

Poisson-Dirichlet statistics for  
the extremes of log-correlated Gaussian fields

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# Outline

## 1. Log-Correlated Fields

- ▶ Hierarchical cases (Polymers on tree, BBM)
- ▶ Non-Hierarchical cases (2D GFF, MRM)

## 2. Main Result: Poisson-Dirichlet Statistics of the Gibbs weights (Log-correlated Gaussian fields are 1-RSB)

## 3. Ideas of the Proof

- ▶ Ghirlanda-Guerra Identities
- ▶ Multiscale Decomposition
- ▶ Bovier-Kurkova Technique
- ▶ Bolthausen-Deuschel-Giacomin tree approximation

## 4. Beyond the Gibbs measure: the Extremal Process

## An example: Gaussian Field on a binary tree

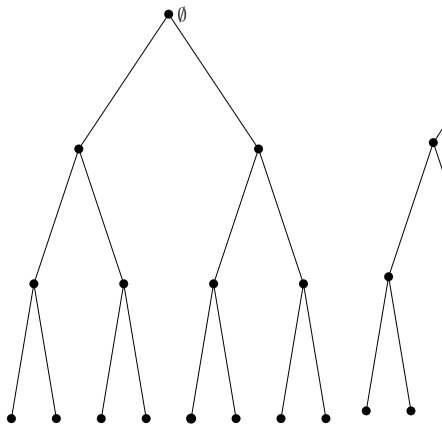
- ▶ Consider a binary tree with  $n$  generations.  
Let  $\mathcal{T}_n$  be the leaves  $|\mathcal{T}_n| = 2^n$ .
- ▶ Let  $(g_e)$  be i.i.d.  $\mathcal{N}(0, 1)$  on each edge  $e$ .  
Consider  $X = (X_v, v \in \mathcal{T}_n)$

$$X_v = \sum_{e: \emptyset \rightarrow v} g_e$$

- ▶  $\mathbb{E}[X_v^2] = n$   
 $\mathbb{E}[X_v X_{v'}] = \text{time of branching}$
- ▶ For any  $0 \leq r \leq 1$

$$\#\{v' : \mathbb{E}[X_v X_{v'}] \geq rn\} = \frac{2^n}{2^{rn}}$$

- ▶ Correlations are **hierarchical**:  
two correlations of a triplet  $v, v', v''$  must be equal.



## Log-correlated Gaussian fields

- ▶ Consider a Gaussian field

$$(X_v, v \in \mathcal{X}_n)$$

indexed by  $2^n$  points in **Euclidean space**, say  $[0, 1]$ .

- ▶  $\mathbb{E}[X_v^2] = n$  and for  $c(v, v') := \mathbb{E}[X_v X_{v'}]$

$$\#\{v' : c(v, v') \geq rn\} = \frac{2^n}{2^{rn}}$$

- ▶ Thus,  $c(v, v')$  must be **log-correlated**

$$c(v, v') \sim -\log \|v - v'\|$$

where  $\|v - v'\|$  is the Euclidean distance

## Non-hierarchical example: 2D discrete GFF

- ▶ Consider a box  $\mathcal{V}_n \subset \mathbb{Z}^2$  with  $2^n$  points.
- ▶  $(X_v, v \in \mathcal{V}_n)$  Gaussian field with

$$\mathbb{E}[X_v X_{v'}] = E^v \left[ \sum_{k=0}^{\tau_{\partial \mathcal{V}_n}} 1_{\{S_k = v'\}} \right].$$

$(S_k)_{k \geq 0}$  SRW starting at  $v$ .

