MTH 513: Chapter 7, Part 1

Last updated: December 1, 2022

$\S7.1 - \S7.2$ Eigenvalues and Eigenvectors

Definition 1. A nonzero vector $\mathbf{x} \in \mathbb{C}^n$ is a **right eigenvector** of $A \in \mathbb{C}^{n \times n}$ if there exists a scalar $\lambda \in \mathbb{C}$, called an **eigenvalue**, such that

$$A\mathbf{x} = \lambda \mathbf{x}$$
.

Similarly, a nonzero vector $\mathbf{y} \in \mathbb{C}^n$ is a **left eigenvector** corresponding to an eigenvalue μ if

$$\mathbf{y}^* A = \mu \mathbf{y}^*.$$

The set of distinct eigenvalues of A, denoted $\Lambda(A)$, is called the **spectrum** of A.

 (λ, \mathbf{x}) is an eigenpair of $A \iff A\mathbf{x} = \lambda\mathbf{x}, \quad \mathbf{x} \neq \mathbf{0}$ $\iff (A - \lambda I)\mathbf{x} = \mathbf{0}, \quad \mathbf{x} \neq \mathbf{0}$ $\iff (A - \lambda I) \text{ is singular (not invertible)}$ $\iff \det(A - \lambda I) = 0$

- (i) $\{\mathbf{x} \neq \mathbf{0}_n : \mathbf{x} \in \mathcal{N}(A \lambda I)\}$ is the set of all eigenvectors associated with λ . From now on, we refer to the subspace $\mathcal{N}(A \lambda I)$ as the **eigenspace** of A associated with eigenvalue λ and denote it by $E_{\lambda}(A)$ or E_{λ} .
- (ii) Let λ is an eigenvalue of A and \mathbf{x} is an associated eigenvector, then (λ, \mathbf{x}) is referred to as an eigenpair of A.
- (iii) The characteristic polynomial for A is $\pi_A(\lambda) = \det(A \lambda I)$. The degree of $\pi_A(\lambda)$ is n, and the leading term in $\pi(\lambda)$ is $(-1)^n \lambda^n$.
- (iv) The characteristic equation for A is $\pi(\lambda) = 0$.
- (v) The eigenvalues of A are the solutions of the characteristic equation, or equivalently, the roots of the characteristic polynomial.

- (vi) Altogether, A has n eigenvalues, but some may be complex numbers (even if the entries of A are real numbers), and some eigenvalues may be repeated.
- (vii) If A contains only real numbers, then its complex eigenvalues must occur in conjugate pairs i.e., if $\lambda \in \Lambda(A)$, then $\overline{\lambda} \in \Lambda(A)$.

Discussion: If $A \in \mathbb{R}^{n \times n}$, then $\pi_A(\lambda) = \det(A - \lambda I)$ is a polynomial of degree n with real coefficients. Consequently, if λ_0 is a root of $\pi_A(\lambda)$, then $\overline{\lambda_0}$ is also a root of $\pi_A(\lambda)$. In other words, if $A \in \mathbb{R}^{n \times n}$, then complex eigenvalues come in conjugate pairs.

Example 2. Let $D = \text{diag}(d_1, \ldots, d_n)$ be an $n \times n$ diagonal matrix. Determine its eigenvalues and associated eigenvectors.

Solution: We start by finding the characteristic polynomial of D which is given by

$$\pi_D(\lambda) = \det(D - \lambda I) = \det \begin{bmatrix} d_1 - \lambda & & & \\ & d_2 - \lambda & & \\ & & \ddots & \\ & & & d_n - \lambda \end{bmatrix} = \prod_{i=1}^n (d_i - \lambda). \tag{1}$$

From (1) it follows that $\pi_D(\lambda) = 0$ for all $\lambda = d_i$, i.e., eigenvalues of D are just diagonal entires d_i . Now in order to determine an e-vector associated with an e-value $\lambda = d_i$ we look at $\mathcal{N}(D - d_i I)$.

From (2) it is easy to see that for $\mathbf{x} = \mathbf{e}_i$ we have $(D - d_i I)\mathbf{x} = (D - d_i I)\mathbf{e}_i = \mathbf{0}$, that is, $\mathbf{x} = \mathbf{e}_i$ is an eigenvector of D associated with an eigenvalue $\lambda = d_i$.

Discussion: Note that here we are not claiming that $\mathbf{x} = \mathbf{e}_i$, or just a scalar multiple of \mathbf{e}_i , is the only eigenvector of D associated with eigenvalue $\lambda = d_i$. This claim would be true if $d_i \neq d_j$ for all $i \neq j$, otherwise, there exist eigenvectors of D other than scalar multiples of \mathbf{e}_i .

¹This is a fact that you have probably encountered the first time in a high school algebra/precalculus course. A more rigorous result from complex analysis is often referred as "Complex Factor Theorem" of "Conjugate Pairs Theorem".

Example 3. Let T be an $n \times n$ upper-triangular matrix. Determine the eigenvalues of T.

Solution: Again, one starts with finding the characteristic polynomial of T, that is,

$$\pi_{T}(\lambda) = \det(T - \lambda I) = \det\begin{bmatrix} t_{1,1} - \lambda & t_{1,2} & t_{1,3} & \cdots & t_{1,n} \\ 0 & t_{2,2} - \lambda & t_{2,3} & \cdots & t_{2,n} \\ 0 & 0 & t_{3,3} - \lambda & \cdots & t_{3,n} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & t_{n,n} - \lambda \end{bmatrix} = \prod_{i=1}^{n} (t_{ii} - \lambda). \quad (3)$$

From (3) it follows that $\pi_T(\lambda) = 0$ when $\lambda = t_{ii}$, that is, eigenvalues of T are exactly the diagonal entries of T.

Theorem 4. If T is a triangular matrix, lower or upper, then the eigenvalues of T are exactly the diagonal entries of T.

Example 5. Let A and B be two square matrices non necessarily of the same size. Show that the characteristic polynomial of $C = \begin{bmatrix} A & \\ & B \end{bmatrix}$ is the product of characteristic polynomials of A and B.

