

# CS-563 Deep Learning

## Matrix and Vector Calculus



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# Matrix Calculus

- ▶ Specialised notation for multivariate calculus.
  - ▶ Simplifies operations such as finding the minimum of a multivariate function.
  - ▶ Different conventions exist. You may choose any as long as you remain consistent.
  - ▶ Purpose of these slides is to set the convention for the rest of the course.
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## Notation

- ▶ Scalars are denoted by lower-case letters like  $s, a, b$ .
- ▶ Vectors are denoted by lower-case bold letters like  $\mathbf{x}, \mathbf{y}, \mathbf{v}$ .
- ▶ Matrices are denoted by upper-case bold letters like  $\mathbf{M}, \mathbf{D}, \mathbf{A}$ .
- ▶ Any vector  $\mathbf{x} \in \mathbb{R}^d$  is by default a column vector.

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix}$$

- ▶ The corresponding row vector is obtained as  $\mathbf{x}^T = [x_1 \quad x_2 \quad \dots \quad x_d]$ .
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# Vectors

For vectors  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$  and  $\mathbf{z} \in \mathbb{R}^k$

- ▶ *Inner product*  $\mathbf{x}^T \mathbf{y} = x_1 y_1 + x_2 y_2 + \dots + x_d y_d$  is a scalar value. Also called *dot product* or *scalar product*.
- ▶ Other representations:  $\mathbf{x} \cdot \mathbf{y}$ ,  $(\mathbf{x}, \mathbf{y})$  and  $\langle \mathbf{x}, \mathbf{y} \rangle$ .
- ▶ Represents similarity of vectors.
  - ▶ If  $\mathbf{x}^T \mathbf{y} = 0$ , then  $\mathbf{x}$  and  $\mathbf{y}$  are orthogonal vectors (in 2D, this means they are perpendicular).
- ▶ *Euclidean norm* of vector

$$\|\mathbf{x}\| = \sqrt{\mathbf{x}^T \mathbf{x}} = \sqrt{x_1 x_1 + x_2 x_2 + \dots + x_d x_d}$$

represents the magnitude of the vector.

- ▶ *Unit vector* has norm 1. Also called *normalised vector*.
  - ▶ If  $\|\mathbf{x}\| = 1$  and  $\|\mathbf{y}\| = 1$ , and  $\mathbf{x}^T \mathbf{y} = 0$ , then  $\mathbf{x}$  and  $\mathbf{y}$  are *orthonormal vectors*.
  - ▶ *Outer-product*  $\mathbf{x} \mathbf{z}^T$  is a  $d \times k$  matrix.
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## Matrix and Vector Calculus

For scalars  $x, y \in \mathbb{R}$ , vectors  $\mathbf{x} \in \mathbb{R}^d$ ,  $\mathbf{y} \in \mathbb{R}^k$  and matrices  $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}$ , we will use the following conventions for writing matrix and vector derivatives.

$$\text{Scalar w.r.t vector: } \nabla_{\mathbf{x}} y = \frac{\partial y}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial y}{\partial x_1} & \frac{\partial y}{\partial x_2} & \cdots & \frac{\partial y}{\partial x_d} \end{bmatrix}$$

$$\text{Vector w.r.t scalar: } \nabla_x \mathbf{y} = \frac{\partial \mathbf{y}}{\partial x} = \begin{bmatrix} \frac{\partial y_1}{\partial x} \\ \frac{\partial y_2}{\partial x} \\ \vdots \\ \frac{\partial y_k}{\partial x} \end{bmatrix}$$

$$\text{Vector w.r.t vector: } \nabla_{\mathbf{x}} \mathbf{y} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{bmatrix} \nabla_{\mathbf{x}} y_1 \\ \nabla_{\mathbf{x}} y_2 \\ \vdots \\ \nabla_{\mathbf{x}} y_k \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \cdots & \frac{\partial y_1}{\partial x_d} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \cdots & \frac{\partial y_2}{\partial x_d} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_k}{\partial x_1} & \frac{\partial y_k}{\partial x_2} & \cdots & \frac{\partial y_k}{\partial x_d} \end{bmatrix}}_{k \times d}$$

# Matrix and Vector Calculus

$$\text{Scalar w.r.t matrix: } \nabla_{\mathbf{x}} y = \frac{\partial y}{\partial \mathbf{X}} = \begin{bmatrix} \frac{\partial y}{\partial x_{11}} & \frac{\partial y}{\partial x_{21}} & \cdots & \frac{\partial y}{\partial x_{m1}} \\ \frac{\partial y}{\partial x_{12}} & \frac{\partial y}{\partial x_{22}} & \cdots & \frac{\partial y}{\partial x_{m2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y}{\partial x_{1n}} & \frac{\partial y}{\partial x_{2n}} & \cdots & \frac{\partial y}{\partial x_{mn}} \end{bmatrix}$$

$$\text{Matrix w.r.t scalar: } \nabla_x \mathbf{Y} = \frac{\partial \mathbf{Y}}{\partial x} = \begin{bmatrix} \frac{\partial y_{11}}{\partial x} & \frac{\partial y_{12}}{\partial x} & \cdots & \frac{\partial y_{1n}}{\partial x} \\ \frac{\partial y_{21}}{\partial x} & \frac{\partial y_{22}}{\partial x} & \cdots & \frac{\partial y_{2n}}{\partial x} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_{m1}}{\partial x} & \frac{\partial y_{m2}}{\partial x} & \cdots & \frac{\partial y_{mn}}{\partial x} \end{bmatrix}$$

# Matrix and Vector Calculus

For vectors  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$  and matrices  $\mathbf{M} \in \mathbb{R}^{k \times d}$  and  $\mathbf{A} \in \mathbb{R}^{d \times d}$

- ▶  $\nabla_{\mathbf{x}}(\mathbf{y}^T \mathbf{x}) = \nabla_{\mathbf{x}}(\mathbf{x}^T \mathbf{y}) = \mathbf{y}^T$
- ▶  $\nabla_{\mathbf{x}}(\mathbf{M}\mathbf{x}) = \mathbf{M}$
- ▶  $\nabla_{\mathbf{x}}(\mathbf{x}^T \mathbf{A}\mathbf{x}) = \mathbf{x}^T(\mathbf{A}^T + \mathbf{A})$
- ▶ For symmetric  $\mathbf{A}$ ,  $\nabla_{\mathbf{x}}(\mathbf{x}^T \mathbf{A}\mathbf{x}) = 2(\mathbf{A}\mathbf{x})^T$

Prove all of the derivatives given above.