

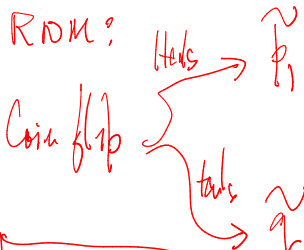
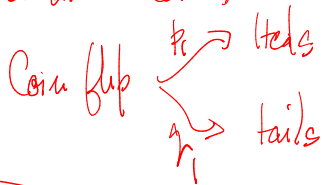
last time's RNM

Equivalent measure \tilde{P} under which

$$E_{\tilde{P}}(D_{u+1} S_{u+1}) = D_u S_u$$

(Doe stock is a \tilde{P} -mg).

Binomial model:



$$\tilde{p}_1 = \frac{(1+r) - d}{u - d}$$

last time

Theorem 4.57. Let X_n represent the wealth of a portfolio at time n . The portfolio is self-financing portfolio if and only if the discounted wealth $D_n X_n$ is a martingale under the risk neutral measure \mathbf{P} .

Remark 4.58. Recall a portfolio is *self financing* if $X_{n+1} = \Delta_n S_{n+1} + (1+r)(X_n - \Delta_n S_n)$ for some adapted process Δ_n .

- (1) That is, self-financing portfolios use only tradable assets when trading, and don't look into the future.
- (2) All replication has to be done using self-financing portfolios.

Proof of Proposition 4.1.

Security Pays V_N at time N

AFP at time $n \leq N$ is

RNP factor

$$V_n = \frac{1}{D_n} \tilde{E}_n (D_N V_N)$$

$$D_n = \text{Discont factor} = \frac{1}{(1+r)^n}$$

Pf. \Rightarrow Want a R. Pf.

\Leftrightarrow Want

a

self fin part

\Rightarrow

$$X_N = V_N.$$



Disc wealth is a \mathbb{P} -mg.

Choose

$$X_{-N} = \frac{1}{D_{-N}} E_{-N}(D_N X_N)$$

&

$$X_N = V_N.$$

Know $X_N = V_N$ (by choice)

$$\Rightarrow D_{-N} X_{-N} = E_{-N}(D_N X_N)$$

NTS $D_n X_n$ is a \tilde{P} -mg

↳ Check: $D_n X_n \approx E_n(D_{n+1} X_{n+1})$

Compute $E_n(D_{n+1} X_{n+1}) = E_n(E_{n+1}(D_N X_N))$

Tower $= E_n(D_N X_N)$

$= D_n X_n$!! Done!!

Example 4.59. Consider two stocks S^1 and S^2 , $u = 2$, $d = 1/2$.

- ▷ The coin flips for S^1 are heads with probability 90%, and tails with probability 10%.
- ▷ The coin flips for S^2 are heads with probability 99%, and tails with probability 1%.
- ▷ Which stock do you like more?
- ▷ Amongst a call option for the two stocks with strike K and maturity N , which one will be priced higher?

↳ Both call options are worth exactly the same

[RNM only depends on u, d, r & N
does not depend on p & q]

Remark 4.60. Even though the stock price changes according to a coin that flips heads with probability p_1 , the arbitrage free price is computed using conditional expectations using the risk neutral probability. So when computing $\tilde{E}_n V_N$, we use our new invented "risk neutral" coin that flips heads with probability \tilde{p}_1 and tails with probability \tilde{q}_1 .

$\rightarrow \tilde{p}_1 \& \tilde{q}_1$ Do not depend on $p_1 \& q_1$

Concepts that will be generalized to continuous time.

- Probability measure: Lebesgue integral, and not a finite sum. Same properties.
- Filtration: Same intuition. No easy description.
- Conditional expectation: Same properties, no formula.
- Risk neutral measure: Formula for \tilde{P} is complicated (Girsanov theorem.)
- Everything still works because of of Theorem 4.57. Understanding why is harder.

Self fin \Leftrightarrow Disc wealth is a \tilde{P} martingale

5. Stochastic Processes

5.1. Brownian motion.

- Discrete time: Simple Random Walk.

