Lecture 21: Reinforcement Learning

Assignment 5: Object Detection

Single-stage detector
Two-stage detector

Due on Monday 12/9, 11:59pm

Assignment 6: Generative Models

Generative Adversarial Networks

Due on Tuesday 12/17, 11:59pm

So far: Supervised Learning

Supervised Learning

Data: (x, y)

x is data, y is label

Goal: Learn a *function* to map x -> y

Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc.

Classification

Cat

So far: Unsupervised Learning

Unsupervised Learning

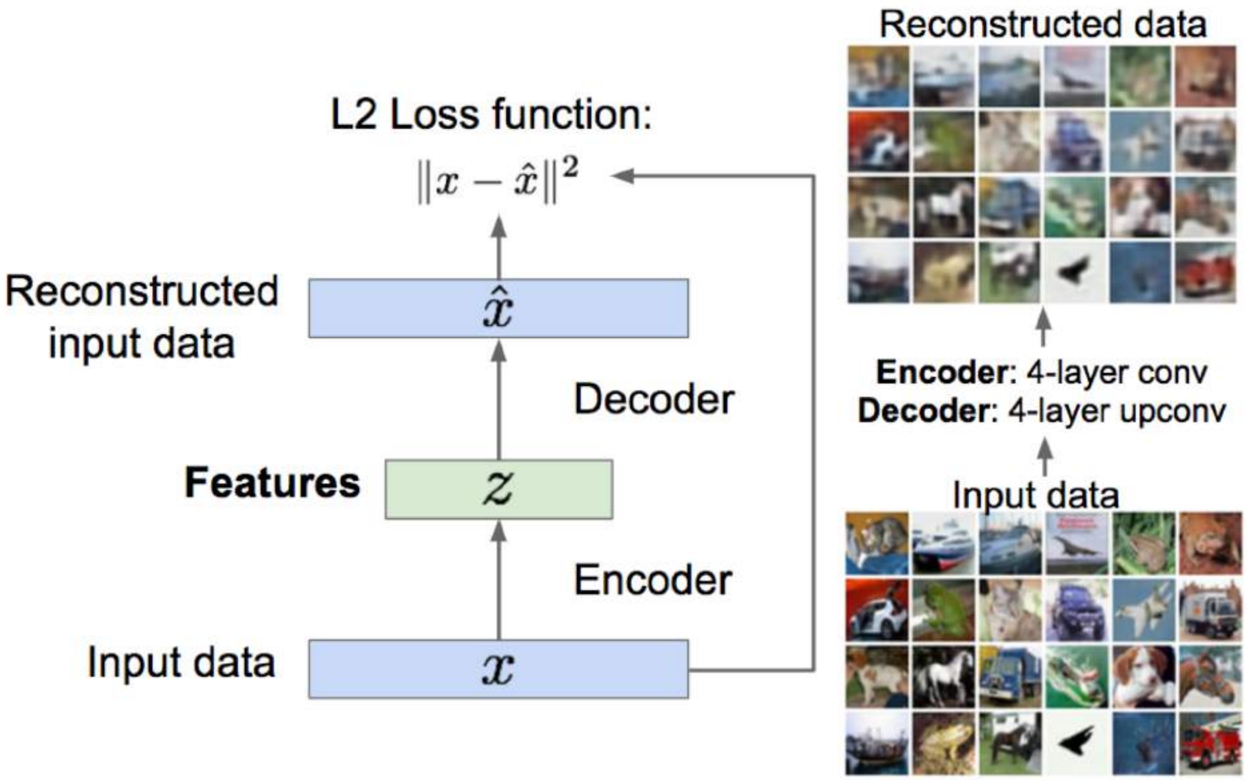
Data: x

Just data, no labels!

Goal: Learn some underlying hidden *structure* of the data

Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

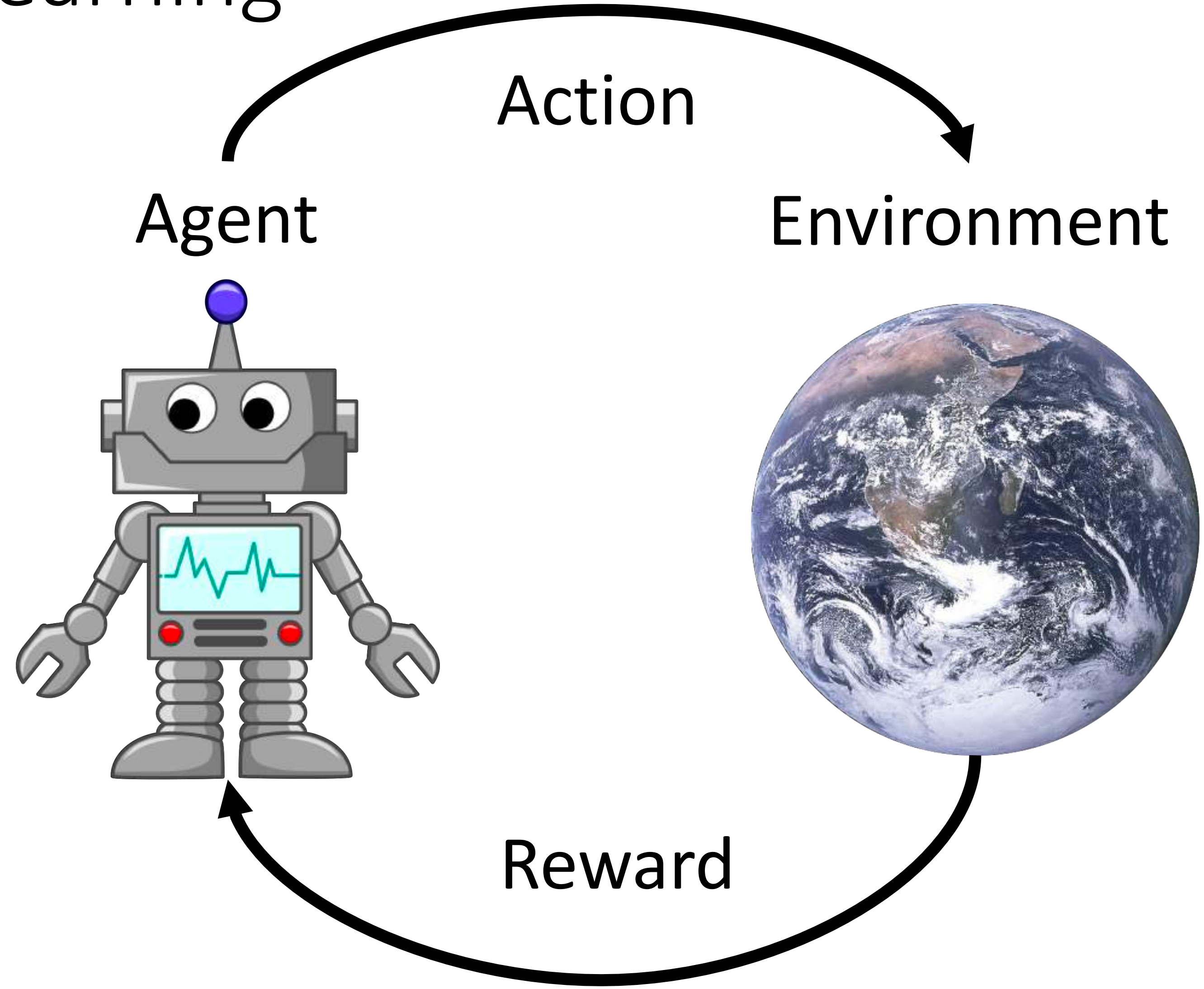
Feature Learning
(e.g. autoencoders)



Today: Reinforcement Learning

Problems where an **agent** performs **actions** in **environment**, and receives **rewards**

Goal: Learn how to take actions that maximize reward



Earth photo is in the public domain
Robot image is in the public domain

Overview

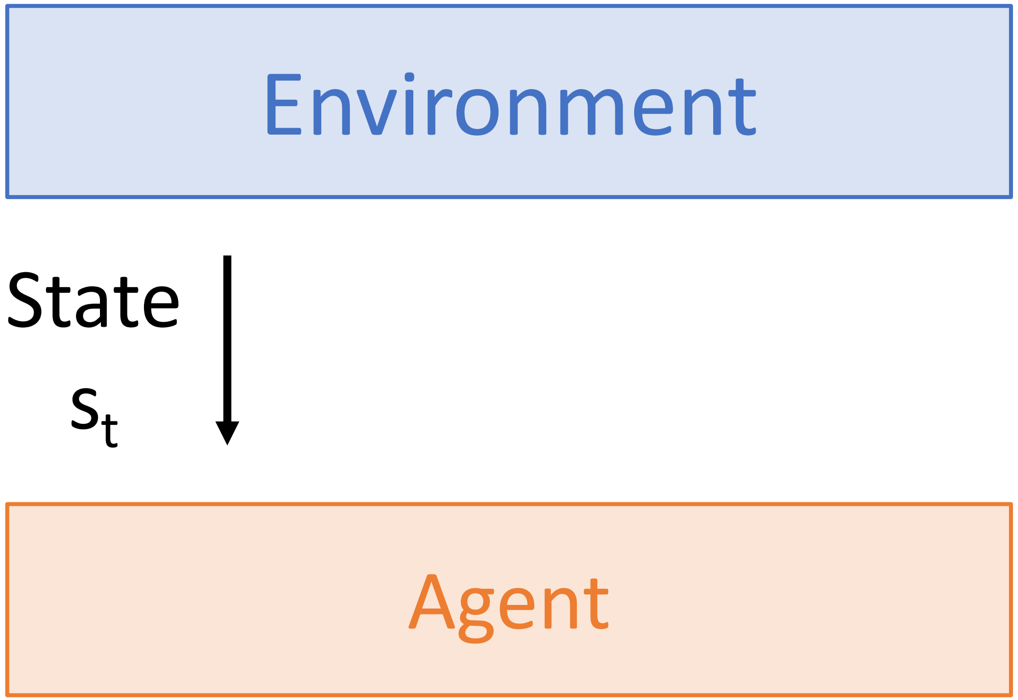
- What is reinforcement learning?
- Algorithms for reinforcement learning
    - Q-Learning
    - Policy Gradients

