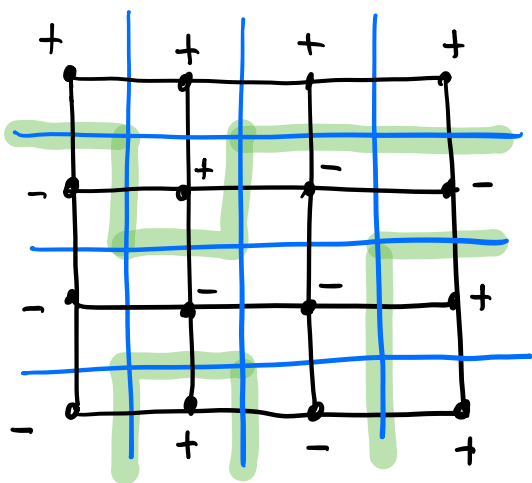


Mapping of the Ising model to a dimer model

Ising model: states are $s: V(\Gamma) \rightarrow \pm 1$

$\Gamma \subset$ square lattice (lattice domain connected simply connected)



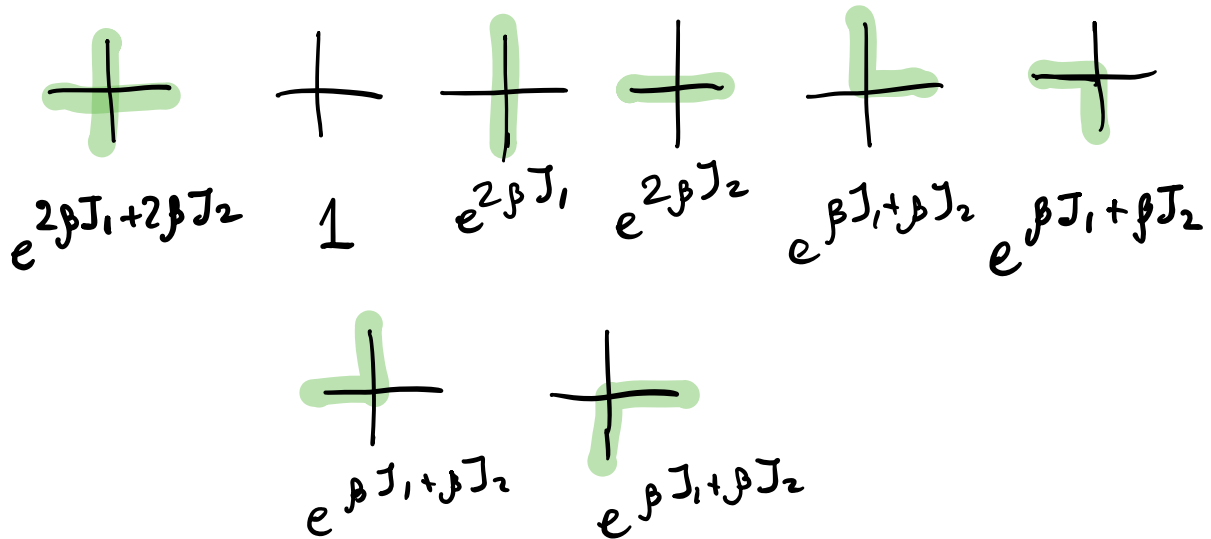
"Domain walls" are paths on Γ^v separating + and - regions

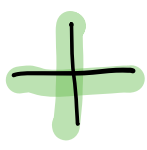
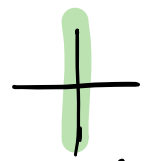
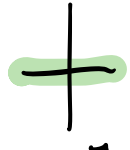
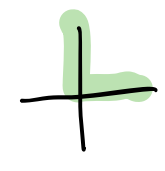
$$E(s) = -J_1 \sum_{\text{vertical edges (i,j)}} \sigma_i \sigma_j - J_2 \sum_{\text{horizontal edges (i,j)}} \sigma_i \sigma_j$$

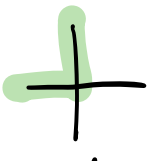
Boltzmann distribution:

$$\text{Prob}(s) = \frac{w(s)}{\sum_{s'} w(s')}, \quad w(s) = e^{-\beta E(s)}$$
$$\beta = \frac{1}{kT}$$

In terms of domain walls:



					
$e^{2\beta J_1 + 2\beta J_2}$	1	$e^{2\beta J_1}$	$e^{2\beta J_2}$	$e^{\beta J_1 + \beta J_2}$	$e^{\beta J_1 + \beta J_2}$

