

Lee 15 Math 62) 11/6/19

1

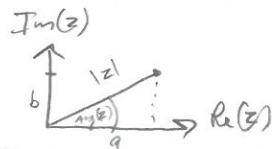
Memorizing functions (mg f's) and
Characteristic functions (cf. f's).

First... a review of imaginary #'s and trigonometry

$a, b \in \mathbb{R}$ $z := a + bi \in \mathbb{C} \leftarrow$ the complex #'s

$\text{Re}(z) := a, \text{Im}(z) := b$ $|z| := \sqrt{a^2 + b^2}, \text{Arg}(z) = \arctan\left(\frac{b}{a}\right)$ usually...

where $i := \sqrt{-1} \Rightarrow i^2 = -1, i^3 = i i^2 = -i, i^4 = (i^2)^2 = 1, i^5 = i i^4 = i, \dots$



Recall $e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!} = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \frac{x^4}{4!} + \frac{x^5}{5!} + \dots$

$e^{ix} = \sum_{k=0}^{\infty} \frac{(ix)^k}{k!} = 1 + ix - \frac{x^2}{2!} - \frac{ix^3}{3!} + \frac{x^4}{4!} + \frac{ix^5}{5!} - \dots$

$\sin(x) = x - \frac{x^3}{3!} + \frac{x^5}{5!} - \dots$

$\cos(x) = 1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \dots$

$i \sin(ix) = ix - \frac{i^3 x^3}{3!} + \frac{i^5 x^5}{5!} - \dots$

$\cos(ix) = 1 - \frac{i^2 x^2}{2!} + \frac{i^4 x^4}{4!} - \dots$

$\Rightarrow e^{ix} = i \sin(ix) + \cos(ix)$ if $ix = \theta \Rightarrow e^{i\theta} = i \sin(\theta) + \cos(\theta)$

if $\theta = \pi \Rightarrow e^{i\pi} = \cos(\pi) = -1 \Rightarrow e^{i\pi} + 1 = 0$ (Euler's identity)

Defn $L' := \left\{ f: \int_{\mathbb{R}} |f(t)| dt < \infty \right\}$ " L' integrable" or "absolutely integrable"

Are all PDF's $\in L'$? Yes! (tho)

If $f \in L' \Rightarrow \exists \hat{f}$, the "Fourier transform" of f :

$$\hat{f}(\omega) := \int_{\mathbb{R}} e^{-2\pi i \omega t} f(t) dt$$

Fourier transformation operator

Further, if $\hat{f} \in L'$ (which is not guaranteed), then we can do a "reverse Fourier transformation operator" to get the original f back!

$$\int_{\mathbb{R}} e^{2\pi i \omega t} \hat{f}(\omega) d\omega = f(t)$$

Fourier Transform Thm: if $f, \hat{f} \in L'$ and f is continuous, then f and \hat{f} are 1:1.

$f(t)$ is known as "time domain" and $\hat{f}(\omega)$ is known as the "frequency domain".

Because $f(t)$ can be decomposed into sines and cosines, and

$|\hat{f}(\omega)|$ provides the amplitudes and $\text{Arg}[\hat{f}(\omega)]$ provides phase shifts.

DEMO

Back to prob. Let X be a r.v. and c.m.f. Therefore,

$$\phi_X(t) := E[e^{itX}] = \int_{\mathbb{R}} e^{itx} f(x) dx$$

if cont. if discrete

which is the Fourier transform in a different unit $t = 2\pi \omega$

Properties of $\phi_X(t)$ (P0) $\phi_X(0) = E[e^{it \cdot 0}] = E[1] = 1$

(P1) If $\phi_X(t) = \phi_Y(t) \Leftrightarrow X \stackrel{d}{=} Y$. Uniqueness

(P2) If $Y = aX + b$ then $\phi_Y(t) = E[e^{it(aX+b)}] = E[e^{itax} e^{itb}] = e^{itb} E[e^{i(at)x}] = e^{itb} \phi_X(at)$

(P3) If X_1, X_2 ind and $T = X_1 + X_2$ then $\phi_T(t) = E[e^{it(X_1+X_2)}] = E[e^{itx_1} e^{itx_2}]$
if X_1, X_2 ind

$$= E[e^{itx_1}] E[e^{itx_2}] = \phi_{X_1}(t) \phi_{X_2}(t)$$

Existence and Boundedness

(P5) $\phi_X(t) \in [-1, 1]$ and this always exists.

$$|\phi_X(t)| = |E[e^{itx}]| = \left| \int e^{itx} f(x) dx \right| \leq \int |e^{itx} f(x)| dx = \int |e^{itx}| |f(x)| dx = \int |f(x)| dx = 1$$

$$\Rightarrow |\sum e^{itx} p(x)| \leq \sum |e^{itx} p(x)| = \sum |e^{itx}| p(x) = \sum p(x) = 1$$

$$|e^{itx}| = |i \sin(tx) + \cos(tx)| = \sqrt{\sin^2(tx) + \cos^2(tx)} = \sqrt{1} = 1$$

Inversion

(P6) If $\phi_X(t) \in L^1$ then ... $f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} \phi_X(t) dt$

Inversion thm

(P7) $P(X \in (a, b)) = \frac{1}{2\pi} \int_{\mathbb{R}} \frac{e^{-ita} - e^{-itb}}{it} \phi_X(t) dt$. No need for $\phi_X(t) \in L^1$!

