

What's so special about Gaussians? One answer:

Def: A probability measure $\mu \in \text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ is **infinitely divisible** if, for each $n \in \mathbb{N}$, $\exists \mu_n \in \text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ s.t. $\mu = \mu_n * \dots * \mu_n$.

I.e. $\exists \{X_{n,k}\}_{k=1}^n$ iid s.t. $S_n = X_{n,1} + \dots + X_{n,n} \stackrel{d}{=} \mu$

I.e. \exists non-constant characteristic function φ_n s.t. $\hat{\mu}(\zeta) = \varphi_n(\zeta)^n \quad \forall \zeta \in \mathbb{R}$.

E.g. If $X_{n,k} \stackrel{d}{=} N(0, \sigma^2/n)$ are independent, then

$$\uparrow S_n = X_{n,1} + \dots + X_{n,n} \stackrel{d}{=} N(0, \sigma^2)$$

$$X_{n,k} \stackrel{d}{=} \frac{\sigma}{\sqrt{n}} Z \text{ for } Z \stackrel{d}{=} N(0, 1) \quad \therefore \varphi_{X_{n,k}}(\zeta) = \varphi_Z\left(\frac{\sigma}{\sqrt{n}} \zeta\right) = e^{-\frac{\sigma^2}{n} \zeta^2 / 2}$$
$$\therefore \varphi_{S_n}(\zeta) = \left(e^{-\frac{\sigma^2}{n} \zeta^2 / 2}\right)^n = e^{-\sigma^2 \zeta^2 / 2}$$
$$\Rightarrow S_n \stackrel{d}{=} \sigma Z \stackrel{d}{=} N(0, \sigma^2).$$
$$= \varphi_Z(\sigma \zeta)$$
$$= \varphi_{\sigma Z}(\zeta)$$

E.g. If $N_{n,k} \stackrel{d}{=} \text{Poisson}(\lambda/n)$ are independent, $S_n = X_{n,1} + \dots + X_{n,n} \stackrel{d}{=} \text{Poisson}(\lambda)$.

Note: if μ, ν are infinitely divisible,

$$\text{so } \mu * \nu = (\mu_1 * \dots * \mu_n) * (\nu_1 * \dots * \nu_n) \\ = (\mu_1 * \nu_1)^{*n}$$

E.g. If $\mu = \frac{1}{2}(\delta_1 + \delta_{-1})$, then $\hat{\mu}(\zeta) = \cos \zeta$.

Suppose $X_1 \stackrel{d}{=} X_2$, independent, s.t. $X_1 + X_2 \stackrel{d}{=} \mu$. \leftarrow Supp $\mu \in [-1, 1]$

$$P(X_1 < -\frac{1}{2})^2 \leq P(X_1 + X_2 < -1) = 0 = P(X_1 + X_2 > 1) \geq P(X_1 > \frac{1}{2})^2$$

$$\{X_1 < -\frac{1}{2}\} \cap \{X_2 < -\frac{1}{2}\} \subseteq \{X_1 + X_2 < -1\} \quad \{X_1 + X_2 > 1\} \supseteq \{X_1 > \frac{1}{2}\} \cap \{X_2 > \frac{1}{2}\}$$

$$\Rightarrow |X_1|, |X_2| \leq \frac{1}{2} \text{ a.s.}$$

$\therefore \mu_{X_1} = \mu_{X_2}$ has finite moments of all orders.

$\therefore \hat{\mu}_{X_1} = \hat{\mu}_{X_2} \in C^\infty$.

$$\cos \zeta = \hat{\mu}(\zeta) = \hat{\mu}_{X_1}(\zeta)^2 \quad \checkmark \\ \uparrow \quad z f(\zeta)^2 \quad f \in C^\infty(\mathbb{R}) \\ 0 = \cos \frac{\pi}{2} = f(\frac{\pi}{2})^2$$

$$\cos \zeta = f(\zeta)^2 \\ \Rightarrow -\sin \zeta = 2f(\zeta) f'(\zeta) \\ -1 = -\sin \frac{\pi}{2} = 2 \cdot 0 \cdot f'(\zeta) \cdot \checkmark$$

Theorem: A probability measure $\mu \in \text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ is infinitely divisible iff \exists a "triangular array"

$$\{X_{n,k}\}_{k=1}^{m_n} \quad m_n \uparrow \infty, \quad n \in \mathbb{N}$$

of random variables s.t. for each n , $\{X_{n,k}\}_{k=1}^{m_n}$

are iid., and

$$S_n = \sum_{k=1}^{m_n} X_{n,k} \xrightarrow{w} \underbrace{X}_\sim \stackrel{d}{=} \mu.$$

Don't need equality, only weak convergence.

