

Eigenvalue problems - Basics / 1

$$A \in \mathbb{C}^{n \times n} \text{ (or } \mathbb{R}^{n \times n}\text{)}$$

(d, x) is (right) eigenpair of $Ax = dx$

(d, y) is left eigenpair if $y^H A = dy^H$

The spectrum of A is the (multi)set of all eigenvalues of A (including multiplicities)

Note that eig. vector only unique up to multiplication by scalar (for a simple eigenvalue).

→ we will often assume some normalization

eg. $\|x\| = 1$, $y^H x = 1$, ... (as useful)

For some matrices finding eigenpairs easy:

1) $A = \text{diag}(a_{ii}) = \begin{pmatrix} a_{11} & & \\ & a_{22} & \\ & & \dots \end{pmatrix}$

$$A e_i = a_{ii} e_i \quad i=1..n$$

2) A triangular (upper or lower)

$$A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ & a_{22} & a_{23} & \dots \\ & & \dots & \dots \\ & & & a_{nn} \end{pmatrix} \quad A e_1 = a_{11} e_1$$

$$Ax = dx \Leftrightarrow (A - dI)x = 0 \rightarrow \det(A - dI) = 0$$

$$\rightarrow (a_{11} - d)(a_{22} - d) \dots (a_{nn} - d) = 0 \rightarrow d = a_{ii} \text{ roots}$$

So, diagonal coefficients are eigenvalues

Eigenvectors?

$$\begin{pmatrix} A_{11} & a_{1k} & A_{1, k+1} \\ & a_{kk} & a_{k, k+1} \\ & & A_{k+1, k+1} \end{pmatrix} \begin{pmatrix} x_1 \\ \xi_k \\ 0 \end{pmatrix} = \begin{pmatrix} a_{kk} \\ \xi_k \\ 0 \end{pmatrix}$$

clear that eig. value $\lambda = a_{kk}$.

$$\begin{cases} A_{11} x_1 + a_{1k} \xi_k = x_1 a_{kk} \\ a_{kk} \xi_k = a_{kk} \xi_k \rightarrow \text{always true} \end{cases}$$

$$(A_{11} - a_{kk} I) x_1 = -a_{1k} \xi_k$$

if a_{kk} not an eigenvalue of A_{11} then always

$$\text{solvable} \rightarrow x_1 = -\xi_k (A_{11} - a_{kk} I)^{-1} a_{1k}$$

So, ξ_k arbitrary (except $\xi_k \neq 0$)

If a_{kk} eigenvalue of A_{11} then

still solvable if $a_{1k} \in \text{range}(A_{11} - a_{kk} I)$
 \rightarrow eig. vector exist & can be computed

not solvable if $a_{1k} \notin \text{range}(A_{11} - a_{kk} I)$

\hookrightarrow eigenvector does not exist
 (discuss this later)

$$\begin{pmatrix} A_{11} & a_{1k} & a_{1, k+1} & A_{1, k+2} \\ & a_{kk} & a_{k, k+1} & a_{k, k+2} \\ & & a_{k+1, k+1} & a_{k+1, k+2} \\ & & & A_{k+2, k+2} \end{pmatrix} \quad \text{where } a_{kk} = a_{k, k+1}$$

$$a_{kk} \notin \Lambda(A_{11})$$

$$\rightarrow (a_{kk}, \begin{pmatrix} -(A_{11} - a_{kk} I)^{-1} a_{1k} \\ 1 \\ 0 \end{pmatrix}) \text{ eig. pair}$$

$$a_{k, k+1} \rightarrow \begin{pmatrix} A_{11} - a_{kk} I & a_{1k} \\ & 0 \end{pmatrix} x = - \begin{pmatrix} a_{1, k+1} \\ a_{k, k+2} \\ \vdots \end{pmatrix}$$

