Review on Probability

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통계적 기계학습(Statistical Machine Learning), 2025 1st semester

Probability Spaces

A probability space is a triple $(\Omega, \mathcal{F}, P)$ where Ω is a set of "outcomes," $\mathcal{F}$ is a set of "events," and $P : \mathcal{F} \to [0,1]$ is a function that assigns probabilities to events.

Definition. Let Ω be a set. A nonempty collection $\mathcal{F}$ of subsets of Ω is called σ-algebra (or field) if
(i) if $A \in \mathcal{F}$ then $\Omega \backslash A \in \mathcal{F}$, and
(ii) if $A_1, A_2, \cdots \in \mathcal{F}$, then $\bigcup\limits_{i=1}^{\infty} A_i \in \mathcal{F}$.

Example. $\mathcal{F} = \{\phi, \Omega\}$ trivial $\sigma-$field
$\mathcal{F} = 2^{\Omega} = \{A |\ A \subset \Omega\}$: power set $\Longrightarrow \sigma-$field

Without P, $(\Omega, \mathcal{F})$ is called a measurable space, i.e., it is a space on which we can put a measure.

Definition. A measure is a nonnegative countably additive set function; that is, for an σ-algebra $\mathcal{F}$, a function $\mu : \mathcal{F} \to [0, \infty]$ is a measure if
(i) $\mu(A) \geq \mu(\phi) = 0$ for all $A \in \mathcal{F}$, and
(iii) For $A_1, A_2, \cdots \in \mathcal{F}$ with $A_i \cap A_j = \phi$ for any $i \neq j$,

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

Definition. (1) $\mu(\Omega) < \infty \Longrightarrow$finite measure
(2) $\mu(\Omega) = 1 \Longrightarrow$probability measure
(3) $\exists$a partition $A_1, A_2, \cdots$ with $\bigcup\limits_{i=1}^{\infty} A_i = \Omega$ and $\mu(A_i) < \infty \Longrightarrow \sigma-$finite measure

Theorem ([1, Theorem 1.1.4])**.** *Let μ be a measure on $(\Omega, \mathcal{F})$.*
(i) Monotonicity. If $A \subset B$ then $\mu(A) \leq \mu(B)$.
(ii) Subadditivity. If $A \subset \bigcup\limits_{i=1}^{\infty} A_i$ then $\mu(A) \leq \sum\limits_{i=1}^{\infty} \mu(A_i)$.
(iii) Continuity from below. $A_n \uparrow A$ (i.e. $A_1 \subset A_2 \subset \cdots$ and $A = \bigcup\limits_{i=1}^{\infty} A_i$) then $\mu(A_i) \uparrow \mu(A)$.
(iv) Continuity from above. $A_n \downarrow A$ (i.e. $A_1 \supset A_2 \supset \cdots$ and $A = \bigcap\limits_{i=1}^{\infty} A_i$) with $\mu(A_1) < \infty$ then $\mu(A_i) \downarrow \mu(A)$.

Definition. Let $\mathcal{A}$ be a class of subsets of Ω. Then $\sigma(\mathcal{A})$ denotes the smallest $\sigma-$algebra that contains $\mathcal{A}$.

For any any $\mathcal{A}$, such $\sigma(\mathcal{A})$ exists and is unique: [1, Exercise 1.1.1].

Definition. Borel $\sigma-$field on $\mathbb{R}^d$, denoted by $\mathcal{R}^d$, is the smallest $\sigma-$field containing all open sets.

Theorem ([1, Theorem 1.1.2]). *There is a unique measure* μ *on* $(\mathbb{R}, \mathcal{R})$ *with*

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

Such measure is called Lebesgue measure.

