

Mathematics, Pusan National University

NUMIRICAL LINEAR ALGEBRA

Projectors

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August 24, 2020



Projectors

- Projectors
- Complementary Projectors
- Orthogonal Projectors
- Projection with an Orthonormal Basis
- Projection with an Arbitrary Basis

Projector in other books

- In Matrix Computations
- In Matrix analysis and applied linear algebra
- In Linear algebra and its application
- In Functions of Matrices
- In Matrix analysis

Projectors[1]

- ▶ Projectors
- ▶ Complementary Projectors
- ▶ Orthogonal Projectors
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Definition

A projector is a square matrix P that satisfies

$$P^2 = P. \quad (1)$$

For $\mathbf{v} \in \text{range}(P)$, $\mathbf{v} = P\mathbf{x}$ for some \mathbf{x}

$$P\mathbf{v} = P^2\mathbf{v} = P\mathbf{x} = \mathbf{v}.$$

This means that $P\mathbf{v} - \mathbf{v} \in \text{null}(P)$.

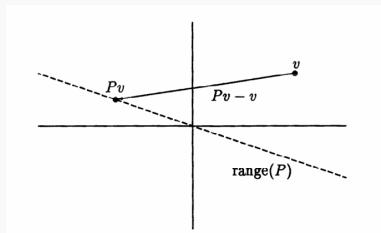


Figure: An oblique projection



If P is a projector, $I - P$ is also a projector,

$$(I - P)^2 = I - 2P - P^2 = I - P$$

The matrix $I - P$ is called the complementary projector to P .

$$\text{range}(I - P) = \text{null}(P) \quad (2)$$

Proof.

$$\forall \mathbf{v} \in \text{null}(P), (I - P)\mathbf{v} = \mathbf{v} - P\mathbf{v} = \mathbf{v}. \Rightarrow \mathbf{v} \in \text{range}(I - P).$$

$$\forall \mathbf{v}, (I - P)\mathbf{v} = \mathbf{v} - P\mathbf{v} = 0 \Rightarrow \mathbf{v} \in \text{null}(P).$$



Also, it is easy to see that $\text{null}(I - P) = \text{range}(P)$.

And $\text{range}(P) \cap \text{null}(P) = 0$

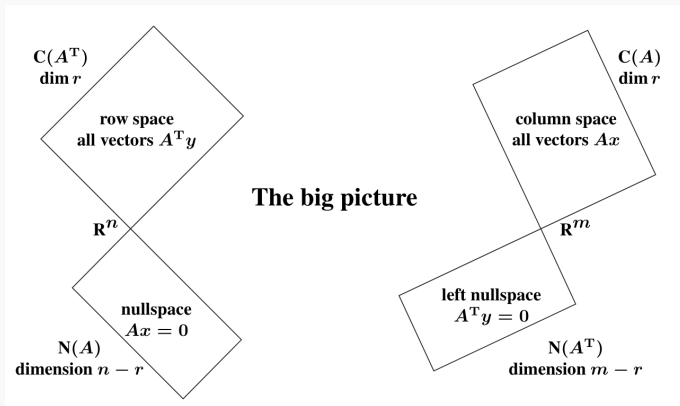


Figure: The Big Picture of Linear Algebra[2]



Let $S_1 = \text{range}(P)$, $S_2 = \text{null}(P)$, P is orthogonal projector if $S_1 \perp S_2$.

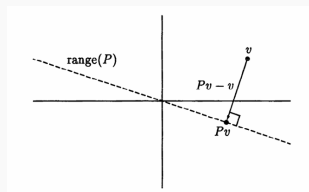


Figure: An orthogonal projection

Theorem

A projector P is orthogonal if and only if $P = P^$*

Proof.

If $P = P^*$, then the inner product between a vector $Px \in S_1$ and a vector $(I - P)y \in S_2$ is zero:

$$x^* P^* (I - P)y = x^* (P - P^2)y = 0$$

Thus the projector is orthogonal.

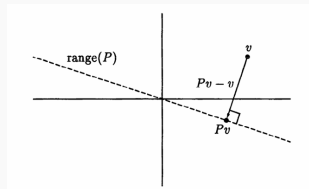


Figure: An orthogonal projection

Proof (Cont.)

