

## VIP Refresher: Linear Algebra and Calculus



**r Vector** – We note  $x \in \mathbb{R}^n$  a vector with  $n$  entries where  $x_i \in \mathbb{R}$  is the  $i$ th entry:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \in \mathbb{R}^n$$

**r Matrix** – We note  $A \in \mathbb{R}^{m \times n}$  a matrix with  $m$  rows and  $n$  columns, where  $A_{ij} \in \mathbb{R}$  is the entry located in the  $i$ th row and  $j$ th column:

$$A = \begin{pmatrix} A_{1,1} & A_{1,2} & \dots & A_{1,n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m,1} & A_{m,2} & \dots & A_{m,n} \end{pmatrix}$$

$A = \dots$

$$\begin{pmatrix} \vdots \\ \vdots \\ \vdots \end{pmatrix} \in \mathbb{R}^{m \times n}$$

*Remark: the vector  $x$  defined above can be viewed as a  $n \times 1$  matrix and is more particularly called a column-vector.*

**r Identity matrix** – The identity matrix  $I \in \mathbb{R}^{n \times n}$  is a square matrix with ones in its diagonal and zero everywhere else:

$$I = \begin{pmatrix} 1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 1 \end{pmatrix}$$

*Remark: for all matrices  $A \in \mathbb{R}^{n \times n}$ , we have  $Ax = Ix = Ax$ .*

**r Diagonal matrix** – A diagonal matrix  $D \in \mathbb{R}^{n \times n}$  is a square matrix with non-zero values in its diagonal and zero everywhere else:

$$D = \begin{pmatrix} d_1 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & d_n \end{pmatrix}$$

$D = 0, \dots, 0$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

$\vdots$

*Remark: we also note  $D$  as  $\text{diag}(d_1, \dots, d_n)$ .*

## Matrix operations

**r Vector-vector multiplication** – There are two types of vector-vector products:

• inner product: for  $x, y \in \mathbb{R}^n$ , we have:

$$x^T y = \sum_{i=1}^n x_i y_i$$

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$$x^T y = \sum_{i=1}^n x_i y_i$$

$$\in \mathbb{R}$$

$$i=1$$

• outer product: for  $x \in \mathbb{R}^m, y \in \mathbb{R}^n$

$$(x y^T)_{ij} = x_i y_j \in \mathbb{R}^{m \times n}$$

**r Matrix-vector multiplication** – The product of matrix  $A \in \mathbb{R}^{m \times n}$  and vector  $x \in \mathbb{R}^n$  is a vector of size  $m$ , such that:

$$(Ax)_i = \sum_{j=1}^n A_{ij} x_j = a_i^T x$$

where  $a_i^T$  are the vector rows and  $a_j$  are the vector columns of  $A$ , and  $x_i$  are the entries of  $x$ .

**r Matrix-matrix multiplication** – The product of matrices  $A \in \mathbb{R}^{m \times n}$  and  $B \in \mathbb{R}^{n \times p}$  is a matrix of size  $m \times p$ , such that:

$$(AB)_{ij} = \sum_{k=1}^n A_{ik} B_{kj} = a_i^T b_j$$

**r Transpose** – The transpose of a matrix  $A \in \mathbb{R}^{m \times n}$ , noted  $A^T$ , is such that its entries are flipped:

$$\forall i, j, A_{ij}^T = A_{ji}$$

*Remark: for matrices  $A, B$ , we have  $(AB)^T = B^T A^T$ .*

**r Inverse** – The inverse of an invertible square matrix  $A$  is noted  $A^{-1}$  and is the only matrix such that:

$$AA^{-1} = A^{-1}A = I$$

*Remark: not all square matrices are invertible. Also, for matrices  $A, B$ , we have  $(AB)^{-1} = B^{-1}A^{-1}$ .*

$$B^{-1}A^{-1}$$

**r Trace** – The trace of a square matrix  $A$ , note

$$\text{tr}(A) = \sum_{i=1}^n A_{ii}$$

*Remark: for matrices  $A, B$ , we have  $\text{tr}(AT) = \text{tr}(A)$  and  $\text{tr}(AB) = \text{tr}(BA)$ .*

**r Determinant** – The determinant of a square matrix  $A \in \mathbb{R}^{n \times n}$ , noted  $|A|$  or  $\det(A)$  is expressed recursively in terms of  $A$  with