Example ([1, Example 1.1.3]). Product space
$(\Omega_i, \mathcal{F}_i, \mathcal{P}_i)$: sequence of probability spaces
Let $\Omega = \Omega_1 \times \cdots \times \Omega_n = \{(\omega_1, \cdots, \omega_n)|\ \omega_i \in \Omega_i\}$
$\mathcal{F} = \mathcal{F}_1 \times \cdots \times \mathcal{F}_n$ =the $\sigma-$field generated by $A_1 \times \cdots \times A_n$, where $A_i \in \mathcal{F}_i$
$P = P_1 \times \cdots \times P_n$ (i.e. $P(A_1 \times \cdots \times A_n) = P_1(A_1) \cdots P_n(A_n)$

Distribution and Random Variables

Definition. Let $(\Omega, \mathcal{F})$ and $(S, \mathcal{S})$ are measurable spaces. A mapping $X : \Omega \to S$ is a measurable map from $(\Omega, \mathcal{F})$ to $(S, \mathcal{S})$ if

$$\text{for all } B \in \mathcal{S},\ X^{-1}(B) := \{\omega \in \Omega :\ X(\omega) \in B\} \in \mathcal{F}.$$

If $(S, \mathcal{S}) = (\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ and $d > 1$ then X is called a random vector. If $d = 1$, X is called a random variable.

Example. A trivial but useful example of a random variable is indicator function 1_A of a set $A \in \mathcal{F}$:

$$1_A(\omega) = \begin{cases} 1 & \omega \in A, \\ 0 & \omega \notin A. \end{cases}$$

If X is a random variable, then X induces a probability measure on $\mathbb{R}$.

Definition. The probability measure μ on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ defined as $\mu(A) = P(X \in A)$ for all $A \in \mathcal{B}(\mathbb{R})$ is called the distribution of X.

Remark. The distribution can be defined similarly for random vectors.

The distribution of a random variable X is usually described by giving its distribution function.

Definition. The distribution function $F(x)$ of a random variable X is defined as $F(x) = P(X \leq x)$.

Theorem ([1, Theorem 1.2.1]). *Any distribution function* F *has the following properties:*
(i) F *is nondecreasing.*
(ii) $\lim_{n\to\infty} F(x) = 1,\ \lim_{n\to-\infty} F(x) = 0.$
(iii) F *is right continuous. i.e.* $\lim_{y\downarrow x} F(y) = F(x)$.
(iv) $P(X < x) = F(x-) = \lim_{y\uparrow x} F(x)$.
(v) $P(X = x) = F(x) - F(x-)$.

Theorem ([1, Theorem 1.2.2]). *If* F *satisfies (i) (ii) (iii) in [1, Theorem 1.2.1], then it is the distribution function of some random variable. That is, there exists a triple* $(\Omega, \mathcal{F}, P)$ *and a random variable* X *such that* $F(x) = P(X \leq x)$.

Theorem. *If* F *satisfies (i) (ii) (iii), then* $\exists!$ *probability measure* μ *on* $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ *such that for all* $a < b$,
$\mu((a, b]) = F(b) - F(a)$

Definition. If X and Y induce the same distribution μ on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$, we say X and Y are equal in distribution. We write

$$X \stackrel{d}{=} Y.$$

Definition. When the distribution function $F(x) = P(X \leq x)$ has the form $F(x) = \int_{-\infty}^{x} f(y)dy$, then we say X has the density function f.

Remark. f is not unique, but unique up to Lebesque measure 0.

Theorem ([1, Theorem 1.3.2])**.** *If $X : (\Omega, \mathcal{F}) \to (S, \mathcal{S})$ and $f : (S, \mathcal{S}) \to (T, \mathcal{T})$ are measurable maps, then $f(X)$ is measurable.*

Theorem. *$f : (S, \mathcal{S}) \to (T, \mathcal{T})$ and suppose $\mathcal{S} = \sigma(\text{open sets})$, $\mathcal{T} = \sigma(\text{open sets})$. Then, if f is continuous then f is measurable.*

Theorem ([1, Theorem 1.3.3])**.** *If $X_1, \cdots, X_n$ are random variables and $f : (\mathbb{R}^n, \mathcal{R}^n) \to (\mathbb{R}, \mathcal{R})$ is measurable, then $f(X_1, \cdots, X_n)$ is a random variable.*

Theorem ([1, Theorem 1.3.4])**.** *If $X_1, \cdots, X_n$ are random variables then $X_1 + \cdots + X_n$ is a random variable.*

Remark. If X, Y are random variables, then

$$cX \text{ (c is scalar)}, \ X \pm Y, \ XY, \ \sin(X), \ X^2, \ \cdots,$$

are all random variables.

