On tropical supereigenvectors

Peter Butkovič

School of Mathematics, University of Birmingham, Birmingham B15 2TT, United Kingdom

Abstract

The task of finding tropical eigenvectors and subeigenvectors, that is non-trivial solutions to $A \otimes x = \lambda \otimes x$ and $A \otimes x \leq \lambda \otimes x$ in the max-plus algebra, has been studied by many authors since the 1960s. In contrast the task of finding supereigenvectors, that is solutions to $A \otimes x \geq \lambda \otimes x$, has attracted attention only recently. We present a number of properties of supereigenvectors focusing on a complete characterization of the values of $\lambda$ associated with supereigenvectors and in particular finite supereigenvectors. The proof of the main statement is constructive and enables us to find a non-trivial subspace of finite supereigenvectors. We also present an overview of key related results on eigenvectors and subeigenvectors.

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1. Introduction

Tropical linear algebra (also called max-algebra or path algebra) is an analogue of linear algebra developed for the pair of operations $(\oplus, \otimes)$ where

$$a \oplus b = \max(a, b)$$

E-mail address: p.butkovic@bham.ac.uk.
and

\[ a \otimes b = a + b \]

for \(a, b \in \mathbb{R} \equiv \mathbb{R} \cup \{-\infty\}\). This pair is extended to matrices and vectors as in conventional linear algebra. That is if \(A = (a_{ij})\), \(B = (b_{ij})\) and \(C = (c_{ij})\) are matrices of compatible sizes with entries from \(\mathbb{R}\), we write \(C = A \oplus B\) if \(c_{ij} = a_{ij} \oplus b_{ij}\) for all \(i, j\) and \(C = A \odot B\) if

\[ c_{ij} = \bigoplus_k a_{ik} \otimes b_{kj} = \max_k (a_{ik} + b_{kj}) \]

for all \(i, j\). If \(\alpha \in \mathbb{R}\) then \(\alpha \otimes A = (\alpha \otimes a_{ij})\). For simplicity we will use the convention of not writing the symbol \(\otimes\). Thus in what follows the symbol \(\otimes\) will usually not be used and unless explicitly stated otherwise, all multiplications indicated are in max-algebra.

The interest in tropical linear algebra was originally motivated by the possibility of dealing with a class of non-linear problems in pure and applied mathematics, operational research, science and engineering as if they were linear due to the fact that \((\mathbb{R}, +, \cdot)\) is a commutative and idempotent semifield. Besides the main advantage of using linear rather than non-linear techniques, tropical linear algebra enables us to efficiently describe and deal with complex sets [6], reveal combinatorial aspects of problems [5] and view a class of problems in a new, unconventional way. The first pioneering papers appeared in the 1960s [15,16,35], followed by substantial contributions in the 1970s and 1980s such as [17,23,39,14]. Since 1995 we have seen a remarkable expansion of this research field following a number of findings and applications in areas as diverse as algebraic geometry [30] and [34], geometry [26], control theory and optimization [2], phylogenetic [33], modelling of the cellular protein production [4] and railway scheduling [24]. A number of research monographs have been published [2,7,24,28,29]. A chapter on max-algebra appears in a handbook of linear algebra [25] and a chapter on idempotent semirings is in a monograph on semirings [21].

Tropical linear algebra covers a range of linear-algebraic problems in the max-linear setting, such as systems of linear equations and inequalities, linear independence and rank, bases and dimension of subspaces, polynomials, characteristic polynomials, matrix equations, matrix orbits and periodicity of matrix powers [2,7,17,24]. Among the most intensively studied questions was the eigenproblem, that is the question, for a given square matrix \(A\) to find all values of \(\lambda \in \mathbb{R}\) and non-trivial vectors \(x\) such that \(A \otimes x = \lambda \otimes x\). This and related questions have been answered [17,23,20,3,19] with numerically stable low-order polynomial algorithms. The same is true about the subeigenproblem that is solution to \(A \otimes x \leq \lambda \otimes x\), which appears to be strongly linked to the eigenproblem (see Section 4). In contrast, until recently [12,38,31] almost no attention has been paid to the supereigenproblem that is solution to \(A \otimes x \geq \lambda \otimes x\), which is trivial for small values of \(\lambda\) but in general the description of the whole solution set seems to be much more difficult than for the eigenproblem [38,31]. This fact triggers in particular the question of finding
finite supereigenvectors. It is the main aim of this paper to identify (in Theorem 5.8) all values of \( \lambda \) for which a given matrix \( A \) has finite supereigenvectors and to find such vectors.

In order to provide a complete picture the results on general and finite supereigenvectors are compared with those for eigenvectors and subeigenvectors. Note that a theory of finite eigenvectors and subeigenvectors is well developed \cite{17,7}. Note also that in the max-times setting, that is for the semifield \((\mathbb{R}_+, \max, .)\) finiteness corresponds to positivity.

We first give in Sections 2–4 a summary of the concepts and known results in tropical linear algebra that will be used in Section 5 to present the results on supereigenvectors.

2. Definitions and notation

Throughout the paper we denote \( -\infty \) by \( \varepsilon \) (the neutral element with respect to \( \oplus \)) and for convenience we also denote by the same symbol any vector, whose all components are \( -\infty \), or a matrix whose all entries are \( -\infty \). If \( a \in \mathbb{R} \) then the symbol \( a^{-1} \) stands for \( -a \). We assume everywhere that \( n \geq 1 \) is an integer and denote \( N = \{1, \ldots, n\} \).

