

Lecture 3



Linear functionals.

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \mapsto \frac{x_1^2 + x_2^2 + 2x_1x_2x_3 \dots x_n}{f \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = f(x)}$$

Does NOT
satisfy
superposition
property.

Fix some $a \in \mathbb{R}^n$

$$f_a: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$x \mapsto a^T x$$

$$f_a(x) = a^T x = \sum_{i=1}^n a_i x_i \quad (*)$$

For any scalars $\alpha, \beta \in \mathbb{R}$

$$f_a(\alpha x + \beta y) = \alpha f_a(x) + \beta f_a(y)$$

$\} \Leftrightarrow$ superposition
property.

$$f_a(x+y) = a^T(x+y) \quad \text{--- (2)}$$

$$\begin{aligned} f_a(\alpha x + \beta y) &= a^T(\alpha x + \beta y) \\ &= a^T(\alpha x) + a^T(\beta y) \\ &= \alpha(a^T x) + \beta(a^T y) \end{aligned}$$

$$f_a(\alpha x + \beta y) = \alpha f_a(x) + \beta f_a(y)$$

Definition: A function $f: \mathbb{R}^n \rightarrow \underline{\mathbb{R}}$ is said to be a linear functional if it satisfies following properties:

- 1) Additivity : $\forall x, y \in \mathbb{R}^n : f(x+y) = f(x) + f(y)$
- 2) Homogeneity : $\forall \alpha \in \mathbb{R}, x \in \mathbb{R}^n : f(\alpha x) = \alpha f(x)$

Clearly: $f_a : x \mapsto a^T x$ is a linear functional from $\mathbb{R}^n \rightarrow \mathbb{R}$.

Homogeneity + additivity \Leftrightarrow superposition

\Rightarrow

$$f(\alpha x) = \alpha f(x)$$

$$f(\beta y) = \beta f(y)$$

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

\Leftarrow $\alpha = \beta = 1$: Additivity
 $\alpha = 1, \beta = 0$: Homogeneity

If f satisfies superposition property, then

$$f(\alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_k x_k) = \alpha_1 f(x_1) + \alpha_2 f(x_2) + \dots + \alpha_k f(x_k)$$

Interesting Q:

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

Ex: $f: x \mapsto x_1 + x_2 + \dots + x_n$ is a linear functional.

Ex: $f: x \mapsto 0$, Ex: $f_i: x \mapsto x_i$ for $1 \leq i \leq n$

Every linear functional f is a linear functional f_a defined by $f_a(x) = a^T x$ for some $a \in \mathbb{R}^n$.

$x = x_1 e_1 + x_2 e_2 + \dots + x_n e_n$... linear combination of unit vectors.

$$\begin{aligned} f(x) &= f(x_1 e_1 + x_2 e_2 + \dots + x_n e_n) \\ &= x_1 f(e_1) + x_2 f(e_2) + \dots + x_n f(e_n) \end{aligned}$$

$$\text{Let } a = \begin{bmatrix} f(e_1) \\ \vdots \\ f(e_n) \end{bmatrix} \in \mathbb{R}^n \Rightarrow f(x) = a^T x$$

The representation of a linear function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ as $\hat{f}(x) = a^T x = f_a(x)$ is 'unique.'

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

$$\begin{aligned} \text{In particular for } x = e_i \quad f(x) &= a^T e_i = a_i = f(e_i) \\ f(x) &= b^T e_i = b_i = f(e_i) \end{aligned}$$

$$\Rightarrow a_i = b_i \quad \forall i \in \{1, 2, \dots, n\}$$

$$\Rightarrow a = b \quad \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = a = b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

a linear functional

$$\longleftrightarrow a \in \mathbb{R}^n ; \text{ unique.}$$

$$\left[\begin{array}{l} \text{The set of all linear functionals} \\ \text{from } \mathbb{R}^n \rightarrow \mathbb{R} \end{array} \right] \longleftrightarrow \mathbb{R}^n$$

$$(\mathbb{R}^n)^* \longleftrightarrow \mathbb{R}^n$$

Examples:

$$1) f(x) = \frac{x_1 + x_2 + \dots + x_n}{n} = \text{avg}(x) = \underbrace{\begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}^T}_{\mathbf{1}^T} x$$

$$2) f(x) = x_1 + \dots + x_n = \mathbf{1}^T x$$

$$3) f(x) = x_i = e_i^T x$$

4) $f(x) = \max \{x_1, \dots, x_n\}$: Is this a linear functional?!

