Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 3

Sep, 12 2016

Lecture on Wed is cancelled

Lecture Overview

Markov Decision Processes

- Formal Specification and example
- Policies and Optimal Policy
- Intro to Value Iteration

Combining ideas for Stochastic planning

- What is a key limitation of decision networks?

Represent (and optimize) only a fixed number of decisions

- What is an advantage of Markov models?

The network can extend indefinitely

Goal: represent (and optimize) an indefinite sequence of decisions

Decision Processes

Often an agent needs to go beyond a fixed set of decisions – Examples?

- Would like to have an **ongoing decision process**

Infinite horizon problems: process does not stop

Robot surviving on planet, Monitoring Nuc. Plant, ...

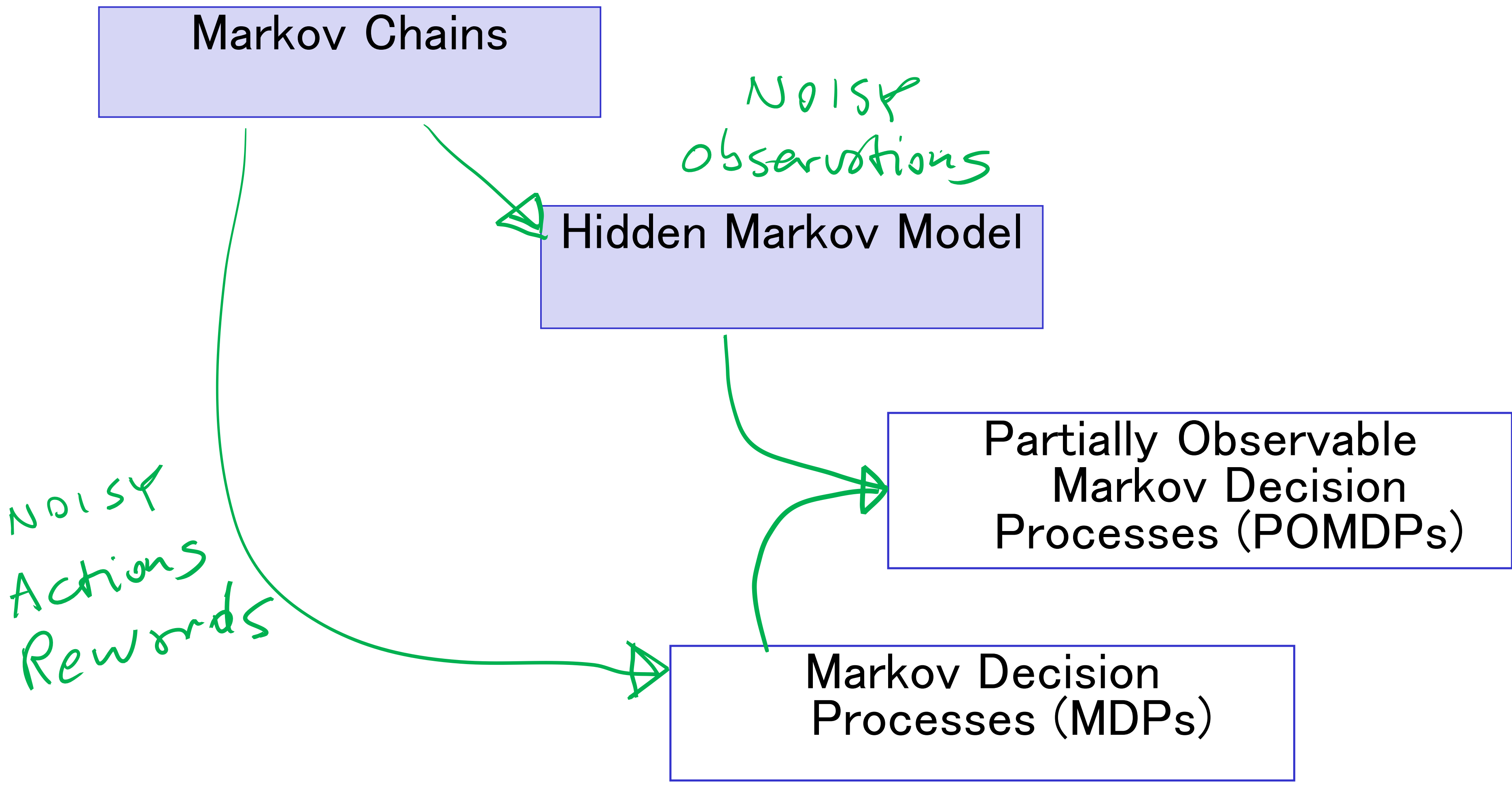
Indefinite horizon problem: the agent does not know when the process may stop

