

# Counting independent sets with the cluster expansion

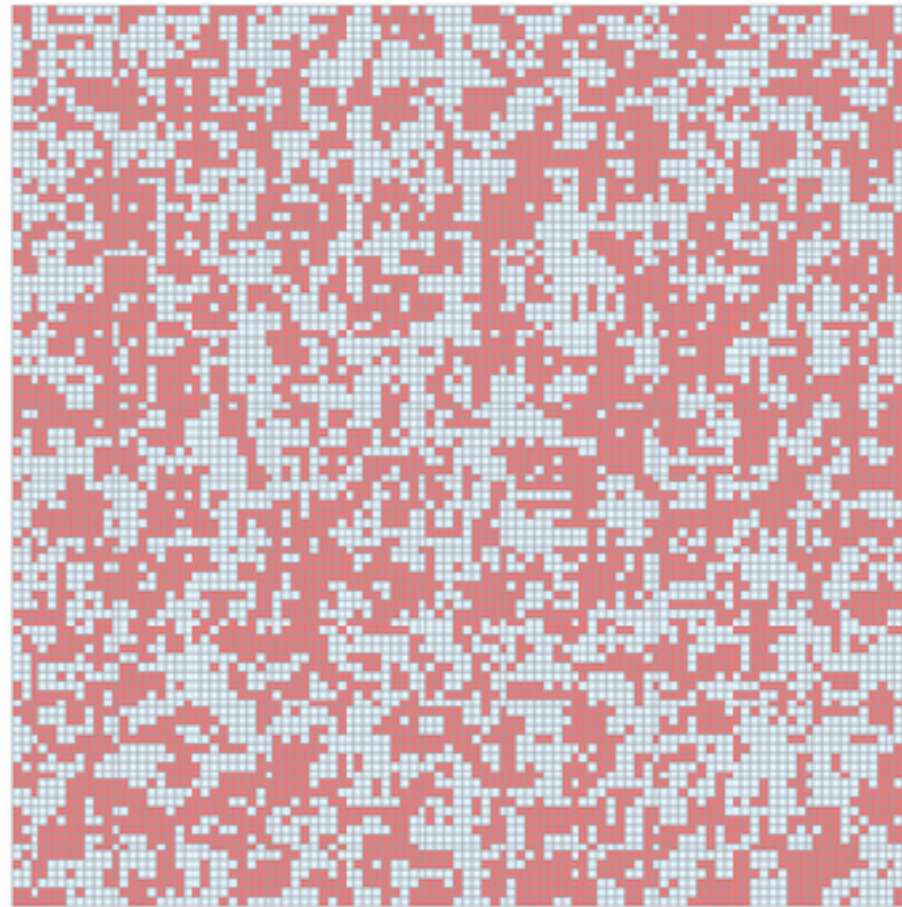
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joint w/ Matthew Jenssen (Oxford)

How can we use **statistical physics** tools and intuition in combinatorics?

The **cluster expansion** is a useful and versatile tool for enumeration

# Statistical physics



Model a physical material (a gas, magnet) as a random **spin configuration** on a graph

Probability distribution determined by **local interactions**.

# Statistical physics

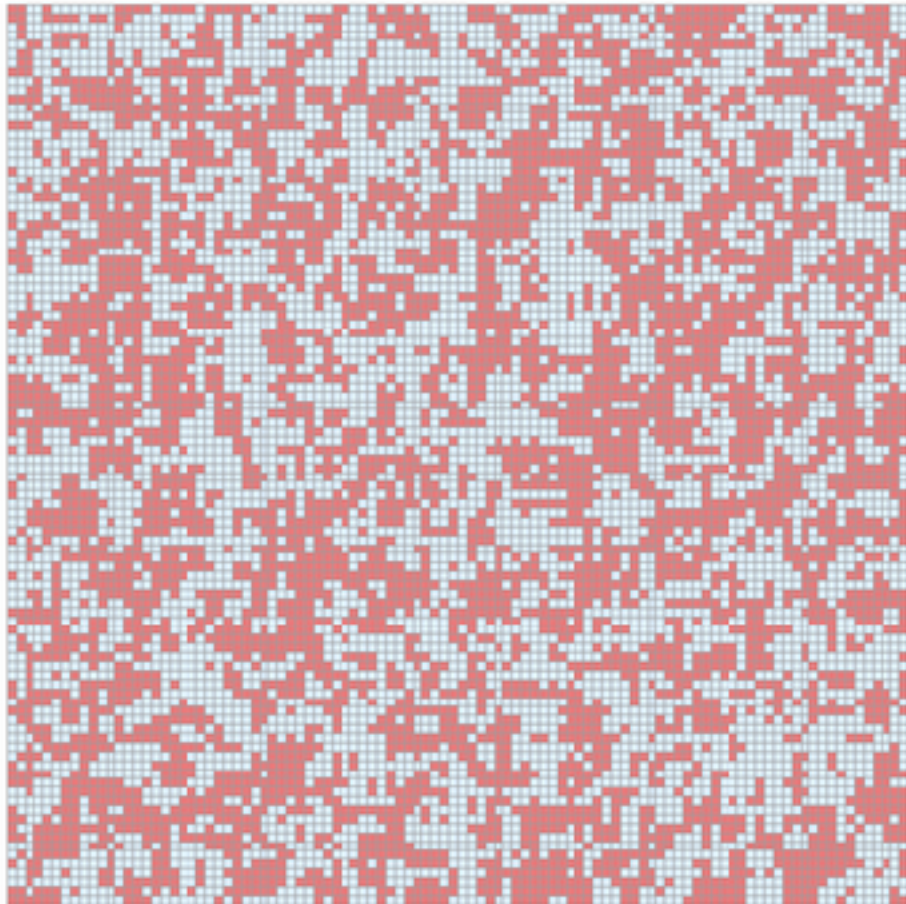
**Ising model:** +1, -1 spins assigned to vertices:

$$\mu(\sigma) = \frac{e^{\beta \sum_{(u,v) \in E} \sigma_u \sigma_v}}{Z_G(\beta)}$$

