

# STA257

Neil Montgomery | HTML is official | PDF versions good for in-class use only  
Last edited: 2016-11-01 22:15

# joint cdf - continuous case

The joint cdf  $F(x, y) = P(X \leq x, Y \leq y)$  can be calculated:

$$F(x, y) = \int_{-\infty}^y \int_{-\infty}^x f(u, v) du dv$$

It is a mystery of multivariable calculus how to obtain  $f$  from  $F$

# "partial" derivatives crash course - I

Maybe you got this far in your co-requisite!

With a function  $g(x, y)$  you can take the derivative with respect to one variable at a time, holding the other variable constant. Notation:

$$\frac{\partial}{\partial x} g(x, y) \quad \text{and} \quad \frac{\partial}{\partial y} g(x, y).$$

When  $g$  is "smooth" you get the nice result:

$$\frac{\partial}{\partial y} \left[ \frac{\partial}{\partial x} g(x, y) \right] = \frac{\partial}{\partial x} \left[ \frac{\partial}{\partial y} g(x, y) \right],$$

and we just call this:

$$\frac{\partial^2}{\partial x \partial y} g(x, y).$$

# joint cdf to joint density

Just take all the "partial" derivatives in any order you like.

$$\frac{\partial^2}{\partial x \partial y} F(x, y) = f(x, y)$$

"Proof: ..."

Examples can be challenging! Consider  $f(x, y) = xy$  on  $0 < x < 1, 0 < y < 2$  (...to be revisited...)

# marginal cdf and marginal density

Just like in the discrete case we can recover information about  $X$  and  $Y$  individually by "integrating out" the other variable. The marginal densities are:

$$f_x(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

$$f_y(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

What about the marginal cdfs?

Continue the example on the previous slide.

picture of  $F(x,y)$

# joint/marginal pdf example

Example D from the book.

$$f(x, y) = \begin{cases} \lambda^2 \exp(-\lambda y) & : 0 \leq x \leq y, \lambda > 0 \\ 0 & : \text{otherwise.} \end{cases}$$

Exercise: review Example E from the book "Bivariate Normal". We will revisit this example.

independent random variables  
(which the book gets a bit wrong)



# recall some definitions and results

Events  $A$  and  $B$  are independent if  $P(A \cap B) = P(A)P(B)$ .

$$A \perp B \iff A^c \perp B \iff A \perp B^c \iff A^c \perp B^c$$

"Experiments"  $\mathcal{E}_A = \{A_1, A_2, \dots\}$  and  $\mathcal{E}_B = \{B_1, B_2, \dots\}$  are independent if  $A_i \perp B_j$  for all  $i, j$ .

**Definition:** Random variables  $X$  and  $Y$  are *independent* if:

$$P(X \in A, Y \in B) = P(X \in A)P(Y \in B)$$

for any\*  $A, B \subset \mathbb{R}$ .

# the book's definition is actually a *theorem*

Theorem:  $X \perp Y$  if and only if the joint cdf  $F(x, y) = F_x(x)F_y(y)$  is the product of the marginal cdfs.

Proof:  $\Leftarrow$  ("only if") too hard;  $\Rightarrow$  left as exercise.

Corollary:  $X \perp Y$  if and only if the joint  $f(x, y) = f_x(x)f_y(y)$

To verify, in practice check two things:

1. The density factors.
2. The non-zero region is a rectangle (possibly infinite in either direction.)

# examples

1.  $f(x, y) = xy$  on  $0 < x < 1$  and  $0 < y < 2$ .

2.  $f(x, y) = \lambda^2 \exp(-\lambda y)$  on  $0 < x < y < \infty$ .

3.  $f(x, y) = \frac{1}{2} \lambda^3 y \exp(-\lambda(x + y))$  on  $x > 0$  and  $y > 0$ .