



**SIMULATION OPTIMIZATION SYSTEMS**  
Research Laboratory

**NOTES ON VECTORS, MATRICES  
AND SENSITIVITIES**

J.W. Bandler and Q.J. Zhang

SOS-86-8-R

September 1986

McMASTER UNIVERSITY  
Hamilton, Canada L8S 4L7  
Department of Electrical and Computer Engineering



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Matrix A

Let

$$\mathbf{A} \triangleq \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

This  $m \times n$  matrix has  $m$  rows and  $n$  columns.

Transpose of A

$$\mathbf{A}^T \triangleq \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{m1} \\ a_{12} & a_{22} & \cdots & a_{m2} \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ a_{1n} & a_{2n} & \cdots & a_{mn} \end{bmatrix}$$

This  $n \times m$  matrix has  $n$  rows and  $m$  columns.

Symmetric Matrix A

A square matrix  $\mathbf{A}$  is said to be symmetric if

$$\mathbf{A}^T = \mathbf{A}$$

Vector a

Let

$$\mathbf{a} \triangleq \begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_n \end{bmatrix}$$

This n-dimensional vector has n rows and 1 column.

Transpose of a

$$\mathbf{a}^T \triangleq [a_1 \quad a_2 \quad \dots \quad a_n]$$

This n-dimensional vector has 1 row and n columns.

**Vector  $\mathbf{a}'$** 

Let

$$\mathbf{a}' \triangleq \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix}$$

This  $m$ -dimensional vector has  $m$  rows and 1 column.

**Transpose of  $\mathbf{a}'$** 

$$\mathbf{a}'^T \triangleq [a_1 \quad a_2 \quad \dots \quad a_m]$$

This  $m$ -dimensional vector has 1 row and  $m$  columns.

Forms of  $A$  and  $A^T$ 

Partitioned forms of  $A$  and  $A^T$  can be written as

$$A^T = [a_1 \quad a_2 \quad \dots \quad a_m] = \begin{bmatrix} a_1^T \\ a_2^T \\ \cdot \\ \cdot \\ a_m^T \end{bmatrix} = A'$$

and

$$A = \begin{bmatrix} a_1^T \\ a_2^T \\ \cdot \\ \cdot \\ a_m^T \end{bmatrix} = [a_1' \quad a_2' \quad \dots \quad a_n'] = A'^T$$

Here,  $a_1, a_2, \dots, a_m$  are  $n$ -dimensional, whereas  $a_1', a_2', \dots, a_n'$  are  $m$ -dimensional.



Rows of A

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \cdot \\ \cdot \\ \cdot \\ \mathbf{a}_m^T \end{bmatrix}$$

This  $m \times n$  matrix has rows which are the transposes of the column vectors

$$\mathbf{a}_1 \triangleq \begin{bmatrix} a_{11} \\ a_{12} \\ \cdot \\ \cdot \\ \cdot \\ a_{1n} \end{bmatrix}, \quad \mathbf{a}_2 \triangleq \begin{bmatrix} a_{21} \\ a_{22} \\ \cdot \\ \cdot \\ \cdot \\ a_{2n} \end{bmatrix}, \quad \dots, \quad \mathbf{a}_m \triangleq \begin{bmatrix} a_{m1} \\ a_{m2} \\ \cdot \\ \cdot \\ \cdot \\ a_{mn} \end{bmatrix}$$

Columns of  $A$ 

$$A = [\mathbf{a}'_1 \quad \mathbf{a}'_2 \quad \dots \quad \mathbf{a}'_n]$$

This  $m \times n$  matrix has columns

$$\mathbf{a}'_1 \triangleq \begin{bmatrix} a_{11} \\ a_{21} \\ \cdot \\ \cdot \\ a_{m1} \end{bmatrix}, \quad \mathbf{a}'_2 \triangleq \begin{bmatrix} a_{12} \\ a_{22} \\ \cdot \\ \cdot \\ a_{m2} \end{bmatrix}, \quad \dots, \quad \mathbf{a}'_n \triangleq \begin{bmatrix} a_{1n} \\ a_{2n} \\ \cdot \\ \cdot \\ a_{mn} \end{bmatrix}$$

Unit Vector  $\mathbf{u}_i$ 

$$\mathbf{u}_i \triangleq \begin{bmatrix} 0 \\ \cdot \\ \cdot \\ \cdot \\ 1 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \leftarrow \text{ith row}$$

This vector is considered as having  $m$  elements, all of which are 0 except the  $i$ th, which is 1.

