

Gap probabilities and individual eigenvalue distr.

- So far we have only studied density correlation functions, $R_{N,U}^{(\beta)}$, i.e. the probability to find an eigenvalue at $x = R_{N,U}^{(\beta)}(x)$, or the probability to find r ev at x and r at y , $R_{N,U}^{(\beta)}(x,y)$ etc
- Now we will consider the probability that an interval I (e.g. $I = (-s,s)$) is empty of eigenvalues, also called gap probability. First $\beta = 2$:

$$A_I = \frac{1}{N!} \int_{\mathbb{R}-I} dx_i P_N^{(\beta=2)}(x_1, \dots, x_N)$$

include to make orthonormal

$$= \frac{1}{N!} \prod_{j=0}^{N-1} h_j \int_{\mathbb{R}-I} dx_i w(x_i) \det [P_{j-1}^{(2)}(x_i)]^2$$

$$= \int_{\mathbb{R}} dx_i \underbrace{(1 - \chi_I(x)) w(x_i)}_{\tilde{w}(x_i)}$$

↑ char. funct on I

$$= \frac{1}{N!} \prod_{j=0}^{N-1} h_j \int_{\mathbb{R}} dx_i \det [\varphi_j(x_i)]^2, \quad \varphi_j(x) = \tilde{w}(x)^{\frac{1}{2}} P_{j-1}(x)$$

Andréief formula $\beta=2$

$$= \det_{1 \leq i, j \leq N} \left[\int_{\mathbb{R}} dx \varphi_i(x) \varphi_j(x) \right] = \det_{1 \leq i, j \leq N} \left[\int_{\mathbb{R}} dx (1 - \chi_I(x)) w(x) P_i(x) P_j(x) \right]$$

$$A_I = \det_{1 \leq i, j \leq N} \left[S_{ij} - \int_I dx w(x) P_i(x) P_j(x) \right] \rightarrow \text{Fredholm determinant}$$

Andrzej formula (integral identity)

Let $\varphi_i(x), \psi_i(x), i=1, 2, \dots, N$ be 2 sets of integrable functions

Then $\int dx_1 \dots \int dx_N \det_{1 \leq i, j \leq N} [\varphi_i(x_j)] \det_{1 \leq i, j \leq N} [\psi_i(x_j)] = N! \det_{1 \leq i, j \leq N} [\int dx \varphi_i(x) \psi_j(x)]$

Proof: - induction: $N=1$ is trivial
 " " assumption: holds for N

$N+1$: expand both det's on l.h.s. w.r.t. column containing x_{n+1} :

$$\int dx_1 \dots \int dx_N \int dx_{n+1} \sum_{j=1}^{N+1} (-1)^{n+1+j} \varphi_j(x_{n+1}) \det_{\substack{j \neq n+1 \\ k \neq i}} [\varphi_k(x_j)] \sum_{l=1}^{N+1} (-1)^{n+1+l} \psi_l(x_{n+1}) \det_{\substack{l \neq n+1 \\ m \neq i}} [\psi_m(x_l)]$$

$$\int dx_{n+1} N! \sum_{i, l=1}^{N+1} (-1)^{i+l} \varphi_i(x_{n+1}) \psi_l(x_{n+1}) \det_{\substack{k \neq i \\ n \neq l}} [\int dx \varphi_k(x) \psi_n(x)]$$

• for fixed i, l : $\sum_{l=1}^{N+1} (-1)^{i+l} \int dx \varphi_i(x) \psi_l(x) \det_{\substack{k \neq i \\ n \neq l}} [\int dx \varphi_k(x) \psi_n(x)]$

is the Laplace expansion w.r.t. row " i " of $\det_{1 \leq k, n \leq N+1} [\int dx \varphi_k(x) \psi_n(x)]$

\Rightarrow we sum over $(N+1)$ such expansions

$$(N+1) N! \det_{1 \leq k, n \leq N+1} [\int dx \varphi_k(x) \psi_n(x)] \quad \square$$

Annotations:
 - Induction assumpt. for N (bracketed on the left)
 - N func. $\varphi_1 \dots \varphi_N$ (under $\det_{k \neq n+1}$)
 - N func. $\psi_1 \dots \psi_N$ (under $\det_{l \neq n+1}$)

$$A_I = \frac{N}{k} (1 - \lambda_j), \quad \lambda_j \text{ eigenvalues of matrix}$$

$$M_{ij} = \int dx w(x) P_i(x) P_j(x)$$

remark:

