

Several Random Variables

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Multiple random variables

We have mostly looked at one random variable X , including whether it is discrete or continuous.

We have also looked at multiple random variables briefly, discussing:

- Joint PMF / PDF and marginal PMF / PDF
- Conditional PMF / PDF and independence
- Expectation and variance of the sum of independent random variables
- Bayes' rule

In this lecture, we will further investigate topics relating to multiple random variables.

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Derived distributions

Procedure

The procedure for transforming one random variable to another is applicable to several random variables.

Given: PDF of X and Y , and $Z = g(X, Y)$, find the PDF of Z .

A two-step procedure:

$$F_Z(z) = \mathbb{P}(Z \leq z) = \mathbb{P}(g(X, Y) \leq z) = \iint_{\{x, y \mid g(x, y) \leq z\}} f_{X, Y}(x, y) \, dx dy$$
$$f_Z(z) = \frac{d}{dz} F_Z(z)$$

(1)

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Example

$X \sim U(0, 1)$ and $Y \sim U(0, 1)$, X and Y are independent, and $Z = \max\{X, Y\}$. What is the PDF of Z ?

ANS: We know $\mathbb{P}(X \leq z) = \mathbb{P}(Y \leq z) = z$.

$$\begin{aligned} F_Z(z) &= \mathbb{P}(\max\{X, Y\} \leq z) = \mathbb{P}(X \leq z, Y \leq z) \\ &= \mathbb{P}(X \leq z) \mathbb{P}(Y \leq z) = z^2 \end{aligned}$$

Differentiating,

$$f_Z(z) = \begin{cases} 2z & 0 \leq z \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

Example

Combining,

$$F_Z(z) = \mathbb{P}\left(\frac{Y}{X} \leq z\right) = \begin{cases} \frac{z}{2} & 0 \leq z \leq 1 \\ 1 - \frac{1}{2z} & z > 1 \\ 0 & \text{otherwise.} \end{cases}$$

Differentiating,

$$f_Z(z) = \begin{cases} \frac{1}{2} & 0 \leq z \leq 1 \\ \frac{1}{2z^2} & z > 1 \\ 0 & \text{otherwise.} \end{cases}$$

Example

$X \sim U(0, 1)$ and $Y \sim U(0, 1)$, X and Y are independent, and $Z = Y/X$. What is the PDF of Z ?

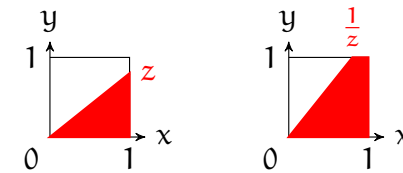
ANS: Case 1: $0 \leq z \leq 1$. We need to find $\mathbb{P}\left(\frac{Y}{X} \leq z\right) = \mathbb{P}(Y \leq zX)$. Consider a small interval from $[x, x + \delta]$.

$$\mathbb{P}(Y \leq zx) \approx zx\delta \implies f_X(x) = zx$$

$$\text{Therefore, } \mathbb{P}(Y \leq zX) = \int_0^1 f_X(x) dx = \int_0^1 (zx) dx = \left[\frac{1}{2}zx^2\right]_0^1 = \frac{1}{2}z.$$

Case 2: $z > 1$. Let $z' = 1/z$.

$$\mathbb{P}(Y/X \leq z) = \mathbb{P}(X/Y \geq z') = 1 - \mathbb{P}(X/Y \leq z') = 1 - \frac{1}{2}z' = 1 - \frac{1}{2z}$$



Example

$X \sim \text{Exp}(\lambda)$ and $Y \sim \text{Exp}(\lambda)$, X and Y are independent, and $Z = X - Y$. What is the PDF of Z ?

ANS: Case 1: $z \geq 0$.

$$\begin{aligned} F_Z(z) &= \mathbb{P}(X - Y \leq z) = 1 - \mathbb{P}(X - Y > z) \\ &= 1 - \int_0^\infty \left(\int_{z+y}^\infty f_{X,Y}(x, y) dx \right) dy \\ &= 1 - \int_0^\infty \lambda e^{-\lambda y} \left(\int_{z+y}^\infty \lambda e^{-\lambda x} dx \right) dy \\ &= 1 - \int_0^\infty \lambda e^{-\lambda y} \left(e^{-\lambda(z+y)} \right) dy \\ &= 1 - e^{-\lambda z} \int_0^\infty \lambda e^{-2\lambda y} dy \\ &= 1 - \frac{1}{2} e^{-\lambda z} \end{aligned}$$

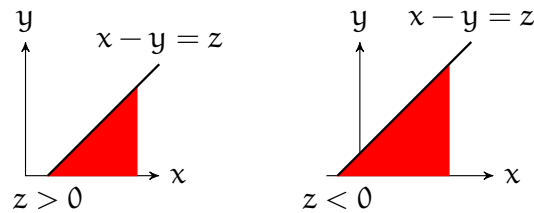
Example

Case 2: $z < 0$. Then, $-Z = Y - X$ which has the same distribution as Z .

$$F_Z(z) = \mathbb{P}(Z \leq z) = \mathbb{P}(-Z \geq -z) = \mathbb{P}(Z \geq -z) = 1 - F_Z(-z)$$

Since $-z > 0$, we can make use of case 1,

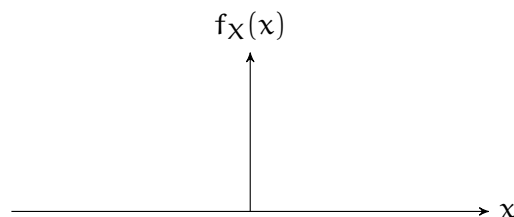
$$F_Z(z) = 1 - \left(1 - \frac{1}{2}e^{-\lambda(-z)}\right) = \frac{1}{2}e^{\lambda z}$$



(4) Laplacian random variable

We can add Laplacian to our list of continuous random variables.

	mean: $\mathbb{E}(X)$	variance: $\text{var}(X)$
Laplacian: $X \sim \text{Lap}(\lambda)$	0	$\frac{2}{\lambda^2}$



Example

Combining,

$$F_Z(z) = \begin{cases} 1 - \frac{1}{2}e^{-\lambda z} & z \geq 0 \\ \frac{1}{2}e^{\lambda z} & z < 0 \end{cases}$$

Differentiating,

$$f_Z(z) = \begin{cases} \frac{\lambda}{2}e^{-\lambda z} & z \geq 0 \\ \frac{\lambda}{2}e^{\lambda z} & z < 0 \end{cases}$$

We can express in a single formula

$$f_Z(z) = \frac{\lambda}{2}e^{-\lambda|z|} \quad (3)$$

called **Laplacian random variable**, and denote $Z \sim \text{Lap}(\lambda)$.

