Paul Klein
Email: paul.klein@uwo.ca
URL: www.ssc.uwo.ca/economics/faculty/klein/

Ergodic properties of Markov processes

1 Introduction to probability theory

1.1 Outcomes, events, expectations

Definition 1. *A non-empty set* Ω *is called a* sample space.

Definition 2. *A* σ-algebra on a the set Ω *is a collection* $\mathcal{F}$ *of subsets of* Ω *such that*

1. $\Omega \in \mathcal{F}$
2. *If* $A \in \mathcal{F}$ *then* $A^c \in \mathcal{F}$
3. *If a countable collection* $\{A_n\}_{n=1}^{\infty}$ *satisfies* $A_n \in \mathcal{F}$ *for each* $n = 1, 2, \ldots$, *then* $(\bigcup_{n=1}^{\infty} A_n) \in \mathcal{F}$

Exercise 1. *Verify that if* $\mathcal{F}$ *is a* σ*-algebra then* $\varnothing \in \mathcal{F}$ *and if the countable collection* $\{A_n\}$ *satisfies* $A_n \in \mathcal{F}$ *for each* $n = 1, 2, \ldots$ *then* $(\bigcap_{n=1}^{\infty} A_n) \in \mathcal{F}$.

Exercise 2. *Verify that if* $\mathcal{F}$ *and* $\mathcal{G}$ *are* σ*-algebras, then* $\mathcal{H} = \mathcal{F} \cap \mathcal{G}$ *is a* σ*-algebra.*

Warning. If $\mathcal{F}$ and $\mathcal{G}$ are σ-algebras, $\mathcal{H} = \mathcal{F} \cup \mathcal{G}$ is not necessarily a σ-algebra unless of course $\mathcal{G} \subset \mathcal{F}$ or vice versa. Indeed, even if $\{\mathcal{F}_n\}$ is a countable collection of σ-algebras satisfying $\mathcal{F}_n \subset \mathcal{F}_{n+1}$ for each $n = 1, 2, \ldots$, the union $\bigcup_{n=1}^{\infty} \mathcal{F}_n$ is not necessarily a σ-algebra. For example, let $\Omega = \mathcal{N}$ and let $\mathcal{F}_n$ be the smallest σ-algebra containing $\{1\}, \{2\}, \ldots, \{n\}$. (This is the power set of $\{1, \ldots, n\}$ and all their complements in $\mathcal{N}$.) Then all $\{2n\}$ are in $\bigcup_{n=1}^{\infty} \mathcal{F}_n$ but their union is not in any $\mathcal{F}_n$ so not in the union either.

Proposition 1. *If G is an arbitrary collection of subsets of a set Ω, then there exists a unique smallest extension to a σ-algebra, i.e. a set $\mathcal{G}$ such that*

1. $G \subset \mathcal{G}$
2. $\mathcal{G}$ *is a σ-algebra*
3. *If $\mathcal{H}$ is a σ-algebra and $G \subset \mathcal{H}$, then $\mathcal{G} \subset \mathcal{H}$.*

In this case, we write $\mathcal{G} = \sigma(G)$.

Proof. Take the set of σ-algebras $\{\mathcal{F}_\alpha\}_{\alpha \in I}$ such that $G \subset \mathcal{F}_\alpha$ for each $\alpha \in I$. This set is not empty since 2^Ω is a member. Now define $\mathcal{G} = \bigcap_{\alpha \in I} \mathcal{F}_\alpha$.

Example 1. *Consider $\mathcal{R}$ (or any set) with the Euclidean topology (or any other topology). Then the smallest σ-algebra containing all the open sets is called the* Borel *σ-algebra.*

Definition 3. *Let $\mathcal{G}$ and $\mathcal{H}$ be σ-algebras. Then $\mathcal{G} \vee \mathcal{H} = \sigma(\mathcal{G} \cup \mathcal{H})$.*

Of course this definition can be extended to arbitrary unions, not just pairwise unions.

Definition 4. *$\mathcal{F}$ be a σ-algebra. A (positive)* measure *is a function $\mu : \mathcal{F} \to \mathcal{R}_+ \cup \{+\infty\}$ such that*

1. $\mu(\varnothing) = 0$
2. *If $\{A_n\}$ is a countable collection of pairwise disjoint members of $\mathcal{F}$, then*

$$\mu\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} \mu(A_n).$$

Definition 5. *A* measure space *is a triple $(\Omega, \mathcal{F}, \mu)$ where Ω is a non-empty set, $\mathcal{F}$ is a σ-algebra of subsets of Ω and $\mu : \mathcal{F} \to \mathcal{R}_+ \cup \{+\infty\}$ is a measure.*

Definition 6. *A* probability space *is a measure space $(\Omega, \mathcal{F}, \mathsf{P})$ such that $\mathsf{P}(\Omega) = 1$. A set $A \in \mathcal{F}$ is called an* event*. An event A is said to occur* P-almost surely *or* P-a.s. *if $\mathsf{P}(A) = 1$.*

Exercise 3. *Let* $\{A_k\}_{k=1}^{\infty}$ *be a seqence of events such that* $A_k \subset A_{k+1}$ *and define* $A = \bigcup_{k=1}^{\infty} A_k$. *(In this situation, we write* $A_k \uparrow A$.*) Show that*

$$\mathsf{P}(A) = \lim_{k\to\infty} \mathsf{P}(A_k).$$

Definition 7. *A* random variable *is a mapping* $X : \Omega \to \mathcal{R}$ *that is* $\mathcal{F}$*-measurable, i.e. such that* $X^{-1}((-\infty, a]) = \{\omega \in \Omega : X(\omega) \leq a\} \in \mathcal{F}$ *for each* $a \in \mathcal{R}$.

Remark 1. *We sometimes write the event* $X^{-1}(B) = \{\omega \in \Omega : X(\omega) \in B\}$ *as* $\{X \in B\}$ *or sometimes just* $X \in B$.

Proposition 2. *Let* $\{X_n\}$ *be a sequence of random variables. Then* $\overline{X}(\omega) = \limsup_{n\to\infty} X_n(\omega)$ *is a random variable and so is* $\underline{X}(\omega) = \liminf_{n\to\infty} X_n(\omega)$.

Proof. Omitted.

Definition 8. *The* law *or* distribution *of a random variable* X *is a probability measure on the Borel* σ*-algebra* $\mathcal{B}$ *on* $\mathcal{R}$ *defined via*

$$\mu_X(B) = \mathsf{P}(X^{-1}(B)).$$

The most elementary random variable is called an indicator, defined as follows.

Definition 9. *Let* $A \in \mathcal{F}$. *Then the random variable* $I_A(\omega)$ *is defined via*

$$I_A(\omega) = \begin{cases} 1 \text{ if } \omega \in A \\ 0 \text{ if } \omega \notin A \end{cases}$$

Definition 10. *A random variable with finite range is called* simple.

