



Probability and Statistics. IDEA-UAB.
Final Exam 2017-18. Prof. J. Caballé.

The exam lasts for 3 hours

1. **(2 points: 1 point for each sub-question)** Consider a random variable \tilde{x} having the Poisson distribution with parameter λ .

(a) Find the moment generating function $M_{\tilde{x}}(t)$ of the random variable \tilde{x} .

(b) Use the moment generating function found in part (a) to compute the mean μ and the variance σ^2 of \tilde{x} .

Hints: (i) The probability function of the Poisson distribution is

$$p(x; \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}, \text{ with } \lambda > 0, \text{ for } x = 0, 1, 2, \dots$$

(ii) For part (a) you should use the Taylor expansion of e^y around $y = 0$.

2. **(4 points: 1 point for each sub-question)** Assume that you have obtained x "successes" in n identical and independent trials.

(a) Find the value $\hat{\theta}_{ML}$ of the maximum likelihood estimator of the probability θ of success in each trial.

(b) Prove that the maximum likelihood estimator $\hat{\theta}_{ML}$ for θ is the most efficient (or the best) estimator in the class of unbiased estimators for θ .

(c) Does the estimator $\hat{\theta}_{ML}$ converge in mean square to θ , $\hat{\theta}_{ML} \xrightarrow{m} \theta$ as $n \rightarrow \infty$? Does $\hat{\theta}_{ML} \xrightarrow{p} \theta$? Does $\hat{\theta}_{ML} \xrightarrow{d} \theta$? Does $\hat{\theta}_{ML} \xrightarrow{a.s.} \theta$?

(d) Using the number of successes in 3 identical and independent trials devise a likelihood ratio test with a level of significance $\alpha = 1/4$ to test the null hypothesis that $\theta = 1/2$ against the alternative hypothesis that $\theta \neq 1/2$. You should provide the test statistic and the critical region for this test.

Hint: For part (d) note that $\lim_{x \rightarrow 0} x^x = 1$ or, equivalently, $\lim_{x \rightarrow 0} (x \cdot \ln x) = 0$, which follows from L'Hôpital's rule.

3. **(4 points: 1 point for each sub-question)** Assume that the density function of the random variable \tilde{x} is

$$f_{\tilde{x}}(x) = \begin{cases} \frac{2-x}{4} & \text{for } x \in (0, 2) \\ \frac{x+2}{4} & \text{for } x \in (-2, 0] \\ 0 & \text{otherwise.} \end{cases}$$

(a) Find the distribution function $F_{\tilde{x}}(x)$ of the random variable \tilde{x} . Draw both $f_{\tilde{x}}(x)$ and $F_{\tilde{x}}(x)$.

(b) Find and draw the distribution function $F_{\tilde{y}}(y)$ and the density function $f_{\tilde{y}}(y)$ of the random variable $\tilde{y} = \tilde{x}^2$.

(c) Consider the random vector (\tilde{x}, \tilde{y}) , where \tilde{x} has the density defined above and \tilde{y} is defined in part (b). Is the random vector (\tilde{x}, \tilde{y}) absolutely continuous, i.e., does its distribution have a density function?

(d) Compute the covariance between \tilde{x} and \tilde{y} , $\text{Cov}(\tilde{x}, \tilde{y})$. Are \tilde{x} and \tilde{y} independent? Answer the latter question using the definition of independence of two random variables.

Answers Final Exam 2017-18. Probability and Statistics.

