

3.5.24. a) If  $x \in \mathbf{R}^n$  is any vector then

$$x^t(A^t A)x = (Ax)^t(Ax) = \|Ax\|_2^2.$$

This is always  $\geq 0$  by the properties of vector norms. Hence  $A^t A$  is positive *semi-definite* for all  $A$ .

b) If  $A \in M_{n \times m}(\mathbf{R})$  and  $n < m$ , then there are fewer equations than variables in the homogeneous system  $Ax = 0$ . This means that there is a nontrivial solution  $x_p \neq 0$  with  $Ax_p = 0$  (set at least one of the free variables to a nonzero value). Hence

$$x_p(A^t A)x_p = \|Ax_p\|_2^2 = 0$$

but  $x_p \neq 0$ . This shows that  $A^t A$  is *not positive-definite*.

c) Now assume  $A \in M_{n \times m}(\mathbf{R})$  and  $n \geq m$ . We want to show that  $A^t A$  is positive definite if and only if  $A$  has full rank. (That is,  $\text{rank}(A) = m$ , or equivalently, that the columns of  $A$  are linearly independent – recall that the rank of a matrix is, by definition, the dimension of its column space.) By the same reasoning as above, we have  $A^t A$  is positive definite if and only if  $x^t(A^t A)x = \|Ax\|_2^2 = 0$  implies  $x = 0$ , so  $Ax = 0$  implies  $x = 0$ . But if  $x \in \mathbf{R}^m$ , then

$$Ax = x_1 a_1 + \cdots + x_m a_m,$$

where  $a_i$  are the columns of  $A$ . Hence  $Ax = 0$  implies  $x = 0$  is equivalent to the assertion that the columns of  $A$  are linearly independent.

3.5.26. Note:  $A, B$  here are  $n \times m$  matrices. a)  $\Rightarrow$ : Assume that  $x$  is the least-squares solution of  $Ax = b$ . Then we know  $b - Ax \in R(A)^\perp = N(A^t)$  by Corollary 3.5.20 in the text. But we are assuming  $R(B) = R(A)$  so by Theorem 3.5.10:

$$N(B^t) = R(B)^\perp = R(A)^\perp = N(A^t).$$

Therefore  $B^t(b - Ax) = 0$ . Rearranging algebraically, we get  $B^t Ax = B^t b$ .

$\Leftarrow$ : Conversely, suppose  $B^t Ax = B^t b$ . Then  $B^t(b - Ax) = 0$ , so  $b - Ax \in N(B^t) = R(B)^\perp$ . Since we assume  $R(A) = R(B)$ ,  $R(A)^\perp = R(B)^\perp$ , so  $b - Ax \in R(A)^\perp$ . Hence  $x$  is the least-squares solution of  $Ax = b$  by Corollary 3.5.20.

b)  $\Leftarrow$ : Assume  $A = BC$  for some nonsingular  $m \times m$  matrix  $C$ . This matrix equation shows that each column of  $A$  is a linear combination of the columns of  $B$  so  $R(A) \subseteq R(B)$  (using 3.5.13 part a). But  $C$  is nonsingular, so we also know  $B = AC^{-1}$ . Then the same reasoning shows that every column of  $B$  is a linear combination of the columns of  $A$ , so  $R(B) \subseteq R(A)$ . The two inclusions show  $R(A) = R(B)$ .

