Probability and Statistics

Omid Safarzadeh

February 10, 2022

Table of contents

***Acknowledgement**: This slide is prepared based on Casella and Berger, 2002

Joint Distribution

- Multivariate models, involve more than one variable.
- Sleeping behaviour of a couple example
- Suppose, for example, that with each point in a sample space we associate an ordered pair of numbers, that is, a point $(x, y) \in \mathbb{R}^2$, where $\mathbb{R}^2$ denotes the plane. Then, we have defined a two-dimensional (or bivariate) random vector (X, Y).

Definition 1.1

An n-dimensional random vector is a function from a sample space Ω into $\mathbb{R}^n$, n-dimensional Euclidean space.

Joint Distribution

Example 1.1

- let

$$X = \text{sum of the two dice} \quad \& \quad Y = |\text{difference of the two dice}|.$$

question: What is, $P(X = 5 \text{ and } Y = 3)$?,
observe that:

$$(3,3) \; :: X = 6 \quad \text{and} \quad Y = 0,$$

$$(4,1) \; :: X = 5 \quad \text{and} \quad Y = 3,$$

Now the bivariate random vector (X, Y) can be defined.

Joint Distribution

- Just two sample points in Ω are (4,1) and (1,4) which are in our interest. Therefore, the event $\{X = 5 \text{ and } Y = 3\}$ will only occur if the event $\{(4,1),(1,4)\}$ occurs. Since each of these sample points in Ω are equally likely,

$$P(\{(4,1),(1,4)\}) = \frac{2}{36} = \frac{1}{18}.$$

  Thus,

$$P(X = 5 \text{ and } Y = 3) = \frac{1}{18}.$$

- For example, can you see why

$$P(X = 7, Y \leq 4) = \frac{1}{9}?$$

  This is because the only sample points that yield this event are (4,3), (3,4), (5,2) and (2,5).

Joint Distribution

Definition 1.2

Let (X, Y) be a discrete bivariate random vector. Then the function $f(x, y)$ form $\mathbb{R}^2$ into $\mathbb{R}$, defined by $f(x, y) = P(X = x, Y = y)$ is called the joint probability mass function or joint pmf (X,Y). If it is necessary to stress the fact that f is the joint pmf of the vector (X, Y) rather than some vector, the notation $f_{X,Y}(x, y)$ will be used.

Joint Distribution

- As before, we can use the joint pmf to calculate the probability of any event defined in terms of (X, Y). For $A \subset \mathbb{R}^2$,

$$P((X, Y) \in A) = \sum_{\{x,y\} \in A} f(x, y).$$

- We could, for example, have $A = \{(x, y) : x = 7 \text{ and } y \leq 4\}$. Then,

$$P((X, Y) \in A) = P(X = 7, Y \leq 4) = f(7, 1) + f(7, 3) = \frac{1}{18} + \frac{1}{18} = \frac{1}{9}.$$

- Let $g(x, y)$ be a real-valued function defined for all possible values (x, y) of the discrete random vector (X,Y). Then, $g(X, Y)$ is itself a random variable and its expected value is

$$E[g(X, Y)] = \sum_{(x,y) \in \mathbb{R}^2} g(x, y) f(x, y).$$

Joint Distribution

Example 1.2

For the (X, Y) whose joint pmf is given in the above Table, what is the expected value of XY? Letting $g(x, y) = xy$, we have

$$E[XY] = 2 * 0 * \frac{1}{36} + 4 * 0 * \frac{1}{36} + ... + 8 * 4 * \frac{1}{36} + 7 * 5 * \frac{1}{18} = 13\frac{1}{18}.$$

- As before,

$$E[ag_1(X, Y) + bg_2(X, Y) + c] = aE[g_1(X, Y)] + E[bg_2(X, Y)] + c.$$

- One very useful result is that any non-negative function from $\mathbb{R}^2$ into $\mathbb{R}$ that is nonzero for at most a countable number of (x, y) pairs sums to 1 is the joint pmf for some bivariate discrete random vector (X, Y).

