MA 361: Probability Theory

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The course

Grading

• Homework: 20%

• Two midterms: 15% each

• Final: 50%

Lecture 1.
Thursday
August 1

Chapter I

Review of discrete probability

Definition I.1 (Discrete probability space). A discrete probability space is a pair (Ω, p) where Ω is a finite or countable set called *sample space* and $p:\Omega\to [0,1]$ is a function giving the *elementary probabilities* of each $\omega\in\Omega$ such that

$$\sum_{\omega \in \Omega} p(\omega) = 1.$$

Examples.

• "Toss a fair n times" is modeled as

$$\Omega = \{0, 1\}^n$$

with

$$p(\omega) \equiv \frac{1}{2^n}.$$

• "Throw r balls randomly into m bins" is modeled as

$$\Omega = [m]^r$$

with p given by the multinomial distribution (assuming uniformity).

• "A box has N coupons, draw one of them."

$$\Omega = [N]$$

$$p = \omega \mapsto \frac{1}{N}.$$

• "Toss a fair coin countably many times." The set of outcomes is clear: $\Omega = \{0, 1\}^{\mathbb{N}}$. What about the elementary probabilities?

Probabilities of some events are also fairly intuitive. For example, the event

$$A = \{ \underline{\omega} \in \Omega \mid \omega_1 = 1, \omega_2 = 1, \omega_3 = 0 \}$$

has probability 1/8. Similarly $B = \{\underline{\omega} \in \Omega \mid \omega_1 = 1, \omega_2 = 0\}$ has probability 1/4. Where does this come from?

What about this event:

$$C = \{ \underline{\omega} \in \Omega \mid \frac{1}{n} \sum_{i=1}^{n} \omega_i \to 0.6 \}$$

What about:

$$D = \{\underline{\omega} \in \Omega \mid \sum_{i=1}^{n} \omega_i = \frac{n}{2} \text{ for infinitely many } n\}^1$$

• "Draw a number uniformly at random from [0, 1]." Ω is obviously [0, 1]. Again some events have obvious probabilities.

$$A = [0.1, 0.3] \implies \mathbf{P}(A) = 0.2$$

Similarly

$$B = [0.1, 0.2] \cup (0.7, 1) \implies \mathbf{P}(B) = 0.4$$

What about $C = \mathbb{Q} \cap [0,1]$? What about D, the $\frac{1}{3}$ -Cantor set?

The $\frac{1}{3}$ -Cantor set is given by the limit of the following sequence of sets.

$$K_0 = [0, 1]$$

 $K_1 = [0, 1/3] \cup [2/3, 1]$
 $K_2 = [0, 1/9] \cup [2/9, 1/3] \cup [2/3, 7/9] \cup [8/9, 1]$
:

where each K_{n+1} is obtained by removing the middle third of each interval in K_n .²

The resolution for the above examples is achieved by taking the 'obvious' cases as definitions.

What we wish for:

What we agree on:

(*)
$$\mathbf{P}([a,b]) = b - a$$
 for all $0 \le a \le b \le 1$.

(#1) If
$$A \cap B = \emptyset$$
, then $\mathbf{P}(A \cup B) = \mathbf{P}(A) + \mathbf{P}(B)$.

(#2) If
$$A_n \downarrow A$$
, then $\mathbf{P}(A_n) \downarrow \mathbf{P}(A)$.

Question: Does there exist a $P: 2^{[0,1]} \to [0,1]$ that satisfies (*), (#1) and (#2)? **No.**

Question: Does there exist a $P: 2^{[0,1]} \to [0,1]$ that satisfies (*), (#1) and even *translational invariance*? **Yes!** However, it is not unique.

$${}^{1}\mathbf{P}(C) = 0 \text{ and } \mathbf{P}(D) = 1.$$

Lecture 1: Discrete probability and σ -algebras

 $^{{}^{2}\}mathbf{P}(C) = \mathbf{P}(D) = 0.$

What about the same for a probability measure on $[0,1]^2$ that is translation and rotation invariant?

What about $[0,1]^3$?

Lack of uniqueness is a disturbing issue. The way out is the following: restrict the class of sets on which ${\bf P}$ is defined to a σ -algebra.

 $^{^3{\}rm The~Banach\text{-}Tarski}$ paradox gives a "no" for the 3D case.

