

# Linear Algebra Problems

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## 1 January 2002, Day 1, Question 8

### Question

Let

$$\mathbf{A} = \begin{pmatrix} 7 & 2 & 4 & 6 & 3 \\ 2 & 5 & 1 & 9 & 8 \\ 4 & 1 & 6 & 4 & 7 \\ 6 & 9 & 4 & 2 & 9 \\ 3 & 8 & 7 & 9 & 6 \end{pmatrix},$$

and let  $\mathbf{v}_{(0)} = (1, 1, 1, 1, 1)^T$  be a column vector. For the iteration scheme

$$\mathbf{v}_{(m+1)} = \mathbf{A}\mathbf{v}_{(m)}, \quad m = 0, 1, 2, \dots,$$

with initial guess  $\mathbf{v}_{(0)}$ , after  $m$  iterations  $\mathbf{v}_{(m)} = \mathbf{A}^m \mathbf{v}_{(0)}$ . Show that as  $m \rightarrow \infty$ ,

$$\frac{\mathbf{v}_{(m)}^T \mathbf{v}_{(m+1)}}{\mathbf{v}_{(m)}^T \mathbf{v}_{(m)}} = \lambda_1 + \mathcal{O}\left(\left(\frac{|\lambda_2|}{\lambda_1}\right)^{2m}\right),$$

where  $\lambda_1 > |\lambda_i|$ ,  $i = 2, 3, 4, 5$ , are the eigenvalues of  $\mathbf{A}$ .

### Answer

Note that  $\mathbf{A}$  is real symmetric, so it is *orthogonally diagonalizable*, i.e. there is an orthogonal matrix  $\mathbf{R}$  such that

$$\mathbf{A} = \mathbf{R} \begin{pmatrix} \lambda_1 & 0 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 & 0 \\ 0 & 0 & \lambda_3 & 0 & 0 \\ 0 & 0 & 0 & \lambda_4 & 0 \\ 0 & 0 & 0 & 0 & \lambda_5 \end{pmatrix} \mathbf{R}^{-1}.$$

Since  $\mathbf{R}$  is orthogonal,  $\mathbf{R}^{-1} = \mathbf{R}^T$ . For simplicity of notation, let  $\mathbf{\Lambda}$  be the diagonal matrix in the factorization above. Note that  $\mathbf{A}^m = \mathbf{R}\mathbf{\Lambda}^m\mathbf{R}^T$ .

$$\begin{aligned} \mathbf{v}_{(m)} &= \mathbf{A}^m \mathbf{v}_{(0)} = \mathbf{R}\mathbf{\Lambda}^m\mathbf{R}^T \mathbf{v}_{(0)} \\ \mathbf{v}_{(m+1)} &= \mathbf{A}^{m+1} \mathbf{v}_{(0)} = \mathbf{R}\mathbf{\Lambda}^{m+1}\mathbf{R}^T \mathbf{v}_{(0)} \\ \mathbf{v}_{(m)}^T \mathbf{v}_{(m+1)} &= (\mathbf{R}\mathbf{\Lambda}^m\mathbf{R}^T \mathbf{v}_{(0)})^T \mathbf{R}\mathbf{\Lambda}^{m+1}\mathbf{R}^T \mathbf{v}_{(0)} \\ &= \mathbf{v}_{(0)}^T \mathbf{R} (\mathbf{\Lambda}^m)^T \mathbf{R}^T \mathbf{R}\mathbf{\Lambda}^{m+1}\mathbf{R}^T \mathbf{v}_{(0)} \\ &= \mathbf{v}_{(0)}^T \mathbf{R}\mathbf{\Lambda}^{2m+1}\mathbf{R}^T \mathbf{v}_{(0)} \quad (\mathbf{R}^T \mathbf{R} = \mathbf{I}; \mathbf{\Lambda} \text{ is symmetric}) \\ \mathbf{v}_{(m)}^T \mathbf{v}_{(m)} &= \mathbf{v}_{(0)}^T \mathbf{R}\mathbf{\Lambda}^{2m}\mathbf{R}^T \mathbf{v}_{(0)} \end{aligned}$$

