

# Super-diffusion and space fractional pde

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# Motivation

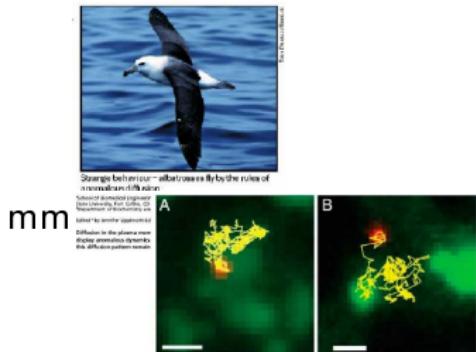


Fig. 1. Overlay image of GFP-tagged Kv2.1 clusters and individual QDs. Kv2.1 clusters are shown in green and QD-tagged channels in red. The trajectories of (A) a clustered and (B) a nonclustered (free) Kv2.1 channels are shown. Interestingly, the nonclustered channel ignores the compartment parameters and the channel travels freely into and out of a cluster. Scale bars: 1  $\mu$ m.

- super-diffusion: mass spreading with  $\infty$  second moment
- observations incompatible with finite 2nd moment [Metzler+ Klafter, (2004)][ Clark, Silman, Kern, Macklin, HilleRisLambers, (1999)]
- tracer tests in rivers: tracer density measured [Deng, Singh Bengtsson, (2004) ][ Benson, Schumer, Meerschaert, Wheatcraft (2001)]

- animal, seeds: sometimes tracer density sometimes individual trajectories
- polymers in biological membranes
- water molecules in porous media [Néel, Bauer, Fleury,(2014)]

# Organisation

- 1. Space fractional diffusion equations
- 2. Fractional integrals and derivatives
- 3. 1D stable Lévy motion
- 4. Stable Lévy motion in higher dimension
- 5. Space fractional diffusion equation : stable Lévy motion density, boundary conditions

# 1. Space fractional diffusion equation

## 1.1. Definition

- in 1D:  $\partial_t C = \partial_x [-uC] + D[p\frac{\partial^\alpha C}{\partial_+ x^\alpha} + (1-p)\frac{\partial^\alpha C}{\partial_- x^\alpha}]$
- in 2D:  
$$\frac{\partial C}{\partial t}(\mathbf{x}, t) + \nabla \cdot \mathbf{u}(\mathbf{x}, t)C(\mathbf{x}, t) = \nabla \cdot \overline{\overline{\mathbf{D}}} \nabla_{\mathbf{p}}^{\alpha-1} C(\mathbf{x}, t) + S_c(\mathbf{x}, t)$$
- $\nabla_{\mathbf{p}}^{\alpha-1} C \equiv \begin{pmatrix} p_1 \frac{\partial^{\alpha_1-1} C}{\partial_+ x_1^{\alpha_1-1}} + (1-p_1) \frac{\partial^{\alpha_1-1} C}{\partial_- x_1^{\alpha_1-1}} \\ p_2 \frac{\partial^{\alpha_2-1} C}{\partial_+ x_2^{\alpha_2-1}} + (1-p_2) \frac{\partial^{\alpha_2-1} C}{\partial_- x_2^{\alpha_2-1}} \end{pmatrix}$
- provided derivatives exist:  $\frac{\partial}{\partial x} \frac{\partial^{\alpha_1-1} C}{\partial_+ x^{\alpha_1-1}} = \frac{\partial^\alpha C}{\partial_+ x^\alpha}$
- Meerschaert+Sikorskii (2012)]

## 1.2. Normal diffusion: a particular case

- in 1D:  $\partial_t C = \partial_x [-uC] + D[p \frac{\partial^2 C}{\partial_+ x^2} + (1-p) \frac{\partial^2 C}{\partial_- x^2}]$
- in 2D:  
$$\frac{\partial C}{\partial t}(\mathbf{x}, t) + \nabla \cdot \mathbf{u}(\mathbf{x}, t)C(\mathbf{x}, t) = \nabla \cdot \overline{\overline{\mathbf{D}}} \nabla_{\mathbf{p}}^1 C(\mathbf{x}, t) + S_c(\mathbf{x}, t)$$
- $\nabla_{\mathbf{p}}^1 C \equiv \begin{pmatrix} \frac{\partial C}{\partial x_1} \\ \frac{\partial C}{\partial x_2} \end{pmatrix}$

