Markov decision process** (POMDP)
- The **environment state** can still be Markov, but the agent does not know it
- We might still be able to construct a Markov agent state

Agent State



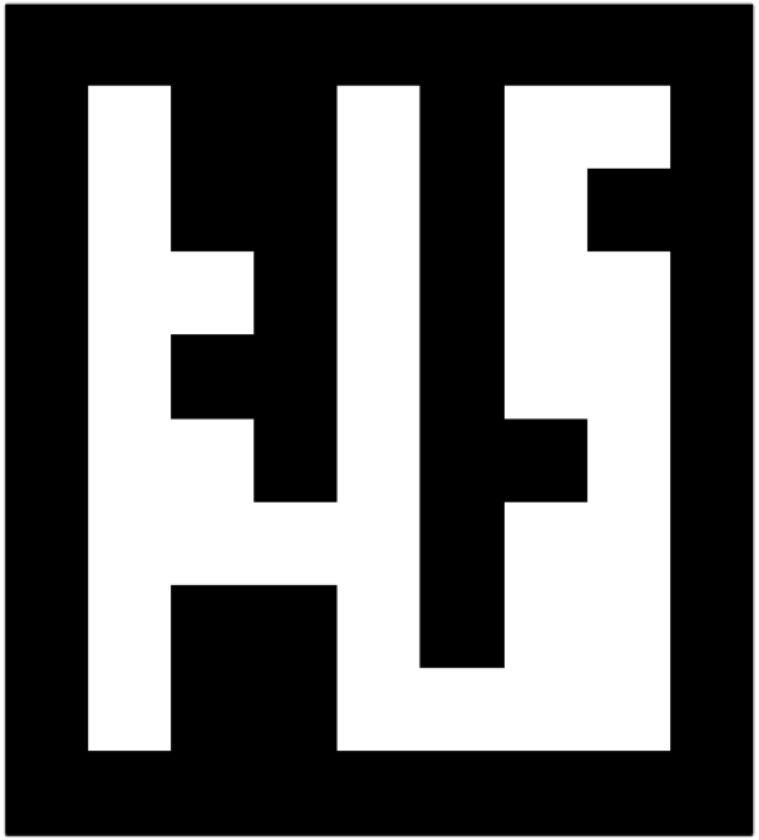
- The agent's actions depend on its state
- The **agent state** is a function of the history
- For instance, $S_t = O_t$
- More generally:

$$S_{t+1} = u(S_t, A_t, R_{t+1}, O_{t+1})$$

  where u is a 'state update function'
- The agent state is often **much** smaller than the environment state

