THE UNIVERSITY OF BRITISH COLUMBIA

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

Lecture 20: 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**

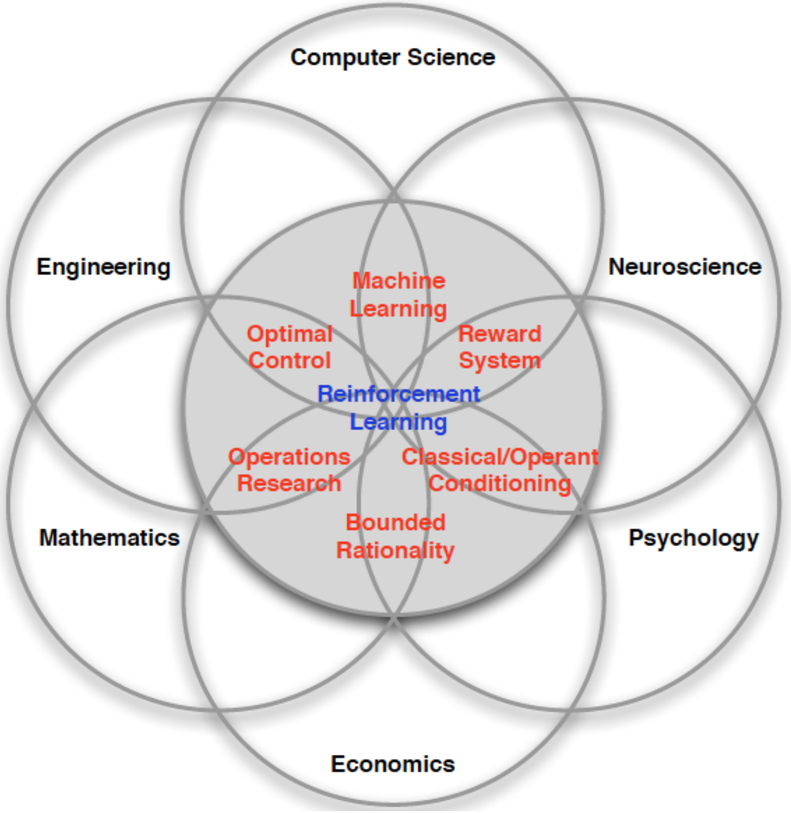
Agent-oriented learning — learning by interacting with an environment to achieve a goal

— More realistic and ambitious than other kinds of machine learning

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

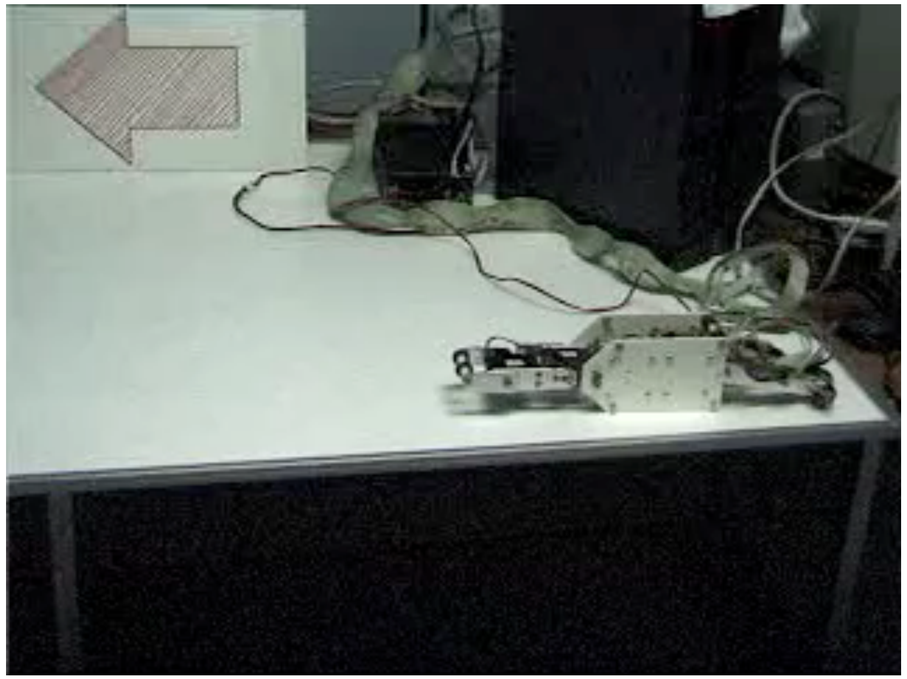
— The kind go machine learning most like natural learning

— Learning that can tell for itself when it is right or wrong



* slide from David Silver

Example: Hajime Kimura's RL Robot



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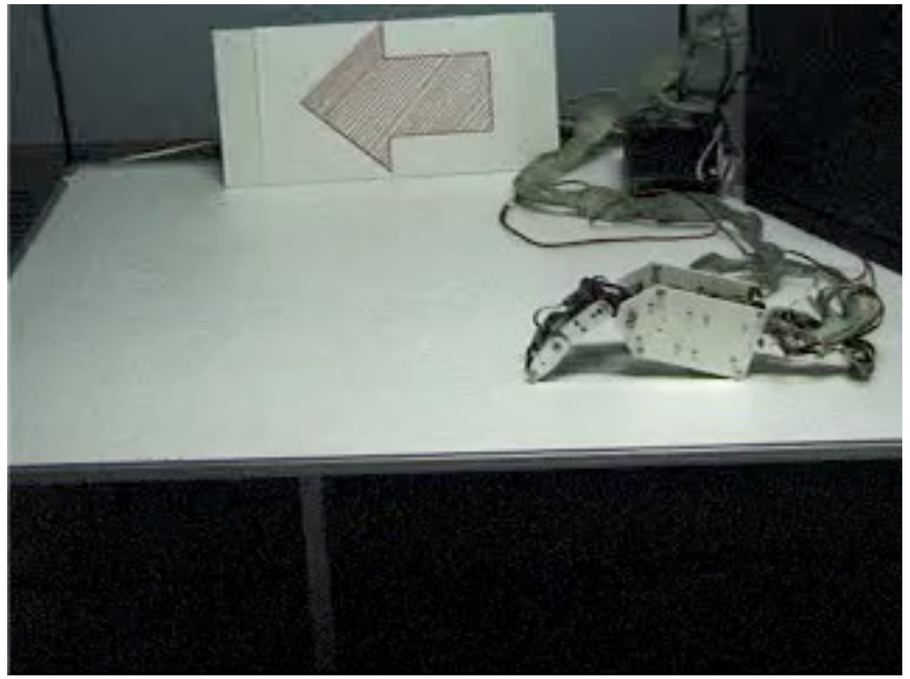

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* slide from Rich Sutton

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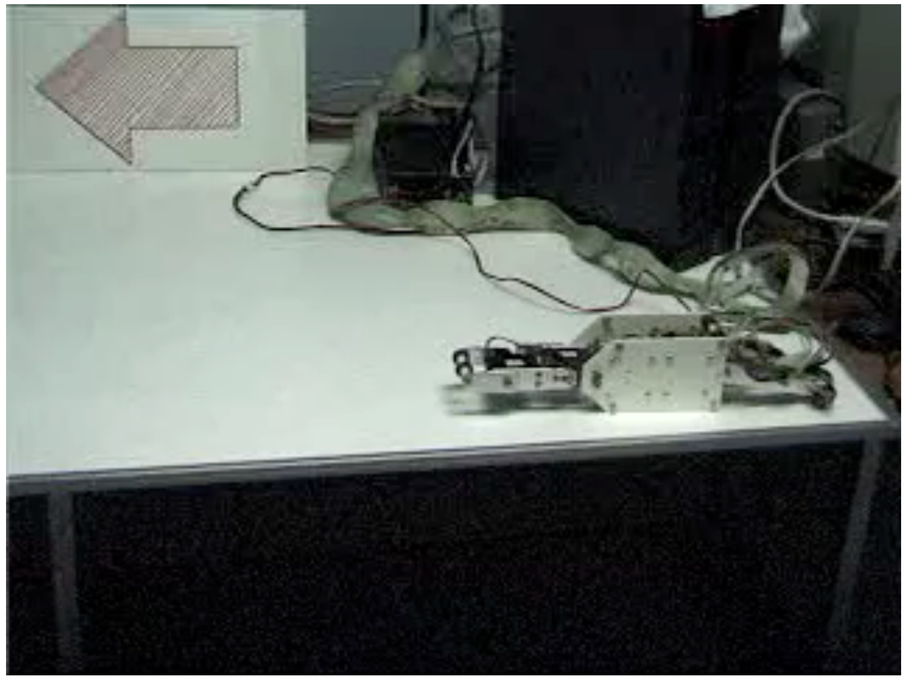

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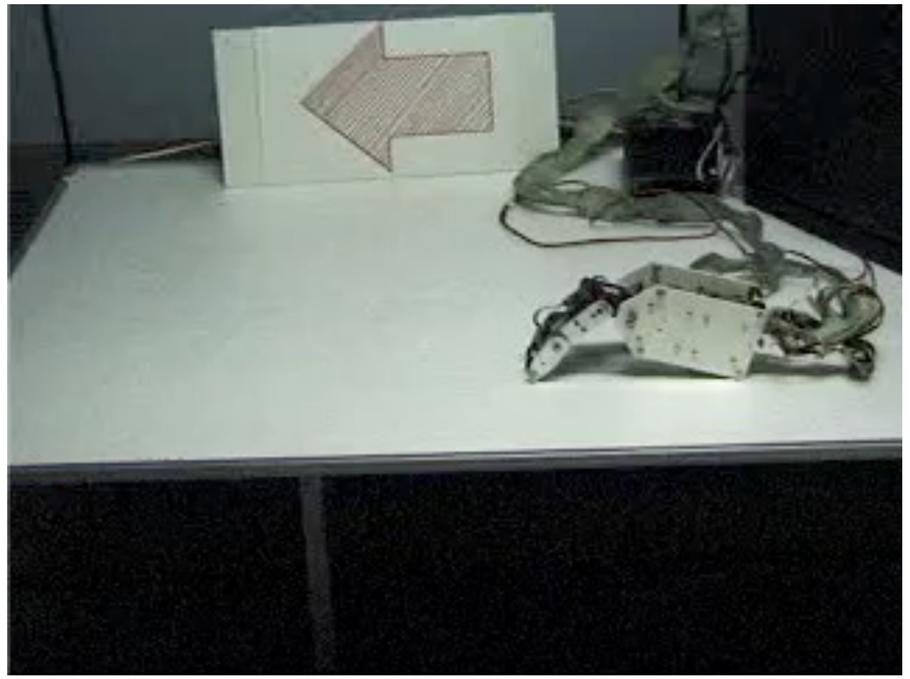

