

Reinforcement learning

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April 4, 2024

(Multi-armed) Bandits



Think about not one but 10 arms you may choose to pull.

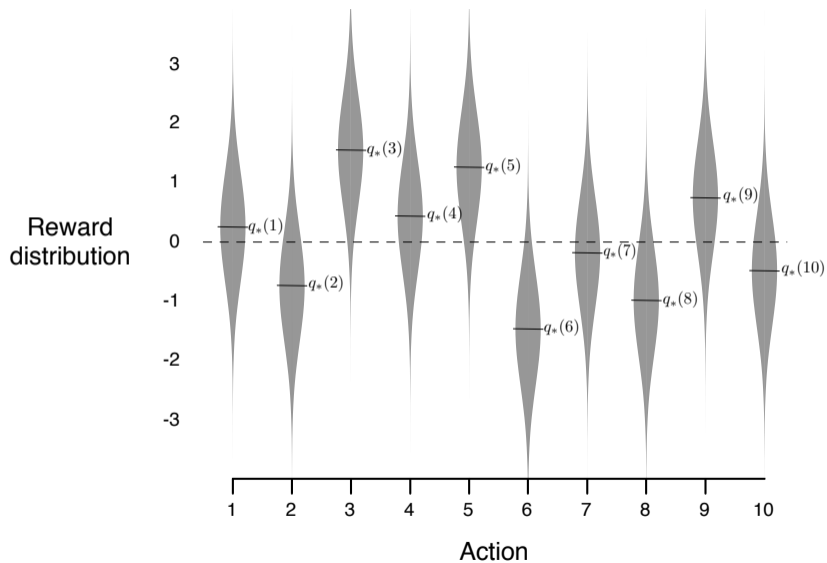
(Multi-armed) Bandits



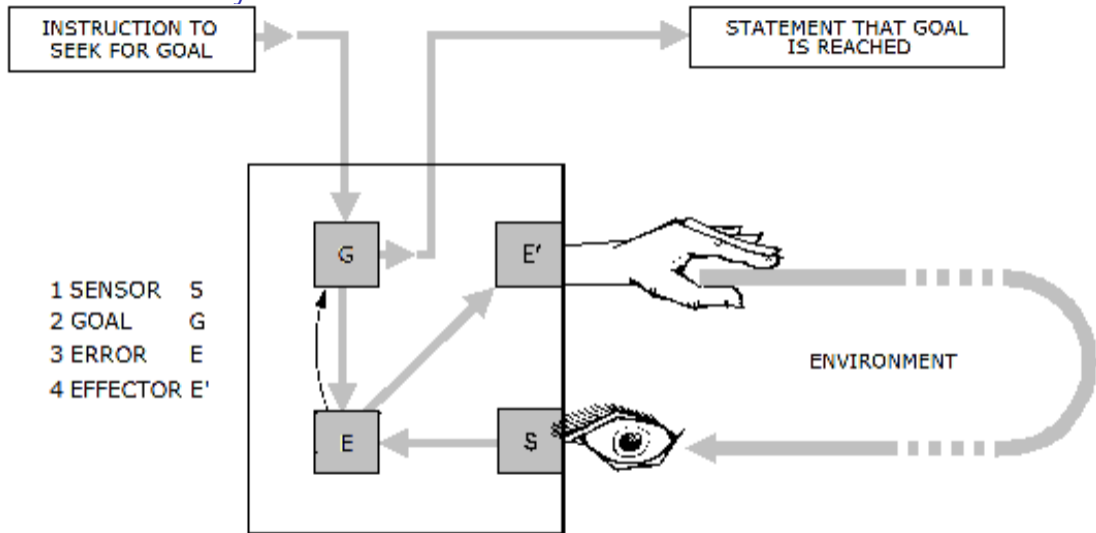
Think about not one but 10 arms you may choose to pull.

$p(s'|s, a)$ and $r(s, a, s')$ not known!

10 armed bandit, what arm to pull?



