

One Dimensional SDEs

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Let's investigate time homogeneous
SDEs in one dimension,

$$dX_t = \mu(X_t)dt + \sigma(X_t)dB_t$$

Assume that μ, σ smooth, Lipschitz.

Solutions:

Step (1) Transform it into a
martingale. Find ψ such that $Y_t = \psi(X_t)$
is a martingale. By Ito,

$$dY_t = \psi'(X_t)\mu(X_t)dt + \psi'(X_t)\sigma(X_t)dB_t \\ + \frac{1}{2}\sigma^2(X_t)\psi''(X_t)dt$$

So we want

$$\psi'(x)\mu(x) + \frac{1}{2}\sigma^2(x)\psi''(x) = 0$$

Set $h(x) = \psi'(x)$

$$\frac{d}{dx} \log(h(x)) = \frac{h'(x)}{h(x)} = - \frac{2\mu(x)}{\sigma^2(x)}$$

r

So

$$h(x) = B \exp\left(-\int \frac{2\mu(x)}{\sigma(x)^2} dx\right)$$

$$\psi(x) = A + B \int \exp\left(-\int \frac{2\mu(x)}{\sigma(x)^2} dx\right)$$

Example:

Brownian motion with drift.

$$X_t = \mu t + B_t$$

$$\begin{aligned}\psi(x) &= A + B \int \exp(-2\mu x) dx \\ &= A + B \exp(-2\mu x)\end{aligned}$$

Example Bessel process

$$dX_t = \frac{d-1}{2} \frac{1}{X_t} dt + dB_t$$

$$\psi(x) = A + B \int \exp\left(\int -\frac{d-1}{x} dx\right)$$

$$= A + B \int \exp(-(d-1) \log x)$$

$$= A + B \int x^{-(d-1)} dx$$

$$= \begin{cases} A + B x^{-(d-2)} & d > 2 \\ \log(x) & d = 2 \\ \dots & \dots \end{cases}$$

$$\begin{cases} \log(x) & d=2 \\ A + B x^{-(d-2)} & d < 2. \end{cases}$$

So

$$dY_t = h(Y_t) \sigma(\varphi^{-1}(Y_t)) dB_t = g(Y_t) dB_t$$

So Y_t is a time changed Brownian motion.

Construction:

Let W_t be Brownian motion, set

$$Y_t = \inf \left\{ s : \int_0^s \frac{1}{g^2(W_u)} du = t \right\},$$

set

$$Y_t = W_{\gamma_t}.$$

Then

$$\langle Y \rangle_t = \langle W_{\gamma_t} \rangle_t = \gamma_t$$

$$\begin{aligned} \text{so } d\langle Y \rangle_t &= d\gamma_t = g^2(W_{\gamma_t}) dt \\ &= g^2(Y_t) dt \end{aligned}$$

$$\text{Let } Z_t = \int_0^t \frac{1}{g(Y_s)} dY_s$$

so Z_t is a martingale and

$$\langle Z \rangle_t = \int_0^t \frac{1}{g(Y_s)^2} d\langle Y \rangle_s$$

- t

$$= \int_0^t ds = t$$

so Z_t is Brownian motion and Y_t solves

$$dY_t = g(Y_t) dZ_t.$$

Now set $X_t = \varphi^{-1}(Y_t)$ and

$$dX_t = \mu(X_t) dt + \sigma(X_t) dZ_t.$$

Hitting probabilities

If $x_0 \in [a, b]$ what is the probability that X_t hits a before b ?

$$\text{Let } T = T_{a,b} = \inf\{t: X_t \in \{a, b\}\}$$

$$\begin{aligned} \mathbb{E} \varphi(X_T) &= \mathbb{E} \varphi(X_0) \\ &= \mathbb{P}[X_T = a] \varphi(a) + \mathbb{P}[X_T = b] \varphi(b). \end{aligned}$$

So

$$\mathbb{P}[X_T = a] = \frac{\varphi(b) - \varphi(x_0)}{\varphi(b) - \varphi(a)}$$

$$\text{If } dX_t = \mu(X_t) dt + dB_t$$

under what conditions on $\mu(x)$ is
 $\mathbb{P}[T_a = \infty] > 0$, i.e. X_t is transient.

If $\lim_{b \rightarrow \infty} \varphi(b) < \infty$ then

$$\lim_{b \rightarrow \infty} \mathbb{P}[X_{T_{a,b}} = a] = \lim_{b \rightarrow \infty} \frac{\varphi(b) - \varphi(a)}{\varphi(b) - \varphi(a)} < 1.$$

Recall

$$\varphi(x) = \int_1^x \exp\left(-2 \int_1^y \mu(u) du\right) dy$$

$\varphi(\infty) < \infty$ if $\mu(x)$ is positive and
 doesn't decay too quickly.

Example: Bessel Process if $\mu(x) = \frac{d-1}{2x}$

$$\begin{aligned} \varphi(x) &= \int_1^x \exp(- (d-1) \log y) \\ &= \int_1^x y^{-(d-1)} dy \\ &= \begin{cases} \frac{1}{(2-d)} (x^{-(d-2)} - 1) & d \neq 2 \\ \log x & d = 2 \end{cases} \end{aligned}$$

So $\lim_{x \rightarrow \infty} \varphi(x) < \infty$ iff $d > 2$.

Example
$$dX_t = (X_t^3 - \gamma X_t^4) dt + X_t^{5/2} dB_t$$

Then

$$\begin{aligned} \varphi(x) &= \int_1^x \exp\left(-2 \int_1^y \frac{u^3 - \gamma u^4}{u^5} du\right) dy \\ &= \int_1^x \exp\left(2u^{-1} + 2\gamma \log u\right) dy \\ &= \int_1^x u^{2\gamma} \exp\left(2u^{-1}\right) dy \end{aligned}$$

For any $\gamma \geq -\frac{1}{2}$ $\varphi(x) \rightarrow \infty$ as

$x \rightarrow \infty$ so X_t is recurrent.

