

# On spectral measures of beta ensembles

Trinh Khanh Duy

Institute of Mathematics for Industry,  
Kyushu University

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# Outline

① Motivation

② Jacobi matrices

③ Gaussian beta ensembles

④ Wishart beta ensembles

## Random Jacobi matrices

- Random Jacobi matrix

$$J = \begin{pmatrix} a_1 & b_1 & & \\ b_1 & a_2 & b_2 & \\ & \ddots & \ddots & \ddots \\ & & b_{N-1} & a_N \end{pmatrix}, \quad \left\{ \begin{array}{l} \{a_i\}_{i=1}^N : \text{real random variables,} \\ \{b_j\}_{j=1}^{N-1} : \text{positive random variables.} \end{array} \right.$$

- Empirical distributions  $L_N$

$$L_N = \frac{1}{N} \sum_{j=1}^N \delta_{\lambda_j}, \quad \left( \{\lambda_1, \dots, \lambda_N\} : (\text{distinct}) \text{ eigenvalues of } J \right).$$

- Asymptotic behaviour of  $L_N$  as  $N \rightarrow \infty$ , i.e.,  $L_N \xrightarrow{w} \exists \mu_\infty$ , or

$$\langle L_N, f \rangle = \frac{1}{N} \sum_{j=1}^N f(\lambda_j) \rightarrow \langle \exists \mu_\infty, f \rangle \quad (f: \text{bounded continuous function}).$$

## Gaussian beta ensembles

- Gaussian beta ensembles.

$$H_N^{(\beta)} = \frac{1}{\sqrt{\beta N}} \begin{pmatrix} \mathcal{N}(0,2) & \chi_{(N-1)\beta} & & \\ \chi_{(N-1)\beta} & \mathcal{N}(0,2) & \chi_{(N-2)\beta} & \\ & \ddots & \ddots & \ddots \\ & & \chi_\beta & \mathcal{N}(0,2) \end{pmatrix}.$$

- Joint probability density function of the eigenvalues

$$(\lambda_1, \dots, \lambda_N) \propto \prod_{i < j} |\lambda_i - \lambda_j|^\beta \exp\left(-\frac{\beta N}{4} \sum_{j=1}^N \lambda_j^2\right).$$

- Semi-circle law.  $\mu_\infty = sc(x) = \sqrt{4 - x^2}/(2\pi)$ ,  $|x| \leq 2$ ,

$$\frac{1}{N} \sum_{j=1}^N f(\lambda_j) \rightarrow \int_{-2}^2 f(x) \frac{\sqrt{4 - x^2}}{2\pi} dx \quad \text{almost surely.}$$

## Example

- Gaussian beta ensembles ( $G\beta E$ ).  $\mu_\infty = sc$ : semi-circle law;
  - Wishart beta ensembles ( $W\beta E$ ).  $\mu_\infty = mp$ : Marchenko-Pastur law.
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- Fluctuations of eigenvalues around the limit:
    - $G\beta E$ . (Johansson 98), for a ‘nice’ function  $f$ ,

$$\sum_{j=1}^N \left( f(\lambda_j) - \langle sc, f \rangle \right) \xrightarrow{d} \mathcal{N}(0, a_f^2).$$

- $W\beta E$ . (Dumitriu & Edelman 2006), for polynomial  $p$ ,

$$\sum_{j=1}^N \left( p(\lambda_j) - \langle mp, p \rangle \right) \xrightarrow{d} \mathcal{N}(0, \hat{a}_p^2).$$

## Spectral measures

- $\mu_N$ : spectral measure of  $(J, e_1)$  if

$$\langle \mu_N, x^k \rangle = (J^k e_1, e_1) = J^k(1, 1), k = 0, 1, \dots.$$

- $\mu_N = \sum_{j=1}^N q_j^2 \delta_{\lambda_j}$ . 1-1 correspondence with Jacobi matrix.

### Main results: Law of large numbers and central limit theorem.

- G $\beta$ E.

LLN.  $\langle \mu_N, f \rangle \rightarrow \langle sc, f \rangle$ , ( $f$ : bounded continuous function);

CLT.  $\sqrt{N}(\langle \mu_N, p \rangle - \mathbf{E}[\langle \mu_N, p \rangle]) \xrightarrow{d} \mathcal{N}(0, \sigma_p^2)$ , ( $p$ : polynomial).

