

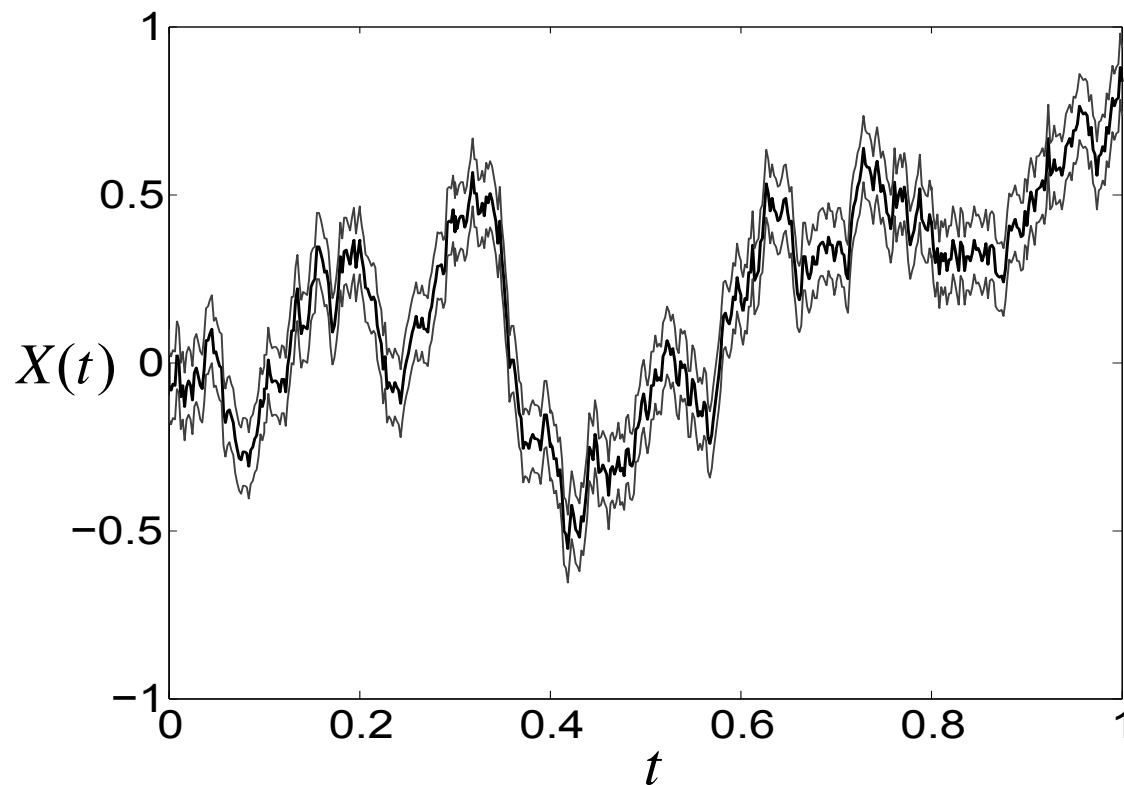
ε -Strong Simulation for Multidimensional
Stochastic Differential Equations
via Rough Path

ε -Strong Simulation for SDEs

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dB(t)$$

A piecewise constant path, X_ε , such that

$$\sup_{0 \leq t \leq T} |X_\varepsilon(t) - X(t)| \leq \varepsilon \text{ w.p. } 1$$

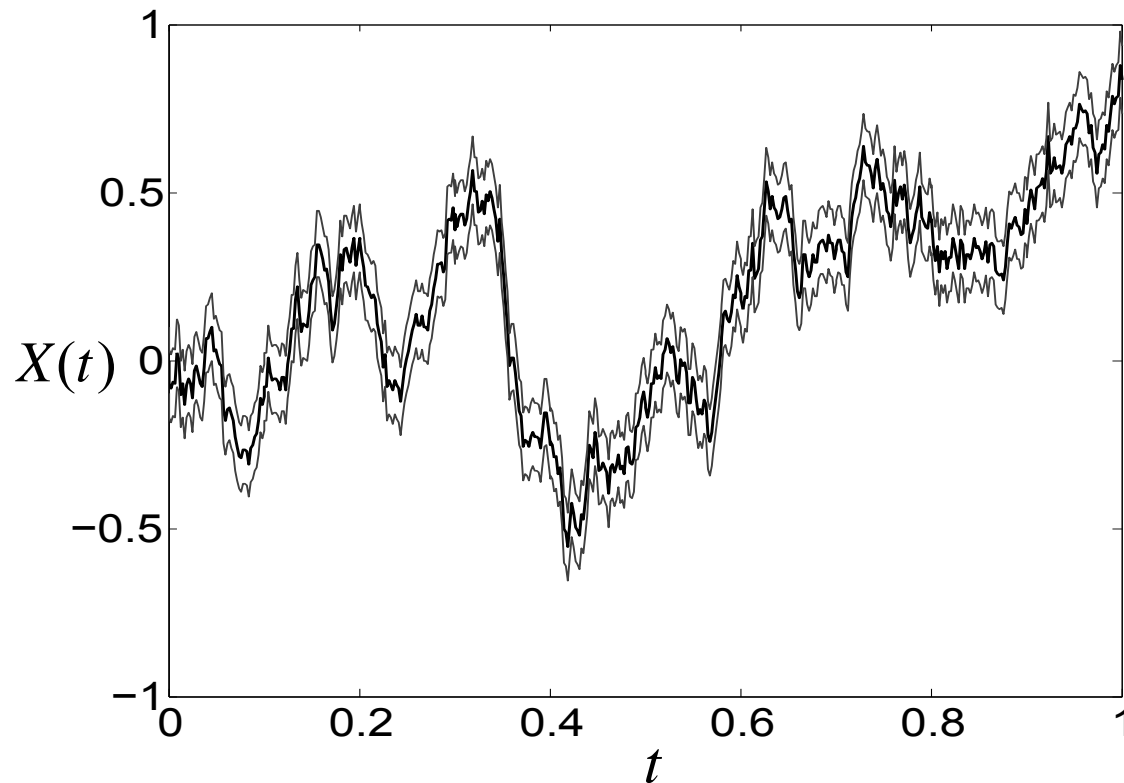


ε -Strong Simulation for SDEs

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dB(t)$$

For any sequence of $0 < \varepsilon_m < \varepsilon_{m-1} < \dots < \varepsilon_1 < 1$, we can simulate X_{ε_m} conditional on $X_{\varepsilon_1}, \dots, X_{\varepsilon_{m-1}}$

Tolerance-Enforced Simulation



Sample Path Simulation for SDEs

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dB(t)$$

	One Dimensional	Multi Dimensional
Finite collection of time point (Exact)	Beskos and Roberts (2004) Beskos, Papaspiliopoulos and Roberts (2006) Chen and Huang (2013) Giesecke and Smelov (2013) ...	Still an open problem...
Sample path (ε -strong)	Beskos, Peluchetti and Roberts (2012)	Blanchet, Chen and Dong (2014): Today's talk!