(4) Laplacian random variable

$$\mathbb{E}(X) = 0 \quad (\text{by symmetry})$$

$$\text{var}(X) = 2 \left(\int_0^\infty x^2 \frac{\lambda}{2} e^{-\lambda x} dx \right) = \lambda \left[\left(-\frac{x^2}{\lambda} - \frac{2x}{\lambda^2} - \frac{2}{\lambda^3} \right) e^{-\lambda x} \right]_0^\infty = \frac{2}{\lambda^2}$$

$$\begin{aligned} M_X(s) &= \int_{-\infty}^\infty e^{sx} \frac{\lambda}{2} e^{-\lambda|x|} dx \\ &= \frac{\lambda}{2} \left[\int_{-\infty}^0 e^{sx} e^{\lambda x} dx + \int_0^\infty e^{sx} e^{-\lambda x} dx \right] \\ &= \frac{\lambda}{2} \left\{ \left[\frac{1}{s+\lambda} e^{(s+\lambda)x} \right]_{-\infty}^0 + \left[\frac{1}{s-\lambda} e^{(s-\lambda)x} \right]_0^\infty \right\} \\ &= \frac{\lambda}{2} \left(\frac{1}{s+\lambda} - \frac{1}{s-\lambda} \right) = \frac{\lambda^2}{\lambda^2 - s^2} \quad \text{where } |s| < \lambda \end{aligned}$$

Example

$X \sim \mathcal{N}(0, 1)$ and $Y \sim \mathcal{N}(0, 1)$, X and Y are independent, and $Z = X + iY$, where $i = \sqrt{-1}$. What are the PDFs of $|Z|$ and $\angle Z$?

ANS: We work out the solution in a few steps.

Step 1: Representing X and Y in a complex plane, we can convert to polar coordinates with random variables $R \geq 0$ and $\Theta \in [0, 2\pi]$, where

$$X = R \cos \Theta \quad Y = R \sin \Theta$$

We also note that the joint PDF of X and Y is

$$f_{X,Y}(x, y) = f_X(x) f_Y(y) = \frac{1}{2\pi} e^{-(x^2+y^2)/2}$$

Example

Step 3: Differentiate $F_{R,\Theta}(r, \theta)$ to obtain $f_{R,\Theta}(r, \theta)$.

$$f_{R,\Theta}(r, \theta) = \frac{\partial^2}{\partial r \partial \theta} F_{R,\Theta}(r, \theta) = \frac{r}{2\pi} e^{-r^2/2} \quad r \geq 0, \theta \in [0, 2\pi]$$

Step 4: Integrate joint PDF to find marginal PDF

$$f_R(r) = \int_0^{2\pi} f_{R,\Theta}(r, \theta) d\theta = r e^{-r^2/2} \quad r \geq 0$$

$$f_\Theta(\theta) = \int_0^\infty \frac{r}{2\pi} e^{-r^2/2} dr = \frac{1}{2\pi} [-e^{-r^2/2}]_0^\infty = \frac{1}{2\pi} \quad \theta \in [0, 2\pi]$$

In our question, $|Z| = R$ and $\angle Z = \Theta$

Example

Step 2: From $f_{X,Y}(x, y)$ we find $F_{R,\Theta}(r, \theta)$.

For a *fixed* set of (r, θ) , the CDF integrates all the points (s, ϕ) with $0 \leq s \leq r$ and $0 \leq \phi \leq \theta$, which is *a sector of a circle with radius r and angle θ* , denoted A .

$$\begin{aligned} F_{R,\Theta}(r, \theta) &= \mathbb{P}(R \leq r, \Theta \leq \theta) \\ &= \iint_A \frac{1}{2\pi} e^{-(x^2+y^2)/2} dx dy \\ &= \frac{1}{2\pi} \int_0^\theta \int_0^r e^{-s^2/2} s ds d\phi \end{aligned}$$

Example

$X \sim \mathcal{N}(0, 1)$ and $Y \sim \mathcal{N}(0, 1)$, X and Y are independent, and $Z = X + iY$, then

- ① The angle follows a *uniform distribution*, $\Theta \sim U(0, 2\pi)$
- ② The magnitude follows a distribution known as *Rayleigh distribution*, $R \sim \text{Ray}(\sigma)$ where

$$f_R(r) = \frac{r}{\sigma^2} e^{-r^2/(2\sigma^2)} \quad (4)$$

with σ^2 being the variance of the normal distributions X and Y .

(5) Rayleigh random variable

We can add Rayleigh to our list of continuous random variables.

	mean: $\mathbb{E}(X)$	variance: $\text{var}(X)$
Rayleigh: $X \sim \text{Ray}(\sigma)$	$\sigma \sqrt{\frac{\pi}{2}}$	$\frac{4 - \pi}{2} \sigma^2$



Sum of two independent random variables

X and Y are two random variables, possibly of different distributions, but independent of each other. We are interested to know the distribution of $Z = X + Y$.

Discrete random variables:

$$\begin{aligned}
 p_Z(z) &= \mathbb{P}(X + Y = z) = \sum_{\{(x,y) \mid x+y=z\}} \mathbb{P}(X = x, Y = y) \\
 &= \sum_x \mathbb{P}(X = x, Y = z - x) \\
 &= \sum_x \mathbb{P}(X = x) \mathbb{P}(Y = z - x) \\
 &= \sum_x p_X(x) p_Y(z - x)
 \end{aligned}$$

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Sum of two independent random variables

Continuous random variables:

$$\begin{aligned}
 \mathbb{P}(Z \leq z \mid X = x) &= \mathbb{P}(X + Y \leq z \mid X = x) \\
 &= \mathbb{P}(x + Y \leq z \mid X = x) \\
 &= \mathbb{P}(x + Y \leq z) \\
 &= \mathbb{P}(Y \leq z - x)
 \end{aligned}$$

Differentiating, we get $f_{Z|X}(z|x) = f_Y(z - x)$.

$$\begin{aligned}
 f_{X,Z}(x, z) &= f_X(x) f_{Z|X}(z|x) = f_X(x) f_Y(z - x) \\
 f_Z(z) &= \int_{-\infty}^{\infty} f_{X,Z}(x, z) dx = \int_{-\infty}^{\infty} f_X(x) f_Y(z - x) dx
 \end{aligned}$$

Sum of two independent random variables

$$\text{Discrete: } p_Z(z) = \sum_x p_X(x) p_Y(z-x) \quad (5)$$

$$\text{Continuous: } f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx \quad (6)$$

The PMF (PDF) of Z is the **convolution** of the PMF (PDF) of X and Y .