Agent State

The full environment state of a maze

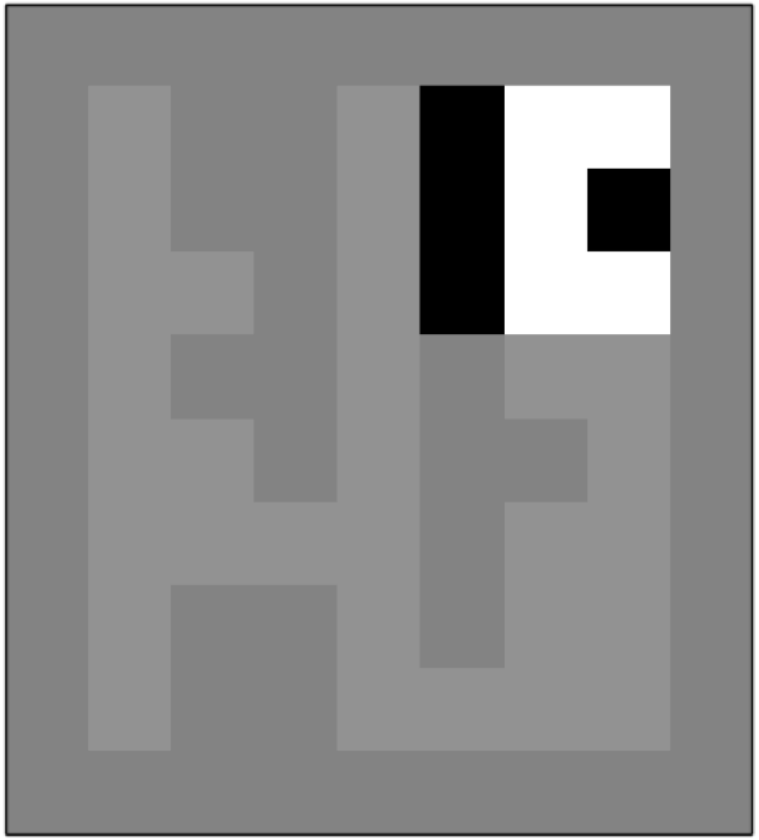


Agent State

A potential observation

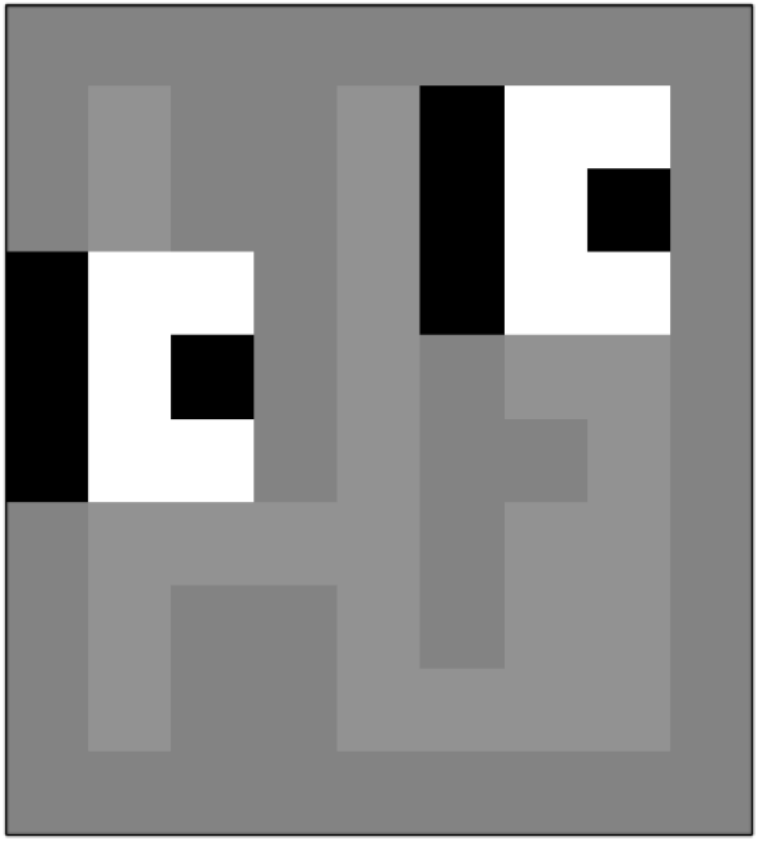
Agent State

An observation in a different location



Agent State

The two observations are indistinguishable



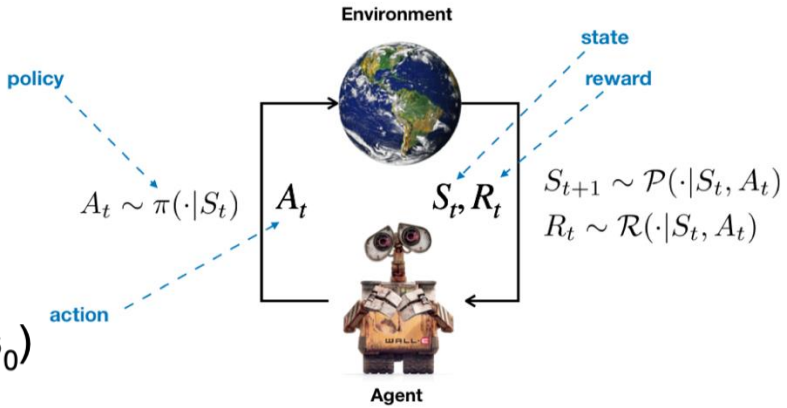
Partially Observable Environments

- To deal with partial observability, agent can construct suitable state representations
- Examples of agent states:
  - Last observation: $S_t = O_t$ (might not be enough)
  - Complete history: $S_t = \mathcal{H}_t$ (might be too large)
  - A generic update: $S_t = u(S_{t-1}, A_{t-1}, R_t, O_t)$ (but how to pick/learn u?)
- Constructing a fully Markovian agent state is often not feasible
- More importantly, the state should allow good policies and value predictions

Markov Decision Process

Defined by: $(\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathbb{P}, \gamma)$

$\mathcal{S}$: set of possible states
$\mathcal{A}$: set of possible actions
$\mathcal{R}$: distribution of reward given (state, action) pair
$\mathbb{P}$: transition probability i.e. distribution over next state given (state, action) pair
γ : discount factor



- At time step t=0, environment samples initial state $s_0 \sim p(s_0)$
- Then, for t=0 until done:
  - Agent selects action a_t
  - Environment samples reward $r_t \sim R(. | s_t, a_t)$
  - Environment samples next state $s_{t+1} \sim P(. | s_t, a_t)$
  - Agent receives reward r_t and next state s_{t+1}

A policy **π** is a function (the agent's behavior) from S to A that specifies what action to take in each state.

- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a|s) = P[a_t=a|s_t=s]$

Objective: find policy **π*** that maximizes cumulative discounted reward: $\sum_{t \geq 0} \gamma^t r_t$

γ is called a discount rate, and it is always $0 \leq \gamma \leq 1$

If γ close to 1, rewards further in the future count more, and we say that the agent is "farsighted"

γ is less than 1 because there is usually a time limit to the sequence of actions needed to solve a task (we prefer rewards sooner rather than later)

The optimal policy π^*

We want to find optimal policy π^* that maximizes the sum of rewards.

How do we handle the randomness (initial state, transition probability…)?
Maximize the **expected sum of rewards!**

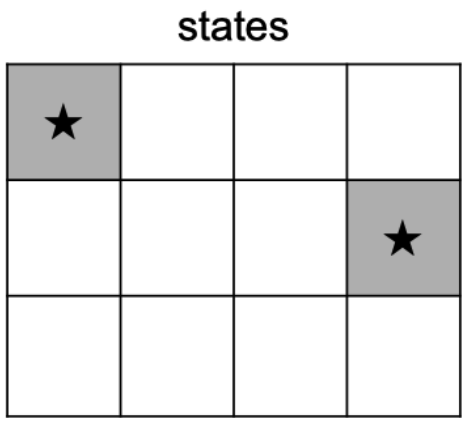
Formally: $\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t \geq 0} \gamma^t r_t | \pi\right]$ with $s_0 \sim p(s_0), a_t \sim \pi(\cdot|s_t), s_{t+1} \sim p(\cdot|s_t, a_t)$

A simple MDP: Grid World

actions = {

1. right
2. left
3. up
4. down

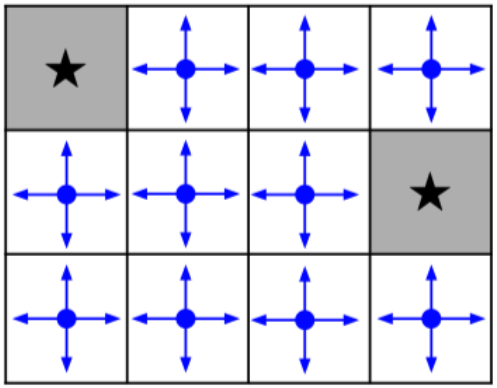
}



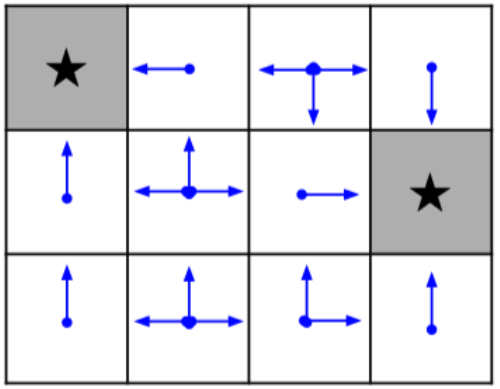
Set a negative "reward" for each transition (e.g. $r = -1$)

Objective: reach one of terminal states (greyed out) in least number of actions

A simple MDP: Grid World



Random Policy



Optimal Policy

Definitions: Value function and Q-value function

Following a policy produces sample trajectories (or paths) $s_0, a_0, r_0, s_1, a_1, r_1, \ldots$

How good is a state?

The **value function** at state s, is the expected cumulative reward from following the policy from state s:

$$V^{\pi}(s) = \mathbb{E}\left[\sum_{t \geq 0} \gamma^t r_t | s_0 = s, \pi\right]$$

How good is a state-action pair?

The **Q-value function** at state s and action a, is the expected cumulative reward from taking action a in state s and then following the policy:

$$Q^{\pi}(s, a) = \mathbb{E}\left[\sum_{t \geq 0} \gamma^t r_t | s_0 = s, a_0 = a, \pi\right]$$

Bellman Equation

The optimal Q-value function Q* is the maximum expected cumulative reward achievable from a given (state, action) pair:

$$Q^*(s,a) = \max_\pi \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | s_0 = s, a_0 = a, \pi\right]$$

Q* satisfies the following **Bellman equation**:

$$Q^*(s,a) = \mathbb{E}_{s'\sim\mathcal{E}}\left[r + \gamma \max_{a'} Q^*(s',a') | s, a\right]$$

Intuition: if the optimal state-action values for the next time-step Q*(s',a') are known, then the optimal strategy is to take the action that maximizes the expected value of $r + \gamma Q^*(s',a')$

The optimal policy **π*** corresponds to taking the best action in any state as specified by Q*

Solving for the optimal policy: Q-learning

Q-learning: Use a function approximator to estimate the action-value function

Value iteration algorithm: Use Bellman equation as an iterative update

$$Q_{i+1}(s,a) = \mathbb{E}\left[r + \gamma \max_{a'} Q_i(s',a') | s,a\right]$$

Q_i will converge to Q* as i -> infinity

- Simplest function approximator: Table!

