

Martingales (discrete time)

Let X_1, X_2, \dots satisfy $E(X_m | \mathcal{X}_{m-1}) = 0$, $\forall m \geq 1$
(we take X_0 to be a constant) + set

$$S_m = \sum_{k=1}^m X_k \quad (S_0 = 0)$$

$\{S_m\}$ is termed a 0-mean martingale. For S_0 a constant (not necessarily 0)

$$S_m = S_0 + \sum_{k=1}^m X_k$$

is called a martingale. Notice $E(S_m) = S_0$, $\forall m$
in this case. It is easily seen that

$$E(S_{m+1} | \mathcal{X}_m) = S_m$$

which is usually taken as the defining property of a martingale. From here we see

$$E(S_m | \mathcal{X}_m) = S_m, \quad m < n$$

& so $E(S_m - S_m | \mathcal{X}_m) = 0$. The X 's are called martingale differences & there is a 1-1 relationship between \mathcal{X}_m & \mathcal{S}_m . One consequence of this is

$$E(S_m | \mathcal{X}_m) = S_m \quad \text{or} \quad E(S_m - S_m | \mathcal{X}_m) = 0,$$

for $m < n$.

If $\{Y_m\}$ is such that X_m/S_m is a f'n of Y_m & $E(S_{m+1} | \tilde{Y}_m) = S_m$ then of course $E(S_{m+1} | \tilde{S}_m) = E[E(S_{m+1} | \tilde{Y}_m) | \tilde{S}_m] = E(S_m | \tilde{S}_m) = S_m$

so that $\{S_m\}$ is a martingale. We often say, in this case, that $\{S_m\}$ is a martingale wrt $\{Y_m\}$.

eg. Let $\{S_m\}$ be a MC so that

$$E[g(S_{m+1}) | \tilde{S}_m] = E[g(S_{m+1}) | S_m]$$

Suppose we can find ψ (psi - lapse) \Rightarrow

$$E[\psi(S_{m+1}) | S_m] = \psi(S_m)$$

which is $P \psi = \psi$, where P is the transition matrix. We would then have

$$E[\psi(S_{m+1}) | \tilde{S}_m] = \psi(S_m)$$

& hence $\{\psi(S_m)\}$ is a martingale (wrt $\{S_m\}$).

We then have $E[\psi(S_m)]$ is constant $\forall m$ which suggests that, for random T , $E[\psi(S_T)]$ will also be this constant. Assume for now this

to be the case ~~for now~~ (it isn't always, but is for stopping times - optional stopping theorem). Consider the simple random walk on $\{0, 1, \dots, N-1, N\}$ where $S_0 = k \in \{1, \dots, N-1\}$, unit steps + absorbing states $0, N$. We wish to calculate the probability that the chain stops at 0 . As before $\{S_m\}$ is a MC & we let p be the prob of a +1 step & $q = 1-p$ the prob of a step to the left. We assume $0 < p < 1$. Let

$$\psi(S_m) = (q/p)^{S_m}$$

It is then easily seen $E[\psi(S_{m+1}) | X_m] = \psi(S_m)$ where X_1, X_2, \dots are the steps. We then have

$$E[\psi(S_m)] = E[\psi(S_0)] = (q/p)^k, \quad \forall m$$

Let $T =$ time to absorption (into 0 or N). It would appear reasonable that

$$E[\psi(S_T)] = (q/p)^k \Rightarrow E[(q/p)^{S_T}] = (q/p)^k$$

Now $S_T = 0$ or N . Let $q_k = P(S_T = 0 | S_0 = k)$ & $p_k = 1 - q_k$.

$$\text{Then } E[(q/p)^{S_T}] = q_k + (q/p)^N p_k = (q/p)^k$$

Set $\rho = q/p$ & assume $\rho \neq 1$. We then get $q_k = \frac{\rho^k - \rho^N}{1 - \rho^N}$

Now $\{S_m\}$ is a martingale (MG) if $E(S_{m+1} | \mathcal{F}_m) = S_m$.
 If $=$ is replaced by \geq then we have a submartingale (SMG). If by \leq then we have a supermartingale. I'll leave it to you to show

Problem (a) $\{S_m\}$ a MG + g convex $\Rightarrow \{g(S_m)\}$ is a SMG.

(b) $\{S_m\}$ a SMG, g convex + inc $\Rightarrow \{g(S_m)\}$ a SMG.