Recall we have also looked at the moment generating functions:

$$M_Z(s) = \mathbb{E}(e^{sZ}) = \mathbb{E}(e^{s(X+Y)}) = \mathbb{E}(e^{sX}e^{sY}) = \mathbb{E}(e^{sX}) \mathbb{E}(e^{sY})$$

$$M_Z(s) = M_X(s)M_Y(s) \quad (7)$$

The moment generating function (MGF) of Z is the **product** of the MGF of X and Y .

Example

$X \sim \text{Exp}(\lambda)$ and $Y \sim \text{Exp}(\lambda)$, X and Y are independent, and $Z = X - Y$. What is the PDF of Z ?

ANS: We have already seen the answer is Laplacian. But we can also proceed by noting that $Z = X + (-Y)$, and $f_{-Y}(y) = f_Y(-y)$ by symmetry, so

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_{-Y}(z-x) dx = \int_{-\infty}^{\infty} f_X(x) f_Y(x-z) dx$$

Now consider $z \geq 0$, so $f_Y(x-z)$ is nonzero only when $x \geq z$.

$$\begin{aligned} f_Z(z) &= \int_z^{\infty} \lambda e^{-\lambda x} \lambda e^{-\lambda(x-z)} dx = \lambda^2 e^{\lambda z} \int_z^{\infty} e^{-2\lambda x} dx \\ &= \lambda^2 e^{\lambda z} \frac{1}{2\lambda} e^{-2\lambda z} = \frac{\lambda}{2} e^{-\lambda z} \end{aligned}$$

The case for $z < 0$ is similar.

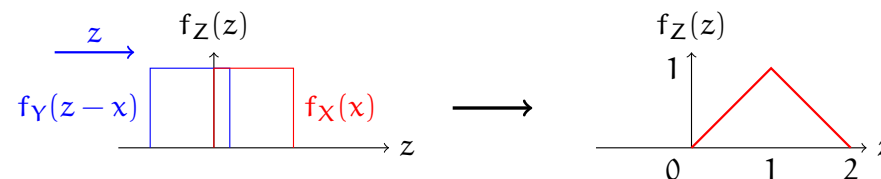
Example

Two random variables X and Y are independent and uniformly distributed between 0 and 1. Find the PDF of $Z = X + Y$.

We make use of the formula

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z-x) dx = \min\{1, z\} - \max\{0, z-1\} \quad \text{for } 0 \leq z \leq 2$$

The integrand is nonzero only when $0 \leq x \leq 1$ and $0 \leq z-x \leq 1$. We can work out the math for different values of z , or do that graphically:



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Definition

The covariance of two random variables X and Y is denoted by $\text{cov}(X, Y)$, and is defined by

$$\text{cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] \quad (8)$$

- $\text{cov}(X, Y) = 0 \implies X$ and Y are uncorrelated.
- $\text{cov}(X, Y)$ is positive $\implies X - \mathbb{E}(X)$ and $Y - \mathbb{E}(Y)$ tend to have the same sign.
- $\text{cov}(X, Y)$ is negative $\implies X - \mathbb{E}(X)$ and $Y - \mathbb{E}(Y)$ tend to have the opposite sign.

Variance measures the “spread” of a random variable. Covariance measures the “spread” across two random variables.

Properties

Some properties (a and b are scalars):

$$\text{cov}(X, X) = \text{var}(X) \quad (10)$$

$$\text{cov}(X, aY + b) = a \cdot \text{cov}(X, Y) \quad (11)$$

$$\text{cov}(X, Y + Z) = \text{cov}(X, Y) + \text{cov}(X, Z) \quad (12)$$

Also, since if X and Y are independent, $\mathbb{E}[XY] = \mathbb{E}[X] \mathbb{E}[Y]$, so

$$X \text{ and } Y \text{ independent} \implies X \text{ and } Y \text{ uncorrelated}$$

Converse is NOT true! (illustrated in the next example)

Definition

Alternative form:

$$\text{cov}(X, Y) = \mathbb{E}[XY] - \mathbb{E}[X] \mathbb{E}[Y] \quad (9)$$

Proof:

$$\begin{aligned} \text{cov}(X, Y) &= \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] \\ &= \mathbb{E}(XY - X\mathbb{E}[Y] - Y\mathbb{E}[X] + \mathbb{E}[X] \mathbb{E}[Y]) \\ &= \mathbb{E}[XY] - \mathbb{E}[X] \mathbb{E}[Y] - \mathbb{E}[X] \mathbb{E}[Y] + \mathbb{E}[X] \mathbb{E}[Y] \\ &= \mathbb{E}[XY] - \mathbb{E}[X] \mathbb{E}[Y] \end{aligned}$$

Example

Consider four points, at $(1, 0)$, $(0, 1)$, $(-1, 0)$, $(0, -1)$, each with probability $1/4$.

They are not independent because fixing Y (e.g. $Y = 1$), it determines X ($X = 0$).

However,

- $\mathbb{E}(X) = \mathbb{E}(Y) = 0$
- $\mathbb{E}(XY) = 0$
- Hence, $\text{cov}(X, Y) = 0$

Covariance

If X and Y are independent (uncorrelated),
 $\text{var}(X + Y) = \text{var}(X) + \text{var}(Y)$. But more generally,

$$\text{var}(X + Y) = \text{var}(X) + \text{var}(Y) + 2\text{cov}(X, Y) \quad (13)$$

Even more generally,

$$\text{var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{var}(X_i) + \sum_{\{(i,j) \mid i \neq j\}} \text{cov}(X_i, X_j) \quad (14)$$

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Covariance

Proof: Let $\tilde{X}_i = X_i - \mathbb{E}(X_i)$.

$$\begin{aligned} \text{var}\left(\sum_{i=1}^n X_i\right) &= \text{var}\left(\sum_{i=1}^n \tilde{X}_i\right) = \mathbb{E}\left[\left(\sum_{i=1}^n \tilde{X}_i\right)^2\right] \\ &= \mathbb{E}\left[\sum_{i=1}^n \sum_{j=1}^n \tilde{X}_i \tilde{X}_j\right] \\ &= \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}[\tilde{X}_i \tilde{X}_j] \\ &= \sum_{i=1}^n \mathbb{E}[\tilde{X}_i^2] + \sum_{\{(i,j) \mid i \neq j\}} \mathbb{E}[\tilde{X}_i \tilde{X}_j] \\ &= \sum_{i=1}^n \text{var}(X_i) + \sum_{\{(i,j) \mid i \neq j\}} \text{cov}(X_i, X_j) \end{aligned}$$

Example

In a class with n students, after the final exam, they were ranked from 1 to n (no two students shared the same rank). The names and the marks were put in a spreadsheet, but a careless teacher sorted the names in some random way without linking them to the marks. Consequently, the matching between the student and his or her actual rank became random. For the student originally with rank k , the new rank now takes a discrete random variable which is uniform between 1 and n . Note that in the new rank, again no two students share the same rank.

