- Home work poll $\rightarrow$ form
- Final exam available for scheduling $\rightarrow$ Prairie test
- Exam 2 stents Friday

Goals:


- review power iteration, shift, invert
- multiple eigenvedors
- Scan factorisation
- methods $>Q R$ ievaction


## Power Iteration

Demo: Motivating Power Iteration [cleared]
Let $A \in \mathbb{R}^{\boldsymbol{n} \times \boldsymbol{n}}$ and $A \boldsymbol{v}_{j}=\lambda_{j} \boldsymbol{v}_{j}(j \in\{1,2, \ldots, n\})$ and
$\left|\lambda_{1}\right|>\left|\lambda_{2}\right|>\cdots>\left|\lambda_{n}\right|$.
Pick some $\boldsymbol{x}_{0}$, consider $\boldsymbol{x}_{i+1}=A \boldsymbol{x}_{i}(i \in\{0, \ldots\})$. Called-Power Iteration.

Let $\boldsymbol{x}_{0}=\sum_{j=1}^{n} \alpha_{j} \boldsymbol{v}_{j}$. Observe that $\boldsymbol{x}_{1}=A^{i} \boldsymbol{x}_{0}=\sum_{i=1}^{n} \alpha_{j} \lambda^{i} \boldsymbol{v}_{j}$. Define $\boldsymbol{e}_{i}=\boldsymbol{x}_{i}\left(\lambda_{1}^{i}\right)-\alpha_{1} \boldsymbol{v}_{1}$.

$$
=\sum_{i=1}^{n} \alpha_{j} \lambda^{i} \mathbf{v}_{j}
$$

$$
\left\|\xlongequal{h^{\prime} r^{\prime}{ }^{\prime} h_{y}}\right\| \frac{\sum_{j=1}^{n} \alpha_{j} \lambda_{j}^{i+1} \boldsymbol{v}_{j}}{\lambda_{1}^{i+1}}-\alpha_{1} \boldsymbol{v}_{1} \|
$$

$$
=\| \sum_{j \neq 2}^{n} \alpha_{j} \underbrace{0}_{\leqslant\left(\left.\frac{\lambda_{2}}{\lambda_{1}}\right|^{(+1}\right)^{i+1} \boldsymbol{v}_{j}\left\|\leqslant\left|\frac{\lambda_{2}}{\lambda_{1}}\right|^{i+1}\right\| \underbrace{\| \sum_{j=2}^{n} \alpha_{j} \boldsymbol{v}_{j} \mid} \|=\left|\frac{\lambda_{2}}{\lambda_{1}}\right|^{i+1} \underbrace{\left\|\boldsymbol{e}_{0}\right\|} .}
$$

le. converges to (al alice of) $\boldsymbol{v}_{1}$ 'linearly' (see later).

[^0]
## Power Iteration: Issues?

What could go wrong with Power Iteration?

- Starting vector has no component along 身 $^{\text {U }}$ Not a problem in practice: Rounding will introduce one.
- Overflow in computing $\lambda_{1}^{i}$
$\rightarrow$ Normalize after each step -
- $\left|\lambda_{1}\right|=\left|\lambda_{2}\right|$
- If $\lambda_{1}=\lambda_{2}$ : multipliclity, defer.
- If $\lambda_{1} \neq \lambda_{2}$ : use shift+invert to separate magnitudes
- Complex eigenvalues
$\rightarrow$ use complex-valued shift, and invert.


## Convergence of Power Iteration: Notation

- $\lambda_{\text {max }}(A)$ : biggest eigenvalue by magnitude
- $\lambda_{\max 2}(A)$ : second-biggest eigenvalue by magnitude.
- $\lambda_{\min 2}(A)$ : second-smallest eigenvalue by magnitude
- $\lambda_{\text {min }}(A)$ : smallest eigenvalue by magnitude
(Not well-defined if there are multiple $\lambda$ with the same magnitudes. Assume that's not the case.)


## Power Iteration: Shift

How does a shift $(A-\sigma I)$ change power iteration?