- W $\beta$ E.

LLN.  $\langle \mu_N, f \rangle \rightarrow \langle mp, f \rangle$ , ( $f$ : bounded continuous function);

CLT.  $\sqrt{N}(\langle \mu_N, p \rangle - \mathbf{E}[\langle \mu_N, p \rangle]) \xrightarrow{d} \mathcal{N}(0, \widehat{\sigma}_p^2)$ , ( $p$ : polynomial).

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## Spectral measures of Jacobi matrices

- Given a Jacobi matrix  $J$ , finite or infinite

$$J = \begin{pmatrix} a_1 & b_1 & & \\ b_1 & a_2 & b_2 & \\ & \ddots & \ddots & \ddots \end{pmatrix}, \quad a_i \in \mathbb{R}, b_i > 0.$$

- There is a measure  $\mu$  on  $\mathbb{R}$ , called spectral measure of  $(J, e_1)$ , s.t.

$$\langle \mu, x^k \rangle = (J^k e_1, e_1) = J^k(1, 1), k = 0, 1, \dots$$

- Uniqueness is equivalent to the essential self-adjointness of  $J$  on  $\ell^2(\mathbb{N})$ .

## Jacobi matrices

$\mu$ : nontrivial prob. meas. on  $\mathbb{R}$  s.t.  $\int |x|^k d\mu(x) < \infty, k = 0, 1, \dots$

- $\{1, x, x^2, \dots\}$  are independent in  $L^2(\mathbb{R}, \mu)$ .
- Define  $\{P_n(x)\}_{n=0}^\infty$  as 
$$\begin{cases} P_n(x) = x^n + \text{lower order,} \\ P_n \perp x^j, \quad j = 0, \dots, n-1. \end{cases}$$
- $p_n := P_n / \|P_n\|_{L^2}$ .

### Theorem

(i)  $xp_n(x) = b_{n+1}p_{n+1}(x) + a_{n+1}p_n(x) + b_np_{n-1}(x), \quad n = 0, 1, \dots,$

where  $b_{n+1} = \frac{\|P_n\|}{\|P_{n+1}\|}, a_{n+1} = \frac{\langle P_n, xP_n \rangle}{\|P_n\|^2}, P_{-1} \equiv 0.$

(ii) Multiplication by  $x$  in the orthonormal set  $\{p_j\}$  has the matrix

$$J = \begin{pmatrix} a_1 & b_1 & & & \\ b_1 & a_2 & b_2 & & \\ & \ddots & \ddots & \ddots & \\ & & & \ddots & \ddots \end{pmatrix}$$

## Jacobi matrices

- $\mu$ : trivial prob. meas., i.e.,

$$\mu = \sum_{j=1}^N q_j^2 \delta_{\lambda_j}, \quad \begin{cases} \{\lambda_j\} : \text{distinct}, \\ \sum q_j^2 = 1, q_j > 0. \end{cases}$$

- $\{x^j\}_{j=0}^{N-1}$ : independent in  $L^2(\mathbb{R}, \mu)$ . Define  $P_0, \dots, P_{N-1}$ .  
 $p_n := P_n / \|P_n\|$ ;

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$$J = \begin{pmatrix} a_1 & b_1 & & & \\ b_1 & a_2 & b_2 & & \\ & \ddots & \ddots & \ddots & \\ & & b_{N-1} & a_N & \end{pmatrix}$$

- $\{\lambda_j\}_{j=1}^N$ : the eigenvalues of  $J$ ,  $\{v_j\}_{j=1}^N$ : the corresponding normalized eigenvectors. Then

$$\mu = \sum_{j=1}^N |v_j(1)|^2 \delta_{\lambda_j} = \sum_{j=1}^N q_j^2 \delta_{\lambda_j}.$$

## Jacobi matrix of semicircle distribution

- Semicircle distribution  $sc$  with density

$$sc(x) = \frac{1}{2\pi} \sqrt{4 - x^2}, \quad |x| \leq 2.$$

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$$J = \begin{pmatrix} 0 & 1 & & \\ 1 & 0 & 1 & \\ & \ddots & \ddots & \ddots & \ddots \end{pmatrix}.$$

