

Basic of Stochastic Finance

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Martingales

Definition

A process X is called *martingale* (relative to $\{F_N\}$) if

1. X is adapted,
2. $E|X_n| < \infty$,
3. $E(X_n|\mathcal{F}_{n-1}) = X_{n-1}$ a. s. ($n \geq 1$).

- *Supermartingale* is defined similarly, except that (3) is replaced by

$$E(X_n|\mathcal{F}_{n-1}) \leq X_{n-1} \text{ a. s. } (n \geq 1)$$

- *Submartingale* is defined with (3) replaced by

$$E(X_n|\mathcal{F}_{n-1}) \geq X_{n-1} \text{ a. s. } (n \geq 1)$$

- A supermartingale decreases on average, a submartingale increases on average in time.

Martingales: examples

One reason martingales are so powerful is that they model a situation where one gains progressively more information over time. Suppose that \mathcal{U} is a set of objects, and $f : \mathcal{U} \rightarrow \mathbb{R}$. Let X be a random variable taking values in \mathcal{U} , and let $\{Y_i\}$ be another sequence of random variables. The associated *Doob martingale* is given by

$$X_i = \mathbb{E}[f(X) \mid Y_0, Y_1, \dots, Y_i].$$

In words, this is our “estimate” for the value of $f(X)$ given the information contained in $\{Y_0, \dots, Y_i\}$. To see that this is always a martingale with respect to $\{Y_i\}$, observe that

$$\mathbb{E}[X_{i+1} \mid Y_0, \dots, Y_i] = \mathbb{E}[\mathbb{E}[f(X) \mid Y_0, \dots, Y_{i+1}] \mid Y_0, \dots, Y_i] = \mathbb{E}[f(X) \mid Y_0, \dots, Y_i] = X_i,$$

where we have used the tower rule of conditional expectations.

$X_n \sim \mathcal{F}$ -adapted ; martingale

$$E[X_n \mid \mathcal{F}_{n-2}] = E[E[X_n \mid \mathcal{F}_{n-1}] \mid \mathcal{F}_{n-2}] = E[X_{n-1} \mid \mathcal{F}_{n-2}] = X_{n-2}$$

Martingales: examples

Balls in bins. Suppose we throw m balls into n bins one at a time. At step i , we place ball i in a uniformly random bin. Let C_1, C_2, \dots, C_m be the sequence of (random) choices, and let C denote the final configuration of the system, i.e. exactly which balls end up in which bins.

Now we can consider a functional like $f(C) = \#$ of empty bins. If $X_i = \mathbb{E}[f(C) \mid C_1, \dots, C_i]$, then $\{X_i\}$ is a (Doob) martingale. It is straightforward to calculate that

$$\mathbb{E}[X_m] = \mathbb{E}[X_0] = \mathbb{E}[f(C)] = n \cdot \left(1 - \frac{1}{n}\right)^m.$$

Suppose we are interested the concentration of $X_m = f(C)$ around its mean value. Of course, we can write $X_m = Z_1 + \dots + Z_m$ where Z_i is the indicator of whether the i th bin is empty after all the balls have been thrown. But note that the $\{Z_i\}$ variables are not independent—in particular, if I tell you that $Z_1 = 1$ (bin 1 is empty), it decreases slightly the likelihood that other bins are empty.

Martingales: examples

The Hoeffding-Azuma inequality

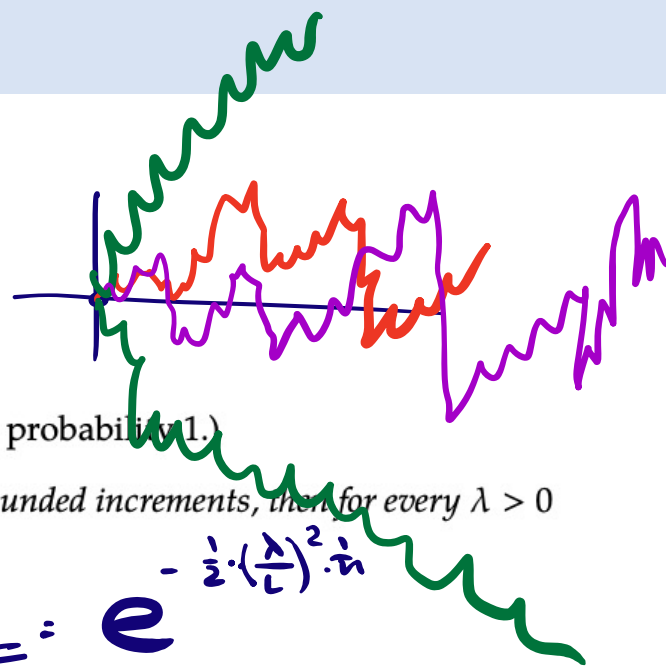
Say that a martingale $\{X_i\}$ has L -bounded increments if

$$|X_{i+1} - X_i| \leq L$$

for all $i \geq 0$. (The preceding inequality is meant to hold with probability 1.)

