

Lecture 5: Collections of Random Variables

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Independent random variables

Independent random variables

- We say that the two random variables are independent conditional on I , and we write:

$$X \perp Y \mid I$$

if and only if conditioning on one does not tell you anything about the other, i.e.,

$$P(x \mid y, I) = P(x \mid I)$$

- When there is no ambiguity, we can drop I .

$$P(x \mid y) = P(x)$$

Independent random variables

- It is easy to show using Bayes' rule that the definition is consistent.

$$X \perp Y \mid I \Rightarrow Y \perp X \mid I$$

- That is, if Y does not give you any information about X , then X does not give you any information about Y , i.e.,

$$\underline{p(x|y)} = p(x)$$

then it follows that \Rightarrow

$$p(y|x) = p(y).$$

Proof: $p(y|x) = \frac{p(x,y)}{p(x)} \stackrel{\text{Bayes' rule}}{=} \dots = p(y)$

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

Properties of independent random variables

- Assume X and Y are independent.
- Then, the joint pdf factorizes:

$$p(x, y) = p(x)p(y).$$

Proof : $X \perp Y \Rightarrow p(x|y) = p(x) \Leftrightarrow p(y|x) = p(y)$
 $X \perp Y$

Bayes' rule : $p(x, y) = \underline{p(x|y)} p(y) = p(x) p(y) \quad \square$

Properties of independent random variables

- Assume X and Y are independent.
- The expectation of the product is the product of the expectation:

$$\mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y].$$

Proof:
$$\begin{aligned}\mathbb{E}[XY] &= \iint xy \, \underline{p(x,y)} \, dx \, dy = \iint xy \, p(x) p(y) \, dx \, dy \\ &= \left(\int x p(x) \, dx \right) \cdot \left(\int y p(y) \, dy \right) \quad (\text{Fubini's Theorem}) \\ &= \mathbb{E}[X] \cdot \mathbb{E}[Y].\end{aligned}$$

Properties of independent random variables

- Assume X and Y are independent.
- The covariance is zero:

$$\mathbb{C}[X, Y] = 0.$$

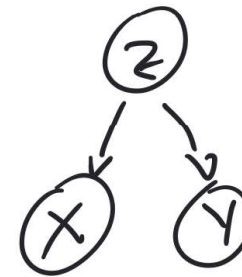
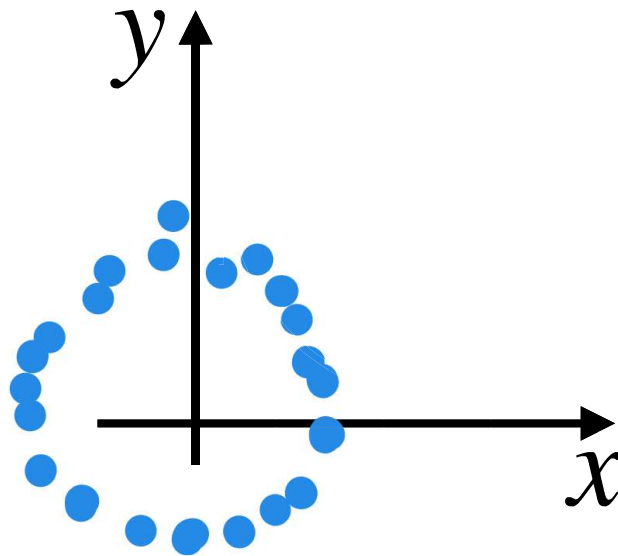
Proof: $C[X, Y] = E[(X - E[X]) \cdot (Y - E[Y])]$
 $= E[XY - X \cdot E[Y] - E[X] \cdot Y + E[X] \cdot E[Y]]$
 $= E[XY] - E[X \cdot \text{const.}] - E[\text{const.} \cdot Y] + E[\text{const.} \cdot \text{const.}]$
 $= E[XY] - E[Y] \cdot E[X] - E[X] \cdot E[Y] + E[X] \cdot E[Y]$
 $= 0$ $\Rightarrow X \perp Y \Rightarrow$ uncorrelated.
 $C[X, Y] = 0$

The reverse is not true! Uncorrelated variables do not have to be independent

$$Z \sim U([0, 2\pi])$$

$$X = \cos Z$$

$$Y = \sin Z$$



$$\mathbb{E}[X, Y] = 0,$$

but X and Y are
very dependent

Properties of independent random variables

- Assume X and Y are independent.
- The variance of the sum of two independent random variables is the sum of the variance of the random variables:

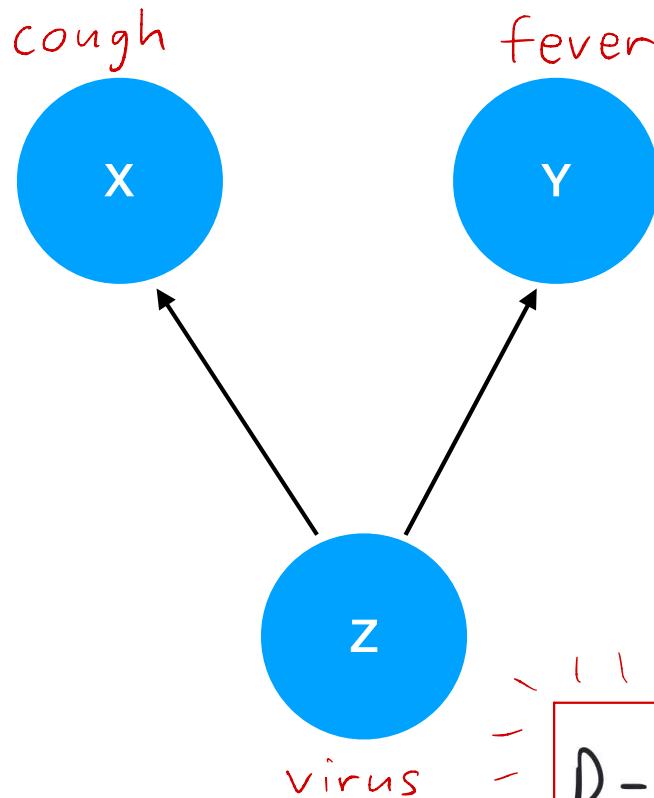
Must remember

$$\mathbb{V}[X + Y] = \mathbb{V}[X] + \mathbb{V}[Y].$$

Proof : $\mathbb{V}[X + Y] = \mathbb{V}[X] + \mathbb{V}[Y] + 2\mathbb{C}[X, Y]$
 $= \mathbb{V}[X] + \mathbb{V}[Y] . \quad \square$

(Note: In the original image, an arrow points from the handwritten '0' above the covariance term to the crossed-out term, indicating it is zero due to independence.)

Reading independence from causal graphs



- X and Y are not independent in general.

$$p(x, y) \neq p(x)p(y)$$

- But X is independent of Y conditioned on Z .

$$p(x, y | z) = p(x | z) p(y | z)$$

D-separation (advanced)

$$p(x=0, y=0) = p(x=0)p(y=0) = (0,3)(0,3) = 0,09$$

$$p(x=0, y=1) = p(x=0)p(y=1) = (0,3)(0,7) = 0,21$$

$$p(x=1, y=1) = p(x=1)p(y=1) = (0,7)(0,7) = 0,49$$

$$E[XY] = E[X]E[Y]$$

$$= \sum_x x p(x) \sum_y y p(y)$$

$$= [0(0,3) + 1(0,7)] [0(0,3) + 1(0,7)]$$

$$= (0,7)(0,7) = 0,49$$