Multil-level Weiner-Hopf Monte-Carlo simulation for Lévy processes

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What is a (one-dimensional) Lévy process?

- Formally: A stochastic process $\{X_t : t \geq 0\}$ which satisfies
  - $X_0 = 0$,
  - X has paths that are right-continuous with left limits (almost surely),
  - For any $0 \leq s \leq t$, $X_t - X_s$ is equal in distribution to X_{t-s},
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- Informally: Some familiar Lévy processes include
  - Linear Brownian motion: $\sigma B_t + \mu t$, $t \geq 0$, where $\sigma^2 \geq 0$ and $\mu \in \mathbb{R}$,
  - Compound Poisson processes: $\sum_{i=1}^{N_t} \xi_i$, where $\{N_t : t \geq 0\}$ is a Poisson arrival process and $\{\xi_i : i \in \mathbb{N}\}$ are i.i.d. random variables.

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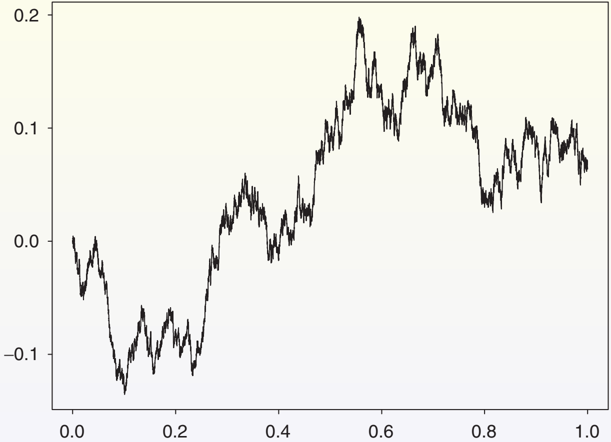
  - If $X_t^{(1)}$, $X_t^{(2)}$ $\cdots$, are independent Lévy processes then, subject to certain conditions, so is

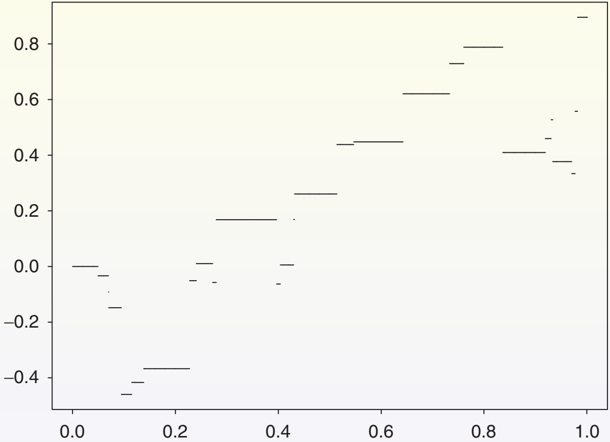
$$\sum_{i \geq 1} X_t^{(i)}$$

.

