

CONSISTENT FAMILIES  
OF BROWNIAN MOTIONS.

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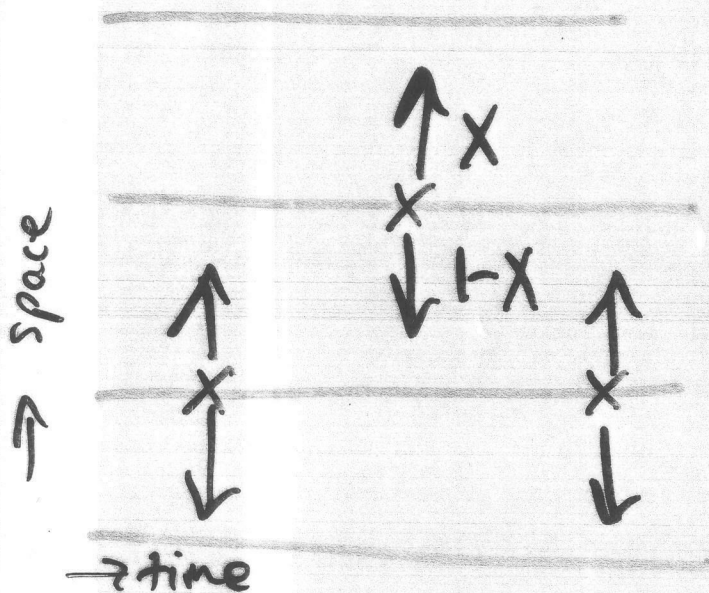
Based on joint work with Chris Howitt.

# Flow of kernels: Model for random evolution of distribution of mass

(1)

time is  $\mathbb{R}$   
space is  $\mathbb{Z}$

parameter  $\mu \in \mathcal{M}_1(\mathbb{R}_0, \mathbb{1})$



- Poisson Point process  $\Lambda$  unit rate on  $\mathbb{R} \times \mathbb{Z}$
- Attached to each pt an independent copy of  $X$  having distribution  $\mu$

Dynamics Mass at a site  $x$  at instant  $t$  with  $(t, x) \in \Lambda$  is divided in ratio  $X : 1-X$ , with parts moving to neighbouring sites  $x+1$  and  $x-1$ .

## Defn of flow

$K_{s,t}(x, A)$  = amount of mass in  $A$  at time  $t$  if unit mass introduced at  $x$  at time  $s$ .  
( $s \leq t$ )

①  $K_{st}$  is a random kernel (from  $\mathbb{Z}$  to  $\mathbb{Z}$ )

②  $K_{st} K_{t,u} = K_{s,u} \quad s < t < u$

③  $K_{t_1,t_2} \perp\!\!\!\perp K_{t_2,t_3} \dots \perp\!\!\!\perp K_{t_{n-1},t_n} \quad t_1 < t_2 < \dots < t_n$

④  $K_{s+dt, t+dt} \stackrel{\text{dot}}{=} K_{st}$

$(K_{s,t}; s \leq t)$  is a stochastic flow of kernels (on  $\mathbb{Z}$ )

Alternative Interpretation: Marked PPP  $(\Lambda, X)$  is a random environment governing motion of a particle.

- jumps at meeting a space/time pt in  $\Lambda$ 
  - up with probability  $X$
  - down with probability  $1-X$ .

then

$K_{st}(x, A) =$  Conditional probability given environment that the particle is in  $A$  at time  $t$  if it is at  $x$  at time  $s$ .

(3)

N part motions : N particles moving conditionally  
independently given environment.

Averaging over environments gives a Markov process  
on  $\mathbb{Z}^N$  with semigroup

$$P_{t-s}^{(N)}(\underline{x}, \underline{A}) = \mathbb{E} \left[ K_{s,t}(\underline{x}, \underline{A}_1) \times \dots \times K_{s,t}(\underline{x}_N, \underline{A}_N) \right]$$

$$\underline{x} = (x_1, \dots, x_N)$$

$$\underline{A} = A_1 \times A_2 \times \dots \times A_N.$$

• clump of  $(n+l)$  particles splits into  $k$  moving up,  $l$  moving down

at rate  $\frac{(n+l)!}{n!l!} p(k:l)$  where  $p(k:l) =$

$$\mathbb{E} [X^k (1-X)^l].$$

So  $(p^{(N)}; N \geq 1)$  determines moments of  $X$   
determines law of the flow  $K$ .