## 2. Fractional integral/derivative

### 2.1. Definitions

Riemann-Liouville derivatives in  $]a, b[$ :

$$\frac{\partial^{\alpha'} f}{\partial_+ x^{\alpha'}}(x) = \frac{\partial}{\partial x}(I_{+x}^{1-\alpha'} f)(x)$$

$$\frac{\partial^{\alpha'} f}{\partial_- x^{\alpha'}}(x) = -\frac{\partial}{\partial x}(I_{-x}^{1-\alpha'} f)(x)$$

$$\alpha' \in ]0, 1]$$

Riemann-Liouville integrals  $I_{+,x}^\gamma$  and  $I_{-,x}^\gamma$  in  $]a, b[$ :

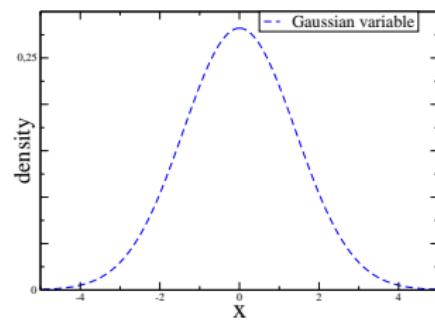
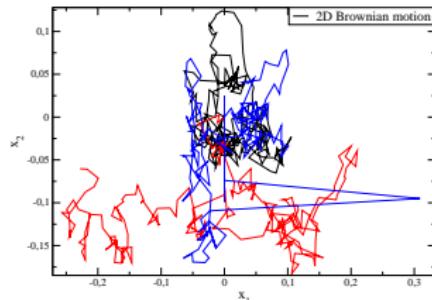
$$I_{+,x}^\gamma f(x) = \frac{1}{\Gamma(\gamma)} \int_a^x \frac{f(x')}{(x-x')^{\gamma-1}} dx' \text{ and } I_{-,x}^\gamma f(x) = \frac{1}{\Gamma(\gamma)} \int_x^b \frac{f(x')}{(x'-x)^{\gamma-1}} dx'$$

## 2.2. Fourier transform

- 1D:  $\hat{f}(k) = \int_{-\infty}^{+\infty} e^{ikx} f(x) dx$
- derivative:  $\frac{\partial f}{\partial x}$ :  $-ik\hat{f}(k)$
- $\frac{\partial^\alpha f}{\partial_+ x^\alpha}$ :  $(-ik)^\alpha \hat{f}(k)$
- $\frac{\partial^\alpha f}{\partial_- x^\alpha}$ :  $(ik)^\alpha \hat{f}(k)$

### 3. Diffusion equation and Brownian motion

#### 3.1. Brownian motion



- in 1D or more
- $\mathbf{B}(t)$ : independent increments
- $d\mathbf{B}([t, t + dt[) \stackrel{d}{=} (2dt)^{1/2} \mathbf{G}$
- $\mathbf{G}$ : standard centered gaussian random variable of  $\mathbb{R}^d$

### 3.2. From Brownian motion to diffusion equation

$$1D: dX([t, t + dt]) = u(X(t))dt + D^{1/2}dB([t, t + dt])$$

$$2D: d\mathbf{X}([t, t + dt]) = \mathbf{u}(\mathbf{X}(t))dt + \begin{pmatrix} D_{11}^{1/2} & 0 \\ 0 & D_{22}^{1/2} \end{pmatrix} d\mathbf{B}([t, t + dt])$$