▷ $X_n = \sum_1^n \xi_i$, where ξ_i 's are i.i.d. $E\xi_i = 0$, and $\text{Range}(\xi_i) = \{\pm 1\}$.

- Continuous time: Brownian motion:

▷ $Y_t = X_n + (t - n)\xi_{n+1}$ if $t \in [n, n + 1)$.

▷ Rescale: $Y_t^\varepsilon = \sqrt{\varepsilon} Y_{t/\varepsilon}$. (Chose $\sqrt{\varepsilon}$ factor to ensure $\text{Var}(Y_t^\varepsilon) \approx t$.)

▷ Let $W_t = \lim_{\varepsilon \rightarrow 0} Y_t^\varepsilon$.

$\text{Var}(\xi_i) = 1$. *Palm*



Weiner Process

Definition 5.1 (Brownian motion). The process W above is called a Brownian motion.

- ▷ Named after Robert Brown (a botanist).

- ▷ Definition is intuitive, but not as convenient to work with.

$X_0 = 0$

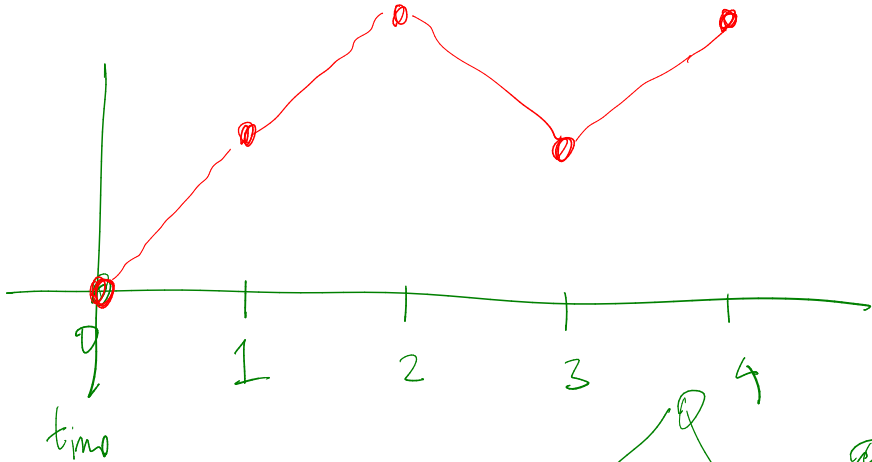
Outcome of k^{th} play is the RV ξ_k

Cum wealth

$X_1 = X_0 + \xi_1$

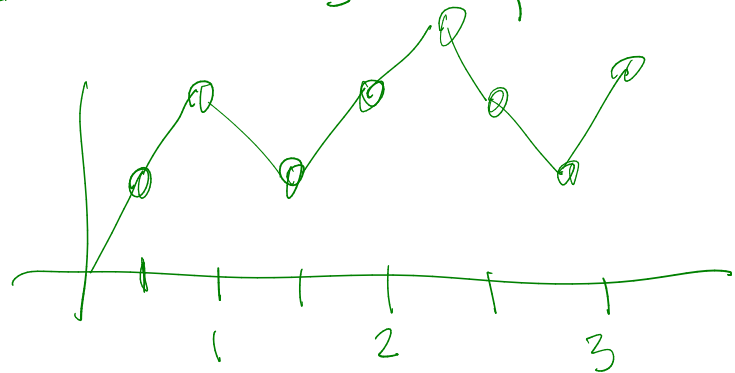
$X_{n+1} = X_n + \xi_{n+1}$

↳



Speed up time

k_1



$$\text{Var}(X_{\underline{n}}) = \text{Var}\left(\sum_1^n \xi_k\right) = \sum_1^n \text{Var}(\xi_k) \quad (\text{indep})$$

$$= \underline{n}$$

$$y_t^e = \sqrt{t} Y_{t/\varepsilon}$$

(So t is an int mult of ε)

$$\text{Var}(Y_t^e) = \varepsilon \quad \text{Var}(Y_{\underline{t/\varepsilon}}) = \cancel{\varepsilon} \quad \cancel{t/\varepsilon}$$

• If t, s are multiples of ε : $Y_t^\varepsilon - Y_s^\varepsilon \sim \sqrt{\varepsilon} \sum_{i=1}^{(t-s)/\varepsilon} \xi_i \xrightarrow{\varepsilon \rightarrow 0} \mathcal{N}(0, t-s)$.