Chapter II

Measure-theoretic probability

σ -algebras **II.1**

Definition II.1 (σ -algebra). Given a set Ω , a collection $\mathcal{F} \subseteq 2^{\Omega}$ is

- $(\varsigma 1) \varnothing \in \mathcal{F}.$ $(\varsigma 2) A \in \mathcal{F} \implies A^c \in \mathcal{F}.$ $(\varsigma 3) \text{ If } A_1, A_2, \dots \in \mathcal{F}, \text{ then } \bigcup_{n=1}^{\infty} A_n \in \mathcal{F}.$

This gives us a modified question.

Question: Does there exist any σ -algebra \mathcal{F} on [0,1] and a function $\mathbf{P} \colon \mathcal{F} \to \mathbf{P}$ [0,1] that satisfies (*), (#1) and (#2)?

Answer: Yes, and it is sort-of unique.

Exercise II.2. Suppose (*) and (#1) hold. Prove that (#2) is equivalent to the following: if $(B_n)_{\mathbb{N}}$ are pairwise disjoint, then

$$\mathbf{P}(\bigcup B_n) = \sum \mathbf{P}(B_n). \tag{II.1}$$

Solution. If $A_1 \supseteq A_2 \supseteq \cdots \supseteq A$, then $A_1^c \subseteq A_2^c \subseteq \cdots \subseteq A^c$. Let $B_n =$ $A_n^c \setminus A_{n-1}^c$, with $B_1 = A_1^c$. First note that (*) and (#1) imply the following:

- (i) $P(A^c) = 1 P(A)$, since $P(A) + P(A^c) = P[0, 1] = 1$.
- (ii) If $A \subseteq B$, then $\mathbf{P}(A) \leq \mathbf{P}(B)$, since $\mathbf{P}(B) = \mathbf{P}(A) + \mathbf{P}(B \setminus A)$. Specifically, $\mathbf{P}(A_1) \ge \mathbf{P}(A_2) \ge \cdots \ge \mathbf{P}(A)$.

Thus $\mathbf{P}(A_n) \downarrow \lim \mathbf{P}(A_n) \geq \mathbf{P}(A)$.

Then

$$\sum_{n=1}^{\infty} \mathbf{P}(B_n) = \lim_{n \to \infty} \mathbf{P}(A_n^c) \quad \text{and} \quad \mathbf{P}(A^c) = \mathbf{P}(\bigcup B_n).$$

If
$$\mathbf{P}(A_n) \downarrow \mathbf{P}(A)$$
, then $\mathbf{P}(A_n^c) \uparrow \mathbf{P}(A^c)$ and so $\sum \mathbf{P}(B_n) = \mathbf{P}(\bigcup B_n)$.
If $\sum \mathbf{P}(B_n) = \mathbf{P}(\bigcup B_n)$, then $\lim \mathbf{P}(A_n^c) = \mathbf{P}(A^c)$ and so $\mathbf{P}(A_n) \downarrow \mathbf{P}(A)$.

A σ -algebra that works for our case is the *smallest* one that contains all intervals.

Exercise II.3. If $\{\mathcal{F}_i\}_{i\in I}$ are σ -algebras on Ω , then $\bigcap_{i\in I} \mathcal{F}_i$ is also a σ -algebra.

Proof. \varnothing is in each \mathcal{F}_i and hence in the intersection. If A is in each \mathcal{F}_i , then so is A^c . If A_1, A_2, \ldots are in each \mathcal{F}_i , then so is $\bigcup_{n=1}^{\infty} A_n$.

This allows us to make sense of the word 'smallest' above.

Definition II.4. Let $S \subseteq 2^{\Omega}$. The *smallest* σ -algebra containing S is given by the intersection of all σ -algebras on Ω that contain S. We denote this by $\sigma(S)$.

This will contain S since 2^{Ω} itself is a σ -algebra.

Example (Borel σ -algebra). The Borel σ -algebra on [0,1] is the smallest σ -algebra containing all intervals in [0,1]. It is denoted by $\mathcal{B}_{[0,1]}$.

II.2 Probability spaces

Definition II.5 (probability space). A probability space is a triple $(\Omega, \mathcal{F}, \mathbf{P})$, where Ω is a non-empty set called the sample space, \mathcal{F} is a σ -algebra on Ω , and \mathbf{P} is a probability measure on \mathcal{F} .

A probability measure on a σ -algebra \mathcal{F} is a function $\mathbf{P} \colon \mathcal{F} \to [0,1]$ such that $\mathbf{P}(\Omega) = 1$ and

$$\mathbf{P}\left(\bigsqcup_{n} A_{n}\right) = \sum_{n} \mathbf{P}(A_{n})$$

for any sequence of pairwise disjoint sets $A_n \in \mathcal{F}$ (countable additivity).

