

Random Matrix Theory: Lecture 3

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CINVESTAV

Density of the matrix

Consider the Wigner GOE model $M_n = \frac{1}{2}(X_n + X_n^\top)$. Then,

$$P(M_n \in dx) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-x_i^2/2} \prod_{1 \leq i < j \leq n} \frac{1}{\sqrt{\pi}} e^{-x_{ij}^2}.$$

or

$$P(M_n \in dx) = c_n \prod_{i,j=1}^n e^{-x_{ij}^2/2} = c_n e^{-\frac{1}{2} \sum_{i,j=1}^n x_{ij}^2} = c_n e^{-\frac{\text{Trace}(M_n^2)}{2}},$$

with $x_{ij} = x_{ji}$.

S_n the space of symmetric $n \times n$ matrices; a manifold of dimension $N = 1 + 2 + \dots + n = \frac{n(n+1)}{2}$.

Represent M_n as a vector $\vec{v} = (v_1, \dots, v_N) \in \mathbf{R}^N$, using the map

$$\phi(\vec{v}) = M_n,$$

where the first n elements of \vec{v} form the diagonal of M_n , then $v_{n+1}, \dots, v_{n+(n-1)}$ form the first row (and also the first column), and so forth.

Joint density of a long vector

the joint probability density of \bar{v} is

$$f(\bar{v}) = c_n e^{-\frac{1}{2} \text{Trace}(\phi(\bar{v})^2)}$$

From the spectral decomposition $M_n = U^\top \Lambda U$, where U is unitary and Λ is the diagonal matrix with the eigenvalues $\lambda_1 \leq \dots \leq \lambda_n$. Given the vector $\bar{w} = (\lambda_1, \dots, \lambda_n, u_1, \dots, u_m)$, where $m = N - n$,

$$\psi(\bar{w}) = M_n = U^\top \Lambda U,$$

where $\bar{\lambda} = (\lambda_1, \dots, \lambda_n)$ form the diagonal matrix Λ , and $\bar{u} = (u_1, \dots, u_m)$ form the matrix U .

Our aim is to find the joint probability density $h_n(\bar{\lambda})$ of $\bar{\lambda}$

The Jacobian

Let $g(\bar{w})$ be the density of \bar{w}

From the spectral decomposition we can see that there is a differentiable map F from \bar{v} to \bar{w} . Then, the probability density of \bar{w} is given by $g(\bar{w}) = f(F^{-1}(\bar{w}))|\det J(\bar{w})|$, where $J(\bar{w})$ is the Jacobian matrix of F .

Notice is that $f(F^{-1}(\bar{w})) = c_n e^{-\frac{\lambda_1^2 + \dots + \lambda_n^2}{2}}$.

So, our task now is to find the Jacobian

$$J = \begin{bmatrix} \frac{dv_1}{d\lambda_1} & \cdots & \frac{dv_1}{d\lambda_n} & \frac{dv_1}{du_1} & \cdots & \frac{dv_1}{du_m} \\ \frac{dv_2}{d\lambda_1} & \cdots & \frac{dv_2}{d\lambda_n} & \frac{dv_2}{du_1} & \cdots & \frac{dv_2}{du_m} \\ & & \vdots & & & \\ \frac{dv_N}{d\lambda_1} & \cdots & \frac{dv_N}{d\lambda_n} & \frac{dv_N}{du_1} & \cdots & \frac{dv_N}{du_m} \end{bmatrix}.$$

derivatives in the manifold

Use $M_n = U^\top \Lambda U$ to find the derivatives. All the information is inside $\left\{ \frac{dM_n}{d\lambda_i}, \frac{dM_n}{du_j} : i = 1, \dots, n; j = 1, \dots, m \right\}$.

We first have that

$$\frac{dM_n}{d\lambda_i} = U^\top \frac{d\Lambda}{d\lambda_i} U \quad \text{and} \quad \frac{dM_n}{du_j} = U^\top \Lambda \frac{dU}{du_j} + \frac{dU^\top}{du_j} \Lambda U.$$

$\frac{d\Lambda}{d\lambda_i}$ is the matrix full of zeros and only one 1 in the (i, i) -entry.

And

$$\frac{dM_n}{du_j} = U^\top \left(\Lambda \frac{dU}{du_j} U^\top + U \frac{dU^\top}{du_j} \Lambda \right) U$$

Also from $I = UU^\top$, we have $0 = U \frac{dU^\top}{du_j} + \frac{dU}{du_j} U^\top$.

Hence

$$\frac{dM_n}{du_j} = U^\top (D_j \Lambda - \Lambda D_j) U,$$

where $D_j = U \frac{dU^\top}{du_j}$ depends solely on the variables u 's.

It occurs that $|\det(J)| = |\det(J')|$, where J' is the $N \times N$ matrix with the columns

$$c'_i = \phi^{-1} \left(\frac{d\Lambda}{d\lambda_i} \right), i = 1, \dots, n;$$

and

$$c'_{n+j} = \phi^{-1} (D_j \Lambda - \Lambda D_j), j = 1, \dots, m.$$

Notice that $D_r \Lambda - \Lambda D_r = [d_{ij}(r)(\lambda_j - \lambda_i)]_{i,j=1}^n$, where $d_{ij}(r)$ are the entries of D_r .

