

# Log-correlated Gaussian fields and linear statistics of $\beta$ -ensembles

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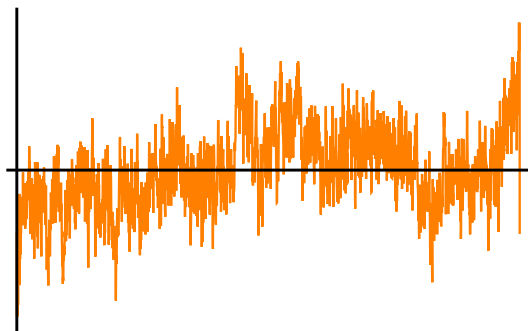
# Outline of the talk

- What are log-correlated Gaussian fields?
- Examples of log-correlated fields in RMT.
- Connection between log-correlated fields in RMT and CLTs for linear statistics.
- A sketch of a proof for a CLT for the circular  $\beta$ -ensemble.

## What is a log-correlated Gaussian field?

Basically a centered Gaussian process  $X(x)$  on a subset of  $\mathbb{R}^d$  with a logarithmic singularity in its covariance:

$$\mathbb{E}X(x)X(y) \sim -\log|x-y|, \quad \text{as } x \rightarrow y.$$



Doesn't make sense as an honest random function.

## Examples of log-correlated fields

- Let  $A_k \sim N_{\mathbb{C}}(0, 1)$  be i.i.d. and

$$X(\theta) = \frac{1}{2} \sum_{k=1}^{\infty} \frac{1}{\sqrt{k}} \left[ A_k e^{ik\theta} + A_k^* e^{-ik\theta} \right].$$

Then formally  $\mathbb{E}X(\theta)X(\theta') = -\frac{1}{2} \log |e^{i\theta} - e^{i\theta'}|$ .

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- Let  $B_k \sim N(0, 1)$  be i.i.d. and for  $x \in (-1, 1)$

$$Y(x) = \sum_{k=1}^{\infty} \sqrt{\frac{1}{k}} B_k T_k(x),$$

where  $T_k(\cos \theta) = \cos k\theta$  (Chebyshev polynomial). Then formally  $\mathbb{E}Y(x)Y(y) = -\frac{1}{2} \log(2|x - y|)$ .

## Examples of log-correlated fields

- Let  $C_k \sim N(0, 1)$  be i.i.d.,  $D \subset \mathbb{R}^2$  nice enough, and  $\Delta\phi_k = -\lambda_k\phi_k$  on  $D$  with zero Dirichlet boundary conditions. Then define the GFF:

$$Z(x) = \sum_{k=1}^{\infty} \frac{C_k}{\sqrt{\lambda_k}} \phi_k(x),$$

Again formally  $\mathbb{E}Z(x)Z(y) = G_D(x, y) \sim -\log|x - y|$  as  $x \rightarrow y$ .

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All of these series converge almost surely in suitable spaces of generalized functions (e.g. Sobolev spaces) and one can make precise sense of everything above.

# Why care about log-correlated fields?

- Universal objects - show up as asymptotic fluctuations in various models: RMT, growth models, combinatorial models, number theory, lattice models, ...



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- Play a critical role in the mathematics of 2-d quantum gravity (Liouville quantum gravity) - conjectured to be related to a suitable scaling limit of random planar maps.
- Can be used to construct conformally invariant random planar curves (SLE type objects).

# Characteristic polynomial of the CUE

Let  $U_N \sim CUE(N)$ , and

$$\begin{aligned} X_N(\theta) &= \log |\det(I - e^{-i\theta} U_N)| \\ &= -\frac{1}{2} \sum_{k=1}^{\infty} \frac{1}{\sqrt{k}} \left[ e^{-ik\theta} \frac{\text{Tr} U_N^k}{\sqrt{k}} + e^{ik\theta} \frac{\text{Tr} U_N^{-k}}{\sqrt{k}} \right]. \end{aligned}$$

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**Theorem (Diaconis and Shahshahani '94)**

For any fixed  $K$ ,  $(\text{Tr} U_N^k / \sqrt{k})_{k=1}^K \xrightarrow{d} (A_k)_{k=1}^K$ , where  $A_k \sim N_{\mathbb{C}}(0, 1)$  i.i.d..