$\varphi(x) \rightarrow -\infty$ as $x \rightarrow 0$ so

X_t never hits 0.

If $\varphi(x) \rightarrow 0$ as $x \rightarrow 0$ fast enough,

X_t may never hit 0.

E.g.
$$dX_t = X_t^\alpha dB_t.$$

Then $X_t = W_{\gamma_t}$, W_t B.M.,

$$\gamma_t = \inf\left\{s: \int_0^s \frac{1}{W_u^{2\alpha}} du = t\right\},$$

Let $\tau_n = \inf\{t: W_t = 2^{-n}\}$

Time spent in $[2^{-k-1}, 2^{-k}]$ from time

τ_k to τ_{k+1} approximately, 2^{-2k} ,

$$\mathbb{E} \int_{\tau_k}^{\tau_{k+1}} \frac{1}{W_n^{2\alpha}} dn \gg 2^{2k(\alpha-1)}$$

So if $\tau^* = \inf\{t: W_t = 0\} = \lim \tau_n$,

$$\int_0^{\tau^*} \frac{1}{W_n^{2\alpha}} dn \gg \sum \int_{\tau_k}^{\tau_{k+1}} \frac{1}{W_n^{2\alpha}} dn \rightarrow \infty$$

$\alpha > 1$ so $\gamma_t < \tau^*$ for all t .

Transition Probabilities

Define the semigroup of operators on bounded functions

$$(T_t f)(x) = \mathbb{E}[f(X_t) | X_0 = x]$$

$$(T_0 f)(x) = f(x) \quad \text{so } T_0 f = f.$$

$$T_{t+s} f(x) = \mathbb{E}[f(X_{t+s}) | X_t = 0]$$

$$= \mathbb{E}[\mathbb{E}[f(X_{t+s}) | X_s] | X_t = 0]$$

$$= \mathbb{E}[T_t(f)(X_s) | X_t = 0]$$

$$= T_s(T_t(f))(x_0).$$

The infinitesimal generator is defined as

$$Af = \lim_{h \downarrow 0} \frac{T_h f - f}{h}$$

By the semigroup property

$$\frac{d}{dt} T_t f(x) = A T_t f(x).$$

$$f(X_t) - f(X_0) = \int_0^t m(X_s) ds + \int_0^t \sigma(X_s) dB_s + \frac{1}{2} \int_0^t \sigma^2(X_s) ds$$

$$\frac{1}{h} \mathbb{E}[f(X_t) - f(X_0)] \rightarrow m(x_0) \frac{d}{dx} f(x_0) + \frac{1}{2} \sigma^2(x_0) \frac{d^2}{dx^2} f(x_0).$$

$$A = m(x) \frac{d}{dx} + \frac{1}{2} \sigma^2(x) \frac{d^2}{dx^2}.$$

If $u(x, t) = T_t f(x)$ then $\frac{du}{dt} = Au$.

Solves the PDE,

(i) $u_t = Au$ u is $C^{1,2}$ on $(0, \infty) \times \mathbb{R}$

(ii) $u(0, x) = f(x)$, u is continuous on $[0, \infty) \times \mathbb{R}$. (*)

If $u(t, x)$ solves (*) then $Y_s = u(t-s, X_s)$

$$Y_s - Y_0 = \int_0^s u_x(t-r, X_r) dr + \int_0^s u_x(t-r, X_r) m(X_r) dr$$

$$\begin{aligned}
& -\frac{1}{2} \int_0^s u_{xx}(t-r, X_r) \sigma^2(X_r) dr \\
& + \int_0^s u_x(t-r, X_r) \sigma(X_r) dr \\
& = \int_0^s u_x(t-r, X_r) \sigma(X_r) dr \\
& \text{martingale}
\end{aligned}$$

Hence $E[Y_t | X_0 = x_0] = E[f(X_t) | X_0 = x_0]$
 $= E[Y_0 | X_0 = x_0] = u(t, x_0).$

What is the density of X_t given $X_0 = x$. Call this $p_t(x, y)$.

Then

$$u(t, x) = E[f(X_t) | X_0 = x] = \int_{\mathbb{R}} p_t(x, y) f(y) dy$$

$$0 = u_t - Au = \int_{\mathbb{R}} f(y) \left[\frac{dp}{dt}(t, x, y) - A p(t, x, y) \right] dy.$$

Theorem: If μ, σ are bounded, Hölder continuous, $\inf \sigma^2 > 0$ then $\exists p_t(x, y)$ s.t.

$$u(t, x) = \int_{\mathbb{R}} p_t(x, y) f(y) dy$$

and $\frac{dp}{dt} = Ap$ applied in x co-ordinate.

This is the fundamental solution to the PDE and gives the transition probability

$$P[X_t \in B | X_0 = x_0] = T_t \mathbb{1}_B(x_0)$$

$$= \int_B P_t(x_0, y) dy$$

Example: Ornstein-Uhlenbeck

$$dX_t = -\theta X_t dt + \sigma dB_t,$$

$$\begin{aligned} \text{Heuristic } X_t &= X_{t-\frac{1}{n}} - \frac{\theta}{n} X_{t-\frac{1}{n}} + \sigma N(0, \frac{1}{n}) \\ &= (1 - \theta/n) X_{t-\frac{1}{n}} + \sigma N(0, \frac{1}{n}) \\ &= (1 - \theta/n)^2 X_{t-\frac{2}{n}} + (1 - \theta/n) \sigma N(0, \frac{1}{n}) \\ &\quad + \sigma N(0, \frac{1}{n}) \\ &= \dots \end{aligned}$$

$$\begin{aligned} X_t &= e^{-\theta t} X_0 + \int_0^t e^{-\theta s} \sigma dB_s \\ &\quad N(0, \sigma^2 \int_0^t e^{-2\theta s} ds) \end{aligned}$$

$$\begin{aligned} P_t(x, y) &= \frac{1}{\sqrt{2\pi(\sigma^2/2\theta)(1-e^{-2\theta t})}} \exp\left(-\frac{(y - e^{-\theta} x)^2}{(\sigma^2/\theta)(1-e^{-2\theta t})}\right) \\ &\sim N(e^{-\theta} x, \frac{\sigma^2}{2\theta}(1-e^{-2\theta t})) \end{aligned}$$

Converges to $N(0, \frac{\sigma^2}{2\theta})$.