The eigenvalues λ_j are the same as the solutions of the integral eq.

$$\int dx w(x) w(y) \frac{1}{k} K_N(x,y) f(y) = \lambda f(x) \quad [\text{see Mehta}]$$

k -th gap probability and k -th eigenvalue : for $\beta = 1, 2, 4$

$$E_k^{(\beta)}(s) = \frac{N!}{(N-k)! k!} \int_{-\infty}^s dx_1 \dots dx_k \int_s^{\infty} dx_{k+1} \dots dx_N P_N^{(\beta)}(x_1, \dots, x_N) \quad \text{kth gap prob.}$$

example: $E_{k=0}(s) = \int_s^{\infty} dx_1 \dots dx_N P_N^{(\beta)}$ prob. that all ev are $\geq s$, $E_{k=0}(s=0) = 1$

general: E_k " " k ev $\leq s$, $N-k \geq s$

$$P_k^{(\beta)}(s) = \frac{k \cdot N!}{k! (N-k)!} \int_{-\infty}^s dx_1 \dots dx_{k-1} \int_s^{+\infty} dx_k \dots dx_N P_N^{(\beta)}(x_1, \dots, x_{k-1}, \lambda_k = s, x_{k+1}, \dots, x_N)$$

if we order $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_N$

$P_k^{(\beta)}(s)$ is the probability to find the k -th eigenvalue at $\lambda_k = s$

it holds $\frac{\partial}{\partial s} E_0^{(\beta)}(s) = -P_0^{(\beta)}(s)$

and $\frac{\partial}{\partial s} E_k^{(\beta)}(s) = \frac{N!}{(N-k)!} \frac{k}{k!} \int_{-\infty}^s dx_1 \dots dx_{k-1} \int_s^{\infty} dx_k \dots dx_N P_N^{(\beta)} \Big|_{\lambda_k = s} - \frac{N!}{(N-k)!} \frac{(N-k)}{k!} \int_{-\infty}^s dx_1 \dots dx_{k-1} \int_s^{\infty} dx_{k+1} \dots dx_N P_N^{(\beta)} \Big|_{\lambda_{k+1} = s}$

$$\Rightarrow \frac{\partial}{\partial s} E_k^{(\beta)}(s) = P_k^{(\beta)}(s) - P_{k+1}^{(\beta)}(s)$$

$$\Leftrightarrow P_k^{(\beta)}(s) = - \sum_{e=0}^{k-1} \frac{\partial}{\partial s} E_e^{(\beta)}(s)$$

• if we know all gaps we know all indiv. eigenvalue distributions

• normalisation: $\forall k \quad \int_{-\infty}^{\infty} dx P_k^{(\beta)}(s) = 1$

exercise or [arxiv 0311171 App A with $w(x) = x^k e^{-x} \Theta(x)$ $E_k \rightarrow k! E_k$]

we will now compute $E_k^{(\beta)}(s)$ in two ways:

i) expressed through $R_{N,k}^{(\beta)}(s)$ in general

ii) expressed through $\langle \text{tr det}^s \rangle$ for $w(x) = x^k e^{-x} \Theta(x)$

i) idea: $(a-b)^j = \sum_{l=0}^j (-1)^l \binom{j}{l} a^{j-l} b^l$

with $a = \int_{-\infty}^{\infty} dx$, $b = \int_{-\infty}^s dx \Rightarrow a-b = \int_s^{\infty} dx$

using the symmetry of $P_N^{(\beta)}$ under permutations of arguments:

$$\Rightarrow E_k^{(\beta)}(s) = \binom{N}{k} \int_{-\infty}^s dx_1 \dots dx_k \sum_{e=0}^{N-k} (-1)^e \binom{N-k}{e} \left(\int_{-\infty}^{\infty} dx_{k+1} \dots dx_{k+e} \right) \left(\int_s^{\infty} dx_{k+e+1} \dots dx_N \right) P_N^{(\beta)}$$

$$= \sum_{e=0}^{N-k} (-1)^e \frac{N!}{k!e!(N-k-e)!} \int_{-\infty}^s dx_1 \dots dx_k \int_{k+e}^{\infty} dx_{k+e+1} \dots dx_N P_N^{(\beta)}$$

