

HW5

(1(a))

Since A is symmetric, $A^T = A$

If A has complex eigenvalues, they must appear in conjugate pairs

Suppose for the sake of contradiction that $\lambda \neq \bar{\lambda}$ are eigenvalues of A

$$A\vec{x} = \lambda\vec{x}, \quad A\vec{x} = \bar{\lambda}\vec{x}$$

$$\vec{x}^T \lambda \vec{x} = \vec{x}^T A \vec{x} = (\vec{x}^T A^T \vec{x})^T = (\vec{x}^T A \vec{x})^T = (\vec{x}^T \bar{\lambda} \vec{x})^T = \vec{x}^T \bar{\lambda} \vec{x}$$

$$\Rightarrow \lambda = \bar{\lambda} \text{ contradict}$$

So all eigenvalues are real

□

(b)

$$R_1 = 2 + 0.3 + 0.7 = 3 \quad D_1 = \{ |z+6| \leq 3 \} = [-9, -6]$$

$$R_2 = 2 + 0.1 + 0.05 = 2.15 \quad D_2 = \{ |z+4| \leq 2.15 \} = [-6.15, -1.95]$$

$$R_3 = 0.3 + 0.1 + 0.1 + 0.1 = 0.6 \quad D_3 = \{ |z-2| \leq 0.6 \} = [1.4, 2.6]$$

$$R_4 = 0.05 + 0.1 = 0.15 \quad D_4 = \{ |z-4| \leq 0.15 \} = [3.85, 4.15]$$

$$R_5 = 0.7 + 0.1 = 0.8 \quad D_5 = \{ |z-6| \leq 0.8 \} = [5.2, 6.8]$$

$$\text{So } D = D_1 \cup D_2 \cup D_3 \cup D_4 \cup D_5 = [-9, -1.95] \cup [1.4, 2.6] \cup [3.85, 4.15] \cup [5.2, 6.8]$$

(c)

No. Since D_1 and D_2 are not disjoint, it is possible that λ with greatest absolute value lies in the intersection of D_1 and D_2 , and thus is a root of multiplicity 2 of $\det(A - \lambda I) = 0$, i.e. λ is not simple.

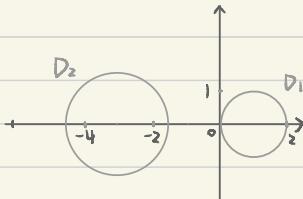
(d)

Since $0 \notin D$, A is invertible.

2(a)

$$R_1 = 1 \quad D_1 = [0, 2]$$

$$R_2 = |1-i| = \sqrt{2} \quad D_2 = [-3-\sqrt{2}, -3+\sqrt{2}]$$



(b)

Since D_1 and D_2 are disjoint, D_3 must intersect with one of the two disks

$$R_3 = |2i| = 2 \quad ([z-2, z+2] \cap D_1) \cup ([z-2, z+2] \cap D_2) \neq \emptyset$$

$$\text{So } z \in [-5-\sqrt{2}, 4]$$

(c)

$$D_1 \cap D_2 \cap D_3 \neq \emptyset$$

$$\text{So } z \in [-2, -1+\sqrt{2}]$$

3(a)

See the code

(b)

See the code

When $x_0 = [1 \ 2 \ -1]^T$, x_k converge to around $[0.7, 0, -0.7]$, λ_i converge to -5.97

When $x_0 = [1 \ 2 \ 1]^T$, x_k converge to around $[0.58, 0.58, 0.58]$, λ_i converge to 3.00

Compared to result of Matlab inbuilt eig function x_k and λ_k converges to the largest $|\lambda_i|$ and its corresponding eigenvector \vec{v}_i .

Note that $[1 \ 2 \ 1]^T \vec{v}_1 = 0$ violates the prerequisite of power method, the algorithm converge to the second largest $|\lambda_2|$.

(c)

See the code

(d)

See the code. As I picked $\alpha_1, \alpha_2, \alpha_3$ each close to $\lambda_1, \lambda_2, \lambda_3$, and with appropriate choice of x_0 , λ each converge to $\lambda_1 \approx -6$, $\lambda_2 \approx 0$, $\lambda_3 \approx 3$, \vec{x}_k each converge to $\vec{v}_1 = [0.7, 0, -0.7]$, $\vec{v}_2 = [-0.4, 0.8, -0.4]$, $\vec{v}_3 = [-0.58, -0.58, -0.58]$, the corresponding eigenvectors.

