



NTNU  
Norwegian University of  
Science and Technology

**Walking randomly in the realm of partial  
differential equations and probability theory**  
**The Laplace operator and Brownian motion**

Department of mathematical sciences  
12 March 2014

# Introduction

We study the following Cauchy problem (heat or diffusion equation)

$$\begin{cases} \partial_t u = \frac{1}{2} \Delta u & (x, t) \in \mathbb{R}^d \times (0, \infty) \\ u(x, 0) = \delta_0(x) & x \in \mathbb{R}^d \end{cases}, \quad (1)$$

where  $\delta_0$  is the Dirac delta centered at the origin. A solution of (1) is called a **fundamental** solution.



# Fundamental solution

Let

$$\hat{\phi}(\xi) := \mathcal{F}(\phi)(\xi) = \frac{1}{(2\pi)^{\frac{d}{2}}} \int_{\mathbb{R}^d} e^{-i\xi \cdot x} \phi(x) dx,$$



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and using that  $\mathcal{F}(\delta_0) = (2\pi)^{-\frac{d}{2}}$  we get

$$\hat{u}(\xi, t) = (2\pi)^{-\frac{d}{2}} e^{-\frac{1}{2} t |\xi|^2}. \quad (2)$$



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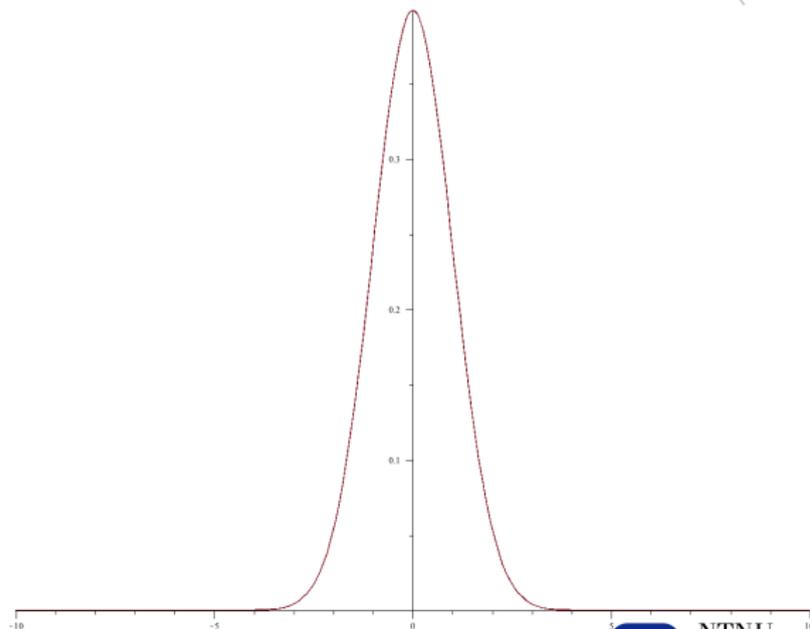
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Hopefully this is a well-known function! It is e.g. the probability density function of the normal distribution (with  $\mu = 0$  and  $\Sigma = tI$ ).



# Normal distribution (or Gaussian distribution) with $\mu = 0$ and $t = 1$



# Family of probability measures

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(All of these properties can be proved using (3).)



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Think of this as assigning a number to each outcome of an experiment.



# Stochastic process

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$$\{X_t\}_{t \in T}$$

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Note that  $X_t = X_t(\omega)$  where  $\omega \in \Omega$ . Here it is useful to think of  $t$  as time, and  $\omega$  as a particle (or an experiment). Then  $t \mapsto X_t(\omega)$  would represent the position (or the result) as a function of time  $t$  of the particle (experiment)  $\omega$ .



# Transition probabilities

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For each  $0 \leq s \leq t < \infty$ ,  $B \in \mathcal{B}(\mathbb{R}^d)$ ,  $x \in \mathbb{R}^d$ , we define

$$P_{s,t}(x, B) = P(X_t \in B | X_s = x)$$

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Note that  $P_{s,t}$  gives the probability of going from the point  $x$  at time  $s$  to the set  $B$  at time  $t$ .



# Chapman-Kolmogorov equations

If we let

$$P_{s,t}(x, dy) = q_{t-s}(y - x) dy = (2\pi(t - s))^{-\frac{d}{2}} e^{-\frac{|y-x|^2}{2(t-s)}} dy,$$



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$$P_{r,t}(x, B) = \int_{\mathbb{R}^d} P_{s,t}(y, B) P_{r,s}(x, dy) \quad (4)$$

for all  $0 \leq r \leq s \leq t < \infty$ ,  $x \in \mathbb{R}^d$ , and  $B \in \mathcal{B}(\mathbb{R}^d)$ .



