

## (I PROBABILITY THEORY)

We will use the following auxiliary result in many calculations below.

Lemma If  $c_n \in \mathbb{C}$  ( $n \in \mathbb{N}$ ),  $c_n \xrightarrow{n \rightarrow \infty} c$ , then

$$\left(1 + \frac{c_n}{n}\right)^n \xrightarrow{n \rightarrow \infty} e^c.$$

Proof: First use triangle inequality

$$\left| \left(1 + \frac{c_n}{n}\right)^n - e^c \right| \leq \left| \left(1 + \frac{c_n}{n}\right)^n - e^{c_n} \right| + \left| e^{c_n} - e^c \right|$$

To estimate the first term, use  $\xrightarrow{0}$  by continuity of exp

$$\begin{aligned} |z^n - w^n| &= |z - w| \cdot |z^{n-1} + z^{n-2}w + z^{n-3}w^2 + \dots + w^{n-1}| \\ &\leq |z - w| \cdot n \cdot M^{n-1} \quad \text{if } |z|, |w| \leq M. \end{aligned}$$

With  $z = 1 + \frac{c_n}{n}$  and  $w = e^{c_n/n}$  and any  $\gamma > |c|$  we have  $|z| \leq e^{\gamma/n}$ ,  $|w| \leq e^{\gamma/n}$  for all large enough  $n$ , and thus

$$\left| \left(1 + \frac{c_n}{n}\right)^n - e^{c_n} \right| \leq \left| 1 + \frac{c_n}{n} - e^{c_n/n} \right| \cdot n \cdot \left(e^{\gamma/n}\right)^{n-1}$$

Finally note that by Taylor series remainder, we have

$$\left| e^{c_n/n} - \left(1 + \frac{c_n}{n}\right) \right| = \mathcal{O}\left(\left(\frac{c_n}{n}\right)^2\right) \quad \text{and obviously } \left(e^{\gamma/n}\right)^{n-1} \leq e^\gamma.$$

We conclude that

$$\left| \left(1 + \frac{c_n}{n}\right)^n - e^{c_n} \right| \leq \mathcal{O}\left(\frac{c_n^2}{n}\right) \xrightarrow{n \rightarrow \infty} 0 \quad \square$$

### I.3 WEAK CONVERGENCE OF REAL RANDOM VARIABLES

In statistical physics, we often <sup>have</sup> consider the following situation

- a probabilistic model (random object) is defined, and it depends on a size parameter  $N$  (the number of microscopic constituents of the system)

- the size parameter in real world systems is large, which is modelled by considering the thermodynamical limit  $N \rightarrow \infty$

► In which sense do the random objects converge as  $N \rightarrow \infty$ ?

Appropriate notion: weak convergence of random variables / probability measures

We discuss weak convergence ~~on~~ ~~in~~ on  $\mathbb{R}$  first  
 (later: ~~in~~ in complete separable metric spaces)

Let's start by examples: in which sense do the following sequences of random variables converge?

### Examples

(1) Continuous dependence on parameters

(a)  $X_n \sim \text{Exp}(\lambda_n)$       $\lambda_n \xrightarrow{n \rightarrow \infty} \lambda$   
 in which sense      $X_n \xrightarrow{n \rightarrow \infty} X \sim \text{Exp}(\lambda)$

(b)  $X_n \sim N(\mu_n, \sigma_n^2)$       $\mu_n \rightarrow \mu, \sigma_n^2 \rightarrow \sigma^2$

$X_n \xrightarrow{n \rightarrow \infty} X \sim N(\mu, \sigma^2)$

(c)  $X_n \sim \text{Bin}(n, p_n)$       $p_n \rightarrow p$

$X_n \xrightarrow{n \rightarrow \infty} X \sim \text{Bin}(n, p)$

(2) The Poisson approximation of binomial distribution

(let  $n \rightarrow \infty$  but  $p_n \rightarrow 0$       $p_n \approx \frac{\lambda}{n}$ )  
 suppose  $(p_n)_{n \in \mathbb{N}}$  is such that  $n \cdot p_n \xrightarrow{n \rightarrow \infty} \lambda$ .

Let  $X_n \sim \text{Bin}(n, p_n)$ .

