Seoul National University

Lecture Note

Introduction to Stochastic Differential Equations

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Chapter 0

Introduction

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Grading

- Mid-terms 1 (15%, 10/10 or 17)
- Mid-terms 2 (15%, 11/7)
- Fianl-term (40%)
- Assignment (20%, 8-10 times)
- Attendance (10%, absent: -2%, late: -1%)

Let X be a standard normal random variable in $\mathbb{R}$. i.e., $\mathbb{P}[X \in [a,b]] = \int_a^b \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$.
(Central Limit Theorem) If $x_1, x_2, \cdots, x_n \in X, E(x_i) = m, Var(x_i) = \sigma^2$, then

$$\frac{\frac{x_1-m}{\sigma} + \frac{x_2-m}{\sigma} + \cdots + \frac{x_n-m}{\sigma}}{\sqrt{n}} \to X$$

In this class, we study dynamic version of this theorem. If $(W_t)_{t\geq 0}$ be a fluctuation, then $(W_t)_{t\geq 0}$ be a random variable in $C[0,T]$
Example. $\frac{dX_t}{dt} = rX_t; dX_1 = rX_t dt$. Then, $X_t = X_0 e^{rt}$ (unrisky assets, bank)
$dX_t = rX_t dt + \sigma X_t dW_t$, σ : volatility (risky assets, stock)
We will study:

1. Probability Space
2. Random Variable
3. Expectation

Textbooks:

1. Stochastic Calculus for Finance II (Shreve), covering chapter 1-3 or 4
2. Introduction to Stochastic Integration (Hui-Hsiung Kuo)

Chapter 1

General Probability Theory

1.1 Infinite Probability Spaces

There are three elements consisting probability space:

- S: Sample space
- $\mathcal{E}$: Family of events $E \subseteq S$ (σ-algebra in measure theory)
- $\mathbb{P}$: probability $\Rightarrow \mathbb{P}(E)$ is defined for all $E \subseteq \mathcal{E}$ (μ with $\mu(S) = 1$)

Example.

1. Toss a coin twice (H for Head, T for Tail)
   Then, $S = \{$HH, HT, TT, TT$\}$
2. Uniform random variable in $[0, 1]^3$
   Then, $S = [0, 1]^3$. If $E = [0, \frac{1}{2}]^3$, then $\mathbb{P}(E) = Vol(E) = \frac{1}{8}$

How to define $\mathcal{E}$?
In example 2, let $\mathcal{E}$ = family of all subsets of $[0, 1]^3$ naively. But Banach-Tarski Paradox says there are disjoint sets E, F with $\mathbb{P}(E \cup F) \neq \mathbb{P}(E) + \mathbb{P}(F)$ in this $\mathcal{E}$. Therefore we cannot naively set $\mathcal{E}$ (Use measure theory)

In example 1, suppose that we cannot see the second flip. If $\{HH\} \notin \mathcal{E}$ and $\{HT, HH\} \in \mathcal{E}$, then $\mathcal{E} = \{\phi, \{HH, HT\}, \{TH, TT\}, \{HH, HT, TH, TT\}\}$

Definition 1.1 (Measure)
Let Ω be non-empty set and $\mathcal{F}$ be family of subsets of Ω with

1. $\phi \in \mathcal{F}$
2. $A \in \mathcal{F} \Rightarrow A^C \in \mathcal{F}$
3. $A_1, A_2, \dots \in \mathcal{F} \Rightarrow \bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$.

We say $\mathcal{F}$ as σ-albegra or σ-field, $A \subseteq \mathcal{F}$ as measurable, and Ω as measurable space.

Exercises.

1) $\Omega \in F$

2) $A_1, A_2, \cdots \in \mathcal{F}$, then $A_1 \cap A_2 \cdots \in \mathcal{F}$

3) $A_1, A_2, \cdots \in A_n \in \mathcal{F}$, then $A_1 \cup \cdots \cup A_n, A_1 \cap \cdots \cap A_n \in \mathcal{F}$.

4) $A, B \in \mathcal{F}$, then $A - B \in \mathcal{F}$

Definition 1.2 (Topological Space)
(See Rudin: *Real and Complex Analysis, Chapter 1.*) Let Θ be non-empty set and τ be family of subsets of Θ with

1. $\phi, \Theta \in \tau$

2. $V_1, \cdots V_n \in \tau \Rightarrow V_1 \cap \cdots \cap V_n \in \tau$

3. $V_\alpha \in \tau \;\; \forall \alpha \in I \Rightarrow \bigcup_{\alpha \in I} V_\alpha \in \tau$.

We say $V \in \tau$ be **open set**, and (Θ, τ) be **topological space**.

