

## Lecture 13: Normal Distribution

### Universality of Uniform

Let  $F$  be a continuous, strictly increasing CDF.

Then  $X = F^{-1}(U) \sim F$  if  $U \sim \text{Unif}(0,1)$ .

Also: (started with  $X$  and we don't have a uniform yet) we just have  $X$  which has CDF  $F$

i.e.,

if  $X \sim F$ , then  $F(X) \sim \text{Unif}(0,1)$

plug  $X$  into  
its own CDF

perfectly valid random variable  
 $F$  is just a function  
function of a random variable  
is a random variable

Started with  
uniform distribution  
computed  $F^{-1}(u)$   
and we claimed that  
it has CDF  $F$ .

$$F(x) = P(X \leq x)$$

$$F(X) = P(X \leq X) = 1 \quad \text{X (wrong)}$$

Ex

$F(x) = 1 - e^{-x}, x > 0$  (Important CDF, exponential distribution)  
Interpretation would be

$$F(X) = 1 - e^{-X}$$

$F(X) \sim \text{Unif}(0,1)$  [Useful in Stats 111, statistical Inference]

→ The interpretation of this is — we first evaluate the function  $F$  as a function (something squared or whatever). Write it as a function, then replace  $x$  by  $X$ .

Example  
(Useful in simulation)

Let  $F(x) = 1 - e^{-x}, x > 0$  ( $\text{expo}(1)$ ),  $U \sim \text{Unif}(0,1)$ ,  
simulate  $X \sim F$ .

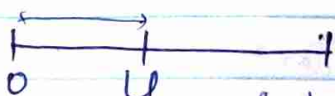
(By  
universality  
theorem)

$$F^{-1}(u) = -\ln(1-u) \Rightarrow F^{-1}(U) = -\ln(1-U) \sim F$$

If we are doing it on a computer and we want 10 random draws from this distribution, we just generate 10 i.i.d. uniforms ~~and~~ ( $U$ ) and just compute as above 10 times and then we will have 10 i.i.d. random draws from the distribution.

$(1-U) \sim \text{Unif}(0,1)$  (Symmetry of Unif)

$a + bU$  is Unif on some interval.  
(0,1)  
→ linear transformation



Note: Non-linear usually leads to non Unif.



## Independence of random variables $X_1, \dots, X_n$

$X_1, X_2, \dots, X_n$  are independent if

$$P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \leq x_n) = P(X_1 \leq x_1) \cdot P(X_2 \leq x_2) \cdots P(X_n \leq x_n)$$

for all  $x_1, x_2, \dots, x_n$

Annotations:  
- Individual CDFs (pointing to the individual probabilities on the right)  
- Joint CDF (pointing to the left-hand side)  
- CDF of all random variables considered jointly as one probability (pointing to the right-hand side)

### Discrete Case

$$P(X_1 = x_1, \dots, X_n = x_n) = P(X_1 = x_1) \cdots P(X_n = x_n)$$

Joint PMF

Individual PMF's

Knowing any collection, any subcollection of these  $X$ 's, knowing their values tells us nothing about the others.

Note :- This is stronger than just pairwise independence. Pairwise independence says if we know one random variable, it does not tell us anything information about any other one random variable.

Full independence means knowing any of them, any collection of <sup>them</sup> tells us nothing about ones that we don't know, no information whatsoever.

Example pairwise independence does not imply independence.

$$X_1, X_2 \sim \text{Bern}(1/2) \text{ i.i.d.}, X_3 = \begin{cases} 1, & \text{if } X_1 = X_2 \\ 0, & \text{otherwise} \end{cases}$$

i.i.d. Coin flips

These are pairwise independent, not independent.

indicator r.v.

i.e. if two pennies match

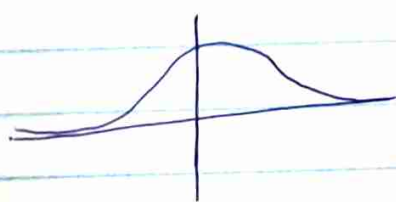
- They are not independent because if we know  $X_1$  and  $X_2$ , then we immediately know  $X_3$  as  $X_3$  is a function of  $X_1$  and  $X_2$ . So, not only does it give us information, it also gives us total information.
- However, just knowing  $X_1$  tells us nothing about  $X_2$  because those are, we assumed, ~~are~~ independent. Just knowing  $X_1$  tells us nothing about  $X_3$  because it's still 50-50. Similarly,  $X_2$  is independent of  $X_3$ . ~~So~~ So, they are pairwise independent, but they are not independent.

