Probability 2017 2

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Probability space

Definition

A probability space is a triple $(\Omega, \mathcal{F}, \mathsf{P})$ of a sample space Ω (set of possible worlds), a σ -algebra \mathcal{F} on Ω , a probability measure $\mathsf{P}: \mathcal{F} \to [0, 1]$. An element $\omega \in \Omega$ is a sample point (world); an element $A \in \mathcal{F}$ is an event; the value $\mathsf{P}(A)$ is the probability of the event A.

- Examples: a finite set, all its subsets, a probability function $p: \Omega \to \mathbb{R}_{>0}$ such that $\sum_{\omega \in \Omega} p(\omega) = 1$; \mathbb{Z}_{\geq} with all its subsets, and a probability function $p: \mathbb{Z}_{\geq} \to \mathbb{R}_{>0}$ such that $\sum_{k=0}^{\infty} p(k) = 1$; the restriction of a probability space to a sub- σ -algebra; the product of two probability spaces.
- Bernoulli trials. Let $\Omega = \{0,1\}^{\mathbb{N}}$ and let $\mathcal{F}_n = \{A \times \{0,1\} \times \{0,1\} \times \cdots | A \subset \{0,1\}^n\}, \ \mathcal{F} = \sigma(\mathcal{F}_n : n \in \mathbb{N}).$ Given $\theta \in [0,1]$, the function $p_n(x_1x_2\cdots x_n\cdots) = \theta \sum_{i=1}^{n} x_i (1-\theta)^{n-\sum_{i=1}^{n} x_i}$ uniquely defines probability spaces $(\Omega, \mathcal{F}_n, \mathbb{P}_n), \ n \in \mathbb{N}$, such that $\mathbb{P}_{n+1}|_{\mathcal{F}_n} = \mathbb{P}_n$, hence a probability measure \mathbb{P} on \mathcal{F} .

Ch. 2 of D. Williams. *Probability with martingales*. Cambridge Mathematical Textbooks. Cambridge University Press, Cambridge, 1991

lim sup and lim inf

Definition

• Let $(a_n)_{n \in \mathbb{N}}$ be a sequence of real numbers.

$$\begin{split} &\limsup_{n \to \infty} a_n = \wedge_{m \in \mathbb{N}} \vee_{n \ge m} a_n \quad (\text{maximum limit}) \\ &\lim_{n \to \infty} \inf a_n = \vee_{m \in \mathbb{N}} \wedge_{n \ge m} a_n \quad (\text{minimum limit}) \end{split}$$

• Let $(E_n)_{n \in \mathbb{N}}$ be a sequence of events in the measurable space (Ω, \mathcal{F}) .

$$\begin{split} &\limsup_{n\to\infty} E_n = \cap_{m\in\mathbb{N}} \cup_{n\geq m} E_n \quad (E_n \text{ infinitely often} \\ &\lim_{n\to\infty} E_n = \cup_{m\in\mathbb{N}} \cap_{n\geq m} E_n \quad (E_n \text{ eventually}) \end{split}$$

Theorem (Fatou lemma)

$$\mathsf{P}\left(\liminf_{n\to\infty} E_n\right) \leq \liminf_{n\to\infty} \mathsf{P}\left(E_n\right) \leq \limsup_{n\to\infty} \mathsf{P}\left(E_n\right) \leq \mathsf{P}\left(\limsup_{n\to\infty} E_n\right)$$

About Fatou lemma

- Notice that $(\limsup_{n} E_{n})^{c} = \liminf_{n} E_{n}^{c}$.
- Notice that $\limsup_{n} \mathbf{1}_{E_n} = \mathbf{1}_{\limsup_{n} E_n}$.
- Proof of FL. Write $\cap_m \cup_{n \ge m} E_n = \cap_m G_m$ so that $G_m \downarrow G = \limsup_n E_n$. We have $P(G_m) \ge \bigvee_{n \ge m} P(E_n)$; monotone continuity implies $P(G_m) \downarrow P(G)$ hence, $\wedge_m P(G_m) = P(G)$.
- BC1. Assume $\sum_{n=1}^{\infty} \mathsf{P}(E_n) < +\infty$. We have for all $m \in \mathbb{N}$ that

$$P\left(\limsup_{n} E_{n}\right) \leq P\left(\bigcup_{n \geq m} E_{n}\right) \leq \sum_{n=m}^{\infty} P\left(E_{n}\right) \to 0 \quad \text{if } m \to \infty$$

hence $P(\limsup_{n} E_n) = 0.$

Measurable function

Definition

Given measurable spaces (S_i, S_i) , i = 1, 2, we say that the function $h: S_1 \to S_2$ is measurable, or is a random variable, if for all $B \in S_2$ the set $h^{-1}(B) = \{s \in S_1 | h(s) \in B\}$ belongs into S_1 .

