

Martingale and Ito's Integral

Def

right-cont. $\{F_t\}_{t \geq 0}$

$$F_t = F_{t+} = \bigcap_{n \geq 1} F_{t+\frac{1}{n}} \quad \forall t \geq 0$$

Lemma: if τ is optional and $c > 0$ -const $\Rightarrow \tau + c$ is
 $\{\tau \wedge f \leq t\} = \{\tau \leq t\} \cup \{f \leq t\}$ a stopping time

page 4: HW ~~proof~~...

$$\int_G X dP = \int_G E(X|g) dP$$

Prop:

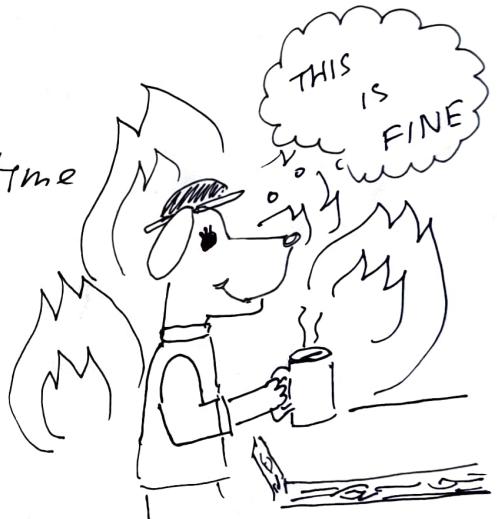
$W_t - F_t - BM$ and τ F_t -stop. time

$\Rightarrow W_{t+\tau} - W_t$ is \perp to F_t

$$X_t, Y_t, Z_t - mg$$

$$mg: \rightarrow X_t Z_t - \langle X_t, Z \rangle + \Rightarrow mg: (\langle X, Z \rangle_t + \langle Y, Z \rangle_t) + []$$

$$mg: \rightarrow Y_t Z_t - \langle Y, Z \rangle$$



Lebesgue- λ Rietjer - gen. of L^1 integrals

$$\frac{dC_t}{dt} = (r(t)dt + m \frac{ds_t}{s_t} + m r(t)dt) =$$

$$= ((1+m)r_t dt + m \frac{ds_t}{s_t})$$

$$d \ln C_t = \frac{dC_t}{C_t} - \frac{1}{2} \cancel{\frac{(dC_t)^2}{C_t^2}} =$$

$$= (1+m)r_t dt + m \frac{ds_t}{s_t} - \frac{1}{2} m^2 \delta_t^2 dt \left(+ \frac{m \cdot \delta_t^2}{2} dt \right)$$

$$(dC_t)^2 = C_t^2 \left\{ (1+m)r_t dt + m \frac{ds_t}{s_t} + \left(\frac{m}{2} - \frac{m^2}{2} \right) \delta_t^2 dt \right.$$

$$\left. + m \cancel{\frac{ds_t}{s_t}} dt + \delta_t dW_t \right)$$

$$= C_t^2 \left((1+m)r_t dt + m \delta_t dW_t \right)^2$$

$$= C_t^2 m^2 \delta_t^2 dt$$

$$\int \ln C_t = \int (1+m)r_t dt + \int m \frac{ds_t}{s_t} \cancel{-} \int \frac{1}{2} m^2 \delta_t^2 dt$$

$$\log C_t - \log C_0 = m(\log s_t - \log s_0) + m \cdot \int \frac{(1+m)r_t}{m} dt$$

$$- m \frac{1}{2} \int m^2 \delta_t^2 dt *$$

$$C_t = C_0 \cdot \left(\frac{s_t}{s_0}^m \right) \cdot \exp \left(a \int r_t dt + b \int \delta_t^2 dt \right)^m$$

$$\exp \left(\cancel{m} \log \left(\frac{s_t}{s_0} \right)^m \right)$$

$$a = \frac{1}{m} + 1$$

$$b = - \frac{1}{2} m \left[\delta_{\frac{m}{2}}^2 - \frac{1}{2} m \right]$$

$$\textcircled{5} \quad dS_t = S_t (\mu(t) dt + \sigma(t) dW_t), \quad S_0 = s$$

$$\frac{dS_t}{S_t} = \mu(t) dt + \sigma(t) dW_t$$

~~W_t = W_t + \mu(t) dt + \sigma(t) dW_t~~

$$d \ln S_t = \frac{dS_t}{S_t} + \frac{1}{2} \sigma^2 \frac{S_t^2}{S_t^2} dt =$$

$$\frac{dS_t}{S_t} = \mu(t) dt + \sigma(t) dW_t - \frac{1}{2} \sigma^2 dt$$

$$= \left(\mu(t) - \frac{1}{2} \sigma^2 \right) dt + \sigma(t) dW_t$$

$$\int d(\ln S_t) = \int_0^t \left(\mu(s) - \frac{1}{2} \sigma^2(s) \right) ds + \int_0^t \sigma(s) dW_s$$

$$\exp(\log S_t - \log S_0) = \exp \left\{ \int (\) ds + \int (\) dW_s \right\}$$

$$\textcircled{6} \quad S \sim S$$

SDE

lecture 2.

Pseudo-random variables

$$X_n = (aX_0 + b) \pmod{c}$$

$\{X_n\}_{n=0,1,\dots,c-1}$

$a, c \in \mathbb{Z}^+$

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$X_n = X_0 \text{ mod } c$

$\{X_n\}$ satisfies a seq. of r.v.
 $\{X_n\}$ are i.i.d. $U(0, 1)$

$\{X_i\}$ seq. of r.v.

