

Stochastic expansions and Hopf algebras

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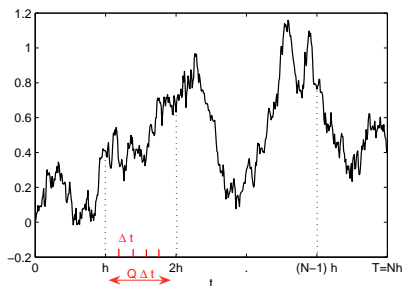
Stochastic differential equations

$$dy_t = V_0(y_t) dt + V_1(y_t) dW_t^1 + \cdots + V_d(y_t) dW_t^d$$

$$y_t = y_0 + \sum_{i=0}^d \int_0^t V_i(y_\tau) dW_\tau^i$$

- ▶ Solution process: $y: \mathbb{R}_+ \rightarrow \mathbb{R}^N$
- ▶ Non-commuting vector fields: $V_i = \sum_{j=1}^n V_i^j(y) \partial_y^j$
- ▶ d -dimensional driving signal: (W^1, \dots, W^d)
- ▶ Convention: $W_t^0 \equiv t$

Wiener process



- ▶ $W_t - W_s \sim N(0, \sqrt{t - s})$
- ▶ Independent increments
- ▶ Continuous, nowhere differentiable (w.p. 1)

Stochastic chain rule

$$y_t = y_0 + \sum_i \int_0^t V_i \circ y_\tau dW_\tau^i$$

Itô lemma (stochastic chain rule) \Rightarrow

$$f \circ y_t = f \circ y_0 + \sum_j \int_0^t V_j \circ f \circ y_\tau dW_\tau^j$$

E.g. choose $f = V_i \Rightarrow$

$$V_i \circ y_t = V_i \circ y_0 + \sum_j \int_0^t V_j \circ V_i \circ y_\tau dW_\tau^j$$

$$y_t = y_0 + \sum_i \int_0^t \left(V_i \circ y_0 + \sum_j \int_0^{\tau_1} V_j \circ V_i \circ y_{\tau_2} dW_{\tau_2}^j \right) dW_{\tau_1}^i$$

Stochastic Taylor series

$$y_t = y_0 + \sum_i \int_0^t dW_{\tau_1}^i V_i \circ y_0 + \sum_{i,j} \int_0^t \int_0^{\tau_1} V_j \circ V_i \circ y_{\tau_2} dW_{\tau_2}^j dW_{\tau_1}^i$$

Now choose $f = V_j \circ V_i \Rightarrow$

$$y_t = y_0 + \sum_i \underbrace{\int_0^t dW_{\tau_1}^i}_{J_i(t)} V_i \circ y_0 + \sum_{i,j} \underbrace{\int_0^t \int_0^{\tau_1} dW_{\tau_2}^j dW_{\tau_1}^i}_{J_{ji}(t)} V_j \circ V_i \circ y_0 + \dots$$

$$J_i(t) \equiv \int_0^t dW_{\tau_1}^i = W_t^i - \underbrace{W_0^i}_0$$

Stochastic Taylor series II

$$J_{ii}(t) \equiv \int_0^t \int_0^{\tau_1} dW_{\tau_2}^i dW_{\tau_1}^i \equiv \frac{1}{2}(W_t^i)^2$$

$$J_{ij}(t) \equiv \int_0^t \int_0^{\tau_1} dW_{\tau_2}^j dW_{\tau_1}^i \equiv \int_0^t W_{\tau_1}^j dW_{\tau_1}^i$$

$$J_{ij}(t) \longrightarrow \hat{J}_{ij}$$

- ▶ Left Riemann sum
- ▶ Karhunen–Loeve
- ▶ K–L + tail distribution approx. (Wiktorsson)

Stochastic Taylor series III

$$y_t = y_0 + \sum_i \underbrace{\int_0^t dW_{\tau_1}^i}_{J_i(t)} V_i \circ y_0 + \sum_{i,j} \underbrace{\int_0^t \int_0^{\tau_1} dW_{\tau_2}^j dW_{\tau_1}^i}_{J_{ji}(t)} V_j \circ V_i \circ y_0 + \dots$$

Strong approximation:

- ▶ Euler-Maruyama: inc. $\hat{J}_i(t)$
- ▶ Milstein method: inc. $\hat{J}_i(t)$ & \hat{J}_{ij}

Deterministic case: V_0 only \Rightarrow

$$\begin{aligned} y_t &= y_0 + tV_0 \circ y_0 + \frac{1}{2}t^2V_0^2 + \frac{1}{6}t^3V_0^3 + \dots \\ &= \exp(tV_0) \circ y_0. \end{aligned}$$

Flow map and exponential Lie series

$$y_t = \varphi_t \circ y_0$$

$$\varphi_t = \text{id} + \sum_i J_i(t) V_i + \sum_{i,j} J_{ij}(t) V_i \circ V_j + \sum_{i,j,k} J_{ijk}(t) V_i \circ V_j \circ V_k + \dots$$

Exponential Lie series:

$$\begin{aligned} \psi_t &= \ln \varphi_t \\ &= (\varphi_t - \text{id}) - \frac{1}{2}(\varphi_t - \text{id})^2 + \frac{1}{3}(\varphi_t - \text{id})^3 + \dots \\ &= \sum_i J_i V_i + \sum_{i,j} J_{ij} V_i V_j + \dots - \frac{1}{2} \left(\sum_i J_i V_i + \dots \right)^2 + \dots \\ &= \sum_i J_i V_i + \sum_{i>j} \frac{1}{2} (J_{ij} - J_{ji}) [V_i, V_j] + \dots \end{aligned}$$

Castell–Gaines (ODE) method

Truncated exponential Lie series across $[t_n, t_{n+1}]$:

$$\hat{\psi}_{t_n, t_{n+1}} = \sum_i \hat{J}_i V_i + \sum_{i>j} + \frac{1}{2}(\hat{J}_{ij} - \hat{J}_{ji})[V_i, V_j].$$

Approximate solution:

$$y_{t_{n+1}} \approx \exp(\hat{\psi}_{t_n, t_{n+1}}) \circ y_{t_n}.$$

Castell–Gaines: solve ODE

$$u'(\tau) = \hat{\psi}_{t_n, t_{n+1}} \circ u(\tau)$$

across $\tau \in [0, 1]$ with $u(0) = y_{t_n}$ gives $u(1) \approx y_{t_{n+1}}$.

Basic idea

- ▶ Construct the new series $\psi_t = F(\varphi_t)$
- ▶ Truncate and use \hat{J}_i, \hat{J}_{ij} to produce $\hat{\psi}_t$
- ▶ Approximate flow-map is $\hat{\varphi}_t = F^{-1}(\hat{\psi}_t)$
- ▶ “Flow error” is the flow remainder $R_t = \varphi_t - \hat{\varphi}_t$
- ▶ Approximate solution is $\hat{y}_t = \varphi_t \circ y_0$
- ▶ Error/remainder is $R_t \circ y_0$
- ▶ Mean-square error measure is

$$\|R_t \circ y_0\|_{L^2}^2 \equiv \mathbb{E}(R_t \circ y_0)^T (R_t \circ y_0)$$

Basic idea

$$\varphi = \text{id} + \sum_{w \in \mathbb{A}^+} J_w V_w$$

Here $\mathbb{A}^+ = \{\text{non-empty words over } \mathbb{A} = \{0, 1, \dots, d\}\}$

$$\psi = F(\varphi) = \sum_{k=1}^{\infty} C_k (\varphi - \text{id})^k = \sum_{w \in \mathbb{A}^+} K_w V_w$$

Goal: choose C_k so that

$$\|R \circ y_0\|_{L^2}^2 \leq \|R^{\text{st}} \circ y_0\|_{L^2}^2$$

Sinh-log series?