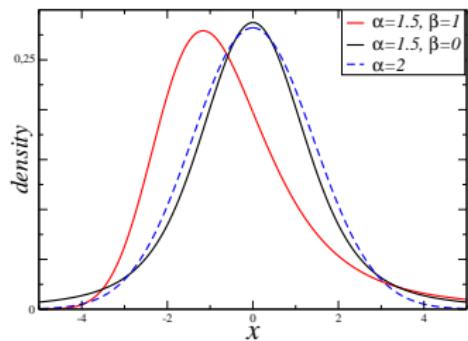
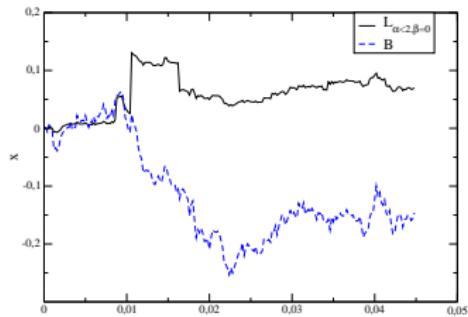
the probability density function  $C$ :  $\frac{\partial C}{\partial t}(\mathbf{x}, t) + \nabla \cdot \mathbf{u}(\mathbf{x}, t)C(\mathbf{x}, t)$

$$= \nabla \cdot \bar{\bar{\mathbf{D}}} \nabla_{\mathbf{p}}^1 C(\mathbf{x}, t), \quad \nabla_{\mathbf{p}}^1 C \equiv \frac{\partial C}{\partial \mathbf{x}}$$
 in 1D

$$\nabla_{\mathbf{p}}^1 C \equiv \left( \frac{\partial C}{\partial x_1}, \frac{\partial C}{\partial x_2} \right)^T$$
 in 2D

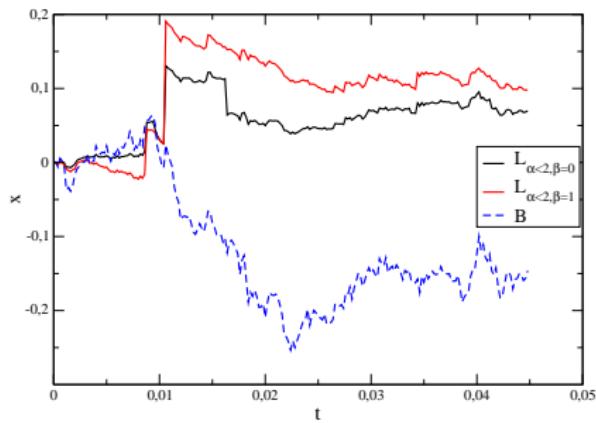
## 4. More general stable Lévy motion

### 4.1. Replace BM by stable motion, in 1D



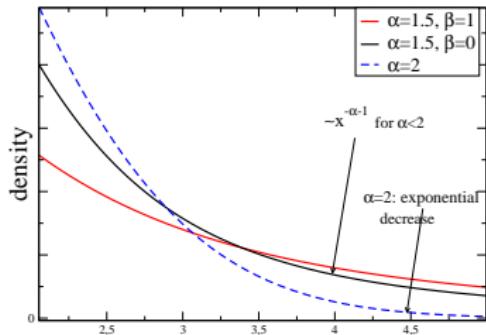
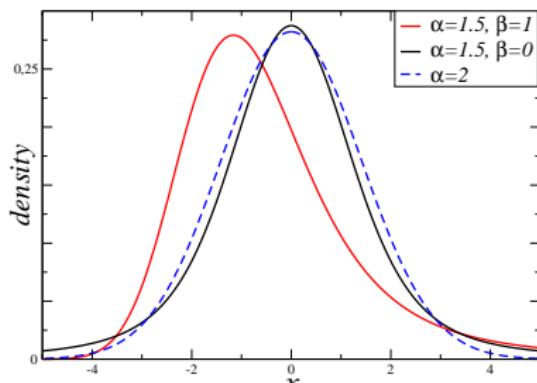
- $dX([t, t + dt]) = u(X(t)dt + D^{1/\alpha}dL_{\alpha,\beta}([t, t + dt]))$  and  $X(0)$ : process of p.d.f  $C$  solution of  $\partial_t C = \partial_x[-uC] + D[p\frac{\partial^\alpha C}{\partial x^\alpha} + (1-p)\frac{\partial^\alpha C}{\partial -x^\alpha}]$  with  $\beta = 2p - 1$
- $dL_{\alpha,\beta}([t, t + dt])$  independent of the past as  $dB([t, t + dt])$
- $dL_{\alpha,\beta}([t, t + dt]) = \frac{d}{-dt^{1/\alpha} \cos \frac{\pi\alpha}{2}} S(\alpha, \beta)$
- $S(\alpha, \beta)$  stable 1D random variable
- $S(2, \beta)$  1D gaussian random variable