Goal-directed system

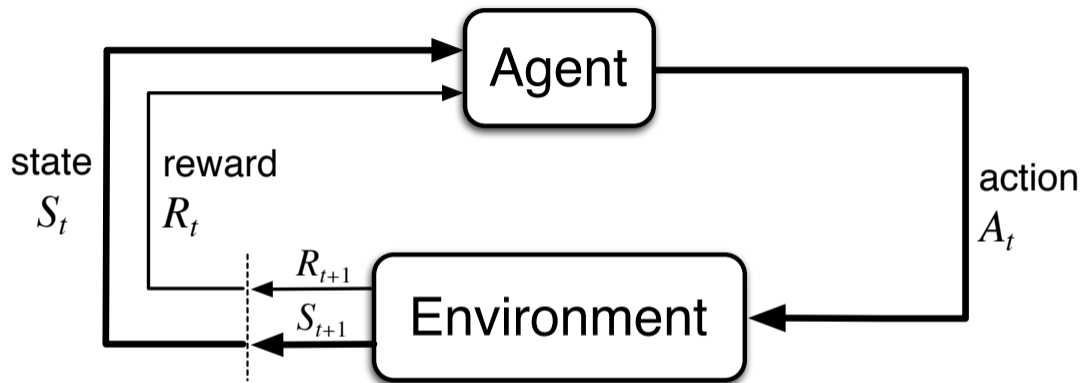


- 1 SENSOR S
- 2 GOAL G
- 3 ERROR E
- 4 EFFECTOR E'

A SIMPLE GOAL-DIRECTED SYSTEM

¹Figure from <http://www.cybsoc.org/gcyb.htm>

Reinforcement Learning - performing actions, learning from rewards



2

- ▶ Feedback in form of **Rewards**
- ▶ Learn to act so as to maximize expected rewards.

²Scheme from [4]

Autonomous Flipper Control with Safety Constraints

Martin Pecka, Vojtěch Šalanský,
Karel Zimmermann, Tomáš Svoboda

experiments utilizing
Constrained Relative Entropy Policy Search

Video: Learning safe policies³

³M. Pecka, V. Salansky, K. Zimmermann, T. Svoboda. Autonomous flipper control with safety constraints. In Intelligent Robots and Systems (IROS), 2016, https://youtu.be/_oUMbBtoRcs

From off-line (MDPs) to on-line (RL)

Markov decision process – MDPs. Off-line search, we know:

- ▶ A set of states $s \in \mathcal{S}$ (map)
- ▶ A set of actions per state. $a \in \mathcal{A}$
- ▶ A transition model $T(s, a, s')$ or $p(s'|s, a)$ (robot)
- ▶ A reward function $r(s, a, s')$ (map, robot)

Looking for the optimal policy $\pi(s)$. We can plan/search before the robot enters the environment.

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Looking for the optimal policy $\pi(s)$. We can plan/search before the robot enters the environment.

On-line problem:

- ▶ Transition model p and reward function r not known.
- ▶ Agent/robot must act and learn from experience.

(Transition) Model-based learning

The main idea: Do something and:

- ▶ Learn an approximate model from experiences.
- ▶ Solve as if the model was correct.

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Learning MDP model:

- ▶ In s try a , observe s' , count (s, a, s') .
- ▶ Normalize to get an estimate of $p(s' | s, a)$.
- ▶ Discover (by observation) each $r(s, a, s')$ when experienced.

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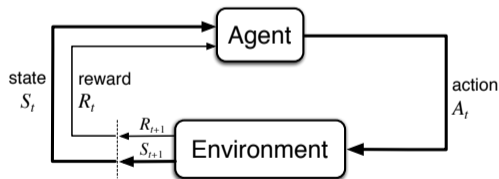
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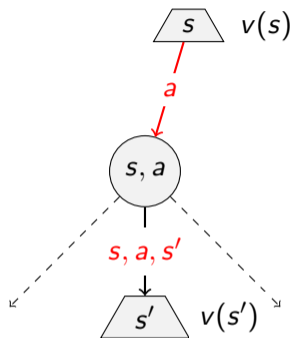
Solve the learned MDP.

