

Introduction to Data Science With Probability and Statistics

Lecture 18 & 19: Joint Distributions & Covariance

CSCI 3022 - Summer 2020

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Joint Distributions of Discrete Random Variables

The joint distribution of two discrete random variables X and Y , defined on the *same* sample space Ω , is given by prescribing the probabilities of all possible values of the pair (X, Y) .

DEFINITION. The *joint probability mass function* p of two discrete random variables X and Y is the function $p : \mathbb{R}^2 \rightarrow [0, 1]$, defined by

$$p(a, b) = \mathbb{P}(X = a, Y = b) \quad \text{for } -\infty < a, b < \infty.$$



Joint Distributions of Discrete Random Variables

List the elements of the event $\{S = 7, M = 4\}$ and compute its probability, where S and M being the sum and the maximum of two independent throws of a die.



Joint Distributions of Discrete Random Variables

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$(3, 4)$ and $(4, 3)$

$$P(S=7, M=4) = \frac{2}{36}$$



Joint Distributions of Discrete Random Variables

Joint probability mass function $p(a, b) = P(S = a, M = b)$

| a | b | | | | | |
|-----|------|------|------|------|------|------|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| 2 | 1/36 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 2/36 | 0 | 0 | 0 | 0 |
| 4 | 0 | 1/36 | 2/36 | 0 | 0 | 0 |
| 5 | 0 | 0 | 2/36 | 2/36 | 0 | 0 |
| 6 | 0 | 0 | 1/36 | 2/36 | 2/36 | 0 |
| 7 | 0 | 0 | 0 | 2/36 | 2/36 | 2/36 |
| 8 | 0 | 0 | 0 | 1/36 | 2/36 | 2/36 |
| 9 | 0 | 0 | 0 | 0 | 2/36 | 2/36 |
| 10 | 0 | 0 | 0 | 0 | 1/36 | 2/36 |
| 11 | 0 | 0 | 0 | 0 | 0 | 2/36 |
| 12 | 0 | 0 | 0 | 0 | 0 | 1/36 |

What about $P(S=a)$?

$$\begin{aligned} P(S=5) &= P(S=5, M=1) \\ &+ P(S=5, M=2) \\ &+ P(S=5, M=3) \\ &+ \dots \\ &P(S=5, M=6) \end{aligned}$$

Joint Distributions of Discrete Random Variables

Joint distribution and marginal distributions of S and M

| a | b | | | | | | $p_S(a)$ |
|----------|------|------|------|------|------|-------|----------|
| | 1 | 2 | 3 | 4 | 5 | 6 | |
| 2 | 1/36 | 0 | 0 | 0 | 0 | 0 | 1/36 |
| 3 | 0 | 2/36 | 0 | 0 | 0 | 0 | 2/36 |
| 4 | 0 | 1/36 | 2/36 | 0 | 0 | 0 | 3/36 |
| 5 | 0 | 0 | 2/36 | 2/36 | 0 | 0 | 4/36 |
| 6 | 0 | 0 | 1/36 | 2/36 | 2/36 | 0 | 5/36 |
| 7 | 0 | 0 | 0 | 2/36 | 2/36 | 2/36 | 6/36 |
| 8 | 0 | 0 | 0 | 1/36 | 2/36 | 2/36 | 5/36 |
| 9 | 0 | 0 | 0 | 0 | 2/36 | 2/36 | 4/36 |
| 10 | 0 | 0 | 0 | 0 | 1/36 | 2/36 | 3/36 |
| 11 | 0 | 0 | 0 | 0 | 0 | 2/36 | 2/36 |
| 12 | 0 | 0 | 0 | 0 | 0 | 1/36 | 1/36 |
| $p_M(b)$ | 1/36 | 3/36 | 5/36 | 7/36 | 9/36 | 11/36 | 1 |

- The marginal distribution of a subset of a collection of random variables is the probability distribution of the variables contained in the subset.
- Summing over the columns of the table yields the marginal distribution of M

Joint Distributions of Continuous Random Variables

- We know that the probability that a single continuous random variable X lies in an interval $[a, b]$, is equal to the area under the probability density function f of X over the interval.
- For the joint distribution of continuous random variables X and Y , the probability that the pair (X, Y) falls in the rectangle $[a_1, b_1] \times [a_2, b_2]$ is equal to the volume under the joint probability density function $f(x, y)$ of (X, Y) over the rectangle.