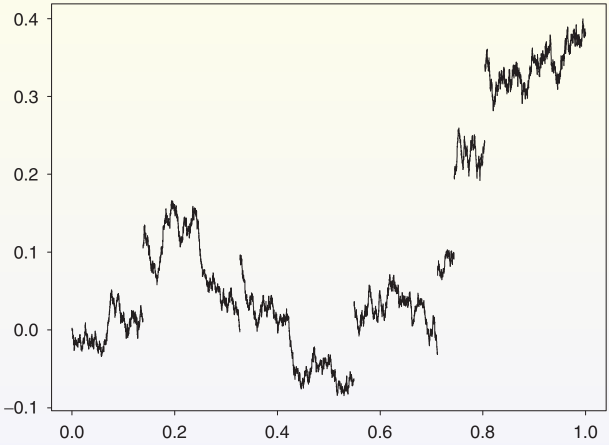
Brownian motion



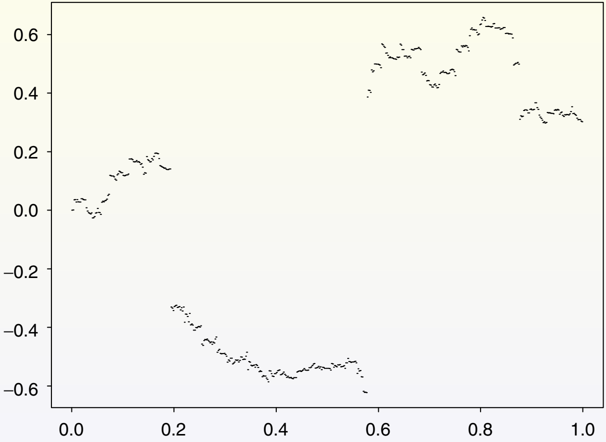
Compound Poisson process



Brownian motion + compound Poisson process



Unbounded variation paths



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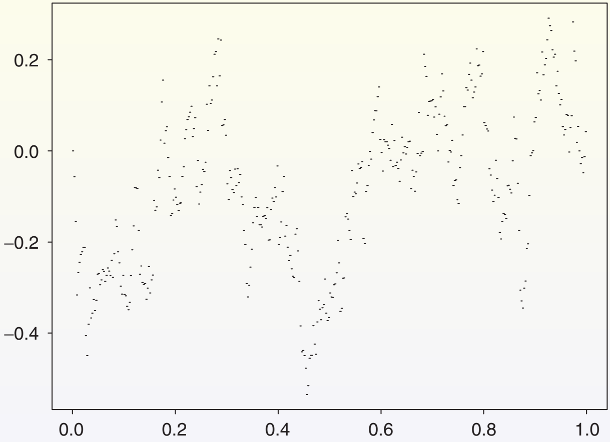

Motivation

- Lévy process. A (one dimensional) process with stationary and independent increments which has paths which are right continuous with left limits and therefore includes Brownian motion with drift, compound Poisson processes, stable processes amongst many others).
- A popular (and often criticised) model in mathematical finance for the evolution of a risky asset is

$$S_t := e^{X_t},\ t \geq 0$$

where $\{X_t : t \geq 0\}$ is a Lévy process. Also used in insurance risk models!
- Barrier options: The value of up-and-out barrier option with expiry date T and barrier b is typically priced as

$$\mathbb{E}_s(f(X_1)\mathbf{1}_{\{\overline{X}_1 \leq b\}})$$

where $\overline{X}_1 = \sup_{u \leq 1} X_u$, f is some nice function.
- One is fundamentally interested in the joint distribution

$$\mathbb{P}(X_1 \in \mathrm{d}x,\ \overline{X}_1 \in \mathrm{d}y)$$

for any Lévy process $(X, \mathbb{P})$.

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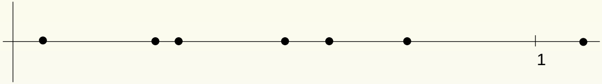

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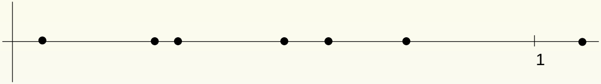

- Note that τ_n is the sum of n i.i.d exponential random variables, each with mean $1/n$. We could therefore write

$$\tau_n = \sum_{i=1}^{n} \frac{1}{n} \mathbf{e}^{(i)},$$

where $\mathbf{e}^{(i)}$ are i.i.d. exponential random variables with unit mean. Hence by the SLLN

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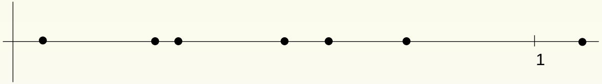

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- Hence for a suitably large n, we have in distribution

$$(X_{\tau_n}, \overline{X}_{\tau_n}) \simeq (X_1, \overline{X}_1).$$

Indeed since 1 is not a jump time with probability 1, we have that $(X_{\tau_n}, \overline{X}_{\tau_n}) \to (X_1, \overline{X}_1)$ almost surely as $n \to \infty$.

