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Particle representations for SPDEs with applications

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Research supported partially by SUST start-up fund

The 14th International Workshop on Markov Processes and Related Topics, Chengdu 2018



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- 1 Weighted particle representation
- 2 System by atomic measure
- 3 Poisson particle representation
- 4 Application to stochastic filtering
- 5 Application to FBSDEs
- 6 Application to superprocesses

1. Weighted particle representation

SPDE we shall study

$$\begin{aligned} \frac{\partial V(t, x)}{\partial t} &= L_2(V(t))V(t, x) \\ &+ \int_U L_1(V(t), u)V(t, x) \frac{W(du dt)}{dt} \end{aligned} \quad (1.1)$$

$W(du ds)$ noise in space-time

$L_1(V(t), u)$ first order diff. operator

$L_2(V(t))$ second order diff. operator



$$\begin{aligned} \langle \phi, V(t) \rangle &= \langle \phi, V(0) \rangle + \int_0^t \langle L_2(V(s))\phi, V(s) \rangle ds \quad (1.2) \\ &+ \int_{U \times [0, t]} \langle L_1(V(s), u)\phi, V(s) \rangle W(duds) \end{aligned}$$

where

$$L_1(\nu, u)\phi(x) = \beta(x, \nu, u)\phi(x) + \alpha^T(x, \nu, u)\nabla\phi(x),$$

$$\begin{aligned} L_2(\nu)\phi(x) &= \frac{1}{2} \sum_{i,j=1}^d a_{ij}(x, \nu) \partial_{x_i} \partial_{x_j} \phi(x) \\ &+ b(x, \nu)^* \nabla\phi(x) + d(x, \nu)\phi(x). \end{aligned}$$

Choose σ and γ s.t.

$$a(x, \nu) = \sigma(x, \nu)\sigma^T(x, \nu) + \int_U \alpha(x, \nu, u)\alpha^T(x, \nu, u)\mu(du)$$

and

$$b(x, \nu) = c(x, \nu) + \sigma(x, \nu)\gamma(x, \nu) + \int_U \beta(x, \nu, u)\alpha(x, \nu, u)\mu(du)$$

Consider system with locations

$$\begin{aligned} X_i(t) &= X_i(0) + \int_0^t \sigma(X_i(s), V(s)) dB_i(s) \\ &\quad + \int_0^t c(X_i(s), V(s)) ds \\ &\quad + \int_{U \times [0, t]} \alpha(X_i(s), V(s), u) W(du ds) \end{aligned} \quad (1.3)$$

with

$$V(t) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n A_i(t) \delta_{X_i(t)} \quad (1.4)$$



and weights

$$\begin{aligned} & A_i(t) \tag{1.5} \\ = & A_i(0) + \int_0^t A_i(s) \gamma^T(X_i(s), V(s)) dB_i(s) \\ & + \int_0^t A_i(s) d(X_i(s), V(s)) ds \\ & + \int_{U \times [0, t]} A_i(s) \beta(X_i(s), V(s), u) W(du ds). \end{aligned}$$

Theorem

$V(t)$ is sol. to (1.4) iff it is a sol. to SPDE (1.2).



Most with constant weight 1:

McKean ('67)

{ Hitsuda & Mitoma ('86) conti.
{ Graham ('96) jump

∞ -dim. { Chiang, Kallianpur & Sundar ('91), Cont.
{ Kallianpur & Xiong ('94) jump
{ Xiong ('95)

non-constant weights { Non-random: Dawson & Vaillancourt ('95)
{ Random: Kotelenez ('95) $A_i(t) \equiv A_i(0)$



Conditions

$$|\sigma(x, \nu)|^2 \leq K^2$$

$$|\sigma(x_1, \nu_1) - \sigma(x_2, \nu_2)|^2 \leq K^2(|x_1 - x_2|^2 + \rho(\nu_1, \nu_2)^2)$$

where

$$\rho(\nu_1, \nu_2) = \sup\{|\langle \phi, \nu_1 - \nu_2 \rangle| : \|\phi\|_\infty \leq 1, Lip(1)\}.$$

Similar conditions for other coeff.