This equation has solution iff $a_{kk} = 0$

$$(a_{kk} = a_{kk})$$

$$(1) \quad A_{11} x_1 + a_{1k} \xi_1 + a_{1kn} \xi_2 = a_{kk} x_1$$

$$(2) \quad \cancel{a_{kk}} \xi_1 + a_{kn} \xi_2 = \cancel{a_{kk}} \xi_1 \quad 0$$

$$(3) \quad a_{kn} \xi_2 = a_{kn} \xi_2 \quad (\text{true})$$

$$(2) \Rightarrow a_{kn} = 0 \quad \text{or} \quad \xi_2 = 0$$

if $\xi_2 = 0 \rightarrow$ get same eig. vec. as for a_{kk}

if $\xi_2 \neq 0$ need $a_{kn} = 0$

(intuitively) simple case: A singular $\rightarrow (0, x)$

s.t. $Ax = 0$ ($x \neq 0$). Such x exists by definition

$$Ax = dx \Leftrightarrow (A - dI)x = 0 \rightarrow (d, x)$$

$$A - dI \text{ singular} \Leftrightarrow \det(A - dI) = 0 \rightarrow$$

polynomial of degree n : characteristic poly.

eig. values of A are roots, $d_1 \dots d_n$ of $\det(A - dI) = 0$

poly of degree n always has n roots, may be repeated

$$P_A(d) = 0 \rightarrow P_A(d) = (d - d_1)^{m_1} (d - d_2)^{m_2} \dots (d - d_k)^{m_k}$$

where k is number of distinct eig. values and

m_i are algebraic multiplicities

$$m_1 + m_2 + \dots + m_k = n$$

Note that $y^H(A - dI) = 0 \Leftrightarrow y^H A = d y^H$
So, "left" and "right" eig. values are the same:

every eigenvalue has left and right eigenvalue.

note each (multiple) eig. value has at least one right and left eig. vector.

A block (upper or lower) triangular

~~$A = \begin{pmatrix} A_{11} & A_{12} & \dots & A_{1k} \\ & A_{22} & \dots & A_{2k} \\ & & \ddots & \vdots \\ & & & A_{kk} \end{pmatrix}$~~

$$A = \begin{pmatrix} A_{11} & A_{12} & \dots & A_{1k} \\ & A_{22} & \dots & A_{2k} \\ & & \ddots & \vdots \\ & & & A_{kk} \end{pmatrix}$$

$$\det(A - dI) = \det(A_{11} - dI) \det(A_{22} - dI) \dots = 0 \Leftrightarrow$$

$$\det(A_{11} - dI) = 0 \text{ or } \det(A_{22} - dI) = 0 \text{ or } \dots$$

$$\text{also } P_A(d) = P_{A_{11}}(d) P_{A_{22}}(d) \dots P_{A_{kk}}(d)$$

$$\text{So, } \Lambda(A) = \Lambda(A_{11}) \cup \Lambda(A_{22}) \cup \dots \cup \Lambda(A_{kk})$$

(counting multiplicities)

$A \in \mathbb{R}^{n \times n} \rightarrow P_A(d)$ has real coefficients \Rightarrow

eigenvalues are real or come in complex conjugate pairs

$$\underline{d \in \Lambda(A) \Rightarrow d \in \mathbb{R} \text{ or } \bar{d} \in \Lambda(A)}$$

Let $A \in \mathbb{R}^{n \times n}$ be singular and let $\{d_1, \dots, d_k\}$ be the set of all eigenvalues associated with d_i :

$$A d_i = d_i d_i \dots d_i$$

~~Then from $A \cdot x = \lambda x$~~

Let $A - dI$ be singular

- if $x \in \text{null}(A - dI) \rightarrow (A - dI)x = 0$

then x eigenvector of A with eigenvalue d

- if $k = \dim \text{null}(A - dI)$ then there exists

basis $\{x_1, \dots, x_k\}$ for $\text{null}(A - dI)$

hence $x \in \text{null}(A - dI) \Rightarrow x = \sum_i \alpha_i x_i$ (some set $\alpha_1, \dots, \alpha_k$)

(there are infinitely many eig. vec.s associated with eig. value d but we can pick only k indep. ones)

- k is called geometric multiplicity of d

- if m is algebraic multiplicity of d then

$$k \leq m$$

* if $k = m$ d has complete set of eigenvectors associated with it.