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$$X_{\mathbf{e}_q} \stackrel{d}{=} S_q + I_q$$

where S_q is independent of I_q and they are respectively equal in distribution to $\overline{X}_{\mathbf{e}_q}$ and $\underline{X}_{\mathbf{e}_q}$. Here $\underline{X}_t = \inf_{s \le t} X_s$.

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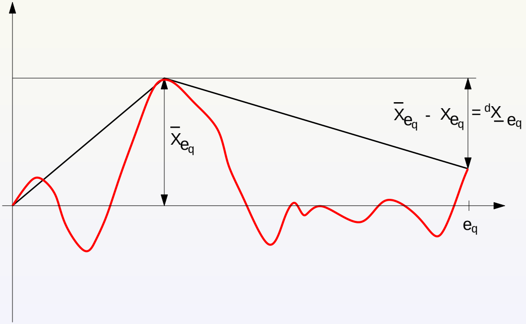

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- Taking advantage of the above, the fact that X has stationary and independent increments and the fact that, as a time, τ_n can be seen as the sum of independent exponential time periods we have the following:

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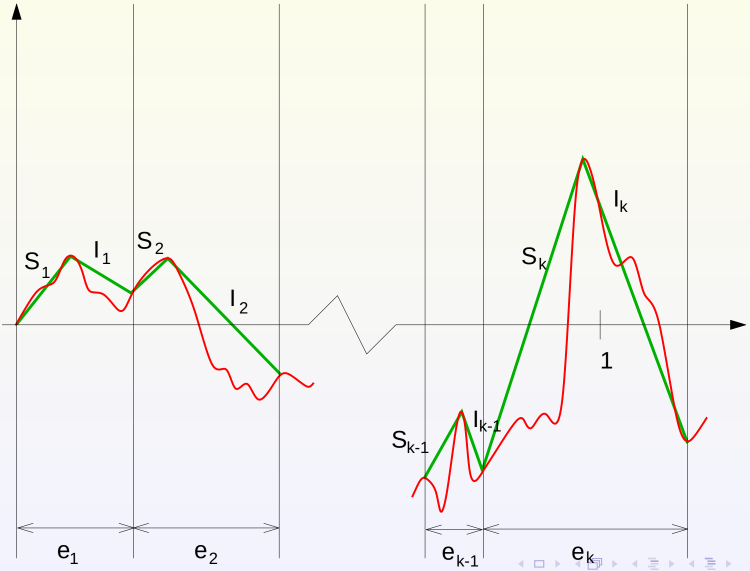

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- For all $n \in \{1, 2, \cdots\}$ and $n > 0$,

$$(X_{\tau_n}, \overline{X}_{\tau_n}) \stackrel{d}{=} (V_n, J_n)$$

where

$$V_n = \sum_{j=1}^{n} \{S_n^{(j)} + I_n^{(j)}\}$$

$$J_n := \bigvee_{i=0}^{n-1} \left(V_i + S_n^{(i+1)} \right).$$

Here, $V_0 = S_n^{(0)} = I_n^{(0)} = 0$, $\{S_n^{(j)} : j \geq 1\}$ are an i.i.d. sequence of random variables with common distribution equal to that of $\overline{X}_{\mathbf{e}_n}$ and $\{I_n^{(j)} : j \geq 1\}$ are another i.i.d. sequence of random variable with common distribution equal to that of $\underline{X}_{\mathbf{e}_n}$.

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- $(V_n, J_n) \stackrel{n\uparrow\infty}{\rightarrow} (X_1, \overline{X}_1)$ in distribution.

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- Sample repeatedly and independently from the distribution $\overline{X}_{\mathbf{e}_n}$ and $\underline{X}_{\mathbf{e}_n}$ and then construct m independent versions of the variables V_n and J_n, say

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- Sampling from $\overline{X}_{\mathbf{e}_n}$ and $\underline{X}_{\mathbf{e}_n}$ is generally impossible for a given Lévy process, but not for a 10 parameter family of processes known as Kuznetsov's β-class (ask me afterwards if interested in the details!).