Theorem ([1, Theorem 1.3.5])**.** $\inf_n X_n, \ \sup_n X_n, \ \limsup_n X_n, \ \liminf_n X_n$ *are random variables.*

Integration

Let μ be a σ-finite measure on $(\Omega, \mathcal{F})$.

Definition. For any predicate $Q(\omega)$ defined on Ω, we say Q is true $(\mu-)$almost everywhere (or a.e.) if $\mu(\{\omega : Q(\omega) \ is \ false\}) = 0$

Step 1.

Definition. φ is a simple function if $\varphi(\omega) = \sum_{i=1}^{n} a_i 1_{A_i}$ with $A_i \in \mathcal{F}$

If φ is a simple function and $\varphi \geq 0$, we let
$\int \varphi d\mu = \sum_{i=1}^{n} a_i \mu(A_i)$

Step 2.

Definition. If f is measurable and $f \geq 0$ then we let
$\int f d\mu = \sup\{\int h d\mu : \ 0 \leq h \leq f \ and \ h \ simple\}$

Step 3.

Definition. We say measurable f is integrable if $\int |f| d\mu < \infty$

let $f^+(x) := f(x) \vee 0$, $f^-(x) := (-f)(x) \vee 0$ where $a \vee b = \max(a, b)$

We define the integral of f by

$\int f d\mu = \int f^+ d\mu - \int f^- d\mu$

we can also define $\int f d\mu$ if $\int f^+ d\mu = \infty$ and $\int f^- d\mu < \infty$, or $\int f^+ d\mu < \infty$ and $\int f^- d\mu = \infty$

Theorem. *(1.4.7) Suppose f and g are integrable.*

(i) If $f \geq 0$ a.e. then $\int f d\mu \geq 0$

(ii) $\forall a \in \mathbb{R}$, $\int a f d\mu = a \int f d\mu$

(iii) $\int f + g d\mu = \int f d\mu + \int g d\mu$

(iv) If $g \leq f$ a.e. then $\int g d\mu \leq \int f d\mu$

(v) If $g = f$ a.e. then $\int g d\mu = \int f d\mu$

(vi) $|\int f d\mu| \leq \int |f| d\mu$

Several techniques of integration

- The pushforward measure of a transformation T is $T_*\mu \coloneqq \mu(T^{-1}(A))$. The change of variables formula for pushforward measures is

$$\int_\Omega f \circ T d\mu = \int_{T(\Omega)} f dT_*\mu.$$

  Now, consider a probability space $(\Omega, \mathcal{F}, P)$, and consider a measurable map $X : (\Omega, \mathcal{F}) \to (S, \mathcal{S})$ as a transformation. Then the distribution measure μ_X of X is in fact the pushforward measure $\mu_X(A) = P(X \in A) = P(X^{-1}(A))$, and hence the change of variable formula becomes

$$\mathbb{E}_P[f(X)] = \int_\Omega f(X(\omega)) dP(\omega) = \int_{X(\Omega)} f(x) d\mu_X(x).$$

- For Lebesgue measure λ and Riemann integrable function f, $\int_{[a,b]} f d\lambda$ is the same as the Riemann integral $\int_a^b f(x) dx$.

- $\int f d\delta_x = f(x)$, where δ_x is the Dirac-delta measure, i.e., $\delta_x(A) = I(x \in A)$.

