

Amendment on last Tutorial

(See Wiki Page
"Spectral Radius"
For more details)

$$\text{" } \|\vec{e}_k\| \leq \rho(M)^k \|\vec{e}_0\| \text{"}$$

Not True in general.

But true as $k \rightarrow \infty$.

$$\|\vec{e}_k\| = \|M^k \vec{e}_0\|$$

$$\leq \|M^k\| \|\vec{e}_0\| \left(\frac{\|A\|}{\det} \sup_{\vec{x} \neq 0} \frac{\|A\vec{x}\|}{\|\vec{x}\|} \right)$$

$$\text{Gelfand's Formula: } \rho(M) = \lim_{k \rightarrow \infty} \|M^k\|^{1/k}$$

$$\text{So, } \|\vec{e}_k\| \leq \|M^k\| \|\vec{e}_0\|$$

$$\rightarrow \rho(M)^k \|\vec{e}_0\| \text{ as } k \rightarrow \infty$$

Explanation on HW 3 Q(5) & (6).

5. Consider the following iterative scheme:

$$x_{k+1} = (\alpha I - tA)x_k + tb$$

where $\alpha \geq 1$. Suppose that A is symmetric positive definite matrix in $\mathbb{R}^{n \times n}$, with eigenvalues $\lambda_n \geq \lambda_{n-1} \geq \dots \geq \lambda_1 > 0$.

(a) Show that the above scheme converges if and only if $\frac{\alpha-1}{\lambda_1} < t < \frac{\alpha+1}{\lambda_n}$.

(b) Prove that the optimal t , in the sense of rate of convergence, is $\frac{2\alpha}{\lambda_1 + \lambda_n}$.

Matrix $\alpha I - tA$ has eigenvalues $\alpha - t\lambda_j$

if $t < 0$,

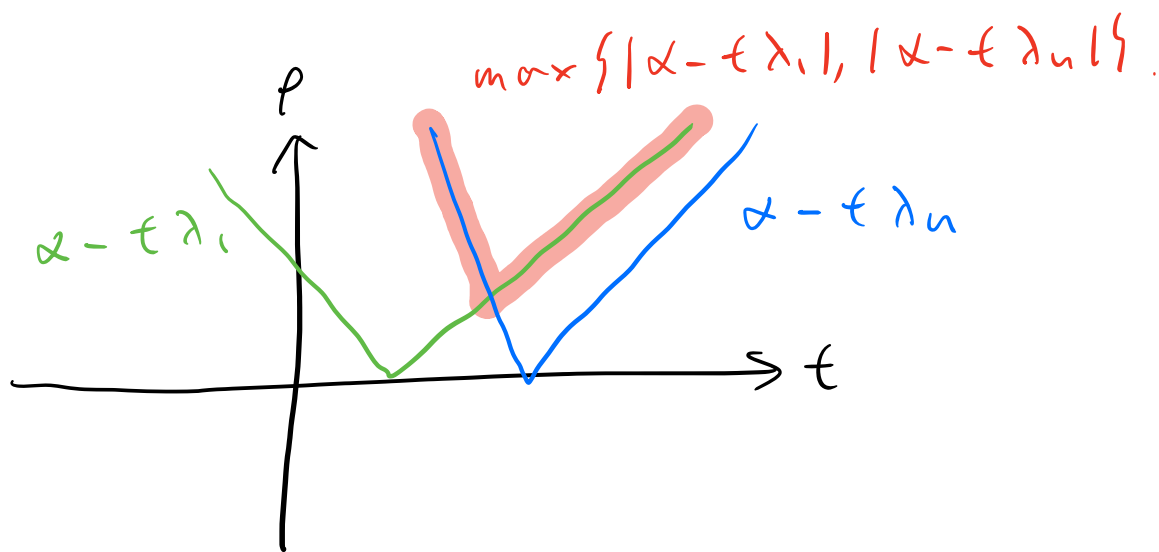
$$\alpha - t\lambda_1 \leq \alpha - t\lambda_j \leq \alpha - t\lambda_n$$

if $t > 0$,

$$\alpha - t\lambda_n \leq \alpha - t\lambda_j \leq \alpha - t\lambda_1$$

In any cases,

$$\begin{aligned} |\alpha - t\lambda_j| &\leq \max\{|\alpha - t\lambda_1|, |\alpha - t\lambda_n|\} \\ &= \rho(\alpha I - tA). \end{aligned}$$



\therefore optimal t satisfy $|\alpha - t\lambda_1| = |\alpha - t\lambda_n|$.

