

Lecture 13 – Martingale (II), Brownian Motion (I)

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1 Review of the Optional Stopping Theorem

Suppose that a stochastic process $\{X_n\}_{n \geq 0}$ is defined on a filtration $\{\mathcal{F}_n\}_{n \geq 0}$. Then $\{X_n\}$ is called a

1. **Martingale** if $\mathbb{E}[X_{n+1} | \mathcal{F}_n] = X_n$;
2. **Supermartingale** if $\mathbb{E}[X_{n+1} | \mathcal{F}_n] < X_n$;
3. **Submartingale** if $\mathbb{E}[X_{n+1} | \mathcal{F}_n] > X_n$.

If $\{X_n\}$ is a martingale with respect to a filtration $\{\mathcal{F}_n\}$, applying the law of total expectation we have $\mathbb{E}[X_n] = \mathbb{E}[X_0]$ for all fixed $n \geq 0$. So we wonder what happens if n is a random variable.

Theorem 1 (Optional Stopping Theorem). *Suppose that $\{X_n\}$ is a martingale with respect to a filtration $\{\mathcal{F}_n\}$ and τ is a stopping time with respect to the same filtration. Then $\mathbb{E}[X_\tau] = \mathbb{E}[X_0]$ if at least one of the following holds*

1. τ is bounded;
2. $\Pr[\tau < \infty] = 1$ and $\exists M$ such that $|X_n| \leq M$ for all $n < \tau$;
3. $\mathbb{E}[\tau] < \infty$ and $\exists c$ such that $\mathbb{E}[|X_{n+1} - X_n| | \mathcal{F}_n] \leq c$ for all $n < \tau$.

Remark. If $\{X_n\}$ is a supermartingale (or submartingale), and at least one of the conditions holds, then the result holds as well, namely, $\mathbb{E}[X_\tau] < \mathbb{E}[X_0]$ (or $\mathbb{E}[X_\tau] > \mathbb{E}[X_0]$).

2 Supermartingale Convergence

Today we are talking about supermartingales.

For a supermartingale, it always holds that $\mathbb{E}[X_{n+1} | \mathcal{F}_n] < \mathbb{E}[X_n]$. So intuitively, the trend of a supermartingale should be declining. Since every decreasing and bounded below sequence of real numbers is convergent, hopefully $\{X_n\}$ should also converge with probability 1 if $\{X_n\}$ is a nonnegative supermartingale.

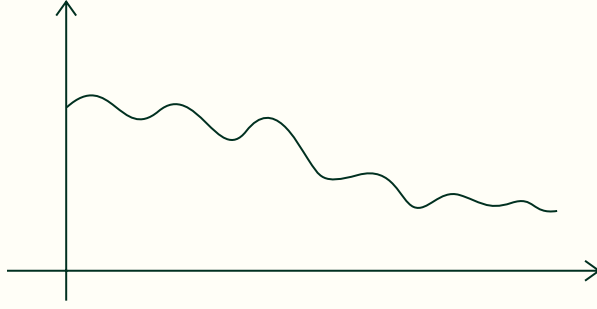


Figure 1: A possible figure of a supermartingale

Now we are going to formalize this idea.

Proposition 2. *Suppose that $\{X_n\}$ is a nonnegative supermartingale with $X_0 \leq a$. For all $b > a$, define T_b by*

$$T_b \triangleq \inf\{t : X_t \geq b\}.$$

Then it holds that

$$\Pr[T_b < \infty] \leq \frac{a}{b}.$$

Proof. Let

$$a \wedge b \triangleq \min\{a, b\},$$

$$a \vee b \triangleq \max\{a, b\}.$$

Fix $t > 0$. Clearly $T_b \wedge t$ is a stopping time. It is an exercise to verify that the condition of optional stopping theorem is satisfied. Therefore, applying the optional stopping theorem, it follows that

$$\mathbb{E}[X_{T_b \wedge t}] \leq \mathbb{E}[X_0] \leq a.$$

On the other hand,

$$X_{T_b \wedge t} = \begin{cases} X_t, & \text{if } T_b > t; \\ \geq b, & \text{if } T_b \leq t. \end{cases}$$

