1 Measures

Let E be any set. A collection $\mathcal{E}$ of subsets of E is called a *σ-algebra* if the following holds:

1. $\emptyset \in \mathcal{E}$.
2. If $A \in \mathcal{E}$, then $A^c = E \setminus A \in \mathcal{E}$.
3. If $(A_n : n \in \mathbb{N})$, $A_n \in \mathcal{E}$, then $\bigcup_n A_n \in \mathcal{E}$.

Examples.

- $\mathcal{E} = \{\emptyset, E\}$
- $\mathcal{E} = \mathcal{P}(E)$, the set of all subsets of E.

Note that $\bigcap_n A_n = (\bigcup_n A_n^c)^c$, any σ-algebra $\mathcal{E}$ is also closed under countable intersection of its elements. Also $B \setminus A = B \cap A^c \in \mathcal{E}$ whenever $A, B \in \mathcal{E}$.

Any set E with a choice of σ-algebra $\mathcal{E}$ is called a *measurable* space, and the elements of $\mathcal{E}$ are called *measurable sets*.

A *measure* μ is a set-function $\mu : \mathcal{E} \to [0, \infty]$ such that $\mu(\emptyset) = 0$, and for any $(A_n : n \in \mathbb{N})$, $A_n \in \mathcal{E}$ pairwise disjoint ($A_n \cap A_m = \emptyset$ for all $n \neq m$) then

$$\mu\left(\bigcup_n A_n\right) = \sum_n \mu(A_n) \qquad \text{(countable additivity of } \mu)$$

If $\mathcal{E}$ is countable, then for any $A \in \mathcal{P}(E)$ and a measure μ

$$\mu(A) = \mu\left(\bigcup_{x \in A} \{x\}\right) = \sum_{x \in A} \mu(\{x\})$$

hence there is a one-to-one correspondence between measures and mass functions on E.

For any collection $\mathcal{A}$ of subsets of E, we define the σ-algebra $\sigma(\mathcal{A})$ generated by $\mathcal{A}$ as

$$\sigma(\mathcal{A}) = \{A \subseteq E : A \in \mathcal{E} \ \forall \sigma\text{-algebras } \mathcal{E} \supseteq \mathcal{A}\}$$

which equals (Example sheet)

$$\sigma(\mathcal{A}) = \bigcap_{\sigma\text{-algebras } \mathcal{E} \supseteq \mathcal{A}} \mathcal{E}$$

To construct good 'generators' we define

1. $\mathcal{A}$ is called a *ring over* E if $\emptyset \in \mathcal{A}$; if $A, B \in \mathcal{A}$ then $B \setminus A \in \mathcal{A}$ and $A \cup B \in \mathcal{A}$.

2. $\mathcal{A}$ is called an *algebra over* E if $\emptyset \in \mathcal{A}$; if $A, B \in \mathcal{A}$ then $A^c \in \mathcal{A}$, $A \cup B \in \mathcal{A}$.

Notice that in a ring $A \Delta B = (B \setminus A) \cup (A \setminus B) \in \mathcal{A}$ and $A \cap B = (A \cup B) \setminus (A \Delta B) \in \mathcal{A}$. Also, $B \setminus A = B \cap A^c = (B^c \cup A)^c \in \mathcal{A}$, so an algebra is a ring.

Fact: If $\bigcup_n A_n$, $A_n \in \mathcal{E}$, $\mathcal{E}$ some σ-algebra (or a ring if the union is finite) - then we can find $B_n \in \mathcal{E}$ disjoint such that $\bigcup_n A_n = \bigcup_n B_n$. Indeed, define $\tilde{A}_n = \bigcup_{j \leq n} A_j$, and set $B_n = \tilde{A}_n \setminus \tilde{A}_{n-1}$, then the fact follows. ["disjointification of countable unions"]

Definition. A *set function* on any collection $\mathcal{A}$ of subsets of E (where $\emptyset \in \mathcal{A}$) is a map $\mu : \mathcal{A} \to [0, \infty]$ such that $\mu(\emptyset) = 0$. We say μ is

1. *increasing* if $\mu(A) \leq \mu(B)$ whenever $A \subseteq B$; $A, B \in \mathcal{A}$
2. *additive* if $\mu(A \cup B) = \mu(A) + \mu(B)$ whenever $A, B \in \mathcal{A}$; $A \cup B \in \mathcal{A}$ and $A \cap B = \emptyset$.
3. *countably additive* if $\mu(\cup_n A_n) = \sum_n \mu(A_n)$ for any $(A_n : n \in \mathbb{N})$ where $A_n \in \mathcal{A}$ disjoint and $\cup_n A_n \in \mathcal{A}$.
4. *countably sub-additive* if $\mu(\cup_n A_n) \leq \sum_n \mu(A_n)$ for all $(A_n : n \in \mathbb{N})$ such that $\cup_n A_n \in \mathcal{A}$

Remark: one can show that a measure μ on a σ-algebra satisfies 1-4 above.

Theorem (Caratheodory)**.** *Let μ be a countably additive set function on a ring $\mathcal{A}$ of subsets of E. Then there exists a measure μ^* on $\sigma(\mathcal{A})$ such that $\mu^*|_{\mathcal{A}} = \mu$.*

Proof. For $B \subseteq E$ define the *outer measure* μ^* as

$$\mu^*(B) = \inf\left\{\sum_{n\in\mathbb{N}} \mu(A_n) : A_n \in \mathcal{A}, B \subseteq \bigcup_n A_n\right\}$$

and set $\mu^*(B) = \infty$ if the set within the infimum is empty.

Define

$$\mathcal{M} = \{A \subseteq E : \mu^*(B) = \mu^*(B \cap A) + \mu^*(B \cap A^c)\ \forall B \subseteq E\}$$

the "μ^*-measurable" sets.

Step 1: μ^* is countably sub-additive on $\mathcal{P}(E)$. For any $B \subseteq E$ and $B_n \subseteq E$ such that $B \subseteq \bigcup_n B_n$ we have

$$\mu^*(B) \leq \sum_n \mu^*(B_n) \tag{†}$$

WLOG we assume $\mu^*(B_n) < \infty$ for all n so for all $\varepsilon > 0$, there exists A_{nm} such that $B_n \subseteq \bigcup_m A_{nm}$ and

$$\mu^*(B_n) + \frac{\varepsilon}{2^n} \geq \sum_m \mu(A_{nm})$$

Now since μ^* and since $B \subseteq \bigcup_n B_n \subseteq \bigcup_{n,m} A_{nm}$, hence

$$\mu^*(B) \leq \mu^*\left(\bigcup_{n,m} A_{nm}\right) \leq \sum_{n,m} \mu(A_{nm}) \leq \sum_n \mu^*(B_n) + \underbrace{\sum_n \frac{\varepsilon}{2^n}}_{=\varepsilon}$$

so (†) follows since ε was arbitrary.

Step 2: μ^* extends μ. Let $A \in \mathcal{A}$. Clearly $A = A \cup \emptyset \cup \ldots \cup \emptyset$, so by definition of μ^*, $\mu^*(A) \leq \mu(A) + 0 + \ldots + 0$. So we need to prove $\mu(A) \leq \mu^*(A)$. Again, assume $\mu^*(A) < \infty$ WLOG, and let $A_n \in \mathcal{A}$ be such that $A \subseteq \bigcup_n A_n$. Then $A = \bigcup_n (\underbrace{A \cap A_n}_{\in \mathcal{A}})$, and since μ is countably sub-additive on $\mathcal{A}$, we have

$$\mu(A) = \mu\left(\bigcup_n (A \cap A_n)\right) \leq \sum_n \mu(\underbrace{A \cap A_n}_{\subseteq A_n}) \leq \sum_n \mu(A_n)$$

so since the (A_n) were arbitrary, by taking infima, we have $\mu(A) \leq \mu^*(A)$.

Step 3: $\mathcal{M} \supseteq \mathcal{A}$. Let $A \in \mathcal{A}$, then $B \subseteq (B \cap A) \cup (B \cap A^c) \cup \emptyset \ldots \cup \emptyset = \bigcup_n B_n$ so by (†) we have

$$\mu^*(B) \leq \mu^*(B \cap A) + \mu^*(B \cap A^c) + 0 \ldots + 0$$

so we need to prove $\mu^*(B) \geq \mu^*(B \cap A) + \mu^*(B \cap A^c)$. Again, WLOG assume $\mu^*(B) < \infty$, and so for all $\varepsilon > 0$ there exist $A_n \in \mathcal{A}$ such that $B \subseteq \bigcup_n A_n$ and

$$\mu^*(B) + \varepsilon \geq \sum_n \mu(A_n) \tag{$\circ$}$$

now $B \cap A \subseteq \bigcup_n (\underbrace{A_n \cap A}_{\in \mathcal{A}})$ and $B \cap A^c \subseteq \bigcup_n (\underbrace{A_n \cap A^c}_{A_n \setminus A \in \mathcal{A}})$. Therefore by definition of inf in μ^* and additivity of μ

$$\begin{aligned}
\mu^*(B \cap A) + \mu^*(B \cap A^c) &\leq \sum_n (\mu(A \cap A_n) + \mu(A^c \cap A_n)) \\
&= \sum_n \mu(A_n) \\
&\underbrace{\leq}_{\circ} \mu^*(B) + \varepsilon
\end{aligned}$$

since ϵ was arbitrary, $\mu^*(B) = \mu^*(B \cap A) + \mu^*(B \cap A^c)$, so $A \in \mathcal{M}$.

Step 4: $\mathcal{M}$ is an algebra. Clearly $\emptyset \in \mathcal{M}$, and by the definition of $\mathcal{M}$ its obvious that $A^c \in \mathcal{M}$ whenever $A \in \mathcal{M}$. So let $A_1, A_2 \in \mathcal{M}$

$$\mu^*(B) = \mu^*(B \cap A_1) + \mu^*(B \cap A_1^c), \text{ since } A_1 \in \mathcal{M}$$

$$= \mu^*(B \cap A_1 \cap A_2) + \mu^*(B \cap A_1 \cap A_2^c) + \mu^*(B \cap A_1^c), \text{ since } A_2 \in \mathcal{M}$$

Clearly $A_1 \cap A_2^c = (A_1 \cap A_2^c) \cap A_1$ and $A_1^c = (A_1 \cap A_2)^c \cap A_1^c$ so

$$\begin{aligned}
&\mu^*(B) \\
&= \mu^*(B \cap A_1 \cap A_2) + \mu^*(B \cap (A_1 \cap A_2)^c \cap A_1) + \mu^*(B \cap (A_1 \cap A_2)^c \cap A_1^c) \\
&= \mu^*(B \cap A_1 \cap A_2) + \mu^*(B \cap (A_1 \cap A_2)^c), \text{ since } A_1 \in \mathcal{M}
\end{aligned}$$

so $A_1 \cap A_2 \in \mathcal{M}$, and $\mathcal{M}$ is an algebra.

Step 5: Let $A = \bigcup_n A_n$, $A_n \in \mathcal{M}$, WLOG A_n disjoint (disjointification). Want $A \in \mathcal{M}$ and $\mu^*(A) = \sum_n \mu^*(A_n)$. By (†) we clearly have

$$\mu^*(B) \leq \mu^*(B \cap A) + \mu^*(B \cap A^c) + 0 + \ldots + 0$$

and

$$\mu^*(A) \leq \sum_n \mu^*(A_n)$$

so we only need two converse inequalities. Similar to before

$$\begin{aligned}
&\mu^*(B)\\
&= \mu^*(B \cap A_1) + \mu^*(B \cap A_1^c)\\
&= \mu^*(B \cap A_1) + \mu^*(B \cap \underbrace{A_1^c \cap A_2}_{=A_2 \text{ as disjoint}}) + \mu^*(B \cap A_1^c \cap A_2^c)\\
&= \sum_{n \le N} \mu^*(B \cap A_n) + \mu^*(B \cap A_1^c \cap \ldots \cap A_N^c)
\end{aligned}$$

since $\bigcup_{n \le N} \subseteq A$ so $\bigcap_{n \le N} A_n^c \supseteq A^c$, taking limits

$$\mu^*(B) \ge \sum_{n=1}^{\infty} \mu^*(B \cap A_n) + \mu^*(B \cap A^c)$$

and by (†)

$$\mu^*(B) \ge \mu^*(B \cap A) + \mu^*(B \cap A^c)$$

so $A \in \mathcal{M}$. Applying the previous with $B = A$, we see

$$\mu^*(A) \ge \sum_{n=1}^{\infty} \mu^*(A \cap A_n) + \mu^*(A \cap A^c) = \sum_n \mu^*(A_n)$$

□

Definition. A collection $\mathcal{A}$ of subsets of E is called a π-*system* if $\emptyset \in \mathcal{A}$ and if $A, B \in \mathcal{A}$, then $A \cap B \in \mathcal{A}$.

Definition. $\mathcal{A}$ is called a *d-system* if $E \in \mathcal{A}$, and if $B_1, B_2 \in \mathcal{A}$ such that $B_1 \subseteq B_2$, then $B_2 \setminus B_1 \in \mathcal{A}$, and if $A_n \in \mathcal{A}$, $A_n \uparrow \bigcup_n A_n = A$, then $A \in \mathcal{A}$.

One shows (Example sheet) that a d-system which is also a π-system is a σ-algebra.

Lemma (Dynkin)**.** *Let $\mathcal{A}$ be a π-system. Then any d-system that conatins $\mathcal{A}$ also contains $\sigma(\mathcal{A})$.*

Proof. Define

$$\mathcal{D} = \bigcap_{\mathcal{D}' \supseteq \mathcal{A} \text{ a d-system}} \mathcal{D}'$$

which is again a d-system (Example sheet). We show that $\mathcal{D}$ is a π-system, hence a σ-algebra containing $\mathcal{A}$. Define

$$\mathcal{D}' = \{B \in \mathcal{D} : B \cap A \in \mathcal{D} \ \forall A \in \mathcal{A}\}$$

which contains $\mathcal{A}$ as $\mathcal{A}$ is a π-system. Next we show $\mathcal{D}'$ is a d-system. Clearly $E \cap A = A \in \mathcal{A} \subseteq \mathcal{D}$, so $E \in \mathcal{D}'$. Next let $B_1, B_2 \in \mathcal{D}'$ such that $B_1 \subseteq B_2$ then $(B_2 \setminus B_1) \cap A = (\underbrace{B_2 \cap A}_{\in \mathcal{D}}) \setminus (\underbrace{B_1 \cap A}_{\in \mathcal{D}}) \in \mathcal{D}$ and so $B_2 \setminus B_1 \in \mathcal{D}'$.

