

Outline

1 Ancillary results

- 1.1 Reviewing results on random variables
- 1.2 0-1 laws

2 Laws of large numbers

3 The strong law

4 Law of iterated logarithm

Generalized Markov's inequality

Proposition 1.

Let

- $h : \mathbb{R} \rightarrow [0, \infty)$ non-negative function
- X random variable with $h(X) \in L^1(\Omega)$

measurable

Then for all $a > 0$ we have

$$\mathbf{P}(h(X) \geq a) \leq \frac{\mathbf{E}[h(X)]}{a}$$

$$h(x) \geq 0 \quad \forall x$$

Proof Define

$$A = \{ \omega ; h(X(\omega)) \geq a \} \quad (EF)$$

Then $h(x) = \overbrace{h(x)}^{\geq a} \mathbf{1}_A + \overbrace{h(x)}^{\geq 0} \mathbf{1}_{A^c}$

$$\Rightarrow h(x) \geq a \mathbf{1}_A$$

$h(x) \in L^1$
 $\Rightarrow E[h(x)] \geq a P(A)$

$$\Rightarrow P(h(x) \geq a) \leq \frac{E[h(x)]}{a}$$

$$P(h(x) \geq a) \leq \frac{E[h(x)]}{a}$$

Case 1 : Take $h(x) = |x|$. Then

$$P(|x| \geq a) \leq \frac{E[|x|]}{a} \quad (\text{Markov})$$

Case 2 : Take $h(x) = x^2$. Then

$$P(|x| \geq a) = P(x^2 \geq a^2)$$

$$\leq \frac{E[x^2]}{a^2}$$

Generalizations

- $P(|X| \geq a) \leq \frac{E[|X|^n]}{a^n}$
- $P(|X| \geq a) \leq E[e^{\beta X}] e^{-\beta a}$

↳ Large deviations

Proof of Proposition 1

Deterministic inequality: Set

$$A = \{h(X) \geq a\}$$

Then we have

$$h(X) \geq a \mathbf{1}_A$$

Expectations: Taking expectations above, we get

$$\mathbf{E}[h(X)] \geq a \mathbf{P}(A)$$

Particular cases of Proposition 1:

Case $h(X) = |X|$: We get Markov's inequality,

$$\mathbf{P}(|X| \geq a) \leq \frac{\mathbf{E}[|X|]}{a}$$

Case $h(X) = X^2$: We get Chebyshev's inequality,

$$\mathbf{P}(|X| \geq a) \leq \frac{\mathbf{E}[|X|^2]}{a^2}$$

Reversed Markov type inequality

Proposition 2.

Let

- $h : \mathbb{R} \rightarrow [0, M)$ non-negative bounded function
- X random variable

Then for all $0 < a < M$ we have

$$\mathbf{P}(h(X) \geq a) \leq \frac{\mathbf{E}[h(X)] - a}{M - a}$$


Proof Consider $A = \{h(x) \geq a\}$. Then

$$h(x) = \underbrace{h(x) \mathbf{1}_A}_{\leq M} + \underbrace{h(x) \mathbf{1}_{A^c}}_{\leq a} \quad h: \mathbb{R} \rightarrow [0, M]$$

$$h(x) \leq M \mathbf{1}_A + a \mathbf{1}_{A^c}$$

$$\Rightarrow E[h(x)] \leq M P(A) + a (1 - P(A))$$

$$\Rightarrow E[h(x)] \leq (M-a)P(A) + a$$

$$\Rightarrow P(A) \geq \frac{E[h(x)] - a}{M-a}$$

Proof of Proposition 2

Deterministic inequality: Set

$$A = \{h(X) \geq a\}$$

Then we have

$$h(X) \leq M \mathbf{1}_A + a \mathbf{1}_{A^c}$$

Expectations: Taking expectations above, we get

$$\begin{aligned} \mathbf{E}[h(X)] &\leq M \mathbf{P}(A) + a(1 - \mathbf{P}(A)) \\ \implies \mathbf{P}(A) &\leq \frac{\mathbf{E}[h(X)] - a}{M - a} \end{aligned}$$

Hölder's inequality

Proposition 3.