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Thus (Hughes, Keating, and O'Connell '01),  $X_N \xrightarrow{d} X$  (in a suitable space).

## Characteristic polynomial of the GUE

Let  $H_N \sim GUE(N)$  (with a suitable normalization). For  $x \in (-1, 1)$ , on the event that  $\sigma(H_N) \subset (-1, 1)$ , one has

$$\begin{aligned} Y_N(x) &= \log |\det(xI - H_N)| \\ &= - \sum_{k=1}^{\infty} \sqrt{\frac{1}{k}} T_k(x) \operatorname{Tr} \left[ \frac{2}{\sqrt{k}} T_k(H_N) \right]. \end{aligned}$$

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*After centering, the random variables  $\operatorname{Tr}[\frac{2}{\sqrt{k}} T_k(H_N)]$  converge jointly in law to i.i.d. standard Gaussians for  $k \leq K$  fixed.*

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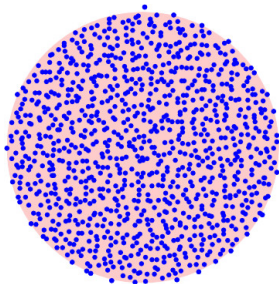
Fyodorov, Khoruzhenko, and Simm '13:  $Y_N(x) - \mathbb{E} Y_N(x) \xrightarrow{d} Y(x)$  (in a suitable space).



# Characteristic polynomial of the Ginibre ensemble

Let  $W_N \sim \text{Ginibre}(N)$  (with a suitable normalization). For  $|z| < 1$ , on the event that  $\sigma(W_N) \subset \mathbb{U} := \{|w| < 1\}$ ,

$$\begin{aligned} Z_N(z) &= \log |\det(zI - W_N)| \\ &= -2\pi \sum_{k=1}^{\infty} \frac{1}{\sqrt{\lambda_k}} \phi_k(z) \text{Tr} \frac{\phi_k(W_N)}{\sqrt{\lambda_k}} - \text{Re} \sum_{k=1}^{\infty} \frac{1}{k} \bar{z}^k \text{Tr} W_N^k. \end{aligned}$$



# Characteristic polynomial of the Ginibre ensemble

## Theorem (Rider and Virág '06)

After centering,  $\text{Tr}f(W_N)$  converges in law to  $N(0, \sigma^2)$ ,

$$\sigma^2 = \frac{1}{4\pi} \int_{\mathbb{U}} |\nabla f|^2 + \frac{1}{2} \sum_{k \in \mathbb{Z}} |k| |\hat{f}(k)|^2.$$

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From this, after centering,  $Z_N$  converges in law (in a suitable space) to  $\tilde{Z}$  with covariance

$$\mathbb{E} \tilde{Z}(z) \tilde{Z}(w) = -\frac{1}{2} \log |z - w|.$$

# The eigenvalue counting function for the GUE

For  $H_N \sim GUE(N)$  (normalized as before) and

$$\tilde{X}_N(x) = \text{Im} \log \det(xI - H_N) = \pi \sum_{j=1}^N \mathbf{1}(x < \lambda_j).$$

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As

$$\int \tilde{X}_N(x) f'(x) dx = \pi \sum_{j=1}^N f(\lambda_j)$$

the CLT implies again that after centering, in the bulk of the spectrum,  $\tilde{X}_N$  converges to a log-correlated field  $\tilde{X}$ .

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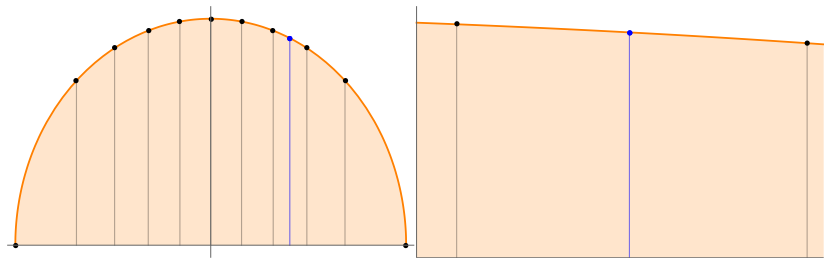
$$\int_{-1}^{\gamma_j} \sigma(x) dx = \frac{j}{N}.$$