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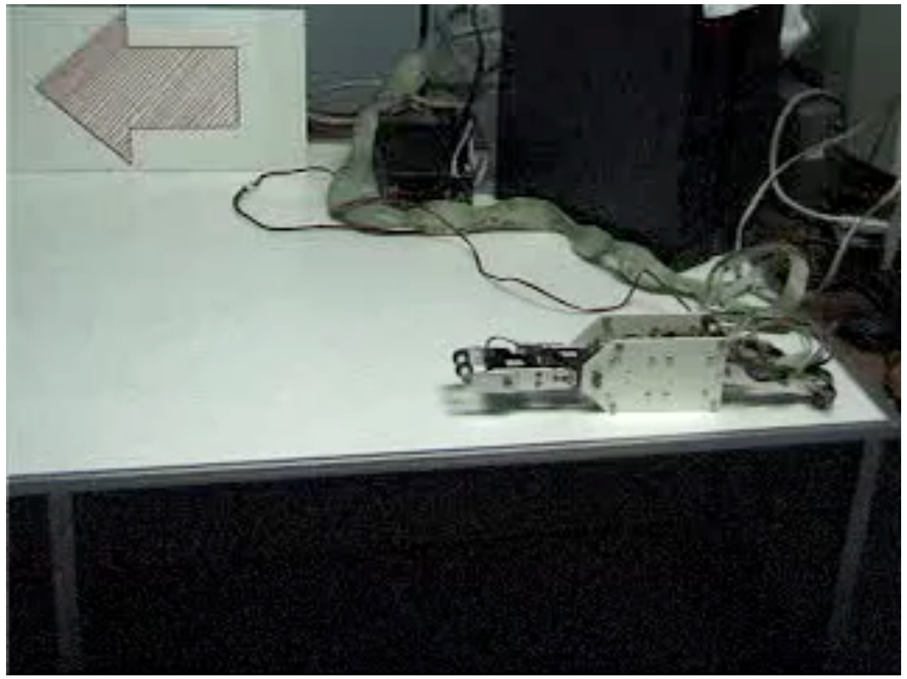

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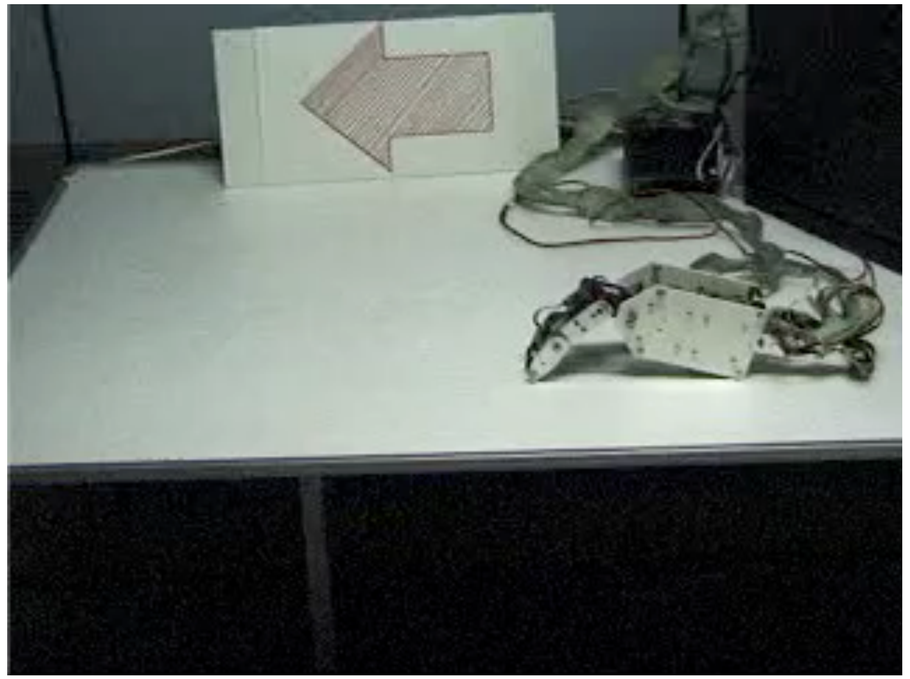

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Human Objectives

“I think it is just the product of a few principles that will be considered very simple in hindsight, so simple that even kids will be able to understand and build intelligent, continually learning, more and more general problem solvers.”

Jurgen Schmidhuber

Human Objectives

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High Level Objectives: Maximize Happiness, Don’t Die

What would be an emergent behavior would evolve

if we have these high level objectives?

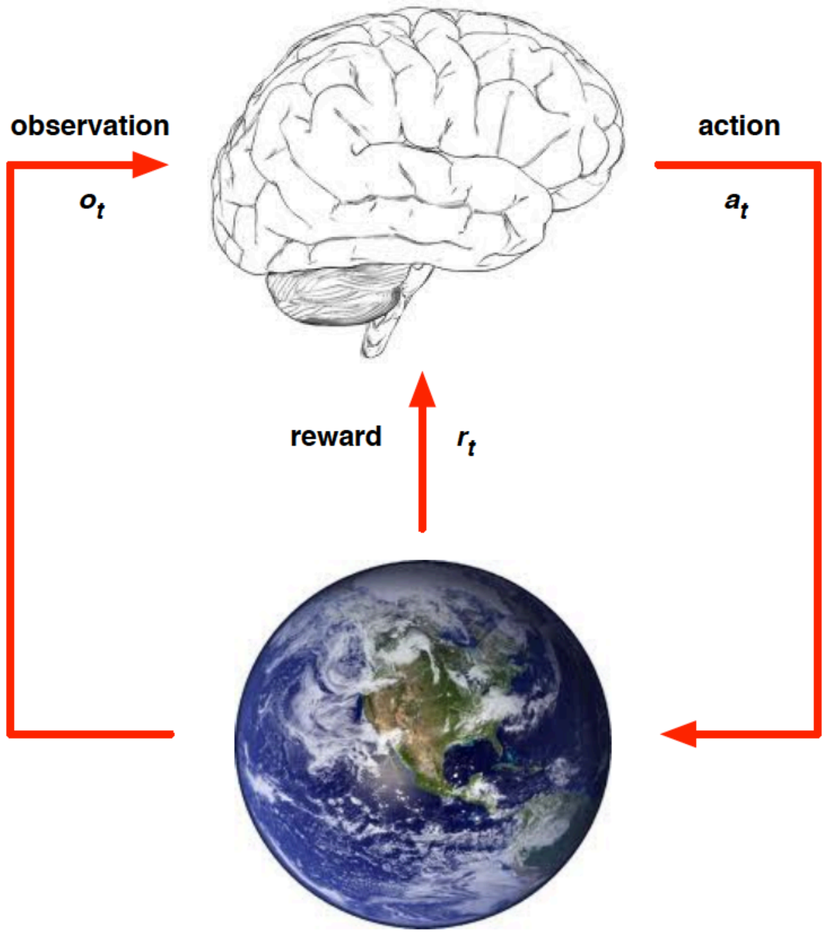
Jurgen Schmidhuber

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

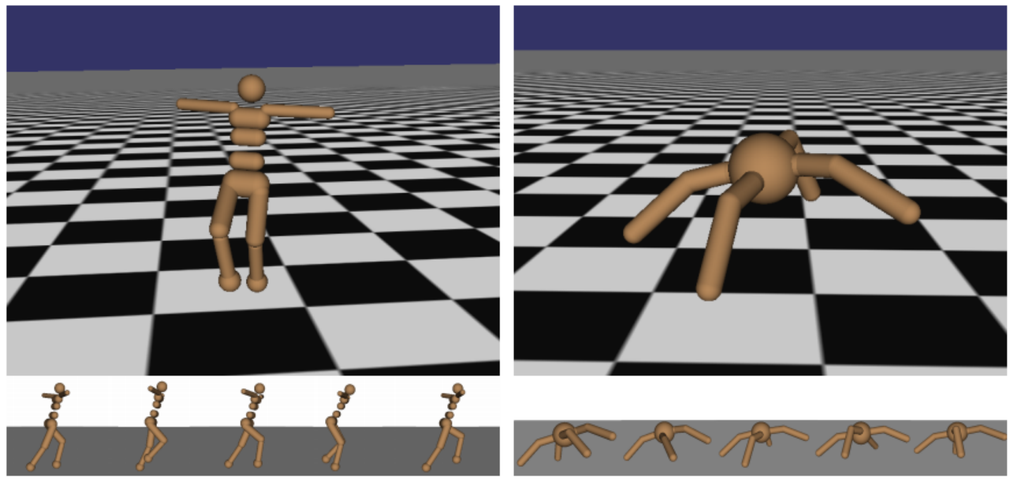
How does **RL** work?



- 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

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

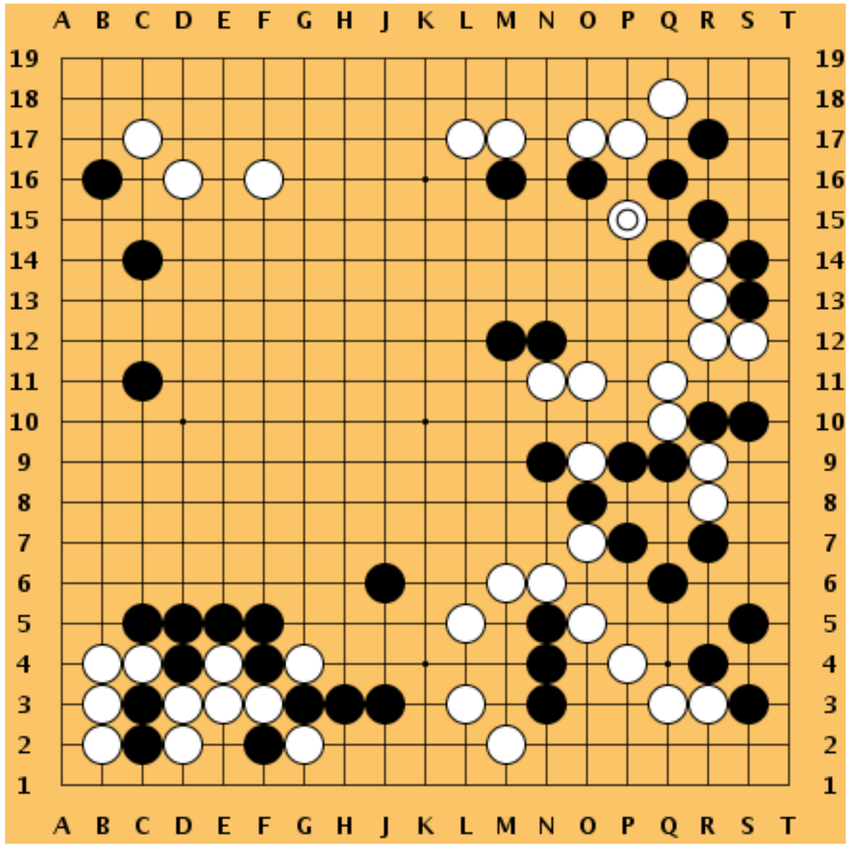
Atari Games

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

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

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

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

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

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

Markov Decision Processes

At times step t=0, environment samples initial state

For time t=0 until done:

- Agent selects action (deterministically or stochastically)
- Environment samples the reward
- Environment samples the next state
- Agent receives reward and next state

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

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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

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

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

Components of the RL Agent

Policy

— How does the agent behave?

Value Function

— How good is each state and/or state-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: $\pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$

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e.g.

State	Action
A	2
B	1

Simple example:

A = You are on the street car approaching
B = You are on the street no car approaching

Action 1 = Cross the street
Action 2 = Stop

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		Action	
		1	2
State	A	0.1	0.9
	B	0.8	0.2

* slide from Dhruv Batra

The **Optimal** Policy

What is a good policy?

* slide from Dhruv Batra

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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?

* slide from Dhruv Batra

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):

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

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✓ **Policy**

— How does the agent behave?

