

Theorem 1 (Portmanteau): let P_n, P be probability measures on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$. The following conditions are equivalent

(i) $P_n \Rightarrow P$

(ii) $\int f dP_n \rightarrow \int f dP$ for all bounded uniformly continuous $f: \mathbb{R} \rightarrow \mathbb{R}$

(iii) $\limsup_{n \rightarrow \infty} P_n(F) \leq P(F) \quad \forall F \text{ -closed}$

(iv) $\liminf_{n \rightarrow \infty} P_n(G) \geq P(G) \quad \forall G \text{ -open}$

(v) $\lim_{n \rightarrow \infty} P_n(A) = P(A) \quad \text{for } A \in \mathcal{B}_{\mathbb{R}}$
 s.t. $P(\partial A) = 0$.

Remark :- Suppose $\{X_n\}_{n \geq 1}$ are r.v. on $(\Omega_n, \mathcal{F}_n, \mathbb{Q}_n)$ and X is a r.v. on $(\mathcal{X}, \mathcal{F}, \mathbb{Q})$. We shall say

$$X_n \xrightarrow{d} X \quad \text{as } n \rightarrow \infty$$

if $\mathbb{Q}_n \cdot X_n^{-1}(\cdot) := P_n(\cdot) \Rightarrow P(\cdot) = \mathbb{Q} \cdot X^{-1}(\cdot)$
 on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$

Proof:

$$(i) \Rightarrow (ii) \Rightarrow (iii) \Leftrightarrow (iv)$$

$\updownarrow$
(v)

(i) $\Rightarrow$ (ii) is from definition of $\mathbb{P}_n \Rightarrow \mathbb{P}$.

(ii) $\Rightarrow$ (iii) let F be a closed set.

Let $\delta > 0$ be given

$$x \in \mathbb{R}, \quad d(x, F) = \inf \{ |x - y| : y \in F \}$$

$$A_k = \{ x \in \mathbb{R} : d(x, F) < \frac{1}{k} \}$$

$$A_k \supseteq A_{k+1} \quad \& \quad \bigcap_{n=1}^{\infty} A_n = A$$

$\therefore \exists \varepsilon > 0$ such that

$$\mathbb{P}(\{x : d(x, F) < \varepsilon\}) < \mathbb{P}(F) + \delta$$

$$\phi(t) = \begin{cases} 1 & \text{for } t \leq 0 \\ 1-t & 0 < t < 1 \\ 0 & t \geq 1 \end{cases}$$

let $f: \mathbb{R} \rightarrow \mathbb{R}$

$$f(x) = \phi\left(\frac{1}{\varepsilon} d(x, F)\right)$$

Ex. :- $f(x) \in [0, 1]$

$$f(x) = 1 \quad x \in F$$

$$f(x) = 0 \quad \text{if } d(x, F) \geq \epsilon$$

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f is
uniformly
continuous.

$$P_n(F) = \int_{F_n} f dP_n \leq \int f dP_n$$

$$\int f dP = \int_{\{x: d(x, F) < \epsilon\}} f dP \leq P(\{x: d(x, F) < \epsilon\}) < P(F) + \delta$$

$$\int f dP_n \longrightarrow \int f dP \quad \text{as } n \rightarrow \infty.$$

$$\Rightarrow \overline{\lim}_{n \rightarrow \infty} P_n(F) \leq P(F) + \delta$$

As $\delta > 0$ was arbitrary $\Rightarrow$ (iii) holds

□

(iii) $\Rightarrow$ (i) let f be a bounded continuous function. $\text{Range}(f) \subseteq [0, 1]$

$\mathbb{Q}$ be a Probability measure on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$

Fix $k \geq 1$. $F_i = \{x \in \mathbb{R} : f(x) \geq \frac{i}{k}\}$, $1 \leq i \leq k$.
be closed sets.

