THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 18: Deep Reinforcement Learning

Types of **Learning**

Supervised training

— Learning from the teacher

— Training data includes desired output

Unsupervised training

— Training data does not include desired output

Reinforcement learning

— Learning to act under evaluative feedback (rewards)

* slide from Dhruv Batra

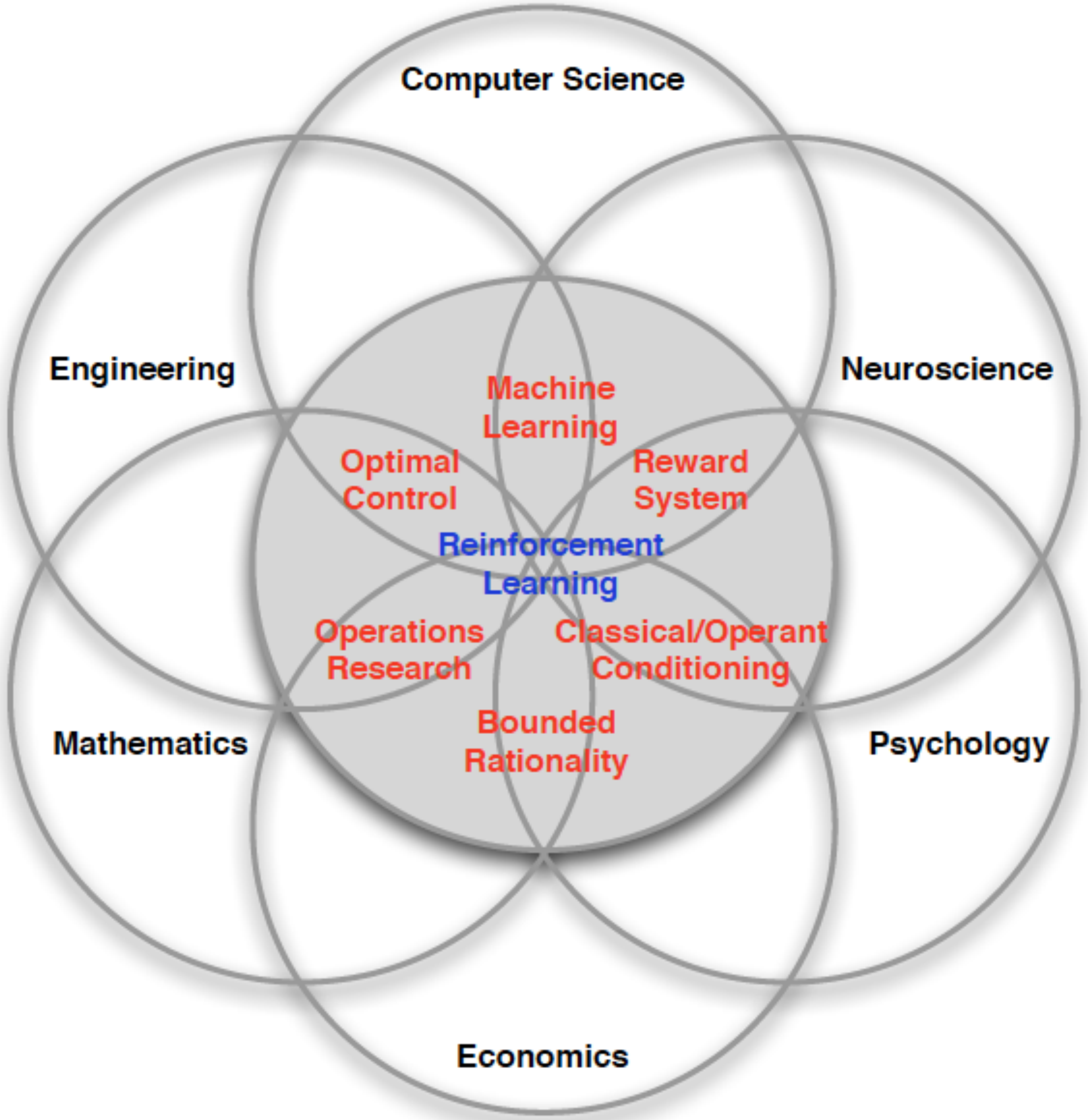
What is Reinforcement Learning

Agent-oriented learning — learning by interacting with an environment to achieve a goal

- More realizing and ambitious than other kinds of machine learning

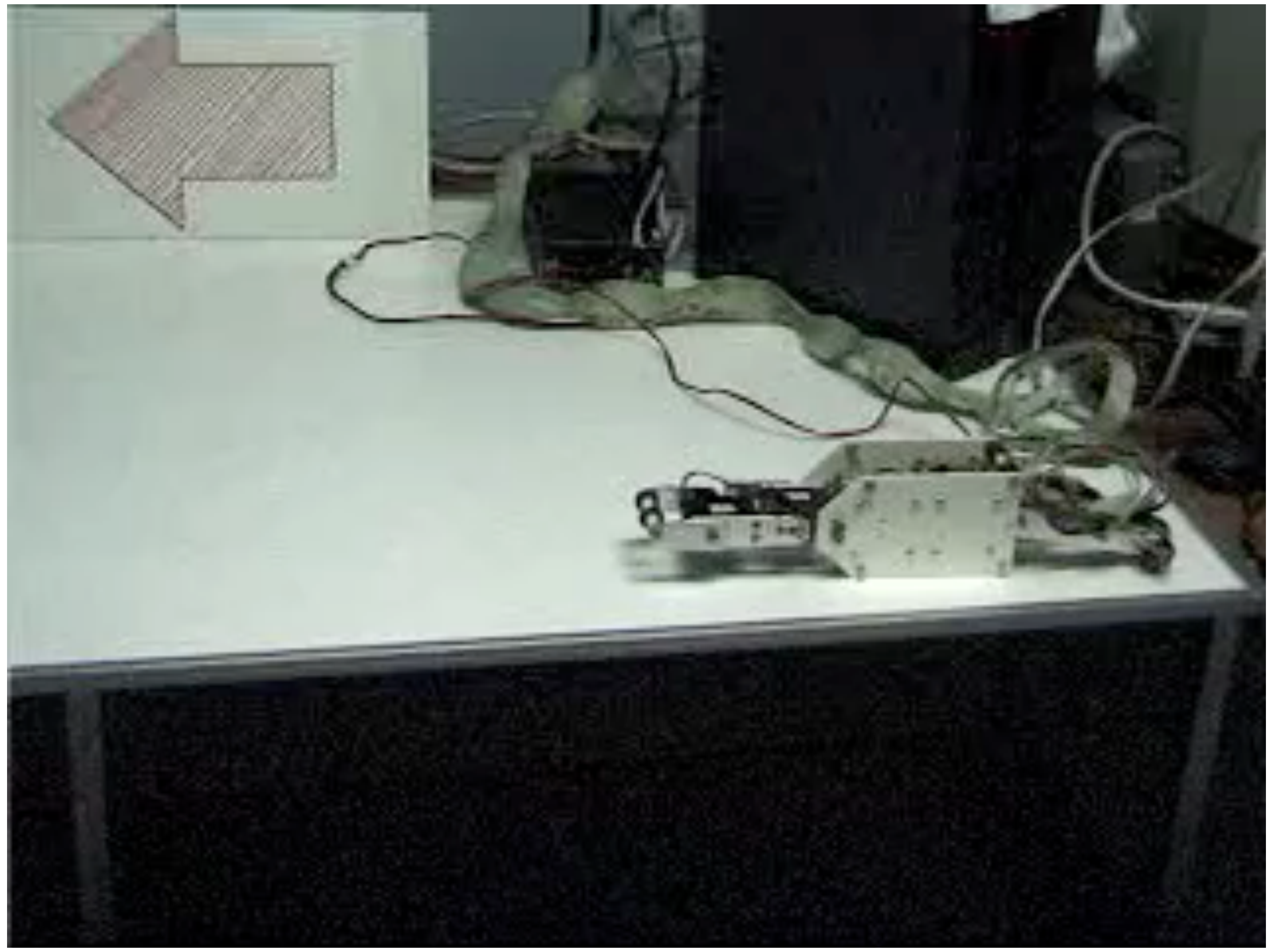
Learning **by trial and error**, with only delayed evaluative feedback (reward)

- The kind go machine learning most like natural learning
- Learning that can tell for itself when it is right or wrong

