

Weyl's Theorem

$$A, E \in \mathbb{C}^{n \times n}$$

$$\lambda_k(A) + \lambda_1(E) \leq \lambda_k(A+E) \leq \lambda_k(A) + \lambda_n(E)$$

Pf: Since $U^*(A+E)U$ & $A+E$ has the same eigenvalue.
we can consider $A+E$, A , & E .

$$\begin{aligned} \lambda_k(A+E) &= \min_{\dim K=k} \max_{K \ni \vec{x} \neq \vec{0}} \frac{\vec{x}^*(A+E)\vec{x}}{\vec{x}^*\vec{x}} \\ &= \min_{\dim K=k} \max_{K \ni \vec{x} \neq \vec{0}} \left\{ \frac{\vec{x}^*A\vec{x}}{\vec{x}^*\vec{x}} + \frac{\vec{x}^*E\vec{x}}{\vec{x}^*\vec{x}} \right\} \end{aligned}$$

Choose $K_{\uparrow} = \{ \vec{x} \mid (\vec{x})_n = (\vec{x})_{n-1} = \dots = (\vec{x})_{k+1} = 0 \} \subseteq \mathbb{R}^n$ dim $K_{\uparrow} = k$

$$\begin{aligned} &\leq \max_{K_{\uparrow} \ni \vec{x} \neq \vec{0}} \left\{ \frac{\vec{x}^*A\vec{x}}{\vec{x}^*\vec{x}} + \frac{\vec{x}^*E\vec{x}}{\vec{x}^*\vec{x}} \right\} \\ &= \max_{K_{\uparrow} \ni \vec{x} \neq \vec{0}} \left\{ \frac{\sum_{i=1}^k \lambda_i(A) x_i^2}{\sum_{i=1}^k x_i^2} + \frac{\vec{x}^*E\vec{x}}{\vec{x}^*\vec{x}} \right\} \\ &\leq \lambda_k(A) + \max_{K_{\uparrow} \ni \vec{x} \neq \vec{0}} \frac{\vec{x}^*E\vec{x}}{\vec{x}^*\vec{x}} \leq \lambda_k(A) + \lambda_n(E) \end{aligned}$$

Since $A = (A+E) + (-E)$

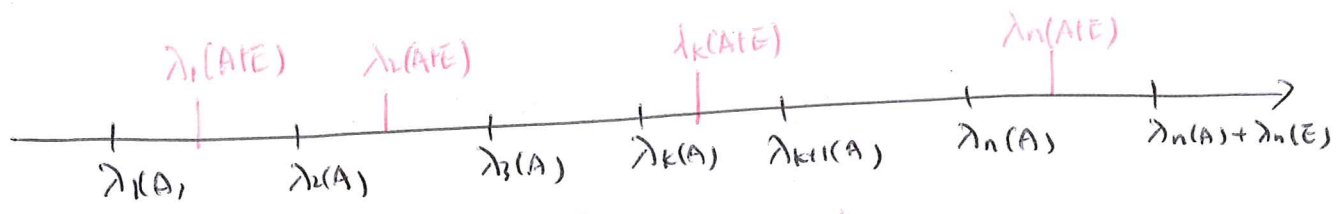
$$\begin{aligned} \lambda_k(A) &\leq \lambda_k(A+E) + \lambda_n(-E) \\ &= \lambda_k(A+E) - \lambda_1(E) \end{aligned}$$

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Corollary Let A, E Hermitian, & $\text{rank}(E)=1, E \geq 0$

then $\lambda_k(A) \leq \lambda_k(A+E) \leq \lambda_{k+1}(E) \quad 1 \leq k \leq n-1$

$\lambda_n(A) \leq \lambda_n(A+E) \leq \lambda_n(A) + \lambda_n(E)$



interlacing property

pf: Diagonalizing E by $U, U^*EU = \begin{pmatrix} l & & 0 \\ & \ddots & \\ 0 & & 0 \end{pmatrix} = \Lambda, l > 0$

Let $U^*AU = B$, since $\lambda_k(A) = \lambda_k(B)$,

w.l.o.g. consider $A + \begin{pmatrix} l & & 0 \\ & \ddots & \\ 0 & & 0 \end{pmatrix} = A + \Lambda$

By Weyl's thm.

