

# Stochastic Calculus - part 1

## Master Programme in Mathematical Finance

ISEG

2016

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Stochastic Calculus - part 1

2016

1 / 20<sup>1</sup>

## Program

- ① Introduction
- ② A review of basic concepts in probability and stochastic processes
- ③ Brownian motion
- ④ The stochastic integral
- ⑤ The Itô formula
- ⑥ Stochastic Differential Equations
- ⑦ Stochastic differential equations and partial differential equations
- ⑧ Girsanov Theorem
- ⑨ Application to financial markets and derivatives pricing

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2016

2 / 20<sup>2</sup>

# Main Bibliography

- ① J. Guerra, Cálculo Estocástico, Lecture Notes (Texto de Apoio), 2012.
- ② B. Oksendal, Stochastic Differential Equations, Springer, 1998.
- ③ D. Nualart, Stochastic Calculus (Lecture notes, Kansas University):  
<http://www.math.ku.edu/~nualart/StochasticCalculus.pdf>
- ④ T. Mikosch, Elementary Stochastic Calculus with Finance in view, World Scientific, 1998.

# Optional Bibliography

- ① Björk, Tomas; Arbitrage Theory in Continuous Time, Oxford University Press, 1998.
- ② I. Karatzas and S. E. Shreve, Brownian Motion and Stochastic Calculus , 2nd edition, Springer, 1991.
- ③ P. E. Kloeden and E. Platen, Numerical Solution of Stochastic Differential Equations , Springer, 1992.
- ④ F. Klebaner, Introduction to Stochastic Calculus with Applications, 3rd edition, Imperial College Press, 2012.
- ⑤ Steven Shreve, Stochastic Calculus for Finance II: Continuous-Time Models, Springer, 2004.

# Introduction

- What is stochastic calculus?
- Study of integral (and differential) calculus with respect to stochastic processes.
- We can define integrals of stochastic processes where the "integrating function" is replaced also by a stochastic process
- The most important stochastic process (paradigm): Brownian motion

## Main topics

- ① Construction of stochastic integrals
- ② Itô formula
- ③ Stochastic differential equations
- ④ Partial differential equations and their relationships with stochastic differential equations
- ⑤ Stochastic calculus for Lévy processes, semimartingales and some processes which are not semimartingales (like the fractional Brownian motion)
- ⑥ Stochastic partial differential equations
- ⑦ Applications to Finance, Physics, Biology, Economics, etc...

# Stochastic Calculus Heroes

See Robert Jarrow and Philip Protter: "A short History of Stochastic Integration and Mathematical Finance" in A festschrift for Herman Rubin, 75–91, IMS Lecture Notes Monogr. Ser., 45, Inst. Math. Statist., Beachwood, OH, 2004.

Download from <http://projecteuclid.org/euclid.lnms/1196285381>

- T. N. Thiele
- Louis Bachelier
- Albert Einstein
- Norbert Wiener
- Kolmogorov
- Vincent Doeblin
- Kiyosi Itô
- Doob
- P. A. Meyer
- Malliavin
- etc...

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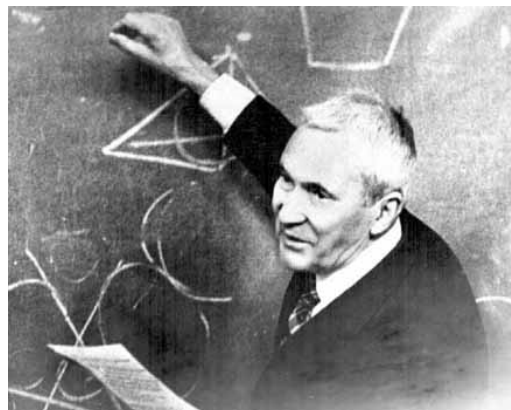
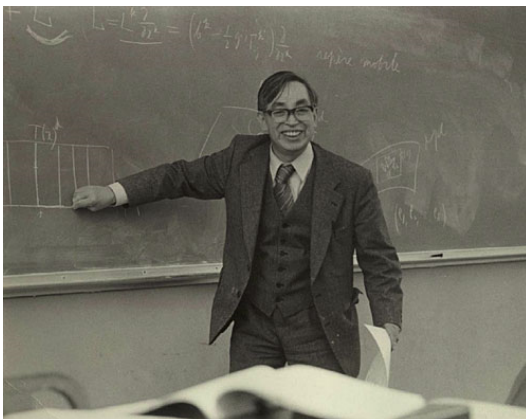
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2016

