CSCE 5218 & 4930
Deep Learning

Advanced Topics

Plan for this lecture

- Alternative representations
  - I. Graph networks
- Alternative learning mechanisms
  - II. Self supervision
  - III. Reinforcement learning
- Alternative tasks
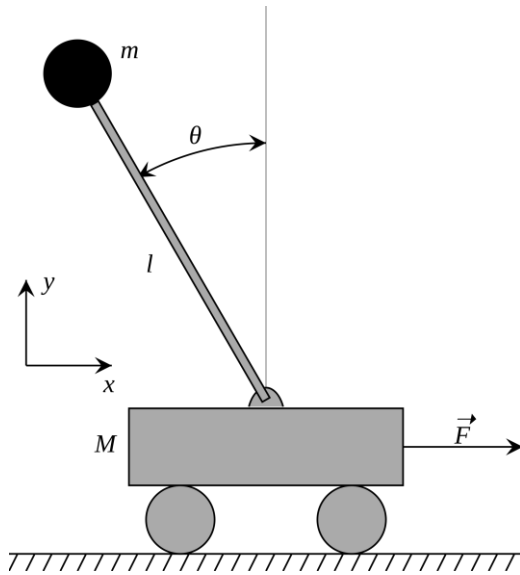 - IV. Generation
- V. Bias and ethics (optional)

Part III: Reinforcement Learning

- Basics: actions, states, rewards, MDP
- Different techniques (Q learning, policy gradients (optional), etc.)
- Example applications

Reinforcement Learning

Agent

Environment

State s_t

Reward r_t
Next state s_{t+1}
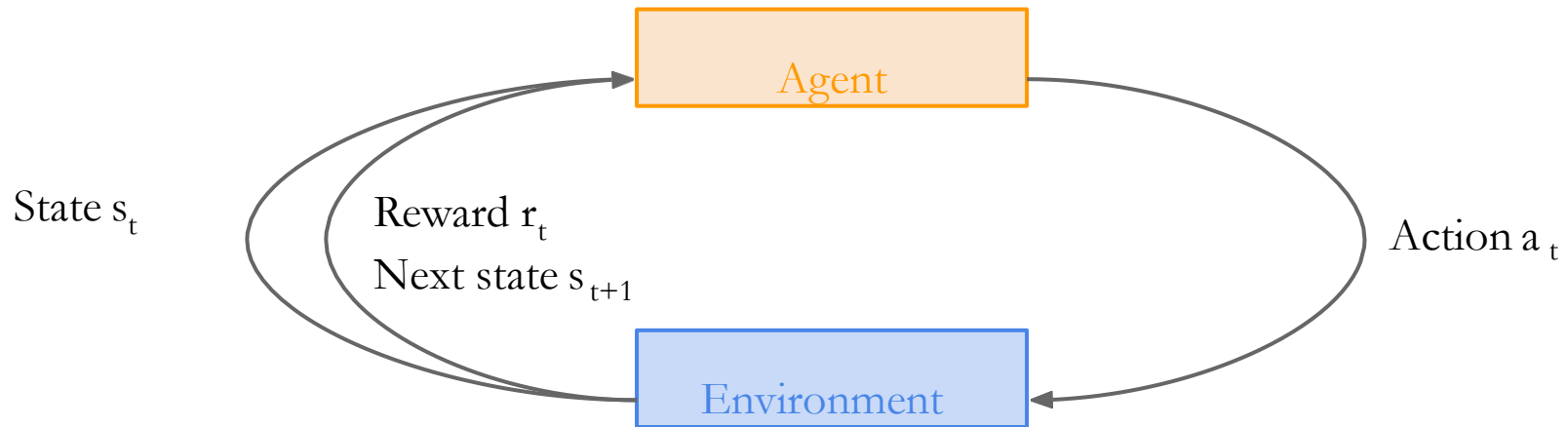
Action a_t