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Note that  $\nu_{t_1, \dots, t_n}$  answers the question "what is the probability of  $X_{t_1} \in B_1$ , and,  $\dots$ , and  $X_{t_n} \in B_n$ ". Hence, it is closely related to transition probabilities.



# Kolmogorov's existence theorem

## Theorem

Given a family of probability measures  $\{\nu_{t_1, \dots, t_n}, t_i \in \mathbb{R}^+ \text{ and } n \in \mathbb{N}\}$  satisfying the Kolmogorov consistency criteria. Then there exists a probability space  $(\Omega, \mathcal{F}, P)$  and a stochastic process  $\{X_t\}_{t \geq 0}$  on  $\Omega$ ;  $X_t : \Omega \rightarrow \mathbb{R}^d$  such that

$$\nu_{t_1, \dots, t_n}(B_1 \times \dots \times B_n) = P(X_{t_1} \in B_1, \dots, X_{t_n} \in B_n),$$

for all  $t_i \in \mathbb{R}^+, k \in \mathbb{N}$  and all Borel sets  $B_j$ .



# Existence of a stochastic process

We "know" that  $\nu_{t_1, \dots, t_n}$  defined by (5) satisfies Kolmogorov's consistency criteria. Hence, there exists a stochastic process  $\{X_t\}_{t \geq 0}$  on  $\Omega$  such that



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that is, the stochastic process  $X_t$  has  $\nu_{t_1, \dots, t_n}$  as its finite dimensional distribution.



# Brownian motion

## Definition

A stochastic process  $B_t : \Omega \times [0, \infty) \rightarrow \mathbb{R}^d$  is called **Brownian motion** if

- i)  $B_0 = 0$
- ii)  $B_{t_n} - B_{t_{n-1}}$  is  $\mathcal{N}(0, (t_n - t_{n-1})I)$
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The process  $X_t$  with finite dimensional distribution given by (5) satisfies all of these axioms! That is, we have constructed Brownian motion using the fundamental solution of (1).



# Why??

Let us write down the finite dimensional distribution

$$\int_{B_1 \times \dots \times B_n} (2\pi(t_1))^{-\frac{d}{2}} e^{-\frac{|x_1|^2}{2(t_1)}} \dots (2\pi(t_n - t_{n-1}))^{-\frac{d}{2}} e^{-\frac{|x_n - x_{n-1}|^2}{2(t_n - t_{n-1})}} dx_1 \dots dx_n.$$



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Consider the second axiom;  $B_{t_n} - B_{t_{n-1}}$  is  $\mathcal{N}(0, (t_n - t_{n-1})I)$ .



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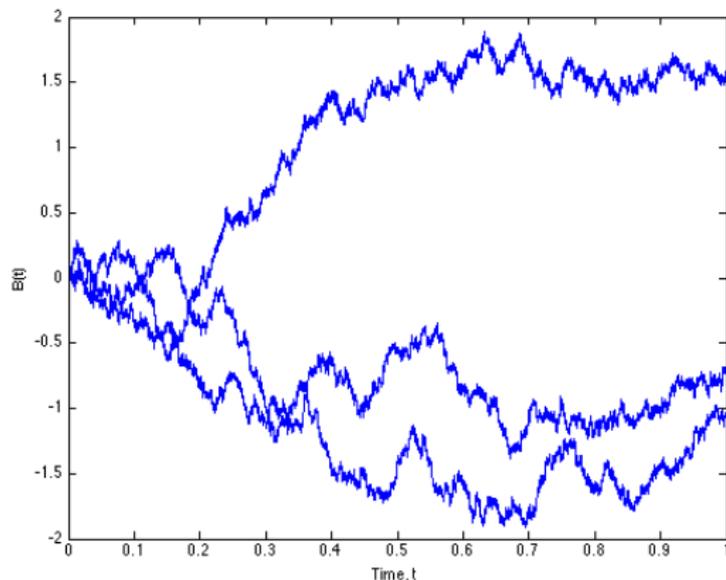
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# Figure of Brownian motion in $\mathbb{R}^1$



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- v)  $\frac{1}{c} B_{c^2 t}$  is also a Brownian motion; it is scalar invariant.



