

# Discrete parametrix method and its applications

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# Model description

The Mc Kean-Singer approach (JDG 67) for «jump-diffusion» processes. Let  $(X_t)_{t \geq 0}$  be a Markov process with values in  $R^d$  with the following generator

$$\begin{aligned} L_t \varphi(x) = & \left\langle b(t, x), \nabla \varphi(x) \right\rangle + \frac{1}{2} \operatorname{tr} \left( a(t, x) D_x^2 \varphi(x) \right) \\ & + \int_{R^d} \left( \varphi(x + y) - \varphi(x) - \frac{\left\langle y, \nabla \varphi(x) \right\rangle}{1 + |y|^2} \right) v(t, x, dy) \end{aligned} \tag{1}$$

# Model description

where

- $a(t, \cdot)$  is a positive semi definite diffusion matrix,  $t \geq 0$  .
- $b(t, \cdot)$  is a drift vector.
- $\nu(t, x, dy)$  is a Levy measure depending on a parameter  $x \in R^d$  .
- $\varphi \in C_0^\infty(R^d)$  is a test function.

## The Mc Kean-Singer approach (JDG, 67)

**Key ideas:** freeze the terminal point  $x'$  and use the Kolmogorov equations satisfied by  $\tilde{p}^{x'}, p$

$$\begin{aligned}\tilde{L}_t^{x'} \varphi(x) &= \langle b(t, x'), \nabla \varphi(x) \rangle + \frac{1}{2} \operatorname{tr}(a(t, x') D_x^2 \varphi(x)) \\ &+ \int_{\mathbb{R}^d} (\varphi(x+y) - \varphi(x) - \frac{\langle y, \nabla \varphi(x) \rangle}{1+|y|^2}) \nu(t, x', dy)\end{aligned}$$

## The Mc Kean-Singer approach (JDG,67)

- $b(t, x')$  is a «frozen» drift,  $t \geq 0$ .
- $\nu(t, x', dy)$  is a «frozen» Levy measure,  $t \geq 0$ .
- $a(t, x')$  is a «frozen» diffusion matrix,  $t \geq 0$ .

**Proposition.** (Mc Kean-Singer Parametrix expansion)

For all  $0 \leq s < t \leq T$

$$p(s, t, x, x') = \sum_{r=0}^{\infty} \tilde{p} \otimes H^{(r)}(s, t, x, x')$$

# Mc Kean-Singer Parametrix expansion

where

$$f \otimes g(s, t, x, y) = \int_s^t du \int_{R^d} f(s, u, x, z) g(u, t, z, x') dz$$
$$\tilde{p} \otimes H^{(0)} = \tilde{p} \quad \text{and} \quad H^{(r)} = H \otimes H^{(r-1)}, r > 0,$$

denotes the  $r$ - fold convolution of the kernel  $H$

Proof.  $(p - \tilde{p}^{x'})(s, t, x, x') =$

$$\int_s^t du \partial_u \int_{R^d} dz p(s, u, x, z) \tilde{p}^{x'}(u, t, z, x')$$

# Mc Kean-Singer Parametrix expansion

$$= \int_s^t du \int_{R^d} dz (\partial_u p(s, u, x, z) \tilde{p}^{x'}(u, t, z, x') \\ + p(s, u, x, z) \partial_u \tilde{p}^{x'}(u, t, z, x'))$$

$$= \int_s^t du \int_{R^d} dz (L_u^* p(s, u, x, z) \tilde{p}^{x'}(u, t, z, x') \\ - p(s, u, x, z) \tilde{L}_u^{x'} \tilde{p}^{x'}(u, t, z, x'))$$

$$= \int_s^t du \int_{R^d} dz p(s, u, x, z) (L_u - \tilde{L}_u^{x'}) \tilde{p}^{x'}(u, t, z, x')$$

## Mc Kean - Singer Parametrix expansion

$$= p \otimes H(s, t, x, x'), \quad \text{where}$$

$$H(u, t, z, x') = (L_u - \tilde{L}_u^{x'}) \tilde{p}^{x'}(u, t, z, x')$$

A simple iteration completes the proof.

