

## Definition: Progressively measurable

$\sigma(\mathbf{s}, \omega)$  is called *progressively measurable* if

- 1 i.  $\sigma(\mathbf{s}, \omega)$  is  $\mathcal{B}[0, \infty) \times \mathcal{F}$  measurable;
- 2 ii. For all  $t \geq 0$ , the map  $[0, t] \times \Omega \rightarrow \mathbb{R}$  given by  $\sigma(\mathbf{s}, \omega)$  is  $\mathcal{B}[0, t] \times \mathcal{F}_t$  measurable.

$\mathcal{B}[0, t]$  denotes the Borel  $\sigma$ -algebra on  $[0, t]$ .

Informally,  $\sigma(\mathbf{s}, \omega)$  is *nonanticipating* = uses information about  $\omega$  contained in  $\mathcal{F}_s$ .

## Definition: Simple Functions

$\sigma(\mathbf{s}, \omega)$  is called *simple* if there exists a partition  $0 \leq s_0 < s_1 < \dots$  of  $[0, \infty)$  and bounded random variables  $\sigma_j(\omega) \in \mathcal{F}_{s_j}$  such that  $\sigma(\mathbf{s}, \omega) = \sigma_j(\omega)$  for  $s_j \leq \mathbf{s} < s_{j+1}$ .

## Definition: Stochastic Integral for Simple Functions

Given such a  $\sigma(s, \omega) = \sigma_j(\omega)$  for  $s_j \leq s < s_{j+1}$ ,  $\sigma_j(\omega) \in \mathcal{F}_{s_j}$  define

$$\int_0^t \sigma(s, \omega) dB(s) = \sum_{j=0}^{J(t)-1} \sigma_j(\omega) (B(s_{j+1}) - B(s_j)) + \sigma_{J(t)}(\omega) (B(t) - B(s_{J(t)}))$$

where  $s_{J(t)} < t \leq s_{J(t)+1}$ .

## Basic properties

- 1  $\int_0^t (c_1 \sigma_1 + c_2 \sigma_2) dB = c_1 \int_0^t \sigma_1 dB + c_2 \int_0^t \sigma_2 dB.$
- 2  $\int_0^t \sigma dB$  is a continuous martingale

## Proof.

Since  $\sigma_j \in \mathcal{F}_{s_j}$ , if  $u \geq s_j$ ,  $E[\sigma_j(B(s_{j+1}) - B(s_j)) | \mathcal{F}_u] = \sigma_j(B(u) - B(s_j))$   
and if  $u < s_j$ ,  $E[\sigma_j(B(s_{j+1}) - B(s_j)) | \mathcal{F}_u] =$   
 $E[E[\sigma_j(B(s_{j+1}) - B(s_j)) | \mathcal{F}_{s_j}] | \mathcal{F}_u] = 0.$  □

## Basic properties

$$3 \quad E[(\int_0^t \sigma(s, \omega) dB(s))^2] = E[\int_0^t \sigma^2(s, \omega) ds]$$

### Proof.

$$\int_0^t \sigma dB = \sum_j \sigma_j (B(s_{j+1} \wedge t) - B(s_j))$$

$$E[(\int_0^t \sigma dB)^2] = \sum_{i,j} E[\sigma_i \sigma_j (B(s_{i+1} \wedge t) - B(s_i))(B(s_{j+1} \wedge t) - B(s_j))]$$

$$i < j : E[E[\sigma_i \sigma_j (B(s_{i+1} \wedge t) - B(s_i))(B(s_{j+1} \wedge t) - B(s_j)) \mid \mathcal{F}_{s_j}]] = 0$$

$$i = j : E[\sigma_j^2 (B(s_{j+1} \wedge t) - B(s_j))^2] =$$

$$E[E[\sigma_j^2 (B(s_{j+1} \wedge t) - B(s_j))^2 \mid \mathcal{F}_{s_j}]] = E[\sigma_j^2] (s_{j+1} \wedge t - s_j)$$

$$E[(\int_0^t \sigma dB)^2] = \sum_j E[\sigma_j^2 (B(s_{j+1} \wedge t) - B(s_j))^2] = E[\int_0^t \sigma^2 ds]$$