Sample Path Simulation for SDEs

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dB(t)$$

One Dimensional

Multi Dimensional

Finite collection of time point
(Exact)

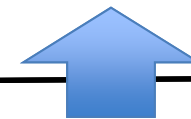
Beskos and Roberts (2004)
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...

Still an open problem...

Sample path
(ϵ -strong)

Beskos, Peluchetti and Roberts (2012)

Blanchet, Chen and Dong (2014): Today's talk!



Sample Path Simulation for SDEs

Beskos and Roberts (2004)

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dB(t)$$

Lamperti Transformation: $Y(t) = \int_y^{X(t)} \frac{1}{\sigma(x)} dx$

$$dY(t) = a(X(t))dt + dB(t)$$

Girsanov's Transformation:

$$\frac{dP}{d\tilde{P}}(\omega) = \exp\left(\int_0^T a(Y(s))dY(s) - \frac{1}{2}\int_0^T a^2(Y(s))dY(s)\right)$$

$$B(t)$$

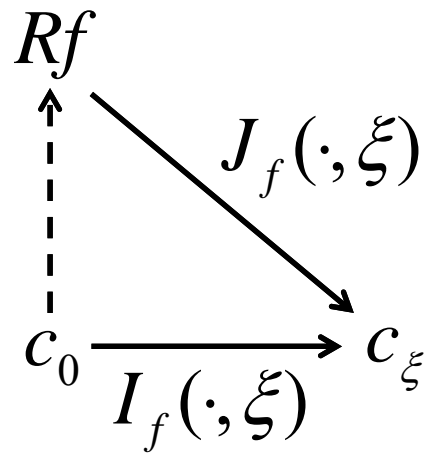
ε -Strong Simulation for SDEs

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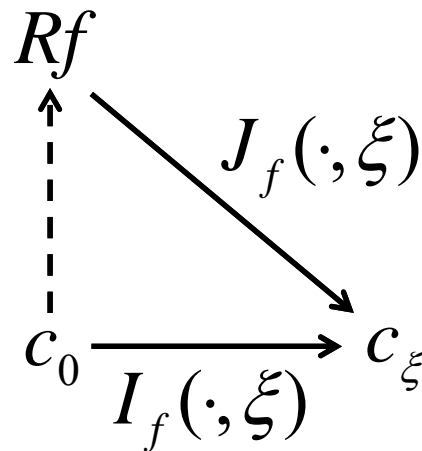
- Theory of Rough Path \rightarrow construct a continuous mapping



ε -Strong Simulation for SDEs

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dB(t)$$

- Theory of Rough Path \rightarrow construct a continuous mapping



- Lévy-Ciesielski construction of $\{B(t): 0 \leq t \leq 1\}$

$$B(t) = W^0 \Lambda^0(t) + \sum_{n=1}^{\infty} \sum_{k=1}^{2^{n-1}} W_k^n \Lambda_k^n(t) \Rightarrow B(t) \approx W^0 \Lambda^0(t) + \sum_{n=1}^N \sum_{k=1}^{2^{n-1}} W_k^n \Lambda_k^n(t)$$

Theory of Rough Paths

Lyons (1998)

$$X_i(t) = X_i(0) + \sum_{j=1}^{d'} \int_0^t \sigma_j(X(s)) dZ_j(t)$$

where $Z(t)$ is continuous but not assume to be differentiable

$$Z(t) = \int_0^t \int_0^{t_1} \dots \int_0^{t_{k-1}} dZ(t_k) \dots dZ(t_1)$$

α -Hölder continuity: $\|Z(t) - Z(s)\|_\infty \leq C |t - s|^\alpha$

1. $\alpha < 1/2$: $Z(t)$

2. $1/3 < \alpha < 1/2$: $Z(t)$ and $A_{i,j}(s,t) := \int_s^t (Z_i(u) - Z_i(s)) dZ_j(t)$

Theory of Rough Paths

$$X_i(t) = X_i(0) + \sum_{j=1}^{d'} \int_0^t \sigma_j(X(s)) dZ_j(t)$$

α -Hölder continuity: $\|Z(t) - Z(s)\|_\infty \leq C |t - s|^\alpha$

➤ $\frac{1}{3} < \alpha \leq \frac{1}{2}$: $Z(t)$ and $A_{i,j}(s,t) := \int_s^t (Z_i(u) - Z_i(s)) dZ_j(t)$

For $0 \leq r < s < t \leq 1$

a) $A_{i,j}(r,t) = A_{i,j}(r,s) + A_{i,j}(s,t) + (Z_i(s) - Z_i(r))(Z_j(t) - Z_j(s))$

b) $A_{i,j}(s,t) + A_{j,i}(s,t) = (Z_i(t) - Z_i(s))(Z_j(t) - Z_j(s))$

Theory of Rough Paths

$[0,1]$

Dyadic discretization: $D_n = \left\{ \frac{k}{2^n}, k = 0, 1, 2, \dots, 2^n \right\}$

$$t_k^n = \frac{k}{2^n} \quad t_k^n = t_{2k}^{n+1}$$

Mesh of D_n : $\Delta_n = 2^{-n}$

Theory of Rough Paths: Davie's estimates

$$X_i(t) = X_i(0) + \sum_{j=1}^{d'} \int_0^t \sigma_j(X(s)) dZ_j(s)$$

$$\|Z\|_\alpha = \sup_n \sup_{s,t \in D_n} \frac{\|Z(t) - Z(s)\|_\infty}{|t - s|^\alpha}, \quad \|A\|_{2\alpha} = \sup_n \sup_{s,t \in D_n} \frac{\|A(t) - A(s)\|_\infty}{|t - s|^{2\alpha}}$$

$$\begin{aligned} \tilde{X}_i^n(t_{k+1}^n) &= \tilde{X}_i^n(t_k^n) + \sum_{j=1}^{d'} \sigma_j(\tilde{X}^n(t_k^n))(Z_j(t_{k+1}^n) - Z_j(t_k^n)) \\ &\quad + \sum_{j=1}^{d'} \sum_{l=1}^d \sum_{m=1}^{d'} \partial_l \sigma_{ij}(\tilde{X}^n(t_k^n)) \sigma_{lm}(\tilde{X}^n(t_k^n)) A_{m,j}(t_k^n, t_{k+1}^n) \end{aligned}$$

$$\tilde{X}^n \rightarrow X$$

$$\|\tilde{X}^n(t) - X(t)\|_\infty \leq G(\|Z\|_\alpha, \|A\|_{2\alpha}) \Delta_n^{3\alpha-1}$$