Reward function $r(s, a, s')$

- ▶ $r(s, a, s')$ - reward for taking a in s and landing in s' .
- ▶ In Grid world, we assumed $r(s, a, s')$ to be the same everywhere.
- ▶ In the real world, it is different (going up, down, ...)

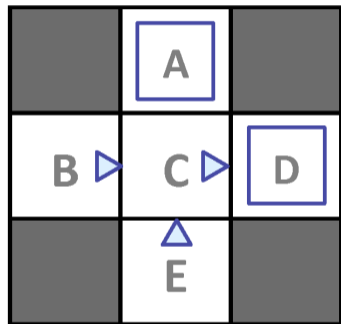


In ai-gym env.`step(action)` returns $s', r(s, \text{action}, s')$.



Model-based learning: Grid example

Input Policy π



Assume: $\gamma = 1$

Observed Episodes (Training)

Episode 1

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2

B, east, C, -1
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Episode 3

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Episode 4

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C, east, A, -1
A, exit, x, -10

4

⁴Figure from [1]

Learning transition model

$$\hat{p}(D \mid C, \text{east}) = ?$$

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Learning reward function

$\hat{r}(C, \text{east}, D) = ?$

Episode 1

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E, north, C, -1
C, east, D, -1
D, exit, x, +10

Episode 4

E, north, C, -1
C, east, A, -1
A, exit, x, -10

Model based vs model-free: Expected age $E[A]$

Random variable age A .

$$E[A] = \sum_a P(A = a)a$$

We do not know $P(A = a)$. Instead, we collect N samples $[a_1, a_2, \dots, a_N]$.

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Model based

$$\hat{P}(a) = \frac{\text{num}(a)}{N}$$

$$E[A] \approx \sum_a \hat{P}(a)a$$

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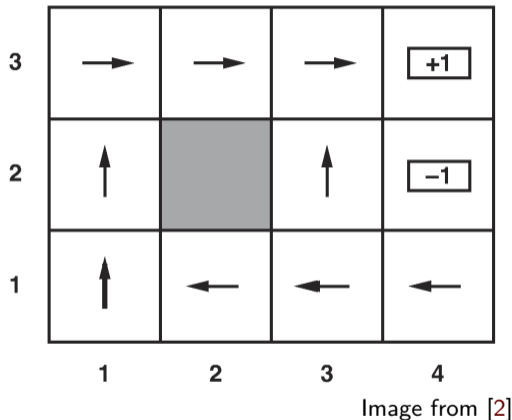
Model free

$$E[A] \approx \frac{1}{N} \sum_i a_i$$

Model-free learning

Passive learning (evaluating given policy)

- ▶ **Input:** a fixed policy $\pi(s)$
- ▶ We want to know how good it is.
- ▶ r, p not known.
- ▶ Execute policy ...
- ▶ and learn on the way.
- ▶ **Goal:** learn the state values $v^\pi(s)$

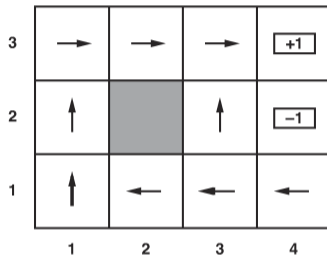


Direct evaluation from episodes

Value of s for π – expected sum of discounted rewards – expected return

$$v^\pi(S_t) = E \left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \right]$$

$$v^\pi(S_t) = E[G_t]$$

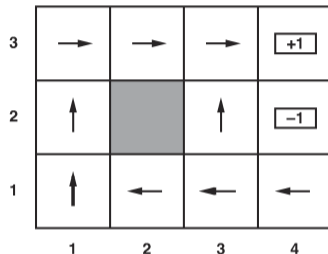


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$(1, 1) \cdot 0.04 \rightsquigarrow (1, 2) \cdot 0.04 \rightsquigarrow (1, 3) \cdot 0.04 \rightsquigarrow (1, 2) \cdot 0.04 \rightsquigarrow (1, 3) \cdot 0.04 \rightsquigarrow (2, 3) \cdot 0.04 \rightsquigarrow (3, 3) \cdot 0.04 \rightsquigarrow (4, 3) + 1$
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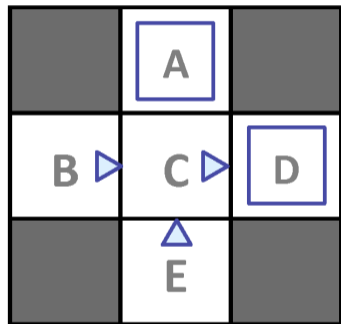
Direct evaluation from episodes, $v^\pi(S_t) = E[G_t]$, $\gamma = 1$