Countable additivity is a stronger condition than finite additivity.

Exercise II.6. Prove that countable additivity is equivalent to the following two conditions taken together:

- (i) finite additivity: if $A \cap B = \emptyset$, then $P(A \sqcup B) = P(A) + P(B)$
- (ii) If $A_n \uparrow A$, then $\mathbf{P}(A_n) \uparrow \mathbf{P}(A)$.

Solution. Identical to theorem II.2.

Lecture 2. Tuesday August 6

Where do Ω , \mathcal{F} , and P come from?

 Ω is simply the set of all possible outcomes.

II.2.1 The σ -algebra

 $\mathcal{F} = 2^{\Omega}$ and $\mathcal{F} = \{\emptyset, \Omega\}$ are bullshit choices. In reality, \mathcal{F} is always chosen to be the smallest σ -algebra containing some specified sets of interest. That is, for some $\mathcal{S} \subseteq 2^{\Omega}$, $\mathcal{F} = \sigma(\mathcal{S})$.

This is sometimes called the σ -algebra "generated by" \mathcal{S} . However, this can create a misconception. Recall the similar notion of the *span* of a set of vectors. We can define the span of a set $S \subseteq V$ of vectors in two ways:

- (external) the smallest subspace containing S.
- (internal) the set of all linear combinations of vectors in S.

For $\sigma(S)$, there is no "internal" definition. $\sigma(S)$ cannot be generated by unions, intersections, etc. of sets in S.

A frequent choice for S is the following.

Definition II.7 (Borel σ -algebra). Let (X, d) be a metric space. The Borel σ -algebra on X is the smallest σ -algebra containing all open sets in X, and is denoted $\mathcal{B}(X)$.

II.2.2 The probability measure

There is some collection $S \subseteq \Omega$ for which we know what the probabilities "should" be, $\mathbf{P} \colon S \to [0, 1]$.

Question II.8. Does **P** extend to a probability measure on $\sigma(S)$? If so, is it unique?

Uniqueness does not hold.

Example. Let $\Omega = \{1, 2, 3, 4\}$ and $S = \{\{1, 2\}, \{2, 3\}, \{3, 4\}\}$. $F = \sigma(S) = 2^{\Omega}$.

Then the probability measures given by

$$\underline{p} = (.25, .25, .25, .25)$$

 $q = (.5, 0, .5, 0)$

agree on \mathcal{S} but differ on \mathcal{F} .

When does uniqueness hold?

Lecture 2: Probability measures and their existence

Uniqueness

Definition II.9 (π -system). A collection $\mathcal{S} \subseteq 2^{\Omega}$ is a π -system if it is closed under finite intersections. That is, for any $A, B \in \mathcal{S}$, $A \cap B \in \mathcal{S}$.

Definition II.10 (λ -system). A collection $\mathcal{C} \subseteq 2^{\Omega}$ is a λ -system if it contains Ω and is closed under

- proper differences: if $A, B \in \mathcal{C}$ and $B \subseteq A$, then $A \setminus B \in \mathcal{C}$.
- increasing limits: if $A_n \in \mathcal{C}$ and $A_n \uparrow A$, then $A \in \mathcal{C}$.

Theorem II.11. If $\mathcal{F} = \sigma(\mathcal{S})$ where \mathcal{S} is a π -system and P, Q are probability measures on \mathcal{F} that agree on \mathcal{S} , then P = Q.

Proof sketch. Consider $\mathcal{G} = \{A \in \mathcal{F} \mid P(A) = Q(A)\}$. Then $\mathcal{G} \supseteq \mathcal{S}$. Further, if $A \in \mathcal{G}$, then $A^c \in \mathcal{G}$ since $P(A^c) = 1 - P(A) = 1 - Q(A) = Q(A^c)$. If $A, B \in \mathcal{G}$ are disjoint, then

$$P(A \sqcup B) = P(A) + P(B) = Q(A) + Q(B) = Q(A \sqcup B).$$

But how do we deal with A, B not disjoint? We need to show that $A, B \in \mathcal{G} \implies A \cap B \in \mathcal{G}$.

Resolution: Show that \mathcal{G} is a λ -system, and then apply the π - λ theorem. Suppose $A, B \in \mathcal{G}$ with $B \subseteq A$. Then $P(A \setminus B) = P(A) - P(B) = Q(A) - Q(B) = Q(A \setminus B)$. Thus \mathcal{G} is closed under proper differences.

