

Linear Transform \circ : $T(av_1 + bv_2) = aT(v_1) + bT(v_2)$

Null space: $N(T) \{ v \in V \mid T(v) = 0 \}$

Range space: $R(T) \{ T(v) \mid v \in V \}$

Rank-Nullity Theorem $\Rightarrow \dim(N(T)) + \dim(R(T)) = \dim(V)$

$A_{m \times n}, B_{n \times p}$ matrices $\text{rank}(AB) \leq \min\{\text{rank}(A), \text{rank}(B)\}$

Division Algorithm: $f = dq + r$ {either $r=0$ or $\deg(r) < \deg(d)$ }

$$f(n) = \phi(n) q(n) + r(n)$$

characteristic equation.

$$f(A) = r(A)$$

$$f(\lambda_i) = r(\lambda_i) \Rightarrow \text{get } \underline{r(\lambda)}$$

* When there are same eigenvalues, use differentiation,

when λ_i is a root of order k , then $\phi(\lambda_i) = 0, \phi'(\lambda_i) = 0, \dots, \phi^{k-1}(\lambda_i) = 0$

But $\phi^k(\lambda_i) \neq 0$

* Issi $\sin(A), \tan(A), e^A, \dots$ sb calculate kr skte hain.

Theorem #2: $z = x + iy$, $f(z)$ has a Taylor series $\sum_{k=0}^{\infty} a_k z^k$, converges for $|z| < R$.
Also for a square matrix A , with eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ s.t. $|\lambda| < R$,
then $f(A) = \sum_{k=0}^{\infty} a_k A^k$, and $f(A)$ is said to be well defined.

Inner Product: $X \rightarrow \text{vector space}$ $x, y \in X$

$$(i) \quad \langle x, x \rangle = \|x\|^2 \geq 0, \quad \langle x, x \rangle = 0 \text{ iff } x = 0$$

$$(ii) \quad \langle x, y \rangle = \langle \bar{y}, x \rangle$$

$$(iii) \quad \langle x + py, z \rangle = \alpha \langle x, z \rangle + \beta \langle y, z \rangle \quad \forall x, y, z \in X$$

$$\langle x, y \rangle = y^* x = \sum_{i=1}^n x_i \bar{y}_i \quad y^* = (\bar{y})^T$$

$$\langle x_i, y_j \rangle = \delta_{ij} = \begin{cases} 0 & i \neq j \\ 1 & i = j \end{cases} \rightarrow \text{orthogonal}$$

\rightarrow orthonormal.

* Every orthonormal set of vectors x_1, \dots, x_n in an inner product space No. 15
linearly independent.

Gram-Schmidt Orthonormalization (GSO)

$$\frac{y_1}{\|y_1\|^2} = \frac{y_1}{y_1}$$

$$\frac{y_2}{\|y_2\|^2} = \frac{y_2}{y_2}$$

$$y = y_1 - \frac{\langle y_1, y \rangle}{\langle y_1, y_1 \rangle} y_1 - \frac{\langle y_2, y \rangle}{\langle y_2, y_2 \rangle} y_2 - \dots - \frac{\langle y_n, y \rangle}{\langle y_n, y_n \rangle} y_n$$

$$\langle E_1, E_i \rangle = 1 \quad \langle y_1, y_i \rangle = 1 = \|E_i\|^2$$

$$\|y\|^2$$

Golden Matrix: two matrices A & E of order n are said to be
if a non-singular matrix P s.t. $P^{-1}AP = E$

IMB: $X_1 = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}, X_2 = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}, \dots, X_n = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$

$[X_1, X_2, \dots, X_n] = \begin{bmatrix} x_1 & x_2 & \dots & x_m \\ x_2 & x_3 & \dots & x_m \\ \vdots & \vdots & \ddots & \vdots \\ x_n & x_n & \dots & x_m \end{bmatrix}$

A & E have same eigenvalues

Theorem: If A has eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ (all distinct)
D degenerate $\Rightarrow \lambda_1, \dots, \lambda_n$, then A is similar to D.

$$P^{-1}AP = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$$

↓

modal matrix spectral matrix
(formed by eigenvectors)

Diagonalizable Matrix: A matrix 'A' is diagonalizable over field F if there exists non-singular matrix P over field F such that $P^{-1}AP$ is a diagonal matrix over F.

Theorem:

$A \rightarrow$ eigenvalues (d_1, d_2, \dots, d_n), eigen vectors (v_1, v_2, \dots, v_n), then $f(A)$ has $f(d_1), f(d_2), \dots, f(d_n)$ as eigen values and v_1, v_2, \dots, v_n as corresponding eigen vectors. But inverse is not true as there can be more eigenvalues other than these.

Lemma:

$f(n) \rightarrow$ polynomial, then $|f(A)| = f(d_1)f(d_2) \dots f(d_n) \rightarrow d_i$'s are eigenvalues of A .

Not all eigen vectors of $f(A)$ are eigen vectors of A .

Theorem:

Eigen vectors associated with distinct eigen values of an n -square matrix A are linearly independent.

Theorem H \rightarrow Hermitian Matrix, there exists a unitary transformation S , such that $S^*HS = \text{diag}(d_1, d_n)$ $d_i \rightarrow$ eigen values of H not necessarily distinct and non-zero. $(S^*S = I)$

Corollary \rightarrow A $\xrightarrow{\text{real}}$ symmetric matrix, there exists orthogonal transformation P , such that $P^TAP = \text{diag}(d_1, d_n)$ d_1, \dots, d_n are eigen values of A not necessarily distinct and non-zero.

