

Telegraph equation from the six-vertex model

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July 2018

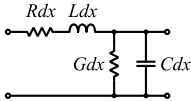
Telegraph equation

Resistance R

Inductance L

Capacitance C

Conductance G



Voltage V Current I

Wiki/Pixabay

$$\frac{\partial V}{\partial x}(x, t) = -L \cdot \frac{\partial I}{\partial t}(x, t) - R \cdot I(x, t)$$

$$\frac{\partial I}{\partial x}(x, t) = -C \cdot \frac{\partial V}{\partial t}(x, t) - G \cdot V(x, t)$$

or

$$\underbrace{V_{xx}}_{\text{Wave equation}} - LC \cdot \underbrace{V_{tt}}_{\text{Effect of losses}} - (RC + GL) \cdot V_t - GR \cdot V = 0$$

Wave equation

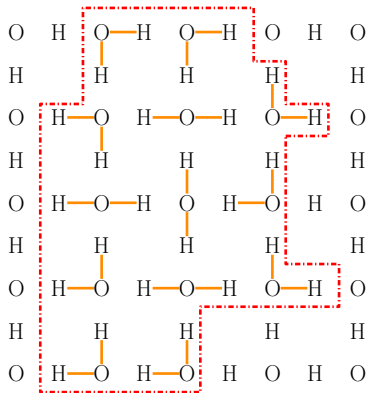
Effect of losses

Six-vertex model

O H O H O H O H O
H H H H H
O H O H O H O H O
H H H H H
O H O H O H O H O
H H H H H
O H O H O H O H O
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Square grid with O in the vertices
and H on the edges.

Six-vertex model



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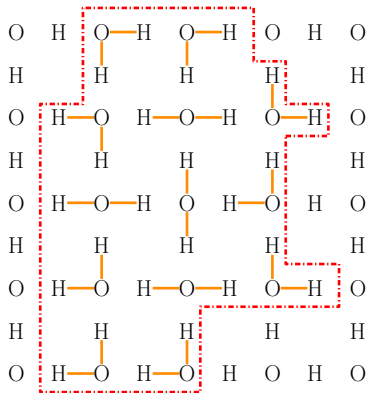
Finite/infinite domain.

Configurations: possible matchings of *all* atoms inside domain into H_2O molecules.

This is **square ice model**.

Real-world ice has somewhat similar (although 3d) structure.

Six-vertex model



Square grid with O in the vertices and H on the edges.

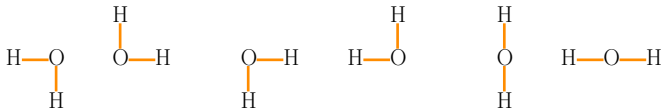
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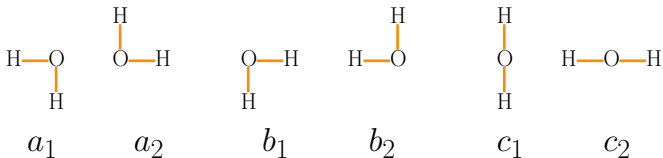
This is **square ice model**.

Real-world ice has somewhat similar (although 3d) structure.

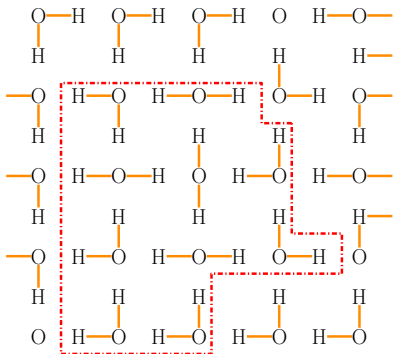
Also known as **six vertex model**.



Six-vertex model: Gibbs measures



Statistical mechanics starting from (Lieb-67):



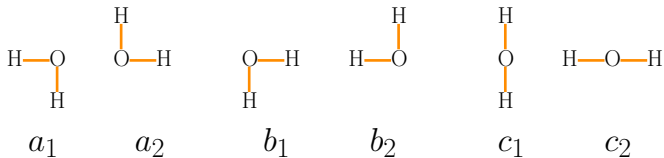
Assign Gibbs weights

$$\frac{a_1^{\#(a_1)} a_2^{\#(a_2)} b_1^{\#(b_1)} b_2^{\#(b_2)} c_1^{\#(c_1)} c_2^{\#(c_2)}}{Z(a_1, a_2, b_1, b_2, c_1, c_2)}$$

[Depends only on $\frac{b_1 b_2}{a_1 a_2}$ and $\frac{c_1 c_2}{a_1 a_2}$.]

**Asymptotic properties of
Gibbs measures?**

Six-vertex model: Gibbs measures



Assign Gibbs weights

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Asymptotic properties of
Gibbs measures?

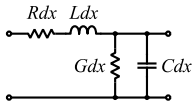
Understanding is still **very limited**.

