Lecture 14: Robot Learning

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: Self-Supervised Learning

Self-Supervised Learning

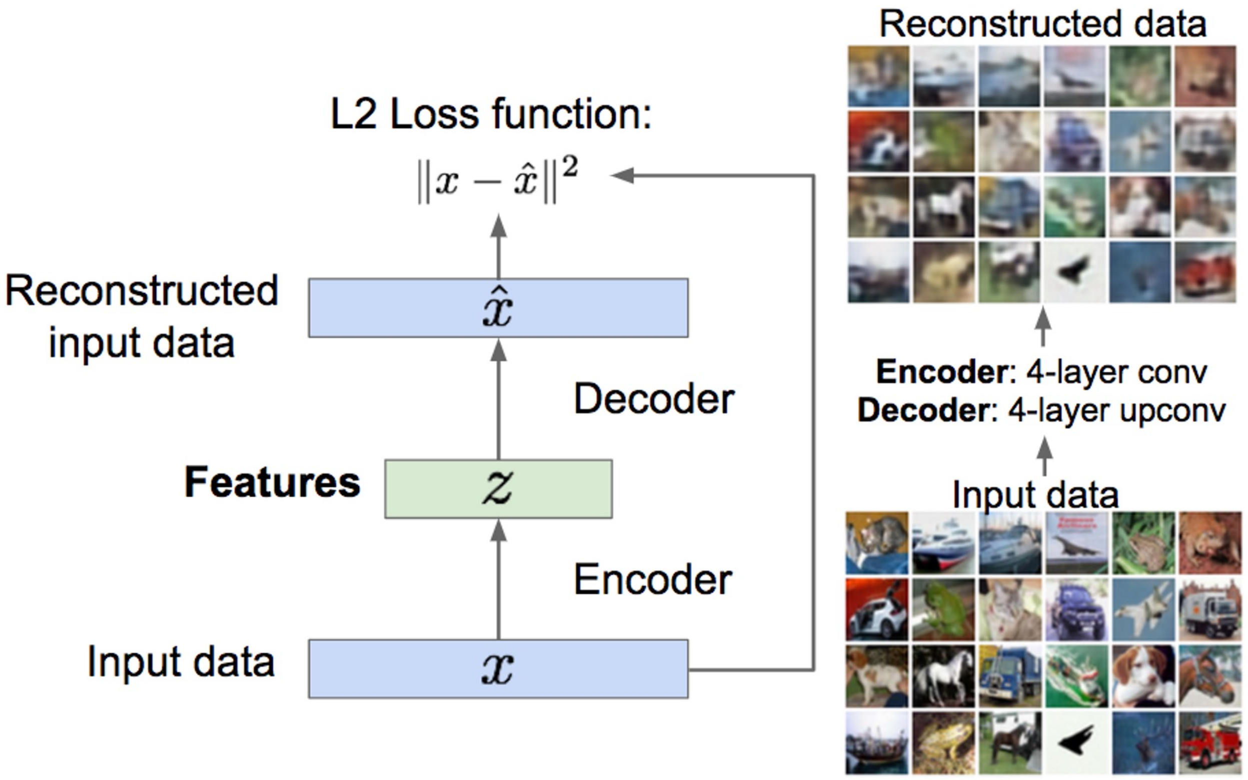
Data: x

Just data, no labels!

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

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

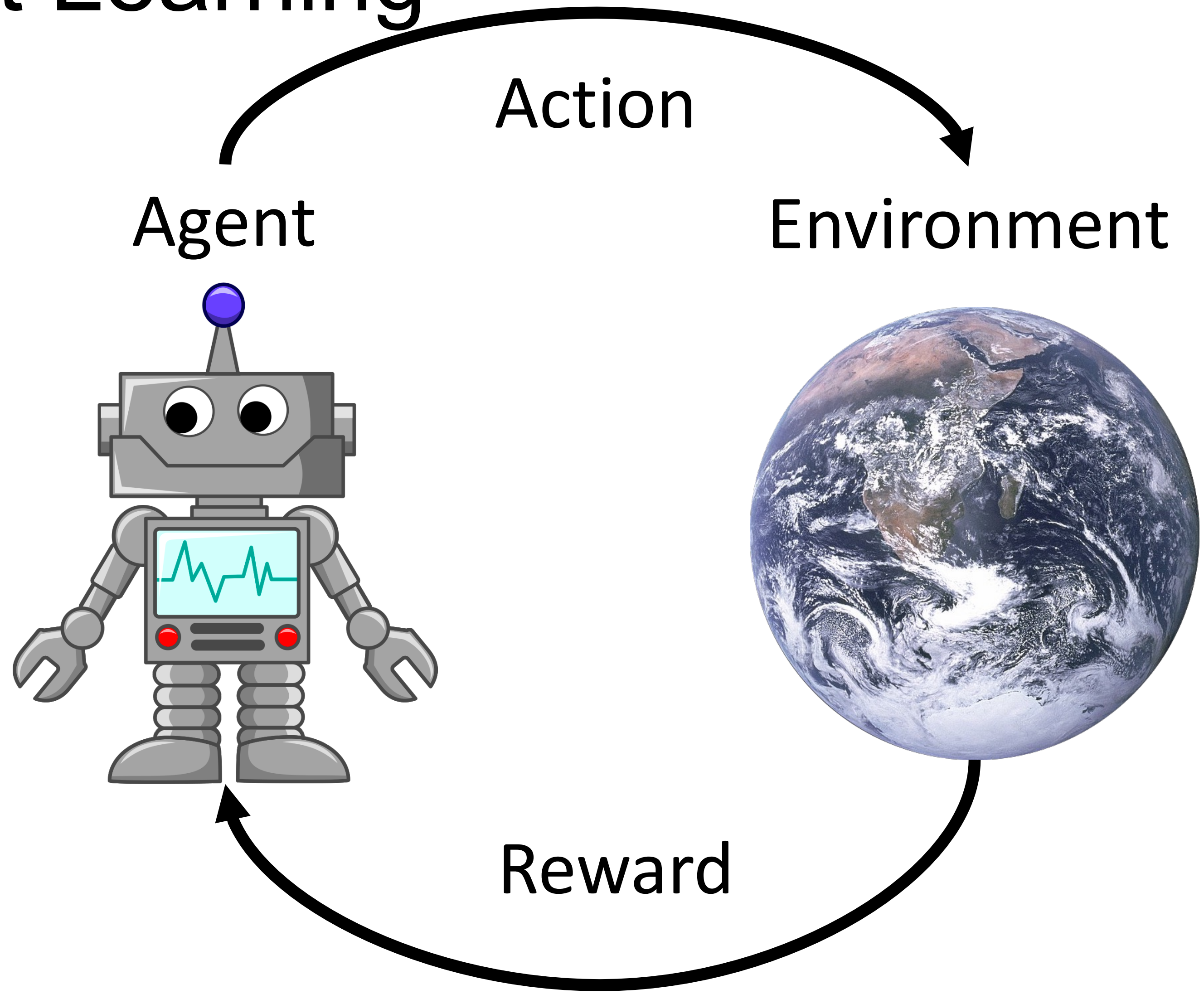
Feature Learning (e.g. autoencoders)



Today: Reinforcement Learning

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

Goal: Learn how to take actions that maximize reward



Overview

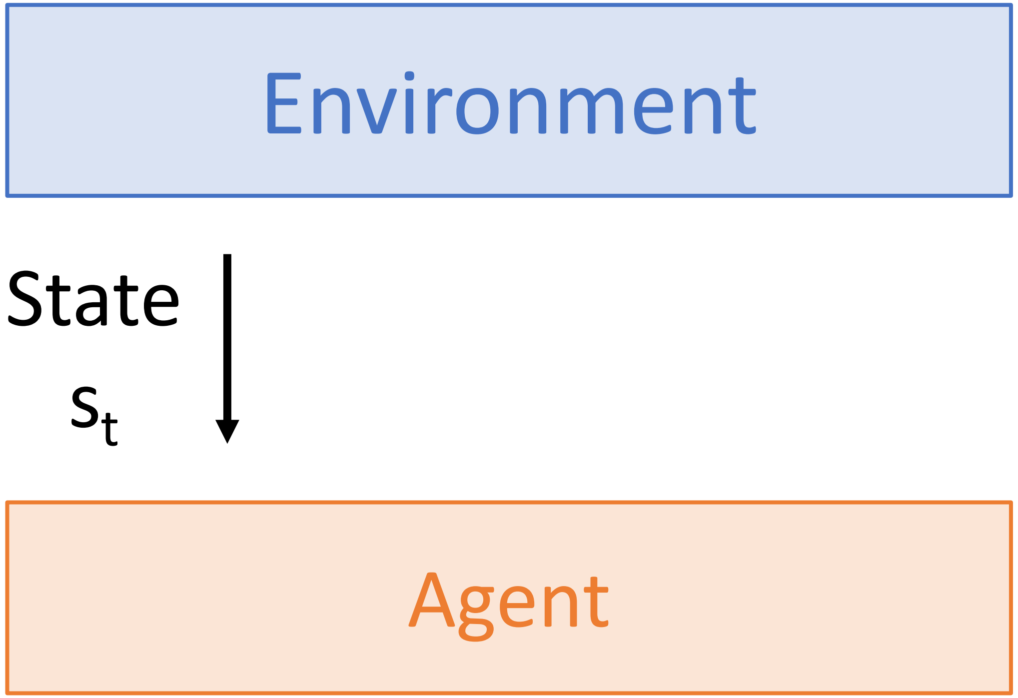
- What is reinforcement learning?
- Algorithms for reinforcement learning
  - Q-Learning
  - Policy Gradients
  - Model-based RL and planning

Reinforcement Learning

Environment

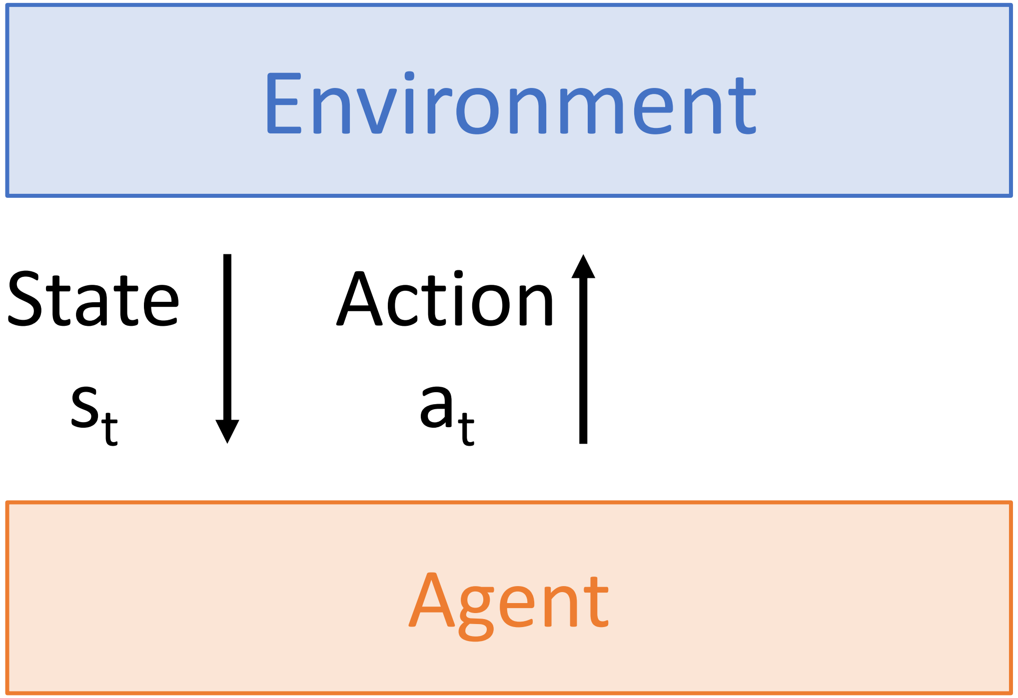
Agent

Reinforcement Learning



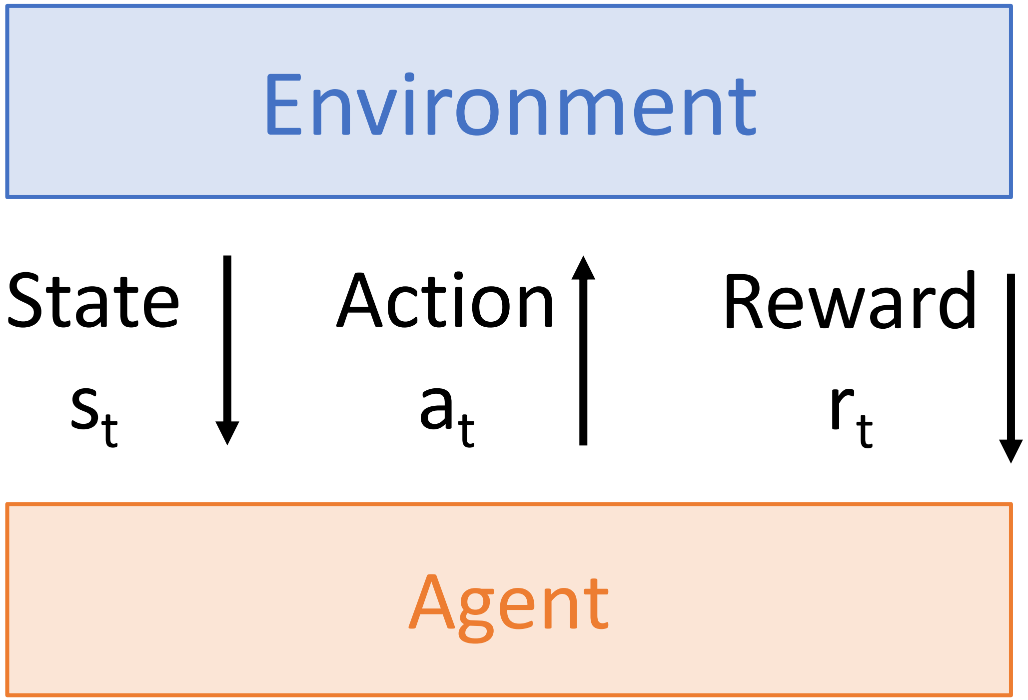
The agent sees a **state**; may be noisy or incomplete