NO!

Affine functions

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is called as an affine function when

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

$\alpha, \beta \in \mathbb{R}$

Every linear function is affine; but converse is not true.

Ex: $f: \mathbb{R}^n \rightarrow \mathbb{R}$ affine.

Fix $a, b \in \mathbb{R}^n$ and for every $x \in \mathbb{R}^n$

$$f(x) = a^T x + b$$

$$f(\alpha x + \beta y) = a^T (\alpha x + \beta y) + b$$

$$\therefore \alpha + \beta = 1$$

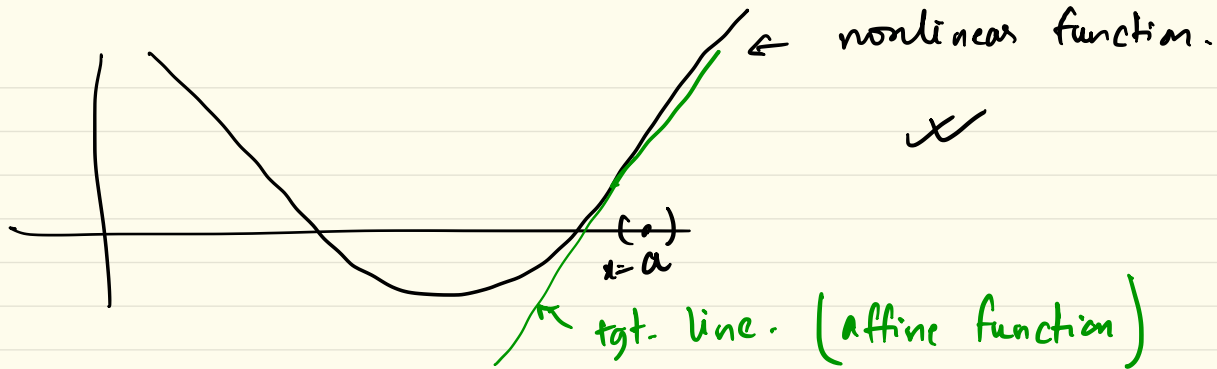
$$= \alpha a^T x + \beta a^T y + (\alpha + \beta) b$$

$$= \alpha a^T x + \alpha b + \beta a^T y + \beta b$$

$$= \alpha (a^T x + b) + \beta (a^T y + b)$$

$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y)$$

$$\Rightarrow f(x) = a^T x + b \text{ is affine.}$$



approximating a
non-linear f in a
small nbd. around pt a .

Every affine function from $\mathbb{R}^n \rightarrow \mathbb{R}$ is of the form

$$f(x) = a^T x + b \quad \text{for some } a \text{ \& } b.$$

$$f(x) = f(0) + x_1(f(e_1) - f(0)) + \dots + x_n(f(e_n) - f(0))$$

$$\underline{a_i = f(e_i) - f(0)} \quad ; \quad \underline{b = f(0)}$$

→ Linear functionals: $\mathbb{R}^n \rightarrow \mathbb{R}$

(every linear functional f)
from $\mathbb{R}^n \rightarrow \mathbb{R}$ $\leftrightarrow a \in \mathbb{R}^n$

$$f(x) = a^T x$$

→ Affine functions from $\mathbb{R}^n \rightarrow \mathbb{R}$

(every affine function f)
from $\mathbb{R}^n \rightarrow \mathbb{R}$ $\leftrightarrow a, b \in \mathbb{R}^n$

$$f(x) = a^T x + b$$

Regression, approximating non-linear functions by an affine function locally. (lazy learning or just in time modeling) ★