Unitarily Similar matrices

Fact 15

Two matrices $A, B \in \mathbb{C}^{n \times n}$ are unitarily similar if there is a unitary matrix $U \in \mathbb{C}^{n \times n}$ such that $B = U^{-1}AU$.

Fact 16

If A, B, and U are all real, then U is orthogonal, and A and B are said to be orthogonally similar.

Fact 17

If $A = A^*$ and A is unitarily similar to B, then $B = B^*$. That is, Hermitian property is preserved under unitary similarity transformations.

Schur's Theorem

Let $A \in \mathbb{C}^{n \times n}$. Then there exists a unitary matrix $U \in \mathbb{C}^{n \times n}$ and an upper triangular matrix $T \in \mathbb{C}^{n \times n}$ such that $T = U^*AU$. Equivalently, $A = UTU^*$, and it is called Schur decomposition of A. Proof on chalkboard.

Remarks on Schur's Theorem

- The main diagonal entries of T are the eigenvalues of A
 - Can we find unitary U such that A is unitarily similar to
 T?
- Proof of Schur's theorem (in Watkin's) book is non-constructive: does not give a way to find U
- Nevertheless, it gives a reason to hope that there may exist an algorithm to create a sequence: $A = A_0, A_1, \cdots$, that converges to upper triangular form
 - Hint: QR algorithm

Remarks on Schur's Theorem

- From the equation $T = U^*AU$: the first column of U is necessarily an eigenvector of A
 - In general, other columns of U are not necessarily eigenvectors of A

Fact 18

(Spectral Theorem for Hermitian Matrices) Suppose $A \in \mathbb{C}^{n \times n}$ is Hermitian. Then there exists a unitary matrix $U \in \mathbb{C}^{n \times n}$ and a diagonal matrix $D \in \mathbb{R}^{n \times n}$ such that $D = U^*AU$. The columns of U are eigenvectors and the main diagonal entries of D are eigenvalues of A.

Reduction to Hessenberg and Tridiagonal Form

Goal: Find an algorithm that reduces the given matrix to triangular form via similarity transform

Note: Due to Abel's theorem, can't expect the algorithm that accomplishes the goal in finite steps Idea:

- Reduce the matrix to upper Hessenberg form
- Find eigenvalues and eigenvectors of Hessenberg matrix
- For Hermitian, it reduces to tridiagonal form (Why?)

Steps to reduce a matrix A to Hessenberg form:

1. Partition A as follows:

$$A = \begin{bmatrix} a_{11} & c^T \\ b & \hat{A} \end{bmatrix}$$

2. Let \hat{Q}_1 be a reflector such that

$$\hat{Q}_1 b = egin{bmatrix} - au_1 \ 0 \ dots \ 0 \end{bmatrix}, \quad ext{where } au = \|b\|_2$$

3. Set

$$Q_1 = egin{bmatrix} 1 & 0^T \ 0 & \hat{Q}_1 \end{bmatrix}, \quad A_{1/2} = Q_1 A = egin{bmatrix} a_{11} & c^T \ - au_1 & \ 0 & \ \hat{Q}_1 \hat{A} \ \vdots & \ 0 & \end{bmatrix},$$

which has the desired zeros in the first column.

- Like the first step of QR algorithm, but less ambitious!
 (Why?)
 - In QR we left one non-zero in first column, but now we left two non-zeros in first column.

4. Compute $A_1 = Q_1 A Q_1^{-1}$, where (recall that) $Q_1^{-1} = Q_1$

$$A_1 = A_{1/2}Q_1 = egin{bmatrix} a_{11} & c^T \hat{Q}_1 \ - au_1 & \ 0 & \ \hat{Q}_1 \hat{A} \hat{Q}_1 \ \vdots & 0 & \end{bmatrix} = egin{bmatrix} a_{11} & * \cdots * \ - au_1 & \ 0 & \ \hat{A}_1 \ \vdots & 0 & \end{bmatrix}$$

- Because of the form of Q_1 , above does not destroy zeros
 - Had we been more ambitious, the zeros may have got destroyed
- Next Steps: Apply the idea recursively on \hat{A}_1

Remaining steps: Create zeros in the second column of A_1 or in the 1st col of \hat{A}_1

