

Scaling Limits and Universality for Random Pinning Models

Francesco Caravenna

Università degli Studi di Milano-Bicocca

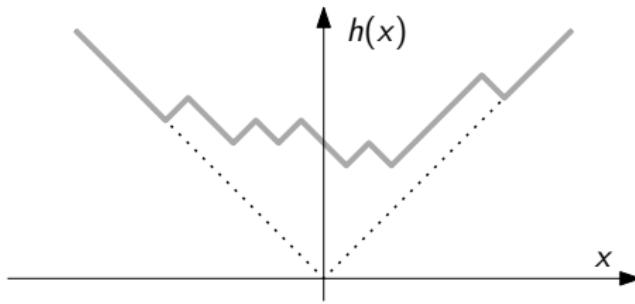
IperMiB ~ September 12, 2013

Outline

1. Hydrodynamics
2. The link with “polymers”
3. The random pinning model
4. Weak disorder regime

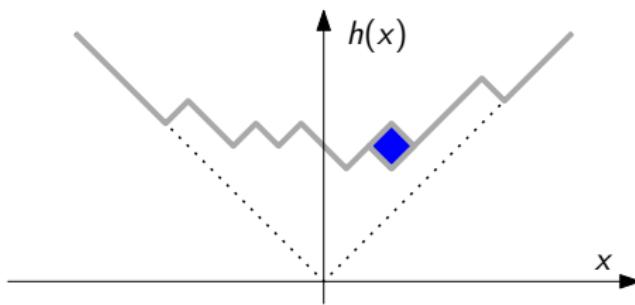
Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$



Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

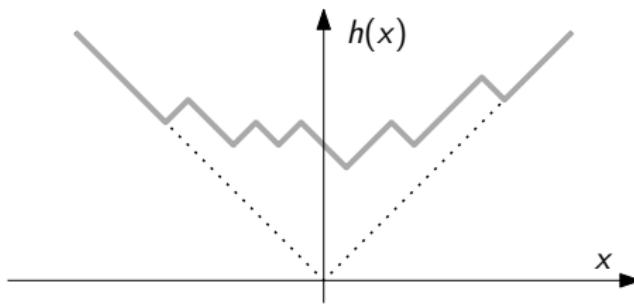


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local valleys become hills at rate $p > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

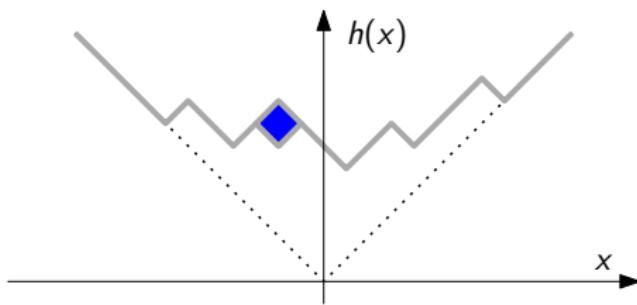


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local valleys become hills at rate $p > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

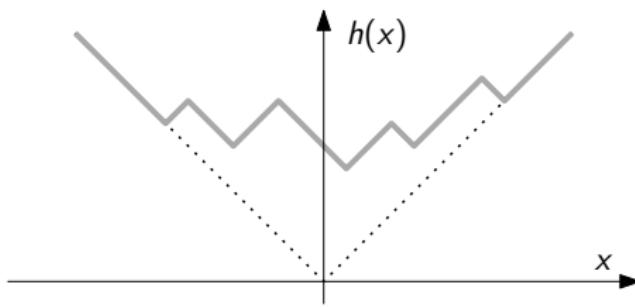


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local valleys become hills at rate $p > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

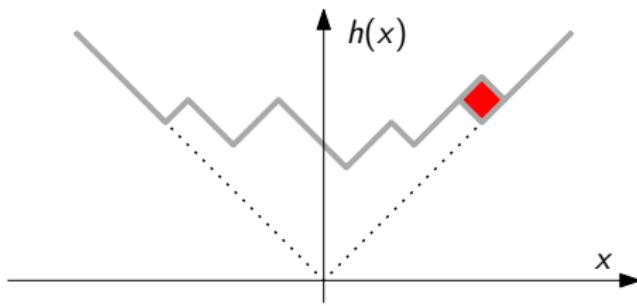


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local valleys become hills at rate $p > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

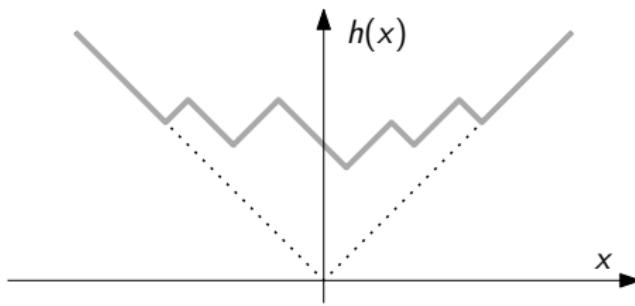


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local **valleys** become **hills** at rate $p > 0$
- ▶ local **hills** become **valleys** at rate $q > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

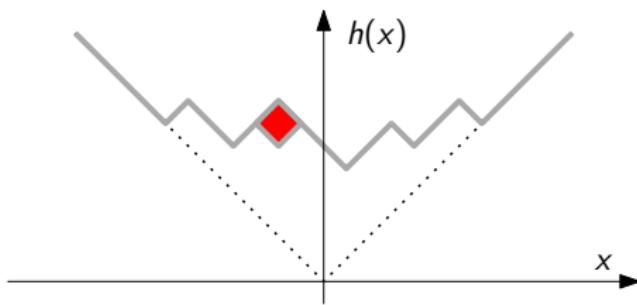


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local **valleys become hills** at rate $p > 0$
- ▶ local **hills become valleys** at rate $q > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

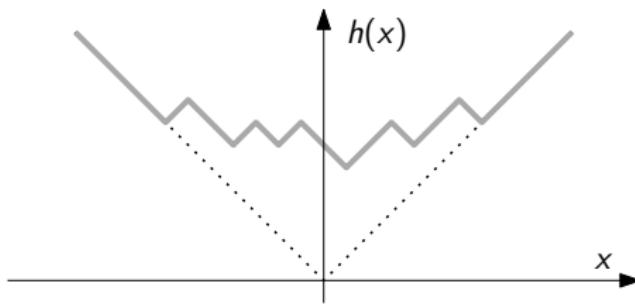


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local **valleys** become **hills** at rate $p > 0$
- ▶ local **hills** become **valleys** at rate $q > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$