Its elements are ind. if $P(X_{n_1} < x_{n_1}, X_{n_2} < x_{n_2}, \dots, X_{n_k} < x_{n_k})$

$\{X_n\} \xrightarrow{n \rightarrow \infty} X$ if
 $= \lim_{n \rightarrow \infty} P(X_{n_i} < x_{n_i})$

Definition:-

$$\lim_{n \rightarrow \infty} \{X_n\} = X \quad \text{if } F_X(x) = \lim_{n \rightarrow \infty} F_{X_n}(x)$$

$\{X_n\}, \{F_{X_n}\}, F_X$
 $\{X_n\}$ is const r.v.s

$C(F_X) = \{X \in \mathbb{R}; F_X(x) \text{ is const}\}$
 $X_n \xrightarrow{n \rightarrow \infty} X$ iff $F_{X_n}(x) \xrightarrow{n \rightarrow \infty} F_X(x), x \in C(F_X)$

$X_n \xrightarrow{n \rightarrow \infty} X \Rightarrow X_n \xrightarrow{n \rightarrow \infty} X \Rightarrow X_n \xrightarrow{n \rightarrow \infty} X$

$X_n \xrightarrow{L^p} X$

by Jensen's inequality $\rightarrow \left(\frac{1}{n} \sum f(u_i)\right)^2 \leq \frac{1}{n} \sum f^2(u_i)$

$$\text{Var} \cdot E \left(\frac{1}{n} \sum f(u_i) \right)^2 \leq E \left(\frac{1}{n} \sum f^2(u_i) \right)$$

by Jensen's inequality.

$= E[f(u_i)^2]$

$f(x) = O(g(x))$, $x \rightarrow a$ for $a < a_0$

f is bounded from above by g



$\{X_i\}_{i \geq 1}$ rep of r.v. i.i.d

$$E(X), E(X^2) \leq \infty$$

$$E \left[\left(\frac{1}{n} \sum_{i=1}^n X_i - \underbrace{E(X_i)}_{\mu} \right)^2 \right] =$$

$$X' u = 0$$

$$X' (\gamma - X\beta) = 0$$

$$X'y - X'X\beta = 0 \quad \Rightarrow \quad E \left[\frac{1}{N^2} \left[\sum_{i=1}^N X_i^2 + 2 \sum_{i < j} X_i X_j \right] - \frac{2}{N} \sqrt{i} \sum_{i=1}^N X_i + \mu^2 \right] =$$

$$Xy = X'X\beta$$

$$= \frac{1}{N^2} E \left[\sum_{i=1}^N a_i^2 \right] + \frac{2}{N^2} n \cdot \mu^2 - \frac{2}{N} n \cdot \mu^2 + \mu^2 =$$

$$= \frac{1}{N} \cdot E [a_i^2] + \frac{2}{N} \cdot \mu^2 - \mu^2 \leq \frac{1}{N} \operatorname{Var}(X_i)$$

Lecture 1

Pseudo-random numbers:

Def. 1. Seq. of unif. dist. r. numbers over $[0, 1]$.)

A seq. $\{X_n\}_{n \geq 1} \subseteq [0, 1]$ is a seq. of r.v. if there exists a p.s. (Ω, \mathcal{F}, P), a seq. $\{U_n\}_{n \geq 1}$ of i.i.d. r.v. with unif. dist. $U[0, 1]$ and we r.s.t. $X_n = U_n(\omega)$, $\forall n \geq 1$.

Pseudo-random generators cons. of deterministic alg. producing a seq. $\{U_n\}_{n \geq 1}$ of $[0, 1]$ real numbers which mimics the stat. properties of a seq. of r.v. (unif. dist. and mut. ind.)

Most algorithms include a linear congruential pseudo-random number generator:

$$X_{n+1} = (aX_n + b) \mod c$$

$a, c \in \mathbb{Z}^+$ ~~where~~

$\Rightarrow U_n = \frac{X_n}{c}$ seem to be unif. dist. on $[0, 1]$

$$\{X_n\} \subseteq \{0, \dots, c-1\}, n=0, 1, \dots$$

$c > 0$ - the "modulus"

$$\{U_n\} \text{ i.i.d. } U[0, 1]$$

$0 < a < m$ - the "multiplier"

$$\bullet \{X_n\} \text{ seq. of r.v.}$$

$0 < b < m$ - the "increment"

$$0 \leq X_0 < m - \text{the "seed"}$$

Properties

or start value

- consider $k > 1$ the first time that

$$X_n = (aX_0 + b) \mod c$$

after this time the seq. repeats itself $\Rightarrow k$ -period

- a congruential seq. which produces $m-1$ distinct values for any seed $X_0 \Rightarrow$ said to have full period

sufficient conditions for a full period seq. are:

- In case $b \neq 0$ and c is a prime number then $\{x_n\}$ has full period if either

$\rightarrow a^{m-1} - 1$ is a multiple of m or

$\rightarrow a^j - 1$, $j \in \{1, \dots, m-2\}$ are not multiples of m

- In case $b \neq 0$, $\{x_n\}$ has full period in each of the following cases:

(i) The GCD of b and a is 1: $\text{GCD}(b, c) = 1$

(ii) Every prime number that divides c also divides $a-1$

(iii) $a-1$ is divisible by 4 if c is divisible by 5

(iv) c is of the form 2^k , b is odd and $a = 4l + 1$ for $l \in \mathbb{N}$

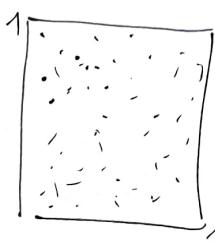
Example: • RANDU ... $a = 2^{16} + 3$, $c = 2^{31}$, $b = 0$