- ▶ The field is **log-correlated**

$$\mathbb{E}[X_v^2] \sim n \log 2$$

$$\mathbb{E}[X_v X_{v'}] \sim \log \frac{2^n}{\|v - v'\|}$$

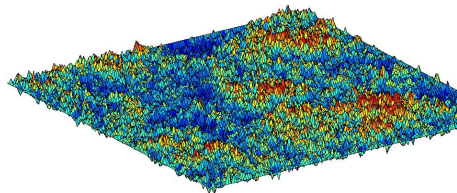


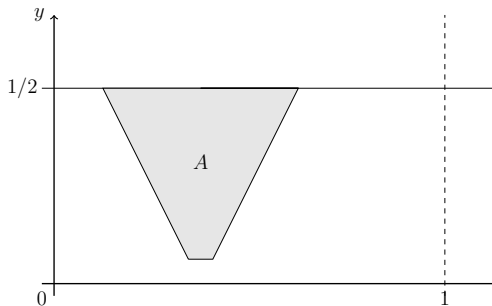
Figure by Samuel April

## Non-hierarchical example in 1D

We focus on a particular representation based on Bacry & Muzy '03  
**Multifractal Random Measure.**

They consider a **random measure**  $\mu$  on  $[0, 1]_{\sim} \times [0, 1/2]$  such that:

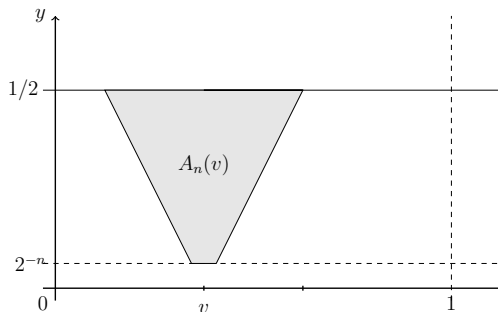
1.  $\mu(A) \sim \mathcal{N}(0, \theta(A))$
2.  $\theta(A) = \int_A y^{-2} dx dy$
3.  $A \cap B = \emptyset \Leftrightarrow \mu(A) \perp \mu(B)$ .



## Example in 1D

We construct a field  $(X_v, v \in \mathcal{X}_n)$  on  $2^n$  points.

- ▶  $\mathcal{X}_n$ :  $2^n$  equidistant points on  $[0, 1]_{\sim}$ .
- ▶  $X_v = \mu(A_n(v))$   
cones of slope  $1/2$   
truncated at  $2^{-n}$



$$\mathbb{E}[X_v^2] = \int_{A_n(v)} y^{-2} dx dy = n \log 2 + O(1)$$

$$\mathbb{E}[X_v X_{v'}] = \int_{A_n(v) \cap A_n(v')} y^{-2} dx dy = -\log |v - v'| + O(1)$$

Correlations are not hierarchical :

For a triplet  $v, v', v''$ , equality of two correlations is not ensured.

## Correlations and Extremal Statistics

To which extent does correlations affect the statistics of high values (extremes) of  $(X_v, v \in \mathcal{X}_n)$ ?

- ▶ Gaussian fields considered have **strong correlations**, of the order of the variance ( $\sim$  spin glasses).

Objects of study

- ▶ **Free energy**:  $\beta > 0$ ,  $Z_n(\beta) = \sum_{v \in \mathcal{X}_n} e^{\beta X_v}$

$$f(\beta) := \lim_{n \rightarrow \infty} \frac{1}{\log 2^n} \log Z_n(\beta)$$

- ▶ **Gibbs measure**: Measure on  $\mathcal{X}_n$  concentrating on extremes

$$\langle \cdot \rangle_{\beta, n} = \frac{\sum_{v \in \mathcal{X}_n} (\cdot) e^{\beta X_v}}{Z_n(\beta)}$$

- ▶ **Overlap distribution**: Normalized covariance  $q(v, v') = \frac{\mathbb{E}[X_v X_{v'}]}{\mathbb{E}[X_v^2]}$

$$x_{\beta, n}(r) := \mathbb{E}[\langle 1_{\{q(v, v') \leq r\}} \rangle_{\beta, n}^{\times 2}]$$



## Extremal Statistics for IID variables (REM model)

Suppose  $(X_v, v \in \mathcal{X}_n)$  are IID of variance  $n \log 2$ .

