

Infinite dimensional polynomial processes

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Innovative Research in Mathematical Finance
in Honor of Yuri Kabanov
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- 1 Introduction and motivation
 - ▶ ... from population genetics
 - ▶ ... from stochastic portfolio theory
 - ▶ ... and some connections to Yuri's work
- 2 The theory of infinite dimensional polynomial processes
- 3 Application: (rough) polynomial forward variance models

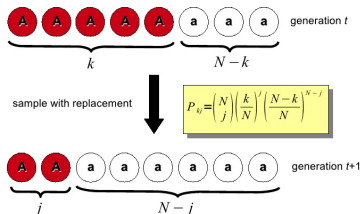
From population genetics to ...

- Neutral 2-allele Wright-Fisher Markov chain model from population genetics

- ▶ Discrete time model of a population with constant size N with two types of alleles, denoted by A and a
- ▶ X_t^N : number of type A individuals at time t
- ▶ X_t^N is modeled as a Markov chain with state space $\{0, \dots, N\}$ and transition probabilities

$$P_{kj} = P(X_{t+1}^N = j | X_t^N = k) = \binom{N}{j} \left(\frac{k}{N}\right)^j \left(1 - \frac{k}{N}\right)^{N-j}.$$

- ▶ Binomial sampling with probability X_t^N/N



... a guiding example of polynomial processes

- Diffusion approximation

- ▶ The process $\frac{1}{N}X_{[Nt]}^N$ converges in law to the **Kimura or Wright-Fisher diffusion** on $[0, 1]$

$$d\lambda_t = \sqrt{(1 - \lambda_t)\lambda_t}dB_t, \quad \lambda_0 \in [0, 1],$$

where B denotes a standard Brownian motion.

⇒ Guiding example of a polynomial process

... a guiding example of polynomial processes

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⇒ Guiding example of a polynomial process

- It has the following **non-standard properties**:

- ▶ **Non-Lipschitz property** of the volatility
- ▶ **Statespace** is not the whole of \mathbb{R}
- ▶ Nevertheless **existence of strong and pathwise unique solutions**

Guiding example of standard polynomial processes

- **Key property and moment formula:** the expected value of **polynomials** of the process' marginals can be computed easily:

$$\mathbb{E} \left[\sum_{j=0}^k y_j \lambda_t^j \right] = \sum_{j=0}^k y_{j,t} \lambda_0^j,$$

where y_t solves the **linear ODE** in \mathbb{R}^{k+1}

$$\partial_t y_t = L_k y_t, \quad y_0 = (y_0, y_1, \dots, y_k) \in \mathbb{R}^{k+1}$$

with L_k the matrix representation of the infinitesimal generator applied to the basis monomials $(1, x, \dots, x^k)$.

\Rightarrow **Tractability:** the Feynman-Kac PDE reduces to a linear $k + 1$ - dimensional ODE, that is solved by matrix exponentiation.

Polynomial jump diffusions on $\mathcal{E} \subseteq \mathbb{R}^d$

Definition

- A linear operator $L : \text{Pol}(\mathbb{R}^d) \rightarrow \text{Pol}(\mathbb{R}^d)$ is called **polynomial** if it maps polynomials to polynomials of same or lower degree.
- Let L be a polynomial operator. Then a **polynomial jump diffusion on \mathcal{E}** is a càdlàg \mathcal{E} -valued solution λ to the martingale problem for L , i.e. for all $p \in \text{Pol}(\mathbb{R}^d)$

$$p(\lambda_t) - \int_0^t Lp(\lambda_s) ds = (\text{local martingale}).$$

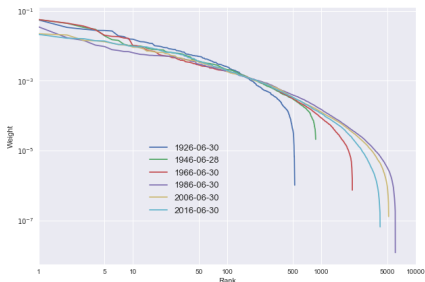
For polynomial operators the **moment formula** holds true and they are of the form