(OR)

Every real symmetric matrix A is orthogonally similar to a diagonal matrix whose diagonal elements are eigen values of A .

Corollary:

For every square matrix A over C , there exists a unitary transform S such that S^*AS is an upper (or lower) triangular matrix (which is not unique) with the eigenvalues of A as diagonal elements.

(using the fact when H is not hermitian.)

Date _____

Determine an orthogonal matrix S s.t. $S^T AS$ is an upper triangular matrix.

$$A = \begin{bmatrix} 0 & 1 & 1 \\ -2 & 3 & 2 \\ -3 & 3 & 4 \end{bmatrix} \quad \begin{array}{l} \lambda_1 = 1 \\ \lambda_2 = 1 \\ \lambda_3 = 5 \end{array}$$

Any. $\lambda = 1 \rightarrow \text{eigen vector} \rightarrow (x + \beta, y, \beta)^T$

$$n_1 = e_1 = (1, 1, 0)^T$$

$$n_3 = e_3 = (0, 0, 1)^T$$

$$n_2 = e_2 = (0, 1, 0)^T$$

n_1, n_2, n_3 should be mutually orthogonal

n_1, n_2, n_3 are L.I. Applying Gram-Schmidt process to get orthonormal vectors.

$$u_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \quad u_2 = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} \quad u_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

$$U = [u_1 \ u_2 \ u_3]$$

$$U^T A U = \begin{bmatrix} 1 & 3 & 3\sqrt{2} \\ 0 & 2 & \sqrt{2} \\ 0 & 3\sqrt{2} & 4 \end{bmatrix}$$

$$\text{Take } G = \begin{bmatrix} 2 & \sqrt{2} \\ 3\sqrt{2} & 4 \end{bmatrix} \quad \rightarrow \text{eigen values} = 1, 5$$

eigen vector for $\lambda = 1 \Rightarrow \begin{pmatrix} 1 \\ -\sqrt{2} \end{pmatrix}$, orthonormal eigenvector is $\frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ -\sqrt{2} \end{pmatrix}$

$$v_1 = \frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ -\sqrt{2} \end{pmatrix} \quad \text{Orthogonal} \quad v_2 = \frac{1}{\sqrt{3}} \begin{pmatrix} \sqrt{2} \\ 1 \end{pmatrix}$$

$$T = [v_1 \ v_2] = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 & \sqrt{2} \\ -\sqrt{2} & 1 \end{bmatrix}$$

$$T^T G T = \begin{bmatrix} 1 & -8\sqrt{2} \\ 0 & 5 \end{bmatrix}$$

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \frac{1}{\sqrt{3}} \begin{bmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & \sqrt{2} \\ 0 & -\sqrt{2} & 1 \end{bmatrix}$$

and the required transformation, $S = UP = \frac{1}{\sqrt{6}} \begin{bmatrix} \sqrt{3} & -1 & -\sqrt{2} \\ \sqrt{3} & 1 & \sqrt{2} \\ 0 & -2 & \sqrt{2} \end{bmatrix}$

$$\text{Thus, } S^T AS = \begin{bmatrix} 1 & \sqrt{2} & 3\sqrt{2} \\ 0 & 1 & -5\sqrt{2} \\ 0 & 0 & 5 \end{bmatrix}$$

upper triangular matrix

* For lower triangular matrix, one has to start with transpose of A .

$AX=0$ has $n-r$ linearly independent eigenvectors

Date _____ / _____ / _____



Theorem: The no. k of independent eigenvectors associated with an eigenvalue λ of multiplicity m of an n -square matrix A is equal to $n - \text{rank}(A\lambda I - A)$

$$k = n - \text{rank}(A\lambda I - A)$$

Theorem: $\text{rank}(AQ) = \text{rank}(Q^T A^T) = \text{rank}(A^T) = \text{rank}(A)$

Also, if P, Q are non-singular, $\text{rank}(A) = \text{rank}(PAQ) = \text{rank}(AQ)$

Theorem: Let λ be an eigenvalue of multiplicity m of a Hermitian Matrix H , then the no. of linearly independent eigenvectors associated with λ is m .

Corollary: The no. of linearly independent eigenvectors associated with an eigenvalue λ of multiplicity m of a real symmetric matrix is m .

Theorem: The eigen vectors associated with distinct eigenvalues of a Hermitian matrix constitute an orthogonal set.
(or real symmetric matrix).

(or real symmetric)

Theorem: $H \rightarrow$ Hermitian Matrix $\xrightarrow{\text{eigenvalue}} \lambda$, multiplicity = m .

Then, there exists a set of m no. of orthogonal (as well as orthonormal) eigen vectors associated with λ .

Theorem: $H \rightarrow$ Hermitian matrix of order n possesses an orthogonal (as well as orthonormal) set of n vectors.

Theorem:

$A \rightarrow$ Hermitian (or real symmetric) matrix of order n with positive eigenvalues.

$B \rightarrow$ Hermitian (or real symmetric) matrix of order n .