So we obtain that

$$X_{T_b \wedge t} \geq b \cdot \mathbb{1}_{\{T_b \leq t\}},$$

which implies that

$$\mathbb{E}[X_{T_b \wedge t}] \geq b \cdot \Pr[T_b \leq t].$$

Combining with $\mathbb{E}[X_{T_b \wedge t}] \leq a$ we conclude that $\Pr[T_b \leq t] \leq a/b$ for all $t > 0$. □

We are ready to show the following theorem.

Theorem 3. *Any nonnegative supermartingale converges with probability 1.*

Proof. Assume that a supermartingale is divergent. Then there are two cases. One is that there exists a subsequence goes to infinity, and another is that there exists an oscillating subsequence. If there exists a subsequence goes to infinity with probability > 0 , then for every $b > 0$, the probability of $\inf\{t : X_t \geq b\} < \infty$ is greater than 0, which contradicts Proposition 2. So it suffices to show that oscillation does not exist.

Suppose that a supermartingale $\{X_n\}$ has two subsequence that converge to different values a and b . W.l.o.g. we further assume that $a < b$. Let $\varepsilon < (b - a)/2$. Then there exists a subsequence of $\{X_n\}$ bounded above by $a' \triangleq a + \varepsilon$ and exists a subsequence bounded below by $b' \triangleq b - \varepsilon$. We now show that this situation happens with probability 0.

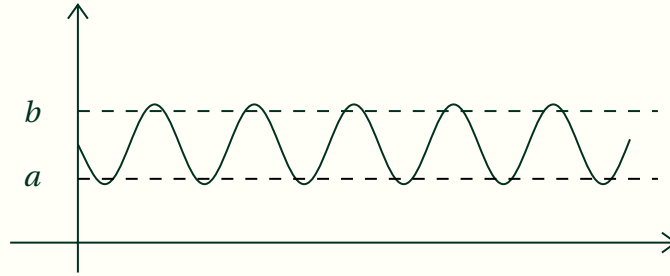


Figure 2: An oscillating sequence

Fix $a < b$ arbitrarily. We define the following stopping times. Let

$$\begin{aligned} T_0 &= 0, \\ S_1 &= \inf\{t : t > T_0 \wedge X_t \leq a\}, \\ T_1 &= \inf\{t : t > S_1 \wedge X_t \geq b\}, \\ S_2 &= \inf\{t : t > T_1 \wedge X_t \leq a\}, \\ &\dots \end{aligned}$$

Since $S_k \leq T_k$ for all $k \in \mathbb{N}$, the optional stopping theorem implies that for all $n \in \mathbb{N}$,

$$\mathbb{E}[X_{S_k \wedge n}] \geq \mathbb{E}[X_{T_k \wedge n}]. \quad (1)$$

Note that

$$X_{T_k \wedge n} = \begin{cases} \geq b, & \text{if } T_k \leq n; \\ X_n, & \text{if } T_k > n. \end{cases}$$

So it follows that

$$X_{T_k \wedge n} \geq b \cdot \mathbb{1}_{[T_k \leq n]} + X_n \cdot (1 - \mathbb{1}_{[T_k \leq n]}),$$

and hence

$$\mathbb{E}[T_k \wedge n] \geq b \cdot \Pr[T_k \leq n] + X_n \cdot (1 - \Pr[T_k \leq n]). \quad (2)$$

Using the same argument we obtain

$$\mathbb{E}[S_k \wedge n] \leq a \cdot \Pr[S_k \leq n] + X_n \cdot (1 - \Pr[S_k \leq n]). \quad (3)$$