# Pollen particles

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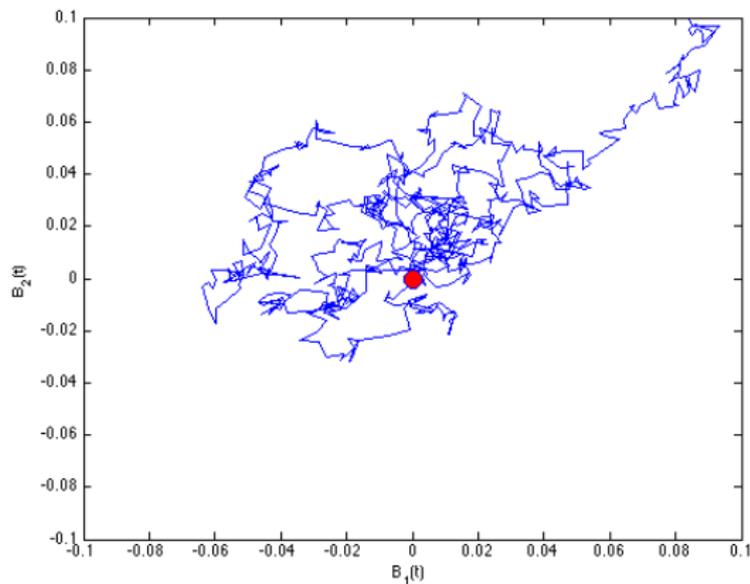
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We then know that the path of one of these particles  $\omega$  will be given by  $(B_1(t, \omega), B_2(t, \omega))$ ; two dimensional Brownian motion.



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# Kolmogorov's forward equation

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Assume that  $B_t$  has a nice, smooth transition probability density  $p_{s,t}(x, y)$ , that is,

$$P(B_t \in B | B_0 = 0) = \int_B p_{0,t}(0, y) dy \quad \forall B \in \mathcal{B}(\mathbb{R}^d).$$



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(Also called the Fokker-Planck equation.)

Assume that  $B_t$  has a nice, smooth transition probability density  $p_{s,t}(x, y)$ , that is,

$$P(B_t \in B | B_0 = 0) = \int_B p_{s,t}(0, y) dy \quad \forall B \in \mathcal{B}(\mathbb{R}^d).$$

Then this density will satisfy

$$\begin{cases} \partial_t p = \frac{1}{2} \Delta_y p & (y, t) \in \mathbb{R}^d \times (0, \infty) \\ p_0(0, y) = \delta_0(y) & (y, t) \in \mathbb{R}^d \times \{0\} \end{cases}.$$



# Fractional Laplace

We turn our attention to the following Cauchy problem (heat or diffusion equation)

$$\begin{cases} \partial_t u = -(-\Delta)^{\frac{\alpha}{2}} u & (x, t) \in \mathbb{R}^d \times (0, \infty) \\ u(x, 0) = \delta_0(x) & x \in \mathbb{R}^d \end{cases}, \quad (6)$$



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for all  $\phi \in \mathcal{S}(\mathbb{R}^d)$ . Note that the (7) is consistent with the Fourier transform of  $\Delta$ .



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# Lévy processes

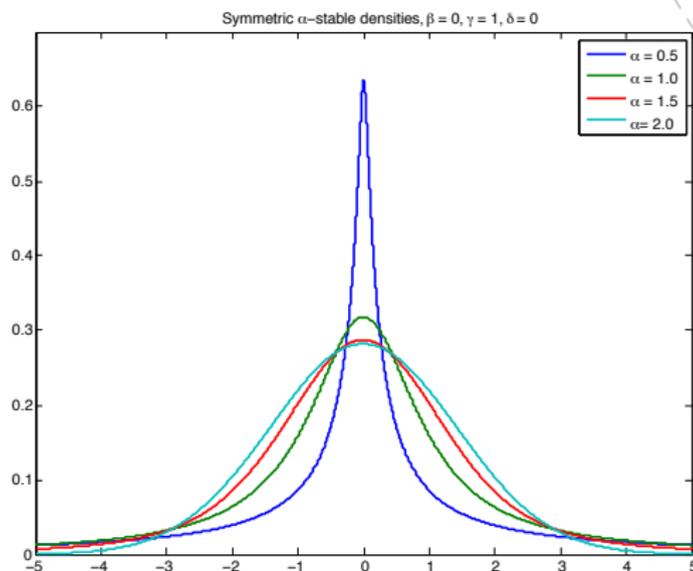
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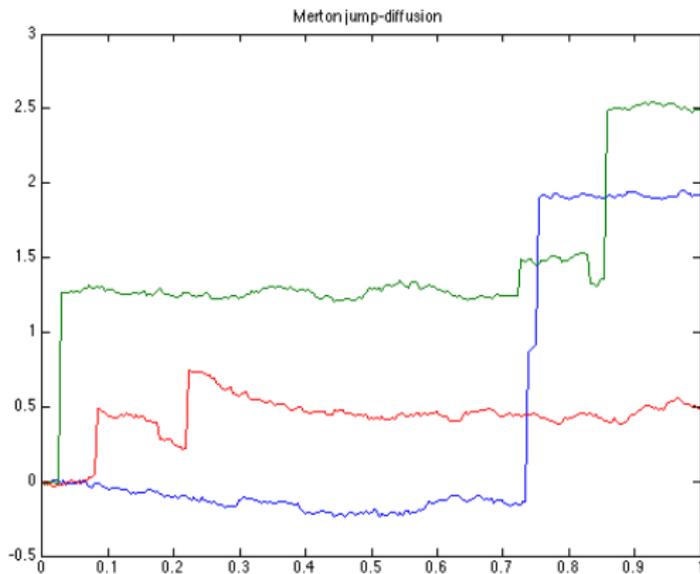
Observe that if we take  $\alpha = 2$  in the above equation, we get Brownian motion up to some constant (there is a one-half missing).