Let  $\mathbf{u} = \mathbf{R}^T \mathbf{v}_{(0)}$ . Then the ratio we seek can be written as

$$\begin{aligned} \frac{\mathbf{v}_{(m)}^T \mathbf{v}_{(m+1)}}{\mathbf{v}_{(m)}^T \mathbf{v}_{(m)}} &= \frac{\lambda_1^{2m+1} u_1^2 + \lambda_2^{2m+1} u_2^2 + \dots}{\lambda_1^{2m} u_1^2 + \lambda_2^{2m} u_2^2 + \dots} \\ &= \frac{\lambda_1^{2m+1} \left[ u_1^2 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m+1} u_2^2 + \dots \right]}{\lambda_1^{2m} \left[ u_1^2 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m} u_2^2 + \dots \right]} \\ &= \lambda_1 \left( \frac{u_1^2 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m+1} u_2^2 + \dots}{u_1^2 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m} u_2^2 + \dots} \right). \end{aligned}$$

If  $u_1 \neq 0$ , then we can re-write this as

$$\frac{\mathbf{v}_{(m)}^T \mathbf{v}_{(m+1)}}{\mathbf{v}_{(m)}^T \mathbf{v}_{(m)}} = \lambda_1 \left( \frac{1 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m+1} \left( \frac{u_2}{u_1} \right)^2 + \dots}{1 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m} \left( \frac{u_2}{u_1} \right)^2 + \dots} \right).$$

Since  $|\lambda_2/\lambda_1| < 1$ , for large-enough  $m$ ,

$$\epsilon = \left( \frac{\lambda_2}{\lambda_1} \right)^{2m} \left( \frac{u_2}{u_1} \right)^2 + \dots < 1.$$

In this case, we can use the series

$$\frac{1}{1 + \epsilon} = \sum_{k=0}^{\infty} (-1)^k \epsilon^k.$$

which converges for  $|\epsilon| < 1$ . We get

$$\frac{\mathbf{v}_{(m)}^T \mathbf{v}_{(m+1)}}{\mathbf{v}_{(m)}^T \mathbf{v}_{(m)}} = \lambda_1 \left( 1 + \left( \frac{\lambda_2}{\lambda_1} \right)^{2m+1} \left( \frac{u_2}{u_1} \right)^2 + \dots \right) (1 - \epsilon + \epsilon^2 - \dots).$$

The largest of the small terms on the right-hand side is  $\epsilon$ , which has terms with exponent  $2m$ . Hence

$$\frac{\mathbf{v}_{(m)}^T \mathbf{v}_{(m+1)}}{\mathbf{v}_{(m)}^T \mathbf{v}_{(m)}} = \lambda_1 (1 - \epsilon + \dots) = \lambda_1 \left[ 1 + \mathcal{O} \left( \left( \frac{|\lambda_2|}{\lambda_1} \right)^{2m} \right) \right].$$

We haven't referred even once to  $\mathbf{v}_{(0)}$ . Does it play a rôle here at all? It does, but it's a minor rôle. The forms of  $\mathbf{v}_{(0)}$  and  $\mathbf{A}$  ensure that each entry in  $\mathbf{v}_{(1)}$  is a positive number. Further, each entry in  $\mathbf{v}_{(m)}$  will be positive for each  $m$ . Thus we are guaranteed to have nonzero  $u_1$  in the manipulations above, so the argument works.

## 2 August 2002, Day 1, Question 4

### Question

Let  $\mathbf{u}$  be a unit vector in  $\mathbb{R}^n$  with  $\mathbf{u}^T \mathbf{u} = 1$ . Let

$$\mathbf{A} = \mathbf{I} - 2\mathbf{u}\mathbf{u}^T$$

be an  $n \times n$  matrix.

- (a) Show that  $\mathbf{A}$  is an orthogonal matrix, that is,  $\mathbf{A}^T \mathbf{A} = \mathbf{I}$ .  
 (b) Find the eigenvalues of  $\mathbf{A}$ . Find the determinant of  $\mathbf{A}$ .

