

# Linear functions

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## Linear equations

consider system of linear equations

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n$$

$$y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n$$

$$\vdots$$

$$y_m = a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n$$

can be written in matrix form as  $y = Ax$ , where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \quad A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

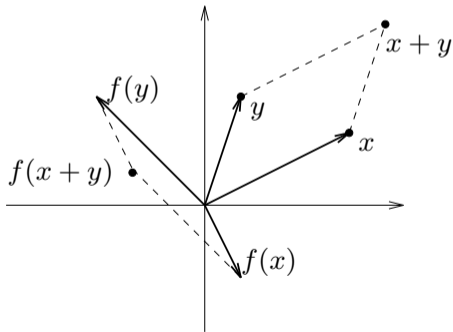
## Linear functions

a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is *linear* if

▶  $f(x + y) = f(x) + f(y), \forall x, y \in \mathbb{R}^n$

▶  $f(\alpha x) = \alpha f(x), \forall x \in \mathbb{R}^n \forall \alpha \in \mathbb{R}$

*i.e.*, *superposition* holds



## Matrix multiplication function

- ▶ consider function  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  given by  $f(x) = Ax$ , where  $A \in \mathbb{R}^{m \times n}$
- ▶ matrix multiplication function  $f$  is linear
- ▶ **converse** is true: **any** linear function  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  can be written as  $f(x) = Ax$  for some  $A \in \mathbb{R}^{m \times n}$
- ▶ representation via matrix multiplication is unique: for any linear function  $f$  there is only one matrix  $A$  for which  $f(x) = Ax$  for all  $x$
- ▶  $y = Ax$  is a concrete representation of a generic linear function

## Interpretations of $y = Ax$

- ▶  $y$  is measurement or observation;  $x$  is unknown to be determined
- ▶  $x$  is 'input' or 'action';  $y$  is 'output' or 'result'
- ▶  $y = Ax$  defines a function or transformation that maps  $x \in \mathbb{R}^n$  into  $y \in \mathbb{R}^m$

## Interpretation of $a_{ij}$

$$y_i = \sum_{j=1}^n a_{ij} x_j$$

$a_{ij}$  is *gain factor* from  $j$ th input ( $x_j$ ) to  $i$ th output ( $y_i$ )

- ▶  $i$ th *row* of  $A$  concerns  $i$ th *output*
- ▶  $j$ th *column* of  $A$  concerns  $j$ th *input*
- ▶  $a_{27} = 0$  means 2nd output ( $y_2$ ) doesn't depend on 7th input ( $x_7$ )
- ▶  $|a_{31}| \gg |a_{3j}|$  for  $j \neq 1$  means  $y_3$  depends mainly on  $x_1$
- ▶  $|a_{52}| \gg |a_{i2}|$  for  $i \neq 5$  means  $x_2$  affects mainly  $y_5$
- ▶  $A$  is lower triangular, *i.e.*,  $a_{ij} = 0$  for  $i < j$ , means  $y_i$  only depends on  $x_1, \dots, x_i$
- ▶  $A$  is diagonal, *i.e.*,  $a_{ij} = 0$  for  $i \neq j$ , means  $i$ th output depends only on  $i$ th input

more generally, **sparsity pattern** of  $A$ , *i.e.*, list of zero/nonzero entries of  $A$ , shows which  $x_j$  affect which  $y_i$

## Linearization

- ▶ if  $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is differentiable at  $x_0 \in \mathbb{R}^n$ , then

$$x \text{ near } x_0 \implies f(x) \text{ very near } f(x_0) + Df(x_0)(x - x_0)$$

where

$$Df(x_0)_{ij} = \left. \frac{\partial f_i}{\partial x_j} \right|_{x_0}$$

is derivative (Jacobian) matrix

- ▶ with  $y = f(x)$ ,  $y_0 = f(x_0)$ , define *input deviation*  $\delta x := x - x_0$ , *output deviation*  $\delta y := y - y_0$
- ▶ then we have  $\delta y \approx Df(x_0)\delta x$
- ▶ when deviations are small, they are (approximately) related by a linear function