Proposition 3. *A simple* $\mathcal{G}$*-measurable random variable* X *has the representation*

$$X(\omega) = \sum_{k=1}^{n} a_k I_{A_k}(\omega) \tag{1}$$

where $a_k \in \mathcal{R}$ *and* $A_k \in \mathcal{G}$.

Proof. Obvious.

Exercise 4. *While it is obvious that a $\mathcal{G}$-measurable random variable with finite range has the representation (1), it is not obvious that any function defined via (1) with $A_k \in \mathcal{G}$ is $\mathcal{G}$-measurable. Nevertheless it is true. Prove it.*

Exercise 5. *Let $\mathcal{G}$ be a σ-algebra of subsets of Ω. Show that the collection $\mathcal{M}$ of sets $A \subset \mathcal{R}$ such that $X^{-1}(A) \in \mathcal{G}$ is a σ-algebra. Hence verify that a mapping X is measurable with respect to a σ-algebra $\mathcal{G}$ if and only if $X^{-1}(B) \in \mathcal{G}$ for each B in the Borel σ-algebra on $\mathcal{R}$.*

Definition 11. *Given a random variable X, we denote by $\sigma(X)$ the smallest σ-algebra $\mathcal{G}$ such that X is $\mathcal{G}$-measurable. By the result of Exercise 5, $\sigma(X)$ is simply the set of sets that can be written $X^{-1}(B)$ with B a Borel subset of $\mathcal{R}$.*

Proposition 4. *Let X be a $\mathcal{G}$-measurable random variable. Then there exists a sequence $\{X_n\}$ of $\mathcal{G}$-measurable simple functions such that $\lim_{n\to\infty} X_n(\omega) = X(\omega)$ for all $\omega \in \Omega$. If $X(\omega) \geq 0$ for all $\omega \in \Omega$ then the convergence can be made monotone, i.e. $X(\omega) \geq X_{n+1}(\omega) \geq X_n(\omega)$ for all ω and all n. In this case we write $X_n \uparrow X$.*

Proof. Define the quantizer function $q : \mathcal{R} \to \mathcal{R}$ via

$$q_n(x) = \begin{cases} n \text{ if } x \geq n \\ (k-1)2^{-n} \text{ if } (k-1)2^{-n} \leq x < k2^{-n};\ k = 1, 2, \ldots, n2^n \\ -(k-1)2^{-n} \text{ if } -k2^{-n} \leq x < -(k-1)2^{-n};\ k = 1, 2, \ldots, n2^n \\ -n \text{ if } x < n \end{cases}$$

and define $X_n(\omega) = q_n(X(\omega))$.

Definition 12. *Let $(\Omega, \mathcal{F}, \mathsf{P})$ be a probability space and let X be a non-negative simple random variable with the representation*

$$X = \sum_{k=1}^{n} a_k I_{A_k}.$$

Then its expectation *is defined via*

$$\mathsf{E}_{\mathsf{P}}[X] = \sum_{k=1}^{n} a_k \mathsf{P}(A_k)$$

where we usually suppress the subscript P *where the choice of measure is clear from the context.*

Exercise 6. *The definition of the expected value of a non-negative simple random variable apparently depends on its precise representation. Show that this is appearance only, i.e. that if, for all* $\omega \in \Omega$*,*

$$X(\omega) = \sum_{k=1}^{n} a_k I_{A_k}(\omega) = \sum_{k=1}^{m} b_k I_{B_k}(\omega)$$

then

$$\sum_{k=1}^{n} a_k \mathsf{P}(A_k) = \sum_{k=1}^{m} b_k \mathsf{P}(B_k).$$

Definition 13. *Let* X *be a non-negative random variable. Then its expectation is defined as follows. Let* F *denote the set of simple random variables* φ *such that* $\varphi \leq X$*. Then*

$$\mathsf{E}[X] = \sup_{\varphi \in F} \mathsf{E}[\varphi]$$

where on the right hand side we invoke Definition 12.

Remark 2. *Notice that Definitions 12 and 13 are equivalent whenever they both apply.*

Definition 14. *Let* X *be a random variable and suppose* $\mathsf{E}[X^+] < \infty$ *and* $\mathsf{E}[X^-] < \infty$.[1] *Then we say that* X *is* integrable *and we define*

$$\mathsf{E}[X] = \mathsf{E}[X^+] - \mathsf{E}[X^-].$$

Remark 3. *This is just the definition of the Lebesgue integral, i.e.*

$$\mathsf{E}[X] = \int_\Omega X(\omega) d\mathsf{P}(\omega).$$

and occasionally we will use this notation. But when we don't we will write $\mathsf{E}[X; A] = \mathsf{E}[I_A \cdot X]$ *instead of the more conventional*

$$\int_A X d\mathsf{P}.$$

When we integrate with respect to measures that are not necessarily probability measures, however, we will always use the more conventional notation.

We end this Section by recalling two fundamental facts about Lebesgue integrals.

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[1] By definition, $X^+(\omega) = \max\{X(\omega), 0\}$ and $X^-(\omega) = \max\{-X(\omega), 0\}$.

Proposition 5 (Monotone convergence)**.** *Let* X *be a random variable and let* $\{X_n\}$ *be a sequence of non-negative random variables such that* $X_n \uparrow X$ *with probability 1. Then*

$$\lim_{n\to\infty} \mathsf{E}[X_n] = \mathsf{E}[X].$$

Remark 4. *The limit may be infinite, in which case* $\mathsf{E}[X] = +\infty$ *as well.*

Proof. Omitted.

Proposition 6 (Dominated convergence)**.** *Let* Y *be an integrable random variable and let* $\{X_n\}$ *be a sequence of random variables such that* $|X_n| \leq Y$ *and suppose* X_n *converges to the random variable* X *with probability one. Then*

$$\lim_{n\to\infty} \mathsf{E}[X_n] = \mathsf{E}[X].$$

Proof. Omitted

Remark 5. *Both these propositions can be strengthened to include qualifiers (*P*-a.s.) in various places.*

Exercise 7. *Let* X *be either integrable or non-negative. Suppose* $\{A_n\}$ *is a sequence of events such that* $A_n \uparrow A$*. Show that*

$$\lim_{n\to\infty} \mathsf{E}[X; A_n] = \mathsf{E}[X; A].$$

Exercise 8. *Suppose* X *is an integrable random variable and that* $\{Y_n\}$ *is a sequence of uniformly bounded random variables, i.e. there is an* $M \geq 0$ *such that* $|Y_n| \leq M$ *for all* $n = 1, \ldots$*. Suppose the event*

$$\lim_{n\to\infty} Y_n(\omega) = X(\omega)$$

has probability 1. Show that

$$\lim_{n\to\infty} \mathsf{E}[|X - Y_n|] = 0$$

i.e. that $Y_n \to X$ *in* $\mathcal{L}^1$*.*

Exercise 9. *Let* X *be integrable. Show that*

$$\lim_{n\to\infty} \mathsf{E}[|X|; |X| > n] = 0.$$

Definition 15. *If $p = 1, 2, \ldots$, then we denote by $\mathcal{L}^p(\Omega, \mathcal{F}, \mathsf{P})$ the set of $\mathcal{F}$-measurable random variables such that $\mathsf{E}[|X|^p] < \infty$ together with the norm*

$$\|X\|_p = \mathsf{E}[|X|^p]^{1/p}.$$

Exercise 10. *Verify that, in any measure space $(\Omega, \mathcal{F}, \mu)$ such that $\mu(\Omega) < \infty$, $\mathcal{L}^1 \subset \mathcal{L}^2$.*

