

Asymptotics of even-even correlations in the Ising model

(joint work with Sébastien OTT)

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Introduction and results

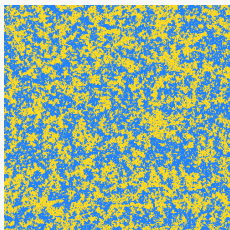
Formal Hamiltonian:
$$\mathcal{H}_\Lambda = - \sum_{\{i,j\} \subset \mathbb{Z}^d} J_{j-i} \sigma_i \sigma_j$$

- ▶ *ferromagnetism:* $J_x \geq 0$ for all $x \in \mathbb{Z}^d$;
- ▶ *symmetry:* $J_x = J_{-x}$ for all $x \in \mathbb{Z}^d$;
- ▶ *finite-range:* $\exists R < \infty$ such that $J_x = 0$ whenever $\|x\|_2 \geq R$;
- ▶ *irreducibility:* $J_x > 0$ for all $x \in \mathbb{Z}^d$ with $\|x\| = 1$.

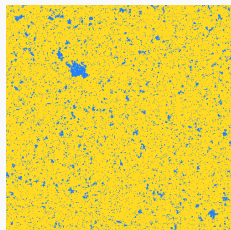
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We assume that $d \geq 2$ and $\beta < \beta_c(d)$, and let μ_β be the unique Gibbs measure.



$\beta < \beta_c(2)$



$\beta > \beta_c(2)$

Let $\text{Cov}_\beta(f, g) = \mu_\beta(fg) - \mu_\beta(f)\mu_\beta(g)$.

Let $[x] \in \mathbb{Z}^d$ be the coordinate-wise integer part of $x \in \mathbb{Z}^d$.

Theorem [Aizenman, Barsky, Fernández 1987]

For all $\beta < \beta_c(d)$ and any unit-vector \mathbf{u} in \mathbb{R}^d , the **inverse correlation length**

$$\xi_\beta(\mathbf{u}) = - \lim_{n \rightarrow \infty} \frac{1}{n} \log \text{Cov}_\beta(\sigma_0, \sigma_{[n\mathbf{u}]})$$

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What about covariances of more general functions?

Asymptotics of correlations

Let f, g be two *local* functions and denote by θ_x the translation by $x \in \mathbb{Z}^d$.

What is the asymptotic behavior of

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Let $\sigma_A = \prod_{i \in A} \sigma_i$. Writing

$$f = \sum_{A \subset \text{supp}(f)} \hat{f}_A \sigma_A, \quad g = \sum_{B \subset \text{supp}(g)} \hat{g}_B \sigma_B,$$

yields

$$\text{Cov}_\beta(f, \theta_{[n\mathbf{u}]}g) = \sum_{\substack{A \subset \text{supp}(f) \\ B \subset \text{supp}(g)}} \hat{f}_A \hat{g}_B \text{Cov}_\beta(\sigma_A, \sigma_{B+n\mathbf{u}}).$$

This motivates the following

Main question

What is the asymptotic behavior of

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Of course, by symmetry, $\mu_\beta(\sigma_C) = 0$ whenever $|C|$ is odd.

In particular, if $|A| + |B|$ is odd, then $\text{Cov}_\beta(\sigma_A, \sigma_B) = 0$.

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There are thus **two cases to consider**:

Odd-odd correlations

$|A|, |B|$ both odd

Even-even correlations

$|A|, |B|$ both even

Theorem [Campanino, Ioffe, V. 2004]

Let $d \geq 2$ and $\beta < \beta_c(d)$. Let $A, B \in \mathbb{Z}^d$ with $|A|$ and $|B|$ odd.

For any unit-vector \mathbf{u} , there exists a constant $0 < C < \infty$ (depending on A, B, \mathbf{u}, β) such that

$$\text{Cov}_\beta(\sigma_A, \sigma_{B+[n\mathbf{u}]}) = \frac{C}{n^{(d-1)/2}} e^{-\xi_\beta(\mathbf{u})n} (1 + o(1)),$$

as $n \rightarrow \infty$.

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as $n \rightarrow \infty$.

