Chapter 0
Measures, Integration, Convergence

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1 Measures

Let Ω be a fixed non-void set.

Definition 1.1 (fields, $\sigma-$fields, monotone classes) A non-void class $\mathcal{A}$ of subsets of Ω is called a:

(i) *field* or *algebra* if $A, B \in \mathcal{A}$ implies $A \cup B \in \mathcal{A}$ and $A^c \in \mathcal{A}$.

(ii) $\sigma-$*field* or $\sigma-$*algebra* if $A, A_1, A_2, \ldots \in \mathcal{A}$ implies $\cup_1^\infty A_n \in \mathcal{A}$ and $A^c \in \mathcal{A}$.

(iii) *monotone class* if A_n is a monotone $\nearrow$ ($\searrow$) sequence in $\mathcal{A}$ implies $\cup_1^\infty A_n \in \mathcal{A}$ ($\cap_1^\infty A_n \in \mathcal{A}$).

(iv) $(\Omega, \mathcal{A})$ with $\mathcal{A}$ a $\sigma-$field of subsets of Ω is called a *measurable space*.

Remark 1.1 (i) $A, B \in \mathcal{A}$ imply $A \cap B \in \mathcal{A}$ for a field.
(ii) $A_1, \ldots, A_n, \ldots \in \mathcal{A}$ implies $\cap_{n=1}^\infty A_n \in \mathcal{A}$ for a $\sigma-$field.
(iii) $\emptyset, \Omega \in \mathcal{A}$ for both a field and $\sigma-$field.
(iv) To prove that $\mathcal{A}$ is a field ($\sigma-$field) it suffices to show that $\mathcal{A}$ is closed under complements and finite (countable) intersections.

Proposition 1.1 (i) Arbitrary intersections of fields ($\sigma-$fields) ((monotone classes)) are fields ($\sigma-$fields) ((monotone classes)).
(ii) There exists a minimal field ($\sigma-$ field) ((monotone class)) $\sigma(\mathcal{C})$ generated by any class of subsets of Ω.
(iii) a $\sigma-$field is a monotone class and conversely if it is a field.

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Proof. (iii) ($\Leftarrow$) $\cup_{n=1}^\infty A_n = \cup_{n=1}^\infty (\cup_{k=1}^n A_k) \equiv \cup_1^\infty B_n$ where $B_n \nearrow$. $\square$

Notation 1.1 If Ω is a set, 2^Ω is the family of all subsets of Ω.
2^Ω is always a $\sigma-$field.

Example 1.1 If $\Omega = R$, let $\mathcal{B}_0$ consist of $\emptyset$ together with all finite unions of disjoint intervals of the form $\cup_{i=1}^n (a_i, b_i]$, or $\cup_{i=1}^n (a_i, b_i] \cup (a_{n+1}, \infty)$, $(-\infty, b_{n+1}] \cup \cup_{i=1}^n (a_i, b_i]$, with $a_i, b_i \in R$. Then $\mathcal{B}_0$ is a field.

Example 1.2 If $\Omega = (0,1]$, let $\mathcal{B}_0$ consist of $\emptyset$ together with all finite unions of disjoint intervals of the form $\cup_{i=1}^n (a_i, b_i]$, $0 \le a_i \le b_i \le 1$. Then $\mathcal{B}_0$ is a field. But note that $\mathcal{B}_0$ does not contain intervals of the form $[a,b]$ or (a,b); however $(a,b) = \cup_{n=1}^\infty (a, b-1/n]$.

Example 1.3 If $\Omega = R$, let $\mathcal{C} = \mathcal{B}_0$ of example 1.1, and let $\mathcal{B}$ be the $\sigma-$field generated by $\mathcal{B}_0$; $\mathcal{B} = \sigma(\mathcal{B}_0)$. $\mathcal{B}$ is a $\sigma-$field which contains all intervals, open, closed or half-open. From real analysis, any open set $O \subset R$ can be written as a countable union of (disjoint) open intervals:

$$O = \cup_{n=1}^\infty (a_n, b_n).$$

Thus $\mathcal{B}$ contains all open sets in R. This particular $\mathcal{B} \equiv \mathcal{B}_1$ is called the family of *Borel sets*. In fact, $\mathcal{B} = \sigma(\mathcal{O})$, where $\mathcal{O}$ is the collection of all open sets in R.

Example 1.4 Suppose that Ω is a metric space with metric ρ. Let $\mathcal{O}$ be the collection of open subsets of Ω. The the $\sigma-$field $\mathcal{B} = \sigma(\mathcal{O})$ is called the Borel $\sigma-$field. In particular, for $\Omega = R^k$ with the Euclidean metric $\rho(x,y) = |x-y| = \{\sum_1^k |x_i - y_i|^2\}^{1/2}$, $\mathcal{B} \equiv \mathcal{B}_k \equiv \sigma(\mathcal{O})$ is the $\sigma-$field of Borel sets.

