Definition 0.1. $\{X(S)\}_{s\geq 0}$ is a martingale w.r.t. a filtration $\{F(s)\}$ if $E[|X(t)|] < \infty$ and E[X(t)|F(s)] = X(s) a.s. for $t\geq s, \geq X(s)$ for submartingale and $\leq x(s)$ for super martingale.

Example: $\{B(t)\}_{t\geq 0}$ is a M.G. w.r.t. $\{F^+(t)\}_{t\geq 0}$.

Proof.

$$E[B(t)|F^{+}(s)]$$
= $E[B(t) - B(s) + B(s)|F^{+}(s)]$
= $E[B(t) - B(s)] + B(s) = B(s)$.

Proposition 0.1. Suppose $\{X(t)\}_{t\geq 0}$ is a M.G. Suppose $S\leq T$ are two stopping times. If $|X(t\wedge T)|\leq X$ for every t and $X\in L^1$. Then E[X(T)|F(S)]=X(S).

Proof. Notation: X(t) for continuous time process and X_T for discrete time process.

Now we proceed by discretization. Fix a positive integer N and consider the discrete-time MG

$$X_n = X(T \wedge n2^{-N}), S_N' = \lfloor 2^N S \rfloor + 1, T_N' = \lfloor 2^N T \rfloor + 1, g(n) = F(n2^{-N}).$$

we can check

- 1. X_n is a discrete M.G. w.r.t. $\{g(n)\}$.
- 2. $S_N' \leq T_N'$ and S_N', T_N' are stopping time w.r.t. $\{g(n)\}$.
- 3. $|X_n| \le X$.

The discrete-time optional stopping theorem gives

$$\mathbb{E}[X_{T_N'}|G_{S_N'}] = X_{S_N'}. (1)$$

Note that

$$X_{T_N'} = X(T \wedge (\lfloor 2^N T \rfloor + 1)2^{-N}), \ (\lfloor 2^N T \rfloor + 1)2^{-N} \geq T, \ hence \ X_{T_N'} = X(T),$$

then (1) is equivalent to

$$\mathbb{E}[X_{T_N'}|g(S_N')] = \mathbb{E}[X(T)|F(2^{-N}S_N')] = X(T \wedge 2^{-N}S_N')$$

Let $S_N := 2^{-N} S_N' \ge S$, $g(S') = F(S'2^{-N})$

$$\mathbb{E}[X_{T_N'}|g(S_N')] = X_{S_N'} \Rightarrow E[X(T)|F(S_N)] = X(T \land S_N).$$

Now for every $A \in S$,

$$\int_A X_T dP = \lim_{n \to \infty} \int_A X(T \wedge S_N) dP.$$

we can take limit because above works for each n. Now, $A \in F(S) \subset F(S_N)$ and because $S_N \to S$ a.s. and by DCT

$$= \int_{A} \lim(X(T \wedge S_{N})dP)$$
$$= \int_{A} X(T \wedge S)dP$$
$$= \int_{A} X(S)dP.$$

Therefore we have that $\{X(T)\}$ is a M.G. and $T \geq S$ and E[X(T)|F(S)] = X(S) a.s. by uniqueness of conditional expectation.

Theorem 0.1. (Doob's maximal inequality) Suppose $\{X(t)\}_{t\geq 0}$ is a Martingale with p>1, then

$$E|X(t)|^p \le E[\sup_{s < t} |X(s)|^p] \le (\frac{p}{p-1})^p E|X(t)|^p.$$

(intuition is that behavior of the max can be achieved by studying an end point)

Proof. Again we partition [0,t] into 2^N pieces $X_n = X(t \wedge n2^{-N})$ with N fixed $n \in [0, 2^N]$, $g_n = F(tn \cdot 2^{-N})$. Therefore $\{X_n\}$ is a discrete-time martingale with respect to filtration g_n . Let $Y_N := \sup_{0 \le n \le 2^N} |X_n|^p$. We have

$$E[\sup_{0\leq n\leq 2^N}|X_n|^p]\leq (\frac{p}{p-1})^pE|X(t)|^p.$$

We let $n \to \infty$, we $Y_N \uparrow \sup_{s \le t} |X(s)|^p \le \text{a.s.}$ by the path-continuity of $\{X(t)\}$. Therefore $N \to \infty$ by MCT

$$\underset{s \leq t}{Esup} |X(s)|^p \leq (\frac{p}{p-1})^p E|X(t)|^p.$$

Theorem 0.2. (Wald's Lemma) $\{B(t)\}_{t\geq 0}$ is a standard Brownian motion. T is a stopping time with respect to $\{F^+(t)\}$ such that either

- 1. $ET < \infty$. or
- 2. $|B(t \wedge T)| \leq X$ for every t and $X \in L^1$,

then we have E[B(T)] = 0.

