MFML: MDP and Reinforcement Learning

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Overview of the course

Up to now:

1. Supervised / unsupervised learning.
   - Data $\mapsto$ model
2. Online learning
   - Decision $\mapsto$ Data $\mapsto$ Decisions

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1. Supervised / unsupervised learning.
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End of the course:

3. Reinforcement learning
   - State $\mapsto$ Decision $\mapsto$ Reward and new state

What is Reinforcement Learning?

And why it differs from supervised or unsupervised learning

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- No labels, but observation of rewards.
- We design an agent, that maps states to actions.

What is Reinforcement Learning?

And why it differs from supervised or unsupervised learning

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Challenges:

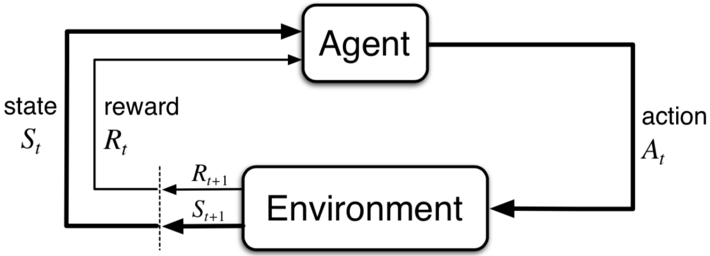
- Many possible states, actions
- Reward can be delayed, or sparse.

Applications

- Games (Go, Atari, StarCraft,...) ▸ StarCraft
- Auto-piloting vehicles ▸ Robots , ▸ Helicopter
- Supply management, energy ▸ data-center
- Trading, bidding ▸ Bidding
- Toy models ▸ AIGym
- . . .

The number of application is increasing.

RL is about interacting with an environment



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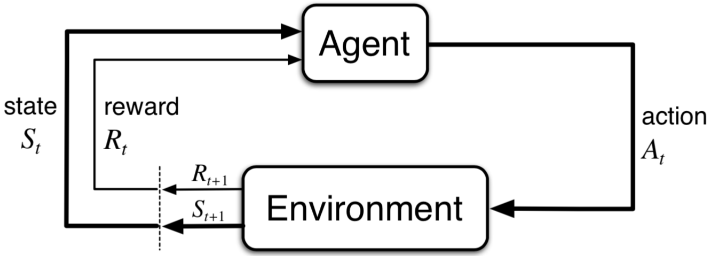

1. Get an observation of the state of the environment
2. Choose an action
3. Obtain a reward

You goal is to select actions to maximize the total reward.

Reward signal

At time t, we observe S_t, take action A_t, and obtain a reward R_{t+1}.

$$S_1, A_1 \qquad R_2, S_2, A_2 \qquad R_3, S_3, A_3 \qquad \dots \qquad R_T, S_T$$

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Impact of actions can be delayed.

- On which actions does the reward depend?

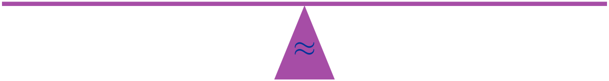
Impact of actions can be weak

- or noisy

Objective of this course

Theory

Practice



MDPs
Tabular RL
Algorithms guarantees
Regret minimization

Deep RL
Policy gradient

Exercises

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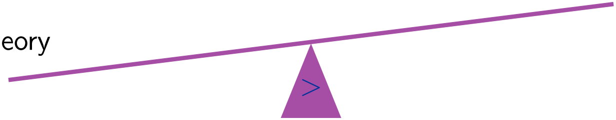
Practice

Theory



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Exercises

Personal work

Week	November 26	Dec 10	Dec 17
Tuesday	MDP	Tabular RL	"Modern" RL

- Mini-exam (Dec 10 and/or Dec 17)
- Final exam in January.

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A few advice:

- Question what you learn
- Try to do some exercises.
  - Program, go deeper, ask follow-up questions.
- Ask questions during or after the course.