7 / 20

7

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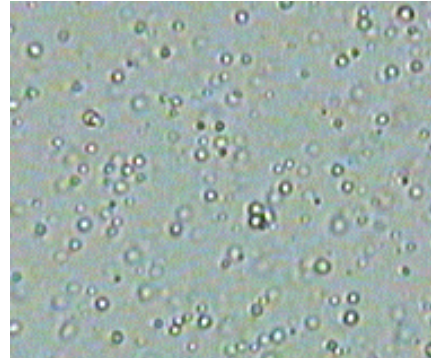
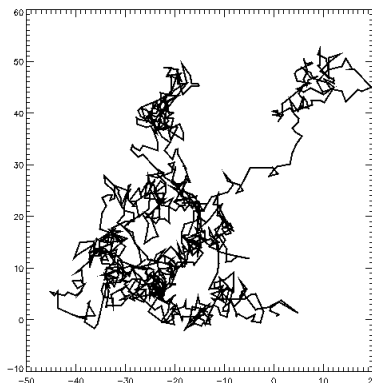
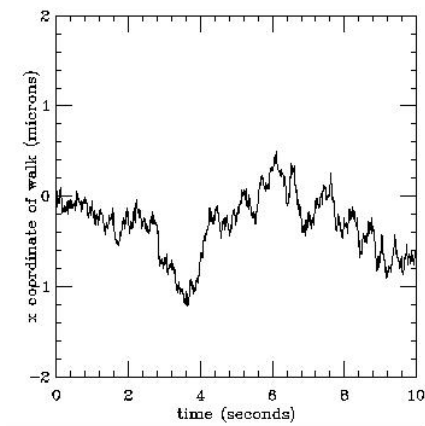
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2016

8 / 20

8

# Brownian motion



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2016 9 / 20

1. A review of basic concepts in probability and stochastic processes

## Stochastic Processes

### Definition

Stochastic Process: is a family of random variables  $\{X_t, t \in T\}$  defined on a probability space  $(\Omega, \mathcal{F}, P)$ .  $T$ : set where the parameter  $t$  is defined. If  $T = \mathbb{N}$ , we have a discrete time process. If  $T = [a, b] \subset \mathbb{R}$  or if  $T = \mathbb{R}$ , we have a continuous time process.

- $\{X_t, t \in T\} = \{X_t(\omega), \omega \in \Omega, t \in T\}$
- $X_t$ : state or position of the process at time  $t$ .
- The space of states (space where the r.v. have values) is usually  $\mathbb{R}$  (continuous state space) or  $\mathbb{N}$  (discrete state space).
- For each fixed  $\omega$  ( $\omega \in \Omega$ ), the map  $t \rightarrow X_t(\omega)$  or  $X(\omega)$  is called a trajectory or sample path of the process.

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2016 10 / 20

## Example

Random walk: Consider a sequence of independent r.v.  $\{Z_t, t \in \mathbb{N}\}$ . Then

$$X_t = Z_1 + Z_2 + \cdots + Z_t = X_{t-1} + Z_t$$

is a stochastic process in discrete time (the random walk).

## Example

A Markov process is a process in which the probability of a future state in time  $t$  depends only on the state previously observed at time  $t_k$ , i.e., if  $t_1 < t_2 < \cdots < t_k < t$ , then

$$P[a < X_t < b | X_{t_1} = x_1, X_{t_2} = x_2, \dots, X_{t_k} = x_k] = P[a < X_t < b | X_{t_k} = x_k].$$

A Markov process with discrete state space is a Markov chain. If it has continuous state space and is in continuous time, then it is a diffusion.

- Probabilistic characterization of a process  $X$ ?

## Definition

Let  $\{X_t, t \in T\}$  be a stochastic process. The finite dimensional distributions (or fidis) of  $X$  are all the distributions of vectors

$$(X_{t_1}, X_{t_2}, \dots, X_{t_n}),$$

where  $n = 1, 2, 3, \dots; t_1, t_2, \dots, t_n \in T$ .

- Distribution of the stochastic process  $\approx$  fidis.

## Example

Gaussian process: when all the fidis are Gaussian. If we know  $\mu$  (mean) and  $\Sigma$  (covariance function or matrix) we can characterize completely the Gaussian distribution. Therefore, in order to know a Gaussian process, we only need to know  $\mu$  and  $\Sigma$ .

