

$$|\mu - \lambda_k| \in \text{cond}(X) \cdot \|E\|$$

4.2 Properties and Transformations

What do the following transformations of the eigenvalue problem $A\mathbf{x} = \lambda\mathbf{x}$ do?

- Shift. $A \rightarrow A - \sigma I$ $(A - \sigma I)\vec{x} = (\lambda - \sigma)\vec{x}$
- Inversion. $A \rightarrow A^{-1}$ $A^{-1}\mathbf{x} = \frac{1}{\lambda}\mathbf{x}$
- Power. $A \rightarrow A^k$ $A^k\mathbf{x} = \lambda^k\mathbf{x}$
- Polynomial $A \rightarrow aA^2 + bA + cI$
 $(aA^2 + bA + cI)\mathbf{x} = (a\lambda^2 + b\lambda + c)\mathbf{x}$
- Similarity $T^{-1}AT$ with T invertible

$$B = T^{-1}AT$$

Schur form

- Show: Every matrix is orthonormally similar to an upper triangular matrix, i.e.

$$A = QUQ^T.$$

$$A = Q \begin{array}{|c|} \hline \text{wavy} \\ \hline 0 \end{array} Q^T$$

This is called the Schur form or Schur factorization.

Also, if we knew how to compute this, how would it help us find eigenvalues?

$$A\vec{x} = \lambda\vec{x} \quad V = \text{span}\{\vec{x}\}$$


$$A : V \rightarrow V$$

$$V^\perp \rightarrow V \oplus V^\perp$$

$$A = \underbrace{\begin{pmatrix} | & & \\ \vec{x} & \vec{x}_1 & \dots & \vec{x}_{n-1} \\ | & & \end{pmatrix}}_{Q_1} \begin{pmatrix} \lambda & & \\ \vdots & \text{X} & \\ \vdots & & \end{pmatrix} \begin{matrix} \\ \\ \hline \\ \hline \\ \\ \\ \end{matrix} Q_1^T$$

$V \quad V^\perp$

if eigenvalue complex,
but if we want real
Schur form,
2x2 bump



4.3 Computing Eigenvalues

Power Iteration

- What are the eigenvalues of A^{1000} ?

Assume $|\lambda_1| > |\lambda_2| > \dots > |\lambda_n|$ with eigenvectors $\mathbf{x}_1, \dots, \mathbf{x}_n$.

Further assume $\|\mathbf{x}_i\| = 1$.

$$\begin{aligned} \vec{x} &= \alpha_1 \vec{x}_1 + \dots + \alpha_n \vec{x}_n \\ \frac{A^{1000} \vec{x}}{\lambda_1^{1000}} &= \frac{\alpha_1 \lambda_1^{1000} \vec{x}_1 + \alpha_2 \left(\frac{\lambda_2}{\lambda_1}\right)^{1000} \vec{x}_2 + \dots + \alpha_n \left(\frac{\lambda_n}{\lambda_1}\right)^{1000} \vec{x}_n}{\lambda_1^{1000}} \end{aligned}$$

"Power iteration"

- Problems:
- overflow (divide by $\|\mathbf{x}\|$)
 - $|\lambda_1| = |\lambda_2| \rightarrow$ **Problem**
 - $\alpha_1 = 0 \rightarrow A^{1000} \vec{x}$ has no comp. in \vec{x}_1
but: rounding error

Power Iteration: Issues?

- What could go wrong with Power Iteration?

What about Eigenvalues?

- Power Iteration generates eigenvectors. What if we would like to know eigenvalues?

$$\lambda \approx \frac{\vec{x}^T A \vec{x}}{\vec{x}^T \vec{x}}$$

\vec{x} : approx eigenvector

↑
Rayleigh quotient

Convergence of Power Iteration

- What can you say about the convergence of the power method?
Say $\mathbf{v}_1^{(k)}$ is the k th estimate of the eigenvector \mathbf{x}_1 , and

$$e_k = \|\mathbf{x}_1 - \mathbf{v}_1^{(k)}\|.$$

$\overset{\circ}{x}_0$

$$x_1 := Ax_0$$

$$x_2 := Ax_1 = A^2x_0$$

$$x_{k+1} = Ax_k$$

$$e_{k+1} \approx \frac{|\lambda_2|}{|\lambda_1|} \cdot e_k \quad \leftarrow \text{linear convergence}$$

↑ too slow

With shift: $e_{k+1} \approx \frac{|\lambda_2 - \sigma|}{|\lambda_1 - \sigma|} \cdot e_k$

With shift and inverse: $e_{k+1} \approx \frac{|\lambda_1 - \sigma|}{|\lambda_2 - \sigma|} \cdot e_k$

Rayleigh Quotient Iteration

- Describe inverse iteration.

$$x_{k+1} := (A - \sigma)^{-1} x_k$$



"new" σ

← amplifies eigenvalue that's closest to sigma

- ~~Describe Rayleigh Quotient Iteration:~~

$$e_{k+1} \approx \left| \frac{\lambda_{\text{closest}} - \sigma}{\lambda_{\text{second-closest}} - \sigma} \right| e_k$$

Pick $\sigma = \frac{x^T A x}{x^T x}$, then this Rayleigh quotient iteration.

Demo: Power Iteration and its Variants

Computing Multiple Eigenvalues

- All Power Iteration Methods compute one eigenvalue at a time.
What if I want *all* eigenvalues?