

Lecture 16

Define $L^1 := \{f: \int_{\mathbb{R}} |f(x)| dx < \infty\}$ all the functions in this set are called L^1 integrable or absolutely integrable

Are PDFs in L^1 ? $\int_{\mathbb{R}} |f(x)| dx = \int_{-\infty}^{\infty} |f(x)| dx = F(\infty) - F(-\infty) = 1 - 0 = 1 \checkmark$ yes.

If $f(x) = x^2$, then $f(x) \notin L^1$ since $\int_{\mathbb{R}} x^2 dx = \infty$.

If $f \in L^1 \Rightarrow \exists \hat{f}$, the Fourier Transform of f :

$$\hat{f}(\omega) = \int_{\mathbb{R}} e^{-i2\pi\omega x} f(x) dx = \mathcal{F}[f]$$

This is called the forward Fourier transform or "Fourier analysis". x is called the "time domain" and ω is called the "frequency domain". One of Fourier's ideas is that functions in L^1 can be decomposed into a sum of sines and cosines with different frequencies, ω , and amplitudes, $|f(\omega)|$, and phase shifts, $\text{Arg}[f(\omega)]$.

Further, if $\hat{f} \in L^1$, then we can do a "reverse/inverse Fourier transform" to restore our original func. f :

$$f(x) = \int_{\mathbb{R}} e^{-i2\pi\omega x} \hat{f}(\omega) d\omega = \mathcal{F}^{-1}(\hat{f}).$$

This is called the "inverse Fourier transform" or "Fourier synthesis".

Fourier Inversion theorem: If f and \hat{f} are in L^1 , then f and \hat{f} are 1:1.

We define the characteristic function (chf) for rv X as:

$$\begin{aligned} \phi_X(t) &:= E[e^{itX}] = \int_{\mathbb{R}} e^{itx} f_X(x) dx \\ &= \sum_{x \in \mathbb{R}} e^{itx} p_X(x) \end{aligned}$$

this is the Fourier transform with a different frequency unit $t = -2\pi\omega$

main properties:

0) $\phi_X(0) = E[e^0] = E[1] = 1 \quad \forall x, \forall t.$

1) $\phi_X(t) = \phi_Y(t) \Leftrightarrow X \stackrel{d}{=} Y$ "Uniqueness"

2) If $Y = aX + b$ where $a, b \in \mathbb{R}$ $\phi_Y(t) = E[e^{it(ax+b)}] = E[e^{itaX} e^{itb}]$
 $= e^{itb} E[e^{itaX}] \stackrel{t'=ta}{=} e^{itb} E[e^{it'X}] = e^{itb} \phi_X(t') = e^{itb} \phi_X(at).$

3) X_1, X_2 are indep. , $T = X_1 + X_2$

$$\phi_T(t) = E[e^{it(X_1+X_2)}] = E[e^{itX_1} e^{itX_2}] = E[e^{itX_1}] E[e^{itX_2}] = \phi_{X_1}(t) \phi_{X_2}(t)$$

4) Moment Generating: $E[X^n] = \frac{\phi_X^{(n)}(0)}{i^n}$

5) $\phi_X(t) \in [-1, 1]$ i.e. the chf exists $\forall x, \forall t$

\Downarrow

$$|\phi_X(t)| \leq 1 \quad \text{Proof} \quad |E[e^{itX}]| = \left| \int_{\mathbb{R}} e^{itx} f_X(x) dx \right| \leq \int_{\mathbb{R}} |e^{itx} f_X(x)| dx$$

$$\leq \int_{\mathbb{R}} |e^{itx}| |f_X(x)| dx = \int_{\mathbb{R}} |\cos(tx) + i \sin(tx)| f_X(x) dx =$$

$$= \int_{\mathbb{R}} \sqrt{\cos^2(tx) + \sin^2(tx)} f(x) dx = \int_{\mathbb{R}} f(x) dx = 1. \quad \square$$

6) Inversion: If $\phi_X(t) \in L^1$ then $f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} \phi_X(t) dt$

7) Levy's CDF formula

$$P(X \in [a, b]) = \frac{1}{2\pi} \int_{\mathbb{R}} \frac{e^{-ita} - e^{-itb}}{it} \phi_X(t) dt$$

8) Levy's Continuity Thm

But first need another concept) Consider a sequence of r.v.'s X_1, X_2, \dots, X_n .

