

ReviewModes of convergence

What can it mean  $X_n \rightarrow X$ ?

Convergence almost surely: There is a set  $\Omega' \subseteq \Omega$  with  $P(\Omega') = 1$  such that  $X_n(\omega) \rightarrow X(\omega)$  for all  $\omega \in \Omega'$ .

Convergence in probability: For all  $\varepsilon > 0$

$$\lim_{n \rightarrow \infty} P[|X - X_n| \geq \varepsilon] = 0.$$

Convergence in expectation (or in  $L^1$ ):  $E[|X - X_n|] \rightarrow 0$  as  $n \rightarrow \infty$

Convergence in  $L^p$  for  $p \geq 1$ :  $E[|X - X_n|^p] \rightarrow 0$  as  $n \rightarrow \infty$

Convergence in distribution:  $F_{X_n}(x) \rightarrow F_X(x)$  at all points  $x$

where  $F_X$  is continuous.

or equivalently

$$E[f(X_n)] \rightarrow E[f(X)] \quad \text{as } n \rightarrow \infty$$

for all bounded, continuous  $f$ .

Relationships:

convergence a.s.  $\Rightarrow$  convergence in probability  
 $\Rightarrow$  convergence in distribution

convergence in  $L^p$   $\Rightarrow$  convergence in prob

convergence in prob  $\Rightarrow$  convergence in distribution  
 $\Rightarrow$  there is a subsequence  $\{X_{n_k}\}$  that converges to  $X$  a.s.

## Analytic Limit Theorems

Basic question: When is  $\lim_{n \rightarrow \infty} E[X_n] = E[\lim_{n \rightarrow \infty} X_n]$ ?

Mondran Convergence Theorem: Assume that  $\{X_n\}$  is an increasing sequence of positive random variables. Then

$$\lim_{n \rightarrow \infty} E[X_n] = E[\lim_{n \rightarrow \infty} X_n]$$

Fatou's Lemma: Assume that  $\{X_n\}$  is a sequence of positive random variables. Then

$$\liminf E[X_n] \geq E[\liminf X_n]$$

Dominated Convergence Theorem: Assume that  $\{X_n\}$  is a sequence of random variables converging a.s. or in probability to  $X$ . Assume that there is an integrable random variable  $Y$  such that  $|X_n| \leq Y$ .

Then

$$\lim_{n \rightarrow \infty} E[X_n] = E[X] = E[\lim_{n \rightarrow \infty} X_n]$$

## Probabilistic Limit Theorems

Laws of Large Numbers: Conditions  $\Rightarrow \frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow 0$

Central Limit Theorem: Conditions  $\Rightarrow \frac{X_1 + X_2 + \dots + X_n}{\sqrt{n}} \rightarrow$  normal distribution

Weak Law of Large Numbers: If  $\{X_n\}$  is an independent sequence of random variables with mean 0 and  $E[X_n^2] \leq \sigma^2$ , then

$$\frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow 0 \text{ in probability}$$

Strong Law of Large Numbers (Kolmogorov): If  $\{X_n\}$  is an independent sequence of random variables with mean 0 and  $E[X_n^4] \leq M$ . Then

$$\frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow 0 \text{ almost surely}$$

Central Limit Theorem (iid case): Assume that  $\{X_n\}$  is a iid-sequence of random variables with mean  $\mu$  and variance  $\sigma^2 > 0$ . Then

$$\frac{X_1 + X_2 + \dots + X_n - n\mu}{\sigma\sqrt{n}} \Rightarrow N(0,1) \text{ in prob.}$$

Central Limit Theorem (Lyapunov's version) Assume that  $\{X_n\}$  is an independent sequence of random variables with mean zero and finite variances  $\sigma_n^2$ . Let  $S_n = X_1 + X_2 + \dots + X_n$  and let

$\Delta_n^2 = \sigma_1^2 + \sigma_2^2 + \dots + \sigma_n^2$ . Assume in addition that  $\gamma_j = E[|X_j|^3]$  exists and that  $\frac{\sum_{j=1}^n \gamma_j}{\Delta_n^3} \rightarrow 0$  as  $n \rightarrow \infty$ . Then

$$\frac{S_n}{\Delta_n} \Rightarrow N(0,1) \text{ in distribution.}$$

Lévy Continuity Theorem: If  $\{X_n\}$  is a sequence of random variables with characteristic functions  $\phi_n$  and  $\phi_n(t) \rightarrow \phi(t)$  for all  $t$  to a function  $\phi$  continuous at 0, then  $\{X_n\}$  converges in distribution to a random variable  $X$ , whose characteristic function is  $\phi$ .

