

INTRODUCTION TO RANDOM MATRIX THEORY II

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- ✻ Jean-Marie Normand reviewed elementary properties of RMT

- ✻ In addition to the methods he proposed, there are two important methods:

- ✻ the Replica Method

- ✻ The Supersymmetric Method

- ✻ These methods can be used in the case standard methods don't work

✻ Problems that can be solved: non Gaussian variables, Laplacian Gaussian Matrices, etc...

A SIMPLE EXAMPLE: HOW TO COMPUTE A RESOLVANT

- ✻ Consider a simple problem: Real Random Symmetric Matrix ensemble
- ✻ Calculate the **resolvent**

$$G(z) = \text{Tr} \frac{1}{z - H}$$

where H_{ij} is a $N \times N$ matrix

- ✻ Density of states

$$\rho(z) = -\frac{1}{N\pi} \text{Im}G(z + i\epsilon)$$

GAUSSIAN IDENTITIES

If A is a symmetric definite positive matrix and u is a real source, one has

$$\int \prod_{i=1}^N dx_i e^{-\frac{1}{2} x_i A_{ij} x_j + u_i x_i} = \frac{(2\pi)^{N/2}}{(\det A)^{1/2}} e^{\frac{1}{2} u_i A_{ij}^{-1} u_j}$$

which implies

$$A_{kl}^{-1} = \frac{\int \prod_{i=1}^N dx_i x_k x_l e^{-\frac{1}{2} x_i A_{ij} x_j}}{\int \prod_{i=1}^N dx_i e^{-\frac{1}{2} x_i A_{ij} x_j}}$$

RESOLVANT

$$\begin{aligned} G(z) &= \text{Tr} \frac{1}{z - H} \\ &= \sum_i (z - H)_{ii}^{-1} \end{aligned}$$

which can be written as

$$G(z + i\epsilon) = \frac{\int \prod_{i=1}^N dx_i \sum_i x_i^2 e^{\frac{i}{2} x_i (z + i\epsilon - H)_{ij} x_j}}{\int \prod_{i=1}^N dx_i e^{\frac{i}{2} x_i (z + i\epsilon - H)_{ij} x_j}}$$

for real z and positive ϵ

One must in fact compute the average of the resolvent over the random matrix elements

$$G(z) = \langle \text{Tr} \frac{1}{z - H} \rangle$$

As it is, it is impossible to average over the matrix elements of H

Difficulty comes from the denominator. To escape, two possibilities

Replicas

Supersymmetry

REPLICAS

In systems with **quenched disorder**, one must average **observables** over the disorder distribution

Example: **the free energy**

$$F = -\frac{1}{\beta} \langle \log Z \rangle$$

The replica trick (SG: Edwards-Anderson, 1975)

$$\langle \log Z \rangle = \frac{d}{dn} \langle Z^n \rangle \Big|_{n=0}$$

Idea: compute for integer n and do the analytic continuation at $n=0$

Practically, introduce n replicas of the system and perform the average

REPLICAS

We have

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \int \prod_{i=1}^N dx_i \sum_i x_i^2 e^{\frac{i}{2} x_i (z + i\epsilon - H)_{ij} x_j} \left(\int \prod_{i=1}^N dx_i \sum_i e^{\frac{i}{2} x_i (z + i\epsilon - H)_{ij} x_j} \right)^{n-1}$$

The limit $n=0$ reconstructs the denominator

Idea: compute the quantity for integer n and do analytic continuation at $n=0$

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^\alpha \sum_i x_i^{(1)2} e^{\frac{i}{2} x_i^\alpha (z + i\epsilon - H)_{ij} x_j^\alpha}$$

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^\alpha e^{\frac{i}{2} x_i^\alpha (z + i\epsilon - H)_{ij} x_j^\alpha}$$

Now it is possible to compute average over the matrices

SUPERSYMMETRY

If we use complex variables

$$\int \prod_i \frac{d\phi_i^* d\phi_i}{\pi} e^{-\phi_i^* A_{ij} \phi_j} = (\det A)^{-1}$$

$$\int \prod_i \frac{d\phi_i^* d\phi_i}{\pi} \phi_k^* \phi_l e^{-\phi_i^* A_{ij} \phi_j} = A_{kl}^{-1} (\det A)^{-1}$$

For anticommuting Grassmann variables (Fermionic)

$$\int \prod_i \frac{d\psi_i^* d\psi_i}{\pi} e^{-\psi_i^* A_{ij} \psi_j} = \det A$$

$$\int \prod_i \frac{d\psi_i^* d\psi_i}{\pi} \psi_k^* \psi_l e^{-\psi_i^* A_{ij} \psi_j} = A_{kl}^{-1} \det A$$

SUPERSYMMETRY

So the resolvent can be expressed as

$$G(z) = \frac{1}{2} \int \prod_i d\phi_i^* d\phi_i d\psi_i^* d\psi_i \sum_i (\phi_i^* \phi_i + \psi_i^* \psi_i) e^{-\phi_i^* (z-H)_{ij} \phi_j - \psi_i^* (z-H)_{ij} \psi_j}$$

Then the determinants cancel

$$G(z) = -\frac{1}{2} \frac{d}{dz} \int \prod_i d\phi_i^* d\phi_i d\psi_i^* d\psi_i e^{-(z-H)_{ij} (\phi_i^* \phi_j + \psi_i^* \psi_j)}$$