Power Method

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

A has eigenvalues $|\lambda_1| > |\lambda_2| \geq \dots \geq |\lambda_n| \geq 0$

and \vec{v}_1 is an eigenvector w.r.t. λ_1 .

Initial Guess:

$$\vec{x}_0 = a_1 \vec{v}_1 + (\text{something else}), a_1 \neq 0.$$

(Random choice of \vec{x}_0 is usually OK)

And iterative scheme:

$$\vec{x}^{k+1} = \frac{A \vec{x}^k}{\|A \vec{x}^k\|_\infty}$$

$$\text{where } \|\vec{v}\|_\infty = \left\| \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} \right\|_\infty = \max_{1 \leq i \leq n} |v_i|$$

$$\text{Then } \|A \vec{x}^k\|_\infty \rightarrow |\lambda_1| = \rho(A)$$

as $k \rightarrow \infty$

(See Lecture Notes).

Remark

$\|\cdot\|_\infty$ is not important,
can be replaced by other norm.

e.g. $\vec{x}^{k+1} = \frac{A \vec{x}^k}{\|A \vec{x}^k\|_2},$

and $\|A \vec{x}^k\|_2$ also converges
to $|\lambda_1| = \rho(A).$

pt exactly the same steps in
lecture notes

Geometric Understanding (Past Homework)

$A \in \mathbb{C}^{n \times n}$ is Normal ($AA^* = A^*A$)
(i.e. A is diagonalizable.)

with eigenvalues:

$$|\lambda_1| > |\lambda_2| > \dots > |\lambda_n| > 0.$$

and eigenvectors: $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$.

$$A = Q D Q^*, \quad Q^* Q = I$$

$$Q = \begin{bmatrix} \frac{1}{\|\vec{v}_1\|} & \frac{1}{\|\vec{v}_2\|} & \dots & \frac{1}{\|\vec{v}_n\|} \\ \vdots & \vdots & \dots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix}$$

Def: For $\vec{x}, \vec{y} \in \mathbb{C}^n$,

$$\cos \angle(\vec{x}, \vec{y}) = \frac{|\langle \vec{x}, \vec{y} \rangle|}{\|\vec{x}\|_2 \|\vec{y}\|_2}$$

$$\sin \angle(\vec{x}, \vec{y}) = \sqrt{1 - \cos^2 \angle(\vec{x}, \vec{y})}$$

$$\tan \angle(\vec{x}, \vec{y}) = \frac{\sin \angle(\vec{x}, \vec{y})}{\cos \angle(\vec{x}, \vec{y})}.$$

$$\text{Recall } \langle \vec{x}, \vec{y} \rangle = \sum x_i \overline{y_i}$$

Consider the iterative scheme

$$\vec{x}^{k+1} = A \vec{x}^k = A^k \vec{x}^0$$

$$T_1: \cos \angle (Q_{\vec{x}}^*, Q_{\vec{y}}^*) = \cos \angle (\vec{x}, \vec{y}).$$

