

Machine Learning for Large-Scale Data Analysis and Decision Making (MATH80629A) Winter 2022

Week #13- Summary

Announcement

- **Project Presentation: in-person**
- Upload your slides/poster to Gradescope due **April 5**
- **Project Report: Group & Individual** due **April 30**
- **Coding question:** we'll schedule it with team-members

Today

- **Last Quiz** on Gradescope!
- Summary of Sequential decision making 2
- Q&A
- Hands on session



Quiz 6

Login to your Gradescope account

Brief recap

- **Markov Decision Processes (MDP)**
 - Offer a framework for sequential decision making
 $\langle \mathbf{A}, \mathbf{S}, \mathbf{P}, \mathbf{R}, \gamma \rangle$
- **Goal:** find the **optimal policy**
 - Dynamic programming and several algorithms (e.g., VI,PI)

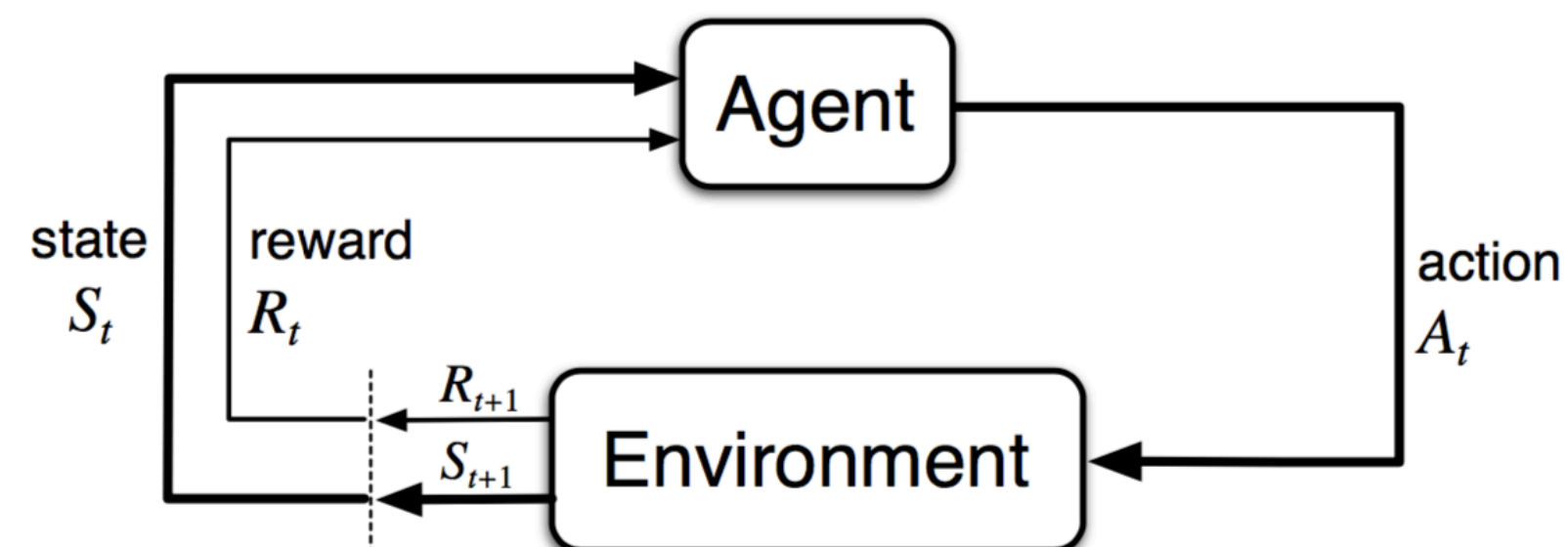


Figure 3.1, RL: An introduction

From MDPs to RL

- In MDPs we assume that we know
 1. **Transition probabilities:** $P(s' | s, a)$
 2. **Reward function:** $R(s)$
- RL is more general
 - **In RL both are typically unknown**
 - **RL agents navigate the world to gather this information**