* if $k < m$ we call d and A defective

* it follows from Schur decomp (later) that $k > m$ impossible.

Defective matrices:

$$A = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \quad A \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} = 0 \cdot \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad (0, \begin{pmatrix} 1 \\ 0 \end{pmatrix}) \text{ eig. pair}$$

but there exists no other eig. vector x for eig. val. 0

$$\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \Rightarrow \begin{cases} x_2 = 0 \\ 0 \cdot x_1 = 0 \end{cases} \rightarrow \begin{pmatrix} x_1 \\ 0 \end{pmatrix} \text{ dependent with } \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

Similarity transformation:

$U \in \mathbb{C}^{n \times n}$ nonsingular: $B = U^{-1}AU$ similarity transformation

B similar to $A \rightarrow \Lambda(B) = \Lambda(A)$ (incl. mult.)

$$Ax = \lambda x \quad (\lambda \in \Lambda(A))$$

$$BU^{-1}x = U^{-1}AU \cdot U^{-1}x = U^{-1}(\lambda x) = \lambda U^{-1}x$$

So, $\lambda \in \Lambda(B)$ and $U^{-1}x$ is corresponding eig. vector.

If x_1 and x_2 are indep eig. vec.s associated with λ , then $U^{-1}x_1$ and $U^{-1}x_2$ are eig. vec.s of B

Moreover, ~~det(B) = det(A)~~

$$\det(\lambda I - B) = \det(\lambda U^{-1}U - U^{-1}AU)$$

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

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

So, B and A have same characteristic poly. \rightarrow

same eigenvalues with same multiplicities
independent

If A has full/complete set of eig. vec.s

$$Ax_i = \lambda_i x_i \quad i = 1 \dots n$$

$$X = [x_1 \ x_2 \ \dots \ x_n] \quad (\text{col.s are eig. vec.s})$$

$$AX = [Ax_1 \ Ax_2 \ \dots \ Ax_n] = [x_1 \lambda_1 \ x_2 \lambda_2 \ \dots \ x_n \lambda_n]$$

$$= X \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$$

$$AX = X\Lambda \Leftrightarrow X^{-1}AX = \Lambda \Leftrightarrow A = X\Lambda X^{-1}$$

(x_i are independent so X^{-1} exists)

So, A diagonalized by similarity transformation defined by its eig. vectors (A diagonalizable)

~ Unfortunately A (general) may not have full set of eig. vec.s

Moreover, X may be ill-conditioned (some eig. vec.s nearly dependent) \rightarrow

working with X^{-1} in practice problematic.

~ better form/decomposition that reveals eig. values and eig. vec.s with "modest" work.

Schur decomp. (theo 1.12). $A \in \mathbb{C}^{n \times n}$. There

is unitary $U \in \mathbb{C}^{n \times n}$ s.t. $U^H A U = T$ where

T is uppertriangular (by choice of U eig. vals of A may be in any order on diagonal of T)

Proof (by induction): let d_1, d_2, \dots, d_n be ordering

eig. val.s of A , and $Ax_1 = d_1 x_1$. (Assume theo true for all mat.s order $n-1$ and smaller)

unitary $X = [x_1 \ x_2]$

$$X^H A X = \begin{pmatrix} x_1^H A x_1 & x_1^H A x_2 \\ x_2^H A x_1 & x_2^H A x_2 \end{pmatrix} = \begin{pmatrix} d_1 & x_1^H A x_2 \\ 0 & x_2^H A x_2 \end{pmatrix}$$