Reinforcement Learning



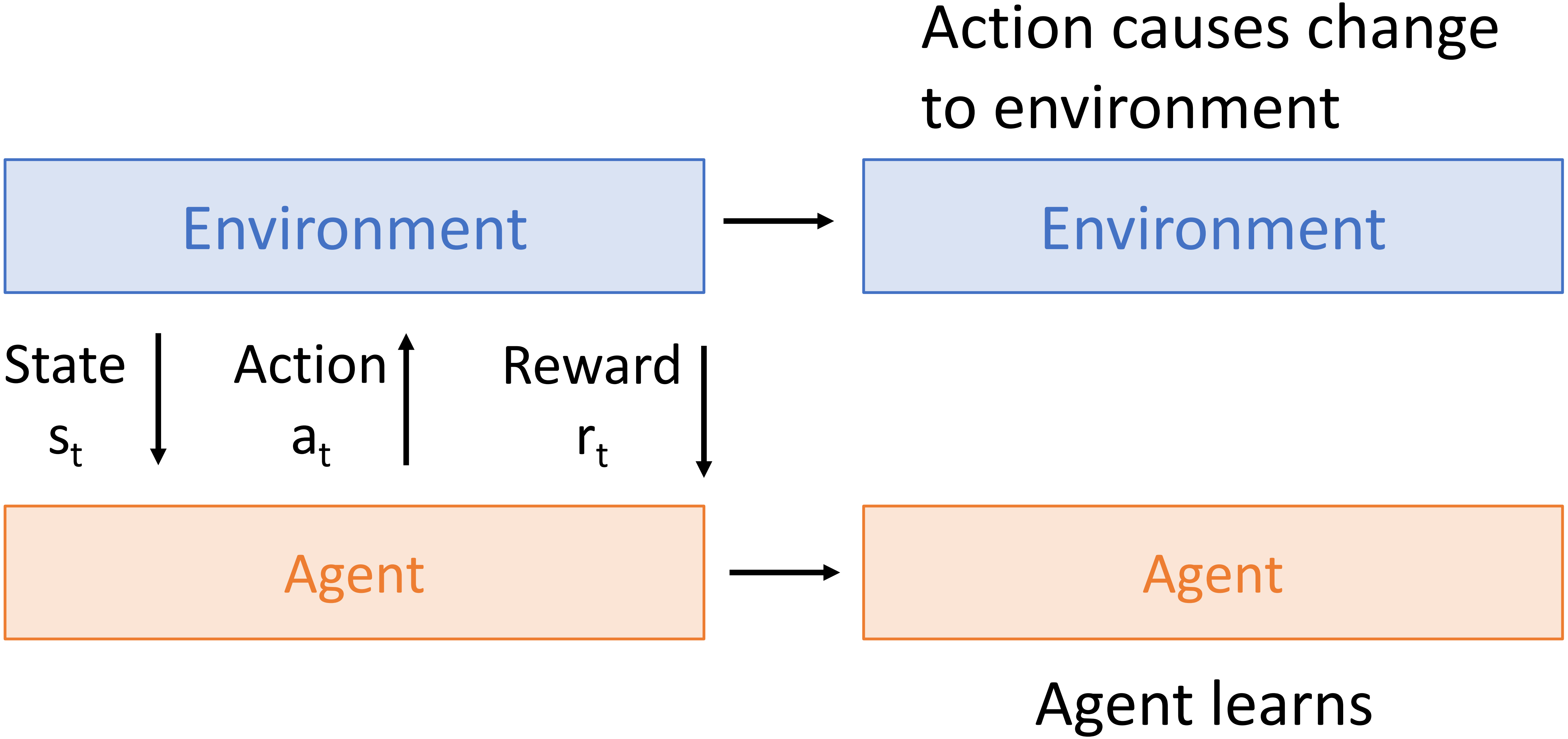
The makes an **action** based on what it sees

Reinforcement Learning



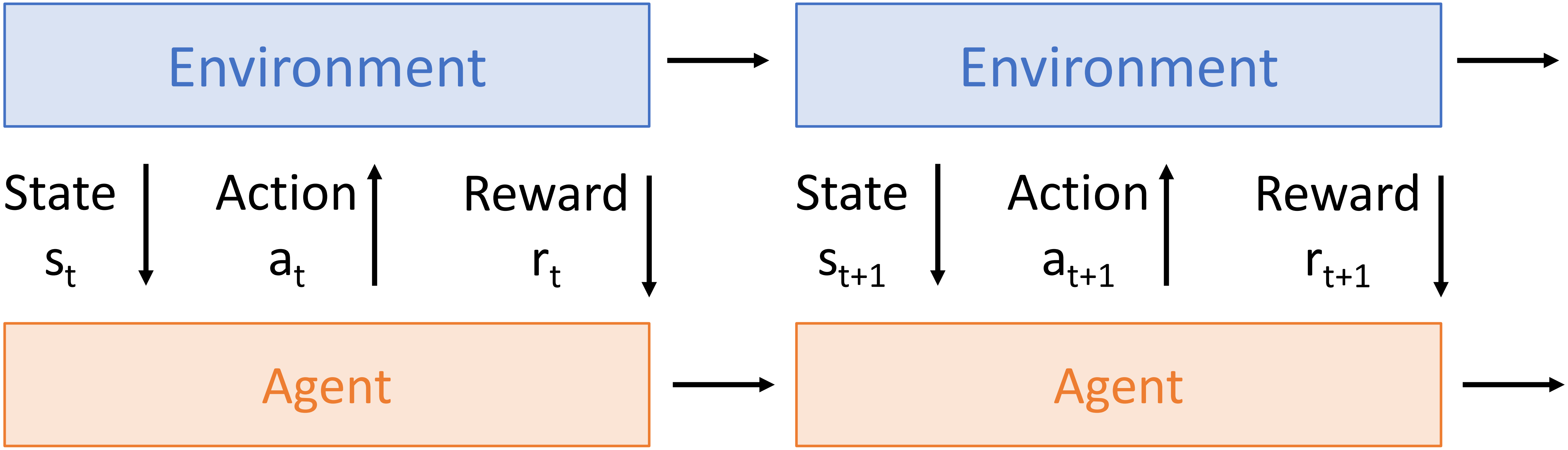
Reward tells the agent how well it is doing

Reinforcement Learning

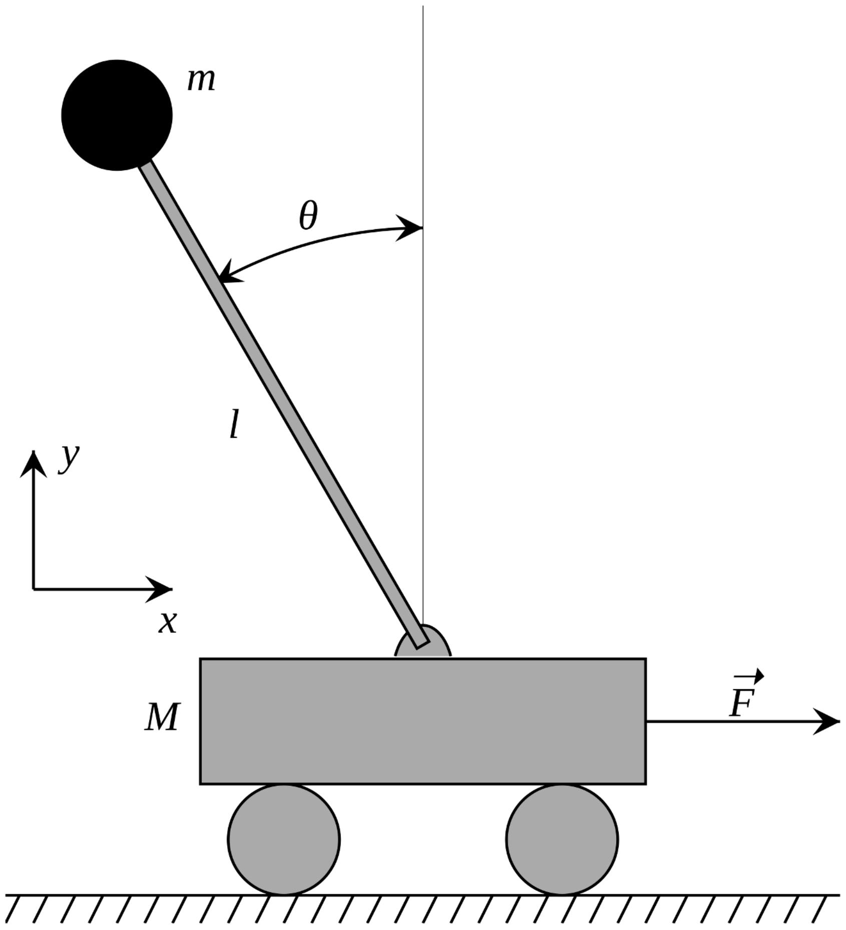


Reinforcement Learning

Process repeats



Example: Cart-Pole Problem



This image is CC0 public domain

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

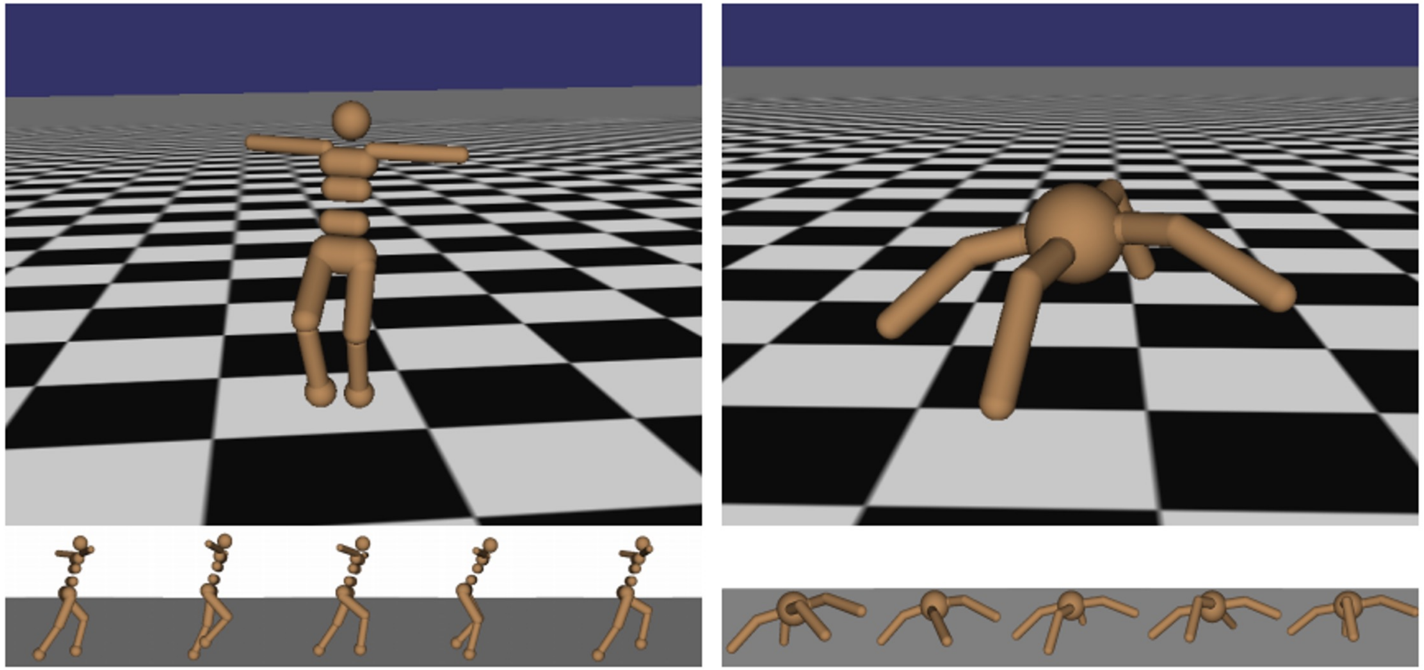


Figure from: Schulman et al, “High-Dimensional Continuous Control Using Generalized Advantage Estimation”, ICLR 2016