reaching location

Finite horizon: the process must end at a give time N

in N steps

Markov Models



Summary Decision Processes: MDPs

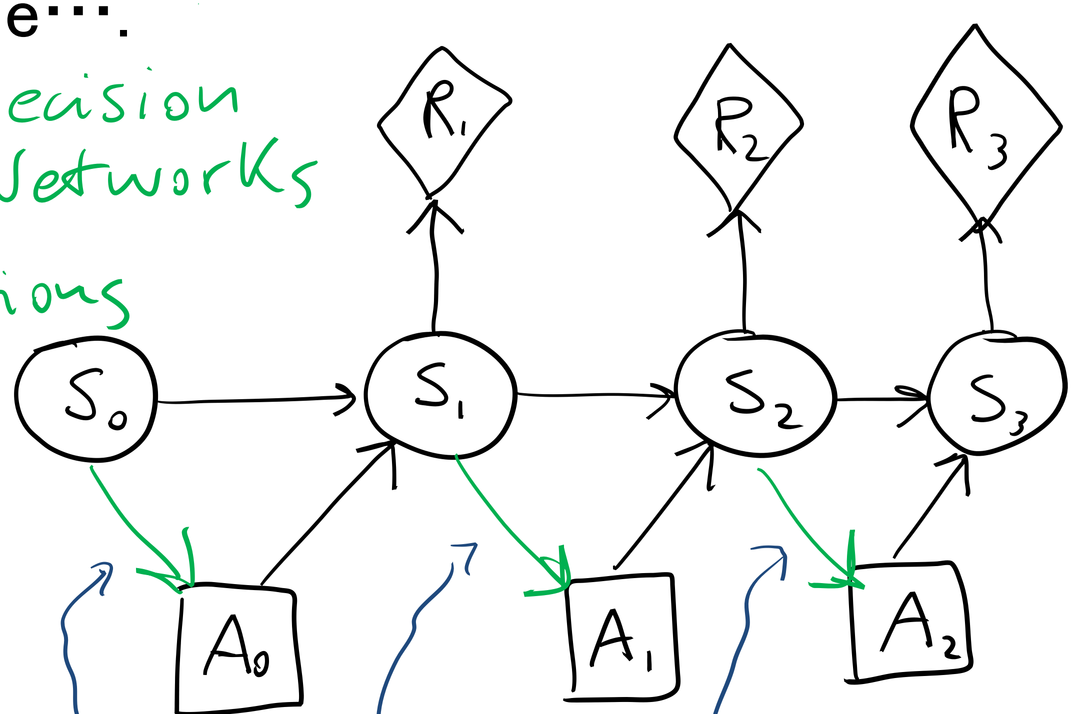
To manage an ongoing (indefinite… infinite) decision process, we combine….