Exercise 11. *Verify that $\mathcal{L}^1$ is dense in $\mathcal{L}^2$.*

Definition 16. *Two events A and B are said to be* independent *if $\mathsf{P}(A \cap B) = \mathsf{P}(A)\mathsf{P}(B)$.*

Definition 17. *Two σ-algebras $\mathcal{F}$ and $\mathcal{G}$ are said to be independent if $\mathsf{P}(F \cap G) = \mathsf{P}(F)\mathsf{P}(G)$ for all $F \in \mathcal{F}$ and $\mathcal{G}$.*

Definition 18. *Two random variables X and Y are said to be independent if $\sigma(X)$ and $\sigma(Y)$ are independent.*

Exercise 12. *Let $X, Y \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathsf{P})$ be independent. Show that $\mathsf{E}[XY] = \mathsf{E}[X]\mathsf{E}[Y]$.*

Proposition 7 (Chebyshev's inequality)**.** *Let X be a non-negative stochastic variable and let $\varphi\colon \mathcal{R} \to R_+$ be a non-decreasing function with $\varphi(x) > 0$ whenever $x > 0$ such that $\varphi(X)$ is integrable. Then, for each $\varepsilon > 0$,*

$$\mathsf{P}\left(\{X(\omega) \geq \varepsilon\}\right) \leq \frac{1}{\varphi(\varepsilon)} \mathsf{E}\left[\varphi(X)\right].$$

Proof.

$$E\left[\varphi(X)\right] \geq \mathsf{E}[\varphi(X); X \geq \varepsilon] \geq$$
$$\mathsf{E}[\varphi(\varepsilon); X \geq \varepsilon] = \varphi(\varepsilon)\mathsf{P}(X \geq \varepsilon).$$

1.2 Conditional expectations

1.2.1 Conditioning on an event

Suppose we know that the event A has occurred and we want to know what to expect of a random variable X given this information.

Definition 19. *Let* X *be an integrable random variable and* A *an event such that* $\mathsf{P}(A) > 0$*. Then we define the number* $\mathsf{E}[X|A]$ *via*

$$\frac{\mathsf{E}[X;A]}{\mathsf{P}(A)}.$$

If, on the other hand, $\mathsf{P}(A) = 0$ *we leave* $\mathsf{E}[X|A]$ *undefined.*

1.2.2 Conditioning on a measurable partition

Now suppose that we have a whole collection of sets that we know whether (or not) they have occurred. We want to define the conditional expectation as a *rule* whose value (prediction) is contingent on which of these known events occurred. To begin with, let this collection be a *measurable partition* of Ω.

Definition 20. *Let* $(\Omega, \mathcal{F}, \mathsf{P})$ *be a probability space. A* measurable partition $\mathbb{P}$ *of* Ω *is a finite collection of sets* $\{A_1, A_2, \ldots, A_n\}$ *such that*

1. $A_k \in \mathcal{F}$ *for all* k
2. $A_j \cap A_k = \varnothing$ *if* $j \neq k$
3. $\bigcup_{k=1}^{n} A_k = \Omega$.

Definition 21. *Let* X *be a random variable and let* $\mathbb{P}$ *be a measurable partition of* Ω*. Then* X *is said to be* $\mathbb{P}$*-measurable if it is* $\sigma(\mathbb{P})$*-measurable.*

Exercise 13. *Let* X *be a random variable and let* $\mathbb{P}$ *be a measurable partition of* Ω*. Verify that* X *is* $\mathbb{P}$*-measurable just in case it is constant on each element of the partition, i.e. if and only if* $X(\omega) = X(\omega')$ *whenever there is an* $A \in \mathbb{P}$ *such that* $\{\omega, \omega'\} \subset A$.

Definition 22. *Let* $\mathbb{P} = \{A_1, A_2, \ldots, A_n\}$ *be a measurable partition of* Ω *and let* X *be an integrable random variable. Then we define the conditional expectation given* $\mathbb{P}$ *via*

$$\mathsf{E}[X|\mathbb{P}] = \sum_{k=1}^{n} I_{A_k} \mathsf{E}[X|A_k].$$

Remark 6. *If* $\mathsf{P}(A_k) = 0$ *for some* k*, this only defines* $\mathsf{E}[X|\mathbb{P}]$ P*-a.s. To complete the definition, let* $\mathsf{E}[X|\mathbb{P}]$ *equal zero (or some other arbitrary constant) on such sets.*

Exercise 14. *Let* X *be an integrable random variable and* $\mathbb{P}$ *be a measurable partition of* Ω*. Define* $Z = \mathsf{E}[X|\mathbb{P}]$*. Verify that* Z *is* $\mathbb{P}$*-measurable and that for each* $A \in \mathbb{P}$*, we have*

$$\mathsf{E}[X; A] = \mathsf{E}[Z; A].$$

1.2.3 Conditioning on a σ-algebra

Inspired by Exercise 14, we would like to define the conditional expectation of an integrable random variable X given the σ-algebra $\mathcal{G}$ as a $\mathcal{G}$-measurable random variable Z such that $\mathsf{E}[Z; G] = \mathsf{E}[X; G]$ for all $G \in \mathcal{G}$. However, at this stage we have no guarantee that such a random variable exists, so a digression on three key theorems is necessary: the Hilbert space projection theorem, the Riesz representation theorem and the Radon-Nikodym theorem. Before we start that endeavor, however, let's establish the basic concept by considering a measurable partition $\mathbb{P} = \{A_k\}_{k=1}^n$. A measure μ on $\mathbb{P}$, or for that matter on the σ-algebra generated by $\mathbb{P}$, is defined by the n numbers

$$\mu_k = \mu(A_k).$$

Now let there be another measure λ. We now want to translate back and forth between these two measures. Might there exist a $\mathbb{P}$-simple function

$$f(\omega) = \sum_{k=1}^{n} a_k I_{A_k}$$

such that

$$\lambda(A_k) = a_k \mu(A_k) \tag{2}$$

for $k = 1, 1, \ldots, n$? Well, let's try to construct such a function. Define

$$a_k = \frac{\lambda(A_k)}{\mu(A_k)}.$$

This of course goes wrong if $\mu(A_k) = 0$, but even then things are not so bad if $\lambda(A_k) = 0$ also; we could then define a_k arbitrarily, and Equation 2 would still hold. So if $\lambda(A_k) = 0$ whenever

$\mu(A_k) = 0$ we say that $\lambda \ll \mu$ and declare that the rescaling function f exists, is $\mathbb{P}$-measurable and is defined uniquely almost everywhere (μ). We call this function the Radon-Nikodym derivative $\frac{d\lambda}{d\mu}$.