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1. (a) Using the Taylor expansion at $y = 0$, we have

$$e^y = \sum_{x=0}^{\infty} \frac{y^x}{x!}. \quad (1)$$

$$\begin{aligned} M_{\tilde{x}}(t) &= \sum_{x=0}^{\infty} \frac{\lambda^x e^{-\lambda}}{x!} e^{tx} = e^{-\lambda} \sum_{x=0}^{\infty} \frac{(\lambda e^t)^x}{x!} = e^{-\lambda} e^{\lambda e^t} \quad (\text{from (1)}) \\ &= e^{\lambda(e^t - 1)}. \end{aligned}$$

- (b)

$$\begin{aligned} M'_{\tilde{x}}(t) &= M_{\tilde{x}}(t) \cdot \lambda e^t \implies \mu = M'_{\tilde{x}}(0) = \underbrace{M_{\tilde{x}}(0)}_1 \cdot \lambda e^0 = \lambda \\ M''_{\tilde{x}}(t) &= M'_{\tilde{x}}(t) \cdot \lambda e^t + M_{\tilde{x}}(t) \cdot \lambda e^t = M_{\tilde{x}}(t) \cdot \lambda^2 e^{2t} + M_{\tilde{x}}(t) \cdot \lambda e^t \\ &= M_{\tilde{x}}(t) \lambda e^t (\lambda e^t + 1) \\ \implies E(\tilde{x}^2) &= M''_{\tilde{x}}(0) = \underbrace{M_{\tilde{x}}(0)}_1 \cdot \lambda e^0 (\lambda e^0 + 1) = \lambda(\lambda + 1) = \lambda^2 + \lambda \\ \implies \sigma^2 &= M''_{\tilde{x}}(0) - [M_{\tilde{x}}(0)]^2 = \lambda^2 + \lambda - \lambda^2 = \lambda. \end{aligned}$$

2. (a) We want to maximize

$$\begin{aligned} L(\theta; x) &= b(x; n, \theta) = \binom{n}{x} \theta^x (1 - \theta)^{n-x} \\ \hat{\theta}_{ML} &= \arg \max_{\theta \in [0,1]} \ln L(\theta; x) = \arg \max_{\theta \in [0,1]} \left\{ \ln \binom{n}{x} + x \ln \theta + (n - x) \ln(1 - \theta) \right\} \\ \frac{d[\ln L(\theta; x)]}{d\theta} &= \frac{x}{\theta} - \frac{n - x}{1 - \theta} = 0 \Rightarrow \hat{\theta}_{ML} = \frac{x}{n} \\ &\Rightarrow \hat{\theta}_{ML} = \frac{\tilde{x}}{n} \end{aligned}$$

Note that

$$\frac{d^2[\ln L(\theta; x)]}{d\theta^2} = -\frac{x}{\theta^2} - \frac{n - x}{(1 - \theta)^2} \leq 0$$

so that we are indeed finding a maximum.

- (b)

$$E(\hat{\theta}_{ML}) = E\left(\frac{\tilde{x}}{n}\right) = \frac{n\theta}{n} = \theta.$$

Thus, $\hat{\theta}_{ML}$ is an unbiased estimator for θ .

$$\text{Var}(\hat{\theta}_{ML}) = \text{Var}\left(\frac{\tilde{x}}{n}\right) = \frac{n\theta(1 - \theta)}{n^2} = \frac{\theta(1 - \theta)}{n}.$$

$$\text{Cramer-Rao lower bound} \equiv CR = \frac{1}{-1E\left[\frac{\partial^2 \ln b(\tilde{x}; n, \theta)}{\partial \theta^2}\right]}$$

$$\begin{aligned} \frac{\partial^2 \ln b(\tilde{x}; n, \theta)}{\partial \theta^2} &= -\frac{\tilde{x}}{\theta^2} - \frac{n - \tilde{x}}{(1 - \theta)^2} \\ E\left[\frac{\partial^2 \ln b(\tilde{x}; n, \theta)}{\partial \theta^2}\right] &= -\frac{n\theta}{\theta^2} - \frac{n - n\theta}{(1 - \theta)^2} = -\frac{n}{\theta(1 - \theta)} \\ CR &= \frac{1}{-\left(-\frac{n}{\theta(1 - \theta)}\right)} = \frac{\theta(1 - \theta)}{n} = \text{Var}(\hat{\theta}_{ML}). \end{aligned}$$

Therefore, $\hat{\theta}_{ML}$ is the best estimator in the class of unbiased estimators for θ .

