Sequential decisions under uncertainty
Markov Decision Processes (MDP)

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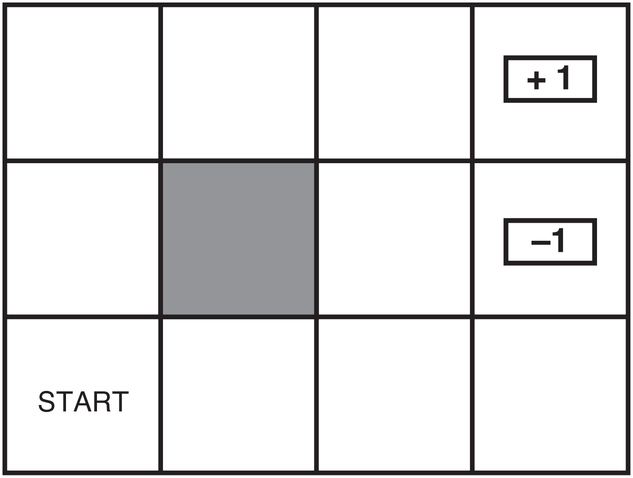
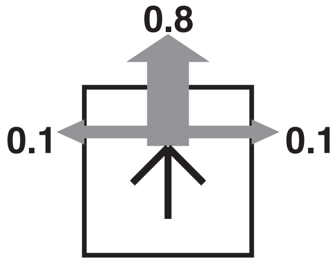
Notes

Unreliable actions in observable grid world





States $s \in \mathcal{S}$, actions $a \in \mathcal{A}$
Model $T(s, a, s') \equiv p(s'|s, a)$ = probability that a in s leads to s'

Notes

Beginning of semester – search – *deterministic* and (fully) *observable* environment
Now:

- Observable – we keep for now – agent knows where it is.
- Deterministic – We introduce "imperfect" agent that does not always obey the command – *stochastic action outcomes*.

There is a treasure (desired goal/end state) but there is also some danger (unwanted goal/end state).
The danger state: think about a mountainous area with safer but longer and shorter but more dangerous paths – a dangerous node may represent a chasm.

Notation note: caligraphic letters like $\mathcal{S}, \mathcal{A}$ will denote the set(s) of all states/actions.

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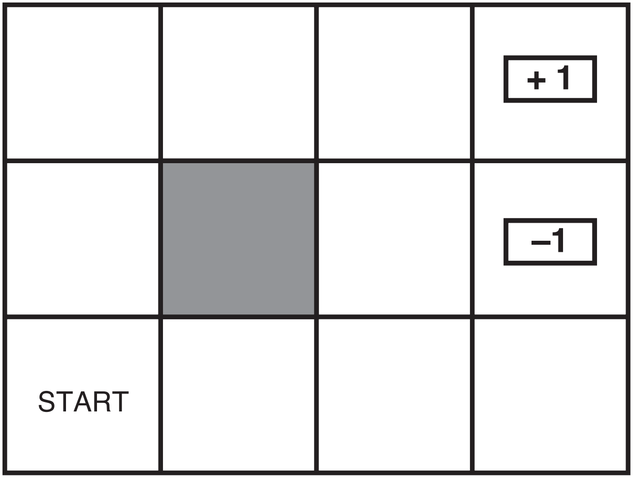

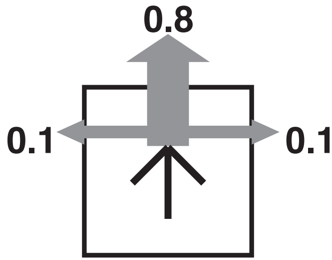

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Unreliable actions

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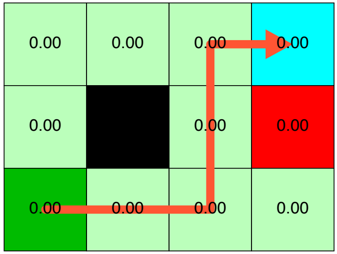
Actions: go over a glacier bridge or around?

Plan? Policy

- In deterministic world: Plan – sequence of actions from Start to Goal.
- MDPs, we need a policy $\pi : \mathcal{S} \rightarrow \mathcal{A}$.
- An action for each possible state.
- What is the best policy?