## Theorem (Le Jan/Raimond 2004)

④

- A stochastic flow of kernels (on any space) is characterized by its  $N$  pt motions
- Any consistent family of (Feller) Markov semigroups  $(P^{(N)}; N \geq 1)$  determines a flow of kernels.
- Consistent means ... any  $M$  cpt's of  $N$ -dim process in family are distributed as  $M$  dimensional member of family.

# Scaling limits

(5)

Do Brownian scaling: lattice is  $\frac{1}{\sqrt{n}} \mathbb{Z}$

Poisson point process intensity  $n$

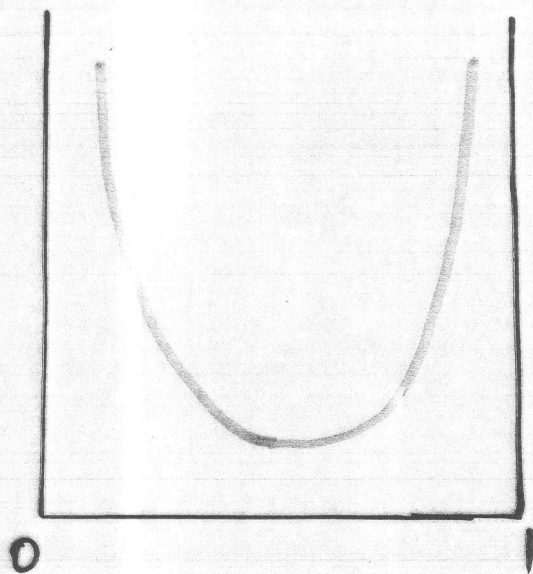
$\mu = \mu_n$  depends on  $n$ .

## Two Examples

(A)

"beta" flow

Le Jan / Raymond / Lemaire



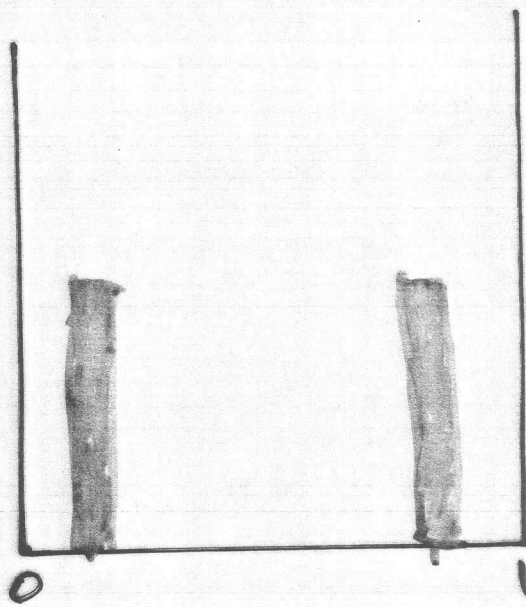
$$\mu_n(dx) = C_n x^{1/\sqrt{n}-1} (1-x)^{1/\sqrt{n}-1} dx$$

N pt motions reversible

→ Dirichlet forms.

(B)

"erosion" flow



$$M_n = \frac{1}{2} \delta_{1/\sqrt{n}} + \frac{1}{2} \delta_{1-1/\sqrt{n}}$$

N point motions not reversible

→ Martingale problem technique s.