$$\begin{aligned} \int f d\mathbb{Q} &\geq \sum_{i=1}^k \frac{i-1}{k} \mathbb{Q}\left(\frac{i-1}{k} \leq f < \frac{i}{k}\right) \\ &= \sum_{i=1}^k \frac{i-1}{k} [\mathbb{Q}(F_{i-1}) - \mathbb{Q}(F_i)] \\ &= \frac{1}{k} \sum_{i=1}^k \mathbb{Q}(F_i) \quad \text{--- (1)} \end{aligned}$$

$$\begin{aligned} \int f d\mathbb{Q} &\leq \sum_{i=1}^k \frac{i}{k} (\mathbb{Q}(F_{i-1}) - \mathbb{Q}(F_i)) \\ &= \frac{1}{k} + \frac{1}{k} \sum_{i=1}^k \mathbb{Q}(F_i) \quad \text{--- (2)} \end{aligned}$$

$$\int f d\mathbb{P}_n \leq \frac{1}{k} + \frac{1}{k} \sum_{i=1}^k \mathbb{P}_n(F_i) \quad \text{(2)}$$

$$\int f d\mathbb{P} \geq \frac{1}{k} \sum_{i=1}^k \mathbb{P}(F_i) \quad \text{(1)}$$

Use (iii) to get

$$\limsup_{n \rightarrow \infty} \int f dP_n \leq \frac{1}{k} + \int f dP$$

$k \geq 1$ was arbitrary $\Rightarrow$

$$\limsup_{n \rightarrow \infty} \int f dP_n \leq \int f dP$$

$$\text{Range}(f) \subseteq [-M, M]$$

$$g(x) = \alpha f(x) + \beta \text{ and } \alpha = \frac{1}{2M}; \quad \beta = \frac{1}{2}$$

$$\text{Range}(g) \subseteq [0, 1]$$

$$\therefore \limsup_n \int g dP_n \leq \int g dP$$

$$\Rightarrow \limsup_{n \rightarrow \infty} \int f dP_n \leq \int f dP \quad \text{--- (3)}$$

Apply (3) to $h = -f$

$$\Rightarrow \liminf_{n \rightarrow \infty} \int f dP_n \geq \int f dP \quad \text{--- (4)}$$

$$\text{(3) and (4)} \Rightarrow \int f dP_n \longrightarrow \int f dP \text{ as } n \rightarrow \infty.$$

$\therefore$ (i) holds

(iii) $\Leftarrow$ (iv) follows by complementation

(iii) $\Rightarrow$ (v) let $A^\circ :=$ interior of A

$\bar{A} =$ closure of A

$$\begin{aligned} \mathbb{P}(\bar{A}) &\geq \overline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(A) \geq \overline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(A^\circ) \\ &\geq \underline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(A^\circ) \geq \underline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(A^\circ) \\ &\geq \mathbb{P}(A^\circ) \quad - (5) \end{aligned}$$

$$\mathbb{P}(\partial A) = 0 \quad \Rightarrow \quad \lim_{n \rightarrow \infty} \mathbb{P}_n(A) = \mathbb{P}(A). \quad (5)$$

$$\bar{A} = A = A^\circ$$

(v) $\Rightarrow$ (iii)

F be closed set

$$F_\delta = \{x \in \mathbb{R} \mid d(x, F) \leq \delta\} \quad \forall \delta > 0$$

$$\partial F_\delta = \{x \in \mathbb{R} \mid d(x, F) = \delta\}$$

Ex: $\exists \delta_k \downarrow 0$ s.t. $\mathbb{P}(\partial F_{\delta_k}) = 0 \quad \forall k \geq 1$

For $k \geq 1$

$$\overline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(F) \leq \overline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(F_{\delta_k}) = \mathbb{P}(F_{\delta_k})$$

$$\text{let } k \rightarrow \infty \quad \overline{\lim}_{n \rightarrow \infty} \mathbb{P}_n(F) \leq \mathbb{P}(F)$$

$\Rightarrow$ (iii) h.o.b
 $\square$

20 Characteristic functions

characteristic functions are "Fourier transforms" of random variables.

Definition 1:- Let $X: \Omega \rightarrow \mathbb{R}$ be a random variable on Probability space $(\Omega, \mathcal{F}, \mathbb{P})$. Its characteristic function $\phi_X: \mathbb{R} \rightarrow \mathbb{C}$ is given by

$$\phi_X(t) = E[e^{itx}] := E[\cos(tx)] + i E[\sin(tx)]$$

Remark 1:

- $\phi_X(\cdot)$ is well defined for all $t \in \mathbb{R}$
- We will denote $\phi_X(\cdot)$ by ϕ
- Ex:- Suppose $E[|x|^k] < \infty$ for some $k \geq 1$.