Then there exist a $n \times n$ non-singular matrix P (not unique) such that,

$$P^T A P = I \text{ and } P^T B P = \text{diag}(c_1, c_2, \dots, c_n)$$

where c_i are real.

(Ans)

$$A = \begin{bmatrix} 6 & 4 & -2 \\ 4 & 12 & -4 \\ -2 & -4 & 13 \end{bmatrix}$$

$$\lambda = 4, 9, 18$$

$$B = \begin{bmatrix} 1 & -1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & 1 \end{bmatrix}$$

defining P such that

$P^T A P = I$, $P^T B P$ is a diag. matrix.

Ans.

$$\begin{pmatrix} -2 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 \\ 4 \\ 5 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \\ -2 \end{pmatrix} \text{ are eigenvectors (orthogonal)}$$

$$\text{Normalising them, } U = \frac{1}{3\sqrt{5}} \begin{bmatrix} -6 & 2 & \sqrt{5} \\ 3 & 4 & 2\sqrt{5} \\ 0 & 5 & -2\sqrt{5} \end{bmatrix} \quad U^T A U = \text{diag}(4, 9, 18)$$

$$\text{Now, take } Q \text{ s.t. } Q^T = \text{diag}(\sqrt{4}, \sqrt{9}, \sqrt{18}) \\ = \text{diag}(2, 3, 3\sqrt{2})$$

$$\text{so } Q = \text{diag}\left(\frac{1}{2}, \frac{1}{3}, \frac{1}{3\sqrt{2}}\right) \quad Q^T = Q$$

$$(UQ)^T A (UQ) = Q^T (U^T A U) Q = I$$

$$\text{Now, } C = (UQ)^T B (UQ) = \frac{1}{180} \begin{bmatrix} 8i & -18 & 9\sqrt{10} \\ -18 & 4 & -2\sqrt{10} \\ 9\sqrt{10} & -2\sqrt{10} & 10 \end{bmatrix}$$

Symmetric.

So, C is an orthogonal matrix R s.t.

$$R^T C R = \text{diag}(c_1, c_2, c_3) \text{ where } c_1, c_2, c_3 \text{ are eigenvalues of } C.$$

$$c_1 = 0 \quad c_2 = 0 \quad c_3 = 19/36$$

Linearly independent eigen vectors $\Rightarrow \begin{pmatrix} -2 \\ -4 \\ \sqrt{10} \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \\ -\sqrt{10} \end{pmatrix}, \begin{pmatrix} 9 \\ -2 \\ \sqrt{10} \end{pmatrix}$

Orthonormalization $\rightarrow y_1 = \frac{1}{\sqrt{30}} \begin{pmatrix} -2 \\ -4 \\ \sqrt{10} \end{pmatrix}; y_2 = \frac{-1}{\sqrt{285}} \begin{pmatrix} 2 \\ -11 \\ -10 \end{pmatrix}; y_3 = \frac{1}{\sqrt{95}} \begin{pmatrix} 9 \\ -2 \\ \sqrt{10} \end{pmatrix}$

$$R = [y_1 \ y_2 \ y_3]$$

$$R^T C R = \text{diag} [0, 0, 19/36]$$

$$P = VQR = \frac{1}{90\sqrt{57}} \begin{bmatrix} 15\sqrt{38} & -120 & -160\sqrt{3} \\ -15\sqrt{38} & -150 & 85\sqrt{3} \\ -30\sqrt{38} & -30 & -40\sqrt{3} \end{bmatrix}$$

But P is not unique, another set of eigenvectors give another P .

Defn: Vector x_m is generalised eigen vector of type P corresponding to matrix A and the eigenvalue λ if $(A - \lambda I)^P x_m = 0$ but $(A - \lambda I)^{P-1} x_m \neq 0$.

Bilinear Form

$$X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \quad A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad Y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix}$$

$X^T A Y$

$$X^T A Y = \sum_{i=1}^m \sum_{j=1}^n a_{ij} x_i y_j$$

Remember to make A symmetric to obtain the correct solⁿ for A .

Quadratic Form ($Q = X^T A X$)

- ① Discriminant of quadratic form ($\det A$) is called discriminant of quadratic form.
 - ② If A is singular ($\det A = 0$), then quadratic form Q is called singular.
 - ③ If it is non-singular, then quadratic form Q is called non-singular.
- Row operation \rightarrow pre-multiplication, Column operation \rightarrow post-multiplication

Normal Form: Matrix A of order $m \times n$ can be reduced to any of these forms.

$$\begin{bmatrix} I_r & 0 \\ 0 & 0 \end{bmatrix} \quad r < m, n$$

$$\begin{bmatrix} I_r \\ 0 \end{bmatrix} \quad r = n < m$$

$$\begin{bmatrix} I_r & 0 \end{bmatrix} \quad r = m < n$$

$$\begin{bmatrix} I_r \end{bmatrix} \quad r = m = n$$

Congruent Form: Two matrices A & B of order n over a field F are said to be congruent over F iff \exists a non-singular matrix P over F such that $B = P^T A P$.

Linear Transform of a quadratic form: Substitution of $x = By$ in the quadratic form is called the linear transform of the quadratic form.

Singular and non-singular transformation: The linear transform $n \circ B$ of a quadratic form $Q = n^T A n$ is singular or non-singular if P is singular or non-singular respectively.