	
$e^{\beta J_1 + \beta J_2}$	$e^{\beta J_1 + \beta J_2}$

Claim

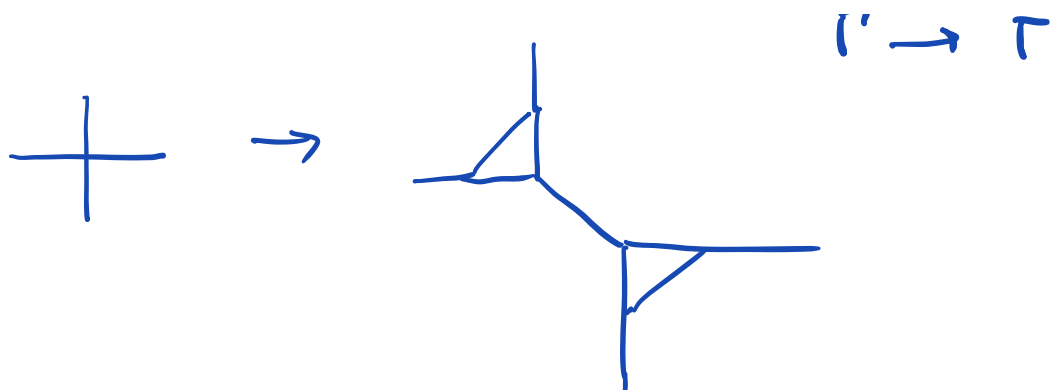
$$e^{-\beta E(\sigma)} = e^{-\beta J_1 |E_v| - \beta J_2 |E_h|} W(\text{domain walls})$$

$$W(\text{domain walls}) = \prod_v W_v(\text{local domain wall near } v)$$

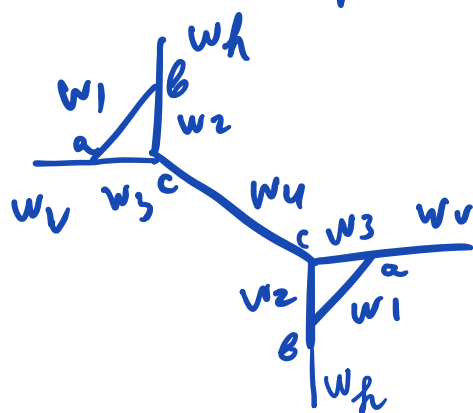
Now let us describe mapping to dimers

a) "Stretch" the dual lattice domain Γ^v :

