

**Regularity and upper density estimates for the law of
an stable process and its supremum:
From simulation to theory**

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Stable process

A general α -stable process starting at 0 is a Lévy process with characteristic function ($\alpha \in (0, 2)$)

$$-\log\left(\mathbb{E}\left[e^{i\theta X_t}\right]\right) = ct|\theta|^\alpha(1 - i\text{sgn}(\theta)\tan(\pi\alpha(2\rho - 1)/2))$$

• Here, $\rho := \mathbb{P}(X_t \geq 0) \in [1 - 1/\alpha, 1/\alpha] \cap (0, 1)$ is the positivity parameter. If $\rho = 1/2$ then the above simplifies to the symmetric stable case and its generator is the fractional Laplacian.

• Our goal: Study of the joint law of $(X_T, \bar{X}_T) \equiv (X_T, \sup_{s \in [0, T]} X_s)$

on the domain $\mathcal{O} := \{(x, y) \in \mathbb{R}^2; y \geq x \vee 0\}$ (including the behavior close to the diagonal and for $x, y \approx 0$ or $x, y \approx \infty$)

• In PDE terms: For a test function f , let $u_t(x, m) := \mathbb{E}_x[f(X_t, m + \bar{X}_T)]$ then for $\nu_\alpha(dz) = |z|^{-1-\alpha} dz$ in the case $\rho = 1/2$

$$\partial_t u_t(x, m) = \int \left(u_t(x+z, m + z1_{[m-x, \infty)}(z)) - u_t(x, m) - \nabla u_t(x, m) \cdot (z, z1_{[m-x, \infty)}(z)) \right) \nu_\alpha(dz)$$

with the boundary conditions $\partial_m^{\alpha-1} u_t(x, -x) = 0$ and $u(0, x, m) = f(x, m)$.

Previous results

- Many previous results: R.A. Doney and M.S. Savov (2010).

$$\partial_y^3 \mathbb{P}(\bar{X}_T \in dy) \stackrel{y \rightarrow \infty}{\approx} T y^{-\alpha-1}; \quad \partial_y^3 \mathbb{P}(\bar{X}_T \in dy) \stackrel{y \rightarrow 0}{\approx} T^{-\rho} y^{\alpha\rho-1}.$$

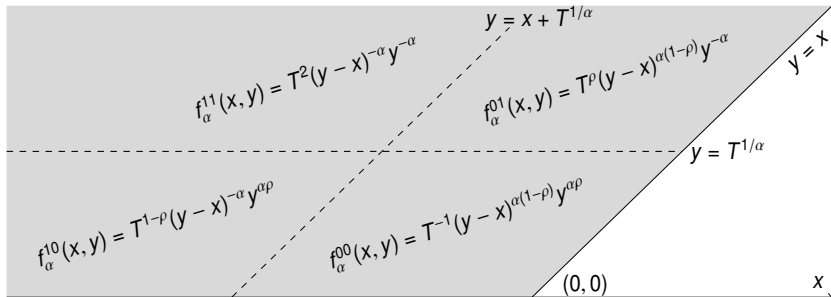
$$\partial_y^3 \mathbb{P}(X_T \in dx) \stackrel{x \rightarrow \infty}{\approx} T x^{-\alpha-1}; \quad \mathbb{P}(X_T \in dx) \stackrel{x \rightarrow 0}{\approx} T^{-1/\alpha}.$$

Analytical arguments based on stable meanders (excursion identities, Wiener-Hopf)

- 4 domains required. Let $\tilde{F}(x, y) := \mathbb{P}(\bar{X}_T \leq x, \bar{X}_T - X_T \leq y)$. We will prove

$$|\partial_x^n \partial_z^m \tilde{F}(x, z)| \leq C x^{-n} \min\{T x^{-\alpha}, T^{-\rho} x^{\alpha\rho}\} \times z^{-m} \min\{T z^{-\alpha}, T^{-(1-\rho)} z^{\alpha(1-\rho)}\}.$$

The density of (X_T, \bar{X}_T) is bounded by: $y^{-1}(y-x)^{-1}f_\alpha^{ij}(x, y)$



The set $O = \{(x, y) \in \mathbb{R}^2 : y > \max\{x, 0\}\}$ (shaded in the figure) is the support of the joint density of (X_T, \bar{X}_T) . According to our Theorem, the support can be partitioned into 4 sub-regions according to which of the functions f_α^{ij} , $i, j \in \{0, 1\}$, is the smallest in the (optimal) case $\alpha' = \alpha$. The dotted lines correspond to the change in time regime.