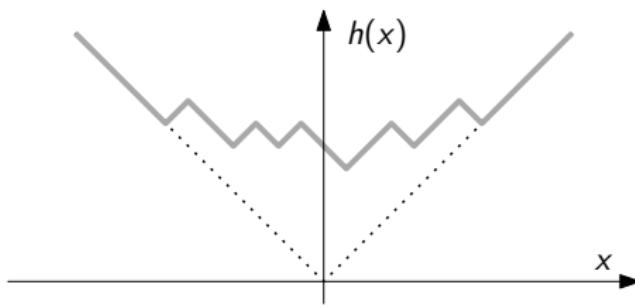


Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local **valleys** become **hills** at rate $p > 0$
- ▶ local **hills** become **valleys** at rate $q > 0$

Corner growth model (in dimension 1)

Random evolution of interface $h : \mathbb{Z} \rightarrow \mathbb{Z}$ $(|h(x+1) - h(x)| = 1)$



Simple probabilistic evolution (exponential clocks \rightsquigarrow Markov process)

- ▶ local **valleys become hills** at rate $p > 0$
- ▶ local **hills become valleys** at rate $q > 0$

$h(t, x) :=$ interface height at time $t \geq 0$, position $x \in \mathbb{Z}$.

Large scale evolution?

Asymmetric case

Assume that $\gamma := p - q > 0$ is fixed ("upward drift")

Asymmetric case

Assume that $\gamma := p - q > 0$ is fixed ("upward drift")

Eulerian scaling: $T = \epsilon t, \quad X = \epsilon x \quad H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon}, \frac{X}{\epsilon}\right)$

Asymmetric case

Assume that $\gamma := p - q > 0$ is fixed ("upward drift")

Eulerian scaling: $T = \epsilon t, \quad X = \epsilon x \quad H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon}, \frac{X}{\epsilon}\right)$

Theorem (Rost '81, Rezakhanlou '91)

As $\epsilon \downarrow 0$, the random function $H_\epsilon(T, X)$ converges a.s. to a **deterministic function** $H(T, X)$, solution of the PDE

$$\partial_T H = \frac{\gamma}{2} (1 - (\nabla H)^2) \quad (\nabla := \partial_X)$$

Asymmetric case

Assume that $\gamma := p - q > 0$ is fixed ("upward drift")

Eulerian scaling: $T = \epsilon t, X = \epsilon x, H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon}, \frac{X}{\epsilon}\right)$

Theorem (Rost '81, Rezakhanlou '91)

As $\epsilon \downarrow 0$, the random function $H_\epsilon(T, X)$ converges a.s. to a **deterministic function** $H(T, X)$, solution of the PDE

$$\partial_T H = \frac{\gamma}{2} (1 - (\nabla H)^2) \quad (\nabla := \partial_X)$$

Then $U := \nabla H$ solves $\partial_T U = -\frac{\gamma}{2} \nabla(U^2)$ (inviscid Burgers)

Asymmetric case

Assume that $\gamma := p - q > 0$ is fixed ("upward drift")

Eulerian scaling: $T = \epsilon t, X = \epsilon x, H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon}, \frac{X}{\epsilon}\right)$

Theorem (Rost '81, Rezakhanlou '91)

As $\epsilon \downarrow 0$, the random function $H_\epsilon(T, X)$ converges a.s. to a **deterministic function** $H(T, X)$, solution of the PDE

$$\partial_T H = \frac{\gamma}{2} (1 - (\nabla H)^2) \quad (\nabla := \partial_X)$$

Then $U := \nabla H$ solves $\partial_T U = -\frac{\gamma}{2} \nabla(U^2)$ (inviscid Burgers)

Law of Large Numbers

Random (micro) model \rightsquigarrow Deterministic (macro) behavior

Weakly asymmetric regime

Consider $p - q = \epsilon$ and diffusive scaling $H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon^2}, \frac{X}{\epsilon}\right)$

Weakly asymmetric regime

Consider $p - q = \epsilon$ and diffusive scaling $H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon^2}, \frac{X}{\epsilon}\right)$

Theorem (Gärtner '88, De Masi, Presutti, Scacciatelli '89)

As $\epsilon \downarrow 0$, $H_\epsilon(T, X)$ converges a.s. to (deterministic) solution of

$$\partial_T H = \frac{1}{2} \Delta H + \frac{1}{2} (1 - (\nabla H)^2) \quad (\text{viscous Burgers})$$

Weakly asymmetric regime

Consider $p - q = \epsilon$ and diffusive scaling $H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon^2}, \frac{X}{\epsilon}\right)$

Theorem (Gärtner '88, De Masi, Presutti, Scacciatelli '89)

As $\epsilon \downarrow 0$, $H_\epsilon(T, X)$ converges a.s. to (deterministic) solution of

$$\partial_T H = \frac{1}{2} \Delta H + \frac{1}{2} (1 - (\nabla H)^2) \quad (\text{viscous Burgers})$$

Fluctuations? (= "second order" corrections to LLN)

Weakly asymmetric regime

Consider $p - q = \epsilon$ and diffusive scaling $H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon^2}, \frac{X}{\epsilon}\right)$

Theorem (Gärtner '88, De Masi, Presutti, Scacciatelli '89)

As $\epsilon \downarrow 0$, $H_\epsilon(T, X)$ converges a.s. to (deterministic) solution of

$$\partial_T H = \frac{1}{2} \Delta H + \frac{1}{2} (1 - (\nabla H)^2) \quad (\text{viscous Burgers})$$

Fluctuations? (= "second order" corrections to LLN)

$\frac{1}{\sqrt{\epsilon}} \{ H_\epsilon(T, X) - H(T, X) \} \rightsquigarrow \text{linear stochastic PDE}$ (typical)

Weakly asymmetric regime

Consider $p - q = \epsilon$ and diffusive scaling $H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon^2}, \frac{X}{\epsilon}\right)$

Theorem (Gärtner '88, De Masi, Presutti, Scacciatelli '89)

As $\epsilon \downarrow 0$, $H_\epsilon(T, X)$ converges a.s. to (deterministic) solution of

$$\partial_T H = \frac{1}{2} \Delta H + \frac{1}{2} (1 - (\nabla H)^2) \quad (\text{viscous Burgers})$$