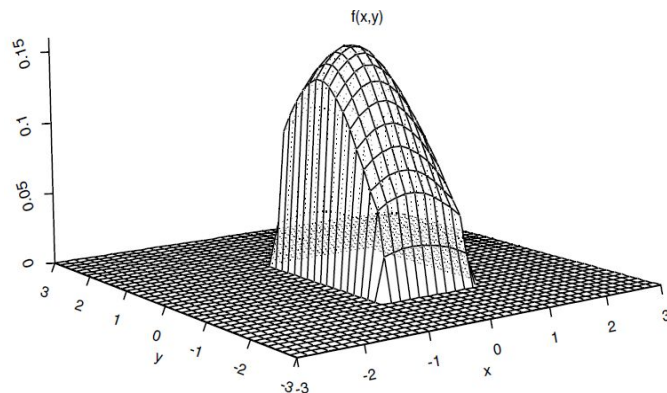


Joint Distributions of Continuous Random Variables

DEFINITION. Random variables X and Y have a *joint continuous distribution* if for some function $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ and for all numbers a_1, a_2 and b_1, b_2 with $a_1 \leq b_1$ and $a_2 \leq b_2$,

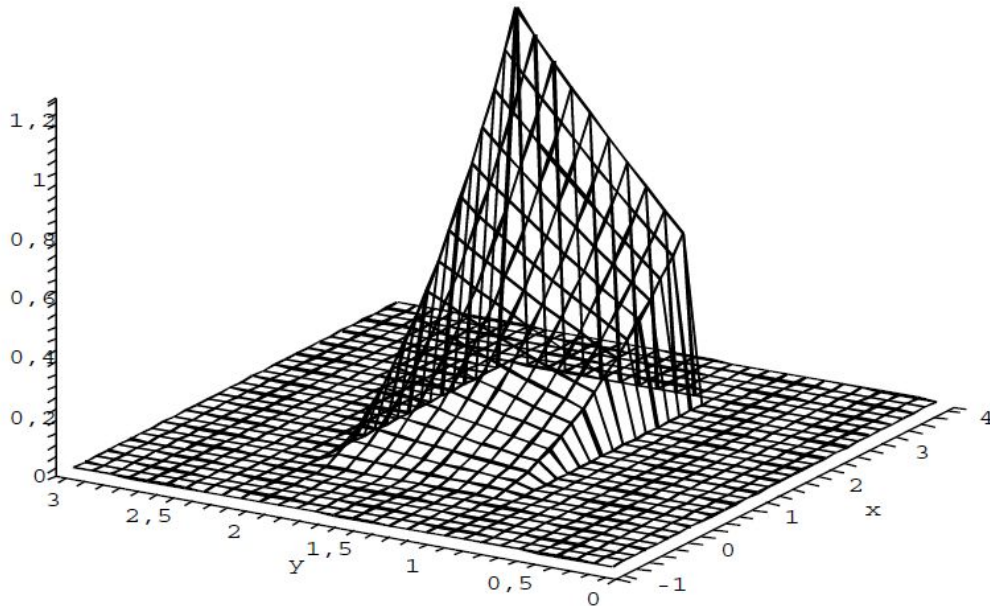
$$P(a_1 \leq X \leq b_1, a_2 \leq Y \leq b_2) = \int_{a_1}^{b_1} \int_{a_2}^{b_2} f(x, y) \, dx \, dy.$$

The function f has to satisfy $f(x, y) \geq 0$ for all x and y , and $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \, dx \, dy = 1$. We call f the *joint probability density function* of X and Y .



Bivariate Normal Probability Density Function

$$f(x, y) = \frac{2}{75}(2x^2y + xy^2) \quad \text{for } 0 \leq x \leq 3 \text{ and } 1 \leq y \leq 2, \text{ and } f(x, y) = 0 \text{ otherwise;}$$



Bivariate Normal Probability Density Function

$$P\left(1 \leq X \leq 2, \frac{4}{3} \leq Y \leq \frac{5}{3}\right) = ?$$



Bivariate Normal Probability Density Function

$$P\left(1 \leq X \leq 2, \frac{4}{3} \leq Y \leq \frac{5}{3}\right) = ? \quad \int_1^2 \int_{4/3}^{5/3} f(x,y) dx dy$$

$$= \frac{2}{75} \int_1^2 \left(\int_{4/3}^{5/3} (2x^2y + xy^2) dy \right) dx$$

$$= \frac{2}{75} \int_1^2 \left(x^2 + \frac{61}{81}x \right) dx = \frac{187}{2025}$$