Example 1.3

Define $f(x, y)$ by

$$f(0,0) = f(0,1) = 1/6,$$

$$f(1,0) = f(1,1) = 1/3,$$

$$f(x,y) = 0 \qquad \text{for any other } (x,y)$$

Marginal Distribution

- Suppose we have a multivariate random variable (X, Y) but are concerned with, say, $P(X = 2)$ only.
- We know the joint pmf $f_{X,Y}(x, y)$ but we need $f_X(x)$ in this case.

Theorem 1.1

Let (X, Y) be a discrete bivariate random vector with joint pmf $f_{X,Y}(x, y)$. Then the marginal pmfs of X and Y, $f_X(x) = P(X = x)$ and $f_Y(y) = P(Y = y)$, are given by

$$f_X(x) = \sum_{y \in \mathbb{R}} f_{X,Y}(x, y) \quad \text{and} \quad f_Y(y) = \sum_{x \in \mathbb{R}} f_{X,Y}(x, y)$$

Marginal Distribution

Example 1.4

Now we can compute the marginal distribution for X and Y from the joint distribution given in the above Table. Then

$$f_Y(0) = f_{X,Y}(2,0) + f_{X,Y}(4,0) + f_{X,Y}(6,0)$$

$$+f_{X,Y}(8,0) + f_{X,Y}(10,0) + f_{X,Y}(12,0)$$

$$= 1/6.$$

As an exercise, you can check that,

$$f_Y(1) = 5/18, \quad f_Y(2) = 2/9, \quad f_Y(3) = 1/6, \quad f_Y(4) = 1/9, \quad f_Y(5) = 1/18.$$

Notice that $\sum_{y=0}^{5} f_Y(y) = 1$, as expected, since these are the only six possible values of Y.

Marginal Distribution

- Now, it is crucial to understand that the marginal distribution of X and Y, described by the marginal pmfs $f_X(x)$ and $f_Y(y)$, do not completely describe the joint distribution of X and Y.
- These are, in fact, many different joint distributions that have the same marginal distributions.

Marginal distribution

Example 1.5

Define a joint pmf by

$$f(0,0) = 1/12, \quad f(1,0) = 5/12, \quad f(0,1) = f(1,1) = 3/12,$$

$$f(x,y) = 0 \qquad \text{for all other values.}$$

- Then,

$$f_Y(0) = f(0,0) + f(1,0) = 1/2,$$
$$f_Y(1) = f(0,1) + f(1,1) = 1/2,$$
$$f_X(0) = f(0,0) + f(0,1) = 1/3,$$

  and

$$f_X(1) = f(1,0) + f(1,1) = 2/3.$$

Example 1.5 cont.

- Now consider the marginal pmfs for the distribution considered in Example (1.3).

$$f_Y(0) = f(0,0) + f(1,0) = 1/6 + 1/3 = 1/2,$$
$$f_Y(1) = f(0,1) + f(1,1) = 1/6 + 1/3 = 1/2,$$
$$f_X(0) = f(0,0) + f(0,1) = 1/6 + 1/6 = 1/3,$$

and

$$f_X(1) = f(1,0) + f(1,1) = 1/3 + 1/3 = 2/3.$$

- We have the same marginal pmfs but the joint distributions are different!

Joint distribution Continuous

Definition 1.3

A function $f(x, y)$ from $\mathbb{R}^2$ to $\mathbb{R}$ is called a joint probability density function or joint pdf of the continuous bivariate random vector (X, Y) if, for every $A \subset \mathbb{R}^2$,

$$P((X, Y) \in A) = \int \int_A f(x, y) dxdy.$$

- The notation $\int \int_A$ means that the integral is evaluated over all $(x, y) \in A$.
- Naturally, for real valued functions $g(x, y)$,

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

- It is important to realise that the joint pdf is defined for all $(x, y) \in \mathbb{R}^2$. The pdf may equal 0 on a large set A if $P((X, Y) \in A) = 0$ but the pdf is still defined for the points in A.