### 0-1 Laws

$\{A_n\}$  a sequence of events:

$$\limsup A_n = \bigcap_{k=1}^{\infty} \bigcup_{n=k}^{\infty} A_n = \{\omega : \omega \text{ belongs to infinitely many } A_n\}$$

$$\liminf A_n = \bigcup_{k=1}^{\infty} \bigcap_{n=k}^{\infty} A_n = \{\omega : \omega \text{ belongs to all but finitely many } A_n\}$$

Borel-Cantelli:

(i) If  $\sum_{n=1}^{\infty} P(A_n) < \infty$ , then  $P[\limsup A_n] = 0$ .

(ii) Assume that  $\{A_n\}$  is independent. Then

a) If  $\sum_{n=1}^{\infty} P(A_n) < \infty$ , then  $P[\limsup A_n] = 0$ .

b) If  $\sum_{n=1}^{\infty} P(A_n) = \infty$ , then  $P[\limsup A_n] = 1$

Assume that  $\{X_n\}$  is a sequence of random variables and put

$$\mathcal{F}_n^* = \sigma(X_{n+1}, X_{n+2}, \dots). \text{ Then } \mathcal{F}_{\infty}^* = \bigcap_{n=1}^{\infty} \mathcal{F}_n^* \text{ is a } \sigma\text{-algebra.}$$

Borel/Kolmogorov 0-1-Law: If  $\{X_n\}$  is an independent sequence of random variables and  $\Delta \in \mathcal{F}_{\infty}^*$ , then  $P(\Delta)$  is either 0 or 1.

## Characteristic functions

$X$  random variable:

$$\varphi_X(t) = E[e^{itX}] = E[\cos tX] + i E[\sin tX]$$

$$\llcorner \int e^{itx} d\mu_X(x) = \int_{-\infty}^{\infty} e^{itx} f(x) dx$$

$\llcorner$  if  $f$  density exist.

Thm: If  $X$  has  $n$ -th moment, then  $\varphi_X$  is  $n$  times differentiable and

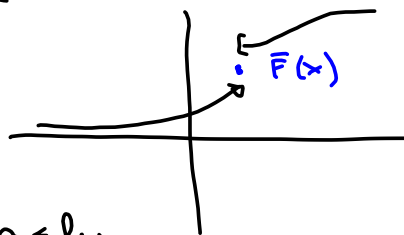
$$\varphi_X(t) = \sum_{j=1}^n \frac{(it)^j}{j!} E[X^j] + o(t^n)$$

Inference: If  $X_1, X_2, \dots, X_n$  are independent

$$\varphi_{X_1 + X_2 + \dots + X_n}(t) = \varphi_{X_1}(t) \varphi_{X_2}(t) \dots \varphi_{X_n}(t)$$

$X$  is normal  $N(\mu, \sigma^2)$ , then  $\varphi_X(t) = e^{-\frac{\sigma^2 t^2}{2} + i\mu t}$

$$\bar{F}(x) = \frac{F(x) + F(x-)}{2}$$



Lévy's inversion formula: For any  $a < b$ ,

$$\bar{F}(b) - \bar{F}(a) = \lim_{\epsilon \downarrow 0} \int_{-\infty}^{\infty} \frac{e^{-itb} - e^{-ita}}{-2\pi i t} e^{-\frac{\epsilon^2 t^2}{2}} \varphi(t) dt.$$

$$= \lim_{T \rightarrow \infty} \int_{-T}^T \frac{e^{-itb} - e^{-ita}}{-2\pi i t} \varphi(t) dt.$$

Corollary: If you know  $\varphi$ , you know  $F$ .

### Inequalities

Chebyshev's inequality:  $P[|X| \geq \lambda] \leq \frac{1}{\lambda^p} E[|X|^p]$

Schwarz' inequality:  $E[XY] \leq E[X^2]^{1/2} E[Y^2]^{1/2}$   
 $|\langle x, y \rangle| \leq \|x\| \|y\|$

Lyapunov's inequalities:  $1 \leq p \leq q$ :

(i)  $E[|X|^p]^{\frac{1}{p}} \leq E[|X|^q]^{\frac{1}{q}}$

(ii)  $E[|X|^p]^{\frac{1}{p}} \leq E[|X|^q]^{\frac{1}{q}}$   
 $\|X\|_p \leq \|X\|_q$

Jensen's inequality: Convex  $\varphi$  & .....  
 (i)  $\varphi(E[X]) \leq E[\varphi(X)]$

(ii)  $\varphi(E[X|G]) \leq E[\varphi(X)|G]$  a.s.

Martingale maximal inequality:  $X$  a positive submartingale:

$$P\left[\max_{k \leq n} X_k \geq \lambda\right] \leq \frac{1}{\lambda} E[|X_n|]$$