

A Note on Independence of Quadratic Forms

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This note is to demonstrate that the extension of Theorem 4.15 of Graybill [1] on the independence of quadratic forms is possible. For the self-contained exposition, Theorem 4.15 is rewritten.

Theorem 4.15 If Y is distributed $N(\mu, \sigma^2 I)$, the positive semidefinite quadratic forms $Y'AY$ and $Y'BY$ are independent if $\text{tr}(AB)=0$.¹⁾

Theorem 4.15 may be extended as follows:

Extension Theorem If Y is distributed $N(\mu, \sigma^2 I)$, the positive semidefinite quadratic forms $Y'AY$ and $Y'BY$ are independent if and only if $\text{tr}(AB)=0$.

It is easy to see that the following theorem together with Theorem 4.10 of Graybill²⁾ proves Extension Theorem.

Theorem $\text{tr}(AB)=0$ if and only if $AB=0$ where

A and B are positive semidefinite and symmetric.

<Proof>

(\Rightarrow) Let $A=P'\Lambda_A P$ and $B=Q'\Lambda_B Q$ where Λ_A and Λ_B are diagonal matrices whose diagonal elements are eigenvalues of A and B , respectively. Then,

$$\begin{aligned}(1) \quad \text{tr}(AB) &= \text{tr}(P'\Lambda_A P Q' \Lambda_B Q) \\ &= \text{tr}(\Lambda_A P Q' \Lambda_B Q P') \\ &= \text{tr}(\Lambda_A R' \Lambda_B R) \quad \text{where } R=QP'\end{aligned}$$

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1) Y denotes an $n \times 1$ random vector. A and B are $n \times n$ positive semidefinite and symmetric matrices. $N(\mu, \sigma^2 I)$ denote the multivariate normal distribution with mean μ and variance-covariance matrix $\sigma^2 I$. The $\text{tr}(\cdot)$ denote trace which is defined as the sum of diagonal elements of a matrix.

2) Graybill, p.84

Theorem 4.10: If Y is distributed $N(\mu, \sigma^2 I)$, the two positive semidefinite quadratic forms $Y'AY$ and $Y'BY$ are independent if and only if $AB=0$.

Rewriting (1),

$$(2) \operatorname{tr}(AB) = \operatorname{tr}\left(\Lambda_A \sum_{i=1}^n \lambda_{Bi} \mathbf{R}_i \mathbf{R}_i'\right)$$

where λ_{Bi} and \mathbf{R}_i are i -th diagonal element of Λ_B and the i -th column vector of \mathbf{R} , respectively.

Or,

$$\begin{aligned} (3) \operatorname{tr}(AB) &= \sum_{i=1}^n \lambda_{Bi} \operatorname{tr}(\Lambda_A \mathbf{R}_i \mathbf{R}_i') \\ &= \sum_{i=1}^n \lambda_{Bi} \mathbf{R}_i' \Lambda_A \mathbf{R}_i \\ &= \sum_{i=1}^n \sum_{j=1}^n \lambda_{Bi} \lambda_{Aj} (R_{ij})^2 \end{aligned}$$

where λ_{Aj} and R_{ji} are the j -th diagonal element of Λ_A and the j -th element of \mathbf{R}_i .

Thus, by assumption,

$$(4) \sum_{i,j} \lambda_{Bi} \lambda_{Aj} (R_{ij})^2 = 0.$$

The positive semidefiniteness of \mathbf{A} and \mathbf{B} implies

$$(5) \lambda_{Bi} \geq 0, \lambda_{Aj} \geq 0; i, j = 1, \dots, n.$$

From (4) and (5),

$$(6) R_{ij} = 0 \text{ if } \lambda_{Bi} \neq 0 \text{ and } \lambda_{Aj} \neq 0.$$

(4), (5), and (6) imply

$$(7) \lambda_{Bi} \lambda_{Aj} R_{ij} = 0.$$

Note that $\lambda_{Bi} \lambda_{Aj} R_{ij}$ is the (j, i) -th element of $\Lambda_A \mathbf{R}' \Lambda_B$, which implies $\Lambda_A \mathbf{R}' \Lambda_B = 0$. Thus, the conclusion is immediate.

(\Leftarrow) It is self-obvious from the definition of trace.

REFERENCE

- [1] Graybill, F.A., *An Introduction to Linear Statistical Models*, Vol. 1, New York: McGraw-Hill, 1961.