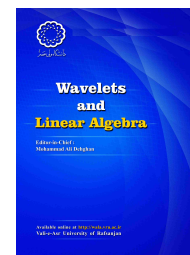


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On L -rays of toeplitz matrices

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ABSTRACT

A toeplitz matrix or diagonal-constant matrix is a matrix in which each descending diagonal from left to right is constant. A matrix R is called integral row stochastic, if each row has exactly a nonzero entry, $+1$, and other entries are zero. In this paper, we present L -rays of integral row stochastic toeplitz matrices, and we provide an algorithm for constructing these matrices.

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1. Introduction

Any n -by- n matrix A of the form

$$\begin{pmatrix} a_0 & a_{-1} & a_{-2} & \dots & \dots & a_{-(n-1)} \\ a_1 & a_0 & a_{-1} & \ddots & & \vdots \\ a_2 & a_1 & \ddots & & \ddots & \vdots \\ \vdots & \ddots & & \ddots & a_{-1} & a_{-2} \\ \vdots & & \ddots & a_1 & a_0 & a_{-1} \\ a_{n-1} & \dots & \dots & a_2 & a_1 & a_0 \end{pmatrix}$$

is a toeplitz matrix. If $A = [a_{ij}]$, then we have $a_{ij} = a_{i+1,j+1} = a_{i-j}$.

A toeplitz matrix may be defined as a matrix $A = [a_{ij}]$ where $a_{ij} = c_{i-j}$, for constants c_{1-n}, \dots, c_{n-1} . The set of n -by- n toeplitz matrices is a subspace of the vector space of n -by- n matrices under matrix addition and scalar multiplication.

Toeplitz matrices are also closely connected with Fourier series, because the multiplication operator by a trigonometric polynomial, compressed to a finite-dimensional space, can be represented by such a matrix. Similarly, one can represent linear convolution as multiplication by a toeplitz matrix.

If each row of a matrix R has exactly a nonzero entry, $+1$, and its other entries zero, R is called integral row stochastic . The collection of all n -by- n integral row stochastic toeplitz matrices is denoted by $\mathcal{TR}(n)$.

For each $1 \leq k \leq n$ define

$$L^{(k)} = \{(k, 1), (k, 2), \dots, (k, k), (k - 1, k), \dots, (1, k)\}.$$

Note that $L^{(k)}$ consists of the first k positions in row k and column k . The sets $L^{(k)}$ are shaped like an L (backward). See [5].

For instance, for $n = 5$

$$\begin{aligned} L^{(1)} &= \{(1, 1)\}, \\ L^{(2)} &= \{(2, 1), (2, 2), (1, 2)\}, \\ L^{(3)} &= \{(3, 1), (3, 2), (3, 3), (2, 3), (1, 3)\}, \\ L^{(4)} &= \{(4, 1), (4, 2), (4, 3), (4, 4), (3, 4), (2, 4), (1, 4)\}, \\ L^{(5)} &= \{(5, 1), (5, 2), (5, 3), (5, 4), (5, 5), (4, 5), (3, 5), (2, 5), (1, 5)\}. \end{aligned}$$

Let $A \in \mathbf{M}_n$. For each $1 \leq k \leq n$ define

$$\sigma_k(A) = \sum_{(i,j) \in L^{(k)}} a_{ij},$$

and

$$\sigma(A) = (\sigma_1(A), \sigma_2(A), \dots, \sigma_n(A)).$$

$\sigma(A)$ is called the L -ray of A .

A matrix in \mathbf{M}_n is doubly stochastic if it is componentwise nonnegative and the entries sum of each row and each column is 1. In [4], the author presented descriptions of L -rays of permutation matrices and doubly stochastic matrices. For more information we refer the reader to [1, 2, 3].

In this paper, we investigate the image set $\sigma(\mathcal{TR}(n)) = \{\sigma(A) : A \in \mathcal{TR}(n)\}$ for the class of integral row stochastic toeplitz matrices. We call this the L -ray problem. We show that they are associated with majorization theory. The book [6] is a comprehensive study of majorization theory and its applications.

2. L -rays of integral row stochastic toeplitz matrices

In this section, we characterize L -rays of integral row stochastic toeplitz matrices.

Example 2.1. Let

$$\mathcal{TR}(2) = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}.$$

Then

$$\sigma(\mathcal{TR}(2)) = \{(1, 1), (0, 2)\}.$$

One can obtain the following proposition directly from the definition of an integral row stochastic toeplitz matrix.

Proposition 2.2. Let $A \in \mathcal{TR}(n)$. Then $0 \leq \sigma_1(A) \leq 1$, and for each k ($2 \leq k \leq n$) $0 \leq \sigma_k(A) \leq 2$.

The notation $x = (x_1, x_2, \dots, x_n) \in \{0, 1, 2\}^n$ means that $x_i \in \{0, 1, 2\}$ for each $1 \leq i \leq n$. A real vector $x = (x_1, x_2, \dots, x_n)$ is called monotone whenever $x_1 \leq x_2 \leq \dots \leq x_n$.

We use the following variation of majorization.

Let $x = (x_1, x_2, \dots, x_n)$ and $y = (y_1, y_2, \dots, y_n)$. Then $x <^* y$ if $\sum_{i=1}^k x_i \leq \sum_{i=1}^k y_i$ for $k < n$ and $\sum_{i=1}^n x_i = \sum_{i=1}^n y_i$.

The following algorithm constructs an integral row stochastic toeplitz matrix $A = (a_{ij})$. Note that $e = (1, 1, \dots, 1)$.

Algorithm

Input: A monotone vector $x = (x_1, x_2, \dots, x_n) \in \{0, 1, 2\}^n$ with $x <^* e$.

