

Today: Symmetric matrices, quadratic forms.  
(end of material of 2<sup>nd</sup> midterm) §5 - §7

Thursday: Preview of differential eq's; other topics on quad. forms.

Next Tue: Q & A for 2<sup>nd</sup> midterm. + election day.

Next Thu: 2<sup>nd</sup> midterm.

open: 11/4 (Wed.) 1pm PST.

close: 11/5 (Thu.) 1pm PST.

(OH: ~~11/6 (Fri.)~~ 12-1:30 pm  $\rightarrow$  11/3 (Tue.) 12-1:30 pm)

Symmetric matrices:  $A = A^T$   
square,  $a_{ij} = a_{ji}$

Prop  $A^T = A \Rightarrow$  any 2 eigenvectors with distinct eigenvalues  
are orthogonal.

pf:  $A\vec{v}_1 = \lambda_1\vec{v}_1, A\vec{v}_2 = \lambda_2\vec{v}_2,$

where  $\vec{v}_1, \vec{v}_2 \neq \vec{0}, \lambda_1 \neq \lambda_2.$

$$\langle A\vec{v}_1, \vec{v}_2 \rangle = \langle \vec{v}_1, A^T\vec{v}_2 \rangle = \langle \vec{v}_1, \underbrace{A\vec{v}_2}_{\parallel} \rangle$$

(HW)

$$\underbrace{\lambda_1\vec{v}_1}_{\parallel} \quad \underbrace{\lambda_2\vec{v}_2}_{\parallel}$$
$$\lambda_1 \langle \vec{v}_1, \vec{v}_2 \rangle \quad \lambda_2 \langle \vec{v}_1, \vec{v}_2 \rangle$$

$$\Rightarrow \langle \vec{v}_1, \vec{v}_2 \rangle = 0$$

□

Def Say a matrix  $A$  is orthogonally diagonalizable

if  $\exists$  orthonormal eigenbasis of  $A$ :  $\{\vec{v}_1, \dots, \vec{v}_n\}$   
 $A\vec{v}_i = \lambda_i \vec{v}_i$

i.e.  $\exists$  orthogonal matrix  $P$  and a diagonal matrix  $D$

s.t.  $A = P D P^T$ . ( $P^T = P^{-1}$ )

$$P = [\vec{v}_1 \dots \vec{v}_n] \quad D = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$$

Thm  $A$  is orthogonally diagonalizable  $\Leftrightarrow A^T = A$

(pf of " $\Rightarrow$ ") :  $A = P D P^T$

$$\begin{aligned} A^T &= (P D P^T)^T = (P^T)^T D^T P^T \\ &= P \underbrace{D^T}_{D^T} P^T \\ &= P D P^T = A. \end{aligned}$$

(pf of " $\Leftarrow$ ").

① If  $A^T = A$  and  $A$  is diagonalizable,  
then  $A$  is orthogonally diagonalizable.

② If  $A^T = A$ , then  $A$  is diagonalizable.

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①:  $\{\lambda_1, \dots, \lambda_k\}$  distinct eigenvalues of  $A \xrightarrow{n \times n}$

$$A - \lambda_1 I, \dots, A - \lambda_k I$$

$$\text{diagonalizable} \sum \dim \text{Nul}(A - \lambda_i I) = n,$$

$$\mathbb{C}^n = \text{Nul}(A - \lambda_1 I) \oplus \dots \oplus \text{Nul}(A - \lambda_k I)$$

If we pick a basis  $\{v_i^{(1)}, \dots, v_i^{(\alpha_i)}\}$  of  $\text{Nul}(A - \lambda_i I)$   
orthogonal for each  $i$ :

then  $\{\underbrace{v_1^{(1)}, \dots, v_1^{(\alpha_1)}}_{\text{is a basis}}, \underbrace{v_2^{(1)}, \dots, v_2^{(\alpha_2)}}, \dots, \underbrace{v_k^{(1)}, \dots, v_k^{(\alpha_k)}}\}$   
 is a basis of  $\mathbb{C}^n$ .

