18.175: Lecture 14

Weak convergence and characteristic functions

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Convergence results

- ▶ **Theorem:** If $F_n \to F_\infty$, then we can find corresponding random variables Y_n on a common measure space so that $Y_n \to Y_\infty$ almost surely.
- **Proof idea:** Take $\Omega = (0,1)$ and $Y_n = \sup\{y : F_n(y) < x\}$.
- ▶ **Theorem:** $X_n \implies X_\infty$ 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 ⇒ X_∞ implies g(X_n) ⇒ 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 µ_n[−M, M] < ε for all n. Define tightness analogously for corresponding real random variables or distributions functions.</p>
- ▶ **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 ||µ − ν|| := sup_B |µ(B) − ν(B)|.
- Intuitively, it 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.
- Corresponds to L₁ distance between density functions when these exist.
- Convergence in total variation norm is much stronger than weak convergence. Discrete uniform random variable U_n on (1/n, 2/n, 3/n, ..., n/n) converges weakly to uniform random variable U on [0, 1]. But total variation distance between U_n and U is 1 for all n.

- Let X be a random variable.
- The characteristic function of X is defined by $\phi(t) = \phi_X(t) := E[e^{itX}].$
- Recall that by definition $e^{it} = \cos(t) + i\sin(t)$.
- ► Characteristic function φ_X similar to moment generating function M_X.
- ► $\phi_{X+Y} = \phi_X \phi_Y$, 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 $E[X^m] = i^m \phi_X^{(m)}(0)$.
- Characteristic functions are well defined at all t for all random variables X.

\$\phi(0) = 1\$
\$\phi(-t) = \overline{\phi(t)}\$
\$|\phi(t)| = |\mathcal{E}e^{itX}| ≤ \mathcal{E}|e^{itX}| = 1\$.
\$|\phi(t+h) - \phi(t)| ≤ \mathcal{E}|e^{ihX} - 1|\$, so \$\phi(t)\$ uniformly continuous on \$(-\infty, \infty)\$)\$
\$\mathcal{E}e^{it(aX+b)} = e^{itb}\phi(at)\$

Characteristic function examples

- **Coin:** If P(X = 1) = P(X = -1) = 1/2 then $\phi_X(t) = (e^{it} + e^{-it})/2 = \cos t$.
- That's periodic. Do we always have periodicity if X is a random integer?
- ▶ **Poisson:** If X is Poisson with parameter λ then $\phi_X(t) = \sum_{k=0}^{\infty} e^{-\lambda} \frac{\lambda^k e^{itk}}{k!} = \exp(\lambda(e^{it} 1)).$
- Why does doubling λ amount to squaring ϕ_X ?
- Normal: If X is standard normal, then $\phi_X(t) = e^{-t^2/2}$.
- ▶ Is ϕ_X always real when the law of X is symmetric about zero?
- ► Exponential: If X is standard exponential (density e^{-x} on (0,∞)) then φ_X(t) = 1/(1 it).
- ▶ **Bilateral exponential:** if $f_X(t) = e^{-|x|}/2$ on \mathbb{R} then $\phi_X(t) = 1/(1+t^2)$. Use linearity of $f_X \to \phi_X$.

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