

Introduction to Probability

Lecture 7: Independence, Covariance and Correlation

Mateja Jamnik, Thomas Sauerwald

University of Cambridge, Department of Computer Science and Technology

email: {mateja.jamnik,thomas.sauerwald}@cl.cam.ac.uk



UNIVERSITY OF
CAMBRIDGE

Independence of Random Variables

Definition of Independence

Two random variables X and Y are **independent** if for all values a, b :

$$\mathbf{P}[X \leq a, Y \leq b] = \mathbf{P}[X \leq a] \cdot \mathbf{P}[Y \leq b].$$



Independence of Random Variables

Definition of Independence

Two random variables X and Y are **independent** if for all values a, b :

$$\mathbf{P}[X \leq a, Y \leq b] = \mathbf{P}[X \leq a] \cdot \mathbf{P}[Y \leq b].$$

For two **discrete** random variables, an equivalent definition is:

$$\mathbf{P}[X = a, Y = b] = \mathbf{P}[X = a] \cdot \mathbf{P}[Y = b].$$



Independence of Random Variables

Definition of Independence

Two random variables X and Y are **independent** if for all values a, b :

$$\mathbf{P}[X \leq a, Y \leq b] = \mathbf{P}[X \leq a] \cdot \mathbf{P}[Y \leq b].$$

For two **discrete** random variables, an equivalent definition is:

$$\mathbf{P}[X = a, Y = b] = \mathbf{P}[X = a] \cdot \mathbf{P}[Y = b].$$

This is useless for continuous random variables.



Independence of Random Variables

This definition covers the **discrete** and **continuous** case!

Definition of Independence

Two random variables X and Y are **independent** if for all values a, b :

$$\mathbf{P}[X \leq a, Y \leq b] = \mathbf{P}[X \leq a] \cdot \mathbf{P}[Y \leq b].$$

For two **discrete** random variables, an equivalent definition is:

$$\mathbf{P}[X = a, Y = b] = \mathbf{P}[X = a] \cdot \mathbf{P}[Y = b].$$

This is useless for continuous random variables.



Independence of Random Variables

This definition covers the **discrete** and **continuous** case!

Definition of Independence

Two random variables X and Y are **independent** if for all values a, b :

$$\mathbf{P}[X \leq a, Y \leq b] = \mathbf{P}[X \leq a] \cdot \mathbf{P}[Y \leq b].$$

For two **discrete** random variables, an equivalent definition is:

$$\mathbf{P}[X = a, Y = b] = \mathbf{P}[X = a] \cdot \mathbf{P}[Y = b].$$

This is useless for continuous random variables.

Remark

Using the **joint probability distribution**, the above is equivalent to for all a, b ,

$$F(a, b) = F_X(a) \cdot F_Y(b).$$



Independence of Random Variables

This definition covers the **discrete** and **continuous** case!

Definition of Independence

Two random variables X and Y are **independent** if for all values a, b :

$$\mathbf{P}[X \leq a, Y \leq b] = \mathbf{P}[X \leq a] \cdot \mathbf{P}[Y \leq b].$$

For two **discrete** random variables, an equivalent definition is:

$$\mathbf{P}[X = a, Y = b] = \mathbf{P}[X = a] \cdot \mathbf{P}[Y = b].$$

This is useless for continuous random variables.

Remark

Using the **joint probability distribution**, the above is equivalent to for all a, b ,

$$F(a, b) = F_X(a) \cdot F_Y(b).$$

All these definitions extend in the natural way to **more than two** variables!



Factorisation

Factorisation

The definition of independence of X and Y implies the following **factorisation** formula: for any “suitable” sets A and B ,

$$\mathbf{P}[X \in A, Y \in B] = \mathbf{P}[X \in A] \cdot \mathbf{P}[Y \in B]$$



Factorisation

The definition of independence of X and Y implies the following **factorisation** formula: for any “suitable” sets A and B ,

$$\mathbf{P}[X \in A, Y \in B] = \mathbf{P}[X \in A] \cdot \mathbf{P}[Y \in B]$$

For **continuous** distributions one obtains by differentiating both sides in the formula for the joint distribution:

$$f_{X,Y}(x,y) = f_X(x) \cdot f_Y(y)$$

Factorisation

Factorisation

The definition of independence of X and Y implies the following **factorisation** formula: for any “suitable” sets A and B ,

$$\mathbf{P}[X \in A, Y \in B] = \mathbf{P}[X \in A] \cdot \mathbf{P}[Y \in B]$$

For **continuous** distributions one obtains by differentiating both sides in the formula for the joint distribution:

$$f_{X,Y}(x,y) = f_X(x) \cdot f_Y(y)$$

Example

Let X and Y be two independent variables. Let $I = (a, b]$ be any interval and define $U := \mathbf{1}_{X \in I}$ and $V := \mathbf{1}_{Y \in I}$. Prove U and V are independent.

