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A characterization of minimal Hermitian matrices

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ABSTRACT

We describe properties of a Hermitian matrix $M \in M_n(\mathbb{C})$ having minimal quotient norm in the following sense:

$$||M|| \leq ||M+D||$$

for all real diagonal matrices $D \in M_n(\mathbb{C})$. Here $\| \|$ denotes the operator norm. We show a constructive method to obtain all the minimal matrices of any size.

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1. Introduction

Let $M_n(\mathbb{C})$ and $D_n(\mathbb{R})$ be, respectively, the algebras of complex and real diagonal $n \times n$ matrices. In this paper we describe Hermitian matrices $M \in M_n(\mathbb{C})$ such that

$$||M|| \leq ||M + D||$$
, for all $D \in D_n(\mathbb{R})$

or equivalently

$$||M|| = \operatorname{dist}(M, D_n(\mathbb{R})),$$

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where $\| \|$ denotes the operator norm. These matrices M will be called minimal. These matrices appeared in the study of minimal length curves in the flag manifold $\mathcal{P}(n) = \mathcal{U}(M_n(\mathbb{C})) / \mathcal{U}(\mathcal{D}_n(\mathbb{C}))$, where $\mathcal{U}(A)$ denotes the unitary matrices of the algebra A, when $\mathcal{P}(n)$ is endowed with the quotient Finsler metric of the operator norm [4]. Minimal length curves δ in $\mathcal{P}(n)$ are given by the left action of $\mathcal{U}(M_n(\mathbb{C}))$ on $\mathcal{P}(n)$. Namely

$$\delta(t) = \left[e^{itM} \right],$$

where *M* is minimal and [U] denotes the class of *U* in $\mathcal{P}(n)$.

The following theorem follows ideas in [4], where this problem was also studied in the context of von Neumann and C* algebras. The next result was stated in Theorem 3.3 of [1] for 3×3 matrices. The same proof holds for $n \times n$ matrices.

Theorem 1. A Hermitian matrix $M \in M_n(\mathbb{C})$ is minimal in the above sense if and only if there exists a positive semidefinite matrix $P \in M_n^h(\mathbb{C})$ such that

- PM² = λ² P for λ = ||M||.
 All the diagonal elements of PM are zero.

Previous attempts to describe minimal matrices were done in [1] for 3×3 matrices. In that paper, all 3×3 minimal matrices were parametrized. We note that, Theorem 1 does not show how to construct $n \times n$ minimal matrices. Our goal in the present paper is to study some properties of $n \times n$ minimal matrices that allow the construction of them.

Minimal operators were studied in [8] where Theorem 2.2 of [1] was used to relate Leibnitz seminorms with quotient norms in C*-algebras.

2. Preliminaries and notation

Let $M_n(\mathbb{C})$ be the algebra of square complex matrices of $n \times n$, $M_n^h(\mathbb{C})$ the real subspace of Hermitian complex matrices, and $D_n(\mathbb{R})$ the real subalgebra of the diagonal real matrices. We denote with $\|A\|$ the usual operator norm of $A \in M_n(\mathbb{C})$ and with $||A||_1 = \operatorname{tr}(|A|) = \operatorname{tr}\left((A^*A)^{1/2}\right)$ the trace norm of A, where tr denotes the usual (non-normalized) trace.

Given a matrix $A \in M_n^h(\mathbb{C})$, $\lambda(A) \subset \mathbb{R}^n$ denotes the set of the eigenvalues of A, in decreasing order and counting multiplicity, that is,

$$\lambda(A) = (\lambda_1, \lambda_2, \dots, \lambda_n),$$

with $\lambda_1 \geqslant \lambda_2 \geqslant \cdots \geqslant \lambda_n$. In this context $\lambda_{min}(A)$ and $\lambda_{max}(A)$ denote the smallest and biggest eigenvalues of A respectively.

The symbol $\sigma(A)$ denotes here the set (unordered) of eigenvalues of A.

We denote with $\{e_i\}_{i=1}^n$ the canonical basis of \mathbb{C}^n . Given a matrix $A \in M_n^h(\mathbb{C})$, we denote with $a_{i,j}$ the i,j entry of A and we write $A = [a_{i,j}]$ for $i,j = 1, \ldots, n$.

