

# Matrix Differentiation.

Formula 1: If  $\Sigma = \bar{x}^T \bar{x}$ ,  $\frac{\partial \Sigma}{\partial \bar{x}} = 2\bar{x}$

Proof:  $\bar{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$   $\bar{x}^T = [x_1 \ x_2 \ \dots \ x_n]$

$$\Sigma = \bar{x}^T \cdot \bar{x} = \sum_{i=1}^n x_i^2$$

$$\Sigma = x_1^2 + x_2^2 + \dots + x_n^2$$

$$\Rightarrow \frac{\partial \Sigma}{\partial x_i} = 2x_i \Rightarrow \frac{\partial \Sigma}{\partial \bar{x}} = 2 \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = 2\bar{x} \quad \text{HP.}$$

Formula 2: If  $\Sigma = \bar{x}^T \bar{y}$ ,  $\frac{\partial \Sigma}{\partial \bar{x}} = \bar{y}$

Proof:  $\bar{x}^T = [x_1 \ x_2 \ \dots \ x_n]_{1 \times n}$   $\bar{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1}$

$$\Sigma = \bar{x}^T \bar{y} = x_1 y_1 + x_2 y_2 + \dots + x_n y_n$$

$$= \sum_{i=1}^n x_i y_i$$

$$\Rightarrow \frac{\partial \Sigma}{\partial x_i} = y_i \Rightarrow \frac{\partial \Sigma}{\partial \bar{x}} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \Rightarrow \frac{\partial \Sigma}{\partial \bar{x}} = \bar{y} \quad \text{HP.}$$

Formula 3: If  $\Sigma = (\bar{x}^T \bar{y})^2$ ,  $\frac{\partial \Sigma}{\partial \bar{x}} = 2(\bar{x}^T \bar{y}) \bar{y}$

Proof:  $\bar{x}^T = [x_1 \ \dots \ x_n]$   $\bar{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$

$$\Sigma = (\bar{x}^T \bar{y})^2 = (x_1 y_1 + x_2 y_2 + \dots + x_n y_n)^2$$

$$\Rightarrow \frac{\partial \Sigma}{\partial x_i} = 2(x_1 y_1 + \dots + x_n y_n) y_i \Rightarrow \frac{\partial \Sigma}{\partial \bar{x}} = 2(\bar{x}^T \bar{y}) \bar{y} \quad \text{HP.}$$

Formula 4:  $\frac{\partial (A\bar{x})}{\partial \bar{x}^T} = A$

Proof:  $A\bar{x} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}^{n \times n} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}^{n \times 1} = \begin{bmatrix} a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + \dots + a_{1n}x_n \\ a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + \dots + a_{2n}x_n \\ \vdots \\ a_{n1}x_1 + a_{n2}x_2 + a_{n3}x_3 + \dots + a_{nn}x_n \end{bmatrix}$

$$A\bar{x} = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_n \end{bmatrix}$$

$a_{ij}x_j \Rightarrow j$  is constant for each row.  
 $i$  is varying

where  $s_i$  is a row

$$s_i = a_{i1}x_1 + a_{i2}x_2 + a_{i3}x_3 + \dots + a_{in}x_n$$

To keep in mind:

$$(A)_{n \times n} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}_{n \times n}$$

$$(B)_{n \times n} = \begin{bmatrix} b_{11} & \dots & b_{1n} \\ \vdots & & \vdots \\ b_{n1} & \dots & b_{nn} \end{bmatrix}_{n \times n}$$

$$\bar{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}_{n \times 1} \quad \bar{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1}$$

$$S_i = a_{i1}x_1 + a_{i2}x_2 + a_{i3}x_3 + \dots + a_{in}x_n$$

$$= \sum_{j=1}^n a_{ij}x_j$$

$$\Rightarrow \frac{\partial S_i}{\partial x_j} = \sum a_{ij} \quad [\text{other terms vanish}]$$