Then for $0 \leq j \leq k$

$$\phi_X^{(j)}(t) = E[(ix)^j e^{itx}] \quad \forall t \geq 0$$

In particular, $\phi_X^{(j)}(0) = i^j E[x^j]$

- For a measure μ on $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$ we can define

the characteristic function of μ as

$$\phi(t) \equiv \hat{\mu}(t) := \int_{\mathbb{R}} e^{itx} \mu(dx)$$

$$:= \int \cos(tx) \mu(dx) + i \int \sin(tx) \mu(dx)$$

If $\mu = \mathbb{P} \circ X^{-1}$ then $\phi = \phi_X$.

Two objectives:-

$$\begin{aligned} \bullet \quad \mathbb{P} \circ X^{-1} = \mathbb{P} \circ Y^{-1} &\iff \phi_X(t) = \phi_Y(t) \quad \forall t \in \mathbb{R} \\ \text{(inversion)} \quad \mu = \nu &\iff \hat{\mu}(t) = \hat{\nu}(t) \end{aligned}$$

$$\begin{aligned} \bullet \quad X_n \xrightarrow{d} X &\iff \phi_{X_n}(t) \longrightarrow \phi_X(t) \quad \forall t \in \mathbb{R} \\ \text{(continuity)} \quad \mu_n \xrightarrow{w} \mu &\iff \hat{\mu}_n(t) \longrightarrow \hat{\mu}(t) \quad \forall t \in \mathbb{R} \end{aligned}$$

Theorem 1: (Fourier Inversion)

let μ be a Probability measure on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$
with characteristic function

$$\hat{\mu}(t) = \int_{\mathbb{R}} e^{itx} \mu(dx)$$

Then if $a < b$

$$\frac{1}{2} \mu(\{a\}) + \frac{1}{2} \mu(\{b\}) + \mu(a, b) = \lim_{T \rightarrow \infty} \frac{1}{2\pi} \int_{-T}^T \frac{e^{ita} - e^{itb}}{it} \hat{\mu}(t) dt$$

Proof:- For $T > 0$,

$$\frac{1}{2\pi} \int_{-T}^T \frac{e^{-ita} - e^{-itb}}{it} \hat{\mu}(t) dt$$

$$= \frac{1}{2\pi} \int_{-T}^T \frac{e^{-ita} - e^{-itb}}{it} \left(\int_{\mathbb{R}} e^{itz} \mu(dz) \right) dt$$

$$\textcircled{I} \stackrel{\text{Fubini}}{=} \frac{1}{2\pi} \int_{\mathbb{R}} \left[\int_{-T}^T \frac{e^{-it(a-x)} - e^{-it(b-x)}}{it} dt \right] \mu(dz)$$

$$\stackrel{\text{Calculus}}{=} \frac{1}{2\pi} \int_{\mathbb{R}} \left[\int_{-T}^T \frac{\sin(t(x-a)) - \sin(t(x-b))}{t} dt \right] \mu(dz) \quad \textcircled{1}$$

We will use the following lemma

Lemma 1: $\theta \in \mathbb{R}$,

$$(a) \quad \lim_{T \rightarrow \infty} \int_{-T}^T \frac{\sin(\theta t)}{t} dt = \pi \text{Sign}(\theta)$$

$$(b) \quad \exists M > 0 \quad \sup_{T > 0, \theta \in \mathbb{R}} \left| \int_{-T}^T \frac{\sin(\theta t)}{t} dt \right| \leq M$$

From ①,

$$\lim_{T \rightarrow \infty} \frac{1}{2\pi} \int_{-T}^T \frac{e^{-ita} - e^{-itb}}{it} \mu(dt) dt$$

lemma 1
= Bounded Convergence Theorem

$$\frac{1}{2\pi} \int_{\mathbb{R}} [\pi \operatorname{Sign}(x-a) - \operatorname{Sign}(x-b)] \mu(dx)$$

$$= \frac{1}{2} \mu(\{a\}) + \mu(a,b) + \frac{1}{2} \mu(\{b\})$$

□

Proof of ① : (Justification of Fubini)

$T > 0$

$$\left| \frac{e^{-ita} - e^{-itb}}{it} e^{itz} \right| \leq \left| \int_a^b e^{-itr} dr \right| \leq \int_a^b |e^{-itr}| dr = b-a$$

$$\therefore \int_{\mathbb{R}} \int_{-T}^T \left| \frac{e^{-ita} - e^{-itb}}{it} e^{itz} \right| dt \mu(dx) \leq 2T(b-a)$$

