

ST 661 Note

Frances Lin

1/13/2022

Outline

Orthogonal matrices (Cont.)

Trace

Eigenvales and eigenvector

- general
- functions of matrices
- symmetric
- pd

Definition

$$C \text{ is orthogonal} \Leftrightarrow C^T C = I \Leftrightarrow C C^T = I \Leftrightarrow C^{-1} = C^T$$

Thm

If C is a $p \times p$ orthogonal and A is $p \times p$,

i) $\det(C) = \pm 1$

This is because $C^T C = I$, $\det(C^T C) = \det(C^T) \det(C) = \det(C) \det(C) = 1$.

ii) $\det(C^T A C) = \det(A)$,

where $C^T A C$ is called conjugate transformation of A .

proof.

$$\det(C^T A C) = \det(A C C^T) = \det(A C C^T) = \det(A I) = \det(A) \quad \square$$

iii) $-1 \leq C_{ij} \leq 1$ for all i, j since they were normalized.

Trace (For Square Matrices Only)

For $n \times n$ matrix $A = (a_{ij})$, $1 \leq i, j \geq n$, trace is a linear scalar function of A s.t. $\text{tr}(A) = \sum_{i=1}^N a_{ii}$.

Thm

i) If A, B are both $n \times n$, then

$$\text{tr}(A + B) = \text{tr}(A) + \text{tr}(B).$$

ii) For A: $n \times p$ and B: $p \times n$,

$$\text{tr}(AB) = \text{tr}(BA).$$

Proof. Exercise. Use definition of trace.

Example. If C is orthogonal, is $\text{tr}(C^T AC) = \text{tr}(A)$?

Proof. Yes, and the proof is similar to $\det(A^T AC) = \det(A)$. Here, we have

$$\text{tr}(C^T AC) = \text{tr}(ACC^T) = \text{tr}(AI) = \text{tr}(A).$$

This is called the conjugate transformation. There are other transformations. Suppose P is nonsingular, then the similarity transformation is given as $P^{-1}AP$ and

$$\text{tr}(P^{-1}AP) = \text{tr}(A).$$

Taking A Step Back

Saying A is $n \times p$ matrix is same as saying that $A \in \mathbb{R}^{n \times p}$. A can also be thought as a linear transformation. If

$$A_{n \times p} X_{p \times 1} = nx1,$$

then $A : \mathbb{R}^p \rightarrow \mathbb{R}^n$ for $x \rightarrow AX$.

If A is $n \times n$, then $A : \mathbb{R}^n \rightarrow \mathbb{R}^n$ for $x \rightarrow AX$.

Next, we want to ask

- For what A, we have $\|x\|$ (length of x) = $\|Ax\|$ for all $x \in \mathbb{R}^n$ (i.e. rotation)?

To make

$$\|x\| = \sqrt{(x^T x)} = \sqrt{((Ax)^T (Ax))} = \sqrt{(x^T A^T Ax)},$$

we need

$$x^T x = x^T A^T A x.$$

Or more like we need

$$x^T I x = x^T A^T A x \Leftrightarrow x^T (A^T A - I) x = 0 \quad \forall x$$

$$\Rightarrow A^T A = I$$

\Leftrightarrow A has to be orthogonal (and A is a rotation matrix). I.e., orthogonal matrices preserve length.

- For what A, do we have x and Ax in the same direction $\forall x$?

x and Ax are in the direction $\forall a$. For scalar a , we need

$$Ax = ax$$

Then

$$A = aI,$$

if a is the same since

$$(A - aI)x = 0 \quad \forall x.$$

Or more flexible A can be

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & \ddots \end{bmatrix}.$$

Relaxing it a bit, we can ask

3. For a given A , what x guarantee that (nontrivial) x and Ax are in the same direction?

Eigenvalues

A is $n \times n$. A scalar λ is called an eigenvalue of A if $\exists x$ s.t.

$$Ax = \lambda x.$$

Such a vector x is called an eigenvector of A .

To find λ and x , set

$$(A - \lambda I)x = 0.$$

Since $(A - \lambda I)$ has to be singular (???) $\Leftrightarrow \det(A - \lambda I) = 0$. This is a degree n polynomial about λ . In addition, root of degree n polynomial has n items and exists, so λ always exists.