• $Y_t^\varepsilon - Y_s^\varepsilon$ only uses coin tosses that are "after s ", and so independent of Y_s^ε .

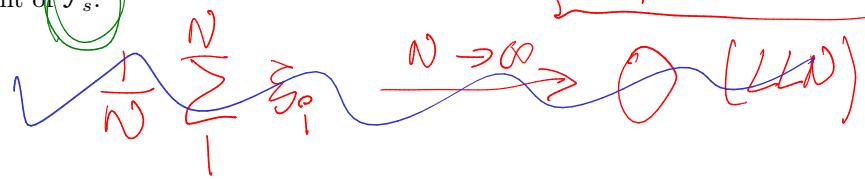
Definition 5.2. Brownian motion is a continuous process such that:

(1) $W_t - W_s \sim \mathcal{N}(0, t-s)$,

(2) $W_t - W_s$ is independent of \mathcal{F}_s .

$$E\xi_i = 0, E\xi_i^2 = 1$$

①



$$\text{CLT } \frac{1}{\sqrt{N}} \sum_{i=1}^N \xi_{i0} \xrightarrow{N \rightarrow \infty} \mathcal{N}(0, 1)$$

Say t & s are mult of ε . ($s = \underline{m}\varepsilon$ & $t = \underline{n}\varepsilon$.)

Then

$$y_t^e - y_s^e = \sqrt{e} \sum_{m+1}^n \varepsilon_m$$

$$= \sqrt{e} \cdot \left(\text{sum of } \underbrace{\left(\frac{t-s}{e} \right)}_N \text{ iid RV's.} \right)$$

$$= \sqrt{t-s} \cdot \left(\frac{1}{\sqrt{N}} \left(\text{sum of } N \text{ iid RV's.} \right) \right)$$

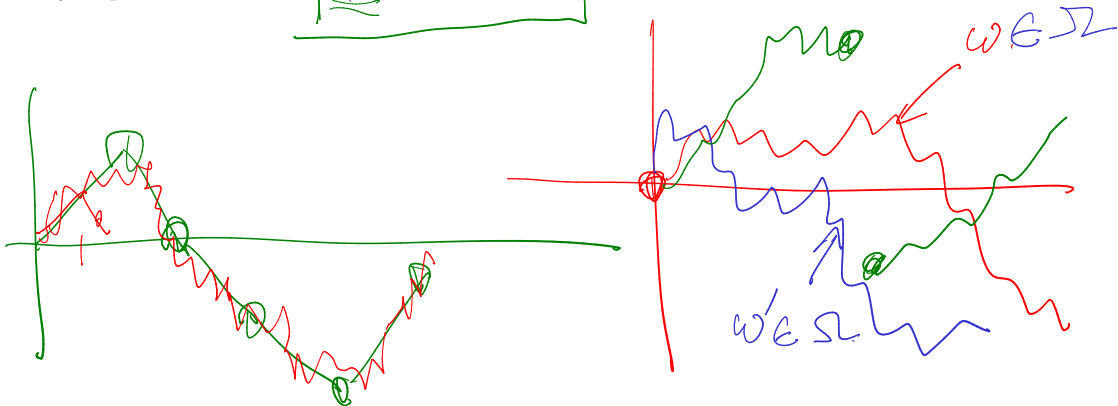
\downarrow
 $N(0, 1)$

$\left| \frac{t-s}{e} = N \right.$

$$\sim N(0, t-s).$$

5.2. Sample space, measure, and filtration.

- Discrete time: Sample space $\Omega = \{(\omega_1, \dots, \omega_N) \mid \omega_i \text{ represents the outcome of the } i^{\text{th}} \text{ coin toss}\}$.
- View $(\omega_1, \dots, \omega_N)$ as the trajectory of a random walk.
- Continuous time: Sample space $\Omega = C([0, \infty))$ (space of continuous functions).
 - ▷ It's infinite. No probability mass function!
 - ▷ Mathematically impossible to define $\underline{P}(A)$ for all $A \subseteq \Omega$.