Markov Chains & Decision Networks

Markovian

Stationary

Assumptions



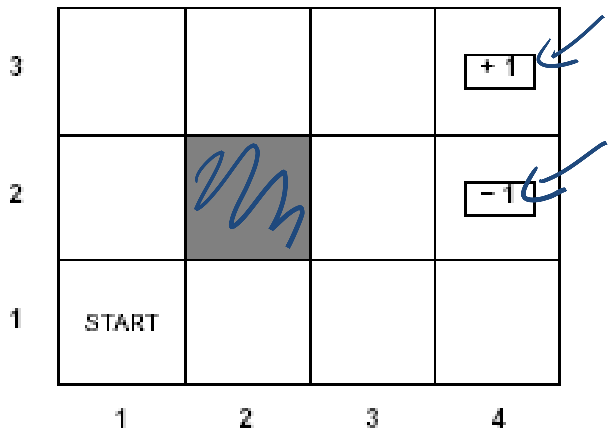
Utility not just at the end

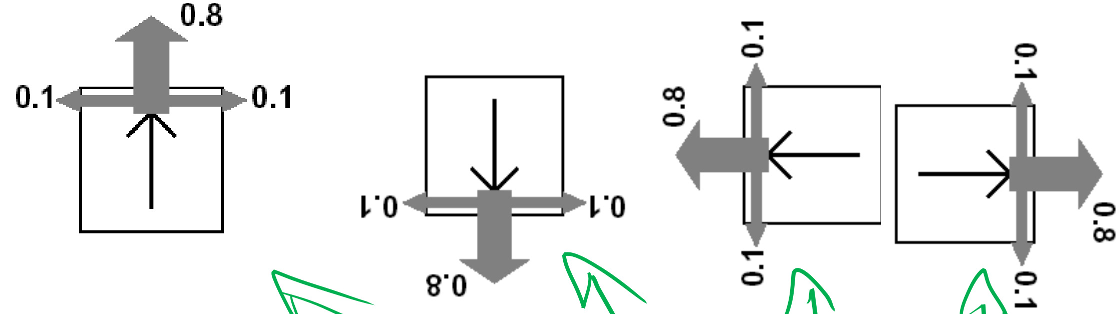
BUT

Sequence of rewards

Fully Observable

Example MDP: Scenario and Actions





Agent moves in the above grid via actions *Up, Down, Left, Right*

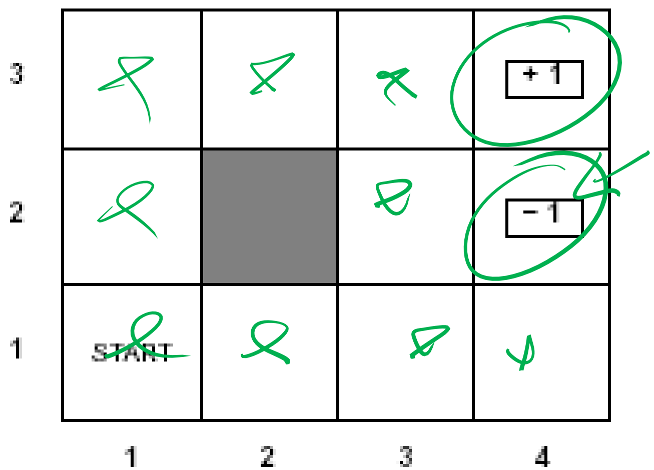
Each action has:

- 0.8 probability to reach its intended effect
- 0.1 probability to move at right angles of the intended direction
- If the agents bumps into a wall, it says there

How many states? 11 {(11),(12), ... ,(24),(34)}

There are two terminal states (3,4) and (2,4)

Example MDP: Rewards

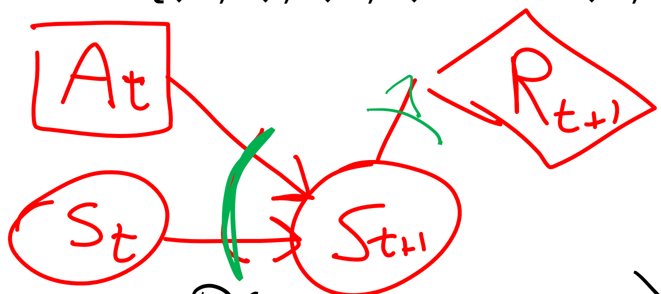


$$R(s) = \begin{cases} -0.04 & \text{(small penalty) for nonterminal states} \\ \pm 1 & \text{for terminal states} \end{cases}$$

