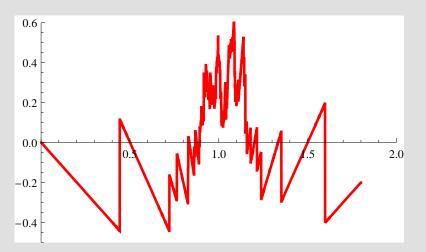
Martingales from pairs of randomized Poisson, Gamma, negative binomial and hyperbolic secant processes

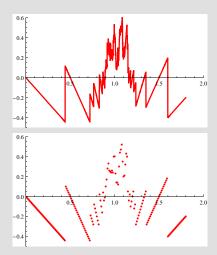
Włodek Bryc¹

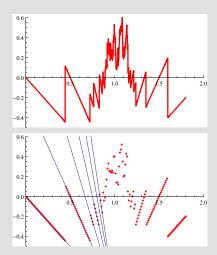
Cincinnati

October 16, 2010

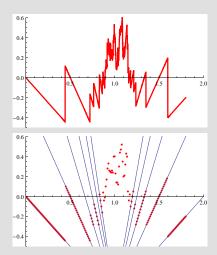




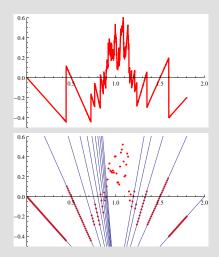




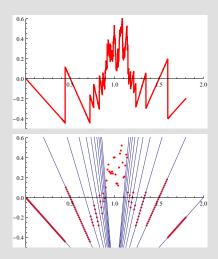


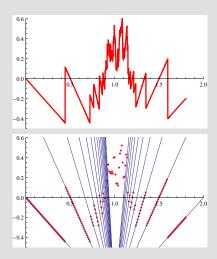


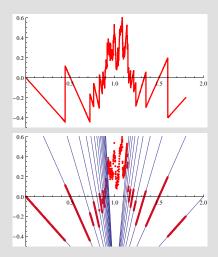


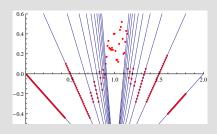




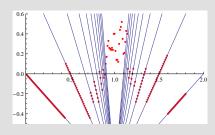






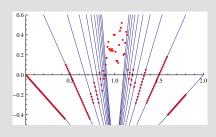


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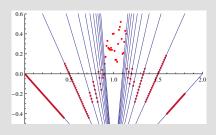
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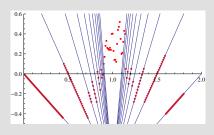


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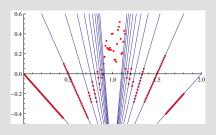
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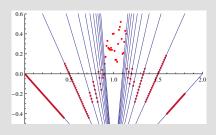
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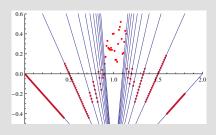
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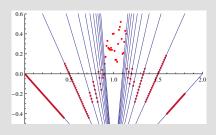


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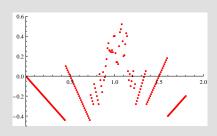


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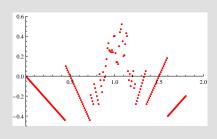


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- t = 1 should be hidden in these formulas!

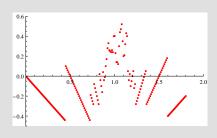




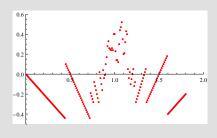
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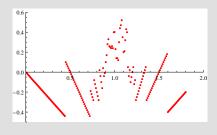
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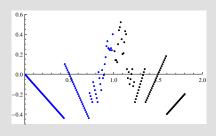
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- But after conversion to "standard form", two-sided conditional variances of bridges based on X_a, X₁ or on X₁, X_b are simpler than for bridges based on X_a, X_b.

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- ① there exist numerical constants $\eta, \theta \in \mathbb{R}$, $\sigma, \tau \geq 0$ and $\rho \in [-2, 2\sqrt{\sigma \tau}]$ such that for all s < t < u,

$$\begin{aligned} \operatorname{Var}[Z_{t}|\mathcal{F}_{s,u}] &= F_{t,s,u} \left(1 + \eta \frac{uZ_{s} - sZ_{u}}{u - s} + \theta \frac{Z_{u} - Z_{s}}{u - s} \right. \\ &+ \sigma \frac{(uZ_{s} - sZ_{u})^{2}}{(u - s)^{2}} + \tau \frac{(Z_{u} - Z_{s})^{2}}{(u - s)^{2}} + \rho \frac{(Z_{u} - Z_{s})(uZ_{s} - sZ_{u})}{(u - s)^{2}} \right), \end{aligned}$$

where $F_{t,s,u}$ is an explicit non-random constant.



