

Large deviations and fluctuation exponents for some polymer models

Timo Seppäläinen

Department of Mathematics
University of Wisconsin-Madison

2011

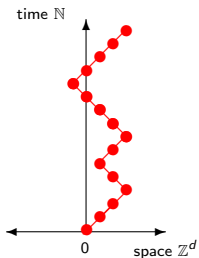
1 Introduction

2 Large deviations

3 Fluctuation exponents

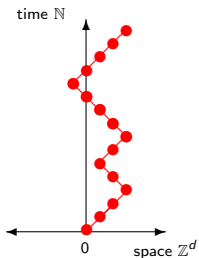
- KPZ equation
- Log-gamma polymer

Directed polymer in a random environment



simple random walk path $(x(t), t)$, $t \in \mathbb{Z}_+$

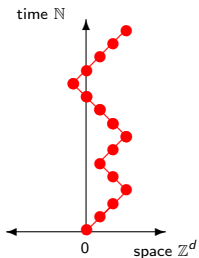
Directed polymer in a random environment



simple random walk path $(x(t), t)$, $t \in \mathbb{Z}_+$

space-time environment $\{\omega(x, t) : x \in \mathbb{Z}^d, t \in \mathbb{N}\}$

Directed polymer in a random environment

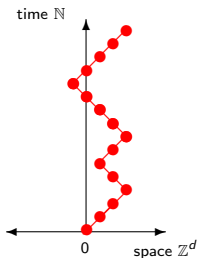


simple random walk path $(x(t), t)$, $t \in \mathbb{Z}_+$

space-time environment $\{\omega(x, t) : x \in \mathbb{Z}^d, t \in \mathbb{N}\}$

inverse temperature $\beta > 0$

Directed polymer in a random environment



simple random walk path $(x(t), t)$, $t \in \mathbb{Z}_+$

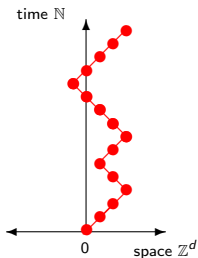
space-time environment $\{\omega(x, t) : x \in \mathbb{Z}^d, t \in \mathbb{N}\}$

inverse temperature $\beta > 0$

quenched probability measure on paths

$$Q_n\{x(\cdot)\} = \frac{1}{Z_n} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$$

Directed polymer in a random environment



simple random walk path $(x(t), t)$, $t \in \mathbb{Z}_+$

space-time environment $\{\omega(x, t) : x \in \mathbb{Z}^d, t \in \mathbb{N}\}$

inverse temperature $\beta > 0$

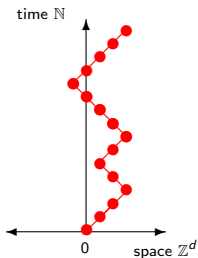
quenched probability measure on paths

$$Q_n\{x(\cdot)\} = \frac{1}{Z_n} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$$

partition function $Z_n = \sum_{x(\cdot)} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$

(summed over all n -paths)

Directed polymer in a random environment



simple random walk path $(x(t), t)$, $t \in \mathbb{Z}_+$

space-time environment $\{\omega(x, t) : x \in \mathbb{Z}^d, t \in \mathbb{N}\}$

inverse temperature $\beta > 0$

quenched probability measure on paths

$$Q_n\{x(\cdot)\} = \frac{1}{Z_n} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$$

partition function $Z_n = \sum_{x(\cdot)} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$

(summed over all n -paths)

\mathbb{P} probability distribution on ω , often $\{\omega(x, t)\}$ i.i.d.

Key quantities again:

- Quenched measure $Q_n\{x(\cdot)\} = Z_n^{-1} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$
- Partition function $Z_n = \sum_{x(\cdot)} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$

Key quantities again:

- Quenched measure $Q_n\{x(\cdot)\} = Z_n^{-1} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$
- Partition function $Z_n = \sum_{x(\cdot)} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$

Questions:

- Behavior of walk $x(\cdot)$ under Q_n on large scales: fluctuation exponents, central limit theorems, large deviations

Key quantities again:

- Quenched measure $Q_n\{x(\cdot)\} = Z_n^{-1} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$
- Partition function $Z_n = \sum_{x(\cdot)} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$

Questions:

- Behavior of walk $x(\cdot)$ under Q_n on large scales: fluctuation exponents, central limit theorems, large deviations
- Behavior of $\log Z_n$ (now also random as a function of ω)

Key quantities again:

- Quenched measure $Q_n\{x(\cdot)\} = Z_n^{-1} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$
- Partition function $Z_n = \sum_{x(\cdot)} \exp\left\{\beta \sum_{t=1}^n \omega(x(t), t)\right\}$

Questions:

- Behavior of walk $x(\cdot)$ under Q_n on large scales: fluctuation exponents, central limit theorems, large deviations
- Behavior of $\log Z_n$ (now also random as a function of ω)
- Dependence on β and d

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Generalize: $E_0 =$ expectation under background RW X_n on \mathbb{Z}^ν .

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Generalize: E_0 = expectation under background RW X_n on \mathbb{Z}^ν .

$$n^{-1} \log Z_n = n^{-1} \log E_0 \left[e^{\beta \sum_{k=0}^{n-1} \omega X_k} \right]$$

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Generalize: E_0 = expectation under background RW X_n on \mathbb{Z}^ν .

$$\begin{aligned} n^{-1} \log Z_n &= n^{-1} \log E_0 \left[e^{\beta \sum_{k=0}^{n-1} \omega_{X_k}} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(\omega_{X_k})} \right] \end{aligned}$$

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Generalize: E_0 = expectation under background RW X_n on \mathbb{Z}^ν .

$$\begin{aligned} n^{-1} \log Z_n &= n^{-1} \log E_0 \left[e^{\beta \sum_{k=0}^{n-1} \omega_{X_k}} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(\omega_{X_k})} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(T_{X_k} \omega, Z_{k+1, k+l})} \right] \end{aligned}$$

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Generalize: E_0 = expectation under background RW X_n on \mathbb{Z}^ν .

$$\begin{aligned} n^{-1} \log Z_n &= n^{-1} \log E_0 \left[e^{\beta \sum_{k=0}^{n-1} \omega_{X_k}} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(\omega_{X_k})} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(T_{X_k} \omega, Z_{k+1, k+l})} \right] \end{aligned}$$

Introduced shift $(T_x \omega)_y = \omega_{x+y}$, steps $Z_k = X_k - X_{k-1} \in \mathcal{R}$,
 $Z_{1, \ell} = (Z_1, Z_2, \dots, Z_\ell)$.

Question: describe quenched limit $\lim_{n \rightarrow \infty} n^{-1} \log Z_n$ (\mathbb{P} -a.s.)

Large deviation perspective.

Generalize: E_0 = expectation under background RW X_n on \mathbb{Z}^ν .

$$\begin{aligned} n^{-1} \log Z_n &= n^{-1} \log E_0 \left[e^{\beta \sum_{k=0}^{n-1} \omega_{X_k}} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(\omega_{X_k})} \right] \\ &= n^{-1} \log E_0 \left[e^{\sum_{k=0}^{n-1} g(T_{X_k} \omega, Z_{k+1, k+l})} \right] \end{aligned}$$

Introduced shift $(T_x \omega)_y = \omega_{x+y}$, steps $Z_k = X_k - X_{k-1} \in \mathcal{R}$,

$Z_{1,\ell} = (Z_1, Z_2, \dots, Z_\ell)$.

$g(\omega, z_{1,\ell})$ is a function on $\Omega_\ell = \Omega \times \mathcal{R}^\ell$.

Define empirical measure $R_n = n^{-1} \sum_{k=0}^{n-1} \delta_{T_{X_k} \omega, Z_{k+1, k+\ell}}$.

It is a probability measure on Ω_ℓ .

Define empirical measure $R_n = n^{-1} \sum_{k=0}^{n-1} \delta_{T_{X_k} \omega, Z_{k+1, k+\ell}}$.