Theory of Rough Paths: Davie's estimates

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Theory of Rough Paths

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$$A_{i,j}(t_{k-1}^n, t_k^n) \approx \tilde{A}_{i,j}^n(t_{k-1}^n, t_k^n)$$

$$R_{i,j}^n(t_l^n, t_m^n) = \sum_{k=l+1}^m (A_{i,j}^n(t_{k-1}^n, t_k^n) - \tilde{A}_{i,j}^n(t_{k-1}^n, t_k^n))$$

For fixed $1 - \alpha < \beta < 2\alpha$

$$\Gamma_R = \sup_n \sup_{s,t \in D_n} \frac{\|R^n(s,t)\|_\infty}{|t - s|^\beta \Delta_n^{2\alpha - \beta}}$$

Theory of Rough Paths: B, Chen, Dong '14

$$X_i(t) = X_i(0) + \sum_{j=1}^{d'} \int_0^t \sigma_j(X(s)) dZ_j(s)$$

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$$\tilde{X}^n \rightarrow X$$

$$\|\tilde{X}^n(t) - X(t)\|_\infty \leq G(\|Z\|_\alpha, \|A\|_{2\alpha}, \Gamma_R) \Delta_n^{2\alpha - \beta}$$

Theory of Rough Paths

$$X_i(t) = X_i(0) + \sum_{j=1}^{d'} \int_0^t \sigma_j(X(s)) dZ_j(t)$$

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$$\begin{aligned} \text{Ito: } A_{i,j}(t_{k-1}^n, t_k^n) &= \int_{t_{k-1}^n}^{t_k^n} (Z_i(t) - Z_i(t_{k-1}^n)) dZ_j(t) \\ &\approx (Z_i(t_{k-1}^n) - Z_i(t_{k-1}^n))(Z_j(t_k^n) - Z_j(t_{k-1}^n)) \\ &= 0 = \tilde{A}_{i,j}^n(t_{k-1}^n, t_k^n) \end{aligned}$$

$$R_{i,j}^n(t_l^n, t_m^n) = \sum_{k=l+1}^m A_{i,j}^n(t_{k-1}^n, t_k^n)$$

For fixed $1 - \alpha < \beta < 2\alpha$,

$$R_{i,j}^n(t_l^n, t_m^n) \leq \Gamma_R (m - l)^\beta \Delta_n^{2\alpha}$$

ε -Strong Simulation

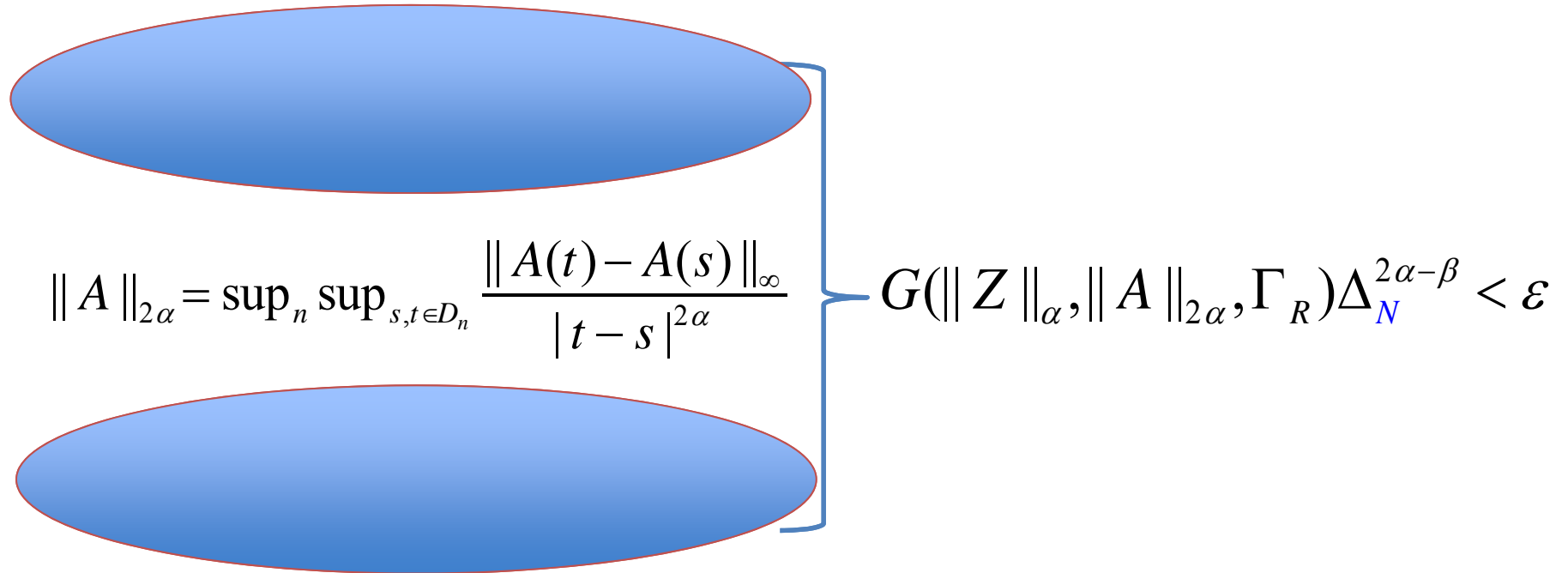
Contribution: Simulate upper bounds for

$$\begin{aligned}
 \|Z\|_\alpha &= \sup_n \sup_{s,t \in D_n} \frac{\|Z(t) - Z(s)\|_\infty}{|t - s|^\alpha} \\
 \|A\|_{2\alpha} &= \sup_n \sup_{s,t \in D_n} \frac{\|A(t) - A(s)\|_\infty}{|t - s|^{2\alpha}} \\
 \Gamma_R &= \sup_n \sup_{0 \leq s < t \leq 1} \frac{\|R^n(s, t)\|_\infty}{|t - s|^\beta \Delta_n^{2\alpha - \beta}}
 \end{aligned}
 \left. \vphantom{\begin{aligned} \|Z\|_\alpha \\ \|A\|_{2\alpha} \\ \Gamma_R \end{aligned}} \right\} G(\|Z\|_\alpha, \|A\|_{2\alpha}, \Gamma_R) \Delta_N^{2\alpha - \beta} < \varepsilon$$

Jointly with $Z(t)$ for t in the dyadic set D_n for any n

ε -Strong Simulation

Contribution: Simulate upper bounds for



The diagram consists of two blue ovals, one above the other, connected by a blue bracket on the right side. The bracket points to a mathematical expression. The expression is the definition of the 2α -norm of A , followed by an inequality involving G , Z , A , Γ_R , and Δ_N .