Let

- X, Y random variables
- $p, q > 1$ such that $p^{-1} + q^{-1} = 1$

Then we have

$$\|X Y\|_{L^1} \leq \|X\|_{L^p} \|Y\|_{L^q}$$

Minkowski's inequality

Proposition 4.

Let

- X, Y random variables
- $p \geq 1$

Then we have

$$\|X + Y\|_{L^p} \leq \|X\|_{L^p} + \|Y\|_{L^p}$$

Remark:

$(L^p(\Omega), \|\cdot\|_{L^p})$ is a Banach space

Limits of sums

Proposition 5.

Let

- X, Y random variables
- X_n, Y_n sequences of random variables

Then we have

- ① $X_n \xrightarrow{\text{a.s.}} X$ and $Y_n \xrightarrow{\text{a.s.}} Y \implies X_n + Y_n \xrightarrow{\text{a.s.}} X + Y$
- ② $X_n \xrightarrow{L^P} X$ and $Y_n \xrightarrow{L^P} Y \implies X_n + Y_n \xrightarrow{L^P} X + Y$
- ③ $X_n \xrightarrow{P} X$ and $Y_n \xrightarrow{P} Y \implies X_n + Y_n \xrightarrow{P} X + Y$
- ④ $X_n \xrightarrow{(d)} X$ and $Y_n \xrightarrow{(d)} Y \not\implies X_n + Y_n \xrightarrow{(d)} X + Y$

Example of $X_n \xrightarrow{\text{a.s.}} X$, $Y_n \xrightarrow{\text{a.s.}} Y$, but

$$X_n + Y_n \not\xrightarrow{\text{a.s.}} X + Y$$

- Take $X_n = z \sim U(0, 1)$
 $Y_n = w = 1 - z \sim U(0, 1)$
- Thus $X_n \xrightarrow{\text{a.s.}} U(0, 1)$ $Y_n \xrightarrow{\text{a.s.}} U(0, 1)$
- However $X_n + Y_n = 1 \sim \delta_1$,
- Thus $X_n + Y_n \not\xrightarrow{\text{a.s.}} "U(0, 1) + U(0, 1)"$

Counter-example for Proposition 5 - item 4

Example of sequence: Consider

- $X_n = X \sim \mathcal{B}\left(\frac{1}{2}\right)$
- $Y_n = Y = 1 - X$

Convergences: We have

$$X_n \xrightarrow{(d)} X, \quad Y_n \xrightarrow{(d)} X.$$

However

$$X_n + Y_n \xrightarrow{(d)} 1$$

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Limsup of sets

Definition 6.

Let

- $\{A_n; n \geq 1\}$ sequence in \mathcal{F}

We define

$$\limsup_{n \rightarrow \infty} A_n = \bigcap_{n=1}^{\infty} \bigcup_{k=n}^{\infty} A_k$$

Interpretation: We also have

$$\limsup_{n \rightarrow \infty} A_n = \{\omega \in \Omega; \omega \text{ belongs to an infinity of } A_n \text{'s}\}$$

Borel-Cantelli lemma

Q. What if $\sum_n P(A_n) = \infty$?

Do we have $P(\limsup A_n) > 0$?

Theorem 7.

Let

- $\{A_n; n \geq 1\}$ sequence in \mathcal{F}

We assume

$$\sum_{n=1}^{\infty} P(A_n) < \infty$$

Then we have

$$P\left(\limsup_{n \rightarrow \infty} A_n\right) = 0$$

Reversed Borel-Cantelli lemma

Theorem 8.

Conclusion: If the A_n 's are II,
then

Let

- $\{A_n; n \geq 1\}$ sequence in \mathcal{F} $P(\limsup A_n) \in \{0,1\}$

We assume

$$\sum_{n=1}^{\infty} P(A_n) = \infty, \quad \text{and} \quad A_n \text{'s independent}$$

Then we have

$$P\left(\limsup_{n \rightarrow \infty} A_n\right) = 1$$