Let  $\mathbf{v}$  be a unit vector in  $\mathbb{R}^n$  with  $\mathbf{v}^T \mathbf{v} = 1$ . Let

$$\mathbf{B} = \mathbf{I} - 2\mathbf{v}\mathbf{v}^T$$

be an  $n \times n$  matrix. Let

$$\mathbf{C} = \mathbf{A}\mathbf{B}.$$

- (c) Show that  $\mathbf{C}$  is an orthogonal matrix, that is,  $\mathbf{C}^T \mathbf{C} = \mathbf{I}$ .  
 (d) Find the determinant of  $\mathbf{C}$ .

### Answer

(a) First note that  $\mathbf{u}\mathbf{u}^T$  is a symmetric matrix:  $(\mathbf{u}\mathbf{u}^T)^T = \mathbf{u}\mathbf{u}^T$ . Since the identity matrix  $\mathbf{I}$  is also symmetric,  $\mathbf{A}$  is symmetric.

$$\begin{aligned} \mathbf{A}^T \mathbf{A} &= \mathbf{A}\mathbf{A} \\ &= (\mathbf{I} - 2\mathbf{u}\mathbf{u}^T)(\mathbf{I} - 2\mathbf{u}\mathbf{u}^T) \\ &= \mathbf{I} - 2\mathbf{u}\mathbf{u}^T - 2\mathbf{u}\mathbf{u}^T + 4\mathbf{u}\mathbf{u}^T \mathbf{u}\mathbf{u}^T \\ &= \mathbf{I} - 4\mathbf{u}\mathbf{u}^T + 4\mathbf{u}(\mathbf{u}^T \mathbf{u})\mathbf{u}^T \\ &= \mathbf{I} - 4\mathbf{u}\mathbf{u}^T + 4\mathbf{u}\mathbf{u}^T \quad (\mathbf{u}^T \mathbf{u} = 1) \\ &= \mathbf{I} \end{aligned}$$

(b) Note immediately that  $\mathbf{u}\mathbf{u}^T$  maps  $\mathbf{u}$  to itself:  $\mathbf{u}\mathbf{u}^T \mathbf{u} = \mathbf{u}(\mathbf{u}^T \mathbf{u}) = \mathbf{u}$ .  $\mathbf{I}$  also maps  $\mathbf{u}$  to itself, so  $\mathbf{A}$  maps  $\mathbf{u}$  to some scalar multiple of itself. Hence  $\mathbf{u}$  is an eigenvector of  $\mathbf{A}$ . In fact,

$$(\mathbf{I} - 2\mathbf{u}\mathbf{u}^T) \mathbf{u} = \mathbf{u} - 2\mathbf{u} = -\mathbf{u},$$

so -1 is the eigenvalue associated with the eigenvector  $\mathbf{u}$ .

We needn't find the other eigenvectors to determine the other eigenvalues. Note that the span of  $\{\mathbf{u}\}$  is a one-dimensional subspace of  $\mathbb{R}^n$ , so there is an  $(n-1)$ -dimensional subspace of vectors orthogonal to  $\mathbf{u}$ . That is, there are linearly

independent vectors  $\mathbf{x}_1, \dots, \mathbf{x}_{n-1}$  such that  $\mathbf{u}^T \mathbf{x}_k = 0$  for  $k = 1, \dots, n-1$ . For each of these  $\mathbf{x}_k$ , then,

$$\begin{aligned} \mathbf{A}\mathbf{x}_k &= (\mathbf{I} - 2\mathbf{u}\mathbf{u}^T)\mathbf{x}_k \\ &= \mathbf{x}_k - 2\mathbf{u}(\mathbf{u}^T \mathbf{x}_k) \\ &= \mathbf{x}_k \quad (\mathbf{u}^T \mathbf{x}_k = 0), \end{aligned}$$

so each  $\mathbf{x}_k$  is an eigenvector with eigenvalue 1.