Plugging (2) and (3) into (1) and using the fact $S_k < T_k$, we have

$$\begin{aligned} & a \cdot \Pr[S_k \leq n] + X_n \cdot (1 - \Pr[S_k \leq n]) \geq b \cdot \Pr[T_k \leq n] + X_n \cdot (1 - \Pr[T_k \leq n]) \\ \implies & a \cdot \Pr[S_k \leq n] \geq b \cdot \Pr[T_k \leq n] + X_n \cdot (\Pr[S_k \leq n] - \Pr[T_k \leq n]) \\ \implies & a \cdot \Pr[S_k \leq n] \geq b \cdot \Pr[T_k \leq n] \\ \implies & \Pr[T_k \leq n] \leq \frac{a}{b} \cdot \Pr[S_k \leq n] \\ \implies & \Pr[T_k \leq \infty] \leq \frac{a}{b} \cdot \Pr[S_k \leq \infty]. \end{aligned}$$

Since $S_k > T_{k-1}$, it implies that for all $k \in \mathbb{N}$,

$$\Pr[T_k \leq \infty] \leq \frac{a}{b} \cdot \Pr[T_{k-1} \leq \infty].$$

Taking the limit to the both sides, we conclude that $\forall \varepsilon > 0$, there exists $n \in \mathbb{N}$ s.t. $\Pr[T_n < \infty] < \varepsilon$. □

3 Stochastic Approximation

We now consider an important application of supermartingales. This example is called *stochastic approximation*.

Suppose a function $f: \mathbb{R} \rightarrow \mathbb{R}$ has an unknown unique zero point (w.l.o.g. we further assume that $f(0) = 0$ but we do not know). To find the zero point we could use the binary search. However we do not know the exact value of f . Every time we ask an oracle for the value of f at some point x , it returns a number $\tilde{f}(x) = f(x) + \eta$ instead. Here η is a random variable with $\mathbb{E}[\eta] = 0$ and $\text{Var}[\eta] = 1$.

Suppose that $f(x) > 0$ if $x >$ the zero point and $f(x) < 0$ if $x <$ the zero point. Then we guess the value of the zero point. Denote our guesses by a sequence X_0, X_1, X_2, \dots . Given X_n , the oracle

returns $Y_n = \tilde{f}(X_n) = f(X_n) + \eta_n$ and we let $X_{n+1} = X_n - a_n \cdot Y_n$ where a_n is to be determined. We hope that $X_n \rightarrow 0$ (the true zero point) with probability 1.

Now our goal is to determine a_n . Intuitively a necessary condition is that $a_n \rightarrow 0$ as $n \rightarrow \infty$ and a_n should not decrease too fast. Formally the following theorem tells us under which condition we will obtain $X_n \rightarrow 0$.

Theorem 4 (Stochastic Approximation). *Let $f: \mathbb{R} \rightarrow \mathbb{R}$ and $X_0, X_1, X_2, \dots, Y_0, Y_1, Y_2, \dots$ are two sequences of random variables such that $\mathbb{E}[(X_0)^2] < \infty$ and*

$$\begin{aligned} Y_n &= f(X_n) + \eta_n, \\ X_{n+1} &= X_n - a_n \cdot Y_n. \end{aligned}$$

Then $X_n \rightarrow 0$ as $n \rightarrow \infty$ if the followings hold

1. $X_0, \eta_1, \eta_2, \dots$ are independent; $\mathbb{E}[\eta_i] = 0$, and $\text{Var}[\eta_i] = 1$;
2. $|f(x)| < c \cdot |x|$ for some $c > 1$; (Lipschitz condition)
3. $\forall \delta > 0, \inf_{|x| > \delta} x \cdot f(x) > 0$;
4. $a_n \geq 0, \sum a_n = \infty$ but $\sum a_n^2 < \infty$.