Reinforcement Learning

Environment

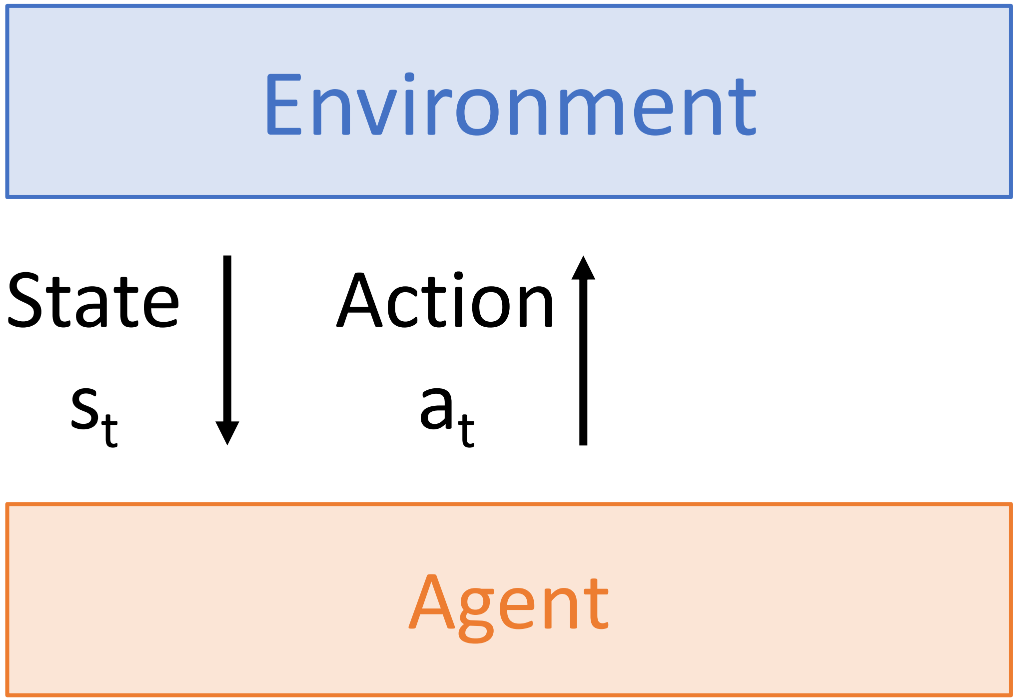
Agent

Reinforcement Learning



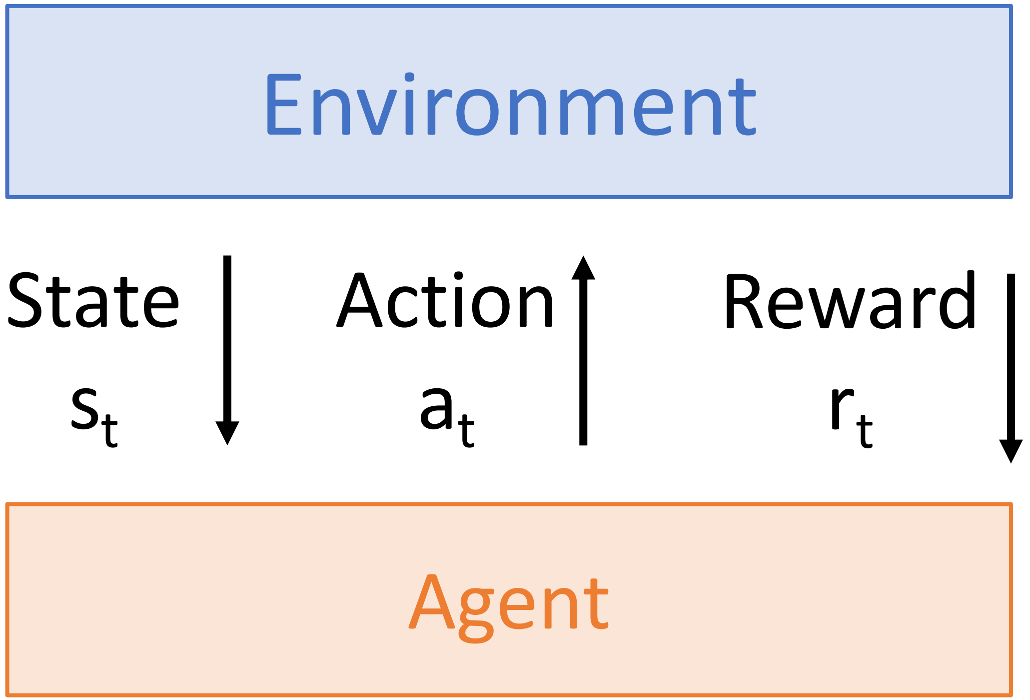
The agent sees a **state**; may be noisy or incomplete

Reinforcement Learning



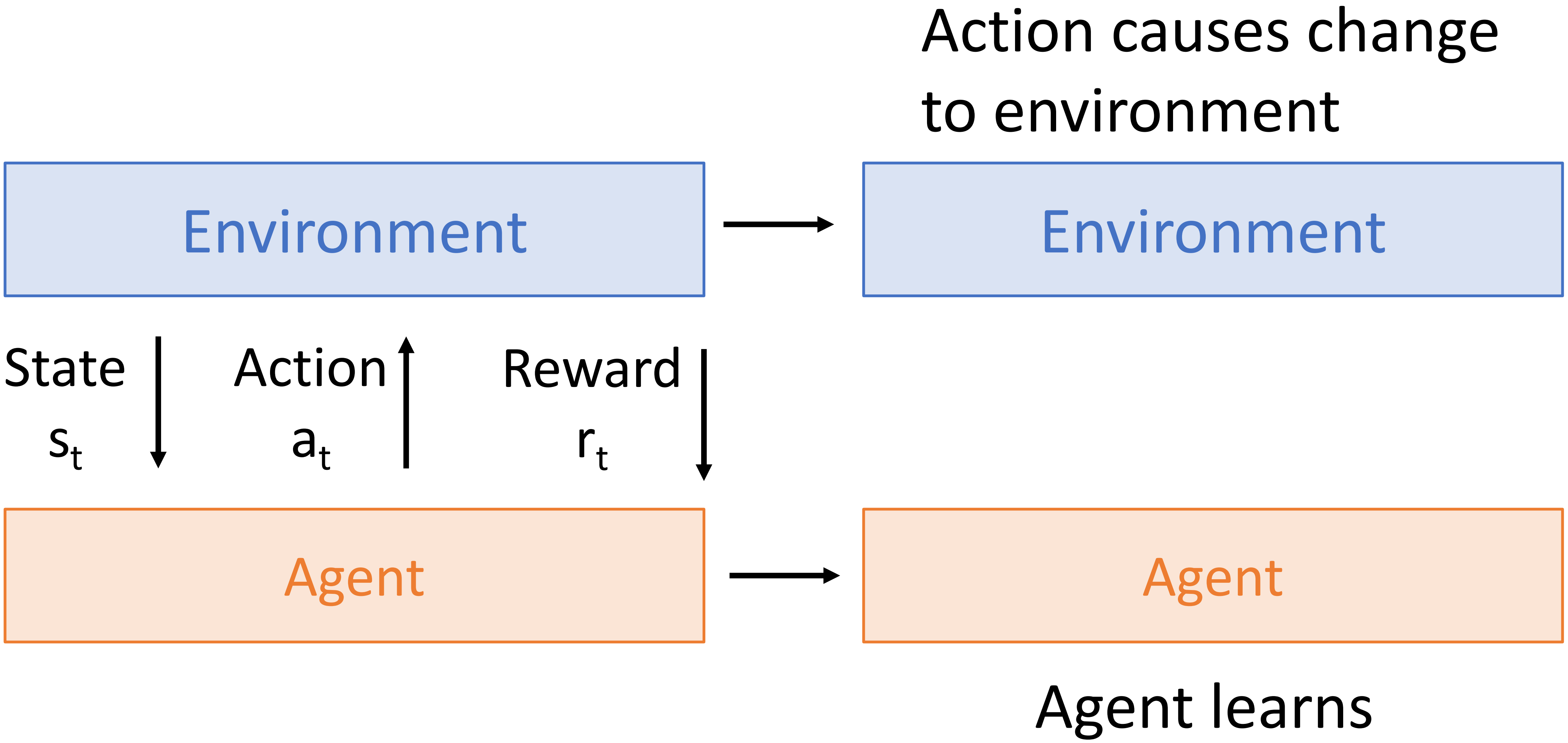
The makes an **action** based on what it sees

Reinforcement Learning



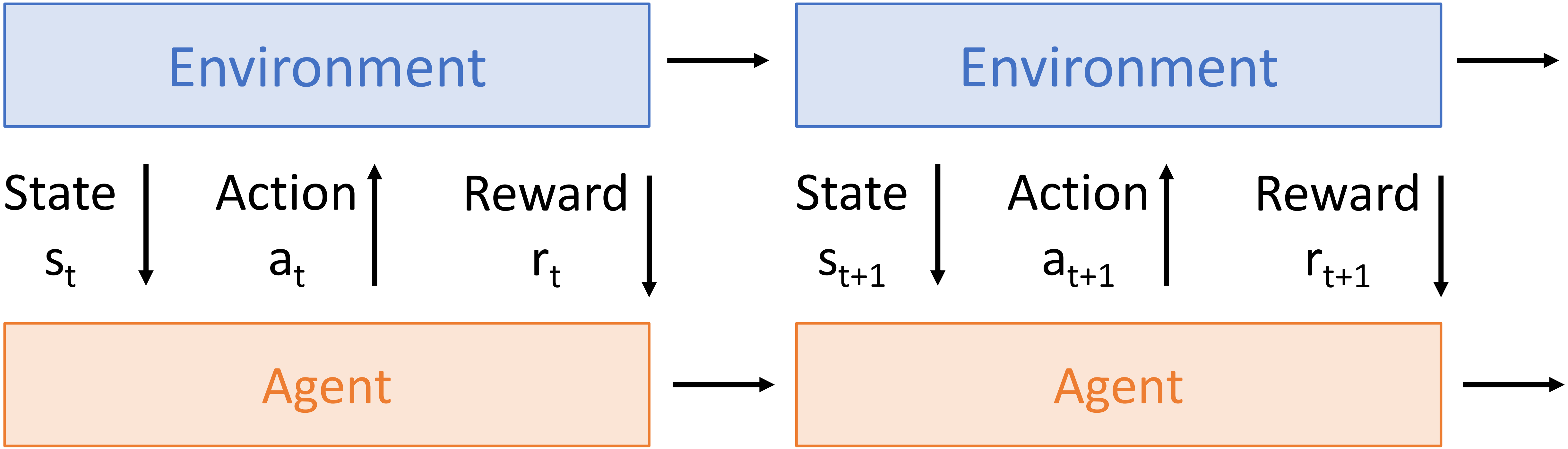
Reward tells the agent how well it is doing