Example: Table for Q-learning

- You're a mouse in this tiny maze. You always **start at the same starting point.**
- The goal is **to eat the big pile of cheese at the bottom right-hand corner** and avoid the poison. After all, who doesn't like cheese?
- The episode ends if we eat the poison, **eat the big pile of cheese**, or if we take more than five steps.
- The learning rate is 0.1
- The discount rate (gamma) is 0.99

https://huggingface.co/learn/deep-rl-course/en/unit2/q-learning-example

Example: Table for Q-learning

Example

- The reward function:
  - 0: Going to a state **with no cheese in it.**
  - +1: Going to a state with a **small cheese in it.**
  - +10: Going to the state with **the big pile of cheese.**
  - -10: Going to the state **with the poison and thus die.**

Example: Table for Q-learning

Example, Step 1

Initialize Q arbitrarily (e.g., $Q(s, a) = 0$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$, and $Q(terminal\text{-}state, \cdot) = 0$)

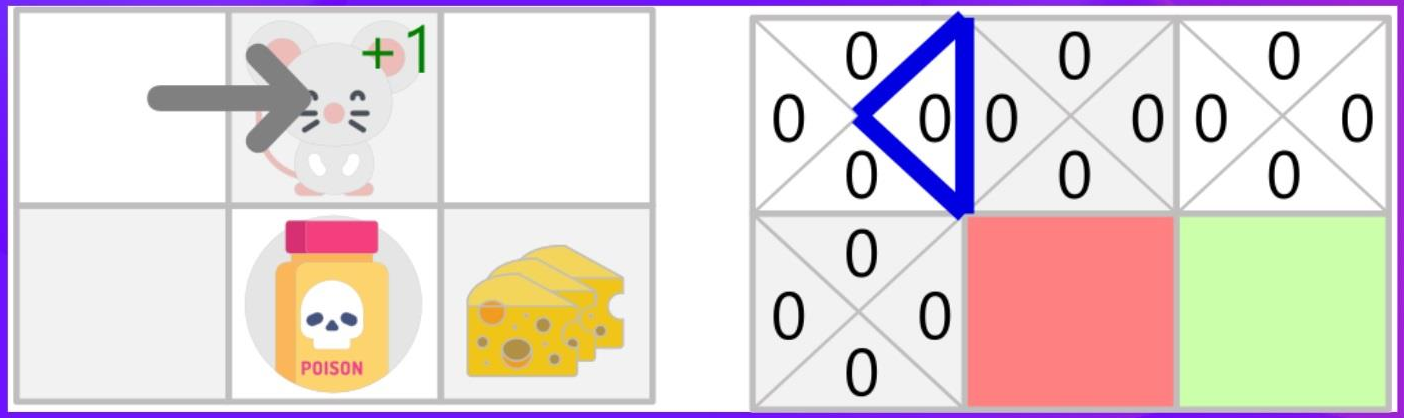
	←	→	↑	↓
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0

We initialize the Q-Table

Example: Table for Q-learning

Example, Step 2

Choose action A_t using policy derived from Q (e.g., ϵ-greedy)