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Read books (and/or research articles)

- (Introduction to Reinforcement Learning (Sutton-Barto, 2018 last ed.))
- Algorithms for Reinforcement Learning (Szepesvari, 2010)
- Deep Reinforcement learning: hands on (Maxim Lapan, 2020)

Content of the course

1. Markov Decision Processes (MDPs)
2. Tabular reinforcement learning
3. Large state-spaces and approximations
4. Monte-Carlo tree search (MCTS)

Outline

Illustrative example: the wheel of fortune

Policy:

number \ time	1	2	3	4	5
1	D			D	D
2	D				D
3					S
⋮		S	S	S	S
10	S	S	S	S	S

$$Q_g(7, \text{STOP}) \overset{?}{>} Q_g(7, \text{DRAW})$$

time — number on the wheel (state) — action

You can draw a wheel indefinitely. After time t:

- If you draw, the wheel stops on $X_t \in \{1 \dots 10\}$ (uniformly).
- You can draw again or stop and earn X_t.

- You can draw the wheel up to $T = 10$ times. How do you play?

The environement lives in a "space"

- $\mathcal{S}$ – state space.
- $\mathcal{A}$ – action space.
- $\mathcal{R}$ – reward space.

$\mathcal{S} = \{1, \dots, 10, \text{STOP}\}$

$\mathcal{A} = \{\text{STOP}, \text{DRAW}\}$

$\mathcal{R} \subseteq \mathbb{R}$

Dynamics:

- (possibly random) evolution of states
- (possibly random) rewards

Markov decision processes

$S_t, A_t \overset{\text{random}}{\underset{\text{transition}}{\rightsquigarrow}} R_{t+1}, S_{t+1}$

A MDPs is defined by:

- $\mathcal{S}$ state space
- $\mathcal{A}$ action set
- Evolution is driven by Markovian transitions

$$\mathbb{P}(S_{t+1} = s', R_{t+1} = r \mid S_t = s, A_t = a) = P(s', r \mid s, a).$$

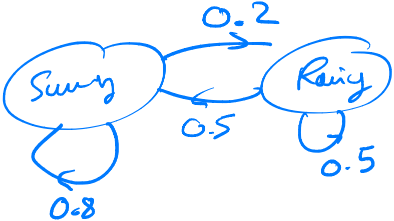
"

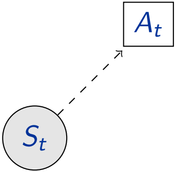
$\mathbb{P}(S_{t+1} = s', R_{t+1} = a \mid S_t = s, A_t = a$ and $H_t)$ history up to "A_t".

MDP = Markov chain + decisions

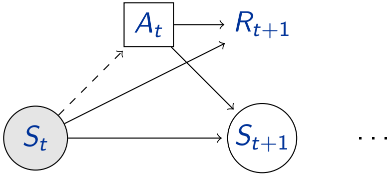
Most reinforcement learning problems can be framed as MDPs.

Graphical representation





Graphical representation



Some examples

- Wind production problem

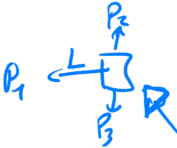
A Wind turbine produces $(W_t)^3 \cos(\theta_t)$ where W_t is the wind speed and θ_t is your angle with respect to wind. Assume that:

- Wind direction changes of ± 1 degree with probability $1/2$.
- Turning your turbine costs you $a > 0$.

Write the MDP for different models:

- Assuming that W_t is constant.
- Assuming that $W(t)$ evolve over time $W(t+1) = \min(1, \max(0, W(t) \pm b))$.
- Assuming that the direction in which the wind changes stays the same with probabilty 90%.

Some examples



- Wind production problem
- Frozen-lake ▸ Link (this is a gridworld example)

S	F	F	F
F	H	F	H
F	F	F	H
H	F	F	G

- ▸ Set space: $\{(0,0),\ldots,(3,3)\}$.
- ▸ Actions: $\{L,R,U,D\}$.
- ▸ Transitions: 1/3 in right direction.
- ▸ Rewards: there are Holes and a Goal.
  - ★ Jumping to the goal gives you "1".