What is the expected number of correct ranking (i.e., new rank is the same as original rank), and its variance?

This question is a work of fiction. Any resemblance to actual persons, living or dead, or actual events is purely coincidental.

Example

Attempt #1: Test some small cases. Let X = correct ranking.

- ① Two students AB; after the randomization, half the time the order remains AB; half the time the order becomes BA.

$$\begin{aligned}\mathbb{E}(X) &= \frac{1}{2} \cdot (2) + \frac{1}{2} \cdot (0) = 1 \\ \mathbb{E}(X^2) &= \frac{1}{2} \cdot (2)^2 + \frac{1}{2} \cdot (0)^2 = 2 \\ \text{var}(X) &= 2 - 1^2 = 1\end{aligned}$$

- ② Three students ABC; There are now $3!$ permutations, with $1/6$ being all correct, $3/6$ having one correct, and $2/6$ being all wrong.

$$\begin{aligned}\mathbb{E}(X) &= \frac{1}{6} \cdot (3) + \frac{3}{6} \cdot (1) + \frac{2}{6} \cdot (0) = 1 \\ \mathbb{E}(X^2) &= \frac{1}{6} \cdot (3)^2 + \frac{3}{6} \cdot (1)^2 + \frac{2}{6} \cdot (0)^2 = 2 \\ \text{var}(X) &= 2 - 1^2 = 1\end{aligned}$$

Guess: $\mathbb{E}(X) = \text{var}(X) = 1$ for all n ?

Example

The calculation of the variance is more complicated because X_i and X_j are correlated, for $i \neq j$. First,

$$\text{var}(X_i) = \frac{1}{n} \left(1 - \frac{1}{n} \right) \quad (\text{Bernoulli})$$

Then, let us calculate $\mathbb{E}(X_i X_j)$ for $i \neq j$.

$$\begin{aligned}\mathbb{E}(X_i X_j) &= \mathbb{P}(X_i = 1 \text{ and } X_j = 1) \\ &= \mathbb{P}(X_i = 1) \mathbb{P}(X_j = 1 | X_i = 1) \\ &= \frac{1}{n} \cdot \frac{1}{n-1} = \frac{1}{n(n-1)}\end{aligned}$$

Hence,

$$\text{cov}(X_i, X_j) = \mathbb{E}(X_i X_j) - \mathbb{E}(X_i) \mathbb{E}(X_j) = \frac{1}{n(n-1)} - \frac{1}{n} \cdot \frac{1}{n} = \frac{1}{n^2(n-1)}$$

Example

Attempt #2: Analytical derivation.

Let $X_i = 1$ if the i th student has the correct rank, and zero otherwise.

So,

$$X = X_1 + X_2 + \dots + X_n$$

For each X_i , we have $\mathbb{P}(X_i = 1) = 1/n$; therefore,

$$\begin{aligned}\mathbb{E}(X_i) &= \frac{1}{n} \cdot 1 + \frac{n-1}{n} \cdot 0 = \frac{1}{n} \\ \mathbb{E}(X) &= \mathbb{E}(X_1) + \dots + \mathbb{E}(X_n) = \frac{1}{n} + \dots + \frac{1}{n} = 1\end{aligned}$$

Hence, although each one having a correct rank decreases with n , there are more students, and the net result is that the expected number of correctness remains 1.

Example

Overall,

$$\begin{aligned}\text{var}(X) &= \text{var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{var}(X_i) + \sum_{\{(i,j) | i \neq j\}} \text{cov}(X_i, X_j) \\ &= n \left[\frac{1}{n} \left(1 - \frac{1}{n} \right) \right] + n(n-1) \left[\frac{1}{n^2(n-1)} \right] \\ &= 1\end{aligned}$$

Hence, the variance also remains 1 irrespective of the number of students.

Quite surprising that irrespective of n , you always expect to get 1 correct and all the rest wrong, and even with the same variance!

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Definition

$\rho(X, Y)$ is normalized in the sense that

$$-1 \leq \rho(X, Y) \leq 1 \quad (16)$$

- $|\rho|$ is a measure of the extent to which $X - \mathbb{E}(X)$ and $Y - \mathbb{E}(Y)$ are “correlated” (i.e., cluster together).
- $|\rho| = 1$ if and only if

$$Y - \mathbb{E}[Y] = c(X - \mathbb{E}[X])$$

where c is a constant of the same sign as ρ

Definition

Often, we work with a “normalized” version of covariance, known as **correlation coefficient**:

$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X) \text{var}(Y)}} \quad (15)$$

Assuming X and Y both have nonzero variance, the numerator determines similar properties as covariance:

- $\rho(X, Y) = 0 \implies X$ and Y are uncorrelated.
- $\rho(X, Y)$ is positive $\implies X - \mathbb{E}(X)$ and $Y - \mathbb{E}(Y)$ tend to have the same sign.
- $\rho(X, Y)$ is negative $\implies X - \mathbb{E}(X)$ and $Y - \mathbb{E}(Y)$ tend to have the opposite sign.

Proof of correlation coefficient magnitude (1)

We start with a lemma known as Schwarz inequality:

$$(\mathbb{E}[XY])^2 \leq \mathbb{E}[X^2] \mathbb{E}[Y^2] \quad (17)$$

for any random variable X and Y .

Proof: We assume $\mathbb{E}[Y^2] \neq 0$, because otherwise we have $Y = 0$ with probability 1, and therefore $\mathbb{E}[XY] = 0$, so equality holds. With this assumption, we start with an expression

$$\mathbb{E}\left[\left(X - \frac{\mathbb{E}[XY]}{\mathbb{E}[Y^2]}Y\right)^2\right]$$

which must be ≥ 0 .