• IBM 360... $a = 7^5$, $c = 2^{31} - 1$, $b = 0$

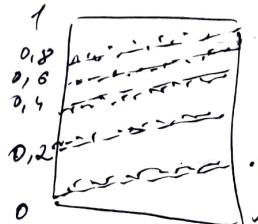
A test for independence

→ Plot successive pairs (v_{2n-1}, v_{2n}) for $n \geq 1$ on the unit square. These points lie on different straight lines of slope a/c and a large number of them should fairly evenly fill the unit square.

$$a = 7^5, c = 2^{31} - 1, b = 0$$



$$a = 1229, c = 2048, b = 1$$

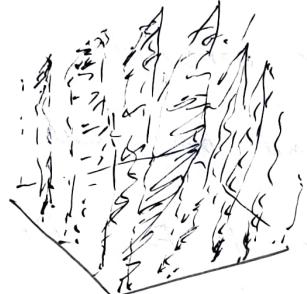


The proceeding test is useful in eliminating glaringly biased generators, but does not guarantee an unbiased generator

(0.8) RANDU: $X_{n+1} = 65539 \pmod{2^{31}}$

appears relatively unbiased, but successive triplets satisfy

$$X_{n+2} = (5X_n - 9X_{n+1}) \pmod{2^{31}}$$



The inverse transform method:

If $X \sim \mu$ the c.d.f. of X is given by

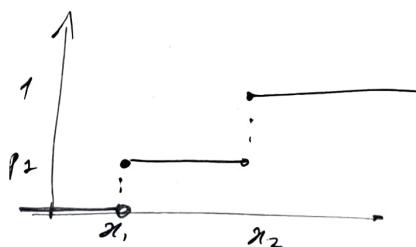
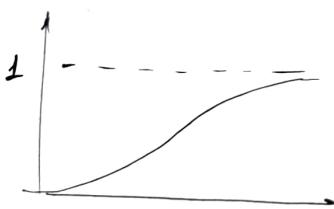
$$F_x(x) = \mu((-\infty, x)) = \int_{-\infty}^x \mu(dy)$$

non-decreasing function and càdlàg functions

(right continuous with left limits =

continuous à droite limite à gauche)

$$\text{s.t. } \lim_{x \rightarrow -\infty} F_x(x) = 0 \quad \text{and} \quad \lim_{x \rightarrow \infty} F_x(x) = 1$$



F_x admits a generalized

inverse G_x which is defined by

$$G_x(u) = \inf \{ x \in \mathbb{R} : F_x(x) \geq u \}, \text{ where } u \in (0, 1)$$

Properties of a gen. inv. function:

o G_x is a \mathbb{R} -valued function defined on $(0, 1)$

non-decreasing and càdlàg, s.t.

$$G_x(u) \leq x \Leftrightarrow u \leq F_x(x), \forall u \in (0, 1), x \in \mathbb{R}$$

- if F_x is strictly increasing cont. function,
then G_x corresponds to the classical inverse
function F_x^{-1} of F_x
- if in addition G_x is cont. differentiable

$$G'_x(u) = \frac{1}{F'_x(G_x(u))}, \quad \forall u \in (0,1)$$

If μ admits a pos. density function $f(x)$
then G_x satisfy the above condition

Prop. If r.v. $U \sim U(0,1)$ and any real r.v. $X \sim \mu$
whose cum. dist. function is F_x , then the real r.v.
 $G_x(U) \sim \mu$

Proof We know that $\{G_x(u) \leq x\} = \{u \leq F_x(x)\}$

$$\Rightarrow P(G_x(u) \leq x) = P(u \leq F_x(x)) = F_x(x)$$

Example:

SP(1)

$(\Omega, \mathcal{F}, \mathbb{P})$ - prob. space, $\omega \in \Omega$ - sample space

Be

$$\#\Omega = 2^{\#A}$$

\mathcal{F} - σ -algebra

$$\#\mathcal{F} = 2^{\#\Omega}$$

(power set)

$$1) \Omega \in \mathcal{F}$$

$$2) A \in \mathcal{F} \Rightarrow \Omega \setminus A \in \mathcal{F}$$

$$3) A_1, \dots, A_n \in \mathcal{F}$$

$$\bigcup_{i=1}^n A_i \in \mathcal{F}$$

④ σ -algebra, that includes all closed (minimal)

[α_β] or [α_β] open intervals is called Borel σ -algebra

$\circ P$ - prob. measure

$$1) P(\Omega) = 1$$

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

$$P(A_1 \cup A_2) = P(A_1) + P(A_2)$$

R.v. - measurable function $f : \Omega \rightarrow \mathbb{R}$
s.t. $\forall B \in \mathcal{B}(\mathbb{R}) : f^{-1}(B) \in \mathcal{F}$

R.function: $X : T \times \Omega \rightarrow \mathbb{R}$

if $\forall t \in T : X(t, \cdot) - \text{r.v. on } (\Omega, \mathcal{F}, \mathbb{P})$

e.g. $T = \mathbb{R}_+ \Rightarrow$ r.function is rand. process

$T = \mathbb{R}_+^\omega \Rightarrow$ r. field

$T = N(\mathbb{Z})$
discr.

$T = \mathbb{R}_+ / \mathbb{R}$
cont.

