MSIAM M1: Probability and Statistics

Solutions to [the most difficult] exercises

1 TD 1

Exercise 1.2. *Provide an example of asymmetric density with $\alpha = 0$.*

Proof. Consider a discrete random variable X, such that $\mathbb{P}(X = 2) = \mathbb{P}(X = -1) = \frac{1}{4}, \mathbb{P}(X = \sqrt{7}) = \frac{1}{4\sqrt{7}}$, and $\mathbb{P}(X = 0) = \frac{1}{2} - \frac{1}{4\sqrt{7}}$. First, note that this r.v. is asymmetric. Indeed, $\mathbb{E}[X] = \frac{1}{2} - \frac{1}{4} - \sqrt{7}\frac{1}{4\sqrt{7}} = 0$. However,

$$F_X(0) = \frac{3}{4} \quad \neq \quad 1 - F_X(0) = \frac{1}{4}.$$

Now, compute the third moment of X:

$$\mathbb{E}[X^3] = 2 - \frac{1}{4} - 7\sqrt{7}\frac{1}{4\sqrt{7}} = 0.$$

Thus, the skewness parameter is 0. □

Exercise 1.4. *Let (ξ_n) and (η_n) be two sequences of r.v. Prove the following statements:*

1°. *If $a \in \mathbb{R}$ is a constant, then when $n \to \infty$:*

$$\xi_n \xrightarrow{D} a \quad \Leftrightarrow \quad \xi_n \xrightarrow{P} a$$

2°. *(**Slutsky's theorem**.) If $\xi_n \xrightarrow{D} a$ and $\eta_n \xrightarrow{D} \eta$ when $n \to \infty$, where $a \in \mathbb{R}$ and η is a random variable, then*

$$\xi_n + \eta_n \xrightarrow{D} a + \eta, \quad \text{as } n \to \infty.$$

Show that if a is a general random variable, these two relations do not hold (construct a counterexample).

3°. *If* $\xi_n \xrightarrow{D} a$ *and* $\eta_n \xrightarrow{D} \eta$ *when* $n \to \infty$*, where* $a \in \mathbb{R}$ *and* η *is a random variable, then*

$$\xi_n \eta_n \xrightarrow{D} a\eta, \quad \text{as } n \to \infty.$$

Would this result continue to hold if we suppose that a is a general random variable?

Proof. 1°. (Anatolii's proof) By the definition of convergence in probability, we want to show that $\lim_{n\to\infty} \mathbb{P}(|\xi_n - a| \geq \varepsilon) = 0$. Let us consider two continuous functions, defined as follows:

$$f_\varepsilon(x) = \begin{cases} 1, & x \in \left(-\infty, a - \frac{3\varepsilon}{2}\right] \bigcup \left[a + \frac{3\varepsilon}{2}, \infty\right) \\ 0, & x \in [a - \varepsilon, a + \varepsilon], \end{cases}$$

$$g_\varepsilon(x) = \begin{cases} 1, & x \in (-\infty, a - \varepsilon] \bigcup [a + \varepsilon, \infty) \\ 0, & x \in \left[a - \frac{\varepsilon}{2}, a + \frac{\varepsilon}{2}\right], \end{cases}$$

Functions f and g are "smoothed" versions of an indicator function, which check if x contains outside of balls of radius ε and $\frac{\varepsilon}{2}$ respectively. Then,

$$\int_{-\infty}^{\infty} f_\varepsilon(x) dF_n(x) \leq \mathbb{P}(|\xi_n - a| \geq \varepsilon) \leq \int_{-\infty}^{\infty} g_\varepsilon(x) dF_n(x),$$

where F_n is a cumulative distribution function of ξ_n. Both left and right sides converge to 0 as $n \to \infty$, since $f_\varepsilon(a) = g_\varepsilon(a) = 0$. Consequently, $\lim_{n\to\infty} \mathbb{P}(|\xi_n - a| \geq \varepsilon) = 0$. It gives the result.