Theorem 2.1. For every $L > 0$, if $\{X_i\}$ is a martingale with L -bounded increments, then for every $\lambda > 0$ and $n \geq 0$, we have

$$\begin{aligned} \mathbb{P}[X_n \geq X_0 + \lambda] &\leq e^{-\frac{\lambda^2}{2L^2n}} \\ \mathbb{P}[X_n \leq X_0 - \lambda] &\leq e^{-\frac{\lambda^2}{2L^2n}} \end{aligned}$$



We will prove this in Section 3. It's useful to note the following special case of the theorem.

Corollary 2.2. Suppose that Z_1, Z_2, \dots, Z_n are independent random variables taking values in the interval $[-L, L]$. Put $Z = Z_1 + \dots + Z_n$ and $\mu = \mathbb{E}[Z]$. Then for every $\lambda > 0$, we have

$$\begin{aligned} \mathbb{P}[Z \geq \mu + \lambda] &\leq e^{-\lambda^2/(2L^2n)} \\ \mathbb{P}[Z \geq \mu - \lambda] &\leq e^{-\lambda^2/(2L^2n)} \end{aligned}$$

Continuous time. Brownian Motion

$$C = 1$$

- By choosing the relationship between Δx and Δt such that $\frac{(\Delta x)^2}{\Delta t} = \text{const} =: C^2$ we get, on the limit, that $X_t \sim N(0, C\sqrt{t})$. The limiting process X_t , preserves some important features of SRW:
- (i) The increments of X ; are independent i.e. for $0 \leq s \leq t \leq u \leq v$ the increments $X_t - X_s$ and $X_v - X_u$ are independent r.v. (the same is valid for any n time intervals).
- (ii) The increments of X_t are stationary i.e. the distribution of $X_{s+t} - X_s$, only depends on t (and not on s).

Definition 6

The random process $\{W_t, t \geq 0\}$ is called Brownian motion (Wiener process), if

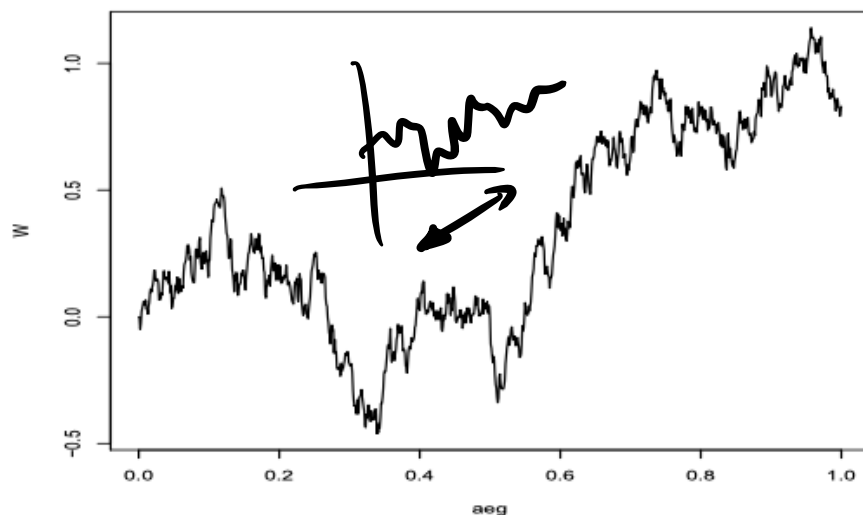
- (i) $W(0) = 0$,
- (ii) for all $t > 0$ the r.v. $W_t \sim N(0, C\sqrt{t})$, where $C > 0$ is a constant.

Continuous time. Brownian Motion

- From the definition of BM it follows that also the increments of BM are normally distributed: by the stationarity of increments

$$W_t - W_s \stackrel{D}{=} W_{t-s} - W_0 = W_{t-s} \sim N(0, \sqrt{t-s}),$$

where $\stackrel{D}{=}$ is to be read as "has same distribution as".



A trajectory of standard Brownian motion

- Note that, in fact, the property (iv) can be deduced from properties (i)-(iii).
- BM is a mathematical model widely used in physics (diffusions), economics (price models) e.t.c.

