

## II Probability & Measure

L1.1

~ Richard Nickl

### 0. Introduction

1) Replace the Riemann integral by the more powerful Lebesgue integral.

A space of 'integrable functions' should be the topological completion of the normed space  $(C[0,1], \|\cdot\|_1)$ ,  $\|f\|_1 = \int_0^1 |f(x)| dx$ ; in the sense that any  $(f_n: n \in \mathbb{N})$  in  $C[0,1]$  that is Cauchy for  $\|\cdot\|_1$  has a limit in the space  $\overline{C[0,1]}$ . It turns out  $\neq \{\text{Riemann integrable}\}$  but equals the space  $L^1$  of Lebesgue-integrable functions.

$L^2$  ... Hilbert space!

2) Axiomatic prob theory

↳ derive key results such as: LLN, CLT, ergodic thm

3) Problem of measure

Does every subset of  $\mathbb{R}^d$  have a volume?

### 1. Measures

Def<sup>n</sup> Let  $E$  be any set; let  $\mathcal{P}(E)$  be the family of all subsets of  $E$ .

A  $\sigma$ -algebra  $\mathcal{E}$  on  $E$  is a family of subsets of  $E$  such that

1)  $\emptyset \in \mathcal{E}$

2)  $A \in \mathcal{E} \Rightarrow A^c = E \setminus A \in \mathcal{E}$

3)  $\forall n, A_n \in \mathcal{E} \Rightarrow \bigcup_n A_n \in \mathcal{E}$

Easy Since  $\bigcap_n A_n = (\bigcup_n A_n^c)^c$ ,  $\mathcal{E}$  closed under ctble intersection

and also  $B \setminus A = B \cap A^c \in \mathcal{E}$  whenever  $A, B \in \mathcal{E}$

We call  $(E, \mathcal{E})$  a measurable space,  $A \in \mathcal{E}$  is a measurable set.

A measure  $\mu$  on  $(E, \mathcal{E})$  is a (non-negative) set function

$\mu: \mathcal{E} \rightarrow [0, \infty]$  such that

1)  $\mu(\emptyset) = 0$

2) for  $(A_n \in \mathcal{E}, n \in \mathbb{N})$  disjoint,  $\mu(\bigcup_{n=1}^{\infty} A_n) = \sum_{n=1}^{\infty} \mu(A_n)$

"countable additivity"

We call  $(E, \mathcal{E}, \mu)$  a measure space.

Remark When  $E$  is countable then any measure  $\mu$  on  $\mathcal{E} = \mathcal{P}(E)$  necessarily satisfies  $\mu(A) = \mu(\bigcup_{a \in A} \{a\}) = \sum_{a \in A} \mu(\{a\})$ .

So  $\mu$  corresponds to a 'mass function'  $m: E \rightarrow [0, \infty]$ ,  $x \mapsto \mu(\{x\})$

When  $E$  is not countable, we generally need to work with  $\sigma$ -algebras  $\mathcal{E} \subseteq \mathcal{P}(E)$  which cannot be described explicitly.

We define, for  $\mathcal{A}$  any collection of subsets of  $E$ ,

$$\sigma(\mathcal{A}) = \left\{ A \subseteq E : A \in \mathcal{E} \text{ for all } \sigma\text{-algebras } \mathcal{E} \ni \mathcal{A} \right\}$$

the  $\sigma$ -algebra generated by  $\mathcal{A}$ : It can be shown (Ex Sheet) that it's just  $\bigcap_{\substack{\mathcal{E}\text{-algebra} \\ \mathcal{E} \ni \mathcal{A}}} \mathcal{E}$  and is a  $\sigma$ -algebra.

Choices for  $\mathcal{A}$  will include

$\rightarrow \mathcal{A}$  is a ring of subsets of  $E$  if  $\emptyset \in \mathcal{A}$ , and if

$$\forall A, B \in \mathcal{A} \Rightarrow \begin{matrix} A^c \\ B \setminus A \end{matrix} \in \mathcal{A}, A \cup B \in \mathcal{A}$$

$\rightarrow \mathcal{A}$  is an algebra if  $\emptyset \in \mathcal{A}$ ,

$$\forall A, B \in \mathcal{A} \Rightarrow A^c \in \mathcal{A}, A \cup B \in \mathcal{A}$$

Remark Since  $A \cap B = (A \cup B) \setminus (A \Delta B)$

where  $A \Delta B = (A \setminus B) \cup (B \setminus A)$ , we see that  $A \cap B \in \mathcal{A}$

when  $A, B$  belong to a ring  $\mathcal{A}$ .

### SET FUNCTIONS

For  $\mathcal{A} \subseteq \mathcal{P}(E)$  st.  $\emptyset \in \mathcal{A}$ , we say that  $\mu$  is a set function if

$$\mu: \mathcal{A} \rightarrow [0, \infty], \mu(\emptyset) = 0$$

We say that  $\mu$  is 1) increasing if  $\forall A, B \in \mathcal{A}$  ~~disjoint~~ st.  $A \subseteq B$

$$\text{we have } \mu(A) \leq \mu(B)$$

2) additive if  $\forall A, B \in \mathcal{A}$  disjoint st.  $A \cup B \in \mathcal{A}$

$$\text{we have } \mu(A \cup B) = \mu(A) + \mu(B)$$

3) ctly additive if  $\forall (A_n) \in \mathcal{A}$  disjoint st.  $\bigcup_n A_n \in \mathcal{A}$

$$\text{we have } \mu\left(\bigcup_n A_n\right) = \sum_n \mu(A_n)$$

41 ctbly subadditive if  $\forall (A_n) \in \mathcal{A}$  s.t.  $\bigcup_n A_n \in \mathcal{A}$  L1.3

$$\text{we have } \mu\left(\bigcup_n A_n\right) \leq \sum_n \mu(A_n)$$

Remark (One shows that) a countably additive set function on a  $\sigma$ -algebra is a measure. One shows that a measure satisfies 1, 2, 4 too.

Theorem (Caratheodory)

Let  $\mathcal{A} \subseteq \mathcal{P}(E)$  be a ring of subsets of  $E$  and let

$\mu: \mathcal{A} \rightarrow [0, \infty]$  be a ctbly additive set function.

Then  $\mu$  extends to a measure on  $\sigma(\mathcal{A})$ .

A ring  $\Rightarrow \emptyset \in \mathcal{A}$

$A, B \in \mathcal{A} \Rightarrow A \cup B, B \setminus A \in \mathcal{A}$

- $\mu$  is countably additive on  $\mathcal{A}$  if  $\forall A_n \in \mathcal{A}$  disjoint  
s.t.  $\bigcup_n A_n \in \mathcal{A} \Rightarrow \mu(\bigcup_n A_n) = \sum_n \mu(A_n)$

"Disjointification Fact"

Let  $A_n \in \mathcal{A}$ ,  $\mathcal{A}$  a ring (or  $\sigma$ -algebra), consider  $\bigcup_n A_n$ .

Then write  $\tilde{A}_n = \bigcup_{j=1}^n A_j$ , so  $\tilde{A}_n$  is increasing ( $\tilde{A}_n \uparrow$ ),  
and defining  $\tilde{B}_1, \dots$  via  $\tilde{B}_n = \tilde{A}_n \setminus \tilde{A}_{n-1}$ .

Then the  $\tilde{B}_n$  are all disjoint, and  $\bigcup_n A_n = \bigcup_n \tilde{B}_n$

note  
 $\tilde{B}_n \in \mathcal{A}$

Theorem  $\mathcal{A}$  a ring on  $E$ ,  $\mu: \mathcal{A} \rightarrow [0, \infty]$  countably additive

- Then  $\exists$  a measure  $\mu^*$  on  $\sigma(\mathcal{A})$  s.t.  $\mu^*|_{\mathcal{A}} = \mu$ .

Proof For  $B \subseteq E$ , define the outer measure

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

set  $\mu^*(B) = \infty$  when no such  $(A_n)$  exists.

Clearly  $\mu^*(\emptyset) = 0$ , and  $\mu^*$  is increasing on  $\mathcal{P}(E)$ .

Let us say that  $A \subseteq E$  is  $\mu^*$ -measurable if  $\forall B \subseteq E$ , we have

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

← KEY IDEA

- and define

$$\mathcal{M} = \{A \subseteq E \mid A \text{ is } \mu^*\text{-measurable}\},$$

the set of all  $\mu^*$ -measurable subsets of  $E$ .

Plan Show  $\mathcal{M}$  is a  $\sigma$ -algebra,  $\mathcal{M} \supseteq \mathcal{A}$ ,  $\mu^*$  is a measure on  $\mathcal{M}$ ,  $\mu^*|_{\mathcal{A}} = \mu$ .

Step I ( $\mu^*$  is countably sub-additive)

For any  $B_n, B \subseteq E$ , suppose  $B \subseteq \bigcup_n B_n$ , then

$$\boxed{\mu^*(B) \leq \sum_n \mu^*(B_n)} \quad (+)$$

● To prove this, may assume  $\mu^*(B_n) < \infty \forall n$ .

Thus  $\forall n \in \mathbb{N}, \forall \epsilon > 0, \exists A_{nm}$  s.t.  $B_n \subseteq \bigcup_m A_{nm}$ ,

where  $A_{nm} \in \mathcal{A}$  s.t.  $\mu^*(B_n) + \frac{\epsilon}{2^n} \geq \sum_m \mu(A_{nm})$

Also,  $B \subseteq \bigcup_n B_n \subseteq \bigcup_n \bigcup_m A_{nm}$ , and  $\mu^* \uparrow$

$$\mu^*(B) \leq \mu^*\left(\bigcup_n \bigcup_m A_{nm}\right) \leq \sum_{n,m} \mu(A_{nm})$$

$$\leq \sum_n \mu^*(B_n) + \epsilon \sum_n 2^{-n}$$

$$= \sum_n \mu^*(B_n) + \epsilon$$

So (t) follows.

STEP II ( $\mu^*$  extends  $\mu$ )

FACT (ExSheet) A countably additive set function on a ring  $\mathcal{A}$ , then it is also additive, increasing and countably subadditive.

Now write  $A \in \mathcal{A}$  as  $A = \bigcup_n (A \cap A_n)$  for any seq  $A_n \in \mathcal{A}$ .

By countable subadditivity, and  $A \cap A_n \subseteq A_n$ , we have

$\uparrow$  s.t.  
 $A \subseteq \bigcup_n A_n$

$$\mu(A) = \mu\left(\bigcup_n (A \cap A_n)\right) \stackrel{inc}{\leq} \sum_n \mu(A_n)$$

so that taking the infimum over all  $A_n$  we see that

$$\mu(A) \leq \mu^*(A), \quad \forall A \in \mathcal{A}$$

It is obvious that  $\mu^*(A) \leq \mu(A)$ , since we can take

$$A_1 = A, \quad A_n = \emptyset \text{ for } n > 1$$

Step III ( $\mathcal{M} \supseteq \mathcal{A}$ )

Let  $A \in \mathcal{A}, B \in \mathcal{E}$ , then we need to check that

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

By countable subadditivity (t), since  $B = (B \cap A) \cup (B \cap A^c)$ ,

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

Need to show  $\geq$  to prove the assertion.

For this, may assume  $\mu^*(B) < \infty$ . Hence as before, let  $\epsilon > 0$ ,

$$\exists A_n \in \mathcal{A} \text{ s.t. } B \subseteq \bigcup_n A_n \text{ and s.t. } \mu^*(B) + \epsilon \geq \sum_n \mu(A_n)$$

Now,  $B \cap A \subseteq \bigcup_n (A_n \cap A)$ ,  $B \cap A^c \subseteq \bigcup_n (A_n \cap A^c)$

and so by (t),

$\uparrow$  elts of ring

$\uparrow$  elts of ring

$$\begin{aligned} & \mu^*(B \cap A) + \mu^*(B \cap A^c) \\ & \leq \sum_n \mu(A_n \cap A) + \sum_n \mu(A_n \cap A^c) \\ & \stackrel{\text{additivity of } \mu}{=} \sum_n \mu(A_n) \leq \mu^*(B) + \varepsilon \end{aligned}$$

So since  $\varepsilon$  arbitrary,  $\mu^*(B \cap A) + \mu^*(B \cap A^c) \leq \mu^*(B)$ .

$M \supseteq A$  follows.

Step IV ( $\mathcal{M}$  is an algebra.)

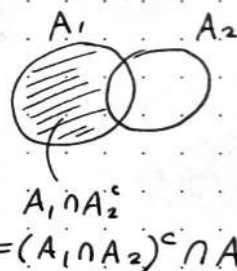
Clearly  $\emptyset \in A \subseteq \mathcal{M}$ . Likewise  $\mathcal{M}$  closed under complements. (symmetry)

Now suppose  $A_1, A_2 \in \mathcal{M}$ ,  $B \in E$ :

$$\begin{aligned} \mu^*(B) &= \mu^*(B \cap A_1) + \mu^*(B \cap A_1^c) \quad (A_1 \in \mathcal{M}) \\ & \quad \downarrow \quad \searrow \\ &= \mu^*(B \cap A_1 \cap A_2) + \mu^*(B \cap A_1 \cap A_2^c) + \mu^*(B \cap A_1^c) \quad (A_2 \in \mathcal{M}) \end{aligned}$$

$$\begin{aligned} &= \mu^*(B \cap A_1 \cap A_2) + \mu^*(B \cap (A_1 \cap A_2)^c \cap A_1) \\ & \quad + \mu^*(B \cap (A_1 \cap A_2)^c \cap A_1^c) \end{aligned}$$

$$= \mu^*(B \cap A_1 \cap A_2) + \mu^*(B \cap (A_1 \cap A_2)^c)$$



Thus  $A_1 \cap A_2 \in \mathcal{M}$ .

Since  $A_1 \cup A_2 = (A_1^c \cap A_2^c)^c$ , have  $\mathcal{M}$  closed under unions.

Step VI ( $\mathcal{M}$  is a  $\sigma$ -algebra,  $\mu^*/\mu$  is a measure)

It suffices to prove (using disjointification) that  $\forall A_n \in \mathcal{M}$  disjoint,  $A = \bigcup_n A_n \in \mathcal{M}$ ,  $\mu^*(A) = \sum_n \mu^*(A_n)$

Now for any  $B \in E$  we write as in V,

$$\begin{aligned} \mu^*(B) &= \mu^*(B \cap A_1) + \mu^*(B \cap A_1^c) \\ &= \mu^*(B \cap A_1) + \mu^*(B \cap \underbrace{A_1^c \cap A_2}_{= A_2}) + \mu^*(B \cap A_1^c \cap A_2^c) \end{aligned}$$

$$= \mu^*(B \cap A_1) + \mu^*(B \cap A_2) + \mu^*(B \cap A_1^c \cap A_2^c)$$

$$\vdots \\ = \sum_{n=1}^N \mu^*(B \cap A_n) + \mu^*(B \cap A_1^c \cap \dots \cap A_N^c)$$

Now,  $A \supseteq \bigcup_{n=1}^N A_n \quad \forall N$ , so  $A^c \subseteq \bigcap_{n=1}^N A_n^c$

$$\text{So } \mu^*(B) \geq \sum_{n=1}^N \mu^*(B \cap A_n) + \mu^*(B \cap A^c) \quad (\mu^* \uparrow)$$

Now let  $N \rightarrow \infty$  to deduce

$$\begin{aligned} \mu^*(B) &\geq \sum_n \mu^*(B \cap A_n) + \mu^*(B \cap A^c) \\ &\stackrel{(+) }{\geq} \mu^*(B \cap \underbrace{\bigcup_n A_n}_A) + \mu^*(B \cap A^c) \end{aligned}$$

Conversely,  $B \in (B \cap A) \cup (B \cap A^c)$  gives other direction.

So  $\mu^*(B) = \mu^*(B \cap A) + \mu^*(B \cap A^c)$  and  $\mathcal{M}$  is a  $\sigma$ -algebra.

Now invoke above inequality with  $B = A$ ,

$$\begin{aligned} \mu^*(A) &\geq \sum_n \mu^*(\underbrace{A \cap A_n}_{A_n}) + \underbrace{\mu^*(A \cap A^c)}_{\text{zero}} \\ &= \sum_n \mu^*(A_n) \end{aligned}$$

Again (+) gives converse  $\mu^*(A) \leq \sum_n \mu^*(A_n)$ .

So indeed  $\mu^*$  is countably additive so a measure on  $\mathcal{M}$ . □

Next topic: check when  $\mu^*$  is a unique extension

(Uniqueness of extension)

A family  $\mathcal{A}$  of subsets of  $E$  is called

1) a  $\pi$ -system if  $\emptyset \in \mathcal{A}$  and  $A, B \in \mathcal{A} \Rightarrow A \cap B \in \mathcal{A}$

2) a d-system if  $E \in \mathcal{A}$  and  $\forall A, B \in \mathcal{A}$  s.t.  $A \subseteq B$ ,  
and all  $A_n \in \mathcal{A}$ ,  $A_n \uparrow$  (increasing), then  $B \setminus A \in \mathcal{A}$ ,  $\bigcup_n A_n \in \mathcal{A}$

One shows (EX Sheet) that if  $\mathcal{A}$  is a d-system and a  $\pi$ -system then  $\mathcal{A}$  is a  $\sigma$ -algebra.

Lemma (Dynkin) Let  $\mathcal{A}$  be a  $\pi$ -system. Then any d-system containing  $\mathcal{A}$  also contains  $\sigma(\mathcal{A})$ .

Theorem (uniqueness of extension)

Let  $\mu_1, \mu_2$  be measures on  $(E, \mathcal{E})$  s.t.

$\mu_1(E) = \mu_2(E) < \infty$ . Suppose  $\mu_1 = \mu_2$  on  $\mathcal{A}$ ,

where  $\mathcal{A}$  is some  $\pi$ -system generating  $\mathcal{E}$  (i.e.  $\mathcal{E} \subseteq \sigma(\mathcal{A})$ )

Then  $\mu_1 = \mu_2$  on  $\mathcal{E}$ .

Proof (Thm) Define the family

$\mathcal{D} = \{A \in \mathcal{E} : \mu_1(A) = \mu_2(A)\}$  of <sup>meas.</sup> subsets of  $E$

where  $\mu_1, \mu_2$  agree. Clearly  $\mathcal{A} \subseteq \mathcal{D}$ ; we will <sup>show</sup>  $\mathcal{D} \supseteq \sigma(\mathcal{A}) \supseteq \mathcal{E}$ .

Clearly,  $E \in \mathcal{D}$ . Also, if  $A, B \in \mathcal{E}$ ,  $A \subseteq B$ , then

$\mu_i(A) + \mu_i(B \setminus A) = \mu_i(B) \leq \mu_i(E) < \infty$  for  $i=1, 2$

So if  $A, B \in \mathcal{D}$ , then  $B \setminus A \in \mathcal{D}$ .

Next if  $A_n \uparrow A$ , where  $A_n \in \mathcal{D}$  and disjoint? (wlog) then

$$\mu_i(A) = \mu_i\left(\bigcup_n \tilde{A}_n\right) = \lim_N \sum_{n=1}^N \mu_i(\tilde{A}_n) = \lim_N \mu_i\left(\bigcup_{n \leq N} \tilde{A}_n\right) = \lim_{n \rightarrow \infty} \mu_i(A_n),$$

so indeed  $A = \bigcup_n A_n$  will lie in  $\mathcal{D}$  too.

Thus  $\mathcal{D}$  is a d-system containing the  $\pi$ -system  $\mathcal{A}$ .

So by Dynkin's lemma,  $\mathcal{D} \supseteq \sigma(\mathcal{A}) \supseteq \mathcal{E}$ , and  $\mu_1 = \mu_2$  □



Proof of Lemma

Def  $\mathcal{D} = \bigcap_{\substack{D_\alpha \text{ d-systems} \\ D_\alpha \ni A}} D_\alpha$ , the intersection of all d-systems containing  $A$ ,

which is again a d-system.

Plan show that  $\mathcal{D}$  is a  $\pi$ -system

Define a new collection of sets

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

Clearly,  $\mathcal{A} \subseteq \mathcal{D}'$  since  $\mathcal{A}$  is a  $\pi$ -system.

Further,  $\mathcal{D}'$  is a d-system: indeed

$$E \cap A = A \in \mathcal{A} \subseteq \mathcal{D} \text{ so } E \in \mathcal{D}'$$

If  $B_1, B_2 \in \mathcal{D}'$  s.t.  $B_1 \subseteq B_2$  then  $\forall A \in \mathcal{A}$

$$(B_2 \setminus B_1) \cap A = \underbrace{(B_2 \cap A)}_{\in \mathcal{D}} \setminus \underbrace{(B_1 \cap A)}_{\in \mathcal{D}} \in \mathcal{D}$$

So  $B_2 \setminus B_1 \in \mathcal{D}'$ .

Finally, if  $B_n \uparrow B$  in  $\mathcal{D}'$ , so  $B \in \mathcal{D}$ , then

for any  $A \in \mathcal{A}$  we have  $\underbrace{(B_n \cap A)}_{\in \mathcal{D}} \uparrow (B \cap A) \in \mathcal{D}$

And so in fact  $B \in \mathcal{D}'$ .

Conclude that  $\mathcal{D}'$  is a d-system containing  $\mathcal{A}$ , hence  $\mathcal{D} \subseteq \mathcal{D}'$ .

But  $\mathcal{D}' \subseteq \mathcal{D}$  so in fact  $\mathcal{D}' = \mathcal{D}$ .

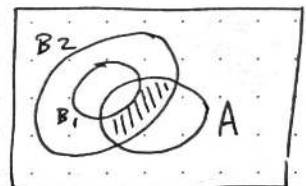
Now define a new system

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

Now from the above,  $\mathcal{A} \subseteq \mathcal{D}''$ .

Repeating the previous steps one shows that  $\mathcal{D}'' = \mathcal{D}$ .

So  $\mathcal{D}$  is a  $\pi$ -system, and a d-system so a  $\sigma$ -algebra containing  $\mathcal{A}$ .  $\square$



L3.3

Remark: A measure  $\mu$  on  $(E, \mathcal{E})$  is finite if  $\mu(E) < \infty$ .

The uniqueness theorem applies to "σ-finite" measures  $\mu$  (i.e.  $\mu$  s.t.

•  $\exists E_n \in \mathcal{E}$  s.t.  $E = \bigcup_n E_n$  and  $\mu(E_n) < \infty \forall n$ ),

as we shall see later (for Lebesgue and other measures).

Borel sets

Let  $E$  be a topological space; the  $\sigma$ -algebra generated by the open sets,  $\mathcal{A} = \{A \subseteq E : A \text{ open}\}$

is called the Borel  $\sigma$ -algebra of  $E$ , we write  $\mathcal{B}(E) = \sigma(\mathcal{A})$ ,  
 $\mathcal{B} = \mathcal{B}(\mathbb{R})$ .

A measure  $\mu$  on  $(E, \mathcal{B}(E))$  is called a Borel measure.

If  $\mu(K) < \infty$  for all compact subsets  $K \subseteq E$  (check  $K \in \mathcal{B}(E)$ ) ← Hausdorff  
 then  $\mu$  is a Radon measure.

CONSTRUCTION OF LEBESGUE MEASURE

Of key importance is the Borel measure  $\mu$  on  $\mathbb{R}$  that assigns to each interval its length,  $\mu((a, b)) = b - a$ ,  $a < b$  in  $\mathbb{R}$ .

Theorem (Lebesgue, 1902)

There exists a unique Borel measure  $\mu$  on  $\mathbb{R}$  s.t.  $\forall a, b \in \mathbb{R}, a < b$ ,  
 $\mu((a, b)) = b - a$ .

Proof Consider the ring  $\mathcal{A}$  of finite unions of disjoint intervals:

$$\mathcal{A} = (a_1, b_1] \cup \dots \cup (a_n, b_n]$$

ring

This ring generates  $\mathcal{B}$  (first it generates  $\sigma(\{(a, b) : a < b\})$ , see Ex Sheet; second for  $a, b \in \mathbb{Q}$  provide basis for topology on  $\mathbb{R}$ .)