Fluctuations? (= "second order" corrections to LLN)

$\frac{1}{\sqrt{\epsilon}} \{ H_\epsilon(T, X) - H(T, X) \} \rightsquigarrow$ linear stochastic PDE (typical)

Interesting: non-linear fluctuations for $p - q = \sqrt{\epsilon}$

Weakly asymmetric regime

Consider $p - q = \epsilon$ and diffusive scaling $H_\epsilon(T, X) := \epsilon h\left(\frac{T}{\epsilon^2}, \frac{X}{\epsilon}\right)$

Theorem (Gärtner '88, De Masi, Presutti, Scacciatelli '89)

As $\epsilon \downarrow 0$, $H_\epsilon(T, X)$ converges a.s. to (deterministic) solution of

$$\partial_T H = \frac{1}{2} \Delta H + \frac{1}{2} (1 - (\nabla H)^2) \quad (\text{viscous Burgers})$$

Fluctuations? (= "second order" corrections to LLN)

$\frac{1}{\sqrt{\epsilon}} \{H_\epsilon(T, X) - H(T, X)\} \rightsquigarrow$ linear stochastic PDE (typical)

Interesting: non-linear fluctuations for $p - q = \sqrt{\epsilon}$

Theorem (Bertini, Giacomin '97)

As $\epsilon \downarrow 0$, $\mathcal{H}_\epsilon(T, X) := \frac{1}{\sqrt{\epsilon}} \{H_\epsilon(T, X) - \frac{T}{2\sqrt{\epsilon}}\}$ converges in distrib. to the "solution" of a non-linear stochastic PDE: the KPZ equation

KPZ equation (Kardar-Parisi-Zhang '86)

The KPZ equation is a **non-linear stochastic** PDE, believed to describe the statistics of several physical systems (**Universality**)

$$\partial_T \mathcal{H} = \frac{1}{2} (\Delta \mathcal{H} - (\nabla \mathcal{H})^2) + \dot{W} \quad (\text{KPZ})$$

\dot{W} space-time white noise (random distribution on \mathbb{R}^2)

KPZ equation (Kardar-Parisi-Zhang '86)

The KPZ equation is a **non-linear stochastic** PDE, believed to describe the statistics of several physical systems (**Universality**)

$$\partial_T \mathcal{H} = \frac{1}{2} (\Delta \mathcal{H} - (\nabla \mathcal{H})^2) + \dot{W} \quad (\text{KPZ})$$

\dot{W} space-time white noise (random distribution on \mathbb{R}^2)

ill-posed: $\nabla \mathcal{H}$ should be distribution \rightsquigarrow meaning of $(\nabla \mathcal{H})^2$?

KPZ equation (Kardar-Parisi-Zhang '86)

The KPZ equation is a **non-linear stochastic** PDE, believed to describe the statistics of several physical systems (**Universality**)

$$\partial_T \mathcal{H} = \frac{1}{2} (\Delta \mathcal{H} - (\nabla \mathcal{H})^2) + \dot{W} \quad (\text{KPZ})$$

\dot{W} space-time white noise (random distribution on \mathbb{R}^2)

ill-posed: $\nabla \mathcal{H}$ should be distribution \rightsquigarrow meaning of $(\nabla \mathcal{H})^2$?

Recent breakthrough (Hairer '13)

KPZ equation (Kardar-Parisi-Zhang '86)

The KPZ equation is a **non-linear stochastic** PDE, believed to describe the statistics of several physical systems (**Universality**)

$$\partial_T \mathcal{H} = \frac{1}{2} (\Delta \mathcal{H} - (\nabla \mathcal{H})^2) + \dot{W} \quad (\text{KPZ})$$

\dot{W} space-time white noise (random distribution on \mathbb{R}^2)

ill-posed: $\nabla \mathcal{H}$ should be distribution \rightsquigarrow meaning of $(\nabla \mathcal{H})^2$?

Recent breakthrough (Hairer '13)

Before that, rigorous meaning through Hopf-Cole transform

$$\mathcal{Z} := e^{-\mathcal{H}}$$

KPZ equation (Kardar-Parisi-Zhang '86)

The KPZ equation is a **non-linear stochastic** PDE, believed to describe the statistics of several physical systems (**Universality**)

$$\partial_T \mathcal{H} = \frac{1}{2} (\Delta \mathcal{H} - (\nabla \mathcal{H})^2) + \dot{W} \quad (\text{KPZ})$$

\dot{W} space-time white noise (random distribution on \mathbb{R}^2)

ill-posed: $\nabla \mathcal{H}$ should be distribution \rightsquigarrow meaning of $(\nabla \mathcal{H})^2$?

Recent breakthrough (Hairer '13)

Before that, rigorous meaning through Hopf-Cole transform

$$\mathcal{Z} := e^{-\mathcal{H}}$$

\mathcal{Z} solves the **Stochastic Heat Equation**, a **linear** stochastic PDE

$$\partial_T \mathcal{Z} = \frac{1}{2} \Delta \mathcal{Z} + \dot{W} \mathcal{Z} \quad (\text{SHE})$$

Outline

1. Hydrodynamics
2. The link with “polymers”
3. The random pinning model
4. Weak disorder regime

"Polymers" enter the game

$$\partial_T \mathcal{Z} = \frac{1}{2} \Delta \mathcal{Z} + \dot{W} \mathcal{Z} \quad (\text{SHE})$$

"Polymers" enter the game

$$\partial_T \mathcal{Z} = \frac{1}{2} \Delta \mathcal{Z} + \dot{W} \mathcal{Z} \quad (\text{SHE})$$

If $\dot{W}(T, X)$ were a function, the solution would be

$$\mathcal{Z}(T, X) = \mathbb{E} \left[e^{- \int_0^T \dot{W}(s, B_s) ds} \right] \quad (\text{Feynman-Kac})$$

with $(B_s)_{s \in [0, T]}$ Brownian Bridge from 0 to X

"Polymers" enter the game

$$\partial_T \mathcal{Z} = \frac{1}{2} \Delta \mathcal{Z} + \dot{W} \mathcal{Z} \quad (\text{SHE})$$

If $\dot{W}(T, X)$ were a function, the solution would be

$$\mathcal{Z}(T, X) = \mathbb{E} \left[e^{- \int_0^T \dot{W}(s, B_s) ds} \right] \quad (\text{Feynman-Kac})$$