- ▶ Diffusion vector fields commute: exponential Lie series has smaller mean-square error (orders 1/2, 1, 3/2)
- ▶ Do not commute: counter-example for order 1
- ▶ Now *assume no drift*: $\mathbb{A} = \{1, \dots, d\}$

Set

$$\psi = \sinh \log \varphi \equiv \sum_{k=1}^{\infty} C_k (\varphi - id)^k$$

$$\hat{\varphi} \equiv \hat{\psi} + \sqrt{id + \hat{\psi}^2}$$

Hopf algebra of words

Shuffle relations:

$$J_{a_1} J_{a_2} = J_{a_1 a_2} + J_{a_2 a_1}$$

$$J_{a_1} J_{a_2 a_3} = J_{a_1 a_2 a_3} + J_{a_2 a_1 a_3} + J_{a_2 a_3 a_1}$$

$$\begin{aligned} J_{a_1 a_2} J_{a_3 a_4} &= J_{a_1 a_2 a_3 a_4} + J_{a_1 a_3 a_2 a_4} + J_{a_1 a_3 a_4 a_2} \\ &\quad + J_{a_3 a_1 a_4 a_2} + J_{a_3 a_1 a_2 a_4} + J_{a_3 a_4 a_1 a_2} \end{aligned}$$

Shuffle product: $J_u J_v \longrightarrow u \sqcup v$

Two Hopf algebra structures, set:

$$\mathcal{H} = \mathbb{R}\langle \mathbb{A} \rangle \otimes \mathbb{R}\langle \mathbb{A} \rangle$$

$$(u \otimes x)(v \otimes y) = (u \sqcup v) \otimes (xy),$$

Pullback to Hopf algebra

$$\varphi = 1 \otimes 1 + \sum_{w \in \mathbb{A}^+} w \otimes w$$

$$\begin{aligned} \Rightarrow \psi &= \sum_{k \geq 1} C_k (\varphi - 1 \otimes 1)^k \\ &= \sum_{k \geq 1} C_k \left(\sum_{w \in \mathbb{A}^+} w \otimes w \right)^k \\ &= \sum_{k \geq 1} C_k \sum_{u_1, \dots, u_k \in \mathbb{A}^+} (u_1 \sqcup \dots \sqcup u_k) \otimes (u_1 \dots u_k) \\ &= \sum_{w \in \mathbb{A}^*} \left(\sum_{k=1}^{|w|} C_k \sum_{\substack{u_1, \dots, u_k \in \mathbb{A}^+ \\ w = u_1 \dots u_k}} u_1 \sqcup \dots \sqcup u_k \right) \otimes w \end{aligned}$$

Concatenation-shuffle operator algebra

$$K \circ w \equiv \sum_{k=1}^{|w|} C_k \sum_{\substack{u_1, \dots, u_k \in \mathbb{A}^+ \\ w = u_1 \dots u_k}} u_1 \sqcup \dots \sqcup u_k$$

$$u_1 \sqcup u_2 \sqcup \dots \sqcup u_k = c^{|u_1|-1} s c^{|u_2|-1} s \dots s c^{|u_k|-1} \otimes w$$

Warning:

$$(b_1 \otimes u_1)(b_2 \otimes u_2) = (b_1 s b_2) \otimes (u_1 u_2),$$

Coefficients

$$|w| = n + 1:$$

$$\begin{aligned} K \circ w &= \sum_{k=1}^{|w|} C_k \sum_{\substack{u_1, \dots, u_k \in \mathbb{A}^+ \\ w = u_1 \sqcup \dots \sqcup u_k}} u_1 \sqcup \dots \sqcup u_k \\ &\rightarrow \sum_{k=1}^{n+1} C_k (c^{n-(k-1)} \sqcup s^{k-1}) \otimes w \\ &= \sum_{k=0}^n C_{k+1} (c^{n-k} \sqcup s^k) \otimes w \\ &= \left(\sum_{k=0}^n C_{k+1} (c^{n-k} \sqcup s^k) \right) \otimes w. \end{aligned}$$

Sinh-log coefficients

Lemma

With

$$C_k = \begin{cases} 1, & k = 1, \\ \frac{1}{2}(-1)^{k+1}, & k \geq 2, \\ \frac{1}{2}(-1)^{n+1} + \epsilon, & k = n, \end{cases}$$

then

$$K = \frac{1}{2}(c^n - \alpha^n) + \epsilon s^n$$

where

$$\alpha^n \circ (a_1 \dots a_{n+1}) \equiv \alpha \circ (a_1 \dots a_{n+1}) \equiv (-1)^n a_{n+1} \dots a_1.$$