$$\Rightarrow \frac{\partial A\bar{x}}{\partial \bar{x}} = \begin{bmatrix} \partial S_1 / \partial x_1 & \partial S_1 / \partial x_2 & \dots & \partial S_1 / \partial x_n \\ \vdots & \vdots & \ddots & \vdots \\ \partial S_n / \partial x_1 & \partial S_n / \partial x_2 & \dots & \partial S_n / \partial x_n \end{bmatrix}$$

$$= \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} = A$$

## Matrix Diff<sup>n</sup> Utilities.

Proposition A: If  $\bar{y}_{m \times 1}$ ,  $\bar{x}_{n \times 1}$ ,  $A_{m \times n}$ ,  $A$  doesn't depend on  $\bar{x}$ :

$$\frac{\partial \bar{y}}{\partial \bar{x}} = A$$

→ diff of  $m \times 1$  w.r.t  $n \times 1$  yields independent  $m \times n$  matrix

Proof:  $i^{\text{th}}$  element of  $\bar{y}$ :  $y_i$

$$y_i = \sum_{j=1}^n a_{ij}x_j$$

[Same as prev. proof but  $y_i$  in place of  $S_i$ ]

$$\frac{\partial y_i}{\partial x_j} = a_{ij}$$

$$\Rightarrow \frac{\partial \bar{y}}{\partial \bar{x}} = A \quad \text{hp.}$$

Proposition B: If  $\bar{y}_{m \times 1}$ ,  $\bar{x}_{n \times 1} = f(\bar{z})$ ,  $A_{m \times n}$ , doesn't depend on  $\bar{x}$  or  $\bar{z}$ :

$$\frac{\partial \bar{y}}{\partial \bar{z}} = A \frac{\partial \bar{x}}{\partial \bar{z}}$$

Proof:  $\bar{y} = A\bar{x}$

$$\text{wkt } y_i = \sum_{j=1}^n a_{ij}x_j \quad [\text{one row}]$$

$$\bar{x} = f(\bar{z})$$

$$\Rightarrow \frac{\partial y_i}{\partial z_j} = \sum_{j=1}^n a_{ij} \frac{\partial x_j}{\partial z_j}$$

$$\Rightarrow \frac{\partial \bar{y}}{\partial \bar{z}} = \frac{\partial \bar{y}}{\partial \bar{x}} \cdot \frac{\partial \bar{x}}{\partial \bar{z}} = A \frac{\partial \bar{x}}{\partial \bar{z}}$$

Proposition C:  $\bar{y}_{m \times 1}$ ,  $\bar{x}_{n \times 1}$ ,  $A$  doesn't depend on  $\bar{x}$  or  $\bar{y}$ .  $\alpha = \text{scalar} = \bar{y}^T A \bar{x}$

$$\frac{\partial \alpha}{\partial \bar{x}} = \bar{y}^T A \quad \frac{\partial \alpha}{\partial \bar{y}} = \bar{x}^T A^T$$

Proof: ①  $\alpha = \bar{y}^T A \bar{x}$

$$\text{Let } \bar{w}^T = \bar{y}^T A$$

$$\Rightarrow \alpha = \bar{w}^T \bar{x}$$

$$\frac{\partial \alpha}{\partial \bar{x}} = \bar{w}^T = \bar{y}^T A \quad \checkmark$$

②

$$\alpha^T = \alpha$$

$$\Rightarrow \alpha^T = (\bar{y}^T A \bar{x})^T$$

$$= \bar{x}^T A^T \bar{y}$$

$$\text{Let } \bar{w}^T = \bar{x}^T A^T$$

$$\Rightarrow \alpha^T = \alpha = \bar{w}^T \bar{y} \quad \checkmark$$

$$\frac{\partial \alpha}{\partial \bar{y}} = \bar{w}^T = \bar{x}^T A^T \quad \text{Hp}$$