## Basic properties

4  $Z(t) = \exp\{\int_0^t \sigma dB - \frac{1}{2} \int_0^t \sigma^2 ds\}$  is a continuous martingale

### Proof.

Suppose  $t \geq u \geq J(t)$ . Then  $E[e^{\int_0^t \sigma dB - \frac{1}{2} \int_0^t \sigma^2 ds} | \mathcal{F}_u]$  can be written

$$e^{\sum_{j=0}^{J(t)-1} \sigma_j (B(s_{j+1}) - B(s_j)) - \frac{1}{2} \sigma_j^2 (s_{j+1} - s_j)} E[e^{\sigma_{J(t)} (B(t) - B(s_{J(t)})) - \frac{1}{2} \sigma_{J(t)}^2 (t - s_{J(t)})} | \mathcal{F}_u].$$

The expectation is just 1, so we have that  $E[Z(t) | \mathcal{F}_u] = Z(u)$  whenever  $t \geq u \geq J(t)$ . It follows by repeated conditioning that  $E[Z(t) | \mathcal{F}_u] = Z(u)$  for any  $u \leq t$ . □

$\mathcal{P}$  = set of progressively measurable functions

### Lemma

For each  $t > 0$ ,  $\mathcal{P} = \text{Closure in } L^2([0, t] \times \Omega, dt \times dP)$  of simple functions

### Proof

Suppose  $\sigma \in \mathcal{P}$  and  $E[\int_0^t \sigma^2(s, \omega) ds] < \infty$   
we need to find a sequence  $\sigma_n$  of simple functions s.t.

$$E[\int_0^t (\sigma(s, \omega) - \sigma_n(s, \omega))^2 ds] \rightarrow 0.$$

We can assume that  $\sigma$  is bounded For if  $\sigma_N = \sigma$  for  $|\sigma| \leq N$  and 0 otherwise then  $\sigma_N \rightarrow \sigma$  and  $|\sigma_N - \sigma|^2 \leq 4|\sigma|^2$  so by the dominated convergence theorem  $E[\int_0^t (\sigma - \sigma_N)^2 ds] \rightarrow 0$ .

## Proof.

Furthermore we can assume that  $\sigma$  is continuous in  $s$

for if  $\sigma$  is bounded then  $\sigma_h = h^{-1} \int_{t-h}^t \sigma ds$  are continuous progressively measurable and converge to  $\sigma$  as  $h \rightarrow 0$ . By the bounded convergence theorem

$$E\left[\int_0^t (\sigma - \sigma_h)^2 ds\right] \rightarrow 0$$

For  $\sigma$  continuous bounded and progressively measurable let

$$\sigma_n(s, \omega) = \sigma\left(\frac{\lfloor ns \rfloor}{n}, \omega\right)$$

These are progressively measurable, bounded and simple functions converging to  $\sigma$  and again by the bounded convergence theorem,

$$E\left[\int_0^t (\sigma - \sigma_n)^2 ds\right] \rightarrow 0$$

## Theorem (Definition of the Itô Integral)

Let  $\sigma(s, \omega)$  be progressively measurable and for each  $t \geq 0$ ,  $E[\int_0^t \sigma^2 ds] < \infty$ . Let  $\sigma_n$  be simple functions with  $E[\int_0^t (\sigma_n - \sigma)^2 ds] \rightarrow 0$  and set

$$X_n(t, \omega) = \int_0^t \sigma_n(s, \omega) dB(s).$$

Then

$$X(t, \omega) = \lim_{n \rightarrow \infty} X_n(t, \omega)$$

exists uniformly in probability, i.e. for each  $T > 0$  and  $\epsilon > 0$ ,

$$\lim_{n \rightarrow \infty} P\left(\sup_{0 \leq t \leq T} |X_n(t, \omega) - X(t, \omega)| \geq \epsilon\right) = 0.$$