Question for today

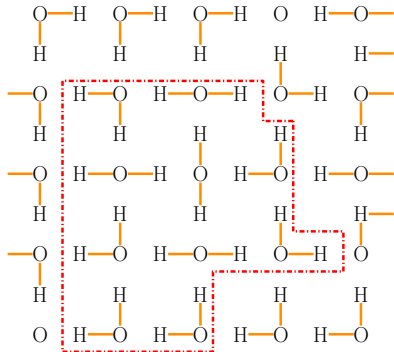
Telegraph equation



$$\mathbf{V}_{xx} - \mathbf{V}_{tt} - \alpha \mathbf{V}_t - \beta \mathbf{V}_x - \gamma \mathbf{V} = 0$$



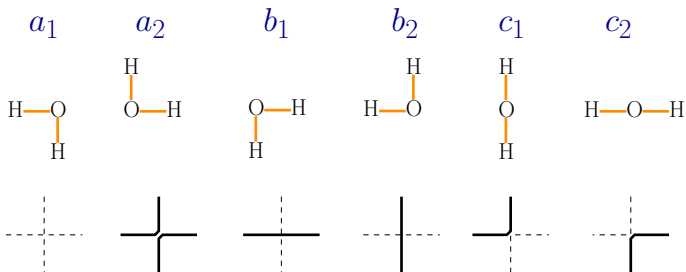
Six-vertex model



$$\frac{a_1^{\#(a_1)} a_2^{\#(a_2)} b_1^{\#(b_1)} b_2^{\#(b_2)} c_1^{\#(c_1)} c_2^{\#(c_2)}}{Z(a_1, a_2, b_1, b_2, c_1, c_2)}$$

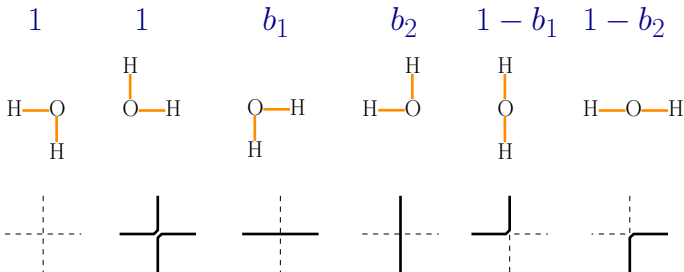
What do they have in common?

Stochastic six-vertex model



An equivalent representation
Collection of **paths** on the plane

Stochastic six-vertex model

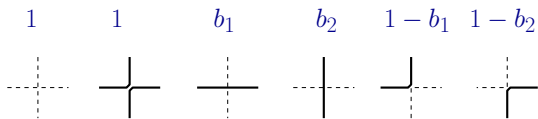


Assumption:
(Gwa-Spohn-92)

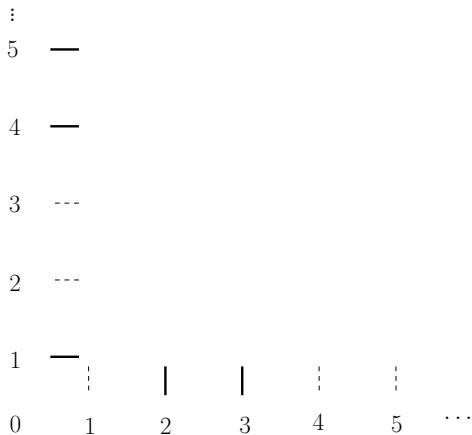
$$a_1 = a_2 = 1, \quad b_1 + c_1 = 1, \quad b_2 + c_2 = 1$$

(Implies $\Delta = \frac{a_1 a_2 + b_1 b_2 - c_1 c_2}{2\sqrt{a_1 a_2 b_1 b_2}} \geq 1$)

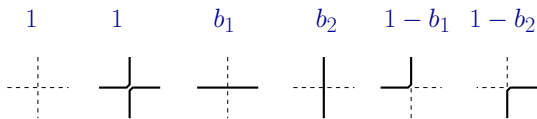
Stochastic six-vertex model



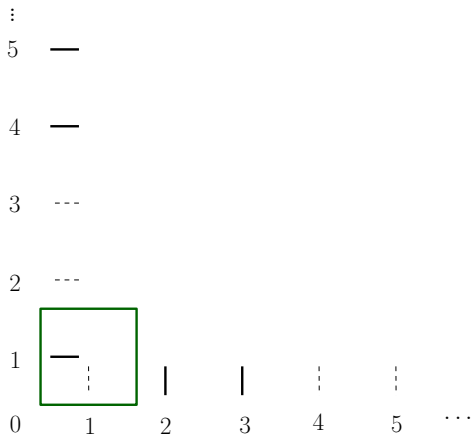
Take arbitrary **boundary conditions** in the quadrant



