

Vectors and their operations No. 2

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October 11, 2016

Dot Product of Two Vectors

Dot Product: Definition

For two vectors $\vec{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$, $\vec{y} = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \in \mathbf{R}^n$, the dot product of \vec{x} and \vec{y} is defined and denoted by

$$(\vec{x}, \vec{y}) := x_1 y_1 + \cdots + x_n y_n$$

Length of Vectors: Definition

The length of $\vec{x} \in \mathbf{R}^n$ is defined and denoted by

$$\|\vec{x}\| = \sqrt{(\vec{x}, \vec{x})} = \sqrt{x_1^2 + \cdots + x_n^2}$$

Basis Properties of Dot Products

Let c

(1.) (Commutativity)

$$(\vec{x}, \vec{y}) = (\vec{y}, \vec{x})$$

(2.) (Bi-linearity (i))

$$(\lambda \vec{x}, \vec{y}) = (\vec{x}, \lambda \vec{y}) = \lambda (\vec{x}, \vec{y})$$

(3.) (Bi-linearity (ii))

$$(\vec{x} + \vec{y}, \vec{z}) = (\vec{x}, \vec{z}) + (\vec{y}, \vec{z}), \quad (\vec{x}, \vec{y} + \vec{z}) = (\vec{x}, \vec{y}) + (\vec{x}, \vec{z})$$

(4.)

$$\|\vec{x}\| \geq 0, \quad \|\vec{x}\| = 0 \Leftrightarrow \vec{x} = 0$$

An Important Formula

An Important Formula

For $\vec{x}, \vec{y} \in \mathbb{R}^n$, we have

$$\|\vec{x} + \vec{y}\|^2 = \|\vec{x}\|^2 + 2(\vec{x}, \vec{y}) + \|\vec{y}\|^2$$

(proof)

$$\begin{aligned} LHS &= (\vec{x} + \vec{y}, \vec{x} + \vec{y}) \\ &= (\vec{x}, \vec{x} + \vec{y}) + (\vec{y}, \vec{x} + \vec{y}) \\ &= (\vec{x}, \vec{x}) + (\vec{x}, \vec{y}) + (\vec{y}, \vec{x}) + (\vec{y}, \vec{y}) \\ &= \|\vec{x}\|^2 + 2(\vec{x}, \vec{y}) + \|\vec{y}\|^2 = RHS \end{aligned}$$

Corollary: Pythagoras Theorem

If $\vec{x}, \vec{y} \in \mathbb{R}^n$ are orthogonal, i.e. $(\vec{x}, \vec{y}) = 0$, then

$$\|\vec{x} + \vec{y}\|^2 = \|\vec{x}\|^2 + \|\vec{y}\|^2$$

Cauchy's Inequality

Cauchy's Inequality

$$(\vec{x}, \vec{y})^2 \leq \|\vec{x}\|^2 \cdot \|\vec{y}\|^2 \quad (\#)$$

A small remark before the proof

$$\|\lambda \vec{x}\| = |\lambda| \cdot \|\vec{x}\|$$

$$(\vec{x}, \vec{0})^2 = 0 \quad \|\vec{x}\|^2 \cdot \|\vec{0}\|^2 = 0$$

(proof) (i) In case $\vec{y} = \vec{0}$, the inequality (#) is OK.

(ii) In case $\vec{y} \neq \vec{0}$, remark that $\|\vec{y}\|^2 > 0$. We develop $\|\vec{x} - \lambda \vec{y}\|^2$ as follows.

$$\begin{aligned} 0 \leq \|\vec{x} - \lambda \vec{y}\|^2 &= \|\vec{x}\|^2 - 2(\vec{x}, \lambda \vec{y}) + \|\lambda \vec{y}\|^2 \\ &= \|\vec{x}\|^2 - 2\lambda(\vec{x}, \vec{y}) + \lambda^2 \|\vec{y}\|^2 \end{aligned} \quad \begin{aligned} \|\lambda \vec{y}\| \\ = |\lambda| \cdot \|\vec{y}\| \end{aligned}$$