(Characteristic function of binomial distribution)

$$\mathbb{P}[B=k] = p^k (1-p)^{n-k} \cdot \binom{n}{k}$$

$$\chi(\theta) = \mathbb{E}[e^{i\theta B}] = \sum_{k=0}^n p^k (1-p)^{n-k} \binom{n}{k} e^{i\theta k} = (1-p + pe^{i\theta})^n$$

Let  $\chi_n$  be the characteristic function of  $X_n$

$$\chi_n(\theta) = (1 - p_n + p_n e^{i\theta})^n = \left(1 - \frac{\lambda(1+o(1))(1-e^{i\theta})}{n}\right)^n$$

$$\xrightarrow{n \rightarrow \infty} \exp(\lambda(e^{i\theta} - 1)) = e^{-\lambda} e^{\lambda e^{i\theta}}$$

(Characteristic function of Poisson distribution)

$$\mathbb{P}[P=k] = \frac{\lambda^k}{k!} e^{-\lambda}$$

$$\chi(\theta) = \mathbb{E}[e^{i\theta P}] = \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} e^{-\lambda} e^{i\theta k} = e^{-\lambda} e^{\lambda e^{i\theta}}$$

in which sense      $X_n \xrightarrow{n \rightarrow \infty} X \sim \text{Poisson}(\lambda)$   
 $\text{Bin}(n, p_n)$

(3) The minimum of independent uniform random variables:

Let  $U_j \sim \text{Unif}([0, 1])$  for  $j=1, 2, 3, \dots$ , independent (II)

Denote  $M_n = \min_{1 \leq j \leq n} U_j$  and  $X_n = n \cdot M_n$ .

The cumulative distribution function of  $X_n$  is

$$\begin{aligned} F_n(x) &= \mathbb{P}[X_n \leq x] = \mathbb{P}\left[M_n \leq \frac{x}{n}\right] \\ &= 1 - \mathbb{P}\left[M_n > \frac{x}{n}\right] = 1 - \mathbb{P}\left[\forall j \in [1, n] : U_j > \frac{x}{n}\right] \\ &\stackrel{\text{II}}{=} 1 - \left(1 - \frac{x}{n}\right)^n \xrightarrow{n \rightarrow \infty} 1 - e^{-x} = F_{\text{Exp}(1)}(x) \end{aligned}$$

(c.d.f. of exponential random variable)

$$X_n \xrightarrow{?} X \sim \text{Exp}(1)$$

In the above examples we considered convergence of random variables in various senses:

- convergence of probabilities of events
- convergence of cumulative distribution functions
- convergence of characteristic functions

In statistical physics the natural notion of convergence is often that observable quantities converge. We idealize that an observable quantity is the expected value of some well-behaved function of the state of the system. By well-behaved we ~~mean~~ here mean continuous and bounded.

Def: A sequence  $(X_n)_{n \in \mathbb{N}}$  of  $\mathbb{R}$ -valued random variables (resp.  $(\nu_n)_{n \in \mathbb{N}}$  of ~~prob-~~measures on  $\mathbb{R}$ ) converges weakly to a random variable  $X$  (resp. to a ~~prob-~~measure  $\nu$ ) if for all bounded ~~meas-~~continuous  $f: \mathbb{R} \rightarrow \mathbb{R}$  we have

$$\mathbb{E}[f(X_n)] \xrightarrow{n \rightarrow \infty} \mathbb{E}[f(X)]$$

$$\text{(resp. } \int_{\mathbb{R}} f \, d\nu_n \rightarrow \int_{\mathbb{R}} f \, d\nu \text{)}$$

We denote

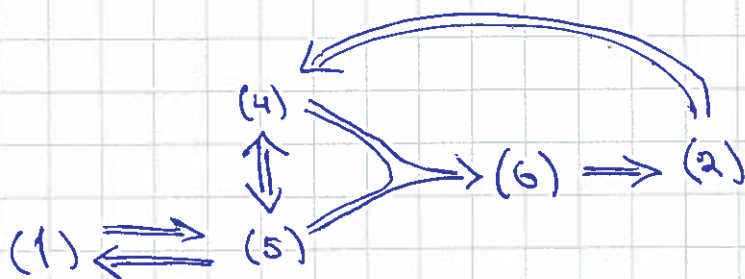
$$X_n \xrightarrow{w} X \quad \text{(resp. } \nu_n \xrightarrow{w} \nu \text{)}$$

The various forms of convergence are essentially equivalent.