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

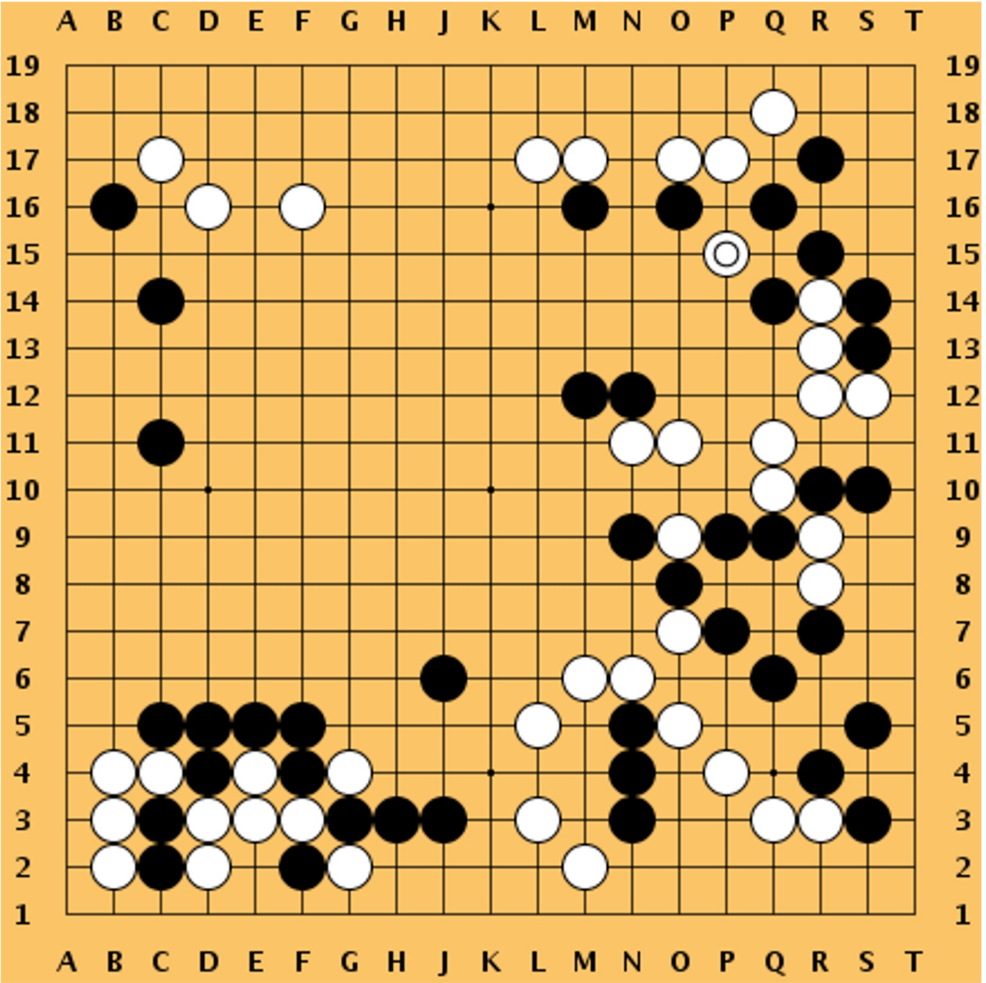
Example: Atari Games

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



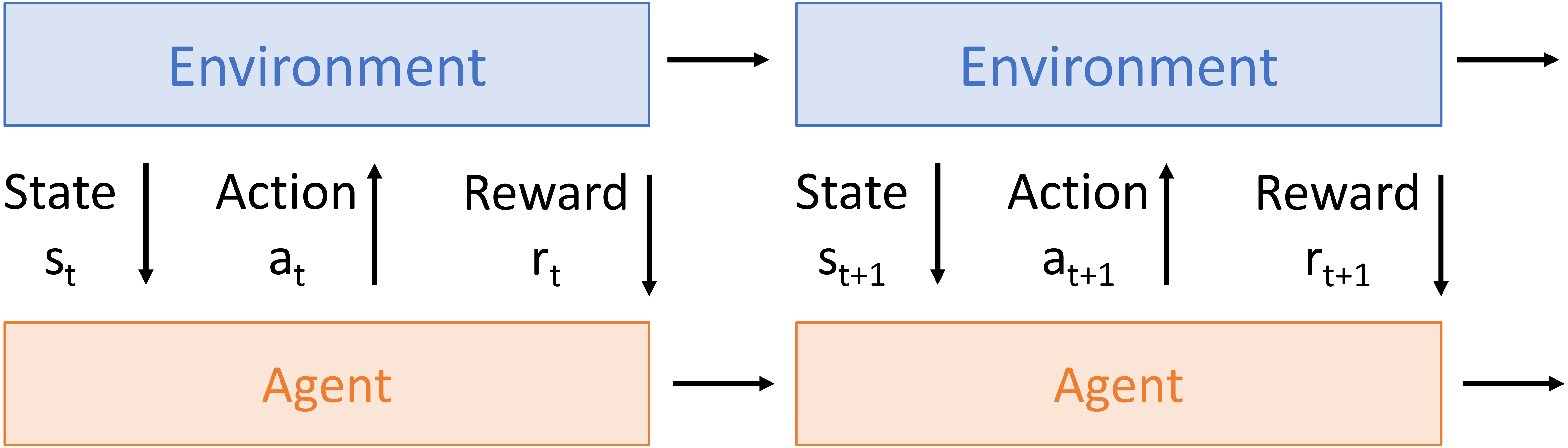
Objective: Win the game!

State: Position of all pieces

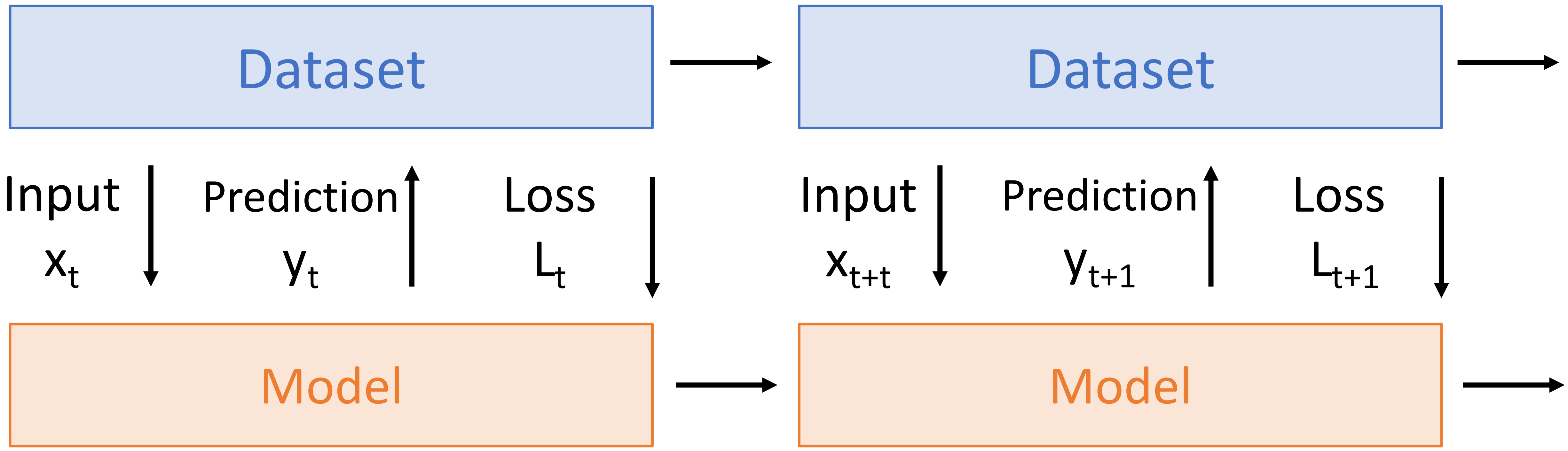
Action: Where to put the next piece down

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

Reinforcement Learning vs Supervised Learning

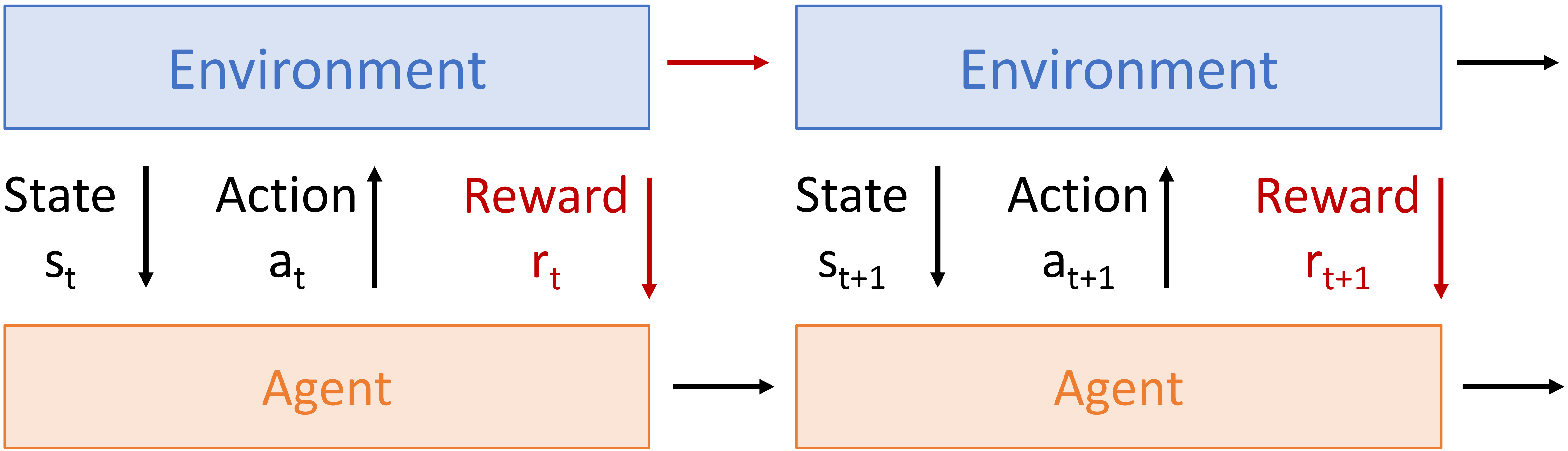


Reinforcement Learning vs Supervised Learning



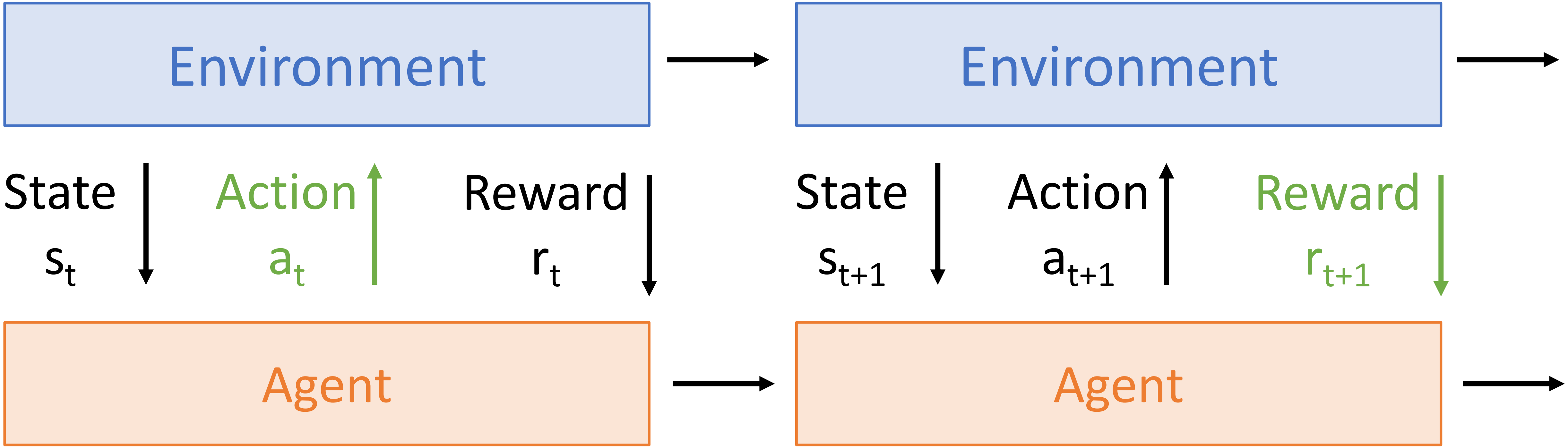
Why is RL different from normal supervised learning?

