

1. Let  $\|A\|_{m,n} = \sup_{x \neq 0} \frac{\|Ax\|_m}{\|x\|_n}$  be the operator (induced) norm and let  $\|A\|_F = (\sum |a_{ij}|^2)^{1/2}$  be the Frobenius norm of the matrix  $A$ . We denote the transpose of the matrix by  $A^T$  and the adjoint by  $A^*$ . Show that:
  - (a)  $\|A\|_\infty = \sup_{x \neq 0} \frac{\|Ax\|_\infty}{\|x\|_\infty} = \max_i \sum_j |a_{ij}| = \text{maximum absolute row sum.}$
  - (b)  $\|A\|_1 = \sup_{x \neq 0} \frac{\|Ax\|_1}{\|x\|_1} = \|A^T\|_\infty = \max_j \sum_i |a_{ij}| = \text{maximum absolute column sum.}$
  - (c)  $\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \sqrt{\lambda_{\max}(A^*A)}$ , where  $\lambda_{\max}$  denotes the maximum eigenvalue.
  - (d)  $\|A\|_2 = \sigma_1$ , where  $\sigma_1$  is the largest singular value of  $A$
  - (e)  $\|A\|_2 = \|A^T\|_2$ .
  - (f) If  $A$  is normal ( $AA^* = A^*A = I$ ), then  $\|A\|_2 = \max_i \lambda_i(A)$ .
  - (g)  $\|QAZ\| = \|A\|$  if  $Q$  and  $Z$  are orthogonal (or unitary) for the Frobenius and the induced 2-norm.
  - (h)  $\|A\|_F = \sqrt{\text{tr}(A^*A)} = \sqrt{\text{tr}(AA^*)}$ .
  - (i) If  $A$  is diagonal, then  $\|A\|_2 = \max_i |a_{ii}|$ .
2. Let  $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ 
  - (a) Calculate the 2-norm of  $A$  using the definition.
  - (b) Calculate the Singular Value Decomposition of  $A$ , i.e.,  $A = U\Sigma V^T$ , with  $U$  and  $V$  orthogonal and  $\Sigma$  diagonal. Determine the 2-norm from singular values.
3. Let  $A \in \mathbb{C}^{m \times m}$  be a square matrix with SVD  $A = U\Sigma V^*$  and let  $H = \begin{bmatrix} 0 & A^* \\ A & 0 \end{bmatrix}$ . Show that eigenvalues and eigenvectors of  $H$  are  $\pm\sigma_i$  and  $\frac{1}{\sqrt{2}} \begin{bmatrix} u_i \\ \pm u_i \end{bmatrix}$ , where  $\sigma_i$  are diagonal elements of  $\Sigma$  and  $u_i$  are columns of  $U$ .
4. Let  $A$  be an  $m \times m$  matrix with distinct eigenvalues  $\lambda_1, \dots, \lambda_k$  and their corresponding eigenspaces  $E_{\lambda_1}, \dots, E_{\lambda_k}$ . Let  $\mathbb{B}_i$  be a basis for  $E_{\lambda_i}$ . Show that the set  $\mathbb{B} = \mathbb{B}_1 \cup \dots \cup \mathbb{B}_k$  is linearly independent.
5. Let  $A$  be an  $m \times m$  Hermitian (self-adjoint) matrix ( $A = A^*$ ). Show that:

- (a) Eigenvalues of  $A$  are real.
- (b) Eigenspaces corresponding to distinct eigenvalues are orthogonal.
- (c)  $A$  is non-defective, i.e.,  $A$  has a  $m$  linearly independent eigenvectors.  
Conclude that  $A$  is orthogonally diagonalizable.
6. Show that if  $A = A^*$ , then singular values of  $A$  are absolute value of eigenvalues of  $A$ .
7. Let  $A = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix}$ . Is  $A$  diagonalizable?
8. Let  $P = P^2$  be a projection. If  $S_1 = \text{Range}(P)$  and  $S_2 = \text{Null}(P)$ , we say that  $P$  is the projector onto  $S_1$  along  $S_2$ . If  $S_1$  and  $S_2$  are orthogonal ( $S_1 \perp S_2$ ), then  $P$  is called an orthogonal projection. Note that orthogonal projections are different from orthogonal matrices. Show that:
- (a)  $S_1 \cap S_2 = \{0\}$ .
- (b)  $I - P$  is a projection ( $I - P$  is called the complementary projection).
- (c)  $\text{Range}(I - P) = \text{Null}(P)$ .
- (d)  $P$  is orthogonal if and only if  $P = P^*$ .
- (e) Let  $q$  be a unit vector. Show that  $P_q = qq^*$  is a rank 1 orthogonal projector. What can you say about  $P_{\perp q} = I - qq^*$ ? Generalize this to arbitrary non unit (non-zero) vectors.
- (f) Let  $Q$  be a unitary (orthonormal in real case) matrix ( $Q^*Q = QQ^* = I$ ) with columns  $\{q_1, \dots, q_n\}$ . Show that  $P = QQ^*$  is the orthogonal projection onto the range of  $Q$ .
- (g) For a given full rank matrix  $A$ , the orthogonal projection onto the  $\text{Range}(A)$  is given by  $P = A(A^*A)^{-1}A^*$ .
- (h) If  $P$  is orthogonal, then  $I - 2P$  is unitary.
- (i)  $\|P\|_2 \geq 1$  with equality if and only if  $P$  is orthogonal.
9. Let  $A$  be an  $m \times n$  full rank matrix with  $m \geq n$  with columns  $\{a_j\}$ . Orthogonal vectors produced by Gram-Schmidt can be written in terms of projections:

$$q_1 = \frac{P_1 a_1}{\|P_1 a_1\|}, \quad q_2 = \frac{P_2 a_2}{\|P_2 a_2\|}, \quad \dots, \quad q_n = \frac{P_n a_n}{\|P_n a_n\|},$$

where  $P_1 = I$  and  $P_j$  for  $j > 1$  is the orthogonal projection onto the space orthogonal to the range of  $Q_{j-1} = [q_1 | \dots | q_{j-1}]$ .

- (a) Show that  $P_j = I - Q_{j-1}Q_{j-1}^* = P_{\perp q_{j-1}} \cdots P_{\perp q_2} P_{\perp q_1}$ .

- (b) In Classical Gram-Schmidt (CGS), we compute  $v_j = P_j a_j$ . In modified GM (MGS), we calculate  $v_j = P_{\perp q_{j-1}} \cdots P_{\perp q_2} P_{\perp q_1} a_j$ :

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for  $j = 1, \dots, n$  do
     $v_j = a_j$ ;
    for  $i = 1, \dots, j - 1$  do
         $r_{ij} = q_i^* a_j$ ;
         $v_j = v_j - r_{ij} q_i$ ;
    end
     $r_{jj} = \|v_j\|_2$ ;
     $q_j = v_j / r_{jj}$ ;
end

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**Algorithm 1: CGS**

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for  $i = 1, \dots, n$  do
     $v_i = a_i$ ;
end
for  $i = 1, \dots, n$  do
     $r_{ii} = \|v_i\|_2$ ;
     $q_i = v_i / r_{ii}$ ;
    for  $j = i + 1, \dots, n$  do
         $r_{ij} = q_i^* v_j$ ;
         $v_j = v_j - r_{ij} q_i$ ;
    end
end

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**Algorithm 2: MGS**

Explain the reason why MGS is more stable than CGS.

- (c) Let

$$A = \begin{bmatrix} 1 & 1 & 1 \\ \epsilon & 0 & 0 \\ 0 & \epsilon & 0 \\ 0 & 0 & \epsilon \end{bmatrix}$$

where  $\epsilon$  is small so that  $1 + \epsilon^2 = 1$  within roundoff errors. Calculate  $q_2^T q_3$  using both algorithms. Comment on your observations.

10. Show that GS can be viewed as an orthogonal triangularization approach  $A \underbrace{R_1 \cdots R_n}_{R^{-1}} = Q$ , where  $R_i$ 's are triangular matrices.

$$[v_1 | \cdots | v_n] = \begin{bmatrix} 1/r_{11} & -r_{12}/r_{11} & \cdots & \\ & 1 & & \\ & & 1 & \\ & & & \ddots \end{bmatrix} [q_1 | v_2^{(2)} | \cdots | v_n^{(2)}].$$

Derive the recursions and write pseudo-code for QR factorization using the GS. Calculate the complexity of the algorithm.

