

MATH 526: Discrete State Stochastic Processes  
Lecture 22-23

**Chapter 5: Martingales**

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## 5.4: Applications

Choosing the proper martingale, we can **estimate certain probabilities**, even if they cannot be computed in closed form.

**Example (Probability of ruin).** Assume that the company's value on day  $n$  is given by

$$S_n = S_{n-1} + X_n, \quad S_0 > 0,$$

where  $\{X_n\}$  are i.i.d. **normal** random variables, with mean  $\mu > 0$  and variance  $\sigma^2 > 0$ :  $X_n \sim N(\mu, \sigma^2)$ . Clearly, we have

$$S_n = S_0 + \sum_{i=1}^n X_i, \quad S_0 > 0.$$

The company goes **bankrupt** when its value drops below zero. Denote by  $\tau$  the first time when the process  $(S_n)$  drops below zero:  $\tau = \min \{n \geq 0 : S_n \leq 0\}$ .

## 5.4: Applications

$$e^{-\frac{2\mu}{\sigma^2} S_n}$$

### Question

How can we estimate the probability that the company will ever go bankrupt:  
 $\mathbb{P}(\tau < \infty) \leq ?$

First, we set up the proper martingale:  $M_n = \exp(-2\mu S_n / \sigma^2)$ . To see that  $(M_n)$  is, indeed, a martingale, we check the “main” property. (At home, verify the finite expectation of the absolute value).

- adaptiveness  $\{X_i\}$
- absolute finite expectation

$$\begin{aligned}
 \bullet \quad \mathbb{E}(M_{n+1} | \mathcal{F}_n^X) &= M_n \mathbb{E}(\exp(-2\mu X_{n+1} / \sigma^2)) \\
 &= M_n \frac{1}{\sigma \sqrt{2\pi}} \int_{\mathbb{R}} e^{-2\mu y / \sigma^2 - (y-\mu)^2 / (2\sigma^2)} dy \\
 &= M_n \frac{1}{\sigma \sqrt{2\pi}} \int_{\mathbb{R}} e^{-\frac{1}{2} \left( \frac{y+\mu}{\sigma} \right)^2} dy \\
 &\stackrel{\downarrow \text{换元}}{=} M_n \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-\frac{1}{2} y^2} dy \\
 &= M_n.
 \end{aligned}$$

$X_{n+1}$   
 $= \frac{1}{\sqrt{\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$   
 $\mathbb{E} e^x = \int f e^x$

$e^{-\frac{2\mu}{\sigma^2}}$   
 $\mathbb{E}[\exp(-cX_i)]^n$   
 $\mathbb{E} e^{(-c)X}$

## 5.4: Applications (Expected Exit Times)

The Optional Sampling theorem implies:

$$\exp(-2\mu S_0/\sigma^2) = \mathbb{E}M_0 = \mathbb{E}M_{n\wedge\tau} = \mathbb{E} \exp(-2\mu S_{n\wedge\tau}/\sigma^2).$$

When  $\tau \leq n$ , we have  $0 \leq -2\mu S_\tau = -2\mu S_{n\wedge\tau}$ . So,

$$\mathbf{1}_{\{\tau \leq n\}} \leq \exp(-2\mu S_{n\wedge\tau}/\sigma^2) \mathbf{1}_{\{\tau \leq n\}} \leq \exp(-2\mu S_{n\wedge\tau}/\sigma^2),$$

Taking expectations in the inequality, we obtain:

$$\mathbb{P}(\tau \leq n) \leq \mathbb{E} \exp(-2\mu S_{n\wedge\tau}/\sigma^2) = \exp(-2\mu S_0/\sigma^2).$$

Due to the continuity of probability, the l.h.s. of the above converges to  $\mathbb{P}(\tau < \infty)$ , as  $n \rightarrow \infty$ . Thus, we obtain

$$\underline{\mathbb{P}(\tau < \infty) \leq \exp(-2\mu S_0/\sigma^2)}.$$

Note:

这个缩放  
有点太大了吧?

Since  $S_0 > 0$   
 $\mu > 0$

$\Rightarrow \text{RHS} < 1$   
 $\Rightarrow \text{good bound}$

## 5.4: Applications (Expected Exit Times)

Martingales can also be used to compute the **expectations** of **exit times**, as well as the expectations of some other **stopping times**.

