

# Exact coefficients of partition functions via stability

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- Arise in combinatorics as graph polynomials.
- Main example: matchings in regular graphs.
- Other examples: independent sets and colourings in regular graphs, triangle-free graphs, etc.

# Matchings in regular graphs

- The **monomer-dimer model** on a graph  $G$  at fugacity  $\lambda > 0$  is the probability distribution on **matchings** such that

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- The function  $Z_G(\lambda) = \sum_M \lambda^{|M|}$  is the **partition function**.
- The same idea can be used for **independent sets**, **colourings**, etc.



## Properties of the partition function

$$Z_G(\lambda) = \sum_M \lambda^{|M|} = \sum_{k \geq 0} m_k(G) \lambda^k$$

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- For  $\lambda = 1$  the partition function **counts** matchings.
- The average size of a matching  $\mathbf{M}$  from the monomer-dimer model is

$$\mathbb{E}|\mathbf{M}| = \frac{\sum_M |M| \lambda^{|M|}}{Z_G(\lambda)} = \frac{\lambda Z'_G(\lambda)}{Z_G(\lambda)} = \lambda \frac{\partial}{\partial \lambda} \log Z_G(\lambda).$$

## Previous work

Consider the family of  $d$ -regular graphs and let  $H_{d,n}$  be the disjoint union of  $n/2d$  copies of  $K_{d,d}$ .

- In previous work we showed that for all  $\lambda > 0$ ,  $H_{d,n}$  maximises the partition function over  $n$ -vertex,  $d$ -regular graphs.

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- In previous work we showed that for all  $\lambda > 0$ ,  $H_{d,n}$  maximises the partition function over  $n$ -vertex,  $d$ -regular graphs.
- In fact, we showed that  $H_{d,n}$  maximises

$$\frac{1}{|E(G)|} \mathbb{E} |\mathbf{M}| = \frac{\lambda}{|E(G)|} \frac{\partial}{\partial \lambda} \log Z_G(\lambda)$$

over all  $d$ -regular graphs.

# Main results

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This is the **upper matching conjecture**.
- 2** If  $G$  contains no copy of  $K_{d,d}$ , should  $Z_G(\lambda)$  be significantly smaller than  $Z_{H_{d,n}}(\lambda)$ ? This is a question of **stability**.

We prove in a general way that a strong form of **2** holds, and that from such a result, **1** follows for a wide range of parameters.



# Stability

In our previous work we showed that for  $\lambda > 0$  and  $d$ -regular  $G$ ,

$$\frac{1}{|V(G)|} \log Z_G(\lambda) \leq \frac{1}{2d} \log Z_{K_{d,d}}(\lambda),$$

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## Theorem

Let  $G$  be a  $d$ -regular graph *which contains no copy of  $K_{d,d}$* . Then there exists a continuous function  $s(d, \lambda)$  which is strictly increasing in  $\lambda$ , and satisfies  $s(d, 0) = 0$ , such that the following holds for  $\lambda \geq 0$ ,

$$\frac{1}{|V(G)|} \log Z_G(\lambda) \leq \frac{1}{2d} \log Z_{K_{d,d}}(\lambda) - s(d, \lambda).$$

## Proof: linear programming with local constraints

- Let  $\alpha_G(\lambda) = \frac{1}{|E(G)|} \mathbb{E}|\mathbf{M}| = \frac{\lambda}{|E(G)|} \frac{\partial}{\partial \lambda} \log Z_G(\lambda)$ .

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- The constraint that  $G$  contains no copy of  $K_{d,d}$  can be naturally added to the program, yielding:

### Lemma

*For any  $d$ -regular  $G$  which contains no copy of  $K_{d,d}$ ,*

$$\alpha_G(\lambda) \leq \alpha_{K_{d,d}}(\lambda) - c(d, \lambda).$$

## Proof: simple calculus gives the stability result

$$\text{Recall } \alpha_G(\lambda) = \frac{1}{|E(G)|} \mathbb{E}|\mathbf{M}| = \frac{\lambda}{|E(G)|} \frac{\partial}{\partial \lambda} \log Z_G(\lambda).$$

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Let  $G$  contain no  $K_{d,d}$ . Then

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$$\begin{aligned} \frac{1}{|V(G)|} \log Z_G(\lambda) &= \frac{d}{2} \int_0^\lambda \frac{\alpha_G(t)}{t} dt \\ &\leq \frac{d}{2} \int_0^\lambda \frac{\alpha_{K_{d,d}}(t) - c(d,t)}{t} dt \\ &= \frac{1}{2d} \log Z_{K_{d,d}}(\lambda) - \underbrace{\frac{d}{2} \int_0^\lambda \frac{c(d,t)}{t} dt}_{s(d,\lambda)} \end{aligned}$$



## Exact bounds on coefficients for almost all sizes

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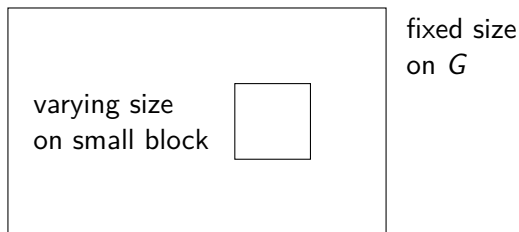
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  - for  $\lambda > 0$ : PART another entropy proof

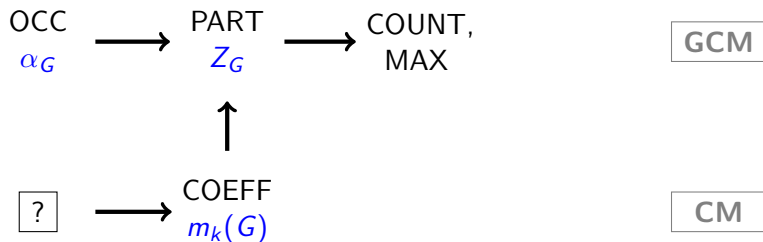
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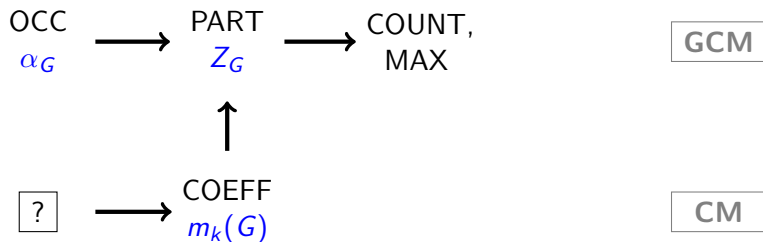
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  - value of each coefficient: COEFF now almost solved

# The big picture



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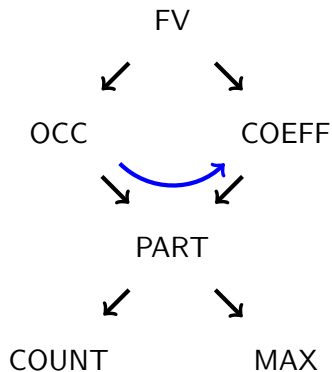
The missing piece is the **free volume**:

$f_G(M)$  = set of edges which could be added to  $M$ ,

$$F_{G,k}(\lambda) = \mathbb{E}|f_G(\mathbf{M}_k)| = (k+1) \frac{m_{k+1}(G)}{m_k(G)},$$

where  $\mathbf{M}_k$  is a uniformly random matching of size  $k$  in  $G$ .

## Another big picture



We conjecture that  $H_{d,n}$  maximises the free volume for all  $k$ , i.e. has property FV.