Trajectory (=path) $T \rightarrow \mathbb{R}$

$\forall t \in T$ fix ω

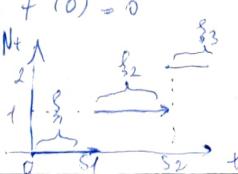
Finite-dimensional dist. $(X_t, \dots, X_{t_n}), t_1, \dots, t_n \in \mathbb{R}$

General process: $S_0 = 0, S_n = S_{n-1} + \xi_n$

(counting) ξ_1, \dots, ξ_n - i.i.d. > 0 a.s.

$$\Leftrightarrow F(0) = 0$$

$$N_t = \arg \max_n \{ S_n \leq t \}$$



s_1, s_2 - renewal times

ξ_1, ξ_2 - interarrival times

$$\text{(i)} \quad \{S_n > t\} = \{N_+ < n\}$$

↑ renewal
time
 $S_n = \sum_{i=1}^n \xi_i$

\uparrow # of events
occurred

$$1) \quad \underline{\text{Convolution}} \quad X \# Y, \quad X \sim F_X, \quad Y \sim F_Y \Rightarrow F_X * F_Y$$

$$F_{X+Y}(x) = \int_{\mathbb{R}} f_X(x-y) dF_Y(y)$$

↓ St. lties Integral

$$2) \quad X \sim P_X, \quad Y \sim P_Y \Rightarrow P_X * P_Y$$

conv. in t. of densities

$$P_{X+Y}(x) = \int_{\mathbb{R}} P_X(x-y) P_Y(y) dy$$

$$F^{n*} = \underbrace{F * \dots * F}_{n \text{ times}}$$

$$1) \quad F^{n*}(x) \leq F(x) \quad \text{if } F(0)=0 \quad (\Rightarrow P(X>0)=1)$$

▷ $\{\xi_1, \dots, \xi_n\}$ - i.i.d. ~ F

$$\{\xi_1 + \dots + \xi_n \leq x\} \subset \{\xi_1 \leq x, \dots, \xi_n \leq x\}$$

$$\begin{aligned} P\{\xi_1 + \dots + \xi_n \leq x\} &\leq \prod_{k=1}^n P\{\xi_k \leq x\} \\ &= F^{n*}(x) \end{aligned}$$

$$2) \quad F^{n*}(x) \geq F^{(n+1)*}(x)$$

$$\{\xi_1 + \dots + \xi_n \leq x\} \supset \{\xi_1 + \dots + \xi_{n+1} \leq x\}$$

3) + commutativity

4) + associativity

Thm: $S_n = \xi_{n-1} + \xi_n, \quad \xi_1, \xi_2 \sim \text{i.i.d. } F, \quad F(0)=0$

Renewal process

$$(i) \quad U(H) = \sum_{n=1}^{\infty} F^{n*}(+) < \infty \quad (\text{converge})$$

$$(ii) \quad E[N_H] = U(H)$$

▷ $E[N_H] = E[\#\{n: S_n \leq H\}] = E\left[\sum_{h=1}^{\infty} \mathbb{1}_{\{S_h \leq H\}}\right] = \sum_{h=1}^{\infty} P\{S_h \leq H\} = \sum_h F^{h*}(H)$ □

Laplace transform: $f : \mathbb{R}_+ \rightarrow \mathbb{R}$

$$\mathcal{L}f(s) = \int_0^\infty e^{-sx} f(x) dx$$

1) f - density function of ξ then $\mathcal{L}f(s) = \mathbb{E}[e^{-s\xi}]$

2) f_1, f_2 : $\mathcal{L}_{f_1 + f_2}(s) = \underbrace{\mathcal{L}f_1(s)}_{\text{in t. of dens.}} + \mathcal{L}f_2(s)$

3) F - dist. funct., $F(0) = 0$, $p = F'$ \Rightarrow

$$\mathcal{L}_F(s) = \frac{\mathcal{L}p(s)}{s}$$

$$\Rightarrow \int_{\mathbb{R}_+} F(x) \frac{d(e^{-sx})}{s} \stackrel{IBP}{=} - \frac{F(x)e^{-sx}}{s} \Big|_0^\infty + \frac{1}{s} \int_{\mathbb{R}_+} p(x)e^{-sx} dx \xrightarrow{\rightarrow 0}$$

(e.g.) 1) $\mathcal{L}x^n(s) = \int_{\mathbb{R}_+} x^n \frac{d(e^{-sx})}{s} = \frac{n}{s} \int_{\mathbb{R}_+} x^{n-1} e^{-sx} dx = \frac{n}{s} \cdot \frac{n-1}{s} \cdots \frac{2}{s} \int_{\mathbb{R}_+} e^{-sx} dx$

2) $\mathcal{L}_{e^{ax}}(s) = \frac{1}{s-a}$ if $a < s$

$$\mathbb{E} N = \mathcal{U}(H) = \sum_{n=1}^{\infty} F^{(n)}(H) = F(H) + \underbrace{\left(\sum_{n=1}^{\infty} F^{(n)} \right)}_{\substack{\text{asym.} \\ \text{property}}} \cdot \underbrace{F(H)}_n$$

$$U = F + U \otimes F = F + U \otimes p \quad \text{if } F' = p$$

dist. dens.

$$\int_{\mathbb{R}} U(x-y) dF(y) = \int_{\mathbb{R}} U(x-y) p(y) dy$$

$$\mathcal{L}_U(s) = \underbrace{\mathcal{L}_F(s)}_{=\frac{\mathcal{L}p(s)}{s}} + \mathcal{L}_u(s) \cdot \mathcal{L}_p(s)$$

$$\Rightarrow \boxed{\mathcal{L}_U(s) = \frac{\mathcal{L}p(s)}{s(1-\mathcal{L}_p(s))}}$$

