ROB311 Quiz 2

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Contents

Single-Agent Decision Problems: Fully-Observable Single-Agent Decision Algorithms

1 Markov

1.1 General

1.1.1 Random Process

Definition: Time-varying random variables $S_0, S_1, S_2, \ldots$.

1.1.2 Markov Process

Definition: Random process + depends on previous time step only (memoryless)
- w.l.o.g. states can contain history of previous states.

1.2 Markov Chains (MCs)

Summary: In a **Markov Chain**, we assume that:
- there are no agents
- state transitions occur automatically
- S_t is the state *after* transition t
- the state transition process is stochastic and memoryless:

$$S_t \perp S_0, \ldots, S_{t-2} \mid S_{t-1}$$

  - S_t is independent of all previous states given S_{t-1}

Name	Function:
initial state distribution	$p_0(s) := \mathbb{P}[S_0 = s]$
transition distribution	$p(s'\|s) := \mathbb{P}[S_{t+1} = s'\|S_t = s]$
Prob. that state of the env. after T transitions is s	$p_T(s) := \mathbb{P}[S_T = s] = \sum_{s'} p_{T-1}(s')p(s\|s')$

- $p_{T-1}(s')$: Prob. s' at T-1 (given)
  - $p_0(s)$: Base case
- $p(s|s')$: Prob. s given s' (from graph)

1.2.1 Bayesian Network

Notes: $S_0, S_1, S_2, \ldots$ form a **Bayesian Network**:

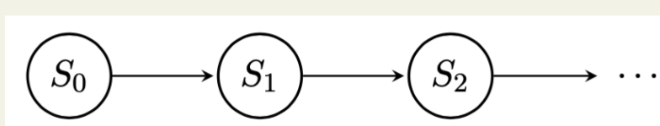

Figure 1

1.3 Markov Reward Processes (MRPs)

Summary: In a **Markov Reward Process**, we assume that:

- there is one agent
- state transitions occur automatically (i.e. agent has no control over actions)
- S_t is the state *after* transition t
- the state transition process is stochastic and memoryless:

$$S_t \perp S_0, \ldots, S_{t-2} \mid S_{t-1}$$

  - S_t is independent of all previous states given S_{t-1}
- R_t is the reward for transition t, i.e., $(S_{t-1}, \varnothing, S_t)$

Name	**Function:**
Initial state distribution	$p_0(s) := \mathbb{P}[S_0 = s]$
Transition distribution	$p(s'\|s) := \mathbb{P}[S_{t+1} = s'\|S_t = s]$
Reward function	$r(s, s') :=$ reward for transition $(s, \varnothing, s')$
Discount factor	$\gamma \in [0, 1]$
Return after T transitions	$\begin{aligned} U_T &= \sum_{t=1}^{T} \gamma^{t-1} R_t \\ &= U_{T-1} + \gamma^{T-1} R_T \end{aligned}$

- i.e. The (possibly discounted) sum of the rewards after T transitions (sequence of rewards)
- **Why?**
  - Future rewards are less valuable than immediate rewards.
  - Won't converge if sum goes to ∞ if $\gamma = 1$.

Expected return after T transitions	$\begin{aligned} \mathbb{E}[U_T] &= \mathbb{E}[U_{T-1}] + \gamma^{T-1}\mathbb{E}[R_t] \\ &= \mathbb{E}[U_{T-1}] + \gamma^{T-1} \sum_{s,s'} p_{T-1}(s) p(s'\|s) r(s, s') \end{aligned}$

- $p_{T-1}(s)p(s'|s)$: Prob. $s \to s'$
- $r(s, s')$: rwd $s \to s'$
- $\mathbb{E}[U_0] := 0$: Base case

1.3.1 Bayesian Network

Notes: $S_0, R_1, S_1, R_2, S_2, \ldots$ form a **Bayesian Network**:

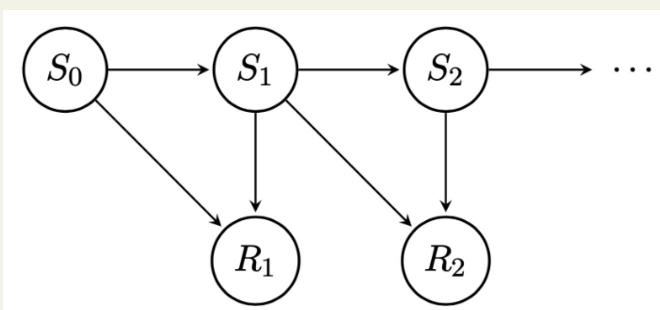

Figure 2

1.4 Markov Decision Processes (MDPs)

1.4.1 Setup

Summary: In a **Markov Decision Process (MDP)**, we assume that:

- there is one agent
- state transitions occur manually (after each action)
- S_t is the state *after* transition t
- A_t is the action inducing transition t
- the state transition process is stochastic and memoryless:

$$S_t \perp S_0, A_1, \ldots, S_{t-2}, A_{t-1} \mid S_{t-1}, A_t$$

  - S_t is independent of all previous states and actions given S_{t-1} and A_t
- R_t is the reward for transition t, i.e., (S_{t-1}, A_t, S_t)

Name	**Function:**
initial state distribution	$p_0(s) := \mathbb{P}[S_0 = s]$
transition distribution	$p(s'\|s,a) := \mathbb{P}[S_t = s'\|A_t = a, S_{t-1} = s]$
reward function	$r(s,a,s') :=$ reward for transition (s,a,s')
a time-invariant policy for choosing actions	$\pi(a\|s) := \mathbb{P}[A_t = a\|S_t = s]$
Maximum number of transitions • A Markov Decision Process can be either: – **Finite**: $T_{\max}$ is finite – **Infinite**: $T_{\max}$ is infinite ∗ For infinite MDPs, we must have $\gamma < 1$.	$T_{\max}$
Prob. that state of the env. after T transitions is s • $p_{T-1}(s)$: Prob. s' at T-1 • $\pi(a\|s')$: Action a from s' • $p(s\|s',a)$: Prob. s given s', a	$p_T(s) = \sum_{a,s'} p_{T-1}(s)\pi(a\|s')p(s\|s',a)$
Expected return after T transitions • $\mathbb{E}_\pi[R_t] = \sum_{s,a,s'} p_{T-1}(s)\pi(a \mid s)p(s' \mid s,a)r(s,a,s')$ • $\mathbb{E}_\pi[U_0] = 0$: Base case.	$\mathbb{E}_\pi[U_T]{=}\mathbb{E}_\pi[U_{T-1}] + \gamma^{T-1}\mathbb{E}_\pi[R_t]$
Future return after τ transitions • Starting at $\tau + 1$ for the future return.	$G_\tau = \sum_{t=\tau+1}^{T} \gamma^{t-(\tau+1)} R_t = R_{\tau+1} + \gamma G_{\tau+1}$
Expected future return after τ transitions given $S_\tau{=}s$ • $\mathbb{E}_\pi[G_{T_{\max}} \mid S_{T_{\max}} = s] = 0$: Base case.	$\mathbb{E}_\pi[G_\tau \mid S_\tau{=}s]{=}\mathbb{E}_\pi[R_{\tau+1} \mid S_\tau{=}s] + \gamma\mathbb{E}_\pi[G_{\tau+1} \mid S_\tau{=}s]$ $= \sum_{a,s'} \pi(a \mid s)p(s' \mid s,a)\left(r(s,a,s') + \gamma\mathbb{E}_\pi[G_{\tau+1} \mid S_{\tau+1}{=}s']\right)$

Summary:

Name	**Function:**
Value function	$v_\pi(s,T) := \mathbb{E}_\pi[G_{T_{\max}-T} \mid S_{T_{\max}-T} = s] = \sum_{a,s'} \pi(a \mid s) p(s' \mid s,a) \left(r(s,a,s') + \gamma v_\pi(s', T-1)\right)$ • Value of state s under the policy π with T transitions remaining. – i.e. How good the state is at time T (e.g. If $v(s,T) = 5$, then the expected future return at T is 5). • $v(s,0) = 0$ for all s: Base case
Optimal action	$a^*(s,T) = \arg\max_{a \in \mathcal{A}(s)} \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma v_{\pi^*}(s', T-1)\right) = \arg\max_{a \in \mathcal{A}(s)} q^*(s,a,T)$
Optimal policy	$\pi^*(a \mid s,T) = \arg\max_{\pi(a \mid s,T)} \mathbb{E}_\pi[G_\tau \mid S_\tau = s] = \begin{cases} 1 & \text{if } a = a^*(s,T) \\ 0 & \text{otherwise} \end{cases}$ • Choose $\pi(\cdot \mid s)$ to maximize the expected future return after T transitions given $S_\tau = s$. • **Note:** Policy always depends on transitions remaining so may omit.
Optimal value function	$v^*(s,T) = \max_a \sum_{s'} p(s' \mid a,s) \left(r(s,a,s') + \gamma v^*(s', \tau+1)\right)$ • Assume we use an optimal policy π^*. • $v^*(s,0) = 0$ for all s: Base case.
Q function (quality)	$q_\pi(s,a,T) := \mathbb{E}_\pi[G_{T_{\max}-T} \mid S_{T_{\max}-T} = s, A_{T_{\max}-(T-1)} = a] = \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma \sum_{a'} \pi(a' \mid s') q_\pi(s', a', T-1) \right)$ • Quality of move (s,a) under policy π with T transitions remaining. • $q_\pi(s,a,0) = 0$ for all s, a: Base case.
Optimal Q function	$q^*(s,a,T) = \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma \max_{a'} q^*(s', a', T-1) \right)$ • $q^*(s,a,0) = 0$ for all s, a: Base case.

1.4.2 Bayesian Network

Notes: $S_0, A_1, R_1, S_1, A_2, R_2, S_2, \ldots$ form a **Bayesian Network**:

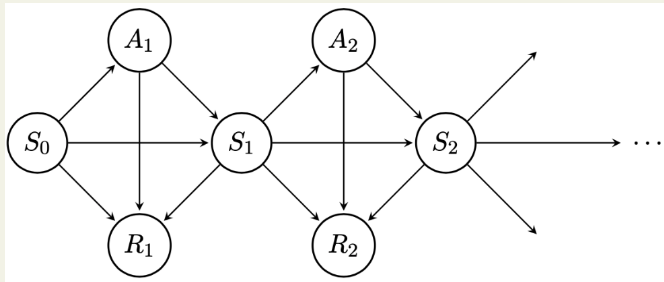

Figure 3

1.4.3 Intuition on Formulae

Notes:

$$\mathbb{E}_\pi[R_{\tau+1} \mid S_\tau = s] = \sum_{a,s'} \pi(a \mid s)p(s' \mid a, s)r(s, a, s')$$

- $\pi(a \mid s)p(s' \mid a, s)$: Prob. of getting to s' from s w/ action a
- $r(s, a, s')$: Reward of getting to s' from s w/ action a

$$\mathbb{E}_\pi[G_{\tau+1} \mid S_\tau = s] = \sum_{a,s'} \pi(a \mid s)p(s' \mid a, s)\mathbb{E}_\pi[G_{\tau+1} \mid S_{\tau+1} = s']$$

- $\pi(a \mid s)p(s' \mid a, s)$: Prob. of getting to s' from s w/ action a
- $\mathbb{E}_\pi[G_{\tau+1} \mid S_{\tau+1} = s']$: Expected future return at $\tau + 1$ from s' at $\tau + 1$.
- $\sum_{a,s'}$: Sum over all possible future states and current actions to get expected future return at $\tau + 1$ from s at τ.

1.5 Canonical Examples

1.5.1 Markov Chains

Example:

1. **Given:** Caveman needs to predict the weather, W, which is either sunny or rainy. Suppose the weather tomorrow depends on the weather today:

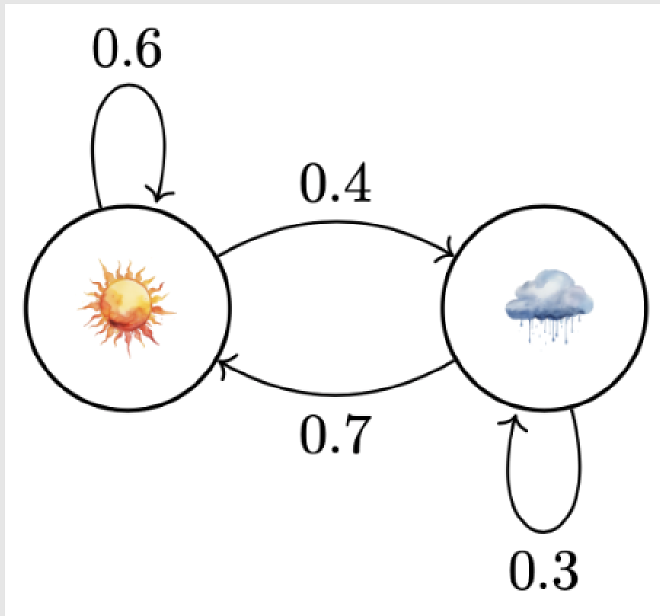

Figure 4

2. **Problem:** Caveman wants to predict the weather on a given day.

1.5.2 Markov Reward Processes

Example:

1. **Given:** Caveman needs to predict the weather, W, which is either sunny or rainy. Suppose the weather tomorrow depends on the weather today:

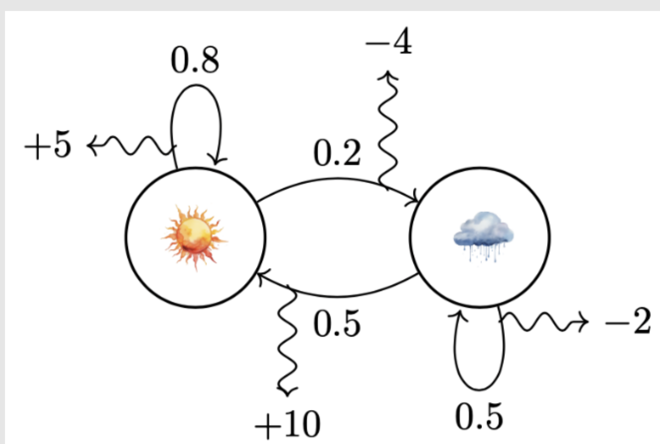

Figure 5

   - Depending on the transition, caveman may feel happier/sadder. This is quantified w/ the rewards.

2. **Problem:** Caveman wants to predict the weather on a given day that maximizes his happiness.

1.5.3 Markov Decision Processes

Process:

1. Set up the base case for $q^*(s,a,0) = 0$ for all s, a.
2. Set up the second base case $q^*(s,a,1) = \sum_{s'} p(s' \mid s,a)\,(r(s,a,s'))$ for all s, a.
3. Set up the recursive case $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$ for all s, a, T.
4. Select the best action for a given state and last time step by selecting the maximum $q^*(s,a,T)$ for a particular s.
5. Write 1 if the action is the best action and 0 otherwise.

Warning:

- $q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$
  - $q^*(s,a,0) = 0$ for all s, a: Base case.
- $a^*(s,T) = \arg\max_{a \in \mathcal{A}(s)} q^*(s,a,T)$
- $\pi^*(a \mid s,T) = \begin{cases} 1 & \text{if } a = a^*(s,T) \\ 0 & \text{otherwise} \end{cases}$

Warning:

- Be careful with the problems. Verify the answers. Go up to at least 2 steps since that tests everything.
- Be able to go through the formula quickly.
- 1st question on the quiz.

Example:

1. **Given:**

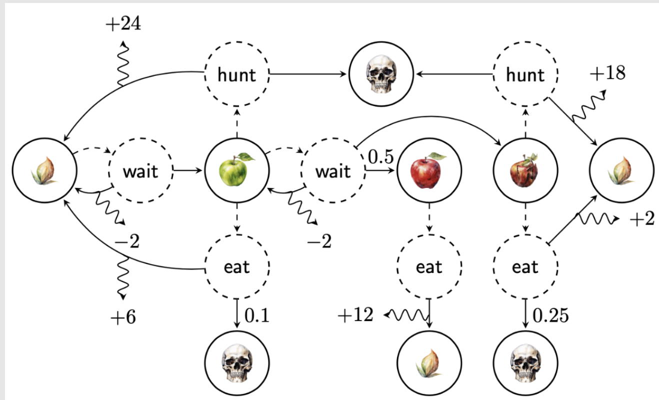

Figure 6

- Solid straight line: Outcome of action a from state s.
- Dotted straight line: Choice of action (policy) from state s.
  - If policy known, then reduced to MRP.
- Squiggly line: Reward for action a from state s to state s'.
- Assume uniform probability.
  - Since $\sum p = 1$, therefore count # of arrows going out of s and divide by 1 to get p.
- Same states have the same connections (i.e. all can use them just to hard to draw)