Theorem Let  $(X_n)$  be  $\mathbb{R}$ -valued r.v.'s,  $(F_n)$  their cumulative distribution functions  $F_n(x) = P[X_n \leq x]$ ,  $(\chi_n)$  their characteristic functions  $\chi_n(\theta) = E[e^{i\theta X_n}]$ , and  $(\nu_n)$  their distributions  $\nu_n[B] = P[X_n \in B]$ . Let also  $X, F, \chi, \nu$  be a r.v., its c.d.f., char. fn., and distribution. Then the following are equivalent:

- (1)  $\forall f: \mathbb{R} \rightarrow \mathbb{R}$  continuous bounded  $E[f(X_n)] \xrightarrow{n \rightarrow \infty} E[f(X)]$  (i.e.  $X_n \xrightarrow{w} X$ )
- (2) For all continuity points  $x \in \mathbb{R}$  of  $F$  we have  $F_n(x) \xrightarrow{n \rightarrow \infty} F(x)$
- (3) For all  $\theta \in \mathbb{R}$  we have  $\chi_n(\theta) \xrightarrow{n \rightarrow \infty} \chi(\theta)$ .
- (4) For all  $U \subset \mathbb{R}$  open we have  $\liminf (\nu_n[U]) \geq \nu[U]$
- (5) For all  $A \subset \mathbb{R}$  closed we have  $\limsup (\nu_n[A]) \leq \nu[A]$
- (6) For all Borel subsets  $B \subset \mathbb{R}$  such that  $\nu[\partial B] = 0$  we have  $\nu_n[B] \xrightarrow{n \rightarrow \infty} \nu[B]$ .

### A map of the proof



We will prove the equivalence with condition (3) in the next lecture, once we have introduced "tightness",



Proof :

$$(4) \iff (5)$$

Just use  $A = \mathbb{R} \setminus U$ .

$$(4) \& (5) \implies (6)$$

Recall

$$B^\circ \subset B \subset \overline{B}$$

$\uparrow$  interior of B  
 $B^\circ = \mathbb{R} \setminus (\mathbb{R} \setminus B)$  (open set)

$\uparrow$  closure of B  
 (closed set)

$$\text{and } \partial B = \overline{B} \setminus B^\circ$$

(boundary)

$$\text{If } \nu[\partial B] = 0 \text{ then } \nu[B^\circ] = \nu[B] = \nu[\overline{B}].$$

In this case we get, assuming (4) and (5),

$$\liminf \nu_n[B_n] \geq \liminf \nu_n[B^\circ]$$

$$\stackrel{(4)}{\geq} \nu[B^\circ] = \nu[B] = \nu[\overline{B}]$$

$$\stackrel{(5)}{\leq} \limsup \nu_n[\overline{B}] \geq \limsup \nu_n[B]$$

Thus the limit  $\lim_{n \rightarrow \infty} \nu_n[B]$  exists and equals  $\nu[B]$ .

$$(6) \implies (2)$$

Note that  $\partial((-\infty, x]) = \{x\}$

and  $\nu[\{x\}] = 0$  iff  $x$  is a continuity point of  $F$ .

Thus by (6), we have  $F_n(x) = \nu_n((-\infty, x]) \rightarrow \nu((-\infty, x]) = F(x)$

$$(2) \implies (4)$$

Assume first that  $U$  is an open interval  $U = (a, b)$ .

Note that since  $F$  has at most countably many points of discontinuity (increasing function) and open sets can be approximated from below, we ~~can~~ can find for any  $\varepsilon > 0$  ~~some~~ continuity points  $a', b'$  such that  $a < a' < b' < b$  and  $\nu[(a', b')] \geq \nu[(a, b)] - \varepsilon$ .

Then, assuming (2), we have

$$\nu[(a, b)] - \varepsilon \leq \nu[(a', b')] = F(b') - F(a')$$

$$\stackrel{(2)}{=} \lim_{n \rightarrow \infty} \underbrace{(F_n(b') - F_n(a'))}_{= \nu_n[(a', b')]} \leq \liminf \nu_n[(a, b)].$$

This proves the claim if  $U$  is an interval.