Definition 1.2 (i) A *measure* (finitely additive measure) is a function $\mu : \mathcal{A} \rightarrow [0, \infty]$ such that $\mu(\emptyset) = 0$ and $\mu(\sum A_n) = \sum \mu(A_n)$ for countable (finite) disjoint sequences A_n in $\mathcal{A}$.
(ii) A *measure space* is a triple $(\Omega, \mathcal{A}, \mu)$ with $\mathcal{A}$ a $\sigma-$field and μ a measure.

Definition 1.3 (i) μ is a *finite measure* if $\mu(\Omega) < \infty$.
(ii) μ is a *probability measure* if $\mu(\Omega) = 1$.
(iii) μ is an *infinite measure* if $\mu(\Omega) = \infty$.
(iv) A measure μ on a field ($\sigma-$field) $\mathcal{A}$ is called *$\sigma-$finite* if there exists a partition $\{F_n\}_{n \ge 1} \subset \mathcal{A}$ such that $\Omega = \sum_1^\infty F_n$ and $\mu(F_n) < \infty$ for all $n \ge 1$.
(v) A *probability space* is a measure space $(\Omega, \mathcal{A}, \mu)$ with μ a probability measure.

Definition 1.4 (i) A measure μ on $(\Omega, \mathcal{A})$ is *discrete* if there are finitely or countably many points ω_i in Ω and masses $m_i \in [0, \infty)$ such that

$$\mu(A) = \sum_{\omega_i \in A} m_i \qquad \text{for} \qquad A \in \mathcal{A}.$$

(ii) If μ is defined on $(\Omega, 2^\Omega)$, Ω arbitrary, by $\mu(A) = \sharp$ of points in A, $\mu(A) = \infty$ if A is not finite, then μ is called *counting measure*.

Example 1.5 (i) A discrete measure μ on $(\Omega, \mathcal{A}) = (R^1, \mathcal{B}_1)$: $x_i = i$, $m_i = 2^i$.
(ii) A discrete measure μ on $(\Omega, \mathcal{A}) = (\mathbb{Z}^+, 2^{\mathbb{Z}^+})$: $x_i = 2i$, $m_i = 1/i$. ($\mathbb{Z}^+ = \{1, 2, \ldots\}$.
(iii) Counting measure on $(R^1, \mathcal{B}_1)$; *not* a $\sigma-$finite measure!
(iv) Counting measure on $(\mathbb{Z}^+, 2^{\mathbb{Z}^+})$.
(v) A probability measure on $\mathbb{Q}$, the rationals: With $\{x_i\}$ an enumeration of the rationals, let $m_i = 6/(\pi^2 i^2)$.

Proposition 1.2 Let $(\Omega, \mathcal{A}, \mu)$ be a measure space.
(i) If $\{A_n\}_{n \ge 1} \subset \mathcal{A}$ with $A_n \subset A_{n+1}$ for all n, then $\mu(\cup_{n=1}^\infty A_n) = \lim_{n \to \infty} \mu(A_n)$.
(ii) If $\mu(A_1) < \infty$ and $A_n \supset A_{n+1}$ for all n, then $\mu(\cap_{n=1}^\infty A_n) = \lim_{n \to \infty} \mu(A_n)$.

Proof. (i)

$$\begin{aligned}
\mu(\cup_1^\infty A_n) &= \mu(\cup_1^\infty (A_n \setminus A_{n-1})) \qquad \text{where} \qquad A_0 = \emptyset \\
&= \sum_1^\infty \mu(A_n \setminus A_{n-1}) \qquad \text{by countable additivity} \\
&= \lim_n \sum_1^n \mu(A_n \setminus A_{n-1}) \\
&= \lim_n \mu(\sum_1^n (A_n \setminus A_{n-1})) \qquad \text{by finite additivity} \\
&= \lim_n \mu(A_n).
\end{aligned}$$

(ii) Let $B_n \equiv A_1 \setminus A_n = A_1 \cap A_n^c$ so that $B_n \nearrow$. Thus, on the one hand we have

$$\begin{aligned}
\lim_n \mu(B_n) &= \mu(\cup_1^\infty B_n) \qquad \text{by part (i)} \\
&= \mu(\cup_1^\infty (A_1 \cap A_n^c)) \\
&= \mu(A_1 \cap \cup_1^\infty A_n^c) \\
&= \mu(A_1 \cap (\cap_1^\infty A_n)^c) \\
&= \mu(A_1) - \mu(\cap_1^\infty A_n) \qquad \text{by finite additivity,}
\end{aligned}$$

while on the other hand,

$$\begin{aligned}
\lim_n \mu(B_n) &= \lim_n \mu(A_1 \setminus A_n) = \lim_n \{\mu(A_1) - \mu(A_n)\} \qquad \text{by finite additivity} \\
&= \mu(A_1) - \lim_n \mu(A_n).
\end{aligned}$$

Combining these two equalities yield the conclusion of (ii). □

Definition 1.5
(i) $\underline{\lim} A_n \equiv \cup_{n=1}^\infty \cap_{k=n}^\infty A_k \qquad \equiv \{\omega \in \Omega : \omega \in \text{all but a finite number of} A_k' s\} \equiv [A_n \;\; a.a.]$;
(ii) $\overline{\lim} A_n \equiv \cap_{n=1}^\infty \cup_{k=n}^\infty A_k \qquad \equiv \{\omega \in \Omega : \omega \in \text{infinitely many} A_k' s\} \equiv [A_n \;\; i.o.]$.