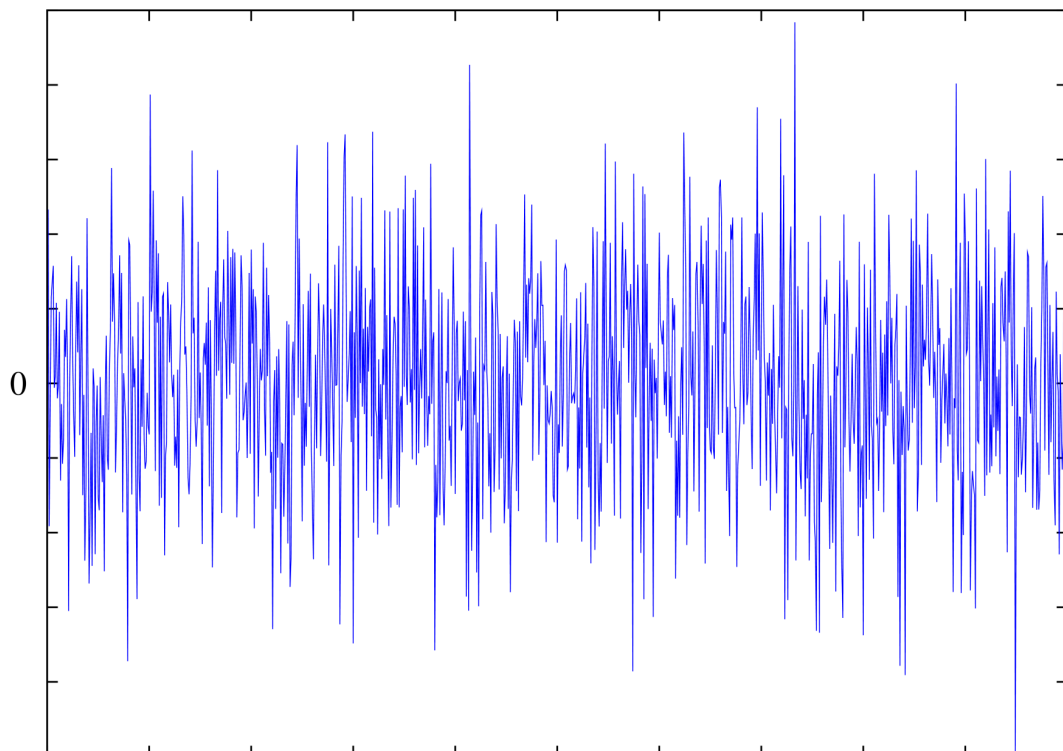
## Example

(white noise) Let  $\{X_t, t \geq 0\}$  and  $X_t \sim N(0, \sigma^2)$ , with all the r.v. independent. Then, the process is Gaussian and the fidis are associated to the distribution functions

$$\begin{aligned} F(x_1, x_2, \dots, x_n) &= P(X_{t_1} \leq x_1, X_{t_2} \leq x_2, \dots, X_{t_n} \leq x_n) \\ &= P(X_{t_1} \leq x_1)P(X_{t_2} \leq x_2) \dots P(X_{t_n} \leq x_n) \\ &= \Phi(x_1)\Phi(x_2) \dots \Phi(x_n). \end{aligned}$$

The expected value and the covariance function of  $X$  are:

$$\begin{aligned} \mu_X(t) &= E[X_t] = 0, \\ c_X(s, t) &= E[(X_t - \mu_X(t))(X_s - \mu_X(s))] = \begin{cases} \sigma^2 & \text{se } s = t \\ 0 & \text{se } s \neq t \end{cases}. \end{aligned}$$



- In general,

$$\mu_X(t) = E[X_t],$$

$$c_X(s, t) = \text{cov}(X_t, X_s) = E[(X_t - \mu_X(t))(X_s - \mu_X(s))].$$

### Definition

A stochastic process  $X$  is said to be strictly (or strongly) stationary if

$$(X_{t_1}, X_{t_2}, \dots, X_{t_n}) \stackrel{d}{=} (X_{t_1+h}, X_{t_2+h}, \dots, X_{t_n+h}),$$

for all the possible choices of  $n$ ;  $t_1, t_2, \dots, t_n \in T$  and  $h$ .

