

18.175: Lecture 12

DeMoivre-Laplace and weak convergence

Scott Sheffield

MIT

DeMoivre-Laplace limit theorem

Weak convergence

Characteristic functions

DeMoivre-Laplace limit theorem

Weak convergence

Characteristic functions

DeMoivre-Laplace limit theorem

- ▶ Let X_i be i.i.d. random variables. Write $S_n = \sum_{i=1}^n X_n$.
- ▶ Suppose each X_i is 1 with probability p and 0 with probability $q = 1 - p$.
- ▶ **DeMoivre-Laplace limit theorem:**

$$\lim_{n \rightarrow \infty} P\left\{a \leq \frac{S_n - np}{\sqrt{npq}} \leq b\right\} \rightarrow \Phi(b) - \Phi(a).$$

- ▶ Here $\Phi(b) - \Phi(a) = P\{a \leq Z \leq b\}$ when Z is a standard normal random variable.
- ▶ $\frac{S_n - np}{\sqrt{npq}}$ describes “number of standard deviations that S_n is above or below its mean”.
- ▶ **Proof idea:** use binomial coefficients and Stirling's formula.
- ▶ Question: Does similar statement hold if X_i are i.i.d. from some other law?
- ▶ **Central limit theorem:** Yes, if they have finite variance.

Local $p = 1/2$ DeMoivre-Laplace limit theorem

- ▶ **Stirling:** $n! \sim n^n e^{-n} \sqrt{2\pi n}$ where \sim means ratio tends to one.
- ▶ **Theorem:** If $2k/\sqrt{2n} \rightarrow x$ then $P(S_{2n} = 2k) \sim (\pi n)^{-1/2} e^{-x^2/2}$.

DeMoivre-Laplace limit theorem

Weak convergence

Characteristic functions

DeMoivre-Laplace limit theorem

Weak convergence

Characteristic functions

Weak convergence

- ▶ Let X be random variable, X_n a sequence of random variables.
- ▶ Say X_n **converge in distribution** or **converge in law** to X if $\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x)$ at all $x \in \mathbb{R}$ at which F_X is continuous.
- ▶ Also say that the $F_n = F_{X_n}$ converge weakly to $F = F_X$.
- ▶ **Example:** X_i chosen from $\{-1, 1\}$ with i.i.d. fair coin tosses: then $n^{-1/2} \sum_{i=1}^n X_i$ converges in law to a normal random variable (mean zero, variance one) by Demoivre-Laplace.
- ▶ **Example:** If X_n is equal to $1/n$ a.s. then X_n converge weakly to an X equal to 0 a.s. Note that $\lim_{n \rightarrow \infty} F_n(0) \neq F(0)$ in this case.
- ▶ **Example:** If X_i are i.i.d. then the empirical distributions converge a.s. to law of X_1 (Glivenko-Cantelli).
- ▶ **Example:** Let X_n be the n th largest of $2n + 1$ points chosen i.i.d. from fixed law.

Convergence results

- ▶ **Theorem:** If $F_n \rightarrow F_\infty$, then we can find corresponding random variables Y_n on a common measure space so that $Y_n \rightarrow Y_\infty$ almost surely.
- ▶ **Proof idea:** Take $\Omega = (0, 1)$ and $Y_n = \sup\{y : F_n(y) < x\}$.
- ▶ **Theorem:** $X_n \Rightarrow X_\infty$ if and only if for every bounded continuous g we have $Eg(X_n) \rightarrow Eg(X_\infty)$.
- ▶ **Proof idea:** Define X_n on common sample space so converge a.s., use bounded convergence theorem.
- ▶ **Theorem:** Suppose g is measurable and its set of discontinuity points has μ_X measure zero. Then $X_n \Rightarrow X_\infty$ implies $g(X_n) \Rightarrow g(X)$.
- ▶ **Proof idea:** Define X_n on common sample space so converge a.s., use bounded convergence theorem.

- ▶ **Theorem:** Every sequence F_n of distribution has subsequence converging to right continuous nondecreasing F so that $\lim F_{n(k)}(y) = F(y)$ at all continuity points of F .
- ▶ Limit may not be a distribution function.
- ▶ Need a “tightness” assumption to make that the case. Say μ_n are **tight** if for every ϵ we can find an M so that $\mu_n[-M, M] < \epsilon$ for all n . Define tightness analogously for corresponding real random variables or distributions functions.
- ▶ **Theorem:** Every subsequential limit of the F_n above is the distribution function of a probability measure if and only if the F_n are tight.

- ▶ If we have two probability measures μ and ν we define the **total variation distance** between them is

$$\|\mu - \nu\| := \sup_B |\mu(B) - \nu(B)|.$$

- ▶ Intuitively, if two measures are close in the total variation sense, then (most of the time) a sample from one measure looks like a sample from the other.
- ▶ Convergence in total variation norm is much stronger than weak convergence.

DeMoivre-Laplace limit theorem

Weak convergence

Characteristic functions

DeMoivre-Laplace limit theorem

Weak convergence

Characteristic functions

Characteristic functions

- ▶ Let X be a random variable.
- ▶ The **characteristic function** of X is defined by $\phi(t) = \phi_X(t) := E[e^{itX}]$. Like $M(t)$ except with i thrown in.
- ▶ Recall that by definition $e^{it} = \cos(t) + i \sin(t)$.
- ▶ Characteristic functions are similar to moment generating functions in some ways.
- ▶ For example, $\phi_{X+Y} = \phi_X \phi_Y$, just as $M_{X+Y} = M_X M_Y$, if X and Y are independent.
- ▶ And $\phi_{aX}(t) = \phi_X(at)$ just as $M_{aX}(t) = M_X(at)$.
- ▶ And if X has an m th moment then $E[X^m] = i^m \phi_X^{(m)}(0)$.
- ▶ But characteristic functions have an advantage: they are well defined at all t for all random variables X .

- ▶ **Lévy's continuity theorem:** if

$$\lim_{n \rightarrow \infty} \phi_{X_n}(t) = \phi_X(t)$$

for all t , then X_n converge in law to X .

- ▶ By this theorem, we can prove the weak law of large numbers by showing $\lim_{n \rightarrow \infty} \phi_{A_n}(t) = \phi_\mu(t) = e^{it\mu}$ for all t . In the special case that $\mu = 0$, this amounts to showing $\lim_{n \rightarrow \infty} \phi_{A_n}(t) = 1$ for all t .
- ▶ **Moment generating analog:** if moment generating functions $M_{X_n}(t)$ are defined for all t and n and $\lim_{n \rightarrow \infty} M_{X_n}(t) = M_X(t)$ for all t , then X_n converge in law to X .

MIT OpenCourseWare
<http://ocw.mit.edu>

18.175 Theory of Probability

Spring 2014

For information about citing these materials or our Terms of Use, visit: <http://ocw.mit.edu/terms> .