Remark 1.2 $\underline{\lim} A_n \subset \overline{\lim} A_n$; $\lim A_n \equiv \underline{\lim} A_n$ provided $\underline{\lim} A_n = \overline{\lim} A_n$.

Proposition 1.3 Monotone $\nearrow$ ($\searrow$) A_n's have $\lim A_n = \cup_1^\infty A_n$ ($= \cap_1^\infty A_n$).

Example 1.6 Let $\mathcal{A} = \mathcal{B} = \sigma(\mathcal{B}_0)$ as in example 1.3. For $B \in \mathcal{B}_0$, let $\mu(B) \equiv$ the sum of the lengths of intervals $A \in \mathcal{B}_0$ composing B. Then μ is a countably additive measure on $\mathcal{B}_0$. Can μ be extended to $\mathcal{B}$? The answers is *yes*, and depends on the following:

Theorem 1.1 (Caratheodory Extension Theorem) A measure μ on a field $\mathcal{C}$ can be extended to a measure on the minimal $\sigma-$field $\sigma-$field $\sigma(\mathcal{C})$ over $\mathcal{C}$. If μ is $\sigma-$finite on $\mathcal{C}$, then the extension is unique and is also $\sigma-$finite.

Proof. See Billingsley (1986), pages 29 - 35 and 137 - 139. □

Example 1.7 (example 1.3, continued.) The extension of the countably additive measure μ on $\mathcal{B}_0$ to $\mathcal{B}_1 = \sigma(\mathcal{B}_0)$, the Boreal $\sigma-$field, is called Lebesgue measure; thus $(R^1, \mathcal{B}_1, \mu)$ where μ is the extension of the Caratheodory extension theorem, is a measure space. The usual procedure is to *complete* $\mathcal{B}_1$ as follows.

Definition 1.6 If $(\Omega, \mathcal{A}, \mu)$ is a measure space such that $B \subset A$ with $A \in \mathcal{A}$ and $\mu(A) = 0$ implies $B \in \mathcal{A}$, then $(\Omega, \mathcal{A}, \mu)$ is a *complete measure space.* If $\mu(A) = 0$, then A is called a *null* set. (Of course there can be non-empty null sets.)

Exercise 1.1 Let $(\Omega, \mathcal{A}, \mu)$ be a measure space. Define

$$\overline{\mathcal{A}} \equiv \{A \cup N : A \in \mathcal{A}, N \subset B \text{ for some } B \in \mathcal{A} \text{ such that } \mu(B) = 0\}$$

and let $\overline{\mu}(A \cup N) \equiv \mu(A)$. Then $(\Omega, \overline{\mathcal{A}}, \overline{\mu})$ is a complete measure space.

Example 1.8 (example 1.3, continued.) Completing $(R^1, \mathcal{B}_1, \mu)$ where μ =Lebesgue measure yields the complete measure space $(R^1, \overline{\mathcal{B}}_1, \overline{\mu})$. $\overline{\mathcal{B}_1}$ is called the $\sigma-$field of *Lebesgue sets.*

So far we know only a few measures. But we will now construct a whole batch of them; and they are just the ones most useful for probability theory.

Definition 1.7 A measure μ on R assigning finite values to finite intervals is called a *Lebesgue - Stieltjes measure.*

Definition 1.8 A function F on R which is finite, increasing, and right continuous is called a *generalized distribution function* (generalized df).

$$F(a, b] \equiv F(b) - F(a)$$

for $-\infty < a \leq b < \infty$ is called the *increment function* of the generalized df F. We identify generalized df's having the same increment function.

Theorem 1.2 (Correspondence theorem.) The relation

$$\mu((a, b]) = F(a, b] \qquad \text{for} \qquad -\infty < a \leq b < \infty$$

establishes a one-to-one correspondence between Lebesgue-Stieltjes measures μ on $\mathcal{B} = \mathcal{B}_1$ and equivalence classes of generalized df's.

Proof. See Billingsley (1986), pages 147, 149 - 151. □

Definition 1.9 (Probability measures on R.) If $\mu(\Omega) = 1$, then μ is called a *probability distribution* or *probability measure* and is denoted by P.

Definition 1.10 An $\nearrow$, right-continuous function F on R such that $F(-\infty) = 0$ and $F(\infty) = 1$ is a *distribution function* (df).

Corollary 1 The relation

$$P((a, b]) = F(b) - F(a) \qquad \text{for} \qquad -\infty < a \leq b < \infty$$

establishes a one-to-one correspondence between probability measures on R and df's.