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- **Notation.**
  - Write $a \lesssim b$ for two positive quantities a and b, if a/b is uniformly bounded (independent of n, M, or any other parameters).
  - Write $F^{n,(i)} := F(V_n^{(i)}, J_n^{(i)})$ for the i-th sample of $F^n := F(V_n, J_n)$ (using the Wiener-Hopf random walk).
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$$e(\widehat{F}^{n,m}_{MC})^2 := \mathbb{E}[(\widehat{F}^{n,m}_{MC} - \mathbb{E}[F(X_1, \overline{X}_1)])^2] = m^{-1}\mathbb{V}(F^n) + (\mathbb{E}[F^n - F(X_1, \overline{X}_1)])^2$$

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- Then we have the following convergence/complexity theorem ...

Numerical Analysis WHMC

Theorem (Single-level WHMC)

Assume that $\exists \alpha > 0$ *s.t.*

(i) $\mathbb{E}[|F^n - F(X_t, \overline{X}_t)|] \lesssim n^{-\alpha}$ *and*

(ii) $\mathcal{C}(F^n) \lesssim n$ (where $\mathcal{C}(F^n)$ is the cost to compute a single sample from F^n)

Then, $\forall \nu \in \mathbb{N} \;\; \exists n, M \in \mathbb{N}$ *s.t.*

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Using the forthcoming analysis we shall shortly present, it will turn out that:

- when X has paths of unbounded variation, $\alpha = \frac{1}{4} \Rightarrow \mathcal{O}(\nu^{-\frac{1}{6}})$ convergence!
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The best one can hope for with such Monte-Carlo schemes is an $\mathcal{O}(\nu^{-\frac{1}{2}})$ converegence.

Multi-level Wiener-Hopf Monte-Carlo [Heinrich, 2001], [Giles, 2007], ...

- Computational gains from exploiting the telescopic sum

$$\mathbb{E}[F^{n_L}] = \mathbb{E}[F^{n_0}] + \sum_{\ell=1}^{L} \mathbb{E}[F^{n_\ell} - F^{n_{\ell-1}}],$$

where $n_\ell = 2^\ell n_0$, $\ell = 1, \ldots, L$, for some small $n_0 \in \mathbb{N}$.

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- Suggesting the multilevel estimator

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- A little algebra again reveals that the means square error satisfies

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- See also **[Dereich, Heidenreich, 2011], [Dereich, 2011], [Giles, Xia, 2012]**.

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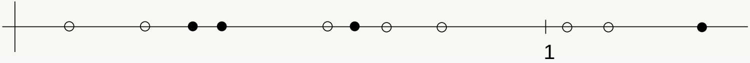
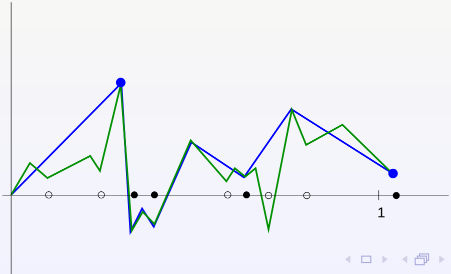
- Recall also that it is **crucial** to have a Poisson process for the time randomisations on **all** levels! How do we sample on two consecutive levels?
- Suppose the "level ℓ" grid is based on a Poisson process of rate n_ℓ. Then by tossing a coin and rejecting arrivals with probability $1/2$ we end up with a Poisson process of rate $n_{\ell-1}$: our new coarser "level $\ell - 1$" Poisson grid. (**Not** a new idea! Also used by **[Glasserman, Merener, 2003], [Giles, Xia, 2012], ...**)





Numerical Analysis (multilevel case)

Theorem (Multilevel WHMC)

Assume $\exists \alpha, \beta > 0$ *with* $\alpha \geq \frac{1}{2}\max\{\beta, 1\}$ *such that*

(i) $|\mathbb{E}[F^{n_\ell} - F(X_t, \overline{X}_t)]| \lesssim n_\ell^{-\alpha}$

(ii) $\mathbb{V}[F^{n_\ell} - F^{n_{\ell-1}}] \lesssim n_\ell^{-\beta}$

(iii) $\mathbb{E}[\mathcal{C}_{n_\ell}] \lesssim n_\ell$.

