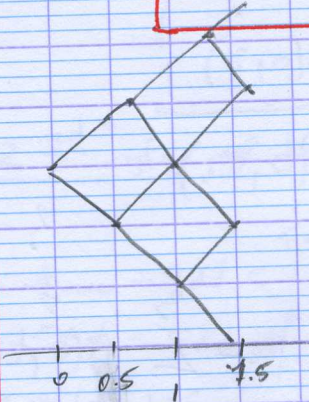


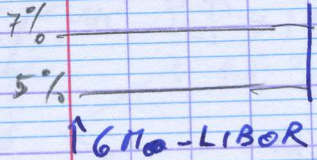
Lecture VI

Introduction to stochastic calculus



Discrete time : $\Delta t = 6M$
 6 months interest rate.

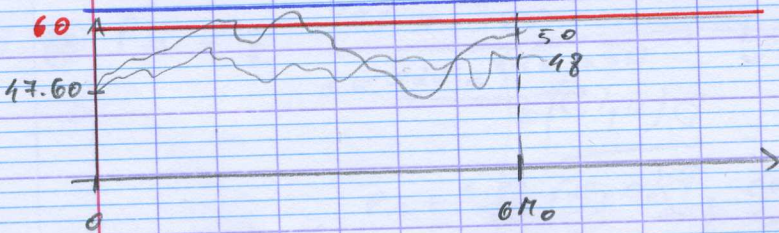
Daily Accrual note:



$Z_{\text{libor}} \times \frac{\text{\# of days LIBOR was at this rate bond } (1+\alpha)}{\text{\# of days in the period}}$

Knock in and knock out options:

JP Morgan



Barrier that should not be crossed.

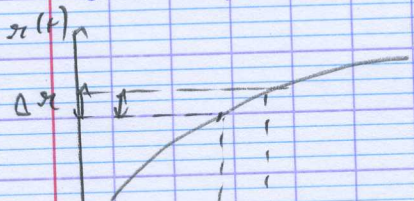
when $\Delta t \rightarrow 0$ (Δt very small), we denote it by dt .
 The rates that we will model are all future spot rates "short rates"

short rate is a random variable (up or down)
 we model change in rate for a very small increment in time (dt)

$r(t+\Delta t) - r(t) = \Delta r$: change in rate.

$\rightarrow \Delta r =$ evolution of interest rates.

or $dS(t) =$ evolution of an asset.



$f(x), f(s)$: asset or stock.

We want $df(s)$

ex 1: $f(s) = s^2 + s$

$$df(s) = \frac{df}{ds} \cdot ds = (2s + 1) ds.$$

ex 2: if $s = 10 \Rightarrow f(10) = 110.$

$$ds = 0.01$$

$$\Rightarrow df(s) = (2 \times 10 + 1) \times 0.01 = 0.21$$

$$\{ f(10.01) = (10.01)^2 + 10.01 = 100.20 + 10.01 = 110.21$$

$$\{ f(10) = 110$$

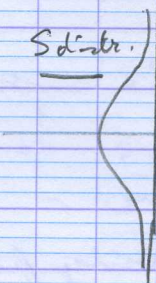
$$\Delta f \approx df = 0.21.$$

• However, s is a random variable,

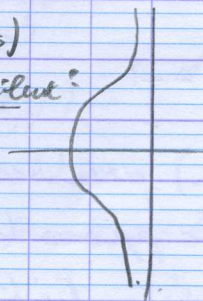
$f(s)$ = option = "is a random".

→ how do we determine $df(s)$? ⇒ **ITO'S LEMMA.**
we look for the link:

S distrib.



between $f(s)$
distribut.



rem: if s is deterministic: $df(s) = f'(s) ds$. (easy)

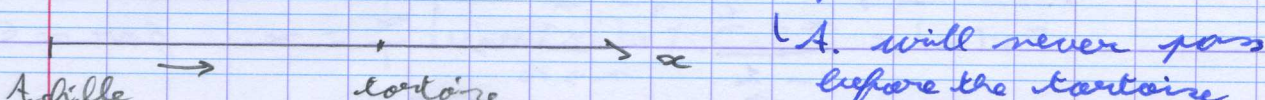
to be able to describe the phenomenon, we have to extend the notion of limit and derivative. (integration).

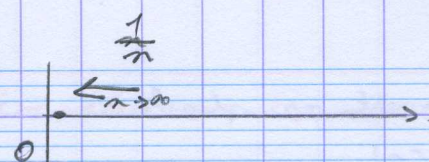
→ **STOCHASTIC CALCULUS.**

Extension of concept of convergence and limit.

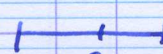
$$\lim_{n \rightarrow \infty} \frac{1}{n} = 0$$

• historical remark: Achille paradox.