Reinforcement Learning

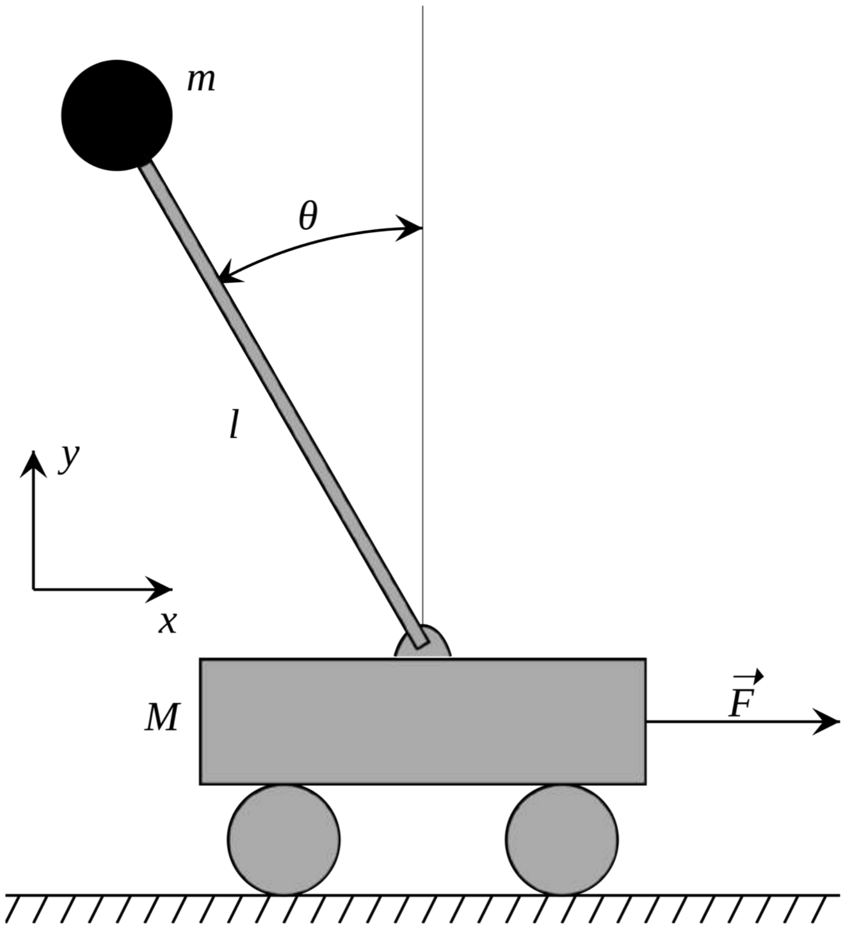


Reinforcement Learning

Process repeats



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

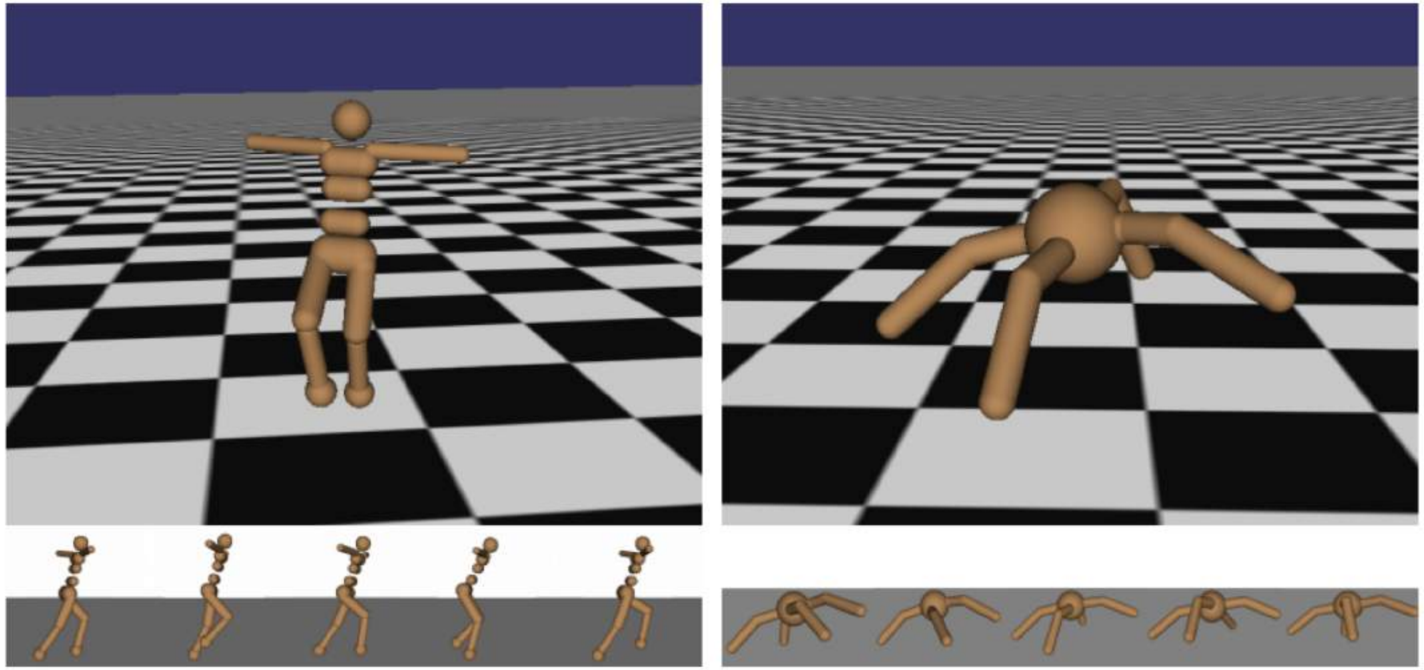


Figure from: Schulman et al, "High-Dimensional Continuous Control Using Generalized Advantage Estimation", ICLR 2016

Objective: Make the robot move forward

State: Angle, position, velocity of all joints

Action: Torques applied on joints

Reward: 1 at each time step upright + forward movement

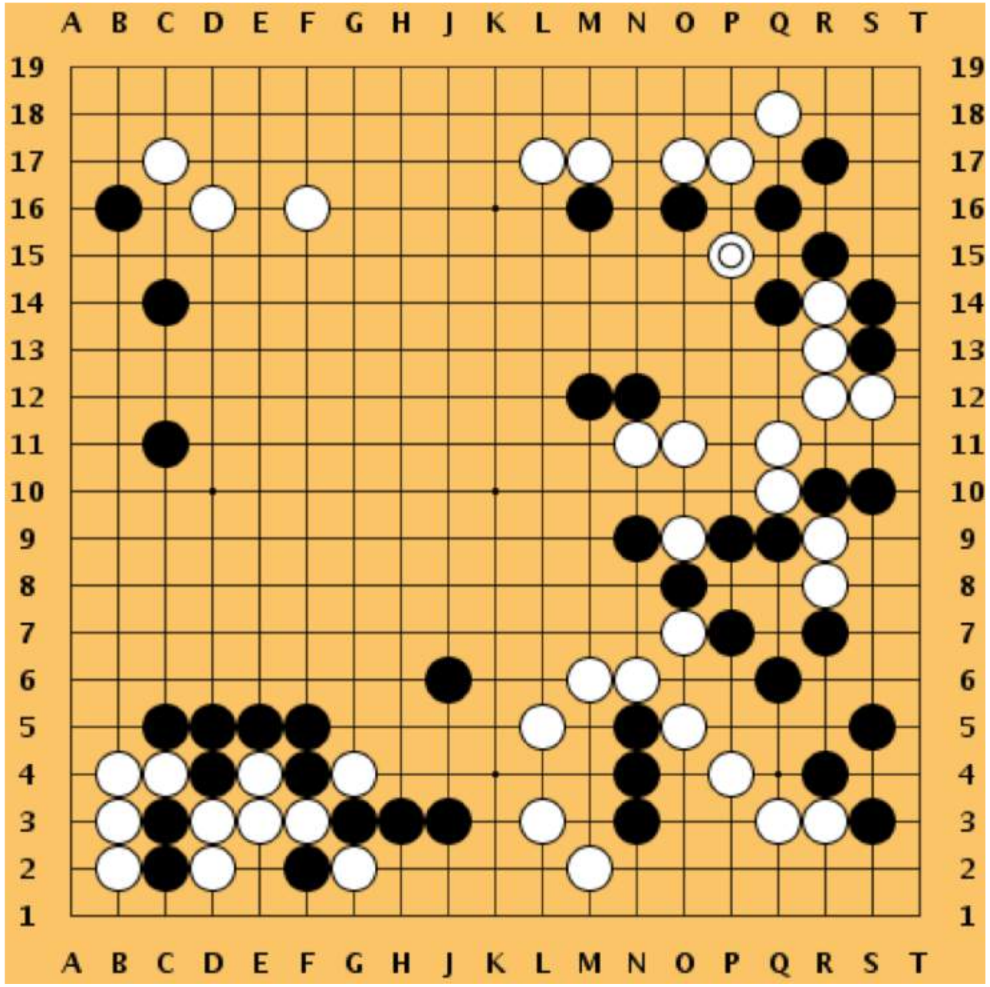
Example: Atari Games

Objective: Complete the game with the highest score

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

Mnih et al, “Playing Atari with Deep Reinforcement Learning”, NeurIPS Deep Learning Workshop, 2013

Example: Go



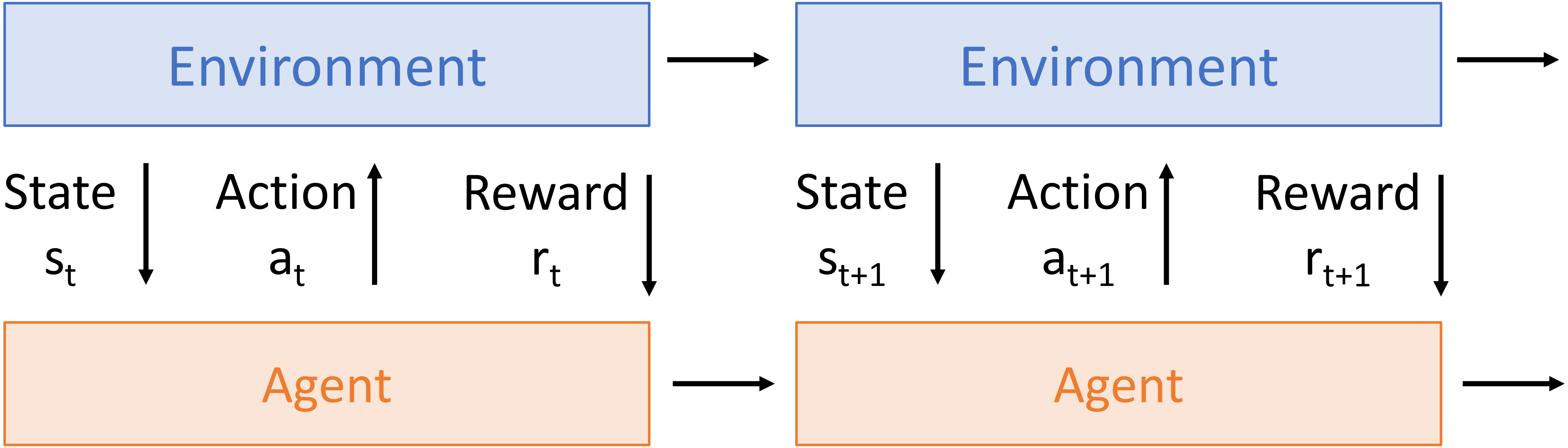
Objective: Win the game!