- There also some deterministic MDPs
  - ▸ Shortest paths probmems
  - ▸ Deterministic games (e.g., go, chess)

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Policies

A (deterministic) policy specifies which action to take in a given state:

$$\pi : \mathcal{S} \to \mathcal{A}.$$

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A stochastic policy specifies a distribution over actions:

$$\pi : \mathcal{S} \times \mathcal{A} \to [0, 1].$$

The agent takes $A_t \sim \pi(\cdot|S_t)$.

$\pi(a|s)$

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Deterministic	Stochastic
Optimal in general	It forces exploration Useful in games / non-Markovian Differentiable

Example of a (deterministic) policy

Return of a policy

We want to compute the best policy... But what is the best policy?

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Do we choose A_t to optimize:

- R_{t+1}? (no: too greedy)

Return of a policy

We want to compute the best policy... But what is the best policy?

Do we choose A_t to optimize:

- R_{t+1}? (no: too greedy)
- R_T? (only final reward?)

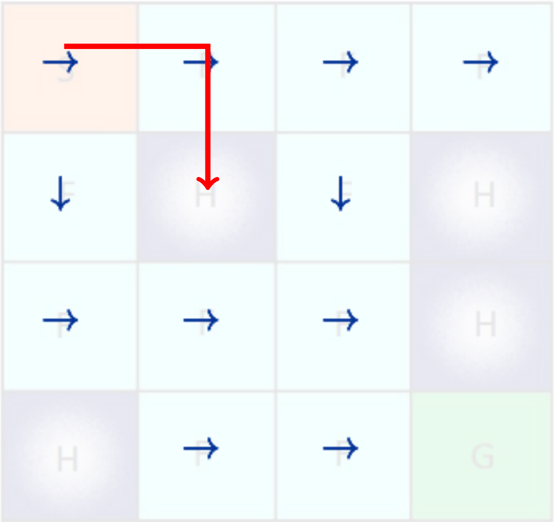
Return of a policy (finite horizon)

Sometimes, a problem has a known finite horizon T. In which case, the return (a.k.a. gain) at time t is:

$$G_t = R_{t+1} + R_{t+2} + \cdots + R_T.$$

The return is random.

Return: example



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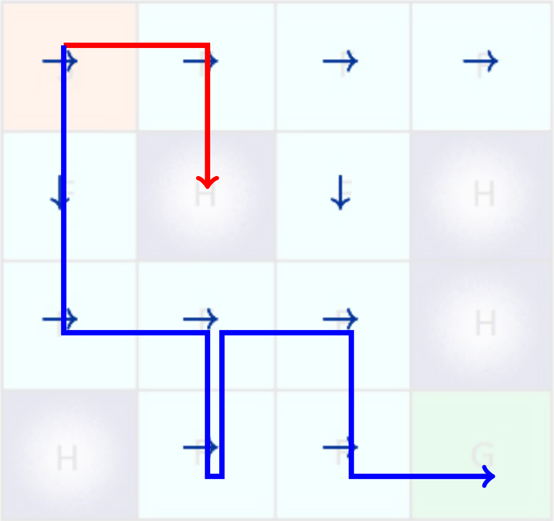

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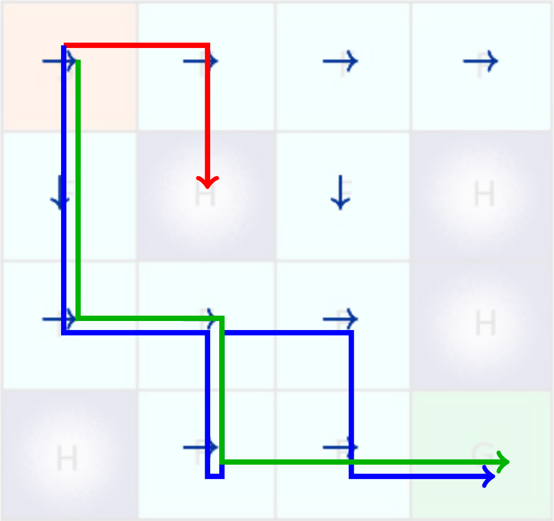

