

History dependent stochastic processes

joint work with

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I 2 models of history dependent st proc

1 • non lin sigma model

II relations, results

III techniques

21d

III techniques

Model I discrete time process on \mathbb{Z}^d $(X_n)_{n \in \mathbb{N}}$

initial weights 'conductances' $(a_e)_{e \in E}$

$E = \{xy \mid x, y \in \mathbb{Z}^d\}$
 in y mean, $|x-y|=1$
 undirected edges

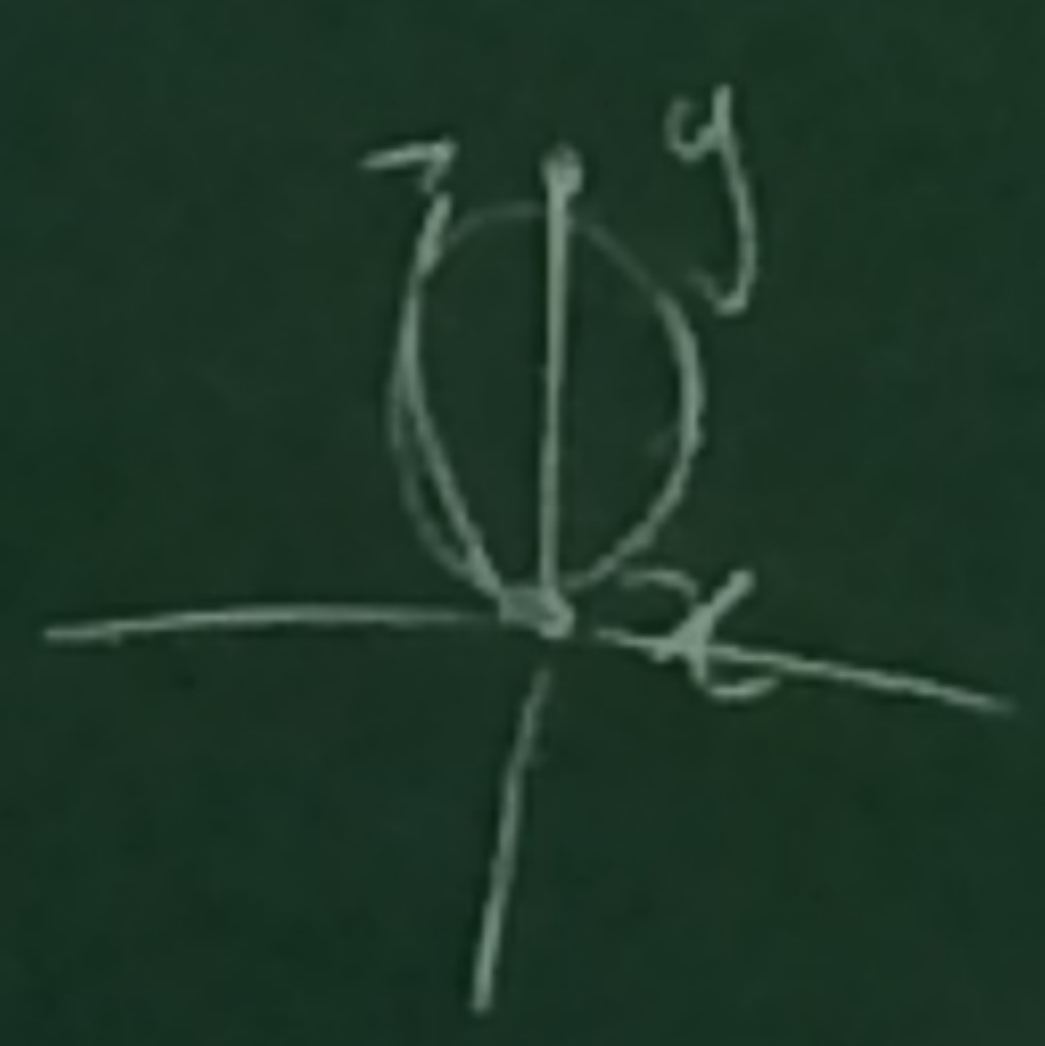
time dependent conductance

$$\omega_e(n) = a_e + T_n(e)$$

$T_n(e) = \# \text{ times } X_m \text{ crossed } e \text{ (both directions) up to time } n$

