

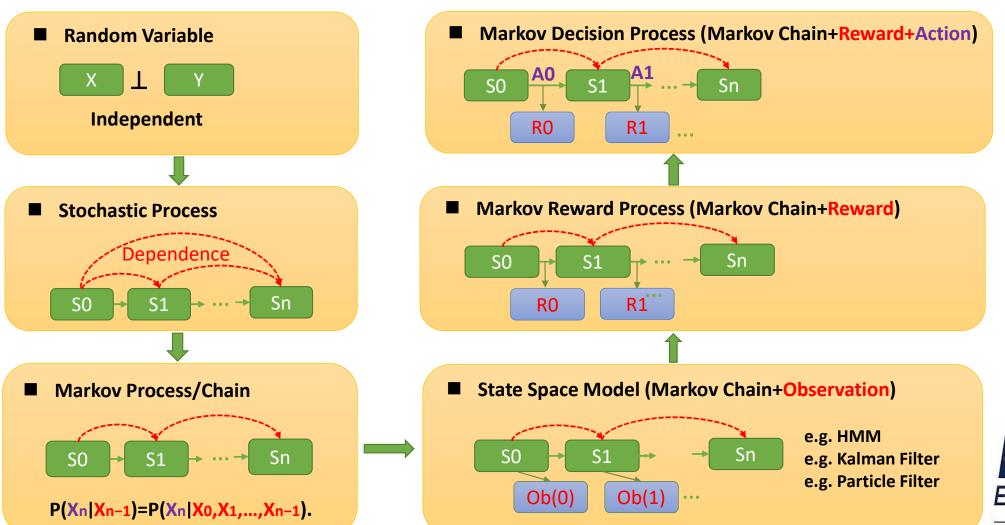
$$V^*(s) = \max_{a} \sum_{s'} T(s, a, s') [R(s, a, s') + \gamma V^*(s')]$$

TP Reinforcement Learning

Adriana TAPUS and Juan Jose Garcia Cardinas and Adnan Saood

<u>adriana.tapus@ensta-paris.fr</u> & <u>juan-jose.garcia@ensta.fr</u> & <u>adnan.saood@ensta-paris.fr</u>

1. Basic knowledge







2. Terminologies

Return: cumulative future reward

$$U_t = R_t + R_{t+1} + R_{t+2} + \dots$$

 R_t and R_{t+1} are important equally?

Discounted Return: discounted cumulative future reward

$$U_t = R_t + \gamma \cdot R_{t+1} + \gamma^2 \cdot R_{t+2} + \dots$$

Action-value function $Q_{\pi}(s_t, a_t)$

$$Q_{\pi}(s_t, \mathbf{a_t}) = \mathbb{E}\left[U_t | S_t = s_t, \mathbf{A_t} = \mathbf{a_t}\right]$$

State-value function (value used in task 2)

$$V_{\pi}(s_t) = \mathbb{E}_{\mathbf{A}}\left[Q_{\pi}(s_t, \mathbf{A})\right] = \sum_{\mathbf{a}} \pi(\mathbf{a}|s_t) \cdot Q_{\pi}(s_t, \mathbf{a})$$



Reinforcement Learning (RL)

- Learning through <u>Interaction with Environment</u>
- Agent is in State s
- Agent executes Action a
- Agent receives a Reward r(s,a) from the environment
- Goal: Maximize long-term discounted Reward

Value-Based RL

Policy Iteration:

- Start with random policy π_0
- Estimate Value-Function of π_i
- Improve $\pi_i \rightarrow \pi_{i+1}$ by making it greedy w.r.t. to the learned value function
- Exploration: Try out random actions to explore the state-space
- Repeat until Convergence

• Learning Algorithms:

- Q-Learning (off-policy), SARSA (on-policy)
- Actor-Critic Methods, etc.

3. Value iteration

Value iteration is a method of computing an optimal policy for an MDP (Markov Decision Process) and its value.

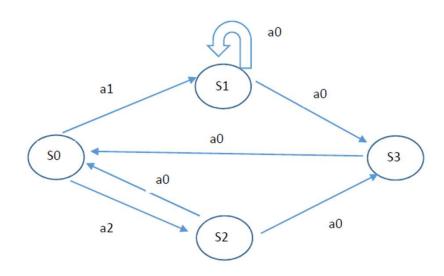
$$egin{aligned} Q_{k+1}\left(s,a
ight) &= R\left(s,a
ight) + \gamma * \sum_{s'} P\left(s' \mid s,a
ight) * V_k\left(s'
ight) \ &= \max_{a} Q_k\left(s,a
ight) \end{aligned}$$

$$\pi[s] = \operatorname{argmax}_{a} R(s,a) + \gamma * \sum_{s'} P(s'|s,a) \cdot V_{k}[s']$$

Interactive Example
https://perso.ensta-paris.fr/~saood/external/RL



4. Task 1



In the figure above, the states are depicted by circles (S0, S1, S2, and S3) and the associated actions are indicated on the arrows: a0, a1, and a2. The transition functions for all the actions are shown below.

Each of the parameters x and y are in the interval [0, 1], and the discounted factor $\gamma \in [0,1)$

The reward is:

$$R(s) = \begin{cases} 10, for state S3\\ 1, for state S2\\ 0, otherwise \end{cases}$$

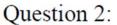


4. Task 1

Question 1:

Enumerate all the possible policies

$$\pi: s \to a$$

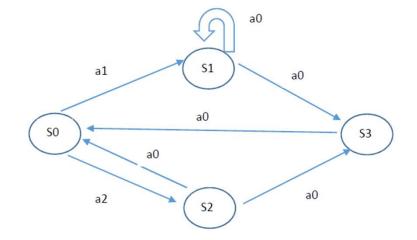


Write the equation for each optimal value function for each state

$$(V^*(s0), V^*(s1), V^*(s2), V^*(s3))$$

Reminder:

$$V^{*}(S) = R(s) + \max_{a} \gamma \sum_{S'} T(S, a, S') V^{*}(S')$$

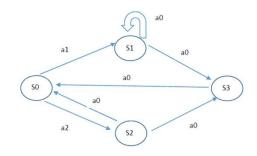




4. Task 1

Question 3:

Is there exist a value for x, that for all $\gamma \in [0,1)$, and $y \in [0,1]$, $\pi^*(s0) = a2$. Justify your answer.



 $R(s) \rightarrow not function of "a"$

Reminder:

$$\pi^*(s) = \arg \max_{a} \sum_{S'} T(S, a, S') V^*(S') \qquad V^*(S) = R(S) + \max_{a} \gamma \sum_{S'} T(S, a, S') V^*(S')$$

Question 4:

Is there exist a value for y, that for all x > 0, and $y \in [0,1]$, $\pi^*(s0) = a1$. Justify your answer.

Question 5: \rightarrow *python code*

Using x=y=0.25 and $\gamma = 0.9$, calculate the π^* and V^* for all states.

$$egin{aligned} Q_{k+1}\left(s,a
ight) &= R\left(s,a
ight) + \gamma * \sum_{s'} P\left(s' \mid s,a
ight) * V_k\left(s'
ight) \ &= \max_{a} Q_k\left(s,a
ight) \end{aligned}$$





Rule

- --In groups
- -- Deadline: before Tuesday 21/10
- Submit:
- -- Code + Readme file with Q1 to Q4
- -- Github or ENSTA gitlab



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Bienvenue sur le serveur GitLab de DaTA, l'association d'informatique de l'ENSTA!







End! Questions?

