

Solution Series 5

Q1. (a) Take $p \in [0, 1]$ and $n \in \mathbb{N} \setminus \{0\}$. We say that $X \sim \text{Bin}(n, p)$ if the distribution of X is

$$\mathbb{P}(X = k) = \binom{n}{k} p^k (1-p)^{n-k}, \quad k \in \{0, 1, \dots, n\}.$$

Show that this is indeed a probability distribution using 2 different methods:

- i. Calculating $\sum_k \mathbb{P}(X = k)$.
- ii. Representing this probability in terms of the box model with replacement.

Calculate the expected value of X using 2 different methods (the one listed above).

(b) Take $K, n \in \mathbb{N}$ and $N \in \mathbb{N} \setminus \{0\}$ with $K, n \leq N$. We say that a random variable $X \sim \text{Hyp}(N, K, n)$ if its distribution is given by

$$\mathbb{P}(X = k) = \frac{\binom{K}{k} \binom{N-K}{n-k}}{\binom{N}{n}} \quad k \in \{\max\{0, n + K - N\}, \dots, \min\{n, K\}\}$$

Show that this is indeed a probability distribution using 2 different methods:

- i. Calculating $\sum_k \mathbb{P}(X = k)$.
Hint: Calculate $(1+x)^n$ in two different ways and identify the terms.
- ii. Representing this probability in the box model without replacement.

Calculate the expectation using both methods.

Solution

(a) Expectation:

i.

$$\begin{aligned} \mathbb{E}[X] &= \sum_{k=1}^n k \binom{n}{k} p^k (1-p)^{n-k} \\ &= \sum_{k=1}^n \frac{n(n-1)!}{(n-k)!(k-1)!} p^{(k-1)+1} (1-p)^{n-k} \\ &= np \sum_{j=0}^{n-1} \binom{n-1}{j} p^j (1-p)^{(n-1)-j} \end{aligned}$$

where we make the change of variables $j = k - 1$. The sum we had is exactly the sum we calculated in the first part for a $\text{Bin}(n-1, p)$, so it is 1. Thus:

$$\mathbb{E}[X] = np.$$

- ii. We know that the amount of red balls that are taken out at time n in an experiment with replacement have the distribution of X . So

$$\begin{aligned}\mathbb{E}[X] &= \mathbb{E} \left[\sum_{j=1}^n \mathbf{1}_{\{\text{In the } j\text{-th draw we get a red ball}\}} \right] \\ &= \sum_{j=1}^n \mathbb{P}(\{\text{In } j\text{-th draw we get a red ball}\}).\end{aligned}$$

The probability that in the j -th draw we get a red ball is p , so:

$$\mathbb{E}[X] = np.$$

(b) Expectation:

i.

$$\begin{aligned}\mathbb{E}[X] &= \sum_{k=\max\{1, N-K-k\}}^{\min\{n, K\}} k \frac{\binom{K}{k} \binom{N-K}{n-k}}{\binom{N}{n}} \\ &= K \sum_{k=\max\{1, N-K-k\}}^{\min\{n, K\}} \frac{\binom{K-1}{k-1} \binom{(N-1)-(K-1)}{(n-1)-(k-1)}}{\binom{N}{n}} \\ &= K \frac{1}{\binom{N}{n}} \sum_{u=\max\{0, N-K-k-1\}}^{\min\{n-1, K-1\}} \binom{K-1}{u} \binom{(N-1)-(K-1)}{(n-1)-u} \\ &= K \frac{\binom{N-1}{n-1}}{\binom{N}{n}} = n \frac{K}{N}.\end{aligned}$$

where we have used the sum we calculated in the first part for a $Hyper(N-1, k-1, n-1)$.

- ii. We see that $X = \sum_{j=1}^n \mathbf{1}_{B_j}$ where B_j is “in the n -th drawing we take a red ball”. We also have

$$\mathbb{P}(B_j) = \mathbb{P}(B_1) = K/N,$$

and since $\sum_{j=1}^n \mathbf{1}_{B_j} = X$ we conclude

$$\mathbb{E}(X) = \mathbb{E} \left[\sum_{j=1}^n \mathbf{1}_{B_j} \right] = n\mathbb{P}(B_1) = n \frac{K}{N}.$$

- Q2.** (a) Let $X \sim \mathcal{E}(\lambda)$ be the exponential random variable with parameter λ . Compute the α -quantile for all $\alpha \in (0, 1)$.
- (b) Let U be uniformly distributed random variable in $\{1, 2, \dots, N\}$. Determine the CDF of U , compute the α -quantile for all $\alpha \in (0, 1)$. For which α the quantile is uniquely determined?