Pairwise independence isn't enough, in general, just to have independence.

### Normal distribution / Gaussian distribution

Central Limit theorem — If we add up a bunch of i.i.d. random variables, the distribution is going to look like a normal distribution.

→ could be either discrete or continuous



$N(0, 1)$  — standard Normal dist. notation  
(mean 0, variance 1)

PDF:  $f(z) = c e^{-z^2/2}$ ,  $c$  is normalizing constant

Value of  $c$

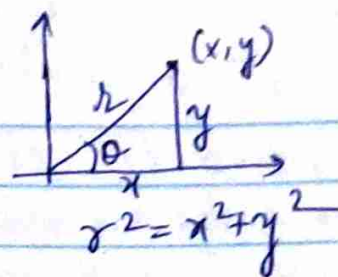
$$\int_{-\infty}^{\infty} e^{-z^2/2} dz$$

$$\int_{-\infty}^{\infty} e^{-z^2/2} dz \int_{-\infty}^{\infty} e^{-z^2/2} dz$$

$$\int_{-\infty}^{\infty} e^{-x^2/2} dx \int_{-\infty}^{\infty} e^{-y^2/2} dy$$



$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-(x^2+y^2)/2} dx dy$$



$$= \int_0^{2\pi} \int_0^{\infty} e^{-r^2/2} \underbrace{r}_{\text{Jacobian}} dr d\theta$$

$$= \int_0^{2\pi} \left( \int_0^{\infty} e^{-u} du \right) d\theta$$

1

$$u = r^2/2$$

$$du = r dr$$

$$= 2\pi$$

$$\int_{-\infty}^{\infty} e^{-z^2/2} dz = \sqrt{2\pi}$$

$$\therefore C = 1/\sqrt{2\pi}$$

$$\text{or, } f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$$

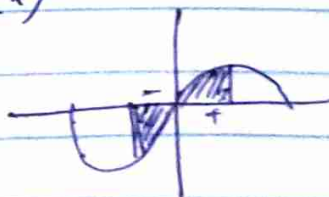
### Mean of Standard Normal

$$Z \sim N(0, 1)$$

$$EZ = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z e^{-z^2/2} dz = 0 \text{ (by symmetry)}$$

if  $g(x)$  is an odd function,  
i.e.,  $g(-x) = -g(x)$

$$\text{then } \int_{-a}^a g(x) dx = 0$$



### Variance

$$\text{Var}(Z) = E(Z^2) - (E(Z))^2$$

$$= E(Z^2)$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z^2 e^{-z^2/2} dz \quad (\text{by LOTUS})$$

Replace  $z$  by  $z^2$

even function

$$= \frac{2}{\sqrt{2\pi}} \int_0^{\infty} z^2 e^{-z^2/2} dz$$

$$= \frac{2}{\sqrt{2\pi}} \int_0^{\infty} \underbrace{z}_{\tilde{u}} \cdot \underbrace{ze^{-z^2/2}}_{dv} dz$$

$$u = z \Rightarrow du = dz$$

$$dv = ze^{-z^2/2}$$

$$v = -e^{-z^2/2}$$

$$= \frac{2}{\sqrt{2\pi}} \left[ (uv) \Big|_0^{\infty} + \int_0^{\infty} e^{-z^2/2} dz \right]$$

$$= \frac{2}{\sqrt{2\pi}} \cdot \frac{1}{2} \sqrt{2\pi}$$

$$= 1$$

### Notation

$\Phi$  is the standard Normal CDF

$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-t^2/2} dt$

$\phi$  →

$$\phi(-z) = 1 - \phi(z) \quad (\text{by symmetry})$$