Equivalent Quadratic form: Two quadratic forms $n^T A n$ and $y^T B y$ are said to be equivalent over F if one can be obtained from the other by a non-singular transform over F defined by $n = Py$ such that $n^T A n = y^T B y$ $B = P^T A P$.
 P is non-singular.

Orthogonal Reduction: Reduction of quadratic form to diagonal form using orthogonal reduction transformation is called orthogonal reduction.

Theorem: Every quadratic form $x^T A x$ (A is symmetric) can be reduced to a diagonal quadratic form $y^T D y$ by means of orthogonal transform P , where the diagonal elements of D are the eigenvalues of A .

Corollary: Every quadratic form $x^T A x$ of rank r (i.e. $A \neq$ rank r) can be reduced by orthogonal transform P to $\lambda_1 y_1^2 + \dots + \lambda_r y_r^2$ where $y = Py$, and $\lambda_1, \lambda_2, \dots, \lambda_r$ are non-zero eigenvalues of A .

Lagrange's reduction:

$$\begin{aligned}
 q(x_1, x_2, x_3) &= 4x_1^2 + 10x_2^2 + 11x_3^2 - 4x_1x_2 + 12x_1x_3 + -12x_2x_3 \\
 &= 4\left(x_1^2 - \frac{1}{2}x_1x_2 - \frac{x_2 - 3x_3}{2}\right) + \left(\frac{x_2 - 3x_3}{2}\right)^2 + 10x_2^2 + 11x_3^2 - 12x_2x_3 \\
 &= (2x_1 - x_2 + 3x_3)^2 + (3x_2 - x_3)^2 + (x_3)^2
 \end{aligned}$$

$y_1 = \frac{1}{2}(2x_1 - x_2 + 3x_3)$
 $y_2 = \frac{1}{3}(3x_2 - x_3)$
 $y_3 = x_3$

$$q = 4y_1^2 + 9y_2^2 + y_3^2 = y^T D y \quad D = \text{diag}(4, 9, 1)$$

$$y = Px$$

$$y = (y_1, y_2, y_3)^T \quad x = (x_1, x_2, x_3)^T \quad P = \begin{bmatrix} 1 & -1/2 & 3/2 \\ 0 & 1 & -1/3 \\ 0 & 0 & 1 \end{bmatrix} \quad |P| = 1$$

$$z_1 = 2y_1$$

$$z_2 = 3y_2 \quad q = z_1^2 + z_2^2 + z_3^2$$

$$z_3 = y_3$$

Definition: If the matrix A is diagonal (respective identity), then its diagonal form is called diagonal (unit) quadratic form.

$x^T A x = x_1^2 + x_2^2 + \dots + x_n^2 \rightarrow$ unit quadratic form $x^T (\text{diag}(a_1, a_2)) x = a_1 x_1^2 + \dots + a_n x_n^2 \rightarrow$ diagonal quadratic form.

Ek baar check
RN.

Date _____

Rank r

Jacobi theorem: A quadratic form $q = \mathbf{x}^T A \mathbf{x} = \sum a_{ij} x_i x_j$ with \mathbf{a} can be transformed by a non-singular transform $\mathbf{x} = P\mathbf{y}$ with $\det(P) = 1$ and P be upper triangular to a diagonal form $q = c_1 y_1^2 + c_2 y_2^2 + \dots + c_r y_r^2$. If and only if c_i 's $i=1, 2, \dots, r$ are non-zero, where

$$y_1 = x_1 + a_{12}x_2 + \dots + a_{1r}x_r + a_{1n+1}x_{r+1} + \dots + a_n x_n$$

$$y_2 =$$

$$y_n =$$

are n linearly independent real linear forms in variables (x_1, x_2, \dots, x_n) . a_i 's are scalars completely determined by a_{ij} 's, $c_i = \frac{a_{ii}}{\Delta_i}$ & Δ_i 's are leading principal minors of A defined as.

$$\Delta_0 = 1; \Delta_1 = a_{11}; \Delta_2 = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}; \Delta_3 = \begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} \dots \Delta_r = \det(A)$$

Hermitian forms: Let $\mathbf{x} = (x_1, \dots, x_n)$ be an n -vector in C^n and $H = (h_{ij})$ be a hermitian matrix of order n over the complex field C , then the form $h(x_1, x_2, \dots, x_n) = \mathbf{x}^T H \mathbf{x} = \sum_{i,j=1}^n h_{ij} \bar{x}_i x_j$ is called the Hermitian form of order n . The matrix H is called matrix of the form and rank of H is called rank of the form.

$(H^* H)^* = H^* H$, as H is hermitian.
Thus $h = \sum_{i,j} h_{ij} \bar{x}_i x_j$ is always real.

Diagonal and unit hermitian form:

Diagonal form can be represented by $h = c_1 \bar{x}_1 x_1 + c_2 \bar{x}_2 x_2 + \dots + c_n \bar{x}_n x_n$ where coefficient c_i 's are real as h is real (since $h = H^* H$). This is called diagonal form and if c_i 's can be 1 it is hermitian, reduced to one, the a hermitian form is given by $h = \bar{x}_1 x_1 + \bar{x}_2 x_2 + \dots + \bar{x}_n x_n = \mathbf{x}^T H \mathbf{x}$ is called unit hermitian form.

Index & signature of a quadratic form.