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Unlike in deterministic environment (also search problems), with stochastic action outcomes, we can end up in any state. Thus, in any state, the robot/agent has to know what to do.

What is the best policy? We will come to that in a minute, ...

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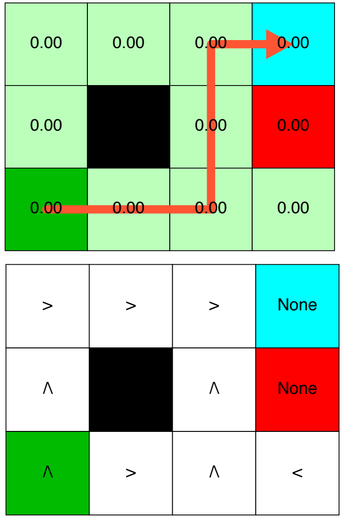

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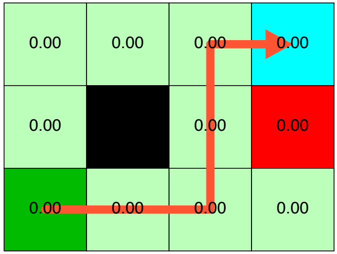

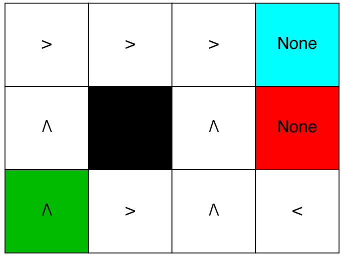

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Rewards

-0.04	-0.04	-0.04	1.00
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Reward : Robot/Agent takes an action a and it is **immediately** rewarded.

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

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

Notes

What do the rewards express? Reward to an agent to be/dwell in that state? Obviously we want the robot to go to the goal and do not stay too long in the maze. The negative reward of 0.04 gives the agent an incentive to reach the goal state quickly, so our environment is a *stochastic generalization of the search problems*.

Thinking about Reward: Robot/Agent takes an action a and it is immediately rewarded for this. The reward may depend on

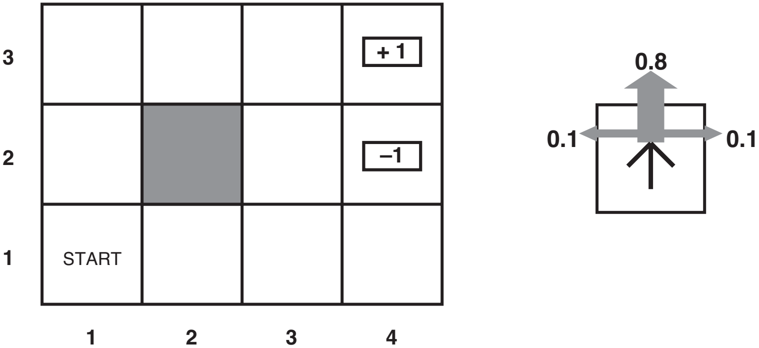
- current state s,
- the action taken a
- the next state s' - result of the action.

Rewards for terminal states can be understood in a way: there is only one action: $a =$ exit. We will come to this soon.

The **reward function** is a property of (is related to) the problem.

Notation remark: lowercase letters will be used for functions like $p, r, v, f, \ldots$

Markov Decision Processes (MDPs)



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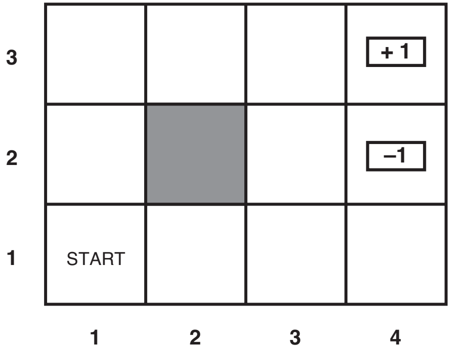

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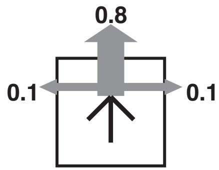

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Markovian property

- Given the present state, the future and the past are independent.
- MDP: Markov means action depends only on the current state.
- In search: successor function (transition model) depends on the current state only.

Notes

Optimal(?) policies

On-line demos.

