

# Independence polynomial on arbitrary recursive graphs

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Auf dem heiligen berg  
Wuppertal

October 25th, 2024

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These dynamical systems have common features, with consequences for partition functions.

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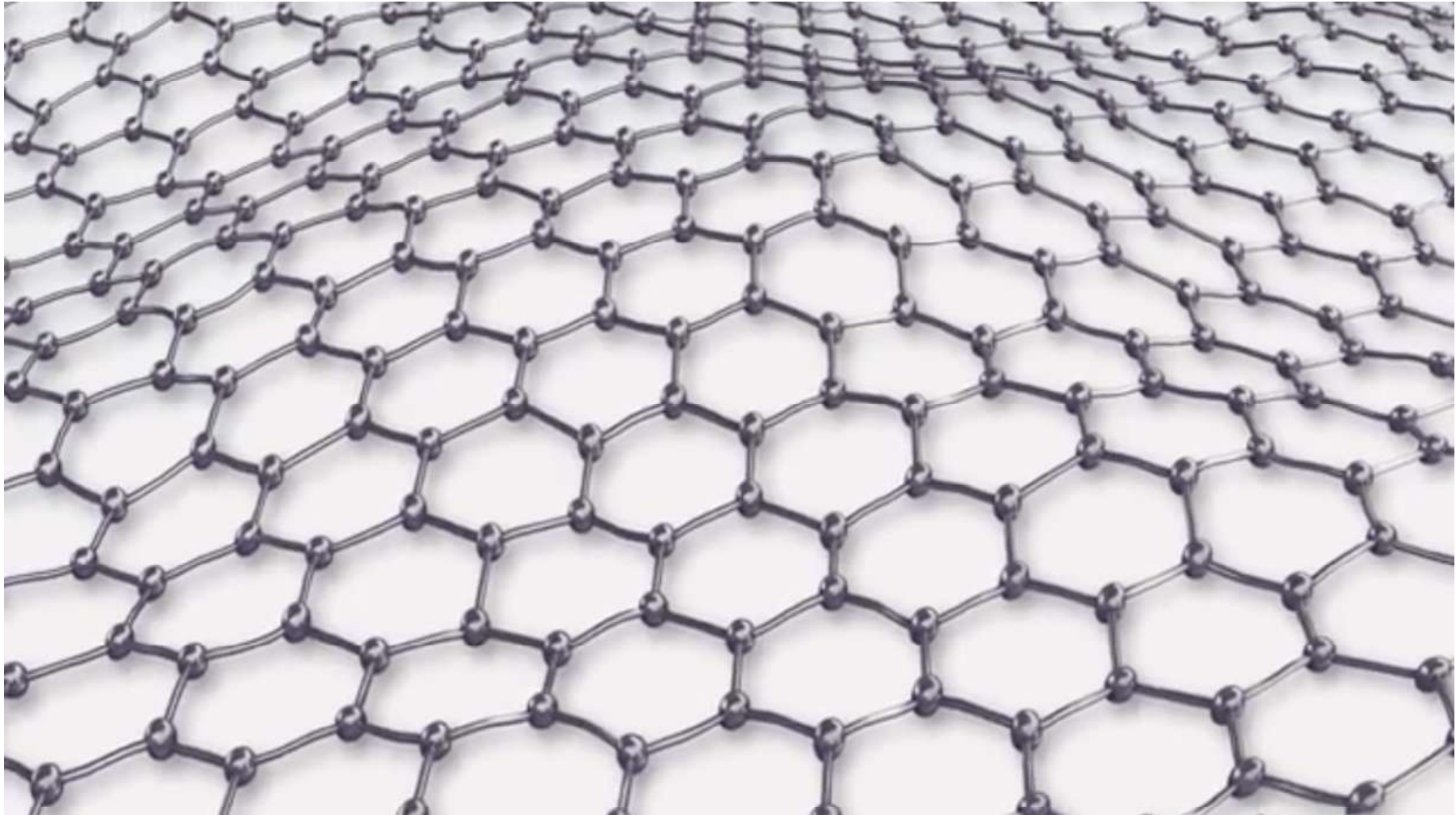
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**Corollary:** For  $G_0$  *maximally independent* the zeros of the independence polynomials are uniformly bounded.