### Definition

A stochastic process  $X$  has stationary increments if

$$X_t - X_s \stackrel{d}{=} X_{t+h} - X_{s+h},$$

for all the possible values of  $s, t$  and  $h$ .

- Exercise: Show that if  $X$  is a Gaussian and strongly stationary process then  $\mu_X(t) = \mu_X(0)$ ,  $\forall t \in T$  and  $c_X(s, t) = f(|s - t|)$  just depends on the distance  $|s - t|$ .

### Definition

A stochastic process has independent increments if the random variables

$$X_{t_2} - X_{t_1}, X_{t_3} - X_{t_2}, \dots, X_{t_n} - X_{t_{n-1}}$$

are independent whenever  $t_1 < t_2 < \dots < t_n$ ,  $n = 1, 2, \dots$

- All the processes with independent increments are Markov processes.



## Example

(Poisson Process) A s. p.  $\{X_t, t \geq 0\}$  is a Poisson process with intensity  $\lambda$  if

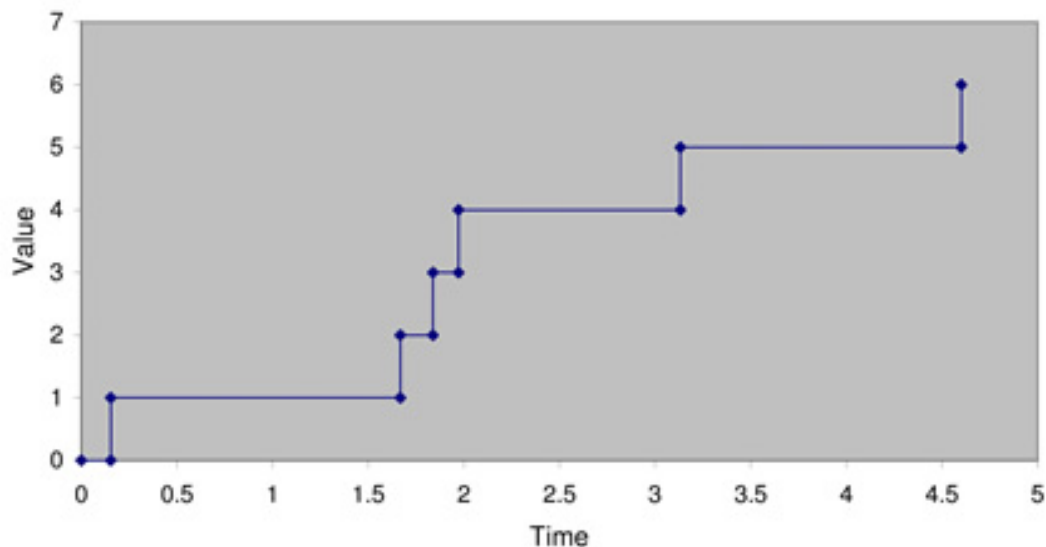
- $X_0 = 0$ ,
- $X$  has stationary and independent increments,
- $X_t \sim Poi(\lambda t)$ .

- If  $Y \sim Poi(\lambda)$  then

$$P(Y = k) = e^{-\lambda} \frac{\lambda^k}{k!}.$$

- Exercise: Show that if  $X$  is a Poisson process then  $X_t - X_s \sim Poi(\lambda(t - s))$  if  $t > s$ .

### Simulation of a Standard Poisson Process



## Definition

A s. p.  $\{X_t, t \in T\}$  is said to be equivalent to the s. p.  $\{Y_t, t \in T\}$  if, for each  $t \in T$ , we have

$$P\{X_t = Y_t\} = 1.$$

In this case, we say that process  $X$  is a version of process  $Y$ .

- 
- Two equivalent processes can have very different trajectories or paths.

## Example

Let  $\varphi$  be a non-negative r. v. with a continuous distribution and consider the s. p.

$$X_t = 0,$$

$$Y_t = \begin{cases} 0 & \text{se } \varphi \neq t \\ 1 & \text{se } \varphi = t \end{cases}$$

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The s. p. are equivalent. However, their trajectories are different.

## Definition

Two s. p.  $\{X_t, t \in T\}$  and  $\{Y_t, t \in T\}$  are said to be undistinguishable if

$$X_t(\omega) = Y_t(\omega) \quad \forall \omega \in \Omega \setminus N,$$

where  $N$  has zero probability ( $P(N) = 0$ ).

- Two s. p. with continuous trajectories which are equivalent are also undistinguishable.