- For a random variable $X \geq 0$,

$$\begin{aligned}
\mathbb{E}_P[X] = \int_\Omega X(\omega) dP(\omega) &= \int_\Omega \int_{[0, X(\omega)]} dt dP(\omega) \\
&= \int_{\{(\omega,t) \in \Omega \times [0,\infty): 0 \leq t \leq X(\omega)\}} dt \times dP(\omega) \\
&= \int_0^\infty \int_{\{\omega \in \Omega: X(\omega) \geq t\}} dP(\omega) dt \\
&= \int_0^\infty P(X \geq t) dt.
\end{aligned}$$

Independence

Definition. Let $(\Omega, \mathcal{F}, P)$ be probability space. Two events $A, B \in \mathcal{F}$ are independent if

$P(A \cap B) = P(A) \times P(B)$

Two random variables X and Y are independent if

$\forall C, D \in \mathcal{R},\ P(X \in C,\ Y \in D) = P(X \in C)P(Y \in D)$

Two σ-fields $\mathcal{F}_1$ and $\mathcal{F}_2(\subset \mathcal{F})$ are independent if

$\forall A \in \mathcal{F}_1,\ \forall B \in \mathcal{F}_2$, A and B are independent.

Remark. An infinite collection of objects ($\sigma-$fields, random variables, or sets) is said to be independent if every finite subcollection is.

Definition. $\sigma-$fields $\mathcal{F}_1, \cdots, \mathcal{F}_n$ are independent if

$P(\bigcap_{i=1}^{n} A_i) = \prod_{i=1}^{n} P(A_i),\ \forall A_i \in \mathcal{F}_i$

random variables $X_1, \cdots, X_n$ are independent if

$P(\bigcap_{i=1}^{n} \{X_i \in B_i\}) = \prod_{i=1}^{n} P(X_i \in B_i),\ \forall B_i \in \mathcal{R}$

Sets $A_1, \cdots, A_n$ are independent if

$P(\bigcap_{i \in I} A_i) = \prod_{i \in I} P(A_i)$ for all $I \subset \{1, \cdots, n\}$

Remark. the definition of independent events is not enough to assume pairwise independent, which is $P(A_i \cap A_j) = P(A_i)P(A_j),\ i \neq j$. It is clear that indenendent events are pairwise independent, but converse is not true.

Example. Let $X_1,\ X_2,\ X_3$be independent random variables with $P(X_i = 0) = P(X_i = 1) = \frac{1}{2}$

Let $A_1 = \{X_2 = X_3\},\ A_2 = \{X_3 = X_1\}$ and $A_3 = \{X_1 = X_2\}$. These events are pairwise independent but not independent.

Theorem ([1, Theorem 1.3.5])**.** *Suppose X and Y are independent, and $f, g : \mathbb{R} \to \mathbb{R}$ are measurable functions with $f, g \geq 0$ or $\mathbb{E}\,|f(X)|\,, \mathbb{E}\,|g(X)| < \infty$, then*

$$\mathbb{E}_P[f(X)g(Y)] = \mathbb{E}_P[f(X)]\mathbb{E}_P[g(Y)].$$

Conditional Expectation

Definition. Let $(\Omega, \mathcal{F}_0, P)$ be a given probability space, a σ-field $\mathcal{F} \subset \mathcal{F}_0$, and a random variable $X \in \mathcal{F}_0$

$E(X|\mathcal{F})$ (conditional expectation of X given $\mathcal{F}$) is a random variable Y such that

(i) $Y \in \mathcal{F}$

(ii) $\forall A \in \mathcal{F},\ \int_A X dP = \int_A Y dP$

Any Y satisfying (i) and (ii) is said to be a version of $E(X|\mathcal{F})$

Lemma ([1, Lemma 5.1.1])**.** *If Y satisfies (i) and (ii), then it is integrable.*

Remark. Uniqueness.

Suppose there are two random variables Y and Y' satisfying (i) and (ii) of the definition of the conditional expectation. Then $Y = Y'$ a.s.

Remark. Existence

$E(X|\mathcal{F})$ exists.