- $r(s) = \{-0.04, 1, -1\}$
- $r(s) = \{-2, 1, -1\}$
- $r(s) = \{-0.01, 1, -1\}$

How to measure quality of a policy?

Notes

We run `mdp_agents.py` changing reward functions.

- $r(s) = \{-0.04, 1, -1\}$
- $r(s) = \{-2, 1, -1\}$ - environment very hostile -
  heading for nearest exit even if it's with negative reward
- $r(s) = \{-0.01, 1, -1\}$ - environment very mildly unpleasant -
  conservative policy (banging head against the wall to avoid negative terminal state at all cost)

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Utilities of sequences

- State reward at time/step t, R_t.
- State at time t, S_t. State sequence $[S_0, S_1, S_2, \ldots,]$

Typically, consider stationary preferences on reward sequences:

$$[R, R_1, R_2, R_3, \ldots] \succ [R, R'_1, R'_2, R'_3, \ldots] \Leftrightarrow [R_1, R_2, R_3, \ldots] \succ [R'_1, R'_2, R'_3, \ldots]$$

If stationary preferences:
Utility (h-history)
$U_h([S_0, S_1, S_2, \ldots,]) = R_1 + R_2 + R_3 + \cdots$

Notes

We consider discrete time t. S_t, R_t notation emphasises the time sequence - not a sequence of particular states. The reward is for an action (transition)

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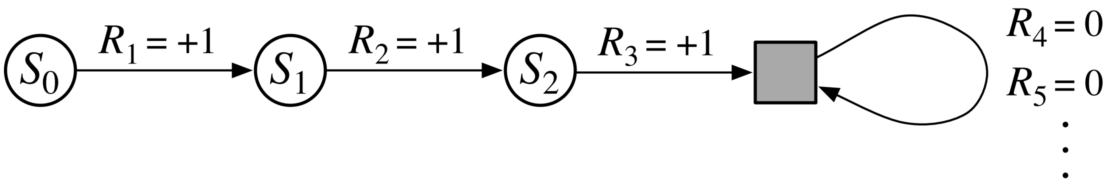
Returns and Episodes

- Executing policy - sequence of states and **rewards**.
- Episode starts at t, ends at T (ending in a terminal state).
- Return (Utility) of the episode (policy execution)

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$$

Notes



Solid

square – *absorbing state* – end of an episode.
(transitions only to itself and generates only rewards of zero)
Allows to unify two formulations of return (G_t) as a finite and infinite sum of rewards.

Comparing policies; Finite vs infinite horizon

Problem: Infinite lifetime $\Rightarrow$ additive utilities are infinite.

- Finite horizon: termination at a fixed time $\Rightarrow$ nonstationary policy, $\pi(s)$ depends on the time left.
- Discounted return , $\gamma < 1$, $R_t \leq R_{\max}$

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- Absorbing (terminal) state.

Returns are successive steps related to each other

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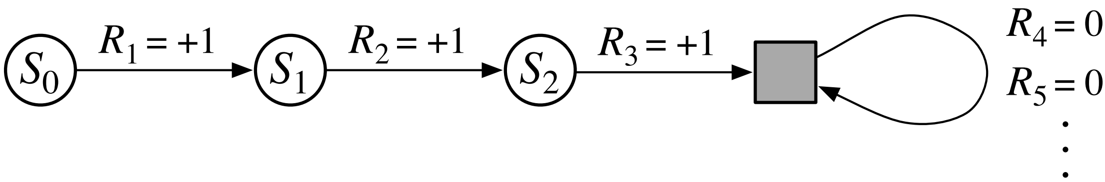

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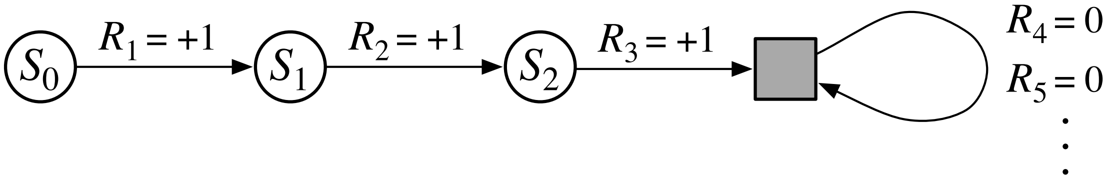