Bivariate Normal Probability Distribution Function

$$F(a,b) = P(X \leq a, Y \leq b)$$

$$= \int_{-\infty}^a \int_{-\infty}^b f(x,y) dy dx$$

$$= \frac{2}{75} \int_0^a \left(\int_1^b (2x^2y + xy^2) dy \right) dx$$

$$= \frac{1}{225} (2a^3b^2 - 2a^3 + a^2b^3 - a^2)$$

Joint Distributions of Continuous Random Variables

FROM JOINT TO MARGINAL PROBABILITY DENSITY FUNCTION. Let f be the joint probability density function of random variables X and Y . Then the *marginal* probability densities of X and Y can be found as follows:

$$f_X(x) = \int_{-\infty}^{\infty} f(x, y) \, dy \quad \text{and} \quad f_Y(y) = \int_{-\infty}^{\infty} f(x, y) \, dx.$$



Joint Distributions of Continuous Random Variables

$$\begin{aligned} f_x(x) &= \int_{-\infty}^{\infty} f(x,y) dy \\ &= \frac{2}{75} \int_1^2 (2x^2y + xy^2) dy \\ &= \frac{2}{225} (9x^2 + 7x) \end{aligned}$$



Independent random variables

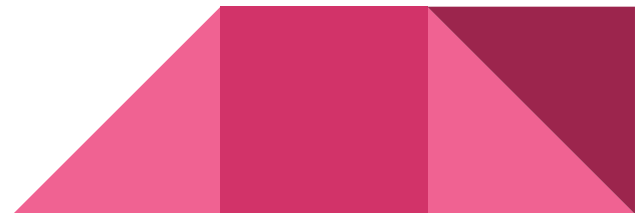
DEFINITION. The random variables X and Y , with joint distribution function F , are *independent* if

$$P(X \leq a, Y \leq b) = P(X \leq a)P(Y \leq b),$$

that is,

$$F(a, b) = F_X(a)F_Y(b) \tag{9.4}$$

for all possible values a and b . Random variables that are not independent are called *dependent*.



Independent random variables

$$1). P(X \in A, Y \in B) = P(X \in A) P(Y \in B)$$

True for both discrete and continuous.

$$2). f(x, y) = f_x(x) \cdot f_y(y) \quad ; \quad f(\cdot) : \text{prob. density functions.}$$

And the general version, with more than 2 R.Vs, also holds.

$$f(x_1, x_2, \dots, x_n) = f_{x_1}(x_1) \cdot f_{x_2}(x_2) \cdot \dots \cdot f_{x_n}(x_n)$$

Propagation of independence

PROPAGATION OF INDEPENDENCE. Let X_1, X_2, \dots, X_n be independent random variables. For each i , let $h_i : \mathbb{R} \rightarrow \mathbb{R}$ be a function and define the random variable

$$Y_i = h_i(X_i).$$

Then Y_1, Y_2, \dots, Y_n are also independent.



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$$Y_i = h_i(X_i).$$

Then Y_1, Y_2, \dots, Y_n are also independent.

for instance; if x, y, z are independent,
then $x^2, 2y, 4z+3$ are also independent.

Expectation and joint distributions

Example:- China vases of various shapes are produced in the Delftware factories in the old city of Delft. One particular simple cylindrical model has height H and radius R centimeters. Due to certain circumstances (manual error), H and R are not constants but are random variables.

The volume of a vase is equal to the random variable $V = \pi H R^2$,

$$E[V] = \int_{-\infty}^{\infty} v f_V(v) dv, \quad f_V \text{ denotes the probability density of } V$$

$$E[V] = E[\pi H R^2] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \pi h r^2 f(h, r) dh dr$$

Expectation and joint distributions

$E[V] = ?$ Suppose, $H = U(25, 35)$ & $R = U(7.5, 12.5)$



Expectation and joint distributions

$$\begin{aligned} E[V] &= \int_{25}^{35} \int_{7.5}^{12.5} \pi h r^2 \cdot \frac{1}{10} \cdot \frac{1}{5} dh dr \\ &= \frac{\pi}{50} \int_{25}^{35} h dh \int_{7.5}^{12.5} r^2 dr \\ &= 9621 \cdot 127 \text{ cm}^2 \end{aligned}$$

Expectation and joint distributions

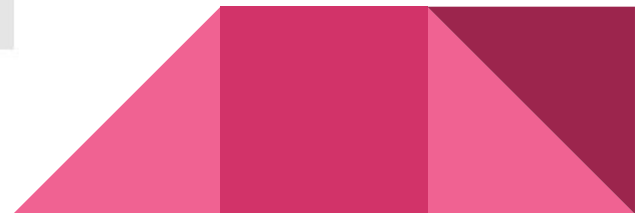
TWO-DIMENSIONAL CHANGE-OF-VARIABLE FORMULA. Let X and Y be random variables, and let $g : \mathbb{R}^2 \rightarrow \mathbb{R}$ be a function.