Alternatively,

$$\begin{aligned} CR &= \frac{1}{1 \cdot E\left[\left(\frac{\partial \ln b(\tilde{x}; n, \theta)}{\partial \theta}\right)^2\right]} \\ \frac{\partial \ln b(\tilde{x}; n, \theta)}{\partial \theta} &= \frac{x}{\theta} - \frac{n - x}{1 - \theta} \\ \left(\frac{\partial \ln b(\tilde{x}; n, \theta)}{\partial \theta}\right)^2 &= \left(\frac{\tilde{x}}{\theta} - \frac{n - \tilde{x}}{1 - \theta}\right)^2 = \frac{(\tilde{x} - n\theta)^2}{\theta^2(1 - \theta)^2} \\ E\left[\left(\frac{\partial \ln b(\tilde{x}; n, \theta)}{\partial \theta}\right)^2\right] &= E\left[\frac{(\tilde{x} - n\theta)^2}{\theta^2(1 - \theta)^2}\right] = \frac{E[(\tilde{x} - n\theta)^2]}{\theta^2(1 - \theta)^2} \\ \frac{E[(\tilde{x} - E(\tilde{x}))^2]}{\theta^2(1 - \theta)^2} &= \frac{\text{Var}(\tilde{x})}{\theta^2(1 - \theta)^2} = \frac{n\theta(1 - \theta)}{\theta^2(1 - \theta)^2} = \frac{n}{\theta(1 - \theta)}. \end{aligned}$$

Therefore,

$$CR = \frac{1}{1 \cdot \mathbb{E} \left[\left(\frac{\partial \ln b(\tilde{x}; n, \theta)}{\partial \theta} \right)^2 \right]} = \frac{\theta(1-\theta)}{n} = \text{Var}(\hat{\theta}_{ML}).$$

(c)

$$\begin{aligned} \mathbb{E} \left[\left(\hat{\theta}_{ML} - \theta \right)^2 \right] &= \mathbb{E} \left[\left(\hat{\theta}_{ML} - \mathbb{E}(\hat{\theta}_{ML}) \right)^2 \right] = \text{Var}(\hat{\theta}_{ML}) = \text{Var} \left(\frac{\tilde{x}}{n} \right) = \frac{\theta(1-\theta)}{n} \\ \Rightarrow \lim_{n \rightarrow \infty} \mathbb{E} \left[\left(\hat{\theta}_{ML} - \theta \right)^2 \right] &= \lim_{n \rightarrow \infty} \frac{\theta(1-\theta)}{n} = 0 \Rightarrow \hat{\theta}_{ML} \xrightarrow{m} \theta. \\ \Rightarrow \hat{\theta}_{ML} &\xrightarrow{p} \theta \Rightarrow \hat{\theta}_{ML} \xrightarrow{d} \theta. \end{aligned}$$

Moreover, since $\hat{\theta}_{ML}$ is equal to the "average" $\bar{\mathbf{y}}_n$ of a random sample $(\tilde{y}_1, \tilde{y}_2, \dots, \tilde{y}_n)$ coming from a Bernoulli population,

$$\hat{\theta}_{ML} = \frac{\tilde{x}_i}{n} = \frac{\sum_{i=0}^n \tilde{y}_i}{n} = \bar{\mathbf{y}}_n,$$

as $\tilde{x}_i = \sum_{i=0}^n \tilde{y}_i \sim B(n, \theta)$, we can apply any of the two Kolmogorov theorems to conclude that $\hat{\theta}_{ML} = \bar{\mathbf{y}}_n \xrightarrow{a.s.} \theta$.