Furthermore the limit is independent of the choice of approximating sequence  $\sigma_n \rightarrow \sigma$ . The limit  $X(t, \omega)$  is the Itô integral

$$X(t) = \int_0^t \sigma(s) dB(s)$$

## Proof.

$X_n(t) - X_m(t) = \int_0^t (\sigma_n - \sigma_m) dB$  is a continuous martingale so by Doob's inequality

$$\begin{aligned} P\left(\sup_{0 \leq t \leq T} |X_n(t) - X_m(t)| \geq \epsilon\right) &\leq \epsilon^{-2} E[(X_n - X_m)^2(T)] \\ &= \epsilon^{-2} E\left[\int_0^T (\sigma_n - \sigma_m)^2 ds\right] \end{aligned}$$

So  $X_n - X_m$  is uniformly Cauchy in probability and therefore there exists a progressively measurable  $X$  with

$$P\left(\sup_{0 \leq t \leq T} |X(t, \omega) - X_n(t, \omega)| \geq \epsilon\right) \xrightarrow{n \rightarrow \infty} 0 \quad \epsilon > 0$$

If  $\sigma'_n \xrightarrow{L^2} \sigma$  and  $X'_n = \int_0^t \sigma'_n dB$ ,  $P(\sup_{0 \leq t \leq T} |X_n - X'_n| \geq \epsilon) \rightarrow 0$  so that  $X_n$  and  $X'_n$  have the same limit.  $\square$



## Basic properties of the Itô Integral

- 1  $\int_0^t (c_1 \sigma_1 + c_2 \sigma_2) dB = c_1 \int_0^t \sigma_1 dB + c_2 \int_0^t \sigma_2 dB.$
- 2  $\int_0^t \sigma dB$  is a continuous martingale.
- 3  $E[(\int_0^t \sigma(s, \omega) dB(s))^2] = E[\int_0^t \sigma^2(s, \omega) ds].$
- 4 If  $|\sigma| \leq C$  then  $Z(t) = \exp\{\int_0^t \sigma dB - \frac{1}{2} \int_0^t \sigma^2 ds\}$  is a continuous martingale

## proof

- 1 By construction
- 2 Continuity follows from the construction. To prove the limit is a martingale we have  $E[X_n(t) | \mathcal{F}_s] = X_n(s)$  and  $X_n \rightarrow X$  in  $L^2$ , therefore in  $L^1$  as well. The  $L^1$  limit of a martingale is a martingale.
- 3  $X_n^2(t) - \int_0^t \sigma_n^2(s) ds$  is a martingale  $\xrightarrow{L^1} X^2(t) - \int_0^t \sigma^2(s) ds$
- 4  $Z_n(t) = \exp\{\int_0^t \sigma_n dB - \frac{1}{2} \int_0^t \sigma_n^2 ds\}$  is a martingale so it suffices to show that  $Z_n(t)$ ,  $n = 1, 2, \dots$  is a uniformly integrable family.

## Proof.

to show that  $Z_n(t) = \exp\{\int_0^t \sigma_n dB - \frac{1}{2} \int_0^t \sigma_n^2 ds\}$ ,  $n = 1, 2, \dots$  is a uniformly integrable family, it is enough to show that there is some fixed  $C < \infty$  for which  $E[(Z_N(t))^2] \leq C$ .

$$\begin{aligned} E[(Z_N(t))^2] &= E[\exp\{2 \int_0^t \sigma_n dB - \int_0^t \sigma_n^2 ds\}] \\ &\leq e^{Ct} E[\exp\{2 \int_0^t \sigma_n dB - \frac{4}{2} \int_0^t \sigma_n^2 ds\}] \\ &= e^{Ct} \end{aligned}$$