Reinforcement Learning vs Supervised Learning



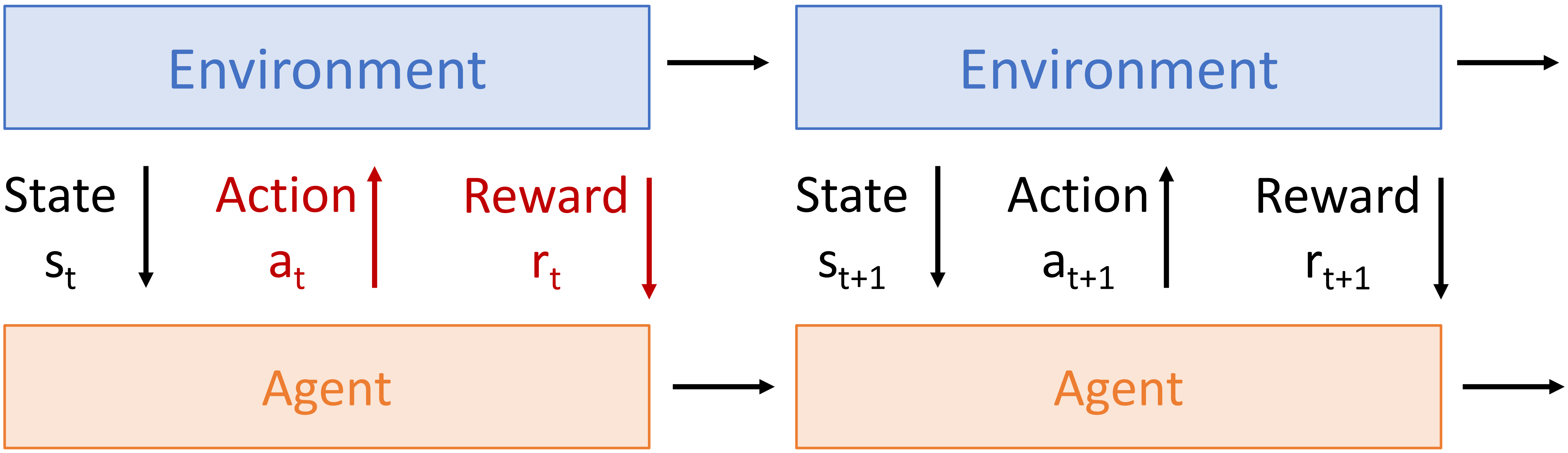
Stochasticity: Rewards and state transitions may be random

Reinforcement Learning vs Supervised Learning



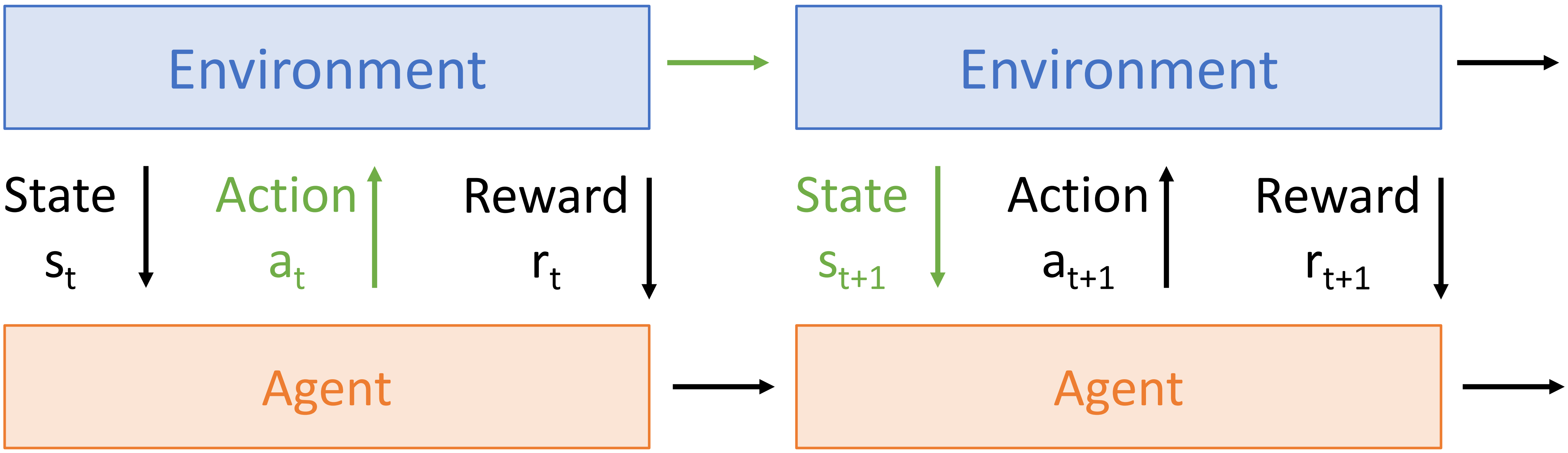
Credit assignment: Reward r_t may not directly depend on action a_t

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)

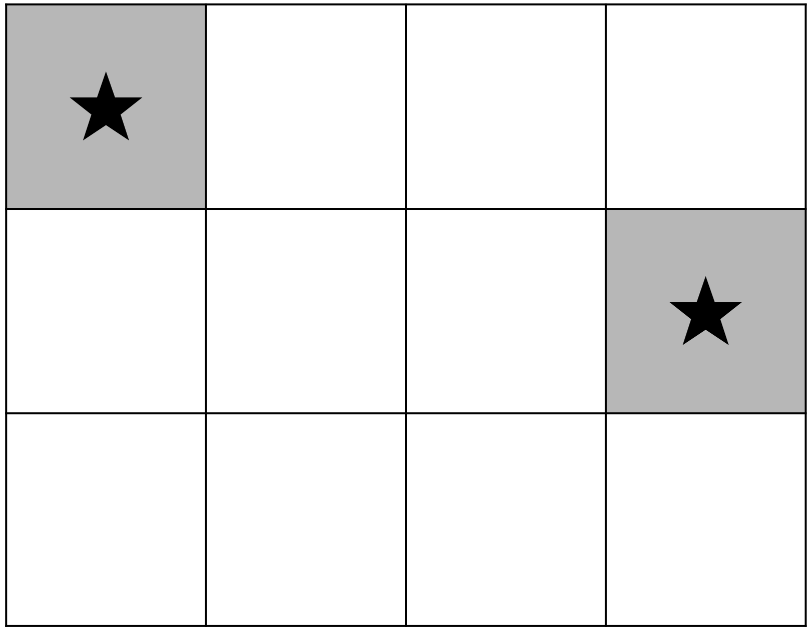
- At time step t=0, environment samples initial state $s_0 \sim p(s_0)$
- Then, for t=0 until done:
  - Agent selects action $a_t \sim \pi(a \mid s_t)$
  - Environment samples reward $r_t \sim R(r \mid s_t, a_t)$
  - Environment samples next state $s_{t+1} \sim P(s \mid s_t, a_t)$
  - Agent receives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

A simple MDP: Grid World

Actions:

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

States



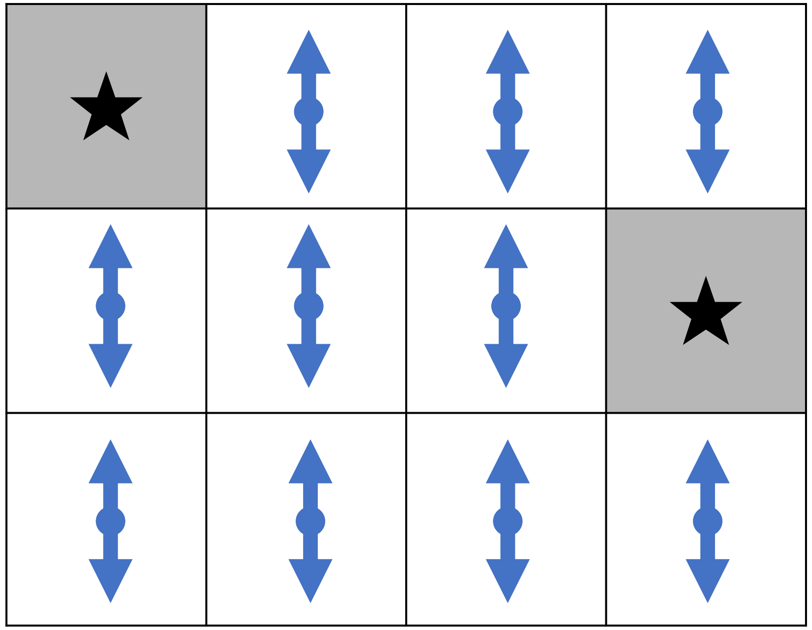
Reward

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

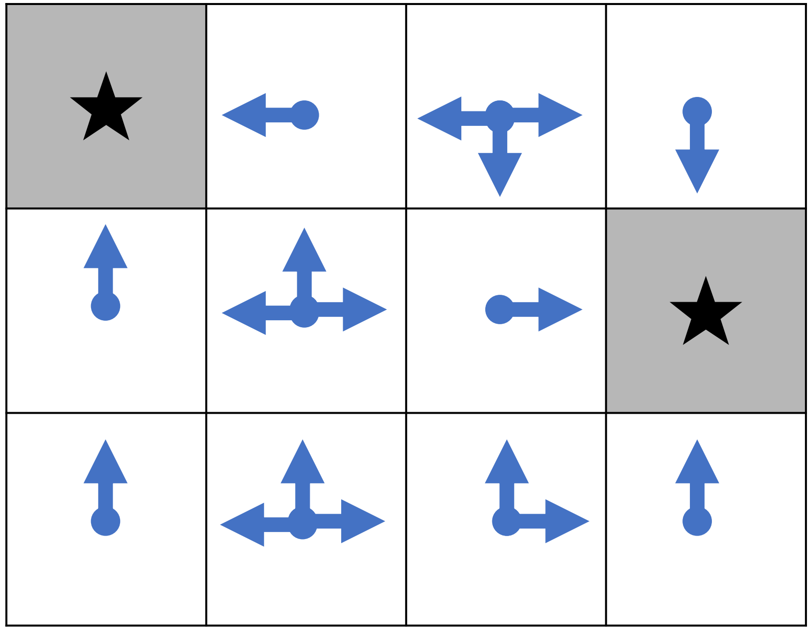
Objective: Reach one of the terminal states in as few moves as possible

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, …

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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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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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Use this to define the loss for training Q: $L(s,a) = \left(Q(s,a;\theta) - y_{s,a,\theta}\right)^2$

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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
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Case Study: Playing Atari Games