$$Z_G(\beta) = \sum_{\sigma} e^{\beta \sum_{(u,v) \in E} \sigma_u \sigma_v}$$

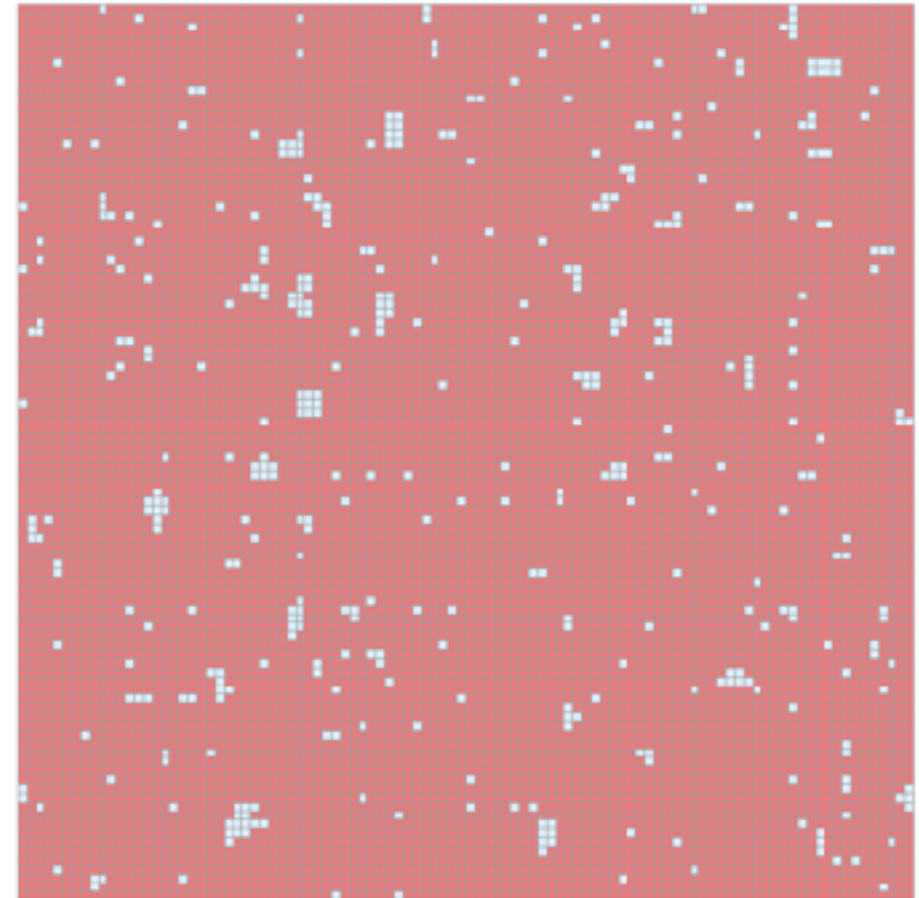
Energy, inverse temperature, partition function

# High and low temperatures



## High temperature

- Weak interactions
- Decay of correlations
- Disorder
- Rapid mixing



## Low temperature

- Strong interactions
- Strong correlations
- Long-range order
- Slow mixing

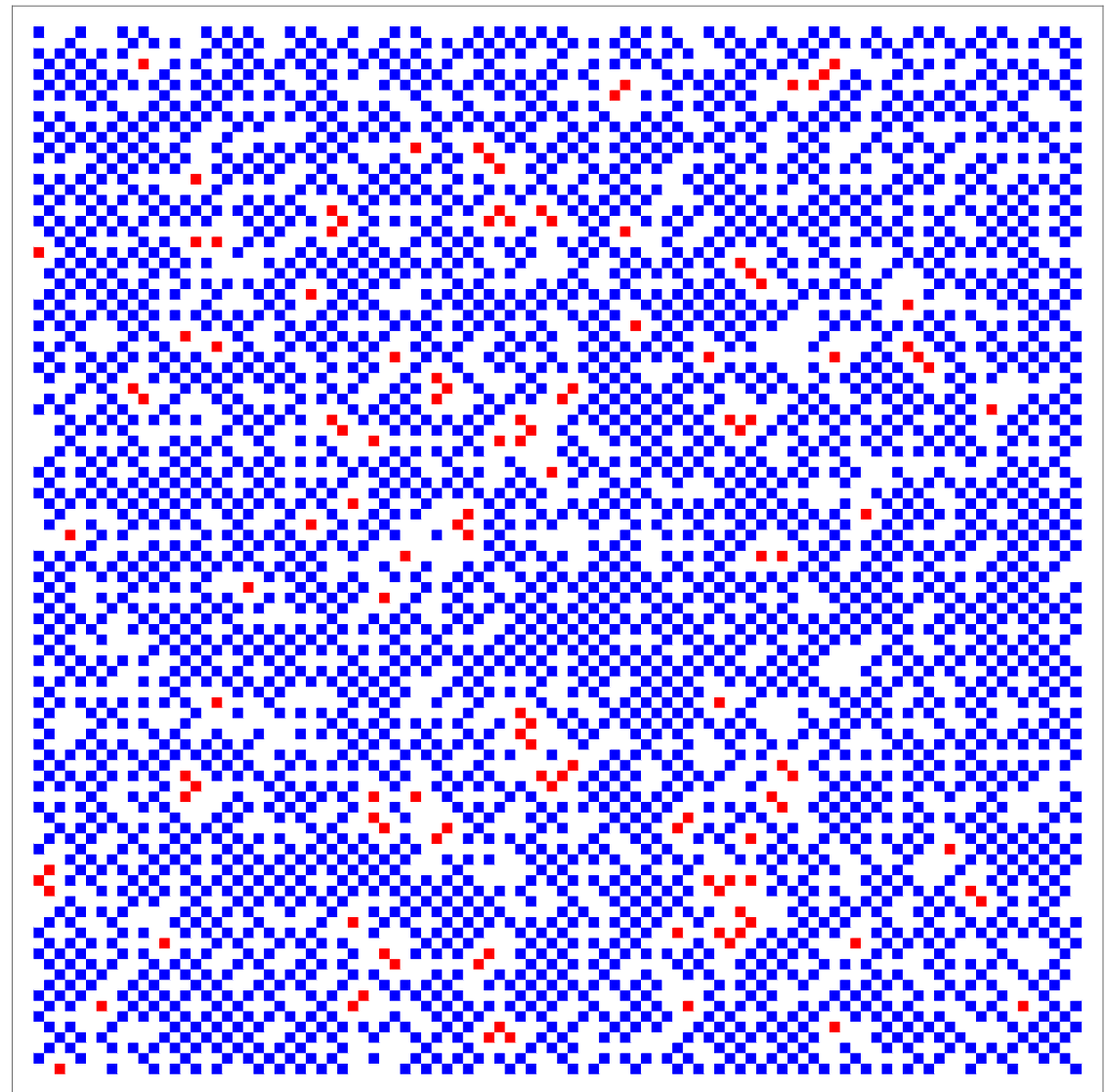


# Hard-core model

**Hard-core model:** weighted independent sets

$$\mu(I) = \frac{\lambda^{|I|}}{Z_G(\lambda)}$$

$$Z_G(\lambda) = \sum_I \lambda^{|I|}$$



Large  $\lambda$  is akin to low temperature. On  $\mathbb{Z}^d$  (bipartite) there are two **ground states** (even/odd)