A *stochastic integral* is an expression of the form

$$X(t, \omega) = \int_0^t \sigma(s, \omega) dB(s) + \int_0^t b(s, \omega) ds + X_0$$

where  $\sigma$  and  $b$  are progressively measurable with  $E[\int_0^t \sigma^2(s, \omega) ds] < \infty$  and  $\int_0^t |b(s, \omega)| ds < \infty$  for all  $t \geq 0$ , and  $X_0 \in \mathcal{F}_0$  is the starting point

The stochastic differential

$$dX = \sigma dB + bdt$$

is shorthand for the same thing

For example the integral formula  $\int_0^t B(s) dB(s) = \frac{1}{2}(B^2(t) - t)$  can be written in differential notation as

$$dB^2 = 2BdB + dt$$

What happens if  $B^2(t)$  is replaced by a more general function  $f(B(t))$  ?

## Itô's Lemma

Let  $f(x)$  be twice continuously differentiable. Then

$$df(B) = f'(B)dB + \frac{1}{2}f''(B)dt$$

## Proof

First of all we can assume without loss of generality that  $f$ ,  $f'$  and  $f''$  are all uniformly bounded, for if we can establish the lemma in the uniformly bounded case, we can approximate  $f$  by  $f_n$  so that all the corresponding derivatives are bounded and converge to those of  $f$  uniformly on compact sets.

Let  $s = t_0 < t_1 < t_2 < \dots < t_n = t$ . We have

$$\begin{aligned} f(B(t)) - f(B(s)) &= \sum_{j=0}^{n-1} [f(B(t_{j+1})) - f(B(t_j))] \\ &= \sum_{j=0}^{n-1} f'(B(t_j))(B(t_{j+1}) - B(t_j)) \\ &\quad + \sum_{j=0}^{n-1} \frac{1}{2} f''(B(\xi_j))(B(t_{j+1}) - B(t_j))^2, \end{aligned}$$

$\xi_j \in [t_j, t_{j+1}]$

Let the width of the partition go to zero. By definition of the stochastic integral

$$\sum_{j=0}^{n-1} f'(B(t_j))(B(t_{j+1}) - B(t_j)) \rightarrow \int_s^t f' dB.$$

As in the computation of the quadratic variation,

$$\begin{aligned} & E \left[ \left( \sum_{j=0}^{n-1} f''(B(\xi_j)) [(B(t_{j+1}) - B(t_j))^2 - (t_{j+1} - t_j)] \right)^2 \right] \\ &= \sum_{j=0}^{n-1} E \left[ (f''(B(\xi_j)))^2 [(B(t_{j+1}) - B(t_j))^2 - (t_{j+1} - t_j)]^2 \right] + o(1) \rightarrow 0 \end{aligned}$$

Hence

$$\sum_{j=0}^{n-1} f''(B(t_j))(B(t_{j+1}) - B(t_j))^2 \xrightarrow{L^2} \int_s^t f''(B(u)) du$$

So we have proved that

$$f(B(t)) - f(B(s)) = \int_s^t f'(B(u)) dB(u) + \frac{1}{2} \int_s^t f''(B(u)) du$$

which is Itô's formula.

- 1 In differential notation Itô's formula reads

$$df(B) = f'(B)dB + \frac{1}{2}f''(B)dt.$$

The Taylor series is  $df(B) = \sum_{n=1}^{\infty} \frac{1}{n!} f^{(n)}(B)(dB)^n$ . In normal calculus we would have  $(dB)^n = 0$  if  $n \geq 2$ , but because of the finite quadratic variation of Brownian paths we have  $(dB)^2 = dt$ , while still  $(dB)^n = 0$  if  $n \geq 3$ .

