

From random matrices to long range dependence

Arijit Chakrabarty

Joint work with Rajat S. Hazra and Deepayan Sarkar

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The problem

- ▶ $(X_{i,j} : i, j \in \mathbb{Z})$ is a stationary, mean zero, variance one Gaussian process.
- ▶ Stationarity means that for $k, l \in \mathbb{Z}$,

$$(X_{i+k, j+l} : i, j \in \mathbb{Z}) \stackrel{d}{=} (X_{i,j} : i, j \in \mathbb{Z}).$$

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- ▶ For $N \geq 1$, define a $N \times N$ matrix

$$W_N(i, j) := X_{i,j} + X_{j,i}, \quad 1 \leq i, j \leq N.$$

- ▶ Denote

$$\mu_N := \text{ESD}(W_N/\sqrt{N}).$$

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- ▶ Denote

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- ▶ **Goal:** To study the limit of μ_N as $N \rightarrow \infty$.

- ▶ Define

$$R(u, v) := \mathbb{E}(X_{0,0}X_{u,v}), \quad u, v \in \mathbb{Z}.$$

- ▶ Herglotz theorem: There exists a finite measure ν on $(-\pi, \pi]^2$ satisfying

$$R(u, v) = \int_{(-\pi, \pi]^2} e^{i(ux+vy)} \nu(dx, dy), \quad u, v \in \mathbb{Z}.$$

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- ▶ Call ν the “spectral measure”.

Assumption

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Free probability

- ▶ Write

$$\nu = \nu_{ac} + \nu_{cs} + \nu_d,$$

where

- ▶ ν_{ac} is absolutely continuous,
- ▶ ν_{cs} is continuous and singular,
- ▶ ν_d is discrete.

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- ▶ ν_{ac} is absolutely continuous,
 - ▶ ν_{cs} is continuous and singular,
 - ▶ ν_d is discrete.
- ▶ **Assumption:** $\nu_{cs} \equiv 0$.
 - ▶ Let

$$\nu_{ac}(dx, dy) = f(x, y) dx dy \text{ on } (-\pi, \pi]^2.$$

Theorem

There exists a deterministic probability measure μ_f , determined solely by the spectral density f , such that

$$\mu_N \rightarrow \mu_f,$$

weakly in probability as $N \rightarrow \infty$.

Theorem

The second moment of the probability measure μ_f is given by

$$\int_{\mathbb{R}} x^2 \mu_f(dx) = 2 \int_{[-\pi, \pi]^2} f(x, y) dx dy .$$

Theorem

If

$$\text{ess inf } f > 0,$$

then μ_f is absolutely continuous.

Theorem

1. For $m \geq 2$, the $(2m)$ -th moment of μ_f is finite if $\|f\|_m < \infty$.
2. If $\|f\|_\infty < \infty$, then μ_f is compactly supported.

Stieltje's transform

Definition

Stieltje's transform of μ_f :

$$\mathcal{G}(z) := \int_{\mathbb{R}} \frac{1}{z-x} \mu_f(dx), z \in \mathbb{C} \setminus \mathbb{R}.$$

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Theorem

Assume that $\|f\|_{\infty} < \infty$. Then,

$$\mathcal{G}(z) = \left[\int_{-\pi}^{\pi} \mathcal{H}(z, x) dx \right], z \in \mathbb{C},$$

where $\mathcal{H}(z, x)$ is the solution of the functional equation

$$z\mathcal{H}(z, x) = 1 + \mathcal{H}(z, x) \int_{-\pi}^{\pi} \mathcal{H}(z, y) f(x, y) dy, z \in \mathbb{C} \setminus \mathbb{R}, |x| < \pi.$$

Theorem

If there exists a function r from $[-\pi, \pi]$ to $[0, \infty)$ such that

$$\frac{1}{2} [f(x, y) + f(y, x)] = r(x)r(y) \text{ for almost all } x, y \in [-\pi, \pi],$$

then

$$\mu_f = \eta_r \boxtimes \text{WSL}(1),$$

where η_r denotes the law of $2^{3/2}\pi r(U)$, U is an Uniform $(-\pi, \pi)$ random variable, and “ \boxtimes ” denotes the free multiplicative convolution.

Theorem

Assume that $(G_n : n \in \mathbb{Z})$ is a one-dimensional stationary Gaussian process with zero mean and positive variance, and whose spectral measure is absolutely continuous. Let $((G_{in} : n \in \mathbb{Z}) : i \in \mathbb{Z})$ be a family of i.i.d. copies of $(G_n : n \in \mathbb{Z})$. Define

$$X_{j,k} := G_{j-k,k}, j, k \in \mathbb{Z}.$$

Then, $(X_{j,k} : j, k \in \mathbb{Z})$ is a stationary Gaussian process, and

$$\mu_f = WSL(2\text{Var}(G_0)).$$

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- ▶ A symmetric matrix A is to be thought of as a Hermitian operator \overline{A} of finite rank acting on the first N coordinates of l^2 .