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

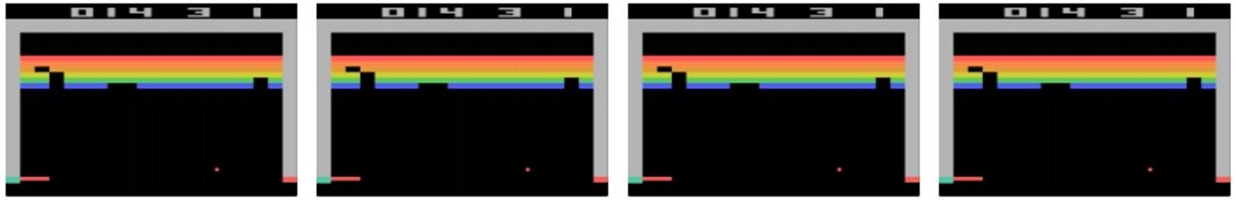
Network output:
Q-values for all actions

FC-A (Q-values)

FC-256

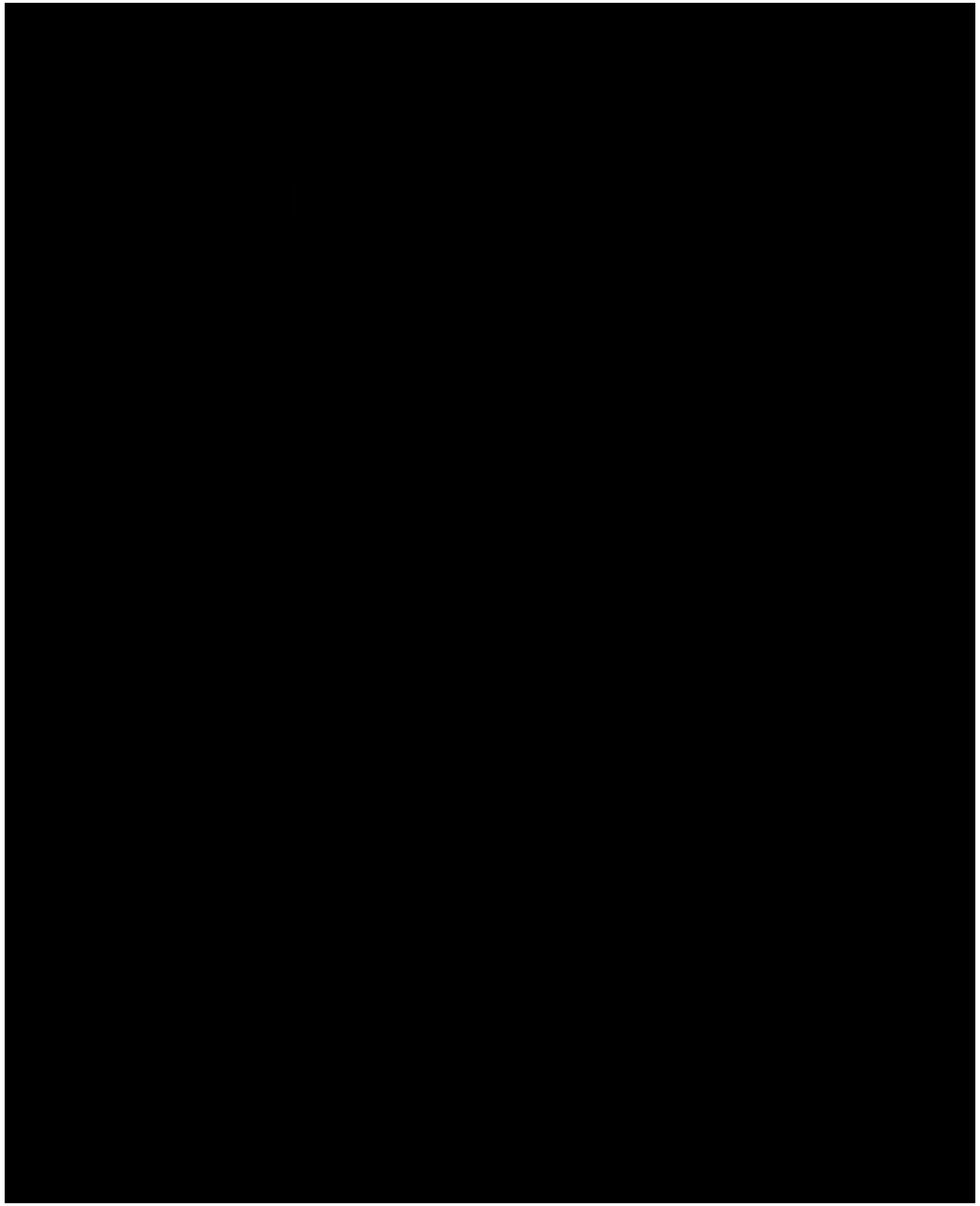
Conv(16->32, 4x4, stride 2)

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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$$\frac{\partial J}{\partial \theta} = \int_X f(x) p_\theta(x) \frac{\partial}{\partial \theta} \log p_\theta(x) \, dx = \mathbb{E}_{x \sim p_\theta}\left[f(x) \frac{\partial}{\partial \theta} \log p_\theta(x)\right]$$

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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1. Initialize random weights θ
2. Collect trajectories x and rewards f(x) using policy π_θ
3. Compute dJ/dθ

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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:

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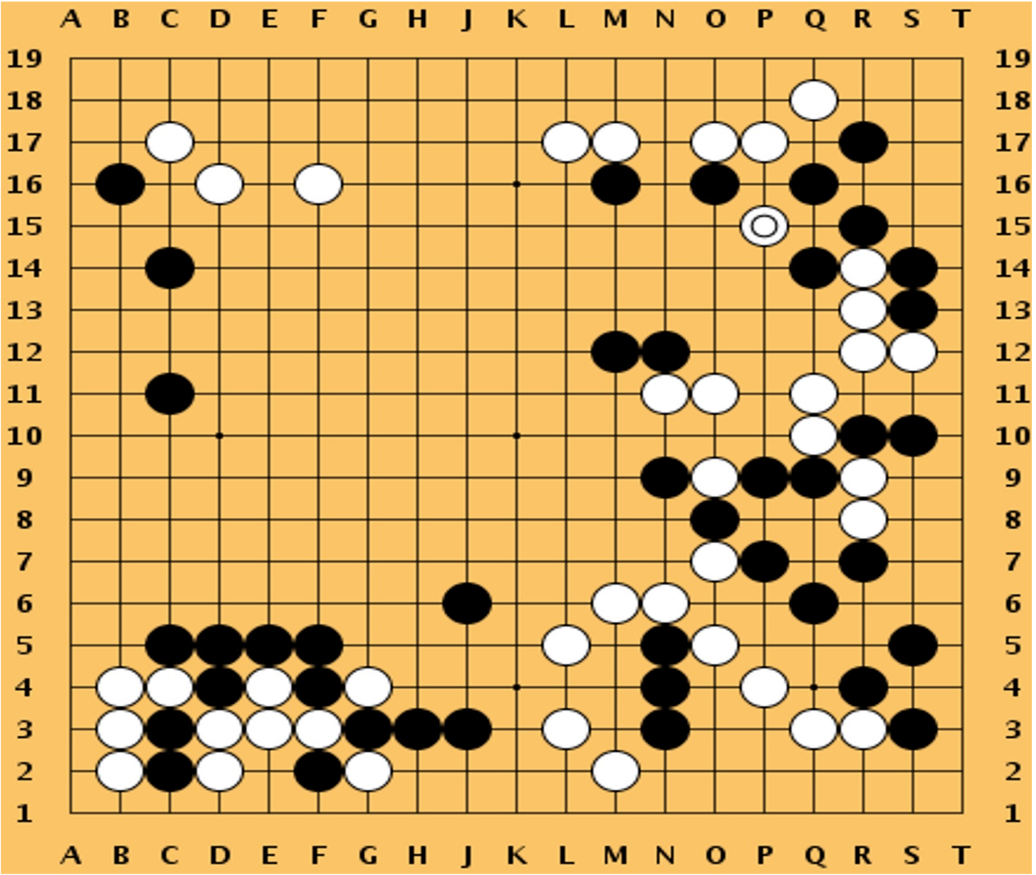
Improving policy gradients: Add **baseline** to reduce variance of gradient estimator

Case Study: Playing Games

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



Silver et al, "Mastering the game of Go with deep neural networks and tree search", Nature 2016
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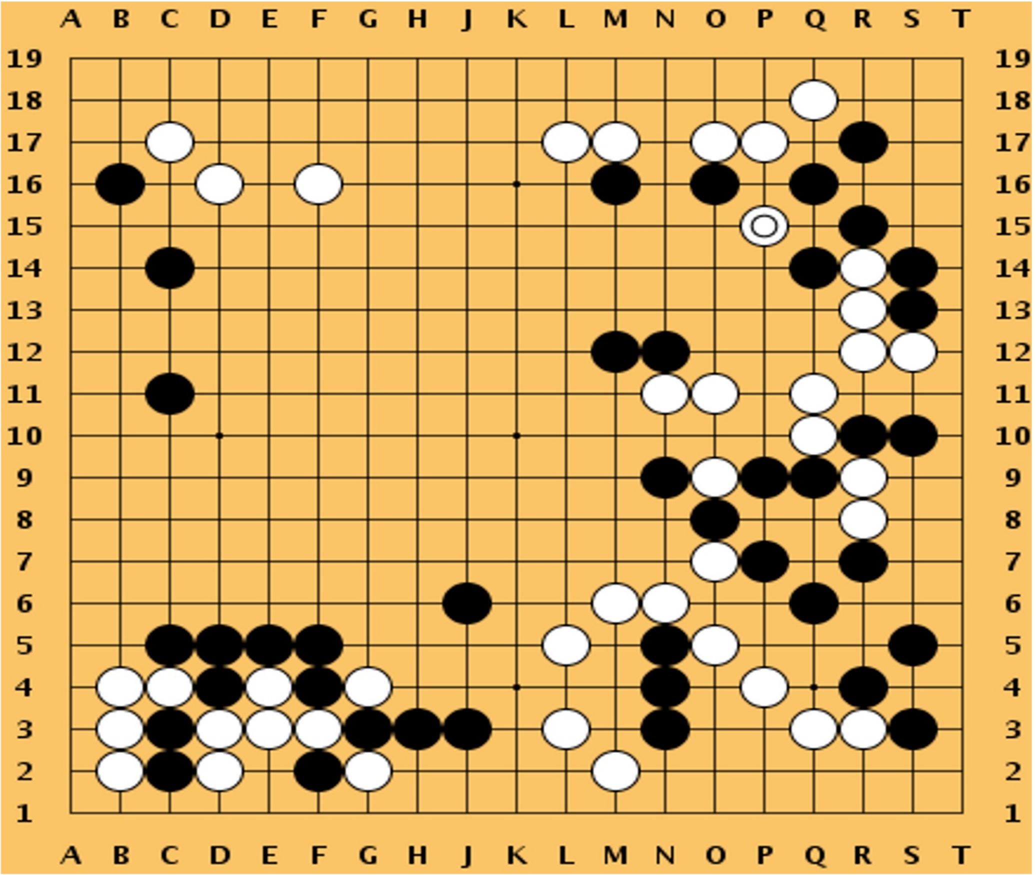