4(a)

$$\begin{aligned} \vec{x}_k &= c_1 \lambda_1^k \vec{v}_1 + \sum_{i=2}^n c_i \lambda_i^k \vec{v}_i = c_1 \lambda_1^k (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i) \\ r_k &= \frac{(c_1 \lambda_1^k (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i))^T A (c_1 \lambda_1^k (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i))}{(c_1 \lambda_1^k (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i))^T c_1 \lambda_1^k (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i)} \\ &= \frac{c_1^2 \lambda_1^{2k} (\vec{v}_1^T + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T)^T A (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i)}{c_1^2 \lambda_1^{2k} (\vec{v}_1^T + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T) (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i)} \\ &= \frac{(\vec{v}_1^T A + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T A) (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i)}{\vec{v}_1^T \vec{v}_1 + \vec{v}_1^T \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T \vec{v}_1 + (\sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T) (\sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i)} \end{aligned}$$

$$\begin{aligned} \vec{v}_1^T \vec{v}_j &= \begin{cases} 0 & i \neq j \\ 1 & i=j \end{cases} \\ &= \frac{\vec{v}_1^T \lambda_1 \vec{v}_1 + \vec{v}_1^T \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \lambda_i \vec{v}_i + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T \lambda_i \vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T \vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \lambda_i \vec{v}_1^T \vec{v}_i}{\vec{v}_1^T \vec{v}_1 + \vec{v}_1^T \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i + \sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T \vec{v}_1 + (\sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i^T) (\sum_{i=2}^n \frac{c_i}{c_1} (\frac{\lambda_i}{\lambda_1})^k \vec{v}_i)} \\ &= \frac{\lambda_1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^k \lambda_i}{1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k}} = \frac{\lambda_1 (1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k+1})}{1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k}} \\ &= \frac{\lambda_1 (1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k} + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k+1} - \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k})}{1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k}} \\ &= \lambda_1 \left(1 + \frac{\sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k} (\frac{\lambda_i}{\lambda_1} - 1)}{1 + \sum_{i=2}^n (\frac{c_i}{c_1})^2 (\frac{\lambda_i}{\lambda_1})^{2k}} \right) \end{aligned}$$

$$a_k \left(\frac{\lambda_2}{\lambda_1} \right)^{-2k} = \frac{\sum_{i=2}^n \left(\frac{c_i}{c_1} \right)^2 \left(\frac{\lambda_2}{\lambda_1} \right)^{2k} \left(\frac{\lambda_i}{\lambda_1} - 1 \right)}{1 + \sum_{i=2}^n \left(\frac{c_i}{c_1} \right)^2 \left(\frac{\lambda_2}{\lambda_1} \right)^{2k}}$$

Since for $|\lambda_1| > |\lambda_2| \geq |\lambda_3| \geq \dots \geq |\lambda_n|$, $\lim_{k \rightarrow \infty} \left(\frac{\lambda_2}{\lambda_1} \right)^{2k} = 0$

$$a_k \left(\frac{\lambda_2}{\lambda_1} \right)^{-2k} = \sum_{i=2}^n \left(\frac{c_i}{c_1} \right)^2 \left(\frac{\lambda_2}{\lambda_1} \right)^{2k} \left(\frac{\lambda_i}{\lambda_1} - 1 \right)$$

$$|\lambda_2| \geq |\lambda_3| \geq \dots \geq |\lambda_j| \geq \dots \geq |\lambda_n|. \text{ consider } \{\lambda_2, \lambda_3, \dots, \lambda_j\} \text{ such that } \lambda_3 = \lambda_4 = \dots = \lambda_j = \lambda_2$$

$$a_k \left(\frac{\lambda_2}{\lambda_1} \right)^{-2k} = \sum_{i=2}^j \left(\frac{c_i}{c_1} \right)^2 \left(\frac{\lambda_2}{\lambda_1} \right)^{2k} \left(\frac{\lambda_i}{\lambda_1} - 1 \right) + \sum_{i=j+1}^n \left(\frac{c_i}{c_1} \right)^2 \left(\frac{\lambda_2}{\lambda_1} \right)^{2k} \left(\frac{\lambda_i}{\lambda_1} - 1 \right) = \sum_{i=2}^j \left(\frac{c_i}{c_1} \right)^2 \left(\frac{\lambda_2}{\lambda_1} \right)^{2k} \left(\frac{\lambda_i}{\lambda_1} - 1 \right) = C$$

Thus $r_k = \lambda_1 (1 + a_k)$ where $a_k \left(\frac{\lambda_2}{\lambda_1} \right)^{-2k} \rightarrow C$ as $k \rightarrow \infty$. C does not depend on k . \square

(b)

By Gershgorin Thm, $\lambda_{\max} \in [20, 22]$

$$\vec{x}_1 = A\vec{x}_0 = \begin{bmatrix} * \\ * \\ * \\ 21 \end{bmatrix} \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 21 \end{bmatrix} = \lambda_{\max} \vec{x}_0 \quad \vec{y}_1 = \frac{\vec{x}_1}{\|\vec{x}_1\|} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 21 \end{bmatrix}$$

Note that $\lambda_{\max} \vec{x}_0 = A\vec{x}_0$, \vec{x}_0 is the corresponding eigenvector of λ_{\max}

\vec{y}_k generated by power method converge to the eigenvector belong to λ_{\max} .