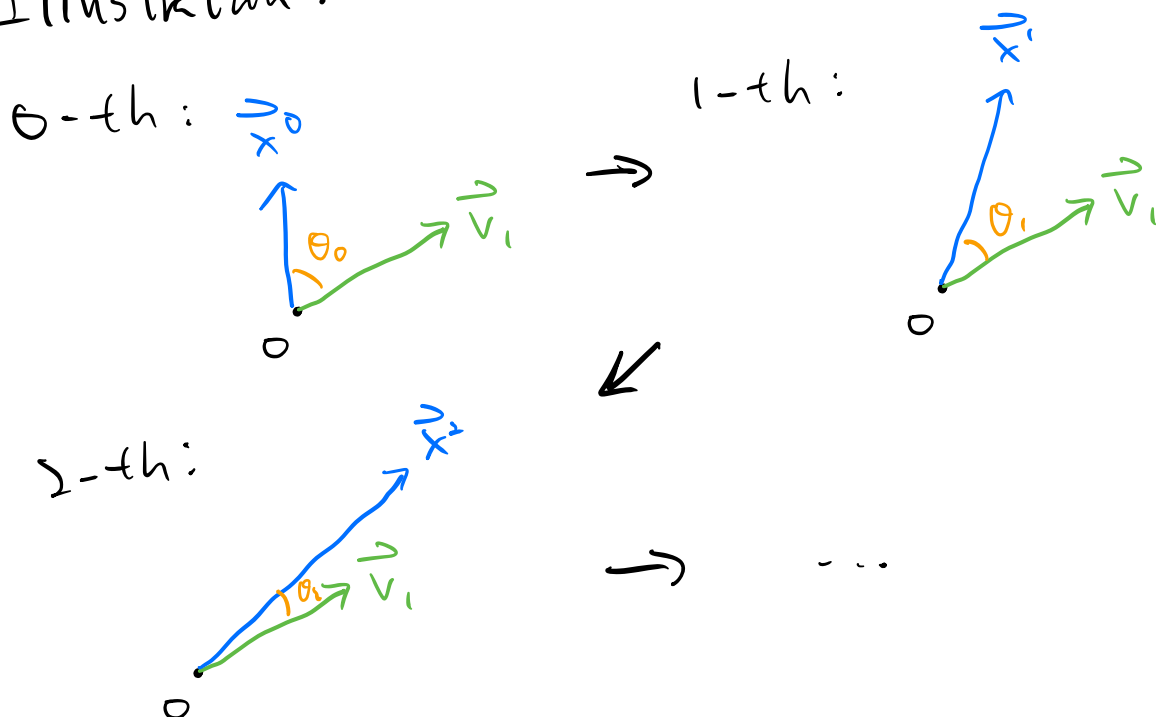
$$\begin{aligned} & \langle Q_{\vec{x}}^*, Q_{\vec{y}}^* \rangle && \|Q_{\vec{x}}^*\|_2^2 \\ &= (Q_{\vec{y}}^*)^* (Q_{\vec{x}}^*) &&= \langle Q_{\vec{x}}^*, Q_{\vec{x}}^* \rangle \\ &= \vec{y}^* Q Q^* \vec{x} &&= \langle \vec{x}, \vec{x} \rangle \\ &= \langle \vec{x}, \vec{y} \rangle &&= \|\vec{x}\|_2^2 \end{aligned}$$

$$T_2: \text{If } \cos \angle (\vec{x}^0, \vec{v}_i) \neq 0,$$

then

$$\tan \angle (\vec{x}^{k+1}, \vec{v}_i) \leq \frac{|\lambda_2|}{|\lambda_1|} \tan \angle (\vec{x}^k, \vec{v}_i).$$

Illustration:



pf (t_2):

$$\vec{x}^{k+1} = A \vec{x}^k$$

$$\Rightarrow \vec{x}^{k+1} = Q D Q^* \vec{x}^k$$

$$\Rightarrow Q^* \vec{x}^{k+1} = D (Q^* \vec{x}^k)$$

$$\Rightarrow \hat{x}^{k+1} = D \hat{x}^k$$

$$\cos^2 \angle (\vec{x}^k, \vec{v}_i)$$

$$= \cos^2 \angle (Q^* \vec{x}^k, Q^* \vec{v}_i)$$

$$= \cos^2 \angle (\hat{x}^k, \vec{e}_i)$$

$$(Q^* \vec{v}_i = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \vec{e}_i)$$

$$= \frac{|\langle \hat{x}^k, \vec{e}_i \rangle|^2}{\|\hat{x}^k\|_2^2 \|\vec{e}_i\|_2^2}$$