State: Position of all pieces

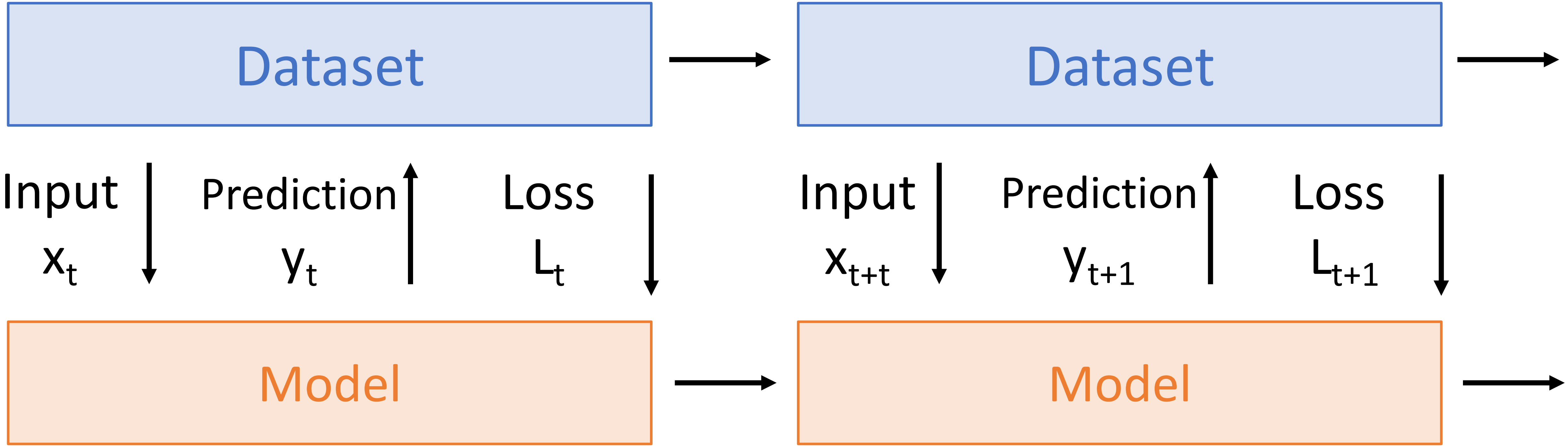
Action: Where to put the next piece down

Reward: On last turn: 1 if you won, 0 if you lost

Reinforcement Learning vs Supervised Learning

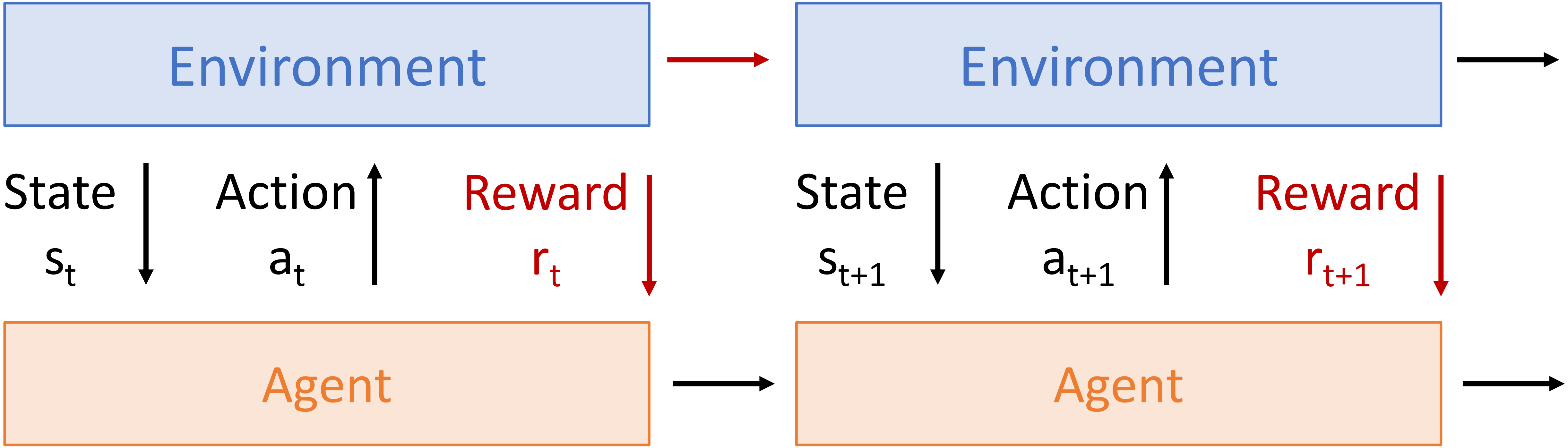


Reinforcement Learning vs Supervised Learning



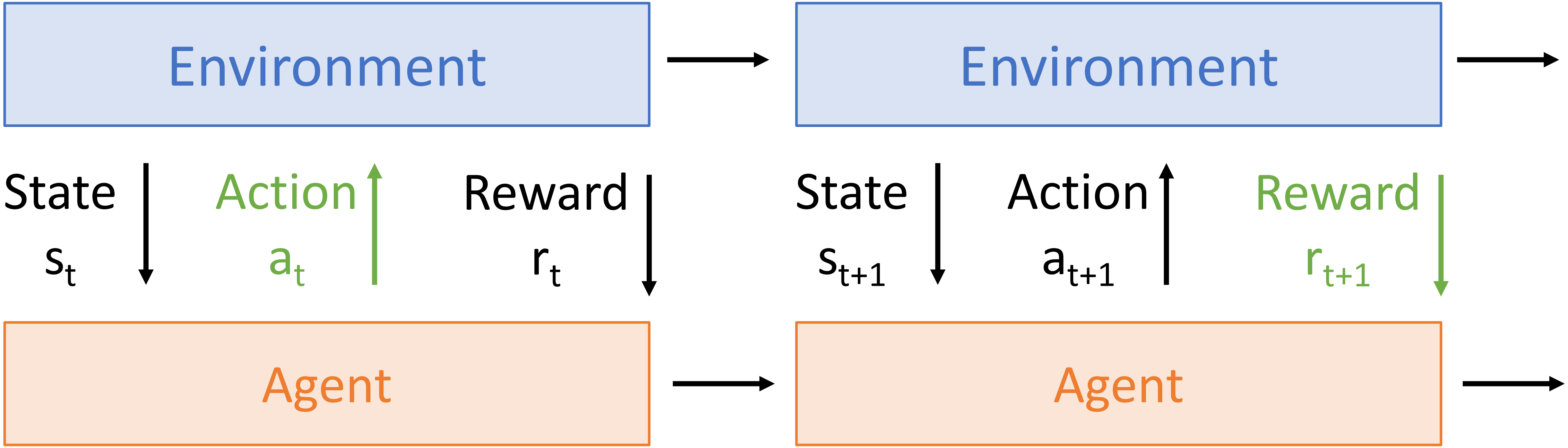
Why is RL different from normal supervised learning?

Reinforcement Learning vs Supervised Learning



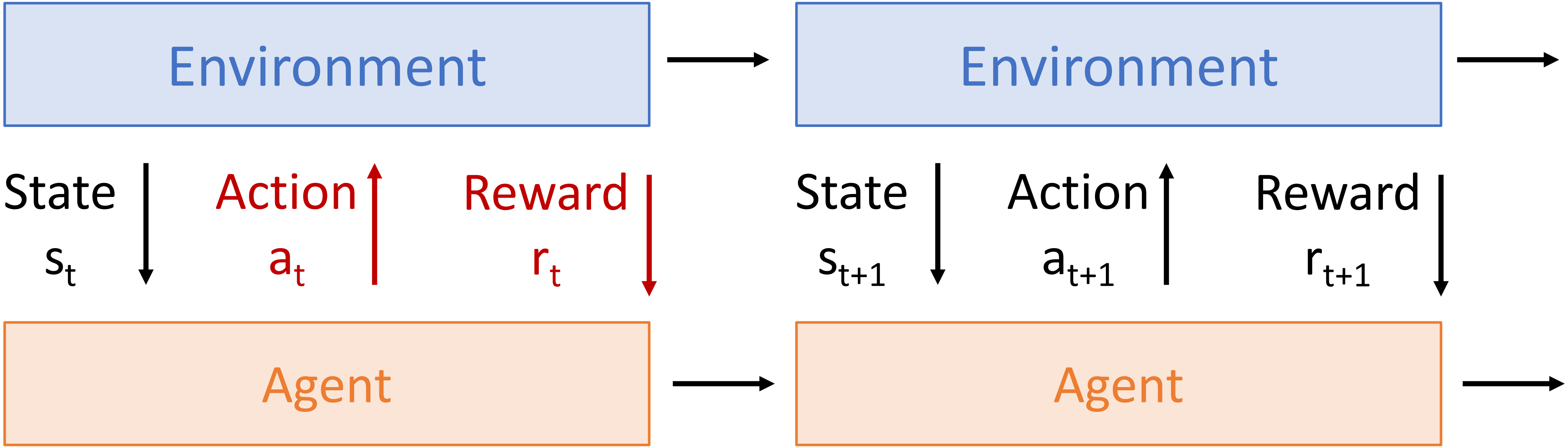
Stochasticity: Rewards and state transitions may be random

Reinforcement Learning vs Supervised Learning



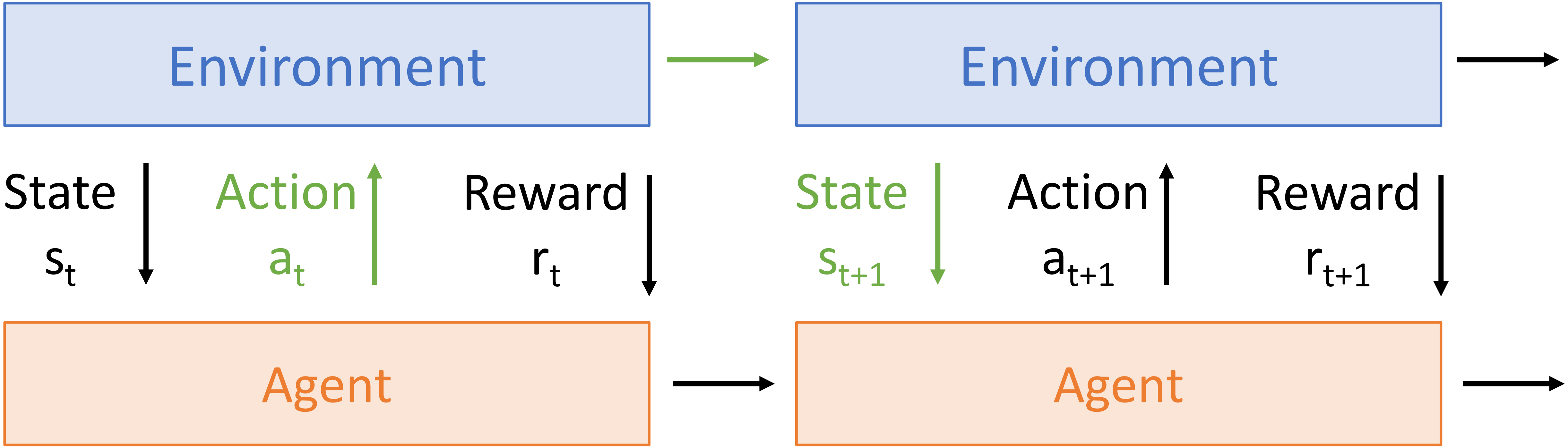
Credit assignment: Reward r_t may not directly depend on action a_t

Reinforcement Learning vs Supervised Learning



Nondifferentiable: Can't backprop through world; can't compute dr_t/da_t

Reinforcement Learning vs Supervised Learning



Nonstationary: What the agent experiences depends on how it acts

Markov Decision Process (MDP)

Mathematical formalization of the RL problem: A tuple (S, A, R, P, γ)

S: Set of possible states
A: Set of possible actions
R: Distribution of reward given (state, action) pair
P: Transition probability: distribution over next state given (state, action)
γ: Discount factor (tradeoff between future and present rewards)

Markov Property: The current state completely characterizes the state of the world. Rewards and next states depend only on current state, not history.