In one set of cases, *every* σ-algebra is generated by a measurable partition. This is when $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ be a finite set and $\mathcal{F}$ is its power set. The probability measure P is defined by the point masses $\mathsf{P}(\{\omega_k\}) = p_k$.

Exercise 15. *Let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ be a finite set and $\mathcal{F}$ be its power set. Let $\mathcal{G} \subset \mathcal{F}$ be a σ-algebra. Let X be a random variable. Let the point masses be denoted by p_k. Describe the conditional expectation $\mathsf{E}[X|\mathcal{G}]$ as explicitly as possible and establish the connection to the Radon-Nikodym derivative.*

A Hilbert space $(\mathscr{H}, (\cdot,\cdot))$ is a vector space associated with an inner product that is complete in the norm generated by this inner product. The details of the definition can be found in many textbooks.

Proposition 8. *The space $\mathcal{L}^2(\Omega, \mathcal{F}, \mathsf{P})$ with the inner product*

$$(X, Y) = \mathsf{E}[X \cdot Y]$$

is a Hilbert space.

Proof. Omitted.

Theorem 9 (The projection theorem)**.** *Let $\mathscr{H}$ be a Hilbert space and let $\mathscr{G} \subset \mathscr{H}$ be another Hilbert space. Then there are unique linear mappings $P : \mathscr{H} \to \mathscr{G}$ and $Q : \mathscr{H} \to \mathcal{G}^{\perp}$ such that $x = Px + Qx$ and $\|x - Px\| = \inf_{y \in \mathscr{G}} \|x - y\|$ for all $x \in \mathscr{H}$.*

Proof. Omitted.

Theorem 10 (Riesz representation)**.** *Let $(\mathscr{H}, (\cdot,\cdot))$ be a Hilbert space and let $f \colon \mathscr{H} \to \mathcal{R}$ be linear and continuous ("a continuous linear functional"). Then there is a $y \in \mathscr{H}$ such that $f(x) = (x, y)$ for all $x \in \mathscr{H}$.*

Proof. Define $M = \{x \in \mathscr{H} \colon f(x) = 0\}$ be the nullspace of f and let $M^\perp = \{x \in \mathscr{H} \colon (x, y) = 0 \text{ for all } y \in M\}$. By the linearity of f, M is a vector space. By the continuity of f, M is closed. Hence M is a Hilbert space. By the Hilbert space projection theorem, every $x \in \mathscr{H}$ can be written as $x = w + z$ where $w \in M$ and $z \in M^\perp$. Evidently (why?) $M^\perp$ is at most one-dimensional. If $M^\perp = \{0\}$ then $M = \mathscr{H}$ and $y = 0$. Otherwise let $y_0 \neq 0$ be a member of $M^\perp$. Every other $z \in M^\perp$ can be written as $z = \alpha y_0$ for some $\alpha \in \mathcal{R}$. In particular, $y = \alpha_0 y_0$. We want $f(y_0) = (y_0, y) = (y_0, \alpha_0 y_0) = \alpha_0 \|y_0\|^2$. So we choose

$$\alpha_0 = \frac{f(y_0)}{\|y_0\|^2}$$

i.e. choose

$$y = \frac{f(y_0)}{\|y_0\|^2} y_0.$$

The remaining details of the proof are left to the reader.

Definition 23. *A linear functional is said to be* bounded *if there is an* $M > 0$ *such that* $\|f(x)\| \leq M\|x\|$ *for all* $x \in \mathscr{H}$.

Proposition 11. *A linear functional is continuous if and only if it is bounded.*

Proof. Exercise.

Definition 24. *Let* λ *and* μ *be two measures with domain* $\mathcal{F}$. *We write* $\lambda \ll \mu$ *(*λ *is absolutely continuous with respect to* μ*) if* $\lambda(A) = 0$ *whenever* $\mu(A) = 0$.

Definition 25. *Let* $(\Omega, \mathcal{F})$ *be a measurable space. A mapping* μ *from* $\mathcal{F}$ *into* $\mathcal{R} \cup \{+\infty\}$ *or* $\mathcal{R} \cup \{-\infty\}$ *is called* signed measure *if*

1. $\mu(\varnothing) = 0$
2. *If* $\{A_n\}$ *is a countable collection of pairwise disjoint members of* $\mathcal{F}$, *then*

$$\mu\left(\bigcup_{n=1}^{\infty} A_n\right) = \sum_{n=1}^{\infty} \mu(A_n).$$

Notice that μ *attains at most one of the values* $+\infty$ *and* $-\infty$.

Theorem 12. *(Hahn decomposition) Let* $(\Omega, \mathcal{F})$ *be a measurable space and let* μ *be a signed measure. Then there exist two sets* $P, N \in \mathcal{F}$ *such that*

1. $P \cap N = \varnothing$
2. $P \cup N = \Omega$
3. *For each* $E \in \mathcal{F}$ *such that* $E \subset P$, $\mu(E) \geq 0$
4. *For each* $E \in \mathcal{F}$ *such that* $E \subset N$, $\mu(E) \leq 0$

Proof. Omitted.

Definition 26 (Hahn-Jordan decomposition)**.** *Let* $(\Omega, \mathcal{F})$ *be a measurable space, let* μ *be a signed measure and let* $P, N \in \mathcal{F}$ *be a Hahn decomposition for* μ*. Then we define, for each* $E \in \mathcal{F}$,

$$\mu^+(E) = \mu(E \cap P)$$

and

$$\mu^-(E) = -\mu(E \cap N).$$

Remark 7. *Notice that* μ^+ *and* μ^- *are both positive measures and that* $\mu = \mu^+ - \mu^-$.

Theorem 13 (Radon-Nikodym, version 1)**.** *Let* $(\Omega, \mathcal{F})$ *be a measurable space. Let* μ *and* λ *be a finite measures such that* $\lambda \ll \mu$*. Then there exists an a.s. (*μ*) unique non-negative function* $f \in \mathcal{L}^1(\Omega, \mathcal{F}, \mu)$ *such that*

$$\lambda(A) = \int_A f d\mu$$

for all $A \in \mathcal{F}$.

Lemma 14. *Let* $(\Omega, \mathcal{F})$ *be a measurable space, Let* μ *be a finite measure, let* f, g *be measurable, non-negative real-valued functions, let* λ *be a finite measure and suppose* f, g *and* λ *are such that*

$$\int_A f d\lambda = \int_A g d\mu$$

for each $A \in \mathcal{F}$*. Then*

$$\int_A g h d\lambda = \int_A f h d\mu$$

for each $A \in \mathcal{F}$ *and each measurable, non-negative real-valued function* h.

Proof (of the lemma).