By Prop., this is an orthogonal set

$\rightarrow$  normalize each vector  $\rightarrow$  orthonormal set  
eigenbasis.  $\square$

② " $A^T = A \Rightarrow$  diagonalizable"

Induction on the size of  $A$ :

$1 \times 1$ : OK.

Assume that any  $(n-1) \times (n-1)$  sym: matrix is diag

$A: n \times n, A^T = A \Rightarrow$  diagonalizable.

Let  $\vec{v}$  be an eigenvector of  $A$ ,  $\|\vec{v}\| = 1$

$$\Rightarrow A\vec{v} = \lambda\vec{v},$$

Choose  $\{\vec{v}_1, \dots, \vec{v}_n\}$  s.t.

$\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$  forms an orthonormal basis of  $\mathbb{C}^n$ .

$$Q = \begin{bmatrix} | & & | \\ \vec{v}_1 & \vec{v}_2 & \cdots & \vec{v}_n \\ | & & | \end{bmatrix} \text{ orthogonal, } Q^T = Q^{-1}$$

$$A\vec{v} = \lambda\vec{v}.$$

$$AQ = \left[ \lambda\vec{v}, A\vec{v}_1, \dots, A\vec{v}_n \right]$$

$$\underline{Q^T A Q} = \left[ \begin{array}{c|ccccc} \vec{v}_1 & & & & & \\ \vec{v}_2 & & & & & \\ \vdots & & & & & \\ \vec{v}_n & & & & & \end{array} \right] \left[ \begin{array}{c} \lambda\vec{v} \\ A\vec{v}_1 \\ \vdots \\ A\vec{v}_n \end{array} \right]$$

$$\begin{bmatrix} \lambda & 0 & \cdots & 0 \\ 0 & \ddots & & \\ \vdots & & \ddots & \\ 0 & & & 0 \end{bmatrix} = \begin{bmatrix} \lambda & * \\ 0 & \ddots \\ \vdots & & A' \\ 0 & & & 0 \end{bmatrix}$$

symmetric  
 $(n-1) \times (n-1)$

$$\Rightarrow -* = 0 \dots 0$$

$$(Q^T A Q)^T = \begin{bmatrix} \lambda & 0 & \cdots & 0 \\ * & (A')^T \end{bmatrix}$$

$A' = (A^T)^T$

$\underline{Q^T A Q} \quad || \quad \underline{A^T = A}$

By inductive hypothesis.  $A'$  is diagonalisable,

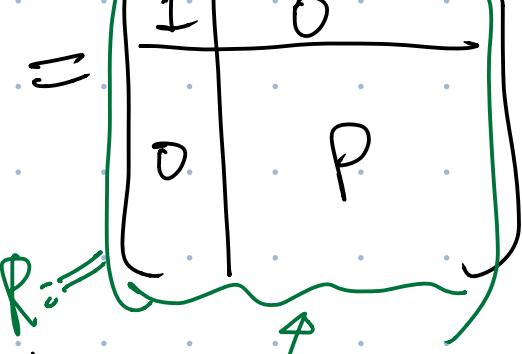
By ①,  $A'$  orthogonally diagonalisable.

$\exists P$  orthogonal &  $D$  diag. s.t.  $A' = PDP^T$ .

$$Q^T A Q =$$

$$\begin{pmatrix} \lambda & 0 \\ 0 & PDP^T \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 0 \\ 0 & P \end{pmatrix} \cdot \begin{pmatrix} \lambda & 0 \\ 0 & D \end{pmatrix} \cdot \begin{pmatrix} 1 & 0 \\ 0 & P^T \end{pmatrix}$$

$P =$    
 $\xrightarrow{\text{orthogonal}}$        $\xrightarrow{\text{diagonal}}$

$$= R \begin{pmatrix} \lambda & 0 \\ 0 & D \end{pmatrix} R^T$$

$$\Rightarrow A = QR \begin{pmatrix} \lambda & 0 \\ 0 & D \end{pmatrix} (QR)^T$$

$\xrightarrow{\text{orthogonal}} \xrightarrow{\text{HW}} \underline{QR \text{ orthogonal}}$

Rmk  $A^T = A \Rightarrow$  all the eigenvalues of  $A$  are real,  
(HW5) real & have real eigenvectors

~~•~~  $A\vec{x} = \lambda\vec{x}, \quad \vec{x} \in \mathbb{C}^n, \lambda \in \mathbb{C}$

WTS:  $\lambda \in \mathbb{R}$ .

