

RECALL: CHARACTERISTIC FUNCTION OF X :

$\Psi_X(t) = \mathbb{E}(e^{i \cdot t \cdot X})$, $t \in \mathbb{R}$

IF X HAS A P.D.F. f , THEN $\Psi_X(t) = \int_{-\infty}^{\infty} e^{i \cdot t \cdot x} \cdot f(x) dx$

THM: IF $\Psi_X(t) = \Psi_Y(t)$ THEN $P(X \leq x) = P(Y \leq x)$
 $\forall t \in \mathbb{R}$ $\forall x \in \mathbb{R}$

(I.E., CHAR. FN. INDEED CHARACTERIZES THE DISTRIBUTION)

INGREDIENTS OF PROOF:

FACT: (A SPECIAL CASE OF FUBINI'S THM)

$g: \mathbb{R}^2 \rightarrow \mathbb{C}$, IF $\mathbb{E}\left(\int_{-\infty}^{\infty} |g(x', t)| dt\right) < +\infty$

THEN $\mathbb{E}\left(\int_{-\infty}^{\infty} g(x', t) dt\right) = \int_{-\infty}^{\infty} \mathbb{E}(g(x', t)) dt$

RECALL: $\gamma_a(x) = \frac{1}{a \cdot \sqrt{2\pi}} \cdot \exp\left(-\frac{x^2}{2 \cdot a^2}\right)$

THEN $\int_{-\infty}^{\infty} e^{i \cdot t \cdot x} \cdot \gamma_a(x) dx = e^{-\frac{1}{2} a^2 \cdot t^2}$

P.D.F. OF $N(0, a^2)$

THUS $\int_{-\infty}^{\infty} e^{i \cdot t \cdot x} \cdot \Psi_a(t) dt \stackrel{A}{=} e^{-\frac{1}{2} \cdot a^2 \cdot x^2}$, THUS

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} e^{i \cdot t \cdot (y-x)} \cdot e^{-\frac{t^2 \cdot \sigma^2}{2}} dt \stackrel{B}{=}$$

$$= \frac{1}{\sigma \cdot \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{i \cdot t \cdot (y-x)} \cdot \Psi_{1/\sigma}(t) dt \stackrel{C}{=} \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot \exp\left(-\frac{(x-y)^2}{2\sigma^2}\right)$$



LET $Y \sim \mathcal{N}(0, 1)$, INDEP. OF X

LET $X_\sigma \stackrel{D}{:=} X + \sigma \cdot Y$, $F_\sigma(x) \stackrel{E}{:=} \mathbb{P}(X_\sigma \leq x)$

$$F_\sigma(x) \stackrel{F}{=} \mathbb{P}\left(Y \leq \frac{x - X}{\sigma}\right) \stackrel{G}{=} \mathbb{E}\left(\Phi\left(\frac{x - X}{\sigma}\right)\right)$$

$$f_\sigma(x) \stackrel{H}{:=} \frac{d}{dx} F_\sigma(x) \stackrel{I}{=} \mathbb{E}\left(\frac{d}{dx} \Phi\left(\frac{x - X}{\sigma}\right)\right) =$$

$$= \mathbb{E}\left(\frac{1}{\sigma} \varphi\left(\frac{x - X}{\sigma}\right)\right) \stackrel{J}{=} \mathbb{E}\left(\varphi_\sigma(x - X)\right) \stackrel{K}{=} \mathbb{E}\left(\frac{1}{\sigma \sqrt{2\pi}} \cdot \exp\left(-\frac{(x - X)^2}{2\sigma^2}\right)\right)$$

$$\Psi_\sigma(t) \stackrel{L}{=} \mathbb{E}\left(e^{i \cdot t \cdot X_\sigma}\right) \stackrel{M}{=} \mathbb{E}\left(e^{i \cdot t \cdot X} \cdot e^{i \cdot t \cdot \sigma \cdot Y}\right) \stackrel{N}{=}$$

$$= \Psi(t) \cdot e^{-\frac{1}{2} \sigma^2 \cdot t^2}$$

LEMMA (INVERSION FORMULA FOR SMOOTHED DISTRIBUTION)

$$f_{\sigma}(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-it \cdot x} \cdot \Psi_{\sigma}(t) dt \quad x \in \mathbb{R}$$

PROOF: LET US FIX $x \in \mathbb{R}$

$$\begin{aligned} \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \cdot \Psi_{\sigma}(t) dt &= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \cdot e^{-\frac{t^2 \cdot \sigma^2}{2}} \cdot \mathbb{E}(e^{itX}) dt \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \underbrace{\mathbb{E}(e^{it \cdot (X-x)} \cdot e^{-\frac{t^2 \cdot \sigma^2}{2}})}_{g(x, t)} dt \end{aligned}$$