Observe that if $M \in M_n^h(\mathbb{C})$ and $D \in D_n(\mathbb{R})$ then $(M+D) \in M_n^h(\mathbb{C})$. Let us consider the quotient $M_n^h(\mathbb{C})/D_n(\mathbb{R})$ and the quotient norm

$$\||M\| \| = \min_{D \in D_n(\mathbb{R})} \|M + D\| = \operatorname{dist}(M, D_n(\mathbb{R}))$$

for $[M] = \{M + D : D \in D_n(\mathbb{R})\} \in M_n^h(\mathbb{C})/D_n(\mathbb{R})$. The minimum is clearly attained.

Definition 1. A matrix $M \in M_n^h(\mathbb{C})$ is called **minimal** if

$$||M|| \leq ||M + D||$$
 for all $D \in D_n(\mathbb{R})$,

or equivalently, if $\|M\| = \||M\|| = \min_{D \in D_n(\mathbb{R})} \|M + D\| = dist(M, D_n(\mathbb{R})).$

Remark 1. Note that if $M \in M_n^h(\mathbb{C})$ is a minimal matrix then its spectrum is centered, i.e. $\|M\|$, $-\|M\| \in \sigma(M)$. In general, for a given matrix $A \in M_n^h(\mathbb{C})$, $\pm \|A\| \in \sigma(A)$ if and only if $\|A\| = \min_{\lambda \in \mathbb{D}} \|A + \lambda I\|$ if and only if $\lambda_{min}(A) + \lambda_{max}(A) = 0$.

For $a_1, a_2, \ldots, a_n \in \mathbb{R}$ we denote with $diag(a_1, a_2, \ldots, a_n)$ the diagonal matrix of $D_n(\mathbb{R})$ with a_1, a_2, \ldots, a_n on the diagonal.

Given $v \in \mathbb{C}^n$, $v \otimes v$ denotes the linear map in \mathbb{C}^n defined by $(v \otimes v)(x) = \langle x, v \rangle v$.

Let us denote with Φ the linear map from $M_n^h(\mathbb{C})$ to $D_n(\mathbb{R})$ defined by

$$\Phi(X) = \text{diag}(x_{1,1}, \dots, x_{n,n}), \text{ for } X = [x_{i,j}] \in M_n^h(\mathbb{C}).$$

Note that

$$\Phi(X) = \sum_{j=1}^{n} \langle Xe_j, e_j \rangle \ e_j \otimes e_j.$$

For $M \in M_n^h(\mathbb{C})$ and $v \in \mathbb{C}^n$ we write \overline{M} and \overline{v} to denote the matrix and vector obtained from M and v by conjugation of its coordinates.

If $M, N \in M_n(\mathbb{C})$ we denote with $M \circ N$ the Schur or Hadamard product of these matrices defined by $(M \circ N)_{i,j} = M_{i,j}N_{i,j}$ for $1 \le i,j \le n$. Therefore, if $v \in \mathbb{C}^n$, with coordinates in the canonical basis given by $v = (v_1, v_2, \dots, v_n)$,

$$v \circ \overline{v} = (|v_1|^2, |v_2|^2, \dots, |v_n|^2) = \sum_{i=1}^n |v_i|^2 e_i \in \mathbb{R}^n_+.$$

Observe that with these notations, if $X \in M_n^h(\mathbb{C})$ and $\{v_i\}_{i=1,\dots,n}$ is an orthonormal basis of \mathbb{C}^n of eigenvectors of X with corresponding eigenvalues $\lambda(X) = (\lambda_1, \dots, \lambda_n)$, then $X = \sum_{i=1}^n \langle X v_i, v_i \rangle \ v_i \otimes v_i = \sum_{i=1}^n \lambda_i \ v_i \otimes v_i$. Direct calculations with the canonical coordinates of these eigenvectors prove that

$$\Phi(X) = \operatorname{diag}\left(\sum_{i=1}^{n} \lambda_i \ (\nu_i \circ \overline{\nu_i})\right). \tag{2.1}$$

For $M, N \in M_n(\mathbb{C})$ the usual matrix product will be denoted with MN and ran(M) will denote the range of the linear transformation M.