If $A_n \uparrow A$ are in \mathcal{G} , then $P(A_n) \uparrow P(A)$ and $Q(A_n) \uparrow Q(A)$. But $P(A_n) = Q(A_n)$ for all n, so P(A) = Q(A). Thus \mathcal{G} is closed under increasing limits.

 \mathcal{G} contains Ω since $P(\Omega) = Q(\Omega) = 1$.

Thus by the π - λ theorem, \mathcal{G} is a σ -algebra and thus $\mathcal{G} \supseteq \mathcal{F}$.

Theorem II.12 (π - λ theorem). Let S be a π -system and C be a λ -system. If $C \supseteq S$, then $C \supseteq \sigma(S)$.

This is due to Sierpiński and Dynkin.

What about existence?

Existence

In the general case, obviously not. Consider $\Omega = [0, 1]$ with

$$S = \{(0, \frac{1}{2}), (0, \frac{1}{4}), (\frac{1}{4}, \frac{1}{2})\}$$
$$\mathbf{P}(a, b) = (b - a)^{2}.$$

Lecture 2: Probability measures and their existence

	\varnothing , Ω	A^c	$\bigcap_{i=1}^{n}$	$\bigcup_{i=1}^{n}$	$\bigcap_{i=1}^{\infty}$	$\bigcup_{i=1}^{\infty}$	$A \setminus B$ $(B \subseteq A)$	$A_n \uparrow A$
π -system			✓					
λ -system	✓	✓					✓	✓
algebra		✓	✓	✓			✓	
σ -algebra	✓	✓	✓	✓	✓	✓	✓	✓

Table II.1: Various systems of sets

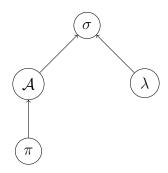


Figure II.1: Heirarchy of systems of sets under inclusion

Then the sum of $\mathbf{P}(0, \frac{1}{4})$ and $\mathbf{P}(\frac{1}{4}, \frac{1}{2})$ is less that $\mathbf{P}(0, \frac{1}{2})$. Let us impose some necessary conditions.

Definition II.13 (Algebra). A collection $\mathcal{A} \subseteq 2^{\Omega}$ is an *algebra* if it is closed under complements and finite unions.

Theorem II.14 (Carathéodory's extension theorem). Let S be an algebra. Assume that $P \colon S \to [0,1]$ is countably additive. Then there exists an extension of P to a probability measure P on $F = \sigma(S)$.

Corollary II.15. The above extension is unique.

Proof. An algebra is a π -system. Theorem II.11 applies.

II.3 Existence of Lebesgue measure

Theorem II.16. There is a unique probability measure λ on [0,1] with the Borel σ -algebra such that

$$\lambda[a,b] = b-a \qquad \forall \ 0 \le a \le b \le 1.$$

Lecture 2: Probability measures and their existence

Proof. Let $\Omega = [0, 1)$.

Let $S_0 = \{[a, b) \mid 0 \le a \le b \le 1\}$. Half-open intervals are nice because they are closed under complements $[a, b)^c = [0, a) \sqcup [b, 1)$ and intersections $[a, b) \cap [c, d) = [a \vee c, b \wedge d)$.

Let

$$\mathcal{S} = \{I_1 \sqcup \cdots \sqcup I_k \mid k \geq 1, I_j \in \mathcal{S}_0 \text{ disjoint}\}\$$

be the collection of all finite disjoint unions of half-open intervals. It is obvious that S is an algebra. Define

$$\lambda_{\mathcal{S}}(I_1 \sqcup \cdots \sqcup I_k) = \sum_{j=1}^k (\sup I_j - \inf I_j).$$

We need to show that this is countably additive, in order that Carathéodory's extension theorem applies. We will proceed via theorem II.6.

- Finite additivity is obvious.
- Let $A_n, A \in \mathcal{S}$ with $A_n \uparrow A$.

By Carathéodory's extension theorem, there exists a unique probability measure λ on $\mathcal{F} = \sigma(\mathcal{S})$ that extends $\lambda_{\mathcal{S}}$.

Lecture 3. Thursday August 8

II.4 New measures from old

Definition II.17. Let (Ω, \mathcal{F}) and (Ω', \mathcal{F}') be two sets with σ -algebras. A function $T \colon \Omega \to \Omega'$ is measurable if

$$T^{-1}(B) \in \mathcal{F}$$
 for all $B \in \mathcal{F}'$.