(P8) Levy's Continuity Thm

(Not covered on modern)

Consider a seq of r.v.'s X_1, X_2, \dots, X_n

We define $X_n \xrightarrow{d} X$ i.e. " X_n converges in distribution to X "

if $\lim_{n \rightarrow \infty} F_{X_n}(x) = F(x) \quad \forall x$ (pointwise function convergence).

If $\lim_{h \rightarrow 0} \phi_{X_h}(t) = \phi_X(t) \Rightarrow X_h \xrightarrow{d} X$. Proof is on PhD qual. exams!

Define $M_X(t) := E(e^{itX})$, the moment generating function (MGF)

Properties (P0) $M_X(0) = 1$

(P1) $M_X(t) = M_Y(t) \Leftrightarrow X \stackrel{d}{=} Y$

(P2) $Y = aX + b \Rightarrow M_Y(t) = e^{itb} M_X(at)$

(P3) $X_1, X_2 \text{ i.i.d.} \Rightarrow M_{X_1+X_2}(t) = M_{X_1}(t) M_{X_2}(t)$

(P4) $E[X^k] = M_X^{(k)}(0)$ this is where it gets its name

The advantage of ch.f.'s is they always exist. MGF's do not have property (P5) \Rightarrow they may not exist. If they do exist, $M_X(t) = \phi_X(-it)$.
 \Rightarrow they may not exist.

\Rightarrow he will be using ch.f.'s because they always exist and they have more properties \Rightarrow more powerful!

P1, P3 together make computations the hard way...

e.g.

$X \sim \text{Bern}(p)$

$$\begin{aligned} \phi_X(t) &= E(e^{itX}) = \sum_{x \in \{0,1\}} e^{itx} p^x (1-p)^{1-x} = e^{it(0)} p^0 (1-p)^{1-0} + e^{it(1)} p^1 (1-p)^{1-1} \\ &= 1-p + pe^{it} \end{aligned}$$

$X \sim \text{Bin}(n, p)$

$$\phi_X(t) = E(e^{itX}) = \sum_{x=0}^n e^{itx} \binom{n}{x} p^x (1-p)^{n-x} = \sum_{x=0}^n \binom{n}{x} (pe^{it})^x (1-p)^{n-x} = (1-p + pe^{it})^n$$

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

$$\begin{aligned}\phi_X(t) &= E[e^{itX}] = \int_0^{\infty} e^{itx} \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} dx = \frac{\beta^\alpha}{\Gamma(\alpha)} \int_0^{\infty} x^{\alpha-1} e^{-(\beta-it)x} dx = \frac{\beta^\alpha}{\Gamma(\alpha)} \frac{\Gamma(\alpha)}{(\beta-it)^\alpha} \\ &= \left(\frac{\beta}{\beta-it}\right)^\alpha\end{aligned}$$

$X_1 \sim \text{Gamma}(\alpha_1, \beta)$ ind. of $X_2 \sim \text{Gamma}(\alpha_2, \beta)$

$$\phi_{X_1+X_2}(t) = \underbrace{\left(\frac{\beta}{\beta-it}\right)^{\alpha_1}}_{(P2)} \underbrace{\left(\frac{\beta}{\beta-it}\right)^{\alpha_2}}_{(P1)} = \left(\frac{\beta}{\beta-it}\right)^{\alpha_1+\alpha_2} \Rightarrow X_1+X_2 \sim \text{Gamma}(\alpha_1+\alpha_2, \beta)$$

Compare this proof to what we did with the convolution!

$X \sim \text{Poisson}(\lambda)$

$$\begin{aligned}\phi_X(t) &= E[e^{itX}] = \sum_{x=0}^{\infty} e^{itx} \frac{\lambda^x e^{-\lambda}}{x!} = \sum_{x=0}^{\infty} \frac{(e^{it}\lambda)^x e^{-\lambda}}{x!} \cdot \frac{e^{-\lambda e^{it}}}{e^{-\lambda e^{it}}} = \frac{e^{-\lambda}}{e^{-\lambda e^{it}}} \underbrace{\sum_{x=0}^{\infty} \frac{(e^{it}\lambda)^x e^{-\lambda e^{it}}}{x!}}_{=1 \text{ since it's P.M.F. of } \text{Poisson}(e^{it}\lambda)} \\ &= e^{-\lambda + \lambda e^{it}} = e^{\lambda(e^{it}-1)}\end{aligned}$$

$X_1 \sim \text{Poisson}(\lambda_1)$ indep of $X_2 \sim \text{Poisson}(\lambda_2)$

$$\phi_{X_1+X_2}(t) = \underbrace{e^{\lambda_1(e^{it}-1)}}_{(P2)} \underbrace{e^{\lambda_2(e^{it}-1)}}_{(P1)} = e^{(\lambda_1+\lambda_2)(e^{it}-1)} \Rightarrow X_1+X_2 \sim \text{Poisson}(\lambda_1+\lambda_2)$$

Consider

X_1, \dots, X_n i.i.d r.v.'s with expectation μ and variance σ^2 ,
Let $T_n = X_1 + \dots + X_n$

Let $\bar{X}_n := \frac{X_1 + \dots + X_n}{n} = \frac{T_n}{n}$ be the r.v. of the sample avg. of n r.v.'s.