3. Minimal matrices

It is apparent that for $X \in M_n^h(\mathbb{C})$

$$\operatorname{tr}(DX) = 0 \ \forall D \in D_n(\mathbb{R}) \iff \Phi(X) = 0.$$
 (3.1)

Then, from the Banach duality formula for the quotient norm and (3.1), it follows that

$$\max_{\substack{X \in M_n^h(\mathbb{C}), \Phi(X) = 0 \\ \|X\|_1 = 1}} |\operatorname{tr}(MX)| = \min_{\substack{D \in D_n(\mathbb{R})}} \|M + D\|.$$
(3.2)

Note that for an orthogonal projection E and $A \in M_n^h(\mathbb{C})$ the condition EA = A is equivalent to $ran(A) \subset ran(E)$.

If $X \in M_n^h(\mathbb{C})$, let X^+ and X^- be the positive and negative parts of X, that is,

$$X^{+} = \frac{|X| + X}{2}$$
 and $X^{-} = \frac{|X| - X}{2}$ (with $|X| = (X^{2})^{1/2} \ge 0$).

Theorem 2. Let $0 \neq M \in M_n^h(\mathbb{C})$ and E_+ (respectively E_-) the spectral projection of M corresponding to the eigenvalue $\lambda_{max}(M)$ (respectively $\lambda_{min}(M)$). The following conditions are equivalent:

- (i) M is minimal.
- (ii) There is a non-zero $X \in M_n^h(\mathbb{C})$ such that

$$\Phi(X) = 0$$
, $E_+X^+ = X^+$, $E_-X^- = X^-$ and $tr(MX) = ||M|| ||X||_1$.

(iii) $\lambda_{max}(M) + \lambda_{min}(M) = 0$, and for any diagonal $D \in D_n(\mathbb{R})$ there exist $y \in ran(E_+)$ and $z \in ran(E_-)$ such that

$$||y|| = ||z|| = 1$$
 and $\langle Dy, y \rangle \leq \langle Dz, z \rangle$.

Proof. We may assume that ||M|| = 1.

(i) \Rightarrow (ii). Since M is minimal, by Remark 1 it must be $\lambda_{max} = 1$ and $\lambda_{min} = -1$. Consider the projections

$$E_1 = E_+, E_2 = E_-$$
 and $E_3 = I - E_1 - E_2$.

Then E_3 is the spectral projection of M corresponding to the open interval (-1, 1), hence $E_3M = ME_3$ and $||ME_3|| < 1$. Now M is written as

$$M = E_1 - E_2 + ME_3$$
.

In view of (3.2) there exists $X \in M_n^h(\mathbb{C})$ such that

$$\Phi(X) = 0, ||X||_1 = 1 \text{ and } tr(MX) = 1.$$
 (3.3)

In terms of the orthogonal decomposition $\mathbb{C}^n = \operatorname{ran}(E_1) \oplus \operatorname{ran}(E_2) \oplus \operatorname{ran}(E_3)$, we can write

$$M = \begin{pmatrix} I & 0 & 0 \\ 0 & -I & 0 \\ 0 & 0 & M_{3,3} \end{pmatrix} \text{ and } X = \begin{pmatrix} X_{1,1} & X_{1,2} & X_{1,3} \\ X_{2,1} & X_{2,2} & X_{2,3} \\ X_{3,1} & X_{3,2} & X_{3,3} \end{pmatrix}.$$

Let us to prove the identities $X_{1,2} = X_{2,1}^* = 0$, $X_{1,3} = X_{3,1}^* = 0$, $X_{2,3} = X_{3,2}^* = 0$ and $X_{3,3} = 0$. The pinching inequality of Chandler Davis [2, IV.52] implies that

$$\left\| \begin{pmatrix} X_{1,1} & X_{1,2} \\ X_{2,1} & X_{2,2} \end{pmatrix} \right\|_{1} + \|X_{3,3}\|_{1} \leqslant \|X\|_{1} = 1$$
(3.4)

and

$$||X_{1,1}||_1 + ||X_{2,2}||_1 \leqslant \left\| \begin{pmatrix} X_{1,1} & X_{1,2} \\ X_{2,1} & X_{2,2} \end{pmatrix} \right\|_1.$$
(3.5)