Three basic partial cases of the model (1)

## Three basic cases

- **Nondegenerate diffusions:**  $\nu = 0, a(t, \cdot)$  is positively definite and UE,  $b(t, \cdot)$  is bounded
- **Degenerated diffusions (Kolmogorov type equations):**  $\nu = 0, a(t, \cdot)$  is positively semi definite,  $b(t, \cdot)$  is **Not bounded!**
- **SDE driven by  $\alpha$ -stable symmetric random processes**

# Three basic cases

We consider SDE driven by  $\alpha$ -stable symmetric process  $Z_s$

$$X_t = x + \int_0^t m(X_{s_-}) ds + \int_0^t \sigma(X_{s_-}) dZ_s,$$

$$\mathbb{E}[\exp(i\langle u, Z_t \rangle)] =$$

$$\exp \left\{ it \langle \gamma, u \rangle - t \int_{S^{d-1}} \left| \langle s, u \rangle \right|^{\alpha} \lambda(ds) \right\}$$

# Three basic cases

For this case

$$\nu(t, x, A) = \nu(x, A) = \nu\{z \in R^d : \sigma(x)z \in A\},$$

$$b(t, x) = m(x) + \sigma(x)\gamma \quad \text{for } 1 < \alpha < 2,$$

$$b(t, x) = 0 \quad \text{for } 0 < \alpha \leq 1, \quad a(t, x) = 0.$$

# Nondegenerate diffusions

$$X_t = x + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dW_s$$

$$(UE): \lambda^{-1} \|z\|^2 \leq \langle a(t, x) z, z \rangle \leq \lambda \|z\|^2, \lambda > 0$$

$$\forall (t, x) \in R^+ \times R^d, a = \sigma \sigma^*.$$

(R):  $b(t, \cdot)$  is bounded and satisfies mild regularity conditions.

# Nondegenerate diffusions

Mc Kean-Singer paramerix series has the following form

$$p(s, t, x, y) = \sum_{r=0}^{\infty} \tilde{p} \otimes H^{(r)}(s, t, x, y),$$

where

$$H(u, t, z, y) = (L_u - \tilde{L}_u^y) \tilde{p}^y(u, t, z, y),$$

$$L_u = \frac{1}{2} \sum_{i,j} a_{ij}(u, z) \partial_{z_i z_j} + \sum_i b_i(u, z) \partial_{z_i},$$

$$\tilde{L}_u^y = \frac{1}{2} \sum_{i,j} a_{ij}(u, y) \partial_{z_i z_j} + \sum_i b_i(u, y) \partial_{z_i}$$

# Discrete Mc Kean Singer parametrix (KMol 84, KM 00,02,09)

Let  $X_{t_i}^h, t_i = ih$ , be a Markov chain with values in  $\mathbb{R}^d$  and with the following dynamics

$$X_{t_{i+1}}^h = X_{t_i}^h + b(t_i, X_{t_i}^h)h + h^{1/2} \xi_{t_{i+1}}^h, \quad X_0^h = x.$$

$$\mathcal{L}(\xi_{t_{i+1}}^h \mid \underset{\sim}{X}_{t_i}^h = x_i, \underset{\sim}{X}_{t_{i-1}}^h = x_{i-1}, \dots) \sim q_{t_i, x_i}(\cdot)$$

depending only on the last values  $(t_i, x_i)$

**The two parameter family of densities  $q_{t,x}(\cdot)$**

## Discrete parametrix

$$(B1) \quad \int z q_{t,x}(z) dz = 0, \forall (t,x) \in R^+ \times R^d$$

$$(B2) \quad \int z_i z_j q_{t,x}(z) dz = a_{ij}(t,x), (t,x) \in R^+ \times R^d$$

$$(B3) \quad \exists \psi : R^d \rightarrow R \quad \text{such that}$$

$$\sup_{x \in R^d} |\psi(x)| < \infty, \quad \int_{R^d} \|x\|^S \psi(x) dx < \infty$$