marginal distribution Continuous Case

- for marginal distributions:

$$f_X(x) = \int_{-\infty}^{\infty} f(x,y)dy, \quad -\infty < x < \infty,$$

$$f_Y(x) = \int_{-\infty}^{\infty} f(x,y)dx, \quad -\infty < y < \infty.$$

- As before, a useful result is that any function $f(x,y)$ satisfying $f(x,y) \geq 0$ for all $(x,y) \in \mathbb{R}^2$ and

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

is the joint pdf of some continuous bi variate random vector (X, Y).

Joint and Marginal distribution

- The joint probability distribution of (X, Y) can be completely described using the joint cdf (cumulative distribution function) rather than with the joint pmf or joint pdf.
- The joint cdf is the function $F(x, y)$ defined by

$$F(x, y) = P(X \leq x, Y \leq y) \quad \text{for all (x,y) } (x, y) \in \mathbb{R}^2.$$

- Although for discrete random vectors it might not be convenient to use the joint cdf, for continuous random variables, the following relationship makes the joint cdf very useful:

$$F(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(s, t) dsdt.$$

- From the bivariate Fundamental Theorem of Calculus,

$$\frac{\partial^2 F(x, y)}{\partial x \partial y}$$

at continuously points of $f(x, y)$. This relationship is very important.

Conditional Distributions and Independence

- We have talked a little bit about conditional probabilities before. Now we will consider conditional distributions.
- The idea is the same. If we have some extra information to make better inference.
- Suppose we are sampling from a population where X is the height (in kgs) and Y is the weight (in cms). What is $P(X > 95)$? Would we have a better/more relevant answer if we knew that the person in question has $Y = 202cms$? Usually, $P(X > 95|Y = 202)$ is supposed to be much larger than $P(X > 95|Y = 165)$.
- Once we have the joint distribution for (X, Y), we can calculate the conditional distributions, as well.
- Notice that now we have three distribution concepts: marginal distribution, conditional distribution and joint distribution.

Conditional Distributions and Independence

Definition 2.1

Let (X, Y) be a discrete bivariate random vector with joint pmf $f(x, y)$ and marginal pmfs $f_X(x)$ and $f_Y(y)$. For any x such that $P(X = x) = f_X(x) > 0$, the conditional pmf of Y given that $X = x$ is the function of y denoted by $f(y|X)$ and defined by

$$f(y|x) = P(Y = y|X = x) = \frac{f(x, y)}{f_X(x)}.$$

$Y = y$ is the function of x denoted by $f(x|y)$ and defined by

$$f(x|y) = P(X = x|Y = y) = \frac{f(x, y)}{f_Y(y)}.$$

- Can we verify that, say, $f(y|x)$ is a pmf? First, since $f(x, y) \geq 0$ and $f_X(x) > 0$. $f(y|x) \geq 0$ for every y. Then,

$$\sum_y f(y|x) = \frac{\sum_y f(x, y)}{f_X(x)} = \frac{f_X(x)}{f_X(x)} = 1.$$

Conditional Distributions

Example 3.1

Define the joint pmf of (X, Y) by

$$f(0,10) = f(0,20) = \frac{2}{18}, \;\; f(1,10) = f(1,30) = \frac{3}{18},$$

$$f(1,20) = \frac{4}{18} \quad \text{and} \quad f(2,30) = \frac{4}{18},$$

while $f(x,y) = 0$ for all other combinations of (x,y).

- Then,

$$f_X(0) = f(0,10) + f(0,20) = \frac{4}{18},$$

$$f_X(1) = f(1,10) + f(1,20) + f(1,30) = \frac{10}{18},$$

$$f_X(2) = f(2,30) = \frac{4}{18}.$$

EXample 2.1 cont.