Theorem

The system (1.3-1.5) has a solution.

Idea of proof

Sequence of approximation

$$B_i^n(t) = B_i \left(\frac{[nt]}{n} \right), \quad D_n(t) = \frac{[nt]}{n}$$

$$W^n(A \times [0, t]) = W \left(A \times \left[0, \frac{[nt]}{n} \right] \right)$$

Solution (X^n, A^n, V^n) weak convergence to (X, A, V)



Theorem

The system (1.3-1.5) has at most one solution.

Idea of proof

Uniqueness of system:

Lipschitz condition is not satisfied: e.g. $(a, x) \mapsto a\beta(x)$

Local Lipschitz, i.e. on

$$\{(a_i) : |a_i| \leq M, i = 1, 2, \dots\}$$

How to truncate?



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How to truncate?

Truncate the average:

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n A_i(t)^2$$

How to prove uniqueness for SPDE (1.2)?

Consider Linear SPDE

$$\begin{aligned}\langle \phi, U(t) \rangle &= \langle \phi, U(0) \rangle + \int_0^t \langle L_{2,s} \phi, U(s) \rangle ds \\ &\quad + \int_{U \times [0,t]} \langle L_{1,s,u} \phi, U(s) \rangle W(duds) \quad (1.6)\end{aligned}$$

where

$$L_{2,s} \phi = L_2(V(s)) \phi$$

$$L_{1,s,u} \phi = L_1(V(s), u) \phi$$



Theorem

If $V_0 \in L^2(\mathbb{R}^d)$, then the linear SPDE (1.6) has at most one solution.

Key: Smooth out by $Z_\delta(t) = T_\delta U(t)$.



Theorem

If $V_0 \in L^2(\mathbb{R}^d)$, then SPDE (1.2) has at most one solution.

Proof

Let $V_1(t)$ be another solution.

Consider

$$X_i(t) = X_i(0) + \int_0^t \sigma(X_i(s), V_1(s)) dB_i(s) + \dots$$

$$A_i(t) = \dots$$



Let

$$V_2(t) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^{\infty} A_i(t) \delta_{X_i(t)}$$

Then V_2 is a solution to

$$\begin{aligned} \langle \phi, U(t) \rangle &= \langle \phi, U(0) \rangle + \int_0^t \langle L_2(V_1(s)) \phi, U(s) \rangle ds \quad (1.7) \\ &+ \int_{U \times [0, t]} \langle L_1(V_1(s), u) \phi, U(s) \rangle W(duds). \end{aligned}$$

V_1 is also a solution to (1.7). By uniqueness, $V_1 = V_2$. V_1 is a solution to (1.3-1.5). $V_1 = V$

2. System by atomic measure

For $i = 1, 2, \dots$, the position of the i th particle is

$$X_t^i = X_0^i + \int_0^t \sigma(X_s^i) dW_s^i + \int_0^t b(X_s^i, N_s) ds + \int_0^t \alpha(X_s^i) dW_s, \quad (2.1)$$

where

$$N_s = \sum_i \delta_{X_s^i}.$$

Condition (B): $\exists c, r > 0$ s.t., $\forall x, z^i \in \mathbb{R}, i = 1, 2, \dots$, we have

$$|\sigma(x)| + |\alpha(x)| + \left| b\left(x, \sum \delta_{z^i}\right) \right| \leq K.$$

Condition (Lip): σ, α Lip., and $\exists c, r > 0$ s.t.,
 $\forall x, \tilde{x}, z^i, \tilde{z}^i \in \mathbb{R}, i = 1, 2, \dots$, we have

$$\begin{aligned} & \left| b(x, N) - b(\tilde{x}, \tilde{N}) \right| \\ & \leq c|x - \tilde{x}| \left(N(S_r(x)) + \tilde{N}(S_r(\tilde{x})) \right) \\ & \quad + c \left(\sum_{|z^i - x| \leq r} |z^i - \tilde{z}^i| + \sum_{|\tilde{z}^i - \tilde{x}| \leq r} |z^i - \tilde{z}^i| \right) \end{aligned} \quad (2.2)$$

where

$$N = \sum \delta_{z^i}.$$



Typical example

$$b(x, \nu) = \phi \left(x, \int h(x - y) \nu(dy) \right)$$

where ϕ bounded Lipschitz in both variables, h bounded Lipschitz w/ compact support.