II.4.1 Push forward

Lemma II.18. Let (Ω, \mathcal{F}, P) be a probability space and (Ω', \mathcal{F}') be a set with a σ -algebra. Let $T: \Omega \to \Omega'$ be measurable. Then $Q := P \circ T^{-1}$ is a probability measure on \mathcal{F}' .

Proof. We need to show that $Q(\Omega') = 1$ and Q is countably additive. The first is immediate as $Q(\Omega') = P(T^{-1}(\Omega')) = P(\Omega) = 1$.

Notice that if B_1 and B_2 are disjoint, so are $T^{-1}(B_1)$ and $T^{-1}(B_2)$. Let $(B_n)_{\mathbb{N}}$ be a sequence of pairwise disjoint sets in \mathcal{F}' . Then $(T^{-1}(B_n))_{\mathbb{N}}$ are

pairwise disjoint in \mathcal{F} . Thus

$$Q(\bigsqcup B_n) = P(T^{-1}(\bigsqcup B_n))$$

$$= P(\bigsqcup T^{-1}(B_n))$$

$$= \sum P(T^{-1}(B_n))$$

$$= \sum Q(B_n).$$

Definition II.19 (cumulative distributive function). A *cumulative* distributive function (CDF) is a function $F: \mathbb{R} \to [0, 1]$ such that

- (i) (increasing) $x \le y \implies F(x) \le F(y)$
- (ii) (right-continuous) $\lim_{h\searrow 0} F(x+h) = F(x)$
- (iii) $\lim_{x\to-\infty} F(x) = 0$ and $\lim_{x\to\infty} F(x) = 1$

Let $P(\mathbb{R})$ be the set of all probability measures on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$. If $\mu \in P(\mathbb{R})$, then $F_{\mu}(x) := \mu(-\infty, x]$ is a CDF (increasing, right-continuous with $F(-\infty) = 0$, $F(\infty) = 1$)).

Lecture 4.
Tuesday
August 13

Theorem II.20. Given a CDF $F: \mathbb{R} \to [0,1]$, there exists a unique probability measure $\mu \in P(\mathbb{R})$ such that $\mu(-\infty, x] = F(x)$ for all $x \in \mathbb{R}$.

Proof. Consider $((0,1),\mathcal{B},\lambda)$ and define

$$T: (0,1) \to \mathbb{R}$$

 $u \mapsto \inf\{x \in \mathbb{R} : F(x) \ge u\}$

The set is non-empty since $F(x) \to 1$ as $x \to \infty$. Moreover, T is increasing since

$$\{x \in \mathbb{R} : F(x) \ge u\} \subseteq \{x \in \mathbb{R} : F(x) \ge v\}$$

whenever $u \leq v$. T is left-continuous.

Finally, $T(u) \leq x \iff F(x) \geq u$. (This is reminiscent of the inverse property: $T(u) = x \iff F(x) = u$.) If $F(x) \geq u$, then $x \in F^{-1}[u, 1)$, so $T(u) \leq x$. If $T(u) \leq x$, then $x + \frac{1}{n} \in F^{-1}[u, 1)$ for all $n \in \mathbb{N}$. By right-continuity, $F(x) \geq u$.

Now T is Borel-measurable, so

$$\mu \coloneqq \lambda \circ T^{-1}$$

is a probability measure on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$.

Further, $\mu(-\infty, x] = \lambda(T^{-1}(-\infty, x]) = \lambda(0, F(x)] = F(x)$. Uniqueness if by the π -system thingy.

Examples.

- Take $f: \mathbb{R} \to [0, \infty)$ measurable whose total integral is 1. Then $F = x \mapsto \int_{-\infty}^{x} f(u) du$ is a CDF.
- (Cantor measure) Consider the $\frac{1}{3}$ -Cantor set $K = K_1 \cap K_2 \cap \ldots$ where

$$K_1 = \left[0, \frac{1}{3}\right] \cup \left[\frac{2}{3}, 1\right]$$

$$K_2 = \left[0, \frac{1}{9}\right] \cup \left[\frac{2}{9}, \frac{1}{3}\right] \cup \left[\frac{2}{3}, \frac{7}{9}\right] \cup \left[\frac{8}{9}, 1\right]$$
:

Notice that

$$K = \{x \in [0,1] : x = \sum_{n=1}^{\infty} \frac{x_n}{3^n}, x_n = 0 \text{ or } 2\}.$$

We can construct the measurable function

$$T: [0,1] \to \mathbb{R}$$

$$\sum_{n=1}^{\infty} \frac{x_n}{2^n} \mapsto \sum_{n=1}^{\infty} \frac{2x_n}{3^n}$$

where we are considering the non-terminating binary expansion of x on the left. It is obvious that T maps only to K. Since $T^{-1}(K) = [0, 1]$, we have that $\mu(K) = 1$. However, $\lambda(K) = 0$. Thus the CDF cannot arise from a density. However, the CDF is continuous!