2. **Problem:** Find the optimal policy for $\gamma = 1$ and $T_{\max} = 5$.
3. **Soln:**

Example:

T	s	a	$q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$
0	-	-	0

- Best Action: $a^*(s,0) = \text{NA}$

1	seed	wait	$q^*(\text{seed},\text{wait},1) = \underbrace{0.5(-2+0)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{ga}} = -1$

- Best Action: $a^*(\text{seed},1) = \text{wait}$

1	ga	wait	$q^*(\text{ga},\text{wait},1) = \underbrace{0.25(-2+0)}_{s'=\text{ga}} + \underbrace{0.5(0+0)}_{s'=\text{rea}} + \underbrace{0.25(0+0)}_{s'=\text{roa}} = -0.5$
1	ga	eat	$q^*(\text{ga},\text{eat},1) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+0)}_{s'=\text{seed}} = 5.4$
1	ga	hunt	$q^*(\text{ga},\text{hunt},1) = \underbrace{0.5(24+0)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 12$

- Best Action: $a^*(\text{ga},1) = \text{hunt}$

1	rea	eat	$q^*(\text{rea},\text{eat},1) = \underbrace{1(12+0)}_{s'=\text{seed}} = 12$

- Best Action: $a^*(\text{rea},1) = \text{eat}$

1	roa	eat	$q^*(\text{roa},\text{eat},1) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+0)}_{s'=\text{seed}} = 1.5$
1	roa	hunt	$q^*(\text{roa},\text{hunt},1) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+0)}_{s'=\text{seed}} = 9$

- Best Action: $a^*(\text{roa},1) = \text{hunt}$

1	dead	-	$q^*(\text{dead},-,1) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$

- Best Action: $a^*(s,1) = -$

- Optimal Policy w/ 1 Transition Remaining: $\pi^*(a \mid s,1) = \begin{cases} 1 & \text{if } a = a^*(s,1) \\ 0 & \text{otherwise} \end{cases}$

Example:

T	s	a	$q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$
2	seed	wait	$q^*(\text{seed}, \text{wait}, 2) = \underbrace{0.5(-2-1)}_{s'=\text{seed}} + \underbrace{0.5(0+12)}_{s'=\text{ga}} = 4.5$

- Best Action: $a^*(\text{seed}, 2) = \text{wait}$

T	s	a	
2	ga	wait	$q^*(\text{ga}, \text{wait}, 2) = \underbrace{0.25(-2+12)}_{s'=\text{ga}} + \underbrace{0.5(0+12)}_{s'=\text{rea}} + \underbrace{0.25(0+9)}_{s'=\text{roa}} = 10.75$
2	ga	eat	$q^*(\text{ga}, \text{eat}, 2) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6-1)}_{s'=\text{seed}} = 4.5$
2	ga	hunt	$q^*(\text{ga}, \text{hunt}, 2) = \underbrace{0.5(24-1)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 11.5$

- Best Action: $a^*(\text{ga}, 2) = \text{hunt}$

T	s	a	
2	rea	eat	$q^*(\text{rea}, \text{eat}, 2) = \underbrace{1(12-1)}_{s'=\text{seed}} = 11$

- Best Action: $a^*(\text{rea}, 2) = \text{eat}$

T	s	a	
2	roa	eat	$q^*(\text{roa}, \text{eat}, 2) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2-1)}_{s'=\text{seed}} = 0.75$
2	roa	hunt	$q^*(\text{roa}, \text{hunt}, 2) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18-1)}_{s'=\text{seed}} = 8.5$

- Best Action: $a^*(\text{roa}, 2) = \text{hunt}$

T	s	a	
2	dead	-	$q^*(\text{dead}, -, 2) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$