We define " X_n converges in distribution to X " (denoted $X_n \xrightarrow{d} X$) as:

$$\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x) \quad \forall x \quad \text{"pointwise convergence"}$$



$$\lim_{n \rightarrow \infty} \phi_{X_n}(t) = \phi_X(t) \Rightarrow X_n \xrightarrow{d} X.$$

$$\text{If } n \text{ large} \quad \phi_{X_n}(t) \approx \phi_X(t) \Rightarrow X_n \approx^d X$$

Chfs can do anything mgfs can do and more!
so emphasis will be on chfs.

ex) $X \sim \text{Gamma}(\alpha, \beta)$

$$\phi_X(t) = E[e^{itX}] = \int_{\mathbb{R}} e^{itx} \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \mathbb{1}_{x>0} dx$$

$$= \frac{\beta^\alpha}{\Gamma(\alpha)} \int_0^\infty x^{\alpha-1} e^{-(\beta-it)x} dx = \frac{\beta^\alpha}{\Gamma(\alpha)} \frac{\Gamma(\alpha)}{(\beta-it)^\alpha} = \left(\frac{\beta}{\beta-it}\right)^\alpha \quad (\text{chf of } \text{Gamma}(\alpha, \beta))$$

$X_1 \sim \text{Gamma}(\alpha_1, \beta)$ indep. of $X_2 \sim \text{Gamma}(\alpha_2, \beta)$, $T = X_1 + X_2$

(P3) $\phi_T(t) = \phi_{X_1}(t) \phi_{X_2}(t) = \left(\frac{\beta}{\beta-it}\right)^{\alpha_1} \left(\frac{\beta}{\beta-it}\right)^{\alpha_2} = \left(\frac{\beta}{\beta-it}\right)^{\alpha_1 + \alpha_2}$

(P1) $\Rightarrow T \sim \text{Gamma}(\alpha_1 + \alpha_2, \beta)$

Lecture 17 consider X_1, \dots, X_n iid rvs of unknown PMF/PDF but we know it has expectation μ and variance σ^2 (both finite).

let $T_n := X_1 + \dots + X_n$, $E[T_n] = n\mu$, $\text{Var}[T_n] = n\sigma^2$

let $\bar{X}_n := \frac{X_1 + \dots + X_n}{n} = \frac{T_n}{n}$, $E[\bar{X}_n] = \mu$, $\text{Var}[\bar{X}_n] = \text{Var}\left[\frac{T_n}{n}\right] = \frac{1}{n^2} \text{Var}[T_n] = \frac{\sigma^2}{n}$

let $Z_n := \frac{\bar{X}_n - \mu}{\frac{\sigma}{\sqrt{n}}} = \frac{\sqrt{n}}{\sigma} \bar{X}_n - \frac{\sqrt{n}}{\sigma} \mu$, $E[Z_n] = 0$, $\text{Var}(Z_n) = \text{Var}\left(\frac{\sqrt{n}}{\sigma} \bar{X}_n\right) = \frac{n}{\sigma^2} \cdot \frac{\sigma^2}{n} = 1 = \text{SD}[Z_n]$

" X_n standardized"

(P3) $\phi_{T_n}(t) = \phi_{X_1}(t) \dots \phi_{X_n}(t) = \left(\frac{\beta}{\beta-it}\right)^{\alpha_1 + \dots + \alpha_n} \Rightarrow T_n \sim \text{Gamma}(\alpha_1 + \dots + \alpha_n, \beta)$

$\stackrel{\text{iid}}{\Rightarrow} (\phi_X(t))^n$

$\phi_{\bar{X}_n}(t) \stackrel{\text{P2}}{=} \phi_{T_n}(t/n) \stackrel{\text{iid}}{=} \phi_X(t/n)^n$

$\phi_{Z_n}(t) \stackrel{\text{P2}}{=} e^{\frac{-it\mu\sqrt{n}}{\sigma}} \phi_{\bar{X}_n}\left(\frac{\sqrt{n}}{\sigma}t\right) \stackrel{\text{iid}}{=} e^{\frac{-it\mu\sqrt{n}}{\sigma}} \phi_X\left(\frac{t}{\sigma\sqrt{n}}\right)^n = e^{\frac{-it\mu\sqrt{n}}{\sigma}} e^{n \ln(\phi_X(\frac{t}{\sigma\sqrt{n}}))}$

$= e^{\frac{-it\mu\sqrt{n}}{\sigma} + n \ln(\phi_X(\frac{t}{\sigma\sqrt{n}}))} = e^{\frac{-it\mu}{\sigma\sqrt{n}} + \ln(\phi_X(\frac{t}{\sigma\sqrt{n}})) \cdot \frac{n}{\sqrt{n}}} = e^{\frac{-it\mu}{\sigma\sqrt{n}} + \ln(\phi_X(\frac{t}{\sigma\sqrt{n}})) \cdot \frac{t^2/\sigma^2}{t^2/\sigma^2}}$

$= e^{\frac{t^2/\sigma^2 (\ln(\phi_X(\frac{t}{\sigma\sqrt{n}})) - \frac{-it\mu}{\sigma\sqrt{n}})}{t^2/\sigma^2}} = \phi_{Z_n}(t)$

We want to examine $\lim \phi(t)$ and if we find it, we can find the limit distribution.