Answer



Buffon's Needle Problem (1/2)



Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)

- A table is ruled with equidistant, parallel lines a distance D apart.

Buffon's Needle Problem (1/2)



Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)

- A table is ruled with equidistant, parallel lines a distance D apart.
- A needle of length L is thrown randomly on the table.

Buffon's Needle Problem (1/2)



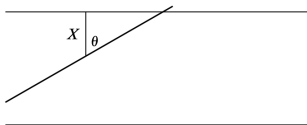
Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)

- A table is ruled with equidistant, parallel lines a distance D apart.
- A needle of length L is thrown randomly on the table.
- What is the probability that the needle will intersect one of the two lines?

Buffon's Needle Problem (1/2)



Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)



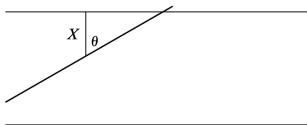
Source: Ross, Probability 8th ed.

- A table is ruled with equidistant, parallel lines a distance D apart.
- A needle of length L is thrown randomly on the table.
- What is the probability that the needle will intersect one of the two lines?

Buffon's Needle Problem (1/2)



Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)



Source: Ross, Probability 8th ed.

- A table is ruled with equidistant, parallel lines a distance D apart.
- A needle of length L is thrown randomly on the table.
- What is the probability that the needle will intersect one of the two lines?

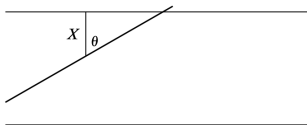
Let X be the distance of the **middle point** of the needle to the closest parallel line. Needle intersects a line if hypotenuse of the triangle is less than $L/2$, i.e.,

$$\frac{X}{\cos(\theta)} < \frac{L}{2} \quad \Leftrightarrow \quad X < \frac{L}{2} \cos(\theta).$$

Buffon's Needle Problem (1/2)



Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)



Source: Ross, Probability 8th ed.

- A table is ruled with equidistant, parallel lines a distance D apart.
- A needle of length L is thrown randomly on the table.
- What is the probability that the needle will intersect one of the two lines?

Let X be the distance of the **middle point** of the needle to the closest parallel line. Needle intersects a line if hypotenuse of the triangle is less than $L/2$, i.e.,

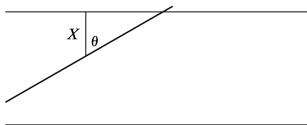
$$\frac{X}{\cos(\theta)} < \frac{L}{2} \quad \Leftrightarrow \quad X < \frac{L}{2} \cos(\theta).$$

We assume that $X \in [0, D/2]$ and $\theta \in [0, \pi/2]$ are **independent** and **uniform**.

Buffon's Needle Problem (1/2)



Georges-Louis Leclerc de Buffon 1707–1788 (Source Wikipedia)



Source: Ross, Probability 8th ed.

- A table is ruled with equidistant, parallel lines a distance D apart.
- A needle of length L is thrown randomly on the table.
- What is the probability that the needle will intersect one of the two lines?

Let X be the distance of the **middle point** of the needle to the closest parallel line. Needle intersects a line if hypotenuse of the triangle is less than $L/2$, i.e.,

$$\frac{X}{\cos(\theta)} < \frac{L}{2} \quad \Leftrightarrow \quad X < \frac{L}{2} \cos(\theta).$$

We assume that $X \in [0, D/2]$ and $\theta \in [0, \pi/2]$ are **independent** and **uniform**.

Can be thought of as: 1. Sample the middle point of needle, 2. Sample the angle.