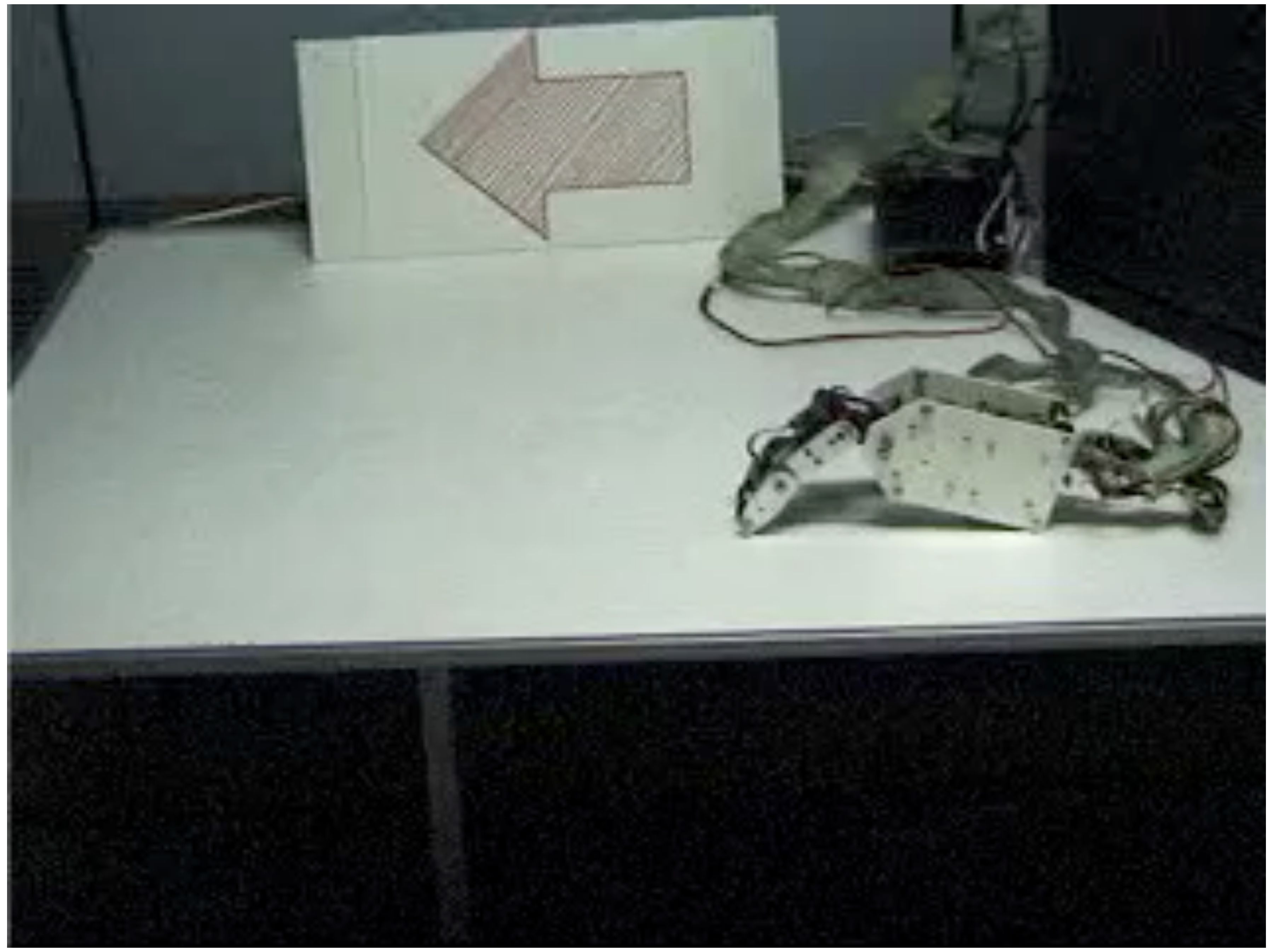


* slide from David Silver

Example: Hajime Kimura's RL Robot



Before



After

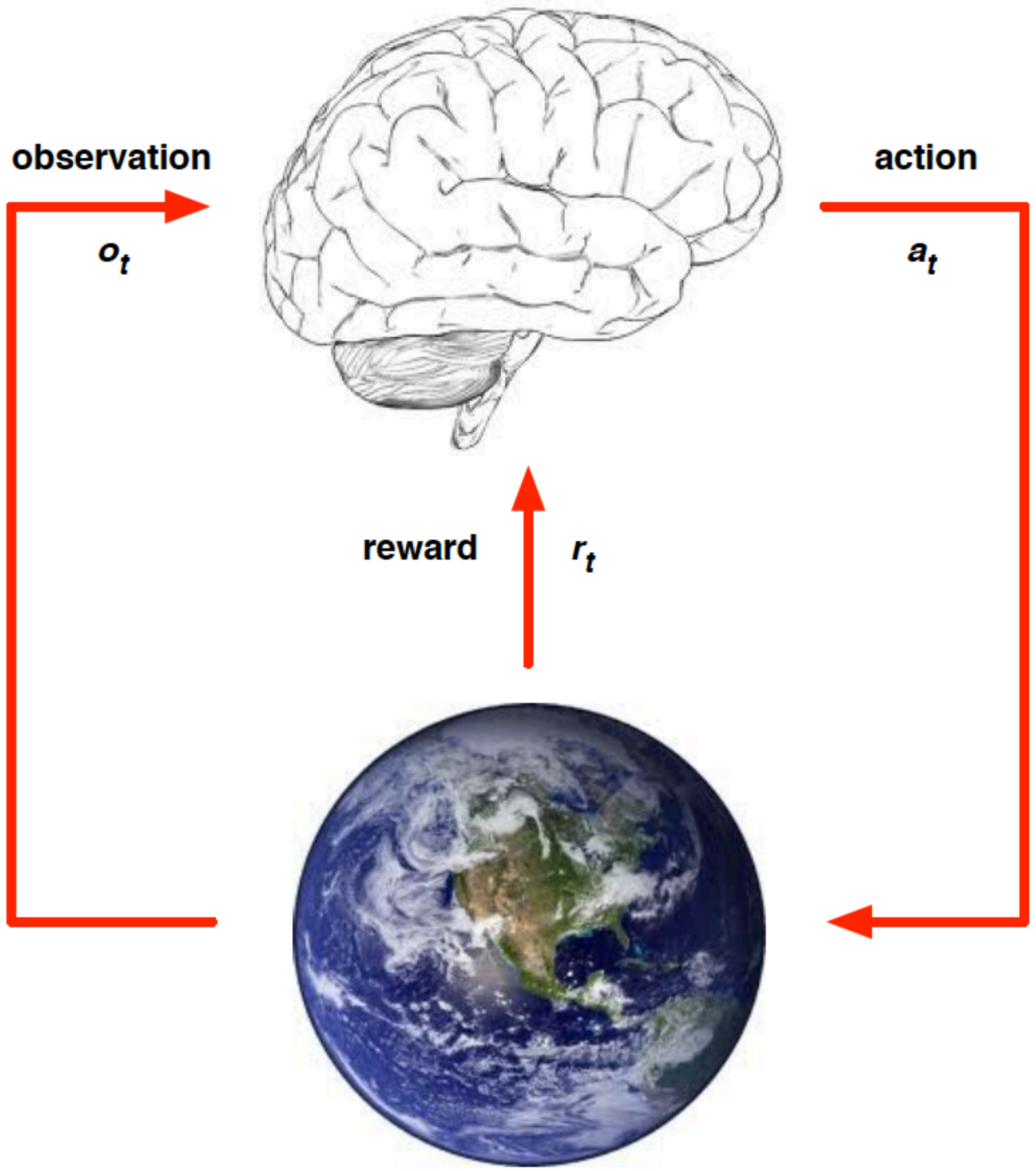
* slide from Rich Sutton

Challenges of RL

- Evaluative feedback (reward)
- Sequentiality, delayed consequences
- Need for trial and error, to explore as well as exploit
- Non-stationarity
- The fleeting nature of time and online data

* slide from Rich Sutton

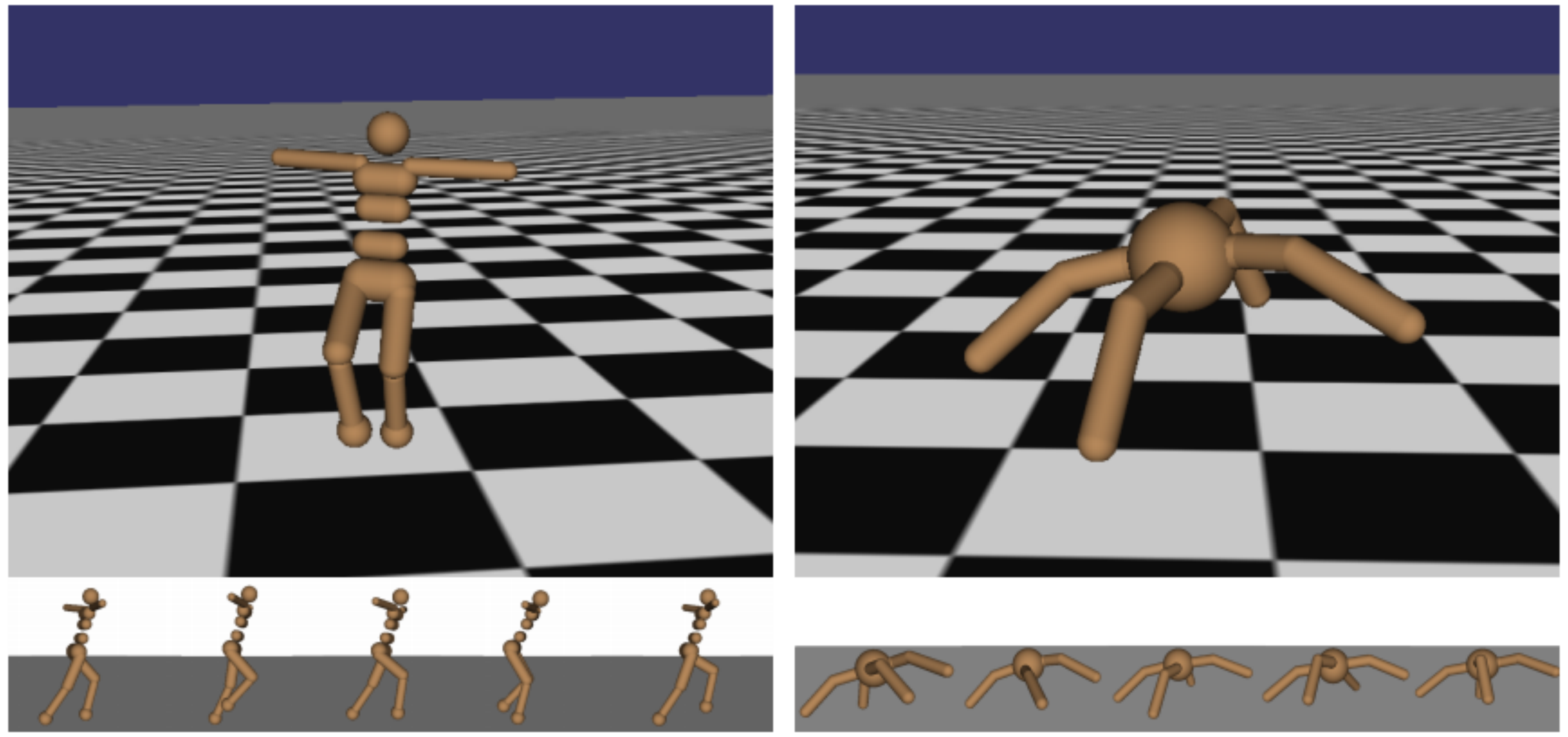
How does **RL** work?



- At each step t the agent:
  - Executes action a_t
  - Receives observation o_t
  - Receives scalar reward r_t
- The environment:
  - Receives action a_t
  - Emits observation o_{t+1}
  - Emits scalar reward r_{t+1}

* slide from David Silver

Robot Locomotion



Objective: Make the robot move forward

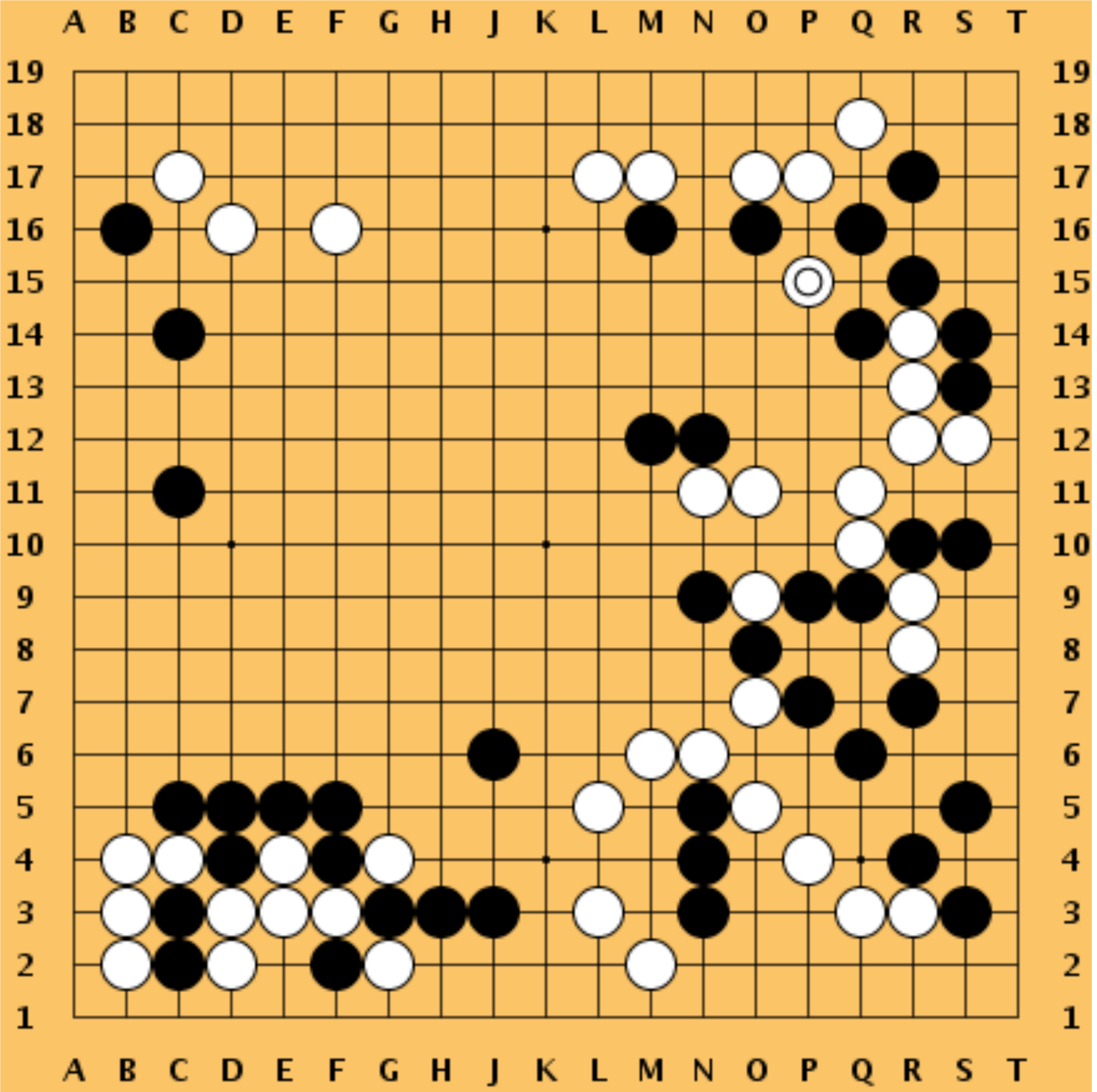
State: Angle and position of the joints
Action: Torques applied on joints
Reward: 1 at each time step upright + forward movement

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 Game (AlphaGo)



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

Markov Decision Processes

— Mathematical **formulation** of the RL problem

Defined by:

$\mathcal{S}$: 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

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- Life is **trajectory**: $\ldots S_t, A_t, R_{t+1}, S_{t+1}, A_{t+1}, R_{t+2}, S_{t+2}, \ldots$

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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— Life is **trajectory**: $\ldots S_t, A_t, R_{t+1}, S_{t+1}, A_{t+1}, R_{t+2}, S_{t+2}, \ldots$

— **Markov property**: Current state completely characterizes the state of the world

$$p(r, s'|s, a) = Prob\left[R_{t+1} = r, S_{t+1} = s' \,\middle|\, S_t = s, A_t = a\right]$$

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Components of the RL Agent

Policy

— How does the agent behave?

Value Function

— How good is each state and/or action pair?

Model

— Agent's representation of the environment

* slide from Dhruv Batra

Policy

- The policy is how the agent acts
- Formally, map from states to actions:

  Deterministic policy: $a = \pi(s)$

  Stochastic policy: $\pi(a|s) = \mathbb{P}[A_t = a | S_t = s]$

e.g.

State	Action
A $\longrightarrow$	2
B $\longrightarrow$	1

* slide from Dhruv Batra

The **Optimal** Policy

What is a good policy?

* slide from Dhruv Batra

The **Optimal** Policy

What is a good policy?

Maximizes current reward? Sum of all future rewards?

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Discounted future rewards!

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The **Optimal** Policy

What is a good policy?

Maximizes current reward? Sum of all future rewards?

Discounted future rewards!

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

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

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Value Function

A value function is a prediction of future reward

“State Value Function" or simply “**Value Function**”

- How good is a state?
- Am I screwed? Am I winning this game?

“Action Value Function” or **Q-function**

- How good is a state action-pair?
- Should I do this now?