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## Gaussian orthogonal ensemble

GOE(N)

$$G_N^{(1)} = \begin{pmatrix} \mathcal{N}(0, 2) & \mathcal{N}(0, 1) & \mathcal{N}(0, 1) & \dots & \mathcal{N}(0, 1) \\ * & \mathcal{N}(0, 2) & \mathcal{N}(0, 1) & \dots & \mathcal{N}(0, 1) \\ * & * & \mathcal{N}(0, 2) & \dots & \mathcal{N}(0, 1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ * & * & * & \dots & \mathcal{N}(0, 2) \end{pmatrix}$$

- Invariant under orthogonal conjugation, i.e.,

$$HG_N^{(1)}H^t \stackrel{d}{=} G_N^{(1)}, \quad H : (\text{deterministic}) \text{ orthogonal matrix.}$$

- Joint distribution of the eigenvalues:

$$(\lambda_1, \dots, \lambda_N) \propto \prod_{i < j} |\lambda_i - \lambda_j| \exp\left(-\frac{1}{4} \sum_{j=1}^N \lambda_j^2\right).$$

## Gaussian unitary ensemble

GUE(N)

$$G_N^{(2)} = \begin{pmatrix} \mathcal{N}(0, 1) & \frac{\mathcal{N}(0, 1) + i\mathcal{N}(0, 1)}{\sqrt{2}} & \dots & \frac{\mathcal{N}(0, 1) + i\mathcal{N}(0, 1)}{\sqrt{2}} \\ * & \mathcal{N}(0, 1) & \dots & \frac{\mathcal{N}(0, 1) + i\mathcal{N}(0, 1)}{\sqrt{2}} \\ \vdots & \vdots & \ddots & \vdots \\ * & * & \dots & \mathcal{N}(0, 1) \end{pmatrix}$$

- Invariant under unitary conjugation, i.e.,

$$UG_N^{(2)}U^* \stackrel{d}{=} G_N^{(2)}, \quad U : (\text{deterministic}) \text{ unitary matrix.}$$

- Joint distribution of the eigenvalues:

$$(\lambda_1, \dots, \lambda_N) \propto \prod_{i < j} |\lambda_i - \lambda_j|^2 \exp\left(-\frac{2}{4} \sum_{j=1}^N \lambda_j^2\right).$$

## Gaussian beta ensembles

$\text{G}\beta\text{E}$  ( $\beta > 0$ )

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$$(\lambda_1, \dots, \lambda_N) \propto \prod_{i < j} |\lambda_i - \lambda_j|^\beta \exp\left(-\frac{\beta}{4} \sum_{j=1}^N \lambda_j^2\right).$$

- $\beta = 1$ , GOE.
- $\beta = 2$ , GUE.
- $\beta = 4$ , GSE (Gaussian symplectic ensemble).

## GOE, Jacobi/tridiagonal matrix model (Dumitriu & Edelman 2002)

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$$G_N^{(1)} = \begin{pmatrix} a_1 & x^t \\ x & B \end{pmatrix}, \quad \begin{cases} a_1 \sim \mathcal{N}(0, 2), \\ x^t \sim (\mathcal{N}(0, 1) \dots \mathcal{N}(0, 1)), \\ B \stackrel{d}{=} G_{N-1}^{(1)}. \end{cases}$$

- $H$ :  $(N - 1) \times (N - 1)$  orthogonal matrix (depending only on  $x$ ) s.t.

$$Hx = (\|x\|_2 0 \dots 0)^t = \|x\|_2 e_1.$$

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$$\begin{aligned} \begin{pmatrix} 1 & 0 \\ 0 & H \end{pmatrix} \begin{pmatrix} a_1 & x^t \\ x & B \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & H^t \end{pmatrix} &= \begin{pmatrix} a_1 & \|x\|_2 e_1^t \\ \|x\|_2 e_1 & HBH^t \end{pmatrix} \\ &\stackrel{d}{=} \begin{pmatrix} a_1 & \|x\|_2 & 0 & \dots & 0 \\ \|x\|_2 & & & & \\ 0 & & & & \\ \vdots & & & & G_{N-1}^{(1)} \\ 0 & & & & \end{pmatrix} \end{aligned}$$

