

• Definition (Probability Measure, Distribution, Distribution Function)

1. Let the probability measure space be (Ω, \mathcal{F}, P) ,
where P is the probability measure.

2. A random variable is a measurable real function X s.t.

$X: (\Omega, \mathcal{F}) \mapsto (R^1, \mathcal{B}^1)$, where \mathcal{B}^1 is the Borel sets of R^1 .

3. The distribution of the r.v. X is defined by

probability measure $M = P X^{-1}$ on (R^1, \mathcal{B}^1) defined by

$$M(A) = P[X \in A] = P X^{-1}(A) = P[\omega : X(\omega) \in A], \quad A \in \mathcal{B}^1.$$

4. The distribution function of X is defined by

$$F(x) = M(-\infty, x] = P[X \leq x] \text{ for real } x$$

• Definition (Expected Values)

The expected value or expectation of $g(X)$ is

$$E[g(X)] = \int g(x) dP = \int_{\Omega} g(X(\omega)) P(d\omega) \text{ w.r.t. the probability measure } P.$$

$$= \int_{R^1} g(x) \mu(dx) \text{ w.r.t. the distribution } M$$

$$= \int_{R^1} g(x) dF(x) \text{ if } F \text{ is the distribution function of } X$$

$$= \int_{R^1} g(x) f(x) dx \text{ if } X \text{ has density } f$$

• Proposition (Monotone Continuity of P)

The measure P is continuous for monotone sequences

(i) If $A_n \uparrow A$, where $A_n \in \mathcal{B}$, then $P(A_n) \uparrow P(A)$.

(ii) If $A_n \downarrow A$, where $A_n \in \mathcal{B}$, then $P(A_n) \downarrow P(A)$.

Pf: (i) Assume

$$A_1 \subset A_2 \subset A_3 \dots$$

and define

$$B_1 = A_1, B_2 = A_2 \setminus A_1, \dots, B_n = A_n \setminus A_{n-1}, \dots$$

Then $\{B_n\}$ is a disjoint sequence of events and

$$\bigcup_{i=1}^{\infty} B_i = A_n, \quad \bigcup_{i=1}^{\infty} B_i = \bigcup_{i=1}^{\infty} A_i = A \quad \text{by } A_1 \subset A_2 \subset \dots$$

By σ -additivity,

$$\begin{aligned} P(A) &= P\left(\bigcup_{i=1}^{\infty} B_i\right) = \sum_{i=1}^{\infty} P(B_i) = \lim_{n \rightarrow \infty} \uparrow \sum_{i=1}^n P(B_i) \\ &= \lim_{n \rightarrow \infty} \uparrow P\left(\bigcup_{i=1}^n B_i\right) = \lim_{n \rightarrow \infty} \uparrow P(A_n). \end{aligned}$$

To prove (i), note if $A_n \uparrow A$, then $A_n^c \downarrow A^c$ and by part (ii)

$$P(A_n^c) = 1 - P(A_n) \uparrow P(A^c) = 1 - P(A)$$

so that $P(A_n) \uparrow P(A)$.

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• Proposition (Fatou's Lemma and Continuity of P)

Suppose $A_n \in \mathcal{B}$, $n \geq 1$.

(i) Fatou Lemma:

$$\begin{aligned} P(\liminf_{n \rightarrow \infty} A_n) &\leq \liminf_{n \rightarrow \infty} P(A_n) \\ &\leq \limsup_{n \rightarrow \infty} P(A_n) \leq P(\limsup_{n \rightarrow \infty} A_n) \end{aligned}$$

(ii) Continuity of P :

If $A_n \rightarrow A$, then $P(A_n) \rightarrow P(A)$

Pf: (ii). Suppose (i) is true.

If $A_n \rightarrow A$, then $\liminf_{n \rightarrow \infty} A_n = \limsup_{n \rightarrow \infty} A_n = A$

$$\begin{aligned} P(A) &= P(\liminf_{n \rightarrow \infty} A_n) \leq \liminf_{n \rightarrow \infty} P(A_n) \\ &\leq \limsup_{n \rightarrow \infty} P(A_n) \leq P(\limsup_{n \rightarrow \infty} A_n) = P(A) \end{aligned}$$

Hence

$$\lim_{n \rightarrow \infty} P(A_n) = P(A), \text{ i.e. } P(A_n) \rightarrow P(A).$$

$$\begin{aligned} (i) \quad P(\liminf_{n \rightarrow \infty} A_n) &= P\left(\lim_{n \rightarrow \infty} \bigcap_{k=n}^{\infty} A_k\right) \\ &= \lim_{n \rightarrow \infty} \uparrow P\left(\bigcap_{k=n}^{\infty} A_k\right) \text{ by the monotone continuity of } P. \\ &\leq \lim_{n \rightarrow \infty} \inf_{k \geq n} P(A_k) \text{ by } A_k \supseteq \bigcap_{k \geq n} A_k \text{ for all } k \geq n. \\ &= \liminf_{n \rightarrow \infty} P(A_n) \end{aligned}$$

Likewise,

$$\begin{aligned} P(\limsup_{n \rightarrow \infty} A_n) &= P\left(\lim_{n \rightarrow \infty} \bigcup_{k=n}^{\infty} A_k\right) \\ &= \lim_{n \rightarrow \infty} \downarrow P\left(\bigcup_{k=n}^{\infty} A_k\right) \text{ by the monotone continuity of } P. \\ &\geq \lim_{n \rightarrow \infty} \sup_{k \geq n} P(A_k) \text{ by } A_k \subseteq \bigcup_{k \geq n} A_k \text{ for all } k \geq n. \\ &= \limsup_{n \rightarrow \infty} P(A_n). \end{aligned}$$

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• Proposition (Distribution Function F).

A function $F: \mathbb{R} \mapsto [0, 1]$ satisfying (i), (ii), (iii) is called a (probability) distribution function (df). Define

$$F(x) = P(-\infty, x] = P[X \leq x]$$

(i) F is right continuous,

(ii) F is monotone non-decreasing.

(iii) F has limits at $\pm\infty$,

$$F(\infty) = \lim_{x \uparrow \infty} F(x) = 1$$

$$F(-\infty) = \lim_{x \downarrow -\infty} F(x) = 0.$$

Pf: (i), we may show F is right continuous as follows:

Let $x_n \downarrow x$, we need to prove $F(x_n) \downarrow F(x)$.