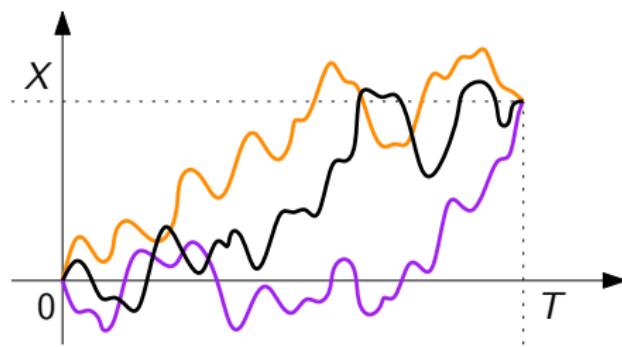
with $(B_s)_{s \in [0, T]}$ Brownian Bridge from 0 to X

Average over paths

$$\mathcal{Z}(T, X) = \int_{C([0, T], \mathbb{R})} e^{- \int_0^T \dot{W}(s, b(s)) ds} P(db)$$

$P(\cdot)$ = Brownian Bridge law = Wiener measure (law of Brownian Motion) conditioned on paths $b(0) = 0$, $b(T) = X$

"Polymers" enter the game



Average over paths

$$\mathcal{Z}(T, X) = \int_{C([0, T], \mathbb{R})} e^{- \int_0^T \dot{W}(s, b(s)) \, ds} P(db)$$

$P(\cdot)$ = Brownian Bridge law = **Wiener measure** (law of Brownian Motion) conditioned on paths $b(0) = 0$, $b(T) = X$

From continuum to discrete

Feynman-Kac is only heuristic, since $\dot{W}(T, X)$ is not a function

From continuum to discrete

Feynman-Kac is only heuristic, since $\dot{W}(T, X)$ is not a function

Possible rigorous meaning through **discretization**:

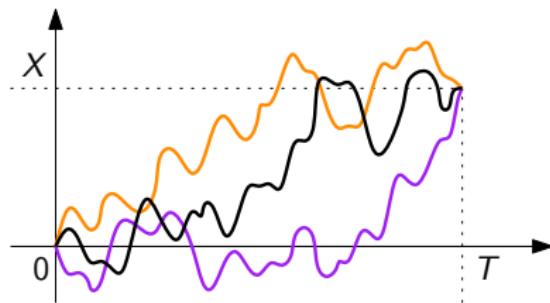
- ▶ $(T, X) \rightsquigarrow (t, x) \in \mathbb{Z}^2$
- ▶ $\dot{W}(T, X) \rightsquigarrow \omega(t, x)$ i.i.d. random variables
- ▶ Brownian Motion $(B_s)_{s \geq 0} \rightsquigarrow$ Random Walk $(S_n)_{n \geq 0}$

From continuum to discrete

Feynman-Kac is only heuristic, since $\dot{W}(T, X)$ is not a function

Possible rigorous meaning through **discretization**:

- ▶ $(T, X) \rightsquigarrow (t, x) \in \mathbb{Z}^2$
- ▶ $\dot{W}(T, X) \rightsquigarrow \omega(t, x)$ i.i.d. random variables
- ▶ Brownian Motion $(B_s)_{s \geq 0} \rightsquigarrow$ Random Walk $(S_n)_{n \geq 0}$

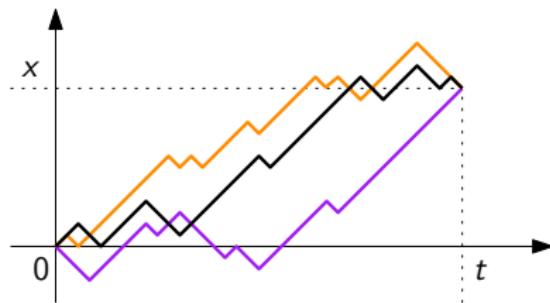


From continuum to discrete

Feynman-Kac is only heuristic, since $\dot{W}(T, X)$ is not a function

Possible rigorous meaning through **discretization**:

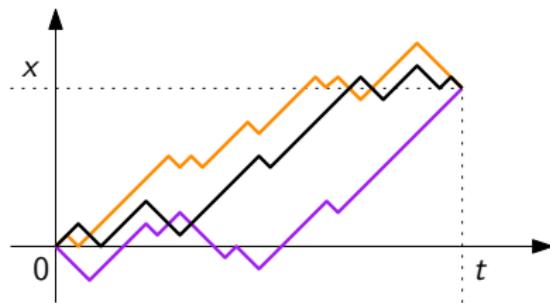
- ▶ $(T, X) \rightsquigarrow (t, x) \in \mathbb{Z}^2$
- ▶ $\dot{W}(T, X) \rightsquigarrow \omega(t, x)$ i.i.d. random variables
- ▶ Brownian Motion $(B_s)_{s \geq 0} \rightsquigarrow$ Random Walk $(S_n)_{n \geq 0}$



"Polymers" enter the game

Directed polymer in random environment

$$\mathcal{Z}(t, x) = \mathbb{E} \left[e^{-\sum_{n=1}^t \omega(n, S_n)} \right] = \sum_{\substack{s: \{0, \dots, t\} \rightarrow \mathbb{Z} \\ s(t) = x}} e^{-\sum_{n=1}^t \omega(n, s_n)} P(\{s\})$$

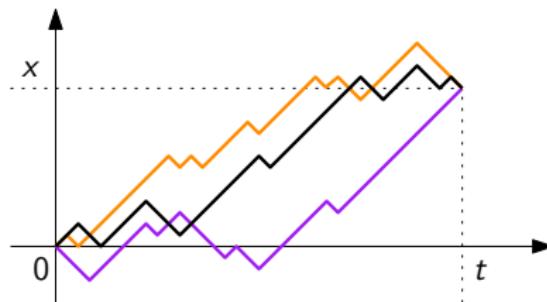


"Polymers" enter the game

Directed polymer in random environment

$$\mathcal{Z}(t, x) = \mathbb{E} \left[e^{-\sum_{n=1}^t \omega(n, S_n)} \right] = \sum_{\substack{s: \{0, \dots, t\} \rightarrow \mathbb{Z} \\ s(t) = x}} e^{-\sum_{n=1}^t \omega(n, s_n)} P(\{s\})$$