1. $F \rightarrow \mathcal{L}_p$

2. $\mathcal{L}_p \rightarrow \mathcal{L}_u$

3. $\mathcal{L}_u \rightarrow \text{guess } U$

Example: $S_n = \xi_{n+1} + \xi_n$
 $\xi_1, \xi_2, \dots - p(x) = \frac{e^{-x}}{2} + e^{-2x}, x > 0$

$E N_t = ?$

- (1) $L_p(s) = \frac{1}{2} L_{e^{-s}}(s) + L_{e^{-2s}}(s) =$
 $= \frac{1}{2(s+1)} + \frac{1}{s+2} = \frac{3s+4}{2(s+1)(s+2)}$

- (2) $L_u(s) = \frac{L_p(s)}{s(s - L_p(s))} = \frac{3s+4}{s^2(2s+3)}$

3) Guess inv. Laplace transform:

$$L_u(s) = \frac{A}{s^2} + \frac{B}{s} + \frac{C}{2s+3}$$

$$A = \frac{4}{3}$$

$$B = 1/9$$

$$C = -2/9$$

$$u(t) = \frac{4}{3}t + \frac{1}{9} - \frac{2}{9} \cdot e^{-\frac{3}{2}t}$$

Limit thems for renewal processes

$$S_n = \xi_{n+1} + \xi_n + \dots + \xi_1, \quad \xi_1, \xi_2, \dots - i.i.d. > 0$$

Theorem 1 $\mu = E \xi_1 < \infty$

Then $\frac{N_t}{t} \xrightarrow[t \rightarrow \infty]{\text{a.s.}} \frac{1}{\mu}$ (convergence)

④ SLLN: $\frac{\xi_1 + \dots + \xi_n}{n} \xrightarrow[n \rightarrow \infty]{\text{a.s.}} \mu$ (analogue for ren process)

Theorem 2 $\sigma^2 = \text{Var } \xi_1 < \infty$

(analogue of CLT)

Then $\frac{N_t - t/\mu}{\sqrt{t\sigma^2/\mu^3}} \xrightarrow[t \rightarrow \infty]{\text{a.s.}} N(0, 1)$

$$P\{Z_t \leq x\} \rightarrow P \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} du$$

④ CLT: $\frac{\xi_1 + \dots + \xi_n - n\mu}{\sigma\sqrt{n}} \xrightarrow{d} N(0, 1)$

1) $S_{N_t} \leq t \leq S_{N_t+1}$



$$\lim_{t \rightarrow \infty} \frac{N_t}{S_t} = \lim_{t \rightarrow \infty} \frac{\ln \frac{N_t}{N_0}}{S_t} = \frac{1}{\mu}$$

$$\lim_{t \rightarrow \infty} \frac{N_t}{S_{t+1}} = \lim_{t \rightarrow \infty} \frac{N_t}{N_{t+1}} \cdot \lim_{t \rightarrow \infty} \frac{N_{t+1}}{S_{t+1}} = \frac{1}{\mu} \Rightarrow \square$$

$\Rightarrow P \left\{ \frac{S_n - n\mu}{\sigma\sqrt{n}} \leq x \right\} \rightarrow \Phi(x), x \in \mathbb{R}$

$$P \left\{ S_n \leq \underbrace{n\mu + \sigma\sqrt{n}x}_n \right\} \rightarrow \Phi(x)$$

$$P \left\{ N_t \geq n \right\}$$

$$n \neq t \cdot \mu$$

$$n = t \cdot \mu - \frac{\sigma\sqrt{n}}{\mu} \cdot x = t \cdot \mu - \frac{\sigma\sqrt{n}}{\mu^{3/2}} x$$

$$P \left\{ Z_t \geq -x \right\} \rightarrow \Phi(x)$$

$$P \left\{ Z_t \leq x \right\} = 1 - P \left\{ Z_t > x \right\} \Rightarrow 1 - \Phi(-x) = \Phi(x)$$

Quant p.e

① Arithmetic BM.

$$dX_t = \mu dt + \sigma dB_t$$

drift diffusion
 term

$$\int_0^T dX_t = \int_0^T \mu dt + \int_0^T \sigma dB_t$$

$$X_T - X_0 = \mu(T-0) + \sigma(B_T - B_0)$$

$$X_T = X_0 + \mu T + \sigma B_T$$

$$\boxed{B_T \sim N[0, T]} \quad B_T - B_0 \sim N[0, T]$$

$$X_T = X_0 + \mu T + \sigma B_T \Rightarrow X_T \sim N[X_0 + \mu T, \sigma^2 T]$$

$$\text{Cov}[X_T, X_S] = \sigma^2 \text{Cov}[B_T, B_S] = \sigma^2 \min(T, S)$$

* cov. of 2 BM is
 the lenght of the
 overlapping time

Q) Geometric BM

$$dX_t = \mu X_t dt + \sigma X_t dB_t \Rightarrow dX_t^2 = \sigma^2 X_t^2 dt$$

drift and diffusion
are proportional to
the value of the process

$$Y_t = \ln X_t$$

$$dY_t = d\ln X_t = \frac{dX_t}{X_t} - \frac{1}{2} \frac{dX_t^2}{X_t^2}$$

$$d\ln X_t = \mu dt + \sigma dB_t - \frac{1}{2} \sigma^2 dt$$

$$d\ln X_t = (\mu - \frac{\sigma^2}{2}) dt + \sigma dB_t$$

$$\int_0^T d\ln X_t = \int_0^T (\mu - \frac{\sigma^2}{2}) dt + \int_0^T \sigma dB_t$$