1°. (Alternative proof) By the definition of convergence in probability, we want to show that $\lim_{n\to\infty} \mathbb{P}(|\xi_n - a| \geq \varepsilon) = 0$. Fix some $\varepsilon > 0$. Denote by $B_\varepsilon(a)$ be the open ball of radius ε around point a, and $\bar{B}_\varepsilon(a)$ its complement. Then

$$\mathbb{P}\left(|\xi_n - a| \geq \varepsilon\right) = \mathbb{P}\left(\xi_n \in \bar{B}_\varepsilon(a)\right)$$

Then we can observe that:

$$\lim_{n\to\infty} \mathbb{P}(|\xi_n - a| \geq \varepsilon) \leq \limsup_{n\to\infty} \mathbb{P}\left(|\xi_n - a| \geq \varepsilon\right) = \\ \limsup_{n\to\infty} \mathbb{P}\left(\xi_n \in \bar{B}_\varepsilon(a)\right) = \mathbb{P}\left(a \in \bar{B}_\varepsilon(a)\right) = 0$$

By definition, it means that the sequence converges to a in probability.

2°*a*. It is a direct consequence of 1°. What we need to show is the following:

$$\mathbb{P}\left(\xi_n + \eta_n \leq t\right) \longrightarrow \mathbb{P}\left(a + \eta \leq t\right) = \mathbb{P}\left(\eta \leq t - a\right).$$

Consider the following event:

$$\{\xi_n + \eta_n - a \le t - a\} = \\ \{\xi_n + \eta_n - a \le t - a, |\xi_n - a| \le \varepsilon\} \bigcup \{\xi_n + \eta_n - a \le t - a, |\xi_n - a| > \varepsilon\}$$

Note that the probability of the second event tends to 0 as $n \to \infty$ (because of the result from 1°). Then, consider

$$\{\eta_n \le t - a - \varepsilon\} \subseteq \{\xi_n + \eta_n - a \le t - a, |\xi_n - a| \le \varepsilon\} \subseteq \{\eta_n \le t - a + \varepsilon\}$$

As a consequence,

$$\mathbb{P}\left(\eta_n \le t - a + \varepsilon\right) \longrightarrow \mathbb{P}\left(\eta \le t - a + \varepsilon\right) \to \mathbb{P}\left(\eta \le t - a\right) \text{ as } \varepsilon \to 0.$$

$2°b$. **(Counterexample)** Consider a sequence ξ_n of Bernoulli variables, such that $\mathbb{P}(\xi_n = 1) = \mathbb{P}(\xi_n = 0) = \frac{1}{2}$, and consider $\eta_n = 1 - \xi_n$. It is easy to see that $\xi_n \xrightarrow{D} \xi$ and $\eta_n \xrightarrow{D} \eta$, where ξ and η are again Bernoulli variables taking values 0 and 1 with equal probability. Obviously, $\xi_n + \eta_n = 1$ is not converging in law to the variable $\xi + \eta$, which is taking values $0, 1, 2$ with probabilities $\frac{1}{4}, \frac{1}{2}, \frac{1}{4}$ respectively.

3°. First note that

$$\xi_n \eta_n = (\xi_n - a)\eta_n + a\eta_n.$$

Note that $a\eta_n \xrightarrow{D} a\eta$ because $\forall a > 0, x \in \mathbb{R}$, $\mathbb{P}\left(a\eta_n \le x\right) = \mathbb{P}\left(\eta_n \le \frac{x}{a}\right) \to \mathbb{P}\left(\eta \le \frac{x}{a}\right) = \mathbb{P}\left(a\eta \le x\right)$. Also, $\forall C < \infty$

$$\left\{|\eta_n(\xi_n - a)| > \varepsilon\right\} \subseteq \left\{|\eta_n| > C\right\} \bigcup \left\{|\xi_n - a| > \frac{\varepsilon}{C}\right\},$$

thus

$$\mathbb{P}\left(|\eta_n(\xi_n - a)| > \varepsilon\right) \le \mathbb{P}\left(|\eta_n| > C\right) + \mathbb{P}\left(|\xi_n - a| > \frac{\varepsilon}{C}\right).$$