Example MDP: Underlying info structures

Four actions *Up, Down, Left, Right*

Eleven States: {(1,1), (1,2)······ (3,4)}



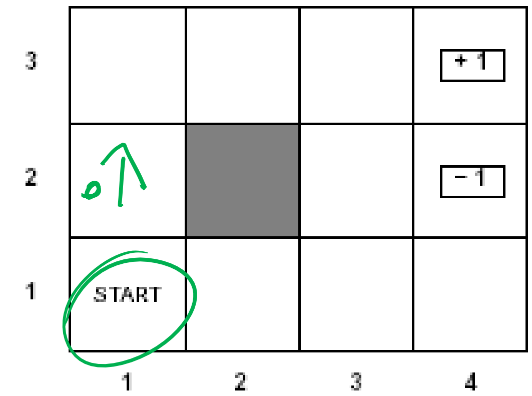


Table 4 x 11 x 11 $P(S_{t+1} \mid S_t, A_t)$

Up

	1,1	2,1	1,2	3,1
1,1	.1	.8	.1	0 0 0 0
2,1	0	.2	0	.8

Down

L

R

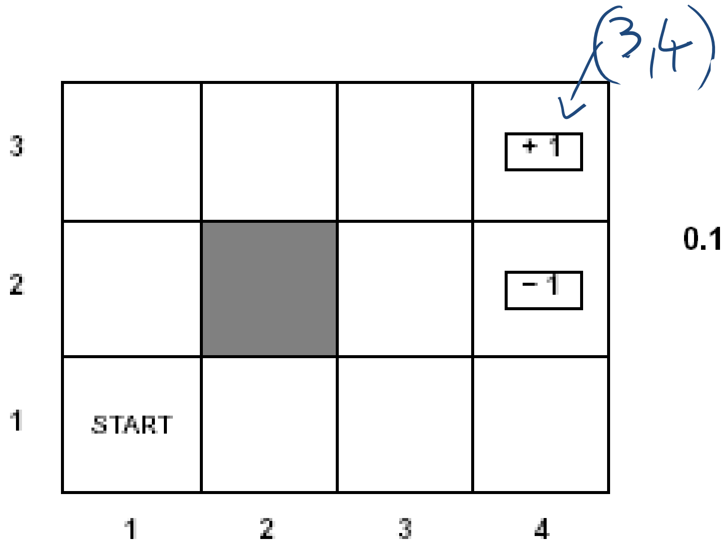
$P(S_0)$

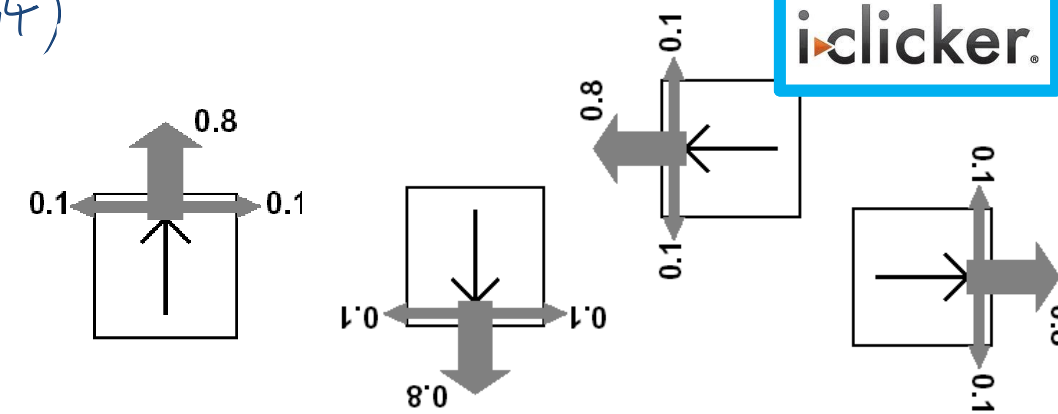
1,1	1
	0
	0
	0
	0
	0
	0

$R(s)$

1 1	−.04
(2 4)	−1
(3 4)	+1

Example MDP: Sequence of actions





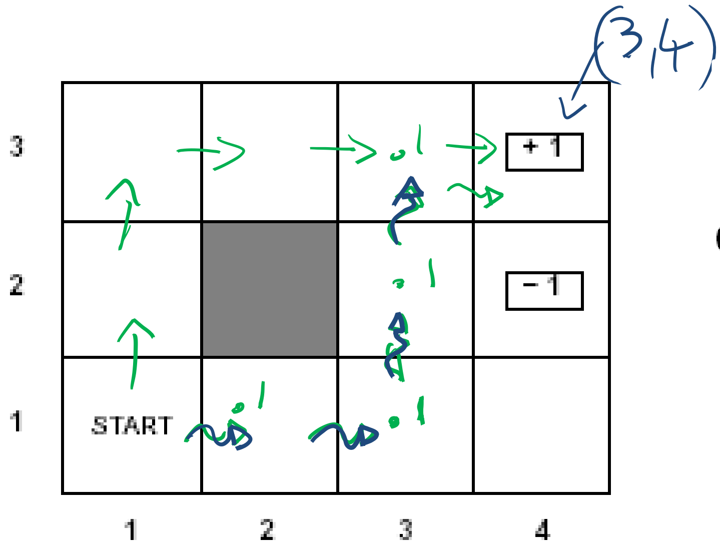
The sequence of actions [*Up, Up, Right, Right, Right*] will take the agent in terminal state (3,4)…