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\mathbf{P} \left[X < \frac{L}{2} \cdot \cos(\theta) \right]$$



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\mathbf{P} \left[X < \frac{L}{2} \cdot \cos(\theta) \right] = \iint_{x < (L/2) \cos y} f_{X,\theta}(x,y) \, dx \, dy$$



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\begin{aligned}\mathbf{P}\left[X < \frac{L}{2} \cdot \cos(\theta)\right] &= \iint_{x < (L/2) \cos y} f_{X,\theta}(x, y) \, dx \, dy \\ &= \iint_{x < (L/2) \cos y} f_X(x) f_\theta(y) \, dx \, dy\end{aligned}$$



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\begin{aligned}\mathbf{P}\left[X < \frac{L}{2} \cdot \cos(\theta)\right] &= \iint_{x < (L/2) \cos y} f_{X,\theta}(x, y) \, dx \, dy \\ &= \iint_{x < (L/2) \cos y} f_X(x) f_\theta(y) \, dx \, dy \\ &= \frac{4}{\pi D} \int_0^{\pi/2} \int_0^{L/2 \cos(y)} dx dy\end{aligned}$$



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\begin{aligned}\mathbf{P}\left[X < \frac{L}{2} \cdot \cos(\theta)\right] &= \iint_{x < (L/2) \cos y} f_{X,\theta}(x, y) \, dx \, dy \\ &= \iint_{x < (L/2) \cos y} f_X(x) f_\theta(y) \, dx \, dy \\ &= \frac{4}{\pi D} \int_0^{\pi/2} \int_0^{L/2 \cos(y)} dx dy \\ &= \frac{4}{\pi D} \int_0^{\pi/2} \frac{L}{2} \cos(y) dy\end{aligned}$$



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\begin{aligned}\mathbf{P}\left[X < \frac{L}{2} \cdot \cos(\theta)\right] &= \iint_{x < (L/2) \cos y} f_{X,\theta}(x, y) \, dx \, dy \\&= \iint_{x < (L/2) \cos y} f_X(x) f_\theta(y) \, dx \, dy \\&= \frac{4}{\pi D} \int_0^{\pi/2} \int_0^{L/2 \cos(y)} dx dy \\&= \frac{4}{\pi D} \int_0^{\pi/2} \frac{L}{2} \cos(y) dy \\&= \frac{2L}{\pi D}.\end{aligned}$$



Buffon's Needle Problem (2/2)

Let us compute the probability that the line intersects:

$$\begin{aligned}\mathbf{P}\left[X < \frac{L}{2} \cdot \cos(\theta)\right] &= \iint_{x < (L/2) \cos y} f_{X,\theta}(x, y) \, dx \, dy \\ &= \iint_{x < (L/2) \cos y} f_X(x) f_\theta(y) \, dx \, dy \\ &= \frac{4}{\pi D} \int_0^{\pi/2} \int_0^{L/2 \cos(y)} dx dy \\ &= \frac{4}{\pi D} \int_0^{\pi/2} \frac{L}{2} \cos(y) dy \\ &= \frac{2L}{\pi D}.\end{aligned}$$

This gives us a method to estimate π !



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.

Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.
- If $\mathbf{Cov}[X, Y] < 0$, then it is the other way around.

Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.
- If $\mathbf{Cov}[X, Y] < 0$, then it is the other way around.

Alternative Formula

Using the linearity of expectation rule, one has the equivalent definition:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y].$$



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.
- If $\mathbf{Cov}[X, Y] < 0$, then it is the other way around.

Alternative Formula

Using the linearity of expectation rule, one has the equivalent definition:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y].$$

- Note that $\mathbf{Cov}[X, X] = \mathbf{V}[X]$.



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.
- If $\mathbf{Cov}[X, Y] < 0$, then it is the other way around.

Alternative Formula

Using the linearity of expectation rule, one has the equivalent definition:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y].$$

- Note that $\mathbf{Cov}[X, X] = \mathbf{V}[X]$.
- Two variables X, Y with $\mathbf{Cov}[X, Y] > 0$ are **positively correlated**.



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.
- If $\mathbf{Cov}[X, Y] < 0$, then it is the other way around.

Alternative Formula

Using the linearity of expectation rule, one has the equivalent definition:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y].$$

- Note that $\mathbf{Cov}[X, X] = \mathbf{V}[X]$.
- Two variables X, Y with $\mathbf{Cov}[X, Y] > 0$ are **positively correlated**.
- Two variables X, Y with $\mathbf{Cov}[X, Y] < 0$ are **negatively correlated**.



Covariance

Definition of Covariance

Let X and Y be two random variables. The **covariance** is defined as:

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

Interpretation:

- If $\mathbf{Cov}[X, Y] > 0$ and X has a realisation larger (smaller) than $\mathbf{E}[X]$, then Y will likely have a realisation larger (smaller) than $\mathbf{E}[Y]$.
- If $\mathbf{Cov}[X, Y] < 0$, then it is the other way around.