$\mathbf{A}$  has one eigenvalue equal to -1 and  $n-1$  eigenvalues equal to 1. Since the determinant is equal to the product of all  $n$  eigenvalues,  $\det \mathbf{A} = (-1)(1)^{n-1} = -1$ .

(c) First note that since that  $\mathbf{B}$  has the same type of structure that  $\mathbf{A}$  does. Hence  $\mathbf{B}$  is symmetric, orthogonal, and has determinant -1. Then note that  $\mathbf{C}^T = (\mathbf{A}\mathbf{B})^T = \mathbf{B}^T \mathbf{A}^T = \mathbf{B}\mathbf{A}$ .

$$\begin{aligned} \mathbf{C}^T \mathbf{C} &= \mathbf{B}\mathbf{A}\mathbf{A}\mathbf{B} \\ &= \mathbf{B}\mathbf{I}\mathbf{B} \quad (\mathbf{A}\mathbf{A} = \mathbf{I}) \\ &= \mathbf{B}\mathbf{B} \\ &= \mathbf{I} \end{aligned}$$

(d) The determinant of a product of matrices is equal to the product of the matrices' determinants, so

$$\det \mathbf{C} = (\det \mathbf{A})(\det \mathbf{B}) = (-1)^2 = 1.$$

#### Comment

It is worth noting here that there are two types of orthogonal matrices: those with determinant 1 and those with determinant -1. Suppose that  $\mathbf{A}$  is an orthogonal (not necessarily symmetric)  $n \times n$  real matrix. Then  $\mathbf{A}^T \mathbf{A} = \mathbf{I}$ , and

$$1 = \det \mathbf{I} = \det (\mathbf{A}^T \mathbf{A}) = (\det \mathbf{A}^T) (\det \mathbf{A}) = (\det \mathbf{A})^2.$$

Here we've used the fact that  $\det \mathbf{A}^T = \det \mathbf{A}$ . The conclusion is that  $\det \mathbf{A}$  is 1 or -1. Those  $n \times n$  orthogonal matrices with determinant 1 form the *special orthogonal group (of order  $n$ )*, often written  $SO(n)$ . Special orthogonal matrices correspond to rotations of  $\mathbb{R}^n$ , while those with determinant -1 correspond to rotations combined with reflections.

Since  $\mathbf{A} = \mathbf{I} - 2\mathbf{u}\mathbf{u}^T$  has determinant -1, it corresponds to reflection in  $\mathbb{R}^n$ . Since  $\mathbf{A}\mathbf{u} = -\mathbf{u}$  and since all of  $\mathbf{A}$ 's other eigenvalues are equal to 1, the mapping  $\mathbf{x} \mapsto \mathbf{A}\mathbf{x}$  performs a reflection in the hyperplane orthogonal to  $\mathbf{u}$ .

A matrix of the form  $\mathbf{A} = \mathbf{I} - 2\mathbf{u}\mathbf{u}^T$ , where  $\mathbf{u}$  is a unit vector, is called a *Householder matrix*, and the transformation it performs is called a *Householder reflection*. It is an essential tool for the computation of the *QR decomposition* of a real square matrix. Each real square matrix can be expressed as a product  $\mathbf{Q}\mathbf{R}$ , where  $\mathbf{Q}$  is orthogonal and  $\mathbf{R}$  is upper triangular.

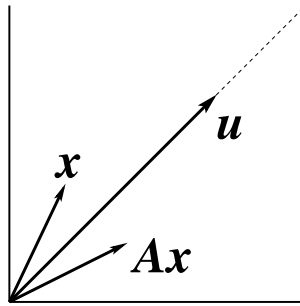


Figure 1: An example of a reflection in  $\mathbb{R}^2$  with  $\mathbf{A} = \mathbf{I} - 2\mathbf{u}\mathbf{u}^T$

### 3 Math 583-A, Fall 2002, Final Exam, Question 1

#### Question

Let  $\mathbb{V}$  be the space of  $2 \times 2$  real matrices and  $F : \mathbb{V} \rightarrow \mathbb{V}$  be the linear map defined by

$$F(\mathbf{A}) = \mathbf{A}\mathbf{M} - \mathbf{M}\mathbf{A},$$

where  $\mathbf{A} \in \mathbb{V}$  and

$$\mathbf{M} = \begin{pmatrix} 1 & 2 \\ 0 & 3 \end{pmatrix}.$$

Find a basis and the dimension of the kernel (null-space) of  $F$ .