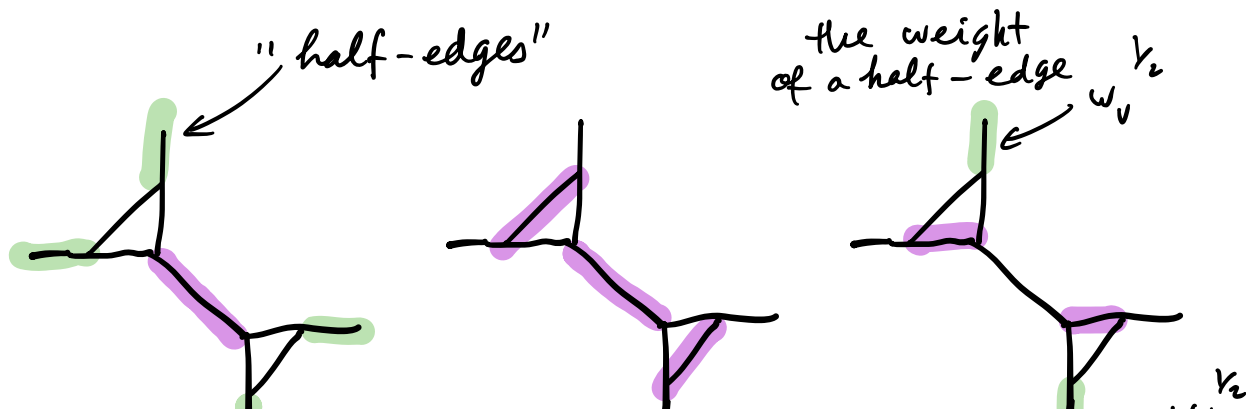
$-v \sim$

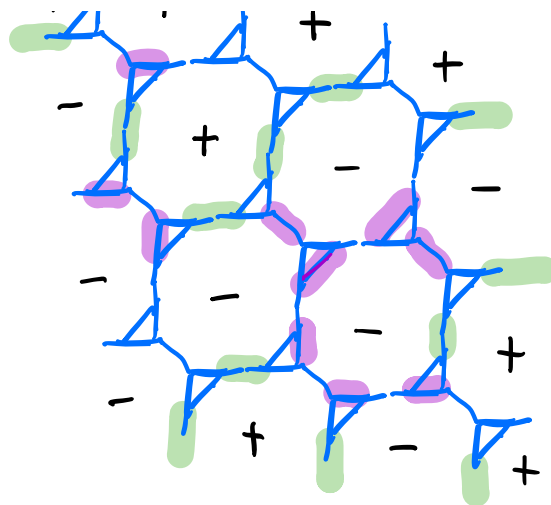
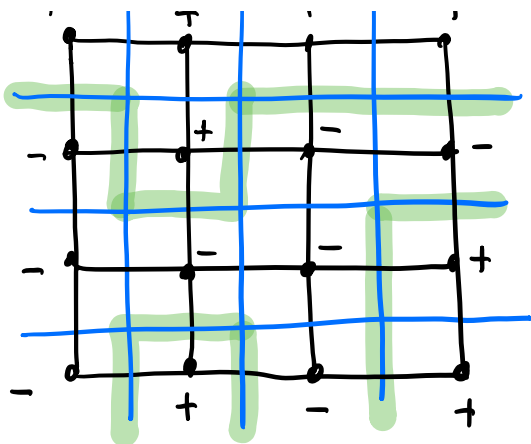


Assign dimer weights $w_1, w_2, w_3, w_4, w_5, w_h$ to edges of the graph $\tilde{\Gamma}$



b) Extend Ising domain walls on $\Gamma^\vee$ to dimer configuration on $\tilde{\Gamma}$:





Proposition When

$$w_4 = e^{2\beta J_1 + 2\beta J_2}, \quad w_3 = e^{\beta J_1}, \quad w_2 = e^{\beta J_2}$$

$$w_1 = e^{-\beta J_1 - \beta J_2}, \quad w_v = w_h = 1$$

the weight of a domain wall configuration on Γ^v is equal to the weight of the corresponding dimer configuration on $\tilde{\Gamma}$.

Corollary

$$Z_{\Gamma}^{\text{Ising}} = Z_{\Gamma^v}^{\text{domain walls}} = Z_{\tilde{\Gamma}}^{\text{dimers}}$$

Note: $\tilde{\Gamma}$ is not bipartite, so no random

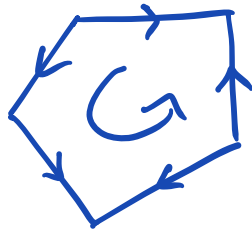
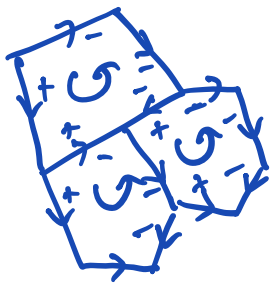
surfaces here.

Kasteleyn solution

Computation of the partition function
and of correlation functions in terms of
Pfaffians.

$$(T \subset \mathbb{R}^2)$$

① Kasteleyn orientation of a plane graph.



$$\prod_{e \in \partial f} \varepsilon(e, f) = -1$$

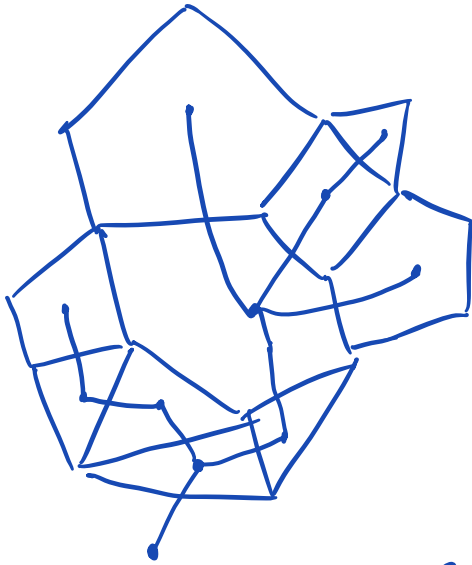
Proposition Kasteleyn orientations exist

Proof. h/w

let us construct a Kasteleyn orientation.