(a) $\lambda_k(A) \leq \lambda_k(A+E) \quad 1 \leq k \leq n \quad (\because \lambda_1(\Lambda) = 0)$

(b) $\lambda_n(A+\Lambda) \leq \lambda_n(A) + \lambda_n(\Lambda)$

n.t.p. $\lambda_k(A+\Lambda) \leq \lambda_{k+1}(A) \quad 1 \leq k \leq n-1$

$\lambda_{k+1}(A) = \min_{\dim K = k+1} \max_{K \ni \vec{x} \neq \vec{0}} \frac{\vec{x}^* A \vec{x}}{\vec{x}^* \vec{x}}$

Let the min occur at $K_+ = \{ \vec{x} \mid \vec{p}_1 \vec{x} = 0, \dots, \vec{p}_{n-k_1} \vec{x} = 0 \}$ $\dim(K_+) = k+1$

Consider $\bar{K} = K_+ \cap \{ (\vec{x})_i = 0 \}$ $\dim \bar{K} = k$

$$\begin{aligned} \lambda_{k+1}(A) &= \max_{K_+ \ni \vec{x} \neq \vec{0}} \frac{\vec{x}^* A \vec{x}}{\vec{x}^* \vec{x}} \geq \max_{\bar{K} \ni \vec{x} \neq \vec{0}} \frac{\vec{x}^* A \vec{x}}{\vec{x}^* \vec{x}} \\ &= \max_{\bar{K} \ni \vec{x} \neq \vec{0}} \frac{\vec{x}^* A \vec{x}}{\vec{x}^* \vec{x}} + \frac{\vec{x}^* \Lambda \vec{x}}{\vec{x}^* \vec{x}} \\ &\geq \min_{\dim K = k} \max_{K \ni \vec{x} \neq \vec{0}} \left\{ \frac{\vec{x}^* (A + \Lambda) \vec{x}}{\vec{x}^* \vec{x}} \right\} \\ &= \lambda_k(A + \Lambda) \end{aligned}$$

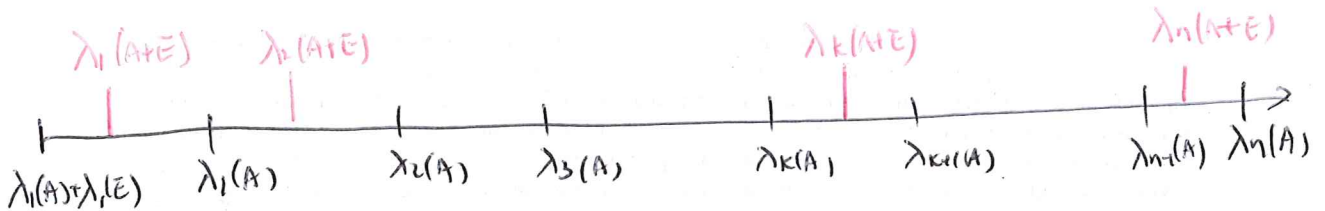
What if one of the \vec{p}_i is $(\vec{x})_i = 0$? *

Corollary Let A, E Hermitian, d $\text{rank}(E)=1, E < 0$

then

$$\lambda_{k+1}(A) \leq \lambda_k(A+E) \leq \lambda_k(A) \quad 1 \leq k \leq n$$

$$\lambda_1(A) + \lambda_1(E) \leq \lambda_1(A+E) \leq \lambda_1(A)$$



Corollary Let A, E Hermitian d $\text{rank}(E) = r$

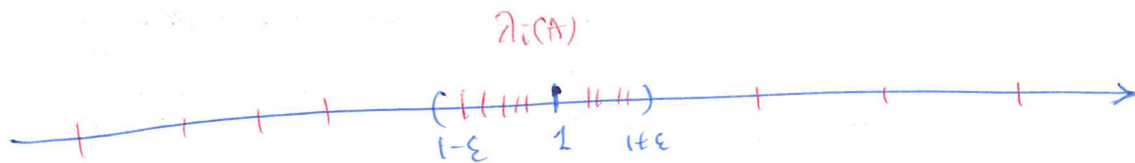
then at most r eigenvalues of $(A+E)$ is outside $[\lambda_1(A), \lambda_n(A)]$

pf: $\text{rank}(E) = r \Rightarrow E = \sum_{i=1}^r L_i, \text{rank}(L_i) = 1$

Ex: Consider $A_n = I_n + L_n + R_n$ all $n \in \mathbb{C}^{n \times n}$ Hermitian.

d $\text{rank}(L_n) \leq p, \|R_n\|_2 \leq \epsilon$. Then $\lambda_i(A) \in [1-\epsilon, 1+\epsilon]$

except at most p outliers.