Condition (I): $X_0^i = i, i \in \mathbb{Z}$.

Lemma

For any $c_1 > 2$ and $t > 0$, there exists a positive constant c_2 such that

$$\mathbb{P}(N_t([-n, n]) > c_1 n) \leq c_2 e^{-(c_1 - 2)n}, \quad \forall n \in \mathbb{N}. \quad (2.3)$$

Corollary

There exists a constant c_3 such that for all n ,

$$\mathbb{E}(N_t([-n, n])^2 1_{N_t([-n, n]) > 3n}) \leq c_2 n e^{-n}.$$

Let c be s.t.

$$\rho(a) = c1_{|a|<1} \exp(-1/(1-a^2)), \quad a \in \mathbb{R}$$

becomes a p.d.f. Let

$$\phi(x) = \int_{\mathbb{R}} e^{-|a|} \rho(x-a) da, \quad x \in \mathbb{R}.$$

Then, ϕ is smooth and

$$c_n e^{-|x|} \leq \phi^{(n)}(x) \leq C_n e^{-|x|}, \quad \forall x \in \mathbb{R}.$$

Also

$$\phi(x^i) \leq \phi(\tilde{x}^j) \exp(|x^i - \tilde{x}^i| + |\tilde{x}^j - \tilde{x}^i|). \quad (2.4)$$



Proposition

The system (2.1) has at most one solution.

Idea of proof Let $\{\tilde{X}_t^i, i \in \mathbb{Z}\}$ be another solution.

$$f(t) \equiv \mathbb{E} \sum_i |X_t^i - \tilde{X}_t^i|^2 \phi(X_t^i) \leq I_0 + I_1 + I_2 \quad (2.5)$$

where



$$I_0 = c \int_0^t \mathbb{E} \sum_i |X_s^i - \tilde{X}_s^i|^2 \phi(X_s^i) ds,$$

$$I_1 = c \int_0^t \mathbb{E} \sum_i \sum_j |X_s^j - \tilde{X}_s^j|^2 \phi(X_s^j) 1_{|X_s^j - X_s^i| \leq 1} ds,$$

$$I_2 = c \int_0^t \mathbb{E} \sum_i \sum_j |X_s^j - \tilde{X}_s^j|^2 \phi(\tilde{X}_s^j) 1_{|\tilde{X}_s^j - \tilde{X}_s^i| \leq 1} ds.$$



$$\begin{aligned} & I_1 \\ \leq & c \int_0^t \mathbb{E} \sum_j |X_s^j - \tilde{X}_s^j|^2 \phi(X_s^j) \#\{i : |X_s^j - X_s^i| \leq 1\} ds \\ \leq & c \int_0^t \mathbb{E} \left\{ \left(\sum_{j: |X_s^j| < n} |X_s^j - \tilde{X}_s^j|^2 \phi(X_s^j) \right) N_s([-n, n]) \right\} ds \\ & + c \int_0^t \mathbb{E} \left\{ \sum_{j: |X_s^j| \geq n} |X_s^j - \tilde{X}_s^j|^2 \phi(X_s^j) \#\{i : |X_s^j - X_s^i| \leq 1\} \right\} ds \\ \equiv & I_{11} + I_{12}. \end{aligned}$$



$$I_{12} \leq ce^{-n/2},$$

$$\begin{aligned} I_{11} &\leq 3cn \int_0^t \mathbb{E} \sum_{j: |X_s^j| < n} |X_s^j - \tilde{X}_s^j|^2 \phi(X_s^j) ds \\ &\quad + c \int_0^t \mathbb{E} \left\{ \left(\sum_{j: |X_s^j| < n} |X_s^j - \tilde{X}_s^j|^2 \phi(X_s^j) \right) \right. \\ &\quad \left. \times N_s([-n, n]) 1_{N_s([-n, n]) > 3n} \right\} ds \\ &\leq cn \int_0^t f(s) ds + ce^{-\delta n}. \end{aligned}$$