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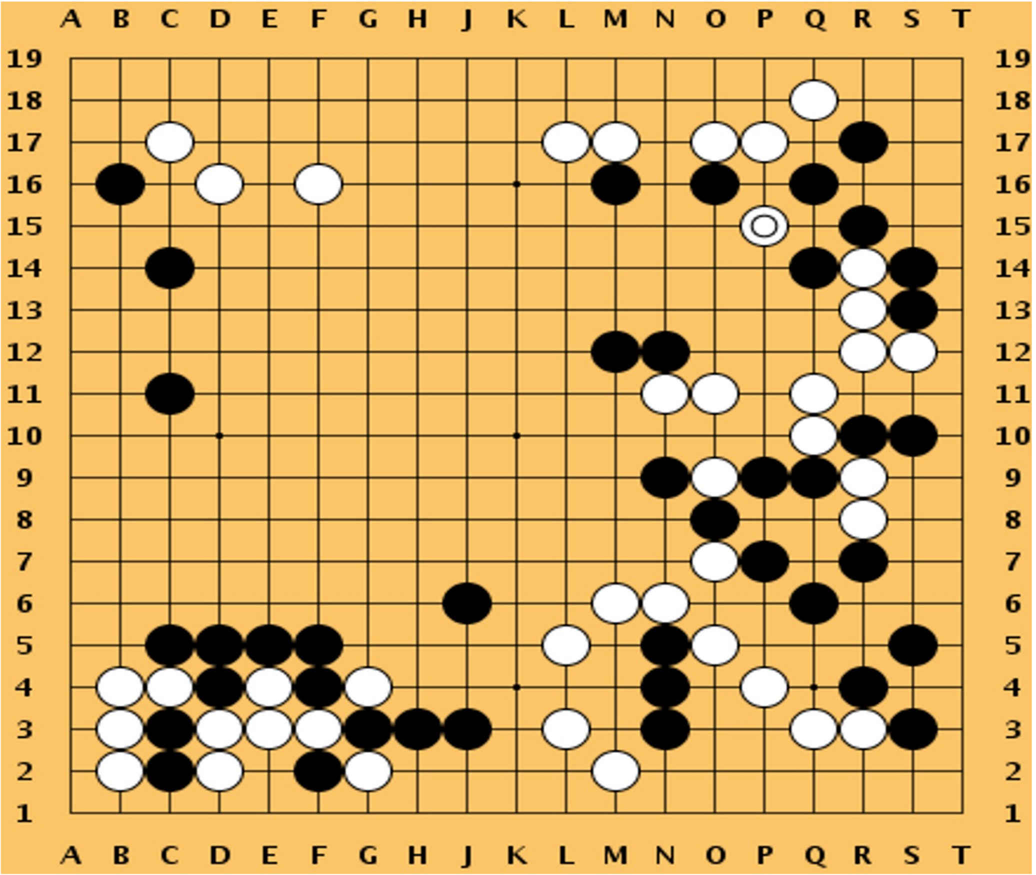

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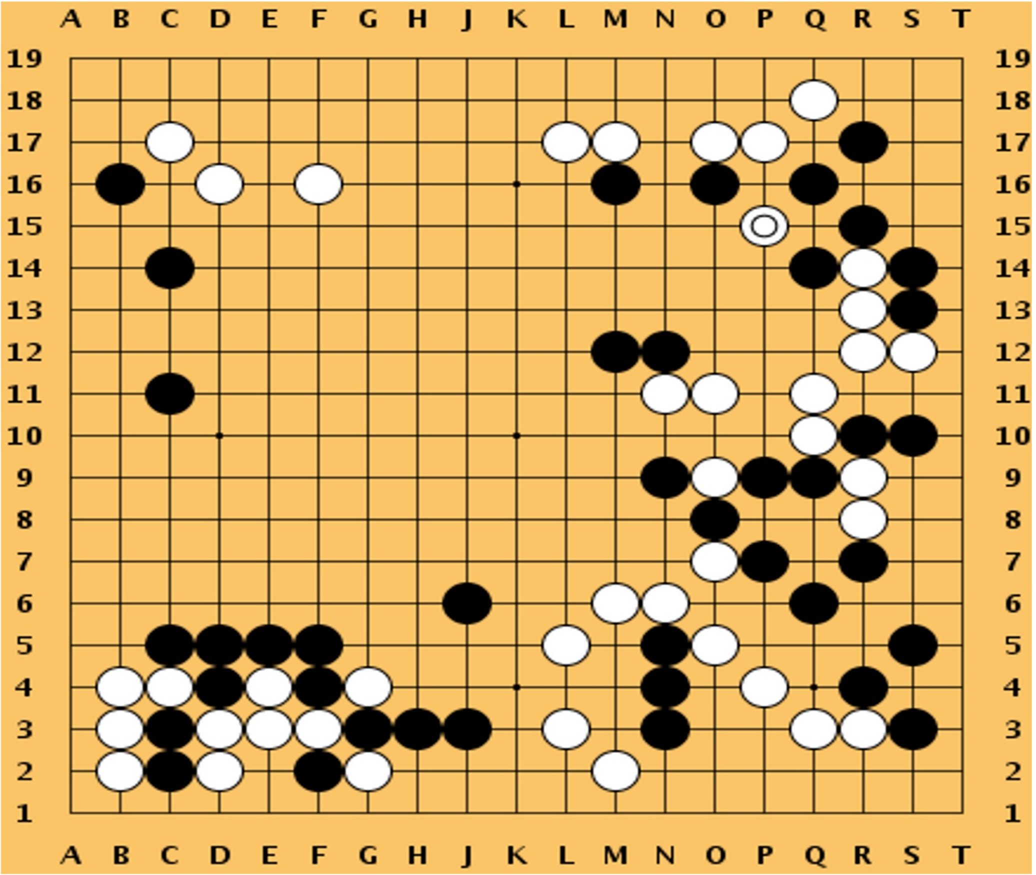

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November 2019: Lee Sedol announces retirement

" 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"

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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

Problems of Model-Free RL

- Learns from trials and error
- Require extensive interactions

AlphaGo Zero: Google DeepMind supercomputer learns 3,000 years of human knowledge in 40 days

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- Safety concerns
- Limited interpretability
  - What if things go wrong?

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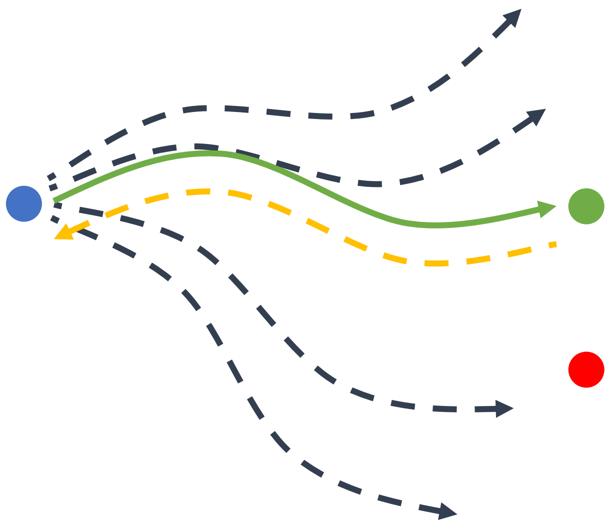
- Humans maintain an intuitive model of the world
  - Widely applicable
  - Sample efficient

Model-Based RL

Model-Based: Learn a model of the world's state transition function $P(s_{t+1}|s_t, a_t)$ and then use planning through the model to make decisions



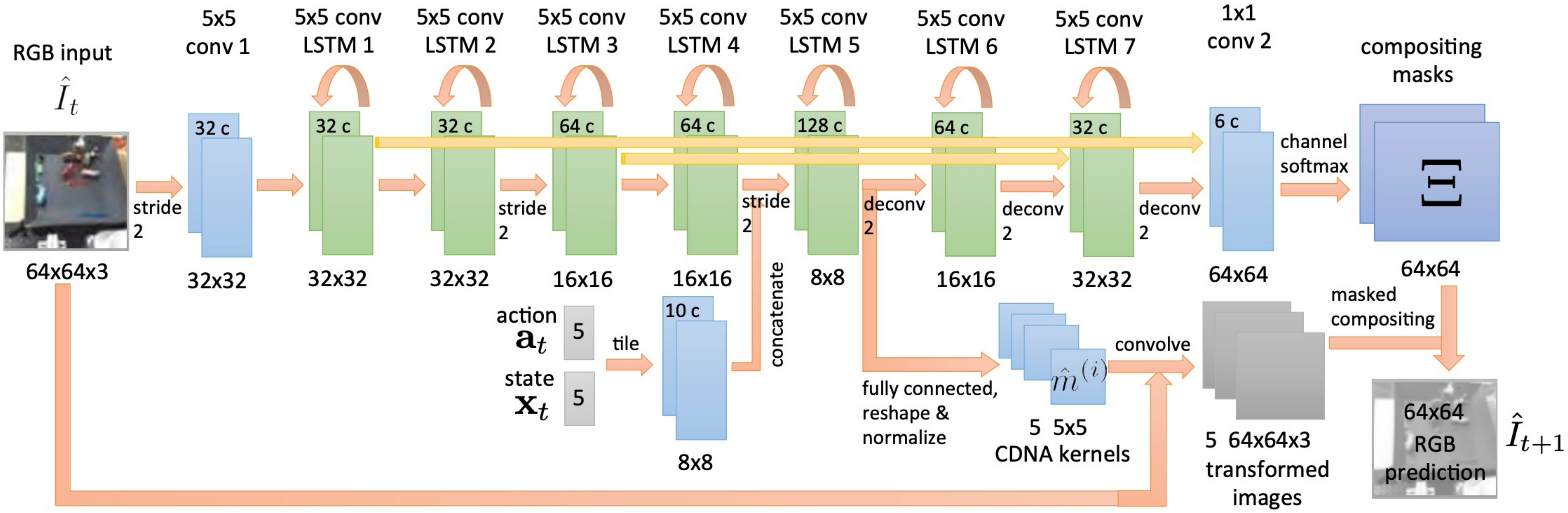
Model might not be accurate enough.

1. Execute the first action
2. Obtain new state
3. Re-optimize the action sequence using gradient descent

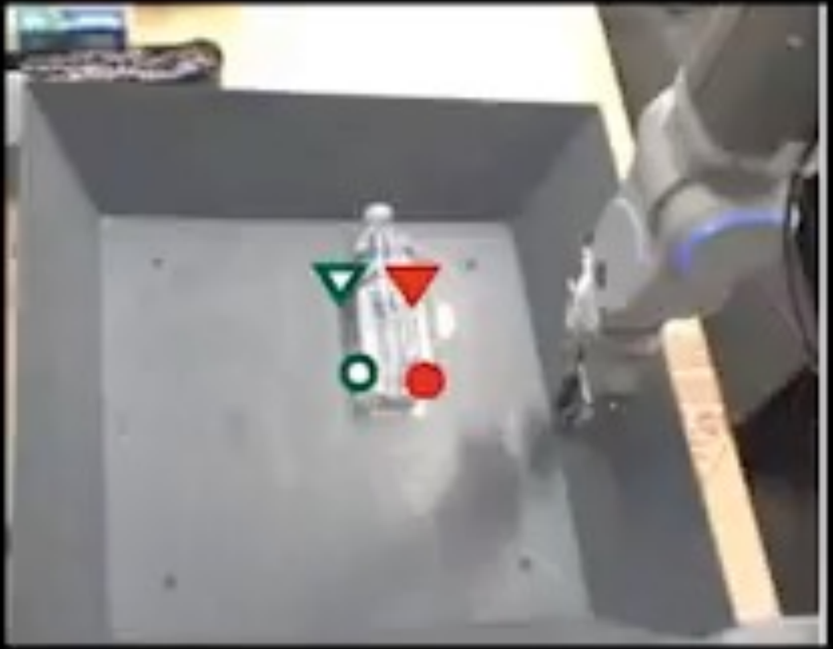
Key: GPU for parallel sampling / gradient descent