- Converges in the continuum limit to the SHE solution

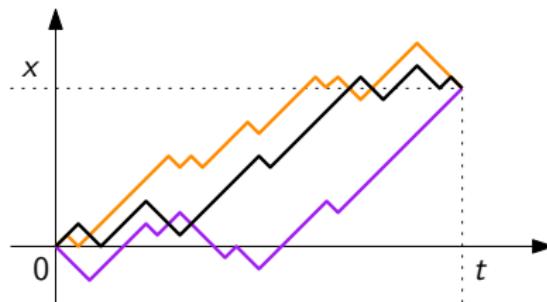


"Polymers" enter the game

Directed polymer in random environment

$$\mathcal{Z}(t, x) = \mathbb{E} \left[e^{-\sum_{n=1}^t \omega(n, S_n)} \right] = \sum_{\substack{s: \{0, \dots, t\} \rightarrow \mathbb{Z} \\ s(t) = x}} e^{-\sum_{n=1}^t \omega(n, s_n)} P(\{s\})$$

- ▶ Converges in the continuum limit to the SHE solution
- ▶ Discretization retains the essence of the problem

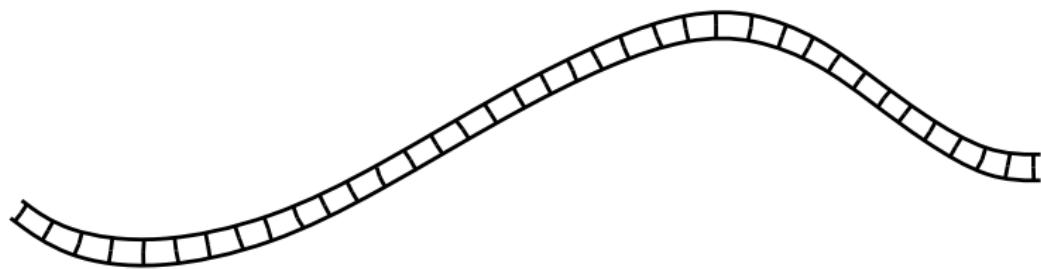


Outline

1. Hydrodynamics
2. The link with “polymers”
3. The random pinning model
4. Weak disorder regime

Some motivations from biology

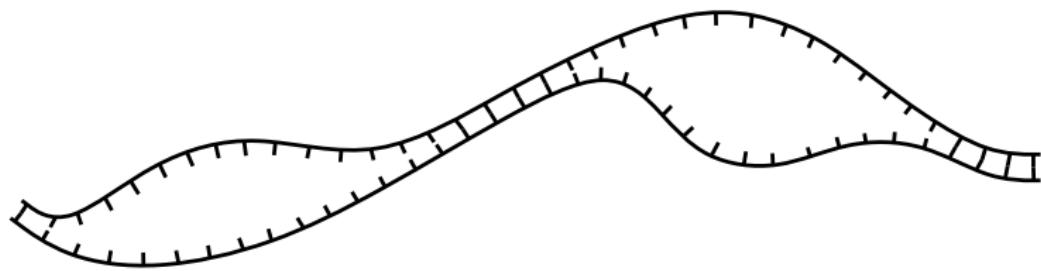
DNA is a long polymer, typically in a **double stranded state**



Strands are tied together by **energetic** (hydrogen) bonds
(otherwise they would be detached, for **entropic** reasons)

Some motivations from biology

DNA is a long polymer, typically in a **double stranded state**



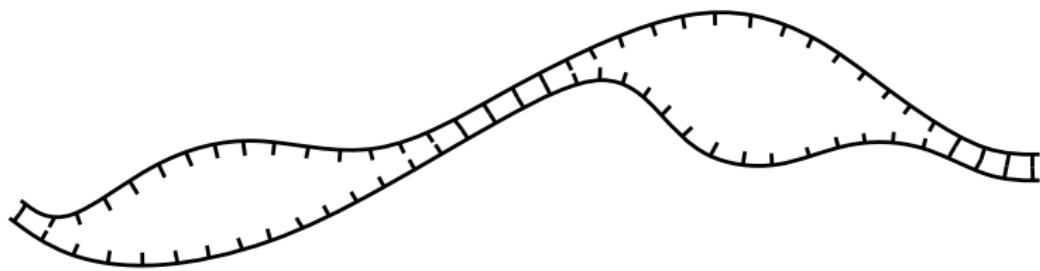
Strands are tied together by **energetic** (hydrogen) bonds
(otherwise they would be detached, for **entropic** reasons)

Denaturation transition

At high temperature there is an **unzipping** transition

Some motivations from biology

DNA is a long polymer, typically in a **double stranded state**



Strands are tied together by **energetic** (hydrogen) bonds
(otherwise they would be detached, for **entropic** reasons)

Denaturation transition

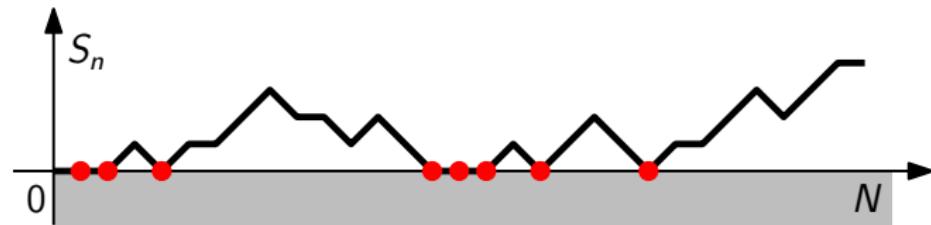
At high temperature there is an **unzipping** transition

How to model such a situation?

