

Lecture 16

Last time

- ▷ Formal construction continued.
- ▷ Markov Property

Today

- ▷ Strong Markov Property
- ▷ Applications

Lemma 2: For bounded measurable f_m , we have

$$\mathbb{E}_\mu \left[\prod_{m=0}^n f_m(x_m) \right] = \int \mu(dx_0) f_0(x_0) \int p(x_0, dx_1) f_1(x_1) \cdots \int p(x_{n-1}, dx_n) f_n(x_n).$$

Proof of Lemma 2: By Tower Law

$$\mathbb{E}_\mu \left[\prod_{m=0}^n f_m(x_m) \right] = \mathbb{E}_\mu \mathbb{E} \left[\prod_{m=0}^n f_m(x_m) \mid \mathcal{F}_{n-1} \right]$$

Take out what you know = $\mathbb{E}_\mu \left[\prod_{m=0}^{n-1} f_m(x_m) \mathbb{E} [f_n(x_n) \mid \mathcal{F}_{n-1}] \right]$

$$\text{Lemma 1} = \mathbb{E}_\mu \left[\prod_{m=0}^{n-1} f_m(x_m) \int p(x_{n-1}, dx_n) f_n(x_n) \right]$$

The result follows by recursing this argument \square

Proof of Markov 1: We prove for a simpler case and extend using $\pi-\lambda$ Thm.

Consider $Y(w) = \prod_{k=1}^n g_k(w_k)$ with g_k bounded and measurable. Let $A = \{w : w_0 \in A_0, \dots, w_m \in A_m\}$

Let $f_k = \begin{cases} 1_{A_k} & k < m, \\ g_0 1_{A_m} & k = m, \\ g_{k-m} & k > m. \end{cases}$ and apply Lemma 2:

$$\begin{aligned} \mathbb{E}_\mu [1_A Y \circ \theta_m] &= \mathbb{E}_\mu [1_A \prod_{k=0}^m g_k(x_{m+k})] \\ &= \int_{A_0} \mu(dx_0) \int_{A_1} p(x_0, dx_1) \dots \int_{A_m} p(x_{m-1}, dx_m) \\ &\quad \left[g_0(x_m) \int p(x_m, dx_{m+1}) g_1(x_{m+1}) \right. \\ &\quad \left. \dots \int p(x_{m+n-1}, dx_{m+n}) g_n(x_{m+n}) \right] \quad (\text{as}) \\ &= \mathbb{E}_\mu [1_A \mathbb{E}_{X_m} Y]. \end{aligned}$$

Again using the $\pi-\lambda$ (as) extends to any $A \in \mathcal{F}_m$. So the result holds for $Y = \prod_{k=0}^n g_k(w_k)$. To finish the proof we use the Mono. Class Thm: Let \mathcal{H} be the collection of Y for which (B) holds, let $S = \{w : w_0 \in A_0, \dots, w_k \in A_k\} : \mathcal{H} \subseteq \{A_i \in \mathcal{G}\}$, taking $g_m = 1_{A_m}$ in (as) shows that (ii) holds, and \mathcal{H} (iii) and (iii₁) by linearity \Rightarrow (B) holds for bounded measurable functions. \square

Strong Markov Property

We prove an extension of Markov 1.
Let N be a stopping time. Define

$$\mathcal{F}_N = \{A : A \cap \{N=n\} \in \mathcal{F}_n \text{ } \forall n\}.$$

Define the random shift operator

$$\Theta_N(\omega) := \begin{cases} \Theta_n(\omega) & \text{on } \{N=n\} \\ * & \text{on } \{N=\infty\} \end{cases}$$

This is a formal symbol we add to Ω .