~ ~~Using~~ By assumption Schur decomp. exists

For $X_2^H A X_2$

$$A = A^H \quad (\text{Hermitian, symm if real})$$

$T = U^H A U$ be Schur Form (decomp) of A

then $T^H = U^H A^H U = U^H A U = T$

So, T uppertri. and lowertri \rightarrow diagonal

Moreover, since $T^H = T \rightarrow$

$$\text{diag}(d_1, \dots, d_n) = \text{diag}(\bar{d}_1, \dots, \bar{d}_n) \rightarrow$$

all $d_i \in \mathbb{R}$

Also $AU = UT = U \begin{pmatrix} d_1 & & \\ & \ddots & \\ & & d_n \end{pmatrix}$

So, columns of U are eigenvectors. (always complete set)

$A = U \Lambda U^H$ spectral decomp. (eigen decomp.)

$$AA^H = A^H A \quad : \quad A \text{ is normal matrix}$$

(obviously an Hermitian matrix is normal)

others \downarrow $A^H = -A$ (skew Hermitian)

$$A^H A = A A^H = I \quad (\text{unitary})$$

Theo A normal matrix has a complete set of orthonormal eigenvectors

Proof:

$$1) \quad A \text{ normal and } \begin{pmatrix} L & H \\ G & M \end{pmatrix} = A$$

$$\text{then } \|G\|_F = \|H\|_F$$

$$A^H A = A A^H \Rightarrow$$

$$L^H L + G^H G = L L^H + H H^H$$

$$\text{diag } \|B\|_F^2 = \sum_{i,j} |b_{ij}|^2$$

$$\text{trace}(B^H B) = b_1^H b_1 + b_2^H b_2 + \dots + b_n^H b_n =$$

$$\sum_i |b_{i1}|^2 + \sum_i |b_{i2}|^2 + \dots = \|B\|_F^2$$

$$\text{similarly } \text{trace}(B B^H) = \|B\|_F^2$$

So, taking trace left and right \rightarrow

$$\|L\|_F^2 + \|G\|_F^2 = \|L\|_F^2 + \|H\|_F^2 \Rightarrow$$

$$\|G\|_F^2 = \|H\|_F^2$$

$$2) \quad T = U^H A U \quad T^H T = U^H A^H U U^H A U =$$

$$U^H A^H A U = U^H A A^H U = T^H T$$

T also normal \therefore but also upper tri

$$T = \begin{pmatrix} t_{11} & t_{12}^H \\ 0 & T_{22} \end{pmatrix} \xrightarrow{\text{theo}} t_{12}^H = 0$$

T_{22} is normal too $\rightarrow T$ diagonal

(The coeff. t_{11}, t_{22}, \dots are in general not real)

How close can we get to diagonal?

$$A = \begin{pmatrix} L & H \\ 0 & M \end{pmatrix} \rightarrow \text{sim. transform that gives block diagonal}$$

product of block uppertri mat.s is uppertri. again

$$U^{-1} A U \text{ with } \begin{pmatrix} I & Q \\ 0 & I \end{pmatrix} = U$$

$$\begin{pmatrix} I & -Q \\ 0 & I \end{pmatrix} \begin{pmatrix} L & H \\ 0 & M \end{pmatrix} \begin{pmatrix} I & Q \\ 0 & I \end{pmatrix} = \begin{pmatrix} * & 0 \\ 0 & * \end{pmatrix}$$

$$\begin{pmatrix} L & H - QM \\ 0 & M \end{pmatrix} \begin{pmatrix} I & Q \\ 0 & I \end{pmatrix} = \begin{pmatrix} L & LQ - QM + H \\ 0 & M \end{pmatrix}$$

block diagonal if

$$LQ - QM = -H$$

Sylvester's eq.