Proposition D: If  $\bar{x}_{n \times 1}$ ,  $A_{m \times n}$  doesn't depend on  $\bar{x}$ ,  $\alpha = \text{scalar} = \bar{x}^T A \bar{x}$

$$\frac{\partial \alpha}{\partial \bar{x}} = \bar{x}^T (A + A^T)$$

Proof:

$$\alpha = \bar{x}^T A \bar{x}$$

$$= \sum_{j=1}^n \sum_{i=1}^m a_{ij} x_i x_j \quad [\text{two for loops}]$$

go row by row. Let  $k$  represent the row.

$$\frac{\partial \alpha}{\partial x_k} = \sum_{j=1}^m a_{kj} x_j + \sum_{i=1}^m a_{ik} x_i$$

$$\frac{\partial \alpha}{\partial \bar{x}} = \bar{x}^T A^T + \bar{x}^T A = \bar{x}^T (A^T + A) \quad \text{Hp.}$$

Proposition E: Same as D, but  $A_{m \times n}$  is symmetric  $\Rightarrow A^T = A$ .

$$\frac{\partial \alpha}{\partial \bar{x}} = 2 \bar{x}^T A$$

$$\text{Proof: } \frac{\partial \alpha}{\partial \bar{x}} = \bar{x}^T (A^T + A)$$

$$= 2 \bar{x}^T A \quad \text{Hp.}$$

Proposition F:  $\bar{y}_{m \times 1} = f(\bar{z})$ ,  $\bar{x}_{n \times 1} = f(\bar{z})$ ,  $\alpha = \text{scalar} = \bar{y}^T \bar{x}$

$$\frac{\partial \alpha}{\partial \bar{z}} = \bar{x}^T \frac{\partial \bar{y}}{\partial \bar{z}} + \bar{y}^T \frac{\partial \bar{x}}{\partial \bar{z}}$$

$$\text{Proof: } \bar{y}^T = [y_1, \dots, y_m] \quad \bar{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

$$\alpha = \bar{y}^T \bar{x} = \sum_{i=1}^n x_i y_i$$

$$\begin{aligned} \frac{\partial \alpha}{\partial z_k} &= \sum_{i=1}^n x_i \frac{\partial y_i}{\partial z_k} + y_i \frac{\partial x_i}{\partial z_k} \Rightarrow \frac{\partial \alpha}{\partial \bar{z}} = \frac{\partial \alpha}{\partial \bar{y}} \cdot \frac{\partial \bar{y}}{\partial \bar{z}} + \frac{\partial \alpha}{\partial \bar{x}} \cdot \frac{\partial \bar{x}}{\partial \bar{z}} \\ &= \bar{x}^T \frac{d\bar{y}}{d\bar{z}} + \bar{y}^T \frac{d\bar{x}}{d\bar{z}} \quad \text{hp.} \end{aligned}$$

$$= \bar{x}^T \frac{\partial \bar{y}}{\partial \bar{z}} + \bar{y}^T \frac{\partial \bar{x}}{\partial \bar{z}} \quad \text{hp.}$$

Proposition G:  $\bar{x}_{n \times 1} = f(\bar{z})$ ,  $\alpha = \text{scalar} = \bar{x}^T \bar{x}$

$$\frac{\partial \alpha}{\partial \bar{z}} = 2 \bar{x}^T \frac{\partial \bar{x}}{\partial \bar{z}}$$

Proof:

$$\begin{aligned} \frac{\partial \alpha}{\partial \bar{z}} &= \frac{\partial \alpha}{\partial \bar{x}} \cdot \frac{\partial \bar{x}}{\partial \bar{z}} + \frac{\partial \alpha}{\partial \bar{y}} \cdot \frac{\partial \bar{y}}{\partial \bar{z}} \\ &= 2 \left[ \frac{\partial \alpha}{\partial \bar{x}} \cdot \frac{\partial \bar{x}}{\partial \bar{z}} \right] \\ &= 2 \bar{x}^T \frac{\partial \bar{x}}{\partial \bar{z}} \quad \text{hp.} \end{aligned}$$