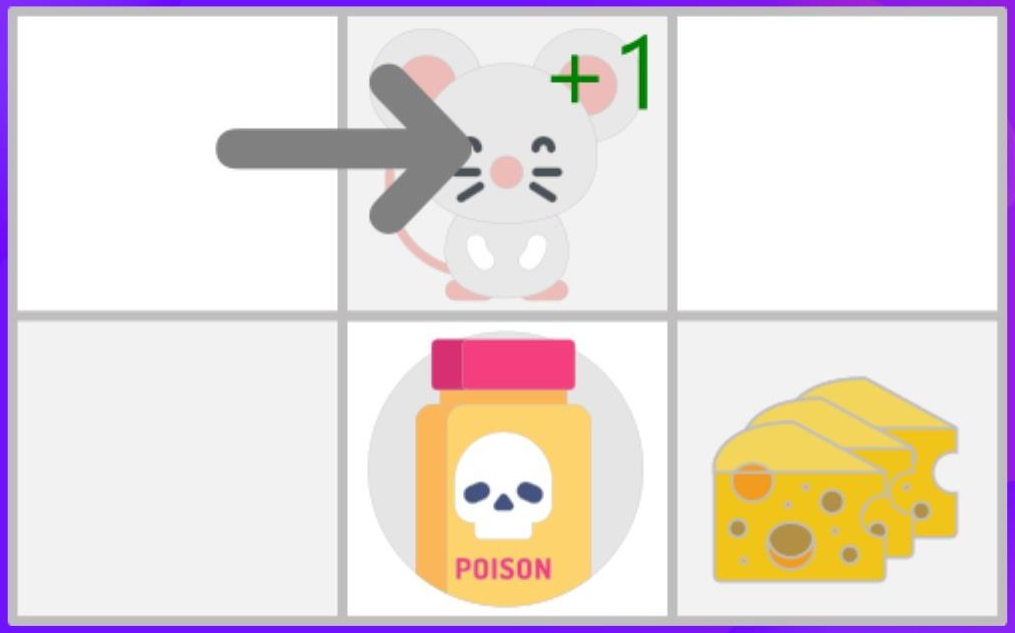


We took a random action (exploration)

Example: Table for Q-learning

Example, Step 3

Take action A_t and observe R_{t+1}, S_{t+1}



Example: Table for Q-learning

Example, Step 4

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma max_a Q(S_{t+1}, a) - Q(S_t, A_t)]$$

New Q-value estimation

Former Q-value estimation

Learning Rate

Immediate Reward

Discounted Estimate optimal Q-value of next state

Former Q-value estimation

TD Target

TD Error

Update our Q-value estimation

Example: Table for Q-learning

Example, Step 4

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t))$$

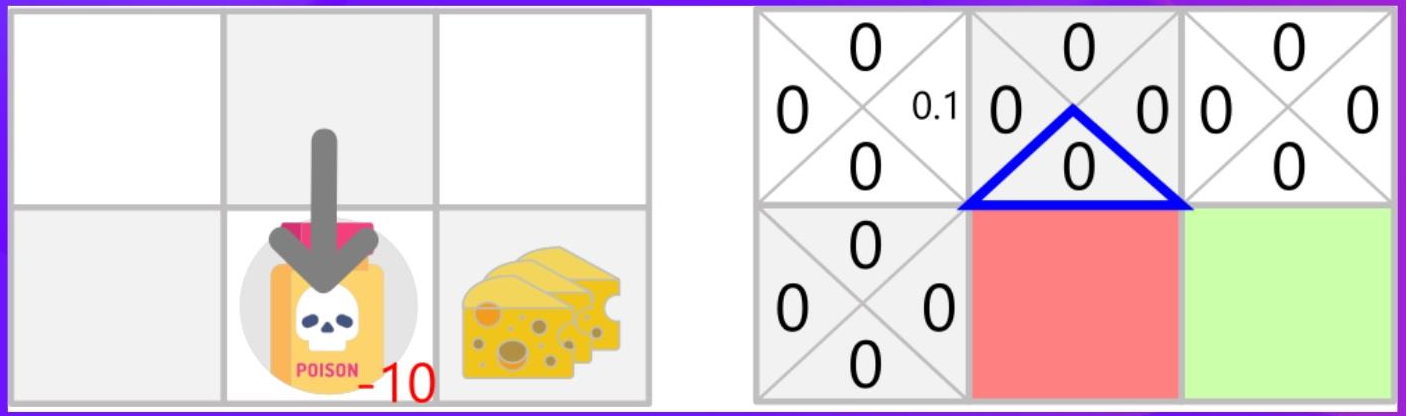
Q(Initial state, Right) = 0 + 0.1 * [1 + 0.99 * 0 - 0]
Q(Initial state, Right) = 0.1

	←	→	↑	↓
	0	0.1	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0

Example: Table for Q-learning

Example, Step 2

Choose action A_t using policy derived from Q (e.g., ϵ-greedy)



We took a random action (exploration)

