

Recall: DCT (Dominated Convergence Theorem):

$\{X_n\}_{n \geq 1}$ - sequence of Random Variables.

$$X_n \rightarrow X$$

Suppose \exists a r.v. Y s.t. $E(Y) < \infty$
and $|X_n| \leq Y \quad \forall n \in \mathbb{N}$.

Then, $E(X_n) \rightarrow E(X)$.

Indeed, $E|X_n - X| = 0$

Lemma: (Fatou's Lemma):

For any sequence $\{X_n\}$ of non-ve r.v.s,

$$E(\liminf X_n) \leq \liminf (E(X_n)).$$

Proof: Define $Y_n = \inf_{k \geq n} X_k$
 $Y_n \geq 0$. $Y_n \uparrow \liminf X_n$ } \Rightarrow $E(Y_n) \rightarrow E(\liminf X_n)$
 (MCT) $E(X_n) \geq E(Y_n) \quad \forall n$
 $\liminf E(X_n) \geq E(\liminf X_n)$ \square

Proof (DCT):

Since $|X_n| \leq Y \quad \forall n$.

& $X_n \rightarrow X$.

we have $|X| \leq Y$.

$$|X_n - X| \leq |X_n| + |X| \leq 2Y$$

$$\leq Y \quad \leq Y$$

$$\text{Set } Z_n := 2Y - |X_n - X|. \quad \therefore E(Z_n) := 2E(Y) - E|X_n - X|.$$

$$\text{non-ve r.v.} \quad \therefore \liminf Z_n = 2Y - \limsup |X_n - X|$$

$$\therefore E(\liminf Z_n) \leq \liminf (E(Z_n)) \quad \text{[By Fatou's Lemma]}$$

$$\Rightarrow 2E(Y) \leq 2E(Y) - \limsup E|X_n - X|$$

$$\therefore 0 \leq \liminf |X_n - X| \leq \limsup |X_n - X| \leq 0$$

$$\Rightarrow ZL(Y) \leq ZL(X) \text{ using } (*)$$

$$\left[\begin{array}{c} \because 0 \leq \liminf_{n \rightarrow \infty} |X_n - X| \leq \limsup_{n \rightarrow \infty} |X_n - X| \leq 0 \\ \downarrow 0 \qquad \qquad \qquad \downarrow 0 \\ \text{as } X_n \rightarrow X. \\ \therefore \lim_{n \rightarrow \infty} |X_n - X| = 0 \end{array} \right]$$

$$\Rightarrow \limsup_{n \rightarrow \infty} E|X_n - X| \leq 0 \quad \left. \begin{array}{l} \&, |X_n - X| \geq 0 \Rightarrow \\ E|X_n - X| \geq 0. \end{array} \right\} \lim_{n \rightarrow \infty} E|X_n - X| = 0.$$



Notation:

for any r.v. X on a probability space, & any $p > 0$,
denote $\|X\|_p = (E|X|^p)^{1/p}$.

$$0 \leq \|X\|_p \leq \infty$$

Holders Inequality:

For any two random variables X, Y on the same probability space

$$E|XY| \leq \|X\|_p \cdot \|Y\|_q, \quad \text{where } p, q > 1 \text{ are conjugate} \\ \left(\text{i.e., } \frac{1}{p} + \frac{1}{q} = 1 \right)$$

Proof:

Case-I: $RHS = 0$

$$\text{Say, } \|X\|_p = 0.$$

$$\Rightarrow E|X|^p = 0.$$

$$\Rightarrow P(X=0) = 1$$

$$\Rightarrow P(XY=0) = 1$$

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$$\Rightarrow LHS = 0.$$

Case - 2: $\|X\|_p > 0$, $\|X\|_q > 0$.

In case atleast one of $\|X\|_p$ and $\|Y\|_q = \infty$,
the inequality holds trivially.

Case - 3: (Non-trivial case)

$$0 < \|X\|_p < \infty , \quad 0 < \|X\|_q < \infty .$$

$$\text{Define } X' := \frac{X}{\|X\|_p} , \quad Y' := \frac{Y}{\|Y\|_q} \quad (\text{"Normalizing"})$$

$$\text{clearly, } \|X'\|_p = \|Y'\|_q = 1.$$

Use inequality:

$$\forall \text{ reals } a, b \geq 0 .$$

$$ab \leq \frac{a^p}{p} + \frac{b^q}{q} .$$

$$\therefore |X'| \cdot |Y'| \leq \frac{1}{p} \cdot |X|^p + \frac{1}{q} \cdot |Y|^q$$

$$\therefore E(|X'| \cdot |Y'|) \leq \frac{1}{p} E|X|^p + \frac{1}{q} E|Y|^q = 1$$