Experience

A. Supervised Learning:

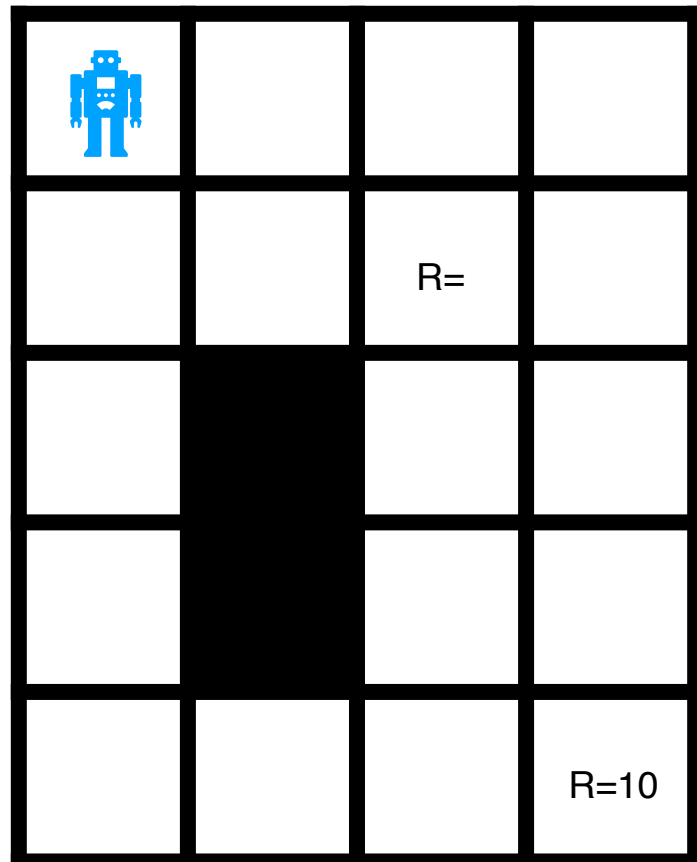
- Given fixed dataset
- Goal: maximize objective on test set (population)

B. Reinforcement Learning

- Collect data as agent interacts with the world
- Goal: maximize sum of rewards

Challenges of reinforcement learning

- **Credit assignment problem:** which action(s) should be credited for obtaining a reward
- **A series of actions** (getting coffee from cafeteria)
- **A small number of actions several time steps ago may be important** (test taking: study before, getting grade long after)
- **Exploration/Exploitation tradeoff:** As agent interacts should it exploit its current knowledge (*exploitation*) or seek out additional information (*exploration*)



Application of RL

- **Robotics**
- **Video games**
- **Financial trading** is the buying and selling of financial assets.
- **Medical treatment/intervention** means the management and care of a patient to combat disease or disorder.
- A **self-driving car** is a vehicle that is capable of sensing its environment and moving safely with little or no human input.
- **Personalized tutoring** is an educational approach that aims to customize learning for each student's strengths, needs, skills, and interests.
- **Feed generation** is an automated platform that helps retailers build product feeds

Algorithm

- **Input:** an environment
 - actions, states, discount factor
 - starting state, method for obtaining next state
- **Output:** an optimal policy
- **In practice:** need a simulator or a real environment for your agent to interact

Algorithms for RL

- **Two main classes of approach**

1. Model-based

- Learns a model of the transition and uses it to optimize a $P(s' | s, a)$ policy given the model

2. Model-free

- Learns an optimal policy without explicitly learning transitions

 π

Prediction vs. control

1. **Prediction:** evaluate a given policy
2. **Control:** Learn a policy
 - Sometimes also called
 - **passive** (prediction)
 - **active** (control)

Monte Carlo Methods

MC for Prediction: First-visit Monte Carlo

- Given a fixed policy (**prediction**)
- Calculate the value function $V(s)$ for each state

First-visit MC prediction, for estimating $V \approx v_\pi$

Initialize:

$\pi \leftarrow$ policy to be evaluated
 $V \leftarrow$ an arbitrary state-value function
 $Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

Repeat forever:

Generate an episode using π
 For each state s appearing in the episode:

$G \leftarrow$ the return that follows the first occurrence of s

Append G to $Returns(s)$
 $V(s) \leftarrow \text{average}(Returns(s))$

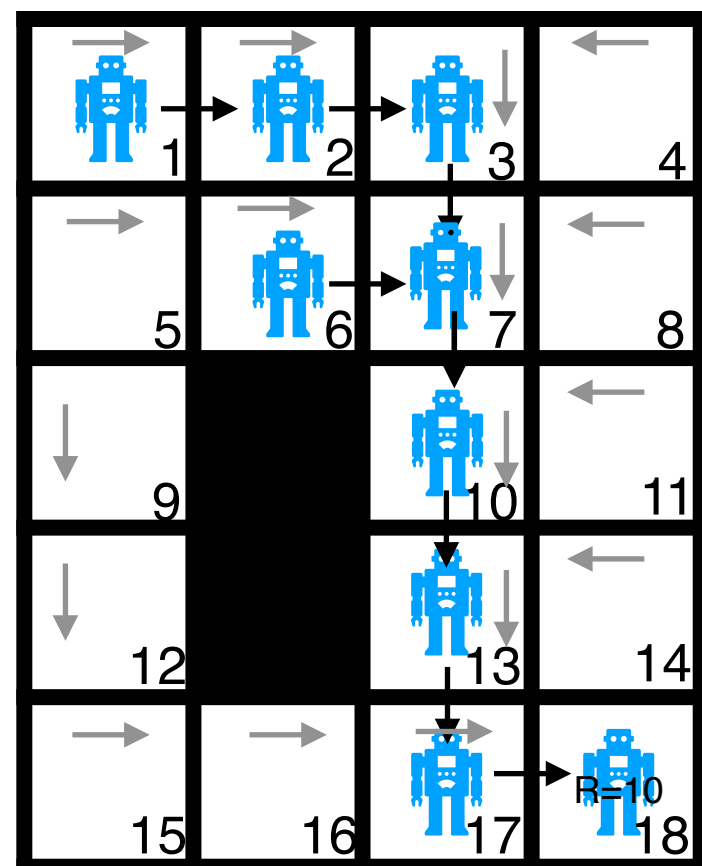
[Sutton & Barto,
RL Book, Ch 5]

- Converges to $V_\pi(\mathbf{s})$ as the number of visits to each state goes to infinity

$$V(\mathbf{s}_t) = \max_{\mathbf{a}_t} \left\{ R(\mathbf{s}_t) + \gamma \sum_{\mathbf{s}_{t+1}} P(\mathbf{s}_{t+1} \mid \mathbf{s}_t, \mathbf{a}_t) V(\mathbf{s}_{t+1}) \right\}$$

Example: grid world

- **Start state is top-left (start of episode)**
- **Bottom right is absorbing (end of episode)**
- **Policy π is given (gray arrows)**



First-visit MC prediction, for estimating $V \approx v_\pi$

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$Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

Repeat forever:

Generate an episode using π

For each state s appearing in the episode:

$G \leftarrow$ the return that follows the first occurrence of s

Append G to $Returns(s)$

$$V(s) \leftarrow \text{average}(\text{Returns}(s))$$

Episode: $(1, \rightarrow) \rightarrow (2, \rightarrow) \rightarrow (3, \downarrow) \rightarrow (7, \downarrow) \rightarrow (6, \rightarrow) \rightarrow (7, \downarrow) \rightarrow (10, \downarrow) \rightarrow (13, \downarrow) \rightarrow (17, \rightarrow)$

For state 7: $\text{return}(7) = \gamma R(6) + \gamma^2 R(7) + \gamma^3 R(10) + \gamma^4 R(13) + \gamma^5 R(17) + \gamma^6 R(18)$
 $= \gamma^6 10$

$$\mathbf{v}(\mathbf{7}) = \gamma^6 * 10$$

Q-value function for control

- We know about state-value functions $V(s)$
- If state transitions are known then they can be used to derive an optimal policy [recall value iteration]:

$$\pi^*(s) = \arg \max_a \left\{ R(s) + \gamma \sum_{s'} P(s' | s, a) V^*(s') \right\} \quad \forall s$$

- When state transitions are unknown what can we do?
- **$Q(s,a)$** the value function of a **(state,action) pair**

$$\pi^*(s) = \arg \max_a \{ Q^*(s, a) \} \quad \forall s$$

MC for Control: Monte Carlo ES

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:

$Q(s, a) \leftarrow$ arbitrary

$\pi(s) \leftarrow$ arbitrary

$Returns(s, a) \leftarrow$ empty list

Repeat forever:

Choose $S_0 \in \mathcal{S}$ and $A_0 \in \mathcal{A}(S_0)$ s.t. all pairs have probability > 0

Generate an episode starting from S_0, A_0 , following π

For each pair s, a appearing in the episode:

$G \leftarrow$ the return that follows the first occurrence of s, a

Append G to $Returns(s, a)$

$Q(s, a) \leftarrow \text{average}(Returns(s, a))$

For each s in the episode:

$\pi(s) \leftarrow \arg\max_a Q(s, a)$

[Sutton & Barto,
RL Book, Ch.5]

First-visit MC prediction, for estimating $V \approx v_\pi$

Initialize:

$\pi \leftarrow$ policy to be evaluated

$V \leftarrow$ an arbitrary state-value function

$Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

Repeat forever:

Generate an episode using π

For each state s appearing in the episode:

$G \leftarrow$ the return that follows the first occurrence of s

Append G to $Returns(s)$

$V(s) \leftarrow \text{average}(Returns(s))$

- Strong reasons to believe that it converges to the optimal policy
- “Exploring starts” requirement may be unrealistic

Monte Carlo without exploring starts (on policy)

On-policy first-visit MC control (for ϵ -soft policies), estimates $\pi \approx \pi_*$

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:

- $Q(s, a) \leftarrow$ arbitrary
- $Returns(s, a) \leftarrow$ empty list
- $\pi(a|s) \leftarrow$ an arbitrary ϵ -soft policy

Repeat forever:

- Generate an episode using π
- For each pair s, a appearing in the episode:
 - $G \leftarrow$ the return that follows the first occurrence of s, a
 - Append G to $Returns(s, a)$
 - $Q(s, a) \leftarrow \text{average}(Returns(s, a))$
- For each s in the episode:
 - $A^* \leftarrow \arg \max_a Q(s, a)$ (with ties broken arbitrarily)
 - For all $a \in \mathcal{A}(s)$:

$$\pi(a|s) \leftarrow \begin{cases} 1 - \epsilon + \epsilon/|\mathcal{A}(s)| & \text{if } a = A^* \\ \epsilon/|\mathcal{A}(s)| & \text{if } a \neq A^* \end{cases}$$

[Sutton & Barto,
RL Book, Ch.5]

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:

- $Q(s, a) \leftarrow$ arbitrary
- $\pi(s) \leftarrow$ arbitrary
- $Returns(s, a) \leftarrow$ empty list

Repeat forever:

- Choose $S_0 \in \mathcal{S}$ and $A_0 \in \mathcal{A}(S_0)$ s.t. all pairs have probability > 0
- Generate an episode starting from S_0, A_0 , following π
- For each pair s, a appearing in the episode:
 - $G \leftarrow$ the return that follows the first occurrence of s, a
 - Append G to $Returns(s, a)$
 - $Q(s, a) \leftarrow \text{average}(Returns(s, a))$
- For each s in the episode:
 - $\pi(s) \leftarrow \arg \max_a Q(s, a)$

- **Policy value cannot decrease**

$$V_{\pi'}(s) \geq V_{\pi}(s), \forall s \in \mathcal{S}$$

π : policy at current step

π' : policy at next step

Monte-Carlo methods summary

- Allow a policy to be learned through interactions
 - **(Does not learn transitions)**
- States are effectively treated as being independent
 - Focus on a subset of states (e.g., states for which playing optimally is of particular importance)
- Episodic (with or without exploring starts)

Temporal Difference

Temporal Difference (TD) Learning

- One of the “central ideas of RL” [Sutton & Barto, RL book]

- Monte Carlo methods

$$V'(s_t) = V(s_t) + \alpha G_t - V(s_t)$$

Observed return : G_t

Step size : α

$$G_t = \sum_t^T \gamma^t R(s_t)$$

- TD(0)

- updates “instantly”

$$V'(s_t) = V(s_t) + \alpha \underbrace{[R(s_t) + \gamma V(s_{t+1})]}_{\approx G_t} - V(s_t)$$

First-visit MC prediction, for estimating $V \approx v_\pi$

Initialize:

$\pi \leftarrow$ policy to be evaluated

$V \leftarrow$ an arbitrary state-value function

$Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

Repeat forever:

Generate an episode using π

For each state s appearing in the episode:

$G \leftarrow$ the return that follows the first occurrence of s

Append G to $Returns(s)$

$V(s) \leftarrow \text{average}(Returns(s))$

TD(0) for prediction VS TD for control

Sarsa (on-policy TD control) for estimating $Q \approx q_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$

Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(\text{terminal}, \cdot) = 0$

Loop for each episode:

Initialize S

Choose A from S using policy derived from Q (e.g., ε -greedy)

Loop for each step of episode:

Take action A , observe R, S'

