

II Università di Roma, Tor Vergata
Dipartimento d'Ingegneria Civile e Ingegneria Informatica
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Complementi di Probabilità e Statistica - Advanced Statistics
Instructors: Roberto Monte & Massimo Regoli
Problems on Conditional Expectation with Solution 2022-12-08

Problem 1 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space and let $X, Y \in \mathcal{L}^2(\Omega; \mathbb{R})$ such that

$$\mathbf{E}[Y | X] = X \quad \text{and} \quad \mathbf{E}[Y^2 | X] = X^2.$$

Prove that $Y = X$, \mathbf{P} -a.s. on Ω .

Solution. We have $Y = X$, \mathbf{P} -a.s. on Ω if and only if there exists an event $E \in \mathcal{E}$ such that $\mathbf{P}(E) = 0$ and $Y(\omega) = X(\omega)$ for every $\omega \in \Omega - E$. By virtue of the properties of the Lebesgue integral, we have

$$Y = X, \mathbf{P}\text{-a.s. on } \Omega \Leftrightarrow \int_{\Omega} (X - Y)^2 d\mathbf{P} = 0.$$

On the other hand,

$$\int_{\Omega} (X - Y)^2 d\mathbf{P} \equiv \mathbf{E}[(X - Y)^2].$$

Hence, we evaluate

$$\mathbf{E}[(X - Y)^2] = \mathbf{E}[X^2 - 2XY + Y^2] = \mathbf{E}[X^2] - 2\mathbf{E}[XY] + \mathbf{E}[Y^2]. \quad (1)$$

Now, by virtue of the properties of the conditional expectation operator, under our assumptions, we have

$$\mathbf{E}[XY] = \mathbf{E}[\mathbf{E}[XY | X]] = \mathbf{E}[X\mathbf{E}[Y | X]] = \mathbf{E}[X^2] \quad (2)$$

and

$$\mathbf{E}[Y^2] = \mathbf{E}[\mathbf{E}[Y^2 | X]] = \mathbf{E}[X^2]. \quad (3)$$

Combining (1)-(3) it follows

$$\mathbf{E}[(X - Y)^2] = 0,$$

which implies the desired result.

Problem 2 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space and let $(\mathbb{R}, \mathcal{B}(\mathbb{R})) \equiv \mathbb{R}$ be the real Borel state space. Let $N \subseteq \mathbb{N}$, let $\{F_n\}_{n \in N}$ be a complete system of mutually exclusive events of Ω and let \mathcal{F} be the σ -algebra generated by $\{F_n\}_{n \in N}$. In symbols $\mathcal{F} \equiv \sigma(\{F_n\}_{n \in N})$. We know that a map $Y : \Omega \rightarrow \mathbb{R}$ is an $(\mathcal{F}, \mathcal{B}(\mathbb{R}))$ -random variable if and only if

$$Y(\omega) = \sum_{n \in N} y_n 1_{F_n}(\omega), \quad \forall \omega \in \Omega,$$

where $(y_n)_{n \in N}$ is a suitable sequence of real numbers.

Consider a random variable $X \in L^2(\Omega; \mathbb{R})$ and let $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$ the subspace $L^2(\Omega; \mathbb{R})$ of space of all \mathcal{F} -random variables. Use the above claim to prove that

$$\mathbf{E}[X | \mathcal{F}] = \arg \min_{Y \in L^2(\Omega_{\mathcal{F}}; \mathbb{R})} \mathbf{E}[(X - Y)^2]$$

As a consequence, show that $\mathbf{E}[X | \mathcal{F}]$ is the orthogonal projection of X on $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$.

Solution. The space $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$ of all real \mathcal{F} -random variables with finite moment of order 2 is a subspace of $L^2(\Omega; \mathbb{R})$ because it fulfills the conditions for a subset of Hilbert space to be a subspace of the Hilbert space. In fact, for all $X, Y \in L^2(\Omega_{\mathcal{F}}; \mathbb{R})$ and all $\alpha, \beta \in \mathbb{R}$ the linear combination $\alpha X + \beta Y$ is also in $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$, to say $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$ is closed for the linear combination. In addition, if $(X_n)_{n \geq 1}$ is a sequence belonging to $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$ and such that $X_n \xrightarrow{L^2} X$, where $X \in L^2(\Omega; \mathbb{R})$, we also have $X \in L^2(\Omega_{\mathcal{F}}; \mathbb{R})$, to say $L^2(\Omega_{\mathcal{F}}; \mathbb{R})$ is a closed subset of $L^2(\Omega; \mathbb{R})$ in the topology induced by the norm.

Now, given $X \in L^2(\Omega_{\mathcal{F}}; \mathbb{R})$, consider the functional $\Delta_X : L^2(\Omega_{\mathcal{F}}; \mathbb{R}) \rightarrow \mathbb{R}_+$ given by

$$\Delta_X(Y) \stackrel{\text{def}}{=} \mathbf{E} \left[(X - Y)^2 \right], \quad \forall Y \in L^2(\Omega_{\mathcal{F}}; \mathbb{R}).$$

Since in the case under concern

$$Y \in L^2(\Omega_{\mathcal{F}}; \mathbb{R}) \Leftrightarrow Y(\omega) = \sum_{n \in N} y_n 1_{F_n}(\omega), \quad \forall \omega \in \Omega,$$

we can write

$$\Delta_X(Y) = \mathbf{E} \left[\left(X - \sum_{n \in N} y_n 1_{F_n} \right)^2 \right] \equiv \Delta_X(y_1, \dots, y_n, \dots).$$

Hence,

$$\begin{aligned} \Delta_X(y_1, \dots, y_n, \dots) &= \mathbf{E} \left[X^2 - 2 \sum_{n \in N} y_n X 1_{F_n} + \sum_{m, n \in N} y_m y_n 1_{F_m} 1_{F_n} \right] \\ &= \mathbf{E} [X^2] - 2 \sum_{n \in N} y_n \mathbf{E} [X 1_{F_n}] + \sum_{m, n \in N} y_m y_n \mathbf{E} [1_{F_m} 1_{F_n}]. \end{aligned}$$

On the other hand,

$$1_{F_m} 1_{F_n} = \begin{cases} 1_{F_n} & \text{if } m = n \\ 1_{\emptyset} & \text{if } m \neq n \end{cases}.$$

Moreover,

$$\mathbf{E} [1_E] = \mathbf{P}(E), \quad \forall E \in \mathcal{E}$$

and

$$\mathbf{E} [X 1_E] = \int_{\Omega} X 1_E d\mathbf{P} = \int_E X d\mathbf{P}, \quad \forall E \in \mathcal{E}.$$

Therefore,

$$\Delta_X(Y) = \mathbf{E} [X^2] - 2 \sum_{n \in N} y_n \int_{F_n} X d\mathbf{P} + \sum_{n \in N} y_n^2 \mathbf{P}(F_n).$$

As a consequence,

$$\partial_{y_m} \Delta_X(y_1, \dots, y_n, \dots) = -2 \int_{F_m} X d\mathbf{P} + 2y_m \mathbf{P}(F_m), \quad \forall m \in N,$$

which implies

$$\partial_{y_m} \Delta_X(y_1, \dots, y_n, \dots) = 0 \Leftrightarrow y_m = \frac{1}{\mathbf{P}(F_m)} \int_{F_m} X d\mathbf{P} = \mathbf{E} [X | F_m], \quad \forall m \in N.$$

Thus, a candidate minimum Y for the functional $\Delta_X : L^2(\Omega_{\mathcal{F}}; \mathbb{R}) \rightarrow \mathbb{R}_+$ takes the form

$$Y = \sum_{n \in N} \mathbf{E} [X | F_n] 1_{F_n} = \mathbf{E} [X | \mathcal{F}].$$

Now, we have

$$\partial_{y_m}^2 \Delta_X(y_1, \dots, y_n, \dots) = \mathbf{P}(F_m) > 0$$

and the functional $\Delta_X : L^2(\Omega_{\mathcal{F}}; \mathbb{R}) \rightarrow \mathbb{R}_+$ is known to be convex¹. It then follow that

$$\mathbf{E}[X \mid \mathcal{F}] = \arg \min_{Y \in L^2(\Omega_{\mathcal{F}}; \mathbb{R})} \mathbf{E}[(X - Y)^2].$$

To complete the proof, it is sufficient to observe that in a Hilbert space the ortogonal projection of a given vector onto a subspace determines the vector in the subspace of the minimum distance from the given vector.