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Agent executes a **policy** π giving distribution of actions conditioned on states
Goal: Find policy π^* that maximizes cumulative discounted reward: $\sum_t \gamma^t r_t$

Markov Decision Process (MDP)

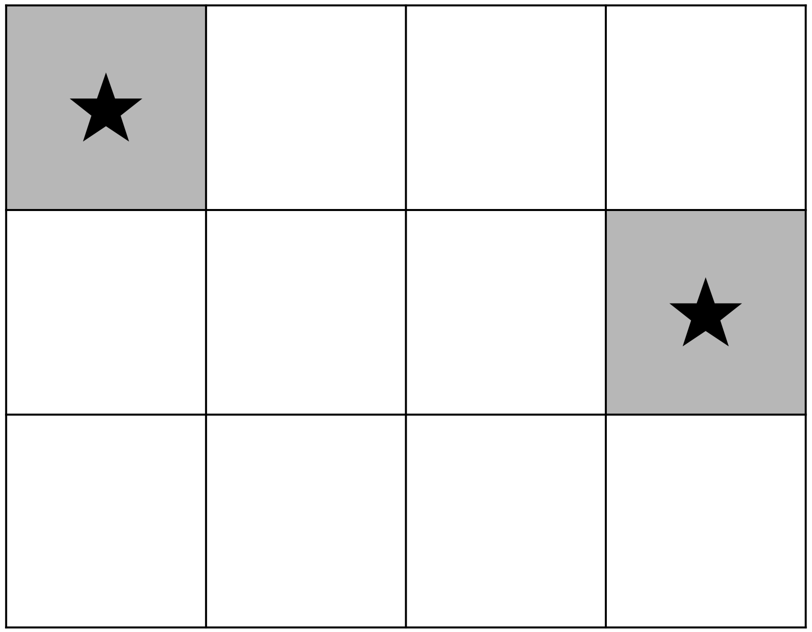
- At time step t=0, environment samples initial state $s_0 \sim p(s_0)$
- Then, for t=0 until done:
  - Agent selects action $a_t \sim \pi(a \mid s_t)$
  - Environment samples reward $r_t \sim R(r \mid s_t, a_t)$
  - Environment samples next state $s_{t+1} \sim P(s \mid s_t, a_t)$
  - Agent receives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

A simple MDP: Grid World

Actions:

1. Right
2. Left
3. Up
4. Down

States



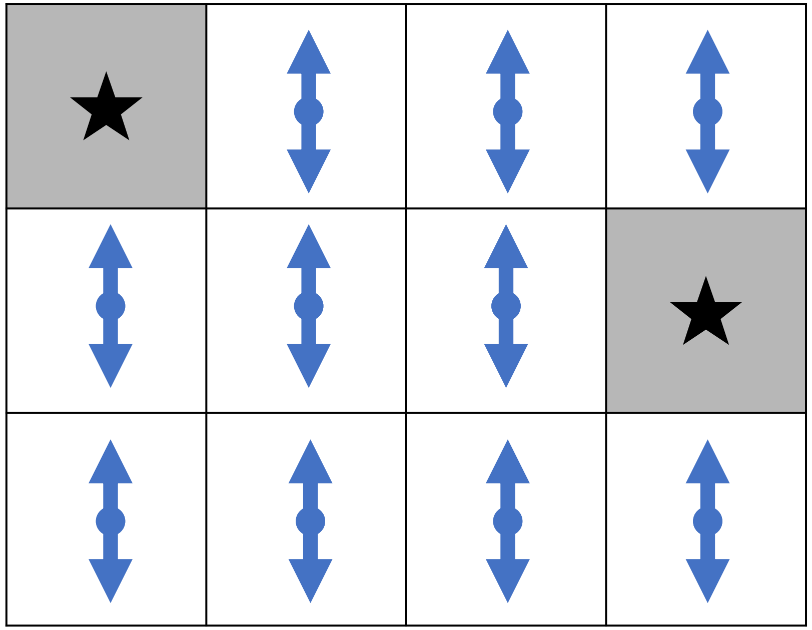
Reward

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

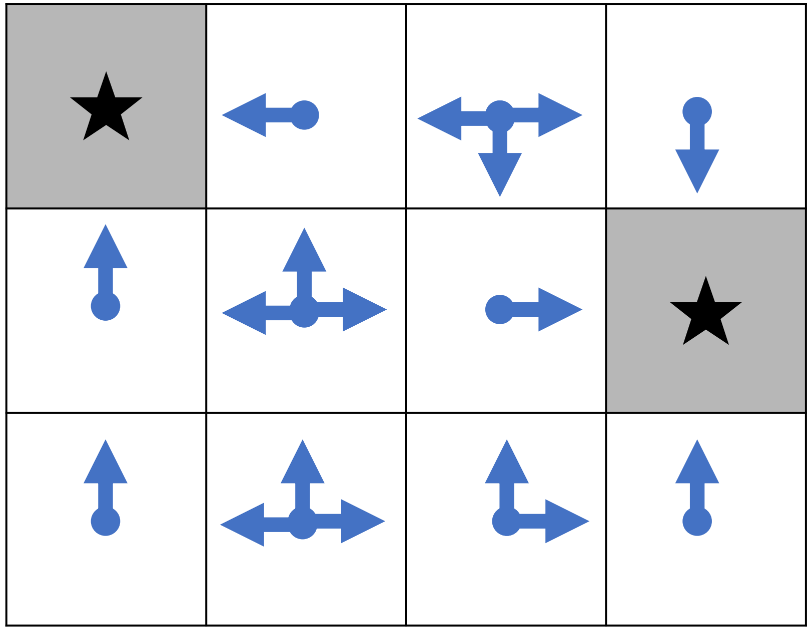
Objective: Reach one of the terminal states in as few moves as possible

A simple MDP: Grid World

Bad policy



Optimal Policy



Finding Optimal Policies

Goal: Find the optimal policy π^* that maximizes (discounted) sum of rewards.

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Solution: Maximize the expected sum of rewards

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t \geq 0} \gamma^t r_t \mid \pi\right]$$

$$s_0 \sim p(s_0)$$
$$a_t \sim \pi(a \mid s_t)$$
$$s_{t+1} \sim P(s \mid s_t, a_t)$$

Value Function and Q Function

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

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

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

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How good is a state-action pair? The **Q 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

Optimal Q-function: $Q^*(s, a)$ is the Q-function for the optimal policy π^*
It gives the max possible future reward when taking action a in state s:

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Where $r \sim R(s,a), s' \sim P(s,a)$

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Intuition: After taking action a in state s, we get reward r and move to a new state s'. After that, the max possible reward we can get is $\max_{a'} Q^*(s',a')$

Solving for the optimal policy: Value Iteration

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Idea: If we find a function Q(s, a) that satisfies the Bellman Equation, then it must be Q^*.

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Start with a random Q, and use the Bellman Equation as an update rule:

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

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Amazing fact: Q_i converges to Q^* as $i \to \infty$
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Solution: Approximate Q(s, a) with a neural network, use Bellman Equation as loss!

Solving for the optimal policy: Deep Q-Learning

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Train a neural network (with weights θ) to approximate Q^*: $Q^*(s,a) \approx Q(s,a;\theta)$

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Use the Bellman Equation to tell what Q should output for a given state and action:

$$y_{s,a,\theta} = \mathbb{E}_{r,s'}\left[r + \gamma \max_{a'} Q(s',a';\theta)\right]$$

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Problem: How to sample batches of data for training?

Case Study: Playing Atari Games

Objective: Complete the game with the highest score

State: Raw pixel inputs of the game screen
Action: Game controls e.g. Left, Right, Up, Down
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Case Study: Playing Atari Games

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

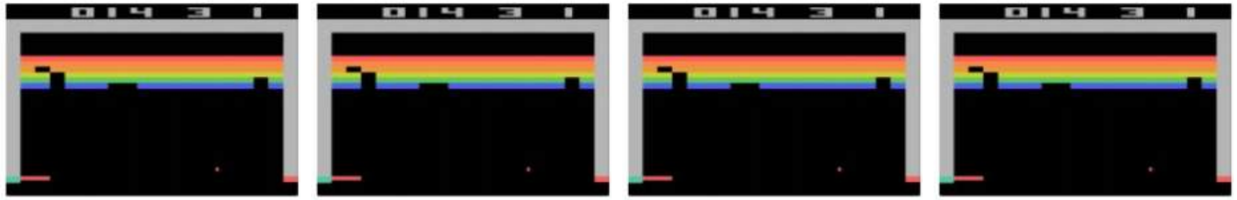
Network output:
Q-values for all actions

FC-A (Q-values)