Unit Vector  $u_j$ 

$$u_j \triangleq \begin{bmatrix} 0 \\ \cdot \\ \cdot \\ \cdot \\ 1 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \leftarrow \text{jth row}$$

This vector is considered as having  $n$  elements, all of which are 0 except the  $j$ th, which is 1.

The Identity Matrix

Let

$$\mathbf{u}_1 \triangleq \begin{bmatrix} 1 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \quad \mathbf{u}_2 \triangleq \begin{bmatrix} 0 \\ 1 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \quad \dots, \quad \mathbf{u}_n \triangleq \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 1 \end{bmatrix}.$$

Then

$$\mathbf{I} = [\mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_n]$$

is called the identity matrix.

Scalar Product

Let

$$\mathbf{a} \triangleq \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}, \quad \mathbf{b} \triangleq \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}.$$

Then

$$\mathbf{a}^T \mathbf{b} \triangleq a_1 b_1 + a_2 b_2 + \dots + a_n b_n$$

The result is a scalar.

Element Selection from Vectors

$$\mathbf{u}_j^T \mathbf{a} \equiv \mathbf{a}^T \mathbf{u}_j = a_j$$

The result is the scalar element  $a_j$ .

$$\mathbf{u}_i^T \mathbf{a}' \equiv \mathbf{a}'^T \mathbf{u}_i = a'_i$$

The result is the scalar element  $a'_i$ .

Row Selection from Matrices

$$\mathbf{u}_i^T \mathbf{A} = \mathbf{u}_i^T \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \cdot \\ \cdot \\ \mathbf{a}_m^T \end{bmatrix} = \mathbf{a}_i^T$$

This result is the row vector corresponding to the  $i$ th row of  $\mathbf{A}$ . In transposed form, we have

$$\mathbf{A}^T \mathbf{u}_i = \mathbf{a}_i$$



Column Selection from Matrices

$$\mathbf{A} \mathbf{u}_j = [\mathbf{a}'_1 \quad \mathbf{a}'_2 \quad \dots \quad \mathbf{a}'_n] \mathbf{u}_j = \mathbf{a}'_j$$

This result is the column vector corresponding to the  $j$ th column of  $\mathbf{A}$ . In transposed form, we have

$$\mathbf{u}_j^T \mathbf{A}^T = \mathbf{a}'_j{}^T$$

Element Selection from Matrices

$$\mathbf{u}_i^T \mathbf{A} \mathbf{u}_j = \begin{cases} \mathbf{u}_i^T (\mathbf{A} \mathbf{u}_j) = \mathbf{u}_i^T \mathbf{a}'_j = a_{ij} \\ (\mathbf{u}_i^T \mathbf{A}) \mathbf{u}_j = \mathbf{a}_i^T \mathbf{u}_j = a_{ij} \end{cases}$$

This result is the scalar element corresponding to the coefficient of  $\mathbf{A}$  obtained from the intersection of row  $i$  and column  $j$ .

Element Representation

$$\mathbf{A} = \begin{bmatrix} \mathbf{u}_1^T \mathbf{a}_1 & \mathbf{u}_2^T \mathbf{a}_1 & \dots & \mathbf{u}_n^T \mathbf{a}_1 \\ \mathbf{u}_1^T \mathbf{a}_2 & \mathbf{u}_2^T \mathbf{a}_2 & \dots & \mathbf{u}_n^T \mathbf{a}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{u}_1^T \mathbf{a}_m & \mathbf{u}_2^T \mathbf{a}_m & \dots & \mathbf{u}_n^T \mathbf{a}_m \end{bmatrix} = \mathbf{A}'^T,$$

where  $\mathbf{u}_j, j = 1, \dots, n$  is  $n$ -dimensional.

$$\mathbf{A}'^T = \begin{bmatrix} \mathbf{u}_1^T \mathbf{a}'_1 & \mathbf{u}_1^T \mathbf{a}'_2 & \dots & \mathbf{u}_1^T \mathbf{a}'_n \\ \mathbf{u}_2^T \mathbf{a}'_1 & \mathbf{u}_2^T \mathbf{a}'_2 & \dots & \mathbf{u}_2^T \mathbf{a}'_n \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{u}_m^T \mathbf{a}'_1 & \mathbf{u}_m^T \mathbf{a}'_2 & \dots & \mathbf{u}_m^T \mathbf{a}'_n \end{bmatrix} = \mathbf{A},$$

where  $\mathbf{u}_i, i = 1, \dots, m$  is  $m$ -dimensional.

