

Week 15 Tuesday.

Recall that.

$$A \in M_{n \times n}(\mathbb{R})$$

In order to diagonalize A , we solve

1) $\det(A - \lambda I) = 0 \rightarrow$ eigenvalue

2) For each eigenvalue λ , solve $(A - \lambda I) \cdot \vec{x} = 0$.

\rightarrow eigenvector(s) $V_\lambda := \{ \vec{v} \mid A \vec{v} = \lambda \vec{v} \}$.

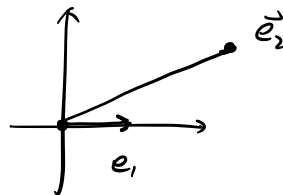
If $\sum_{\lambda} \dim(V_\lambda) = n$, then we can find a basis $S = \{ \vec{v}_1, \dots, \vec{v}_n \}$

of \mathbb{R}^n that are all eigenvectors. $\Rightarrow P^{-1} A P = D$

$$P = \left(\begin{array}{c|c|c} \vec{v}_1 & \dots & \vec{v}_n \end{array} \right)$$

Not always diagonalizable:

ex. $A = \begin{pmatrix} 1 & 2 \\ 0 & 1 \end{pmatrix} \quad \mathbb{R}^2$



For symmetric matrix, such bad situation never happens.

Thm. $A \in M_{n \times n}(\mathbb{R}) \quad A = A^T$. then A can always be diagonalized.

Prk. Recall. last time: if $\lambda_1 \neq \lambda_2$ are different eigenvalue.

then V_{λ_1} and V_{λ_2} are orthogonal to each other.

So. if A can be diagonalized, then A can also be orthogonally diagonalized.

Prep: Block Matrix.

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} a' & b' \\ c' & d' \end{pmatrix} = \begin{pmatrix} a \cdot a' + b \cdot c' & a \cdot b' + b \cdot d' \\ c \cdot a' + d \cdot c' & c \cdot b' + d \cdot d' \end{pmatrix}$$

$$\left(\begin{array}{c|c} A & B \\ \hline C & D \end{array} \right) \left(\begin{array}{c|c} A' & B' \\ \hline C' & D' \end{array} \right) = \begin{pmatrix} A \cdot A' + B \cdot C' & A \cdot B' + B \cdot D' \\ C \cdot A' + D \cdot C' & C \cdot B' + D \cdot D' \end{pmatrix}$$

Pf. Firstly, we can always find at least one eigenvalue λ_1 for A . then. solve $(A - \lambda_1 I) \cdot \vec{x} = 0$. so we can find at least one eigenvector \vec{v}_1 for A .

Assume \vec{v}_1 is normalized, and extend it to an orthonormal basis. $\{\vec{v}_1, \dots, \vec{v}_n\}$. take $P = \begin{pmatrix} \downarrow & \downarrow & \downarrow \\ v_1 & \dots & v_n \end{pmatrix}$
(use Gram-Schmidt)

$$P^T A P = \left(\begin{array}{c|c} \lambda_1 & A_1 \\ \hline 0 & A_2 \end{array} \right) \rightarrow \begin{pmatrix} \lambda_1 & 0 \\ 0 & A_2 \end{pmatrix}$$

Since A is symmetric, P is orthogonal matrix. ($P \cdot P^T = I$)

$$(P^T A P)^T = P^T A^T (P^T)^T = P^T A P \text{ is symmetric}$$

$$\Rightarrow A_1 = \overline{1 \ 0 \ 0 \ 0} \quad A_2 = A_2^T$$

Use induction: ① For $n=1$. A is scalar. always true.

② Assume for $k < n$ $A \in M_{k \times k}(\mathbb{R})$ is always diagonalizable

Now. by ②. we can pick $Q \in M_{(n-1) \times (n-1)}$ orthonormal. s.t.

$$Q^T \cdot A_2 \cdot Q = D \text{ is diag}$$

Therefore. $\tilde{Q} := \left(\begin{array}{c|c} 1 & 0 \\ \hline 0 & Q \end{array} \right) \quad \tilde{Q}^{-1} = \left(\begin{array}{c|c} 1 & 0 \\ \hline 0 & Q^{-1} \end{array} \right)$

we can get $\tilde{Q}^{-1} \cdot \left(\begin{array}{c|c} \lambda_1 & 0 \\ \hline 0 & A_2 \end{array} \right) \cdot \tilde{Q}$

$$= \left(\begin{array}{c|c} 1 & 0 \\ \hline 0 & Q^{-1} \end{array} \right) \left(\begin{array}{c|c} \lambda_1 & 0 \\ \hline 0 & A_2 \end{array} \right) \cdot \left(\begin{array}{c|c} 1 & 0 \\ \hline 0 & Q \end{array} \right)$$

$$= \left(\begin{array}{c|c} \lambda_1 & 0 \\ \hline 0 & Q^{-1} A_2 Q \end{array} \right) = \left(\begin{array}{c|c} \lambda_1 & 0 \\ \hline 0 & \begin{matrix} d_1 & & \\ & \ddots & \\ & & d_{n-1} \end{matrix} \end{array} \right) \quad \text{D}$$

□.