- Then define the "fluctuation field": for  $x \in (\gamma_{j-1}, \gamma_j]$ ,

$$\tilde{Y}_N(x) = N\sigma(\gamma_j) \left[ \lambda_j - N \int_{\gamma_{j-1}}^{\gamma_j} y\sigma(y) dy \right].$$



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One can then show that

$$\int \tilde{Y}_N(x) f'(x) = \sum_{j=1}^N [f(\lambda_j) - \mathbb{E}f(\lambda_j)] + \text{error},$$

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Moral of the story: **CLTs equivalent to log-correlated fields describing global fluctuations.**

# Gaussian multiplicative chaos

Log-correlated fields relevant to Liouville quantum gravity and the construction of SLE type curves through random measures of the form  $e^{X(x) - \frac{1}{2}\mathbb{E}X(x)^2} dx$ .

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Theorem (W '14, Berestycki, W, Wong '16)

For small enough  $\gamma > 0$ ,  $\frac{e^{\gamma X_N(\theta)}}{\mathbb{E}e^{\gamma X_N(\theta)}} d\theta$  (CUE) and  $\frac{e^{\gamma Y_N(x)}}{\mathbb{E}e^{\gamma Y_N(x)}} dx$  (GUE) converge to chaos measures.

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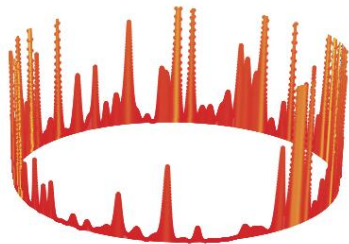
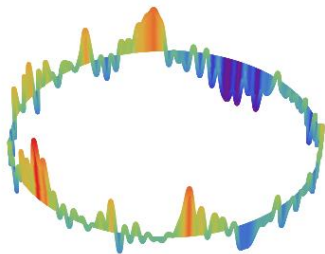
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Proof through RHP estimates (due to Deift, Its, and Kraosvsky; and others).

# Gaussian multiplicative chaos





## Central limit theorems

- CLTs proven in great generality and with different methods for one-cut regular  $\beta$ -ensembles - even in the discrete case (Diaconis and Shahshahani; Johansson; Pastur; Shcherbina; Rider and Virág; Ameur, Hedenmalm, and Makarov; Borot and Guionnet; Dumitriu and Paquette; Döbler and Stolz; Forrester and Witte; Jiang and Matsumoto; Borodin, Gorin, and Guionnet,...).

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- Log-correlated objects appearing generically in  $\beta$ -ensembles (though 2d for  $\beta \neq 2$  open?).
- Chaos measures and behavior of the maximum of the fields universal?
- I can't prove it, but the following came out of an attempt.

## A Gaussian approximation result

- Assume that  $W \sim N(0, \sigma^2)$  and  $W'$  is a "small perturbation" of this preserving the law:  $W' \sim N(0, \sigma^2)$  and  $\mathbb{E}(WW') = \sigma^2(1 - \epsilon)$ .

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- Then one has

$$\mathbb{E}(W' - W|W) = -\epsilon W \quad (1)$$

$$\mathbb{E}[(W' - W)^2|W] = 2\epsilon\sigma^2 + \mathcal{O}(\epsilon^2) \quad (2)$$

$$\mathbb{E}|W' - W|^3 = \mathcal{O}(\epsilon^{3/2}) \quad (3)$$

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- Perhaps if this nearly holds,  $W$  is nearly Gaussian?