# Statistical physics perspective

1. Computing (approximately)  $Z_G$  is the central task

**Weighted counting**

2. Understand **correlations** between spins

**Properties of a 'typical' object**

3. Understand changes in correlations as  $\lambda, \beta$  changes

**Extra parameter can help**

# Combinatorics at low temperature

## Combinatorics

- Find an **extremal** object satisfying a property
- Count the **number** of such objects
- Describe a **typical** such object

## Physics

- Find a **ground state**
- Compute the **partition function**
- Describe the **Gibbs measure**



# Independent sets in the hypercube

Let  $Q_d$  be the **discrete hypercube** and consider its independent sets.

**Theorem 1** (Korshunov–Sapozhenko, 1983)

$$i(Q_d) = Z_{Q_d}(1) = (2 + o(1))\sqrt{e}2^{2^{d-1}}$$

Sapozhenko's later simplification of the proof has proved very influential: an example of the method of **graph containers**

# Independent sets in the hypercube

**Theorem 2.** (Galvin, 2011)

For  $\lambda > \sqrt{2} - 1$ ,

$$Z(\lambda) = (2 + o(1)) \cdot \exp \left[ \frac{\lambda}{2} \left( \frac{2}{1 + \lambda} \right)^d \right] (1 + \lambda)^{2^{d-1}}$$

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For  $\lambda = \Omega(\log d \cdot d^{-1/3})$ , asymptotics of  $\log Z$

# Independent sets in the hypercube

## Theorem 3. (Jenssen, P.)

1) Asymptotics of  $Z_{Q_d}(\lambda)$  for all fixed  $\lambda$ . E.g

$$Z = (2 + o(1)) \cdot \exp \left[ \frac{\lambda}{2} \left( \frac{2}{1 + \lambda} \right)^d \left( 1 + \frac{(2\lambda^2 + \lambda^3)d(d-1) - 2}{4(1 + \lambda)^d} \right) \right] (1 + \lambda)^{2^{d-1}} \text{ for } \lambda > 2^{1/3} - 1$$

2) Expansion to arbitrary precision, e.g.

$$i(Q_d) = 2\sqrt{e} \cdot 2^{2^{d-1}} \left( 1 + \frac{3d^2 - 3d - 2}{8 \cdot 2^d} + \frac{243d^4 - 646d^3 - 33d^2 + 436d + 76}{384 \cdot 2^{2d}} + O(d^6 \cdot 2^{-3d}) \right)$$

3) Essentially **complete probabilistic understanding** of the structure typical (weighted) independent sets (Poisson limits, CLT's, large deviations, correlation decay...)

# Perturbative tools

**Idea:** precisely measure **deviations** from a simple, known distribution or configuration.

**High temperature:** expand around iid spins

**Low temperature:** expand around the constant configurations

**Mathematically:** control an infinite series expansion of the log partition function: **the cluster expansion**

# Cluster expansion

Infinite series representation for  $\log Z$

- How to compute the terms?
- When does the series converge?

Setting: multivariate hard-core model

$$Z_G(\vec{\lambda}) = \sum_I \prod_{v \in I} \lambda_v$$

Series for  $\log Z_G(\vec{\lambda})$

# Cluster expansion

**Cluster:** multiset of vertices that induce a connected subgraph in  $G$

**Ursell function:**

$$\phi(H) = \frac{1}{|V(H)|!} \sum_{\substack{A \subseteq E(H) \\ \text{spanning, connected}}} (-1)^{|A|}$$

Example:



# Cluster expansion

Formally,

$$\log Z_G(\vec{\lambda}) = \sum_{\Gamma} \phi(H(\Gamma)) \prod_{v \in \Gamma} \lambda_v$$

Example:

# Convergence?

When does the cluster expansion converge?

Classic topic in statistical physics (Mayer, Penrose,...)

