

Lecture 15

Numerical Analysis

March 26, 2018

Last time:

- Eigenvalue review

$$A\underline{v} = \lambda\underline{v}$$

$$\Leftrightarrow \det(A - \lambda I) = 0$$

- Gerschgorin's Theorem

All  $\lambda$  lie in  $\bigcup_i D_i$  with

$$D_i = \left\{ z \in \mathbb{C} \text{ s.t. } |z - a_{ii}| \leq \sum_{j \neq i} |a_{ij}| \right\}$$

- The Power Method

If  $|\lambda_j| > |\lambda_l|$  for all  $l \neq j$ , then

$$A^k \underline{v} = c_1 \lambda_1^k \hat{\underline{v}}_1 + \dots + c_n \lambda_n^k \hat{\underline{v}}_n$$

$$\begin{array}{l} \nearrow \\ \text{randomly chosen vector} \end{array} \quad \approx c_j \lambda_j^k \hat{\underline{v}}_j \quad \left( \hat{\underline{v}} \text{ denotes a unit vector} \right)$$

This means that

$$\frac{A^{k+1} \underline{v}}{\|A^k \underline{v}\|} \approx \frac{c_j \lambda_j^{k+1} \hat{\underline{v}}_j}{|c_j| |\lambda_j^k| \|\hat{\underline{v}}_j\|} \approx \lambda_j \hat{\underline{v}}_j$$

$\uparrow$   
 unit vector,  
 $j^{\text{th}}$  eigenvector.

## The Power Method

Start with random  $\underline{w}_0$ .

① compute  $\hat{\underline{w}}_0 = \frac{\underline{w}_0}{\|\underline{w}_0\|}$  ← 2-norm.

② set  $\underline{w}_{k+1} = A \hat{\underline{w}}_k$ .

③ (normalize  $\hat{\underline{w}}_{k+1} = \frac{\underline{w}_{k+1}}{\|\underline{w}_{k+1}\|}$ )  
 (approximate)

To calculate  $\lambda_1$ , where  $|\lambda_1| > |\lambda_l|$ ,  $l \neq 1$ ,  
 there are two basic options:

①  $\lambda_1 \approx (A \hat{\underline{w}}_k)_i / (\hat{\underline{w}}_k)_i$  ← this may be small  
 ←  $i^{\text{th}}$  component

② set  $\lambda_1 \approx (A \hat{\underline{w}}_k, \hat{\underline{w}}_k)$  (since  $\|\hat{\underline{w}}_k\| = 1$ )

How fast does the power method converge?

Examine the quantity  $\underline{\hat{W}}_k - \underline{\hat{V}}_1$ :

If  $k$  is sufficiently large, then

$\underline{\hat{W}}_k \approx c_1 \lambda_1^k \underline{\hat{V}}_1$ , then (assume  $c_1 > 0$ )

$$\begin{aligned}\underline{\hat{W}}_k &\approx \frac{1}{|c_1| |\lambda_1|^k} \left( c_1 \lambda_1^k \underline{\hat{V}}_1 + c_2 \lambda_2^k \underline{\hat{V}}_2 + \dots + c_n \lambda_n^k \underline{\hat{V}}_n \right) \\ &= \underline{\hat{V}}_1 + \frac{c_2}{c_1} \frac{\lambda_2^k}{|\lambda_1|^k} \underline{\hat{V}}_2 + \dots\end{aligned}$$

Therefore

$$\| \underline{\hat{W}}_k - \underline{\hat{V}}_1 \| \approx \left\| \underline{\hat{V}}_1 + \frac{c_2}{c_1} \frac{\lambda_2^k}{|\lambda_1|^k} \underline{\hat{V}}_2 + \dots - \underline{\hat{V}}_1 \right\|$$

$$\sim \mathcal{O}\left(\left|\frac{\lambda_2}{\lambda_1}\right|^k\right)$$

↖ the convergence of the Power Method depends on the gap in the eigenvalues.