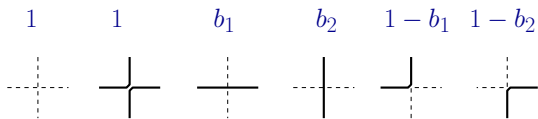
Stochastic six-vertex model



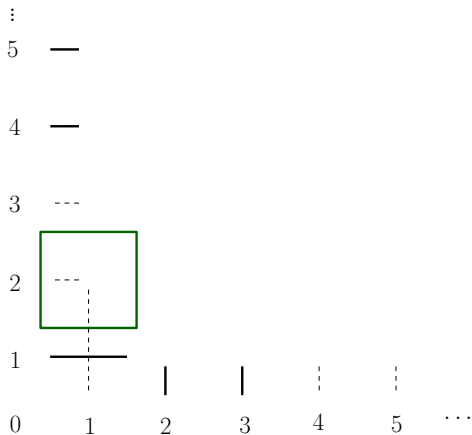
Proceed with **sequential stochastic sampling**



Stochastic six-vertex model

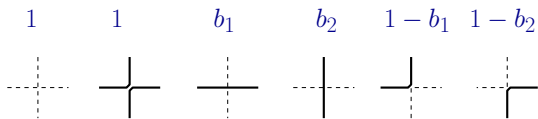


Proceed with **sequential stochastic sampling**

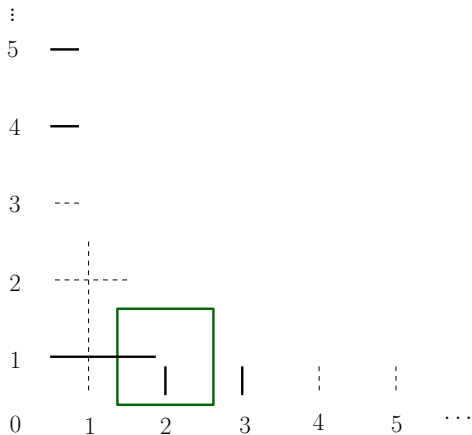


no choice

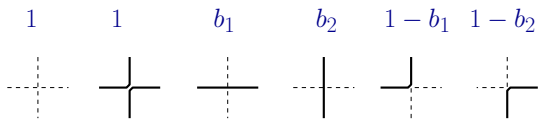
Stochastic six-vertex model



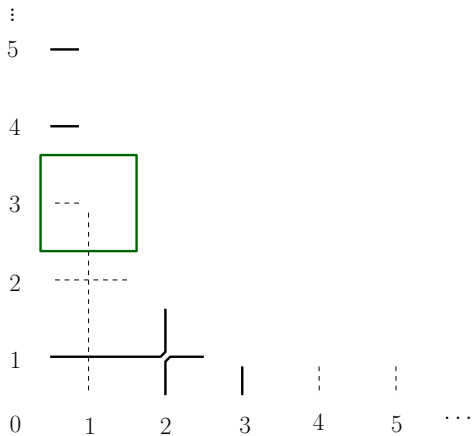
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Stochastic six-vertex model