If X and Y are *discrete* random variables with values a_1, a_2, \dots and b_1, b_2, \dots , respectively, then

$$\mathbb{E}[g(X, Y)] = \sum_i \sum_j g(a_i, b_j) \mathbb{P}(X = a_i, Y = b_j).$$

If X and Y are *continuous* random variables with joint probability density function f , then

$$\mathbb{E}[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f(x, y) \, dx \, dy.$$



Expectation and joint distributions

Example: Take $g(x, y) = xy$ for discrete random variables X and Y with the joint probability distribution given in table below. The expectation of XY is computed as follows: $E[XY] = ?$

$$\begin{aligned} E[XY] &= \sum_x \sum_y (xy) \cdot P(X=x, Y=y) \\ &= (0 \cdot 0) \cdot 0 + (1 \cdot 0) \cdot 1/4 + (2 \cdot 0) \cdot 0 \\ &\quad + (0 \cdot 1) \cdot 1/4 + (1 \cdot 1) \cdot 0 + (2 \cdot 1) \cdot 1/4 \\ &\quad + (0 \cdot 2) \cdot 0 + (1 \cdot 2) \cdot \frac{1}{4} + (2 \cdot 2) \cdot 0 \\ &= 1. \end{aligned}$$

| b | a | | |
|-----|-----|-----|-----|
| | 0 | 1 | 2 |
| 0 | 0 | 1/4 | 0 |
| 1 | 1/4 | 0 | 1/4 |
| 2 | 0 | 1/4 | 0 |

Covariance

We saw $E[X + Y] = E[X] + E[Y]$

Does such a simple relation also hold for the variance of the sum $\text{Var}(X + Y)$ or for expectation of the product $E[XY]$?

Let X and Y be two random variables with joint probability density as

$$f(x, y) = \frac{2}{75} (2x^2y + xy^2) \quad \text{for } 0 \leq x \leq 3 \text{ and } 1 \leq y \leq 2.$$

$$\begin{aligned} \text{Var}(X + Y) &= 939/2000 \\ \text{Var}(X) + \text{Var}(Y) &= \frac{4747}{10000} \end{aligned} \quad \neq$$

Covariance

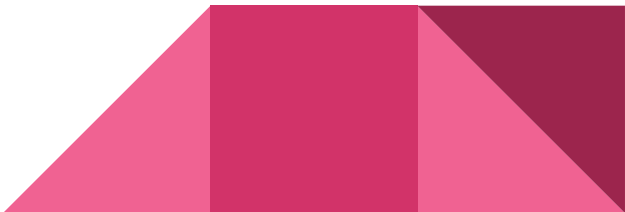
$$\begin{aligned}\text{Var}(x+y) &= E[(x+y - E[x+y])^2] \\&= E\left[\left(\underbrace{(x - E[x])}_{\text{Var}(x)} + \underbrace{(y - E[y])}_{\text{Var}(y)}\right)^2\right] \\&= E[(x - E[x])^2] + E[(y - E[y])^2] \\&\quad + 2E[(x - E[x])(y - E[y])]\end{aligned}$$

$$\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y) + \underbrace{2E[(x - E[x])(y - E[y])]}_{\text{Covariance}}$$

Covariance

DEFINITION. Let X and Y be two random variables. The *covariance* between X and Y is defined by

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

- If the covariance of X and Y is positive, we say that X and Y are positively correlated.
 - If the covariance of X and Y is negative, we say that X and Y are negatively correlated.
 - If the covariance of X and Y is zero, we say that X and Y are uncorrelated.
- 

Covariance

AN ALTERNATIVE EXPRESSION FOR THE COVARIANCE. Let X and Y be two random variables, then

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




Independent versus uncorrelated

Let X and Y be two independent random variables.

$$\begin{aligned} \mathbb{E}[XY] &= \sum_i \sum_j a_i b_j \mathbb{P}(X = a_i, Y = b_j) \\ &= \sum_i \sum_j a_i b_j \mathbb{P}(X = a_i) \mathbb{P}(Y = b_j) \\ &= \left(\sum_i a_i \mathbb{P}(X = a_i) \right) \left(\sum_j b_j \mathbb{P}(Y = b_j) \right) \\ &= \mathbb{E}[X] \mathbb{E}[Y]. \end{aligned}$$

Independent versus uncorrelated: If two random variables X and Y are independent, then X and Y are uncorrelated.



