

Probability and Statistics

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Table of contents

- 1 Joint and Marginal Distribution
- 2 Conditional Distributions and Independence
- 3 Bivariate Transformations
- 4 Hierarchical Models and Mixture Distribution
- 5 Bivariate Normal Distribution
- 6 Multivariate Distribution
- 7 Inequalities
- 8 Reference

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

Joint and Marginal Distribution

- So far, our interest has been on events involving a single random variable only. In other words, we have only considered "univariate models."
- Multivariate models, on the other hand, involve more than one variable.
- Consider an experiment about health characteristics of the population. Would we be interested in one characteristic only, say weight? Not really. There are many important characteristics.

Definition 1.1

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

- 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) .

Joint and Marginal Distribution

Example 1.1

Consider the experiment of tossing two fair dice. The sample space has 36 equally likely points. For example:

$(3, 3)$: both dices show a 3,

$(4, 1)$: first dice shows a 4 and the second die a 1.

- Now, let

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

Then,

$(3, 3) :: X = 6$ and $Y = 0$,

$(4, 1) :: X = 5$ and $Y = 3$,

and so we can define the bivariate random vector (X, Y) thus.

Joint and Marginal Distribution

- What is, $P(X = 5 \text{ and } Y = 3)$? One can verify that the two relevant sample points in Ω are $(4,1)$ and $(1,4)$. 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 $(2,5)$.

- Note that from now on we will use $P(\text{event a, event b})$ rather than $P(\text{event a and event b})$.

Definition 1.2

Let (X, Y) be a discrete bivariate random vector. Then the function $f(x, y)$ from \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 and Marginal 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,

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

- Expectations are also dealt with in the same way as before. 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

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

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

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

- 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

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

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

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

Joint and 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

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

Joint and 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

$$\begin{aligned}f_Y(0) &= f_{X,Y}(2, 0) + f_{X,Y}(4, 0) + f_{X,Y}(6, 0) \\&\quad + f_{X,Y}(8, 0) + f_{X,Y}(10, 0) + f_{X,Y}(12, 0) \\&= 1/6.\end{aligned}$$

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 .

Joint and 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.
- The knowledge of the marginal distributions only does not allow us to determine the joint distribution (except under certain assumptions).

Example 1.5

Define a joint pmf by

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

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

- 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 and Marginal distribution

- Consider now the corresponding definition for continuous random variables.

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 $A \subset \mathbb{R}^2$,

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

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

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

- 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 .

Joint and Marginal distribution

- Again, naturally,

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

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

- 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

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

is the joint pdf of some continuous bivariate 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

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

- 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:

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

- 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 $Y = 202\text{cms}$? 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

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

$f(x|y)$ 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,

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

Example 2.1

Define the joint pmf of (X, Y) by

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

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

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.

Conditional Distributions and Independence

- 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 and Independence

- The analogous definition for continuous random variables is given next.

Definition 2.2

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 Distributions and Independence

- Note that for discrete random variables, $P(X = x) = f_X(x)$ and $P(X = x, Y = y) = f(x, y)$. Then Definition (2.1) is actually parallel to the definition of $(P(Y = y|X = x))$ in Definition (2.1). The same interpretation is not valid for continuous random variables since $(P(X = x) = 0)$ for every x . However, replacing pmfs with pdfs lead to Definition (2.2).
- The **conditional expected value** of $g(Y)$ given $X = x$ is given by

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

in the discrete and continuous cases, respectively.

- The conditional expected value has all of the properties of the usual expected value listed in Theorem (2.1)

Definition 2.3

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 $y \in \mathbb{R}$,

$$f(x, y) = f_X(x)f_Y(y). \quad (1)$$

Conditional Distributions and 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 2.2

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???

Conditional Distributions and Independence

Example 2.3

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,

$$\begin{aligned} P(X = Y) &= f(0,0) + f(1,1) + f(2,2) \\ &= 0.01 * 0.7 + 0.09 * 0.25 + 0.9 * 0.05 = 0.0745. \end{aligned}$$

Theorem 2.1

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!

Theorem 2.2

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!

Theorem 3.1

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 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.

Bivariate Transformations

- Then,

$$U = X + Y \sim N(0, 2).$$

- What about V ? Define $Z = -Y$ and notice that

$$Z = -Y \sim N(0, 1).$$

- Then, by Theorem (3.2)

$$V = X - Y = X + Z \sim N(0, 2),$$

as well.

Theorem 3.3

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!

Hierarchical Models and Mixture Distribution

- 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 4.1

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, $f_X(\cdot)$ and $f_{X|Y}(\cdot|Y=y)$.
- This result is widely known as the Law of Iterated Expectations.