We use SVD to show the “only if”. Suppose that P is orthogonal. And S_1 has dimension n . Then an SVD of P can be expressed as follows. Let $\{\mathbf{q}_1, \dots, \mathbf{q}_m\}$ be an orthogonal basis of \mathbb{C}^m , where $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$ is a basis of S_1 and $\{\mathbf{q}_{n+1}, \dots, \mathbf{q}_m\}$ is a basis of S_2 . For $j \leq n$, $P\mathbf{q}_j = \mathbf{q}_j$, and for $j > n$, $P\mathbf{q}_j = 0$. Let Q be the unitary matrix such that j th column is \mathbf{q}_j .

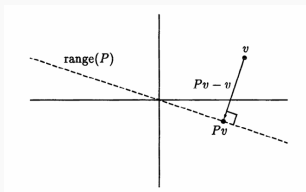


Figure: An orthogonal projection

Proof (Cont.)

$$PQ = \begin{bmatrix} q_1 & \cdots & q_n & 0 & \cdots \end{bmatrix}$$

so that

$$Q^*PQ = \begin{bmatrix} 1 & & & & \\ & \ddots & & & \\ & & 1 & & \\ & & & 0 & \\ & & & & \ddots \end{bmatrix} = \Sigma$$

a diagonal matrix with ones in the first n entries and zeros everywhere else.

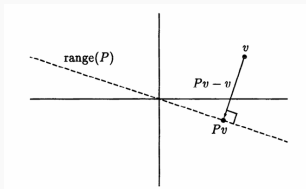


Figure: An orthogonal projection

Proof.

Thus we have constructed a singular value decomposition of P :

$$P = Q\Sigma Q^*$$

Since $P^* = (Q\Sigma Q^*)^* = Q^*\Sigma^*Q = Q\Sigma Q^* = P$, $P = P^*$ □



Since an orthogonal projector has some singular values equal to zero, We will use reduced SVD. We obtain the marvelously simple expression

$$P = \hat{Q}\hat{Q}^* \quad (3)$$

where the columns of \hat{Q} are orthonormal. Let $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$ be an any set n orthogonal vectors in \mathbb{C}^m , and \hat{Q} be the corresponding $m \times n$ matrix. Consider \mathbf{v} can be expressed as

$$\mathbf{v} = \mathbf{r} + \sum_{i=1}^n (\mathbf{q}_i \mathbf{q}_i^*) \mathbf{v}$$

So the map

$$\mathbf{v} \mapsto \sum_{i=1}^n (\mathbf{q}_i \mathbf{q}_i^*) \mathbf{v} \quad (4)$$

is an orthogonal projector onto $\text{range}(P)$.

Projectors

Projection with an Orthonormal Basis



It can be written $y = \hat{Q}\hat{Q}^*v$:

$$y = \hat{Q} \hat{Q}^* v$$

The complement of an orthogonal projector is also an orthogonal projector.
($\because I - \hat{Q}\hat{Q}^*$ is hermitian.)

The complement projects onto the space orthogonal to $range(\hat{Q})$.



Example

An important special case of orthogonal projectors is the rank-one orthogonal projector that isolates the component in a single direction \mathbf{q} , which can be written

$$P^* = \mathbf{q}\mathbf{q}^*. \quad (5)$$

These are the pieces from which higher-rank projectors can be made, as in (4). Their complements are the rank $m - 1$ orthogonal projectors that eliminate the component in the direction of \mathbf{q} :

$$P_{\perp \mathbf{q}} = I - \mathbf{q}\mathbf{q}^*.$$

For arbitrary nonzero vectors \mathbf{a} , the analogous formulas are

$$P_{\mathbf{a}} = \frac{\mathbf{a}\mathbf{a}^*}{\mathbf{a}^*\mathbf{a}}, \quad P_{\perp \mathbf{a}} = I - \frac{\mathbf{a}\mathbf{a}^*}{\mathbf{a}^*\mathbf{a}}. \quad (6)$$



Suppose that the subspace is spanned by the linearly independent vectors $\{\mathbf{a}_1, \dots, \mathbf{a}_n\}$, and let A be the $m \times n$ matrix whose j th column is \mathbf{a}_j . In passing from \mathbf{v} to its orthogonal projection $\mathbf{y} \in \text{range}(A)$, the difference $\mathbf{y} - \mathbf{v}$ must be orthogonal to $\text{range}(A)$.