$$\downarrow$$

$$\left(\frac{|X| \cdot |Y|}{\|X\|_p \cdot \|Y\|_q} \right)$$

$$\therefore E|XY| \leq \|X\|_p \cdot \|Y\|_q .$$

Cauchy - Schwarz Inequality:

$$E|XY| \leq \|X\|_p \cdot \|Y\|_q$$

Cauchy-Schwarz inequality

$$E|XY| \leq \|X\|_2 \cdot \|Y\|_2$$

Fact: for any r.v. X ,

$$\|X\|_{p_1} \leq \|X\|_{p_2} \quad \forall \quad 0 < p_1 < p_2.$$

Proof:

$$E|X|^{p_1} = E|WZ| \quad \begin{matrix} W = |X|^{p_1} \\ Z = 1 \end{matrix}$$

$$\leq (E(W^p))^{1/p} \cdot (E(Z^q))^{1/q}$$

[By Holder's inequality]

$$= (E|X|^{p_2})^{p_1/p_2}$$

$p = p_2/p_1 > 1$, q -conjugate of p .

$$\therefore (E|X|^{p_1})^{1/p_1} \leq E(|X|^{p_2})^{1/p_2}$$

$$\Rightarrow \|X\|_{p_1} \leq \|X\|_{p_2}$$

Minkowski's Inequality:

Let $p \geq 1$.

for any two X, Y

$$\|X+Y\|_p \leq \|X\|_p + \|Y\|_p$$

Proof: $p=1$: (trivial)

$$\therefore |X+Y| \leq |X| + |Y|$$

$p > 1$: Let q be the conjugate of p . i.e., $\frac{1}{p} + \frac{1}{q} = 1$

$$\begin{aligned} \therefore E|X+Y|^p &\leq E(|X| \cdot |X+Y|^{p-1}) + E(|Y| \cdot |X+Y|^{p-1}) \quad (\text{triangle ineq.}) \\ &\leq \|X\|_p \cdot \| |X+Y|^{p-1} \|_q + \|Y\|_p \cdot \| |X+Y|^{p-1} \|_q \quad (\text{Holder's inequality}) \end{aligned}$$

$$= (\|X\|_p + \|Y\|_p) \left(\| |X+Y|^{p-1} \|_q \right)$$

$$\frac{1}{p} + \frac{1}{q} = 1$$

$$= (\|X\|_p + \|Y\|_p) \cdot \left(E|X+Y|^{(p-1) \cdot q} \right)^{1/q}$$

$$\therefore (p-1)q = p$$

$$= (\|X\|_p + \|Y\|_p) \cdot \left(E|X+Y|^p \right)^{1/q}$$

$$\text{if } (E|X+Y|^p)^{1/q} = 0$$

$$= (\|X\|_p + \|Y\|_p) \cdot (E|X+Y|^p)^{1/p}$$

$$(E|X+Y|^p)^{1-\frac{1}{p}} \leq (\|X\|_p + \|Y\|_p)$$

$$\Rightarrow (E|X+Y|^p)^{1/p} \leq (\|X\|_p + \|Y\|_p) \quad \square$$

if $(E|X+Y|^p)^{1/p} = 0$
Minkowski holds trivially.
← if not,

Jensen's Inequality:

Let X be a real random variable with $E(X) < \infty$ (i.e., finite)

Then, for convex function $\varphi: \mathbb{R} \rightarrow \mathbb{R}$ with $E(\varphi(X))$ finite,

$$\varphi(E(X)) \leq E(\varphi(X)).$$

Some facts about Convex functions:

① $\forall a, b, c, d$.

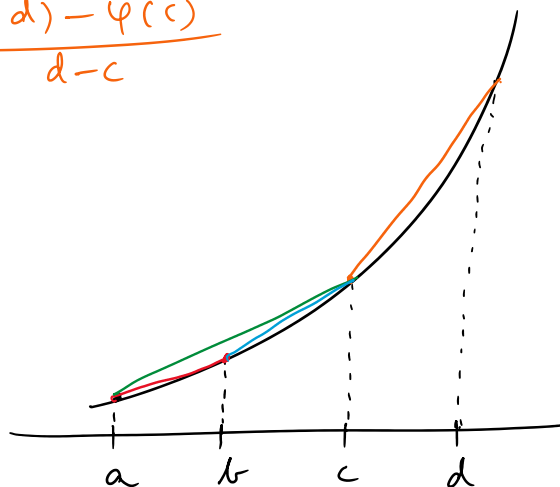
$$\frac{\varphi(b) - \varphi(a)}{b - a} \leq \frac{\varphi(d) - \varphi(c)}{d - c}$$

② $\forall a, b, c$

$$\frac{\varphi(c) - \varphi(a)}{c - a} < \frac{\varphi(c) - \varphi(b)}{c - b}$$

③ For $a < b < c$.

$$\frac{\varphi(c) - \varphi(a)}{c - a} \geq \frac{\varphi(b) - \varphi(a)}{b - a}$$



Consequence:

$\forall x \in \mathbb{R}$, $\varphi'(x^-)$ & $\varphi'(x^+)$ exist &
 $\varphi'(x^-) \leq \varphi'(x^+)$

In particular, φ is continuous.