Characteristic Equation

$(A - \lambda I)x = 0$ is called the characteristic (or polynomial) equation of A . λ is an eigenvalue of A and x is a corresponding eigenvector.

$$Ax = \lambda x$$

Claim. $2x$ is also eigenvector of A corresponding to λ .

Proof.

$$A(2x) = 2Ax = 2\lambda x = \lambda(2x)$$

In general, cx is also an eigenvector of A , where c is a scalar and $\neq 0$. Among this class of eigenvectors, we often require $\|x^T x\| = 1$ for eigenvector.

Ques. Suppose λ is an eigenvalue of A with corresponding eigenvector x , when does $g(A)$ has the same λ ?

- i) $g(A) = cA$ where c is a scalar

Proof.

$$Ax = \lambda x \Rightarrow (cA)x = c\lambda x,$$

so $c\lambda$ is an eigenvalue of cA .

ii) $g(A) = cA + bI$

$$g(A)x = (cA + bI)x = cAx + bIx = cAx + bx = c\lambda x + bx = (c\lambda + b)x,$$

so $(c\lambda + b)$ is an eigenvalue of $g(A) = cA + bI$.

iii) Suppose $g(A) = A^2$, is λ^2 an eigenvalue of A^2 ? Yes.

Proof.

$$(A^2x) = A(Ax) = A(\lambda x) = \lambda(Ax) = \lambda(\lambda x) = \lambda^2 x \quad \square$$

In general, A^k has λ^k as an eigenvalue.

iv) Combining ii) and iii), we get that

$$(A^3 + 4A^2 - 3A + 3I)x = A^3x + 4A^2x - 3A + 3x = \lambda^3x + 4\lambda^2x - 3\lambda x + 3x = (\lambda^3 + 4\lambda^2 - 3\lambda + 3)x.$$

v) Suppose A is nonsingular (has inverse), $g(A) = A^{-1}$ has $\frac{1}{\lambda}$ as an eigenvalue.

Claim. If A is nonsingular, then $\lambda \neq 0$.

Proof. If $\lambda = 0$, then $\exists x \neq 0$ s.t. $Ax = 0$ $x = 0$.

Thm

A is $n \times n$,

- i) If P is nonsingular, then $P^{-1}AP$ and A share the same eigenvalue.
- ii) If C is orthogonal, then C^TAC and A share the same eigenvalue.

Proof. HW. Remark. Eigenvectors may be different.

(!Important) Thm

A is $n \times n$ symmetric (i.e. $A = A^T$ or $a_{ij} = a_{ji}$), then

- i) The eigenvalue $\lambda_1, \lambda_2, \dots, \lambda_n$ are real (some of them have the same eigenvector).
- ii) The eigenvector x_1, x_2, \dots, x_k of A corresponding to the distinct eigenvalue $\lambda_1, \lambda_2, \dots, \lambda_k$ are mutually orthogonal and the eigenvector $x_{k+1}, x_{k+2}, \dots, x_{k+n}$ corresponding to the nondistinct eigenvalue can be chosen to be mutually orthogonal, so $x_i^T x_j^T = 0 \forall i \neq j$.

Ques. Why though? C is $n \times n$

$$C = [c_1 \ c_2 \ \cdots \ c_n] = [x_1 \ x_2 \ \cdots \ x_n] = [| \ | \ \cdots \ |]$$

C is an orthogonal matrix because using this thm, there is a way to make sure we have orthogonal vectors.

$$AC = A(x_1, x_2, \dots, x_n) = (Ax_1, Ax_2, \dots, Ax_n) = (\lambda_1 x_1, \lambda_2 x_2, \dots, \lambda_n x_n) = C \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix} = (\text{or } CD),$$

where x_i are eigenvectors.

$AC = CD$ where C is an orthogonal matrix.

$\Rightarrow A = CDC^T$ for any symmetric A (This is called spectral decomposition.)

$\Leftrightarrow C^T AC = D$ This is called the diagonalization of matrix.