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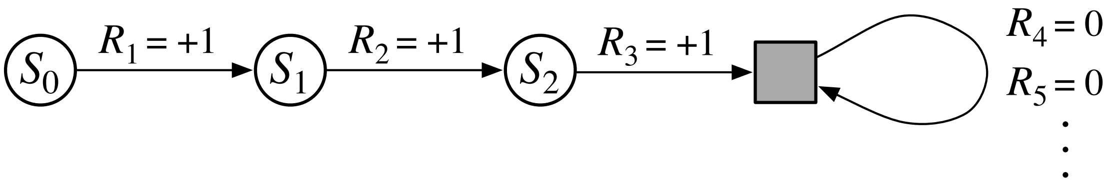

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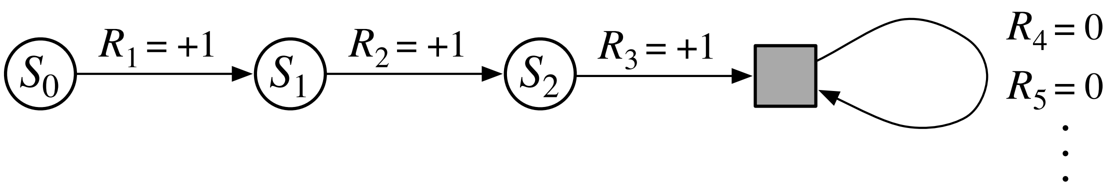

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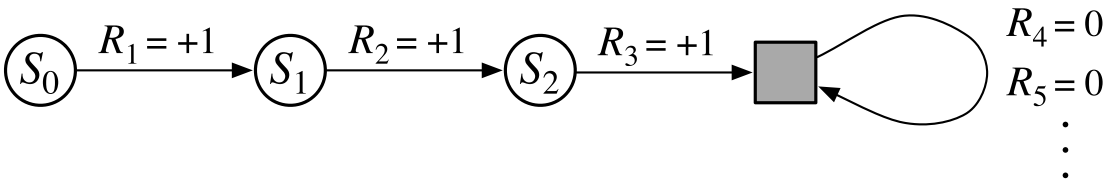

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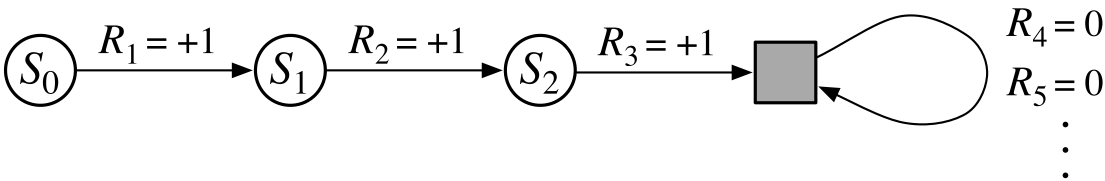

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$$\begin{aligned} G_t &= R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 R_{t+4} + \cdots \\ &= R_{t+1} + \gamma(R_{t+2} + \gamma^1 R_{t+3} + \gamma^2 R_{t+4} + \cdots) \\ &= R_{t+1} + \gamma G_{t+1} \end{aligned}$$

Solid square – *absorbing state* – end of an episode.
(transitions only to itself and generates only rewards of zero)

Allows to unify two formulations of return (G_t) as a finite and infinite sum of rewards.

Comparing policies; Finite vs infinite horizon

Problem: Infinite lifetime ⇒ additive utilities are infinite.

- Finite horizon: termination at a fixed time ⇒ nonstationary policy, $\pi(s)$ depends on the time left.
- Discounted return , $\gamma < 1, R_t \leq R_{\max}$

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \leq \frac{R_{\max}}{1-\gamma}$$

- Absorbing (terminal) state.

Returns are successive steps related to each other

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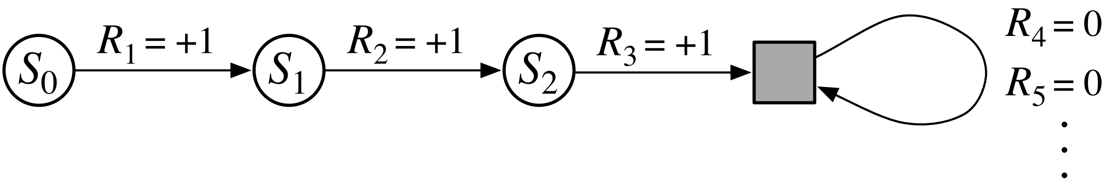
Notes

Discounting is quite natural choice. Think about your preferences/rewards. Go to pub with friends tonight, studying (for the far future reward of getting A in the course)?