Proof: step 1

Partial integration formula:

$$a_1 \dots a_{n+1} = (a_1 \dots a_n) \sqcup a_{n+1} - (a_1 \dots a_{n-1}) \sqcup (a_{n+1} a_n) \\ + \dots + (-1)^n a_{n+1} \dots a_1$$

$$c^n = -c^{n-1}s - c^{n-2}s\alpha - c^{n-3}s\alpha^2 - \dots - \alpha^n$$

$$\alpha^n = -c^n - \sum_{k=0}^{n-1} c^k s \alpha^{n-k-1}$$

Proof: step 2

Antipode polynomial:

$$\alpha^n \equiv -(c - s)^n.$$

True for $n = 1, 2$, assume true for $k = 1, 2, \dots, n - 1$. Direct expansion \Rightarrow

$$(c - s)^n = c^n - \sum_{k=0}^{n-1} c^k s (c - s)^{n-k-1}$$

Use induction.

Proof: step 3

Recall:

$$\begin{aligned}K &= \frac{1}{2}c^n + \frac{1}{2} \sum_{k=0}^n (-1)^k (c^{n-k} \sqcup s^k) + \epsilon s^n \\ &= \frac{1}{2}c^n + \frac{1}{2}(c - s)^n + \epsilon s^n \\ &= \frac{1}{2}c^n - \frac{1}{2}\alpha^n + \epsilon s^n\end{aligned}$$

Hence

$$K_w = \frac{1}{2}(J_w - J_{\alpha \circ w}) + \epsilon \prod_{i=1}^{n+1} J_{w_i}$$

Sinh-log remainder is smaller I

$$\|R^{\text{st}} \circ y_0\|_{L^2}^2 = \|R^{\text{sl}} \circ y_0\|_{L^2}^2 + E$$

where with $R^{\text{st}} = R^{\text{sl}} + \bar{R}$:

$$E \equiv \mathbb{E} (\bar{R} \circ y_0)^{\text{T}} (R^{\text{sl}} \circ y_0) + \mathbb{E} (R^{\text{sl}} \circ y_0)^{\text{T}} (\bar{R} \circ y_0) + \mathbb{E} (\bar{R} \circ y_0)^{\text{T}} (\bar{R} \circ y_0)$$

$$R^{\text{sl}} = \sum_{\substack{w \in \mathbb{A}^+ \\ |w| \geq n+1}} K_w V_w + \dots$$

$$\bar{R} = \sum_{\substack{w \in \mathbb{A}^+ \\ |w|=n+1}} \underbrace{J_w - K_w}_{\bar{J}_w} V_w$$

Sinh-log remainder is smaller II

$$E = \sum_{\substack{u, v \in \mathbb{A}^+ \\ |u|=|v|=n+1}} \mathbb{E} (\bar{J}_u K_v + K_u \bar{J}_v + \bar{J}_u \bar{J}_v) (V_u \circ y_0)^T (V_v \circ y_0)$$

$$\text{Recall } K_u = \frac{1}{2}(J_u - J_{\alpha \circ u}) + \epsilon \prod_{i=1}^{n+1} J_{u_i} \Rightarrow$$

$$\begin{aligned} & \bar{J}_u K_v + K_u \bar{J}_v + \bar{J}_u \bar{J}_v \\ &= \epsilon^0 \left(\frac{1}{2}(J_u J_v - J_{\alpha \circ u} J_{\alpha \circ v}) + \frac{1}{4}(J_u + J_{\alpha \circ u})(J_v + J_{\alpha \circ v}) \right) \\ & \quad - \epsilon^1 \left(\frac{1}{2}(J_u - J_{\alpha \circ u}) \prod_{i=1}^{n+1} J_{v_i} + \frac{1}{2}(J_v - J_{\alpha \circ v}) \prod_{i=1}^{n+1} J_{u_i} \right) \\ & \quad - \epsilon^2 \left(\prod_{i,j=1}^{n+1} J_{u_i} J_{v_j} \right) \end{aligned}$$

Concluding remarks

- ▶ Drift?
- ▶ Measure?
- ▶ Lévy processes
- ▶ Fractional Brownian motion
- ▶ Combinatorics \leftrightarrow analysis