

# Fluctuations of Rank Based Stochastic Differential Equations

Praveen Kolli

joint work with Misha Shkolnikov

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# Rank Based Stochastic Differential Equations

Consider the following  $n$  interacting diffusions (particles) on the real line where the  $i^{\text{th}}$  diffusion evolves according to the SDE

$$dX_i(t) = b(F_n(t, X_i(t))) dt + \sigma(F_n(t, X_i(t))) dW_i(t) \quad (1)$$

Here  $b, \sigma$  are Lipschitz continuous functions from  $[0, 1]$  to  $\mathbb{R}$ ,  $F_n(t, x)$  is

the empirical cdf  $\frac{\sum_{i=1}^n \mathbb{I}(X_i(t) \leq x)}{n}$ . We observe that the drift and volatility terms of the  $i^{\text{th}}$  particle depends on its rank. If  $Y_1, Y_2$  and  $Y_3$  are 3 real numbers with  $Y_3 < Y_1 < Y_2$ , then  $\text{Rank}(Y_1)=2$ ,  $\text{Rank}(Y_2)=3$  and  $\text{Rank}(Y_3)=1$ . This implies  $b(F_n(t, X_i(t))) = b(\frac{\text{rank}(X_i(t))}{n})$  and we have a similar term for the volatility coefficient.

# Law of Large numbers

Theorem (Shkolnikov '12, Jourdain, Reygner '13)

For the aforementioned interaction diffusions with  $b, \sigma$  continuous and  $X_i(0), i = 1, 2, \dots, n$  IID drawn from  $\lambda$ , then  $F_n(t, x) \rightarrow F(t, x)$  where  $F(t, x)$  is a non random CDF and satisfies the following porous medium PDE with the initial condition  $F(0, x) = F_\lambda(x)$

$$F_t(t, x) = -\left(b(F(t, x))F_x(t, x)\right) + \left(\frac{\sigma^2(F(t, x))}{2}F_x(t, x)\right)_x \quad (2)$$

## Derivation of PME

For any test function  $f(x) \in C_c^\infty$ , we have

$$\begin{aligned}
 \int_{\mathbb{R}} f(x) d(F_n(t, x) - F_n(0, x)) &= \frac{\sum_{i=1}^n (f(X_i(t)) - f(X_i(0)))}{n} \\
 &= \int_0^t \int_{\mathbb{R}} \left( f'(x) b(F_n(s, x)) + f''(x) \frac{\sigma^2(F_n(s, x))}{2} \right) dF_n(s, x) ds \quad (3) \\
 &+ \sum_{i=1}^n \int_0^t \frac{f'(X_i(s)) \sigma(F_n(s, X_i(s)))}{n} dW_i(s)
 \end{aligned}$$

Now as  $n \rightarrow \infty$ , we expect  $F_n(t, x)$  to converge to  $F(t, x)$  and we also expect the integrals to converge appropriately.

## Proof Cont'd

Upon letting  $n \rightarrow \infty$ , we obtain

$$\begin{aligned} & \int_{\mathbb{R}} f(x) d(F(t, x) - F(0, x)) = \\ & = \int_0^t \int_{\mathbb{R}} \left( f'(x) b(F(s, x)) + f''(x) \frac{\sigma^2(F(s, x))}{2} \right) dF(s, x) ds \end{aligned} \quad (4)$$

Differentiating wrt  $t$  and using the fact that the limiting distribution  $F(t, x)$  has a density  $F_x(t, x)$ , we get

$$\begin{aligned} & \int_{\mathbb{R}} f(x) F_{xt}(t, x) dx = \\ & = \int_{\mathbb{R}} \left( f'(x) b(F(t, x)) + f''(x) \frac{\sigma^2(F(t, x))}{2} \right) F_x(t, x) dx \end{aligned} \quad (5)$$

Integration by parts gives us the Porous Medium PDE.

## Proof Cont'd

What happened to the Martingale Term ?