$$AX - XB = C \quad (\text{solve for } X)$$

$$A \in \mathbb{C}^{n \times n}, \quad B \in \mathbb{C}^{m \times m}$$

Sylvester operator $S: \mathbb{C}^{n \times m} \rightarrow \mathbb{C}^{n \times m}$

$$SX := AX - XB \rightarrow SX = C$$

S is linear

$$S(X_1 + X_2) = S X_1 + S X_2$$

$$\begin{aligned}
S(\alpha X_1 + \beta X_2) &= A(\alpha X_1 + \beta X_2) - (\alpha X_1 + \beta X_2)B \\
&= \alpha AX_1 - \alpha X_1 B + \beta AX_2 - \beta X_2 B \\
&= \alpha SX_1 + \beta SX_2
\end{aligned}$$

So, solution exists (unique) if S nonsingular

Theo 1.16 : S nonsingular iff (if and only if)

$$\Lambda(A) \cap \Lambda(B) = \emptyset$$

I: $Ax = \lambda x$, $y^H B = \mu y^H$ and let $x = xy^H$

$$\text{Then } SX = Ax y^H - x y^H B = \lambda X - \mu X = (\lambda - \mu) X$$

~~if $\lambda \in \Lambda(A) \cap \Lambda(B)$ then~~

if $\hat{\lambda} \in \Lambda(A) \cap \Lambda(B)$, then \hat{x}, \hat{y} exist s.t.

$$A \hat{x} = \hat{\lambda} \hat{x}, \quad \hat{y}^H B = \hat{\lambda} \hat{y}^H \quad \text{and hence}$$

$$\hat{X} = \hat{x} \hat{y}^H \neq 0 \quad \text{and} \quad S \hat{X} = 0 \quad (\text{singular})$$

II (if $\Lambda(A) \cap \Lambda(B) = \emptyset \Rightarrow S$ nonsingular)

Solve $SX = C$ (show solution exists)

$$\text{Let } T = V^H B V \rightarrow \quad (T \text{ upper tri})$$

$$AXV - XB V = CV \Leftrightarrow A(XV) - (XV)V^H B V = (CV)$$

$$\Leftrightarrow AY - YT = D \quad \text{with } Y = XV, \quad D = CV$$

$$\text{columnwise: } A y_i - y_i t_{ii} = d_i \Leftrightarrow$$

$$(A - t_{ii} I) y_i = d_i \quad \text{has solution because } t_i \in \Lambda(B) \text{ and } \Lambda(A) \cap \Lambda(B) = \emptyset$$

→ compute y_1

$$A y_2 - y_1 t_{12} - y_2 t_{22} = d_2 \iff$$

$$(A - t_{22} I) y_2 = d_2 + y_1 t_{12}$$

again, since $t_{22} \in \Lambda(B)$ and $\Lambda(A) \cap \Lambda(B) = \emptyset$
we know $t_{22} \notin \Lambda(A)$ and system solvable.

etc

Hence we can compute (solve for y) for any

D. ~~So that $X = YV$~~ $y = XV \rightarrow X = YV^H$

So, we can compute X (X exists) for any c .

Therefore S nonsingular.

Let $SX = \sigma X$. ~~\iff~~

$$AX - XB = \sigma X \iff (A - \sigma I)X - XB = 0$$

So that $S_\sigma X := (A - \sigma I)X - XB$ singular

$$\implies \Lambda(A - \sigma I) \cap \Lambda(B) \neq \emptyset$$

$$d \in \Lambda(A) \rightarrow d - \sigma \in \Lambda(A - \sigma I)$$

So, there must be $d \in \Lambda(A)$, $\mu \in \Lambda(B)$ s.t.

$$d - \sigma = \mu \iff \sigma = d - \mu \quad (\text{reverse holds as well})$$

Eigenvalues of S are diff. s of eig. vals of
 A and eig. vals of B

~~Ex~~ $A = \begin{pmatrix} L & H \\ 0 & M \end{pmatrix}$ and $\Lambda(L) \cap \Lambda(M) = \emptyset$

then Q exists s.t. $LQ - QM = -H$

and sim. transform

$$\begin{pmatrix} I & -Q \\ 0 & I \end{pmatrix} \begin{pmatrix} L & H \\ 0 & M \end{pmatrix} \begin{pmatrix} I & Q \\ 0 & I \end{pmatrix} = \begin{pmatrix} L & 0 \\ 0 & M \end{pmatrix}$$

Apply recursively.