It is a probability measure on Ω_ℓ .

Then $n^{-1} \log Z_n = n^{-1} \log E_0 [e^{nR_n(g)}]$

Define empirical measure $R_n = n^{-1} \sum_{k=0}^{n-1} \delta_{T_{X_k} \omega, Z_{k+1, k+\ell}}$.

It is a probability measure on Ω_ℓ .

Then $n^{-1} \log Z_n = n^{-1} \log E_0 [e^{nR_n(g)}]$

Task: understand large deviations of $P_0\{R_n \in \cdot\}$ under \mathbb{P} -a.e. fixed ω (quenched).

Define empirical measure $R_n = n^{-1} \sum_{k=0}^{n-1} \delta_{T_{X_k} \omega, Z_{k+1, k+l}}$.

It is a probability measure on Ω_ℓ .

Then $n^{-1} \log Z_n = n^{-1} \log E_0 [e^{nR_n(g)}]$

Task: understand large deviations of $P_0\{R_n \in \cdot\}$ under \mathbb{P} -a.e. fixed ω (quenched).

Process on Ω_ℓ is $(T_{X_n} \omega, Z_{n+1, n+l})$, under a fixed ω .

Define empirical measure $R_n = n^{-1} \sum_{k=0}^{n-1} \delta_{T_{X_k} \omega, Z_{k+1, k+\ell}}$.

It is a probability measure on Ω_ℓ .

Then $n^{-1} \log Z_n = n^{-1} \log E_0 [e^{nR_n(g)}]$

Task: understand large deviations of $P_0\{R_n \in \cdot\}$ under \mathbb{P} -a.e. fixed ω (quenched).

Process on Ω_ℓ is $(T_{X_n} \omega, Z_{n+1, n+\ell})$, under a fixed ω .

Evolution: pick random step z from \mathcal{R} , then execute move $S_z : (\omega, z_{1, \ell}) \rightarrow (T_{z_1} \omega, z_{2, \ell} z)$.

Define empirical measure $R_n = n^{-1} \sum_{k=0}^{n-1} \delta_{T_{X_k} \omega, Z_{k+1, k+l}}$.

It is a probability measure on Ω_ℓ .

Then $n^{-1} \log Z_n = n^{-1} \log E_0 [e^{nR_n(g)}]$

Task: understand large deviations of $P_0\{R_n \in \cdot\}$ under \mathbb{P} -a.e. fixed ω (quenched).

Process on Ω_ℓ is $(T_{X_n} \omega, Z_{n+1, n+l})$, under a fixed ω .

Evolution: pick random step z from \mathcal{R} , then execute move

$$S_z : (\omega, z_{1, \ell}) \rightarrow (T_{z_1} \omega, z_{2, \ell} z).$$

Defines kernel p on Ω_ℓ : $p(\eta, S_z \eta) = |\mathcal{R}|^{-1}$.

Entropy

Let $\mu_0 = \Omega$ -marginal of $\mu \in \mathcal{M}_1(\Omega_\ell)$. Define

$$H_{\mathbb{P}}(\mu) = \begin{cases} \inf \{ H(\mu \times q \mid \mu \times p) : \mu q = \mu \} & \text{if } \mu_0 \ll \mathbb{P} \\ \infty & \text{otherwise.} \end{cases}$$

Infimum over Markov kernels q that fix μ .

Entropy

Let $\mu_0 = \Omega$ -marginal of $\mu \in \mathcal{M}_1(\Omega_\ell)$. Define

$$H_{\mathbb{P}}(\mu) = \begin{cases} \inf \{ H(\mu \times q | \mu \times p) : \mu q = \mu \} & \text{if } \mu_0 \ll \mathbb{P} \\ \infty & \text{otherwise.} \end{cases}$$

Infimum over Markov kernels q that fix μ .

Inside the braces the familiar relative entropy

$$H(\mu \times q | \mu \times p) = \int_{\Omega_\ell} \sum_{z \in \mathcal{R}} q(\eta, S_z \eta) \log \frac{q(\eta, S_z \eta)}{p(\eta, S_z \eta)} \mu(d\eta).$$

Entropy

Let $\mu_0 = \Omega$ -marginal of $\mu \in \mathcal{M}_1(\Omega_\ell)$. Define

$$H_{\mathbb{P}}(\mu) = \begin{cases} \inf \{ H(\mu \times q \mid \mu \times p) : \mu q = \mu \} & \text{if } \mu_0 \ll \mathbb{P} \\ \infty & \text{otherwise.} \end{cases}$$

Infimum over Markov kernels q that fix μ .

Inside the braces the familiar relative entropy

$$H(\mu \times q \mid \mu \times p) = \int_{\Omega_\ell} \sum_{z \in \mathcal{R}} q(\eta, S_z \eta) \log \frac{q(\eta, S_z \eta)}{p(\eta, S_z \eta)} \mu(d\eta).$$

$H_{\mathbb{P}}$ is convex but not lower semicontinuous.

Assumptions.

- Environment $\{\omega_x\}$ IID under \mathbb{P} .
- g local function on Ω_ℓ s.t. $\mathbb{E}|g|^p < \infty$ for some $p > 2(\nu + 1)$.

Assumptions.

- Environment $\{\omega_x\}$ IID under \mathbb{P} .
- g local function on Ω_ℓ s.t. $\mathbb{E}|g|^p < \infty$ for some $p > 2(\nu + 1)$.

Theorem. (Rassoul-Agha, S, Yilmaz) Deterministic limit

$$\Lambda(g) = \lim_{n \rightarrow \infty} n^{-1} \log E_0 [e^{nR_n(g)}]$$

exists \mathbb{P} -a.s. and

$$\Lambda(g) = H_{\mathbb{P}}^{\#}(g) \equiv \sup_{\mu} \sup_{c > 0} \{E^{\mu}[g \wedge c] - H_{\mathbb{P}}(\mu)\}.$$

Assumptions.

- Environment $\{\omega_x\}$ IID under \mathbb{P} .
- g local function on Ω_ℓ s.t. $\mathbb{E}|g|^p < \infty$ for some $p > 2(\nu + 1)$.

Theorem. (Rassoul-Agha, S, Yilmaz) Deterministic limit

$$\Lambda(g) = \lim_{n \rightarrow \infty} n^{-1} \log E_0 [e^{nR_n(g)}]$$

exists \mathbb{P} -a.s. and

$$\Lambda(g) = H_{\mathbb{P}}^{\#}(g) \equiv \sup_{\mu} \sup_{c>0} \{E^{\mu}[g \wedge c] - H_{\mathbb{P}}(\mu)\}.$$

Remark. True more generally, e.g. ergodic \mathbb{P} if g is bounded.

Quenched weak LDP (large deviation principle) under Q_n .

$$Q_n(A) = \frac{1}{E_0[e^{nR_n(g)}]} E_0[e^{nR_n(g)} \mathbf{1}_A(\omega, Z_{1,\infty})]$$

Quenched weak LDP (large deviation principle) under Q_n .

$$Q_n(A) = \frac{1}{E_0[e^{nR_n(g)}]} E_0[e^{nR_n(g)} \mathbf{1}_A(\omega, Z_{1,\infty})]$$

Rate function $I(\mu) = \sup_{\varphi \in \mathcal{U}(\Omega_\ell)} \{E^\mu(\varphi) - \Lambda(\varphi + g)\} + \Lambda(g)$.

Quenched weak LDP (large deviation principle) under Q_n .

$$Q_n(A) = \frac{1}{E_0[e^{nR_n(g)}]} E_0[e^{nR_n(g)} \mathbf{1}_A(\omega, Z_{1,\infty})]$$

Rate function $I(\mu) = \sup_{\varphi \in \mathcal{U}(\Omega_\ell)} \{E^\mu(\varphi) - \Lambda(\varphi + g)\} + \Lambda(g)$.