$$\nabla p(\lambda)^\top b(\lambda) + \frac{\text{Tr}(c(\lambda)\nabla^2 p(\lambda))}{2} + \int (p(\lambda + \xi) - p(\xi) - \nabla p(\lambda)^\top \xi) K(\lambda, d\xi)$$

with $\lambda \mapsto b(\lambda)$ affine, $\lambda \mapsto c_{ij}(\lambda) + \int \xi_i \xi_j K(\lambda, d\xi)$ quadratic, $\lambda \mapsto \int \xi^{\mathbf{k}} K(\lambda, d\xi)$ polynomial up to degree $|\mathbf{k}|$ for $|\mathbf{k}| \geq 3$.

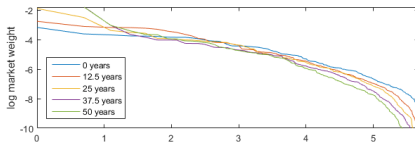
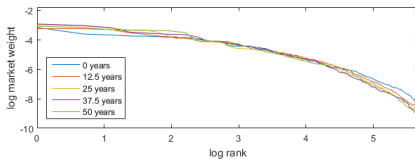
From stochastic portfolio theory to...

- **Stochastic portfolio theory (SPT)** (introduced by Robert Fernholz, Ioannis Karatzas, etc.) analyzes **high dimensional stock markets**, typically the constituents of large equity indices like S&P 500 and the **capital distribution curves**.
- That is, the mapping $\log k \mapsto \log(\mu_t^{(k)})$, where $\mu_t^{(1)}, \dots, \mu_t^{(d)}$ are the ordered market weights of the d considered companies.
- They are of **remarkable stability** between 1926 -2016 for the US stock market (see the graph by J. Ruf below).



...to polynomial models for the market weights

- Polynomial models allow to overcome certain shortcomings of existing models (see [C.'18; Polynomial processes in stochastic portfolio theory]).
- Within the Financial Maths Team Challenge 2016 South Africa, we performed a **calibration of a 300 dimensional polynomial process**.
- **Shape preservation and “correct” dynamic behavior over 50 years.**
- Comparison between the polynomial model and a Black & Scholes model:



From large financial markets in SPT...

- Consider a set of stocks with market capitalizations S_t^1, \dots, S_t^d and the corresponding market weights $\mu_t^i = \frac{S_t^i}{S_t^1 + \dots + S_t^d}$ taking values in the unit simplex $\Delta^d = \{z \in [0, 1]^d : z_1 + \dots + z_d = 1\}$, i.e. the space of probability measures on a set of d points.
- Large financial market as $d \rightarrow \infty$, e.g. for analyzing the capitalization curves.
- \Rightarrow Probability measure valued setting with an (uncountably) infinite dimensional underlying space.
- Possible approach: Linear factor models, i.e. view (μ^1, \dots, μ^d) as the projection of a single tractable infinite dimensional model.
 - ▶ Let X be a probability measure valued polynomial process.
 - ▶ For functions $g_i^d \geq 0$ such that $g_1^d + \dots + g_d^d \equiv 1$, set $\mu_t^{i,d} = \int g_i^d(x) X_t(dx)$. \Rightarrow much richer class than polynomial models on Δ^d but similar tractability.
 - ▶ Consider limits as $d \rightarrow \infty$.

...to some open questions inspired by Yuri's work



...to some open questions inspired by Yuri's work

- When does such a model satisfy NAA1, i.e. **no (relative) asymptotic arbitrage of the first kind**, as introduced in the context of large financial markets by **Y. Kabanov and D. Kramkov (1994, 1998)**?
⇒ Existence of supermartingale deflators?
- Construction of **stochastic integrals** with respect to the measure valued process, in a similar spirit as in **T.Björk, G. Di Masi, Y. Kabanov, W.Runggaldier (1997)**, by reversing the role of integrands (measure valued processes) and integrators (continuous function valued processes)?
 - ▶ Evolution of the value of a portfolio corresponding to a trading strategy which is a predictable process with values in continuous functions. The measure valued process could for instance represent an **electricity forward price**.
 - ▶ **Functionally generated portfolios** (also in a modelfree sense based on Itô-type formulas in the sense of H. Föllmer)