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MDPs recap

Markov decition processes (MDPs):

- Set of states $\mathcal{S}$
- Set of actions $\mathcal{A}$
- Transitions $p(s'|s, a)$ or $T(s, a, s')$
- Reward function $r(s, a, s')$; and discount γ

MDP quantities:

- (deterministic) Policy $\pi(s)$ – choice of action for each state
- Return (Utility) of an episode (sequence) – sum of (discounted) rewards.

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Notes

Value functions

- Executing policy π - sequence of states (and rewards).
- Utility of a state sequence.
- But actions are unreliable - environment is stochastic.
- Expected return of a policy π.

Starting at time t, i.e. S_t,

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

Value function

$$v^\pi(s) = \mathrm{E}^\pi\left[G_t \mid S_t = s\right] = \mathrm{E}^\pi\left[\sum_{k=0}^{\infty}\gamma^k R_{t+k+1}\,\middle|\, S_t = s\right]$$

Action-value function (q-function)

$$q^\pi(s,a) = \mathrm{E}^\pi\left[G_t \mid S_t = s, A_t = a\right] = \mathrm{E}^\pi\left[\sum_{k=0}^{\infty}\gamma^k R_{t+k+1}\,\middle|\, S_t = s, A_t = a\right]$$

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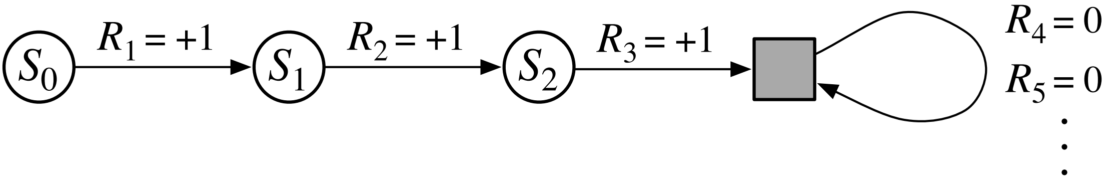

Contrast *return* of a particlar episode vs. *value* – expected utility of a state sequence in general – *expected return*
Expected value can be also computed by running (executing) the policy many times and then computing average - Monte Carlo simulation methods.

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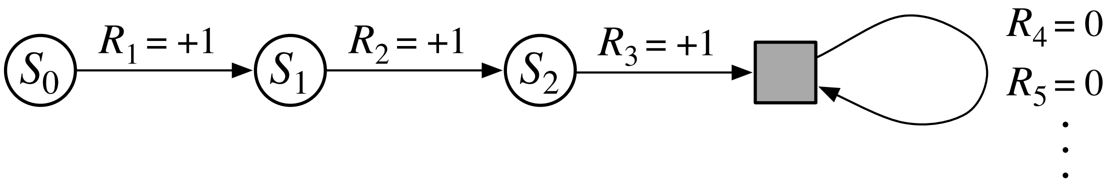

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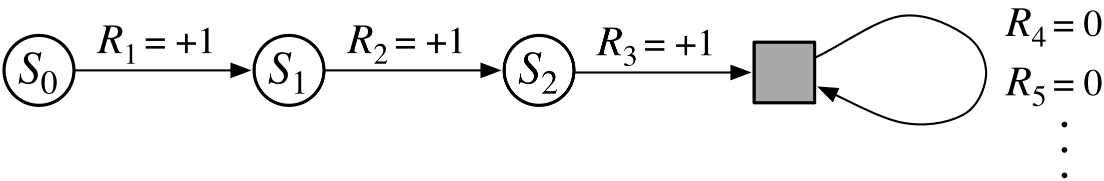

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Optimal policy π^*, and optimal value $v^*(s)$

$v^*(s)$ = expected (discounted) sum of rewards (until termination) assuming *optimal* actions.