A vector or matrix are called finite if all their entries are real numbers. A square matrix is called diagonal if all its diagonal entries are real numbers and off-diagonal entries are \( \varepsilon \). A diagonal matrix with all diagonal entries equal to \( 0 \) is called the unit matrix and denoted \( I \). Obviously, \( AI = IA = A \) whenever \( A \) and \( I \) are of compatible sizes.

If \( A \) is a square matrix then the iterated product \( AA \ldots A \) in which the symbol \( A \) appears \( k \)-times will be denoted by \( A^k \). By definition \( A^0 = I \).

It is easily proved that if \( A, B \) and \( C \) are of compatible sizes then:

\[
A \geq B \implies AC \geq BC \quad \text{and} \quad CA \geq CB. \tag{1}
\]

Tropical linear algebra often benefits from close links between matrices and digraphs. A digraph is an ordered pair \( D = (V, E) \) where \( V \) is a nonempty finite set (of nodes) and \( E \subseteq V \times V \) (the set of arcs).

Let \( D = (V, E) \) be a digraph. A sequence \( \pi = (v_1, \ldots, v_p) \) of nodes in \( D \) is called a path (in \( D \)) if \( p = 1 \) or \( p > 1 \) and \( (v_i, v_{i+1}) \in E \) for all \( i = 1, \ldots, p-1 \). The number \( p-1 \) is called the length of \( \pi \) and will be denoted by \( l(\pi) \). If \( u \) is the starting node and \( v \) is the endnode of \( \pi \) then we say that \( \pi \) is a \( u \rightarrow v \) path. If there is a \( u \rightarrow v \) path in \( D \) then \( v \) is said to be reachable from \( u \), notation \( u \rightarrow v \). Thus \( u \rightarrow u \) for any \( u \in V \).

A path \( (v_1, \ldots, v_p) \) is called a cycle if \( v_1 = v_p \) and \( p > 1 \) and it is called an elementary cycle if, moreover, \( v_i \neq v_j \) for \( i, j = 1, \ldots, p-1, i \neq j \). If there is no cycle in \( D \) then \( D \) is called acyclic.

A digraph \( D \) is called strongly connected if \( u \rightarrow v \) for all nodes \( u, v \) in \( D \). A subdigraph \( D' \) of \( D \) is called a strongly connected component of \( D \) if it is a maximal strongly connected subdigraph of \( D \), that is, \( D' \) is a strongly connected subdigraph of \( D \) and if \( D' \)
is a subdigraph of a strongly connected subdigraph $D''$ of $D$ then $D' = D''$. Note that a digraph consisting of one node and no arc is strongly connected and acyclic; however, if a strongly connected digraph has at least two nodes then it obviously cannot be acyclic.

If $D = (N, E)$ is a digraph and $K \subseteq N$ then $D[K]$ denotes the induced subgraph of $D$, that is

$$D[K] = (K, E \cap (K \times K)).$$

A **weighted digraph** is $D = (V, E, w)$, where $(V, E)$ is a digraph and $w$ is a real function on $E$. All definitions for digraphs are naturally extended to weighted digraphs. If $\pi = (v_1, \ldots, v_p)$ is a path in $(V, E, w)$ then the **weight** of $\pi$ is $w(\pi) = w(v_1, v_2) + w(v_2, v_3) + \ldots + w(v_{p-1}, v_p)$ if $p > 1$ and $\varepsilon$ if $p = 1$.

Given $A = (a_{ij}) \in \mathbb{R}^{n \times n}$ the symbol $D_A$ will denote the weighted digraph $(N, E, w)$ where $E = \{(i, j) \mid a_{ij} > \varepsilon\}$ and $w(i, j) = a_{ij}$ for all $(i, j) \in E$. The digraph $D_A$ is said to be **associated** with the matrix $A$. If $\pi = (i_1, \ldots, i_p)$ is a path in $D_A$ then we denote $w(\pi)$ by $w(\pi, A)$ and it now follows from the definitions that $w(\pi, A) = a_{i_1i_2} + a_{i_2i_3} + \ldots + a_{i_{p-1}i_p}$ if $p > 1$ and $\varepsilon$ if $p = 1$.

If $D_A$ is strongly connected then $A$ is called **irreducible** and **reducible** otherwise.

Given $A \in \mathbb{R}^{n \times n}$, the symbol $\lambda(A)$ will stand for the **maximum cycle mean** of $A$, that is:

$$\lambda(A) = \max_\sigma \mu(\sigma, A),$$

where the maximization is taken over all elementary cycles in $D_A$, and

$$\mu(\sigma, A) = \frac{w(\sigma, A)}{l(\sigma)}$$

denotes the **mean** of a cycle $\sigma$. With the convention $\max \emptyset = \varepsilon$ the value $\lambda(A)$ always exists since the number of elementary cycles is finite. However, it is easy to show [7] that $\lambda(A)$ remains the same if the word “elementary” is removed from the definition. It can be computed in $O(n^3)$ time [27], see also [7]. Observe that $\lambda(A) = \varepsilon$ if and only if $D_A$ is acyclic.

Let $A \in \mathbb{R}^{n \times n}$ and $\lambda \in \mathbb{R}$. A cycle $\sigma$ in $D_A$ is called **$\lambda$-critical** if $\mu(\sigma, A) = \lambda$. We denote by $N_c(A, \lambda)$ the set of **$\lambda$-critical nodes**, that is nodes on $\lambda$-critical cycles. The **$\lambda$-critical digraph** of $A$ is the digraph $C_A$ with the set of nodes $N$; the set of arcs, notation $E_c(A)$, is the set of arcs of all $\lambda$-critical cycles. If $i, j \in N_c(A, \lambda)$ belong to the same $\lambda$-critical cycle then $i$ and $j$ are called **$\lambda$-equivalent** and we write $i \sim_\lambda j$. Clearly, $\sim_\lambda$ constitutes a relation of equivalence on $N_c(A, \lambda)$. The letter $\lambda$ or prefix $\lambda$- will be omitted when $\lambda = \lambda(A)$.

