

Random Matrices in Multivariate Analysis

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Johnstone's introductory talk

Three groups of attendees

Statistics

Applications

Mathematics

I will oscillate between the three groups

Brief comments on some earlier lectures

Zeitouni's tutorial

$O(p)$: The group of $p \times p$ orthogonal matrices

H : A generic member of G

dH : normalized Haar measure on $O(p)$

A and B : symmetric $p \times p$ matrices

$$\int_{O(p)} \exp(\operatorname{tr} AHBH^*) dH$$

The integral appears in the density of the eigenvalues of a Wishart matrix

Tracy's tutorial

The zonal polynomial expansion

$$\int_{O(p)} \exp(\operatorname{tr} AHBH^*) dH = \sum_{k=0}^{\infty} \frac{1}{k!} \sum_{|\tau|=k} \frac{C_{\tau}(A) C_{\tau}(B)}{C_{\tau}(I)}$$

$C_{\tau}(A)$: No “explicit” formula

WLOG, $A = \operatorname{diag}(a_1, \dots, a_p)$ and $B = \operatorname{diag}(b_1, \dots, b_p)$

For $p = 2$, an explicit formula:

$$\int_{O(2)} \exp(\operatorname{tr} AHBH^*) dH = c \exp(\dots) I_{\nu}(|a_1 - a_2| \cdot |b_1 - b_2|)$$

I_{ν} is a modified Bessel function

Eichinger (1980's): polymer chemistry, Gaussian macromolecules

Gross and D.R., *Trans. Amer. Math. Soc.*, 1987

Open Problem: Generalize Eichinger's formula to general p

The integral is a generalized Bessel function: Opdam, Heckman

$U(p)$: Similar expansion, but with different zonal polynomials

$C_\tau(A)$ is a multiple of the well-known Schur function, $s_\tau(A)$

$$\tau = (\tau_1, \dots, \tau_p), \tau_1 \geq \dots \geq \tau_p \geq 0$$

A is Hermitian, $A = \text{diag}(a_1, \dots, a_p)$

Vandermonde: $V(A) = \prod_{i < j} (a_i - a_j)$

$$s_\tau(A) = \frac{\det (a_i^{\tau_j + p - j})}{V(A)}$$

$$\begin{aligned}
& \int_{U(p)} \exp(\operatorname{tr} AHBH^*) dH \\
&= \frac{c}{V(A)V(B)} \sum_{\tau_1 \geq \dots \geq \tau_p \geq 0} \det(a_i^{\tau_j + p - j}) \det(b_i^{\tau_j + p - j}) \prod_{j=1}^p c_{\tau_j + p - j}
\end{aligned}$$

Apply Cauchy-Binet/Andréief/Pólya-Szegő Formula:

$$\begin{aligned}
& \int \cdots \int \det(f_i(x_j)) \det(g_i(x_j)) \prod_{j=1}^p d\mu(x_j) \\
&= p! \det\left(\int f_i(x)g_j(x)d\mu(x)\right)
\end{aligned}$$

$$\int_{U(p)} \exp(\operatorname{tr} AHBH^*) dH = c \frac{\det(e^{a_i b_j})}{V(A)V(B)}$$

Hua Loo-Keng, "Harmonic Analysis of Functions of Several Complex Variables in the Classical Domains," AMS Transl., 1963.

C. G. Khatri (1970), Sankhyā: A statistician!

Harish-Chandra-Itzykson-Zuber formula

Gross and D.R. (1992, 1995), J. Approximation Theory: Total positivity

2-D normal p.d.f., $f(x, y) \propto \exp(-x^2 - y^2) \exp(xy)$,

For $x_j, y_j \in \mathbb{R}$, $j = 1, \dots, p$, when is $\det(f(x_i, y_j)) \geq 0$?

Karlin, Lehmann, Perlman-Olkin, ...

