$$\frac{f_{x}(t)}{f_{x}(t)} = E\left[e^{itx}\right] = \int \underbrace{\sum_{x \in supp(x)} e^{itx}}_{x \in supp(x)} e^{itx} \int_{supp(x)} e^{itx} f(x) discrete$$

$$= \int \underbrace{\sum_{x \in supp(x)} e^{itx}}_{supp(x)} f(x) discrete$$

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consider
$$\phi_{\chi}'(t) = \frac{d}{dt} \left[E[e^{itx}] \right] = \frac{d}{dt} \left[\int_{iR} e^{itx} dx \right] =$$

conditions;
(a) ItEA s.t. [g(x,t)dx converges A[a,b] CIR

(b) g(x,t) cont. Y teA (e) g(x,t) cont. Y XEIR

(d) ttEA, Sofg(x,t) dt convergen uniformly.

$$Q'(t) = \int f(x)ix - e^{itx} dx$$

 $\int_{X}^{R} [R] (x) - \int_{R}^{R} [R] (x) - \int_{R}^{R} [R] (x) dx = i \int_{R}^{R} [R] (x) dx$

$$\phi_{x}''(t) = \int_{\mathbb{R}} f(x) e^{2x^{2}} e^{itx} dx$$

$$\phi_{X}^{\prime\prime}(0) = i \int_{\mathbb{R}} X^{2} f(x) dx = i^{2} E \left[X^{2} \right]$$

*Bern: PMF So \$x(0) = 23 E[x3] bean doesn't have $= \sum_{n=1}^{\infty} E[X^n] = \frac{\varphi_x^{(n)}(0)}{z^n}$ (6) $P(x \in (a,b)) = \frac{1}{2\pi} \int \frac{e^{-ita} - itb}{it} \varphi_{x}(t) dt$ Motivation: If \$\phi_x \in L' (\delta_x is integrable) a => $f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{\frac{z}{c}tx} \phi(t) dt$ $P(X \in (a,b)) = \int_{a}^{b} f(x) dx = \int_{a}^{b} \int_{a}^{e^{itx}} g(t) dt dx$ $= \frac{1}{2\pi} \int_{\mathbb{R}} \left(\int_{a}^{b} e^{-tx} dx \right) \phi_{x}(t) dt = \frac{1}{2\pi} \int_{\mathbb{R}} \frac{e^{-ita} - itb}{it} dt$ $(f) \Rightarrow \phi_{\chi}(t) = \phi_{\chi}(t) \iff \chi \stackrel{d}{=} \chi \quad uniqueness property.$ (8) of (t) is a ch. funct. for Xn if $\forall t \mid \lim_{n \to \infty} \phi_{x_n}(t) = \phi_{x_n}(t) = \rangle$ $\lim_{n\to\infty} F_{x_n}(x) = F_{x}(x)$ also --- $\lim_{n\to\infty} x_n \stackrel{q}{=} x$ or Xn d X Convergence in distribution / Ian

Examples:

$$\begin{array}{l} x \, \text{nGramma} \, (k, \lambda) \\ \varphi_{x}(t) = \int^{\infty} e^{ztx} \, \frac{\lambda k e^{-Ax} x^{k-1}}{\Gamma(k)} \, dx = \frac{\lambda}{\Gamma(k)} \int_{x}^{x} x^{k-1} e^{(t+A)x} dx \\ \text{Let } u = (\lambda - zt) x \cdot \Rightarrow x = \frac{1}{\lambda - zt} u \cdot dx \\ dx = \frac{1}{\lambda - zt} \cdot du & \text{sign} \, dx \end{array}$$

$$\varphi_{x}(t) = \frac{\lambda^{k}}{\Gamma(k)} \cdot \int_{0}^{\infty} \frac{u^{k-1}}{(\lambda^{-i}t)^{k-1}} e^{-u} \frac{1}{\lambda^{-i}t} du$$