## Discrete parametrix

and  $\forall (t, x, z) \in [0, T] \times R^d \times R^d$

$$\left| D_z^\nu q_{t,x}(z) \right| \leq \psi(z), |\nu| = 0, 1, 2, 3, 4.$$

$$\left| D_x^\nu q_{t,x}(z) \right| \leq \psi(z), |\nu| = 0, 1, 2.$$

(B4) mild regularity conditions on  $b(t, x)$  and  
 $a(t, x)$

## Discrete parametrix

**Example.** The Euler scheme. For this case

$$X_{t_{i+1}}^h = X_{t_i}^h + b(t_i, X_{t_i}^h)h + \sigma(t_i, X_{t_i}^h)(W_{t_{i+1}} - W_{t_i}),$$

$$\xi_{t_{i+1}}^h = h^{-1/2} \sigma(t_i, X_{t_i}^h)(W_{t_{i+1}} - W_{t_i}),$$

and  $q_{t,x}(z)$  is the family of Gaussian densities

$$q_{t,x}(z) = \phi_{0,a(t,x)}(z)$$

# Discrete parametrix

**Goal: handle more general random sources**

**than**  $(W_{t_{i+1}} - W_{t_i})$

**Error analysis:** get a scheme that admits a «parametrix» representation comparable to the continuous case. **Frozen Markov chain**

$$\tilde{X}_{t_{i+1}}^{h,x'} = \tilde{X}_{t_i}^{h,x'} + b(t_i, x')h + h^{1/2} \tilde{\xi}_{t_{i+1}}^h, \quad \tilde{X}_0^{h,x'} = x,$$

$$\mathcal{L}(\xi_{t_{i+1}}^h \mid X_{t_i}^h = x_i, X_{t_{i-1}}^h = x_{i-1}, \dots) \sim q_{t_i, x'}(\cdot)$$

## Discrete parametrix

Consider for a test function  $\varphi \in C_0^\infty(\mathbb{R}^d)$

$$L_{t_j}^h \varphi(x) = h^{-1} \left\{ E[\varphi(X_{t_j+h}^h \mid X_{t_j}^h = x)] - \varphi(x) \right\}$$

$$\tilde{L}_{t_j}^{h,x'} \varphi(x) = h^{-1} \left\{ E[\varphi(\tilde{X}_{t_j+h}^{h,x'} \mid \tilde{X}_{t_j}^{h,x'} = x)] - \varphi(x) \right\}$$

$$H^h(t_i, t_j, x, x') = (L_{t_j}^h - \tilde{L}_{t_j}^{h,x'}) \tilde{p}^h(t_{j+h}, t_{j'}, x, x')$$

## Discrete parametrix

The following discrete Mc Kean-Singer type expansion holds

$$p^h(t_j, t_{j'}, x, x') = \sum_{r=0}^{j'-j} \tilde{p}^h \otimes_h H^{h,(r)}(t_j, t_{j'}, x, x'), \quad (2)$$

$$f \otimes_h g(t_j, t_{j'}, x, x') =$$

$$\sum_{k=0}^{j'-j-1} h \int_{R^d} f(t_j, t_{j+k}, x, z) g(t_{j+k}, t_{j'}, z, x') dz$$

# Discrete parametrix

Main idea: comparison of two series (1) and (2)

Main tool: classical local limit theorems

$$p(0, T, x, y) = \sum_{r=0}^{\infty} \tilde{p} \otimes H^{(r)}(0, T, x, y) \quad (1)$$

$$p^h(0, T, x, y) = \sum_{r=0}^{(T/h)-1} \tilde{p}^h \otimes_h H^{h,(r)}(0, T, x, y) \quad (2)$$

# Discrete parametrix

1. Control of the tails of these series
2. Control of the replacement  $\otimes$  by  $\otimes_h$   
(replacement of integrals by Riemannian sums )
3. Control of the convergence of  $\tilde{p}^h$  to  $\tilde{p}$   
(classical local limit multidimensional theorems)
4. Control of the difference of kernels  $H$  and  $H^h$