Solution: Suppose $A \in \mathbb{C}^{n \times n}$ and $B \in \mathbb{C}^{m \times m}$ so that $C \in \mathbb{C}^{(m+n) \times (m+n)}$. Then the characteristic polynomial of C is given by

$$\pi_{C}(\lambda) = \det(C - \lambda I_{n+m}) = \det\left(\left[\frac{A}{B}\right] - \lambda \left[\frac{I_{n}}{I_{m}}\right]\right)$$

$$= \det\left[\frac{A - \lambda I_{n}}{B - \lambda_{m}}\right]$$

$$= \det(A - \lambda I_{n}) \cdot \det(A - \lambda I_{m})$$

$$= \pi_{A}(\lambda) \cdot \pi_{B}(\lambda).$$

Theorem 6. Let $D = \operatorname{diag}(A_1, A_2, \dots, A_k)$ be a block-diagonal matrix with square block A_i ,

(i)
$$\pi_D(\lambda) = \prod_{i=1}^k \pi_{A_i}(\lambda)$$
.

$$\begin{array}{ll} (\mathrm{i}) \ \pi_D(\lambda) \ = \ \prod_{i=1}^k \pi_{A_i}(\lambda) \,. \\ \\ (\mathrm{ii}) \ \varLambda(D) \ = \ \bigcup_{i=1}^k \varLambda(A_i) \,. \end{array} \qquad (eigenvalues \ of \ D \ is \ just \ a \ union \ of \ eigenvalues \ of \ A_i) \end{array}$$

Example 7. Let $J_k(\lambda_0)$ be a $k \times k$ matrix of the form

$$J_k(\lambda_0) = \begin{bmatrix} \lambda_0 & 1 & 0 & \cdots & 0 \\ & \lambda_0 & 1 & \cdots & 0 \\ & & \ddots & \ddots & \vdots \\ & & & \lambda_0 & 1 \\ & & & & \lambda_0 \end{bmatrix}_{k \times k}.$$

(a) What are the eigenvalues of $J_4(13)$?

Solution: Since $J_4(13)$ is an upper triangular matrix, by Example 3 we know its eigenvalues are exactly its diagonal entries, that is, $\lambda = 13$.

(b) What is the dimension of associated eigenspace(s)?

Solution: This is exactly one of your homework problems. More specifically, $J_4(13) - 13 \cdot I_4$ is given by

$$J_4(13) - 13 \cdot I_4 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

Clearly, rank $(J_4(13) - 13 \cdot I_4) = 4 - 1 = 3$. From the Rank-Nullity Theorem we know that $\dim \mathcal{N}(J_4(13) - 13 \cdot I_4) = 1$ and a basis for $\mathcal{N}(J_4(13) - 13 \cdot I_4)$ is

$$\left\{ \begin{bmatrix} 1\\0\\0\\0 \end{bmatrix} \right\}.$$

(c) Determine the eigenvalues and dimensions of associated eigenspaces of the matrix

$$J = \begin{bmatrix} J_k(a) & & & \\ & J_\ell(b) & & \\ & & J_m(c) \end{bmatrix}.$$

Solution: From Example 5 it follows that the set of eigenvalues of J is just the union of eigenvalues of diagonal blocks, which from the previous part we know are exactly $\lambda = a$, $\lambda = b$, and $\lambda = c$. Finally, from our homework assignment we know that a basis for each of the associated eigenspaces are given by

Basis for
$$E_{\lambda=a} = \left\{ \begin{bmatrix} 1\\0\\\vdots\\0\\\hline \hline \mathbf{0}_{\ell\times 1}\\\hline \mathbf{0}_{m\times 1} \end{bmatrix}_{(k+\ell+m)\times 1} \right\}$$

Basis for
$$E_{\lambda=b} = \left\{ \begin{bmatrix} \mathbf{0}_{k\times 1} \\ 1 \\ 0 \\ \vdots \\ \mathbf{0}_{m\times 1} \end{bmatrix}_{(k+\ell+m)\times 1} \right\}$$

Basis for
$$E_{\lambda=c}$$
 =
$$\left\{ \begin{bmatrix} \frac{\mathbf{0}_{k\times 1}}{\mathbf{0}_{\ell\times 1}} \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{(k+\ell+m)\times 1} \right\}$$

Example 8. Compute eigenvalues and associated eigenspaces of $A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & -5 & 0 \\ 1 & 8 & 1 \end{bmatrix}$.

Solution: We start by computing the characteristic polynomial of A.

$$\pi_{A}(\lambda) = \det (A - \lambda I) = \det \begin{bmatrix} 1 - \lambda & 2 & 1 \\ 0 & -5 - \lambda & 0 \\ 1 & 8 & 1 - \lambda \end{bmatrix}$$

$$= (-5 - \lambda) \det \begin{bmatrix} 1 - \lambda & 1 \\ 1 & 1 - \lambda \end{bmatrix}$$

$$= -(5 + \lambda) ((1 - \lambda)^{2} - 1)$$

$$= -(5 + \lambda) ((1 - \lambda - 1)(1 - \lambda + 1))$$

$$= \lambda (5 + \lambda)(2 - \lambda)$$
(4)

From (4) we see that the eigenvalues of A are $\lambda_1 = 0$, $\lambda_2 = -5$, and $\lambda_3 = 2$. Next we look for the associated eigenvectors.