Then, $\forall \nu \in \mathbb{N} \;\; \exists L$ *and* $\{M_\ell\}_{\ell=0}^{L}$ *s.t.* $\mathcal{C}\left(\widehat{F}_{\mathrm{ML}}^{n_0, L, \{M_\ell\}}\right) \lesssim \nu$ *and* L^2 *error*

$$e\left(\widehat{F}_{\mathrm{ML}}^{n_0, L, \{M_\ell\}}\right) \lesssim \begin{cases} \nu^{-\frac{1}{2}} & \text{if } \beta > 1\,, \\ \nu^{-\frac{1}{2}} \log^2 \nu & \text{if } \beta = 1\,, \\ \nu^{-\frac{1}{2+(1-\beta)/\alpha}} & \text{if } \beta < 1\,. \end{cases}$$

Numerical Analysis (multilevel case)

Theorem (Multilevel WHMC)

Assume $\exists \alpha, \beta > 0$ *with* $\alpha \geq \frac{1}{2}\max\{\beta, 1\}$ *such that*

(i) $|\mathbb{E}[F^{n_\ell} - F(X_t, \overline{X}_t)]| \lesssim n_\ell^{-\alpha}$

(ii) $\mathbb{V}[F^{n_\ell} - F^{n_{\ell-1}}] \lesssim n_\ell^{-\beta}$

(iii) $\mathbb{E}[\mathcal{C}_{n_\ell}] \lesssim n_\ell$.

Then, $\forall \nu \in \mathbb{N} \;\; \exists L$ *and* $\{M_\ell\}_{\ell=0}^{L}$ *s.t.* $\mathcal{C}\left(\widehat{F}_{\mathrm{ML}}^{n_0, L, \{M_\ell\}}\right) \lesssim \nu$ *and* L^2 *error*

$$e\left(\widehat{F}_{\mathrm{ML}}^{n_0, L, \{M_\ell\}}\right) \lesssim \begin{cases} \nu^{-\frac{1}{2}} & \text{if } \beta > 1\,, \\ \nu^{-\frac{1}{2}} \log^2 \nu & \text{if } \beta = 1\,, \\ \nu^{-\frac{1}{2+(1-\beta)/\alpha}} & \text{if } \beta < 1\,. \end{cases}$$

- For Kuznetsov's β-class of Lévy processes also Assumption (iii) holds.
- Recall that $\alpha = (1/4)1/2$ for (un)bounded variation paths & shortly we shall see $\beta = 1/2 \;\Rightarrow\; (\mathcal{O}(\nu^{-\frac{1}{4}}))\; \mathcal{O}(\nu^{-\frac{1}{3}})$.
- Compare with former (single-level) rates $(\mathcal{O}(\nu^{-\frac{1}{6}}))\; \mathcal{O}(\nu^{-\frac{1}{4}})$.

Numerical analysis MLWH

Remains to verify the assumptions (i) $|\mathbb{E}[F^{n_\ell} - F(X_t, \overline{X}_t)]| \lesssim n_\ell^{-\alpha}$ and (ii) $\mathbb{V}[F^{n_\ell} - F^{n_{\ell-1}}] \lesssim n_\ell^{-\beta}$.