Choose A' from S' using policy derived from Q (e.g., ε -greedy)

$Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma Q(S', A') - Q(S, A)]$

$S \leftarrow S'; A \leftarrow A';$

until S is terminal

Tabular TD(0) for estimating v_π

Input: the policy π to be evaluated

Initialize $V(s)$ arbitrarily (e.g., $V(s) = 0$, for all $s \in \mathcal{S}^+$)

Repeat (for each episode):

Initialize S

Repeat (for each step of episode):

$A \leftarrow$ action given by π for S

Take action A , observe R, S'

$V(S) \leftarrow V(S) + \alpha [R + \gamma V(S') - V(S)]$

$S \leftarrow S'$

until S is terminal

[Sutton & Barto,
RL Book, Ch.6]

Q-learning for control

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Initialize $Q(s, a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\text{terminal-state}, \cdot) = 0$

Repeat (for each episode):

Initialize S

Repeat (for each step of episode):

Choose A from S using policy derived from Q (e.g., ϵ -greedy)

Take action A , observe R, S'

$$Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$$

$$S \leftarrow S'$$

until S is terminal

[Sutton & Barto,
RL Book, Ch.6]

- Converges to Q^* as long as all (s,a) pairs continue to be updated and with minor constraints on learning rate

$$\epsilon\text{-greedy policy} \quad \mathbf{a} = \begin{cases} \arg \max_a Q(\mathbf{a}, s) & \text{with probability } 1 - \epsilon, \\ \text{random } a & \text{with probability } \epsilon. \end{cases}$$

Comparing TD and MC

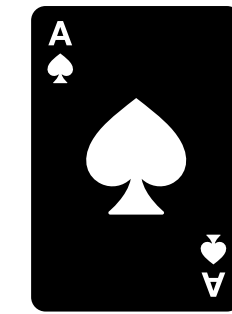
- MC requires going through full episodes before updating the value function. Episodic.
- Converges to the optimal solution
- TD updates each $V(s)$ after each transition. Online.
- Converges to the optimal solution (some conditions on α)
- Empirically TD methods tend to converge faster

Practical difficulties

- **Compared to supervised learning** setting up an RL problem is often **harder**
 - Need an **environment** (or at least a simulator)
- **Rewards**
 - In some domains it's clear (e.g., in games)
 - In others it's much more subtle (e.g., you want to please a human)

**Hand on Session
+
Extra material
(Some will be used for this week's exercises)**

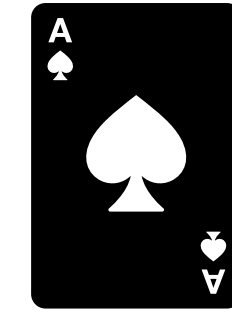
Black Jack



The most widely played casino banking game in the world, also known as Twenty-One.