- Moreover,

$$f(10|0) = \frac{f(0,10)}{f_X(0)} = \frac{2/18}{4/18} = \frac{1}{2},$$

$$f(20|0) = \frac{f(0,20)}{f_X(0)} = \frac{2/18}{4/18} = \frac{1}{2},$$

Therefore, given the knowledge that $X = 0$, Y is equal to either 10 or 20, with equal probability.

- In addition,

$$f(10|1) = f(30|1) = \frac{3/18}{10/18} = \frac{3}{10},$$

$$f(20|1) = \frac{4/18}{10/18} = \frac{4}{10},$$

$$f(30|2) = \frac{4/18}{4/18} = 1.$$

Interestingly, when $X = 2$, we know for sure that Y will be equal to 30.

- Finally,

$$P(Y > 10|X = 1) = f(20|1) + f(30|1) = \frac{7}{10},$$

$$P(Y > 10|X = 0) = f(20|0) = \frac{1}{2},$$

etc...

Conditional Distributions

Definition 3.1

Let (X, Y) be a continuous bivariate random vector with joint pdf $f(X, y)$ and marginal pdfs $f_X(x)$ and $f_Y(y)$. For any x such that $f_X(x) > 0$, the conditional pdf of Y given that $X = x$ is the function of y denoted by $f(y|x)$ and defined by

$$f(y|x) = \frac{f(x, y)}{f_X(x)}.$$

For any y such that $f_Y(y) > 0$, the conditional pdf of X given that $Y = y$ is the function of x denoted by $f(x|y)$ and defined by

$$f(x|y) = \frac{f(x, y)}{f_Y(y)}.$$

Conditional Expected Values

- The conditional expected value of $g(Y)$ given $X = x$ is given by

$$E[g(Y)|x] = \sum_y g(y)f(y|x) \quad \text{and} \quad E[g(Y)|x] = \int_{-\infty}^{\infty} g(y)f(y|x)dx,$$

Independence

Definition 3.2

Let (X, Y) be a bivariate random vector with joint pdf or pmf $f(x, y)$ and marginal pdfs or pmfs $f_X(x)$ and $f_Y(y)$. Then X and Y are called independent random variables if, for every $x \in \mathbb{R}$ and $y \in \mathbb{R}$,

$$f(x, y) = f_X(x) f_Y(y). \tag{1}$$

Independence

- Now, in the case of independence, clearly,

$$f(y|x) = \frac{f(x,y)}{f_X(x)} = \frac{f_X(x)f_Y(y)}{f_X(x)} = f_Y(y).$$

- We can either start with the joint distribution and check independence for each possible value of x and y, or start with the assumption that X and Y are independent and model the joint distribution accordingly. In this latter direction, our economic intuition might have to play an important role.
- "Would information on the value of X really increase our information about the likely value of Y?"

Example 3.2

Consider the discrete bivariate random vector (X, Y), with joint pmf given by

$$f(10,1) = f(20,1) = f(20,2) = 1/10,$$

$$f(10,2) = f(10,3) = 1/5 \quad \text{and} \quad f(20,3) = 3/10.$$

- The marginal pmfs are then given by

$$f_X(10) = f_X(20) = 0.5 \quad \text{and} \quad f_Y(1) = 0.2, f_Y(2) = 0.3 \quad \text{and} \quad f_Y(3) = 0.5.$$

Example 2.2 cont.

- Now, for example,

$$f(10,3) = \frac{1}{5} \neq \frac{1}{2}\frac{1}{2} = f_X(10)f_Y(3),$$

although

$$f(10) = \frac{1}{10} = \frac{1}{2}\frac{1}{5} = f_X(10)f_Y(1).$$

- Do we always have to check all possible pairs, one by one???

