

Math 525: Lecture 21

March 29, 2018

So far, we have worked primarily with (stationary) Markov chains whose transition matrices are “constant”. In this lecture, we explore the following question: what if we could “control” the transition matrix? In this context, we will have a transition matrix $P(\pi)$ that depends on some quantity π which we, the “controller”, get to choose.

1 Markov decision processes

For this lecture, our setting is as follows:

- $S = \{1, \dots, m\}$ is a finite state space.
- To each state i in S is associated a nonempty countable set \mathcal{A}_i which we can intuitively think of as all the “actions” available at state i .

Definition 1.1. A *stationary policy* π_0 is a function whose domain is S and which satisfies $\pi_0(i) \in \mathcal{A}_i$ for all i . The set of all stationary policies is denoted Π_0 .

Definition 1.2. A *randomized policy* $(\pi_n)_{n \geq 0}$ is a sequence in which each $\pi_n(i)$ is a random variable satisfying

- $\pi_n(i)$ takes values in \mathcal{A}_i a.s. and
- $\{\pi_n(i) = a\} \in \mathcal{F}_n$ for each a in \mathcal{A}_i .¹

The set of all randomized policies is denoted Π .

For each state i in S and action a in \mathcal{A}_i , let $p_i(a)$ denote a nonnegative column vector satisfying $p_i(a)^\top e = 1$. Given a randomized policy π , let $(X_n^\pi)_{n \geq 0}$ denote a Markov chain satisfying

$$\mathbb{P}(X_{n+1}^\pi = j \mid X_n^\pi = i) = p_i(\pi_n(i))^\top e_j.$$

That is, the transition matrix at time n is

$$P(\pi_n) = \begin{pmatrix} p_1(\pi_n(1))^\top \\ p_2(\pi_n(2))^\top \\ \vdots \\ p_m(\pi_n(m))^\top \end{pmatrix}.$$

¹We have purposely neglected to specify \mathcal{F}_n yet (we’ll come back to this).

While we write X_n^π , it should be noted that this quantity only depends on π_0, \dots, π_{n-1} . In light of this, we sometimes write $X_0, X_1^{\pi_0}, X_2^{\pi_0, \pi_1}$, etc. to stress this independence. In light of this, we can unambiguously define $\mathcal{F}_n = \sigma(X_0^\pi, \dots, X_n^\pi)$.

Now, let $c : S \rightarrow \mathbb{R}$, $0 \leq d < 1$, and

$$J(i, \pi) = \mathbb{E} \left[\sum_{n \geq 0} d^n c(X_n^\pi) \middle| X_0^\pi = i \right]. \quad (1)$$

We can think of

- $c(X_n^\pi)$ as the cost incurred at time n and
- d^n as a discount factor which attempts to capture the fact that costs incurred in the “future” are not as bad as costs incurred “today”.

Our objective is to pick π so as to minimize $J(i, \pi)$. That is, we are interested in the quantity

$$\boxed{v(i) = \inf_{\pi \in \Pi} J(i, \pi)} \quad (2)$$

We call (2) a *Markov decision process* (MDP).

Proposition 1.3. *$v(i)$ is bounded for each i .*

Proof. This is a trivial consequence of the discount factor being strictly less than one:

$$|v(i)| \leq \sum_{n \geq 0} d^n \max_j |c(j)| = \frac{1}{1-d} \max_j |c(j)|. \quad \square$$

2 Dynamic programming

By the Markov property,

$$\begin{aligned} J(i, \pi) &= \mathbb{E}^i \left[c(X_0^\pi) + \sum_{n \geq 1} d^n c(X_n^\pi) \right] = c(i) + d \mathbb{E}^i \left[\sum_{n \geq 0} d^n c(X_{n+1}^\pi) \right] \\ &= c(i) + d \mathbb{E}^i [J(X_1^\pi, (\pi_n)_{n \geq 1})] \geq c(i) + d \sum_j (P(\pi_0))_{ij} v(j) \end{aligned}$$

where π_0 is some stationary policy. Taking infimums of both sides of this equality,

$$v(i) \geq \inf_{\pi_0 \in \Pi_0} \left\{ c(i) + d \sum_j (P(\pi_0))_{ij} v(j) \right\}. \quad (3)$$