This result has a **long history**. Some milestones:

- | | | |
|---|-----------------|----------------------|
| ▶ Ornstein–Zernike 1914, Zernike 1916: | $ A = B = 1$ | non-rigorous |
| ▶ Abraham–Kunz 1977, Paes–Leme 1978: | $ A = B = 1$ | $\beta \ll 1$ |
| ▶ Bricmont–Fröhlich 1985, Minlos–Zhizhina 1988, 1996: | $ A , B $ odd | $\beta \ll 1$ |
| ▶ Campanino–Ioffe–V. 2003: | $ A = B = 1$ | $\beta < \beta_c(d)$ |

Substantially more delicate!

The analysis started with the case $|A| = |B| = 2$. Physicists quickly understood that

$$\text{Cov}_\beta(\sigma_A, \sigma_{B+[nu]}) = e^{-2\xi_\beta(\mathbf{u})n(1+o(1))}.$$

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However, concerning the prefactor, two conflicting predictions were put forward:

Polyakov 1969		Camp-Fisher 1971
n^{-2}	$d = 2$	n^{-d} for all $d \geq 2$
$(n \log n)^{-2}$	$d = 3$	
$n^{-(d-1)}$	$d \geq 4$	

(Note that both coincide with the exact computation when $d = 2$.)

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It turns out that Polyakov was right. This was first shown in

- ▶ *Bricmont-Fröhlich 1985*: $|A| = |B| = 2$ $\beta \ll 1$ $d \geq 4$
- ▶ *Minlos-Zhizhina 1988, 1996*: $|A|, |B|$ even $\beta \ll 1$ $d \geq 2$

Even-even correlations

$$\text{Let } \Xi(n) = \begin{cases} n^2 & \text{when } d = 2, \\ (n \log n)^2 & \text{when } d = 3, \\ n^{d-1} & \text{when } d \geq 4. \end{cases}$$

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Our main result is

Theorem [Ott, V. 2018]

Let $d \geq 2$ and $\beta < \beta_c(d)$. Let $A, B \in \mathbb{Z}^d$ with $|A|$ and $|B|$ even.

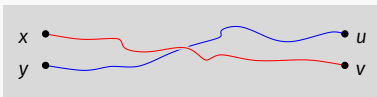
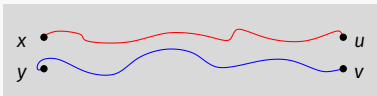
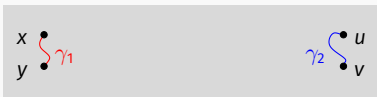
For any unit vector \mathbf{u} in \mathbb{R}^d , there exist constants $0 < C_- \leq C_+ < \infty$ (depending on A, B, \mathbf{u}, β) such that, for all n large enough,

$$\frac{C_-}{\Xi(n)} e^{-2\xi_\beta(\mathbf{u})n} \leq \text{Cov}_\beta(\sigma_A, \sigma_{B+[n\mathbf{u}]}) \leq \frac{C_+}{\Xi(n)} e^{-2\xi_\beta(\mathbf{u})n}.$$

Heuristics

Heuristics

Let $A = \{x, y\}$ and $B + [nu] = \{u, v\}$. **High-temperature expansion** of $\mu_\beta(\sigma_x \sigma_y \sigma_u \sigma_v)$ yields 3 types of configurations:

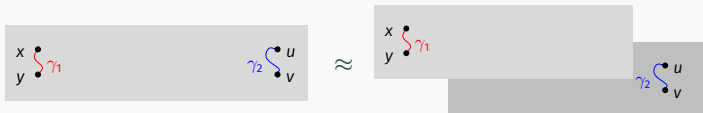


High-temperature expansion of $\mu_\beta(\sigma_x \sigma_y) \mu_\beta(\sigma_u \sigma_v)$ yields



Heuristics (and difficulties)

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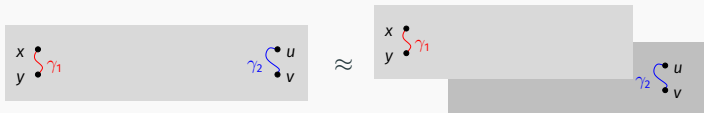


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Heuristics (and difficulties)

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Then, neglecting the interactions between γ_1, γ_2 would yield

$$\text{Cov}_\beta(\sigma_A, \sigma_{B+[nu]}) \approx \mu_\beta(\sigma_x \sigma_u) \mu_\beta(\sigma_y \sigma_v) + \mu_\beta(\sigma_x \sigma_v) \mu_\beta(\sigma_y \sigma_u) \approx n^{-(d-1)} e^{-2\xi_\beta(\mathbf{u})n},$$

which is what we want when $d \geq 4$. Assuming that the paths behave as random walk bridges and taking into account the non-intersection constraint would then yield the correct behavior also when $d = 2$ or 3 ...