□

Problem 3 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space and let $(\mathbb{R}, \mathcal{B}(\mathbb{R})) \equiv \mathbb{R}$ be the real Borel state space. Let $X, Y \in L^2(\Omega; \mathbb{R})$.

1. Prove in all details that $\mathbf{E}[Y \mid X] = \mathbf{E}[Y]$ a.e. on Ω implies $\text{Cov}(X, Y) = 0$, but X and Y may not be independent.
2. Prove in all details that $\text{Cov}(X, Y) = 0$ does not imply $\mathbf{E}[Y \mid X] = \mathbf{E}[Y]$.

Hint: in the first case, to generate a suitable counterexample one may consider the random variables $X \sim \text{Ber}(p)$, $Z \sim N(0, 1)$, independent of X , and $Y = XZ$. In the second case consider $X \sim N(0, 1)$ and $Y = X^2$.

¹To prove the convexity of the functional $\Delta_X : L^2(\Omega_{\mathcal{F}}; \mathbb{R}) \rightarrow \mathbb{R}_+$, we may observe that thanks, to the Cauchy-Schwarz inequality and the convexity of the standard quadratic function $f(u) \stackrel{\text{def}}{=} u^2$, we have

$$\begin{aligned} \Delta_X(\theta Y + (1 - \theta)Z) &= \mathbf{E}[(X - (\theta Y + (1 - \theta)Z))^2] \\ &= \mathbf{E}[(\theta(X - Y) + (1 - \theta)(X - Z))^2] \\ &= \mathbf{E}[\theta^2(X - Y)^2 + 2\theta(1 - \theta)(X - Y)(X - Z) + (1 - \theta)^2(X - Z)^2] \\ &= \theta^2 \mathbf{E}[(X - Y)^2] + 2\theta(1 - \theta) \mathbf{E}[(X - Y)(X - Z)] + (1 - \theta)^2 \mathbf{E}[(X - Z)^2] \\ &\leq \theta^2 \mathbf{E}[(X - Y)^2] + 2\theta(1 - \theta) |\mathbf{E}[(X - Y)(X - Z)]| + (1 - \theta)^2 \mathbf{E}[(X - Z)^2] \\ &\leq \theta^2 \mathbf{E}[(X - Y)^2] + 2\theta(1 - \theta) \mathbf{E}[(X - Y)^2]^{1/2} \mathbf{E}[(X - Z)^2]^{1/2} + (1 - \theta)^2 \mathbf{E}[(X - Z)^2] \\ &= \left(\theta \mathbf{E}[(X - Y)^2]^{1/2} + (1 - \theta) \mathbf{E}[(X - Z)^2]^{1/2} \right)^2 \\ &\leq \theta \mathbf{E}[(X - Y)^2] + (1 - \theta) \mathbf{E}[(X - Z)^2], \end{aligned}$$

for every $\theta \in [0, 1]$.

To show the convexity of the standard quadratic function, $f(u) \stackrel{\text{def}}{=} u^2$, we may observe that the inequality

$$(u - v)^2 \geq 0,$$

which holds true for every $u, v \in \mathbb{R}$, implies

$$-\theta(1 - \theta)(u - v)^2 \leq 0,$$

which holds true for every $u, v \in \mathbb{R}$ and $\theta \in [0, 1]$. The latter can be rewritten as

$$-\theta(1 - \theta)(u^2 - 2uv + v^2) \leq 0$$

or equivalently

$$\theta^2 u^2 - \theta u^2 + 2\theta(1 - \theta)uv + (1 - \theta)^2 v^2 - (1 - \theta)v^2.$$

This implies

$$\theta^2 u^2 + 2\theta(1 - \theta)uv + (1 - \theta)^2 v^2 \leq \theta u^2 + (1 - \theta)v^2.$$

Hence,

$$(\theta u + (1 - \theta)v)^2 \leq \theta u^2 + (1 - \theta)v^2,$$

which proves the desired result.

Solution.

1. Under the assumption $\mathbf{E}[Y | X] = \mathbf{E}[Y]$ a.e. on Ω , by virtue of the properties of the conditional expectation operator, we can write

$$\mathbf{E}[XY] = \mathbf{E}[\mathbf{E}[XY | X]] = \mathbf{E}[X\mathbf{E}[Y | X]] = \mathbf{E}[X\mathbf{E}[Y]] = \mathbf{E}[X]\mathbf{E}[Y]$$

Therefore,

$$\text{Cov}(X, Y) = \mathbf{E}[XY] - \mathbf{E}[X]\mathbf{E}[Y] = 0.$$

Now, if we consider the random $X \sim \text{Ber}(p)$, $Z \sim N(0, 1)$, independent of X , and $Y = XZ$, we have

$$\begin{aligned}\text{Cov}(X, Y) &= \mathbf{E}[XY] - \mathbf{E}[X]\mathbf{E}[Y] = \mathbf{E}[X^2Z] - \mathbf{E}[X]\mathbf{E}[XZ] \\ &= \mathbf{E}[X^2]\mathbf{E}[Z] - \mathbf{E}[X]^2\mathbf{E}[Z] \\ &= 0.\end{aligned}$$

On the other hand, we have

$$\mathbf{P}(X \leq 0) = q,$$

and, on account that X and Z are independent,

$$\begin{aligned}\mathbf{P}(Y \leq 0) &= \mathbf{P}(XZ \leq 0) \\ &= \mathbf{P}(XZ \leq 0, X = 0) + \mathbf{P}(XZ \leq 0, X = 1) \\ &= \mathbf{P}(XZ \leq 0 | X = 0)\mathbf{P}(X = 0) + \mathbf{P}(XZ \leq 0 | X = 1)\mathbf{P}(X = 1) \\ &= \mathbf{P}(0 \leq 0 | X = 0)\mathbf{P}(X = 0) + \mathbf{P}(Z \leq 0 | X = 1)\mathbf{P}(X = 1) \\ &= \mathbf{P}(\Omega)\mathbf{P}(X = 0) + \mathbf{P}(Z \leq 0)\mathbf{P}(X = 1) \\ &= q + \frac{1}{2}p.\end{aligned}$$

Furthermore, the same arguments as above shows that

$$\begin{aligned}\mathbf{P}(X \leq 0, Y \leq 0) &= \mathbf{P}(X \leq 0, XZ \leq 0) \\ &= \mathbf{P}(X = 0, XZ \leq 0) \\ &= \mathbf{P}(XZ \leq 0 | X = 0)\mathbf{P}(X = 0) \\ &= q.\end{aligned}$$

Hence, we have

$$\mathbf{P}(X \leq 0)\mathbf{P}(Y \leq 0) = q\left(q + \frac{1}{2}p\right) \neq q = \mathbf{P}(X \leq 0, Y \leq 0)$$

which shows that X and Y are not independent.

2. To show that $\text{Cov}(X, Y) = 0$ does not imply $\mathbf{E}[Y | X] = \mathbf{E}[Y]$, we consider $X \sim N(0, 1)$ and $Y = X^2$. We have

$$\begin{aligned}\text{Cov}(X, Y) &= \mathbf{E}[XY] - \mathbf{E}[X]\mathbf{E}[Y] \\ &= \mathbf{E}[X^3] - \mathbf{E}[X]\mathbf{E}[X^2] \\ &= 0,\end{aligned}$$

but

$$\mathbf{E}[Y | X] = \mathbf{E}[X^2 | X] = X^2 \neq \mathbf{E}[X^2] = \mathbf{E}[Y].$$

□

Problem 4 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space and let X and Y be independent standard Gaussian distributed random variables on Ω . Set

$$U \stackrel{\text{def}}{=} X + Y, \quad V \stackrel{\text{def}}{=} X - Y.$$

1. Compute the distributions of U and V .
2. Prove that U and V are independent.
3. Compute $\mathbf{E}[X | U]$, $\mathbf{E}[X | V]$, $\mathbf{E}[Y | U]$, $\mathbf{E}[Y | V]$.
4. Compute $\mathbf{E}[XY | U]$.

Exercise 5 Hint: First, concentrate your attention on the circumstance that X and Y are independent and standard Gaussian distributed. Second, it might be useful to consider $\mathbf{E}[X^2 | U]$ and $\mathbf{E}[Y^2 | U]$.

Solution.