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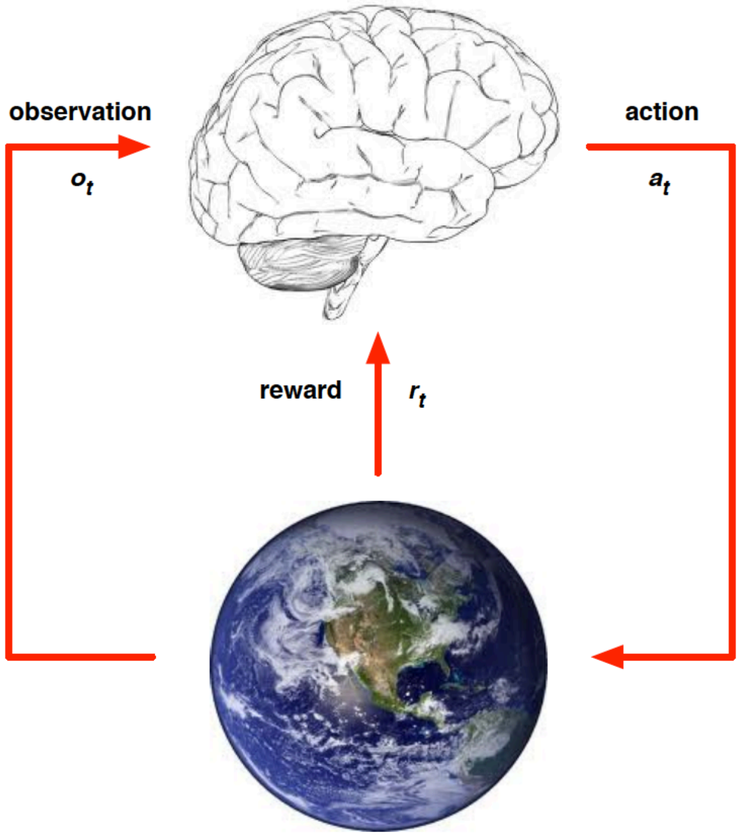
Model

Model predicts what the world will do next



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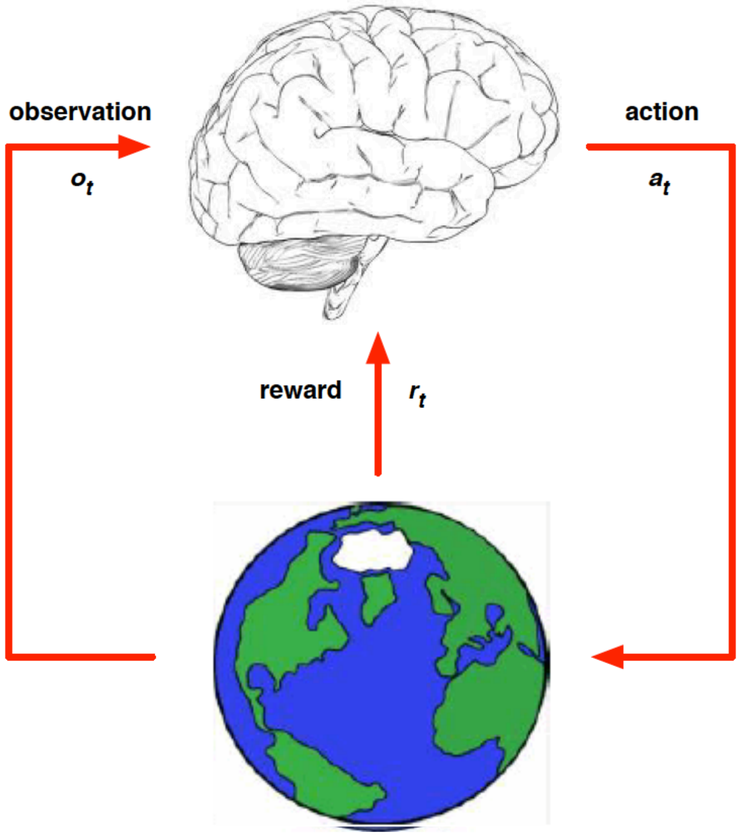

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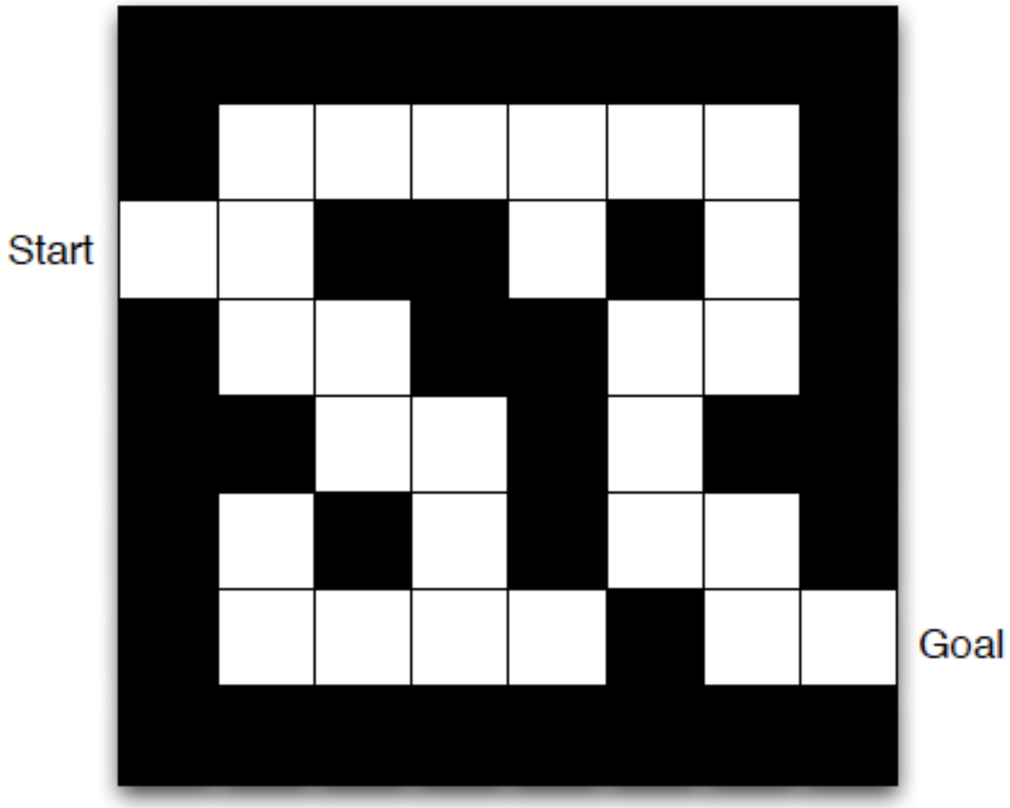
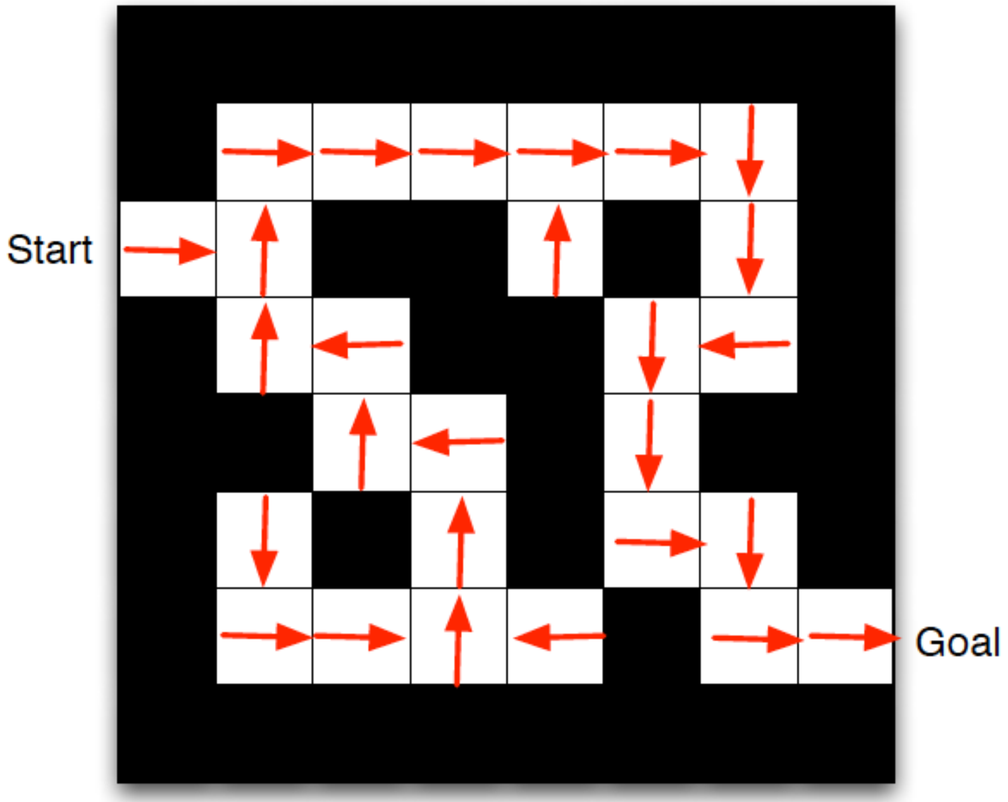
Maze Example