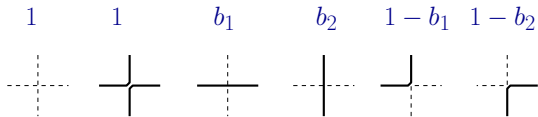


Proceed with **sequential stochastic sampling**

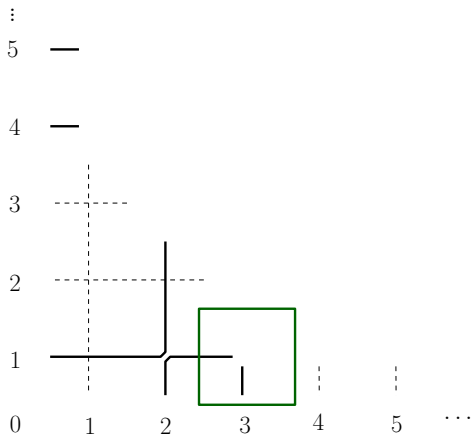


no choice

Stochastic six-vertex model

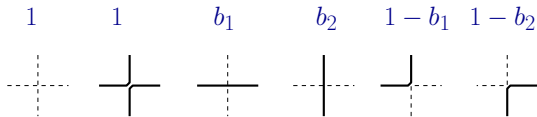


Proceed with **sequential stochastic sampling**

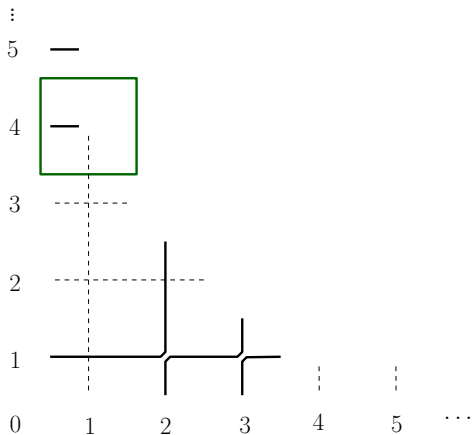


no choice

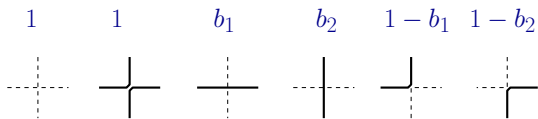
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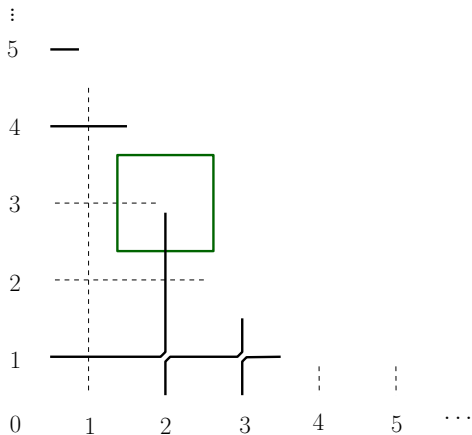
Proceed with **sequential stochastic sampling**



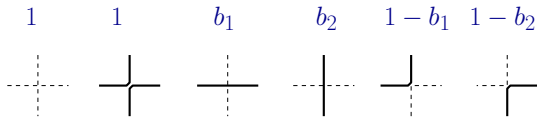
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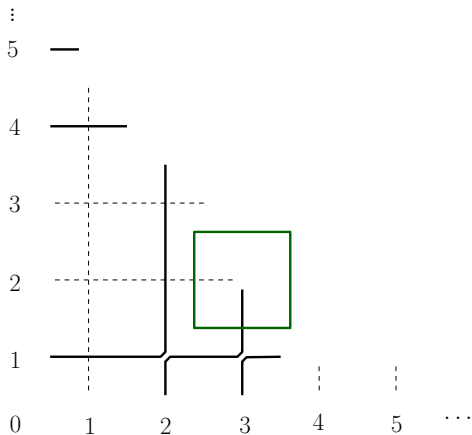
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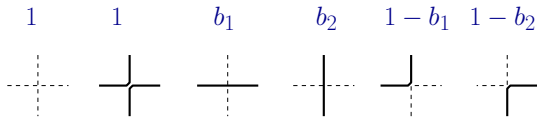
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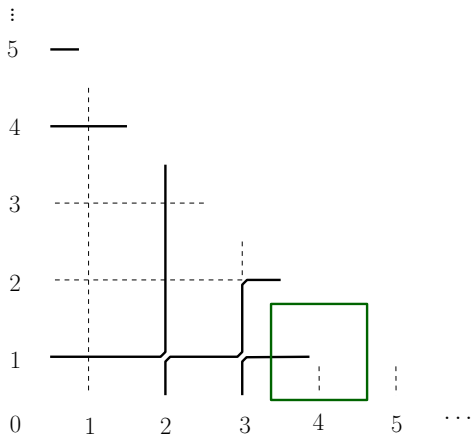
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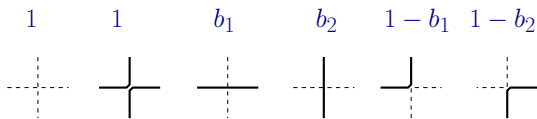
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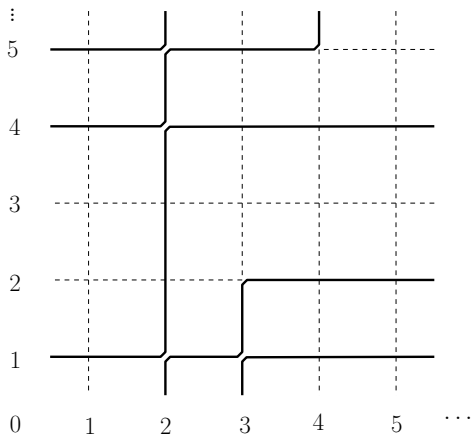
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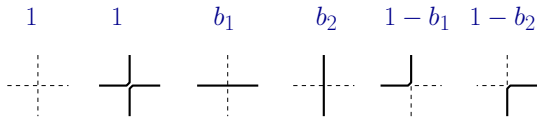
Stochastic six-vertex model



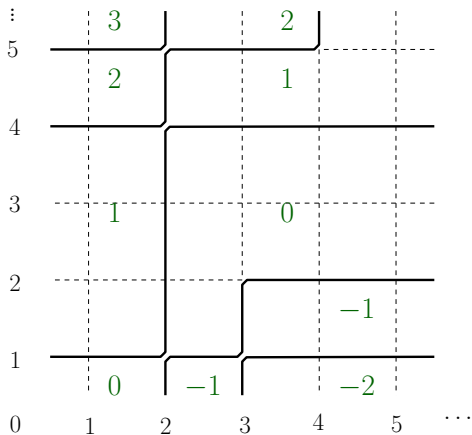
Until the quadrant is **filled**



Stochastic six-vertex model

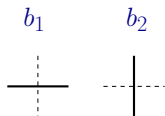
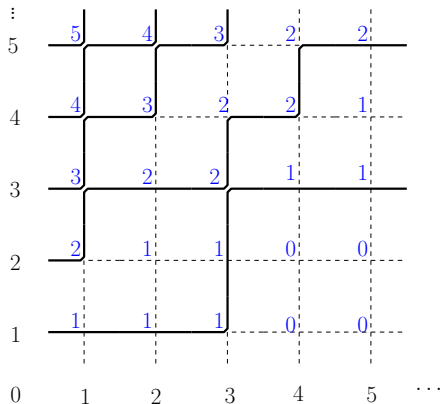


The resulting paths are level lines of the **height function**



- Height is 0 at the origin,
- increases up,
- decreases to the right.