## Main result for the non-degenerate case

**Theorem (KMam 00).** Assume (UE), (B), (B1)-(B4). Then

$$\sup_{(x,y) \in R^{2d}} \left\{ T^{d/2} \left( 1 + \left( \frac{|y-x|}{\sqrt{T}} \right)^{S'} \right) \times \left| p^h(0, T, x, y) - p(0, T, x, y) \right| \right\} = O(n^{-1/2})$$

where

$$t \in [0, T], h = T/n, S' = (S - 2d - 4)/d$$

## Main result for the non-degenerate case

Homogeneous case:  $q_{t,x}(\cdot) = q_x(\cdot)$

(B5) For all  $(x, y) \in R^d \times R^d$ ,  $j \geq j_0$  with a bound  $j_0$  that does not depend on  $x$

$$\left| D_x^\nu q_x^{(j)}(y) \right| \leq C j^{-d/2} \psi(j^{-1/2} y), |\nu| = 0, 1, 2, 3.$$

for a constant  $C < \infty$ . Here  $q_x^{(j)}(y)$  denotes the  $j$ -fold convolution of  $q$  for fixed  $x$  as a function of  $y$ :  $q_x^{(j)}(y) = \int q_x^{(j-1)}(u) q_x(y-u) du$

## Main result for the non-degenerate case

**Theorem (KMam 09).** Assume (UE), (B), (B1)-(B5). Then there exists  $\delta > 0$  such that

$$\sup_{(x,y) \in R^{2d}} T^{d/2} \left( 1 + \left( \frac{|y-x|}{\sqrt{T}} \right)^{S'} \right) \times \left| p^h(0, T, x, y) - p(0, T, x, y) - h^{1/2} \pi_1(0, T, x, y) - h \pi_2(0, T, x, y) \right| = O(n^{-1-\delta})$$

**Open question: is it possible to take  $\delta=1/2$  ?**

## Main result for the non-degenerate case

where

$$\pi_1(0, T, x, y) = (p \otimes \mathcal{F}_2[p])(0, T, x, y),$$

$$\pi_2(0, T, x, y) = (p \otimes \mathcal{F}_2[p])(0, T, x, y)$$

$$+ (p \otimes \mathcal{F}_1[p \otimes \mathcal{F}_1[p]])(0, T, x, y)$$

$$+ \frac{1}{2} p \otimes (L_*^2 - L^2) p(0, T, x, y),$$

## Main result for the non-degenerate case

$$\mathcal{F}_i[f](s, t, x, y) = \sum_{|\nu|=i+2} \frac{\chi_\nu(y)}{\nu!} D_x^\nu f(s, t, x, y),$$

$i = 1, 2.$

$\chi_\nu(y)$  is the  $\nu$ -th cumulant of the density  $q_y(\cdot)$ ,  
 $L_*$  is the operator  $L$  with the coefficients  
frozen at  $x$  (not at  $y$  like in  $\tilde{L}$  ! )

## Degenerate diffusions. Kolmogorov example.

A.Kolmogorov (1934) example in  $R^2$

$$L = \frac{1}{2} \partial_{xx}^2 + bx\partial_y, b \neq 0.$$

Solution  $(X_t, Y_t)$  is given by

$$\begin{aligned} X_t &= x + W_t \\ Y_t &= y + b\left(xt + \int_0^t W_s ds\right) \end{aligned}$$

## Kolmogorov example

Two important properties of this example:

- Transportation of the initial condition  $x$  to the second component
- Different time scales.

$$\begin{pmatrix} X_t \\ Y_t \end{pmatrix} \sim \mathfrak{N} \left( \begin{pmatrix} x \\ y + bxt \end{pmatrix}, \begin{pmatrix} t & \frac{bt^2}{2} \\ \frac{bt^2}{2} & \frac{b^2t^2}{3} \end{pmatrix} \right)$$

# Degenerate diffusion

Model description.

$$\left\{ \begin{array}{l} X_t = x + \int_0^t b(X_s, Y_s) ds + \int_0^t \sigma(X_s, Y_s) dW_s \\ Y_t = y + \int_0^t F(X_s) ds \end{array} \right.$$

(A1)  $b, \sigma$  are  $C^1$ , bounded, resp.  $R^d$  and  $R^d \otimes R^d$  valued Lipchitz continuous,  $\sigma\sigma^*$  u.e.

