

Power iteration & inverse iteration.

Note Title

(I) Power iteration - this method finds the abs. value of the largest e-value of A & its corr. e-vector.

Algorithm: choose x_0 (initial vector)

$i=0$ to convergence

$$y_1 = Ax_0$$

$$x_1 = \frac{Ax_0}{\|Ax_0\|}$$

$$y_2 = A \left(\frac{Ax_0}{\|Ax_0\|} \right)$$

$$= \frac{A^2 x_0}{\|A^2 x_0\|}$$

$$x_2 = \frac{A^2 x_0}{\|A^2 x_0\|}$$

$$y_{i+1} = Ax_i$$

$$x_{i+1} = y_{i+1} / \|y_{i+1}\|_2 \quad (\text{approx. e-vector})$$

$$\lambda_{i+1} = x_{i+1}^T A x_{i+1} \quad (\text{approx. e-value})$$

end.

- Consider the simplest case where $A = \text{diag}(\lambda_1, \dots, \lambda_n)$ with $|\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_n|$

In this case the e-vectors are columns e_i of the identity matrix.

Note that x_i can be written as $x_i = \frac{A^i x_0}{\|A^i x_0\|}$.

$$\text{Let } x_0 = \begin{pmatrix} \xi_1 \\ \vdots \\ \xi_n \end{pmatrix}, \quad \xi_1 \neq 0.$$

$$\text{Then } A^i x_0 = A^i \begin{pmatrix} \xi_1 \\ \vdots \\ \xi_n \end{pmatrix} = \begin{pmatrix} \xi_1 \lambda_1^i \\ \vdots \\ \xi_n \lambda_n^i \end{pmatrix} = \xi_1 \lambda_1^i \begin{pmatrix} 1 \\ \frac{\xi_2}{\xi_1} \left(\frac{\lambda_2}{\lambda_1}\right)^i \\ \vdots \\ \frac{\xi_n}{\xi_1} \left(\frac{\lambda_n}{\lambda_1}\right)^i \end{pmatrix}$$

Since each $|\lambda_i| \leq |\lambda_1|$, $A^i x_0 \mapsto \pm \xi_1 \lambda_1^i e_1$

$$\therefore x_i = \frac{A^i x_0}{\|A^i x_0\|} \mapsto \pm e_1 = \text{e-vector corr. to largest e-value } \lambda_1.$$

$$x_i \mapsto \pm e_1 \Rightarrow x_i^T A x_i \mapsto \lambda_1 = \text{largest e-value.}$$

- Now let A be a diagonalizable matrix i.e. \exists invertible matrix P such that $A = P \Lambda P^{-1}$, $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$
 $|\lambda_1| \geq \dots \geq |\lambda_n|$.

Let $P = [p_1 | \dots | p_n]$, where p_1, \dots, p_n are e-vectors with $\|p_i\|_2 = 1$.

Let $x_0 = P \begin{pmatrix} \xi_1 \\ \vdots \\ \xi_n \end{pmatrix}$, $\xi_1 \neq 0$.

Then $A^i = (P \Lambda P^{-1})^i = P \Lambda^i P^{-1}$

So $A^i x_0 = P \Lambda^i P^{-1} P \begin{pmatrix} \xi_1 \\ \vdots \\ \xi_n \end{pmatrix} = P \Lambda^i \begin{pmatrix} \xi_1 \\ \vdots \\ \xi_n \end{pmatrix} = P \begin{pmatrix} \xi_1 \lambda_1^i \\ \vdots \\ \xi_n \lambda_n^i \end{pmatrix} = P \xi_1 \lambda_1^i \begin{pmatrix} 1 \\ \frac{\xi_2}{\xi_1} \left(\frac{\lambda_2}{\lambda_1}\right)^i \\ \vdots \\ \frac{\xi_n}{\xi_1} \left(\frac{\lambda_n}{\lambda_1}\right)^i \end{pmatrix}$

$\therefore A^i x_0 \mapsto \xi_1 \lambda_1^i p_1 \quad (p_1 = p_1)$

$\therefore x_i = \frac{A^i x_0}{\|A^i x_0\|} \mapsto p_1 \text{ (e-vector corr. to } \lambda_1) \quad \left(\text{as } i \rightarrow \infty \right)$

$\& \lambda_i = x_i^T A x_i \mapsto p_1^T A p_1 = p_1^T \lambda_1 p_1 = \lambda_1$.