Proof. Suppose (ii) holds, then by the previous proposition with S=0, Then

$$E[B(T)|F(0)] = B(0) \ a.s.$$

Suppose (i) holds, define

$$M_k = \max_{0 \le t \le 1} |B(t+k) - B(k)|, \ M = \sum_{k=1}^{\lceil T \rceil} M_k(my \ control \ function)$$

and note that $|B(t \wedge T)| \leq M$. (by triangle inequality for every t) Then

$$EM = E\left[\sum_{k=1}^{\lceil T \rceil} M_k\right]$$

$$= E\left[\sum_{k=1}^{\infty} 1_{T>k-1} M_k\right]$$

$$= \sum_{k=1}^{\infty} E\left[1_{T>k-1} M_k\right]$$

$$= \sum_{k=1}^{\infty} P(T>k-1) EM_k$$

$$= E\left[M_1\right] \sum_{k=1}^{\infty} P(T>k-1)$$

$$= E\left[M_1\right] E(T+1) < \infty$$

because $M_1 < \infty$ (continuity in a compact set) and E(T+1) by assumption (1). Above, $\{T \le k-1\}^c \in F(k-1)$ and $M_k \in F(k).(\{T > k\} \in F(k).$

Lemma 0.1. $\{B^2(t)-t\}$ is a M.G. Suppose X_i iid mean zero and variance 1 then S_n^2-n is a martingale.

$$E[B^{2}(t) - t|F(s)]$$

$$= E[(B(t) - B(s))^{2}] + B(s)^{2} - t$$

$$= t - s + B^{2}(s) - t = B^{2}(s) - s.$$

Theorem 0.3. (continuous time Optional stopping lemma) Suppose $\{X(t)\}_{t\geq 0}$ is a continuous MG W.R.T. F, and T is a stopping time w.r.t. F. If the process $\{X(T \wedge t)\}_{t\geq 0}$ is dominated by an integrable RV X, then

$$\mathbb{E}[X(T)] = X(0),$$

almost surely.

Theorem 0.4. (Wald's lemma 2) Suppose T is a stopping time and $ET < \infty$. then $E(B^2(T) - T) = 0$.)

Proof. Define $T_n := \inf\{t \ge 0 | |B(t)| = n\}$. Then

$$B^2(t \wedge T \wedge T_n) - t \wedge T \wedge T_n$$

is dominated by $n^2 + T$. Also it is a martingale by Lemma 10.1., we can apply walds lemma 1(thm about continuous martingale), (actually we apply Optional stopping theorem for continuous martingale)

$$E(B^2(T \wedge T_n)) = E[T \wedge T_n] \tag{0}$$

when n goes to infinity, $E[T \wedge T_n) \uparrow E(T)$ by MCT

$$E(B^2(T \wedge T_n)) \le E(B^2(T))$$

$$limsupE(B^{2}(T \wedge T_{n})) \le E(B^{2}(T)) \tag{1}$$

Also, by Fatou

$$E(B^2(T)) \le liminf E(B^2(T \land T_n)) \tag{2}$$

then by taking limit to above (0)

$$ET = E(B^2(T)).$$

Theorem 0.5. (Gambler's ruin) $T = \inf\{t : B(t) \in \{a, b\}\}$ where a < 0 < b.

1. $P(B(T) = a) = \frac{b}{|a|+b}$

2. ET = |a|b

Proof. We need to observe that $ET < \infty$ bounded by geometric as in discrete case.

$$E(B(T)) = 0 = aP(B(T) = a) + b(1 - P(B(T) = a))) \rightarrow P(B(T) = a) = \frac{b}{|a| + b}$$

$$E(B^{2}(T)) = ET$$

$$a^{2} \frac{b}{|a| + b} + b^{2}(1 - \frac{b}{|a| + b}) = |a|b.$$

Definition 0.2. A martingale $\{X_n\}$ is binary splitting if whenever the event

$$A(X_0, X_1, ..., X_n) = \{X_{=}x_0, ..., X_n = x_n\}$$

has positive probability, X_{n+1} given A is supported on at most two values.