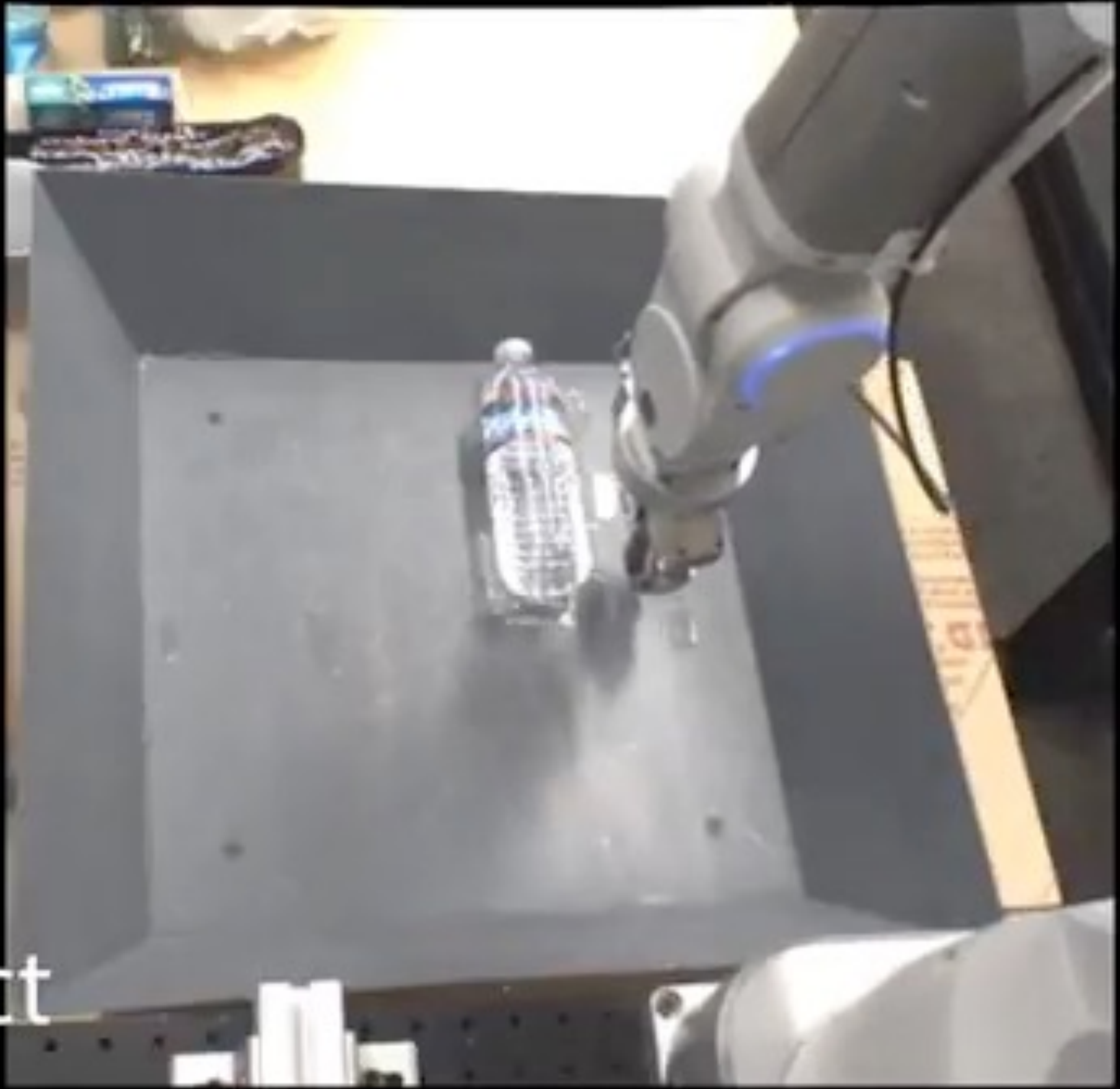
Key question: what should be the form of s_t?

Pixel Dynamics - Deep Visual Foresight



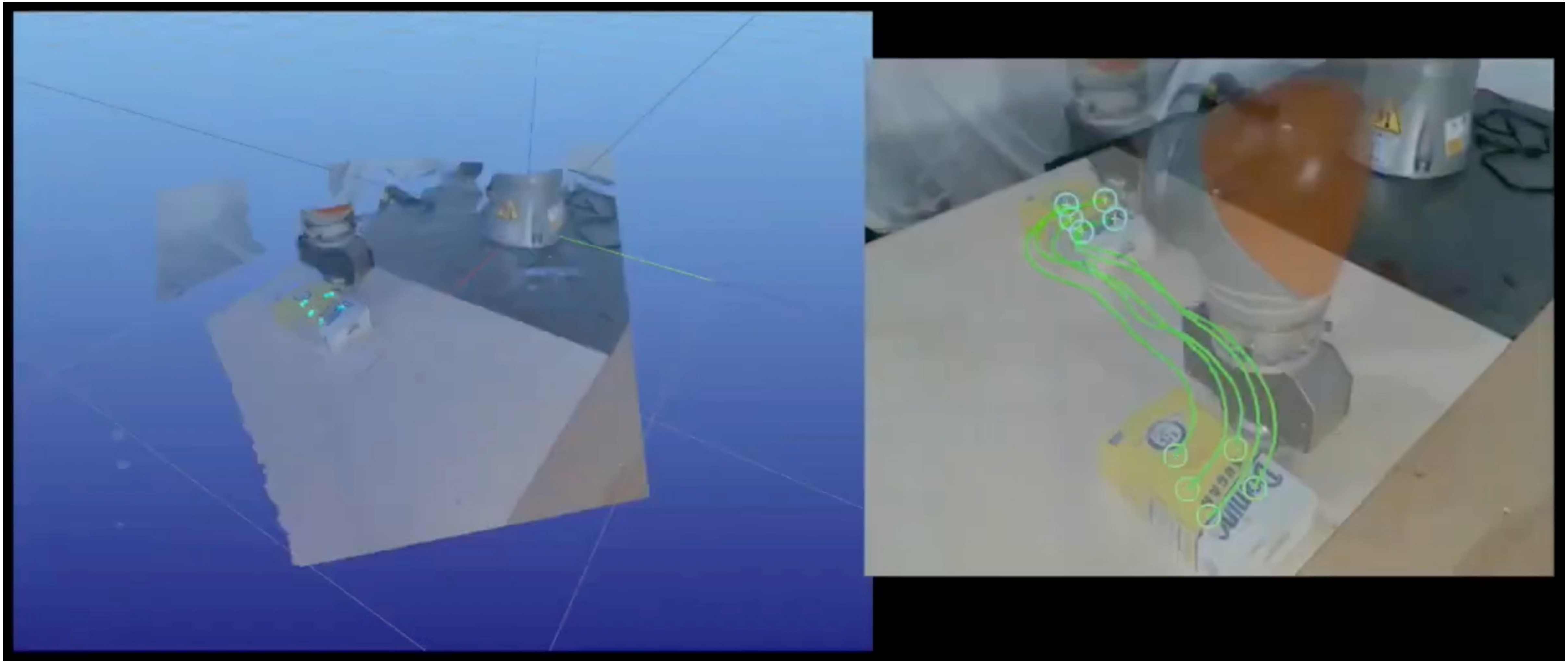
Finn and Levine, "Deep Visual Foresight for Planning Robot Motion", ICRA 2017



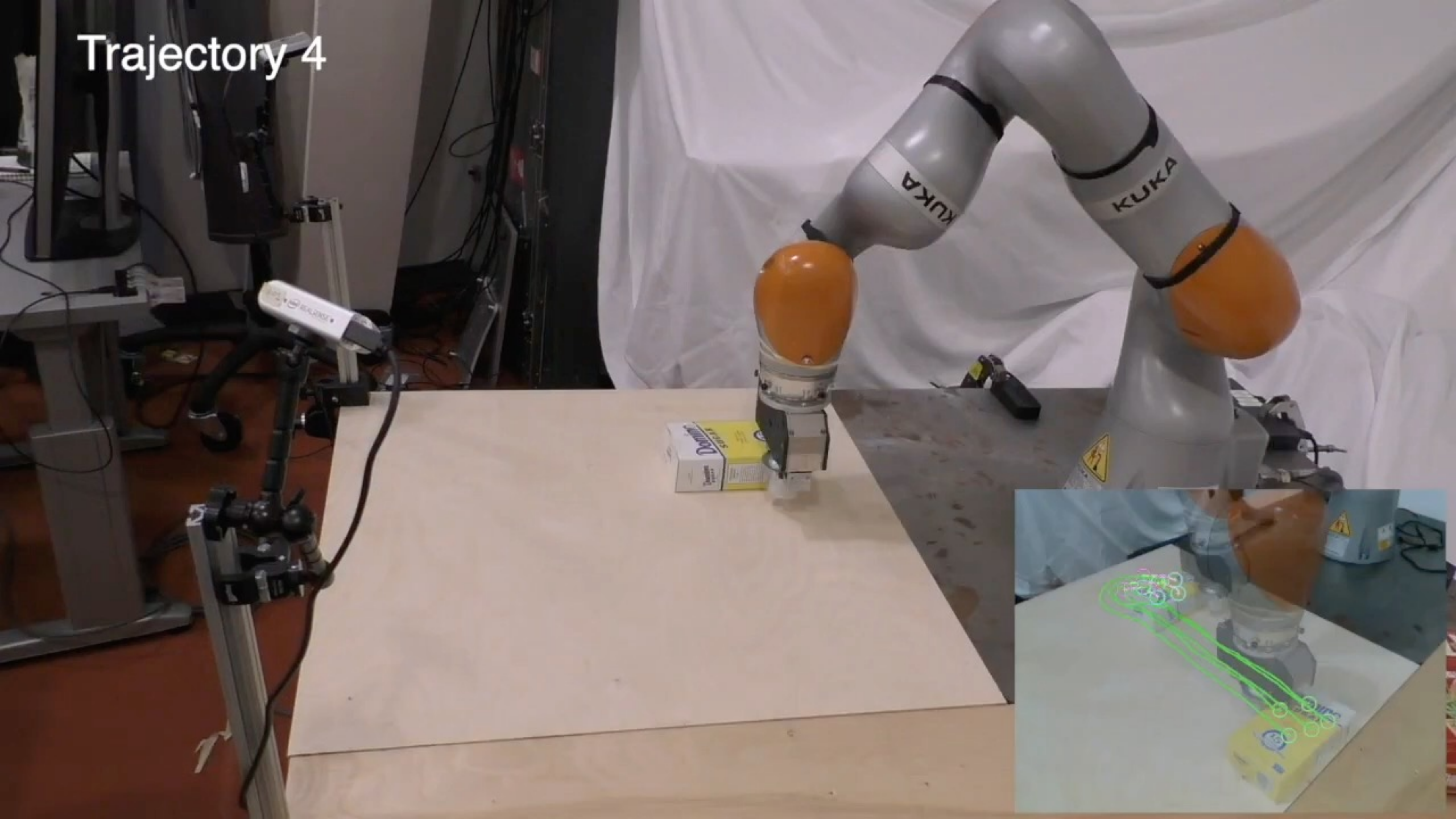


transparent object

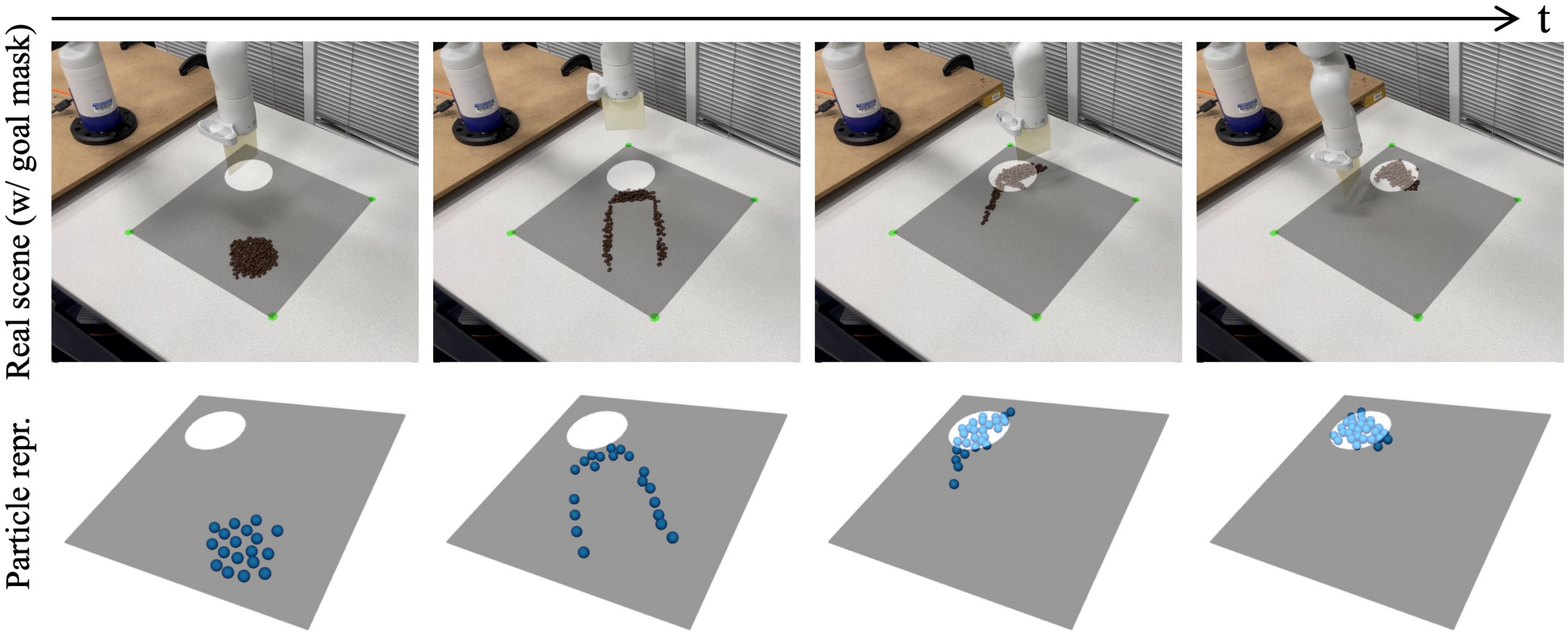
Keypoint Dynamics



Manuelli, Li, Florence, Tedrake, “Keypoints into the Future: Self-Supervised Correspondence in Model-Based Reinforcement Learning”, CoRL 2020