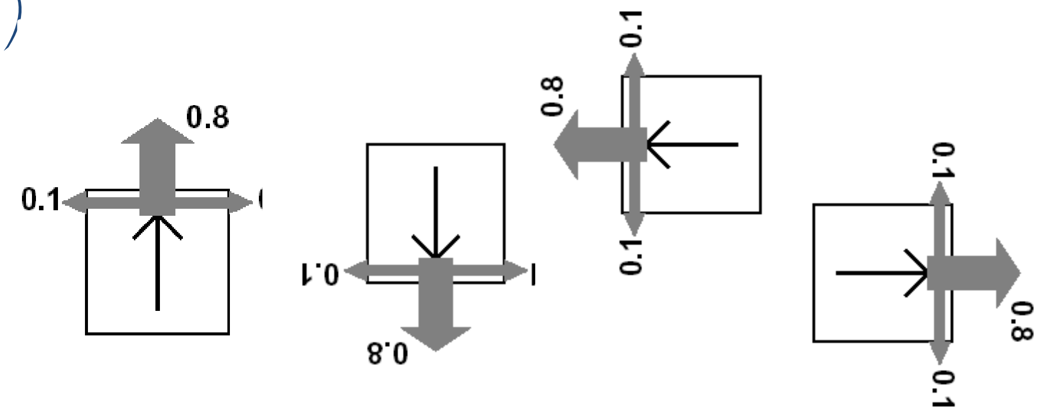
A. *always* B. *never* C. *Only sometimes*

With what probability?

A. $(0.8)^5$ B. $(0.8)^5 + ((0.1)^4 \times 0.8)$ C. $((0.1)^4 \times 0.8)$

Example MDP: Sequence of actions





Can the sequence [*Up, Up, Right, Right, Right*] take the agent in terminal state (3,4)?

$(.8)^5$

Can the sequence reach the goal in any other way?

$(.1)^4 \, .8$ ← with prob

yes

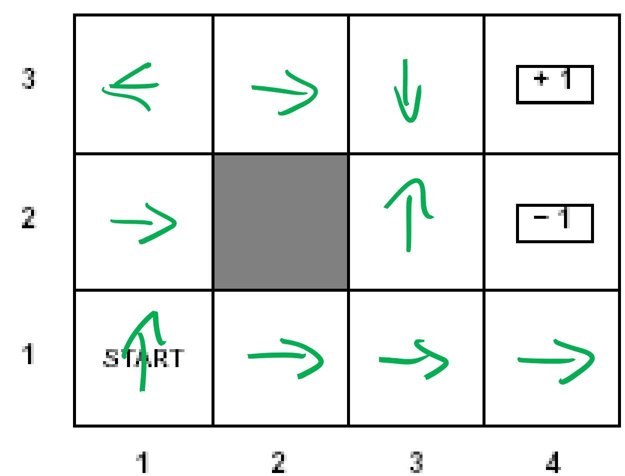
MDPs: Policy

- The robot needs to know what to do as the decision process unfolds…
- It starts in a state, selects an action, ends up in another state selects another action….

- Needs to make the same decision over and over: Given the current state what should I do?