• choose a spanning tree T for T^V

- orient edges of Γ that do not intersect T arbitrarily

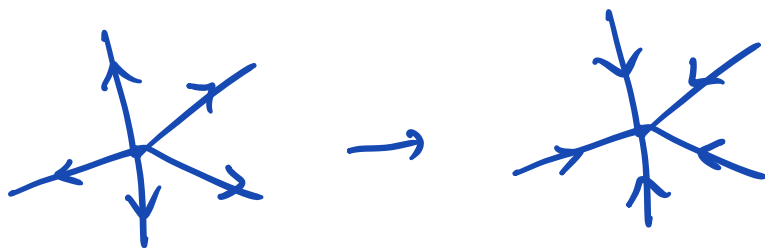


- orient edges on the boundary of faces corresponding to leaves of T such that they will be K -oriented.

remove these faces and consider remaining cell complex with the corresponding spanning tree T' .

- continue this procedure.
- The result will be a K -orientation of Γ .

Def. Two K -orientations K, K' are equivalent if K' can be obtained from K by a sequence of orientation reversing maps :



Thm. All K-orientations of a plane graph are equivalent.

Proof. h/w.

let K_1, K_2 be two Kasteleyn orientations

define

$$\varepsilon_{K_1 K_2}(e) = \begin{cases} 1, & K_1 \text{ orientation of } e \text{ coincide with } K_2 \text{-orientation} \\ -1, & \text{otherwise} \end{cases}$$

Clearly

$$\prod_{e \in \partial f} \varepsilon_{K_1 K_2}(e) = 1$$

for any face f .

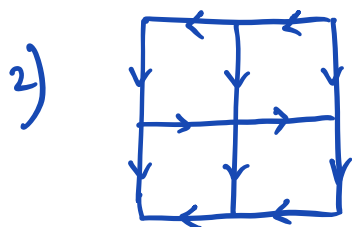
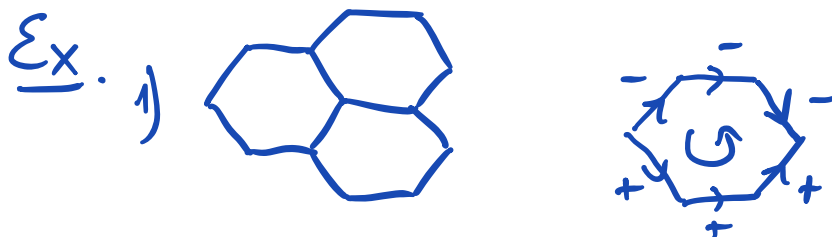
Therefore $\varepsilon_{K_1 K_2}$ defines a representation

$$\rho_{K_1 K_2}: \pi_1(\Sigma) \rightarrow \mathbb{Z}_2. \quad \text{Clearly } \varepsilon_{K_1 K_2} = \varepsilon_{K_2 K_1}$$

Lemma. • Each representation can be obtained in this way.

- If $K_1 \sim K_1'$, then $P_{K_1 K_2} = P_{K_1' K_2}$.

Proof. h/w.



② Kasteleyn matrix :

Let $w(e) > 0$ be weights of edges
and K be a Kasteleyn orientation

$$A_{ij}^K = \begin{cases} w(ij), & i \rightarrow j \\ -w(ij), & i \leftarrow j \\ 0, & \text{not connected} \end{cases}$$

Theorem (Kasteleyn)

$$\text{Pf}(A^K) = \varepsilon^K \sum_{D \subset E} \prod_{e \in D} w(e)$$

where

$$\text{Pf}(A) = \frac{1}{2^{n/2} (n/2)!} \sum_{\sigma \in S_n} (-1)^\sigma \prod_{i=1}^{n/2} A_{\sigma_i \sigma_{i+1}}$$

$A: n \times n$, skew symmetric, n is even

and
$$\varepsilon^K = (-1)^\sigma \varepsilon_{\sigma_1 \sigma_2}^K \cdots \varepsilon_{\sigma_{n-1} \sigma_n}^K$$

does not depend on the permutation σ .

Proof. (see LN-38)

Digression on Grassman integrals and Pfaffians.