Then,

$$I_1 \leq cn \int_0^t f(s) ds + 2ce^{-\delta n}.$$

Similarly

$$I_2 \leq cn \int_0^t \tilde{f}(s) ds + ce^{-\delta n}. \quad (2.6)$$

Hence,

$$f(t) \leq cn \int_0^t (f(s) + \tilde{f}(s)) ds + ce^{-\delta n}.$$

Similarly, we can prove that

$$\tilde{f}(t) \leq cn \int_0^t (f(s) + \tilde{f}(s)) ds + ce^{-\delta n}.$$



Adding two equations, we get

$$f(t) + \tilde{f}(t) \leq cn \int_0^t (f(s) + \tilde{f}(s)) ds + ce^{-\delta n}.$$

By Gronwall's inequality, for $t < \delta$, we have

$$f(t) + \tilde{f}(t) \leq ce^{-\delta n} e^{nt} \rightarrow 0$$

This gives us uniqueness for $t < \delta$.

How to get uniqueness for any t ?



Adding two equations, we get

$$f(t) + \tilde{f}(t) \leq cn \int_0^t (f(s) + \tilde{f}(s)) ds + ce^{-\delta n}.$$

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$$f(t) + \tilde{f}(t) \leq ce^{-\delta n} e^{nt} \rightarrow 0$$

This gives us uniqueness for $t < \delta$.

How to get uniqueness for any t ?

We get uniqueness by replacing $e^{-|x|}$ by $e^{-\lambda|x|}$.

3. Poisson particle representation

Consider system: For $i = 1, 2, \dots$,

$$\begin{aligned} X_t^i &= X_0^i + \int_0^t \sigma(X_s^i) dW_i(s) + \int_0^t b(X_s^i, V_s) ds \\ &\quad + \int_{U \times [0, t]} \alpha(X_s^i, u) W(duds) \end{aligned} \quad (3.1)$$

and

$$\begin{aligned} U_t^i &= U_0^i + \int_0^t U_s^i \gamma(X_s^i) dW_i(s) + \int_0^t U_s^i a(X_s^i, V_s) ds \\ &\quad + \int_{U \times [0, t]} U_s^i \beta(X_s^i, u) W(duds), \end{aligned} \quad (3.2)$$



where V is the measure-valued process given by

$$V(t) = \lim_{u \rightarrow \infty} \frac{1}{u} \sum_{U_t^i \leq u} \delta_{X_t^i}. \quad (3.3)$$



Remark

i) Given V ,

$$\sum_i \delta_{(X_t^i, U_t^i)}$$

is a Poisson random measure on $\mathbb{R} \times \mathbb{R}_+$ with intensity measure $V(t) \times m$, where m is the Lebesgue measure on \mathbb{R}_+ .

ii) Advantages of Poisson representation: $V(t)$ can be infinite measure.

iii)

$$\begin{aligned} V(t) &= \lim_{\epsilon \rightarrow 0^+} \epsilon \sum_{i=1}^{\infty} e^{-\epsilon U_t^i} \delta_{X_t^i} \\ &= \lim_{\epsilon \rightarrow 0^+} \epsilon^2 \sum_{i=1}^{\infty} U_t^i e^{-\epsilon U_t^i} \delta_{X_t^i}. \end{aligned}$$

Condition (B) remains true.