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**Key idea:** The almost infinite system is a limit of larger and larger finite systems.

# Two spin models on graphs

Assume interaction energies are constant. Obtain a *graph*  $G$  and states  $\sigma : G \rightarrow \{\text{spins}\}$ .

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## Hard-core model

Let

$$Z_G(\lambda) = \sum_{\sigma \text{ ind.}} \prod_{v \in V(G)} \lambda^{\sigma(v)},$$

summing over *independent*  $\sigma$ :  $\sigma(v) \cdot \sigma(w) = 0$  for every  $(v, w) \in E(G)$ .

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Related are the *Tutte polynomial* and the *Chromatic polynomial*, which consider  $q$  as a parameter.

# Modeling infinite graphs as limits of a sequence $(G_n)$

To each graph  $G_n$  we associate a normalized free energy:

$$\rho_n(\lambda) = \frac{\log |Z_G(\lambda)|}{|V(G_n)|}$$

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## Yang-Lee (1952)

If the zeros of the polynomials  $Z_{G_n}(\lambda)$  avoid a **complex neighborhood** of the parameter  $\lambda_0$ , then the limiting free energy is real analytic at  $\lambda_0$ .

# Partition functions on regular lattices

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How can it be that such a simple question is still open?

- 1 Regular lattices are not trivial.
- 2 Computation of  $G_n$  is “hard”.

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A precise description of  $U$  is still lacking.

# Relevance of zero-sets of partition functions

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A recent result:

de Boer-Buys-P.-Regts, 2024

Consider an increasing sequence of  $d$ -dimensional torus-graphs. If the tori are balanced, the zeros are bounded. If the tori are highly unbalanced, the zeros are unbounded.