# A Gaussian approximation result

## Theorem (Meckes '09; Döbler and Stolz '11)

Assume:  $(W, W_t) \in \mathbb{C}^{2d}$  exchangeable,  $Z \sim N_{\mathbb{C}}(0, I_{d \times d})$ ,  $\exists$  deterministic  $\Lambda \in \mathbb{C}^{d \times d}$  and  $\Sigma \in \mathbb{C}^{d \times d}$  positive definite, and random  $R \in \mathbb{C}^d$  and  $S, T \in \mathbb{C}^{d \times d}$ :

$$\lim_{t \rightarrow 0} \frac{1}{t} \mathbb{E}(W_t - W | W) = -\Lambda W + R \quad (1)$$

$$\lim_{t \rightarrow 0} \frac{1}{t} \mathbb{E}((W_t - W)(W_t - W)^* | W) = 2\Lambda\Sigma + S \quad (2)$$

$$\lim_{t \rightarrow 0} \frac{1}{t} \mathbb{E}((W_t - W)(W_t - W)^T | W) = T \quad (2')$$

$$\lim_{t \rightarrow 0} \frac{1}{t} \mathbb{E}|W_t - W|^3 = 0. \quad (3)$$

$$\Rightarrow d(W, \sqrt{\Sigma}Z) \lesssim \|\Lambda^{-1}\|_{op} [\mathbb{E}\|R\|_2 + \|\Sigma^{-1/2}\|_{op} \mathbb{E}(\|S\|_{HS} + \|T\|_{HS})].$$



## A CLT for the $C\beta E$

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- Döbler and Stolz '11: multivariate generalization.

### Theorem (W '15)

Let  $(e^{ix_j})_{j=1}^N \sim C\beta E(N)$  ( $\beta > 0$ ),  $T_K = \left( \sum_{j=1}^N e^{ikx_j} \right)_{k=1}^K$ , and  $G_K = \left( \sqrt{\frac{2}{\beta}} j Z_j \right)_{j=1}^K$  ( $Z_j \sim N_{\mathbb{C}}(0, 1)$  i.i.d.). Then

$$d(T_K, G_K) = \mathcal{O} \left( \frac{K^{7/2}}{N} \right).$$

## Remarks

- Gives a (far from optimal?) rate of convergence for the CLT.
- $K$  can increase with  $N$ !
- Implies CLTs for smooth functions through Fourier expanding.
- For the proof, only need to estimate (mixed) moments up to order 4.
- Not strong enough to estimate maximum of  $X_N$ : would need to have  $K \sim N$  for this.

## Sketch of proof

- Take  $W = T_K$ , and  $W_t = \left( \sum_{j=1}^N e^{ikx_j(t)} \right)_{k=1}^K$ , where

$$dx_j(t) = \frac{\beta}{2} \sum_{i \neq j} \cot \frac{x_j(t) - x_i(t)}{2} dt + \sqrt{2} dB_j(t)$$

(circular DBM) started from  $(x_j)$ .

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(circular DBM) started from  $(x_j)$ .

- $(W, W_t)$  exchangeable as C $\beta$ E is reversible for the dynamics.
- Limits of the conditional expectations can be expressed in terms of the generator of cDBM

$$L_\beta = \frac{\beta}{2} \sum_j \sum_{i \neq j} \cot \frac{x_j - x_i}{2} \partial_{x_j} + \sum_{j=1}^N \partial_{x_j}^2$$

acting on power sums  $p_k(x) = \sum_{j=1}^N e^{ikx_j}$  (and their products).

## Sketch of proof

e.g. 
$$\lim_{t \rightarrow 0} \frac{1}{t} \mathbb{E}(W_t - W | W) = (L_\beta p_k(x))_{k=1}^K.$$



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Doing the calculations:

$$\Lambda_{k,l} = \delta_{k,l} N k \frac{\beta}{2} \tag{1}$$

$$\Sigma_{k,l} = \frac{2}{\beta} k \delta_{k,l} \tag{2}$$

$$R_k = -k^2 \left[ \frac{\beta}{2} - 1 \right] p_k(x) - k \frac{\beta}{2} \sum_{l=1}^{k-1} p_l(x) p_{k-l}(x) \tag{3}$$

$$S_{k,l} = (1 - \delta_{k,l}) 2k l p_{k-l}(x) \tag{4}$$

$$T_{k,l} = -2k l p_{k+l}(x). \tag{5}$$

## Sketch of proof

- One concludes by bounding relevant moments.
- Best ones I know of (for the  $C\beta E$ ): Jiang and Matsumoto '11.
- Weaker ones would suffice if you're happy with weaker  $K$ .
- Approach should work for other models too (works at least for the Gaussian  $\beta$ -ensemble).