The above bounds are in accordance with known asymptotic results.

Main statement

Let $O = \{(x, y) \in \mathbb{R}^2 : y > x \vee 0\}$, $n, m \geq 1$, $T > 0$.

Theorem

Let $F(x, y) := \mathbb{P}(X_T \leq x, \bar{X}_T \leq y)$ be the law of (X_T, \bar{X}_T) . Then $F \in C^\infty(O)$.
Moreover, for any fixed $\alpha' \in [0, \alpha)$ there is $C > 0$ s.t. for all $(x, y) \in O$,

$$\begin{aligned} |\partial_x^n \partial_y^m F(x, y)| &\leq C y^{-m} (y-x)^{1-n-m} (2y-x)^{m-1} \\ &\quad \times \min \{f_{\alpha'}^{00}(x, y), f_{\alpha'}^{01}(x, y), f_{\alpha'}^{10}(x, y), f_{\alpha'}^{11}(x, y)\}, \\ C \min \{ &T^{2\frac{\alpha'}{\alpha}} (y-x)^{-n-\alpha'} y^{-m-\alpha'}, T^{\frac{\alpha'}{\alpha}(1-\rho)} (y-x)^{-n-\alpha'} y^{-m+\alpha'\rho}, \\ &T^{\frac{\alpha'}{\alpha}\rho} (y-x)^{-n+\alpha'(1-\rho)} y^{-m-\alpha'}, T^{-\frac{\alpha'}{\alpha}} (y-x)^{-n+\alpha'(1-\rho)} y^{-m+\alpha'\rho} \}. \end{aligned}$$

4 Domains: **Behavior at ∞** . **Behavior at 0**. This result is optimal in time and almost optimal in space taking $\alpha' \approx \alpha$. The main reason is that there is some Chebyshev's type argument used.

Some consequences

- Assume that $\alpha \in (0, 2)$. Then the distribution function $F(x) := \mathbb{P}(\bar{X}_T \leq x) \in C^\infty(0, \infty)$ and, for every $\alpha' \in [0, \alpha)$ and $n \geq 1$, there exists some constant $C > 0$ such that for all $x > 0$ and $T > 0$, we have for $n \geq 1$

$$|\partial_x^n F(x)| \leq Cx^{-n} \min\{T^{\frac{\alpha'}{\alpha}} x^{-\alpha'}, T^{-\frac{\alpha'}{\alpha}\rho} x^{\alpha'\rho}\}.$$

- Define $\tau_L := \inf\{t > 0 : X_t > L\}$. Then the density of τ_L is smooth and the following estimate is satisfied for $n \geq 1$:

$$|\partial_t^n \mathbb{P}(\tau_L \leq t)| \leq Ct^{-\frac{1}{\alpha}-n} \min\{L^{-\alpha'} t^{\frac{\alpha'}{\alpha}}, L^{\alpha'\rho} t^{-\frac{\alpha'\rho}{\alpha}}\}.$$

- If $\alpha(1 - \rho) \geq 1$ there is no blow up of the density at the boundary $y = x$. Blow up appears with density derivatives.
- One can also obtain bounds for the derivatives of (related to overshooting) $y \geq T^{1/\alpha}$, $x \leq 0$. Then for any $\alpha' \in (0, \alpha)$

$$\mathbb{P}(X_T \leq x, \tau_y < T) \leq CT^{2\frac{\alpha}{\alpha'}} y^{-\alpha'} \times \min\{y^{-\alpha'}, (-x)^{-\alpha'}\}$$

Interpolation

Finite dimensional calculus based on a indep. increment process
 X uses

$$D_s = \frac{\partial}{\partial \Delta X_s}$$

Are there any other variations of this definition?

If the functional $F(X)$ can be approximated using functions F_n

$$F_n(E_1, \dots, E_n, G_1, \dots, G_n, U_1, \dots, U_n) \stackrel{\mathcal{L}}{\Rightarrow} F(X)$$

One may try to do the analysis based on the i.i.d. sequence
 $\{E_i, G_i, U_i\}_{i \in \mathbb{N}}$ is densities are explicit.