5. Pick a reflector $\hat{Q}_2 \in \mathbb{C}^{(n-2)\times (n-2)}$ same way as in 1st step, except that A replaced by A_1 . That is, set

$$Q_2 = egin{bmatrix} 1 & 0 & 0 & \cdots & 0 \ 0 & 1 & 0 & \cdots & 0 \ 0 & 0 & & & \ dots & dots & \hat{Q}_2 & \ 0 & 0 & & & \end{bmatrix}$$

6. Apply Q_2 on A_1 to get $A_{3/2}$

$$A_{3/2} = Q_2 A_1 = egin{bmatrix} a_{11} & * & * & * \cdots * \ \hline - au_1 & * & * \cdots * \ \hline 0 & - au_2 & \ \hline \vdots & \vdots & \hat{Q}_2 \hat{A}_2 \ \hline 0 & 0 & \end{bmatrix}$$

7. Complete the similarity transformation: $A_2 = A_{3/2}Q_2$

$$A_{2} = A_{3/2}Q_{2} = \begin{bmatrix} a_{11} & * & * \cdots * \\ -\tau_{1} & * & * \cdots * \\ \hline 0 & -\tau_{2} \\ \vdots & \vdots & \hat{Q}_{2}\hat{A}_{2}\hat{Q}_{2} \\ 0 & 0 \end{bmatrix}$$

6. Next steps creates zeros in the 3rd column, and so on. After n-2 steps, the reduction is complete. Result is: $B=Q^*AQ$,

$$Q=Q_1Q_2\cdots Q_{n-2}$$
 and $Q^*=Q_{n-2}Q_{n-3}\cdots Q_1$

Algorithm-Reduction to Hessenberg i

```
1: for k = 1, ..., n-2 do
    \beta \leftarrow \max\{|a_{ik}| \mid i = k+1,\ldots,n\}
 3: \gamma_k \leftarrow 0
 4: if \beta \neq 0 then
           % Set up the reflector
 5:
           a_{k+1:n,k} \leftarrow \beta^{-1} a_{k+1:n,k}
 6:
          \tau_k \leftarrow \sqrt{a_{k+1,k}^2 + \cdots + a_{n,k}^2}
 7:
           if a_{k+1,k} < 0 then
 8:
 9:
               \tau_k = -\tau_k
           end if
10:
11:
     \eta \leftarrow a_{k+1,k} + \tau_k
```

Algorithm-Reduction to Hessenberg ii

12:
$$a_{k+1,k} \leftarrow 1$$

13: $a_{k+2:n,k} \leftarrow a_{k+2:n,k}/\eta$
14: $\gamma_k \leftarrow \eta/\tau_k$
15: $\tau_k \leftarrow \tau_k \beta$
16: % Multiply on the left by \hat{Q}_k
17: $b_{k+1:n,1}^T \leftarrow a_{k+1:n,k}^T a_{k+1:n,k+1:n}$
18: $b_{k+1:n,1}^T \leftarrow -\gamma b_{k+1:n,1}^T$
19: $a_{k+1:n,k+1:n} \leftarrow a_{k+1:n,k+1:n} + a_{k+1:n,b_{k+1:n,1}}$
20: % Multiply on the right by \hat{Q}_k
21: $b_{1:n} \leftarrow a_{1:n,k+1:n} a_{k+1:n,k}$
22: $b_{1:n} \leftarrow -\gamma_k b_{1:n,1}$
23: $a_{1:n,k+1:n} \leftarrow a_{1:n,k+1:n} + b_{1:n,1} a_{k+1:n,k}^T$

Algorithm-Reduction to Hessenberg iii

- 24: $a_{k+1,k} \leftarrow -\tau_k$
- 25: **end if**
- 26: **end for**
- 27: $\tau_{n-1} \leftarrow -a_{n,n-1}$
 - The input is A, and output is $B = Q^T A Q$ stored in A
 - The zeros below the subdiagonal are used to store u_k
 - Scalar γ_k stored in separate array γ
 - Note for symmetric A, B will be triadiagonal! (See page 353 in Watkins)

The QR Algorithm

Goal: Compute eigenvalue of $A \in \mathbb{R}^{n \times n}$

Idea: Use QR algorithm as follows:

- 1: Set $A_0 = A$
- 2: **for** $i = 1, \dots, do$
- 3: $A_{m-1} = Q_m R_m$
- 4: $R_m Q_m = A_m$
- 5: end for
 - In step 1, A_{m-1} is decomposed into Q_m and R_m (using QR)
 - In step 2, the factors R_m and Q_m are multiplied in reverse order to get A_m
 - $A_m = Q_m^* A_{m-1} Q_m$, the sequence $A_j \to T$, upper triangular form (Why? Later!)