Now, fix $\epsilon > 0$. For each i , let $\pi^i = (\pi_n^i)_{n \geq 0}$ be a randomized policy which satisfies

$$v(i) \geq J(i, \pi^i) + \epsilon.$$

Let π_0 be an arbitrary stationary policy. Define a new randomized policy $\pi^\epsilon = (\pi_n^\epsilon)_{n \geq 0}$ by

$$\pi_n^\epsilon = \begin{cases} \pi_0 & \text{if } n = 0 \\ \mathbf{1}_{\{i\}}(X_1^{\pi_0})\pi_{n-1}^i & \text{if } n > 0. \end{cases}$$

Note that

$$v(i) \leq J(i, \pi^\epsilon) = c(i) + d \sum_j (P(\pi_0))_{ij} J(j, \pi^j) \leq c(i) + d \sum_j (P(\pi_0))_{ij} v(j) - \epsilon.$$

Now, take infimums of both sides to get

$$v(i) \leq \inf_{\pi_0 \in \Pi_0} \left\{ c(i) + d \sum_j (P(\pi_0))_{ij} v(j) \right\} - \epsilon. \quad (4)$$

We can take $\epsilon \downarrow 0$ and combine (3) and (4) to arrive at

$$v(i) = \inf_{\pi_0 \in \Pi_0} \left\{ c(i) + d \sum_j (P(\pi_0))_{ij} v(j) \right\}. \quad (5)$$

The implications of this are amazing! We started out with an objective function (1) that was daunting: minimizing it would require picking a stationary policy for each time n . However, we were able to use the Markov property to reduce this to a “local” problem that only involves minimizing over all stationary policies π_0 . In fact, we can simplify (5) even further. First, we need some notation:

for $\{y_\alpha\}_\alpha \in \mathbb{R}^n$, $\inf_\alpha y_\alpha$ is the vector with entries $\inf_\alpha (y_\alpha)_i$.

Theorem 2.1 (Dynamic programming). *Let $v = (v(1), \dots, v(m))^\top$ and $c = (c(1), \dots, c(m))^\top$ where $v(i)$ is the quantity defined by (2). Then,*

$$\sup_{\pi_0 \in \Pi_0} \{(I - dP(\pi_0))v - c\} = 0$$

Proof. We can rewrite (5) as

$$v = \inf_{\pi_0 \in \Pi} \{c + dP(\pi_0)v\}. \quad (6)$$

Moving some terms around, we obtain the desired result. \square

In fact, the situation is much more general than we have let on. We can allow for more general discount factors and costs:

$$J(i, \pi) = \mathbb{E} \left[\sum_{n \geq 0} d(\pi_n, X_n^\pi)^n c(\pi_n, X_n^\pi) \middle| X_0^\pi = i \right].$$

However, in this case, it is no longer necessarily the case that $v(\cdot)$ is bounded. When it is, the corresponding dynamic programming equation is

$$\sup_{\pi_0 \in \Pi_0} \{(I - D(\pi_0)P(\pi_0))v - c(\pi_0)\} = 0 \quad (7)$$

where $D(\pi_0) = \text{diag}(d(\pi_0(1), 1), \dots, d(\pi_0(m), m))$ and $c(\pi_0) = (c(\pi_0(1), 1), \dots, c(\pi_0(m), m))^\top$.

In light of this, the remainder of this lecture is focused on (7). In particular, we would like to know if an arbitrary vector v satisfies (7), is it necessarily equal to the MDP (2)? Moreover, can we use (7) to compute the MDP?

3 Matrix classes

First, we will need to recall some more linear algebra.

3.1 Monotone matrices

Definition 3.1. A *monotone matrix* is a real square matrix A such that $Ax \geq 0$ implies $x \geq 0$ for all real vectors x .

Proposition 3.2. *Monotone matrices are nonsingular.*

Proof. Let A be a monotone matrix and assume there exists x with $Ax = 0$. Then, by monotonicity, $x \geq 0$ and $-x \geq 0$, and hence $x = 0$. \square

Proposition 3.3. *A real square matrix A is monotone if and only if A^{-1} exists and is nonnegative.*

Proof. Suppose A is monotone. Denote by x the i -th column of A . Then, Ax is the i -th standard basis vector, and hence $x \geq 0$ by monotonicity. For the reverse direction, suppose A admits a nonnegative inverse. Then, if $Ax \geq 0$, $x = A^{-1}Ax \geq A^{-1}0 = 0$, and hence A is monotone. \square

3.2 M-matrices

Definition 3.4. An *M-matrix* is any square matrix A which can be written in the form

$$A = sI - B \tag{8}$$

where $s \geq \rho(B)$ and B is nonnegative.