## Kotecky-Preiss

Given  $a : V \rightarrow [0, \infty)$ , suppose for all  $v$ ,

$$\sum_{u \in \{v\} \cup N(v)} e^{a(u)} |\lambda_u| \leq a(v).$$

Then the cluster expansion **converges absolutely**, and

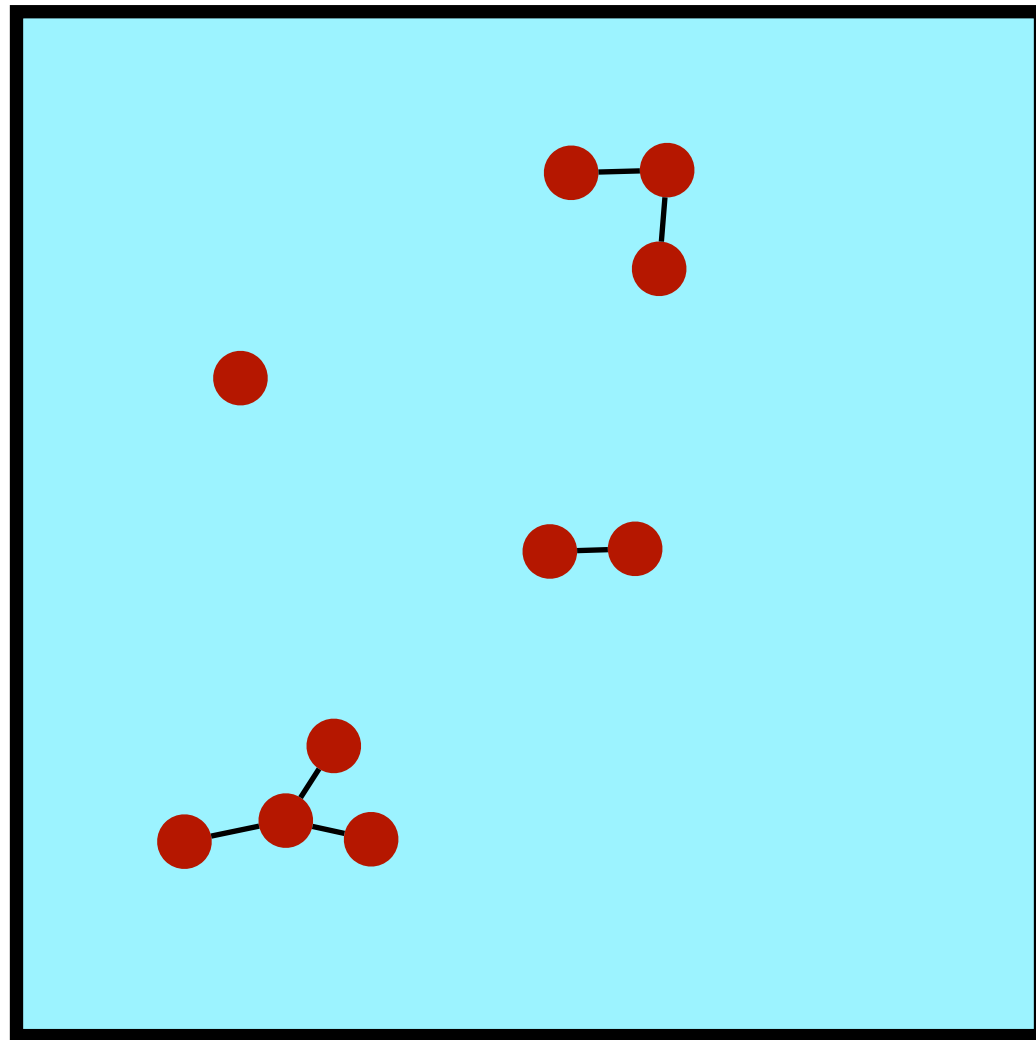
$$\sum_{\Gamma \ni v} \left| \phi(H(\Gamma)) \prod_{u \in \Gamma} \lambda_u \right| \leq a(v).$$

# Convergence?

**Example:**  $G$  has max degree  $\Delta$  and  $|\lambda_v| \leq \lambda$

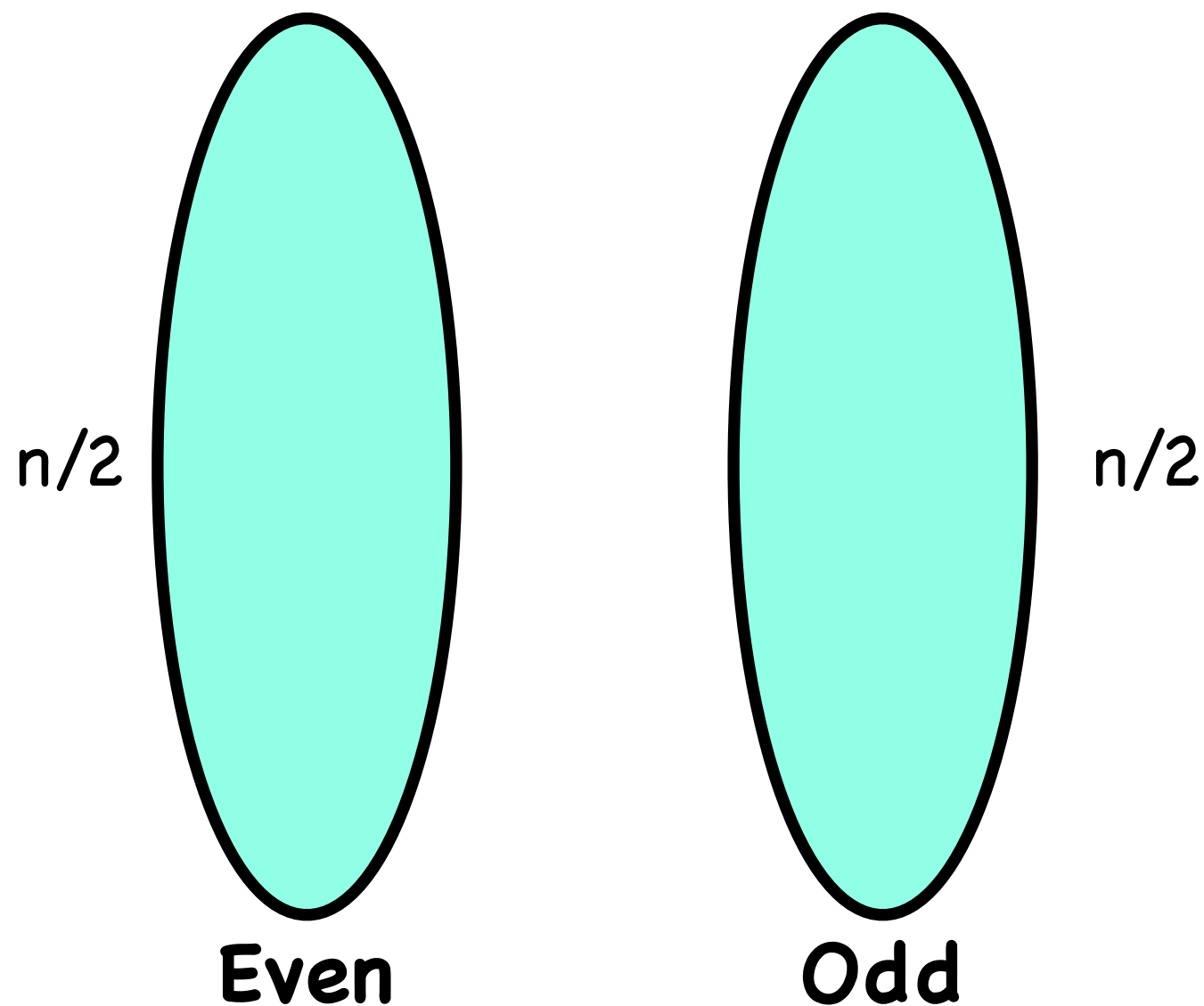
# Combinatorics at low temperature

We can use the cluster expansion to account for **deviations** from a ground state.