2 Measurable Functions and Integration

Let $(\Omega, \mathcal{A})$ be a measurable space.
Let X denote a function, $X : \Omega \to R$.

Definition 2.1 $X : \Omega \to R$ is *measurable* if $[X \in B] \equiv X^{-1}(B) = \{\omega \in \Omega : X(\omega) \in B\} \in \mathcal{A}$ for all $B \in \mathcal{B}_1$.

Definition 2.2 (i) For $A \in \mathcal{A}$ the *indicator function* of A is the function

$$1_A(\omega) = \begin{cases} 1 & \text{if } \omega \in A \\ 0 & \text{if } \omega \in A^c \end{cases} .$$

(ii) A *simple function* is $X(\omega) \equiv \sum_{i=1}^n x_i 1_{A_i}(\omega)$ for $\sum_1^n A_i = \Omega$, $A_i \in \mathcal{A}$, $x_i \in R$.
(iii) An *elementary function* is $X(\omega) \equiv \sum_{i=1}^\infty x_i 1_{A_i}(\omega)$ for $\sum_{i=1}^\infty A_i = \Omega$, $A_i \in \mathcal{A}$, $x_i \in R$.

Proposition 2.1 X is measurable if and only if $X^{-1}(\mathcal{C}) \equiv \{X^{-1}(C) : C \in \mathcal{C}\} \subset \mathcal{A}$ where $\sigma(\mathcal{C}) = \mathcal{B}$. Hence X is measurable if and only if $X^{-1}((x,\infty)) \equiv [X > x] \in \mathcal{A}$ for all $x \in R$.

Proof. $(\Rightarrow)$ This direction is trivial.
$(\Leftarrow)$ $X^{-1}(\mathcal{B}) = X^{-1}(\sigma(\mathcal{C})) = \sigma(X^{-1}(\mathcal{C}))$ since X^{-1} preserves all set operations and since $X^{-1}(\mathcal{C}) \subset \mathcal{A}$ with $\mathcal{A}$ a $\sigma-$field by hypothesis.
Further, $\sigma(\{(x,\infty) : x \in R\}) = \mathcal{B}_1$ since $(a,b] = (a,\infty) \cap (b,\infty)^c$, and $\mathcal{B}_1$ is generated by intervals of the form $(a,b]$. $\square$ Note that the assertion of the propostion would work with (x,∞) replaced

by any of $[x,\infty)$, $(-\infty, x]$, $(-\infty, x)$.

Proposition 2.2 Suppose that $\{X_n\}$ are measurable. Then so are $\sup_n X_n$, $-X_n$, $\inf_n X_n$, $\overline{\lim} X_n$, $\underline{\lim} X_n$, and $\lim X_n$.

Proof. $[\sup X_n > x] = \cup_n [X_n > x]$;
$[-X_n > x] = [X_n < -x]$;
$\inf X_n = -\sup_n(-X_n)$;
$\overline{\lim} X_n = \inf_n(\sup_{k \geq n} X_k)$;
$\underline{\lim} X_n = -\overline{\lim}(-X_n)$;
$\lim_n X_n = \overline{\lim} X_n$ when $\lim X_n$ exists. $\square$

Proposition 2.3 X is measurable if and only if it is the limit of a sequence of simple functions:

$$X_n = -n 1_{[X < -n]} + \sum_{k=-n2^n+1}^{n2^n} \frac{k-1}{2^n} 1_{[(k-1)/2^n \leq X < k/2^n]} + n 1_{[X > n]}.$$

Proof. $(\Rightarrow)$ The X_n's exhibited above have $|X_n(\omega) - X(\omega)| < 2^{-n}$ for $|X(\omega)| < n$.
$(\Leftarrow)$ The exhibited X_n's are simple, converge to X, and $\lim X_n$ is measurable by prop 2.2. $\square$

Remark 2.1 If $X \geq 0$, then $0 \leq X_n \nearrow X$.

Proposition 2.4 Let X, Y be measurable. Then $X \pm Y$, XY, X/Y, $X^+ \equiv X1_{[X\geq 0]}$, $X^- \equiv -X1_{[X\leq 0]}$, $|X|$, $g(X)$ for measurable g are all measurable.

Proof. Let X_n, Y_n be simple functions, $X_n \to X$, $Y_n \to Y$. Then $X_n \pm Y_n$, X_nY_n, X_n/Y_n are simple functions converging to $X \pm Y$, XY, and X/Y, and hence the limits are measurable by prop 2.3. X^+ and X^- are easy by prop 2.3, and $|X| = X^+ + X^-$. For $g : R \to R$ measurable we have, for $B \in \mathcal{B}_1$,

$$\begin{aligned} (gX)^{-1}(B) &= X^{-1}(g^{-1}(B)) = X^{-1}(\text{ a Borel set }) \qquad \text{since} \quad g \text{ is measurable} \\ &\in \mathcal{A} \qquad \text{since} \qquad X^{-1} \text{ is measurable.} \end{aligned}$$