FC-256

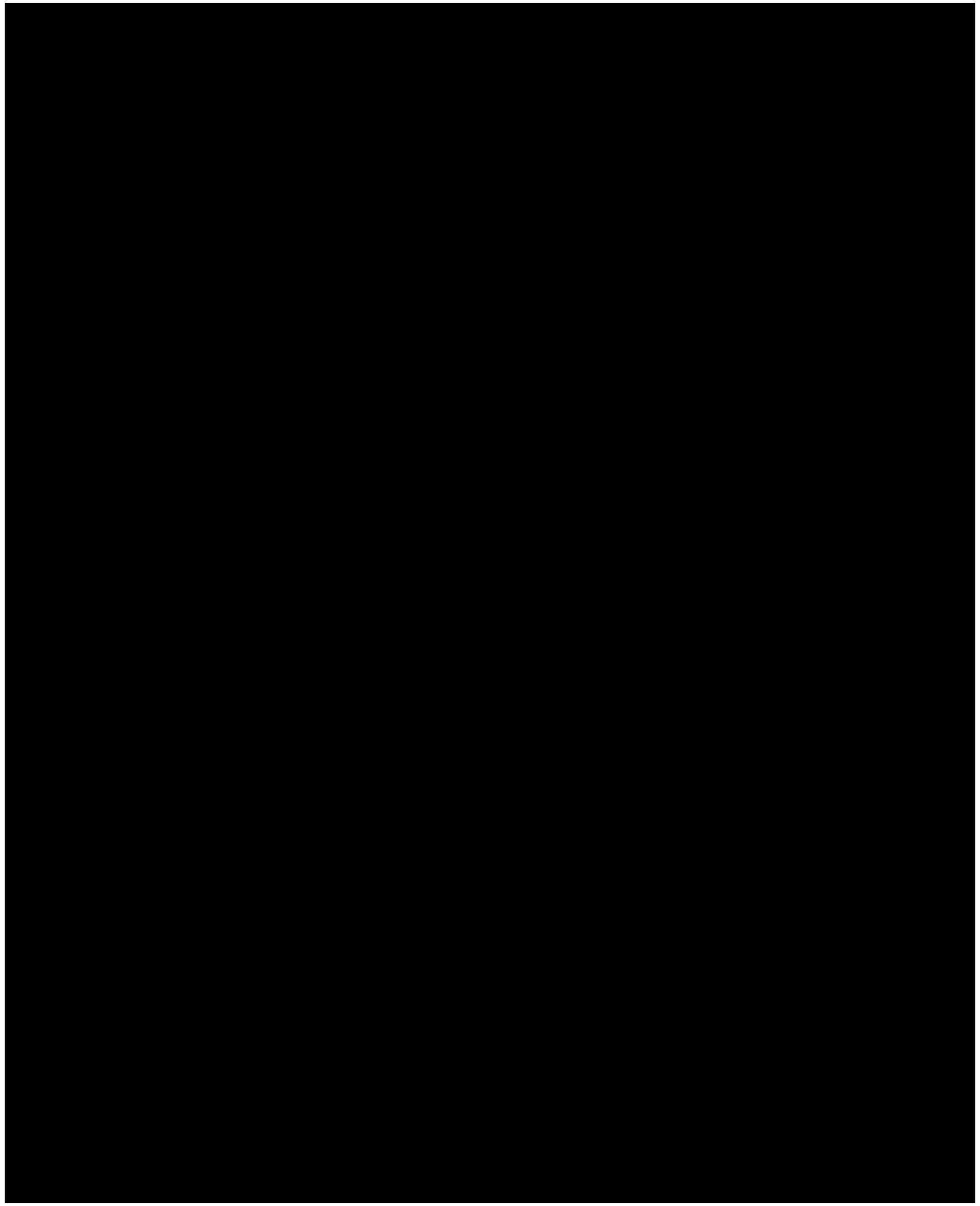
Conv(16->32, 4x4, stride 2)

Conv(4->16, 8x8, stride 4)



With 4 actions: last layer gives values $Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$, $Q(s_t, a_4)$

Network input: state s_t: 4x84x84 stack of last 4 frames
(after RGB->grayscale conversion, downsampling, and cropping)



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

Q-Learning

Q-Learning: Train network $Q_\theta(s, a)$ to estimate future rewards for every (state, action) pair

Problem: For some problems this can be a hard function to learn.
For some problems it is easier to learn a mapping from states to actions

Q-Learning vs Policy Gradients

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Objective function: Expected future rewards when following policy π_θ:

$$J(\theta) = \mathbb{E}_{r \sim p_\theta}\left[\sum_{t \geq 0} \gamma^t r_t\right]$$

Find the optimal policy by maximizing: $\theta^* = \arg\max_\theta J(\theta)$ **(Use gradient ascent!)**

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General formulation: $J(\theta) = \mathbb{E}_{x\sim p_\theta}[f(x)]$ Want to compute $\frac{\partial J}{\partial \theta}$

Policy Gradients: REINFORCE Algorithm

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Approximate the expectation via sampling!

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Sequence of states and actions when following policy π_θ

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Reward we get from state sequence x

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Gradient of predicted action scores with respect to model weights. Backprop through model π_θ!

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2. Collect trajectories x and rewards f(x) using policy π_θ
3. Compute dJ/dθ

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2. Collect trajectories x and rewards f(x) using policy π_θ
3. Compute dJ/dθ
4. Gradient ascent step on θ
5. GOTO 2

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Intuition:
When f(x) is high: Increase the probability of the actions we took.
When f(x) is low: Decrease the probability of the actions we took.

So far: Q-Learning and Policy Gradients

Q-Learning: Train network $Q_\theta(s, a)$ to estimate future rewards for every (state, action) pair
Use Bellman Equation to define loss function for training Q:

$$y_{s,a,\theta} = \mathbb{E}_{r,s'}\left[r + \gamma \max_{a'} Q(s', a'; \theta)\right] \qquad \text{Where } r \sim R(s,a), s' \sim P(s,a)$$

$$L(s,a) = \left(Q(s,a;\theta) - y_{s,a,\theta}\right)^2$$

Policy Gradients: Train a network $\pi_\theta(a \mid s)$ that takes state as input, gives distribution over which action to take in that state. Use REINFORCE Rule for computing gradients:

$$J(\theta) = \mathbb{E}_{x \sim p_\theta}[f(x)] \qquad \frac{\partial J}{\partial \theta} = \mathbb{E}_{x \sim p_\theta}\left[f(x) \sum_{t \geq 0} \frac{\partial}{\partial \theta} log\, \pi_\theta(a_t | s_t)\right]$$

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Improving policy gradients: Add **baseline** to reduce variance of gradient estimator

Other approaches: Model Based RL

Actor-Critic: Train an actor that predicts actions (like policy gradient) and a critic that predicts the future rewards we get from taking those actions (like Q-Learning)

Sutton and Barto, "Reinforcement Learning: An Introduction", 1998; Degris et al, "Model-free reinforcement learning with continuous action in practice", 2012; Mnih et al, "Asynchronous Methods for Deep Reinforcement Learning", ICML 2016

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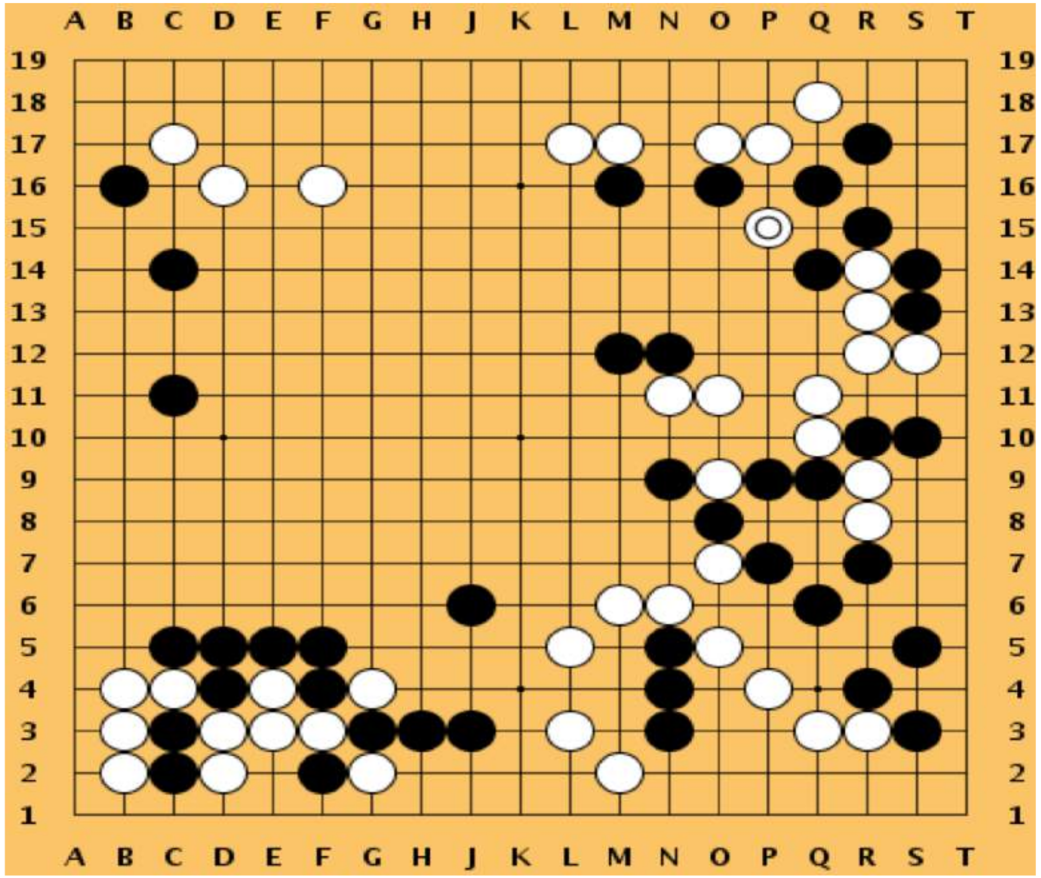
Adversarial Learning: Learn to fool a discriminator that classifies actions as real/fake

Ho and Ermon, "Generative Adversarial Imitation Learning", NeurIPS 2016

Case Study: Playing Games

AlphaGo: (January 2016)
- Used imitation learning + tree search + RL
- Beat 18-time world champion Lee Sedol