Note that $\mathbb{P}\left(|\xi_n - a| > \frac{\varepsilon}{C}\right)$ converges to 0 as $n \to \infty$ due to 1°. Now it only remains to note that $\mathbb{P}\left(|\eta_n| > C\right) \to \mathbb{P}\left(|\eta| > C\right) < \frac{\delta}{4}$ for $C = C(\delta)$ sufficiently large.

□

Exercise 1.9. *Let $\xi_1, \ldots, \xi_n$ be independent r.v. and let*

$$\xi_{\min} = \min(\xi_1, \ldots, \xi_n), \quad \xi_{\max} = \max(\xi_1, \ldots, \xi_n).$$

1. *Show that*

$$\mathbb{P}(\xi_{\min} \ge x) = \prod_{i=1}^{n} \mathbb{P}(\xi_i \ge x), \quad \mathbb{P}(\xi_{\max} < x) = \prod_{i=1}^{n} \mathbb{P}(\xi_i < x)$$

2. *Suppose, furthermore, that* $\xi_1, \ldots, \xi_n$ *are identically distributed with uniform distribution* $\mathcal{U}[0, a]$. *Compute* $\mathbb{E}[\xi_{\min}], \mathbb{E}[\xi_{\max}], Var[\xi_{\min}], Var[\xi_{\max}]$

Proof. We consider the variable $\xi_{\max}$. The proof for $\xi_{\min}$ is identical.

1. Thanks to the independence of $\xi_1, \ldots, \xi_n$ we have:

$$\mathbb{P}\left(\max_{i=1,\ldots,n} \xi_i\right) = \mathbb{P}(\xi_1 < x, \ldots, \xi_n < x) = \mathbb{P}(\xi_1 < x) \ldots \mathbb{P}(\xi_n < x).$$

2. Since $\xi_i \sim \mathcal{U}[0, a]$, we have the following c.d.f. $F^*(x)$ of $\xi_{\max}$:

$$F^*(x) = \prod_{i=1}^{n} \frac{x}{a} = \left(\frac{x}{a}\right)^n \quad \forall 0 \le x \le a.$$

From that, we can easily derive the density of $\xi_{\max}$:

$$f^*(x) = \frac{nx^{n-1}}{a^n}.$$

Then, it is easy to obtain the expressions for the first and the second moments:

$$\mathbb{E}[\xi_{\max}] = \int_0^a xn\frac{x^{n-1}}{a^n}dx = \frac{an}{n+1}$$
$$\mathbb{E}[\xi_{\max}^2] = \int_0^a x^2 n\frac{x^{n-1}}{a^n}dx = \frac{a^2 n}{n+2}.$$

From that we compute the varaince:

$$Var[\xi_{\max}] = \mathbb{E}[\xi_{\max}^2] - (\mathbb{E}[\xi_{\max}])^2 = a^2\frac{n}{(n+1)^2(n+2)}.$$

It gives the statement.

□

Exercise 1.10. *Let* $\xi_1, \ldots, \xi_n$ *be i.i.d. Bernoulli r.v. with*

$$\mathbb{P}(\xi_i = 0) = 1 - \lambda_i \Delta, \quad \mathbb{P}(\xi_i = 1) = \lambda_i \Delta,$$

where $\lambda_i > 0$ *and* $\Delta > 0$ *is small. Show that*

$$\mathbb{P}\left(\sum_{i=1}^{n} \xi_i = 1\right) = \left(\sum_{i=1}^{n} \lambda_i\right)\Delta + O(\Delta^2), \quad \mathbb{P}\left(\sum_{i=1}^{n} \xi_i > 1\right) = O(\Delta^2).$$