- ▶ **Free energy:**

$$\lim_{n \rightarrow \infty} \frac{1}{\log 2^n} \log Z_n(\beta) := \begin{cases} \log 2 + \frac{\beta^2 \log 2}{2} & \beta \leq \beta_c := \sqrt{2} \\ \sqrt{2} \log 2\beta & \beta \geq \beta_c \end{cases}$$

- ▶ **Overlap distribution:** Normalized covariance  $q(v, v') = \delta_{vv'}$

$$x_\beta(dr) := \lim_{n \rightarrow \infty} \mathbb{E}[\langle 1_{\{q(v, v') \in dr\}} \rangle_{\beta, n}^{\times 2}] = \frac{\beta_c}{\beta} \delta_0 + (1 - \frac{\beta_c}{\beta}) \delta_1$$

- ▶ **Gibbs measure:** For  $\beta > \beta_c$ , the Gibbs weights

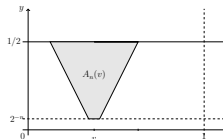
$$(\langle \delta_v \rangle_{\beta, n}, v \in \mathcal{X}_n)_\downarrow \rightarrow \text{PD}(\beta_c/\beta)$$

$\text{PD}(\alpha) = (\eta_i / \sum_j \eta_j, i \in \mathbb{N})_\downarrow$  where  $(\eta_i)$  is Poisson( $s^{-\alpha-1} ds$ ) on  $\mathbb{R}^+$ .

The REM is said to exhibit 1-RSB.

## Main results: Free energy

The Gaussian field  $(X_v, v \in \mathcal{X}_N)$  (cones) is **1-RSB**:



Theorem (A-Zindy '12)

The free energy is the same as the **REM**:

$$\lim_{n \rightarrow \infty} \frac{1}{\log 2^n} \log Z_n(\beta) = \begin{cases} \log 2 + \frac{\beta^2 \log 2}{2} & \beta \leq \beta_c := \sqrt{2} \\ \sqrt{2} \log 2\beta & \beta \geq \beta_c \end{cases} \text{ a.s. and in } L^1$$

- ▶ This was shown for BBM (hierarchical) by **Derrida & Spohn '88** based on the work of Bramson '78.
- ▶ The result for non-hierarchical field was conjectured by Carpentier & Ledoussal '00.
- ▶ The result follows from the works on 2DGGF of Bolthausen, Deuschel & Giacomin '01, and Daviaud '06.

## Main results: 1-RSB and PD weights

### Theorem (A-Zindy '12)

The joint distribution of overlaps is the same as the REM: for  $\beta \geq \beta_c$

1.

$$x_\beta(dr) = \lim_{n \rightarrow \infty} \mathbb{E} \left[ \left\langle 1_{\{q(v, v') \in dr\}} \right\rangle_{\beta, n}^{\times 2} \right] = \frac{\beta_c}{\beta} \delta_0 + \left(1 - \frac{\beta_c}{\beta}\right) \delta_1$$

2.

$$\mathbb{E} \left[ \left\langle F(\{q(v_k, v_l)\}) \right\rangle_{\beta, n}^{\times s} \right] \rightarrow E \left[ \sum_{i_1, \dots, i_s} \xi_{i_1} \dots \xi_{i_s} F(\{\delta_{kl}\}) \right]$$

where  $(\xi_i, i \in \mathbb{N})_\downarrow$  are PD( $\beta_c/\beta$ ).

- ▶ This was shown in the hierarchical case by Bovier & Kurkova '04.
- ▶ This shows the **Ultrametricity Conjecture** for the field considered: Correlations not hierarchical for finite  $n$ , but are in the limit  $n \rightarrow \infty$ !
- ▶ **Open questions:** What about other test-functions ?  
Conjectured in Duplantier, Rhodes, Sheffield & Vargas '12

## Ideas of the Proofs

The method of proof is **robust** and is applicable to other log-correlated fields

- ▶ Bacry & Muzy construction on  $[0, 1]^d$  (Multifractal Random Measure)
- ▶ 2D discrete Gaussian free field

We restrict to the 1D case for simplicity.

