

# Characteristic Functions

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# Raindrops Again and Again and ...

## Raindrops in two seconds

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But why?

# Sum of Independent Normals

## The Normal Sum Problem

$X_1 \sim N(\mu_1, \sigma_1^2), X_2 \sim N(\mu_2, \sigma_2^2)$ .  $X_1, X_2$  are independent. Distribution of  $Y = X_1 + X_2$ ?

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Observation:

- $E[Y] = E[X_1] + E[X_2]$
- $Var[Y] = Var[X_1] + Var[X_2]$

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Observation:

- $E[Y] = E[X_1] + E[X_2]$
- $\text{Var}[Y] = \text{Var}[X_1] + \text{Var}[X_2]$

But what is the distribution?

# Characteristic Functions

To deal with the sums of random variables, **characteristic function** is a powerful weapon for us.

## Definition

Let  $X$  be a random variable and denote by  $F$  the cumulative distribution function of  $X$  (or  $f$  the probability density function). The characteristic function  $\varphi = \varphi_X$  of  $X$  (or of  $F$ , in which case we also write  $\varphi_F$ ) is defined by

$$\varphi_X(t) := E[e^{itX}] = \int_{-\infty}^{\infty} e^{itx} dF(x) = \int_{-\infty}^{\infty} e^{itx} f(x) dx, t \in \mathbb{R}$$



# Recall Complex Numbers

If you have forgotten everything about complex numbers, all you need to recall is the following:

- $i$  is the imaginary unit,
- $i^2 = -1$ ,
- $e^{i\theta} = \cos \theta + i \sin \theta$ . (This formula comes from Taylor Series)

## Theorem (Uniqueness Theorem)

*Let  $X$  be a real random variable with distribution function  $F$  and characteristic function  $\varphi$ . Similarly, let  $Y$  have distribution function  $G$  and characteristic function  $\psi$ . If  $\varphi(t) = \psi(t)$  for all  $t \in \mathbb{R}$  then  $F(x) = G(x)$  for all  $x \in \mathbb{R}$ .*

From this we may easily conclude the distribution of a random variable if we can prove that its characteristic function is of the same form as a known distribution.

# Properties

Even if we cannot find the distribution in the lookup table, we may also retrieve it from characteristic functions by hand:

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## Theorem (Inversion Formula)

*If  $\int_{\mathbb{R}} |\varphi(t)| dt < \infty$  then  $X$  has bounded continuous density*

$$f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} \varphi(t) dt$$

## Theorem

*If  $X$  and  $Y$  are independent random variables then the characteristic function of their sum is*

$$\varphi_{X+Y}(t) = \varphi_X \cdot \varphi_Y.$$

This gives us a much simpler way than convolution.

## Theorem

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If  $X$  and  $Y$  are random variables such that  $\varphi_{X+Y} = \varphi_X \cdot \varphi_Y$ , then in general we do not conclude  $X$  and  $Y$  are independent. This is called **subindependence**.

## Theorem

For any  $a, b \in \mathbb{R}$ ,

$$\varphi_{aX+b}(t) = e^{ibt} \varphi_X(at).$$

# Distributions and Their Characteristic Functions

## Example (Characteristic Function for Exponential)

Find the characteristic function for  $X \sim \text{Exponential}(\lambda)$ .



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$$\begin{aligned}\varphi_X(t) &:= E[e^{itX}] \\&= \int_{-\infty}^{\infty} e^{itx} f(x) dx \\&= \int_0^{\infty} e^{itx} \cdot \lambda e^{-\lambda x} dx && \text{By distribution of } x \\&= \frac{\lambda}{it - \lambda} e^{(it - \lambda)x} \Big|_0^{\infty} \\&= \frac{\lambda}{\lambda - it} && \text{By Squeeze Theorem}\end{aligned}$$

# Distributions and Their Characteristic Functions

The last two steps

$$\left. \frac{\lambda}{it - \lambda} e^{(it - \lambda)x} \right|_0^\infty = \frac{\lambda}{\lambda - it}$$

can be justified by

$$\lim_{x \rightarrow \infty} |e^{(it - \lambda)x}| = \lim_{x \rightarrow \infty} |e^{-\lambda x}| = 0 \text{ for positive } \lambda$$

# Distributions and Their Characteristic Functions

The table below shows some common distributions and their characteristic functions:

**Table:** Characteristic Functions for Common Distributions

Distribution	Characteristic Function
Constant $X \equiv a$	$\varphi_X(t) = e^{iat}$ .
Binomial $X \sim \text{Binomial}(m, p)$	$\varphi_X(t) = (pe^{it} + (1 - p))^m$
Poisson $X \sim \text{Poisson}(\lambda)$	$\varphi_X(t) = e^{\lambda(e^{it}-1)}$
Exponential $X \sim \text{Exponential}(\lambda)$	$\varphi_X(t) = \frac{\lambda}{\lambda - it}$
Normal $X \sim N(0, 1)$	$\varphi_X(t) = e^{-\frac{t^2}{2}}$
Normal $Y \sim N(\mu, \sigma^2)$	$\varphi_Y(t) = e^{it\mu - \frac{\sigma^2 t^2}{2}}$

# Statistics and Probability

So what "characteristics" are these weird "characteristic functions" talking about?

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To understand this, first we need some knowledge about **moments**.