FUBINI

FUBINI IS APPLICABLE:

$$\mathbb{E} \left(\int_{-\infty}^{\infty} |g(x, t)| dt \right) = \mathbb{E} \left(\int_{-\infty}^{\infty} e^{-\frac{t^2 \cdot \sigma^2}{2}} dt \right) < +\infty$$

$$\mathbb{E} \left(\frac{1}{2\pi} \int_{-\infty}^{\infty} e^{it \cdot (X-x)} \cdot e^{-\frac{t^2 \cdot \sigma^2}{2}} dt \right)$$

$$\mathbb{E} \left(\frac{1}{\sigma \sqrt{2\pi}} \cdot \exp \left(-\frac{(x-X)^2}{2\sigma^2} \right) \right) = f_{\sigma}(x)$$

FACT: IF X HAS A CONTINUOUS P.D.F. $f(x)$

THEN $f(x) \stackrel{A}{=} \lim_{\sigma \rightarrow 0} f_{\sigma}(x) \stackrel{B}{=} \lim_{\sigma \rightarrow 0} \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \cdot e^{-\frac{1}{2}\sigma^2 t^2} \cdot \Psi(t) dt$

PROOF: HOMEWORK 8.1

CLAIM: IF X HAS A CONTINUOUS P.D.F. $f(x)$ AND

IF $\int_{-\infty}^{\infty} |\Psi(t)| dt < +\infty$ THEN $f(x) \stackrel{D}{=} \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \cdot \Psi(t) dt$

PROOF: $\lim_{\sigma \rightarrow 0} \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \cdot e^{-\frac{1}{2}\sigma^2 t^2} \cdot \Psi(t) dt \stackrel{F}{=} \dots$

BY DOMINATED CONVERGENCE THM:

$$\forall \sigma > 0 : \left| e^{-itx} \cdot e^{-\frac{1}{2}\sigma^2 t^2} \cdot \Psi(t) \right| \leq |\Psi(t)|$$

PROOF OF THM STATED ON PAGE 101:

GIVEN $\Psi(t), t \in \mathbb{R}$, WE CAN RECOVER

$F_{\sigma}(x) \stackrel{H}{=} \int_{-\infty}^x f_{\sigma}(u) du$ BY LEMMA FROM PAGE 103,

AND $F_{\sigma} \Rightarrow F$ AS $\sigma \rightarrow 0$ BY SLUTSKY. THUS

WE CAN RECOVER F FROM Ψ . ✓

PAGE 104

DEF: CAUCHY DISTRIBUTION

$$\boxed{X \sim \text{CAU}(1)} \quad \text{IF} \quad \boxed{F(x) = \frac{1}{2} + \frac{1}{\pi} \cdot \arctan(x)}$$

THUS $f(x) = F'(x) = \frac{1}{\pi} \cdot \frac{1}{1+x^2}$

$$\boxed{X \sim \text{CAU}(a)} \quad \text{IF} \quad \boxed{\frac{X}{a} \sim \text{CAU}(1)}$$

NOTE: IF $X \sim \text{CAU}(1)$ THEN $E(|X|) = +\infty$

INDEED: $\int_{-\infty}^{\infty} |x| \cdot \frac{1}{\pi} \cdot \frac{1}{1+x^2} dx = 2 \cdot \int_0^{\infty} x \cdot \frac{1}{\pi} \cdot \frac{1}{1+x^2} dx \geq$

$$\geq \frac{1}{\pi} \int_1^{\infty} \frac{1}{x} dx = +\infty$$

$$Z(\lambda) = E(e^{\lambda X}) = \begin{cases} 1 & \text{IF } \lambda = 0 \\ +\infty & \text{IF } \lambda \in \mathbb{R} \setminus \{0\} \end{cases}$$

CLAIM: IF $X \sim \text{CAU}(1)$ THEN $\Psi(t) = e^{-|t|}$

PROOF: WE KNOW FROM HW 6.2(a) THAT

$$\int_{-\infty}^{\infty} e^{itx} \cdot \frac{1}{2} e^{-|x|} dx = \frac{1}{1+t^2}$$

NOW $X \mapsto \frac{1}{2} e^{-|x|}$ IS CONTINUOUS AND

$$\int_{-\infty}^{\infty} \frac{1}{1+t^2} dt \stackrel{A}{<} +\infty \quad \text{THUS BY CLAIM ON PAGE 104}$$

WE HAVE $\frac{1}{2} e^{-|x|} \stackrel{B}{=} \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \cdot \frac{1}{1+t^2} dt$

THUS $\int_{-\infty}^{\infty} e^{itx} \cdot \frac{1}{\pi} \cdot \frac{1}{1+x^2} dx \stackrel{C}{=} e^{-|-t|} = e^{-|t|}$ ✓

THUS: $X \sim \text{CAU}(a) \iff E(e^{itX}) = e^{-a \cdot |t|}$

CLAIM: IF $X \sim \text{CAU}(a)$, $Y \sim \text{CAU}(b)$, INDEP.