1. GG Identities and AC Stochastic Stability
2. Multi-scale decomposition
3. Bovier & Kurkova technique '04
4. Tree approximation (Bolthausen-Deuschel-Giacomin '01 and Daviaud '06)

# 1. Gibbs Measures of Gaussian Fields

## Theorem (Panchenko '10)

If the free energy is differentiable at  $\beta > 0$ , then the field concentrates:

$$\frac{1}{\log 2^n} \mathbb{E} \langle |X_v - \mathbb{E}[\langle X_v \rangle_{\beta, n}]| \rangle_{\beta, n} \rightarrow 0 .$$

In particular, by integration by parts, for any smooth  $F$ ,

$$\begin{aligned} \mathbb{E} \left[ \left\langle q(v_1, v_{s+1}) F(\{q(v_i, v_j)\}_{i, j \leq s}) \right\rangle_{\beta, n}^{\times s+1} \right] = \\ \frac{1}{s} \mathbb{E} \left[ \left\langle q(v_1, v_2) \right\rangle_{\beta, n}^{\times 2} \right] \mathbb{E} \left[ \left\langle F(\{q(v_i, v_j)\}) \right\rangle_{\beta, n}^{\times s} \right] \\ + \frac{1}{s} \sum_{k=2}^s \mathbb{E} \left[ \left\langle q(v_1, v_k) F(\{q(v_i, v_j)\}) \right\rangle_{\beta, n}^{\times s} \right] + o(1) \end{aligned}$$

Ghirlanda-Guerra Identities

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- ▶ Similar results obtain for **Stochastic Stability** (Aizenman-Contucci '98, A-Chatterjee '10).
- ▶ In the case where  $q(v, v') \rightarrow \delta_{vv'}$ , the GG identities characterizes PD distributions (Talagrand '03).
- ▶ **GG identities and Stochastic stability** are at the core of **Ultrametricity** (Aizenman-A '08, Panchenko '09 '12).

# 1. Gibbs Measures of Gaussian Fields

## Theorem (Panchenko '10)

If the free energy is differentiable at  $\beta > 0$ , then the field concentrates:

$$\frac{1}{\log 2^n} \mathbb{E} \left| \langle X_v \rangle_{\beta, n} - \mathbb{E}[\langle X_v \rangle_{\beta, n}] \right| \rightarrow 0 .$$

In particular, by integration by parts, for any smooth  $F$ ,

$$\begin{aligned} \mathbb{E} \left[ \left\langle q(v_1, v_{s+1}) F(\{q(v_i, v_j)\}) \right\rangle_{\beta, n}^{\times s+1} \right] = \\ \frac{1}{s} \mathbb{E} \left[ \left\langle q(v_1, v_2) \right\rangle_{\beta, n}^{\times 2} \right] \mathbb{E} \left[ \left\langle F(\{q(v_i, v_j)\}) \right\rangle_{\beta, n}^{\times s} \right] \\ + \frac{1}{s} \sum_{k=2}^s \mathbb{E} \left[ \left\langle q(v_1, v_k) F(\{q(v_i, v_j)\}) \right\rangle_{\beta, n}^{\times s} \right] + o(1) \end{aligned}$$

