

Lec 13

Convergence of Martingale.

Prop. X_0, X_1, \dots nonnegative supermartingale. $X_0 \leq a$.

$$\forall b > a, \quad T_b \stackrel{\Delta}{=} \inf \{t : X_t \geq b\}. \quad \Pr [T_b < \infty] \leq a/b.$$

Pf. $\forall t > 0$.

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

If $T \leq t$. $X_{T \wedge t} \geq b$.

$$\Rightarrow X_{T \wedge t} \geq b \mathbf{1}[T \leq t].$$

$$\Rightarrow a \geq E[X_{T \wedge t}] \geq b \cdot \Pr[T \leq t].$$

$$\Rightarrow \Pr[T \leq t] \leq a/b.$$

$$\Rightarrow \Pr[T < \infty] \leq \Pr[T \leq t] \leq a/b.$$

OST for supermartingale.

if. OST conditions
are satisfied.

then $E[X_s] = E[X_T]$.

Thm. A nonnegative supermartingale converges w.p. 1.

Pf. ① $E[X_t] \leq E[X_0] \Rightarrow X_t \xrightarrow{t \rightarrow \infty} \infty$.

② $0 \leq a < b$.

$$T_0 = 0.$$

$$S_1 = \inf \{t \geq T_0 : X_t \leq a\}.$$

$$T_1 = \inf \{t \geq S_1 : X_t \geq b\}.$$

:

$$S_k = \inf \{t \geq T_{k-1} : X_t \leq a\}$$

$$T_k = \inf \{t \geq S_k : X_t \geq b\}.$$

$$\forall n \in \mathbb{N}, \text{ OS } \bar{T} \Rightarrow E[X_{T_k \wedge n} - X_{S_k \wedge n}] \leq 0.$$

* If $T_k \leq n$, then $X_{T_k \wedge n} \geq b$.

* If $T_k > n$, then $X_{T_k \wedge n} = X_n$.

$$\Rightarrow X_{T_k \wedge n} \geq b \cdot \mathbf{1}[T_k \leq n] + X_n \mathbf{1}[T_k > n]$$

$$X_{S_k \wedge n} \leq a \cdot \mathbf{1}[S_k \leq n] + X_n \mathbf{1}[S_k > n].$$

$$X_{T_k \wedge n} - X_{S_k \wedge n} \geq b \cdot \mathbf{1}[T_k \leq n] - a \cdot \mathbf{1}[S_k \leq n] + X_n (\mathbf{1}[T_k > n] - \mathbf{1}[S_k > n])$$

$$\geq b \mathbf{1}[T_k \leq n] - a \mathbf{1}[S_k \leq n]$$

$$\Rightarrow b \Pr[T_k \leq n] - a \Pr[S_k \leq n] \leq 0.$$

$$\Rightarrow \Pr[T_k < \infty] \leq \left(\frac{a}{b}\right) \Pr[S_k < \infty] \leq \Pr[T_{k-1} < \infty].$$

Stochastic Approximation

Goal: Find the zero of a function. but the value may contain noise.

Thm: $f: \mathbb{R} \rightarrow \mathbb{R}$. $\mathbb{E}[f(x_0)] < \infty$.

$$Y_n = f(X_n) + \eta_n.$$

$$X_{n+1} = X_n - a_n Y_n.$$

²f. ① $X_0, \eta_0, \eta_1, \dots$ are independent, $\mathbb{E}[\eta_i] = 0$, $\text{Var}[\eta_i] = 1$.

② $|f(x)| \leq c|x|$ for some $1 < c < \infty$.

③ $\forall \delta > 0 \quad \inf_{|x| > \delta} (xf(x)) > 0$.

④ $a_n \geq 0, \sum a_n = \infty$.

⑤ $\sum a_n^2 < \infty$.

$X_n \rightarrow 0$ w.p. 1 as $n \rightarrow \infty$.

$$\text{Pf. } \mathbb{E}[\ X_{n+1}^2 \mid \bar{X}_{0,n}]$$

$$= \mathbb{E} \left[\left(X_n - a_n (f(X_n) + \gamma_n) \right)^2 \mid \bar{X}_{0,n} \right]$$

$$= X_n^2 - 2a_n X_n f(X_n) + a_n^2 (f(X_n)^2 + 1).$$

$$|f'(x)| \leq c(x)$$

$$\leq X_n^2 - 2a_n X_n f(X_n) + a_n^2 c^2 (X_n^2 + 1)$$

$$= X_n^2 (1 + a_n^2 c^2) - 2a_n X_n f(X_n) + a_n^2 c^2.$$

$$\text{Define } W_n = b_n (X_n^2 + 1), \quad b_n = \left(\prod_{k=1}^{n-1} (1 + a_k^2 c^2) \right)^{-1}$$

$$\mathbb{E}[W_{n+1} \mid \bar{X}_{0,n}] = b_{n+1} \mathbb{E}[X_{n+1}^2 \mid \bar{X}_{0,n}] + b_{n+1}$$

$$\leq b_{n+1} \left(X_n^2 (1 + a_n^2 c^2) + a_n^2 c^2 \right) + b_{n+1}$$

$$= b_{n+1} (1 + a_n^2 c^2) (X_n^2 + 1) = b_n (X_n^2 + 1) = W_n.$$

$\{W_n\}$ is a nonnegative supermartingale.