Next take $B_n \uparrow B$, $B_n \in \mathcal{D}'$ then $\underbrace{B_n \cap A}_{\in \mathcal{D}} \uparrow B \cap A \in \mathcal{D}$ so $B \in \mathcal{D}'$.

Hence $\mathcal{D}'$ is a d-system containing $\mathcal{A}$, so by minimality of $\mathcal{D}'$, $\mathcal{D} \subseteq \mathcal{D}'$. Conversely, by construction $\mathcal{D}' \subseteq \mathcal{D}$, so $\mathcal{D}' = \mathcal{D}$.

Next define

$$\mathcal{D}'' = \{B \in \mathcal{D} : B \cap A \in \mathcal{D} \ \forall A \in \mathcal{D}\}$$

which by the preceding step ($\mathcal{D}' = \mathcal{D}$) contains $\mathcal{A}$. Just as before, one shows that $\mathcal{D}'' = \mathcal{D}$ and so $\mathcal{D}$ is a π-system (as $\mathcal{D}''$ is by construction). □

Theorem (Uniqueness of extension)**.** *Let μ_1, μ_2 be measures on $(E, \mathcal{E})$ such that $\mu_1(E) = \mu_2(E) < \infty$, and suppose $\mu_1 = \mu_2$ on a π-system $\mathcal{A}$ such that $\mathcal{E} \subseteq \sigma(\mathcal{A})$. Then $\mu_1 = \mu_2$ on $\mathcal{E}$.*

Proof. Define

$$\mathcal{D} = \{A : \mu_1(A) = \mu_2(A)\}$$

which contains $\mathcal{A}$ by hypothesis. We show that $\mathcal{D}$ is a d-system, and hence by Dynkin's Lemma, contains $\sigma(\mathcal{A})$, so the theorem follows.

To see this, note first that $E \in \mathcal{D}$ by hypothesis. Next, by additivity and finiteness of μ_1, μ_2, for $B_1 \subseteq B_2$, $B_1, B_2 \in \mathcal{D}$.

$$\mu_1(B_2 \setminus B_1) = \mu_1(B_2) - \mu_1(B_1) = \mu_2(B_2) - \mu_2(B_1) = \mu_2(B_2 \setminus B_1)$$

so $B_2 \setminus B_1 \in \mathcal{D}$. Finally take $B_n \uparrow B$, $B_n \in \mathcal{D}$. This implies $B \setminus B_n \downarrow \emptyset$ and (by Example sheet) $\mu_i(B \setminus B_n) \to \mu_i(\emptyset) = 0$ for $i = 1, 2$. This implies for $\mu_i(B) < \infty$ that $\mu_i(B_n) \to \mu_i(B)$ as $n \to \infty$ for both $i = 1, 2$. But then

$$\mu_1(B) = \lim_{n\to\infty} \mu_1(B_n) = \lim_{n\to\infty} \mu_2(B_n) = \mu_2(B)$$

and so $B \in \mathcal{D}$, and thus $\mathcal{D}$ is a d-system. $\square$

Remark: the above theorem applies to finite measures μ such that $\mu(E) < \infty$. The above theorem extends (as we will see) to σ-finite measures μ for which $E = \bigcup_{n\in\mathbb{N}} E_n$ such that $\mu(E_n) < \infty$.

Borel-σ-algebras

Definition. Let E be a topological space (Hausdorff, or metric space). The σ-algebra generated by $\mathcal{A} = \{B \subseteq E : B \text{ is open}\}$ is called the *Borel-σ-algebra*, denoted by $\mathcal{B}(E)$, or just $\mathcal{B}$ when $E = \mathbb{R}$. Elements of $\mathcal{B}(E)$ are the Borel subsets of E. A measure μ on $(E, \mathcal{B}(E))$ is called a *Borel measure on E*. A *Radon* measure μ is a Borel measure such that $\mu(K) < \infty$ for all $K \subseteq E$ compact (closed in Hausdorff spaces, hence measurable).

Construction of Lebesgue measure

We will (eventually) construct a unique Borel measure μ on $\mathbb{R}^d$ such that

$$\mu\left(\prod_{i=1}^{d}[a_i, b_i]\right) = \prod_{i=1}^{d}|b_i - a_i|,\ a_i < b_i,\ i = 1, \dots, d$$

We will do $d = 1$ first.

Theorem. *There exists a unique Borel measure (called the Lebesgue measure) μ on $\mathbb{R}$ such that*

$$\mu((a, b]) = b - a,\ \forall a < b \tag{†}$$

Proof. Consider the collection $\mathcal{A}$ of subsets of $\mathbb{R}$ of the form

$$A = (a_1, b_1] \cup \ldots \cup (a_n, b_n]$$

(intervals pairwise disjoint) which form a ring ($\emptyset = ((a, a])$, unions and differences are clear), which generates (Example sheet) generates the same σ-algebra on the open such intervals, and open intervals with rational endpoints generate $\mathcal{B}$, so $\sigma(\mathcal{A}) \supseteq \mathcal{B}$.

Define a set function μ on $\mathcal{A}$ by

$$\mu(A) = \sum_{i=1}^{n} (b_i - a_i)$$

μ is clearly additive, and well-defined since if $A = \bigcup_j C_j$ and $A = \bigcup_k D_k$ for distinct disjoint unions, then $C_j = \bigcup_k (C_j \cap D_k)$ and $D_k = \bigcup_j (D_K \cap C_k)$, so

$$\mu(A) = \mu\left(\bigcup_j C_j\right) = \sum_j \mu(C_j) = \sum_j \mu\left(\bigcup_k (C_j \cap D_k)\right)$$

$$= \sum_{j,k} \mu(C_j \cap D_k) = \ldots = \mu\left(\bigcup_k D_k\right) = \mu(A)$$

by additivity of μ. Now to prove existence of μ, we apply Caratheodory's theorem and need to check that μ is countably additive on $\mathcal{A}$. By the Example sheet, it suffices to show that for all $A_n \in \mathcal{A}$ such that $A_n \downarrow \emptyset$ we have $\mu(A_n) \to 0$.

Assume this is not the case, so there exists some $\varepsilon > 0$ and $B_n \in \mathcal{A}$ such that $B_n \downarrow \emptyset$ but $\mu(B_n) \geq 2\varepsilon$ for all n. We can approximate B_n from within by $C_n = \bigcup_{i=1}^{N_n} \left(a_{n_i} + \frac{\varepsilon 2^{-n}}{N_n}, b_{n_i}\right] \in \mathcal{A}$ such that $\mu(B_n \setminus C_n) = \varepsilon 2^{-n} \cdot \frac{N_n}{N_n} = \varepsilon 2^{-n}$.

Now since $B_n \downarrow$, we have $B_N = \bigcap_{n \leq N} B_n$ and

$$B_N \setminus (C_1 \cap \ldots \cap C_N) = B_N \cap \left(\bigcup_{n \leq N} C_n^c\right) = \bigcup_{n \leq N} B_N \setminus C_n \subseteq \bigcup_{n \leq N} B_n \setminus C_n$$

Hence since μ is increasing

$$\mu\left(B_N \setminus (C_1 \cap \ldots \cap C_N)\right) \leq \mu\left(\bigcup_{n \leq N} B_n \setminus C_n\right) \leq \sum_{n \leq N} \mu(B_n \setminus C_n) \leq \varepsilon$$

Hence the "length" of what was removed $(C_1 \cap \ldots \cap C_N)$ must be at least ε, i.e

$$\mu(C_1 \cap \ldots \cap C_N) \geq \varepsilon > 0$$

This means that $C_1 \cap \ldots \cap C_N$ is non-empty for all N, and so is

$$K_N = \overline{C_1} \cap \ldots \cap \overline{C}_N$$

($\overline{C}_i$ denotes the closure of C_i) Thus K_N is a nested sequence of non-empty closed intervals, so $\emptyset \neq \bigcap_N K_N$. But $K_N \subseteq \overline{C}_N \subseteq B_N$, so $\emptyset \neq \bigcap_N K_N \subseteq \bigcap_N B_n = \emptyset$, a contradiction. So a measure μ satisfying (†) must exist.

For uniqueness, suppose μ, λ measures such that (†) holds, and define $\mu_n(A) = \mu(A \cap (n, n+1])$, $\lambda(A) = \lambda(A \cap (n, n+1])$ for $n \in \mathbb{Z}$, which are finite measures such that $\mu_n(E) = 1 = \lambda_n(E)$ and $\mu_n = \lambda_n$ on the π-system $\mathcal{A}$. So by the uniqueness theorem, we must have $\mu_n = \lambda_n$ on $\mathcal{B}$, and

$$\mu(A) = \mu\left(\bigcup_n A \cap (n, n+1]\right) = \sum_n \mu(A \cap (n, n+1]) = \sum_n \mu_n(A)$$

$$= \sum_n \lambda_n(A) = \ldots = \lambda(A)$$

so $\lambda = \mu$. □

Remarks:

1. a set $B \in \mathcal{B}$ is called a Lebesgue null set if $\mu(B) = 0$. Can write $\{x\} = \bigcap_n \left(x - \frac{1}{n}, x\right]$ and so $\mu(\{x\}) = \lim_n \frac{1}{n} = 0$. In particular $\mu((a, b)) = \mu((a, b]) = \mu([a, b])$, and any countable set Q satisfies $\mu(Q) = \mu\left(\bigcup_{q \in Q} \{q\}\right) = \sum_{q \in Q} \mu(\{q\}) = 0$. But there exist C uncountable (and measurable) in $\mathcal{B}$ such that $\mu(C) = 0$ [Cantor set].

2. Translation invariance of μ: let $x \in \mathbb{R}$, then $B + x = \{b + x : b \in B\}$ is in $\mathcal{B}$ whenever $B \in \mathcal{B}$ and we can define

$$\mu_x(B) = \mu(B + x)$$

and by uniqueness in the preceding theorem

$$\mu_x((a, b]) = \mu((a + x, b + x]) = (b + x) - (a + x) = b - a$$

so $\mu_x = \mu$.

3. Lebesgue-measurable sets: in the extension theorem, μ was assigned on the class $\mathcal{M}$, which can be shown (Example sheet) to equal

$$\mathcal{M} = \{M = A \cup N : A \in \mathcal{B}, N \subseteq B \in \mathcal{B} \text{ s.t } \mu(B) = 0\}$$

Existence of non-measurable sets

Consider $E = (0, 1]$ with addition "+" modulo 1, and Lebesgue measure μ is still translation invariant modulo 1.

Consider the subgroup $Q = E \cap \mathbb{Q}$ of E and declare $x \sim y$ if $x - y \in Q$. This gives equivalence classes $[x] = \{y \in E : x \sim y\}$ on E. Assuming the axiom of choice, we can select a representative of $[x]$, and denote by S the set of selections running over all equivalence classes. Then we can partition E into the union of its cosets,

$$E = \bigcup_{q \in Q} (S + q)$$

a disjoint union.

Assume S is a Borel set (in $\mathcal{B}(E)$), then $S + q$ is also a Borel set for all $q \in Q$, and we can write (by countable additivity and translation invariance)

$$1 = \mu(E) = \mu\left(\bigcup_{q \in Q} (S + q)\right) = \sum_{q \in Q} \mu(S + q) = \sum_{q \in Q} \mu(S)$$

which is a contradiction. So $S \notin \mathcal{B}(E)$.

One can further show that μ cannot exted to $\mathcal{P}(E)$,

Theorem (Banach,Kuretowski)**.** *Assuming the continuum hypothesis, there exists no measure on* $([0, 1])$ *such that* $\mu((0, 1]) = 1$ *and* $\mu(\{x\}) = 0$ *for all* $x \in (0, 1]$.

Proof. Not given [see Dudley, 2002]. $\square$

Probability Spaces

If $(E, \mathcal{E}, \mu)$ (a measure space) is such that $\mu(E) = 1$, we often call it a *probability space* and write $(\Omega, \mathcal{F}, \mathbb{P})$, where Ω is the set of outcomes/the sample space; $\mathcal{F}$ is the set of events and $\mathbb{P}$ is the probability measure.

The axioms of probability theory (Kolmogorov, 1933) are

1. $\mathbb{P}(\Omega) = 1$
2. $0 \leq \mathbb{P}(E) \leq 1, \forall E \in \mathcal{F}$
3. If $(A_n : n \in \mathbb{N})$ are disjoint, $A_n \in \mathcal{F}$, then $\mathbb{P}\left(\bigcup_n A_n\right) = \sum_n \mathbb{P}(A_n)$ [so $\mathbb{P}$ is a measure on a σ-algebra

We further say that $(A_i : i \in I)$ are *independent* if for all $J \subseteq I$ finite, we have

$$\mathbb{P}\left(\bigcap_{j\in J} A_j\right) = \prod_{j\in J} \mathbb{P}(A_j)$$

We further say σ-algebras $(\mathcal{A}_i : i \in I)$ are *independent* if for any $A_j \in \mathcal{A}_j$, $j \in J$, $j \subseteq I$ finite, the A_j's are independent.

Proposition. Let $\mathcal{A}_1, \mathcal{A}_2$ be π-systems of sets in $\mathcal{F}$, and suppose $\mathbb{P}(A_1 \cap A_2) = \mathbb{P}(A_1)\mathbb{P}(A_2)$ for all $A_1 \in \mathcal{A}_1$, $A_2 \in \mathcal{A}_2$. Then the σ-algebras $\sigma(\mathcal{A}_1), \sigma(\mathcal{A}_2)$ are independent.