$$\ln X_T - \ln X_0 = (\mu - \frac{\sigma^2}{2}) T + \sigma B_T$$

$$X_T = X_0 e^{(\mu - \frac{\sigma^2}{2}) T + \sigma B_T}$$

$$= e^{\underbrace{\ln X_0 + \dots}_{=z} + \dots}$$

$$Y_T = e^Z \sim LN \left[\ln X_0 + \left(\mu - \frac{\sigma^2}{2} \right) T, \sigma^2 T \right]$$

$$Z \sim N[0, 1] \quad E[e^{tZ}] = e^{t^2/2}$$

$$E[e^{t(a+\sigma z)}] = e^{at + \frac{(t\sigma)^2}{2}}$$

$$\frac{C_t}{C_0} = \left(\frac{S_t}{S_0} \right)^m \exp(a \int_0^t r(s) ds + b \int_0^t s^2 ds)^m$$

$\log C_t - \log C_0 = m \left(\log \left(\frac{S_t}{S_0} \right) + \underbrace{(a \int_0^t r(s) ds + b \cdot \int_0^t s^2 ds)}_{\text{Sto}} \right)$

$$\log \frac{C_t}{C_0} \stackrel{!}{=} \underbrace{\log \frac{S_t}{S_0}}_{\text{Sto}}$$

$$\log \frac{C_t}{C_0} = \underbrace{m \log \frac{S_t}{S_0}}_{\text{Sto}} + m$$

$$\int_0^t \frac{dC_s}{C_s} = m \cdot \int_0^t \frac{dS_s}{S_s} + m \left(a \int_0^t r(s) ds + b \int_0^t s^2 ds \right)$$

$$\frac{dC_t}{C_t} = m \left(\frac{dS_t}{S_t} + \underbrace{(a \cdot r(t) + b \cdot t^2)}_{\delta(t)} \right)$$

$$dC_t = C_t \cdot m \left(\quad \right)$$

$S_t \approx S$

$$\frac{dC_t}{C_t} = (\gamma(t) dt + m\left(\frac{ds^+}{s^+} + \gamma, dt\right))$$

$$\int_0^t d \log C_s = \underbrace{\int_0^t \gamma(s) ds}_{\downarrow} + \underbrace{\int_0^t m(\dots) ds}_{\downarrow}$$

$$\log C_t - \log C_0 = \underbrace{\int_0^t \cancel{m(\frac{ds^+}{s^+}, ds)}}_{\circlearrowleft} + \underbrace{\int_0^t m\left(\frac{ds^+}{s^+}, dt\right) + m(\cancel{ds^+}, dt)}_{\circlearrowleft} + \underbrace{\int_0^t m(\mu dt + \sigma dw, dt)}_{\cancel{\circlearrowleft}}$$

$$\int f dg = g f \cdot \int g df \quad \int m\left(\mu \frac{ds^+}{s^+}, dt\right) =$$

$$\left(\frac{s^+}{s_0}\right)^h \quad \cancel{\text{or}} \quad \left(e^{x^c}\right)^n = e^{x \cdot n}$$

$$\int m(\dots) dt^+ t^{\cdot n} - \int t^{\cdot n} dm$$

$$\int m(\mu dt, dt) dt + \int m(b dw, dt) dt$$

$$\frac{dS_t}{S_t} = \mu(t) dt + \sigma(t) dW_t$$

$$\underline{d(\log(S_t))} = \frac{dS_t}{S_t} - \frac{1}{2} \frac{\sigma^2 P^2 dt}{P^2}$$

$$= \left(\mu - \frac{\sigma^2}{2} \right) dt + \sigma dW_t$$

$$\int dS_t = S_0 \left(\left(\mu - \frac{\sigma^2}{2} \right) dt + \sigma dW_t \right)$$

~~$$S_t = \int_0^t S_u \left(\mu - \frac{\sigma^2}{2} \right) du + \int_0^t S_u \sigma dW_u$$~~

~~$$= \int_0^t S_u \left(\mu - \frac{\sigma^2}{2} \right) du + \int_0^t S_u \sigma dW_u$$~~

$$\int_0^t \frac{dS_u}{S_u} = \int_0^t \left(\mu - \frac{\sigma^2}{2} \right) du + \int_0^t \sigma dW_u$$

$$\log \frac{S_t}{S_0} = \int_0^t \left(\mu - \frac{\sigma^2}{2} \right) du + \int_0^t \sigma dW_u$$

$$\log S_t - \log S_0 = \left[\int_0^t \sigma dW_u \right] - \log S_0$$

$$S_t = S_0 e^{\left[\int_0^t \sigma dW_u \right]}$$

$$dS_t = d\left(g \exp \left[\dots \right] \right) = g \cdot S_t \cdot d \left[\int_0^t (\dots) ds + \int_0^t \sigma(s) dw_s \right]$$

$$\left(\int x dt \right)' = x dt$$

$$\frac{\partial}{\partial x} \left(\int x dx \right)$$

$$\textcircled{d} \left[\int_0^t (\dots) ds + \int_0^t \sigma(s) dw_s \right] =$$

$$= \left[\dots \right] \textcircled{dt} + \left[\dots \right] dw + \frac{1}{2} \left[\dots \right] dt$$