Error in solving linear systems

P7

$$A\vec{x} = \vec{b}, \quad A\hat{x} = \hat{b}$$

Then

$$\frac{\|\vec{x} - \hat{x}\|}{\|\vec{x}\|} \leq K(A) \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|}$$

pf:

$$A(\vec{x} - \hat{x}) = \vec{b} - \hat{b}$$

$$\Rightarrow (\vec{x} - \hat{x}) = A^{-1}(\vec{b} - \hat{b})$$

$$\Rightarrow \|\vec{x} - \hat{x}\| \leq \|A^{-1}\| \|\vec{b} - \hat{b}\| \quad (1)$$

$$A\vec{x} = \vec{b}$$

$$\Rightarrow \|\vec{b}\| \leq \|A\| \|\vec{x}\|$$

$$\Rightarrow \frac{1}{\|\vec{x}\|} \leq \frac{\|A\|}{\|\vec{b}\|} \quad (2)$$

$$(1) \text{ and } (2) \Rightarrow \frac{\|\vec{x} - \hat{x}\|}{\|\vec{x}\|} \leq \|A\| \|A^{-1}\| \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|}$$

Note: $\text{Mat}(=6) \cdot 10^{-16} \Rightarrow \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|} = 10^{-16}$

$$\text{If } K(A) = \|A\| \|A^{-1}\| = 10^8$$

expect $\frac{\|\vec{x} - \hat{x}\|}{\|\vec{x}\|} = 10^{-8}$

What if A is also accurate?

Thm $A\vec{x} = \vec{b}$, $\hat{A}\hat{x} = \hat{b}$, and $\kappa(A) \frac{\|A - \hat{A}\|}{\|A\|} < 1$

Then

$$\frac{\|\vec{x} - \hat{x}\|}{\|\vec{x}\|} \leq \frac{\kappa(A)}{1 - \kappa(A) \frac{\|A - \hat{A}\|}{\|A\|}} \left(\frac{\|A - \hat{A}\|}{\|A\|} + \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|} \right)$$

Pf:-

$$\begin{aligned} A(\vec{x} - \hat{x}) &= A\vec{x} - A\hat{x} \\ &= \vec{b} - A\hat{x} + \hat{A}\hat{x} - \hat{A}\hat{x} \\ &= \vec{b} - (A - \hat{A})\hat{x} - \hat{b} \end{aligned}$$

$$\therefore (\vec{x} - \hat{x}) = A^{-1}(\vec{b} - \hat{b}) - A^{-1}(A - \hat{A})\hat{x}$$

$$\frac{\|\vec{x} - \hat{x}\|}{\|\vec{x}\|} \leq \|A^{-1}(A - \hat{A})\| \frac{\|\hat{x}\|}{\|\vec{x}\|} + \|A^{-1}\| \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|} \frac{\|A\vec{x}\|}{\|\vec{x}\|}$$

$$\leq \|A^{-1}(A - \hat{A})\| \frac{\|\hat{x} - \vec{x}\|}{\|\vec{x}\|} + \|A^{-1}(A - \hat{A})\| \frac{\|\vec{x}\|}{\|\vec{x}\|} + \|A^{-1}\| \|A\| \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|} \frac{\|\vec{x}\|}{\|\vec{x}\|}$$

$$\leq \|A\| \|A^{-1}\| \frac{\|A - \hat{A}\|}{\|A\|} \frac{\|\hat{x} - \vec{x}\|}{\|\vec{x}\|} + \|A\| \|A^{-1}\| \frac{\|A - \hat{A}\|}{\|A\|} + \kappa(A) \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|}$$

$$\left(1 - \kappa(A) \frac{\|A - \hat{A}\|}{\|A\|}\right) \frac{\|\hat{x} - \vec{x}\|}{\|\vec{x}\|} \leq \kappa(A) \left\{ \frac{\|A - \hat{A}\|}{\|A\|} + \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|} \right\}$$

$$\therefore \frac{\|\hat{x} - \vec{x}\|}{\|\vec{x}\|} \leq \frac{\kappa(A)}{1 - \kappa(A) \frac{\|A - \hat{A}\|}{\|A\|}} \left\{ \frac{\|A - \hat{A}\|}{\|A\|} + \frac{\|\vec{b} - \hat{b}\|}{\|\vec{b}\|} \right\} \quad \#$$