Proof of correlation coefficient magnitude (2)

Proof:

$$\begin{aligned}
 0 &\leq \mathbb{E} \left[\left(X - \frac{\mathbb{E}[XY]}{\mathbb{E}[Y^2]} Y \right)^2 \right] \\
 &= \mathbb{E} \left[X^2 - 2 \frac{\mathbb{E}[XY]}{\mathbb{E}[Y^2]} XY + \frac{(\mathbb{E}[XY])^2}{(\mathbb{E}[Y^2])^2} Y^2 \right] \\
 &= \mathbb{E}[X^2] - 2 \frac{\mathbb{E}[XY]}{\mathbb{E}[Y^2]} \mathbb{E}[XY] + \frac{(\mathbb{E}[XY])^2}{(\mathbb{E}[Y^2])^2} \mathbb{E}[Y^2] \\
 &= \mathbb{E}[X^2] - \frac{(\mathbb{E}[XY])^2}{\mathbb{E}[Y^2]}
 \end{aligned}$$

Therefore, $(\mathbb{E}[XY])^2 \leq \mathbb{E}[X^2] \mathbb{E}[Y^2]$, and thus $\frac{(\mathbb{E}[XY])^2}{\mathbb{E}[X^2] \mathbb{E}[Y^2]} \leq 1$.

Proof of correlation coefficient magnitude (4)

Next, we show what happens when $Y - \mathbb{E}[Y] = c(X - \mathbb{E}[X])$, or $\tilde{Y} = c\tilde{X}$:

- $\mathbb{E}(\tilde{X}\tilde{Y}) = c\mathbb{E}(\tilde{X}^2)$
- $\mathbb{E}(\tilde{Y}^2) = c^2\mathbb{E}(\tilde{X}^2)$

Therefore,

$$\rho(X, Y) = \frac{c\mathbb{E}[\tilde{X}^2]}{\sqrt{c^2\mathbb{E}[\tilde{X}^2] \mathbb{E}[\tilde{X}^2]}} = \frac{c}{|c|} = \begin{cases} 1 & c > 0 \\ -1 & c < 0 \end{cases}$$

Proof of correlation coefficient magnitude (3)

For general random variables X and Y , we first “center” them to form

$$\tilde{X} = X - \mathbb{E}[X]$$

$$\tilde{Y} = Y - \mathbb{E}[Y]$$

- $\text{var}(\tilde{X}) = \text{var}(X) = \mathbb{E}[\tilde{X}^2]$
- $\text{cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = \mathbb{E}[\tilde{X}\tilde{Y}]$

Then, we make use of Schwarz inequality

$$(\rho(X, Y))^2 = \frac{(\text{cov}(X, Y))^2}{\text{var}(X) \text{var}(Y)} = \frac{(\mathbb{E}[\tilde{X}\tilde{Y}])^2}{\mathbb{E}[\tilde{X}^2] \mathbb{E}[\tilde{Y}^2]} \leq 1$$

So $|\rho(X, Y)| \leq 1$.

Proof of correlation coefficient magnitude (5)

We now show the reverse: when $\rho(X, Y) = \pm 1$,

$$\begin{aligned}
 \mathbb{E} \left[\left(\tilde{X} - \frac{\mathbb{E}[\tilde{X}\tilde{Y}]}{\mathbb{E}[\tilde{Y}^2]} \tilde{Y} \right)^2 \right] &= \mathbb{E}[\tilde{X}^2] - \frac{(\mathbb{E}[\tilde{X}\tilde{Y}])^2}{\mathbb{E}[\tilde{Y}^2]} \\
 &= \mathbb{E}[\tilde{X}^2] (1 - [\rho(X, Y)]^2) = 0
 \end{aligned}$$

This means, with probability 1, $\tilde{X} - \frac{\mathbb{E}[\tilde{X}\tilde{Y}]}{\mathbb{E}[\tilde{Y}^2]} \tilde{Y}$ is equal to zero. It follows that, with probability 1,

$$\tilde{X} = \frac{\mathbb{E}[\tilde{X}\tilde{Y}]}{\mathbb{E}[\tilde{Y}^2]} \tilde{Y} = \sqrt{\frac{\mathbb{E}[\tilde{X}^2]}{\mathbb{E}[\tilde{Y}^2]}} \rho(X, Y) \tilde{Y}$$

i.e., the ratio of $\tilde{X}$ and $\tilde{Y}$ is determined by the sign of $\rho(X, Y)$.

Example

For n independent coin toss, let X be the number of heads and Y be the number of tails. What is the correlation coefficient $\rho(X, Y)$?

ANS: Since $X + Y = n$, they are “perfectly correlated.” We expect $\rho(X, Y) = \pm 1$. Moreover, since $X + Y = \mathbb{E}(X) + \mathbb{E}(Y) = n$, we have

$$X - \mathbb{E}(X) = -(Y - \mathbb{E}(Y))$$

so the sign of $\rho(X, Y)$ should be negative, i.e., it is equal to -1 .

Alternatively, we can apply the formula

$$\text{cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = -\mathbb{E}[(X - \mathbb{E}[X])^2] = -\text{var}(X)$$

and note that $\text{var}(X) = \text{var}(Y)$, by symmetry, and therefore

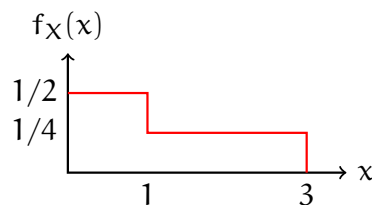
$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X) \text{var}(Y)}} = \frac{-\text{var}(X)}{\sqrt{\text{var}(X) \text{var}(X)}} = -1$$

Motivating example

A continuous random variable X has the PDF

$$f_X(x) = \begin{cases} \frac{1}{2} & 0 \leq x \leq 1 \\ \frac{1}{4} & 1 < x \leq 3 \\ 0 & \text{otherwise.} \end{cases}$$

as depicted below. What is $\mathbb{E}(X)$ and $\text{var}(X)$?