 $\lambda_1 = 0$ We start by looking at $\mathcal{N}(A - \lambda_1 I) = \mathcal{N}(A)$

$$(A - 0 \cdot I)\mathbf{x} = \mathbf{0} \qquad \Longleftrightarrow \qquad \begin{bmatrix} 1 - 0 & 2 & 1 & 0 \\ 0 & -5 - 0 & 0 & 0 \\ 1 & 8 & 1 - 0 & 0 \end{bmatrix}$$

$$\xrightarrow{\text{rref}} \qquad \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

And so a basis for the associated eigenspace $E_{\lambda_1=0}$ is

$$\left\{ \left[\begin{array}{c} -1\\0\\1 \end{array} \right] \right\}$$

 $\lambda_2 = -5$ We start by looking at $\mathcal{N}(A - \lambda_2 I) = \mathcal{N}(A + 5I)$

$$(A+5 \cdot I)\mathbf{x} = \mathbf{0} \qquad \iff \begin{bmatrix} 1+5 & 2 & 1 & 0 \\ 0 & -5+5 & 0 & 0 \\ 1 & 8 & 1+5 & 0 \end{bmatrix}$$

$$\xrightarrow{\mathbf{rref}} \qquad \begin{bmatrix} 1 & 0 & -\frac{2}{23} & 0 \\ 0 & 1 & \frac{35}{46} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

And so a basis for the associated eigenspace $E_{\lambda_2=-5}$ is

$$\left\{ \left[\begin{array}{c} 4 \\ -35 \\ 46 \end{array} \right] \right\}$$

 $\lambda_3 = 2$ We start by looking at $\mathcal{N}(A - \lambda_3 I) = \mathcal{N}(A - 2I)$

$$(A - 2 \cdot I)\mathbf{x} = \mathbf{0} \qquad \iff \qquad \begin{bmatrix} 1 - 2 & 2 & 1 & 0 \\ 0 & -5 - 2 & 0 & 0 \\ 1 & 8 & 1 - 2 & 0 \end{bmatrix}$$

$$\xrightarrow{\text{rref}} \qquad \begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

And so a basis for the associated eigenspace $E_{\lambda_3=2}$ is

$$\left\{ \begin{bmatrix} 1\\0\\1 \end{bmatrix} \right\}$$

Example 9. Let A be an $n \times n$ matrix.

(a) Prove A and A^T have exactly the same characteristic polynomials.

Proof. The desired conclusion follows directly from the following chain of equalities

$$\pi_{A^T}(\lambda) = \det(A^T - \lambda I)$$

$$= \det(A^T - \lambda I^T)$$

$$= \det((A - \lambda I)^T)$$

$$= \det(A - \lambda I)$$

$$= \pi_A(\lambda)$$

(b) Show that if λ is an eigenvalue of A, then $\overline{\lambda}$ is an eigenvalue of A^* .

Proof. Assume that λ is an eigenvalue of A an \mathbf{x} an associated eigenvector. Then

$$A\mathbf{x} = \lambda \mathbf{x} \,. \tag{5}$$

Taking a complex conjugate of equation (5) gives

$$\mathbf{x}^* A^* = \overline{\lambda} \mathbf{x}^*$$
,

and so $\overline{\lambda}$ is an eigenvalue of A^* with an associated *left* eigenvector \mathbf{x} .

(c) Show that if (λ, \mathbf{x}) is an eigenpair of A, then $(\lambda, c \cdot \mathbf{x})$ is an eigenpair of A, where c is an arbitrary nonzero constant.

Proof. Let (λ, \mathbf{x}) be an eigenpair of A so that

$$A\mathbf{x} = \lambda \mathbf{x}. \tag{6}$$

Multiplying equation (6) by a nonzero scalar c we obtain

$$A(c \cdot \mathbf{x}) = \lambda(c \cdot \mathbf{x}). \tag{7}$$

Since \mathbf{x} is an eigenvector by assumption it is nonzero. Further, since $c \neq 0$, it follows that $c\mathbf{x} \neq \mathbf{0}$. Therefore, it follows from (7) that $(\lambda, c \cdot \mathbf{x})$ is an eigenpair of A.

Special Case: If \mathbf{x} is an eigenvector of A associated with an eigenvalue λ , then $\pm \frac{1}{||\mathbf{x}||_2}\mathbf{x}$ is also an eigenvector of A associated with λ . In other words, with any eigenvalue there are at least two eigenvectors of unit length (norm equals to one).

(d) Show that if (λ, \mathbf{x}) is an eigenpair of A, then $(\lambda + \varepsilon, \mathbf{x})$ is an eigenpair of $A + \varepsilon I_n$, where ε is an arbitrary constant.

Proof. Assume that (λ, \mathbf{x}) is an eigenpair of A so that

$$A\mathbf{x} = \lambda \mathbf{x}. \tag{8}$$

Adding $\varepsilon \mathbf{x}$ to the both sides of equation (8) gives

$$A\mathbf{x} + \varepsilon \mathbf{x} = \lambda \mathbf{x} + \varepsilon \mathbf{x}$$
$$(A + \varepsilon I)\mathbf{x} = (\lambda + \varepsilon)\mathbf{x},$$

and so $(\lambda + \varepsilon, \mathbf{x})$ is an eigenpair of $A + \varepsilon I$.

(e) Assume that A is a nonsingular matrix. Show that if (λ, \mathbf{x}) is an eigenpair of A, then $(\lambda^{-1}, \mathbf{x})$ is an eigenpair of A^{-1} .

Proof. Assume that (λ, \mathbf{x}) is an eigenpair of A so that

$$A\mathbf{x} = \lambda \mathbf{x} \,. \tag{9}$$

Multiplying from the left the both sides of equation (9) by A^{-1} gives

$$\mathbf{x} = \lambda A^{-1} \mathbf{x} \tag{10}$$

Furthermore, dividing by λ both sides of (10) (why can we do this?) gives

$$\frac{1}{\lambda} \mathbf{x} = A^{-1} \mathbf{x} \,. \tag{11}$$

Therefore, from (11) it follows that $(\frac{1}{\lambda}, \mathbf{x})$ is an eigenpair of A^{-1} .

(f) Prove that if (λ, \mathbf{x}) is an eigenpair of A, then (λ^k, \mathbf{x}) is an eigenpair of A^k .