What is the stationary distribution
in general?

Three approaches

(1) Find $\pi(x)$ such that

$$\int \pi(x) p_t(x, y) dx = \pi(y).$$

(2) Take limit $\lim_{t \rightarrow \infty} p_t(x, y) = \pi(y)$.

(3) If π is stationary

$$\mathbb{E}_\pi f(X_0) = \mathbb{E} f(X_t)$$

$$\text{So } \frac{d}{dt} \mathbb{E}_\pi f(X_t) = 0$$

$$= \int \pi(x) A f(x) dx$$

$$= \int \pi(x) \left[\mu(x) \frac{d}{dx} f(x) + \frac{1}{2} \sigma^2(x) \frac{d^2}{dx^2} f(x) \right]$$

$$= \int \left[-\frac{d}{dx} [\pi(x) \mu(x)] + \frac{d^2}{dx^2} \left[\frac{1}{2} \sigma^2(x) \pi(x) \right] \right] f(x) dx$$

$$\text{So } \frac{d}{dx} \left[-\pi(x) \mu(x) + \frac{d}{dx} \left[\frac{1}{2} \sigma^2(x) \pi(x) \right] \right] = 0$$

$$\text{Solve } -\pi(x) \mu(x) + \frac{d}{dx} \left[\frac{1}{2} \sigma^2(x) \pi(x) \right] = 0$$

$$-(\mu(x) - \sigma(x) \sigma'(x)) \pi(x) + \frac{1}{2} \sigma^2(x) \pi'(x) = 0$$

$$d \ln(\pi(x)) = \frac{\pi'(x)}{\pi(x)} = \frac{2(\mu(x) - \sigma(x) \sigma'(x))}{\sigma^2(x)}$$

$$\frac{d}{dx} \log(\pi(x)) = \frac{\pi'(x)}{\pi(x)} = \frac{2(M(x) - \sigma'(x)\sigma(x))}{\sigma^2(x)}$$

$$\pi(x) = \frac{1}{2} \exp\left(\int_0^x \frac{2(M(y) - \sigma'(y)\sigma(y))}{\sigma^2(y)} dy\right)$$

For the Ornstein-Uhlenbeck process, $M = -\theta x$

$$\pi(x) = \frac{1}{2} \exp\left(\frac{-\theta x^2}{\sigma^2}\right) = \frac{1}{2} \exp\left(-\frac{x^2}{2(\sigma^2/\theta)}\right)$$

For $dX_t = (X_t^3 - \gamma X_t^4) dt + X_t^{5/2} dB_t$,

$$\pi(x) = \exp\left(\int_1^x \frac{2(y^3 - \gamma y^4 - \frac{5}{2} y^3 \cdot y^{\frac{5}{2}})}{y^5} dy\right)$$

$$= \exp\left(\int_1^x 2y^{-2} - (2\gamma + 5)y^{-1} dy\right)$$

$$= \exp(-2x^{-1} - (2\gamma + 5) \log x)$$

$$= x^{-(2\gamma+5)} \exp(-2x^{-1})$$

Inverse Gamma $(2\gamma+4, 2)$.

Connection to PDEs

Dirichlet Problem on \mathbb{R}^d

$$\Delta u = 0 \quad \text{in } D, \quad u \text{ is } C^2$$

$u = g$ on ∂D . and continuous

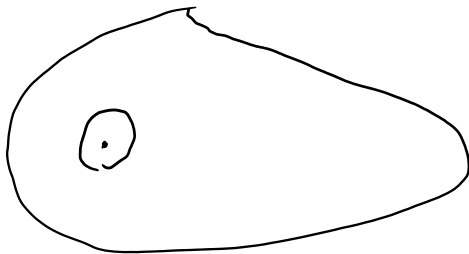
Assume D is open, bounded, ∂D is C^∞ manifold.

Let τ be first exit time of D ,

$$u(x) = \mathbb{E}[f(B_\tau) | X_0 = x].$$

Then $u(B_{t \wedge \tau})$ is a martingale.

Mean value property



$\{f\}$ B ball around x_0 ,

$$\begin{aligned} u(x_0) &= \mathbb{E}[f(B_\tau) | \tau_B] \\ &= \mathbb{E}[u(B_{\tau_B})] \\ &= \int_{\partial B} u(y) dy \end{aligned}$$

So by the mean value property

u is C^∞ , $\Delta u = 0$.

Without PDE's

• Smoothness:

Let $\psi: [0, \infty)$ be C^∞

supported on $[\frac{\delta}{2}, \delta]$, positive on $(\frac{\delta}{2}, \delta)$.

Then
$$\int_{\mathbb{R}^2} u(y) \psi(|x-y|) dy = C_4$$

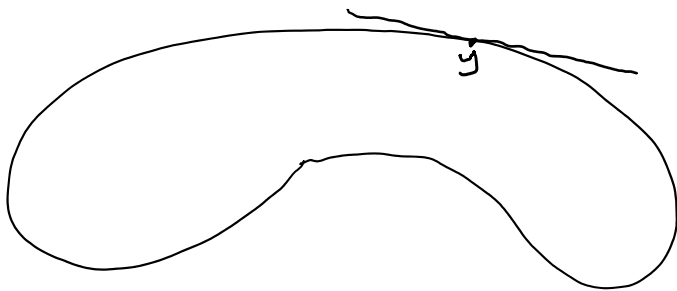
so u is C^∞ .