①

$$\begin{aligned}
 W_t &\sim \text{Wiener's Proc.} \quad N(0; t) \\
 E[W_t] &= E[W_t - 0] = E[W_t - W_0] = 0 \\
 E[W_t^2] &= \text{Var}(W_t) + E^2(W_t) = \text{Var}(W_t - W_0) = t - 0 = t \\
 t > s \quad E[W_t \cdot W_s] &= \text{Corr}(W_t, W_s) + E[W_t] \cdot E[W_s] = \\
 &= \text{Corr}(W_t, W_s) = \text{Corr}(W_t - W_s, W_s) \\
 &= \text{Corr}(W_t - W_s, W_s) = \text{Corr}(W_t - W_s, W_s) = \text{Corr}(W_t - W_s, W_s) \\
 &= \text{Corr}(W_t - W_s, W_s) = \text{Corr}(W_t - W_s, W_s) = \text{Corr}(W_t - W_s, W_s) \\
 t > s \quad E[W_t \cdot W_s] &= s \\
 E[W_t \cdot W_s] &= \min(t, s) \\
 \text{Corr}(W_t, W_s) &= \frac{\min(t, s)}{\sqrt{t \cdot s}} = \begin{cases} \frac{s}{t} & \text{if } s < t \\ \frac{t}{s} & \text{if } t < s \end{cases} = \sqrt{\frac{\min(t, s)}{\max(t, s)}}
 \end{aligned}$$

Finite-dimensional distributions of SBM

- The joint distribution of $(W_{t_1}, W_{t_2}, \dots, W_{t_n})$ where $0 < t_1 < t_2 < \dots < t_n$ can easily be calculated.
- For each t_i , the density of W_{t_i} is

$$f_{W_{t_i}}(x) = \frac{1}{\sqrt{2\pi t_i}} e^{-\frac{x^2}{2t_i}}$$

Provided that $C = 1$.

Since the equalities $\begin{cases} W_{t_1} = x_1 \\ W_{t_2} = x_2 \\ \dots \\ W_{t_n} = x_n \end{cases}$ are equivalent to the equalities $\begin{cases} W_{t_1} = x_1 \\ W_{t_2} = x_2 \\ \dots \\ W_{t_n} = x_n \end{cases}$

And since the increments are independent, we have

$$\begin{aligned} f_{W_{t_1}, \dots, W_{t_n}}(x_1, \dots, x_n) &= f_{W_{t_1}, W_{t_2} - W_{t_1}, \dots, W_{t_n} - W_{t_{n-1}}}(x_1, x_2 - x_1, \dots, x_n - x_{n-1}) = f_{W_{t_1}}(x_1) \cdot \\ &f_{W_{t_2} - W_{t_1}}(x_2 - x_1) \cdot \dots \cdot f_{W_{t_n} - W_{t_{n-1}}}(x_n - x_{n-1}) = \frac{1}{\sqrt{2\pi t_1}} e^{-\frac{x_1^2}{2t_1}} \frac{1}{\sqrt{2\pi(t_2 - t_1)}} e^{-\frac{(x_2 - x_1)^2}{2(t_2 - t_1)}} \cdot \dots \cdot \\ &\frac{1}{\sqrt{2\pi(t_n - t_{n-1})}} e^{-\frac{(x_n - x_{n-1})^2}{2(t_n - t_{n-1})}} \end{aligned}$$

- The formula obtained can be used for many purposes.

② W_t is a martingale $t > s$

$$E[W_t | \mathcal{F}_s] = E[W_t - W_s + W_s | \mathcal{F}_s] = E[W_t - W_s | \mathcal{F}_s] + E[W_s | \mathcal{F}_s] = 0 + W_s = W_s$$

③ Brownian Bridge $s < t$

$$\{W_t^2 - t\}_{t \geq 0} \text{ is a martingale?}$$

$$E[W_t^2 - t | \mathcal{F}_s] = E[W_t^2 | \mathcal{F}_s] - E[t | \mathcal{F}_s] = E[W_t^2 | \mathcal{F}_s] - t = W_s^2 - s$$

$$E[W_t^2 | \mathcal{F}_s] = E[(W_t - W_s + W_s)^2 | \mathcal{F}_s] = E[(W_t - W_s)^2 | \mathcal{F}_s] + 2E[(W_t - W_s)W_s | \mathcal{F}_s] + E[W_s^2 | \mathcal{F}_s]$$

$$= E[(W_t - W_s)^2 | \mathcal{F}_s] + 2E[W_t - W_s | \mathcal{F}_s]W_s + E[W_s^2 | \mathcal{F}_s] = (t - s) + 0 + W_s^2 = t - s + W_s^2$$