## Definition (Moment)

For probability density functions  $f$  (or cumulative density function  $F$ ), the moments are given by

$$\mu'_n = E[X^n] = \int_{-\infty}^{\infty} x^n dF(x) = \int_{-\infty}^{\infty} x^n f(x) dx$$

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**Relation with statistics.** Observe that the first moment is simply the expectation. The second moment is related to the variance:

$$\text{Var}[X] = E[X^2] - (E[X])^2.$$

What about the third moment?

# Statistics and Probability

What about the third moment?

A related concept is **skewness**:

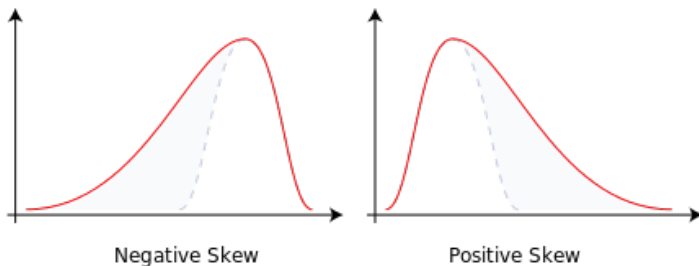


Figure: Same expectation and variance, but different skewness



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## Solution

Let  $X, Y$  be two independent  $Poisson(\lambda)$  random variables. Let  $Z = X + Y$ . Notice that characteristic functions for  $X$  (and respectively  $Y$ ) is

$$\varphi_X(t) = e^{\lambda(e^{it}-1)}$$

Therefore we have

$$\varphi_Z(t) = \varphi_{X+Y}(t) = (\varphi_X(t))^2 = e^{2\lambda(e^{it}-1)}$$

By uniqueness of characteristic functions we know that  $Z \sim Poisson(2\lambda)$ .

Conclusion:

- This is the same as our intuition.
- By similar ideas, one can show that the sum of two independent poisson random variables has a poisson distribution with an expectation of the sum of both expectations

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## Solution

Similarly to previous problem

$$\varphi_Y(t) = \varphi_{X_1+X_2}(t) = e^{it\mu_1 - \frac{\sigma_1^2 t^2}{2}} \cdot e^{it\mu_2 - \frac{\sigma_2^2 t^2}{2}}$$

Therefore we have

$$\varphi_Y(t) = e^{it(\mu_1 + \mu_2) - \frac{(\sigma_1^2 + \sigma_2^2)t^2}{2}}$$

which implies that  $Y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

# Sum of Independent Normals

Conclusion:

- Our result is consistent with the statistics.
- Sum of two independent normal random variables is still normal.

# From Binomial To Poisson

## Example

Show that  $Poisson(\lambda)$  is the same as  $\lim_{n \rightarrow \infty} Binomial(n, \frac{\lambda}{n})$ .



# From Binomial To Poisson

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## Solution

Take the limit of the characteristic function of the binomial distribution.

$$\begin{aligned}\lim_{n \rightarrow \infty} \varphi_B(t) &= \lim_{n \rightarrow \infty} \left( \frac{\lambda}{n} e^{it} + \left(1 - \frac{\lambda}{n}\right) \right)^n \\ &= \lim_{n \rightarrow \infty} \left( 1 + (e^{it} - 1) \frac{\lambda}{n} \right)^n \\ &= e^{\lambda(e^{it} - 1)}\end{aligned}$$

# Central Limit Theorem

First we need to prove a lemma that gives us the common characteristics of all distributions:

## Lemma

For any random variable  $X$  with  $E[X] = 0$ ,  $Var[X] = 1$ , we have  $\varphi_X(t) = 1 - \frac{1}{2}t^2 + o(t^2)$ .

## Proof.

Directly from the definition and Taylor Series we have

$$\varphi_X(t) = E[e^{itX}] = E[1 + itX + \frac{1}{2}i^2t^2X^2 + o((tX)^2)]$$

By linearity of expectation,

$$\varphi_X(t) = E[1] + itE[X] - \frac{1}{2}t^2E[X^2] + o(t^2)$$

Also

$$E[X^2] = \text{Var}[X] - (E[X])^2 = 1$$

Therefore

$$\varphi_X(t) = 1 - \frac{1}{2}t^2 + o(t^2)$$



# Central Limit Theorem

## Theorem (Central Limit Theorem)

*If  $X_i$  are independent identically distributed random variables with  $E[X_i] = \mu$ ,  $\text{Var}[X_i] = \sigma^2$ , then  $S_n^* = \frac{1}{\sigma\sqrt{n}} \sum_{i=1}^n (X_i - \mu)$  converges weakly to  $N(0, 1)$ .*

## Proof.

By Lemma 20 we denote the characteristic function of  $\frac{X_i - \mu}{\sigma}$  by  $\varphi(t)$ , then  $\varphi(t) = 1 - \frac{1}{2}t^2 + o(t^2)$ . Therefore the characteristic function of  $S_n^*$  is

$$\varphi^n(t/\sqrt{n}) = [1 - \frac{t^2}{2n} + o(t^2/n)]^n$$

Take  $n \rightarrow \infty$  and we get the characteristic function of  $\lim_{n \rightarrow \infty} S_n^*$

$$\Phi(t) = \lim_{n \rightarrow \infty} \varphi^n(t/\sqrt{n}) = \lim_{n \rightarrow \infty} [1 - \frac{t^2}{2n}]^n = e^{-\frac{t^2}{2}}$$

Therefore  $\lim_{n \rightarrow \infty} S_n^*$  converges to  $N(0, 1)$ . □

Thanks for your attention!