Reduces the problem to computing prove

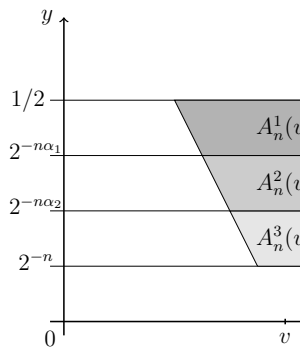
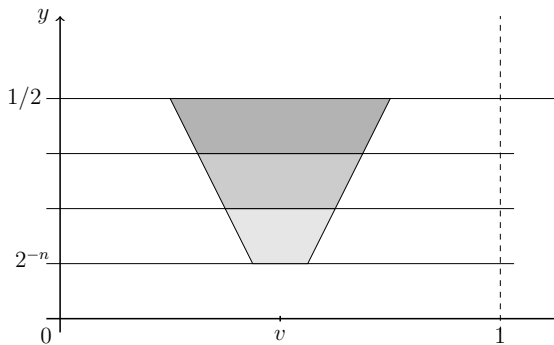
$$x_{\beta}(r) = \lim_{n \rightarrow \infty} \mathbb{E} \left\langle 1_{\{q(v, v') \leq r\}} \right\rangle_{\beta, n}^{\times 2} \text{ is 1-RSB.}$$

## 2. Multi-scale Decomposition

- ▶ Independence of disjoint sets  $\rightarrow$  **multiscale decomposition** in strips
- ▶ Pick  $\alpha = (\alpha_1, \alpha_2)$ ,  $0 < \alpha_1 < \alpha_2 < 1$ , and  $\sigma = (\sigma_1, \sigma_2, \sigma_3)$ .
- ▶ Write  $Y^{(\sigma, \alpha)} = (Y_v^{(\sigma, \alpha)}, n \in \mathcal{X}_n)$  for the Gaussian field

$$Y_v^{(\sigma, \alpha)} = \sigma_1 \mu(A_n^1(v)) + \sigma_2 \mu(A_n^2(v)) + \sigma_3 \mu(A_n^3(v))$$

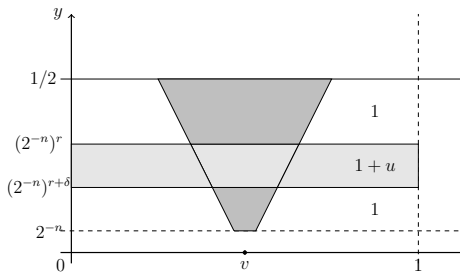
- ▶ This is similar to a **GREM** (Derrida '85).





### 3. The Bovier-Kurkova technique

- ▶ Bovier & Kurkova '04 obtained the **overlap distribution** of a continuous version of the GREM by considering perturbation of the model.
- ▶ For  $0 < r < 1$ ,  $\delta$  and  $u$  small.



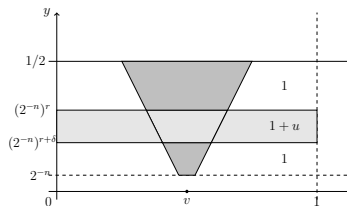
### 3. The Bovier-Kurkova technique

- For  $0 < r < 1$ ,  $\delta$  small and  $u$  close to 1

$$x_\beta(r) = \lim_{n \rightarrow \infty} \mathbb{E} \left\langle 1_{\{q(v, v') \leq r\}} \right\rangle_{\beta, n}^{\times 2} \quad Z_n^{(u, r, \delta)}(\beta) = \sum_{v \in \mathcal{X}_n} e^{\beta Y^{(u, r, \delta)}(v)}$$

Lemma (Bovier & Kurkova '04)

$$\beta^2 \int_r^{r+\delta} x_\beta(s) ds = \frac{d}{du} \left( \lim_{n \rightarrow \infty} \frac{1}{n \log 2} \mathbb{E} \log Z_n^{(u, r, \delta)}(\beta) \right) \Big|_{u=0}$$



## 4. BDG tree approximation

To compute the free energy, it suffices to compute the log-number of high points

$$\mathcal{E}^{(\sigma, \alpha)}(\gamma) = \lim_{n \rightarrow \infty} \frac{\log \#\{v \in \mathcal{X}_n : Y_v^{(\sigma, \alpha)} \geq \gamma \sqrt{2} \log 2n\}}{\log 2^n} \quad \text{in prob.}$$