5.1.1. Examples

Example. (5.1.1) If $X \in \mathcal{F}$, $E(X|\mathcal{F}) = X$

Example. (5.1.2) If $X \perp \mathcal{F},\ E(X|\mathcal{F}) = E(X)$

Example. (5.1.3) Let $\Omega_1, \Omega_2, \cdots$ be a countable partition of Ω into disjoint sets and let $\mathcal{F} = \sigma(\Omega_1, \Omega_2, \cdots)$

Then $E(X|\mathcal{F})(\omega) = \sum_{k=1}^{\infty} c_k I(\omega \in \Omega_k)$

where $c_k = \begin{cases} \frac{\int_{\Omega_k} X dP}{P(\Omega_k)} & if\ P(\Omega_k) > 0 \\ arbitrary & if\ P(\Omega_k) = 0 \end{cases}$

Definition. $P(A|\mathcal{F}) = E(1_A|\mathcal{F})$

$P(A|B) = P(A \cap B)/P(B)$

Remark. $P(A|\sigma(B)) = \begin{cases} P(A|B) & if\ \omega \in B \\ P(A|B^c) & if\ \omega \in B^c \end{cases}$

Definition. Conditional expectation given random variable

$E(X|Y) = E(X|\sigma(Y))$

Definition. Conditional expectation given $Y = y$, i.e. $E(X|Y = y)$

Consider $E(X|Y)$, which is $\sigma(Y)$-measurable

Then there exists a measurable function $h : \mathbb{R} \to \mathbb{R}$ s.t. $E(X|Y) = h(Y)$ (Exercise 1.3.8)

We can define

$E(X|Y = y) = h(y)$

Definition. $P(A|Y = y) = E(I_A|Y = y)$

Example. (5.1.4) $(X, Y) \sim pdf\ f(x, y)$ (w.r.t. Lebesque measure)

Then $E(g(X)|Y) = \frac{\int g(x)f(x,Y)dx}{\int f(x,Y)dx}$

provided $f(x, y) > 0\ \forall (x, y)$

Example. (5.1.5) Suppose $X \perp Y$. Let φ be a function wit $E|\varphi(X, Y)| < \infty$ and let $g(x) = E(\varphi(x, Y))$. Then

$E(\varphi(X, Y)|X) = g(X)$

Example. Convolution formula

$X \perp Y$

Let $\varphi_z(x, y) = I(x + y \leq z)$

Then $g(x) = E(\varphi_z(x, Y)) = P(Y \leq z - x)$

Hence $P(X + Y \leq z|X) = F_Y(z - X)$

which implies

$P(X + Y \leq z) = E(P(X + Y \leq z|X))$

$= E(F_Y(z - X))$

$= \int_{-\infty}^{\infty} F_Y(z - x)dF_X(x) = F_X * F_Y$

Properties

Theorem. *(5.1.2) (a) Linearlity.*

$E(aX + Y|\mathcal{F}) = aE(X|\mathcal{F}) + E(Y|\mathcal{F})$

(b) Monotonicity.

If $X \leq Y$*, then* $E(X|\mathcal{F}) \leq E(Y|\mathcal{F})$

(c) Monotone convergence theorem.

If $X_n \geq 0$ *and* $X_n \uparrow X$ *with* $E|X| < \infty$*, then* $E(X_n|\mathcal{F}) \uparrow E(X|\mathcal{F})$

Theorem. *(5.1.3) Jensen Inequality*
If φ is convex and $E|X| < \infty$ and $E|\varphi(X)| < \infty$, then
$\varphi(E(X|\mathcal{F})) \leq E(\varphi(X)|\mathcal{F})$

Theorem. *(5.1.4) Conditional expectation is a contraction in L^p, $p \geq 1$*
i.e., $E(|E(X|\mathcal{F})|^p) \leq E|X|^p$ for $p \geq 1$

Theorem. *(5.1.5) If $\mathcal{F} \subset \mathcal{G}$ and $E(X|\mathcal{G}) \in \mathcal{F}$, then $E(X|\mathcal{F}) = E(X|\mathcal{G})$*

Theorem. *(5.1.6) If $\mathcal{F}_1 \subset \mathcal{F}_2$, then*
(i) $E(E(X|\mathcal{F}_1)|\mathcal{F}_2) = E(X|\mathcal{F}_1)$
(ii) $E(E(X|\mathcal{F}_2)|\mathcal{F}_1) = E(X|\mathcal{F}_1)$

Theorem. *(5.1.7) If $X \in \mathcal{F}$ and $E|X| < \infty$, then*
$E(XY|\mathcal{F}) = XE(Y|\mathcal{F})$