Problem 6 Let N be a geometric random variable with success probability p , which models the first occurrence of success in n independent trials, and let $(X_n)_{n \geq 1}$ be a sequence of independent and normally distributed random variables with mean μ and variance σ^2 , which are also independent of N . Study the conditional expectation

$$\mathbf{E} \left[\sum_{k=1}^N X_k \mid N \right].$$

Use the properties of the conditional expectation to compute the expectation and the variance of the random sum

$$S_N \stackrel{\text{def}}{=} \sum_{k=1}^N X_k.$$

Solution. Since the random variables of the sequence $(X_n)_{n \geq 1}$ are independent and are also inde-

pendent of N , which is geometrically distributed, we can write

$$\begin{aligned}
\mathbf{E} \left[\sum_{k=1}^N X_k \mid N \right] &= \sum_{n=1}^{\infty} \mathbf{E} \left[\sum_{k=1}^N X_k \mid N = n \right] 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\Omega} \left(\sum_{k=1}^N X_k \right) 1_{\{N=n\}} d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\{N=n\}} \left(\sum_{k=1}^N X_k \right) d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\{N=n\}} \left(\sum_{k=1}^n X_k \right) d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\Omega} \left(\sum_{k=1}^n X_k \right) 1_{\{N=n\}} d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \mathbf{E} \left[\left(\sum_{k=1}^n X_k \right) 1_{\{N=n\}} \right] \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \left(\sum_{k=1}^n \mathbf{E}[X_k] \right) \mathbf{E}[1_{\{N=n\}}] \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \left(\sum_{k=1}^n \mu \right) \mathbf{P}(N=n) \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} n \mu 1_{\{N=n\}} \\
&= \mu \sum_{n=1}^{\infty} n 1_{\{N=n\}} \\
&\stackrel{\mathbf{P}\text{-a.s.}}{=} \mu N.
\end{aligned}$$

Now, we can write

$$\mathbf{E} \left[\sum_{k=1}^N X_k \right] = \mathbf{E} \left[\mathbf{E} \left[\sum_{k=1}^N X_k \mid N \right] \right] = \mathbf{E}[\mu N] = \mu \mathbf{E}[N] = \frac{\mu}{p}.$$

and

$$\mathbf{D}^2 \left[\sum_{k=1}^N X_k \right] = \mathbf{E} \left[\left(\sum_{k=1}^N X_k \right)^2 \right] - \mathbf{E} \left[\sum_{k=1}^N X_k \right]^2 = \mathbf{E} \left[\mathbf{E} \left[\left(\sum_{k=1}^N X_k \right)^2 \mid N \right] \right] - \frac{\mu^2}{p^2}.$$

Thus, we are left with computing

$$\mathbf{E} \left[\left(\sum_{k=1}^N X_k \right)^2 \mid N \right].$$

A straightforward computation yields

$$\begin{aligned}
\mathbf{E} \left[\left(\sum_{k=1}^N X_k \right)^2 \mid N \right] &= \sum_{n=1}^{\infty} \mathbf{E} \left[\left(\sum_{k=1}^N X_k \right)^2 \mid N = n \right] 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\Omega} \left(\sum_{k=1}^N X_k \right)^2 1_{\{N=n\}} d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\{N=n\}} \left(\sum_{k=1}^N X_k \right)^2 d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\{N=n\}} \left(\sum_{k=1}^n X_k \right)^2 d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \int_{\Omega} \left(\sum_{k=1}^n X_k \right)^2 1_{\{N=n\}} d\mathbf{P} \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \mathbf{E} \left[\left(\sum_{k=1}^n X_k \right)^2 1_{\{N=n\}} \right] \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \mathbf{E} \left[\left(\sum_{k=1}^n X_k \right)^2 \right] \mathbf{E} [1_{\{N=n\}}] \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \left(\frac{1}{\mathbf{P}(N=n)} \mathbf{E} \left[\left(\sum_{k=1}^n X_k \right)^2 \right] \mathbf{P}(N=n) \right) 1_{\{N=n\}} \\
&= \sum_{n=1}^{\infty} \mathbf{E} \left[\left(\sum_{k=1}^n X_k \right)^2 \right] 1_{\{N=n\}},
\end{aligned}$$

where

$$\begin{aligned}
\mathbf{E} \left[\left(\sum_{k=1}^n X_k \right)^2 \right] &= \mathbf{E} \left[\sum_{k=1}^n X_k^2 + \sum_{k,\ell=1}^n X_k X_{\ell} \right] \\
&= \sum_{k=1}^n \mathbf{E} [X_k^2] + \sum_{k,\ell=1}^n \mathbf{E} [X_k] \mathbf{E} [X_{\ell}] \\
&= \sum_{k=1}^n (\mu^2 + \sigma^2) + \sum_{k,\ell=1}^n \mu^2 \\
&= (\mu^2 + \sigma^2) n + \mu^2 (n-1) n \\
&= \sigma^2 n + \mu^2 n^2.
\end{aligned}$$

Therefore,

$$\begin{aligned}
\mathbf{E} \left[\left(\sum_{k=1}^N X_k \right)^2 \mid N \right] &= \sum_{n=1}^{\infty} (\sigma^2 n + \mu^2 n^2) 1_{\{N=n\}} \\
&= \sigma^2 \sum_{n=1}^{\infty} n 1_{\{N=n\}} + \mu^2 \sum_{n=1}^{\infty} n^2 1_{\{N=n\}} \\
&= \sigma^2 N + \mu^2 N^2.
\end{aligned}$$

It then follows

$$\begin{aligned}
\mathbf{E} [\sigma^2 N + \mu^2 N^2] &= \sigma^2 \mathbf{E} [N] + \mu^2 \mathbf{E} [N^2] \\
&= \frac{\sigma^2}{p} + \mu^2 (\mathbf{D}^2 [N] + \mathbf{E} [N]^2) \\
&= \frac{\sigma^2}{p} + \mu^2 \left(\frac{2-p}{p^2} \right).
\end{aligned}$$

In the end,

$$\mathbf{D}^2 \left[\sum_{k=1}^N X_k \right] = \frac{\sigma^2}{p} + \mu^2 \left(\frac{2-p}{p^2} \right) - \frac{\mu^2}{p^2} = \frac{\sigma^2}{p} + \mu^2 \left(\frac{1-p}{p^2} \right).$$

Problem 7 Let N be a Poisson random variable with rate parameters λ and let $(X_k)_{k=1}^n$ a finite sequence of independent standard Bernoulli random variables with success parameter p , which are also independent of N . Study the conditional expectation

$$\mathbf{E} \left[\sum_{k=1}^N X_k \mid N \right].$$

Use the properties of the conditional expectation to compute the expectation and the variance of the random sum

$$S_N \stackrel{\text{def}}{=} \sum_{k=1}^N X_k.$$

Solution.

Problem 8 Let B be a binomial random variable with number of trials parameter n and success probability p , which models the number of successes in n independent trials, and let $(X_k)_{k=1}^n$ be a finite sequence of independent and exponentially distributed random variables with rate parameter λ , which are also independent of B . Study the conditional expectation

$$\mathbf{E} \left[\sum_{k=1}^B X_k \mid B \right].$$

Use the properties of the conditional expectation to compute the expectation (and the variance) of the random sum

$$S_B \stackrel{\text{def}}{=} \sum_{k=1}^B X_k.$$

Solution.

Problem 9 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let X and Y be independent standard Rademacher random variables² on Ω . Set $Z \stackrel{\text{def}}{=} X + Y$.

1. Compute $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$.
2. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ uncorrelated?
3. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with standard Rademacher random variables, can you compute $\mathbf{E}[(X + Y)^2 | Z]$ and $\mathbf{E}[XY | Z]$?