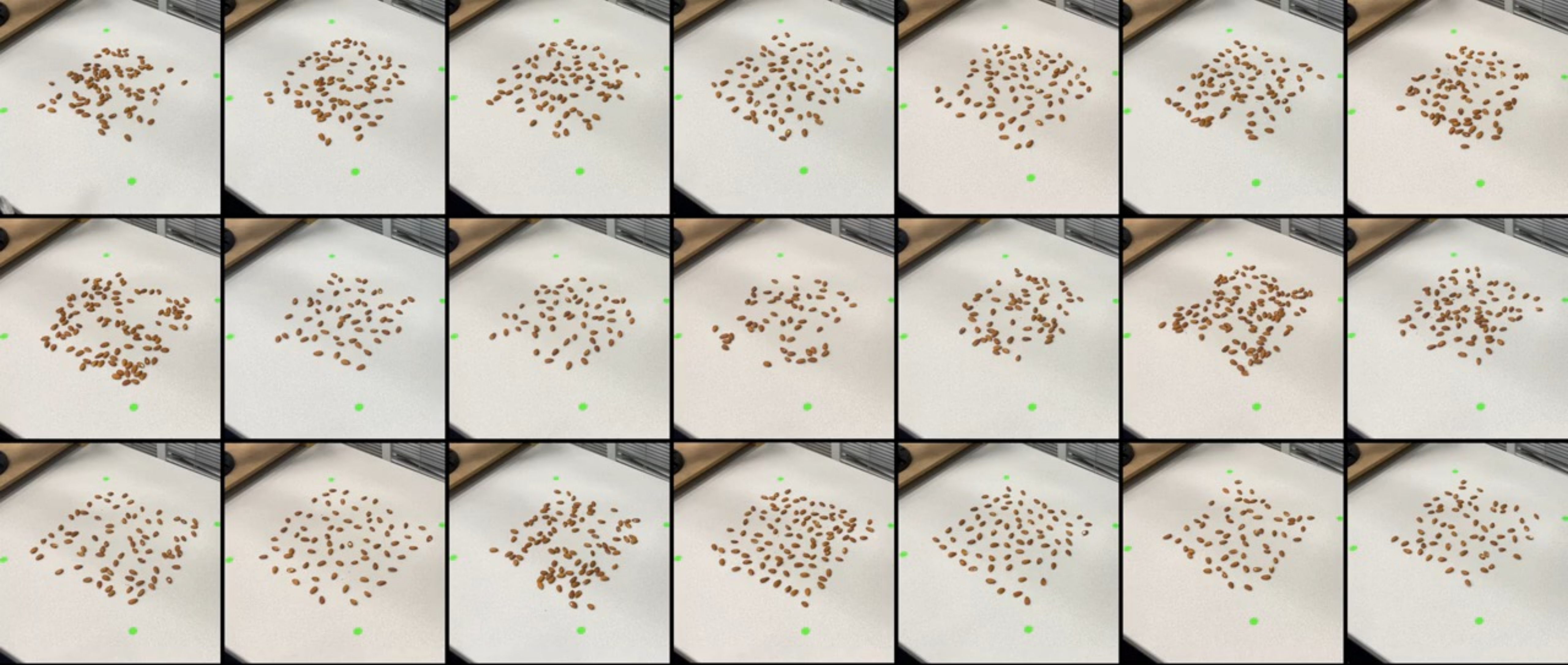

Trajectory 4
KUKA
KUKA

Particle Dynamics



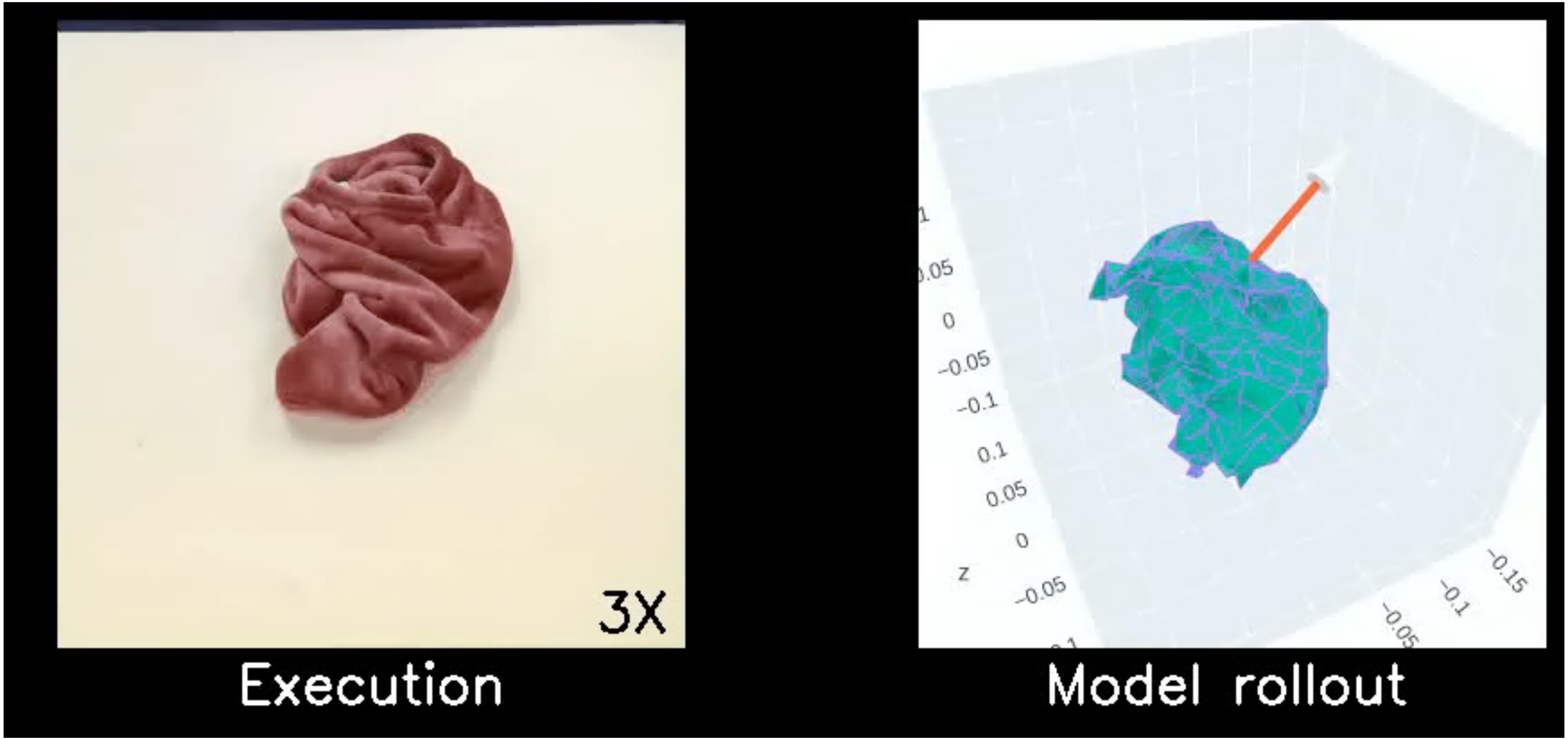
Wang, Li, Driggs-Campbell, Fei-Fei, Wu, “Dynamic-Resolution Model Learning for Object Pile Manipulation”, RSS 2023


Granola
Rice
Carrot
Candy
24x speed




Push to all letters
24x speed

Mesh-Based Dynamics



Huang, Lin, Held, “Mesh-based Dynamics with Occlusion Reasoning for Cloth Manipulation”, RSS 2022

Other approaches

Model-Based: Learn a model of the world's state transition function $P(s_{t+1}|s_t, a_t)$ and then use planning through the model to make decisions

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Ng et al, "Algorithms for Inverse Reinforcement Learning", ICML 2000

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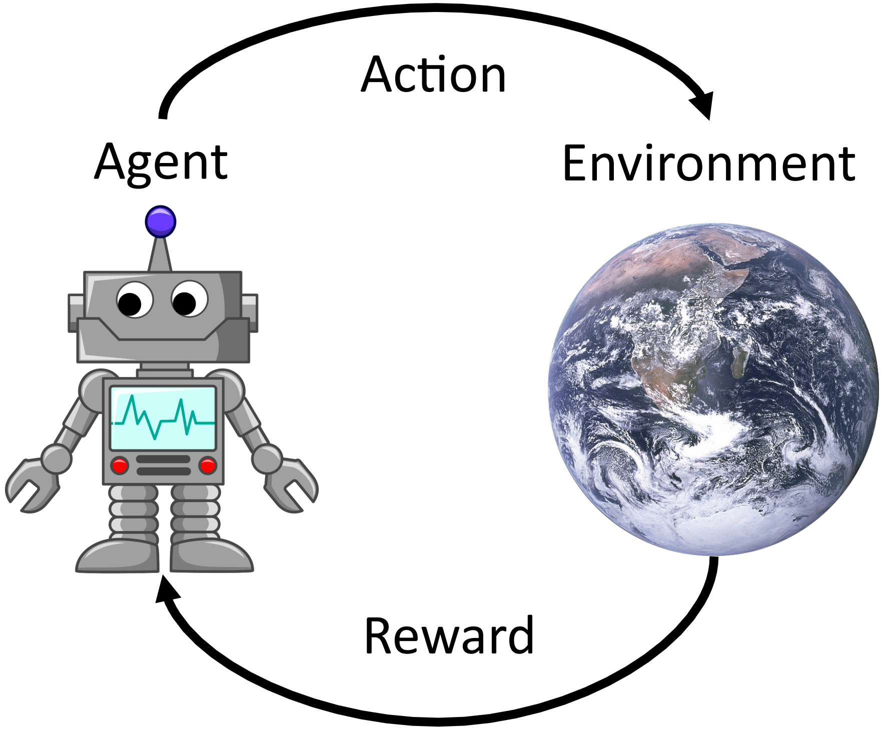
Adversarial Learning: Learn to fool a discriminator that classifies actions as real/fake

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

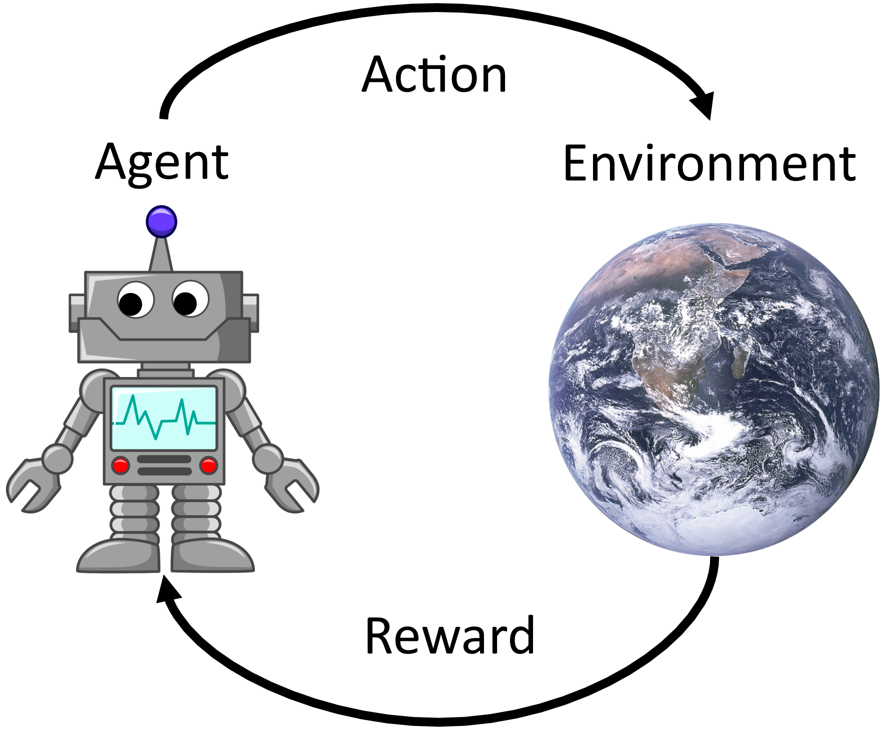
Reinforcement Learning: Interacting With World



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

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: Generative Models

Guest Lecture by Dr. Ruiqi Gao from Google Brain