#### Answer

Let

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}.$$

Then the matrix equation  $\mathbf{A}\mathbf{M} - \mathbf{M}\mathbf{A} = \mathbf{O}$ , where the left-hand side is

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} 1 & 2 \\ 0 & 3 \end{pmatrix} - \begin{pmatrix} 1 & 2 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} = \begin{pmatrix} -2a_{21} & 2a_{11} + 2a_{12} - 2a_{22} \\ -2a_{21} & 2a_{21} \end{pmatrix},$$

is equivalent to a system of four scalar linear equations:

$$\begin{aligned} -2a_{21} &= 0, \\ 2a_{11} + 2a_{12} - 2a_{22} &= 0, \\ -2a_{21} &= 0, \\ 2a_{21} &= 0. \end{aligned}$$

Note that we do not have four independent equations here, so the solution is not unique. In fact the solutions are the form

$$\begin{pmatrix} a_{11} \\ a_{12} \\ a_{21} \\ a_{22} \end{pmatrix} = \begin{pmatrix} a_{11} \\ a_{12} \\ 0 \\ -a_{11} - a_{12} \end{pmatrix}.$$

where  $a_{11}$  and  $a_{12}$  can be any real numbers. The corresponding  $2 \times 2$  matrix is

$$\begin{pmatrix} a_{11} & a_{12} \\ 0 & -a_{11} - a_{12} \end{pmatrix} = a_{11} \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} + a_{12} \begin{pmatrix} 0 & 1 \\ 0 & -1 \end{pmatrix}.$$

Each  $2 \times 2$  real matrix  $\mathbf{A}$  of this form satisfies  $F(\mathbf{A}) = \mathbf{O}$ , so the kernel of  $F$  is 2-dimensional, and one example of a basis for this kernel is

$$\left\{ \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}, \begin{pmatrix} 0 & 1 \\ 0 & -1 \end{pmatrix} \right\}.$$

## 4 Math 583-A, Fall 2002 Final Exam, Question 2

### Question

(a) For a general  $2 \times 2$  matrix  $\mathbf{A}$ , write down expressions for the eigenvalues of  $\mathbf{A}$  in terms of the determinant and trace of  $\mathbf{A}$ , *i.e.*  $\det \mathbf{A}$  and  $\text{Tr} \mathbf{A}$ .

(b) Let  $\mathbf{A}$  and  $\mathbf{B}$  be  $2 \times 2$  matrices such that

$$\mathbf{AB} - 2\mathbf{BA} = \mathbf{O}.$$

Show that all the eigenvalues of the matrix  $\mathbf{C} = \mathbf{AB}$  are equal to zero.

### Answer

(a) First we compute the determinant of  $\mathbf{A} - \lambda \mathbf{I}$ :

$$\begin{aligned} \begin{vmatrix} a_{11} - \lambda & a_{12} \\ a_{21} & a_{22} - \lambda \end{vmatrix} &= (a_{11} - \lambda)(a_{22} - \lambda) - a_{21}a_{12} \\ &= \lambda^2 - \underbrace{(a_{11} + a_{22})}_{\text{Tr} \mathbf{A}} \lambda + \underbrace{a_{11}a_{22} - a_{21}a_{12}}_{\det \mathbf{A}}. \end{aligned}$$

The solutions of the quadratic equation are

$$\lambda_{\pm} = \frac{1}{2} \left( \text{Tr} \mathbf{A} \pm \sqrt{(\text{Tr} \mathbf{A})^2 - 4 \det \mathbf{A}} \right).$$