Plan to Compute All Eigenvalues of a Matrix

Steps to compute eigenvalues and eigenvectors:

- 1. Reduce the matrix to upper Hessenberg form by applying unitary similarity transforms (See previous slides)
- 2. Apply QR algorithm to reduce this upper hessenberg matrix to upper triangular form

Speeding up Eigenvalue Computations

Gaol: Speedup the computation of eigenvalues

Idea: As the iteration progresses, the entries of the matrix A^m goes to zero, and the diagonal entries tend to get closer to eigenvalues of A, so choose appropriate shifts.

Fact 19

The subdiagonal entries $a_{i+1,i}^m \to 0$ as $m \to \infty$. More precisely, $|\lambda_i| > |\lambda_{i+1}|$, then $a_{i+1,i}^m \to 0$ linearly with convergence ratio $|\lambda_{i+1}/\lambda_i|$, as $m \to \infty$.

Steps to Speedup Computation of Eigenvalues

- If $\lambda_n \neq \lambda_{n-1}$, then we may want to make the ratio $(\lambda_n \rho)/(\lambda_{n-1} \rho)$ provided we have can find a ρ close to λ_n .
- Since, in the QR iteration, diagonal entries are getting closer to eigenvalues, choose

$$\rho_n = a_{n,n}^m$$

and apply QR iteration on shifted matrix: $A - \rho_n I$

Shifted QR Algorithm

```
Require: A
 1: \rho_0 = 1
2: for i = 1, ... do
3: A_{m-1} - \rho_{m-1}I = Q_m R_m
 4: R_m Q_m + \rho_{m-1} I =: A_m
5: \rho_m = a_{n,n} (Choose shift)
6: if a_{n,n-1} < tol then
         A_m = A_m(1: n-1, 1: n-1) (Delete last row and
7:
         column)
      end if
8:
9: end for
```

 It may happen that one of the subdiagonal entries other than last one becomes zero, in that case, the matrix becomes block upper triangular

Applications of Eigenvalue Algorithms: SVD

Recall basic LA

Recall the following spaces:

$$\mathcal{N}(A) = \{ x \in \mathbb{R}^m \mid Ax = 0 \}$$

$$\mathcal{R}(A) = \{ Ax \mid x \in \mathbb{R}^m \}$$

- The null space is a subspace of \mathbb{R}^m
- The range space is a subspace of \mathbb{R}^n

Recall the rank-nullity theorem:

$$m = \dim(\mathcal{N}(A)) + \dim(\mathcal{R}(A))$$

Properties of AA^T and A^TA

Fact 20

Prove that A^TA and AA^T are symmetric and positive definite.

Fact 21

$$\mathcal{N}(A^TA) = \mathcal{N}(A)$$

Fact 22

$$rank(A^TA) = rank(A) = rank(A^T) = rank(AA^T)$$

Fact 23

If v is an eigenvector of A^TA associated with a non-zero eigenvalue λ , then Av is an eigenvector of AA^T associated with the same eigenvalue.

Fact 24

Let v_1 and v_2 be eigenvectors of A^TA . If v_1 and v_2 are orthogonal, then Av_1 and Av_2 are also orthogonal.

Fact 25

Let $B \in \mathbb{R}^{n \times n}$ be a symmetric matrix with eigenvectors u_i and u_j associated with eigenvalues λ_i and λ_j , with $\lambda_i \neq \lambda_j$. Then u_i and u_j are orthogonal.

Geometric SVD

Fact 26

Let $A \in \mathbb{R}^{n \times m}$ be a nonzero matrix with rank r. Then \mathbb{R}^m has an orthonormal basis $v_1, v_2, \ldots, v_m, \mathbb{R}^n$ has an orthonormal basis u_1, \ldots, u_n , and there exists $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r > 0$ such that

$$Av_i = \begin{cases} \sigma_i u_i & i = 1, \dots, r \\ 0 & i = r + 1, \dots, m \end{cases}$$

and

$$A^{T}u_{i} = \begin{cases} \sigma_{i}v_{i} & i = 1, \dots, r \\ 0 & i = r + 1, \dots, n \end{cases}$$