# GOE, Jacobi/tridiagonal matrix model (Dumitriu & Edelman 2002)

- $a_1 \sim \mathcal{N}(0, 2)$ .
- $\|x\|_2 = \left( \underbrace{\mathcal{N}(0, 1)^2 + \cdots + \mathcal{N}(0, 1)^2}_{N-1} \right)^{1/2} \sim \chi_{N-1}$ : chi distribution.
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$$G_N^{(1)} \stackrel{1^{st} step}{\sim\!\!\!\sim} \begin{pmatrix} \mathcal{N}(0, 2) & \chi_{N-1} & 0 & \dots & 0 \\ \chi_{N-1} & & & & \\ \vdots & & G_{N-1}^{(1)} & & \\ 0 & & & & \\ & & & & \end{pmatrix}$$

*finally*

$$\stackrel{\sim\!\!\!\sim}{\sim\!\!\!\sim} \begin{pmatrix} \mathcal{N}(0, 2) & \chi_{N-1} & & & \\ \chi_{N-1} & \mathcal{N}(0, 2) & \chi_{N-2} & & \\ & \ddots & \ddots & \ddots & \\ & & \chi_1 & \mathcal{N}(0, 2) & \end{pmatrix}$$

- $\exists H$ : (random) orthogonal matrix s.t.

$$\begin{aligned} & \begin{pmatrix} 1 & 0 \\ 0 & H \end{pmatrix} \left( G_N^{(1)} \right) \begin{pmatrix} 1 & 0 \\ 0 & H^t \end{pmatrix} \\ & =: J_N^{(1)} \stackrel{d}{=} \begin{pmatrix} \mathcal{N}(0, 2) & \chi_{N-1} & & & \\ \chi_{N-1} & \mathcal{N}(0, 2) & \chi_{N-2} & & \\ & \ddots & \ddots & \ddots & \\ & & \chi_1 & \mathcal{N}(0, 2) & \end{pmatrix} \end{aligned}$$

- The eigenvalues of  $G_N^{(1)}$  are the same as those of  $J_N^{(1)}$ .
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$$\left( G_N^{(1)} \right)^k (1, 1) = \left( J_N^{(1)} \right)^k (1, 1).$$

- $H_N^{(\beta)} := \frac{1}{\sqrt{\beta N}} \begin{pmatrix} \mathcal{N}(0,2) & \chi_{(N-1)\beta} & & \\ \chi_{(N-1)\beta} & \mathcal{N}(0,2) & \chi_{(N-2)\beta} & \\ & \ddots & \ddots & \ddots \\ & & \chi_\beta & \mathcal{N}(0,2) \end{pmatrix}$
- The eigenvalues of  $H_N^{(\beta)}$  have (scaled)  $G\beta E$  distribution, i.e.,

$$(\lambda_1, \dots, \lambda_N) \propto \prod_{i < j} |\lambda_i - \lambda_j|^\beta \exp\left(-\frac{\beta N}{4} \sum_{j=1}^N \lambda_j^2\right).$$

- $(q_1, \dots, q_N)$  is distributed as  $(\chi_\beta, \dots, \chi_\beta)$  normalized to unit length, independent of  $(\lambda_1, \dots, \lambda_N)$ .

## Empirical distributions: semi circle law & CLT (Johansson '98)

- Empirical distributions

$$L_N^{(\beta)} := \sum_{j=1}^N \frac{1}{N} \delta_{\lambda_j}, \quad (\lambda_1, \dots, \lambda_N) : \text{(scaled) G}\beta\text{E}.$$

- $f: \mathbb{R} \rightarrow \mathbb{R}$ : bounded continuous function,

$$\langle L_N^{(\beta)}, f \rangle = \frac{1}{N} \sum_{j=1}^N f(\lambda_j) \rightarrow \langle sc, f \rangle \text{ a.s. as } N \rightarrow \infty.$$

- $f$ : 'nice' function

$$\sum_{j=1}^N (f(\lambda_j) - \langle sc, f \rangle) \xrightarrow{d} \mathcal{N}(0, a_f^2),$$

where  $a_f^2$  is a quadratic functional of  $f$ .