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Motivating example

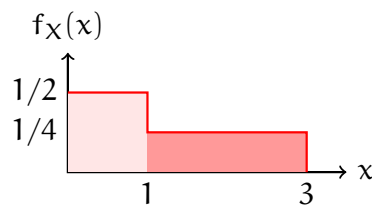
We can solve it directly:

$$\begin{aligned} \mathbb{E}(X) &= \int_0^1 x \frac{1}{2} dx + \int_1^3 x \frac{1}{4} dx \\ &= \frac{1}{4} [x^2]_0^1 + \frac{1}{8} [x^2]_1^3 = \frac{1}{4} + \frac{9}{8} - \frac{1}{8} = \frac{5}{4} \end{aligned}$$

$$\begin{aligned} \mathbb{E}(X^2) &= \int_0^1 x^2 \frac{1}{2} dx + \int_1^3 x^2 \frac{1}{4} dx \\ &= \frac{1}{6} [x^3]_0^1 + \frac{1}{12} [x^3]_1^3 = \frac{1}{6} + \frac{27}{12} - \frac{1}{12} = \frac{7}{3} \end{aligned}$$

$$\text{var}(X) = \frac{7}{3} - \left(\frac{5}{4}\right)^2 = \frac{37}{48}$$

Motivating example



It seems we can “divide” X in two ranges: $[0, 1]$ and $[1, 3]$.

Let us define an auxiliary random variable Y where

$$Y = \begin{cases} 1 & x < 1 \\ 2 & x \geq 1 \end{cases}$$

Can we compute $\mathbb{E}(X)$ and $\text{var}(X)$ in terms of $\mathbb{E}(X|Y)$ and $\text{var}(X|Y)$?

Definition

We therefore have this *law of iterated expectation*:

$$\mathbb{E}[X] = \mathbb{E}[\mathbb{E}[X|Y]] = \mathbb{E}_Y[\mathbb{E}_X[X|Y]] \quad (20)$$

Note that we put in the subscript X and Y to emphasize what the random variable is with each expectation operation. We do not always make that designation.

Definition

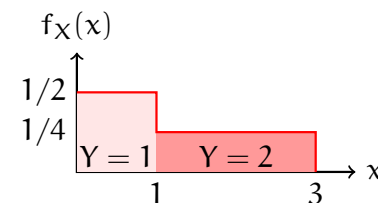
Let us first consider $\mathbb{E}[X|Y]$. Remember that *unconditional average* = *averaging the conditional averages*:

$$\mathbb{E}(X) = \sum_y p_Y(y) \mathbb{E}(X|Y=y) \quad (18)$$

$$\mathbb{E}(X) = \int_{-\infty}^{\infty} \mathbb{E}(X|Y=y) f_Y(y) dy \quad (19)$$

- ④ $\mathbb{E}[X|Y=y]$ is a constant (for a fixed value of y). So more generally, it is a function of y .
- ② $\mathbb{E}[X|Y]$ is therefore a function of Y , i.e., with PMF $p_Y(y)$ or PDF $f_Y(y)$.
- ③ So, the above are formulas for *expectation of $\mathbb{E}[X|Y]$* .

Motivating example



Note that $\mathbb{P}(Y=1) = \mathbb{P}(Y=2) = 1/2$. Also, conditioning on $Y=1$ or $Y=2$, the r.v. X is uniform, such that

$$\mathbb{E}(X|Y=1) = \frac{1}{2} \quad \text{and} \quad \mathbb{E}(X|Y=2) = 2$$

Therefore,

$$\begin{aligned} \mathbb{E}(X) &= \mathbb{E}(\mathbb{E}[X|Y]) = \mathbb{P}(Y=1) \mathbb{E}[X|Y=1] + \mathbb{P}(Y=2) \mathbb{E}[X|Y=2] \\ &= \frac{1}{2} \left(\frac{1}{2} \right) + \frac{1}{2} (2) = \frac{5}{4} \end{aligned}$$

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Total variance

To show the law of total variance, we first define two quantities:

$$\hat{X} = \mathbb{E}(X|Y) \quad (22)$$

$$\tilde{X} = \hat{X} - X \quad (23)$$

$\hat{X}$ is an **estimator** of X given Y , whereas $\tilde{X}$ is the estimation **error**.

In our example:

$$\hat{X} = \begin{cases} \frac{1}{2} & y = 1 (0 \leq X < 1) \\ 2 & y = 2 (1 \leq X < 3) \end{cases}$$

$$\tilde{X} = \begin{cases} \frac{1}{2} - X & y = 1 (0 \leq X < 1) \\ 2 - X & y = 2 (1 \leq X < 3) \end{cases}$$

Total variance

There's also a law of total variance:

$$\text{var}(X) = \mathbb{E}[\text{var}(X|Y)] + \text{var}(\mathbb{E}[X|Y]) \quad (21)$$

Both the law of iterated expectation and law of total variance allow us to start with expressions of $\mathbb{E}(X|Y)$ and $\text{var}(X|Y)$ to arrive at $\mathbb{E}(X)$ and $\text{var}(X)$.

Total variance

We aim to show:

- 1 We can divide X into two parts, such that

$$\text{var}(X) = \text{var}(\tilde{X}) + \text{var}(\hat{X})$$

The second term $\text{var}(\hat{X})$ is $\text{var}(\mathbb{E}(X|Y))$.

- 2 The variance of the estimator is

$$\text{var}(\tilde{X}) = \mathbb{E}(\text{var}(X|Y))$$

To show $\text{var}(X) = \text{var}(\tilde{X}) + \text{var}(\hat{X})$, we need to demonstrate that the *estimator is uncorrelated with the estimation error*. We will do that later.

Total variance

Instead, we first look at the estimator. We want to show in two steps:

- 1 Its expected value is zero:

$$\mathbb{E}(\tilde{X}) = 0$$

- 2 Its variance is then:

$$\text{var}(\tilde{X}) = \mathbb{E}(\tilde{X}^2) = \mathbb{E}(\text{var}(X|Y))$$

Total variance

The error has an expected value of 0, but what about its variance, $\text{var}(\tilde{X})$?

By definition,

$$\text{var}(X|Y) = \mathbb{E}[(X - \mathbb{E}[X|Y])^2 | Y] = \mathbb{E}[(X - \hat{X})^2 | Y] = \mathbb{E}[\tilde{X}^2 | Y]$$

Therefore,

$$\text{var}(\tilde{X}) = \mathbb{E}(\tilde{X}^2) - (\mathbb{E}(\tilde{X}))^2 = \mathbb{E}(\mathbb{E}[\tilde{X}^2 | Y]) = \mathbb{E}(\text{var}(X|Y))$$

Total variance

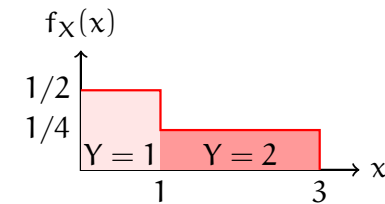
The estimator $\hat{X} = \mathbb{E}(X|Y)$ is *unbiased*, because

$$\mathbb{E}(X) = \mathbb{E}[\mathbb{E}(X|Y)] = \mathbb{E}(\hat{X}),$$

and therefore $\mathbb{E}(\tilde{X}) = \mathbb{E}(\hat{X} - X) = 0$.