(c)

$$\varepsilon_k = |r_k - \lambda_1| = |\lambda_1 (1 + a_k) - \lambda_1| = |\lambda_1 a_k|$$

$$\varepsilon_{k+5} = |\lambda_1 a_{k+5}|$$

Since $\lambda_1 \approx 21$, $\lambda_2 \approx -9$, $a_k \left(\frac{\lambda_2}{\lambda_1} \right)^{-2k} \rightarrow C$ as $k \rightarrow \infty$

$$\lim_{k \rightarrow \infty} \frac{|\varepsilon_{k+5}|}{|\varepsilon_k|} = \lim_{k \rightarrow \infty} \frac{|a_{k+5}|}{|a_k|} = \lim_{k \rightarrow \infty} \frac{|C \left(\frac{\lambda_2}{\lambda_1} \right)^{2(k+5)}|}{|C \left(\frac{\lambda_2}{\lambda_1} \right)^{2k}|} = \left(\frac{\lambda_2}{\lambda_1} \right)^{10}$$

$$\rho = -\log_{10} \left(\left(\frac{\lambda_2}{\lambda_1} \right)^{10} \right) \approx 3.68$$

So we could gain 3 to 4 more correct decimals

5(a)

Prove by induction

Base Case: $- A_P^{(3)} = \begin{bmatrix} 0 & 0 & -a_0 \\ 1 & 0 & -a_1 \\ 0 & 1 & -a_2 \end{bmatrix}$ A of odd size

$$\det(A_P^{(3)} - xI) = -x(-x(-a_2 - x) + a_1) - a_0 = -x^3 - a_2x^2 - a_1x - a_0 = -P^{(3)}(x)$$

$$\det(A_P^{(3)} - xI) = 0 \Leftrightarrow P^{(3)}(x) = 0$$

$$- A_P^{(4)} = \begin{bmatrix} 0 & 0 & 0 & -a_0 \\ 1 & 0 & 0 & -a_1 \\ 0 & 1 & 0 & -a_2 \\ 0 & 0 & 1 & -a_3 \end{bmatrix} \quad \text{A of even size}$$

$$\det(A_P^{(4)} - xI) = -x(-x(-x(-a_3 - x) + a_2) - a_1) + a_0$$

$$= x^4 + a_3x^3 + a_2x^2 + a_1x + a_0 = P^{(4)}(x)$$

$$\det(A_P^{(4)} - xI) = 0 \Leftrightarrow P^{(4)}(x) = 0$$

Induction:

$$A_P^{(n)} = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 & -a_0 \\ 1 & 0 & 0 & \cdots & 0 & -a_1 \\ \vdots & & & & & \\ 0 & 0 & 0 & \cdots & 1 & -a_{n-1} \end{bmatrix} \quad A_P^{(n+1)} = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 & -a_0 \\ 1 & 0 & 0 & \cdots & 0 & -a_1 \\ \vdots & & & & & \\ 0 & 0 & 0 & \cdots & 1 & -a_n \end{bmatrix} \quad \text{triangular}$$

$$\det(A_P^{(n+1)} - xI) = -x \cdot \det \begin{bmatrix} -x & 0 & 0 & \cdots & 0 & -a_1 \\ 1-x & 0 & 0 & \cdots & 0 & -a_2 \\ \vdots & & & & & \\ 0 & 0 & 0 & \cdots & 1 & -a_{n-1} \end{bmatrix} + (-1)^{n+2}(-a_0) \cdot \det \begin{bmatrix} 1-x & 0 & 0 & \cdots & 0 \\ 0 & 1-x & 0 & \cdots & 0 \\ \vdots & & & & \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}$$

- When n is even, $n+1$ is odd

$$\det(A_P^{(n+1)} - xI) = -x(x^n + a_nx^{n-1} + \cdots + a_1) - a_0 = -x^{n+1} - a_nx^n - \cdots - a_1x - a_0 = -P^{(n+1)}(x)$$

- When n is odd, $n+1$ is even

$$\det(A_P^{(n+1)} - xI) = -x(-x^n - a_nx^{n-1} - \cdots - a_1) + a_0 = x^{n+1} + a_nx^n + \cdots + a_1x + a_0 = P^{(n+1)}(x)$$

$$\text{In either case, } \det(A_P^{(n+1)} - xI) = 0 \Leftrightarrow P^{(n+1)}(x) = 0$$

Thus the roots of $P(x)$ could be computed as the eigenvalues of A_P . □

(b)

See the code

6.