The pinning model

1. Configuration space $\Omega = (\mathbb{N}_0)^N$ (N = system size)

S_n = distance of the n -th monomers of the two strands



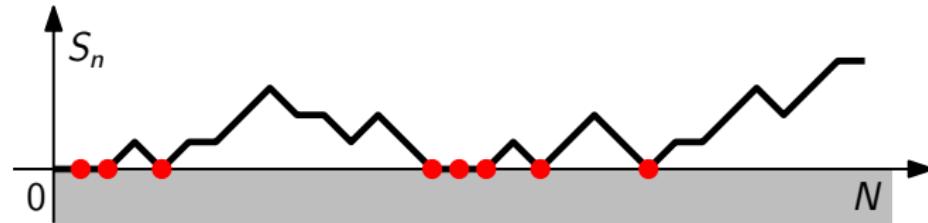
The pinning model

1. Configuration space $\Omega = (\mathbb{N}_0)^N$ (N = system size)

S_n = distance of the n -th monomers of the two strands

2. A priori measure P on Ω (non-interacting system)

P = law of a random walk or Markov chain



The pinning model

1. Configuration space $\Omega = (\mathbb{N}_0)^N$ (N = system size)

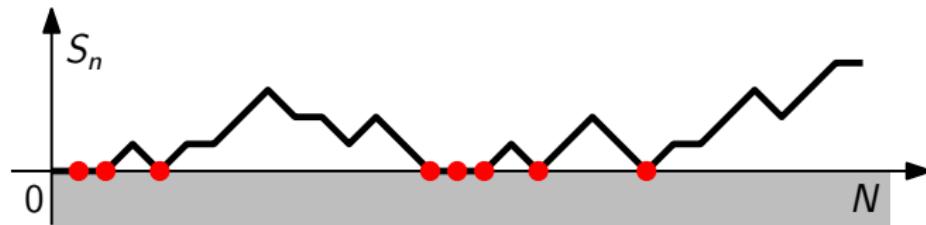
S_n = distance of the n -th monomers of the two strands

2. A priori measure P on Ω (non-interacting system)

P = law of a random walk or Markov chain

3. Energy function $H : \Omega \rightarrow \mathbb{R}$

$H(S) = - \sum_{n=1}^N \xi_n \mathbb{1}_{\{S_n=0\}}$ (ξ_n = energy of n -th bond)



The pinning model

1. Configuration space $\Omega = (\mathbb{N}_0)^N$ (N = system size)

S_n = distance of the n -th monomers of the two strands

2. A priori measure P on Ω (non-interacting system)

P = law of a random walk or Markov chain

3. Energy function $H : \Omega \rightarrow \mathbb{R}$

$H(S) = - \sum_{n=1}^N \xi_n \mathbb{1}_{\{S_n=0\}}$ (ξ_n = energy of n -th bond)

Gibbs measure: $P_{N,\beta}^\xi(\{S\}) = \frac{1}{Z_{N,\beta}} \exp(-\beta H(S)) P(\{S\})$

The pinning model

1. Configuration space $\Omega = (\mathbb{N}_0)^N$ (N = system size)

S_n = distance of the n -th monomers of the two strands

2. A priori measure P on Ω (non-interacting system)

P = law of a random walk or Markov chain

3. Energy function $H : \Omega \rightarrow \mathbb{R}$

$H(S) = - \sum_{n=1}^N \xi_n \mathbb{1}_{\{S_n=0\}}$ (ξ_n = energy of n -th bond)

Gibbs measure: $P_{N,\beta}^\xi(\{S\}) = \frac{1}{Z_{N,\beta}} \exp(-\beta H(S)) P(\{S\})$

In thermal equilibrium at temperature $T > 0$, setting $\beta := \frac{1}{k_B T}$, the probability of observing a configuration S is $P_{N,\beta}^\xi(\{S\})$

The pinning model

1. Configuration space $\Omega = (\mathbb{N}_0)^N$ (N = system size)

S_n = distance of the n -th monomers of the two strands

2. A priori measure P on Ω (non-interacting system)

P = law of a random walk or Markov chain

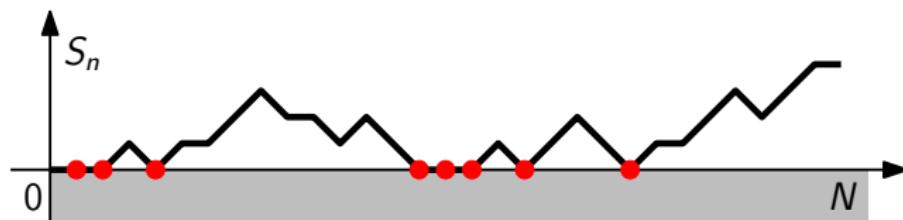
3. Energy function $H : \Omega \rightarrow \mathbb{R}$

$H(S) = - \sum_{n=1}^N \xi_n \mathbb{1}_{\{S_n=0\}}$ (ξ_n = energy of n -th bond)

Gibbs measure: $P_{N,\beta}^\xi(\{S\}) = \frac{1}{Z_{N,\beta}} \exp(-\beta H(S)) P(\{S\})$

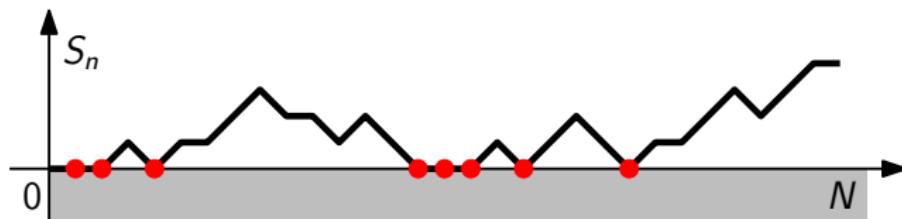
In thermal equilibrium at temperature $T > 0$, setting $\beta := \frac{1}{k_B T}$, the probability of observing a configuration S is $P_{N,\beta}^\xi(\{S\})$

Phase transition



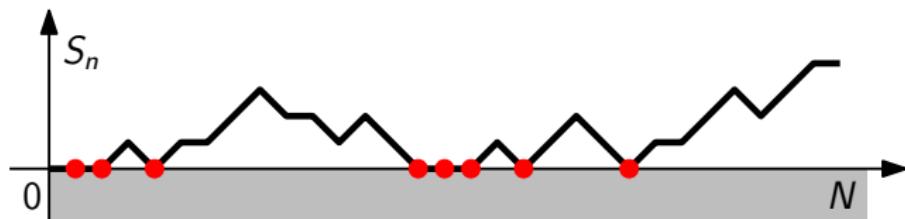
- ▶ Parameters N , $\beta = \frac{1}{k_B T}$, $\xi = (\xi_n)_{1 \leq n \leq N}$ (bond energies)

Phase transition



- ▶ Parameters N , $\beta = \frac{1}{k_B T}$, $\xi = (\xi_n)_{1 \leq n \leq N}$ (bond energies)
- ▶ $P_{N,\beta}^\xi$ probability on a space $\Omega = (\mathbb{N}_0)^N$ of discrete paths
It tells us whether the strands are attached or detached