Let $X = \text{diag}(x_i)$, $Y = \text{diag}(y_i)$. Then

$$\det(e^{\rho x_i y_j}) = c V(X) V(Y) \int_{U(p)} \exp(\text{tr} X H Y H^*) dH$$

Conclude: $\det(f(x_i, y_j)) \geq 0$ if the x_i and y_i are similarly ordered

Gross and D.R., JAT (1995): Many types of total positivity, related to compact Lie groups

Open Area: Develop a theory of variation-diminishing transformations for these theories of total positivity

Ingram Olkin: I've heard that he knows $N \gg 8$ derivations of the Wishart distribution

I myself know four

The formula for the multivariate gamma function,

$$\Gamma_p(a) = \pi^{p(p-1)/4} \prod_{j=1}^p \Gamma(a - \frac{1}{2}(j-1)),$$

is implicit in Wishart's derivation of his distribution

John Wishart (1898–1956)

Ingham (1939?) read Wishart's paper and noted the importance of Wishart's formula for $\Gamma_p(a)$ for analytic number theory

C. L. Siegel (1940?) gave an independent calculation of $\Gamma_p(a)$

The Ingham-Siegel formula

H. Maass, "Siegel's Modular Forms and Dirichlet Series," 1971.

A remarkable calculation of $\Gamma_p(a)$ (and more) using integration-by-parts on the space of positive definite matrices, treated as a Riemannian manifold.

Back to applications

In all noncentral multivariate problems we find the “troublesome” factors, the hypergeometric functions of matrix argument

Perlman and Olkin (1980), Bondar (1980’s)

When is

$$\frac{\partial^2}{\partial a_1 \partial a_2} \log V(A)V(B) \int_{O(p)} \exp(\text{tr } AHBH^*) dH \geq 0?$$

How about

$$\frac{\partial^2}{\partial a_1 \partial b_1} \log V(A)V(B) \int_{O(p)} \exp(\text{tr } AHBH^*) dH \geq 0?$$

Replace $O(p)$ by $U(p)$, then both are true for all Hermitian A, B

D.R. (J. Statist. Phys., 2004) used the condensation formulas of C. L. Dodgson [Lewis Carroll]

Hegerl

When Hegerl mentioned “missing data,” I had this happy feeling.

Monotone missing data: The matrix-argument hypergeometric functions appear even in the central problems

$(p + q)$ -dimensional normal random vector, $\begin{pmatrix} X \\ Y \end{pmatrix} \sim N(\mu, \Sigma)$

Random sample

$$\begin{array}{cccccc} X_1 & \cdots & X_n & * & \cdots & * \\ Y_1 & \cdots & Y_n & Y_{n+1} & \cdots & Y_N \end{array}$$

Panel survey data, astronomy, early detection of diseases, wildlife research, covert communications, mental-health research, ...

Explicit formulas for the MLE's of μ and Σ are available, but nothing yet for the EXACT (fixed n, N) distributions

In some applications, it could be unethical to hope for large sample sizes.

Calling Alan Edelman! Lots and lots of random matrices ...

Theorem (Wan-Ying Chang and D.R., November 1, 2006):

$$\hat{\mu} \stackrel{\mathcal{L}}{=} V_1 + \sqrt{1 - \frac{n}{N}} R \begin{pmatrix} V_2 \\ 0 \end{pmatrix}$$

where $V_1 \sim N_{p+q}(\mu, \Omega)$, R is a positive r.v., and $V_2 \sim N_p(0, \dots)$

$\hat{\Sigma}$ has a density function of the form

$$W(\hat{\Sigma}_{11.2}) W(\hat{\Sigma}_{22}) {}_1F_1(\hat{\Sigma}_{12} \hat{\Sigma}_{22}^{-1} \hat{\Sigma}_{21})$$

What is this ${}_1F_1$? The confluent hypergeometric function which appears at the beginning of Johnstone's Ann. Statist. paper on principal components for high-dimensional random matrices.

Resistance is futile: You will be assimilated into the area of world of matrix-argument hypergeometric functions.

Wan-Ying and still can establish optimality properties of classical statistical hypothesis tests

Testing $H_0 : \mu = \mu_0$ against $H_a : \mu \neq \mu_0$: We have modified likelihood ratio test statistics which are unbiased

Testing $H_0 : (\mu, \Sigma) = (\mu_0, \Sigma_0)$ against $H_a : (\mu, \Sigma) \neq (\mu_0, \Sigma_0)$

Ditto

The sphericity test: $H_0 : \Sigma \propto I$

We have the distribution of the LRT statistic, but unbiasedness continues to evade us

Testing $\Sigma_{12} = 0$: Eaton and Kariya (1983)