# STAT 516: Multivariate Distributions Joint Density Function and its Role 

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## Basics

- Similarly to the case of a single continuous random variables, we talk about the joint probability density function (pdf) - not about individual pdfs
- Notes of caution:

1. The joint density function of all the variables does not equal the probability of a specific point in the multidimensional space
2. The joint density function reflects a relative importance of a particular point
3. For a general set $A$ in the multidimensional space, the probability that a random vector $\mathbb{X}$ belongs to $A$ is obtained by integrating the joint density function over the set $A$

## Definition

- Let $\mathbb{X}=\left(X_{1}, \ldots, X_{n}\right)$ be an $n$ - dimensional random vector taking values in $R^{n}$ for some $n, 1<n<\infty$
- We say that $f\left(x_{1}, \ldots, x_{n}\right)$ is the joint density or simply the density of $\mathbb{X}$ if, for all $a_{1}, \ldots, a_{n}, b_{1}, \ldots, b_{n}$ with

$$
-\infty<a_{i} \leq b_{i}<\infty
$$

$$
\begin{aligned}
& P\left(a_{1} \leq X_{1} \leq b_{1}, a_{2} \leq X_{2} \leq b_{2}, \ldots, a_{n} \leq X_{n} \leq b_{n}\right) \\
& =\int_{a_{n}}^{b_{n}} \cdots \int_{a_{2}}^{b_{2}} \int_{a_{1}}^{b_{1}} f\left(x_{1}, x_{2}, \ldots, x_{n}\right) d x_{1} \cdots d x_{n}
\end{aligned}
$$

## PDF properties

- In order that a function $f: R^{n} \rightarrow R$ be a density function of some $n$-dimensional random vector, it is necessary and sufficient that

1. $f\left(x_{1}, \ldots, x_{n}\right) \geq 0$ for any $\left(x_{1}, \ldots, x_{n}\right) \in R^{n}$
2. $\int_{R^{n}} f\left(x_{1}, \ldots, x_{n}\right) d x_{1} \ldots d x_{n}=1$

## The joint cumulative density function (CDF)

- Let $\mathbb{X}$ be an $n$ - dimensional random vector with the density function $f\left(x_{1}, \ldots, x_{n}\right)$. The joint CDF, or simply the CDF, of $\mathbb{X}$ is

$$
F\left(x_{1}, \ldots, x_{n}\right)=\int_{-\infty}^{x_{1}} \cdots \int_{-\infty}^{x_{1}} f\left(t_{1}, \ldots, t_{n}\right) d t_{1} \ldots d t_{n}
$$

- Both the CDF and the pdf completely specify the distribution of a continuous random vector
- The relation between the CDF and the pdf is

$$
f\left(x_{1}, \ldots, x_{n}\right)=\frac{\partial^{n}}{\partial x_{1} \ldots \partial x_{n}} F\left(x_{1}, x_{2}, \ldots, x_{n}\right)
$$

## Marginal densities

- Let $\mathbb{X}=\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ be a continuous random vector with a joint density $f\left(x_{1}, x_{2}, \ldots, x_{n}\right)$. Let $1 \leq p \leq n$. Then, the marginal joint density of $\left(X_{1}, X_{2}, \ldots, X_{p}\right)$ is given by

$$
f_{1,2, \ldots, p}\left(x_{1}, x_{2}, \ldots, x_{p}\right)=\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f\left(x_{1}, x_{2}, \ldots, x_{n}\right) d x_{p+1} \ldots, d x_{n}
$$

## Independence

- Let $\mathbb{X}=\left(X_{1}, X_{2}, \ldots, X_{n}\right)$ be a continuous random vector with a joint density $f\left(x_{1}, x_{2}, \ldots, x_{n}\right)$. Then, $X_{1}, X_{2}, \ldots, X_{n}$ are independent if and only if

$$
f\left(x_{1}, x_{2}, \ldots, x_{n}\right)=\prod_{i=1}^{n} f_{i}\left(x_{i}\right)
$$

- To prove one way, you have to integrate both sides of the factorization identity
- To prove the other way, you have to take the classical definition of independence

$$
F\left(x_{1}, \ldots, x_{n}\right)=\prod_{i=1}^{n} F_{i}\left(x_{i}\right)
$$

and partially differentiate both sides successively with respect to $x_{1}, \ldots, x_{n}$

## Example I

- Bivariate Uniform $-f(x, y)=1$ in the $[0,1] \times[0,1]$ rectangle and 0 otherwise
- Note that $f$ is always non-negative; moreover,

$$
\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) d x d y=\int_{0}^{1} \int_{0}^{1} f(x, y) d x d y=1
$$

- Thus, $f$ is a valid bivariate density function
- Check that the marginal density

$$
f(x)=\int_{0}^{1} f(x, y) d y=1
$$

for any $0 \leq x \leq 1$; thus, both $X \sim \operatorname{Unif}[0,1]$ and $Y \sim \operatorname{Unif}[0,1]$

- Furthermore, for any $x, y f(x, y)=f_{1}(x) f_{2}(y)$ and so $X$ and $Y$ are independent


## Example II

- Uniform distribution on a triangle: $f(x, y)=2$ for any $x, y \geq 0$ and $x+y \leq 1$
- In that case, the marginal density of $X$ is

$$
f_{1}(x)=\int_{0}^{1-x} 2 d y=2(1-x)
$$

for $0 \leq x \leq 1$

- Similarly, the marginal density of $Y$ is $f_{2}(y)=2(1-y)$ for $0 \leq y \leq 1$.
- Note that $P\left(\left.X>\frac{1}{2} \right\rvert\, Y>\frac{1}{2}\right)=0$; at the same time,

$$
P\left(x>\frac{1}{2}\right)=\int_{1 / 2}^{1} 2(1-x) d x=\frac{1}{4} \neq 0
$$

- Thus, $X$ and $Y$ are not independent


## Example III

- A joint density $f(x, y)=x \exp (-x(1+y))$ for $x, y \geq 0$
- It is obviously non-negative; note that

$$
\begin{aligned}
& \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) d x d y=\int_{0}^{\infty} \int_{0}^{\infty} x \exp (-x(1+y)) d x d y \\
& =\int_{0}^{\infty} \frac{1}{(1+y)^{2}} d y=\int_{1}^{\infty} \frac{1}{y^{2}} d y=1
\end{aligned}
$$

- Verify that $f_{1}(x)=\exp (-x)$ for any $x \geq 0$ and $f_{2}(y)=\frac{1}{(1+y)^{2}}$ for any $y \geq 0$
- Thus, the factorization identity is not true and $X$ and $Y$ are not independent