Domain-wall and fixed weights



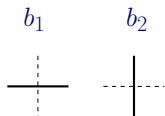
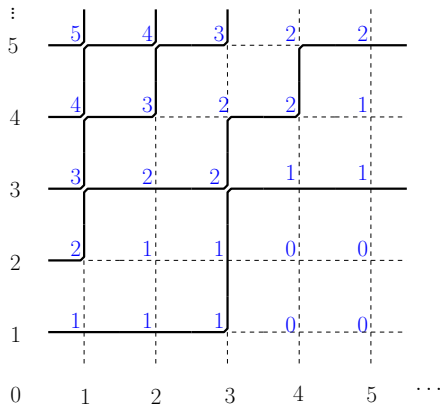
$$\mathfrak{s} = \frac{1 - b_1}{1 - b_2}$$

$$\frac{1}{L}H(Lx, Ly) \rightarrow \mathfrak{h}(x, y) = \begin{cases} 0, & \frac{x}{y} > \mathfrak{s}^{-1}, \\ \frac{(\sqrt{\mathfrak{s}x} - \sqrt{y})^2}{1 - \mathfrak{s}}, & \mathfrak{s} \leq \frac{x}{y} \leq \mathfrak{s}^{-1} \\ y - x, & \frac{x}{y} < \mathfrak{s}. \end{cases}$$

Theorem. (Borodin–Corwin–Gorin-14) For **domain-wall** boundary conditions and **fixed** $0 < b_2 < b_1 < 1$, $\frac{1}{L}H(Lx, Ly) \rightarrow \mathfrak{h}(x, y)$ with fluctuations on $L^{1/3}$ scale given by the **Tracy–Widom** distribution.

TW = universal law for the largest eigenvalue of Hermitian matrices **and** for particle system in Kardar–Parisi–Zhang class

Domain-wall and fixed weights



$$\mathfrak{s} = \frac{1 - b_1}{1 - b_2}$$

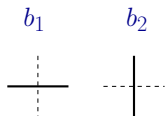
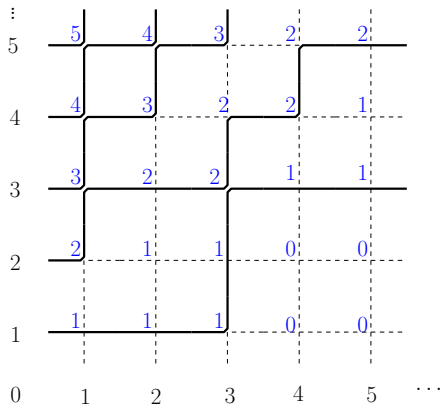
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$$\rho_x \cdot \mathfrak{s} + \rho_y \cdot (\mathfrak{s} + (\mathfrak{s} - 1)\rho)^2 = 0, \quad \rho = \mathfrak{h}_x.$$

1st-order non-linear PDE (Gwa–Spohn-92) (Reshetikhin–Sridhar-16)

Domain-wall and fixed weights



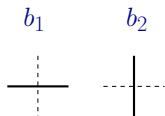
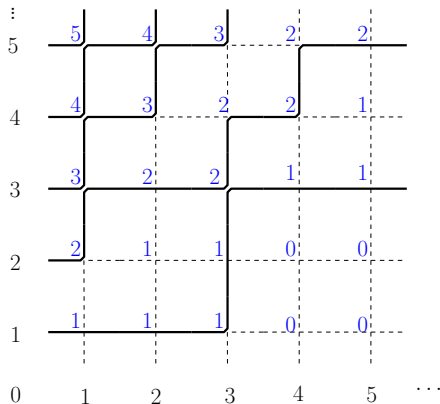
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- Instead of b_1, b_2 , only \mathfrak{s} . Where is the **second parameter**?
- Where is the **linear** telegraph equation?