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
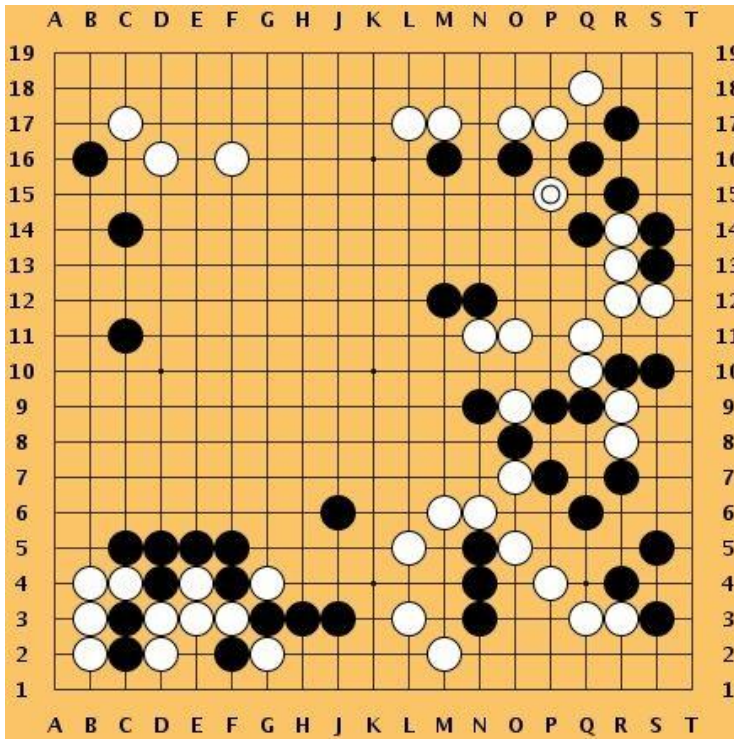**Reward:** 1 at each time step if the pole is upright

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
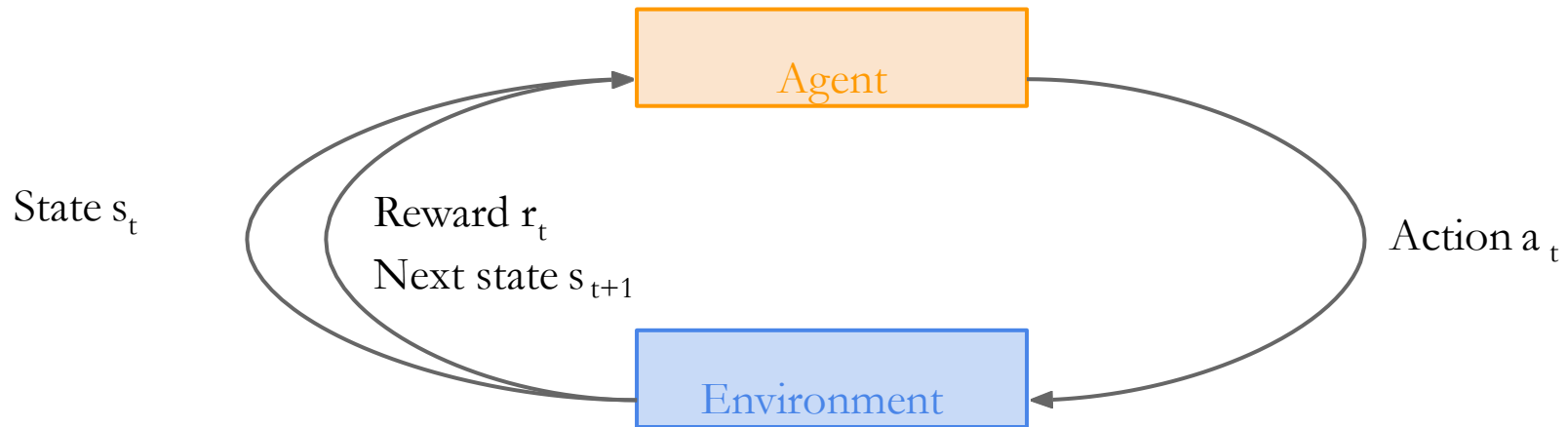
Go

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

How can we mathematically formalize the RL problem?