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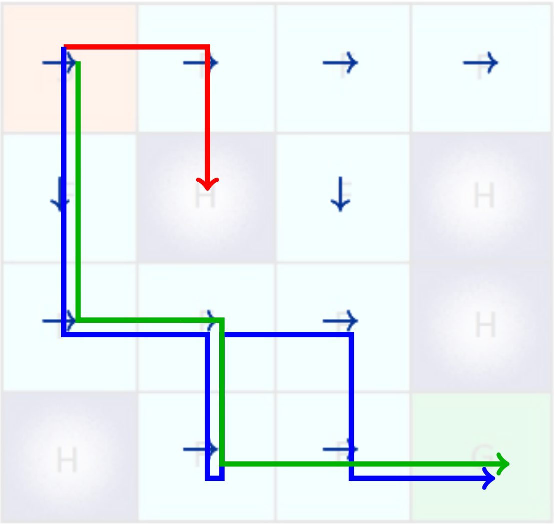

Return(Red) = 0
Return(Green)=1
Return(Blue) = 1.

The return is random.

In practice, we will look at the expected return $\mathbb{E}[G_t]$.

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Value function

state

The value function of a policy π is

$$V_t^{\pi}(s) = \mathbb{E}^{\pi}\left[G_t \mid S_t = s\right],$$

where $\mathbb{E}^{\pi}[\cdot]$ means $\mathbb{E}\left[\cdot \mid A_{t+k} \sim \pi(S_{t+k}) \quad (k \geq 0)\right]$.

time

Value function

The value function of a policy π is

$$V_t^{\pi}(s) = \mathbb{E}^{\pi}\left[G_t \mid S_t = s\right],$$

where $\mathbb{E}^{\pi}\left[\cdot\right]$ means $\mathbb{E}\left[\cdot \mid A_{t+k} \sim \pi(S_{t+k}) \quad (k \geq 0)\right]$.

It specifies the expected return. For each t, it is a vector of $|\mathcal{S}|$ values. If $\mathcal{S} = \{s_1 \dots s_4\}$

	s_1	s_2	s_3	s_4
V				

Bellman's Equation (policy evaluation, finite horizon)

We have $V_t^\pi(s) = \mathbb{E}^\pi[G_t \mid S_t = s]$ and

$$\begin{aligned} G_t &= R_{t+1} + R_{t+2} + \dots R_T \\ &= R_{t+1} + G_{t+1}. \end{aligned}$$

Hence:

$$\begin{aligned} V_t^\pi(s) &= \mathbb{E}^\pi[R_{t+1} + G_{t+1} \mid S_t = s] \\ &= \mathbb{E}^\pi[R_{t+1} \mid S_t = s] + \mathbb{E}^\pi[G_{t+1} \mid S_t = s] \\ &= r(S_t, A_t) + \sum_{s'} \mathbb{E}^\pi[G_{t+1} \mid S_{t+1} = s'] \mathbb{P}^\pi(S_{t+1} = s' \mid S_t = s) \\ &= r(S_t, \pi(S_t)) + \sum_{s'} V_{t+1}^\pi(s') P(s' \mid s, \pi(s)) \end{aligned}$$

where $r(s, a) = \sum_{r'} r' p(r' \mid s, a) = \mathbb{E}[R_{t+1} \mid S_t = s, A_t = a]$

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Hence:

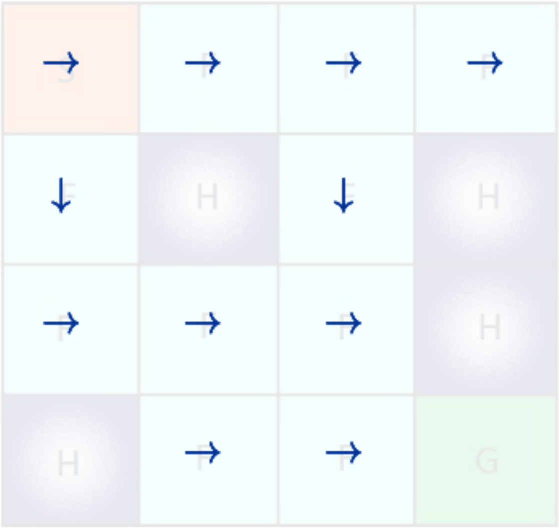
$$\begin{aligned} V_t^\pi(s) &= \underbrace{\sum_{s',r}(r + V^\pi(s'))p(s', r \mid s, a = \pi(s)).}_{=Q_{t+1}^\pi(s,\pi(s))} \\ &= \mathrm{r}(s, \pi(s)) + \sum_{s'} V_{t+1}^\pi(s')p(s' \mid s, a = \pi(s)), \end{aligned}$$

Bellman's equation

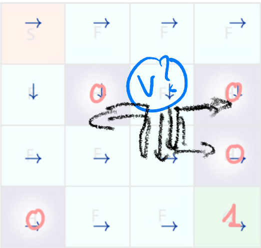
where $\mathrm{r}(s, a) = \sum_{r'} r' p(r' \mid s, a)$.

Algorithm: backward induction

Example : Finite-horizon Bellman's equation (evaluation)



Example : Finite-horizon Bellman's equation (evaluation)

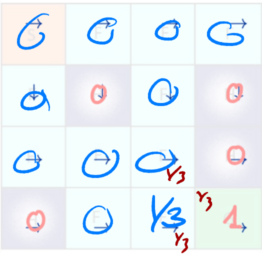


$t = 1$

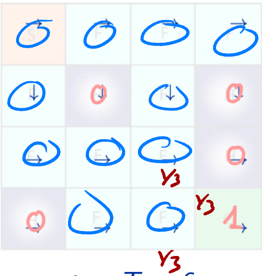
$t = 2$

$t = 3$

$t = 4$



$t = 5$



$t = T = 6$

Action-Value function

The action-value function of a policy π is

$$Q^{\pi}(s, a) = \mathbb{E}^{\pi}[G_t \mid S_t = s \wedge A_t = a].$$

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It is a table of $|\mathcal{S}| \times |\mathcal{A}|$ values. If $\mathcal{S} = \{s_1 \dots s_4\}$ and $\mathcal{A} = \{a_1, a_2\}$:

Q	a_1	a_2
s_1		
s_2		
s_3		
s_4		

From Q, we can define a greedy policy: $a_t = \arg\max_{a \in \mathcal{A}} Q(s_t, a)$.

Optimal policy

We denote by $V_t^*(s) = \max_\pi V_t^\pi(s)$ and $Q_t^*(s,a) = \max_\pi Q_t^\pi(s, a)$
For a finite-horizon T, a policy is a function $\pi : \mathcal{S} \times \{1 \dots T\} \to \mathcal{A}$.

$$V_t^*(s) = \max_a Q_t^*(s,a)$$
$$Q_t^*(s,a) = r(s,a) + \sum_{s'} V_{t+1}^*(s') P(s'|s,a)$$

$$V_T^*(s) = 0$$

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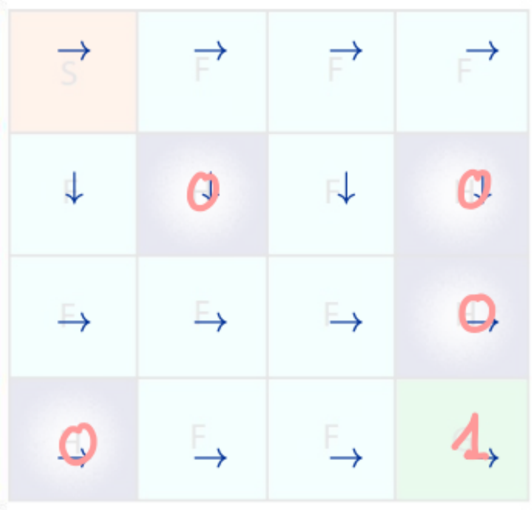
$$V_t^*(s) = \max_a Q_t(s,a)$$
$$Q_t^*(s,a) = \sum_{s',a} (r + V_{t+1}^*(s')) P(s', r \mid s, a)$$