By Itô's formula,

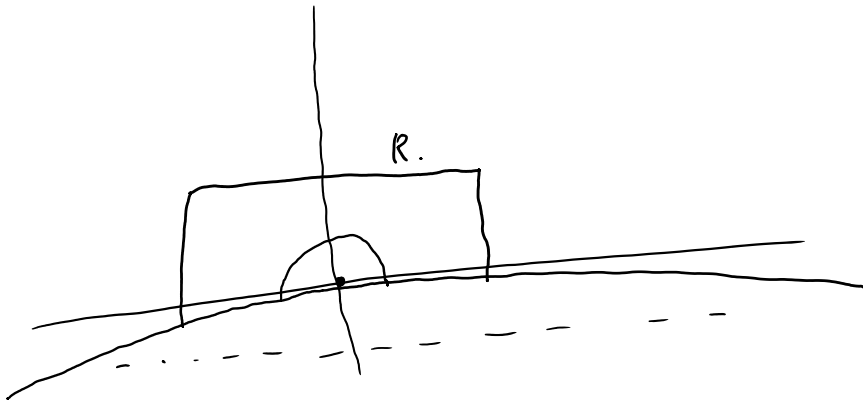
$$u(B_{t \wedge \tau}) - u(B_0) = \sum_i \int_0^t u_{x_i}(B_s) dB_s^i + \frac{1}{2} \int_0^t \Delta u(B_s) ds$$

and since $u(B_s)$ is a martingale.

- Need to check u is continuous on ∂D .



Suppose $y \in \partial D$.
Translate & rotate so that y is at the origin and the tangent plane is the x -axis



Suppose the surface is the graph of a function $f(x)$ locally and $|f(x)| \leq \delta |x|$ for $|x| \leq R$.

Pick R small enough so that $|f(x) - f(0)| \leq \frac{\epsilon}{2}$ for $|x| \leq R$.

If $|z| < \delta R$ then, let A be the event

$$\left\{ \sup_{0 \leq s \leq \theta R^2} |B_s^{(1)}| \leq R/2, \inf_{0 \leq s \leq \theta R^2} B_s^{(2)} \leq -2\delta R \right\}$$

$$\begin{aligned} \mathbb{P}[A^c] &\leq 4 \mathbb{P}[|B_{\theta R^2}| \geq \frac{R}{2}] + \mathbb{P}[|B_{\theta R^2}| \leq 2\delta R] \\ &= 4 \mathbb{P}[N(0,1) \geq \frac{1}{2} \theta^{-1/2}] + \mathbb{P}[N(0,1) \leq 2\delta \theta^{-1/2}] \\ &\leq \epsilon. \end{aligned}$$

if $\delta \ll \sqrt{\theta} \ll 1$.

On the event A ,

$$\mathbb{E}[|f(B_c) - f(B_0)|] \leq \epsilon \mathbb{P}[A] + 2\|f\| \mathbb{P}[A^c]$$

. b . . . F T . ?

• What if I wanted to know $E\tau$?

• Let $f(x_1, x_2) = -x_1^2$ u solves the Dirichlet problem for $\Delta u \equiv 0$, $u = f$ on ∂D .

Then if $v = u - f$, $\Delta v = -2$, $v \equiv 0$ on ∂D .

$$v(x_t) - v(x_0) = \sum_{x_i} \int v_{x_i}(x_s) dB_s^{(i)} + \frac{1}{2} \int_0^\tau \Delta v(x_s) ds$$

$$-v(x_0) = E - \int_0^\tau ds = -E\tau$$

$$v(x_0) = E\tau.$$

Hitting Measure

What is the density h on ∂D ?

Half plane



$$H := \{(x, y) : x \in \mathbb{R}^{d-1}, y \in \mathbb{R}, y > 0\}$$

...

... \mathbb{R}^{d-1}

$$H := \{(x, y) : x \in \mathbb{R}^d, y > 0\}$$

$$\text{Let } h_\theta(x, y) = \frac{C_d y}{((x - \theta)^2 + y^2)^{d/2}} \text{ for } \theta \in \mathbb{R}^{d-1}$$

$$\text{such that } \int_{\mathbb{R}^{d-1}} h_\theta(0, 1) d\theta = 1.$$

$$\Delta h_\theta = \sum_i \frac{d^2}{dx_i^2} h_\theta(x, y) + \frac{d}{dy^2} h_\theta(x, y) = 0$$

Set

$$u(x, y) = \int_{\mathbb{R}^{d-1}} h_\theta(x, y) f(\theta) d\theta.$$

$$\Delta u = 0,$$

If $x_n \rightarrow x, y_n \rightarrow 0$ then

$$u(x_n, y_n) \rightarrow f(x)$$

So

$$u(x, y) = \mathbb{E}[f(B_{\tau_H}) \mid B_0 = (x, y)]$$

and the hitting density from $(x, y) \in H$ to $\theta \in \partial H$ is $h_\theta(x, y)$.

$$h_\theta(0, 1) = \frac{1}{\pi(1 + \theta^2)} \quad \text{Cauchy Distribution}$$