Wasserstein distance by

$$\rho_x(\nu_1, \nu_2) = \sup \left\{ \left| \int_{|y-x| \leq 1} f(y)(\nu_1 - \nu_2)(dy) \right| : f \in \mathbb{B}_1 \right\},$$

where \mathbb{B}_1 is the unit ball under Lipschitz norm, i.e.,

$$\mathbb{B}_1 = \{f : \mathbb{R} \rightarrow \mathbb{R}, |f(x)| \leq 1, |f(x) - f(y)| \leq |x - y|\}.$$

Condition (Lip): $\exists K$ s.t. $\forall x, \tilde{x} \in \mathbb{R}$ and $\nu, \tilde{\nu} \in M(\mathbb{R})$, we have

$$\begin{aligned} & |b(x, \nu) - b(\tilde{x}, \tilde{\nu})| \\ & \leq K (|x - \tilde{x}| (1 + \nu(S_1(x)) + \tilde{\nu}(S_1(\tilde{x}))) + \rho_x(\nu, \tilde{\nu}) + \rho_{\tilde{x}}(\nu, \tilde{\nu})), \end{aligned}$$

where $S_1(x)$ denotes the interval $(x - 1, x + 1)$.

Suppose that (3.1-3.3) has two solutions (X_i, U_i, V) and $(\tilde{X}_i, \tilde{U}_i, \tilde{V})$, $i = 1, 2, \dots$.



We will need the following large ball type estimate.

Lemma

Suppose that

$$\sup_{y \in \mathbb{R}} \left(V_0(S_2(y)) + \int_{|x-y|>2} \frac{V_0(dx)}{|x-y-1|} \right) < \infty,$$

where $S_2(y)$ is the interval with center y and radius 2. Then, there are constants $c, \delta > 0$ such that for any $s \in [0, T]$ and $n \in \mathbb{N}$, we have

$$\mathbb{P} \left(\sup_{|y| \leq n} V_s(S_1(y)) > \sqrt{n} \right) \leq ce^{-\delta n}. \quad (3.4)$$



Key in the proof i) V solution to (1.2).

ii) By the exponential formula of Boué-Dupuis, we have

$$-\log \mathbb{E}e^{f(W)} = \inf_u \mathbb{E} \left(\frac{1}{2} \|u\|^2 - f \left(W + \int_0^\cdot u_s ds \right) \right), \quad (3.5)$$

where the infimum is taken over all processes u that are \mathcal{F}_t^W -predictable such that

$$\|u\|^2 = \int_0^T u_t^2 dt < \infty, \quad a.s.$$



Theorem

The infinite system (3.1-3.3) has a unique solution.

Idea of proof Let

$$f(t) \equiv \lim_{\epsilon \rightarrow 0} \sum_i \epsilon e^{-\epsilon U_t^i} |X_t^i - \tilde{X}_t^i|^2 \phi(X_t^i),$$

and

$$g(t) = \lim_{\epsilon \rightarrow 0} \mathbb{E} \sum_i \epsilon^3 e^{-\epsilon U_t^i} (U_t^i - \tilde{U}_t^i)^2 \phi(X_t^i).$$

\tilde{f} and \tilde{g} are defined similarly.



Let $h(t)$ be the sum of $f(t)$, $g(t)$, $\tilde{f}(t)$ and $\tilde{g}(t)$. Then,

$$h(t) \leq cn \int_0^t h(s) ds + ce^{-\delta n}.$$

The uniqueness then follows from Gronwall's inequality.

4. Application to stochastic filtering

Signal process

$$dX_t = b(X_t)dt + \sigma(X_t)dB_t.$$

Observation process

$$Y_t = \int_0^t h(X_s)ds + W_t.$$

Information

$$\mathcal{G}_t = \sigma\{Y_s : s \leq t\}.$$

Optimal filter

$$\langle f, \pi_t \rangle = \mathbb{E}(f(X_t)|\mathcal{G}_t).$$

Kallianpur-Striebel formula,

$$\langle f, \pi_t \rangle = \frac{\langle f, \mu_t \rangle}{\langle 1, \mu_t \rangle},$$

where

$$\langle f, \mu_t \rangle = \hat{\mathbb{E}}(f(X_t)M_t|\mathcal{G}_t)$$

and $\hat{\mathbb{E}}$ is expectation wrt \hat{P} under which (B, Y) is B.M.