Total variance

In our example:



Conditioning on $Y = 1$ or $Y = 2$, the r.v. X is uniform, such that

$$\text{var}(X|Y=1) = \frac{1^2}{12} \quad \text{and} \quad \text{var}(X|Y=2) = \frac{2^2}{12}$$

Therefore,

$$\begin{aligned} \mathbb{E}(\text{var}(X|Y)) &= \mathbb{P}(Y=1) \text{var}(X|Y=1) + \mathbb{P}(Y=2) \text{var}(X|Y=2) \\ &= \frac{1}{2} \left(\frac{1}{12} \right) + \frac{1}{2} \left(\frac{4}{12} \right) = \frac{5}{24} \end{aligned}$$

Total variance

Now, we go back to show that *the estimator is uncorrelated with the estimation error*:

$$\text{cov}(\hat{X}, \tilde{X}) = 0 \quad (24)$$

First, we have

$$\mathbb{E}(\tilde{X} | Y) = \mathbb{E}(\hat{X} - X | Y) = \mathbb{E}(\hat{X} | Y) - \mathbb{E}(X | Y) = 0$$

because given Y , then $\hat{X}$ is a fixed value, and therefore $\mathbb{E}(\hat{X} | Y) = \hat{X}$.

The second term, $\mathbb{E}(X | Y)$ is $\hat{X}$ by definition.

Total variance

Third,

$$\text{cov}(\hat{X}, \tilde{X}) = \mathbb{E}(\hat{X}\tilde{X}) - \mathbb{E}(\hat{X})\mathbb{E}(\tilde{X}) = 0 - \mathbb{E}(X) \cdot 0 = 0$$

Because $\text{cov}(\hat{X}, \tilde{X}) = 0$, we can conclude

$$\text{var}(X) = \text{var}(\tilde{X}) + \text{var}(\hat{X})$$

The law of total variance is precisely the same equation:

$$\text{var}(X) = \underbrace{\mathbb{E}[\text{var}(X | Y)]}_{\text{var}(\tilde{X})} + \underbrace{\text{var}(\mathbb{E}[X | Y])}_{\text{var}(\hat{X})}$$

Total variance

Second, note that for any function $g(\cdot)$, we have

$$\mathbb{E}(Xg(Y) | Y) = g(Y)\mathbb{E}(X | Y),$$

because given the value of Y , the function $g(Y)$ is a constant and therefore can be pulled outside the expectation.

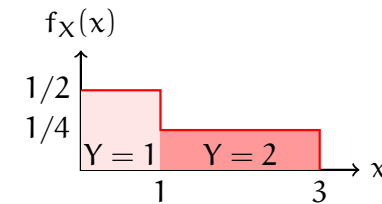
As a special case, we have

$$\mathbb{E}(\hat{X}\tilde{X}) = \mathbb{E}(\mathbb{E}[\hat{X}\tilde{X} | Y]) = \mathbb{E}(\hat{X}\mathbb{E}[\tilde{X} | Y]) = 0$$

because $\hat{X}$ is a function of Y only, and $\mathbb{E}[\tilde{X} | Y] = 0$ as calculated earlier.

Total variance

In our example:



We already note that $\mathbb{E}(X) = \frac{5}{4}$, which we call μ here.

$$\begin{aligned} \text{var}(\mathbb{E}[X | Y]) &= \mathbb{P}(Y = 1) (\mathbb{E}[X | Y = 1] - \mu)^2 + \mathbb{P}(Y = 2) (\mathbb{E}[X | Y = 2] - \mu)^2 \\ &= \frac{1}{2} \left(\frac{1}{2} - \frac{5}{4} \right)^2 + \frac{1}{2} \left(2 - \frac{5}{4} \right)^2 = \frac{9}{16} \\ \text{var}(X) &= \mathbb{E}[\text{var}(X | Y)] + \text{var}(\mathbb{E}[X | Y]) = \frac{5}{24} + \frac{9}{16} = \frac{37}{48} \end{aligned}$$

Example

We have a biased coin where the probability of heads, denoted by Y , is a continuous uniform random variable in the range of $[0, 1]$. We toss the coin n times, and let X be the number of heads obtained. Find $\mathbb{E}(X)$ and $\text{var}(X)$.

ANS: X is dependent on Y , so Eq. (20) and (21) would be useful.

Since $\mathbb{E}(X|Y = y) = ny$, we have $\mathbb{E}(X|Y) = nY$.

$$\mathbb{E}(X) = \mathbb{E}(\mathbb{E}[X|Y]) = \mathbb{E}(nY) = n\mathbb{E}(Y) = \frac{n}{2}$$

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Example

Similarly, since $\text{var}(X|Y = y) = ny(1 - y)$, so $\text{var}(X|Y) = nY(1 - Y)$.

$$\mathbb{E}(\text{var}(X|Y)) = \mathbb{E}(nY(1 - Y)) = n\mathbb{E}(Y) - n\mathbb{E}(Y^2) = \frac{n}{2} - \frac{n}{3} = \frac{n}{6}$$

because $\mathbb{E}(Y^2) = \text{var}(Y) + (\mathbb{E}(Y))^2 = \frac{1}{12} + (\frac{1}{2})^2 = \frac{1}{3}$. Also,

$$\text{var}(\mathbb{E}[X|Y]) = \text{var}(nY) = n^2 \cdot \frac{1}{12}$$

Combining,

$$\text{var}(X) = \mathbb{E}[\text{var}(X|Y)] + \text{var}(\mathbb{E}[X|Y]) = \frac{n}{6} + \frac{n^2}{12}$$

Example

You visit a number of bookstores in search of a particular textbook on probability. Any given bookstore carries the book with probability p , independent of the others. In a typical bookstore, the amount of time you spend is exponentially distributed with parameter λ , and independent of the time you spend in other bookstores. You will keep on visiting bookstores until you find the book (because the lectures are too boring, you'd rather learn from a book). What are the mean, variance, and PDF of the total time spent in search of the book?

It is a sum of a *geometric number* of independent exponential random variables.