Theorem. *(5.1.8) Suppose $EX^2 < \infty$*
then $E(X|\mathcal{F})$ is a random variable $Y \in \mathcal{F}$ that minimizes $E(X-Y)^2$ among all random variables$\in \mathcal{F}$

Weak laws of large numbers

Various modes of convergence

$\{X_n\}$ and X are random variables defined on $(\Omega, \mathcal{F}, P)$

Definition. $X_n \to X$ almost surely (a.s.) (with probability 1(w.p. 1), almost everywhere(a.e.)) if $P\{\omega : X_n(\omega) \to X(\omega)\} = 1$

Equivalent definition : $\forall \epsilon$, $\lim_{m\to\infty} P\{\omega : |X_n(\omega) - X(\omega)| \leq \epsilon \ \forall n \geq m\} = 1$
or $\forall \epsilon$, $\lim_{m\to\infty} P\{\omega : |X_n(\omega) - X(\omega)| > \epsilon \ \forall n \geq m\} = 0$

Definition. $X_n \to X$ in probability (in pr, $\xrightarrow{p}$) if $\lim_{n\to\infty} P\{|X_n - X| > \epsilon\} = 0$

Theorem. $X_n \to X$ *a.s.* $\Longrightarrow X_n \xrightarrow{p} X$

Remark. $X_n \xrightarrow{p} X \not\Rightarrow X_n \to X$ a.s.

Definition. $X_n \to X$ in L_p, $0 < p < \infty$
if $\lim_{n\to\infty} E(|X_n - X|^p) = 0$ provided $E|X_n|^p < \infty$, $E|X|^p < \infty$.

Theorem. $X_n \to X$ *in* $L_p \implies X_n \xrightarrow{p} X$

Theorem. *(Chebyshev inequality)*
$P(|X| \geq \epsilon) \leq \frac{E|X|^p}{\epsilon^p}$

Remark. $X_n \xrightarrow{p} X \not\Rightarrow X_n \to X$ in L_p

Example. $\Omega = [0,1]$, $\mathcal{F} = \mathcal{B}[0,1]$, $P = Unif[0,1]$
$X(\omega) = 0$, $X_n(\omega) = nI(0 \leq \omega \leq \frac{1}{n})$
Then $P\{|X_n(\omega) - X(\omega)| > \epsilon\} = P\{0 \leq \omega \leq \frac{1}{n}\} = \frac{1}{n} \to 0$
But $E|X_n - X| = E|X_n| = 1$

Theorem. *$X_n \xrightarrow{p} X$ and there exists a random variables Z s.t.*

$|X_n| \le Z$ and $E|Z|^p < \infty$

Then $X_n \to X$ in L_p.

Remark. If $E|X| < \infty$, then

$\lim_{n\to\infty} \int_{A_n} |X| dP \to 0$ whenever $P(A_n) \to 0$

2..2.1. L_2 weak law

Theorem ([1, Theorem 2.2.3])**.** *Let $X_1, X_2, \cdots$ be uncorrelated random variables with $EX_i = \mu$ and $Var(X_i) \le C < \infty$*

Let $S_n = \sum_{i=1}^{n} X_i$. Then

$\frac{S_n}{n} \to \mu$ in L_2 and so in pr.

Theorem ([1, Theorem 2.2.9])**.** *Weak law of large numbers*

Let $X_1, X_2, \cdots$ be i.i.d. random variables with $E|X_i| < \infty$.

Let $S_n = X_1 + \cdots + X_n$ and let $\mu = EX_1$.

Then $\frac{S_n}{n} \to \mu$ in pr.

Weak Convergence

Definition. A sequence of distribution function F_n converges weakly to a limit F ($F_n \Rightarrow F,\ F_n \xrightarrow{w} F$)

if $F_n(y) \to F(y)\ \forall y$ that are continuity points of F.

Definition. A sequence of random variables $\{X_n\}$ converges weakly or converges in distribution to a limit X

($X_n \Rightarrow X,\ X_n \xrightarrow{w} X,\ X_n \xrightarrow{d} X$)

If the distribution function F_n of X_n converges weakly to the distribution of X.

