# **CHAPTER 1**

#### Solution 1.1

(a) For k = 2,  $(A + B)^2 = A^2 + AB + BA + B^2$ . If AB = BA, then  $(A + B)^2 = A^2 + 2AB + B^2$ . In general if AB = BA, then the *k*-fold product  $(A + B)^k$  can be written as a sum of terms of the form  $A^j B^{k-j}$ , j = 0, ..., k. The number of terms that can be written as  $A^j B^{k-j}$  is given by the binomial coefficient  $\begin{pmatrix} k \\ j \end{pmatrix}$ . Therefore AB = BA implies

$$(A+B)^{k} = \sum_{j=0}^{k} {k \choose j} A^{j} B^{k-j}$$

(b) Write

$$\det \left[\lambda I - A(t)\right] = \lambda^n + a_{n-1}(t)\lambda^{n-1} + \cdots + a_1(t)\lambda + a_0(t)$$

where invertibility of A(t) implies  $a_0(t) \neq 0$ . The Cayley-Hamilton theorem implies

$$A^{n}(t) + a_{n-1}(t)A^{n-1}(t) + \cdots + a_{0}(t)I = 0$$

for all t. Multiplying through by  $A^{-1}(t)$  yields

$$A^{-1}(t) = \frac{-a_1(t)I - \dots - a_{n-1}(t)A^{n-2}(t) - A^{n-1}(t)}{a_0(t)}$$

for all *t*. Since  $a_0(t) = \det [-A(t)]$ ,  $|a_0(t)| = |\det A(t)|$ . Assume  $\varepsilon > 0$  is such that  $|\det A(t)| \ge \varepsilon$  for all *t*. Since  $||A(t)|| \le \alpha$  we have  $|a_{ij}(t)| \le \alpha$ , and thus there exists a  $\gamma$  such that  $|a_j(t)| \le \gamma$  for all *t*. Then, for all *t*,

$$||A^{-1}(t)|| = \frac{||a_1(t)I + \dots + A^{n-1}(t)||}{|\det A(t)|}$$
$$\leq \frac{\gamma + \gamma \alpha + \dots + \alpha^{n-1}}{\varepsilon} \triangleq \beta$$

#### Solution 1.2

(a) If  $\lambda$  is an eigenvalue of A, then recursive use of  $Ap = \lambda p$  shows that  $\lambda^k$  is an eigenvalue of  $A^k$ . However to show multiplicities are preserved is more difficult, and apparently requires Jordan form, or at least results on similarity to upper triangular form.

(b) If  $\lambda$  is an eigenvalue of invertible A, then  $\lambda$  is nonzero and  $Ap = \lambda p$  implies  $A^{-1}p = (1/\lambda)p$ . As in (a), addressing preservation of multiplicities is more difficult.

(c)  $A^T$  has eigenvalues  $\lambda_1, \ldots, \lambda_n$  since det  $(\lambda I - A^T) = \det (\lambda I - A)^T = \det (\lambda I - A)$ .

(d)  $A^H$  has eigenvalues  $\overline{\lambda_1}, \ldots, \overline{\lambda_n}$  using (c) and the fact that the determinant (sum of products) of a conjugate is the conjugate of the determinant. That is

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$$\det (\lambda I - A^H) = \det (\overline{\lambda I} - A)^H = \det (\overline{\lambda I} - A)$$

(e)  $\alpha A$  has eigenvalues  $\alpha \lambda_1, \ldots, \alpha \lambda_n$  since  $Ap = \lambda p$  implies  $(\alpha A)p = (\alpha \lambda)p$ .

(f) Eigenvalues of  $A^{T}A$  are not nicely related to eigenvalues of A. Consider the example

$$A = \begin{bmatrix} 0 & \alpha \\ 0 & 0 \end{bmatrix}, \quad A^T A = \begin{bmatrix} 0 & 0 \\ 0 & \alpha \end{bmatrix}$$

where the eigenvalues of A are both zero, and the eigenvalues of  $A^{T}A$  are 0,  $\alpha$ . (If A is symmetric, then (a) applies.)

#### Solution 1.3

(a) If the eigenvalues of *A* are all zero, then det  $(\lambda I - A) = \lambda^n$  and the Cayley-Hamilton theorem shows that *A* is nilpotent. On the other hand if one eigenvalue, say  $\lambda_1$  is nonzero, let *p* be a corresponding eigenvector. Then  $A^k p = \lambda_1^k p \neq 0$  for all  $k \ge 0$ , and *A* cannot be nilpotent.

(b) Suppose Q is real and symmetric, and  $\lambda$  is an eigenvalue of Q. Then  $\overline{\lambda}$  also is an eigenvalue. From the eigenvalue/eigenvector equation  $Qp = \lambda p$  we get  $p^H Qp = \lambda p^H p$ . Also  $Q\overline{p} = \overline{\lambda}\overline{p}$ , and transposing gives  $p^H Qp = \overline{\lambda}p^H p$ . Subtracting the two results gives  $(\lambda - \overline{\lambda})p^H p = 0$ . Since  $p \neq 0$ , this gives  $\lambda = \overline{\lambda}$ , that is,  $\lambda$  is real.