Also,

$$h_0 \sim B_\tau^{(1)}$$

$$\text{where } \tau = \inf\{t: B_t^{(2)} - B_0^{(2)} = -1\}.$$

By Brownian Scaling

$$h_0 \sim \sqrt{\tau} N(0,1)$$

$$P[\tau \leq t] = P[\min_{0 \leq s \leq t} B_s^{(2)} \leq -1]$$

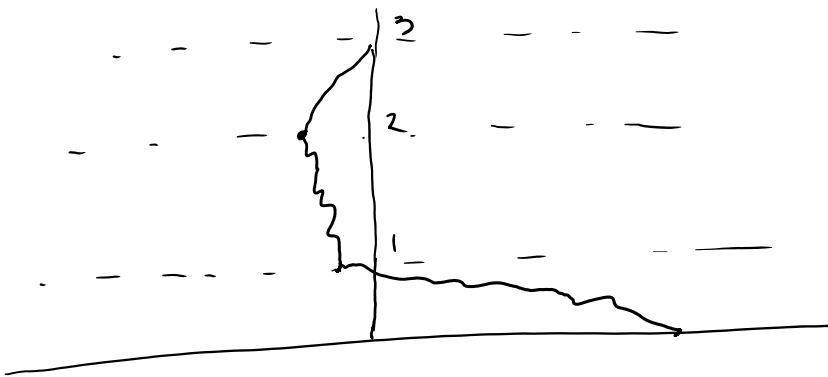
$$= P[\max_{0 \leq s \leq t} B_s \geq 1] = P[|B_t| \geq 1]$$

$$= P[|N(0,1)| \geq 1/\sqrt{t}] = P\left[\frac{1}{|N(0,1)|^2} \leq t\right]$$

So $h_0 = \frac{1}{W}$ ratio of independent normals

Another reason it must be Cauchy.

The Cauchy distribution is the only symmetric 1-self similar process (up to scaling)



Starting from $(0, h)$ let $\tau_h = \inf\{t: B_t^{(2)} = h\}$.

Then set $Y_j = B_{T_j}^{(1)} - B_{T_{j-1}}^{(1)} \sim h_\theta(0,1)$
independent

$$B_{T_n}^{(1)} - B_{T_0}^{(1)} \sim h_\theta(0, k)$$

So h_θ is 1-self similar.

Other Domains

A map $f: D \rightarrow D'$, $D, D' \in \mathbb{C}$ is conformal if it is holomorphic and has derivative that is no-where vanishing.

$\Delta f = 0$ so $f(B_t)$ is a martingale.

Let $f(z) = u(z) + i v(z)$, $u(B_t) = U_t$, $v(B_t) = V_t$.

Thm: If M_t is a d -dimensional martingale

$$\langle M^{(i)}, M^{(j)} \rangle_t = \begin{cases} 0 & \text{if } i \neq j \\ t & \text{if } i = j \end{cases}$$

then M_t is d -dimensional B.M.

Proof: $\sum a_i M_t^{(i)}$ is a one dimensional martingale with $\langle \sum a_i M_t^{(i)}, \sum a_i M_t^{(i)} \rangle = t \sum a_i^2$

So is B.M. $\times \sqrt{\Sigma \alpha_i^2}$. Follows that jointly Gaussian with same covariance as B.M. \square

$$U_t - U_0 = \int_0^t u_x(B_s) dB_s^{(1)} + \int_0^t u_y(B_s) dB_s^{(2)}$$

$$V_t - V_0 = \int_0^t v_x(B_s) dB_s^{(1)} + \int_0^t v_y(B_s) dB_s^{(2)}$$

Cauchy - Riemann Relations

$$\boxed{u_x = v_y \quad u_y = -v_x}$$

$$\begin{aligned} \mathbb{E} \langle U \rangle_t &= \int_0^t (u_x(B_s))^2 + (u_y(B_s))^2 ds \\ &= \langle V \rangle_t \end{aligned}$$

$$\begin{aligned} \langle U+V \rangle_t &= \int_0^t (u_x + v_x)^2 + (u_y + v_y)^2 ds \\ &= \int_0^t u_x^2 + v_x^2 + u_y^2 + v_y^2 ds \\ &= \langle U \rangle_t + \langle V \rangle_t \end{aligned}$$

$$\begin{aligned} \mathbb{E} \langle U, V \rangle_t &= \frac{1}{2} (\langle U+V \rangle_t - \langle U \rangle_t - \langle V \rangle_t) \\ &= 0. \end{aligned}$$

If $\gamma_t = \inf \{s : \langle U \rangle_s = t\}$ then

$W_t = f(B_{\gamma_t})$ is 2-d B.M.

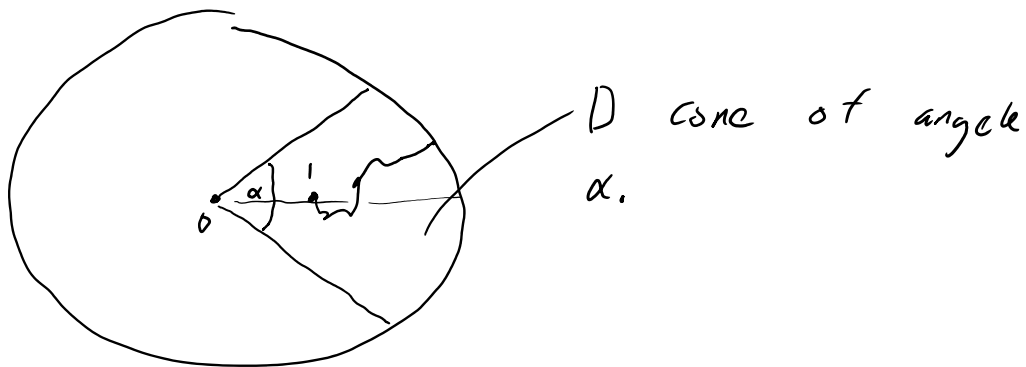
So $f(B_t)$ is time changed Brownian Motion.

By the Riemann - Mapping Theorem there is a conformal map between any simply connected open subdomains of \mathbb{C}

$$f: H \rightarrow D'$$

and the hitting measure on D' starting from z is the push forward of $h_0(f^{-1}(z))$.