Lemma 0.2. (Dubin's embedding) Let X is a random variable with finite 2nd moment. Then we have a binary splitting $MG\{X_n\}_{n=1}^{\infty}$ such that $X_n \to X$ in L^2 and a.s.

Proof. We define $\{X_n\}$ and $\{g_n\}$ in the following recursive way.

$$g_0 = \{\phi, \Omega\}$$
 and $X_0 = EX$.

$$\xi_0 = \begin{cases} 1 & \text{if } X \ge X_0 \\ -1 & \text{if } X < X_0. \end{cases}$$

For every n > 0 we define $g_n = \sigma(\xi_0, ..., \xi_{n-1})$ and $X_n = E[X|g_n]$ and $\xi_n = \begin{cases} 1 & \text{if } X \ge X_n \\ -1 & \text{if } X < X_n \end{cases}$. $g_1 = \sigma(\xi_0) = \sigma(\{\xi_0 = 1\}, \{\xi_0 = -1\})$

$$X_1 = E[X|X \ge EX]1_{X > EX} + E[X|X < EX]1_{X < EX}.$$

Check

- 1. $\{X_n\}$ is a MG. ($E[X_n|g_{n-1}] = X_{n-1}$ by the law small wins and by definition of conditional expectation, $X_n \in g_n$)
- 2. $\{X_n\}$ is a binary splitting converging to X.

(key observation is that by using tower, $EXX_n = E[E[XX_n|g_n]] = EX_n^2$. So crossterm goes to 0 in the following)

Theorem 0.6. (Skorohkod embedding) Suppose $\{B(t)\}$ is a S.B.M. and that X is a RV with mean zero and finite 2nd moment. Then there exists a stopping time T with respect to $\{F^+(t)\}$ such that B(T) has the law of X ($B(T) \stackrel{d}{=} X$) $AND \mathbb{E}[T] = \mathbb{E}[X^2]$.

https://people.math.wisc.edu/roch/grad-prob/gradprob-notes29.pdf

Theorem 0.7. (converge in distribution in metric space) Suppose (E,P) is a metric space and A is a σ -algebra of E. Suppose X_{01} and X are E-valued random variable then $X_n \to_d X$ if $g: E \to R$, we have

$$\lim_{n\to\infty} \mathbb{E}[g(X_n)] = E[g(X)].$$

Remark: If E=R, $\rho=Euclidean$ distance, then this is equivalent to converge in distribution in usual sense. We will view the B.M. on [0,1] as a C[0,1] (continuous function on [0,1] to R)-valued r.v.

B(t,w) as $\Omega \to C[0,1]$ and $w \to B(\cdot,w)$ from [0,1]R. $\rho(f,g) = ||f-g||_{\infty}$. Suppose $\{X_n\}$ a set of E-valued r.v.s then $X_n \to_d X \iff \limsup p(X_n \in K) \le P(X \in k)$ for every closed set k in E.

Theorem 0.8. Given mean 0 variance 1 $\{X_n\}$ we look at $S_n = \sum X_i$, then define interpolate linearly $S_t = S_{\lfloor t \rfloor} + (t - \lfloor t \rfloor)(S_{\lfloor t \rfloor + 1} - S_{\lfloor t \rfloor})$. Then we can define $S_n^*(t) = \frac{S(nt)}{\sqrt{n}}$, $t \in [0,1]$. Then $\{S_n^*\} \to_d \{B(t), t \in [0,1]\}$ converge in the sense of viewing both LHS and RHS as C[0,1]-valued r.v.s. In a special case, put t=1

$$\frac{S_n}{\sqrt{n}} \to_d B(1)$$

this is a functional clt.

Proof. See the notes.

Theorem 0.9. $\{X_k\}$ iid with $EX'_k = 0$, $var(X_k) = 1$ Let $M_n = max\{S_k, k \leq n\}$. Then

$$limP(M_n \ge X\sqrt{n}) = \frac{2}{\sqrt{2\pi}} \int_0^\infty e^{-x^2/2} dy.$$

$$(P(B(n)) > X\sqrt{n}).$$