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Free probability

- ▶ A symmetric matrix A is to be thought of as a Hermitian operator \overline{A} of finite rank acting on the first N coordinates of l^2 .
- ▶ If $\lambda_1 \leq \dots \leq \lambda_N$ are the eigenvalues of A counted with multiplicity, then the spectrum of \overline{A} is $\{0, \lambda_1, \dots, \lambda_N\}$, where 0 has infinite multiplicity.

Eigen measure

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- ▶ **Eigen measure** of A :

$$\text{EM}(A) := \infty\delta_0 + \sum_{j=1}^N \delta_{\lambda_j}.$$

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- ▶ **Eigen measure** of A :

$$\text{EM}(A) := \infty\delta_0 + \sum_{j=1}^N \delta_{\lambda_j}.$$

- ▶ The measure $\text{EM}(A)$ is to be viewed as an element of the set \mathcal{P} of point measures ξ of the form

$$\xi := \infty\delta_0 + \sum_{j=1}^{\infty} \delta_{\theta_j},$$

where $(\theta_j : j \geq 1)$ is some sequence of real numbers.

$$\mathcal{C}_p := \left\{ \mu \in \mathcal{P} : \int_{\mathbb{R}} |x|^p \mu(dx) < \infty \right\}, p \in [1, \infty).$$

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$$\mathcal{C}_p := \left\{ \mu \in \mathcal{P} : \int_{\mathbb{R}} |x|^p \mu(dx) < \infty \right\}, \quad p \in [1, \infty).$$

- ▶ For $p \geq 1$ and $\xi \in \mathcal{C}_p$, there exist unique real numbers

$$\alpha_1(\xi) \geq \alpha_2(\xi) \geq \dots \geq 0 \geq \dots \alpha_{-2}(\xi) \geq \alpha_{-1}(\xi),$$

such that

$$\xi = \infty \delta_0 + \sum_{j \neq 0} \delta_{\alpha_j(\xi)}.$$

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such that

$$\xi = \infty \delta_0 + \sum_{j \neq 0} \delta_{\alpha_j(\xi)}.$$

$$d_p(\xi_1, \xi_2) := \left[\sum_{j \neq 0} |\alpha_j(\xi_1) - \alpha_j(\xi_2)|^p \right]^{1/p}, \quad \xi_1, \xi_2 \in \mathcal{C}_p.$$

Theorem

There exists a random point measure ξ which is almost surely in \mathcal{C}_2 such that

$$d_4(\text{EM}(W_N/N), \xi) \xrightarrow{P} 0,$$

as $N \rightarrow \infty$. Furthermore, the distribution of ξ is determined by ν_d .

Theorem

There exists a random point measure ξ which is almost surely in \mathcal{C}_2 such that

$$d_4(\text{EM}(W_N/N), \xi) \xrightarrow{P} 0,$$

as $N \rightarrow \infty$. Furthermore, the distribution of ξ is determined by ν_d .

Remark

If $f \equiv 0$, then d_4 can be improved to d_2 .

Theorem

If $\nu_d((-\pi, \pi]^2) > 0$, then the random variable

$$\int_{\mathbb{R}} x^2 \xi(dx)$$

is positive almost surely, and non-degenerate.

Long range dependence

- | | | |
|----|--|--|
| 1. | The component ν_{ac} determines the limiting ESD | The component ν_d determines the limiting EM |
|----|--|--|

Long range dependence

1.

The component ν_{ac}
determines the limiting ESD
 μ_f , of W_N/\sqrt{N} .

The component ν_d
determines the limiting EM
 ξ , of W_N/N .

Long range dependence

1.	The component ν_{ac} determines the limiting ESD μ_f , of W_N/\sqrt{N} .	The component ν_d determines the limiting EM ξ , of W_N/N .
2.	The measure μ_f is deterministic.	The measure ξ is random.

Long range dependence

1.	The component ν_{ac} determines the limiting ESD μ_f , of W_N/\sqrt{N} .	The component ν_d determines the limiting EM ξ , of W_N/N .
2.	The measure μ_f is deterministic.	The measure ξ is random.

Definition

A mean zero stationary Gaussian process with positive variance indexed by \mathbb{Z}^2 is **short range dependent** if the corresponding spectral measure is absolutely continuous, and the same is **long range dependent** if the spectral measure is discrete, that is, supported on a countable set.

