

## 0.1 Property of Integral

**Theorem 0.1. Jensen's inequality.** Suppose  $\varphi$  is convex, that is,

$$\lambda\varphi(x) + (1 - \lambda)\varphi(y) \geq \varphi(\lambda x + (1 - \lambda)y), \forall \lambda \in (0, 1), x, y \in \mathbb{R}.$$

If  $\mu$  is a probability measure, and  $f$  and  $\varphi(f)$  are integrable, then:

$$\varphi\left(\int f d\mu\right) \leq \int \varphi(f) d\mu$$

**Theorem 0.2. Holder's inequality.** If  $p, q \in (1, \infty)$  with  $1/p + 1/q = 1$ . Then:

$$\int |fg| d\mu \leq \|f\|_p \|g\|_q$$

The special case  $p = q = 2$  is called **Cauchy-Schwarz inequality**

**Theorem 0.3. Bounded Convergence Theorem.** Let  $E$  be a set,  $\mu(E) < \infty$ . Suppose  $f_n$  vanishes on  $E^c$ ,  $|f_n(x)| \leq M$ , and  $f_n \rightarrow f$  in measure. Then:

$$\int f d\mu = \lim_{n \rightarrow \infty} \int f_n d\mu$$

**Theorem 0.4. Fatou's Lemma.** If  $f_n \geq 0$ , then:

$$\liminf_{n \rightarrow \infty} \int f_n d\mu \geq \int \left( \liminf_{n \rightarrow \infty} f_n \right) d\mu$$

**Theorem 0.5. Monotone Convergence Theorem.** If  $f_n \geq 0$ , and  $f_n \uparrow f$ , then

$$\int f_n d\mu \uparrow \int f d\mu$$

**Theorem 0.6. Dominated Convergence Theorem.** If  $f_n \rightarrow f$  a.e.,  $|f_n| \leq g, \forall n$ , and  $g$  is integrable, then:

$$\int f_n d\mu \rightarrow \int f d\mu$$

Let  $(X, \mathcal{A}, \mu_1), (Y, \mathcal{B}, \mu_2)$  be two  $\sigma$ -finite measure spaces. Let

$$\begin{aligned} \Omega &= X \times Y \\ \mathcal{S} &= \{A \times B \mid A \in \mathcal{A}, B \in \mathcal{B}\} \\ \mathcal{F} &= \mathcal{A} \times \mathcal{B} = \sigma(\mathcal{S}). \end{aligned}$$

**Theorem 0.7.** There is a unique measure  $\mu$  on  $\mathcal{F}$  with:

$$\mu(A \times B) = \mu_1(A) \mu_2(B)$$

**Theorem 0.8. Fubini's Theorem.** If  $f \geq 0$  or  $\int |f| d\mu < \infty$  then:

$$\int_X \int_Y f(x, y) \mu_2(dy) \mu_1(dx) = \int_{X \times Y} f d\mu = \int_Y \int_X f(x, y) \mu_1(dx) \mu_2(dy)$$

# 1 Laws of Large Number

## 1.1 Independence

**Definition 1.1.**  $(\Omega, \mathcal{F}, \mathbb{P})$ ;  $A, B \in \mathcal{F}$  are called independent if  $\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B)$

Two  $\sigma$ -fields  $\mathcal{G}, \mathcal{H}$  are independent if  $\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B), \forall A \in \mathcal{G}, B \in \mathcal{H}$ .

Two random variable  $X, Y$  are independent iff  $\sigma(X), \sigma(Y)$  are independent.

**Definition 1.2.**  $\mathcal{A}$  is a  $\pi$ -system if it is closed under intersection.  $\mathcal{L}$  is a  $\lambda$ -system if (i)  $\Omega \in \mathcal{L}$ , (ii)  $\forall A, B \in \mathcal{L}, A \subset B$  then  $B - A \in \mathcal{L}$ , and (iii) If  $A_n \in \mathcal{L}, A_n \uparrow A$  then  $A \in \mathcal{L}$ .

**Theorem 1.1.**  $\pi$ - $\lambda$  Theorem. If  $\mathcal{P}$  is a  $\pi$ -system and  $\mathcal{L}$  is a  $\lambda$ -system that contains  $\mathcal{P}$  then  $\sigma(\mathcal{P}) \subset \mathcal{L}$ .

**Theorem 1.2.** Suppose  $\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_n$  are independent and each  $\mathcal{A}_i$  is a  $\pi$ -system, then  $\sigma(\mathcal{A}_1), \sigma(\mathcal{A}_2), \dots, \sigma(\mathcal{A}_n)$  are independent.