Example: Table for Q-learning

Example, Step 3

Take action A_t and observe R_{t+1}, S_{t+1}

Example: Table for Q-learning

Example, Step 4

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t))$$

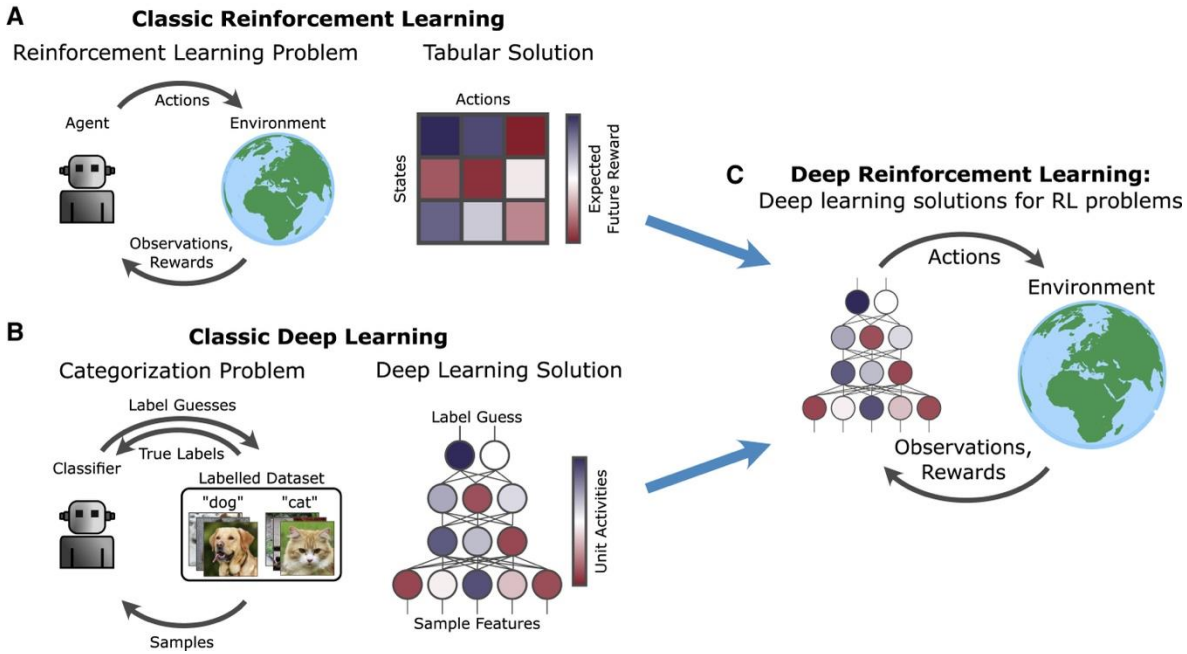
Q(State 2, Down) = 0 + 0.1 * [-10 + 0.99 * 0 - 0]
Q(State 2, Down) = -1

	←	→	↑	↓
	0	0.1	0	0
	0	0	0	-1
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0

Deep Q-Learning

What's the problem with this?
Not scalable. Must compute Q(s,a) for every state-action pair. If state is e.g. current game state pixels, computationally infeasible to compute for entire state space!

Solution: use a function approximator to estimate Q(s,a). E.g. a neural network!



Q-learning: Use a function approximator to estimate the action-value function

$$Q(s, a; \theta) \approx Q^*(s, a)$$

function parameters (weights)

If the function approximator is a deep neural network => **deep q-learning**!

From https://www.sciencedirect.com/science/article/pii/S0896627320304682

Deep Q-Learning

Remember: want to find a Q-function that satisfies the Bellman Equation:

$$Q^*(s,a) = \mathbb{E}_{s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q^*(s',a') | s, a \right]$$

Forward Pass

Loss function: $L_i(\theta_i) = \mathbb{E}_{s,a \sim \rho(\cdot)} \left[(y_i - Q(s,a;\theta_i))^2 \right]$

where $y_i = \mathbb{E}_{s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q(s',a';\theta_{i-1}) | s, a \right]$

Backward Pass

Gradient update (with respect to Q-function parameters θ):

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a \sim \rho(\cdot); s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q(s',a';\theta_{i-1}) - Q(s,a;\theta_i)) \nabla_{\theta_i} Q(s,a;\theta_i) \right]$$

Deep Q-Learning

Remember: want to find a Q-function that satisfies the Bellman Equation:

$$Q^*(s,a) = \mathbb{E}_{s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q^*(s',a') | s, a \right]$$

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where $y_i = \mathbb{E}_{s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q(s',a';\theta_{i-1}) | s, a \right]$

Iteratively try to make the Q-value close to the target value (y_i) it should have, if Q-function corresponds to optimal Q* (and optimal policy π^*)