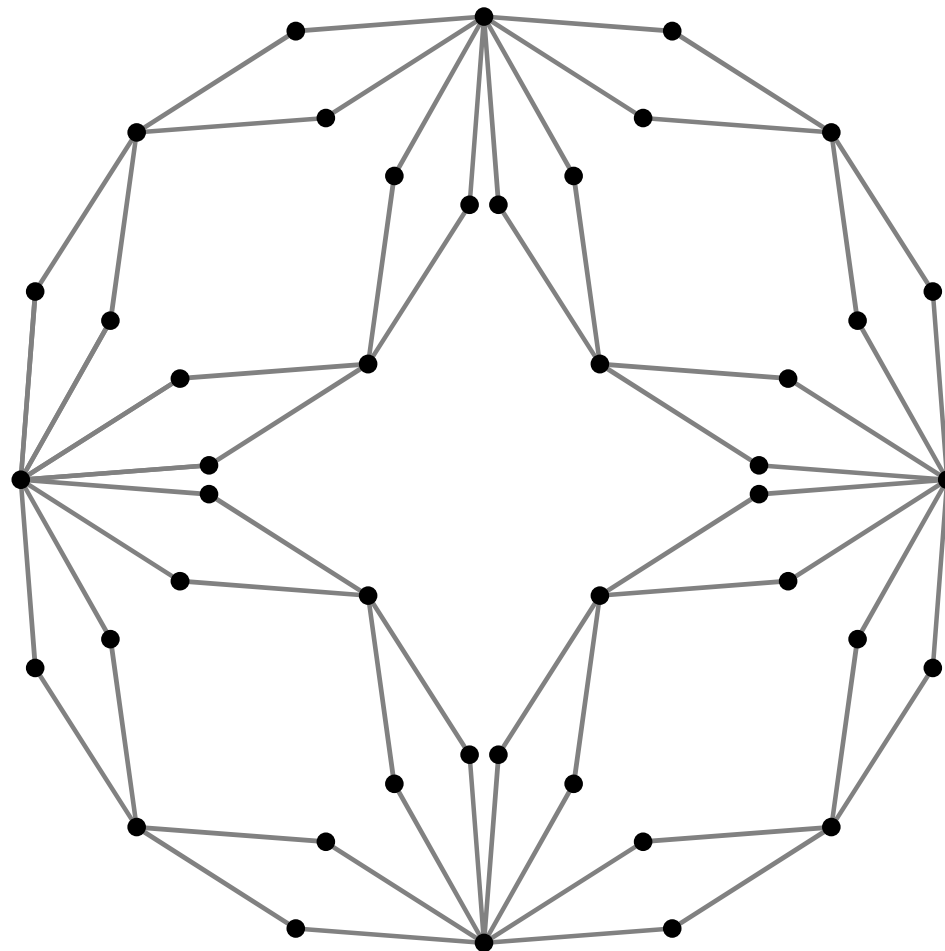
# Example of recursive graphs, I



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Bleher-Lyubich-Roeder (2010), Chio-Roeder (2021)

Consider the Ising model on *diamond hierarchical lattices*. Then there is a unique phase transition.



# Example of recursive graphs, II

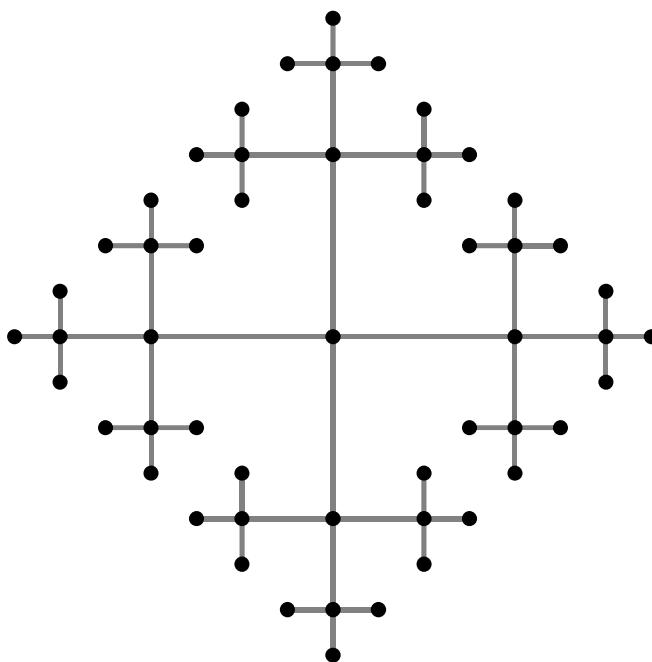
# Example of recursive graphs, II

Rivera-Letelier & Sombra (talk at Fields Institute, 2019)

Consider the Hard-Core model on  $d$ -ary trees. Then zeros accumulate at a unique parameter in  $\mathbb{R}_+$ :

$$\lambda(d) = \frac{d^d}{(d+1)^{d-1}},$$

the unique phase transition **of infinite order**.