Proof. (by induction) Let (λ, \mathbf{x}) be an eigenpair of A, so that,

$$A\mathbf{x} = \lambda \mathbf{x}.\tag{12}$$

Multiplying (12) on the left by A gives

$$A^{2}\mathbf{x} = A \cdot (\lambda \mathbf{x}) = \lambda \cdot A\mathbf{x} = \lambda \cdot \lambda \mathbf{x} = \lambda^{2}\mathbf{x}. \tag{13}$$

Now assume that $(\lambda^{k-1}, \mathbf{x})$ is an eigenpair of A^{k-1} , so that

$$A^{k-1}\mathbf{x} = \lambda^{k-1}\mathbf{x} \,. \tag{14}$$

Multiplying (14) on the left by A gives

$$A^k \mathbf{x} \, = \, A \cdot \left(\lambda^{k-1} \mathbf{x} \right) \, = \, \lambda^{k-1} \cdot A \mathbf{x} \, = \, \lambda^{k-1} \cdot \lambda \mathbf{x} \, = \, \lambda^k \mathbf{x} \, ,$$

as desired. \Box

Last updated: December 1, 2022

$\S7.1 - \S7.2$ Eigenvalues and Eigenvectors

Definition 10. Two $n \times n$ matrices A and B are said to be **similar** whenever there exists a nonsingular matrix P such that $P^{-1}AP = B$. The product $P^{-1}AP$ is called a **similarity transformation** of A.

Example 11. Let $B = P^{-1}AP$, for some nonsingular matrix P. Prove that characteristic polynomials of A and B are the same. Conclude that the eigenvalues of A and B are the same.

Proof. We start by computing the characteristic polynomial of B

$$\pi_{B}(\lambda) = \det (B - \lambda I)$$

$$= \det (P^{-1}AP - \lambda I)$$

$$= \det (P^{-1} \cdot (A - \lambda I) \cdot P)$$

$$= \det (P^{-1}) \cdot \det (A - \lambda I) \cdot \det (P)$$

$$= \det (A - \lambda I) \cdot \det (P^{-1}) \cdot \det (P)$$

$$= \pi_{A}(\lambda) \cdot \det (P^{-1} \cdot P)$$

$$= \pi_{A}(\lambda) \cdot \det (I)$$

$$= \pi_{A}(\lambda) \cdot 1$$

$$= \pi_{A}(\lambda)$$

Since the characteristic polynomials of A and B are identical, then their eigenvalues are also identical.

Main Message: Similar matrices have identical eigenvalues. Hence one possible strategy for computing eigenvalues of a matrix is to transform it via similarity to a matrix whose eigenvalues are easy to compute, e.g., a diagonal or a triangular matrix.

Question: Can every matrix be transformed to a diagonal matrix via similarity?

Answer: NO. We have already seen this in Section 4.9. But here it is again. To see why that is the case let A be an $n \times n$ nonzero matrix such that $A^k = 0_{n \times n}$. Assume that there exists an invertible matrix P such that

$$P^{-1}AP = D = \begin{bmatrix} d_1 & & & \\ & d_2 & & \\ & & \ddots & \\ & & & d_n \end{bmatrix}.$$

Then one obtains

$$D^{k} = \begin{bmatrix} d_{1}^{k} & & & \\ & d_{2}^{k} & & \\ & & \ddots & \\ & & & d_{n}^{k} \end{bmatrix} = \underbrace{(P^{-1}AP) \cdot (P^{-1}AP) \cdots (P^{-1}AP)}_{k \ times} = P^{-1}A^{k}P = 0_{n \times n}.$$

Now it follows that for all i = 1, 2, ..., n,

$$d_i^k = 0 \implies d_i = 0 \implies D = 0_{n \times n}$$
.

Consequently, $A = PDP^{-1} = 0_{n \times n}$ which contradicts the assumption that A is nonzero.

Definition 12. A square matrix A is said to be **nilpotent** if $A^k = 0$ for some positive integer k.

Proposition 13. Let A be an $n \times n$ matrix. The following statements are equivalent.

- (a) A is nilpotent.
- (b) All eigenvalues of A are zero.
- (c) The characteristic polynomial of A is $\pi_A(\lambda) = \lambda^n$.

Proof. $\underline{(a) \Longrightarrow (b)}$ Assume that A is a nilpotent matrix and so $A^k = 0_{n \times n}$ for some k. Now let (λ, \mathbf{x}) be an arbitrary eigenpair of A so that

$$A\mathbf{x} = \lambda \mathbf{x}. \tag{15}$$

Multiplying (15) by A^{n-1} on the left gives

$$A^{n}\mathbf{x} = \lambda^{n}\mathbf{x} \qquad \Longleftrightarrow \qquad \mathbf{0} = \lambda^{n}\mathbf{x}. \tag{16}$$

Since **x** is an eigenvector and is nonzero, it follows that (16) only holds if $\lambda^n = 0$, or equivalently, $\lambda = 0$.

 $\underline{(b)\Longrightarrow(c)}$ Assume that all eigenvalues of A are zero. Since $\det(A-\lambda I)$ is a polynomial of degree n whose roots are exactly eigenvalues of A, it must be that $\det(A-\lambda I)=\pm\lambda^n$.

$$(c) \Longrightarrow (a)$$
 We will do this in a few pages.

Definition 14. An $n \times n$ matrix A is said to be diagonalizable if there exists an invertible matrix P such that $P^{-1}AP = D$, where D is a diagonal matrix.

Question: What matrices are diagonalizable?

Answer: Let $A \in \mathbb{C}^{n \times n}$ and assume that there exists an invertible matrix P such that

$$P^{-1}AP = D = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix} \iff AP = PD. \tag{17}$$

Looking at AP = PD column-wise we have that for each i = 1, ..., n it holds that

$$A \cdot \begin{bmatrix} P_{*1} & P_{*2} & \cdots & P_{*n} \end{bmatrix} = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix} \begin{bmatrix} P_{*1} & P_{*2} & \cdots & P_{*n} \end{bmatrix}$$

$$\begin{bmatrix} AP_{*1} & AP_{*2} & \cdots & AP_{*n} \end{bmatrix} = \begin{bmatrix} \lambda_1 P_{*1} & \lambda_2 P_{*2} & \cdots & \lambda_n P_{*n} \end{bmatrix}$$
$$AP_{*i} = \lambda_i P_{*i}$$

that is, (λ_i, P_{*i}) is an eigenpair of A.