Proof (of the theorem). Define a new measure via $\nu(A) = \mu(A) + \lambda(A)$. For any $g \in \mathcal{L}^2(\Omega, \mathcal{F}, \nu)$, we can define the linear function

$$\Phi(g) = \int_\Omega g d\lambda.$$

By the triangle and Cauchy-Schwartz inequalities, we have

$$|\Phi(g)| \leq \left| \int_\Omega g d\lambda \right| \leq \int_\Omega |g| d\lambda \leq \int_\Omega |g| d\nu \leq \sqrt{\nu(\Omega)} \cdot \|g\|_{\mathcal{L}^2(\Omega, \mathcal{F}, \nu)}$$

so that Φ is bounded and hence continuous by Proposition 11. Hence by Theorem 10 there is an $h \in \mathcal{L}^2(\Omega, \mathcal{F}, \nu)$ such that

$$\int_\Omega g d\lambda = \int_\Omega g h d\nu \tag{3}$$

for all $g \in \mathcal{L}^2(\Omega, \mathcal{F}, \nu)$. By setting $g = I_A$ for an arbitrary $A \in \mathcal{F}$ and using the fact that $0 \leq \lambda(A) \leq \nu(A)$, we see that $0 \leq h \leq 1$. Now rewrite Equation 3 as

$$\int_\Omega g d\lambda = \int_\Omega g h d\lambda + \int_\Omega g h d\mu,$$

i.e.

$$\int_\Omega g(1 - h) d\lambda = \int_\Omega g h d\mu \tag{4}$$

for all $g \in \mathcal{L}^2(\Omega, \mathcal{F}, \nu)$. In particular, it holds for all indicator functions. But then by Lemma 14 we have

$$\int_A d\lambda = \int_A \frac{h}{1 - h} \, d\mu$$

for every $A \in \mathcal{F}$, provided $1/(1 - h)$ is well-defined a.e. (λ) and (μ). So we proceed to show that $h \neq 1$ a.e. (μ) and hence also (λ). For that purpose, define $A = \{\omega \in \Omega : h(\omega) = 1\}$ and set $g = I_A$. From Equation 4, we obtain

$$\int_A h d\mu = \int_A (1 - h) d\lambda$$

which implies that $\mu(A) = 0$. Since $\lambda \ll \mu$, it follows that $\lambda(A) = 0$ also. We can then, with a good conscience, define

$$f = \frac{h}{1 - h}$$

and this function is non-negative since $0 \leq h \leq 1$ as we have seen. For integrability, notice that

$$\lambda(\Omega) = \int_\Omega f d\mu < \infty$$

by the finiteness of λ.

Definition 27. *A measure μ on $(\Omega, \mathcal{F})$ is said to be σ-*finite *if there exists a countable collection $\{B_n\}$ of members of $\mathcal{F}$ such that*

1. $|\mu(B_n)| < \infty$ *for all* n
2. $\bigcup_n B_n = \Omega$

Theorem 15 (Radon-Nikodym, version 2)**.** *Let $(\Omega, \mathcal{F})$ be a measurable space. Let μ be a σ-finite measure and let λ be a finite*[2] *measure such that $\lambda \ll \mu$. Then there exists an a.s. (μ) unique $\mathcal{F}$-measurable function $f \in \mathcal{L}^1(\Omega, ,\mu)$ such that*

$$\lambda(A) = \int_A f d\mu$$

for all $A \in \mathcal{F}$.

Proof. Let $\{B_n\}$ be a countable measurable covering of Ω such that each B_n has finite measure under μ. Define $\lambda_n(A) = \lambda(A \cap B_n)$ for each $A \in \mathcal{F}$. On each B_n, define f_n as the Radon-Nikodym derivative $\dfrac{d\lambda_n}{d\mu}$. Define $f = f_n$ on B_n for each n and the proof is done.

Exercise 16. *Verify that f in the previous proof is measurable. What if $\{B_n\}$ is uncountable?*

Example 2. *Let $\Omega = [0, 1]$ and let $\mathcal{F} = \mathcal{B}$ be the Borel σ-algebra generated by the Euclidean topology. Let μ be the counting measure and m be the Lebesgue measure. Apparently $m \ll \mu$ but there is no f such that $dm = f d\mu$.*

Theorem 16 (Radon-Nikodym, version 3)**.** *Let $(\Omega, \mathcal{F})$ be a measurable space. Let μ be a σ-finite measure and let λ be a finite signed measure (both the negative and the positive parts are finite)*

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[2] If λ is merely σ-finite, then we may lose integrability of f, but we still have existence and $\mathcal{F}$-measurability. This result is omitted only because the proof is a bit more complicated.

such that $\lambda \ll \mu$. Then there exists an a.s. (μ) unique $\mathcal{F}$-measurable function $f \in \mathcal{L}^1(\Omega, \mathcal{F}, \mu)$ such that

$$\lambda(A) = \int_A f d\mu$$

for all $A \in \mathcal{F}$.

Proof. Take the Hahn-Jordan decomposition $\lambda = \lambda^+ - \lambda^-$ and apply 13 to λ^+ and to λ^-, yielding two Radon-Nikodym derivatives; call them (without abuse of notation!) f^+ and f^-. For integrability, notice that

$$\lambda^+(\Omega) = \int_\Omega f^+ d\mu < \infty$$

and

$$\lambda^-(\Omega) = \int_\Omega f^- d\mu < \infty$$

by assumption.

Theorem 17 (Radon-Nikodym, version 4)**.** *Let $(\Omega, \mathcal{F})$ be a measurable space. Let μ be a finite measure and let λ be a finite signed measure such that $\lambda \ll \mu$. Then there exists an a.s. (μ) unique $\mathcal{F}$-measurable function $f\colon \Omega \to \mathcal{R}$ such that*

$$\lambda(A) = \int_A f d\mu$$

for all $A \in \mathcal{F}$. If neither $+\infty$ nor $-\infty$ are in the range of λ, then $f \in \mathcal{L}^1(\Omega, \mathcal{F}, \mu)$.

With the Radon-Nikodym theorem in hand, we can define the conditional expectation via the following recipe.