Dense

6

$$P_n(k:l) = \int_0^1 x^k (1-x)^l \mu_n(dx)$$

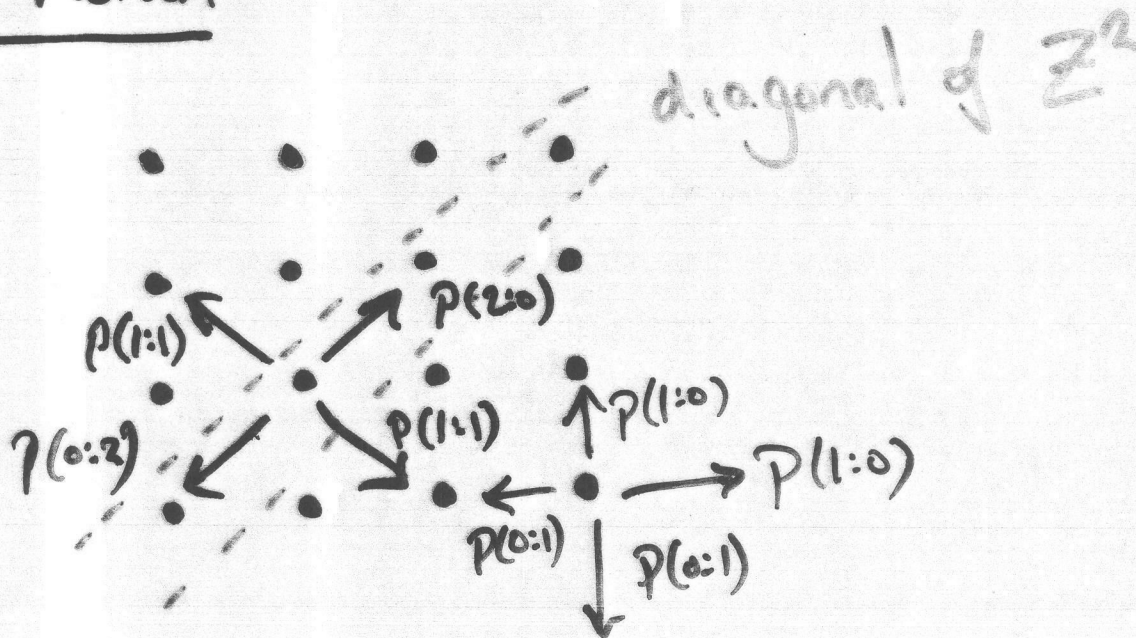
Assume  $\mu_n$  symmetric  
about  $1/2 \Rightarrow$

$$P_n(0:1) = P_n(1:0) = 1/2$$

### One pt motion

Simple symmetric random walk  $\xRightarrow{n \rightarrow \infty}$  BM

### Two pt motion



Scaling limit if  $\sqrt{n} P_n(1:1) \rightarrow \theta \in (0, \infty)$   
as  $n \rightarrow \infty$

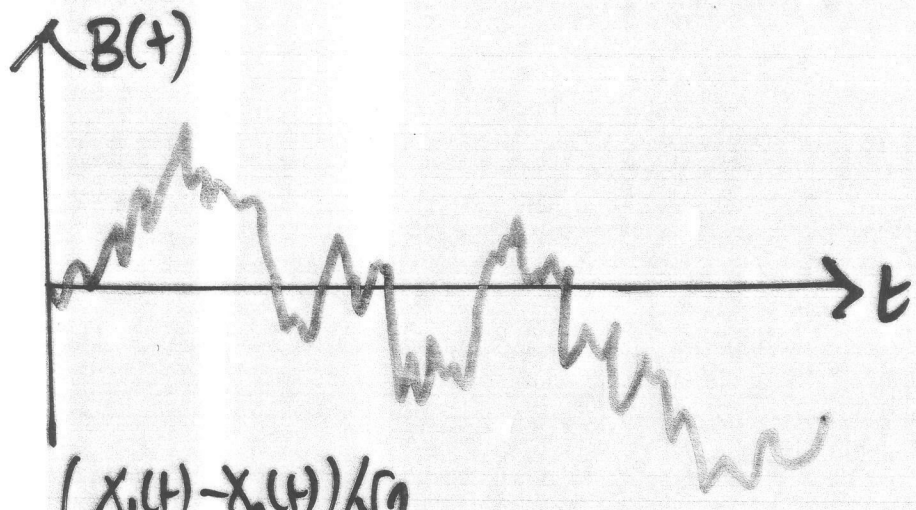
Scaling limit is a diffusion  $(X_1, X_2)$  on  $\mathbb{R}^2$  with