Note for matlab, r.e. = 10^{-16} , if $\kappa(A) = 10^8$

$$\text{r.e. in } \vec{x} = \frac{10^8}{1 - 10^8 \cdot 10^{-16}} \cdot \{10^{-16} + 10^{-16}\}$$

$$\approx 10^{-8} \quad \#$$

Conjugate Gradient Method

Conjugate Direction: Q Hermitian, \vec{d}_i, \vec{d}_j are conjugate (w.r.t. Q) if
$$\vec{d}_i^* Q \vec{d}_j = 0$$

Thm 1: $Q > 0$, $\{\vec{d}_0, \dots, \vec{d}_{k-1}\}$ conjugate $\Rightarrow \{\vec{d}_i\}_{i=0}^{k-1}$ linearly independent

Pf: Suppose $\sum_{i=0}^{k-1} \alpha_i \vec{d}_i = 0$ for some α_i

$$\forall j \quad 0 = \vec{d}_j^* Q \left(\sum_{i=0}^{k-1} \alpha_i \vec{d}_i \right) = \sum_{i=0}^{k-1} \alpha_i \vec{d}_j^* Q \vec{d}_i = \alpha_j \vec{d}_j^* Q \vec{d}_j$$

$$\because Q > 0, \vec{d}_j^* Q \vec{d}_j > 0 \Rightarrow \alpha_j = 0 \quad \forall j$$

Note: Suppose we solve $Q\vec{x} = \vec{b}$ & solution is \vec{x}_+

Suppose we have found n conjugate directions $\{\vec{d}_0, \dots, \vec{d}_{n-1}\}$ li.

$$\vec{x}_+ = \sum_{i=0}^{n-1} \alpha_i \vec{d}_i$$

$$Q\vec{x}_+ = \sum_{i=0}^{n-1} \alpha_i Q\vec{d}_i$$

where
$$\vec{d}_j^* Q \vec{x}_+ = \sum_{i=0}^{n-1} \alpha_i \vec{d}_j^* Q \vec{d}_i = \alpha_j \vec{d}_j^* Q \vec{d}_j$$

$$\Rightarrow \alpha_j = \frac{\vec{d}_j^* Q \vec{x}_+}{\vec{d}_j^* Q \vec{d}_j} = \frac{\vec{d}_j^* \vec{b}}{\vec{d}_j^* Q \vec{d}_j} \quad \left(\begin{array}{l} \text{no reference to} \\ \vec{x}_+ \text{ is needed} \\ \text{in computing } \alpha_j \end{array} \right)$$

$$\vec{x}_+ = \sum_{i=0}^{n-1} \frac{\vec{d}_i^* \vec{b}}{\vec{d}_i^* Q \vec{d}_i} \vec{d}_i$$

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Can we find n conjugate directions easily??

Conjugate Direction Algorithm

Let $\{\vec{d}_0, \dots, \vec{d}_{n-1}\}$ be conjugate directions

Given \vec{x}_0 , define $\vec{x}_{k+1} = \vec{x}_k + \alpha_k \vec{d}_k$

$$\text{where } \alpha_k = -\frac{\vec{g}_k^T \vec{d}_k}{\vec{d}_k^T Q \vec{d}_k} \quad (*)$$

$$\vec{g}_k = Q\vec{x}_k - \vec{b} \quad (= Q(\vec{x}_{k-1} + \alpha_{k-1} \vec{d}_{k-1}) - \vec{b})$$

$$\text{then } \vec{x}_n = Q^{-1} \vec{b} = \vec{x}_* = \vec{g}_{k-1} + \alpha_{k-1} Q \vec{d}_{k-1} \quad \text{only one matrix-vector multiplication per iteration!}$$

$$\text{pf: } \{\vec{d}_i\}_{i=0}^{n-1} \text{ l.i. } \therefore \vec{x}_* - \vec{x}_0 = \sum_{i=0}^{n-1} \beta_i \vec{d}_i$$

$$Q(\vec{x}_* - \vec{x}_0) = \sum_{i=0}^{n-1} \beta_i Q \vec{d}_i$$

$$\vec{d}_j^T Q(\vec{x}_* - \vec{x}_0) = \sum_{i=0}^{n-1} \beta_i \vec{d}_j^T Q \vec{d}_i = \beta_j \vec{d}_j^T Q \vec{d}_j \quad 0 \leq j \leq n-1$$

$$\therefore \beta_j = \frac{\vec{d}_j^T Q(\vec{x}_* - \vec{x}_0)}{\vec{d}_j^T Q \vec{d}_j} = \frac{\vec{d}_j^T (\vec{b} - Q\vec{x}_0)}{\vec{d}_j^T Q \vec{d}_j} \quad (1)$$