Since the above inequality holds for any $\lambda \in \mathbb{R}$, the Discriminants of quadratic equation is

$$(\vec{x}, \vec{y})^2 - \|\vec{x}\|^2 \cdot \|\vec{y}\|^2 \leq 0 \rightarrow (\vec{x}, \vec{y})^2 \leq \|\vec{x}\|^2 \cdot \|\vec{y}\|^2$$

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$$\vec{y} = \vec{0} \Leftrightarrow \|\vec{y}\| = 0$$

Triangle Inequality

Corollary to Cauchy's Inequality

$$\|\vec{x} + \vec{y}\| \leq \|\vec{x}\| + \|\vec{y}\|$$

(proof) We have

$$\|\vec{y} + \vec{y}\|^2 = \|\vec{x}\|^2 + 2(\vec{x}, \vec{y}) + \|\vec{y}\|^2 \leq \|\vec{x}\|^2 \cdot \|\vec{y}\|^2$$

Moreover

$$2(\vec{x}, \vec{y}) \leq 2|(\vec{x}, \vec{y})| \leq 2\|\vec{x}\| \cdot \|\vec{y}\|$$

Accordingly

$$\begin{aligned} \|\vec{x} + \vec{y}\|^2 &\leq \|\vec{x}\|^2 + 2\|\vec{x}\| \cdot \|\vec{y}\| + \|\vec{y}\|^2 \\ &= (\|\vec{x}\| + \|\vec{y}\|)^2 \end{aligned}$$

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Application

problem

Let $\vec{a} = \begin{pmatrix} 1 \\ 1 \\ -1 \\ 2 \end{pmatrix}$, $\vec{b} = \begin{pmatrix} -1 \\ 2 \\ 1 \\ 1 \end{pmatrix}$. Then we try to find the minimum value of

$$f(t) := \|\vec{b} - t\vec{a}\|^2$$

We develop $\|\vec{b} - t\vec{a}\|^2$ by

$$\|\vec{b} - t\vec{a}\|^2 = t^2\|\vec{a}\|^2 - 2t(\vec{a}, \vec{b}) + \|\vec{b}\|^2$$

We have moreover $\|\vec{a}\|^2 = 7$, $(\vec{a}, \vec{b}) = 2$, $\|\vec{b}\|^2 = 7$. Thus

$$f(t) = 7t^2 - 2t + 7 = t\left(t - \frac{2}{7}\right)^2 + \frac{45}{7}$$

Accordingly we find that $f(t)$ has the minimum value $\frac{45}{7}$ when $t = \frac{2}{7}$.

$$\begin{aligned} & 1 \cdot (-1) + 1 \cdot 2 \\ & + (-1) \cdot 1 + 2 \cdot 1 \\ & = 2 \end{aligned}$$

Problem in general

Problem

Let $\vec{a}, \vec{b} \in \mathbb{R}^n$ and assume that $\vec{a} \neq \vec{0}$. Problem is to find the minimum value of

$$f(t) = \|\vec{b} - t\vec{a}\|^2$$

First we make the same approach by developing $\|\vec{b} - t\vec{a}\|^2$ by

$$\begin{aligned} \|\vec{b} - t\vec{a}\|^2 &= t^2\|\vec{a}\|^2 - 2t(\vec{a}, \vec{b}) + \|\vec{b}\|^2 \\ &= \|\vec{a}\|^2 \left(t - \frac{(\vec{a}, \vec{b})}{\|\vec{a}\|^2} \right)^2 + \|\vec{b}\|^2 - \frac{(\vec{a}, \vec{b})^2}{\|\vec{a}\|^2} \end{aligned}$$

minimum value.

Thus $f(t)$ takes its minimum value when $t = \frac{(\vec{a}, \vec{b})}{\|\vec{a}\|^2}$.

Geomtric Interpretation

In case $n = 2$ or $n = 3$, it is clear that $\|\vec{b} - t\vec{a}\|^2$ is minimum when

$$(\vec{b} - t\vec{a}) \perp \vec{a}$$

This condition is equivalent to

$$(\vec{b} - t\vec{a}, \vec{a}) = (\vec{b}, \vec{a}) - t\|\vec{a}\|^2 = 0 \quad \text{namely} \quad t = \frac{(\vec{a}, \vec{b})}{\|\vec{a}\|^2}$$

This is identical to the result obtained by minimizing the square functions of t .

