

Ch11 Definition

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Definition 11.1 Dot Product $\vec{u} = \begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix}$ $\vec{v} = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}$

$$\vec{u} \cdot \vec{v} = u_1 v_1 + u_2 v_2 + \dots + u_n v_n$$

$$= \begin{pmatrix} \vec{u} \end{pmatrix}^T \vec{v}$$

Definition 11.4 Norm

$$\|\vec{u}\| := \sqrt{\vec{u} \cdot \vec{u}}$$

Definition 11.5 Distance

$$\|\vec{u} - \vec{v}\| = \sqrt{(\vec{u} - \vec{v}) \cdot (\vec{u} - \vec{v})}$$

Definition 11.7 Orthogonal vectors

$$\theta = \arccos \frac{a \cdot b}{\|a\| \|b\|}$$

\vec{u}, \vec{v} orthogonal if $\vec{u} \cdot \vec{v} = 0$

Definition 11.9 Orthogonal basis, Orthonormal basis

Orthogonal: $\vec{v}_i \cdot \vec{v}_j = 0$ for $i \neq j$

Orthonormal: $\| \vec{v}_i \| = 1$ for every i .

Definition 11.12 Orthogonal matrix (orthonormal)

If $Q^{-1} = Q^T$. Then Q is orthogonal

Column of Q forms orthonormal basis.

Proposition 11.2

$$(1) \vec{u} \cdot \vec{v} = \vec{v} \cdot \vec{u}$$

$$(\vec{u} + \vec{v}) \cdot \vec{w} = \vec{u} \cdot \vec{w} + \vec{v} \cdot \vec{w}$$

$$(c\vec{u}) \cdot \vec{v} = c(\vec{u} \cdot \vec{v})$$

Proposition 11.10

If B is orthonormal basis of \mathbb{R}^n , e.g. $B = \{\vec{v}_1, \dots, \vec{v}_n\}$

$$x, y \in \mathbb{R}^n$$

$$[\vec{x}]_B = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

$$[\vec{y}]_B = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$$

$$\text{THEN } [\vec{x}]_B \cdot [\vec{y}]_B = \vec{x} \cdot \vec{y}$$

$$= (x_1 v_1 + \dots + x_n v_n) \cdot (y_1 v_1 + \dots + y_n v_n)$$

$$= x_1 y_1 (v_1 \cdot v_1) + \dots + (x_n y_n) (v_n \cdot v_n) \quad (\text{e.g. } v_1 \cdot v_2 = 0 \text{ (orthogonal)})$$

$$= x_1 y_1 + \dots + x_n y_n$$

Theorem 11.14 For any $\vec{v}, \vec{w} \in \mathbb{R}^n$,

$$Q\vec{v} \cdot Q\vec{w} = \vec{v} \cdot \vec{w}$$

Definition 11.16 Orthogonal projection a onto b

$$\text{proj}_b a = \frac{a \cdot b}{b \cdot b} b$$

Definition 11.17 The Gram-Schmidt Process

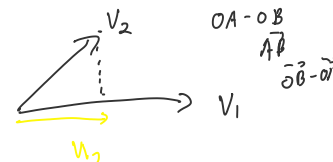
Every vector space has an orthogonal basis

$$u_1 = \vec{v}_1$$

$$u_2 = \vec{v}_2 - \text{proj}_{u_1} \vec{v}_2$$

$$u_3 = \vec{v}_3 - \text{proj}_{u_1} \vec{v}_3 - \text{proj}_{u_2} \vec{v}_3$$

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Definition 11.17 Orthogonally diagonalizable matrix

- if exist orthogonal matrix Q
- diagonal matrix D

$$\Rightarrow Q^T A Q = D$$

$$\Rightarrow A = Q D Q^T$$

$$A = Q D Q^{-1}$$

↑
the orthonormal basis
of the eigenvectors

Q is simply P in eigendecomposition,
but each column normalized!

- Symmetric matrices have orthogonal eigenvectors!

Theorem 11.25 The Singular Value Decomposition

$$A = U \Sigma Q^T \quad (A = P^{-1} D P, \quad P = A^T A, \quad P^{-1} = (A^T A)^{-1} = A^{-1} A^T)$$

$m \times n$ $n \times m$ $n \times n$ $n \times n$

- U : orthogonal $m \times m$ matrix U (eigenvectors of AA^T)
- V : orthogonal $n \times n$ matrix V (eigenvectors of $A^T A$)

Σ : block diagonal matrix (no need $n \times n$) ($\sigma_i = \sqrt{\lambda_i}$)

$$\text{e.g. } \begin{pmatrix} * & 0 & \sigma_1 & 0 \\ 0 & * & 0 & \sigma_2 \\ 0 & 0 & * & 0 \\ 0 & 0 & 0 & * \end{pmatrix} \quad \begin{matrix} m > n \\ n > m \end{matrix}$$

Definition 11.26

Let A be $m \times n$ matrix.

Let $\vec{v}_1, \dots, \vec{v}_n$ be an orthonormal basis of \mathbb{R}^n of eigenvectors for $A^T A$.

Singular values of A $\sigma_i := \|A \vec{v}_i\|$

$$= \sqrt{\lambda_i}$$

$$\vec{v}_m = \vec{v}_m - \text{proj}_{\vec{v}_1} \vec{v}_m - \dots - \text{proj}_{\vec{v}_{m-1}} \vec{v}_m$$

$\{\vec{v}_1, \dots, \vec{v}_m\}$ is orthogonal. \rightarrow divide by norm gives orthonormal.

Theorem 11.21 (Spectral Theorem)

- Orthogonally diagonalizable if and only if $A = A^T$

Not necessarily square.

Proposition 11.23

A : $m \times n$ matrix

$$\text{e.g. } A = \begin{pmatrix} 2 & 0 \\ 0 & 2 \\ 1 & 0 \end{pmatrix}$$

$$A^T A = \begin{pmatrix} 2 & 0 & 1 \\ 0 & 2 & 0 \end{pmatrix} \begin{pmatrix} 2 & 0 \\ 0 & 2 \\ 1 & 0 \end{pmatrix}$$

$$= \begin{pmatrix} 5 & 0 \\ 0 & 4 \end{pmatrix}$$

$$(5 - \lambda)(4 - \lambda) = 0$$

$$\lambda = 5 \text{ or } \lambda = 4.$$

$$\sigma_1 = \sqrt{5} \quad \sigma_2 = 2$$

It means matrix A stretches some vector/space
in direction of $A^T A$'s eigenvector by $\sqrt{\lambda_i}$.
↑
 $A^T A$'s A .

'''' eigenvalue of $A'A$