18.175: Lecture 18

Poisson random variables

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Extend CLT idea to stable random variables

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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. • Let X be a random variable.

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- 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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- We already saw that this should work for Cauchy random variables.

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- ▶ If $X_1, X_2, ...$ have same law as X_1 then we have $E \exp(itS_n/n^{1/\alpha}) = \phi(t/n^{\alpha})^n = (1 - (1 - \phi(t/n^{1/\alpha})))$. As $n \to \infty$, this converges pointwise to $\exp(-C|t|^{\alpha})$.

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- Conclude by continuity theorems that $X_n/n^{1/\alpha} \implies Y$ where Y is a random variable with $\phi_Y(t) = \exp(-C|t|^{\alpha})$
- Let's look up stable distributions. Up to affine transformations, this is just a two-parameter family with characteristic functions exp[−|t|^α(1 − iβsgn(t)Φ)] where Φ = tan(πα/2) where β ∈ [−1, 1] and α ∈ (0, 2].

• Let's think some more about this example, where $P(X_1 > x) = P(X_1 < -x) = x^{-\alpha}/2$ for $0 < \alpha < 2$ and X_1, X_2, \ldots are i.i.d.

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- More generally {m ≤ n : X_m/n^{1/α} ∈ (a, b)} converges in law to Poisson with mean ∫_A ^α/_{2|x|^{α+1}} dx < ∞.</p>

▶ More generality: suppose that $\lim_{x\to\infty} P(X_1 > x)/P(|X_1| > x) = \theta \in [0, 1] \text{ and }$ $P(|X_1| > x) = x^{-\alpha}L(x) \text{ where } L \text{ is slowly varying (which means } \lim_{x\to\infty} L(tx)/L(x) = 1 \text{ for all } t > 0).$

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- ▶ **Theorem:** Then $(S_n b_n)/a_n$ converges in law to limiting random variable, for appropriate a_n and b_n values.

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- More general constructions are possible via Lévy Khintchine representation.

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- The inversion theorems and continuity theorems that apply here are essentially the same as in the one-dimensional case.