State s_t

Reward r_t
Next state s_{t+1}

Action a_t

Agent

Environment

Markov Decision Process

- Mathematical formulation of the RL problem
- **Markov property**: Current state completely characterises the state of the world

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

Markov Decision Process

- 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 $r_t \sim R(\,.\mid s_t, a_t)$
    - Environment samples next state $s_{t+1} \sim P(\,.\mid s_t, a_t)$
    - Agent receives reward r_t and next state s_{t+1}

- A policy π is a function from S to A that specifies what action to take in each state
- **Objective**: find policy π^* that maximizes cumulative discounted reward: $\sum_{t \geq 0} \gamma^t r_t$

A simple MDP: Grid World

actions = {

  1.   right •——→

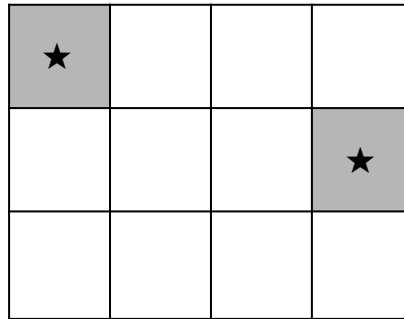 2.   left   ←——•

  3.   up   ↑•

  4.   down •↓

}

states

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

A simple MDP: Grid World

states

actions = {
1. right $\bullet\!\!-\!\!\rightarrow$
2. left $\leftarrow\!\!-\!\!\bullet$
3. up
4. down
}
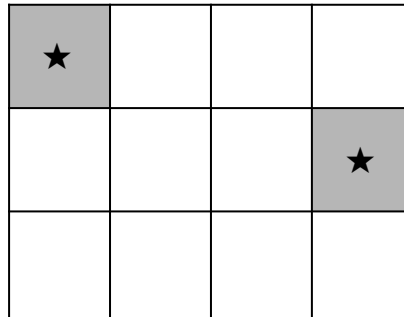
How do we set the reward?

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

A simple MDP: Grid World

states

actions = {

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

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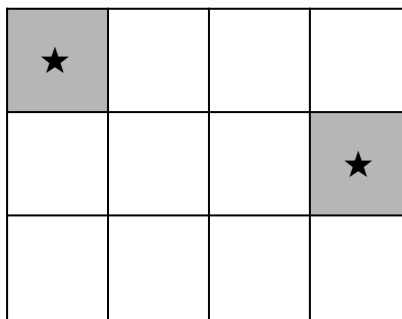
Set a negative "reward" for each transition (e.g. $r = -1$)

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

A simple MDP: Grid World
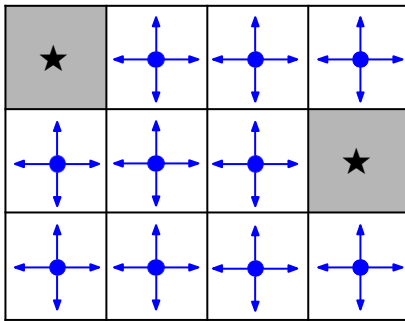
Random Policy
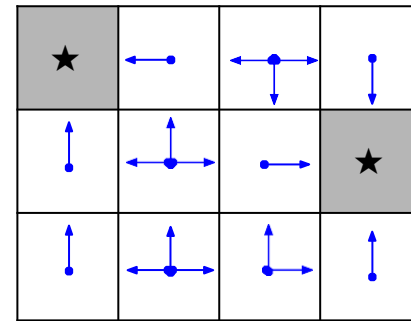
Optimal Policy

Fei-Fei Li, Andrej Karpathy, Justin Johnson, Serena Yeung

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…)?

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 $s_0 \sim p(s_0), a_t \sim \pi(\cdot|s_t), s_{t+1} \sim p(\cdot|s_t, a_t)$

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, ...

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

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

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:

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

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

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

function parameters (weights)

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

Q-network Architecture

$Q(s, a; \theta)$:

neural network
with weights θ

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

| FC-4 (Q-values) |
| FC-256 |
| 32 4x4 conv, stride 2 |
| 16 8x8 conv, stride 4 |
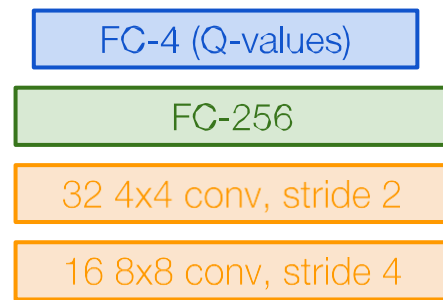
Last FC layer has 4-d
output (if 4 actions),
corresponding to
$Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$, $Q(s_t, a_4)$