Proof. Exercise. □

The Borel-Cantelli Lemmas

For a sequence $(A_n : n \in \mathbb{N})$, $A_n \in \mathcal{F}$, define

$$\limsup_n A_n = \bigcap_n \bigcup_{m\geq n} A_m = \{A_n \text{ infinitely often "i.o."}\}$$

$$\liminf_n A_n = \bigcup_n \bigcap_{m\geq n} A_m = \{A_n \text{ eventually}\}$$

Lemma (1st Borel-Cantelli Lemma)**.** *If $A_n \in \mathcal{F}$ are such that $\sum_n \mathbb{P}(A_n) < \infty$ then $\mathbb{P}(A_n$ i.o.$) = 0$*

Proof.

$$\mathbb{P}\left(\bigcap_n \bigcup_{m\geq n} A_m\right) \leq \mathbb{P}\left(\bigcup_{m\geq n} A_m\right) \leq \sum_{m\geq n} \mathbb{P}(A_m) \to 0$$

□

Remark: the proof actually works for any measure μ.

Lemma (2nd Borel-Cantelli Lemma)**.** *Suppose $A_n \in \mathcal{F}$ are independent and $\sum_n \mathbb{P}(A_n) = \infty$. Then $\mathbb{P}(A_n$ i.o.$) = 1$.*

Proof. By independence, for any $N \geq n$ and using $1 - a \leq e^{-a}$,

$$\mathbb{P}\left(\bigcap_{m=n}^{N} A_m^c\right) = \prod_{m=n}^{N} (1 - \mathbb{P}(A_m)) \leq \exp\left(-\sum_{m=n}^{N} \mathbb{P}(A_m)\right) \to 0 \text{ as } N \to \infty$$

Since $\bigcap_{m=n}^{N} A_m^c \downarrow \bigcap_{m\geq n} A_m^c$, by countable additivity we have

$$\mathbb{P}\left(\bigcap_{m\geq n} A_m^c\right) = 0$$

But then

$$\mathbb{P}(A_n \text{ i.o.}) = \mathbb{P}\left(\bigcup_n \bigcap_{m \geq n} A_m\right) = 1 - \mathbb{P}\left(\bigcup_n \bigcap_{m \geq n} A_m^c\right)$$

$$\geq 1 - \sum_n \underbrace{\mathbb{P}\left(\bigcap_{m \geq n} A_m^c\right)}_{=0} = 1$$

$\square$

2 Measurable functions

Let $(E, \mathcal{E})$, $(G, \mathcal{G})$ be measurable spaces and let $f : E \to G$. We say that f is $\mathcal{E}$-$\mathcal{G}$-*measurable* if $f^{-1}(A) \in \mathcal{E}$ for all $A \in \mathcal{G}$. If $G = \mathbb{R}$ with $\mathcal{G} = \mathcal{B}(\mathbb{R})$, we just say $f : (E, \mathcal{E}) \to \mathbb{R}$ is *measurable*.

Moreover, if E is a topological space and $\mathcal{E} = \mathcal{B}(E)$, we say f is *Borel measurable*.

Preimages preserve set operations: $f^{-1}\left(\bigcup_i A_i\right) = \bigcup_i f^{-1}(A_i)$ and $f^{-1}(G \setminus A) = E \setminus f^{-1}(A)$, which implies that $\{f^{-1}(A) : A \in \mathcal{G}\}$ is a σ-algebra over E, and likewise $\{A : f^{-1}(A) \in \mathcal{E}\}$ is also a σ-algebra over G.

This implies that if $\mathcal{A}$ is a collection of subsets of G generating $\mathcal{G}$ and such that $f^{-1}(A) \in \mathcal{E}$ for all $A \in \mathcal{A}$, then $\{A : f^{-1}(A) \in \mathcal{E}\}$ is a σ-algebra containing $\mathcal{A}$, and hence $\mathcal{G}$. In particular, it suffices to check $f^{-1}(A) \in \mathcal{E}$, $\forall A \in \mathcal{A}$ to conclude that f is measurable.

If f takes real values, then

$$\mathcal{A} = \{(-\infty, y] : y \in \mathbb{R}\}$$

generates $\mathcal{B}(\mathbb{R})$ (Example sheet), and so f will be measurable whenever $f^{-1}((-\infty, y]) = \{x \in E : f(x) \le y\} \in \mathcal{E}$ for all $y \in \mathbb{R}$. Moreover, if E is a topological space with $\mathcal{E} = \mathcal{B}(E)$, then if $f : E \to \mathbb{R}$ is continuous, it is Borel measurable.

The indicator function

$$1_A(x) = \begin{cases} 1 & \text{when } x \in A \\ 0 & \text{when } x \notin A \end{cases}$$

is measurable if and only if $A \in \mathcal{E}$.

One shows that compositions of measurable maps are measurable, and so are $f_1 + f_2$, $f_1 \cdot f_2$, $\inf_n f_n$, $\liminf_n f_n$,$\limsup_n f_n$ whenever the f_n are.

Moreover, given a collection of maps $\{f_i : E \to (G, \mathcal{G}), i \in I\}$ we can make them all measurable for

$$\sigma\left(f_i^{-1}(A) : A \in \mathcal{G}, i \in I\right)$$

Theorem (Monotone class theorem)**.** *Let $\mathcal{A}$ be a π-system generating the σ-algebra $\mathcal{E}$ over E. Let further $\mathcal{V}$ be a vector space of bounded maps from E to $\mathbb{R}$ such that*

1. $1_E \in \mathcal{V}$, $1_A \in \mathcal{V}$, $\forall A \in \mathcal{A}$.
2. *If f is bounded and $f_n \in \mathcal{V}$ is such that $0 \le f_n \uparrow f$ pointwise on E, then $f \in \mathcal{V}$.*

Then $\mathcal{V}$ contains all bounded measurable $f : E \to \mathbb{R}$.

Proof. Define $\mathcal{D} = \{A \in \mathcal{E} : 1_A \in \mathcal{V}\}$. By hypothesis, $\mathcal{D}$ contains the π-system $\mathcal{A}$ and we now show it is also a d-system, so by Dynkind's lemma, $\mathcal{E} = \mathcal{D}$. Indeed, $E \in \mathcal{D}$ since $1_E \in \mathcal{V}$ by hypothesis. Also if $A \subseteq B$, $A, B \in \mathcal{D}$, then $1_{B \setminus A} = 1_B - 1_A \in \mathcal{V}$ as $\mathcal{V}$ is a vector space. Finally, if $A_n \in \mathcal{D}$ and $A_n \uparrow A$, then $1_{A_n} \uparrow 1_A$ pointwise and so $1_A \in \mathcal{V}$ by hypothesis, so $A \in \mathcal{D}$. In particular $A \in \mathcal{V}$ for all $A \in \mathcal{E}$.

Let now $f : E \to \mathbb{R}$ be bounded, non-negative and measurable. Define

$$f_n = \sum_{j=0}^{n2^n} \frac{j}{2^n} 1_{A_{n_j}}$$

where $A_{n_j} = \{x \in E : \frac{j}{2^n} < f(x) \leq \frac{j+1}{2^n}\} = f^{-1}((\frac{j}{2^n}, \frac{j+1}{2^n}]) \in \mathcal{E}$ for $j = 0, \ldots, n2^n - 1$, and $A_{n_{n2^n}} = \{x \in E : f(x) > n\} = f^{-1}((n, \infty)) \in \mathcal{E}$.

Clearly since f is bounded, for $n > ||f||_\infty$, we see

$$f_n \leq f \leq f_n + 2^{-n}$$

so $|f_n - f| \leq 2^{-n} \to 0$. So by hypothesis $f \in \mathcal{V}$. For general f bounded and measurable, we can decompose $f = f^+ - f^-$ where $f^\pm \geq 0$, and repeat the argument above. $\square$

Image Measures

If $f : (E, \mathcal{E}) \to (G, \mathcal{G})$ is $\mathcal{E}$-$\mathcal{G}$ measurable, and μ is a measure on $\mathcal{E}$, then the image measure $\nu = \mu \circ f^{-1}$ is obtained from

$$\nu(A) = \mu(f^{-1}(A)), \ \forall A \in \mathcal{G}$$

which is indeed a measure on $\mathcal{G}$ (Example sheet).

Lemma. *Let $g : \mathbb{R} \to \mathbb{R}$ be a right-continuous,monotone increasing function, and set $g(\pm\infty) = \lim_{z\to\pm\infty} g(z)$. On $I = (g(-\infty), g(\infty))$ define*

$$f(x) = \inf\{y \in \mathbb{R} : x \leq g(y)\},\ \ x \in I$$

Then f is monotone increasing, left-continuous and

$$f(y) \leq y \iff x \leq g(y)\ \forall x, y$$

Proof. Define $J_x = \{y \in \mathbb{R} : x \leq g(y)\}$. Since $x > g(-\infty)$, J_x is non-empty and bounded below, so $f(x) \in \mathbb{R}$. Now if $y \in J_x$ then $y' \geq y$ implies $y' \in J_x$ as well since $g \uparrow$. Moreover if $y_n \downarrow y$, $y_n \in J_x$, then we can take limits in $x \leq g(y_n)$ to see $x \leq \lim_n g(y_n) = g(y)$ as g is right-continuous, so $y \in J_x$. We conclude that $J_x = [f(x), \infty)$, which shows the equivalence.

Moreover, if $x \leq x'$, then $J_x \supseteq J_{x'}$ since $g \uparrow$. So by properties of the infimum $f(x) \leq f(x')$. Likewise if $x_n \uparrow x$, then $J_x = \bigcap_n J_{x_n}$ so $f(x_n) \to f(x)$ as $x_n \to x$. □

We call f the *generalised inverse of g.*

Theorem. *Let g be as in the above lemma. Then there exists a unique Radon measure μ_g on $\mathbb{R}$ such that $\mu_g((a, b]) = g(b) - g(a)$ for all $a < b$. Every Radon measure on $\mathbb{R}$ can be obtained in this way.*

Proof. For f as defined in the previous lemma, note that for all $z \in \mathbb{R}$

$$f^{-1}((-\infty, z]) = \{x : f(x) \leq z\} = \{x : x \leq g(y)\} = (g(-\infty), g(z)] \in \mathcal{B}(I)$$

Where the 2nd equality follows again from the lemma. So f is $\mathcal{B}$-$\mathcal{B}(I)$ measurable, and the image measure $\mu \circ f^{-1} = \mu_g$, where μ is the Lebesgue measure on I, exists.

Then for $-\infty < a < b < \infty$ we have

$$\mu_g((a, b]) = \mu(f^{-1}((a, b])) = \mu(x \in I : a < f(x) \leq b) = \mu((g(a), g(b)]) = g(b) - g(a)$$

Which uniquely determines μ_g by the same arguments as for the Lebesgue measure on $\mathbb{R}$. (Since g maps into $\mathbb{R}$, μ_g is a Radon measure).

Conversely, let ν be any Radon measure on $\mathbb{R}$, define

$$g(y) = \begin{cases} \nu((0, y]) & y \geq 0 \\ -\nu((y, 0]) & y < 0 \end{cases}$$

Which is clearly increasing in y (since ν is increasing). If $y_n \downarrow y$, then $(0, y_n] \downarrow (0, y]$ so $g(y_n) \to g(y)$ since ν is countably additive, so g is right-continuous. Finally (assuming $a < 0 < b$, the other cases are similar),

$$\nu((a, b]) = \nu((a, 0]) + \nu((0, b]) = -g(a) + g(b) = g(b) - g(a)$$

And by uniqueness as before, the result follows. □

Remark: The μ_g are called Lebesgue-Stieltjes measures, with Stieltjes distribution g.

For example, the Dirac measure δ_x at $x \in \mathbb{R}$, defined by

$$\delta_x(A) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases}$$

Which has Stieltjes distribution $g = 1_{[x,\infty)}$.

Random Variables

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space, and $(E, \mathcal{E})$ a measurable space.

Definition. An *E-valued random variable* X is any $\mathcal{F}$-$\mathcal{E}$ measuable map

$$X : \Omega \to E$$

When $E = \mathbb{R}, \mathbb{R}^d$ (with Borel σ-algebras) we call X a *random variable*, or random vector. The *law* or *distribution* μ_X of a random variable is given by $\mu_X = \mathbb{P} \circ X^{-1}$ (the image measure) with, for $E = \mathbb{R}$ distribution function

$$F_X(z) = \mu_X((-\infty, z]) = \mathbb{P}(X^{-1}(-\infty, z]) = \mathbb{P}\left(\omega \in \Omega : X(\omega) \leq z\right) = \mathbb{P}(X \leq z)$$

which uniquely determines μ_X.

Using properties of measures one shows that any distribution function satisfies

1. $F_X \uparrow$
2. F_X is right-continuous
3. $\lim_{z \to -\infty} F_X(z) = \mu_X(\emptyset) = 0$ and $\lim_{z \to \infty} F_X(z) = \mu_X(\mathbb{R}) = \mathbb{P}(\Omega) = 1$

Given any distribution function F_X satisfying 1,2 & 3, we can on $(\Omega, \mathcal{F}, \mathbb{P}) = ((0,1), \mathcal{B}(0,1), \mu)$, where μ is the Lebesgue measure obatin a random variable $X : \Omega \to \mathbb{R}$ by

$$X(\omega) = \inf\{x : \omega \leq F_X(x)\}$$

with distribution function F_X.

Definition. A countable collection $(X_i : (\Omega, \mathcal{F}, \mathbb{P} \to (E, \mathcal{E}))$ of random variables is said to be *independent* whenever the σ-algebras $\sigma(X_i^{-1}(A) : A \in \mathcal{E})$ are independent. For $(E, \mathcal{E}) = (\mathbb{R}, \mathcal{B})$ one shows (Example sheet) that this is equivalent (for $I = \{1, \dots, n\}$) to

$$\mathbb{P}(X_1 \leq x_1, \dots, X_n \leq x_n) = \prod_{i=1}^{n} \mathbb{P}(X_i \leq x_i),\ \forall x_i \in \mathbb{R}$$

We now construct on $(\Omega, \mathcal{F}, \mathbb{P}) = ((0,1), \mathcal{B}, \mu|_{(0,1)})$ with $\mu|_{(0,1)}$ the Lebesgue measure on $(0,1)$ an infinite sequence of independent random variables with prescribed distribution functions F_n.