Notes

Showing cases for

- $r(s) = \{-0.04, 1, -1\}$, $\gamma = 0.999999$, $\epsilon = 0.03$
- $r(s) = \{-0.01, 1, -1\}$, $\gamma = 0.999999$, $\epsilon = 0.03$

What is the difference in the optimal policy? Try to explain why it happened.
We still do not know *how* to compute the optimality, ... right?

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	0	1	2	3	
0	0.81	0.87	0.92	1.00	0
1	0.76		0.66	-1.00	1
2	0.70	0.65	0.61	0.39	2
	0	1	2	3	

	0	1	2	3	
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1	∧		∧	-1.00	1
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0	0.95	0.96	0.98	1.00	0
1	0.94		0.89	-1.00	1
2	0.92	0.91	0.90	0.80	2
	0	1	2	3	

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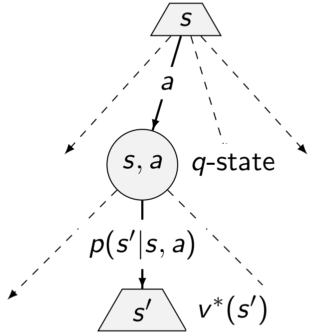
MDP search tree

The value of a q-state (s, a):

$$q^*(s,a) = \sum_{s'} p(s'|a,s)\left[r(s,a,s') + \gamma\, v^*(s')\right]$$

The value of a state s:

$$v^*(s) = \max_a q^*(s,a)$$



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Recall Expectimax algorithm from the last lecture.
How to compute $V(s)$? Well, we could solve the expectimax search - but it grows quickly. We can see $R(s)$ as the price for leaving the state s just anyhow.

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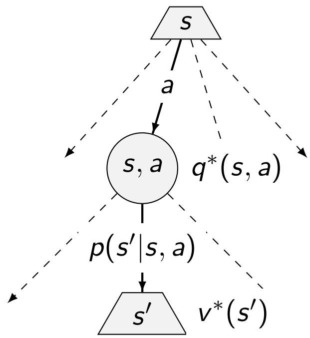

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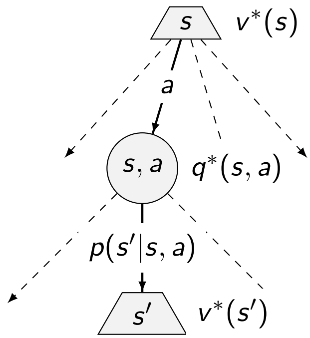

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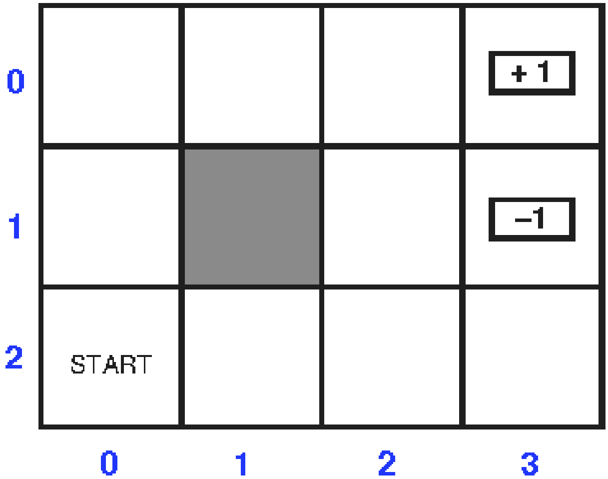
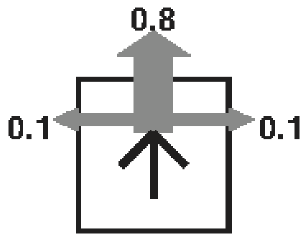
Bellman (optimality) equation

$$v^*(s) = \max_{a \in A(s)} \sum_{s'} p(s'|a,s) \left[r(s,a,s') + \gamma v^*(s') \right]$$





Notes

v computation on the table - one row for each action. We got n equations for n unknown - n states. But max is a non-linear operator!

Value iteration

- Start with arbitrary $V_0(s)$ (except for terminals)
- Compute Bellman update (one ply of expectimax from each state)

$$V_{k+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} p(s'|s,a) V_k(s')$$

- Repeat until convergence

The idea: Bellman update makes local consistency with the Bellmann equation. Everywhere locally consistent $\Rightarrow$ globally optimal.

