

**THE CHINESE UNIVERSITY OF HONG KONG**  
**Department of Mathematics**  
**MATH3310 2024-2025**  
**Assignment 5**  
**Due Date: December 7 before 11:59 PM**

1. Below are the simultaneous iteration method with shift and the QR iteration method with shift.

**Shifted Simultaneous Iteration**

Let  $Q^{(0)} = I$

For  $k = 0, 1, 2, \dots$

- Choose shift  $s_k$
- $Y = (A - s_k I) \bar{Q}^{(k)}$
- QR factorization of  $Y$ :  $Y = \bar{Q}^{(k+1)} R^{(k+1)}$

Denote  $\bar{R}^{(k)} = R^{(k)} R^{(k-1)} \dots R^{(1)}$

**Shifted QR Iteration**

Let  $A^{(0)} = A$

For  $k = 0, 1, 2, \dots$

- Choose shift  $s_k$
- $Q_{QR}^{(k+1)} R_{QR}^{(k+1)} = A^{(k)} - s_k I$
- $A^{(k+1)} = R_{QR}^{(k+1)} Q_{QR}^{(k+1)} + s_k I$

Denote  $\bar{Q}_{QR}^{(k)} = Q_{QR}^{(1)} Q_{QR}^{(2)} \dots Q_{QR}^{(k)}$ ,  $\bar{R}_{QR}^{(k)} = R_{QR}^{(k)} R_{QR}^{(k-1)} \dots R_{QR}^{(1)}$

- (a) According to the definition of shifted QR iteration, directly prove  $A^{(k+1)} = \left(Q_{QR}^{(k+1)}\right)^T A^{(k)} Q_{QR}^{(k+1)}$  and  $A^{(k)} = \left(\bar{Q}_{QR}^{(k)}\right)^T A \bar{Q}_{QR}^{(k)}$ .
- (b) To prove the following properties, you may need mathematical induction.
- i.  $(A - s_k I)(A - s_{k-1} I) \dots (A - s_0 I) = \bar{Q}^{(k+1)} \bar{R}^{(k+1)}$
  - ii.  $(A - s_k I)(A - s_{k-1} I) \dots (A - s_0 I) = \bar{Q}_{QR}^{(k+1)} \bar{R}_{QR}^{(k+1)}$
- (Hint: using the conclusion in (a), show  $A - s_k I = \bar{Q}_{QR}^{(k+1)} (A^{(k+1)} - s_k I) \left(\bar{Q}_{QR}^{(k+1)}\right)^T$ )
- iii.  $\bar{Q}^{(k+1)} = \bar{Q}_{QR}^{(k+1)}$  and  $\bar{R}^{(k+1)} = \bar{R}_{QR}^{(k+1)}$
2. Suppose  $A$  is real symmetric positive definite, and let the nonzero  $\mathbf{p}_i$ 's be  $A$ -orthogonal, that is.  $\mathbf{p}_i^T A \mathbf{p}_j = 0$  if  $i \neq j$ . let  $\mathbf{x}_k = \mathbf{x}_0 + \sum_{j=0}^{k-1} \alpha_j \mathbf{p}_j$ , and  $f(\mathbf{x}) = \frac{1}{2} \mathbf{x}^T A \mathbf{x} - \mathbf{b}^T \mathbf{x}$
- (a) show that  $\mathbf{p}_i$ 's are linearly independent.
  - (b) Given a fixed integer  $k$ , show that if  $\mathbf{x}_k$  was chosen to minimize the  $f(\mathbf{x})$ ,  $\forall \mathbf{x} \in \mathbf{x}_0 + \text{span}\{\mathbf{p}_0, \dots, \mathbf{p}_{k-1}\}$ , then determining the  $\alpha_k$  such that  $\mathbf{x}_k + \alpha_k \mathbf{p}_k$  minimizing  $f(\mathbf{x})$  is the same as choosing  $\mathbf{x}_{k+1}$  to minimize  $f(\mathbf{x})$ ,  $\forall \mathbf{x} \in \mathbf{x}_0 + \text{span}\{\mathbf{p}_0, \dots, \mathbf{p}_{k-1}, \mathbf{p}_k\}$ . Moreover, what are the values of  $\alpha_0, \dots, \alpha_{k-1}$  such that  $\mathbf{x}_k = \underset{\alpha_0, \alpha_1, \dots, \alpha_{k-1}}{\operatorname{argmin}} f\left(\mathbf{x}_0 + \sum_{j=0}^{k-1} \alpha_j \mathbf{p}_j\right)$ ?
  - (c) Denote  $\mathcal{K}_{m+1}(A; r_0) = \text{span}\{r_0, Ar_0, A^2 r_0, \dots, A^m r_0\}$ , and here is an equivalent statement of conjugate gradient method.