$$\mathbf{a}_j^*(\mathbf{y} - \mathbf{v}) = 0 \text{ for every } j$$

$$\mathbf{y} \in \text{range}(A) \Rightarrow \exists \mathbf{x} \text{ such that } \mathbf{y} = A\mathbf{x}$$

$$\Rightarrow \mathbf{a}_j^*(A\mathbf{x} - \mathbf{v}) = 0 \text{ for every } j$$

$$\Rightarrow A^*(A\mathbf{x} - \mathbf{v}) = 0$$

$$\Rightarrow A^*A\mathbf{x} = A^*\mathbf{v}$$

$$\Rightarrow \mathbf{x} = (A^*A)^{-1}A^*\mathbf{v} \quad (7)$$

$$\Rightarrow P = A(A^*A)^{-1}A^* (\because \mathbf{y} = A\mathbf{x}) \quad (8)$$

Projector in other books

- ▶ Matrix Computations [3]
- ▶ Matrix analysis and applied linear algebra [4]
- ▶ Linear algebra and its application [5]
- ▶ Functions of Matrices [6]
- ▶ Matrix Analysis [7]



There are several important orthogonal projections associated with the singular value decomposition. Suppose $A = U\Sigma V^T \in \mathbb{R}^{m \times n}$ is SVD of A and that $r = \text{rank}(A)$. If we have the U and V partitionings

$$U = \begin{bmatrix} U_r & \tilde{U}_r \\ r & m-r \end{bmatrix}, \quad V = \begin{bmatrix} V_r & \tilde{V}_r \\ r & n-r \end{bmatrix}$$

Then

$$V_r V_r^T = \text{projection on to } \text{null}(A)^\perp = \text{range}(A^T)$$

$$\tilde{V}_r \tilde{V}_r^T = \text{projection on to } \text{null}(A)$$

$$U_r U_r^T = \text{projection on to } \text{range}(A)$$

$$\tilde{U}_r \tilde{U}_r^T = \text{projection on to } \text{range}(A)^\perp = \text{null}(A^T)$$



Projectors

Let \mathcal{X} and \mathcal{Y} be complementary subspaces of a vector space \mathcal{V} so that each $\mathbf{v} \in \mathcal{V}$ can be uniquely resolved as $\mathbf{v} = \mathbf{x} + \mathbf{y}$, where $\mathbf{x} \in \mathcal{X}$ and $\mathbf{y} \in \mathcal{Y}$. The unique linear operator \mathbf{P} defined by $\mathbf{P}\mathbf{v} = \mathbf{x}$ is called the *projector onto \mathcal{X} along \mathcal{Y}* , and \mathbf{P} has the following properties.

- $\mathbf{P}^2 = \mathbf{P}$ (\mathbf{P} is idempotent). (5.9.8)
- $\mathbf{I} - \mathbf{P}$ is the complementary projector onto \mathcal{Y} along \mathcal{X} . (5.9.9)
- $R(\mathbf{P}) = \{\mathbf{x} \mid \mathbf{P}\mathbf{x} = \mathbf{x}\}$ (the set of “fixed points” for \mathbf{P}). (5.9.10)
- $R(\mathbf{P}) = N(\mathbf{I} - \mathbf{P}) = \mathcal{X}$ and $R(\mathbf{I} - \mathbf{P}) = N(\mathbf{P}) = \mathcal{Y}$. (5.9.11)
- If $\mathcal{V} = \mathbb{R}^n$ or \mathbb{C}^n , then \mathbf{P} is given by

$$\mathbf{P} = [\mathbf{X} \mid \mathbf{0}] [\mathbf{X} \mid \mathbf{Y}]^{-1} = [\mathbf{X} \mid \mathbf{Y}] \begin{pmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} [\mathbf{X} \mid \mathbf{Y}]^{-1}, \quad (5.9.12)$$

where the columns of \mathbf{X} and \mathbf{Y} are respective bases for \mathcal{X} and \mathcal{Y} . Other formulas for \mathbf{P} are given on p. 634.

Figure: Projectors in Matrix analysis and applied linear algebra



Angle between Complementary Subspaces.

Let angle of nonzero vectors \mathbf{u} and \mathbf{v} , denoted as θ , is defined to be the number $0 \leq \theta \leq \pi/2$ such that

$$\cos \theta = \frac{\mathbf{v}^T \mathbf{u}}{\|\mathbf{v}\|_2 \|\mathbf{u}\|_2}.$$

How about “angle between subspaces of \mathbb{R}^n ”?