Proposition 18. *Let $(\Omega, \mathcal{F}, \mathsf{P})$ be a probability space, let $X \in \mathcal{L}^1(\Omega, \mathcal{F}, \mathsf{P})$ and let $\mathcal{G} \subset \mathcal{F}$ be a σ-algebra. Then there exists a $Z \in \mathcal{L}^1(\Omega, \mathcal{G}, \mathsf{P})$ such that $\mathsf{E}[Z; G] = \mathsf{E}[X; G]$ for all $G \in \mathcal{G}$. This Z is a.s. (P) unique and we denote it by $\mathsf{E}[X|\mathcal{G}]$.*

Proof. Apparently $(\Omega, \mathcal{G})$ is a measurable space and $\mathsf{P}_\mathcal{G}$, the restriction of P to $\mathcal{G}$, is a finite measure; from now on, abusing the notation somewhat, we will call it P. Now define the signed measure $\mu\colon \mathcal{G} \to \mathcal{R}$ via

$$\mu(G) = \mathsf{E}[X; G]$$

and apparently $\mu \ll \mathsf{P}$ on $(\Omega, \mathcal{G})$. By the Radon-Nikodym, theorem, there exists an essentially unique $Z \in \mathcal{L}^1(\Omega, \mathcal{G}, \mathsf{P})$ such that

$$\mu(G) = \mathsf{E}[Z; G].$$

Definition 28. *Let $\mathcal{G}$ be a σ-algebra and let $A \in \mathcal{F}$ be an event. Its* conditional probability *is defined via*

$$\mathsf{P}[A|\mathcal{G}] = \mathsf{E}[I_A|\mathcal{G}].$$

Exercise 17. *Let $\mathcal{G} \subset \mathcal{H}$ be two σ-algebras and let X be an integrable random variable. Verify the law of iterated expectations, i.e. that*

$$\mathsf{E}\left[\mathsf{E}[X|\mathcal{H}]|\mathcal{G}\right] = \mathsf{E}\left[X|\mathcal{G}\right].$$

Exercise 18. *Let X and Y be square integrable, let $\mathcal{G} \subset \mathcal{F}$ be a σ-algebra and suppose Y is $\mathcal{G}$-measurable. Then*

$$\mathsf{E}[XY|\mathcal{G}] = Y\mathsf{E}[X|\mathcal{G}].$$

Exercise 19. *Let X be an integrable random variable and suppose the σ-algebras $\mathcal{G}$ and $\sigma(X)$ are independent. Show that $\mathsf{E}[X|\mathcal{G}] = \mathsf{E}[X]$. Hence (or otherwise) verify that $\mathsf{E}[X|\{\varnothing, \Omega\}] = \mathsf{E}[X]$.*

1.2.4 Conditioning on a random variable

Definition 29. *Let Z be an integrable random variable and let X be an arbitrary random variable. Then we define*

$$\mathsf{E}[Z|X] = \mathsf{E}[Z|\sigma(X)].$$

Preferably, though, we would like to give precise meaning to the following expression: $\mathsf{E}[Z|X = x]$. For this we need the following Proposition.

Proposition 19. *Let X be a random variable and let Y be a $\sigma(X)$-measurable random variable. Then there exists a Borel measurable function $f : \mathcal{R} \to \mathcal{R}$ such that $Y(\omega) = f(X(\omega))$ for all $\omega \in \Omega$.*

Proof. Let $\{Y_n\}$ be a sequence of $\sigma(X)$-measurable simple random variables such that $\lim_{n\to\infty} Y_n(\omega) = Y(\omega)$ for each $\omega \in \Omega$. Fix n and let $\{a_1, a_2, \ldots, a_N\}$ be the range of Y_n, where without loss of generality we assume that $a_j \neq a_k$ whenever $j \neq k$. Form the sets $A_k = Y_n^{-1}(\{a_k\})$ and the sets $B_k = X(A_k)$. By the $\sigma(X)$-measurability of Y_n and the distinctness of the a_k:s, the B_k:s are pairwise disjoint. Hence we can define $f_n(x) = a_k$ on B_k and zero elsewhere. Finally, define $f(x) = \lim_{n\to\infty} f_n(x)$ wherever the limit exists and 0 elsewhere.

Using this result, we define $Y = \mathsf{E}[Z|X]$ and define $\mathsf{E}[Z|X = x] = f(x)$.

Exercise 20. *Suppose* $X \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathsf{P})$ *and let* $\mathcal{G} \subset \mathcal{F}$ *be a* σ*-algebra. Without using the Hilbert space projection theorem, show that* $Z^* = \mathsf{E}[X|\mathcal{G}]$ *solves*

$$\min_{Z \in \mathcal{L}^2(\Omega,\mathcal{G},\mathsf{P})} \mathsf{E}\left[(X - Z)^2\right].$$

Hint: Start by showing that $\mathsf{E}[Z(X - Z^*)] = 0$ *for each* $Z \in \mathcal{L}^2(\Omega, \mathcal{G}, \mathsf{P})$.

1.2.5 Alternative definition of the conditional expectation

The material so far suggests that there is an alternative approach to defining the conditional expectation.

Definition 30. *Let* $X \in \mathcal{L}^2(\Omega, \mathcal{F}, \mathsf{P})$ *and let* $\mathcal{G} \subset \mathcal{F}$ *be a* σ*-algebra. Then* $\mathsf{E}[X|\mathcal{G}]$ *is the projection of* X *on* $\mathcal{L}^2(\Omega, \mathcal{G}, \mathsf{P})$.

Exercise 21. *If* $X \notin \mathcal{L}^2(\Omega, \mathcal{F}, \mathsf{P})$ *but* $X \in \mathcal{L}^1(\Omega, \mathcal{F}, \mathsf{P})$ *then let* $\{X_n\}$ *be a sequence in* $\mathcal{L}^2$ *that converges to* X *in* $\mathcal{L}^1$*. (Such a sequence exists by Exercise 11.) Now define the sequence* $Z_n = \mathsf{E}[X_n|\mathcal{G}]$*. Verify that this sequence converges to a limit* Z *in* $\mathcal{L}^1(\Omega, \mathcal{G}, \mathsf{P})$*. (This is of course our definition of* $\mathsf{E}[X|\mathcal{G}]$*.)*

Definition 31. *Let* $(\Omega, \mathcal{F}, \mathsf{P})$ *be a probability space and let* $X : \Omega \to \mathbb{R}^n$ *be a random vector. This vector is said to be* normally distributed *with mean* μ *and (non–singular) variance matrix* Σ *if, for each Borel set* $A \subset \mathbb{R}^n$,

$$\mathsf{P}(X^{-1}(A)) = (2\pi)^{-n/2}|\Sigma|^{-1/2} \int\limits_A \exp\left\{-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu)\right\} dm(x)$$

where m is Lebesgue measure on $\mathbb{R}^n$. If Σ is singular, then, with probability 1, X is confined to a subspace.

A nice thing about normal vectors is that the conditional expectation function is linear in the following sense. Suppose

$$Z = \begin{bmatrix} X \\ Y \end{bmatrix}$$

is a normal vector with mean

$$\mu = \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

and variance matrix

$$\Sigma = \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{xy}^T & \Sigma_{yy} \end{bmatrix}.$$

Then the conditional expectation function is linear, i.e. there exists a matrix M such that

$$\mathsf{E}[Y|X] = \mu_y + M(X - \mu_x).$$

We can use the (Hilbert space) projection theorem to compute M. Setting the prediction error orthogonal to all the elements of X, we get

$$\mathsf{E}[(X - \mu_x)(Y - \mu_y - M(X - \mu_x))^T] = 0$$

which implies

$$\Sigma_{xy} = \Sigma_{xx} M^T$$

and it follows that, if Σ_{xx} is invertible,

$$M = \Sigma_{xy}^T \Sigma_{xx}^{-1}.$$

Thus

$$\mathsf{E}[Y|X] = \mu_y + \Sigma_{xy}^T \Sigma_{xx}^{-1}(X - \mu_x).$$

Incidentally, this formula gives the best (in a mean square error sense) linear predictor even if Z is not normal. This is also a consequence of the Hilbert space projection theorem.

