

신경망 네트워크와 수학적 기반

Linear functions Superposition and linear functions



- $f: \mathbb{R}^n \to \mathbb{R}$ means f is a function mapping n-vectors to numbers
- lacktriangledown f satisfies the *superposition property* if

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

holds for all numbers α , β , and all *n*-vectors x, y

◆ a function that satisfies superposition is called *linear*

Linear functions The inner product function



◆ with *a* an *n*-vector, the function

$$f(x) = a^{T}x = a_1x_1 + a_2x_2 + \dots + a_nx_n$$

is the *inner product function*

- \bullet f(x) is a weighted sum of the entries of x
- the inner product function is linear:

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

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

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

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

Linear functions all linear functions are inner products



- suppose $f: \mathbb{R}^n \to \mathbb{R}$ is linear
- then it can be expressed as $f(x) = a^T x$ for some a
- specifically: $a_i = f(e_i)$
- follows from

$$f(x) = f(x_1e_1 + x_2e_2 + \dots + x_ne_n)$$

= $x_1f(e_1) + x_2f(e_2) + \dots + x_nf(e_n)$

Linear functions Affine functions



- ◆ a function that is linear plus a constant is called *affine*
- general form is $f(x) = a^T x + b$, with a an n-vector and b a scalar
- \bullet a function $f: \mathbb{R}^n \to \mathbb{R}$ is affine if and only if

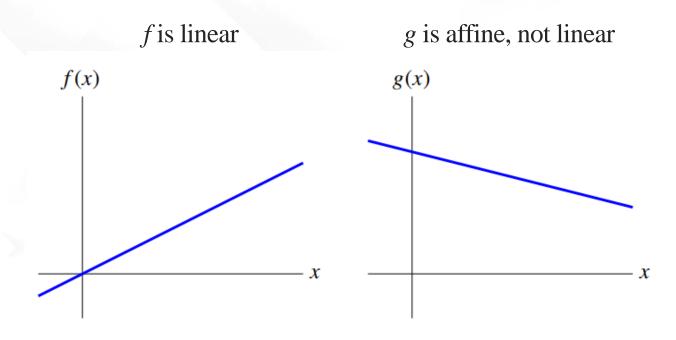
$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y)$$

holds for all α , β with $\alpha + \beta = 1$, and all *n*-vectors x, y

sometimes people refer to affine functions as linear

Linear functions Linear versus affine functions





Linear functions

CAU

First-order Taylor approximation

- \bullet suppose $f: \mathbb{R}^n \to \mathbb{R}$
- \bullet *first-order Taylor approximation* of f, near point z:

$$\hat{f}(x) = f(z) + \frac{\partial f}{\partial x_1}(z)(x_1 - z_1) + \dots + \frac{\partial f}{\partial x_n}(z)(x_n - z_n)$$

- $\hat{f}(x)$ is very close to f(x) when x_i are all near z_i
- \hat{f} is an **affine function** of x
- can write using inner product as

$$\hat{f}(x) = f(z) + \nabla f(z)^{T} (x - z)$$

• where *n*-vector $\nabla f(z)$ is the **gradient** of f at z

$$\nabla f(z) = \left(\frac{\partial f}{\partial x_1}(z), \dots, \frac{\partial f}{\partial x_n}(z)\right)$$