For such  $A \in \mathcal{A}$ , define a set function

$$\mu(A) = \sum_{i=1}^n (b_i - a_i), \quad \text{clearly is additive, subadditive,}$$

and also well-defined: suppose  $A$  can be written as two distinct disjoint unions of intervals, say  $A = \bigcup_j C_j$ ,  $A = \bigcup_k D_k$ ,

then each  $C_j = \bigcup_k (C_j \cap D_k)$ ,  $D_k = \bigcup_j (D_k \cap C_j)$

$$\text{and obtain } \mu(A) = \sum_j \mu(C_j) = \sum_{j,k} \mu(C_j \cap D_k) = \sum_k \mu(D_k)$$

By virtue of Carathéodory's theorem, the result will follow if we

can show that  $\mu$  is countably additive on  $\mathcal{A}$ .

FACT (Ex Sheet) A finite-valued <sup>additive</sup> set function on a ring  $\mathcal{A}$  is countably additive iff for any decreasing  $A_n \downarrow$  with  $\bigcap_n A_n = \emptyset$ ,  $\mu(A_n) \rightarrow 0$  as  $n \rightarrow \infty$ . We will argue by contradiction; suppose  $B_n \in \mathcal{A}$  is s.t.  $B_n \downarrow \emptyset$  but  $\mu(B_n) \not\rightarrow 0$ . Then  $\exists \epsilon > 0$  s.t. for infinitely many  $n \in \mathbb{N}$ ,

$$\mu(B_n) \geq 2\epsilon > 0.$$

Now we approximate each  $B_n$  from within by  $C_n \in \mathcal{A}$  s.t.  $\overline{C_n} \subseteq B_n$  and  $\mu(B_n \setminus C_n) \leq \epsilon 2^{-n}$ .

(take unions of intervals  $(a_i, b_i]$  to  $(a_i + \frac{\epsilon 2^{-n}}{N_n}, b_i]$  where  $N_n$  is no. of ints in  $B_n$ )

$$\begin{aligned} \text{Now, } \mu(B_n \setminus (C_1 \cap \dots \cap C_n)) &\leq \mu((B_n \setminus C_1) \cup \dots \cup (B_n \setminus C_n)) \\ &\leq \sum_{i \leq n} \mu(B_n \setminus C_i) \leq \epsilon \sum_{i \leq n} 2^{-i} \leq \epsilon \end{aligned}$$

Since  $\mu(B_n) \geq 2\epsilon$ , "before removal",

we must have  $\mu(C_1 \cap \dots \cap C_n) \geq \epsilon$ , in particular the union of intervals

$C_1 \cap \dots \cap C_n$  is non-empty.

Likewise  $\overline{C_1} \cap \dots \cap \overline{C_n} = K_n$  is non-empty, (oh... shit... here it comes...)

compact, so by compactness properties  $\bigcap_n K_n \neq \emptyset$ .

But  $\bigcap_n K_n \subseteq \bigcap_n B_n = \emptyset$ , ~~✗~~

All in all,  $\mu$  is countably additive and extends to a Borel measure.

Remains to prove uniqueness.

$$\mu((b, a)) = a - b$$

Let  $\lambda$  be any other measure on  $\mathcal{B}$  s.t.  $\lambda((a, b]) = b - a$

For any  $n \in \mathbb{N}$ , consider new measures

$$\mu_n(A) = \mu(A \cap (n, n+1]), \quad \lambda_n = \lambda(A \cap (n, n+1]),$$

which are finite measures that coincide on  $\mathcal{A}$ , which forms a  $\pi$ -system generating  $\sigma$ -algebra. Hence by the uniqueness theorem applied to the finite measures  $\lambda_n, \mu_n$  we must have that they coincide on  $\mathcal{B}$ .

But for any  $A \in \mathcal{B}$ ,

$$\mu(A) = \sum_{n \in \mathbb{Z}} \mu(A \cap (n, n+1]) = \sum_{n \in \mathbb{Z}} \mu_n(A) = \sum_{n \in \mathbb{Z}} \lambda_n(A) = \dots = \lambda(A).$$

□

😊

Remark

1) A set  $A \in \mathcal{B}$  is called a Lebesgue-null-set if  $\mu(A) = 0$ .

Since  $\{x\} = \bigcap_n (x - \frac{1}{n}, x]$ , but since  $\mu$  is a measure we also have  $\mu(\{x\}) = \lim_{n \rightarrow \infty} \mu((x - \frac{1}{n}, x]) = \lim_{n \rightarrow \infty} \frac{1}{n} = 0$ , hence any singleton  $\{x\}$ ,  $x \in \mathbb{R}$  has Lebesgue measure zero. In fact for any countable subset of  $\mathbb{R}$ ,

e.g.  $\mathbb{Q}$ , we have  $\mu(\mathbb{Q}) = \mu\left(\bigcup_{q \in \mathbb{Q}} \{q\}\right) = \sum_{q \in \mathbb{Q}} \underbrace{\mu(\{q\})}_{=0} = 0$

2) The measure  $\mu$  is defined on  $\mathcal{B}$ , but in fact also on the class  $\mathcal{M}$  of (outer) Lebesgue-measurable sets. One shows (Ex Sheet) that

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

so  $\mathcal{M}$  contains any subset of a Borel null-set.

3) If we define the translation by  $x$  of  $B \in \mathcal{B}$  to equal

$$B + x = \{ b + x : b \in B \} \quad (\text{lies in } \mathcal{B})$$

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

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

we have  $\mu_x = \mu$  by the uniqueness theorem.

So  $\mu_x = \mu$  on  $\mathcal{B}(\mathbb{R})$  but also on  $\mathcal{B}((0, 1])$  if " $+x$ " is mod 1.

We say that Lebesgue measure  $\mu$  is translation invariant.

Non-measurable sets

One may ask:  $\mathcal{B} \subsetneq \mathcal{P}(\mathbb{R})$ ,  $\mathcal{M} \subsetneq \mathcal{P}(\mathbb{R})$ ?

Similarly  $\mathcal{B}((0, 1]) \subsetneq \mathcal{P}((0, 1])$ ?

For  $x, y \in (0, 1]$ , let us write  $x \sim y$  if  $x - y \in \mathbb{Q}$ , where " $-$ " is mod 1 and  $\mathbb{Q} = \mathbb{Q} \cap (0, 1]$ .

Now (using AOC) we select exactly one element from each equivalence class  $[x] = \{y \in (0, 1] \text{ s.t. } y \sim x\}$  and let  $S \subseteq (0, 1]$  denote the resulting set.

Define further  $S + q = \{s + q \text{ mod } 1, s \in S\}$ , so

$$(0, 1] = \bigcup_{q \in \mathbb{Q}} (S + q), \text{ a disjoint union of cosets.}$$

L5.2

Now by translation invariance of  $\mu|_{(0,1]} = \mu$ ,

$\mu(S) = \mu(S+q)$  for each  $q$  and hence

$$\mu((0,1]) = \sum_{q \in \mathbb{Q}} \mu(S+q) = 1 \quad \text{iii} \quad \begin{array}{l} \text{either } 0 \\ \text{or } \infty, \text{ no} \end{array}$$

Therefore  $S$  cannot lie in  $\mathcal{B}$ , or in  $\mathcal{M}$ .

Is there another way to extend  $\mu$  to  $\mathcal{P}((0,1])$ ?

Theorem (Banach-Kuratowski)

Assume the continuum hypothesis. Then there exists no measure  $\mu$  on  $\mathcal{P}((0,1])$  s.t.  $\mu((0,1]) = 1$  and  $\mu(\{x\}) = 0 \quad \forall x \in (0,1]$ .

(see RMDudley, Real Analysis & Prob p526)

PROBABILITY MEASURES  $\mu(\Omega) = 1$

Call  $(E, \mathcal{E}, \mu)$  a probability space.

We write  $(\Omega, \mathcal{A}, \mathbb{P})$  for it, where

$\Omega$  ... outcome / sample space

$\mathcal{A}$  ... events ( $\sigma$ -algebra)

$\mathbb{P}$  ... prob measure

Axioms of probability (Kolmogorov, 1933)

1)  $\mathbb{P}(\Omega) = 1 \quad (\Leftrightarrow \mu(E) = 1, \mu(\emptyset) = 0)$

2)  $\mathbb{P}(E) \geq 0 \quad \forall E \in \mathcal{A}$

3)  $\mathbb{P}(\bigcup_n A_n) = \sum_n \mathbb{P}(A_n)$  for  $A_n \in \mathcal{A}$  disjoint

Let us say events  $(A_i : i \in I)$  are independent if  $\forall J \subseteq I$  finite

$$\mathbb{P}\left(\bigcap_{i \in J} A_i\right) = \prod_{i \in J} \mathbb{P}(A_i)$$

Sub- $\sigma$ -algebras  $\mathcal{A}_i \subseteq \mathcal{F}$ ,  $(\mathcal{A}_i : i \in I)$  are said to be independent if  $\forall J \subseteq I$  finite, the events  $(A_i, i \in I)$  for  $A_i \in \mathcal{A}_i$  are independent

L5.3

Thm Let  $\mathcal{A}_1, \mathcal{A}_2$  be  $\pi$ -systems of subsets in  $\mathcal{F}$ .

Suppose  $IP(A_1 \cap A_2) = IP(A_1)IP(A_2)$  for all  $A_1 \in \mathcal{A}_1, A_2 \in \mathcal{A}_2$ .

Then  $\sigma(\mathcal{A}_1), \sigma(\mathcal{A}_2)$  are independent.

L6.1

Thm Let  $\mathcal{A}_1, \mathcal{A}_2$  be  $\pi$ -systems of subsets in  $\mathcal{F}$ .

Suppose  $IP(A_1 \cap A_2) = IP(A_1)IP(A_2) \quad \forall A_1 \in \mathcal{A}_1, A_2 \in \mathcal{A}_2$

● Then  $\sigma(\mathcal{A}_1), \sigma(\mathcal{A}_2)$  are independent

Proof Fix  $A_1 \in \mathcal{A}_1$ , define two measures

$$\mu(A) = IP(A_1 \cap A), \quad \nu(A) = IP(A_1)IP(A),$$

which are finite measures s.t.  $\mu(\Omega) = IP(A_1) = \nu(\Omega)$ .

They coincide on the  $\pi$ -system  $\mathcal{A}_2 \Rightarrow$  hence also on  $\sigma(\mathcal{A}_2)$

Repeat the argument fixing  $A_2 \in \mathcal{A}_2$ . (not quite but eh) □

In proving 'asymptotic' results in probability, it is useful to consider

● events (or sets)  $\limsup A_n = \bigcap_n \bigcup_{m \geq n} A_m = \{A_n \text{ i.o.}\}$   
 $\liminf A_n = \bigcup_n \bigcap_{m \geq n} A_m = \{A_n \text{ eventually}\}$  ↑  
infinitely often

Lemma (1<sup>st</sup> Borel-Cantelli Lemma)

If  $\sum_n IP(A_n) < \infty$  then  $IP(A_n \text{ i.o.}) = 0$

Pf We can write, for any  $n$

$$\begin{aligned} IP(A_n \text{ i.o.}) &= IP\left(\bigcap_n \bigcup_{m \geq n} A_m\right) \\ &\leq IP\left(\bigcup_{m \geq n} A_m\right) \\ &\leq \sum_{m \geq n} IP(A_m) \rightarrow 0 \text{ as } n \rightarrow \infty \end{aligned}$$
□

● 2<sup>nd</sup> Borel-Cantelli Lemma

Suppose  $(A_n : n \in \mathbb{N}) \subseteq \mathcal{F}$  are independent

If  $\sum_n IP(A_n) = \infty$  then  $IP(A_n \text{ i.o.}) = 1$

Proof We use  $1-a \leq e^{-a}$  for  $a = a_n = IP(A_n)$

Then  $\forall n, N \geq n$ , by independence of  $A_n$ 's (hence  $A_n^c$ 's)

$$IP\left(\bigcap_{m=n}^N A_m^c\right) = \prod_{m=n}^N (1-a_m) \leq \prod_{m=n}^N e^{-a_m} = \exp\left(-\sum_{m=n}^N a_m\right)$$

So necessarily  $\rightarrow 0$  as  $N \rightarrow \infty$  and since  $\bigcap_{m=n}^N A_m^c \downarrow \bigcap_{m=n}^{\infty} A_m^c$

● we will deduce  $IP\left(\bigcap_{m \geq n} A_m^c\right) = 0 \quad \forall n$ .

Conclude that  $IP(A_n \text{ i.o.}) = 1 - \lim IP\left(\bigcup_n \bigcap_{m \geq n} A_m^c\right) = 1$  □



## 2. MEASURABLE FUNCTIONS & RANDOM VARIABLES

### Measurable functions

Let  $(E, \mathcal{E})$ ,  $(G, \mathcal{G})$  be measurable spaces. A function

$$f: E \rightarrow G$$

is called measurable (or  $\mathcal{E}$ - $\mathcal{G}$  meas) if the inverse image (preimage)

$$f^{-1}(A) \in \mathcal{E} \quad \forall A \in \mathcal{G}$$

Recall  $f^{-1}(A) = \{x \in E : f(x) \in A\}$

When the range space  $(G, \mathcal{G}) = (\mathbb{R}, \mathcal{B})$ , we simply say that  $f: E \rightarrow \mathbb{R}$  is ~~Borel~~ measurable. If  $E$  is a topological space,  $\mathcal{E} = \mathcal{B}(E)$ , we say that  $f: E \rightarrow \mathbb{R}$  is Borel measurable.

Note that inverse images preserve set operations

$$f^{-1}\left(\bigcup_{i \in I} A_i\right) = \bigcup_{i \in I} f^{-1}(A_i)$$

$$f^{-1}\left(\bigcap_{i \in I} A_i\right) = \bigcap_{i \in I} f^{-1}(A_i)$$

so we deduce that

$\{f^{-1}(A) : A \in \mathcal{G}\}$  is itself a  $\sigma$ -algebra.

Likewise  $\{A \in \mathcal{G} : f^{-1}(A) \in \mathcal{E}\}$  is a  $\sigma$ -algebra as well

In particular, to check measurability, the following is useful:

If  $\mathcal{G} = \sigma(\mathcal{A})$  and  $f^{-1}(A) \in \mathcal{E} \quad \forall A \in \mathcal{A}$  then

$\{A : f^{-1}(A) \in \mathcal{E}\}$  is a  $\sigma$ -algebra containing  $\mathcal{A}$ , so  $\mathcal{G}$ ,

so  $f$  is measurable.

In particular, when  $(G, \mathcal{G}) = (\mathbb{R}, \mathcal{B})$ , then the intervals

$\{(-\infty, y] : y \in \mathbb{R}\}$  generate  $\mathcal{B}$

and so if  $\{x \in E : f(x) \leq y\} \in \mathcal{E} \quad \forall y \in \mathbb{R}$

then  $f$  is 'Borel'-measurable.

If  $E$  is a topological space, and  $f: E \rightarrow \mathbb{R}$  is continuous,

then  $f^{-1}(U)$  is open in  $E$  whenever  $U$  is open in  $\mathbb{R}$ .

Since open sets generate  $\mathcal{B}$ , we see that  $f$  is measurable (Borel)

L6.3

If  $A \in \mathcal{E}$  is measurable, then the indicator function

$$1_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{o/w} \end{cases}$$

is measurable, clearly.

One shows also (ExSheet) that  $f_1 + f_2$ ,  $f_1 \cdot f_2$ ,  $\inf_n f_n$ ,  $\sup_n f_n$ ,  
 $\liminf_n f_n$ ,  $\limsup_n f_n$

are all measurable when the  $f_n$  are.

Also  $\{x \in E : f_n(x) \text{ converges as } n \rightarrow \infty\}$  is measurable.

Finally Given any maps  $f_i : E \rightarrow G$ ,

we can make them all  $\mathcal{E}$ - $\mathcal{G}$  measurable by setting

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

the  $\sigma$ -algebra generated by  $(f_i)_{i \in I}$

Theorem (monotone classes)

Let  $(E, \mathcal{E})$  be a measurable space, and consider  $\mathcal{A}$  a  $\pi$ -system generating  $\mathcal{E}$ .

Let  $\mathcal{V}$  be a vector space of bounded maps  $f : E \rightarrow \mathbb{R}$

(i.e.  $\sup_{x \in E} f(x) < \infty$  for each  $f \in \mathcal{V}$ ) s.t.

1)  $1 = (1_E) \in \mathcal{V}$  and  $1_A \in \mathcal{V} \forall A \in \mathcal{A}$

2) whenever  $f_n \in \mathcal{V}$ ,  $f$  bounded s.t.  $0 \leq f_n \uparrow f$  pointwise  
 $\Rightarrow f \in \mathcal{V}$

Then  $\mathcal{V}$  contains all bounded measurable functions.

Proof Define  $\mathcal{D} = \{A \in \mathcal{E} : 1_A \in \mathcal{V}\}$ ,

which contains  $E$ ,  $1_{B \setminus A} = 1_B - 1_A \in \mathcal{V}$  (vector space)

and  $0 \leq 1_{A_n} \uparrow 1_A \in \mathcal{V}$  and so  $A_n \uparrow A \Rightarrow A \in \mathcal{D}$ , so  $\mathcal{D}$  is a d-system.

It contains  $\mathcal{A}$  ( $\pi$ -system), so by Dynkin's lemma,

$$\mathcal{D} \supseteq \sigma(\mathcal{A}) \supseteq \underset{\substack{\uparrow \\ \text{gen} \\ E}}{\mathcal{E}} \supseteq \mathcal{D} \Rightarrow E = \mathcal{D}$$

~~sub...~~  
 $B \setminus A \checkmark$

L6.4

Now let  $f: E \rightarrow [0, \infty)$  be any bounded non-negative measurable function.

We define a piecewise-constant approximation as follows

$$f_n(x) = 2^{-n} \sum_{j=0}^{n2^n} j \mathbb{1}_{A_{j,n}}$$

where  $A_{j,n} = \left\{ x \in E : \frac{j}{2^n} \leq f(x) \leq \frac{j+1}{2^n} \right\}$  for  $j = 0, 1, \dots, n2^n - 1$ .

$$= f^{-1} \left( \left( \frac{j}{2^n}, \frac{j+1}{2^n} \right] \right) \in \mathcal{E} \quad \text{if } j > 0?$$

$$A_{n2^n, n} = \{ x \in E : f(x) > n \}$$

$$= f^{-1}((n, \infty)) \in \mathcal{E}$$

since  $f$  is measurable.

In particular  $f_n \in \mathcal{V}$ .

Clearly  $0 \leq f_n \leq n$ , so for  $n$  large enough, we then must have  $f_n(x) \leq f(x) \leq f_n(x) + \frac{1}{2^n}$ .

So  $f_n \uparrow f$  pointwise. Therefore by hypothesis,  $f \in \mathcal{V}$ .

For an arbitrary  $f: E \rightarrow \mathbb{R}$  bounded measurable, we can write

$$f = f^+ - f^- \text{ and apply the above to } f^+, f^-$$

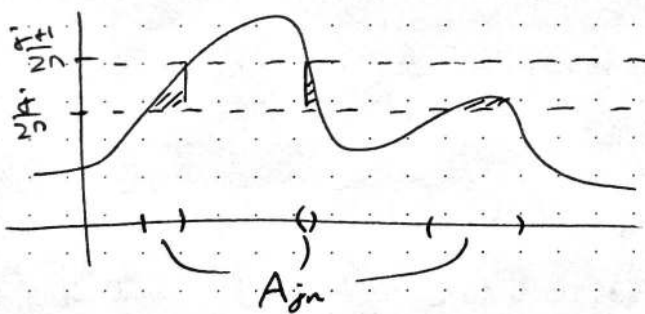


Image Measures



Image Measures

Let  $(E, \mathcal{E})$  and  $(G, \mathcal{G})$  measurable spaces,

$f: E \rightarrow G$  measurable map,

and let  $\mu$  be a measure on  $E$ . Then we can define a measure  $\nu$  on  $G$

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

which indeed is a measure on  $G$  (Ex Sheet)

It is called the image measure  $\nu \equiv \mu \circ f^{-1}$

Lemma Let  $g: \mathbb{R} \rightarrow \mathbb{R}$  be non-constant, right continuous, non-decreasing (1)

Define  $I = (g(-\infty), g(\infty))$  and a map  $f: I \rightarrow \mathbb{R}$

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

the smallest  $y \in \mathbb{R}$  s.t.  $g(y) \geq x$ . Then  $f$  is left-continuous, non-decreasing and  $\lceil f(x) \leq y \iff x \leq g(y) \rceil$

Proof For  $x \in I$ , define

$$J_x = \{ y \in \mathbb{R} : x \leq g(y) \}$$

is non-empty (since  $g(y) > g(-\infty)$ ,  $x > g(-\infty)$  <sup>← want</sup>). (& bold below)

So the infimum  $f(x) = \inf J_x$  exists in  $\mathbb{R}$ .

If  $y \in J_x$ ,  $y' \geq y$  then  $x \leq g(y) \leq g(y') \Rightarrow y' \in J_x$ .

Also, for any sequence  $y_n \in J_x$  s.t.  $y_n \downarrow y$ , by right-continuity,

$g(y_n) \downarrow g(y)$  and  $x \leq g(y)$ , i.e.  $y \in J_x$ .

So  $J_x = [f(x), \infty)$  and  $f(x) \leq y \iff y \in J_x \iff x \leq g(y)$   $\circ$

Next note  $x' \leq x \Rightarrow J_{x'} \supseteq J_x \Rightarrow f(x') \leq f(x)$ .

Finally, if  $x_n \uparrow x$  then  $J_x = \bigcap_n J_{x_n}$  and by def<sup>n</sup> of inf,

$$f(x_n) \rightarrow f(x) \text{ as } n \rightarrow \infty$$

□

$$\left\{ \bigcap_n [a_n, \infty) = \left[ \sup_n a_n, \infty) \right] \right\}$$

Theorem Let  $g: \mathbb{R} \rightarrow \mathbb{R}$  be as in the previous lemma.

Then  $\exists!$  Radon measure  $\mu_g$  on  $\mathbb{R}$  (on  $\mathcal{B}(\mathbb{R})$ ) st.

$$\mu_g((a, b]) = g(b) - g(a) \quad \forall a, b \in \mathbb{R}, a < b$$

Moreover, any Radon measure on  $\mathbb{R}$  can be represented in this way.

Remark We call  $\mu_g$  the Lebesgue-Stieltjes measure with distr  $f^n g$

Proof Let  $f, I$  be as in the lemma, and  $\mu$  the Lebesgue measure on  $\mathbb{R}$ .

$$\begin{aligned} \text{The } \{x \in I : f(x) \leq z\} &\stackrel{\text{lemma}}{=} \{x \in I : x \leq g(z)\} \\ &= (g(-\infty), g(z)] \in \mathcal{B}(I) \end{aligned}$$

$\forall z$ , and since  $\{(-\infty, z] : z \in \mathbb{R}\}$  generate  $\mathcal{B}(\mathbb{R})$ , we deduce that  $f$  is measurable.

So the image measure  $\mu_g = \mu \circ f^{-1}$  exists on  $\mathcal{B}(\mathbb{R})$

We also have

$$\begin{aligned} \mu_g((a, b]) &= \mu(x : f(x) > a, f(x) \leq b) \\ &\stackrel{\text{lemma}}{=} \mu((g(a), g(b)]) \\ &= g(b) - g(a) \quad \square \end{aligned}$$

By the uniqueness argument for  $\mu$ , we see that  $\mu_g$  is the unique such measure, and it is Radon since any compact  $K \in \mathcal{B}(\mathbb{R})$

necessarily satisfies  $\mu_g(K) \leq \mu_g([-n, n]) \leq \mu_g((a, b]) < \infty$

Conversely, let  $\nu$  be any Radon measure, and define

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

which is clearly increasing and satisfies  $(a < 0 < b)$

$$\begin{aligned} \nu((a, b]) &= \nu((a, 0]) + \nu((0, b]) \\ &= g(b) - g(a), \quad \text{with a similar calculation for} \end{aligned}$$

$$0 < a < b, \quad a < b < 0.$$

Clearly  $g$  is right continuous since  $A_n = (0, y_n] \downarrow (0, y]$

so  $\nu(A_n) \rightarrow \nu(A)$  by countable additivity  $\sim$

By uniqueness  $\mu_g = \nu$ . □

Example The 'Dirac' point mass measure  $\delta_x$  at  $x \in \mathbb{R}$  is

$$\delta_x(A) = 1 \text{ iff } x \in A, \text{ else zero,}$$

is a Radon measure with df  $g(t) = 1_{[x, \infty)}(t)$

### 2.3 RANDOM VARIABLES

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space, and  $(E, \mathcal{E})$  a measurable space. A measurable map  $X: \Omega \rightarrow E$  is called a random variable (r.v.) in  $E$ . If  $E = \mathbb{R}$ , we just say r.v. The image measure on  $E$  obtained in this way  $\mu_X = \mathbb{P} \circ X^{-1}$  is called the law or distribution of  $X$ .