$$= \frac{\lambda^{k}}{\Gamma(k) \cdot (\lambda^{-i}t)^{k}} \int_{0}^{\infty} \frac{u^{k-1}}{(\lambda^{-i}t)^{k}} e^{-u} du = \frac{\lambda^{k}}{\Gamma(k) \cdot (\lambda^{-i}t)^{k}} e^{-u} du$$

$$= \left(\frac{\lambda}{\lambda^{-i}t}\right)^{k}$$

$$= \left(\frac{\lambda}{\lambda^{-i}t}\right)^{k}$$

$$(N-it)$$

$$(N-it)$$

$$X_{1} \times Gamma (k_{1}, \lambda) \text{ fnd of } X_{2} \sim Gamma (k_{2}, \lambda).$$

$$X_{1} + X_{2} \sim Gamma (k_{1} + k_{2}, \lambda)$$

$$(K_{1} + k_{2}, \lambda) \times (K_{2} + k_{2}) \times (K_{3} + k_{2}) \times (K_{3}$$

$$\begin{array}{lll}
\text{Poisson}(A) \\
\text{Poisson}(A) \\
\text{Poisson}(A) \\
\text{PMF of Poisson}(Ae^{it}) \\
\text{PMF of Poisson}(Ae^{it}) \\
\text{PMF of Poisson}(Ae^{it})
\end{array}$$

$$\begin{array}{lll}
\text{Poisson}(Ae^{it}) \\
\text{Poisson}(Ae^{it})
\end{array}$$

(*)
$$X_1 \sim Poisson(A_1)$$
 and of $X_2 \sim Poisson(A_2)$.
 $X_1 + X_2 \sim Poisson(A_1 + A_2)$ $= A_1(e^{it}-1)e^{A_2(e^{it}-1)}e^{$

*(X1)..., Xn rid some dist. with finite mean M and finite variance σ^2 , $X = \frac{1}{D} \sum_{i=1}^{D} X_i$ EDJ=M $Var[X] = \sigma^2$ Define $Z_n = \frac{\overline{X_n - M}}{\overline{S_n}}$ Var(Zn)=12 0>0> N(0,1) Standardization SE(Zn) $\varphi_{x}(t) \neq \varphi_{x}(t)$ Rule #2 $\varphi_{x}(t) \neq \varphi_{x}(t)$ $\varphi_{x}(t) \neq \varphi_{x}(t)$ $\varphi_{x}(t) = (\varphi_{x}(t))^{n}$ $\phi_{z,c}(t) = \phi_{x_0}\left(\frac{t}{s_0}\right)e^{it}\left(\frac{-u}{s_0}\right) = \phi_{x_0}\left(\frac{t}{s_0}\right)e^{it}\frac{t}{s_0}\frac{u}{u}$ = PXp(EJD) e it MA = $\lim_{n\to\infty} e^{\ln(\phi_x(\frac{t}{\sigma_{Jn}})^n} e^{-\frac{it}{\sigma_{Jn}}}) \frac{\text{let}_y = e^{\ln(y)}}{\sqrt{1+\frac{t}{\sigma_{Jn}}}}$ = lim enln (\$\phi_x(\frac{1}{\phi_v})) - \frac{it \mu n}{\phi_v} = $\lim_{n\to\infty} e^{n(\ln(\phi_{x}(\frac{t}{\sigma_{Jn}}))} - \frac{it\mu}{\sigma_{Jn}})$ $= e^{\lim n} \left(\ln \left(\sqrt{\frac{t}{s_n}} \right) - \frac{it \mu}{\sigma v_n} \right)$ $= e^{\lim \ln \left(\phi_{X} \left(\frac{t}{\sigma vn} \right) \right) - \frac{itM}{\sigma vn}} \cdot \frac{t^{2}/\sigma^{2}}{t^{2}/\sigma^{2}}$ $= e^{\frac{t^2}{02} \lim_{n \to \infty} \ln \left(\phi_{\chi} \left(\frac{t}{\sigma v_n} \right) \right) - \frac{it}{\sigma v_n}}$

Let
$$u = \frac{t}{\sigma \sqrt{n}}$$
 $t = \frac{t^2}{\sigma \sqrt{n}}$ $t = \frac$

