

Last time: Conditional Exp.

$$(\Omega, \mathcal{G}, P)$$

$\mathcal{F} \subseteq \mathcal{G}$  a  $\sigma$ -sub alg of  $\mathcal{G}$ .

$X \rightarrow \mathcal{G}$  meas RV.

$E(X|\mathcal{F}) \rightarrow$  "best approx of  $X$  as an  $\mathcal{F}$  meas RV"

$E(X|\mathcal{F}) = \begin{cases} \textcircled{1} \text{ Is an } \mathcal{F}\text{-meas RV.} \end{cases}$

$\begin{cases} \textcircled{2} \text{ for every } A \in \mathcal{F}, \int_A X dP = \int_A E(X|\mathcal{F}) dP \end{cases}$

Amongst all  $\mathcal{F}$ -meas RV's,  $Y$ ,  $E(X-Y)^2$  is minimized when  
 $Y = E(X|\mathcal{F})$ .

Proof: ① Suppose  $X$  is an  $\mathcal{F}$ -meas RV,

$$\text{then } E(X | \mathcal{F}) = \cancel{EX} \\ X$$

② Suppose  $X$  is a  $\mathcal{G}$ -meas RV that is Independent of  $\mathcal{F}$ .

(i.e. If  $A \in \sigma(X)$ ,  $B \in \mathcal{F}$ , then  $A$  ind of  $B$   
( $P(A \cap B) = P(A)P(B)$ ))

$$\text{then } E(X | \mathcal{F}) = EX$$

Intuition ②: Say  $X = \sum_{i=1}^n a_i \mathbb{1}_{A_i}$ ,  $A_i \in \mathcal{G}$

& each  $A_i$  is ind of every event in  $\mathcal{F}$ .

Let  $B \in \mathcal{F}$  be some event.

Know  $A_i$  is ind of  $B$  for all  $i$ .

$$\begin{aligned} \text{Compute } \int_B X dP &= \int_B (\sum a_i \mathbb{1}_{A_i}) dP \\ &= \sum a_i \int_B \mathbb{1}_{A_i} dP \\ &= \sum a_i P(A_i \cap B) \\ &= \sum a_i P(A_i) P(B) \quad (\because A_i \text{ is ind of } B) \\ &= P(B) \left[ \sum a_i P(A_i) \right] = P(B) EX = \int_B (EX) dP \end{aligned}$$

$$\Rightarrow \int_B X dP \implies \int_B (EX) dP. \text{ for EVERY } B \in \mathcal{F}.$$

$$\left. \begin{array}{l} \parallel \text{ (def of cond exp) } \\ \int_B \underline{E(X|\mathcal{F})} dP \end{array} \right\} \implies E(X|\mathcal{F}) = EX.$$

(Note:  $EX$  is a const r.v. & is  $\mathcal{F}$ -measurable).

$$Z(\omega) = \cancel{f(\omega)} \cdot 1 \leftarrow \text{const R.V.}$$

$$\left. \begin{array}{l} \{Z \leq \alpha\} \rightarrow \Omega \\ \qquad \qquad \rightarrow \emptyset \end{array} \right\} \begin{array}{l} \alpha \geq 1 \\ \alpha < 1 \end{array}$$

Independence lemma: (Examples in Recitation tomorrow).

$t \rightarrow f(x, y) \rightarrow$  fn of two variables

$X \rightarrow$  ~~meas~~  $\mathcal{G}$ -meas R.V.  $X$  is ind of  $\mathcal{G}$ .

$Y \rightarrow \mathcal{F}$  meas R.V.

$E(f(X, Y) | \mathcal{F}) = g(Y)$  where

$g = g(y)$  is a (non-random) function defined by

$$g(y) = E f(X, y)$$

Martingales:  $\rightarrow$  Fair game.

$\hookrightarrow$  ① Filtration:

$W =$  Brownian Motion.

$\sigma(W(t)) \leftarrow$  info obtained by observing  $W(t)$

Let  $\mathcal{F}_t = \sigma\left(\bigcup_{s \leq t} \sigma(W_s)\right)$ .

$=$   $\sigma$ -alg generated by  $\left\{\bigcup_{s \leq t} \sigma(W_s)\right\}$ .