When  $E = \mathbb{R}$ ,  $\mathcal{E} = \mathcal{B}$ , this law is determined by the  $\pi$ -system

$$\begin{aligned} \{(-\infty, x] : x \in \mathbb{R}\} \text{ as } F_X(x) &= \mu_X((-\infty, x]) \\ &= \mathbb{P}(\omega \in \Omega : X(\omega) \leq x) \\ &=: \mathbb{P}(X \leq x), \end{aligned}$$

called the cumulative distribution function (cdf). By properties of measures,

we see 1)  $\lim_{z \downarrow x} F(z) = F(x)$

2)  $\lim_{z \rightarrow \infty} F(z) = 1$

3)  $\lim_{z \rightarrow -\infty} F(z) = 0$ , and  $F \uparrow$

and we say that any  $F$  with the preceding properties is a cdf.

Indeed, if  $\Omega = (0, 1)$ ,  $\mathcal{F} = \mathcal{B}((0, 1))$ ,  $\overset{\mathbb{P}}{\mu} = \mu|_{(0, 1)}$  Lebesgue measure restricted to  $(0, 1)$ , then  $F = g$  in the lemma from earlier gives that

$$X(\omega) = \inf \{x : \omega \in F(x)\}, \omega \in (0, 1)$$

is a random variable with distribution function

$$\begin{aligned} \mathbb{P}(\omega \in \Omega : X(\omega) \leq x) &= \mathbb{P}(\omega \in \Omega : \omega \in F(x)) \\ &= F(x) - 0 = F(x) \end{aligned}$$

so any probability distribution can be realised by a prob dist  $f^n$ .

## L8.1

We say that a countable family of random variables  $(X_i : i \in \mathbb{I})$  is independent if the family of  $\sigma$ -algebras  $(\sigma(X_i) : i \in \mathbb{I})$  is independent.

One can check (ExSheet) that this is equivalent to (for real rvs)

$$\mathbb{P}(X_1 \leq x_1, \dots, X_n \leq x_n) = \mathbb{P}(X_1 \leq x_1) \cdots \mathbb{P}(X_n \leq x_n)$$

$\forall x_i \in \mathbb{R}$ , for all finite subsets  $X_1, \dots, X_n$  of  $(X_i : i \in \mathbb{I})$

To construct examples of such sequences of indep rvs, consider a prob space

$$(\Omega, \mathcal{F}, \mathbb{P}) = ((0,1), \mathcal{B}(0,1), \mu|_{(0,1)})$$

Recall that any  $\omega \in \Omega = (0,1)$  has a binary expansion

$$\omega = 0.\omega_1\omega_2\omega_3 \dots, \quad \omega_i \in \{0,1\}$$

$$= 0 + \frac{1}{2}\omega_1 + \frac{1}{4}\omega_2 + \dots$$

which is unique if we exclude  $\infty$ -many zeros

(in this case  $\frac{1}{2} = 0 + \frac{1}{4} + \frac{1}{8} + \frac{1}{16} + \dots$   $\square$ )

Hence define Rademacher rvs

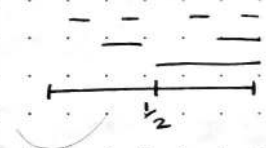
$$R_n : (0,1) \rightarrow \{0,1\}$$

$$\omega \mapsto \omega_n$$

$$\text{One sees } R_1 = 1_{(\frac{1}{2}, 1)}$$

$$R_2 = 1_{(\frac{1}{4}, \frac{1}{2}]} + 1_{(\frac{3}{4}, 1)}$$

$$R_3 = 1_{(\frac{1}{8}, \frac{1}{4}]} + 1_{(\frac{3}{8}, \frac{1}{2}]} + 1_{(\frac{5}{8}, \frac{3}{4}]} + 1_{(\frac{7}{8}, 1)}$$



"percolate"

all the  $R_n$  are indeed measurable,

$$\mathbb{P}(R_n=1) = \mathbb{P}(R_n=0) = \frac{1}{2}$$

Notice next that, for  $x_i \in \{0,1\}^n$

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

and also  $\mathbb{P}(\bigotimes_{i=1}^n R_i = x_i) \cdots \mathbb{P}(R_n = x_n) = (\frac{1}{2})^n = 2^{-n} \quad \square$

Hence the  $R_n$  are all independent and identically distributed (iid) rvs

Thus we have constructed an infinite sequence of iid rvs s.t.

$$\mathbb{P}(R_n=1) = \mathbb{P}(R_n=0) = \frac{1}{2}$$

L8.2

Now take a bijection  $m: \mathbb{N}^2 \leftrightarrow \mathbb{N}$  (e.g.  $m = 2^{k-1}(2n-1)$ )

and define new variables

$$Y_{nk} = R_{m(n,k)} \quad (\text{iid})$$

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

← measurable

which are also all independent (the series converges  $\forall \omega \in \Omega$  since  $|Y_{nk}(\omega)| \leq 1$ )

Now consider intervals  $(\frac{i}{2^m}, \frac{i+1}{2^m})$  with dyadic rational endpoints and observe

$$\mathbb{P}\left(\frac{i}{2^m} < Y_n \leq \frac{i+1}{2^m}\right)$$

$$= \mathbb{P}\left(\frac{i}{2^m} \leq \sum_k 2^{-k} Y_{nk} \leq \frac{i+1}{2^m}\right)$$

$$= \mathbb{P}(Y_{n_1} = y_1, \dots, Y_{n_m} = y_m) = 2^{-m}$$

with a.s.

where  $(y_1, \dots, y_m) \in \{0, 1\}^m$  corresponds to  $i, m$

Since these intervals form a  $\pi$ -system generating  $\mathcal{B}((0, 1))$ , we see

$\mathcal{L}(Y_n) = \mu|_{(0, 1)} \forall n$ , and hence the  $Y_n$  form an infinite sequence of iid  $U(0, 1)$  variables.

Prop<sup>n</sup> Let  $(F_n: n \in \mathbb{N})$  be any sequence of probability dist<sup>n</sup> functions on  $\mathbb{R}$ . Then there exist <sup>indep</sup> r.v.s  $(X_n: n \in \mathbb{N})$  defined on  $(\Omega, \mathcal{F}, \mathbb{P}) = ((0, 1), \mathcal{B}, \mu|_{(0, 1)})$

s.t. their prob distributions  $\mathbb{P}X_n = F_n \forall n \in \mathbb{N}$

Proof Take  $Y_n \stackrel{\text{iid}}{\sim} U(0, 1)$ , set  $G_n(y) = \inf \{x: y \leq F_n(x)\}$ , and  $X_n = G_n(Y_n)$ , a r.v. with distribution

$$\mathbb{P}(X_n \leq x) = \mathbb{P}(G_n(Y_n) \leq x)$$

$$= \mathbb{P}(Y_n \leq F_n(x))$$

gen (increases)

$$= F_n(x)$$

□



## §2.5 Convergence of meas $f_n^s$ and rvs

Let  $(E, \mathcal{E}, \mu)$  be a measure space.

- A property defining  $A \in \mathcal{E}$  is said to hold almost everywhere (a.e.) if  $\mu(A^c) = 0$ .

When  $(E, \mathcal{E}, \mu) = (\Omega, \mathcal{F}, \mathbb{P})$  we say  $\mathbb{P}$ -almost surely (a.s.)

A sequence of measurable  $f_n: (E, \mathcal{E}, \mu) \rightarrow \mathbb{R}$  is said to converge  $\mu$ -a.e. to  $f: E \rightarrow \mathbb{R}$  if  $\mu(\{x \in E : f_n(x) \not\rightarrow f(x)\}) = 0$

Next, if  $f_n, f$  are measurable maps on  $E$ , we say that  $f_n \xrightarrow{n \rightarrow \infty} f$  in  $\mu$ -measure if  $\forall \varepsilon > 0$ ,  $\mu(\{x \in E : |f_n(x) - f(x)| > \varepsilon\}) \rightarrow 0$  as  $n \rightarrow \infty$ .

- For r.v.s  $X_n, X$  (so that  $\mu(E) = \mathbb{P}(\Omega) = 1$ ) we say

$X_n \rightarrow X$  almost surely  $X_n \xrightarrow{\text{a.s.}} X$ ,

$X_n \rightarrow X$  in probability  $X_n \xrightarrow{\mathbb{P}} X$

respectively:

For rvs (on  $\mathbb{R}$ ), we say

$X_n \rightarrow X$  in distribution,  $X_n \xrightarrow{d} X$

if the distribution functions

$$F_{X_n}(t) \rightarrow F_X(t) \quad \forall t \in \mathbb{R}$$

- where  $F_X$  is continuous.

Theorem Let  $(f_n : n \in \mathbb{N})$  be a sequence of meas  $f_n$  on  $(E, \mathcal{E}, \mu)$

1) if  $\mu(E) < \infty$ , if  $f_n \xrightarrow{\text{a.e.}} 0 \rightarrow f_n \rightarrow 0$  in measure

2) if  $f_n \rightarrow 0$  in measure, then  $f_{n_k} \rightarrow 0$  a.e. along a subsequence  $n_k$

Proof 1) Let  $\varepsilon > 0$ .

$$\mu(|f_n| \leq \varepsilon) \geq \mu\left(\bigcap_{m \geq n} \overbrace{\{ |f_m| \leq \varepsilon \}}^{A_m}\right)$$

$$\uparrow \mu\left(\bigcup_n \bigcap_{m \geq n} A_m\right) = \mu(|f_n| \leq \varepsilon \text{ eventually})$$

$$\geq \mu(f_n \rightarrow 0 \text{ as } n \rightarrow \infty) = \mu(E) < \infty$$

- Taking complements,  $\lim_n \mu(|f_n| > \varepsilon) = 0$

and so  $f_n \rightarrow 0$  in measure.

L8.4

b) Choose  $\varepsilon = \frac{1}{k}$ ,  $k \in \mathbb{N}$ , select a subsequence  $n_k$  st.

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

By the first Borel-Cantelli lemma,

$$\mu(|f_{n_k}| > \frac{1}{k} \text{ i.o.}) = 0$$

$$\Rightarrow f_{n_k} \rightarrow 0 \text{ a.e.}$$

□

L9.1

Remark 1) The requirement  $\mu(E) < \infty$  is necessary in the previous theorem:

$$f_n = 1_{(n, \infty)} \longrightarrow 0 \text{ a.e. as } n \longrightarrow \infty,$$

● but  $\mu(\{x : |f_n(x)| > \varepsilon\}) = \mu((n, \infty)) = \infty$  ( $\mu$  Lebesgue)

2) Take independent  $(A_n : n \in \mathbb{N})$  s.t.  $P(A_n) = \frac{1}{n} (\rightarrow 0)$

Then  $\sum_n P(A_n) = \infty$ , so by Borel-Cantelli

$$P(\{1_{A_n} = 1 \text{ i.o.}\}) = 1, \text{ so}$$

$$1_{A_n} \not\rightarrow 0 \text{ } P\text{-a.s.}$$

In contrast,  $P(\{1_{A_n} > \varepsilon\}) = P(A_n) = \frac{1}{n} \rightarrow 0$ , so

$$1_{A_n} \rightarrow 0 \text{ in } P \text{ as } n \rightarrow \infty.$$

3) One shows further that  $X_n \xrightarrow{P} X$  then  $X_n \xrightarrow{d} X$

● Moreover, if  $X_n \xrightarrow{d} X$  then  $\exists \tilde{X}_n, \tilde{X} : (\Omega, \mathcal{F}, P) \rightarrow \mathbb{R}$  s.t.

$$\text{Law}(\tilde{X}_n) = \text{Law}(X_n), \quad \text{Law}(\tilde{X}) = \text{Law}(X)$$

and  $\tilde{X}_n \rightarrow \tilde{X}$  a.s. as  $n \rightarrow \infty$ .

Example Consider  $(X_n : n \in \mathbb{N})$  iid with cdf  $P(X_n \leq x) = 1 - e^{-x}$

Consider  $A_n = \{X_n \geq \alpha \log n\}$ ,  $\alpha > 0$

so that  $P(A_n) = e^{-\alpha \log n} = n^{-\alpha}$ , hence

$$\sum_n P(A_n) < \infty \iff \alpha > 1, \text{ so}$$

● by the Borel-Cantelli lemmas,

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

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

hence  $\limsup_n \frac{X_n}{\log n} = 1$  a.s.

### TAIL EVENTS

For  $(X_n : n \in \mathbb{N})$  any sequence of rvs, set

$$\mathcal{T}_n = \sigma(X_{n+1}, X_{n+2}, \dots)$$

$$\mathcal{T} = \bigcap_n \mathcal{T}_n,$$

● where  $\mathcal{T}$  is called the tail- $\sigma$ -algebra

L9.2

### Theorem (Kolmogorov)

Let  $(X_n: n \in \mathbb{N})$  be independent vrs

If  $A \in \mathcal{T}$  then  $IP(A) \in \{0, 1\}$

If  $Y: (\Omega, \mathcal{T}, IP) \rightarrow \mathbb{R}$  is measurable,

then  $Y$  is a.s. constant.

### Remark "0-1-law"

Proof The  $\sigma$ -algebra  $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$

is generated by the  $\pi$ -system

$$A = \{X_1 \leq x_1, \dots, X_n \leq x_n\}, \quad x_i \in \mathbb{R}$$

while  $\mathcal{T}_n$  is generated by the  $\pi$ -system of sets

$$B = \{X_{n+1} \leq x_{n+1}, \dots, X_{n+k} \leq x_{n+k}\}, \quad k \in \mathbb{N}$$

By independence, for any such  $A, B$ ,

$$IP(A \cap B) = IP(A) \cdot IP(B),$$

so by a theorem from earlier, the  $\sigma$ -algebras  $\mathcal{F}_n, \mathcal{T}_n$  are independent.

Then  $\bigcup_n \mathcal{F}_n$  is another  $\pi$ -system generating

$$\mathcal{F}_\infty = \sigma(X_1, X_2, \dots) = \sigma(X_n: n \in \mathbb{N}),$$

so we deduce, again by the theorem from earlier, that  $\mathcal{F}_\infty, \mathcal{T}$  are indep.

But  $\mathcal{T} \subseteq \mathcal{T}_n \subseteq \mathcal{F}_\infty$ , \*whereas\*, so if  $A \in \mathcal{T}$ ,

$A$  is independent from itself and  $IP(A) = IP(A \cap A) = IP(A)^2$ .

Finally, if  $Y$  is  $\mathcal{T}$ -measurable, the

$$Y^{-1}((-\infty, y]) = \{Y \leq y\} \in \mathcal{T}$$

has probability 1 or 0, so  $Y = c$ , [a.s.]

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

□

### 3. Integration

For  $(E, \mathcal{E}, \mu)$  a measure space, and  $f$  a measurable function on  $E$ , we will define its integral

$$\mu(f) = \int_E f d\mu = \int_E f(x) d\mu(x) = \int_E f(x) \mu(dx)$$

whenever  $f \geq 0$ , or when  $f$  is integrable.

Equally we will define the expectation of rvs  $X$  as

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

To start, let us say a function  $f: E \rightarrow \mathbb{R}$  is simple if it is of the form  $f = \sum_{k=1}^m a_k 1_{A_k}$ ,  $a_k \geq 0$ ,  $A_k \in \mathcal{E}$ ,  $m \in \mathbb{N}$ .

For such  $f$ , we set its integral to be

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

which is well-defined (easy) and one further shows

$$1) \mu(\alpha f) = \alpha \mu(f), \quad \mu(f+g) = \mu(f) + \mu(g), \quad f, g \text{ simple}, \alpha \geq 0$$

$$2) f \leq g \Rightarrow \mu(f) \leq \mu(g)$$

$$3) f = 0 \text{ a.e.} \Rightarrow \mu(f) = 0$$

For a general measurable, non-negative

$$f: E \rightarrow [0, \infty]$$

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

Remark: We will see the sup can be realised for a particular  $g$  simple chosen as

$$f_n = 2^{-n} \lfloor 2^n f \rfloor \wedge n$$

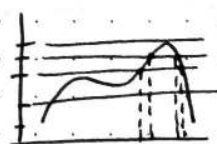
$$= 2^{-n} \sum_{j=0}^{n2^n-1} j 1_{A_{nj}}$$

$$A_{nj} = f^{-1} \left( \frac{j}{2^n}, \frac{j+1}{2^n} \right]$$

Riemann



Lebesgue



get owned

Now if  $0 \leq f \leq g \Rightarrow \mu(f) \leq \mu(g)$

If  $f: E \rightarrow [-\infty, \infty]$  is measurable, then set

$$f^+ = f \vee 0, \quad f^- = (-f) \vee 0,$$

the positive, negative parts

L9.4

Then  $f = f^+ - f^-$ ,  $|f| = f^+ + f^-$

If  $\mu(|f|) < \infty$ , then we say  $f$  is integrable, then we define

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

Clearly,  $|\mu(f)| \leq \mu(|f|) \quad \forall$  integrable  $f$

Theorem (Monotone convergence theorem)

Let  $f_n, f$  be measurable  $(E, \mathcal{E}, \mu) \rightarrow [0, \infty)$ ,

suppose  $f_n \uparrow f$  (pointwise). Then  $\mu(f_n) \uparrow \mu(f)$

Remark  $x_n \uparrow x$  if  $x_n \leq x_{n+1}$ ,  $x_n \rightarrow x$

For (meas) functions  $f_n \uparrow f$  if  $f_n(x) \uparrow f(x)$  for each  $x$ .

Theorem (Monotone convergence)

Let  $f_n, f: (E, \mathcal{E}, \mu) \rightarrow [0, \infty]$  be measurable.

Suppose  $f_n \uparrow f$  (pointwise). Then  $\mu(f_n) \uparrow \mu(f)$ .

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

$M = \sup_n \mu(f_n)$ , so  $\mu(f_n) \uparrow M$  (since  $(f_n)$  monotone increasing)

and since  $f_n \leq f \forall n$ ,  $\mu(f_n) \leq \mu(f) \forall n \Rightarrow M \leq \mu(f)$

We will show that  $\mu(f) \leq M$  via  $\mu(g) \leq M \forall g \text{ simple}, g \leq f$

WLOG, take  $g = \sum_{k=1}^m a_k 1_{A_k}$ ,  $A_k$  disjoint

Define a new simple function

$$g_n = \underbrace{(2^{-n} \lfloor 2^n f_n \rfloor)}_{\bar{f}_n} \wedge g, \quad \text{so that } \bar{f}_n \leq f_n$$

implies  $g_n \leq f_n$ . Since  $f_n \uparrow f$ ,  $\Rightarrow \bar{f}_n \uparrow f$  and since  $f \geq g$ ,

we see  $g_n = \bar{f}_n \wedge g \uparrow f \wedge g = g$

Fix  $\varepsilon > 0$  and define sets

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

and note  $g = a_k$  on  $A_k$ . Since  $g_n \uparrow g$ , we must have  $A_k(n) \uparrow A_k$  ( $n \rightarrow \infty$ )

so since  $\mu$  is a measure,  $\mu(A_k(n)) \uparrow \mu(A_k)$

$$\text{Also, } 1_{A_k} g_n \geq (1-\varepsilon)a_k 1_{A_k(n)} \quad (\text{on } E)$$

so since  $\mu(\cdot)$  is increasing,

$$\mu(1_{A_k} g_n) \geq (1-\varepsilon)a_k \mu(A_k(n))$$

Finally since the  $A_k$  are disjoint, we write

$$g_n = \left( \sum_{k=1}^m 1_{A_k} \right) g_n$$

Now using additivity of simple function integrals,

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

$$\uparrow_{n \rightarrow \infty} (1-\varepsilon) \sum_{k=1}^m a_k \mu(A_k) = (1-\varepsilon) \mu(g)$$

So we see  $\mu(g_n) \leq \mu(f_n) \leq M$

and overall,  $\mu(g) \leq \frac{M}{1-\varepsilon}$  and since  $\varepsilon$  arbitrary, result follows  $\square$

## Some remarks

1) Another way of writing the last result is

$$\lim_n \int f_n d\mu = \lim_n \mu(f_n) \stackrel{!}{=} \mu(f) = \mu(\lim_n f_n) = \int \lim_n f_n d\mu$$

as long as  $0 \leq f_n \uparrow f$  pointwise.

Also, for  $g_n \geq 0$  measurable  $f_n$ 's, we have

$$\sum_n \mu(g_n) = \mu\left(\sum_n g_n\right)$$

2) The requirement  $f_n \uparrow f$  pointwise can be weakened to  $f_n \uparrow f$  a.e.

3) If  $(f_n: \mathbb{N})$ ,  $f$  are measurable,  $f_n \uparrow f$ ,  $\mu(f_1) > -\infty$ ,

then  $\mu(f_n) \uparrow \mu(f)$  as  $n \rightarrow \infty$  (not required that  $f_n \geq 0$ )

The condition  $\mu(f_1) > -\infty$  is necessary as the example

$$f_n = -1_{(n, \infty)} \text{ shows } (\uparrow 0, \mu(f_n) = -\infty \forall n)$$

4) A symmetric version where  $f_n \downarrow f$ ,  $\mu(f_1) < \infty$  implies  $\mu(f_n) \downarrow \mu(f)$  also exists.

Theorem Let  $f, g \geq 0$  measurable functions. Then

a)  $\mu(\alpha f + \beta g) = \alpha \mu(f) + \beta \mu(g)$ ,  $\alpha, \beta \in \mathbb{R}_{\geq 0}$  (additivity)

b)  $g \leq f \Rightarrow \mu(g) \leq \mu(f)$

c)  $\mu(f) = 0 \Leftrightarrow f = 0$  a.e.

Proof a) Take simple functions  $f_n = (2^{-n} \lfloor 2^n f \rfloor) \wedge n$

$$g_n = (2^{-n} \lfloor 2^n g \rfloor) \wedge n$$

so  $0 \leq f_n \uparrow f$ ,  $0 \leq g_n \uparrow g$ ,

and also  $0 \leq \alpha f_n + \beta g_n \uparrow \alpha f + \beta g$ , as  $n \rightarrow \infty$ .