- Empirical distributions

$$L_N^{(\beta)} := \sum_{j=1}^N \frac{1}{N} \delta_{\lambda_j}.$$

- Spectral measures

$$\mu_N^{(\beta)} = \sum_{j=1}^N q_j^2 \delta_{\lambda_j}.$$

- $\mathbf{E}[q_j^2] = \frac{1}{N} \cdot (q_1, \dots, q_N)$  independent of  $(\lambda_1, \dots, \lambda_N)$ .

Consequently,  $\bar{L}_N = \bar{\mu}_N$ , namely,

$$\mathbf{E}[\langle \mu_N, f \rangle] = \sum_{j=1}^N \mathbf{E}[q_j^2] \mathbf{E}[f(\lambda_j)] = \sum_{j=1}^N \frac{1}{N} \mathbf{E}[f(\lambda_j)] = \mathbf{E}[\langle L_N, f \rangle].$$

## Theorem

- (i) *The spectral measures  $\mu_N$  converges weakly to the semicircle distribution, almost surely, i.e.,*

$$\langle \mu_N, f \rangle \rightarrow \langle sc, f \rangle \text{ a.s. as } N \rightarrow \infty.$$

- (ii) *For any polynomial  $p$  of positive degree,*

$$\sqrt{\beta N} \left( \langle \mu_N, p \rangle - \mathbf{E}[ \cdot ] \right) \xrightarrow{d} \mathcal{N}(0, \sigma_p^2) \text{ as } N \rightarrow \infty,$$

where  $\sigma_p^2 > 0$  (does not depend on  $\beta$ ).

- Recall that for a ‘nice’ function  $f$ ,

$$\langle L_N^{(\beta)}, f \rangle \xrightarrow{a.s.} \langle sc, f \rangle \text{ as } N \rightarrow \infty.$$

$$N \left( \langle L_N^{(\beta)}, f \rangle - \langle sc, f \rangle \right) \xrightarrow{d} \mathcal{N}(0, a_f^2) \text{ as } N \rightarrow \infty.$$

## Related results: spectral measures of Wigner matrices

- $\{\xi_{ii}\}_i$ : i.i.d.  $\mathbf{E}[\xi_{11}] = 0$ ;  $\mathbf{E}[|\xi_{11}|^k] < \infty, k = 2, 3, \dots$
- $\{\xi_{ij}\}_{i < j}$ : i.i.d.  $\mathbf{E}[\xi_{12}] = 0$ ,  $\mathbf{E}[\xi_{12}^2] = 1$ ;  $\mathbf{E}[|\xi_{11}|^k] < \infty, k = 3, 4, \dots$
- $X_N$ : symmetric matrix

$$X_N := \frac{1}{\sqrt{N}} \begin{pmatrix} \xi_{11} & \xi_{12} & \xi_{13} & \dots & \xi_{1N} \\ * & \xi_{22} & \xi_{23} & \dots & \xi_{2N} \\ * & * & \xi_{33} & \dots & \xi_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ * & * & * & \dots & \xi_{NN} \end{pmatrix}$$

called a (real) Wigner matrix.

- $\nu_N$ : spectral measure, i.e.,  $\langle \nu_N, x^k \rangle = X_N^k(1, 1)$ .
- $\nu_N$  converges weakly to the semicircle law.

## Central limit theorems

(i)  $k = 1$ ,  $\langle \nu_N, x \rangle = X_N(1, 1) = \frac{\xi_{11}}{\sqrt{N}}$ . Therefore

$$\sqrt{N}(\langle \nu_N, x \rangle - \mathbf{E}[\langle \nu_N, x \rangle]) = \xi_{11} \xrightarrow{d} \xi_{11}.$$

In general, the limit distribution is not Gaussian.