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

* slide from David Silver

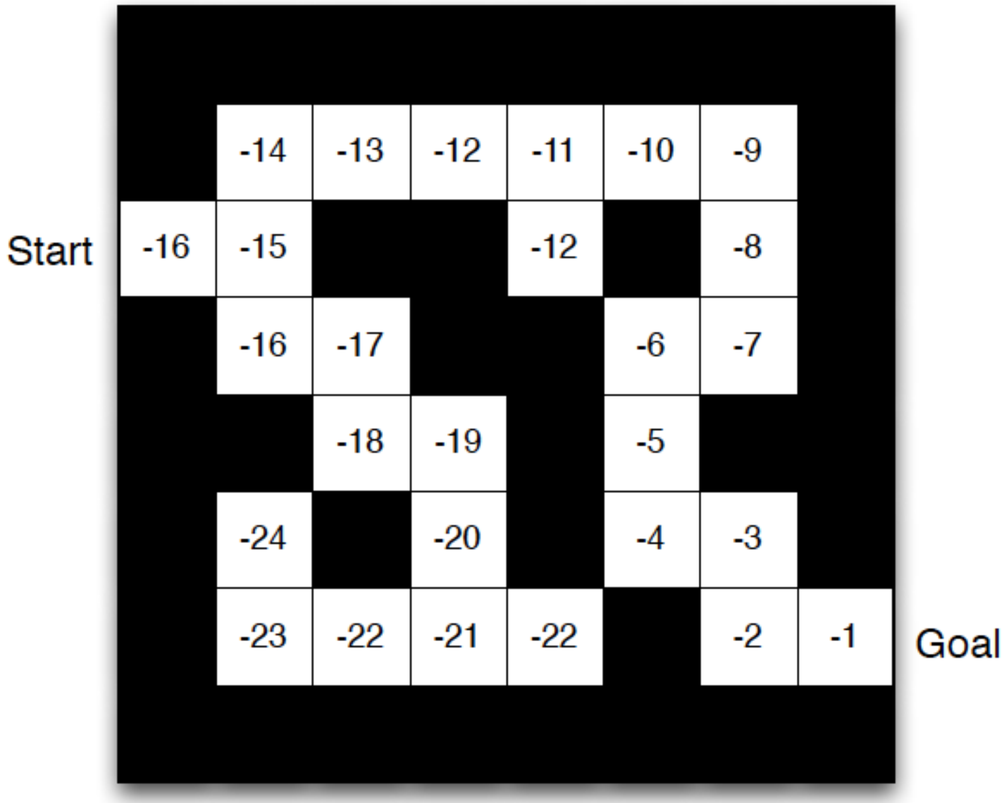
Maze Example: Policy



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

* slide from David Silver

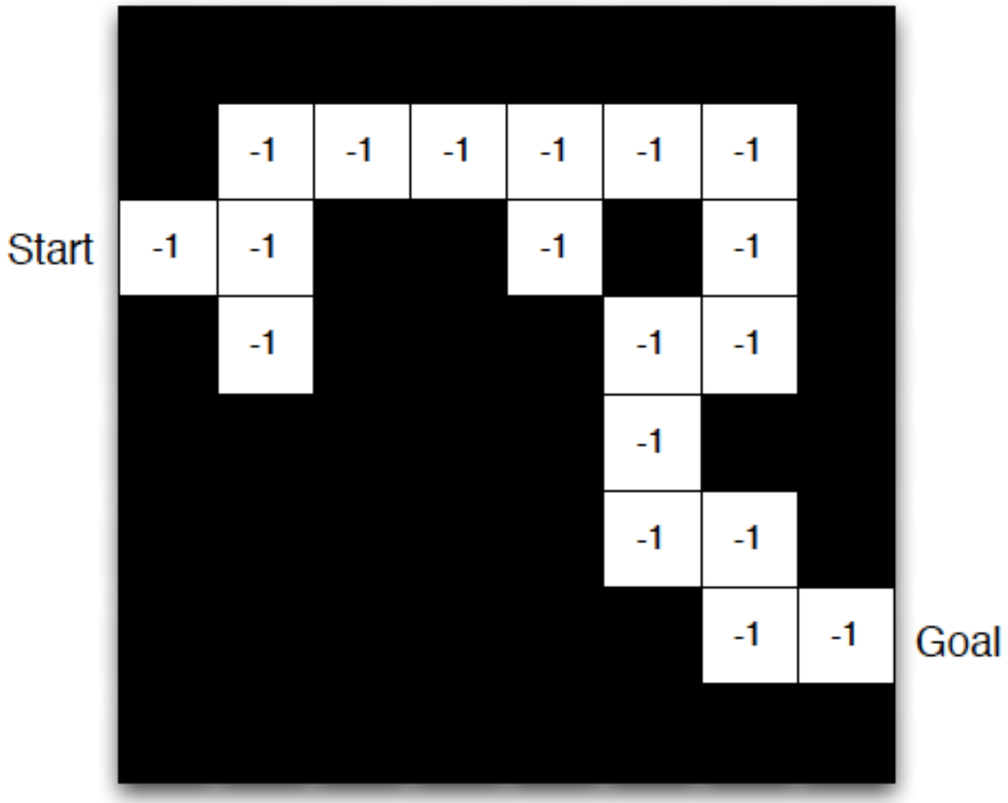
Maze Example: Value



Numbers represent value $\mathbf{v}_\pi(s)$ 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

* slide from Dhruv Batra

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Actor-critic RL

- — Value function
- — Policy function

Model-based RL

- — Build a model of the world
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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

— Use neural nets to represent the policy π_θ

$$\pi_{\theta^*} \approx \pi^*$$

Model-based RL

— Use neural nets to represent and learn the model

* slide from Dhruv Batra

Approaches to RL

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Optimal Value Function

Optimal Q-function is the maximum achievable value

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) = Q^{\pi^*}(s,a)$$

* slide from David Silver

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Once we have it, we can act optimally

$$\pi^*(s) = \operatorname*{argmax}_a Q^*(s,a)$$

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Optimal value maximizes over all future decisions

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

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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

* 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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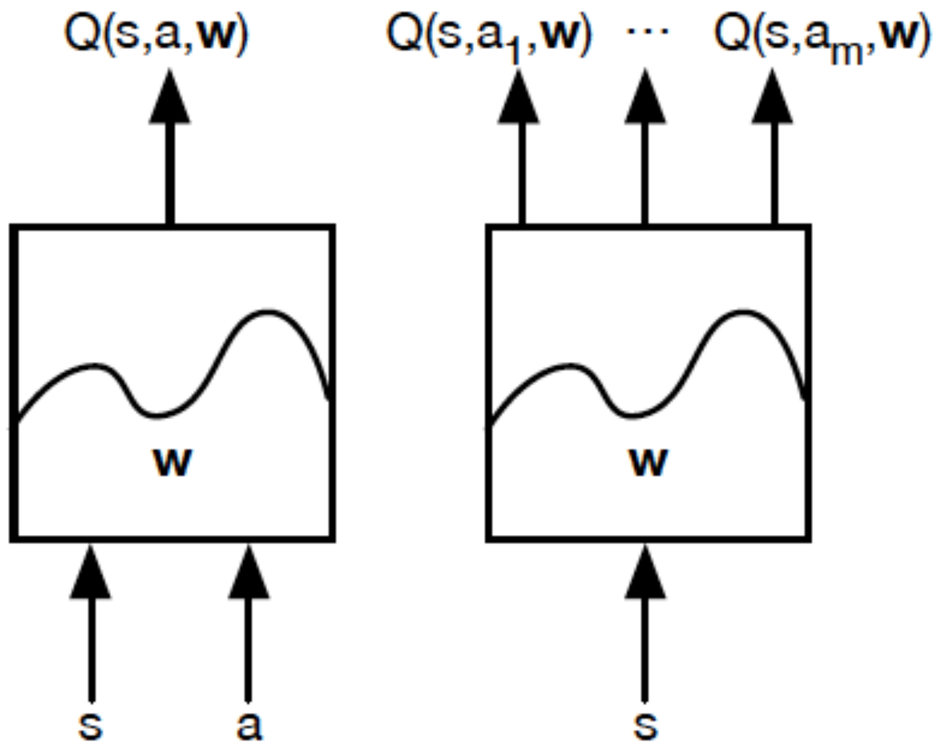
Q-Networks

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



* slide from David Silver

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
Action: Game controls e.g. Left, Right, Up, Down
Reward: Score increase/decrease at each time step

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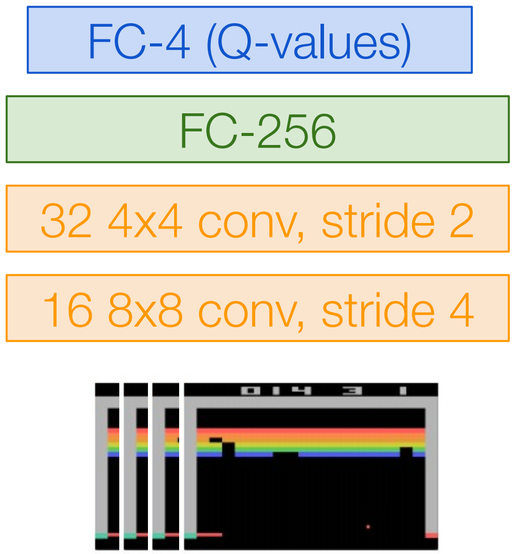
Q-Network Architecture

[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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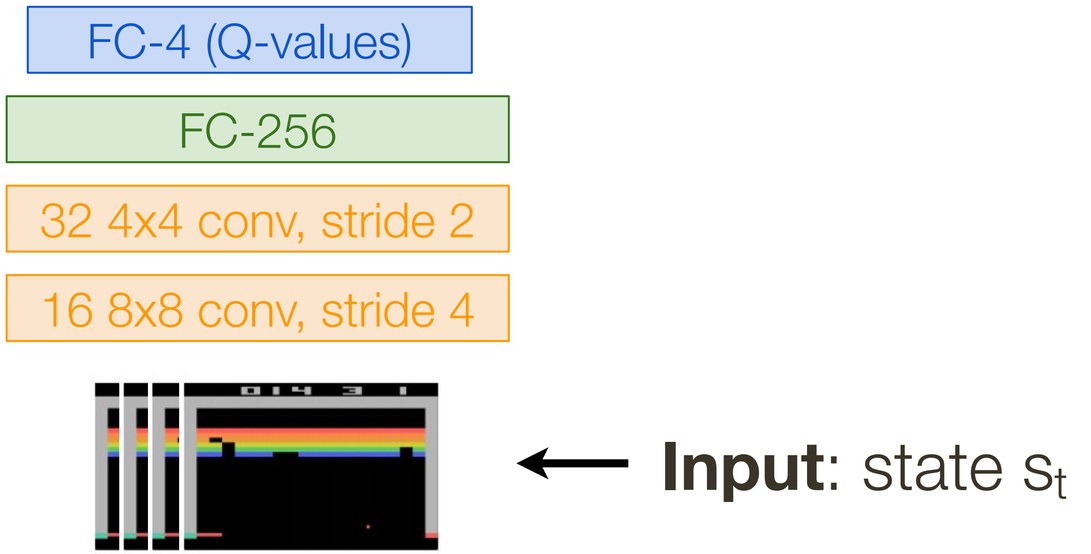

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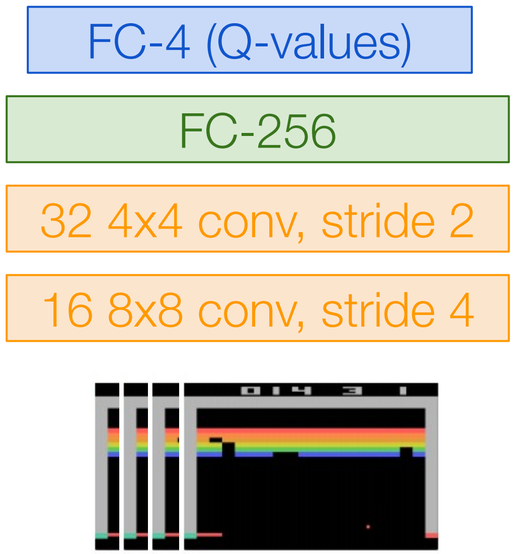

← familiar conv and fc layers

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

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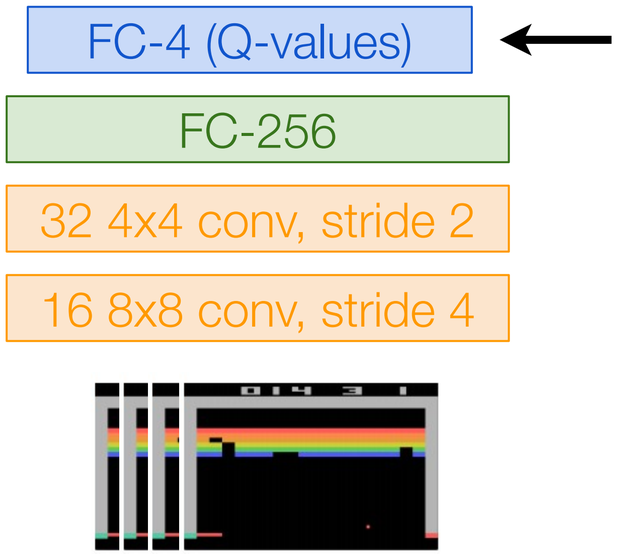
Q-Network Architecture

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

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



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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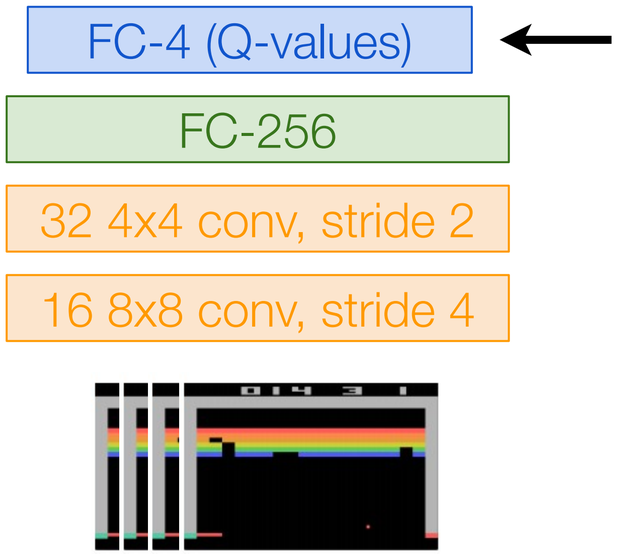

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Number of actions between 4-18 depending on Atari game

