

Quick review of linear algebra

Matrices yield linear maps

A map $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is *linear* if $f(ax + by) = af(x) + bf(y)$ for all $x, y \in \mathbb{R}^n$ and all $a, b \in \mathbb{R}$.

$f(x+y) = f(x) + f(y)$
 $f(ax) = a f(x)$

An $m \times n$ matrix A yields a linear map from \mathbb{R}^n to \mathbb{R}^m via matrix multiplication $x \mapsto Ax$.

Examples

- The identity matrix/identity linear map from \mathbb{R}^n to itself.

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

$$A = \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix}$$

$n \times n$

$A(x+y) = Ax + Ay$
 $Acx = cAx$

A $m \times n$ matrix $x \in \mathbb{R}^n$ $x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$ $m \times n$ $n \times 1$ $Ax \rightarrow \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \in \mathbb{R}^m$

- The zero map from $\mathbb{R}^n \rightarrow \mathbb{R}^m$

$$f: \mathbb{R}^n \rightarrow \mathbb{R}^m \quad f(x) = 0 \text{ for all } x$$

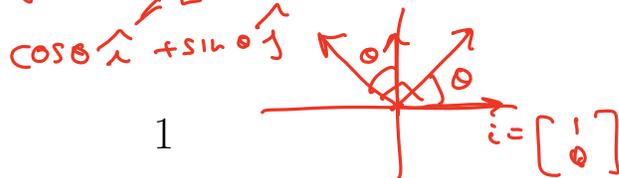
$$m \times n \begin{pmatrix} 0 & \dots & 0 \\ \vdots & & \vdots \\ 0 & & 0 \end{pmatrix}$$

- The rotation matrix $M(\theta) = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix}$

$$\theta \in \mathbb{R}$$

$$M(\theta) \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}$$

$$M(\theta) \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -\sin \theta \\ \cos \theta \end{bmatrix}$$



Every linear map comes from a matrix

Given a linear map $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$, we can associate to it an $m \times n$ matrix A with entries (a_{ij}) by computing

$$T(\underline{\mathbf{e}}_j) = \sum_{i=1}^m a_{ij} \mathbf{f}_i$$

where \mathbf{e}_j and \mathbf{f}_i are the n - and m - dimensional column vectors with a one in position j (resp. i) and zeros elsewhere.

$$\mathbb{R}^n \ni \mathbf{e}_j = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$$\mathbb{R}^m \ni \mathbf{f}_i = \begin{bmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$$T(\mathbf{e}_j) = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$$

" $x_1 \mathbf{f}_1 + x_2 \mathbf{f}_2 + \dots + x_m \mathbf{f}_m$

$$T(\mathbf{e}_j) = \sum_{i=1}^m a_{ij} \mathbf{f}_i$$

for $j=1, \dots, n$.

$$A = (a_{ij})$$

$$\begin{pmatrix} \dots & \overset{j}{\dots} & \dots \\ \dots & a_{1j} & \dots \\ \dots & a_{2j} & \dots \\ \dots & \vdots & \dots \\ \dots & a_{mj} & \dots \end{pmatrix} \begin{pmatrix} \mathbf{e}_j \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} = \begin{pmatrix} a_{1j} \\ \vdots \\ a_{mj} \end{pmatrix} = T(\mathbf{e}_j)$$

$$A(\mathbf{e}_1) = 2\mathbf{f}_1 + \mathbf{f}_2$$

$$A(\mathbf{e}_2) = 5\mathbf{f}_1 - 6\mathbf{f}_2$$

$$A = \begin{pmatrix} 2 & 5 \\ 1 & -6 \end{pmatrix}$$

$$A\mathbf{e}_1 = A \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} = 2\mathbf{f}_1 + \mathbf{f}_2$$

Matrix Multiplication is composition of linear maps

If $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $V : \mathbb{R}^m \rightarrow \mathbb{R}^p$ are linear maps with associated matrices A and B , then the matrix associated to the composition

$V \circ T$ is the matrix product BA .