Diagonalizability

- A complete set of eigenvectors of $A \in \mathbb{F}^{n \times n}$ is any set of n linearly independent eigenvectors for A. Not all matrices have a complete sets of eigenvectors, e.g., nilpotent matrices. Matrices that fail to posses complete sets of eigenvectors are sometimes called deficient or defective matrices.
- Matrix $A \in \mathbb{F}^{n \times n}$ is diagonalizable if and only if A possesses a complete set of eigenvectors. Moreover, $P^{-1}AP = \operatorname{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$ if and only if the columns of P constitute a complete set of eigenvectors and the λ_j 's are the associated eigenvalues that is, each (λ_j, P_{*j}) is an eigenpair for A.

Make sure you do a few computational examples here!!!

Example 15. (cont. of Ex. 8) Determine if A is a diagonalizable matrix, where $A = \begin{bmatrix} 1 & 2 & 1 \\ 0 & -5 & 0 \\ 1 & 8 & 1 \end{bmatrix}$.

Solution: From Example 8 we have

$$P^{-1}AP = D = \begin{bmatrix} 0 & & \\ & -5 & \\ & & 2 \end{bmatrix},$$

where

$$P = \begin{bmatrix} -1 & 4 & 1 \\ 0 & -35 & 0 \\ 1 & 46 & 1 \end{bmatrix}.$$

Remark 16. Note that the eigenvalues in matrix D can be put in any order, as long as one re-orders the corresponding eigenvectors in P. For example, one can check that

$$\widetilde{P}^{-1} A \widetilde{P} = \widetilde{D} = \begin{bmatrix} 2 & & \\ & 0 & \\ & & -5 \end{bmatrix},$$

where

$$\widetilde{P} = \begin{bmatrix} 1 & -1 & 4 \\ 0 & 0 & -35 \\ 1 & 1 & 46 \end{bmatrix}.$$

Last updated: December 1, 2022

$\S7.1 - \S7.2$ Schur's Theorem and Implications

As a preparation, we start by reviewing some basic facts.

Definition 17. An $n \times n$ matrix A is said to be unitary if $A^*A = AA^* = I_n$. Equivalently, A is a unitary matrix if its columns (rows) form an orthonormal basis for \mathbb{C}^n .

Lemma 18. Let $A \in \mathbb{C}^{n \times n}$ and $B \in \mathbb{C}^{m \times m}$ be unitary matrices. Then

$$C = \left[\begin{array}{c|c} A & \\ \hline & B \end{array} \right]$$

is unitary.

Lemma 19. Let $A \in \mathbb{C}^{n \times n}$ and $B \in \mathbb{C}^{n \times n}$ be unitary matrices. Then $A \cdot B$ is also a unitary matrix.

Theorem 20 (Schur's Triangularization Theorem). Every square matrix is unitarily similar to an upper-triangular matrix. That is, for each $A \in \mathbb{C}^{n \times n}$, there exists a unitary matrix U (not unique) and an upper-triangular matrix T (not unique) such that $U^*AU = T$ (or $A = UTU^*$), and the diagonal entries of T are the eigenvalues of A.

Proof. We prove this statement by induction. For n=1, this result holds trivially. Namely,

$$A = \begin{bmatrix} a_{11} \end{bmatrix} = \begin{bmatrix} 1 \end{bmatrix} \cdot \begin{bmatrix} a_{11} \end{bmatrix} \cdot \begin{bmatrix} 1 \end{bmatrix} = \begin{bmatrix} 1 \end{bmatrix} \cdot \begin{bmatrix} a_{11} \end{bmatrix} \cdot \begin{bmatrix} 1 \end{bmatrix}^* = U \cdot T \cdot U^*.$$

For the inductive hypothesis, we assume that all $(n-1) \times (n-1)$ matrices are unitarily similar to an upper triangular matrix.

Next we let A be $n \times n$ matrix and suppose that (λ, \mathbf{x}) is an eigenpair for A, i.e., $A\mathbf{x} = \lambda \mathbf{x}$. Without loss of generality, assume that \mathbf{x} is of unit length, otherwise, $\frac{1}{||\mathbf{x}||_2}\mathbf{x}$ is one such eigenvector. Now let Q be a unitary matrix such that

$$Q = \left[\mathbf{x} \mid \widetilde{Q} \right],$$

where $\widetilde{Q} \in \mathbb{C}^{n \times (n-1)}$. (Why and how can this be done?) Then we have the following chain of equalities

$$Q^*AQ = \left[\frac{\mathbf{x}^*}{\widetilde{Q}^*}\right] A \left[\mathbf{x} \mid \widetilde{Q}\right] = \left[\frac{\mathbf{x}^*}{\widetilde{Q}^*}\right] \left[A\mathbf{x} \mid A\widetilde{Q}\right]$$

$$= \left[\frac{\mathbf{x}^*}{\widetilde{Q}^*}\right] \left[\lambda\mathbf{x} \mid A\widetilde{Q}\right] = \left[\frac{\lambda\mathbf{x}^*\mathbf{x} \mid \mathbf{x}^*A\widetilde{Q}}{\lambda\widetilde{Q}^*\mathbf{x} \mid \widetilde{Q}^*A\widetilde{Q}}\right]$$

$$= \left[\frac{\lambda \mid \mathbf{x}^*A\widetilde{Q}}{\mathbf{0}_{n-1} \mid A_2}\right], \tag{18}$$

where (18) follows from the fact that \mathbf{x} is a unit vector by assumption, columns of \widetilde{Q} are orthogonal to \mathbf{x} , and $A_2 = \widetilde{Q}^* A \widetilde{Q}$.