Theorem

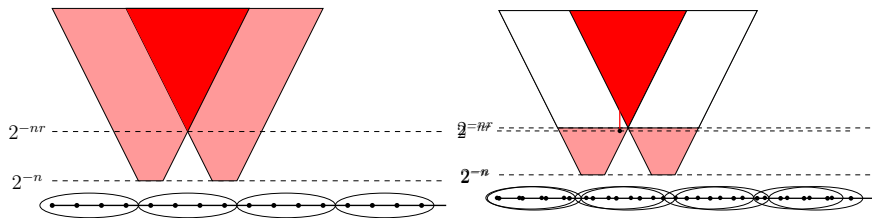
- ▶ Daviaud '06: Case  $\sigma_1 = \sigma_2 = \sigma_3 = 1$

$$\mathcal{E}(\gamma) = 1 - \gamma^2 \quad (\text{like IID})$$

- ▶ A-Zindy '12: The number of high points  $\mathcal{E}^{(\sigma, \alpha)}(\gamma)$  is the same as for the  $\text{GREM}(\sigma, \alpha)$ .

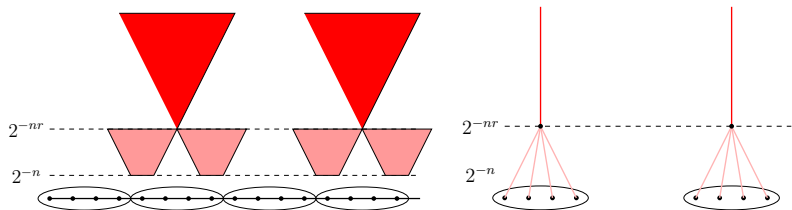
## 4. BDG tree approximation

- ▶ Divide the  $2^n$  points into  $2^{nr}$  boxes with  $2^{n(1-r)}$  points/box (offspring)
- ▶ Contribution at scale  $2^{-nr}$  is not the same for the points in the box.
- ▶ **Log-Miracle #1:**  
Non-common part is smaller than the common part:  $1 \ll rn \log 2$ .



## 4. BDG tree approximation

- ▶ The offspring within a box are not independent.
- ▶ **Log-Miracle #2:**  
The offspring of two boxes are independent at scale below  $2^{-nr}$ .  
Enough independent boxes for the offspring to reach a high value.



- ▶ Bolthausen, Deuschel & Giacomin '01 and Daviaud '06 uses this approximation to compute the first order of the maximum and the log-number of high points in the 2D GFF.

## Beyond the Gibbs measure: the Extremal Process

The analysis of the extremal process

$$(X_v, v \in \mathcal{X}_n) \text{ close to } \max_v X_v$$

is much more delicate than the one of the Gibbs measure.

Not in the same universality class as the REM.

### Hierarchical case

- ▶ Bramson '78: for BBM,  $\max_v X_v - m(n)$  converges as  $n \rightarrow \infty$  for an appropriate  $m(n)$ .
- ▶ The limit law is **not Gumbel** as in the REM.
- ▶  $(X_v - m(n), v \in \mathcal{T}_n)$  converges to a **Poisson cluster process** (A, Bovier & Kistler '11, Aïdekon, Berestycki, Brunet & Shi '11).

## Beyond the Gibbs measure: the Extremal Process

The analysis of the extremal process

$$(X_v, v \in \mathcal{X}_n) \text{ close to } \max_v X_v$$

is much more delicate than the one of the Gibbs measure.

### Universality class of log-correlated fields

#### Non-Hierarchical case (cones, 2DGFF, etc)

- ▶ The extremal process should be like the one of BBM: Carpentier & Ledoussal '00, Fyodorov & Bouchaud '08.
- ▶ Recent results: BDG '01, Bramson & Zeitouni '10, Ding & Zeitouni '12, Duplantier, Rhodes, Sheffield & Vargas '12
- ▶ **Convergence of max not proved...**