Infinite dimensional setting

- Y : real **Banach algebra** with identity element 1 for the multiplication
- Y^* : **dual space** equipped with the weak- $*$ -topology, which is the weakest topology making all **linear functionals** $\lambda \mapsto \lambda(y) = \langle y, \lambda \rangle$ on Y^* continuous.
- $y_1 \otimes y_2$: symmetric tensor product for two elements $y_1, y_2 \in Y$
- We fix a (reasonable) **crossnorm** $\|\cdot\|_X$ on $Y \otimes Y$, i.e. a norm $\|\cdot\|_X$ on $Y \otimes Y$ such that
 - 1 $\|y_1 \otimes y_2\|_X = \|y_1\| \|y_2\|$ for each $y_1, y_2 \in Y$, and
 - 2 $\sup_{y \in Y \otimes Y, \|y\|_X \leq 1} |(\lambda_1 \otimes \lambda_2)(y)| = \|\lambda_1\|_{Y^*} \|\lambda_2\|_{Y^*}$ for each $\lambda_1, \lambda_2 \in Y^*$.
- $Y \widehat{\otimes} Y$: **completion** of $Y \otimes Y$ with respect to $\|\cdot\|_X$
- $y^{\otimes k}, Y^{\otimes k}, Y \widehat{\otimes}^k, \lambda^{\otimes k}$ for $k \in \mathbb{N}$ are defined analogously. For $k = 0$, we identify $Y \widehat{\otimes}^0$ with \mathbb{R} .

Guiding example and polynomials on Y^*

Example (important setting for SPT)

- Let $E \subseteq \mathbb{R}$ be compact.
- $Y := C(E)$: Banach space of continuous functions
- $Y^* = M(E)$: space of finite signed measures
- Letting $\|\cdot\|_\infty$ be the supremum norm on $C(E)^{\otimes k}$, we get that $Y^{\widehat{\otimes} k}$ is the space of symmetric continuous functions $f : E^k \rightarrow \mathbb{R}$.

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- Letting $\|\cdot\|_\infty$ be the supremum norm on $C(E)^{\otimes k}$, we get that $Y^{\widehat{\otimes} k}$ is the space of symmetric continuous functions $f : E^k \rightarrow \mathbb{R}$.
- A polynomial on Y^* with coefficients $y := (y_0, \dots, y_k) \in \bigoplus_{j=0}^k Y^{\widehat{\otimes} j}$ is defined as $p(\lambda) = \sum_{j=0}^k \langle y_j, \lambda^{\otimes j} \rangle$ with $\langle y_j, \lambda^{\otimes j} \rangle := \lambda^{\otimes j}(y_j)$ for $y_j \in Y^{\widehat{\otimes} j}$.
- $P := \{\lambda \mapsto p(\lambda) \mid p \text{ is a polynomial on } Y^*\}$ algebra of all polynomials on Y^*
- The space of **cylindrical polynomials with coefficients in a dense linear subspace $D \subseteq Y$** is defined by

$$P^D = \{\varphi(\langle y_1, \lambda \rangle, \dots, \langle y_k, \lambda \rangle) \mid \text{polynomials } \varphi : \mathbb{R}^k \rightarrow \mathbb{R}, k \in \mathbb{N}_0, y_i \in D\}.$$

Differentiability

Definition

- A map $f : Y^* \rightarrow \mathbb{R}$ is said to be **Fréchet differentiable** at $\lambda \in Y^*$ if there exists a linear functional $y_\lambda^{**}(\cdot) = \langle y_\lambda^{**}, \cdot \rangle \in Y^{**}$ such that

$$\lim_{\tilde{\lambda} \rightarrow 0} \frac{|f(\lambda + \tilde{\lambda}) - f(\lambda) - y_\lambda^{**}(\tilde{\lambda})|}{\|\tilde{\lambda}\|_{Y^*}} = 0.$$

We write $\partial f(\lambda) := y_\lambda^{**}$.