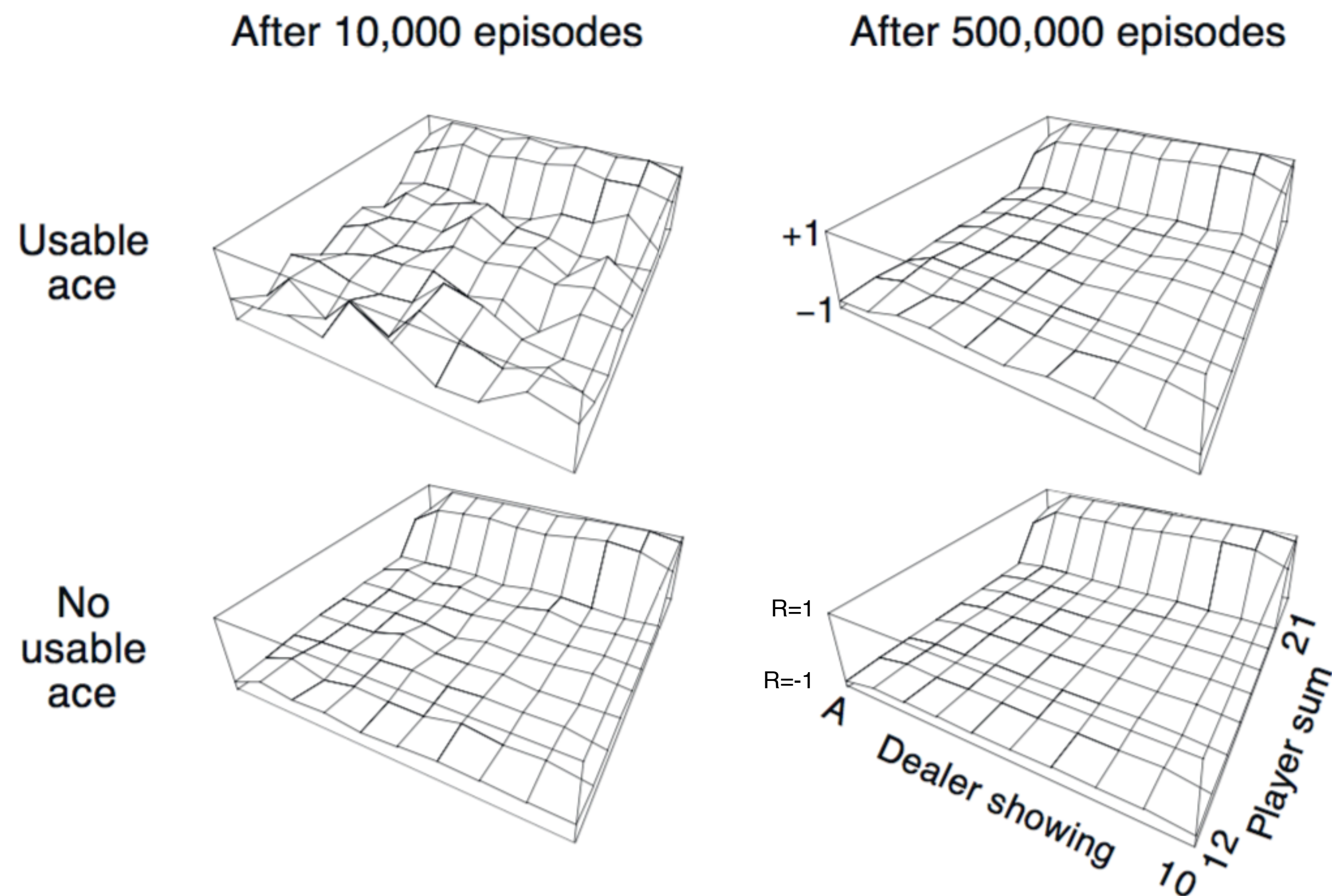


Black Jack



- **Episode: one hand**
- **States: Sum of player's cards, dealer's card, usable ace**
- **Actions: {Stay, Hit}**
- **Rewards: {Win +1, Tie 0, Loose -1}**
- **A few other assumptions: infinite deck**

- Evaluates the policy that hits except when the sum of the cards is 20 or 21



[Figure 5.1, Sutton & Barto]

Approximation techniques

- Methods we studied are “tabular”
- State value functions (and Q) can be approximated
 - **Linear approximation:** $V(\mathbf{s}) = \mathbf{w}^\top \mathbf{x}(\mathbf{s})$
 - Coupling between states through $\mathbf{x}(\mathbf{s})$
 - **Adapt the algorithms for this case.**
 - Updates to the value function now imply updating the weights \mathbf{w} using a gradient

Approximation techniques (prediction)

- **Linear approximation:** $V(s) = \mathbf{w}^\top \mathbf{x}(s)$
- **Objective:** $\sum_{s \in \mathcal{S}} [\mathbf{v}_\pi(s) - \mathbf{w}^\top \mathbf{x}(s)]^2$
- **Gradient update:** $\mathbf{w}_{t+1} = \mathbf{w}_t - 2\alpha \sum_{s \in \mathcal{S}} [\mathbf{v}_\pi(s) - \mathbf{w}^\top \mathbf{x}(s)] \mathbf{x}(s)$

[Sutton & Barto,
RL Book, Ch.9]

Gradient Monte Carlo Algorithm for Estimating $\hat{v} \approx v_\pi$

Input: the policy π to be evaluated
 Input: a differentiable function $\hat{v} : \mathcal{S} \times \mathbb{R}^d \rightarrow \mathbb{R}$
 Initialize value-function weights \mathbf{w} as appropriate (e.g., $\mathbf{w} = \mathbf{0}$)
 Repeat forever:
 Generate an episode $S_0, A_0, R_1, S_1, A_1, \dots, R_T, S_T$ using π
 For $t = 0, 1, \dots, T-1$:
 $\mathbf{w} \leftarrow \mathbf{w} + \alpha [G_t - \hat{v}(S_t, \mathbf{w})] \nabla \hat{v}(S_t, \mathbf{w})$