- 2 If the function  $f$  depends on  $t$  as well as  $B(t)$ , the formula is

$$df(t, B(t)) = \frac{\partial f}{\partial t}(t, B(t))dt + \frac{\partial f}{\partial x}(t, B(t))dB(t) + \frac{1}{2} \frac{\partial^2 f}{\partial x^2}(t, B(t))dt.$$

The proof is about the same as the special case above.

- 3 If  $B(t)$  is a  $d$ -dimensional Brownian motion and  $f(t, x)$  is a function on  $[0, \infty) \times \mathbf{R}^d$  which has one continuous derivative in  $t$  and two continuous derivatives in  $x$ , then the formula reads

$$df(t, B(t)) = \frac{\partial f}{\partial t}(t, B(t))dt + \nabla f(t, B(t)) \cdot dB(t) + \frac{1}{2} \Delta f(t, B(t))dt.$$

## Local time

$f$  continuous function on  $\mathbb{R}_+$

$$L_t(x) = \int_0^t \delta_x(f(s)) ds = \lim_{\epsilon \downarrow 0} (2\epsilon)^{-1} |\{0 \leq s \leq t : |f(s) - x| \leq \epsilon\}|$$

$$\int_0^t 1_A(f(s)) ds = \int_A L_t(x) dx$$

$f \in C^1$   $L_t(x) = \sum_{s_j \in [0, t]: f(s_j) = x} |f'(s_j)|^{-1}$  discontinuous in  $t$   
Itô's lemma applied to  $|B_t - x|$  gives

### Tanaka's formula for Brownian Local Time

$$L_t(x) = |B_t - x| - |B_0 - x| - \int_0^t \operatorname{sgn}(B_s - x) dB_s$$

In particular,  $L_t(x)$  continuous in  $t$  a.s.



But  $|x|$  not differentiable, so no fair!!!

Proof.

$$f'_\epsilon(x) = (2\epsilon)^{-1} 1_{[-\epsilon, \epsilon]}$$

Itô

$$(2\epsilon)^{-1} |\{0 \leq s \leq t : |B_s| \leq \epsilon\}| = f_\epsilon(B_t) - f_\epsilon(B_0) - \int_0^t f'_\epsilon(B_s) dB_s$$

$$\epsilon \downarrow 0$$

$$L_t(x) = |B_t - x| - |B_0 - x| - \int_0^t \operatorname{sgn}(B_s - x) dB_s$$

Note: To be honest, we have to do a little bit more convolution to make  $f''$  continuous. □

## Feynman-Kac formula

$V$  a nice function (say bounded).  $u \in C^{1,2}$  solves

$$\frac{\partial u}{\partial t} = \frac{1}{2} \frac{\partial^2 u}{\partial x^2} + Vu, \quad u(0, x) = u_0(x)$$

$\int u(x) \exp\{-x^2/2t\} dx < \infty$ . Then

$$u(t, x) = E_x \left[ e^{\int_0^t V(B(s)) ds} u_0(B(t)) \right]$$

### Proof.

For  $0 \leq s \leq t$  let  $Z(s) = u(t-s, B(s)) e^{\int_0^s V(B(u)) du}$ . By Itô's lemma

$$\begin{aligned} Z(t) - Z(0) &= \int_0^t \left\{ -\frac{\partial u}{\partial s} + \frac{1}{2} \frac{\partial^2 u}{\partial x^2} + Vu \right\} e^{\int_0^s V(B(u)) du} ds = 0 \\ &\quad + \int_0^t \frac{\partial u}{\partial x} (t-s, B(s)) e^{\int_0^s V(B(u)) du} ds = \text{martingale} \end{aligned}$$

so  $E_x[Z(t)] = E_x[Z(0)]$

□

- 1 In  $d > 1$  if  $u \in C^{1,2}$  solves

$$\frac{\partial u}{\partial t} = \frac{1}{2} \Delta u + Vu, \quad u(0, x) = u_0(x)$$

