

Derivatives of matrices, vectors and scalar forms.

(You can find more details and properties in "matrix cookbook").

Notations: $\beta = [\beta_1, \beta_2, \dots, \beta_n]^T$ be an $n \times 1$ column vector of variables.

$a = [a_1, a_2, \dots, a_n]^T$ be an $n \times 1$ constant column vector.

A be an $m \times n$ constant matrix; Y be an $n \times n$ matrix of variables.

Examples: Please compute the following first-order derivative $\frac{\alpha f(\beta)}{\alpha \beta}$:

1. Let $f(\beta) = a^T \beta$, so that $f(\beta) : \mathbb{R}^n \mapsto \mathbb{R}^1$.

2. Let $f(\beta) = \beta^T a$, so that $f(\beta) : \mathbb{R}^n \mapsto \mathbb{R}^1$.

3. Let $f(\beta) = A\beta$, so that $f(\beta) : \mathbb{R}^n \mapsto \mathbb{R}^m$.

4. Let $f(\beta) = \beta^T A^T$, so that $f(\beta) : \mathbb{R}^n \mapsto \mathbb{R}^{m \times 1}$.

5. Let $f(\beta) = \beta^T (A^T A) \beta$, so that $f(\beta) : \mathbb{R}^n \mapsto \mathbb{R}^1$.

6. please compute $\frac{\alpha f(Y)}{\alpha Y}$, where $f(Y) = \text{tr}(Y a a^T)$, so that $f(Y) : \mathbb{R}^{n \times n} \mapsto \mathbb{R}^1$.

Solution 1:

$$f(\beta) = a^T \beta = [a_1, a_2, \dots, a_n] \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} = \sum_{i=1}^n a_i \beta_i.$$

By definition, we have $\frac{\alpha f(\beta)}{\alpha \beta} = \begin{bmatrix} \frac{\alpha f(\beta)}{\alpha \beta_1} \\ \frac{\alpha f(\beta)}{\alpha \beta_2} \\ \vdots \\ \frac{\alpha f(\beta)}{\alpha \beta_n} \end{bmatrix} = \begin{bmatrix} \frac{\alpha \sum_{i=1}^n a_i \beta_i}{\alpha \beta_1} \\ \frac{\alpha \sum_{i=1}^n a_i \beta_i}{\alpha \beta_2} \\ \vdots \\ \frac{\alpha \sum_{i=1}^n a_i \beta_i}{\alpha \beta_n} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = a$

\downarrow
 $\frac{\alpha \text{ scalar}}{\alpha \text{ vector}}$

Solution 2:

$$f(\beta) = \beta^T a = a^T \beta = \sum_{i=1}^n a_i \beta_i, \text{ similar we can derive:}$$

$$\frac{\alpha f(\beta)}{\alpha \beta} = \begin{bmatrix} \frac{\alpha f(\beta)}{\alpha \beta_1} \\ \frac{\alpha f(\beta)}{\alpha \beta_2} \\ \vdots \\ \frac{\alpha f(\beta)}{\alpha \beta_n} \end{bmatrix} = \begin{bmatrix} \frac{\alpha \sum_{i=1}^n a_i \beta_i}{\alpha \beta_1} \\ \frac{\alpha \sum_{i=1}^n a_i \beta_i}{\alpha \beta_2} \\ \vdots \\ \frac{\alpha \sum_{i=1}^n a_i \beta_i}{\alpha \beta_n} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = a$$

\downarrow
 $\frac{\alpha \text{ scalar}}{\alpha \text{ vector}}$

Solution 3:

$$f(\beta) = A\beta = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}_{m \times n} \cdot \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}_{n \times 1} = \left[\underbrace{\sum_{j=1}^n a_{1j} \beta_j}_{f_1(\beta)}, \underbrace{\sum_{j=1}^n a_{2j} \beta_j}_{f_2(\beta)}, \dots, \underbrace{\sum_{j=1}^n a_{mj} \beta_j}_{f_m(\beta)} \right]_{m \times 1}^T$$

By definition, we have

$\frac{\alpha f(\beta)}{\alpha \beta}$
 \downarrow
 α vector
 α vector

$$\frac{\alpha f(\beta)}{\alpha \beta} = \begin{bmatrix} \frac{\alpha f_1(\beta)}{\alpha \beta_1} & \frac{\alpha f_2(\beta)}{\alpha \beta_1} & \dots & \frac{\alpha f_m(\beta)}{\alpha \beta_1} \\ \frac{\alpha f_1(\beta)}{\alpha \beta_2} & \frac{\alpha f_2(\beta)}{\alpha \beta_2} & \dots & \frac{\alpha f_m(\beta)}{\alpha \beta_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\alpha f_1(\beta)}{\alpha \beta_n} & \frac{\alpha f_2(\beta)}{\alpha \beta_n} & \dots & \frac{\alpha f_m(\beta)}{\alpha \beta_n} \end{bmatrix}_{m \times n}$$