A quadratic form $Q = n^T A n$ can be reduced to diagonal form using non-singular transform. Let the reduced form be

$$Q = c_1 y_1^2 + c_2 y_2^2 + \dots + c_r y_r^2 \quad (1)$$

which we may write as,

$$Q = x_1 y_1^2 + x_2 y_2^2 + \dots + x_r y_r^2 \text{ where } x_i's \text{ are free.} \quad (2)$$

Then no. of +ve terms in (1) is called the index and the difference between the no. of +ve and -ve terms which is, $r - (r-k) = 2k - r$ is called the signature of the quadratic form.

Theorem: Under a unitary transform ($n = P\bar{n}$, P is a unitary matrix) a hermitian form $h = n^* H n$ can be reduced to diagonal form $h = d_1 \bar{y}_1 y_1 + d_2 \bar{y}_2 y_2 + \dots + d_r \bar{y}_r y_r$, where d_i 's are eigenvalues of H .

Theorem: Sylvester's law of inertia for Hermitian form:

Under all non-singular transforms, the rank r and the index k are invariants of a Hermitian form
does not change under transformations.

Defn: Equivalent Hermitian form: $n^* H n$ and $\bar{y}^* Q y$ are equivalent
if $n^* H n = \bar{y}^* P^* H P y = \bar{y}^* Q y$.
or $n = P\bar{y}$. P is non-singular.

When same rank, index, they are form equivalent.

Corollary $Q = n^T A n$ $n = P\bar{y}$ k = index, r = rank of Q ,

$$Q = y_1^2 + y_2^2 + \dots + y_r^2 - y_{r+1}^2 - y_{r+2}^2 - \dots - y_n^2 \text{ can be obtained}$$

Date / /

Definition

A real quadratic hermitian form $q(n)$ is said to be

- (a) positive definite (PD) if $q(n) > 0$ for $n \neq 0$
- (b) negative definite (ND) if $q(n) < 0$ for $n \neq 0$
- (c) positive semidefinite (PSD) if $q(n) \geq 0$ for $n \neq 0$
- (d) negative semidefinite (NSD) if $q(n) \leq 0$ for $n \neq 0$
- (e) indefinite if $q(n) \geq 0$ for $n \neq 0$

Imp: the under consideration must be given. ($n_1^2 + n_2^2$ is PSD) $\begin{matrix} n_1 = 0 \\ n_2 = 0 \\ n_3 = \text{any} \end{matrix}$ (and is PD in $R \times R$)

Theorem: $q(n) \rightarrow \text{order } n$, rank r , signature p , real quadratic form of hermitian.

- (a) PD iff $r=p=n$
- (b) PSD iff $r=p < n$
- (c) ND iff $r=-p=n$
- (d) NSD iff $r=-p < n$
- (e) indefinite iff $|p| < r$.

Defn Minor determinant of order p : $\det \begin{pmatrix} i_1 & i_2 & \dots & i_p \\ j_1 & j_2 & \dots & j_p \end{pmatrix}$ where $1 \leq i_1 < i_2 < \dots < i_p \leq n$ and

$1 \leq j_1 < j_2 < \dots < j_p \leq n$, $1 \leq p \leq n$ be p row and column indices,

$$A = \begin{pmatrix} i_1 & i_2 & \dots & i_p \\ j_1 & j_2 & \dots & j_p \end{pmatrix} = \begin{vmatrix} a_{i_1 j_1} & a_{i_1 j_2} & \dots & a_{i_1 j_p} \\ a_{i_2 j_1} & a_{i_2 j_2} & \dots & a_{i_2 j_p} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i_p j_1} & a_{i_p j_2} & \dots & a_{i_p j_p} \end{vmatrix} \quad \begin{pmatrix} 1 & 3 & 5 \\ 1 & 2 & 5 \end{pmatrix} = \begin{vmatrix} a_{11} & a_{12} & a_{15} \\ a_{31} & a_{32} & a_{35} \\ a_{51} & a_{52} & a_{55} \end{vmatrix}$$

Defn

Principal Minor

Selecting identical row & column matrices

$$\text{above } A = \begin{pmatrix} i_1 & i_2 & \dots & i_p \\ j_1 & j_2 & \dots & j_p \end{pmatrix} \rightarrow \text{Both are same}$$

Leading - principal Minor

$i_1=1, i_2=2, \dots, i_p=p$ in principal

minor is now leading principal minor

$$A = \begin{pmatrix} 1 & 2 & \dots & p \\ 1 & 2 & \dots & p \end{pmatrix}$$

Corollary: If the quadratic form $q = n^T A n$ (respectively Hermitian form $n^T H n$) is PD, then \exists a non-singular transformation $n = Py$ (respectively $n = Qy$) s.t. $n^T A n = y^T J_n y$ (resp. $n^T H n = y^T J_n y$)

Theorem: If $q(n) = n^T A n$ is the definite,

- (a) $\det A > 0$
- (b) Every principal minor of A is the
- (c) $a_{ii} > 0$, $i=1, 2, \dots, n$ where $A = (a_{ij})$

Theorem: If a real quadratic form $q(n) = n^T A n$ is PSD then

- (a) $|A| = 0$
- (b) Every principal minor of A is non-negative
- (c) $a_{ii} \geq 0$ iff n_i^2 appears in $q(n)$.