Assembly of an Element into a Column Vector

To place the parameter  $\phi$  into the  $i$ th row of a column vector we write

$$\mathbf{u}_i \phi = \begin{bmatrix} 0 \\ \cdot \\ \cdot \\ \cdot \\ \phi \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \leftarrow \text{ith row}$$

This results in a column vector containing zeros everywhere except in the  $i$ th row, which contains  $\phi$ .

Assembly of an Element into a Row Vector

To place the parameter  $\phi$  into the  $j$ th column of a row vector we write

$$\phi \mathbf{u}_j^T = [0 \quad \dots \quad \phi \quad \dots \quad 0]$$

↑  
jth col

This results in a row vector containing zeros everywhere except in the  $j$ th column, which contains  $\phi$ .

Assembly of a Vector into a Row of a Matrix

To place the n-dimensional vector  $\mathbf{a}$  into the  $i$ th row of a matrix we write

$$\mathbf{u}_i \mathbf{a}^T = \begin{bmatrix} 0 & 0 & & 0 \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ 0 & 0 & & 0 \\ a_1 & a_2 & \dots & a_n \\ 0 & 0 & & 0 \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ 0 & 0 & & 0 \end{bmatrix} \leftarrow \text{ith row}$$

This results in a matrix containing zeros everywhere except in the  $i$ th row, which contains  $\mathbf{a}^T$ .

Assembly of a Vector into a Column of a Matrix

To place the  $m$ -dimensional vector  $\mathbf{a}'$  into the  $j$ th column of a matrix we write

$$\mathbf{a}' \mathbf{u}_j^T = \begin{bmatrix} 0 & \dots & 0 & a'_1 & 0 & \dots & 0 \\ 0 & \dots & 0 & a'_2 & 0 & \dots & 0 \\ & & & \vdots & & & \\ & & & \vdots & & & \\ & & & \vdots & & & \\ 0 & \dots & 0 & a'_m & 0 & \dots & 0 \end{bmatrix}$$

↑  
jth col

This results in a matrix containing zeros everywhere except in the  $j$ th column, which contains  $\mathbf{a}'$ .

Assembly of an Element into a Matrix

To place the parameter  $\phi$  into the intersection of row  $i$  and column  $j$  we write

$$\mathbf{u}_i \phi \mathbf{u}_j^T = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ \dots & \phi & \dots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix} \begin{array}{l} \text{ith row} \\ \text{jth col} \end{array}$$

This results in a matrix containing zeros everywhere except in the  $i,j$  location, which contains  $\phi$ .

Two other forms are convenient to represent. The first one is

$$\mathbf{u}_i (\phi \mathbf{u}_j^T) = \begin{bmatrix} \mathbf{0}^T \\ \mathbf{0}^T \\ \vdots \\ \vdots \\ \vdots \\ \phi \mathbf{u}_j^T \\ \vdots \\ \vdots \\ \mathbf{0}^T \end{bmatrix} \leftarrow \text{ith row}$$

The other form is

$$(\mathbf{u}_i \phi) \mathbf{u}_j^T = [\mathbf{0} \quad \mathbf{0} \quad \dots \quad \mathbf{u}_i \phi \quad \dots \quad \mathbf{0}]$$

↑  
jth col



Assembly of a Matrix

To assemble **A** we may write

$$\mathbf{A} = \sum_{i=1}^m \sum_{j=1}^n \mathbf{u}_i a_{ij} \mathbf{u}_j^T$$

Assembly of the  $i$ th Row of a Matrix

To assemble the  $i$ th row of  $\mathbf{A}$  we write

$$\mathbf{a}_i^T = \sum_{j=1}^n a_{ij} \mathbf{u}_j^T$$

Assembly of the jth Column of a Matrix

To assemble the jth column of **A** we write

$$\mathbf{a}_j = \sum_{i=1}^m \mathbf{u}_i a_{ij}$$

Dyadic Product of  $\mathbf{a}$  and  $\mathbf{b}$ 

Let

$$\mathbf{a} \triangleq \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}, \quad \mathbf{b} \triangleq \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

Then

$$\mathbf{a} \mathbf{b}^T \triangleq \begin{bmatrix} a_1 b_1 & a_1 b_2 & \dots & a_1 b_m \\ a_2 b_1 & a_2 b_2 & \dots & a_2 b_m \\ \vdots & \vdots & & \vdots \\ a_n b_1 & a_n b_2 & \dots & a_n b_m \end{bmatrix}$$

This result is the  $n$  by  $m$  matrix containing all possible products  $a_i b_j$ ,  $i = 1, 2, \dots, n$ ;  $j = 1, 2, \dots, m$ .