$\because (-\infty, x_n] \downarrow (-\infty, x]$, by the monotone continuity of P ,

$$F(x_n) = P(-\infty, x_n] \downarrow P(-\infty, x] = F(x).$$

(ii) If $x < y$, then $(-\infty, x] \subset (-\infty, y]$,

by the monotonicity of P ,

$$F(x) = P(-\infty, x] \leq P(-\infty, y] = F(y).$$

$$(iii) F(\infty) = \lim_{x_n \uparrow \infty} F(x_n) \quad \text{for any sequence } x_n \uparrow \infty$$

$$= \lim_{x_n \uparrow \infty} \uparrow P(-\infty, x_n])$$

$$= P(\lim_{x_n \uparrow \infty} \uparrow (-\infty, x_n]) \quad \text{by monotone continuity of } P$$

$$= P(\bigcup_n (-\infty, x_n]) = P(\mathbb{R})$$

$$= P(\mathbb{R}) = P(\Omega) = 1$$

$$F(-\infty) = \lim_{x_n \downarrow -\infty} F(x_n) = \lim_{x_n \downarrow -\infty} \downarrow P(-\infty, x_n])$$

$$= P(\lim_{x_n \downarrow -\infty} \downarrow (-\infty, x_n]) \quad \text{by monotone continuity of } P$$

$$= P(\bigcap_n (-\infty, x_n]) = P(\emptyset) = 0.$$

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• Proposition (Borel-Cantelli Lemma)

Let $\{A_n\}$ be any events. If

$$\sum_n P(A_n) < \infty,$$

then

$$P([A_n \text{ i.o.}]) = P(\limsup_{n \rightarrow \infty} A_n) = 0.$$

Note: the basic tool for proving almost sure convergence!

$$\text{Pf: } P([A_n \text{ i.o.}]) = P(\lim_{n \rightarrow \infty} \cup_{j=n}^{\infty} A_j)$$

$$= \lim_{n \rightarrow \infty} P(\cup_{j=n}^{\infty} A_j) \quad \text{by monotone continuity of } P.$$

$$\leq \limsup_{n \rightarrow \infty} \sum_{j=n}^{\infty} P(A_j) \quad \text{by subadditivity of } P.$$

$$= 0$$

Since $\sum_n P(A_n) < \infty$ implies $\sum_{j=n}^{\infty} P(A_j) \rightarrow 0$ as $n \rightarrow \infty$.

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• Example

Suppose $\{X_n, n \geq 1\}$ are Bernoulli r.v.'s with

$$P[X_n=1] = p_n = 1 - P[X_n=0]$$

We assert that $P[\lim_{n \rightarrow \infty} X_n = 0] = 1$ if $\sum_n p_n < \infty$.

$$\text{If } \sum_n p_n = \sum_n P[X_n=1] < \infty,$$

then by the Borel-Cantelli Lemma,

$$P([X_n=1] \text{ i.o.}) = 0$$

$$\Rightarrow P((\limsup_{n \rightarrow \infty} [X_n=1])^c) = P(\liminf_{n \rightarrow \infty} [X_n=0]) = 1$$

That is, with probability 1, the r.v.'s $\{X_n\}$ must converge to 0.

Hence $X_n \rightarrow 0$ with probability 1, a.s..

• Proposition (Borel Zero-One Law).

If $\{A_n\}$ is a sequence of "independent" events, then

$$P([A_n \text{ i.o.}]) = \begin{cases} 0 & \text{iff } \sum_n P(A_n) < \infty, \\ 1 & \text{iff } \sum_n P(A_n) = \infty. \end{cases}$$

Note: The Borel-Cantelli Lemma does not require "independence", but the Borel Zero-One Law does.

Pf: From the Borel-Cantelli Lemma, if

$$\sum_n P(A_n) < \infty,$$

$$\text{then } P([A_n \text{ i.o.}]) = 0.$$

Conversely, suppose $\sum_n P(A_n) = \infty$, then

$$\begin{aligned} P([A_n \text{ i.o.}]) &= P(\limsup_{n \rightarrow \infty} A_n) \\ &= 1 - P(\liminf_{n \rightarrow \infty} A_n^c) = 1 - P(\lim_{n \rightarrow \infty} \bigcap_{k=n}^{\infty} A_k^c) \\ &= 1 - \lim_{n \rightarrow \infty} P(\bigcap_{k=n}^{\infty} A_k^c) = 1 - \lim_{n \rightarrow \infty} P(\lim_{m \rightarrow \infty} \bigcap_{k=n}^m A_k^c) \text{ by monotone continuity} \\ &= 1 - \lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} P(\bigcap_{k=n}^m A_k^c) \text{ by monotone continuity of } P. \\ &= 1 - \lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} \prod_{k=n}^m (1 - P(A_k)) \text{ by independence of } \{A_k\}. \end{aligned}$$

To prove $\lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} \prod_{k=n}^m (1 - P(A_k)) = 0$.

use the inequality $1-x < e^{-x}$, $0 < x < 1$. (*)

Now we have

$$\begin{aligned} \lim_{n \rightarrow \infty} \prod_{k=n}^m (1 - P(A_k)) &\leq \lim_{n \rightarrow \infty} \prod_{k=n}^m e^{-P(A_k)} = \lim_{n \rightarrow \infty} e^{-\sum_{k=n}^m P(A_k)} \\ &= e^{-\sum_{k=n}^{\infty} P(A_k)} = e^{-\infty} = 0 \text{ since } \sum_n P(A_n) = \infty. \end{aligned}$$

This is true for all n , so

$$\lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} \prod_{k=n}^m (1 - P(A_k)) = 0.$$

To verify (*), for $0 < x < 1$,

$$-\log(1-x) = \sum_{k=1}^{\infty} \frac{x^k}{k} \geq x \Rightarrow \frac{1}{1-x} \geq e^x, e^{-x} \leq 1-x.$$

#

• Example

Suppose $\{X_n, n \geq 1\}$ are independent in addition to being Bernoulli, with

$$P[X_k=1] = p_k = 1 - P[X_k=0]$$

Then we assert that

$$P[X_n \rightarrow 0] = 1 \text{ iff } \sum_n p_n < \infty.$$

$$\therefore P[X_n \rightarrow 0] = P\left(\liminf_{n \rightarrow \infty} [X_n = 0]\right) = 1$$

∴ we need to show

$$P\left(\left(\liminf_{n \rightarrow \infty} [X_n = 0]\right)^c\right) = P\left(\limsup_{n \rightarrow \infty} [X_n = 1]\right) = P([X_n = 1] \text{ i.o.}) = 0$$

iff

$$\sum_n P[X_n = 1] = \sum_n p_n < \infty.$$

by the Borel Zero-One Law. #

• Theorem (A Second Pf of the Second Borel-Cantelli Lemma)

For a sequence A_1, A_2, \dots of events, let $N_n = I_{A_1} + \dots + I_{A_n}$, $p_k = P(A_k)$.