## 4.1. 1D stable process



- stable process
  - $\alpha < 2$ : more very large jumps than  $\alpha = 2$
  - $\beta > 0$  and  $\alpha < 2$ : larger large jumps
  - $\beta > 0$  and  $\alpha < 2$ : jumps of moderate size made smaller

## 4.2. Stable RV



- stable random variable  $S(\alpha, \beta)$ , stability exponent  $0 < \alpha \leq 2$ , skewness  $-1 \leq \beta \leq 1$
- $\infty$  variance except NORMAL RV  $\alpha = 2$
- characteristic function  $\langle e^{ikS(\alpha,\beta)} \rangle = e^{-\varphi_{\alpha,\beta}(k)}$
- $\varphi_{\alpha,\beta}(k) = |k|^\alpha (1 - i\beta \text{sign}(k) \tan \frac{\pi\alpha}{2})$ ,  $\varphi_{\alpha,-\beta}(k) = \varphi_{\alpha,\beta}(-k)$

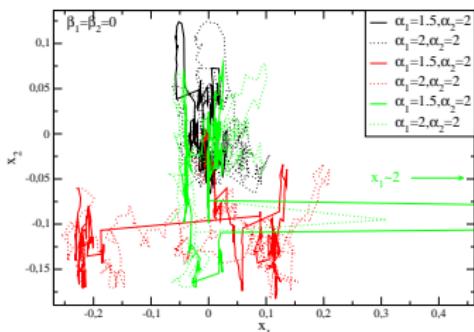
## 4.3. The word “stable”

- stable w.r.t what? for random variables
- the distribution of the sum of independent identically distributed variables
- $\mathcal{S}_1$  and  $\mathcal{S}_2$  independent, distributed as  $S(\alpha, \beta) \Rightarrow \mathcal{S}_1 + \mathcal{S}_2 \stackrel{d}{=} 2^{1/\alpha} S(\alpha, \beta)$
- $\mathcal{S}_1, \dots, \mathcal{S}_n$  independent, distributed as  $S(\alpha, \beta) \Rightarrow \mathcal{S}_1 + \dots + \mathcal{S}_n \stackrel{d}{=} n^{1/\alpha} S(\alpha, \beta)$
- consequence:  $dL_{\alpha, \beta}([t, t + dt]) \stackrel{d}{=} -dt^{1/\alpha} \cos \frac{\pi\alpha}{2} S(\alpha, \beta)$  can hold for all  $dt$ , and  $L_{\alpha, \beta}(t) \stackrel{d}{=} -t^{1/\alpha} \cos \frac{\pi\alpha}{2} S(\alpha, \beta)$

## 4.4. Stable variables are attractors

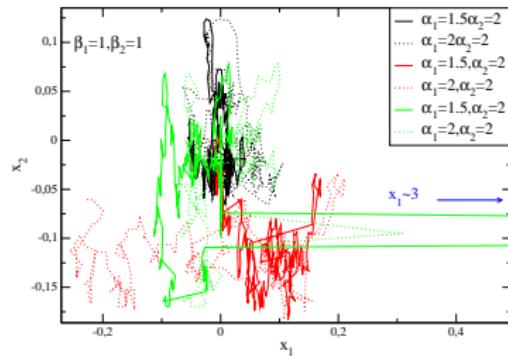
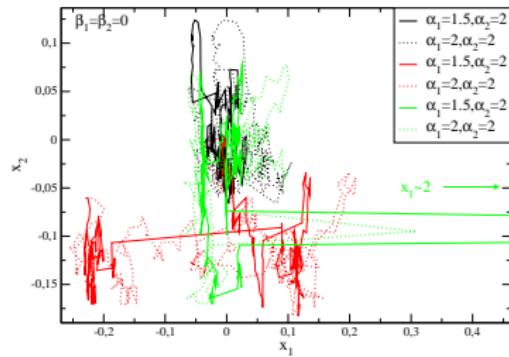
- why studying stable random variables?
- because they are attractors
- Gaussian variables are attractors:  $Y_i$  independent copies of  $Y$  whose variance is finite, there exist  $a_n$  and  $b_n$  s.t  $\sum a_i Y_i - b_i \Rightarrow G$
- if  $Y_i$  independent, distributed as  $Y$  whose p.d.f falls off as  $x^{-\alpha-1}$  at  $\infty$ :  $\sum a_i Y_i - b_i \Rightarrow S(\alpha, \beta)$
- ubiquitous in Nature