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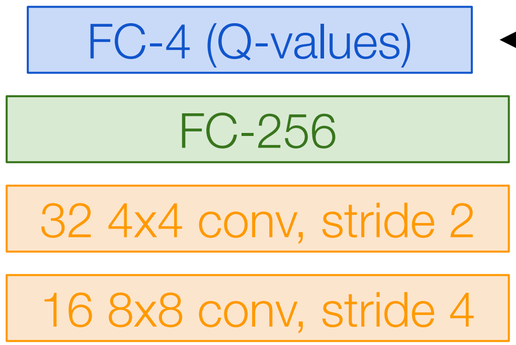

Last FC layer has 4-d output (if 4 actions), corresponding to $Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$, $Q(s_t, a_4)$

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

Current state s_t: 84x84x4 stack of last 4 frames
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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):

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

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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 $\boldsymbol{\pi}^*$)

Backward Pass:

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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

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Experience Replay

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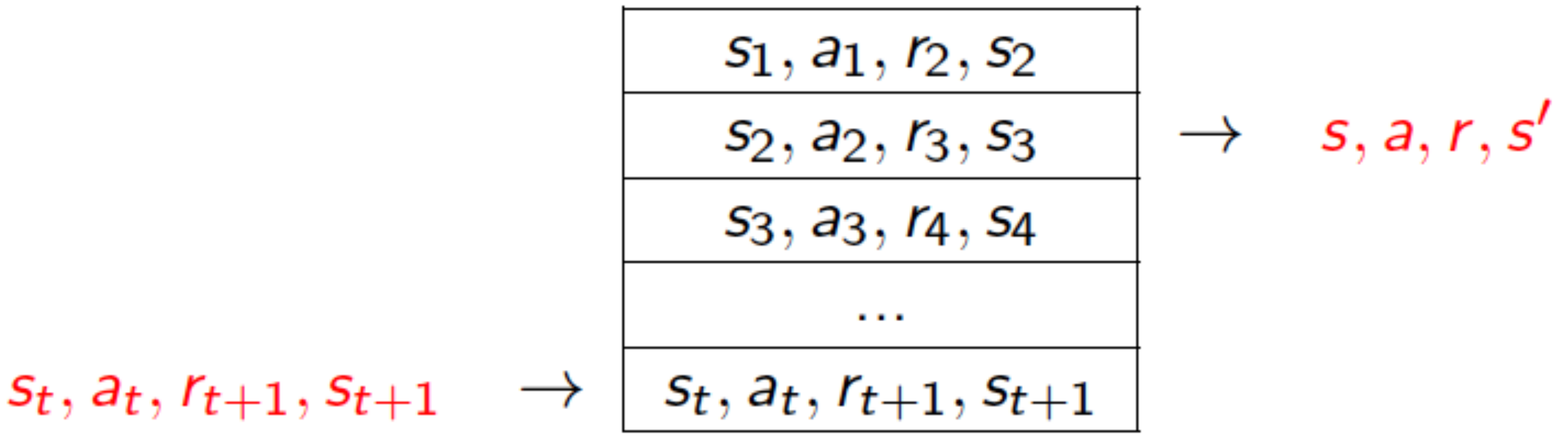
Experience Replay

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



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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}
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    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
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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
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Initialize replay memory, Q-network

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Play M episodes (full games)

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Initialize state (start geme screen pixes) at beggining of each episode

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end for

For each timestep T of the game
(T is max steps but can return early)

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With small probability take random action (explore)

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Otherwise select greedy action from current policy (implicit in Q function)

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Take action and observe the reward and next state

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Store transition replay in memory

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Sample a random mini-batch from replay memory and perform a gradient descent step

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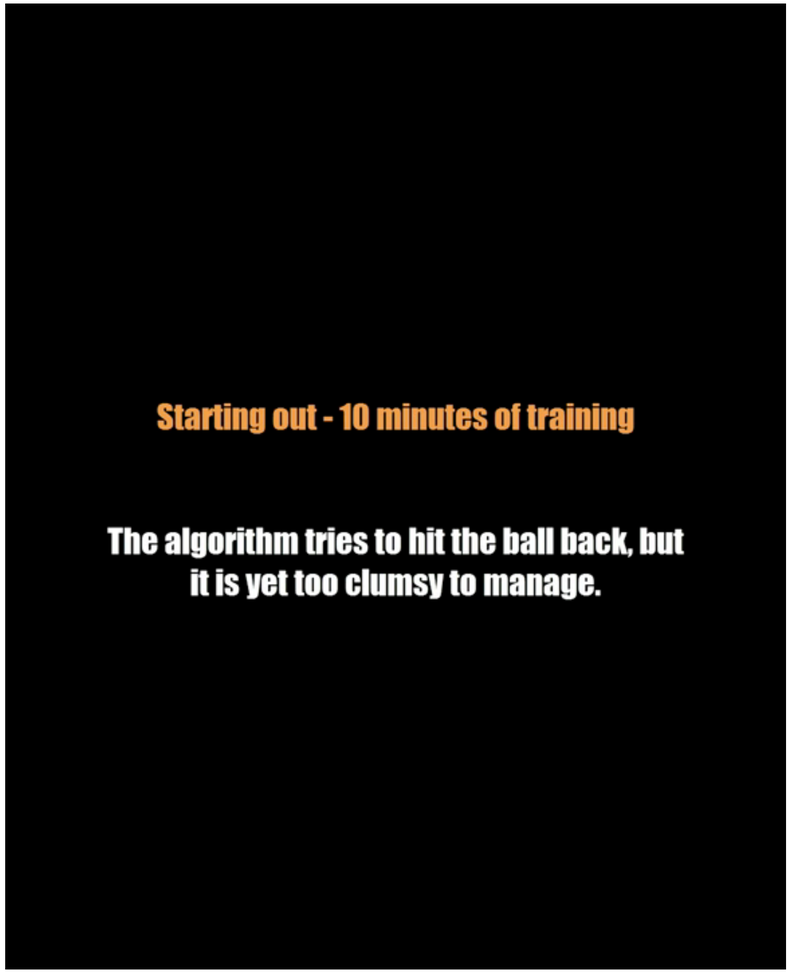
Example: Atari Playing



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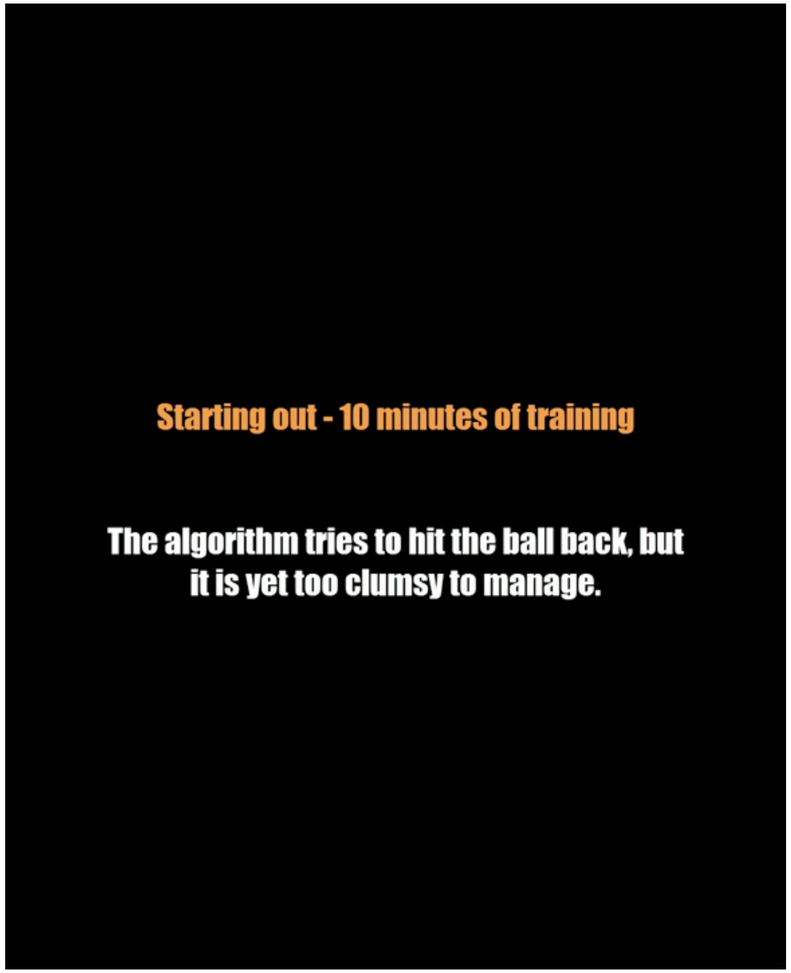

Deep RL

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

— Use neural nets to represent the policy π_θ

$$\pi_{\theta^*} \approx \pi^*$$

Model-based RL

— Use neural nets to represent and learn the model

* slide from Dhruv Batra

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* slide from Dhruv Batra

Policy Gradients

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

For each policy, define its value:

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

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

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How can we do this?

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How can we do this?

Gradient ascent on policy parameters!

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REINFORCE algorithm

Expected reward:

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

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

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

REINFORCE algorithm

Expected reward:

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

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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

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

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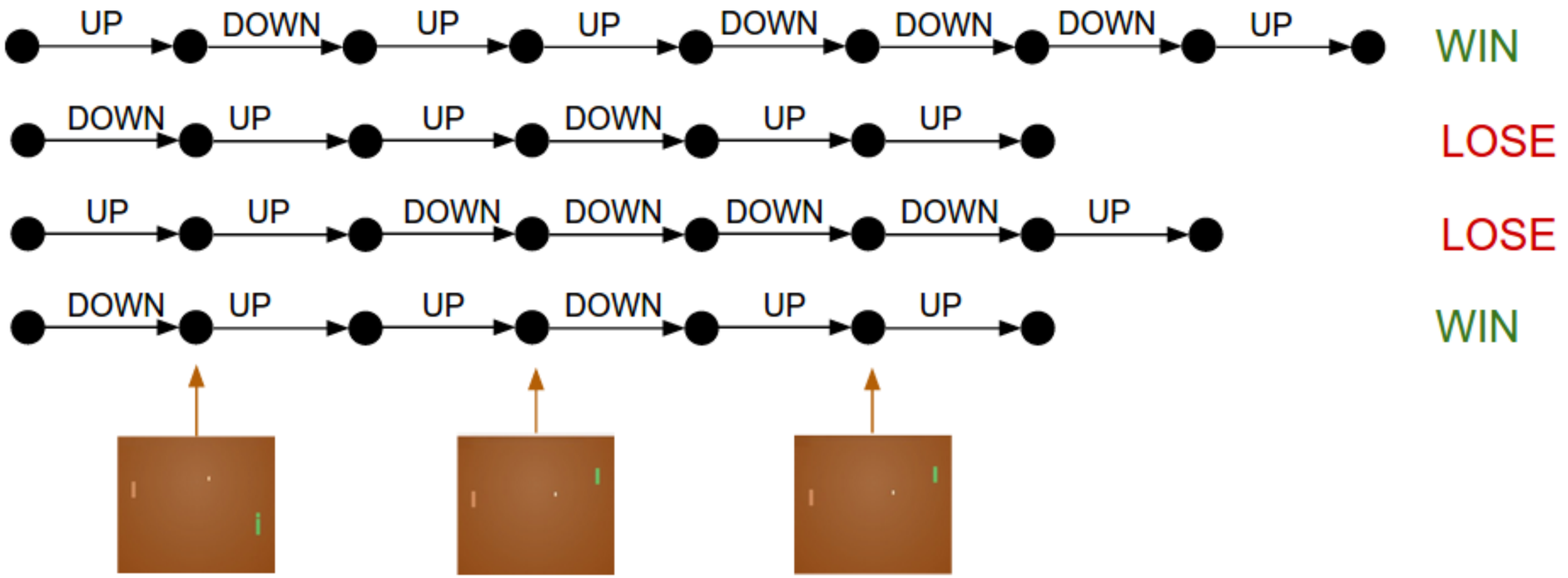
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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?