11. Householder algorithm constructs a sequence of unitary matrices  $Q_k$  so that  $Q_n \cdots Q_2 Q_1 A = R$  is upper triangular. Here

$$Q_k = \begin{bmatrix} I & 0 \\ 0 & F \end{bmatrix}$$

where  $I$  is  $(k-1) \times (k-1)$  identity matrix and  $F$  is an  $(m-k+1) \times (m-k+1)$  unitary matrix that reflects the space  $\mathcal{C}^{m-k+1}$  across the hyperplane  $H$  orthogonal to  $v = \|x\|e_1 - x$ .

- (a) Describe the geometry of the Householder algorithm
- (b) Derive a formula for the Householder reflector  $F$  ( $F = I - 2\frac{vv^*}{v^*v}$ ).
- (c) Write the pseudo-code of Householder QR factorization. What is the algorithmic complexity?
12. Let  $u_1, \dots, u_n$  be a sequence of unit vectors and let the first  $i - 1$  components of  $u_i$  be zero. Let  $P = P_n P_{n-1} \dots P_1$ , where  $P_i = I - 2u_i u_i^T$  is a Householder transformation. Show that there is an  $n \times n$  lower triangular matrix  $T$  such that  $P = I - UTU^T$ , where  $U = [u_1 | \dots | u_n]$ . Provide an algorithm for computing the entries of  $T$ .
13. Let  $H$  be a *hyperplane* in  $\mathbb{R}^n$  with orthonormal basis  $\{u_1, u_2, \dots, u_{n-1}\}$ . A hyperplane can be characterized as a set of points orthogonal to a fixed non-zero vector  $v$ . Let  $P$  be the orthogonal projection onto  $H$  and let  $P^\perp$  be its complementary projection.
- (a) Describe  $P$  in terms of the basis of  $H$ .
- (b) Describe  $P$  in terms of the basis of the complementary subspace  $H^\perp$ .
- (c) Let  $F = I - 2P^\perp$ . Show that  $F$  is unitary and give a geometric interpretation of  $F$ .
14. (Overdetermined systems) Consider a system of linear equations  $Ax = b$ , where  $A$  is  $m \times n$ ,  $m \geq n$  with full (column) rank. This kind of system is called overdetermined. The least-squares solution is to find  $x$  that minimizes  $\|Ax - b\|$ . Show that this minimization is achieved by

$$Ax = b \iff A^T Ax = A^T b \iff x = (A^T A)^{-1} A^T b$$

The matrix  $A^\dagger = (A^T A)^{-1} A^T$  is called Moore-Penrose pseudo-inverse.

15. (Underdetermined systems) For the system  $Ax = b$ , where  $A$  is  $m \times n$ ,  $m < n$  or if  $\text{rank}(A) < n$ , the  $n \times n$  matrix  $A^T A$  is non invertible. This is because  $\text{rank}(A^T A) = \text{rank}(A) < n$  (prove this). In such cases, we can still define a pseudo-inverse using singular value decomposition. Let  $A = U \Sigma V^T$  with  $U$ ,  $m \times m$  orthogonal,  $\Sigma$ ,  $m \times n$  diagonal and  $V$ ,  $n \times n$  orthogonal.

$$Ax = b \iff U \Sigma V^T x = b \iff \Sigma V^T x = U^T b$$

Define  $y = V^T x$  and let  $b' = U^T b$ . Then the system  $Ax = b$  is equivalent to the diagonal system:

$$\Sigma y = b'.$$

If we can solve this diagonal system for  $y$ , we can then compute  $x = Vy$ . The diagonal matrix  $\Sigma$  is of the form

$$\Sigma = \begin{bmatrix} \tilde{\Sigma} & 0 \\ 0 & 0 \end{bmatrix}$$

with  $\tilde{\Sigma}$  is an  $r \times r$  diagonal matrix of the form

$$\tilde{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_r \end{bmatrix}$$

where  $\sigma_1 \geq \cdots \geq \sigma_r > 0$  are the non-zero singular values of  $A$ , with  $r \leq \min(m, n)$ . Since  $\Sigma$  may not be invertible due to singularities, we resort to defining a pseudo inverse of  $\Sigma$  as

$$\Sigma^{-1} = \begin{bmatrix} \tilde{\Sigma}^{-1} & 0 \\ 0 & 0 \end{bmatrix}$$

and

$$\tilde{\Sigma}^{-1} = \begin{bmatrix} 1/\sigma_1 & 0 & \cdots & 0 \\ 0 & 1/\sigma_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1/\sigma_r \end{bmatrix}$$

Now, let  $\hat{y} = \Sigma^{-1}b'$ . Show that this solution minimizes  $\|\Sigma y - b'\|$  with the additional constraint that  $\|\hat{y}\|$  is minimum among all possible solutions. The pseudo-inverse of  $A$  can be obtained by  $A^\dagger = V\Sigma^{-1}U^T$ .