Definitions of Derivative Operators

$$\frac{\partial}{\partial \mathbf{a}} \triangleq \begin{bmatrix} \frac{\partial}{\partial a_1} \\ \frac{\partial}{\partial a_2} \\ \vdots \\ \frac{\partial}{\partial a_n} \end{bmatrix}$$

$$\frac{\partial}{\partial \mathbf{A}} \triangleq \begin{bmatrix} \frac{\partial}{\partial a_{11}} & \frac{\partial}{\partial a_{12}} & \dots & \frac{\partial}{\partial a_{1n}} \\ \frac{\partial}{\partial a_{21}} & \frac{\partial}{\partial a_{22}} & \dots & \frac{\partial}{\partial a_{2n}} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial}{\partial a_{m1}} & \frac{\partial}{\partial a_{m2}} & \dots & \frac{\partial}{\partial a_{mn}} \end{bmatrix}$$

Derivatives of Scalar Products

$$\frac{\partial(\mathbf{a}^T \mathbf{b})}{\partial \mathbf{a}} = \left( \frac{\partial \mathbf{a}^T}{\partial \mathbf{a}} \right) \mathbf{b} = \mathbf{b}$$

Also,

$$\frac{\partial(\mathbf{b}^T \mathbf{a})}{\partial \mathbf{a}} = \frac{\partial(\mathbf{a}^T \mathbf{b})}{\partial \mathbf{a}} = \mathbf{b}$$

Jacobian Matrix [ $\mathbf{b} \neq \mathbf{a}$ ]

Let

$$\mathbf{a} \triangleq \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}, \quad \mathbf{b} \triangleq \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

Then

$$\frac{\partial \mathbf{b}^T}{\partial \mathbf{a}} \triangleq \left( \frac{\partial}{\partial \mathbf{a}} \right) \mathbf{b}^T = \begin{bmatrix} \frac{\partial b_1}{\partial a_1} & \frac{\partial b_1}{\partial a_2} & \cdots & \frac{\partial b_1}{\partial a_n} \\ \frac{\partial b_2}{\partial a_1} & \frac{\partial b_2}{\partial a_2} & \cdots & \frac{\partial b_2}{\partial a_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial b_m}{\partial a_1} & \frac{\partial b_m}{\partial a_2} & \cdots & \frac{\partial b_m}{\partial a_n} \end{bmatrix}^T$$

$$= \begin{bmatrix} \left( \frac{\partial b_1}{\partial \mathbf{a}} \right)^T \\ \left( \frac{\partial b_2}{\partial \mathbf{a}} \right)^T \\ \vdots \\ \left( \frac{\partial b_m}{\partial \mathbf{a}} \right)^T \end{bmatrix}^T = \begin{bmatrix} \frac{\partial b_1}{\partial a_1} & \frac{\partial b_1}{\partial a_2} & \cdots & \frac{\partial b_1}{\partial a_n} \\ \frac{\partial b_2}{\partial a_1} & \frac{\partial b_2}{\partial a_2} & \cdots & \frac{\partial b_2}{\partial a_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial b_m}{\partial a_1} & \frac{\partial b_m}{\partial a_2} & \cdots & \frac{\partial b_m}{\partial a_n} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\partial \mathbf{b}}{\partial a_1} & \frac{\partial \mathbf{b}}{\partial a_2} & \cdots & \frac{\partial \mathbf{b}}{\partial a_n} \end{bmatrix}^T$$