Consider \mathcal{R} and \mathcal{N} such that the nonzero subspaces and $\mathbb{R}^n = \mathcal{R} \oplus \mathcal{N}$.

The angle between \mathcal{R} and \mathcal{N} is defined to be the number $0 \leq \theta \leq \pi/2$ such that

$$\cos \theta = \max_{\substack{\mathbf{u} \in \mathcal{R} \\ \mathbf{v} \in \mathcal{N}}} \frac{\mathbf{v}^T \mathbf{u}}{\|\mathbf{v}\|_2 \|\mathbf{u}\|_2} = \max_{\substack{\mathbf{u} \in \mathcal{R}, \mathbf{v} \in \mathcal{N} \\ \|\mathbf{u}\|_2 = \|\mathbf{v}\|_2 = 1}} \mathbf{v}^T \mathbf{u}$$

This is a good definition, but it's not easy to compute.

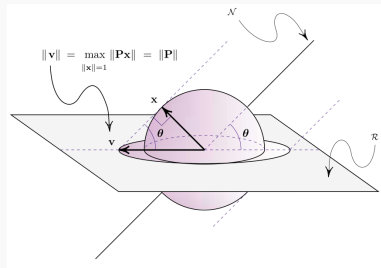


Angle between Complementary Subspaces.

Let P be the projector such that $\text{range}(P) = \mathcal{R}$ and $\text{null}(P) = \mathcal{N}$.

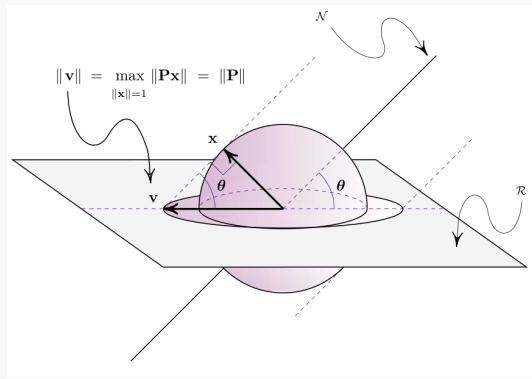
Recall the matrix 2-norm of P is

$$\|P\|_2 = \max_{\|x\|_2=1} \|Px\|_2$$



In other words, $\|P\|_2$ is the length of a longest vector in the image of the unit sphere under transformation by P . Consider the situation in \mathbb{R}^3 . The image of the unit sphere under P is obtained by projecting the sphere onto \mathcal{R} along lines parallel to \mathcal{N} .

Angle between Complementary Subspaces.



The norm of a longest vector \mathbf{v} on this ellipse equals the norm of P . That is,

$$\|\mathbf{v}\|_2 = \max_{\|\mathbf{x}\|_2=1} \|\mathbf{P}\mathbf{x}\|_2 = \|\mathbf{P}\|_2.$$

Therefore,

$$\sin \theta = \frac{\|\mathbf{x}\|_2}{\|\mathbf{v}\|_2} = \frac{1}{\|\mathbf{v}\|_2} = \frac{1}{\|\mathbf{P}\|_2}$$



There is example of projection(projector) matrix.

Least-Squares Fitting of Data

The cost of producing t books like this one is nearly linear, $\mathbf{b} = c + dt$, with editing and typesetting in c and then printing and binding in d . c is the set-up cost and d is the cost for each additional book.

$$\begin{array}{rcl} c + dt_1 & = & b_1 \\ c + dt_2 & = & b_2 \\ \vdots & & \\ c + dt_m & = & b_m \end{array} \quad \Rightarrow \quad \begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}, \quad \text{or} \quad A\mathbf{x} = \mathbf{b}$$

The best solution (\hat{c}, \hat{d}) is the $\hat{\mathbf{x}}$ that minimizes the squared error E^2 :

$$\text{Minimize} \quad E^2 = \|\mathbf{b} - A\mathbf{x}\|^2 = (b_1 - C - Dt_1)^2 + \cdots + (b_m - C - Dt_m)^2.$$



Example

Let $(t_1, b_1) = (-1, 1)$, $(t_2, b_2) = (1, 1)$ and $(t_3, b_3) = (2, 3)$, then

$$Ax = \mathbf{b} \quad \text{is} \quad \begin{matrix} c - d = 1 \\ c + d = 1 \\ c + 2d = 3 \end{matrix} \quad \text{or} \quad \begin{bmatrix} 1 & -1 \\ 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 3 \end{bmatrix}$$

Since there is no straight line through all three points, they are solved by least squares:

$$A^T A \hat{\mathbf{x}} = A^T \mathbf{b} \quad \Rightarrow \quad \begin{bmatrix} 3 & 2 \\ 2 & 6 \end{bmatrix} \begin{bmatrix} \hat{c} \\ \hat{d} \end{bmatrix} = \begin{bmatrix} 5 \\ 6 \end{bmatrix}$$

The best solution is $\hat{c} = \frac{9}{7}$, $\hat{d} = \frac{4}{7}$ and the best line is $\frac{9}{7} + \frac{4}{7}t$.