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Value Function and **Q-value** Function

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

— The **value function** (how good is the state) at state s, is the expected cumulative reward from state s (and following the policy thereafter):

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

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— The **Q-value function** (how good is a state-action pair) at state s and action a, is the expected cumulative reward from taking action a in state s (and following the policy thereafter):

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

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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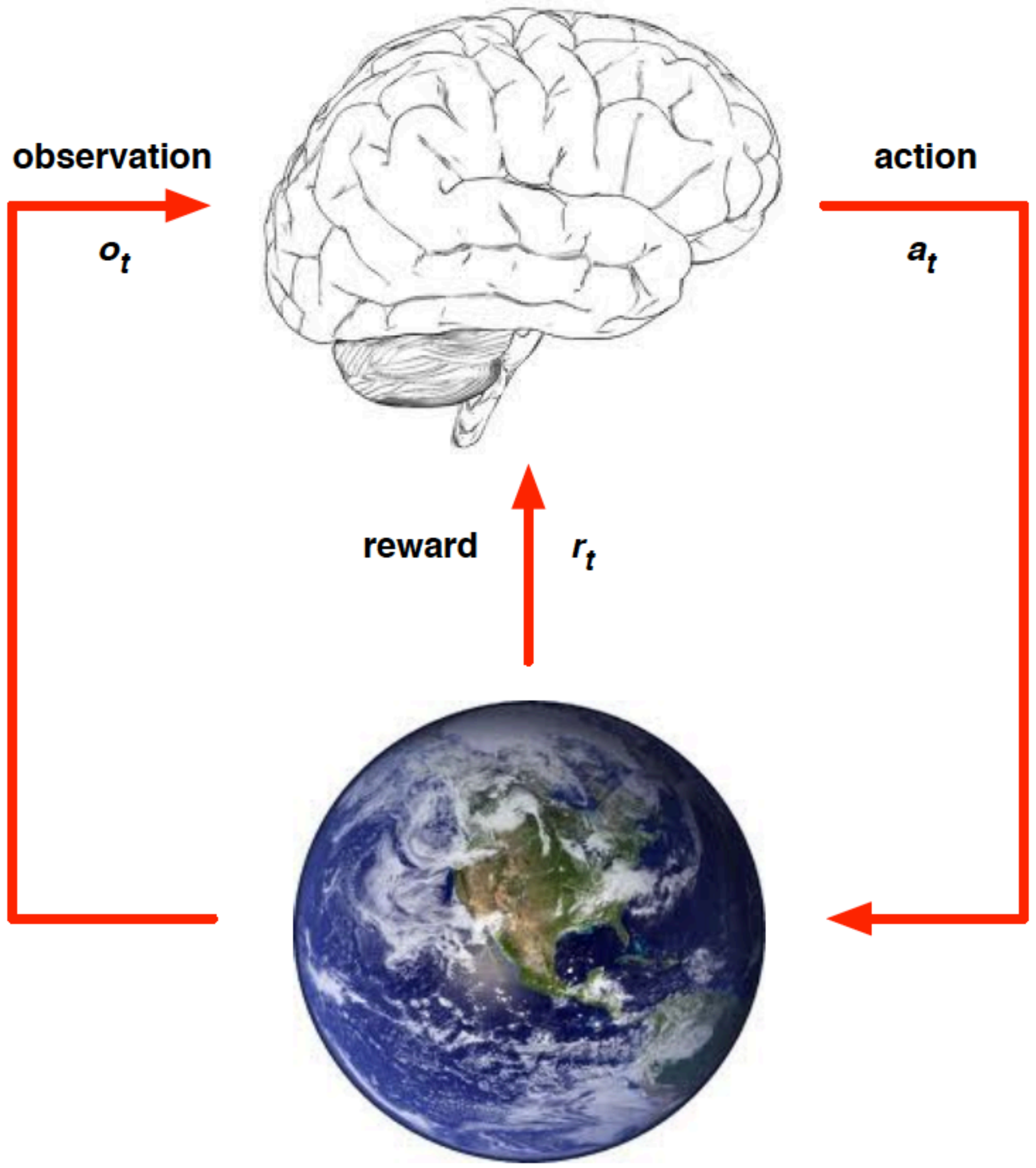
Model

Model predicts what the world will do next



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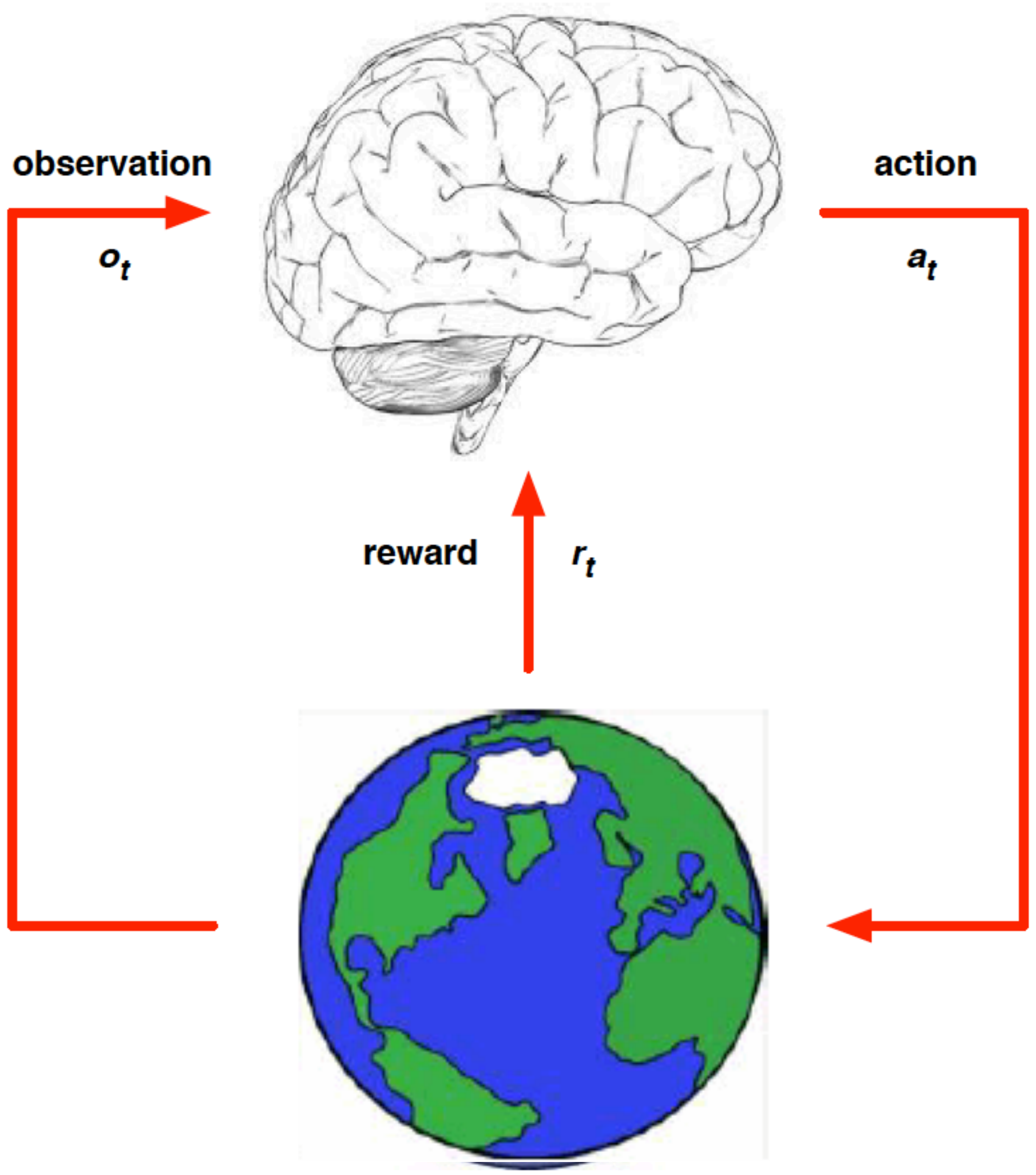

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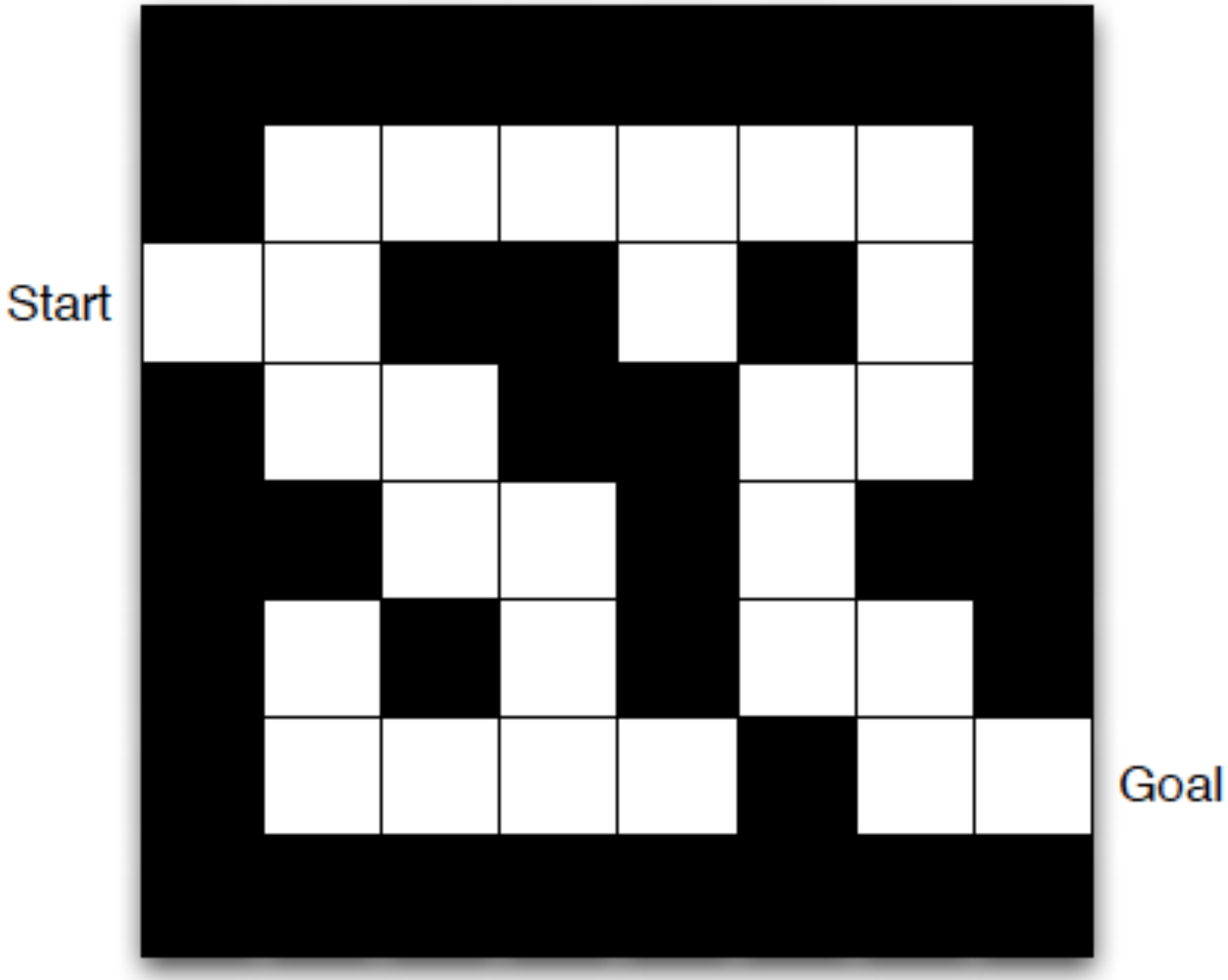
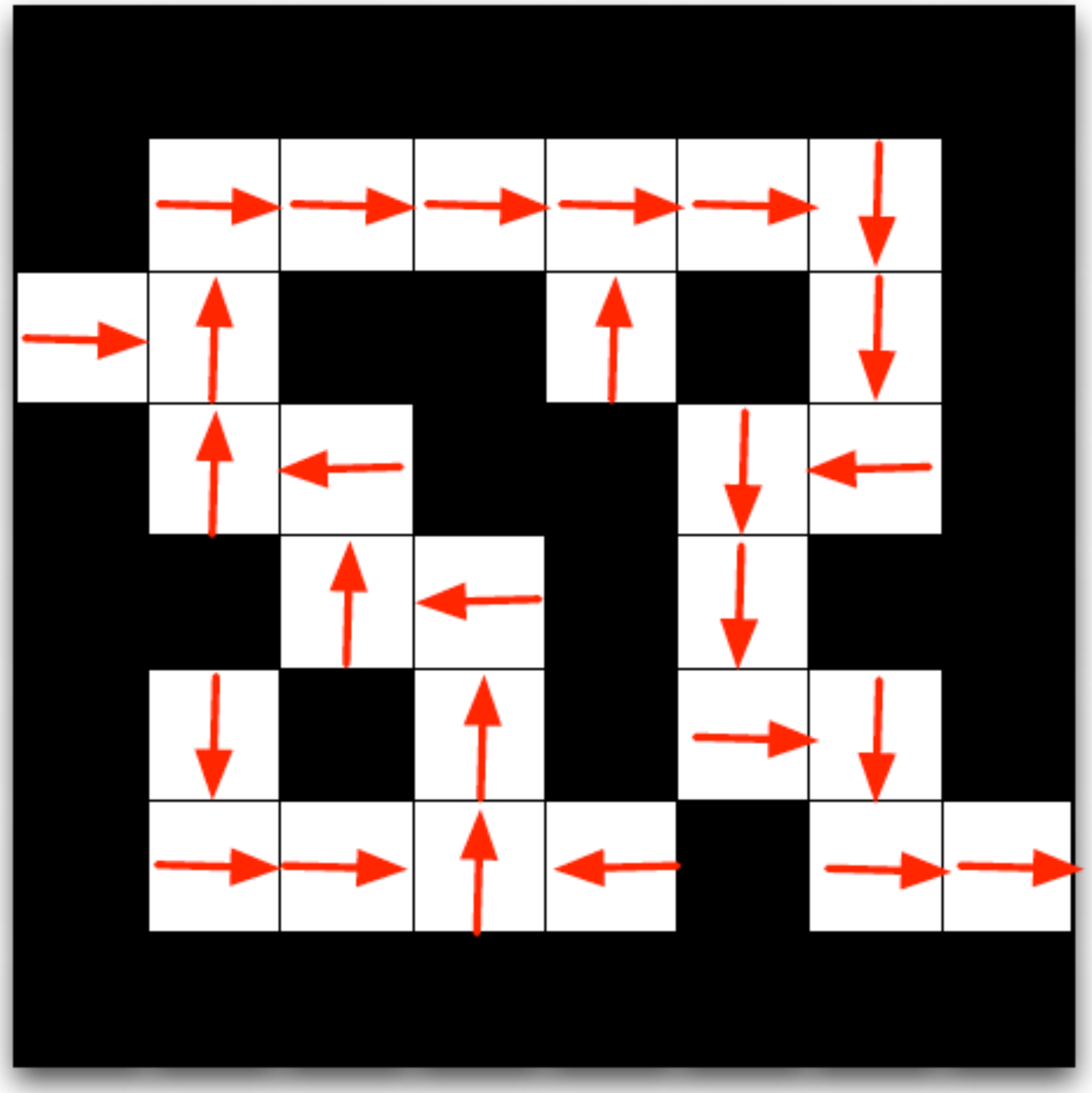
Maze Example