No need to worry about it since we assume $N < \infty$

Theorem (Markov 2): For each n , let $y_n : \Omega_0 \rightarrow \mathbb{R}$ be measurable with $|y_n| \leq M$ for some $M > 0$. Then,

$$\mathbb{E}_\mu [y_n \circ \Theta_N | \mathcal{F}_N] = \mathbb{E}_{X_N} y_N \text{ on } \{N < \infty\}.$$

This is $\varphi(x, n) = \mathbb{E}_x(y_n)$ evaluated at $x = X_N$, $n = N$.

Proof: Let $A \in \mathcal{F}_N$. Let's partition depending on the value of N ,

$$\mathbb{E}_\mu [(y_n \circ \Theta_N) \mathbf{1}_{A \cap \{N < \infty\}}]$$

$$\textcircled{*} = \sum_{n=0}^{\infty} \mathbb{E}_m [(\gamma_n \circ \theta_N) \mathbf{1}_{A \cap \{N=n\}}]$$

Notice that $A \cap \{N=n\} \in \mathcal{F}_n$ so

Markov 1 gives

$$\textcircled{*} = \sum_{n=0}^{\infty} \mathbb{E}_m [(\mathbb{E}_{X_n} Y_n) \mathbf{1}_{A \cap \{N=n\}}]$$

$$= \mathbb{E}_m [(\mathbb{E}_{X_N} Y_N) \mathbf{1}_{A \cap \{N < \infty\}}].$$

□

Applications

We will use Markov 2 to prove a formula that will be key in the next few lectures.

Assume that S is countable.

Let $T_y^0 = 0$ and for $k \geq 1$, let

$$T_y^{(k)} = \inf \{n > T_y^{(k-1)} : X_n = y\}.$$

↑ k th time we visit y .

We let $T_y = T_y^{(1)}$ and $P_{xy} = \mathbb{P}(T_y < \infty)$.

Theorem: Assume S is countable:

$$P_x(T_y^{(k)} < \infty) = P_{xy} P_{yy}^{k-1}$$

Proof If $K=1$, it follows by definition.
Suppose $K \geq 2$, define

$$Y(\omega) = \mathbb{1}_{\{\exists x_n = y\}}(\omega) = \begin{cases} 1 & \exists \omega_n = y, \\ 0 & \text{otherwise.} \end{cases}$$

Set $N = T_y^{(K-1)} \Rightarrow Y \circ \theta_N = 1 \text{ if } T_y^{(K)} < \infty.$
Markov 2 states that on $\{N < \infty\}$

$$\mathbb{E}_x[Y \circ \theta_N | \mathcal{F}_N] = \mathbb{E}_{X_N} Y$$

$$X_N = y \text{ on } \{N < \infty\} \Rightarrow \mathbb{E}_y Y$$

$$\begin{aligned} (\text{B}) &= P_y(T_y < \infty) \\ &= P_{yy}. \end{aligned}$$

We can now analyze the probability we care about

$$\begin{aligned} P_x(T_y^K < \infty) &= \mathbb{E}_x[(Y \circ \theta_N) \mathbb{1}_{\{N < \infty\}}] \\ &= \mathbb{E}_x[\mathbb{E}_x[Y \circ \theta_N | \mathcal{F}_N] \mathbb{1}_{\{N < \infty\}}] \\ (\text{B}) &= \mathbb{E}_x[P_{yy} \mathbb{1}_{\{N < \infty\}}] \end{aligned}$$

$$= P_{yy} \mathbb{P}_x [T_y^{(k-1)} < \infty]$$

Induction \rightarrow :

$$= P_{yy}^{k-1} \mathbb{P}_x [T_y < \infty]$$

$$= P_{yy}^{k-1} P_{xy}.$$

□

A second application:

Theorem: Let ξ_1, ξ_2, \dots be iid rv with a symmetric distribution around 0. Then

$$\mathbb{P}(\sup_{m \leq n} S_m \geq a) \leq 2 \mathbb{P}(S_n \geq a)$$

—

Exercise for the break read the proof in Durrett (Thm 5.2.7) and interiorize the ideas.