- Best Action: $a^*(s, 2) = -$

- Optimal Policy w/ 2 Transitions Remaining: $\pi^*(a \mid s, 2) = \begin{cases} 1 & \text{if } a = a^*(s,2) \\ 0 & \text{otherwise} \end{cases}$

Example:

T	s	a	$q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\right)$
3	seed	wait	$q^*(\text{seed}, \text{wait}, 3) = \underbrace{0.5(-2+4.5)}_{s'=\text{seed}} + \underbrace{0.5(0+11.5)}_{s'=\text{ga}} = 7$

- Best Action: $a^*(\text{seed}, 3) = \text{wait}$

3	ga	wait	$q^*(\text{ga}, \text{wait}, 3) = \underbrace{0.25(-2+11.5)}_{s'=\text{ga}} + \underbrace{0.5(0+11)}_{s'=\text{rea}} + \underbrace{0.25(0+8.5)}_{s'=\text{roa}} = 10$
3	ga	eat	$q^*(\text{ga}, \text{eat}, 3) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+4.5)}_{s'=\text{seed}} = 9.45$
3	ga	hunt	$q^*(\text{ga}, \text{hunt}, 3) = \underbrace{0.5(24+4.5)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 14.25$

- Best Action: $a^*(\text{ga}, 3) = \text{hunt}$

3	rea	eat	$q^*(\text{rea}, \text{eat}, 3) = \underbrace{1(12+4.5)}_{s'=\text{seed}} = 16.5$

- Best Action: $a^*(\text{rea}, 3) = \text{eat}$

3	roa	eat	$q^*(\text{roa}, \text{eat}, 3) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+4.5)}_{s'=\text{seed}} = 4.875$
3	roa	hunt	$q^*(\text{roa}, \text{hunt}, 3) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+4.5)}_{s'=\text{seed}} = 11.25$

- Best Action: $a^*(\text{roa}, 3) = \text{hunt}$

3	dead	-	$q^*(\text{dead}, -, 3) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$

- Best Action: $a^*(s, 3) = -$

- Optimal Policy w/ 3 Transitions Remaining: $\pi^*(a \mid s, 3) = \begin{cases} 1 & \text{if } a = a^*(s,3) \\ 0 & \text{otherwise} \end{cases}$

Example:

T	s	a	$q^*(s,a,T) = \sum_{s'} p(s' \mid s,a)\Big(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1)\Big)$
4	seed	wait	$q^*(\text{seed},\text{wait},4) = \underbrace{0.5(-2+7)}_{s'=\text{seed}} + \underbrace{0.5(0+14.25)}_{s'=\text{ga}} = 9.625$
			• Best Action: $a^*(\text{seed},4) = \text{wait}$
4	ga	wait	$q^*(\text{ga},\text{wait},4) = \underbrace{0.25(-2+14.25)}_{s'=\text{ga}} + \underbrace{0.5(0+16.5)}_{s'=\text{rea}} + \underbrace{0.25(0+11.25)}_{s'=\text{roa}} = 14.125$
4	ga	eat	$q^*(\text{ga},\text{eat},4) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+7)}_{s'=\text{seed}} = 11.7$
4	ga	hunt	$q^*(\text{ga},\text{hunt},4) = \underbrace{0.5(24+7)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 15.5$
			• Best Action: $a^*(\text{ga},4) = \text{hunt}$
4	rea	eat	$q^*(\text{rea},\text{eat},4) = \underbrace{1(12+7)}_{s'=\text{seed}} = 19$
			• Best Action: $a^*(\text{rea},4) = \text{eat}$
4	roa	eat	$q^*(\text{roa},\text{eat},4) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+7)}_{s'=\text{seed}} = 6.75$
4	roa	hunt	$q^*(\text{roa},\text{hunt},4) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+7)}_{s'=\text{seed}} = 12.5$
			• Best Action: $a^*(\text{roa},4) = \text{hunt}$
4	dead	-	$q^*(\text{dead},-,4) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$
			• Best Action: $a^*(s,4) = -$

- Optimal Policy w/ 4 Transitions Remaining: $\pi^*(a \mid s, 4) = \begin{cases} 1 & \text{if } a = a^*(s,4) \\ 0 & \text{otherwise} \end{cases}$

Example:

T	s	a	$q^*(s,a,T) = \sum_{s'} p(s' \mid s,a) \left(r(s,a,s') + \gamma \max_{a'} q^*(s',a',T-1) \right)$
5	seed	wait	$q^*(\text{seed}, \text{wait}, 5) = \underbrace{0.5(-2+9.625)}_{s'=\text{seed}} + \underbrace{0.5(0+15.5)}_{s'=\text{ga}} = 11.5625$

- Best Action: $a^*(\text{seed}, 5) = \text{wait}$

5	ga	wait	$q^*(\text{ga}, \text{wait}, 5) = \underbrace{0.25(-2+15.5)}_{s'=\text{ga}} + \underbrace{0.5(0+19)}_{s'=\text{rea}} + \underbrace{0.25(0+12.5)}_{s'=\text{roa}} = 16$
5	ga	eat	$q^*(\text{ga}, \text{eat}, 5) = \underbrace{0.1(0+0)}_{s'=\text{dead}} + \underbrace{0.9(6+9.625)}_{s'=\text{seed}} = 14.0625$
5	ga	hunt	$q^*(\text{ga}, \text{hunt}, 5) = \underbrace{0.5(24+9.625)}_{s'=\text{seed}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 16.8125$

- Best Action: $a^*(\text{ga}, 5) = \text{hunt}$

5	rea	eat	$q^*(\text{rea}, \text{eat}, 5) = \underbrace{1(12+9.625)}_{s'=\text{seed}} = 21.625$

- Best Action: $a^*(\text{rea}, 5) = \text{eat}$

5	roa	eat	$q^*(\text{roa}, \text{eat}, 5) = \underbrace{0.25(0+0)}_{s'=\text{dead}} + \underbrace{0.75(2+9.625)}_{s'=\text{seed}} = 8.71875$
5	roa	hunt	$q^*(\text{roa}, \text{hunt}, 5) = \underbrace{0.5(0+0)}_{s'=\text{dead}} + \underbrace{0.5(18+9.625)}_{s'=\text{seed}} = 13.8125$

- Best Action: $a^*(\text{roa}, 5) = \text{hunt}$

5	dead	-	$q^*(\text{dead}, -, 5) = \underbrace{1(0+0)}_{s'=\text{end}} = 0$

- Best Action: $a^*(s, 5) = -$

- Optimal Policy w/ 5 Transitions Remaining: $\pi^*(a \mid s, 5) = \begin{cases} 1 & \text{if } a = a^*(s,5) \\ 0 & \text{otherwise} \end{cases}$

Example:
1. **Given:**

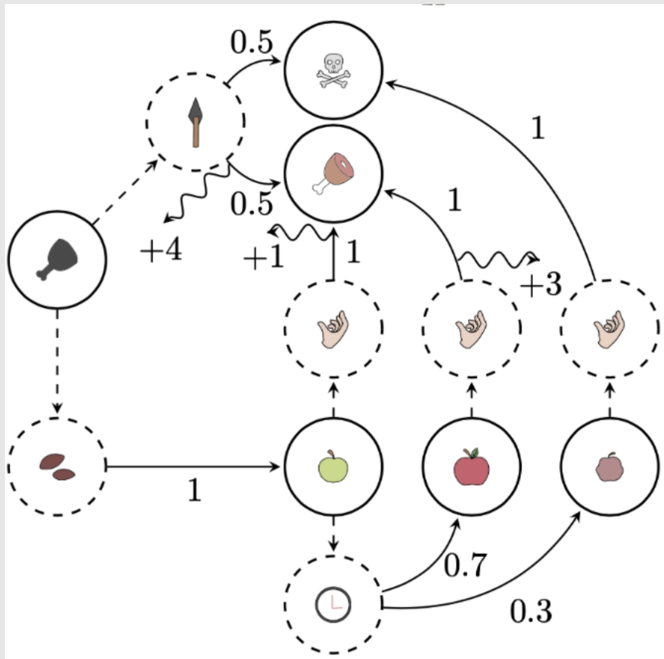

Figure 7

2. **Problem:** What is the optimal policy for cavemen with $T = 3$ w/ $\gamma = 1$?
3. **Solution:**

s	a	$q^*(s,a,0)$	$q^*(s,a,1)$	$q^*(s,a,2)$	$q^*(s,a,3)$	$a^*(s,2)$	$\pi^*(a \mid s,2)$
empty	hunt	0	2	2	2	seed	0
empty	seed	0	0	1	2.1		1

