Lecture XIII
Nonnegative Matrices

Key Points:

- **Markov matrices**
- **Stochastic and doubly stochastic matrices**
- **Theorem of Perron on convergence**
- **Perron-Frobenius theory**
- **Examples and applications**

Nonnegative and Positive Matrices

A matrix $M = \left(m_{ij}\right)$ is said to be nonnegative, if $m_{ij} \geq 0$ for all $i,\ j$.

It is said to be positive, if $m_{ij} > 0$ for all $i,\ j$.

Comments

Positive matrix ≠ Positive-definite matrix

Nonnegative matrix ≠ Nonnegative definite matrix (also known as positive semi-definite matrix)

A Motivating Example

Consider a particle taking values from the set $\{1,\ 2,\ \ldots,\ N\}$ and moving at discrete points in time $n = 0, 1, 2, \ldots$.

Let $M = \left(m_{ij}\right)$ be the (presumably time-invariant) transition matrix,

with m_{ij} the probability the particle jumping from state j at time n to state i at time $n+1$.

A Motivating Example (cont'd)

Such a stochastic process is usually called a discrete Markov process.

$M = \left(m_{ij} \right)$ is a (nonnegative) Markov matrix satisfying the following conditions:

$i)\ \ m_{ij} \geq 0;$

$ii)\ \ \sum_{i=1}^{N} m_{ij} = 1, \forall j = 1, 2, \ldots, N.$

A Motivating Example (cont'd)

Let $x_i(n)$ be the probability the particle is in state i at time n. Then, the following relations hold:

$$x_i\left(n+1\right)=\sum_{j=1}^{N} m_{ij}x_j\left(n\right),\quad 1\le i\le N$$

or, in compact matrix notation,

$$x\left(n+1\right)=Mx(n),\quad n=0,1,2,\ldots \qquad x\triangleq\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

Fundamental Question:

What is the limiting behavior of x(n)?

Remark: For any n, $x(n)$ is a probability vector, i.e.,

all components $x_i(n)$ are nonnegative,

and satisfy $\sum_{i=1}^{N} x_i(n) = 1$.

Question 1: Markov matrices

What is the range of parameters λ so that a linear combination $\lambda P + (1-\lambda) Q$ of two Markov matrices $P,\ Q$ remains to be Markov?

Question 2: Probability Vector

Assume M is a Markov matrix and x is a probability vector. Is Mx a probability vector? Why?

Remarkable Result

For any *positive* Markov matrix M and any probability vector $x(0)$, the solution $x(n)$ to $x(n+1) = Mx(n)$ settles at a fixed probability vector y, that is,

$$\lim_{n\to\infty} x(n) = y$$

In addition, y is independent of $x(0)$, and is an eigenvector of M associated with eigenvalue 1.

Comment 1

It should be noted that this result does not hold, if M is only nonnegative matrix, but not positive. A counter-example is

$$M = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}.$$

Indeed, in this case, $M^n x = x$ is dependent on initial condition x!

Comment 2

This type of matrix-theoretic results has been applied recently to address engineering and bio-problems, such as

- Coordination and control of groups of robots
- Consensus in biological multi-agents: bird flocking, fish schooling …

See: “Jadbabaie, Lin and Morse, IEEE Transactions on Automat. Control, 2003” and many references on distributed control and computation.

Sketch of Proof

Noting that

$$\langle x(n),\ b\rangle = \langle M^n x(0), b\rangle = \langle x(0), (M^T)^n b\rangle,$$

it suffices to show that, for any b,

$$(M^T)^n b \to b_l,\quad as\quad n \to \infty.$$

With this in mind, consider

$$z(n) = (M^T)^n b$$

obeying the difference equation

$$z\left(n+1\right) = M^T z(n),\quad \text{with } z(0) = b.$$

Sketch of Proof (cont'd)

Let $u(n)$ be the largest component of $z(n)$, and $v(n)$ the smallest component of $z(n)$.