Defn: A real symmetric matrix A (respectively Hermitian H) is called the definite matrix (resp. the definite Hermitian matrix) iff the corresponding form $n^T A n$ ($n^T H n$) is the definite and is denoted by $A > 0$ ($H > 0$).

Theorem: A real matrix A is symmetric and p.d. iff one of the following statements hold

- (i) $P^T A P$ is symmetric and PD for any real and non-singular P .
- (ii) $A = P^T P$ for a real and non-singular P [i.e., \exists a non-singular matrix P s.t. $A = P^T P$]

Real Symmetric \leftrightarrow Hermitian

Date _____



Theorem: Sylvester's Criteria for positive definiteness

A quadratic form $q(x_1, x_2, \dots, x_n) = n^T A n = \sum_{i,j=1}^n a_{ij} x_i x_j$ is p.d.

(iff) the leading principal minors are +ve i.e., all the determinants, $\Delta_1 = a_{11}$, $\Delta_2 = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}, \dots, \Delta_n = \begin{vmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{vmatrix}$ are +ve

Theorem: A quadratic form $q = n^T A n = \sum_{i,j=1}^n a_{ij} x_i x_j$ with rank r can be transformed by a non-singular ($i,j=1$) transformation $n = P y$ with $|P|=1$, and P upper triangular to the diagonal form $q = c_1 y_1^2 + \dots + c_r y_r^2$ iff Δ_i 's, $i=1, \dots, r$ are non-zero where $c_i = \frac{\Delta_i}{\Delta_{i-1}}$, $\Delta_0 = 1$, $\Delta_1 = a_{11}$, $\Delta_2 = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}$.

Now, $\Delta_n = \begin{vmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{vmatrix} \Rightarrow |\Delta| > 0$; thus full rank of quadratic form \Rightarrow all the terms will be there.

$$q = n^T A n \Rightarrow q = \sum \frac{\Delta_i}{\Delta_{i-1}} y_i^2 \quad \Delta_0 = 1 \quad \Delta_i > 0 \Rightarrow q > 0$$

Theorem: $n^T A n$ is p.d. \Leftrightarrow all principal minors of A are +ve

Theorem: $q(x_1, x_2, \dots, x_n) = \sum_{i,j} a_{ij} x_i x_j$ is p.d. $\Leftrightarrow a_{11} > 0, \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} > 0, \dots, \begin{vmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{vmatrix} > 0$

$$\begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} < 0, -ve.$$

even order \rightarrow the } principal minors of A .
odd order \rightarrow -ve. }

* if $\lambda_k = 0$, $|A - \lambda I| = 0 \Rightarrow |A| = 0 \Rightarrow A$ is singular.
Hence PSD or NSD only when A is singular.

Date: _____



Theorem: A real quadratic form $n^T A n$ is {real symmetric or Hermitian}

- (a) p.d. iff all the eigenvalues of A are +ve.
- (b) n.d. iff all the eigenvalues of A are -ve.
- (c) p.s.d. iff all the eigenvalues of A are non-negative with at least one zero eigenvalue.
- (d) nsd iff all the eigenvalues of A are non-positive with at least one zero eigenvalue.
- (e) indefinite iff A has atleast one positive and one negative eigenvalue.

Theorem: A quadratic form $q(n) = n^T A n \rightarrow \text{PSD} \iff A \rightarrow \text{singular} +$
all principal minors are ~~non~~ non-negative.

Theorem: $q(n) = n^T A n = \sum a_{ij} n_i n_j \rightarrow \text{PSD} \text{ if } |A| = 0 \text{ and leading principal minors}$
 a_1, a_2, \dots, a_{n-1} of A are +ve.

Norm/Vector Norm: Let X be a vector space of a real valued function $f(x)$
on X satisfies following properties,

$$(1) \|x\| \geq 0 \text{ and } \|x\| = 0 \iff x = 0$$

$$(2) \|cx\| = |c| \|x\|$$

$$(3) \|x+y\| \leq \|x\| + \|y\|$$

e.g. $\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p} \Rightarrow \|x\|_\infty = \max_i |x_i|$

p.v.i

is basically a norm, satisfies its properties.

Date _____

Inequalities

① Let $p > 1$ and define q by $\frac{1}{p} + \frac{1}{q} = 1$ (then p & q are called conjugate exponents).

Let α, β be any two no. then $\alpha\beta \leq \frac{\alpha^p}{p} + \frac{\beta^q}{q}$.

② Hölder's inequality: Let $x = (x_1, x_2, \dots, x_n)^T$ $(p > 1)$

$$\sum_{i=1}^n |z_i \cdot x_i| \leq \left(\sum_{i=1}^n |z_i|^p \right)^{1/p} \cdot \left(\sum_{i=1}^n |x_i|^q \right)^{1/q} \quad \text{where } p, q \text{ are any two no. satisfying } \frac{1}{p} + \frac{1}{q} = 1$$

③ Cauchy-Schwarz Inequality: $p=q=2$; $\sum_{i=1}^n |z_i x_i| \leq \left(\sum_{i=1}^n |z_i|^2 \right)^{1/2} \left(\sum_{i=1}^n |x_i|^2 \right)^{1/2}$

④ Minkowski's Inequality: $\|nx\|_p \leq \|nx\|_p + \|y\|_p$

$$\text{or, } \left(\sum_{i=1}^n |z_i + y_i|^p \right)^{1/p} \leq \left(\sum_{i=1}^n |z_i|^p \right)^{1/p} + \left(\sum_{i=1}^n |y_i|^p \right)^{1/p}$$

Metric: A metric in a vector space V is a real valued $f: V \times V \rightarrow \mathbb{R}$ of ordered pairs of elements of V which satisfies following.