Any $\omega \in (0,1)$ has a binary representation $(\omega_i) \in \{0,1\}^{\mathbb{N}}$, where $\omega = \sum_{i=1}^{n} \omega_i 2^{-i}$, which is unique if we exclude sequences which terminate with infinitely many 0's (so rationals end in a sequence of 1's). Then we can define $R_n(\omega) = \omega_n$ ("Radenmacher functions"), which are of the form

$$\begin{aligned}
&R_1(\omega) = 1_{(1/2,1)} \\
&R_2(\omega) = 1_{(1/4,1/2]} + 1_{(3/4,1)} \\
&R_3(\omega) = 1_{(1/8,1/4]} + 1_{(3/8,1/2]} + 1_{(5/8,3/4]} + 1_{(7/8,1)}
\end{aligned}$$

So the R_n are random variables such that $\mathbb{P}(R_n = 1) = \frac{1}{2} = \mathbb{P}(R_n = 0)$, so the R_n are Bernoulli for all n. Moreover for $(x_i)_{i=1}^{n} \in \{0,1\}^n$

$$\mathbb{P}(R_1 = x_1, \dots, R_n = x_n) = 2^{-n} = \underbrace{\mathbb{P}(R_1 = x_1)}_{\frac{1}{2}} \dots \mathbb{P}(R_n = x_n)$$

So the R_n are all independent. Now take a bijection $m : \mathbb{N}^2 \to \mathbb{N}$ and define $Y_{nk} = R_{m(n,k)}$ which are again independent and define

$$Y_n = \sum_k 2^{-k} Y_{nk}$$

which converge for all $\omega \in \Omega$ since $|Y_{nk}| \leq 1$ are still independent. To determine the law of Y_n we consider the π-system of intervals $\left(\frac{i}{2^m}, \frac{i+1}{2^m}\right]$, $i = 0, \dots, 2^m - 1$, $m \in \mathbb{N}$, with dyadic endpoints, which generate $\mathcal{B}$ and

$$\begin{aligned}
\mathbb{P}\left(Y_n \in \left(\frac{i}{2^m}, \frac{i+1}{2^m}\right]\right) &= \mathbb{P}\left(\frac{i}{2^m} < \sum_k 2^{-k} Y_{nk} \leq \frac{i+1}{2^m}\right) = 2^{-m} \\
&= \mu|_{(0,1)}\left(\left(\frac{i}{2^m}, \frac{i+1}{2^m}\right]\right)
\end{aligned}$$

so the law $\mu_{Y_n} = \mu|_{(0,1)}$ by the uniqueness theorem, and so the Y_n's are an infinite sequene of independent uniform random variables. Now if F_n are probability distribution functions (satisfy axioms 1-3 from earlier), then taking the generalised inverse $f_n = F_n^{-1}$ from the lemma, we see that the $F_n^{-1}(Y_n)$ are independent and have distribution function F_n.

Convergence of measurable functions

Definition. We say that a property defining a set $A \in \mathcal{E}$ holds μ-*almost everywhere* if $\mu(A^c) = 0$ for a measure μ on $\mathcal{E}$. If $\mu = \mathbb{P}$, we say it holds $\mathbb{P}$-*almost surely*, or *with probability* 1, if $\mathbb{P}(A) = 1$.

If f_n, f are measurable maps on $(E, \mathcal{E}|_\mu)$ we say $f_n \to f$ μ-*almost always* if

$$\mu(x \in E : f_n(x) \not\to f(x) \text{ as } n \to \infty) = 0$$

We say $f_n \to f$ in μ-measure if for all $\varepsilon > 0$

$$\mu(x \in E : |f_n(x) - f(x)| > \varepsilon) \to 0 \text{ as } n \to \infty$$

For random variables say $X_n \to X$ $\mathbb{P}$-*almost surely* or $X_n \to X$ in $\mathbb{P}$-*probability* respectively.

If $E = \mathbb{R}$, we say $X_n \xrightarrow{d} X$ *in distribution* if $\mathbb{P}(X_n \leq x) \to \mathbb{P}(X \leq x)$ for all $x \in \mathbb{R}$ such that $x \mapsto \mathbb{P}(X \leq x)$ is continuous. One shows $X_n \xrightarrow{P} X$ implies $X_n \xrightarrow{d} X$.

Theorem. *Let $f_n : (E, \mathcal{E}) \to \mathbb{R}$ be measurable functions.*

1. *If $\mu(E) < \infty$, then whenever $f_n \to 0$ a.e (almost everywhere) we have $f_n \to 0$ in measure.*
2. *If $f_n \to 0$ in measure, then $f_{n_k} \to 0$ a.e along some subsequence n_k.*

Proof.

1. For all $\varepsilon > 0$ we have

$$\begin{aligned}
\mu(|f_n| \leq \varepsilon) &\geq \mu\left(\bigcap_{m \geq n} \underbrace{\{|f_m| \leq \varepsilon\}}_{:= A_m}\right) \\
&\uparrow \mu\left(\bigcup_n \bigcap_{m \geq n} A_m\right) \\
&= \mu(|f_n| \leq \varepsilon \text{ eventually}) \\
&\geq \mu\left(f_n \to 0 \text{ as } n \to \infty\right) \\
&= \mu(E)
\end{aligned}$$

   so $\liminf_n \mu(|f_n| \leq \varepsilon) \geq \mu(E)$. So we see $\limsup_n \mu(|f_n| > \varepsilon) \leq \mu(E) - \mu(E) = 0$, so $\mu(|f_n| > \varepsilon) \to 0$ as $n \to \infty$ as desired.

2. By hypothesis, for all $\varepsilon > 0$ $\mu(|f_n| > \frac{1}{k}) < \varepsilon$ for n large enough. So choosing $\varepsilon = \frac{1}{k^2}$ we see that along some subsequence n_k we have $\mu(|f_{n_k}| > \frac{1}{k}) \leq \frac{1}{k^2}$ so

$$\sum_k \mu(|f_{n_k}| > \frac{1}{k}) < \infty$$

and by the 1st Borel-Cantelli Lemma, we have $\mu\left(|f_{n_k}| > \frac{1}{k} \text{ i.o}\right) = 0$, so $f_{n_k} \to 0$ a.e.

$\square$

Remarks: (1) is false if $\mu(E) = \infty$, as the example $1_{(n,\infty)}$ on $(\mathbb{R}, \mathcal{B}, \mu)$, μ Lebesgue measure shows. (2) is false without restricting to subsequences: take A_n independent such that $\mathbb{P}(A_n) = \frac{1}{n}$ then $1_{A_n} \to 0$ in $\mathbb{P}$-probability since $\mathbb{P}(1_{A_n} > \varepsilon) = \mathbb{P}(A_n) = \frac{1}{n} \to 0$ but $\sum_n \mathbb{P}(A_n) = \infty$, so by the 2nd Borel-Cantelli Lemma, $\mathbb{P}(1_{A_n} > \varepsilon \text{ i.o}) = 1$, so $1_{A_n} \not\to 0$ a.s.

Example. Let $(X_n : n \in \mathbb{N})$ be independent and identically distributed (iid) exponential random variables with $\mathbb{P}(X_1 \leq x) = 1 - e^{-x}$, $x \geq 0$. Define $A_n = \{X_n \geq \alpha \log n\}$, $\alpha > 0$, s.t $\mathbb{P}(A_n) = n^{-\alpha}$ and $\sum_n \mathbb{P}(A_n) < \infty$ if and only if $\alpha > 1$. So by the Borel-Cantelli lemmas, we have

$$\mathbb{P}\left(\frac{X_n}{\log n} \geq 1 \text{ i.o}\right) = 1$$

while

$$\mathbb{P}\left(\frac{X_n}{\log n} \geq 1 + \varepsilon \text{ i.o}\right) = 0 \ \forall \varepsilon > 0$$

So $\limsup_n \frac{X_n}{\log n} = 1$ almost surely.

Kolmogorov's 0-1 Law

For $(X_n : n \in \mathbb{N})$ random variables, define $\mathcal{T} = \sigma(X_{n+1}, X_{n+2}, \ldots)$ and set $\mathcal{T} = \bigcap_{n \in \mathbb{N}} \mathcal{T}_n$, the "tail σ-algebra" which contains all events in $\mathcal{F}$ which depend only on the limiting behaviour of the sequence.

Theorem. *For $(X_n : n \in \mathbb{N})$ independent random variables, if $A \in \mathcal{T}$ then $\mathbb{P}(A) = 1$ or $\mathbb{P}(A) = 0$. Moreover if $Y : (\Omega, \mathcal{T}) \to (\mathbb{R}, \mathcal{B})$ is meaurable, then Y is constant almost surely.*

Proof. Define $\mathcal{F}_n = \sigma(X_1, \ldots, X_n)$ which is a σ-algebra generated by the π-system of sets

$$A = (X_1 \leq x_1, \ldots, X_n \leq x_n), \ x_i \in \mathbb{R}$$

and note that the π-system of sets

$$B = (X_{n+1} \leq x_{n+1}, \ldots, X_{n+k} \leq x_{n+k}), \ k \in \mathbb{N}, \ x_i \in \mathbb{R}$$

generates $\mathcal{T}_n$. By independence of X_n, $\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$, so by the theorem from earlier we see that $\mathcal{T}_n$ and $\mathcal{F}_n$ are independent. If we set $\mathcal{F}_\infty = \sigma(X_1, X_2, \ldots)$, then $\bigcup_n \mathcal{F}_n$ is a π-system generating $\mathcal{F}_\infty$, and if $A \in \bigcup_n \mathcal{F}_n$, there exists $\bar{n}$ such that $B \in \mathcal{T}_{\bar{n}}$ is independent of A, in particular A is independent of elements in $\mathcal{T} = \bigcap_{\bar{n}} \mathcal{T}_{\bar{n}}$, hence as before $\mathcal{F}_\infty$ is independent of $\mathcal{T}$. But clearly $\mathcal{T} \subseteq \mathcal{F}_\infty$, so if $A \in \mathcal{T}$ it is independent to $A \in \mathcal{F}_\infty$! Now $\mathbb{P}(A) = \mathbb{P}(A \cap A) = \mathbb{P}(A)^2$, so $\mathbb{P}(A) = 0$ or 1. Finally, if Y is $\mathcal{T}$ measurable, then $\{Y \leq y\}$ lies in $\mathcal{T}$ for all y, hence have probability 1 or 0. Then let

$$c = \inf\{y : F_Y(y) = 1\}$$

so $Y = c$ almost surely. □

3 Integration

For $f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ measurable or "integrable" we will define the integral with respect to μ:

$$\mu(f) = \int_E f \mathrm{d}\mu = \int_E f(x) \mathrm{d}\mu(x)$$

and if X is a random variable, we define its ("mathematical") expectation as

$$\mathbb{E}X = \int_\Omega X \mathrm{d}\mathbb{P} = \int_\Omega X(\omega)\mathrm{d}\mathbb{P}(\omega)$$

To start, call $f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ *simple* if it is of the form

$$f = \sum_{k=1}^m a_k 1_{A_k},\ a_k \geq 0,\ A_k \in \mathcal{E},\ m \in \mathbb{N}$$

We define its μ-integral to be

$$\mu(f) = \sum_{k=1}^m a_k \mu(A_k)$$

which is well-defined (Example sheet) and it satisfies the following properties:

1. $\mu(\alpha f + \beta g) = \alpha\mu(f) + \beta\mu(g)$ for all $\alpha, \beta \geq 0$ and f, g simple
2. If $g \leq f$ then $\mu(g) \leq \mu(f)$
3. If $f = 0$ almost everywhere $\mu(f)$

For general $f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ non-negative, we define its μ-integral as

$$\mu(f) = \sup\{\mu(g) : g \leq f,\ g \text{ simple}\}$$

which is consistent with the definition for simple functions, and takes values in $[0, \infty]$.

For $f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ measurable (but not necessarily non-negative), we define $f^+ = \max(f, 0)$, $f^- = \max(-f, 0)$, so that $f = f^+ - f^-$ and $|f| = f^+ + f^-$. We say that f is μ-integrable if $\mu(|f|) < \infty$. In this case we define

$$\mu(f) = \mu(f^+) - \mu(f^-)$$

which is well-defined (i.e not $\infty - \infty$).

Theorem (Monotone Convergence Theorem)**.** *Let $f_n, f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ be measurable and non-negative such that $0 \leq f_n \uparrow f$ (i.e $f_n(x) \leq f_{n+1}(x) \leq f(x)$ and $f_n(x) \to f(x)$ for all $x \in E$). Then $\mu(f_n) \to \mu(f)$ as $n \to \infty$.*

Remark: if we take the approximating sequence $\tilde{f}_n$ $(= \min(2^{-n}\lfloor 2^n f \rfloor, n))$ then $0 \leq \tilde{f} \uparrow f$ so $\mu(f) = \lim_n \mu(\tilde{f}_n)$.

Proof. Recall $\mu(f) = \sup\{\mu(g) : g \leq f,\ g \text{ simple}\}$. Since $0 \leq f_n \uparrow$ we have $\mu(f_n) \uparrow \sup_n \mu(f_n) = M$. But then since $f_n \leq f$ we must have $\mu(f_n) \leq \mu(f)$ so taking suprema $M \leq \mu(f)$, and if $M < \infty$ we have $\lim_n \mu(f_n) \leq \mu(f)$.

We will now show $\mu(g) \leq M$ for all simple functions g such that $g \leq f$ so that taking suprema $\mu(f) = \sup_g \mu(g) \leq M$ so $\mu(f) = \lim_n \mu(f_n)$ follows.