Note that $||M_{3,3}|| < 1$. First let us show that $X_{3,3} = 0$. Suppose, that $||X_{3,3}||_1 \neq 0$. Then by (3.3) and the inequalities (3.4) and (3.5) we have

$$||X||_1 = 1 = \operatorname{tr}(MX) = \operatorname{tr}(X_{1,1}) - \operatorname{tr}(X_{2,2}) + \operatorname{tr}(M_{3,3}X_{3,3})$$

$$\leq ||X_{1,1}||_1 + ||X_{2,2}||_1 + ||M_{3,3}|| ||X_{3,3}||_1$$

$$< ||X_{1,1}||_1 + ||X_{2,2}||_1 + ||X_{3,3}||_1 \leq ||X||_1 = 1,$$

a contradiction. Hence $X_{3,3} = 0$. Incidentally, we have proved that

$$tr(X_{1,1}) = ||X_{1,1}||_1$$
 and $tr(-X_{2,2}) = ||-X_{2,2}||_1$.

Therefore, by the well-known fact that $tr(Y) = ||Y||_1$ occurs only if $Y \ge 0$, we have that

$$X_{1,1} \geqslant 0 \text{ and } -X_{2,2} \geqslant 0.$$
 (3.6)

Moreover by (3.3)

$$\operatorname{tr}(MX) = \operatorname{tr} \begin{pmatrix} X_{1,1} & X_{1,2} & X_{1,3} \\ -X_{2,1} & -X_{2,2} & -X_{2,3} \\ M_{3,3}X_{3,1} & M_{3,3}X_{3,2} & 0 \end{pmatrix} = 1 = \begin{pmatrix} X_{1,1} & X_{1,2} & X_{1,3} \\ -X_{2,1} & -X_{2,2} & -X_{2,3} \\ M_{3,3}X_{3,1} & M_{3,3}X_{3,2} & 0 \end{pmatrix}_{1}.$$

Then, by the same argument, the matrix MX should be positive semidefinite, which implies that $X_{1,3} =$ $X_{3,1}^* = 0$ and $X_{2,3} = X_{3,2}^* = 0$. In the same way from the relation

$$\operatorname{tr}\begin{pmatrix} X_{1,1} & X_{1,2} \\ -X_{2,1} & -X_{2,2} \end{pmatrix} = \left\| \begin{pmatrix} X_{1,1} & X_{1,2} \\ -X_{2,1} & -X_{2,2} \end{pmatrix} \right\|_{1}$$

we can conclude that $\begin{pmatrix} X_{1,1} & X_{1,2} \\ -X_{2,1} & -X_{2,2} \end{pmatrix} \ge 0$, and then $X_{1,2} = X_{2,1}^* = 0$.

Therefore

$$X = \begin{pmatrix} X_{1,1} & 0 & 0 \\ 0 & X_{2,2} & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \text{with } X_{1,1} \geqslant 0 \text{ and } X_{2,2} \leqslant 0,$$

which proves that $X^+ = E_+ X_{1,1} E_+$ and $X^- = -E_- X_{2,2} E_-$, hence $E_+ X^+ = X^+$ and $E_- X^- = X^-$.

(ii) \Rightarrow (i) is immediate from (3.2).

(ii) \Rightarrow (iii). Take a non-zero $X \in M_n^h(\mathbb{C})$ such that $\Phi(X) = 0$, $E_+ = X^+$, $E_-X^- = X^-$ and $\|X\|_1 = 0$ $\operatorname{tr}(MX)$. Pick a diagonal $D \in D_n(\mathbb{R})$. Note that $X \neq 0$ and $\Phi(X) = 0$ imply that $\Phi(X^+) = \Phi(X^-) \neq 0$. Since $X^+, X^- \ge 0$, it follows that

$$\|X^+\|_1 = \|\Phi(X^+)\|_1 = \|\Phi(X^-)\|_1 = \|X^-\|_1 \neq 0.$$

The inequalities

$$\operatorname{tr}\left(\Phi(X^{+})D\right) = \operatorname{tr}\left(X^{+}D\right) \geqslant \|X^{+}\|_{1} \min_{y \in \operatorname{ran}(E_{+}), \ \|y\| = 1} \langle Dy, y \rangle$$

and

$$\operatorname{tr}\left(\Phi(X^{-})D\right) = \operatorname{tr}\left(X^{-}D\right) \leqslant \|X^{-}\|_{1} \max_{z \in \operatorname{ran}(E_{-}), \|z\| = 1} \langle Dz, z \rangle$$

prove (iii).