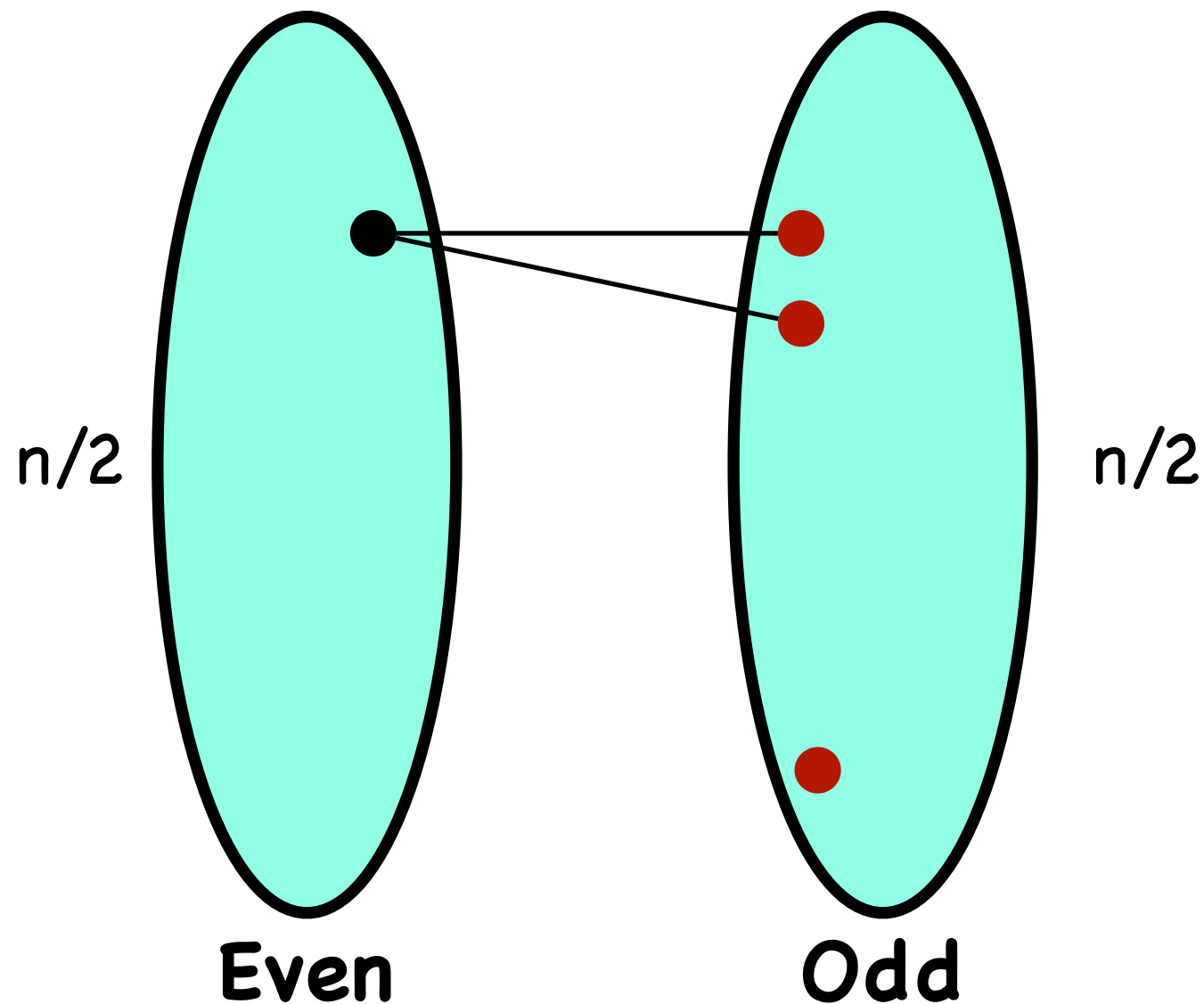
For the Ising model, deviations from the blue ground state are **connected components of red vertices**

# Independent sets in bipartite graphs



Two **ground states**: **Even** (no odds), **Odd** (no evens)  
each of weight  $(1 + \lambda)^{n/2}$  (or  $2^{n/2}$  for unweighted case)