Let $\Lambda(A)$ be partitioned in disjoint multisets

$$\Lambda(A) = R_1 \cup R_2 \cup \dots \cup R_k$$

then Schur decomp. exists s.t.

$T = X^H A X$ with eigenvalues in order of R_1, R_2, \dots

$$T = \begin{pmatrix} L_1 & H \\ 0 & M \end{pmatrix} \text{ and exist sim. transform } \hat{Q}$$

$$\hat{Q}^{-1} T \hat{Q} = \begin{pmatrix} L_1 & 0 \\ 0 & M \end{pmatrix}$$

now apply same steps to get ~~the~~ L_2

(separated out of M) and so on.

Thm 1.19: Let $\Lambda(A)$ be $R_1 \cup R_2 \cup \dots \cup R_k$

where $R_i \cap R_j = \emptyset$ $i \neq j$. Then X exists s.t.

$$X^{-1} A X = \text{diag}(L_1, L_2, \dots, L_k)$$

$$\text{and } \Lambda(L_i) = R_i$$

Note we can apply this to partition R_i such that

each R_i has one eigenvalue only, repeated with alg. multiplicity

Jordan Form / decomposition

Jordan block $J_m(d) = \underbrace{\begin{pmatrix} d & & 0 \\ & \ddots & \\ 0 & & d \end{pmatrix}}_m \in \mathbb{C}^{m \times m}$

Note $J_m(d)$ has exactly 1 eigenvector (e_i)

d : alg. multiplicity $= m$

geom " " 1

Theo 1.22 : Let A have k distinct eigenvalues

$d_1 \dots d_k$ with alg. mult. m_1, m_2, \dots, m_k

Then there are unique integers

$$m_{ij} \quad i=1 \dots k, \quad j=1 \dots l_i : m_i = \sum_{j=1}^{l_i} m_{ij}$$

and nonsingular X s.t. $X^{-1}AX = \text{diag}(\eta_1, \dots, \eta_k)$

where

$$\eta_i = \text{diag} \left(\underbrace{J_{m_{i1}}(d_i)}_{m_{i1}}, \underbrace{J_{m_{i2}}(d_i)}_{m_{i2}}, \dots, \underbrace{J_{m_{il_i}}(d_i)}_{m_{il_i}} \right)$$

Take $X = (X_1 \dots X_k) \rightarrow AX_i = X_i \eta_i$

$$X_i = (X_{i1} \dots X_{il_i}) \rightarrow AX_{ij} = X_{ij} J_{m_{ij}}(d_i)$$

~~$$X_{ij} = \begin{pmatrix} x_{ij}^{(1)} & \dots & x_{ij}^{(m_{ij})} \\ \vdots & & \vdots \\ x_{ij}^{(1)} & \dots & x_{ij}^{(m_{ij})} \end{pmatrix} \begin{pmatrix} x_1^{(ij)} & x_2^{(ij)} & \dots & x_{m_{ij}}^{(ij)} \end{pmatrix}$$~~

$$A x_1^{(ij)} = d_i x_1^{(ij)}$$

$$A x_p^{(ij)} = d_i x_p^{(ij)} + x_{p-1}^{(ij)} \quad p=2 \dots m_{ij}$$

(Section 2, read def.s of norms)

Operator norm (induced matrix norm)

Let μ be vector norm on \mathbb{R}^m

v " " " " " \mathbb{R}^n

$$\|A\|_{\mu, v} := \max_{v(x)=1} \mu(Ax)$$

is matrix norm subordinate to μ and v

rounding error: $P(A)$ result of rounding elements of A
(assume IEEE arithm.)