Dangers in this method:

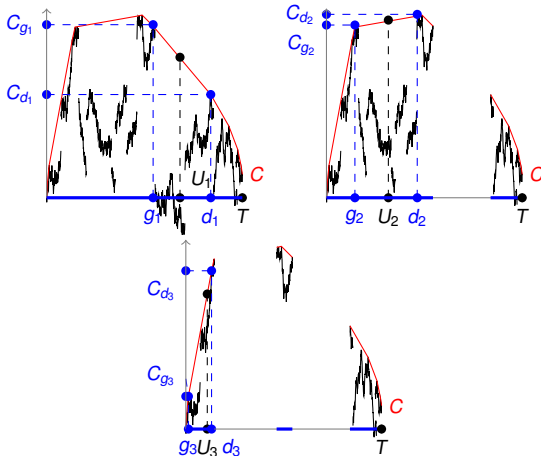
- ▶ The convergence rate is not good enough. R.N.
Bhattacharaya and R. Ranga Rao, Normal Approximation and Asymptotic Expansions. SIAM Classics, 2010
- ▶ The used variables $\{E_i\}_{i \in \mathbb{N}}$ are not explaining the main density behavior of $F(X)$
- ▶ Because one concentrates on $F(X)$ one may loose track of all path behavior

Interpolation techniques

Can it be used?

- Fournier-Printems, Bally, V. and Caramellino: L. Stochastic Integration by Parts. Advanced Courses in Mathematics - CRM Barcelona, 2016
- Key questions:
 - 1) How to choose the approximations?
 - 2) Which random variables to use? (Partial Malliavin Calculus)
- Main answers:
 - 1) Convex majorants of Lévy processes (50's~) with multi-level (2008)
 - 2) Chambers-Mallows-Stuck decomposition method (recall that explicit stable laws are not available)('76). Base the calculations on exponential r.v.'s $\{E_i\}_{i \in \mathbb{N}}$. That is, the "length" of stable increments.

Convex majorants



Selecting the first three faces of the concave majorant: the total length of the thick blue segment(s) on the abscissa equal the stick sizes T , $T - (d_1 - g_1)$ and $T - (d_1 - g_1) - (d_2 - g_2)$, respectively. The independent random variables U_1, U_2, U_3 are uniform on the sets $[0, T]$, $[0, T] \setminus (g_1, d_1)$, $[0, T] \setminus \cup_{i=1}^2 (g_i, d_i)$, respectively. Note that the residual length of unsampled faces after n samples is L_n .

Mathematical Definition

Exponentially converging stick-breaking process: $\ell = (\ell_k)_{k \geq 1}$ on $[0, T]$, defined using $U_k \sim U[0, 1]$

$$\ell_1 = T(1 - U_1)$$

$$\ell_k = T U_1 \dots U_{k-1} (1 - U_k)$$

$$\triangle \quad \mathbb{E}[\ell_k^{r/\alpha}] = T^r \left(1 + \frac{r}{\alpha}\right)^{-k}.$$

i.i.d. stable r.v.'s $(S_k)_{k \geq 1}$ with parameters (α, ρ) (i.e. $S_k \stackrel{d}{=} X_1$).

$$\bar{X}_T = X_+ = \sum_{k=1}^{\infty} \ell_k^{1/\alpha} [S_k]^+$$

$$X_T = X_+ - X_- = X_+ - \sum_{k=1}^{\infty} \ell_k^{1/\alpha} [S_k]^-.$$

Remark: One loses some information about the path!

Chambers-Mallows-Stuck

Next step: Probabilistic representation:(Chambers-Mallows-Stuck, $\alpha \in (0, 1) \cup \{1\} \cup (1, 2)$). E_k : length. G_k : oscillations

$$S_k \stackrel{\mathcal{L}}{=} E_k^{1-1/\alpha} G_k \quad \text{and} \quad G_k = g(V_k), \quad k \in \mathbb{N},$$

for i.i.d. $\text{Exp}(1) \sim (E_k)_{k \geq 1} \perp (V_k)_{k \geq 1} \sim \text{U}(-\frac{\pi}{2}, \frac{\pi}{2})$

$$g(x) = \frac{\sin(\alpha(x + \pi(\rho - \frac{1}{2})))}{\cos^{1/\alpha}(x) \cos^{1-1/\alpha}((1-\alpha)x - \alpha\pi(\rho - \frac{1}{2}))}, \quad x \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right).$$

Note that indeed $\mathbb{P}(S_k > 0) = \rho$.