Solution. Since X and Y be independent standard Rademacher random variables, we have

$$Z(\omega) = (X + Y)(\omega) = \begin{cases} -2, & \text{if } \omega \in \{X = -1, Y = -1\}, \\ 0, & \text{if } \omega \in \{X = -1, Y = 1\} \cup \{X = 1, Y = -1\}, \\ 2, & \text{if } \omega \in \{X = 1, Y = 1\}. \end{cases}$$

That is to say,

$$X + Y = -2 \cdot 1_{\{X=-1, Y=-1\}} + 2 \cdot 1_{\{X=1, Y=1\}} + 0 \cdot 1_{\{X=-1, Y=1\} \cup \{X=1, Y=-1\}},$$

equivalently

$$Z = -2 \cdot 1_{\{Z=-2\}} + 2 \cdot 1_{\{Z=2\}} + 0 \cdot 1_{\{Z=0\}}.$$

Furthermore,

$$\mathbf{P}(Z = -2) = \mathbf{P}(X + Y = -2) = \mathbf{P}(X = -1, Y = -1) = \mathbf{P}(X = -1) \mathbf{P}(Y = -1) = \frac{1}{4},$$

$$\mathbf{P}(Z = 2) = \mathbf{P}(X + Y = 2) = \mathbf{P}(X = 1, Y = 1) = \mathbf{P}(X = 1) \mathbf{P}(Y = 1) = \frac{1}{4},$$

and

$$\begin{aligned} \mathbf{P}(Z = 0) &= \mathbf{P}(X + Y = 0) = \mathbf{P}(\{X = -1, Y = 1\} \cup \{X = 1, Y = -1\}) \\ &= \mathbf{P}(X = -1, Y = 1) + \mathbf{P}(X = 1, Y = -1) \\ &= \mathbf{P}(X = -1) \mathbf{P}(Y = 1) + \mathbf{P}(X = 1) \mathbf{P}(Y = -1) \\ &= \frac{1}{2}. \end{aligned}$$

1. Since Z is a discrete random variable, to compute $\mathbf{E}[X | Z]$ we can apply the formula

$$\mathbf{E}[X | Z] = \mathbf{E}[X | Z = -2] 1_{\{Z=-2\}} + \mathbf{E}[X | Z = 2] 1_{\{Z=2\}} + \mathbf{E}[X | Z = 0] 1_{\{Z=0\}},$$

where

$$\begin{aligned} \mathbf{E}[X | Z = -2] &= \frac{1}{\mathbf{P}(Z = -2)} \int_{\{Z=-2\}} X d\mathbf{P} = 4 \int_{\{X=-1, Y=-1\}} X d\mathbf{P} \\ &= -4 \int_{\{X=-1, Y=-1\}} d\mathbf{P} = -4 \mathbf{P}(X = -1, Y = -1) \\ &= -1, \end{aligned}$$

²A standard Rademacher random variable R is given by

$$R \stackrel{\text{def}}{=} \begin{cases} 1, & \mathbf{P}(R = 1) = 1/2, \\ -1, & \mathbf{P}(R = -1) = 1/2. \end{cases}$$

$$\begin{aligned}
\mathbf{E}[X \mid Z = 2] &= \frac{1}{\mathbf{P}(Z = 2)} \int_{\{Z=2\}} X d\mathbf{P} = 4 \int_{\{X=1, Y=1\}} X d\mathbf{P} \\
&= 4 \int_{\{X=1, Y=1\}} d\mathbf{P} = 4\mathbf{P}(X = 1, Y = 1) \\
&= 1,
\end{aligned}$$

and

$$\begin{aligned}
\mathbf{E}[X \mid Z = 0] &= \frac{1}{\mathbf{P}(Z = 0)} \int_{\{Z=0\}} X d\mathbf{P} = 2 \left(\int_{\{X=-1, Y=1\} \cup \{X=1, Y=-1\}} X d\mathbf{P} \right) \\
&= 2 \left(\int_{\{X=-1, Y=1\}} X d\mathbf{P} + \int_{\{X=1, Y=-1\}} X d\mathbf{P} \right) \\
&= 2(-1 \cdot \mathbf{P}(X = -1, Y = 1) + 1 \cdot \mathbf{P}(X = 1, Y = -1)) \\
&= 2 \left(-1 \cdot \frac{1}{4} + 1 \cdot \frac{1}{4} \right) \\
&= 0.
\end{aligned}$$

It follows

$$\mathbf{E}[X \mid Z] = -1 \cdot 1_{\{Z=-2\}} + 1 \cdot 1_{\{Z=-2\}} + 0 \cdot 1_{\{Z=0\}} = \frac{1}{2}Z.$$

In addition, since X and Y clearly play the same role,

$$\mathbf{E}[Y \mid Z] = \frac{1}{2}Z.$$

Another argument, based on the properties of the conditional expectation, is the following. Observe that

$$Z = \mathbf{E}[Z \mid Z] = \mathbf{E}[X + Y \mid Z] = \mathbf{E}[X \mid Z] + \mathbf{E}[Y \mid Z].$$

On the other hand, we know that

$$\mathbf{E}[X \mid Z] = g_X(Z) \quad \text{and} \quad \mathbf{E}[Y \mid Z] = g_Y(Z)$$

where $g_X : \mathbb{R} \rightarrow \mathbb{R}$ and $g_Y : \mathbb{R} \rightarrow \mathbb{R}$ are suitable Borel functions. The structure of the function $g_X : \mathbb{R} \rightarrow \mathbb{R}$ [resp. $g_Y : \mathbb{R} \rightarrow \mathbb{R}$] depends on the joint distribution of X and Z [resp. Y and Z] and on the distribution of Z . However, in our case, it is not difficult to show that

$$F_{X,Z}(u, z) = F_{Y,Z}(u, z),$$

for every $(u, z) \in \mathbb{R}^2$. In fact,

$$\begin{aligned}
&F_{X,Z}(u, z) \\
&= \mathbf{P}(X \leq u, Z \leq z) \\
&= \mathbf{P}(X \leq u, X + Y \leq z) \\
&= \mathbf{P}(X \leq u, X + Y \leq z, X = 1) + \mathbf{P}(X \leq u, X + Y \leq z, X = -1) \\
&= \mathbf{P}(X \leq u, X + Y \leq z \mid X = 1) \mathbf{P}(X = 1) + \mathbf{P}(X \leq u, X + Y \leq z \mid X = -1) \mathbf{P}(X = -1) \\
&= \frac{1}{2} (\mathbf{P}(X \leq u, X + Y \leq z \mid X = 1) + \mathbf{P}(X \leq u, X + Y \leq z \mid X = -1)) \\
&= \frac{1}{2} (\mathbf{P}(1 \leq u, 1 + Y \leq z \mid X = 1) + \mathbf{P}(-1 \leq u, -1 + Y \leq z \mid X = -1)) \\
&= \frac{1}{2} (\mathbf{P}(1 \leq u, Y \leq z - 1 \mid X = 1) + \mathbf{P}(-1 \leq u, Y \leq z + 1 \mid X = -1)) \\
&= \begin{cases} 0, & \text{if } u < -1, \\ \frac{1}{2} \mathbf{P}(Y \leq z + 1 \mid X = -1) = \frac{1}{2} \mathbf{P}(Y \leq z + 1), & \text{if } -1 \leq u < 1, \\ \frac{1}{2} (\mathbf{P}(Y \leq z - 1 \mid X = 1) + \mathbf{P}(Y \leq z + 1 \mid X = -1)) = \frac{1}{2} (\mathbf{P}(Y \leq z - 1) + \mathbf{P}(Y \leq z + 1)), & \text{if } 1 \leq u. \end{cases}
\end{aligned}$$

Similarly,

$$F_{Y,Z}(u, z) = \begin{cases} 0, & \text{if } u < -1, \\ \frac{1}{2} \mathbf{P}(X \leq z+1 \mid Y = -1) = \frac{1}{2} \mathbf{P}(X \leq z+1), & \text{if } -1 \leq u < 1, \\ \frac{1}{2} (\mathbf{P}(X \leq z-1 \mid Y = 1) + \mathbf{P}(X \leq z+1 \mid Y = -1)) = \frac{1}{2} (\mathbf{P}(X \leq z-1) + \mathbf{P}(X \leq z+1)), & \text{if } 1 \leq u. \end{cases}$$

Therefore, on account that X and Y have the same distribution, we obtain the desired result. As a consequence, we can asses that

$$g_X = g_Y,$$

which implies

$$\mathbf{E}[X \mid Z] = \mathbf{E}[Y \mid Z].$$

It then follows

$$2\mathbf{E}[X \mid Z] = 2\mathbf{E}[Y \mid Z] = Z,$$

which yields

$$\mathbf{E}[X \mid Z] = \mathbf{E}[Y \mid Z] = \frac{1}{2}Z,$$

as expected.