(d) Likelihood function under the null hypothesis:

$$L \left(\frac{1}{2}; x \right) = \binom{3}{x} \left(\frac{1}{2} \right)^x \left(\frac{1}{2} \right)^{3-x} = \binom{3}{x} \left(\frac{1}{2} \right)^3.$$

$$\arg \sup_{\theta \in [0,1]} L(\theta; x) = \arg \max_{\theta \in [0,1]} \binom{3}{x} \theta^x (1-\theta)^{3-x} = \hat{\theta}_{ML} = \frac{x}{3}$$

$$\sup_{\theta \in [0,1]} L(\theta; x) = \binom{3}{x} \left(\frac{x}{3} \right)^x \left(\frac{3-x}{3} \right)^{3-x}$$

Thus, the test statistic is

$$\tilde{\lambda} = \frac{L \left(\frac{1}{2}; \tilde{x} \right)}{\sup_{\theta \in [0,1]} L(\theta; \tilde{x})} = \frac{\binom{3}{\tilde{x}} \left(\frac{1}{2} \right)^3}{\binom{3}{\tilde{x}} \left(\frac{\tilde{x}}{3} \right)^{\tilde{x}} \left(\frac{3-\tilde{x}}{3} \right)^{3-\tilde{x}}} = \frac{\left(\frac{1}{2} \right)^3}{\left(\frac{\tilde{x}}{3} \right)^{\tilde{x}} \left(\frac{3-\tilde{x}}{3} \right)^{3-\tilde{x}}}$$

$$= \frac{\frac{1}{8}}{\frac{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}}{3^3}} = \frac{\frac{27}{8}}{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}}.$$

The critical region is defined by a constant $k > 0$ such that we reject the null hypothesis if

$$\tilde{\lambda} = \frac{\frac{27}{8}}{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}} \leq k$$

If $\tilde{x} = 0$, then $\tilde{\lambda} = \lim_{x \rightarrow 0} \frac{27/8}{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}} = \frac{27/8}{1 \cdot 3^3} = 1/8$. Under the null hypothesis this occurs with probability $\binom{3}{0} \left(\frac{1}{2} \right)^3 = 1/8$.

If $\tilde{x} = 1$, then $\tilde{\lambda} = \frac{27/8}{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}} = 27/32$. Under the null hypothesis this occurs with probability $\binom{3}{1} \left(\frac{1}{2} \right)^3 = 3/8$.

If $\tilde{x} = 2$, then $\tilde{\lambda} = \frac{27/8}{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}} = 27/32$. Under the null hypothesis this occurs with probability $\binom{3}{1} \left(\frac{1}{2} \right)^3 = 3/8$.

If $\tilde{x} = 3$, then $\tilde{\lambda} = \lim_{x \rightarrow 3} \frac{27/8}{\tilde{x}^{\tilde{x}} (3-\tilde{x})^{3-\tilde{x}}} = \frac{27/8}{3^3 \cdot 1} = 1/8$. Under the null hypothesis this occurs with probability $\binom{3}{0} \left(\frac{1}{2} \right)^3 = 1/8$.

Note that

$$\lim_{x \rightarrow 0} (x \cdot \ln x) = \lim_{x \rightarrow 0} \left(\frac{\ln x}{\frac{1}{x}} \right) = \frac{\lim_{x \rightarrow 0} \left(\frac{1}{x} \right)}{\lim_{x \rightarrow 0} \left(-\frac{1}{x^2} \right)} = \lim_{x \rightarrow 0} \left(-\frac{x^2}{x} \right) = \lim_{x \rightarrow 0} (-x) = 0.$$

Thus,

$$\lim_{x \rightarrow 0} x^x = \lim_{x \rightarrow 0} \exp(x \cdot \ln x) = \exp \left[\lim_{x \rightarrow 0} (x \cdot \ln x) \right] = e^0 = 1.$$

Therefore, the probability function of $\tilde{\lambda}$ under the null hypothesis $\theta = \frac{1}{2}$ is $f_{\tilde{\lambda}} \left(\frac{27}{32} \right) = \frac{3}{8} + \frac{3}{8} = \frac{3}{4}$ and $f_{\tilde{\lambda}} \left(\frac{1}{8} \right) = \frac{1}{8} + \frac{1}{8} = \frac{1}{4}$.