## Power Iteration: Shift

How does a shift $(A-\sigma l)$ change power iteration?

- Converges to eigenvector for $\lambda_{\max }(A-\sigma l)$ with convergence factor $\left|\frac{\lambda_{\max } 2(A-\sigma l)}{\lambda_{\max }(A-\sigma l)}\right|$.
- Can help guide convergence to eigenvalues 'on boundary' of spectrum.


Power Iteration: Inversion
How does inversion ( $A^{-1}$ ) change power iteration?

$$
\begin{aligned}
& A \vec{x}=\lambda \vec{x} \Leftrightarrow \stackrel{l}{\mid A^{-1}} \Leftrightarrow \vec{x}=\lambda A^{-10} x \\
\Leftrightarrow & A^{-1} \vec{x}=\frac{1}{\lambda} \vec{x} \\
& \left|\frac{\lambda_{\max 2}\left(A^{-1}\right)}{\lambda_{\text {max }}\left(A^{4}\right)}\right|=\left|\frac{1 / \lambda_{\min 2}(A)}{1 / \lambda_{\min }(A)}\right|=\left|\frac{\lambda_{\min }(A)}{\lambda_{\min }(A)}\right|
\end{aligned}
$$

## Power Iteration: Inversion

How does inversion ( $A^{-1}$ ) change power iteration?

- Converges to eigenvector for $\lambda_{\max }\left(A^{-1}\right)=1 / \lambda_{\min }(A)$ with convergence factor

$$
\left|\frac{\lambda_{\max 2}\left(A^{-1}\right)}{\lambda_{\max }\left(A^{-1}\right)}\right|=\left|\frac{1 / \lambda_{\min 2}(A)}{1 / \lambda_{\min }(A)}\right|=\left|\frac{\lambda_{\min }(A)}{\lambda_{\min 2}(A)}\right| .
$$

- Guide convergence to smallest eigenvalues.



## Power Iteration: Shift and Inversion

How does shift-invert $\left((A-\sigma I)^{-1}\right)$ change power iteration?


## Power Iteration: Shift and Inversion

How does shift-invert $\left((A-\sigma I)^{-1}\right)$ change power iteration?

- Converges to eigenvector for
$\lambda_{\max }\left((A-\sigma I)^{-1}\right)=1 / \lambda_{\min }(A-\sigma I)$ with convergence factor

$$
\left|\frac{\lambda_{\max 2}\left((A-\sigma I)^{-1}\right)}{\lambda_{\max }\left((A-\sigma I)^{-1}\right)}\right|=\left|\frac{\lambda_{\min }(A-\sigma I)}{\lambda_{\min 2}(A-\sigma I)}\right| .
$$

- Guide convergence to eigenvalue closest to $\sigma$.


What about Eigenvalues?

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


Demo: Power Iteration and its Variants [cleared]

Schur forth
Show: Every matrix is orthonormally similar to an upper triangular matrix, ie. $A=Q U Q^{T}$. This is called the Schur form or Schur factorization.

$$
A_{v}=\lambda_{1} \vec{v} \quad V_{=\text {span }}\{\vec{v}\}
$$

$$
\begin{aligned}
& A: V \rightarrow V \\
& V^{+} \rightarrow \mathbb{R}^{n}-V_{\oplus} V^{2} \\
& A=\underbrace{\left[\begin{array}{ll}
\vec{v}-\text { Basisot } V^{ \pm}-
\end{array}\right]\left(\begin{array}{ll}
\lambda & \\
0 & ? O^{+}
\end{array}\right] Q_{1}^{+} .}_{Q_{1}}
\end{aligned}
$$

## Schur Form: Comments, Eigenvalues, Eigenvectors

$A=Q U Q^{T}$. For complex $\lambda$ :

- Either complex matrices, or
- $2 \times 2$ blocks on diag.

If we had a Schur form of $A$ (no $2 \times 2$ blocks), can we find the eigenvalues?
$\square$
And the eigenvectors?


[^0]:    $<1$