Example ([1, Example 3.2.1])**.** Let $X_1, X_2, \cdots$ be iid with $P(X_1 = 1) = P(X_1 = -1) = \frac{1}{2}$.

Let $S_n = X_1 + \cdots + X_n$.

Then $F_n(y) = P(S_n/\sqrt{n} \le y) \to \int_{-\infty}^{y} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx\ \forall y$

That is, $F_n \Rightarrow N(0,1)$

Example ([1, Example 3.2.3])**.** Let $X \sim F$ and $X_n = X + \frac{1}{n}$

Then $F_n(x) = P(X_n \le x) = F(x - \frac{1}{n}) \to F(x-)$

Hence $F_n(x) \to F(x)$ only when $F(x) = F(x-)$

(i.e. x is a continuity point of F)

so $X_n \to X$

Example ([1, Example 3.2.4])**.** $X_p \sim Geo(p)$ (i.e. $P(X_p \ge m) = (1-p)^{m-1}$)

Then $P(X_p > \frac{x}{p}) = (1-p)^{\frac{x}{p}} \to e^{-x}$ as $p \to 0$

Central Limit Theorem

Theorem ([1, Theorem 3.4.1])**.** *Let $X_1, X_2, \cdots$ be iid with $EX_i = \mu$ and $Var(X_i) = \sigma^2 > 0$.*

If $S_n = X_1 + \cdots + X_n$, then

$(S_n - n\mu)/(\sqrt{n}\sigma) \xrightarrow{d} N(0,1)$

Theorem ([1, Theorem 3.4.9]). *Berry-Essen theorem*

Let $X_1, X_2, \cdots$ be i.i.d. with $EX_i = 0$, $EX_i^2 = \sigma^2$ and $E|X_1|^3 = \rho < \infty$

Let $F_n(x)$ be the distribution function of $(X_1 + \cdots + X_n)/(\sigma\sqrt{n})$ and $\Phi(x)$ be the standard normal distribution.

Then $\sup_x |F_n(x) - \Phi(x)| \le 3\rho/(\sigma^3\sqrt{n})$

Stochastic Order Notation

The classical order notation should be familiar to you already.

1. We say that a sequence $a_n = o(1)$ if $a_n \to 0$ as $n \to \infty$. Similarly, $a_n = o(b_n)$ if $a_n/b_n = o(1)$.
2. We say that a sequence $a_n = O(1)$ if the sequence is eventually bounded, i.e. for all n large, $|a_n| \le C$ for some constant $C \ge 0$. Similarly, $a_n = O(b_n)$ if $a_n/b_n = O(1)$.
3. If $a_n = O(b_n)$ and $b_n = O(a_n)$ then we use either $a_n = \Theta(b_n)$ or $a_n \asymp b_n$.

When we are dealing with random variables we use stochastic order notation.

1. We say that $X_n = o_P(1)$ if for every $\epsilon > 0$, as $n \to \infty$

$$\mathbb{P}(|X_n| \ge \epsilon) \to 0,$$

   i.e. X_n converges to zero in probability.

2. We say that $X_n = O_P(1)$ if for every $\epsilon > 0$ there is a finite $C(\epsilon) > 0$ such that, for all n large enough:

$$\mathbb{P}(|X_n| \ge C(\epsilon)) \le \epsilon.$$

The typical use case: suppose we have $X_1, \ldots, X_n$ which are i.i.d. and have finite variance, and we define:

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i.$$

1. $\hat{\mu} - \mu = o_P(1)$ (Weak Law of Large Number)
2. $\hat{\mu} - \mu = O_P(1/\sqrt{n})$ (Central Limit Theorem)

As with the classical order notation, we can do some simple "calculus" with stochastic order notation and observe that for instance: $o_P(1) + O_P(1) = O_P(1)$, $o_P(1)O_P(1) = o_P(1)$ and so on.

References

[1] Rick Durrett. *Probability: theory and examples*, volume 31 of *Cambridge Series in Statistical and Probabilistic Mathematics*. Cambridge University Press, Cambridge, fourth edition, 2010.