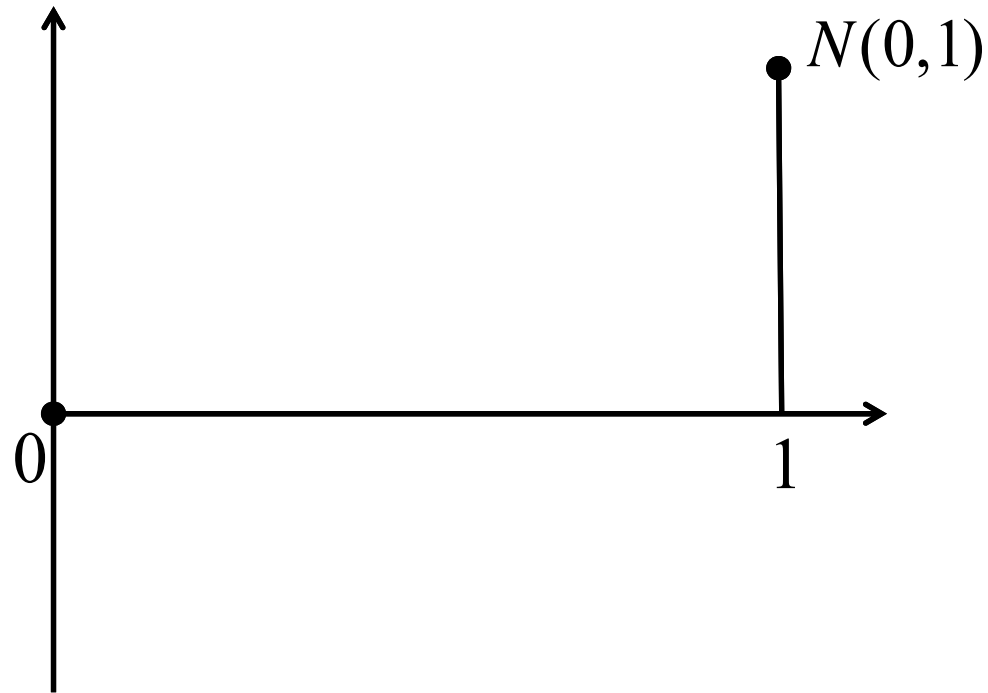
$$\|A\|_{2\alpha} = \sup_n \sup_{s,t \in D_n} \frac{\|A(t) - A(s)\|_\infty}{|t - s|^{2\alpha}}$$
$$G(\|Z\|_\alpha, \|A\|_{2\alpha}, \Gamma_R) \Delta_N^{2\alpha - \beta} < \varepsilon$$

Jointly with $Z(t)$ for t in the dyadic set D_n for any n

Wavelet Construction of Brownian Motion

Lévy-Ciesielski Construction:

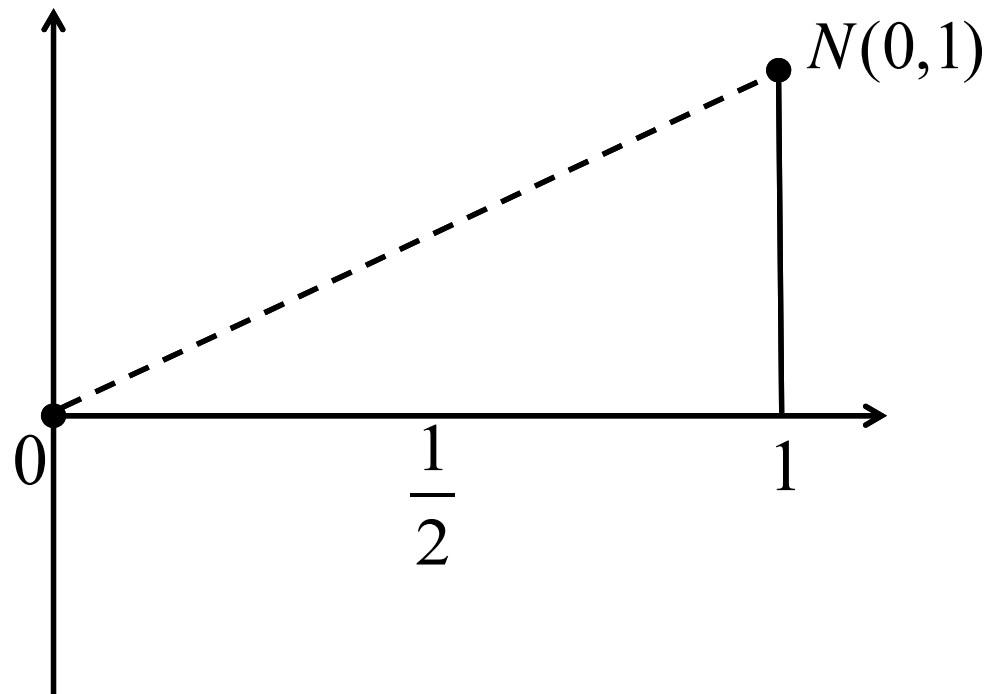
$$Z(t) = W^0 \Lambda^0(t) + \sum_{n=1}^{\infty} \sum_{k=1}^{2^{n-1}} W_k^n \Lambda_k^n(t)$$



Wavelet Construction of Brownian Motion

Lévy-Ciesielski Construction:

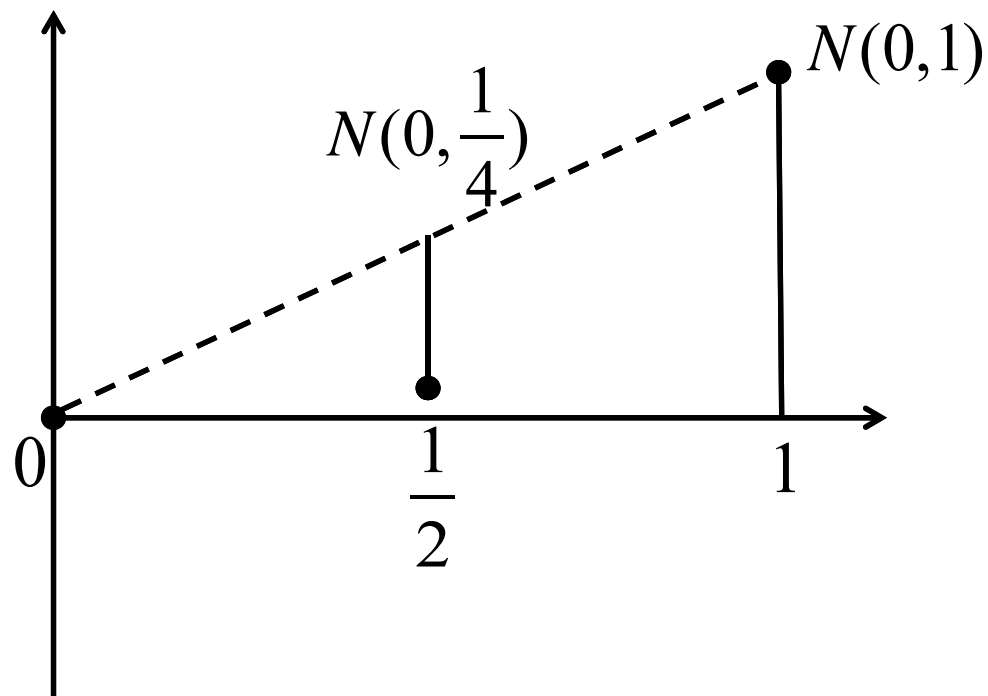
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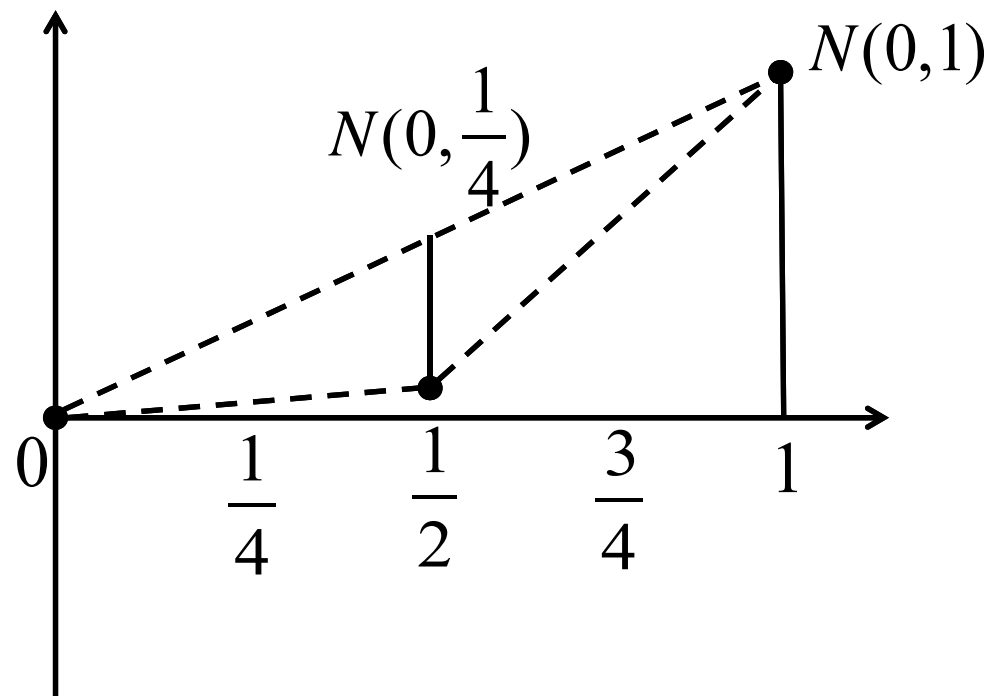
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Wavelet Construction of Brownian Motion

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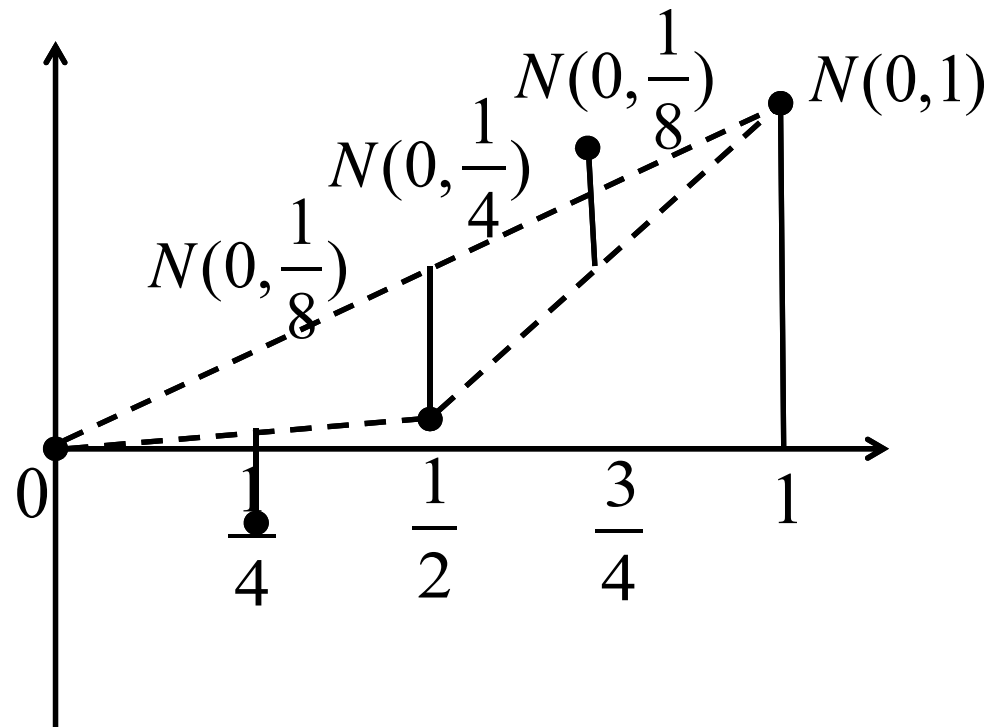
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Wavelet Construction of Brownian Motion