□

Remark 2.2 Any continuous function g is measurable since

$$g^{-1}(\mathcal{B}) = g^{-1}(\sigma(\mathcal{O})) = \sigma(g^{-1}(\mathcal{O})) = \sigma(\text{ a subcollection of open sets }) \subset \mathcal{B}.$$

Now let $(\Omega, \mathcal{A}, \mu)$ be a measure space, and leet X, Y denote measurable functions from $(\Omega, \mathcal{A})$ to $(\overline{R}, \overline{\mathcal{B}})$, $\overline{R} \equiv R \cup \{\pm\infty\}$, $\overline{\mathcal{B}} \equiv \sigma(\mathcal{B} \cup \{\infty\} \cup \{-\infty\})$.
CONVENTIONS: $0 \cdot \infty = 0 = \infty \cdot 0$, $x \cdot \infty = \infty \cdot x = \infty$ if $0 < x < \infty$; $\infty \cdot \infty = \infty$.

Definition 2.3 (i) For $X \equiv \sum_1^m x_i 1_{A_i}$ with $x_i \geq 0$, $\sum_1^m A_i = \Omega$, then $\int X\,d\mu = \sum_1^m x_i \mu(A_i)$.
(ii) For $X \geq 0$, $\int X\,d\mu \equiv \lim_n \int X_n d\mu$ where $\{X_n\}$ is any ≥ 0, $\nearrow$ sequence of simple functions, $X_n \to X$.
(iii) For general X, $\int X\,d\mu \equiv \int X^+ d\mu - \int X^- d\mu$ if one of $\int X^+ d\mu$, $\int X^- d\mu$ is finite.
(iv) If $\int X\,d\mu$ is finite, then X is *integrable*.

JUSTIFICATION: See Loève pages 120 - 123 or Billingsley (1986), page 176.

Proposition 2.5 (Elementary properties.) Suppose that $\int X\,d\mu$, $\int Y\,d\mu$, and $\int X\,d\mu + \int Y\,d\mu$ exist. Then:
(i) $\int (X+Y) d\mu = \int X\,d\mu + \int Y\,d\mu$, $\int cX\,d\mu = c\int X\,d\mu$;
(ii) $X \geq 0$ implies $\int X\,d\mu \geq 0$; $X \geq Y$ implies $\int X\,d\mu \geq \int Y\,d\mu$; and $X = Y$ a.e. implies $\int X\,d\mu = \int Y\,d\mu$.
(iii) (integrability). X is integrable if and only if $|X|$ is integrable, and either implies that X is a.e. finite. $|X| \leq Y$ with Y integrable implies X integrable; X and Y integrable implies that $X + Y$ is integrable.

Proof. (iii) That X is integrable if and only if $\int X^+ d\mu$ and $\int X^- d\mu$ finite if and only if $|X|$ integrable is easy. Now $\int X^+ d\mu < \infty$ implies X^+ finite a.e.; if not, then $\mu(A) > 0$ where $A \equiv \{\omega : X^+(\omega) = \infty\}$, and then $\int X^+ d\mu \geq \int X^+ 1_A d\mu = \infty \cdot \mu(A) = \infty$, a contradiction. Now $0 \leq X^+ \leq Y$, thus $0 \leq \int X^+ d\mu \leq \int Y\,d\mu < \infty$. Likewise $\int X^- d\mu < \infty$. □

Theorem 2.1 (Monotone convergence theorem.) If $0 \leq X_n \nearrow X$, then $\int X_n d\mu \to \int X\,d\mu$.

Corollary 1 If $X_n \geq 0$ then $\int \sum_{n=1}^\infty X_n d\mu = \sum_{n=1}^\infty \int X_n d\mu$.

Proof. Note that $0 \le \sum_1^n X_k \nearrow \sum_1^\infty X_k$ and apply the monotone convergence theorem. □

Theorem 2.2 (Fatou's lemma.) If $X_n \ge 0$ for all n, then $\int \underline{\lim} X_n d\mu \le \underline{\lim} \int X_n d\mu$.

Proof. Since $X_n \ge \inf_{k \ge n} X_k \equiv Y_n \nearrow \underline{\lim} X_n$, it follows from the MCT that

$$\int \underline{\lim} X_n d\mu = \int \lim Y_n d\mu = \lim \int Y_n d\mu \le \underline{\lim} \int X_n d\mu.$$

□

Definition 2.4 A sequence X_n *converges almost everywhere* (or *converges* a.e. for short), denoted $X_n \to_{a.e.} X$, if $X_n(\omega) \to X(\omega)$ for all $\omega \in \Omega \setminus N$ where $\mu(N) = 0$ (i.e. for a.e. ω). Note that $\{X_n\}$, X, are all defined on one measure space $(\Omega, \mathcal{A})$. If μ is a probability measure, $\mu = P$ with $P(\Omega) = 1$, we will write $\to_{a.s.}$ for $\to_{a.e.}$.

Proposition 2.6 Let $\{X_n\}$, X be finite measurable functions. Then $[X_n \to X] = \cap_{k=1}^\infty \cup_{n=1}^\infty \cap_{m=n}^\infty [|X_m - X| < 1/k]$, and is a measurable set.