Since A_2 is an $(n-1) \times (n-1)$ and the inductive hypothesis applies and so there exists an $(n-1) \times (n-1)$ unitary matrix \widetilde{R} such that $\widetilde{R}^*A_2\widetilde{R} = \widetilde{T}$, where \widetilde{T} is an $(n-1) \times (n-1)$ upper triangular matrix. Consider a new matrix

$$R = \left\lceil \frac{1}{\widetilde{R}} \right\rceil \in \mathbb{C}^{n \times n},$$

and observe that R is also unitary and

$$R^* = \left[\begin{array}{c|c} 1 \\ \hline & \widetilde{R}^* \end{array}\right] \in \mathbb{C}^{n \times n}.$$

Going back to (18) we obtain the following chain of equalities

$$R^{*}(Q^{*}AQ)R = \begin{bmatrix} 1 & \lambda & \mathbf{x}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & A_{2} \end{bmatrix} \cdot \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & A_{2} \end{bmatrix} \cdot \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \hline 0_{n-1} & \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix} 1 & \lambda & \overline{X}^{*}A\widetilde{Q} \\ \overline{X}^{*}A\widetilde{Q} \end{bmatrix} = \begin{bmatrix}$$

Clearly, U = QR is a unitary matrix since the product of unitary matrices is again a unitary matrix, and T is an upper triangular matrix. Finally, from (19) the desired conclusion follows. \Box

Remark 21. One can always arrange for eigenvalues of A to appear "consecutively" along the diagonal of T, that is, all repeating eigenvalues appear consequently, and so on. Furthermore, Schur's form is not unique, that is, neither T nor U is unique. Also, note that even if A is real, then T and U might be complex. Finally, there is something called "real Schur form" so if you would like to know more, I am happy to provide you with additional references.

Theorem 22. Let $A \in \mathbb{C}^{n \times n}$. Then

$$\operatorname{trace}(A) = \sum_{i=1}^{n} \lambda_i$$
 and $\det(A) = \prod_{i=1}^{n} \lambda_i$,

where λ_i are eigenvalues of A.

Remark 23. If you have not reviewed properties of determinants, now is the time to go over determinant review.

Proof. From the Schur's Triangularization Theorem we know that there exists an upper triangular matrix T whose diagonal entires are the eigenvalues of A and the unitary matrix U such that

$$T = U^*AU. (20)$$

Taking trace of the both sides of (20), together with the facts that $\operatorname{trace}(XY) = \operatorname{trace}(YX)$ for all $X, Y \in \mathbb{C}^{n \times n}$ and $U^*U = U^*U = I_n$ for a unitary matrix U, imply that

$$\operatorname{trace}(T) = \operatorname{trace}(U^*AU) = \operatorname{trace}(UU^*A) = \operatorname{trace}(I_nA)$$

$$\sum_{i=1}^n \lambda_i = \operatorname{trace}(A).$$

On the other hand, taking det of the both sides of (20), together with the facts that $\det(XY) = \det(X) \det(Y)$ for all $X, Y \in \mathbb{C}^{n \times n}$, imply that

$$\det(T) \ = \ \det(U^*AU) \ = \ \det(U^*)\det(A)\det(U)$$

$$\prod_{i=1}^{n} \lambda_{i} = \frac{1}{\det(U)} \det(A) \det(U) = \det(A).$$

Remark 24. Note that nearly identical argument would work for square matrices that are diagonalizable. However, the argument via Schur's Theorem (or via Jordan Canonical Form - not covered yet!) hold for all matrices.

Theorem 25. Let $A \in \mathbb{C}^{n \times n}$ be a normal matrix, that is, $A^*A = AA^*$. Prove that A is unitarily diagonalizable.

Proof. By the Schur's Triangularization Theorem we know that there exist a unitary matrix U such that $U^*AU = T_A$, where T_A is an upper triangular matrix. Equivalently, we have that

$$A = U T_A U^* \quad \text{and} \quad A^* = U T_A^* U^*. \tag{21}$$

Since A is normal we have the following chain of equalities

$$AA^{*} = A^{*}A$$

$$(UT_{A}U^{*})(UT_{A}^{*}U^{*}) = (UT_{A}^{*}U^{*})(UT_{A}U^{*})$$

$$UT_{A}(U^{*}U)T_{A}^{*}U^{*} = UT_{A}^{*}(U^{*}U)T_{A}U^{*}$$

$$UT_{A}T_{A}^{*}U^{*} = UT_{A}^{*}T_{A}U^{*}$$

$$T_{A}T_{A}^{*} = T_{A}^{*}T_{A}.$$
(22)

From (22) it follows that T_A is also normal. Furthermore, from our take-home exam we know that since T_A is an upper triangular and a normal matrix, then it must be diagonal.

Theorem 26 (Spectral Theorem for Hermitian Matrices). Let $A \in \mathbb{C}^{n \times n}$ be a Hermitian matrix. The following statements are true.

- (i) A is unitarily diagonalizable.
- (ii) All eigenvalues of A are real.
- (iii) Eigenvectors of A corresponding to distinct eigenvalues are orthogonal.

Proof. Assume A is Hermitian. Then $A^*A = AA = AA^*$ and so A is also normal. By Theorem 25 it follows that A is unitarily diagonalizable, that is, there exists a unitary matrix U and a diagonal matrix D such that

$$U^* A U = D. (23)$$

Taking a complex conjugate of (23) implies that

$$U^* A^* (U^*)^* = D^*$$

$$U^* A U = D^*$$

$$D = D^*.$$
(24)

But (24) implies that D is also a Hermitian matrix and so

$$\overline{d_i} = d_i, \qquad i = 1, 2, \dots, n. \tag{25}$$

But (25) implies that each d_i must be real and so all eigenvalues of A are real.

Finally, to prove (iii) let (λ, \mathbf{x}) and (μ, \mathbf{y}) be eigenpairs of A where $\lambda \neq \mu$. Then

$$A\mathbf{x} = \lambda \mathbf{x}$$
 and $A\mathbf{y} = \mu \mathbf{y}$.

Then

$$\mathbf{y}^* A \mathbf{x} = \lambda \mathbf{y}^* \mathbf{x}$$

$$\mathbf{y}^* A^* \mathbf{x} = \lambda \mathbf{y}^* \mathbf{x}$$

$$\mu \mathbf{y}^* \mathbf{x} = \lambda \mathbf{y}^* \mathbf{x}$$
(26)

$$(\lambda - \mu)\mathbf{y}^*\mathbf{x} = 0, (27)$$

where (26) follows from the assumption that A is Hermitian. Finally, the assumption that $\lambda \neq \mu$, together with (26), imply that $\mathbf{y}^*\mathbf{x} = 0$, as desired.