A matrix $A \in \mathbb{R}^{n \times n}$ is called **definite** if $\lambda(A) = 0$ [13,17]. Thus a matrix is definite if and only if all cycles in $D_A$ are nonpositive and at least one has weight zero. It is easy to
check that \( \lambda(\alpha A) = \alpha \lambda(A) \) for any \( \alpha \in \mathbb{R} \). Hence \((\lambda(A))^{-1} A\) is definite whenever \( \lambda(A) \) is finite. The matrix \( \lambda^{-1} A \) for \( \lambda \in \mathbb{R} \) will be denoted by \( A_\lambda \).

The (tropical) column span of a matrix \( A \) will be denoted by \( \text{span}(A) \) that is for \( A \) with columns \( A_1, \ldots, A_n \)

\[
\text{span}(A) = \left\{ \sum_i \ominus \alpha_i A_i; \alpha_1, \ldots, \alpha_n \in \mathbb{R} \right\}.
\]

We also define

\[
\text{span}^+(A) = \left\{ \sum_i \ominus \alpha_i A_i; \alpha_1, \ldots, \alpha_n \in \mathbb{R} \right\}.
\]

Given \( A \in \mathbb{R}^{n \times n} \) it is standard \([17,2,24,7]\) in max-algebra to define the infinite series

\[
A^+ = A \oplus A^2 \oplus A^3 \oplus \ldots
\]

and

\[
A^* = I \oplus A^+ = I \oplus A \oplus A^2 \oplus A^3 \oplus \ldots.
\]

The matrix \( A^+ \) is called the weak transitive closure of \( A \) and \( A^* \) is the strong transitive closure of \( A \), also called the Kleene star.

It follows from the definitions that every entry of the matrix sequence

\[
\{ A \oplus A^2 \oplus \ldots \oplus A^k \}_{k=0}^\infty
\]

is a nondecreasing sequence in \( \mathbb{R} \) and therefore either it is convergent to a real number (when bounded) or its limit is \(+\infty\) (when unbounded). If \( \lambda(A) \leq 0 \) then

\[
A^+ = A \oplus A \oplus \ldots \oplus A^k
\]

and

\[
A^* = I \oplus A \oplus A^2 \oplus \ldots \oplus A^{k-1}
\]

for every \( k \geq n \) and can be found using the Floyd–Warshall algorithm in \( O(n^3) \) time \([7]\). If \( A \) is also irreducible and \( n > 1 \) then both \( A^+ \) and \( A^* \) are finite.

If \( \lambda \in \mathbb{R} \) then \( A_\lambda^+ \) will be shortly written as \( A_\lambda^+ \), similarly \( A_\lambda^* \). If \( \lambda = \lambda(A) \) then the symbol \( A_\lambda^+ \) stands for the matrix consisting of the columns of \( A_\lambda^+ \) with indices \( j \in N_c(A) \). The following will be useful and is easily proved.

**Lemma 2.1.** (See \([17,24,7]\).) Let \( A \in \mathbb{R}^{n \times n} \), \( \lambda = \lambda(A) > \varepsilon \) and \( A_\lambda^+ = (\gamma_{ij}) \). Then \( j \in N_c(A) \) if and only if \( \gamma_{jj} = 0 \).
Let \( S \subseteq \mathbb{R}^n \). The set \( S \) is called a **tropical subspace** if

\[
\alpha u \oplus \beta v \in S
\]

for every \( u, v \in S \) and \( \alpha, \beta \in \mathbb{R} \). The adjective “tropical” will usually be omitted.

If \( S \subseteq \mathbb{R}^m \) is a finite set then as a slight abuse of notation we will denote by \( \text{span}\,(S) \) the set \( \text{span}\,(A) \), where \( A \) is the matrix whose columns are exactly the elements of \( S \). If \( \text{span}\,(S) = T \) then \( S \) is called a **set of generators** for \( T \) and \( T \) is called **finitely generated**.

Let \( v \in \mathbb{R}^m \). The **max-norm** or just norm of \( v \) is the value of the greatest component of \( v \), notation \( \|v\| \); \( v \) is called scaled if \( \|v\| = 0 \). The set \( S \) is called scaled if all its elements are scaled.

The set \( S = \{v_1, \ldots, v_n\} \subseteq \mathbb{R}^m \) is called **dependent** if \( v_k \in \text{span}\{v_1, \ldots, v_{k-1}, v_{k+1}, \ldots, v_n\} \) for some \( k \in \mathbb{N} \). Otherwise \( S \) is **independent**.

Let \( S, T \subseteq \mathbb{R}^m \). The set \( S \) is called a **basis** of \( T \) if it is an independent set of generators for \( T \). The following is of fundamental importance as it shows that every subspace has an essentially unique basis.

**Theorem 2.2.** (See [36,37,11,7].) Every non-trivial finitely generated subspace has a unique scaled basis.

Finally, for \( A \in \mathbb{R}^{n \times n} \) and \( \lambda \in \mathbb{R} \) we denote

\[
V(A, \lambda) = \left\{ x \in \mathbb{R}^n ; Ax = \lambda x \right\},
\]

\[
V_+(A, \lambda) = \left\{ x \in \mathbb{R}^n ; Ax \leq \lambda x \right\},
\]

\[
V^*(A, \lambda) = \left\{ x \in \mathbb{R}^n ; Ax \geq \lambda x \right\},
\]

\[
FV(A, \lambda) = \left\{ x \in \mathbb{R}^n ; Ax = \lambda x \right\},
\]

\[
FV_+(A, \lambda) = \left\{ x \in \mathbb{R}^n ; Ax \leq \lambda x \right\},
\]

\[
FV^*(A, \lambda) = \left\{ x \in \mathbb{R}^n ; Ax \geq \lambda x \right\},
\]

\[
\Lambda(A) = \left\{ \lambda \in \mathbb{R} ; V(A, \lambda) \neq \{\varepsilon\} \right\}.
\]

The set \( \Lambda(A) \) or just \( \Lambda \) will be called the **spectrum** of \( A \).