$(1, 1)_{-.04} \rightsquigarrow (1, 2)_{-.04} \rightsquigarrow (1, 3)_{-.04} \rightsquigarrow (1, 2)_{-.04} \rightsquigarrow (1, 3)_{-.04} \rightsquigarrow (2, 3)_{-.04} \rightsquigarrow (3, 3)_{-.04} \rightsquigarrow (4, 3)_{+1}$
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What is $v(3, 2)$ after these episodes?

Direct evaluation: Grid example

Input Policy π



Assume: $\gamma = 1$

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Episode 1

B, east, C, -1
C, east, D, -1
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Episode 3

E, north, C, -1
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Episode 4

E, north, C, -1
C, east, A, -1
A, exit, x, -10

Direct evaluation: Grid example, $\gamma = 1$

What is $v(C)$ after the 4 episodes?

Episode 1

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2

B, east, C, -1
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Episode 3

E, north, C, -1
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Episode 4

E, north, C, -1
C, east, A, -1
A, exit, x, -10

Direct evaluation: Grid example, $\gamma = 1$

What is $v(C)$ after the 4 episodes?

Let M be the number of recorded episodes.
Let N be the number of samples used
to compute the averages.

What is the relation of M and N ?

- A** $N = M$
- B** $N \leq M$
- C** $N \geq M$
- D** N has no relation to M

Episode 1

B, east, C, -1
C, east, D, -1
D, exit, x, +10

Episode 2

B, east, C, -1
C, east, D, -1
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E, north, C, -1
C, east, D, -1
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Direct evaluation algorithm (every-visit version)

$(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) \xrightarrow{+1}$
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Input: a policy π to be evaluated

Initialize:

$V(s) \in \mathbb{R}$, arbitrarily, for all $s \in \mathcal{S}$

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

Loop forever (for each episode):

Generate an episode following π : $S_0, A_0, R_1, S_1, A_1, R_2, \dots, S_{T-1}, A_{T-1}, R_T$

$G \leftarrow 0$

Loop backwards for each step of episode, $t = T - 1, T - 2, \dots, 0$:

$G \leftarrow R_{t+1} + \gamma G$

Append G to $Returns(S_t)$

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

Direct evaluation algorithm (first-visit version)

$(1, 1)_{-.04} \rightsquigarrow (1, 2)_{-.04} \rightsquigarrow (1, 3)_{-.04} \rightsquigarrow (1, 2)_{-.04} \rightsquigarrow (1, 3)_{-.04} \rightsquigarrow (2, 3)_{-.04} \rightsquigarrow (3, 3)_{-.04} \rightsquigarrow (4, 3)_{+1}$
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$G \leftarrow R_{t+1} + \gamma G$

If S_t does not appear in S_0, S_1, \dots, S_{t-1} : // Use the return for the first visit only

Append G to $Returns(S_t)$

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

Direct evaluation: analysis

The good:

- ▶ Simple, easy to understand and implement.
- ▶ Does not need p, r and eventually it computes the true v^π .

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- ▶ Each state value learned in isolation.
- ▶ State values are not independent
- ▶ $v^\pi(s) = \sum_{s'} p(s' | s, \pi(s)) [r(s, \pi(s), s') + \gamma v^\pi(s')]$

(on-line) Policy evaluation?

In MDP, we did:

- ▶ Initialize the values: $V_0^\pi(s) = 0$
- ▶ In each iteration, replace V with a one-step-look-ahead:
$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} p(s' | s, \pi(s)) [r(s, \pi(s), s') + \gamma V_k^\pi(s')]$$

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Problem: both $p(s' | s, \pi(s))$ and $r(s, \pi(s), s')$ unknown!