# $\alpha$ -stable distributions with $\mu = 0$



# Figures of Lévy processes

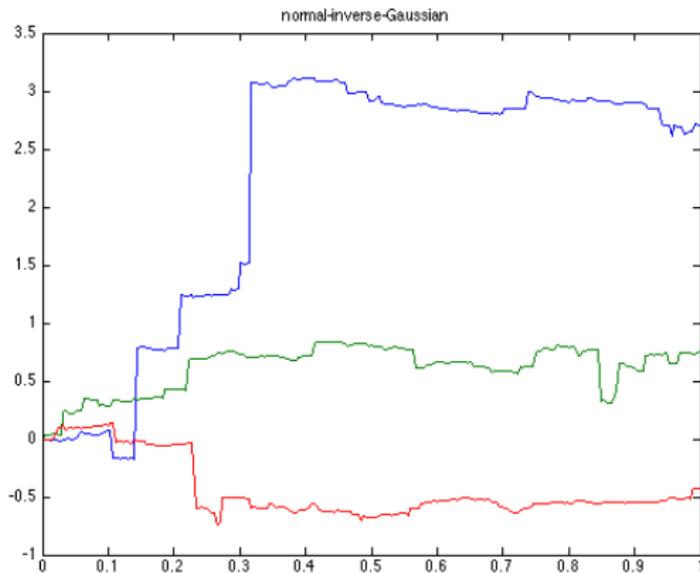


Picture due to A. Meucci (2009).



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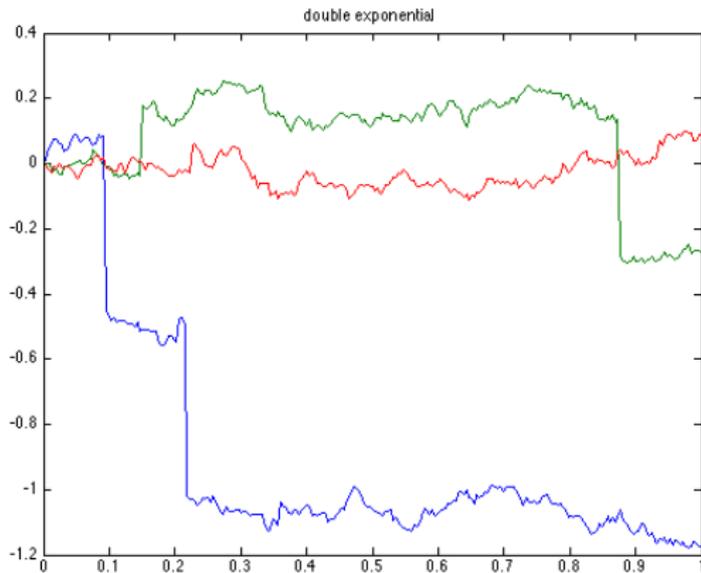


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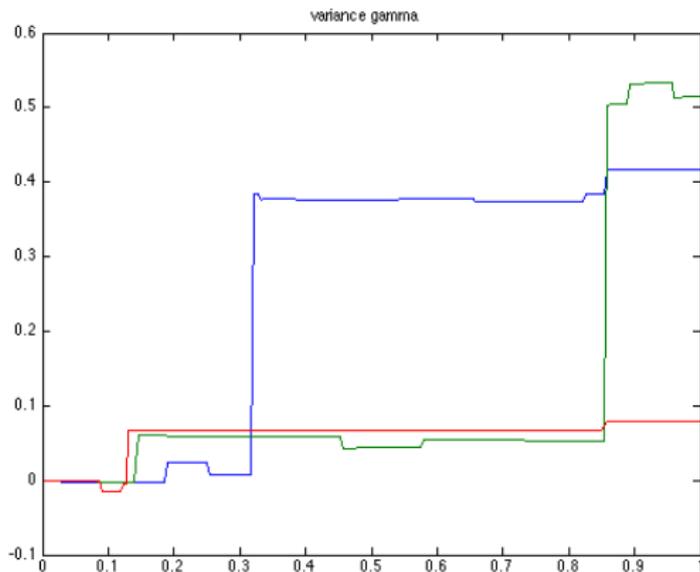