Theorem. (RSY) Assumptions as above and $\Lambda(g)$ finite. Then \mathbb{P} -a.s. for compact $F \subseteq \mathcal{M}_1(\Omega_\ell)$ and open $G \subseteq \mathcal{M}_1(\Omega_\ell)$:

$$\overline{\lim}_{n \rightarrow \infty} n^{-1} \log Q_n\{R_n \in F\} \leq - \inf_{\mu \in F} I(\mu),$$

$$\underline{\lim}_{n \rightarrow \infty} n^{-1} \log Q_n\{R_n \in G\} \geq - \inf_{\mu \in G} I(\mu).$$

Return to $d + 1$ dim directed polymer in i.i.d. environment.

Return to $d + 1$ dim directed polymer in i.i.d. environment.

Question: Is the path $x(\cdot)$ diffusive or not, that is, does it scale like standard RW?

Return to $d + 1$ dim directed polymer in i.i.d. environment.

Question: Is the path $x(\cdot)$ diffusive or not, that is, does it scale like standard RW?

Early results: diffusive behavior for $d \geq 3$ and small $\beta > 0$:

1988 Imbrie and Spencer: $n^{-1} E^Q(|x(n)|^2) \rightarrow c$ \mathbb{P} -a.s.

1989 Bolthausen: quenched CLT for $n^{-1/2}x(n)$.

Return to $d + 1$ dim directed polymer in i.i.d. environment.

Question: Is the path $x(\cdot)$ diffusive or not, that is, does it scale like standard RW?

Early results: diffusive behavior for $d \geq 3$ and small $\beta > 0$:

1988 Imbrie and Spencer: $n^{-1} E^Q(|x(n)|^2) \rightarrow c$ \mathbb{P} -a.s.

1989 Bolthausen: quenched CLT for $n^{-1/2}x(n)$.

In the opposite direction: if $d = 1, 2$, or $d \geq 3$ and β large enough, then $\exists c > 0$ s.t.

$$\overline{\lim}_{n \rightarrow \infty} \max_z Q_n\{x(n) = z\} \geq c \quad \mathbb{P}\text{-a.s.}$$

(Carmona and Hu 2002, Comets, Shiga, and Yoshida 2003)

Definition of fluctuation exponents ζ and χ

Definition of fluctuation exponents ζ and χ

- Fluctuations of the path $\{x(t) : 0 \leq t \leq n\}$ are of order n^ζ .

Definition of fluctuation exponents ζ and χ

- Fluctuations of the path $\{x(t) : 0 \leq t \leq n\}$ are of order n^ζ .
- Fluctuations of $\log Z_n$ are of order n^χ .

Definition of fluctuation exponents ζ and χ

- Fluctuations of the path $\{x(t) : 0 \leq t \leq n\}$ are of order n^ζ .
- Fluctuations of $\log Z_n$ are of order n^χ .
- Conjecture for $d = 1$: $\zeta = 2/3$ and $\chi = 1/3$.

Definition of fluctuation exponents ζ and χ

- Fluctuations of the path $\{x(t) : 0 \leq t \leq n\}$ are of order n^ζ .
- Fluctuations of $\log Z_n$ are of order n^χ .
- Conjecture for $d = 1$: $\zeta = 2/3$ and $\chi = 1/3$.

Results: these exact exponents for three particular 1+1 dimensional models.

Earlier results for $d = 1$ exponents

Past rigorous bounds give $3/5 \leq \zeta \leq 3/4$ and $\chi \geq 1/8$:

Earlier results for $d = 1$ exponents

Past rigorous bounds give $3/5 \leq \zeta \leq 3/4$ and $\chi \geq 1/8$:

- Brownian motion in Poissonian potential: Wüthrich 1998, Comets and Yoshida 2005.

Earlier results for $d = 1$ exponents

Past rigorous bounds give $3/5 \leq \zeta \leq 3/4$ and $\chi \geq 1/8$:

- Brownian motion in Poissonian potential: Wüthrich 1998, Comets and Yoshida 2005.
- Gaussian RW in Gaussian potential: Petermann 2000 $\zeta \geq 3/5$, Mejane 2004 $\zeta \leq 3/4$

Earlier results for $d = 1$ exponents

Past rigorous bounds give $3/5 \leq \zeta \leq 3/4$ and $\chi \geq 1/8$:

- Brownian motion in Poissonian potential: Wüthrich 1998, Comets and Yoshida 2005.
- Gaussian RW in Gaussian potential: Petermann 2000 $\zeta \geq 3/5$, Mejane 2004 $\zeta \leq 3/4$
- Licea, Newman, Piza 1995-96: corresponding results for first passage percolation

Rigorous $\zeta = 2/3$ and $\chi = 1/3$ results

- (1) Log-gamma polymer: $\beta = 1$ and $e^{-\omega(x,t)} \sim \text{Gamma}$, plus appropriate boundary conditions

Rigorous $\zeta = 2/3$ and $\chi = 1/3$ results

- (1) Log-gamma polymer: $\beta = 1$ and $e^{-\omega(x,t)} \sim \text{Gamma}$, plus appropriate boundary conditions
- (2) Polymer in a Brownian environment. (Joint with B. Valkó.) Model introduced by O'Connell and Yor 2001.

Rigorous $\zeta = 2/3$ and $\chi = 1/3$ results

- (1) Log-gamma polymer: $\beta = 1$ and $e^{-\omega(x,t)} \sim \text{Gamma}$, plus appropriate boundary conditions
- (2) Polymer in a Brownian environment. (Joint with B. Valkó.) Model introduced by O'Connell and Yor 2001.
- (3) Continuum directed polymer, or Hopf-Cole solution of the Kardar-Parisi-Zhang (KPZ) equation:
 - (i) Initial height function given by two-sided Brownian motion. (Joint with M. Balázs and J. Quastel.)
 - (ii) Narrow wedge initial condition. (Amir, Corwin, Quastel)

Rigorous $\zeta = 2/3$ and $\chi = 1/3$ results

- (1) Log-gamma polymer: $\beta = 1$ and $e^{-\omega(x,t)} \sim \text{Gamma}$, plus appropriate boundary conditions
- (2) Polymer in a Brownian environment. (Joint with B. Valkó.) Model introduced by O'Connell and Yor 2001.
- (3) Continuum directed polymer, or Hopf-Cole solution of the Kardar-Parisi-Zhang (KPZ) equation:
 - (i) Initial height function given by two-sided Brownian motion. (Joint with M. Balázs and J. Quastel.)
 - (ii) Narrow wedge initial condition. (Amir, Corwin, Quastel)

Next details on (3.i), then details on (1).

Hopf-Cole solution to KPZ equation

KPZ eqn for height function $h(t, x)$ of a 1+1 dim interface:

$$h_t = \frac{1}{2} h_{xx} - \frac{1}{2} (h_x)^2 + \dot{W}$$

where \dot{W} = Gaussian space-time white noise.

Hopf-Cole solution to KPZ equation

KPZ eqn for height function $h(t, x)$ of a 1+1 dim interface:

$$h_t = \frac{1}{2} h_{xx} - \frac{1}{2} (h_x)^2 + \dot{W}$$

where \dot{W} = Gaussian space-time white noise.

Initial height $h(0, x) =$ two-sided Brownian motion for $x \in \mathbb{R}$.

Hopf-Cole solution to KPZ equation

KPZ eqn for height function $h(t, x)$ of a 1+1 dim interface:

$$h_t = \frac{1}{2} h_{xx} - \frac{1}{2} (h_x)^2 + \dot{W}$$

where \dot{W} = Gaussian space-time white noise.

Initial height $h(0, x)$ = two-sided Brownian motion for $x \in \mathbb{R}$.

$Z = \exp(-h)$ satisfies $Z_t = \frac{1}{2} Z_{xx} - Z \dot{W}$ that can be solved.

Hopf-Cole solution to KPZ equation

KPZ eqn for height function $h(t, x)$ of a 1+1 dim interface:

$$h_t = \frac{1}{2} h_{xx} - \frac{1}{2} (h_x)^2 + \dot{W}$$

where \dot{W} = Gaussian space-time white noise.