Use samples for evaluating policy?

MDP (p, r known) : Update V estimate by a weighted average:

$$V_{k+1}^{\pi}(s) \leftarrow \sum_{s'} p(s' | s, \pi(s)) [r(s, \pi(s), s') + \gamma V_k^{\pi}(s')]$$

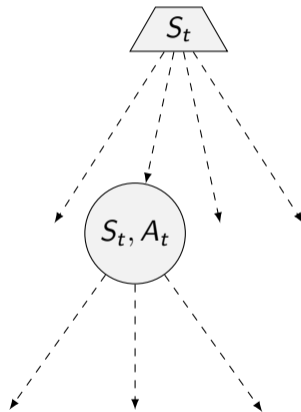
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What about stop, try, try, ..., and average?

Trials at time t . $\pi(S_t) \rightarrow A_t$, repeat A_t .



Use samples for evaluating policy?

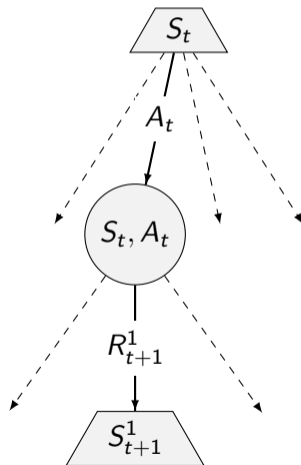
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Trials at time t . $\pi(S_t) \rightarrow A_t$, repeat A_t .

$$\text{trial}^1 = R_{t+1}^1 + \gamma V(S_{t+1}^1)$$



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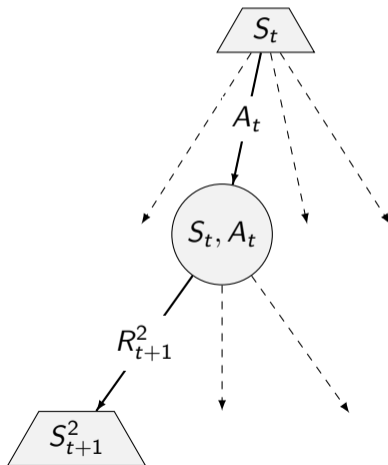
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$$\text{trial}^1 = R_{t+1}^1 + \gamma V(S_{t+1}^1)$$

$$\text{trial}^2 = R_{t+1}^2 + \gamma V(S_{t+1}^2)$$



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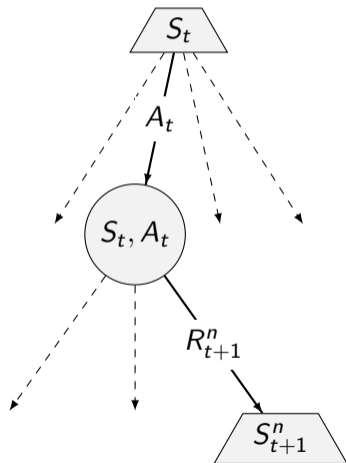
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$$\vdots = \vdots$$

$$\text{trial}^n = R_{t+1}^n + \gamma V(S_{t+1}^n)$$



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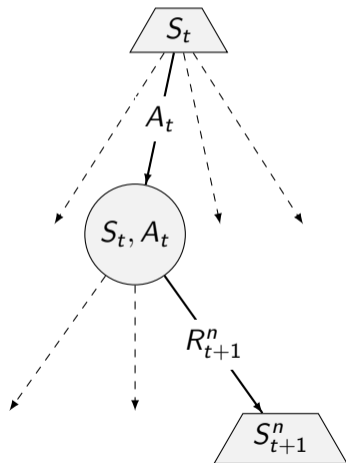
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$$V(S_t) \leftarrow \frac{1}{n} \sum_i \text{trial}^i$$