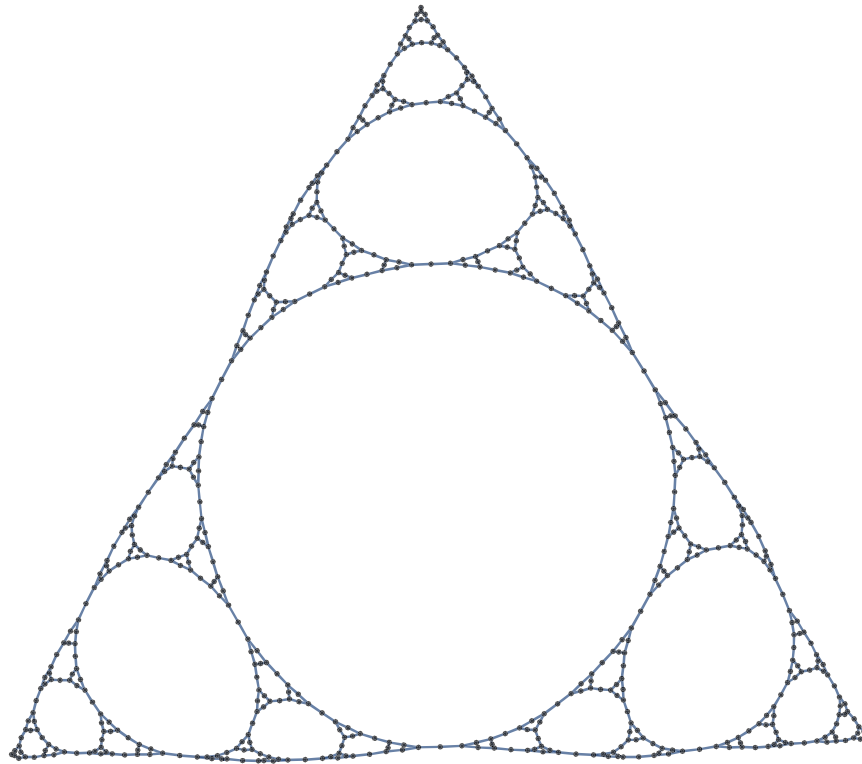


# Example of recursive graphs, III

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Nguyen-Bac Dang, Rostislav Grigorchuk, Mikhail Lyubich, 2021

Spectrum of the Laplacian on Schreier graphs of some self-similar groups.



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In all of these examples, the recursion induces a rational dynamical system, which can be studied to describe the zeros.

The purpose of this project is to present a **general framework**, to study the induced dynamical systems, and to draw conclusions regarding the partition functions.



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We call  $(H, \Sigma, \Phi)$  the *gluing data*.

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**Step 4.** Mark  $k$  vertices of  $G_{n+1}$  using the function  $\Phi : \{1, \dots, k\} \rightarrow E(H)$ . If  $e = \Phi(j)$  has multiple vertices, label the marked vertex of  $\Sigma_e$ .

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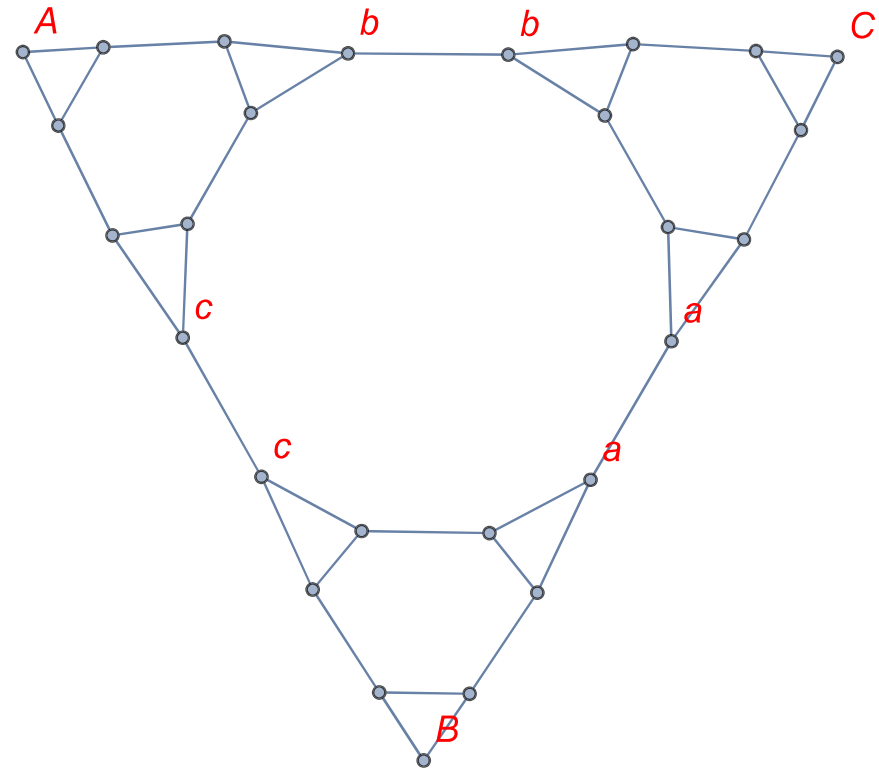
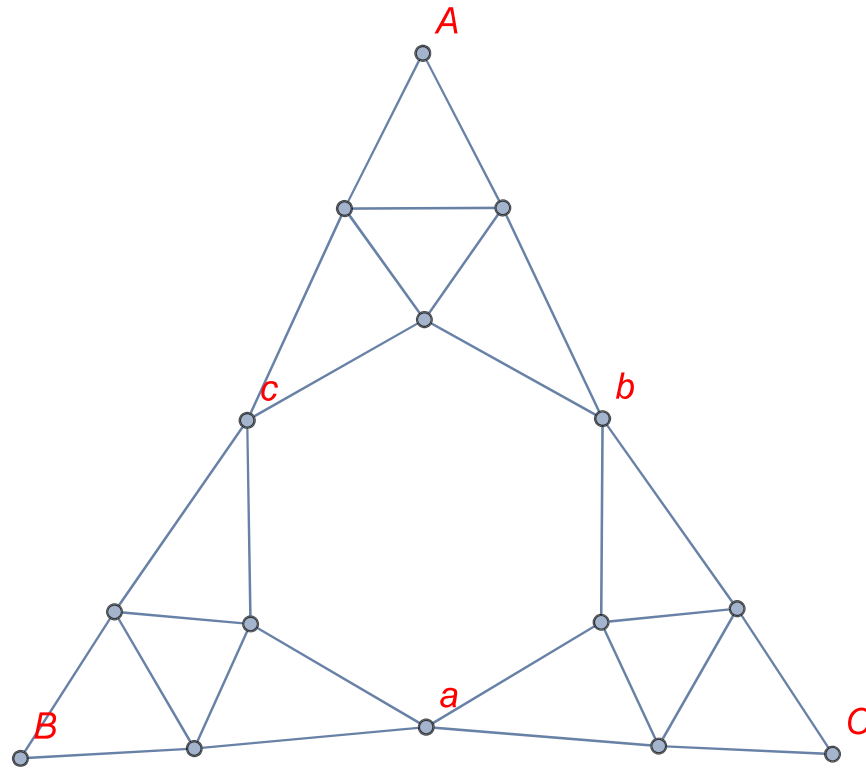
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**Step 4.** Define  $\Phi(j) = \{v_j(j)\}$ .