$\left. \begin{matrix} X_1 \\ X_2 \end{matrix} \right\}$  each BMs

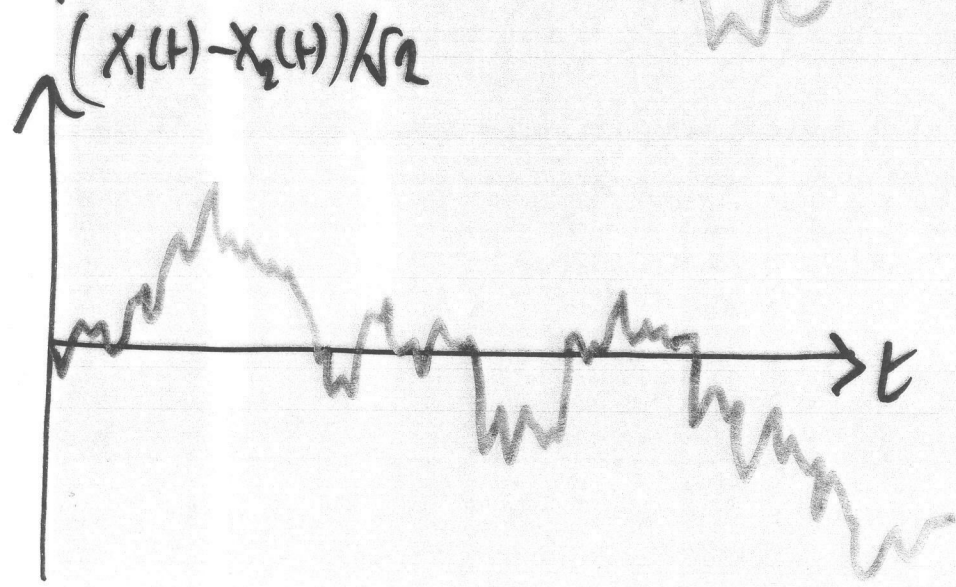
$$\langle X_1, X_2 \rangle(t) = \int_0^t 1_{(X_1(s) = X_2(s))} ds$$

$$L^0(|X_1 - X_2|)(t) = 4\theta \int_0^t 1_{(X_1(s) = X_2(s))} ds$$

" $\theta$  Coupled BMs"



• SAME EXCURSIONS



•  $\{t : X_1(t) = X_2(t)\}$   
 is Cantor set with  
 +ve Lebesgue measure.



- Action of generator of  $(X_1, X_2)$  on  $C^2$ -functions  
doesn't characterize

- By Tanaka

$$|X_1(t) - X_2(t)| - 4\theta \int_0^t \mathbb{1}_{(X_1(s) = X_2(s))} ds$$

is a martingale.

Need to apply generator to piecewise

linear function  $f(x_1, x_2) = |x_1 - x_2|$

to characterize.

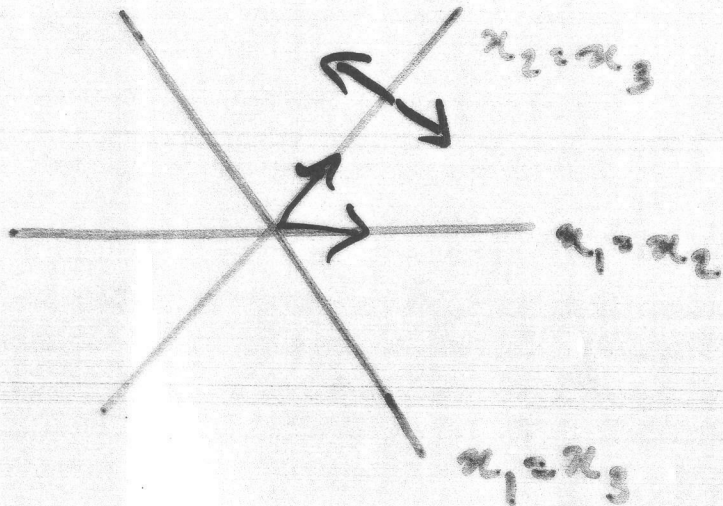
- Need some multidimensional generalization  
to characterize  $N$  pt motions.