Proof. We would like to construct a supermartingale. To achieve this goal, we first compute $\mathbb{E}[X_{n+1}^2 | \bar{X}_{0,n}]$. By $\mathbb{E}[\eta_n] = 0, \mathbb{E}[\eta_n^2] = 1$ and $|f(x)| < c|x|$, we have that

$$\begin{aligned} \mathbb{E}[X_{n+1}^2 | \bar{X}_{0,n}] &= \mathbb{E}[(X_n - a_n(f(X_n) + \eta_n))^2 | \bar{X}_{0,n}] \\ &= \mathbb{E}[X_n^2 | \bar{X}_{0,n}] - \mathbb{E}[2a_n X_n (f(X_n) + \eta_n) | \bar{X}_{0,n}] + \mathbb{E}[a_n^2 (f(X_n) + \eta_n)^2 | \bar{X}_{0,n}] \\ &= X_n^2 - 2a_n X_n f(X_n) + a_n^2 (\mathbb{E}[f(X_n)^2 | \bar{X}_{0,n}] + 1) \\ &\leq X_n^2 + a_n^2 (c^2 X_n^2 + c^2) \\ &= (a_n^2 c^2 + 1) X_n^2 + a_n^2 c^2. \end{aligned}$$

Now, it is clear to justify that $\{W_n \triangleq b_n (X_n^2 + 1)\}_{n \geq 0}$ is supermartingale with respect to $\{X_n\}$, where b_n is given by

$$b_n \triangleq \prod_{k=1}^{n-1} (1 + a_k^2 c^2)^{-1}.$$

Applying Theorem 3, it follows that

$$\lim_{n \rightarrow \infty} W_n = \xi \quad \text{for some } \xi > 0.$$

Note that

$$W_n = \frac{X_n^2 + 1}{\prod_{k=1}^{n-1} (1 + a_k^2 c^2)}.$$

Since $1 + a_k^2 c^2 \leq e^{a_k^2 c^2}$, we obtain that

$$\prod_{k=1}^{n-1} (1 + a_k^2 c^2) \leq e^{c^2 \sum_{k=1}^{n-1} a_k^2}$$

converge as $n \rightarrow \infty$. Therefore $\{X_n^2\}_{n \geq 0}$ is convergent.

We now show that $X_n \rightarrow \delta$ for some $\delta > 0$ with positive probability is impossible. Fix $\delta > 0$.

$\forall m > 0$, we define the following *bad event*. Let

$$\mathcal{B}_m \triangleq \bigcap_{n \geq m} \{X_n \in D\}$$

where $D \triangleq \{x : |x| > \delta\}$. It is sufficient to show $\Pr[\mathcal{B}_m] = 0$ for all m .

By Condition 3, there exists $\varepsilon > 0$ s.t. $\inf_{x \in D} x \cdot f(x) \geq \varepsilon$. So we obtain that

$$X_n \cdot f(X_n) \geq \varepsilon \cdot \mathbb{1}_{\{X_n \in D\}}.$$

Taking the expectation to the both sides, it implies that

$$\mathbb{E}[X_n \cdot f(X_n)] \geq \varepsilon \cdot \Pr[X_n \in D] \geq \varepsilon \cdot \Pr[\mathcal{B}_m].$$

Recall that $\{W_n\}$ is a supermartingale, and we further have (by the computation above) that

$$\mathbb{E}\left[W_{n+1} \mid \bar{X}_{0,n}\right] < W_n - 2a_n b_{n+1} X_n \cdot f(X_n).$$

Taking the expectation to the both sides, it yields that

$$\begin{aligned} \mathbb{E}[W_{n+1}] &< \mathbb{E}[W_n] - 2a_n b_{n+1} \mathbb{E}[X_n \cdot f(X_n)] \\ &< \mathbb{E}[W_n] - 2a_n b_{n+1} \varepsilon \cdot \Pr[\mathcal{B}_m] \\ &< \mathbb{E}[W_m] - 2\varepsilon \sum_{k=m}^n a_k b_{k+1} \cdot \Pr[\mathcal{B}_m], \end{aligned}$$

which yields that

$$\Pr[\mathcal{B}_m] \leq \frac{\mathbb{E}[W_m] - \mathbb{E}[W_{n+1}]}{2\varepsilon \sum_{k=m}^n a_k b_{k+1}} \rightarrow 0.$$