Initial height $h(0, x)$ = two-sided Brownian motion for $x \in \mathbb{R}$.

$Z = \exp(-h)$ satisfies $Z_t = \frac{1}{2} Z_{xx} - Z \dot{W}$ that can be solved.

Define $h = -\log Z$, the **Hopf-Cole solution** of KPZ.

Hopf-Cole solution to KPZ equation

KPZ eqn for height function $h(t, x)$ of a 1+1 dim interface:

$$h_t = \frac{1}{2} h_{xx} - \frac{1}{2} (h_x)^2 + \dot{W}$$

where \dot{W} = Gaussian space-time white noise.

Initial height $h(0, x)$ = two-sided Brownian motion for $x \in \mathbb{R}$.

$Z = \exp(-h)$ satisfies $Z_t = \frac{1}{2} Z_{xx} - Z \dot{W}$ that can be solved.

Define $h = -\log Z$, the **Hopf-Cole solution** of KPZ.

Bertini-Giacomin (1997): h can be obtained as a weak limit via a smoothing and renormalization of KPZ.

WASEP connection

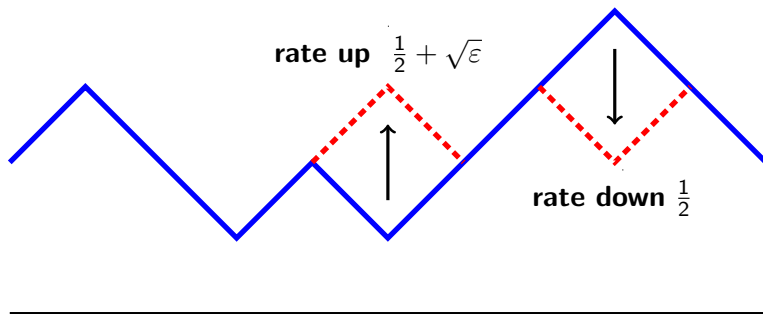
$\zeta_\varepsilon(t, x)$ height process of weakly asymmetric simple exclusion s.t.

$$\zeta_\varepsilon(x+1) - \zeta_\varepsilon(x) = \pm 1$$

WASEP connection

$\zeta_\varepsilon(t, x)$ height process of weakly asymmetric simple exclusion s.t.

$$\zeta_\varepsilon(x+1) - \zeta_\varepsilon(x) = \pm 1$$



WASEP connection

Jumps:

$$\zeta_\varepsilon(x) \longrightarrow \begin{cases} \zeta_\varepsilon(x) + 2 & \text{with rate } \frac{1}{2} + \sqrt{\varepsilon} \text{ if } \zeta_\varepsilon(x) \text{ is a local min} \\ \zeta_\varepsilon(x) - 2 & \text{with rate } \frac{1}{2} \text{ if } \zeta_\varepsilon(x) \text{ is a local max} \end{cases}$$

WASEP connection

Jumps:

$$\zeta_\varepsilon(x) \longrightarrow \begin{cases} \zeta_\varepsilon(x) + 2 & \text{with rate } \frac{1}{2} + \sqrt{\varepsilon} \text{ if } \zeta_\varepsilon(x) \text{ is a local min} \\ \zeta_\varepsilon(x) - 2 & \text{with rate } \frac{1}{2} \text{ if } \zeta_\varepsilon(x) \text{ is a local max} \end{cases}$$

Initially: $\zeta_\varepsilon(0, x+1) - \zeta_\varepsilon(0, x) = \pm 1$ with probab $\frac{1}{2}$.

WASEP connection

Jumps:

$$\zeta_\varepsilon(x) \longrightarrow \begin{cases} \zeta_\varepsilon(x) + 2 & \text{with rate } \frac{1}{2} + \sqrt{\varepsilon} \text{ if } \zeta_\varepsilon(x) \text{ is a local min} \\ \zeta_\varepsilon(x) - 2 & \text{with rate } \frac{1}{2} \text{ if } \zeta_\varepsilon(x) \text{ is a local max} \end{cases}$$

Initially: $\zeta_\varepsilon(0, x+1) - \zeta_\varepsilon(0, x) = \pm 1$ with probab $\frac{1}{2}$.

$$h_\varepsilon(t, x) = \varepsilon^{1/2} (\zeta_\varepsilon(\varepsilon^{-2}t, [\varepsilon^{-1}x]) - v_\varepsilon t)$$

WASEP connection

Jumps:

$$\zeta_\varepsilon(x) \longrightarrow \begin{cases} \zeta_\varepsilon(x) + 2 & \text{with rate } \frac{1}{2} + \sqrt{\varepsilon} \text{ if } \zeta_\varepsilon(x) \text{ is a local min} \\ \zeta_\varepsilon(x) - 2 & \text{with rate } \frac{1}{2} \text{ if } \zeta_\varepsilon(x) \text{ is a local max} \end{cases}$$

Initially: $\zeta_\varepsilon(0, x+1) - \zeta_\varepsilon(0, x) = \pm 1$ with probab $\frac{1}{2}$.

$$h_\varepsilon(t, x) = \varepsilon^{1/2} (\zeta_\varepsilon(\varepsilon^{-2}t, [\varepsilon^{-1}x]) - v_\varepsilon t)$$

Thm. As $\varepsilon \searrow 0$, $h_\varepsilon \Rightarrow h$ (Bertini-Giacomin 1997).

Fluctuation bounds

From coupling arguments for WASEP

$$C_1 t^{2/3} \leq \text{Var}(h_\varepsilon(t, 0)) \leq C_2 t^{2/3}$$

Fluctuation bounds

From coupling arguments for WASEP

$$C_1 t^{2/3} \leq \text{Var}(h_\varepsilon(t, 0)) \leq C_2 t^{2/3}$$

Thm. (Balázs-Quastel-S) For the Hopf-Cole solution of KPZ,

$$C_1 t^{2/3} \leq \text{Var}(h(t, 0)) \leq C_2 t^{2/3}$$

Fluctuation bounds

From coupling arguments for WASEP

$$C_1 t^{2/3} \leq \text{Var}(h_\varepsilon(t, 0)) \leq C_2 t^{2/3}$$

Thm. (Balázs-Quastel-S) For the Hopf-Cole solution of KPZ,

$$C_1 t^{2/3} \leq \text{Var}(h(t, 0)) \leq C_2 t^{2/3}$$

The lower bound comes from control of rescaled correlations

$$S_\varepsilon(t, x) = 4\varepsilon^{-1} \text{Cov}[\eta(\varepsilon^{-2}t, \varepsilon^{-1}x), \eta(0, 0)]$$

Rescaled correlations:

$$S_\varepsilon(t, x) = 4\varepsilon^{-1} \text{Cov}[\eta(\varepsilon^{-2}t, \varepsilon^{-1}x), \eta(0, 0)]$$

Rescaled correlations:

$$S_\varepsilon(t, x) = 4\varepsilon^{-1} \text{Cov}[\eta(\varepsilon^{-2}t, \varepsilon^{-1}x), \eta(0, 0)]$$

$S_\varepsilon(t, x)dx \Rightarrow S(t, dx)$ with control of moments:

$$\int |x|^m S_\varepsilon(t, x) dx \sim O(t^{2m/3}), \quad 1 \leq m < 3.$$

(A second class particle estimate.)

Rescaled correlations:

$$S_\varepsilon(t, x) = 4\varepsilon^{-1} \text{Cov}[\eta(\varepsilon^{-2}t, \varepsilon^{-1}x), \eta(0, 0)]$$

$S_\varepsilon(t, x)dx \Rightarrow S(t, dx)$ with control of moments:

$$\int |x|^m S_\varepsilon(t, x) dx \sim O(t^{2m/3}), \quad 1 \leq m < 3.$$

(A second class particle estimate.)

$$S(t, dx) = \frac{1}{2} \partial_{xx} \text{Var}(h(t, x)) \quad \text{as distributions.}$$

Rescaled correlations:

$$S_\varepsilon(t, x) = 4\varepsilon^{-1} \text{Cov}[\eta(\varepsilon^{-2}t, \varepsilon^{-1}x), \eta(0, 0)]$$

$S_\varepsilon(t, x)dx \Rightarrow S(t, dx)$ with control of moments:

$$\int |x|^m S_\varepsilon(t, x) dx \sim O(t^{2m/3}), \quad 1 \leq m < 3.$$

(A second class particle estimate.)