Conditional Distribution

- Let's use the formula above to solve one particular problem. Suppose we know that at time t BM has taken value $W_t = B$. Let s be an earlier time, $s < t$.
- What is the conditional distribution of W_s given the event $W_t = B$? It is known that the conditional density is the ratio of joint density and the density of the condition, we can calculate

$$f_{W_s|W_t}(x|B) = \frac{f_{W_s, W_t}(x, B)}{f_{W_t}(B)} = \frac{\frac{1}{\sqrt{2\pi s}} e^{-\frac{x^2}{2s}} \cdot \frac{1}{\sqrt{2\pi(t-s)}} e^{-\frac{(B-x)^2}{2(t-s)}}}{\frac{1}{\sqrt{2\pi t}} e^{-\frac{B^2}{2t}}} = \dots = \frac{1}{\sqrt{2\pi \frac{t}{s}(t-s)}} e^{-\frac{t(x-B)^2}{2s(t-s)}}$$

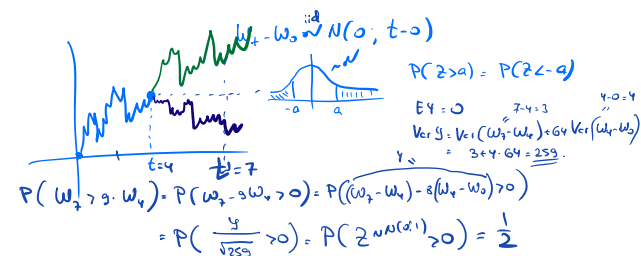
- Hence, the conditional distribution of W_s is normal distribution with mean and variance $\frac{s(t-s)}{t}$.

Maxima of Brownian Motion

- If $a > 0$, then $P\left\{\max_{0 \leq s \leq t} W_s \geq a\right\} = P\{T_a \leq t\} = 2[1 - \Phi\left(\frac{|a|}{\sqrt{t}}\right)]$
- If $a < 0$, then $P\left\{\max_{0 \leq s \leq t} W_s \geq a\right\} = 1$

$$P(\max X_i > \dots) = 1 - P(\max X_i < \dots)$$

$$\left(P(X_i < \dots) \right)^n$$



Brownian Motion between Two Boundaries

Let $A > 0, B > 0$. Let us find the probability that, starting from 0, BM reaches level A before $-B$. Recall that in the case of SRW the answer to the same question is $\frac{B}{A+B}$. As the same answer remains true for any time and space steps sizes, we have

$$P\{W_t \text{ reaches } A \text{ before } -B\} = P\{T_A < T_B\} = \frac{B}{A+B}$$

Exercise

Let W_t be a standard Brownian motion. Assume that $W_1 = 2$. Find the probability that $W_5 < 0$.

- Without any given condition we would have $P\{W_5 < 0\} = \frac{1}{2}$, since $W_t \sim N(0, \sqrt{t})$.
- However, under the condition $W_1 = 2$ the increment $W_5 - W_1 \sim N(0, \sqrt{4})$ – this distribution only depends on the length of the time interval and not on its location. Therefore we have

$$\begin{aligned} P\{W_5 < 0 | W_1 = 2\} &= P\{W_5 - W_1 < -2 | W_1 = 2\} = \\ &= P\{W_5 - W_1 < -2\} = P\{W_4 < -2\} = \\ &= P\{N(0, \sqrt{4}) < -2\} = \Phi\left(\frac{-2}{2}\right) = \Phi(-1) = 0.16 \end{aligned}$$

Continuous time. Filtration

- Many important concepts and results that are known for martingales with discrete time can be transferred to continuous time without any major change.
- Let $(\Omega, \mathcal{F}, \mathbf{P})$ be a probability space and let t be a real-valued parameter interpreted as time. Most often, t takes values from the half-line R^+ or finite interval $(0, T)$.

Definition 7

A family of σ -algebras $\{\mathcal{F}_t, t \geq 0\}$ is called a *filtration*, if

- 1) all its members \mathcal{F}_t are sub- σ -algebras of \mathcal{F} and,
- 2) for $s < t$ one has $\mathcal{F}_s \subseteq \mathcal{F}_t$.

As in the case of discrete time, we are mainly interested in the natural filtration $\{\mathcal{F}_t^X, t \geq 0\}$, generated by a random process X . As before, \mathcal{F}_t^X contains the information induced by the random process X within the time interval $[0, t]$. It means that an event $A \in \mathcal{F}_t^X$ if and only if one can decide whether A occurred or not on the basis of the trajectory $\{X_s, 0 \leq s \leq t\}$ that the process X generates by time t .