1. Initialize: Let $A = (a_{ij}) = 0_n$ (the zero matrix).

2. for $k = 1, 2, \dots, n$ do

(a) If $x_k = 1$,

If $k = \min\{1 \leq i \leq k : x_i \neq 0\}$, let $a_{1k} = 1$.

Else $s = \max\{1 \leq i \leq k - 1 : x_i \neq 0\}$ and $l =$ the number of obtained rows in the stage $x_s = 1$, let $a_{(l+1)k} = 1$.

(b) If $x_k = 2$,

Let m be the number 2's in the vector x .

for $i = 1, 2, \dots, m$ do

Let $a_{ki} = a_{(k-m)k} = 1$.

Output: A .

In the following theorem we describe the L -rays of integral row stochastic toeplitz matrices. Remember that $\text{card}(A)$ is the number of its elements, where A is a finite set.

Theorem 2.3. $\sigma(\mathcal{TR}(n)) = \{x \in \{0, 1, 2\}^n \mid x <^* e, x \text{ is monotone}\}$.

Furthermore, if $x \in \{0, 1, 2\}^n, x <^ e$ and x is monotone, then Algorithm offers an integral row stochastic toeplitz matrix A with $\sigma(A) = x$.*

Proof. First, assume that $x = \sigma(A)$ where $A \in \mathcal{TR}(n)$. Proposition 2.2 ensures that $x \in \{0, 1, 2\}^n$. We see that for each $k \leq n$

$$\begin{aligned}\sum_{r=1}^k x_r &= \sum_{r=1}^k \sigma_r(A) \\ &= \sum_{i,j \leq k} r_{ij} \leq k,\end{aligned}$$

and

$$\begin{aligned}\sum_{r=1}^n x_r &= \sum_{r=1}^n \sigma_r(A) \\ &= \sum_{i,j \leq n} r_{ij} \\ &= n.\end{aligned}$$

These imply that $x <^* e$. Now, we claim that x is monotone. As A is an integral row stochastic toeplitz matrix, we have two steps.

Step 1. If $A = I_n$, then $x = e$, and so x is monotone.

Step 2. If

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

where $a_{1k}, a_{2(k+1)}, \dots, a_{tm}, a_{(t+1)1}, a_{(t+2)2}, \dots, a_{n(k-1)} \neq 0$, we consider three cases.

Case 1. $k = t + 1$;

We observe that

$$\sigma_1(A) = \dots = \sigma_{k-1}(A) = 0,$$

and

$$\sigma_k(A) = \dots = \sigma_n(A) = 2.$$

That is, $x = (0, \dots, 0, 2, \dots, 2)$.

Case 2. $k > t + 1$;

Then

$$\begin{aligned} \sigma_1(A) &= \dots = \sigma_t(A) = 0, \\ \sigma_{t+1}(A) &= \dots = \sigma_{k-1}(A) = 1, \end{aligned}$$

and

$$\sigma_k(A) = \dots = \sigma_n(A) = 2.$$

Thus, $x = (0, \dots, 0, 1, \dots, 1, 2, \dots, 2)$.

Case 3. $k < t + 1$;

In this case,

$$\begin{aligned} \sigma_1(A) &= \dots = \sigma_{k-1}(A) = 0, \\ \sigma_k(A) &= \dots = \sigma_t(A) = 1, \end{aligned}$$

and

$$\sigma_{t+1}(A) = \dots = \sigma_n(A) = 2.$$

Hence $x = (0, \dots, 0, 1, \dots, 1, 2, \dots, 2)$.

In any case, we deduce that x is monotone.

For the converse, suppose that $x \in \{0, 1, 2\}^n$, $x <^* e$ and x is monotone. We claim that Algorithm constructs some $A \in \mathcal{TR}(n)$ such that $x = \sigma(A)$.

Claim: After each iteration k (of step 2) the present matrix A has the property $\sigma_i(A) = x_i$ for each $i = 1, 2, \dots, k$.

Proof of Claim: By induction on k we prove it. If $k = 1$ there is nothing to prove. Suppose that $k \leq n$ and the statement holds for $k' < k$. We consider three cases.

Case 1. If $x_k = 0$;

We see A is not modified. So $\sigma_k(A) = 0$, and the induction statement holds in this case.

Case 2. If $x_k = 1$;

If $k = \min\{1 \leq i \leq k : x_i \neq 0\}$ then $a_{1k} = 1$, and so $\sigma_k(A) = x_k$. If not; $a_{l+1k} = 1$ and hence $\sigma_k(A) = x_k$.

Case 3. If $x_k = 2$;

Algorithm ensures that $a_{ki} = a_{(k-m)k} = 1$ for each $1 \leq i \leq m$. This follows that $\sigma_k(A) = x_k$.

So the induction statement holds, and then $\sigma(A) = x$.

It remains to prove that $A \in \mathcal{TR}(n)$.

Define

$$\begin{aligned} I_0 &= \{1 \leq i \leq n : x_i = 0\}, \\ I_1 &= \{1 \leq i \leq n : x_i = 1\}, \end{aligned}$$

and

$$I_2 = \{1 \leq i \leq n : x_i = 2\}.$$

We see that

$$n = \text{card}(I_0) + \text{card}(I_1) + \text{card}(I_2). \tag{2.1}$$

Step 1. $\text{card}(I_0) = 0$;

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

(iii) Let $x = (0, 0, 0, 1, 1, 2, 2, 2)$. So $x <^* e$ and the desired matrix is

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

(iv) If $x = (1, 2, 0)$, then we can not use the Algorithm.

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