(iii) \Rightarrow (ii). Suppose that there is no $0 \neq X \in M_n^h(\mathbb{C})$ satisfying the requirements of (ii). Consider the following two compact convex subsets of $M_n^h(\mathbb{C})$

$$A = \{Y : E_+Y = Y \ge 0, \text{ tr}(Y) = 1\} \text{ and } B = \{Z : E_-Z = Z \ge 0, \text{ tr}(Z) = 1\}.$$

Since the assumption implies that $\Phi(A) \cap \Phi(B) = \emptyset$, the compact convex sets $\Phi(A)$ and $\Phi(B)$ in \mathbb{R}^n are separated by a linear form, that is, there is a non-zero vector $d=(d_1,\ldots,d_n)\in\mathbb{R}^n$ such that

$$\min_{Y \in A} \langle \Phi(Y), d \rangle > \max_{Z \in \mathcal{B}} \langle \Phi(Z), d \rangle.$$

This contradicts the condition (iii): taking $D = diag(d_1, \ldots, d_n)$,

$$\min_{Y \in \mathcal{A}} \langle \Phi(Y), d \rangle = \min_{y \in \operatorname{ran}(E_+), \|y\| = 1} \langle Dy, y \rangle$$

and

$$\max_{Z \in \mathcal{B}} \langle \Phi(Z), d \rangle = \max_{z \in \operatorname{ran}(E_-), \|z\| = 1} \langle Dz, z \rangle.$$

This completes the proof. \Box

Remark 2. Let $M \in M_n^h(\mathbb{C})$ be a minimal matrix and $X \in M_n^h(\mathbb{C})$ be as in (ii) of the previous theorem. The functional $\psi(\cdot) = \operatorname{tr}(X \cdot)$ is a witness for the fact that 0 is a best approximation to M in $D_n(\mathbb{R})$ as defined in [8]. That is, ψ is a norm one functional such that $\psi|_{D_n(\mathbb{R})} = 0$ and $\psi(M) = \|M - 0\|$.

4. An algorithm to construct minimal matrices

It is now clear that Theorem 2 can be used to construct all minimal matrices.

Theorem 3. (step 1) Take non-zero $X \in M_n^h(\mathbb{C})$ with 0 diagonal (hence $X^+ \neq 0, X^- \neq 0$ and $ran(X^+) \perp ran(X^-)$).

(step 2) Take non-zero orthoprojections E_+ and E_- such that $E_+E_-=0$, $E_+X^+=X^+$ and $E_-X^-=X^-$.

(step 3) Take $R \in M_n^h(\mathbb{C})$ such that $R(E_+ + E_-) = 0$ and $\|R\| < 1$. Then $M = E_+ - E_- + R$ is a minimal matrix with $\|M\| = 1$.

Conversely every minimal matrix M with ||M|| = 1 is obtained in this way.

Remark 3. Note that for different $X \in M_n^h(\mathbb{C})$ with zero diagonal, the construction detailed in Theorem 3 may give the same orthoprojections E_+ and E_- onto $\operatorname{ran}(X^+)$ and $\operatorname{ran}(X^-)$, and therefore the same

minimal matrices. Take for example the 3 \times 3 unitary $U=\frac{1}{\sqrt{3}}\begin{pmatrix}1&1&1\\1&w&w^2\\1&w^2&w\end{pmatrix}$ with $w=e^{i\frac{2\pi}{3}}$. Then

define $X_t = U \operatorname{diag}(1, t-1, -t) U^*$ for $t \in \mathbb{R}$ and 0 < t < 1. It is apparent that $X_t \in M_n^h(\mathbb{C})$, $\Phi(X_t) = 0$ and $\|X_t\|_1 = 2$. By construction, if $t_1 \neq t_2$, the matrices X_{t_1} and X_{t_2} are different. However $\operatorname{ran}((X_{t_1})^+) = \operatorname{ran}((X_{t_2})^+)$ and $\operatorname{ran}((X_{t_1})^-) = \operatorname{ran}((X_{t_2})^-)$ for $t_1, t_2 \in (0, 1)$.

The following corollary is a slight variation of Theorem 1.

Corollary 1. A non-zero matrix $M \in M_n^h(\mathbb{C})$ is minimal if and only if there exists a non-zero positive semidefinite matrix $P \in M_n^h(\mathbb{C})$ such that

- $PM^2 = \lambda^2 P$ for $\lambda = ||M||$.
- All the diagonal elements of PM are zero.
- *P* commutes with *M*.