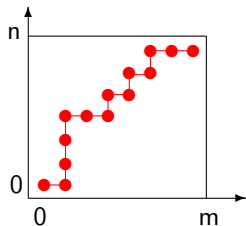
$$S(t, dx) = \frac{1}{2} \partial_{xx} \text{Var}(h(t, x)) \quad \text{as distributions.}$$

With some control over tails we arrive at

$$\text{Var}(h(t, 0)) = \int |x| S(t, dx) \sim O(t^{2/3}).$$

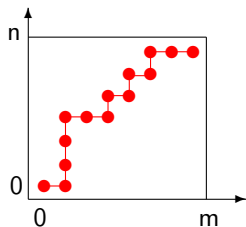
1+1 dimensional lattice polymer with log-gamma weights

Fix both endpoints.



1+1 dimensional lattice polymer with log-gamma weights

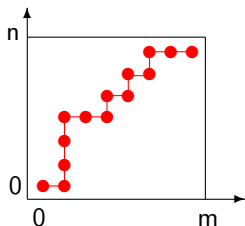
Fix both endpoints.



$\Pi_{m,n}$ = set of admissible paths

1+1 dimensional lattice polymer with log-gamma weights

Fix both endpoints.

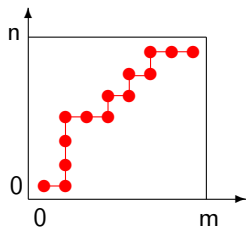


$\Pi_{m,n}$ = set of admissible paths

independent weights $Y_{i,j} = e^{\omega(i,j)}$

1+1 dimensional lattice polymer with log-gamma weights

Fix both endpoints.



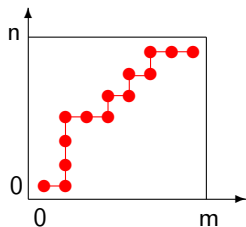
$\Pi_{m,n}$ = set of admissible paths

independent weights $Y_{i,j} = e^{\omega(i,j)}$

environment $(Y_{i,j} : (i,j) \in \mathbb{Z}_+^2)$

1+1 dimensional lattice polymer with log-gamma weights

Fix both endpoints.



$\Pi_{m,n}$ = set of admissible paths

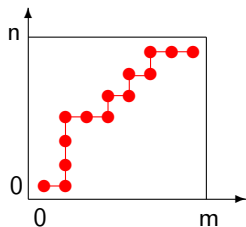
independent weights $Y_{i,j} = e^{\omega(i,j)}$

environment $(Y_{i,j} : (i,j) \in \mathbb{Z}_+^2)$

$$Z_{m,n} = \sum_{x_\bullet} \prod_{k=1}^{m+n} Y_{x_k}$$

1+1 dimensional lattice polymer with log-gamma weights

Fix both endpoints.



$\Pi_{m,n}$ = set of admissible paths

independent weights $Y_{i,j} = e^{\omega(i,j)}$

environment $(Y_{i,j} : (i,j) \in \mathbb{Z}_+^2)$

$$Z_{m,n} = \sum_{x_\cdot} \prod_{k=1}^{m+n} Y_{x_k}$$

quenched measure $Q_{m,n}(x_\cdot) = Z_{m,n}^{-1} \prod_{k=1}^{m+n} Y_{x_k}$

averaged measure $P_{m,n}(x_\cdot) = \mathbb{E}Q_{m,n}(x_\cdot)$

Weight distributions

- Parameters $0 < \theta < \mu$.

Weight distributions

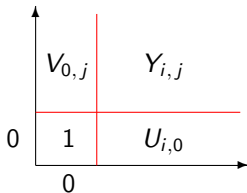
- Parameters $0 < \theta < \mu$.
- **Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$

Weight distributions

- Parameters $0 < \theta < \mu$.
- **Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$
- **Boundary weights** $U_{i,0} = Y_{i,0}$ and $V_{0,j} = Y_{0,j}$.

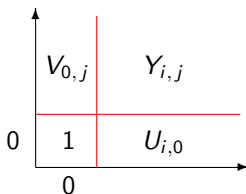
Weight distributions

- Parameters $0 < \theta < \mu$.
- **Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$
- **Boundary weights** $U_{i,0} = Y_{i,0}$ and $V_{0,j} = Y_{0,j}$.



Weight distributions

- Parameters $0 < \theta < \mu$.
- Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$
- Boundary weights** $U_{i,0} = Y_{i,0}$ and $V_{0,j} = Y_{0,j}$.



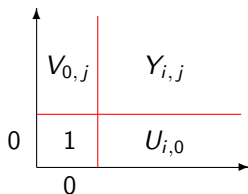
$$U_{i,0}^{-1} \sim \text{Gamma}(\theta)$$

$$V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

Weight distributions

- Parameters $0 < \theta < \mu$.
- Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$
- Boundary weights** $U_{i,0} = Y_{i,0}$ and $V_{0,j} = Y_{0,j}$.



$$U_{i,0}^{-1} \sim \text{Gamma}(\theta)$$

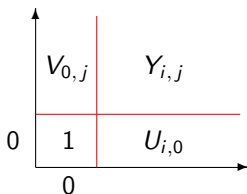
$$V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

- Gamma(θ) density: $\Gamma(\theta)^{-1} x^{\theta-1} e^{-x}$ on \mathbb{R}_+

Weight distributions

- Parameters $0 < \theta < \mu$.
- Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$
- Boundary weights** $U_{i,0} = Y_{i,0}$ and $V_{0,j} = Y_{0,j}$.



$$U_{i,0}^{-1} \sim \text{Gamma}(\theta)$$

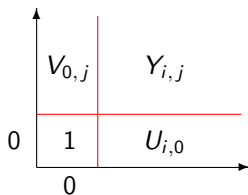
$$V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

- Gamma(θ) density: $\Gamma(\theta)^{-1} x^{\theta-1} e^{-x}$ on \mathbb{R}_+
- $\Psi_n(s) = (d^{n+1}/ds^{n+1}) \log \Gamma(s)$

Weight distributions

- Parameters $0 < \theta < \mu$.
- Bulk weights** $Y_{i,j}$ for $i, j \in \mathbb{N}$
- Boundary weights** $U_{i,0} = Y_{i,0}$ and $V_{0,j} = Y_{0,j}$.



$$U_{i,0}^{-1} \sim \text{Gamma}(\theta)$$

$$V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

- Gamma(θ) density: $\Gamma(\theta)^{-1} x^{\theta-1} e^{-x}$ on \mathbb{R}_+
- $\Psi_n(s) = (d^{n+1}/ds^{n+1}) \log \Gamma(s)$
- $\mathbb{E}(\log U) = -\Psi_0(\theta)$ and $\text{Var}(\log U) = \Psi_1(\theta)$

Variance bounds for $\log Z$

With $0 < \theta < \mu$ fixed and $N \nearrow \infty$ assume

$$|m - N\Psi_1(\mu - \theta)| \leq CN^{2/3} \quad \text{and} \quad |n - N\Psi_1(\theta)| \leq CN^{2/3} \quad (1)$$

Variance bounds for $\log Z$

With $0 < \theta < \mu$ fixed and $N \nearrow \infty$ assume

$$|m - N\Psi_1(\mu - \theta)| \leq CN^{2/3} \quad \text{and} \quad |n - N\Psi_1(\theta)| \leq CN^{2/3} \quad (1)$$

Theorem

For (m, n) as in (1), $C_1 N^{2/3} \leq \text{Var}(\log Z_{m,n}) \leq C_2 N^{2/3}$.