Proof. Note that

$$\{\xi_1 + \cdots + \xi_n = 1\} = \bigcup_{i=1}^{n} \{\xi_i = 1, \xi_{j \neq i} = 0\}.$$

Since all the variables are independent, the following holds:

$$\begin{aligned}
\mathbb{P}(\xi_1 + \cdots + \xi_n = 1) &= \sum_{i=1}^{n} \mathbb{P}\left(\xi_i = 1, \xi_{j \neq i} = 0\right) \\
&= \sum_{i=1}^{n} \mathbb{P}(\xi_i = 1) \prod_{j \neq i} \mathbb{P}\left(\xi_j = 0\right) = \sum_{i=1}^{n} \lambda_i \Delta \prod_{i \neq j} (1 - \lambda_j \Delta) \\
&= \sum_{i=1}^{n} \lambda_i \Delta + O(\Delta^2).
\end{aligned}$$

What about the second statement, note that

$$\mathbb{P}\left(\sum_{i=1}^{n} \xi_i > 1\right) = 1 - \mathbb{P}\left(\sum_{i=1}^{n} \xi_i = 0\right) - \mathbb{P}\left(\sum_{i=1}^{n} \xi_i = 1\right)$$

Let us compute the second term:

$$\mathbb{P}\left(\sum_{i=1}^{n} \xi_i = 0\right) = \prod_{i=1}^{n} \mathbb{P}(\xi_i = 0) = \prod_{i=1}^{n} \mathbb{P}(1 - \lambda_i \Delta) = 1 - \sum_{i=1}^{n} \lambda_i \Delta + O(\Delta^2).$$

That, in addition with the result for $\mathbb{P}(\xi_1 + \cdots + \xi_n = 1)$, gives the statement of the exercise. □

Exercise 1.11. *1. Prove that* $\inf_{a \in \mathbb{R}} \mathbb{E}[(\xi - a)^2]$ *is attained for* $a = \mathbb{E}[\xi]$ *and so*

$$\inf_{a \in \mathbb{R}} \mathbb{E}[(\xi - a)^2] = Var[\xi].$$

2. Let ξ *be a nonnegative r.v. with c.d.f.* F *and finite expectation. Prove that*

$$\mathbb{E}[\xi] = \int_0^{\infty} (1 - F(x))\, dx.$$

3. Show, using the result from 2. that if M *is the median of the c.d.f.* F *of* ξ*,*

$$\inf_{a \in \mathbb{R}} \mathbb{E}[|\xi - a|] = \mathbb{E}[|\xi - M|].$$

Proof. 1. Trivial (write an expression as a polynom depending on a, take the derivative w.r.t a, find zeroes).

2. Note that by the statement of the exercise, we have

$$\int_t^\infty x dF(x) \to 0 \quad t \to \infty.$$

As $\int_t^\infty x dF(x) \geq t(1-F(t))$, it implies that $t(1-F(t)) \to 0, t \to \infty$. Now we can use the integration by part formula, which results in:

$$\begin{aligned}\mathbb{E}[x] = \int_0^\infty x dF(x) = -\int_0^\infty x d(1-F(x)) \\ = -x((1-F(x))\Big|_0^\infty + \int_0^\infty (1-F(x))dx = \int_0^\infty (1-F(x))dx\end{aligned}$$

3. The previous formula actually gives the remaining result. First, we note that $\mathbb{P}(|\xi - a| > x) = \mathbb{P}(\xi > x + a) + \mathbb{P}(\xi > -x + a)$, thus

$$\begin{aligned}\mathbb{E}(|\xi - a|) = \int_0^\infty \mathbb{P}(|\xi - a| > x)\, dx = \int_0^\infty \mathbb{P}(\xi > x+a) dx + \int_0^\infty \mathbb{P}(\xi > -x + a)\, dx \\ = \int_a^\infty \mathbb{P}(\xi > z) dz - \int_a^\infty \mathbb{P}(\xi < z) dz\end{aligned}$$

The result can be obtained by computing the derivative w.r.t. a.