Reward: -1 per time-step
Actions: N, E, S, W
States: Agent's location

* slide from David Silver

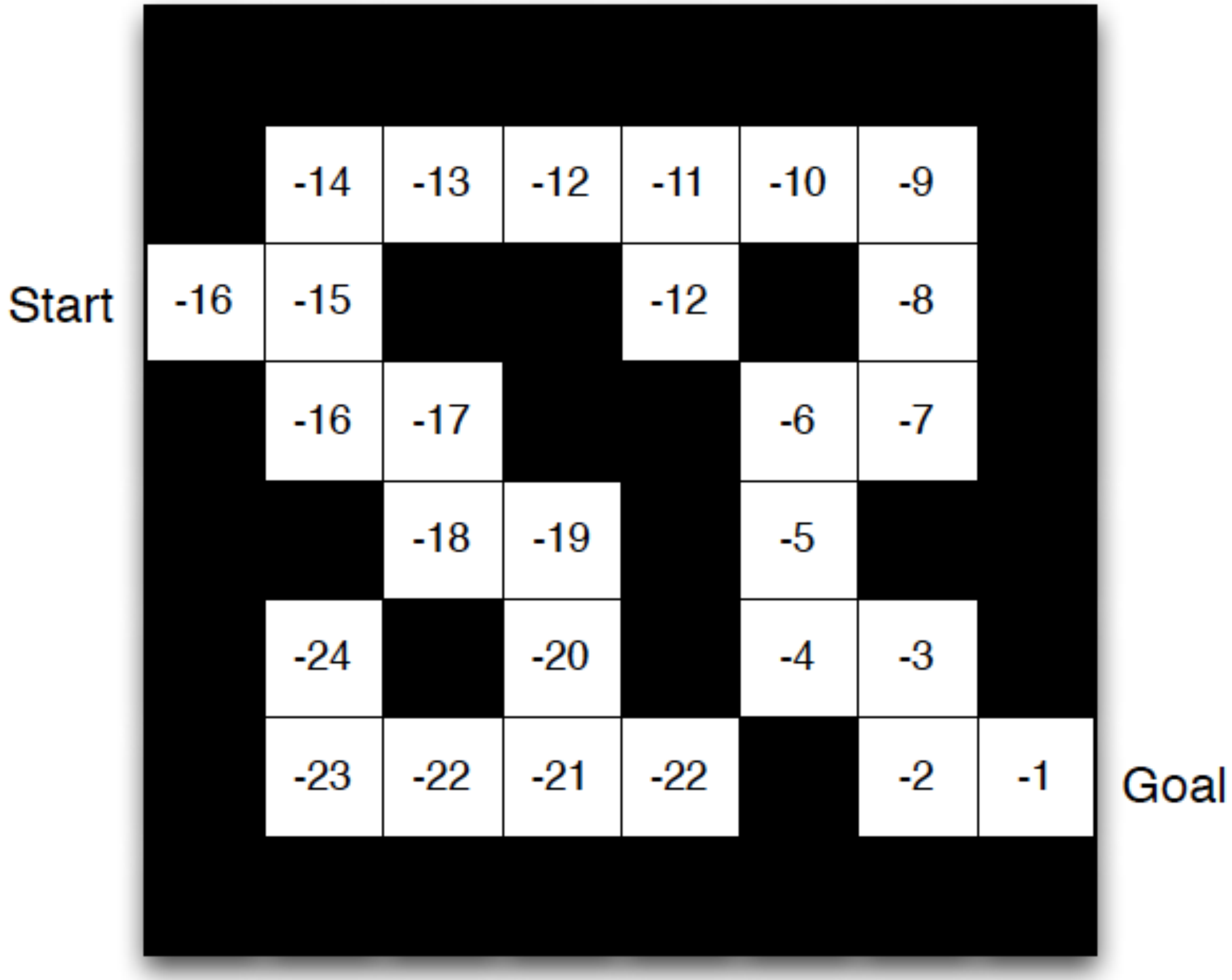
Maze Example: Policy



Arrows represent a policy $\pi(s)$ for each state s

* slide from David Silver

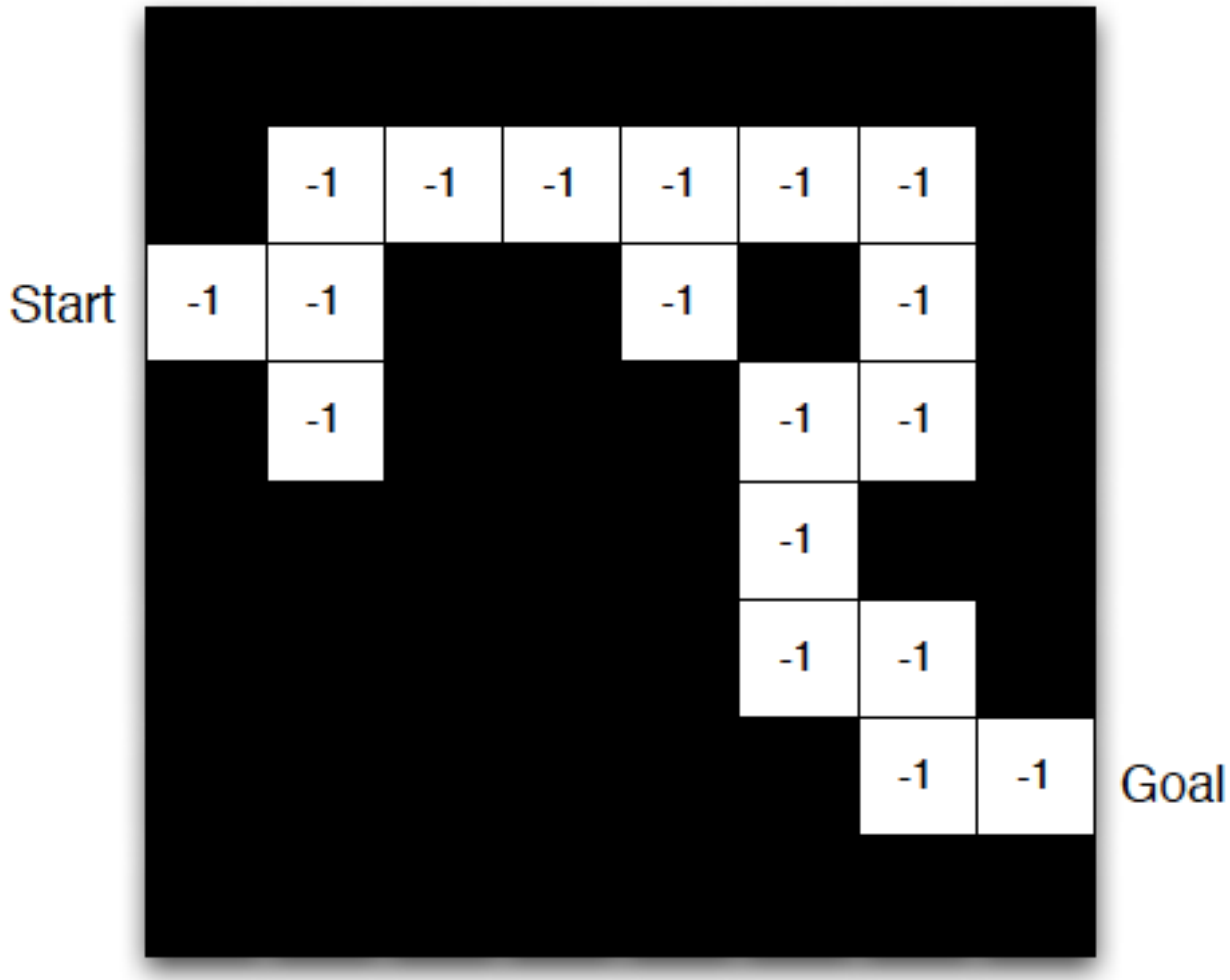
Maze Example: Value



Numbers represent value $v_\pi(s)$ of each state s

* slide from David Silver

Maze Example: Model



Grid layout represents transition model

Numbers represent the immediate reward for each state (same for all states)

* slide from David Silver

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* slide from Dhruv Batra

Approaches to RL: Taxonomy

Model-free RL

Value-based RL

- Estimate the optimal action-value function $Q^*(s,a)$
- No policy (implicit)

Policy-based RL

- Search directly for the optima policy π^*
- No value function

Model-based RL

- Build a model of the world
- Plan (e.g., by look-ahead) using model

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Actor-critic RL

- Value function
- Policy function

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* slide from Dhruv Batra

Deep RL

Value-based RL

— Use neural nets to represent Q function $Q(s, a; \theta)$

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

Policy-based RL

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Optimal Q-function is the maximum achievable value

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Once we have it, we can act optimally

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Optimal value maximizes over all future decisions

$$\begin{aligned} Q^*(s,a) &= r_{t+1} + \gamma \max_{a_{t+1}} r_{t+2} + \gamma^2 \max_{a_{t+2}} r_{t+3} + \ldots \\ &= r_{t+1} + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1}) \end{aligned}$$

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Formally, Q* satisfied Bellman Equations

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

* slide from David Silver

Solving for the Optimal Policy

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

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* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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Not scalable. Must compute Q(s,a) for every state-action pair. If state is e.g. game pixels, computationally infeasible to compute for entire state space!

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

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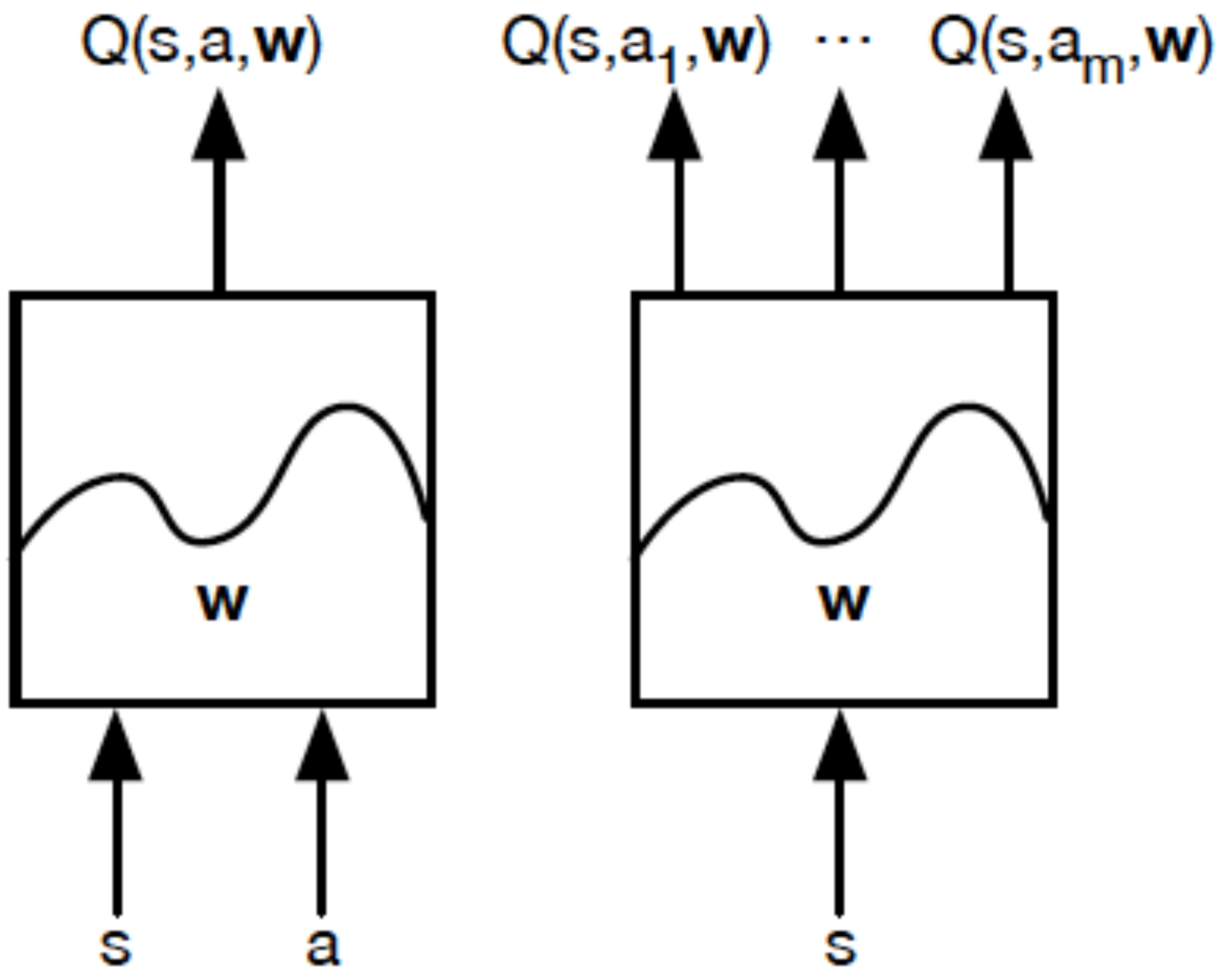
Q-Networks

$$Q(s, a, \mathbf{w}) \approx Q^*(s, a)$$



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Case Study: Playing **Atari** Games