then

$$u(t, x) = E_x \left[ e^{\int_0^t V(B(s)) ds} u_0(B(t)) \right]$$

where  $B(t)$  is  $d$ -dimensional Brownian motion

- 2 If  $V = V(t, x)$

$$u(t, x) = E_x \left[ e^{\int_0^t V(t-s, B(s)) ds} u_0(B(t)) \right]$$

- 3 Historical remark. Feynman's thesis was that solution  $u$  of it Schrödinger equation  $\frac{\partial u}{\partial t} = i \left[ \frac{1}{2} \frac{\partial^2 u}{\partial x^2} + Vu \right]$  should have representation

$$u(x, t) = \int e^{i \int_0^t V(f_s) ds - \frac{i}{2} \int_0^t |f'|^2 ds} u_0(f_t)$$

where  $\int$  is supposed to be average over functions starting at  $x$ . Kac pointed out that it is rigorous if  $i \mapsto 1$

## Arcsin law

$\xi(t) = \frac{1}{t} \int_0^t \mathbf{1}_{[0,\infty)}(B(s)) ds$  = the fraction of time that Brownian motion is positive up to time  $t$

$$P(\xi(t) \leq a) = \begin{cases} 0 & a < 0; \\ \frac{2}{\pi} \arcsin \sqrt{a} & 0 \leq a \leq 1; \\ 1 & a > 1. \end{cases}$$

Simple explanation why distribution of  $\xi(t)$  indep of  $t$

$$\xi(t) = \int_0^1 \mathbf{1}_{[0,\infty)}(B(ts)) ds = \int_0^1 \mathbf{1}_{[0,\infty)}\left(\frac{1}{\sqrt{t}} B(ts)\right) ds = \int_0^1 \mathbf{1}_{[0,\infty)}(\tilde{B}(s)) ds$$

$$\xi(t) \stackrel{d}{=} \xi(1)$$

## Proof

By Feynman-Kac if we can find a nice solution of

$$\frac{\partial u}{\partial t} = \frac{1}{2} \frac{\partial^2 u}{\partial x^2} - u \mathbf{1}_{[0, \infty)} \quad u(0, x) = 1$$

Then

$$u(t, x) = E_x \left[ e^{-\int_0^t \mathbf{1}_{[0, \infty)}(B(s)) ds} \right]$$

and

$$u(t, 0) = \int_0^1 e^{-at} dP(\xi \leq a)$$

$$\alpha > 0, \phi_\alpha(x) = \alpha \int_0^\infty u(t, x) e^{-\alpha t} dt \rightarrow -\frac{1}{2} \phi_\alpha'' + (\alpha + \mathbf{1}_{[0, \infty)}) \phi_\alpha = \alpha$$

$$\phi_\alpha(x) = \begin{cases} \frac{\alpha}{\alpha+1} + A e^{x\sqrt{2(\alpha+1)}} + B e^{-x\sqrt{2(\alpha+1)}}, & x \geq 0, \\ 1 + C e^{x\sqrt{2\alpha}} + D e^{-x\sqrt{2\alpha}}, & x \leq 0. \end{cases}$$

$$u \leq 1 \Rightarrow \phi_\alpha \leq 1 \Rightarrow A = D = 0$$

## Proof.

$$\phi_\alpha(0_-) = \phi_\alpha(0_+), \phi'_\alpha(0_-) = \phi'_\alpha(0_+)$$

$$\Rightarrow B = \frac{\alpha^{1/2}}{(1+\alpha)(\sqrt{\alpha}+\sqrt{\alpha+1})}, C = \frac{1}{(1+\alpha)^{1/2}(\sqrt{\alpha}+\sqrt{\alpha+1})^{1/2}}$$

$$\phi_\alpha(0) = \sqrt{\frac{\alpha}{\alpha+1}} = \int_0^\infty E[e^{-t\xi} \alpha e^{-\alpha t}] dt$$