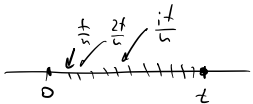
Definition 8

If $\{Y_t, t \geq 0\}$ is a random process such that for each t the random variable Y is \mathcal{F}_t -measurable, then it is said that the process Y is *adapted to filtration* $\{\mathcal{F}_t, t \geq 0\}$.

Examples

1. The random process $Z_t = \int_0^t X_s ds$ is adapted to the filtration $\{\mathcal{F}_t^X, t \geq 0\}$, since knowing the path of X within time interval $[0, t]$ is sufficient to determine Z_t .
2. The process $M_t = \max_{0 \leq s \leq t} W_s$ is adapted to the filtration $\{\mathcal{F}_t^W, t \geq 0\}$.
 $W_t - W_s \sim N(0, t-s)$
3. The process $Z_t = W_{t+1}^2 - W_t^2$ is not adapted to the filtration $\{\mathcal{F}_t^W, t \geq 0\}$.

$$J_n = \sum_{i=1}^n (Y_i - Y_{i-1})^2$$

$$Y_i = W_{\frac{i}{n}}$$


$$E[J_n] = E\left[\sum_{i=1}^n (Y_i - Y_{i-1})^2\right] = \sum_{i=1}^n E[(Y_i - Y_{i-1})^2] = \sum_{i=1}^n \underbrace{\text{Var}(Y_i - Y_{i-1})}_{\text{Var}(W_{\frac{i}{n}} - W_{\frac{i-1}{n}})} + E[(Y_i - Y_{i-1})]^2 = \sum_{i=1}^n \frac{1}{n} = n \cdot \frac{1}{n} = t$$

$$\text{Var}[J_n] = \text{Var}\left[\sum_{i=1}^n (Y_i - Y_{i-1})^2\right] = \sum_{i=1}^n \text{Var}((Y_i - Y_{i-1})^2) = \sum_{i=1}^n \text{Var}\left[\left(\frac{Y_i - Y_{i-1}}{\sqrt{t/n}}\right)^2 \cdot \frac{t}{n}\right] = \frac{t^2}{n^2} \sum_{i=1}^n \text{Var}\left(\left(\frac{Y_i - Y_{i-1}}{\sqrt{t/n}}\right)^2\right)$$

$X \sim N(0, 1)$
 $X^2 \sim \chi^2$
 $\text{Var}(X^2) = 2$

$Y_i - Y_{i-1} \sim N(0, \frac{t}{n})$
 $\frac{Y_i - Y_{i-1}}{\sqrt{t/n}} \sim N(0, 1)$

$$= \frac{t^2}{n^2} \sum_{i=1}^n 2 = \frac{2t^2}{n}$$

$$E[J_n] = t$$

$$\text{Var}(J_n) = \frac{2t^2}{n} \xrightarrow{n \rightarrow \infty} 0 \Rightarrow J_n \xrightarrow{n \rightarrow \infty} t$$

dt
 $(dw_t)^2 \rightarrow dt$

~~$$\int_0^t W_u dW_u = \frac{1}{2}(W_t^2 - W_0^2)$$~~

$$\begin{aligned}
 & dt \cdot dt = 0 \quad dt \cdot dW_t = 0 \quad dW_t \cdot dW_t = dt \\
 & (dW_t)^2 = dW_t^2 = dt \cdot dW_t = 0 \quad \text{Itô's Lemma} \\
 & (dW_t)^4 = 0
 \end{aligned}$$

Continuous time. Martingales

$$f(t, W_t) \quad df = f'_t \cdot dt + f'_W \cdot dW + \frac{1}{2} f''_{WW} (dW_t)^2$$

Definition 9

Let $(\Omega, \mathcal{F}, \mathbf{P})$ be a probability space endowed with a filtration $\{\mathcal{F}_t, t \geq 0\}$. A random process $\{M_t, t \geq 0\}$ is called a martingale, if

1. M is adapted to the filtration $\{\mathcal{F}_t, t \geq 0\}$,
2. $E|M_t| < \infty, \forall t$
3. For any $s \leq t$ we have $E(M_t | \mathcal{F}_s) = M_s$ a.s.

- If the equality in (3) is replaced by the inequality \leq (or \geq), then we speak about a supermartingale (respectively submartingale).

Remark: Similarly, a martingale can be defined on a finite time interval $[0, T]$. In the following mostly the filtration $\{\mathcal{F}_t^W, t \geq 0\}$, generated by a standard Brownian motion W , is used.