- Restrict our attention to \mathcal{G} , a subset of some sets $A \subseteq \Omega$, on which \mathbf{P} can be defined.
 - ▷ \mathcal{G} is a σ -algebra. (Closed countable under unions, complements, intersections.)

• \mathbf{P} is called a *probability measure* on (Ω, \mathcal{G}) if:

▷ $\mathbf{P}: \mathcal{G} \rightarrow [0, 1]$, $\mathbf{P}(\emptyset) = 0$, $\mathbf{P}(\Omega) = 1$.

▷ $\mathbf{P}(A \cup B) = \mathbf{P}(A) + \mathbf{P}(B)$ if $A, B \in \mathcal{G}$ are disjoint.

▷ If $A_n \in \mathcal{G}$, $\mathbf{P}\left(\bigcup_{n=1}^{\infty} A_n\right) = \lim_{n \rightarrow \infty} \mathbf{P}(A_n)$. (& $A_n \subseteq A_{n+1}$)

• Random variables are measurable functions of the sample space:

▷ Require $\{X \in A\} \in \mathcal{G}$ for every "nice" $A \subseteq \mathbb{R}$.

▷ E.g. $\{X = 1\} \in \mathcal{G}$, $\{X > 5\} \in \mathcal{G}$, $\{X \in [3, 4]\} \in \mathcal{G}$, etc.

▷ Recall $\{X \in A\} = \{\omega \in \Omega \mid X(\omega) \in A\}$.

Is $X > 0$?

↓
 $\{X > 0\} = \{\omega \mid X(\omega) > 0\}$

Q: $\mathbf{P}(X > 0)$

$$X: \Omega \longrightarrow \mathbb{R}$$

Given any $\omega \in \Omega$, $X(\omega) \in \mathbb{R}$.

• Expectation is a *Lebesgue Integral*: Notation $\underline{EX} = \int_{\Omega} \underline{X} d\underline{P} = \int_{\Omega} \underline{X(\omega)} d\underline{P(\omega)}$.

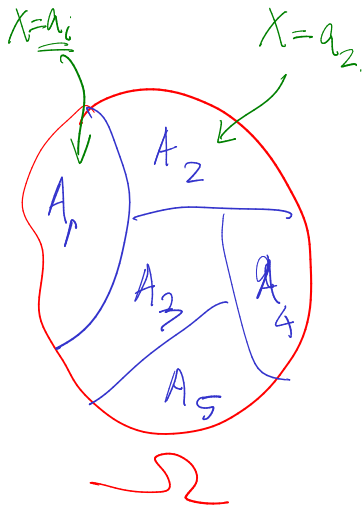
▷ No simple formula.

▷ If $\underline{X} = \sum \underline{a_i} \underline{1_{A_i}}$, then $\underline{EX} = \sum \underline{a_i} \underline{P(A_i)} = \sum \underline{a_i} \underline{P(X = a_i)}$

▷ $\underline{1_A}$ is the indicator function of A: $\underline{1_A(\omega)} = \begin{cases} \underline{1} & \omega \in A \\ \underline{0} & \omega \notin A \end{cases}$

Discrete case

$$EX = \sum_{x_i \in \text{Range}(X)} x_i P(X = x_i)$$



Proposition 5.3 (Useful properties of expectation).

α, β not random.

(1) (Linearity) $\alpha, \beta \in \mathbb{R}$, X, Y random variables, $\mathbf{E}(\alpha X + \beta Y) = \alpha \mathbf{E}X + \beta \mathbf{E}Y$.