~~•~~  $\overline{\vec{x}^T A \vec{x}} \in \mathbb{R}$  actually is a real number.

b/c:

$$\begin{aligned}\overline{\vec{x}^T A \vec{x}} &= \vec{x}^T \overline{A} \vec{x} = \underline{\vec{x}^T A \vec{x}} \\ &= \vec{x}^T A^T \vec{x} = \overline{\vec{x}^T A \vec{x}}.\end{aligned}$$

$\vec{x}^T A \vec{x} = \vec{x}^T \lambda \vec{x} = \lambda \underbrace{\vec{x}^T \vec{x}}_{\neq 0}$

$$\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix},$$

$$\vec{x}^T \vec{x} = [\bar{x}_1 \dots \bar{x}_n] \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$$= [x_1]^2 + \dots + [x_n]^2 \in \mathbb{R}$$

Quadratic forms.: homogeneous deg. 2 poly. in

$x_1, \dots, x_n$  variables

$$Q(x_1, \dots, x_n) = \sum_{i=1}^n b_{ii} x_i^2 + \sum_{i < j} 2b_{ij} x_i x_j$$

$$Q_A(\vec{x}) = \vec{x}^T A \vec{x}$$

Symmetric matrix  $A$   
 $n \times n$

$$\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \sum_{i=1}^n a_{ii} x_i^2 + \sum_{1 \leq i < j \leq n} 2a_{ij} x_i x_j$$

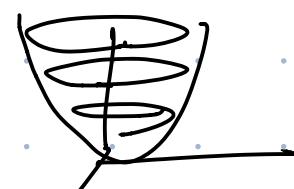
e.g.  $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, Q_A(x_1, x_2) = x_1^2 + 2x_1 x_2 + x_2^2$

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} x_1 + x_2 \\ x_1 + x_2 \end{bmatrix} = x_1^2 + x_1 x_2 + x_1 x_2 + x_2^2$$

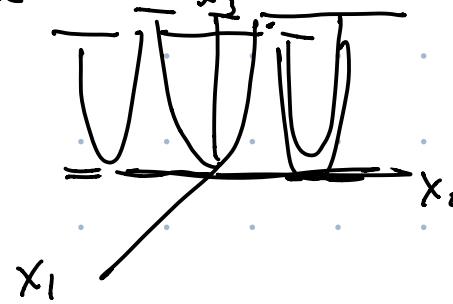
e.g.  $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, Q_A(\vec{x}) = x_1^2 + x_2^2$

↑  
positive definite



$$A = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, Q_A(\vec{x}) = x_1^2$$

