Probability

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1 Measure theory review

1.1 Measurable space and mapping

Definition (σ-field)**.** A collection of subsets $\Sigma \subset 2^{\Omega}$ is a σ-field if

- $\emptyset \in \Sigma$.
- If $A \in \Sigma$, then $A^c \in \Sigma$.
- If $\{A_i\}_{i=1}^{\infty} \subset \Sigma$, then $\bigcup_{i=1}^{\infty} A_i \in \Sigma$.

The pair (Ω, Σ) is called a measurable space.

Definition (atom)**.** Let Σ be a σ-field. Say $A \in \Sigma$ is an atom if for all $B \in \Sigma$ either $A \subset B$ or $A \cap B = \emptyset$.

Proposition. For all $\omega \in \Omega$, there exists atom $A \in \Sigma$ containing ω if Ω is finite or countable.

Proof. Define $\widetilde{A} = \bigcap \{B \in \Sigma : \omega \in B\}$. We can check that $\widetilde{A} \in \Sigma$ and $\widetilde{A}$ is an atom containing ω. □

Corollary. If Ω is finite or countable, there exists a partition $\Omega = \bigsqcup_i \Omega_i$, where each Ω_i is an atom of Σ. With this partition, Σ is just the power set with respect to $\{\Omega_i\}_i$.

Definition. If $F \subset 2^{\Omega}$, then the σ-field generated by F is the smallest σ-field containing all elements of F. Write this σ-field as $\sigma(F)$.

Example. Let $\Omega = \{1, 2, 3, 4, 5\}$ and $F = \{\{2, 3\}, \{3, 4\}\}$. Construct σ-field Σ generated by F. Σ is all possible union of sets from the collection $\{\{2\}, \{3\}, \{4\}, \{1, 5\}\}$.

Definition (measurable mapping)**.** Given two measurable spaces (Ω, Σ) and $(\widetilde{\Omega}, \widetilde{\Sigma})$. Then $f : \Omega \to \widetilde{\Omega}$ is measurable if $f^{-1}(B) \in \Sigma$ for all $B \in \widetilde{\Sigma}$.

Definition (Borel σ-field)**.** Let (T, τ) be a topological space. Then the Borel σ-field $\mathcal{B}(T, \tau)$ is defined as the smallest σ-field containing all open sets.

Definition (product measurable space)**.** Given two measurable spaces (Ω, Σ) and $(\widetilde{\Omega}, \widetilde{\Sigma})$. We can define the product measurable space as follows: let the ground set be $\Omega \times \widetilde{\Omega}$, and let $\Sigma \otimes \widetilde{\Sigma}$ be the smallest σ-field containing all rectangles $B \times \widetilde{B}$ where $B \in \Sigma$ and $\widetilde{B} \in \widetilde{\Sigma}$.

More generally, let Λ be an index set and $(\Omega_\lambda, \Sigma_\lambda)_{\lambda \in \Lambda}$. Define the product σ-field $\bigotimes_{\lambda \in \Lambda} \Sigma_\lambda$ be the smallest σ-field containing all elements in the form of $\prod_{\lambda \in \Lambda} B_\lambda$ where $B_\lambda \in \Sigma_\lambda$ and $B_\lambda = \Omega_\lambda$ for all but countably many indices.

Proposition. Let $(\Omega_i, \Sigma_i)_{i=1}^n$ be measurable spaces and $(\prod_{i=1}^n \Omega_i, \bigotimes_{i=1}^n \Sigma_i)$ be the product space. Let (Ω, Σ) be the domain and $f = (f_1, \ldots, f_n) : (\Omega, \Sigma) \to (\prod_{i=1}^n \Omega_i, \bigotimes_{i=1}^n \Sigma_i)$. Suppose f is measurable, then every coordinate projection $f_i : \Omega \to \Omega_i$ is measurable.

This is also true for arbitrary index set.

Proposition. If $f : (\Omega, \Sigma) \to (\Omega_f, \Sigma_f)$ and $g : (\Omega, \Sigma) \to (\Omega_g, \Sigma_g)$, then the concatenation (f, g) is measurable w.r.t. the product space $(\Omega_f \times \Omega_g, \Sigma_f \otimes \Sigma_g)$.

Proof. Let $A \times B$ be such that $A \in \Sigma_f$ and $B \in \Sigma_g$. Then the preimage

$$(f, g)^{-1}(A \times B) = f^{-1}(A) \cap g^{-1}(B) \in \Sigma.$$

By definition, the product σ-field is generated by rectangles, so the proof is complete. □

1.2 Measure space

Definition (measure)**.** Let (Ω, Σ) be a measurable space. Then $\mu : \Sigma \to [0, \infty]$ is a measure if

- $\mu(\emptyset) = 0$.
- If $A_i \in \Sigma$ is pairwise disjoint then $\mu\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mu(A_i)$.

Proposition (continuity of measure)**.** If $A_1 \subset A_2 \subset \dots$ is a nested sequence of elements of Σ and μ be any measure on (Ω, Σ). Then

$$\mu\left(\bigcup_{i=1}^{\infty} A_i\right) = \lim_{i\to\infty} \mu(A_i).$$

If $A_1 \supset A_2 \supset \dots$ is a nested sequence of elements of Σ and $\mu(A_n) < \infty$ for some n. Then

$$\mu\left(\bigcap_{i=1}^{\infty} A_i\right) = \lim_{i\to\infty} \mu(A_i).$$

Definition. Let (Ω, Σ, μ) be a measure space.

Say μ is σ-finite if there is a representation $\Omega = \bigcup_{i=1}^{\infty} \Omega_i$ where $\Omega_i \in \Sigma$ and $\mu(\Omega_i) < \infty$.

Say μ is a probability measure if $\mu(\Omega) = 1$.

Definition (completion of measure space)**.** Let (Ω, Σ, μ) be a measure space. Let

$$\widetilde{\Sigma} = \{A \cup B : A \in \Sigma, B \subset \Omega, \text{there exists } C \in \Sigma \text{ with } \mu(C) = 0 \text{ and } B \subset C\}.$$

We can check $\widetilde{\Sigma}$ is a σ-field. If $\widetilde{\mu}$ is a measure on $(\Omega, \widetilde{\Sigma})$ which agrees with μ on Σ, then $(\Omega, \widetilde{\Sigma}, \widetilde{\mu})$ is called a completion of (Ω, Σ, μ).