Zakai equation: Special case of (1.1) with $W = Y$ and

$$L_2\phi(x) = \frac{1}{2} \sum_{i,j=1}^d a_{ij}(x) \partial_{x_i} \partial_{x_j} \phi(x) + b(x)^* \nabla \phi(x),$$

$$L_1\phi(x) = h(x)\phi(x).$$

Kushner-FKK equation: Special case of (1.1) with W being the innovation process and

$$L_1(\nu, u)\phi(x) = h(x) - \langle h, \nu \rangle.$$

5. Application to FBSDEs

Consider

$$\begin{cases} dX(t) &= b(X(t), Y(t), Z(t))dt + \sigma(X(t), Y(t), Z(t))dW(t), \\ dY(t) &= g(X(t), Y(t), Z(t))dt + Z(t)dW(t), \\ X(0) &= x, \quad Y(T) = h(X(T)). \end{cases}$$

How to solve FBSDE numerically?



Try $Y(t) = u(t, X(t))$. By Itô's formula, we get

$$\begin{aligned}dY(t) &= \partial_t u dt + \partial_x u dX(t) + \frac{1}{2} \partial_x^2 u (dX(t))^2 \\&= \partial_t u dt + \partial_x u b dt + \partial_x u \sigma dW_t + \frac{1}{2} \partial_x^2 u \sigma^2 dt \\&= \left(\partial_t u + b \partial_x u + \frac{1}{2} \sigma^2 \partial_x^2 u \right) dt + \partial_x u \sigma dW_t.\end{aligned}$$



Compare with FBSDE, we get

$$\begin{aligned} & h(t, X(t), u(t, X(t)), Z(t)) \\ = & \partial_t u(t, X(t)) + b(t, X(t), u(t, X(t)), Z(t)) \partial_x u(t, X(t)) \\ & + \frac{1}{2} \sigma^2(t, X(t), u(t, X(t)), Z(t)) \partial_x^2 u(t, X(t)) \end{aligned} \quad (5.6)$$

and

$$Z(t) = \sigma(t, X(t), u(t, X(t)), Z(t)) \partial_x u(t, X(t)).$$



Four step scheme (Ma-Protter-Yong):

Step 1: Find function $z(t, x, y, p)$ satisfying

$$z(t, x, y, p) = \sigma(t, x, y, z(t, x, y, p))p. \quad (5.7)$$

Step 2: Solve PDE

$$\begin{cases} \partial_t u + b(t, x, u, z(t, x, u, \partial_x u))\partial_x u \\ \quad + \frac{1}{2}\sigma^2(t, x, u, z(t, x, u, \partial_x u))\partial_x^2 u \\ \quad = h(t, x, u, z(t, x, u, \partial_x u)) \\ u(T, x) = g(x), \quad x \in \mathbb{R}. \end{cases} \quad (5.8)$$



Step 3: Solve SDE

$$dX(t) = \tilde{b}(t, X(t))dt + \tilde{\sigma}(t, X(t))dW_t, \quad X_0 = x, \quad (5.9)$$

where

$$\tilde{b}(t, x) = b(t, x, u(t, x), z(t, x, u, \partial_x u(t, x))).$$

Step 4:

$$\begin{cases} Y(t) &= u(t, X(t)) \\ Z(t) &= z(t, X(t), Y(t), \partial_x u(t, X(t))). \end{cases} \quad (5.10)$$



(A1) The generator g has the following form: for $z = (z_1, \dots, z_l)$,

$$g(x, y, z) = C(x, y)y + \sum_{j=1}^l D_j(x, y)z_j,$$

and $b(x, y)$, $\sigma(x)$, $g(x, y, z)$, $f(x)$, $C(x, y)$ and $D(x, y)$ are all bounded and Lipschitz continuous maps with bounded partial derivatives up to order 2. Furthermore, the matrix $\sigma\sigma^*$ is uniformly positive definite, and the function f is integrable. Here σ^* denote the transpose of the matrix σ .