Jacobian Matrix [ $\mathbf{b} \equiv \mathbf{a}$ ]

$$\begin{aligned} \frac{\partial \mathbf{a}^T}{\partial \mathbf{a}} &= \left[ \frac{\partial a_1}{\partial \mathbf{a}} \quad \frac{\partial a_2}{\partial \mathbf{a}} \quad \dots \quad \frac{\partial a_n}{\partial \mathbf{a}} \right] \\ &= [\mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_n] = \mathbf{1} \\ &= \left[ \frac{\partial \mathbf{a}}{\partial a_1} \quad \frac{\partial \mathbf{a}}{\partial a_2} \quad \dots \quad \frac{\partial \mathbf{a}}{\partial a_n} \right]^T \\ &= [\mathbf{u}_1 \quad \mathbf{u}_2 \quad \dots \quad \mathbf{u}_n]^T = \mathbf{1} \end{aligned}$$

where,

$$\mathbf{a} = \sum_{i=1}^n a_i \mathbf{u}_i$$

and

$$\frac{\partial}{\partial \mathbf{a}} = \sum_{i=1}^n \frac{\partial}{\partial a_i} \mathbf{u}_i$$

Hence,

$$\frac{\partial \mathbf{a}}{\partial a_i} \equiv \frac{\partial a_i}{\partial \mathbf{a}} \equiv \mathbf{u}_i$$



Jacobian Matrix [ $\mathbf{b} = \mathbf{A} \mathbf{a}$ ]

$$\frac{\partial \mathbf{b}^T}{\partial \mathbf{a}} = \frac{\partial (\mathbf{a}^T \mathbf{A}^T)}{\partial \mathbf{a}} = \mathbf{A}^T$$

Jacobian Matrix [ $\mathbf{b} = \mathbf{A}^T \mathbf{a}$ ]

$$\frac{\partial \mathbf{b}^T}{\partial \mathbf{a}} = \frac{\partial (\mathbf{a}^T \mathbf{A})}{\partial \mathbf{a}} = \mathbf{A}$$

Jacobian Matrix [ $\mathbf{b} = \mathbf{c}^T \mathbf{A} \mathbf{a}$ ]

$$\frac{\partial \mathbf{b}}{\partial \mathbf{a}} = \mathbf{A}^T \mathbf{c}$$

Jacobian Matrix [ $\mathbf{b} = \mathbf{a}^T \mathbf{A} \mathbf{c}$ ]

$$\frac{\partial \mathbf{b}}{\partial \mathbf{a}} = \mathbf{A} \mathbf{c}$$

Jacobian Matrix [ $\mathbf{b} = \mathbf{a}^T \mathbf{A} \mathbf{a}$ ]

$$\frac{\partial \mathbf{b}}{\partial \mathbf{a}} = \mathbf{A} \mathbf{a} + \mathbf{A}^T \mathbf{a} = (\mathbf{A} + \mathbf{A}^T) \mathbf{a}$$

Derivative of an Element of a Matrix w.r.t. A

$$\frac{\partial a_{ij}}{\partial A} = \begin{bmatrix} \cdot \\ \cdot \\ \cdot \\ \cdot \\ \dots & 1 & \dots \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \begin{array}{l} \\ \\ \\ \\ \text{ith row} \\ \\ \\ \\ \\ \end{array}$$

jth col

$$= \mathbf{u}_i \mathbf{u}_j^T$$

The result is a matrix with zeros everywhere except at the intersection of row  $i$  and column  $j$ , which has a 1.

Derivative of  $\mathbf{A}$  w.r.t.  $a_{ij}$

$$\frac{\partial \mathbf{A}}{\partial a_{ij}} = \mathbf{u}_i \mathbf{u}_j^T \equiv \frac{\partial a_{ij}}{\partial \mathbf{A}}$$

Derivative of  $\mathbf{A}^{-1}$  where  $m = n$ 

We have, by definition

$$\mathbf{A}^{-1} \mathbf{A} = \mathbf{1}$$

from which

$$\frac{\partial \mathbf{A}^{-1}}{\partial \phi} = -\mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi} \mathbf{A}^{-1}$$