[Mnih *et al.*, 2013; Nature 2015]

Objective: Complete the game with the highest score

State: Raw pixel inputs of the game state
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Reward: Score increase/decrease at each time step

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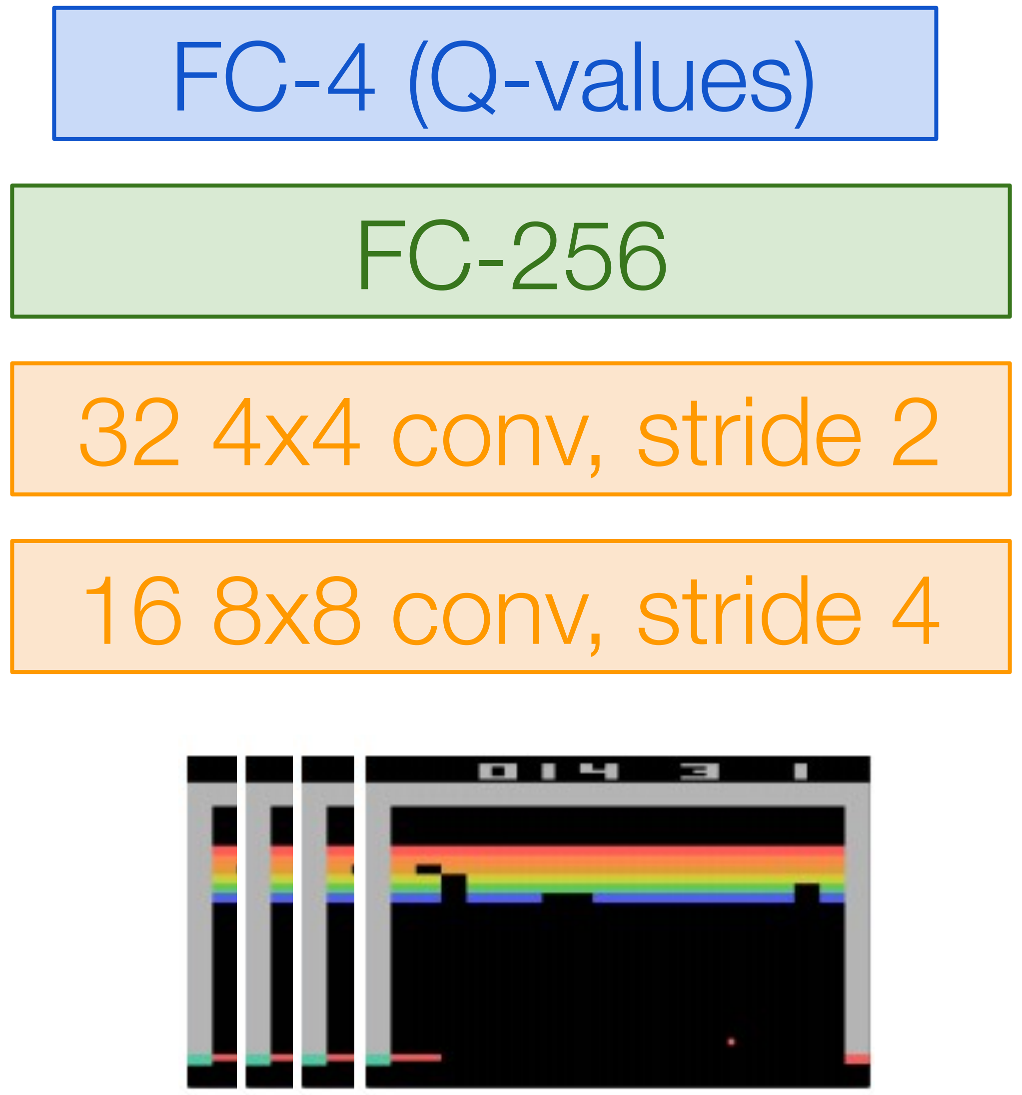
Q-Network Architecture

[Mnih *et al.*, 2013; Nature 2015]

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



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

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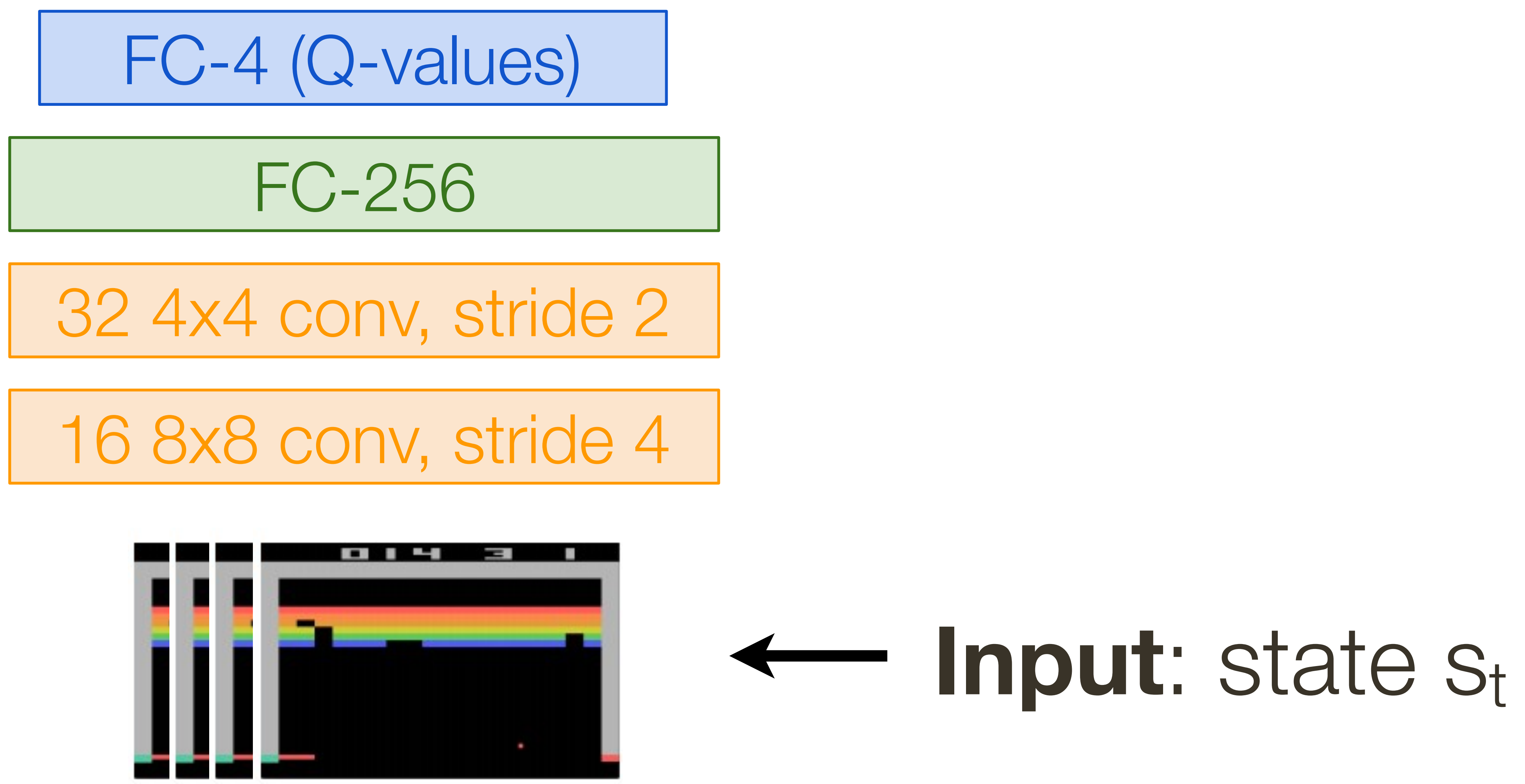

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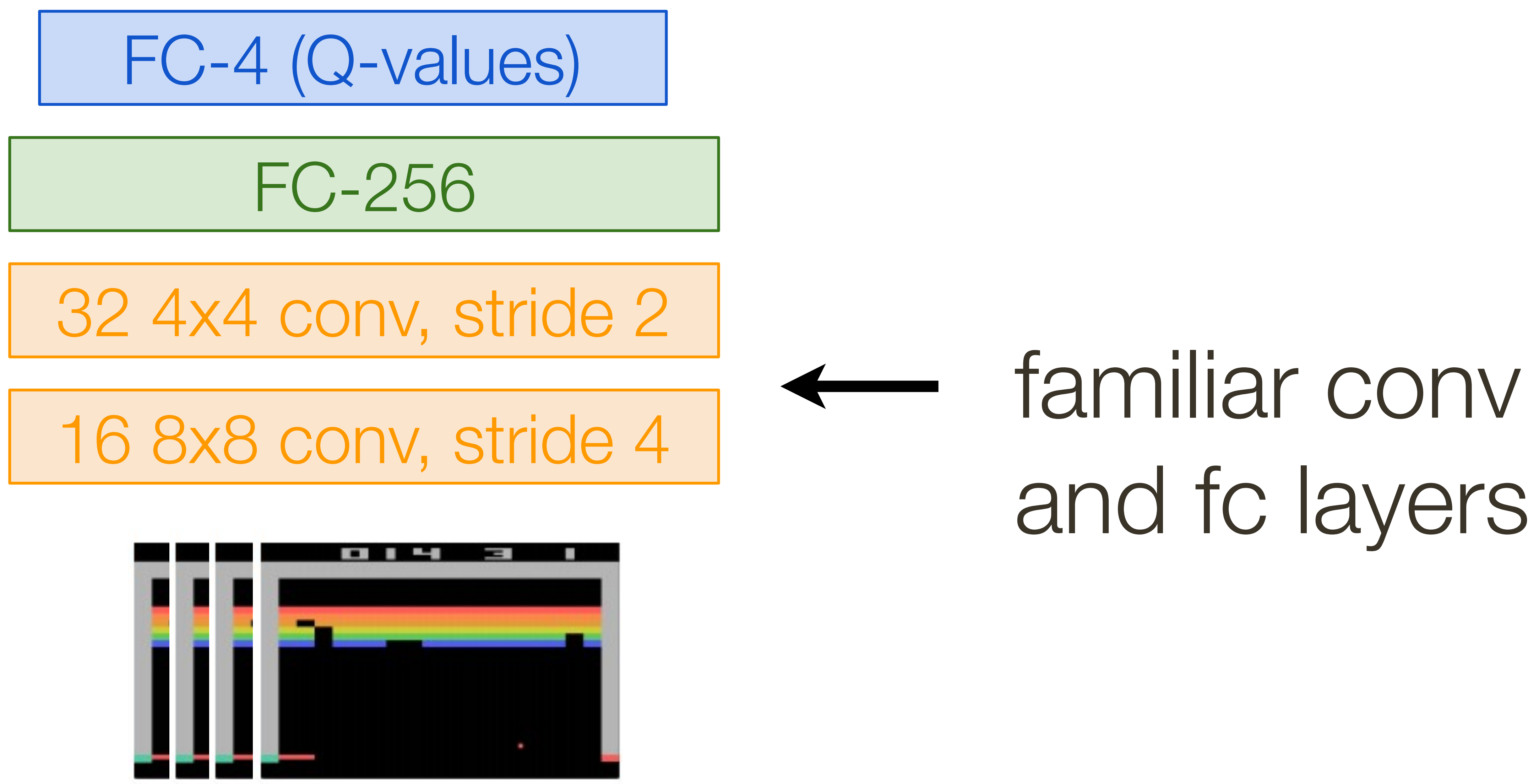