1.3 π-λ theorem

Definition (π-system)**.** Let Ω be a set and $\mathcal{P}$ be a collection of subsets of Ω. Then $\mathcal{P}$ is a π-system if it is closed with respect to taking finite intersections. That is, $A, B \in \mathcal{P}$ implies $A \cap B \in \mathcal{P}$.

Example. On the real line $\mathbb{R}$, both $\mathcal{P}_1 = \{(a,b) : a < b\}$ and $\mathcal{P}_2 = \{(-\infty, a] : a \in \mathbb{R}\}$ are π-systems.

Definition (λ-system)**.** Let Ω be a set and $\mathcal{L}$ be a collection of subsets of Ω. Say $\mathcal{L}$ is a λ-system if

- $\emptyset \in \mathcal{L}$.
- $A \in \mathcal{L}$ implies $A^c \in \mathcal{L}$.
- for all countable collection of disjoint elements $A_i \in \mathcal{L}$, we have $\bigcup_{i=1}^{\infty} A_i \in \mathcal{L}$.

For an alternative definition, say $\mathcal{L}$ is a λ-system if

- $\Omega \in \mathcal{L}$.
- If $A, B \in \mathcal{L}$ and $A \subset B$, then $B \setminus A \in \mathcal{L}$.
- If $A_n \in \mathcal{L}$ and $A_n \uparrow A$, then $A \in \mathcal{L}$.

Theorem (π-λ theorem)**.** Let Ω be a set, $\mathcal{P}$ be a π-system and $\mathcal{L}$ be a λ-system. Also suppose $\mathcal{P} \subset \mathcal{L}$, then $\sigma(\mathcal{P}) \subset \mathcal{L}$.

Proof. Let $\ell(\mathcal{P})$ be the smallest λ-system on Ω containing $\mathcal{P}$. The goal is to show that $\ell(\mathcal{P})$ is a σ-field. We need to show that if $A_i \in \ell(\mathcal{P})$ for $1 \leq i < \infty$, then $\bigcup_{i=1}^{\infty} A_i \in \ell(\mathcal{P})$. Note that

$$\bigcup_{i=1}^{\infty} A_i = \bigcup_{i=1}^{\infty} \left(A_i \setminus \bigcup_{j=1}^{i-1} A_i \right),$$

so it suffices to show that $A, B \in \ell(\mathcal{P})$ implies $A \cap B \in \ell(\mathcal{P})$.

For $A \in \ell(\mathcal{P})$ we define

$$W_A = \{B \subset \Omega : A \cap B \in \ell(\mathcal{P})\}.$$

It can be directly verified that W_A is a λ-system.

Take $A \in \mathcal{P}$, then for any $B \in \mathcal{P}$ we have $A \cap B \in \mathcal{P} \subset \ell(\mathcal{P})$. Hence, $\mathcal{P} \subset W_A$ and thus $\ell(\mathcal{P}) \subset W_A$ for all $A \in \mathcal{P}$, as $\ell(\mathcal{P})$ is the smallest λ-system on Ω containing $\mathcal{P}$. Now take $A \in \ell(\mathcal{P})$, we have $A \in W_B$ for all $B \in \mathcal{P}$. It follows that $A \cap B \in \ell(\mathcal{P})$ and thus $B \in W_A$. Hence similarly $\ell(\mathcal{P}) \subset W_A$ for all $A \in \ell(\mathcal{P})$.

Now for any pair $B, C \in \ell(\mathcal{P})$, we have $C \in W_B$ and thus $B \cap C \in \ell(\mathcal{P})$. This completes the proof. □

1.4 Extension theorems

Definition (semi-field)**.** A collection of subsets $S \subset 2^{\Omega}$ is a semi-field if

- $\emptyset \in S$ and $\Omega \in S$.
- $A, B \in S$ implies $A \cap B \in S$.
- If $A \in S$, then A^c is a finite disjoint union of sets in S.

Theorem (Caratheorody's extension theorem)**.** Let S be a semi-field and let μ be a non-negative function on S satisfying:

- $\mu(\emptyset) = 0$.
- If $A_1, \dots, A_n$ are disjoint and $\bigcup_{i=1}^n A_i \in S$, then $\mu(\bigcup_{i=1}^n A_i) = \sum_{i=1}^n \mu(A_i)$.
- If $A_1, A_2, \dots$ are such that $\bigcup_{i=1}^\infty A_i \in S$, then $\mu(\bigcup_{i=1}^\infty A_i) \leq \sum_{i=1}^\infty \mu(A_i)$.

Then μ admits a unique extension $\overline{\mu}$ which is a measure on $\overline{S}$, the field (algebra) generated by S. Moreover, if $\overline{\mu}$ is σ-finite then $\overline{\mu}$ admits a unique extension $\widetilde{\mu}$ to $\sigma(S)$.

Notation. Let T be any set. Write

$$\mathbb{R}^T = \left\{ (\omega_t)_{t \in T} : \omega_t \in \mathbb{R} \right\}.$$

Also write $\mathcal{R}^T$ as the σ-field generated by rectangles of the form $\prod_{t \in T} I_t$, where for each $t \in T$, I_t is either a semi-open interval of the form $(a, b]$ with $a < b$ or $I_t = \mathbb{R}$, and $I_t = \mathbb{R}$ for all but finitely many $t \in T$.

Theorem (Kolmogorov's extension theorem)**.** For each finite non-empty subset $J \subset T$, let μ_J be a Borel probability measure in $\mathbb{R}^J$, and assume that the measures $(\mu_J)_{J \subset T, |J| < \infty}$ are compatible, in the sense that whenever $J_1 \subset J_2 \subset T$ with $0 \leq |J_1| \leq |J_2| < \infty$, $I_j \subset \mathbb{R}$ with $j \in J_1$ are Borel subsets of $\mathbb{R}$, and

$$\widetilde{I_j} = \begin{cases} I_j & (j \in J_1) \\ \mathbb{R} & (j \in J_2 \setminus J_1), \end{cases}$$

one has

$$\mu_{J_2}\left(\prod_{j \in J_2} \widetilde{I_j} \right) = \mu_{J_1}\left(\prod_{j \in J_1} I_j \right).$$

Then there exists a unique probability measure μ on $(\mathbb{R}^T, \mathcal{R}^T)$ consistent with $(\mu_J)_{J \subset T, |J| < \infty}$. That is, one has

$$\mu\left(\prod_{t \in T} I_t \right) = \mu_J\left(\prod_{j \in J} I_j \right)$$

whenever $J \subset T$ with $|J| < \infty$ and $I_t = \mathbb{R}$ for all $t \notin J$.

1.5 Lebesgue Integration

Here we provide a proof for dominated convergence theorem that uses the truncation technique, which will be a useful technique later in the course.