## 4.5. Stable Lévy motion in 1D and 2D



- $dX([t, t + dt]) = u(X(t)dt + D^{1/\alpha} dL_{\alpha, \beta}([t, t + dt]))$  and  
 $X(0)$ : process of p.d.f  $C$   
solution of  $\partial_t C = \partial_x [-uC] + D[p \frac{\partial^\alpha C}{\partial_{+x}^\alpha} + (1-p) \frac{\partial^\alpha C}{\partial_{-x}^\alpha}]$  with  
 $\beta = 2p - 1$
  - $dL_{\alpha_1, \alpha_2, \beta_1, \beta_2}([t, t + dt])$   
independent of the past
  - $dL_{\alpha_1, \alpha_2, \beta_1, \beta_2}([t, t + dt]) \stackrel{d}{=} - \begin{pmatrix} dt^{1/\alpha_1} \cos \frac{\pi \alpha_1}{2} & 0 \\ 0 & dt^{1/\alpha_2} \cos \frac{\pi \alpha_2}{2} \end{pmatrix}$   
 $= \nabla \cdot \bar{D} \nabla_p^{\alpha-1} C(x, t) + S_c(x, t)$   
 $- p_1 \frac{\partial^{\alpha_1-1} C}{\partial_{-x_1^{\alpha_1-1}}} \quad \left. \begin{array}{l} \\ \\ \end{array} \right)$   
 $- p_2 \frac{\partial^{\alpha_2-1} C}{\partial_{-x_2^{\alpha_2-1}}} \quad \left. \begin{array}{l} \\ \\ \end{array} \right)$

## 4.6. Skewness parameter and trajectories



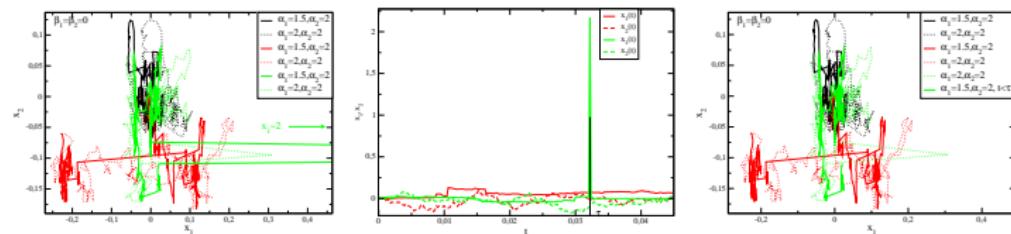
## 5. Stable Lévy motion density and space fractional diffusion

