

# 18.175: Lecture 11

## Central limit theorem variants

Scott Sheffield

MIT

# Outline

CLT idea

CLT variants

More on random walks and local CLT

Poisson random variable convergence

Extend CLT idea to stable random variables

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## Recall Fourier inversion formula

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- ▶ **Observation:** can define Fourier transforms of generalized functions. Can interpret finite measure as generalized function.

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- ▶ Given function  $\phi$  and points  $t_1, \dots, t_n$ , consider matrix with  $i, j$  entry given by  $\phi(t_i - t_j)$ . Call  $\phi$  **positive definite** if this matrix is always positive semidefinite Hermitian.

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$$Y\bar{Y} = \sum_{j=1}^n \sum_{k=1}^n a_j \bar{a}_k e^{(t_i - t_j)X},$$

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- ▶ **Fourier transform:** natural one-to-one map from set of probability measures on  $\mathbb{R}$  (describable by distribution functions  $F$ ) to set of possible characteristic functions.

## Recall continuity theorem

- ▶ **Strong continuity theorem:** If  $\mu_n \implies \mu_\infty$  then  $\phi_n(t) \rightarrow \phi_\infty(t)$  for all  $t$ . Conversely, if  $\phi_n(t)$  converges to a limit that is continuous at 0, then the associated sequence of distributions  $\mu_n$  is tight and converges weakly to a measure  $\mu$  with characteristic function  $\phi$ .



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- ▶ When we zoom in on a twice differentiable function near zero (scaling vertically by  $n$  and horizontally by  $\sqrt{n}$ ) the picture looks increasingly like a parabola.

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- ▶ **Proof idea:** Use characteristic functions  $\phi_{n,m} = \phi_{X_{n,m}}$ . Try to get some uniform handle on how close they are to their quadratic approximations.

# Berry-Esseen theorem

- ▶ If  $X_i$  are i.i.d. with mean zero, variance  $\sigma^2$ , and  $E|X_i|^3 = \rho < \infty$ , and  $F_n(x)$  is distribution of  $(X_1 + \dots + X_n)/(\sigma\sqrt{n})$  and  $\Phi(x)$  is standard normal distribution, then  $|F_n(x) - \Phi(x)| \leq 3\rho/(\sigma^3\sqrt{n})$ .

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- ▶ 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.

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

- ▶ **Proof idea:** Use characteristic functions, reduce to periodic integral problem. Look up “Fourier series”. Note that for  $Y$  supported on  $a + \theta\mathbb{Z}$ , we have

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- ▶ What is the probability that the walk is back at the origin after one step? Two steps? Three steps?
- ▶ One could compute this in Mathematica by writing out the characteristic function  $\phi_X$  for one-step increment  $X$  and calculating  $\int_0^{2\pi} \phi_X^k(t) dt / 2\pi$ .



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- ▶ Example: suppose we have random walk on  $\mathbb{Z}$  that at each step tosses fair 4-sided coin to decide whether to go 1 unit left, 1 unit right, 2 units left, or 2 units right?
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- ▶ Can one use this to establish when a random walk on  $\mathbb{Z}^d$  is recurrent versus transient?

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- ▶ **Key idea for all these examples:** Divide time into large number of small increments. Assume that during each increment, there is some small probability of thing happening (independently of other increments).

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- ▶ Then  $\text{Var}[X] = E[X^2] - E[X]^2 = \lambda(\lambda+1) - \lambda^2 = \lambda$ .

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- ▶ **Proof idea:** Just write down the log characteristic functions for Bernoulli and Poisson random variables. Check the conditions of the continuity theorem.

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## Recall continuity theorem

- ▶ **Strong continuity theorem:** If  $\mu_n \implies \mu_\infty$  then  $\phi_n(t) \rightarrow \phi_\infty(t)$  for all  $t$ . Conversely, if  $\phi_n(t)$  converges to a limit that is continuous at 0, then the associated sequence of distributions  $\mu_n$  is tight and converges weakly to a measure  $\mu$  with characteristic function  $\phi$ .

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- ▶ When we zoom in on a twice differentiable function near zero (scaling vertically by  $n$  and horizontally by  $\sqrt{n}$ ) the picture looks increasingly like a parabola.

- ▶ Question? Is it possible for something like a CLT to hold if  $X$  has infinite variance? Say we write  $V_n = n^{-a} \sum_{i=1}^n X_i$  for some  $a$ . Could the law of these guys converge to something non-Gaussian?

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- ▶ Let's look up stable distributions.

## Infinitely divisible laws

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- ▶ More general constructions are possible via Lévy Khintchine representation.