Corollary 1 Let $\{X_n\}$, X be finite measurable functions. Then $X_n \to_{a.e.} X$ if and only if

$$\mu(\cap_{n=1}^\infty \cup_{m=n}^\infty [|X_m - X| \ge \epsilon) = 0$$

for all $\epsilon > 0$. If $\mu(\Omega) < \infty$, $X_n \to_{a.e.} X$ if and only if

$$\mu(\cup_{m=n}^\infty [|X_m - X| \ge \epsilon) \to 0 \qquad \text{as} \qquad n \to \infty$$

for all $\epsilon > 0$.

Proof. First note that

$$[X_n \to X]^c = \cup_{k=1}^\infty \cap_{n=1}^\infty \cup_{m=n}^\infty [|X_m - X| \ge 1/k] \equiv \cup_{k=1}^\infty A_k$$

with $A_k \nearrow$; and $A_k = \cap_{n=1}^\infty B_{nk}$ with $B_{nk} \searrow$ in n. Applying prop 1.2 gives the result. □

Definition 2.5 (Convergence in measure; convergence in probability.) A sequence of finite measurable functions X_n *converge in measure* to a measurable function X, denoted $X_n \to_\mu X$, if

$$\mu([|X_n - X| \ge \epsilon]) \to 0$$

for all $\epsilon > 0$. If μ is a probability measure, $\mu(\Omega) = 1$, call $\mu = P$, write $X_n \to_p X$, and say X_n *converge in probability* to X.

Proposition 2.7 Let X_n's be finite a.e.
(i) If $X_n \to_\mu X$ then there exist a subsequence $\{n_k\}$ such that $X_{n_k} \to_{a.e.} X$.
(ii) If $\mu(\Omega) < \infty$ and $X_n \to_{a.e.} X$, then $X_n \to_\mu X$.

Theorem 2.3 (Dominated Convergence Theorem) If $|X_n| \le Y$ a.e. with Y integrable, and if $X_n \to_\mu X$ (or $X_n \to_{a.e.} X$), then $\int |X_n - X| d\mu \to 0$ and $\lim \int X_n d\mu = \int X d\mu$.

Proof. We give the proof under the assumption $X_n \to_{a.e.} X$. Then $Z_n \equiv |X_n - X| \to 0$ a.e. and $Z_n \le |X_n| + |X| \le 2Y \equiv Z$. Thus $Z - Z_n \ge 0$ and by Fatou's lemma

$$\int Z d\mu = \int \underline{\lim}(Z - Z_n) d\mu \le \underline{\lim} \int (Z - Z_n) d\mu = \int Z d\mu - \overline{\lim} \int Z_n d\mu,$$

and this implies

$$\overline{\lim} \int Z_n = \overline{\lim} \int |X_n - X| d\mu \le 0.$$

Thus

$$|\int X_n - \int X| = |\int (X_n - X) d\mu| \le \int |X_n - X| d\mu \to 0.$$

□

Definition 2.6 Let X be a finite meaurable function on a probability space $(\Omega, \mathcal{A}, P)$ (so that $P(\Omega) = 1$). Then X is called a *random variable* and

$$P_X(B) \equiv P(X \in B) = P(\{\omega \in \Omega : X(\omega) \in B\})$$

for all $B \in \mathcal{B}$ is called the (induced) probability distribution of X (on R). The df associated with P_X is denoted by F_X and is called the *df of the random variable* X. Thus $(R, \mathcal{B}, P_X)$ is a probability space.

Theorem 2.4 (Theorem of the unconscious statistician.) If g is a finite measurable function from R to R, then

$$\int_\Omega g(X(\omega)) dP(\omega) = \int_R g(x) dP_X(x) = \int_R g(x) dF_X(x).$$

Proposition 2.8 (Interchange of integral and limit or derivative.) Suppose that $X(\omega, t)$ is measurable for each $t \in (a, b)$.
(i) If $X(\omega, t)$ is a.e. continuous in t at t_0 and $|X(\omega, t) \le Y(\omega)$ a.e. for $|t - t_0| < \delta$ with Y integrable, then $\int X(\cdot, t) d\mu$ is continuous in t at t_0.
(ii) Suppose that $\frac{\partial}{\partial t} X(\omega, t)$ exists for a.e. ω, all $t \in (a, b)$, and $|\frac{\partial}{\partial t} X(\omega, t)| \le Y(\omega)$ integrable a.e. for all $t \in (a, b)$. Then

$$\frac{\partial}{\partial t} \int_\Omega X(\omega, t) d\mu(\omega) = \int_\Omega \frac{\partial}{\partial t} X(\omega, t) d\mu(\omega).$$