We define $g_n = \min(\bar{f}_n, g) = \bar{f}_n \wedge g$, where $\bar{f}_n$ is the approximation of f_n by simple functions from the monotone class theorem, $[\tilde{f}_n]_n = \bar{f}_n = \min(2^{-n}\lfloor 2^n f_n \rfloor, n)$. Now since $f_n \uparrow f$ we must have $\bar{f}_n \uparrow f$ too, and so $g_n \uparrow \min(f, g) = g$, and since $\bar{f}_n \leq f_n$ we also have $g_n \leq f_n$ for all n.

Now let g be an arbitrary simple function, of the form

$$g = \sum_{k=1}^{m} a_k 1_{A_k}$$

with $m \in \mathbb{N}$, $a_k \geq 0$ and $A_k \in \mathcal{E}$ disjoint (wlog). We define for $\varepsilon > 0$ arbitrary

$$A_k(n) = \{x \in A_k : g_n(x) \geq (1-\varepsilon)a_k$$

Since $g = a_k$ on A_k and since $g_n \uparrow g$, we have $A_k(n) \uparrow A_k$ for all k. Also since μ is a measure, we must have $\mu(A_k(n)) \uparrow \mu(A_k)$. We have $g_n 1_{A_k} \geq g_n 1_{A_k(n)} \geq (1-\varepsilon)a_k 1_{A_k(n)}$ on E. Moreover

$$g_n = \sum_{k=1}^{m} g_n 1_{A_k}$$

since the A_k's are disjoint and support g_n (if $1_{A_n} = 0$ for all n, then $g = 0$ and $f_n = 0$). Now

$$\mu(g_n) = \sum_{k=1}^{m} \mu(g_n 1_{A_k}) \geq (1-\varepsilon)\sum_{k=1}^{n} a_k \mu(A_k(n)) \uparrow (1-\varepsilon)\sum_{k=1}^{m} a_k \mu(A_k) = (1-\varepsilon)\mu(g)$$

So $\mu(g) \leq \frac{1}{1-\varepsilon} \limsup_n \mu(g_n) \leq \frac{1}{1-\varepsilon} \limsup_n \mu(f_n) \leq \frac{M}{1-\varepsilon}$. Since ε was arbitrary we have $\mu(g) \leq M$ as required. □

Remarks: we have shown $\mu(f) = \mu(\lim_n f_n) = \lim_n \mu(f)$, so we can interchange $\int(\cdot)\mathrm{d}\mu$ and the limit. If $g_n \geq 0$, then $\mu\left(\sum_n g_n\right) = \sum_n \mu(g_n)$. Moreover it suffices to require $f_n \uparrow f$ almost everywhere and the $f_n \geq 0$ hypothesis is not necessary as long as f_1 is integrable (then just subtract f_1 from all terms).

Theorem. *Let $f, g : (E, \mathcal{E}, \mu) \to \mathbb{R}$ be measurable and non-negative. Then*

1. $\mu(\alpha f + \beta g) = \alpha\mu(f) = \beta\mu(g)$ *for all* $\alpha, \beta \geq 0$
2. *If* $g \leq f$ *then* $\mu(g) \leq \mu(f)$

3. *$f = 0$ almost everywhere if and only if $\mu(f) = 0$.*

Proof. If $\tilde{f}_n, \tilde{g}_n$ are the approximations of f, g from the monotone class theorem, then $\alpha\tilde{f}_n \uparrow \alpha f$, $\beta\tilde{g}_n \uparrow \beta g$, $\alpha\tilde{f}_n + \beta\tilde{g}_n \uparrow \alpha f + \beta g$. And from earlier

$$\mu(\alpha\tilde{f}_n + \beta\tilde{g}_n) = \alpha\mu(\tilde{f}_n) + \beta\mu(\tilde{g}_n)$$

So taking limits the monotone convergence theorem implies

$$\mu(\alpha f + \beta g) = \alpha\mu(f) + \beta\mu(g)$$

(2) follows in a similar way. Now we show (3): if $f = 0$ almost everywhere, then $0 \leq \tilde{f}_n \leq f = 0$ a.e, so $\tilde{f}_n = 0$ a.e for all n, so $\mu(\tilde{f}_n) = 0$, so $\mu(\tilde{f}_n) \uparrow \mu(f) = 0$. Conversely if $\mu(f) = 0$ then $0 \leq \mu(\tilde{f}) \uparrow \mu(f) = 0$ so $\mu(\tilde{f}_n) = 0$ for all n, so $\tilde{f}_n = 0$ a.e. Since $0 \leq \tilde{f}_n \uparrow f$ we have that $f = 0$ a.e. □

Remark: functions such as $1_{\mathbb{Q}}$ have $\mu(1_{\mathbb{Q}}) = 0$, and are 'identified' with 0.

Theorem. *Let $f, g : (E, \mathcal{E}, \mu) \to \mathbb{R}$ be integrable. Then*

1. *$\mu(\alpha f + \beta g) = \alpha\mu(f) + \beta\mu(g)$ for all $\alpha, \beta \in \mathbb{R}$*
2. *$g \leq f$ implies $\mu(g) \leq \mu(f)$*
3. *If $f = 0$ almost everywhere then $\mu(f) = 0$*

Proof. Clearly if f is integrable, so is αf, and $\mu(-f) = -\mu(f)$. And for $\alpha \geq 0$, $\mu(\alpha f) = \mu((\alpha f)^+) - \mu((\alpha f)^-) = \alpha\mu(f^+) - \alpha\mu(f^-) = \alpha\mu(f)$. So we can restrict to $\alpha = \beta = 1$.

Define $h = f + g = h^+ - h^- = f^+ - f^- + g^+ - g^-$. This is the same as $h^+ + f^- + g^- = h^- + f^+ + g^+$, and all of these functions are non-negative. Hence by the previous theorem

$$\mu(h^+) + \mu(f^-) + \mu(g^-) = \mu(h^-) + \mu(f^+) + \mu(g^+)$$

so $\mu(h) = \mu(f) + \mu(g)$ follows.

Now we show (2). Clearly $0 \leq f - g$ so $\mu(0) \leq \mu(f - g)$ by the previous theorem, and $\mu(f - g) = \mu(f) - \mu(g)$ by (1) of this theorem.

Finally we show (3): if $f = 0$ almost everywhere, $f^+ = f^- = 0$ almost everywhere, so $\mu(f) = \mu(f^+) - \mu(f^-) = 0 - 0$. □

Lemma (Fatou). *Let $f_n, f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ be measurable and non-negative. Then $\mu(\liminf_n f_n) \leq \liminf_n \mu(f_n)$.*

Remark: recall that for $x_n \in \mathbb{R}$

$$\liminf_n x_n = \sup_n \inf_{m \geq n} x_m$$

$$\limsup_n x_n = \inf_n \sup_{m \geq n} x_m$$

In particular, if $\limsup_n x_n = \liminf_n x_n$ then $\lim_n x_n = \liminf_n x_n$. Therefore if $f = \lim_n f_n$ exists in Fatou's lemma, we have $\mu(f) \leq \liminf_n \mu(f_n)$.

Proof. We have $\inf_{m \geq n} f_m \leq f_k$ for all $k \geq n$, and integrating this implies $\mu(\inf_{m \geq n} f_m) \leq \mu(f_k)$ for all $k \geq n$. So

$$\mu(\inf_{m \geq n} f_m) \leq \mu(f_k)$$

$$\mu(\inf_{m \geq n} f_m) \leq \inf_{k \geq n} \mu(f_k) \leq \sup_n \inf_{k \geq n} \mu(f_k) = \liminf_n \mu(f_n)$$

Also, $0 \leq \inf_{m \geq n} f_m \uparrow \sup_n \inf_{m \geq n} f_m$ so by the monotone convergence theorem

$$\mu(\liminf_n f_n) = \lim_n \mu(\inf_{m \geq n} f_m) \leq \liminf_n \mu(f_n)$$

□

Theorem (Dominated convergence theorem). *Let $f_n, f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ be measurable such that $|f_n| \leq g$ almost everywhere on E and g is μ-integrable ($\mu(g) < \infty$). Suppose $f_n \to f$ pointwise (or almost everywhere) on E. Then f_n and f are integrable and $\mu(f_n) \to \mu(f)$ as $n \to \infty$.*

Proof. Clearly $\mu(|f_n|) \leq \mu(g) < \infty$ so the f_n are integrable and taking limits in $|f_n| \leq g$ we have $|f| \leq g$, so $\mu(|f|) < \infty$.

Next

$$0 \leq g \pm f_n \xrightarrow{\text{ptws on } E} g \pm f$$

By Fatou's lemma

$$\mu(g)+\mu(f) = \mu(g+f) = \mu(\liminf_n (g+f_n)) \leq \liminf_n (\mu(g)+\mu(f_n)) = \mu(g)+\liminf_n \mu(f_n)$$

So $\mu(f) \leq \liminf_n \mu(f_n)$. Likewise

$$\mu(g) - \mu(f) = \mu(\liminf_n (g - f_n)) \leq \mu(g) - \limsup_n \mu(f_n)$$

So $\limsup_n \mu(f_n) \leq \mu(f)$. Therefore $\limsup_n \mu(f_n) = \liminf_n \mu(f_n) = \lim_n \mu(f_n) = \mu(f)$. □

Example. On $E = [0,1]$ with the Lebesgue measure, suppose $f_n \to f$ pointwise and $\sup_n ||f_n||_\infty \leq g < \infty$. Then since $\mu(g) \leq g$ the dominated convergence theorem implies $\mu(f_n) \to \mu(f)$ as $n \to \infty$ (no uniform convergence of $f_n \to f$ required).

Remark: the proof of the Fundamental Theorem of Calculus (FTC) requires only $\int_x^{x+h} \mathrm{d}t = h$. Therefore for any continuous $f : [0,1] \to \mathbb{R}$

$$\underbrace{\int_0^x f(t)\mathrm{d}t}_{\text{Riemann-integral}} = F(x) = \underbrace{\int_0^x f(t)\mathrm{d}\mu(t)}_{\text{Lebesgue-integral}},\ x \in [0,1]$$

So these integrals coincide for continuous maps.

One shows that all Riemann-integrable functions are μ^*-measurable (μ is Lebesgue measure) but that there exist Riemann-integrable functions that are not Borel measurable.

A bounded μ^*-measurable function is Riemann-integrable if and only if

$$\mu(x \in [0,1] : f \text{ if discontinuous at } x) = 0$$

All standard formulae for the Riemann-integral (substitution, integration, by parts etc) extend to all bounded measurable functions by the monotone class theorem (see Example sheet).

Theorem. *Let $U \subseteq \mathbb{R}$ be open, $(E, \mathcal{E}, \mu)$ a measure space, and $f : U \times E \to \mathbb{R}$ such that*

- *$x \mapsto f(t,x)$ for all $t \in U$ is measurable*
- *$t \mapsto f(t,x)$ is differentiable for all $x \in E$, with $\left|\frac{\partial f(t,x)}{\partial t}\right| \leq g(x)$ for all $t \in U$ where g is μ-integrable.*

Then if

$$F(t) = \int_E f(t,x)\mathrm{d}\mu(x)$$

we have

$$F'(t) = \int_E \frac{\partial f}{\partial t}(t,x)\mathrm{d}\mu(x)$$

Proof. By the MVT

$$|g_h(x)| := \left|\frac{f(t+h,x) - f(t,x)}{h} - \frac{\partial f}{\partial t}(t,x)\right| = \left|\frac{\partial f(\tilde{t},x)}{\partial t} - \frac{\partial f(t,x)}{\partial t}\right|$$

For some $\tilde{t} \in U$. SO $|g_h(x)| \leq 2g(x)$ which is μ-integrable. By differentiability, we have $g_h \to 0$ as $h \to 0$, so applying the dominated convergence theorem, $\mu(g_h) \to \mu(0) = 0$, or by linearity of μ

$$\mu(g_h) = \frac{\int_E \left(f(t+h,x) - f(t,x)\right)\mathrm{d}\mu(x)}{h} - \int_E \frac{\partial f}{\partial t}(t,x)\mathrm{d}\mu(x)$$

$$= \frac{F(t+h) - F(t)}{h} - F'(t) \to 0 \text{ as } h \to 0$$

□

Integrals with respect to image measures

For $f : (E, \mathcal{E}, \mu) \to (G, \mathcal{G})$ measurable, $g : G \to \mathbb{R}$ measurable and non-negative, we have

$$\mu \circ f^{-1}(g) = \int_G g \mathrm{d}\mu \circ f^{-1} = \int_E g(f(x)) \mathrm{d}\mu(x) = \mu(g \circ f)$$

On a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, and for a G-valued random variable X,

$$\mathbb{E}g(X) = \mu_X(g) = \int_\Omega g(X(\omega)) \mathrm{d}\mathbb{P}(\omega) = \int_\Omega g \mathrm{d}\mathbb{P}$$

Measures with densities

If $f : (E, \mathcal{E}, \mu) \to \mathbb{R}$ is measurable and non-negative, we can define $\nu_f(A) = \mu(f 1_A)$ for any $A \in \mathcal{E}$, which is again a measure (by the monotone convergence theorem), and if $g : (E, \mathcal{E}) \to \mathbb{R}$ is measurable, then $\nu_f(g) = \int_E g(x) f(x) \mathrm{d}\mu(x) = \int_E g \mathrm{d}\nu_f$. We call f the density of ν_f with respect to μ.

Product measures

Let $(E_1, \mathcal{E}_1, \mu_1)$ and $(E_2, \mathcal{E}_2, \mu_2)$ be finite measure spaces. On $E = E_1 \times E_2$, we consider the π-system of 'rectangles' $\mathcal{A} = \{A_1 \times A_2 : A_1 \in \mathcal{E}_1, A_2 \in \mathcal{E}_2\}$, which generates the σ-algebra $\sigma(\mathcal{A}) \equiv \mathcal{E}_1 \otimes \mathcal{E}_2 = \mathcal{E}$.