2. Thanks to what shown above, we have

$$\mathbf{E}[X \mid Z] \mathbf{E}[Y \mid Z] = \frac{1}{4}Z^2 \sim \text{Ber}\left(\frac{1}{2}\right).$$

Hence,

$$\mathbf{E}[\mathbf{E}[X \mid Z] \mathbf{E}[Y \mid Z]] = \frac{1}{2}.$$

On the other hand,

$$\mathbf{E}[\mathbf{E}[X \mid Z]] = \mathbf{E}[\mathbf{E}[Y \mid Z]] = \mathbf{E}\left[\frac{1}{2}Z\right] = \frac{1}{2}\mathbf{E}[Z] = 0.$$

Hence, $\mathbf{E}[X \mid Z]$ and $\mathbf{E}[Y \mid Z]$ are not uncorrelated.

3. Since $\mathbf{E}[X \mid Z]$ and $\mathbf{E}[Y \mid Z]$ are not not uncorrelated, they cannot be independent.

4. By virtue of the properties of the conditional expectation, we have

$$\mathbf{E}[(X+Y)^2 \mid Z] = \mathbf{E}[Z^2 \mid Z] = Z^2.$$

On the other hand,

$$\begin{aligned} \mathbf{E}[(X+Y)^2 \mid Z] &= \mathbf{E}[X^2 + 2XY + Y^2 \mid Z] \\ &= \mathbf{E}[X^2 \mid Z] + 2\mathbf{E}[XY \mid Z] + \mathbf{E}[Y^2 \mid Z]. \end{aligned}$$

Now, since $X \sim Y \sim \text{Rad}(1/2)$, we have $X^2 \sim Y^2 \sim \text{Dir}(1)$. We then obtain

$$Z^2 = \mathbf{E}[(X+Y)^2 \mid Z] = \mathbf{E}[1 \mid Z] + 2\mathbf{E}[XY \mid Z] + \mathbf{E}[1 \mid Z] = 2 + 2\mathbf{E}[XY \mid Z].$$

The latter yields

$$\mathbf{E}[XY \mid Z] = \frac{1}{2}Z^2 - 1.$$

Problem 10 Let Z [resp. R] be a standard Gaussian [Rademacher] random variable on a probability space Ω . In symbols, $X \sim N(0, 1)$ and $R \sim \text{Rad}(1/2)$. Assume that X and R are independent and define $Y \equiv R \cdot X$.

1. Is the random variable Y Gaussian?
2. Are the random variables X and Y uncorrelated? Are X and Y independent?
3. Are the random variables R and Y uncorrelated? Are R and Y independent?
4. Does the random vector $(X, Y)^\top$ have a bivariate Gaussian distribution? Hint: consider the possibility that $(X, Y)^\top$ has a bivariate Gaussian distribution; how the random variable $Z \equiv X + Y$ should be distributed?
5. Can you compute $\mathbf{E}[Y | X]$ and $\mathbf{E}[X | Y]$?

Solution. .

Problem 11 Let X [resp. B] be a standard Gaussian [Bernoulli] random variable on a probability space Ω . In symbols, $X \sim N(0, 1)$ and $B \sim \text{Ber}(1/2)$. Assume that X and B are independent and define $Y \equiv B \cdot X$. **Specifying carefully the properties used**, answer the following questions:

1. Is the random variable Y Gaussian? Is Y absolutely continuous?
2. Are the random variables X and Y uncorrelated? Are X and Y independent?
3. Are the random variables B and Y uncorrelated? Are B and Y independent?
4. Does the random vector $(X, Y)^\top$ have a bivariate Gaussian distribution?
5. Can you compute $\mathbf{E}[Y | X]$? What about $\mathbf{E}[X | Y]$?

Solution. /

Problem 12 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let X and Y be independent standard Rademacher random variables³ on Ω . Set $Z \stackrel{\text{def}}{=} X + Y$.

1. Compute $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$.
2. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ uncorrelated?
3. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with standard Rademacher random variables, can you compute $\mathbf{E}[(X + Y)^2 | Z]$ and $\mathbf{E}[XY | Z]$?

Solution. .

³A standard Rademacher random variable R is given by

$$R \stackrel{\text{def}}{=} \begin{cases} 1, & \mathbf{P}(R = 1) = 1/2, \\ -1, & \mathbf{P}(R = -1) = 1/2. \end{cases}$$

Problem 13 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let X and Y be independent standard Bernoulli random variables on Ω . Define $Z \stackrel{\text{def}}{=} X + Y$.

1. Compute $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$.
2. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ uncorrelated?
3. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with Bernoulli random variables, can you compute $\mathbf{E}[(X + Y)^2 | Z]$ and $\mathbf{E}[XY | Z]$?

Solution. .

Problem 14 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let R be a standard Rademacher random variable on Ω , and let X be a real random variable on Ω symmetric about 0 with finite second order moment. Assume that X and R are independent and define $Y \stackrel{\text{def}}{=} R \cdot X$.

1. Has the random variable Y the same distribution of X ?
2. Are the random variables X and Y uncorrelated?
3. Are the random variables X and Y independent?
4. Can you compute $\mathbf{E}[Y | X]$?

Solution. .

Problem 15 Let X [resp. R] be a standard Gaussian [Rademacher] random variable on a probability space Ω . In symbols, $X \sim N(0, 1)$ and $R \sim \text{Rad}(1/2)$. Assume that X and R are independent and define $Y \equiv R \cdot X$.

1. Is the random variable Y Gaussian?
2. Are the random variables X and Y independent?
3. Does the random vector $(X, Y)^\top$ have a bivariate Gaussian distribution? Hint: consider the possibility that $(X, Y)^\top$ has a bivariate Gaussian distribution; how the random variable $Z \equiv X + Y$ should be distributed?
4. Can you compute $\mathbf{E}[Y | X]$ and $\mathbf{E}[X | Y]$?

Solution. .

Problem 16 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space, let \mathcal{F} be a sub- σ -algebra of \mathcal{E} , and let X, Y be real random variables on Ω with finite second order moment.

1. Show that

$$\mathbf{E}[(X - \mathbf{E}[X | \mathcal{F}])^2] \leq \mathbf{E}[(X - \mathbf{E}[X])^2].$$

2. Show that

$$\mathbf{E}[XY | \mathcal{F}]^2 \leq \mathbf{E}[X^2 | \mathcal{F}] \mathbf{E}[Y^2 | \mathcal{F}]. \quad (4)$$

Solution.

1. In the space $\mathcal{L}^2(\Omega_{\mathcal{F}}; \mathbb{R})$ of the real \mathcal{F} -random variables having finite moment of the second order the conditional expectation of X given \mathcal{F} is characterized as

$$\mathbf{E}[X | \mathcal{F}] = \arg \min_{Y \in \mathcal{L}^2(\Omega_{\mathcal{F}}; \mathbb{R})} \mathbf{E}[(X - Y)^2].$$

This means that

$$\mathbf{E}[(X - \mathbf{E}[X | \mathcal{F}])^2] \leq \mathbf{E}[(X - Y)^2],$$

for every $Y \in \mathcal{L}^2(\Omega_{\mathcal{F}}; \mathbb{R})$. In particular, since the deterministic random variable $\mathbf{E}[X] \equiv \mathbf{E}[X] \cdot 1_{\Omega}$ is clearly in $\mathcal{L}^2(\Omega_{\mathcal{F}}; \mathbb{R})$, setting $Y \equiv \mathbf{E}[X]$ we obtain the desired inequality.

2. Note first that for all real random variables X, Y on Ω we have

$$|XY| \leq \frac{1}{2}(X^2 + Y^2).$$

Therefore, the assumption that X and Y have finite second moment implies that XY has finite first order moment. Hence, both the sides of (5) are well defined. Now, given any $z \in \mathbb{R}$, the random variable $X + zY$ has finite second order moment and, by virtue of the positivity of the conditional expectation operator, we have

$$\mathbf{E}[(X + zY)^2 | \mathcal{F}] \geq 0.$$

On the other hand, the linearity of the conditional expectation operator implies

$$\mathbf{E}[(X + zY)^2 | \mathcal{F}] = \mathbf{E}[X^2 | \mathcal{F}] + 2z\mathbf{E}[XY | \mathcal{F}] + z^2\mathbf{E}[Y^2 | \mathcal{F}].$$

As a consequence, we can write

$$\mathbf{E}[X^2 | \mathcal{F}] + 2z\mathbf{E}[XY | \mathcal{F}] + z^2\mathbf{E}[Y^2 | \mathcal{F}] \geq 0$$

for every $z \in \mathbb{R}$. It follows that

$$\Delta \equiv \mathbf{E}[XY | \mathcal{F}]^2 - \mathbf{E}[X^2 | \mathcal{F}]\mathbf{E}[Y^2 | \mathcal{F}] \leq 0,$$

which is the desired (5).