By the monotone convergence theorem we see

$$\mu(f_n) \uparrow \mu(f), \quad \mu(g_n) \uparrow \mu(g), \quad \mu(\alpha f_n + \beta g_n) \uparrow \mu(\alpha f + \beta g)$$

Since  $\mu(\cdot)$  additive on the simple functions,

$$\mu(\alpha f_n + \beta g_n) = \alpha \mu(f_n) + \beta \mu(g_n) \quad \text{and done by above}$$

b) Blindingly obvious

c) If  $f = 0$  a.e., then  $f_n = 0 \forall n$  a.e.  $\Rightarrow \mu(f_n) = 0 \uparrow \mu(f) = 0$  {  $\because f_n = 0$  a.e.  $\forall n$   
 $\because f = 0$  a.e.  
(pointwise limit)  $\square$

Conversely, if  $\mu(f) = 0$ , then  $0 \leq \mu(f_n) \leq \mu(f) = 0 \Rightarrow \mu(f_n) = 0 \forall n$  { somewhat subtle?  $\downarrow$



L10.3

Theorem Let  $f, g: E \rightarrow \mathbb{R}$  be  $\mu$ -integrable,

then 1)  $\forall \alpha, \beta \in \mathbb{R}$ ,  $\mu(\alpha f + \beta g) = \alpha \mu(f) + \beta \mu(g)$  (additivity)

2)  $\mu(g) \leq \mu(f)$  whenever  $g \leq f$

3)  $f=0$  a.e.  $\Rightarrow \mu(f) = 0$

Proof 1) For  $\alpha \geq 0$ ,  $\alpha f$  is also integrable, and

$$\begin{aligned} \mu(\alpha f) &= \mu(\alpha f^+) - \mu(\alpha f^-) \\ &= \alpha \mu(f^+) - \alpha \mu(f^-) \quad (\text{previous thm}) \\ &= \alpha \mu(f) \end{aligned}$$

and combine this with  $\mu(-f) = -\mu(f)$  to get  $\mu(\alpha f) = \alpha \mu(f) \quad \forall \alpha \in \mathbb{R}$

Now set  $h = f + g$  can be written

$$h^+ + f^- + g^- = h^- + f^+ + g^+ \quad (\text{all non-negative})$$

$$\therefore \mu(h^+) + \mu(f^-) + \mu(g^-) = \mu(h^-) + \mu(f^+) + \mu(g^+) \quad \text{by previous theorem}$$

$$\therefore \mu(h) = \mu(f) + \mu(g) \quad \square$$

$$2) \text{ If } f \leq g \Rightarrow \mu(g) - \mu(f) = \mu(\underbrace{g-f}_{\geq 0}) \geq 0$$

$$\text{So } \mu(f) \leq \mu(g)$$

$$3) \text{ If } f=0 \text{ a.e.} \Rightarrow f^+ = f^- = 0 \text{ a.e.}$$

$$\Rightarrow \mu(f^+) = \mu(f^-) = 0$$

$$\Rightarrow \mu(f) = 0 \quad \square$$

Remark about 3)

We cannot expect the converse to hold, but we can check that  $f=0$  a.e.

by checking i)  $\mu(|f|) = 0 \Rightarrow |f| = 0$  a.e.  $\Rightarrow f=0$  a.e.

ii)  $\mu(f1_A) = 0 \quad \forall A \in \mathcal{A}$ , where  $\mathcal{A}$   $\pi$ -system generating  $\mathcal{E}$ , with  $E \in \mathcal{A}$

(uniqueness theorem for measures)

Lemma (Fatou)

Let  $f_n: (E, \mathcal{E}, \mu) \rightarrow [0, \infty)$  be measurable.

Then  $\mu(\liminf_n f_n) \leq \liminf_n \mu(f_n)$

Remark Recall that  $(x_n \in \mathbb{R})$

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

$$\limsup_n x_n \equiv \overline{\lim} x_n = \inf_m \sup_{n \geq m} x_n$$

Note:  $\underline{\lim} f_n, \overline{\lim} f_n$  are measurable

$$\underline{\lim} x_n = \overline{\lim} x_n = x \iff \lim_n x_n = x$$

If  $f_n \rightarrow f$  pointwise, then Fatou's lemma says

$$\mu(f) \leq \underline{\lim} \mu(f_n)$$

Proof For any  $k \geq n$ ,  $\inf_{m \geq n} f_m \leq f_k$

So

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

$\therefore \mu(\inf_{m \geq n} f_m) \leq \inf_{k \geq n} \mu(f_k) \leq \sup_n \inf_{k \geq n} \mu(f_k) = \underline{\lim} \mu(f_k)$

Also, the  $f_n$ 's  $\inf_{m \geq n} f_m \nearrow \sup_n \inf_{m \geq n} f_m$  as  $n \rightarrow \infty$

So by monotone convergence theorem,

$$\mu(\inf_{m \geq n} f_m) \nearrow \mu(\underline{\lim} f_n)$$

The result  $\mu(\underline{\lim} f_n) \leq \underline{\lim} \mu(f_n)$  follows □

Theorem (Dominated convergence)

Let  $f_n, f: (E, \mathcal{E}, \mu) \rightarrow \mathbb{R}$  be measurable  $f_n$ 's,

and suppose  $f_n \rightarrow f$  pointwise on  $E$ ,

and that  $|f_n| \leq g \quad \forall n$ , where  $g$  is  $\mu$ -integrable

Then  $f_n, f$  are integrable, and

$$\mu(f_n) \rightarrow \mu(f) \quad \text{as } n \rightarrow \infty.$$

Proof Taking limits in  $|f_n| \leq g$ , deduce  $|f| \leq g$ ,

so  $\mu(|f|) \leq \mu(g) < \infty \Rightarrow f$  (and  $f_n$ ) is integrable.

Now write

$$0 \leq g \pm f_n \xrightarrow{n \rightarrow \infty} g \pm f = \underline{\lim} (g \pm f_n)$$

So applying Fatou's Lemma twice

$$\begin{aligned} \mu(g) + \mu(f) &= \mu(g+f) = \mu(\underline{\lim} (g+f_n)) \\ &\stackrel{\text{Fatou}}{\leq} \underline{\lim} \mu(g+f_n) = \underline{\lim} (\mu(g) + \mu(f_n)) \\ &= \mu(g) + \underline{\lim} \mu(f_n) \end{aligned}$$

$$\begin{aligned} \mu(g) - \mu(f) &= \mu(\underline{\lim} (g-f_n)) \stackrel{\text{Fatou}}{\leq} \underline{\lim} (\mu(g) - \mu(f_n)) \\ &\leq \mu(g) - \overline{\lim} \mu(f_n) \end{aligned}$$

So collecting these inequalities, obtain

$$\overline{\lim} \mu(f_n) \leq \mu(f) \leq \underline{\lim} \mu(f_n) \leq \overline{\lim} \mu(f_n)$$

$$\therefore \underline{\lim} \mu(f_n) = \mu(f) \quad \square$$

An immediate application:

On  $E = [0, 1]$  (or  $\mu(E) < \infty$ ),

suppose  $f_n \rightarrow f$  pointwise and

$$\sup_n \|f_n\|_\infty = g < \infty$$

Then  $\mu(g) < \infty$ , so by the Dominated Convergence Theorem,

$$\mu(f_n) \rightarrow \mu(f)$$

Theorem (Diff under an integral)

Let  $U \subseteq \mathbb{R}$  be open and let  $f: U \times E \rightarrow \mathbb{R}$

satisfying 1)  $x \mapsto f(t, x)$  is integrable  $\forall t \in U$

2)  $t \mapsto f(t, x)$  is diff'ble  $\forall x \in E$

$$3) \left| \frac{\partial f}{\partial t}(t, x) \right| \leq g(x) \quad \forall t, x$$

s.t.  $g$  is integrable

Then  $x \mapsto \frac{\partial f}{\partial t}(t, x)$  is integrable  $\forall t$ , if  $F(U) \rightarrow \mathbb{R}$ ,

$$F(t) = \int_E f(t, x) d\mu(x) \quad \text{then} \quad \frac{dF}{dt} = \int_E \frac{\partial f}{\partial t}(t, x) d\mu(x)$$

He's wearing airpods!

L11.3

Proof For  $h_n \rightarrow 0$  set

$$g_n(x) = \frac{f(t+h_n, x) - f(t, x)}{h_n} - \frac{\partial f}{\partial t}(t, x)$$

[well defined?  
t fixed!]

$\rightarrow 0$  as  $n \rightarrow \infty$  (pointwise in  $x$ )

By the Mean Value Thm,

$$|g_n(x)| = \left| \frac{\partial f}{\partial t}(\tilde{t}_n, x) - \frac{\partial f}{\partial t}(t, x) \right| \leq 2g(x), \text{ } \mu\text{-integrable}$$

So by the dominated conv theorem,

$$\mu(g_n) \rightarrow \mu(\lim g_n) = 0$$

In other words,

$$\int_E \frac{f(t+h_n, x) - f(t, x)}{h_n} d\mu(x)$$

$$= \frac{F(t+h_n) - F(t)}{h_n} \rightarrow \int_E \frac{\partial f}{\partial t}(t, x) d\mu(x) = \frac{dF}{dt} \quad \square$$

A few more remarks about the Riemann integral

1) One shows that if  $f: [0, 1] \rightarrow \mathbb{R}$  is Riemann-integrable, then it defines a Lebesgue integrable function on  $([0, 1], \mathcal{E}^{\mu}, \mu)$

$\mathcal{E}^{\mu} = \mathcal{M}$  Lebesgue-measurable sets

Lebesgue measure on  $[0, 1]$

and  $\mu(f) = \int_0^1 f(x) dx$  [But  $\exists f$  Riemann integrable that is not Borel-measurable]

But note that  $1_{\mathbb{Q}}$  is not Riemann-integrable, but  $\mu(1_{\mathbb{Q}}) = \mu(\mathbb{Q}) = 0$  so  $1_{\mathbb{Q}}$  is Lebesgue-integrable.

2) For continuous functions on  $[0, 1] \rightarrow \mathbb{R}$ , the fundamental thm of calculus for the Lebesgue integral is proved in the same way as for the Riemann integral.

In fact, Lebesgue proved a stronger / more general assertion to the effect that for  $f: [0,1] \rightarrow \mathbb{R}$  Lebesgue integrable, if  $F(x) = \int_0^x f(y) d\mu(y)$ , then

$$\lim_{h \rightarrow 0} \frac{F(x+h) - F(x)}{h} = \lim_{h \rightarrow 0} \frac{1}{h} \int_x^{x+h} f(y) d\mu(y) = f(x) \quad \mu\text{-a.e. } x$$

("Lebesgue's differentiation theorem")

<<look it up  
in a book>>

Transformations of integrals

Proposition Let  $\phi: [a, b] \rightarrow \mathbb{R}$  be continuously diff, strictly increasing

Then for any Borel meas  $g: [\phi(a), \phi(b)] \rightarrow [0, \infty]$ , we have

$$\int_{\phi(a)}^{\phi(b)} g(y) dy = \int_a^b g(\phi(x)) \phi'(x) dx$$

Proof (sketch, left as exercise)

First check indicators of intervals  $g = \mathbb{1}_{(\phi(a_i), \phi(b_i))}$ ,  $a \leq a_i < b_i \leq b$

in which case the FTC gives the result.

Then apply an approximation argument with the monotone class theorem.  $\square$

More generally, if  $f: (E, \mathcal{E}) \rightarrow (G, \mathcal{G})$  is measurable; and  $\nu = \mu \circ f^{-1}$  is

the image measure on  $\mathcal{G}$ ; then for any map  $g: \mathcal{G} \rightarrow [0, \infty]$ ,

$$\text{then } \mu \circ f^{-1}(g) = \int_G g d\nu = \int_E g(f(x)) d\mu(x) = \int_E g \circ f d\mu = \mu(g \circ f),$$

see Ex Sheet. In particular if  $X: (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow \mathbb{R}$  has law  $\mu_X$ , and if

$g: \mathbb{R} \rightarrow \mathbb{R}$  is Borel, then

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

Prop Let  $f: (E, \mathcal{E}, \mu) \rightarrow \mathbb{R}$  be measurable and define

$$\nu_f(A) = \mu(f \mathbb{1}_A), \quad A \in \mathcal{E}$$

Then  $\nu_f$  defines a new measure on  $\mathcal{E}$  and

$$\nu_f(g) = \int g d\nu_f = \int_E g f d\mu$$

for any  $g: (E, \mathcal{E}) \rightarrow [0, \infty]$  meas.

Proof Exercise.  $\square$

We call  $f$  the density of  $\nu_f$  wrt  $\mu$ .

In particular, if  $\overset{\nu_f}{\mu_X}$  is the law of a random variable on  $\mathbb{R}$ , then we say that  $f$  is the prob density function of  $\nu_f$ . Expectations are then

$$\text{often written as } \mathbb{E} g(X) = \int_{\mathbb{R}} g(x) f(x) d\mu(x)$$

PRODUCT MEASURES & FUBINI'S THEOREM

Let  $(E_1, \mathcal{E}_1, \mu_1)$ ,  $(E_2, \mathcal{E}_2, \mu_2)$  be finite measure spaces ( $\mu_i(E_i) < \infty$ )

We define 'rectangles'

$$A_1 \times A_2 = \{ (a_1, a_2) \in E_1 \times E_2 : a_1 \in A_1, a_2 \in A_2 \}$$

and the product space  $E = E_1 \times E_2$ , on which the family of subsets

$$\mathcal{A} = \{ A_1 \times A_2 : A_1 \in \mathcal{E}_1, A_2 \in \mathcal{E}_2 \}$$

defines a  $\pi$ -system. We define the product  $\sigma$ -algebra

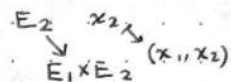
$$\mathcal{E} = \mathcal{E}_1 \otimes \mathcal{E}_2 = \sigma(\mathcal{A})$$

We need two lemmas:

Lemma Let  $f: E \rightarrow \mathbb{R}$  be  $\mathcal{E}$ -measurable

Then for any  $x_1 \in E_1$ , the map

$$x_2 \mapsto f(x_1, x_2) \text{ is } \mathcal{E}_2\text{-measurable.}$$



Proof We use the monotone class theorem with

$\mathcal{A}$  the  $\pi$ -system generating  $\mathcal{E}$  and

vector space  $\mathcal{V} = \{ f: E \rightarrow \mathbb{R} \text{ bounded, } \mathcal{E}\text{-meas s.t. Lemma holds} \}$ .

Then clearly  $1_A \in \mathcal{V} \forall A \in \mathcal{A}$  since  $1_A = 1_{A_1}(x_1) 1_{A_2}(x_2) = c 1_{A_2}(x_2)$

is  $\mathcal{E}_2$ -measurable.

Then  $f_n \in \mathcal{V}$  s.t.  $0 \leq f_n \uparrow f$  then

$$f(x_1, \cdot) = \lim_n f_n(x_1, \cdot)$$

is also  $\mathcal{E}_2$ -measurable as the limit of  $\mathcal{E}_2$ -meas  $f_n$ 's, hence by the monotone class theorem  $\mathcal{V}$  contains all bounded meas  $f$ 's.

The general meas  $f$  can be approx by  $f_n = (-n) \vee f \wedge n \uparrow f$ , so satisfies the condition of the lemma too.  $\square$

L12.3

Lemma Let  $f: (E, \mathcal{E}) \rightarrow [-\infty, \infty]$  be bounded or non-negative, and measurable. Then define

$$f_1(x_1) = \int_{E_2} f(x_1, x_2) \cdot d\mu_2(x_2)$$

If  $f$  is bounded then  $f_1: E_1 \rightarrow \mathbb{R}$  is bounded,  $\overset{E_1}{\leftarrow}$  measurable.

If  $f$  is non-negative then  $f_1: E_1 \rightarrow \mathbb{R}$  is non-negative,  $\mathcal{E}_1$ -meas.

Proof Note that  $f_1$  is well-defined as an integral by the previous lemma.

We apply again a monotone class argument with  $\pi$ -system  $\mathcal{A}$  and vector space

$$\mathcal{V} = \{ f: E \rightarrow \mathbb{R}, \text{ bounded meas., lemma is true} \}$$

To see  $1_A \in \mathcal{V}$  for  $A \in \mathcal{A}$ , notice that for  $1_{A_1 \times A_2}$ , we have

$$f_1(x_1) = 1_{A_1}(x_1) \mu_2(A_2) \quad \text{which is } \geq 0, \text{ bounded } \overset{E_1}{\leftarrow} \text{ meas.}$$

$\mu_2(E_2) < \infty$

Next by the monotone convergence theorem ( $x_1$  fixed), (applied to  $\mu_2$ -integral)

$$\int_{E_2} f(x_1, x_2) \cdot d\mu_2(x_2) = \lim_n \underbrace{\int_{E_2} f_n(x_1, x_2) \cdot d\mu_2(x_2)}_{\text{are } \mathcal{E}_1\text{-meas}}$$

$f$  monotone  $f_n \uparrow$

so the LHS is  $\mathcal{E}_1$ -meas as the limit of  $\mathcal{E}_1$ -meas  $f_n$ 's.

Clearly  $f_1 \geq 0$  if all  $f_n \uparrow$  are non-negative, and if  $f_n$  are bounded the limit is bounded by  $\|f\|_\infty \mu_2(E_2) < \infty$ .

So  $\mathcal{V}$  contains all bounded measurable  $f$ 's by the monotone class theorem.  $\square$

Theorem (Product measure)

There exists a unique  $\mu = \mu_1 \otimes \mu_2$  measure on  $(E, \mathcal{E})$  s.t.

$$\mu(A_1 \times A_2) = \mu_1(A_1) \mu_2(A_2) \quad (*)$$

$\forall A_1 \in \mathcal{E}_1, A_2 \in \mathcal{E}_2$ .

Proof Since  $\mathcal{A}$  is a  $\pi$ -system generating  $\mathcal{E} = \sigma(\mathcal{A})$ , if such a measure exists, it is necessarily unique. To prove existence, define

$$\mu(A) = \int_{E_1} \left( \int_{E_2} 1_A(x_1, x_2) \cdot d\mu_2(x_2) \right) \cdot d\mu_1(x_1) \quad \forall A \in \mathcal{E}$$

This is well-defined by the previous lemmas.

Clearly  $\mu(\emptyset) = 0$ , and it satisfies  $(*)$  since for  $A = A_1 \times A_2$ ,

$$\mu(A) = \int_{E_1} 1_{A_1}(x_1) \left( \int_{E_2} 1_{A_2}(x_2) \cdot d\mu_2(x_2) \right) \cdot d\mu_1(x_1) = \mu_1(A_1) \mu_2(A_2)$$



L12.4

To check countable additivity, let  $A_n \in \mathcal{E}$  be disjoint, so

$$1_{\bigcup_n A_n} = \sum_n 1_{A_n} = \lim_{N \rightarrow \infty} \sum_{n \in N} 1_{A_n} \quad (\text{monotone limit}), \text{ so}$$

$$\mu(\bigcup_n A_n) = \int_{E_1} \left( \int_{E_2} \sum_n 1_{A_n}(x_1, x_2) d\mu_2(x_2) \right) d\mu_1(x_1)$$

$$= \int_{E_1} \sum_n \left( \int_{E_2} 1_{A_n}(x_1, x_2) d\mu_2(x_2) \right) d\mu_1(x_1)$$

↓  
monotone  
convergence

$$= \sum_n \int_{E_1} \left( \int_{E_2} 1_{A_n}(x_1, x_2) d\mu_2(x_2) \right) d\mu_1(x_1)$$

$$= \sum_n \mu(A_n), \text{ so } \mu \text{ is indeed a measure}$$

Remark The construction is symmetric in  $1 \leftrightarrow 2$

Remark It is clear that on  $\bar{\mathcal{E}} = \mathcal{E}_2 \otimes \mathcal{E}_1$ , we can define  $\bar{\mu} = \mu_2 \otimes \mu_1$ , and if  $\bar{f}: E_2 \times E_1 \rightarrow [0, \infty]$  is defined as

$$\bar{f}(x_2, x_1) = f(x_1, x_2), \text{ then}$$

$$\bar{\mu}(\bar{f}) = \mu(f), \text{ simply because}$$

$$\mu_1(A_1)\mu_2(A_2) = \mu_2(A_2)\mu_1(A_1) \text{ on } \pi\text{-system } \mathcal{A}$$

### Theorem (Fubini)

Consider a product space  $(E, \mathcal{E}, \mu) = (E_1 \times E_2, \mathcal{E}_1 \otimes \mathcal{E}_2, \mu_1 \otimes \mu_2)$   $\uparrow \mu_1, \mu_2$   
finite

a) Let  $f: (E, \mathcal{E}, \mu) \rightarrow [0, \infty]$ . Then

$$\begin{aligned} \mu(f) &\stackrel{(1)}{=} \int_{E_1} \left( \int_{E_2} f(x_1, x_2) d\mu_2(x_2) \right) d\mu_1(x_1) \\ &\stackrel{\text{symm}}{=} \int_{E_2} \left( \int_{E_1} f(x_1, x_2) d\mu_1(x_1) \right) d\mu_2(x_2) \end{aligned}$$

b) Let  $f: (E, \mathcal{E}, \mu) \rightarrow \mathbb{R}$  be  $\mu$ -integrable

$$\text{Set } A_1 = \{x \in E_1 : \int_{E_2} |f(x_1, x_2)| d\mu_2(x_2) < \infty\}$$

$$\begin{aligned} \text{and } f_1(x_1) &= \int_{E_2} f(x_1, x_2) d\mu_2(x_2) \text{ for } x_1 \in A_1 \\ &= 0 \text{ otherwise} \end{aligned}$$

Then  $\mu_1(A_1^c) = 0$  and  $f_1$  is  $\mu_1$ -integrable and

$$\mu_1(f_1) = \mu(f)$$

Proof a) By the definition of the product measure  $\mu$  in the previous proof, we know that the result is true (i.e. (1) holds) for  $f = 1_{A_1 \times A_2}$ ,

so by uniqueness<sup>(1)</sup>, this extends to all  $A \in \mathcal{E}$ .

By linearity of the  $\mu, \mu_1, \mu_2$  integrals, (1) extends to all simple functions

For general  $f$  take a simple approximation  $f_n = \lfloor 2^n f \rfloor \frac{1}{2^n} \wedge n$ , so

$0 \leq f_n \uparrow f$ , so (1) holds for  $f_n$  and by monotone convergence theorem,

we see  $\mu(f_n) \uparrow \mu(f)$ , and also  $\forall x_1 \in E_1$ ,

$$0 \leq \int_{E_2} f_n(x_1, x_2) d\mu_2(x_2) \uparrow \int_{E_2} f(x_1, x_2) d\mu_2(x_2)$$

$$\begin{aligned} \text{so overall } \mu(f) &= \lim_n \mu(f_n) \stackrel{(1)}{=} \lim_n \int_{E_1} \left( \int_{E_2} f_n(x_1, x_2) d\mu_2(x_2) \right) d\mu_1(x_1) \\ &\stackrel{(1)}{=} \int_{E_1} \left( \int_{E_2} f(x_1, x_2) d\mu_2(x_2) \right) d\mu_1(x_1) \end{aligned}$$

which proves a)

L13.2

b)  $f: E \rightarrow \mathbb{R}$  is s.t.  $\mu(|f|) < \infty$

The map  $x_1 \mapsto \int_{E_2} |f(x_1, x_2)| d\mu_2(x_2)$   
 $E_1 \rightarrow [0, \infty]$

is  $\mathcal{E}_1$ -measurable by the lemma from last lecture, ~~and~~ by a) the  $\mu_1$ -integral of this map satisfies

$$\int_{E_1} \left( \int_{E_2} |f(x_1, x_2)| d\mu_2(x_2) \right) d\mu_1(x_1) = \mu(|f|) < \infty$$

In particular,  $\mu_1(E_1 \setminus A_1) = 0$

So the map  $f_1$  is  $\mu_1$ -integrable. Now we can decompose

$$f_1^{(\pm)} = \int_{E_2} f^{\pm}(x_1, x_2) d\mu_2(x_2)$$

and  $f_1 = (f_1^{(+)} - f_1^{(-)}) 1_{A_1}$ , by linearity of  $\mu_2$ -integral ~~and~~

Then using a) we deduce

$$\begin{aligned} \mu(f) &= \mu(f^+) - \mu(f^-) \\ &= \mu_1(f_1^{(+)} - f_1^{(-)}) \\ &= \mu_1(f_1) \end{aligned}$$

□

Remarks 1) Clearly  $\mu_1(f_1) = \mu_1(f_1 1_{A_1})$

2) The theorem extends to  $\sigma$ -finite measures (such as Lebesgue-measure on  $\mathbb{N}$ )

3) By a  $\pi$ -system argument, check

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

so by induction we can extend the previous arguments to any  $n \in \mathbb{N}$

In particular, on  $(\mathbb{R}^n, \mathcal{B}^{\otimes n})$ ,  $\mathcal{B}^{\otimes n} = \bigotimes_{i=1}^n \mathcal{B}(\mathbb{R})$

one defines the  $n$ -dimensional Lebesgue measure  $\mu^n = \bigotimes_{i=1}^n \mu$ ,

where  $\mu$  is standard Lebesgue measure on  $\mathbb{R}$ . The resulting integral

$$\begin{aligned} \text{is written as } \int_{\mathbb{R}^n} f d\mu^n &= \int_{\mathbb{R}^n} f(x) dx \\ &= \int_{\mathbb{R}} \dots \int_{\mathbb{R}} f(x_1, \dots, x_n) d\mu_1(x_1) \dots d\mu_n(x_n) \end{aligned}$$

for  $f: (\mathbb{R}^n, \mathcal{B}^{\otimes n}) \rightarrow \mathbb{R}$ .