**Example (Symmetric simple random walk)**  $\{X_n\}$  are i.i.d. random variables, taking values 1 and  $-1$  with **probability  $1/2$** .

$$S_n = x + \sum_{i=1}^n X_i, \quad S_0 = x.$$

Choose integers  $a < x < b$  and introduce:

$$\tau = V_a \wedge V_b = \min \{n \geq 0 : S_n \notin (a, b)\}.$$

上次是  $P(V_a < V_b)$   
这次计算  $E\tau$

### Question

What is the **expected time until the process  $(S_n)$  leaves the interval  $(a, b)$** :

$$E\tau = ?$$

As usual, we, first, need to **find the proper martingale**:

$$(M_n := S_n^2 - n)_{n=0}^\infty.$$

这里的  $mG$  是  
Compensated Square of  
 $mG$ ,  $S_n$  本身是一个  $mG$ .

**Check:**  $M_n$  is a martingale w.r.t.  $(X_n)$ :

## 5.4: Applications

Due to the **Optional Sampling theorem**,  $(M_{n \wedge \tau})$  is a martingale as well. In particular

$$x^2 = \mathbb{E} M_0 = \mathbb{E} M_{n \wedge \tau}.$$

Notice that  $|M_{n \wedge \tau}|$  is not bounded uniformly, hence, we cannot apply the DCT to pass to the limit, as  $n \rightarrow \infty$ , inside the expectation!

这里的  $M_n$  非 bounded.

Indeed, we need to make few more transformations before we can pass to the limit:

$$x^2 = \mathbb{E} M_{n \wedge \tau} = \mathbb{E} (S_{n \wedge \tau}^2) - \mathbb{E} (n \wedge \tau).$$

WT Find another method to express it!

We have shown before (using Markov chains) that

simple symmetric RW

$$\mathbb{P}(\tau < \infty) = 1.$$

is recurrent.

Therefore, with probability one, we have,

$$\lim_{n \rightarrow \infty} \tau \wedge n = \tau, \quad \lim_{n \rightarrow \infty} S_{n \wedge \tau}^2 = S_\tau^2.$$

Since  $|S_{n \wedge \tau}^2| \leq \max(a^2, b^2)$ , we can apply ~~DCT~~ to conclude that

$$\lim_{n \rightarrow \infty} \mathbb{E} S_{n \wedge \tau}^2 = \mathbb{E} S_\tau^2.$$

$S_n$  是一个 bounded  $M_n$ .

## 5.4: Applications

In addition, the following **monotonicity** property holds:

$$\tau \wedge n \leq \tau \wedge (n+1).$$

### Remark

Recall the **Monotone Convergence theorem (MCT)**: Let  $X$  and  $\{X_n\}$  be random variables, such that, with probability one:  $X_n \leq X_{n+1}$ , for each  $n$ , and  $\lim_{n \rightarrow \infty} X_n = X$ . Then,  $\lim_{n \rightarrow \infty} \mathbb{E}X_n = \mathbb{E}X$ .

Thus, due to MCT:

$$\mathbb{E}(n \wedge \tau) \rightarrow \mathbb{E}\tau,$$

as  $n \rightarrow \infty$ .

$$\Rightarrow \lim_{n \rightarrow \infty} \mathbb{E}M_{n \wedge \tau} = \mathbb{E}M_\tau$$

Collecting the above, we conclude:

$$x^2 = \lim_{n \rightarrow \infty} \mathbb{E}M_{n \wedge \tau} = \mathbb{E}M_\tau = \mathbb{E}S_\tau^2 - \mathbb{E}\tau,$$

$$x^2 = a^2 \mathbb{P}(V_a \leq V_b) + b^2 (1 - \mathbb{P}(V_a \leq V_b)) - \mathbb{E}\tau$$

Since we also know the formula for  $\mathbb{P}(V_a < V_b)$ , we obtain:

$$\mathbb{E}\tau = a^2 \frac{b-x}{b-a} + b^2 \frac{x-a}{b-a} - x^2 = (b-x)(x-a).$$

$$f_1 \leq \dots \leq f_n \leq \dots$$

$$\begin{aligned} & \lim_{n \rightarrow \infty} \int f_n dx \\ &= \int \lim_{n \rightarrow \infty} f_n dx \\ &= \int f dx \end{aligned}$$

## 5.4: Applications

if  $\mu \neq 0$ , we can use mG

When the mean of  $X_n$ , denoted  $\mu$ , is **not zero**, there is an even easier way to compute the **expected exit time** – by considering  $M_n = S_n - \mu n$ . Below is a general statement that summarizes this result.

