## MVE055 2018 Lecture 4

Marco Longfils<br>Department of Mathematical Sciences, Chalmers University of Technology and University of Gothenburg

Wednesday $12^{\text {th }}$ September, 2018

## Joint distribution

- Up to now: univariate distribution $\rightarrow$ a single random value.
- Typically we need to consider multivariate distribution, used to model many uncertain values. In this way, we can take into account the dependencies between these quantities.
- We will now focus on bivariate distribution, but generalization to more variables is straightforward.


## Joint density function/1

## Definition (discrete joint density)

Let $X, Y$ be two discrete random variables. The vector $(X, Y)$ is a bivariate discrete random variable and a function $f_{X Y}$ which satisfies

$$
f_{X Y}(x, y)=\operatorname{Pr}[X=x, Y=y], \text { for } \operatorname{all}(x, y) \in \mathbb{R}^{2}
$$

is called joint density for the vector $(X, Y)$.

## Theorem

A function $f(x, y)$ is a discrete joint density if and only if

- $f(x, y) \geq 0$
- $\sum_{\text {all }(x, y)} f(x, y)=1$


## Definition (discrete marginal density)

Let $(X, Y)$ be a bivariate discrete random vector with joint density $f_{X Y}$. The marginal density $f_{X}$ for $X$ is given by

$$
f_{X}(x)=\sum_{\text {all } y} f_{X Y}(x, y)
$$

and similarly the marginal density for $Y$ is

$$
f_{Y}(y)=\sum_{\text {all } x} f_{X Y}(x, y)
$$

## Joint density function/2

## Definition (continuous joint density)

Let $X, Y$ be two continuous random variables. The vector $(X, Y)$ is a bivariate continuous random variable and a function $f_{X Y}$ which satisfies

- $f(x, y) \geq 0$
- $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) d y d x=1$
- $\operatorname{Pr}[X \in[a, b], Y \in[c, d]]=\int_{a}^{b} \int_{c}^{d} f(x, y) d y d x$, for all $a, b, c, d \in \mathbb{R}$ is called joint density for the vector $(X, Y)$.
Furthermore, the marginal densities $f_{X}$ and $f_{Y}$ for, respectively, $X$ and $Y$ are given by

$$
\begin{aligned}
& f_{X}(x)=\int_{-\infty}^{\infty} f_{X Y}(x, y) d y \\
& f_{Y}(y)=\int_{-\infty}^{\infty} f_{X Y}(x, y) d x
\end{aligned}
$$

## Independence of random variable

- Recall: two events $A, B$ are said to be independent if $\operatorname{Pr}[A \cap B]=\operatorname{Pr}[A] \operatorname{Pr}[B]$.


## Definition (independence for random variables)

Two random variables $X$ and $Y$ with joint density $f_{X Y}$ and marginal densities $f_{X}, f_{Y}$ are independent if and only if

$$
f_{X Y}(x, y)=f_{X}(x) f_{Y}(y)
$$

for all $x$ and $y$

## Expected value

- In general, the expected value of a function of $H(X, Y)$ is given by

$$
\mathbb{E}[H(X, Y)]=\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} H(x, y) f_{X Y}(x, y) d x d y
$$

if $X, Y$ are discrete and by

$$
\mathbb{E}[H(X, Y)]=\sum_{\text {all }(x, y)} H(x, y) f_{X Y}(x, y)
$$

- Same properties as in the discrete case.
- If $X, Y$ are independent then

$$
\mathbb{E}[X Y]=\mathbb{E}[X] \mathbb{E}[Y]
$$

(the viceversa is not true in general).

## Covariance

## Definition (Covariance)

Let $X$ and $Y$ be two random variables. The covariance between $X$ and $Y$ is defined as

$$
\operatorname{Cov}(X, Y)=\mathbb{E}[(X-\mathbb{E}[X])(Y-\mathbb{E}[Y])]
$$

It holds that

$$
\operatorname{Cov}(X, Y)=\mathbb{E}[X Y]-\mathbb{E}[X] \mathbb{E}[Y] .
$$

- If $X, Y$ are independent $\rightarrow \mathbb{E}[X Y]=\mathbb{E}[X] \mathbb{E}[Y] \rightarrow \operatorname{Cov}(X, Y)=0$ (the viceversa is not true in general).
- $\operatorname{Cov}(X, Y)$ gives an indication of association between $X$ and $Y$
- $\operatorname{Cov}(X, Y)$ can be any real value $\rightarrow$ no information about the strength of the dependence.


## Correlation

## Definition (Correlation)

Let $X$ and $Y$ be two random variables. The correlation between $X$ and $Y$ is defined as

$$
\rho_{X Y}=\frac{\operatorname{Cov}(X, Y)}{\sqrt{\operatorname{Var}[X] \operatorname{Var}[Y]}} .
$$

- $\rho_{X Y}$ measures linear dependence between $X$ and $Y$.
- $\rho_{X Y}$ can be any real value between -1 and 1 .
- $\left|\rho_{X Y}\right|=1$ if and only if $Y=\beta_{0}+\beta_{1} X$ for some $\beta_{0}$ and $\beta_{1} \neq 0$.


US spending on science, space, and technology
correlates with
Suicides by hanging, strangulation and suffocation


## Conditional density

- Recall: given two events $A, B$ (if $\operatorname{Pr}[B]>0)$ we have $\operatorname{Pr}[A \mid B]=\frac{\operatorname{Pr}[A \cap B]}{\operatorname{Pr}[B]}$.


## Definition (conditional density)

Given two random variables $X$ and $Y$ with joint density $f_{X Y}$ and marginal densities $f_{X}, f_{Y}$ we define the conditional density for $X$ given $Y=y$ as

$$
f_{X \mid y}=\frac{f_{X Y}(x, y)}{f_{Y}(y)}, \text { if } f_{Y}(y)>0
$$

## Transformation of variables

## Theorem

Let $(X, Y)$ be a continuous bivariate vector with density $f_{X Y}$. Moreover, let $(U, V)$ be a continuous bivariate vector with density $f_{U V}$ and

$$
(X, Y)=\left(h_{1}(U, V), h_{2}(U, V)\right)
$$

where $h_{1}$ and $h_{2}$ define a one-to-one transformation and have continuous partial derivatives. Then

$$
f_{U V}(u, v)=f_{X Y}\left(h_{1}(u, v), h_{2}(u, v)\right)|J|
$$

where $J$ is the given by

$$
J=\operatorname{det}\left[\begin{array}{ll}
\frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\
\frac{\partial y}{\partial u} & \frac{\partial y}{\partial v}
\end{array}\right]
$$