(c) If A is upper triangular, then  $\lambda I - A$  is upper triangular. Recursive Laplace expansion of the determinant about the first column gives

det 
$$(\lambda I - A) = (\lambda - a_{11}) \cdots (\lambda - a_{nn})$$

which implies the eigenvalues of A are the diagonal entries  $a_{11}, \ldots, a_{nn}$ .

### Solution 1.4

**(a)** 

$$A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \text{ implies } A^{T}A = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \text{ implies } ||A|| = 1$$

**(b)** 

$$A = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix} \text{ implies } A^T A = \begin{bmatrix} 10 & 6 \\ 6 & 10 \end{bmatrix}$$

Then

$$\det (\lambda I - A^T A) = (\lambda - 16)(\lambda - 4)$$

which implies ||A|| = 4. (c)

$$A = \begin{bmatrix} 1-i & 0\\ 0 & 1+i \end{bmatrix} \text{ implies } A^{H}A = \begin{bmatrix} (1+i)(1-i) & 0\\ 0 & (1-i)(1+i) \end{bmatrix} = \begin{bmatrix} 2 & 0\\ 0 & 2 \end{bmatrix}$$

This gives  $||A|| = \sqrt{2}$ .

# Solution 1.5 Let

 $A = \left[ \begin{array}{cc} 1/\alpha & \alpha \\ 0 & 1/\alpha \end{array} \right] \ , \quad \alpha > 1$ 

Then the eigenvalues are  $1/\alpha$  and, using an inequality on text page 7,

$$||A|| \ge \max_{1 \le i, j \le 2} |a_{ij}| = \alpha$$

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# **Solution 1.6** By definition of the spectral norm, for any $\alpha \neq 0$ we can write

$$||A|| = \max_{||x|| = 1} ||Ax|| = \max_{||x|| = 1} \frac{||Ax||}{||x||}$$
$$= \max_{||\alpha x|| = 1} \frac{||A\alpha x||}{||\alpha x||} = \max_{||x|| = 1/|\alpha|} \frac{|\alpha|||Ax||}{|\alpha|||x||}$$

Since this holds for any  $\alpha \neq 0$ ,

$$||A|| = \max_{||x|| \neq 0} \frac{||Ax||}{||x||} = \max_{x \neq 0} \frac{||Ax||}{||x||}$$

Therefore

$$||A|| \ge \frac{||Ax||}{||x||}$$

for any  $x \neq 0$ , which gives

$$||A x|| \le ||A|| \, ||x||$$

**Solution 1.7** By definition of the spectral norm,

$$||AB|| = \max_{||x|| = 1} ||(AB)x|| = \max_{||x|| = 1} ||A(Bx)||$$
  
$$\leq \max_{||x|| = 1} \{ ||A|| ||Bx|| \}, \text{ by Exercise 1.6}$$
  
$$= ||A|| \max_{||x|| = 1} ||Bx|| = ||A|| ||B||$$

If *A* is invertible, then  $A A^{-1} = I$  and the obvious ||I|| = 1 give

$$1 = ||A A^{-1}|| \le ||A|| ||A^{-1}||$$

Therefore

$$||A^{-1}|| \ge \frac{1}{||A||}$$

**Solution 1.8** We use the following easily verified facts about partitioned vectors:

$$\| \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \| \ge \|x_1\|, \|x_2\|; \quad \| \begin{bmatrix} x_1 \\ 0 \end{bmatrix} \| = \|x_1\|, \quad \| \begin{bmatrix} 0 \\ x_2 \end{bmatrix} \| = \|x_2\|$$

Write

$$Ax = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} A_{11}x_1 + A_{12}x_2 \\ A_{21}x_1 + A_{22}x_2 \end{bmatrix}$$

Then for  $A_{11}$ , for example,

$$||A|| = \max_{||x|| = 1} ||Ax|| \ge \max_{||x|| = 1} ||A_{11}x_1 + A_{12}x_2||$$
$$\ge \max_{||x_1|| = 1} ||A_{11}x_1|| = ||A_{11}||$$

The other partitions are handled similarly. The last part is easy from the definition of induced norm. For example if

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$$A = \left[ \begin{array}{c} 0 & A_{12} \\ 0 & 0 \end{array} \right]$$

then partitioning the vector x similarly we see that

$$\max_{||x|| = 1} ||A x|| = \max_{||x_2|| = 1} ||A_{12}x_2|| = ||A_{12}||$$

**Solution 1.9** By the Cauchy-Schwarz inequality, and  $||x^{T}|| = ||x||$ ,  $|x^{T}A x| \le ||x^{T}A|| ||x|| = ||A^{T}x|| ||x|| \le ||A^{T}|| ||x||^{2} = ||A|| ||x||^{2}$ 

$$x^{T}A x \ge -||A|| ||x||^{2}$$

If  $\lambda$  is an eigenvalue of A and x is a corresponding unity-norm eigenvector, then

$$|\lambda| = |\lambda| ||x|| = ||\lambda x|| = ||A x|| \le ||A|| ||x|| = ||A||$$