• (just for fun) Fix a $\theta > 2$ and define

$$T_{\theta} \colon [0,1] \to [0,1]$$

$$\sum_{n=1}^{\infty} \frac{x_n}{2^n} \mapsto \sum_{n=1}^{\infty} \frac{x_n}{\theta^n}$$

define $\mu_{\theta} = \lambda \circ T_{\theta}^{-1}$. $\mu_2 = \lambda$. It is known that for $\theta > 2$, μ_{θ} has no density. What about $1 < \theta < 2$? This is an open problem. "Bernoulli convolution problem".

II.4.2 Structure of $P(\Omega, \mathcal{F})$

What is the structure of $P(\Omega, \mathcal{F})$? Is it a vector space? A group?

One thing to note is that $P(\Omega, \mathcal{F})$ is convex. That is, given any $\mu, \nu \in P(\Omega, \mathcal{F})$ and $0 \le t \le 1$, $(1 - t)\mu + t\nu \in P(\Omega, \mathcal{F})$. This is called a *mixture* of μ and ν .

We would like to study *closeness* of probability measures. Consider a computer generating a random number between 0 and 1, by generating a

sequence of 8 random bits. The computer is actually sampling from the uniform distribution

$$\mu_{2^8} = \text{Unif}\left\{\frac{0}{2^8}, \frac{1}{2^8}, \dots, \frac{2^8 - 1}{2^8}\right\}.$$

However, we do accept μ as an approximation of λ . We will thus attempt to define a metric on $P(\mathbb{R})$.

Attempt 1. (total variation distance) Define

$$d(\mu, \nu) = \sup_{A \in \mathcal{B}_{\mathbb{R}}} |\mu(A) - \nu(A)|.$$

This does not work for out for our use case, as

$$d(\mu_{2^8}, \lambda) = 1.$$

Attempt 2. (Kolmogorov-Smirnov metric) Choose a suitable $\mathcal{C} \in \mathcal{B}_{\mathbb{R}}$ and define

$$d(\mu,\nu)=\sup_{A\in\mathcal{C}}\lvert\mu(A)-\nu(A)\rvert.$$
 \mathcal{C} should be "measure-determining".

Attempt 3. (Lévy metric)

$$d(\mu, \nu) = \inf\{\varepsilon > 0 : F_{\mu}(x + \varepsilon) + \varepsilon \ge F_{\nu}(x) \text{ and } F_{\nu}(x + \varepsilon) + \varepsilon \ge F_{\mu}(x) \text{ for all } x \in \mathbb{R}\}.$$

This is symmetric by sheer obviousness. For \triangle , consider three measures μ, ν, ρ .

$$t > d(\mu, \nu)$$
 $\Longrightarrow F_{\mu}(x+t) + t \ge F_{\nu}(x)$
 $s > d(\nu, \rho)$ $\Longrightarrow F_{\nu}(x+s) + s \ge F_{\rho}(x)$

Thus

$$F_{\mu}(x+t+s) + t + s \ge F_{\nu}(x+s) + t \ge F_{\rho}(x)$$

Thus $t + s \ge d(\mu, \rho)$. \triangle holds.

Finally, suppose $d(\mu, \nu) = 0$. Let $\varepsilon_n \downarrow 0$ be a sequence such that $F_{\mu}(x+\varepsilon_n)+\varepsilon_n\geq F_{\nu}(x)$ for all x for all n. Taking limits, we have $F_{\mu}(x) \geq F_{\nu}(x)$ by right-continuity. By symmetry, $F_{\mu}(x) = F_{\nu}(x).$

Definition II.21. If $\mu_n, \mu \in P(\mathbb{R})$ and $d(\mu_n, \mu) \to 0$ then we say that μ_n converges in distribution to μ and write $\mu_n \stackrel{d}{\to} \mu$.

