## Fractal Structure of Zeros in Hierarchical Models (after Derrida, De Seze, and Itzykson)

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# I. Preliminaries.

#### Diamond hierarchical lattice.

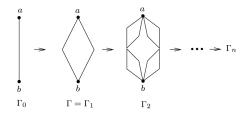


Figure : The first few graphs in the DHL

Let  $\Gamma$  be the diamond graph. The **diamond hierarchical lattice** is the sequence of graphs {  $\Gamma_n$  }<sub> $n \in \mathbb{N}$ </sub> such that

• 
$$\Gamma_1 := \Gamma$$
.

•  $\Gamma_{n+1}$  has two marked vertices *a*, *b* and is obtained from  $\Gamma_n$  by replacing each edge of  $\Gamma_n$  by  $\Gamma_1$ .

Let 
$$\Gamma_n = (V_n, E_n)$$

#### Potts model on the DHL

A configuration of spins is a mapping

$$\sigma: V_n \longrightarrow \{1, 2, \ldots, q\}$$

The Ising model is the case q = 2. The *Energy* of  $\sigma$  is

$$\mathcal{H}_n(\sigma) := -J \sum_{(i,j)\in E_n} \delta_{\sigma_i, \sigma_j}$$

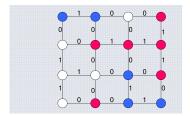


Figure : Here, q = 3 and  $\mathcal{H} = -10J$ .

### $P_n(\sigma)$ and the partition function.

A configuration  $\sigma$  occurs with probability proportional to the  $\mathit{Gibbs}$   $\mathit{weight}$ 

$$W_n(\sigma) := e^{-H_n(\sigma)/T}$$

Note that

- When T is close to zero, then minimal energy configurations have much higher probabilities.
- When T is close to  $\infty$ , all configurations have more or less the same probability.

Hence,

$$P_n(\sigma) = \frac{W_n(\sigma)}{Z_n}$$

where  $Z_n := \sum_{\sigma} W(\sigma)$  is the partition function.

#### the partition function

we introduce the change of variables

$$y := e^{J/T}$$

so that  $Z_n$  becomes a polynomial in y of degree  $|E_n|$ :

$$Z_n(y) = \sum_{\sigma} y^{I(\sigma)}$$

where  $I(\sigma) := \sum_{(i,j)\in E_n} \delta_{\sigma(i),\sigma(j)}$  is the *interaction of*  $\sigma$ . There are exactly q configurations such that the spins are alligned, so:

$$Z_n(y) = q \prod_{i=1}^{|E_n|} (y - y_i)$$

The zeros of  $Z_n$ ,  $\{y_i\}_{1 \le i \le |E_n|}$  are called the *Fisher zeros*.

# II. Computing the Fisher zeros: Migdal - Kadanoff renormalization equations.

#### two conditional partition functions

Let

$$U_n := \sum_{\substack{\sigma \text{ s.t.} \\ \sigma(a) = \sigma(b) = 1}} W_n(\sigma)$$

$$V_n := \sum_{\substack{\sigma \text{ s.t.} \\ \sigma(a)=1, \sigma(b)=2}} W_n(\sigma)$$

 $(U_n \text{ and } V_n \text{ are functions of } y)$ . Clearly,

$$Z_n = qU_n + q(q-1)V_n$$

Finding an expression for  $U_n$  and  $V_n$  in terms of  $U_{n-1}$  and  $V_{n-1}$  is not hard (see blackboard) and since

$$U_0=y, \quad V_0=1$$

we can compute  $Z_n$  via an iterative procedure.

We have obtained:

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$$Z_n(y) = L \circ R^n(y, 1)$$

where  $R: \mathbb{C}^2 \to \mathbb{C}^2$  is given by

$$R(U, V) := \left( \left( U^2 + (q-1)V^2 \right)^2, \ V^2 (2U + (q-2)V)^2 \right)$$
  
nd  $L : \mathbb{C}^2 \to \mathbb{C}$  is

$$L(U, V) := qU + q(q-1)V$$

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In the paper of **Derrida**, **De Seze and Itzykson (1983)** a different iterative procedure is used: Define  $T : \mathbb{C} \to \mathbb{C}$  as

$$T(y) := \left(\frac{y^2 + q - 1}{2y + q - 2}\right)^2$$

Then  $Z_n(y)$  are the  $4^{n-1}$  preimages of 1 - q by the (n - 1)-th iterate of T.

**Derrida, De Seze and Itzykson (1983)** studies numerically what happens in the *thermodynamic limit*  $n \rightarrow \infty$ .

Recall that

- The *Julia set* of *T*, *J*(*T*), is the closure of the set of repelling periodic points of *T*.
- Mikhail Lyubich and Alexandre Freires, Artur Lopes, and Ricardo Mañé have shown (1983) that if a point y<sub>0</sub> is not exceptional for T (see below) then the probability measures μ<sub>n</sub>(y<sub>0</sub>) supported on { T<sup>-n</sup>(y<sub>0</sub>) } converge, as n→∞ to the measure of maximal entropy, which is supported on J(T).
- $y_0 = 1 q$  is not exceptional, since it is not a critical value of T.

Hence, in the thermodynamic limit  $n \to \infty$ , the Fisher zeros converge, in the sense explained above, to  $\mathcal{J}(T)$ .

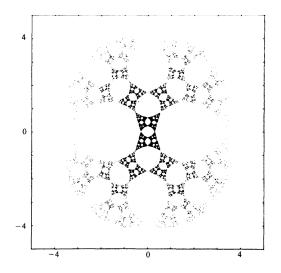


Figure : Here, q = 2. No bias in the Monte Carlo procedure.

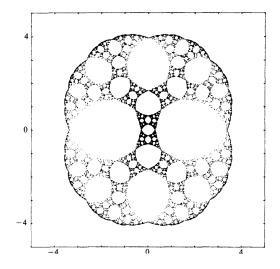


Figure : Here, q = 2, as before. Biased Monte Carlo procedure.

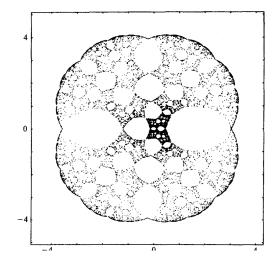


Figure : Here, q = 1.5. Biased Monte Carlo procedure.

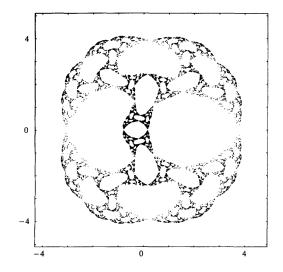


Figure : Here, q = 2.5. Biased Monte Carlo procedure.

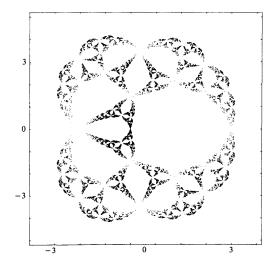


Figure : Here, q = 3. Biased Monte Carlo procedure.

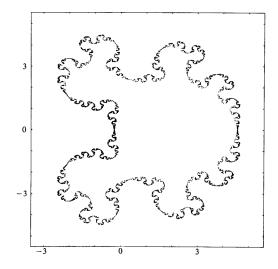


Figure : Here, q = 4. Biased Monte Carlo procedure.