## Example 2: Towers of Hanoi



The Sierpinsky triangle  $G_2$  and the towers of Hanoi  $G_2$ , where the connecting graphs are *edges*.



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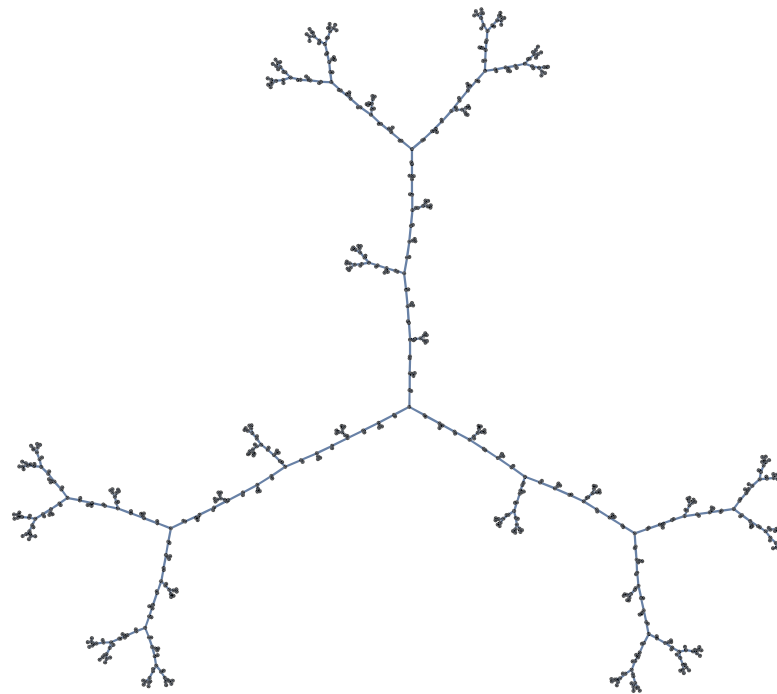
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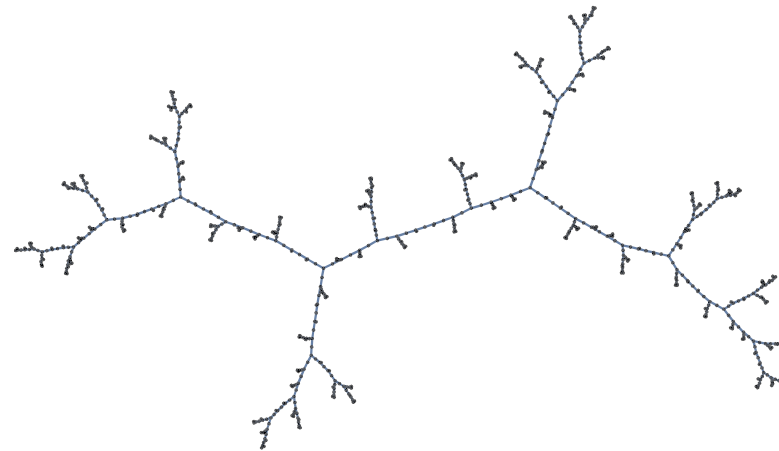
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Formula for  $(x_1, \dots, x_k)_{n+1}$ :