Derivative of  $\mathbf{A}^{-1}$  w.r.t.  $a_{ij}$ 

$$\frac{\partial \mathbf{A}^{-1}}{\partial a_{ij}} = -\mathbf{A}^{-1} \mathbf{u}_i \mathbf{u}_j^T \mathbf{A}^{-1}$$

$$= -\mathbf{p}_i \mathbf{q}_j^T$$

where  $\mathbf{p}_i$  and  $\mathbf{q}_j$  are solutions to

$$\mathbf{A} \mathbf{p}_i = \mathbf{u}_i$$

$$\mathbf{A}^T \mathbf{q}_j = \mathbf{u}_j$$

Derivatives of the Solution of  $\mathbf{Ax} = \mathbf{b}$

Let  $\mathbf{A}$  be  $n \times n$ ,  $\mathbf{x}$  and  $\mathbf{b}$  be  $n$ -dimensional. Then,

$$\begin{aligned} \frac{\partial \mathbf{x}}{\partial a_{ij}} &= \frac{\partial (\mathbf{A}^{-1} \mathbf{b})}{\partial a_{ij}} \\ &= -\mathbf{A}^{-1} \mathbf{u}_i \mathbf{u}_j^T \mathbf{A}^{-1} \mathbf{b} = -\mathbf{p}_i x_j \end{aligned}$$

Derivative of an Element of the Solution of  $\mathbf{Ax} = \mathbf{b}$

Let

$$\begin{aligned} \frac{\partial x_k}{\partial a_{ij}} &= \mathbf{u}_k^T \frac{\partial \mathbf{x}}{\partial a_{ij}} = -\mathbf{u}_k^T \mathbf{A}^{-1} \mathbf{u}_i \mathbf{u}_j^T \mathbf{A}^{-1} \mathbf{b} \\ &= -\hat{\mathbf{x}}_k^T \mathbf{u}_i \mathbf{u}_j^T \mathbf{x} \\ &= -\hat{x}_{ki} x_j \end{aligned}$$

Hence,

$$\frac{\partial x_k}{\partial \mathbf{A}} = -\hat{\mathbf{x}}_k \mathbf{x}^T$$

where  $\hat{\mathbf{x}}_k$  is the solution of

$$\mathbf{A}^T \hat{\mathbf{x}}_k = \mathbf{u}_k$$

Derivative of a Linear Combination of the Elements of the Solution of  $\mathbf{A} \mathbf{x} = \mathbf{b}$ 

Let  $\bar{x} = \mathbf{u}^T \mathbf{x}$

Then

$$\begin{aligned} \frac{\partial \bar{x}}{\partial a_{ij}} &= \frac{\partial(\mathbf{u}^T \mathbf{x})}{\partial a_{ij}} = -\mathbf{u}^T \mathbf{p}_i \mathbf{q}_j^T \mathbf{b} \\ &= -(\mathbf{u}^T \mathbf{p}_i)(\mathbf{b}^T \mathbf{q}_j) \end{aligned}$$

The result comes from the appropriate linear combinations of  $\mathbf{p}_i$  and  $\mathbf{q}_j$ .

Alternatively,

$$\begin{aligned} \frac{\partial \bar{x}}{\partial a_{ij}} &= -\mathbf{q}_i^T \mathbf{u}_i \mathbf{u}_j^T \mathbf{x} \\ &= -\mathbf{q}_i \mathbf{x}_j \end{aligned}$$

where  $\mathbf{q}$  is the solution of

$$\mathbf{A}^T \mathbf{q} = \mathbf{u}$$

Hence

$$\frac{\partial \bar{x}}{\partial \mathbf{A}} = -\mathbf{q} \mathbf{x}^T$$

Also,

$$\frac{\partial \bar{x}}{\partial a_{ij}} = \mathbf{u}_i^T \frac{\partial \bar{x}}{\partial \mathbf{A}} \mathbf{u}_j$$

Hence

$$\frac{\partial \bar{x}}{\partial \phi} = \sum_{i=1}^n \sum_{j=1}^n \frac{\partial \bar{x}}{\partial a_{ij}} \frac{\partial a_{ij}}{\partial \phi} = \sum_{i=1}^n \sum_{j=1}^n \mathbf{u}_i^T \frac{\partial \bar{x}}{\partial \mathbf{A}} \mathbf{u}_j \frac{\partial a_{ij}}{\partial \phi}$$

Special Case 1

Let

$$\frac{\partial \mathbf{A}}{\partial \phi} \equiv \mathbf{u} \mathbf{u}_i^T - \mathbf{u} \mathbf{u}_j^T$$

Then

$$\begin{aligned} \frac{\partial \bar{x}}{\partial \phi} &= -\mathbf{u}^T \frac{\partial \mathbf{x}}{\partial \phi} = -\mathbf{u}^T \mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \phi} \mathbf{A}^{-1} \mathbf{b} \\ &= -\mathbf{u}^T \mathbf{A}^{-1} \mathbf{u} (\mathbf{u}_i - \mathbf{u}_j)^T \mathbf{A}^{-1} \mathbf{b} \\ &= -\mathbf{u}^T \mathbf{p} (x_i - x_j) \end{aligned}$$