Example



Ball of radius r . $B_0 = 1$.

$$T_r = \inf\{s: B_s = r\}$$

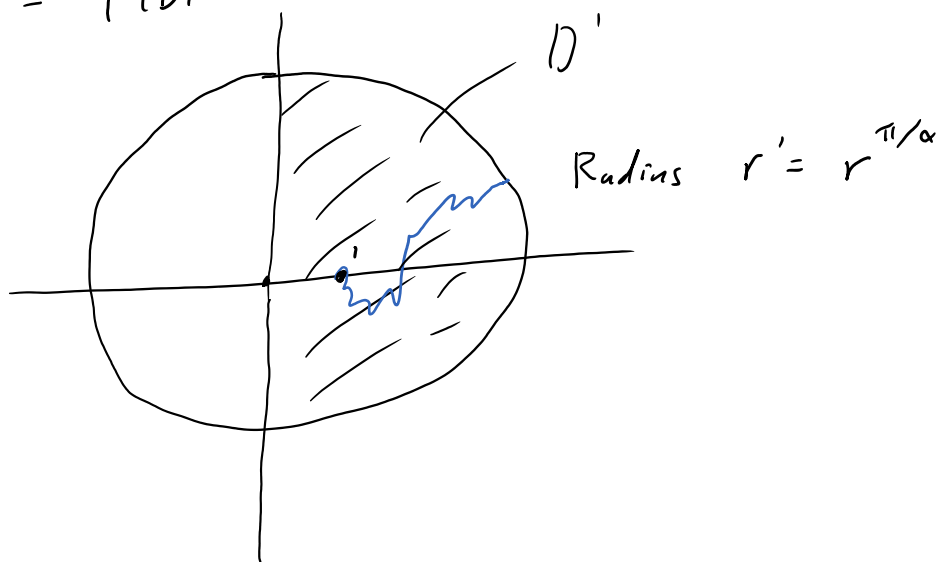
$$\mathbb{P}\{T_{\partial D} = T_r\}$$

i.e. exits cone through circle.

Set $f(x) = x^{\pi/\alpha}$

Set $f(z) = z^\alpha$

$$D' = f(D)$$



$$\mathbb{P}[T_{\partial D'} = T_{r'}] = \mathbb{P}[T_{\partial D} = T_r]$$

Let $S = \inf \{t : \operatorname{Re}(B_t) = 0\}$

$$\tilde{B}_t = \begin{cases} B_t & t \leq S \\ B_t - 2\operatorname{Re}(B_t) & t \geq S \end{cases} \quad \text{Reflection Principles}$$

$$B_t \stackrel{d}{=} \tilde{B}_t$$

$$\mathbb{P}[\operatorname{Re}(B_{T_{r'}}) > 0]$$

$$= \mathbb{P}[\operatorname{Re}(B_{T_{r'}}) > 0, S > T_{r'}] + \mathbb{P}[\operatorname{Re}(B_{T_{r'}}) > 0, S < T_{r'}]$$

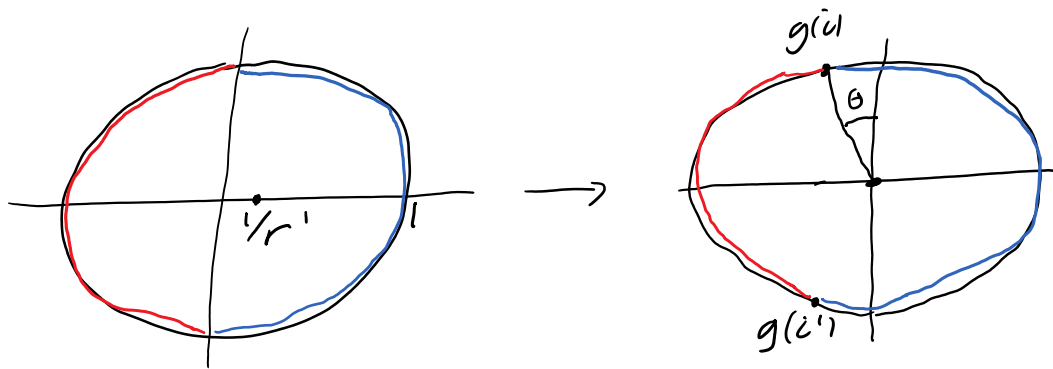
$$= \mathbb{P}[S > T_{r'}] + \mathbb{P}[\operatorname{Re}(\tilde{B}_{T_{r'}}) < 0]$$

$$\mathbb{P}[S > T_{r'}]$$

$$= \mathbb{P}[\operatorname{Re}(B_{T_{r'}}) > 0] - \mathbb{P}[\operatorname{Re}(B_{T_{r'}}) < 0]$$

$$= \mathbb{P} [\text{Re}(B_{T_{r'}}) > 0] - \mathbb{P} [\text{Re}(B_{T_{r'}}) < 0]$$

Now map to unit disc with $B_0 = 1/r'$.



Let g be the Moebius Transform

$$g(z) = \frac{z - 1/r'}{1 - z/r'}$$

which maps $B(1)$ to itself and 1 to 0 .

$$g(i) = \frac{i - 1/r'}{1 - i/r'} = \frac{(r'i - 1)(r' + i)}{(r' - i)(r' + i)} = \frac{((r')^2 - 1)i - 2r'}{(r')^2 + 1}$$

$$| \text{Blue} - \text{Red} | = 4\theta$$

$$\theta = \arctan\left(\frac{2r'}{(r')^2 - 1}\right)$$

$$\mathbb{P} [S > T_{r'}] = \frac{1}{2\pi} \cdot 4 \arctan\left(\frac{2r'}{(r')^2 - 1}\right)$$

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$$= \frac{2}{\pi} \arctan \left(\frac{2r^{1/\alpha}}{r^{2/\alpha} - 1} \right)$$

Hausdorff Dimension of Brownian Motion

α -Hausdorff content

$$\mathcal{H}^\alpha(E) = \inf \left\{ \sum_i |E_i|^\alpha : E \subseteq \bigcup E_i \right\}$$

$|E_i|$ = diameter of E .

