

# Rayleigh Quotient Iteration

- Describe inverse iteration.

$$(A^{-1})^k x_0$$

- Describe Rayleigh Quotient Iteration.

$$\frac{x^T A x}{x^T x}$$

$$\begin{array}{c}
 x_0 \\
 A A A A x_0 \\
 A^k x_0
 \end{array}$$



$$\left( (A - \sigma I)^{-1} \right)^k x_0$$

## 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?

- Suppose I know  $\lambda$  so that  $Ax = \lambda x$

$$A = Q \begin{pmatrix} \lambda & & & \\ & \times & & \\ & & \times & \\ & & & \times \\ & & & & \times \end{pmatrix} Q^T$$

↳ Deflation

- Power it. w/ multiple vectors

## Simultaneous Iteration

- What happens if we carry out power iteration on multiple vectors simultaneously?

$$X_0 \in \mathbb{R}^{n \times p}$$

$$X_{k+1} = A X_k$$

↗ Drawbacks: -  $p$  times same answer  
(eigvec for largest ev.)  
- expensive  
- ill-conditioned

## Orthogonal Iteration

$$\circ X_0 \in \mathbb{R}^{n \times p}$$

$$Q_k R_k = X_k$$

$$X_{k+1} = A Q_k$$

$$Q_0 R_0 = X_0$$

$$\underline{X_1 = A Q_0} \Rightarrow A = Q_0 R_0 Q_0^T$$

$$Q_1 R_1 = X_1$$

$$X_2 = A Q_1$$

$$\underline{Q_n R_n = X_n} \Rightarrow A = Q_n R_n Q_n^T$$

$$\underline{X_n = A Q_n}$$

( $p \leq n$ ) starting vectors

- expensive

- slow / linear convergence

$$A = Q \left( \begin{array}{c|c} \text{diag} & \\ \hline & \end{array} \right) Q^T$$

$$A \approx Q_n R_n Q_n^T$$

$$\hat{X}_2 = Q_n^T A Q_n \approx R_n$$

## Demo: Orthogonal Iteration

## In-class activity: Eigenvalue Iterations

## QR Iteration/QR Algorithm

Orthogonal iteration:

$$X_0 = A$$

$$Q_k R_k = X_k$$

$$X_{k+1} = A Q_k$$

→ QR iteration:

$$\bar{X}_0 = A$$

$$\bar{Q}_k \bar{R}_k = \bar{X}_k$$

$$\bar{X}_{k+1} = \bar{R}_k \bar{Q}_k$$

Tracing through reveals:

- $\hat{X}_k = \bar{X}_{k+1}$

- $Q_0 = \bar{Q}_0$

$$Q_1 = \bar{Q}_0 \bar{Q}_1$$

$$Q_k = \bar{Q}_0 \bar{Q}_1 \cdots \bar{Q}_k$$

- slow-ish convergence  
(still same as PT)

- expensive ( $O(n^3)$ /it.)

Orthogonal iteration showed:  $\hat{X}_k = \bar{X}_{k+1}$  converge. Also:

$$\bar{X}_{k+1} = \bar{R}_k \bar{Q}_k = \bar{Q}_k^T \bar{X}_k \bar{Q}_k,$$

so the  $\bar{X}_k$  are all similar → all have the same eigenvalues.

→ QR iteration produces Schur form.



## QR Iteration: Incorporating a Shift

- How can we accelerate convergence of QR iteration using shifts?

$$\tilde{X}_0 = A$$

$$\tilde{Q}_k \tilde{R}_k = \tilde{X}_k - \sigma_k I \quad \leadsto \quad \tilde{R}_k = \tilde{Q}_k^\dagger [\tilde{X}_k - \sigma_k I]$$

$$\tilde{X}_{k+1} = \tilde{R}_k \tilde{Q}_k + \sigma_k I$$

$$\tilde{X}_{k+1} = \tilde{R}_k \tilde{Q}_k + \sigma_k I = \tilde{Q}_k^\dagger [\tilde{X}_k - \sigma_k I] \tilde{Q}_k + \sigma_k I$$

$$= \tilde{Q}_k^\dagger \tilde{X}_k \tilde{Q}_k - \cancel{\sigma_k \tilde{Q}_k^\dagger I \tilde{Q}_k} + \sigma_k I$$

$$= \tilde{Q}_k^\dagger \tilde{X}_k \tilde{Q}_k - \cancel{\sigma_k I} + \cancel{\sigma_k I}$$

(1) Picking  $\sigma_k \approx (\tilde{X}_k)_{nn}$

(2) Pick two eigen values  $\left( \begin{array}{c} \square \\ \square \end{array} \right)$  in the BR of  $\tilde{X}_k$

$$Ax = \lambda x$$

$$(A - \lambda I)x = 0$$

## QR Iteration: Computational Expense

- A full QR factorization at each iteration costs  $O(n^3)$ —can we make that cheaper?

## 4.4 Krylov Space Methods