Proof. If M is minimal and X is as in (ii) of Theorem 2 then $P = X^+ + X^-$ fulfills all the required conditions. That these conditions are necessary follows from Theorem 1. \square

Recall that E_+ and E_- are the spectral projections corresponding respectively to the eigenvalues $\lambda_{max}(M)$ and $\lambda_{min}(M)$.

Corollary 2. A non-zero matrix $M \in M_n^h(\mathbb{C})$ is minimal if and only if $\lambda_{min}(M) + \lambda_{max}(M) = 0$ and there exist two non-zero positive semidefinite matrices $P, Q \in M_n^h(\mathbb{C})$ such that

- $ran(P) \subset ran(E_+)$ and $ran(Q) \subset ran(E_-)$.
- $\Phi(P) = \Phi(Q).$
- PQ = 0.

Proof. If M is minimal and X is as in (ii) of Theorem 2, then $P = X^+$ and $Q = X^-$ satisfy all the required conditions. That these conditions are necessary for M to be minimal follows picking $X = \frac{1}{\|P - Q\|_1}(P - Q)$, which satisfies condition (ii) of Theorem 2. \square

5. Spectral eigenspaces corresponding to λ_{min} and λ_{max} for a minimal matrix

In this section we describe some properties of the subspaces $ran(E_+)$ and $ran(E_-)$, where E_+ and E_- are the spectral projections of a minimal matrix M corresponding to the eigenvalues $\lambda_{max}(M)$ and $\lambda_{min}(M)$. As seen in Theorem 3 these are the building blocks of all the minimal matrices.

 $\lambda_{min}(M)$. As seen in Theorem 3 these are the building blocks of all the minimal matrices. For given vectors $\{w_k\}_{k=1}^m \subset \mathbb{C}^n$ we denote with $\operatorname{co}(\{w_k\}_{k=1}^m)$ the convex hull generated by them.

Corollary 3. Let $M \in M_n^h(\mathbb{C})$ be a non-zero matrix such that $\lambda_{max}(M) + \lambda_{min}(M) = 0$. Then the following properties are equivalent:

- (a) *M* is minimal.
- (b) There exist orthonormal sets $\{v_i\}_{i=1}^r \subset \operatorname{ran}(E_+)$ and $\{v_j\}_{j=r+1}^{r+s} \subset \operatorname{ran}(E_-)$ such that

$$\operatorname{co}(\{v_i \circ \overline{v_i}\}_{i=1}^r) \cap \operatorname{co}\left(\{v_j \circ \overline{v_j}\}_{j=r+1}^{r+s}\right) \neq \emptyset. \tag{5.1}$$

Proof. Suppose that M is minimal. By using Theorem 2 there exists a non-zero $X \in M_n^h(\mathbb{C})$ that satisfies (ii) of that theorem. Fix a basis of $\operatorname{ran}(X^+)$ of orthonormal eigenvectors $\{v_i\}_{i=1}^r$ corresponding to the (strictly) positive eigenvalues $\{a_i\}_{i=1}^r$ of X^+ , and a basis of $\operatorname{ran}(X^-)$ of orthonormal eigenvectors $\{v_j\}_{j=r+1}^{r+s}$ corresponding to the (strictly) positive eigenvalues $\{a_j\}_{j=r+1}^{r+s}$ of X^- (note that $\operatorname{ran}(X^+) \perp \operatorname{ran}(X^-)$). Then, since $X^+ = \sum_{i=1}^r a_i(v_i \otimes v_i)$ and $X^- = \sum_{j=r+1}^{r+s} a_j(v_j \otimes v_j)$, using the formula (2.1) for $\Phi(X^+)$ and $\Phi(X^-)$, it can be shown that

$$\Phi(X) = \Phi(X^+) - \Phi(X^-) = \operatorname{diag}\left(\sum_{i=1}^r a_i \ (v_i \circ \overline{v_i})\right) - \operatorname{diag}\left(\sum_{j=r+1}^{r+s} a_j \ (v_j \circ \overline{v_j})\right).$$