Problem 17 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space and let $(\mathbb{R}, \mathcal{B}(\mathbb{R})) \equiv \mathbb{R}$ be the real Borel state space. Let $X, Y \in L^2(\Omega; \mathbb{R})$.

1. Prove in all details that $\mathbf{E}[Y | X] = \mathbf{E}[Y]$ a.e. on Ω implies $\text{Cov}(X, Y) = 0$, but X and Y may not be independent.
2. Prove in all details that $\text{Cov}(X, Y) = 0$ does not imply $\mathbf{E}[Y | X] = \mathbf{E}[Y]$.

Hint: in the first case, to generate a suitable counterexample one may consider the random variables $X \sim \text{Ber}(p)$, $Z \sim N(0, 1)$, independent of X , and $Y = XZ$. In the second case consider $X \sim N(0, 1)$ and $Y = X^2$.

Solution.

1. Under the assumption $\mathbf{E}[Y | X] = \mathbf{E}[Y]$ a.e. on Ω , by virtue of the properties of the conditional expectation operator, we can write

$$\mathbf{E}[XY] = \mathbf{E}[\mathbf{E}[XY | X]] = \mathbf{E}[X\mathbf{E}[Y | X]] = \mathbf{E}[X\mathbf{E}[Y]] = \mathbf{E}[X]\mathbf{E}[Y]$$

Therefore,

$$\text{Cov}(X, Y) = \mathbf{E}[XY] - \mathbf{E}[X]\mathbf{E}[Y] = 0.$$

Now, if we consider the random $X \sim \text{Ber}(p)$, $Z \sim N(0, 1)$, independent of X , and $Y = XZ$, we have

$$\begin{aligned} \text{Cov}(X, Y) &= \mathbf{E}[XY] - \mathbf{E}[X]\mathbf{E}[Y] = \mathbf{E}[X^2Z] - \mathbf{E}[X]\mathbf{E}[XZ] \\ &= \mathbf{E}[X^2]\mathbf{E}[Z] - \mathbf{E}[X]^2\mathbf{E}[Z] \\ &= 0. \end{aligned}$$

On the other hand, we have

$$\mathbf{P}(X \leq 0) = q,$$

and, on account that X and Z are independent,

$$\begin{aligned} \mathbf{P}(Y \leq 0) &= \mathbf{P}(XZ \leq 0) \\ &= \mathbf{P}(XZ \leq 0, X = 0) + \mathbf{P}(XZ \leq 0, X = 1) \\ &= \mathbf{P}(XZ \leq 0 | X = 0)\mathbf{P}(X = 0) + \mathbf{P}(XZ \leq 0 | X = 1)\mathbf{P}(X = 1) \\ &= \mathbf{P}(0 \leq 0 | X = 0)\mathbf{P}(X = 0) + \mathbf{P}(Z \leq 0 | X = 1)\mathbf{P}(X = 1) \\ &= \mathbf{P}(\Omega)\mathbf{P}(X = 0) + \mathbf{P}(Z \leq 0)\mathbf{P}(X = 1) \\ &= q + \frac{1}{2}p. \end{aligned}$$

Furthermore, the same arguments as above shows that

$$\begin{aligned} \mathbf{P}(X \leq 0, Y \leq 0) &= \mathbf{P}(X \leq 0, XZ \leq 0) \\ &= \mathbf{P}(X = 0, XZ \leq 0) \\ &= \mathbf{P}(XZ \leq 0 | X = 0)\mathbf{P}(X = 0) \\ &= q. \end{aligned}$$

Hence, we have

$$\mathbf{P}(X \leq 0)\mathbf{P}(Y \leq 0) = q\left(q + \frac{1}{2}p\right) \neq q = \mathbf{P}(X \leq 0, Y \leq 0)$$

which shows that X and Y are not be independent.

2. To show that $\text{Cov}(X, Y) = 0$ does not imply $\mathbf{E}[Y | X] = \mathbf{E}[Y]$, we consider $X \sim N(0, 1)$ and $Y = X^2$. We have

$$\begin{aligned} \text{Cov}(X, Y) &= \mathbf{E}[XY] - \mathbf{E}[X]\mathbf{E}[Y] \\ &= \mathbf{E}[X^3] - \mathbf{E}[X]\mathbf{E}[X^2] \\ &= 0, \end{aligned}$$

but

$$\mathbf{E}[Y | X] = \mathbf{E}[X^2 | X] = X^2 \neq \mathbf{E}[X^2] = \mathbf{E}[Y].$$

□

Problem 18 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space, let $(\mathbb{R}, \mathcal{B}(\mathbb{R})) \equiv \mathbb{R}$ be the Euclidean real line endowed with the Borel σ -algebra, and let $X, Y \in L^2(\Omega; \mathbb{R})$. Fixed any sub- σ -algebra \mathcal{F} of \mathcal{E} , we call conditional variance of X given \mathcal{F} the random variable

$$\mathbf{D}^2[X | \mathcal{F}] \stackrel{\text{def}}{=} \mathbf{E} \left[(X - \mathbf{E}[X | \mathcal{F}])^2 | \mathcal{F} \right].$$

Prove that:

1. we have

$$\mathbf{D}^2[X | \mathcal{F}] = \mathbf{E}[X^2 | \mathcal{F}] - \mathbf{E}[X | \mathcal{F}]^2;$$

2. if X is an \mathcal{F} -random variable, then we have

$$\mathbf{D}^2[X | \mathcal{F}] = 0;$$

3. if X is \mathcal{F} -independent, then we have

$$\mathbf{D}^2[X | \mathcal{F}] = \mathbf{D}^2[X];$$

4. if X is an \mathcal{F} -random variable and Y is \mathcal{F} -independent, then we have

$$\mathbf{D}^2[X + Y | \mathcal{F}] = \mathbf{D}^2[Y].$$

Solution.

Problem 19 Let X [resp. B] be a standard Gaussian [Bernoulli] random variable on a probability space Ω . In symbols, $X \sim N(0, 1)$ and $B \sim \text{Ber}(1/2)$. Assume that X and B are independent and define $Y \equiv B \cdot X$. **Specifying carefully the properties used**, answer the following questions:

1. Is the random variable Y Gaussian? Is Y absolutely continuous?
2. Are the random variables X and Y uncorrelated? Are X and Y independent?
3. Are the random variables B and Y uncorrelated? Are B and Y independent?
4. Does the random vector $(X, Y)^\top$ have a bivariate Gaussian distribution?
5. Can you compute $\mathbf{E}[Y | X]$? What about $\mathbf{E}[X | Y]$?

Solution.

1. To check whether Y is Gaussian we compute $\mathbf{P}(Y \leq y)$, for every $y \in \mathbb{R}$. On account that $\{B = 0\}, \{B = 1\}$ constitute a partition of Ω , the random variables B and X are independent, and $X \sim N(0, 1)$, we can write

$$\begin{aligned} \mathbf{P}(Y \leq y) &= \mathbf{P}(BX \leq y) \\ &= \mathbf{P}(BX \leq y, B = 0) + \mathbf{P}(BX \leq y, B = 1) \\ &= \mathbf{P}(BX \leq y | B = 0) \mathbf{P}(B = 0) + \mathbf{P}(BX \leq y | B = 1) \mathbf{P}(B = 1) \\ &= \frac{1}{2} (\mathbf{P}(0 \leq y | B = 0) + \mathbf{P}(X \leq y | B = 1)) \\ &= \frac{1}{2} (\mathbf{P}(0 \leq y) + \mathbf{P}(X \leq y)) \\ &= \begin{cases} \frac{1}{2} \mathbf{P}(X \leq y) = \frac{1}{2} F_X(x), & \text{if } y < 0, \\ \frac{1}{2} (1 + \mathbf{P}(X \leq y)) = \frac{1}{2} (1 + F_X(x)) & \text{if } 0 \leq y. \end{cases} \end{aligned}$$

Now, we have

$$\lim_{y \rightarrow 0^-} \mathbf{P}(Y \leq y) = \lim_{y \rightarrow 0^-} \frac{1}{2} F_X(x) = \frac{1}{4}$$

and

$$\lim_{y \rightarrow 0^+} \mathbf{P}(Y \leq y) = \lim_{y \rightarrow 0^+} \frac{1}{2} (1 + F_X(x)) = \frac{3}{4}$$

This proves that Y is not Gaussian.