THEN $(X+Y) \sim \text{CAU}(a+b)$

PROOF: $\Psi_{X+Y}(t) \stackrel{F}{=} \Psi_X(t) \cdot \Psi_Y(t) \stackrel{G}{=} e^{-a \cdot |t|} \cdot e^{-b \cdot |t|} = e^{-(a+b) \cdot |t|}$

NOTE:

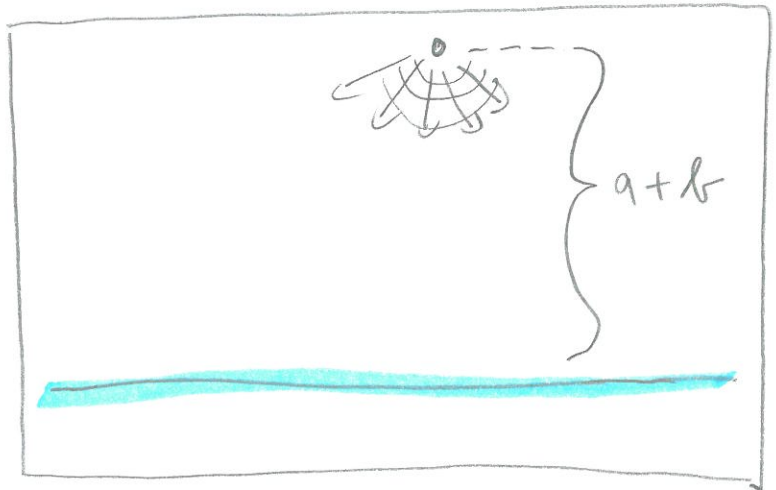
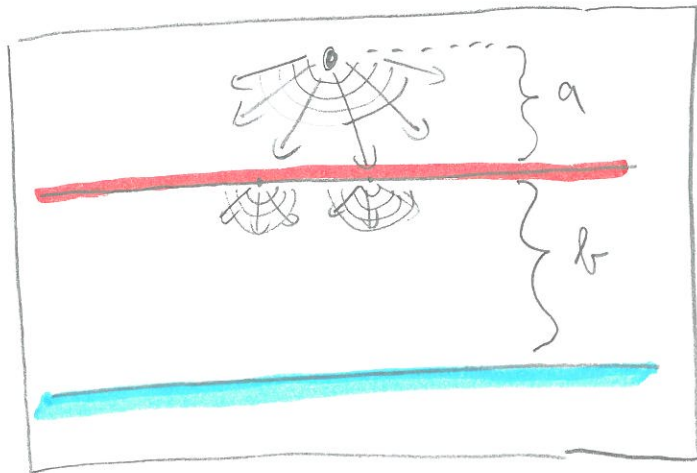


A LIGHTBULB THAT EMITS UNIT AMOUNT OF LIGHT

THEN THE LIGHT INTENSITY DISTRIBUTION ON THE RED LINE IS $\text{CAU}(a)$

(EASY TO CHECK USING DEF OF arctan FUNCTION)

THUS: DIFFRACTION (HUYGENS-FRESNEL PRINCIPLE)



ON THE LEFT PICTURE, THE RED LINE IS MADE OF "MILK GLASS", I.E., LIGHT IS "DIFFUSED". ON BOTH PICTURES, THE LIGHT DISTRIBUTION ON BLUE LINE IS $CAU(a+b)$.

ON THE LEFT, WE USED THAT THE CONVOLUTION OF $CAU(a)$ AND $CAU(b)$ IS $CAU(a+b)$.

LAW OF LARGE NUMBERS FAILS FOR CAUCHY DISTRIBUTION:

IF X_1, X_2, \dots I.I.D. $CAU(1)$, THEN

$S_m = X_1 + \dots + X_m$, $S_m \sim CAU(m)$, THUS

$$\frac{S_m}{m} \sim CAU(1)$$

THUS $\frac{S_m}{m}$ DOES NOT CONVERGE TO A DETERMINISTIC NUMBER AS $m \rightarrow \infty$.