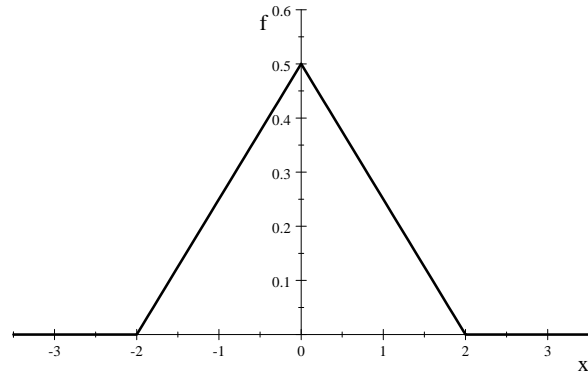
If we want that the level of significance be $1/4$, then

$$P \left(\tilde{\lambda} \leq k; \frac{1}{2} \right) = \frac{1}{4}.$$

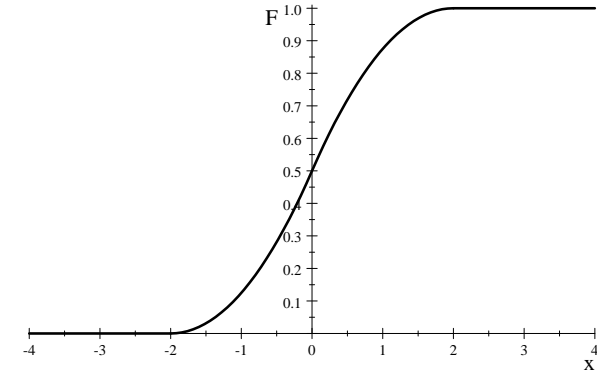
Therefore, we must choose for the threshold value k any real number lying in the left semiclosed interval $\left[\frac{1}{8}, \frac{27}{32} \right)$. Thus, we reject the null hypothesis when

$\tilde{\lambda} = 1/8$, that is, when we get 0 or 3 successes in 3 trials.

3. (a) $f_{\tilde{x}}(x)$



$$F_{\tilde{x}}(x) = \begin{cases} 0 & \text{for } x \leq -2 \\ \int_{-2}^x \frac{x+2}{4} dx = \frac{x^2}{8} + \frac{x}{2} + \frac{1}{2} & \text{for } x \in (-2, 0] \\ \int_{-2}^0 \frac{x+2}{4} dx + \int_0^x \frac{2-x}{4} dx = \frac{1}{2} + \int_0^x \frac{2-x}{4} dx = -\frac{x^2}{8} + \frac{x}{2} + \frac{1}{2} & \text{for } x \in (0, 2) \\ 1 & \text{for } x \geq 2. \end{cases}$$



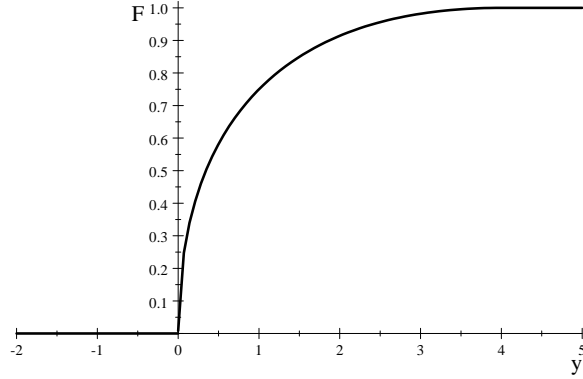
(b) Since

$$F_{\tilde{y}}(y) = P(\tilde{y} \leq y) = P(\tilde{x}^2 \leq y) = P(-y^{1/2} \leq \tilde{x} \leq y^{1/2})$$

$$= \int_{-y^{1/2}}^0 \frac{x+2}{4} dx + \int_0^{y^{1/2}} \frac{2-x}{4} dx = y^{1/2} - \frac{y}{4} \quad \text{for } x \in (-2, 2) \iff y \in (0, 4).$$