$$\rho = \mathbb{P}(S_k > 0) \in [1 - 1/\alpha, 1/\alpha] \cap (0, 1).$$

semi-linear structure in the representation for $(X_T, \bar{X}_T) \equiv (X_+, X_-)$

$$\bar{X}_T = X_+ = \sum_{k=1}^{\infty} \ell_k^{1/\alpha} E_k^{1-1/\alpha} [G_k]^+$$

$$X_T = X_+ - X_- = X_+ - \sum_{k=1}^{\infty} \ell_k^{1/\alpha} E_k^{1-1/\alpha} [G_k]^-.$$

coordinate change and n -th order approx. to $X = (X_+, X_-)$:

$$X_n = (X_{+,n}, X_{-,n})$$

$a_n := T^{1/\alpha} \kappa^n$ with $\kappa \in (0, 1)$. Let η_+ and $\eta_- \sim \text{Exp}(1)$

$$X_{\pm,n} = \sum_{k=1}^n \ell_k^{1/\alpha} E_k^{1-1/\alpha} [G_k]^{\pm} + a_n \eta_{\pm}^{1-1/\alpha}.$$

$n = 0$, $X_{\pm,0} \equiv 0$, $[x]^+ = \max\{x, 0\}$,

$$0 \neq X_{\pm,n} - X_{\pm,n-1} = \ell_n^{1/\alpha} E_n^{1-1/\alpha} [G_n]^{\pm} + (a_n - a_{n-1}) \eta_{\pm}^{1-1/\alpha}$$

Intuitively, if the sequence $\{a_n\}$ decays too fast, then it will not serve its purpose. In particular, given the assumption below moments estimates will follow.

Assumption[A- κ] $a_n := T^{1/\alpha} \kappa^n$, $n \in \mathbb{N}$ where $\kappa^\alpha \in [\rho \vee (1 - \rho), 1)$.

Reconstructive derivative operator and IBP

$$\mathcal{D}_n^\pm = \eta_\pm \partial_{\eta_\pm} + \sum_{k=1}^n E_k \mathbf{1}_{\{[G_k]^\pm > 0\}} \partial_{E_k},$$

⚠ The factor (η_\pm, E_k) cancels boundary terms and has a regenerative property for $\mathcal{D}_n^\pm X_{\pm, n} = (1 - 1/\alpha) X_{\pm, n}$. **This keeps the stable moments controlled!** . It also shows that G_k does not need to be differentiated.

$$S_n(\Omega) = \{\Phi \in L^0(\Omega); \exists \phi \in S_\infty((0, \infty)^{3n+3}; \mathbb{R}), \Phi = \phi(\bar{E}_n, \bar{U}_n, \bar{V}_n, \eta_+, \eta_-)\},$$

Theorem (The approx. but exploding IBP formula)

Fix $n, m \in \mathbb{N}$ with $m \geq n$. Then for any $\Phi \in S_m(\Omega)$ and f smooth,

$$\mathbb{E}[\partial_\pm f(X_n) \Phi] = \mathbb{E}[f(X_n) H_{n,m}^\pm(\Phi)],$$

$$H_{n,m}^\pm(\Phi) := \frac{\alpha/(\alpha-1)}{X_{\pm, n}} \left(\left(\eta_\pm - \frac{1}{\alpha} + \sum_{k=1}^m (E_k - 1) \mathbf{1}_{\{[G_k]^\pm > 0\}} \right) \Phi - \mathcal{D}_m^\pm[\Phi] \right).$$

m : number of variables used for the IBP

n : approximation parameter

⚠ The numerator grows polynomially fast w.r.t. m . \rightarrow Explosion

⚠ Note that time rescaling is clear in the denominator. **Malliavin variance**

Multi-level in IBP as an interpolation method

$$H_{n,m}^{\pm,k+1}(\Phi) = H_{n,m}^{\pm}(H_{n,m}^{\pm,k}(\Phi)) \quad \text{for } k \geq 0, \text{ where} \quad H_{n,m}^{\pm,0}(\Phi) = \Phi.$$

Theorem (The ∞ -dim. IBP formula)