If E_1, E_2 are topological spaces with a countable base, then $\mathcal{B}(E_1 \times E_2)$ for the product topology on $E_1 \times E_2$ coincides with $\mathcal{B}(E_1) \otimes \mathcal{B}(E_2)$ (see Dudley).

Lemma. *Let $f : (E, \mathcal{E}) \to \mathbb{R}$ be measurable. Then for all $x_1 \in E_1$ fixed the map $x_2 \mapsto f(x_1, x_2)$ is $\mathcal{E}_2$-measurable.*

Proof. Define a vector space

$$\mathcal{V} = \{f : (E, \mathcal{E}) \to \mathbb{R} \text{ bounded and measurable, s.t Lemma holds}\}$$

This is indeed a vector space, and contains $1_E, 1_A$ for all $A \in \mathcal{A}$, since $1_A = 1_{A_1}(x_1) 1_{A_2}(x_2)$ is $\mathcal{E}_2$ measurable as $A_2 \in \mathcal{E}_2$. Next let $0 \leq f_n \uparrow f$, $f_n \in \mathcal{V}$, then $f(x_1, \cdot) = \lim_n f_n(x_1, \cdot)$ hence is $\mathcal{E}_2$-measurable as the limit of a sequence of measurable functions, so by the monotone class theorem, $\mathcal{V}$ contains all bounded measurable functions. This extends to all f (not necessarily bounded) by taking $\min(\max(-n, f), n) \in \mathcal{V}$, which converges to f. $\square$

Lemma. *Let $f : (E, \mathcal{E}) \to \mathbb{R}$ be measurable, such that either*

1. *f is bounded or;*
2. *$f \geq 0$*

Then $x_1 \mapsto \int_{E_2} f(x_1, x_2) \mathrm{d}\mu_2(x_2)$ is $\mathcal{E}_1$ measurable, and is (in the case of 1) bounded on E_1, (in the case of 2) ≥ 0, respectively.

Remarks: in 2, the mapping may evaluate to ∞, but $\{x_1 \in E_1 : \int_{E_2} f(x_1, x_2)\mathrm{d}\mu(x_2) = \infty\} \in \mathcal{E}_1$

Proof. Define a vector space

$$\mathcal{V} = \{f : (E, \mathcal{E}) \to \mathbb{R} \text{ bounded and measurable, s.t Lemma holds}\}$$

Which is indeed a vector space, and contains 1_E since $1_{E_1}\mu(E_2) \geq 0$ is bounded and also $1_A = 1_{A_1}(x_1)1_{A_2}(x_2)$ since $1_{A_1}(x_1)\mu_2(A_2)$ is $\mathcal{E}_1$-measurable, non-negative and bounded since $0 \leq \mu_2(E_2) < \infty$.

Now let $0 \leq f_n \uparrow f$ be a sequence in $\mathcal{V}$. Then by the monotone convergence theorem,

$$\int_{E_2} \lim_n f_n(x_1, x_2)\mathrm{d}\mu_2(x_2) = \lim_n \int_{E_2} f_n(x_1, x_2)\mathrm{d}\mu_2(x_2)$$

which is $\mathcal{E}_1$-measurable as the limit of $\mathcal{E}_1$-measurable functions. Also (in the case of 1) it is bounded by $\mu_2(E_2)||f||_\infty$ and non-negative, so $f \in \mathcal{V}$, so by the monotone class theorem, $\mathcal{V}$ contains all bounded measureable functions. In the case of 2, we approximate f by $\min(f, n) \in \mathcal{V}$. □

Theorem (Product measure)**.** *Let $\mu_1(E_1), \mu_2(E_2) < \infty$. Then there exists a unique measure μ on $(E_1 \times E_2, \mathcal{E}_1 \otimes \mathcal{E}_2)$ such that $\mu(A_1 \times A_2) = \mu_1(A_1)\mu_2(A_2)$ for all $A_1 \in \mathcal{E}_1$, $A_2 \in \mathcal{E}_2$.*

Proof. By the uniqueness theorem and since $\mathcal{A}$ generates $\mathcal{E}_1 \otimes \mathcal{E}_2$, there can only be one such measure. Define

$$\mu(A) = \int_{E_1} \left(\int_{E_2} 1_A(x_1, x_2)\mathrm{d}\mu_2(x_2) \right) \mathrm{d}\mu_1(x_1)$$

, so $\mu(A_1 \times A_2) = \int_{E_1} 1_{A_1}(x_1)\mu_2(A_2)\mathrm{d}\mu_1(x_1) = \mu_1(A_1)\mu_2(A_2)$, and $\mu(\emptyset) = 0$, so to prove the theorem we need to show μ is countably additive (and thus a measure). Let $A_n \in \mathcal{E}_1 \otimes \mathcal{E}_2$ be disjoint, so $1_{\bigcup_n A_n} = \sum_n 1_{A_n} = \lim_{N\to\infty} \sum_{n \leq N} 1_{A_n}$. Thus

$$\mu\left(\bigcup_n A_n\right) = \int_{E_1} \left(\int_{E_2} \lim_{N\to\infty} \sum_{n \leq N} 1_{A_n}(x_1, x_2)\mathrm{d}\mu_2(x_2) \right) \mathrm{d}\mu_1(x_1)$$

Which upon applying the monotone convergence theorem twice (once for each integral), in conjunction with the previous lemmas, gives

$$\mu\left(\bigcup_n A_n\right) = \lim_{N\to\infty} \sum_{n \leq N} \int_{E_1} \left(\int_{E_2} 1_{A_n}(x_1, x_2)\mathrm{d}\mu_2(x_2) \right) \mathrm{d}\mu_1(x_1) = \sum_{n=1}^{\infty} \mu(A_n)$$

□

Theorem (Fubini's Theorem)**.** *Let $(E, \mathcal{E}, \mu) = (E_1 \times E_2, \mathcal{E}_1 \otimes \mathcal{E}_2, \mu_1 \otimes \mu_2)$. Then*

(a) Let $f : (E, \mathcal{E}) \to \mathbb{R}$ be measurable and non-negative. Then

$$\mu(f) = \int_E f \mathrm{d}\mu = \int_{E_1} \left(\int_{E_2} f(x_1, x_2) \mathrm{d}\mu_2(x_2) \right) \mathrm{d}\mu_1(x_1) \qquad (\dagger)$$

$$= \int_{E_2} \left(\int_{E_1} f(x_1, x_2) \mathrm{d}\mu_1(x_1) \right) \mathrm{d}\mu_2(x_2) \qquad (\circ)$$

(b) If $f : (E, \mathcal{E}) \to \mathbb{R}$ is μ-integrable, then if

$$A_1 = \left\{ x_1 \in E_1 : \int_{E_2} |f(x_1, x_2)| \mathrm{d}\mu_2(x_2) < \infty \right\}$$

and for $f_1(x_1) = \int_{E_2} f(x_1, x_2) \mathrm{d}\mu_2(x_2)$ for $x_1 \in A_1$, and $f_1(x_1) = 0$ on A_1^c, we have $\mu_1(A_1^c) = 0$, and $\mu(f) = \mu_1(f_1) = \mu_1(f_1 1_{A_1})$.

Remark: in (b), if f is bounded, $A_1 = E_1$. The same statement holds for f_2, A_2 with the obvious modifications in (b), so $\mu_1(f_1) = \mu_2(f_2)$. But for $f(x_1, x_2) = \frac{x_1^2 - x_2^2}{(x_1^2 + x_2^2)}$ on $(0,1)^2$, we have $\mu_1(f_1) \neq \mu_2(f_2)$ but f is not Lebesgue measurable on $(0,1)^2$.

Proof. By the construction of $\mu(A)$ for rectangles $A = A_1 \times A_2 \in \mathcal{A}$ generating $\mathcal{E}$, the identities $(\dagger)$ and $(\circ)$ hold for $f = 1_A$, and by uniqueness of extenion, this extends to 1_A, $A \in \mathcal{E}$, and by linearity of the integral this extends to simple functions. By the monotone convergence theorem (applied 5 times) on simple functions $0 \leq f_n \uparrow f$, the result (a) follows.

If $h(x_1) = \int_{E_2} |f(x_1, x_2)| \mathrm{d}\mu_2(x_2)$, then by (a) $\mu_1(|h|) \leq \mu(|f|) < \infty$ since f is μ-integrable. So f_1 is μ_1-integrable and $\mu_1(A_1^c) = 0$. Then $f_1^{\pm} = \int_{E_2} f^{\pm}(x_1, x_2) \mathrm{d}\mu_2(x_2)$ so $\mu_1(f_1) = \mu_1(f_1^+) - \mu_1(f_1^-)$. Thus

$$\mu(f) = \mu(f^+) - \mu(f^-) = \mu_1(f_1^+) - \mu_1(f_1^-) = \mu_1(f_1)$$

by (a). $\square$

Remark: the preceding results for product measures extend to σ-finite measures μ.

For $(E_i, \mathcal{E}_i)$ for $i = 1, \dots, n$ with σ-finite μ_i, then since

$$(\mathcal{E}_1 \otimes \mathcal{E}_2) \otimes \mathcal{E}_3 = \mathcal{E}_1 \otimes (\mathcal{E}_2 \otimes \mathcal{E}_3)$$

by a π-system argument and Dynkin's lemma, we can iterate the construction of product measures to obtain $\mu_1 \otimes \ldots \otimes \mu_n$, a unique product measure on $(\bigotimes_{i=1}^n E_i, \bigotimes_{i=1}^n \mathcal{E}_i)$ such that $\mu_1 \otimes \ldots \otimes \mu_n(A_1 \times \ldots \times A_n) = \prod_{i=1}^n \mu_i(A_i)$.

In particular, on $\mathbb{R}^n$ with Borel-σ-algebra $\mathcal{B}(\mathbb{R}^n) = \bigotimes_{i=1}^n \mathcal{B}(\mathbb{R})$ (product topology), we obtain the n-dimensional Lebesgue measure

$$\mu^n = \bigotimes_{i=1}^n \mu$$

and Fubini's theorem (applied $n-1$ times) implies

$$\mu^n(f) = \int_{\mathbb{R}^n} f \mathrm{d}\mu^n = \int_{\mathbb{R}} \dots \int_{\mathbb{R}} f(x_1, \dots, x_n) \mathrm{d}\mu(x_1) \dots \mathrm{d}\mu(x_n)$$

whenever f is measurable and non-negative, or μ^n-integrable.

Product Probability Spaces & Independence

Proposition. Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space, and $(E, \mathcal{E}) = (\bigoplus_{i=1}^n E_i, \bigoplus_{i=1}^n \mathcal{E}_i)$. Consider $X : (\Omega, \mathcal{F}, \mathbb{P}) \to (E, \mathcal{E})$ measurable and such that $X(\omega) = (X_1(\omega), \dots, X_n(\omega))$. The following are equivalent:

(i) $X_1, \dots, X_n$ are independent

(ii) $\mu_X = \oplus_{i=1}^n \mu_{X_i}$

(iii) For all $f_i : E_i \to \mathbb{R}$ bounded and measurable,

$$\mathbb{E}\left[\prod_{i=1}^n f_i(X_i)\right] = \prod_{i=1}^n \mathbb{E} f(X_i)$$

Proof. First we show (i) implies (ii): for rectangles $A = \times_{i=1}^n A_i$, $A_i \in \mathcal{E}_i$, we have (by the definition of image measure)

$$\mu_X(A_1, \dots, A_n) = \mathbb{P}(X_1 \in A_1, \dots, X_n \in A_n) = \prod_{i=1}^n \mathbb{P}(X_i \in A_i) = \prod_{i=1}^n \mu_{X_i}(A_i)$$

Now we show (ii) implies (iii): by Fubini's theorem,

$$\mathbb{E}\left[\prod_{i=1}^n f(X_i)\right] = \mu_X\left(\prod_{i=1}^n f(X_i)\right) = \int_{E_1} \dots \int_{E_n} f_1(x_1) \dots f_n(x_n) \mathrm{d}\mu_{X_1}(x_1) \dots \mu_{X_n}(x_n)$$

$$= \prod_{i=1}^n \int_{E_i} f_i(x_i) \mathrm{d}\mu_{X_i}(x_i) = \prod_{i=1}^n \mathbb{E} f_i(X_i)$$

Finally we show (iii) implies (i): take $f_i = 1_{A_i}$ for any $A_i \in \mathcal{E}_i$, which is bounded and measurable. So

$$\mathbb{P}(X_1 \in A_1, \dots, X_n \in A_n) = \mathbb{E}\left[\prod_{i=1}^n 1_{A_i}(X_i)\right] = \prod_{i=1}^n \mathbb{E} 1_{A_i} = \prod_{i=1}^n \mathbb{P}(X_i \in A_i)$$

so $X_1, \dots, X_n$ are independent. $\square$

4 L^p-spaces and norms

Definition. A *norm* on a vector space V (over $\mathbb{R}$) is a map $||\cdot||_V : V \to \mathbb{R}_+$ such that

1. $||\lambda v|| = |\lambda| \cdot ||v||$
2. $||u+v|| \leq ||u|| + ||v||$
3. $||v|| = 0 \iff v = 0$

Definition. For $(E, \mathcal{E}, \mu)$ a measure space, we define $L^p(E,\mathcal{E},\mu) = L^p(\mu) = L^p$ by

$$L^p(E,\mathcal{E},\mu) = \{f : E \to \mathbb{R} \text{ measurable s.t } ||f||_p < \infty\}$$

where

$$||f||_p = \left(\int_E |f(x)|^p \mathrm{d}\mu(x)\right)^{1/p},\ 1 \leq p < \infty$$

$$||f||_\infty = \operatorname{en\,sup}|f| := \inf\{\lambda > 0 : |f| \leq \lambda \text{ a.e}\}$$

The property (1) of a norm holds for $||\cdot||_p$ whenever $1 \leq p \leq \infty$. Property (2) holds for $p = 1, \infty$ and also for $1 < p < \infty$ (to be proved). For (3), note that $f = 0$ implies $||f||_p = 0$, but $||f||_p = 0$ implies $f = 0$ almost everywhere on E. We can define quotient spaces

$$\mathcal{L}_p = L^p/\{f = 0 \text{ a.e}\} = \{[f] : f \in L^p\}$$

where the equivalence classes are $[f] = \{g \in L^p : g = f \text{ a.e}\}$. The functional $||\cdot||_p$ is then a norm on $\mathcal{L}_p$.

