## Probabilistic Aspects of Computer Science: TD Bonus Average Reward for Unichains

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## October 25, 2017

A Markov Decision Process  $\mathcal{M}$  is said to be a *unichain* if the finite-state Markov chain  $\mathcal{M}^{\pi}$ , induced by any deterministic stationary policy  $\pi = d^{\infty}$ , has exactly one recurrent strongly connected component plus a possibly empty set of transient states (it is often said to be *recurrent* in case this set of transient states is empty). Otherwise, the MDP is said to be *multichain*. We are interested in the following in studying the limsup and liminf average optimal rewards

$$\mathbf{g}_{+}^{*}[s] = \sup_{\pi \in \Pi^{MR}} (\mathbf{g}_{+}^{\pi}[s]) \qquad \text{where} \qquad \mathbf{g}_{+}^{\pi} = \limsup_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} \mathbf{E}^{\pi}(r(X_{i}, Y_{i}))$$
$$\mathbf{g}_{-}^{*}[s] = \sup_{\pi \in \Pi^{MR}} (\mathbf{g}_{-}^{\pi}[s]) \qquad \text{where} \qquad \mathbf{g}_{-}^{\pi} = \liminf_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} \mathbf{E}^{\pi}(r(X_{i}, Y_{i}))$$

and the average optimal reward in case  $\mathbf{g}_{+}^{*} = \mathbf{g}_{-}^{*}$  (we denote it  $\mathbf{g}^{*}$  in that case).

**Exercise 1** (Average rewards in unichains). We consider in this exercise a unichain  $\mathcal{M}$ .

- 1. We start by studying a particular deterministic stationary policy  $d^{\infty}$ . Let  $\mathbf{P}_d$  be the matrix of the finite-state Markov chain  $\mathcal{M}^{d^{\infty}}$ . Describe precisely the matrix  $\mathbf{P}_d^*$  defined as the Cesaro-limit of the sequence  $\{\mathbf{P}_d^n\}_{n\in\mathbb{N}}$ . Show that  $\mathbf{g}^{d^{\infty}}$  exists and is a constant vector.
- 2. We consider the system of equations (E), with variables  $g \in \mathbb{R}$  and  $\mathbf{h} \in \mathbb{R}^S$ :

$$\forall s \in S \qquad g + \mathbf{h}[s] = \max\{r(s, a) + \sum_{s' \in S} p(s' \mid s, a) \mathbf{h}[s'] \mid a \in A_s\}$$

Using Theorem 3.38, show that

- let  $d^{\infty}$  be a Blackwell optimal policy. Then  $((\mathbf{P}_d^*\mathbf{r}_d)[s_0], \mathbf{D}_d\mathbf{r}_d)$  is a solution of (E), for every state  $s_0$ ;<sup>1</sup>
- if  $(g, \mathbf{h})$  is a solution of (E), then  $g = \mathbf{g}^*[s]$  for every state  $s \in S$ , and there exists  $c \in \mathbb{R}$  such that  $\mathbf{h}[s] = (\mathbf{D}_d \mathbf{r}_d)[s] + c$  for every state s, with  $d^{\infty}$  a Blackwell optimal policy.
- 3. Consider the MDP schematized below:

$$a, 1/2, 5$$
  $a, 1, -1$   
 $a, 1/2, 5$   
 $1$   
 $b, 1, 10$ 

Show that it is a unichain, and write the system of equations (E). Solve it. Among all the deterministic stationary policies of this MDP, which one(s) is/are optimal? a Blackwell optimal policy?

<sup>&</sup>lt;sup>1</sup>We denote by  $\mathbf{D}_d$  the deviation matrix defined by  $(\mathbf{Id} - \mathbf{P}_d + \mathbf{P}_d^*)^{-1} - \mathbf{P}_d^*$ .

- 4. For  $\mathbf{h} \in \mathbb{R}^{S}$ , a decision rule d is  $\mathbf{h}$ -improving if  $\mathbf{r}_{d} + \mathbf{P}_{d}\mathbf{h} = \max_{d'}(\mathbf{r}_{d'} + \mathbf{P}_{d'}\mathbf{h})$ . Let  $(g, \mathbf{h})$  be a solution of (E), and let d be an  $\mathbf{h}$ -improving decision rule. Show that  $d^{\infty}$  is an optimal policy, i.e.,  $\mathbf{g}^{d^{\infty}} = \mathbf{g}^{*}$ .
- 5. What becomes of the policy iteration presented in the course in this special case?

**Exercise 2** (coNP-completeness of deciding if an MDP is a unichain). Show that the problem of deciding whether a given MDP is a unichain is in coNP (equivalently that deciding if it is a multichain is in NP. By reduction of 3-SAT, show that it is indeed a coNP-complete problem. (*Hint: starting from an instance*  $\varphi$  of 3-SAT, construct an MDP  $\mathcal{M}_{\varphi}$  such that  $\varphi$  is satisfiable if, and only if,  $\mathcal{M}_{\varphi}$  is a multichain. You may think of using as states of the MDP: one state  $c_j$  per clause  $(j \in \{1, \ldots, m\})$ , 4 states  $s_i, s_i^*, t_i, f_i$  per litteral  $(i \in \{1, \ldots, n\})$ , and two special states a and b, one encoding a truth assignment, and the other encoding its converse.)