We consider the following FBSDE in the fixed duration $[0, T]$:

$$\begin{cases} dX(t) = b(X(t), Y(t)) dt + \sigma(X(t)) dW(t), \\ -dY(t) = g(X(t), Y(t), Z(t))dt - Z(t)dW(t), \\ X(0) = x, Y(T) = f(X(T)), \end{cases} \quad (5.11)$$

where $b : \mathbb{R}^d \times \mathbb{R}^k \rightarrow \mathbb{R}^d$, $\sigma : \mathbb{R}^d \rightarrow \mathbb{R}^{d \times l}$,
 $g : \mathbb{R}^d \times \mathbb{R}^k \times \mathbb{R}^{k \times l} \rightarrow \mathbb{R}^k$ and $f : \mathbb{R}^d \rightarrow \mathbb{R}^k$.

The PDE becomes

$$\begin{cases} -\frac{\partial u(t,x)}{\partial t} &= Lu(t,x) + C(x, u(t,x))u(t,x) \\ &+ \sum_{j=1}^l \sigma_j(x) D_j(x, u(t,x)) \partial_x u(t,x) \\ u(T,x) &= f(x), \end{cases}$$

and

$$L = \frac{1}{2} \sum_{i,j=1}^d a_{ij} \partial_{x_i, x_j} + \sum_{i=1}^d b_i \partial_{x_i},$$

with $a_{ij} = (\sigma \sigma^T)_{ij}$, $\sigma = (\sigma_1, \dots, \sigma_l)$ and b_i being the i th coordinate of b .



For $0 \leq t \leq T$, assume $v(t, x) = u(T - t, x)$. Then

$$\begin{cases} \frac{\partial v(t, x)}{\partial t} = Lv(t, x) + C(x, v(t, x))v(t, x) \\ \quad + \sum_{j=1}^l \sigma_j(x) D_j(x, v(t, x)) \partial_x v(t, x) \\ v(0, x) = f(x). \end{cases} \quad (5.12)$$



PDE (5.12) can be rewritten as

$$\begin{aligned} \frac{\partial v(t, x)}{\partial t} = & \frac{1}{2} \sum_{i,j=1}^d \partial_{x_i, x_j} (a_{ij}(x) v(t, x)) \\ & - \sum_{i=1}^d \partial_{x_i} \left(\tilde{b}_i(x, v) v(t, x) \right) \\ & + \tilde{c}(x, v(t, x)) v(t, x) \end{aligned}$$

where



$$\begin{aligned}\tilde{c}(x, v) &= C(x, v) - \sum_{i=1}^d \partial_{x_i} b_i(x, v) \\ &\quad - \sum_{i=1}^d \partial_{x_i} \tilde{D}_i(x, v) + \frac{1}{2} \sum_{i,j=1}^d \partial_{x_i, x_j} a_{ij}(x),\end{aligned}$$

$$\tilde{b}_i(x, v) = \sum_{j=1}^d \partial_{x_j} a_{ij}(x) - b_i(x, v) - \tilde{D}_i(x, v),$$

and

$$\tilde{D}_i(x, v) = \sum_{j=1}^l D_j(x, v) \sigma_{ij}(x).$$



Theorem (Extension of Kurtz-X. (1999))

For $0 < t \leq T$, $i = 1, 2, \dots$, let

$$\begin{cases} dX_i(t) = \tilde{b}(X_i(t), v(t, X_i(t)))dt + \sigma(X_i(t))dB_i(t), \\ dA_i(t) = A_i(t)\tilde{c}(X_i(t), v(t, X_i(t))) dt \\ V(t) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n A_j(t)\delta_{X_j(t)} \end{cases} \quad (5.13)$$

with i.i.d initial random sequence $\{(X_i(0), A_i(0)), i \in \mathbb{N}\}$ taking values in $\mathbb{R}^d \times \mathbb{R}$, where $\{B_i(t), i \in \mathbb{N}\}$ are independent standard Brownian motions, $V(t)$ has density $v(t, x)$ and $v(0, x) = f(x)$. Then, $v(t, x)$ solves SPDE (5.12).

6. Application to superprocesses

At time $t = 0$, k_n particles at locations

$$x_i^n \in \mathbb{R}, \quad i = 1, 2, \dots, k_n.$$

- Each has $expo.(n)$ clock (indep. from each other).