$$E_k^{(\beta)}(s) = \sum_{e=0}^{N-k} (-1)^e \frac{1}{k!e!} \int_{-\infty}^s dx_1 \dots dx_k \int_{k+e}^{\infty} dx_{k+e+1} \dots dx_N R_{N,k+e}^{(\beta)}(x_1, \dots, x_{k+e})$$

here we define $R_{N,0}^{(\beta)} \equiv 1 \quad (= \frac{E_N^{(\beta)}}{Z_N^{(\beta)}}$)

eg. $E_0^{(\beta)}(s) = 1 - \int_{-\infty}^s dx_1 R_{N,1}^{(\beta)}(x_1) + \frac{1}{2} \int_{-\infty}^s \int_{-\infty}^s dx_1 dx_2 R_{N,2}^{(\beta)}(x_1, x_2) + \dots$

- numerically this sum converges very rapidly
- in the limit $N \rightarrow \infty$ this is the def. of a Fredholm det., alternatively to p. 25

Remark: We may also introduce a generating functional

$$E(s; \xi) \equiv \sum_{e=0}^N (-\xi)^e \frac{1}{e!} \int_{-\infty}^s d\lambda_1 \dots d\lambda_e R_{N,e}^{(\beta)}(\lambda_1, \dots, \lambda_e)$$

$$\Rightarrow E_k^{(\beta)}(s) = \left. \frac{(-)^k}{k!} \frac{\partial^k}{\partial \xi^k} E(s; \xi) \right|_{\xi=1} \quad (\text{for } k=0, 1, \dots, N)$$

ii) let us choose the chiral or Virchard-Laguerre ensembles (N x N matrices)

with weight $\omega_w^{(\beta)}(x) = x^{\frac{\beta}{2}(\nu+1)-1} e^{-x}$ on \mathbb{R}_+ \Rightarrow all lower bounds are at 0

consider $E_{0,N}^{(\beta)}(s)$: display ν -dep

$$E_{0,N}^{(\beta)}(s) = \frac{1}{N! \prod_{j=0}^{\nu} h_j^{(\beta)}} \int_S \prod_{b=1}^N dx_b e^{x_b} x_b^{\frac{\beta}{2}(\nu+1)-1} e^{-x_b} \prod_{n \geq m} |x_n - x_m|^\beta$$

shift $x_n - s = y_n$

$$= \frac{1}{N! \prod_{j=0}^{\nu} h_j^{(\beta)}} \int_{\mathbb{R}} \prod_{e=1}^N dy_e e^{(y_e + s)} y_e^{\frac{\beta}{2}(\nu+1)-1} e^{-(y_e + s)} \prod_{n \geq m} |y_n - y_m|^\beta$$

if we compare to

$$\left\langle \frac{1}{\prod_{j=1}^L \det(z_j - H H^\dagger)} \right\rangle_{N, \nu} = \frac{1}{N! \prod_{j=0}^{\nu} h_j^{(\beta)}} \int_{\mathbb{R}} \prod_{e=1}^N dy_e e^{-y_e} y_e^{\frac{\beta}{2}(\nu+1)-1} e^{-y_e} \prod_{j=1}^L \prod_{i=1}^N (z_j - y_i) |\Delta_N|^\beta$$

• we have that $E_{0,v}^{(\beta)}(s)$ is the ave. of $\frac{\beta}{2}(v+1)-1$ char. polynomials with argument $z_1 = \dots = z_L = -s$
 (for $\beta=4$ because of the degeneracy $\Theta_0 = \begin{pmatrix} \lambda_0 & 0 \\ 0 & \lambda_0 \end{pmatrix}$ the eigenvalues always appear in pairs)

• for this interpretation we need $\frac{\beta}{2}(v+1)-1 \in \mathbb{N}$ (and even for $\beta=4$)

$\beta=1$: $\frac{1}{2}(v+1)-1 = \frac{(v-1)}{2} \in \mathbb{N} \Leftrightarrow v=2\ell+1, \ell \in \mathbb{N}$

$\beta=4$: $\frac{4}{2}(v+1)-1 = 2v+1$ even ($\Leftrightarrow v = k - \frac{1}{2}$)