Note that $[A_n \text{ i.o.}] = [w : \sup_n N_n(w) = \infty]$.

If the A_n are independent and $\sum p_n = \infty$, then

$$P[A_n \text{ i.o.}] = P[w : \sup_n N_n(w) = \infty] = 1.$$

This is the second Borel-Cantelli lemma.

Pf: Put $p_k = P(A_k)$ and $m_n = p_1 + \dots + p_n$.

From $E[I_{A_K}] = p_k$, $\text{Var}[I_{A_K}] = p_k(1-p_k) \leq p_k$ follow

$$E[N_n] = \sum p_k = m_n, \quad \text{Var}[N_n] = \sum p_k(1-p_k) \leq m_n. \quad \text{by the } A_n \text{ indep.}$$

If $m_n > x$, then

$$\begin{aligned} P[N_n \leq x] &= P[N_n - m_n \leq x - m_n] \quad \text{by } x - m_n < 0 \\ &= P[N_n - m_n \leq -|m_n - x|] \quad \text{by } m_n - x > 0 \\ &\leq P[|N_n - m_n| \geq |m_n - x|] \\ &\leq \frac{\text{Var}[N_n]}{(m_n - x)^2} \leq \frac{m_n}{(m_n - x)^2}. \quad \text{by Chebychev's inequality} \end{aligned}$$

If $\sum p_n = \infty$, so that $m_n \rightarrow \infty$, thus

$$\lim_n P[N_n \leq x] = 0 \text{ for each } x.$$

Since $P[\sup_k N_k \leq x] \leq P[N_n \leq x]$,

$$P[\sup_k N_k \leq x] = 0, \text{ and hence}$$

$$\begin{aligned} P[\sup_k N_k < \infty] &= P\left(\bigcup_x [\sup_k N_k \leq x]\right) \\ &\leq \sum_x P[\sup_n N_n \leq x] = 0. \end{aligned}$$

Hence $P[A_n \text{ i.o.}] = P[\sup_n N_n = \infty] = 1$. #

• Theorem (A Refinement of the Second Borel-Cantelli Lemma)

If $\sum P(A_n) = \infty$ and

$$\liminf_n \frac{\sum_{j,k} P(A_j \cap A_k)}{\left(\sum_{k=1}^n P(A_k)\right)^2} \leq 1, \quad (*)$$

then $P[A_n : \text{a.s.}] = 1$

Remark:

As the proof will show, the ratio in (*) ≥ 1 ;

if (*) holds, then $\liminf_n \frac{\sum_{j,k} P(A_j \cap A_k)}{\left(\sum_{k=1}^n P(A_k)\right)^2} = 1$.

Pf: Let $\theta_n = \frac{\sum_{j,k} P(A_j \cap A_k)}{\left(\sum_{k=1}^n P(A_k)\right)^2} = \frac{\sum_{j,k} P(A_j \cap A_k)}{m_n^2}$

where $m_n = E[N_n] = \sum_{k=1}^n E[I_{A_k}] = \sum_{k=1}^n P(A_k)$.

$$\begin{aligned} \text{Var}[N_n] &= E[N_n^2] - m_n^2 \\ &= \sum_{j,k} E[I_{A_j} I_{A_k}] - m_n^2 \\ &= \sum_{j,k} P(A_j \cap A_k) - m_n^2 \\ &= (\theta_n - 1) m_n^2 \geq 0 \end{aligned}$$

So that $\theta_n - 1 \geq 0$, i.e. $\theta_n \geq 1$.

If $m_n > x$, then

$$\begin{aligned} P[N_n \leq x] &= P[N_n - m_n \leq -(m_n - x)] \quad \text{by } m_n > x. \\ &\leq P[|N_n - m_n| \geq m_n - x] \\ &\leq \frac{\text{Var}[N_n]}{(m_n - x)^2} = \frac{(\theta_n - 1) m_n^2}{(m_n - x)^2} \quad \text{by Chebychev's inequality.} \end{aligned}$$

If $\sum p_n = \infty$, so that $m_n \rightarrow \infty$, thus $m_n^2 / (m_n - x)^2 \rightarrow 1$.

Since $\theta_n - 1 \geq 0$ and by the hypothesis $\liminf_n \theta_n \leq 1$,
thus $\liminf_n (\theta_n - 1) = 0$, and hence

$$\liminf_n P[N_n \leq x] = 0 \text{ for each } x.$$

Since $P[\sup_n N_k \leq x] \leq P[N_n \leq x]$, then $P[\sup_n N_k \leq x] = 0$, hence

$$\begin{aligned} P[\sup_n N_k < \infty] &= P\left(\bigcup_x P[\sup_n N_k \leq x]\right) \\ &\leq \sum_x P[\sup_n N_k \leq x] = 0 \end{aligned}$$

Hence $P[A_n : \text{a.s.}] = P[\sup_n N_n = \infty] = 1$. *

• Corollary (Cor of the Refinement of the Second Borel-Cantelli Lemma)

If, as in the second Borel-Cantelli lemma,
the A_n are independent (or even if they are merely pairwise independent),
then $\sum P(A_n) = \infty$ implies that

$$\liminf_n \frac{\sum_{j \leq n} P(A_j \cap A_k)}{(\sum_{k \leq n} P(A_k))^2} \leq 1$$

then $P[A_n \text{ i.o.}] = 1$ by the refinement of the second Borel-Cantelli lemma.

p.f.: Put $p_k = P(A_k)$. Suppose $\sum p_n = \infty$.

suppose the A_n are independent (or pairwise independent),
by the refinement of the second Borel-Cantelli lemma,
it suffices to check that

$$\liminf_n \frac{\sum_{j \leq n} P(A_j \cap A_k)}{(\sum_{k \leq n} P(A_k))^2} \leq 1$$

$$\frac{\sum_{j \leq n} P(A_j \cap A_k)}{(\sum_{k \leq n} P(A_k))^2} = \frac{\sum_{j \leq n} p_k + \sum_{j \neq k} p_j p_k}{m_n^2} \quad \text{by } \begin{cases} \text{pairwise independent} \\ \text{independent} \end{cases}$$

$$= \frac{m_n^2 + \sum_{k \leq n} p_k - \sum_{k \leq n} p_k^2}{m_n^2} \quad \text{by } m_n^2 = (p_1 + \dots + p_n)^2 = \sum_{k \leq n} p_k^2 + \sum_{j \neq k} p_j p_k$$

$$= 1 + \frac{\sum_{k \leq n} (p_k - p_k^2)}{m_n^2}$$

$$\leq 1 + \frac{m_n}{m_n^2} = 1 + \frac{1}{m_n} \quad \text{by } \sum_{k \leq n} (p_k - p_k^2) \leq \sum_{k \leq n} p_k = m_n$$

$$\rightarrow 1 \quad \text{by } m_n = \sum_{k \leq n} p_k \rightarrow \sum p_n = \infty$$

Hence this proves the second Borel-Cantelli lemma again. #.