Initial condition:

$$V_T^*(s) = \max_a r(s,a)$$

Optimal policy (finite horizon): illustration



$T = 6$

$Q_5^*((2,3),D) = 1/3$

$Q_5^*((2,3),R) = 1/3$

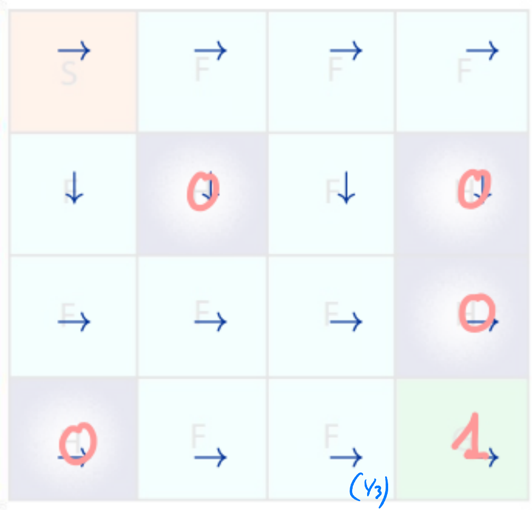
$Q_5^*((2,3),L) = 0$

$Q_5^*((2,3),U) = 1/3$

$$V_5^*((2,3)) = \frac{1}{3}$$

$$\pi_5^*((2,3)) \in \{D, R, U\}$$

Optimal policy (finite horizon): illustration



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$Q_5^*((2,3), U) =$ 1/3

$V_5^*((2,3)) = 1/3$

$Q_4^*((2,3), D) =$ 4/9

$Q_4^*((2,3), R) =$ 4/9

$Q_4^*((2,3), L) =$ 1/9

$Q_4^*((2,3), U) =$ 1/3

$V_4^*((2,3)) = 4/9$

$\pi^*((2,3)) \in \{D, R\}$

Optimal policy (finite horizon): illustration

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.33  1
L L L L
L L L L
L L L L
L L D L
```

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.11 0.00
0.00 0.11 0.44  1
L L L L
L L L L
L L L L
L D D L
```

```
0.00 0.00 0.00 0.00
0.00 0.00 0.04 0.00
0.00 0.07 0.15 0.00
0.00 0.19 0.52  1
L L L L
L L L L
L D L L
L D D L
```

```
0.00 0.00 0.01 0.00
0.00 0.00 0.05 0.00
0.02 0.11 0.21 0.00
0.00 0.26 0.57  1
L L L L
L L L L
D D L L
L R D L
```

```
0.00 0.00 0.02 0.00
0.01 0.00 0.07 0.00
0.05 0.16 0.24 0.00
0.00 0.31 0.61  1
L D L L
L L L L
D D L L
L R D L
```

```
0.00 0.01 0.03 0.01
0.02 0.00 0.09 0.00
0.07 0.20 0.28 0.00
0.00 0.36 0.64  1
D R L U
L L L L
U D L L
L R D L
```

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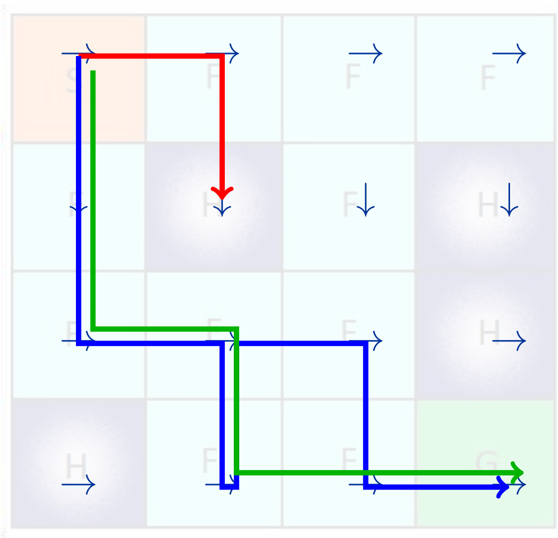
Which trajectory is best?