Domain-wall and fixed weights



$$\mathfrak{s} = \frac{1 - b_1}{1 - b_2}$$

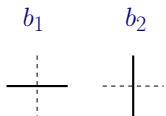
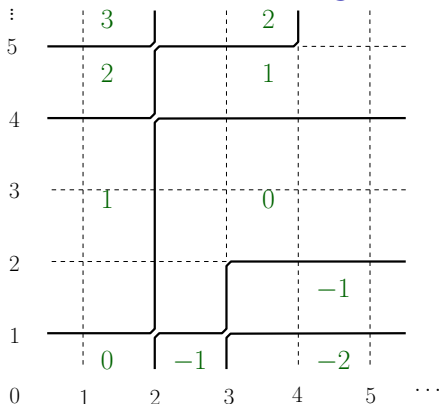
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- Instead of b_1, b_2 , only \mathfrak{s} . Where is the **second parameter**?
- Where is the **linear** telegraph equation?

(Borodin–Gorin–18): One needs to **rescale** weights b_1, b_2 .

Rescaled weights: Law of Large Numbers



Low density of corners

$$b_1 = \exp\left(-\frac{\beta_1}{L}\right)$$

$$b_2 = \exp\left(-\frac{\beta_2}{L}\right)$$

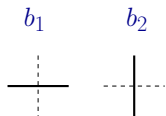
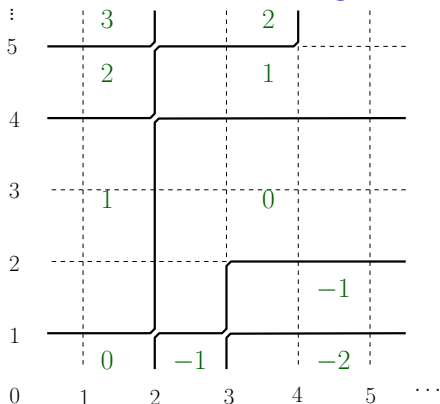
$$q = \left(\frac{b_2}{b_1}\right)^L = e^{\beta_1 - \beta_2}$$

Theorem. (Borodin–Gorin–18) For **arbitrary** boundary conditions and **rescaled weights**, $\frac{1}{L}H(Lx, Ly) \rightarrow h(x, y)$ with

$$\frac{\partial^2}{\partial x \partial y} (q^{h(x,y)}) + \beta_2 \frac{\partial}{\partial x} (q^{h(x,y)}) + \beta_1 \frac{\partial}{\partial y} (q^{h(x,y)}) = 0,$$

$$q^{h(x,0)} = \chi(x), \quad q^{h(0,y)} = \psi(y).$$

Rescaled weights: Law of Large Numbers



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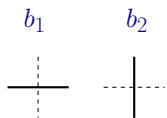
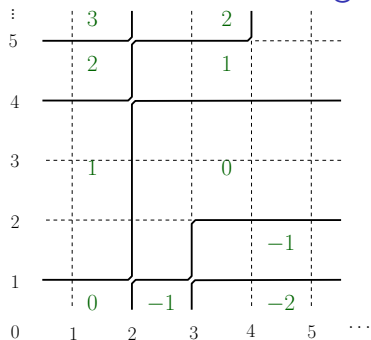
$$q = \left(\frac{b_2}{b_1}\right)^L = e^{\beta_1 - \beta_2}$$

$$(q^{h(x,y)})_{xy} + \beta_2 (q^{h(x,y)})_x + \beta_1 (q^{h(x,y)})_y = 0$$

$$q^{h(x,0)} = \chi(x), \quad q^{h(0,y)} = \psi(y).$$

- In $t = x + y$, $z = x - y$, a version of the **Telegraph equation**.
- **Characteristic** Cauchy problem has a unique solution.

Rescaled weights: Law of Large Numbers



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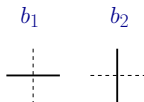
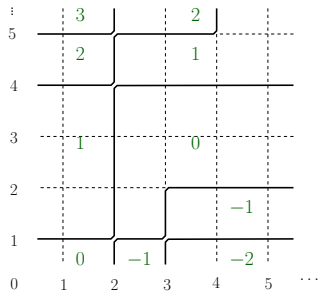
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$$\left(q^{h(x,y)}\right)_{xy} + \beta_2 \left(q^{h(x,y)}\right)_x + \beta_1 \left(q^{h(x,y)}\right)_y = 0$$

2nd order **hyperbolic** limit shape equation is **strange**:

- Diffusions: **parabolic** equations (e.g. Brownian motion)
- Interacting particle systems: **1st order** equations (e.g. TASEP)
- $2d$ statistical mechanics: 2nd order **elliptic** Euler–Lagrange equations through variational principles (e.g. random tilings)

Rescaled weights: Fluctuations



$$b_1 = \exp\left(-\frac{\beta_1}{L}\right) \quad b_2 = \exp\left(-\frac{\beta_2}{L}\right)$$

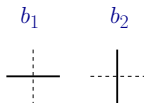
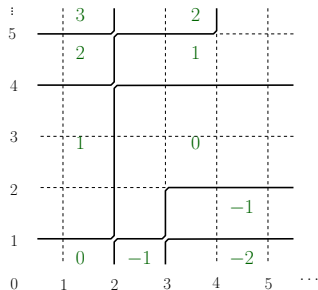
$$q = \frac{b_2}{b_1} = q^{1/L}$$

$$\frac{1}{L}H(Lx, Ly) \rightarrow \mathfrak{h}(x, y).$$

What about **fluctuations** $H(Lx, Ly) - \mathbb{E}H(Lx, Ly)$?