$$\vec{x}_k - \vec{x}_0 = \alpha_0 \vec{d}_0 + \dots + \alpha_{k-1} \vec{d}_{k-1} \quad k \geq 1$$

$$Q(\vec{x}_k - \vec{x}_0) = \sum_{i=0}^{k-1} \alpha_i Q \vec{d}_i$$

$$\vec{d}_k^T Q(\vec{x}_k - \vec{x}_0) = \sum_{i=0}^{k-1} \alpha_i \vec{d}_k^T Q \vec{d}_i = 0$$

$$\Rightarrow \vec{d}_k^T Q \vec{x}_k = \vec{d}_k^T Q \vec{x}_0 \quad (2)$$

$$\therefore (2) \rightarrow (1) \Rightarrow \beta_j = \frac{\vec{d}_j^T (\vec{b} - Q\vec{x}_0)}{\vec{d}_j^T Q \vec{d}_j}$$

$$= -\frac{\vec{d}_j^T \vec{g}_j}{\vec{d}_j^T Q \vec{d}_j} = \alpha_j \quad (*)$$

$$\vec{x}_* = \vec{x}_0 + \sum_{i=0}^{n-1} \alpha_i \vec{d}_i = \vec{x}_n$$

Expanding Subspace Theorem

$\{\vec{d}_i\}_{i=0}^{k-1}$ conjugate direction & $\{\vec{x}_i\}_{i=0}^k$ from conjugate direction method

Then $\vec{x}_k = \underset{\vec{x} \in \vec{x}_0 + B_k}{\text{min}} \left\{ \frac{1}{2} \vec{x}^T Q \vec{x} - \vec{b}^T \vec{x} \right\}$

where $B_k = \{\vec{d}_0, \dots, \vec{d}_{k-1}\}$

pf: $f(x) \equiv \frac{1}{2} \vec{x}^T Q \vec{x} - \vec{b}^T \vec{x}$ strictly convex

$\vec{x}_0 + B_k$ is affine

need to move $\nabla f(\vec{x}_k) \perp B_k$

$\nabla f(\vec{x}_k) = Q \vec{x}_k - \vec{b} = \vec{g}_k$

By induction, show $\vec{g}_k \perp B_k \quad \forall k$

$k=0$ $B_k = \emptyset$, okay

Suppose true for all $i \leq k$, i.e. $\vec{g}_i \perp B_i, i \leq k$

for $k+1$:

$$\begin{aligned} \vec{g}_{k+1} &= Q \vec{x}_{k+1} - \vec{b} \\ &= Q(\vec{x}_k + \alpha_k \vec{d}_k) - \vec{b} \\ &= Q \vec{x}_k + \alpha_k Q \vec{d}_k - \vec{b} \\ &= \vec{g}_k + \alpha_k Q \vec{d}_k \end{aligned}$$

so for $i=0, \dots, k$

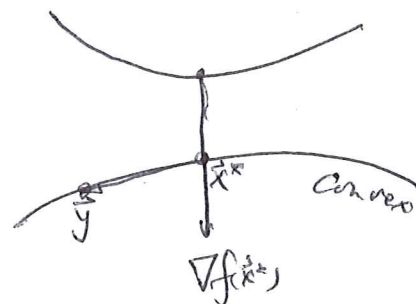
$$\vec{d}_i^T \vec{g}_{k+1} = \underbrace{\vec{d}_i^T \vec{g}_k}_0 + \alpha_k \underbrace{\vec{d}_i^T Q \vec{d}_k}_0 = 0$$

(hypothesis) (conjugate)

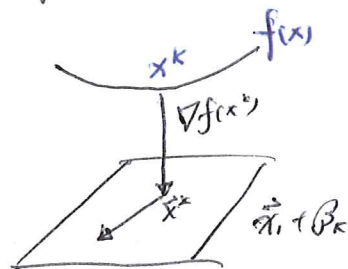
for k

$$\vec{d}_k^T \vec{g}_{k+1} = \vec{d}_k^T \vec{g}_k + \alpha_k \vec{d}_k^T Q \vec{d}_k = 0 \quad (\text{by definition of } \alpha_k)$$

$\therefore \vec{g}_{k+1} \perp \{\vec{d}_0, \dots, \vec{d}_k\} = B_{k+1}$



$\nabla f(\vec{x}^*) \cdot (\vec{y} - \vec{x}^*) \geq 0$



Corollary

$\vec{g}_k^T \vec{d}_i = 0 \quad \forall i=1, \dots, k-1$