2 Dynamical systems

In elementary treatments of stochastic processes, they are defined as arbitrary sequences of random variables, i.e. mappings $X : I \times \Omega \to \mathcal{R}$, where I is some suitable index set such as $\mathcal{Z}_+$ or $\mathcal{Z}$. Here, however, we will employ a different approach that is no less general.

Definition 32. *A* dynamical system *is a quadruple* $(\Omega, \mathcal{F}, \mathsf{P}, T)$ *where* Ω *is a non-empty set,* $\mathcal{F}$ *is a* σ*-algebra on* Ω*,* $\mathsf{P} : \mathcal{F} \to [0, 1]$ *is a probability measure and* $T : \Omega \to \Omega$ *is an* $\mathcal{F}$*-measurable mapping.*

Example 3. *Let* Ω *be the set of doubly infinite sequences from* $\mathcal{R}$*, i.e. let each* $\omega \in \Omega$ *be a mapping* $\omega : \mathcal{Z} \to \mathcal{R}$ *and define* T *via* $(T\omega)(t) = \omega(t + 1)$*.*

Once a dynamical system is in place, each random variable $X(\omega)$ defines a stochastic process via the following recipe: $X_n(\omega) = X(T^n\omega)$. This is of course a sequence of random variables, as expected.

Example 4. *Suppose* $|\rho| < 1$ *and define* X *via*

$$X(\omega) = \sum_{k=0}^{\infty} \rho^k \omega(-k).$$

Then

$$X_n(\omega) = X(T^n\omega) = \sum_{k=0}^{\infty} \rho^k \omega(n - k).$$

Notice that this process satisfies

$$X_{n+1} = \rho X_n + \omega(n + 1).$$

Definition 33. *A dynamical system is called* stationary *if* $\mathsf{P}(T^{-1}(F)) = \mathsf{P}(F)$ *for all* $F \in \mathcal{F}$*.*

Exercise 22. *Let* $(\Omega, \mathcal{F}, \mathsf{P}, T)$ *be a stationary dynamical system and let* X *be an integrable random variable. Show that*

$$\mathsf{E}[X(\omega)] = \mathsf{E}[X(T\omega)].$$

Lemma 20 (Hopf's maximal ergodic lemma)**.** *Let* $(\Omega, \mathcal{F}, \mathsf{P}, T)$ *be a stationary dynamical system and let* X *be an integrable random variable. Define, for* $n = 1, 2, \ldots,$

$$S_n(\omega) = \sum_{k=0}^{n-1} X(T^k \omega)$$

and

$$M_n(\omega) = \max_{1 \le k \le n} S_k(\omega).$$

Then

$$\mathsf{E}[X; M_n > 0] \ge 0.$$

Proof. We begin by noting that $M_n(\omega) = M_{n-1}^+(T\omega) + X(\omega)$ and that $M_n^+(T\omega) \ge M_{n-1}^+(T\omega)$. Evidently

$$X(\omega) + M_n^+(T\omega) \ge X(\omega) + M_{n-1}^+(T\omega) = M_n(\omega)$$

and it follows that

$$X(\omega) \ge M_n(\omega) - M_n^+(T\omega).$$

Now integrate over the set $\{M_n(\omega) > 0\}$. We get

$$\mathsf{E}[X(\omega); M_n(\omega) > 0] \ge$$

$$\mathsf{E}\left[M_n^+(\omega); M_n(\omega) > 0\right] - \mathsf{E}\left[M_n^+(T\omega); M_n(\omega) > 0\right] =$$

$$\mathsf{E}\left[M_n^+(\omega)\right] - \mathsf{E}\left[M_n^+(T\omega); M_n(\omega) > 0\right] \ge$$

$$\mathsf{E}\left[M_n^+(\omega)\right] - \mathsf{E}\left[M_n^+(T\omega)\right] = 0.$$

Definition 34. *Let* $(\Omega, \mathcal{F}, \mathsf{P}, T)$ *be a dynamical system. A set* $A \in \mathcal{F}$ *is called* invariant *if* $T^{-1}(A) = A$.

Exercise 23. *Verify that if* T *is one-one and onto, then any invariant set* A *satisfies* $A = T(A)$. *What matters? Injectiveness or surjectiveness?*

Exercise 24. *Verify that the set $\mathcal{I}$ of invariant sets is a σ-algebra.*

Exercise 25. *Let $(\Omega, \mathcal{F}, \mathsf{P}, T)$ be a dynamical system and let $\mathcal{I}$ be the σ-algebra of invariant sets. Let X be integrable. Show that*

$$\mathsf{E}[X(\omega)|\mathcal{I}] = \mathsf{E}[X(T\omega)|\mathcal{I}].$$

Exercise 26. *Let Let $(\Omega, \mathcal{F}, \mathsf{P}, T)$ be a dynamical system and let $\mathcal{I}$ be the σ-algebra of invariant sets. Let X be a random variable. Suppose $X(\omega) \equiv X(T\omega)$. Show that X is $\mathcal{I}$-measurable. (Such a random variable is called invariant.)*

Definition 35. *The dynamical system $(\Omega, \mathcal{F}, \mathsf{P}, T)$ is said to be* ergodic *if any event $A \in \mathcal{I}$ satisfies $\mathsf{P}(A) = 0$ or $\mathsf{P}(A) = 1$.*

Theorem 21 (Birkhoff's ergodic theorem)**.** *Let $(\Omega, \mathcal{F}, \mathsf{P}, T)$ be a dynamical system, let $\mathcal{I}$ be the σ-algebra of invariant sets and let X be an integrable random variable. Then, P-almost surely and in $\mathcal{L}^1$,*

$$\lim_{n\to\infty} \frac{1}{n} \sum_{k=0}^{n-1} X(T^k\omega) = \mathsf{E}[X|\mathcal{I}].$$

Corollary 22. *If $(\Omega, \mathcal{F}, \mathsf{P}, T)$ is ergodic, then, P-almost surely,*

$$\lim_{n\to\infty} \frac{1}{n} \sum_{k=0}^{n-1} X(T^k\omega) = \mathsf{E}[X]$$

Proof (of the corollary). All we need to do is to verify that $\mathsf{E}[X]$ qualifies as a version of the conditional expectation $\mathsf{E}[X|\mathcal{I}]$. Evidently it is $\mathcal{I}$-measurable. Now consider an invariant event A. Either $\mathsf{P}(A) = 1$ which means that $\mathsf{E}[\mathsf{E}[X]; A] = \mathsf{E}[X]$ and $\mathsf{E}[X; A] = \mathsf{E}[X]$ or $\mathsf{P}(A) = 0$ in which case $\mathsf{E}[\mathsf{E}[X]; A] = 0$ and $\mathsf{E}[X; A] = 0$.