(c) $\{S_m\}$ a SMG $\Rightarrow \{S_m^+\}$ a SMG

Note - $X^+ = \max(0, X)$. Another notation used is $\overset{\max}{\downarrow} X$

- $X \wedge Y$ denotes $\min(X, Y)$ + $X \vee Y$ the max.

If $\{S_m\}$ is a martingale wrt $\{Y_m\}$ then

$$S_m = E(S_{m+N} | \mathcal{F}_m)$$

If S_{m+N} converged to S_∞ , with $E|S_0| < \infty$, we might then conclude

$$S_m = E(S_\infty | \mathcal{F}_m) \quad (*)$$

If we start with S_∞ having finite mean + define S_m via (*) then $\{S_m\}$ is a martingale (the Doob martingale).

If we are willing to assume 2nd moments (*) may be interpreted in a least-squares prediction context.

Kolmogorov's Inequality Let $\{S_m\}$ be a 0-mean martingale & $c > 0$. Then

$$P\left(\max_{1 \leq k \leq m} |S_k| > c\right) \leq \frac{\text{Var}(S_m)}{c^2} = \frac{E(S_m^2)}{c^2}$$

Proof: Let $M_j = \max_{1 \leq k \leq j} |S_k|$ & $A_j = \{M_{j-1} \leq c < M_j\}$, $j=1, \dots, m$ ($M_0 = 0$). Then $\{\max_{1 \leq k \leq m} |S_k| > c\} = \bigcup_{j=1}^m A_j$ &

the A 's are disjoint. Now,

$$\begin{aligned} E(S_m^2 I_{A_j}) &= E[(S_m - S_j + S_j)^2 I_{A_j}] \\ &= E(S_j^2 I_{A_j}) + E[(S_m - S_j)^2 I_{A_j}] \\ &\quad + 2 \underbrace{E(S_j (S_m - S_j) I_{A_j})}_0 \\ &\geq E(S_j^2 I_{A_j}) \end{aligned}$$

since $E[(S_m - S_j)^2 I_{A_j}] \geq 0$ & $E[(S_m - S_j) f^m(X_j)] = 0$.

$\therefore E(S_m^2 I_{A_j}) \geq E(S_j^2 I_{A_j}) \geq E(c^2 I_{A_j}) = c^2 P(A_j)$,
since $A_j \Rightarrow |S_j| > c \therefore E(S_m^2) \geq \sum_{j=1}^m E(S_m^2 I_{A_j}) \geq c^2 \sum_{j=1}^m P(A_j)$

\forall so $P(\max_{1 \leq k \leq m} |S_k| > c) \leq E(S_m^2)/c^2$ qed

This inequality in the i.i.d case leads to a proof of the SLLN. We can extend the SLLN to the dependent case quite easily with a generalization of the inequality (due to Hajek + Renyi)

Theorem (The KHR Inequality) Let $\{S_m\}$ be a 0-mean martingale & $0 = c_0 < c_1 \leq \dots$ constants.

Then $P(|S_k| \leq c_k, k=1, \dots, m) \geq 1 - \sum_{k=1}^m \frac{E(X_k^2)}{c_k^2}$

Remark Note $S_m = \sum_{k=1}^m X_k$ & the X 's are uncorrelated with $E(X_k) = 0$. If $c_k = c > 0$ for $k > 0$ this result reduces to the Kolmogorov Inequality as $\text{Var}(S_m) = E(S_m^2) = \sum_{k=1}^m E(X_k^2)$

Proof

Let $B_m = \{|S_1| \leq c_1, \dots, |S_m| \leq c_m\}$. Then

$$\begin{aligned} P(B_m) &= E[I(B_m)] \\ &= E[I(B_{m-1}) I(|S_m| \leq c_m)] \\ &= E[I(B_{m-1}) (1 - I(|S_m| > c_m))] \\ &> E[I(B_{m-1}) (1 - S_m^2 / c_m^2)] \\ &= E[I(B_{m-1}) (1 - (S_{m-1} + X_m)^2 / c_m^2)] \\ &= E[I(B_{m-1}) (1 - S_{m-1}^2 / c_m^2 - X_m^2 / c_m^2)] \end{aligned}$$

since $E(X_m S_{m-1} I(B_{m-1})) = 0$.

$$P(B_m) \geq E\left[I(B_{m-1}) \left(1 - \frac{S_{m-1}^2}{C_m^2}\right)\right] - E\left[I(B_{m-1}) \frac{X_m^2}{C_m^2}\right]$$

$$\geq E\left[I(B_{m-1}) \left(1 - \frac{S_{m-1}^2}{C_{m-1}^2}\right)\right] - E\left(\frac{X_m^2}{C_m^2}\right)$$

$$\left(\begin{matrix} 0 \\ 0 \end{matrix} \begin{matrix} C_m^2 \geq C_{m-1}^2 \\ X_m^2 \geq I(B_{m-1}) \frac{X_m^2}{C_m^2} \end{matrix}\right)$$