Return of a policy (discounted infinite horizon)

$\beta \quad \sqrt{\beta} \quad \beta^{1/3} \quad \beta^{1/4} \quad \dots$

$e^{-\alpha} \quad e^{-2\alpha} \quad e^{-3\alpha} \quad \dots$

When T is not specified, it is common to look at the discounted return:

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots$$
$$= \sum_{k=0}^{\infty} \gamma^k R_{t+1+k},$$

with $\gamma \in [0, 1)$.

$$G_t = R_{t+1} + \gamma G_{t+1}$$

- $\gamma = 0$: myopic (greedy).
- $\gamma = 1$: total reward.

Finite h~~orizon~~

$$V_t^{\pi}(s) = r(s,\pi(s)) + \sum_{s'} V_{t+1}^{\pi}(s')\, P(s' \mid s,\pi(s))$$

Discount:

$$V_t^{\pi}(s) = r(s,\pi(s)) + \gamma \sum_{s'} V_{t+1}^{\pi}(s')\, P(s' \mid s,\pi(s))$$

$$G_t = R_{t+1} + \gamma\, G_{t+1}$$

Value of a policy and value iteration

Call T^π the operator that associates to a vector V the vector $T^\pi V$:

$$T^\pi V(s) = \mathrm{r}(s, \pi(s)) + \gamma \sum_{s'} V(s') p(s' \mid s, a = \pi(s))$$

The value of a policy is the unique vector V^π such that $T^\pi V^\pi = V^\pi$.

$$V_t(s) = (T^\pi V_{t+1})(s)$$

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The value of a policy is the unique vector V^π such that $T^\pi V^\pi = V^\pi$.

Proof. T^π is contracting for the $\|v\| = \max_s |v(s)|$.

$$\| T^\pi V - T^\pi V' \| \leq \gamma \| V - V' \|$$

How to compute V^π

$$\leftarrow \cdots \quad V_{T-2} \leftarrow V_{T-1} \leftarrow V_T$$

$$V^{(2)} \leftarrow V^{(1)} \leftarrow V^{(0)}$$

Two solutions:

1. Solve the linear system.
2. Initialize $V^{(0)} = 0$ and apply $V^{(k+1)} = T^\pi V^{(k)}$ until convergence.

The optimal policy

We denote by $V^*(s) = \max_\pi V^\pi(s)$ and $Q^*(s,a) = \max_\pi Q^\pi(s,a)$.

The optimal policy π^* is such that:

$$\pi^* = \arg\max_\pi V^\pi(s) \qquad \forall s \in \mathcal{S}$$

or equivalently:

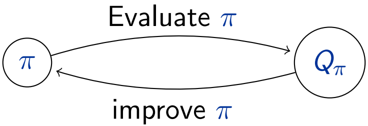
$$\pi^* = \arg\max_\pi Q^\pi(s,a) \qquad \forall s \in \mathcal{S}, s \in \mathcal{A}$$

Iterative solutions

$$\begin{tikzcd} \pi \arrow[r, bend left, "\text{Evaluate } \pi"] & Q_\pi \arrow[l, bend left, "\text{improve } \pi"] \end{tikzcd}$$

If you know the transitions and reward: value iteration or policy iteration.

Iterative solutions



If you know the transitions and reward: value iteration or policy iteration.
Value iteration:

- Initialize V^0 (for instance to 0).
- For $k \geq 0$ and $s \in \mathcal{S}$, do:
  $$V^{k+1}(s) := \max_{a\in\mathcal{A}} \left(\mathrm{r}(s,a) + \gamma \sum_{s'} V^k(s')p(s' \mid s,a)\right)$$

"Theorem": If $\gamma < 1$, then $\|V^k - V^*\| = O(\gamma^k)$.