Number of actions between 4-18
depending on Atari game
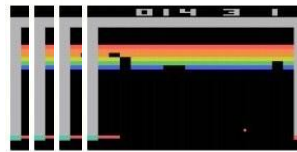
Current state s_t: 84x84x4 stack of last 4 frames
(after RGB->grayscale conversion, downsampling, and cropping)

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**
    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 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 $\phi_1 = \phi(s_1)$
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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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Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
    Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$ ⟵ Initialize state (starting game screen pixels) at the beginning of each episode
    for $t = 1, T$ **do**
        With probability ϵ select a random action a_t
        otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
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    for $t = 1, T$ **do**   ← For each timestep t of the game
        With probability ϵ select a random action a_t
        otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
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    end for
end for

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

Fei-Fei Li, Andrej Karpathy, Justin Johnson, Serena Yeung

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← 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

Algorithm 1 Deep Q-learning with Experience Replay

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　　end for
end for

Store transition in replay memory

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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

https://arxiv.org/pdf/1312.5602.pdf

Policy Gradients (review on your own)

What is a problem with Q-learning?
The Q-function can be very complicated!

Example: a robot grasping an object has a very high-dimensional state => hard to learn exact value of every (state, action) pair

But the policy can be much simpler: just close your hand
Can we learn a policy directly, e.g. finding the best policy from a collection of policies?

Policy Gradients

Formally, let's define a class of parameterized policies: $\Pi = \{\pi_\theta, \theta \in \mathbb{R}^m\}$

For each policy, define its value:

$$J(\theta) = \mathbb{E}\left[\sum_{t \geq 0} \gamma^t r_t | \pi_\theta\right]$$

We want to find the optimal policy $\theta^* = \arg\max_\theta J(\theta)$

How can we do this?

Gradient ascent on policy parameters!

REINFORCE Algorithm (Williams 1992)

Gradient estimator:

$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} r(\tau) \nabla_\theta \log \pi_\theta(a_t | s_t)$$
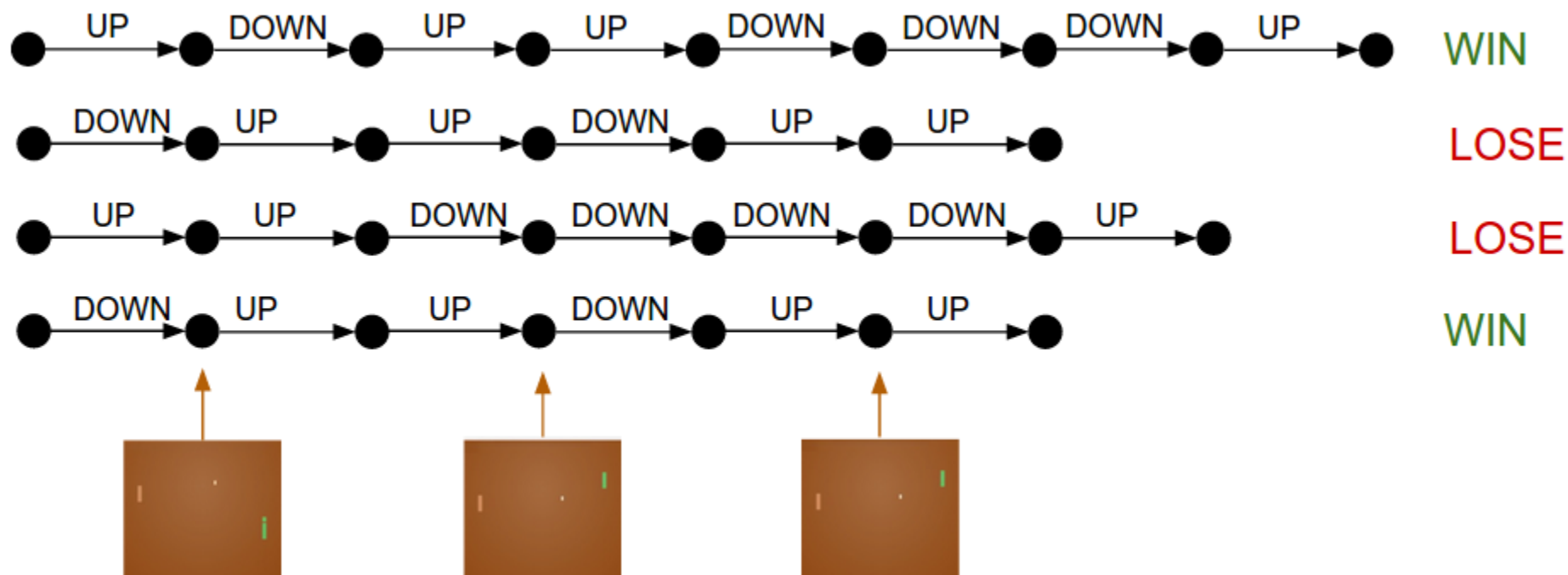
Interpretation:
- If $r(\tau)$ is high, push up the probabilities of the actions seen
- If $r(\tau)$ is low, push down the probabilities of the actions seen