# Independent sets in bipartite graphs

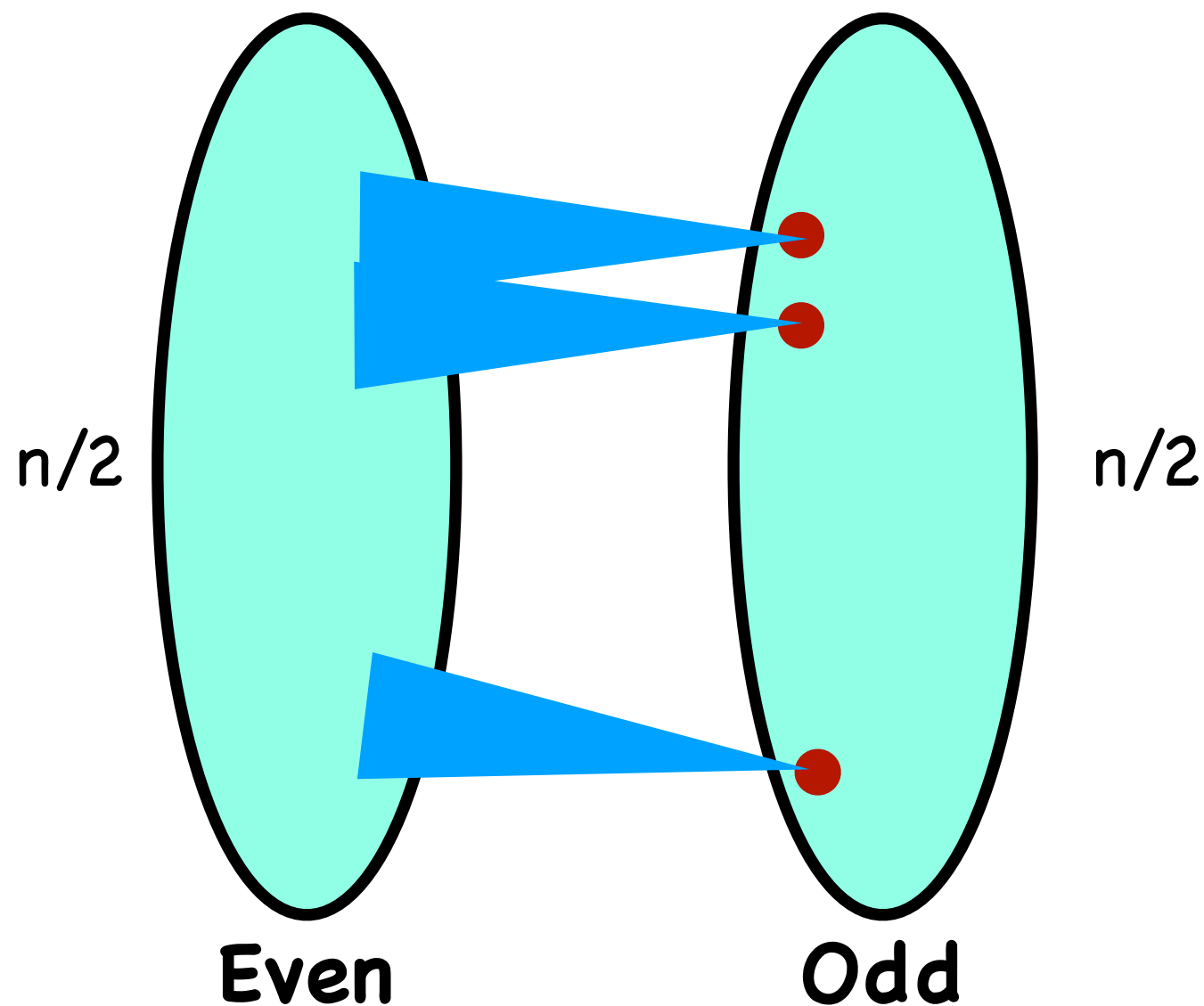


Deviations from **Even** are **2-linked components of odd vertices**.

How much does a deviation **cost** (relative to ground state)?



# Independent sets in bipartite graphs



A deviation  $\gamma$  costs  $\frac{\lambda^{|\gamma|}}{(1 + \lambda)^{|N(\gamma)|}}$ . The cost **factorizes** over deviations!

# Independent sets in bipartite graphs

Now we rewrite the partition function in terms of deviations (**polymers**):

$$Z = (1 + \lambda)^{n/2} \sum_{\Gamma} \prod_{\gamma \in \Gamma} \frac{\lambda^{|\gamma|}}{(1 + \lambda)^{|N(\gamma)|}}$$

sum is over all collections of **compatible** polymers (union is not 2-linked)

We want to measure contributions from **mostly even** or **mostly odd** configurations separately.

# Independent sets in bipartite graphs

Define a **polymer** as a defect of size at most  $n/10$ , say.

Define the **even partition function**:

$$Z_{\text{even}} = (1 + \lambda)^{n/2} \cdot \Xi_{\text{even}} = (1 + \lambda)^{n/2} \sum_{\Gamma} \prod_{\gamma \in \Gamma} \frac{\lambda^{|\gamma|}}{(1 + \lambda)^{|N(\gamma)|}}$$

sum is over all collections of **compatible** (small) polymers.

Define  $Z_{\text{odd}}$  analogously.

# Independent sets in bipartite graphs

What have we gained by defining  $Z_{\text{even}}, Z_{\text{odd}}$ ?

Depends on the graph  $G$  (and the value of  $\lambda$ )!

If  $G$  is a **sufficiently good expander** and  $\lambda$  is large enough then:

- 1)  $Z \approx Z_{\text{even}} + Z_{\text{odd}}$  (exponentially small rel. error)
- 2) **Cluster expansion** for  $\Xi_{\text{even}}, \Xi_{\text{odd}}$  converges

**Cluster expansion convergence** allows us to **approximate  $Z$**  very accurately (algorithmically!) and gives strong **correlation decay** properties

# Independent sets in bipartite graphs

**Warm-up example:** random  $\Delta$ -regular bipartite expander graphs (paper w/ Jenssen & Keevash)

**Hypercube:** not a great expander for large sets but **graph containers** to the rescue

# Expander graphs

Let  $G$  be a  $\Delta$ -regular bipartite graph on  $n$  vertices so that  $|N(S)| \geq (1 + \alpha) |S|$  for every  $|S| \leq n/4$  on one side of the bipartition.

With  $w(\gamma) = \frac{\lambda^{|\gamma|}}{(1 + \lambda)^{|N(\gamma)|}}$ , we have:

$$\Xi_{\text{even}} = \sum_{\Gamma} \prod_{\gamma \in \Gamma} w(\gamma)$$

This is a **multivariate hard-core model!**  
(with the incompatibility graph on polymers)

The **larger**  $\lambda$  the smaller the fugacities



# Expander graphs

Check the Kotecky–Preiss condition:

$$\sum_{\gamma' \neq \gamma} e^{|\gamma'|} w(\gamma') \leq |\gamma|$$

Expansion gives the bound:  $w(\gamma) \leq \frac{\lambda^{|\gamma|}}{(1 + \lambda)^{(1+\alpha)|\gamma|}}$

# Expander graphs

Need an approximation lemma:

$$\frac{Z - Z_{\text{odd}} - Z_{\text{even}}}{Z} \leq e^{-n}$$

This is a kind of Markov chain **slow-mixing** result:  
it says there is a bottleneck in the state space

**The algorithm:** compute cluster expansion up to size  $\log n$  for  $\Xi_{\text{even}}, \Xi_{\text{odd}}$ , exponentiate, add together, and multiply by  $(1 + \lambda)^{n/2}$ .

# Hypercube

Back to  $Q_d$ .

Small sets are **very good expanders**:  $|S| \leq d^2$   
expand by  $cd$ .

Large sets are **not**: expand by factor  $(1 + O(1/\sqrt{d}))$ .  
Using the same argument we'd need large  $\lambda$ .