Example 3.3

Let X be the number of living parents of a student randomly selected from an elementary school in Kansas city and Y be the number of living parents of a retiree randomly selected from Sun City. Suppose, furthermore, that we have

$$f_X(0) = 0.01 \quad f_X(1) = 0.09 \quad f_X(2) = 0.9,$$

$$f_Y(0) = 0.7 \quad f_Y(1) = 0.25 \quad f_Y(2) = 0.05.$$

- It seems reasonable that X and Y will be independent: knowledge of the number of parents of the student does not give us any information on the number of parents of the retiree and vice versa. Therefore, we should have

$$F_{X,Y}(x, Y) = f_X(x)f_Y(y).$$

Example 2.3 cont.

- Then, for example

$$f_{X,Y}(0,0) = 0.007, \quad f_{X,Y}(0,1) = 0.0025,$$

  etc.

- We can thus calculate quantities such as,

$$P(X = Y) = f(0,0) + f(1,1) + f(2,2)$$

$$= 0.01 * 0.7 + 0.09 * 0.25 + 0.9 * 0.05 = 0.0745.$$

Independence and Expectation

Theorem 3.1

Let X and Y be independent random variables.

1. For any $A \subset \mathbb{R}$ and $B \subset \mathbb{R}$, $P(X \in A, Y \in B) = P(X \in A)P(Y \in B)$; that is, the events $\{X \in A\}$ and $\{Y \in B\}$ are independent events.
2. Let $g(x)$ be a function only of x and $h(y)$ be a function only of y. Then

$$E[g(X)h(Y)] = E[g(X)]E[h(Y)].$$

- **Proof**: Exercise!

Independent Normal Variables

Theorem 3.2

Let $X \sim N(\mu_X, \sigma_x^2$ and $Y \sim N(\mu_Y, \sigma_y^2)$ be independent normal variables. Then the random variable $Z = X + Y$ has a $N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$ distribution.

- **Proof**: Exercise!

Bivariate Transformations

Theorem 4.1

If $X \sim \text{Poisson}(\theta)$, $Y \sim \text{Poisson}(\lambda)$ and X and Y are independent, then $X + Y \sim \text{Poisson}(\theta + \lambda)$

Theorem 4.2

Let $X \sim N(\mu_x, \sigma_x^2)$ and $Y \sim N(\mu_Y, \sigma_Y^2)$ be independent normal variables. Then the random variable $Z = X + Y$ has a $N(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$ distribution.

Bivariate Transformations

Theorem 4.3

Let $X \perp\!\!\!\perp Y$ be two random variables. Define $U = g(X)$ and $V = h(Y)$, where $g(x)$ is a function only of x and $h(y)$ is a function only of y. Then $U \perp\!\!\!\perp V$.

- **Proof**: Exercise!

- Now comes a very useful theorem which you will, most likely, use frequently in the future.
- Remember that $E[X[Y]]$ is a function of y and $E[X|Y]$ is a random variable whose value depends on the value of Y.

Theorem 5.1

If X and Y are two random variables, then

$$E_X[X] = E_Y\{E_{X|Y}[X|Y]\},$$

provided that the expectations exist.

- It is important to notice that the two expectations are with respect to two different probability densities, $f_X(.)$ and $f_{X|Y}(.|Y = y)$.
- This result is widely known as the Law of Iterated Expectations.

Definition 5.1

A random variable X is said to have a mixture distributionif the distribution of X depends on a quantity that also has a distribution.

- Therefore, the mixture distribution is a distribution that is generated through a hierarchical mechanism.

Example 5.1

Now, consider the following hierarchical model:

$$\begin{aligned} X|Y &\sim \text{binomial}(Y, p), \\ Y|\Lambda &\sim \text{Poisson}(\Lambda), \\ \Lambda &\sim \text{exponential}(\beta), \end{aligned}$$

- Then,

$$E_X[X] = E_Y\{E_{X|Y}[X|Y]\} = E_Y[pY]$$
$$= E_\Lambda\{E_{Y|\Lambda}[pY|\Lambda]\} = pE_\Lambda\{E_{Y|\Lambda}[Y|\Lambda]\}$$
$$= pE_\Lambda[\Lambda] = p\beta,$$

Example 4.1 cont.

Which is obtained by successive application of the Law of Iterated Expectations.