Lecture 5. Tuesday August 20

Remark. This is also called weak convergence and hence sometimes written $\mu_n \stackrel{\text{w}}{\to} \mu$. Yet others write $\mu_n \Rightarrow \mu$.

Proposition II.22. Let $\mu_n, \mu \in P(\mathbb{R})$. Then

 $\mu_n \xrightarrow{d} \mu \iff F_{\mu_n}(x) \to F_{\mu}(x) \text{ for all } x \text{ where } F_{\mu} \text{ is continuous.}$

Examples.

• $\delta_{\frac{1}{2}} \xrightarrow{d} \delta_0$ because

$$\lim_{n \to \infty} F_{\delta_{1/n}}(x) = \begin{cases} 0 & \text{if } x \le 0, \\ 1 & \text{if } x > 0. \end{cases}$$

So $F_{\delta_1/n}(x) \to F_{\delta_0}(x)$ for all $x \neq 0$.

• $\delta_{-\frac{1}{2}}(x) \to \delta_0(x)$ everywhere.

Proof. Write $F_{\mu} = F$ and $F_{\mu_n} = F_n$.

Suppose $\mu_n \xrightarrow{d} \mu$ and let F be continuous at $x \in \mathbb{R}$. Let $\varepsilon > 0$. Then

$$F(x+\varepsilon) + \varepsilon \ge F_n(x)$$
$$F_n(x) + \varepsilon \ge F(x-\varepsilon)$$

for all large n. Thus we have

$$\limsup_{n \to \infty} F_n(x) \le F(x + \varepsilon) + \varepsilon$$
$$\liminf_{n \to \infty} F_n(x) \ge F(x - \varepsilon) - \varepsilon.$$

But this holds for all $\varepsilon > 0$. Letting $\varepsilon \downarrow 0$ gives

$$\limsup_{n \to \infty} F_n(x) \le F(x)$$
$$\liminf_{n \to \infty} F_n(x) \ge F(x).$$

Thus $\lim_{n\to\infty} F_n(x) = F(x)$.

Now suppose $F_n(x) \to F(x)$ for all x where F is continuous. Fix $\varepsilon > 0$ and pick $x_1 < \cdots < x_p$ such that

- each x_j is a continuity point of F,
- $x_{j+1} x_j < \varepsilon$ for all j,
- $F(x_1) \le \varepsilon$ and $F(x_p) \ge 1 \varepsilon$.

Then $\exists N \in \mathbb{N}$ such that $\forall n \geq N$ we have

$$|F_n(x_j) - F(x_j)| < \varepsilon \text{ for all } j.$$
 (II.2)

Let $x \in \mathbb{R}$ and $n \geq N$. We have three cases.

 $(x_j \le x \le x_{j+1})$ Then

$$F_n(x+\varepsilon) + \varepsilon \ge F_n(x_{j+1}) + \varepsilon \ge F(x_{j+1}) \ge F(x).$$

The first and last inequalities are by the increasing nature of CDFs. The middle inequality is by equation (II.2). Similarly

$$F(x+\varepsilon)+\varepsilon \geq F(x_{i+1})+\varepsilon \geq F_n(x_{i+1}) \geq F_n(x)$$
.

 $(x < x_1)$ Then

$$F_n(x+\varepsilon) + \varepsilon \ge \varepsilon \ge F(x_1) \ge F(x)$$
.

The other direction requires a bigger jump.

$$F(x+2\varepsilon) + 2\varepsilon \ge 2\varepsilon \ge F(x_1) + \varepsilon \ge F_n(x_1) \ge F_n(x)$$
.

$$(x > x_p)$$

Thus
$$d(\mu_n, \mu) \to 0$$
.

Remark. Notice that the converse did not use the continuity of F at all. All that was required is that the points of continuity of F are dense. Thus we have the following proposition immediately.

Proposition II.23. Let $\mu_n, \mu \in P(\mathbb{R})$ and let D be a dense subset of \mathbb{R} . Then

$$F_{\mu_n}(x) \to F_{\mu}(x) \text{ for all } x \in D \implies \mu_n \xrightarrow{d} \mu.$$

 $(P(\mathbb{R}), d_{\text{Lévy}})$ is a metric space. It is interesting to ask what the *compact* subsets of this space are.

Definition II.24. A subset $A \subseteq P(\mathbb{R})$ is *tight* if for all $\varepsilon > 0$ there exists a compact set K_{ε} such that

$$\mu(K_{\varepsilon}^c) \leq \varepsilon \text{ for all } \mu \in \mathcal{A}.$$

For \mathbb{R} , it only makes sense to consider $K_{\varepsilon} = [-M_{\varepsilon}, M_{\varepsilon}]$. Such an M_{ε} exists for each $\mu \in \mathcal{A}$ individually, but not necessarily for all $\mu \in \mathcal{A}$ simultaneously.