Now, we only need to prove that

$$u(n) - v(n) \to 0.$$

Since

$$z_i(n+1) = \sum_{j=1}^{N} m_{ji} z_j(n),$$

with $\sum_{j=1}^{N} m_{ji} = 1, m_{ji} > 0,$ we have

Sketch of Proof (cont'd)

we have

$$u(n+1) \le u(n) \text{ and } v(n+1) \ge v(n).$$

So, the decreasing sequence $u(n)$ and the increasing sequence $v(n)$ *both* converge:

$$u(n) \to u,\ v(n) \to v.$$

Next, we need to show that $u = v$.

Sketch of Proof (cont'd)

Let d be the positive lower bound for m_{ij}.

Using the component form of $z(n+1) = M^T z(n)$, it follows that

$$(*)\begin{cases} u(n+1) \le (1-d)u(n) + dv(n), \\ v(n+1) \ge (1-d)v(n) + du(n). \end{cases}$$

$\Rightarrow$

$$u(n+1) - v(n+1) \le (1-2d)\big(u(n) - v(n)\big)$$

Remark: Detailed derivations of (*)

To illustrate the idea, let's first look at the Case of $N = 2$. It suffices to prove the following

$$c = \alpha a + \beta b \leq \left(1 - d\right) a + db$$

for any $a \geq b \geq 0$ and $\alpha + \beta = 1$.

Of course, the above is equivalent to

$$0 \leq \left(1 - \alpha - d\right) a - \left(\beta - d\right) b \Leftrightarrow \left(\beta - d\right)(a - b) \geq 0.$$

The latter clearly holds, because $d \leq \beta$.

To prove the general case $N \geq 2,$ note that we can assume that $v = u_N$. Also note that

$$\sum_{j=1}^{N} m_{ji} u_j \leq (1-d)u + dv$$

holds if

$$0 \leq \left(1 - \sum_{j=1}^{N-1} m_{ji} - d \right) u - (m_{Ni} - d)v$$

$$\Leftrightarrow (m_{Ni} - d)(u - v) \geq 0.$$

The latter clearly holds, because $d \leq m_{Ni}$.

Sketch of Proof (cont'd)

Since $d \le 0.5$ when $N \ge 2$,

$u(n+1) - v(n+1) \le (1-2d)\big(u(n) - v(n)\big)$

implies that $u(n) - v(n) \to 0$, as $n \to \infty$.

As a result, $z(n)$ converges to a vector z with the components being equal. That is,

$z = (a_1, \cdots, a_1)^T$. So, $x(n) \to y$.

Using $\langle x(n),\ b \rangle = \langle x(0), (M^T)^n b \rangle$, and letting $c = x(0)$,

$\langle y, b \rangle = \langle c, z \rangle = a_1 (c_1 + \cdots + c_N) = a_1$.

Since a_1 depends only on b, y is independent of c!

Sketch of Proof (end)

Finally, we need to show that y is an eigenvector of M associated with eigenvalue 1. Indeed,

$$y = \lim_{n\to\infty} M^{n+1}c = M \lim_{n\to\infty} M^{n}c = My.$$

$Note\ that\ y > 0.$

Property 1 of Markov Matrices

For any eigenvalue λ of a Markov matrix M,

$|\lambda| \le 1.$

Proof

Since M^T shares the same eigenvalues with M, let us take an eigenvector x of M^T associated with the eigenvalue λ. That is,

(*) $$\lambda x = M^T x.$$

Let m be the absolute value of a component of x of greatest magnitude, then using l_∞-norm, (*) implies:

$$|\lambda| m \le m \sum_{j=1}^{N} m_{ji} = m \;\Rightarrow\; |\lambda| \le 1.$$

Remark *(Jie Du, 2013.12.10)*

- We can prove it using the Gersgorin disk Theorem.

Property 2 of Markov Matrices

If M is a *positive* Markov matrix, then $\lambda = 1$ is the only eigenvalue of absolute value one.

Proof

Assume that μ is another eigenvalue with $|\mu| = 1$,

and $\omega + jz$ an associated eigenvector.

Choose a big enough t_1 to make $\omega + t_1 y$ and $z + t_1 y$

both positive vectors, with y the limit of $M^n x(0)$.