## Degenerate diffusion

(A2)  $F$  is  $R^d$  valued,  $C^{2+\alpha}$ ,  $\alpha > 0$ , Lipschitz continuous mapping, **NOT bounded**, and  $|\nabla F| \geq C > 0$ .

➤  $(W_s)_{s \geq 0}$  standard d-dimensional BM.

**How to choose correctly the frozen process?**

Frozen diffusion process should **compensate the additional singularity** arising from the transportation of the initial condition.

## Degenerate diffusion

Our assumptions and Ito formula imply that the process  $(\bar{X}_s, \bar{Y}_s)_{s \geq 0} = (F(X_s), Y_s)_{s \geq 0}$  follows the dynamics of the same type with  $F(x) = x$ :

$$\left\{ \begin{array}{l} X_t = x + \int_0^t b(X_s, Y_s) ds + \int_0^t \sigma(X_s, Y_s) dW_s \\ Y_t = y + \int_0^t X_s ds \end{array} \right.$$

## Degenerate diffusion

Frozen diffusion process should be chosen to  
**compensate the additional singularity** arising  
from the transportation of the initial condition

$$\left\{ \begin{array}{l} \tilde{X}_s^{1,x'} = x_1 + \int_0^s \sigma(x'_1, x'_2 - x'_1(t-u)) dW_u + b(x'_1, x'_2) s \\ \tilde{X}_s^{2,x'} = x_2 + \int_0^s \tilde{X}_u^{1,x'} du \\ x' = (x'_1, x'_2), s \in [0, t]. \end{array} \right.$$

## Degenerate diffusion

**Remark.** Compensated value of the second component  $\theta_u^2 = x'_2 - x'_1(t-u), u \in [0, s]$  is a solution of the system of ODE

$$d\theta_u^2 = x'_1 du, \theta_t^2 = x'_2, u \in [0, s]$$

## Degenerate diffusion

**«Aronson type» bounds for the transition density.** Assume (A1) and (A2). Then  $\exists C, c$  such that  $\forall (t, x, x') \in (0, T] \times R^d \times R^d$

$$C^{-1} p_{c^{-1}}(t, x, x') \leq p(t, x, x') \leq C p_c(t, x, x')$$

where

## Aronson type bounds

$$p_c(t, x, x') = \left( \frac{\sqrt{3}c}{2\pi(t-s)^2} \right)^{d/2} \times \exp \left\{ -c \left\{ \frac{|x'_1 - x_1|^2}{4t} + 3 \frac{\left| x'_2 - x_2 - \frac{x_1 + x'_1}{2} t \right|^2}{t^3} \right\} \right\}$$

## Aronson type bounds

Upper bound and partial lower bound were proved in (KMM, 2010), lower bound for more general model was proved in (DM, 2010).

### Markov chain approximation

Two scales. «**Micro**» scale with the step  $h_0$ , and «**macro**» scale with the step  $h = nh_0$ . The initial Markov chain «lives» in micro scale and the aggregated Markov chain «lives» in macro scale.