- Thm (Bernstein's Version of The Weierstrass Approximation Thm).

Let $f: [0, 1] \rightarrow \mathbb{R}$ be continuous, and

define the "Bernstein polynomial of degree n " by

$$B_n(x) = \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k}, \quad 0 \leq x \leq 1.$$

Then

$B_n(x) \rightarrow f(x)$ uniformly for $x \in [0, 1]$.

Pf: Let $\{\delta_k, k=1, \dots, n\}$ be iid Bernoulli r.v.'s with

$P[\delta_i = 1] = x = 1 - P[\delta_i = 0]$, hence have finite mean x .

• Define $S_n = \sum_{i=1}^n \delta_i$ s.t. $S_n \sim \text{binomial}(n, x)$.

• The weak law of large numbers implies that

$$\frac{S_n}{n} \xrightarrow{P} x.$$

• $\therefore f$ is continuous on $[0, 1]$, a compact set

$\therefore f\left(\frac{S_n}{n}\right) \xrightarrow{P} f(x)$ and f is bounded, uniformly continuous
the dominated convergence theorem implies that

$$E f\left(\frac{S_n}{n}\right) = \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} = B_n(x) \rightarrow f(x) \text{ as } n \rightarrow \infty.$$

• Define the modulus of continuity

$$w(\delta) = \sup_{\substack{0 \leq x, y \leq 1 \\ |x-y| \leq \delta}} |f(x) - f(y)|,$$

the uniformly continuity of f implies $\lim_{\delta \downarrow 0} w(\delta) = 0$.

$$\begin{aligned} \sup_{x \in \mathbb{R}} |B_n(x) - f(x)| &= \sup_x |E f\left(\frac{S_n}{n}\right) - f(x)| \leq \sup_x E |f\left(\frac{S_n}{n}\right) - f(x)| \\ &\leq \sup_x \left\{ E \left(|f\left(\frac{S_n}{n}\right) - f(x)| \mathbf{1}_{\left\{ \left|\frac{S_n}{n} - x\right| \leq \epsilon \right\}} \right) + E \left(|f\left(\frac{S_n}{n}\right) - f(x)| \mathbf{1}_{\left\{ \left|\frac{S_n}{n} - x\right| > \epsilon \right\}} \right) \right\} \\ &\leq w(\epsilon) P \left[\left| \frac{S_n}{n} - x \right| \leq \epsilon \right] + 2 \|f\| \sup_x P \left[\left| \frac{S_n}{n} - x \right| > \epsilon \right], \\ &\because |f\left(\frac{S_n}{n}\right) - f(x)| \leq \|f\| \left| \frac{S_n}{n} - x \right| + \|f\| \leq 2 \|f\|, \\ &\leq w(\epsilon) + \frac{2 \|f\|}{\epsilon^2} \sup_x \text{Var} \left(\frac{S_n}{n} \right) = w(\epsilon) + \frac{2 \|f\|}{\epsilon^2} \sup_x \frac{x(1-x)}{n} \\ &\leq w(\epsilon) + \frac{2 \|f\|}{\epsilon^2} \frac{1}{4n}. \end{aligned}$$

$$\limsup_{n \rightarrow \infty} \sup_x |B_n(x) - f(x)| \leq w(\epsilon) \rightarrow 0 \text{ as } \epsilon \rightarrow 0.$$

- Definition (Tail σ -field)

Let $\{X_n\}$ be a sequence of r.v.'s and define

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

The "tail σ -field" T is defined as

$$T = \bigcap_n F'_n = \lim_{n \rightarrow \infty} \downarrow \sigma(X_{n+1}, X_{n+2}, \dots)$$

These are events which depend on the tail of the $\{X_n\}$ sequence.

A : tail event if $A \in T$

X : tail r.v. if $X: (\Omega, \mathcal{B}) \rightarrow (R, \mathcal{B}(R))$ s.t. $X^{-1}(B(R)) \subset T$.

- Theorem (Kolmogorov Zero-One Law).

If $\{X_n\}$ are "independent" r.v.'s with tail σ -field T ,

then $\Lambda \in T$ implies $P(\Lambda) = 0$ or 1 .

Pf: Suppose $\Lambda \in T$. We show that Λ is independent of itself s.t

$$P(\Lambda) = P(\Lambda \cap \Lambda) = P(\Lambda)P(\Lambda), \text{ therefore } P(\Lambda) = 0 \text{ or } 1.$$

We define $F_n = \sigma(X_1, \dots, X_n)$ s.t. $F_n \uparrow$ and $F_\infty = \sigma(X_1, X_2, \dots)$.

Note that

$$\Lambda \in T \subset F'_n = \sigma(X_{n+1}, X_{n+2}, \dots) \subset \sigma(X_1, X_2, \dots) = F_\infty.$$

For all n , we have $\Lambda \in F'_n$,

Since $F_n \perp\!\!\!\perp F'_n$, we have $\Lambda \perp\!\!\!\perp F_n, \forall n$,

and therefore $\Lambda \perp\!\!\!\perp \bigcup_n F_n$.

Let $C_1 = \{\Lambda\}$, $C_2 = \bigcup_n F_n$. Then C_i is a π -system, $i=1, 2$, $C_1 \perp\!\!\!\perp C_2$ and

$$\sigma(C_1) = \{\emptyset, \Lambda, \Lambda^c, \Omega\} \perp\!\!\!\perp \sigma(C_2) = F_\infty.$$

Now $\Lambda \in \sigma(C_1)$ and $\Lambda \in F_\infty$,

thus Λ is independent of itself.