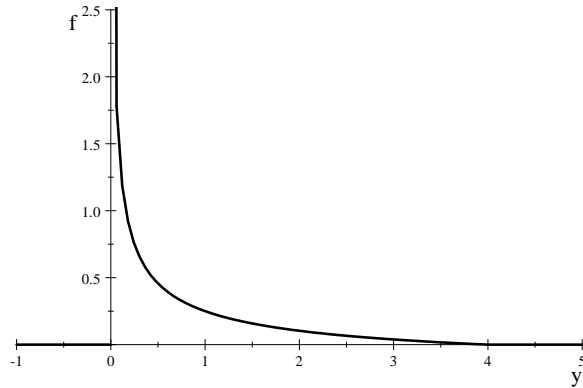
Therefore,

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ y^{1/2} - \frac{y}{4} & \text{for } y \in (0, 4) \\ 1 & \text{for } y \geq 4. \end{cases}$$



We know that $f_{\tilde{y}}(y) = F'_{\tilde{y}}(y)$ for all y where the distribution function $F_{\tilde{y}}$ is differentiable. Thus,

$$f_{\tilde{y}}(y) = \begin{cases} \frac{y^{-1/2}}{2} - \frac{1}{4} & \text{for } y \in (0, 4) \\ 0 & \text{otherwise} \end{cases}$$



Note that the density $f_{\tilde{y}}$ is continuous at $y = 4$ and, hence, the distribution

function $F_{\tilde{y}}$ is differentiable at $y = 4$. However, the density $f_{\tilde{y}}$ is discontinuous at $y = 0$ and thus the distribution function $F_{\tilde{y}}$ is non-differentiable at $y = 0$.

We see that

$$\lim_{y \rightarrow 0^-} f_{\tilde{y}}(y) = 0 \neq \infty = \lim_{y \rightarrow 0^+} f_{\tilde{y}}(y).$$

Note: This exercise could be also solved using the density function technique instead of the distribution function technique. To this end we first need to make the transformation $\tilde{z} = |\tilde{x}|$ and find the distribution function $F_{\tilde{z}}$ of \tilde{z} . Note that

$$\begin{aligned} F_{\tilde{z}}(z) &= P(\tilde{z} \leq z) = P(|\tilde{x}| \leq z) = P(-z \leq \tilde{x} \leq z) \\ &= \int_{-z}^0 \frac{x+2}{4} dx + \int_0^z \frac{2-x}{4} dx = z - \frac{z^2}{4} \text{ for } z \in (-2, 2) \iff z \in (0, 2). \end{aligned}$$

Therefore,

$$F_{\tilde{z}}(z) = \begin{cases} 0 & \text{for } z \leq 0 \\ z - \frac{z^2}{4} & \text{for } z \in (0, 2) \\ 1 & \text{for } z \geq 2. \end{cases}$$

Therefore, the density of \tilde{z} is

$$f_{\tilde{z}}(z) = \begin{cases} F'_{\tilde{z}}(z) = 1 - \frac{z}{2} & \text{for } z \in (0, 2) \\ 0 & \text{otherwise} \end{cases}$$

Then, define $\tilde{y} = g(\tilde{z}) = \tilde{z}^2$. Note that $g : (0, 2) \rightarrow (0, 4)$ is a one-to-one correspondence. Thus, $z = g^{-1}(y) = y^{1/2}$ and $\frac{dz}{dy} = \frac{dg^{-1}(y)}{dy} = \frac{y^{-1/2}}{2} > 0$ for