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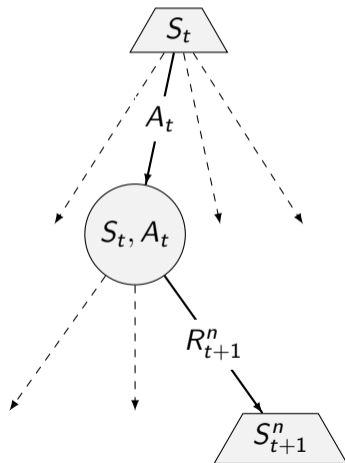
$$\text{trial}^2 = R_{t+1}^2 + \gamma V(S_{t+1}^2)$$

$$\vdots = \vdots$$

$$\text{trial}^n = R_{t+1}^n + \gamma V(S_{t+1}^n)$$

$$V(S_t) \leftarrow \frac{1}{n} \sum_i \text{trial}^i$$

Problem: We cannot re-set to S_t easily.



Temporal-difference value learning

$(1, 1)_{-.04} \rightsquigarrow (1, 2)_{-.04} \rightsquigarrow (1, 3)_{-.04} \rightsquigarrow (1, 2)_{-.04} \rightsquigarrow (1, 3)_{-.04} \rightsquigarrow (2, 3)_{-.04} \rightsquigarrow (3, 3)_{-.04} \rightsquigarrow (4, 3)_{+1}$

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$$\gamma = 1$$

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$\gamma = 1$

From first trial (episode): $V(2, 3) =$, $V(1, 3) =$, ...

Temporal-difference value learning

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From first trial (episode): $V(2, 3) = 0.92$, $V(1, 3) = 0.84, \dots$

Temporal-difference value learning

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$$V(1, 3) = R_{t+1} + V(2, 3) = -0.04 + 0.92 = 0.88$$

Temporal-difference value learning

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- ▶ Update ($\alpha \times$ difference): $V(S_t) \leftarrow V(S_t) + \alpha \left([R_{t+1} + \gamma V(S_{t+1})] - V(S_t) \right)$
- ▶ α is the learning rate.

Temporal-difference value learning

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- ▶ α is the learning rate.
- ▶ $V(S_t) \leftarrow (1 - \alpha)V(S_t) + \alpha$ (new sample)

Exponential moving average

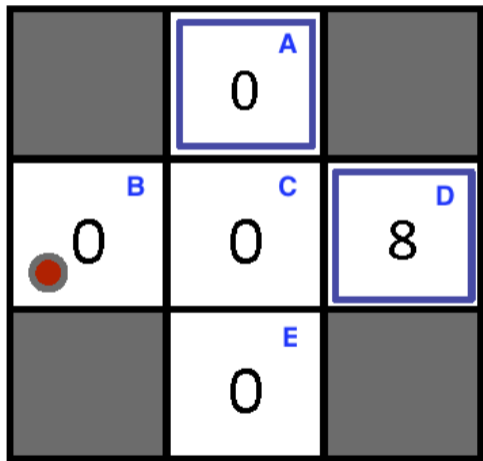
$$\bar{x}_n = (1 - \alpha)\bar{x}_{n-1} + \alpha x_n$$

What does it remember about the past? Try to derive:

$$\bar{x}_n = f(\alpha, x_n, x_{n-1}, x_{n-2}, x_{n-3}, \dots)$$

Example: TD Value learning

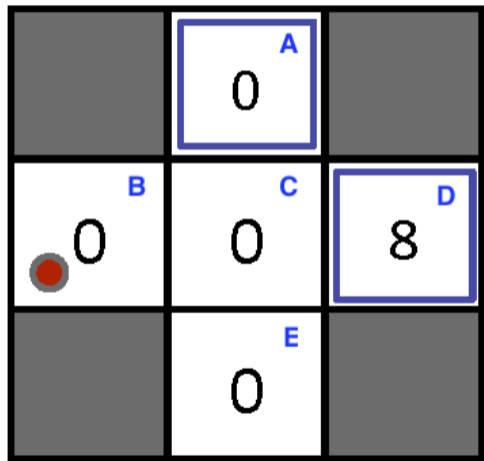
$$V(S_t) \leftarrow V(S_t) + \alpha(R_{t+1} + \gamma V(S_{t+1}) - V(S_t))$$