### 3. Known results on eigenvectors and subeigenvectors

The tropical **eigenvalue–eigenvector problem** (briefly eigenproblem) is the following:

**Given** \( A \in \mathbb{R}^{n \times n} \), **find all** \( \lambda \in \mathbb{R} \) (eigenvalues) and \( x \in \mathbb{R}^n \), \( x \neq \varepsilon \) (eigenvectors) such that

\[
Ax = \lambda x.
\]
This problem has been studied since the work of R.A. Cuninghame-Green [16]. A full solution of the eigenproblem in the case of irreducible matrices has been presented by R.A. Cuninghame-Green [17,18] and M. Gondran and M. Minoux [22], see also N.N. Vorobyov [35]. The general (reducible) case was first presented by S. Gaubert [20] and R.B. Bapat, D. Stanford and P. van den Driessche [3]. See also [9] and [7].

**Theorem 3.1.** (See [16,17,22].) If \( A \in \mathbb{R}^{n \times n} \) is irreducible then \( \Lambda(A) = \{ \lambda(A) \} \) and all eigenvectors of \( A \) are finite.

The value \( \lambda(A) \) is usually called the *principal eigenvalue*. For a matrix \( A \) to have finite eigenvectors it is not necessary that \( A \) is irreducible:

**Theorem 3.2.** (See [17].) Let \( A = (a_{ij}) \in \mathbb{R}^{n \times n} \) and \( \lambda(A) > \varepsilon \). Then \( A \) has finite eigenvectors if and only if for every \( i \in N \) there is a \( j \in N(A) \) such that \( i \to j \). All finite eigenvectors (if any) are associated with \( \lambda = \lambda(A) \).

The following theorem identifies an essentially unique basis of the eigenspace of \( A \) corresponding to the principal eigenvalue. Note that this statement for irreducible matrices was already proved in [17]. The case when \( \lambda(A) = \varepsilon \) is trivial [7] and will not be discussed here.

**Theorem 3.3.** (See [1].) Suppose that \( A \in \mathbb{R}^{n \times n} \), \( \lambda = \lambda(A) > \varepsilon \) and \( g_1, \ldots, g_n \) are the columns of \( A^+_\lambda \). Then

\[
V(A, \lambda(A)) = \text{span} \left( \widetilde{A}^+_{\lambda} \right)
\]

and we obtain a basis of \( V(A, \lambda(A)) \) by taking exactly one \( g_j \) for each equivalence class in \((N_c(A), \sim)\).

Reducible \( n \times n \) matrices have up to \( n \) eigenvalues. In order to identify all of them \( A \) is transformed by simultaneous permutations of the rows and columns (which do not change the spectrum) to a *Frobenius normal form* (FNF)

\[
A' = \begin{pmatrix}
A_{11} & \varepsilon & \cdots & \varepsilon \\
A_{21} & A_{22} & \cdots & \varepsilon \\
& \ddots & \ddots & \ddots \\
& & \ddots & \cdots \\
A_{r1} & A_{r2} & \cdots & A_{rr}
\end{pmatrix}, \quad (6)
\]

where \( A_{11}, \ldots, A_{rr} \) are irreducible square submatrices of \( A' \). This form is unique up to the order of the blocks and simultaneous permutations of the rows and columns within each block. If \( A \) is in the Frobenius normal form (6) then the corresponding partition subsets of the node set \( N \) of \( D_A \) will be denoted as \( N_1, \ldots, N_r \) and called *classes* (of \( A \)). It follows that each of the induced subgraphs \( D_A[N_i] (i = 1, \ldots, r) \) is strongly connected
and an arc from $N_i$ to $N_j$ in $D_A$ exists only if $i \geq j$. As a slight abuse of language we will also say for simplicity that $\lambda(A_{jj})$ is the eigenvalue of $N_j$.

If $A$ is in the Frobenius normal form (6) then the reduced digraph, notation $R_A$, is the digraph with nodes $N_1, \ldots, N_r$ and the set of arcs $\{(N_i, N_j); (\exists k \in N_i)(\exists \ell \in N_j)a_{k\ell} > \varepsilon\}$. Observe that $R_A$ is acyclic and represents a partially ordered set. Any class that has no incoming (outcoming) arcs in $R_A$ is called initial (final), similarly for diagonal blocks. Recall that the symbol $N_i \rightarrow N_j$ means there is a directed path from $N_i$ to $N_j$ in $R_A$ (and therefore from each node in $N_i$ to each node in $N_j$ in $D_A$).

It is intuitively clear that all eigenvalues of $A$ in an FNF are among the unique eigenvalues of diagonal blocks. However, in general some of these values are not eigenvalues of $A$. The following key result appeared for the first time independently in the thesis [20] and report [3], see also [7] and [9].