$y \in (0, 4)$. Therefore, the density of \tilde{y} is

$$f_{\tilde{y}}(y) = \begin{cases} f_{\tilde{z}}(g^{-1}(y)) \left| \frac{g^{-1}(y)}{dy} \right| = \left(1 - \frac{y^{1/2}}{2}\right) \frac{y^{-1/2}}{2} = \frac{y^{-1/2}}{2} - \frac{1}{4} & \text{for } y \in (0, 4) \\ 0 & \text{otherwise.} \end{cases}$$

and, thus, the distribution function is

$$F_{\tilde{y}}(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \int_0^y \left(\frac{y^{-1/2}}{2} - \frac{1}{4} \right) dy = y^{1/2} - \frac{y}{4} & \text{for } y \in (0, 4) \\ 1 & \text{for } y \geq 4. \end{cases}$$

(c) The distribution of the random vector (\tilde{x}, \tilde{y}) does NOT have a density $f_{(\tilde{x}, \tilde{y})}(x, y)$. To see this, let us define the following subset C of \mathbb{R}^2 :

$$C = \{(x, y) \in \mathbb{R}^2 \mid y = x^2\}$$

The set C is the graph of a parabola on the plane. Then, on the one hand,

$$P((x, y) \in C) = 1.$$

but, on the other hand, if the density $f_{(\tilde{x}, \tilde{y})}(x, y)$ exists, we should have

$$\int_C f_{(\tilde{x}, \tilde{y})}(x, y) d(x, y) = 1,$$

which is a contradiction since the set C has zero Lebesgue measure on \mathbb{R}^2 .

(d)

$$\begin{aligned} E(\tilde{x}) &= \int_{-2}^0 x \cdot \frac{x+2}{4} dx + \int_0^2 x \cdot \frac{2-x}{4} dx = 0, \\ E(\tilde{y}) &= E(\tilde{x}^2) = \int_{-2}^0 x^2 \cdot \frac{x+2}{4} dx + \int_0^2 x^2 \cdot \frac{2-x}{4} dx = \frac{2}{3} \end{aligned}$$

or

$$E(\tilde{y}) = \int_0^4 y \left(\frac{y^{-1/2}}{2} - \frac{1}{4} \right) dy = \frac{2}{3},$$

$$E(\tilde{x} \cdot \tilde{y}) = E(\tilde{x}^3) = \int_{-2}^0 x^3 \cdot \frac{x+2}{4} dx + \int_0^2 x^3 \cdot \frac{2-x}{4} dx = 0$$

$$\text{Cov}(\tilde{x}, \tilde{y}) = E(\tilde{x} \cdot \tilde{y}) - E(\tilde{x}) \cdot E(\tilde{y}) = 0 - 0 \cdot \frac{2}{3} = 0.$$

However, even if \tilde{x} and \tilde{y} are uncorrelated, they are not independent. It is obvious that the values taken by \tilde{y} depend on the values taken by \tilde{x} . According to the definition of independence between two random variables, if \tilde{x} and \tilde{y} are independent we should have that

$$P(\tilde{x} \in B_1, \tilde{y} \in B_2) = P(\tilde{x} \in B_1) \cdot P(\tilde{y} \in B_2)$$

for all pairs B_1 and B_2 of Borel sets. Then, we can check that the random variables \tilde{x} and \tilde{y} are not independent. For instance,

$$P(\tilde{x} \in (-1, 0), \tilde{y} \in (2, 4)) = 0$$

as $\{\tilde{x} \in (-1, 0)\} \cap \{\tilde{y} \in (2, 4)\} = \emptyset$ because $\tilde{x} \in (-1, 0) \Rightarrow \tilde{y} \in (0, 1)$.

Moreover,

$$\begin{aligned} P(\tilde{x} \in (-1, 0)) &= \int_{-1}^0 \frac{x+2}{4} dx = \frac{3}{8} \\ P(\tilde{y} \in (2, 4)) &= \int_2^4 \left(\frac{y^{-1/2}}{2} - \frac{1}{4} \right) dy = \frac{3}{2} - \sqrt{2}, \end{aligned}$$

Therefore,

$$P(\tilde{x} \in (-1, 0), \tilde{y} \in (2, 4)) \neq P(\tilde{x} \in (-1, 0)) \cdot P(\tilde{y} \in (2, 4)).$$