Product prob spaces & independence

Prop Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a prob space, and let  $(E_i, \mathcal{E}_i)$ ,  $i=1, \dots, n$  be measurable spaces, with product  $(E, \mathcal{E}) = (\prod_{i=1}^n E_i, \otimes_{i=1}^n \mathcal{E}_i)$ .

Consider a measurable map

$$X(\omega) = (X_1(\omega), \dots, X_n(\omega)), \quad X: \Omega \rightarrow E$$

TFAE a)  $X_1, \dots, X_n$  are independent

$$b) \mu_X = \mu_{X_1} \otimes \dots \otimes \mu_{X_n}$$

c)  $\forall f_1, \dots, f_n$  bounded  $\overset{\mathcal{E}_i}{\text{meas}}$  on  $E_i$ ,  $i=1, \dots, n$

$$\text{then } \mathbb{E} \left( \prod_{k=1}^n f_k(X_k) \right) = \prod_{k=1}^n \mathbb{E} (f_k(X_k))$$

Proof Set  $\nu = \mu_{X_1} \otimes \dots \otimes \mu_{X_n}$  which on the  $\pi$ -system

$$A = \left\{ \prod_{k=1}^n A_k : A_k \in \mathcal{E}_k \right\} \text{ generating } \mathcal{E}$$

$$\begin{aligned} \text{satisfies } \forall A \in A, \quad \mu_X(A) &= \mathbb{P}(X_k \in A_k \forall k) \\ &= \mathbb{P} \left( \bigcap_k \{X_k \in A_k\} \right) \\ &= \prod_k \mathbb{P}(X_k \in A_k) \quad \downarrow \text{ indep} \\ &= \prod_k \mu_{X_k}(A_k) \\ &= \nu(A) \end{aligned}$$

which by uniqueness theorem yields  $\mu_X = \nu$ . So a)  $\Rightarrow$  b).

Next suppose b) holds. Use Fubini's theorem  $n$ -times to see

$$\begin{aligned} \mathbb{E} \left( \prod_{k=1}^n f_k(X_k) \right) &= \int_E \prod_{k=1}^n f_k(x_k) d\mu_{X \in E}(x) \\ &= \int_E \prod_{k=1}^n f_k(x_k) d\mu_{X_k}(x_k) \quad \downarrow \text{ by a)} \\ &= \prod_{k=1}^n \int_{E_k} f_k(x_k) d\mu_{X_k}(x_k) \quad \downarrow \text{ Fubini} \\ &= \prod_{k=1}^n \mathbb{E} (f_k(X_k)) \end{aligned}$$

So b)  $\Rightarrow$  c)

Finally, c)  $\Rightarrow$  a) by taking  $f_k = 1_{A_k}$ ,  $A_k \in \mathcal{E}_k$ ,  $k=1, \dots, n$  □

L13.4

One can in fact construct infinite product prob spaces.

Suppose  $(\Omega_i, \mathcal{F}_i, \mathbb{P}_i)_{i=1}^{\infty}$  and set  $\Omega = \prod_{i=1}^{\infty} \Omega_i$

On  $\Omega$  we define cylinder subsets

$$\mathcal{C} = \left\{ C \subseteq \Omega : C = A \times \prod_{i \geq n} \Omega_i, A \in \bigotimes_{i=1}^n \mathcal{F}_i, n \in \mathbb{N} \right\}$$

which is a  $\pi$ -system generating the 'cylindrical'  $\sigma$ -algebra  $\mathcal{F} = \sigma(\mathcal{C})$

Then  $\exists!$   $\nu$  on  $\mathcal{F}$  s.t.

$$\nu(C) = (\nu_1 \otimes \dots \otimes \nu_n)(A)$$

extending a sequence of prob measures  $\nu_1, \dots$  to  $\sigma(\mathcal{C})$ . (Kolmogorov's extension thm.)

Specifically, ~~we~~ we can in this way realise an  $\infty$  seq

of independent rvs with law  $\nu_i$ ;  $i=1, \dots$  by just taking coordinate

projection  $X_{ni}(\omega) = \omega_i$ ;  $\omega \in \Omega$ .

$L^p$ -spaces, norms, inequalities

Let  $(E, \mathcal{E}, \mu)$  be a measure space, and let  $p \in [1, \infty]$ .

Then we define spaces

$$L^p(E, \mathcal{E}, \mu) = L^p(\mu) = L^p \\ = \{ f \text{ measurable, } \|f\|_p < \infty \}$$

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

$$\|f\|_\infty = \operatorname{ess\,sup}_{x \in E} |f(x)| = \inf \{ \lambda \in \mathbb{R} : f \leq \lambda \text{ a.e.} \}$$

Clearly if  $\mu(E) < \infty$  then

$$\|f\|_p \leq \|f\|_\infty (\mu(E))^{1/p}, \text{ so in this case}$$

$$L^\infty \subseteq L^p \quad \forall p.$$

We say  $f_n \rightarrow f$  in  $L^p$  as  $n \rightarrow \infty$  if  $\|f_n - f\|_p \rightarrow 0$  as  $n \rightarrow \infty$ .

Markov's (Chebyshev's) inequality

Prop Let  $f \geq 0$  meas. Then  $\forall \lambda \geq 0$ ,

$$\mu(\{x \in E : f(x) \geq \lambda\}) = \mu(f \geq \lambda) \leq \left( \frac{\lambda}{\mu(f)} \right)^{-1}$$

Proof Integrate wrt  $\mu$  the inequality

$$\lambda 1_{\{f \geq \lambda\}} \leq f \quad \text{on } E. \quad \square$$

So if  $g \in L^p(\mu)$ , then applying Markov's ineq. to  $f = |g|^p$  gives

$$\begin{aligned} \mu(|g| > \lambda) &= \mu(|g|^p > \lambda^p) \\ &\leq \frac{\|g\|_p^p}{\lambda^p} = O(\lambda^{-p}) \quad \text{as } \lambda \rightarrow \infty. \end{aligned}$$

Jensen's inequality

Let  $I \subseteq \mathbb{R}$  be an interval. A map  $c: I \rightarrow \mathbb{R}$  is convex if

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

For Since  $c$  is continuous on int  $I$ , one shows that  $c$  is Borel

One also shows that a convex function (equivalently) satisfies

$$\forall x < t < y \text{ in } I, \quad \frac{c(t) - c(x)}{t - x} \leq \frac{c(y) - c(t)}{y - t} \quad (0)$$

Lemma For  $c: I \rightarrow \mathbb{R}$  convex and any  $m \in \text{int } I$ , there exist  $a, b \in \mathbb{R}$  s.t.  $c(x) \geq ax + b \quad \forall x \in I$ , with equality at  $x = m$ .

Proof Applying (0) with  $t = m$  we set

$$a = \sup_{x < m} \left\{ \frac{c(m) - c(x)}{m - x} : x \in I \right\}$$

which exists by (0). Now for  $y > m$ , by (0) we have

$$a \leq \frac{c(y) - c(m)}{y - m} \quad \text{or} \quad c(y) \geq a(y - m) + c(m) \\ = ay + b \quad \text{for } b = c(m) - am.$$

For  $x < m$ , we know

$$\frac{c(m) - c(x)}{m - x} \leq a \quad \text{so} \quad c(x) \geq a(x - m) + c(m) \\ = ax + b \quad \Rightarrow$$

Also,  $c(m) = am + b$ , so we are done. □

Theorem (Jensen's inequality).

Let  $X$  be an integrable r.v. ( $\mathbb{E}|X| < \infty$ ) taking values in  $I \subset \mathbb{R}$ .

Let  $c: I \rightarrow \mathbb{R}$  be convex. Then  $\mathbb{E}c(X)$  is well-defined, and

$$\mathbb{E}c(X) \geq c(\mathbb{E}X)$$

Proof Assume first  $m = \mathbb{E}X \in \text{int } I$ .

Now by the previous lemma we see

$$c(X) \geq aX + b \quad \text{and} \quad \mathbb{E}c^-(X) \leq |a|\mathbb{E}|X| + |b| < \infty$$

since  $X$  integrable

$$\therefore \mathbb{E}c(X) = \mathbb{E}c^+(X) - \mathbb{E}c^-(X) \text{ is well defined in } (-\infty, \infty]$$

Now integrating the preceding ineq gives

$$\mathbb{E}c(X) \geq a\mathbb{E}X + b = am + b = c(m) = c(\mathbb{E}X) \quad \text{as desired}$$

If  $m = \mathbb{E}X$  lies at  $\inf I$  or  $\sup I$  then  $X = \text{const. a.s.}$  and so

$$\mathbb{E}c(X) = c(\mathbb{E}X)$$

$\square$

L14.3

A direct implication, with convex function  $c(x) = |x|^{q/p}$ ,  $1 \leq p < q < \infty$ ,  
 is  $\|X\|_p = (\mathbb{E}|X|^p)^{1/p} = (c(\mathbb{E}|X|^p))^{1/q}$

$$\begin{aligned} &\leq \underset{\text{Jensen}}{(\mathbb{E}(c(|X|^p)))^{1/q}} \\ &= (\mathbb{E}|X|^q)^{1/q} = \|X\|_q \quad \Rightarrow L^q(P) \subseteq L^p(P) \end{aligned}$$

for all  $p \leq q$ .

### Hölder and Minkowski's inequality

Theorem (Hölder), C-S for  $p=q=2$

Let  $p, q \in [1, \infty]$  s.t.  $\frac{1}{p} + \frac{1}{q} = 1$  ("conjugate")

Then  $\mu(|fg|) \leq \|f\|_p \|g\|_q \quad \forall f, g \text{ meas.}$

Proof If  $\|f\|_p = \infty$  or  $\|g\|_q = \infty$  ✓

and if  $f=0$  or  $g=0$  a.e. ✓

Then  $\|f\|_p \neq 0$  as  $d\mu$   $|f|^p = 0$  a.e.  $\Rightarrow f=0$  a.e.

We can thus divide desired ineq by  $\|f\|_p$  and assume wlog  $\|f\|_p = 1$ .

In particular,  $\mu(A) = \int_A |f|^p d\mu$ ,  $A \in \mathcal{E}$

defines a p.m. on  $(\mathcal{E}, \mathcal{E})$  with density  $|f|^p$ .

So we can write, noting also that  $q(p-1) = p$  for conjugate indices,

$$\begin{aligned} \mu(|fg|) &= \int_{\mathcal{E}} |fg| d\mu \\ &= \int_{\mathcal{E}} |g| \frac{|f|^p}{|f|^{p-1}} \mathbb{1}_{\{|f|>0\}} d\mu \end{aligned}$$

$$= \mathbb{E} \left[ \frac{|g|}{|f|^{p-1}} \mathbb{1}_{\{|f|>0\}} \right]$$

$$L^q(P) \subseteq L^1(P) \leq \left( \mathbb{E} \left[ \frac{|g|^q}{|f|^{q(p-1)}} \mathbb{1}_{\{|f|>0\}} \right] \right)^{1/q}$$

$$= \left( \int_{\mathcal{E}} |g|^q \frac{|f|^p}{|f|^p} \mathbb{1}_{\{|f|>0\}} d\mu \right)^{1/q}$$

$$\leq \mu(|g|^q)^{1/q} = \|g\|_q \|f\|_p$$

□



Theorem (Minkowski)

Let  $p \in [1, \infty]$ ,  $f, g$  measurable. Then

$$\|f+g\|_p \leq \|f\|_p + \|g\|_p \quad (\Delta\text{-ineq. for } L^p\text{-"norms"})$$

Proof  $p=1, \infty$  are clear. Also if  $\|f\|_p = \infty$  or  $\|g\|_p = \infty$  the result is also clear. So assume  $q/w$ .

Using the basic (pointwise) inequality

$$|f+g|^p \leq 2^p (|f|^p + |g|^p) \quad \text{we see}$$

$$\mu(|f+g|^p) \leq 2^p (\|f\|_p^p + \|g\|_p^p) < \infty, \text{ so } f+g \in L^p$$

If  $\|f+g\|_p = 0$ , nothing to prove.

So assume  $> 0$ , in particular

$$\mu(|f+g|^p) = \|f+g\|_p^p > 0, \text{ and so}$$

for conjugate  $p, q$ ,

$$\| |f+g|^{p-1} \|_q = (\mu(|f+g|^p))^{1-\frac{1}{p}}$$

Now we use Hölder's inequality

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

$$\stackrel{\text{Hölder}}{\leq} \left( \int_E |f+g|^{q(p-1)} d\mu \right)^{1/q} \left( \int |f|^p d\mu \right)^{1/p}$$

$$+ \left( \int_E |f+g|^{q(p-1)} d\mu \right)^{1/q} \left( \int |g|^p d\mu \right)^{1/p}$$

$$= (\|f\|_p + \|g\|_p) (\|f+g\|_p^{p/q})$$

so dividing by  $\|f+g\|_p^{p/q} > 0$  we obtain

$$\|f+g\|_p^{p-\frac{p}{q}} \leq \|f\|_p + \|g\|_p$$

which proves the theorem since  $p(1-\frac{1}{q}) = 1$ .  $\square$

By linearity of  $\int \cdot d\mu$  and Minkowski's inequality, the  $\|\cdot\|_p$ -functionals satisfy 1) + 2), but not 3); since  $\|f\|_p = 0 \Rightarrow |f|^p = 0$  a.e.  $\Rightarrow f = 0$  a.e.,

with the qualification 'a.e.':

Define equivalence classes  $[f] = \{h \text{ meas.}; \text{ s.t. } h = f \text{ a.e.}\}$ , we can define

$$\begin{aligned} \mathcal{L}^p(\mu) &= L^p(\mu) / \{h \text{ meas.}, h = 0 \mu \text{ a.e.}\} \\ &= \{[f] : f \in L^p\} \end{aligned}$$

which equipped with the  $\|\cdot\|_p$ -norm is a normed vector space ( $[0] = 0$ ).

Since  $\|[f]\|_p = \|f\|_p$  this distinction of spaces is often notationally suppressed:

A normed space  $(V, \|\cdot\|)$  is called complete if every Cauchy sequence  $(v_n)$  in  $V$  converges to some  $v \in V$ . More precisely, recall that  $v_n$  is Cauchy for  $\|\cdot\|$  if  $\forall \varepsilon > 0, \exists N \in \mathbb{N}$  s.t.  $\forall m, n \gg N,$

$$\|v_n - v_m\| \leq \varepsilon,$$

and in a complete space,  $\exists v \in V$  s.t.  $v_n \rightarrow v$ .

Terminology a complete normed linear space is called a Banach space

Theorem ( $\mathcal{L}^p$  is a Banach space)

Let  $1 \leq p < \infty$ , and let  $(f_n : n \in \mathbb{N})$  be s.t.

$$\|f_n - f_m\|_p \rightarrow 0 \text{ as } m, n \rightarrow \infty \text{ (Cauchy for } L^p\text{-norm)}$$

Then  $\exists f \in L^p$  s.t.  $\|f_n - f\|_p \rightarrow 0$  as  $n \rightarrow \infty$ .

Proof ( $p = \infty$  exercise)

By hypothesis we can find a subsequence  $n_k$  ( $\varepsilon = 2^{-k}$ ) s.t.

$$\|f_{n_{k+1}} - f_{n_k}\|_p \leq 2^{-k} \quad \forall k \in \mathbb{N},$$

$$\text{so } S = \sum_{k=1}^{\infty} \|f_{n_{k+1}} - f_{n_k}\|_p < \infty$$

By Minkowski's inequality, for any finite integer  $K$ ,

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

So by the monotone convergence theorem,

$$\left\| \sum_{k=1}^{\infty} |f_{n_{k+1}} - f_{n_k}| \right\|_p \leq S$$

So in particular

$$\sum_{k=1}^{\infty} |f_{n_{k+1}} - f_{n_k}| < \infty \quad \text{a.e.}; \quad \text{hence } \forall x \in A, \quad \mu(E \setminus A) = 0,$$

the real series  $\sum_{k=1}^K (f_{n_{k+1}}(x) - f_{n_k}(x)) = f_{n_{K+1}}(x) - f_{n_0}(x)$

so by the completeness of  $\mathbb{R}$ ,  $f_{n_{k+1}}(x) \rightarrow \lim_{K \rightarrow \infty} f_{n_k}(x)$  as  $K \rightarrow \infty$

for  $x \in A$ . Define

$$f(x) = \begin{cases} \lim_{k \rightarrow \infty} f_{n_k}(x), & \text{for } x \in A \\ 0 & \text{o/w} \end{cases} \quad (\text{meas})$$

and by what precedes we have shown that

$$f_{n_k} \rightarrow f \quad \text{a.e.}$$

Now let  $\varepsilon > 0$  be fixed and choose  $N$  large enough s.t.

$$\|f_n - f_m\|_p^p < \varepsilon \quad \forall m, n \geq N.$$

$$\text{Then } \|f_n - f\|_p^p = \mu(|f_n - f|_p^p)$$

$$= \mu\left(\lim_K |f_n - f_{n_k}|^p\right)$$

$$\stackrel{\text{Fatou}}{\leq} \lim_K \mu(|f_n - f_{n_k}|^p) \stackrel{\text{Cauchy prop}}{\leq} \varepsilon$$

So in particular,  $f \in L^p$ ,

$$\|f\|_p \leq \|f - f_N\|_p + \|f_N\|_p < \infty \quad (N \text{ fixed})$$

and  $f_n \rightarrow f$  in  $L^p$ .  $\square$

Remark If  $f_n \in C([0,1])$  or  $f_n$  is simple, and Cauchy for  $\|\cdot\|_1$  ( $\mu$  Lebesgue measure) on  $(0,1)$ , then  $\exists f \in L^1(\mu)$  s.t.  $f_n \rightarrow f$  in  $L^1(\mu)$ . One further shows that  $C([0,1])$  or  $V = \{f \text{ simple}\}$  are dense in  $L^1(\mu)$  for  $\|\cdot\|_1$ -norm ( $\forall f \in L^1(\mu) \exists v_f \in C([0,1])$ ;  $v_f \in V$  resp s.t.  $\|f - v_f\|_1 < \varepsilon$ ;  $\varepsilon$  arbitrary). In this sense,  $L^1(\mu)$  is the completion of  $C([0,1])$  or  $V$  for the  $\|\cdot\|_1$ -norm. (Same for  $L^p$ ,  $p < \infty$ )

$L^2(\mu)$  as a Hilbert Space

A symmetric bilinear map  $\langle \cdot, \cdot \rangle$ .

$$(v, w) \mapsto \langle v, w \rangle; V \times V \rightarrow \mathbb{R}$$

on a vector space  $V$  is called an inner product if

$$\langle v, v \rangle \geq 0, \quad = 0 \text{ iff } v = 0.$$

Then  $\|v\| = \sqrt{\langle v, v \rangle}$  is a norm on  $V$ .

Then  $L^2(\mu)$  is an inner product space for

$$\langle f, g \rangle = \int_E fg \, d\mu, \quad \text{inducing the norm } \|\cdot\|_2.$$

A complete inner product space (such as  $L^2(\mu)$ ) is called a Hilbert space.

Basic geometric properties are

$$\bullet \text{ 1) (Pythagoras) } \|f+g\|_2^2 = \|f\|_2^2 + 2\langle f, g \rangle + \|g\|_2^2.$$

We say  $f$  is orthogonal to  $g$  in  $L^2$  if  $\langle f, g \rangle = \int_E fg \, d\mu = 0$ .

2) (parallelogram identity)

$$\|f+g\|_2^2 + \|f-g\|_2^2 = 2\|f\|_2^2 + 2\|g\|_2^2.$$

~~Theorem~~ For  $V \subseteq L^2$ , we define the orthogonal complement

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

A subset  $V$  of  $L^2$  is closed if for any  $f_n \in V$  s.t.  $f_n \rightarrow f$  in  $L^2$  we know  
(or  $L^2$ )  $f \in V$  ( $f = v$  a.e.,  $v \in V$ ).

Theorem (orthogonal projection)

Let  $V \subseteq L^2$  be a closed vector subspace (of  $L^2$ )

Then for each  $f \in L^2$  there exists a (a.e. unique) orthogonal decomposition

$$f = v + u, \quad v \in V, \quad u \in V^\perp.$$

s.t.  $\|f - v\|_2 \stackrel{(*)}{\leq} \|f - g\|_2 \quad \forall g \in V$ , with equality iff  $v = g$  a.e.

[We call  $v$  the orthogonal projection of  $f$  onto  $V$ .]

Proof  $\|\cdot\| = \|\cdot\|_2$  For this proof

Define a minimal distance:  $d(f, V) = \inf_{g \in V} \|f - g\|$

and take a sequence  $g_n \in V$  s.t.  $\|f - g_n\| \rightarrow d(f, V)$ .

By the  $\sum_{j=1}^n \vec{a}_j$ -Law  $\rangle m, n \in \mathbb{N}$

$$2 \|f - g_n\|^2 + 2 \|f - g_m\|^2 = \underbrace{\|2(f - \frac{g_m + g_n}{2})\|^2}_{\in V} + \|g_n - g_m\|^2$$

$$\geq 4 d(f, V)^2$$

so rearranging,

$$0 \leq \|g_n - g_m\|^2 \leq 2(\|f - g_n\|^2 + \|f - g_m\|^2) - 4d(f, V)^2$$

$$\rightarrow 0 \text{ as } n, m \rightarrow \infty$$

So we conclude that  $g_n$  is Cauchy for  $\|\cdot\|$ , hence  $\rightarrow g$  in  $L^2$ , and since  $V$  was closed,  $g \in V$  too

Then  $\|f - g\| = \lim \|f - g_n\| = d(f, V)$  as desired,

so  $g$  indeed minimises the distance and (+) holds (a.e. shenanigans.)

In particular the map

$$F: t \mapsto \|f - (g + th)\|^2, \quad t \in \mathbb{R}, h \in V$$

is minimised at  $t=0$ , and

$$F(t) = \|f - g\|^2 - 2t \langle f - g, h \rangle + t^2 \|h\|^2$$

$$F'(t) = -2 \langle f - g, h \rangle + 2t \|h\|^2$$

$$F''(t) = 2 \|h\|^2 > 0$$

so necessarily we must have  $0 = F'(0) = -2 \langle f - g, h \rangle \quad \forall h \in V$

This means  $\langle f - g, h \rangle = 0 \quad \forall h \in V$ , so  $u = f - g \in V^\perp$

and we have our decomposition  $f = uv$ :

Uniqueness, suppose  $f = w + z$  for some  $w \in V, z \in V^\perp$ . Then

$$(v - w) + (u - z) = 0 \text{ and using Pythagoras}$$

$$0 = \|v - w\|^2 + \|u - z\|^2 \Rightarrow v = w, u = z. \quad \square$$

L16.1

When the Hilbert space is  $L^2(\mathbb{P})$ , then the covariance of r.v.s  $X, Y$  in  $L^2(\mathbb{P})$  is

$$\begin{aligned} \text{cov}(X, Y) &= \mathbb{E}((X - \mathbb{E}X)(Y - \mathbb{E}Y)) \\ &= \langle X - \mathbb{E}X, Y - \mathbb{E}Y \rangle \end{aligned}$$

$\text{var}(X) = \text{cov}(X, X)$ ; and we may declare

$X \perp Y$  in  $L^2(\mathbb{P})$  if  $\mathbb{E}X = \mathbb{E}Y = 0$ ,  $\text{cov}(X, Y) = 0$ .

