

Stochastic processes: translate maths to sense

Debdas Paul

Institute for Systems Theory and Automatic Control (IST)
University of Stuttgart

October 28, 2015

Overview

- 1 Definition
- 2 Questions of interest
- 3 Fundamental stochastic processes
 - Simple random walk
 - Markov chains
 - Martingales
 - Brownian motion
- 4 Stochastic calculus
 - Itô's calculus
 - Girsanov's theorem
- 5 References

Overview

1 Definition

2 Questions of interest

3 Fundamental stochastic processes

- Simple random walk
- Markov chains
- Martingales
- Brownian motion

4 Stochastic calculus

- Itô's calculus
- Girsanov's theorem

5 References

Definition(s)

Definition(s)

A collection of **random variables** indexed by **time**

$$Z(t) = \begin{cases} \{X_0, X_1, X_2, \dots\} & \text{Discrete time} \\ \{X_t\}_{t \geq 0} & \text{Continuous time} \end{cases}$$

Definition(s)

A collection of **random variables** indexed by **time**

$$Z(t) = \begin{cases} \{X_0, X_1, X_2, \dots\} & \text{Discrete time} \\ \{X_t\}_{t \geq 0} & \text{Continuous time} \end{cases}$$

Alternate definition: Probability distribution over a space of paths

Definition(s)

A collection of **random variables** indexed by **time**

$$Z(t) = \begin{cases} \{X_0, X_1, X_2, \dots\} & \text{Discrete time} \\ \{X_t\}_{t \geq 0} & \text{Continuous time} \end{cases}$$

Alternate definition: Probability distribution over a space of paths

Example

① $f(t) = t$ with prob. 1

② $f(t) = \begin{cases} t & \forall t \\ -t & \forall t \end{cases}$ with prob. 0.5
with prob. 0.5

③ For each t , $f(t) = \begin{cases} t & \forall t \\ -t & \forall t \end{cases}$ with prob. 0.5
with prob. 0.5

Overview

- 1 Definition
- 2 Questions of interest
- 3 Fundamental stochastic processes
 - Simple random walk
 - Markov chains
 - Martingales
 - Brownian motion
- 4 Stochastic calculus
 - Itô's calculus
 - Girsanov's theorem
- 5 References

Questions of interest

Questions of interest

- 1 What are the dependencies in the sequence of values?

$$\{X_{t_{i+1}} - X_{t_i}, i = 0, 1, 2 \dots\}$$

are mutually independent or not?

Questions of interest

- ① What are the dependencies in the sequence of values?

$$\{X_{t_{i+1}} - X_{t_i}, i = 0, 1, 2 \dots\}$$

are mutually independent or not?

- ② What is the long term behaviour (LLN, CLT)?

$$(Z(t) \xrightarrow{fdd} W, t \rightarrow \infty)$$

fdd : Finite dimensional distribution (rem: Kolmogorov's extension theorem)

Questions of interest

- ① What are the dependencies in the sequence of values?

$$\{X_{t_{i+1}} - X_{t_i}, i = 0, 1, 2, \dots\}$$

are mutually independent or not?

- ② What is the long term behaviour (LLN, CLT)?

$$(Z(t) \xrightarrow{fdd} W, t \rightarrow \infty)$$

fdd : Finite dimensional distribution (rem: Kolmogorov's extension theorem)

- ③ What is the probability of a boundary (rare) event (how often something extreme happens)?

$$\mathbb{P}(Z(t) > \text{high level})$$

Overview

1 Definition

2 Questions of interest

3 Fundamental stochastic processes

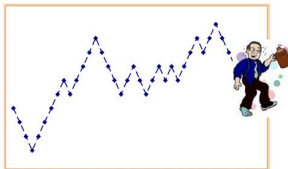
- Simple random walk
- Markov chains
- Martingales
- Brownian motion

4 Stochastic calculus

- Itô's calculus
- Girsanov's theorem

5 References

Simple Random Walk: simplest stochastic process



Definition

Let Y_i be i.i.d random variables such that:

$$Y_i = \begin{cases} 1 & \text{with prob. } 0.5 \\ -1 & \text{with prob. } 0.5 \end{cases}$$

and

$$X_t = \sum_{i=1}^t Y_i, X_0 = 0$$

Then $Z(t) = \{X_0, X_1, X_2, \dots\}$ is a one dimensional simple random walk

Simple Random Walk: properties

- 1 Expectation: $E(X_t) = 0$
- 2 Independent increments: For $0 = t_0 \leq t_1 \leq \dots \leq t_k$,
 $\{X_{t_{i+1}} - X_{t_i}, i = 0, 1, 2 \dots k - 1\}$ are mutually independent
Remark: what happens from time 20 to 30 is irrelevant to what happens from 40 to 50
- 3 (Stationary?) $\forall h \geq 1, t \geq 0$ the distribution of $X_{t+h} - X_t$ is same as the distribution of X_h
Remark: If we look at the same amount of time, then what happens inside the time interval is irrelevant of starting point as the distribution is same.