$$P(a_{ij}) = a_{ij}(1 + \varepsilon_{ij}) \quad |\varepsilon_{ij}| \leq \varepsilon_M$$

$$P(A) = A + E \quad E = (a_{ij} \varepsilon_{ij})$$

$$|E| \leq |A| \varepsilon_M \quad |\cdot| \text{ comp. wise abs value}$$

$$\text{absolute norm: } \| |A| \| = \|A\| \rightarrow \|E\| \leq \|A\| \varepsilon_M$$

$$\frac{\|E\|}{\|A\|} \leq \varepsilon_M \quad (\text{normwise relative error})$$

$$\text{Ex. } x = \begin{pmatrix} 1 \\ 10^{-3} \\ 10^{-5} \end{pmatrix} \quad \tilde{x} = \begin{pmatrix} 1.00001 \\ 1.01 \cdot 10^{-3} \\ 2 \cdot 10^{-5} \end{pmatrix}$$

$$\frac{\|\tilde{x} - x\|}{\|x\|} = 10^{-5} \quad \text{but} \quad \frac{|\tilde{x}_3 - x_3|}{|x_3|} = 1 \quad (100\% \text{ error})$$

Def 2.3

Let $\|\cdot\|_{l,m}$, $\|\cdot\|_{m,n}$, $\|\cdot\|_{l,n}$ be matrix norms defined on $\mathbb{C}^{l \times m}$, $\mathbb{C}^{m \times n}$, and $\mathbb{C}^{l \times n}$. These norms are consistent if for all $A \in \mathbb{C}^{l \times m}$, $B \in \mathbb{C}^{m \times n}$ we have $\|AB\|_{l,n} \leq \|A\|_{l,m} \cdot \|B\|_{m,n}$

$\|\cdot\|_1$, $\|\cdot\|_2$, $\|\cdot\|_\infty$, $\|\cdot\|_F$ are consistent norms

Many ways to construct useful norms

On a finite dim. vector space all norms are equivalent.

$A \in \mathbb{C}^{n \times n}$. $\rho(A) := \max_{\lambda \in \Lambda(A)} |\lambda|$ is called

spectral radius

$\rho(A)$ is not a norm, but closely related.

consider $\rho\left(\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}\right)$

(λ, x) with $|\lambda| = \rho$ is dominant eigenpair

(vector, value)

Theo 2.7. $\rho(A) \leq \|A\|$ for any consistent norm $\|\cdot\|$

let (λ, x) be dom. eigenpair. Then

$$\begin{aligned} \|Ax\| &= \|\lambda x\| = |\lambda| \|x\| \quad \text{and} \\ \|Ax\| &\leq \|A\| \cdot \|x\| \end{aligned}$$

So, ~~||A||~~ $|d| \leq \|A\|$

Theo 2.8. $A \in \mathbb{C}^{n \times n}$. For any $\varepsilon > 0$ there is a consistent norm $\|\cdot\|_{A,\varepsilon}$ s.t.

$$\|A\|_{A,\varepsilon} \leq \rho(A) + \varepsilon$$

If dom. eigenvalues nondefective, there is a consistent norm $\|\cdot\|_A$ s.t.

$$\|A\| = \rho(A)$$

Proof:

Schur. Form

$$U^H A U = \Lambda + N$$

upper tri part

$$\eta > 0 \text{ let } D_\eta = \text{diag}(1, \eta, \eta^2, \dots, \eta^{n-1})$$

$$\text{Consider } D_\eta^{-1} U^H A U D_\eta = \Lambda + D_\eta^{-1} N D_\eta$$

$$(D_\eta^{-1} N D_\eta)_{ij} = \begin{cases} 0 & \text{if } i \geq j \\ n_{ij} \eta^{j-i} & \text{if } i < j \end{cases}$$

So, for $\alpha \eta < 1$ we can make upper tri part arbitrarily small (but not zero)

$$\text{Pick } \eta \text{ s.t. } \|D_\eta^{-1} N D_\eta\|_\infty \leq \varepsilon$$

$$\begin{aligned} \|B\|_{A,\varepsilon} &= \|D_\eta^{-1} U^H B U D_\eta\|_\infty \leq \|\Lambda\|_\infty + \|D_\eta^{-1} N D_\eta\|_\infty \\ &\leq \rho(A) + \varepsilon \end{aligned}$$