$$\mathbb{P}(X_{n+1}=y \mid X_n=x, X_{n-1}, \dots, X_0) = \frac{\omega_{xy}(n)}{\sum_{z \sim x} \omega_{zx}(n)}$$

reinforcement on the edges



meaning of a_e

first time we visit the edge e

ω_e goes from $a_e \rightarrow a_{e+1}$

$$a_e \ll 1$$

$$a_e \gg 1$$

$$a_{e+1} \gg a_e$$

$$a_{e+1} \sim a_e$$

strong regf

weak regf

IMP simplification : this process = RW in Rand Env
 $\Lambda \subset \mathbb{Z}^d$ finite E_Λ

$$\mathbb{P}_\Lambda^{ERRW}(\cdot) = \int d\rho(\omega) \mathbb{P}_\Lambda^\omega(\cdot)$$

\uparrow law for \uparrow RW environment
 Rand environment with conduct ω_e

del 2

continuous time ~~process~~

(Y)

and

$$D) dg(\omega) = \frac{1}{K} \frac{\prod_{e \in E_\Lambda} \omega_e^{a_e}}{\prod_{j \neq j_0} \left(\sum_{e \ni j} \omega_e \right)^{\frac{1}{2} + \frac{\sum_{e \ni j} a_e}{2}}} \sqrt{D[m]} \prod_{\substack{e \in E_\Lambda \\ e \neq e_0}} \frac{d\omega_e}{\omega_e} \delta_{\omega_{e_0} = 1}$$

log

$D[m]$ = diagonal minor of the matrix $\Lambda \times \Lambda$

$$m_{ij} = \begin{cases} -\omega_{ij} & i \neq j \\ \sum_{k=k-1} \omega_{ik} & i = k \end{cases}$$

$$D[m] = \sum_T \prod_{e \in T} \omega_e$$

T spanning tree on Λ

$$P_{\Lambda}^{ERRW}(\cdot) = \int d\rho(\omega) \uparrow \text{law for} \uparrow \text{rand environment} P_{\Lambda}^{\omega}(\cdot) \uparrow \text{RW environment with conduct } \omega_e$$

Model 2 continuous time ~~process~~ ^{jump} process $(Y_t)_{t \geq 0}$ on \mathbb{Z}^d

Vertex Reinforced Jump Process

rates of jump over the edge e depend on time $\omega_e(\tau)$

initial rate $\omega_e(0) = \beta_e$

local time $T_x(\tau) = \text{total time } Y \text{ spent at } x \text{ up to time } \tau$

reinforcement scheme

$$\omega_{xy}(\tau) = \begin{cases} \beta_e [1 + T_y(\tau)] \neq \omega_{yx}(\tau) & \text{Volkov, Davies} \\ \beta_e e^{T_x(\tau) + T_y(\tau)} = \omega_{xy}(\tau) & \begin{matrix} x & y \\ \text{Subut-Torres} \end{matrix} \end{cases}$$

conditioned on $(Y_s)_{s \leq \tau}$

the process jumps from $x = Y_{\tau}$ to y with rate $\omega_{xy}(\tau)$

meaning of β

$\beta_c \gg 1$ initial jump rate from $x \rightarrow y$ large

$T_x(\tau)$ does not grow much

\Rightarrow weak zenyf

$\beta_c \ll 1$

takes a long time to do the

first jump $\Rightarrow T_x(\tau)$ large

\Rightarrow strong zenyf

discrete time process associated to γ

$$Z_n = \prod_{i=1}^n \tau_i$$

τ_n : time before n^{th} jump

$$D) dg(\omega) = \frac{1}{K} \frac{\prod_{e \in E \setminus \Lambda} \omega_e^{ae}}{\prod_{j \neq j_0} \left(\sum_{e \ni j} \omega_e \right)^{\frac{1}{2} + \frac{\sum_{e \ni j} ae}{2}}} \sqrt{D[m]} \prod_{\substack{e \in E \setminus \Lambda \\ e \neq e_0}} \frac{d\omega_e}{\omega_e} \delta_{\omega_{e_0} = 1}$$

leg.