□

Exercise 1.12. *Let X_1 and X_2 be two independent r.v. with exponential distribution $\mathscr{E}(\lambda)$. Show that $\min(X_1, X_2)$ and $|X_1 - X_2|$ are r.v. with distributions, respectively, $\mathscr{E}(2\lambda)$ and $\mathscr{E}(\lambda)$.*

Proof. The first result is the direct consequence of Exercise 10. For the second result, consider a r.v. $\zeta = X_1 - X_2$. As both variables X_1 and X_2 are independent, we can use the Fubini theorem, and find the c.d.f of ζ as follows:

$$\begin{aligned}F_\zeta(z) = \mathbb{P}(\zeta < z) &= \int_{x\geq 0, y\geq 0, x-y\leq z} dF(x)dF(y) = \int_{x,y\geq 0} \mathbb{1}_{x-y\leq z} dF(x)dF(y) \\ &= \int_0^\infty dF(x)\left[\int_0^\infty \mathbb{1}_{y\geq x-z} dF(y)\right] \\ &= \int_0^\infty dF(x)\left[\mathbb{1}_{x-z\geq 0}\int_{x-z}^\infty dF(y) + \mathbb{1}_{x-z<0}\int_0^\infty dF(y)\right] \\ &= \int_0^\infty dF(x)\,[\mathbb{1}_{x\geq z}(1-F(x-z)) + \mathbb{1}_{x<z}]\end{aligned}$$

Then, two cases are possible:

$z < 0$:

$$F_\zeta(z) = \int_0^\infty dF(x)(1-F(x-z)) = e^{\lambda z}\lambda \int_0^\infty e^{-2\lambda x} dx = \frac{1}{2}e^{\lambda z}$$

$z \geq 0$:

$$F_\zeta(z) = \int_0^z dF(x) + \int_z^\infty dF(x)(1 - F(x-z)) = F(z) + \lambda \int_z^\infty e^{\lambda(z-x)} e^{-\lambda x} dx$$
$$= (1 - e^{-\lambda z}) + \frac{1}{2} e^{-\lambda z} = 1 - \frac{e^{-\lambda z}}{2}$$

It only remains to note that $F_{|\zeta|}(x) = F_\zeta(x) - F_\zeta(-x)$ for all $x \geq 0$. □

Exercise 1.14. *Suppose that r.v. $\xi_1, \ldots, \xi_n$ are mutually independent and identically distributed with the c.d.f. F. For $x \in \mathbb{R}$, let us define the random variable $\hat{F}_n(x) = \frac{1}{n}\mu_n$, where μ_n is the number of $\xi_1, \ldots, \xi_n$ which satisfy $\xi_k \leq x$. Show that for any x,*

$$\hat{F}_n(x) \xrightarrow{P} F(x).$$

The function $\hat{F}_n(x)$ is called ***the empirical distribution function****.*

Proof. Consider a sequence of random variables $\zeta_1, \ldots, \zeta_n$ such that $\zeta_i = \mathbb{1}_{\xi_k \leq x}$. Note that $\{\zeta_i\}_{i=1,n}$ is a sequence of i.i.d. Bernoulli random varaibles with the probability of success $F(x)$. Observe that

$$\hat{F}_n(x) = \frac{1}{n} \sum_{i=1}^n \zeta_i.$$

$n\hat{F}_n(x)$ is a Binomial random variable with the expectation and variance being $F(x)$ and $\frac{F(x)(1-F(x))}{n}$ respectively. Then, by Chebyshev's inequality, we have the following result $\forall \varepsilon > 0$:

$$\mathbb{P}\left(|F_n(x) - F(x)| \geq \varepsilon\right) \leq \frac{F(x)(1 - F(x))}{n\varepsilon^2}$$