$\forall i, j$ , which is the matrix  $A$  without its row  $i$  and column  $j$ , as follows:

$$\det(A) = \sum_{j=1}^n (-1)^{i+j} A_{i,j} |A_{i \setminus j, j \setminus i}|$$

Remark: A is invertible if and only if

$$|A| \neq 0. \text{ Also, } |AB| = |A| |B| \text{ and } |A^T| = |A|.$$

## Matrix properties

**Symmetric decomposition** – A given matrix A can be expressed in terms of its symmetric and antisymmetric parts as follows:

$$A = \frac{A + A^T}{2} + \frac{A - A^T}{2}$$

Symmetric      Antisymmetric

**Norm** – A norm is a function  $N : V \rightarrow [0, +\infty]$  where V is a vector space, and such that

for all  $x, y \in V$ , we have:

- $N(x+y) \leq N(x) + N(y)$
- $N(ax) = |a| N(x)$  for a scalar
- if  $N(x) = 0$ , then  $x = 0$

For  $x \in V$ , the most commonly used norms are summed up in the table below:

### Norm Notation D

**Definition** Use cases: Manhattan, L1,  $\sum |x_i|$ , LASSO regularization

$\sqrt{\sum x_i^2}$ , Euclidean, L2,  $\sqrt{\sum x_i^2}$ , Ridge regularization

$(\sum_{i=1}^n |x_i|^p)^{1/p}$ , p-norm, Lp,  $(\sum |x_i|^p)^{1/p}$ , Hölder inequality = 1

$\max_i |x_i|$ , Infinity, L $\infty$ , Uniform convergence

**Linearly dependence** – A set of vectors is said to be linearly dependent if one of the vectors in the set can be defined as a linear combination of the others.

Remark: if no vector can be written this way, then the vectors are said to be linearly independent.

**Matrix rank** – The rank of a given matrix A is noted  $\text{rank}(A)$  and is the dimension of the vector space generated by its columns. This is equivalent to the maximum number of linearly independent columns of A.

**Positive semi-definite matrix** – A matrix  $A \in \mathbb{R}^{n \times n}$  is positive semi-definite (PSD)

$$A = A^T \text{ and } \forall x \in \mathbb{R}^n, x^T A x \geq 0$$

Remark: similarly, a matrix A is said to be positive definite, and is noted A

0, if it is a PSD

matrix which satisfies for all non-zero vector  $x$ ,  $x^T A x > 0$ .

**Eigenvalue, eigenvector** – Given a matrix  $A \in \mathbb{R}^{n \times n}$ ,  $\lambda$  is said to be an eigenvalue of A if

there exists a vector  $z \in \mathbb{R}^n \setminus \{0\}$ , called eigenvector, such that we have:

$$Az = \lambda z$$

**Spectral theorem** – Let  $A \in \mathbb{R}^{n \times n}$ . If A is symmetric, then A is diagonalizable by a real

orthogonal matrix U

$\in \mathbb{R}^{n \times n}$ . By noting  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ , we have:

$$\exists \Lambda \text{ diagonal, } A = U \Lambda U^T$$

**Singular-value decomposition** – For a given matrix A of dimensions m

$\times n$ , the singular-value decomposition (SVD) is a factorization technique that guarantees the existence of U  $m \times m$

unitary,  $\Sigma$   $m \times n$  diagonal and V  $n \times n$  unitary matrices, such that:

$A = U \Sigma V^T$

## Matrix calculus

**Gradient** – Let  $f : \mathbb{R}^m \times \mathbb{R}^n \rightarrow \mathbb{R}$  be a function. A  $\in \mathbb{R}^m \times \mathbb{R}^n$  f

with respect to A is a  $m \times n$  matrix

(The gradient of  $f(A)$ , such that:  $\nabla f(A) = (\partial f / \partial A_{i,j})$ )

Remark: the gradient of f is only defined when f is a function that returns a scalar.

**Hessian** – Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a function and  $x \in \mathbb{R}^n$  be a vector. The hessian of f with

respect to x is a  $n \times n$  symmetric m

$$(\partial^2 f / \partial x_i \partial x_j) = (\partial^2 f / \partial x_j \partial x_i)$$

Remark: the hessian of f is only defined when f is a function that returns a scalar.

**Gradient operations** – For matrices A, B, C, the following gradient properties are worth having in mind:

$$\nabla \text{tr}(AB) = B^T \nabla f(A^T) = (\nabla f(A))^T$$

$$\nabla \text{tr}(ABATC) = CAB + CTAB^T \nabla - 1^T A |A| = |A| (A)$$