Variance bounds for $\log Z$

With $0 < \theta < \mu$ fixed and $N \nearrow \infty$ assume

$$|m - N\Psi_1(\mu - \theta)| \leq CN^{2/3} \quad \text{and} \quad |n - N\Psi_1(\theta)| \leq CN^{2/3} \quad (1)$$

Theorem

For (m, n) as in (1), $C_1 N^{2/3} \leq \text{Var}(\log Z_{m,n}) \leq C_2 N^{2/3}$.

Theorem

Suppose $n = \Psi_1(\theta)N$ and $m = \Psi_1(\mu - \theta)N + \gamma N^\alpha$ with $\gamma > 0$, $\alpha > 2/3$.
Then

$$N^{-\alpha/2} \left\{ \log Z_{m,n} - \mathbb{E}(\log Z_{m,n}) \right\} \Rightarrow \mathcal{N}(0, \gamma \Psi_1(\theta))$$

Fluctuation bounds for path

$v_0(j)$ = leftmost, $v_1(j)$ = rightmost point of x_\cdot on horizontal line:

$$v_0(j) = \min\{i \in \{0, \dots, m\} : \exists k : x_k = (i, j)\}$$

$$v_1(j) = \max\{i \in \{0, \dots, m\} : \exists k : x_k = (i, j)\}$$

Fluctuation bounds for path

$v_0(j) =$ leftmost, $v_1(j) =$ rightmost point of x_\cdot on horizontal line:

$$v_0(j) = \min\{i \in \{0, \dots, m\} : \exists k : x_k = (i, j)\}$$

$$v_1(j) = \max\{i \in \{0, \dots, m\} : \exists k : x_k = (i, j)\}$$

Theorem

Assume (m, n) as previously and $0 < \tau < 1$. Then

$$(a) P\left\{v_0(\lfloor \tau n \rfloor) < \tau m - bN^{2/3} \text{ or } v_1(\lfloor \tau n \rfloor) > \tau m + bN^{2/3}\right\} \leq \frac{C}{b^3}$$

(b) $\forall \varepsilon > 0 \exists \delta > 0$ such that

$$\overline{\lim}_{N \rightarrow \infty} P\left\{\exists k \text{ such that } |x_k - (\tau m, \tau n)| \leq \delta N^{2/3}\right\} \leq \varepsilon.$$

Results for log-gamma polymer summarized

With reciprocals of gammas for weights, both endpoints of the polymer fixed and the right boundary conditions on the axes, we have identified the one-dimensional exponents

$$\zeta = 2/3 \quad \text{and} \quad \chi = 1/3.$$

Results for log-gamma polymer summarized

With reciprocals of gammas for weights, both endpoints of the polymer fixed and the right boundary conditions on the axes, we have identified the one-dimensional exponents

$$\zeta = 2/3 \quad \text{and} \quad \chi = 1/3.$$

Next step is to

- eliminate the boundary conditions and
- consider polymers with fixed length and free endpoint

Results for log-gamma polymer summarized

With reciprocals of gammas for weights, both endpoints of the polymer fixed and the right boundary conditions on the axes, we have identified the one-dimensional exponents

$$\zeta = 2/3 \quad \text{and} \quad \chi = 1/3.$$

Next step is to

- eliminate the boundary conditions and
- consider polymers with fixed length and free endpoint

In both scenarios we have the upper bounds for both $\log Z$ and the path.

But currently do not have the lower bounds.

Results for log-gamma polymer summarized

With reciprocals of gammas for weights, both endpoints of the polymer fixed and the right boundary conditions on the axes, we have identified the one-dimensional exponents

$$\zeta = 2/3 \quad \text{and} \quad \chi = 1/3.$$

Next step is to

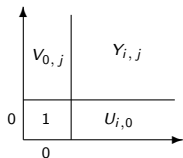
- eliminate the boundary conditions and
- consider polymers with fixed length and free endpoint

In both scenarios we have the upper bounds for both $\log Z$ and the path.

But currently do not have the lower bounds.

Next some key points of the proof.

Burke property for log-gamma polymer with boundary

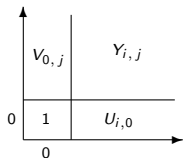


Given initial weights $(i, j \in \mathbb{N})$:

$$U_{i,0}^{-1} \sim \text{Gamma}(\theta), \quad V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

Burke property for log-gamma polymer with boundary



Given initial weights $(i, j \in \mathbb{N})$:

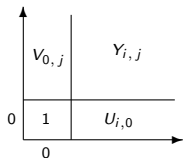
$$U_{i,0}^{-1} \sim \text{Gamma}(\theta), \quad V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

Compute $Z_{m,n}$ for all $(m, n) \in \mathbb{Z}_+^2$ and then define

$$U_{m,n} = \frac{Z_{m,n}}{Z_{m-1,n}} \quad V_{m,n} = \frac{Z_{m,n}}{Z_{m,n-1}} \quad X_{m,n} = \left(\frac{Z_{m,n}}{Z_{m+1,n}} + \frac{Z_{m,n}}{Z_{m,n+1}} \right)^{-1}$$

Burke property for log-gamma polymer with boundary



Given initial weights $(i, j \in \mathbb{N})$:

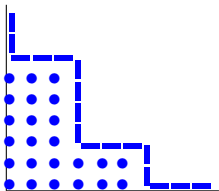
$$U_{i,0}^{-1} \sim \text{Gamma}(\theta), \quad V_{0,j}^{-1} \sim \text{Gamma}(\mu - \theta)$$

$$Y_{i,j}^{-1} \sim \text{Gamma}(\mu)$$

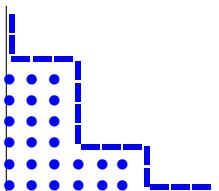
Compute $Z_{m,n}$ for all $(m, n) \in \mathbb{Z}_+^2$ and then define

$$U_{m,n} = \frac{Z_{m,n}}{Z_{m-1,n}} \quad V_{m,n} = \frac{Z_{m,n}}{Z_{m,n-1}} \quad X_{m,n} = \left(\frac{Z_{m,n}}{Z_{m+1,n}} + \frac{Z_{m,n}}{Z_{m,n+1}} \right)^{-1}$$

For an undirected edge f :
$$T_f = \begin{cases} U_x & f = \{x - e_1, x\} \\ V_x & f = \{x - e_2, x\} \end{cases}$$



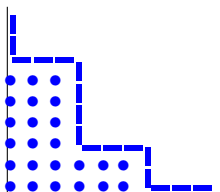
- down-right path (z_k) with edges $f_k = \{z_{k-1}, z_k\}$, $k \in \mathbb{Z}$
- interior points \mathcal{I} of path (z_k)



- down-right path (z_k) with
edges $f_k = \{z_{k-1}, z_k\}$, $k \in \mathbb{Z}$
- interior points \mathcal{I} of path (z_k)

Theorem

Variables $\{T_{f_k}, X_z : k \in \mathbb{Z}, z \in \mathcal{I}\}$ are independent with marginals $U^{-1} \sim \text{Gamma}(\theta)$, $V^{-1} \sim \text{Gamma}(\mu - \theta)$, and $X^{-1} \sim \text{Gamma}(\mu)$.



- down-right path (z_k) with
edges $f_k = \{z_{k-1}, z_k\}$, $k \in \mathbb{Z}$
- interior points \mathcal{I} of path (z_k)

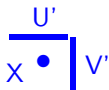
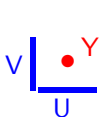
Theorem

Variables $\{T_{f_k}, X_z : k \in \mathbb{Z}, z \in \mathcal{I}\}$ are independent with marginals $U^{-1} \sim \text{Gamma}(\theta)$, $V^{-1} \sim \text{Gamma}(\mu - \theta)$, and $X^{-1} \sim \text{Gamma}(\mu)$.

“Burke property” because the analogous property for last-passage is a generalization of Burke’s Theorem for M/M/1 queues, via the last-passage representation of M/M/1 queues in series.