Note: If  $s \leq t$ , then  $\mathcal{F}_s \subseteq \mathcal{F}_t$

① A filtration  $\{\mathcal{F}_t\}$  is a collection of  $\sigma$ -algebras such that if  $s \leq t$   $\mathcal{F}_s \subseteq \mathcal{F}_t$ .

② The filtration generated by a process  $X$  is denoted by  $\mathcal{F}_t^X = \sigma\left(\bigcup_{s \leq t} \sigma(X_{\frac{t}{s}})\right)$ .

③ Most of the time  $\mathcal{F}_t =$  filtration generated by B.M.

Def: ① Let  $\{\mathcal{F}_t\}$  be a filtration

We say a process  $X$  is adapted to the filtration  $\{\mathcal{F}_t\}$  if for every  $t \geq 0$ ,

$X(t)$  is an  $\mathcal{F}_t$ -meas R.V.

② We say  $M$  is a martingale (wrt the filtration  $\{\mathcal{F}_t\}$ ) if -

①  $M$  is adapted (i.e.  $M(t)$  is  $\mathcal{F}_t$  meas).

② If  $s \leq t$ ,  $E(M(t) | \mathcal{F}_s) = M(s)$



Sub Martingale : ~~the~~ Require  $E(M(t) | \mathcal{F}_s) \geq M(s)$ .

Super-Martingale : Require  $E(M(t) | \mathcal{F}_s) \leq M(s)$ .

~~Proof~~ ~~Prp~~ If  $M$  is a mg,  $EM(t) = EM(0)$

Proof: Know  $M(0) = E(M(t) | \mathcal{F}_0)$  (mg prop).

$$\Rightarrow EM(0) = E E(M(t) | \mathcal{F}_0) = EM(t).$$

Warning: If  $EM(t) = EM(0)$  for every  $t$   
must  $M$  be a mg? **NO** (Eg in Redation)

Eg: B.M. is a mg

Filtration  $\rightarrow$  Brownian filtration.

$W \rightarrow$  std Brownian motion.

To check BM is a mg, need to check

for every  $s \leq t$ ,

$$\boxed{E(W(t) | \mathcal{F}_s) = W(s)}$$

Proof of  $(*)$ :  $E(W(t) | \mathcal{F}_s) = E(W(t) - W(s) + W(s) | \mathcal{F}_s)$

$$= E(W(t) - W(s) | \mathcal{F}_s) + E(W(s) | \mathcal{F}_s)$$

$$E(W(t) - W(s)) + W(s)$$

( $\circ$ ,  $\circ$ ) ①  $W(t) - W(s)$  is independ. of  $\mathcal{F}_s$ .

②  $W(s)$  is <sup>(ind inc)</sup>  $\mathcal{F}_s$  meas.

$$\Rightarrow E(W(t) | \mathcal{F}_s) = W(s) + 0 = W(s) //$$

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Stochastic Integration:

Stock  $\rightarrow$  price at time  $t = S(t)$ .

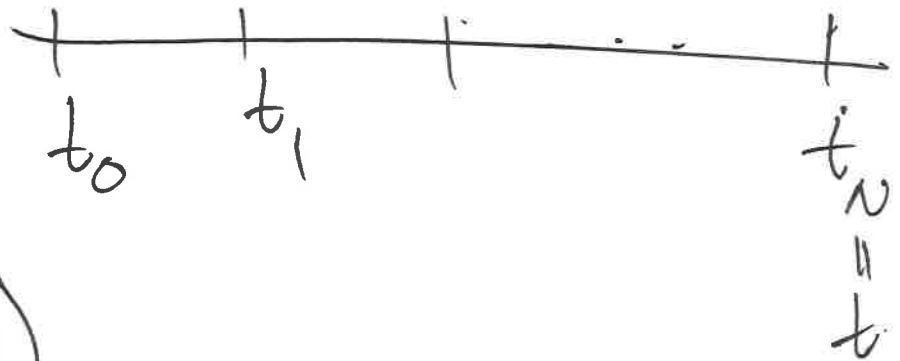
$\Delta(t) =$  position on the stock = # shares held at time  $t$ .

Only trade at times  $0 = t_0 < t_1 < \dots < t_N$ .