**Theorem 3.4 (Spectral theorem).** Let (6) be a Frobenius normal form of a matrix $A \in \mathbb{R}^{n \times n}$. Then

$$\Lambda(A) = \{\lambda \in \mathbb{R}; (\exists j)\lambda = \lambda(A_{jj}) = \max_{N_i \rightarrow N_j} \lambda(A_{ii})\}.$$

**Corollary 3.5.** Every $n \times n$ matrix $A$ has up to $n$ eigenvalues and the greatest eigenvalue is $\lambda(A)$ (which will therefore also be denoted by $\lambda_{\text{max}}$).

Note that if a diagonal block, say $A_{jj}$ has $\lambda(A_{jj}) \in \Lambda(A)$, it still may not satisfy the condition $\lambda(A_{jj}) = \max_{N_i \rightarrow N_j} \lambda(A_{ii})$ and may not provide any eigenvectors. It is therefore necessary to identify blocks that satisfy this condition: If

$$\lambda(A_{jj}) = \max_{N_i \rightarrow N_j} \lambda(A_{ii})$$

then $A_{jj}$ (and also $N_j$ or just $j$) is called spectral. Thus $\lambda(A_{jj}) \in \Lambda(A)$ if $j$ is spectral but not necessarily the other way round. We immediately deduce that all initial blocks as well as the blocks with maximum cycle mean $\lambda(A)$ are spectral. The smallest eigenvalue of $A$ that is

$$\min \Lambda(A) = \min \{\lambda(N_i); N_i \text{ spectral}\}$$

will be denoted $\lambda_{\text{min}}$.

We now explain how to find a basis of the eigenspace associated with a general eigenvalue $\lambda \in \Lambda(A)$. Let $A \in \mathbb{R}^{n \times n}$ be in the Frobenius normal form (6), $N_1, \ldots, N_r$ be the classes of $A$ and $R = \{1, \ldots, r\}$. The case $\lambda = \varepsilon$ is trivial [7] and will not be discussed here. Suppose that $\lambda \in \Lambda(A), \lambda > \varepsilon$ and denote

$$I(\lambda) = \{i \in R; \lambda(N_i) = \lambda, N_i \text{ spectral}\}.$$
Note that $\lambda(\lambda^{-1}A) = \lambda^{-1}\lambda(A)$ may be positive since $\lambda \leq \lambda(A)$ and thus $A^+_\lambda = (\gamma_{ij})$ may now include entries equal to $+\infty$. Let us denote

$$N'_c(A, \lambda) = \bigcup_{i \in I(\lambda)} N_c(A_{ii}, \lambda) = \left\{ j \in N; \gamma_{jj} = 0, j \in \bigcup_{i \in I(\lambda)} N_i \right\}.$$  

**Theorem 3.6.** (See [9,7].) Suppose that $A \in \mathbb{R}^{n \times n}$ and $\lambda \in \Lambda(A), \lambda > \varepsilon$. Let $g_1, \ldots, g_n$ be the columns of $A^+_\lambda$ and $\tilde{A}^+_\lambda$ consist of $g_j, j \in N'_c(A, \lambda)$. Then

$$V(A, \lambda) = \text{span} \left( \tilde{A}^+_\lambda \right)$$

and a basis of $V(A, \lambda)$ can be obtained by taking exactly one $g_j, j \in N'_c(A, \lambda)$ for each $\sim_\lambda$ equivalence class.

**Corollary 3.7.** The spectrum $\Lambda(A)$ and bases of $V(A, \lambda)$ for all $\lambda \in \Lambda(A)$ can be found in $O(n^3)$ time.

### 4. Subeigenvectors

If $A \in \mathbb{R}^{n \times n}$ and $\lambda \in \mathbb{R}$ then a vector $x \in \mathbb{R}^n, x \neq \varepsilon$ satisfying

$$Ax \leq \lambda x$$

is called a subeigenvector of $A$ with associated subeigenvalue $\lambda$.

The question of existence of subeigenvectors and finite subeigenvectors has been studied for some time and the theorem below summarizes the main results. The case when $\lambda(A) = \varepsilon$ is trivial [7] and will not be discussed here.

**Theorem 4.1.** (See [10,7].) Let $A \in \mathbb{R}^{n \times n}, \lambda(A) > \varepsilon$. Then

(a) $FV_* (A, \lambda) \neq \emptyset$ if and only if $\lambda \geq \lambda(A)$ and $FV_* (A, \lambda) = \text{span}^+ (A^*_\lambda)$ for $\lambda \geq \lambda(A)$.

(b) $V_* (A, \lambda) \neq \{\varepsilon\}$ if and only if $\lambda \geq \lambda_{\text{min}}$ and $V_* (A, \lambda) = \text{span} (G)$, for $\lambda \geq \lambda_{\text{min}}$, where $G$ is the matrix consisting of the columns $g_j$ of the matrix $A^*_\lambda$ with indices $j \in \bigcup_{i \in I_*(\lambda)} N_i$, where

$$I_*(\lambda) = \{i \in R; \lambda(N_i) \leq \lambda, N_i \text{ spectral}\}.$$  

It follows that bases of $FV_* (A, \lambda) \neq \emptyset$ and $V_* (A, \lambda) \neq \{\varepsilon\}$ can be found in $O(n^3)$ time [32].
5. Supereigenvectors

If $A \in \mathbb{R}^{n \times n}$ and $\lambda \in \mathbb{R}$ then a vector $x \in \mathbb{R}^n$, $x \neq \varepsilon$ satisfying

$$Ax \geq \lambda x$$

is called a supereigenvector of $A$ with associated supereigenvalue $\lambda$.

In contrast to eigenvectors and subeigenvectors the questions of existence and full description are more difficult for supereigenvectors, although there is a trivial answer for $\lambda$ small enough as stated in the next proposition. In what follows we denote $\min_{i=1,\ldots,n} a_{ii}$ by $\overline{\lambda}(A)$ or just $\overline{\lambda}$. Clearly, $\overline{\lambda}(A) \leq \lambda_{\text{min}}$.