- Analogously, whenever it exists, we denote by $\partial^k f(\lambda)$ the element of $(Y^{\widehat{\otimes} k})^{**}$ corresponding to the k -th iterated Fréchet derivative of f at λ .

For a $p \in P^D$ of the form $p(\lambda) := \varphi(\langle y_1, \lambda \rangle, \dots, \langle y_d, \lambda \rangle)$ we have

$$\partial^k p(\lambda) = \sum_{i_1, \dots, i_k=1}^d y_{i_1} \otimes \dots \otimes y_{i_k} \varphi_{i_1, \dots, i_k}(\langle y_1, \lambda \rangle, \dots, \langle y_d, \lambda \rangle).$$

and thus $\partial^k p(\lambda) \in D^{\otimes k}$ for each $\lambda \in Y^*$.

Lévy type operator

Definition

Let $L : P^D \rightarrow P$ be a linear operator and fix $\lambda \in Y^*$. The operator L is said to be of **Lévy type** on $\mathcal{E} \subseteq Y^*$ at λ if $p \mapsto Lp(\lambda)$ can be represented as

$$Lp(\lambda) = -\Gamma(\lambda)p(\lambda) + B(\partial p(\lambda), \lambda) + \frac{1}{2}Q(\partial^2 p(\lambda), \lambda) \\ + \int p(\xi) - p(\lambda) - \langle \partial p(\lambda), \xi - \lambda \rangle K(\lambda, d\xi),$$

where the quadruplet $(\Gamma(\lambda), B(\cdot, \lambda), Q(\cdot, \lambda), K(\lambda, \cdot))$ consists of some constant $\Gamma(\lambda) \in \mathbb{R}_+$, some linear operators

$$B(\cdot, \lambda) : D \rightarrow \mathbb{R}, \quad \text{and} \quad Q(\cdot, \lambda) : D \otimes D \rightarrow \mathbb{R},$$

and some (nonnegative) measure $K(\lambda, \cdot)$ on $\mathcal{E} \setminus \{\lambda\}$ satisfying

$$Q(y \otimes y, \lambda) \geq 0 \quad \text{and} \quad \int \langle y, \xi - \lambda \rangle^2 K(\lambda, d\xi) < \infty, \quad \forall y \in D.$$

Polynomial operators

Definition

Fix $\mathcal{E} \subseteq Y^*$. A linear operator $L: P^D \rightarrow P$ is called **\mathcal{E} -polynomial** if for every $p \in P^D$ there is some $q \in P$ such that $q|_{\mathcal{E}} = Lp|_{\mathcal{E}}$ and $\deg(q) \leq \deg(p)$.

Proposition (C. & Svaluto-Ferro '18)

A linear operator $L: P^D \rightarrow P$ of Lévy type is \mathcal{E} -polynomial if and only if

$$\Gamma(\lambda) = \text{const}, \quad B(y, \lambda) = B_0(y) + \langle B_1(y), \lambda \rangle$$

$$Q(y \otimes y, \lambda) + \int \langle y, \xi - \lambda \rangle^2 K(\lambda, d\xi) = \sum_{i=0}^2 \langle Q_i(y \otimes y), \lambda^{\otimes i} \rangle$$

$$\int \langle y, \xi - \lambda \rangle^k K(\lambda, d\xi) = \sum_{i=0}^k \langle J_i^k(y^{\otimes k}), \lambda^{\otimes i} \rangle, \quad k \geq 3$$

for some linear operators $B_0: D \rightarrow \mathbb{R}$, $B_1: D \rightarrow Y$, $Q_i: D \otimes D \rightarrow Y^{\hat{\otimes} i}$, $i \in \{0, 1, 2\}$, $J_i^k: D^{\otimes k} \rightarrow Y^{\hat{\otimes} i}$, $i \in \{0, \dots, k\}$ for $k \geq 3$.

Dual operator

Definition

Let $L: P^D \rightarrow P$ be an \mathcal{E} -polynomial operator and fix $k \in \mathbb{N}$.

