

# cs229 notes

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## 1 Matrix Derivatives

Good link: <https://www.math.uwaterloo.ca/~hwolkowi/matrixcookbook.pdf>

### 1.1 Some useful identities

1.

$$\frac{\partial}{\partial X} \log |X| = X^{-1}$$

Proof:

$$\frac{\partial}{\partial X} \log |X| = \frac{1}{|X|} \frac{\partial |X|}{\partial X}$$

We know that

$$\left( \frac{\partial |X|}{\partial X} \right)_{ij} = \frac{\partial}{\partial X_{ij}} * \det(X)$$

and

$$\det(X) = X_{i1}C_{i1} + X_{i2}C_{i2} + \dots + X_{in}C_{in}$$

where  $C_{ij}$  is the cofactor of  $X_{ij}$ . So,

$$\frac{\partial}{\partial X_{ij}} * \det(X) = C_{ij}$$

$$\frac{\partial |X|}{\partial X} = C = \text{adj}(X)^T$$

where  $C$  is the cofactor matrix of  $X$ .  $\text{adj}(X)$  is the adjugate matrix of  $X$  and  $X^{-1} = \frac{\text{adj}X}{|X|}$ .

so we get

$$\frac{\partial}{\partial X} \log |X| = \frac{1}{|X|} \frac{\partial |X|}{\partial X} = \frac{1}{|X|} \text{adj}(X)^T = (X^{-1})^T$$

Reference: [kamper matrix calculus](#)

$$2. \frac{\partial}{\partial X} (z^T X^{-1} z) = -(X^{-1}) z z^T (X^{-1})$$

Proof:

$$\frac{\partial}{\partial X} (z^T X^{-1} z)$$

Lets first compute the derivative of  $z^T X^{-1} z$  with respect to  $X_{ij}$

$$\frac{\partial}{\partial X_{ij}} (z^T X^{-1} z)$$

Lets first derive  $\frac{\partial X^{-1}}{\partial X_{ij}}$

$$\frac{\partial X^{-1}}{\partial X_{ij}}$$

Using  $X * X^{-1} = I$  we get

$$X^{-1} \frac{\partial X}{\partial X_{ij}} + \frac{\partial X^{-1}}{\partial X_{ij}} X = 0$$

i.e.

$$\frac{\partial X^{-1}}{\partial X_{ij}} = -X^{-1} \frac{\partial X}{\partial X_{ij}} X^{-1}$$

where  $\frac{\partial X}{\partial X_{ij}}$  is the matrix of partial derivatives of  $X$  with respect to  $X_{ij}$  and it's elements are 0 except for the element at  $i, j$  which is 1.

So lets say  $H = \frac{\partial \text{tr}(z^T X^{-1} z)}{\partial X}$

$$H_{ij} = \frac{\partial}{\partial X_{ij}} \text{tr}(z^T X^{-1} z)$$

Using cyclic property of trace we get

$$H_{ij} = \frac{\partial}{\partial X_{ij}} \text{tr}(z^T X^{-1} z) = \frac{\partial}{\partial X_{ij}} \text{tr}(z z^T (X^{-1}))$$

We know that

$$\partial(\text{Tr}(A)) = \text{Tr}(\partial(A))$$

because trace is linear. so

$$H_{ij} = \text{tr}(z z^T \frac{\partial}{\partial X_{ij}} (X^{-1})) = \text{tr}(z z^T (-X^{-1} \frac{\partial X}{\partial X_{ij}} X^{-1}))$$

Using cyclic property of trace we get

$$H_{ij} = \text{tr}(X^{-1} z z^T X^{-1} \frac{\partial X}{\partial X_{ij}})$$

Now suppose that

$$F = X^{-1} z z^T X^{-1}$$

then

$$\text{tr}(F \frac{\partial X}{\partial X_{ij}}) = F_{ji} = F_{ij}$$

since  $F$  is symmetric. Hint: You can think of the fact only the  $j$ th row of  $F$  is multiplied by the  $j$ th column, and only  $i$ th column of  $j$ th row of  $F$  is multiplied by the  $i$ th row of  $j$ th column of  $F$  leading to element at  $F_{jj}$  contributing and the rest being zero.

Hence:  $H = -X^{-1} z z^T X^{-1}$

**2 Prove that if  $z^T H z \geq 0$  then  $H$  is positive semi-definite and cost function  $J$  is convex.  $H$  is Hessian matrix of  $J$ .**