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- Denote particle by a multi-index α .
- Between branching times, particle α moves according to

$$dx_t^\alpha = b(x_t^\alpha)dt + c(x_t^\alpha)dW_t + e(x_t^\alpha)dB_t^\alpha$$

W , B^α indep. B.M.



Define **measure-valued process**

$$\mu_t^n = \frac{1}{n} \sum_{\alpha \sim t} \delta_{x_\alpha^n(t)}$$

where $\alpha \sim t$ means particle α is alive at time t .



Convergence Theorem

$(\mu_t^n) \Rightarrow (\mu_t)$ unique sol. to **MP**: μ_t is $\mathcal{M}(R)$ -valued

$$M_t(f) \equiv \langle \mu_t, f \rangle - \langle \mu, f \rangle - \int_0^t \langle \mu_s, bf' + af'' \rangle ds$$

continuous martingale with

$$\langle M(f) \rangle_t = \int_0^t \left(\langle \mu_s, f^2 \rangle + \langle \mu_s, cf' \rangle^2 \right) ds$$

where $a(x) = \frac{1}{2}(e(x)^2 + c(x)^2)$.

Studied by **Adler and Skoulakis (2001)** and **Wang (1998)** among others.



(CMP)

$$N_t(f) \equiv \langle \mu_t, f \rangle - \langle \mu, f \rangle - \int_0^t \langle \mu_s, bf' + df'' \rangle ds \\ - \int_0^t \langle \mu_s, cf' \rangle dW_s$$

P^W -martingale w/

$$\langle N(f) \rangle_t = \int_0^t \langle \mu_s, f^2 \rangle ds$$



Formally,

$$\begin{aligned} N_t(f) &= \langle \mu_t, f \rangle - \langle \mu, f \rangle \\ &\quad - \int_0^t \langle \mu_s, (b + c\dot{W}_s)f' + df'' \rangle ds, \end{aligned}$$

Therefore,

$$E^W \exp(-\langle \mu_t, f \rangle) = \exp(-\langle \mu, y_{0,t} \rangle),$$



where

$$y_{s,t} = f + \int_s^t c \partial_x y_{r,t} \dot{W}_r dr + \int_s^t (b \partial_x y_{r,t} + a \partial_x^2 y_{r,t} - y_{r,t}(x)^2) dr.$$

Stochastic integral is backward Itô integral.



Theorem (Xiong, 2004, AP)

$$\mathbb{E}^W \exp(-\langle \mu_t, f \rangle) = \exp(-\langle \mu, y_{0,t} \rangle),$$

where $Lf = af'' + bf'$,

$$y_{s,t} = f + \int_s^t c \partial_x y_{r,t} \hat{d}W_r \\ + \int_s^t (Ly_{r,t} - y_{r,t}(x)^2) dr.$$



Forward version:

$$\begin{aligned} v_t(x) = & f(x) + \int_0^t \left(Lv_r(x) - \frac{\gamma}{2} v_r(x)^2 \right) dr \\ & + \int_0^t \int_U h(y, x) \nabla v_r(x) W(dr dy). \end{aligned} \quad (6.14)$$

Theorem

i) The SLLE (6.14) has a unique solution $v_t(x)$.

ii) v_t is the unique solution of the following infinite particle system: $i = 1, 2, \dots$,

$$d\xi_t^i = dB_i(t) - \int_U h(y, \xi_t^i) W(dt dy) + \left(2a'(\xi_t^i) - \int_U h(y, \xi_t^i) \nabla h(y, \xi_t^i) \mu(dy) \right) dt, \quad (6.15)$$

$$dm_t^i = m_t^i \left((a''(\xi_t^i) - v_t(\xi_t^i)) dt - \int_U \nabla h(y, \xi_t^i) W(dt dy) \right), \quad (6.16)$$

$$\nu_t = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n m_t^i \delta_{\xi_t^i}, \quad a.s. \quad (6.17)$$

where for any $t \geq 0$, ν_t is absolutely continuous with respect to Lebesgue measure with v_t as the Radon-Nikodym derivative.



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Thanks!