$D[m]$ = diagonal minor of the matrix $\Lambda \times \Lambda$

$$m_{ij} = \begin{cases} -\omega_{ij} & i \sim j \\ \sum_{k \sim i} \omega_{ik} & i = k \end{cases}$$

$$D[m] = \sum_T \prod_{e \in T} \omega_e$$

↑ spanning tree on Λ

$$2) dp(t) = \prod_{i \sim j} e^{-\beta_{ij} [\chi_i(t_i) - 1]} \sqrt{D[m]} \prod_{\substack{e \in \Lambda \\ j \neq j_0}} \frac{dt_j e^{-t_j}}{\int_0^\infty dt_j e^{-t_j}} \delta_{t_0 = 0}$$

$D[m]$ = diag minor of

$$m_{ij} = \begin{cases} -\beta_{ij} e^{t_i + t_j} & i \sim j \\ \sum_{k \sim i} \beta_{ik} e^{t_i + t_k} & i = j \end{cases}$$

1, 2 gradient measures
 $t_j \rightarrow t_j + t$ V_j meas does
 $\omega_e \rightarrow \omega_e e^c$ V_e not change

Model 3 $H^{2|2}$ non-linear sigma model introduced in the context of AMT

non $U(1)$ σ -model gradient $e^{-\int (\nabla\phi)^2}$
Zambauer 92

ϕ takes values in a non linear manifold

manifold here $U(1,1|2)$ SOSY

\rightarrow 2 real variables (t_d, s_d) $d \in \mathbb{Z}^d$

$$\rightarrow m_{ij} = \begin{cases} -\rho_{ij} e^{t_i + t_j} & (i=j) \\ \sum_k \rho_{ik} e^{t_i + t_k} & (i \neq j) \end{cases}$$

1, 2 gradient measures
 $t_j \rightarrow t_j + t$ V_j meas does
 $w_e \rightarrow w_e c$ V_e not change

$$d\nu(t, s) = \prod_{ij} e^{-\rho_{ij} L_{ij} s_j^2 + \dots}$$

$$\cdot D[m] \prod \frac{dL_{ij} ds_j}{\sqrt{2\pi}} e^{-t_j} \delta_{t_j=0} \delta_{s_j=0}$$

$$m_{ij} = \int e^{-\frac{1}{2} (s, m s)} ds = \frac{1}{\sqrt{D[m]}}$$

VRJP = marginal of H^{2k} integrate out S

Relation between LERRW and VRTJP in the context of HMT
 [Subot-Tarcea's]

VRTJP with p_e indep. RV. = LERRW

$$\mathbb{P}_{Na}^{LERRW} = \int \prod e^{\frac{d\gamma(p_e)}{p_e}} \frac{e^{-p_e} p_e^{a-1}}{\Gamma(a)} \mathbb{P}_{\Lambda, \beta}^{RT} = \int \prod_{+} d\gamma(p_e) dN_{\Lambda, \beta}^{+} \mathbb{P}^{\overbrace{U(+/\beta)}^{\omega}}$$

low for RW environment
 rand environment with conduct ω_e

Results/Conj

H^{212} ext. localiz. high temp = $\rho_e \leq \beta, < c_1 \quad \forall e \in E$

VAJT $\int d\mu(H) e^{\frac{t_x}{2}} \leq e^{-|x|c} \rightarrow$ positive recurrence $\forall d \geq 1$

$d=1$ exp loc $\forall \beta$

ext states low T $\rho_e \geq \beta_2 \gg 1 \quad \forall e \quad d \geq 3$

t_x aligned $\int (d t_x - t_y)^m d\mu(H) < 2 \quad \forall x, y$ any in Λ

Roller Trick

stup

exp local $\forall \beta$

\rightarrow transience

LEPRAW

$d \geq 1$ strong renf. $a_e \leq a_2 \ll 1$
positive recurrence ST

$d \geq 3$ weak renf. $a_1 \gg a_2 \gg 1$
transience \mathbb{P} Tarsos

$d=1$, strip local Rollos Merkle
weak pos in $d=2$