Proposition (Chebyshev's/Markov's inequality)**.** Let $f \geq 0$ be non-negative and measurable. Then for all $\lambda > 0$, $\mu(f \geq \lambda) = \mu(\{x : f(x) \geq \lambda\}) \leq \frac{\mu(f)}{\lambda}$.

Proof. Integrate $\lambda 1_{\{f \geq \lambda\}} \leq f$ on E. □

Definition. Let $I \subseteq \mathbb{R}$ be an interval, then a map $c : I \to \mathbb{R}$ is called *convex* if

$$c(tx + (1-t)y) \leq tc(x) + (1-t)c(y),\ \forall x, y \in I,\ \forall t \in (0,1)$$

which is easily seen to be equivalent to the condition that for all $x, y \in I$ and t with $x < t < y$,

$$\frac{c(t) - c(x)}{t - x} \leq \frac{c(y) - c(t)}{y - t} \tag{$\circ$}$$

Since c is continuous on the interior of I, it is Borel-measurable.

Lemma. *Let $m \in int(I)$. Then if c is convex on I, there exist a, b such that $c(x) \geq ax + b$ with equality when $x = m$.*

Proof. Define
$$a = \sup\{\frac{c(m) - c(x)}{m - x} : x < m\}$$
which exists in $\mathbb{R}$ by ($\circ$). Let $y \in I$, $y > m$, then by ($\circ$), $a \leq \frac{c(y)-c(m)}{y-m}$, so we get
$$c(y) \geq ay + \underbrace{(-am + c(m))}_{=b}$$
Likewise for $x < m$, by definition of a
$$\frac{c(m) - c(y)}{m - y} \leq a$$
so $c(y) \geq ay - b$. Also $c(m) = am + b$. ☐

Theorem (Jensen's inequality)**.** *Let X be a random variable taking values in $I \subseteq \mathbb{R}$ and such that $\mathbb{E}|X| < \infty$. If $c : I \to \mathbb{R}$ is convex, then $\mathbb{E}c(X) \geq c(\mathbb{E}X)$, in particular $\mathbb{E}c(X) = \mathbb{E}c^+(X) - \mathbb{E}c^-(X)$ is will defined in $(-\infty, \infty]$.*

Proof. Define $m = \mathbb{E}X = \int_I z \mathrm{d}\mu_X(z)$, and if $m \notin \mathrm{int}(I)$, then $X = m$ almost surely and the result follows. If $m \in \mathrm{int}(I)$, then we can apply the lemma to see $c^-(X) \leq |a||X| + |b|$. So $\mathbb{E}c^-(X) \leq |a|\mathbb{E}|X| + |b| < \infty$, and $\mathbb{E}c(X) = \mathbb{E}c^+(x) - \mathbb{E}c^-(X)$ is well-defined in $(-\infty, \infty]$.

Then integrating the inequality from the lemma
$$\mathbb{E}c(X) \geq a\mathbb{E}X + b = am + b = c(m) = c(\mathbb{E}X)$$
☐

Remark: a consequence of this is that if X is a bounded random variable (in $L^\infty(\mathbb{P})$), and if $1 \leq p < q < \infty$ then $c(x) = |x|^{q/p}$ is convex and
$$||X||_p = (\mathbb{E}|X|^p)^{1/p} = c(\mathbb{E}|X|^p)^{1/q} \leq \mathbb{E}\left(c(|X|^p)\right)^{1/q} = ||X||_q$$
Using the monotone convergence theorem, this extends to all $X \in L^q(\mathbb{P})$. In particular $L^q(\mathbb{P}) \subseteq L^p(\mathbb{P})$ for all $1 \leq p \leq q \leq \infty$.

Theorem (Holders inequality)**.** *Let f, g be measurable on $(E, \mathcal{E}, \mu)$. If p, q are conjugate, i.e $\frac{1}{p} + \frac{1}{q} = 1$ and $1 \leq p, q \leq \infty$, then*
$$\mu(|fg|) = \int_E |gf| \mathrm{d}\mu \leq ||f||_p ||g||_q$$
(for $p = q = 2$, this is the Cauchy-Schwarz inequality on L^2)

Proof. The cases $p = 1, \infty$ are obvious, and we can assume $f \in L^p, g \in L^q$ (or else we're done). We can also assume that we dont have $f = 0$ almost everywhere (else done), hence $||f||_p > 0$, so by dividing we can assume $||f||_p = 1$. Then

$$\mu(|fg|) = \int_E |g| \frac{1}{|f|^{p-1}} 1_{\{|f|>0\}} \underbrace{|f|^p \mathrm{d}\mu}_{\mathrm{d}\mathbb{P}} \leq \left(\int_E |g|^q \frac{1}{|f|^{q(p-1)}} |f|^p \mathrm{d}\mu \right)^{1/q} = ||g||_q$$

□

Theorem (Minkowski's inquality)**.** *Let $f, g : (E, \mathcal{E}, \mu) \to \mathbb{R}$ be measurable. Then for all $1 \leq p \leq \infty$*

$$||f+g||_p \leq ||f||_p + ||g||_p$$

Proof. $p = 1, \infty$ are clear, so assume $1 < p < \infty$. We may assume $f, g \in L^p$ or else it is obvious. We can integrate the pointwise inequality

$$|f+g|^p \leq \leq 2^p(|f|^p + |g|^p)$$

to deduce

$$||f+g||_p^p \leq 2^p \left(||f||_p^p + ||g||_p^p\right) < \infty$$

So we can assume $0 < ||f+g||_0 < \infty$. Now

$$||f+g||_p^p = \int_E |f+g|^{p-1}|f+g|\mathrm{d}\mu = \int_E |f+g|^{p-1}|f|\mathrm{d}\mu + \int_E |f+g|^{p-1}|g|\mathrm{d}\mu$$

So by Holders inequality with q conjugate to p

$$||f+g||_p^p \leq \underbrace{\left(\int_E |f+g|^{q(p-1)}\mathrm{d}\mu\right)^{1/q}}_{||f+g||_p^{p/q}} (||f||_p + ||g||_p)$$

So obtain $||f+g||_p \leq ||f||_p + ||g||_p$. □

Theorem ($\mathcal{L}^p$ is a Banach space)**.** *Let $1 \leq p \leq \infty$, and let $f_n \in L^p$ be a Cauchy sequence. Then there exists $f \in L^p$ such that $f_n \to f$ in L^p.*

Proof. We assume $p < \infty$, the proof when $p = \infty$ is easier. or all $\varepsilon > 0$ there exists $N \in \mathbb{N}$ such that $\forall m, n \geq N$, $||f_n - f_m|| \leq \varepsilon$. Using this with $\varepsilon = 2^{-k}$ we can extract a subsequence f_{N_k} such that $S = \sum_{k=1}^{\infty} ||f_{N_{k+1}} - f_{N_k}||_p \leq \sum_{k=1}^{\infty} 2^{-k} < \infty$. By Minkowski's inequality, for any K

$$\left\|\sum_{k=1}^{K} |f_{N_{k+1}} - f_{N_k}|\right\|_p \leq \sum_{k=1}^{K} ||f_{N_{k+1}} - f_{N_k}||_p \leq S$$

So by the monotone convergence theorem applied to $\left|\sum_{k=1}^{K} |f_{N_{k+1}} - f_{N_k}|\right|^p \uparrow \left|\sum_{k=1}^{\infty} |f_{N_{k+1}} - f_{N_k}|\right|^p$ we see that

$$\left\|\sum_{k=1}^{\infty} |f_{N_{k+1}} - f_{N_k}|\right\|_p \leq S < \infty$$

Since the integral is finite, we see that $\sum_{k=1}^{\infty} |f_{N_{k+1}} - f_{N_k}| < \infty$ almost everywhere. Then $\sum_{k=1}^{K}(f_{N_{k+1}}(x) - f_{N_n}(x)) = f_{N_{K+1}}(x) - f_{N_1}(x)$ converges in $\mathbb{R}$ for all x in some set A with $\mu(A^c) = 0$. Since $\mathbb{R}$ is complete, $f_{N_k}(x)$ converges in $\mathbb{R}$ and we define

$$f(x) = \begin{cases} \lim_{k\to\infty} f_{N_k}(x) & x \in A \\ 0 & x \notin A \end{cases}$$

So $f_{N_k} \to f$ as $k \to \infty$ almost everywhere. Next

$$||f_n - f||_p^p = \mu(|f_n - f|^p) = \mu\left(\lim_k |f_n - f_{N_k}|^p\right) \leq \liminf_k \mu(|f_n - f_{N_k}|^p)$$

where the last inequality follows from Fatou's lemma. Using the Cauchy property, $||f||_p \leq ||f - f_N||_p + ||f_N||_p < \infty$, so $f \in L^p$ and $||f_n - f_{N_k}||_p^p \leq \varepsilon^p$ for $n, N_k \geq N$, so $f_n \to f$ in L^p. $\square$

Remark: if V is any of the spaces $C([a,b])$, $\{f \text{ simple}\}$ or $\{f \text{ a linear combination of indicators of intervals}\}$, then V is dense in $L^1(\mu)$, for μ the Lebesgue measure on $\mathcal{B}([a,b])$, and so the completion $\overline{(V, ||\cdot||_1)} = L^1(\mu)$.

$\mathcal{L}^2(\mu)$ as a Hilbert space

Definition. A symmetric bilinear form $\langle\cdot,\cdot\rangle : V \times V \to \mathbb{R}$ on a vector space V is called a *inner product* if $\langle v, v\rangle \geq 0$ with equality only when $v = 0$. In this case we can define a norm $||v|| = \sqrt{\langle v, v\rangle}$ on V, and if $(V, \langle\cdot,\cdot\rangle)$ is complete for $||\cdot||$, we call this space a *Hilbert space*.

Corollary. *$\mathcal{L}^2(\mu)$ is a Hilbert space for $\langle f, g\rangle = \int_E fg\mathrm{d}\mu$.*

Proof. Trivial by previous theorem. $\square$

Pythagoras rule: for $f, g \in L^2$, $||f + g||_2^2 = ||f||_2^2 + 2\langle f, g\rangle + ||g||_2^2$.

We say that f is orthogonal to g if $\langle f, g\rangle = \int_E fg\mathrm{d}\mu = 0$, and write $f \perp g$. For centred (mean 0) random variables X, Y, we have $\langle X, Y\rangle = \mathbb{E}(XY) = \mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)] = \mathrm{Cov}(X, Y) = 0$ whenever $X \perp Y$.

Parallelogram identity: $||f + g||_2^2 + ||f - g||_2^2 = 2(||f||_2^2 + ||g||_2^2)$

For $V \subseteq \mathcal{L}^2(\mu)$, we define its orthogonal complement

$$V^\perp = \{f \in L^2(\mu) : \langle f, v\rangle = 0 \ \forall v \in V\}$$

We say that a subset V of $\mathcal{L}^2$ is closed if for any sequence f_n in V, which converges to some $f \in \mathcal{L}^2$, we have $f = v$ almost everywhere for some $v \in V$.

Theorem. *Let V be a closed linear subspace of $\mathcal{L}^2(\mu)$. Then for all $f \in \mathcal{L}^2$ there exists a decomposition $f = v + u$, for $v \in V$, $u \in V^\perp$ such that $||f - v||_2 \leq ||f - g||_2$ for all $g \in V$, with equality only if $g = v$ almost everywhere. We call v the projection of f onto V.*

Proof. Define (throughout this proof we write $||\cdot||$ for $||\cdot||_2$) $d(f,V) = \inf_{g\in V} ||g - f||$ and take $g_n \in V$ approximating the infimum. By the parallelogram-law

$$\begin{aligned} 2||f-g_n||^2 + 2||f-g_m||^2 &= ||2f - (g_n+g_n)||^2 + ||g_n - g_m||^2 \\ &= 4\left\| f - \underbrace{\frac{g_n+g_m}{2}}_{\in V} \right\|^2 + ||g_n-g_m||^2 \\ &\geq 4d(f,V)^2 + ||g_n - g_m||^2 \end{aligned}$$

So $\limsup_{m,n} |g_n - g_m||^2 \leq 4d(f,V)^2 - 4d(f,V)^2 = 0$. So (g_n) is Cauchy in L^2, so by completness, it converges $g_n \to v$ for some $v \in L^2$, and since V is closed, $v \in V$. In particular, $\inf_{g\in V} ||g-f|| = ||v - f||$.

We further have

$$d(f,V)^2 \leq F(t) := \|f - (v+th)\|^2,\ t\in\mathbb{R},\ h \in V$$

from which we obtain the first order condition $F'(0) = 2\langle f - v, h\rangle = 0$ for all $h \in V$. So if we define $f - v = u$, we have $f = u + v$ and $u \in V^\perp$ since h was arbitrary. If $f = w + z$ with $w \in V$, $z \in V^\perp$ then

$$v - w + u - z = f - f = 0$$

so $||v-w+u-z||^2 = 0$ with $v - w \in V$, $u - z \in V^\perp$ so by Pythagoras $||v-w+u-z||^2 = 0 = ||v-w||^2 + ||u-z||^2$, i.e $v = w$ and $u = z$ (almost everywhere). □

Convergence in $L^1(\Omega, \mathcal{F}, \mathbb{P})$ and uniform integrability (UI)

Theorem (Bounded convergence)**.** *Let X_n be random variables on $(\Omega,\mathcal{F},\mathbb{P})$ such that $|X_n| \leq C < \infty$ for all n, and $X_n \xrightarrow{\mathbb{P}} X$ as $n \to \infty$. Then $X_n \to X$ in $L^1(\mathbb{P})$.*

Proof. We know $X_{n_k} \to X$ almost surely along a subsequence, so

$$|X| =^{\text{a.s}} \lim_k |X_{n_k}| \leq C$$

so X is also bounded by C. Then

$$\mathbb{E}|X_n - X| \left(1_{|X_n - X|>\varepsilon/2} + 1_{|X_n-X|\leq\varepsilon/2}\right) \leq 2C\mathbb{P}(|X_n - X| > \varepsilon/2) + \varepsilon/2$$

Which is less than ε for all n sufficiently large. □

If $X \in L^1(\mathbb{P})$, then on $\delta \to 0$,

$$I_X(\delta) := \sup\{\mathbb{E}(|X|1_A) : A \in \mathcal{F},\ \mathbb{P}(A) \leq \delta\} \downarrow 0$$

Suppose not, then there exists $\varepsilon > 0$ and $A_n \in \mathcal{F}$ such that $\mathbb{P}(A_n) \leq 2^{-n}$ but $\mathbb{E}(|X|1_{A_n}) \geq \varepsilon > 0$ for all n.