### 5.1. In $R^2$

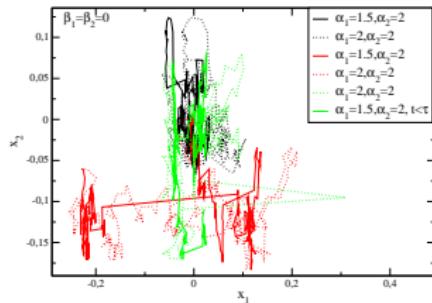
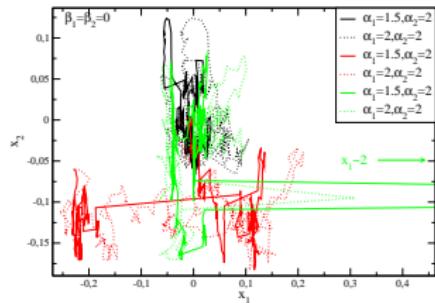
- $d\mathbf{X}([t, t + dt]) = \mathbf{u}(\mathbf{X}(t))dt + D^{1/\alpha} \begin{pmatrix} D_1^{1/\alpha_1} & 0 \\ 0 & D_2^{1/\alpha_2} \end{pmatrix} d\mathbf{L}_{\alpha, \beta}([t, t + dt])$
- $\mathbf{X}(0)$  random variable of  $\mathbb{R}^2$ ,  $\beta = 2\mathbf{p} - \mathbf{1}$
- $\frac{\partial C}{\partial t}(\mathbf{x}, t) + \nabla \cdot \mathbf{u}(\mathbf{x}, t)C(\mathbf{x}, t) = \nabla \cdot \bar{\bar{\mathbf{D}}} \nabla_{\mathbf{p}}^{\alpha-1} C(\mathbf{x}, t) + S_c(\mathbf{x}, t)$
- $\nabla_{\mathbf{p}}^{\alpha-1} C \equiv \begin{pmatrix} p_1 \frac{\partial^{\alpha_1-1} C}{\partial_+ x_1^{\alpha_1-1}} + (1-p_1) \frac{\partial^{\alpha_1-1} C}{\partial_- x_1^{\alpha_1-1}} \\ p_2 \frac{\partial^{\alpha_2-1} C}{\partial_+ x_2^{\alpha_2-1}} + (1-p_2) \frac{\partial^{\alpha_2-1} C}{\partial_- x_2^{\alpha_2-1}} \end{pmatrix}$

## 5.2. In bounded domain $\Omega$ , $C = 0$ on $\partial\Omega$

Killing  $\mathbf{X}(t)$  at 1st exit time  $\tau$  from  $\Omega$  yields  $\mathbf{X}^\Omega(t)$  [Chen, Meerschaert, Nane (2012)] .



## 5.2. Killing $\mathbf{X}(t)$ at 1st exit time $\tau$ from $\Omega$



$$\Omega = [-1, 1] \times [-1, 1]$$

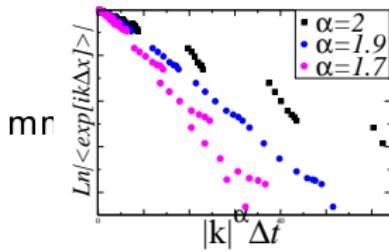
## 5.2. In bounded domain $\Omega$ , $C = 0$ on $\partial\Omega$

The density of  $\mathbf{X}^\Omega(t)$  satisfies

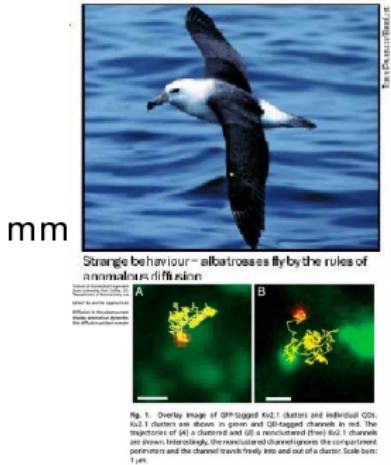
$$\frac{\partial C}{\partial t}(\mathbf{x}, t) + \nabla \cdot \mathbf{u}(\mathbf{x}, t)C(\mathbf{x}, t) = \nabla \cdot \bar{\bar{\mathbf{D}}} \nabla_p^{\alpha-1} C(\mathbf{x}, t) + S_c(\mathbf{x}, t) \text{ and}$$
$$C = 0 \text{ on } \partial\Omega$$

## Conclusion

- 2 approaches of super-dispersion.  
why?
  - numerical simulation: the equivalence validates codes
  - experiments: sometimes we measure tracer concentrations, sometimes we measure other functionals related to the statistics of molecular motion.
- 
- Example: the characteristic function of water molecule displacement  $\langle e^{ik\Delta x} \rangle$ . If stable motion rules molecular motion,  $= e^{iku\Delta t - D\Delta t \varphi}$ ,  
 $\varphi = |k|^\alpha (1 - i\beta \text{sign}(k) \tan \frac{\pi\alpha}{2})$



# Conclusion



- sometimes we measure individual trajectories, and some mathematical properties attached to parameter  $\alpha$  help us discriminating between models