$x \in \mathbb{R}^N$  belongs to cell

$$\{y \in \mathbb{R}^N : y_i \leq y_j \text{ if } a_i \leq a_j\}$$

$N=3$

$$x_1 + x_2 + x_3 = 0$$



13 cells

For each  $x \in \mathbb{R}^N$   $V(x)$  set of vectors

"pointing out" to neighbouring cells with form

$$V = V_{IJ} \text{ with cpts } v(i) = \begin{cases} 0 & \text{if } i \notin I \cup J \\ +1 & \text{if } i \in I \\ -1 & \text{if } i \in J \end{cases}$$

GIVEN a family of parameters

$(\theta(\kappa: l); \kappa, l \geq 1)$  Satisfying CONSISTENCY

$$\theta(\kappa: l) = \theta(\kappa+1: l)$$

$$+ \theta(\kappa: l+1)$$

$$\text{Put } \theta(V_{IJ}) = \theta(|I|, |J|)$$

+ SYMMETRY

• Say  $f \in \mathcal{L}^N$  if  $f: \mathbb{R}^N \rightarrow \mathbb{R}$  cts, linear on each cell.

• Set

$$A_N^\theta f(x) = \sum_{v \in V(x)} \theta(v) \nabla_v f(x)$$

Defn An  $\mathbb{R}^N$ -valued process  $(X(t); t \geq 0)$  solves the  $A_N^\theta$ -martingale problem if

- Each cpt  $X_i$  is a BM

-  $\langle X_i, X_j \rangle(t) = \int_0^t 1_{\{X_i(s) = X_j(s)\}} ds$

-  $f(X(t)) - \int_0^t A_N^\theta f(X(s)) ds$  is a martingale for each  $f \in \mathcal{L}^N$ .

THEOREM The  $A_N^\theta$ -martingale problem is well-posed.

Moreover:

Consistent  $\theta \Rightarrow$  Consistent diffusions as  $N$  varies.

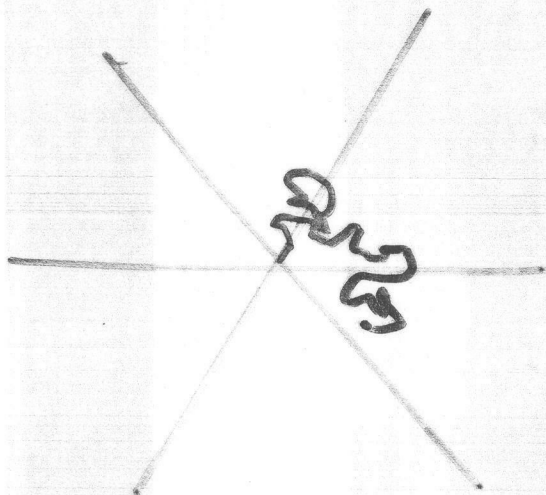
Existence By scaling limits with

(11)

$$\sqrt{n} P_n(n:l) \rightarrow \theta(n:l)$$

Uniqueness Martingale problem describes how  
clump of  $(n+l)$  particles splits into clumps  
of size  $n$  and  $l$ .

(N=3) [Ikeda-Watanabe]



Excursion from diagonal  $D$   
"leaves" in a direction  
given by some  $v \in V(\circ)$

$$E(v) = \{x + \alpha v : x \in D, \alpha > 0\}$$

Proposition -  $X$  solves  $\mathbb{R}_N^0$ -mart problem starting  
from diagonal  $D$

$$- T_\varepsilon = \inf \{t \geq 0 : |X_i(t) - X_j(t)| = \varepsilon \text{ some } i, j\}$$

Then

$$\lim_{\varepsilon \downarrow 0} P(X(T_\varepsilon) \in E(v)) = \frac{\theta(v)}{\sum_{u \in V(D)} \theta(u)}$$