## LECTURE: MULTIVARIATE DISTRIBUTIONS

## 1. Conditional Distribution

Another question we might ask is:
Question: What is the distribution of $Y_{1}$ given that $\left(Y_{2}=y_{2}\right)$ ?

## Example 1:

In the exam-coffee example, what is the distribution of the number of cups of coffee drunk today $X_{2}$ given that a student has a midterm this week ( $X_{1}=$ yes)?

Recall: We can display the joint probability distribution for the pair $\left(X_{1}, X_{2}\right)$ in a $2 \times 3$ table:

\[

\]

To answer the question, we look at the first row of the table, which corresponds to ( $X_{1}=$ yes)

$$
2 / 20 \quad 3 / 20 \quad 3 / 20
$$

This is not a valid probability mass function, because the elements do not sum to 1 . To fix that, we just need to divide by the marginal probability

$$
p_{1}(\text { yes })=P\left(X_{1}=\text { yes }\right)=2 / 20+3 / 20+3 / 20=8 / 20
$$

We then get the conditional probability for $X_{2}$ given ( $X_{1}=$ yes $)$, which we can write as $p\left(y_{2} \mid\right.$ yes $)$ or $p\left(y_{2} \mid Y_{1}=\right.$ yes $)$ :

$$
\begin{array}{ll}
\hline y_{2} & p\left(y_{2} \mid \text { yes }\right) \\
\hline 0 & (2 / 20) /(8 / 20)=2 / 8 \\
1 & (3 / 20) /(8 / 20)=3 / 8 \\
2 & (3 / 20) /(8 / 20)=3 / 8 \\
\hline
\end{array}
$$

## Definition:

Let $Y_{1}$ and $Y_{2}$ be discrete random variables with joint pmf $p\left(y_{1}, y_{2}\right)$ and let $p_{2}\left(y_{2}\right)$ be the marginal distribution of $Y_{2}$.

Then the conditional distribution of $Y_{1}$ given $\left(Y_{2}=y_{2}\right)$ is:

$$
p\left(y_{1} \mid y_{2}\right)=P\left(Y_{1}=y_{1} \mid Y_{2}=y_{2}\right)=\frac{P\left(Y_{1}=y_{1}, Y_{2}=y_{2}\right)}{P\left(Y_{2}=y_{2}\right)}=\frac{p\left(y_{1}, y_{2}\right)}{p_{2}\left(y_{2}\right)}
$$

In words, the conditional distribution is the joint distribution divided by the marginal distribution.

We can similarly define the cond. distribution of $Y_{2}$ given $\left(Y_{1}=y_{1}\right)$ as

$$
p\left(y_{2} \mid y_{1}\right)=\frac{p\left(y_{1}, y_{2}\right)}{p_{1}\left(y_{1}\right)}
$$

Just like we did in the example above

## 2. INDEPENDENCE

The final question to settle is independence. Roughly speaking, two random variables are independent of if the probabilities of each one are
not affected by the value of the other one. The following will serve as our definition for independence of two discrete random variables.

## Definition:

Let $Y_{1}$ and $Y_{2}$ be discrete random variables with joint pmf $p\left(y_{1}, y_{2}\right)$ and let $p_{1}\left(y_{1}\right)$ and $p_{2}\left(y_{2}\right)$ the marginal distributions of $Y_{1}$ and $Y_{2}$.

Then $Y_{1}$ and $Y_{2}$ are independent if

$$
p\left(y_{1}, y_{2}\right)=p_{1}\left(y_{1}\right) p_{2}\left(y_{2}\right) \quad \text { for all } y_{1}, y_{2}
$$

In other words, two random variables are independent if their joint distribution is the product of the two marginal distributions, compare this with $P(A \cap B)=P(A) P(B)$ for independent events.

## Example 2:

In the exam-coffee example above, are $Y_{1}$ and $Y_{2}$ independent?

NO because, for example

$$
p(\text { yes }, 1)=\frac{3}{20} \neq p_{1}(\text { yes }) p_{2}(1)=\left(\frac{8}{20}\right)\left(\frac{7}{20}\right)
$$

I mean, did we really expect coffee consumption and exams to be independent? ©

## 3. Distribution of Two Continuous Variables

Video: What is a Double Integral

## Video: Changing the Order of Integration

We will repeat the same discussion but for a pair of continuous random variables. This will require integration in two dimensions, cf. the videos above.

Joint Probability Density: For two continuous random variables, we have a joint density function, which is the continuous analogue of the joint pmf.