Theorem (dominated convergence theorem)**.** Let $\{f_n\}_{n=1}^{\infty}$ be a sequence of measurable functions on (Ω, Σ, μ) and $g \geq 0$ be another measurable function. Suppose

1. $\int g \, d\mu < \infty$.
2. $|f_n|(\omega) \leq g(\omega)$ for all $\omega \in \Omega$ and $n \geq 1$.
3. $f_n \to f$ pointwise.

Then

$$\lim_{n\to\infty} \int f_n \, d\mu = \int f \, d\mu.$$

Proof. **Claim 1.** If h is a function on (Ω, Σ, μ) with $h \geq 0$ and $\int h \, d\mu < \infty$. Let $\{A_n\}_{n=1}^{\infty}$ be any sequence of elements of Σ with $\mu(A_n) \to 0$. Then

$$\int_{A_n} h \, d\mu \to 0.$$

Proof of claim. WLOG assume $\mu(A_n) \leq 2^{-n}$ for all n. Define $h_n = h \, \mathbb{1}_{\bigcup_{i=n}^{\infty} A_i}$. We then have

1. The sequence $\{h_n\}_{n=1}^{\infty}$ is monotone.
2. h_n converges to 0 almost everywhere.

Monotone convergence theorem then implies $\lim_{n\to\infty} \int h_n \, d\mu = 0$. Meanwhile,

$$0 \leq \int_{A_n} h \, d\mu \leq \int h_n \, d\mu,$$

and the proof is complete.

Claim 2. Suppose $h \geq 0$ and $\int h \, d\mu < \infty$. Let $\{\varepsilon_n\}_{n=1}^{\infty}$ be a sequence of strictly positive numbers converging to zero. Define

$$B_n = \{\omega \in \Omega : h(\omega) \leq \varepsilon_n\} \in \Sigma.$$

Then

$$\int_{B_n} h \, d\mu \to 0.$$

Proof of this claim is left as an exercise.

Now we prove the theorem. Fix $\varepsilon > 0$. By the previous two claims, there exists $M > 0$ and $\delta > 0$ such that

$$\int_{\{g \geq M\}} g \, d\mu < \varepsilon, \quad \int_{\{g \leq \delta\}} g \, d\mu < \varepsilon.$$

Let $U = \{\omega : \delta < g(\omega) < M\}$. Since g is integrable, $\mu(U) < \infty$. For $\omega \in U$, let $n_\varepsilon(\omega)$ be the smallest index such that $n \geq n_\varepsilon(\omega)$ implies $|f_n(\omega) - f(\omega)| \leq \varepsilon \mu(U)^{-1}$. It follows that there exists N such that

$$\mu\left(\{\omega \in U : n_\varepsilon(\omega) > N\}\right) \leq \frac{\varepsilon}{M}.$$

Then, for $n \geq N$, we have

$$\left|\int_U (f_n - f)\, d\mu\right| \leq \int_{n_\varepsilon(\omega) \leq N} |f_n - f|\, d\mu + \int_{n_\varepsilon(\omega) > N} |f_n - f|\, d\mu \leq 3\varepsilon.$$

Now for $n \geq N$, we have

$$\left|\int (f_n - f)\, d\mu\right| \leq 3\varepsilon + \int_{U^c} |f - f_n|\, d\mu \leq 3\varepsilon + 2\int_{U^c} g\, d\mu \leq 7\varepsilon.$$

□

Theorem (Markov-Chebyshev inequality)**.** Suppose we have probability measure space $(\Omega, \Sigma, \mathbb{P})$ and $f \geq 0$. Suppose also $\int f\, d\mathbb{P} < \infty$. Then

$$\mathbb{P}\left(\{\omega : f(\omega) > t\}\right) \leq \frac{1}{t} \int f\, d\mathbb{P}.$$

for all $t > 0$.

Remark. Let $1 \leq p < \infty$. Suppose $f : (\Omega, \Sigma, \mathbb{P}) \to [0, \infty]$ and $\int f^p\, d\mathbb{P} < \infty$. Then

$$\mathbb{P}\left(\{\omega : f(\omega) > t\}\right) \leq \frac{1}{t^p} \int f^p\, d\mathbb{P}.$$

for all $t > 0$.

Remark. Suppose $\int e^{\lambda f}\, d\mathbb{P} < \infty$ for all $\lambda \in \mathbb{R}$ and $f : (\Omega, \Sigma, \mathbb{P}) \to [0, \infty]$. Then

$$\mathbb{P}\left(\{\omega : f(\omega) > t\}\right) \leq \frac{1}{e^{\lambda t}} \int e^{\lambda f}\, d\mathbb{P}$$

for all $t > 0$ and $\lambda > 0$.

Theorem (Hölder inequality)**.** Let $p, q \in [1, \infty]$ and $p^{-1} + q^{-1} = 1$. Let (Ω, Σ, μ) be a probability space. For any measurable functions f, g, we have

$$\int |fg|\, d\mathbb{P} \leq \left(\int |f|^p\, d\mathbb{P}\right)^{1/p} \left(\int |g|^q\, d\mathbb{P}\right)^{1/q}.$$

Theorem (Jensen's inequality)**.** Let (Ω, Σ, μ) be a probability space and f be integrable. Let $\varphi : \overline{\mathbb{R}} \to \overline{\mathbb{R}}$ be convex and suppose $\varphi(\infty) = \lim_{x \to \infty} \varphi(x)$ and $\varphi(-\infty) = \lim_{x \to -\infty} \varphi(x)$. Then

$$\varphi\left(\int f\, d\mathbb{P}\right) \leq \int \varphi(f)\, d\mathbb{P}.$$

1.6 Product measures and Fubini theorem

Let $(\Omega_1, \Sigma_1, \mu_1)$, $(\Omega_2, \Sigma_2, \mu_2)$ be σ-finite measure spaces. We already defined the product $\Sigma_1 \otimes \Sigma_2$. To define a product measure, we first consider the algebra of rectangles

$$S = \{A \in \Sigma_1 \otimes \Sigma_2 : A = A_1 \times A_2 \text{ for some } A_1 \in \Sigma_1, A_2 \in \Sigma_2\}.$$

Then we can define $\mu = \mu_1 \times \mu_2$ on S by

$$\mu(A) = \mu_1(A_1)\mu_2(A_2)$$

for $A = A_1 \times A_2$. We can check that the definition is self-consistent. That is, if $A = A_1 \times A_2$ is a countable union of disjoint rectangles $\{A_1^{(j)} \times A_2^{(j)}\}_{j=1}^{\infty}$, we have

$$\mu(A_1 \times A_2) = \sum_{j=1}^{\infty} \mu(A_1^{(j)} \times A_2^{(j)}).$$

This can be verified with monotone convergence theorem. Now μ is a premeasure and can be uniquely extended to $\Sigma_1 \otimes \Sigma_2$.