Proof of Burke property

Induction on \mathcal{I} by flipping a growth corner:

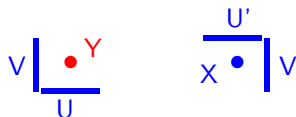


$$U' = Y(1 + U/V) \quad V' = Y(1 + V/U)$$

$$X = (U^{-1} + V^{-1})^{-1}$$

Proof of Burke property

Induction on \mathcal{I} by flipping a growth corner:



$$U' = Y(1 + U/V) \quad V' = Y(1 + V/U)$$

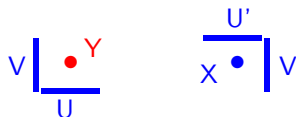
$$X = (U^{-1} + V^{-1})^{-1}$$

Lemma. Given that (U, V, Y) are independent positive r.v.'s, $(U', V', X) \stackrel{d}{=} (U, V, Y)$ iff (U, V, Y) have the gamma distr's.

Proof. “if” part by computation, “only if” part from a characterization of gamma due to Lukacs (1955). \square

Proof of Burke property

Induction on \mathcal{I} by flipping a growth corner:



$$\begin{aligned}
 U' &= Y(1 + U/V) & V' &= Y(1 + V/U) \\
 X &= (U^{-1} + V^{-1})^{-1}
 \end{aligned}$$

Lemma. Given that (U, V, Y) are independent positive r.v.'s, $(U', V', X) \stackrel{d}{=} (U, V, Y)$ iff (U, V, Y) have the gamma distr's.

Proof. “if” part by computation, “only if” part from a characterization of gamma due to Lukacs (1955). \square

This gives all (z_k) with finite \mathcal{I} . General case follows.

Proof of off-characteristic CLT

Recall that

$$\begin{cases} n = \Psi_1(\theta)N \\ m = \Psi_1(\mu - \theta)N + \gamma N^\alpha \end{cases} \quad \gamma > 0, \alpha > 2/3.$$

Proof of off-characteristic CLT

Recall that
$$\begin{cases} n = \Psi_1(\theta)N \\ m = \Psi_1(\mu - \theta)N + \gamma N^\alpha \end{cases} \quad \gamma > 0, \alpha > 2/3.$$

Set $m_1 = \lfloor \Psi_1(\mu - \theta)N \rfloor$.

Proof of off-characteristic CLT

Recall that
$$\begin{cases} n = \Psi_1(\theta)N \\ m = \Psi_1(\mu - \theta)N + \gamma N^\alpha \end{cases} \quad \gamma > 0, \alpha > 2/3.$$

Set $m_1 = \lfloor \Psi_1(\mu - \theta)N \rfloor$. Since $Z_{m,n} = Z_{m_1,n} \cdot \prod_{i=m_1+1}^m U_{i,n}$

Proof of off-characteristic CLT

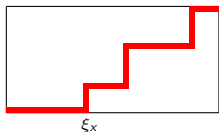
Recall that
$$\begin{cases} n = \Psi_1(\theta)N \\ m = \Psi_1(\mu - \theta)N + \gamma N^\alpha \end{cases} \quad \gamma > 0, \alpha > 2/3.$$

Set $m_1 = \lfloor \Psi_1(\mu - \theta)N \rfloor$. Since $Z_{m,n} = Z_{m_1,n} \cdot \prod_{i=m_1+1}^m U_{i,n}$

$$N^{-\alpha/2} \overline{\log Z_{m,n}} = N^{-\alpha/2} \overline{\log Z_{m_1,n}} + N^{-\alpha/2} \sum_{i=m_1+1}^m \overline{\log U_{i,n}}$$

First term on the right is $O(N^{1/3-\alpha/2}) \rightarrow 0$. Second term is a sum of order N^α i.i.d. terms. \square

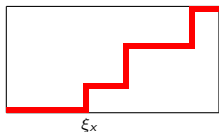
Variance identity



Exit point of path from x -axis

$$\xi_x = \max\{k \geq 0 : x_i = (i, 0) \text{ for } 0 \leq i \leq k\}$$

Variance identity



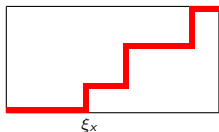
Exit point of path from x -axis

$$\xi_x = \max\{k \geq 0 : x_i = (i, 0) \text{ for } 0 \leq i \leq k\}$$

For $\theta, x > 0$ define positive function

$$L(\theta, x) = \int_0^x (\Psi_0(\theta) - \log y) x^{-\theta} y^{\theta-1} e^{x-y} dy$$

Variance identity



Exit point of path from x -axis

$$\xi_x = \max\{k \geq 0 : x_i = (i, 0) \text{ for } 0 \leq i \leq k\}$$

For $\theta, x > 0$ define positive function

$$L(\theta, x) = \int_0^x (\Psi_0(\theta) - \log y) x^{-\theta} y^{\theta-1} e^{x-y} dy$$

Theorem. For the model with boundary,

$$\text{Var}[\log Z_{m,n}] = n\Psi_1(\mu - \theta) - m\Psi_1(\theta) + 2 E_{m,n} \left[\sum_{i=1}^{\xi_x} L(\theta, Y_{i,0}^{-1}) \right]$$

Variance identity, sketch of proof

$$\begin{array}{ccc} N = \log Z_{m,n} - \log Z_{0,n} & & \\ W = \log Z_{0,n} & \boxed{\phantom{S = \log Z_{m,0}}} & E = \log Z_{m,n} - \log Z_{m,0} \\ & S = \log Z_{m,0} & \end{array}$$

Variance identity, sketch of proof

$$\begin{array}{ccc}
 N = \log Z_{m,n} - \log Z_{0,n} & & \\
 W = \log Z_{0,n} & \boxed{\phantom{S = \log Z_{m,0}}} & E = \log Z_{m,n} - \log Z_{m,0} \\
 & S = \log Z_{m,0} &
 \end{array}$$

$$\begin{aligned}
 \mathbb{V}\text{ar}[\log Z_{m,n}] &= \mathbb{V}\text{ar}(W + N) \\
 &= \mathbb{V}\text{ar}(W) + \mathbb{V}\text{ar}(N) + 2 \mathbb{C}\text{ov}(W, N) \\
 &= \mathbb{V}\text{ar}(W) + \mathbb{V}\text{ar}(N) + 2 \mathbb{C}\text{ov}(S + E - N, N) \\
 &= \mathbb{V}\text{ar}(W) - \mathbb{V}\text{ar}(N) + 2 \mathbb{C}\text{ov}(S, N) \quad (E, N \text{ ind.}) \\
 &= n\Psi_1(\mu - \theta) - m\Psi_1(\theta) + 2 \mathbb{C}\text{ov}(S, N).
 \end{aligned}$$

To differentiate w.r.t. parameter θ of S while keeping W fixed, introduce a separate parameter $\rho (= \mu - \theta)$ for W .

$$-\text{Cov}(S, N) = \frac{\partial}{\partial \theta} \mathbb{E}(N)$$

To differentiate w.r.t. parameter θ of S while keeping W fixed, introduce a separate parameter $\rho (= \mu - \theta)$ for W .

$$-\text{Cov}(S, N) = \frac{\partial}{\partial \theta} \mathbb{E}(N) = \tilde{\mathbb{E}} \left[\frac{\partial}{\partial \theta} \log Z_{m,n}(\theta) \right]$$

To differentiate w.r.t. parameter θ of S while keeping W fixed, introduce a separate parameter $\rho (= \mu - \theta)$ for W .

$$-\text{Cov}(S, N) = \frac{\partial}{\partial \theta} \mathbb{E}(N) = \tilde{\mathbb{E}} \left[\frac{\partial}{\partial \theta} \log Z_{m,n}(\theta) \right]$$

when $Z_{m,n}(\theta) = \sum_{x \in \Pi_{m,n}} \prod_{i=1}^{\xi_x} H_{\theta}(\eta_i)^{-1} \cdot \prod_{k=\xi_x+1}^{m+n} Y_{x_k}$ with

$$\eta_i \sim \text{IID Unif}(0, 1), \quad H_{\theta}(\eta) = F_{\theta}^{-1}(\eta), \quad F_{\theta}(x) = \int_0^x \frac{y^{\theta-1} e^{-y}}{\Gamma(\theta)} dy.$$