Cauchy: 

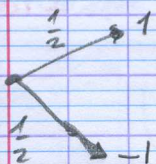
$\lim_{n \rightarrow \infty} \frac{1}{n} = 0$ means:
 $\forall \epsilon > 0, \exists N \in \mathbb{N}, \forall n > N, \left| \frac{1}{n} \right| \leq \epsilon$

\Rightarrow given any interval  we have, after a while, there is $N_0(\epsilon)$ such that, for all $n > N_0(\epsilon), \left| \frac{1}{n} - 0 \right| \leq \epsilon$.

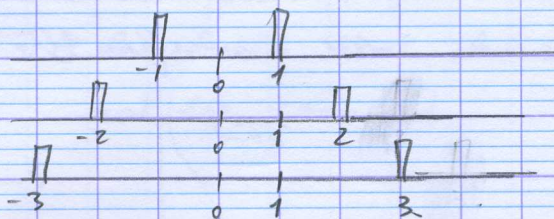
generally: $\lim_{n \rightarrow \infty} f(n) = L$
 $\Leftrightarrow \forall \epsilon > 0, \exists N_0 \in \mathbb{N}, \forall n > N_0, |f(n) - L| \leq \epsilon$

$f(n) = x^{\frac{1}{n}}, x > 0$
 $\lim_{n \rightarrow \infty} f(n) = \lim_{n \rightarrow \infty} x^{\frac{1}{n}} = f(x)$
 if given $\forall x, \lim_{n \rightarrow \infty} f(n) = f(x)$

ex ①:



$$\begin{cases} S_1 = X_1 \\ S_2 = X_1 + X_2 \\ S_3 = X_1 + X_2 + X_3 \end{cases}$$



(S_n) are random variable.

Suppose (X_i) are random var.

Let $F_i(x)$ the cumulative density functⁿ of X_i :

$$F_i(x) = P(X_i \leq x)$$

def:

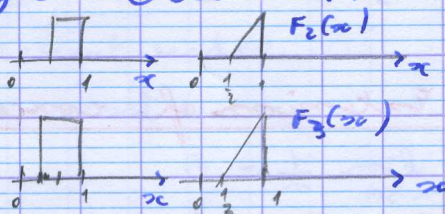
$X_n \xrightarrow[n \rightarrow \infty]{} X$ in distribution if $\lim_{n \rightarrow \infty} F_n(x) = F(x)$
 we say: convergence in distribution.

ex ②: (X_n) are uniformly distributed between $[\frac{1}{n}, 1]$

$$X_2 \sim U\left(\left[\frac{1}{2}, 1\right]\right)$$

$$X_3 \sim U\left(\left[\frac{1}{3}, 1\right]\right)$$

$$X_{100} \sim U\left(\left[\frac{1}{100}, 1\right]\right)$$



for X_n : $f_n(x) = \frac{1}{1 - \frac{1}{n}}$

$$F_n(x) = \frac{x - \frac{1}{n}}{1 - \frac{1}{n}} \xrightarrow[n \rightarrow \infty]{} \frac{x}{1} = x \text{ for } x \in [0, 1]$$

Central limit theorem:

If (X_i) are iid (independent and identically distributed) random variables (RV) with

$$\{ E[X_i] = \mu$$

$$\text{Var}[X_i] = \sigma^2$$

$$S_n = \frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}}$$

then:

$$S_n \xrightarrow[n \rightarrow \infty]{} N(0, 1)$$

: normal $(0, 1)$
mean variance.

ex 1 (following) $S_1 = X_1$

$$S_2 = X_1 + X_2$$

$$S_n = \sum_{i=1}^n X_i$$

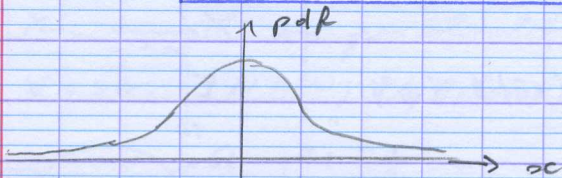
we suppose $E[X_i] = 0$ and (X_i) iid.
 $\text{Var}[X_i] = 1$

then: $S'_n = \frac{\sum_{i=1}^n X_i - 0}{\sqrt{n} \times 1} \Rightarrow N(0, 1)$

$$\Rightarrow S'_n = \frac{1}{\sqrt{n}} \sum_{i=1}^n X_i \sim N(0, 1)$$

$$\Rightarrow S_n = \sum X_i \sim \sqrt{n} N(0, 1)$$

$$\Rightarrow \boxed{S_n \sim N(0, n)} \text{ when } n \text{ large.}$$



ex 2:

Let $n = \left\lceil \frac{T}{\Delta x} \right\rceil$ where $\left\lceil \frac{T}{\Delta x} \right\rceil$ is the largest integer $\leq \frac{T}{\Delta x}$

$$\lceil x \rceil = \max \{ n \in \mathbb{N} / n \leq x \}$$

Note $W_n = \Delta x (X_1 + X_2 + \dots + X_n) = \Delta x \times \left(\sum_{i=1}^n X_i \right)$

(X_i) are iid, $E[X_i] = 0$.

$$\text{Var}[X_i] = 1$$

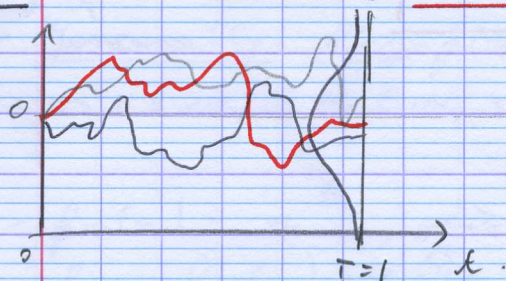
$$E[W_n] = E(\Delta x \times \sum_{i=1}^n X_i) = \Delta x \times \left(\sum_{i=1}^n E(X_i) \right) = 0$$

$$\text{Var}[W_n] = \text{Var}(\Delta x \times \sum_{i=1}^n X_i) = \Delta x^2 \times \left(\sum_{i=1}^n \text{Var}(X_i) \right) \text{ by independence} \\ = \Delta x^2 \times n$$

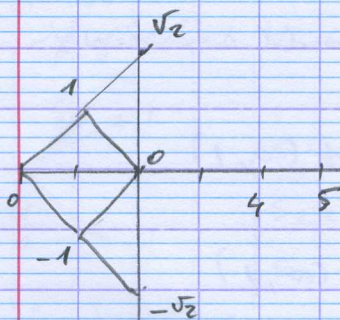
$$\text{If } \Delta x = \frac{1}{\sqrt{n}} \Rightarrow \begin{cases} E[W_n] = 0 \\ \text{Var}[W_n] = 1 \end{cases}$$

$$W_n = \frac{\sum_{i=1}^n X_i - 0}{1 \times \sqrt{n}} \xrightarrow{n \rightarrow \infty} N(0, 1)$$

def: W_n is called a Wiener process or a Brownian Motion



$$\begin{cases} \text{mean} = 0 \\ \text{Var} = \sqrt{t} \end{cases}$$

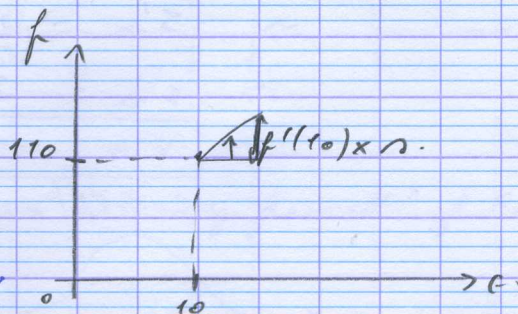


pply 1: all paths are continuous.
(no jumps)

ex: $f(t) = t^2 + t$

$$f(10) = 110$$

$$f'(t) = 2t + 1 \Rightarrow f'(10) = 30$$



pply 2: the paths are almost nowhere differentiable.

Convergence in probability!

Almost equivalent to convergence in norm.

Kolmogorov: $(\Omega, \mathcal{F}, \mu)$

Ω = sample space.

$\mathcal{F} = \{1, 2, 3, \dots\} = \{0, \infty\}$.

\mathcal{F} : is a collection of subsets of Ω .

def: $\emptyset \in \mathcal{K}$

$A \in \mathcal{K} \Rightarrow A^c \in \mathcal{K}$.

$\mathcal{K}_i \in \mathcal{K}$ and $\mathcal{K}_j \in \mathcal{K} \Rightarrow \mathcal{K}_i \cup \mathcal{K}_j \in \mathcal{K}$.

If $\forall i \in \mathbb{N}, \infty, F_i \in \mathcal{K} \Rightarrow \cup F_i \in \mathcal{K} \Rightarrow \sigma$ -additivity.
 \mathcal{K} is called a σ -field.

ex: $\mathcal{K} = \{\emptyset, \Omega, \{2, 4, 6\}, \{1, 3, 5\}\}$.

$\mathcal{K}_1 = \{\emptyset, \Omega\}$.

$\mathcal{K}_2 = \{\emptyset\}$.

def: μ called probability measure is defined by:

$\mu: \mathcal{K} \rightarrow [0, 1]$

$\forall A \neq \emptyset, \mu(A) \geq 0$.