Remarks: ① We need to choose x_0 such that its first component is non-zero. This is mostly okay if x_0 is chosen at random.

② The rate of convergence is completely dependent on the gap between λ_1 & λ_2 (the eigengap).

If $\lambda_1 \gg \lambda_2$, then convergence is fast;

on the other hand, if $\frac{\lambda_2}{\lambda_1}$ is close to 1, the

convergence is very slow.

③ If A is real & the largest e -value is complex then there are 2 complex-conjugate e -values with the same abs. value; then this method does not work (same case if 2 real nos. k & $-k$ are e -values of A)

(II) Inverse iteration (inverse power method)

useful when we know (or have a good approx, say σ) for an e -value λ and we want to find the corr. e -vector.

Idea: apply power method to a 'shift': $(A - \sigma I)^{-1}$

This makes the power method converge to an e -value closest to σ .

Algorithm: $i=0$ to convergence (x_0 : initial vector)

$$\left| \begin{array}{l} y_{i+1} = (A - \sigma I)^{-1} x_i \\ x_{i+1} = y_{i+1} / \|y_{i+1}\|_2 \quad (\text{approx. } e\text{-vector}) \\ \lambda_{i+1} = x_{i+1}^T A x_{i+1} \quad (\text{approx. } e\text{-value}). \end{array} \right.$$

end.

Note: $A = P \Lambda P^{-1} \Rightarrow A - \sigma I = P (\Lambda - \sigma I) P^{-1}$

$\Lambda = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}$

$\therefore (A - \sigma I)^{-1} = P \underbrace{(\Lambda - \sigma I)^{-1}} P^{-1}$

$\therefore (A - \sigma I)^{-1}$ has the same e -vectors as A with corr. e -values $(\lambda_j - \sigma)^{-1}$.

Suppose $\lambda_k - \sigma \leq \lambda_i - \sigma \quad \forall i$ (ie. λ_k is the e -value closest to σ)

ie. $(\lambda_i - \sigma)^{-1} \leq (\lambda_k - \sigma)^{-1} \quad \forall i$

$$\begin{aligned}
 \text{Then } (A - \sigma I)^{-i} x_0 &= P (A - \sigma I)^{-i} P^{-1} P \begin{pmatrix} \xi_1 \\ \vdots \\ \xi_n \end{pmatrix} \\
 &= P \begin{pmatrix} \xi_1 (\lambda_1 - \sigma)^{-i} \\ \vdots \\ \xi_n (\lambda_n - \sigma)^{-i} \end{pmatrix} \\
 &= \xi_k (\lambda_k - \sigma)^{-i} P \begin{pmatrix} \frac{\xi_1}{\xi_k} \left(\frac{\lambda_k - \sigma}{\lambda_1 - \sigma} \right)^i \\ \vdots \\ 1 \\ \vdots \\ \frac{\xi_n}{\xi_k} \left(\frac{\lambda_k - \sigma}{\lambda_n - \sigma} \right)^i \end{pmatrix} \quad k^{\text{th}} \text{ spot}
 \end{aligned}$$

$$\text{Since } \left| \frac{\lambda_k - \sigma}{\lambda_i - \sigma} \right| < 1, \quad \text{as } i \rightarrow \infty, \quad \frac{(A - \sigma I)^{-i} x_0}{\|(A - \sigma I)^{-i} x_0\|} \mapsto P e_k = P_k$$

" e-vector
corr. to λ_k .

$$\therefore \lambda_i = x_i^T A x_i \mapsto \lambda_k \quad \text{as } i \rightarrow \infty$$