16. Show that the Moore-Penrose pseudo-inverse of  $A$  satisfies the following identities

- (a)  $AA^\dagger A = A$ .
- (b)  $A^\dagger AA^\dagger = A^\dagger$ .
- (c)  $A^\dagger A = (A^\dagger A)^T$ .
- (d)  $AA^\dagger = (AA^\dagger)^T$ .

17. Cholesky Factorization: A  $n \times n$  positive definite matrix  $A$  can be factorized into  $A = LL^T$ , where  $L$  is lower triangular. Derive the recursions for Cholesky Factorization as presented in the following pseudo code:

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 $\ell_{11} = \sqrt{a_{11}};$ 
for  $j = 2, \dots, n$  do
  |  $\ell_{j1} = a_{j1}/\ell_{11};$ 
end
for  $i = 2, \dots, n-1$  do
  |  $\ell_{ii} = (a_{ii} - \sum_{k=1}^{i-1} \ell_{ik}^2)^{1/2};$ 
  | for  $j = i+1, \dots, n$  do
  | |  $\ell_{ji} = (a_{ji} - \sum_{k=1}^{i-1} \ell_{jk}\ell_{ik})/\ell_{ii};$ 
  | end
  |  $\ell_{nn} = (a_{nn} - \sum_{k=1}^{n-1} \ell_{nk}^2)^{1/2};$ 
end

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18. Let  $A = \begin{bmatrix} 4 & 8 \\ 8 & 32 \end{bmatrix}$

(a) Use the  $LU$  decomposition to write  $PA = LU$  using Gaussian elimination with partial pivoting.

(b) Find the Cholesky decomposition of  $A$ , i.e.,  $A = LL^T$ :

$$A = \begin{bmatrix} a_{11} & w^* \\ w & K \end{bmatrix} = \begin{bmatrix} \sqrt{a_{11}} & 0 \\ w/\sqrt{a_{11}} & I \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & K - ww^*/a_{11} \end{bmatrix} \begin{bmatrix} \sqrt{a_{11}} & w^*/\sqrt{a_{11}} \\ 0 & I \end{bmatrix}$$

(c) Find  $LDL^T$  decomposition of  $A$ .

19. (Need for pivoting in Gaussian Eliminations). In the following use three-decimal digit floating point arithmetic. Let

$$A = \begin{bmatrix} 0.0001 & 1 \\ 1 & 1 \end{bmatrix}$$

(a) Show that  $\kappa(A) = \|A\|_{\infty} \|A^{-1}\|_{\infty} \approx 4$ . (Hence  $A$  is well conditioned).

(b) Calculate the  $LU$  decomposition of  $A$  without partial pivoting and compute the product  $LU$  and compare with  $A$ . Comment on your results.

(c) Solve the system  $Ax = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$  using this  $LU$  decomposition. Compare with exact solution and comment on your results.

(d) Repeat the above steps this time with partial pivoting and show that the problem is eliminated.

20. Let  $A$  be an  $m \times m$  real matrix.

(a) Describe the sequence of similarity transformations that can transform  $A$  to a Hessenberg matrix  $H$ . Describe the relation between eigenvalues and eigenvectors of  $A$  and  $H$ .

- (b) Show that if  $A$  is symmetric, then the Hessenberg matrix  $H$  is tridiagonal.
- (c) Show that the  $QR$  decomposition of a Hessenberg matrix  $H = QR$ , yields a Hessenberg matrix  $Q$ . Deduce that  $RQ$  remains a Hessenberg matrix.
21. Let  $A$  be a symmetric  $m \times m$  matrix with distinct eigenvalues  $\lambda_1, \dots, \lambda_k$  and let  $W(A) = \left\{ \frac{x^T A x}{x^T x} \mid x \in \mathbb{R}^m \right\}$  denote the set of all Rayleigh Quotients of  $A$ . Show that  $W(A)$  is the convex hull of the eigenvalues of  $A$ , i.e.,

$$W(A) = \left\{ \sum_{i=1}^k \alpha_i \lambda_i \mid \alpha_i \geq 0 \text{ and } \sum_{i=1}^k \alpha_i = 1 \right\}.$$