Theorem (Fubini-Tonelli)**.** Let $(\Omega_1, \Sigma_1, \mu_1)$, $(\Omega_2, \Sigma_2, \mu_2)$ be σ-finite measure spaces and let (Ω, Σ, μ) be the product space. Suppose f is measurable on the product space. Suppose either f is non-negative or $\int_\Omega |f| \, d\mu < \infty$. Then

- $y \mapsto f(x, y)$ is Σ_2 measurable for all $x \in \Omega_1$.
- $x \mapsto \int_{\Omega_2} f(x, y) \, d\mu_2(y)$ is Σ_1 measurable.
- We have
$$\int_{\Omega_1} \int_{\Omega_2} f(x, y) \, d\mu_2(y) \, d\mu_1(x) = \int_\Omega f(x, y) \, d\mu(x, y).$$

Proof. First suppose $f = \mathbb{1}_A$ for $A \in \Sigma$. Also suppose μ_1, μ_2 are finite. Define section

$$A_x = \{y \in \Omega_2 : (x, y) \in A\}.$$

The goal is to show that $A_x \in \Sigma_2$ for all $x \in \Omega_1$. Define a family of sets

$$\mathcal{F}_x = \{B \in \Sigma : B_x \text{ is } \Sigma_2\text{-measurable}\}.$$

It can be verified that $\mathcal{F}_x$ is a σ-field for all $x \in \Omega_1$. Also, $\mathcal{F}_x$ contains all rectangles and thus $\Sigma \subset \mathcal{F}_x$. Hence, we have shown that $y \mapsto \mathbb{1}_A(x, y) = \mathbb{1}_{A_x}(y)$ is measurable for all $x \in \Omega_1$.

Next we show $x \mapsto \mu_2(A_x)$ is measurable and its integral over Ω_1 is equal to $\mu(A)$. Define

$$\mathcal{U} = \left\{B \in \Sigma : x \mapsto \mu_2(B_x) \text{ is } \Sigma_1\text{-measurable and } \int_{\Omega_1} \mu_2(B_x) \, d\mu_1 = \mu(B)\right\}$$

It can be verified that $\mathcal{U}$ is a λ-system. Note that $\mathcal{U}$ also contains all rectangles in Σ. It follows that $\mathcal{U} = \Sigma$ and the proof for indicator functions are complete.

Then use linearity to extend to simple functions, and use monotone convergence theorem to prove the statement for non-negative functions. For the case where f is integrable, consider the positive and negative part about f to complete the proof. □

2 Probability theory basics

2.1 Distributions and densities

Definition. Let $F : \mathbb{R} \to [0,1]$. Suppose F is

- right-continuous.
- non-decreasing.
- $\lim_{t\to-\infty} F(t) = 0$ and $\lim_{t\to\infty} f(t) = 1$.

Then F is a cumulative distribution function (CDF).

Remark. If we want to define CDF in $\mathbb{R}^2$ then the axioms are

- right-continuous: $F(\widetilde{s}, \widetilde{t}) \to F(s,t)$ as $t \downarrow \widetilde{t}$ and $s \downarrow \widetilde{s}$.
- coordinate-wise non-decreasing.
- $\lim_{s,t\to\infty} F(s,t) = 1$, $\lim_{s\to-\infty} F(s,t) = 0$ for any t, and $\lim_{t\to-\infty} F(s,t) = 0$ for any s.
- For a rectangle with bottom left vertex (a_1, a_2) and top right vertex (b_1, b_2),

$$F(b_1, b_2) - F(b_1, a_2) - F(a_1, b_2) + F(a_1, a_2) \geq 0.$$

Now we can connect the notion of CDF with randomness.

Suppose X-random real-valued variable on $(\Omega, \Sigma, \mathbb{P})$ that is almost everywhere finite. Define

$$F_X(t) = \mathbb{P}\{X(\omega) \leq t\}$$

for $-\infty < t < \infty$. It can be verified that F_X is a CDF.

Conversely, for any CDF F, there exists a probability space $(\Omega, \Sigma, \mathbb{P})$ and a real valued random variable on $(\Omega, \Sigma, \mathbb{P})$ with CDF F.

Definition. If X is random variable on $(\Omega, \Sigma, \mathbb{P})$ real valued and a.e. finite. Then we can define the induced Borel probability measure μ_X on $(\mathbb{R}, \mathcal{B}_\mathbb{R})$ by

$$\mu_X(B) := \mathbb{P}\{X \in B\}$$

for all $B \in \mathcal{B}_\mathbb{R}$.

Now suppose μ is any Borel probability measure on $\mathbb{R}$. Consider probability space $(\mathbb{R}, \mathcal{B}_\mathbb{R}, \mu)$ and formal identity mapping id on $\mathbb{R}$. Then $\mu_{\text{id}} \equiv \mu$.

Theorem. There is a one-to-one correspondence between the family of CDFs and the family of Borel probability measure on $\mathbb{R}$.

Proof. For any Borel probability measure μ, $F_\mu(t) = \mu((-\infty, t])$ is a valid CDF.

Conversely, for any CDF F, there exists unique probability measure μ_F on $\mathbb{R}$ such that $\mu_F((-\infty, t]) = F(t)$ for all $-\infty < t < \infty$. This is a corollary of Caratheorody extension theorem. For detailed proof see notes or textbook. □

Remark. Suppose $X = (X_1, X_2)$ is a random vector in $\mathbb{R}^2$. We can define

$$F_X(s,t) = \mathbb{P}\{X_1 \leq s, X_2 \leq t\}.$$

Corresponding results are also true.

Definition (Probability mass function)**.** Let $(\Omega, \Sigma, \mathbb{P})$ be a probability space and $X : \Omega \to \mathbb{R}$ be random variable. Suppose there exists $S \subset \mathbb{R}$ countable such that $\mathbb{P}\{X \in S\} = 1$. We can define the probability mass function (PMF) f_X via

$$f_X(t) = \mathbb{P}\{X = t\}$$

for $t \in \mathbb{R}$. Due to the restriction, this gives complete description of the distribution, and we can construct CDF F_X via

$$F_X(t) = \sum_{s \leq t} f_X(s).$$

This sum makes sense since the $f_X(s) = 0$ for all but countably many s. Conversely, we can also reconstruct f_X from a CDF F_X.