Since $\sum_n \mathbb{P}(A_n) < \infty$, we use the Borel-Cantelli lemma to see

$$\mathbb{P}\left(\bigcap_n \bigcup_{m\geq n} A_m\right) = 0$$

But $\mathbb{E}(|X|1_{A_n}) \leq \mathbb{E}(|X|1_{\bigcup_{m\geq n} A_m})$ and noting that $1\left(\bigcup_{m\geq n} A_m\right) \to 1\left(\bigcap_n \bigcup_{m\geq n} A_m\right)$, we have that $\mathbb{E}|X|1_{\bigcup_{m\geq n} A_m} \to \mathbb{E}|X|1_{\bigcap_n \bigcup_{m\geq n} A_m}$ by the dominated convergence theorem with dominating function $g(x) = |X|1_\Omega$. So $\mathbb{E}|X|1_{A_n} \to 0$, a contradiction.

For a collection $\mathcal{X} \subseteq L^1(\mathbb{P})$ of random variables, we say $\mathcal{X}$ is *uniformly integrable* if it is bounded in $L^1(\mathbb{P})$ and

$$I_{\mathcal{X}}(\delta) = \sup\left\{\mathbb{E}|X|1_A : A \in \mathcal{F},\ \mathbb{P}(A) \leq \delta,\ X \in \mathcal{X}\right\} \downarrow 0$$

as $\delta \to 0$. Note that $X_n = n1_{(0,1/n)}$ for μ Lebesgue measure on $(0,1)$ is bounded in $L^1(\mathbb{P})$ but not uniformly integrable. If $\mathcal{X}$ is bounded in $L^p(\mathbb{P})$ for $p > 1$, then by Holder's inequality

$$\mathbb{E}|X|1_A \leq \underbrace{||X||_p}_{\leq C} \underbrace{\mathbb{P}(A)^{1/q}}_{\leq \delta^{1/q}} \to 0 \text{ uniformly}$$

so such $\mathcal{X}$ is uniformly integrable.

Lemma. *$\mathcal{X} \subseteq L^1(\mathbb{P})$ is uniformly integrable if and only if* $\sup_{X\in\mathcal{X}} \mathbb{E}(|X|1_{\{|X|>k\}}) \to 0$ *as $k \to \infty$.*

Proof. If $\mathcal{X}$ is uniformly integrable, then by Markov's inequality

$$\mathbb{P}(|X| > k) \leq \frac{\mathbb{E}|X|1_\Omega}{k} \leq \frac{I_{\mathcal{X}}(1)}{k} \to 0 \text{ as } k \to \infty$$

so $\mathbb{P}(|X| > k) < \delta$ uniformly for k sufficiently large. So using the uniformly integrable property with $A = \{|X| > k\}$ we get the required limit.

Conversely, we have $\mathbb{E}|X| = \mathbb{E}|X|\left(1_{\{|X|\leq k\}} + 1_{\{|X|>k\}}\right) \leq k + \varepsilon/2$ for k large enough, so $\mathcal{X}$ is bounded in $L^1(\mathbb{P})$. Next for A such that $\mathbb{P}(A) \leq \delta$

$$\mathbb{E}|X|1_A\left(1_{\{|X|\leq k\}} + 1_{\{|X|>k\}}\right) \leq k\mathbb{P}(A) + \mathbb{E}|X|1_{\{|X|>k\}} \leq k\delta + \varepsilon/2$$

for k large. $\square$

Theorem. *Let X_n, X be random variables on $(\Omega, \mathcal{F}, \mathbb{P})$. Then the following are equivalent*

1. *$X_n, X \in L^1(\mathbb{P})$, $X_n \to X$ in $L^1(\mathbb{P})$ as $n \to \infty$.*

2. *$(X_n : n \in \mathbb{N})$ is uniformly integrable and $X_n \xrightarrow{\mathbb{P}} X$ as $n \to \infty$.*

Proof. We first show (1) implies (2): clearly $\mathbb{P}(|X_n - X| > \varepsilon) \leq \frac{\mathbb{E}|X_n - X|}{\varepsilon} \to 0$, so $X_n \to X$ in probability. Since any finite collection is uniformly integrable, so are $X_1, \ldots, X_N$, and for $n \geq N$ and A with $\mathbb{P}(A) \leq \delta$ we have $\mathbb{E}|X_n|1_A \leq \mathbb{E}|X_n - X|1_A + \mathbb{E}|X|1_A \leq \varepsilon/2 + \varepsilon/2$ for N large enough and δ small enough.

Now we show (2) implies (1). Since $X_{n_k} \to X$ almost surely along a subsequence,

$$\mathbb{E}|X| = \mathbb{E}\liminf_k |X_{n_k}| \leq \liminf_k \mathbb{E}|X_{n_k}| \leq I_{\mathcal{X}}(1) < \infty$$

So $X \in L^1(\mathbb{P})$. Next define

$$X_n^K = \min(\max(-k, X_n), k) = g(X_n)$$

$$X^K = \min(\max(-k, X), k) = g(X)$$

Then

$$\mathbb{P}(|g(X_n) - g(X)| > \varepsilon) \leq \mathbb{P}(|X_n - X| > \varepsilon') \text{ for some } \varepsilon' > 0$$

And since $X_n \xrightarrow{\mathbb{P}} X$, the RHS converges to 0 as $n \to \infty$. Now by bounded convergence, $X_n^K \to X^K$ in $L^1(\mathbb{P})$ and so

$$\mathbb{E}|X_n - X| \leq \underbrace{\mathbb{E}|X_n - X_n^K|}_{\mathbb{E}|X_n|1_{\{|X_n|>K\}} \to 0} + \mathbb{E}|X_n^K - X^K| + \underbrace{\mathbb{E}|X^K - X|}_{\mathbb{E}|X|1_{\{|X|>K\}} \to 0} < \varepsilon$$

□

Fourier transforms

In this section, we will write $L^p(\mathbb{R}^d)$ for the set of measurable functions $f : \mathbb{R}^d \to \mathbb{C}$ such that $||f||_p = \left(\int_{\mathbb{R}^d} |f(x)|^p \mathrm{d}x\right)^{1/p} < \infty$.

We can extend the integral as a complex linear map $L^1(\mathbb{R}^d) \to \mathbb{C}$ by $\int_{\mathbb{R}^d}(u+iv)(x)\mathrm{d}x := \int_{\mathbb{R}^d} u(x)\mathrm{d}x + i\int_{\mathbb{R}^d} v(x)\mathrm{d}x$.

Note that

$$\left\|\int_{\mathbb{R}^d} f(x)\mathrm{d}x\right\| = \int_{\mathbb{R}^d} \alpha f(x)\mathrm{d}x$$

for some $\alpha \in \mathbb{C}$ with $|\alpha| = 1$ (take α to have complementary argument to the integral). Then write $\alpha f = u + iv$ so

$$\begin{aligned}\left\|\int_{\mathbb{R}^d} f(x)\mathrm{d}x\right\| &= \int_{\mathbb{R}^d} u(x)\mathrm{d}x + i\underbrace{\int_{\mathbb{R}^d} v(x)\mathrm{d}x}_{=0} \\ &\leq \int_{\mathbb{R}^d} |f(x)|\mathrm{d}x\end{aligned}$$

since $u \leq |u| \leq |\alpha f| = |f|$.
For $f \in L^1(\mathbb{R}^d)$ we define the *Fourier transform* $\hat{f}$ by

$$\hat{f}(u) = \int_{\mathbb{R}^d} f(x)e^{i\langle u,x\rangle}\mathrm{d}x$$

Where $\langle u, x\rangle$ is the usual dot product on $\mathbb{R}^d$, i.e $\sum_{i=1}^d u_i x_i$.

Note that $|\hat{f}(u)| \leq ||f||_1$. Also, if $u_n \to u$, then $e^{i\langle u_n,x\rangle} \to e^{i\langle u,x\rangle}$, so by the dominated convergence theorem (dominated by $|f|$), $\hat{f}(u_n) \to \hat{f}(u)$. So $\hat{f}$ is a continuous bounded function.

For $f \in L^1(\mathbb{R}^d)$, with $\hat{f} \in L^1(\mathbb{R}^d)$, we say that the *Fourier inversion formula* holds for f if

$$f(x) = \frac{1}{(2\pi)^d}\int_{\mathbb{R}^d} \hat{f}(u)e^{-i\langle u,x\rangle}\mathrm{d}u$$

for almost all $x \in \mathbb{R}^d$.

For $f \in L^1(\mathbb{R}^d) \cap L^2(\mathbb{R}^d)$ (neither L^1 nor L^2 is contained in the other with the Lebesgue measure), we say the *Plancherel identity* holds if $||\hat{f}||_2 = (2\pi)^{d/2}||f||_2$.

We'll show the inversion formula holds whenever $\hat{f} \in L^1$, and Plancherel holds for all $f \in L^1 \cap L^2$.

For a finite Borel-measure μ on $\mathbb{R}^d$, we define the *Fourier transform* $\hat{\mu}$ by

$$\hat{\mu}(u) = \int_{\mathbb{R}^d} e^{i\langle u,x\rangle} \mathrm{d}\mu(x),\ u \in \mathbb{R}^d$$

Then $|\hat{\mu}| \leq \mu(\mathbb{R}^d)$. If μ has a density f with respect to the Lebesgue measure $\mathrm{d}x$, then $\hat{\mu} = \hat{f}$.

For a random variable X in $\mathbb{R}^d$, the *characteristic function* ϕ_X is given by $\phi_X(u) = \mathbb{E}(e^{i\langle u,X\rangle}) = \hat{\mu_X}(u)$, where μ_X is the Law of X.

Convolutions

For $f \in L^1(\mathbb{R}^d)$ and a probability measure ν on $\mathbb{R}^d$, we define the convolution $f * \nu$ by

$$f * \nu(x) = \begin{cases} \int_{\mathbb{R}^d} f(x-y)d\nu(y) & \text{if } f(x-\cdot) \in L^1(\nu) \\ 0 & \text{otherwise} \end{cases}$$

Note that for $p \in [1,\infty)$

$$\begin{aligned} \int_{\mathbb{R}^d} \left(\int_{\mathbb{R}^d} |f(x-y)| \mathrm{d}\nu(y) \right)^p \mathrm{d}x &\leq \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} |f(x-y)|^p \mathrm{d}\nu(y) \mathrm{d}x \\ &= \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} |f(x)|^p \mathrm{d}x \mathrm{d}\nu(x) \\ &= ||f||_p^p \end{aligned}$$

Where the inequality follows from Jensen, the swapping of integration from Fubini and using translation invariance of the Lebesgue measure.

So for $f \in L^p$, have $f(x-\cdot) \in L^p(v)$ at almost all x, and

$$||f * \nu||_p^p = \int_{\mathbb{R}^d} \left| \int_{\mathbb{R}^d} f(x-y) \mathrm{d}\nu(y) \right|^p \mathrm{d}x \leq ||f||_p^p$$

So $f \mapsto f * \nu$ is a contraction on $L^p(\mathbb{R}^d)$. In the case ν has a density g with a respect to the Lebesgue measure $\mathrm{d}x$, we write $f * g = f * v$.

For probability measures μ, ν on $\mathbb{R}^d$, we define $\mu * \nu$, another probability measure on $\mathbb{R}^d$ as the law of $X + Y$ where X, Y are independent with laws μ, ν. i.e

$$\begin{aligned} \mu * \nu(A) = \mathbb{P}(X + Y \in A) &= \int_{\mathbb{R}^d \times \mathbb{R}^d} 1_A(x+y) \mathrm{d}(\mu \otimes \nu)(x,y) \\ &= \int_{\mathbb{R}^d} \left(\int_{\mathbb{R}^d} 1_A(x+y) \mathrm{d}\mu(x) \right) \mathrm{d}\nu(y) \end{aligned}$$

by Fubini. If μ has density f with respect to $\mathrm{d}x$, then $\mu * \nu$ has density $f * \nu$ with respect to $\mathrm{d}x$.

Indeed

$$\begin{aligned}\int_{\mathbb{R}^d}\left(\int_{\mathbb{R}^d} 1_A(x+y)\mathrm{d}\mu(x)\right)\mathrm{d}\nu(y) &= \int_{\mathbb{R}^d}\left(\int_{\mathbb{R}^d} 1_A(x+y)f(x)\mathrm{d}x\right)\mathrm{d}\nu(y)\\ &= \int_{\mathbb{R}^d}\left(\int_{\mathbb{R}^d} 1_A(v)f(v-y)\mathrm{d}v\right)\mathrm{d}\nu(y)\\ &= \int_{\mathbb{R}^d} 1_A(v)\underbrace{\int_{\mathbb{R}^d} f(v-y)\mathrm{d}\nu(y)}_{=f*\nu(v)\text{ a.e}}\mathrm{d}v\end{aligned}$$

Exercise: $f \hat{*}\, \nu(u) = \hat{f}(u)\hat{\nu}(u)$