Let

$$\mathbf{u} = \mathbf{u}_i - \mathbf{u}_j$$

Then

$$\frac{\partial \bar{x}}{\partial \phi} = -(p_i - p_j)(x_i - x_j)$$

and



$$\frac{\partial \mathbf{A}}{\partial \phi} = (\mathbf{u}_i - \mathbf{u}_j)(\mathbf{u}_i - \mathbf{u}_j)^T$$

$$= \begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots \\ \dots & 1 & \dots & -1 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \dots & -1 & \dots & 1 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \begin{array}{l} \leftarrow \text{ith row} \\ \leftarrow \text{jth row} \end{array}$$

$\begin{array}{cc} \uparrow & \uparrow \\ \text{ith col} & \text{jth col} \end{array}$

Special Case 2

Let

$$\frac{\partial \mathbf{A}}{\partial \phi} \equiv (\mathbf{u}_k - \mathbf{u}_\ell)(\mathbf{u}_k - \mathbf{u}_\ell)^T$$

Then

$$\begin{aligned} \frac{\partial \bar{\mathbf{x}}}{\partial \phi} &= -\mathbf{u}^T \mathbf{A}^{-1} (\mathbf{u}_k - \mathbf{u}_\ell) (\mathbf{u}_k - \mathbf{u}_\ell)^T \mathbf{A}^{-1} \mathbf{b} \\ &= -(\mathbf{q}_k - \mathbf{q}_\ell)(\mathbf{x}_k - \mathbf{x}_\ell) \end{aligned}$$

where  $\mathbf{q}$  is the solution to

$$\mathbf{A}^T \mathbf{q} = \mathbf{u}$$

and  $\mathbf{u}$  is the vector leading to  $\bar{\mathbf{x}} = \mathbf{u}^T \mathbf{x}$ .

Placing Elements Arbitrarily

Let

$$\mathbf{u}_0 \triangleq \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}$$

$$\mathbf{u}_1 \triangleq \begin{bmatrix} 1 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}$$

$$\mathbf{u}_2 \triangleq \begin{bmatrix} 0 \\ 1 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}$$

$$\mathbf{u}_n \triangleq \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 1 \end{bmatrix}$$

and denote

$$\mathbf{u}_{i,j} \triangleq \mathbf{u}_i - \mathbf{u}_j$$

$$\mathbf{u}_{rs,kl} \triangleq \mathbf{u}_r + \mathbf{u}_s - \mathbf{u}_k - \mathbf{u}_l$$

hence

$$\mathbf{u}_{i_1 i_2 \dots i_p, j_1 j_2 \dots j_q} \triangleq \sum_{k=1}^p \mathbf{u}_{i_k} - \sum_{\ell=1}^q \mathbf{u}_{j_\ell}$$

For example,

$$\mathbf{u}_{345,16} = \begin{bmatrix} -1 \\ 0 \\ 1 \\ 1 \\ 1 \\ -1 \end{bmatrix}$$

Then if

$$\mathbf{u} \equiv \mathbf{u}_{345,16}$$

we have

$$\mathbf{u}^T \mathbf{u} = \text{card} \{3, 4, 5, 1, 6\} = 5$$

and

$$\mathbf{u} \mathbf{u}^T = \begin{array}{cccccc} \left[ \begin{array}{cccccc} 1 & 0 & -1 & -1 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 1 & 1 & 1 & -1 \\ -1 & 0 & 1 & 1 & 1 & -1 \\ -1 & 0 & 1 & 1 & 1 & -1 \\ 1 & 0 & -1 & -1 & -1 & 1 \end{array} \right] & \begin{array}{l} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{array} \\ \begin{array}{cccccc} 1 & 2 & 3 & 4 & 5 & 6 \end{array} & \end{array}$$

$$= (\mathbf{u}_3 + \mathbf{u}_4 + \mathbf{u}_5 - \mathbf{u}_1 - \mathbf{u}_6)(\mathbf{u}_3 + \mathbf{u}_4 + \mathbf{u}_5 - \mathbf{u}_1 - \mathbf{u}_6)^T$$