Reminder. For **fixed** b_1, b_2 , they were Tracy–Widom on $L^{1/3}$ scale.

Rescaled weights: Fluctuations

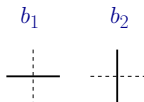
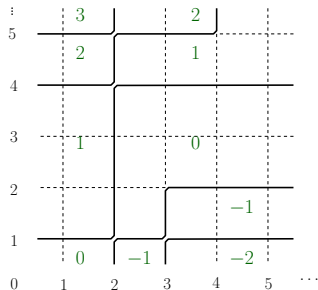


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$$q = \frac{b_2}{b_1} = q^{1/L}$$

Claim. $H(Lx, Ly) - \mathbb{E}H(Lx, Ly) \approx L^{1/2} \times \text{Gaussian}.$

Rescaled weights: Fluctuations



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$$q = \frac{b_2}{b_1} = q^{1/L}$$

Claim. $H(Lx, Ly) - \mathbb{E}H(Lx, Ly) \approx L^{1/2} \times \text{Gaussian}$.

Theorem. (Borodin–Gorin–18, Shen–Tsai–18)

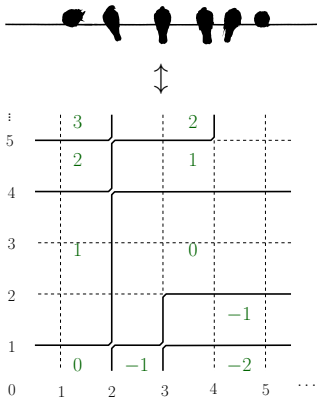
$\lim_{L \rightarrow \infty} \sqrt{L} (q^{H(Lx, Ly)} - \mathbb{E}q^{H(Lx, Ly)})$ solves **Stochastic Telegraph**

$$\phi_{xy} + \beta_2 \phi_x + \beta_1 \phi_y = \dot{W} \sqrt{V(x, y)}$$

$$V(x, y) = (\beta_1 + \beta_2) q_x^h q_y^h + (\beta_2 - \beta_1) \beta_2 q^h q_x^h - (\beta_2 - \beta_1) \beta_1 q^h q_y^h$$

R.H.S. = 2d white noise \times non-linear functional of the limit shape

Six-vertex and Telegraph



Stochastic six-vertex model in the quadrant in low corner density asymptotic regime.

- Deterministic limit (LLN) for $q^{H(x,y)}$ is given by the homogeneous Telegraph equation.
- Gaussian fluctuations (CLT) are given by Stochastic Telegraph equation.

Why?

Feynman–Kac for Heat equation

For a second, switch to (parabolic) **Heat equation**.

$$H_t = \frac{1}{2} H_{xx}, \quad t \geq 0, \quad H(0, x) = f(x).$$

The Feynman–Kac formula expresses the solution:

$$H(t, x) = \mathbb{E}f(B_t),$$

where B_t is the **Brownian motion** started at $B_0 = x$.

Similar representation is possible for the Telegraph equation!

Feynman–Kac for Telegraph

Persistent random walk.



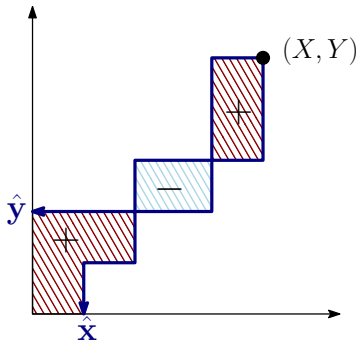
Turns down/to the left at Poisson
random times.

Feynman–Kac for Telegraph

Persistent random walk.



Turns down/to the left at Poisson random times.



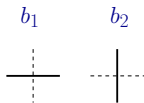
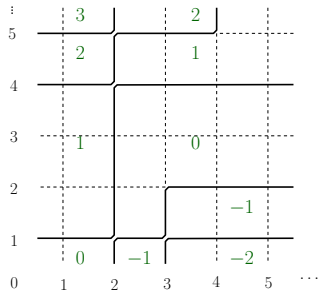
Theorem. (Borodin–Gorin–18; following Goldstein–51, Kac–74)

$$\phi_{xy} + \beta_2 \phi_x + \beta_1 \phi_y = u, \quad x, y > 0; \quad \phi(x, 0) = \chi(x), \quad \phi(0, y) = \psi(y).$$

Then **random characteristics** solve the inhomogeneous Telegraph:

$$\phi(X, Y) = \mathbb{E}\chi(\hat{x}) + \mathbb{E}\psi(\hat{y}) + \mathbb{E} \left[\int_0^X \int_0^Y \mathcal{I}_{\text{between}}^\pm(x, y) u(x, y) dx dy \right].$$

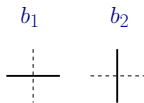
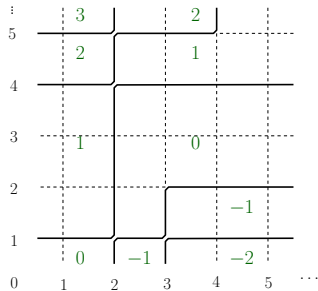
Six-vertex and persistent random walks



$$b_1 = \exp\left(-\frac{\beta_1}{L}\right) \quad b_2 = \exp\left(-\frac{\beta_2}{L}\right)$$

If paths are **rare** (low density limit), then each of them becomes a persistent random walk. They are essentially independent.