To differentiate w.r.t. parameter θ of S while keeping W fixed, introduce a separate parameter $\rho (= \mu - \theta)$ for W .

$$-\text{Cov}(S, N) = \frac{\partial}{\partial \theta} \mathbb{E}(N) = \tilde{\mathbb{E}} \left[\frac{\partial}{\partial \theta} \log Z_{m,n}(\theta) \right]$$

when $Z_{m,n}(\theta) = \sum_{x \in \Pi_{m,n}} \prod_{i=1}^{\xi_x} H_{\theta}(\eta_i)^{-1} \cdot \prod_{k=\xi_x+1}^{m+n} Y_{x_k}$ with

$$\eta_i \sim \text{IID Unif}(0, 1), \quad H_{\theta}(\eta) = F_{\theta}^{-1}(\eta), \quad F_{\theta}(x) = \int_0^x \frac{y^{\theta-1} e^{-y}}{\Gamma(\theta)} dy.$$

Differentiate: $\frac{\partial}{\partial \theta} \log Z_{m,n}(\theta) = -E^{Q_{m,n}} \left[\sum_{i=1}^{\xi_x} L(\theta, Y_{i,0}^{-1}) \right].$

Together:

$$\begin{aligned}\mathbb{V}\text{ar}[\log Z_{m,n}] &= n\Psi_1(\mu - \theta) - m\Psi_1(\theta) + 2\mathbb{C}\text{ov}(S, N) \\ &= n\Psi_1(\mu - \theta) - m\Psi_1(\theta) + 2E_{m,n}\left[\sum_{i=1}^{\xi_x} L(\theta, Y_{i,0}^{-1})\right].\end{aligned}$$

This was the claimed formula. \square

Sketch of upper bound proof

The argument develops an inequality that controls both $\log Z$ and ξ_x simultaneously. Introduce an auxiliary parameter $\lambda = \theta - bu/N$.

Sketch of upper bound proof

The argument develops an inequality that controls both $\log Z$ and ξ_x simultaneously. Introduce an auxiliary parameter $\lambda = \theta - bu/N$. The weight of a path x_\cdot such that $\xi_{x_\cdot} > 0$ satisfies

$$W(\theta) = \prod_{i=1}^{\xi_x} H_\theta(\eta_i)^{-1} \cdot \prod_{k=\xi_x+1}^{m+n} Y_{x_k}$$

Sketch of upper bound proof

The argument develops an inequality that controls both $\log Z$ and ξ_x simultaneously. Introduce an auxiliary parameter $\lambda = \theta - bu/N$. The weight of a path x , such that $\xi_x > 0$ satisfies

$$W(\theta) = \prod_{i=1}^{\xi_x} H_{\theta}(\eta_i)^{-1} \cdot \prod_{k=\xi_x+1}^{m+n} Y_{x_k} = W(\lambda) \cdot \prod_{i=1}^{\xi_x} \frac{H_{\lambda}(\eta_i)}{H_{\theta}(\eta_i)}.$$

Sketch of upper bound proof

The argument develops an inequality that controls both $\log Z$ and ξ_x simultaneously. Introduce an auxiliary parameter $\lambda = \theta - bu/N$. The weight of a path x , such that $\xi_x > 0$ satisfies

$$W(\theta) = \prod_{i=1}^{\xi_x} H_{\theta}(\eta_i)^{-1} \cdot \prod_{k=\xi_x+1}^{m+n} Y_{x_k} = W(\lambda) \cdot \prod_{i=1}^{\xi_x} \frac{H_{\lambda}(\eta_i)}{H_{\theta}(\eta_i)}.$$

Since $H_{\lambda}(\eta) \leq H_{\theta}(\eta)$,

$$Q^{\theta, \omega} \{ \xi_x \geq u \} = \frac{1}{Z(\theta)} \sum_x \mathbf{1} \{ \xi_x \geq u \} W(\theta) \leq \frac{Z(\lambda)}{Z(\theta)} \cdot \prod_{i=1}^{\lfloor u \rfloor} \frac{H_{\lambda}(\eta_i)}{H_{\theta}(\eta_i)}.$$

For $1 \leq u \leq \delta N$ and $0 < s < \delta$,

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \mathbb{P}\left\{ \prod_{i=1}^{\lfloor u \rfloor} \frac{H_\lambda(\eta_i)}{H_\theta(\eta_i)} \geq \alpha \right\} \\ + \mathbb{P}\left(\frac{Z(\lambda)}{Z(\theta)} \geq \alpha^{-1} e^{-su^2/N} \right).$$

For $1 \leq u \leq \delta N$ and $0 < s < \delta$,

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \mathbb{P}\left\{ \prod_{i=1}^{\lfloor u \rfloor} \frac{H_\lambda(\eta_i)}{H_\theta(\eta_i)} \geq \alpha \right\} \\ + \mathbb{P}\left(\frac{Z(\lambda)}{Z(\theta)} \geq \alpha^{-1} e^{-su^2/N} \right).$$

Choose α right. Bound these probabilities with Chebychev which brings $\text{Var}(\log Z)$ into play. In the characteristic rectangle $\text{Var}(\log Z)$ can be bounded by $E(\xi_x)$. The end result is this inequality:

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \frac{CN^2}{u^4} E(\xi_x) + \frac{CN^2}{u^3}$$

For $1 \leq u \leq \delta N$ and $0 < s < \delta$,

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \mathbb{P}\left\{ \prod_{i=1}^{\lfloor u \rfloor} \frac{H_\lambda(\eta_i)}{H_\theta(\eta_i)} \geq \alpha \right\} \\ + \mathbb{P}\left(\frac{Z(\lambda)}{Z(\theta)} \geq \alpha^{-1} e^{-su^2/N} \right).$$

Choose α right. Bound these probabilities with Chebychev which brings $\text{Var}(\log Z)$ into play. In the characteristic rectangle $\text{Var}(\log Z)$ can be bounded by $E(\xi_x)$. The end result is this inequality:

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \frac{CN^2}{u^4} E(\xi_x) + \frac{CN^2}{u^3}$$

Handle $u \geq \delta N$ with large deviation estimates. In the end, integration gives the moment bounds.

For $1 \leq u \leq \delta N$ and $0 < s < \delta$,

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \mathbb{P}\left\{ \prod_{i=1}^{\lfloor u \rfloor} \frac{H_\lambda(\eta_i)}{H_\theta(\eta_i)} \geq \alpha \right\} \\ + \mathbb{P}\left(\frac{Z(\lambda)}{Z(\theta)} \geq \alpha^{-1} e^{-su^2/N} \right).$$

Choose α right. Bound these probabilities with Chebychev which brings $\text{Var}(\log Z)$ into play. In the characteristic rectangle $\text{Var}(\log Z)$ can be bounded by $E(\xi_x)$. The end result is this inequality:

$$\mathbb{P}[Q^\omega \{\xi_x \geq u\} \geq e^{-su^2/N}] \leq \frac{CN^2}{u^4} E(\xi_x) + \frac{CN^2}{u^3}$$

Handle $u \geq \delta N$ with large deviation estimates. In the end, integration gives the moment bounds. **END.**

Polymer in a Brownian environment

Environment: independent Brownian motions B_1, B_2, \dots, B_n

Partition function (without boundary conditions):

$$Z_{n,t}(\beta) = \int_{0 < s_1 < \dots < s_{n-1} < t} \exp[\beta(B_1(s_1) + B_2(s_2) - B_2(s_1) + B_3(s_3) - B_3(s_2) + \dots + B_n(t) - B_n(s_{n-1})))] ds_{1,n-1}$$