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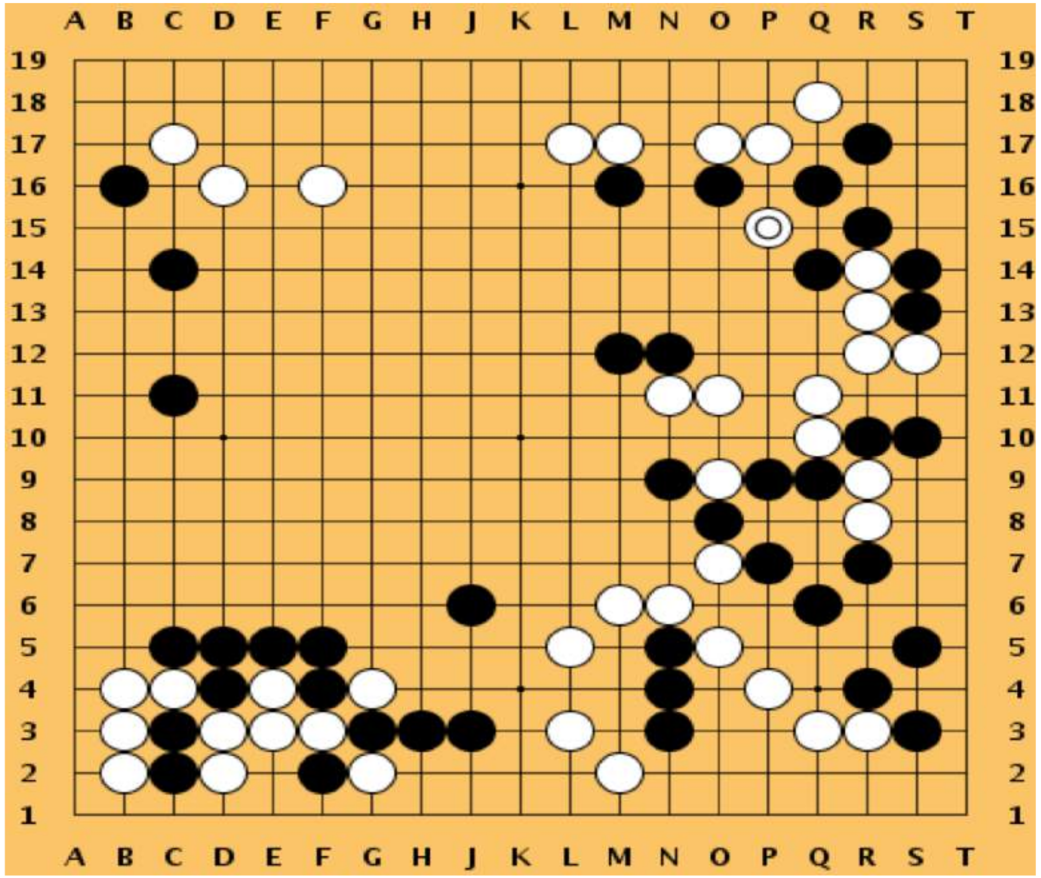

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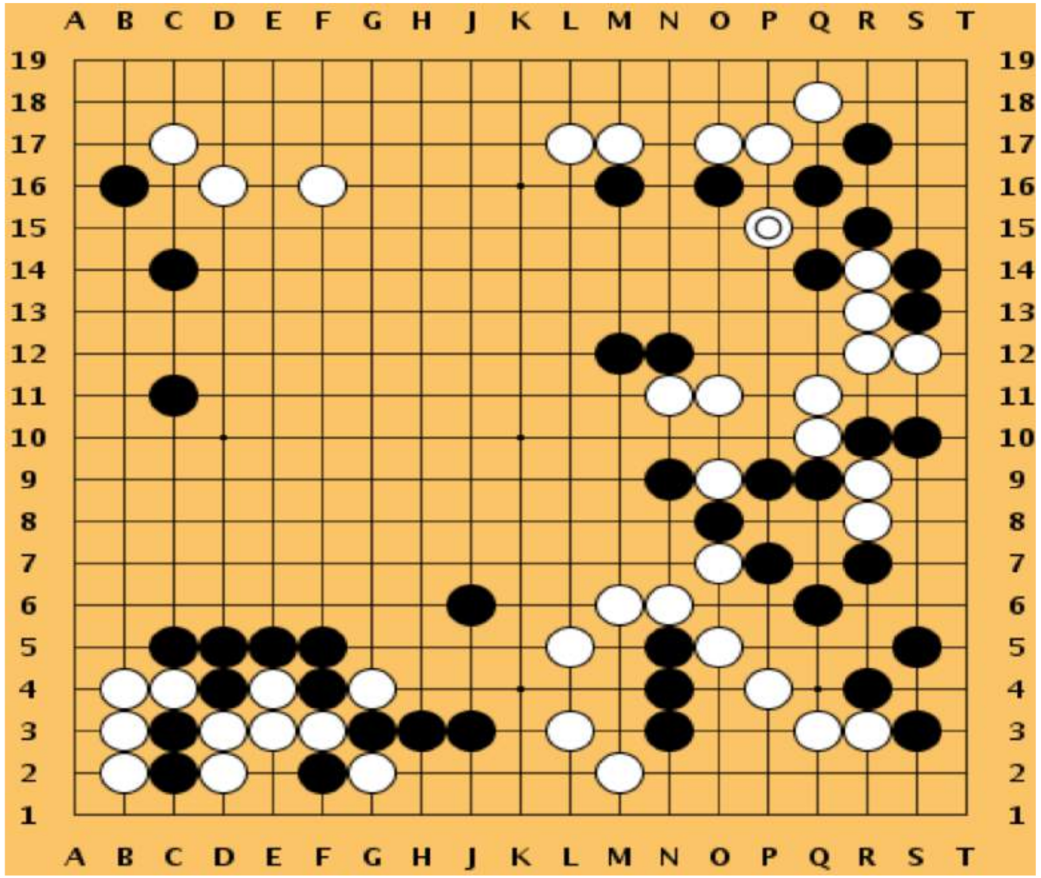

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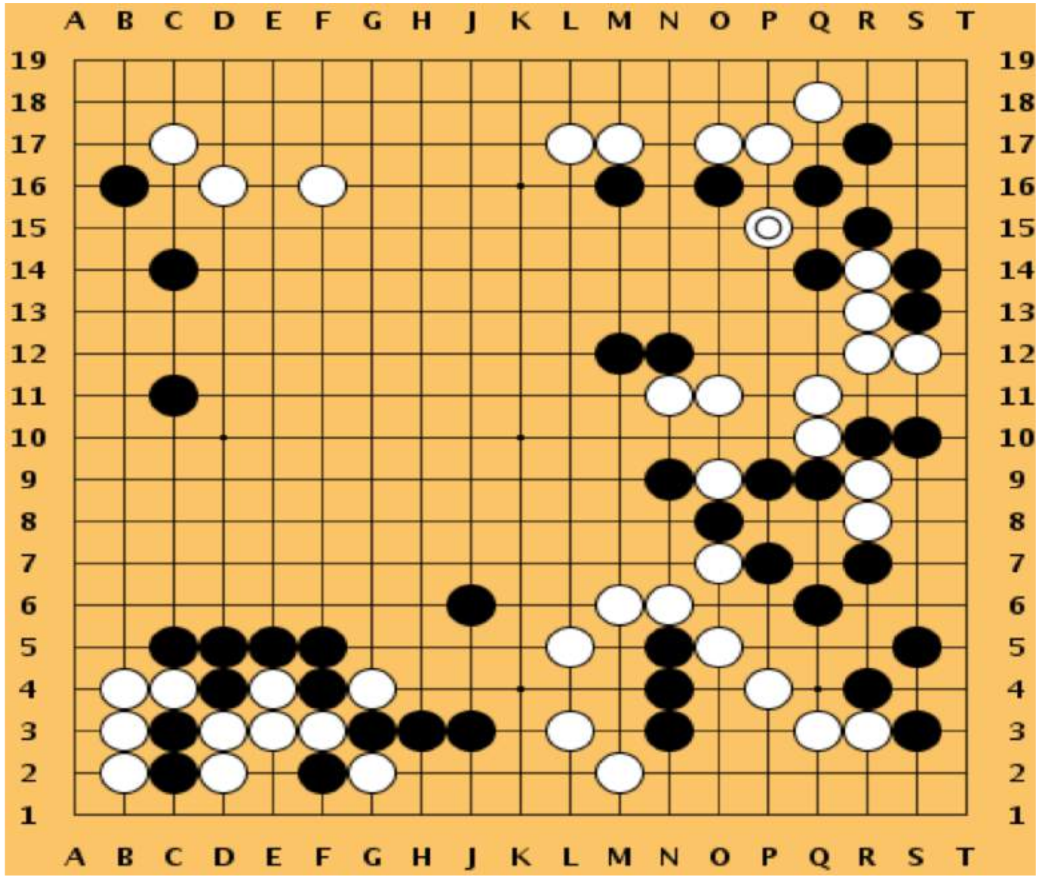

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- Plans through a learned model of the game

November 2019: Lee Sedol announces retirement

"With the debut of AI in Go games, I've realized that I'm not at the top even if I become the number one through frantic efforts"
"Even if I become the number one, there is an entity that cannot be defeated"

Silver et al, "Mastering the game of Go with deep neural networks and tree search", Nature 2016
Silver et al, "Mastering the game of Go without human knowledge", Nature 2017
Silver et al, "A general reinforcement learning algorithm that masters chess, shogi, and go through self-play", Science 2018
Schrittwieser et al, "Mastering Atari, Go, Chess and Shogi by Planning with a Learned Model", arXiv 2019

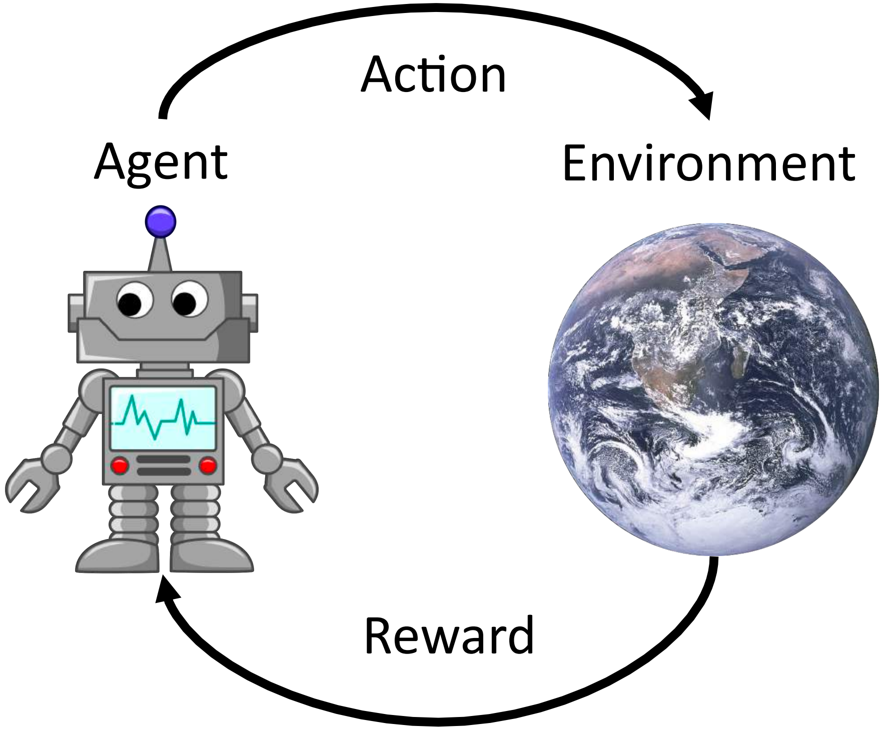
Quotes from: https://en.yna.co.kr/view/AEN20191127004800315

More Complex Games

StarCraft II: AlphaStar (October 2019)
Vinyals et al, "Grandmaster level in StarCraft II using multi-agent reinforcement learning", Science 2018

Dota 2: OpenAI Five (April 2019)
No paper, only a blog post:
https://openai.com/five/#how-openai-five-works

Reinforcement Learning: Interacting With World



Normally we use RL to train **agents** that interact with a (noisy, nondifferentiable) **environment**

Reinforcement Learning: Stochastic Computation Graphs

Can also use RL to train neural networks with **nondifferentiable** components!