Example 27. Let
$$A = \begin{bmatrix} 0 & a_{12} & a_{13} & a_{14} \\ 0 & 0 & a_{23} & a_{24} \\ 0 & 0 & 0 & a_{34} \\ 0 & 0 & 0 & 0 \end{bmatrix}$$
. Compute A^2, A^3, A^4 .

Solution:

Lemma 28. Let J be a $k \times k$ upper-triangular matrix with diagonal entries equal to zero. Prove that $J^k = 0_{k \times k}$.

Lemma 29. Let k be a positive integer and let T_i be a $k \times k$ block matrices such that

$$T_{i} = \begin{bmatrix} C_{11}^{(i)} & \star & \cdots & \star \\ & C_{22}^{(i)} & \cdots & \star \\ & & \ddots & \vdots \\ & & & C_{kk}^{(i)} \end{bmatrix}, \qquad i = 1, 2, \dots, k.$$

Further, assume $C_{ii}^{(i)}$ is the zero matrix for each i. Then the product $T_1T_2\cdots T_k$ is the zero matrix of the appropriate size.

Just to get a feel how Lemma 29 works, let us consider the case when k=3. Then

$$T_{1}T_{2}T_{3} = \begin{bmatrix} \mathbf{0} & \star & \star \\ 0 & X & \star \\ 0 & 0 & Y \end{bmatrix} \begin{bmatrix} A & \star & \star \\ 0 & \mathbf{0} & \star \\ 0 & 0 & B \end{bmatrix} \begin{bmatrix} P & \star & \star \\ 0 & Q & \star \\ 0 & 0 & \mathbf{0} \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0 & \bullet \\ 0 & 0 & \bullet \\ 0 & 0 & YB \end{bmatrix} \begin{bmatrix} P & \star & \star \\ 0 & Q & \star \\ 0 & 0 & \mathbf{0} \end{bmatrix}$$
(28)

$$= \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}. \tag{30}$$

Definition 30. Let q(t) be a scalar polynomial such that

$$q(t) = a_k t^k + a_{k-1} t^{k-1} + \dots + a_1 t + a_0.$$

If $A \in \mathbb{R}^{n \times n}$, then q(A) is an $n \times n$ matrix such that

$$q(A) = a_k A^k + a_{k-1} A^{k-1} + \dots + a_1 A + a_0 I.$$

Lemma 31. Let q(t) be an arbitrary scalar polynomial. Then for any matrix A and a nonsingular matrix S we have that

$$q(S^{-1}AS) = S^{-1}q(A)S$$
.

Proof. Let
$$q(t) = a_k t^k + a_{k-1} t^{k-1} + \cdots + a_1 t + a_0$$
 so that

$$q(S^{-1}AS) = a_k(S^{-1}AS)^k + a_{k-1}(S^{-1}AS)^{k-1} + \dots + a_1(S^{-1}AS) + a_0(S^{-1}AS)$$

$$= a_kS^{-1}A^kS + a_{k-1}S^{-1}A^{k-1}S + \dots + a_1S^{-1}AS + a_0S^{-1}AS$$

$$= S^{-1}(a_kA^k + a_{k-1}A^{k-1} + \dots + a_1A + a_0I)S$$

$$= S^{-1}q(A)S.$$

Theorem 32 (Cayley-Hamilton Theorem). Let $A \in \mathbb{C}^{n \times n}$. Then $p(A) = 0_{n \times n}$, that is, A satisfies its own characteristic equation.

Proof. Let $\lambda_1, \ldots, \lambda_k$ be distinct eigenvalues of A with algebraic multiplicities m_1, m_2, \ldots, m_k , respectively. Then the characteristic polynomial of A is of the form

$$p(\lambda) = \det(A - \lambda I) = (\lambda - \lambda_1)^{m_1} \cdot (\lambda - \lambda_2)^{m_2} \cdots (\lambda - \lambda_k)^{m_k},$$

where $m_1 + \cdots + m_k = n$. By the Schur's Triangularization Theorem we know that there exists a unitary matrix U such that

$$U^*AU = T_A = \begin{bmatrix} T_1 & \star & \cdots & \star \\ & T_2 & \cdots & \star \\ & & \ddots & \vdots \\ & & & T_k \end{bmatrix}, \quad \text{where} \quad T_i = \begin{bmatrix} \lambda_i & \star & \cdots & \star \\ & \lambda_i & \cdots & \star \\ & & \ddots & \vdots \\ & & & \lambda_i \end{bmatrix}_{m_i \times m}$$

for i = 1, ..., k. By Lemma 28 we know have that $(T_i - \lambda_i I)^{m_i} = 0_{m_i \times m_i}$ and

$$(T_A - \lambda_i I)^{m_i} = \begin{bmatrix} \star & \cdots & \star & \cdots & \star \\ & \ddots & \vdots & & \vdots \\ & & \mathbf{0} & \cdots & \star \\ & & & \ddots & \vdots \\ & & & \star \end{bmatrix}$$

By Lemma 29 it follows that

$$(T_A - \lambda_1 I)^{m_1} (T_A - \lambda_2 I)^{m_2} \cdots (T_A - \lambda_k I)^{m_k} = 0_{n \times n}.$$

Finally, Lemma 31 implies that

$$U^*p(A)U = p(U^*AU) = p(T_A) = (T_A - \lambda_1 I)^{m_1} (T_A - \lambda_2 I)^{m_2} \cdots (T_A - \lambda_k I)^{m_k} = 0_{n \times n},$$
 and consequently, $p(A) = 0_{n \times n}$.

Multiplicities

For $\lambda \in \Lambda(A) = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$, we adopt the following definitions.