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk
- Situtation: I will play untill I win €100 or loose €100

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk
- Situation: I will play untill I win €100 or loose €100
- Question: What is the probabilty that I will stop playing after winining €100?

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk
- Situtation: I will play untill I win €100 or loose €100
- Question: What is the probabilty that I will stop playing after winining €100?
- Answer : $1/2$

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk
- Situtation: I will play untill I win €100 or loose €100
- Question: What is the probabilty that I will stop playing after winining €100?
- Answer : $1/2$
- Situtation: I will play untill I win €100 or loose €50

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk
- Situation: I will play untill I win €100 or loose €100
- Question: What is the probabiltiy that I will stop playing after winining €100?
- Answer : $1/2$
- Situation: I will play untill I win €100 or loose €50
- Question: What is the probabiltiy that I will stop playing after winining €100?

Simple Random Walk: example

- Game: **Coin toss**
- Rule: Toss a fair coin– if head, I win 1 € else I loose 1 €(Assume start from 0 balance)
- My balance will follow a simple random walk
- Situation: I will play untill I win €100 or loose €100
- Question: What is the probabilty that I will stop playing after winining €100?
- Answer : $1/2$
- Situation: I will play untill I win €100 or loose €50
- Question: What is the probabilty that I will stop playing after winining €100?
- Answer: $1/3$ (Martingale theory; comes later)

Markov chains

- A stochastic process is called a Markov chain if it has a specific property : Markov property

Markov chains

- A stochastic process is called a Markov chain if it has a specific property : Markov property
- Markov property: Future depends ONLY on the present and not on the past.

Markov chains

- A stochastic process is called a Markov chain if it has a specific property : Markov property
- Markov property: Future depends ONLY on the present and not on the past.
- Mathematically:

$$Pr(X_{t+1} = x | X_1 = x_1, \dots, X_t = x_t) = Pr(X_{t+1} = x | X_t = x_t)$$

if $Pr(X_1 = x_1, \dots, X_t = x_t) > 0$, conditional probabilities are well defined

Markov chains: some interesting facts

- Simple random walk is a Markov chain, why? New coin toss every time, past does not matter !

Markov chains: some interesting facts

- Simple random walk is a Markov chain, why? New coin toss every time, past does not matter !
- Transition matrix: collection of probabilities of moving from one state to another.

Markov chains: some interesting facts

- Simple random walk is a Markov chain, why? New coin toss every time, past does not matter !
- Transition matrix: collection of probabilities of moving from one state to another.
- State space of SWR is infinite \implies No transition matrix

Markov chains: some interesting facts

- Simple random walk is a Markov chain, why? New coin toss every time, past does not matter !
- Transition matrix: collection of probabilities of moving from one state to another.
- State space of SWR is infinite \implies No transition matrix
- N-step transition probability is called the famous **Chapman-Kolmogorov** (C-K) equation.

Markov chains: some interesting facts

- Simple random walk is a Markov chain, why? New coin toss every time, past does not matter !
- Transition matrix: collection of probabilities of moving from one state to another.
- State space of SWR is infinite \implies No transition matrix
- N-step transition probability is called the famous **Chapman-Kolmogorov** (C-K) equation.
- Differential form of C-K equation is called the **Master equation**

Markov chains: some interesting facts

- Simple random walk is a Markov chain, why? New coin toss every time, past does not matter !
- Transition matrix: collection of probabilities of moving from one state to another.
- State space of SWR is infinite \implies No transition matrix
- N-step transition probability is called the famous **Chapman-Kolmogorov** (C-K) equation.
- Differential form of C-K equation is called the **Master equation**
- Master equation for biochemical reactions \rightarrow **Chemical Master Equation** (CME)- the fundamental equation for stochastic modelling of biochemical processes

Martingales: be fair!

Martingales: be fair!

- Stochastic processes for "fair" games: In **expectation** you will not win any money at all or it exclude the possibility of winning strategies based on game history.
- Mathematically:

$$\mathbb{E}(X_{t+1}|X_1, \dots, X_t) = X_t$$

- Example : simple random walk

Martingales: be fair!

- Stochastic processes for "fair" games: In **expectation** you will not win any money at all or it exclude the possibility of winning strategies based on game history.

- Mathematically:

$$\mathbb{E}(X_{t+1}|X_1, \dots, X_t) = X_t$$

- Example : simple random walk
- The Optional Stopping Time theorem:
 - ▶ **Main concept**: If one plays a Martingale game, no matter what strategy he/she uses, the expected value will remain same.