Definition 1.3 (Measurable Function)
$f : (\Omega, \mathcal{F}) \to (\Theta, \tau)$ is **measurable** if $f^{-1}(V) \in \mathcal{F} \;\; \forall V \in \tau$

Definition 1.4 (Positive Measure)
Let Ω be non-empty set and $\mathcal{F}$ be σ-algebra. Then $\mu : \mathcal{F} \to [0, \infty]$ is called **measurable** if

1. $A_1, A_2, \cdots$: disjoint members of $\mathcal{F} \Rightarrow \mu(A_1 \cup A_2 \cup \cdots) = \sum_{i=1}^{\infty} \mu(A_i)$

2. $\mu(A) < \infty$ for some $A \in \mathcal{F}$,

and $(\Omega, \mathcal{F}, \mu)$ is called **measrue space**.

Definition 1.5 (probability space, random variable)

1. $(\Omega, \mathcal{F}, \mathbb{P})$ is called as **probability space** if $\mathbb{P}(\Omega) = 1$.

2. X is called as **random varaible** if it is a function from $(\Omega, \mathcal{F}, \mathbb{P})$ to $\mathbb{R}$

<u>Next Class</u>

- Borel sets on $\mathbb{R}$ or $\mathbb{R}^d$

- Lebesgue Measure

- Lebesgue Integral (Define Expectation of random variable)

Last class, we define a sample space Ω, a σ-algebra $\mathcal{F}$, and a (positive) measure $\mu : \mathcal{F} \to [0, \infty]$.

Exercises.

- $A_1 \subseteq A_2 \subseteq \cdots \Rightarrow \mu(\bigcup_{i=1}^{\infty} A_i = \lim_{n\to\infty} \mu(A_n)$
- $A_1 \subseteq A_2 \subseteq \cdots, \mu(A_1) < \infty \Rightarrow \mu(\bigcup_{i=1}^{\infty} A_i = \lim_{n\to\infty} \mu(A_n)$

Theorem 1.6 (Rudin 1.10)
Let $\mathcal{F}_0$ be a collection of subset of Ω. Then, $\exists! \mathcal{F}^*$ minimal σ-algebra containing $\mathcal{F}_0$.

Proof. Let $\{\mathcal{F}_\alpha, \alpha \in I\}$ be family of σ-algebra containing $\mathcal{F}_0$. Then, $\mathcal{F}^* = \bigcap_{\alpha \in I} F_\alpha$ satisfies the three condition: 1) contain $\mathcal{F}_0$ 2) σ-algebra 3) minimal (trivial, $\mathcal{F}^* \subseteq \mathcal{F}_\alpha$) $\square$

Definition 1.7 (Borel measurable)
$\mathcal{B}$ is called a **Borel σ-algebra** on topological space (Θ, τ) if $\mathcal{B}$ is minimal σ-algebra containing τ, and B is called **Borel measurable** if $B \in \mathcal{B}$.

Remark (Completion of measure space, Rudin 1.15).
Consider an extension $(\Omega, \mathcal{F}, \mu) \to (\Omega, \overline{\mathcal{F}}, \mu)$ where

1. $\overline{\mathcal{F}} = \{A \cup N : A \in \mathcal{F}, N \subseteq A_0 \subseteq \mathcal{F}, \mu(A_0) = 0\}$
2. $\mu(A \cup N) = \mu(A)$

Then, (Check!)

1. (well-definedness) $A_1 \cup N_1 = A_2 \cup N_2 \Rightarrow \mu(A_1) = \mu(A_2)$
2. $\mu : \overline{\mathcal{F}}$ is σ-algebra.
3. $\mu : \overline{\mathcal{F}} \to [0, \infty]$ is a measure

Example.

1) $\mathbb{R}$

$$\mathcal{F}_0 = \tau \xrightarrow{1.10} \mathcal{B} \xrightarrow{\text{completion}} \overline{\mathcal{B}}$$
$$\mathcal{L} \xrightarrow{\text{Rudin CH2}} \mathcal{L} \xrightarrow{\text{completion}} \mathcal{L}$$

2) $C[0,T] = \Omega = \{f; f : [0,T] \to \mathbb{R}, \text{continuous}\}$.
Define $\mathcal{F}_0 = \{\bigcup_{t_1, t_2, \cdots, t_k}(A_1, A_2, \cdots, A_k) : 0 \le t_1 < t_2 < \cdots < t_k \le T; A_1, \cdots A_k \in \overline{\mathcal{B}}\}$. We call $\{f \in C[0,T] : f(t_1) \in A_1, f(t_2) \in A_2, \cdots, f(t_k) \in A_k\}$ as **cylindrical set**. Consider

$$\mathcal{F}_0 \xrightarrow{1.10} \quad \mathcal{B} \xrightarrow{\text{completion}} \overline{\mathcal{B}}$$
$$\mathbb{P}_{\text{BM}} \xrightarrow{\text{KET}} \mathbb{P}_{\text{BM}} \xrightarrow{\text{completion}} \mathbb{P}^*_{\text{BM}}$$

(KET refers Kolmogorov's Extension Thm)

1.2 Random Variables and Distributions

Definition 1.8
$f : \Omega \to \mathbb{R}$ is measurable if $f^{-1}(V) \in \mathcal{F}$ for any open set $V \subseteq \mathbb{R}$.