- Note that in this example we considered both discrete and continuous random variables. This is fine.

Theorem 5.2

For any two random variables X and Y,

$$Var_X(X) = E_Y[Var_{X|Y}(X|Y)] + Var_Y\{E_{X|Y}[X|Y]\}$$

- **Proof**: Exercise!

Example 5.2

Consider the following generalisation of the binomial distribution, where the probability of success varies according to a distribution.

- Specifically,

$$\begin{aligned} X|P &\sim \text{binomial}(n, P), \\ P &\sim \text{beta}(\alpha, \beta), \end{aligned}$$

- Then

$$E_X[X] = E_P\{E_{X|P}[X|P]\} = E_P[nP] = n\frac{\alpha}{\alpha+\beta},$$

  where the last result follows from the fact that for $P \sim \text{beta}(\alpha, \beta)$, $E[P] = \alpha/(\alpha+\beta)$.

Example 5.3

Now, let's calculate the variance of X. By Theorem (4.2),

$$Var_X(X) = Var_p\{E_{X|P}[X|P]\} + E_P[Var_{X|P}(X|P)].$$

- Now, $E_{X|P}[X|P] = nP$ and since $P \sim$beta$(\alpha + \beta)$,

$$Var_P(E_{X|P}[X|P]) = Var_p(nP) = n^2 \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}.$$

- Moreover, $Var_{X|P}(X|P) = nP(1-P)$, due to $X|P$ being a *binomial* random variable.

Bivariate Normal Distribution

- We now introduce the bivariate normal distribution.

Definition 6.1

Let $-\infty < \mu_X < \infty$, $-\infty < \mu_Y < \infty$, $\sigma_X > 0$, $\sigma_Y > 0$ and $-1 < \rho < 1$. The bivariate normal pdf with means μ_X and μ_y, variances σ_X^2 and σ_Y^2, and correlation ρ is the bivariate pdf given by

$$f_{X,Y}(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{1-\rho^2}}$$

$$x \; exp\{-\frac{1}{2(1-\rho^2)}[u^2 - 2\rho uv + v^2]\},$$

where $u = (\frac{y-\mu_Y}{\sigma_Y})$ and $v = (\frac{x-\mu_X}{\sigma_X})$, while $-\infty < x < \infty$ and $-\infty < y < \infty$.

Bivariate Normal Distribution

- More concisely, this would be written as

$$\binom{X}{Y} \sim N\left\{\begin{pmatrix}\mu_X \\ \mu_Y\end{pmatrix}, \begin{pmatrix}\sigma_X^2 & \rho\sigma_X\sigma_Y \\ \rho\sigma_X\sigma_Y & \sigma_Y^2\end{pmatrix}\right\}.$$

- In addition, starting from the bivariate distribution, one can show that

$$Y|X = x \sim N\{\mu_Y + \rho\sigma_Y(\frac{x-\mu_X}{\sigma_X}, \sigma_Y^2(1-\rho^2)\},$$

  and, likewise,

$$X|Y = y \sim N\{\mu_X + \rho\sigma_X(\frac{y-\mu_Y}{\sigma_Y}, \sigma_X^2(1-\rho^2)\}.$$

- Finally, again, starting from the bivariate distribution, it can be shown that

$$X \sim N(\mu_X, \sigma_X^2) \quad \text{and} \quad Y \sim N(\mu_Y, \sigma_Y^2).$$

- Therefore, joint normality implies conditional and marginal normality. However, this does not go in the opposite direction; marginal or conditional normality does not necessarily imply joint normality.

Bivariate Normal Distribution

- The normal distribution has another interesting property.
- Remember that although independence implies zero covariance, the reverse is not necessarily true.
- The normal distribution is an exception to this: if two normally distributed random variables have zero correlation (or, equivalently, zero covariance) then they are independent.
- Why? Remember that independence is a property that governs all moments, not just the second order ones (such as variance or covariance).
- However, as the preceding discussion reveals, the distribution of a bivariate normal random variable is entirely determined by its mean and covariance matrix. In other words, the first and second order moments are sufficient to characterise the distribution.
- Therefore, we do not have to worry about any higher order moments. Hence, zero covariance implies independence in this particular case.