(ii)  $k = 2$ ,  $\langle \nu_N, x^2 \rangle = X_N^2(1, 1) = \sum_{i=1}^N \frac{1}{N} \xi_{1i}^2$ . We consider

$$\begin{aligned} & \sqrt{N}(\langle \nu_N, x^2 \rangle - \mathbf{E}[\langle \nu_N, x^2 \rangle]) \\ &= \frac{\xi_{11}^2 - \mathbf{E}[\xi_{11}^2]}{\sqrt{N}} + \frac{\sqrt{N-1}}{\sqrt{N}} \frac{(\xi_{12}^2 - 1) + (\xi_{13}^2 - 1) + \cdots + (\xi_{1N}^2 - 1)}{\sqrt{N-1}} \\ &\xrightarrow{d} \mathcal{N}(0, \mathbf{E}[(\xi_{12}^2 - 1)^2]). \end{aligned}$$

The limit distribution is Gaussian!!

## Spectral measures of Wigner matrices

Theorem (Pizzo et al. (J. Stat. Phys. 2012), D. (Osaka J. Math. 2016))

Let  $S_{N,k} := \sqrt{N} (\langle \nu_N, x^k \rangle - \mathbf{E}[\cdot])$ .

(i)  $k = 3, 5, \dots$ ,

$$S_{N,k} \xrightarrow{d} c_k Y + Z_k,$$

where  $c_k$  is a constant,  $Y \sim \xi_{11}$ ,  $Z_k \sim \mathcal{N}(0, a_k^2)$  and  $Y$  and  $Z_k$  are independent.

(ii)  $k = 2, 4, \dots$ ,

$$S_{N,k} \xrightarrow{d} Z_k \sim \mathcal{N}(0, a_k^2).$$

(iii) Multidimensional version. There are jointly Gaussian random variables  $\{Z_k\}$  independent of  $Y \sim \xi_{11}$  such that

$$\{S_{N,k}\}_{k=1}^K \xrightarrow{d} (Y, Z_2, c_3 + Z_3, Z_4, \dots).$$

## Chi distribution

What is  $\chi_n$ ,  $n > 0$ ?

- $n = 1, 2, \dots,$

$$\left( \underbrace{\mathcal{N}(0, 1)^2 + \cdots + \mathcal{N}(0, 1)^2}_n \right)^{1/2} \sim \chi_n.$$

- For  $n > 0$ ,

$$p.d.f. = \frac{2}{\Gamma(\frac{n}{2})} x^{n-1} e^{-x^2}, \quad x > 0.$$

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$$\chi_n = \sqrt{2} \Gamma \left( \frac{n}{2}, 1 \right)^{1/2},$$

where  $\Gamma(k, \theta)$  denotes the gamma distribution.

- As  $n \rightarrow \infty$ ,

$$\chi_n - \sqrt{n} \xrightarrow{d} \mathcal{N}(0, \frac{1}{2}).$$

## Decomposition of $\mathbf{G}\beta\mathbf{E}$ matrix

$$\begin{aligned} & \frac{1}{\sqrt{\beta N}} \begin{pmatrix} \mathcal{N}(0,2) & \chi_{(N-1)\beta} & & \\ \chi_{(N-1)\beta} & \mathcal{N}(0,2) & \chi_{(N-2)\beta} & \\ & \ddots & \ddots & \ddots \\ & & \chi_\beta & \mathcal{N}(0,2) \end{pmatrix} \\ & \approx \begin{pmatrix} 0 & 1 & & \\ 1 & 0 & 1 & \\ & \ddots & \ddots & \ddots \\ & & \ddots & \ddots \end{pmatrix} + \frac{1}{\sqrt{\beta N}} \begin{pmatrix} \mathcal{N}(0,2) & \mathcal{N}(0,\frac{1}{2}) & & \\ \mathcal{N}(0,\frac{1}{2}) & \mathcal{N}(0,2) & \mathcal{N}(0,\frac{1}{2}) & \\ & \ddots & \ddots & \ddots \end{pmatrix} \end{aligned}$$

This implies the semi-circle law and the CLT for  $\langle \mu_N, p \rangle$  with polynomial  $p$ .