$$V \circ T : \mathbb{R}^n \rightarrow \mathbb{R}^p$$

$$A \leftrightarrow T \quad m \times n$$

$$B \leftrightarrow V \quad p \times m$$

$$\underbrace{BA}_{V \circ T} \quad p \times n$$

$$A \leftrightarrow T$$

$$T(e_j) = \sum_{i=1}^m a_{ij} f_i \quad j=1, \dots, n$$

$$V(f_i) = \sum_{k=1}^p b_{ki} t_k \quad t_k \quad k=1, \dots, p$$

$$V T(e_j) = V\left(\sum_{i=1}^m a_{ij} f_i\right) = \sum_{i=1}^m a_{ij} V(f_i)$$

$$= \sum_{i=1}^m a_{ij} \left(\sum_{k=1}^p b_{ki} t_k \right)$$

$$= \sum_{k=1}^p \left(\sum_{i=1}^m a_{ki} a_{ij} \right) t_k$$

$$c_{kj} = \sum_{i=1}^m b_{ki} a_{ij}$$

$$c_{kj}$$

$$C = BA.$$

A linear map is bijective if its matrix is invertible

- If $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is bijective then its inverse is also linear and the associated matrix is the inverse matrix A^{-1} . Conversely if the associated matrix is invertible then T is bijective. In particular the inverse of a bijective linear map is ~~bijective~~ linear.

all correspond to the same thing. $\left\{ \begin{array}{l} \text{invertible linear maps} \\ \text{invertible matrices} \\ \text{matrices } A \text{ with } \det(A) \neq 0 \end{array} \right.$

A matrix is invertible if and only if it has nonzero determinant

The inner product (dot product)

Definition: The Euclidean inner product on \mathbb{R}^n is the dot product

$$\left(\sum_{i=1}^n a_i \mathbf{e}_i\right) \cdot \left(\sum_{i=1}^n b_i \mathbf{e}_i\right) = \sum_{i=1}^n a_i b_i.$$

If $x, y \in \mathbb{R}^n$ this is also written $\langle x, y \rangle$.

$$\langle x, y \rangle = x \cdot y$$

$$\begin{aligned} & (3, 5) \cdot (2, 7) \\ &= 3 \cdot 2 + 5 \cdot 7 \\ &= 41 \end{aligned}$$

Properties of the inner product

Proposition: The inner product is:

- symmetric, so $\langle x, y \rangle = \langle y, x \rangle$

$$(\sum a_i e_i) \cdot (\sum b_i e_i) = \sum a_i b_i$$

$$\langle x+y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$$

- bilinear, so $\langle x, y+z \rangle = \langle x, y \rangle + \langle x, z \rangle$ and $\langle ax, y \rangle = a \langle x, y \rangle$ for $x, y \in \mathbb{R}^n$ and $a \in \mathbb{R}$.

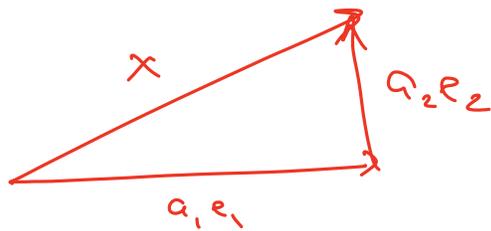
$$\begin{aligned} x \cdot (y+z) &= x \cdot y + x \cdot z & \Leftrightarrow x &= \sum a_i e_i \\ \sum a_i (b_i + c_i) &= \sum a_i b_i + \sum a_i c_i & y &= \sum b_i e_i \\ ax \cdot y &= a \sum a_i b_i & z &= \sum c_i e_i \end{aligned}$$

- positive definite, so $\langle x, x \rangle \geq 0$ for all x and is zero only if $x = 0$.

$$\langle x, x \rangle = \sum a_i^2 \geq 0$$

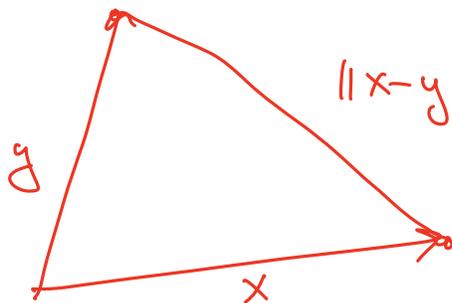
$$x = \sum a_i e_i \quad \sum a_i^2 = 0 \Leftrightarrow \text{all } a_i = 0 \Leftrightarrow x = 0$$

Given a vector x , the quantity $x \cdot x = \|x\|^2$ is called the norm of x ; geometrically it is the length of the vector x .



$$\|x\|^2 = a_1^2 + a_2^2$$

Given two vectors x and y , the quantity $(x - y) \cdot (x - y) = \|x - y\|^2$ is the square of the Euclidean distance between x and y .



$$\|x - y\|^2 = \text{squared distance from } x \text{ to } y$$