Proposition 3.5. *The M-matrix (8) is nonsingular if and only if $s > \rho(B)$.*

Proof. Note that A is nonsingular if and only if s is an eigenvalue of B since

$$Ax = sx - Bx = 0 \iff Bx = sx.$$

Therefore, if $s > \rho(B)$, then A is nonsingular. Conversely, if $s = \rho(B)$, by the Perron-Frobenius theorem, s is an eigenvalue of B . \square

Proposition 3.6. *Nonsingular M-matrices are monotone.*

Proof. Divide (8) by s so that

$$s^{-1}A = I - s^{-1}B.$$

Noting that $\rho(s^{-1}B) < 1$, the inverse of the right hand side of the above is the Neumann series

$$(I - s^{-1}B)^{-1} = \sum_{k \geq 0} (s^{-1}B)^k.$$

In particular, this Neumann series consists only of powers of nonnegative matrices, and therefore converges to a nonnegative matrix. In other words, sA^{-1} is nonnegative, and hence so too is A^{-1} . \square

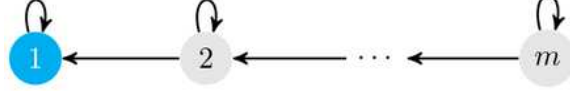


Figure 1: Graph of (10)

3.3 Weakly chained diagonally dominant matrices

Definition 3.7. Let $A = (A_{ij})$ be a matrix. We say its i -th row is *strictly diagonally dominant* (s.d.d.) if

$$|A_{ii}| > \sum_{i \neq j} |A_{ij}|. \quad (9)$$

We say the matrix is s.d.d. if all of its rows are s.d.d. Weakly diagonally dominant (w.d.d.) is defined with weak inequality (\geq) instead.

Example 3.8. The matrix

$$\begin{pmatrix} 1 & & & \\ -1 & 1 & & \\ & -1 & 1 & \\ & & -1 & 1 \end{pmatrix} \quad (10)$$

is not strictly diagonally dominant, but it is weakly diagonally dominant.

Definition 3.9. Let $A = (A_{ij})$ be a matrix. Let

$$J = \{i: i \text{ satisfies (9)}\}$$

denote the set of all s.d.d. rows of A . We say A is *weakly chained diagonally dominant* (w.c.d.d.) if

1. A is w.d.d.
2. For each row $i \notin J$, there is a walk $i \rightarrow j$ with $j \in J$.

Example 3.10. The matrix (10) is w.c.d.d. (see Figure 1).

Proposition 3.11. *w.c.d.d. matrices are nonsingular.*²

Proof. Let A be w.c.d.d. If A is singular, we can find a nonzero vector x such that $Ax = 0$. Without loss of generality, let i_1 be such that $|x_{i_1}| = 1 \geq |x_j|$ for all j . Since A is w.c.d.d., we may pick a walk $i_1 \rightarrow i_2 \rightarrow \dots \rightarrow i_k$ ending at an s.d.d. row $i_k \in J$.

Taking moduli on both sides of

$$-a_{i_1 i_1} x_{i_1} = \sum_{j \neq i_1} a_{i_1 j} x_j$$

²Shivakumar, P. N., and Kim Ho Chew. "A sufficient condition for nonvanishing of determinants." Proceedings of the American mathematical society (1974): 63-66.

yields

$$|a_{i_1 i_1}| = |a_{i_1 i_1} x_{i_1}| = \left| \sum_{j \neq i_1} a_{i_1 j} x_j \right| \leq \sum_{j \neq i_1} |a_{i_1 j}| |x_j| \leq \sum_{j \neq i_1} |a_{i_1 j}|.$$

Since A is w.d.d., the above must hold with equality. Therefore, $|x_j| = 1$ whenever $a_{i_1 j}$ is nonzero. In particular, $|x_{i_2}| = 1$, and we can repeat the same argument as above to get that row i_2 is not s.d.d., row i_3 is not s.d.d., etc. until we conclude that row i_k is not s.d.d., a contradiction. \square

To be continued...