Orthogonal Projection

Orthogonal Projection

$$\vec{w} = \frac{(\vec{a}, \vec{b})}{\|\vec{a}\|^2} \vec{a}$$

is called the **orthogonal projection** of \vec{b} in the direction of \vec{a} .

\vec{w} satisfies the conditions

- (i) $(\vec{b} - \vec{w}) \perp \vec{a}$
- (ii) $\vec{w} = t\vec{a}$ for some $t \in \mathbb{R}$.

$$\|\vec{c} - s\vec{a} - t\vec{e}\|^2 \quad s, t \in \mathbb{R}.$$

Matrices and their operations No. 1

Multiplication of 2×2 Matrices

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Review 1: 2×2 Matrices

2×2 matrices

$$A = (\vec{a}_1 \ \vec{a}_2) = \begin{pmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

A 2×2 matrix is given in the following ways.

- (i) Combining two column vectors $\vec{a}_1, \vec{a}_2 \in \mathbf{R}^2$
- (ii) Combining two row vectors \mathbf{a}_1 and \mathbf{a}_2
- (iii) Giving 2×2 components.

NB a_{ij} is used for the component of the i th row and of the j th column.

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$$= (\vec{a}_1, \vec{a}_2) = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

Review 2

Multiplication of 2-dim. vectors to 2×2 matrices

$$A \begin{pmatrix} x \\ y \end{pmatrix} = x\vec{a} + y\vec{a}_2$$

$$= x \begin{pmatrix} a_{11} \\ a_{21} \end{pmatrix} + y \begin{pmatrix} a_{12} \\ a_{22} \end{pmatrix} = \begin{pmatrix} xa_{11} + ya_{12} \\ xa_{21} + ya_{22} \end{pmatrix}$$

$$= \begin{pmatrix} \mathbf{a}_1 \begin{pmatrix} x \\ y \end{pmatrix} \\ \mathbf{a}_2 \begin{pmatrix} x \\ y \end{pmatrix} \end{pmatrix}$$

$$(a_{11} \ a_{12}) \begin{pmatrix} x \\ y \end{pmatrix}$$

$$(a_{21} \ a_{22}) \begin{pmatrix} x \\ y \end{pmatrix}$$

Here we use the multiplication of a row vector and a column vector defined by

$$(\alpha \ \beta) \begin{pmatrix} x \\ y \end{pmatrix} = \alpha x + \beta y$$

Review 3: Multiplication of two 2×2 matrices

Take another 2×2 matrix

$$B = (\vec{b}_1 \ \vec{b}_2) = \begin{pmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{pmatrix}.$$

Then

$$AB = (A\vec{b}_1 \ A\vec{b}_2) = \begin{pmatrix} \mathbf{a}_1 \vec{b}_1 & \mathbf{a}_1 \vec{b}_2 \\ \mathbf{a}_2 \vec{b}_1 & \mathbf{a}_2 \vec{b}_2 \end{pmatrix}$$

Linear Map defined by using A

A Map defined by A

Given a 2×2 matrix

$$A = (\vec{a}_1 \ \vec{a}_2) = \begin{pmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix},$$

we can define a map

$$F_A : \mathbf{R}^2 \longrightarrow \mathbf{R}^2$$
$$\begin{pmatrix} s \\ t \end{pmatrix} \mapsto A \begin{pmatrix} s \\ t \end{pmatrix} = s\vec{a}_1 + t\vec{a}_2$$

Linearity of F_A

Linearity of F_A

F_A satisfies the following basic properties called **Linearity**.

- (i) $F_A(\vec{x} + \vec{y}) = F_A(\vec{x}) + F_A(\vec{y})$
- (ii) $F_A(\lambda\vec{x}) = \lambda F_A(\vec{x})$
- (iii) $F_A(\lambda\vec{x} + \mu\vec{y}) = \lambda F_A(\vec{x}) + \mu F_A(\vec{y})$

These three properties are identical to the following.

