# Theoretical Machine Learning - Assignment 1

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## 1. Problem 1

#### 1.1.

of order  $n \times 1$ .

Their matrix multiplication gives a vector = 
$$\begin{vmatrix} a_{11}x_1 + a_{12}x_2 + \dots a_{1n}x_n \\ a_{21}x_1 + a_{22}x_2 + \dots a_{2n}x_n \\ a_{31}x_1 + a_{32}x_2 + \dots a_{3n}x_n \\ & & & \\ & &$$

Now we use differentiation of one vector, Ax by another vector, x. This will give us a matrix of dimension m x n.

which gives us matrix A itself. Hence, Proven.

#### 1.2.

$$\begin{vmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{vmatrix}$$
 of order n x 1. Hence,  $x^T = |x_1 \ x_2 \ x_3 \ \dots \ x_n |$  of order 1 x n. 
$$x^T A = \left| \begin{array}{ccc} \sum_{i=1}^N (a_{i1}x_i) & \sum_{i=1}^N (a_{i2}x_i) & \dots & \sum_{i=1}^N (a_{in}x_i) \end{array} \right|$$
 of order 1 x n.

Hence,  $x^T A x = \sum_{i=1}^N \sum_{j=1}^N (a_{ij} x_i x_j)$ , which is a scalar. Now we differentiate a scalar wrt a vector.

$$\begin{vmatrix} \frac{\partial}{\partial x_1} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} x_i x_j) & \frac{\partial}{\partial x_1} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} x_i x_j) & \frac{\partial}{\partial x_3} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} x_i x_j) & \frac{\partial}{\partial x_1} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} x_i x_j) & \frac{\partial}{\partial x_i} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} x_i x_j) & \frac{\partial}{\partial$$

$$\left| \begin{array}{l} \sum\limits_{i=1}^{N} (a_{i1}x_i) + \sum\limits_{j=1}^{N} (a_{1j}x_j) & \sum\limits_{i=1}^{N} (a_{i2}x_i) + \sum\limits_{j=1}^{N} (a_{2j}x_j) & \sum\limits_{i=1}^{N} (a_{i3}x_i) + \sum\limits_{j=1}^{N} (a_{3j}x_j) & \dots & \sum\limits_{i=1}^{N} (a_{in}x_i) + \sum\limits_{j=1}^{N} (a_{nj}x_j) \end{array} \right|$$

This can be split into addition of 2 matrices as:

$$\left| \begin{array}{ccc} \sum_{i=1}^{N} (a_{i1}x_i) & \sum_{i=1}^{N} (a_{i2}x_i) & \dots & \sum_{i=1}^{N} (a_{in}x_i) \end{array} \right| + \left| \begin{array}{ccc} \sum_{j=1}^{N} (a_{1j}x_j) & \sum_{j=1}^{N} (a_{2j}x_j) & \dots & \sum_{j=1}^{N} (a_{nj}x_j) \end{array} \right|$$

This basically is,  $x^TA + x^TA^T = x^T(A + A^T)$ . Hence, Proven.

# 2. Problem 2

On differentiating a mx1 vector by a kx1 vector we get an mxk matrix. Now consider n such mx1 vectors stacked to form a m x n matrix, then the final dimension of the differentiation will be m x nk.

## 3. Problem 3

#### 3.1. Solve

$$\frac{\mathrm{d} \begin{vmatrix} 2sin^2(x)cos(y) \\ x^2 + 3e^y \end{vmatrix}}{\mathrm{d} \begin{vmatrix} x \\ y \end{vmatrix}}$$

$$= \begin{vmatrix} \frac{\partial (2sin^2(x)cos(y))}{\partial x} & \frac{\partial (2sin^2(x)cos(y))}{\partial y} \\ \frac{\partial (x^2 + 3e^y)}{\partial x} & \frac{\partial (x^2 + 3e^y)}{\partial y} \end{vmatrix} = \begin{vmatrix} 2sin(2x)cos(y) & -2sin^2(x)sin(y) \\ 2x & 3e^y \end{vmatrix}$$

#### 3.2. Solve

$$\frac{\mathrm{d} \begin{vmatrix} 3x^2y + xyzw \\ \sin(x^2 + yw - z) \end{vmatrix}}{\mathrm{d} \begin{vmatrix} x \\ y \\ w \\ z \end{vmatrix}}$$

$$= \begin{vmatrix} \frac{\partial(3x^2y + xyzw)}{\partial x} & \frac{\partial(3x^2y + xyzw)}{\partial y} & \frac{\partial(3x^2y + xyzw)}{\partial z} & \frac{\partial(3x^2y + xyzw)}{\partial z} & \frac{\partial(3x^2y + xyzw)}{\partial w} \\ \frac{\partial(\sin(x^2 + yw - z)}{\partial x} & \frac{\partial(\sin(x^2 + yw - z)}{\partial y} & \frac{\partial(\sin(x^2 + yw - z)}{\partial z} & \frac{\partial(\sin(x^2 + yw - z)}{\partial w} \end{vmatrix}$$

$$= \begin{vmatrix} 6xy + yzw & 3x^2 + xzw & xyw & xyz \\ 2x\cos(x^2 + yw - z) & w\cos(x^2 + yw - z) & -\cos(x^2 + yw - z) & y\cos(x^2 + yw - z) \end{vmatrix}$$

$$= \begin{vmatrix} 6xy + yzw & 3x^2 + xzw & xyw & xyz \\ 2x\cos(x^2 + yw - z) & w\cos(x^2 + yw - z) & -\cos(x^2 + yw - z) & y\cos(x^2 + yw - z) \end{vmatrix}$$

### 4. Problem 4

$$\text{Consider } \beta = \left| \begin{array}{c} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_n \end{array} \right| \text{ and } \mathbf{x} = \left| \begin{array}{c} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{array} \right|, \text{ both vectors of order n x 1.}$$

Then  $\beta^T x = \sum_{i=1}^{N} (\beta_i x_i)$ . So,  $e^{\sum_{i=1}^{N} (\beta_i x_i)}$ is a scalar, which is to be differentiated by the vector  $\mathbf{x}$ . This gives us the transpose a vector.

$$\begin{vmatrix} \sum_{\frac{N}{2}(\beta_{i}x_{i})}^{N} & \sum_{\frac{N}{2}(\beta_{i}x_{i})}^{N} & \sum_{\frac{N}{2}(\beta_{i}x_{i})}^{N} & \sum_{\frac{N}{2}(\beta_{i}x_{i})}^{N} & \dots & \sum_{\frac{N}{2}(\beta_{i}x_{i})}^{N} \end{vmatrix}$$

$$= \begin{vmatrix} \sum_{\beta_{1}}^{N}(\beta_{i}x_{i}) & \sum_{\beta_{2}}^{N}(\beta_{i}x_{i}) & \sum_{\beta_{3}}^{N}(\beta_{i}x_{i}) & \sum_{\beta_{3}}^{N}(\beta_{i}x_{i}) & \dots & \beta_{n}e^{i=1} \end{vmatrix}$$

$$= \begin{vmatrix} \beta_{1}e^{\beta^{T}x} & \beta_{2}e^{\beta^{T}x} & \beta_{3}e^{\beta^{T}x} & \dots & \beta_{n}e^{\beta^{T}x} \end{vmatrix} = e^{\beta^{T}x} \begin{vmatrix} \beta_{1} & \beta_{2} & \beta_{3} & \dots & \beta_{n} \end{vmatrix} = \beta^{T}e^{\beta^{T}x}$$

$$\mathbf{Ans} \mathbf{)} \beta^{T}e^{\beta^{T}x}$$