This means that if  $|\frac{\lambda_2}{\lambda_1}| \approx 1$  then convergence is very slow.

How can this idea be accelerated?

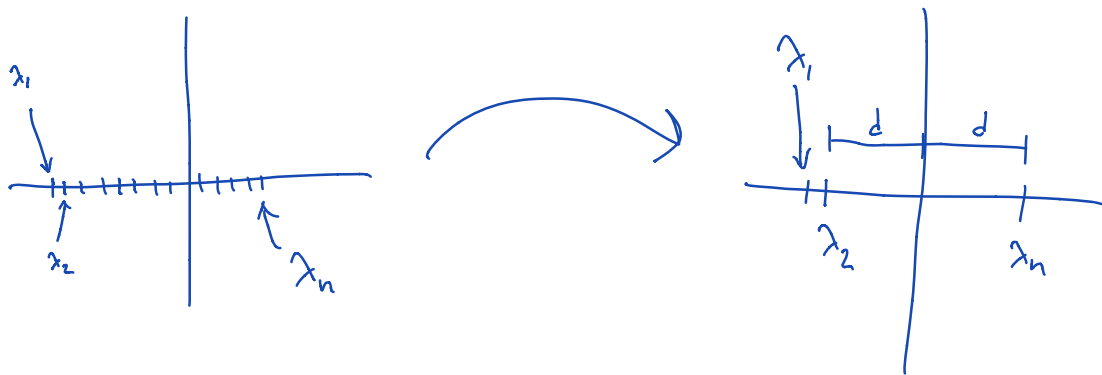
Idea one: Power method with shifts:

If  $A$  has eigenvalues  $\lambda_1, \dots, \lambda_n$ ,  
then  $A - \lambda I$  has eigenvalues  $\lambda_1 - \lambda, \dots, \lambda_n - \lambda$ .

PF:

$$\begin{aligned}(A - \lambda I)\underline{v}_\lambda &= A\underline{v}_\lambda - \lambda\underline{v}_\lambda \\ &= \lambda_\ell \underline{v}_\lambda - \lambda\underline{v}_\lambda \\ &= (\lambda_\ell - \lambda)\underline{v}_\lambda\end{aligned}$$

Pick  $\lambda$  to increase the convergence rate:



choose  $\lambda$  so that

$$\frac{\lambda_2 + \lambda_n}{2} \rightarrow 0$$

$$\Rightarrow \lambda = \frac{\lambda_2 + \lambda_n}{2}$$

Idea Two Apply the Power Method to the eigenvalues of  $A^{-1}$  (or better yet,

$$(A - sI)^{-1}.$$

This is called Inverse Power<sup>v</sup> with Shift Method.

If  $A$  has eigenvalues  $\lambda_1, \dots, \lambda_n$ , then

$A^{-1}$  has eigenvalues  $\frac{1}{\lambda_1}, \dots, \frac{1}{\lambda_n}$ , and

$(A - sI)^{-1}$  has eigenvalues  $\frac{1}{\lambda_1 - s}, \dots, \frac{1}{\lambda_n - s}$ .

The proper choice of  $s$  can cause very rapid convergence.

Choosing  $s$  close to  $\lambda_l$  causes  $\frac{1}{\lambda_l - s}$  to grow very large, while  $\frac{1}{\lambda_j - s}$ ,  $j \neq l$ , remains bounded.

This scheme is of course more expensive, since "applying"  $A^{-1}$  requires solving a linear system.

### Inverse Power Method with Shift

① set  $\hat{\underline{b}}_0$  to be random.

② solve  $(A - sI) \underline{b}_1 = \hat{\underline{b}}_0$

$$\Leftrightarrow \underline{b}_1 = (A - sI)^{-1} \hat{\underline{b}}_0$$

③ set  $\hat{\underline{b}}_1 = \frac{\underline{b}_1}{\|\underline{b}_1\|}$ .

④ Proceed as in the Power Method...