By Fubini's theorem this reads  $E\left[\frac{\alpha}{\alpha+\xi}\right] = \sqrt{\frac{\alpha}{\alpha+1}}$  or

$$\int_0^1 \frac{1}{1+\gamma a} dP(\xi \leq a) = \frac{1}{\sqrt{1+\gamma}}$$

Looking up a table of transforms we find

$$dP(\xi \leq a) = \frac{2}{\pi} \frac{1}{\sqrt{a(1-a)}} da \quad 0 \leq a \leq 1$$

which is the density of the arcsin distribution □

# Stochastic differential equations

$\sigma(x, t), b(x, t)$  mble

## Definition

A stochastic process  $X_t$  is a solution of a stochastic differential equation

$$dX_t = b(X_t, t)dt + \sigma(X_t, t)dB_t, \quad X_0 = x_0$$

on  $[0, T]$  if  $X_t$  is progressively measurable with respect to  $\mathcal{F}_t$ ,  $\int_0^T |b(X_t, t)|dt < \infty$ ,  $\int_0^T |\sigma(X_t, t)|^2 dt < \infty$  a.s. and

$$X_t = x_0 + \int_0^t b(X_s, s)ds + \int_0^t \sigma(X_s, s)dB_s \quad 0 \leq t \leq T$$

The main point is that  $\sigma(\omega, t) = \sigma(X_t, t)$ ,  $b(\omega, t) = b(X_t, t)$

# Ornstein-Uhlenbeck Process

$X_t, t \geq 0$  is the solution of the *Langevin equation*

$$dX_t = -\alpha X_t dt + \sigma dB_t$$

To solve it

$$de^{\alpha t} X_t = \alpha e^{\alpha t} X_t dt + e^{\alpha t} (-\alpha X_t dt + \sigma dB_t) = \sigma e^{\alpha t} dB_t$$

so

$$X_t = X_0 e^{-\alpha t} + \sigma \int_0^t e^{-\alpha(t-s)} dB_s$$

If  $X_0 \sim \mathcal{N}(m, V)$  indep of  $B_t, t \geq 0 \Rightarrow X_t$  Gaussian process

$$m(t) = E[X_t] = m e^{-\alpha t}$$

$$c(s, t) = \text{Cov}(X_s, X_t) = [V + \frac{\sigma^2}{2\alpha} (e^{2\alpha \min(t,s)} - 1)] e^{-\alpha(t+s)}$$

$m = 0, V = \frac{\sigma^2}{2\alpha} \Rightarrow X_t$  stationary Gaussian  $c(s, t) = \frac{\sigma^2}{2\alpha} e^{-\alpha(t-s)}$

$Y_t = \int_0^t X_s ds$  "Physical" Brownian motion



# Geometric Brownian motion

$$dS_t = \mu S_t dt + \sigma S_t dB_t \quad \mu = \text{drift} \quad \sigma = \text{volatility}$$

By Ito's formula

$$S_t = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma B_t}$$

## Bessel process ( $d = 2$ )

Let  $B_t = (B_t^1, B_t^2)$  be 2d Brownian motion starting at 0,

$$r_t = |B_t| = \sqrt{(B_t^1)^2 + (B_t^2)^2}.$$

By Ito's lemma,

$$dr_t = \frac{B_t^1}{|B_t|} dB_t^1 + \frac{B_t^2}{|B_t|} dB_t^2 + \frac{1}{2} \frac{1}{|B_t|} dt.$$

As it stands this is *not* a stochastic differential equation.

Let  $Y_t$  be the solution of

$$dY = \frac{B_t^1}{|B_t|} dB_t^1 + \frac{B_t^2}{|B_t|} dB_t^2, \quad Y_0 = 0.$$

Let  $f(x)$  be a smooth function and use Ito's lemma to show that

$$f(t, Y_t) - f(0, Y_0) - \frac{1}{2} \int_0^t (\partial_t f + \partial_x^2 f)(s, Y_s) ds$$

is a martingale