(b) Multiplying an  $n \times n$  matrix by a scalar  $\alpha$  multiplies each column by that same scalar, so  $\det(\alpha \mathbf{A}) = \alpha^n \det(\mathbf{A})$ . In the case at hand, we're told that  $\mathbf{AB} = 2\mathbf{BA}$ , so

$$\det \mathbf{C} = \det(\mathbf{AB}) = \det(2\mathbf{BA}) = 2^2 \det(\mathbf{BA}).$$

But  $\det(\mathbf{BA}) = \det(\mathbf{AB})$ , so

$$\det \mathbf{C} = 4 \det(\mathbf{BA}) = 4 \det(\mathbf{AB}) = 4 \det \mathbf{C}.$$

The conclusion is that  $\det \mathbf{C} = 0$ .

**Comment**

Each  $n \times n$  matrix  $\mathbf{A}$  has  $n$  eigenvalues, when the eigenvalues are counted according to (algebraic) multiplicity.

$n \times n$  matrices  $\mathbf{A}$  and  $\mathbf{B}$  are called *similar* (to each other) if there is some invertible matrix  $\mathbf{C}$  such that  $\mathbf{B} = \mathbf{C}\mathbf{A}\mathbf{C}^{-1}$ . Recall that the eigenvalues of  $\mathbf{B}$  are the zeroes of its characteristic polynomial ( $\det(\mathbf{B} - \lambda\mathbf{I})$ ); how are the characteristic polynomials of similar matrices related?

$$\begin{aligned} \det(\mathbf{B} - \lambda\mathbf{I}) &= \det(\mathbf{C}\mathbf{A}\mathbf{C}^{-1} - \lambda\mathbf{I}) \\ &= \det(\mathbf{C}\mathbf{A}\mathbf{C}^{-1} - \lambda\mathbf{C}\mathbf{I}\mathbf{C}^{-1}) \\ &= \det(\mathbf{C}(\mathbf{A} - \lambda\mathbf{I})\mathbf{C}^{-1}) \\ &= (\det \mathbf{C})(\det(\mathbf{A} - \lambda\mathbf{I}))(\det \mathbf{C}^{-1}) \\ &= (\det \mathbf{C})(\det \mathbf{C})^{-1}(\det(\mathbf{A} - \lambda\mathbf{I})) \\ &= \det(\mathbf{A} - \lambda\mathbf{I}) \end{aligned}$$

Similar matrices have identical characteristic polynomials; thus they also have identical eigenvalues and identical multiplicities of eigenvalues.

Each  $n \times n$  matrix  $\mathbf{A}$  (real or complex) has a *Schur factorization*:

$$\mathbf{A} = \mathbf{Q}\mathbf{T}\mathbf{Q}^*,$$

where  $\mathbf{Q}$  is unitary ( $\mathbf{Q}^*\mathbf{Q} = \mathbf{I}$ , i.e.  $\mathbf{Q}^* = \mathbf{Q}^{-1}$ ) and  $\mathbf{T}$  is upper triangular. You should be able to convince yourself that the characteristic polynomial of an upper triangular matrix has the form

$$\det(\mathbf{T} - \lambda\mathbf{I}) = \prod_{k=1}^n (t_{kk} - \lambda),$$

where  $t_{kk}$  is the  $k$ th element on the diagonal of  $\mathbf{T}$ . This indicates that the eigenvalues of an upper triangular matrix are found on the diagonal of such a matrix.

Let  $\mathbf{A}$  have Schur factorization  $\mathbf{Q}\mathbf{T}\mathbf{Q}^*$ , so that

$$\begin{aligned} \det \mathbf{A} &= \det(\mathbf{Q}\mathbf{T}\mathbf{Q}^*) \\ &= (\det \mathbf{Q})(\det \mathbf{T})(\det \mathbf{Q}^*) \\ &= (\det \mathbf{Q})(\det \mathbf{T})(\det \mathbf{Q}^{-1}) \\ &= (\det \mathbf{Q})(\det \mathbf{T})(\det \mathbf{Q})^{-1} \\ &= (\det \mathbf{Q})(\det \mathbf{Q})^{-1}(\det \mathbf{T}) \\ &= \det \mathbf{T} = \prod_{k=1}^n t_{kk} = \prod_{k=1}^n \lambda_k, \end{aligned}$$