$$\sum_{x \sim y \in \{0,1\}^{km}} \prod_{i=1}^m (y_1(i), \dots, y_k(i)) \cdot \prod_{e \in E(H)} \frac{Z_{\Sigma_e}(\lambda, y|_e, x|_e)}{\lambda^{|y|_e}}$$

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## Observation

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Hence the equations

$$\frac{(x_1, \dots, x_{j-1}, 1, x_{j+1}, \dots, x_k)}{(x_1, \dots, x_{j-1}, 0, x_{j+1}, \dots, x_k)} = \frac{(0, \dots, 0, 1, 0, \dots, 0)}{(0, \dots, 0, 0, 0, \dots, 0)}$$

define a  $k$ -dimensional manifold in  $\mathbb{C}^{2^k}$  and in  $\mathbb{P}^{2^k-1}$ .

# Example: Dendrite recursion

When passing from  $G_{n+1}$  to  $G_n$ , the action on the labels is:

$$a \rightarrow c$$

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As a consequence, the invariant 3-manifold is mapped onto a periodic 2-manifold, which is a graph over the variables

$$[1, 0, 0]_n = \frac{(1, 0, 0)_n}{(0, 0, 0)_n} \quad \text{and} \quad [0, 0, 1]_n = \frac{(0, 0, 1)_n}{(0, 0, 0)_n}$$

For the second iterate this 2-manifold in  $\mathbb{P}^2$  consists of fixed points.



# Understanding the dynamics near the fixed manifold

Assume that none of the periodic labels are *critical*.

## Theorem

*The periodic manifold is normally super-attracting.*

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**Proof by Mathematica.**

```
In[21]:= Eigenvalues[jacobiansurface]
```

```
Out[21]= {0, 0, 0, 0, 0, 1, 1}
```

# Maximally independent

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## Definition

A labeled graph  $G_n$  is *maximally independent* if for every assignment  $x = (x_1, \dots, x_k)$  the maximal independent  $I(x) \subset V(G_0)$  is unique, and moreover

$$|I(1, \dots, 1)| - |I(0, \dots, 0)| = k.$$

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## Example

For the Dendrite recursion the tripod  $G_0$  is not maximally independent, but  $G_1$  is.

For the Antenna recursion the edge  $G_0$  is not maximally independent, but  $G_2$  is.

## Theorem

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When summing the coordinates, the terms  $(1, \dots, 1)_n$  will dominate the others, hence no zeros. □

# Conclusion and future work

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This is just a start:

- ① When are zeros bounded away from  $\mathbb{R}_+$ ?
- ② When do zeros equidistribute?
- ③ Does the behavior depend on  $(G_0, \Sigma)$ , or only on  $(H, \Phi)$ ?
- ④ What about other partition functions?
- ⑤ ...

# Thank you.