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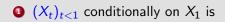
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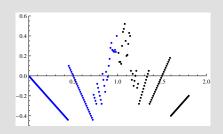
The inverse transformation

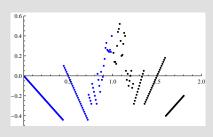
$$X_t = (1-t)W_{t/(1-t)}$$

represents the Brownian bridge in terms of the Wiener process.



$$(1-t)N_{t/(1-t)}$$

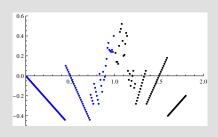




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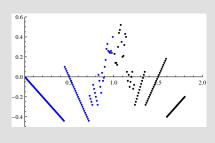
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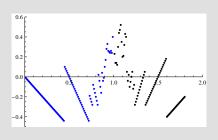


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Question

Which other Lévy processes could be "put together" into a quadratic harness? Into a martingale?



$$\begin{aligned} \operatorname{Var}[Z_{t}|\mathcal{F}_{s,u}] &\sim 1 + \eta \frac{uZ_{s} - sZ_{u}}{u - s} + \theta \frac{Z_{u} - Z_{s}}{u - s} \\ &+ \sigma \frac{(uZ_{s} - sZ_{u})^{2}}{(u - s)^{2}} + \tau \frac{(Z_{u} - Z_{s})^{2}}{(u - s)^{2}} + \rho \frac{(Z_{u} - Z_{s})(uZ_{s} - sZ_{u})}{(u - s)^{2}} \end{aligned}$$

Suppose $\exists T > 0$ such that $\{Z_t : t < T\}$ conditioned on Z_T , leads to QH Y with

$$\operatorname{Var}(Y_t|\mathcal{F}_{s,u}) \sim 1 + \theta_Y \frac{Y_u - Y_s}{u - s} + \tau_Y \frac{(Y_u - Y_s)^2}{(u - s)^2} + \rho_Y \dots$$

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$$\rho = 0$$
, $\sigma = \tau = 0$ and $\eta = \theta = 0$. (Then $(Z_t) = (W_t)$.)

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$$\eta\sqrt{\tau}=\theta\sqrt{\sigma}$$
, and $\rho=2\sqrt{\sigma\tau}$. (Then $T=\sqrt{\tau/\sigma}$, $\rho_Y=0$, and ...)

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$$\operatorname{Var}(Y_t|\mathcal{F}_{s,u}) = \frac{(u-t)(t-s)}{u-s+\tau} \left(1 + \theta_Y \frac{Y_u - Y_s}{u-s} + \tau_Y \frac{(Y_u - Y_s)^2}{(u-s)^2}\right),$$

- **1** $\tau = 0, \theta = 0$, and (Y_t) is the Wiener processes,
- **2** $\tau = 0, \theta \neq 0$, and (Y_t) is a Poisson type processes
- **3** $\tau > 0$ and $\theta^2 > 4\tau$, and (Y_t) is a Pascal (negative-binomial) type process,
- **4** $\sigma = 0$ $\sigma = 0$ **4** $\sigma = 0$ **5** $\sigma = 0$ **6** $\sigma = 0$ **7** $\sigma = 0$ **9** $\sigma = 0$ **9** $\sigma = 0$ **1** $\sigma =$
- **5** $\theta^2 < 4\tau$, and (Y_t) is a Meixner (hyperbolic-secant) type process

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- conditionally independent hyperbolic secant processes with random parameter $\alpha \in (-\pi, \pi)$, where X_t has density

$$f(x; t, \alpha) = \frac{(2\cos\frac{\alpha}{2})^{2t}}{2\pi\Gamma(2t)} |\Gamma(t + ix)|^2 e^{\alpha x}, \ t > 0.$$

Proposition (B..-Wesolowski - in prep)

For random $\Pi \in (0,1)$, define Y_t as Π -conditionally negative binomial process $\Pr(Y_t = k | \Pi = p) = \frac{\Gamma(t+k)}{\Gamma(t)k!} p^t (1-p)^k$, $k = 0, 1, \ldots$