$\underbrace{\frac{\alpha f_1(\beta)}{\alpha \beta_n}}_{\frac{\alpha f_1(\beta)}{\alpha \dots}}$ $\underbrace{\frac{\alpha f_2(\beta)}{\alpha \beta_n}}_{\frac{\alpha f_2(\beta)}{\alpha \dots}}$ $\underbrace{\frac{\alpha f_m(\beta)}{\alpha \beta_n}}_{\frac{\alpha f_m(\beta)}{\alpha \dots}}$

$$= \begin{bmatrix} \frac{\alpha \sum_{j=1}^n a_{1j} \beta_j}{\alpha \beta_1} & \frac{\alpha \sum_{j=1}^n a_{2j} \beta_j}{\alpha \beta_1} & \dots & \frac{\alpha \sum_{j=1}^n a_{mj} \beta_j}{\alpha \beta_1} \\ \frac{\alpha \sum_{j=1}^n a_{1j} \beta_j}{\alpha \beta_2} & \frac{\alpha \sum_{j=1}^n a_{2j} \beta_j}{\alpha \beta_2} & \dots & \frac{\alpha \sum_{j=1}^n a_{mj} \beta_j}{\alpha \beta_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\alpha \sum_{j=1}^n a_{1j} \beta_j}{\alpha \beta_n} & \frac{\alpha \sum_{j=1}^n a_{2j} \beta_j}{\alpha \beta_n} & \dots & \frac{\alpha \sum_{j=1}^n a_{mj} \beta_j}{\alpha \beta_n} \end{bmatrix}_{m \times n} = \begin{bmatrix} a_{11} & a_{21} & \dots & a_{m1} \\ a_{12} & a_{22} & \dots & a_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{mn} \end{bmatrix}_{m \times n} = A^T$$

Solution 4:

$$f(\beta) = \beta^T A^T = [\beta_1, \beta_2, \dots, \beta_n]_{1 \times n} \begin{bmatrix} a_{11} & a_{21} & \dots & a_{m1} \\ a_{12} & a_{22} & \dots & a_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{mn} \end{bmatrix}_{n \times m} = \left[\underbrace{\sum_{j=1}^n a_{1j} \beta_j}_{f_1(\beta)}, \underbrace{\sum_{j=1}^n a_{2j} \beta_j}_{f_2(\beta)}, \dots, \underbrace{\sum_{j=1}^n a_{mj} \beta_j}_{f_m(\beta)} \right]_{1 \times m}$$

since $\frac{\alpha f^T(\beta)}{\alpha \beta} = \frac{\alpha (\beta^T A^T)^T}{\alpha \beta} = \frac{\alpha A \beta}{\alpha \beta} = A^T$ (from solution 3).

so we have $\frac{\alpha f(\beta)}{\alpha \beta} = \left(\frac{\alpha f^T(\beta)}{\alpha \beta} \right)^T = (A^T)^T = A$

Solution 5:

Using the formula $\frac{dh(x)g(x)}{dx} = \frac{dh(x)}{dx}g(x) + \frac{dg(x)}{dx}h(x)$,

Let $h(x) = h^T(\beta) = \beta^T A^T$; $g(x) = g(\beta) = A\beta$

then we have $\frac{\partial f(\beta)}{\partial \beta} = \frac{\partial h^T(\beta)g(\beta)}{\partial \beta} = \frac{\partial h(\beta)}{\partial \beta}g(\beta) + \frac{\partial g(\beta)}{\partial \beta}h(\beta)$

$$= A^T A \beta + A^T A \beta$$

$$= 2A^T A \beta$$

Notice that $h(\beta) = g(\beta) = A\beta$ in this example

Exercise: please calculate $\frac{\partial f(\beta)}{\partial \beta}$, where $f(\beta) = \beta^T X \beta$, X is an $n \times n$ constant matrix.

Answer: $\frac{\partial (\beta^T X \beta)}{\partial \beta} = (X^T + X)\beta$

Solution 6:

$$f(Y) = \text{tr}(Y A A^T) = \text{tr} \begin{bmatrix} \sum_{i=1}^n Y_{i1} a_{i1} & \dots & \sum_{i=1}^n Y_{i2} a_{i2} & \dots & \sum_{i=1}^n Y_{in} a_{in} \\ \vdots & & \vdots & & \vdots \\ \vdots & & \vdots & & \vdots \\ \vdots & & \vdots & & \vdots \\ \vdots & & \vdots & & \vdots \end{bmatrix}_{n \times n} = \sum_{j=1}^n \sum_{i=1}^n Y_{ji} a_{ij}$$

By definition:

$\frac{\partial f(Y)}{\partial Y} = \begin{bmatrix} \frac{\partial f(Y)}{\partial Y_{11}} & \frac{\partial f(Y)}{\partial Y_{12}} & \dots & \frac{\partial f(Y)}{\partial Y_{1n}} \\ \frac{\partial f(Y)}{\partial Y_{21}} & \frac{\partial f(Y)}{\partial Y_{22}} & \dots & \frac{\partial f(Y)}{\partial Y_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f(Y)}{\partial Y_{n1}} & \frac{\partial f(Y)}{\partial Y_{n2}} & \dots & \frac{\partial f(Y)}{\partial Y_{nn}} \end{bmatrix}_{n \times n} = \begin{bmatrix} a_1^2 & a_2 a_1 & \dots & a_n a_1 \\ a_1 a_2 & a_2^2 & & a_n a_2 \\ \vdots & \vdots & \ddots & \vdots \\ a_1 a_n & a_2 a_n & \dots & a_n^2 \end{bmatrix}_{n \times n} = A A^T$

\downarrow
 $\frac{\partial \text{scalar}}{\partial \text{matrix}}$

Exercise: please calculate $\frac{\partial f(Y)}{\partial Y}$, where $f(Y) = \text{tr}(Y X)$, X is an $n \times n$ constant matrix.

Answer: $\frac{\partial \text{tr}(Y X)}{\partial X} = X^T$