$\beta=2$: $\frac{2}{2}(v+1)-1 = v \in \mathbb{N} \quad \forall$ (for all $v=0,1,2,\dots$)

• in $E_{0,v}^{(\beta)}(s)$ the "effective" v_{eff} leads to $\frac{\beta}{2}(v_{\text{eff}}+1)-1 = 0$

$$E_{0,v}^{(\beta=2)}(s) = \left\langle \prod_{\ell=1}^v \det(-s - H H^T) \right\rangle_{N_1, v_{\text{eff}}=0} (-)^{vN} e^{-Ns}$$

$$E_{0,v=2\ell+1}^{(\beta=1)}(s) = \left\langle \prod_{j=1}^{\ell} \det(-s - H H^T) \right\rangle_{N_1, v_{\text{eff}}=1}^{-Ns} e^{-N\ell}$$

$\Leftrightarrow v_{\text{eff}} = \frac{2}{\beta} - 1 \in \mathbb{N}$

$= \begin{cases} 1 & \beta=1 \\ 0 & \beta=2 \\ -\frac{1}{2} & \beta=4 \end{cases}$

example:
 $\beta=2, v=0$
 or $\beta=1, \ell=0$: $E_0(s) = e^{-Ns}$

• the computation of $E_{0,v=2\ell}^{\beta=4}, E_0^{\beta=4}$ is an open problem
 (see however Edelmann, J. Matrix Anal. Appl. 9 (88) for a recursion)

• the two problems are related, solving one solves the other

• E_k can also be expressed in terms of $\langle \bar{u} \det \rangle$:

$E_k \sim \int_0^s \int_0^{\infty} \dots \int_0^{\infty} d\lambda_1 \dots d\lambda_{k+1} \dots d\lambda_N P_N$

↑
meas

shift $\hookrightarrow \langle \det^k \rangle_{N-k}$

Computation of averages of characteristic polynomials

• we will focus again on $\beta=2$, for $\beta=1$, see [Molita, Normand arXiv 0101463]

Theorem Brézin-Hilgami [CMP 214(2000) 111]

cond-mat using de Bruijn

$$\left\langle \prod_{c=1}^L \det(X_c - H) \right\rangle_N = \frac{1}{\Delta_L(\{x_j\})} \begin{vmatrix} \tilde{P}_N(x_1) & \dots & \tilde{P}_N(x_L) \\ \tilde{P}_N(x_2) & \dots & \tilde{P}_N(x_L) \\ \vdots & & \vdots \\ \tilde{P}_N(x_L) & \dots & \tilde{P}_N(x_L) \end{vmatrix}$$

where $\tilde{P}_c(x)$ are the monic orthogonal polynomials w.r.t weight $w(x)$
 $\int dx w(x) \tilde{P}_n(x) \tilde{P}_c(x) = h_n \delta_{nc}$ (Note: for $w(x) \propto \prod \det(x_j - H H^\dagger)$)

Proof [Baik, Deift, Strahov arXiv 0304016 math-ph]

Consider the weight $w^{[e]}(x) = \left(\prod_{j=1}^e (x_j - x) \right) w(x)$ ($0 \leq e \leq L$)

Then $\tilde{P}_n^{[e]}(t) \equiv \frac{1}{(t-x_1)\dots(t-x_e)} \begin{vmatrix} \tilde{P}_n(x_1) & \dots & \tilde{P}_n(x_L) \\ \tilde{P}_n(x_2) & \dots & \tilde{P}_n(x_L) \\ \vdots & & \vdots \\ \tilde{P}_n(x_L) & \dots & \tilde{P}_n(x_L) \end{vmatrix}$

are the monic orthogonal polyn. w.r.t $w^{[e]}(x)$ ($e=1, \dots, L$):

$$\begin{vmatrix} \tilde{P}_n(x_1) & \dots & \tilde{P}_n(x_L) \\ \tilde{P}_n(x_2) & \dots & \tilde{P}_n(x_L) \\ \vdots & & \vdots \\ \tilde{P}_n(x_L) & \dots & \tilde{P}_n(x_L) \end{vmatrix}$$