Definition (Probability density function)**.** Suppose F is a CDF which is absolutely continuous. That is, there exists Borel measurable non-negative function ρ on $\mathbb{R}$ such that

$$F(t) = \int_{-\infty}^{t} \rho(s)\, ds$$

for all $-\infty < t < \infty$. This implies F is almost everywhere differentiable and the derivative is ρ. In this case, say ρ is the density function.

If random variable X is such that F_X is absolutely continuous, then the corresponding ρ_X is the probability density function for X.

Remark. Recall that a Borel σ-finite measure μ on the real line is absolutely continuous w.r.t the Lebesgue measure m on $\mathbb{R}$ if $\mu(A) = 0$ whenever $A \in \mathcal{B}_\mathbb{R}$ is Lebesgue null. In this case, Randon-Nikodym theorem implies existence of non-negative Borel measurable function f such that $\mu(A) = \int_A f\, dm$.

Theorem. Suppose X RV on $(\Omega, \Sigma, \mathbb{P})$ is real-valued and a.e. finite. The following are equivalent:

1. F_X is absolutely continuous.
2. μ_X is absolutely containing w.r.t. Lebesgue measure.

Moreover, ρ_X is also the derivative of μ_X w.r.t. Lebesgue measure. That is, for any $A \in \mathcal{B}_{\mathbb{R}}$,

$$\mu_X(A) = \int_A \rho_X(t)\, dt.$$

2.2 Independence

Definition. Say two events $A, B \in \Sigma$ are independent if $\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$.

It is easy to verify that A, B are independent implies A^c, B are independent.

Remark. Suppose $\mathbb{P}(B) > 0$, then the conditional probability of A given B is defined as

$$\mathbb{P}(A \mid B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

Then, independence of A and B is equivalent to $\mathbb{P}(A \mid B) = \mathbb{P}(A)$.

Definition. Let $A_1, \ldots, A_n$ be events. Say they are mutually independent if for any $\emptyset \neq I \subset [n]$, we have

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

This is equivalent to saying that for every $2 \leq i \leq n$, the event A_i is independent from any event generated by $A_1, \ldots, A_{i-1}$, or A_i is independent from $\sigma(A_1, \ldots, A_{i-1})$.

Remark. The events $A_1, \ldots, A_n$ are called k-wise independent if any k-subset of the events are mutually independent. For $k < n$, this notion is strictly weaker than mutual independence of all n events. As an example, consider $\mathbb{P}$ to be the uniform distribution on $\{1, \ldots, 4\}$. Let $A_1 = \{1, 2\}$, $A_2 = \{1, 3\}$, and $A_3 = \{2, 3\}$. Then they are pairwise independent but not mutually independent.

Definition. A collection of events $\{A_\lambda\}_{\lambda \in \Lambda}$ on $(\Omega, \Sigma, \mathbb{P})$ are mutually independent if any finite subset of events are mutually independent.

Definition. Let $(\Omega, \Sigma, \mathbb{P})$ be a probability space. Two σ-subfields are independent if for any $A \in \Sigma_1$ and $B \in \Sigma_2$, A, B are independent.

Definition. Let $(\Omega, \Sigma, \mathbb{P})$ be a probability space and X, Y be two real-valued random variables. Say X and Y are independent if

$$\mathbb{P}\{X \in A, Y \in B\} = \mathbb{P}\{X \in A\}\, \mathbb{P}\{Y \in B\}$$

for any $A, B \in \mathcal{B}_{\mathbb{R}}$.

Equivalently, let Σ_X, Σ_Y be the σ-field generated by X and Y. Then independence of X and Y is equivalent to independence of Σ_X and Σ_Y.

Now we explore how this connect with product structure.

Proposition. Let $(\Omega_1, \Sigma_1, \mathbb{P}_1)$ and $(\Omega_2, \Sigma_2, \mathbb{P}_2)$ be two probability spaces and let $(\Omega, \Sigma, \mathbb{P})$ be the product space. Let X and Y be two random variables on $(\Omega, \Sigma, \mathbb{P})$. Suppose there exists some measurable functions such that $X(\omega_1, \omega_2) = g(\omega_1)$, and $Y(\omega_1, \omega_2) = h(\omega_2)$. Then X and Y are independent.

Proof. Let $A, B \in \mathcal{B}_{\mathbb{R}}$. Then

$$\begin{aligned} \mathbb{P}\{X \in A, Y \in B\} &= \mathbb{P}\left\{(\omega_1, \omega_2) : \omega_1 \in g^{-1}(A), \omega_2 \in h^{-1}(B)\right\} \\ &= \mathbb{P}\left(\left\{\omega_1 \in g^{-1}(A)\right\} \times \left\{\omega_2 \in h^{-1}(B)\right\}\right) \\ &= \mathbb{P}_1\left(\omega_1 \in g^{-1}(A)\right) \mathbb{P}_2\left(\omega_2 \in h^{-1}(B)\right). \end{aligned}$$

However,

$$\begin{aligned} \mathbb{P}_1\left(\omega_1 \in g^{-1}(A)\right) &= \mathbb{P}\left\{(\omega_1, \omega_2) : \omega_1 \in g^{-1}(A), \omega_2 \in \Omega_2\right\} \\ &= \mathbb{P}\{X \in A\}, \end{aligned}$$

and similarly for Y. □

Remark. Let $(\Omega, \Sigma, \mathbb{P})$ be a probability space and suppose X, Y be two random variables that are independent and a.e. finite. They then generate two Borel probability measure μ_X and μ_Y on $\mathbb{R}$. Define a product probability space as of $(\mathbb{R}^2, \mathcal{B}_{\mathbb{R}^2}, \mu_X \times \mu_Y)$. Define $\widetilde{X}(x, y) = x$ and $\widetilde{Y}(x, y) = y$ as random variables on the product space. By definition, $\widetilde{X}$ is equidistributed with X. That is, $\mu_{\widetilde{X}} = \mu_X$ and $F_{\widetilde{X}} = F_X$. Similarly $\mu_{\widetilde{Y}} = \mu_Y$. Also, $\widetilde{X}, \widetilde{Y}$ are independent. Now (X, Y) and $(\widetilde{X}, \widetilde{Y})$ have the same distribution.