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# The Black-Scholes option pricing model

Let us look at an European call option. That is, the right to buy one stock for  $K$  NOK at a fixed time  $T > t$ . We call  $K$  the strike price (the agreed price) and  $S_t$  the spot price (the price of the stock at time  $t$ ). If we are lucky we earn  $S_T - K$  NOK, so the pay-off is  $\max\{S_T - K, 0\}$ .



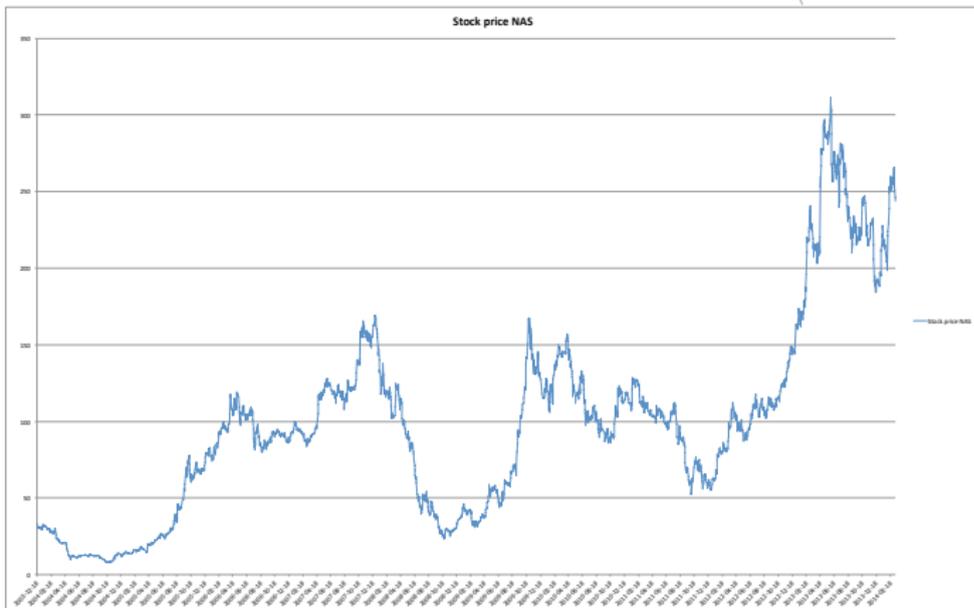
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The problem is how much does this European call option cost? Or, how do we get a good estimate on  $S_t$ ?



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In 1997, Fischer Black and Myron Scholes won the Nobel Prize in Economics for the equation

$$\begin{cases} \frac{\partial V}{\partial t} + \frac{\sigma^2}{2} S^2 \frac{\partial^2 V}{\partial S^2} + rS \frac{\partial V}{\partial S} - rV = 0 & t \in [0, T) \\ V(S, T) = \max\{S - K, 0\} & t = T \end{cases},$$

where  $V = V(S, t)$  is the price of the option,  $r$  is the risk-free interest rate, and  $\sigma$  is the volatility of the stock.



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where  $V = V(S, t)$  is the price of the option,  $r$  is the risk-free interest rate, and  $\sigma$  is the volatility of the stock.

The solution of this problem is given by the Feynman-Kac formula

$$V(S, t) = E \left[ e^{-r(T-t)} \max\{S_T^{t,x} - K, 0\} \right].$$



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This model has a lot of weaknesses. One crucial example is that Brownian motion has a continuous version; so, this model cannot model sudden jumps in price (which we know occurs in real life). Furthermore, since the tail of a gaussian distribution is very thin, the probability of extreme events is very low.

This is where Lévy processes enter. We allow sudden discontinuous jumps in such processes, and this is a very useful tool when modelling stock prices.



# The Black-Scholes option pricing model

As a consequence of this fact, it is common nowadays (at least in finance) to add

$$\int_{|y|>0} u(x+y, t) - u(x, t) - (e^y - 1) \partial_x u(x, t) \nu(dy)$$

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The solution is still given by a formula similar to Feynman-Kac', but  $S_t$  is now a Lévy process.