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• Lemma (Tail r.v. X is constant a.s.).

Let \mathcal{G} be a σ -field s.t. for $A \in \mathcal{G}$, $P(A) = 0$ or 1 , and

X be a r.v. measurable w.r.t \mathcal{G} . Then there exists c s.t. $P[X=c]=1$.

Pf: Let $F(x) = P[X \leq x]$, which is non-decreasing.

Since $[X \leq x] \in \sigma(X) \subset \mathcal{G}$,

$F(x) = 0$ or 1 , $\forall x \in \mathbb{R}$.

Let $c = \sup_{x \in \mathbb{R}} \{x : F(x) = 0\}$.

The df F must have a jump of size 1 at c and

thus $P[X=c]=1$. #

• Corollary (Cor. of the Kolmogorov Zero-One Law).

Let $\{X_n\}$ be "indep." r.v.'s and $S_n = \sum_{i=1}^n X_i$. Then

(i) $P[\sum_n X_n \text{ converges}] = 0$ or 1

(ii) $\limsup_{n \rightarrow \infty} X_n$, $\liminf_{n \rightarrow \infty} X_n$ are constants a.s.

(iii) $P[\omega : \frac{S_n(\omega)}{n} \rightarrow 0] = 0$ or 1

Pf: (ii) $\because \sum_{n=1}^{\infty} X_n(\omega) \text{ converges iff } \sum_{n=m+1}^{\infty} X_n \text{ converges for any } m$.

$\therefore [\sum_{n=1}^{\infty} X_n(\omega) \text{ converges}] = [\sum_{n=m+1}^{\infty} X_n \text{ converges}] \in \mathcal{F}_m^{'}, \forall m$.

Then $[\sum_{n=1}^{\infty} X_n(\omega) \text{ converges}] \in \mathcal{T}$.

(ii) $\because \limsup$ of the sequence $\{X_n\} = \limsup$ of the sequence $\{X_m, X_{m+1}, \dots\}, \forall m$

so we have $\limsup_{n \rightarrow \infty} X_n \in \mathcal{T}$.

(iii) For any m ,

$$\lim_{n \rightarrow \infty} \frac{S_n(\omega)}{n} = \lim_{n \rightarrow \infty} \frac{\sum_{i=1}^n X_i(\omega)}{n} = \lim_{n \rightarrow \infty} \frac{\sum_{i=m+1}^n X_i(\omega)}{n} \text{ for any } m.$$

So for any m , $\lim_{n \rightarrow \infty} \frac{S_n(\omega)}{n} \in \mathcal{F}_m^{'}$, and hence $\lim_{n \rightarrow \infty} \frac{S_n(\omega)}{n} \in \mathcal{T}$. #

- Definition (Simple Functions)

A simple real function is one with finite range; that is,

$$f = \sum_{i=1}^n x_i \mathbf{1}_{A_i}$$

where the A_i form a finite decomposition of Ω ; that is,

$$\bigcup_{i=1}^n A_i = \Omega \text{ and } A_i \cap A_j = \emptyset \text{ for } i \neq j$$

f is measurable \mathcal{F}_t if each $A_i \in \mathcal{F}_t$.

- Theorem (Approximation Sequence of Real Measurable Function)

If f is real and measurable \mathcal{F}_t , there exists a sequence $\{f_n\}$ of simple functions, each measurable \mathcal{F}_t , s.t.

$$0 \leq f_n(\omega) \uparrow f(\omega) \text{ if } f(\omega) \geq 0$$

$$0 \geq f_n(\omega) \downarrow f(\omega) \text{ if } f(\omega) \leq 0$$

Pf: Define

$$\begin{aligned} f_n = & -n \mathbf{1}_{\{f \leq -n\}} + \sum_{k=1}^{2^n - (k-1)} \frac{1}{2^n} \mathbf{1}_{\left[\frac{k-1}{2^n} \leq f \leq \frac{k}{2^n}\right]} \\ & + \sum_{k=1}^{2^n - (k-1)} \frac{1}{2^n} \mathbf{1}_{\left[\frac{k-1}{2^n} \leq f \leq \frac{k}{2^n}\right]} + n \mathbf{1}_{\{f \geq n\}}. \end{aligned}$$

This sequence has the desired property. #

• Definition (The Integral)

- Let f be real, nonnegative measurable function on a measurable space $(\Omega, \mathcal{F}, \mu)$.

The integral of f is defined by

$$\int f d\mu = \sup \sum_i \left[\inf_{w \in A_i} f(w) \right] \mu(A_i),$$

the supremum extends over all finite decompositions $\{\Omega_i\}$ of Ω into \mathcal{F} -sets.

- For general f (not necessarily nonnegative), its "positive part" is

$$f^+(w) = f(w) \vee 0, \text{ so } f^+ \geq 0.$$

its "negative part" is

$$f^-(w) = (-f(w)) \vee 0, \text{ so } f^- \geq 0.$$

$$\text{Then } f = f^+ - f^-.$$

The integral of f is defined by

$$\int f d\mu = \int f^+ d\mu - \int f^- d\mu. \quad (1)$$

Note:

- f is integrable if

$\int f^+ d\mu < \infty$ and $\int f^- d\mu < \infty$; thus has (1) as its definite integral.

- f is not integrable if

1. $\int f^+ d\mu = \infty$ and $\int f^- d\mu < \infty$; but has definite integral $+\infty$;

2. $\int f^+ d\mu < \infty$ and $\int f^- d\mu = \infty$; but has definite integral $-\infty$;

3. $\int f^+ d\mu = \infty$ and $\int f^- d\mu = \infty$; no definite integral.

- f is integrable iff $|f|$ is integrable

Pf: f is integrable

$$\Leftrightarrow \int f^+ d\mu < \infty \text{ and } \int f^- d\mu < \infty$$

$$\Leftrightarrow \int f^+ d\mu + \int f^- d\mu = \int (f^+ + f^-) d\mu = \int |f| d\mu < \infty$$

$\Leftrightarrow |f|$ is integrable.

#

• Definition (Integration over Sets)

The integral of f over a set A in \mathcal{F}_ϵ is defined by.

$$\int_A f d\mu = \int I_A f d\mu.$$

Note:

• The definition applies if f is defined only on A (Set $f=0$ outside A).

• $\int_A f d\mu = 0$ if $\mu(A) = 0$.