Multivariate Distribution

- Let $\mathbf{X} = (X_1, ..., X_n)$. Then the sample space for $\mathbf{X}$ is a subset of $\mathbb{R}^n$, the n-dimensional Euclidian space.
- If this sample space is countable, then $\mathbf{X}$ is a discrete random vector and its joint pmf is given by

$$f(\mathbf{x}) = f(x_1, ..., x_n) = P(X_1 = x_1, ..., X_n = x_n) \text{ for each } (x_1, ..., x_n) \in \mathbb{R}^n.$$

- For any $A \subset \mathbb{R}^n$,

$$P(\mathbf{X} \in A) = \sum_{\mathbf{x} \in A} f(\mathbf{x}).$$

- Similarly, for the continuous random vector, we have the joint pdf given by $f(\mathbf{x}) = f(x_1, ..., x_n)$ which satisfies

$$P(\mathbf{X} \in A) = \int ... \int_A f(\mathbf{x}) d\mathbf{x} = \int ... \int_A f(x_1, ..., x_n) dx_1 ... dx_n.$$

- Note that $\int ... \int_A$ is an n-fold integration, where the limits of integration are such that the integral is calculated over all points $\mathbf{x} \in A$.

Multivariate Distribution

- Let $g(\mathbf{x}) = g(x_1, ..., x_n)$. be a real-valued function defined on the sample space of $\mathbf{X}$. Then, for the random variable $g(\mathbf{X})$,

$$\text{(discrete)} \quad : \quad E[g(\mathbf{X}] = \sum_{x \in \mathbb{R}^n} g(\mathbf{x}) f(\mathbf{x}),$$

$$\text{(continuous)} \quad : \quad E[g(\mathbf{X}] = \int_{-\infty}^{\infty} ... \int_{-\infty}^{\infty} g(\mathbf{x}) f(\mathbf{x}) dx.$$

- The marginal pdf or pmf of $(X_1, ..., X_k)$, the first k coordinates of $(X_1, ..., X_n)$, is given by

$$\text{(discrete)} \quad : \quad f(x_1, ..., x_k) = \sum_{(x_{k+1}, \ldots, x_n) \in \mathbb{R}^{n-k}} f(x_1, ..., x_n),$$

$$\text{(discrete)} \quad : \quad f(x_1, ..., x_k) = \int_{-\infty}^{\infty} ... \int_{-\infty}^{\infty} f(x_1, ..., x_n), dx_{k+1} ... dx_n,$$

for every $(x_1, ..., x_k) \in \mathbb{R}^k$.

Multivariate Distribution

Definition 7.1

Let $\mathbf{X}_1, ..., \mathbf{X}_n$ be random vectors with joint pdf or pmf $f(\mathbf{x}_1, ..., \mathbf{x}_n)$. Let $f_{\mathbf{X}_i}(\mathbf{x}_i)$ denote the marginal pdf of pmf of $\mathbf{X}_i$. Then, $\mathbf{X}_1, ...\mathbf{X}_n$ are called mutually independent random vectors if, for every $(\mathbf{x}_1, ...\mathbf{x}_n)$,

$$f(\mathbf{x}_1, ..., \mathbf{x}_n) = f_{\mathbf{X}_1}(\mathbf{x}_1)......f_{\mathbf{X}_n}(\mathbf{x}_n) = \prod_{i=1}^{n} f_{\mathbf{X}_i}(\mathbf{x}_i)$$

- If the $\mathbf{X}_i$s are all one-dimensional, then $X_1, ..., X_n$ are called mutually independent random variables.

Reference

Casella, G., & Berger, R. (2002). *Statistical inference*. Cengage Learning.
https://books.google.fr/books?id=FAUVEAAAQBAJ