The right part converges to 0 as $n \to \infty$, which gives the result. □

2 TD 2

Exercise 2.1. *Two random vectors $X \in \mathbb{R}^p$ and $Y \in \mathbb{R}^q$ are independent iff the characteristic function $\phi_Z(u)$ of the vector $Z = (X,Y)^T$ can be represented, for any $u = (a,b)^T$, $a \in \mathbb{R}^p$ and $b \in \mathbb{R}^q$, as*

$$\phi_Z(u) = \phi_X(a)\phi_Y(b)$$

Proof. The necessity is evident (i.e., if we can represent the characteristic function as a product, the variables are independent). Let us show the sufficiency in the continuous case (assuming that the common density (X,Y) exists). The density of $f_Z(x,y)$ of Z, $x \in \mathbb{R}^p$ and $y \in \mathbb{R}^q$ is given by

$$\begin{aligned} f_Z(x,y) &= (2\pi)^{-(p+q)} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} e^{-iu^T z}\phi_Z(u)du \\ &= \left[(2\pi)^{-p}\int_{-\infty}^{\infty} e^{-ia^T x}\phi_X(a)da\right]\left[(2\pi)^{-q}\int_{-\infty}^{\infty} e^{-ib^T y}\phi_Y(b)db\right] \\ &= f_X(x)f_Y(y) \end{aligned}$$

□

Exercise 2.2. *Let the joint density of r.v.'s X and Y satisfy*

$$f(x,y) = \frac{1}{2\pi}e^{-\frac{x^2}{2}}e^{-\frac{y^2}{2}}\left[1 + xy\mathbb{1}_{-1\le x,y\le 1}.\right]$$

What is the distribution of X, of Y?

Proof. To find a marginal density of Y we only need to integrate the joint density on the whole space:

$$\begin{aligned} \int_{-\infty}^{\infty} f(x,y)dx &= \frac{1}{2\pi}\int_{-\infty}^{\infty} e^{-\frac{x^2}{2}}e^{-\frac{y^2}{2}}\left[1 + xy\mathbb{1}_{-1\le x,y\le 1}dx\right] \\ &= \frac{1}{2\pi}e^{-\frac{y^2}{2}}\left[\int_{-\infty}^{\infty} e^{-\frac{x^2}{2}}dx + y\int_{-1}^{1} xe^{-\frac{x^2}{2}}dx\right] \\ &= \frac{1}{2\pi}e^{-\frac{y^2}{2}}\left[\sqrt{2\pi} + 0\right] = \frac{1}{\sqrt{2\pi}}e^{-\frac{y^2}{2}} \end{aligned}$$

Thus, Y follows a standard normal distribution. The proof for X is analogous.

□

Exercise 2.3. *Consider $X \sim \mathcal{N}_p(\mu,\Sigma)$, where $\mu \in \mathbb{R}^p$ and $\Sigma \in \mathbb{R}^{p\times p}$ Prove that any linear transformation of a normal vector is again a normal vector: if $Y = AX + c$ where $A \in \mathbb{R}^{q\times p}$ and $c \in \mathbb{R}^q$ are some fixed matrix and vector (non-random),*

$$Y \sim \mathcal{N}_q\left(A\mu + c, A\Sigma A^T\right)$$

Proof. Note that any projection of Y is a normal univariate random variable. So, indeed for all $b \in \mathbb{R}^q$ the following holds:

$$b^T Y = b^T AX + b^T c = a^T X + d,$$

with $a = A^T b$ and $d = b^T c$. Using the Theorem 2.2 from course we deduce that Y is $q-$variate normal vector. Its mean and covariance matrix are given by:

$$\mathbb{E}[Y] = A\mu + c, \quad Var(Y) = A\Sigma A^T.$$

□

Exercise 2.11. *Given 2 independent r.v. X_1 and X_2 with exponential distribution with parameters λ_1 and λ_2. Find the distribution $Z = \frac{X_1}{X_2}$. Compute $\mathbb{P}(X_1 < X_2)$.*