Let $\Phi \in \bigcap_{n \in \mathbb{N}} \mathcal{S}_n(\Omega)$. For any $n \geq 1$, $k_+, k_- \geq 0$ and $f \in C_\epsilon^{k_+,k_-}(\mathbb{R}_+^2)$ we have

$$\begin{aligned} \mathbb{E}[\partial_+^{k_+} \partial_-^{k_-} f(X_+, X_-) \Phi] &= \mathbb{E}[f(X_n) H_{n,n}^{+,k_+}(H_{n,n}^{-,k_-}(\Phi))] \\ &+ \sum_{j=n}^{\infty} \mathbb{E}[f(X_{j+1}) H_{j+1,j+1}^{+,k_+}(H_{j+1,j+1}^{-,k_-}(\Phi)) - f(X_j) H_{j,j+1}^{+,k_+}(H_{j,j+1}^{-,k_-}(\Phi))]. \end{aligned}$$

⚠ The convergence in the above sum is **geometric** in j due to the difference $X_{j+1} - X_j$.

⚠ The weight $H_{j,j+1}^{+,k_+}$ **only grows polynomially** in j .

⚠ Positive and negative moment estimates are needed!

⚠ To correctly balance these terms one uses basic interpolation inequalities

The moment estimates

Let $f(x_+, x_-) = [x_+ - x]^{k_+} [x_- - y]^{k_-}$ and $Z_m = \eta_+ + \eta_- + \sum_{k=1}^m E_k$

$$\begin{aligned} & \left| f(X_{n+1}) H_{n+1, n+1}^{+, k_+} (H_{n+1, n+1}^{-, k_-}(\Phi)) - f(X_n) H_{n, n+1}^{+, k_+} (H_{n, n+1}^{-, k_-}(\Phi)) \right|^p \\ &= \left| \frac{f(X_{n+1})}{X_{+, n+1}^{k_+} X_{-, n+1}^{k_-}} - \frac{f(X_n)}{X_{+, n}^{k_+} X_{-, n}^{k_-}} \right|^p \left| H_{n, n+1}^{+, k_+} (H_{n, n+1}^{-, k_-}(\Phi)) X_{+, n}^{k_+} X_{-, n}^{k_-} \right|^p \\ &\leq \left| \frac{f(X_{n+1})}{X_{+, n+1}^{k_+} X_{-, n+1}^{k_-}} - \frac{f(X_n)}{X_{+, n}^{k_+} X_{-, n}^{k_-}} \right|^p p_{k_+, k_-}^\phi(Z_{n+1}, n+1)^p. \end{aligned}$$

Here p is a polynomial of order $k_+ + k_-$. Now, recall

$$0 \leq X_{\pm, n} - X_{\pm, n-1} \leq \ell_n^{1/\alpha} [S_n]^+ + (a_n - a_{n-1}) \eta_+^{1-1/\alpha}$$

How the moments are used: At infinity, there is an exchange of space variable and random variable. At zero, something more complicated (but similar) happens. For example,

$$\mathbf{1}_{X_+ > x} \leq \frac{X_+^p}{x^p}.$$

Simple interpolation inequalities for moment estimates

Moreover, we frequently apply the following basic interpolating inequalities: $\mathbf{1}_{\{y>x\}} \leq y^v x^{-v}$ for all $v \geq 0$ where we interpret the upper bound as 1 if $v = 0$. Also, if $y, z \geq 0$ then for all $r \in [0, 1]$

$$y \wedge z \leq y^r z^{1-r}$$

$$y \vee z \geq y^r z^{1-r}.$$

Define $(m_{\pm,n}, M_{\pm,n}) := (X_{\pm,n} \wedge X_{\pm,n+1}, X_{\pm,n} \vee X_{\pm,n+1})$ then $m_{\pm,n} = X_{\pm,n+1} \wedge X_{\pm,n} \geq \kappa X_{\pm,n}$ since $X_{\pm,n+1} \geq \kappa X_{\pm,n}$. Similarly, $M_{\pm,n} \leq \kappa^{-1} X_{\pm,n+1}$.

Some main points

- ▶ We have used an approximation method which converges exponentially fast to the limit of interest.
- ▶ In this construction which involves three different types of random variables, we recognize that the exponential random variables generate the supremum of the process.
- ▶ A finite dimensional calculus is obtained using these exponential random variables. The estimates explode polynomially fast.
- ▶ Using the Multi-level method as an interpolation technique we can use the exponential convergence in order to “kill ” the polynomial blow-up. (First interpolation)
- ▶ Two different situations: positive moments and negative moments are needed. In order to do this optimally additional simple algebraic interpolation inequalities are used.

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