

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.,

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

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

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

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.,

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

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

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

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: $\mathbb{C}[X, Y] = \mathbb{E}[(X - \mathbb{E}[X]) \cdot (Y - \mathbb{E}[Y])]$

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

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

const. *const.* *const.*

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

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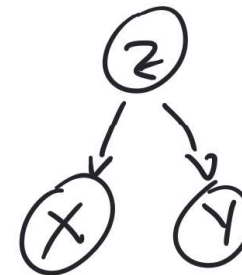
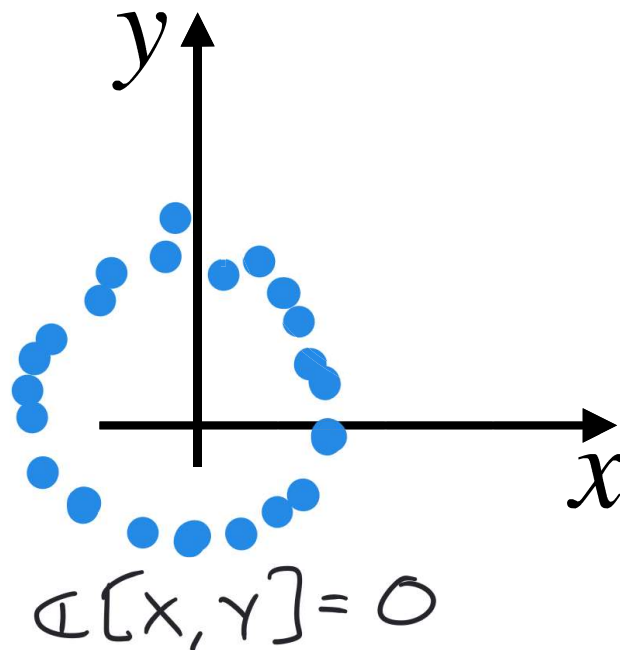
$$\mathbb{E}[X] \cdot \mathbb{E}[Y] \quad (X \perp Y) \quad = 0 \quad \& \quad X \perp Y \Rightarrow \text{uncorrelated.}$$

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

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

$$X = \cos Z$$

$$Y = \sin Z$$



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:

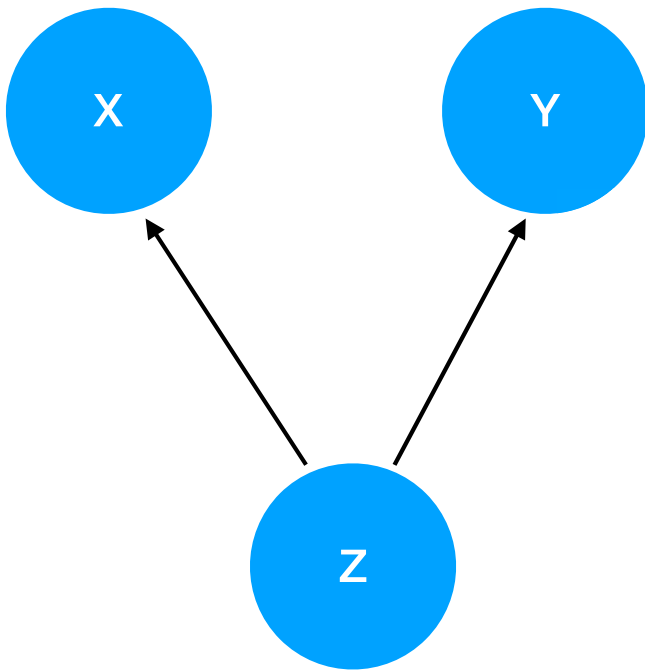
Must remember

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

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)