Solution:

(a) The distribution function of an exponentially distributed random variable X is given by

$$F_X(x) = \mathbb{P}(X \leq x) = 1 - e^{-\lambda x}.$$

For a α -quantile q_α one has

$$\mathbb{P}(X \leq q_\alpha) \geq \alpha \text{ and } \mathbb{P}(X \geq q_\alpha) \geq 1 - \alpha.$$

Since X has density (so $\mathbb{P}(X = x) = 0$ for every x),

$$1 - e^{-\lambda q_\alpha} = \mathbb{P}(X \leq q_\alpha) = \alpha.$$

That is

$$q_\alpha = -\ln(1 - \alpha)/\lambda.$$

(b) The distribution function is

$$F_U(u) = \mathbb{P}(U \leq u) = \begin{cases} 0, & u < 1 \\ k/N, & u \in [k, k+1), k \in \{1, \dots, N-1\} \\ 1, & u \geq N \end{cases}.$$

For quantile, if $\alpha = k/N$ for some $k \in \{1, \dots, N-1\}$, then the quantile can be chosen in $[k, k+1)$.

If $\alpha \in (k/N, (k+1)/N)$, then the quantile is uniquely determined: $q_\alpha = k+1$.

Q3. Let X and Y be random variables with joint density distribution given by

$$f_{X,Y}(x, y) = e^{-x^2 y} \mathbf{1}_{\{x \geq 1\}} \mathbf{1}_{\{y \geq 0\}}$$

(a) Why is this a probability measure?

(b) What is the density function of X .

(c) Compute $\mathbb{P}(Y \leq 1/X^2)$.

Solution:

(a) We just have to prove that $\int_{\mathbb{R}^2} f_{X,Y}(x, y) dx dy = 1$.

$$\begin{aligned} \int_1^\infty \int_0^\infty e^{-x^2 y} dy dx &= \int_1^\infty \left(-\frac{e^{-x^2 y}}{x^2} \right) \Big|_0^\infty dx \\ &= \int_1^\infty \frac{1}{x^2} dx = 1. \end{aligned}$$

(b) We now that $f_X(x) = \int_{\mathbb{R}} f_{X,Y}(x, y) dy$, then

$$f_X(x) = \int_0^\infty e^{-x^2 y} dy \mathbf{1}_{\{x \geq 1\}} = \frac{1}{x^2} \mathbf{1}_{\{x \geq 1\}}.$$

(c) Let's compute:

$$\begin{aligned}\mathbb{P}\left(Y \leq \frac{1}{X^2}\right) &= \int_1^\infty \int_0^{1/x^2} e^{-x^2 y} dx dy \\ &= \int_1^\infty \frac{1}{x^2} - e^{-1} \frac{1}{x^2} = 1 - e^{-1}.\end{aligned}$$

Q4. Let X and Y be two independent exponential random variables with parameter λ . Let $a > 0$.

(a) What is the joint density of the couple of random variables $(X, X + Y)$?

(b) Let $b \leq a$, what is the probability of $X \leq b$ conditioned on the event

$$B := \{X \leq a \text{ and } X + Y \geq a\}.$$

(c) What is the conditional density of X given the event B ?

Solution

(a) $X \sim \mathcal{E}(\lambda)$ so it has density

$$f_X(x) = \mathbf{1}_{x \geq 0} \lambda e^{-\lambda x}$$

as well as for Y ,

$$f_Y(y) = \mathbf{1}_{y \geq 0} \lambda e^{-\lambda y}.$$

The joint density of $(X, Z) := (X, X + Y)$ is

$$\begin{aligned}f_{X,Z}(x, z) &= f_{X,Y}(x, z - x) \\ (\text{independence of } X \text{ and } Y) &= f_X(x) f_Y(z - x) \\ &= \mathbf{1}_{x \geq 0} \lambda e^{-\lambda x} \mathbf{1}_{z-x \geq 0} \lambda e^{-\lambda(z-x)} \\ &= \mathbf{1}_{0 \leq x \leq z} \lambda^2 e^{-\lambda z}\end{aligned}$$

(b) The event B has probability:

$$\begin{aligned}\mathbb{P}(B) &= \int_a^\infty \int_0^a f_{X,Z}(x, z) dx dz \\ &= \int_a^\infty \int_0^a \mathbf{1}_{0 \leq x \leq z} \lambda^2 e^{-\lambda z} dx dz \\ &= a \lambda^2 \int_a^\infty e^{-\lambda z} dz \\ &= a \lambda e^{-\lambda a}.\end{aligned}$$

Note that it is also the probability that a $\text{Poisson}(a\lambda)$ random variable equals to 1 (it is also the probability of a Poisson process with intensity λ having exactly one point on

the interval $[0, a]$. Similarly, for $0 \leq b \leq a$,

$$\begin{aligned}\mathbb{P}(X \leq b | B) &= \frac{\mathbb{P}(X \leq b, Z \geq a)}{\mathbb{P}(B)} \\ &= \frac{\int_a^\infty \int_0^b f_{X,Z}(x, z) dx dz}{a\lambda e^{-\lambda a}} \\ &= \frac{b}{a}.\end{aligned}$$

- (c) The density is obtained by taking the derivative of $\mathbb{P}(X \leq b | B)$ with respect to b , which gives

$$f_{X|B}(x) = \mathbf{1}_{0 \leq x \leq a} \frac{1}{a}.$$

We conclude that the conditional law of X given B is the uniform distribution on $[0, a]$.