Next, if  $\mathcal{G}$  is a sub- $\sigma$ -algebra of  $\mathcal{F}$  generated by  $\{\mathcal{G}_i : i \in \mathbb{I}\}$ ,  $\mathbb{I}$  countable,  $\mathcal{G}_i \in \mathcal{F}$ , and  $L^2(\Omega, \mathcal{G}, \mathbb{P})$  is a closed subspace of  $L^2(\Omega, \mathcal{F}, \mathbb{P})$ ; and one defines the conditional expectation of  $X \in L^2(\Omega, \mathcal{F}, \mathbb{P})$

given  $\mathcal{G}$  as  $Y = \sum_{i \in \mathbb{I}} \mathbb{E}(X | \mathcal{G}_i) 1_{\mathcal{G}_i}$ ,

$$\mathbb{E}(X | \mathcal{G}_i) = \frac{\mathbb{E}(X 1_{\mathcal{G}_i})}{\mathbb{P}(\mathcal{G}_i)}, \quad \mathbb{P}(\mathcal{G}_i) > 0$$

One shows that the law of  $Y$  coincides with the law of the  $L^2(\mathbb{P})$ -projection of  $X$  onto  $L^2(\Omega, \mathcal{G}, \mathbb{P})$ . (Dudley p350)

### Convergence in $L^1(\mathbb{P})$

In what follows,  $L^1 = L^1(\Omega, \mathcal{F}, \mathbb{P})$  for some prob space [could take  $\mu(E) < \infty$ ]:

#### Theorem (Bounded convergence)

Let  $(X_n : n \in \mathbb{N})$  s.t.  $X_n \xrightarrow[n \rightarrow \infty]{\mathbb{P}} X$ , and  $|X_n| \leq c \quad \forall n \in \mathbb{N}, c < \infty$ ,

then  $X_n \xrightarrow[n \rightarrow \infty]{L^1} X$  in  $L^1$

Proof: From earlier, we know that  $X_{n_k} \xrightarrow{\text{a.s.}} X$  along a subsequence  $n_k$

$$|X| = \lim_{n \rightarrow \infty} |X_{n_k}| \leq c, \quad \Rightarrow X \in L^1(\mathbb{P})$$

Then

$$\begin{aligned} \mathbb{E}|X_n - X| &= \mathbb{E}|X_n - X| 1_{\{|X_n - X| > \varepsilon/2\}} + \mathbb{E}|X_n - X| 1_{\{|X_n - X| \leq \varepsilon/2\}} \\ &\leq 2c \mathbb{P}(|X_n - X| > \varepsilon/2) + \varepsilon/2 < \varepsilon \end{aligned}$$

for  $n = n(\varepsilon)$  large enough by def<sup>n</sup> of conv in  $\mathbb{P}$ .  $\square$

Next, a lemma.

Lemma Let  $X \in L^1(\mathbb{P})$ . Then

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

$\downarrow$   
0 as  $\delta \rightarrow 0$

pf suppose not, so  $\forall \varepsilon > 0$ ,  $\exists A_n \in \mathcal{F}$  ( $\delta = 2^{-n}$ ) s.t.  $P(A_n) \leq 2^{-n}$  but  $E(|X|1_{A_n}) \geq \varepsilon$

Then  $\sum_n P(A_n) < \infty$  so by Borel-Cantelli we see that

$$P(A_n \text{ i.o.}) = 0.$$

Now use the dominated convergence theorem to deduce

$$\varepsilon \leq E(|X|1_{A_n}) \leq E(|X|1_{\bigcup_{m \geq n} A_m}) \rightarrow E(|X|1_{\{A_n \text{ i.o.}\}})$$

a contradiction.  $\square$

The previous limit can be required to hold uniformly in a collection  $\mathcal{X}$  of r.v.s in  $L^1(P)$ , specifically define

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

Clearly  $I_{\mathcal{X}}(1) < \infty$  iff  $\mathcal{X}$  is bounded in  $L^1$  (i.e.  $\sup_{X \in \mathcal{X}} \|X\|_1 < \infty$ ), and we say  $\mathcal{X}$  is uniformly integrable (UI) if it is bounded in  $L^1(P)$  and satisfies  $I_{\mathcal{X}}(\delta) \rightarrow 0$  as  $\delta \rightarrow 0$ .

Remark If  $\mathcal{X}$  is bounded in  $L^p(P)$  for  $1 < p \leq \infty$ , then by Hölder's inequality (conjugate  $q$ )

$$E(|X|1_A) \leq \underbrace{(E|X|^p)^{1/p}}_{\leq C} \cdot \underbrace{(P(A))^{1/q}}_{\leq \delta} \rightarrow 0 \text{ as } \delta \rightarrow 0$$

so  $\mathcal{X}$  is UI. (Not true for  $p=1$ ;  $P$  is Lebesgue m. on  $(0,1)$ ,  $\{X_n = n1_{(0,1/n)}\}$  is bounded in  $L^1$ ; but not UI.)

Lemma  $\mathcal{X}$  is UI  $\Leftrightarrow \sup \{ E|X|1_{\{|X|>k\}} : X \in \mathcal{X} \} \rightarrow 0$  as  $k \rightarrow \infty$

Proof  $\Rightarrow$ : Choose  $\delta$  such that  $I_{\mathcal{X}}(\delta) < \varepsilon$ ,  $k$  large enough s.t.  $I_{\mathcal{X}}(1) \leq k\delta$ . By Markov's inequality,

$$P(|X| > k) \leq \frac{E|X|}{k} \leq \frac{I_{\mathcal{X}}(1)}{k} \leq \delta, \text{ hence}$$

$$E|X|1_{\{|X|>k\}} \leq I_{\mathcal{X}}(\delta) < \varepsilon \text{ for such } k \quad \square$$

even  $k, P(A \leq \delta)$

" $\Leftarrow$ " Conversely, take  $K$  s.t.

$$\sup_{X \in \mathcal{L}} \mathbb{E}(|X| \mathbb{1}_{\{|X| > K\}}) < \varepsilon/2$$

then  $X$  is bounded in  $L^1(\mathbb{P})$  since

$$\begin{aligned} \mathbb{E}|X| &\leq \mathbb{E}(|X| \mathbb{1}_{\{|X| \leq K\}}) + \mathbb{E}(|X| \mathbb{1}_{\{|X| > K\}}) \\ &\leq K + \varepsilon/2 < \infty, \end{aligned}$$

and if  $A \in \mathcal{F}$ ,  $\mathbb{P}(A) \leq \delta$ , then

$$\begin{aligned} \mathbb{E}|X| \mathbb{1}_A &\leq \mathbb{E}(|X| \mathbb{1}_A \mathbb{1}_{\{|X| > K\}}) + \mathbb{E}(|X| \mathbb{1}_A \mathbb{1}_{\{|X| \leq K\}}) \\ &\leq \varepsilon/2 + K \mathbb{P}(A) \\ &\leq \varepsilon/2 + K \delta < \varepsilon \end{aligned}$$

for  $\delta = \delta(K, \varepsilon)$  small enough.  $\square$

Theorem Let  $(X_n : n \in \mathbb{N})$ ,  $X$  be r.v.s in  $(\Omega, \mathcal{F}, \mathbb{P})$ . TFAE

(a)  $X, X_n \in L^1(\mathbb{P}) \forall n$ ;  $X_n \xrightarrow{n \rightarrow \infty} X$  in  $L^1(\mathbb{P})$

(b)  $\mathcal{X} = (X_n : n \in \mathbb{N})$  is U.I. and  $X_n \xrightarrow[n \rightarrow \infty]{\mathbb{P}} X$

Proof "a"  $\Rightarrow$  "b" By Markov's inequality,

$$\mathbb{P}(|X_n - X| > \varepsilon) \leq \frac{\mathbb{E}|X_n - X|}{\varepsilon} \rightarrow 0 \quad \text{as } n \rightarrow \infty,$$

so  $X_n \xrightarrow{\mathbb{P}} X$ . Since any finite collection of r.v.s is U.I., we have

$\forall A \in \mathcal{F}$  s.t.  $\mathbb{P}(A) \leq \delta$  that

$\mathbb{E}|X| \mathbb{1}_A \leq \varepsilon/2$ ,  $\mathbb{E}|X_n| \mathbb{1}_A \leq \varepsilon/2 \quad \forall n \in \mathbb{N}$ ,  $N = N(\varepsilon)$  chosen  
s.t.  $\mathbb{E}|X_n - X| < \varepsilon/2 \quad \forall n > N$ .

$$\begin{aligned} \text{Then } \mathbb{E}(|X_n| \mathbb{1}_A) &\leq \mathbb{E}(|X_n - X| \mathbb{1}_A) + \mathbb{E}(|X| \mathbb{1}_A) \\ &\leq \varepsilon/2 + \varepsilon/2 \quad \text{for } n > N \end{aligned}$$

so  $(X_n)$  is U.I.

Next "b"  $\Rightarrow$  "a". From earlier we know  $X_n \xrightarrow[n \rightarrow \infty]{\mathbb{P}} X \Rightarrow X_{n_k} \xrightarrow[n \rightarrow \infty]{a.s.} X$  as  $k \rightarrow \infty$ ,

so by Fatou's lemma

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

So  $X \in L^1(\mathbb{P})$ . Now for  $K$  to be chosen

$$X_n^k = (-k) \vee X_n \wedge k, \quad X^k = (-k) \vee X \wedge k, \quad \text{so that}$$

$$X_n^k \xrightarrow[n \rightarrow \infty]{\mathbb{P}} X^k \quad \text{as } n \rightarrow \infty$$



since  $P(|X_n^k - X^k| > \epsilon) \leq P(|X_n - X| > \epsilon) \rightarrow 0$

and by the lemma from earlier applied to  $|X_n^k| \leq K = C$ , we deduce

$$\mathbb{E}|X_n^k - X^k| \xrightarrow{n \rightarrow \infty} 0$$

Now write

$$\mathbb{E}|X_n - X| \leq \mathbb{E}|X_n - X_n^k| + \mathbb{E}|X_n^k - X^k| + \mathbb{E}|X^k - X|$$

$$\leq \mathbb{E}|X_n|_{\{|X_n| > k\}} + \epsilon/3 + \mathbb{E}|X|_{\{|X| > k\}}$$

↑  
for  $n(k)$   
large  
enough

$$\stackrel{\text{UI lemma.}}{<} \epsilon/3 + \epsilon/3 + \epsilon/3 \quad \text{for } k \text{ large enough, } n \text{ large enough}$$

So  $X_n \rightarrow X$  in  $L^1(P)$  as  $n \rightarrow \infty$ .  $\square$

In this section,  $L^p = L^p(\mathbb{R}^d)$ ,  $1 \leq p < \infty$ , denote spaces of complex-valued integrable functions  $f: \mathbb{R}^d \rightarrow \mathbb{C}$  st:

$$\bullet \quad \|f\|_p^p = \int_{\mathbb{R}^d} |f(x)|^p dx < \infty,$$

$dx$  is (product) Lebesgue-measure  $\mu^d$  on  $\bigotimes_{j=1}^d \mathcal{B}(\mathbb{R}) = \mathcal{B}$ .

The integral of a complex valued map  $f = (\operatorname{Re}f) + i(\operatorname{Im}f)$  is defined as

$$\int f(x) dx = \int \operatorname{Re}f(x) dx + i \int \operatorname{Im}f(x) dx$$

where we assume  $\int |f(x)| dx < \infty$ . Then  $L^p$  is a complex vector space,

satisfying  $|\int f(x) dx| \leq \int |f(x)| dx$ .

On  $L^2(\mathbb{R}^d)$  the inner product  $\langle \cdot, \cdot \rangle_{L^2}$  is now given by

$$\bullet \quad \langle f, g \rangle_{L^2} = \int_{\mathbb{R}^d} f(x) \overline{g(x)} dx$$

Moreover,  $dx$  is translation-invariant (see Ex Sheet) in that

$$\int_{\mathbb{R}^d} f(x-y) dx = \int_{\mathbb{R}^d} f(x) dx = \int_{\mathbb{R}^d} f(-x) dx$$

(Fourier's idea: write  $f = \sum_k c_k(f) e^{ikx}$ , an 'orthogonal' decomposition of  $f$  in  $L^2([0, 2\pi])$ )

A 'continuous' version of this idea is based on Fourier transforms  $\hat{f}: \mathbb{R}^d \rightarrow \mathbb{C}$  of  $f \in L^1(\mathbb{R}^d)$  defined as

$$\bullet \quad \hat{f}(u) = \int_{\mathbb{R}^d} f(x) e^{i\langle u, x \rangle} dx, \quad u \in \mathbb{R}^d, \langle u, x \rangle = \sum_{i=1}^d u_i x_i$$

Clearly, since  $|e^{i\langle u, x \rangle}| = 1$ , we see  $|\hat{f}(u)| \leq \|f\|_1 \quad \forall u$

Likewise, by the dominated convergence theorem, if  $u_n \rightarrow u$  in  $\mathbb{R}^d$ ,

then  $\hat{f}(u_n) \rightarrow \hat{f}(u)$ , so  $\hat{f}: \mathbb{R}^d \rightarrow \mathbb{C}$  is lhd continuous

"TRAILER" 1) Fourier Inversion,  $f, \hat{f} \in L^1$  then  $f(x) = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \hat{f}(y) e^{-i\langle x, y \rangle} dy$

2) Plancherel's theorem,  $f \in L^1 \cap L^2$ , then

$$\bullet \quad \|\hat{f}\|_{L^2} = (2\pi)^{d/2} \|f\|_{L^2}, \quad \langle f, g \rangle_{L^2} = (2\pi)^d \langle \hat{f}, \hat{g} \rangle_{L^2} \quad \curvearrowright$$

3) Proof of CLT (cheese lettuce tomato) from prob theory

Some more defns: For a prob. measure (or finite)  $\mu$  we define the Fourier transform  $\hat{\mu}(u) = \int_{\mathbb{R}^d} e^{i\langle u, x \rangle} d\mu(x)$ ,  $u \in \mathbb{R}^d$ ,

again  $|\hat{\mu}(u)| \leq \mu(\mathbb{R}^d) = 1$

If  $\mu = \mu_f$  arises from prob density  $f$ , then  $\hat{\mu}_f = \hat{f}$

Related to this is the characteristic function of a r.v.  $X$  taking values in  $\mathbb{R}^d$ ,

$$\begin{aligned} \phi_X(u) &= \mathbb{E}(e^{i\langle u, X \rangle}) \\ &= \int_{\mathbb{R}^d} e^{i\langle u, x \rangle} d\mu_X(x) = \hat{\mu}_X(u) \end{aligned}$$

where  $\mu_X$  is the law of the r.v.  $X$ .

A key concept in Fourier analysis is the notion of convolution of  $f^n$ s or measures. For  $f \in L^p$ ,  $1 \leq p < \infty$ , and  $\nu$  a prob. measure on  $\mathbb{R}^d$ , set

$$\begin{aligned} f * \nu(x) &= \int_{\mathbb{R}^d} f(x-y) d\nu(y), \quad x \in \mathbb{R}^d \\ &= \nu(f(x-\cdot)) \end{aligned}$$

By Jensen's inequality and Fubini's theorem,

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

$$\stackrel{\text{Jensen}}{\leq} \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} |f(x-y)|^p d\nu(y) \right) dx$$

$$= \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} |f(x-y)|^p dx \right) d\nu(y) = \|f\|_p^p \cdot 1$$

which implies  $\|f * \nu\|_p^p \leq \|f\|_p^p$ , in particular,  $f * \nu \in L^p$  and hence is  $< \infty$  a.e. ~~This was for  $p=1$~~

When  $\nu$  has a density  $g \in L^1$  so that  $d\nu(x) = g(x)dx$ , then we write  $f * g$  for  $f * \nu_g$  ( $g \in L^1$ )

For two prob. measures  $\mu, \nu$  on  $\mathbb{R}^d$  we define their convolution as the new measure

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

So if  $\mu$  has density  $f$ , then by translation invariance of  $dx$  and Fubini's theorem,

$$\begin{aligned}\mu * \nu(A) &= \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} 1_A(x+y) f(x) dx d\nu(y) \\ &= \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} 1_A(x) f(x-y) d\nu(y) dx \\ &= \int_{\mathbb{R}^d} 1_A(x) f * \nu(x) dx, \quad A \in \mathcal{B}\end{aligned}$$

so  $\mu * \nu$  has density  $f * \nu$  (in  $L^1$ )

A key observation is that,  $f \in L^1$

$$\begin{aligned}\widehat{f * \nu}(u) &= \int_{\mathbb{R}^d} f * \nu(x) e^{i\langle u, x \rangle} dx \\ &= \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} f(x-y) \cancel{dx} e^{i\langle u, x-y+y \rangle} d\nu(y) dx \\ &\stackrel{\text{Fubini}}{=} \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} \underset{z}{f(x-y)} e^{i\langle u, \underset{z}{x-y} \rangle} dx \right) e^{i\langle u, y \rangle} d\nu(y) \\ &= \widehat{f}(u) \underbrace{\int_{\mathbb{R}^d} e^{i\langle u, y \rangle} d\nu(y)}_{\widehat{\nu}(u)} = \widehat{f}(u) \widehat{\nu}(u) \quad \forall u \in \mathbb{R}^d\end{aligned}$$

Likewise, by independence of  $X \sim \mu, Y \sim \nu$ ,

$$\begin{aligned}\widehat{\mu * \nu} &= \mathbb{E}(e^{i\langle u, X+Y \rangle}) \\ &\stackrel{\text{indep}}{=} \mathbb{E}(e^{i\langle u, X \rangle}) \mathbb{E}(e^{i\langle u, Y \rangle}) \\ &= \widehat{\mu}(u) \widehat{\nu}(u), \quad u \in \mathbb{R}^d\end{aligned}$$

### Fourier transforms of Gaussians

Recall that the Gaussian density of a  $N(0, t)$  variable on  $\mathbb{R}$  is

$$g_t(x) = \frac{1}{(2\pi t)^{1/2}} e^{-|x|^2/2t}, \quad x \in \mathbb{R}$$

In particular, for a  $X \sim N(0, 1)$  variable, the c.f.

$$\phi_X(u) = \mathbb{E}(e^{iuX}) \quad \text{satisfies}$$

$$\frac{d}{du} \phi_X(u) = \frac{1}{\sqrt{2\pi}} \frac{d}{du} \int_{\mathbb{R}} e^{iux} e^{-x^2/2} dx$$

$$\stackrel{\text{diff under } \int}{=} \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{iux} ix e^{-x^2/2} dx$$

$$\stackrel{\text{by parts}}{=} 0 + i^2 u \int_{\mathbb{R}} e^{iux} e^{-x^2/2} \frac{1}{\sqrt{2\pi}} dx$$

$$= -u \phi_X(u)$$

$$\text{So we obtain } \frac{d}{du} (e^{u^2/2} \phi_X(u)) = u e^{u^2/2} \phi_X(u) + e^{u^2/2} (-u \phi_X(u)) \\ = 0 \quad \text{on } \mathbb{R}$$

$$\text{So } \phi_X(u) = \phi_X(0) e^{-u^2/2} = e^{-u^2/2} \quad \ddot{\smile}$$

$$\text{So in } d=1, \quad \hat{g}_1(u) = \sqrt{2\pi} g_1(u)$$

We have shown in  $d=1$  that

$$\hat{g}_1(u) = \sqrt{2\pi} g_1(u) \quad \forall u \in \mathbb{R}$$

● Next let  $Z_1, \dots, Z_d$  be  $\overset{\text{i.i.d.}}{\sim} N(0,1)$ ,  $Z = (Z_1, \dots, Z_d) \sim N(0, I_{\mathbb{R}^d})$ ,  
 which has pdf  $g_t(x) = \frac{1}{(2\pi t)^{d/2}} \exp\left(-\frac{|x|^2}{2t}\right)$ ,  $x \in \mathbb{R}^d$ .  
 then  $\sqrt{t}Z \sim N(0, tI)$ ,  
 $t > 0$

$$\begin{aligned} \hat{g}_t(u) &= \mathbb{E}(e^{i\langle u, \sqrt{t}Z \rangle}) \\ &= \mathbb{E}\left(\prod_{j=1}^d e^{i u_j \sqrt{t} Z_j}\right) \\ &\stackrel{\text{i.i.d.}}{=} \prod_{j=1}^d \mathbb{E}\left(e^{i \underbrace{u_j \sqrt{t}}_{=: u} Z_j}\right) \\ &= \prod_{j=1}^d e^{-u_j^2 t/2} \\ &= e^{-|u|^2 t/2} \end{aligned}$$

● In other words,  $\hat{g}_t(u) = (2\pi)^{d/2} t^{-d/2} g_{1/t}(u)$ ,

and Fourier-transforming again we see

$$\hat{\hat{g}}_t = (2\pi)^d g_t \Rightarrow g_t = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \hat{g}(u) e^{-iux} du$$

Hence 'Fourier inversion' holds for (centred) Gaussians. (translation invariance)

A Gaussian convolution of  $f \in L^1(\mathbb{R}^d)$  is

$$f * g_t = \int_{\mathbb{R}^d} f(\cdot - y) g_t(y) dy, \text{ where } g_t \text{ is a Gaussian}$$

● pdf as above. As before,  $f * g_t$  is bounded and its on  $\mathbb{R}^d$ , and

$\|f * g_t\|_1 \leq \|f\|_1$  and also, since

$$|f * g_t(x)| \leq \frac{1}{(2\pi t)^{d/2}} \int |f(x-y)| \underbrace{e^{-|y|^2/2t}}_{\leq 1} dy = \frac{\|f\|_1}{(2\pi t)^{d/2}} \quad \forall x \in \mathbb{R}^d$$

Also  $\widehat{f * g}(u) = \hat{f}(u) e^{-|u|^2 t/2}$ , so

$$\|\widehat{f * g}\|_1 \leq \|f\|_1 \int_{\mathbb{R}^d} e^{-|u|^2 t/2} du = \left(\frac{2\pi}{t}\right)^{d/2} \|f\|_1$$

$$\|\widehat{f * g}\|_\infty \leq \|f\|_1$$

recall  
 $\|\hat{f}\|_\infty \leq \|f\|_1$

Remark If  $\mu$  is a prob measure, then writing  $g_t = g_{t/2} * g_{t/2}$

$$\mu * g_t = \underbrace{(\mu * g_{t/2})}_{\in L^1} * g_{t/2} \text{ is also a Gaussian conv}^n$$

Lemma Fourier inversion holds for all Gaussian convolutions.