Six-vertex and persistent random walks

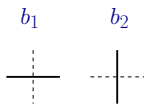
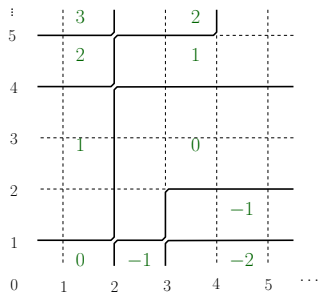


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Conclusion. LLN/CLT for the height at **low density** is the same as LLN/CLT for a family of independent persistent random walks. Hence, connection to the Telegraph equation.

Six-vertex and persistent random walks



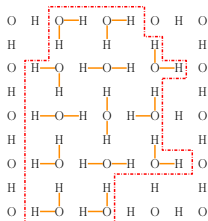
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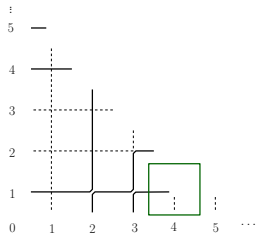
Conclusion. LLN/CLT for the height at **low density** is the same as LLN/CLT for a family of independent persistent random walks. Hence, connection to the Telegraph equation.

How to explain the same connection at **high densities** and the appearance of $q^{H(x,y)}$?

Summary



$$\phi_{xy} + \beta_2 \phi_x + \beta_1 \phi_y = \dot{W} \sqrt{V}$$



- Stochastic **six-vertex model** in the rare corners regime unexpectedly connects to **hyperbolic PDEs**.
- $\lim_{L \rightarrow \infty} q^{H(Lx, Ly)}$ solves Telegraph equation.
- $q \rightarrow 0$: fixed weights 1st order nonlinear PDE for LLN.
- $\lim_{L \rightarrow \infty} \sqrt{L}(q^H - \mathbb{E}q^H) =$ Stochastic Telegraph.
- Links to persistent random walks — Feynman–Kac formula for Telegraph.

Main tool: four point relation

Proofs rely on **exact discrete analogue** of stochastic Telegraph.

$$\begin{array}{cccccc}
 1 & & 1 & & b_1 & & b_2 & & 1 - b_1 & & 1 - b_2 \\
 \\
 \begin{array}{|c|c|} \hline H & H \\ \hline \hline H & H \\ \hline \end{array} & & \begin{array}{|c|c|} \hline H+1 & H \\ \hline \hline H & H-1 \\ \hline \end{array} & & \begin{array}{|c|} \hline H+1 \\ \hline \hline H \\ \hline \end{array} & & \begin{array}{|c|c|} \hline H & H-1 \\ \hline \hline H & H-1 \\ \hline \end{array} & & \begin{array}{|c|c|} \hline H+1 & \\ \hline \hline & H \\ \hline \end{array} & & \begin{array}{|c|} \hline H \\ \hline \hline & \\ \hline \end{array} & & \begin{array}{|c|} \hline & \\ \hline \hline & H-1 \\ \hline \end{array}
 \end{array}$$

Theorem. (Borodin–Gorin–18; with help of Wheeler) For the stochastic six-vertex model in the quadrant with **arbitrary** boundary conditions, and each $x, y = 1, 2, \dots$, set for $q = \frac{b_2}{b_1}$:

$$\xi(x, y) = q^{H(x,y)} - b_1 q^{H(x-1,y)} - b_2 q^{H(x,y-1)} + (b_1 + b_2 - 1) q^{H(x-1,y-1)}.$$

Then ξ is a **martingale** with explicit variance:

- $\mathbb{E}[\xi(x, y) \mid H(u, v), u < x \text{ or } v < y] = 0.$

- $\mathbb{E}[\xi^2(x, y) \mid H(u, v), u < x \text{ or } v < y] =$

$$(b_1(1 - b_1) + b_1(1 - b_2))\Delta_x\Delta_y + b_1(1 - b_2)(1 - q)q^{H(x,y)}\Delta_x - b_1(1 - b_1)(1 - q)q^{H(x,y)}\Delta_y,$$

with $\Delta_x = q^{H(x,y-1)} - q^{H(x-1,y-1)}, \quad \Delta_y = q^{H(x-1,y)} - q^{H(x-1,y-1)}$