Proposition H:  $\bar{y}_{m \times 1} = f(\bar{z})$ ,  $\bar{x}_{n \times 1} = f(\bar{z})$ ,  $A_{m \times n}$  doesn't depend on  $\bar{z}$ ,  $\alpha = \text{scalar} = \bar{y}^T A \bar{x}$

$$\frac{\partial \alpha}{\partial \bar{z}} = \bar{x}^T A^T \frac{\partial \bar{y}}{\partial \bar{z}} + \bar{y}^T A \frac{\partial \bar{x}}{\partial \bar{z}}$$

Proof: wkt  $\frac{\partial \alpha}{\partial \bar{z}} = \frac{\partial \alpha}{\partial \bar{y}} \cdot \frac{\partial \bar{y}}{\partial \bar{z}} + \frac{\partial \alpha}{\partial \bar{x}} \cdot \frac{\partial \bar{x}}{\partial \bar{z}} = \bar{x}^T \frac{\partial \bar{y}}{\partial \bar{z}} + \bar{y}^T \frac{\partial \bar{x}}{\partial \bar{z}}$

let  $\bar{w}^T = \bar{y}^T A$

$\Rightarrow \alpha = \bar{w}^T \bar{x}$

$$\begin{aligned} \frac{\partial \alpha}{\partial \bar{z}} &= \bar{x}^T \frac{\partial \bar{w}}{\partial \bar{z}} + \bar{w}^T \frac{\partial \bar{x}}{\partial \bar{z}} \\ &= \bar{x}^T A^T \frac{\partial \bar{y}}{\partial \bar{z}} + \bar{y}^T A \frac{\partial \bar{x}}{\partial \bar{z}} \quad \text{hp.} \end{aligned}$$

Proposition I:  $\bar{y}_{m \times 1} = f(\bar{z})$ ,  $\bar{x}_{n \times 1} = f(\bar{z})$ ,  $A_{m \times n} \neq f(\bar{z})$ ,  $\alpha = \text{scalar} = \bar{x}^T A \bar{x}$

$$\frac{\partial \alpha}{\partial \bar{z}} = \bar{x}^T (A + A^T) \frac{\partial \bar{x}}{\partial \bar{z}}$$

Proof: same as before.

Proposition J: same as I, but  $A_{n \times n}$  is symmetric

$$\frac{\partial \alpha}{\partial \bar{z}} = 2 \bar{x}^T A \frac{\partial \bar{x}}{\partial \bar{z}}$$

Proof: same as before

Proposition K:  $A$  is a non-singular matrix,  $\{a_{ij}\} \in A$ ,  $a_{ij} = f(\alpha)$

$$\frac{\partial A^{-1}}{\partial \alpha} = -A^{-1} \frac{\partial A}{\partial \alpha} A^{-1}$$

Proof:  $A$  is non-singular  $\Rightarrow AA^{-1} = I$

$$\frac{\partial A}{\partial \alpha} A^{-1} + \frac{\partial A^{-1}}{\partial \alpha} A = 0$$

$$-\frac{\partial A}{\partial \alpha} A^{-1} = \frac{\partial A^{-1}}{\partial \alpha} A$$

$$\Rightarrow \frac{\partial A^{-1}}{\partial \alpha} = -A^{-1} \frac{\partial A}{\partial \alpha} A^{-1}$$

$$\frac{\partial A}{\partial \alpha} = \begin{bmatrix} \frac{\partial a_{11}}{\partial \alpha} & \frac{\partial a_{12}}{\partial \alpha} & \dots & \frac{\partial a_{1n}}{\partial \alpha} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial a_{n1}}{\partial \alpha} & \dots & \dots & \frac{\partial a_{nn}}{\partial \alpha} \end{bmatrix}$$

$$\frac{\partial A^{-1}}{\partial \alpha} = -A^{-1} \frac{\partial A}{\partial \alpha} A^{-1}$$