- A **k -th dual operator** $L_k: \bigoplus_{j=0}^k D^{\otimes j} \rightarrow \bigoplus_{j=0}^k Y^{\hat{\otimes} j}$ is a linear operator that maps the coefficients vector of p to the coefficients vector of Lp , for each $p \in P^D$ with $\deg(p) \leq k$ such that $L_k y := (L_k^0 y, \dots, L_k^k y)$ satisfies

$$Lp(\lambda) = \sum_{j=0}^k \langle L_k^j y, \lambda^{\otimes j} \rangle, \quad \text{for all } \lambda \in Y^*$$

$$\text{for } p(\lambda) = \sum_{j=0}^k \langle y_j, \lambda^{\otimes j} \rangle.$$

Polynomial processes

Let $\mathcal{E} \subseteq Y^*$ and $L : P^D \rightarrow P$ be a linear operator. An \mathcal{E} -valued process $(\lambda_t)_{t \geq 0}$ defined on some filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ is called a **solution to the martingale problem for L** with initial condition $\lambda_0 \in \mathcal{E}$ if

- $\lambda_0 = \lambda$ \mathbb{P} -a.s.,
- for every $p \in P^D$ there exists a **measurable version of $(p(\lambda_t))_{t \geq 0}$** and **$(Lp(\lambda_t))_{t \geq 0}$** and
- the process

$$N_t^p := p(\lambda_t) - p(\lambda_0) - \int_0^t Lp(\lambda_s) ds$$

defines a **local martingale** for every $p \in P^D$.

Definition

Let L be \mathcal{E} -polynomial. A solution to the martingale problem for L is called an \mathcal{E} -valued **polynomial jump diffusion** if $(N_t^p)_{t \geq 0}$ is a **true martingale** for all $p \in P^D$.

Moment formula

Theorem (C.& Svaluto-Ferro '18)

Let $(\lambda_t)_{t \geq 0}$ be a polynomial jump diffusion corresponding to L and fix a dual operator $(L_k)_{k \in \mathbb{N}}$. Suppose that

- the k -th dual operator L_k is closable, and that the coefficients vector $y \in \bigoplus_{j=0}^k D^{\otimes j}$ is in the domain of its closure \bar{L}_k .
- Suppose that there is a weak solution $(y_t)_{t \geq 0} = (y_{t,0}, \dots, y_{t,k})_{t \geq 0}$ with $y_{t,j} \in Y^{\widehat{\otimes} j}$ (satisfying certain technical conditions) of the $k+1$ dimensional system of linear ODEs on $\bigoplus_{j=0}^k Y^{\widehat{\otimes} j}$

$$\partial_t y_t = \bar{L}_k y_t, \quad y_0 = y$$

Then the following conditional *moment formula* holds true

$$\mathbb{E} \left[\left(\sum_{j=0}^k \langle y_j, \lambda_T^{\otimes j} \rangle \right) \mid \mathcal{F}_t \right] = \sum_{j=0}^k \langle y_{T-t,j}, \lambda_t^{\otimes j} \rangle.$$

Interpretation

- The infinite dimensional Y^* valued Feynman Kac PDE reduces to a $k + 1$ dimensional systems of linear ODEs on $\bigoplus_{j=0}^k Y^{\widehat{\otimes} j}$.
- When $Y^* = M(E)$ for some compact set $E \subseteq \mathbb{R}$, this corresponds to a system of linear PDES, where the j -th component is a function on E^j .
 - ▶ When E consists of one point, we are back to the one-dimensional guiding example of the Wright-Fisher diffusion and we obtain a $k + 1$ dimensional ODE.

Polynomial foward variance models

- Log price dynamics: $dX_t = -\frac{1}{2} V_t dt + \sqrt{V_t} dW_t$
- Forward variance dynamics

$$\lambda_t(x) = \frac{d}{dx} \lambda_t(x) dt + dM_t^x$$

where $V_t = \lambda_t(0)$ (actually $\lambda_t(x) = \mathbb{E}[V_{t+x} | \mathcal{F}_t]$), W is a Brownian motion and (M_t^x) is a continuous martingale for all $x \in \mathbb{R}_+$.