Remark. $\mathcal{B}(\mathbb{R})$ = Borel σ-algebra in $\mathbb{R}$.

Remark. If f: measurable, then $f^{-1}(B) \in \mathcal{F}$ for any $B \in \mathcal{B}(\mathbb{R})$.

Proof. Let $G = \{A \subseteq \mathbb{R} : f^{-1}(A) \in \mathcal{F}\}$. Then, $\tau \subseteq G$, G : σ-algebra (check!), hence $\mathcal{B}(\mathbb{R}) \subseteq G$. $\square$

Definition 1.9

- $(\Omega, \mathcal{F}, \mathbb{P})$ is a **probability space** if $(\mathbb{P}(\Omega) = 1$.
- X is **random variable** if $X : \Omega \to \mathbb{R}$ is measruable.

Example.

1. Toss a coin Twice.
   $\Omega = \{HH, HT, TH, TT\}$, $\mathcal{F} = 2^{\Omega} = \{$ all subsets of $\Omega\}$, $\mathbb{P}(A) = \frac{1}{4}|A|, \;\; A \in \mathcal{F}$.
   Then, X = # of H's is random variable with $X(HH) = 2, X(HT) = X(TH) = 1, X(TT) = 1$.

2. Uniform random variable in $[0,1]$
   $\Omega = [0,1]$, $\mathcal{F} = \{B \in \mathcal{B}(\mathbb{R}) : B \subseteq [0,1]\}$, $\mathbb{P}(B) = \mathcal{L}(B)$ $(\mathbb{P}([0,1]) = \mathcal{L}([0,1]) = 1)$.
   Then, $X : [0,1] \to \mathbb{R}$ with $X(x) = x$ be a (uniform) random variable in $[0,1]$.

Remark. $\mathcal{L}$: Lebesgue measrue on $\mathbb{R}$. i.e.,$\mathcal{L}(a,b) = b - a$. Then, $\mathcal{L}(\{a\}) = 0$
$(\because \{a\} = \bigcap_{i=1}^{\infty}(a - \frac{1}{n}, a + \frac{1}{n}) \Rightarrow \mathcal{L}(\{a\}) = \lim_{n\to\infty} \mathcal{L}((a - \frac{1}{n}, a + \frac{1}{n})) = 0)$
Similarly, $\mathcal{L}([a,b]) = \mathcal{L}([a,b)) = \mathcal{L}((a,b]) = b - a$, $\mathcal{L}(\mathbb{Q}) = \sum_{q \in \mathbb{Q}} \mathcal{L}(\{q\}) = 0$.

Return to uniform random variable,

$$\mathbb{P}[X \in (a,b)] = \mathbb{P}[\{x : X(x) \in (a,b)\}] = \mathbb{P}[(a,b)] = b - a.$$

Definition 1.10 (Distribution measure on X)
X is a random variable in $(\Omega, \mathcal{F}, \mathbb{P})$. μ_X is a **distribution measure on** X if μ_X is a probability measrue on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ such that

$$\mu_X(B) = \mathbb{P}[X \in B] \; \forall B \in \mathcal{B}(\mathbb{R}) = \mathbb{P}[\{\omega : X(\omega) \in B\}] = \mathbb{P}[X^{-1}(B)]$$

Definition 1.11 (Probability density function)
f is a **probability density function** of X if $\mu_X((a,b)) = \int_a^b f(x)dx$

Remark. Lebesgue-Radon-Nikodym decomposition implies that any measure can be decomposed as density part and non-density part.

Example (Standard Normal random variable).
Let $\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$. Define $F : (0,1) \to \mathbb{R}$ by $F(x) = N^{-1}(x)$ for $N(X) = \int_{-\infty}^{x} \phi(y) dy$.
Let $\Omega = (0,1), \mathcal{F} = \{B \in \mathcal{B}(\mathbb{R}) : B \subseteq (0,1)\}, \mathbb{P}(A) = \mathcal{L}(A) : A \in \mathcal{B}(\mathbb{R})$.
Then, $Y : \Omega \ni x \mapsto F(x) \in \mathbb{R}$ is a random variable with

$$\begin{aligned} \mathbb{P}[Y \in (a,b)] &= \mathcal{P}[\{x : Y(x) \in (a,b)\}] \\ &= \mathbb{P}[\{x \in (N(a), N(b))\}] \\ &= N(b) - N(a) = \int_a^b \phi(x) dx, \end{aligned}$$

and a density function is ϕ.