

On the distribution of the largest root of a matrix
in multivariate analysis*

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1. Introduction and Summary. Distribution problems in multivariate analysis are often related to the joint distribution of the characteristic roots of a matrix derived from sample observations. This well-known Fisher-Girshick-Hsu-Mood-Roy distribution (under certain null hypotheses) of s non-null characteristic roots can be expressed in the form

$$(1.1) \quad f(\theta_1, \dots, \theta_s) = C(s, m, n) \prod_{i=1}^s \theta_i^m (1-\theta_i)^n \prod_{i>j} (\theta_i - \theta_j)$$

$$0 < \theta_1 \leq \dots \leq \theta_s < 1 \quad ,$$

where

$$(1.2) \quad C(s, m, n) = \pi^{\frac{1}{2}s^2} \Gamma_s(m+n+s+1) / \{ \Gamma_s(\frac{1}{2}(2m+s+1)) \Gamma_s(\frac{1}{2}(2n+s+1)) \Gamma_s(\frac{1}{2}s) \} \quad ,$$

$\Gamma_s(\cdot)$ is the multivariate gamma function defined in [2], and m and n are defined differently for various situations described in [4], [6]. Pillai [3], [5] has given the density function of the larger of two roots, i.e. when $s = 2$, as a hypergeometric function. In this paper, the result is extended to the

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general case giving the density function of the largest of s roots as a generalized hypergeometric function [1],[2]. The density function of the largest root of a sample covariance matrix derived by Sugiyama [7] can be obtained from the one derived here by considering the transformation $\frac{1}{2}\lambda_s = n\theta_s$ and making n tend to infinity.

2. The distribution of the largest root. Let us recall first the definition of the hypergeometric function of matrix argument [2]. If \underline{S} and \underline{T} are $(p \times p)$ symmetric matrices, then

$$(2.1) \quad {}_2F_1(a_1, a_2; b; \underline{S}) \\ = \frac{\Gamma_p(b)}{\Gamma_p(a_1)\Gamma_p(b-a_1)} \int_{\underline{0}}^{\underline{I}} |\underline{I}-\underline{S} \underline{T}|^{-a_2} |\underline{T}|^{a_1 - \frac{1}{2}(p+1)} |\underline{I}-\underline{T}|^{b-a_1 - \frac{1}{2}(p+1)} (d\underline{T}).$$

Now make the following transformation [3],[5],[7] in (1.1):

$$(2.2) \quad \theta_s = \theta_s, \quad l_i = \theta_i / \theta_s, \quad i = 1, \dots, s-1.$$

We get

$$(2.3) \quad f_1(l_1, l_2, \dots, l_{s-1}, \theta_s) \\ = C(s, m, n) \theta_s^{ms + (s-1)(1 + \frac{1}{2}s)} (1 - \theta_s)^n \prod_{i=1}^{s-1} \{l_i^m (1 - l_i \theta_s)^n (1 - l_i)\} \prod_{i>j=1}^{s-1} (l_i - l_j).$$

Now for the integration of (2.3) with respect to the l 's in the range

$0 < l_1 \leq \dots \leq l_{s-1} < 1$, note that in the multivariate beta function form the $(s-1)$ -fold integral will reduce to (2.1) with $a_1 = m + \frac{1}{2}s$, $a_2 = -n$, $b = m + s + 1$,

$\underline{S} = \theta_s \underline{I}_{s-1}$, $p = s-1$, and the limits $\underline{0}$ and \underline{I}_{s-1} except that the result thus

obtained should be multiplied by $\Pi^{-\frac{1}{2}(s-1)^2} \Gamma_{s-1}(\frac{s-1}{2})$ since the integrand of (2.1) is equivalent to that of (2.3) only after an orthogonal transformation to diagonalize the matrix \tilde{T} and integrating out the elements of this orthogonal matrix. Thus we get

$$(2.4) \quad f_2(\theta_s) = \{C(s,m,n) \Gamma_{s-1}(m + \frac{1}{2}s) \Gamma_{s-1}(1 + \frac{1}{2}s) \Gamma_{s-1}(\frac{s-1}{2}) / \Pi^{\frac{1}{2}(s-1)^2} \Gamma_{s-1}(m+s+1)\} \\ e^{ms+(s-1)(1+\frac{1}{2}s)} (1-\theta_s)^n {}_2F_1(m+\frac{1}{2}s, -n; m+s+1; \theta_s \tilde{I}_{s-1}).$$

When $s = 2$, (2.4) reduces to the result given by Pillai [3],[5]. Further, the density function of the smallest root, θ_1 , can be obtained from (2.4) by changing $1-\theta_s$ to θ_1 and m to n [3],[5]. In addition, the density function of the largest root of a sample covariance matrix [7] can be obtained from (2.4) by the method given in the last section.

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