Since $\Phi(X)=0$, it is apparent that $\sum_{i=1}^r a_i \ (v_i \circ \overline{v_i})=\sum_{j=r+1}^{r+s} a_j \ (v_j \circ \overline{v_j})$ and $\operatorname{tr}(X^+)=\operatorname{tr}(X^-)>0$, which proves that $\sum_{i=1}^r a_i=\sum_{j=r+1}^{r+s} a_j$. Therefore,

$$\sum_{i=1}^r \frac{a_i}{\sum_{i=1}^r a_i} \ (\nu_i \circ \overline{\nu_i}) = \sum_{j=r+1}^{r+s} \frac{a_j}{\sum_{j=r+1}^{r+s} a_j} \ (\nu_j \circ \overline{\nu_j}) \ .$$

Then, since $ran(X^+) \subset ran(E_+)$ and $ran(X^-) \subset ran(E_-)$, (b) holds.

Conversely, if (b) holds, there exist α_i , $\beta_j > 0$ satisfying $\sum_{i=1}^r \alpha_i = 1 = \sum_{i=r+1}^{r+s} \beta_j$, and orthonormal sets $\{v_i\}_{i=1}^r \subset \operatorname{ran}(E_+)$ and $\{v_j\}_{j=r+1}^{r+s} \subset \operatorname{ran}(E_-)$, such that

$$\sum_{i=1}^{r} \alpha_i(\nu_i \circ \overline{\nu_i}) = \sum_{j=r+1}^{r+s} \beta_j(\nu_j \circ \overline{\nu_j}) \in \operatorname{co}(\{\nu_i \circ \overline{\nu_i}\}_{i=1}^r) \cap \operatorname{co}\left(\{\nu_j \circ \overline{\nu_j}\}_{j=r+1}^{r+s}\right).$$

Put

$$X = \frac{1}{2} \left(\sum_{i=1}^{r} \alpha_i \ (\nu_i \otimes \nu_i) - \sum_{j=r+1}^{r+s} \beta_j \ (\nu_j \otimes \nu_j) \right).$$

It is straightforward that *X* satisfies condition (ii) of Theorem 2. Therefore *M* is minimal. □

The previous corollary could have been proved with similar techniques as in the proof of (ii) \Rightarrow (iii) in Theorem 2. Moreover, define the following subsets of \mathbb{R}^n_+

$$\mathcal{P}_{+} = \bigcup_{\substack{\text{o.n. set } \{v_i\}_{i=1}^r \\ \{v_i\}_{i=1}^r \subset \operatorname{ran}(E_{+})}} \operatorname{co}(\{v_i \circ \overline{v_i}\}_{i=1}^r) \quad \text{and} \quad \mathcal{P}_{-} = \bigcup_{\substack{\text{o.n. set } \{v_j\}_{j=r+1}^{r+s} \\ \{v_j\}_{j=r+1}^{r+s} \subset \operatorname{ran}(E_{-})}} \operatorname{co}\left(\{v_j \circ \overline{v_j}\}_{j=r+1}^{r+s}\right).$$

Then \mathcal{P}_+ and \mathcal{P}_- induce the subsets $\Phi(\mathcal{A})$ and $\Phi(\mathcal{B}) \subset D_n(\mathbb{R})$, where \mathcal{A} and \mathcal{B} are the compact convex sets defined in the proof of Theorem 2. Then, \mathcal{P}_+ and \mathcal{P}_- are compact and convex sets of \mathbb{R}^n . Therefore for a matrix M such that $\lambda_{min}(M) + \lambda_{max}(M) = 0$, the property $\mathcal{P}_+ \cap \mathcal{P}_- \neq \emptyset$ is equivalent to being minimal.

A different way to construct minimal matrices is the following. Take $a_i > 0$, for $1 \le i \le r$, $a_j > 0$ for $r+1 \le j \le r+s$ with $1 \le r, s, r+s \le n$ and such that $\sum_{i=1}^r a_i = \sum_{j=r+1}^{r+s} a_j$. If we define $\vec{a} = (a_1, \ldots, a_r, -a_{r+1}, \ldots, -a_{r+s}, 0, \ldots, 0) \in \mathbb{R}^n$, it follows that \vec{a} majorizes $\vec{0} = (0, \ldots, 0) \in \mathbb{R}^n$, and we will denote $\vec{0} \prec \vec{a}$ as usual (see [6] for basic facts on majorization). Then a concrete unitary matrix $U \in M_n(\mathbb{C})$ can be found (see [5–7]) such that $(U \circ \overline{U}) \in M_n(\mathbb{R}_+)$ satisfies that $(U \circ \overline{U}) \vec{a} = \vec{0}$. This last equality can be written as

