18.175: Lecture 16 Central limit theorem variants

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CLT variants

CLT variants

Recall Fourier inversion formula

• If $f : \mathbb{R} \to \mathbb{C}$ is in L^1 , write $\hat{f}(t) := \int_{-\infty}^{\infty} f(x) e^{-itx} dx$.

- Fourier inversion: If f is nice: $f(x) = \frac{1}{2\pi} \int \hat{f}(t) e^{itx} dt$.
- Easy to check this when f is density function of a Gaussian. Use linearity of $f \rightarrow \hat{f}$ to extend to linear combinations of Gaussians. or to convolutions with Gaussians.
- Show $f \rightarrow \hat{f}$ is an isometry of Schwartz space (endowed with L^2 norm). Extend definition to L^2 completion.
- Convolution theorem: If

$$h(x) = (f * g)(x) = \int_{-\infty}^{\infty} f(y)g(x-y)dy,$$

then

$$\hat{h}(t) = \hat{f}(t)\hat{g}(t).$$

Observation: can define Fourier transforms of generalized functions. Can interpret finite measure as generalized 18 175 I

Recall Bochner's theorem

- ► Given any function φ and any points x₁,..., x_n, we can consider the matrix with i, j entry given by φ(x_i x_j). Call φ **positive definite** if this matrix is always positive semidefinite Hermitian.
- Bochner's theorem: a continuous function from ℝ to ℝ with φ(1) = 1 is a characteristic function of a some probability measure on ℝ if and only if it is positive definite.
- Positive definiteness kind of comes from fact that variances of random variables are non-negative.
- The set of all possible characteristic functions is a pretty nice set.
- ► The Fourier transform is a natural map from set of all probability measures on ℝ (which can be described by their distribution functions F) to the set of possible characteristic functions.

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Strong continuity theorem: If µ_n ⇒ µ_∞ then φ_n(t) → φ_∞(t) for all t. Conversely, if φ_n(t) converges to a limit that is continuous at 0, then the associated sequence of distributions µ_n is tight and converges weakly to a measure µ with characteristic function φ.

Recall CLT idea

- Let X be a random variable.
- The characteristic function of X is defined by $\phi(t) = \phi_X(t) := E[e^{itX}].$
- And if X has an *m*th moment then $E[X^m] = i^m \phi_X^{(m)}(0)$.
- ▶ In particular, if E[X] = 0 and $E[X^2] = 1$ then $\phi_X(0) = 1$ and $\phi'_X(0) = 0$ and $\phi''_X(0) = -1$.
- ► Write $L_X := -\log \phi_X$. Then $L_X(0) = 0$ and $L'_X(0) = -\phi'_X(0)/\phi_X(0) = 0$ and $L''_X = -(\phi''_X(0)\phi_X(0) - \phi'_X(0)^2)/\phi_X(0)^2 = 1.$
- If $V_n = n^{-1/2} \sum_{i=1}^n X_i$ where X_i are i.i.d. with law of X, then $L_{V_n}(t) = nL_X(n^{-1/2}t)$.
- When we zoom in on a twice differentiable function near zero (scaling vertically by n and horizontally by √n) the picture looks increasingly like a parabola.

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- CLT is pretty special. What other kinds of sums are approximately Gaussian?
- ► Triangular arrays: Suppose X_{n,m} are independent expectation-zero random variables when 1 ≤ m ≤ n.
- ► Suppose $\sum_{m=1}^{n} EX_{n,m}^2 \to \sigma^2 > 0$ and for all ϵ , $\lim_{n \to \infty} E(|X_{n,m}|^2; |X_{n,m}| > \epsilon) = 0.$
- ► Then $S_n = X_{n,1} + X_{n,2} + \ldots + X_{n,n} \implies \sigma \chi$ (where χ is standard normal) as $n \to \infty$.
- ▶ Proof idea: Use characteristic functions φ_{n,m} = φ_{X_{n,m}}. Try to get some uniform handle on how close they are to their quadratic approximations.

- ▶ If X_i are i.i.d. with mean zero, variance σ^2 , and $E|X_i|^3 = \rho < \infty$, and $F_n(x)$ is distribution of $(X_1 + \ldots + X_n)/(\sigma\sqrt{n})$ and $\Phi(x)$ is standard normal distribution, then $|F_n(x) \Phi(x)| \le 3\rho/(\sigma^3\sqrt{n})$.
- Provided one has a third moment, CLT convergence is very quick.
- Proof idea: You can convolve with something that has a characteristic function with compact support. Play around with Fubini, error estimates.

Local limit theorems for walks on $\mathbb Z$

- Suppose $X \in b + h\mathbb{Z}$ a.s. for some fixed constants b and h.
- Observe that if φ_X(λ) = 1 for some λ ≠ 0 then X is supported on (some translation of) (2π/λ)Z. If this holds for all λ, then X is a.s. some constant. When the former holds but not the latter (i.e., φ_X is periodic but not identically 1) we call X a **lattice random variable**.

• Write
$$p_n(x) = P(S_n/\sqrt{n} = x)$$
 for $x \in \mathcal{L}_n := (nb + h\mathbb{Z})/\sqrt{n}$
and $n(x) = (2\pi\sigma^2)^{-1/2} \exp(-x^2/2\sigma^2)$.

► Assume X_i are i.i.d. lattice with $EX_i = 0$ and $EX_i^2 = \sigma^2 \in (0, \infty)$. Theorem: As $n \to \infty$,

$$\left|\sup_{x\in\mathcal{L}^n}|n^{1/2}/hp_n(x)-n(x)|\to 0.\right.$$

▶ **Proof idea:** Use characteristic functions, reduce to periodic integral problem. Note that for Y supported on $a + \theta \mathbb{Z}$, we have $P(Y = x) = \frac{1}{2\pi/\theta} \int_{-\pi/\theta}^{\pi/\theta} e^{-itx} \phi_Y(t) dt$. 18.175 Lecture 16 MIT OpenCourseWare http://ocw.mit.edu

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