**Proposition 5.1.** If $\lambda \leq \overline{\lambda}$ then $V^*(A, \lambda) = \mathbb{R}^n$.

**Proof.** If $\lambda \leq a_{ii}$ for every $i$ then for every $x$ and every $i$ we have

$$\lambda \otimes x_i \leq a_{ii} \otimes x_i \leq (A \otimes x)_i$$

and so $\lambda x \leq Ax$. \qed

In order to describe the values of $\lambda$ associated with supereigenvectors we start with a necessary condition for finite supereigenvectors (which later turns out to be insufficient in general).

**Lemma 5.2.** If $Ax \geq \lambda x$, $x$ finite then $\lambda \leq \lambda(A)$.

**Proof.** Take any $i = i_1 \in N$. Then

$$\lambda + x_{i_1} \leq a_{i_1 i_2} + x_{i_2}$$

for some $i_2 \in N$. Similarly

$$\lambda + x_{i_2} \leq a_{i_2 i_3} + x_{i_3}$$

for some $i_3 \in N$ and so on. By finiteness and by omitting, if necessary, a few first indices we get for some $k$:

$$\lambda + x_{i_k} \leq a_{i_k i_1} + x_{i_1}.$$  

After adding up and simplifying we have

$$\lambda \leq \frac{a_{i_1 i_2} + \ldots + a_{i_k i_1}}{k} \leq \lambda(A). \quad \square$$
Given $A \in \mathbb{R}^{n \times n}$ and non-empty sets $J, K \subseteq N$ the symbol $A(J, K)$ will denote the submatrix of $A$ consisting of entries with row indices from $J$ and column indices from $K$. The principal submatrix $A(J,J)$ will be written briefly as $A(J)$.

We are ready to characterize all $\lambda$ associated with supereigenvectors. This result first appeared in [8] and then independently in [38].

**Theorem 5.3.** $V^*(A, \lambda) \neq \{\varepsilon\}$ if and only if $\lambda \leq \lambda(A)$.

**Proof.** Suppose first $Ax \geq \lambda x, x \neq \varepsilon$. Let $J = \text{supp}(x)$, then

$$A(J)x(J) \geq \lambda x(J).$$

By **Lemma 5.2** we have $\lambda \leq \lambda(A(J)) \leq \lambda(A)$.

Suppose $\lambda \leq \lambda(A)$. Let $x \in V(A, \lambda(A)), x \neq \varepsilon$, then

$$A \otimes x = \lambda(A) \otimes x \geq \lambda \otimes x. \quad \square$$

**Corollary 5.4.** If $\lambda(A) = \varepsilon$ and $V^*(A, \lambda) \neq \{\varepsilon\}$ then $\lambda = \varepsilon$ and $V^*(A, \varepsilon) = \mathbb{R}^n$.

The size of a minimal set of generators of $V^*(A, \lambda)$ can be exponentially large in terms of $n$ [38]. An algorithm for finding a set of generators of $V^*(A, \lambda)$ has been presented in [38]. This method is incrementally polynomial. It can be decided about each generator whether it is an extremal (an element of an essentially unique basis, see **Theorem 2.2**) of $V^*(A, \lambda)$ in $O(n^3)$ time [31]. However, the question of finding a basis in an efficient way remains open.

The next two statements show that compared to eigenvectors there is a greater level of freedom in choosing infinite components for a supereigenvector and unlike for eigenvectors we can associate a supereigenvector with any cycle in $D_A$.

**Proposition 5.5.** For every $J \subseteq N, J \neq \emptyset$ there exists an $x \in V^*(A, \lambda), x \neq \varepsilon$, where $\lambda = \lambda(A(J))$ and $x(N-J) = \varepsilon$.

**Proof.** Let $J \subseteq N, J \neq \emptyset$. Then by **Theorem 3.4** there exists a $z \neq \varepsilon$ such that $A(J)z = \lambda(A(J))z$. Set $x(J) = z$ and $x(N-J) = \varepsilon$. Hence

$$A \otimes x = \begin{pmatrix}
A(J,J) & A(J,N-J) \\
A(N-J,J) & A(N-J,N-J)
\end{pmatrix}
\begin{pmatrix}
x(J) \\
\varepsilon
\end{pmatrix}
\geq \lambda(A(J))
\begin{pmatrix}
x(J) \\
\varepsilon
\end{pmatrix}
= \lambda(A(J))x. \quad \square$$
Proposition 5.6. If \( A \otimes x \geq \lambda(A(J))x, x \neq \varepsilon, \) where \( J = \text{supp}(x) \) then there exists a critical cycle \((i_1, i_2, \ldots, i_k)\) in \( D_{A(J)} \) such that

\[
A(C)x(C) = \lambda(A(J))x(C),
\]

where \( C = \{i_1, i_2, \ldots, i_k\} \).

Proof. If \( \lambda(A(J)) = \varepsilon \) then every cycle is critical and at least one component, say \( i, \) of \( A(J) \otimes x \) is \( \varepsilon \) because \( A(J) \) has an \( \varepsilon \) row. Then we can take \( C = \{i\} \).