Chapter 4

Generalize eigenvectors \rightarrow Eigenspaces

$A \in \mathbb{C}^{n \times n}$, X subspace of \mathbb{C} (subset and ^{vector} space)

Then X is invariant subspace or eigenspace of

$$AX := \{Ax : x \in X\} \subset X$$

The span of an eigenvector is invariant _{subspace}

Let $A \in \mathbb{R}^{n \times n}$ with complex eig. pair

$$(d, x) \equiv: \begin{cases} d \in \mathbb{C} \text{ (no } d \in \mathbb{R}) \\ x = y + iz, y, z \in \mathbb{R} \end{cases}$$

Then $A \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} y \\ z \end{bmatrix} L$ (all real)

where $d, \bar{d} \in \Lambda(L)$

So, we can work strictly with real vectors and matrices (up to 2×2 blocks)

Theo 1.2 p. 243

Let X be eigenspace and X (col.s) form basis for X . Then

$$AX = XL, \quad L = X^I A X$$

where X^I is left inverse of X : $X^I X = I$

(but in general $XX^I \neq I$ or not even def'd)

L is representation of A on eigenspace X with basis X

let $x \in X$ and $Ax = dx$. Then

$$x = Xu \quad (X \text{ basis}) \text{ and } Ax = AXu = XLu$$

$$Ax = dx = dXu = XLu$$

$$X^T X (du) = X^T X Lu \Leftrightarrow Lu = du$$

(also works the other way around)

So, if (d, x) eig. pair of A then $(d, X^T x)$ eig. pair of L
and if (d, u) eig. pair of L then (d, Xu) eig. pair of A

There is a one-one correspondence between
eigenvectors of A lying in X and eigenvectors
of L

Exploit this when interested in few (relatively)
eigenpairs of A

Def 1.3

$$A \in \mathbb{C}^{n \times n}, \quad X \in \mathbb{C}^{n \times k}, \quad L \in \mathbb{C}^{k \times k}$$

If X full ~~rank~~ rank and $\exists AX = XL$

(L, X) is (right) eigenpair of order k of A

similarly (L, Y) is left eigenpair if $Y^H A = LY^H$

(and $\mathcal{R}(Y)$ is left eigenspace of A)

If X orthonormal $\rightarrow (L, X)$ orthonormal

Theo 1.4 let (L, X) be eig. pair of A .

If $U \in \mathbb{C}^{k \times k}$ nonsingular, then

$(U^{-1}LU, XU)$ is also eig. pair of A .

If $W \in \mathbb{C}^{n \times n}$ nonsingular, then

$(L, W^{-1}X)$ eig. pair of $W^{-1}AW$

$$AXU = XLU = XU \cdot U^{-1}LU \quad \underline{etc}$$

U represents (arbitrary) change of basis \rightarrow

basis for X (eigenspace) in principle not relevant (in practice it is)

\rightarrow eigenvalues do not change $U^{-1}LU$ similar to L
~~choice of basis of the space~~ \hookrightarrow space determines eigenvals not basis.

$$W^{-1}AW \cdot W^{-1}X = W^{-1}AX = W^{-1}XL$$

Theo 1.5

let $R = \{d_1, \dots, d_k\}$ be a multiset of eig. vals.

Then there is subspace X that is eig. space of A

with eigenvalues $d_1 \dots d_k$ (U_1, U_2)

(Block) Schur Form: $A(U_1, U_2) = \begin{pmatrix} T_{11} & T_{12} \\ 0 & T_{22} \end{pmatrix} \begin{pmatrix} U_1 \\ U_2 \end{pmatrix}$

where T_{ii} has elements of R on diagonal (with)

mult. s. $AU_1 = U_1 T_1$ and $X = R(U_1)$