

Deriving some Matrix Cookbook identities

Linear algebra without matrix notation

Proving identities in (Petersen & Pedersen, 2008) using standard matrix notation can be cumbersome. It can be helpful to employ explicit tensor notation with a basis of vectors $\{e_i\}$ and dual vectors $\{e^i\}$. Dual vectors act on vectors as $e^j(e_i) = \delta_i^j$.

To agree with the standard meaning of juxtaposition as matrix multiplication, juxtaposing (dual) vectors means either *application* $e^i e_j = e_i(e_j)$ or the *tensor product* $e_i e^j = e_i \otimes e^j$ depending on the order. Note that $e_i e_j$ and $e^i e^j$ are left undefined (in the same way that row-row or column-column multiplications are undefined).

In tensorial notation, we have

$$\begin{pmatrix} u^1 \\ \vdots \\ u^n \end{pmatrix} \equiv u^i e_i, \quad (v_1 \cdots v_m) \equiv v_j e^j, \quad \begin{pmatrix} A_1^1 & \cdots & A_m^1 \\ \vdots & \ddots & \vdots \\ A_1^n & \cdots & A_m^n \end{pmatrix} \equiv A_j^i e_i e^j.$$

With this scheme, matrix multiplication looks like

$$Ax \equiv A_j^i x^k e_i e^j e_k = A_j^i x^k e_i \delta_k^j = A_j^i x^j e_i$$

with implicit summation over i, j, k .

For transposition, define $(e_i)^T = e^i$. If $a = a^i e_i$ and $a^T = a_i e^i$, then $a^i = a_i$.

The derivative of a function from matrices to scalars

Suppose $f : \mathbb{K}^{n \times m} \rightarrow \mathbb{K}$ is a scalar-valued function of matrices. The derivative $\partial f(X)/\partial X$ is understood to be the matrix whose ij component is the derivative of $f(X)$ with respect to the ij component of the input matrix X .

This can be expressed concretely as

$$\frac{\partial}{\partial X} f(X) \equiv \sum_{ij} \frac{d}{dt} f(X + t e_i e^j) \Big|_{t=0} e_i e^j$$

where the matrix form of $e_i e^j$ is the matrix with ij component one and others zero.

Identities from the Matrix Cookbook

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

$$\begin{aligned} \frac{\partial}{\partial X} (a^T X b) &= \sum_{ij} \frac{d}{dt} a^T (X + t e_i e^j) b \Big|_{t=0} e_i e^j \\ &= \sum_{ij} (a^T e_i e^j b) e_i e^j \\ &= \sum_{ij} (e^i a)^T (e^j b) e_i e^j \\ &= \sum_{ij} (a^i) (b^j) e_i e^j && \text{since } e^i a = a^j e^i (e_j) = a^j \delta_j^i \\ &= a^i b_j e_i e^j && \text{since } b^j = b_j \\ &= a^i e_i b_j e^j \\ &= ab^T \end{aligned}$$

$$\frac{\partial}{\partial X} \text{tr}(AXB) = A^T B^T$$

$$\begin{aligned} \frac{\partial}{\partial X} \text{tr}(AXB) &= \frac{d}{dt} \text{tr}(A(X + t e_i e^j)B) \Big|_{t=0} e_i e^j \\ &= \text{tr}(A e_i e^j B) e_i e^j \\ &= \text{tr}(A_b^a e_a e^b e_i e^j B_d^c e_c e^d) e_i e^j \\ &= A_b^a B_d^c \text{tr}(e_a e^b e_i e^j e_c e^d) e_i e^j \\ &= A_b^a B_d^c \delta_a^b \delta_c^d \text{tr}(e_a e^d) e_i e^j \\ &= A_b^a B_d^c \delta_a^d e_i e^j \\ &= B_d^c A_b^a e_i e^j \\ &= (BA)^j_i e_i e^j \\ &= ((BA)^T)^i_j e_i e^j \\ &= A^T B^T \end{aligned}$$

$$\frac{\partial}{\partial X} \text{tr}(X^2) = 2X^T$$

$$\begin{aligned} \frac{\partial}{\partial X} \text{tr}(X^2) &= \frac{d}{dt} \text{tr}((X + t e_i e^j)^2) \Big|_{t=0} e_i e^j \\ &= \frac{d}{dt} \text{tr}(X^2 + t X e_i e^j + t e_i e^j X + \mathcal{O}(t^2)) \Big|_{t=0} e_i e^j \\ &= \text{tr}(X e_i e^j + e_i e^j X) e_i e^j \\ &= 2X_b^a \text{tr}(e_a e^b e_i e^j) e_i e^j \\ &= 2X_b^a \delta_a^b \text{tr}(e_a e^j) e_i e^j \\ &= 2X_b^a \delta_a^j e_i e^j \\ &= 2X_b^j e_i e^j \\ &= 2(X^T)^i_j e_i e^j \\ &= 2X^T \end{aligned}$$

References

Petersen, K. B., & Pedersen, M. S. (2008,). *The Matrix Cookbook*.