Hausdorff Dimension

$$\text{Dim}(E) = \inf \{ \alpha \geq 0 : \mathcal{H}^\alpha(E) > 0 \}$$

A box in \mathbb{R}^d dimension d , line $\text{dim } 1$, point $\text{dim } 0$.

What about the range of 2 dimensional B.M?

Upper bound:

If $f(x)$ is β -Hölder continuous then

$$E = \text{Range}(f) := \{ f(x) : x \in [0, 1] \}$$

has Hausdorff dimension at most $\frac{1}{\beta}$.

Proof: $|f(x) - f(y)| \leq C|x - y|^\beta$

So let $E_i^{(n)} = B_{r/n}(f(i/n))$ for $1 \leq i \leq n$.

So let $E_i = B_{cn^{-\beta}}(f(\frac{i}{n}))$ for $1 \leq i \leq n$.

Then $f(x) \in E_i^{(n)}$ for $\frac{i-1}{n} \leq x \leq \frac{i}{n}$,

$$|E_i^{(n)}| \leq 2Cn^{-\beta}.$$

For $\alpha > 1/\beta$,

$$\sum |E_i^{(n)}|^\alpha \leq (2Cn^{-\beta})^\alpha \cdot n$$

$$\rightarrow 0.$$

Hence $H^\alpha(E) = 0$ so $\dim(E) \leq 1/\beta$.

Lemma: Brownian motion on $[0,1]$ is

α -Hölder continuous for all $\alpha < 1/2$.

Proof:

Let $A_i^n = [(i-1)2^{-n}, (i)2^{-n}]$.

If $x, y \in [0,1]$, $2^{-(n+1)} \leq x-y \leq 2^{-n}$

then $x, y \in A_i^n$ for some $1 \leq i \leq 2^n$.

For $L > 0$, let $D_i^n(L)$ be the event

$$D_i^n(L) := \left\{ \max_{x, y \in A_i^n} |B(x) - B(y)| \leq L 2^{-(n+1)\alpha} \right\}.$$

If $\bigcap_{n \geq 0} \bigcap_{i=1}^{2^n} D_i^n(L)$ holds then

$B(t)$ is α -Hölder with constant L .

By Markov property $\mathbb{P}[D_i^n] = \mathbb{P}[D_1^n]$.

By Brownian Scaling,

$$\begin{aligned}\mathbb{P}[D_1^n(L)] &= \mathbb{P}\left[\max_{0 \leq x, y \leq 2 \cdot 2^{-n}} |B(x) - B(y)| \leq L 2^{-\alpha(n+1)}\right] \\ &= \mathbb{P}\left[\max_{0 \leq x, y \leq 2} |B(x) - B(y)| \cdot 2^{-n/2} \leq L 2^{\left(\frac{1}{2} - \alpha\right)n} 2^{-\alpha}\right] \\ &= \mathbb{P}\left[D_1^0(L 2^{\left(\frac{1}{2} - \alpha\right)n})\right]\end{aligned}$$

$\mathbb{P}[D_1^0(L)]$

$$= \mathbb{P}\left[\max_{0 \leq x \leq 2} B(x) - \min_{0 \leq x \leq 2} B(x) \leq L 2^{-\alpha}\right]$$

$$\leq 2 \mathbb{P}\left[\max_{0 \leq x \leq 2} B(x) \leq L 2^{-\alpha-1}\right]$$

$$\leq \exp(-c L^2).$$

$\mathbb{P}\left[\bigcap_n \bigcap_i D_i^n(L)\right]$

$$= \sum_n 2^{n+1} \exp(-c_2 L^2 2^{\left(\frac{1}{2} - \alpha\right)n})$$

$< \infty$

$\rightarrow 0$ as $L \rightarrow \infty$.

So $B(E)$ is a.s. α -Hölder.

Corollary: $\text{Range}(B(E)) \leq 2$ for $d \geq 2$.

Lower Bound:

Define the α -energy of a measure μ as

$$I_\alpha(\mu) := \iint |x-y|^{-\alpha} d\mu(x) d\mu(y).$$

Theorem: If μ is a measure supported on E ,

$$\mathcal{H}^\alpha(E) \geq \frac{\mu(E)^2}{I_\alpha(E)}$$

Proof: If A_n is a pairwise disjoint

covering of E , such that $\mathcal{H}^\alpha(E) \leq \sum_n |A_n|^\alpha \leq \mathcal{H}^\alpha(E) + \delta$,

$$I_\alpha(E) \geq \sum_n \int_{A_n} \int_{A_n} |x-y|^{-\alpha} \mu(dx) \mu(dy)$$

$$\geq \sum_n \frac{\mu(A_n)^2}{|A_n|^\alpha}$$

$$\mu(E) \leq \sum_n \mu(A_n) = \sum_n |A_n|^{\alpha/2} \frac{\mu(A_n)}{|A_n|^{\alpha/2}}$$

By Cauchy-Schwarz,

$$\begin{aligned} \mu(E)^2 &\leq \left(\sum |A_n|^\alpha \right) \sum \frac{\mu(A_n)^2}{|A_n|^\alpha} \\ &\leq (\mathcal{H}(E) + \delta) \cdot I_\alpha(\mu) \end{aligned}$$

Take the occupation measure of d -dimensional
Brownian motion

$$\mu(A) = \int_0^1 \mathbb{I}(B(t) \in A) dt.$$

Then

$$\begin{aligned} \mathbb{E} I_\alpha(\mu) &= \int_0^1 \int_0^1 \mathbb{E} |B(t) - B(s)|^{-\alpha} ds dt \\ &= \int_0^1 \int_0^1 \mathbb{E} |B(t-s)|^{-\alpha} ds dt \\ &\leq 2 \int_0^1 \mathbb{E} |B(t)|^{-\alpha} dt \\ &= 2 \mathbb{E} |B(1)|^{-\alpha} \int_0^1 t^{-\frac{\alpha}{2}} dt \end{aligned}$$

If $d \geq 2$, $\alpha < 2$ then

$$\mathbb{E} |B(1)|^{-\alpha} = \int_{\mathbb{R}^d} |x|^{-\alpha} \frac{1}{(\sqrt{2\pi})^d} e^{-|x|^2/2} dx < \infty$$

So $\mathbb{E} I_\alpha(\mu) < \infty$.