Might seem simplistic to say that if a trajectory is good then all its actions were good.
But in expectation, it averages out!

Policy Gradients

REINFORCE Algorithm (Williams 1992)

Gradient estimator:
$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} r(\tau) \nabla_\theta \log \pi_\theta(a_t | s_t)$$

Interpretation:
- If $r(\tau)$ is high, push up the probabilities of the actions seen
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Might seem simplistic to say that if a trajectory is good then all its actions were good.
But in expectation, it averages out!

However, this also suffers from high variance because credit assignment is really hard. Can we help the estimator?

Variance Reduction

Gradient estimator:
$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} r(\tau) \nabla_\theta \log \pi_\theta(a_t | s_t)$$

First idea: Push up probabilities of an action seen, only by the cumulative future reward from that state

$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} \left(\sum_{t' \geq t} r_{t'} \right) \nabla_\theta \log \pi_\theta(a_t | s_t)$$

Second idea: Use discount factor γ to ignore delayed effects

$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} \left(\sum_{t' \geq t} \gamma^{t'-t} r_{t'} \right) \nabla_\theta \log \pi_\theta(a_t | s_t)$$

Fei-Fei Li, Ranjay Krishna, Danfei Xu

Variance Reduction: Baseline

Problem: The raw value of a trajectory isn't necessarily meaningful. For example, if rewards are all positive, you keep pushing up probabilities of actions.

What is important then? Whether a reward is better or worse than what you expect to get

Idea: Introduce a baseline function dependent on the state.
Concretely, estimator is now:

$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} \left(\sum_{t' \geq t} \gamma^{t'-t} r_{t'} - b(s_t) \right) \nabla_\theta \log \pi_\theta(a_t | s_t)$$

Fei-Fei Li, Ranjay Krishna, Danfei Xu

How to choose the baseline?

Want to push up the probability of an action from a state, if this action was better than the **expected value of what we should get from that state**.

Intuitively, we are happy with an action a_t in a state s_t if $\qquad Q^\pi(s_t, a_t) - V^\pi(s_t)$ is large. On the contrary, we are unhappy with an action if it's small.

Using this, we get the estimator:

$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} (Q^{\pi_\theta}(s_t, a_t) - V^{\pi_\theta}(s_t)) \nabla_\theta \log \pi_\theta(a_t|s_t)$$

Policy Gradients tl;dr

- Objective: $\sum_i A_i \log p(y_i|x_i)$

- x_i = state

- y_i = sampled action

- A_i = "advantage" e.g. +1/-1 for win/lose in simplest version, or discounted, or improvement over "baseline"

Policy Gradients vs Q-Learning

- Policy gradients suffers from high variance and instability; might want to make gradients smaller (e.g. relative to a baseline)
- Policy gradients can handle continuous action spaces (Gaussian policy)
- Estimating exact value of state-action pairs vs choosing what actions to take (value not important)
- Step-by-step (did I correctly estimate the reward at this time) vs delayed feedback (run policy and wait until game terminates)

Actor-Critic Algorithm

We can combine Policy Gradients and Q-learning by training both an **actor** (the policy) and a **critic** (the Q-function).

