

Positive Definite Matrices

Yangang Cao

June 3, 2019

For any symmetric matrix A , the product $x^T Ax$ is a pure quadratic form $f(x_1, \dots, x_n)$:

$$\begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i x_j$$

Each of the following tests is a **necessary and sufficient** condition for the real symmetric matrix A to be **positive definite**:

- $x^T Ax > 0$ for all nonzero real vectors x
- All the eigenvalues of A satisfy $\lambda_i > 0$
- All the upper left submatrices A_k have positive determinants
- All the pivots (without row exchanges) satisfy $d_k > 0$
- There is a matrix R with independent columns such that $A = R^T R$

Each of the following tests is a **necessary and sufficient** condition for the real symmetric matrix A to be **positive semidefinite**:

- $x^T Ax \geq 0$ for all vectors x
- All the eigenvalues of A satisfy $\lambda_i \geq 0$
- No principal submatrices have negative determinants
- No pivots are negative
- There is a matrix R , possibly with dependent columns, such that $A = R^T R$