where  $\lambda_1, \dots, \lambda_n$  are the eigenvalues of  $\mathbf{T}$ . Since  $\mathbf{A}$  and  $\mathbf{T}$  are similar, these are also the eigenvalues of  $\mathbf{A}$ . Hence for general  $n \times n$  matrix  $\mathbf{A}$ ,

$$\det \mathbf{A} = \prod_{k=1}^n \lambda_k.$$

Now we prove a related fact concerning the trace. Let  $\mathbf{A}$  again have Schur factorization  $\mathbf{QTQ}^*$ .

$$\begin{aligned} \text{Tr} \mathbf{A} &= \sum_{k=1}^n a_{kk} \\ &= \sum_{k=1}^n (\mathbf{ATQ}^*)_{kk} \\ &= \sum_{k=1}^n \sum_{j=1}^n (\mathbf{QT})_{kj} (\mathbf{Q}^*)_{jk} \\ &= \sum_{k=1}^n \sum_{j=1}^n \left( \sum_{i=1}^n q_{ki} t_{ij} \right) (\mathbf{Q}^*)_{jk} \\ &= \sum_{i=1}^n \sum_{j=1}^n t_{ij} \left( \sum_{k=1}^n (\mathbf{Q}^*)_{jk} q_{ki} \right) \\ &= \sum_{i=1}^n \sum_{j=1}^n t_{ij} (\mathbf{Q}^* \mathbf{Q})_{ji} \\ &= \sum_{i=1}^n \sum_{j=1}^n t_{ij} \delta_{ji} \quad (\mathbf{Q} \text{ is unitary}) \\ &= \sum_{j=1}^n t_{jj} = \sum_{j=1}^n \lambda_j, \quad (\mathbf{T} \text{ is upper triangular}) \end{aligned}$$

where  $\lambda_1, \dots, \lambda_n$  are the eigenvalues of  $\mathbf{T}$ . Since  $\mathbf{A}$  is similar to  $\mathbf{T}$ , these are the eigenvalues of  $\mathbf{A}$  as well. We see, then, that the trace of  $\mathbf{A}$  is equal to the sum of  $\mathbf{A}$ 's eigenvalues, counted according to multiplicity.

## 5 January 2003, Day 1, Question 4

### Question

Let  $\mathbf{A}$  be a complex rectangular  $m \times n$  matrix, and let  $\mathbf{A}^*$  be its conjugate transpose. Show that  $\mathbf{A}^* \mathbf{A}$  and  $\mathbf{A} \mathbf{A}^*$  have the same nonzero eigenvalues.

### Answer

Each matrix, regardless of whether it is square, has unique *singular value decomposition*:

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^*,$$

where  $\mathbf{U}$  is an  $m \times m$  complex unitary matrix,  $\mathbf{V}$  is an  $n \times n$  complex unitary matrix, and  $\mathbf{\Sigma}$  is an  $m \times n$  real “diagonal” matrix.  $\mathbf{\Sigma}$ , which is non-square if  $m \neq n$ , is diagonal in the sense that largest upper-left square sub-matrix of  $\mathbf{\Sigma}$  is diagonal. The non-zero entries in  $\mathbf{\Sigma}$  are called the *singular values* of  $\mathbf{A}$ . The rank of  $\mathbf{A}$  is equal to the number of singular values  $\mathbf{A}$  has, *i.e.* the number of non-zero entries in  $\mathbf{\Sigma}$ . This number is bounded by  $\min\{m, n\}$ .