1. In fact,

$$\begin{matrix} x \\ y \end{matrix} \int_{\gamma_1} \begin{matrix} u \\ v \end{matrix} \int_{\gamma_2} - \begin{matrix} x \\ y \end{matrix} \int_{\gamma_1} \begin{matrix} u \\ v \end{matrix} \int_{\gamma_2} = e^{-2\xi_{\beta}(\mathbf{u})n(1+o(1))}$$

and thus cannot be neglected!

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$$\int_x^y \int_u^v \gamma_1 \gamma_2 - \int_x^y \int_u^v \gamma_1 \gamma_2 = e^{-2\xi_\beta(\mathbf{u})n(1+o(1))}$$

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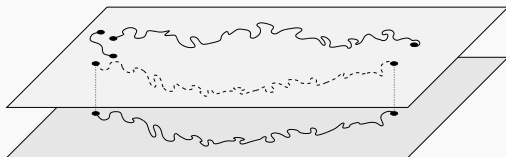
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2. The paths γ_1, γ_2 have long-distance (self)interactions. In particular, $w(\gamma_1, \gamma_2) \neq w(\gamma_1)w(\gamma_2)$.
3. It is not at all obvious why the non-intersection constraint should yield the same behavior as if γ_1 and γ_2 were random walk bridges.

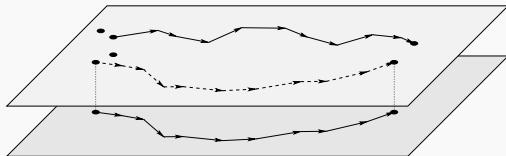
Problems with this argument

To solve these problems, we use

- ▶ The random-current & high-temperature, or the FK representations, in order to reduce to two **independent** objects (HT paths or FK clusters), conditioned on not intersecting:



- ▶ The Ornstein-Zernike theory (Campanino-Ioffe-V. 2003, 2008 and Ott-V. 2017), in order to approximate these objects using directed random walks on \mathbb{Z}^d :



Sketch of the lower bound

Sketch of the lower bound: Step 1

The first step is to prove that, for any $x, y \in A$ and $u, v \in B$ with $x \neq y$ and $u \neq v$, the following bound holds:

$$\frac{\text{Cov}_\beta(\sigma_A, \sigma_B)}{\mu_\beta(\sigma_x \sigma_u) \mu_\beta(\sigma_y \sigma_v)} \geq \sum_{\substack{C_1 \ni x, u \\ C_2 \ni y, v}} \mathbb{1}_{\{C_1 \cap C_2 = \emptyset\}} \mathbb{P}^{\text{FK}}(C_{x,u} = C_1 \mid x \leftrightarrow u) \mathbb{P}^{\text{FK}}(C_{y,v} = C_2 \mid y \leftrightarrow v),$$

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Note that the RHS is precisely the probability that the two clusters $C_{x,u}$ and $C_{y,v}$, sampled **independently** from $\mathbb{P}^{\text{FK}}(\cdot \mid x \leftrightarrow u)$ and $\mathbb{P}^{\text{FK}}(\cdot \mid y \leftrightarrow v)$, are disjoint.

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Note also that the denominator in the LHS provides the main “squared OZ” behavior. The RHS can then be used to find the corrections due to the non-intersection constraint.

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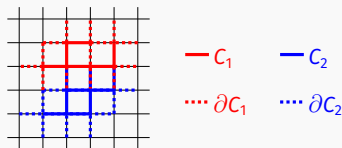
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Sketch of the lower bound: Step 1

Next, we partition the event in the last expression according to the realizations of clusters C_1, C_2 such that $x, u \in C_1$, $y, v \in C_2$ and $C_1 \cap C_2 = \emptyset$.