- Recalling that F is Lipschitz

$$\begin{aligned}\mathbb{V}(F^{n_\ell} - F^{n_{\ell-1}}) &= \mathbb{V}(F(X_{\tau_{n_\ell}}, \overline{X}_{\tau_{n_\ell}}) - F(X_{\tau_{n_\ell - 1}}, \overline{X}_{\tau_{n_\ell - 1}})) \\ &\leq \mathbb{E}[(X_{\tau_{n_\ell}} - X_{\tau_{n_\ell - 1}})^2] + \mathbb{E}[(\overline{X}_{\tau_{n_\ell}} - \overline{X}_{\tau_{n_\ell - 1}})^2]\end{aligned}$$

Numerical analysis MLWH

Remains to verify the assumptions (i) $|\mathbb{E}[F^{n_\ell} - F(X_t, \overline{X}_t)]| \lesssim n_\ell^{-\alpha}$ and (ii) $\mathbb{V}[F^{n_\ell} - F^{n_{\ell-1}}] \lesssim n_\ell^{-\beta}$.

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- [Unbounded variation case]:Working with our Lévy process as a Markovian semi-martingale we get for $\mathbf{s}$ and $\mathbf{t}$ random times independent of X,

(1) $\mathbb{E}[(X_{\mathbf{t}} - X_{\mathbf{s}})^2] = \mathbb{V}(X_1)\mathbb{E}[|\mathbf{t} - \mathbf{s}|] + \mathbb{E}[X_1]^2\mathbb{E}[(\mathbf{t} - \mathbf{s})^2]$

(2) $\mathbb{E}[(\overline{X}_{\mathbf{t}} - \overline{X}_{\mathbf{s}})^2] \leq 16\mathbb{V}(X_1)\mathbb{E}[|\mathbf{t} - \mathbf{s}|] + 2(\max\{\mathbb{E}[X_1], 0\})^2\mathbb{E}[(\mathbf{t} - \mathbf{s})^2]$,

[Better estimates for bounded variation case!]

Numerical analysis MLWH

Remains to verify the assumptions (i) $|\mathbb{E}[F^{n_\ell} - F(X_t, \overline{X}_t)]| \lesssim n_\ell^{-\alpha}$ and (ii) $\mathbb{V}[F^{n_\ell} - F^{n_{\ell-1}}] \lesssim n_\ell^{-\beta}$.

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- [Unbounded variation case]:Working with our Lévy process as a Markovian semi-martingale we get for $\mathbf{s}$ and $\mathbf{t}$ random times independent of X,

  (1) $\mathbb{E}[(X_\mathbf{t} - X_\mathbf{s})^2] = \mathbb{V}(X_1)\mathbb{E}[|\mathbf{t}-\mathbf{s}|] + \mathbb{E}[X_1]^2\mathbb{E}[(\mathbf{t}-\mathbf{s})^2]$

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  [Better estimates for bounded variation case!]

- Finally, recalling that τ_{n_ℓ} is a (n_ℓ, n_ℓ)-gamma distribution with mean 1,

$$\mathbb{E}[(\tau_{n_\ell} - 1)^2] \lesssim n_\ell^{-1} \quad \text{and} \quad \mathbb{E}[|\tau_{n_\ell} - 1|] \lesssim n_\ell^{-\frac{1}{2}}.$$

Numerical analysis MLWH

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- Recalling that F is Lipschitz

$$\begin{aligned}\mathbb{V}(F^{n_\ell} - F^{n_{\ell-1}}) &= \mathbb{V}(F(X_{\tau_{n_\ell}}, \overline{X}_{\tau_{n_\ell}}) - F(X_{\tau_{n_\ell-1}}, \overline{X}_{\tau_{n_\ell-1}})) \\ &\leq \mathbb{E}[(X_{\tau_{n_\ell}} - X_{\tau_{n_\ell-1}})^2] + \mathbb{E}[(\overline{X}_{\tau_{n_\ell}} - \overline{X}_{\tau_{n_\ell-1}})^2]\end{aligned}$$

- [Unbounded variation case]:Working with our Lévy process as a Markovian semi-martingale we get for $\mathbf{s}$ and $\mathbf{t}$ random times independent of X,