Lévy-Ciesielski Construction:

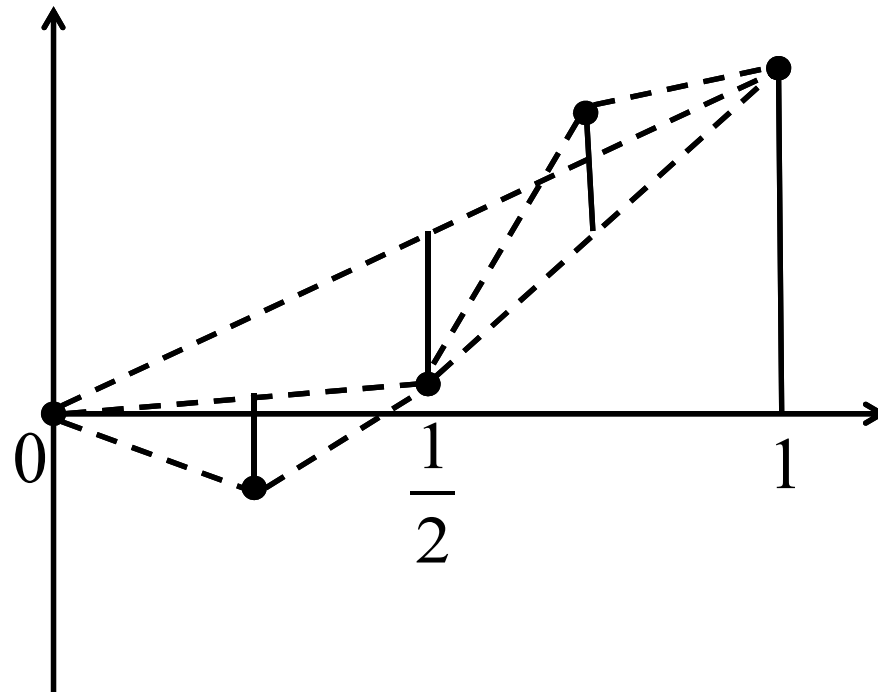
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Wavelet Construction of Brownian Motion

Lévy-Ciesielski Construction:

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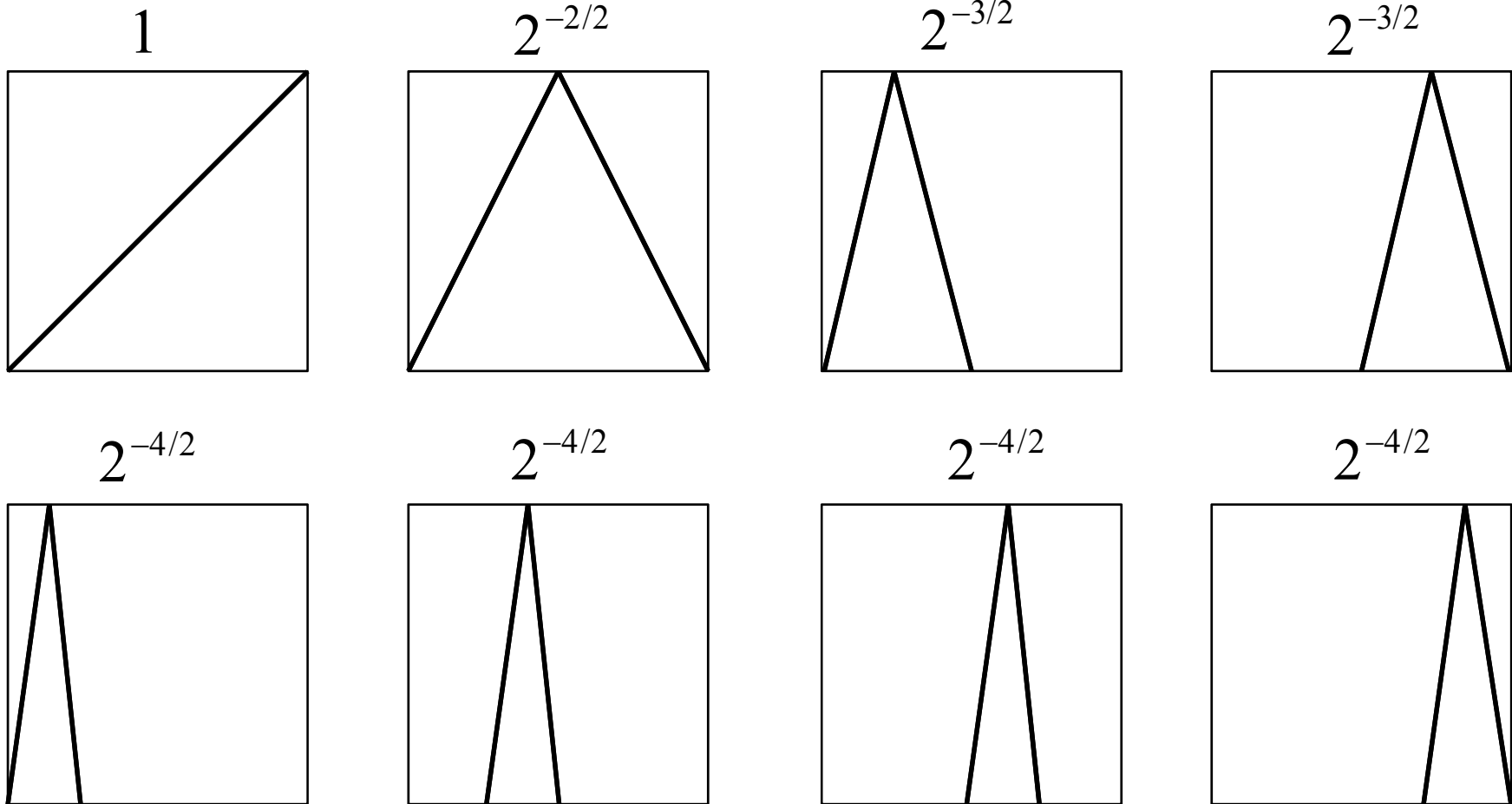


$N(0, 2^{-(n+1)})$

Wavelet Construction of Brownian Motion

Lévy-Ciesielski Construction:

$$Z(t) = W^0 \Lambda^0(t) + \sum_{n=1}^{\infty} \sum_{k=1}^{2^{n-1}} W_k^n \Lambda_k^n(t)$$