• Properties

(i) If f and g are nonnegative and

$$\int_A f d\mu = \int_A g d\mu \text{ for all } A \text{ in } \mathcal{F}_\epsilon,$$

and if μ is σ -finite, then $f=g$ a.e.

(ii) If f and g are integrable and

$$\int_A f d\mu = \int_A g d\mu \text{ for all } A \text{ in } \mathcal{F}_\epsilon, \text{ then } f=g \text{ a.e.}$$

(iii) If f and g are integrable and

$$\int_A f d\mu = \int_A g d\mu \text{ for all } A \in \mathcal{P} \text{ where}$$

\mathcal{P} is a π -system generating \mathcal{F}_ϵ and

Ω is a finite or countable union of \mathcal{P} -sets, then $f=g$ a.e.

Remark:

The results about integrals are proved

1. for indicator functions
2. then for simple functions.
3. then for nonnegative functions
4. then for integrable functions.

• Theorem (Monotone Convergence Thm, MCT).

If $0 \leq X_n \uparrow X$, then

$$E(X_n) \uparrow E(X), \text{ or equivalently, } \lim_{n \rightarrow \infty} E(X_n) = E(\lim_{n \rightarrow \infty} X_n).$$

Note: MCT allows the interchange of limits and expectation.

Pf: Suppose we have $X_n, X \in \bar{\mathcal{E}}_f := \{X \geq 0, X: (\Omega, \mathcal{B}) \mapsto (R, \mathcal{B}(R))\}$.

We may find simple functions $Y_m^{(n)} \in \mathcal{E}_f := \{X \geq 0, X \text{ is simple r.v.}\}$, to act as approximation to X_n , s.t.

$$Y_m^{(n)} \uparrow X_n, \quad m \rightarrow \infty.$$

We need to find a sequence of simple functions $\{Z_m\}$ approximating X ,

$$Z_m \uparrow X, \quad m \rightarrow \infty,$$

which can be expressed in terms of the approximation $\{X_n\}$.

So define

$$Z_m = \bigvee_{n \leq m} Y_m^{(n)} \quad \because Y_m^{(n)} \geq 0 \Rightarrow Z_m \in \mathcal{E}_f$$

Note that Z_m is non-decreasing since

$$\begin{aligned} Z_m &\leq \bigvee_{n \leq m} Y_{m+1}^{(n)} \quad \text{since } Y_m \leq Y_{m+1} \\ &\leq \bigvee_{n \leq m+1} Y_{m+1}^{(n)} = Z_{m+1} \end{aligned}$$

For $n \leq m$,

$$\textcircled{1} \quad Y_m^{(n)} \leq Y_m^{(m)} \leq \bigvee_{j \leq m} Y_m^{(j)} = Z_m;$$

$$\textcircled{2} \quad Z_m \leq \bigvee_{j \leq m} X_j = X_m \quad \text{since } Y_m^{(j)} \leq X_j \text{ which is monotone in } j.$$

$$\Rightarrow Y_m^{(n)} \leq Z_m \leq X_m$$

We conclude that for all n

$$X_n = \lim_{m \rightarrow \infty} Y_m^{(n)} \leq \lim_{m \rightarrow \infty} Z_m \leq \lim_{m \rightarrow \infty} X_m$$

So

$$X = \lim_{n \rightarrow \infty} X_n \leq \lim_{n \rightarrow \infty} Z_n \leq \lim_{n \rightarrow \infty} X_m = X.$$

(next pg. cont)

Hence $X = \lim_{n \rightarrow \infty} X_n = \lim_{m \rightarrow \infty} Z_m$ and.

it follows that $\{Z_m\}$ is a simple function approximation to X .

Because expectation is monotone on \mathcal{E} ; simple r.v.'s,

$$E(X_n) = \lim_{m \rightarrow \infty} \uparrow E(Y_m^n) \quad \text{by expectation definition.}$$

$$\leq \lim_{m \rightarrow \infty} \uparrow E(Z_m) \leq \lim_{m \rightarrow \infty} \uparrow E(X_m) \quad \text{from above}$$

$\therefore Z_m \in \mathcal{E}_f$ and $\{Z_m\}$ is a simple function approximation to X ,

$$E(X) = E(\lim_{m \rightarrow \infty} \uparrow Z_m) = \lim_{m \rightarrow \infty} \uparrow E(Z_m) \quad \text{by expectation definition.}$$

$$\therefore E(X_n) \leq E(X) = \lim_{m \rightarrow \infty} \uparrow E(Z_m) \leq \lim_{m \rightarrow \infty} \uparrow E(X_m),$$

$$\text{So } \lim_{n \rightarrow \infty} E(X_n) \leq E(X) \leq \lim_{n \rightarrow \infty} E(X_n),$$

hence the result follows.

#

Corollary (Series Version of MCT)

If $X_k \geq 0, k \geq 1$, then

$$E\left(\sum_{k=1}^{\infty} X_k\right) = \sum_{k=1}^{\infty} E(X_k).$$

So that the expectation and infinite sum can be exchanged.

$$\begin{aligned} \text{Pf: } E\left(\sum_{k=1}^{\infty} X_k\right) &= E\left(\lim_{n \rightarrow \infty} \sum_{k=1}^n X_k\right) \\ &= \lim_{n \rightarrow \infty} E\left(\sum_{k=1}^n X_k\right) \quad \because \sum_{k=1}^n X_k \uparrow \sum_{k=1}^{\infty} X_k \text{ and then by MCT} \\ &= \lim_{n \rightarrow \infty} \sum_{k=1}^n E(X_k) \\ &= \sum_{k=1}^{\infty} E(X_k). \end{aligned}$$

#

• Theorem (Fatou's Lemma)

If $X_n \geq 0$, then

$$E(\liminf_{n \rightarrow \infty} X_n) \leq \liminf_{n \rightarrow \infty} E(X_n).$$

More generally, if there exists $Z \in L_1$ s.t. $X_n \geq Z$, then the inequality holds.