It can be directly checked that

$$M\left(\omega + jz + t_1(1+j)y\right) = \mu(\omega + jz) + t_1(1+j)y.$$

So,

$$M^n\left(\omega + jz + t_1(1+j)y\right) = \mu^n(\omega + jz) + t_1(1+j)y.$$

Proof (Cont'd)

On the other hand, as $n \to \infty$,

$M^n\left(\omega + jz + t_1(1+j)y\right) = M^n((\omega + t_1 y) + j(z + t_1 y))$.

As shown previously, $M^n(\omega + t_1 y)$ and $M^n(z + t_1 y)$

converge to a scalar multiple of ones, resp.

However, $\mu^n(\omega + jz)$ converges only when $\mu = 1$,

under the constraint $|\mu| = 1$.

Exercise

For any positive Markov matrix, if λ is an eigenvalue with an associated *positive* eigenvector, then $\lambda = 1$.

Detailed Solution

By hypothesis, $Mx = \lambda x$, with M a positive Markov matrix and x a positive eigenvector.

Clearly, λ can only be a positive real eigenvalue.

Without loss of generality, we can assume that x is a positive probability vector.

By the remarkable result, $M^n x = \lambda^n x$ must converge to a probability vector. If $\lambda < 1$, then a contradiction occurs.

Another Proof (by Matt)

Let $x = (x_1, x_2, ..., x_n)^T$ be the positive eigenvector associated with λ. Then, $Mx = \lambda x$ implies:

$$m_{i1}x_1 + \cdots + m_{in}x_n = \lambda x_i, \ \forall i = 1, 2, \cdots, n.$$

Summing up these equations, and using the fact that M is a Markov matrix, it holds:

$$x_1 + \cdots + x_n = \lambda(x_1 + \cdots + x_n)$$

$\Rightarrow \lambda = 1.$

Note: indeed, we only need to assume $x_1 + \cdots + x_n \neq 0.$

Positive Matrices

The following linear equations often occur as a simple model for the growth of a set of biological objects:

$$x_i(n+1) = \sum_{j=1}^{N} a_{ij} x_j(n), \ i = 1, 2, \cdots, N.$$

Or, in compact matrix notation,

$$x(n+1) = Ax(n),$$

where $A = \left(a_{ij}\right)_{N \times N}$ is a positive matrix, i.e. $a_{ij} > 0$.

Problem

Determine the behavior of $x_i[n]$ as $n \to \infty$?

Theorem of Perron (1907)

(1) If A is a positive matrix, there is a unique eigenvalue of A, denoted as $\lambda_{\max}(A)$, which has the greatest absolute value.

(2) This eigenvalue $\lambda_{\max}(A)$ is positive and simple, and its associated eigenvector may be taken positive.

Proof. See the textbook.

Application: A Limit Theorem

Let $c \neq 0$ be any nonnegative vector. Then,

$$v = \lim_{n \to \infty} A^n c / \lambda_{\max}(A)^n$$

exists and is an eigenvector of A associated with $\lambda_{\max}(A)$, unique up to a scalar multiple determined by the choice of c, but otherwise independent of the initial state c.

See the textbook.

As a result,

the solution of $x(n+1) = Ax(n)$, with $A = \left(a_{ij}\right)$ a positive matrix, asymptotically looks like

$$x\left(n\right) \sim \lambda^n \gamma, \quad \lambda = \lambda_{\max}\left(A\right): \text{ Perron root}$$

where γ is a (positive) eigenvector associated with λ, or a positive multiple of a special normalized eigenvector.

For the population example described by

$x(n+1) = Ax(n)$,

the above result implies that:

regardless of the initial population, we will approach a steady-state situation where the total population grows exponentially, but the proportions of the total various species remain constant.

Continuous Growth Processes

Starting with a discrete-time process with a small time interval Δ, then

$$x_i\left(t+\Delta\right)=\left(1+a_{ii}\Delta\right)x_i(t)+\Delta\sum_{j\neq i}a_{ij}x_j(t)$$

$i=1,2,\cdots,N;\ a_{ij}=$ rates of production.