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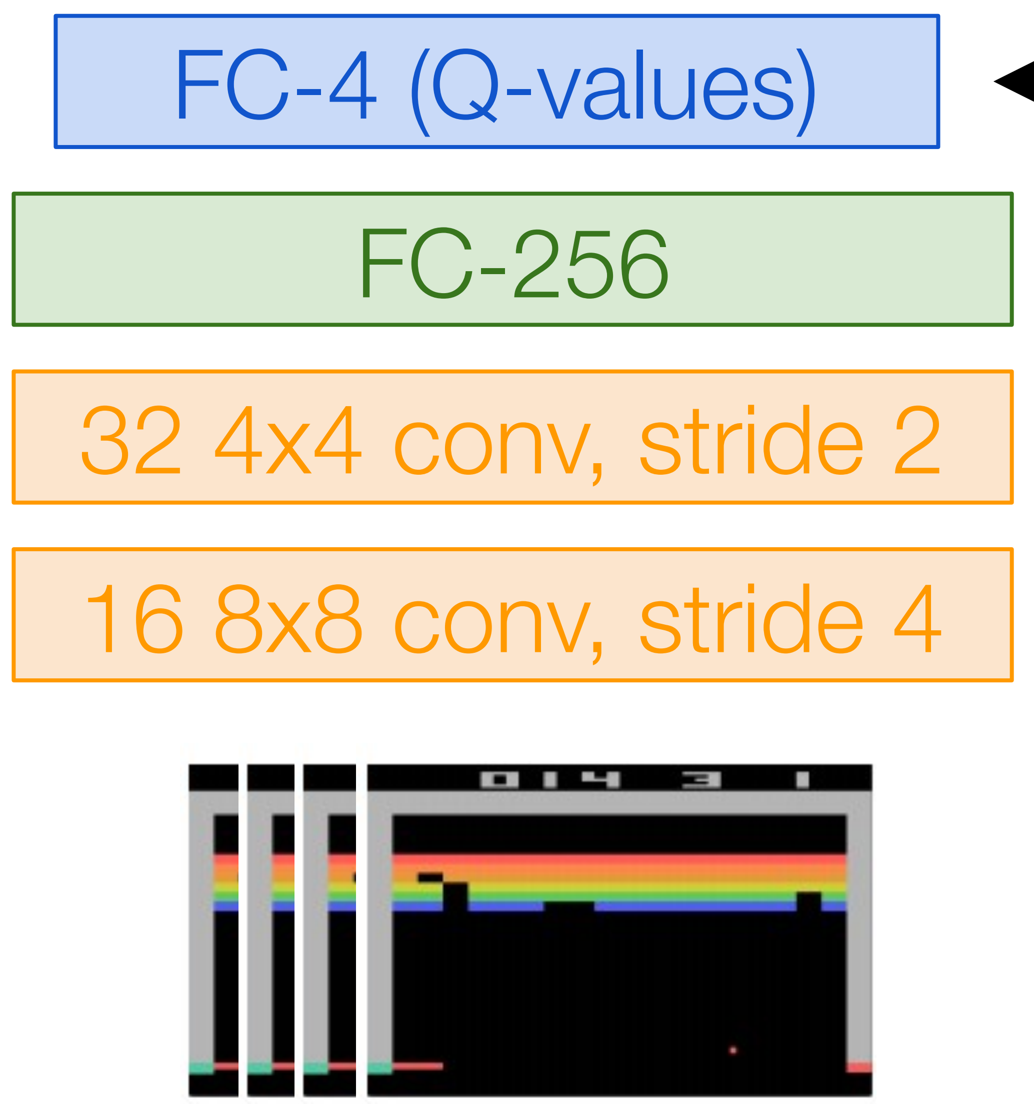

Last FC layer has 4-d output (if 4 actions), corresponding to $Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$, $Q(s_t,a_4)$

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Q-Network Architecture

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

FC-256

32 4x4 conv, stride 2

16 8x8 conv, stride 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)

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

Number of actions between 4-18 depending on Atari game

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Q-Network Learning

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

$$Q^*(s,a) = \mathbb{E}[r + \gamma \max_{a'} Q^*(s',a') \mid s,a]$$

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Forward Pass:

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

where $y_i = \mathbb{E}[r + \gamma \max_{a'} Q^*(s',a') \mid s,a]$

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Backward Pass:

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

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

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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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***)

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Training the Q-Network: **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

Experience Replay

To remove correlations, build data-set from agent's own experience

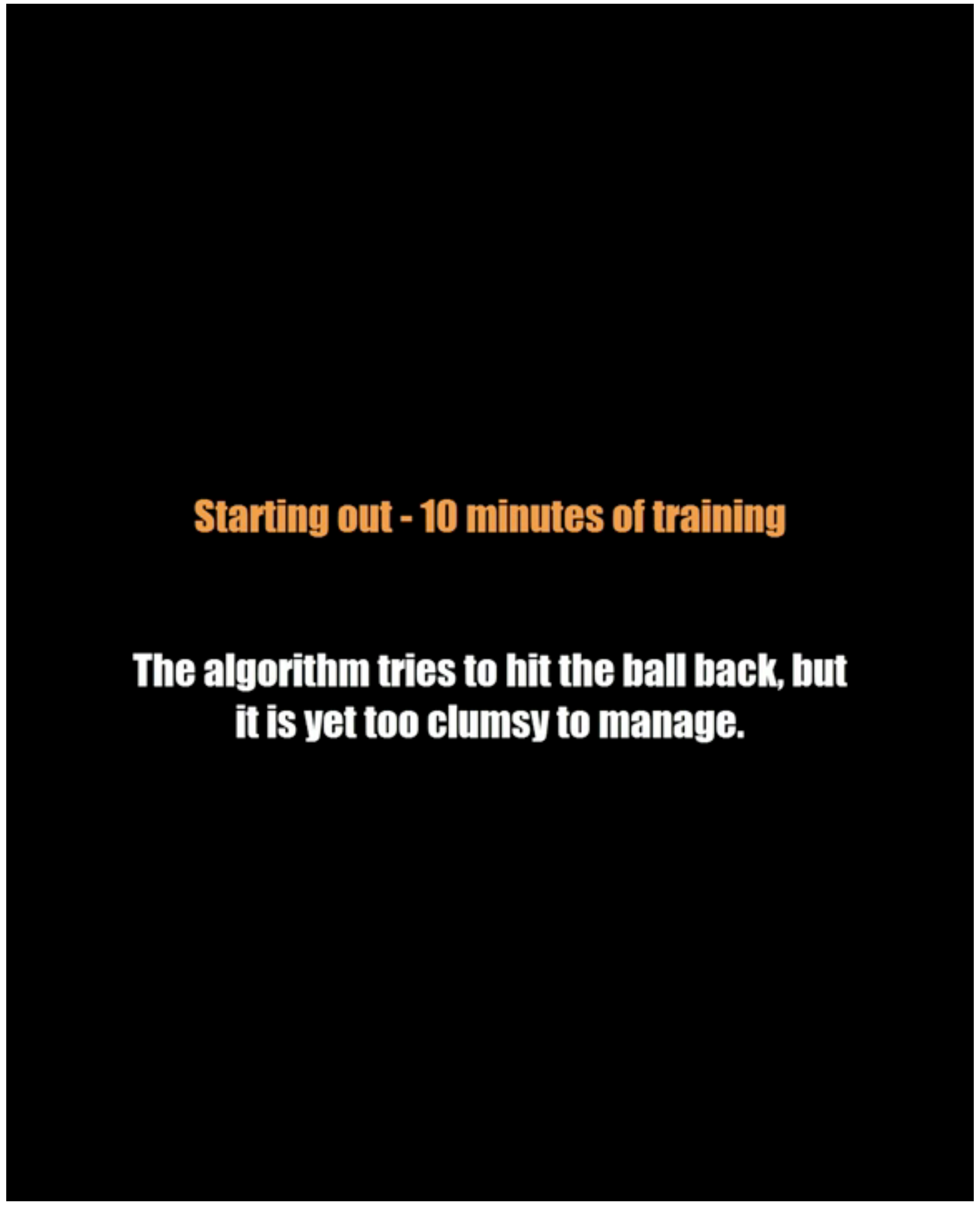
s_1, a_1, r_2, s_2
s_2, a_2, r_3, s_3
s_3, a_3, r_4, s_4
$\ldots$
$s_t, a_t, r_{t+1}, s_{t+1}$

$s_2, a_2, r_3, s_3 \rightarrow s, a, r, s'$

$s_t, a_t, r_{t+1}, s_{t+1} \rightarrow s_t, a_t, r_{t+1}, s_{t+1}$

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Example: Atari Playing



Deep RL

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Policy Gradients

Formally, let's define a class of parameterized policies:

For each policy, define its value:

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

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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 $\theta^* = \arg\max_\theta J(\theta)$

Policy Gradients

Formally, let's define a class of parameterized policies:

For each policy, define its value:

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

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How can we do this?

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How can we do this?

Gradient ascent on policy parameters!

REINFORCE algorithm

Expected reward:

$$J(\theta) = \mathbb{E}_{\tau \sim p(\tau;\theta)}\left[r(\tau)\right]$$
$$= \int_{\tau} r(\tau)p(\tau;\theta)\mathrm{d}\tau$$

Where r(τ) is the reward of a trajectory $\tau = (s_0, a_0, r_0, s_1, \ldots)$

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Now let's differentiate this: $\nabla_\theta J(\theta) = \int_\tau r(\tau) \nabla_\theta p(\tau;\theta) \mathrm{d}\tau$

Intractable! Expectation of gradient is
problematic when p depends on θ

REINFORCE algorithm

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Now let's differentiate this: $\nabla_\theta J(\theta) = \int_\tau r(\tau) \nabla_\theta p(\tau;\theta) \mathrm{d}\tau$

However, we can use a nice trick: $\nabla_\theta p(\tau;\theta) = p(\tau;\theta) \frac{\nabla_\theta p(\tau;\theta)}{p(\tau;\theta)} = p(\tau;\theta) \nabla_\theta \log p(\tau;\theta)$

If we inject this back:

$$\nabla_\theta J(\theta) = \int_\tau \left(r(\tau) \nabla_\theta \log p(\tau;\theta) \right) p(\tau;\theta) \mathrm{d}\tau$$
$$= \mathbb{E}_{\tau \sim p(\tau;\theta)} [r(\tau) \nabla_\theta \log p(\tau;\theta)]$$

Can estimate with Monte Carlo sampling

Intuition

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(τ) is high, push up the probabilities of the actions seen
- If r(τ) is low, push down the probabilities of the actions seen

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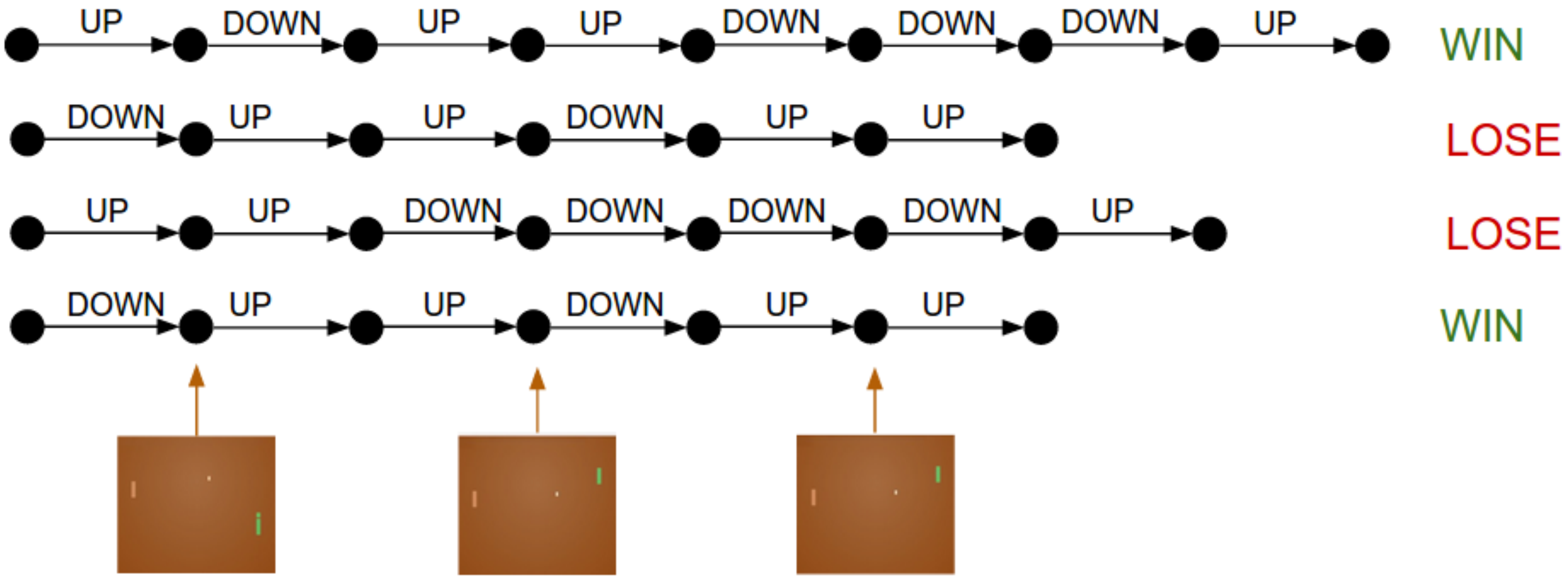
Intuition



* slide from Dhruv Batra

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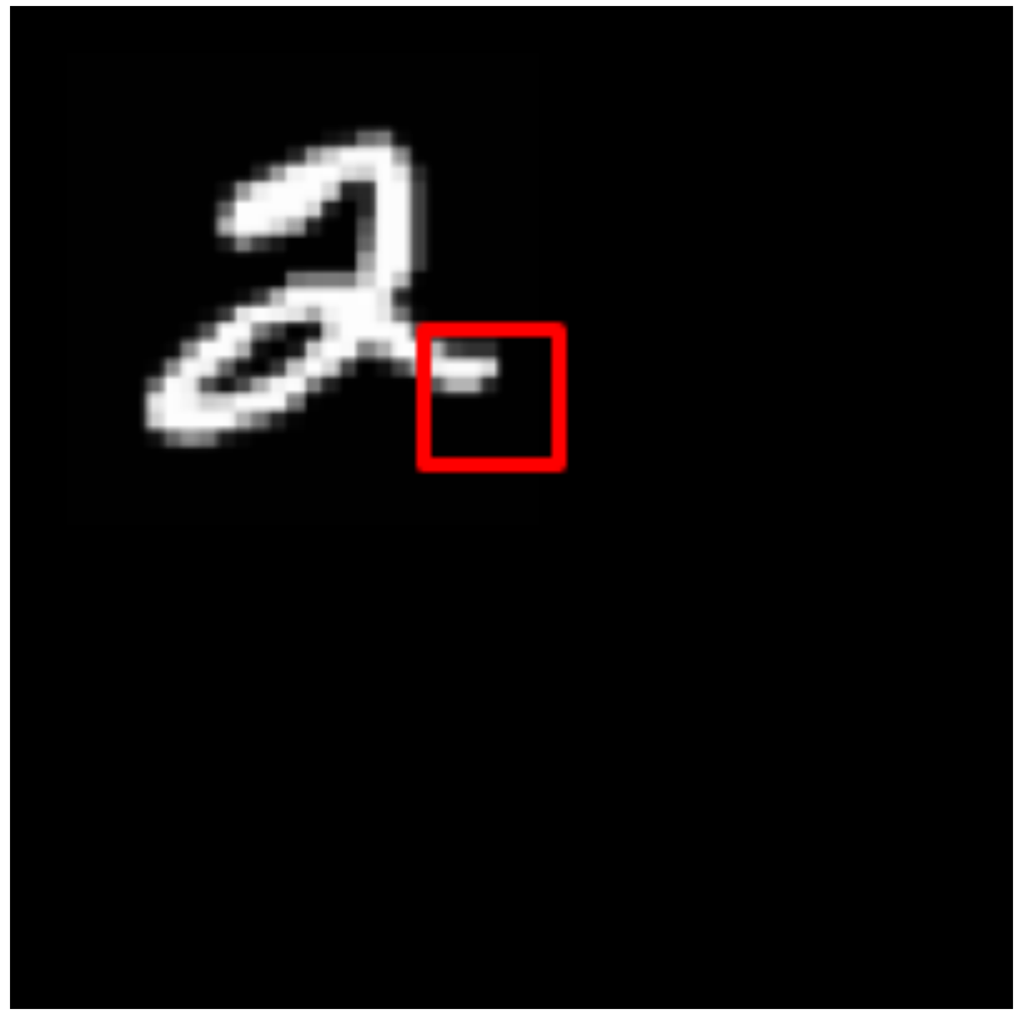
However, this also suffers from high variance because credit assignment is really hard. Can we help the estimator?