- $q^*(\text{empty}, \text{hunt}, 1) = 0.5(4+0) + 0.5(0+0) = 2$
- $q^*(\text{empty}, \text{seed}, 1) = 1(0+0) = 0$
- $q^*(\text{empty}, \text{hunt}, 2) = 0.5(4+0) + 0.5(0+0) = 2$
- $q^*(\text{empty}, \text{seed}, 2) = 1(0+1\cdot 1) = 1$
- $q^*(\text{empty}, \text{hunt}, 3) = \underbrace{0.5(4+0)}_{s'=\text{full}} + \underbrace{0.5(0+0)}_{s'=\text{dead}} = 2$
- $q^*(\text{empty}, \text{seed}, 3) = \underbrace{1(0+1\cdot 2.1)}_{s'=\text{ga}} = 2.1$

s	a	$q^*(s,a,0)$	$q^*(s,a,1)$	$q^*(s,a,2)$	$q^*(s,a,3)$	$a^*(s,2)$	$\pi^*(a \mid s,2)$
ga	grab	0	1	1	1	clock	0
ga	clock	0	0	2.1	2.1		1

- $q^*(\text{ga}, \text{grab}, 1) = 1(1+0) = 1$
- $q^*(\text{ga}, \text{clock}, 1) = 0.7(0+0) + 0.3(0+0) = 0$
- $q^*(\text{ga}, \text{grab}, 2) = 1(1+0) = 1$
- $q^*(\text{ga}, \text{clock}, 2) = 0.7(0+3) + 0.3(0+0) = 2.1$
- $q^*(\text{ga}, \text{grab}, 3) = \underbrace{1(1+0)}_{s'=\text{full}} = 1$
- $q^*(\text{ga}, \text{clock}, 3) = \underbrace{0.7(0+3)}_{s'=\text{ra}} + \underbrace{0.3(0+0)}_{s'=\text{roa}} = 2.1$

s	a	$q^*(s,a,0)$	$q^*(s,a,1)$	$q^*(s,a,2)$	$q^*(s,a,3)$	$a^*(s,2)$	$\pi^*(a \mid s,2)$
dead	-	0	0	0	0	-	1

- $q^*(\text{dead}, -, 1) = 1(0+0) = 0$
- $q^*(\text{dead}, -, 2) = 1(0+0) = 0$
- $q^*(\text{dead}, -, 3) = 1(0+0) = 0$

s	a	$q^*(s,a,0)$	$q^*(s,a,1)$	$q^*(s,a,2)$	$q^*(s,a,3)$	$a^*(s,2)$	$\pi^*(a \mid s,2)$
full	-	0	0	0	0	-	1

- $q^*(\text{full}, -, 1) = 1(0+0) = 0$
- $q^*(\text{full}, -, 2) = 1(0+0) = 0$
- $q^*(\text{full}, -, 3) = 1(0+0) = 0$

s	a	$q^*(s,a,0)$	$q^*(s,a,1)$	$q^*(s,a,2)$	$q^*(s,a,3)$	$a^*(s,2)$	$\pi^*(a \mid s,2)$
ra	grab	0	3	3	3	grab	1

- $q^*(\text{ra}, \text{grab}, 1) = 1(3+0) = 3$
- $q^*(\text{ra}, \text{grab}, 2) = 1(3+0) = 3$
- $q^*(\text{ra}, \text{grab}, 3) = \underbrace{1(3+0)}_{s'=\text{full}} = 3$

s	a	$q^*(s,a,0)$	$q^*(s,a,1)$	$q^*(s,a,2)$	$q^*(s,a,3)$	$a^*(s,2)$	$\pi^*(a \mid s,2)$
roa	grab	0	0	0	0	grab	1

- $q^*(\text{roa}, \text{grab}, 1) = 1(0+0) = 0$
- $q^*(\text{roa}, \text{grab}, 2) = 1(0+0) = 0$
- $q^*(\text{roa}, \text{grab}, 3) = \underbrace{1(0+0)}_{s'=\text{dead}} = 0$