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- ▶ Assume: $\gamma = 1, \alpha = 0.5, \pi(s) \Rightarrow$

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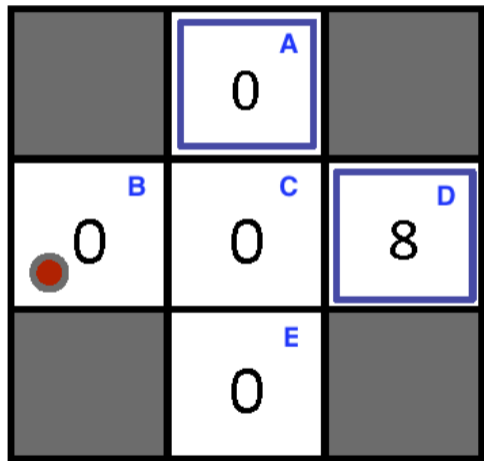
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- ▶ $(B, \rightarrow, C), -2, \Rightarrow V(B)?$

Example: TD Value learning

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- ▶ Values represent initial $V(s)$
- ▶ Assume: $\gamma = 1, \alpha = 0.5, \pi(s) \Rightarrow$
- ▶ $(B, \rightarrow, C), -2, \Rightarrow V(B)?$
- ▶ $(C, \rightarrow, D), -2, \Rightarrow V(C)?$

Temporal difference value learning: algorithm

Input: the policy π to be evaluated

Algorithm parameter: step size $\alpha \in (0, 1]$

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

Loop for each episode:

 Initialize S

 Loop 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

What is wrong with the temporal difference Value learning?

The Good: Model-free value learning by mimicking Bellman updates.

What is wrong with the temporal difference Value learning?

The Good: Model-free value learning by mimicking Bellman updates.

The Bad: How to turn values into a (new) policy?

$$\blacktriangleright \pi(s) = \arg \max_a \sum_{s'} p(s' | s, a) [r(s, a, s') + \gamma V(s')]$$

What is wrong with the temporal difference Value learning?

The Good: Model-free value learning by mimicking Bellman updates.

The Bad: How to turn values into a (new) policy?

$$\blacktriangleright \pi(s) = \arg \max_a \sum_{s'} p(s' | s, a) [r(s, a, s') + \gamma V(s')]$$

$$\blacktriangleright \pi(s) = \arg \max_a Q(s, a)$$

Q-learning

Reminder: V , Q -value iteration for MDPs

Value/Utility iteration (depth limited evaluation):

▶ Start: $V_0(s) = 0$

▶ In each step update V by looking one step ahead:

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} p(s' | s, a) [r(s, a, s') + \gamma V_k(s')]$$

Q values more useful (think about updating π)

▶ Start: $Q_0(s, a) = 0$

▶ In each step update Q by looking one step ahead:

$$Q_{k+1}(s, a) \leftarrow \sum_{s'} p(s' | s, a) \left[r(s, a, s') + \gamma \max_{a'} Q_k(s', a') \right]$$

Q-learning (one episode of)

$$\text{MDP update: } Q_{k+1}(s, a) \leftarrow \sum_{s'} p(s' | s, a) \left[r(s, a, s') + \gamma \max_{a'} Q_k(s', a') \right]$$

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Learn Q values as the robot/agent goes (temporal difference)

- ▶ Drive the robot and fetch rewards (s, a, s', R)

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Learn Q values as the robot/agent goes (temporal difference)

- ▶ Drive the robot and fetch rewards (s, a, s', R)
 - ▶ We know old estimates $Q(s, a)$ (and $Q(s', a')$), if not, initialize.
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-
- ▶ A new trial/sample estimate at time t

$$\text{trial} = R_{t+1} + \gamma \max_a Q(S_{t+1}, a)$$

Q-learning (one episode of)

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- ▶ α update

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(\text{trial} - Q(S_t, A_t))$$

or (the same)

$$Q(S_t, A_t) \leftarrow (1 - \alpha)Q(S_t, A_t) + \alpha \text{trial}$$

Q-learning (one episode of)

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In each step Q approximates the optimal q^* function.