Remark. If X and Y are independent, then their joint distribution $F_{(X,Y)}$ is uniquely determined by the individual distributions of F_X, F_Y. Indeed,

$$F_{(X,Y)}(s, t) = F_X(s) F_Y(t).$$

Remark. Let $(\Omega, \Sigma, \mathbb{P})$ be a probability space and suppose X, Y be two random variables that are independent. Suppose they have densities ρ_X, ρ_Y, then the distribution density of vector (X, Y) is $\rho_{(X,Y)}(s, t) = \rho_X(s)\rho_Y(t)$.

Remark. If X and Y are independent random variable, and f, g are measurable functions. Then $f(X)$ and $g(Y)$ are independent as well.

Remark. Given probability space $(\Omega, \Sigma, \mathbb{P})$ and random variable X. It may not exists another random variable Y that is independent from X on the same probability space. See the following example.

Example. As an example, consider $([0, 1], \mathcal{B}_{[0,1]}, m)$ and $X(\omega) = \omega$, so X is uniform on $[0, 1]$. The goal is to construct variable Y such that $Y \sim \text{Bernoulli}(\frac{1}{2})$.

Proof. Let $A \in \mathcal{B}_{[0,1]}$ and $t \in [0,1]$. Define the density of set A at point t to be

$$\lim_{\varepsilon \to 0} \frac{m(A \cap [t-\varepsilon, t+\varepsilon])}{2\varepsilon}.$$

The Lebesgue density theorem says this is well defined and takes values in $\{0,1\}$ for m-a.e. $t \in [0,1]$.

Suppose such Y exists, we can vies Y as an indicator of a set $A \subset [0,1]$ of probability $\frac{1}{2}$. That is, $Y = \mathbb{1}_A$ and $\mathbb{P}(A) = \frac{1}{2}$. Choose any point $t \in (0,1)$ such that density of A at t is well-defined. WLOG assume the density is 1. Pick $\varepsilon > 0$ such that $m(A \cap [t-\varepsilon, t+\varepsilon]) \geq \frac{3}{2}\varepsilon$. Now,

$$\begin{aligned} m(A \cap [t-\varepsilon, t+\varepsilon]) &= \mathbb{P}\{Y = 1, X \in [t-\varepsilon, t+\varepsilon]\} \\ &= \mathbb{P}\{Y = 1\}\, \mathbb{P}\{X \in [t-\varepsilon, t+\varepsilon]\} \\ &= \varepsilon, \end{aligned}$$

a contradiction.

Alternatively, we can derive a contradiction using $m(A) = \mathbb{P}\{Y = 1, X \in A\}$. □

Remark. The goal is to have statements “independent” from the underlying probability space.

2.3 Convolution

Definition (convolution)**.** Let μ, ν be Borel probability measures on $\mathbb{R}$. The convolution of μ and ν is a probability measure on $\mathbb{R}$ such that

$$(\mu * \nu)(S) = \int_{\mathbb{R}^2} \mathbb{1}_S(x+y) d(\mu \times \nu)$$

for all $S \in \mathcal{B}_{\mathbb{R}}$.

Remark. Suppose both μ and ν have densities ρ_μ and ρ_ν. That is, $\mu \ll m$ and $\nu \ll m$. It follows that

$$\begin{aligned} (\mu * \nu)(S) &= \int_{\mathbb{R}} \left(\int_{\mathbb{R}} \mathbb{1}_S(x+y) \rho_\mu(x)\, dx \right) \rho_\nu(y)\, dy \\ &= \int_{\mathbb{R}} \left(\int_S \rho_\mu(w-y)\, dw \right) \rho_\nu(y)\, dy \\ &= \int_S \left(\int_{\mathbb{R}} \rho_\mu(w-y) \rho_\nu(y)\, dy \right) dw \end{aligned}$$

Note that this implies $\mu * \nu \ll m$ and

$$\rho_{\mu*\nu}(w) = \int_{\mathbb{R}} \rho_\mu(w-y) \rho_\nu(y)\, dy,$$

which is the convolution of funtion ρ_μ and ρ_ν.

Remark. If X and Y are two independent random variables and μ_X and μ_Y are the corresponding induced Borel measure $\mathbb{R}$, then $\mu_{X+Y} = \mu_X * \mu_Y$.

Remark. Suppose X and Y are independent and their CDF is F_X and F_Y, then

$$F_{X+Y}(t) = \int_{\mathbb{R}} F_X(t-w)\, d\mu_Y(w) = \int_{\mathbb{R}} F_X(t-w)\, dF_Y(w).$$

2.4 Moments

In this section we explore the computation and basic properties of moments.

Definition (moments)**.** Let X be a random variable on $(\Omega, \Sigma, \mathbb{P})$. The p-th absolute moment of X is

$$\mathbb{E}\,|X|^p = \int_\Omega |X|^p \, d\mathbb{P}.$$

This is always well-defined but can be infinite.

If p is positive integer, the p-th moment of X is

$$\mathbb{E}X^p = \int_\Omega X^p \, d\mathbb{P}$$

whenever it is defined.

In particular, $\mathbb{E}X$ is the mean or expectation, the variance is $\operatorname{var}(X) = \mathbb{E}(X - \mathbb{E}X)^2$ whenever the expectation is defined, and the standard deviation is $\sqrt{\operatorname{var}(X)}$.

Proposition. Let X be random variable $(\Omega, \Sigma, \mathbb{P})$ and $0 < p < q < \infty$. Then,

$$\left(\mathbb{E}\,|X|^p\right)^{1/p} \le \left(\mathbb{E}\,|X|^q\right)^{1/q}.$$

Proof. Define $Y = |X|^p$, then we want to show that $\mathbb{E}Y \le (\mathbb{E}Y^{q/p})^{p/q}$. Note that $t \mapsto |t|^{q/p}$ is convex. Therefore, by Jensen's inequality,

$$(\mathbb{E}Y)^{q/p} \le \mathbb{E}\left(Y^{q/p}\right).$$

□

Now we want to show that moments only depends on the distribution of the random variable, and it does not carry unnecessary information about the underlying probability space. To do this, we first show the following proposition.

Proposition. Let g be measurable and X a random variable. Then,

$$\mathbb{E}\,|g(X)| = \int_{\mathbb{R}} |g(t)| \, d\mu_X(t).$$

Moreover, if $\mathbb{E}\,|g(X)| < \infty$, then

$$\mathbb{E}g(X) = \int_{\mathbb{R}} g(t)\, d\mu_X(t).$$

Corollary. If $\mathbb{E}X$ is well-defined, then

$$\mathbb{E}X = \int_{\mathbb{R}} t\, d\mu_X(t).$$

Moreover, if X has distribution density ρ_X, then $\mathbb{E}X = \int_{\mathbb{R}} t\rho_X(t)\, dt$.