Proof For  $f \in L^1$ ,  $t > 0$ , use Fourier inversion for  $g_t$  and Fubini's theorem

$$\begin{aligned}
 (2\pi)^d f * g_t(x) &= (2\pi)^d \int_{\mathbb{R}^d} f(x-y) g_t(y) dy \\
 &= \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} f(x-y) \hat{g}_t(u) e^{-i\langle u, y \rangle} du dy \\
 &= \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} f(x-y) e^{i\langle u, x-y \rangle} dy \right) \hat{g}_t(u) e^{-i\langle u, x \rangle} du \\
 &= \int_{\mathbb{R}^d} \hat{f}(u) \hat{g}_t(u) e^{-i\langle u, x \rangle} du \\
 &= \int_{\mathbb{R}^d} \widehat{f * g_t}(u) e^{-i\langle u, x \rangle} du \quad \square
 \end{aligned}$$

The next step uses that  $f * g_t \approx f$  as  $t \rightarrow 0$

$$\left( \text{Gaussian curve} \quad \text{Narrower Gaussian curve} \quad \text{Very narrow Gaussian curve} \rightarrow \delta_0 \right)$$

Lemma Let  $f \in L^p$ ,  $1 \leq p < \infty$ . Then

$$\|f * g_t - f\|_p \rightarrow 0 \text{ as } t \rightarrow 0$$

Proof  $\forall \varepsilon > 0$ ,  $\exists h \in C_c(\mathbb{R}^d)$  s.t.  $\|f - h\|_p < \varepsilon/3$  (see Ex Sheet)

Then by linearity of  $*$  we see

$$\|(f * g_t - h * g_t)\|_p = \|(f - h) * g_t\|_p \leq \|f - h\|_p$$

Next define  $e(y) = \int_{\mathbb{R}^d} |h(x-y) - h(x)|^p dx$  which satisfies

$$0 \leq e(y) \leq 2^p \|h\|_p^p \quad \forall y; \text{ which is } dx\text{-integrable on } K_h \text{ (bdd)}$$

Then since  $h(x-y) - h(x) \rightarrow 0$  as  $y \rightarrow 0$ ,

the dominated convergence theorem implies  $e(y) \rightarrow 0$  as  $y \rightarrow 0$  (†)

Next

$$\|h * g_t - h\|_p^p \stackrel{Minkowski}{=} \int_{\mathbb{R}^d} \left| \int_{\mathbb{R}^d} (h(x-y) - h(x)) g_t(y) dy \right|^p dx$$

$$\leq \int_{\mathbb{R}^d} e(y) g_t(y) dy$$

$$\stackrel{\substack{y = \sqrt{t}z \\ \rightarrow 0}}{=} \int_{\mathbb{R}^d} e(\sqrt{t}z) g_1(z) dz \rightarrow 0 \text{ as } t \rightarrow 0 \text{ by bounded convergence}$$

L18.3

Summarising, by Minkowski's inequality

$$\begin{aligned} \|f * g_t - f\|_p &\leq \|f * g_t - h * g_t\|_p + \|h * g_t - h\|_p + \|h - f\|_p \\ &\leq 2\epsilon/3 + \epsilon/3 \end{aligned}$$

for  $t$  small enough.  $\square$

Theorem (Fourier inversion) Suppose  $f \in L^1(\mathbb{R}^d)$  and  $\hat{f} \in L^1(\mathbb{R}^d)$  ( $\hat{f} \in$  Fourier algebra). Then

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

for a.e.  $x \in \mathbb{R}^d$ .

Remark 1) The identity holds everywhere for the unique  $f \in [F]$ .

2) If  $\hat{f} = 0$  a.e.  $\rightarrow f = 0$  a.e.

Proof Set  $f_t = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \hat{f}(u) \underbrace{e^{-|u|^2 t/2}}_{= \widehat{f * g_t}(u)} e^{-i\langle u, x \rangle} du$

so  $f_t = f * g_t$  so by the previous lemma,

$$\|f_t - f\|_1 = \|f * g_t - f\|_1 \rightarrow 0 \text{ as } t \rightarrow 0.$$

At the same time, since  $\frac{1}{(2\pi)^d} \hat{f}(u) e^{-|u|^2 t/2} \rightarrow \hat{f}(u)$  as  $t \rightarrow 0$  and  $\hat{f} \in L^1$ , the dominated convergence theorem implies

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

But since  $L^1$ -conv  $\Rightarrow f_{t_n} \rightarrow f$  a.e. along a subsequence, then by uniqueness of limits,

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

Theorem (Plancherel) Let  $f \in L^1 \cap L^2$ . Then

$$\|\hat{f}\|_{L^2} = (2\pi)^{d/2} \|f\|_{L^2}$$

Proof First assume  $\hat{f} \in L^1$ , so Fourier inversion applies

$$\Rightarrow f, \hat{f} \in L^\infty \Rightarrow f, \hat{f} \in L^2 \text{ We see}$$

$(x, u) \mapsto f(x) \hat{f}(u)$  is  $dx du$ -integrable, so

$$(2\pi)^d \|f\|_{L^2}^2 = (2\pi)^d \int_{\mathbb{R}^d} f(x) \overline{f(x)} dx$$



L18.4

$$\stackrel{\text{Fourier inversion}}{=} \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} \hat{f}(u) e^{-i\langle u, x \rangle} du \right) \overline{f(x)} dx$$

$$\stackrel{\text{Fubini}}{=} \int_{\mathbb{R}^d} \hat{f}(u) \int_{\mathbb{R}^d} f(x) e^{i\langle u, x \rangle} dx du$$

$$= \int_{\mathbb{R}^d} \hat{f}(u) \overline{\hat{f}(u)} du = \|\hat{f}\|_{L^2}^2$$

To extend this to general  $f \in L^1 \cap L^2$ , take the Gaussian conv.

$f_t = f * g_t$ , then  $f_t \rightarrow f$  in  $L^2$  by the lemma from earlier,

so  $\|f_t\|_2 \rightarrow \|f\|_2$  as  $t \rightarrow 0$ .

Likewise  $|\hat{f}_t| = |\hat{f}| e^{-|u|^2 t/2} \nearrow |\hat{f}|$  as  $t \rightarrow 0$ .

So by the monotone convergence theorem,

$$\|\hat{f}_t\|_2^2 \nearrow \|\hat{f}\|_2^2 \text{ as } t \rightarrow 0$$

$$\text{Then } (2\pi)^d \|f\|_2^2 = \lim_{t \rightarrow 0} (2\pi)^d \|f_t\|_2^2$$

$$= \lim_{t \rightarrow 0} \|\hat{f}_t\|_2^2 \quad \text{by Plancherel, since } \hat{f}_t \in L^1$$

$$= \|\hat{f}\|_2^2 \quad \square$$

Weak convergence and characteristic f<sup>n</sup>s

We say that Borel p.m.  $(\mu_n : n \in \mathbb{N})$  on  $\mathbb{R}^d$  converge weakly to a Borel

● p.m.  $\mu$  on  $\mathbb{R}^d$  if

$$\mu_n(f) = \int_{\mathbb{R}^d} f d\mu_n \longrightarrow \int_{\mathbb{R}^d} f d\mu$$

$\forall f: \mathbb{R}^d \rightarrow \mathbb{R}$  bounded and continuous.

If  $X_n \sim \mu_n, X \sim \mu$  are r.v.s then we say  $X_n \rightarrow X$  weakly.

A few facts are (see Ex. Sheet)

1) If  $\int f d\mu = \int f d\nu \quad \forall f: \mathbb{R}^d \rightarrow \mathbb{R}$  and  $\mu, \nu$  p.m.  $\Rightarrow \mu = \nu$

2) If  $d=1$  then  $\mu_{X_n} \rightarrow \mu_X$  weakly for r.v.'s  $X_n, X \Leftrightarrow X_n \xrightarrow[n \rightarrow \infty]{d} X$

3) In fact since  $\mu$  (and then also the  $\mu_n$ ) is a Radon measure,

● it concentrates its mass on a compact subset of  $\mathbb{R}^d$ , and one then shows further that  $\mu_n \rightarrow \mu$  weakly  $\Leftrightarrow \int f d\mu_n \rightarrow \int f d\mu$

$$\forall f \in C_c^\infty(\mathbb{R}^d)$$

infinitely diff maps  
of compact support

A famous theorem due to P. Lévy is that to establish weak convergence, it

suffices to check pointwise conv of c.f.s  $\phi_{X_n} \rightarrow \phi_X$ .

Theorem 1) Let  $X$  be a r.v. in  $\mathbb{R}^d$ . Then the law  $\mu_X$  of  $X$  is uniquely determined by  $\phi_X (= \hat{\mu}_X)$  and if  $\phi_X \in L^1$  then

●  $\mu_X$  has a pdf  $f_X(x) = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \phi_X(u) e^{-iux} du$

2) If  $(X_n : n \in \mathbb{N}), X$  are r.v.s in  $\mathbb{R}^d$  s.t.  $\phi_{X_n}(u) \xrightarrow{p.w.} \phi_X(u)$  as  $n \rightarrow \infty$  then  $X_n \rightarrow X$  ( $\mu_{X_n} \rightarrow \mu_X$ ) weakly.

Proof We can take  $Z \sim N(0, I)$  with density  $g_I$ , independent of  $X$  (later also,  $X_n$ ) (if necessary enrich the prob space to be  $(\Omega, \mathcal{F}, \mathbb{P}) \times (\mathbb{R}^d, \mathcal{B}, g_I dx)$  and note that all statements are about 'laws' only)

a) Then  $\sqrt{t}Z$  has density  $g_t$  and  $X + \sqrt{t}Z$  has density  $f_t = \mu_X * g_t$

● (a Gaussian convolution)

By Fourier inversion for Gaussian convolutions,

$$f_t(x) = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \phi_X(u) e^{-|u|^2 t/2} e^{-i\langle u, x \rangle} du$$

L19.2

and if we test against any  $g: \mathbb{R}^d \rightarrow \mathbb{R}$  bdd. ds

$$\int_{\mathbb{R}^d} g(x) f_t(x) dx = \mathbb{E} g(X + \sqrt{t} Z) \xrightarrow{\text{bounded convergence}} \mathbb{E}(g(X)) = \int_{\mathbb{R}^d} g(x) d\mu_X(x)$$

so  $\phi_X$  determines  $\int g d\mu \forall g$  bdd. and ds.

so by the remark from earlier, also  $\mu_X$

Next if  $\phi_X \in L^1$ , then  $|f_t| \leq \frac{1}{(2\pi)^d} \|\phi_X\|$

and applying the dom. conv. theorem with  $\leq |\phi_X|$ ,  $f_t(x) \rightarrow f_X(x)$  p.w. as  $t \rightarrow 0$

But  $f_t = \mu_X * g_t (= \int (X + \sqrt{t} Z))$

$\geq 0 \forall t$ , so the limit  $f_X \geq 0$  as well

And for  $g \in C_c(\mathbb{R}^d)$ ,

$$\int_{\mathbb{R}^d} g d\mu_X = \lim_{t \rightarrow 0} \int_{\mathbb{R}^d} g(x) f_t(x) dx = \int_{\mathbb{R}^d} g(x) f_X(x) dx$$

by dominated convergence, so  $f_X$  is the pdf of  $\mu_X$ .

b) Now let  $X_n$  be st.  $\phi_{X_n}(u) \rightarrow \phi_X(u)$ , and let  $g: \mathbb{R}^d \rightarrow \mathbb{R}$  be compactly supported and Lipschitz. ( $|g(x) - g(y)| \leq \|g\|_{Lip} |x - y| \forall x, y \in \mathbb{R}^d$ )

Then let  $\varepsilon > 0$ , choose  $t$  s.t.  $\sqrt{t} \|g\|_{Lip} \mathbb{E}|Z| \leq \varepsilon/3$

so that

$$\mathbb{E} |g(X_n + \sqrt{t} Z) - g(X_n)| \leq \sqrt{t} \|g\|_{Lip} \mathbb{E}|Z| \leq \varepsilon/3$$

$$\mathbb{E} |g(X + \sqrt{t} Z) - g(X)| \leq \dots \leq \varepsilon/3 ; \text{ now}$$

$$\left| \int g d\mu_{X_n} - \int g d\mu_X \right| = \left| \mathbb{E} g(X_n) - \mathbb{E} g(X) \right|$$

$$\leq \left| \mathbb{E} g(X_n) - \mathbb{E} g(X_n + \sqrt{t} Z) \right|$$

$$+ \left| \mathbb{E} g(X_n + \sqrt{t} Z) - \mathbb{E} g(X + \sqrt{t} Z) \right|$$

$$+ \left| \mathbb{E} g(X + \sqrt{t} Z) - \mathbb{E} g(X) \right|$$

$\leq \frac{2}{3} \varepsilon + \text{middle term}$ , so suffices to show convergence to zero of middle term as  $n \rightarrow \infty$

Indeed,  $\mathbb{E} g(X_n + \sqrt{t} Z) = \int_{\mathbb{R}^d} g(x) f_{t,n}(x) dx \xrightarrow{\mu_{X_n} * g_t}$

$$\stackrel{\text{Fubini}}{\text{inv}} = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} g(x) \int_{\mathbb{R}^d} \phi_{X_n}(u) e^{-|u|^2/2} e^{-i\langle x, u \rangle} du dx$$

but  $|g(x)| e^{-|u|^2/2}$  is  $du dx$  integrable

and  $|\phi_{X_n}(u)| \leq 1$ ,  $\phi_{X_n} \rightarrow \phi_X$  pointwise

so by the dominated convergence theorem,

$$\xrightarrow{n \rightarrow \infty} \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} g(x) \phi_X(u) e^{-|u|^2/2} e^{-i\langle x, u \rangle} du dx$$

$$= \int_{\mathbb{R}^d} g(x) f_\varepsilon(x) dx = \mathbb{E} g(X + \sqrt{\varepsilon} Z)$$

So overall,  $|\int g d\mu_{X_n} - \int g d\mu_X| < \varepsilon$  for all  $n$  large enough.

for any  $g \in C_c^\infty$ , so  $\mu_{X_n} \rightarrow \mu_X$  weakly.  $\square$

### Multivariate Gaussian distributions

Def. A r.v.  $X$  in  $\mathbb{R}^d$  is Gaussian if  $\langle u, X \rangle = \sum_{i=1}^d u_i X_i$  is one-dimensional Gaussian  $\forall u \in \mathbb{R}^d$ .

(Remark A 1-d-Gaussian is a normal distribution with pdf  $f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

for some  $\mu \in \mathbb{R}$ ,  $\sigma > 0$ . [ $N(\mu, \sigma^2)$ ,  $N(\mu, 0) \sim \delta_\mu$ ].

Theorem Let  $X = (X_1, \dots, X_n)$  be Gaussian in  $\mathbb{R}^n$ .

a) if  $A$  is a  $n \times n$  matrix,  $b \in \mathbb{R}^n$  then  $AX + b$  is Gaussian in  $\mathbb{R}^n$

b)  $X \in L^2$ ,  $\mu = \mathbb{E}X$  exists, and the covariance matrix

$V = \text{var}(X) = (\text{cov}(X_i, X_j))_{i,j=1}^n$  exists

c)  $\phi_X(u) = e^{i\langle u, \mu \rangle - \langle u, V u \rangle / 2}$   $\forall u \in \mathbb{R}^n$

d) if  $V^{-1}$  exists then  $X$  has a pdf on  $\mathbb{R}^n$  given by:

$$f_X(x) = (2\pi)^{-\frac{n}{2}} (\det V)^{-\frac{1}{2}} \exp \left\{ -\frac{\langle x - \mu, V^{-1}(x - \mu) \rangle}{2} \right\}$$

e) if  $X = \begin{pmatrix} X_{(1)} \\ X_{(2)} \end{pmatrix}$  is s.t.  $\text{cov}(X_{(1)}, X_{(2)}) = 0$ , then  $X_{(1)}, X_{(2)}$  are independent

L19.4

Proof Use Ex Sheet + uniqueness of c.f.s

+ props. of 1-dim Gaussians  $\square$

Sums of independent rvs

$X_1, \dots, X_n$  iid rvs,  $\text{Var}(X_i) = 1$ ,  $\mathbb{E} X_i = 0$ , then  $\forall \varepsilon > 0$

$$\mathbb{P}\left(\left|\frac{1}{n} \sum_{i=1}^n X_i\right| > \varepsilon\right) \leq \frac{\frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right)}{\varepsilon^2} = \frac{1}{n\varepsilon^2} \rightarrow 0$$

So  $\frac{1}{n} \sum_{i=1}^n X_i \xrightarrow{\mathbb{P}} \mathbb{E} X = 0$  (weak LLN)

Theorem Let  $(X_n : n \in \mathbb{N})$  be independent; s.t.

$$\mathbb{E} X_n = \mu \quad \forall n, \quad \mathbb{E} X_n^4 \leq M \quad \forall n$$

Then if  $S_n = \sum_{i=1}^n X_i$ , then

$$\frac{S_n}{n} \rightarrow \mu \quad \text{a.s. as } n \rightarrow \infty$$

Proof We can assume  $\mu = 0$ ; since  $Y_n = X_n - \mu$ , then

$$\mathbb{E} Y_n = 0 \quad \forall n \quad \text{and} \quad \mathbb{E} Y_n^4 \leq \mathbb{E}(2^4(X_n^4 + \mu^4)) \leq 16(M + \mu^4) = \tilde{M}$$

Now to prove the result; notice

$$X_n, X_n^2, X_n^3 \text{ are integrable. } (L^4(\mathbb{P}) \subseteq L^p(\mathbb{P}); 1 \leq p \leq 4)$$

and by independence,  $\mu = 0$ ;

$$\mathbb{E} X_i X_j^3 = \mathbb{E} X_i X_j X_k^2 = \mathbb{E} X_i X_j X_k X_l = 0$$

for distinct  $i, j, k, l$ . Thus

$$\mathbb{E}(S_n^4) = \mathbb{E}\left(\sum_{i \leq n} X_i^4 + 6 \sum_{i < j} X_i^2 X_j^2\right)$$

$$\text{Now } \mathbb{E} X_i^2 X_j^2 \stackrel{\text{ind}}{=} (\mathbb{E} X_i^2)(\mathbb{E} X_j^2) \stackrel{\text{C-S}}{\leq} \sqrt{\mathbb{E} X_i^4} \sqrt{\mathbb{E} X_j^4} \leq M \quad \text{so}$$

$$\mathbb{E}(S_n^4) \leq nM + 3n(n-1)M \leq 3n^2M$$

$$\text{so } \mathbb{E}\left(\sum_n \left(\frac{S_n}{n}\right)^4\right) \leq 3M \sum_n \frac{1}{n^2} < \infty$$

So in particular,  $\sum_n \left(\frac{S_n}{n}\right)^4 < \infty$  a.s.

So  $\frac{S_n}{n} \rightarrow 0$  a.s. (woah!)  $\square$

Qu's How fast is the convergence of  $\frac{S_n}{n} \rightarrow \mathbb{E}X (= \mu)$

Theorem (Cheese Lettuce Tomato)

Let  $X_1, \dots, X_n$  be iid r.v.s on  $\mathbb{R}$  st:

$$\mathbb{E}X_i = 0 \quad \forall i, \quad \text{Var}(X_i) = 1$$

Then for  $S_n = \sum_{i=1}^n X_i$  we have, for all  $x \in \mathbb{R}$ ,

$$\begin{aligned} \mathbb{P}\left(\frac{1}{\sqrt{n}} S_n \leq x\right) &\longrightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy \\ &= \mathbb{P}(Z \leq x), \quad Z \sim N(0,1) \end{aligned}$$

Proof Apply to theorem from last lecture, and recall that weak convergence of  $\frac{1}{\sqrt{n}} S_n \rightarrow Z$  as  $n \rightarrow \infty$  will imply the result ( $d=1$ )

If  $\phi(u) = \mathbb{E} e^{iuX_1} \Rightarrow \phi(0) = 1$ , but

differentiating  $\phi$  wrt  $u$  under the integral, using  $\mathbb{E}|X_1| \leq \sqrt{\mathbb{E}|X_1|^2} = 1$ ,

$$\phi'(u) = i \mathbb{E} X_1 e^{iuX_1} \Rightarrow \phi'(0) = i \mathbb{E} X_1 = 0$$

and likewise

$$\phi''(u) = i^2 \mathbb{E} X_1^2 e^{iuX_1} \Rightarrow \phi''(0) = -1$$

So applying Taylor's theorem to  $\phi$  we see that as  $u \rightarrow 0$ ,

$$\phi(u) = 1 - \frac{u^2}{2} + o(u^2)$$

Then if  $\phi_n$  is the c.f. of  $S_n/\sqrt{n}$ , we see

$$\begin{aligned} \phi_n(u) &= \mathbb{E}(e^{iu(X_1 + \dots + X_n)/\sqrt{n}}) \stackrel{\text{iid.}}{=} \left(\phi\left(\frac{u}{\sqrt{n}}\right)\right)^n \\ &\stackrel{\substack{n \rightarrow \infty \\ u \text{ fixed}}}{=} \left(1 - \frac{u^2}{2n} + o\left(\frac{u^2}{n}\right)\right)^n \end{aligned}$$

Using that the complex logarithm satisfies  $\log(1+z) = z + o(|z|)$

$$\text{so } \log \phi_n(u) = n \log\left(1 - \frac{u^2}{2n} + o\left(\frac{u^2}{n}\right)\right) = -\frac{u^2}{2} + o(1) \quad \text{as } n \rightarrow \infty$$

hence  $\forall u \in \mathbb{R}$ ,  $\phi_n(u) \rightarrow e^{-u^2/2}$  as  $n \rightarrow \infty$ .  $\square$

$$\uparrow \\ \mathbb{E}(e^{iuZ})$$

Remarks 1) A  $d$ -dimensional version can be proved either in the same way (Dudley, p306), or also using the Cramér-Wold device:  $X_n \xrightarrow{d} X$  in  $\mathbb{R}^k$

•  $\Leftrightarrow \langle u, X_n \rangle \xrightarrow{d} \langle u, X \rangle$  in  $\mathbb{R} \quad \forall u \in \mathbb{R}^k$

2) The theorem says

$$\sqrt{n} \left( \frac{1}{n} \sum_{i=1}^n X_i - \mathbb{E} X \right) \xrightarrow{d} N(0, 1), \text{ non-deg.}$$

but this limit does not hold a.s. / in  $\mathbb{P}$ .

One proves the law of the iterated logarithm (LIL)

$$\limsup_n \frac{S_n}{\sqrt{2n \log \log n}} \stackrel{\text{a.s.}}{=} +1$$

$$(\liminf) \quad \quad \quad \stackrel{\text{a.s.}}{=} -1 \quad \quad \quad \circ$$

The following results are often useful in applications of the CLT

Proposition 1) (Continuous mapping) If  $X_n \rightarrow X$  weakly in  $\mathbb{R}^d$ ,

$X_n$  takes values in  $\mathcal{X} \subseteq \mathbb{R}^d$ , and  $g: \mathcal{X} \rightarrow \mathbb{R}^k$  is continuous, then  $g(X_n) \rightarrow g(X)$  weakly in  $\mathbb{R}^k$ .

2) (Slutsky's Lemma)

If  $X_n \rightarrow X$  weakly in  $\mathbb{R}^k$ ,  $Y_n \xrightarrow{\mathbb{P}} c$ ,  $c$  a constant (a.s.) then

$$(X_n, Y_n) \rightarrow (X, c) \text{ weakly (jointly) in } \mathbb{R}^k \times \mathbb{R}^k$$

• In particular,  $X_n + Y_n \rightarrow X + c$ ,  $X_n Y_n \rightarrow X c$

$$X_n / Y_n \rightarrow X / c \text{ if } c \neq 0$$

Proof 1) Use that  $f \circ g: \mathcal{X} \rightarrow \mathbb{R}$  is bounded, continuous and so

$$\int f d\mu_{g(X_n)} = \int f \circ g d\mu_{X_n} \rightarrow \int f \circ g d\mu_X = \int f d\mu_{g(X)}$$

2) First we prove an auxiliary result that if

$$\textcircled{1} \quad X_n \xrightarrow{w} X \text{ as } n \rightarrow \infty \text{ and } |X_n - Y_n| \xrightarrow{\mathbb{P}} 0$$

then  $Y_n \xrightarrow{w} X$  as  $n \rightarrow \infty$ .

For any  $f$  bounded and Lipschitz

$$|\mathbb{E}(f(Y_n)) - \mathbb{E} f(X)| \leq |\mathbb{E} f(X_n) - \mathbb{E} f(X)| + |\mathbb{E} f(Y_n) - \mathbb{E} f(X_n)|$$

$\rightarrow 0$  as  $n \rightarrow \infty$  since  $X_n \xrightarrow{w} X$



$$\begin{aligned} & \leq \left| \mathbb{E}(f(Y_n) - f(X_n)) \mathbb{1}_{\{|X_n - Y_n| \leq \varepsilon/2\}} \right| \\ & \quad + \left| \mathbb{E}(f(Y_n) - f(X_n)) \mathbb{1}_{\{|X_n - Y_n| > \varepsilon/2\}} \right| \\ & \leq \|f\|_{\text{Lip}} \varepsilon/2 + \|f\|_{\infty} \mathbb{P}(|X_n - Y_n| > \varepsilon/2) \\ & \leq \varepsilon \quad \text{for } n \text{ large enough.} \quad \square \end{aligned}$$

Now Slutsky's Lemma follows from (o) with

$$|(X_n, Y_n) - (X_n, c)| = |Y_n - c| \xrightarrow{\mathbb{P}} 0$$

Also  $(X_n, c) \xrightarrow{w} (X, c)$  weakly since for  $f: \mathbb{R}^k \times \mathbb{R}^k \rightarrow \mathbb{R}$  bdd & continuous the map  $x \mapsto f(x, c)$  is bdd & cts on  $\mathbb{R}^k$

so  $\mathbb{E} f(X_n, c) \rightarrow \mathbb{E} f(X, c)$  by weak conv of  $X_n \rightarrow X$  in  $\mathbb{R}^k$ .