① $d(u, v) \geq 0$ and $d(u, v) = 0$ iff $u=v$

② $d(u, v) = d(v, u)$ (Symmetry)

③ $d(u, v) \leq d(u, w) + d(w, v)$ (triangular inequality)

A vector space for which a metric is defined is called a metric space.

\Rightarrow d induced by the norm $\|nx\|_p$ means, $d(x, y) = \|nx-y\|_p$

Matrix

Norm:

- ① $\|A\| \geq 0$ and $\|A\|=0$ iff $A=0$
- ② $\|\alpha A\| = |\alpha| \|A\|$ for $\alpha \in \mathbb{C} \times \mathbb{R}$
- ③ $\|A+B\| \leq \|A\| + \|B\|$
- ④ $\|AB\| \leq \|A\| \cdot \|B\|$

⑤

$$\|A\|_1 = \sum |a_{ij}|$$

$$\|A\|_\infty = \max_j \left(\sum_i |a_{ij}| \right) \quad \text{Row sum}$$

⑥

$$\|A\|_F = \sqrt{\sum |a_{ij}|^2}$$

$$\|A\|_F = \left(\sum_{ij} |a_{ij}|^2 \right)^{1/2}$$

Column sum

$$\|I\| \geq 1$$

$$\|A^{-1}\| \leq \frac{1}{\|A\|}$$

$$\|A^n\| \leq \|A\|^n$$

$$\|AU\|$$

→ Cholesky factorisation: For every symmetric & pos. definite matrix,

there exists a lower triangular matrix L s.t $A = LL^T$

$$A = \begin{bmatrix} a_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}; \quad L = \begin{bmatrix} l_{11} & 0 \\ l_{21} & l_{22} \end{bmatrix} \quad l_{11} = \sqrt{a_{11}} \quad l_{21} = \frac{1}{l_{11}} A_{21}$$

$$l_{22} l_{22}^T = A_{22} - \frac{1}{l_{11}} A_{21} A_{21}^T$$

L is symmetric & pos. definite.

Defⁿ Matrix Norm compatible with vector norm: Let A be matrix in $V^{m \times n}$ over \mathbb{K} and x be any vector in \mathbb{K}^n then a matrix norm is said to be compatible with the vector norm iff $\forall x \quad \|Ax\|_A \leq \|A\|_A \|x\|_A$
 so $\|A\|_A$ is compatible with $\|x\|_A$.

Theorem: (a) Let x & y be in $V(n)$. If $x \neq y$ then real no. $\|x\| \rightarrow \|y\|$ and $\|x-y\| \rightarrow 0$

(b) Let A & B be in $V_{n \times n}$. If $A \rightarrow B$, then real no. $\|A\| \rightarrow \|B\|$ and $\|A-B\| \rightarrow 0$

Defn

Equivalent Vector Norm: Let $\|\cdot\|_a$ and $\|\cdot\|_b$ be two vector norms in \mathbb{C}^n , then $\|\cdot\|_a$ is said to be equivalent to $\|\cdot\|_b$ if there exist two no. $m & M$ s.t.

$$m \|\cdot\|_a \leq \|\cdot\|_b \leq M \|\cdot\|_a \quad \forall n \in \mathbb{C}^n$$
Theorem

Equivalence of vector norm satisfy (i) reflexive (ii) symmetric (iii) transitive properties.

Theorem: All norms on \mathbb{C}^n are equivalent.

Theorem: All norms on $\mathbb{C}^{n \times n}$ are equivalent, i.e. if $\|\cdot\|_a$ and $\|\cdot\|_b$ are two different norms on $\mathbb{C}^{n \times n}$, then there exists real no. m and M s.t. $m \|\cdot\|_a \leq \|\cdot\|_b \leq M \|\cdot\|_a$ for any $A \in \mathbb{C}^{n \times n}$.

$\Rightarrow \|\cdot\|_p, p = 1, 2, \dots, \infty$ satisfy the following inequalities.

$$(a) \|\cdot\|_\infty \leq \|\cdot\|_1 \leq n \|\cdot\|_\infty, \quad \|\cdot\|_\infty \leq \|\cdot\|_2 \leq \sqrt{n} \|\cdot\|_\infty$$

$$(b) \|\cdot\|_2 \leq \|\cdot\|_1 \leq \sqrt{n} \|\cdot\|_2, \quad \sqrt{n} \|\cdot\|_1 \leq \|\cdot\|_2 \leq \|\cdot\|_1$$

$$(c) \frac{1}{n} \|\cdot\|_1 \leq \|\cdot\|_\infty \leq \|\cdot\|_1, \quad \frac{1}{\sqrt{n}} \|\cdot\|_2 \leq \|\cdot\|_\infty \leq \|\cdot\|_2$$

Householder Transform

Defn

If w is a unit vector in \mathbb{C}^n , then a matrix P in $\mathbb{C}^{n \times n}$ of the form $P = I - 2w w^*$ ($w^* w = 1$ (norm)) is called the Householder transform, elementary hermitian matrix or an elementary reflector.