$$\frac{\partial F}{\partial t} dt + \frac{\partial F}{\partial w} dw + \frac{1}{2} \frac{\partial^2 F}{\partial w^2} dw^2$$

$$\left(\mu - \frac{\sigma^2}{2} \right) dt + \sigma dw + \frac{1}{2} \sigma^2 dw^2$$

$$F = f(g(x))$$

$$dF = \frac{df}{dg} \cdot \frac{dg}{dx}$$

$$(dF)^2$$

$$\frac{dx}{ds} \cdot \frac{ds}{dz}$$

~~At~~

$$\frac{d^2k}{ds^2} = \frac{d}{dx} \left(\frac{df}{dy} \cdot \frac{dg}{dx} \right) \cdot \frac{dx}{dy}$$

$$\int_m \frac{ds_+}{s_+} = \int_m \left(s_+ (\mu(t) dt + \delta(t) dW_+) \right)$$

$$\left[\int_m \frac{ds_+}{s_+} + \frac{1}{2} \int s_+^2 ds_+ \right]$$

~~$\int_m \frac{ds_+}{s_+}$~~

$$\int_m \frac{ds_+}{s_+} = \int_m \mu(t) dt + \int_m \delta(t) dW_+$$

$$dX_t = \frac{\beta - X_t}{1-t} dt + dW_t, \quad X_0 = 0$$

$$X_t = Y_t(1-t)$$

$$d(Y_t(1-t)) = \frac{\beta - Y_t(1-t)}{(1-t)} dt + dW_t, \quad Y_0 = 0$$

$$dX_t = \frac{\beta}{1-t} dt - Y_t dt + dW_t$$

$$= \frac{X}{1-t} dt + dW_t$$

~~$dX_t = dY_t(1-t) - Y_t dt =$~~

~~$= \frac{\beta}{1-t} dt = Y_t dt + dW_t$~~

~~Let's take it~~

$$dY_t = \frac{\beta}{(1-t)^2} dt + \frac{1}{1-t} dW_t$$

$$\int_0^t dY_s = \int \frac{\beta}{(1-s)^2} ds + \int \frac{1}{1-s} dW_s$$

$$Y_t = \frac{X_t}{1-t} \Rightarrow X_t = (1-t) \int_0^t \frac{\beta}{(1-s)^2} ds + \int \frac{1-t}{1-s} dW_s$$

$$X_t = \xi + \int_0^t \frac{1-s}{1-s} dW_s, \quad t \in [0, 1]$$

① $X_t = \int_0^t ds + \int \cdot dW_t$ is cont. and adapted to F_t

$$\textcircled{2} \quad P(X_0 = \xi) = 1$$

$$\textcircled{3} \quad |X_t| \leq |\xi| + \int_0^t \left| \frac{1-t}{1-s} \right| dW_s$$

$$\mathbb{E}|X_t| \leq \mathbb{E}|\xi|$$

$$\mathbb{E}|X_t| \leq \xi \text{ a.s.}$$

$$\mathbb{E} \left[\int \left| \frac{\xi - X_s}{1-s} \right| ds + \cancel{\int \dots ds} + \int_0^t \left(\frac{1-s}{1-s} \right)^2 ds \right]$$

$$= \int \frac{\xi - \mathbb{E}[X_s]}{1-s} ds + t$$

$$\leq \int \frac{\xi - t\xi}{1-s} ds + t < \infty$$

$$\textcircled{4} \quad X_t = \int_0^t ds + \int \cdot dW_s$$

$$\xi \sim N(m, \sigma^2)$$

$$dX_t = \frac{\xi - X_t}{1-t} dt + dW_t, \quad X_0 = 0$$

$$X_t = Y_t(1-t)$$

$$d(Y_t(1-t)) = \frac{\xi - Y_t(1-t)}{(1-t)} dt + dW_t, \quad Y_0 = 0$$

~~obviously~~

$$dY_t(1-t) - Y_t dt = \frac{\xi}{1-t} dt - Y_t dt + dW_t$$

$$dY_t = \frac{\xi}{(1-t)^2} dt + \frac{1}{1-t} dW_t$$

$$\int_0^t dY_s = \int_0^t \frac{\xi}{(1-s)^2} ds + \int_0^t \frac{1}{1-s} dW_s$$

$$Y_t = \int_0^t \frac{\xi}{(1-s)^2} ds + \int_0^t \frac{1}{1-s} dW_s, \quad Y_t = \frac{X_t}{1-t}$$

$$X_t = (1-t) \cdot \xi \cdot \left(\frac{t}{1-t} \right) + \int_0^t \frac{1-t}{1-s} dW_s$$

$$X_t = t \xi + \int_0^t \frac{1-t}{1-s} dW_s, \quad t \in [0, 1]$$

Show uniqueness

$$\textcircled{1} \quad X_t = 0 + \int_0^t \frac{\zeta - X_s}{1-s} ds + \int_0^t dW_s$$

is cont. and adapted to F_t

$$\textcircled{2} \quad P(X_0 = 0) = 1$$

$$\textcircled{3} \quad |X_t| \leq |t\zeta| + \int_0^t \frac{1-t}{1-s} dW_s$$

$$E[|X_t|] \leq E[|t\zeta|]$$

$$E[|X_t|] \leq \cancel{tE|\zeta|} + E[|\zeta|], \quad \zeta \sim N(\mu, \sigma^2)$$

$$E[|X_t|] \leq mt$$

$$E \left[\int_0^t \frac{\zeta - X_s}{1-s} ds + \int_0^t ds \right] =$$

$$= \int_0^t \frac{m - E[|X_s|]}{1-s} ds + t \leq$$

$$= \int_0^t \frac{m - mt}{1-s} ds + t < \infty$$

$$\textcircled{4} \quad X_t = 0 + \int_0^t \frac{\zeta - X_s}{1-s} ds + \int_0^t dW_s$$

then $(X_t^1; t \geq 0)$ and $(X_t^2; t \geq 0)$ are indistinguishable $\Leftrightarrow P(X_t^1 = X_t^2, t \geq 0) = 1$