The last claim follows from continuity of  $+, \cdot, /$  on  $\mathbb{R}^k \times \mathbb{R}^k \rightarrow \mathbb{R}^k$  and the continuous mapping theorem.  $\square$

## § Ergodic Theory

A dynamical system consists of a state space  $E$  and a transformation

$\Theta: E \rightarrow E$ . If we apply  $\Theta$   $n$ -times we write

$$\Theta^n = \underbrace{\Theta \circ \dots \circ \Theta}_{n\text{-times}}$$

In ergodic theory one studies the long-term 'statistical' behaviour of the orbits  $\Theta^{(n)}(x)$ ,  $x \in E$ , specifically we will consider averages

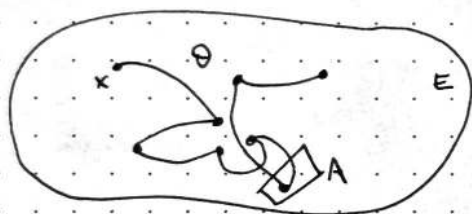
$$\frac{1}{N} \sum_{k=1}^N \Theta^k(x), \quad x \in E \text{ and } E \text{ endowed with some measure } \mu.$$

For instance, for  $A \subseteq E$  we can ask whether

$$\frac{1}{N} \sum_{k=1}^N \mathbb{1}_A \circ \Theta^k(x) = \frac{1}{N} \sum_{k=1}^N \mathbb{1}_{\{\Theta^k(x) \in A\}}$$

stabilises as  $N \rightarrow \infty$  at some "invariant" measure  $\mu(A)$ .

Ex (Boltzmann's ergodic hypothesis)



$\int$  no. of times the system visits  $A$   
is approx  $\approx \text{vol}(A) (\mu(A))$  ?

### Some definitions

Let  $(E, \mathcal{E}, \mu)$  be a measure space.

A measurable map/transformation  $\Theta: E \rightarrow E$  is called measure-preserving

(m.p.) if  $\mu(\Theta^{-1}(A)) = \mu(A) \quad \forall A \in \mathcal{E}$ . In this case, if  $f: E \rightarrow \mathbb{R}$  is measurable then necessarily  $\int_E f \circ \Theta d\mu = \int_E f d\mu$

A meas map  $f$  is called invariant (under  $\Theta$ ) if  $f = f \circ \Theta$ ; and  $A \in \mathcal{E}$  is called invariant if  $\Theta^{-1}(A) = A$ .

The collection of invariant subsets of  $E$ , denoted  $\mathcal{E}_\Theta$ , is a  $\sigma$ -algebra and  $f: E \rightarrow \mathbb{R}$  is invariant  $\Leftrightarrow f$  is  $\mathcal{E}_\Theta$ -measurable.

Def<sup>n</sup> We say that  $\Theta$  is ergodic ( $\mu$ -ergodic) if  $A \in \mathcal{E}_\Theta$

$$\Rightarrow \mu(A) = 0 \text{ or } \mu(A^c) = 0$$

Fact If  $\theta$  is ergodic and  $f$  is invariant (for  $\theta$ ), then  $f = c$  const.  $\mu$ -a.e.

Some examples

1) On the  $n$ -torus  $E = (0,1]^n$ ,  $\mathcal{E} = \hat{\otimes}_{i=1}^n B((0,1])$ ,  $\mu = \mu^n$   
product Lebesgue measure, then the translation map

$$\theta_a(x_1, \dots, x_n) = (x_1 + a_1, \dots, x_n + a_n) \pmod{1}$$

is measure-preserving by translation invariance of  $\mu$ ; for  $n=1$ ,  $\theta_a$  is ergodic  $\Leftrightarrow a$  is irrational. (see Ex Sheet)

2) On  $E = (0,1]$  with  $\mu =$  Lebesgue measure on  $(0,1]$   
the map  $x \mapsto 2x \pmod{1}$  is ~~m.p.~~ ergodic for  $\mu$  (Ex Sheet)

[It is also ergodic...]

3) Recall from earlier that on the infinite product space

$$E = \mathbb{R}^{\mathbb{N}} = \{x = (x_n : n \in \mathbb{N}) : x_n \in \mathbb{R}\}$$

we can consider the cylindrical  $\sigma$ -algebra  $\sigma(\mathcal{C})$  generated by

$$\mathcal{C} = \left\{ \prod_{n \in \mathbb{N}} A_n : A_n \in \mathcal{B}, A_n = \mathbb{R} \text{ for } n \text{ large enough} \right\}$$

One shows that

$$\sigma(\mathcal{C}) = \sigma(X_n : n \in \mathbb{N}), \quad X_n(x) = x_n$$

Now let  $m$  be any prob meas on  $\mathbb{R}$ ; then we have shown earlier the existence of an infinite sequence  $(Y_n : n \in \mathbb{N})$  iid of law  $m$

on  $\mathbb{R}$ ; defined on  $(\Omega, \mathcal{F}, \mathbb{P}) = ((0,1), \mathcal{B}, \mu_{(0,1)})$

which can be injected into  $(\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}))$  by  $\leftarrow$  Lebesgue

$$Y : \Omega \rightarrow E, \quad Y(\omega) = (Y_n(\omega) : n \in \mathbb{N})$$

which is  $\mathcal{F}$ - $\sigma(\mathcal{C})$  measurable since for any cylinder  $C = A_1 \times \dots \times A_n \times \dots$

$$Y^{-1}(C) = Y_1^{-1}(A_1) \cap \dots \cap Y_n^{-1}(A_n) \in \mathcal{F}$$

We define on  $(\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}))$  the image measure

$$\mu = \mathbb{P} \circ Y^{-1}, \quad \text{which satisfies}$$

$$\mu\left(\prod_{n \in \mathbb{N}} A_n\right) = \prod_{n \in \mathbb{N}} m(A_n) \quad \forall \text{ cylinders,}$$

the unique 'product measure' on  $\sigma(\mathcal{C})$ .

One calls  $(\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}), \mu) = (E, \Sigma, \mu)$  the 'canonical model' for an infinite sequence of iid variables.

● On  $(E, \Sigma, \mu)$  we can define the (Bernoulli-) shift map  
 $\Theta(x_1, x_2, \dots) = (x_2, x_3, \dots)$

Theorem on  $(\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}), \mu)$ , the shift map  $\Theta$  is measure-preserving and ergodic.

Proof For  $A \in \mathcal{C}$  of the form

$$A = \prod_{i \leq n} (-\infty, x_i] \times \mathbb{R} \times \dots \quad \text{we can check}$$

$$\begin{aligned} \mu(A) &= \mathbb{P}(Y_1 \leq x_1, \dots, Y_n \leq x_n) \\ &= m((-\infty, x_1]) \cdots m((-\infty, x_n]) \\ &= \mathbb{P}(Y_2 \leq x_1, \dots, Y_{n+1} \leq x_n) \\ &= \mu(\Theta \circ 1_A) = \mu \circ \Theta^{-1}(A) \end{aligned}$$

So  $\Theta$  is m.p. (by Dynkin's Lemma).

To prove ergodicity, recall the tail- $\sigma$ -algebra

$$\mathcal{T} = \bigcap_n \mathcal{T}_n \quad \text{where} \quad \mathcal{T}_n = \sigma(X_m : m \geq n+1)$$

Then for  $A \in \mathcal{C}$ ,  $A = \prod_k A_k$

$$\Theta^{-n}(A) = \{ X_{n+k} \in A_k \quad \forall k \} \in \mathcal{T}_n$$

● so since  $\mathcal{T}_n$  is itself a  $\sigma$ -algebra, this extends to all  $A \in \sigma(\mathcal{C})$ .

Now suppose  $A$  is invariant, then

$$\Theta^{-n}(A) = A \quad \text{for all } n, \quad \text{so } A \in \mathcal{T}_n \quad \forall n, \quad \text{so } A \in \mathcal{T}$$

Thus  $\mathcal{E}_\Theta \subseteq \mathcal{T}$ , and by Kolmogorov's 0-1 law, we deduce

$$\mu(A) = 0 \quad \text{or} \quad 1 \quad \text{for any invariant set}$$

∴  $\Theta$  is ergodic.  $\square$

● next time:  $\frac{1}{n} S_n(f) = \frac{1}{n} \sum_{m=1}^n \Theta^m \circ f \rightarrow ?$

ergodic theorem

Ergodic theorems

Let  $(E, \mathcal{E}, \mu)$  be a  $\sigma$ -finite measure space with

$\theta: E \rightarrow E$  a measure preserving transf. ( $\mu \circ \theta^{-1} = \mu$ )

Set  $S_0 = 0$ , and for  $f: E \rightarrow \mathbb{R}$  meas.,

$$S_n = S_n(f) = f + f \circ \theta + \dots + f \circ \theta^{n-1} \\ = \sum_{k=0}^{n-1} f \circ \theta^k \quad (\theta^0 = \text{id})$$

Theorem (Birkhoff)

Let  $f \in L^1(\mu)$ . Then  $\exists \bar{f}: (E, \mathcal{E}) \rightarrow \mathbb{R}$   $\theta$ -invariant st.

$$\mu(|\bar{f}|) \leq \mu(|f|) \quad \text{and} \quad \frac{S_n(f)}{n} \rightarrow \bar{f} \quad \text{a.e.}$$

The proof is based on a key lemma.

Lemma (maximal ergodic lemma)

For  $f \in L^1(\mu)$ , set  $S^* = S^*(f) = \sup_{n \geq 0} S_n(f)$

Then  $\int_{\{S^* > 0\}} f \, d\mu \geq 0$

Proof Define  $S_n^* = \max_{0 \leq m \leq n} S_m$  ( $S_n^* \nearrow S^*$ )

Then  $S_m \leq S_n^*$  ( $\forall n \in \mathbb{N}$ )  $\forall 0 \leq m \leq n$ ,

and  $S_{m+1} = S_m \circ \theta + f$  (def)

$$\leq S_n^* \circ \theta + f \quad (*)$$

Now define  $A_n = \{S_n^* > 0\}$  ( $\nearrow \{S^* > 0\}$ )

On  $A_n$ ,  $S_n^* = \max_{1 \leq m \leq n} S_m$  (since  $S_0 = 0$ ), so

$$S_n^* = \max_{1 \leq m \leq n} S_m \leq \max_{0 \leq m \leq n} S_{m+1} \stackrel{(*)}{\leq} S_n^* \circ \theta + f$$

Now integrating this inequality wrt  $d\mu$ ,

$$\int_{A_n} S_n^* \, d\mu \leq \int_{A_n} (S_n^* \circ \theta) \, d\mu + \int_{A_n} f \, d\mu$$

On  $A_n^c$  we must have  $S_n^* = 0 \leq S_n^* \circ \theta$  which implies

$$\int_E S_n^* \, d\mu \leq \underbrace{\int_E S_n^* \circ \theta \, d\mu}_{= \int_E S_n^* \, d\mu \text{ since } \theta \text{ is m.p.}} + \int_{A_n} f \, d\mu$$

Hence  $\int_{A_n} f \, d\mu \geq 0$ .

Since  $f 1_{A_n} \rightarrow f 1_{\{S^* > 0\}}$  and  $|f 1_{A_n}| \leq |f|$ ,  $f \in L^1(\mu)$  we deduce from the dominated convergence theorem that

$$\int_{\{S^* > 0\}} f d\mu = \lim_{n \rightarrow \infty} \int_{A_n} f d\mu \geq 0. \quad \square$$

Now to prove Birkhoff's theorem, notice that

$$\limsup_{n \rightarrow \infty} \frac{S_n(f)}{n} = \limsup_{n \rightarrow \infty} \frac{S_n(f) \circ \theta}{n}$$

are invariant functions and hence

$$\frac{S_{n+1}(f) - f}{n+1} = \frac{S_n(f) \circ \theta}{n}$$

their inverse images

$$D = D_{a,b} = \left\{ \liminf_n \frac{S_n(f)}{n} < a < b < \overline{\lim}_n \frac{S_n(f)}{n} \right\}$$

are measurable and invariant ( $\theta^{-1}D = D$ ).

Wlog we can assume  $b > 0$ . Then take  $B \in \mathcal{E}$ ,  $B \subseteq D$  s.t.  $\mu(B) < \infty$  and set

$$g = f - b 1_B \in L^1(\mu)$$

Then

$$\begin{aligned} S_n(g) &= S_n(f) - b S_n(1_B) \\ &\geq S_n(f) - bn \quad (\text{since } 1_B + 1_B \circ \theta + \dots + 1_B \circ \theta^{n-1} \leq n) \\ (*) &> 0 \quad \text{on } D \text{ for some } n \in \mathbb{N} \quad (\text{def. of } \overline{\lim}) \end{aligned}$$

Now we apply the maximal ergodic lemma with  $E = D$ ,  $\mu = \mu|_D$

which is still  $\theta$ -invariant:  $\mu|_D(A) = \mu(A \cap D) \stackrel{\text{inv}}{=} \mu(\theta^{-1}(A \cap D))$

$$= \mu(\theta^{-1}(A) \cap \underbrace{\theta^{-1}(D)}_D)$$

$$= \mu|_D(\theta^{-1}(A)) \quad (\text{still mp})$$

And note that  $\{S^* > 0\} \subseteq D$  as we are restricting,

but by (\*) get in fact  $\{S^*(g) > 0\} \supseteq D$ .

$$0 \leq \int_{\{S^* > 0\}} g d\mu = \int_D g d\mu = \int_D f d\mu - b\mu(B)$$

$$\text{So } b\mu(B) \leq \int_D f d\mu.$$

By  $\sigma$ -finiteness, this inequality extends to  $D$  (take  $B_n \uparrow D, \mu(B_n) < \infty$ ) and take limits  $b\mu(D) = b \lim_n \mu(B_n) \leq \int_D f d\mu$  (1)

Repeating this argument with  $-f, -a$  we deduce

$$(-a)\mu(D) \leq \int_D (-f) d\mu \quad (2)$$

$$\therefore a\mu(D) \geq \int_D f d\mu$$

which combined give

$$b\mu(D) \leq \int_D f d\mu \leq a\mu(D)$$

but  $a < b$ , so necessarily  $\mu(D) = 0$ .

$$\text{Now define } \Delta = \left\{ \liminf_n \frac{S_n(t)}{n} < \overline{\lim}_n \frac{S_n}{n} \right\}$$

$$= \bigcup_{\substack{a, b \in \mathbb{Q} \\ a < b}} \left\{ \liminf_n \frac{S_n}{n} < a < b < \overline{\lim}_n \frac{S_n}{n} \right\}$$

Hence since  $\mu(D_{a,b}) = 0$  by the above,  $\mu(\Delta) = 0$ .

On  $\Delta^c$ ,  $\frac{S_n}{n}$  converges in  $[-\infty, \infty]$  and, has invariant

$$\bar{f} = \begin{cases} \lim_n \frac{S_n}{n} & \text{on } \Delta^c, \\ 0 & \text{on } \Delta, \end{cases}$$

so that  $\frac{S_n}{n} \rightarrow \bar{f}$  a.e. as  $n \rightarrow \infty$ .

Finally, since  $\mu(|f \circ \theta^{n-1}|) = \mu(|f|)$  so

$$\mu(|S_n|) \leq n \mu(|f|) \quad \text{and thus}$$

$$\mu(|\bar{f}|) = \mu\left(\lim_n \left| \frac{S_n}{n} \right|\right) \stackrel{\text{Fatou}}{\leq} \lim_n \mu\left(\left| \frac{S_n}{n} \right|\right) \leq \mu(|f|) < \infty,$$

in particular  $|\bar{f}| < \infty$  a.e.  $\square$

Theorem (von Neumann's  $L^p$  ergodic theorem)

Assume  $\mu(E) < \infty$ ,  $1 \leq p < \infty$ . Then  $\forall f \in L^p(\mu)$ ,

$$\bullet \quad \frac{S_n(f)}{n} = \frac{f + f \circ \theta + \dots + f \circ \theta^{n-1}}{n} \rightarrow \bar{f}$$

as  $n \rightarrow \infty$  in  $L^p(\mu)$ .

Proof Since  $\theta$  is m.p., so

$$\|f \circ \theta^i\|_p^p = \int_E |f| \circ \theta^i \, d\mu = \int_E |f| \, d\mu = \|f\|_p^p \quad \forall i \geq 0$$

So by Minkowski's inequality, for any  $f \in L^p(\mu)$ ,

$$\bullet \quad \left\| \frac{S_n(f)}{n} \right\|_p \leq \frac{n}{n} \|f\|_p = \|f\|_p \quad (*)$$

Now let  $\varepsilon > 0$  be given, choose  $K$  large enough such that for

$$f_K = (-K) \vee f \wedge K,$$

$$\|f - f_K\|_p^p = \int_{\{|f| > K\}} (|f(x)| - K)^p \, d\mu(x) < (\varepsilon/3)^p$$

possible since  $|f(x)|^p \mathbb{1}_{\{|f| > K\}} \rightarrow 0$  a.e. as  $K \rightarrow \infty$ ,

and using dominated convergence.

Now  $f_K$  is bounded and hence in  $L^1(\mu)$  (for  $\mu(E) < \infty$ ), so by

Birkhoff's theorem we know that

$$\bullet \quad \frac{S_n(f_K)}{n} \xrightarrow[n \rightarrow \infty]{\text{a.e.}} \bar{f}_K, \quad \bar{f}_K \text{ invariant}$$

Since  $\left| \frac{S_n(f_K)}{n} \right| \leq K$  for all  $n$ , bounded convergence implies that the

last limit extends to  $L^p$ -convergence ( $g_n \rightarrow g$  a.e.,  $|g_n| < K$ )

so choose  $N$  large enough s.t.

$$\Rightarrow g_n \rightarrow g \text{ in } L^1(\mu),$$

for  $n \geq N$ ,

$$\|g_n - g\|_p \leq K^{p-1} \|g_n - g\|_1 \rightarrow 0$$

$$\left\| \frac{S_n(f_K)}{n} - \bar{f}_K \right\|_p < \varepsilon/3$$



Finally, for  $\bar{f}$  the limit in Birkhoff's theorem of  $\frac{S_n(f)}{n}$  (noting  $L^p \subseteq L^1$ )

$$\|\bar{f} - \bar{f}_k\|_p^p = \int \lim_{n \rightarrow \infty} \left| \frac{S_n(f)}{n} - \frac{S_n(f_k)}{n} \right|^p d\mu$$

$$\stackrel{\text{Fatou's lemma}}{\leq} \lim_n \int \left| \frac{S_n(f-f_k)}{n} \right|^p d\mu$$

$$\stackrel{\text{for } f-f_k}{(+) \leq} \|f-f_k\|_p^p < (\epsilon/3)^p \text{ by choice of } k$$

Collecting all terms, using Minkowski's inequality

$$\begin{aligned} \left\| \frac{S_n(f)}{n} - \bar{f} \right\|_p &\leq \left\| \frac{S_n(f-f_k)}{n} \right\|_p + \left\| \frac{S_n(f_k)}{n} - \bar{f}_k \right\|_p + \|\bar{f}_k - \bar{f}\|_p \\ &\leq \stackrel{(+)}{\leq} \frac{\epsilon}{3} + \frac{\epsilon}{3} = \epsilon \text{ for } n \text{ large enough. } \square \end{aligned}$$

### The strong law of large numbers

The previous ergodic theorems apply to the shift map

$$\Theta(x_1, x_2, \dots) = (x_2, x_3, \dots)$$

on the canonical p-space  $(E, \mathcal{E}, \mu) = (\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}), \bigotimes_{i=1}^{\infty} m)$

where  $m$  is any p.m. on  $\mathbb{R}$ .

Theorem Let  $m$  be a p.m. on  $\mathbb{R}$  s.t.  $\int_{\mathbb{R}} |x| dm(x) < \infty$ ,  $\int_{\mathbb{R}} x dm(x) = \nu$

Then

$$\mu\left(x \in \mathbb{R}^{\mathbb{N}} : \frac{x_1 + \dots + x_n}{n} \rightarrow \nu \text{ as } n \rightarrow \infty\right) = 1$$

Proof Choose  $f(x) = x_1$ ,  $f \in L^1(\mu)$ ,

so by the ergodic theorems

$$\frac{S_n(f)}{n} = \frac{f + f \circ \Theta + \dots + f \circ \Theta^{n-1}}{n} = \frac{x_1 + x_2 + \dots + x_n}{n} \xrightarrow[L^1(\mu)]{\text{a.e.}} \bar{f}$$

where  $\bar{f}$  is invariant, and  $= \text{const}$  a.e. since  $\Theta$  was shown to be ergodic. Also

$$\text{const} = \mu(\bar{f}) \stackrel{L^1 \text{ limit}}{=} \lim_{n \rightarrow \infty} \mu\left(\frac{S_n(f)}{n}\right) = n \cdot \frac{\nu}{n} = \nu \quad \square \Rightarrow$$

Theorem (Kolmogorov - Khinchine)

Let  $(X_n : n \in \mathbb{N})$  be a sequence of iid r.v.'s defined on some p.space

●  $(\Omega, \mathcal{F}, \mathbb{P})$  s.t.  $\mathbb{E}|X_1| < \infty$ ,  $\mathbb{E}X_1 = \nu$ . Then if

$$S_n = \sum_{i=1}^n X_i, \text{ we have } \frac{S_n}{n} \xrightarrow{\text{a.s.}} \nu \text{ as } n \rightarrow \infty$$

Proof Denote by  $m$  the law of  $X_1$ , and define

$$X : (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow (\mathbb{R}^{\mathbb{N}}, \sigma(\mathcal{C}))$$

by  $X(\omega) = (X_1, X_2, \dots)$ , which is measurable by arguments from earlier.

$$\mu = \mathbb{P} \circ X^{-1} = \bigotimes_{i=1}^{\infty} m$$

Using this injection

$$\mathbb{P} \left( \frac{S_n}{n} \rightarrow \nu \text{ as } n \rightarrow \infty \right)$$

$$= \mu \left( x \in \mathbb{R}^{\mathbb{N}} : \frac{x_1 + \dots + x_n}{n} \rightarrow \nu \text{ as } n \rightarrow \infty \right)$$

$$= 1 \text{ by the previous theorem. } \square$$

To show that  $\mathbb{E}|X_1| < \infty$  is necessary, we finally prove

Prop Let  $X_1, \dots, X_n$  be iid s.t.  $\mathbb{E}|X_1| = \infty$ . Then a.s.,

$\frac{S_n}{n}$  does not converge to any finite limit

Proof Suppose to the contrary that  $\frac{S_n}{n}$  converges a.s. to some limit.

● Then  $\frac{S_{n-1}}{n-1} = \frac{X_1 + \dots + X_{n-1}}{n-1} \cdot \frac{n-1}{n}$  converges to the same limit,

and hence  $\frac{X_n}{n} = \frac{S_n - S_{n-1}}{n} \rightarrow 0$  as  $n \rightarrow \infty$  a.s.

But for any non-negative r.v.  $Y$  (see ExSheet)

$$\mathbb{E}Y \leq \sum_n \mathbb{P}(Y > n), \text{ so for } Y = |X_1|,$$

we have

$$\infty = \mathbb{E}|X_1| \leq \sum_n \mathbb{P}(|X_1| > n)$$

$$\stackrel{\text{iid}}{=} \sum_n \mathbb{P}(|X_n| > n)$$

● so by the second Borel-Cantelli lemma,

$$\mathbb{P} \left( \frac{|X_n|}{n} > 1 \text{ i.o.} \right) = 1 \text{ * to } \frac{X_n}{n} \rightarrow 0 \text{ a.s. } \square$$