

Lecture #24

03/08/2023

Recap of basics on eig. values & eig. vectors

- ① Computing eig. values $\{\lambda_i\}_{i=1}^n$ of $A \in \mathbb{R}^{n \times n}$ reduces to solving for the roots of a monic polynomial equation in degree n :

$$\det(\lambda I - A) = 0 \Rightarrow \lambda^n + c_1 \lambda^{n-1} + c_2 \lambda^{n-2} + \dots + c_{n-1} \lambda + c_n = 0$$

Characteristic polynomial

$$\text{Charpoly}(\lambda) = 0$$

→ has n roots

→ Some roots maybe real, some maybe complex conjugates, some maybe repeated

② Roots of charpoly(λ) have sensitive dependence on its coefficients c_1, c_2, \dots, c_n , which in turn depend on a complicated manner on the entries of A :

For example, $A \in \mathbb{R}^{2 \times 2}$:

$$\text{charpoly}(\lambda) \equiv \lambda^2 - \text{trace}(A)\lambda + \det(A) = 0$$

$$\begin{aligned} \text{Here, } c_1 &= -\text{trace}(A) \\ c_2 &= \det(A) \end{aligned}$$

But for general $A \in \mathbb{R}^{n \times n}$:

$$\text{charpoly}(\lambda) \equiv \sum_{k=0}^n (-1)^k \underbrace{\text{trace}(\Lambda^k A)}_{\text{trace of the } k^{\text{th}} \text{ exterior power of } A} \lambda^{n-k}$$

③ Structural info. about $A \rightsquigarrow$ Structural info on eig. values

Example:

- If $A = A^T$ (symmetric) then all eig. values λ_i of A are real.
- If A is symmetric and positive (semi)definite, then $\lambda_i > 0$ (≥ 0) for all $i = 1, \dots, n$

④ Similarity transformation: $A \mapsto MAM^{-1}$

where M is any nonsingular matrix, preserves the eig. values of A :

$$\lambda_i(A) = \lambda_i(MAM^{-1}) \text{ for all } i = 1, \dots, n$$

⑤ Let $A \in \mathbb{R}^{m \times n}$, $B \in \mathbb{R}^{n \times m}$

Then: $\underbrace{AB}_{m \times m}$ and $\underbrace{BA}_{n \times n}$ have the same nonzero eig. values.

⑥ The following sentences are equivalent:

A is (unitarily) diagonalizable



Matrix A is normal / non-defective



$AA^T = A^T A$ (Matrix A commutes with its transpose)



$A = V \Lambda V^{-1}$ } Λ is the diagonal matrix with eig. values along main diagonal

and Matrix V is invertible
stacking of eig. vector columns

\Updownarrow
 A has linearly independent eig. vectors $\{ \underline{v}^{(i)} \}_{i=1}^n$

where $\underline{v}^{(1)}$, $\underline{v}^{(2)}$, ..., $\underline{v}^{(n)}$
 \uparrow \uparrow \uparrow
eig. vector eig. vector eig. vector
corresponding corresponding corresponding
to λ_1 to λ_2 to λ_n

Last topic: Algorithms to solve special eig. value problems

Problem statement:

Compute the "dominant" / largest magnitude eig. value and its corresponding "dominant" eig. vector for a given $A \in \mathbb{R}^{n \times n}$ diagonalizable.

We order the eigen values as:

$$|\lambda_1| > |\lambda_2| \geq |\lambda_3| \geq \dots \geq |\lambda_n|$$

Strictly greater than \leftarrow needed for our algorithm for solving this problem

IDEA: perform vector fixed point recursion:

- Make a random guess for initial vector \underline{v}_0 .
- for $k = 0, 1, 2, \dots$ This algorithm

$$\underline{v}_{k+1} = \frac{A \underline{v}_k}{\|A \underline{v}_k\|_2};$$

← This algorithm is called the Power Iteration Algorithm

end

We claim: $\{v_k\} \xrightarrow{k \rightarrow \infty} v$
 \uparrow
 dominant eig. vector of A

Once we get converged \underline{v} , then extract the corresponding dominant eig. value as:

$$\lambda = \frac{\underline{v}^T A \underline{v}}{\underline{v}^T \underline{v}}$$

