

# STA286 Lecture 08

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## a note on “identically distributed”

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Define:

$$X_1 = \begin{cases} 1 & : 3 \text{ or } 4 \text{ appears} \\ 0 & : \text{otherwise} \end{cases} \quad \text{and} \quad X_2 = \begin{cases} 1 & : 5 \text{ or } 6 \text{ appears} \\ 0 & : \text{otherwise} \end{cases}$$

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$X_1$  and  $X_2$  are not the same functions. But they have the same p.m.f.:

$$p(x) = \left(\frac{1}{3}\right)^x \left(\frac{2}{3}\right)^{1-x}, \quad x \in \{0, 1\}.$$

We say  $X_1$  and  $X_2$  are *identically distributed*.

joint distributions

## more than one random variable at a time

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The approach is to consider a random vector such as  $(X, Y)$ ,  $(X_1, X_2)$ ,  $(X_1, X_2, \dots, X_n)$  and so on. At first we'll consider two at a time:  $(X, Y)$ .

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Main interest is in statements like:

$$P(X = x, Y = y) \quad \text{or} \quad P(a < X < b, c < Y < d)$$

where the “comma” notation is a compact way of writing, say:

$$P(\{X = x\} \cap \{Y = y\})$$

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They also have cdfs:

$$F(x, y) = P(X \leq x, Y \leq y)$$

but we won't focus much on these.

## a joint pmf

A gas distribution company has pipes with diameters 1, 1.5, and 1.75 inches. The pipes are used at pressures of 2, 1, and 0.5 pounds per square inch.

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$X$  and  $Y$  might have the following *joint probability mass function*:

$Y$	$X$		
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e.g. the probability that a randomly selected pipe has diameter  $X = 1.5$  and pressure  $Y = 0.5$  is:

$$P(X = 1.5, Y = 0.5) = 0.1$$

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A joint density also must be non-negative and integrate to 1 over all  $\mathbb{R}^2$ .

## joint density example - I

Two electronic components fail at times  $X$  and  $Y$  according to the following joint density (measured in years):

$$f(x, y) \begin{cases} 2e^{-x-2y} & : x > 0, y > 0 \\ 0 & : \text{otherwise} \end{cases}$$

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Is this actually a valid joint density? It is non-negative, and:

$$\iint_{\mathbb{R}^2} f(x, y) \, dx dy = \int_0^{\infty} \int_0^{\infty} 2e^{-x-2y} \, dx dy = \int_0^{\infty} e^{-x} \, dx \int_0^{\infty} 2e^{-2y} \, dy = 1$$

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## marginal distributions

A joint distribution contains *all* information about both  $X$  and  $Y$  together.

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A statement about  $X$  alone could be something like  $P(X = 1)$ , which is just  $0.075 + 0.11 + 0.16 = 0.345$

## marginal pmf

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Here are the “marginals” for both  $X$  and  $Y$  in the gas example:

Y	X			Marginal
	1	1.5	1.75	
0.5	0.075	0.100	0.150	0.325
1	0.110	0.080	0.090	0.280
2	0.160	0.140	0.095	0.395
Marginal	0.345	0.320	0.335	1.000



## marginal density

Reconsider the two electronic components example:

$$f(x, y) \begin{cases} 2e^{-x-2y} & : x > 0, y > 0 \\ 0 & : \text{otherwise} \end{cases}$$

A statement about, say,  $Y$  alone might be  $P(Y > 1)$ , which would be the integral on the entire half plane  $y > 1$ :

$$\int\int_{y>1} f(x, y) \, dx dy$$

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But in the end, the calculation only ever involved  $2e^{-2y}$  once  $x$  was “integrated out.”

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e.g. Consider the following function:

$$f(x, y) = \begin{cases} 2 & : 0 < x < 1, 0 < y < 1, x + y < 1 \\ 0 & : \text{otherwise} \end{cases}$$

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This is a valid density. Let  $X$  and  $Y$  have this joint density.



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## conditional distributions

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$$P(X = 1.5|Y = 2) = \frac{0.14}{0.395} \qquad P(X = 1.75|Y = 2) = \frac{0.095}{0.395}$$

## conditional pmf and conditional density

Given the joint pmf  $p(x, y)$  for  $X$  and  $Y$ , the conditional pmf for  $X$  given  $Y = y$  is:

$$p(x|y) = \frac{p(x, y)}{p_Y(y)},$$

provided  $P(Y = y) > 0$ .



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## conditional density example

Reconsider the two electronic components example:

$$f(x, y) \begin{cases} 2e^{-x-2y} & : x > 0, y > 0 \\ 0 & : \text{otherwise} \end{cases}$$

The marginal density for  $Y$  is  $2e^{-2y}$  on  $y > 0$ .

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Heck, the conditional density for  $X$  given  $Y$  equals anything greater than 0 is still always  $e^{-x}$  on  $x > 0$ .

That's because  $X$  and  $Y$  have a special relationship... to be revisited.

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$$f(x, y) = \begin{cases} 2 & : 0 < x < 1, 0 < y < 1, x + y < 1 \\ 0 & : \text{otherwise} \end{cases}$$

The marginal density for  $X$  was found to be  $f_X(x) = 2x$  for  $0 < x < 1$ .

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The conditional density of  $Y$  given  $X = 0.5$  will be 0 when  $y$  is outside  $(0, 0.5)$ .

Otherwise it will be:

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Unlike marginal densities, conditional densities can sometimes be visualized. They are just “slices” of the joint density.