Alternative Formula

Using the linearity of expectation rule, one has the equivalent definition:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y].$$

- Note that $\mathbf{Cov}[X, X] = \mathbf{V}[X]$.
- Two variables X, Y with $\mathbf{Cov}[X, Y] > 0$ are **positively correlated**.
- Two variables X, Y with $\mathbf{Cov}[X, Y] < 0$ are **negatively correlated**.
- Two variables X, Y with $\mathbf{Cov}[X, Y] = 0$ are **uncorrelated**.



Illustration of 3 Cases for $\text{Cov}[X, Y]$

500 outcomes of randomly generated pairs of RVs (X, Y) with different joint distributions

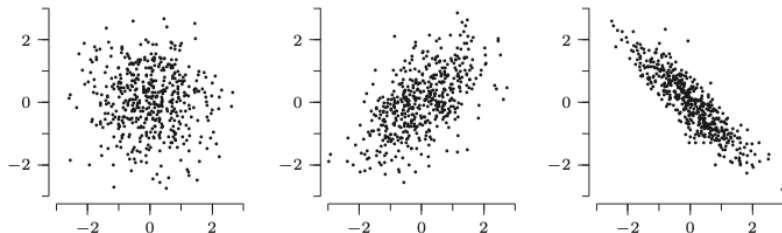


Fig. 10.1. Some scatterplots.
Source: Textbook by Dekking

1. What is the covariance (positive, negative, neutral)?
2. Where is the covariance the largest (in magnitude)?

Independence implies Uncorrelated

Example

Let X and Y be two independent random variables. Then X and Y are uncorrelated, i.e., $\text{Cov}[X, Y] = 0$.

Answer

We give a proof for the discrete case:



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.
 $\Rightarrow X \cdot Y = 0$ (for all outcomes), and thus



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.
- $\Rightarrow X \cdot Y = 0$ (for all outcomes), and thus

$$\mathbf{E}[X \cdot Y] = 0.$$



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.
 $\Rightarrow X \cdot Y = 0$ (for all outcomes), and thus

$$\mathbf{E}[X \cdot Y] = 0.$$

- Further, $\mathbf{E}[X] = 0$ (and $\mathbf{E}[Y] = 1/3$), and hence:



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **un-correlated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.
 $\Rightarrow X \cdot Y = 0$ (for all outcomes), and thus

$$\mathbf{E}[X \cdot Y] = 0.$$

- Further, $\mathbf{E}[X] = 0$ (and $\mathbf{E}[Y] = 1/3$), and hence:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y] = 0.$$



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.
 $\Rightarrow X \cdot Y = 0$ (for all outcomes), and thus

$$\mathbf{E}[X \cdot Y] = 0.$$

- Further, $\mathbf{E}[X] = 0$ (and $\mathbf{E}[Y] = 1/3$), and hence:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y] = 0.$$

- On the other hand, $\mathbf{P}[X = 0] = 1/3$ and $\mathbf{P}[Y = 0] = 2/3$, and thus



Uncorrelated may not imply Independence

Example

Find a (simple) example of two random variables X and Y which are **uncorrelated but dependent**.

Answer

- Let X be uniformly sampled from $\{-1, 0, +1\}$ and $Y := \mathbf{1}_{X=0}$.
 $\Rightarrow X \cdot Y = 0$ (for all outcomes), and thus

$$\mathbf{E}[X \cdot Y] = 0.$$

- Further, $\mathbf{E}[X] = 0$ (and $\mathbf{E}[Y] = 1/3$), and hence:

$$\mathbf{Cov}[X, Y] = \mathbf{E}[X \cdot Y] - \mathbf{E}[X] \cdot \mathbf{E}[Y] = 0.$$

- On the other hand, $\mathbf{P}[X = 0] = 1/3$ and $\mathbf{P}[Y = 0] = 2/3$, and thus

$$1 = \mathbf{P}[X \cdot Y = 0] > \mathbf{P}[X = 0] \cdot \mathbf{P}[Y = 0] = 2/9.$$



Variance of Sum Formula

- For any two random variables X, Y ,

$$\mathbf{V}[X + Y] = \mathbf{V}[X] + \mathbf{V}[Y] + 2 \cdot \mathbf{Cov}[X, Y].$$