2. Since $Y \equiv B \cdot X$, the intuition is that the observation of the values taken by X transmits information on the values taken by Y . That is X and Y are not independent. In fact, thanks to the independence of X and B and on account that $X \sim N(0, 1)$, we have

$$\mathbf{E}[XY] = \mathbf{E}[XBX] = \mathbf{E}[BX^2] = \mathbf{E}[B] \mathbf{E}[X^2] = \frac{1}{2} \cdot 1 = \frac{1}{2}.$$

On the other hand,

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

Hence,

$$\mathbf{E}[XY] - \mathbf{E}[X] \mathbf{E}[Y] = \frac{1}{2}$$

This shows that X and Y are correlated, which prevents that X^2 and Y^2 are independent.

3. Still thanks to the independence of X and B and on account that $X \sim N(0, 1)$ and $B^2 \sim \text{Ber}(1/2)$, we have

$$\mathbf{E}[BY] = \mathbf{E}[BBX] = \mathbf{E}[B^2X] = \mathbf{E}[B^2] \mathbf{E}[X] = \frac{1}{2} \mathbf{E}[X] = 0.$$

On the other hand,

$$\mathbf{E}[B] \mathbf{E}[Y] = \mathbf{E}[B] \mathbf{E}[BX] = \mathbf{E}[B] \mathbf{E}[B] \mathbf{E}[X] = \frac{1}{4} \mathbf{E}[X] = 0.$$

This shows that B and Y are uncorrelated. Here, the intuition is that the observation of the values taken by B transmits information on the values taken by Y . Hence, the intuition is that B and Y are not independent. To prove this, we show that B^2 and Y^2 are correlated. In fact, thanks to the independence of X and B and on account that $B^4 \sim B^2 \sim \text{Ber}(1/2)$, we have

$$\mathbf{E}[B^2Y^2] = \mathbf{E}[B^2B^2X^2] = \mathbf{E}[B^4X^2] = \mathbf{E}[B^4] \mathbf{E}[X^2] = \frac{1}{2} \cdot 1 = \frac{1}{2}$$

and

$$\mathbf{E}[B^2] \mathbf{E}[Y^2] = \mathbf{E}[B^2] \mathbf{E}[B^2X^2] = \mathbf{E}[B^2] \mathbf{E}[B^2] \mathbf{E}[X^2] = \frac{1}{2} \cdot \frac{1}{2} \cdot 1 = \frac{1}{4}.$$

This shows that B^2 and Y^2 are correlated, which prevents that B^2 and Y^2 are independent. Eventually, B and Y cannot be independent.

4. Since $B \sim \text{Ber}(1/2)$ is independent of X , we have

$$\mathbf{E}[Y | X] = \mathbf{E}[BX | X] = X \mathbf{E}[B | X] = \mathbf{E}[B] X = \frac{1}{2} X$$

$$\mathbf{E}[X | Y] = \mathbf{E}[X | BX]$$

By virtue of what shown above and the properties of the conditional expectation, on account that B and X are independent, we have,

$$\mathbf{E}[Y | X] = \mathbf{E}[BX | X] = X\mathbf{E}[B | X] = X\mathbf{E}[B] = \frac{1}{2}X.$$

Now, to compute $\mathbf{E}[X | Y]$, observe preliminarily that

$$B(\omega) = 1_{\{B=1\}}(\omega)$$

for every $\omega \in \Omega$. In fact,

$$1_{\{B=1\}}(\omega) = \begin{cases} 1 & \text{if } B(\omega) = 1 \\ 0 & \text{if } B(\omega) = 0 \end{cases}$$

Hence,

$$Y = BX = X1_{\{B=1\}}.$$

As a consequence, on account that

$$1_{\{B=1\}} + 1_{\{B=0\}} = 1_\Omega,$$

we have

$$\begin{aligned} \mathbf{E}[X | Y] &= \mathbf{E}[X(1_{\{B=1\}} + 1_{\{B=0\}}) | Y] \\ &= \mathbf{E}[X1_{\{B=1\}} | Y] + \mathbf{E}[X1_{\{B=0\}} | Y] \\ &= \mathbf{E}[Y | Y] + \mathbf{E}[X1_{\{B=0\}} | Y] \\ &= Y + \mathbf{E}[X1_{\{B=0\}} | Y] \\ &= BX + \mathbf{E}[X1_{\{B=0\}} | Y]. \end{aligned}$$

Thus, we are left with computing

$$\mathbf{E}[X1_{\{B=0\}} | Y].$$

To this goal, observe that

$$\int_{\{Y \in C\}} \mathbf{E}[X1_{\{B=0\}} | Y] d\mathbf{P}_{|\sigma(Y)} = \int_{\{Y \in C\}} X1_{\{B=0\}} d\mathbf{P} = \int_{\{Y \in C\} \cap \{B=0\}} X d\mathbf{P},$$

where

$$\{Y \in C\} \cap \{B=0\} = \{BX \in C\} \cap \{B=0\} = \begin{cases} \{B=0\}, & \text{if } 0 \in C, \\ \emptyset, & \text{if } 0 \notin C. \end{cases}$$

Hence,

$$\int_{\{Y \in C\}} \mathbf{E}[X1_{\{B=0\}} | Y] d\mathbf{P}_{|\sigma(Y)} = \begin{cases} \int_{\{B=0\}} X d\mathbf{P}, & \text{if } 0 \in C, \\ 0, & \text{if } 0 \notin C, \end{cases}$$

for every $C \in \mathcal{B}(\mathbb{R})$. On the other hand,

$$\int_{\{B=0\}} X d\mathbf{P} = \mathbf{E}[X1_{\{B=0\}}] = \mathbf{E}[X] \mathbf{E}[1_{\{B=0\}}] = \mathbf{E}[X] \mathbf{P}(B=0) = \frac{1}{2} \mathbf{E}[X].$$

It then follows,

$$\int_{\{Y \in C\}} \mathbf{E}[X1_{\{B=0\}} | Y] d\mathbf{P}_{|\sigma(Y)} = \begin{cases} \frac{1}{2} \mathbf{E}[X], & \text{if } 0 \in C, \\ 0, & \text{if } 0 \notin C. \end{cases}$$

We then claim that

$$\mathbf{E}[X1_{\{B=0\}} | Y] = \mathbf{E}[X] 1_{\{Y=0\}}, \quad \mathbf{P}_{|\sigma(Y)}\text{-a.s. on } \Omega.$$

In fact, we have

$$\{Y = 0\} = \{XB = 0\} = \{X \in \mathbb{R}, B = 0\} \cup \{X = 0, B = 1\},$$

where

$$\{X \in \mathbb{R}, B = 0\} \cap \{X = 0, B = 1\} = \emptyset.$$

This, on account of the independence of X and B and that X is a continuous random variable, implies

$$\begin{aligned} \mathbf{P}(Y = 0) &= \mathbf{P}(X \in \mathbb{R}, B = 0) + \mathbf{P}(X = 0, B = 1) \\ &= \mathbf{P}(X \in \mathbb{R}) \mathbf{P}(B = 0) + \mathbf{P}(X = 0) \mathbf{P}(B = 1) \\ &= \mathbf{P}(B = 0) \\ &= \frac{1}{2}. \end{aligned}$$

In addition, since

$$\{Y \in C\} \cap \{Y = 0\} = \begin{cases} \{Y = 0\} & \text{if } 0 \in C \\ \emptyset & \text{if } 0 \notin C \end{cases},$$

for every $C \in \mathcal{B}(\mathbb{R})$, we have

$$\begin{aligned} \int_{\{Y \in C\}} \mathbf{E}[X] 1_{\{Y=0\}} d\mathbf{P}_{|\sigma(Y)} &= \mathbf{E}[X] \int_{\{Y \in C\} \cap \{Y=0\}} d\mathbf{P}_{|\sigma(Y)} \\ &= \mathbf{E}[X] \mathbf{P}(\{Y \in C\} \cap \{Y = 0\}) \\ &= \begin{cases} \mathbf{E}[X] \mathbf{P}(Y = 0) & \text{if } 0 \in C \\ 0 & \text{if } 0 \notin C \end{cases} \\ &= \begin{cases} \frac{1}{2} \mathbf{E}[X] & \text{if } 0 \in C \\ 0 & \text{if } 0 \notin C \end{cases}, \end{aligned}$$

for every $C \in \mathcal{B}(\mathbb{R})$. From what shown above, we can write

$$\int_{\{Y \in C\}} \mathbf{E}[X 1_{\{B=0\}} | Y] d\mathbf{P}_{|\sigma(Y)} = \int_{\{Y \in C\}} \mathbf{E}[X] 1_{\{Y=0\}} d\mathbf{P}_{|\sigma(Y)},$$

for every $C \in \mathcal{B}(\mathbb{R})$. This implies our claim. Summarizing we obtain

$$\mathbf{E}[X | Y] = BX + \mathbf{E}[X] 1_{\{Y=0\}}, \quad \mathbf{P}_{|\sigma(Y)}\text{-a.s. on } \Omega,$$

which completes the solution of 5.