The Idea of Record Breakers for Brownian Path

Record breakers: $\{(n, k, i) : |W_{i,k}^n| > 4\sqrt{\log(2^{n-1} + k)}\}$

$$N_1 = \max\{n \geq 1 : 4\sqrt{\log(2^{n-1} + k)} \text{ for some } 1 \leq k \leq 2^{n-1}\}$$

➤ $EN_1 < \infty$

➤ $\|Z\|_\alpha \leq \sum_{n=1}^{\lceil \log_2 N_1 \rceil} 2^{-n(1/2-\alpha)} \max_k \{W_k^n\} + \frac{(\lceil \log_2 N_1 \rceil + 1)^{-1/2(1/2-\alpha)}}{1 - 2^{-1/2(1/2-\alpha)}}$

Simulation of the Brownian Path

Let $l = 2^{n-1} + k$ and $V_{i,l} = W_{i,k}^n$ for $n \geq 1$

$$V_{i,1} = W_i^0$$

$$\{(i,l) : |V_{i,l}| > a\sqrt{\log l}\}$$

$$J_i(0) = 1$$

$$J_i(k) = \{l > J_i(k-1) : V_{i,l} > a\sqrt{\log l}\}$$

$$\gamma_i = \min\{k : J_i(k) = \infty\}$$

Simulation of the Brownian Path

$$J_i(0) = 1$$

$$J_i(k) = \{l > J_i(k-1) : V_{i,l} > a\sqrt{\log l}\}$$

$$\gamma_i = \min\{k : J_i(k) = \infty\}$$

$$U(\infty) = P(J_i(1) = \infty) = \prod_{l=2}^{\infty} P(|V_{i,l}| \leq a\sqrt{\log(l)})$$

$$U(h) = P(J_i(1) > h) = \prod_{l=2}^h P(|V_{i,l}| \leq a\sqrt{\log(l)})$$

Simulation of the Brownian Path

$$J_i(0) = 1$$

$$J_i(k) = \{l > J_i(k-1) : V_{i,l} > a\sqrt{\log l}\}$$

$$\gamma_i = \min\{k : J_i(k) = \infty\}$$

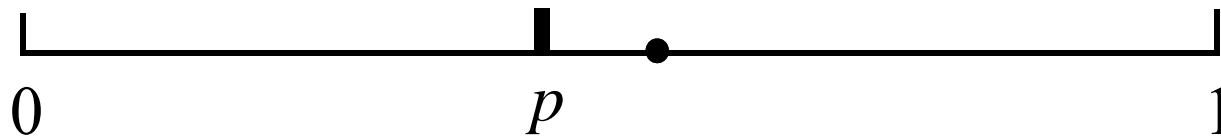
$$p = P(J_i(1) = \infty) = \prod_{l=2}^{\infty} P(|V_{i,l}| \leq a\sqrt{\log(l)})$$

$$U(h) = P(J_i(1) > h) = \prod_{l=2}^h P(|V_{i,l}| \leq a\sqrt{\log(l)})$$

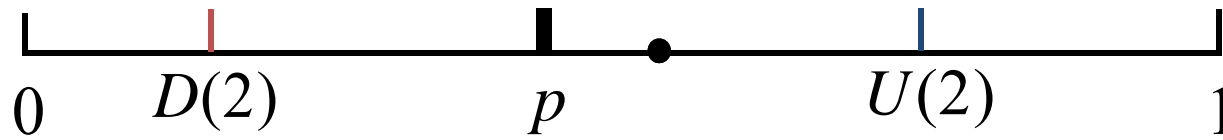
$$P(J_i(1) = \infty) \geq U(h)(1 - h^{1-a^2/2}) = D(h)$$

$$P(J_i(1) = h) = U(h-1) - U(h)$$

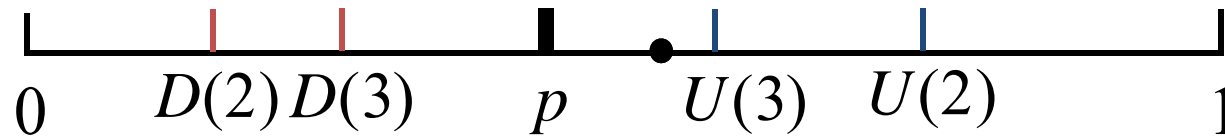
Simulation of the Brownian Path



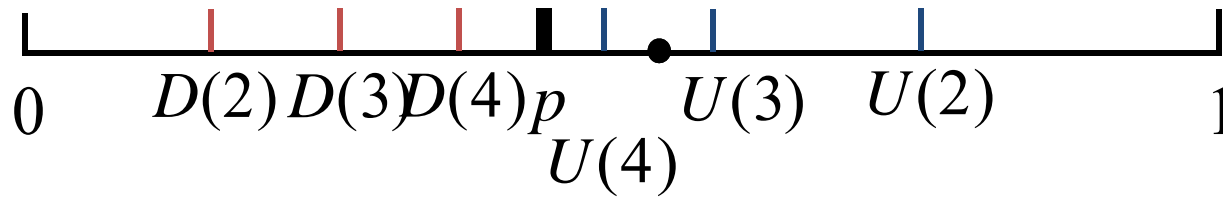
Simulation of the Brownian Path



Simulation of the Brownian Path



Simulation of the Brownian Path



$$J(1) = 4$$

Simulation of the Brownian Path

1. Find all the record breakers $\{(n, k, i) : |W_{i,k}^n| > 4\sqrt{\log(2^{n-1} + k)}\}$
2. Simulate $W_{i,k}^n$ conditional on the information of the record breakers

Infinite Sum Representation of Lévy Area

$$L_{i,j}^n(k) = L_{i,j}^n(k-1) + \Xi_i^n(t_{2k-1}^n) \Xi_j^n(t_{2k}^n)$$

Let $\Xi_i^n(t_r^n) = Z_i(t_r^n) - Z_i(t_{r-1}^n)$

$$\Xi_i^n(t_{2k-1}^n) = \frac{1}{2} \Xi_i^{n-1}(t_k^{n-1}) + \Delta_{n+1}^{1/2} W_{i,k}^n$$

$$\Xi_i^n(t_{2k}^n) = \frac{1}{2} \Xi_i^{n-1}(t_k^{n-1}) - \Delta_{n+1}^{1/2} W_{i,k}^n$$

$$A_{i,j}(t_k^n, t_{k+1}^n) = \sum_{h=n+1}^{\infty} (L_{i,j}^h(2^{h-n}(k+1)) - L_{i,j}^h(2^{h-n}k))$$

$$R_{i,j}(t_k^n, t_{k'}^n) = \sum_{h=n+1}^{\infty} (L_{i,j}^h(2^{h-n}k') - L_{i,j}^h(2^{h-n}k))$$

