

1 Show that each  $A_k$  [ $A(1 : k, 1 : k)$  in matlab notation] is SPD.

**Solution:** Let  $x$  be any vector in  $\mathbb{R}^k$  and consider the vector  $y$  of  $\mathbb{R}^n$  obtained by stacking  $x$  followed by  $n - k$  zeros. Then it can be easily seen that:  $(A_k x, x) = (A y, y)$  and since  $A$  is SPD then  $(A y, y) > 0$  and therefore  $(A_k x, x) > 0$  for any  $x$  in  $\mathbb{R}^k$ . Hence  $A_k$  is SPD.  $\square$

2 Consequence  $\det(A_k) > 0$

**Solution:** This is because the determinant is the product of the eigenvalues which are real positive (see notes).  $\square$

3 If  $A$  is SPD then for any  $n \times k$  matrix  $X$  of rank  $k$ , the matrix  $X^T A X$  is SPD.

**Solution:** For any  $v \in \mathbb{R}^k$  we have  $(X^T A X v, v) = (A X v, X v)$ . In addition, since  $X$  is of full rank,

then  $Xv$  cannot be zero if  $v$  is nonzero. Therefore we have  $(AXv, Xv) > 0$ .  $\square$

**Ex 4** Show that if  $A^T = A$  and  $(Ax, x) = 0 \forall x$  then  $A = 0$ .

**Solution:** The condition implies that for all  $x, y$  we have  $(A(x + y), x + y) = 0$ . Now expand this as:  
 $(Ax, x) + (Ay, y) + 2(Ax, y) = 0$  for all  $x, y$  which shows that  $(Ax, y) = 0 \forall x, y$ . This implies that  $A = 0$  (e.g. take  $x = e_j, y = e_i$ )...  $\square$

**Ex 5** Show: A nonzero matrix  $A$  is indefinite iff  $\exists x, y : (Ax, x)(Ay, y) < 0$ .

**Solution:**

$\leftarrow$  Trivial. The matrix can't be PSD or NSD under the condition

$\rightarrow$  Need to prove: If  $A$  is indefinite then there exist such that  $x, y : (Ax, x)(Ay, y) < 0$ . Assume contrary is true, i.e.,  $\forall x, y (Ax, x)(Ay, y) \geq 0$ . There is at least one  $x_0$  such that  $(Ax_0, x_0)$  is nonzero, otherwise  $A = 0$  from previous question. Assume  $(Ax_0, x_0) > 0$ . Then  $\forall y (Ax_0, x_0)(Ay, y) \geq 0$ .

which implies  $\forall \mathbf{y} : (\mathbf{A}\mathbf{y}, \mathbf{y}) \geq 0$ , i.e.,  $\mathbf{A}$  is positive semi-definite. This contradicts the assumption that  $\mathbf{A}$  is neither positive nor negative semi-definite  $\square$

6 The (standard) LU factorization of an SPD matrix  $\mathbf{A}$  exists.

**Solution:** This is an immediate consequence of the main theorem on existence (Lec. notes. set #5) and Exercise 1 in this set which showed that  $\det(\mathbf{A}_k) > 0$  for  $k = 1, \dots, n$ .  $\square$

*Example:*

$$\mathbf{A} = \begin{pmatrix} 1 & -1 & 2 \\ -1 & 5 & 0 \\ 2 & 0 & 9 \end{pmatrix}$$

7 Is  $\mathbf{A}$  symmetric positive definite?

**Solution:** Answer is yes because  $\det(A_k) > 0$  for  $k = 1, 2, 3$ .  $\square$

**8** What is the  $LDL^T$  factorization of  $A$  ?

**Solution:** The LU factorization is:

$$L = \begin{pmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 2 & 1/2 & 1 \end{pmatrix} \quad U = \begin{pmatrix} 1 & -2 & 1 \\ 0 & 4 & 2 \\ 0 & 0 & 4 \end{pmatrix}$$

Therefore  $A = LDL^T$  where  $L$  is as given above and

$$D = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 4 \end{pmatrix} \quad \square$$

**9** What is the Cholesky factorization of  $A$  ?

**Solution:** From the above LDLT factorization we have  $A = GG^T$  with

$$G = \begin{pmatrix} 1 & 0 & 0 \\ -1 & 2 & 0 \\ 2 & 1 & 2 \end{pmatrix} \quad \square$$

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## Gradient of $\psi(x) = (Ax, x)$

In practice exercise # 6 it is asked: Let  $A$  be symmetric and  $\psi(x) = (Ax, x)$ . What is the partial derivative  $\frac{\partial \psi(x)}{\partial x_k}$ ? What is the gradient of  $\psi$ ?

**Solution:** First note that

$$\psi(x) = \sum_{i=1}^n x_i \left[ \sum_{j=1}^n a_{ij} x_j \right]$$

and so, using basic rules for derivatives of products:

$$\begin{aligned} \frac{\partial \psi(x)}{\partial x_k} &= \sum_{i=1}^n \frac{\partial x_i}{\partial x_k} \left[ \sum_{j=1}^n a_{ij} x_j \right] + \sum_{i=1}^n x_i \left[ \frac{\partial x_i}{\partial x_k} \sum_{j=1}^n a_{ij} x_j \right] \\ &= \sum_{j=1}^n a_{kj} x_j + \sum_{i=1}^n x_i a_{ik} \\ &= 2 \sum_{j=1}^n a_{kj} x_j \end{aligned}$$

which is nothing but twice the  $k$ -th component of  $A\mathbf{x}$  or  $\frac{\partial\psi(\mathbf{x})}{\partial x_k} = 2(A\mathbf{x})_k$ . Therefore the gradient of  $\psi$  is

$$\nabla\psi(\mathbf{x}) = 2A\mathbf{x}.$$

A somewhat simpler solution for finding the gradient is to expand  $\psi(\mathbf{x} + \boldsymbol{\delta}) = (A(\mathbf{x} + \boldsymbol{\delta}), (\mathbf{x} + \boldsymbol{\delta})) = \dots$  and to write that the linear term should be of the form  $[\nabla\psi]^T \boldsymbol{\delta}$ .  $\square$