(2) (Positivity) If $X \geq 0$ then $\mathbf{E}X \geq 0$. If $X \geq 0$ and $\mathbf{E}X = 0$ then $X = 0$ almost surely.

(3) (Layer Cake) If $X \geq 0$, $\mathbf{E}X = \int_0^\infty \mathbf{P}(X \geq t) dt$.

(4) More generally, if φ is increasing, $\varphi(0) = 0$ then $\mathbf{E}\varphi(X) = \int_0^\infty \varphi'(t) \mathbf{P}(X \geq t) dt$.

(5) (Unconscious Statistician Formula) If PDF of X is p , then $\mathbf{E}f(X) = \int_{-\infty}^\infty f(x)p(x) dx$.

lazy

$(X=0 \text{ a.s. means } \mathbf{P}(X=0) = 1)$.

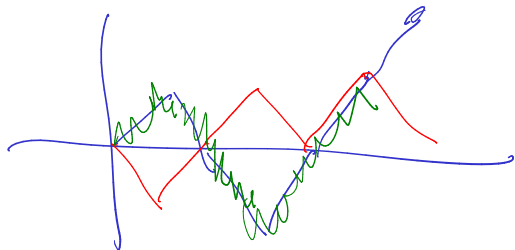
$\varphi' =$ derivative of φ

PDF of X is f , then $\mathbf{E}f(X) = \int_{\mathbb{R}} f(x) p(x) dx$

• Filtrations:

- ▷ Discrete time: $\mathcal{F}_n =$ events described using the first n coin tosses.
- ▷ Coin tosses doesn't translate well to continuous time.
- ▷ Discrete time try #2: $\mathcal{F}_n =$ events described using the trajectory of the SRW up to time n .
- ▷ Continuous time: $\mathcal{F}_t =$ events described using the trajectory of the Brownian motion up to time t .
- ▷ If $t_i \leq t$, $A_i \subseteq \mathbb{R}$ then $\{W_{t_1} \in A_1, \dots, W_{t_n} \in A_n\} \in \mathcal{F}_t$. (Need all $t_i \leq t$!)
- ▷ As before: if $s \leq t$, then $\mathcal{F}_s \subseteq \mathcal{F}_t$.
- ▷ Discrete time: $\mathcal{F}_0 = \{\emptyset, \Omega\}$. Continuous time: $\mathcal{F}_0 = \{A \in \mathcal{G} \mid P(A) \in \{0, 1\}\}$.

$$X_{n+1} = X_n + \xi_{n+1} \quad (\xi_{n+1} = \text{outcome of } (n+1)^{\text{th}} \text{ coin toss})$$



E.g.: $\{W_s > 0\} \in \mathcal{F}_t$

$\{W_s > 0\} \in \mathcal{F}_t$

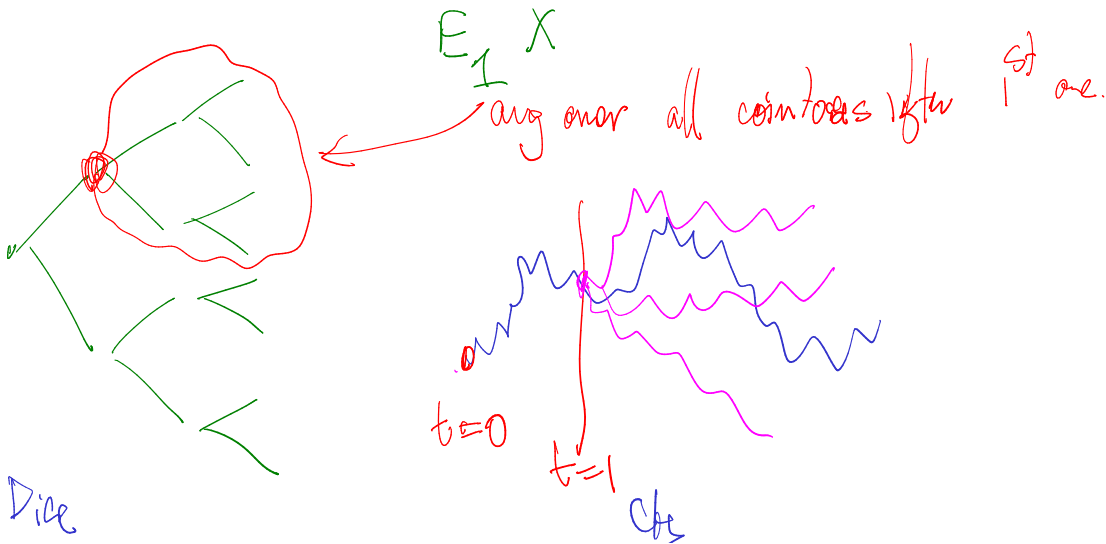
$\{W_s \in [1, 2] \& W_t < 0\} \in \mathcal{F}_t$