- We consider $x \mapsto \lambda_t(x)$ on the following Hilbert space Y^* (c.f. Filipovic 2001),

$$Y^* = Y = \{y \in AC(\mathbb{R}_+, \mathbb{R}) \mid \int_0^\infty |y'(x)|^2 \alpha(x) dx < \infty\}$$

for a specified strictly positive weight function $\alpha > 0$.

- ▶ Scalar product $\langle y, \lambda \rangle_\alpha = y(0)\lambda(0) + \int y'(x)\lambda'(x)\alpha(x)dx$.
- ▶ $x \mapsto M_t^x \in Y^*$ for every $t \geq 0$ \mathbb{P} -a.s.
- Polynomial structure: $d[\langle y, M_t^x \rangle_\alpha, \langle y, M_t^x \rangle_\alpha] = \sum_{i=0}^2 \langle Q_i(y \otimes y), \lambda^{\otimes i} \rangle_\alpha dt$

Special case: rough polynomial variance models

- Consider an $E \subset \mathbb{R}$ -valued **polynomial Volterra process**, i.e.

$$V_t = f(t) + \int_0^t K(t-s) \sqrt{C(V_s)} dB_s,$$

where f is a deterministic function, $C(v) = \Gamma v^2 + \gamma v + c$ for constants Γ, γ, c , B a Brownian motion and K a kernel in $L^2_{\text{loc}}(\mathbb{R}_+, \mathbb{R})$. In rough volatility models the kernel is typically fractional, i.e. $K(t) = \frac{t^{\alpha-1}}{\Gamma(\alpha)}$ for $\alpha \in (\frac{1}{2}, 1)$.

- As in C. & Teichmann '18, lift the stochastic Volterra processes to Y^* and consider the following SPDE

$$d\lambda_t(x) = \frac{d}{dx} \lambda_t(x) + K(x) \sqrt{C(\langle \lambda_t, 1 \rangle_\alpha)} dB_t,$$

- ▶ Then $M_t^x = K(x) \sqrt{C(\langle \lambda_t, 1 \rangle_\alpha)} B_t$.
- ▶ $Q(y \otimes y; \lambda) = \frac{1}{2} \langle y, K \rangle_\alpha^2 (\Gamma \langle \lambda, 1 \rangle_\alpha^2 + \gamma \langle \lambda, 1 \rangle_\alpha + c)$

Futures and options on VIX

- Define the VIX at time t via the continuous time monitoring formula

$$VIX_t^2 = \mathbb{E} \left[\frac{1}{\Delta} \int_0^\Delta V_{t+x} dx \middle| \mathcal{F}_t \right] = \frac{1}{\Delta} \int_0^\Delta \lambda_t(x) dx$$

- The risk neutral valuation formula for an option on VIX with payoff φ (for the VIX future $\varphi(x) = \sqrt{x}$) is then

$$\mathbb{E} [\varphi(VIX_t^2)] = \mathbb{E} \left[\varphi \left(\frac{1}{\Delta} \int_0^\Delta \lambda_t(x) dx \right) \right].$$

- Since $\int_0^\Delta \lambda_t(x) dx = \langle y, \lambda_t \rangle_\alpha$ for some y , for all polynomials φ up to degree k , this expectation can be computed by solving a $k + 1$ dimensional system of PDEs. \Rightarrow Polynomial approximation for other payoffs.

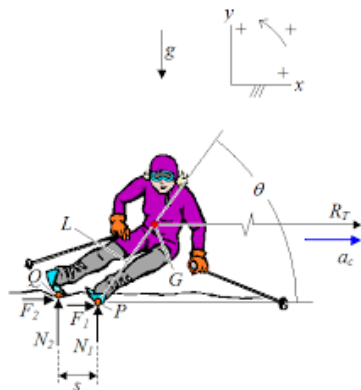
Conclusion

Framework of infinite dimensional polynomial processes for

- ... (probability) measure valued processes, e.g. for stochastic portfolio theory or population genetics;
- ... function valued processes, for term structure modeling, in particular forward variance models and rough volatility;
- ... interacting particle systems.

Thank you for your attention!

Thanks Yuri, for all your inspiring ideas, in particular for bringing each year skiing and mathematics together!



Happy birthday!