↑  
positive semidefinite



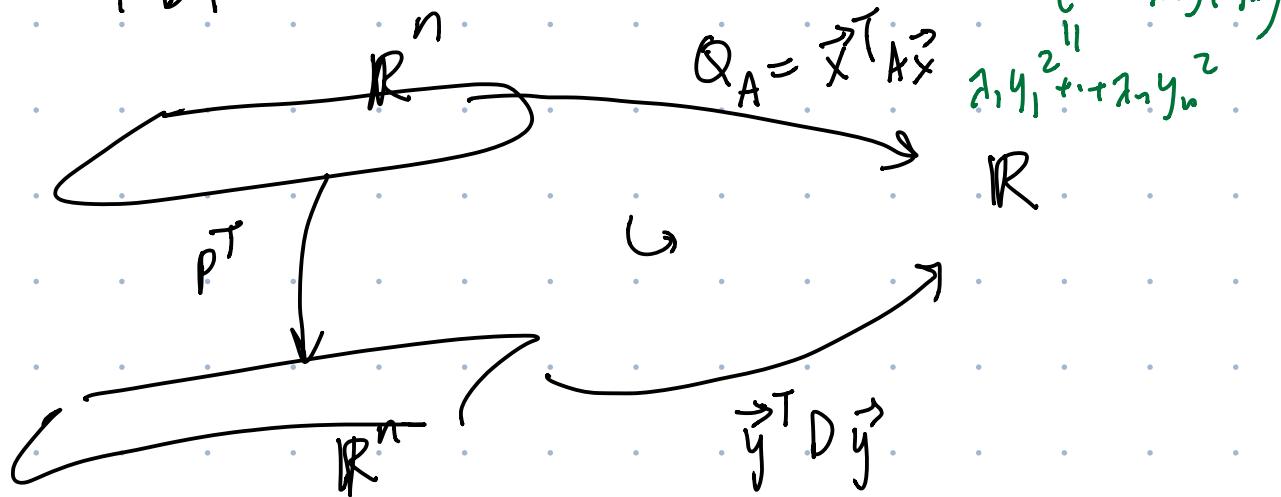
$$A = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \quad Q_A(\vec{x}) = x_1^2 - x_2^2$$

↑  
Indefinite.



$$Q_A(\vec{x}) = \vec{x}^T A \vec{x} = \vec{x}^T P D P^T \underbrace{\vec{x}}_{\vec{y}} = \vec{y}^T D \vec{y}$$

$\vec{y} = [y_1, \dots, y_n]^T$



i.e. we can use  $P^T$  to do a "change of variables" to repn the quadratic form by a diagonal matrix.

e.g.  $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = P D P^T$

$$\text{Null}(A - 0\mathbb{I}) = \text{Span}\left\{\begin{bmatrix} \sqrt{2} \\ -\sqrt{2} \end{bmatrix}\right\} \quad P = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}, \quad D = \begin{bmatrix} 0 & 0 \\ 0 & 2 \end{bmatrix}$$

$$\text{Null}(A - 2\mathbb{I}) = \text{Span}\left\{\begin{bmatrix} \sqrt{2} \\ \sqrt{2} \end{bmatrix}\right\} \quad P^T = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$\vec{y} = p^T \vec{x} = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{aligned} Q_A(\vec{x}) &= \vec{y}^T D \vec{y} = \vec{y}^T \begin{bmatrix} 0 & 0 \\ 0 & 2 \end{bmatrix} \vec{y} \\ &= 2 y_2^2 = 2 \frac{1}{2} (x_1 + x_2)^2 = \underline{(x_1 + x_2)^2} \end{aligned}$$


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Def A symmetric matrix.,  $Q_A(\vec{x}) = \vec{x}^T A \vec{x}$ .

- Say A or  $Q_A$  is positive definite if  $Q_A(\vec{x}) > 0 \quad \forall \vec{x} \neq \vec{0}$
  - Positive semidefinite if  $Q_A(\vec{x}) \geq 0 \quad \forall \vec{x} \neq \vec{0}$ .
  - negative definite, negative semidefinite
  - indefinite if it's not any of the above
- 

Thm. A symmetric,

- It's positive def.  $\Leftrightarrow$  all eigenvalues  $> 0$ .
- It's positive semidef.  $\Leftrightarrow$      $\geq 0$

Similarly for negative (semi)def,

$$x^T A x$$

$$X = \underbrace{v_1 + \dots + v_n}$$

||

$$(v_1^T + \dots + v_n^T) \underbrace{A(v_1 + \dots + v_n)}$$

||

$$\sum_{i,j} v_i^T \underbrace{A v_j}_{y} = \sum_{i,j} \lambda_j v_i^T v_j$$

$\lambda_j v_j = \sum_i \lambda_i v_i^T v_i$