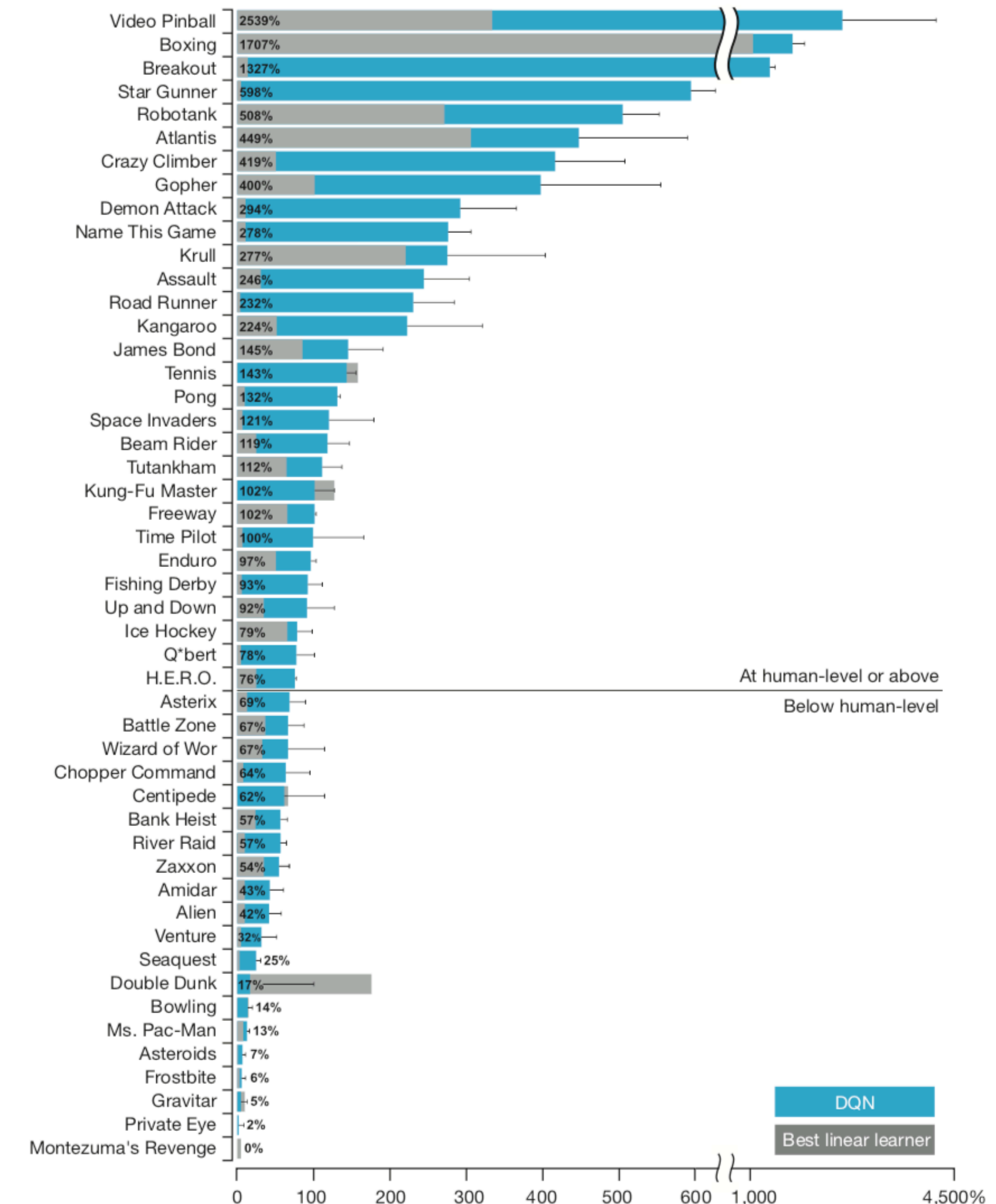
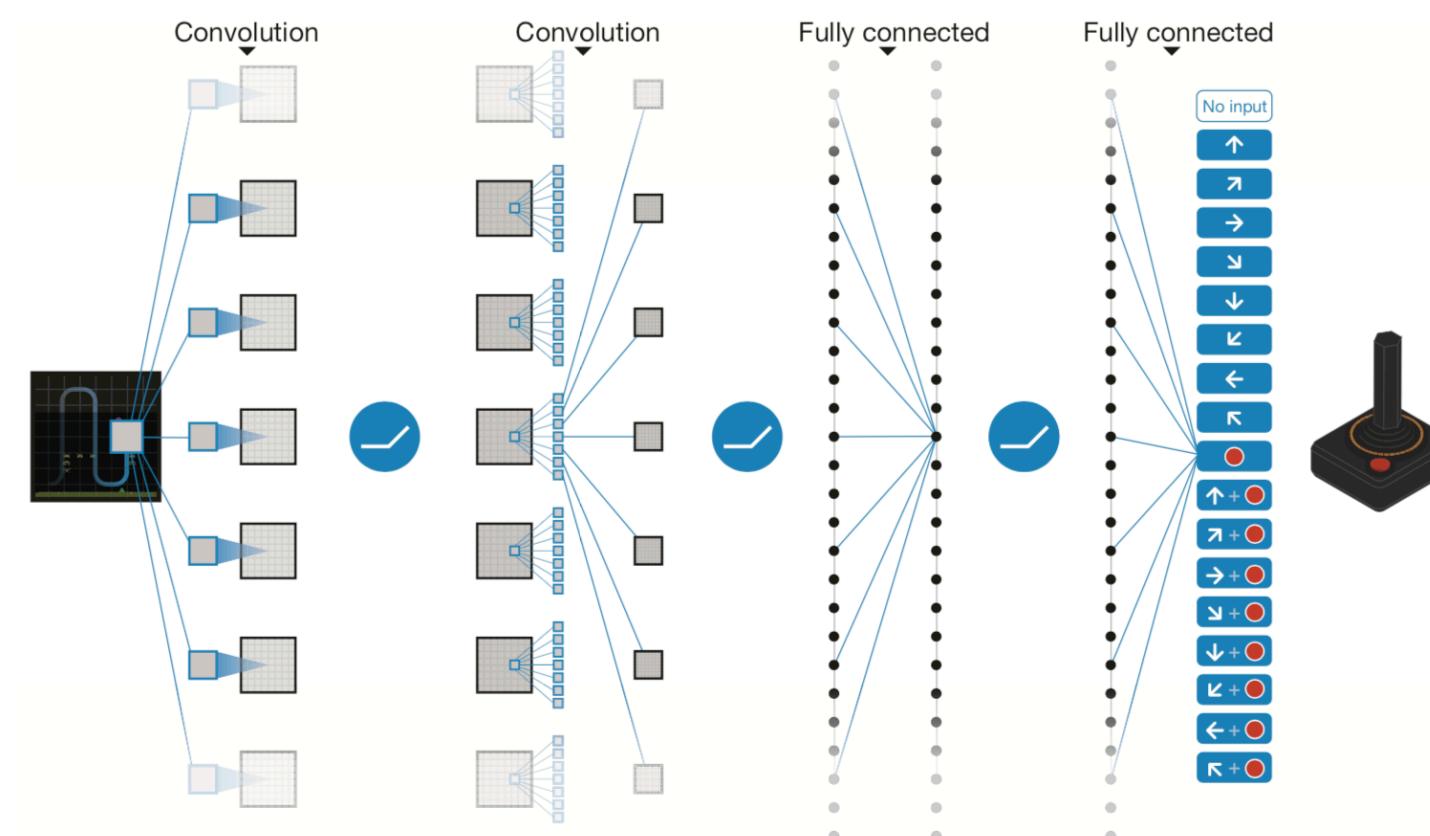
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 Repeat forever:
 Generate an episode using π
 For each state s appearing in the episode:
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 Append G to $Returns(s)$
 $V(s) \leftarrow \text{average}(Returns(s))$

G_t is an unbiased estimator of $\mathbf{v}_\pi(s_t)$

Approximation techniques

- Works both for prediction and control
- Any model can be used to approximate
- Recent work using deep neural networks yield impressive performance on computer (Atari) games



Summary

- Today we have defined RL studied several algorithms for solving RL problems (mostly for for tabular case)
- **Main challenges**
 - Credit assignment
 - Exploration/Exploitation tradeoff
- **Algorithms**
 - Prediction
 - Monte Carlo and TD(0)
 - Control
 - Q-learning
- **Approximation algorithms can help scale reinforcement learning**