Proof. Let us compute the following probability:

$$\begin{aligned}
\mathbb{P}(Z \geq t) = \mathbb{P}(Z \geq t) = & \iint_{\{(x_1,x_2):x_1 \geq tx_2 \geq 0\}} \lambda_1\lambda_2 e^{-\lambda_1 x_1} e^{-\lambda_2 x_2} dx_1 dx_2 \\
&= \lambda_2 \int_0^\infty e^{-\lambda_2 x_2} \left(\int_{tx_2}^\infty e^{-\lambda_1 x_1} d(\lambda_1 x_1) \right) dx_2 = \lambda_2 \int_0^\infty e^{-\lambda_2 x_2} e^{-\lambda_1 t x_2} dx_2 \\
&= \lambda_2 \int_0^\infty e^{-x_2(\lambda_1 t + \lambda_2)} dx_2 = \frac{\lambda_2}{\lambda_1 t + \lambda_2}
\end{aligned}$$

Then,

$$F_Z(t) = \frac{\lambda_1 t}{\lambda_1 t + \lambda_2}$$

Then, it is easy to compute $\mathbb{P}(X_1 < X_2)$, which is given as:

$$\mathbb{P}(X_1 < X_2) = \mathbb{P}(Z < 1) = \frac{\lambda_1}{\lambda_1 + \lambda_2}.$$

□

Exercise 2.15. *Show that if ϕ is a characteristic function of some r.v., then $\phi^\star$, $|\phi|^2$ and $Re(\phi)$ are also characteristic functions (of certain r.v.).*

Hint: for $Re(\phi)$ consider 2 independent random variables X and Y, where Y takes values -1 and 1 with probabilities $\frac{1}{2}$, X has characteristic function ϕ, then compute the characteristic function of XY.

Proof.

- For the complex conjugate:

$$\phi^\star = \mathbb{E}[\cos(tX) - i\sin(tX)] = \mathbb{E}[\cos(-tX) + i\sin(-tX)] = \mathbb{E}\left[e^{it(-X)}\right]$$

Thus, we see that $\phi^\star$ is a characteristic function of the variable $-X$.

- It is easy to see that $|\phi|^2 = 1$, so that it is a characteristic function of a constant 0.

- Note that:

$$Re(\phi) = \frac{\phi + \phi^\star}{2}$$

We have seen previously that $\phi^\star$ is the characteristic function of the variable $-X$. Consider a variable Y taking 1 and -1 with probability $\frac{1}{2}$ (independently of X). Let us write the characteristic function of the product (using the result of the exercise 2.1):

$$\mathbb{E}[\exp(itXY)] = \frac{\mathbb{E}\left[\left(e^{itX} + e^{-itX}\right)\right]}{2} = \frac{\phi + \phi^\star}{2} = Re(\phi)$$

□

Exercise 2.17. *Let (X, Y) be a random vector with density*

$$f(x, y) = C\exp\left(-x^2 + xy - \frac{y^2}{2}\right).$$

1. *Show that (X, Y) is a normal vector. Compute the expectation, the covariance matrix and the characteristic function of (X, Y). Compute the correlation coefficient ρ_{XY} of X and Y.*

2. *What is the distribution of X? Of Y? Of $2X - Y$?*

3. *Show that X and $Y - X$ are independent random variables with the same distribution.*

Proof. 1. The fact that it is normal is (more or less) obvious. We only need to find a constant C to obtain the density. Note that

$$C\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \exp\left(-x^2 + xy - \frac{y^2}{2}\right) dxdy = 2\pi C.$$

Since the double integral over the density must be equal to 1, $C = \frac{1}{2\pi}$. Let us proceed to computing the expectation and so on.

$$\mathbb{E}[X] = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x\exp\left(-x^2 + xy - \frac{y^2}{2}\right) dxdy = 0$$

Idem for $\mathbb{E}[Y]$. Then, the mean vector is given by $(0,0)^T$. Let us compute the second moments:

$$\mathbb{E}[X^2] = \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^2\exp\left(-x^2 + xy - \frac{y^2}{2}\right) dxdy = 1$$