Backward Pass

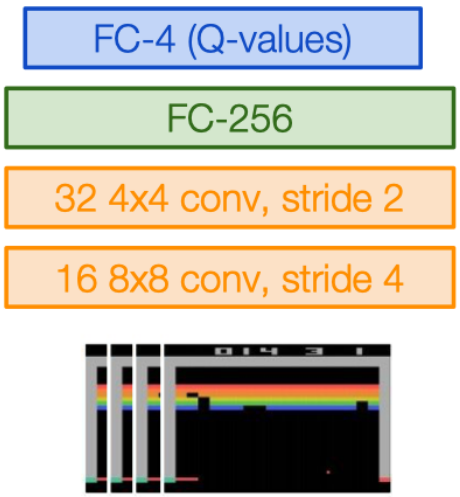
Gradient update (with respect to Q-function parameters θ):

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a \sim \rho(\cdot); s' \sim \mathcal{E}} \left[r + \gamma \max_{a'} Q(s',a';\theta_{i-1}) - Q(s,a;\theta_i)) \nabla_{\theta_i} Q(s,a;\theta_i) \right]$$

Deep Q-Learning

$Q(s, a; \theta)$:
neural network
with weights θ

A single feedforward pass to compute Q-values for all actions from the current state => efficient!



Last FC layer has 4-d output (if 4 actions), corresponding to $Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$, $Q(s_t, a_4)$

Number of actions between 4-18 depending on Atari game

Current state s_t: 84x84x4 stack of last 4 frames
(after RGB->grayscale conversion, downsampling, and cropping)

Deep Q-Learning: Experience Replay

Learning from batches of consecutive samples is problematic:

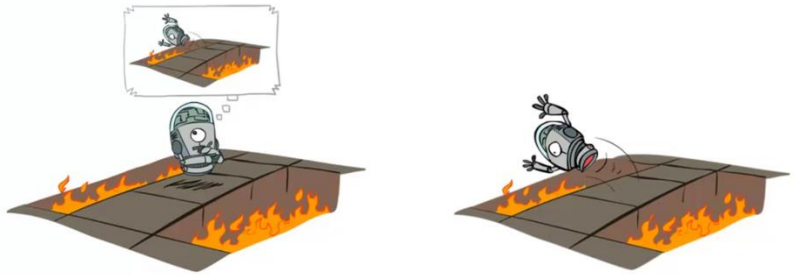
- Samples are correlated => inefficient learning
- Current Q-network parameters determines next training samples (e.g. if maximizing action is to move left, training samples will be dominated by samples from left-hand size) => can lead to bad feedback loops

Address these problems using **experience replay**

- Continually update a **replay memory** table of transitions (s_t, a_t, r_t, s_{t+1}) as game (experience) episodes are played
- Train Q-network on random minibatches of transitions from the replay memory, instead of consecutive samples

Exploration vs. Exploitation

Learning: We don't know which states are good or what the actions do. We must try out the actions and states to learn what to do



- If we knew how the world works (embodied in P), then the policy should be deterministic
  - just select optimal action in each state
- Reinforcement learning is like trial-and-error learning
- The agent should discover a good policy from its experiences of the environment
- Without losing too much reward along the way
- Since we do not have complete knowledge of the world, taking what appears to be the optimal action may prevent us from finding better states/actions
- Interesting trade-off:
  - immediate reward (exploitation) vs. gaining knowledge that might enable higher future reward (exploration)

Examples

- Restaurant Selection
  - Exploitation: Go to your favourite restaurant
  - Exploration: Try a new restaurant
- Online Banner Advertisements
  - Exploitation: Show the most successful advert
  - Exploration: Show a different advert
- Oil Drilling
  - Exploitation: Drill at the best known location
  - Exploration: Drill at a new location
- Game Playing
  - Exploitation: Play the move you believe is best
  - Exploration: Play an experimental move

Q Learning: Exploration/Exploitation

- Have not specified how actions chosen (during learning)
- Can choose actions to maximize $\hat{Q}(s, a)$
- Good idea?
- Can instead employ stochastic action selection (policy):

$$P(a_i|s) = \frac{\exp(k\hat{Q}(s, a_i))}{\sum_j \exp(k\hat{Q}(s, a_j))}$$

- Can vary k during learning
  - more exploration early on, shift towards exploitation

Or a simpler way (**ε-greedy**): Exploits the best-known action with probability (1-ε) and explores a random action with probability ε, balancing between exploration and exploitation.