Phase transition



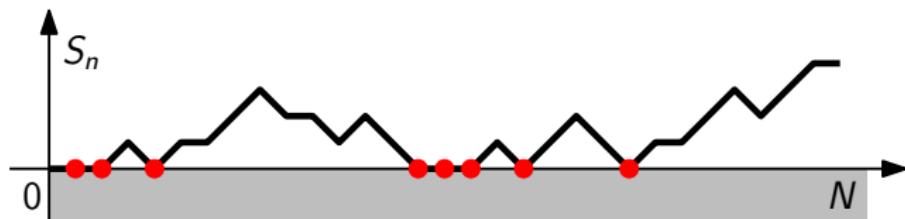
- ▶ Parameters $N, \beta = \frac{1}{k_B T}, \xi = (\xi_n)_{1 \leq n \leq N}$ (bond energies)
- ▶ $P_{N,\beta}^\xi$ probability on a space $\Omega = (\mathbb{N}_0)^N$ of discrete paths
It tells us whether the strands are attached or detached

Phase Transition

There exists $\beta_c > 0$ such that for $N \gg 1$:

- ▶ if $\beta < \beta_c$, $P_{N,\beta}^\xi$ supported by paths with $O(\log N)$ contacts

Phase transition



- ▶ Parameters $N, \beta = \frac{1}{k_B T}, \xi = (\xi_n)_{1 \leq n \leq N}$ (bond energies)
- ▶ $P_{N,\beta}^\xi$ probability on a space $\Omega = (\mathbb{N}_0)^N$ of discrete paths
It tells us whether the strands are attached or detached

Phase Transition

There exists $\beta_c > 0$ such that for $N \gg 1$:

- ▶ if $\beta < \beta_c$, $P_{N,\beta}^\xi$ supported by paths with $O(\log N)$ contacts
- ▶ if $\beta > \beta_c$, $P_{N,\beta}^\xi$ supported by paths with $\sim cN$ contacts

Assumptions on P (a priori law)

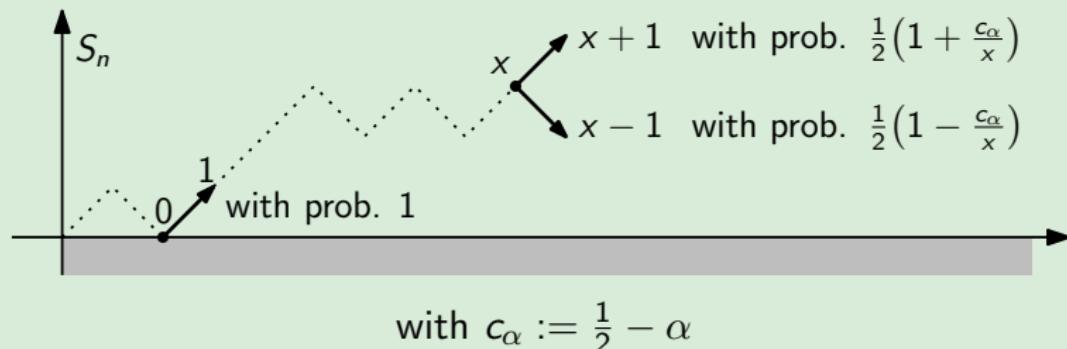
P = law of a Markov chain on \mathbb{N}_0 such that for some $\alpha \in (0, \infty)$

$$P(\text{first return to zero} = n) \sim \frac{(\text{const.})}{n^{1+\alpha}} \quad (\text{loop probability})$$

Assumptions on P (a priori law)

$P =$ law of a Markov chain on \mathbb{N}_0 such that for some $\alpha \in (0, \infty)$

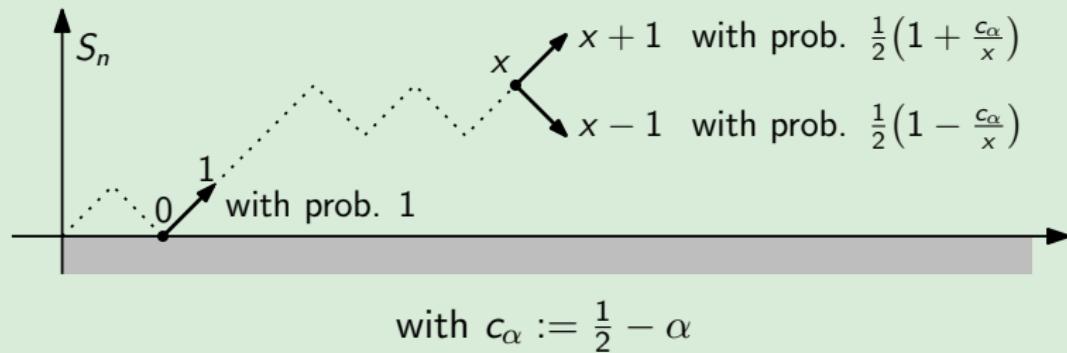
$$P(\text{first return to zero} = n) \sim \frac{(\text{const.})}{n^{1+\alpha}} \quad (\text{loop probability})$$



Assumptions on P (a priori law)

$P =$ law of a Markov chain on \mathbb{N}_0 such that for some $\alpha \in (0, \infty)$

$$P(\text{first return to zero} = n) \sim \frac{(\text{const.})}{n^{1+\alpha}} \quad (\text{loop probability})$$



Discretization of Bessel process: $dS_t = dB_t + \frac{c_\alpha}{S_t} dt$

Assumptions on ξ (bond energies)

How to choose the bond energies $\xi = (\xi_n)_{n \in \mathbb{N}}$ defining $P_{N,\beta}^\xi$?
(linked to the base pairs sequence)

Assumptions on ξ (bond energies)

How to choose the bond energies $\xi = (\xi_n)_{n \in \mathbb{N}}$ defining $P_{N,\beta}^\xi$?
(linked to the base pairs sequence)

In a **random** way! (\rightsquigarrow disordered system)

$(\xi_n)_{n \in \mathbb{N}}$ i.i.d. random variables with mean h and variance 1
(with finite exponential moments)

Assumptions on ξ (bond energies)

How to choose the bond energies $\xi = (\xi_n)_{n \in \mathbb{N}}$ defining $P_{N,\beta}^\xi$?
(linked to the base pairs sequence)