$$\vec{x} = \vec{b} = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \quad \vec{v}' = \vec{x} + c\vec{e}_1 = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} + 3\vec{e}_1 = \begin{bmatrix} 4 \\ 2 \\ 2 \end{bmatrix} \quad \vec{v} = \begin{bmatrix} 0 \\ 4 \\ 2 \end{bmatrix}$$

$$H_1 = I - \frac{2}{\vec{v}^T \vec{v}} \vec{v} \vec{v}^T = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -\frac{2}{3} & -\frac{2}{3} & -\frac{2}{3} \\ 0 & -\frac{2}{3} & \frac{2}{3} & -\frac{2}{3} \\ 0 & -\frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \end{bmatrix} \quad H_1 A H_1 = \begin{bmatrix} 2 & -3 & 0 & 0 \\ -3 & 1 & 3 & 4 \\ 0 & 3 & -3 & -9 \\ 0 & 4 & -9 & -2 \end{bmatrix}$$

$$\vec{x} = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \quad \vec{v}' = \vec{x} + c\vec{e}_1 = \begin{bmatrix} 3 \\ 4 \end{bmatrix} + 5\vec{e}_1 = \begin{bmatrix} 8 \\ 4 \end{bmatrix} \quad \vec{v} = \begin{bmatrix} 0 \\ 0 \\ 8 \\ 4 \end{bmatrix}$$

$$H_2 = I - \frac{2}{\vec{v}'^T \vec{v}'} \vec{v}' \vec{v}'^T = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -\frac{3}{5} & -\frac{4}{5} \\ 0 & 0 & -\frac{4}{5} & \frac{3}{5} \end{bmatrix} \quad H_2 H_1 A H_1 H_2 = \begin{bmatrix} 2 & -3 & 0 & 0 \\ -3 & 1 & -5 & 0 \\ 0 & -5 & -11 & -3 \\ 0 & 0 & -3 & 6 \end{bmatrix}$$

$$Q = H_2 H_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -\frac{1}{3} & -\frac{2}{3} & -\frac{2}{3} \\ 0 & \frac{14}{15} & -\frac{2}{15} & -\frac{1}{3} \\ 0 & \frac{2}{15} & -\frac{11}{15} & \frac{2}{3} \end{bmatrix}$$

7(a)(b)

See the code

(c)

From the graph, we can see that larger k leads to a wider spread in the value of eigenvalues.

Note that power method iterations $\vec{x}_k = c_1 \lambda_1^k (\vec{v}_1 + \sum_{i=2}^n \frac{c_i}{c_1} (\lambda_i/\lambda_1)^k \vec{v}_i)$

$\vec{x}_k - c_1 \lambda_1^k \vec{v}_1 \approx C \left(\frac{\lambda_2}{\lambda_1} \right)^k$, so the sequence converges at the speed $\frac{|\lambda_2|}{|\lambda_1|}$.
When $k < 1$, $\frac{|\lambda_2|}{|\lambda_1|}$ is smaller, with λ_1 fixed at one.

So $k < 1$ improves the speed of convergence.

8(a)

$L_k(x_i) = \begin{cases} 1 & i=k \\ 0 & i \neq k \end{cases}$ could be constructed as a linear combination of basis of P_n .

So $L_k(x_i) \in P_n$

$$\forall i \in \{0, \dots, n\}, \sum_{k=0}^n \alpha_k L_k(x_i) = 0$$

$$\alpha_0 L_0(x_i) + \alpha_1 L_1(x_i) + \dots + \alpha_n L_n(x_i) = \alpha_i L_i(x_i) = \alpha_i = 0$$

$$\text{So } \alpha_0 = \alpha_1 = \dots = \alpha_n = 0$$

(b)

$$\forall i \in \{0, \dots, n\}, \alpha_0 L_0(x_i) + \alpha_1 L_1(x_i) + \dots + \alpha_n L_n(x_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_n x_i^n$$

$$\alpha_i = \alpha_i L_i(x_i) = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \dots + \beta_n x_i^n = (1 \ x_i \ x_i^2 \ \dots \ x_i^n) \vec{\beta}$$

$$\vec{\alpha} = \begin{bmatrix} \beta_0 + x_0 \beta_1 + x_0^2 \beta_2 + \dots + x_0^{n-1} \beta_{n-1} + x_0^n \beta_n \\ \beta_0 + x_1 \beta_1 + x_1^2 \beta_2 + \dots + x_1^{n-1} \beta_{n-1} + x_1^n \beta_n \\ \vdots \\ \beta_0 + x_n \beta_1 + x_n^2 \beta_2 + \dots + x_n^{n-1} \beta_{n-1} + x_n^n \beta_n \end{bmatrix} = V \vec{\beta}$$

(c)

$\text{cond}(V) \gg 1$, this basis transform cannot be performed accurately.