Pf: • If $X_n \geq 0$, then

$$E(\liminf_{n \rightarrow \infty} X_n) = E\left(\lim_{n \rightarrow \infty} \bigcap_{k \geq n} X_k\right)$$

$$= \lim_{n \rightarrow \infty} \bigcup E\left(\bigcap_{k \geq n} X_k\right) \text{ by MCT: } \bigcap_{k \geq n} X_k \geq 0$$

$$\because \bigcap_{k \geq n} X_k \leq X_k, \forall k \geq n, \therefore E\left(\bigcap_{k \geq n} X_k\right) \leq E(X_k), \forall k \geq n$$

$$\leq \liminf_{n \rightarrow \infty} E(X_k) = \liminf_{n \rightarrow \infty} E(X_n).$$

• For the case: $X_n \geq Z$, we have $X_n - Z \geq 0$, and

$$E(\liminf_{n \rightarrow \infty} (X_n - Z)) \leq \liminf_{n \rightarrow \infty} E(X_n - Z)$$

$$\text{so } E(\liminf_{n \rightarrow \infty} X_n) - E(Z) \leq \liminf_{n \rightarrow \infty} E(X_n) - E(Z),$$

then the result follows. \star

• Corollary (More Fatou Lemma)

If $X_n \leq Z$ s.t. $Z \in L_1$. Then

$$\limsup_{n \rightarrow \infty} E(X_n) \leq E\left(\limsup_{n \rightarrow \infty} X_n\right).$$

Pf: If $X_n \leq Z$, then $-X_n \geq -Z \in L_1$, and

the Fatou Lemma implies

$$E(\liminf_{n \rightarrow \infty} (-X_n)) \leq \liminf_{n \rightarrow \infty} E(-X_n)$$

$$E(-\liminf_{n \rightarrow \infty} (-X_n)) \geq -\liminf_{n \rightarrow \infty} E(-X_n)$$

The result follows by $-\liminf - = \limsup$. \star

• Proposition (More Fatou's Lemma)

(a) If $X_n \xrightarrow{a.s.} X$, then for every $r > 0$,

$$E(|X|^r) \leq \liminf_{n \rightarrow \infty} E(|X_n|^r)$$

(b) If $X_n \xrightarrow{P} X$, or $X_n \Rightarrow X$, then the above also holds.

Pf: (a) Suppose $X_n \xrightarrow{a.s.} X$,

$$E(|X|^r) = E(\liminf_n |X_n|^r)$$

$$\leq \liminf_n E(|X_n|^r) \quad \text{by Fatou's lemma: } |X_n|^r \geq 0.$$

(b) Suppose $X_n \xrightarrow{P} X$, hence $X_n \xrightarrow{d} X$.

By Skorohod's thm, we know that

there exist $Y_n, n \geq 1, Y$ s.t. $Y_n \stackrel{d}{=} X_n, n \geq 1, Y \stackrel{d}{=} X, Y_n \xrightarrow{a.s.} Y$.

From (a) we get that for every $r > 0$,

$$E(|Y|^r) \leq \liminf_{n \rightarrow \infty} E(|Y_n|^r)$$

$\because Y_n \stackrel{d}{=} X_n, n \geq 1, Y \stackrel{d}{=} X,$

$$\therefore E(|X|^r) \leq \liminf_{n \rightarrow \infty} E(|X_n|^r).$$

#

• Theorem (DCT and Lebesgue Dominated Convergence)

(a) Dominated Convergence Thm (DCT)

If $X_n \xrightarrow{a.s.} X$ and \exists a dominating r.v. Z s.t. $|X_n| \leq Z \in L_1$, then

$$E(X_n) \rightarrow E(X)$$

(b) Lebesgue Dominated Convergence Thm

If $X_n \xrightarrow{P} X$ and \exists a dominating r.v. Z s.t. $|X_n| \leq Z \in L_1$, then

$$E(X_n) \rightarrow E(X)$$

(c) If $X_n \Rightarrow X$ and \exists a dominating r.v. Z s.t. $|X_n| \leq Z \in L_1$, then

$$E(X_n) \rightarrow E(X)$$

pf: (a) If $|X_n| \leq Z$, then $-Z \leq X_n \leq Z$, and $Z \in L_1$, $-Z \in L_1$.

$$\because X_n \xrightarrow{a.s.} X \therefore \lim_{n \rightarrow \infty} X_n = \liminf_{n \rightarrow \infty} X_n = \limsup_{n \rightarrow \infty} X_n$$

The Fatou's Lemma implies that

$$E(X) = E\left(\liminf_{n \rightarrow \infty} X_n\right) \leq \liminf_{n \rightarrow \infty} E(X_n)$$

$$\leq \limsup_{n \rightarrow \infty} E(X_n) \leq E\left(\limsup_{n \rightarrow \infty} X_n\right) = E(X).$$

Thus all inequalities are equality.

(b) It suffices to show that

every convergent subsequence $\{E(X_{n_k})\}$ converges to $E(X)$

Suppose $E(X_{n_k})$ converges. Then since $X_n \xrightarrow{P} X$,

$\{X_{n_k}\}$ contains an a.s. convergent subsequence $\{X_{n_{k(i)}}\}$ s.t. $X_{n_{k(i)}} \xrightarrow{a.s.} X, i \rightarrow \infty$.

Then DCT implies $E(X_{n_{k(i)}}) \rightarrow E(X)$. So $E(X_n) \rightarrow E(X)$.

(c) Since \exists r.v. Z s.t. $|X_n| \leq Z \in L_1 \Rightarrow \{X_n\}$ is ui

Since $X_n \Rightarrow X$, by Skorohod's theorem,

$\exists Y_n, n \geq 1, Y$ with $Y_n \stackrel{d}{=} X_n, Y \stackrel{d}{=} X$ s.t. $Y_n \xrightarrow{a.s.} Y$, thus $Y_n \xrightarrow{P} Y$.

$\{X_n\}$ is ui $\Rightarrow \{Y_n\}$ is ui by $Y_n \stackrel{d}{=} X_n$

$\therefore Y_n \xrightarrow{P} Y$ and $\{Y_n\}$ is ui $\Leftrightarrow Y_n \xrightarrow{L^1} Y$ (Result)

$\therefore E(X_n) = E(Y_n) \rightarrow E(Y) = E(X)$. #

- (c) If X, Y are random variables with distribution functions $F(x), G(x)$ which have no common discontinuities, then

$$E(F(Y)) + E(G(X)) = 1.$$

Interpret the sum of expectations on the left as a probability.

- (d) Even if F and G have common jumps, if $X \perp\!\!\! \perp Y$ then

$$E(F(Y)) + E(G(X)) = 1 + P[X = Y].$$

6. Suppose $X \in L_1$ and A and A_n are events.

✓ (a) Show

$$\int_{[|X|>n]} X dP \rightarrow 0.$$

✓ (b) Show that if $P(A_n) \rightarrow 0$, then

$$\int_{A_n} X dP \rightarrow 0.$$

Hint: Decompose

$$\int_{A_n} |X| dP = \int_{A_n[|X| \leq M]} |X| dP + \int_{A_n[|X| > M]} |X| dP$$

for large M .