Variance of Sum Formula

- For any two random variables X, Y ,

$$\mathbf{V}[X + Y] = \mathbf{V}[X] + \mathbf{V}[Y] + 2 \cdot \mathbf{Cov}[X, Y].$$

- Hence if X and Y are **uncorrelated** variables,

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

Variance of Sum Formula

- For any two random variables X, Y ,

$$\mathbf{V}[X + Y] = \mathbf{V}[X] + \mathbf{V}[Y] + 2 \cdot \mathbf{Cov}[X, Y].$$

- Hence if X and Y are **uncorrelated** variables,

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

Generalisation of the case where
 X and Y are even **independent**!

Variance of Sum Formula

- For any two random variables X, Y ,

$$\mathbf{V}[X + Y] = \mathbf{V}[X] + \mathbf{V}[Y] + 2 \cdot \mathbf{Cov}[X, Y].$$

- Hence if X and Y are **uncorrelated** variables,

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

Generalisation of the case where X and Y are even **independent**!

- For any random variables $X_1, X_2, \dots, X_n$:

$$\mathbf{V}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbf{V}[X_i] + 2 \cdot \sum_{i=1}^n \sum_{j=i+1}^n \mathbf{Cov}[X_i, X_j].$$

Computing Variances of Sums of Uncorrelated Variables

Example

Recall the example where $X \in \{-1, 0, +1\}$ uniformly and $Y := \mathbf{1}_{X=0}$. Compute $\mathbf{V}[X + Y]$.

_____ Answer _____



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:

- If X increases by a factor of α , then **Cov** $[X, Y]$ increases by a factor of α .



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:

- If X increases by a factor of α , then **Cov** $[X, Y]$ increases by a factor of α .
- ⇒ Even if X and Y both increase by α , then **Cov** $[X, Y]$ will change.
(Exercise: It changes by?)



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:

- If X increases by a factor of α , then $\mathbf{Cov}[X, Y]$ increases by a factor of α .
- ⇒ Even if X and Y both increase by α , then $\mathbf{Cov}[X, Y]$ will change.
(Exercise: It changes by?)

Correlation Coefficient

Let X and Y be two random variables. The **correlation coefficient** $\rho(X, Y)$ is defined as:

$$\rho(X, Y) = \frac{\mathbf{Cov}[X, Y]}{\sqrt{\mathbf{V}[X] \cdot \mathbf{V}[Y]}}.$$

If $\mathbf{V}[X] = 0$ or $\mathbf{V}[Y] = 0$, then it is defined as 0.



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:

- If X increases by a factor of α , then $\mathbf{Cov}[X, Y]$ increases by a factor of α .
- ⇒ Even if X and Y both increase by α , then $\mathbf{Cov}[X, Y]$ will change.
(Exercise: It changes by?)

Correlation Coefficient

Let X and Y be two random variables. The **correlation coefficient** $\rho(X, Y)$ is defined as:

$$\rho(X, Y) = \frac{\mathbf{Cov}[X, Y]}{\sqrt{\mathbf{V}[X] \cdot \mathbf{V}[Y]}}.$$

If $\mathbf{V}[X] = 0$ or $\mathbf{V}[Y] = 0$, then it is defined as 0.

Properties:



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:

- If X increases by a factor of α , then $\mathbf{Cov}[X, Y]$ increases by a factor of α .
- ⇒ Even if X and Y both increase by α , then $\mathbf{Cov}[X, Y]$ will change.
(Exercise: It changes by?)

Correlation Coefficient

Let X and Y be two random variables. The **correlation coefficient** $\rho(X, Y)$ is defined as:

$$\rho(X, Y) = \frac{\mathbf{Cov}[X, Y]}{\sqrt{\mathbf{V}[X] \cdot \mathbf{V}[Y]}}.$$

If $\mathbf{V}[X] = 0$ or $\mathbf{V}[Y] = 0$, then it is defined as 0.

Properties:

1. The correlation coefficient is **scaling-invariant**, i.e.,
 $\rho(X, Y) = \rho(\alpha \cdot X, \beta \cdot Y)$ for any $\alpha, \beta > 0$.



Correlation Coefficient: Normalising the Covariance

The definition of covariance is **not scaling invariant**:

- If X increases by a factor of α , then $\mathbf{Cov}[X, Y]$ increases by a factor of α .
- ⇒ Even if X and Y both increase by α , then $\mathbf{Cov}[X, Y]$ will change.
(Exercise: It changes by?)