$$\prod (1 + a_n^2 c^2) \leq e^{c^2 \sum a_n^2} \downarrow \Rightarrow X_n^2 \downarrow$$

What we have is

$$\mathbb{E}[W_{n+1} \mid \bar{X}_{0,n}] \leq W_n - \frac{2a_n b_{n+1}}{\text{red line}} X_n f(X_n) > \varepsilon.$$

$$\forall \delta > 0. \quad D \triangleq \{x : |x| > \delta\}.$$

$$\text{Bad event} \quad B_m \triangleq \bigcap_{n \geq m} X_n \in D.$$

$$\varepsilon = \inf_{x \in D} x f(x).$$

$$X_n f(X_n) \geq \mathbb{I}[X_n \in D] \cdot \varepsilon \quad \text{for all } m \leq n$$

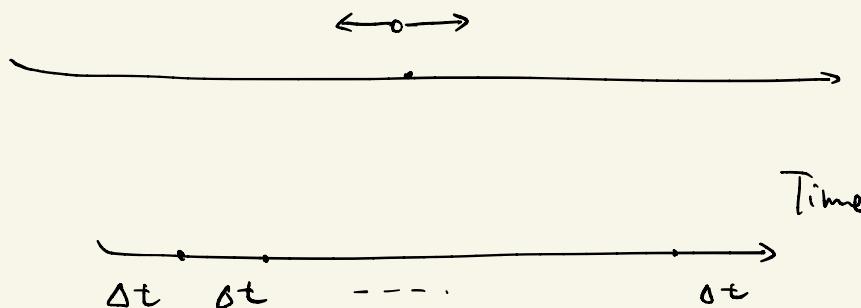
$$\Rightarrow \mathbb{E}[X_n f(X_n)] \geq \varepsilon \cdot P_r[X_n \in D] \geq \varepsilon P(B_m)$$

$$\begin{aligned} \Rightarrow \mathbb{E}[W_{n+1}] &\leq \mathbb{E}[W_n] - 2a_n b_{n+1} \varepsilon P(B_m) \\ &\leq \mathbb{E}[W_m] - 2\varepsilon P(B_m) \sum_{k=m}^{n-1} a_k b_{k+1}. \end{aligned}$$

$$\Rightarrow P(B_m) \leq \frac{\mathbb{E}[W_m]}{2 \sum_{k=m}^{n-1} a_k b_{k+1}} \rightarrow 0.$$

Brownian Motion

1-D Random walk.



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

$$X_i \in \{+1, -1\}.$$

$$\text{Var}(X_i) = 1.$$

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

$$\text{Var}(X(t)) = \frac{\delta^2}{\delta t} \cdot t. \quad \text{Let } \delta = \sigma \sqrt{\delta t}.$$

$$= \sigma^2 t.$$

Thm. X_1, X_2, \dots a sequence of i.i.d. r.v. mean μ , variance σ^2 .

$$\frac{\bar{X}_n - n\mu}{\sigma \sqrt{n}} \xrightarrow{n \rightarrow \infty} N(0, 1)$$

$$\Pr \left[\frac{X_1 + \dots + X_n - n\mu}{\sigma \sqrt{n}} \leq a \right] \rightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^a e^{-x^2/2} dx.$$

Cor. When $\Delta t \rightarrow 0$. $\text{Var}(X_i) = \sigma^2 \Delta t$.

$$E[X_i] = 0.$$

$$X(t) \sim \mathcal{N}(\bar{X}_t, \sqrt{\frac{t}{\Delta t}} \cdot N(0, 1)) = N(0, \sigma^2 t).$$

If $t_1 < t_2 < \dots < t_n$.

$$X(t_n) - X(t_{n-1}), X(t_{n-1}) - X(t_{n-2}), \dots, X(t_2) - X(t_1), X(t_1)$$

are independent.

$X(t+s) - X(t)$ only depends on s .

Def. $\{X(t), t \geq 0\}$ is said to be a Brownian motion process if.

(1) $X(0) = 0$.

(2)

(3) $X(t) \sim N(0, \sigma^2 t)$.