Consider $\mathbb{C}^n$,

$$\wedge^n \mathbb{C}^n = \langle a_i \mid a_i a_j = -a_j a_i, i, j = 1 \dots n \rangle$$

Choose a basis in $\wedge^n \mathbb{C}^n$, say $a_1 \dots a_n$

Any $f \in \wedge^n \mathbb{C}^n$ can be written as

$$f = f_n a_1 \wedge \dots \wedge a_n + \text{lower order terms}$$

Def. $f_n = \int f da$

Remark. Usually $da = da_n \dots da_1$,

and the integral is computed by the rules

$$\int a_i da_i = 1, \int da_i = 0, da_i a_j = -a_j da_i$$

Lemma. Let $A = (a_{ij})_i^n$ be a skew

symmetric matrix, then

$$\int \exp\left(\frac{1}{2}(a, Aa)\right) da = \text{Pf}(A)$$

$$\exp(x) = \sum_{k \geq 0} \frac{1}{k!} x^k,$$

h.w Use Grassman integrals to prove

- $\text{Pf}(A)^2 = \det(A)$
- If $\mathbb{C}^n = B \oplus W$, $\dim B = \dim W = \frac{n}{2}$

$$A = \begin{pmatrix} 0 & K^{BW} \\ K^{WB} & 0 \end{pmatrix}$$

$$\begin{aligned} \text{Pf}(A) &= \det_B(K^{BW} K^{WB}) = \\ &= \det_W(K^{WB} K^{BW}) \end{aligned}$$

Lemma Let $A^t = -A$, $2n \times 2n$

$$(1) \quad \frac{\partial^k \text{Pf}(A)}{\partial a_{i_1 j_1} \dots \partial a_{i_k j_k}} = (-1)^{\sigma(I)} \text{Pf}(A_I)$$

where A_I = matrix A with columns and rows $i_1 j_1 \dots i_k j_k$ being removed

and $\sigma: (1, 2, \dots, 2n) \mapsto (i_1 j_1 \dots i_k j_k 1 \dots \hat{i}_1 \hat{j}_1 \dots \hat{i}_k \hat{j}_k \dots 2n)$

$$(2) \quad (-1)^{\sigma(I)} \text{Pf}(A_I) = (-1)^k \text{Pf}(A) \text{Pf}((A^{-1})_{a\theta})_{a, \theta \in I}$$

Thm when $(i_a j_a) \neq (i_b j_b)$

$$\langle \sigma_{a_1 j_1} \dots \sigma_{i_k j_k} \rangle = (-1)^k a_{i_1 j_1}^k \dots a_{i_k j_k}^k \cdot$$

$$\cdot \text{Pf}((A^k)_{a\theta}^{-1})_{a, \theta \in \{i_1 \dots i_k j_1 \dots j_k\}}$$

Proof.

$$\langle \sigma_{e_1} \dots \sigma_{e_k} \rangle = \frac{1}{Z} w(e_1) \dots w(e_k) \frac{\partial^k Z}{\partial w(e_1) \dots \partial w(e_k)} =$$

$$\partial^k \dots \text{Pf}(A^k)$$

$$= \frac{1}{Z} w(e_1) \dots w(e_k) \frac{\partial^k \log Z}{\partial w(e_1) \dots \partial w(e_k)} =$$

$$= \frac{1}{\text{pf}(A)} a_{i_1 j_1}^K \dots a_{i_k j_k}^K \frac{\partial^k \text{pf}(A^K)}{\partial a_{i_1 j_1}^K \dots \partial a_{i_k j_k}^K},$$

we can assume $i_1 < j_1 \dots i_k < j_k$

Then use Lemma.



In particular:

$$\langle \sigma_{ij} \rangle = - a_{ij} (A^K)^{-1}_{ij}$$

For two point correlation function:

$$\begin{aligned} \langle \sigma_{i_1 j_1} \sigma_{i_2 j_2} \rangle &= a_{i_1 j_1} a_{i_2 j_2} \left((A^{-1})_{i_1 j_1} (A^{-1})_{i_2 j_2} + \right. \\ &\quad \left. + (A^{-1})_{i_1 j_2} (A^{-1})_{i_2 j_1} - (A^{-1})_{i_1 i_2} (A^{-1})_{j_1 j_2} \right) \end{aligned}$$

graphically these three terms are:

$$+ \begin{array}{c} \text{---} \text{---} \text{---} \text{---} \\ \text{---} \text{---} \text{---} \text{---} \end{array} + \begin{array}{c} \text{---} \text{---} \text{---} \text{---} \\ \text{---} \text{---} \text{---} \text{---} \end{array} + \begin{array}{c} \text{---} \text{---} \text{---} \text{---} \\ \text{---} \text{---} \text{---} \text{---} \end{array}$$