$$\sum_{i=1}^{r} a_i(\nu_i \circ \overline{\nu_i}) - \sum_{i=r+1}^{r+s} a_j(\nu_j \circ \overline{\nu_j}) = \vec{0},$$

where $\{v_k\}_{k=1}^n$ are the columns of the unitary *U*. Then any matrix of the form

$$M = \lambda \sum_{i=1}^{r} v_i \otimes v_i - \lambda \sum_{i=r+1}^{r+s} v_j \otimes v_j + \sum_{h=r+s+1}^{n} \lambda_h (v_h \otimes v_h)$$
 (5.2)

is minimal, provided that $\lambda > 0$, $\lambda_h \in \mathbb{R}$, $|\lambda_h| < \lambda$. These computations provide a different way to construct examples of minimal matrices of any size.

In [3] several algorithms are produced to find unitary (or orthogonal) matrices U that satisfy $(U \circ \overline{U})\vec{a} = \vec{0}$ for a given \vec{a} . Nevertheless, the set of all possible unitaries U that satisfy $(U \circ \overline{U})\vec{a} = 0$ is not known in general. The papers [9] and [10] study this problem.

The method to obtain minimal matrices as in (5.2) has the disadvantage that M relies on the construction of the unitary U.

Remark 4. In [1] a different characterization of minimal 3×3 matrices was obtained. It is shown that given a 3×3 matrix M, with $\lambda(M) = (\lambda, \mu, -\lambda)$, $|\mu| \le \lambda = ||M||$, then, M is minimal, if and only if, there exists a normalized eigenvector v_{λ} of the eigenvalue λ and a normalized eigenvector $v_{-\lambda}$ of the eigenvalue $-\lambda$ such that $v_{\lambda} \circ \overline{v_{\lambda}} = v_{-\lambda} \circ \overline{v_{-\lambda}}$. The statement remains valid if any of the eigenvalues has multiplicity two ($\mu = \pm \lambda$). The following is an example of a 4×4 minimal Hermitian matrix where this condition does not hold. Let

$$M = \begin{pmatrix} \frac{9}{14} & -\frac{15}{14} - \frac{i}{7} & -\frac{1}{7} + \frac{5i}{7} & \frac{2}{7} + \frac{6i}{7} \\ -\frac{15}{14} + \frac{i}{7} & \frac{13}{14} & -\frac{1}{7} + i & \frac{6i}{7} \\ -\frac{1}{7} - \frac{5i}{7} & -\frac{1}{7} - i & \frac{5}{7} & -1 - \frac{2i}{7} \\ \frac{2}{7} - \frac{6i}{7} & -\frac{6i}{7} & -1 + \frac{2i}{7} & \frac{5}{7} \end{pmatrix}.$$

Then $\lambda(M) = (2, 2, 1, -2)$, and the eigenspace of the eigenvalue 2 is generated by the orthonormal eigenvectors

$$v_1 = \frac{1}{5\sqrt{2}} (-1 - 2i, 5, -3 - i, 1 - 3i)$$
 and
 $v_2 = \frac{1}{10\sqrt{14}} (17 - 11i, -15 + 5i, -9 + 17i, 3 - 19i).$

The vector $w=\frac{1}{2\sqrt{2}}$ (1-i,1-i,1+i,1+i) is a normalized eigenvector of eigenvalue -2. A direct calculation shows that for $\alpha=\frac{2}{9}$, $\alpha(v_1\circ\overline{v_1})+(1-\alpha)(v_2\circ\overline{v_2})=w\circ\overline{w}=(\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4})$, which proves that M is minimal (using Corollary 3). However, there is not an eigenvector v in the eigenspace of the eigenvalue 2 such that $v\circ\overline{v}=w\circ\overline{w}$. This follows writing $v=\beta v_1+\gamma v_2$ with $\beta,\gamma\in\mathbb{C}$, and $|\beta|^2+|\gamma|^2=1$, and proving that $v\circ\overline{v}=w\circ\overline{w}$ cannot happen (note that it can be supposed that $\gamma=\sqrt{1-|\beta|^2}$).

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