The Martingale term  $M_t^n = \sum_{i=1}^n \int_0^t \frac{f'(X_i(s))\sigma(F_n(s, X_i(s)))}{n} dW_i(s)$  vanishes as  $n \rightarrow \infty$ . To see this, look at  $\langle M^n \rangle_t$

$$\langle M^n \rangle_t = \int_0^t \int_{\mathbb{R}} \frac{(f'(x)\sigma(F_n(s, x)))^2}{n} dF_n(s, x) ds \rightarrow 0 \text{ as } n \rightarrow \infty \quad (6)$$

We have  $F_n(t, x) \rightarrow F(t, x)$ , the next natural question to ask is, What can we say about the fluctuations  $G_n(t, x) = \sqrt{n}(F_n(t, x) - F(t, x))$  ?

## Theorem (Kolli, Shkolnikov '16)

$G_n(t, x) \rightarrow G(t, x)$ , where  $G(t, x)$  is the mild solution of the SPDE with the initial condition  $G(0, x) = \beta(F_\lambda(x))$

$$G_t(t, x) = - \left( b(F(t, x)) G(t, x) \right)_x + \frac{\left( \sigma^2(F(t, x)) G(t, x) \right)_{xx}}{2} + \sigma(F(t, x)) \sqrt{F_x(t, x)} \dot{W}(t, x) \quad (7)$$

where  $\dot{W}$  is space time white noise and  $\beta$  is an Independent standard Brownian Bridge.



# Solution of the SPDE

,We can solve the SPDE explicitly and the solution is as follows

$$\begin{aligned}
 G(t, x) = & \int_{\mathbb{R}} p(0, y, t, x) G(0, y) dy \\
 & + \int_0^t \int_{\mathbb{R}} \sigma(F(s, y)) \sqrt{F_x(s, y)} p(s, y, t, x) dW(s, y)
 \end{aligned} \tag{8}$$

where  $p(s, y, t, x)$  is the transition density of the diffusion

$$d\bar{X}_i(t) = b(F(t, \bar{X}_i(t))) dt + \sigma(F(t, \bar{X}_i(t))) dW_i(t) \tag{9}$$

# Proof

There are two parts in the proof

- Tightness
- Identification of the limit

As  $n \rightarrow \infty$ , For every  $i$ , we expect  $X_i(t)$  to fluctuate around  $\bar{X}_i(t)$ . The SDEs for  $X_i(t)$  and  $\bar{X}_i(t)$  are as follows

$$dX_i(t) = b(F_n(t, X_i(t))) dt + \sigma(F_n(t, X_i(t))) dW_i(t) \quad (10)$$

$$d\bar{X}_i(t) = b(F(t, \bar{X}_i(t))) dt + \sigma(F(t, \bar{X}_i(t))) dW_i(t) \quad (11)$$

We expect  $X_i(t)$  to be close to  $\bar{X}_i(t)$  and the following propagation of chaos estimate gives us the exact sense in which the two particles are close

## Brief review of Wasserstein distance on the Real line

Let  $F(x)$  and  $G(x)$  be two Probability distributions on the Real line, then the  $p$  Wasserstein distance between  $F$  and  $G$  is defined as follows

$$W_p^p(F, G) = \int_0^1 |F^{-1}(t) - G^{-1}(t)|^p dt \quad (12)$$

In view of Kantorovich duality, the 1 Wasserstein distance admits the following representation

$$W_1(F, G) = \int_{-\infty}^{\infty} |F(x) - G(x)| dx \quad (13)$$

# Propogation of Chaos Estimate

## Theorem (Kolli, Shkolnikov '16)

For all  $p > 0$  and  $T > 0$  there exists a constant  $C = C(p, T) < \infty$  such that

$$\sum_{i=1}^n \mathbb{E} \left[ \sup_{0 \leq t \leq T} |X_i(t) - \bar{X}_i(t)|^p \right] \leq \frac{C}{n^{p/2-1}}. \quad (14)$$

In particular, when  $p \geq 1$  one has

$$\mathbb{E} \left[ \sup_{0 \leq t \leq T} W_p^p(F_n(t, x), \bar{F}_n(t, x)) \right] \leq C n^{-p/2}. \quad (15)$$

where  $F_n(t, x)$  and  $\bar{F}_n(t, x)$  are the empirical CDFs corresponding to the particle systems  $X_i(t)$  and  $\bar{X}_i(t)$  respectively.