**Solution 1.10** Since  $Q = Q^T$ ,  $Q^T Q = Q^2$ , and the eigenvalues of  $Q^2$  are  $\lambda_1^2, \ldots, \lambda_n^2$ . Therefore  $||Q|| = \sqrt{\lambda_{\max}(Q^2)} = \max_{1 \le i \le n} |\lambda_i|$ 

For the other equality Cauchy-Schwarz gives

$$|x^{T}Qx| \leq ||x^{T}Q|| ||x|| = ||Qx|| ||x||$$
  
$$\leq ||Q|| ||x||^{2} = [\max_{1 \leq i \leq n} |\lambda_{i}|] x^{T}x$$

Therefore  $|x^T Qx| \le ||Q||$  for all unity-norm *x*. Choosing  $x_a$  as a unity-norm eigenvector of *Q* corresponding to the eigenvalue that yields  $\max_{1 \le i \le n} |\lambda_i|$  gives

$$|x_a^T Q x_a| = x_a^T \left[ \max_{1 \le i \le n} |\lambda_i| \right] x_a = \max_{1 \le i \le n} |\lambda_i|$$

Thus  $\max_{||x|| = 1} |x^T Q x| = ||Q||.$ 

Solution 1.11 Since 
$$||A x|| = \sqrt{(A x)^T (A x)} = \sqrt{x^T A^T A x}$$
,  
 $||A|| = \max_{||x|| = 1} \sqrt{x^T A^T A x}$ 
$$= \left[\max_{||x|| = 1} x^T A^T A x\right]^{1/2}$$

The Rayleigh-Ritz inequality gives, for all unity-norm *x*,

$$x^{T}A^{T}A x \leq \lambda_{\max}(A^{T}A) x^{T}x = \lambda_{\max}(A^{T}A)$$

and since  $A^T A \ge 0$ ,  $\lambda_{\max}(A^T A) \ge 0$ . Choosing  $x_a$  to be a unity-norm eigenvector corresponding to  $\lambda_{\max}(A^T A)$  gives

$$x_a^T A^T A x_a = \lambda_{\max}(A^T A)$$

Thus

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$$\max_{||x|| = 1} x^T A^T A x = \lambda_{\max}(A^T A)$$

so we have  $||A|| = \sqrt{\lambda_{\max}(A^T A)}$ .

**Solution 1.12** Since  $A^T A > 0$  we have  $\lambda_i(A^T A) > 0$ , i = 1, ..., n, and  $(A^T A)^{-1} > 0$ . Then by Exercise 1.11,

$$|A^{-1}||^{2} = \lambda_{\max}((A^{T}A)^{-1}) = \frac{1}{\lambda_{\min}(A^{T}A)}$$
$$= \frac{\prod_{i=1}^{n} \lambda_{i}(A^{T}A)}{\lambda_{\min}(A^{T}A) \cdot \det(A^{T}A)} \leq \frac{[\lambda_{\max}(A^{T}A)]^{n-1}}{(\det A)^{2}}$$
$$= \frac{||A||^{2(n-1)}}{(\det A)^{2}}$$

Therefore

$$||A^{-1}|| \le \frac{||A||^{n-1}}{|\det A|}$$

**Solution 1.13** Assume  $A \neq 0$ , for the zero case is trivial. For any unity-norm x and y,

$$|y^{T}Ax| \le ||y^{T}|| ||Ax||$$
  
 $\le ||y|| ||A|| ||x|| = ||A||$ 

Therefore

$$\max_{\|y\|_{1} \le \|y\|_{1} \le 1} |y^{T}A x| \le ||A||$$

Now let unity-norm  $x_a$  be such that  $||A x_a|| = ||A||$ , and let

$$y_a = \frac{Ax_a}{||A||}$$

Then  $||y_a|| = 1$  and

$$|y_a^T A x_a| = \frac{|x_a^T A^T A x_a|}{||A||} = \frac{||A x_a||^2}{||A||} = \frac{||A||^2}{||A||} = ||A||$$

Therefore

$$\max_{||x||, ||y|| = 1} |y^T A x| = ||A||$$

**Solution 1.14** The coefficients of the characteristic polynomial of a matrix are continuous functions of matrix entries, since determinant is a continuous function of the entries (sum of products). Also the roots of a polynomial are continuous functions of the coefficients. (A proof is given in Appendix A.4 of E.D. Sontag, Mathematical Control Theory, Springer-Verlag, New York, 1990.) Since a composition of continuous functions is a continuous function, the pointwise-in-t eigenvalues of A(t) are continuous in t.

This argument gives that the (nonnegative) eigenvalues of  $A^{T}(t)A(t)$  are continuous in *t*. Then the maximum at each *t* is continuous in *t* — plot two eigenvalues and consider their pointwise maximum to see this. Finally since square root is a continuous function of nonnegative arguments, we conclude ||A(t)|| is continuous in *t*.

However for continuously-differentiable A(t), ||A(t)|| need not be continuously differentiable in t. Consider the

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