**Conjugate gradient method for solving  $Ax = b$  (not optimized)**

Let  $\mathbf{x}_0$  be the initial vector and  $\mathbf{r}_0 = A\mathbf{x}_0 - \mathbf{b}$ ,  $\mathbf{p}_0 = -\mathbf{r}_0$ .

For  $k = 0, 1, \dots$ ,

$$\begin{aligned}\alpha_k &= -\frac{\mathbf{p}_k^T \mathbf{r}_k}{\mathbf{p}_k^T A \mathbf{p}_k} \\ \mathbf{x}_{k+1} &= \mathbf{x}_k + \alpha_k \mathbf{p}_k \\ \mathbf{r}_{k+1} &= A\mathbf{x}_{k+1} - \mathbf{b} \\ \beta_k &= -\frac{\mathbf{r}_{k+1}^T A \mathbf{p}_k}{\mathbf{p}_k^T A \mathbf{p}_k} \\ \mathbf{p}_{k+1} &= -\mathbf{r}_{k+1} - \beta_k \mathbf{p}_k.\end{aligned}$$

in the class, we have proven the following several properties by induction.

i. for  $k = 0, 1, \dots, n$ ,

$$\text{span}\{\mathbf{r}_0, \mathbf{r}_1, \dots, \mathbf{r}_k\} = \text{span}\{\mathbf{p}_0, \mathbf{p}_1, \dots, \mathbf{p}_k\} = \mathcal{K}_{k+1}(A; \mathbf{r}_0)$$

ii. for  $1 \leq i, j \leq n$  and  $i \neq j$ ,

$$\mathbf{r}_i^T \mathbf{r}_j = 0 \quad \text{and} \quad \mathbf{p}_i^T A \mathbf{p}_j = 0$$

Using these properties and conclusion in (b), prove that

$$\mathbf{x}_k = \underset{\mathbf{x} \in \mathbf{x}_0 + \mathcal{K}_k(A; \mathbf{r}_0)}{\text{argmin}} f(\mathbf{x})$$

3. Suppose  $A$  is a real symmetric matrix and  $A = QDQ^T$  where  $Q^T Q = I$  and  $D = \text{diag}(\lambda_1, \dots, \lambda_n)$ . Assume

$$|\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_k| > |\lambda_{k+1}| \geq \dots \geq |\lambda_n|.$$

Let  $E_k$  denote the subspace spanned by the first  $k$  columns of  $Q$ , equivalently, subspace spanned by eigenvectors associated with  $\lambda_1, \lambda_2, \dots, \lambda_k$ , and let  $\cos \angle(\mathbf{x}^{(0)}, E_k) \neq 0$ . We define

$$\begin{aligned}\cos \angle(\mathbf{x}, E_k) &:= \max \{ \cos \angle(\mathbf{x}, \mathbf{y}) : \mathbf{y} \in E_k \setminus \{0\} \}, \\ \sin \angle(\mathbf{x}, E_k) &:= \min \{ \sin \angle(\mathbf{x}, \mathbf{y}) : \mathbf{y} \in E_k \setminus \{0\} \}, \\ \tan \angle(\mathbf{x}, E_k) &:= \frac{\sin \angle(\mathbf{x}, E_k)}{\cos \angle(\mathbf{x}, E_k)}.\end{aligned}$$

Let  $\mathbf{x}^{(m)} = A^m \mathbf{x}^{(0)} = A \mathbf{x}^{(m-1)}$ ,

- (a) Suppose  $\mathbf{x}^{(0)} = \sum_{i=1}^n a_i \vec{q}_i$ , where  $\vec{q}_i$  is the eigenvector associated with  $\lambda_i$ , show that

$$\tan^2 \angle(\mathbf{x}^{(m+1)}, E_k) = \frac{\sum_{i=k+1}^n (a_i)^2 |\lambda_i|^{2(m+1)}}{\sum_{i=1}^k (a_i)^2 |\lambda_i|^{2(m+1)}}$$

- (b) prove that

$$\tan \angle(\mathbf{x}^{(m+1)}, E_k) \leq \frac{|\lambda_{k+1}|}{|\lambda_k|} \tan \angle(\mathbf{x}^{(m)}, E_k)$$