2. Quadratic Form.

$$f(x,y) = x^2 + 2xy - 3y^2 \quad \xrightarrow{1/y^2} \quad \tilde{x} = x/y$$

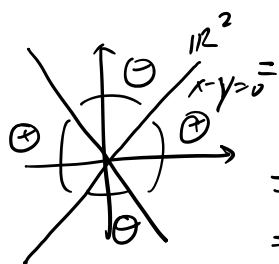
$$\tilde{x}^2 + 2\tilde{x} - 3$$

$$= (\tilde{x} + \alpha)^2 + \beta$$

$$\tilde{x}^2 + 2\tilde{x} + 1 - 1 - 3$$

$$= (\tilde{x} + 1)^2 - 4$$

$$(\tilde{x} + 1)^2 - 4$$



$$x^2 + 2xy + y^2 - y^2 - 3y^2$$

$$= (x+y)^2 - 4y^2$$

$$= [(x+y) + 2y] \cdot [(x+y) - 2y]$$

$$g(x,y) = x \cdot y = g_1(x,y) \pm$$

$$g_2(x,y)^2$$

$$\frac{1}{4}(x+y)^2 - \frac{1}{4}(x-y)^2$$

$$ax^2 + bxy + cy^2 = \overset{?}{g}_1(x,y)^2 \pm \overset{?}{g}_2(x,y)^2$$

$$\begin{aligned}
 f(x,y) &= ax^2 + 2bxy + cy^2 \stackrel{??}{=} \underbrace{(x \ y)}_{\leftarrow} \begin{pmatrix} a & b \\ b & c \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \vec{x}^T \cdot A \cdot \vec{x} \\
 &= (ax+by \quad bx+cy) \cdot \begin{pmatrix} x \\ y \end{pmatrix} \\
 &= ax^2 + bxy + bxy + cy^2
 \end{aligned}$$

We see a bijection between.

homogeneous quadratic polynomials \longleftrightarrow symmetric matrices

complete the square \longleftrightarrow A is diagonal

In general if $P^T A P = D$ then $A = P D P^{-1}$

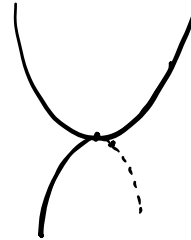
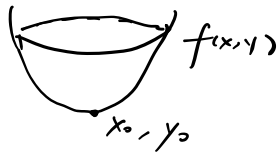
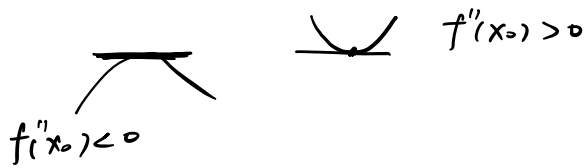
$$\text{then } \vec{x}^T \cdot A \cdot \vec{x} = \underline{\vec{x}^T \cdot P} \cdot D \cdot \underline{P^{-1} \cdot \vec{x}}$$

$$\begin{aligned}
 \text{then } \vec{y} &= P^{-1} \cdot \vec{x} \quad \text{linear transformation of } \begin{pmatrix} x \\ y \end{pmatrix} \\
 &= \begin{pmatrix} P_1x + P_2y \\ P_3x + P_4y \end{pmatrix}
 \end{aligned}$$

Recall calculus

$$\begin{aligned}
 f(x,y) &= f(x_0, y_0) + \frac{\partial f}{\partial x}(x_0, y_0) \cdot (x-x_0) + \frac{\partial f}{\partial y}(x_0, y_0) \cdot (y-y_0) \\
 &+ \left[\frac{\partial^2 f}{\partial x^2}(x_0, y_0) \cdot \frac{(x-x_0)^2}{2} + \frac{\partial^2 f}{\partial y^2}(x_0, y_0) \cdot \frac{(y-y_0)^2}{2} \right. \\
 &\left. + \frac{\partial^2 f}{\partial x \partial y}(x_0, y_0) \cdot \frac{(x-x_0) \cdot (y-y_0)}{2} \right] + \dots
 \end{aligned}$$

$$f(x) = f(x_0) + \frac{df}{dx}(x_0) \cdot (x-x_0) + \frac{d^2f}{dx^2}(x_0) \frac{(x-x_0)^2}{2} + \dots$$



local
min
positive det.

local max
negative det.

saddle
indefinite

Def: $Q(x, y) = ax^2 + 2bxy + cy^2$ then.

if $Q(x, y) > 0$ for every $(x, y) \neq (0, 0) \Rightarrow$ positive definite

$Q(x, y) < 0$ \Rightarrow negative definite

$Q(x, y)$ can be both positive and negative \Rightarrow indefinite