Proof. (ii). By the mean value theorem

$$\frac{X(\omega, t+h) - X(t)}{h} = \frac{\partial}{\partial t} X(\omega, t)|_{t=s}$$

for some $t \le s \le t + h$. Also the left side of the display converges to $\frac{\partial}{\partial t} X(\omega, t)$ as $h \to 0$ for a.e. ω, and by the equality of the display and the hypothesized bound, the difference quotient on the left side of the display is bounded in absolute value by Y. Therefore

$$\begin{aligned} \frac{\partial}{\partial t} \int X(\omega, t) d\mu(\omega) &= \lim_{h \to 0} \frac{1}{h} \left\{ \int X(\omega, t+h) d\mu(\omega) - \int X(\omega, t) d\mu(\omega) \right\} \\ &= \lim_{h \to 0} \int \left\{ \frac{X(\omega, t+h) - X(\omega, t)}{h} \right\} d\mu(\omega) \\ &= \int \frac{\partial}{\partial t} X(\omega, t) d\mu(\omega) \end{aligned}$$

where the last equality holds by the dominated convergence theorem. □

3 Absolute Continuity, Radon-Nikodym Theorem, Fubini's Theorem

Let $(\Omega, \mathcal{A}, \mu)$ be a measure space, and let X be a non-negative measurable function on Ω. For $A \in \Omega$, set

$$\nu(A) \equiv \int_A X \, d\mu = \int_\Omega 1_A X \, d\mu.$$

Then ν is another measure on $(\Omega, \mathcal{A})$ and ν is finite if and only if X is integrable ($X \in L_1(\mu)$).

Definition 3.1 The measure ν defined by ?? is said to have *density X with respect to μ.*

Note that $\mu(A) = 0$ implies that $\nu(A) = 0$.

Definition 3.2 If μ, ν are any two measures on $(\Omega, \mathcal{A})$ such that $\mu(A) = 0$ implies $\nu(A) = 0$ for any $A \in \mathcal{A}$, then ν is said to be *absolutely continuous with respect to μ*, and we write $\nu \prec\prec \mu$. We also say that *ν is dominated by μ.*

Theorem 3.1 (Radon-Nikodym theorem.) Let $(\Omega, \mathcal{A}, \mu)$ be a $\sigma-$finite measure space, and let ν be a measure on $(\Omega, \mathcal{A})$ with $\nu \prec\prec \mu$. Then there exists a measurable function $X \geq 0$ such that $\nu(A) = \int_A X\mu$ for all $A \in \mathcal{A}$. The function $X \equiv \frac{d\nu}{d\mu}$ is unique in the sense that if Y is another such function, then $Y = X$ a.e. with respect to μ. X is called the *Radon-Nikodym derivative* of ν with respect to μ.

Proof. See Billingsley (1986), page 376. □

Corollary 1 (Change of Variable Theorem.) Suppose that ν, μ are $\sigma-$finite measures defined on a measure space $(\Omega, \mathcal{A})$ with $\nu \prec\prec \mu$, and suppose that Z is a measurable function such that $\int Z d\nu$ is well-defined. Then for all $A \in \mathcal{A}$,

$$\int_A Z d\nu = \int_A Z \frac{d\nu}{d\mu} d\mu.$$

Proof. (i) If $Z = 1_B$; then

$$\int_A 1_B d\nu = \nu(A \cap B) = \int_{A \cap B} \frac{d\nu}{d\mu} d\mu = \int_A 1_B \frac{d\nu}{d\mu} d\mu.$$

(ii) If $Z = \sum_1^m z_i 1_{A_i}$, then

$$\begin{aligned} \int_A Z d\nu &= \sum_1^m z_i \int_A 1_{A_i} d\nu \\ &= \sum_1^m z_i \int_A 1_{A_i} \frac{d\nu}{d\mu} d\mu \qquad \text{by (i)} \\ &= \int_A Z \frac{d\nu}{d\mu} d\mu \end{aligned}$$

(iii) If $Z \geq 0$, let $Z_n \geq 0$ be simple functions $\nearrow Z$. Then

$$\begin{aligned} \int_A Z d\nu &= \lim \int_A Z_n d\nu \qquad \text{by the monotone convergence thm.} \\ &= \lim \int Z_n \frac{d\nu}{d\mu} d\mu \qquad \text{by part (ii)} \\ &= \int_A Z \frac{d\nu}{d\mu} d\mu \qquad \text{by the monotone convergence thm.} \end{aligned}$$

(iv) If Z is measurable, $Z = Z^+ - Z^-$ where one of Z^+, Z^- is $\nu-$integrable, then

$$\begin{aligned} \int_A Z d\nu &= \int_A Z^+ d\nu - \int_A Z^- d\nu \\ &= \int_A Z^+ \frac{d\nu}{d\mu} d\mu - \int_A Z^- \frac{d\nu}{d\mu} d\mu \qquad \text{by (iii)} \\ &= \int_A Z \frac{d\nu}{d\mu} d\mu. \end{aligned}$$

□

Example 3.1 Let $(\Omega, \mathcal{A}, P)$ be a probability space; often this will be $(R^n, \mathcal{B}_n, P)$. Often in statistics we suppose that P has a density f with respect to a $\sigma-$finite measure μ on $(\Omega, \mathcal{A})$ so that

$$P(A) = \int_A f d\mu \qquad \text{for} \qquad A \in \mathcal{A}.$$

If μ is Lebesgue measure on R^n, then f is the *density function*. If μ is counting measure on a countable set, then f is the *frequency function* or *mass function*.