$$\left(V = \underbrace{R + \gamma P V}_{T^\pi V} \right)$$

Illustration

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00    1
L L L L
L L L L
L L L L
L L L L
```

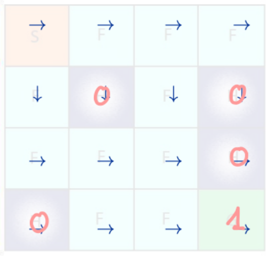
$\gamma = 0.8$

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00    1
L L L L
L L L L
L L L L
L L L L
```

$\gamma = 0.9$

Iteration $k = 0$

Illustration



```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.33   1
L L L L
L L L L
L L L L
L L D L
```

$\gamma = 0.8$

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.33   1
L L L L
L L L L
L L L L
L L D L
```

$\gamma = 0.9$

Iteration $k = 1$

Illustration

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.09 0.00
0.00 0.09 0.42   1
L  L  L  L
L  L  L  L
L  L  L  L
L  D  D  L
```

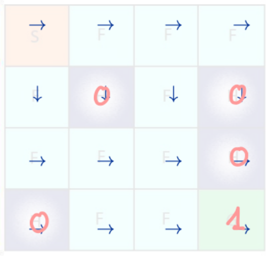
$\gamma = 0.8$

```
0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
0.00 0.00 0.10 0.00
0.00 0.10 0.43   1
L  L  L  L
L  L  L  L
L  L  L  L
L  D  D  L
```

$\gamma = 0.9$

Iteration $k = 2$

Illustration



```
0.00 0.00 0.00 0.00
0.00 0.00 0.02 0.00
0.00 0.05 0.11 0.00
0.00 0.14 0.47   1
L  L  L  L
L  L  L  L
L  D  L  L
L  D  D  L
```

$\gamma = 0.8$

```
0.00 0.00 0.00 0.00
0.00 0.00 0.03 0.00
0.00 0.06 0.13 0.00
0.00 0.16 0.49   1
L  L  L  L
L  L  L  L
L  D  L  L
L  D  D  L
```

$\gamma = 0.9$

Iteration $k = 3$

Illustration

```
0.00 0.00 0.01 0.00
0.01 0.00 0.04 0.00
0.03 0.10 0.17 0.00
0.00 0.21 0.52   1
D R L U
L L L L
U D L L
L R D L
```

$\gamma = 0.8$

```
0.00 0.01 0.02 0.01
0.01 0.00 0.06 0.00
0.05 0.14 0.22 0.00
0.00 0.28 0.57   1
D R L U
L L L L
U D L L
L R D L
```

$\gamma = 0.9$

Iteration $k = 4$

Illustration

0.02	0.02	0.03	0.02
0.03	0.00	0.06	0.00
0.06	0.13	0.20	0.00
0.00	0.25	0.54	1

```
D U R U
L L L L
U D L L
L R D L
```

$\gamma = 0.8$

0.07	0.06	0.07	0.06
0.09	0.00	0.11	0.00
0.15	0.25	0.30	0.00
0.00	0.38	0.64	1

```
L U L U
L L L L
U D L L
L R D L
```

$\gamma = 0.9$

Iteration $k = 90$

$$\frac{\gamma^k}{1-\gamma}$$

Policy iteration

Policy iteration:

- Initialize π^0 (to some random value).
- For $k \geq 0$:

  Compute Q^{π^k} (=linear system)

  For all $a \in \mathcal{A}$: $\pi^{k+1}(s) := \arg\max_{a \in \mathcal{A}} Q^{\pi^k}(s, a)$.

"Theorem": If $\gamma < 1$, then after a finite number of iterations: $V^k = V^*$.

Exercise: the wheel of fortune

You can draw a wheel indefinitely. After time t:

- If you draw, the wheel stops on $X_t \in \{1 \dots 10\}$ (uniformly). You earn X_t.
- You can draw again or keep $X_{t+1} := X_t$.

How do you play knowing that you want to maximize your discounted reward: $\mathbb{E}\left[\sum_{t=1}^{\infty} \delta^t X_t\right]$ with $\gamma = 0.9$?

- Compare value iteration and policy iteration algorithms.

Table of contents

Important concepts

(to be filled by you!)