REINFORCE in Action: **Recurrent Attention Model** (REM)

Objective: Image Classification

Take a sequence of “glimpses” selectively focusing on regions of the image, to predict class

- Inspiration from human perception and eye movements
- Saves computational resources => scalability
- Able to ignore clutter / irrelevant parts of image



glimpse

[Mnih *et al.*, 2014]

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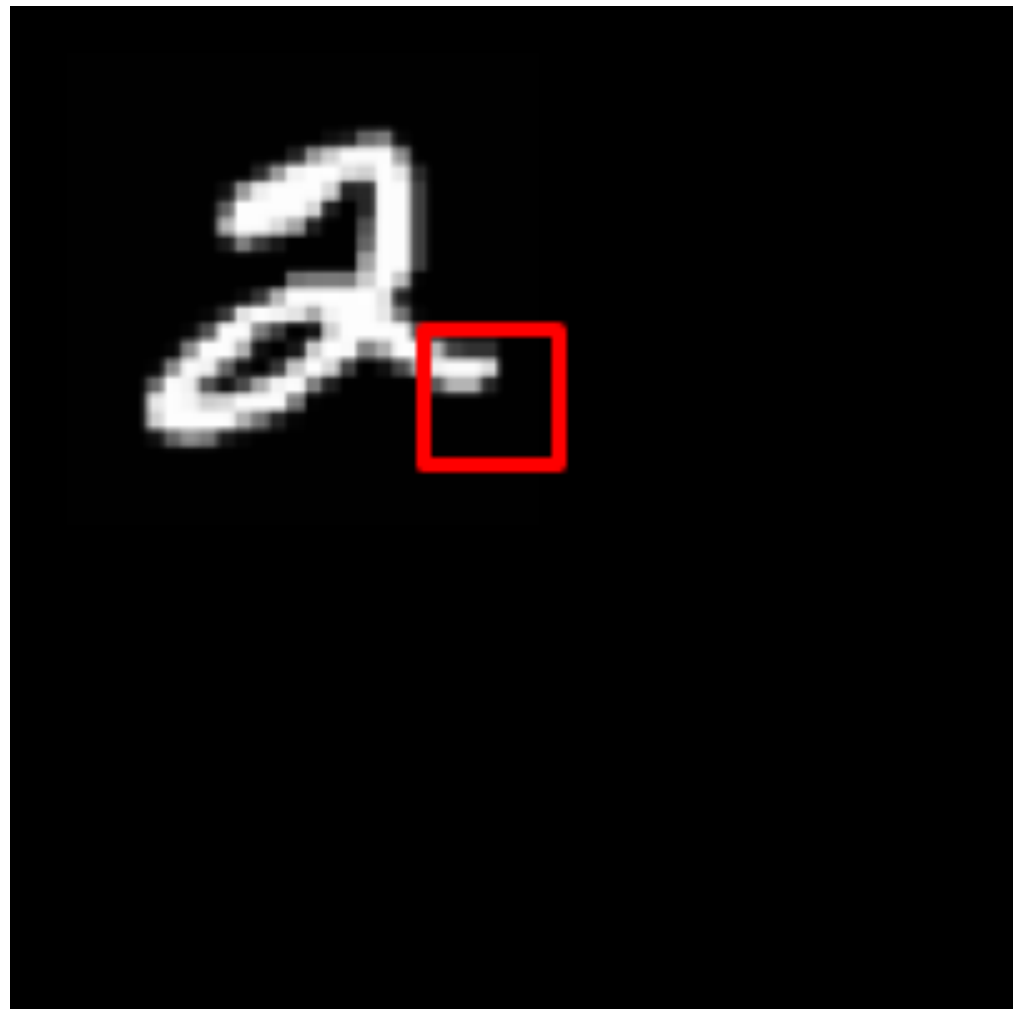

glimpse

State: Glimpses seen so far
Action: (x,y) coordinates (center of glimpse) of where to look next in image
Reward: 1 at the final timestep if image correctly classified, 0 otherwise

[Mnih *et al.*, 2014]

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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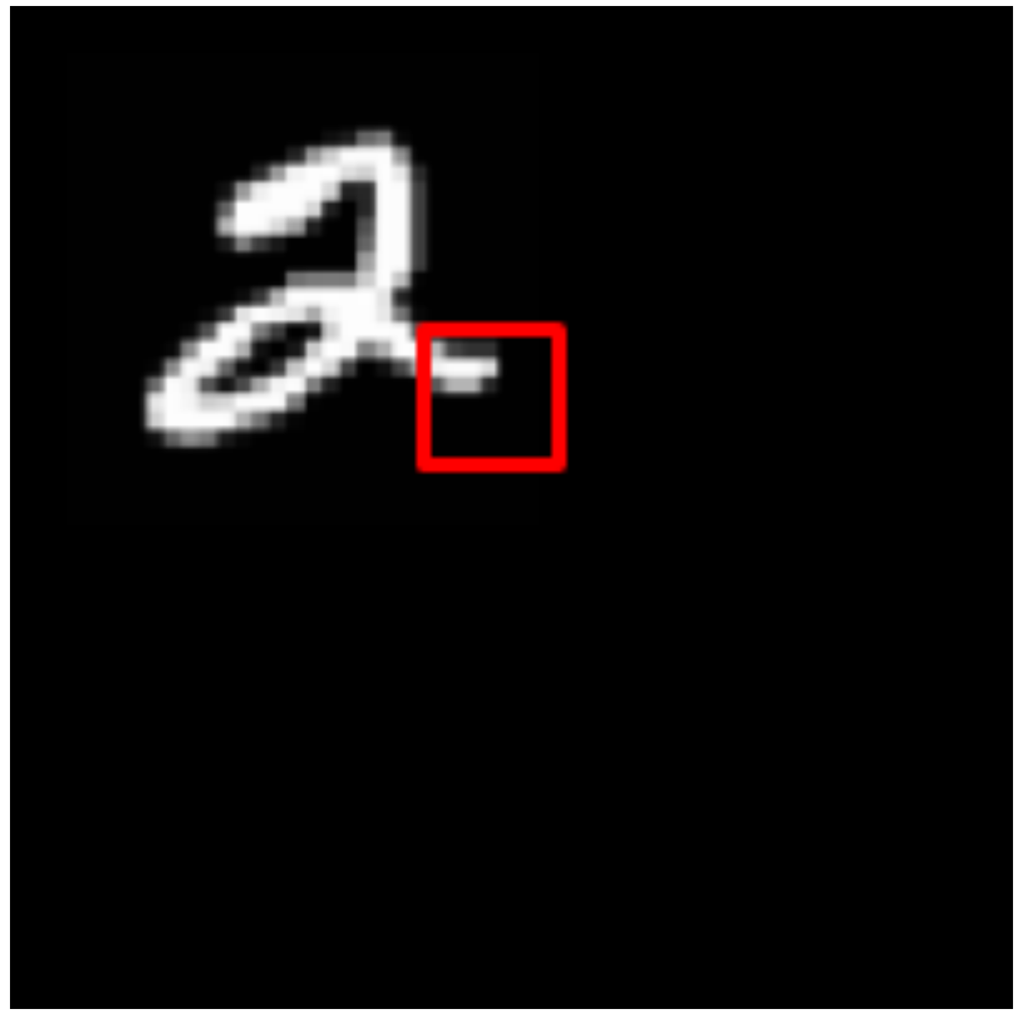

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Glimpsing is a **non-differentiable operation** => learn policy for how to take glimpse actions using REINFORCE
Given state of glimpses seen so far, use RNN to model the state and output next action

[Mnih *et al.*, 2014]

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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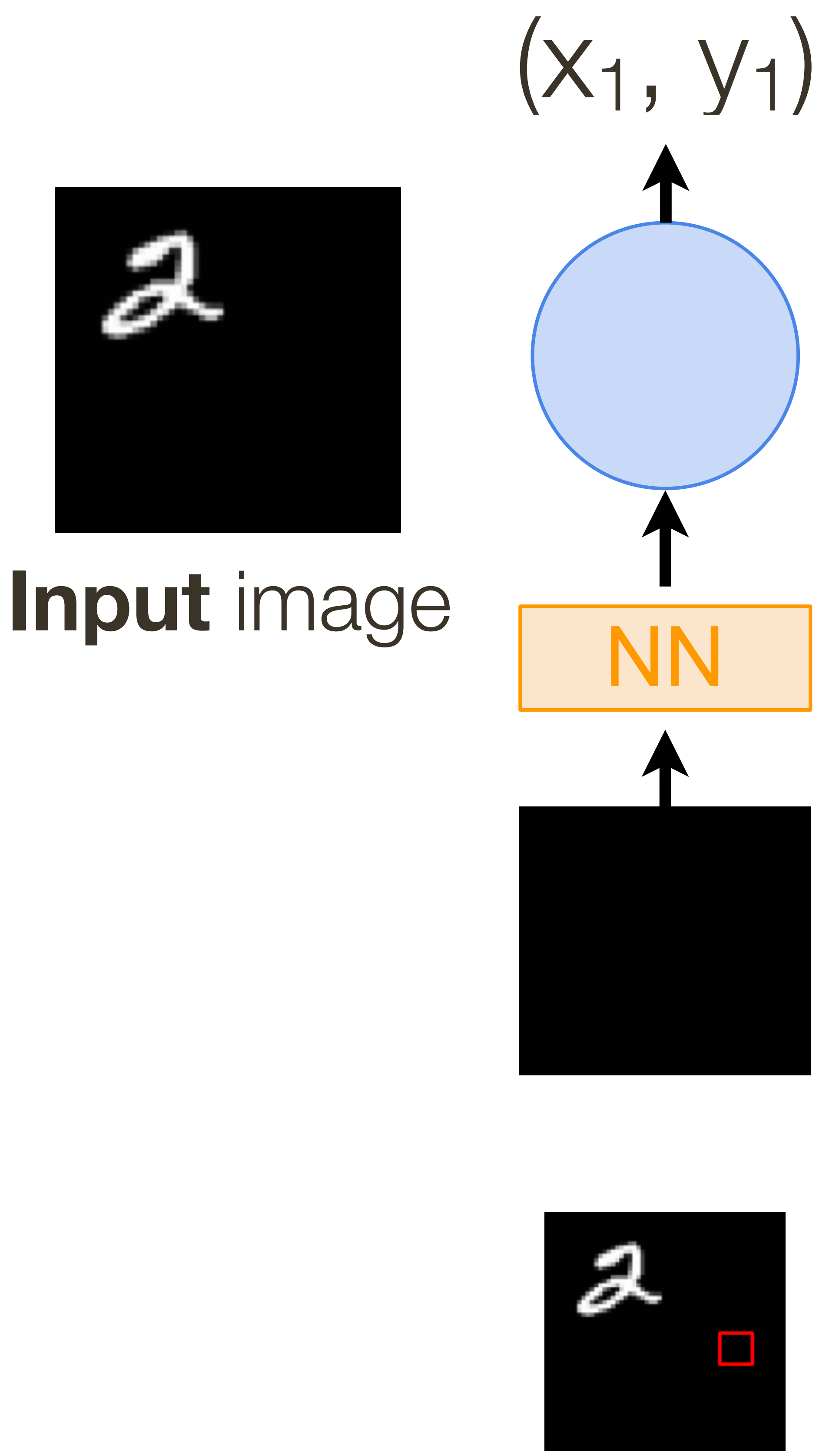