(1) $\mathbb{E}[(X_\mathbf{t} - X_\mathbf{s})^2] = \mathbb{V}(X_1)\mathbb{E}[|\mathbf{t} - \mathbf{s}|] + \mathbb{E}[X_1]^2\mathbb{E}[(\mathbf{t} - \mathbf{s})^2]$

(2) $\mathbb{E}[(\overline{X}_\mathbf{t} - \overline{X}_\mathbf{s})^2] \leq 16\mathbb{V}(X_1)\mathbb{E}[|\mathbf{t} - \mathbf{s}|] + 2(\max\{\mathbb{E}[X_1], 0\})^2\mathbb{E}[(\mathbf{t} - \mathbf{s})^2]$,

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- All together we get $\mathbb{V}(F^{n_\ell} - F^{n_{\ell-1}}) \lesssim n_\ell^{-\frac{1}{2}}$, and so $\beta = \frac{1}{2}$.

Numerical analysis MLWH

Remains to verify the assumptions (i) $|\mathbb{E}[F^{n_\ell} - F(X_t, \overline{X}_t)]| \lesssim n_\ell^{-\alpha}$ and (ii) $\mathbb{V}[F^{n_\ell} - F^{n_{\ell-1}}] \lesssim n_\ell^{-\beta}$.

- Recalling that F is Lipschitz

$$\begin{aligned} \mathbb{V}(F^{n_\ell} - F^{n_{\ell-1}}) &= \mathbb{V}(F(X_{\tau_{n_\ell}}, \overline{X}_{\tau_{n_\ell}}) - F(X_{\tau_{n_\ell - 1}}, \overline{X}_{\tau_{n_\ell - 1}})) \\ &\leq \mathbb{E}[(X_{\tau_{n_\ell}} - X_{\tau_{n_\ell - 1}})^2] + \mathbb{E}[(\overline{X}_{\tau_{n_\ell}} - \overline{X}_{\tau_{n_\ell - 1}})^2] \end{aligned}$$

- [Unbounded variation case]:Working with our Lévy process as a Markovian semi-martingale we get for $\mathbf{s}$ and $\mathbf{t}$ random times independent of X,

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  (2) $\mathbb{E}[(\overline{X}_{\mathbf{t}} - \overline{X}_{\mathbf{s}})^2] \leq 16\mathbb{V}(X_1)\mathbb{E}[|\mathbf{t} - \mathbf{s}|] + 2(\max\{\mathbb{E}[X_1], 0\})^2\mathbb{E}[(\mathbf{t} - \mathbf{s})^2]$,

  [Better estimates for bounded variation case!]
- Finally, recalling that τ_{n_ℓ} is a (n_ℓ, n_ℓ)-gamma distribution with mean 1,

$$\mathbb{E}[(\tau_{n_\ell} - 1)^2] \lesssim n_\ell^{-1} \quad \text{and} \quad \mathbb{E}[|\tau_{n_\ell} - 1|] \lesssim n_\ell^{-\frac{1}{2}}.$$

- All together we get $\mathbb{V}(F^{n_\ell} - F^{n_{\ell-1}}) \lesssim n_\ell^{-\frac{1}{2}}$, and so $\beta = \frac{1}{2}$.
- Via Jensen's inequality we then easily also get $\alpha = \frac{1}{4}$ ...

Kuznetsov's β-class

- The characteristic exponent ($\Psi(\theta) = -\log \mathbb{E}(\mathrm{e}^{\mathrm{i}\theta X_1}), \theta \in \mathbb{R}$) is given by

$$\begin{aligned}\Psi(\theta) \quad &= \quad \mathrm{i}az + \frac{1}{2}\sigma^2 z^2 + \frac{c_1}{\beta_1}\left\{\mathsf{B}(\alpha_1, 1-\lambda_1) - \mathsf{B}(\alpha_1 - \frac{\mathrm{i}\theta}{\beta_1}, 1-\lambda_1)\right\} \\ &\quad + \frac{c_2}{\beta_2}\left\{\mathsf{B}(\alpha_2, 1-\lambda_2) - \mathsf{B}(\alpha_2 + \frac{\mathrm{i}\theta}{\beta_2}, 1-\lambda_2)\right\}\end{aligned}$$

where $\mathsf{B}(x,y) = \Gamma(x)\Gamma(y)/\Gamma(x+y)$ is the Beta function, with parameter range $a \in \mathbb{R}, \sigma, c_i, \alpha_i, \beta_i > 0$ and $\lambda_1, \lambda_2 \in (0,3) \setminus \{1,2\}$.