Pf. (\Rightarrow) If μ is infinitely divisible, can find $\{X_{n,k}\}_{k=1}^n$ iid
s.t. $S_n = X_{n,1} + \dots + X_{n,n} \xrightarrow{d} \mu$

(\Leftarrow) Step 1 is to show that if such a triangular array exists, so does one with $m_n = n$.

We'll skip this step, which involves some kind of involved tail bound estimates. We'll prove the theorem with $m_n = n$.

We have $\{X_{n,k}\}_{k=1}^n$ iid for each n s.t.

$$S_n = X_{n,1} + \dots + X_{n,n} \xrightarrow{w} X \stackrel{d}{=} \mu.$$

Fix $l \in \mathbb{N}$. Consider $S_{nl} = \sum_{k=1}^{nl} X_{nl,k} = \sum_{i=1}^l S_n^i$

iid for $1 \leq i \leq l$ $S_n^i = \sum_{j=n(i-1)+1}^{ni} X_{nl,j}$

Since $S_{nl} \xrightarrow{n \rightarrow \infty} X$, we know that $\{\mu_{S_{nl}}\}_{n \in \mathbb{N}}$ is tight.

$$\begin{aligned} & \sup_{n \in \mathbb{N}} P(|S_{nl}| > r) \\ & \quad \text{can make } < \text{ any } \varepsilon \text{ with} \\ & \quad \hookrightarrow \text{decreasing as } r \nearrow \infty \text{ - suff. large } r > 0. \\ & \quad \hookrightarrow \leq \varepsilon(r) \downarrow 0 \text{ as } r \nearrow \infty. \end{aligned}$$

$$\begin{aligned} P(S_n^1 > r)^l &= P(S_n^1 > r, \dots, S_n^l > r) \leq P(S_{nl} > lr) \\ &\Rightarrow S_{nl} > lr. \quad \leq P(|S_{nl}| > lr) \leq \varepsilon(lr) \end{aligned}$$

Similarly $P(-S_n^1 > r)^l \leq \varepsilon(lr)$

$$\begin{aligned} & \therefore P(|S_n^1| > r) \leq \varepsilon(lr)^{1/l} \downarrow 0 \text{ as } r \nearrow \infty \\ & \therefore \{\mu_{S_n^i}\}_{n=1}^\infty \text{ is tight.} \end{aligned}$$

So $\{S_n^1\}_{n=1}^\infty$ is tight, and \therefore by Helly/Prokhorov,
 \exists subsequence $\{n_j\}_{j=1}^\infty$ with $S_{n_j}^1 \xrightarrow{j \rightarrow \infty} w \gamma$ for some γ .

\therefore since $S_{n_j}^1, S_n^l$ are iid, can select Y_1, \dots, Y_l iid.

$$\text{s.t. } S_{n_j}^i \xrightarrow{j \rightarrow \infty} w Y_i$$

$$\therefore S_{n_j l} = \sum_{i=1}^l S_{n_j}^i \xrightarrow{j \rightarrow \infty} w Y_1 + \dots + Y_l$$

$$X \xrightarrow{w} \varphi_{S_{n_j}^1 + \dots + S_{n_j}^l}(\gamma) = \varphi_{S_{n_j}^1}(\gamma) \cdots \varphi_{S_{n_j}^l}(\gamma) \quad \forall \{\gamma\} \in \mathbb{R}.$$

$$X \stackrel{d}{=} Y_1 + \dots + Y_l \quad \varphi_{Y_1}(\gamma) \cdots \varphi_{Y_l}(\gamma) = \varphi_{Y_1 + \dots + Y_l}(\gamma)$$

$\underbrace{\text{i.i.d.}}$ $\Rightarrow \mu_X$ is Inf-div. //

It turns out we can even weaken the iid. condition on the "rows" of the triangular array. We'll explore this in the Gaussian case.