✓ (c) Show $E(|X|) = \int_{\Omega} |X| dP = 0$ iff $P[|X| > 0] = 0$, i.e. $|X| = 0$ a.s.
 $\int_A |X| dP = 0$ iff $P(A \cap [|X| > 0]) = 0$.

- (d) If $X \in L_2$, show $\text{Var}(X) = 0$ implies $P[X = E(X)] = 1$ so that X is equal to a constant with probability 1.

- (e) Suppose that (Ω, \mathcal{B}, P) is a probability space and $A_i \in \mathcal{B}$, $i = 1, 2$. Define the distance $d : \mathcal{B} \times \mathcal{B} \mapsto \mathbb{R}$ by

$$d(A_1, A_2) = P(A_1 \Delta A_2).$$

Check the following continuity result: If $A_n, A \in \mathcal{B}$ and

$$d(A_n, A) \rightarrow 0$$

then

$$\int_{A_n} X dP \rightarrow \int_A X dP$$

so that the map

$$A \mapsto \int_A X dP$$

is continuous.

Ex 5-6

Pf: (a) $\int_{\{|X|>n\}} |X| dP = E(|X| \mathbb{1}_{\{|X|>n\}})$

$$|E(|X| \mathbb{1}_{\{|X|>n\}})| \leq E(|X| \mathbb{1}_{\{|X|>n\}})$$

$$\because |X| \mathbb{1}_{\{|X|>n\}} \downarrow |X| \cdot 0 = 0 \text{ as } n \rightarrow \infty$$

$$\text{and } |X| \mathbb{1}_{\{|X|>n\}} \leq |X| < L_1,$$

\therefore by DCT

$$|E(|X| \mathbb{1}_{\{|X|>n\}})| \leq E(|X| \mathbb{1}_{\{|X|>n\}}) \rightarrow 0 \text{ as } n \rightarrow \infty$$

Hence

$$E(|X| \mathbb{1}_{\{|X|>n\}}) \rightarrow 0 \text{ as } n \rightarrow \infty$$

(b) $\int_{A_n} |X| dP$

$$= E(|X| \mathbb{1}_{A_n} \mathbb{1}_{\{|X| \leq M\}}) + E(|X| \mathbb{1}_{A_n} \mathbb{1}_{\{|X|>M\}})$$

$$\leq M P(A_n) + E(|X| \mathbb{1}_{\{|X|>M\}})$$

$$\rightarrow 0 + E(|X| \mathbb{1}_{\{|X|>M\}}) \text{ as } n \rightarrow \infty$$

$$\rightarrow 0 \text{ as } M \rightarrow \infty \text{ from (a)}$$

(c) ① Show $P(A \cap \{|X|>0\}) = 0 \Rightarrow E(|X| \mathbb{1}_A) = 0$

$$\begin{aligned} E(|X| \mathbb{1}_A) &= E(|X| \mathbb{1}_{A \cap \{|X|>0\}}) + E(|X| \mathbb{1}_{A \cap \{|X|=0\}}) \\ &= E(|X| \mathbb{1}_{A \cap \{|X|>0\}}) \end{aligned}$$

$$\because \mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}} \uparrow \mathbb{1}_{A \cap \{|X|>0\}}$$

$$\text{and } |\mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}}| \leq 1,$$

$$\therefore P(A \cap \{|X| \geq \frac{1}{n}\}) = E(\mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}}) \rightarrow E(\mathbb{1}_{A \cap \{|X|>0\}}) = P(A \cap \{|X|>0\}) = 0 \text{ by DCT}$$

Hence

$$\int_{A \cap \{|X| \geq \frac{1}{n}\}} |X| dP = E(|X| \mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}}) \rightarrow E(|X| \mathbb{1}_{A \cap \{|X|>0\}}) = 0 \text{ from (b).}$$

② Show $E(|X| \mathbb{1}_A) = 0 \Rightarrow P(A \cap \{|X|>0\}) = 0$

$$\because \frac{1}{n} \mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}} \leq |X| \mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}} \leq |X| \mathbb{1}_A$$

$$\therefore \frac{1}{n} P(A \cap \{|X| \geq \frac{1}{n}\}) \leq E(|X| \mathbb{1}_A) = 0 \Rightarrow P(A \cap \{|X| \geq \frac{1}{n}\}) = 0$$

$$\therefore \mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}} \uparrow \mathbb{1}_{A \cap \{|X|>0\}} \text{ & } |\mathbb{1}_{A \cap \{|X| \geq \frac{1}{n}\}}| \leq 1$$

$$\therefore \text{by DCT, } 0 = P(A \cap \{|X| \geq \frac{1}{n}\}) \rightarrow P(A \cap \{|X|>0\}) = 0.$$

• Theorem (Fubini's Thm)

If (X, \mathcal{X}, μ) and (Y, \mathcal{Y}, ν) are probability spaces,

let $\pi(A \times B) = \mu(A) \cdot \nu(B)$ be the product measure

for measurable rectangles $A \times B, A \in \mathcal{X}, B \in \mathcal{Y}$. Then

(1) for nonnegative f , the functions

(*) $\int_Y f(x, y) \nu(dy)$, $\int_X f(x, y) \mu(dx)$ are measurable \mathcal{X}, \mathcal{Y} , respectively;

$$\begin{aligned} (***) \int_{X \times Y} f(x, y) \pi(dx, dy) &= \int_X \left[\int_Y f(x, y) \nu(dy) \right] \mu(dx) \\ &= \int_Y \left[\int_X f(x, y) \mu(dx) \right] \nu(dy) \end{aligned}$$

(2) If f (not necessarily nonnegative) is integrable w.r.t. π , the product measure, then (*) and (**) again hold.

Remark:

- Fubini's thm implies that double integrals can be calculated as the iterated integrals.
- Application of Fubini's thm:
usually follows a two step procedure,
 - check $\int_X \left[\int_Y |f(x, y)| \nu(dy) \right] \mu(dx)$ or $\int_Y \left[\int_X |f(x, y)| \mu(dx) \right] \nu(dy) < \infty$
 - If the result of ① is finite,
then the double integral (w.r.t. π) of $|f(x, y)|$ must be finite,
so that f is integrable w.r.t. π ;
then the value of the double integral of f is found by computing one of the iterated integrals of f ;
 If the result of ① is infinite,
 f is not integrable π .