The line $\frac{9}{7} + \frac{4}{7}t$ has $\frac{5}{7}, \frac{13}{7}, \frac{17}{7}$ at $-1, 1, 2$. This vector is the projection. ($P = A(A^T A)^{-1} A^T$)

Projectors

In Linear algebra and its application

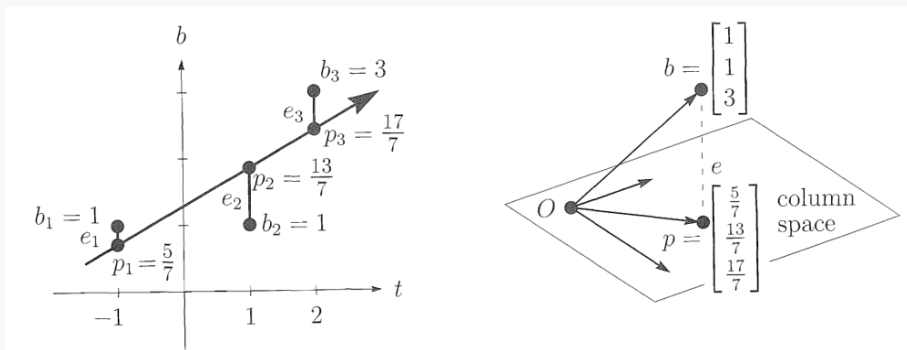


Figure: Example of straight-line approximation matches the projection p of b



The pseudoinverse $X \in \mathbb{C}^{m \times m}$ of $A \in \mathbb{C}^{m \times n}$ is the unique matrix satisfying the four Moore–Penrose conditions:

$$\begin{aligned} \text{(i)} \quad & AXA = A, & \text{(ii)} \quad & XAX = X, \\ \text{(iii)} \quad & AX = (AX)^*, & \text{(iv)} \quad & XA = (XA)^*. \end{aligned} \tag{9}$$

The pseudoinverse is denoted by A^+ .

Let S be a subspace of \mathbb{C}^m , and let $P_S \in \mathbb{C}^{m \times m}$.

- ▶ P_S is the projector onto S if $\text{range}(P_S) = S$ and $P_S^2 = P_S$.
The projector is not unique.
- ▶ P_S is the orthogonal projector onto S if $\text{range}(P_S) = S$ and $P_S^2 = P_S$ and $P_S^* = P_S$.
The orthogonal projector is unique.
In terms of the pseudoinverse, $P_{\text{range}(A)} = AA^+$ and $P_{\text{range}(A^*)} = A^+A$.



Theorem

Let $A \in M_n$ be given. There exists a unique monic polynomial $q_A(t)$ of minimum degree that annihilates A . The degree of $q_A(t)$ is at most n . If $p(t)$ is any monic polynomial such that $p(A) = 0$, then $q_A(t)$ divides $p(t)$, that is, $p(t) = h(t)q_A(t)$ for some monic polynomial $h(t)$.

Definition

Let $A \in M_n$ be given. The unique monic polynomial $q_A(t)$ of minimum degree that annihilates A is called the minimal polynomial of A .

Example

Let $A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, then the minimal polynomial of A is $q_A(t) = t^2 - 1$.



Definition

Thought of as a formal polynomial in t , the characteristic polynomial of $A \in M_n$ is

$$p_A(t) = \det(tI - A)$$

We refer to the equation $p_A(t) = 0$ as the characteristic equation of A .

Example

Let $A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, then the characteristic polynomial of A is $p_A(t) = t^3 - t^2 - t + 1$.

And since $p_A(A) = 0$, $p_A(t) = (t - 1)(t^2 - 1) = h(t)q_A(t)$ where $h(t) = t - 1$ and $q_A(t) = t^2 - 1$.