# Convergence

For larger  $\gamma$ , we use the **container lemma** of **Sapozhenko** and **Galvin**: let  $\mathcal{G}(a, b)$  be the family of 2-linked  $A$  with  $|[A]| = a, |N(A)| = b$ .

$$\text{For all } \lambda \geq \frac{C_0 \log d}{d^{1/3}}, a \leq 2^{d-2}$$
$$\sum_{A \in \mathcal{G}(a, b)} \frac{\lambda^{|A|}}{(1 + \lambda)^b} \leq 2^d \exp \left( -\frac{C_1(b - a) \log d}{d^{2/3}} \right).$$

This **works perfectly** to verify the K-P condition for large polymers!

# Consequences

With cluster expansion convergence + approximation lemma we can derive many consequences:

$$Z \approx 2(1 + \lambda)^{2^{d-1}} \cdot \Xi_{\text{even}}$$

**Approximation to  $\mu$ :**

pick **even/odd** at random

sample a **configuration  $X$  of polymers** with probability

$$\prod_{\gamma \in X} w(\gamma) / \Xi_{\text{even}}$$

Independently sample **unblocked even vertices**.

# Terms of the cluster expansion

The cluster expansion gives an **asymptotic expansion** for the log partition function

**Theorem 6.** (Jenssen, P.)

For  $\lambda = \Omega(\log d \cdot d^{-1/3})$ ,

$$Z(\lambda) = 2(1 + \lambda)^{2^{d-1}} \cdot \exp \left[ \sum_{j=1}^k L_j + \epsilon_k \right]$$

The term  $L_j$  only depends on clusters of size  $j$ ,  
and  $\epsilon_k = o(L_k)$ .

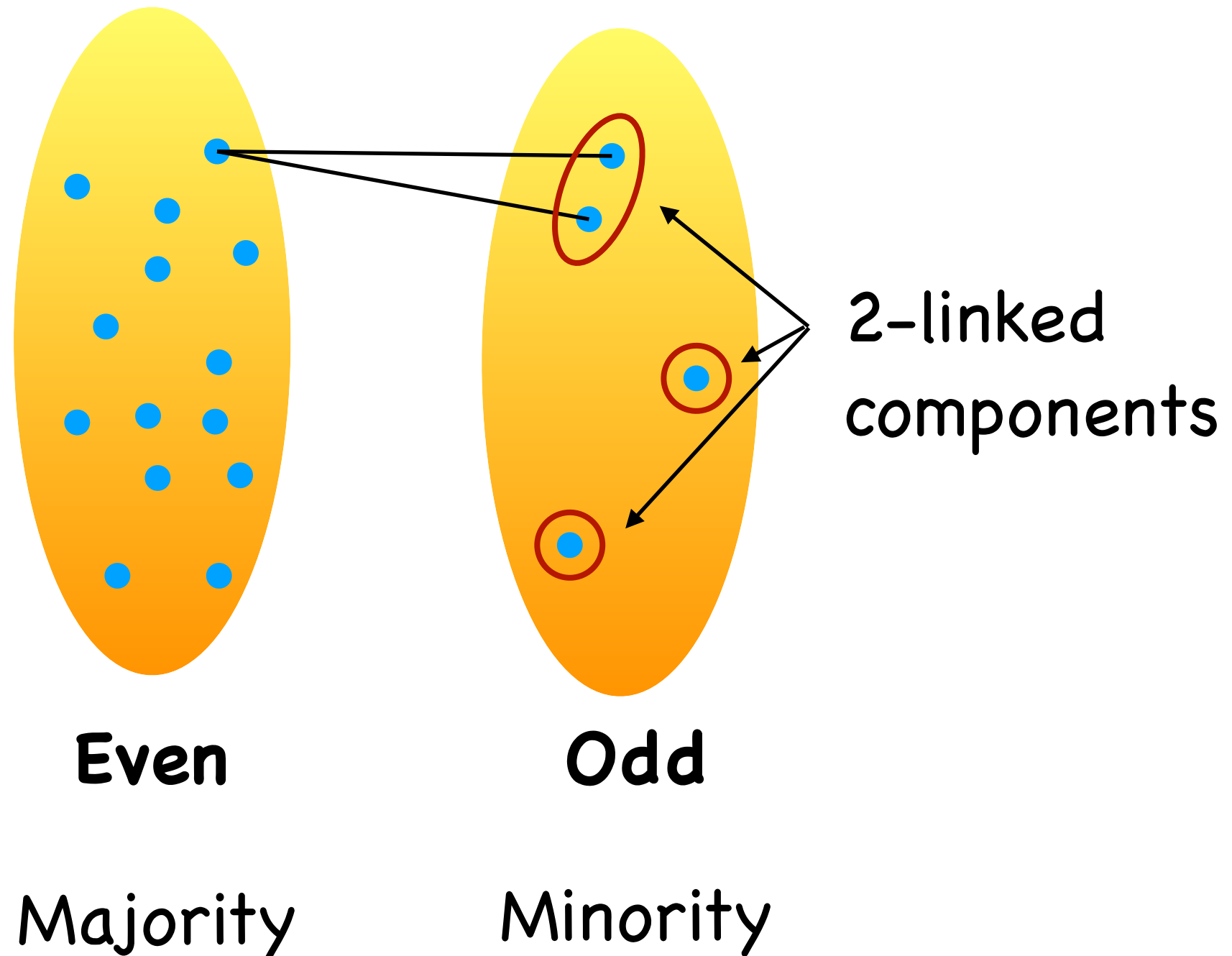


# Terms of the cluster expansion

What do the terms  $L_j$  look like?

# The hard-core model

What does a **typical independent set** from  $\mu_\lambda$  look like?

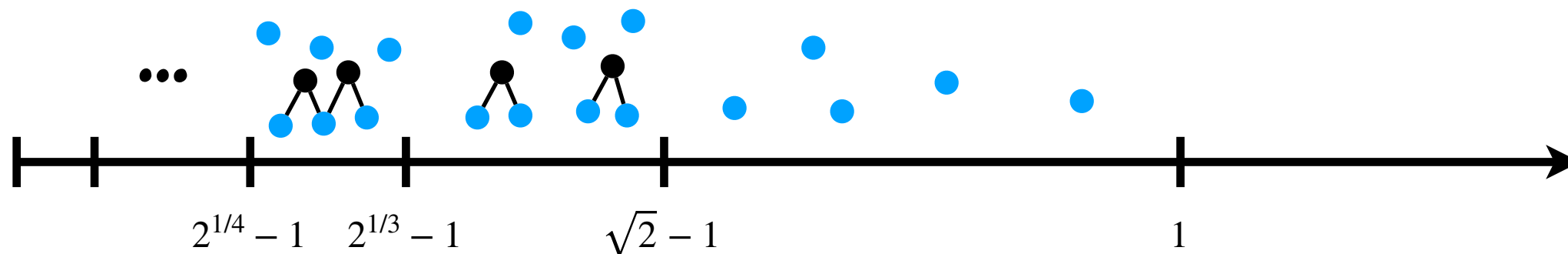


# The hard-core model

## Theorem 3. (Galvin, 2011)

For  $\lambda = 1 + s/d$ , the number of occupied vertices on the minority side is **asymptotically Poisson** with mean  $e^{-s/2}/2$