Martingales: be fair!

- Stochastic processes for "fair" games: In **expectation** you will not win any money at all or it exclude the possibility of winning strategies based on game history.

- Mathematically:

$$\mathbb{E}(X_{t+1}|X_1, \dots, X_t) = X_t$$

- Example : simple random walk
- The Optional Stopping Time theorem:
 - ▶ **Main concept**: If one plays a Martingale game, no matter what strategy he/she uses, the expected value will remain same.
 - ▶ **Stopping time**: A positive integer valued r.v. which provides rules to stop a random process. The decision depends on all the events up to that time. NO future dependencies (why?)

Martingales: be fair!

- Stochastic processes for "fair" games: In **expectation** you will not win any money at all or it exclude the possibility of winning strategies based on game history.

- Mathematically:

$$\mathbb{E}(X_{t+1}|X_1, \dots, X_t) = X_t$$

- Example : simple random walk
- The Optional Stopping Time theorem:

- ▶ **Main concept**: If one plays a Martingale game, no matter what strategy he/she uses, the expected value will remain same.
- ▶ **Stopping time**: A positive integer valued r.v. which provides rules to stop a random process. The decision depends on all the events up to that time. NO future dependencies (why?)

Examples: In our coin toss game, the first time we win €100 or loose €50; time of first peak (not a stopping time ! why?)

Optional Stopping Time theorem

Theorem

(Informal way) Let there is a martingale with stopping time T , and suppose there is a constant K such that $T \leq K$ always. In this case the expectation value at the stopping time is always equal to the value at the beginning.

Optional Stopping Time theorem

Theorem

(Informal way) Let there is a martingale with stopping time T , and suppose there is a constant K such that $T \leq K$ always. In this case the expectation value at the stopping time is always equal to the value at the beginning.

Coin toss revisited

- consider the second situation: I will play until I win €100 or loose €50

Now, we can define a stopping time for this (strategy) say τ . According to the above theorem:

$$E(X_\tau) = X_0 = 0 \implies 100p + (1 - p) * (-50) = 0 \implies p = 1/3$$

Brownian motion: simplest continuous time stochastic process

Denoted by $B(t)$ - serves basic model for the cumulative noise.

Definition

$B(t)$ is a stochastic process having the following properties:

- For any $0 < u < s < t$, $\{B(t) - B(s)\}$ and $\{B(u) - B(0)\}$ are independent of each other (Independent increments)
- $\{B(t) - B(s)\} \sim \mathcal{N}(0, t - s)$
- $B(t)$ is continuous everywhere.

Path properties of $B(t)$

- Has infinite variation on any interval
- Quadratic variation on $[0, t]$ equal to t

Overview

- 1 Definition
- 2 Questions of interest
- 3 Fundamental stochastic processes
 - Simple random walk
 - Markov chains
 - Martingales
 - Brownian motion
- 4 Stochastic calculus
 - Itô's calculus
 - Girsanov's theorem
- 5 References

Quadratic variation: invitation to Itô calculus

Definition

If g is a function of real variable, define its quadratic variation over the interval $[0, t]$ as the limit (when it exists)

$$[g](t) = \lim_{\delta_n \rightarrow 0} \sum_{i=1}^n (g(t_i^n) - g(t_{i-1}^n))^2$$

Where the limit is taken over the partitions: $0 = t_0^n < t_1^n, \dots, < t_n^n = t$, with $\delta_n = \max_{1 \leq i \leq n} (t_i^n - t_{i-1}^n)$

Important facts:

- For enough smooth function having finite variation, this quadratic variation is zero! \implies We can apply Riemannian calculus.
- For $B(t)$, quadratic variation is not zero hence we can not apply classical calculus \rightarrow starting point of Itô calculus

Glimpse of Itô calculus: differentiation

Motivation: We want to compute infinitesimal differences of $f(B(t))$, where f is a smooth and nice function

Glimpse of Itô calculus: differentiation

Motivation: We want to compute infinitesimal differences of $f(B(t))$, where f is a smooth and nice function

- Now suppose $B(t)$ is differentiable then, $df = \frac{dB(t)}{dt} dt$ – easy!

Glimpse of Itô calculus: differentiation

Motivation: We want to compute infinitesimal differences of $f(B(t))$, where f is a smooth and nice function

- Now suppose $B(t)$ is differentiable then, $df = \frac{dB(t)}{dt} dt$ – easy!
- But we can not do that! reason: quadratic variation of $B(t)$ is $dB(t)^2 = dt$
- How about $df = f'(B(t))dB(t)$?