In a **random** way! (\rightsquigarrow disordered system)

$(\xi_n)_{n \in \mathbb{N}}$ i.i.d. random variables with mean h and variance 1
(with finite exponential moments)

1. Fix parameters $\beta \geq 0$ (inverse temp.), $h \in \mathbb{R}$ (disorder mean)

Assumptions on ξ (bond energies)

How to choose the bond energies $\xi = (\xi_n)_{n \in \mathbb{N}}$ defining $P_{N,\beta}^\xi$?
(linked to the base pairs sequence)

In a **random** way! (\rightsquigarrow disordered system)

$(\xi_n)_{n \in \mathbb{N}}$ i.i.d. random variables with mean h and variance 1
(with finite exponential moments)

1. Fix parameters $\beta \geq 0$ (inverse temp.), $h \in \mathbb{R}$ (disorder mean)
2. Sample a typical realization of disorder sequence $\xi = (\xi_n)_{n \in \mathbb{N}}$

Assumptions on ξ (bond energies)

How to choose the bond energies $\xi = (\xi_n)_{n \in \mathbb{N}}$ defining $P_{N,\beta}^\xi$?
(linked to the base pairs sequence)

In a **random** way! (\rightsquigarrow disordered system)

$(\xi_n)_{n \in \mathbb{N}}$ i.i.d. random variables with mean h and variance 1
(with finite exponential moments)

1. Fix parameters $\beta \geq 0$ (inverse temp.), $h \in \mathbb{R}$ (disorder mean)
2. Sample a typical realization of disorder sequence $\xi = (\xi_n)_{n \in \mathbb{N}}$
3. Plug these “external parameters” in the Gibbs measure $P_{N,\beta,h}^\xi$

Some key observations

Large scale properties of the Gibbs measure $P_{N,\beta,h}^\xi$ (as $N \rightarrow \infty$)

Some key observations

Large scale properties of the Gibbs measure $P_{N,\beta,h}^\xi$ (as $N \rightarrow \infty$)

- ▶ do not depend on the realization of disorder $\xi = (\xi_n)_{n \in \mathbb{N}}$
(Warning: they depend on the law of ξ !)

Some key observations

Large scale properties of the Gibbs measure $P_{N,\beta,h}^\xi$ (as $N \rightarrow \infty$)

- ▶ do not depend on the realization of disorder $\xi = (\xi_n)_{n \in \mathbb{N}}$
(Warning: they depend on the law of ξ !)
- ▶ are encoded in the partition function $Z_{\beta,h}^\xi(N, x)$

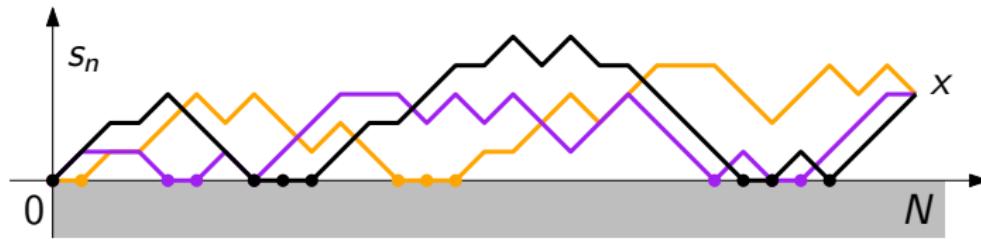
$$Z_{\beta,h}^\xi(N, x) = E[e^{-H(S)} \mathbb{1}_{\{S_N=x\}}] = \sum_{\substack{s: \{0, \dots, N\} \rightarrow \mathbb{N}_0 \\ s_N=x}} e^{-H(s)} P(\{s\})$$

Some key observations

Large scale properties of the Gibbs measure $P_{N,\beta,h}^\xi$ (as $N \rightarrow \infty$)

- ▶ do not depend on the realization of disorder $\xi = (\xi_n)_{n \in \mathbb{N}}$
(Warning: they depend on the law of ξ !)
- ▶ are encoded in the partition function $Z_{\beta,h}^\xi(N, x)$

$$Z_{\beta, h}^{\xi}(N, x) = \mathbb{E}\left[e^{-H(S)} \mathbb{1}_{\{S_N=x\}}\right] = \sum_{\substack{s: \{0, \dots, N\} \rightarrow \mathbb{N}_0 \\ S_N=x}} e^{-H(s)} \mathbb{P}(\{s\})$$



Outline

1. Hydrodynamics
2. The link with “polymers”
3. The random pinning model
4. Weak disorder regime

From discrete to continuum

The pinning model for $\alpha \in (\frac{1}{2}, 1)$ is “disorder relevant” \rightsquigarrow
Interesting behavior in the weak disorder regime $\beta, h \rightarrow 0$

From discrete to continuum

The pinning model for $\alpha \in (\frac{1}{2}, 1)$ is “disorder relevant” \rightsquigarrow
Interesting behavior in the weak disorder regime $\beta, h \rightarrow 0$

Continuum partition function

Choosing appropriately $\beta_N \rightarrow 0, h_N \rightarrow 0$, the diffusively rescaled partition function has a **universal** non-trivial **random** limit

$$Z_{\beta_N, h_N}^\xi(NT, \sqrt{N}X) \xrightarrow[N \rightarrow \infty]{d} \mathcal{Z}(T, X)$$

(which formally solves an irregular stochastic linear PDE)

From discrete to continuum

The pinning model for $\alpha \in (\frac{1}{2}, 1)$ is “disorder relevant” \rightsquigarrow
Interesting behavior in the weak disorder regime $\beta, h \rightarrow 0$

Continuum partition function

Choosing appropriately $\beta_N \rightarrow 0, h_N \rightarrow 0$, the diffusively rescaled partition function has a **universal** non-trivial **random** limit

$$Z_{\beta_N, h_N}^\xi(NT, \sqrt{N}X) \xrightarrow[N \rightarrow \infty]{d} \mathcal{Z}(T, X)$$

(which formally solves an irregular stochastic linear PDE)

Continuum pinning model

The diffusively rescaled Gibbs measure converges to a **random** distribution on $C([0, 1], \mathbb{R})$ (“perturbation” of a Bessel processes)

[Joint work with N. Zygouras (Warwick) and R. Sun (Singapore)]

Thanks.