In the following, we will use replicas

REPLICAS

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^\alpha e^{\frac{i}{2} x_i^\alpha (z + i\epsilon - H)_{ij} x_j^\alpha}$$

Assume the matrix entries are Gaussian
identically distributed variables

$$H_{ij} = H_{ji}$$

with

$$P(H_{ii}) = \sqrt{\frac{1}{2\pi H_0^2}} e^{-\frac{H_{ii}^2}{2H_0^2}}$$

$$P(H_{ij}) = \sqrt{\frac{N}{2\pi H^2}} e^{-\frac{NH_{ij}^2}{2H^2}}$$

Note the Wigner scaling which allows good scaling limit

To simplify, assume

$$H_{ii} = 0$$

and perform Gaussian average

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^\alpha e^{\frac{i}{2}(z+i\epsilon)x_i^{(\alpha)2} - \frac{H^2}{2N} \sum_{i < j, \alpha, \beta} x_i^\alpha x_i^\beta x_j^\alpha x_j^\beta}$$

which can be rewritten as

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^\alpha e^{\frac{i}{2}(z+i\epsilon)x_i^{(\alpha)2} - \frac{H^2}{4N} \sum_{\alpha, \beta} (\sum_i x_i^\alpha x_i^\beta)^2}$$

or finally

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^\alpha e^{\frac{i}{2}(z+i\epsilon)x_i^{(\alpha)2} - \frac{H^2}{4N} \sum_{\alpha} (\sum_i x_i^{(\alpha)2})^2 - \frac{H^2}{2N} \sum_{0 \leq \alpha < \beta \leq n} (\sum_i x_i^\alpha x_i^\beta)^2}$$

Using inverse Gaussian transforms,
we get (up to normalizations)

$$e^{-\frac{H^2}{4N} \sum_{\alpha} (\sum_i x_i^{(\alpha)})^2} = \int \prod_{\alpha=1}^n dq_{\alpha} e^{-Nq_{\alpha}^2 - iHq_{\alpha} \sum_i x_i^{(\alpha)}}$$

$$e^{-\frac{H^2}{2N} \sum_{0 \leq \alpha < \beta \leq n} (\sum_i x_i^{\alpha} x_i^{\beta})^2} = \int \prod_{\alpha < \beta} dq_{\alpha\beta} e^{-\frac{N}{2} \sum_{\alpha < \beta} q_{\alpha\beta}^2 - iHq_{\alpha\beta} \sum_i x_i^{\alpha} x_i^{\beta}}$$

Introduce the $n \times n$ matrix

$$Q_{\alpha\alpha} = 2q_{\alpha}$$

$$Q_{\alpha\beta} = q_{\alpha\beta}$$

we have

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{i=1}^N \prod_{\alpha=1}^n dx_i^{\alpha} \prod_{\alpha, \beta} dQ_{\alpha\beta} e^{\frac{i}{2}(z+i\epsilon) \sum_i x_i^{(\alpha)} - \frac{N}{4} \text{Tr} Q^2 - i \frac{H}{2} \sum_i x_i^{\alpha} x_i^{\beta}}$$

Now the replicated variables can be integrated and we obtain

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} \int \prod_{\alpha, \beta} dQ_{\alpha\beta} e^{-\frac{N}{2} \left(\frac{1}{2} \text{Tr} Q^2 + \text{Tr} \log(z + i\epsilon - HQ_{\alpha\beta}) \right)}$$

where we have used the matrix identity

$$\log \det A = \text{Tr} \log A$$

When $N \rightarrow \infty$ we use the saddle-point method

$$Q - H(z - HQ)^{-1} = 0$$

equivalent to the matrix equation

$$HQ^2 - zQ + H = 0$$

This equation determines only the eigenvalues of Q

$$\lambda_{\pm} = \frac{z \pm \sqrt{z^2 - 4H^2}}{2H}$$

This equation does not determine the degeneracy of the eigenvalues.

Let nq be the degeneracy of the + solution and $n(1-q)$ that of the - solution with $0 < q < 1$

We have

$$G(z + i\epsilon) = \lim_{n \rightarrow 0} \frac{2}{in} \frac{d}{dz} e^{-\frac{nN}{2} \left(\frac{q}{2} \lambda_+^2 + \frac{(1-q)}{2} \lambda_-^2 + q \log(z + i\epsilon - H\lambda_+) + (1-q) \log(z + i\epsilon - H\lambda_-) \right)}$$

q is chosen so as to maximize the exponent of G

One can see easily that

$$q = 1 \text{ for } z > 2H$$

$$q = 0 \text{ for } z < -2H$$

$$G(z + i\epsilon) = 2iN \frac{d}{dz} \left(\frac{q}{2} \lambda_+^2 + \frac{(1-q)}{2} \lambda_-^2 + q \log(z + i\epsilon - H\lambda_+) + (1-q) \log(z + i\epsilon - H\lambda_-) \right)$$

More work (complex analysis) allows to compute
the density of states.

One finds of course the **semi-circle law**

CONCLUSION

- ✻ Simple and elegant method
- ✻ Can be generalized to non Gaussian distributions with Wigner scaling
- ✻ Allows calculation of corrections to saddle-point
- ✻ Can be generalized to many other problems: Optimization, time dependent systems, etc..