We remark that tightness is a simple consequence of the above estimate.

## Identification of the limit

for any smooth test function  $h(t, x)$

$$\begin{aligned}
 \int_{\mathbb{R}} h(t, x) (G_n(t, x) - G_n(0, x)) dx &= \int_0^t \int_{\mathbb{R}} h_t(s, x) G_n(s, x) dx ds \\
 &+ \int_0^t \int_{\mathbb{R}} \sqrt{n} \left( h_x(s, x) (B_n - B)(F_n(s, x)) + h_{xx}(s, x) (\Sigma_n - \Sigma)(F_n(s, x)) \right) dx ds \\
 &+ \int_0^t \int_{\mathbb{R}} \sqrt{n} h_x(s, x) (B(F_n(s, x)) - B(F(s, x))) dx ds \\
 &+ \int_0^t \int_{\mathbb{R}} \sqrt{n} h_{xx}(s, x) (\Sigma(F_n(s, x)) - \Sigma(F(s, x))) dx ds + \text{Martingale term}(M_t^n)
 \end{aligned}
 \tag{16}$$

## Proof Cont'd

$$\text{Martingale term}(M_t^n) = - \sum_{i=1}^n \int_0^t \frac{h(s, X_i(s)) \sigma(F_n(s, X_i(s))) dW_i(s)}{\sqrt{n}} \quad (17)$$

where  $B(x) = \int_0^x b(y) dy$ ,  $\Sigma(x) = \int_0^x \frac{\sigma^2(y)}{2} dy$ ,  $B_n(\frac{i}{n}) = \frac{\sum_{j=1}^i b(\frac{j}{n})}{n}$  and

$\Sigma_n(\frac{i}{n}) = \frac{\sum_{j=1}^i \sigma^2(\frac{j}{n})}{2n}$ , We also notice that  $(B_n - B)(F_n(s, x)) = O(\frac{1}{n})$  and similarly  $(\Sigma_n - \Sigma)(F_n(s, x)) = O(\frac{1}{n})$ . Upon letting  $n \rightarrow \infty$ , we expect  $G_n(t, x)$  to converge to  $G(t, x)$  and we also expect the integrals to converge appropriately.

## Proof Cont'd

The limit  $G(t,x)$  satisfies the following

$$\begin{aligned}
 \int_{\mathbb{R}} h(t,x)(G(t,x) - G(0,x)) dx &= \int_0^t \int_{\mathbb{R}} h_t(s,x) G(s,x) dx ds \\
 + \int_0^t \int_{\mathbb{R}} \left( h_x(s,x) b(F(s,x)) + h_{xx} \frac{\sigma^2(F(s,x))}{2} \right) G(s,x) dx ds & \quad (18) \\
 + \text{Martingale term}(M_t) &
 \end{aligned}$$

## Proof Cont'd

To find out the limit of the Martingale  $M_t^n$ , we look at the quadratic variation  $\langle M^n \rangle_t$

$$\langle M^n \rangle_t = \int_0^t \int_{\mathbb{R}} (h(s, x) \sigma(F_n(s, x)))^2 dF_n(s, x) ds \quad (19)$$

Now as  $n \rightarrow \infty$ ,  $\langle M^n \rangle_t \rightarrow \langle M \rangle_t$  and  $\langle M \rangle_t$  is as follows

$$\langle M \rangle_t = \int_0^t \int_{\mathbb{R}} (h(s, x) \sigma(F(s, x)))^2 F_x(s, x) dx ds \quad (20)$$

From this we infer that

$$M_t = \int_0^t \int_{\mathbb{R}} h(s, x) \sigma(F(t, x)) \sqrt{F_x(t, x)} dW(s, x) \quad (21)$$






## Proof Cont'd

Differentiating wrt  $t$  and Integration by parts gives us the SPDE that we want

$$G_t(t, x) = - \left( b(F(t, x)) G(t, x) \right)_x + \frac{\left( \sigma^2(F(t, x)) G(t, x) \right)_{xx}}{2} + \sigma(F(t, x)) \sqrt{F_x(t, x)} \dot{W}(t, x) \quad (22)$$

# References

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# Thank You