Hence

$$\mathcal{H}^\alpha(E) \geq \frac{1}{I_{\alpha}(L)} > 0 \quad \text{a.s.}$$

So $\dim(E) \geq \alpha$.

Taylor's Theorem The range of Brownian motion is 2 for $d \geq 2$.

Dimension of zero set and record times.

Let $Z = \{t: B(t) = 0\}$.

Let $R = \{t: B(t) = M(t)\}$ $M(t) = \max_{0 \leq s \leq t} B(s)$.

For $\alpha < \frac{1}{2}$, B.M. is α -Hölder a.s. and hence so is $M(t)$. If $\{A_n\}$ is a union of disjoint intervals covering E , $A_n = (a_n, b_n)$

$$\begin{aligned} \mathcal{H}^\alpha(E) &\geq \sum_n |A_n|^\alpha - \delta \\ &\geq \sum_n |b_n - a_n|^\alpha - \delta \\ &\geq \sum_n \frac{M(b_n) - M(a_n)}{L} - \delta \\ &\geq \frac{1}{L} [M(1) - M(0)] - \delta \\ &> 0. \end{aligned}$$

So $\dim(R) \geq \frac{1}{2}$.

Let $Y_t = M_t - B_t$.

Theorem: $\{Y_t\} \stackrel{d}{=} \{B_t\}$ and is a Markov process

Proof:

(M_t, B_t) is a Markov process.

Since if $X = \max_{0 \leq u \leq s} B_{t+u} - B_t$,

$$Z = B_{t+s} - B_t$$

Then (X, Z) is independent of \mathcal{F}_t

and

$$(M_{t+s}, B_t) = (M_t \vee B_t + X, B_t + Z).$$

Now

$$\begin{aligned} Y_{t+s} &= (M_t \vee B_t + X) - (B_t + Z) \\ &= Y_t \vee X - Z \end{aligned}$$

which only involves (M_t, B_t) through Y_t so

Y_t is also a Markov chain.

To show that $Y_t \stackrel{d}{=} |B_t|$ it suffices to show that

$$\begin{aligned} \mathbb{P}[Y_{t+s} > a \mid Y_t = y] &= \mathbb{P}[|B_{t+s}| > a \mid |B_t| = y] \\ &= \mathbb{P}[|N(y, s)| > a]. \end{aligned}$$

As this will imply equal finite dimensional distributions and they both have continuous paths.

$$\text{Let } \hat{M}_s = y \vee M_s, \quad \hat{Y}_s = \hat{M}_s - B_s$$

$$P[Y_{t+s} > a \mid Y_t = y]$$

$$= P[\hat{Y}_s > a]$$

Now

$$P[\hat{Y}_t > a]$$

$$= P[y - B_s > a]$$

$$+ P[y - B_s \leq a, M_s - B_s > a] \quad \leftarrow \text{since } M_s > y$$

$$= (I) + (II)$$

$$(I) = P[N(y, s) > a]$$

For (II) set $W_u = B_{s-u} - B_s$ also B.M.

$$\text{Let } N_t = \max_{0 \leq u \leq t} N_u = \left(\max_{0 \leq u \leq t} M_{s-u} \right) - B_s$$

$$\text{so } N_s = M_s - B_s$$

So applying reflection principle to W_s at a ,

$$(II) = P[y + W_s \leq a, N_s > a]$$

$$= P[y + 2a - W_s^* \leq a, N_s^* > a]$$

$$\begin{aligned}
&= \mathbb{P}[y - W_s^* \leq -a] \\
&= \mathbb{P}[N(y, s) \leq -a]
\end{aligned}$$

$$\text{So } (I) + (II) = \mathbb{P}[|N(y, s)| > a].$$

Stronger Result

$$\{(|B_t|, L_t^0)\}_{t \geq 0} \stackrel{d}{=} \{ (M_t - B_t, M_t) \}_{t \geq 0}.$$

Lemma: $\dim(Z) \leq \frac{1}{2}$.

$$\text{Let } A_i^{(n)} = [in, (i+1)n].$$

$$\begin{aligned}
\text{Then } &\mathbb{P}[Z \cap A_i \neq \emptyset] \\
&= \mathbb{P}\left[\max_{\frac{i}{n} \leq t \leq \frac{i+1}{n}} B_t - B_{in} > |B_{in}| \right] \\
&= \mathbb{P}[|N(0, \frac{1}{n})| > |N(0, i/n)|] \\
&\approx C i^{-\frac{1}{2}}.
\end{aligned}$$

So

$$\begin{aligned}
\mathbb{E} |H^\alpha(Z)| &\leq \mathbb{E} \sum_i \left(\frac{1}{n}\right)^\alpha I(A_i^{(n)} \cap Z) \\
&\leq C \sum_i n^{-\alpha} i^{-\frac{1}{2}} \approx C' n^{\frac{1}{2}-\alpha} \\
&\rightarrow 0 \text{ if } \alpha > \frac{1}{2}.
\end{aligned}$$