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

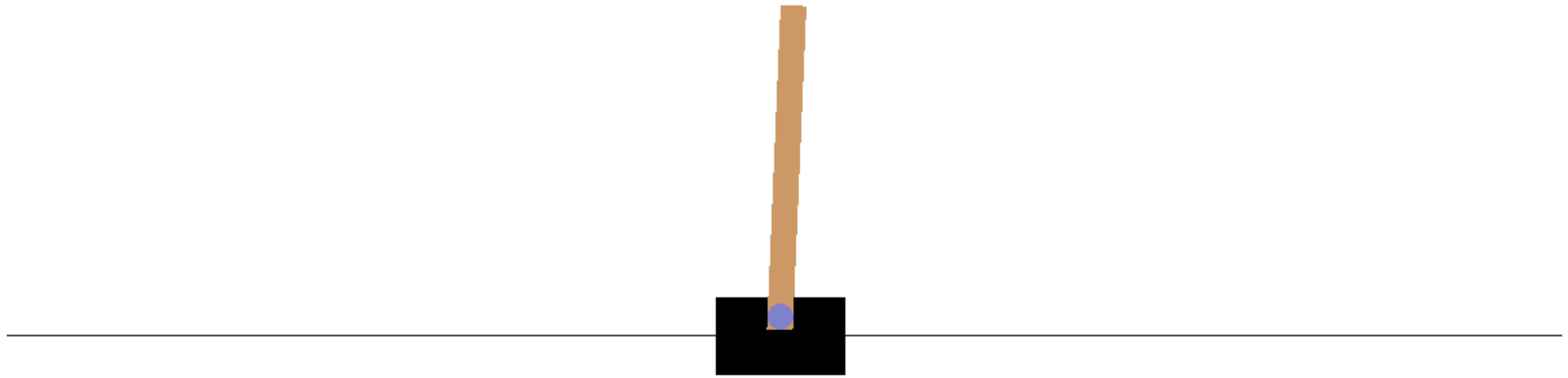
CartPole Environment

Unstable system. Poll will fall if left to own devices.

Goal: Keep the poll upright by applying +1 / -1 force (move cart left or right)

Reward: +1 for every frame for every time step pole remains upright

State: 4-D (position + velocity of cart, angle + velocity of pole)



https://medium.com/@fork.tree.ai/understanding-baseline-techniques-for-reinforce-53a1e2279b57

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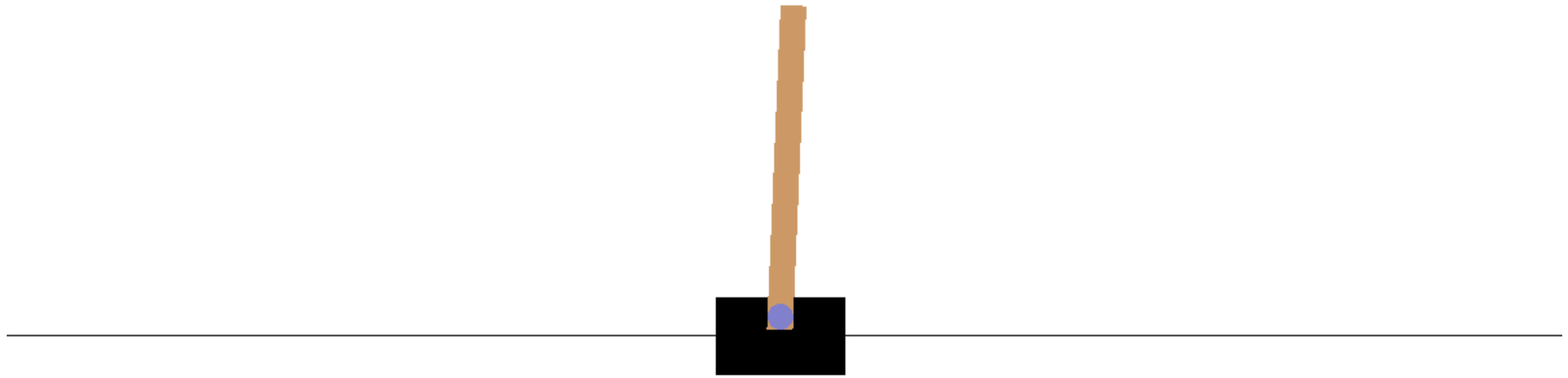

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CartPole Environment

$$R + \gamma R + \gamma^2 R + \gamma^3 R + \ldots = \frac{R}{1 - \gamma}$$

Note: we can focus on short-term horizon policy by setting gamma = 0

on long-term horizon policy by setting gamma close to 1

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What happens if we delayed our reward, e.g., only receive 1 if pole is upright after 500 time steps?

$$\gamma^{499} R$$

REINFORCE with **Whitening Baseline**

Subtract mean over rewards in a rollout and divide by the standard deviation

$$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} r(\tau) \nabla_\theta \log \pi_\theta(a_t|s_t) \qquad r(\tau) = \sum \gamma^t r_t \qquad r(\tau) = \frac{\sum \gamma^t r_t - \mu_{r_t}}{\sigma_{r_t}}$$

1 iteration = 1 episode + gradient update step

1 interaction = 1 action taken in the environment

REINFORCE with **Whitening Baseline**

Does not solve a game, even after 1000 iterations!!

Algorithm unstable (variance is high)

1 iteration = 1 episode + gradient update step

1 interaction = 1 action taken in the environment

REINFORCE with **Learned Baseline** (self-critic)

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

$$r(\tau) = \sum \gamma^t r_t - V_\phi(s_t)$$

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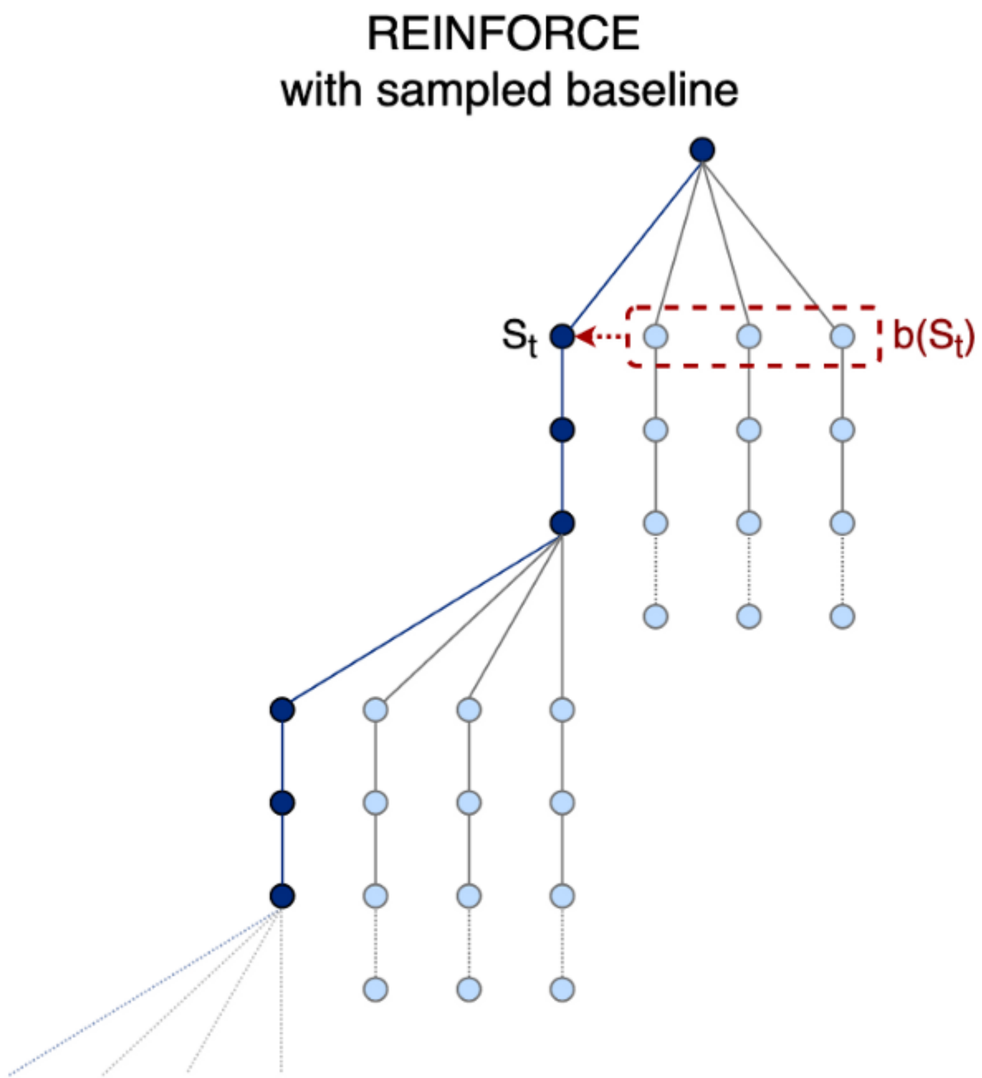
REINFORCE with **Sampled Baseline**

https://medium.com/@fork.tree.ai/understanding-baseline-techniques-for-reinforce-53a1e2279b57

$$\hat{v}(S_t) = \frac{1}{N_b} \sum_{b=1}^{N_b} G_t^{(b)} \quad \text{(sample rollouts)}$$

$$\hat{v}(S_t) = G_t^{(greedy)} \quad \text{(greedy rollout)}$$

$$\theta_{t+1} = \theta_t + \alpha \left(G_t - \hat{v}(S_t) \right) \nabla \log \pi(A_t | S_t, \theta)$$



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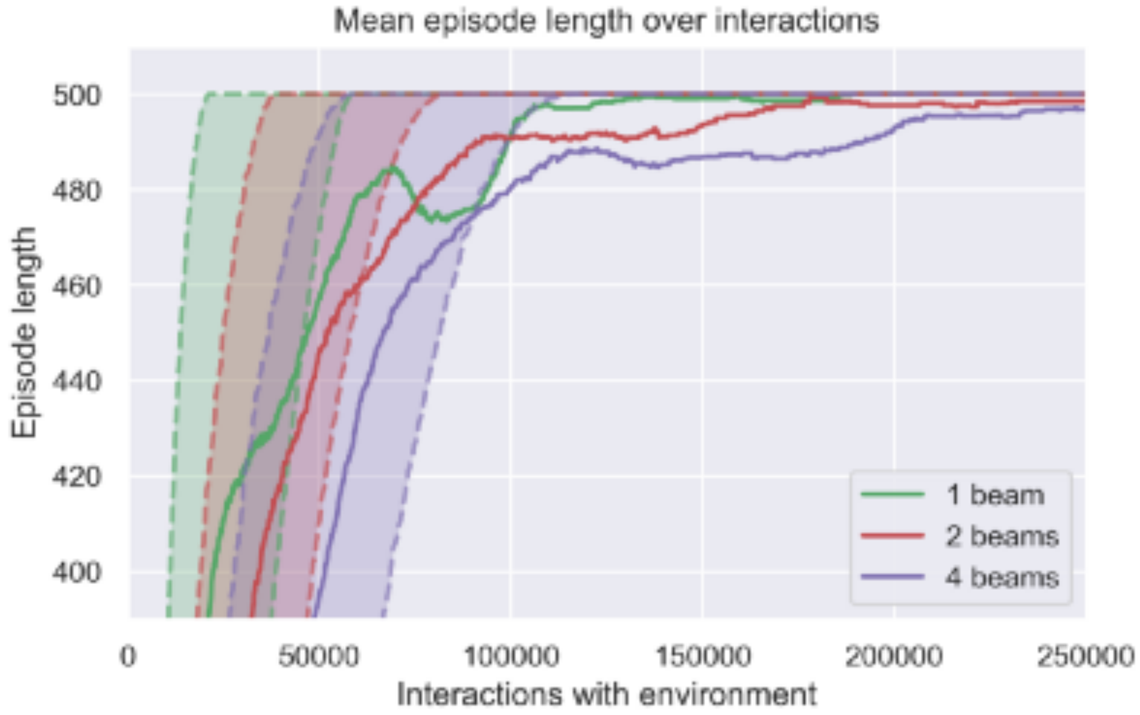