Proposition 3.1 (Scheffé's theorem.) Suppose that $\nu_n(A) = \int_A f_n d\mu$, that $\nu(A) = \int_A f d\mu$ where f_n are densities and $\nu_n(\Omega) = \nu(\Omega) < \infty$ for all n, and that $f_n \to f$ a.e. μ. Then

$$\sup_{A \in \mathcal{A}} |\nu_n(A) - \nu(A)| = \frac{1}{2} \int_\Omega |f_n - f| \to 0.$$

Proof. For $A \in \mathcal{A}$,

$$\begin{aligned} |\nu_n(A) - \nu(A)| &= |\int_A (f_n - f) d\mu| \\ &\leq \int_A |f_n - f| d\mu \leq \int_\Omega |f_n - f| d\mu, \end{aligned}$$

and this implies that

$$\sup_{A \in \mathcal{A}} |\nu_n(A) - \nu(A)| \leq \int_\Omega |f_n - f| d\mu.$$

Let $g_n \equiv f - f_n$. Now $g_n^+ \to 0$ a.e. μ, and $g_n^+ \leq f$ which is integrable. Thus by the dominated convergence theorem $\int g_n^+ d\mu \to 0$. But

$$0 = \int g_n d\mu = \int_\Omega (f - f_n) d\mu = \int_\Omega (g_n^+ - g_n^-) d\mu,$$

so $\int g_n^+ d\mu = \int g_n^- d\mu$, and hence

$$\int |g_n| d\mu = \int g_n^+ d\mu + \int g_n^- d\mu = 2\int g_n^+ d\mu \to 0,$$

proving the claimed convergence. To prove that equality holds as claimed in the statement of the proposition, note that for the event $B \equiv [f - f_n \geq 0]$ we have

$$\begin{aligned} \sup_{A\in\mathcal{A}} |\nu_n(A) - \nu(A)| &\geq |\nu_n(B) - \nu(B)| = |\int_{[f-f_n\geq 0]} (f_n - f) d\mu| \\ &= \int_{[g_n^+\geq 0]} g_n^+ d\mu = \int g_n^+ d\mu \\ &= \frac{1}{2}\int |f_n - f| d\mu. \end{aligned}$$

But on the other hand

$$\begin{aligned} |\nu_n(A) - \nu(A)| &= |\int_A f_n d\mu - \int_A f d\mu| \\ &= |\int_A (f - f_n) d\mu| \\ &= |\int_{A\cap B} (f - f_n) d\mu + \int_{A\cap B^c} (f - f_n) d\mu| \\ &\leq \int g_n^+ d\mu, \end{aligned}$$

so

$$\sup_{A\in\mathcal{A}} |\nu_n(A) - \nu(A)| \leq \int g_n^+ d\mu = \frac{1}{2}\int |f_n - f| d\mu.$$

□

Now supppose that $(\mathbb{X}, \mathcal{X}, \mu)$ and $(\mathbb{Y}, \mathcal{Y}, \nu)$ are two $\sigma-$finite measure spaces. If $A \in \mathcal{X}$, $B \in \mathcal{Y}$, a *measurable rectangle* is a set of the form $A \times B \subset \mathbb{X} \times \mathbb{Y}$.

Let $\mathcal{X} \times \mathcal{Y} \equiv \sigma(\{A \times B : A \in \mathcal{X}, B \in \mathcal{Y}\})$. Define a measure π on $(\mathbb{X} \times \mathbb{Y}, \mathcal{X} \times \mathcal{Y})$ by

$$\pi(A \times B) = \mu(A)\nu(B)$$

for measurable rectangles $A \times B$.

Theorem 3.2 (Fubini - Tonelli theorem.) Suppose that $f : \mathbb{X} \times \mathbb{Y} \to R$ is $\mathcal{X} \times \mathcal{Y}-$measurable and $f \geq 0$. Then

$$\int_{\mathbb{Y}} f(x, y) d\nu(y) \quad \text{is} \quad \mathcal{X}\text{ - measurable },$$

$$\int_{\mathbb{X}} f(x, y) d\mu(x) \quad \text{is} \quad \mathcal{Y}\text{ - measurable },$$

and

$$(1) \qquad \int_{\mathbb{X}\times\mathbb{Y}} f(x, y) d\pi(x, y) = \int_{\mathbb{X}} \left\{ \int_{\mathbb{Y}} f(x, y) d\nu(y) \right\} d\mu(x) = \int_{\mathbb{Y}} \left\{ \int_{\mathbb{X}} f(x, y) d\mu(x) \right\} d\nu(y).$$

If $f \in L_1(\pi)$ (so $\int_{\mathbb{X}\times\mathbb{Y}} |f| d\pi < \infty$), then (1) holds.