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Example: Small "routing" network sends image to one of K networks

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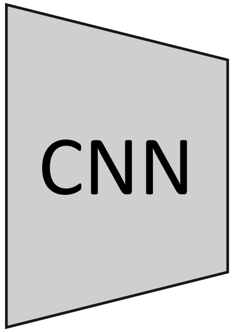
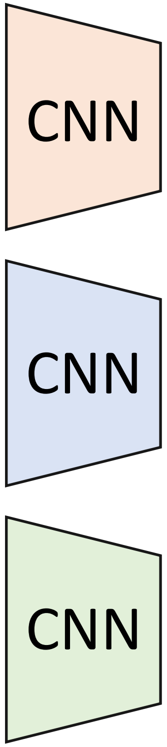


Which network to use?

P(orange) = 0.2

P(blue) = 0.1

P(green) = 0.7



Reinforcement Learning: Stochastic Computation Graphs

Can also use RL to train neural networks with **nondifferentiable** components!

Example: Small “routing” network sends image to one of K networks

CNN

Which network to use?

P(orange) = 0.2

P(blue) = 0.1

P(green) = 0.7

Sample:

Green

CNN

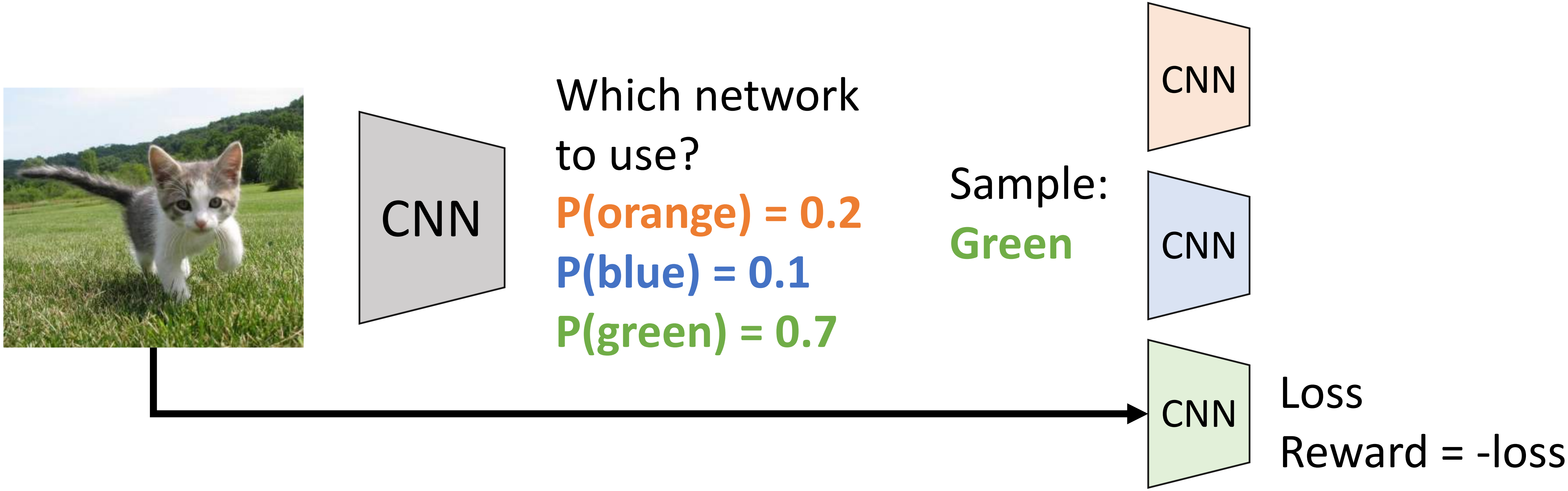
CNN

CNN

Reinforcement Learning: Stochastic Computation Graphs

Can also use RL to train neural networks with **nondifferentiable** components!

Example: Small "routing" network sends image to one of K networks



Reinforcement Learning: Stochastic Computation Graphs

Can also use RL to train neural networks with **nondifferentiable** components!

Example: Small "routing" network sends image to one of K networks

Update routing net with policy gradient

CNN

Which network to use?

P(orange) = 0.2

P(blue) = 0.1

P(green) = 0.7

Sample:

Green

CNN

CNN

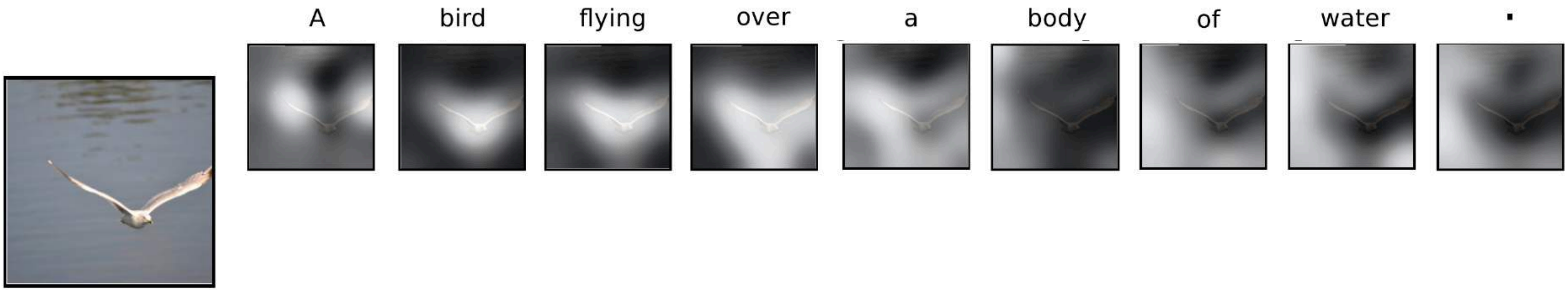
CNN

Loss

Reward = -loss

Stochastic Computation Graphs: Attention

Recall: Image captioning with attention. At each timestep use a weighted combination of features from different spatial positions (Soft Attention)



Xu et al, "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Stochastic Computation Graphs: Attention

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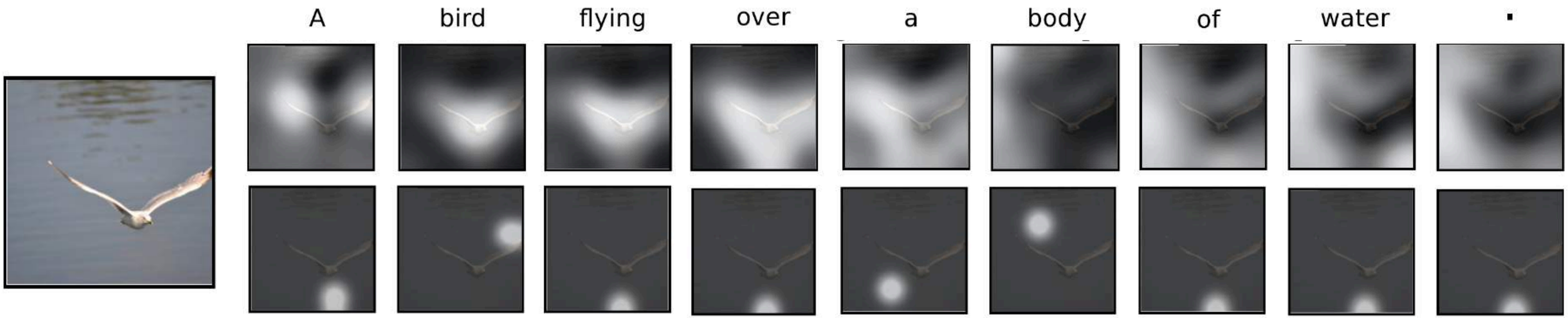
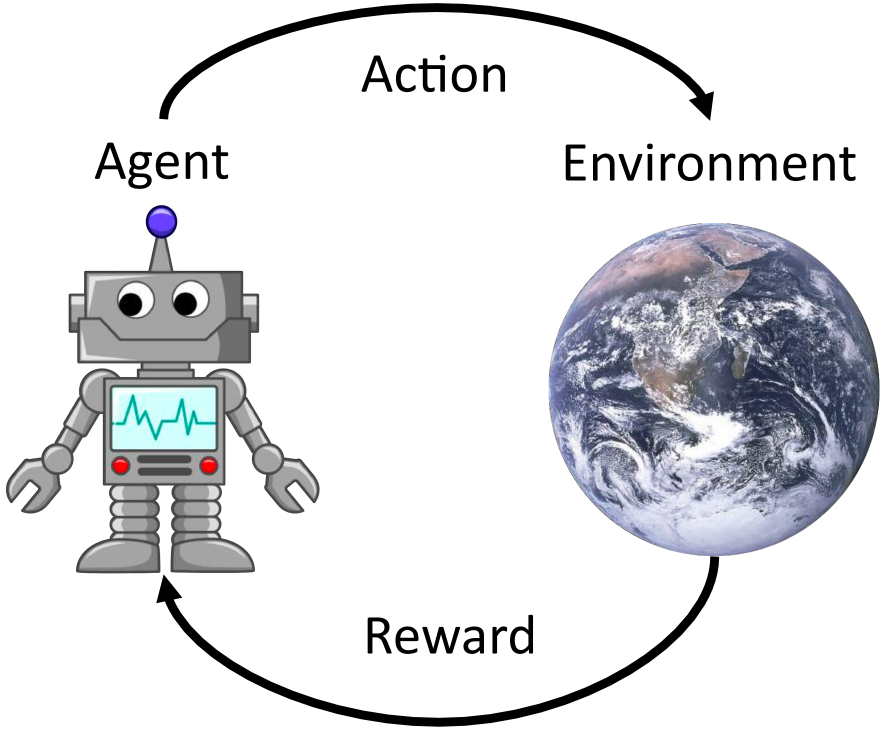


Hard Attention: At each timestep, select features from exactly one spatial location. Train with policy gradient.

Xu et al, "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Summary: Reinforcement Learning

RL trains **agents** that interact with an **environment** and learn to maximize **reward**



Q-Learning: Train network $Q_\theta(s, a)$ to estimate future rewards for every (state, action) pair. Use Bellman Equation to define loss function for training Q

Policy Gradients: Train a network $\pi_\theta(a \mid s)$ that takes state as input, gives distribution over which action to take in that state. Use REINFORCE Rule for computing gradients

Next Time:
Course Recap
Open Problems in Computer Vision