Proposition. If $X \geq 0$, then

$$\mathbb{E}X = \int_0^\infty \mathbb{P}\left\{X \geq t\right\}\, dt.$$

In particular, if X is non-negative and integer valued, then $\mathbb{E}X = \sum_{i=1}^\infty \mathbb{P}\left\{X \geq i\right\}$.

Proof. With Fubini-Tonelli, we have

$$\mathbb{E}X = \int_0^\infty s\, d\mu_X(s) = \int_0^\infty \int_0^s 1\, dt\, d\mu_X(s) = \int_0^\infty \int_t^\infty 1\, d\mu_X\, dt = \int_0^\infty \mathbb{P}\left\{X \geq t\right\}\, dt.$$

□

Proposition. Let $X_1, \ldots, X_n$ are random variables on $(\Omega, \Sigma, \mathbb{P})$. Suppose they are either all non-negative or all integrable. Suppose also that they are mutually independent. Then,

$$\mathbb{E}\left(\prod_{i=1}^n X_i\right) = \prod_{i=1}^n \mathbb{E}X_i.$$

Proof. It suffices to show the statement for $n = 2$. Define independent variables $\widetilde{X_1}$ and $\widetilde{X_2}$ on the product space $(\mathbb{R}^2, \mathcal{B}_{\mathbb{R}^2}, \mu_{X_1} \times \mu_{X_2})$ by coordinate projection. We know $\widetilde{X_i}$ is equidistributed with X_i, so

$$\mathbb{E}[X_1 X_2] = \mathbb{E}[\widetilde{X_1}\widetilde{X_2}] = \mathbb{E}[\widetilde{X_1}\mathbb{E}\widetilde{X_2}] = \mathbb{E}[X_1 \mathbb{E}X_2],$$

where in the second equality we used Fubini-Tonelli. □

Remark. Recall that whenever $\mathbb{E}X$ is finite, $\operatorname{var} X = \mathbb{E}(X - \mathbb{E}X)^2 = \mathbb{E}X^2 - (\mathbb{E}X)^2$. If $X_1, \ldots, X_n$ are pairwise independent and have well-defined variances, then

$$\operatorname{var}(X_1 + \cdots + X_n) = \sum_{i=1}^n \operatorname{var} X_i.$$

Definition (moment generating function)**.** Let X be a random variable, and $\lambda \in \mathbb{R}$. Define the moment generating function of X via

$$M_X(\lambda) = \mathbb{E}\exp(\lambda X).$$

Suppose $M_X(\lambda)$ is finite in some neighborhood of 0. Then,

$$M_X(\lambda) = \mathbb{E}\left[\sum_{n=1}^{\infty} \frac{(\lambda x)^n}{n!}\right] = \sum_{n=1}^{\infty} \frac{\lambda^n \mathbb{E}X^n}{n!}.$$

It follows that $M_X'(0) = \mathbb{E}X$. Now to justify the exchang of integral and summation, note that

$$S_N = \sum_{i=1}^{N} \frac{(\lambda x)^n}{n!} \to e^{\lambda x},$$

and

$$|S_N| \leq \sum_{i=1}^{N} \frac{|\lambda x|^n}{n!} \leq e^{|\lambda x|}.$$

However, $e^{|\lambda X|} \leq e^{\lambda X} + e^{-\lambda X}$. The expectation of RHS is finite for small λ by assumption, so the claim follows from dominated convergence theorem.

Proposition. Let X be a non-negative random variable. Then TFAE:

1. M_X is finite in some neighborhood of 0.
2. $\sup_{p\geq 1} p^{-1}(\mathbb{E}X^p)^{1/p} < \infty$.

Proof. (1) $\implies$ (2). Suppose $M_X(\varepsilon) = \mathbb{E}\left[\sum_{n=1}^{\infty} \frac{\varepsilon^n X_n}{n!}\right] < \infty$. This implies that $\sup_{n\geq 1} \mathbb{E}\left[\frac{\varepsilon^n X^n}{n!}\right] < \infty$. Let $1 \leq C < \infty$ be such that $\mathbb{E}\left[\frac{\varepsilon^n X^n}{n!}\right] < C$ for all $n \geq 1$. We then have

$$\left(\frac{\varepsilon}{n!}\right)^{1/n} (\mathbb{E}X^n)^{1/n} \leq C^{1/n}$$

It follows from Sterling's formula $n! \sim (n/e)^n$ that

$$\frac{1}{n} (\mathbb{E}X^n)^{1/n} \leq C$$

for some other constant C.

(2) $\implies$ (1). Suppose $\sup_{p\geq 1} p^{-1} (\mathbb{E}X^p)^{1/p} \leq C < \infty$. It follows that for any $n \geq 1$

$$\frac{1}{n!} (\mathbb{E}X^n) \leq C^n \frac{n^n}{n!} \leq C^n$$

for some other constant C. Take $\varepsilon = \frac{1}{2C}$, we then have

$$\mathbb{E}\left[\frac{\varepsilon^n X^n}{n!}\right] \leq 2^{-n}.$$

Therefore, $M_X(\varepsilon) = \mathbb{E}\left[\sum_{n=1}^{\infty} \frac{\varepsilon^n X^n}{n!}\right] < \infty$. □

Now we present an example of moment method for approximating random variables.

Example. Let $G \sim G(n, \frac{1}{2})$ be the Erdos-Renyi random graph. The goal is to estimate the number of triangles in G. Let N be the number of triangles in G. We have

$$N = \sum_{\substack{S \subset [n] \\ |S|=3}} b_S,$$

where b_S is the indicator that S is a triangle in G. It follows that $\mathbb{E}N = \frac{1}{8}\binom{n}{3}$. Also,

$$\mathbb{E}N^2 = \sum_{|S|=3} \sum_{|S'|=3} \mathbb{E}[b_S b_{S'}]$$

To compute this, we consider several cases.

1. If $S \cap S' = \emptyset$, then $\mathbb{E}[b_S b_{S'}] = \frac{1}{64}$.
2. If $|S \cap S'| = 1$, then $\mathbb{E}[b_S b_{S'}] = \frac{1}{64}$.
3. If $|S \cap S'| = 3$, then $\mathbb{E}[b_S b_{S'}] = \frac{1}{8}$.
4. If $|S \cap S'| = 2$, then $\mathbb{E}[b_S b_{S'}] = \frac{1}{32}$.