Covariance

Consider the random variables X and Y with the joint distribution given in below. Check that X and Y are dependent, but that also $E[XY] = E[X]E[Y]$.

$$P(X=0, Y=0) \neq P(X=0) P(Y=0)$$

$0 \qquad \qquad \qquad \frac{1}{4} \qquad \qquad \frac{1}{4}$

$$E[XY] = 1 = E[X] E[Y]$$

$$0 \cdot \frac{1}{4} + 1 \cdot \frac{1}{2} + 2 \cdot \frac{1}{4} = 1$$

| | | a | | | |
|----------|---------------|---------------|---------------|---------------|---------------|
| | | | | | |
| b | | 0 | 1 | 2 | $P(Y=b)$ |
| 0 | 0 | 0 | $\frac{1}{4}$ | 0 | $\frac{1}{4}$ |
| 1 | $\frac{1}{4}$ | 0 | 0 | $\frac{1}{4}$ | $\frac{1}{2}$ |
| 2 | 0 | $\frac{1}{4}$ | 0 | 0 | $\frac{1}{4}$ |
| $P(X=a)$ | | $\frac{1}{4}$ | $\frac{1}{2}$ | $\frac{1}{4}$ | |

Covariance

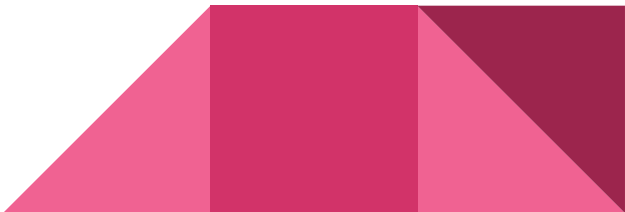
VARIANCE OF THE SUM. Let X and Y be two random variables.
Then always

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y).$$

If X and Y are *uncorrelated*,

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y).$$

We always have that $E[X + Y] = E[X] + E[Y]$, whereas $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$ only holds for uncorrelated random variables (and hence for independent random variables!)



Covariance Change of Units

COVARIANCE UNDER CHANGE OF UNITS. Let X and Y be two random variables. Then

$$\text{Cov}(rX + s, tY + u) = rt \text{Cov}(X, Y)$$

for all numbers r, s, t , and u .

For instance;

X, Y be temperatures in F

$rX + s, tY + u$ are in $^{\circ}C$.

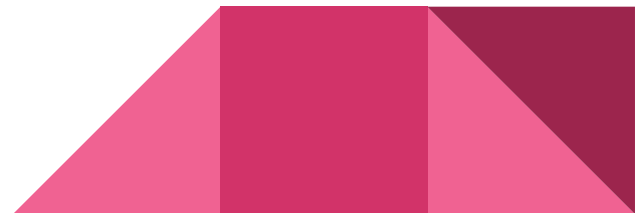


Covariance Change of Units

For X and Y having joint probability distribution function as below:-

$$f(x, y) = \frac{2}{75}(2x^2y + xy^2) \quad \text{for } 0 \leq x \leq 3 \text{ and } 1 \leq y \leq 2, \text{ and } f(x, y) = 0 \text{ otherwise;}$$

Find $\text{Cov}(-2X + 7, 5Y - 3)$



Covariance Change of Units

For X and Y having joint probability distribution function as below:-

$$f(x, y) = \frac{2}{75}(2x^2y + xy^2) \quad \text{for } 0 \leq x \leq 3 \text{ and } 1 \leq y \leq 2, \text{ and } f(x, y) = 0 \text{ otherwise;}$$



The correlation coefficient

A standardized version of the covariance called the correlation coefficient of X and Y

DEFINITION. Let X and Y be two random variables. The *correlation coefficient* $\rho(X, Y)$ is defined to be 0 if $\text{Var}(X) = 0$ or $\text{Var}(Y) = 0$, and otherwise

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}}.$$

Important Property:



The correlation coefficient

For X and Y in the previous problem, find $\rho(-2X + 7, 5Y - 3)$



The correlation coefficient

For X and Y in the previous problem, find $\rho(-2X + 7, 5Y - 3)$