$$\{W_{t+1} > 0\} \notin \mathcal{F}_t$$

$$\{W_{t+1} > 0\} \in \mathcal{F}_{t+1}$$

5.3. Conditional expectation.

- Notation $\underline{E}_t(X) = \underline{E}(X | \underline{\mathcal{F}}_t)$ (read as conditional expectation of X given \mathcal{F}_t)
- No formula! But same intuition as discrete time.
- $E_t X(\omega) =$ “average of X over $\Pi_t(\omega)$ ”, where $\Pi_t(\omega) = \{\omega' \in \Omega \mid \omega'(s) = \omega(s) \forall s \leq t\}$.
- Mathematically problematic: $\mathbf{P}(\Pi_t(\omega)) = 0$ (but it still works out.)



Definition 5.4. $E_t X$ is the unique random variable such that:

(1) $E_t X$ is \mathcal{F}_t -measurable.

(2) For every $A \in \mathcal{F}_t$, $\int_A E_t X dP = \int_A X dP$

Remark 5.5. Choosing $A = \Omega$ implies $E(E_t X) = EX$.

Proposition 5.6 (Useful properties of conditional expectation).

(1) If $\alpha, \beta \in \mathbb{R}$ are constants, X, Y , random variables $E_t(\alpha X + \beta Y) = \alpha E_t X + \beta E_t Y$.

(2) If $X \geq 0$, then $E_t X \geq 0$. Equality holds if and only if $X = 0$ almost surely.

(3) (Tower property) If $0 \leq s \leq t$, then $E_s(E_t X) = E_s X$.

(4) If X is \mathcal{F}_t measurable, and Y is any random variable, then $E_t(XY) = X E_t Y$.

(5) If X is \mathcal{F}_t measurable, then $E_t X = X$ (follows by choosing $Y = 1$ above).

(6) If Y is independent of \mathcal{F}_t , then $E_t Y = EY$.

Remark 5.7. These properties are exactly the same as in discrete time.

Lemma 5.8 (Independence Lemma). If X is \mathcal{F}_t measurable, Y is independent of \mathcal{F}_t , and $f = f(x, y): \mathbb{R}^2 \rightarrow \mathbb{R}$ is any function, then

$$\mathbf{E}_t f(X, Y) = g(Y), \quad \text{where} \quad g(y) = \mathbf{E} f(X, y).$$

Remark 5.9. If p_Y is the PDF of Y , then $\mathbf{E}_t f(X, Y) = \int_{\mathbb{R}} f(X, y) p_Y(y) dy$.

$$\underline{g(x)} = \mathbf{E} \underbrace{f(x, Y)}$$

\swarrow
 subset $x = X$

$g(X) =$ ~~the~~ Avg $f(X, Y)$ in Y & leave X alone

5.4. Martingales.

Definition 5.10. An adapted process M is a martingale if for every $0 \leq s \leq t$, we have $\mathbf{E}_s M_t = M_s$.

Remark 5.11. As with discrete time, a martingale is a fair game: stopping based on information available today will not change your expected return.

Proposition 5.12. *Brownian motion is a martingale.*

Proof.