The following is an equivalent expression of the singular value decomposition and will be easier to use in this problem:

$$\mathbf{A} = \sum_{j=1}^r \sigma_j \mathbf{u}_j \mathbf{v}_j^*,$$

where  $r$  is the rank of  $\mathbf{A}$ ,  $\sigma_j$  is the  $j$ th element on the diagonal of  $\mathbf{\Sigma}$ ,  $\mathbf{u}_j$  is the  $j$ th column of  $\mathbf{U}$ , and  $\mathbf{v}_j$  is the  $j$ th column of  $\mathbf{V}$ .

$$\begin{aligned} \mathbf{A}^* \mathbf{A} &= \left( \sum_{j=1}^r \sigma_j \mathbf{u}_j \mathbf{v}_j^* \right)^* \left( \sum_{k=1}^r \sigma_k \mathbf{u}_k \mathbf{v}_k^* \right) \\ &= \left( \sum_{j=1}^r \sigma_j \mathbf{v}_j \mathbf{u}_j^* \right) \left( \sum_{k=1}^r \sigma_k \mathbf{u}_k \mathbf{v}_k^* \right) \\ &= \sum_{j=1}^r \sum_{k=1}^r \sigma_j \sigma_k \mathbf{v}_j (\mathbf{u}_j^* \mathbf{u}_k) \mathbf{v}_k^* \\ &= \sum_{j=1}^r \sum_{k=1}^r \sigma_j \sigma_k \mathbf{v}_j \delta_{jk} \mathbf{v}_k^* \quad (\text{columns of a unitary matrix form an orthonormal set}) \\ &= \sum_{j=1}^r \sigma_j^2 \mathbf{v}_j \mathbf{v}_j^*, \\ \mathbf{A}^* \mathbf{A} \mathbf{v}_\ell &= \sum_{j=1}^r \sigma_j^2 \mathbf{v}_j \mathbf{v}_j^* \mathbf{v}_\ell = \sum_{j=1}^r \sigma_j^2 \mathbf{v}_j \delta_{j\ell} = \sigma_\ell^2 \mathbf{v}_\ell \end{aligned}$$

The eigenvalues of  $\mathbf{A}^* \mathbf{A}$ , which is an  $n \times n$  matrix, are  $\sigma_\ell^2$ ,  $\ell = 1, \dots, n$ . On the

other hand,

$$\begin{aligned}
\mathbf{AA}^* &= \left( \sum_{j=1}^r \sigma_j \mathbf{u}_j \mathbf{v}_j^* \right) \left( \sum_{k=1}^r \sigma_k \mathbf{u}_k \mathbf{v}_k^* \right)^* \\
&= \left( \sum_{j=1}^r \sigma_j \mathbf{u}_j \mathbf{v}_j^* \right) \left( \sum_{k=1}^r \sigma_k \mathbf{v}_k \mathbf{u}_k^* \right) \\
&= \sum_{j=1}^r \sum_{k=1}^r \sigma_j \sigma_k \mathbf{u}_j (\mathbf{v}_j^* \mathbf{v}_k) \mathbf{u}_k^* \\
&= \sum_{j=1}^r \sum_{k=1}^r \sigma_j \sigma_k \mathbf{u}_j \delta_{jk} \mathbf{u}_k^* \\
&= \sum_{j=1}^r \sigma_j^2 \mathbf{u}_j \mathbf{u}_j^*, \\
\mathbf{AA}^* \mathbf{u}_\ell &= \sum_{j=1}^r \sigma_j^2 \mathbf{u}_j \mathbf{u}_j^* \mathbf{u}_\ell = \sum_{j=1}^r \sigma_j^2 \mathbf{u}_j \delta_{j\ell} = \sigma_\ell^2 \mathbf{u}_\ell.
\end{aligned}$$

The eigenvalues of  $\mathbf{AA}^*$ , which is an  $m \times m$  matrix, are  $\sigma_\ell^2$ ,  $\ell = 1, \dots, m$ .  $\mathbf{A}^* \mathbf{A}$  and  $\mathbf{AA}^*$  have the same non-zero eigenvalues  $\sigma_1^2, \dots, \sigma_r^2$ , where  $r$  is the rank of  $\mathbf{A}$ ; if  $m \neq n$ , then  $\mathbf{A}^* \mathbf{A}$  and  $\mathbf{AA}^*$  have different numbers of zero eigenvalues.