Examples.

- $\mathcal{A} = \{\delta_n\}_{n \in \mathbb{Z}}$ is *not* tight. No matter what M is chosen, $\delta_{\lceil M+1 \rceil}$ will have all of its mass outside of [-M, M].
- Similarly, $\{N(\mu,1)\}_{\mu\in\mathbb{R}}$ is not tight, but $\{N(\mu,1)\}_{-16\leq\mu\leq32768}$ is tight.
- $\{N(\mu, \sigma^2)\}_{\substack{-10 \le \mu \le 10 \ 0 < \sigma < 10}}$ is not tight, but $\{N(\mu, \sigma^2)\}_{\substack{-10 \le \mu \le 10 \ 0 < \sigma < 10}}$ is.
- $\{\delta_{\frac{1}{n}}\}_{n\in\mathbb{N}}$ is tight.

Definition II.25. A set $E \subseteq (X, d)$ is *pre-compact* if its closure \overline{E} is compact.

Theorem II.26. Any $A \subseteq P(\mathbb{R})$ is pre-compact iff it is tight.

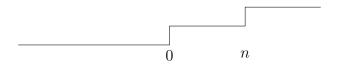
Theorem II.27 (Helly's selection principle). Let $\mu_n \in P(\mathbb{R})$. Then there is a subsequence $n_1 < n_2 < \dots$ and an increasing, right continuous functio $F \colon \mathbb{R} \to [0,1]$ such that

$$F_{\mu_n}(x) \to F(x)$$
 for all x where F is continuous.

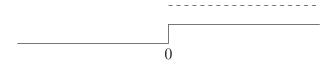
F may be a "defective CDF". It need not go to 0 to the left, nor 1 to the right.

Examples.

• Let $\mu_n = \frac{1}{2}\delta_0 + \frac{1}{2}\delta_n$. $F_{\mu_n}(x)$ looks like



The pointwise limit of any subsequence is



This is not a CDF.

• The limit for $\mu_n = N(0, n)$ is the constant function $F(x) = \frac{1}{2}$.

Proof. Fix a dense countable set $D = \{x_1, x_2, \ldots\} \subseteq \mathbb{R}$. By compactness of [0, 1], there exists a subsequence $(n_k)_{k \in \mathbb{N}}$ such that $F_{n_k}(x_1)$ converges, say to c_1 .

Choose a further subsequence $(n_{k_l})_{l\in\mathbb{N}}$ such that $F_{n_{k_l}}(x_2)$ converges, say to c_2 .

Choose a further subsequence $(n_{k_{l_m}})_{m\in\mathbb{N}}$ such that $F_{n_{k_{l_m}}}(x_3)$ converges, say to c_3 .

The limit of doing this infinitely many times may give an empty subsequence. The key is *diagonalization*.

Let us relabel these subsequences as $(n_{1,k})_{k\in\mathbb{N}}$, $(n_{2,k})_{k\in\mathbb{N}}$, $(n_{3,k})_{k\in\mathbb{N}}$,

Walk the diagonal. $F_{n_{j,j}}(x_i) \to c_i$ for each i.

Thus we have constructed a subsequence, which we will finally label $(n_k)_{k\in\mathbb{N}}$ such that

$$F_{n_k}(x_i) \to c_i$$
 for all i .

All that remains is to extend this preserving right-contiunity. Define

$$F(x) := \inf\{c_i \mid i \in \mathbb{N} \text{ such that } x < x_i\}.$$

All that remains is to check that

- F is increasing and right-continuous,
- $F_{n_k}(x) \to F(x)$ if F is continuous at x.

Suppose $x_1 \le x_2$. Then $F(x_1) = \inf\{c_i \mid x_i > x_1\} \le \inf\{c_i \mid x_i > x_2\} = F(x_2)$ since the second set is a subset of the first.

Now let $x \in \mathbb{R}$ and $\varepsilon > 0$. Then $F(x) \geq c_i - \varepsilon$ for some i such that $x_i \geq x$. Let $y \in (x, x_i)$. Then $F(y) \leq c_i$ by definition of $F(c_i)$ is a witness for y). Thus $F(x) \leq F(y) \leq F(x) + \varepsilon$.