# Degenerate Markov chain

**The «frozen» model. Micro scale.**

$$\tilde{X}_{t_{i+1}}^{h_0,1,t,x'} = \tilde{X}_{t_i}^{h_0,1,t,x'} + b(x')h_0$$

$$+ \sigma(x'_1, x'_2 - x'_1 t) \sqrt{h_0} \tilde{\xi}_{i+1},$$

$$\tilde{X}_{t_{i+1}}^{h_0,2,t,x'} = \tilde{X}_{t_i}^{h_0,2,t,x'} + \tilde{X}_{t_{i+1}}^{h_0,1,t,x'} h_0 =$$

$$\tilde{X}_{t_i}^{h_0,2,t,x'} + h_0 \tilde{X}_{t_i}^{h_0,1,t,x'} + h_0^2 b(x') +$$

$$h_0^{3/2} \sigma(x'_1, x'_2 - x'_1 t) \tilde{\xi}_{i+1}$$

## Degenerate Markov chain

Where  $(\xi_i)_{i \in N^*}$  are centered, i.i.d. with unit covariance matrix and with a density  $q(\cdot)$ . Note that  $\begin{pmatrix} \tilde{\xi}_{i+1} \\ \tilde{\xi}_{i+1} \end{pmatrix}$  **does Not have a density in  $R^{2d}$  !**

To get a density **we have to iterate  $n$**  times and to consider our chain **in macro scale**.

# Degenerate Markov chain

**Aggregated frozen Markov chain. Marco scale.**

$$\tilde{X}_{t_n}^{h_0, 1, t, x'} = x_1 + (nh_0)b(x'_1, x'_2)$$

$$+ \sigma(x'_1, x'_2 - x'_1 t) \sqrt{nh_0} \tilde{\xi}_n^{(1)},$$

$$\tilde{X}_{t_n}^{h_0, 2, t, x'} = x_2 + (nh_0)x_1 + \frac{\gamma_n}{2}(nh_0)^2 b(x'_1, x'_2)$$

$$+ (nh_0)^{3/2} \sigma(x'_1, x'_2 - x'_1 t) \tilde{\xi}_n^{(2)},$$

# Degenerate Markov chain

where

$$\gamma_n = 1 + \frac{1}{n}, \tilde{\xi}_n^{(1)} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \tilde{\xi}_i,$$

$$\tilde{\xi}_n^{(2)} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{n-i+1}{n} \tilde{\xi}_i,$$

$$\begin{pmatrix} \tilde{\xi}_n^{(1)} \\ \tilde{\xi}_n^{(2)} \end{pmatrix} \rightarrow \begin{pmatrix} W_1 \\ \int_0^1 W_s ds \end{pmatrix}$$

# Degenerate Markov chain

By Fourier methods  $\Rightarrow \begin{pmatrix} \tilde{\xi}_n^{(1)} \\ \tilde{\xi}_n^{(2)} \end{pmatrix}$  admits a regular

density  $q_n(\cdot)$  in  $R^{2d}$ . This gives an idea how to construct the unfrozen Markov chain in macro scale.

# Degenerate Markov chain

**Unfrozen Markov chain. Macro scale.**

$$X_{t_{i+1}}^{h,1} = X_{t_i}^{h,1} + b(X_{t_i}^h)h + \sigma(X_{t_i}^h)\sqrt{h}\eta_{i+1}^1,$$

$$X_{t_{i+1}}^{h,2} = X_{t_i}^{h,2} + \left\{ X_{t_i}^{h,1} + \frac{\gamma_n}{2} b(X_{t_i}^h)h + \sigma(X_{t_i}^h)\sqrt{h}\eta_{i+1}^2 \right\} h$$

$\begin{pmatrix} \eta_{i+1}^1 \\ \eta_{i+1}^2 \end{pmatrix}$  also has the same density  $q_n(\cdot)$

## LLT for the densities

$$(A3) \int_{R^d} |u|^S |D_u^\nu q_n(u)| du < \infty, |\nu| \leq 4, S > 4(d+1) + 2d^2.$$

**Theorem.** Assume (A1) - (A3). Then  $\exists c > 0$  such that

$$\sup_{x, x' \in R^{2d}} \left[ (1 + |x_1| + |x'_1|) \sup_{0 \leq \delta \leq 1} p_c(T(1 + \delta), x, x') + \chi_{T^{1/2}} \left( x'_1 - x_1, x'_2 - x_2 - T \left( \frac{x_1 + x'_1}{2} \right) \right) \right] \times$$