$\mu(\emptyset) = 0$

$\mu(\Omega) = 1$

$A \cap B = \emptyset \Rightarrow \mu(A \cup B) = \mu(A) + \mu(B)$

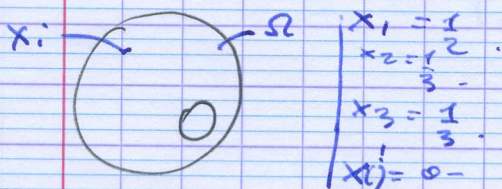
σ -additivity; if $\forall (i,j) F_i \in \mathcal{K}, F_i \cap F_j = \emptyset$

then: $\mu(\bigcup_{i=1}^{\infty} F_i) = \sum_{i=1}^{\infty} \mu(F_i)$

def: A random variable is a function $X: \Omega \rightarrow \mathbb{R}$.

def: $X_n \xrightarrow[n \rightarrow \infty]{} X$ in probability \Leftrightarrow

$\forall \epsilon > 0, \exists N \in \mathbb{N}, \forall n > N, \forall \eta > 0, \forall n > N, P(|X_n - X| \leq \eta) \leq \epsilon$.



$\forall \epsilon > 0, \lim_{n \rightarrow \infty} P[\omega: \omega \in \Omega, |X_n(\omega) - X(\omega)| > \epsilon] = 0$

$\Leftrightarrow \forall \epsilon > 0, \lim_{n \rightarrow \infty} P[\omega, |X_n(\omega) - X(\omega)| < \epsilon] = 1$

* Kolmogorov: $(\Omega, \mathcal{K}, \mu)$: we flip a coin H : head

$\Omega = \{H, T\}$

T : tail

$\mathcal{K} = \{\emptyset, \Omega, \{H\}, \{T\}\}$

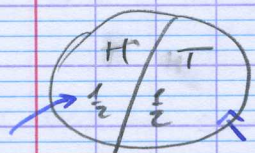
Convergence in distribution:

$$X_1: H \mapsto 1 \quad \mu(H) = \mu(T) = \frac{1}{2}$$

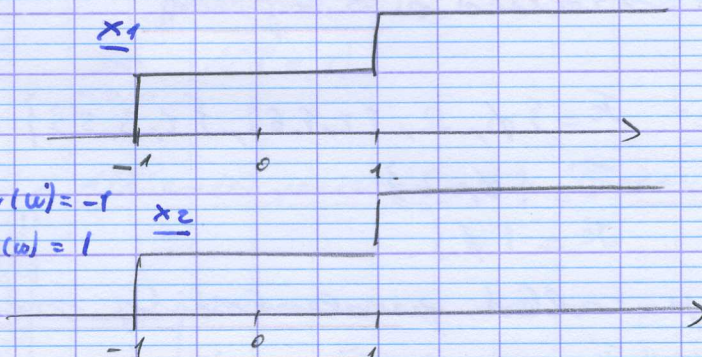
$$T \mapsto -1$$

$$X_2: H \mapsto -1$$

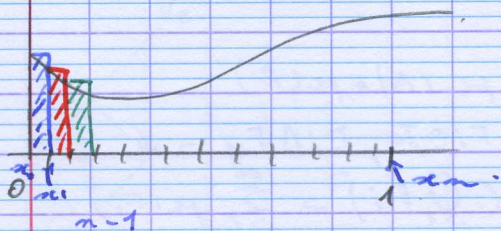
$$T \mapsto 1$$



$$\begin{cases} X_1(\omega) = 1 \\ X_2(\omega) = -1 \end{cases} \quad \begin{cases} X_1(\omega) = -1 \\ X_2(\omega) = 1 \end{cases}$$



- $\int_0^1 f(x) dx$: definite integral.
- Riemann integral.

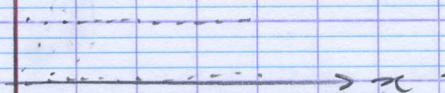


$$\text{def: } \left[\lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} f(x_i) (x_{i+1} - x_i) = \int_0^1 f(x) dx. \right.$$

which is the Riemann integral.

counter-ex: $f(x) = \begin{cases} 1 & \text{if } x \text{ is irrational} \\ 0 & \text{if } x \text{ is rational } \frac{p}{q} \end{cases}$

notation: $f(x) = \chi_{\mathbb{R}}(x)$



→ the Riemann integral does not exist.

$$\begin{cases} \sum f(x_i) (x_{i+1} - x_i) = 0 \\ \sum f(x_i) (x_{i+1} - x_i) = 1 \end{cases}$$

⇒ depending on the subdivision of $(0, \alpha)$