

Linear algebra for AI & ML

Basis and dimension.

In \mathbb{R}^n , the maximal linearly independent collection contains n vectors.

A basis is a collection of n linearly independent vectors in \mathbb{R}^n .

Any vector $v \in \mathbb{R}^n$ can be written as a unique linear combination of basis vectors.

$B = \{v_1, \dots, v_n\}$ is a basis of \mathbb{R}^n .

$$v \in \mathbb{R}^n$$

Consider the linear combination,

$$\alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n + \beta v = 0$$

Linear functions

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is called as a linear function if $\forall x, y \in \mathbb{R}^n$ and $\alpha, \beta \in \mathbb{R}$

$$\boxed{f(\alpha x + \beta y) = \alpha f(x) + \beta f(y)} \quad \therefore \text{superposition principle}$$

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$$\boxed{\begin{aligned} f(\alpha x) &= \alpha f(x) \\ f(x+y) &= f(x) + f(y) \end{aligned}} \quad \leftarrow$$

$$f\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = x_1^2 + x_2^2 + \dots + x_n^2 \quad \leftarrow \text{not linear}$$

$$= |x_1| + |x_2| + \dots + |x_n| \quad \leftarrow \text{not linear}$$

$$= \alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_n x_n \quad \leftarrow \text{linear}$$

for scalars α_i 's $\in \mathbb{R}$

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a linear map.

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

$$= x_1 e_1 + x_2 e_2 + \dots + x_n e_n$$

$$e_i = \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} \leftarrow i^{\text{th}} \text{ position.}$$

$$f(x) = f(x_1 e_1 + x_2 e_2 + \dots + x_n e_n)$$

$$= x_1 \underbrace{f(e_1)}_{x_1} + x_2 \underbrace{f(e_2)}_{x_2} + \dots + x_n \underbrace{f(e_n)}_{x_n}$$

$$a = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} f(e_1) \\ \vdots \\ f(e_n) \end{bmatrix}$$

$$f(x) = a^T x \quad - \text{inner product of } a \in \mathbb{R}^n \text{ with } x \in \mathbb{R}^n$$

$$= \langle a, x \rangle$$

outer product ax^T

Affine maps:

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is an affine map if

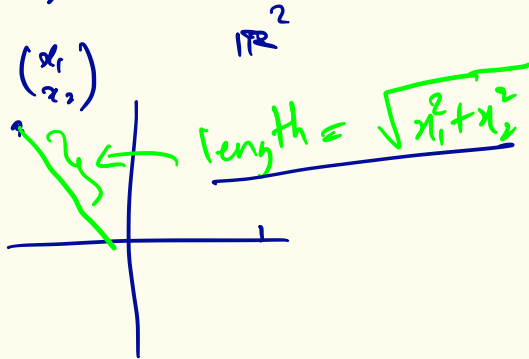
$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y) \quad \text{where } \alpha + \beta = 1$$

Every affine map is of the form

$$f(x) = a^T x + b \quad \text{where } a \in \mathbb{R}^n \text{ and } b \in \mathbb{R}$$

Norm of a vector.

$$f \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$$



$$f(x) = \|x\|$$

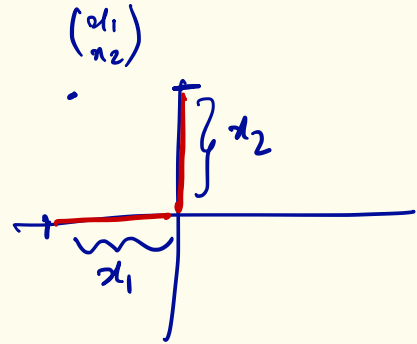
$\|\cdot\|: \mathbb{R}^n \rightarrow \mathbb{R}$ is a norm if

i) $\|x\| \geq 0$ and $\|x\| = 0 \Leftrightarrow x = 0$

ii) $\|\alpha x\| = |\alpha| \|x\|$

iii) $\|x + y\| \leq \|x\| + \|y\|$

\therefore 2-norm of $x \in \mathbb{R}^n$



$$\text{length} = |x_1| + |x_2|$$

$f(x)$

$$\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}$$

- vector p -norm

where $p \geq 1$

Distance : consider $\| \cdot \| : \mathbb{R}^n \rightarrow \mathbb{R}$

$\forall x, y \in \mathbb{R}^n$

$$d(x, y) = \|x - y\|$$