.....  
If  $\lambda > 2^{1/(m+1)} - 1$  then whp the largest 2-linked occupied component on the minority side is of size at most  $m$



# New results

## Theorem 4. (Jenssen, P.)

The **threshold** for emergence of 2-linked components of size  $m$  is:

$$\lambda = 2^{1/m} - 1 + \frac{2^{1+1/m}(m-1)\log d}{md} + \frac{s}{d}$$

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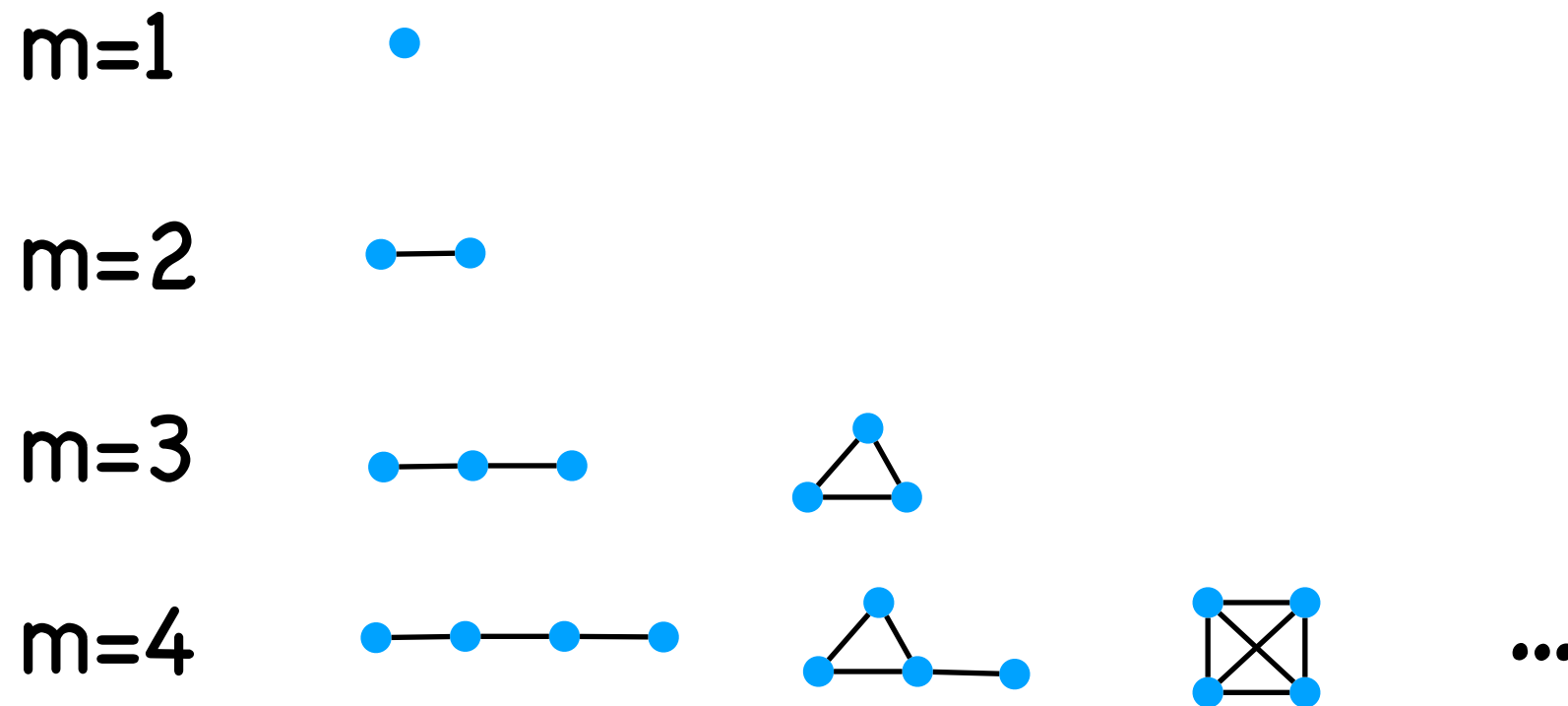
If  $s \rightarrow \infty$  then whp there are no components of size  $m$

If  $s \rightarrow -\infty$  then whp there are components of size  $m$

If  $s$  is constant, then the number of  $m$ -components is  
**asymptotically Poisson**

# New results

2-linked components have an **isomorphism type** as a graph:



What is the **joint distribution** of the numbers of each type of 2-linked component on the minority side?

**Independent Normals, Poissons!**

# Further applications of the method

**Balogh, Garcia, Li:** asymptotics for number of independent sets in middle 2 layers of  $Q_d$

**Jenssen, Keevash:** asymptotics for number of  $q$ -colorings of  $Q_d$  for all  $q$ . (Galvin  $q=3$ , Kahn–Park  $q=4$ )

**Davies, Jenssen, P.:** proof of the Upper Matching Conjecture for large  $n$ . Cluster expansion for  $i_k(G)$ .

Many **low-temperature** algorithmic results.

# Further reading

**This paper:** <https://arxiv.org/abs/1907.00862>

**Galvin:** <https://www3.nd.edu/~dgalvin1/pdf/countingindsetsinQd.pdf>

**Friedli-Vilenik:** <https://www.unige.ch/math/folks/velenik/smbook/>

**Scott-Sokal:** <https://people.maths.ox.ac.uk/scott/Papers/llshort.pdf>

**algorithms:** <https://arxiv.org/abs/1806.11548>

# Open problems

1. Can we apply the cluster expansion to other applications of graph containers?
2. What about hypergraph containers?
3. Further applications of statistical physics tools?

Thank you!