Putting it together: Deep Q-Learning with Experience Replay

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N ← Initialize replay memory, Q-network
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

Putting it together: Deep Q-Learning with Experience Replay

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do** ← Play M episodes (full games)
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
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  end for
end for

Initialize state (starting game screen pixels) at the beginning of each episode

Putting it together: Deep Q-Learning with Experience Replay

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  end for
end for

For each timestep t of the game

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    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

With small probability, select a random action (explore), otherwise select greedy action from current policy

Putting it together: Deep Q-Learning with Experience Replay

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  end for
end for

Take the action (a_t), and observe the reward r_t and next state s_{t+1}

Putting it together: Deep Q-Learning with Experience Replay

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    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

Store transition in replay memory

Putting it together: Deep Q-Learning with Experience Replay

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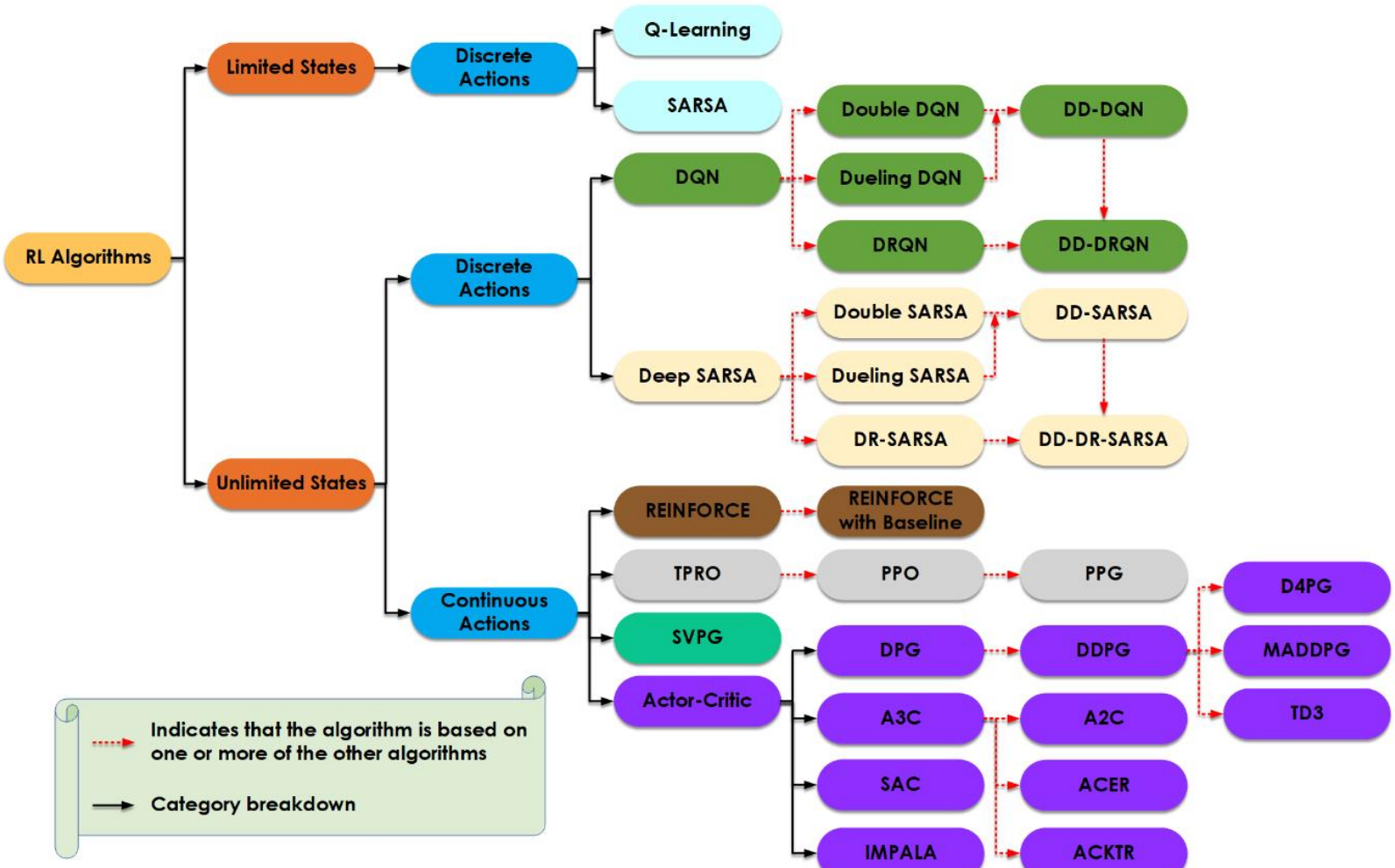
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

Experience Replay: Sample a random minibatch of transitions from replay memory and perform a gradient descent step

Reinforcement Learning Algorithms



AlMahamid, Fadi, and Katarina Grolinger. "Reinforcement learning algorithms: An overview and classification." 2021 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE). IEEE, 2021.

Questions?

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