- (i) $A(\vec{x} + \vec{y}) = A\vec{x} + A\vec{y}$
- (ii) $A(\lambda\vec{x}) = \lambda(A\vec{x})$
- (iii) $A(\lambda\vec{x} + \mu\vec{y}) = \lambda(A\vec{x}) + \mu(A\vec{y})$

Moreover remark that (iii) can be easily derived from (i) and (ii).

In fact

$$A(\lambda\vec{x} + \mu\vec{y}) = A(\lambda\vec{x}) + A(\mu\vec{y})$$
$$= \lambda(A\vec{x}) + \mu(A\vec{y})$$

Proof

Proof for (i)

$$LHS = A \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \right) = A \left(\begin{pmatrix} x_1 + y_1 \\ x_2 + y_2 \end{pmatrix} \right)$$

$$= (x_1 + y_1) \vec{a}_1 + (x_2 + y_2) \vec{a}_2$$

$$= x_1 \vec{a}_1 + y_1 \vec{a}_1 + x_2 \vec{a}_2 + y_2 \vec{a}_2$$

$$= (x_1 \vec{a}_1 + x_2 \vec{a}_2) + (y_1 \vec{a}_1 + y_2 \vec{a}_2)$$

$$= A \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right) + A \left(\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \right) = RHS$$

($\vec{a}_1 \vec{a}_2$)

$\vdash \vec{a} \in \mathbb{R}^n$

$$(\lambda + \mu) \vec{a} = \lambda \vec{a} + \mu \vec{a}$$

Proof for (ii)

$$LHS = A \left(\begin{pmatrix} \lambda x_1 \\ \lambda x_2 \end{pmatrix} \right)$$

$$= (\lambda x_1) \vec{a}_1 + (\lambda x_2) \vec{a}_2$$

$$= \lambda (x_1 \vec{a}_1) + \lambda (x_2 \vec{a}_2)$$

$$= \lambda (x_1 \vec{a}_1 + x_2 \vec{a}_2) = RHS$$

($\vec{a}_1 \vec{a}_2$)

$$(\lambda \mu) \vec{a} = \lambda (\mu \vec{a})$$

$$\boxed{\lambda (\vec{a} + \vec{b}) = \lambda \vec{a} + \lambda \vec{b}}$$

$$\lambda (A \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \right))$$

Associativity

Thanks to the Linearity, we can prove the following theorem about **Associativity**.

Theorem: Associativity

Given 2×2 matrices A and B . Then we have for $\vec{x} \in \mathbb{R}^2$.

$$(AB)\vec{x} = A(B\vec{x})$$

$$A B \vec{x}$$

In fact,

$$RHS = A(x_1 \vec{b}_1 + x_2 \vec{b}_2)$$

$$(iii) \rightarrow x_1(A\vec{b}_1) + x_2(A\vec{b}_2)$$

$$= (A\vec{b}_1 \ A\vec{b}_2) \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = (AB)\vec{x} = RHS$$

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Associativity 2

Theorem: Associativity

Given 2×2 matrices A , B and C . Then

$$(AB)C = A(BC)$$

$$\begin{aligned} \text{RHS} &= ((AB)\vec{c}_1 \quad (AB)\vec{c}_2) \\ &= (A(B\vec{c}_1) \quad A(B\vec{c}_2)) \\ &\stackrel{\text{By the last theorem}}{=} A(B\vec{c}_1 \quad B\vec{c}_2) \\ &= A(BC) = \text{RHS}. \end{aligned}$$

Scalar Multiplication to Matrices

Scalar Multiplication to 2×2 Matrices

Given a 2×2 matrix

$$A = (\vec{a}_1 \quad \vec{a}_2) = \begin{pmatrix} \vec{a}_1 \\ \vec{a}_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix},$$

we define a scalar multiplication by λ to A as follows:

$$\lambda A = (\lambda \vec{a}_1 \quad \lambda \vec{a}_2) = \begin{pmatrix} \lambda \vec{a}_1 \\ \lambda \vec{a}_2 \end{pmatrix} = \begin{pmatrix} \lambda a_{11} & \lambda a_{12} \\ \lambda a_{21} & \lambda a_{22} \end{pmatrix}$$