Theorem

Let $A \in M_n$ be given. There is a nonsingular $S \in M_n$, positive integers q and n_1, \dots, n_q with $n_1 + \dots + n_q = n$ and scalars $\lambda_1, \dots, \lambda_q \in \mathbb{C}$ such that

$$A = S \begin{bmatrix} J_{n_1}(\lambda_1) & & \\ & \ddots & \\ & & J_{n_q}(\lambda_q) \end{bmatrix} S^{-1} \quad (10)$$

The Jordan matrix $J_A = J_{n_1}(\lambda_1) \oplus \dots \oplus J_{n_q}(\lambda_q)$ is uniquely determined by A up to permutation of its direct summands. If A is real and has only real eigenvalues, then S can be chosen to be real.

Fact : J_A is similar to A . (has same eigenvalues)



We may assume that $J = J_{m_1}(\lambda) \oplus \cdots \oplus J_{m_p}(\lambda) \oplus \hat{J}$, in which the Jordan matrix \hat{J} is a direct sum of Jordan blocks with eigenvalues different from λ . Then

$$\begin{aligned} J - \lambda I &= (J_{m_1}(\lambda) - \lambda I) \cdots (J_{m_p}(\lambda) - \lambda I) \oplus (\hat{J} - \lambda I) \\ &= J_{m_1}(0) \oplus \cdots \oplus J_{m_p}(0) \oplus (\hat{J} - \lambda I) \end{aligned}$$

is similar to $A - \lambda I$. Moreover, $(J - \lambda I)^k$ is similar to $(A - \lambda I)^k$. And rank is similarity invariant,

$$\text{rank}(A - \lambda I)^k = \text{rank}(J - \lambda I)^k = \text{rank} J_{m_1}(0)^k + \cdots + \text{rank} J_{m_p}(0)^k + \text{rank}(\hat{J} - \lambda I)^k \quad (11)$$

Now let $A \in M_n$, let $\lambda \in \mathbb{C}$, let k be a positive integer, let

$$r_k(A, \lambda) = \text{rank}(A - \lambda I)^k, \quad r_0(A, \lambda) := n \quad (12)$$

and define

$$w_k(A, \lambda) = r_{k-1}(A, \lambda) - r_k(A, \lambda), \quad w_1(A, \lambda) := n - r_1(A, \lambda) \quad (13)$$



Using (11) and (12), we can explain the algebraic meaning of $w_k(A, \lambda)$:

$$\begin{aligned}w_k(A, \lambda) &= (\text{rank } J_{m_1}(0)^{k-1} - \text{rank } J_{m_1}(0)^k) + \cdots + (\text{rank } J_{m_p}(0)^{k-1} - \text{rank } J_{m_p}(0)^k) \\&= (1 \text{ if } m_1 \geq k) + \cdots + (1 \text{ if } m_p \geq k) \\&= \text{number of blocks with eigenvalue } \lambda \text{ that have size at least } k\end{aligned}\tag{14}$$

Definition

The Weyr characteristic of $A \in M_n$ associated with $\lambda \in \mathbb{C}$ is

$$w(A, \lambda) = (w_1(A, \lambda), \dots, w_q(A, \lambda))$$

in which the sequence of integers $w_j(A, \lambda)$ is defined by (13)



Definition

Let $\lambda \in \mathbb{C}$ be given, let $q \geq 1$ be a given positive integer, let $w_1 \geq \dots \geq w_q \geq 1$ be a given nonincreasing sequence of positive integers, and let $w = (w_1, \dots, w_q)$. The Weyr block $W(w, \lambda)$ associated with λ and w is the upper triangular $q \times q$ block bidiagonal matrix

$$W(w, \lambda) = \begin{bmatrix} \lambda I_{w_1} & G_{w_1, w_2} & & & \\ & \lambda I_{w_2} & G_{w_2, w_3} & & \\ & & \ddots & \ddots & \\ & & & \ddots & G_{w_{q-1}, w_q} \\ & & & & I_{w_q} \end{bmatrix} \quad (15)$$

$$\text{in which } G_{w_i, w_j} = \begin{bmatrix} I_{w_j} \\ 0 \end{bmatrix} \in M_{w_i, w_j}, \quad 1 \leq i < j$$



For any $A \in M_n$, let q be the index of an eigenvalue λ of A , let $w_k = w_k(A, \lambda)$, $k = 1, 2, \dots$ be the Weyr characteristic of A associated with λ . Define the Weyr block of A associated with the eigenvalue λ to be

$$W_A(\lambda) = W(w(A, \lambda), \lambda)$$

Theorem

Let $\lambda_1, \dots, \lambda_d$ be distinct eigenvalues of $A \in M_n$.