Glimpse of Itô calculus: differentiation

Motivation: We want to compute infinitesimal differences of $f(B(t))$, where f is a smooth and nice function

- Now suppose $B(t)$ is differentiable then, $df = \frac{dB(t)}{dt}dt$ – easy!
- But we can not do that! reason: quadratic variation of $B(t)$ is $dB(t)^2 = dt$
- How about $df = f'(B(t))dB(t)$? WRONG!
- Using Taylor expansion,

$$f(t+x) - f(t) = f'(t)x \text{ (classical calculus)}$$

Now for $f(B(t))$

$$\begin{aligned} f(B(t+x)) - f(B(t)) &= f'(B(t))dB(t) + 1/2f''(B(t))(dB(t))^2 + \dots \\ df &= f'(B(t))dB(t) + 1/2f''(B(t))dt \end{aligned}$$

This is Itô's lemma

Glimpse of Itô calculus: integration

Integrations is nothing but 'inverse' of differentiation

So Let us define:

$$F(t, B(t)) = \int f(t, B(t))dB(t) + \int g(t, B(t))dt$$

if $dF = fdB(t) + gdt$

- **Question:** Does there exists Riemannian sum type description?

Glimpse of Itô calculus: integration

Integrations is nothing but 'inverse' of differentiation

So Let us define:

$$F(t, B(t)) = \int f(t, B(t))dB(t) + \int g(t, B(t))dt$$

if $dF = fdB(t) + gdt$

- **Question:** Does there exists Riemannian sum type description?
- **Answer:** Itô integral is the limit of Riemannian sums when always take leftmost point of each interval → You can not see the future!

Glimpse of Itô calculus: integration

Integrations is nothing but 'inverse' of differentiation

So Let us define:

$$F(t, B(t)) = \int f(t, B(t))dB(t) + \int g(t, B(t))dt$$

if $dF = fdB(t) + gdt$

- **Question:** Does there exists Riemannian sum type description?
- **Answer:** Itô integral is the limit of Riemannian sums when always take leftmost point of each interval → You can not see the future!
- **Reason:** Due to quadratic variance the two limits(left and right) are different (variance accumulates)!

Girsanov's theorem: change of measure

Motivation: Consider

$$\begin{cases} B(t) & \text{without drift} \\ \widehat{B}(t) & \text{with drift} \end{cases}$$

Girsanov's theorem: change of measure

Motivation: Consider

$$\begin{cases} B(t) & \text{without drift} \\ \widehat{B}(t) & \text{with drift} \end{cases}$$

- Q: Can we switch between $B(t)$ and $\widehat{B}(t)$ by change of measure

Girsanov's theorem: change of measure

Motivation: Consider

$$\begin{cases} B(t) & \text{without drift} \\ \widehat{B}(t) & \text{with drift} \end{cases}$$

- Q: Can we switch between $B(t)$ and $\widehat{B}(t)$ by change of measure
- A: Yes. According to the theorem $\widehat{B}(t)$ and $B(t)$ can be converted to each other using simple multiplication (multiply with Radon-Nikodym derivative)!

Girsanov's theorem: change of measure

Motivation: Consider

$$\begin{cases} B(t) & \text{without drift} \\ \widehat{B}(t) & \text{with drift} \end{cases}$$

- Q: Can we switch between $B(t)$ and $\widehat{B}(t)$ by change of measure
- A: Yes. According to the theorem $\widehat{B}(t)$ and $B(t)$ can be converted to each other using simple multiplication (multiply with Radon-Nikodym derivative)!
- Utility: convert a non-martingale process (with non-zero drift term) (might be risky) to a martingale process (safe!)

Overview

- 1 Definition
- 2 Questions of interest
- 3 Fundamental stochastic processes
 - Simple random walk
 - Markov chains
 - Martingales
 - Brownian motion
- 4 Stochastic calculus
 - Itô's calculus
 - Girsanov's theorem
- 5 References

References

- ① Klebaner, Fima C. Introduction to stochastic calculus with applications. Vol. 57. London: Imperial College Press, 2005.
—Excellent book to start with; notational simplicity
- ② Van Kampen, Nicolaas Godfried. Stochastic processes in physics and chemistry. Vol. 1. Elsevier, 1992.—Classic but hard to digest!
- ③ Karlin, Samuel. A first course in stochastic processes. Academic press, 2014.—Easy to read
- ④ Grimmett, Geoffrey, and David Stirzaker. Probability and random processes. Oxford university press, 2001.—Good for revision of prerequisites
- ⑤ Øksendal, Bernt. Stochastic differential equations. Springer Berlin Heidelberg, 2003.—mathematically intensive
- ⑥ Ikeda, Nobuyuki, and Shinzo Watanabe. Stochastic differential equations and diffusion processes. Elsevier, 2014.—High notational complexity; more abstract and analytical