Correlation Coefficient

Let X and Y be two random variables. The **correlation coefficient** $\rho(X, Y)$ is defined as:

$$\rho(X, Y) = \frac{\mathbf{Cov}[X, Y]}{\sqrt{\mathbf{V}[X] \cdot \mathbf{V}[Y]}}.$$

If $\mathbf{V}[X] = 0$ or $\mathbf{V}[Y] = 0$, then it is defined as 0.

Properties:

1. The correlation coefficient is **scaling-invariant**, i.e.,
 $\rho(X, Y) = \rho(\alpha \cdot X, \beta \cdot Y)$ for any $\alpha, \beta > 0$.
2. For any two random variables X, Y , $\rho(X, Y) \in [-1, 1]$.



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer

- We will only prove $\rho(X, Y) \geq -1$ (the other direction follows in analogous way).



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer

- We will only prove $\rho(X, Y) \geq -1$ (the other direction follows in analogous way).
- Let σ_x^2 and σ_y^2 denote the variances of X and Y , and σ_x and σ_y their standard deviations.



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer

- We will only prove $\rho(X, Y) \geq -1$ (the other direction follows in analogous way).
- Let σ_x^2 and σ_y^2 denote the variances of X and Y , and σ_x and σ_y their standard deviations.
- Then:

$$0 \leq \mathbf{v} \left[\frac{X}{\sigma_x} + \frac{Y}{\sigma_y} \right]$$



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer

- We will only prove $\rho(X, Y) \geq -1$ (the other direction follows in analogous way).
- Let σ_x^2 and σ_y^2 denote the variances of X and Y , and σ_x and σ_y their standard deviations.
- Then:

$$\begin{aligned} 0 &\leq \mathbf{V} \left[\frac{X}{\sigma_x} + \frac{Y}{\sigma_y} \right] \\ &= \mathbf{V} \left[\frac{X}{\sigma_x} \right] + \mathbf{V} \left[\frac{Y}{\sigma_y} \right] + 2\mathbf{Cov} \left[\frac{X}{\sigma_x}, \frac{Y}{\sigma_y} \right] \end{aligned}$$



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer

- We will only prove $\rho(X, Y) \geq -1$ (the other direction follows in analogous way).
- Let σ_x^2 and σ_y^2 denote the variances of X and Y , and σ_x and σ_y their standard deviations.
- Then:

$$\begin{aligned} 0 &\leq \mathbf{V} \left[\frac{X}{\sigma_x} + \frac{Y}{\sigma_y} \right] \\ &= \mathbf{V} \left[\frac{X}{\sigma_x} \right] + \mathbf{V} \left[\frac{Y}{\sigma_y} \right] + 2 \mathbf{Cov} \left[\frac{X}{\sigma_x}, \frac{Y}{\sigma_y} \right] \\ &= \frac{\mathbf{V}[X]}{\mathbf{V}[X]} + \frac{\mathbf{V}[Y]}{\mathbf{V}[Y]} + 2 \cdot \frac{\mathbf{Cov}[X, Y]}{\sigma_X \cdot \sigma_Y} \end{aligned}$$



Range of the Correlation Coefficient

Example

Verify that the correlation coefficients' range satisfies $\rho(X, Y) \in [-1, 1]$.

Answer

- We will only prove $\rho(X, Y) \geq -1$ (the other direction follows in analogous way).
- Let σ_x^2 and σ_y^2 denote the variances of X and Y , and σ_x and σ_y their standard deviations.
- Then:

$$\begin{aligned} 0 &\leq \mathbf{V} \left[\frac{X}{\sigma_x} + \frac{Y}{\sigma_y} \right] \\ &= \mathbf{V} \left[\frac{X}{\sigma_x} \right] + \mathbf{V} \left[\frac{Y}{\sigma_y} \right] + 2 \mathbf{Cov} \left[\frac{X}{\sigma_x}, \frac{Y}{\sigma_y} \right] \\ &= \frac{\mathbf{V}[X]}{\mathbf{V}[X]} + \frac{\mathbf{V}[Y]}{\mathbf{V}[Y]} + 2 \cdot \frac{\mathbf{Cov}[X, Y]}{\sigma_X \cdot \sigma_Y} \\ &= 2 \cdot (1 + \rho(X, Y)). \end{aligned}$$