- The algebraic multiplicity of λ is the number of times it is repeated as a root of the characteristic polynomial. In other words, $alg\ mult_A(\lambda_i) = m_i$ if and only if $(x \lambda_1)^{m_1} \cdot (x \lambda_2)^{m_2} \cdot \ldots \cdot (x \lambda_s)^{m_s} = 0$ is the characteristic equation for A.
- When alg $mult_A(\lambda_0) = 1$, then λ_0 is called a simple eigenvalue.
- The **geometric multiplicity** of λ_0 is dim $\mathcal{N}(A \lambda_0 I)$. In other words, geo $mult_A(\lambda_0)$ is the maximal number of linearly independent eigenvectors associated with λ_0 .
- Eigenvalues such that $alg\ mult_A(\lambda_0) = geo\ mult_A(\lambda_0)$ are called **semi simple eigenvalues** of A.

Multiplicity Inequality

For every $A \in \mathbb{F}^{n \times n}$, and for each $\lambda \in \Lambda(A)$,

$$geo\ mult_A(\lambda) \leq ald\ mult(\lambda).$$
 (31)

Proof. Suppose $alg \, mult_A(\lambda) = k$. By Schur's Triangularization Theorem we know that there exist a unitary matrix U such that

$$U^*AU = T_A = \left[\begin{array}{c|c} T_{11} & T_{12} \\ \hline 0 & T_{22} \end{array} \right] ,$$

where T_{11} is a $k \times k$ upper triangular matrix with diagonal entires λ , and T_{22} is an $(n-k) \times (n-k)$ upper-triangular matrix such that $\lambda \notin \Lambda(T_{22})$. Consequently, $T_{22} - \lambda I_{n-k}$ is nonsingular, and

$$\operatorname{rank}(A - \lambda I) = \operatorname{rank}\left(U^*(A - \lambda I)U\right) = \operatorname{rank}(U^*AU - \lambda I) = \operatorname{rank}(T_A - \lambda I)$$

$$= \operatorname{rank} \left(\left[\frac{T_{11} - \lambda I_k}{0} \middle| \frac{T_{12}}{T_{22} - \lambda I_{n-k}} \right] \right) \ge \operatorname{rank} (T_{22} - \lambda I_{n-k}) = n - k.$$

Now we have that

$$alg \ mult_A(\lambda) = k \ge n - \operatorname{rank}(A - \lambda I) = \dim \mathcal{N}(A - \lambda I) = geo \ mult_A(\lambda).$$

Independent Eigenvectors

Let $\{\lambda_1, \lambda_2, \dots, \lambda_k\}$ be a set of distinct of A.

- If $\{(\lambda_1, \mathbf{x}_1), (\lambda_2, \mathbf{x}_2), \dots, (\lambda_k, \mathbf{x}_k)\}$ is a set of eigenpairs for A, then $S = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k\}$ is a linearly independent set.
- If \mathcal{B}_i is a basis for $\mathcal{N}(A \lambda_i I)$, then $\mathcal{B}_1 \cup \mathcal{B}_2 \cup \cdots \cup \mathcal{B}_k$ is a linearly independent set.

Proof. Read the proof on page 512.

Diagonalizability and Multiplicities

A matrix $A \in \mathbb{C}^{n \times n}$ is diagonalizable if and only if

$$deo \ mult_A(\lambda) = alg \ mult_A(\lambda)$$

for each $\lambda \in \Lambda(A)$ – that is, if and only if every eigenvalues is semisimple.

Distinct Eigenvalues

If no eigenvalue of A is repeated, then A is diagonalizable. However, the converse is not true!

MTH 513: Chapter 7, Part 4

Last updated: December 1, 2022

A Few Remarks on the Jordan Canonical Form

Recall that for a positive integer k and an arbitrary scalar λ , we define the **Jordan block** as

$$J_k(\lambda) = \begin{bmatrix} \lambda & 1 & 0 & \cdots & 0 \\ & \lambda & 1 & \cdots & 0 \\ & & \ddots & \ddots & \\ & & & \lambda & 1 \\ & & & & \lambda \end{bmatrix}_{k \times k}.$$

Block-diagonal matrix consisting of Jordan blocks is called the **Jordan segment**, namely,

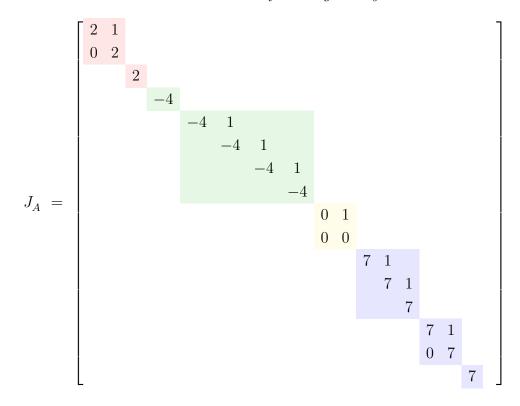
$$\mathcal{J}(\lambda) = \begin{bmatrix} J_1(\lambda) & & & & \\ & J_2(\lambda) & & & \\ & & \ddots & & \\ & & & J_t(\lambda) \end{bmatrix}.$$

Theorem 33. Let A be an $n \times n$ arbitrary matrix, and assume that $\lambda_1, \ldots, \lambda_r$ are the only distinct eigenvalues of A. Then there exists a nonsingular matrix P such that

$$P^{-1}AP = J_A = \begin{bmatrix} \mathcal{J}(\lambda_1) & & & & \\ & \mathcal{J}(\lambda_2) & & & \\ & & \ddots & & \\ & & & \mathcal{J}(\lambda_r) \end{bmatrix},$$

where J_A has ONE Jordan segment $\mathcal{J}(\lambda_j)$ for each distinct eigenvalue λ_j . Moreover, J_A is unique up to permutation of Jordan segments and Jordan blocks within each segment.

Example 34. Let A be the matrix whose Jordan form is given by



- (a) What are the eigenvalues of A and their algebraic and geometric multiplicities?
- (b) What is rank of A?
- (c) What is determinant of A?
- (d) What is trace of A?
- (e) Find a polynomial $q(\lambda)$ of the minimal degree such that $q(A) = 0_{16 \times 16}$.