The last quantity converges to zero because $\mathbb{E}[W_m] - \mathbb{E}[W_{n+1}]$ is bounded for all $n > m$, and

$$2\varepsilon \sum_{k=m}^n a_k b_{k+1} > 2\varepsilon b_n \sum_{k=m}^n a_k > 2\varepsilon \cdot e^{-c^2 \sum_{k=m}^n a_k^2} \sum_{k=m}^n a_k \rightarrow \infty$$

as $n \rightarrow \infty$ (since $\sum a_k^2$ converges and $\sum a_k \rightarrow \infty$). That completes our proof. \square

4 Introduction to Brownian Motion

Brownian motion describes the random motion of small particles suspended in a liquid or in a gas. This process was named after the botanist Robert Brown, who observed and studied a jittery motion of pollen grains suspended in water under a microscope. Later, Albert Einstein gave a physical explanation of this phenomenon.

In mathematics, Brownian motion is characterized by the *Wiener process*, named after Norbert Wiener, a famous mathematician and the originator of cybernetics. Consider a uniform one-dimensional random walk starting from 0. Denote by X_i the i -th step. Then X_i is a uniform random variable in $\{-1, +1\}$. Now suppose that each time unit Δt we take a step of length δ . Let $X(t)$ be our position at time t . So it holds that

$$X(t) = \delta \cdot (X_1 + X_2 + \dots + X_{t/\Delta t}).$$

Now we are interested in what happens if Δt and $\delta \rightarrow 0$. Since $\mathbb{E}[X_i] = 0$ and $\text{Var}[X_i] = 1$, we have that

$$\begin{aligned} \mathbb{E}[X(t)] &= 0, \\ \text{Var}[X(t)] &= \delta^2 \cdot \frac{t}{\Delta t}. \end{aligned}$$

We would like to obtain a non-trivial stochastic process, so a natural idea is to fix $\delta^2/\Delta t$ to be a constant. Let

$$\delta = \sigma \cdot \sqrt{\Delta t}$$

for some constant $\sigma > 0$. Thus $\text{Var}[X(t)] = \sigma^2 t$. The next question is what the distribution of $X(t)$ is? The central limit theorem tells us $X(t)$ has a normal distribution $\mathcal{N}(0, \sigma^2 t)$.

Theorem 5 (Central Limit Theorem). *Suppose that X_1, X_2, \dots , is a sequence of i.i.d. random variables with mean μ and variance σ^2 . Then for $n \rightarrow \infty$, it holds that*

$$\frac{\sum X_i - n\mu}{\sigma\sqrt{n}} \sim \mathcal{N}(0, 1).$$

Or equivalently,

$$\lim_{n \rightarrow \infty} \Pr \left[\frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}} \leq a \right] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^a e^{-x^2/2} dx.$$

Let $Y_i = \delta X_i$ in our setting. Then $\text{Var}[Y_i] = \sigma^2 \Delta t$. Applying the central limit theorem, it follows that

$$X(t) = \sum_{k=1}^{t/\Delta t} Y_k \sim \sigma^2 \Delta t \cdot \sqrt{\frac{t}{\Delta t}} \cdot \mathcal{N}(0, 1) = \mathcal{N}(0, \sigma^2 t)$$

as $\Delta t \rightarrow 0$. This argument gives an intuition of Wiener process. We now formalize the definition.

Definition 1 (Brownian Motion (Wiener Process)). A stochastic process $\{X(t)\}_{t \geq 0}$ is said to be a *Brownian motion* if

- $X(0) = 0$.
- **Independent increments.** $\forall 0 = t_0 < t_1 < \dots < t_n$,

$$X(t_n) - X(t_{n-1}), \quad X(t_{n-1}) - X(t_{n-2}), \quad \dots, \quad X(t_1) - X(t_0)$$

are independent.

- **Stationary increments.** $\forall t, s > 0$, $X(t+s) - X(t)$ only depends on s , and has a normal distribution $\mathcal{N}(0, \sigma^2 s)$ for some constant σ .
- $X(t)$ is continuous.