## Definition:

Let $Y_{1}$ and $Y_{2}$ be two continuous random variables. Then the joint density of $Y_{1}$ and $Y_{2}$ is any function $f\left(y_{1}, y_{2}\right)$ such that
(1) $f\left(y_{1}, y_{2}\right) \geq 0$ for all $y_{1}, y_{2}$

$$
\begin{equation*}
\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f\left(y_{1}, y_{2}\right) d y_{1} d y_{2}=1 \tag{2}
\end{equation*}
$$

In other words, $f\left(y_{1}, y_{2}\right)$ is non-negative and integrates/sums up to 1 .
In the single variable case, we had

$$
P(a \leq X \leq b)=\int_{a}^{b} f(x) d x
$$

Here we have the same thing except we integrate the joint density over a region:

## Definition:

Let $Y_{1}$ and $Y_{2}$ be two continuous random variables with joint density $f\left(y_{1}, y_{2}\right)$. Let $A$ be a region of the plane. Then

$$
P\left(\left(Y_{1}, Y_{2}\right) \in A\right)=\iint_{A} f\left(y_{1}, y_{2}\right) d y_{1} d y_{2}
$$

Interpretation of $f$ : Just as in the single-variable case, we have

$$
f(a, b) \approx \frac{P\left(\left(a \leq Y_{1} \leq a+h\right) \text { and }\left(b \leq Y_{2} \leq b+k\right)\right)}{h k}
$$

So $f(a, b)$ is the probability that $\left(Y_{1}, Y_{2}\right)$ lies in the rectangle $[a, a+h] \times[b, b+k]$ but scaled by the area $h k$ of that rectangle.

## Example 3:

Let $X$ and $Y$ be random variables with joint density $f(x, y)$ where

$$
f(x, y)= \begin{cases}k x y & 0 \leq y \leq x \leq 1 \\ 0 & \text { otherwise }\end{cases}
$$

(a) Find the value of $k$ such that $f(x, y)$ is a valid joint density function.

$$
\text { We need } \iint_{A} f(x, y) d x d y=1
$$

The bounds of the density function are the following:

$$
A=\{y \geq 0, x \leq 1, y \leq x\}
$$

This describes the triangular region illustrated below.


Note: Whenever we have a double integral, we have two choices when we do our integration. We can integrate in $x$ direction first, or we can integrate in the $y$ direction first. Both ways give the same answer, but sometimes one is easier than the other. We will show both of them here.

Method 1: Let's start by integrating in the $y$ direction first.

2. Integrate in the $x$ direction next; $x$ goes from 0 to 1 . You can think of this as "summing" the slices you made in the first step, following this bottom arrow.
$y$ goes from 0 to the diagonal line $y=x$, so those are the limits for the integral with respect to $y$ (inner integral). Then $x$ goes from 0 to 1 , so those are the limits for the integral with respect to $x$ (outer integral).

Putting this together, we have:

$$
\begin{aligned}
1 & =\int_{0}^{1} \int_{0}^{x} k x y d y d x \\
& =k \int_{0}^{1} x\left[\frac{y^{2}}{2}\right]_{y=0}^{y=x} d x \\
& =\frac{k}{2} \int_{0}^{1} x^{3} d x \\
& =\frac{k}{2}\left[\frac{x^{4}}{4}\right]_{0}^{1}=\frac{k}{8}
\end{aligned}
$$

Therefore $k=8$
Method 2: This time we integrate in the $x$ direction first.

$x$ starts at the diagonal line $y=x$ and goes to $x=1$. The diagonal line has the equation $y=x$, which we solve for $x$ to get $x=y$. Thus
the lower limit is the function $x=y$. The upper limit is 1 , so the limits of the integral with respect to $x$ (inner integral) are $y$ and 1 . Then $y$ goes from 0 to 1 , so those are the limits for the integral with respect to $y$ (outer integral). Putting this together, we have:

$$
\begin{aligned}
1 & =\int_{0}^{1} \int_{y}^{1} k x y d x d y \\
& =k \int_{0}^{1} y\left[\frac{x^{2}}{2}\right]_{x=y}^{x=1} d y \\
& =\frac{k}{2} \int_{0}^{1} y\left(1-y^{2}\right) d y \\
& =\frac{k}{2} \int_{0}^{1}\left(y-y^{3}\right) d y \\
& =\frac{k}{2}\left[\frac{y^{2}}{2}-\frac{y^{4}}{4}\right]_{0}^{1}=\frac{k}{8}
\end{aligned}
$$

We get the same answer! Which one was easier?
Aside: Fubini's theorem says that for "nice" functions $f$, both ways will always give the same answer.