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Free probability

- ▶ $(G_n : n \in \mathbb{Z})$: a zero mean stationary Gaussian process with spectral density $|x|^{-1/2}$,
- ▶ $((G_{in} : n \in \mathbb{Z}) : i \in \mathbb{Z})$: a family of i.i.d. copies of $(G_n : n \in \mathbb{Z})$,

▶

$$X_{j,k} := G_{j-k,k}, j, k \in \mathbb{Z}.$$

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- ▶ $((G_{in} : n \in \mathbb{Z}) : i \in \mathbb{Z})$: a family of i.i.d. copies of $(G_n : n \in \mathbb{Z})$,

▶

$$X_{j,k} := G_{j-k,k}, j, k \in \mathbb{Z}.$$

▶

$$\mu_f = WSL(2\text{Var}(G_0)).$$

Example 2



$$f(x, y) := \mathbf{1}(-\pi/2 \leq x, y \leq \pi/2), \quad -\pi \leq x, y \leq \pi.$$

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$$\mu_f = \eta_r \boxtimes WSL(1),$$

where

- ▶ η_r is the law of $2^{3/2}\pi\mathbf{1}(|U| \leq \pi/2)$,
- ▶ $U \sim (-\pi, \pi)$.

Example 2



$$f(x, y) := \mathbf{1}(-\pi/2 \leq x, y \leq \pi/2), \quad -\pi \leq x, y \leq \pi.$$



$$\mu_f = \eta_r \boxtimes WSL(1),$$

where

- ▶ η_r is the law of $2^{3/2}\pi\mathbf{1}(|U| \leq \pi/2)$,
- ▶ $U \sim (-\pi, \pi)$.
- ▶ μ_f is the law of $2\pi BW$ where
 - ▶ $B \sim \text{Bernoulli}(1/2)$,
 - ▶ $W \sim WSL(1)$,
 - ▶ B, W are **classically** independent.

Example 3

▶

$$f(x, y) := |xy|^{-1/2}, \quad -\pi \leq x, y \leq \pi.$$

▶

$$\mu_f = \eta_r \boxtimes WSL(1).$$

▶

$$\int_{\mathbb{R}} x^4 \mu_f(dx) = \infty.$$

The main ingredient

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Fact

Let $(X_{j,k} : j, k \in \mathbb{Z})$ be a stationary mean zero Gaussian process. Then, there exist $c_{j,k} \in \mathbb{R}$ satisfying

$$\sum_{j,k} c_{j,k}^2 < \infty,$$

and

$$(X_{j,k} : j, k \in \mathbb{Z}) \stackrel{d}{=} \left(\sum_{l,m} c_{l,m} G_{j-l, k-m} : j, k \in \mathbb{Z} \right),$$

if and only if, the spectral measure of $(X_{j,k})$ is absolutely continuous.

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Proof of the main result

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Theorem

There exists a deterministic probability measure μ_f , determined solely by the spectral density f , such that

$$\mu_N \rightarrow \mu_f,$$

weakly in probability as $N \rightarrow \infty$, where

$$\mu_N := \text{ESD}(W_N/\sqrt{N}).$$

Proof

- ▶ Assume that $\nu \equiv \nu_{ac}$.

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Free probability

Proof

▶ Assume that $\nu \equiv \nu_{ac}$.

▶

$$(X_{j,k} : j, k \in \mathbb{Z}) \stackrel{d}{=} \left(\sum_{l,m} c_{l,m} G_{j-l, k-m} : j, k \in \mathbb{Z} \right),$$

Proof

- ▶ Assume that $\nu \equiv \nu_{ac}$.



$$(X_{j,k} : j, k \in \mathbb{Z}) \stackrel{d}{=} \left(\sum_{l,m} c_{l,m} G_{j-l,k-m} : j, k \in \mathbb{Z} \right),$$

- ▶ Usual moments method works for

$$\sum_{l,m=-n}^n c_{l,m} G_{j-l,k-m}$$

for fixed n .

Proof

- ▶ Assume that $\nu \equiv \nu_{ac}$.



$$(X_{j,k} : j, k \in \mathbb{Z}) \stackrel{d}{=} \left(\sum_{l,m} c_{l,m} G_{j-l,k-m} : j, k \in \mathbb{Z} \right),$$

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- ▶ Hoffman-Wielandt inequality completes the proof.

Free probability

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Theorem

Let μ be a probability measure on \mathbb{R} such that

$$\text{Support}(\mu) \subset [\delta, \infty) \text{ for some } \delta > 0,$$

and

$$\int_0^{\infty} x \mu(dx) < \infty.$$

Then, there exists a probability measure ν on \mathbb{R} and $\varepsilon > 0$ such that

$$\text{WSL}(1) \boxtimes \mu = \text{WSL}(\varepsilon) \boxplus \nu.$$

Corollary

If μ is as in the previous result, then $WSL \boxtimes \mu$ is absolutely continuous.

Future work

- ▶ The ν_{CS} component.

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Future work

- ▶ The ν_{CS} component.
- ▶ Growth rate of the largest eigenvalue, especially when the LSD has unbounded support.

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Future work

- ▶ The ν_{CS} component.
- ▶ Growth rate of the largest eigenvalue, especially when the LSD has unbounded support.
- ▶ The asymmetric case.

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