The Idea of Record Breakers for Lévy Area

Record breakers: $\{(n, k, k', i, j) : |L_{i,j}^n(k') - L_{i,j}^n(k)| > (k' - k)^\beta \Delta_n^{2\alpha}\}$

$N_2 = \max\{n \geq 1 : |L_{i,j}^n(k') - L_{i,j}^n(k)| > (k' - k)^\beta \Delta_n^{2\alpha} \text{ for some } 0 \leq k < k' \leq 2^{n-1}\}$

➤ $P(N_2 < \infty) = 1$

➤ $\Gamma_R \leq \frac{2^{-(2\alpha-\beta)}}{1-2^{-(2\alpha-\beta)}} \max_{n \leq N_2} \max_{0 \leq k < k' \leq 2^{n-1}} \frac{\|L^n(k') - L^n(k)\|_\infty}{(k' - k)^\beta \Delta_n^{2\alpha}}$

The Idea of Record Breakers for Lévy Area

Record breakers: $\{(n, k, k', i, j) : |L_{i,j}^n(k') - L_{i,j}^n(k)| > (k' - k)^\beta \Delta_n^{2\alpha}\}$

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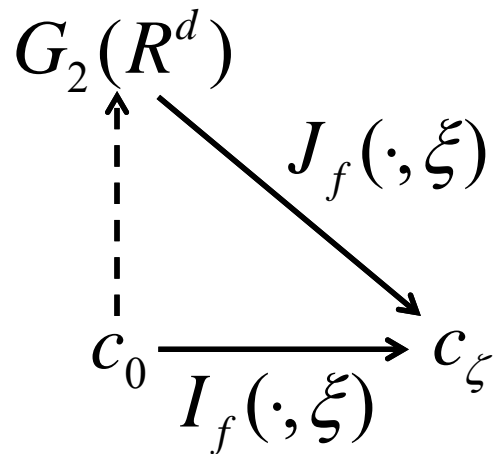
➤ $\Gamma_R \leq \frac{2^{-(2\alpha-\beta)}}{1-2^{-(2\alpha-\beta)}} \max_{n \leq N_2} \max_{0 \leq k < k' \leq 2^{n-1}} \frac{\|L^n(k') - L^n(k)\|_\infty}{(k' - k)^\beta \Delta_n^{2\alpha}}$

➤ $\|A\|_{2\alpha} \leq \Gamma_R \frac{2}{1-2^{-2\alpha}} + \|Z\|_\alpha^2 \frac{2^{1-\alpha}}{1-2^{-\alpha}}$

Summary

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dZ(t)$$

- Theory of Rough Path → construct a continuous mapping



$$Z(t)$$

$$A_{i,j}(s,t) = \int_s^t (Z_i(u) - Z_i(s))dZ_j(u)$$

- Lévy-Ciesielski construction of $\{Z(t): 0 \leq t \leq 1\}$

$$Z(t) \approx W^0 \Lambda^0(t) + \sum_{n=1}^N \sum_{k=1}^{2^{n-1}} W_k^n \Lambda_k^n(t)$$

Thank you !

Record Breakers

Negative drifted random walk

$$S_n = X_1 + X_2 + \dots + X_n \text{ with } E[X_1] < 0$$

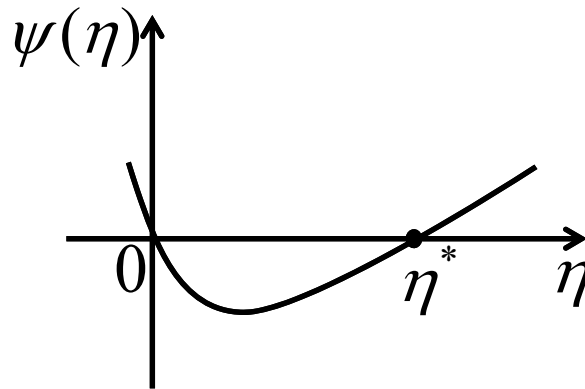
$$T_a = \inf\{n \geq 0 : S_n \geq a\}$$

$$P(T_a = \infty) > 0$$

Negative drifted random walk

$$f_\eta(y) = \exp(\eta y - \psi(\eta))f(y) \text{ where } \psi(\eta) := \log E[\exp(\eta Y_i)]$$

$$\eta^* : \psi(\eta^*) := \log E[\exp(\eta^* Y_i)] = 0$$



$$f_{\eta^*}(y) = f(y)\exp(\eta^* y)$$

$$P(T_a < \infty) = E_{\eta^*} \left[\exp(-\eta^* S_{T_a}) 1_{\{T_a < \infty\}} \right] = E_{\eta^*} \left[\exp(-\eta^* S_{T_a}) \right]$$

$$U \leq \exp(-\eta^* S_{T_a})$$

Simulation of the Lévy Area

$$P_n[\cdot] = P[\cdot | \mathbb{F}_n]$$

$$L_{i,j}^{n+m}(k) = \sum_{r=1}^k \Xi_i^{n+m}(t_{2r-1}^{n+m}) \Xi_j^n(t_{2r}^{n+m})$$

$$\Xi_i^n(t_{2k-1}^n) = \frac{1}{2} \Xi_i^{n-1}(t_k^{n-1}) + \Delta_{n+1}^{1/2} W_{i,k}^n$$

$$\Xi_i^n(t_{2k}^n) = \frac{1}{2} \Xi_i^{n-1}(t_k^{n-1}) - \Delta_{n+1}^{1/2} W_{i,k}^n$$

$$E_n[E_{n+1}[\dots E_{n+m-1}[\exp(\theta_0 \{L_{i,j}^{n+m}(k') - L_{i,j}^{n+m}(k)\})]\dots]]$$

Simulation of the Lévy Area

1. Simulate $M = m, I = i, J = j, K = k, K' = k'$
2. Simulate $\omega_{n:n+m}$
3. Simulate $U \square \text{Uniform}[0,1]$

If $U \leq L_n(m, i, j, k, k', \omega_{n:n+m})$ output $\omega_{n:n+m}$

else we got $N_2 = n$