In the general case  $U$  is an at most countable union of disjoint open intervals, ~~we~~  $U = \bigcup_{j \in \mathbb{N}} (a_j, b_j)$

By the above argument we ~~can~~ get  $\nu[(a_j, b_j)] - \varepsilon \cdot 2^{-j} \leq \liminf \nu_n[(a_j, b_j)]$

By Fatou's lemma then  $\nu[U] - \varepsilon \leq \liminf \nu_n[U]$ .

(1)  $\Rightarrow$  (5) Let  $A \subset \mathbb{R}$  be closed and assume  $A \neq \emptyset$ .

$x \mapsto d(x, A) := \inf_{y \in A} |x - y|$  is continuous  $\mathbb{R} \rightarrow [0, \infty)$   
 For  $\varepsilon > 0$  set  $f_\varepsilon(x) = \begin{cases} 1 - \frac{d(x, A)}{\varepsilon} & \text{if } d(x, A) \leq \varepsilon \\ 0 & \text{if } d(x, A) \geq \varepsilon \end{cases}$

Then  $f_\varepsilon: \mathbb{R} \rightarrow [0, 1]$  is bounded and continuous, and

we have  $\mathbb{1}_A \leq f_\varepsilon \leq \mathbb{1}_{A_\varepsilon}$

where  $A_\varepsilon = \{x \in \mathbb{R} \mid d(x, A) \leq \varepsilon\}$  is the  $\varepsilon$ -thickening of  $A$ .

Thus

~~$$\nu[A] = \int_{\mathbb{R}} \mathbb{1}_A d\nu \leq \int_{\mathbb{R}} f_\varepsilon d\nu \leq \int_{\mathbb{R}} \mathbb{1}_{A_\varepsilon} d\nu = \nu[A_\varepsilon].$$~~

Similarly  $\limsup \nu_n[A] \leq \limsup \int_{\mathbb{R}} f_\varepsilon d\nu_n \stackrel{(1)}{=} \int_{\mathbb{R}} f_\varepsilon d\nu \leq \nu[A_\varepsilon].$

But  $A_\varepsilon$  approximates the closed set  $A$  from above,  $A_\varepsilon \downarrow A$  as  $\varepsilon \downarrow 0$ .

Thus  $\nu[A_\varepsilon] \rightarrow \nu[A]$  as  $\varepsilon \rightarrow 0$  and (5) follows.

(5)  $\Rightarrow$  (1) In (1) we may without loss of generality consider  $0 < f < 1$ .  
 (add a constant to  $f$ , and multiply  $f$  by constant, if necessary)

Fix temporarily  $N \in \mathbb{N}$  and set

$$A_i = \{x \in \mathbb{R} \mid f(x) \geq \frac{i}{N}\} \quad (i=0, 1, 2, \dots, N)$$

$\uparrow$  closed set, because  $f$  continuous.

Approximate  $f$  from above and below by elementary functions

$$\sum_{i=1}^N \frac{i-1}{N} \mathbb{1}_{A_{i-1} - A_i} \leq f \leq \sum_{i=1}^N \frac{i}{N} \mathbb{1}_{A_{i-1} - A_i}$$

Integrate against  $\nu$  to get

$$\sum_{i=1}^N \frac{i-1}{N} \nu[A_{i-1} - A_i] \leq \int_{\mathbb{R}} f d\nu \leq \sum_{i=1}^N \frac{i}{N} \nu[A_{i-1} - A_i]$$

$$\frac{1}{N} \sum_{i=1}^N \nu[A_i] \leq \int_{\mathbb{R}} f d\nu \leq \frac{1}{N} + \frac{1}{N} \sum_{i=1}^N \nu[A_i]$$

By (5) then (using a similar estimate for  $\nu_n$ )

~~$$\limsup \int_{\mathbb{R}} f d\nu_n \leq \frac{1}{N} + \limsup \int_{\mathbb{R}} f d\nu_n \leq \frac{1}{N} \sum_{i=1}^N \limsup \nu_n[A_i]$$~~

$$\stackrel{(5)}{\leq} \frac{1}{N} \sum_{i=1}^N \nu[A_i] \leq \int_{\mathbb{R}} f d\nu. \quad \text{Take } N \rightarrow \infty.$$

We get  $\limsup \int_{\mathbb{R}} f d\nu_n \leq \int_{\mathbb{R}} f d\nu$ . Consider  $-f$  to get  $\liminf \int_{\mathbb{R}} f d\nu_n \geq \int_{\mathbb{R}} f d\nu$ .  $\square$