Change in wealth

$$= X(t_N) - X(0)$$

$$= \sum_{i=0}^{n-1} \Delta(t_i) (S(t_{i+1}) - S(t_i))$$



$$P = \{ 0 = t_0 < t_1 < t_2 \dots t_N = t \}$$

↑ partition of  $[0, t]$ .

$$\|P\| = \max_i t_{i+1} - t_i$$

Trade cost:

$$\text{Expect } X(t) - X(0) = \lim_{\|P\| \rightarrow 0} \sum \Delta_i(t) (S(t_{i+1}) - S(t_i))$$

$$= \int_0^t \Delta(s) dS(s).$$

(Riemann-Stieltjes Integral).

From calculus: This limiting process only works.

for "processes of finite 1<sup>st</sup> variation".

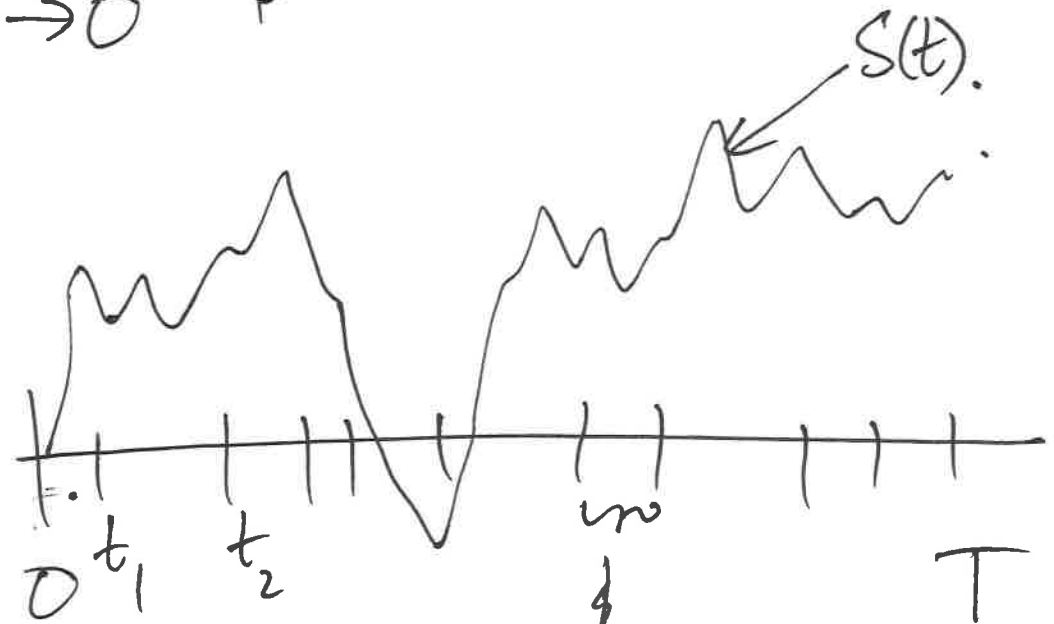
Stock prices typically don't have this.

Instead: Use the "Itô Integral".

① First variation.

$S \rightarrow$  some process.

$$V_{[0, T]}(S) \stackrel{\text{def}}{=} \lim_{|P| \rightarrow 0} \sum_{i=0}^{n-1} |S(t_{i+1}) - S(t_i)|.$$

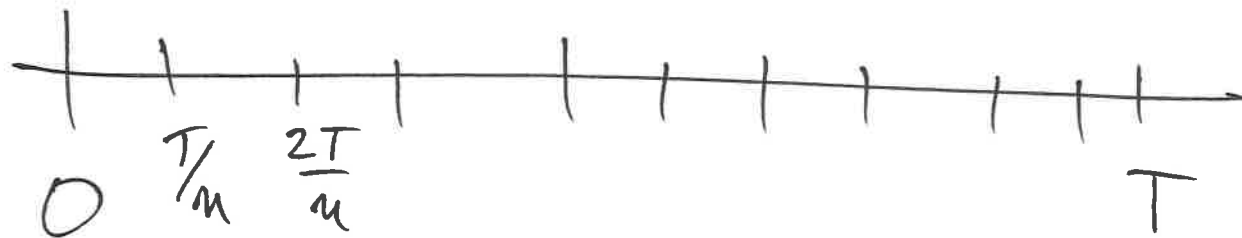


lim as  $|t_{i+1} - t_i| \rightarrow 0$

Claim: Brownian Motion does NOT  
have finite 1<sup>st</sup> variation.