$X_t = t\zeta + \int_0^t \frac{1-t}{1-s} dW_s$ is Gaussian

$$X_t \sim N(tm, \sigma^2 + \frac{(1-t)^2}{(1-t)}t) \Rightarrow X_t \sim N(tm, \sigma^2 + t(1-t))$$

$$\begin{aligned}
 & \left(\frac{s_+}{s_n} \right)^m \\
 C_0 & \cdot \exp \left\{ \int_0^+ \left(m v_{ls} - m \frac{\dot{v}_s^2}{2} \right) ds + m \int_0^+ v_s dv_s \right\} \\
 & \exp \left\{ \int_0^+ \left(m - \frac{1}{2} m^2 \right) \dot{v}_s^2 ds + \int_0^+ r_s / (m+1) ds \right\}
 \end{aligned}$$

$$C_0 \cdot \exp$$

$$\begin{aligned}
 \exp(m) &= \exp(\log e^m) \\
 \exp(m \cdot f) &\neq \exp(f)^m \\
 e^{ma} &= (e^a)^m
 \end{aligned}$$

P.82

$$dX = g X dW$$

$$X(0) = 1$$

$$X(t) = e^{-\frac{1}{2} \int_0^t g^2 ds + \int_0^t g dW}$$

$$Y(t) := e^{X(t)}$$

$$dx = d(e^{X(t)}) = e^{X(t)} \cdot d(X(t)) \cdot dx$$

~~WZT~~
~~dx/dt~~

$$u(x) = e^x$$

$$F(x,t) = e^y$$

$$\frac{\partial F}{\partial y} dy + \frac{1}{2} \frac{\partial^2 F}{\partial y^2} (dy)^2$$

$$\underbrace{\frac{\partial F}{\partial W} dW + \frac{\partial F}{\partial t} dt + \frac{1}{2} \frac{\partial^2 F}{\partial W^2} dt}_{\text{dF}}$$

$$\cancel{\frac{\partial F}{\partial W} dW}$$

$$= e^y \cdot (dy)$$

$$(dy)^2 = \cancel{x_1} \frac{dt^2}{0} + x_2 dt dW + \cancel{g_2} \frac{(dW^2)}{dx}$$

$$P_0 + \int_0^+ \mu E(P(s)) ds =$$

$$P_0 + \int_0^+ \mu E\left(P_0 e^{2W_s} + \left(\mu - \frac{\delta^2}{2}\right)t\right) ds =$$

$$= P_0 + \int_0^+ \mu \cdot P_0 e^{\left(\mu t + \frac{\delta^2}{2}t\right)} \cdot E(e^{2W_s}) ds$$

~~$E(e^X) = e^{E(X)}$~~

$$\downarrow \infty \quad P_0 + \int_0^+ \mu P_0 e^{\mu t} ds$$

$$P_0 + \cancel{\left(P_0 e^{\mu t} \right)} \int_0^+$$

$$E[e^{2\delta W_s}] = e^{2\delta \cdot 0 + \frac{4\delta^2 t}{2}}$$

$$\int_0^+ e^{2\delta W_s} ds =$$

And

$$E(X) \\ = \int_X x f(x) dx \\ = \int_X x dF(x)$$

$$y = f(a+bz) = at + btz \sim N[at, \sigma^2 t^2]$$

$$\mathbb{E}[e^y] = e^{\mathbb{E}[y] + 1/2 \text{Var}[y]}$$

$$X_T = e^{\ln X_0 + (\mu - \sigma^2/2)T + \sigma B_T} = e^y$$

$$y \sim N[\ln X_0 + (\dots)T, \sigma^2 T]$$

$$y \sim N[\mathbb{E}[y], \text{Var}[y]] \quad \text{Delete}$$

$$\mathbb{E}[X_T] = \mathbb{E}[e^y] = e^{\ln X_0 + (\mu - \sigma^2/2)T + 1/2 \sigma^2 T} = X_0 e^{\mu T}$$

$$\text{Var}[X_T] = \mathbb{E}[X_T^2] - \mathbb{E}[X_T]^2$$

$$\begin{aligned} \mathbb{E}[X_T^2] &= \mathbb{E}[e^{2y}] = e^{\mathbb{E}[2y] + 1/2 \text{Var}[2y]} \\ &= e^{2\mathbb{E}[y] + 2\text{Var}[y]} = e^{2(\ln X_0 + \dots) + 2\sigma^2 T} \\ &= \dots = X_0^2 e^{2\mu T + \sigma^2 T} \end{aligned}$$

$$\text{Var}[X_T] = X_0^2 e^{2\mu T + \sigma^2 T} - X_0^2 e^{2\mu T}$$

$$= X_0^2 e^{2\mu T} (e^{\sigma^2 T} - 1)$$

$$\text{Cov}(X_t, X_s) = \mathbb{E}(X_t X_s) - \mathbb{E}(X_t) \mathbb{E}(X_s)$$

$$= X_0^2 e^{\mu(T+s) + \sigma^2 s} - X_0^2 e^{\mu(T+s)}$$