Definition 4.1

A random variable X is said to have a **mixture distribution** if 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 4.1

Now, consider the following hierarchical model:

$$X|Y \sim \text{binomial}(Y, p),$$

$$Y|\Lambda \sim \text{Poisson}(\Lambda),$$

$$\Lambda \sim \text{exponential}(\beta),$$

- Then,

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

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 4.2

For any two random variables X and Y ,

$$\text{Var}_X(X) = E_Y[\text{Var}_{X|Y}(X|Y)] + \text{Var}_Y\{E_{X|Y}[X|Y]\}$$

- **Proof:** Exercise!

Example 4.2

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

- Specifically,

$$X|P \sim \text{binomial}(n, P),$$

$$P \sim \text{beta}(\alpha, \beta),$$

- 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 4.3

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

$$\text{Var}_X(X) = \text{Var}_P\{E_{X|P}[X|P]\} + E_P[\text{Var}_{X|P}(X|P)].$$

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

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

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

Bivariate Normal Distribution

- We now introduce the bivariate normal distribution.

Definition 5.1

Let $-\infty < \mu_X < \infty$, $-\infty < \mu_Y < \infty$, $\sum_X > 0$, $\sum_Y > 0$ and $-1 < \rho < 1$. The bivariate normal pdf with means μ_X and μ_Y , variances \sum_X^2 and \sum_Y^2 , and correlation ρ is the bivariate pdf given by

$$f_{X,Y}(x,y) = \frac{1}{2\pi \sum_X \sum_Y \sqrt{1-\rho^2}} \\ \times \exp\left\{-\frac{1}{2(1-\rho^2)}[u^2 - 2\rho uv + v^2]\right\},$$

where $u = \left(\frac{y-\mu_Y}{\sum_Y}\right)$ and $v = \left(\frac{x-\mu_X}{\sum_X}\right)$, while $-\infty < x < \infty$ and $-\infty < y < \infty$.

Bivariate Normal Distribution

- More concisely, this would be written as

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

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

$$Y|X = x \sim N\left\{\mu_Y + \rho \frac{\sum_Y}{\sum_X} \left(\frac{x - \mu_X}{\sum_X}\right), \sum_Y^2 (1 - \rho^2)\right\},$$

and, likewise,

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

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

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

- 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 $\mathbf{X} = (X_1, \dots, X_n)$. 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

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

- 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 $f(\mathbf{x}) = f(x_1, \dots, x_n)$ which satisfies

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

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

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

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

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

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

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

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

Definition 6.1

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

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

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

Theorem 6.1

Generalisation of Theorem 3.3: Let $\mathbf{X}_1, \dots, \mathbf{X}_n$ be independent random vectors. Let $g_i(\mathbf{x}_i)$ be a function of \mathbf{x}_i , $i = 1, \dots, n$. Then, the random variables $U_i = g_i(\mathbf{X}_i)$, $i = 1, \dots, n$, are mutually independent.

- We will now cover some basic inequalities used in statistics and econometrics.
- Most of the time, more complicated expressions can be written in terms of simpler expressions. Inequalities on these simpler expressions can then be used to obtain an inequality, or often a bound, on the original complicated term.
- This part is based on Sections 3.6 and 4.7 in Casella & Berger.

- We start with one of the most famous probability inequalities.

Theorem 7.1

Chebychev's Inequality: Let X be a random variable and let $g(x)$ be a non-negative function. Then, for any $r > 0$,

$$P(g(X) \geq r) \leq \frac{E[g(X)]}{r}.$$

- **Proof:** Using the definition of the expected value,

$$\begin{aligned} E[g(X)] &= \int_{-\infty}^{\infty} g(x)f_X(x)dx \\ &\geq \int_{\{x:g(x)\geq r\}} g(x)f_X(x)dx \\ &\geq r \int_{\{x:g(x)\geq r\}} f_X(x)dx \\ &= rP(g(X) \geq r). \end{aligned}$$

- Hence,

$$E[g(X)] \geq rP(g(X) \geq r),$$

implying

$$P(g(X) \geq r) \leq \frac{E[g(X)]}{r}.$$

Inequalities

- This result comes in very handy when we want to turn a probability statement into an expectation statement. For example, this would be useful if we already have some moment existence assumptions and we want to prove a result involving a probability statement.