Properties: ① P is hermitian, $P^* = P$

② P is unitary, $P^* P = P P^* = I$

③ P is involutory, $P^2 = I$

④ If $Pn = y$, then $\|n\|_2 = \|y\|_2 \quad \{ n^* n = y^* y \}$

Thus, norm is preserved

$$= n^* n \text{ as } P^* P = I$$

Theorem: Given a non-zero vector $n = (n_1, \dots, n_k)^T$ in \mathbb{R}^k , there exists a householder transformation $P_n = I - 2ww^T$ of order k such that $P_n n = \alpha e$, where α is real no., $e = (1, 0, \dots, 0)^T$ is an elementary vector in \mathbb{R}^k and I is identity matrix of order k .

Orthogonal reduction to a triangular form and Q-R decomposition by householder transform.

$Q \Rightarrow$ orthogonal matrix $R \Rightarrow$ upper-triangular matrix.

$$A = QR$$

Algorithm: Given $n = (n_1, \dots, n_k)^T$, compute

$$\textcircled{a} \quad m = (n_1^2 + n_2^2 + \dots + n_k^2)^{1/2}$$

$$\|n\|_2$$

$$\textcircled{b} \quad 2q^2 = m^2 + m n_1 \text{ sgn } n_1$$

$$\begin{matrix} \text{sgn } n_1 & 1 & 1 & - \\ n > 0 & n = 0 & n < 0 \end{matrix}$$

$$\textcircled{c} \quad u = [n_1 + m \text{ sgn } n_1, n_2, \dots, n_k]^T$$

$$\textcircled{d} \quad P_m = I - \frac{uu^T}{q^2}$$

$$P_{m-1} = I - \frac{uv^T}{q^2}$$

$$Q^T = V_r V_{r-1} \dots V_1$$

$$\text{and } Q^T A = R$$

$$(Q^T)^{-1} = Q$$

in less order k .

$$V_2 \xrightarrow{A} \begin{bmatrix} 1 & 0 \\ 0 & P_{m-1} \end{bmatrix}; \quad V_3 \xrightarrow{A} \begin{bmatrix} I_2 & 0 \\ 0 & P_{m-2} \end{bmatrix}; \quad V_4 \xrightarrow{A} \begin{bmatrix} I_3 & 0 \\ 0 & P_{m-3} \end{bmatrix}$$

orthogonal

Induced Matrix Norms

$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \max_{\|y\|=1} \|Ay\|$$

Theorem

Every induced matrix norm is a compatible matrix norm.

In other words,

(a) $\|A\| = \max_{\|u\|=1} \|Au\|$ is a matrix norm.

(b) The induced matrix norm defined in (a) is compatible with the vector norm $\|u\|$, i.e., $\|Au\| \leq \|A\| \cdot \|u\|$.

Axiom 1:

$\|A\| \geq 0$ always, $A=0 \Rightarrow \|A\|=0$ \Leftarrow

Axiom 2:

$\|\alpha A\| = |\alpha| \|A\| \quad \left\{ \max_{\|u\|=1} \|\alpha Au\| = |\alpha| \max_{\|u\|=1} \|Au\| \right\}$

Axiom 3:

$\|A+B\| \leq \|A\| + \|B\|$.

Weierstrass theorem: A continuous f defined on closed and bounded set of points attains a max. and a min. in its domain ($\|A\|$) is a continuous f and set of points for $\|u\|=1$ is a closed and bounded set then if \exists u_0 s.t. $\|u_0\|=1$ and $\|A\| = \max_{\|u\|=1} \|Au\| = \|Au_0\|$

so

$$\begin{aligned} \|AB\| &= \max_{\|u\|=1} \|ABu\| = \|ABu_0\| \\ \|AB\| &\leq \|A\| \|B\| \\ &= \|A(Bu_0)\| \leq \|A\| \|Bu_0\| \\ &\leq \|A\| \|B\| \|u_0\| \end{aligned}$$

* A maxima should occur in the given domain for this theorem to hold true.

* Every induced matrix norm is a matrix norm.

$$\| \mathbf{1} \|_2 = (\sum_{i=1}^n 1^2)^{\frac{1}{2}}$$

Date _____ / _____ / _____

Q Show that the matrix norms.

notation to show eigenvalues of $\mathbf{A}^* \mathbf{A}$.

(a) $\| \mathbf{A} \|_1 = \max_i \sum_j |a_{ij}|$

(b) $\| \mathbf{A} \|_\infty = \max_j \sum_i |a_{ij}|$

(c) $\| \mathbf{A} \|_2 = \sqrt{\lambda_{\max}(\mathbf{A}^* \mathbf{A})}$

are induced respectively by the vector norms,

(a) $\| \mathbf{x} \|_1 = \sum_{i=1}^n |x_i|$

(b) $\| \mathbf{x} \|_\infty = \max_i |x_i|$

$\| \mathbf{A} \|_m = n \max_{i,j} |a_{ij}|$

$\| \mathbf{A} \|_F = (\sum_{i,j} |a_{ij}|^2)^{\frac{1}{2}}$

$\| \mathbf{A} \|_q = \sqrt{\sum_{i,j} |a_{ij}|^2}$