Let us now suppose that \( \lambda(A(J)) > \varepsilon \) and denote \( \lambda = \lambda(A(J)) \). Let \( i_1 \in J \). Then

\[
\lambda + x_{i_1} \leq \max_j (a_{i_1j} + x_j) = a_{i_1i_2} + x_{i_2}
\]

for some \( i_2 \in J \). Similarly we have

\[
\lambda + x_{i_2} \leq \max_j (a_{i_2j} + x_j) = a_{i_2i_3} + x_{i_3}
\]

for some \( i_3 \in J \), and so on. By finiteness and by omitting, if necessary, a few first indices we get for some \( k \):

\[
\lambda + x_{i_k} \leq \max_j (a_{i_kj} + x_j) = a_{i_ki_1} + x_{i_1}.
\]

After adding up and simplifying we have

\[
\lambda \leq \frac{a_{i_1i_2} + \ldots + a_{i_ki_1}}{k} \leq \lambda(A(J)).
\]

Hence none of the inequalities can be strict and (9) follows. \( \square \)

Our main result is a full characterization of all values of \( \lambda \) associated with finite supereigenvectors. Suppose that \( A \) is in an FNF (6). Recall that for \( i, j \in N \) the symbol \( i \rightarrow j \) means that there is a path from \( i \) to \( j \) in \( D_A \) and similarly \( N_i \rightarrow N_j \) means that there is a path from \( N_i \) to \( N_j \) in \( R_A \). On the other hand \( N_i \Rightarrow N_j \) will mean that there is a path from \( N_i \) to \( N_j \) in \( R_A \) containing only nodes \( N_t \) such that \( \lambda_t \leq \lambda_j \).

We denote

\[
\lambda^*(A) = \min \{ \lambda(A_{jj}); N_j \text{ is a final class} \}.
\]

We also use \( \lambda^* \) for \( \lambda^*(A) \) if appropriate. Note that in the above definition it does not matter whether \( N_j \) is spectral or not.

The following immediate corollary of Theorem 3.2 will be useful for proving our main result, Theorem 5.8 below. In both statements we assume that \( A \in \mathbb{R}^{n \times n} \) is in the FNF (6) with classes \( N_1, \ldots, N_r, R = \{1, \ldots, r\} \) and the symbol \( \lambda_j, j \in R \) stands for \( \lambda(A_{jj}) \).
**Proposition 5.7.** Let \( j \in R \),

\[
\mathcal{M}_j = \{ i \in R; N_i \Rightarrow N_j \},
\]

\[
M_j = \bigcup_{i \in \mathcal{M}_j} N_i
\]

and

\[
B^{(j)} = A(M_j).
\]

Then \( FV(B^{(j)},\lambda_j) \neq \emptyset \).

**Theorem 5.8.** \( FV^*(A,\lambda) \neq \emptyset \iff \lambda \leq \lambda^*(A) \).

**Proof.** Let \( N_j \) be final and \( \lambda(A_{jj}) = \lambda^*(A) \). Let \( A \otimes x \geq \lambda \otimes x, x \) finite. Then \( A_{jj} \otimes x(N_j) \geq \lambda \otimes x(N_j), x(N_j) \) finite and so by Lemma 5.2 \( \lambda \leq \lambda(A_{jj}) = \lambda^*(A) \).

For the converse it is sufficient to prove that \( FV^*(A,\lambda^*) \neq \emptyset \). Let \( j \in R \) be such that \( N_j \) is final and \( \lambda^* = \lambda_j \). By Proposition 5.7 (using the same notation) there exists a finite vector \( y^{(j)} \) such that \( B^{(j)} \otimes y^{(j)} = \lambda_j \otimes y^{(j)} \). Let \( A^{(1)} = A, A^{(2)} = A(N - M_j) \) and \( l \in R \) be such that \( N_l \) is final in \( A^{(2)} \) and \( \lambda^*(A^{(2)}) = \lambda_l \). If \( N_l \) is also final in \( A^{(1)} \) then \( \lambda_l \geq \lambda_j \) from the definition of \( \lambda_j \). If \( N_l \) is not final in \( A^{(1)} \) then \( N_l \Rightarrow N_j \) and so \( \lambda_l > \lambda_j \) (since otherwise \( l \) would have been included in \( \mathcal{M}_j \)). In any case \( \lambda_l \geq \lambda_j \) and again by Proposition 5.7 there exists a finite vector \( y^{(l)} \) such that

\[
B^{(l)} \otimes y^{(l)} = \lambda_l \otimes y^{(l)}.
\]

Continue in this way with \( A^{(3)} = A(N - M_j - M_l) \) and so on until some \( A^{(s)} \) has a finite eigenvector – this is guaranteed to happen when \( B^{(s)} \) consists of all the remaining parts of \( A \).

This process creates a sequence of finite vectors \( y^{(j)}, y^{(l)}, \ldots \). Set \( x = (x_1, \ldots, x_n)^T \) so that \( x(M_k) = y^{(k)} \) for all sets \( M_k \) created in the process. Then \( x \) is finite and

\[
A \otimes x = A \otimes \begin{pmatrix} \vdots \\ x(M_k) \\ \vdots \end{pmatrix} \geq \begin{pmatrix} \vdots \\ A(M_k) \otimes x(M_k) \\ \vdots \end{pmatrix}
\]
\[
\begin{pmatrix}
\vdots \\
\lambda_k \otimes x(M_k) \\
\vdots \\
\end{pmatrix} 
\geq \lambda^* \otimes \begin{pmatrix}
\vdots \\
x(M_k) \\
\vdots \\
\end{pmatrix} = \lambda^* \otimes x.
\]

The last inequality follows because \( \lambda_k \geq \lambda^* \) for every \( k \).

It is easily seen that the identification of \( \mathcal{M}_j \) in Proposition 5.7 can be done in polynomial time. Therefore the constructive proof above provides a method to find a non-trivial subset of a set of generators of finite supereigenvectors in polynomial time. If (in the notation of this proof) \( B \) is the \( n \times t \) matrix (for some positive integer \( t \)) of the form

\[
\begin{pmatrix}
\vvdots \\
\varepsilon \\
\varepsilon B^{(j)} \\
\varepsilon \\
\varepsilon \\
\vvdots
\end{pmatrix}
\]

then \( \text{span}^+(B) \subseteq FV^*(A, \lambda^*) \).