- ②

$$(t, x) \longrightarrow \frac{e^{-ita} - e^{-itb}}{it} e^{itz}$$

is jointly measurable
on $\mathbb{R}_+ \times \mathbb{R}$

- ③

②, ③ $\Rightarrow$ Fubini's Theorem applies. $\square$

Proof of lemma 1 :-

$T > 0$

$$\theta = 0. \quad \Rightarrow \quad \int_{-T}^T \frac{\sin(\theta t)}{t} dt = 0$$

$$\therefore \lim_{T \rightarrow \infty} \int_{-T}^T \frac{\sin(\theta t)}{t} dt = 0 = \text{Sign}(\infty) \equiv \text{Sign}(\theta) \quad - (4)$$

$\theta \neq 0$

$$\int_{-T}^T \frac{\sin(\theta t)}{t} dt \stackrel{s = |\theta|t}{=} \text{Sign}(\theta) \int_{-|\theta|T}^{|\theta|T} \frac{\sin(s)}{s} ds$$

$$= 2 \text{Sign}(\theta) \int_0^{|\theta|T} \frac{\sin(s)}{s} ds \quad - (5)$$

Ex:-

$$(i) \int_0^{|\theta|T} \frac{\sin(s)}{s} du = \int_0^{\infty} \left[\int_0^{|\theta|T} \sin(s) e^{-us} ds \right] du \quad (\text{Fubini})$$

$$(ii) \int_0^{|\theta|T} \sin(s) e^{-us} ds = \frac{1 + h(\theta, T) - u g(\theta, T)}{1 + u^2} \quad (\text{Integration by parts})$$

where $g(\theta, T) \rightarrow 0$ as $T \rightarrow \infty$.
 $h(\theta, T) \rightarrow 0$

$$(iii) \quad \lim_{T \rightarrow \infty} \int_0^{T\theta} \frac{\sin(cs)}{s} ds = \int_0^{\infty} \frac{1}{1+u^2} du = \frac{\pi}{2}$$

(Dominated Convergence)

Part (A) follows from (iii), (B) follows from (5) $\square$

We are now ready to resolve the first objective)

Corollary 1 (Fourier Uniqueness - "characteristic")

let X, Y be random variables on $(\mathcal{X}, \mathcal{F}, \mathbb{P})$.

Then

$$\phi_X(t) = \phi_Y(t) \quad \forall t \in \mathbb{R}$$

$$\Leftrightarrow \mathbb{P}_X \tilde{X}^{-1}(\cdot) = \mathbb{P}_Y \tilde{Y}^{-1}(\cdot)$$

Proof:-

$\Leftarrow$ obvious.

$\Rightarrow$ Theorem 1 $\Rightarrow a < b$

$$\underbrace{\mathbb{P}_X \tilde{X}^{-1}(\{a\}) + \mathbb{P}_X \tilde{X}^{-1}(\{b\})}_{2} + \mathbb{P}_X \tilde{X}^{-1}(a, b) = \underbrace{\mathbb{P}_Y \tilde{Y}^{-1}(\{a\}) + \mathbb{P}_Y \tilde{Y}^{-1}(\{b\})}_{2} + \mathbb{P}_Y \tilde{Y}^{-1}(a, b)$$

$\Rightarrow$ outside a countable collection of $\{d_n\}_{n \geq 1}$
 $a, b \notin \{d_n\}$

$$\mathbb{P} \cdot \bar{X}^1(\{a\}) = \mathbb{P} \cdot \bar{X}^1(\{b\}) = \mathbb{P} \cdot \bar{Y}^1(\{a\}) = \mathbb{P} \cdot \bar{Y}^1(\{b\}) = 0$$

$$\Rightarrow \mathbb{P} \cdot \bar{X}^1((a, b]) = \mathbb{P} \cdot \bar{Y}^1((a, b])$$

for $a < b$ such $b, a \notin \{d_n\}_{n \geq 1}$

$$\stackrel{\text{Ex}}{\Rightarrow} \mathbb{P} \cdot \bar{X}^1 = \mathbb{P} \cdot \bar{Y}^1 \quad \square$$