- Q5.** (a) Take X a random variable. Prove that for all $\lambda \geq 0$

$$\mathbb{P}(X \geq t) \leq \exp(-\lambda t) \mathbb{E}(\exp(\lambda X)).$$

- (b) Define $\phi_X(\lambda) := \ln(\mathbb{E}(e^{\lambda X}))$. Prove that $\phi(\lambda) \geq \lambda \mathbb{E}(X)$.

- (c) Prove that

$$\mathbb{P}(X \geq t) \leq \exp(-\sup_{\lambda \geq 0} \{\lambda t - \phi_X(\lambda)\}).$$

- (d) If $X \sim N(0, \sigma)$, calculate $\phi_X(\lambda)$.

- (e) Prove that if X is a positive random variable

$$\mathbb{E}(X) = \int_0^\infty \mathbb{P}(X \geq t) dt$$

- (f) Show that if $X \sim N(0, \sigma)$ and Y is a random variable such that $\phi_Y(\lambda) \leq \phi_X(\lambda)$, then

$$\mathbb{E}(Y^2) \leq 4\sigma^2.$$

Solution:

- (a) For $\lambda = 0$ the property is trivial. If $\lambda > 0$, using Markov (Tchebyshev) inequality we have that

$$\begin{aligned}\mathbb{P}(X \geq t) &= \mathbb{P}(\exp(\lambda X) \geq \exp(\lambda t)) \\ &\leq \frac{1}{\exp(\lambda t)} \mathbb{E}(\exp(\lambda X)).\end{aligned}$$

- (b) Given that $\exp(\lambda \cdot)$ is a convex function, thanks to Jensen inequality (Thm 3.6) we have that:

$$\begin{aligned}\mathbb{E}(\exp(\lambda X)) &\geq \exp(\mathbb{E}(\lambda X)) \\ \Rightarrow \phi(\lambda) = \ln(\mathbb{E}(\exp(\lambda X))) &\geq \lambda \mathbb{E}(X).\end{aligned}$$

(c) Using part a) we have that for all $\lambda > 0$

$$\begin{aligned}\mathbb{P}(X \geq \lambda) &\leq \exp(-\lambda t)\mathbb{E}(e^{\lambda X}) = \exp(\phi_X(\lambda) - \lambda t) \\ \Rightarrow \mathbb{P}(X \geq \lambda) &\leq \exp(-\sup_{\lambda \geq 0}\{\lambda t - \phi_X(\lambda)\}),\end{aligned}$$

where we have just taken the infimum of the exponential term over $\lambda \geq 0$.

(d) Let's compute

$$\begin{aligned}\mathbb{E}(e^{\lambda X}) &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} \exp(\lambda x) \exp\left(-\frac{x^2}{2\sigma^2}\right) dx \\ &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} \exp\left(-\frac{x^2 - 2\lambda\sigma^2}{2\sigma^2}\right) dx \\ &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} \exp(\lambda x) \exp\left(-\frac{(x - \lambda\sigma^2)^2}{2\sigma^2}\right) \exp\left(\frac{\lambda^2\sigma^2}{2}\right) dx \\ &= \exp\left(\frac{\lambda^2\sigma^2}{2}\right),\end{aligned}$$

then $\phi(\lambda) = \frac{1}{2}\lambda^2\sigma^2$.

(e) We just have to use Fubini's Theorem to compute

$$\begin{aligned}\mathbb{E}(X) &= \mathbb{E}\left(\int_0^{\infty} \mathbf{1}_{\{t \leq X\}} dt\right) \\ &= \int_0^{\infty} \mathbb{E}(\mathbf{1}_{\{X \geq t\}}) dt \\ &= \int_0^{\infty} \mathbb{P}(X \geq t) dt.\end{aligned}$$

(f) First let's compute:

$$\sup_{\lambda > 0} \left\{ \lambda t - \frac{1}{2}\lambda^2\sigma^2 \right\},$$

this is just a quadratic function on λ , so it attains its maximum in $\lambda_{\max} = t/\sigma^2 > 0$. Then its supremum is just $t^2/2\sigma^2$. So thanks to problem c) we have that

$$\begin{aligned}\mathbb{P}(Y \geq t) &\leq \exp(-\sup_{\lambda \geq 0}\{\lambda t - \phi_Y(\lambda)\}) \\ &\leq \exp(-\sup_{\lambda \geq 0}\{\lambda t - \phi_X(\lambda)\}) \\ &= \exp\left(-\frac{t^2}{2\sigma^2}\right).\end{aligned}$$

Thus, thanks to part e) we have that

$$\begin{aligned}\mathbb{E}(Y^2) &= \int_0^\infty P(Y^2 \geq t)dt = \int_0^\infty P(Y \geq \sqrt{t})dt + \int_0^\infty P(-Y \geq \sqrt{t})dt \\ &\leq 2 \int_0^\infty \exp\left(-\frac{t}{2\sigma^2}\right) dt \\ &= 4\sigma^2.\end{aligned}$$

Where we have used also

$$\phi_{-Y}(\lambda) = \phi_Y(-\lambda) \leq \phi_X(-\lambda) = \phi_{-X}(\lambda) = \phi_X(\lambda),$$

hence the previous step can also be applied to $\mathbb{P}(-Y \geq \sqrt{t})$.