Corollary 23. *If $X \in \mathcal{L}^p$ for some $p > 1$, then $\lim_{n\to\infty} \frac{1}{n} \sum_{k=0}^{n-1} X(T^k\omega) = \mathsf{E}[X|\mathcal{I}]$ in $\mathcal{L}^p$ as well.*

Proof (of the corollary).

Proof (of Birkhoff's theorem). Since we can always replace X with $X - \mathsf{E}[X|\mathcal{I}]$ we can assume without loss of generality that $\mathsf{E}[X|\mathcal{I}] = 0$. Now define $\overline{\eta} = \limsup_{n\to\infty} \dfrac{S_n}{n}$ and $\underline{\eta} = \liminf_{n\to\infty} \dfrac{S_n}{n}$. For a.s. convergence, it suffices to prove that $\overline{\eta} \leq 0$ with probability 1; by considering $-X$ it follows immediately that $\underline{\eta} \geq 0$ with probability 1 as well and consequently $\underline{\eta} = \overline{\eta} = 0$ with probability 1. Let $\varepsilon > 0$ and define $A^\varepsilon = \{\overline{\eta}(\omega) > \varepsilon\}$. Evidently $A^\varepsilon \in \mathcal{I}$. Also, define

$$X^\varepsilon(\omega) = (X(\omega) - \varepsilon) I_{A^\varepsilon}(\omega),$$

and define S_n^ε and M_n^ε accordingly. Now consider the sequence of events $B_n^\varepsilon = \{M_n^\varepsilon > 0\}$. We want to show that $B_n^\varepsilon \uparrow A^\varepsilon$. Clearly $B_n^\varepsilon \subset B_{n+1}^\varepsilon$.

$$\bigcup_{n=1}^{\infty} B_n^\varepsilon = \{\sup_n S_n^\varepsilon > 0\} = \{\sup_n \frac{S_n^\varepsilon}{n} > 0\} = \{\sup_n \frac{S_n}{n} > \varepsilon\} \cap A^\varepsilon = A^\varepsilon.$$

Since $|X^\varepsilon(\omega)| \leq |X(\omega)| + \varepsilon$, X^ε is integrable and hence the dominated convergence theorem and Lemma 20 guarantees that

$$\mathsf{E}[X^\varepsilon; A^\varepsilon] = \lim_{n\to\infty} \mathsf{E}[X^\varepsilon; B_n^\varepsilon] \geq 0.$$

It follows that

$$0 \leq \mathsf{E}[X^\varepsilon; A^\varepsilon] = \mathsf{E}[X - \varepsilon; A^\varepsilon] = \mathsf{E}[X; A^\varepsilon] - \varepsilon \mathsf{P}(A^\varepsilon) =$$

$$\mathsf{E}\left[\mathsf{E}[X|\mathcal{I}]; A^\varepsilon\right] - \varepsilon \mathsf{P}(A^\varepsilon) = -\varepsilon \mathsf{P}(A^\varepsilon).$$

Thus $P(A^\varepsilon) = 0$ for all $\varepsilon > 0$ and it follows that we must have $\underline{\eta} \leq 0$ almost surely. To prove $\mathcal{L}^1$ convergence, consider...

3 Markov processes

We started our discussion of Birkhoff's theorem by noting that we could think of stochastic processes in two ways: (1) given a probability space, a stochastic process is an arbitrary sequence of random variables or (2) given a dynamical system, a stochastic process is a sequence of random variables of the form $X \circ T^n$ where X is a random variable. Here we will adopt a third perspective. Think of a stochastic process as a probability space, where the sample space Ω is the set of mappings $\omega : I \to \mathcal{R}$ where I is either $\mathcal{Z}$ or $\mathcal{Z}_+$. We can then create an associated dynamical system by defining the mapping T as the shift operator

$$(T\omega)(t) = \omega(t+1).$$

It is in this sense that the dynamical system approach involves no loss of generality.

Intuitively, a Markov process is a process such that if the present (period t) value is known, knowing its values at earlier times $t-1$, $t-2$ etc. is useless for predicting its future. To formalize this, we need to define the flow of information generated by a stochastic process. From now on, we will assume that $I = \mathcal{Z}_+$. Let $\mathcal{F}$ be the product σ-algebra $\otimes_{i \in I} \mathcal{B}_i$, where $\mathcal{B}_i = \mathcal{B}$ is the Borel σ-algebra on $\mathcal{R}$.

Definition 36. *Let I be a non-empty ordered set and let $\{(\Omega_i, \mathcal{F}_i)\}$ be a family of measurable spaces. A* measurable rectangle *is a Cartesian product of the form*

$$\prod_{i \in I} A_i;\ A_i \neq \Omega_i \text{ for finitely many } i \in I$$

where $A_i \in \mathcal{F}_i$ for all i.

Definition 37. *Let I be a set and let $\{(\Omega_i, \mathcal{F}_i)\}$ be a family of measurable spaces. Then the* product σ-algebra *is defined via*

$$\otimes_{i \in I} \mathcal{F}_i = \sigma(\textit{measurable rectangles})$$

Notice that, for each t, $\omega(t)$ is a random variable. Hence we can define, for $s \leq t$,

$$\mathcal{F}_n^m = \sigma\left(\omega(m), \omega(m+1), \ldots, \omega(n)\right).$$

Given this information structure, define a stochastic process in the usual way via $X \circ T^n$, where X is some given random variable.

Definition 38. *A stochastic process $X_n = X \circ T^n$ is said to be* Markov *if for every Borel set $B \subset \mathcal{R}$ and all $s \leq t$ we have*

$$\mathsf{P}(X_t \in B | F_s^0) = \mathsf{P}(X_{t+1} \in B | F_s^s)$$

Exercise 27. *Show that X_t is Markov if and only if*

$$\mathsf{P}(X_{t+1} \in B | F_t^0) = \mathsf{P}(X_{t+1} \in B | F_t^t)$$

for all Borel sets B and all t.

Definition 39. *A Markov process is said to be* time homogeneous *if there exists a function P* ...

Kolmogorov's extension theorem.

Let $\mathscr{D} = (\Omega,$ be the dynamical system and X a time homogeneous Markov process with probability transition function P. Then .

Ergodicity characterized. Invariant sets characterized.

Definition 40. *Let $(\Omega, \mathcal{F}, \mathsf{P})$ be a probability space. Two events $A, B \in \mathcal{F}$ are said to be* equivalent *if they differ by a set of measure zero, i.e. $\mathsf{P}(A \bigtriangleup B) = 0$ where we define $A \bigtriangleup B = (A \cap B^c) \cup (A^c \cap B)$.*

4 Stationary measures

The Feller property and existence. Uniqueness for deterministic reasons. Uniqueness for probabilistic reasons; convergence. Uniqueness implies ergodicity.