Now $I(B_{m-1}) = I(B_{m-2}) I(|S_{m-1}| \leq C_{m-1})$. Since $I(|S_{m-1}| \leq C_{m-1}) \left(1 - \frac{S_{m-1}^2}{C_{m-1}^2}\right) \geq 1 - \frac{S_{m-1}^2}{C_{m-1}^2}$ we have

$$P(B_m) \geq E\left[I(B_{m-1}) \left(1 - \frac{S_{m-1}^2}{C_{m-1}^2}\right)\right] \quad (*)$$

$$\geq E\left[I(B_{m-2}) \left(1 - \frac{S_{m-1}^2}{C_{m-1}^2}\right)\right] - E\left(\frac{X_m^2}{C_m^2}\right) \quad (**)$$

Now apply the reduction from (*) to (**) to the 1st term of (**) repeatedly to finally obtain (set $B_0 = \Omega$)

$$P(B_m) \geq 1 - \sum_{k=1}^m \frac{E(X_k^2)}{C_k^2}$$

qed

Note When $m=2$ & going from (*) to (**) the 1st term in (**) will be $1 - \frac{E(S_1^2)}{C_1^2} = 1 - \frac{E(X_1^2)}{C_1^2}$

Theorem Let $\{X_n\}$ have constant finite variance σ^2 and satisfy $E(X_n | X_{n-1}) = 0$.
Then

$$\bar{X}_n = \frac{S_n}{n} \xrightarrow{a.s.} 0$$

Proof For any $N > 0$ the sequence $0, S_N, \underbrace{S_N + X_{N+1}}_{S_{N+1}}, \dots$ is a 0-mean martingale. Now let $\epsilon > 0$ & consider

$$P\left(\left|\frac{S_n}{n}\right| \leq \epsilon, \forall n \geq N_0\right)$$

$$= P\left(|S_{N_0}| \leq N_0 \epsilon, |S_{N_0+1}| \leq (N_0+1)\epsilon, \dots\right)$$

$$\stackrel{\text{KHR}}{>} 1 - \left[\frac{E(S_{N_0}^2)}{\epsilon^2 N_0^2} + \sum_{k=N_0+1}^{\infty} \frac{\sigma^2}{\epsilon^2 k^2} \right]$$

Since $\frac{E(S_{N_0}^2)}{\epsilon^2 N_0^2} = \frac{N_0 \sigma^2}{\epsilon^2 N_0^2} \rightarrow 0$ as $N_0 \rightarrow \infty$ as

does $\sum_{k=N_0+1}^{\infty} \frac{\sigma^2}{\epsilon^2 k^2}$ we conclude $\bar{X}_n \xrightarrow{a.s.} 0$

qed

Note $\frac{S_n}{a_n} \xrightarrow{a.s.} 0$ for any $a_n > 0$ with $\sum \frac{1}{a_n^2} < \infty$.

The Martingale Convergence Theorem

Let $\{S_m\}$ be a 0-mean martingale with $\sup_m E(S_m^2) < \infty$. Then \exists a rv $S_\infty \in L_2$ st $S_m \xrightarrow{ms} S_\infty$.

Remark (a) The 0-mean assumption can easily be relaxed as any nonzero mean martingale is a constant + a 0-mean one. More importantly the 2nd moment condition can be weakened to $\sup_m E|S_m| < \infty$ & then the conclusion is $S_m \xrightarrow{as} S_\infty$ with $E(|S_\infty|) < \infty$. If $\{S_m\}$ is ui we also have $S_m \xrightarrow{L_1} S_\infty$.

(b) The remarks in (a) continue to apply if $\{S_m\}$ is a SMG.