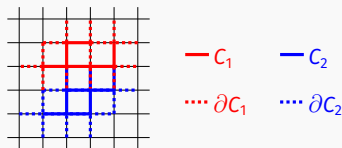
$$\begin{aligned}\mathbb{P}^{\text{FK}}(x \leftrightarrow u, y \leftrightarrow v, x \not\leftrightarrow y) &= \sum_{C_1, C_2} \mathbb{P}^{\text{FK}}(C_{x,u} = C_1, C_{y,v} = C_2) \\ &= \sum_{C_1, C_2} \mathbb{P}^{\text{FK}}(\mathcal{O}(C_1), \mathcal{C}(\partial C_1), \mathcal{O}(C_2), \mathcal{C}(\partial C_2))\end{aligned}$$



Sketch of the lower bound: Step 1

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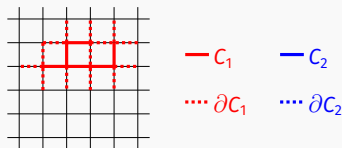
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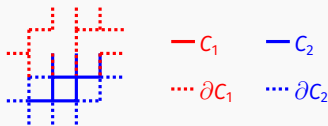
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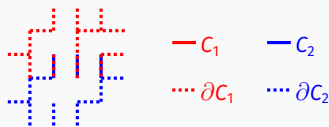
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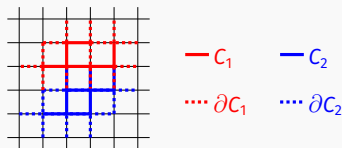
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Sketch of the lower bound: Step 1

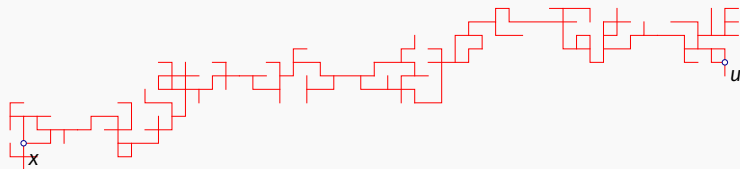
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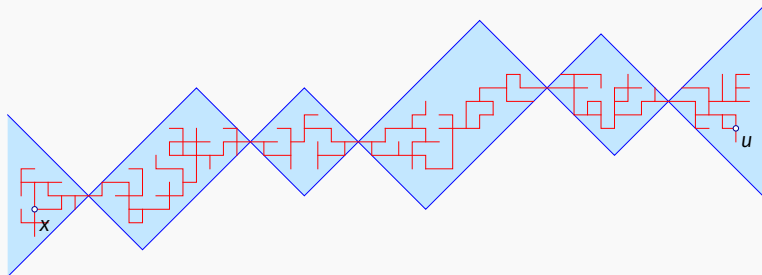
Sketch of the lower bound: Step 2

- ▶ We now only need to understand the asymptotic behavior of the probability that the two clusters do not intersect.
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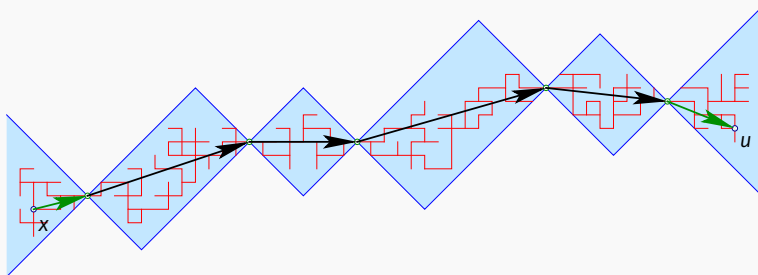
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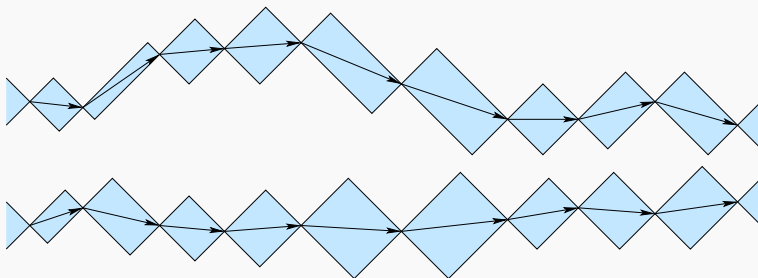


The resulting directed random walk has increments with exponential tails and thus approximates well the original cluster.

Sketch of the lower bound: Step 2

► Whenever the two “necklaces” are disjoint, the corresponding clusters are also necessarily disjoint.

↪ Lower bound in terms of a random walk event, with the same asymptotic behavior as non-crossing constraint.



Conclusion

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- ▶ It would be nice to obtain *sharp* asymptotics, but this seems difficult. Maybe by developing a version of OZ applicable directly in the (double)random-current representation...
- ▶ Extension to models with richer symmetry group seems interesting (even just a classification of possible behaviors). We could not find literature on the subject.

Thank you for your attention!