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- **1** Then $Y = (Y_t)_{t \ge 0}$ is Markov.
- **2** Assume $\beta = \mathbf{E}(1/\Pi) 1$ and $v^2 = \text{Var}(1/\Pi) > 0$. Then

$$Z_t = c(1-t)Y_{\frac{t}{cv(1-t)}} - t\frac{\beta}{v}.$$

is a quadratic harness on (0,1) with parameters

$$\eta = \theta = \frac{(2\beta + 1) v}{(\beta + 1) \beta}, \ \sigma = \tau = \frac{v^2}{\beta(\beta + 1)}, \ \rho = 2\sqrt{\sigma \tau}.$$

Here
$$c = \frac{v}{v^2 + \beta^2 + \beta}$$
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Let $\Pi \in (0,1)$ be a random variable such that $\mathbf{E}(1/\Pi) < \infty$. Suppose Y is a Π -conditionally negative binomial process and $Z_t = c(1-t)Y_{\frac{t}{cv(1-t)}} - t\frac{\beta}{v}$ with some coefficients $\beta, v > 0$. Then the following are equivalent:

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- **①** $(Z_t)_{t\in[0,1)}$ is a martingale with respect to its natural filtration $(\mathcal{F}_{\leq t})$.
- **2** Π has the beta $B_I(a, b)$ density

$$h(p) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1} 1_{(0,1)}(p), \tag{1}$$

with $a = 2 + \beta(\beta + 1)/v^2$ and $b = \beta + \beta^2(\beta + 1)/v^2$.

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Proof: Special case of Diaconis-Ylvisaker, *Conjugate priors for exponential families*, Ann. Statist., 1979.



Let Y and Y' be Π -conditionally independent negative binomial processes. With $\beta = \mathbf{E}(1/\Pi) - 1$, $v^2 = \text{Var}(1/\Pi)$, define

$$Z_{t} = \begin{cases} c(1-t)Y_{\frac{t}{cv(1-t)}} - t\frac{\beta}{v} & \text{if } 0 \leq t < 1, \\ \left(\frac{1-\Pi}{\Pi} - \beta\right)/v & \text{if } t = 1, \\ c(t-1)Y_{\frac{1}{cv(t-1)}}' - \frac{\beta}{v} & \text{if } t > 1. \end{cases}$$
 (2)

$$c=\tfrac{v}{v^2+\beta^2+\beta}.$$

 $C - \frac{1}{v^2 + \beta^2 + \beta}$. Time-inversion: $(Z_t) \sim (tZ_{1/t})$.

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- laws for randomization (except Poisson) can be deduced from results in [Diaconis-Ylvisaker (1979)]

• A pair of Λ -conditionally independent Poisson processes (N_t) , (\tilde{N}_t) makes a martingale on $(0,\infty)$ iff Λ has gamma density $h(d\lambda) = C\lambda^{p-1}e^{-r\lambda}1_{(0,\infty)}(\lambda)d\lambda$



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- A pair of W-conditionally independent hyperbolic secant processes makes a martingale on $(0,\infty)$ iff $h(d\alpha) = C (1 + \cos \alpha)^p \exp(r\alpha) 1_{(-\pi,\pi)}(\alpha) d\alpha$

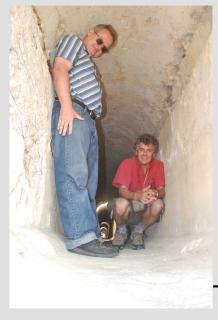


Conclusions

• For a process $(X_t)_{t \in (0,\infty)}$ with linear two-sided regressions, non-constant quadratic conditional variances, and product covariance $\text{cov}(X_s, X_t) = (as + b)(ct + d)$ for s < t, the existence of a "special time" T can be recognized by a calculation.

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- 2 Then (X_t) is put together from one of the "randomized pairs" of Poisson, negative binomial, gamma, or hyperbolic secant processes.



Thank you

Abstract

Consider a pair of independent Poisson processes, or a pair of Negative Binomial processes, or Gamma, or hyperbolic secant processes with a shared randomly selected parameter. Under appropriate randomization, one can deterministically re-parametrize the time and scale for both processes so that the first process runs on time interval (0,1), the second process runs on time interval $(1,\infty)$, and the two processes seamlessly join into one Markov martingale on $(0,\infty)$. In fact, a property stronger than martingale holds: we stitch together two processes into a single quadratic harness on $(0,\infty)$