Q-learning: algorithm (repeating episodes, until terminal or exhausted)

step size $0 < \alpha \leq 1$

initialize $Q(s, a)$ for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$

repeat episodes:

 initialize S

for for each step of episode: **do**

 choose A from $\mathcal{A}(S)$

 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

until Time is up, ...

From Q-learning to Q-learning agent

- ▶ Drive the robot and fetch rewards. (s, a, s', R)
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Technicalities for the Q-learning agent

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Technicalities for the Q-learning agent

- ▶ How to represent the Q-function?

From Q-learning to Q-learning agent

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Technicalities for the Q-learning agent

- ▶ How to represent the Q-function?
- ▶ What is the value for terminal? $Q(s, \text{Exit})$ or $Q(s, \text{None})$

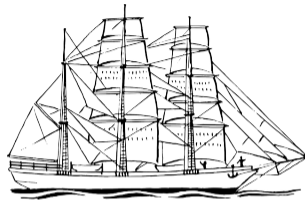
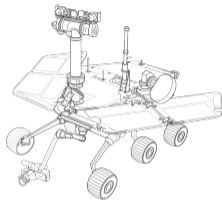
From Q-learning to Q-learning agent

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Technicalities for the Q-learning agent

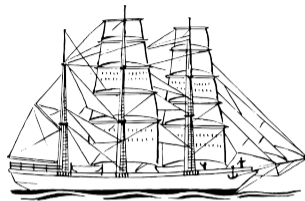
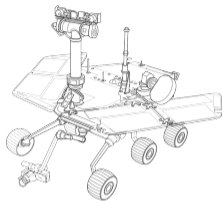
- ▶ How to represent the Q-function?
- ▶ What is the value for terminal? $Q(s, \text{Exit})$ or $Q(s, \text{None})$
- ▶ How to drive? Where to drive next? Does it change over the course?

Exploration vs. Exploitation



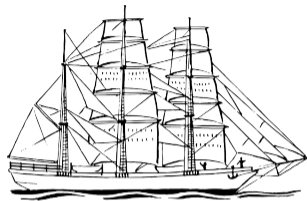
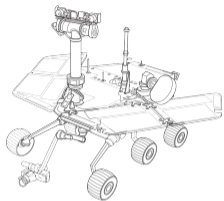
► Drive the known road or try a new one?

Exploration vs. Exploitation



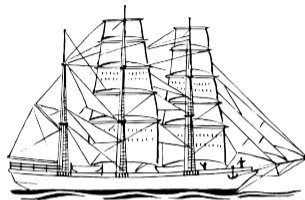
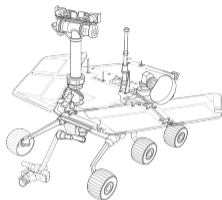
- ▶ Drive the known road or try a new one?
- ▶ Go to the university menza or try a nearby restaurant?

Exploration vs. Exploitation



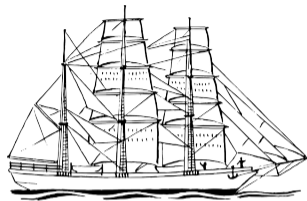
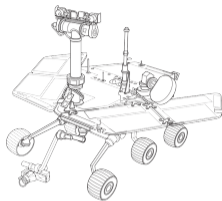
- ▶ Drive the known road or try a new one?
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Exploration vs. Exploitation



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Exploration vs. Exploitation



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- ▶ ...

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Random (ϵ -greedy):

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- ▶ ϵ same everywhere?

What we have learned

- ▶ Agent/robot may learn by acting and getting rewards
- ▶ Model based vs. model-free methods
- ▶ Direct learning vs. temporal-difference learning
- ▶ From learning state values to Q-learning

References I

Further reading: Chapter 21 of [2] (chapter 23 of [3]). More detailed discussion in [4], chapters 5 and 6.

[1] Dan Klein and Pieter Abbeel.

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[2] Stuart Russell and Peter Norvig.

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[4] Richard S. Sutton and Andrew G. Barto.

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