- The actor decides which action to take, and the critic tells the actor how good its action was and how it should adjust
- Also alleviates the task of the critic as it only has to learn the values of (state, action) pairs generated by the policy
- Can also incorporate Q-learning tricks e.g. experience replay
- Define by the advantage function how much an action was better than expected

$$A^\pi(s, a) = Q^\pi(s, a) - V^\pi(s)$$
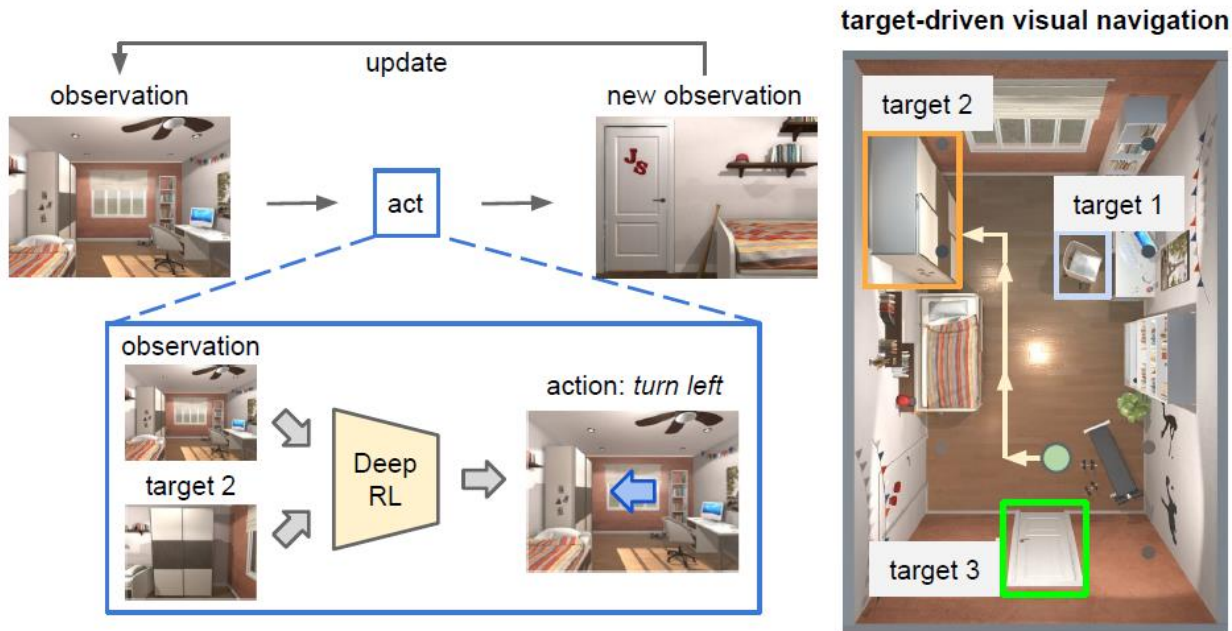
RL for navigation

Fig. 1. The goal of our deep reinforcement learning model is to navigate towards a visual target with a minimum number of steps. Our model takes the current observation and the image of the target as input and generates an action in the 3D environment as the output. Our model learns to navigate to different targets in a scene without re-training.

Zhu et al., "Target-driven Visual Navigation in Indoor Scenes using Deep Reinforcement Learning", ICRA 2017

RL for navigation

(a)   (b)