Proof (the L_2 version)

$$\begin{aligned} \sup E(S_m^2) < \infty &\Rightarrow \sum_{k=1}^{\infty} E(X_k^2) < \infty \\ &\Rightarrow \sum_{k=1}^m X_k \xrightarrow{ms} S_\infty \end{aligned}$$

with $E(S_\infty^2) < \infty$. It remains to show that $\sum_{k=1}^m X_k \xrightarrow{as}$. If it does then the limit must be S_∞ .
($\circ \circ$ a subseq of $\sum_{k=1}^m X_k \xrightarrow{as} S_\infty$)

Now for every n the sequence $0, S_{m+1} - S_m, S_{m+2} - S_m, \dots$ is a 0-mean martingale. Now apply Kolmogorov's Inequality to get

$$P(|S_m - S_n| \leq \epsilon; \forall m > n) \geq 1 - \frac{1}{\epsilon^2} \sum_{k=n+1}^{\infty} E(X_k^2)$$

$\rightarrow 1$

Hence $\{S_m\}$ is mutually convergent (ie has the Cauchy property) & so $S_m \xrightarrow{a.s.} (\cdot)$ as $m \rightarrow \infty$. The limit must be S_∞ (w.p.1).

qed

The Optional Stopping Theorem

Let $\{S_m\}$ be a martingale with mean S_0 . If T is a stopping time for $\{S_m\}$ and

(a) $T \stackrel{a.s.}{\leq} \infty$ (b) $E(|S_T|) < \infty$ (c) $E[S_m I(T \geq m)] \rightarrow 0$

then $E(S_T) = E(S_m) = S_0$.

Remarks

- T is a stopping time if $\forall m \{T \leq m\}$ is a \mathcal{F}_m event

- If (a) & (c) hold & $\sup_m E|S_m| < \infty$ then (b) holds

- If $1 \leq T_1 \leq T_2 \leq \dots$ are stopping times then $\{S_{T_n}\}$ is a MG

- The result holds if $E(T) < \infty$ & \exists a constant M st

$$\sup_m E(|X_{m+1}| | X_m) \leq M$$

This can be further weakened by only taking the sup over $m \leq T$.

Proof For $m > j$

$$E[S_m I(T=j)] = E[(S_m - S_j) I(T=j)] + E[S_j I(T=j)]$$

$$= E[S_j I(T=j)]$$

\therefore for any m

$$S_0 = E(S_m) = E[S_m I(T \geq m)] + E[S_m I(T < m)]$$

$$= E[S_m I(T \geq m)] + \sum_{j=1}^{m-1} E[S_m I(T=j)]$$

$$= E[S_m I(T \geq m)] + \sum_{j=1}^{m-1} E[S_j I(T=j)]$$

But $E[S_T I(T < m)] = \sum_{j=1}^{m-1} E[S_T I(T=j)] = \sum_{j=1}^{m-1} E[S_j I(T=j)]$

so that

$$E(S_T) - S_0 = E[S_T I(T \geq m)] - E[S_m I(T \geq m)]$$

Now, $E(S_m I(T \geq m)) \rightarrow 0$ by assumption and

$$|E(S_T I(T \geq m))|$$

$$\leq E(|S_T| I(T \geq m)) = \sum_{j=m}^{\infty} E(|S_T| I(T=j))$$

$$= \sum_{j=m}^{\infty} E(|S_j| I(T=j)) \rightarrow 0 \text{ as } m \rightarrow \infty$$

since

$$\infty > E(|S_T|) = E(|S_T| \sum_{j=1}^{\infty} I(T=j))$$

$$= \sum_{j=1}^{\infty} E(|S_T| I(T=j))$$

$$= \sum_{j=1}^{\infty} E(|S_j| I(T=j))$$

Hence

$$E(S_T) = S_0$$

qed

Theorem Let $\{S_m\}$ be a martingale, $T \geq 1$ a stopping time & $Z_m = S_{T \wedge m}$. Then $\{Z_m\}$ is a martingale.

Proof $Z_m = Z_m I(T < m) + Z_m I(T \geq m)$
 $= \sum_{j=1}^{m-1} Z_m I(T=j) + S_m I(T \geq m)$
 $= \sum_{j=1}^{m-1} S_j I(T=j) + S_m I(T \geq m)$

which is a f'm of \tilde{S}_m . Now

$$E(Z_{m+1} | \tilde{S}_m) = \sum_{j=1}^m S_j I(T=j) + E(S_{m+1} I(T \geq m+1) | \tilde{S}_m)$$

Since $\{T \geq m+1\} = \{T \leq m\}^c$ is an \tilde{S}_m -event
 we get $E(S_{m+1} I(T \geq m+1) | \tilde{S}_m) = I(T \geq m+1) E(S_{m+1} | \tilde{S}_m)$
 $= I(T > m) S_m$

$$\begin{aligned} \therefore E(Z_{m+1} | \tilde{S}_m) &= S_m I(T > m) + Z_m I(T \leq m) \\ &= Z_m I(T > m) + Z_m I(T \leq m) \\ &= Z_m \end{aligned}$$

qed