**Remark 5.9.** \( \lambda^*(A) \) ranges over the whole discrete set \( \{\lambda(A_{jj}); j \in R\} \) and may be smaller or greater than \( \lambda_{\min} \), or equal to \( \lambda_{\min} \), for instance when

\[
A = \begin{pmatrix}
\alpha & \varepsilon & \varepsilon \\
0 & 2 & \varepsilon \\
\varepsilon & 0 & 1
\end{pmatrix}
\]

then for any \( \alpha \in \mathbb{R} \) we have \( \lambda(A) = \max(2, \alpha), \lambda_{\min} = 1 \) and \( \lambda^*(A) = \alpha \).

Fig. 1 shows a comparison of values of \( \lambda \) associated with general/finite eigenvectors, subeigenvectors and supereigenvectors.

We conclude with an example. Let \( A \) be the matrix

\[
\begin{pmatrix}
3 \\
5 \\
1 \\
0 & 0 & 0 & 2 \\
0 & 0 & -1 & 1 \\
0 & -1 & -2 \\
0 & 0 & -6 \\
\end{pmatrix}
\]
Fig. 1. Values of $\lambda$ with associated eigenvectors, subeigenvectors and supereigenvectors.

where (and in the matrices below) all missing entries are $\varepsilon$. This matrix is in an FNF with $n = 7$, $r = 6$, $N_1 = \{i\}$ for $i = 1, 2, 3, 4$, $N_5 = \{5, 6\}$ and $N_6 = \{7\}$. Clearly, $\lambda_1 = 3$, $\lambda_2 = 5$, $\lambda_3 = 1$, $\lambda_4 = 2$, $\lambda_5 = 0$, $\lambda_6 = 6$, $\Lambda(A) = \{5, 2, 0, 6\}$, $\lambda_{\text{max}} = \lambda(A) = 6$, $\lambda_{\text{min}} = 0, \lambda^*(A) = 1 = \lambda(N_3), \bar{\lambda}(A) = -2$. Initial classes are $N_5$, $N_6$, final classes are $N_1$, $N_2$ and $N_3$. The algorithm in the proof chooses first $j = 3$. Hence $M_3 = \{3, 5\}$, $M_3 = \{3, 5, 6\}$, $\lambda_3 = 1$ and

$$B^{(3)} = A(\{3, 5, 6\}) = \begin{pmatrix} 1 & -1 & 1 \\ 0 & -1 & -2 \end{pmatrix}.$$ 

We then get

$$B_{\lambda_3}^{(3)} = \begin{pmatrix} 0 & -2 & 0 \\ -1 & -2 & -3 \end{pmatrix}, \quad \left(B_{\lambda_3}^{(3)}\right)^+ = \begin{pmatrix} 0 & -1 & -2 \\ -1 & -2 & -2 \end{pmatrix}$$

and

$$\tilde{B}_{\lambda_3}^{(3)} = \begin{pmatrix} 0 \\ -1 \\ -1 \end{pmatrix}$$

since only the first column is critical. Hence the eigenspace of $B^{(3)}$ (in which all vectors are finite) is the set of multiples of $y^{(3)} = (0, -1, -1)^T$.

In the next iteration

$$A^{(2)} = \begin{pmatrix} 3 & 5 \\ 0 & 2 \\ 0 & 6 \end{pmatrix},$$
\[ l = 1, \quad M_1 = \{1, 4\} = M_1, \quad \lambda_1 = 3 \text{ and } \]

\[ B^{(2)} = A(\{1, 4\}) = \begin{pmatrix} 3 & 0 \\ 0 & 2 \end{pmatrix}. \]

Similarly as before the eigenspace of \( B^{(2)} \) (in which all vectors are finite) is the set of multiples of \( y^{(2)} = (0, -3)^T \).

In the next iteration

\[ A^{(3)} = \begin{pmatrix} 5 \\ 6 \end{pmatrix}, \]

\[ l = 2, \quad M_2 = \{2\} = M_2, \quad \lambda_2 = 5 \text{ and } y^{(3)} = (0)^T. \]

Finally,

\[ A^{(4)} = \begin{pmatrix} 6 \end{pmatrix}, \]

\[ l = 6, \quad M_7 = \{7\} = M_6, \quad \lambda_6 = 6 \text{ and } y^{(4)} = (0)^T. \]

We conclude that finite supereigenvectors of \( A \) associated with \( \lambda \) exist if and only if \( \lambda \leq 1 \) and for any such \( \lambda \) we have \( \text{span}^+ (B) \subseteq FV^* (A, \lambda) \), where

\[ B = \begin{pmatrix} 0 & 0 \\ 0 & -3 \\ -1 & -1 \\ -1 & \end{pmatrix}. \]

We also observe that \( FV^* (A, \lambda) = \mathbb{R}^7 \) and \( V^* (A, \lambda) = \mathbb{R}^7 \) for all \( \lambda \leq -2 \).

6. Conclusions

We have presented an overview of previously proved criteria for the existence of general and finite eigenvectors and subeigenvectors. We have then proved such criteria for general and finite supereigenvectors. A method for finding a non-trivial subset of a set of generators of finite supereigenvectors follows from the proof. However, efficient finding of a set of generators and a basis of the subspace of all general or finite supereigenvectors associated with a given \( \lambda \in \mathbb{R} \) remains open.

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References