Example 7.1

Let $g(x) = (x - \mu)^2 / \sigma^2$, where $\mu = E[X]$ and $\sigma^2 = \text{Var}(X)$. Let, for convenience, $r = t^2$. Then,

$$P\left[\frac{(X - \mu)^2}{\sigma^2} \geq t^2\right] \leq \frac{1}{t^2} E\left[\frac{(X - \mu)^2}{\sigma^2}\right] = \frac{1}{t^2}.$$

- This implies that

$$P[|X - \mu| \geq t\sigma] \leq \frac{1}{t^2},$$

and, consequently,

$$P[|X - \mu| < t\sigma] \geq 1 - \frac{1}{t^2}.$$

Example 8.1 cont.

- Therefore, for instance for $t = 2$, we get

$$P[|X - \mu| \geq 2\sigma] \leq 0.25 \quad \text{or} \quad P[|X - \mu| < 2\sigma] \geq 0.75.$$

This says that, there is at least a 75% chance that a random variable will be within 2σ of its mean (**independent of the distribution of X**).

- This information is useful. However, many times, it might be possible to obtain an even **tighter** bound in the following sense.

Example 7.2

Let $Z \sim N(0, 1)$. Then,

$$\begin{aligned} P(Z \geq t) &= \frac{1}{\sqrt{2\pi}} \int_t^{\infty} e^{-x^2/2} dx \\ &\leq \frac{1}{\sqrt{2\pi}} \int_t^{\infty} \frac{x}{t} e^{-x^2/2} dx \\ &= \frac{1}{\sqrt{2\pi}} \frac{e^{-t^2/2}}{t}. \end{aligned}$$

The second inequality follows from the fact that for $x > t$, $x/t > 1$. Now, since Z has a symmetric distribution, $P(|Z| \geq t) = 2P(Z \geq t)$. Hence,

$$P(|Z| \geq t) \leq \sqrt{\frac{2}{\pi}} \frac{e^{-t^2/2}}{t}.$$

Example 8.2 cont.

- Set $t = 2$ and observe that

$$P(|Z| \geq 2) \leq \sqrt{\frac{2}{\pi}} \frac{e^{-2}}{2} = 0.054.$$

and, consequently,

$$P[|X - \mu| < t\sigma] \geq 1 - \frac{1}{t^2}.$$

This is a much tighter bound compared to the one given by Chebychev's Inequality.

- Generally Chebychev's Inequality provides a more conservative bound.

- A related inequality is [Markov's Inequality](#).

Lemma 7.1

If $P(Y \geq 0) = 1$ and $P(Y = 0) < 1$, then, for any $r > 0$,

$$P(Y \geq r) \leq \frac{E[Y]}{r},$$

and the relationship holds with equality if and only if $P(Y = r) = p = 1 - P(Y = 0)$, where $0 < p \leq 1$.

- The more general form of Chebychev's Inequality, provided in White (2001), is as follows.

White Proposition

Proposition (White 2001): Let X be a random variable such that $E[|X|^r] < \infty$, $r > 0$. Then, for every $t > 0$,

$$P(|X| \geq t) \leq \frac{E[|X|^r]}{t^r}.$$

Setting $r = 2$, and some re-arranging, gives the usual Chebychev's Inequality. If we let $r = 1$, then we obtain Markov's Inequality. See White (2001, pp.29-30).

Theorem 7.2

(Hölder's Inequality): Let X and Y be any two random variables, and let p and q be such that

$$\frac{1}{p} + \frac{1}{q} = 1.$$

Then,

$$E[|XY|] \leq \{E[|X|^p]\}^{1/p} \{E[|Y|^q]\}^{1/q}.$$

• **Proof:** Exercise!

Theorem 7.3

(Cauchy-Schwarz Inequality): For any two random variables X and Y ,

$$E[|XY|] \leq \{E[|X|^2]\}^{1/2} \{E[|Y|^2]\}^{1/2}.$$

- **Proof:** Set $p = q = 2$.

Theorem 7.4

(Minkowski's Inequality): Let X and Y be any two random variables. Then, for $1 \leq p < \infty$,

$$\{E[|X + Y|^p]\}^{1/p} \leq \{E[|X|^p]\}^{1/p} + \{E[|Y|^p]\}^{1/p}.$$

• **Proof:** Exercise!

Definition 7.1

A function $g(x)$ is **convex** if

$$g(\lambda x + (1 - \lambda)y) \leq \lambda g(x) + (1 - \lambda)g(y), \quad \text{for all } x \text{ and } y, \text{ and } 0 < \lambda < 1.$$

The function $g(x)$ is **concave** if $-g(x)$ is convex.

- Now we can introduce **Jensen's Inequality**.

Theorem 7.5

For any random variable X , if $g(x)$ is a convex function, then

$$E[g(X)] \geq g\{E[X]\}.$$

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