In a similar way we obtain $\mathbb{E}\left[Y^2\right] = 2$ and $\mathbb{E}[XY] = 1$. Thus, the covariance matrix is given as:

$$\Sigma = \begin{pmatrix} 1 & 1 \\ 1 & 2 \end{pmatrix}$$

Then, we can find the correlation coefficient by computing $\rho = \frac{2}{\sqrt{2}\sqrt{4}} = \frac{1}{\sqrt{2}}$. Characteristic function is given by $\exp\left(-\frac{1}{2}(z^T \Sigma z)\right)$.

2. To find the marginal density function of Y, we have to integrate the joint density, thus we have:

$$f(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \exp\left(-x^2 + xy - \frac{y^2}{2}\right) dy = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$
$$f(y) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \exp\left(-x^2 + xy - \frac{y^2}{2}\right) dx = \frac{1}{2\sqrt{\pi}} e^{-\frac{y^2}{4}}$$

Easy to see that X is a standard normal variable, while Y is a centered normal with the variance 2. In order to find the distribution of $2X - Y$ we can use the characteristic functions. Note that $\phi_X(t) = \exp\left(-t^2\right)$ and $\phi_Y(t) = \exp\left(-\frac{t^2}{2}\right)$

$$\phi_{2X-Y}(t) = \mathbb{E}\left[\exp\left(-it(2X - Y)\right)\right] =$$
$$\frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \exp\left(-it(2X - Y)\right) f(x, y)dxdy = \frac{1}{2\sqrt{\pi}} e^{-t^2}$$

Then, by Theorem 2.1. from course, $2X - Y$ is a again a normal variable with mean 0 and variance 2.

Analogously, we can compute the mean and the variance by linear algebra (knowing that $2X - Y$ follows normal distribution). $\mu_{2X-Y} = 0$, and

$$\begin{aligned} Var(2X - Y) &= Var(2X + (-Y)) = Var(2X) + Var(-Y) + 2Cov(2X, -Y) \\ &= 4Var(X) + Var(Y) - 2Cov(X, Y) = 4 + 2 - 2 = 4. \end{aligned}$$

3. Note that the vector $Z = (X, Y - X)$ is a linear transformation of a normal vector (X, Y). More precisely,

$$Z = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}\begin{pmatrix} X \\ Y \end{pmatrix}$$

Then, Z follows a normal distribution with the mean 0 and the covariance matrix given by

$$\Sigma_Z = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}\begin{pmatrix} 1 & 1 \\ 1 & 2 \end{pmatrix}\begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}^T = I_2$$

Since Σ_Z is an identity matrix, both X and $Y - X$ are distributed by the same law and are independent.

$\square$

Exercise 2.19. *Let ξ and η be independent r.v. with uniform distribution $U[0,1]$. Prove that*

$$X = \sqrt{-2\ln\xi}\cos(2\pi\eta), \quad Y = \sqrt{-2\ln\xi}\cos(2\pi\eta)$$

satisfy $Z = (X,Y)^T \sim N_2(0,I)$.

Hint: Let $(X,Y)^T \sim N_2(0,I)$. Change to the polar coordinates.

Proof. Recall that we can switch to the polar coordinates by applying the following transformation:

$$X = r\cos(\varphi)$$
$$Y = r\sin(\varphi).$$

Recall that the density function of the standard bivariate normal distribution is given by:

$$f(x,y) = \frac{1}{2\pi}\exp\left(-\frac{x^2+y^2}{2}\right).$$

We can verify that in the polar coordinates the density function of the normal bivariate distribution satisfies:

$$f_{\rho,\phi}(r,\varphi) = \frac{re^{-r^2/2}}{2\pi}\mathbb{1}_{0\le\varphi<2\pi}.$$

Thus, we see that ρ and ϕ are independent. $\square$