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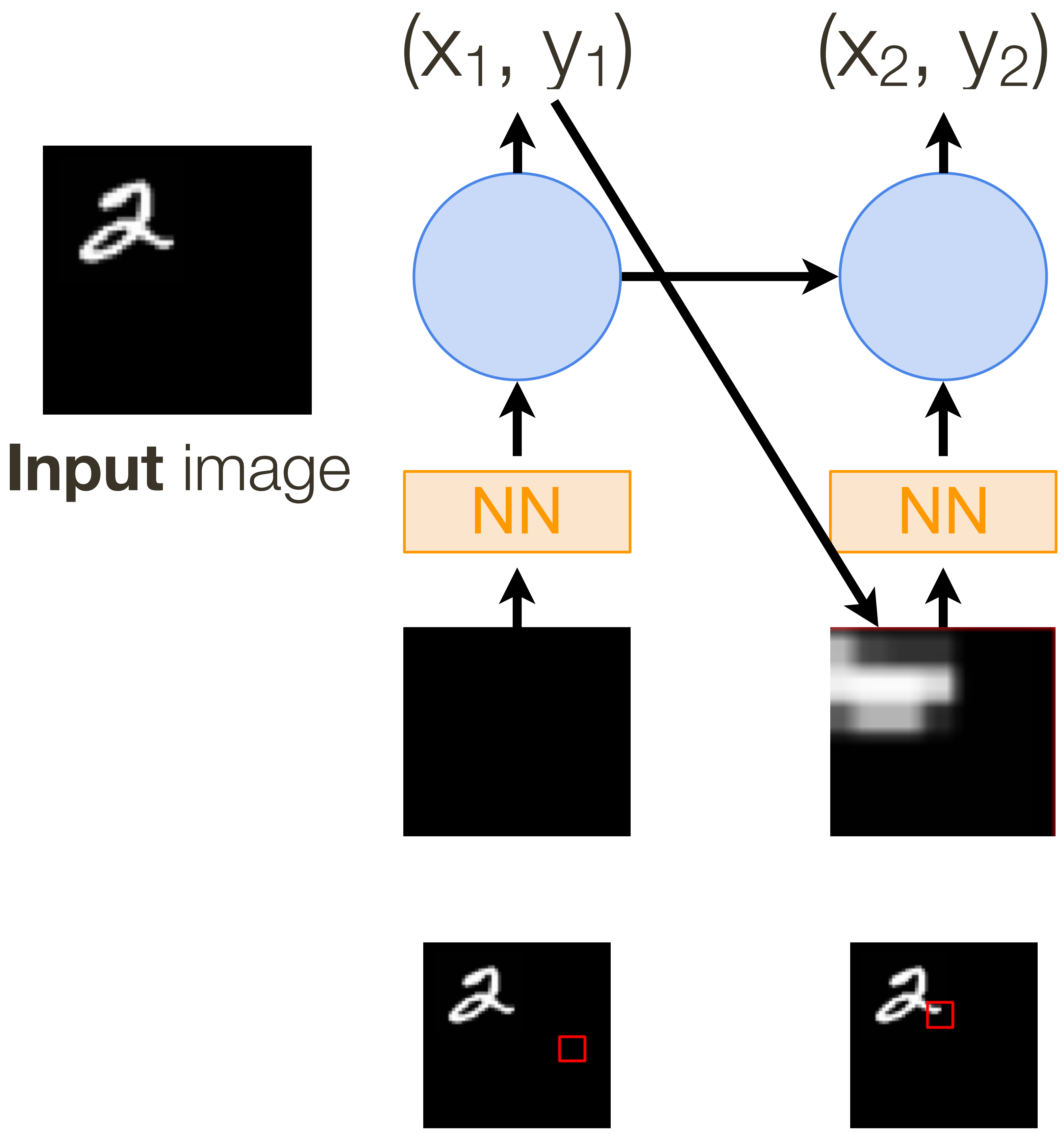

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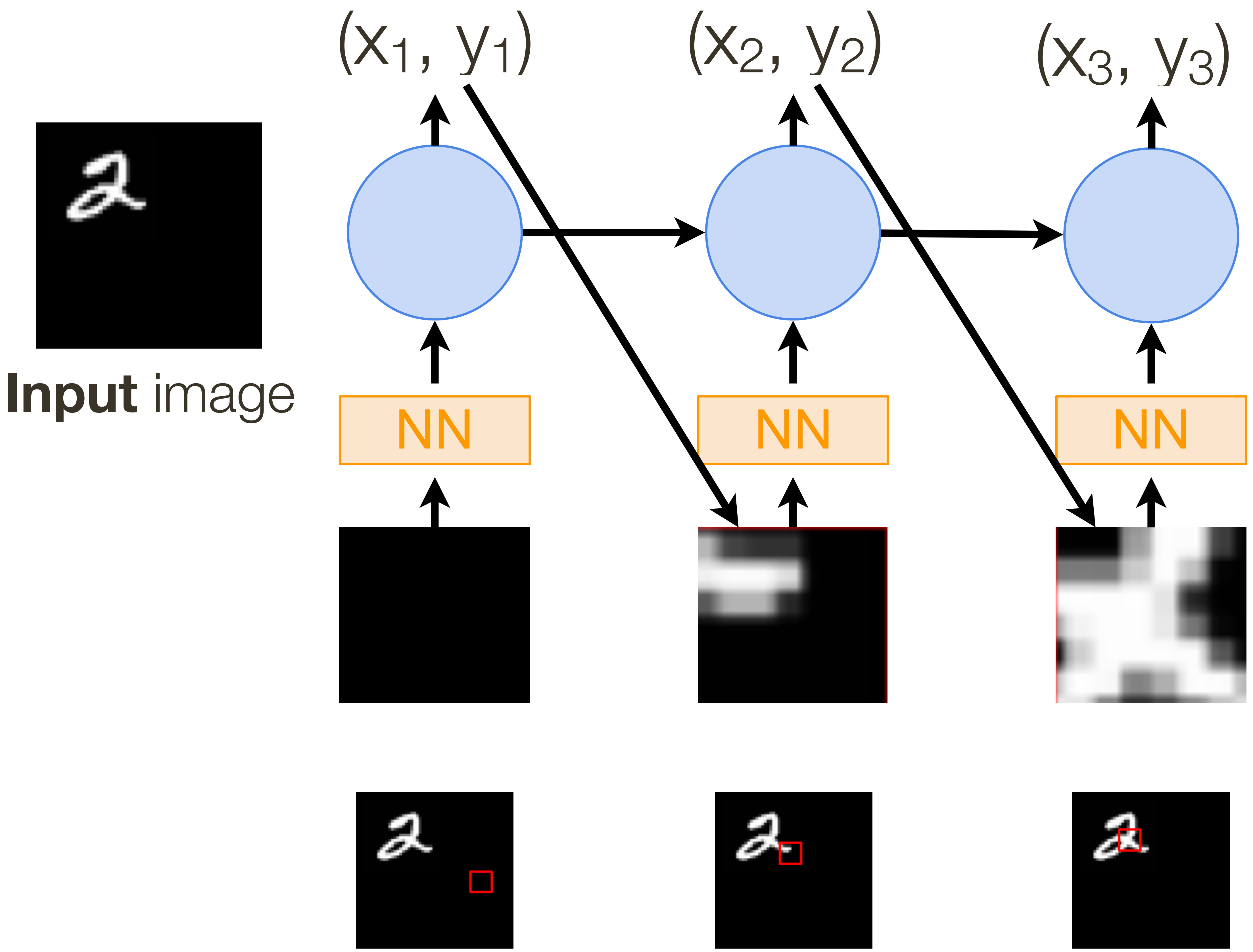

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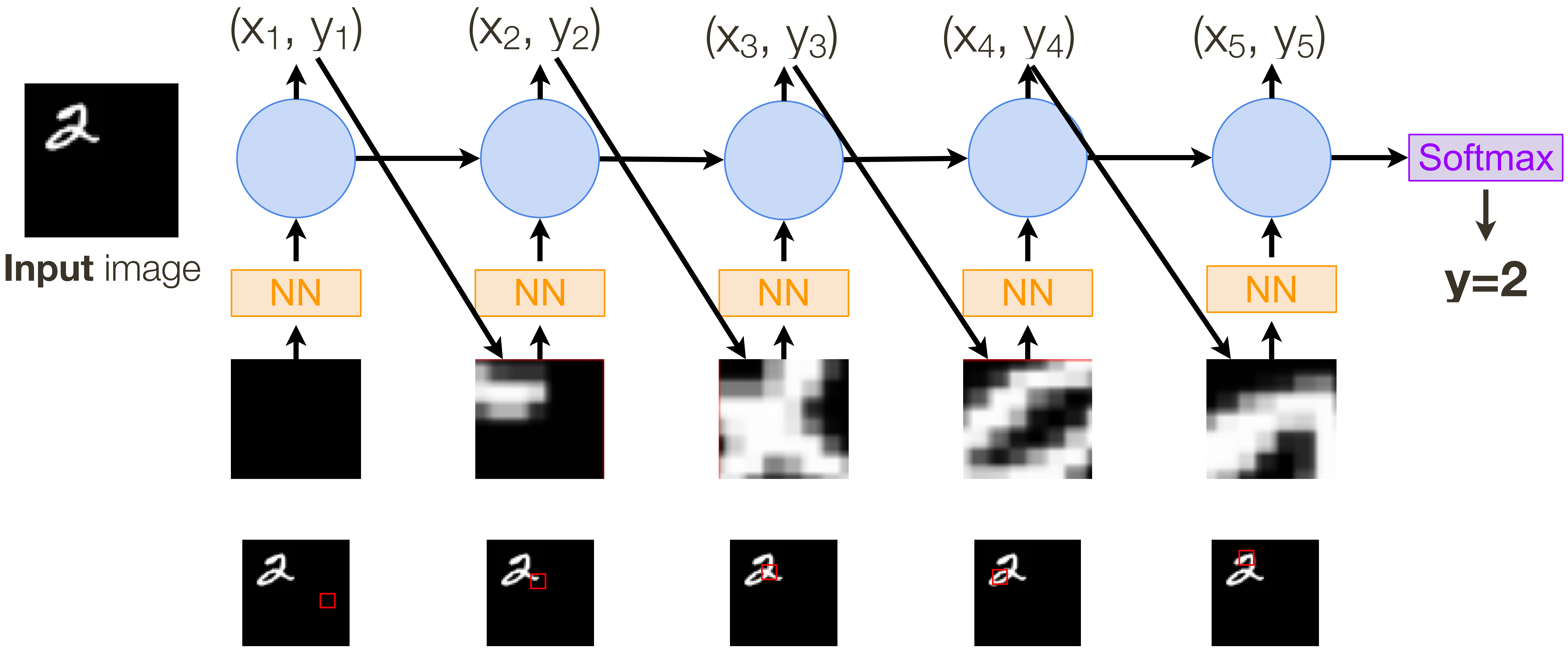

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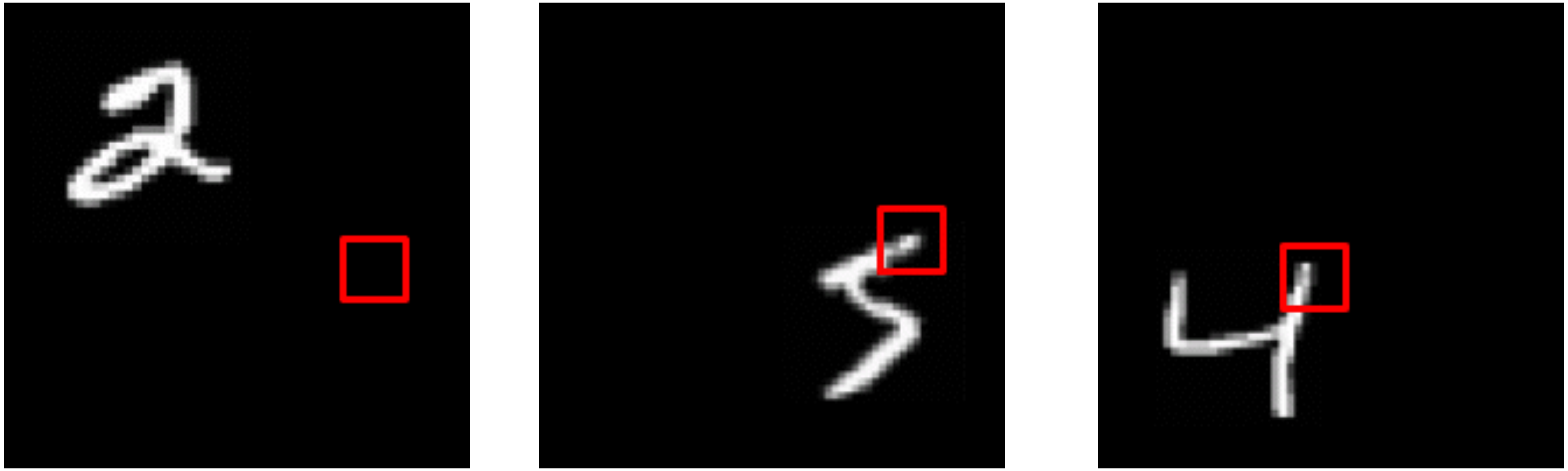

Has also been used in many other tasks including fine-grained image recognition, image captioning, and visual question-answering!

[Mnih *et al.*, 2014]

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Summary

Policy gradients: very general but suffer from high variance so requires a lot of samples. ***Challenge***: sample-efficiency

Q-learning: does not always work but when it works, usually more sample-efficient. ***Challenge***: exploration

Guarantees:
— Policy Gradients: Converges to a local minima of $J(\theta)$, often good enough!
— Q-learning: Zero guarantees since you are approximating Bellman equation with a complicated function approximator