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Fact:

For every $x \in \mathbb{R}$.

\exists real nos. $a(=a_x)$ and $b(=b_x)$.

s.t. $a+by \leq \varphi(y)$

with equality holding only at $y=x$, φ -convex.

Proof: take any $x \in \mathbb{R}$.


take any real b such that $\varphi'(x^-) \leq b \leq \varphi'(x^+)$

take $a = \varphi(x) - bx$.

Clearly, $\varphi(x) = a + bx$.

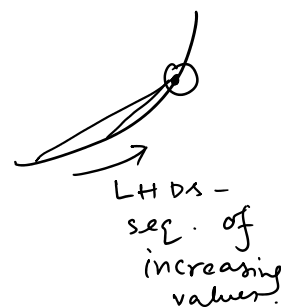
take $y \neq x$.

W.L.O.G., take $y > x$.

$$\frac{\varphi(y) - \varphi(x)}{y - x} \geq \varphi'(x^+) \geq b. \quad \text{(RHS - seq. of decreasing values)}$$


$$\Rightarrow \varphi(y) - (a + bx) \geq by - bx$$

$$\Rightarrow \varphi(y) \geq a + by.$$



... proof of Jensen's (... contd):

$\therefore E(X)$ is finite.

$E(X) \in \mathbb{R}$.

$\therefore \exists$ reals a, b s.t.

$$a + by \leq \varphi(y) \quad \forall y.$$

(using the result above).

$$\&, a + bE(X) \leq \varphi(E(X))$$

$$\rightarrow a + bX \leq \varphi(X).$$

$$\therefore \underline{a + bE(X)} \leq E(\varphi(X))$$

$$\underbrace{\quad}_{\varphi(E(X))}$$

Aim: X is a real random variable with density f - non-ve.

This means, f is Riemann integrable on \mathbb{R} with $\int_{-\infty}^{\infty} f(x) dx = 1$, and, for any interval I ,

$$P(X \in I) = \int_I f(x) dx.$$

If $h: \mathbb{R} \rightarrow \mathbb{R}$ is a function such that, $h(X)$ is a random variable, then $h(X)$ has finite expectation iff $\int_{-\infty}^{\infty} |h(x)| \cdot f(x) dx < \infty$.

& in that case, $E(h(X)) = \int_{-\infty}^{\infty} h(x) \cdot f(x) dx$.

Proof: Start with $0 \leq X \leq M$.

X has density function $f: \int_0^M f(x) dx = 1$.

Define $X_n := \sum_{0 \leq k \leq M \cdot 2^n - 1} \frac{k}{2^n} \cdot 1_{\frac{k}{2^n} \leq X \leq \frac{k+1}{2^n}}$

Each X_n is non-negative simple r.v., $X_n \nearrow X$

$$\Rightarrow E(X) = \lim_{n \rightarrow \infty} E(X_n)$$

$$= \sum_{0 \leq k \leq M \cdot 2^n - 1} \frac{k}{2^n} \cdot \int_{\frac{k}{2^n}}^{\frac{k+1}{2^n}} f(x) dx.$$

proof:
(exercise)

$$= \int_0^M x f(x) dx.$$

Now, X has density f : $\int_0^{\infty} f(x) dx = 1$.

Claim: $E(X) = \int_0^{\infty} x \cdot f(x) dx$.

Fix M :

define $X_M = \begin{cases} X, & \text{if } X \leq M \\ 0, & \text{if } X > M \end{cases}$.

$$X_M \geq 0.$$

$$X_M \nearrow X.$$

$$\Rightarrow E(X) = \lim_{M \rightarrow \infty} E(X_M).$$

(by MCT)

$$X_{n,M} = \sum_{0 \leq k \leq M \cdot 2^n - 1} \frac{k}{2^n} \cdot \mathbb{1}_{\frac{k}{2^n} < X < \frac{k+1}{2^n}}$$

$$\therefore E(X_M) = \lim_{n \rightarrow \infty} E(X_{n,M}) = \int_0^M x f(x) dx$$

$$\therefore E(X) = \lim_{M \rightarrow \infty} E(X_M) = \lim_{M \rightarrow \infty} \int_0^M x \cdot f(x) dx = \int_0^{\infty} x f(x) dx$$