Figure 1: Our goal is to use scene priors to improve navigation in unseen scenes and towards novel objects. (a) There is no mug in the field of view of the agent, but the likely location for finding a mug is the cabinet near the coffee machine. (b) The agent has not seen a mango before, but it infers that the most likely location for finding a mango is the fridge since similar objects such as apple appear there as well. The most likely locations are shown with the orange box.
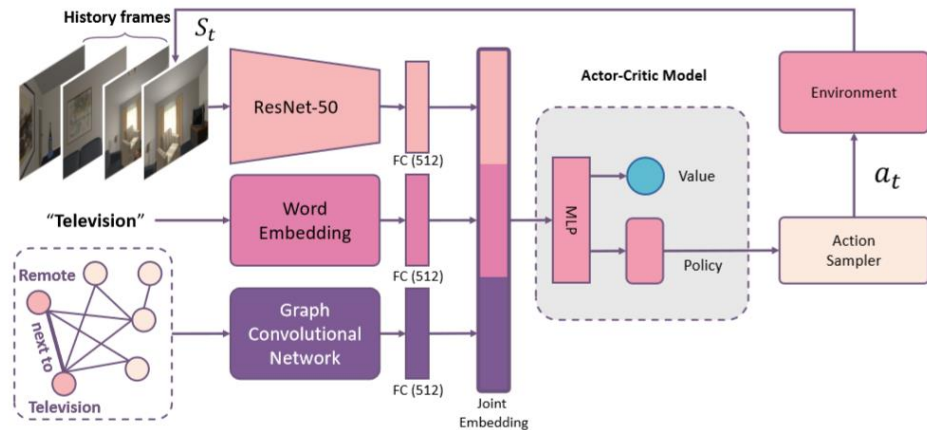

Figure 2: **Overview of the architecture.** Our model to incorporate semantic knowledge into semantic navigation. Specifically, we learn a policy network that decides an action based on the visual features of the current state, the semantic target category feature and the features extracted from the knowledge graph. We extract features from the parts of the knowledge graph that are activated.

Yang et al., "Visual Semantic Navigation using Scene Priors", ICLR 2019
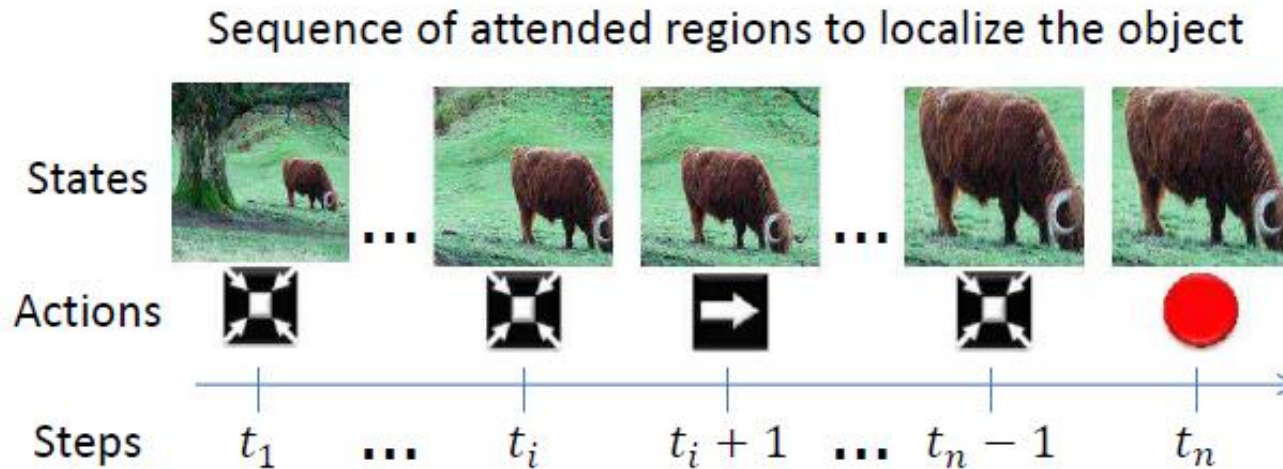
RL for object detection

Figure 1. A sequence of actions taken by the proposed algorithm to localize a cow. The algorithm attends regions and decides how to transform the bounding box to progressively localize the object.

Caicedo and Lazebnik, "Active Object Localization with Deep Reinforcement Learning", ICCV 2015

RL for object detection

Figure 2. Illustration of the actions in the proposed MDP, giving 4 degrees of freedom to the agent for transforming boxes.

$$R_a(s, s') = sign\left(IoU(b', g) - IoU(b, g)\right) \qquad R_\omega(s, s') = \begin{cases} +\eta & \text{if } IoU(b, g) \geq \tau \\ -\eta & \text{otherwise} \end{cases}$$

Caicedo and Lazebnik, "Active Object Localization with Deep Reinforcement Learning", ICCV 2015