We have sufficient tools now to approach such type of problems involving summing of a random number of independent random variables.

Setting

We consider

$$Y = X_1 + \dots + X_N$$

where

- N is a random variable that takes nonnegative integer values.
- $X_1, X_2, \dots$ are identically distributed random variables.
- $N, X_1, X_2, \dots$ are independent, meaning that any finite subcollection of these random variables are independent.
- $\mathbb{E}(X)$ and $\text{var}(X)$ are the common mean and variance of each X_i .

Variance

Similarly, to compute $\text{var}(Y)$:

$$\begin{aligned}\text{var}(Y | N = n) &= \text{var}(X_1 + \dots + X_N | N = n) \\ &= \text{var}(X_1 + \dots + X_n | N = n) \\ &= \text{var}(X_1 + \dots + X_n) \\ &= n\text{var}(X)\end{aligned}$$

This is true for every nonnegative integer n and, therefore,

$$\text{var}(Y | N) = N\text{var}(X)$$

Using the law of total variance, we obtain

$$\begin{aligned}\text{var}(Y) &= \mathbb{E}[\text{var}(Y | N)] + \text{var}(\mathbb{E}[Y | N]) \\ &= \mathbb{E}[N\text{var}(X)] + \text{var}(N\mathbb{E}[X]) \\ &= \mathbb{E}(N) \text{var}(X) + (\mathbb{E}[X])^2 \text{var}(N)\end{aligned}$$

Expectation

We first calculate $\mathbb{E}(Y)$:

$$\begin{aligned}\mathbb{E}(Y | N = n) &= \mathbb{E}(X_1 + \dots + X_N | N = n) \\ &= \mathbb{E}(X_1 + \dots + X_n | N = n) \\ &= \mathbb{E}(X_1 + \dots + X_n) \\ &= n\mathbb{E}(X)\end{aligned}$$

This is true for every nonnegative integer n and, therefore,

$$\mathbb{E}(Y | N) = N\mathbb{E}(X)$$

Using the law of iterated expectations, we obtain

$$\mathbb{E}(Y) = \mathbb{E}(\mathbb{E}[Y | N]) = \mathbb{E}(N\mathbb{E}[X]) = \mathbb{E}(N) \mathbb{E}(X)$$

Putting together

Summary:

$$\mathbb{E}(Y) = \mathbb{E}(N) \mathbb{E}(X) \quad (25)$$

$$\text{var}(Y) = \mathbb{E}(N) \text{var}(X) + (\mathbb{E}[X])^2 \text{var}(N) \quad (26)$$

Furthermore, through the transform method, we can derive the overall distribution.

Moment generating function

To find $M_Y(s)$:

$$\begin{aligned}\mathbb{E}(e^{sY} | N = n) &= \mathbb{E}(e^{s(X_1 + \dots + X_N)} | N = n) \\ &= \mathbb{E}(e^{sX_1} \dots e^{sX_n} | N = n) \\ &= \mathbb{E}(e^{sX_1}) \dots \mathbb{E}(e^{sX_n}) \\ &= (M_X(s))^n\end{aligned}$$

where $M_X(s)$ is the transform associated with (identically distributed) X_i for each i . Later on, we will also make use of the representation

$$(M_X(s))^n = e^{\log(M_X(s))^n} = e^{n \log M_X(s)}$$

Example

You visit a number of bookstores in search of a particular textbook on probability. Any given bookstore carries the book with probability p , independent of the others. In a typical bookstore, the amount of time you spend is exponentially distributed with parameter λ , and independent of the time you spend in other bookstores. You will keep on visiting bookstores until you find the book (because the lectures are too boring, you'd rather learn from a book). What are the mean, variance, and PDF of the total time spent in search of the book? $\implies$ *A sum of a geometric number of independent exponential random variables*

N = number of bookstores $\sim \text{Geo}(p)$

Y = total time spent

Moment generating function

Now, we consider two formulas:

$$\begin{aligned}M_Y(s) &= \mathbb{E}(e^{sY}) = \mathbb{E}(\mathbb{E}[e^{sY} | N = n]) = \mathbb{E}((M_X(s))^N) \\ &= \sum_{n=0}^{\infty} (M_X(s))^n f_N(n) \\ &= \sum_{n=0}^{\infty} e^{n \log M_X(s)} f_N(n) \\ M_N(n) &= \mathbb{E}(e^{sN}) = \sum_{n=0}^{\infty} e^{ns} f_N(n)\end{aligned}$$

So we can conclude

$$M_Y(s) = M_N(\log M_X(s)) \quad (27)$$

Example

Now we make use of the results derived above, and that

$$M_X(s) = \frac{\lambda}{\lambda - s} \quad M_N(s) = \frac{pe^s}{1 - (1-p)e^s},$$

we can derive

$$\begin{aligned}\mathbb{E}(Y) &= \mathbb{E}(N) \mathbb{E}(X) = \frac{1}{p} \cdot \frac{1}{\lambda} \\ \text{var}(Y) &= \mathbb{E}(N) \text{var}(X) + (\mathbb{E}[X])^2 \text{var}(N) = \frac{1}{p} \cdot \frac{1}{\lambda^2} + \frac{1}{\lambda^2} \cdot \frac{1-p}{p^2} = \frac{1}{\lambda^2 p^2} \\ M_Y(s) &= M_N(\log M_X(s)) = \frac{p \cdot \frac{\lambda}{\lambda - s}}{1 - (1-p) \frac{\lambda}{\lambda - s}} = \frac{p\lambda}{p\lambda - s}\end{aligned}$$

which is the transform of an exponentially distributed r.v. with parameter $p\lambda$,

$$f_Y(y) = p\lambda e^{-p\lambda y} \quad y \geq 0$$

Example

How about a *sum of a geometric number of independent geometric random variables*?

$$N \sim \text{Geo}(p)$$

$$X_i \sim \text{Geo}(q)$$

$$Y = X_1 + \dots + X_N$$

We have

$$\begin{aligned} M_Y(s) &= M_N(\log M_X(s)) = \frac{p \frac{q e^s}{1 - (1-q)e^s}}{1 - (1-p) \frac{q e^s}{1 - (1-q)e^s}} \\ &= \frac{p q e^s}{1 - (1-pq)e^s} \end{aligned}$$

which is the transform of a geometrically distributed r.v. with parameter pq .

Conclusions

By now, we have covered both basic and several advanced topics dealing with discrete and continuous random variables, including cases involving multiple random variables and their interactions.