- Variance formula:

$$\begin{aligned}\text{Var}[\langle \mu_N, f \rangle] &= \frac{\beta N}{\beta N + 2} \text{Var}[\langle L_N, f \rangle] \\ &\quad + \frac{2}{N\beta + 2} (\mathbf{E}[\langle \mu_N, f^2 \rangle] - \mathbf{E}[\langle \mu_N, f \rangle]^2).\end{aligned}$$

- Consequently

$$N\beta \text{Var}[\langle \mu_N, f \rangle] \rightarrow \langle sc, f^2 \rangle - \langle sc, f \rangle^2,$$

provided that  $\text{Var}[\langle L_N, f \rangle] = o(N)$ .

## Theorem (D. 2016)

For a 'nice' function  $f$ ,

$$\frac{\sqrt{N\beta}}{\sqrt{2}} (\langle \mu_N, f \rangle - \mathbf{E}[\langle \mu_N, f \rangle]) \xrightarrow{d} \mathcal{N}(0, \sigma_f^2),$$

where  $\sigma_f^2 = \langle sc, f^2 \rangle - \langle sc, f \rangle^2$ .

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## Jacobi matrices for $W\beta E$

- $m \in \mathbb{N}, n > m - 1,$

$$B_m = \begin{pmatrix} \chi_{\beta n} & & & \\ \chi_{\beta(m-1)} & \chi_{\beta(n-1)} & & \\ & \ddots & \ddots & \\ & & \chi_{\beta} & \chi_{\beta(n-m+1)} \end{pmatrix}, W_m = B_m B_m^t.$$

- Eigenvalues of  $W_m$ , ( $a = \beta n/2, p = 1 + \beta(m-1)/2$ ),

$$(\lambda_1, \dots, \lambda_m) \propto |\Delta(\lambda)|^\beta \prod_{i=1}^m \lambda_i^{a-p} \exp\left(-\frac{1}{2} \sum_{i=1}^m \lambda_i\right).$$

- $(q_1, \dots, q_m)$  is distributed as  $(\chi_{\beta}, \dots, \chi_{\beta})$  normalized to unit length, independent of  $(\lambda_1, \dots, \lambda_m)$ .

## Decomposition of Wishart beta ensemble matrices

- $m, n \rightarrow \infty, m/n \rightarrow \gamma \in (0, 1), c_j \sim \chi_{\beta(n-j+1)}, d_j \sim \chi_{\beta(m-j)}$

$$\begin{aligned}\widetilde{W}_m &= \frac{1}{\beta n} \begin{pmatrix} c_1^2 & c_1 d_1 & & & \\ c_1 d_1 & c_2^2 + d_1^2 & c_2 d_2 & & \\ & \ddots & \ddots & \ddots & \\ & & c_{m-1} d_{m-1} & c_m^2 + d_{m-1}^2 & \end{pmatrix} \\ &= \begin{pmatrix} 1 & \sqrt{\gamma} & & & \\ \sqrt{\gamma} & 1+\gamma & \sqrt{\gamma} & & \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & \ddots \end{pmatrix} + \frac{1}{\sqrt{\beta n}} \begin{pmatrix} 2\bar{c}_1 & \sqrt{\gamma}\bar{c}_1 + \bar{d}_1 & & & \\ \sqrt{\gamma}\bar{c}_1 + \bar{d}_1 & 2(\bar{c}_2 + \sqrt{\gamma}\bar{d}_1) & \sqrt{\gamma}\bar{c}_2 + \bar{d}_2 & & \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & \ddots \end{pmatrix},\end{aligned}$$

- $\bar{c}_i, \bar{d}_j$ : i.i.d.  $\sim \mathcal{N}(0, \frac{1}{2})$ .

$$\begin{cases} c_j \approx \sqrt{\beta n} + \bar{c}_j, & d_j \approx \sqrt{\beta n}\sqrt{\gamma} + \bar{d}_j, \\ c_j^2 \approx \beta n + 2\sqrt{\beta n}\bar{c}_j, & d_j^2 \approx \beta n\gamma + 2\sqrt{\beta n}\sqrt{\gamma}\bar{d}_j, \\ c_j d_j \approx \beta n\sqrt{\gamma} + \sqrt{\beta n}(\sqrt{\gamma}\bar{c}_j + \bar{d}_j). \end{cases}$$

- For more details, see arXiv:1601.01146

Thank you very much for your attention!