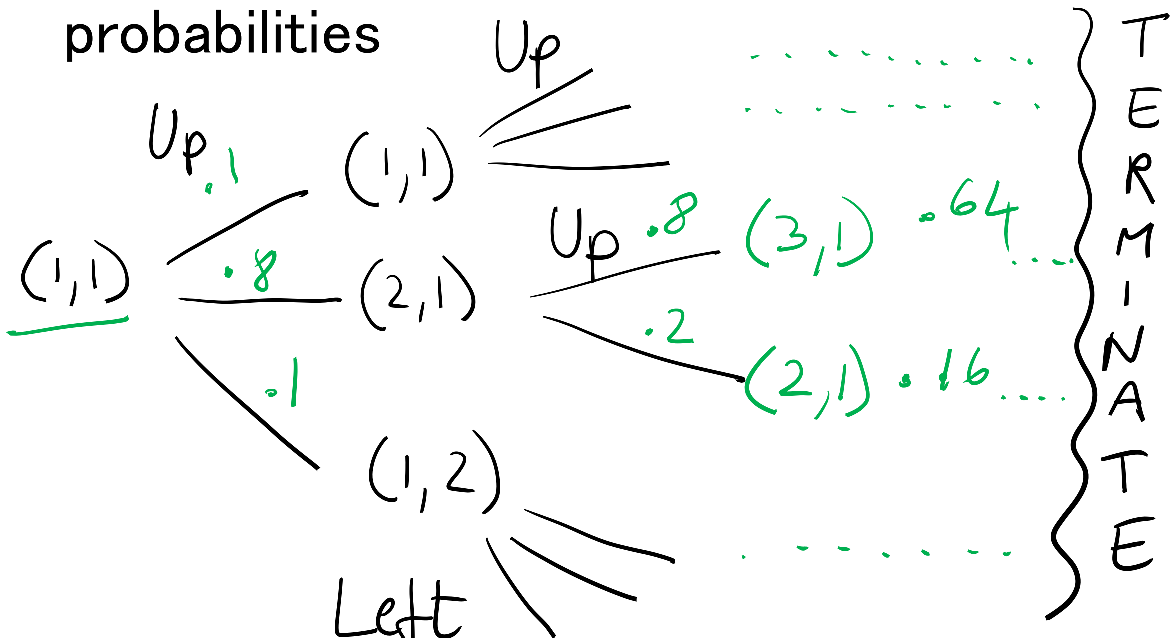
policy

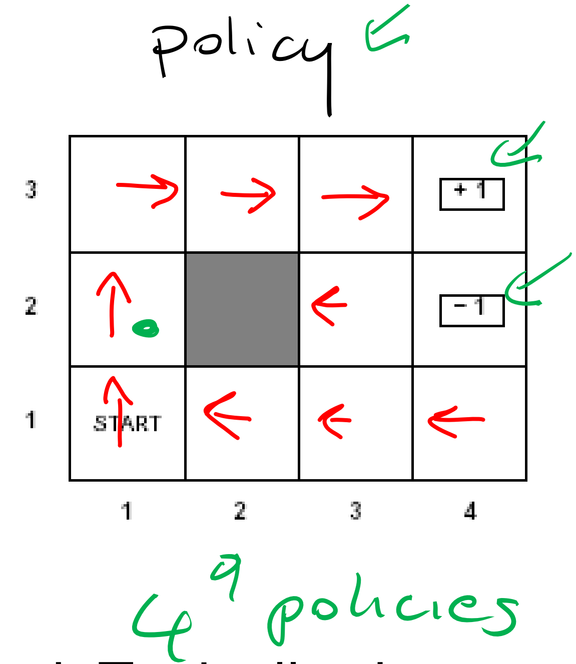
- So a policy for an MDP is a single decision function $\pi(s)$ that specifies what the agent should do for each state s



How to evaluate a policy

A policy can generate a set of state sequences with different probabilities





Each state sequence has a corresponding reward. Typically the (*discounted*) sum of the rewards for each state in the sequence

$$\sum \underset{-.04}{(1,1)} \rightarrow \underset{-.04}{(1,1)} \rightarrow (2,1) \rightarrow (3,1) \rightarrow (3,1) \rightarrow (3,2) \rightarrow (3,3) \rightarrow \underset{+1}{(3,4)}$$

$+.72$

MDPs: expected value/total reward of a policy and optimal policy

Each sequence of states (environment history) associated with a policy has

- a certain **probability** of occurring
- a given amount of total **reward** as a function of the rewards of its individual states

Expected value /total reward

$$\sum \overbrace{P(s_0, s_1, \ldots, s_{\text{TERMINAL}})}^{\text{probability}} * \overbrace{\sum R(s_0) \ldots R(s_T)}^{\text{rewards}}$$

For all the sequences of states generated by the policy

we sum the product of its probability times its reward

Optimal policy is the policy that maximizes *expected total reward*

Lecture Overview

Markov Decision Processes

- Formal Specification and example
- Policies and Optimal Policy
- **Intro to Value Iteration**

Sketch of ideas to find the optimal policy for a MDP (Value Iteration)

We first need a couple of definitions

- $V^{\pi}(s)$: the expected value of following policy π in state s
- $Q^{\pi}(s, a)$, where a is an action: expected value of performing *a* in *s*, and then following policy π.