Theorem

- Let $C \subset S_2$ and $\sigma(C) = S_2$. If $h^{-1}: C \to S_1$, then h is measurable.
- Given measurable spaces (S_i, S_i), i = 1, 2, 3, if both h: S₁ → S₂, g: S₂ → S₃ are measurable functions, then g ∘ f : S₁ → S₃ is a measurable function.
- Given measurable spaces (S_i, S_i) , i = 0, 1, 2 and $h_i \colon S_0 \to S_j$, j = 1, 2, consider $h = (h_1, h_2) \colon S_0 \to S_1 \times S_2$. with product space $(S_1 \times S_2, S_1 \otimes S_2)$, Then both h_1 and h_2 are measurable if, and only if, h is measurable.

Ch. 3 of Ch. 2 of D. Williams. Probability with martingales. Cambridge Mathematical Textbooks. Cambridge University Press, Cambridge, 1991.

Image measure

Definition

Given measurable spaces (S_i, S_i) , i = 1, 2, a measurable function $h: S_1 \to S_2$, and a measure μ_1 on (S_1, S_1) , then $\mu_2 = \mu_1 \circ h^{-1}$ is a measure on (S_2, S_2) . We write $h_{\#}\mu_1 = \mu_2 \circ h^{-1}$ and call it image measure. If μ_1 is a probability measure, we say that $h_{\#}\mu_1$ is the distribution of the random variable h.

• Bernoulli scheme Let $(\Omega, \mathcal{F}, \mathsf{P})$ be the Bernoulli scheme, and define $X_t \colon \Omega \to \{0, 1\}$ to be the *t*-projection, $X_t(x_1x_2\cdots) = x_t$. It is a random variable with Bernoulli distribution $\mathsf{B}(\theta)$. The random variable $Y_n = X_1 + \cdots + X_n$ has distribution $\mathsf{Bin}(\theta, n)$. The random variable $T = \inf \{k \in \mathbb{N} | X_k = 1\}$ has distribution $\mathsf{Geo}(\theta)$.

Real random variable

Definition

Let (S, S) be a measurable space. A real random variable is a real function $h: S \to \mathbb{R}$ with is measurable into (\mathbb{R}, B) .

Theorem

- h: S → ℝ is a real random variable if, and only if, for all c ∈ ℝ the level set {s ∈ S} h(s) ≤ c is measurable. The same property holds with ≤ replaced by < or ≥ or >. The condition can be taken as a definition of extended random variable i.e. h: S → ℝ = ℝ ∪ {-∞, +∞}.
- If g, h: S → ℝ are real random variables and Φ: ℝ² → ℝ is continuous, then Φ ∘ (g, h) is a real random variable.
- Let (h_n)_{n∈N} be a sequence of real random variables on (S,S). Then sup_n f_n, inf_n f_n, lim sup_n f_n, lim inf_n f_n are real random variable.

A monotone-class theorem

Theorem

Let $\mathcal H$ be a vector space of bounded real functions of a set S and assume $1\in \mathcal H.$ Assume

- 1. \mathcal{H} is a monotone class i.e., if for each bounded increasing sequence $(f_n)_n \in \mathbb{N}$ in \mathcal{H} the function $\vee_n f_n$ belong to \mathcal{H} .
- 2. \mathcal{H} contains the indicator functions of a π -system \mathcal{I} .

Then, \mathcal{H} contains all bounded measurable functions of $(S, \sigma(I))$.

• Application. Consider measurable spaces $(\Omega_i, \mathcal{F}_i)$, i = 1, 2. Define $\Omega = \Omega_1 \times \Omega_2$ and $\mathcal{I} = \{A_1 \times A_2 | A_1 \in \mathcal{F}_1, A_2 \in \mathcal{F}_2\}$. Then $\mathcal{F}_1 \otimes \mathcal{F}_2 = \sigma(\mathcal{I})$. Let \mathcal{H} be the set of all bounded real functions $f: \Omega_1 \times \Omega_2 \to \mathbb{R}$ such that for each fixed $x \in \Omega_1$ the mapping $\Omega_2 \ni y \mapsto f(x, y)$ is \mathcal{F}_2 -measurable and for each fixed $y \in \Omega_2$ the mapping $\Omega_1 \ni x \mapsto f(x, y)$ is \mathcal{F}_1 -measurable.

 ^{§3.14} and §A3.1 of D. Williams. Probability with martingales. Cambridge Mathematical Textbooks. Cambridge University Press, Cambridge, 1991