Problem 20 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space and let $B \sim \text{Ber}(1/2)$ [resp. $R \sim \text{Rad}(1/2)$] a standard Bernoulli [resp. Rademacher] random variable on Ω . Assume that B and R are independent and define $X \stackrel{\text{def}}{=} B + R$.

1. Compute $\mathbf{E}[X | B]$, $\mathbf{E}[X | R]$, $\mathbf{E}[B | X]$, and $\mathbf{E}[R | X]$. In addition, **specifying carefully the properties used**, answer the following questions:
2. Are the random variables $\mathbf{E}[X | B]$, $\mathbf{E}[X | R]$ uncorrelated? Are $\mathbf{E}[X | B]$, $\mathbf{E}[X | R]$ independent?
3. Are the random variables $\mathbf{E}[B | X]$ and $\mathbf{E}[R | X]$ uncorrelated? Are $\mathbf{E}[B | X]$ and $\mathbf{E}[R | X]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with a Bernoulli and a Rademacher random variable, can you compute $\mathbf{E}[BR | X]$?

Solution. .

Problem 21 Let U, V real random variables on a probability space Ω such that $U \sim V \sim N(0, 1)$, the vector $(U, V)^\top$ is Gaussian, and $\text{Corr}(U, V) \equiv \rho < 1$. Consider the real random variables

$$X \stackrel{\text{def}}{=} U - \rho V \quad \text{and} \quad Y \stackrel{\text{def}}{=} \sqrt{1 - \rho} V.$$

1. Can you prove that the vector $(X, Y)^\top$ is Gaussian?
2. Are the random variables X and Y independent?
3. Compute the distributions of X and Y ;
4. Compute $\mathbf{E}[X^2 Y^2]$, $\mathbf{E}[X Y^3]$, $\mathbf{E}[Y^4]$.
5. Compute $\mathbf{E}[U^2 V^2]$.

Solution. .

Problem 22 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space and let B_1 and B_2 be standard Bernoulli random variables on Ω . In symbols, $B_k \sim \text{Ber}(1/2)$, for $k = 1, 2$. Assume that B_1 and B_2 are independent and set

$$X \stackrel{\text{def}}{=} B_1 + B_2, \quad Y \stackrel{\text{def}}{=} B_1 \cdot B_2$$

1. Compute $\mathbf{E}[B_k | X]$ and $\mathbf{E}[B_k | Y]$ for $k = 1, 2$.
2. Are the random variables $\mathbf{E}[B_1 | X]$ and $\mathbf{E}[B_2 | X]$ uncorrelated? Are they independent?
3. Are the random variables $\mathbf{E}[B_1 | Y]$ and $\mathbf{E}[B_2 | Y]$ uncorrelated? Are they independent?
4. Compute $\mathbf{E}[X | Y]$ and $\mathbf{E}[Y | X]$.
5. Are the random variables $\mathbf{E}[X | Y]$ and $\mathbf{E}[Y | X]$ uncorrelated? Are they independent?
6. Compute $\mathbf{E}[X^2 | Y]$ and $\mathbf{E}[Y^2 | X]$.

Solution. .

Problem 23 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let X and Y be independent standard Bernoulli random variables on Ω . Define $Z \stackrel{\text{def}}{=} X + Y$.

1. Compute $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$.
2. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ uncorrelated?
3. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with Bernoulli random variables, can you compute $\mathbf{E}[(X + Y)^2 | Z]$ and $\mathbf{E}[XY | Z]$?

Solution. .

Problem 24 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space and let R_1 and R_2 be standard Rademacher random variables on Ω . In symbols, $R_k \sim \text{Rad}(1/2)$, for $k = 1, 2$. Assume that R_1 and R_2 are independent and set

$$X \stackrel{\text{def}}{=} R_1 - R_2, \quad Y \stackrel{\text{def}}{=} -R_1 \cdot R_2$$

1. Compute $\mathbf{E}[R_k | X]$ and $\mathbf{E}[R_k | Y]$ for $k = 1, 2$.
2. Are the random variables $\mathbf{E}[R_1 | X]$ and $\mathbf{E}[R_2 | X]$ uncorrelated? Are they independent?
3. Are the random variables $\mathbf{E}[R_1 | Y]$ and $\mathbf{E}[R_2 | Y]$ uncorrelated? Are they independent?
4. Compute $\mathbf{E}[X | Y]$ and $\mathbf{E}[Y | X]$.
5. Are the random variables $\mathbf{E}[X | Y]$ and $\mathbf{E}[Y | X]$ uncorrelated? Are they independent?
6. Compute $\mathbf{E}[X^2 | Y]$ and $\mathbf{E}[Y^2 | X]$.

Solution. .

Problem 25 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let X and Y be independent standard Rademacher random variables⁴ on Ω . Set $Z \stackrel{\text{def}}{=} X + Y$.

1. Compute $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$.
2. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ uncorrelated?
3. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with standard Rademacher random variables, can you compute $\mathbf{E}[(X + Y)^2 | Z]$ and $\mathbf{E}[XY | Z]$?

Solution. .

Problem 26 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let X and Y be independent standard Bernoulli random variables on Ω . Define $Z \stackrel{\text{def}}{=} X + Y$.

1. Compute $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$.
2. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ uncorrelated?
3. Are the random variables $\mathbf{E}[X | Z]$ and $\mathbf{E}[Y | Z]$ independent?
4. By using the properties of the conditional expectation, on account that you are dealing with Bernoulli random variables, can you compute $\mathbf{E}[(X + Y)^2 | Z]$ and $\mathbf{E}[XY | Z]$?

Solution. .

⁴A standard Rademacher random variable R is given by

$$R \stackrel{\text{def}}{=} \begin{cases} 1, & \mathbf{P}(R = 1) = 1/2, \\ -1, & \mathbf{P}(R = -1) = 1/2. \end{cases}$$

Problem 27 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ a probability space, let R be a standard Rademacher random variable on Ω , and let X be a real random variable on Ω symmetric about 0 with finite second order moment. Assume that X and R are independent and define $Y \stackrel{\text{def}}{=} R \cdot X$.

1. Has the random variable Y the same distribution of X ?
2. Are the random variables X and Y uncorrelated?
3. Are the random variables X and Y independent?
4. Can you compute $\mathbf{E}[Y | X]$?

Solution. .

Problem 28 Let X [resp. R] be a standard Gaussian [Rademacher] random variable on a probability space Ω . In symbols, $X \sim N(0, 1)$ and $R \sim \text{Rad}(1/2)$. Assume that X and R are independent and define $Y \equiv R \cdot X$.

1. Is the random variable Y Gaussian?
2. Are the random variables X and Y independent?
3. Does the random vector $(X, Y)^\top$ have a bivariate Gaussian distribution? Hint: consider the possibility that $(X, Y)^\top$ has a bivariate Gaussian distribution; how the random variable $Z \equiv X + Y$ should be distributed?
4. Can you compute $\mathbf{E}[Y | X]$ and $\mathbf{E}[X | Y]$?

Solution. .

Problem 29 Let $(\Omega, \mathcal{E}, \mathbf{P}) \equiv \Omega$ be a probability space, let \mathcal{F} be a sub- σ -algebra of \mathcal{E} , and let X, Y be real random variables on Ω with finite second order moment.

1. Show that

$$\mathbf{E} \left[(X - \mathbf{E}[X | \mathcal{F}])^2 \right] \leq \mathbf{E} \left[(X - \mathbf{E}[X])^2 \right].$$

2. Show that

$$\mathbf{E}[XY | \mathcal{F}]^2 \leq \mathbf{E}[X^2 | \mathcal{F}] \mathbf{E}[Y^2 | \mathcal{F}]. \quad (5)$$

Solution. .