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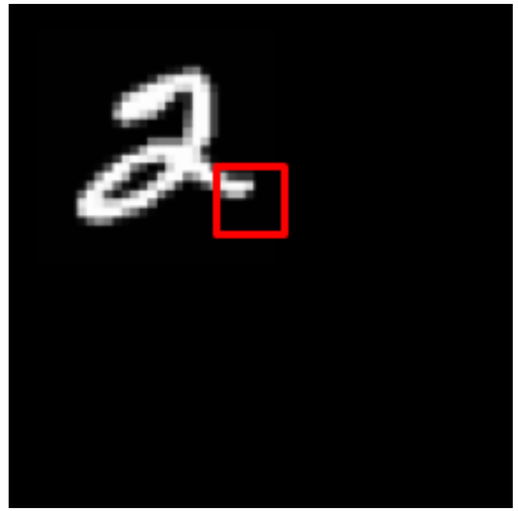
REINFORCE in Action: **Recurrent Attention Model** (REM)

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]

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

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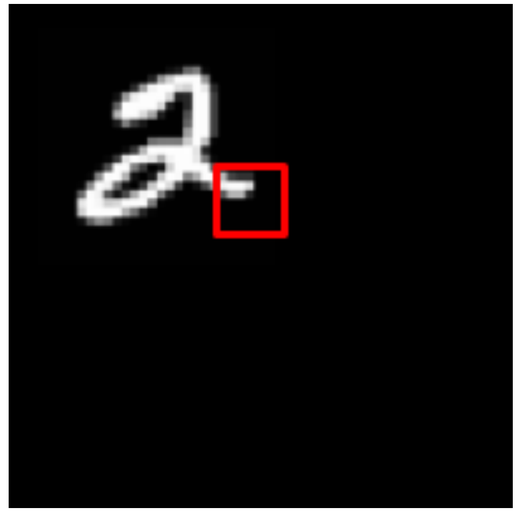

glimpse

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

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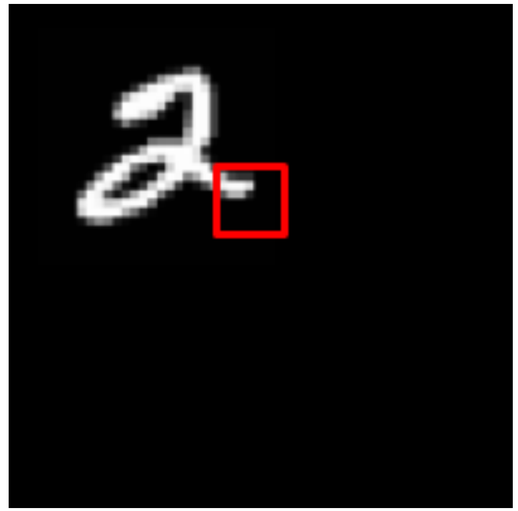

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Glimpsing is a **non-differentiable operation** => learn policy for how to take glimpse actions using REINFORCE
Given state of glimpses seen so far, use RNN to model the state and output next action

[Mnih *et al.*, 2014]

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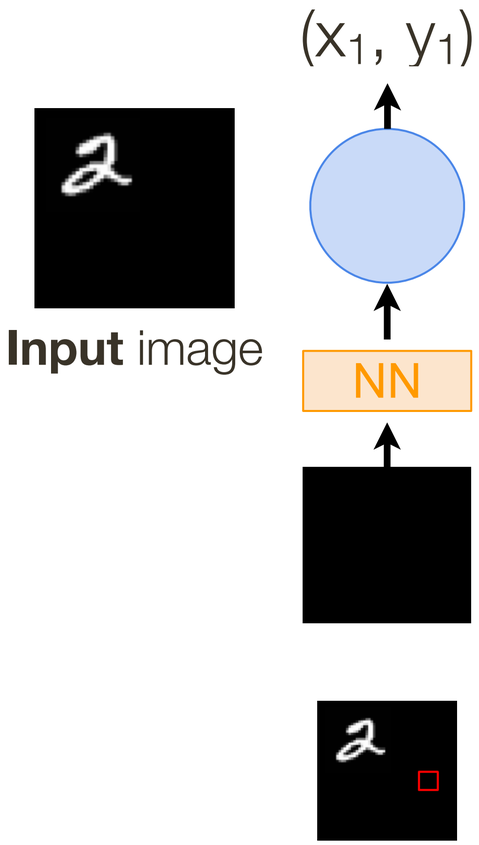

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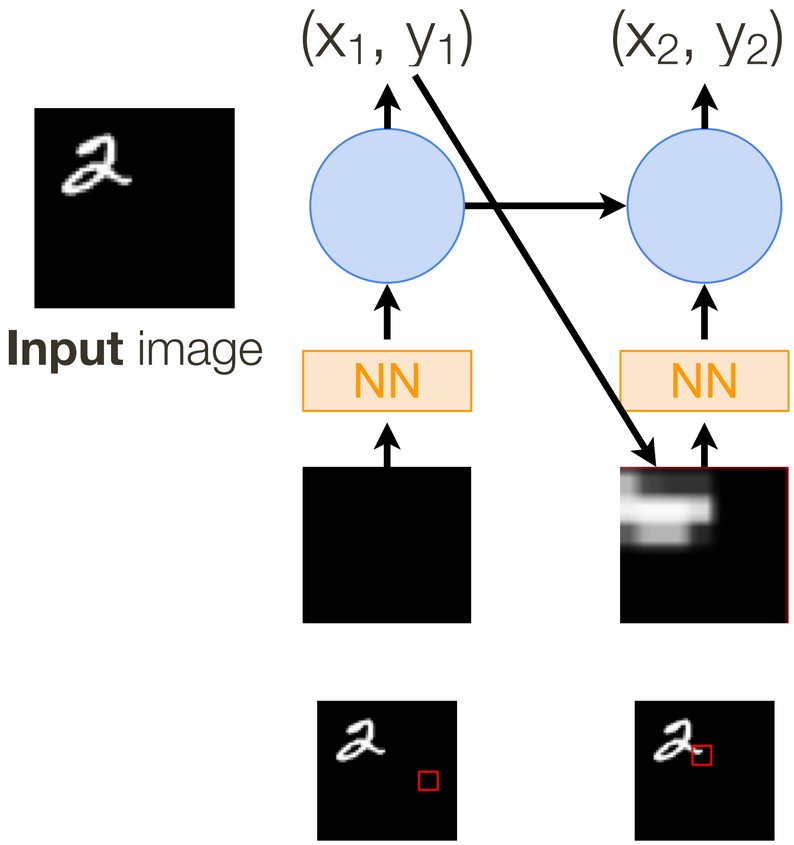

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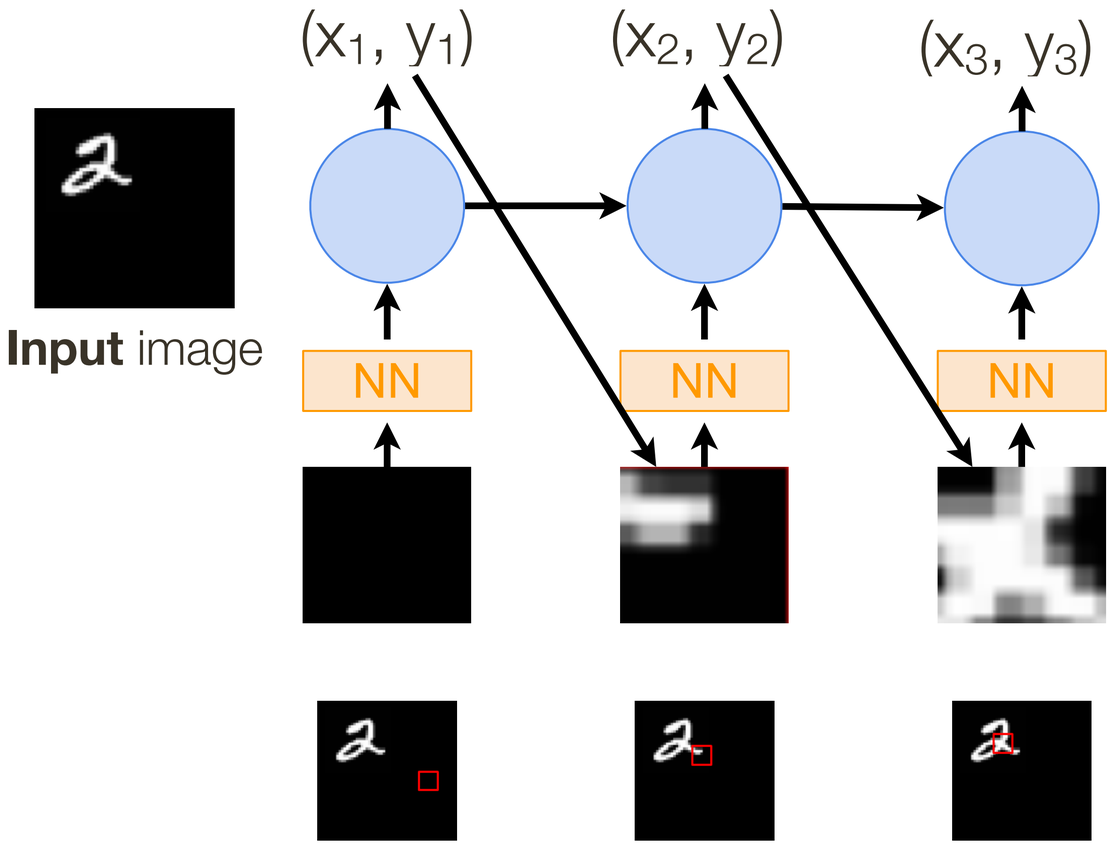