$$= \frac{|(\hat{x}^k)_i|^2}{\|\hat{x}^k\|_2^2}$$

$$\sin^2 \angle (\vec{x}^k, \vec{v}_i)$$

$$= 1 - \cos^2 \angle (\vec{x}^k, \vec{v}_i)$$

$$= \frac{\|\hat{x}^k\|_2^2 - |(\hat{x}^k)_i|^2}{\|\hat{x}^k\|_2^2}$$

$$= \frac{\sum_{i=2}^n |(\hat{x}^k)_i|^2}{\|\hat{x}^k\|_2^2}$$

$$\tan^2 \angle(\vec{x}^k, \vec{v}_1)$$

$$= \frac{\sin^2 \angle(\vec{x}^k, \vec{v}_1)}{\cos^2 \angle(\vec{x}^k, \vec{v}_1)}$$

$$= \frac{\sum_{i=2}^n |(\hat{x}^k)_i|^2}{|(\hat{x}^k)_1|^2}$$

$$= \frac{\sum_{i=1}^n |(\text{D} \hat{x}^{k-1})_i|^2}{|(\text{D} \hat{x}^{k-1})_1|^2}$$

$$= \frac{\sum_{i=1}^n |\lambda_i (\hat{x}^{k-1})_i|^2}{|\lambda_1 (\hat{x}^{k-1})_1|^2}$$

$$\leq \frac{|\lambda_2|^2 \sum_{i=1}^n |(\hat{x}^{k-1})_i|^2}{|\lambda_1|^2 |(\hat{x}^{k-1})_1|^2}$$

$$= \left| \frac{\lambda_2}{\lambda_1} \right|^2 \tan^2 \angle(\vec{x}^{k-1}, \vec{v}_1)$$

□

Exercise (Power Method with Shift).

With the above notation,

let $\mu \in \mathbb{R}$, $A - \mu I$ invertible,

$$|\lambda_1 - \mu| < |\lambda_2 - \mu| \leq \dots \leq |\lambda_n - \mu|,$$

consider the iterative scheme:

$$\vec{x}^{k+1} = (A - \mu I)^{-1} \vec{x}^k$$

Show

$$\tan \angle(\vec{x}^{k+1}, \vec{v}_1) \leq \frac{|\lambda_1 - \mu|}{|\lambda_2 - \mu|} \tan \angle(\vec{x}^k, \vec{v}_1)$$

Solution:

$$\text{Let } \hat{A} = (A - \mu I)^{-1}$$

Note $A - \mu I$

has eigenvalues: $\lambda_1 - \mu, \lambda_2 - \mu, \dots, \lambda_n - \mu$

$$|\lambda_1 - \mu| < |\lambda_2 - \mu| \leq \dots \leq |\lambda_n - \mu|$$

and shares the same eigenvectors with A .

$\therefore \hat{A}$ has eigenvalues:

$$\hat{\lambda}_1 = \frac{1}{\lambda_1 - \mu}, \hat{\lambda}_2 = \frac{1}{\lambda_2 - \mu}, \dots, \hat{\lambda}_n = \frac{1}{\lambda_n - \mu}$$

$$|\hat{\lambda}_1| > |\hat{\lambda}_2| \geq \dots \geq |\hat{\lambda}_n|$$

$$(A - \mu I) \vec{v}_i = (\lambda_i - \mu) \vec{v}_i$$

$$\Rightarrow \frac{1}{\lambda_i - \mu} \vec{v}_i = (A - \mu I)^{-1} \vec{v}_i$$

$\therefore \hat{A}$ and A share the same eigenvectors.

So, by (12),

$$\begin{aligned} \tan \angle(\vec{x}^{k+1}, \vec{v}_i) &\leq \frac{|\hat{\lambda}_2|}{|\hat{\lambda}_1|} \tan \angle(\vec{x}^k, \vec{v}_i) \\ &= \frac{|\lambda_1 - \mu|}{|\lambda_2 - \mu|} \tan \angle(\vec{x}^k, \vec{v}_i) \end{aligned}$$