Hence,

$$\mathbb{E}N^2 = \frac{1}{64}\binom{n}{3}^2 \pm O(n^4),$$

where the $O(n^4)$ term comes from the cases where $|S \cap S'| = 2$ or 3. Therefore,

$$\operatorname{var} N = \mathbb{E}N^2 - (\mathbb{E}N)^2 = O(n^4).$$

Using Chebyshev's inequality, for each $t > 0$ we have

$$\mathbb{P}\left\{|N - \mathbb{E}N| \geq t \cdot \mathbb{E}N\right\} \leq \frac{\operatorname{var} N}{t^2(\mathbb{E}N)^2} = t^{-2}O(n^{-2}) \to 0.$$

as $n \to \infty$.

We have the following proposition on sub-Gaussian decay of moments.

Proposition. Let X be a random variable, TFAE:

1. $\sup_{p\geq 1}(\mathbb{E}\,|X|^p)^{1/p}p^{-1/2} < \infty$.
2. there exists $c > 0$ such that $\mathbb{P}\left\{|X| > t\right\} \leq 2\exp(-ct^2)$ for all $t > 0$.

If any of these statement is satisfied, X is called a *subgaussian variable*.

Proof. Exercise. □

Theorem (Khintchine's inequality)**.** There exists a universal constant $C < \infty$ such that for any $n \in \mathbb{N}$, $a_1, \dots, a_n \in \mathbb{R}$, and $p \geq 1$, we have

$$\left(\mathbb{E}\left|\sum_{i=1}^n a_i r_i\right|^p\right)^{1/p} \leq C\sqrt{p}\left\|a\right\|_2,$$

where $r_1, \dots, r_n$ are i.i.d. Rademacher variables: $\mathbb{P}\left\{r_i = 1\right\} = \mathbb{P}\left\{r_i = -1\right\} = \frac{1}{2}$.

Proof. WLOG assume $\left\|a\right\|_2 = 1$. Let $\lambda > 0$. For any $t > 0$, we have

$$\mathbb{P}\left\{\sum_{i=1}^n a_i r_i > t\right\} = \mathbb{P}\left\{\exp\left(\lambda\sum_{i=1}^n a_i r_i\right) > \exp(\lambda t)\right\} \leq \frac{\mathbb{E}\exp\left(\lambda\sum_{i=1}^n a_i r_i\right)}{\exp(\lambda t)}$$

from Markov's inequality. By independence, we have

$$\mathbb{P}\left\{\sum_{i=1}^n a_i r_i > t\right\} \leq \frac{\prod_{i=1}^n \mathbb{E}\exp(\lambda a_i r_i)}{\exp(\lambda t)} = \frac{\prod_{i=1}^n \frac{1}{2}\left(\exp(\lambda a_i) + \exp(-\lambda a_i)\right)}{\exp(\lambda t)}.$$

Now we use $\exp(x) \leq x + \exp(x^2)$ to obtain

$$\mathbb{P}\left\{\sum_{i=1}^n a_i r_i > t\right\} \leq \frac{\prod_{i=1}^n \exp(\lambda^2 a_i^2)}{\exp(\lambda t)} = \exp\left(\lambda^2\left\|a\right\|_2^2 - \lambda t\right).$$

This holds for any $\lambda > 0$. Substituting $\lambda = \frac{1}{2}t\left\|a\right\|_2^{-2}$, we have

$$\mathbb{P}\left\{\sum_{i=1}^n a_i r_i > t\right\} \leq \exp\left(-\frac{1}{4}\frac{t^2}{\left\|a\right\|_2^2}\right)$$

Similarly we can bound $\mathbb{P}\left\{\sum_{i=1}^n a_i r_i < -t\right\}$ as the Rademacher variables are symmetric. Hence we have

$$\mathbb{P}\left\{\left|\sum_{i=1}^n a_i r_i\right| > t\right\} \leq 2\exp\left(-\frac{1}{4}t^2\right).$$

The theorem follows from the previous proposition. □

Theorem (Anti-concentration inequalities)**.** Let X be a non-negative random variable and $1 \leq p < q < \infty$. Suppose $\left(\mathbb{E}X^p\right)^{1/p} \leq C \left(\mathbb{E}X^q\right)^{1/q}$ for some constant C. Then there exsits $\varepsilon > 0$ depending only on p, q, C such that

$$\mathbb{P}\left\{X \geq \varepsilon \left(\mathbb{E}X^p\right)^{1/p}\right\} \geq \varepsilon.$$

2.5 Convergence of random variable

Definition. Let $\{X_n\}_{n=1}^{\infty}$ be a sequence of random variables and X is also a random variable. Say X_n converges to X *in distribution* or *weakly* if for any compactly supported continuous function f, we have

$$\int_{\mathbb{R}} f(t)\, d\mu_{X_n}(t) \to \int_{\mathbb{R}} f(t)\, d\mu_X(t).$$

Write $X_n \xrightarrow{d} X$ or $X_n \xrightarrow{w} X$.

Proposition. $X_n \xrightarrow{w} X$ iff $F_{X_n}(t) \to F_X(t)$ at every point t where F_X is continuous.

Definition. Let $\{X_n\}_{n=1}^{\infty}$ be a sequence of random variables and X is also a random variable defined on the same probability space. Say X_n converges to X *in probability* if for any $\varepsilon > 0$,

$$\mathbb{P}\left\{|X_n - X| < \varepsilon\right\} \to 1.$$

Write $X_n \xrightarrow{\mathbb{P}} X$.

Proposition. If $X_n \xrightarrow{\mathbb{P}} X$, then $X_n \xrightarrow{d} X$.

Proof. Let $t \in \mathbb{R}$ be such that F_X is continuous at point t and let $\varepsilon > 0$. Let $\delta > 0$ be such taht $F_X(t+\delta) \leq F_X(t) + \varepsilon$ and $F_X(t-\delta) \geq F_X(t) - \varepsilon$. Since $\mathbb{P}\left\{|X - X_n| < \delta\right\} \to 1$, there exists n_0 such that $n \geq n_0$ implies

$$\mathbb{P}\left\{|X_n - X| < \delta\right\} \geq 1 - \varepsilon.$$

Take $n \geq n_0$. We have

$$\begin{aligned} F_{X_n}(t) &= \mathbb{P}\left\{X_n \leq t\right\} \\ &\leq \mathbb{P}\left\{|X_n - X| > \delta\right\} + \mathbb{P}\left\{X \leq t + \delta\right\} \\ &\leq \varepsilon + F_X(t) + \varepsilon \\ &\leq F_X(t) + 2\varepsilon. \end{aligned}$$

Similarly for the other side. □