- ▶ *There is a nonsingular $S \in M_n$ and there are Weyr blocks W_1, \dots, W_d such that*
- ▶ *$A = S(W_1 \oplus \dots \oplus W_d)S^{-1}$*
- ▶ *The Weyr matrix $W_1 \oplus \dots \oplus W_d$ is similar to A .*

where $W_j = W_A(\lambda_j)$ for each $j = 1, \dots, d$.

Let $W_A = W_A(\lambda_1) \oplus \dots \oplus W_A(\lambda_d)$, then $A = SW_AS^{-1}$ is Weyr canonical form of A .



Example

Consider the Jordan matrix $J = J_3(\lambda) \oplus J_2(\lambda)$, then $w_J(J, \lambda) = 2, 2, 1$:

$$J = \left[\begin{array}{ccc|cc} \lambda & 1 & 0 & & \\ 0 & \lambda & 1 & & \\ 0 & 0 & \lambda & & \\ \hline & & & \lambda & 1 \\ & & & 0 & \lambda \end{array} \right] \Rightarrow W_J(\lambda) = \left[\begin{array}{cc|cc|c} \lambda & 0 & 1 & 0 & \\ 0 & \lambda & 0 & 1 & \\ \hline & & \lambda & 0 & 1 \\ & & 0 & \lambda & 0 \\ \hline & & & & \lambda \end{array} \right]$$

The eigenvalue of J is $(\lambda, \lambda, \lambda, \lambda, \lambda)$, considering multiplicity and there are two eigenvectors corresponding to the eigenvalue. The cycle for the first eigenvector of $(J - \lambda I)$ is 3 and the second eigenvector is 2.

Theorem

Let $\lambda_1, \dots, \lambda_d$ be the distinct eigenvalues of a given $A \in M_n$ in any prescribed order, let q_1, \dots, q_d be their respective indices, and let $q = q_1 + \dots + q_d$. Then A is unitarily similar to an upper triangular matrix of the form

$$F = \begin{bmatrix} \mu_1 I_{n_1} & F_{12} & F_{13} & \cdots & F_{1p} \\ & \mu_2 I_{n_2} & F_{23} & \cdots & F_{2p} \\ & & \mu_1 I_{n_1} & \ddots & \vdots \\ & & & \ddots & F_{p-1p} \\ & & & & \mu_p I_{n_p} \end{bmatrix} \quad \text{in which}$$

- (a) $\mu_1 = \dots = \mu_{q_1} = \lambda_1; \mu_{q_1+1} = \dots = \mu_{q_1+q_2} = \lambda_2; \dots; \mu_{p-q_d+1} = \dots = \mu_p = \lambda_d$
- (b) For each $j = 1, \dots, d$ the q_j integers n_i, \dots, n_{i+q_j-1} for which $\mu_i = \dots = \mu_{i+q_j-1} = \lambda_j$ are the Weyr characteristic of λ_j as an eigenvalue of A , that is, $n_i = w_1(A, \lambda_j) \geq \dots \geq n_{i+q_j-1} = w_{q_j}(A, \lambda_j)$
- (c) if $\mu_i = \mu_{i+1}$ then $n_i \geq n_{i+1}$, $F_{i,i+1} \in M_{n_i, n_{i+1}}$ is upper triangular, and its diagonal entries are real and positive



Corollary

Let $A \in M_n$ be a projector: $A^2 = A$. Let

$$\sigma_1 \geq \cdots \geq \sigma_g > 1 \geq \sigma_{g+1} \geq \cdots \geq \sigma_r > 0 = \sigma_{r+1} = \cdots$$

be the singular values of A , so $r = \text{rank} A$ and g is the number of singular values of A that are greater than 1. Then A is unitarily similar to

$$\begin{bmatrix} 1 & (\sigma_1^2 - 1)^{1/2} \\ 0 & 0 \end{bmatrix} \oplus \cdots \oplus \begin{bmatrix} 1 & (\sigma_g^2 - 1)^{1/2} \\ 0 & 0 \end{bmatrix} \oplus I_{r-g} \oplus 0_{n-r-g}$$



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Thank you!