Take $q_n^{[e]}(t)$ to be the det in the num

it holds $q_n^{[e]}(x_j) = 0$ for $j=1, \dots, e$, polyn of deg $\leq n+e$

$\Rightarrow \frac{q_n^{[e]}(t)}{(t-x_1)\dots(t-x_e)}$ is a poly of deg $\leq n$

It holds $\int t^j \frac{q_n^{[e]}(t)}{(t-x_1)\dots(t-x_e)} w(t) dt = \int t^j \frac{q_n^{[e]}(t)}{(t-x_1)\dots(t-x_e)} w^{(e)}(t) dt = 0$ for $j=0, \dots, n-1$

The normalisation follows from

looking at $t \gg 1$ (it can be shown that det in denom is $\neq 0$, see Baik, Deift, Strahov)

Theorem (2-point fnc.) [BDS]

$$\left\langle \prod_{j=1}^k \det(x_j - H) \det(y_j - H) \right\rangle_N = \frac{\prod_{e=1}^{N+k-1} h_e}{\Delta_k(x) \Delta_k(y)} \det \left[K_{N+k}(x_i, y_j) \right]$$

Proof see BDS (who state this using Christoffel-Darboux)

Note that using the previous theorem this also equals a det of size $2k \times 2k$ of polynomials only. In fact a more general Th holds.

Thm [14 arXiv 0212051 [hep-th]]

Let $k \geq \ell$:
$$\left\langle \prod_{i=1}^k \det(x_i - H) \prod_{j=1}^{\ell} \det(y_j - H) \right\rangle_N = \frac{\prod_{i=1}^{N+k-1} h_i \prod_{j=N}^{N+k-1} h_j}{\Delta_k(x) \Delta_{\ell}(y)}$$

$$\det \begin{array}{c|c} K_{N+k}(x_e, y_m) & m=1, \dots, \ell \\ \hline P_{N+m-1}(x_e) & m=\ell+1, \dots, k \end{array}$$

Proof: for non-Hermit, valid in Hermit case $e=1, \dots, k$

Back to gap probabilities:

for $\beta=2$ and $w(x) = x^{\nu} e^{-x}$ we have $\tilde{P}_N^{(\nu)}(x) = (-1)^N N! \sum_N^{(\nu)}(x)$

$$E_{0, \nu}^{(\beta=2)}(s) = \lim_{\substack{x_0 \rightarrow s \\ 0 \rightarrow \nu}} \frac{(-1)^{\nu N}}{\Delta_{\nu}(x)} \det \begin{array}{c} (-1)^N N! \sum_N^{(\nu)}(-x_1) \dots (-1)^{N+\nu-1} (N+\nu-1)! \sum_{N+\nu-1}^{(\nu)}(-x_1) \\ \vdots \\ (-1)^N N! \sum_N^{(\nu)}(-x_{\nu}) \dots \end{array}$$

index = ν if = 0

this limit can be computed by doing a Taylor expansion.

Alternatively Mehta, Normad computed the average of a char. polynomial to some power directly:

The Brezin-Mikhailov II (see also Melnik-Normand)

Define $\langle \det(x-H)^m \rangle_N = \frac{I_2(N, m; x)}{I_2(N, 0; x)}$ for $\beta=2$
 it holds $I_2(N, 0; x) = Z_N^{(\beta=2)}$

$$I_2(N, m; x) = \frac{N!}{\prod_{l=0}^{m-1} l!} \prod_{j=0}^{N-m} h_j \det \begin{bmatrix} \tilde{p}^{(l)}(x) \\ N+k \end{bmatrix}_{0 \leq k, l \leq m-1}$$

where $\tilde{p}^{(l)}(x)$ is the l -th derivative of the monic OP

For an explicit expression for $w(x) = x^\nu e^{-x}$ for $E_{\alpha, \nu}^{(\beta)}$ see

- Forrester, Hughes JMP 35 (1994) 6736 $\beta=2$
- Nagao, Forrester Nucl. Phys. B 509 (1998) 561 $\beta=1$ ν odd only

These $E_0(s)$ is given by a Pfaffian of Laguerre polynomials

→ See also arXiv 1103.5617 for summarizing what is known on individual eigenvalue distributions

Duality: Melnik-Normand

$$I_2(N, m; x) = \text{const} \cdot I_2(m, N; ix)$$

exchanging $N \leftrightarrow m$ matrix dimension and # of defuncts