$\Rightarrow$ : We must show that if  $R(A) = R(B)$ , then there is a nonsingular matrix  $C$  such that  $A = BC$ . First, note that  $R(A) = R(B)$  implies  $\text{rank}(A) = \text{rank}(B)$ . Let us consider the special case first where the first  $k$  columns of  $A$  form a basis for  $R(A)$  and similarly the first  $k$  columns of  $B$  form a basis for  $R(B)$ . Write  $A = (\hat{A} \ A')$  and  $B = (\hat{B} \ B')$  where  $\hat{A}$  and  $\hat{B}$  are the first  $k$  columns in each case. Since the columns of  $\hat{A}$  and  $\hat{B}$  are bases of  $R(A) = R(B)$ , each of the first  $k$  columns of  $A$  can be written uniquely as a linear combination of the first  $k$  columns of  $B$ , and vice versa. This says that there are  $k \times k$  matrices  $\hat{C}$  and  $\hat{D}$  such that

$$(1) \quad \hat{A}\hat{D} = \hat{B}$$

and

$$(2) \quad \hat{B}\hat{C} = \hat{A}.$$

It follows that  $\hat{A}(\hat{D}\hat{C}) = \hat{A}$  and  $\hat{B}(\hat{C}\hat{D}) = \hat{B}$ . Then, since the columns of  $\hat{A}$  and  $\hat{B}$  are linearly independent, we get  $\hat{C}\hat{D} = I_k$  and  $\hat{D}\hat{C} = I_k$ , so  $\hat{C}$  and  $\hat{D}$  are inverse matrices of each other.

Furthermore, since the first  $k$  columns of  $B$  form a basis for  $R(B)$  again, the last  $m-k$  columns of  $A$  (the matrix  $A'$ ) can be written in terms of the entries in the matrix  $B$  in the form

$$(3) \quad A' = B' + \hat{B}P$$

for some  $k \times (m-k)$  matrix  $P$ . Similarly,

$$(4) \quad B' = A' + \hat{A}Q$$

for some  $k \times (m-k)$  matrix  $Q$ . But then consider the  $m \times m$  matrices

$$C = \begin{pmatrix} \hat{C} & P \\ 0 & I_{m-k} \end{pmatrix}$$

and

$$D = \begin{pmatrix} \hat{D} & Q \\ 0 & I_{m-k} \end{pmatrix}$$

We have

$$BC = (\hat{B} \ B') \begin{pmatrix} \hat{C} & P \\ 0 & I_{m-k} \end{pmatrix} = (\hat{A} \ A') = A$$

by (2) and (3) above. Furthermore,  $C$  is invertible since  $\hat{C}$  is invertible as above.

(In fact, although this is not necessary for the problem, it can be seen that  $C^{-1} = D$ . This is true since

$$B(CD) = (\hat{B} \ B') \begin{pmatrix} \hat{C} & P \\ 0 & I_{m-k} \end{pmatrix} \begin{pmatrix} \hat{D} & Q \\ 0 & I_{m-k} \end{pmatrix} = (\hat{B}(\hat{C}\hat{D}) \ \hat{B}\hat{C}Q + \hat{B}P + B').$$

From (2), (3), and (4),

$$\hat{B}\hat{C}Q + \hat{B}P + B' = \hat{A}Q + \hat{B}P + B' = B' - A' + A' - B' + B' = B'$$

But this shows

$$\hat{B}(\hat{C}Q + P) = 0,$$

so, since the columns of  $\hat{B}$  are linearly independent,  $\hat{C}Q + P = 0$ . Hence  $CD = I_m$ , and similarly  $DC = I_m$ .)

The general case now follows since we can find some collections of columns of  $A$  and  $B$  that are bases for  $R(A)$  and  $R(B)$  respectively and reorder the columns to put those bases in the first  $k$  columns. This can be done by multiplying by suitable  $m \times m$  permutation matrices  $\Pi, \Sigma$ . Let

$$A_1 = A\Pi \quad \text{and} \quad B_1 = B\Sigma.$$

Then by the above if  $R(A) = R(A_1) = R(B_1) = R(B)$ , there is an invertible  $m \times m$  matrix  $C$  such that  $B_1C_1 = A_1$ . But then

$$A = A_1\Pi^{-1} = B_1C_1\Pi^{-1} = B(\Sigma C_1\Pi^{-1}),$$

so  $A = BC$  where  $C = \Sigma C_1\Pi^{-1}$ . This is invertible since  $\Pi, \Sigma, C_1$  are.