- The corresponding Lévy measure Π has density

$$\pi(x) = c_1 \frac{\mathrm{e}^{-\alpha_1\beta_1 x}}{(1-\mathrm{e}^{-\beta_1 x})^{\lambda_1}} \mathbf{1}_{\{x>0\}} + c_2 \frac{\mathrm{e}^{\alpha_2\beta_2 x}}{(1-\mathrm{e}^{\beta_2 x})^{\lambda_2}} \mathbf{1}_{\{x<0\}}.$$

The β-class of Lévy processes includes another recently introduced family of Lévy processes known as Lamperti-stable processes.

Meromorphic Lévy processes (contains the β-class)

(i) The characteristic exponent $\Psi(z)$ is a meromorphic function which has poles at points $\{-\mathrm{i}\rho_n, \mathrm{i}\hat{\rho}_n\}_{n\ge 1}$, where ρ_n and $\hat{\rho}_n$ are positive real numbers.

(ii) For $q \ge 0$ function $q + \Psi(z)$ has roots at points $\{-\mathrm{i}\zeta_n, \mathrm{i}\hat{\zeta}_n\}_{n\ge 1}$ where ζ_n and $\hat{\zeta}_n$ are nonnegative real numbers (strictly positive if $q > 0$). We will write $\zeta_n(q)$, $\hat{\zeta}_n(q)$ if we need to stress the dependence on q.

(iii) The roots and poles of $q + \Psi(\mathrm{i}z)$ satisfy the following interlacing condition

$$\dots - \rho_2 < -\zeta_2 < -\rho_1 < -\zeta_1 < 0 < \hat{\zeta}_1 < \hat{\rho}_1 < \hat{\zeta}_2 < \hat{\rho}_2 < \dots$$

(iv) The Wiener-Hopf factors are expressed as convergent infinite products,

$$\mathbb{E}\left[\mathrm{e}^{-z\overline{X}_{\mathbf{e}_q}}\right] = \prod_{n\ge 1} \frac{1 + \frac{z}{\rho_n}}{1 + \frac{z}{\zeta_n}}$$

$$\mathbb{E}\left[\mathrm{e}^{z\underline{X}_{\mathbf{e}_q}}\right] = \prod_{n\ge 1} \frac{1 + \frac{z}{\hat{\rho}_n}}{1 + \frac{z}{\hat{\zeta}_n}}.$$

Distribution of extrema

- For $x \geq 0$

$$\mathbb{P}(\overline{X}_{\mathsf{e}_q} \in \mathsf{d}x) = \mathsf{a}_0(\rho, \zeta)\delta_0(\mathsf{d}x) + \sum_{n=1}^{\infty} \mathsf{a}_n(\rho, \zeta)\zeta_n \mathrm{e}^{-\zeta_n x}\mathsf{d}x$$

- Here

$$\mathsf{a}_0(\rho, \zeta) = \lim_{n \to +\infty} \prod_{k=1}^{n} \frac{\zeta_k}{\rho_k}, \quad \mathsf{a}_n(\rho, \zeta) = \left(1 - \frac{\zeta_n}{\rho_n}\right) \prod_{\substack{k \geq 1 \\ k \neq n}} \frac{1 - \frac{\zeta_n}{\rho_k}}{1 - \frac{\zeta_n}{\zeta_k}}$$

- A similar expression holds for $\mathbb{P}(-\underline{X}_{\mathsf{e}_q} \in \mathsf{d}x)$.

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