Can we express $Q^{\pi}(s, a)$ in terms of $V^{\pi}(s)$?

$$Q^{\pi}(s, a) = V^{\pi}(s) + R(s)$$

A.

$$Q^{\pi}(s, a) = R(s) + \sum_{s' \in X} P(s' | s, a) * V^{\pi}(s')$$

B.

$$Q^{\pi}(s, a) = R(s) + \sum_{s' \in X} V^{\pi}(s')$$

C.

D. None of the above

X: set of states reachable from *s* by doing *a*

Discounted Reward Function

- Suppose the agent goes through states s_1, s_2,...,s_k and receives rewards r_1, r_2,...,r_k
- We will look at ***discounted reward*** to define the reward for this sequence, i.e. its *utility* for the agent

$$\gamma \ \textbf{\textit{discount factor}},\ 0 \le \gamma \le 1$$

$R_{\max}$ bound on R(s) for every s

$$U[s_1, s_2, s_3, ..] = r_1 + \gamma r_2 + \gamma^2 r_3 + ...$$

$$= \sum_{i=0}^{\infty} \gamma^i r_{i+1} \le \sum_{i=0}^{\infty} \gamma^i R_{\max} = \frac{R_{\max}}{1-\gamma}$$

Sketch of ideas to find the optimal policy for a MDP (Value Iteration)

We first need a couple of definitions STOP HERE

- $V^{\pi}(s)$: the expected value of following policy π in state *s*
- $Q^{\pi}(s, a)$, where *a* is an action: expected value of performing *a* in *s*, and then following policy π.

We have, by definition

$$Q^{\pi}(s, a) = R(s) + \gamma \sum_{s'} P(s' \mid s, a) V^{\pi}(s')$$

reward obtained in *s*

Discount factor

states reachable from *s* by doing *a*

Probability of getting to *s'* from *s* via *a*

expected value of following policy π in *s'*

Value of a policy and Optimal policy

We can also compute $V^{\pi}(s)$ in terms of $Q^{\pi}(s, a)$

$$V^{\pi}(s) = Q^{\pi}(s, \pi(s))$$

Expected value of following π in s

Expected value of performing the action indicated by π in s and following π after that

action indicated by π in s

For the optimal policy $\pi *$ we also have

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

Value of Optimal policy

$$V^{\pi^*}(s) \;=\; Q^{\pi^*}(s, \pi^*(s))$$

Remember for any policy π

$$Q^{\pi}(s, \pi(s)) = R(s) + \gamma \sum_{s'} P(s' | s, \pi(s)) \times V^{\pi}(s'))$$

But the Optimal policy π * is the one that gives the action that maximizes *the future reward* for each state

$$\overset{V^{\pi^*}(s)}{\cancel{Q^{\pi^*}(s, \pi^*(s))}} = R(s) + \gamma \max_a \sum_{s'} P(s' | s, a) \times V^{\pi^*}(s')$$

$\Downarrow$

So…

$$V^{\pi^*}(s) = R(s) + \gamma \max_a \sum_{s'} P(s' | s, a) \times V^{\pi^*}(s'))$$

Value Iteration Rationale

- Given *N* states, we can write an equation like the one below for each of them

$$\boxed{V(s_1) = R(s_1) + \gamma \max_a \sum_{s'} P(s'|s_1,a)V(s')}$$

$$\boxed{V(s_2) = R(s_2) + \gamma \max_a \sum_{s'} P(s'|s_2,a)V(s')}$$

- Each equation contains *N* unknowns – the V values for the *N* states
- N equations in N variables (Bellman equations): It can be shown that they have a unique solution: the values for the optimal policy
- Unfortunately the N equations are non-linear, because of the max operator: Cannot be easily solved by using techniques from linear algebra
- **Value Iteration Algorithm**: Iterative approach to find the optimal policy and corresponding values

Learning Goals for today's class

You can:

- Compute the probability distribution on states given a sequence of actions in an MDP
- Define a policy for an MDP
- Define and Justify a discounted reward function
- Derive the Bellman equations on which Value Iteration is based (we will likely finish this in the next lecture)

Lecture on Wed is cancelled ☹

TODO for Fri

Read textbook

- 9.5.3 Value Iteration