Letting $\Delta\to 0$, we have

$$\dot{x}_i=a_{ii}x_i+\sum_{j\neq i}a_{ij}x_j,\quad 1\leq i\leq N.$$

Continuous Version of Perron's Theorem

If $a_{ij} > 0,\ i \neq j,$ then the eigenvalue of A with largest real part, denoted as $\rho(A),$ is real and simple. There is an associated positive eigenvector which is unique up to a multiplicative constant.

Note: The asymptotic behavior of $x_i(t),$ as $t \to \infty,$ is determined by $\rho(A).$

Exercise from Mathematical Economics

(K.D. Arrow & A.C. Enthoven, 1956)

If A has all negative diagonal elements, and no negative off-diagonal elements, if D is a diagonal matrix, and if the real parts of the eigenvalues of both A and DA are negative, then the diagonal elements of D are positive.

Other Notions and Extensions

- **Irreducible matrix**
- **Perron-Frobenuis theory**
- **Stochastic and doubly stochastic matrices**

Irreducible Matrix

A nonnegative matrix $A \in \mathbb{R}_+^{n \times n}$ is said to be irreducible, if for every pair (i, j), $\exists k \geq 1$ such that the (i, j) entry of A^k is positive.

Example 1: Positive Markov matrices

Example 2: Any matrix $A \in \mathbb{R}_+^{n \times n}$ with the property that $A^k > 0$ for some $k \geq 1$. Such a matrix is known as "primitive matrix".

Is the converse true?

Remark: Irreducible Matrices may not be primitive

A Counter-Example:

The following matrix

$$A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

is a (nonnegative) irreducible matrix, but A^k is not a positive matrix for *any* k.

(Do you know why?)

Comment (*Primitive matrices*)

Definition: A matrix $A \in \mathbb{R}_+^{n\times n}$ is primitive, if it is irreducible and has only one nonzero eigenvalue of maximum modulus.

Theorem

For any matrix $A \in \mathbb{R}_+^{n\times n}$, A is primitive, if and only if A^m is a positive matrix for some $m \geq 1$.

(See the text of Horn-Johnson, 2013, page 540, for a proof.)

Examples

- Show that the matrix

$$A = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix}$$

  is irreducible.

- How about an upper-triangular matrix

like $A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$?

Interesting Result

Let $A \in \mathbb{R}^{n\times n}$ be a nonnegative irreducible matrix.

Then, $\left(I_n + A\right)^{n-1}$ is a positive matrix.

Proof: follows from the following identity

$$\left(I_n + A\right)^{n-1} = \sum_{k=1}^{n-1} \binom{n-1}{k} A^{n-1-k}$$

and Caley-Hamilton Theorem.

Exercise

For any nonnegative matrix $A \in \mathbb{R}^{n\times n}$ and a diagonal matrix $D \in \mathbb{R}^{n\times n}$ with positive entries in the diagonal.

The following statements are equivalent:

1) A is irreducible;

2) AD is irreducible;

3) DA is irreducible.

Perron-Frobenius Theory

For any nonnegative irreducible matrix $A \in \mathbb{R}^{n\times n}$, it holds:

1) the spectral radius $\rho(A) \triangleq \max\{|\lambda| : \lambda \in \sigma(A)\}$ is an eigenvalue of A.

2) $\exists u \in \mathbb{R}^{n}_{>0}$, such that $Au = \rho(A)u$.

3) The algebraic multiplicity of $\rho(A)$ is one.

Stochastic and Doubly Stochastic Matrices

Consider a nonnegative matrix $P = \left(p_{ij} \right) \in \mathbb{R}_{+}^{n \times n}$.

1) It is stochastic, if $\sum_{j=1}^{n} p_{ij} = 1, \ \forall i.$

2) It is doubly stochastic, if both P and P^T are stochastic.

Theorem of Birkhoff-von Neumann

Any doubly stochastic matrix $P \in \mathbb{R}^{n \times n}$ is a convex combination of finitely many permutation matrices. That is,

$$P = \sum_{i=1}^{m} \lambda_i P_i, \quad \text{with } \lambda_i \geq 0, \sum_i \lambda_i = 1,$$

where P_i is a permutation matrix derived from I_n after interchanging some of the rows.