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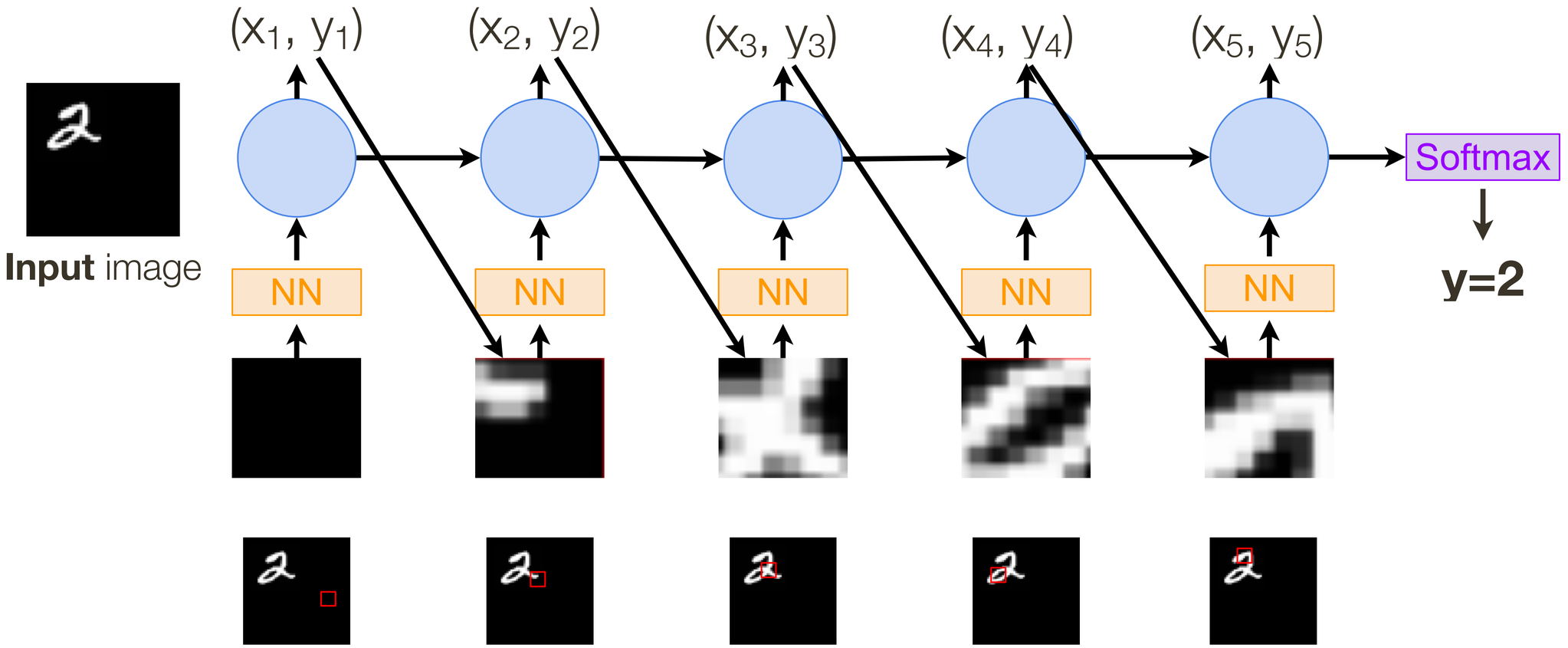

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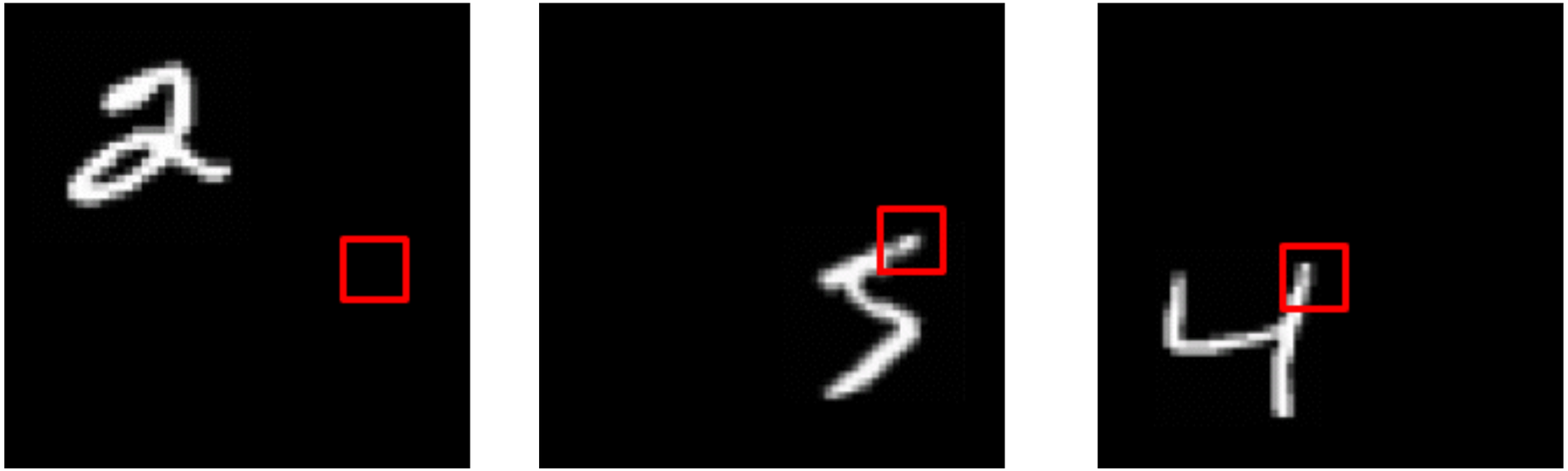

Has also been used in many other tasks including fine-grained image recognition, image captioning, and visual question-answering!

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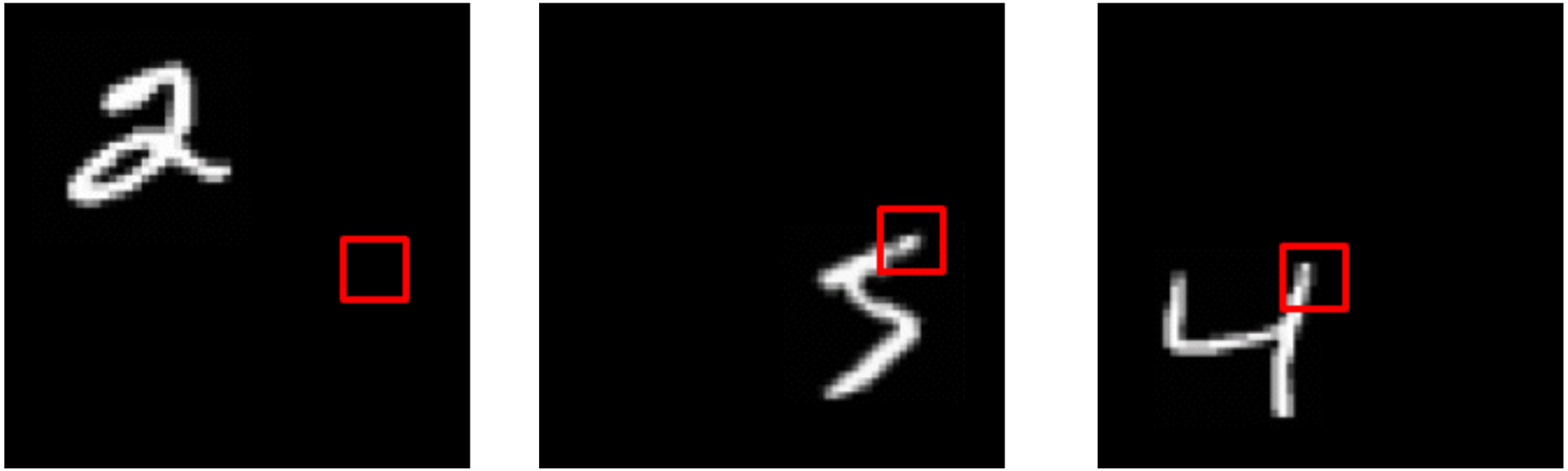

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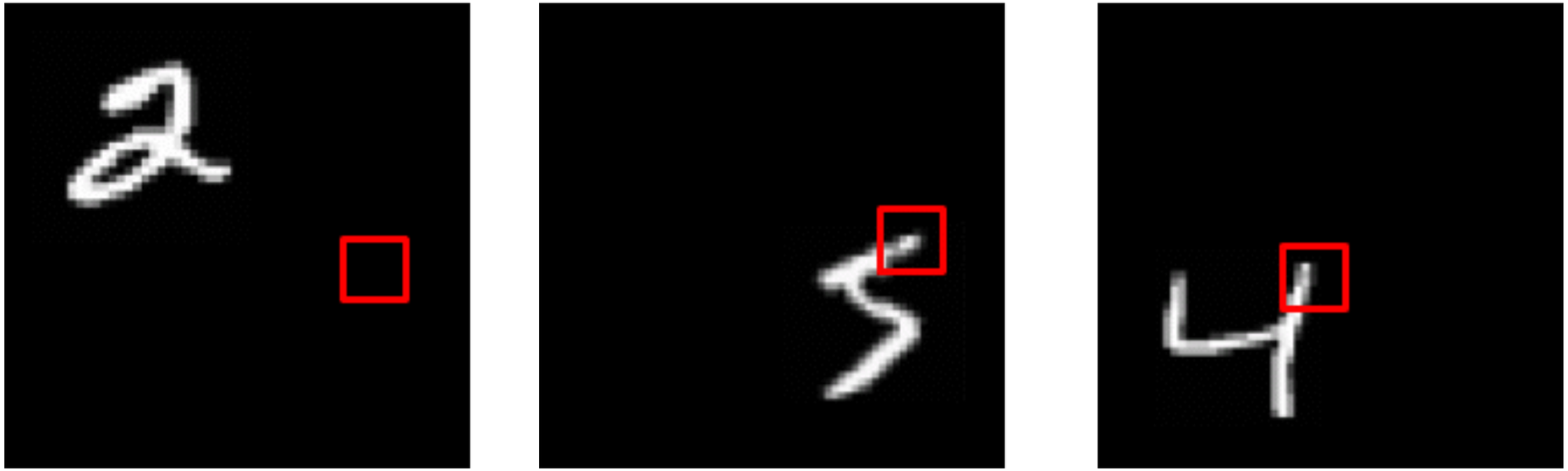

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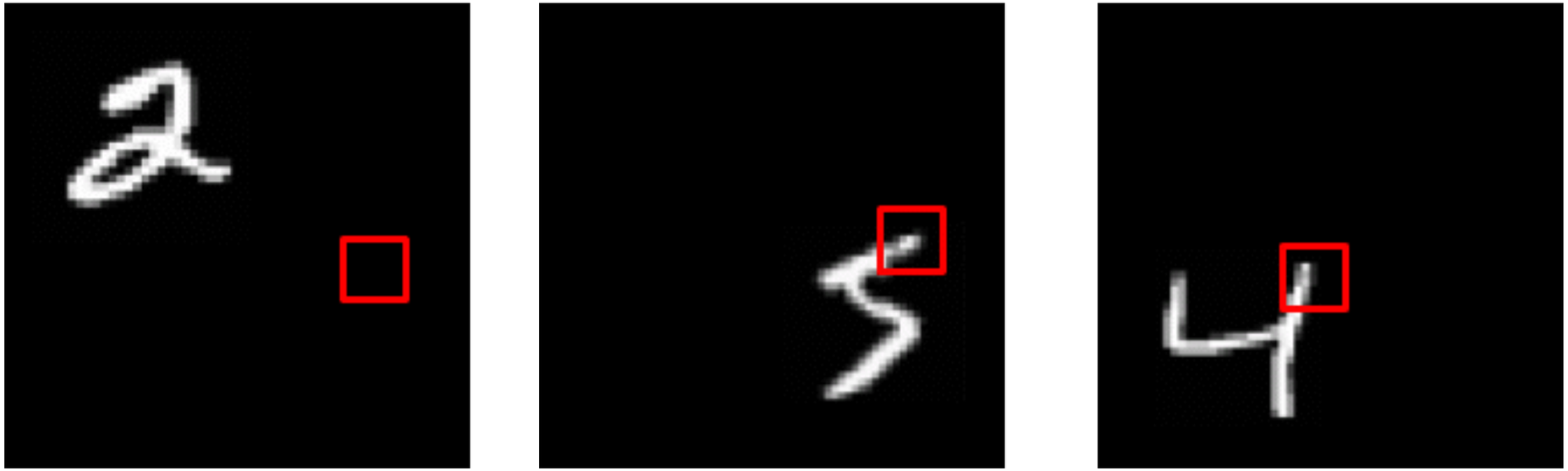

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Summary

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(θ), often good enough!

— Q-learning: Zero guarantees since you are approximating Bellman equation with a complicated function approximator

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