↖ because the definition
of eig. value: $A \underline{v} = \lambda \underline{v}$

Power Iteration:

\underline{v}_0 = random initial guess vector

for $k = 1, 2, \dots$

$$\underline{v}_k = \frac{A \underline{v}_{k-1}}{\|A \underline{v}_{k-1}\|_2};$$

$$\lambda = (\underline{v}(:, \text{end}))^T A \underline{v}(:, \text{end});$$

Theorem: Given $A \in \mathbb{R}^{n \times n}$ diagonalizable with eig. values ordered as

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

For "almost every" initial guess (\Leftrightarrow with probability 1),
the power iteration algorithm converges

linearly to the eig. vector $\underline{v}^{(1)}$ corresponding
to λ_1 , with worst-case convergence rate

$$|\lambda_2 / \lambda_1|.$$

Derivation / Proof:

Choose an initial vector \underline{x}_0 and decompose it into eig. vectors $\underline{v}^{(j)}$ of A :

$$\underline{x}_0 = \sum_{j=1}^n c_j \underline{v}^{(j)} \quad \left. \vphantom{\sum_{j=1}^n} \right\} \begin{array}{l} \text{This is always possible} \\ \text{for diagonalizable } A \end{array}$$

$\{c_j\}$ are constant coefficients

"almost every" $\Leftrightarrow c_1 \neq 0$

$$\begin{aligned} \text{Then, } A \underline{x}_0 &= \sum_{j=1}^n c_j \boxed{A \underline{v}^{(j)}} \\ &= \sum_{j=1}^n c_j \boxed{\lambda_j \underline{v}^{(j)}} \end{aligned}$$

$$\begin{aligned} \Rightarrow A^2 \underline{x}_0 &= A(A \underline{x}_0) \\ &= \sum_{j=1}^n c_j \lambda_j (A \underline{v}^{(j)}) \end{aligned}$$

$$= \sum_{j=1}^n c_j \lambda_j^2 \underline{v}^{(j)}$$

$$\begin{aligned} &\vdots \\ A^k \underline{x}_0 &= \sum_{j=1}^n c_j \lambda_j^k \underline{v}^{(j)} \quad \text{for any } k = 0, 1, 2, \dots \end{aligned}$$

$$\begin{aligned}
\therefore \underline{x}_{k+1} &= \frac{A \underline{x}_k}{\|A \underline{x}_k\|_2} \\
&= \frac{A^k \underline{x}_0}{\|A^k \underline{x}_0\|_2} \\
&= \frac{\sum_{j=1}^n c_j \lambda_j^k \underline{v}^{(j)}}{\left\{ \sum_{j=1}^n (c_j \lambda_j)^2 \right\}^{1/2}}
\end{aligned}$$

because $(\underline{v}^{(i)})^T \underline{v}^{(j)} = 1 \Rightarrow \|\underline{v}^{(i)}\|_2 = 1$ and $(\underline{v}^{(i)})^T \underline{v}^{(j)} = 0$ for all $i \neq j$

$$\Rightarrow \underline{x}_{k+1} = \cancel{c_1} \cancel{\lambda_1}^k \left\{ \underline{v}^{(1)} + \sum_{j=2}^n \frac{c_j}{c_1} \left(\frac{\lambda_j}{\lambda_1} \right)^k \underline{v}^{(j)} \right\}$$

$$\cancel{c_1} \cancel{\lambda_1}^k \left[1 + \sum_{j=2}^n \left(\frac{c_j}{c_1} \right)^2 \left(\frac{\lambda_j}{\lambda_1} \right)^{2k} \right]^{1/2}$$

($\because c_1 \neq 0$
with probability 1) ($\because \lambda_1 \neq 0$)

$$\Rightarrow \lim_{k \rightarrow \infty} \underline{x}_{k+1} = \underline{v}^{(1)} \quad \text{since } |\lambda_1| > |\lambda_j| \quad \text{for all } j=2, \dots, n$$

with convergence rate $\leq |\lambda_2/\lambda_1|$

" " " " = $|\lambda_2/\lambda_1|$ if $c_2 \neq 0$ 