Proof:  $\lim_{n \rightarrow \infty} \sum \left| W\left(\frac{(i+1)T}{n}\right) - W\left(\frac{iT}{n}\right) \right| = +\infty$   
almost surely!

(Proof in notes).  
No time in lecture.



# What Saves Use Quadratic Variation

Def: Let  $M$  be any process.

Define the quadratic variation of  $M$ . by

$$[M, M](T) = \lim_{\|P\| \rightarrow 0} \sum_{i=0}^{n-1} \left( M(t_{i+1}) - M(t_i) \right)^2$$

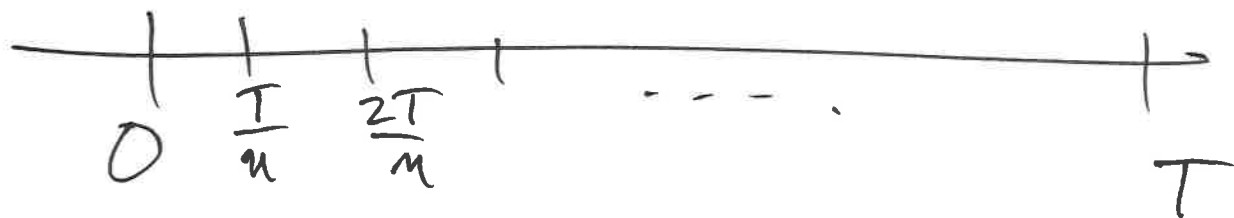
Compute  $[W, W]$ :

Let  $W =$  std 1D B.M.

Claim:  $[W, W](T) = T$



Proof: For simplicity assume  $t_i = \frac{T \cdot i}{n}$  (uniform partition).



$$\begin{aligned} \text{Let } \Delta_i W &= W(t_{i+1}) - W(t_i) \\ &= W\left(\frac{T(i+1)}{n}\right) - W\left(\frac{T i}{n}\right). \end{aligned}$$

$$\text{NTS: } \lim_{n \rightarrow \infty} \sum (\Delta_i W)^2 = T.$$

Note:

$$\sum_{i=0}^{n-1} (\Delta_i W)^2 - T = \underbrace{\sum_{i=0}^{n-1} \left[ W\left(\frac{(i+1)T}{n}\right) - W\left(\frac{iT}{n}\right) \right]^2 - \frac{T}{n}}_{\xi_i}$$

Note:  $\xi_i$  are all iid RV's.

$$\xi_i \sim \left[ N\left(0, \frac{T}{n}\right)^2 - \frac{T}{n} \right].$$

$$\Rightarrow E \xi_i = 0 \quad \& \quad E \xi_i^2 = \frac{T^2}{n^2} \left( E N(0, 1)^4 - 1 \right).$$

$$\Rightarrow \text{Var} \left( \sum_{i=0}^{n-1} \xi_i \right) = \sum_{i=0}^{n-1} \text{Var}(\xi_i).$$

$$= \sum_{i=0}^{n-1} \frac{T^2}{n^2} (E N(0,1)^4 - 1)$$

$$\xrightarrow{n \rightarrow \infty} 0$$

$$\Rightarrow \lim_{n \rightarrow \infty} \text{Var} \left( \sum_{i=0}^{n-1} (\Delta_i W)^2 - T \right) \longrightarrow 0$$

$$\Rightarrow \lim_{n \rightarrow \infty} \sum_{i=0}^{n-1} (\Delta_i W)^2 = T$$

$$[W, W](T)$$

// ,

$$E N(0, \sigma^2) = 0$$

$$E N(0, \sigma^2)^2 = \sigma^2,$$

$$\parallel$$

$$\text{Var}(N(0, \sigma^2)),$$

$$\xi_i \sim \left[ N\left(0, \frac{T}{n}\right)^2 - \frac{T}{n} \right].$$

$$E \xi_i^2 = E \left( N\left(0, \frac{T}{n}\right)^4 + \frac{T^2}{n^2} - 2 \frac{T}{n} N\left(0, \frac{T}{n}\right)^2 \right),$$

$$= E N\left(0, \frac{T}{n}\right)^4 + \cancel{\frac{T^2}{n^2}} - \cancel{2} \frac{T^2}{n^2}$$

$$\lim_{n \rightarrow \infty} \text{Var}(X_n - T) = 0$$