### Theorem

*(Wald's first identity)* Let  $\{X_n\}$  be i.i.d. random variables, with mean  $\mu$ . Let  $\tau$  be a stopping time with respect to  $(X_n)$ , such that  $\mathbb{E}\tau < \infty$ . Set for any  $n \geq 1$ ,

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

Then,

$$\mathbb{E}S_\tau = \mu \mathbb{E}\tau.$$

Stronger

Recall Compound Poisson Process:  $\{X_n\}$ ,  $N_t \sim PP(\lambda)$

$\hookrightarrow X_t = \sum_{i=1}^{N_t} X_i \xrightarrow{\text{Independent}}$

$$\begin{aligned}\mathbb{E}(X_t) &= \mathbb{E}(\mathbb{E}(X_t | N_t)) \\ &= \mu \mathbb{E}(N_t)\end{aligned}$$



## 5.4 Applications

### Theorem

(Wald's first identity) Let  $\{X_n\}$  be i.i.d. random variables, with mean  $\mu$ . Let  $\tau$  be a stopping time with respect to  $(X_n)$ , such that  $\mathbb{E}\tau < \infty$ . Set for any  $n \geq 1$ ,

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

Then,

$$\mathbb{E}S_\tau = \mu\mathbb{E}\tau.$$

$$S_\tau := \sum_{i=1}^{\infty} X_i \mathbf{1}_{\{\tau \geq i\}}.$$

$$|S_{\tau \wedge n}| = \left| \sum_{i=1}^{\infty} X_i \mathbf{1}_{\{\tau \wedge n \geq i\}} \right|.$$

**Proof.** The proof follows similar lines. Start with the monotone convergence theorem that yields  $\mathbb{E}[\tau \wedge n] \rightarrow \mathbb{E}[\tau]$ . Next,

$$|S_{\tau \wedge n}| \leq \underbrace{Y}_{\text{circled}} \quad \text{where} \quad Y = \sum_{m=1}^{\infty} |X_m| \mathbf{1}_{\{\tau \geq m\}}.$$

WTS  $\mathbb{E}Y < \infty$   
to use DCT

Since  $\{\tau \geq m\} = \{\tau \leq m-1\}^c$  is determined by  $X_1, \dots, X_{m-1}$ , it is independent of  $X_m$ , and

$$\mathbb{E}[Y] = \mathbb{E}|X_1| \sum_{m=1}^{\infty} \mathbb{P}(\tau \geq m) = \underbrace{\mathbb{E}|X_1|}_{\text{circled}} \underbrace{\mathbb{E}[\tau]}_{\text{circled}} < \infty.$$

$\therefore \tau > 0$

Finally, the dominated convergence theorem implies that  $\mathbb{E}[S_{\tau \wedge n}] \rightarrow \mathbb{E}[S_\tau]$ . As before, we use the martingale  $\{S_n - \mu n\}_n$  to conclude that

$$0 = \mathbb{E}[S_0 - 0] = \mathbb{E}[S_{\tau \wedge n}] - \mu \mathbb{E}[\tau \wedge n] \rightarrow \mathbb{E}[S_\tau] - \mu \mathbb{E}[\tau]. \quad \blacksquare$$

See 5.5

### Theorem (Maximal inequality for supermartingales)

Let  $(X_n)$  be a **supermartingale**, such that  $X_n \geq 0$ , for all  $n$  and consider an arbitrary constant  $\lambda > 0$ . Then,

$$\mathbb{P} \left( \max_{n \geq 0} X_n > \lambda \right) \leq \frac{\mathbb{E}X_0}{\lambda}.$$

$$\sum_{\lambda^-} \int \mathbb{P}(X_n > \lambda) = \mathbb{E}$$

**Proof.** Think at home.

Suggested Exercises (Durrett, 3rd ed.), not for submission

Exercises 5.8.