## LLT for the densities

$$\times |p_h(T, x, x') - p(T, x, x')| = O(h^{1/2}).$$

Where  $p_c(t, x, x')$  is the Gaussian density defined above and

$$\chi_\rho(u_1, u_2) = \rho^{-4d} \frac{1}{1 + \left( \left| \frac{u_1}{\rho} \right|^2 + \left| \frac{u_2}{\rho^{3/2}} \right|^2 \right)^{\frac{s-4}{4d-1}}}$$

# SDE's driven by $\alpha$ -stable symmetric processes

We consider

$$X_t = x + \int_0^t m(X_{s_-}) ds + \int_0^t \sigma(X_{s_-}) dZ_s,$$

where  $Z_s$  is  $\alpha$ -stable symmetric process in  $R^d$ ,  $\alpha \in (0,2)$ . The Brownian case  $\alpha=2$  was considered in [KMam 02]. **The Euler scheme:**

$$X_{t_{i+1}}^h = X_{t_i}^h + m(X_{t_i}^h)h + \sigma(X_{t_i}^h)(Z_{t_{i+1}} - Z_{t_i})$$

# SDE's driven by $\alpha$ -stable symmetric processes

Assume:

(A1) For  $d \geq 2$  the spherical measure  $\lambda$  has a surface density of class  $C^q(S^{d-1})$  and for  $d \geq 1$ , there exist  $0 < C_1 \leq C_2 < \infty, \forall p \in R^d$ , such that

$$C_1|p|^\alpha \leq \int_{S^{d-1}} |\langle p, s \rangle|^\alpha \lambda(ds) \leq C_2|p|^\alpha$$

# SDE's driven by $\alpha$ -stable symmetric processes

(A2)  $m, \sigma$  and their derivatives up to the order  $q$  are bounded. For  $1 < \alpha < 2$ ,  
 $b(x) = m(x) + \sigma(x)\gamma$  is uniformly bounded.  
For  $0 < \alpha \leq 1$  we suppose that  $b(x) = 0$   
For all  $x \in R^d$ .

(A3)  $\exists \Lambda \geq 1$  such that

$$\Lambda^{-1}|\xi|^2 \leq \langle \sigma(x)\xi, \xi \rangle \leq \Lambda|\xi|^2$$

# SDE's driven by $\alpha$ -stable symmetric processes

**Theorem.** Suppose that  $q > d + 4$  and (A1) – (A3). Let  $0 < M \leq q - (d + 4)$ . Then there exists a function  $R_M(T, x, y)$ ,

$$|R_M(T, x, y)| \leq C_M(T) \frac{1}{1 + |y - x|^{d+\alpha}} = \rho_{\alpha, M}(T, y - x),$$

$C_M(T) < \infty$ , such that

# SDE's driven by $\alpha$ -stable symmetric processes

$$(p - p^h)(T, x, y) =$$

$$\sum_{l=1}^{M-1} \frac{h^l}{(l+1)!} \pi_l^h(T, x, y) + h^M R_M(T, x, y),$$

where  $\sum_{l=1}^{M-1} |\pi_l^h(T, x, y)| \leq \rho_{\alpha, M}(T, y - x).$

# SDE's driven by $\alpha$ -stable symmetric processes

**Example.** For  $M=2$

$$(p - p^h)(T, x, y) =$$

$$\frac{h}{2}(p \otimes (L^2 - \tilde{L}_*^2)p)(T, x, y) + h^2 R_2(T, x, y),$$

$$|R_2(T, x, y)| \leq \rho_{\alpha, 2}(T, y - x), \quad \tilde{L}_*^2 p = \tilde{L}_*(\tilde{L}_* p),$$

$\tilde{L}_*$  is a generator (1) with a drift vector  $b(x)$  and with a Levy measure  $\nu(x, dy)$  frozen at  $x$ .

# References

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