Notes

What is the complexity of each iteration? $O(S^2 A)$

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Convergence

$$V_{k+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) V_k(s')$$

$$\gamma < 1$$

$$-R_{\max} \le R(s) \le R_{\max}$$

Max norm:

$$\|V\| = \max_s |V(s)|$$

$$U([s_0, s_1, s_2, \ldots, s_\infty]) = \sum_{t=0}^{\infty} \gamma^t R(s_t) \le \frac{R_{\max}}{1-\gamma}$$

Notes

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Notes

Convergence cont'd

$V_{k+1} \leftarrow BV_k$
$\|BV_k - BV'_k\| \leq \gamma \|V_k - V'_k\|$
$\|BV_k - V_{\text{true}}\| \leq \gamma \|V_k - V_{\text{true}}\|$
Rewards are bounded, at the beginning then Value error is
$\|V_0 - V_{true}\| \leq \frac{2R_{\max}}{1-\gamma}$
We run N iterations and reduce the error by factor γ in each and want to stop the error is below ϵ:
$\gamma^N 2R_{\max}/(1-\gamma) \leq \epsilon$ Taking logs, we find: $N \geq \frac{\log(2R_{\max}/\epsilon(1-\gamma))}{\log(1/\gamma)}$
To stop the iteration we want to find a bound relating the error to the size of *one* Bellman update for any given iteration.
We stop if

$$\|V_{k+1} - V_k\| \leq \frac{\epsilon(1-\gamma)}{\gamma}$$

then also: $\|V_{k+1} - V_{\text{true}}\| \leq \epsilon$ Proof on the next slide

Notes

Try to proove that:

$$\|\max f(a) - \max g(a)\| \leq \max \|f(a) - g(a)\|$$

Convergence cont'd

$\|V_{k+1} - V_{\text{true}}\| \leq \epsilon$ is the same as $\|V_{k+1} - V_{\infty}\| \leq \epsilon$
Assume $\|V_{k+1} - V_k\| = \text{err}$
In each of the following iteration steps we reduce the error by the factor γ. Till ∞, the total sum of reduced errors is:

$$\text{total} = \gamma \text{err} + \gamma^2 \text{err} + \gamma^3 \text{err} + \gamma^4 \text{err} + \cdots = \frac{\gamma \text{err}}{(1-\gamma)}$$

We want to have total $< \epsilon$.

$$\frac{\gamma \text{err}}{(1-\gamma)} < \epsilon$$

From it follows that

$$\text{err} < \frac{\epsilon(1-\gamma)}{\gamma}$$

Hence we can stop if $\|V_{k+1} - V_k\| < \epsilon(1-\gamma)/\gamma$

Notes

Value iteration demo

$$V_{k+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a) V_k(s')$$

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Notes

Run `mdp_agents.py` and try to compute next state value in advance. Remind the $R(s) = -0.04$ and $\gamma = 1$ in order to simplify computation. Then discuss the course of the Values.

Value iteration algorithm

function VALUE-ITERATION(env,ϵ) **returns:** state values V
    input: env - MDP problem, ϵ
    $V' \leftarrow 0$ in all states
    repeat $\triangleright$ iterate values until convergence
        $V \leftarrow V'$ $\triangleright$ keep the last known values
        $\delta \leftarrow 0$ $\triangleright$ reset the max difference
        for each state s **in** S **do**
            $V'[s] \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s,a)V(s')$
            if $|V'[s] - V[s]| > \delta$ **then** $\delta \leftarrow |V'[s] - V[s]|$
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Notes

References

Some figures from [1] (chapter 17) but notation slightly changed in order to adapt notation from [2] (chapters 3, 4) which will help us in the Reinforcement Learning part of the course. Note that the book [2] is available on-line.

[1] Stuart Russell and Peter Norvig.
Artificial Intelligence: A Modern Approach.
Prentice Hall, 3rd edition, 2010.
http://aima.cs.berkeley.edu/.

[2] Richard S. Sutton and Andrew G. Barto.
Reinforcement Learning; an Introduction.
MIT Press, 2nd edition, 2018.
http://www.incompleteideas.net/book/the-book-2nd.html.

Notes