**Theorem 1.3.** In order for  $X_1, X_2, \dots, X_n$  to be independent, it is sufficient that for all  $x_1, \dots, x_n \in \mathbb{R}$ ,

$$\mathbb{P}[X_1 \leq x_1, \dots, X_n \leq x_n] = \prod_{i=1}^n \mathbb{P}[X_i \leq x_i]$$

**Theorem 1.4.** Suppose  $X_1, \dots, X_n$  are independent random variables and  $X_i$  has distribution  $\mu_i$ , then  $(X_1, \dots, X_n)$  has distribution  $\mu_1 \times \mu_2 \times \dots \times \mu_n$ .

**Theorem 1.5.** If  $X$  and  $Y$  are independent, then:

$$\mathbb{P}[X + Y \leq z] = \int F(z - y) dG(y)$$

## 1.2 Weak Laws of Large Number

**Definition 1.3.** We say  $Y_n$  converges to  $Y$  in probability if  $\forall \epsilon > 0, \lim_{n \rightarrow \infty} \mathbb{P}[|Y_n - Y| < \epsilon] = 0$ .

**Lemma 1.1.** If  $p > 0$  and  $\mathbb{E}|Z_n|^p \rightarrow 0$  then  $Z_n \rightarrow 0$  in probability.

**Theorem 1.6.**  $L^2$  weak law. Let  $X_1, X_2, \dots$  be uncorrelated random variables with  $\mathbb{E}X_i = \mu$  and  $\text{Var}(X_i) \leq C < \infty$ . If  $S_n = X_1 + \dots + X_n$  then  $S_n/n \rightarrow \mu$  in  $L^2$  and in probability.

**Theorem 1.7.**  $L^1$  weak law. Let  $X_1, X_2, \dots$  be i.i.d with  $\mathbb{E}|X_i| < \infty$ . Then  $S_n/n \rightarrow \mathbb{E}X_1$  in probability

## 1.3 Borel-Cantelli Lemmas

**Definition 1.4.**  $A_n \subset \Omega$ .

$$\begin{aligned} \limsup A_n &= \lim_{m \rightarrow \infty} \bigcup_{n=m}^{\infty} A_n = \{\omega \text{ that are in infinitely many } A_n\} \\ \liminf A_n &= \lim_{m \rightarrow \infty} \bigcap_{n=m}^{\infty} A_n = \{\omega \text{ that are in all but finitely many } A_n\} \end{aligned}$$

**Theorem 1.8.** The First Borel-cantelli Lemma. If  $\sum_{n=1}^{\infty} \mathbb{P}A_n < \infty$  then:

$$\mathbb{P}[A_n \text{ i.o.}] = 0$$

**Theorem 1.9.** Relation between Convergence in Probability and Almost Surely.

$X_n \rightarrow X$  in probability iff for every subsequence  $X_{n(m)}$  there is a further subsequence  $X_{n(m_k)}$  that converges almost surely to  $X$ .

**Theorem 1.10.** *If  $f$  is continuous and  $X_n \rightarrow X$  in probability then  $f(X_n) \rightarrow f(X)$  in probability. If, in addition,  $f$  is bounded then  $\mathbb{E}f(X_n) \rightarrow \mathbb{E}f(X)$ .*

**Theorem 1.11.**  *$L^4$  Strong Law of Large Number 1. Let  $X_1, X_2, \dots$  be i.i.d with  $\mathbb{E}X_i = \mu$  and  $\mathbb{E}X_i^4 < \infty$ . Then  $S_n/n \rightarrow \mu$  a.s.*

**Theorem 1.12.** *The Second Borel-Cantelli Lemma. If  $A_n$  are independent then  $\sum \mathbb{P}A_n = \infty$  implies  $\mathbb{P}[A_n \text{ i.o.}] = 1$ .*

**Theorem 1.13.** *“Anti” LLN. If  $X_i$  are i.i.d with  $\mathbb{E}|X_i| = \infty$ , then  $\mathbb{P}[|X_n| \geq n \text{ i.o.}] = 1$ . So  $\mathbb{P}[\lim S_n/n = a \in (-\infty, \infty)] = 0$*

**Theorem 1.14.** *If  $A_1, A_2, \dots$  are pairwise independent and  $\sum_{n=1}^{\infty} \mathbb{P}(A_n) = \infty$  then as  $n \rightarrow \infty$*

$$\frac{\sum_{m=1}^n \mathbb{I}[A_m]}{\sum_{m=1}^n \mathbb{P}[A_m]} \rightarrow 1 \text{ a.s.}$$

## 1.4 Strong Law of Large Numbers

**Theorem 1.15.** *SLLN. Let  $X_1, X_2, \dots$  be pairwise independent identically distributed random variables with  $\mathbb{E}|X_i| = \mu < \infty$ . Then  $S_n/n \rightarrow \mu$  a.s. as  $n \rightarrow \infty$ .*