1 Part 1: probability review

Exercise 1.1

Let X be a random variable taking values between 0 and π with pdf given by $f(x) = c \sin(x), x \in [0, \pi]$. What is the value of c?

Solution: Since the integral of the pdf is always 1 (by definition),

$$1 = \int_0^{\pi} f(x) dx = \int_0^{\pi} c \sin x dx = -c \Big|_0^{\pi} \cos x = -c(\cos \pi - \cos 0) = -c(-2) = 2c.$$

And so, 2c = 1 and $c = \frac{1}{2}$. B

Exercise 1.2

What is $\mathbb{E}[X]$?

Solution: By the definition of expectation,

$$\mathbb{E}[X] = \int_0^{\pi} x f(x) \, \mathrm{d}x = \int_0^{\pi} cx \sin x \, \mathrm{d}x = c \Big|_0^{\pi} (\sin x - x \cos x) = c(-\pi \cos \pi + \sin \pi - 0 \cos 0 + \sin 0) = \pi c.$$

We know from the previous problem that $c = \frac{1}{2}$, so $\mathbb{E}[X] = \frac{\pi}{2}$. A.

Exercise 1.3

Let X be a Gaussian random variable with mean $\mu > 0$ and variance μ^2 . What is $\mathbb{E}[X]$?

Solution: The mean, that is $\mathbb{E}[X]$, is μ by definition. B

Exercise 1.4

What is $\mathbb{E}[X^2]$?

Solution: By definition of variance,

$$\mu^2 = \text{Var}[X] = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \mathbb{E}[X^2] - \mu^2,$$

so $\mathbb{E}[X^2] = 2\mu^2$. C

Exercise 1.5

What is $\mathbb{E}[X^3]$?

Solution: Using the binomial theorem,

$$\mathbb{E}[X^3] = \mathbb{E}[((X - \mu) + \mu)^3]$$

$$= \mathbb{E}[(X - \mu)^3] + 3\mathbb{E}[(X - \mu)^2\mu] + 3\mathbb{E}[(X - \mu)\mu^2] + \mathbb{E}[\mu^3]$$

$$= 3\mu\mathbb{E}[(X - \mu)^2] + \mu^3.$$

Since $X - \mu$ is a Gaussian random variable with mean 0 and variance μ^2 , $\mathbb{E}[(X - \mu)^2] = \mu^2$,

$$\mathbb{E}[X^3] = 3\mu^3 + \mu^2 4\mu^3.3$$

C

Exercise 1.6

What is $Var[X^2]$?

Solution: For a normal random variable with mean μ and standard deviation σ , $\mathbb{E}[X^4] = 3\sigma^4 + 6\mu^2\sigma^2 + \mu^4$. Since our mean and standard deviation are both μ in this case, $\mathbb{E}[X^4] = 10\mu^4$. Using this,

$$Var[X^{2}] = \mathbb{E}[X^{4}] - \mathbb{E}[X^{2}]^{2}$$
$$= 10\mu^{4} - (2\mu^{2})^{2}$$
$$= 6\mu^{4}.$$

B.

Exercise 1.7

What is $\mathbb{P}[X > 0]$ in terms of the CDF Φ of the standard Gaussian distribution?

Solution: By definition of the cdf,

$$\mathbb{P}[X>0] = \mathbb{P}\left[\frac{X-\mu}{\sigma} > -\frac{\mu}{\sigma}\right] = \mathbb{P}\left[\frac{X-\mu}{\sigma} > -1\right] = \mathbb{P}\left[\frac{X-\mu}{\sigma} < \right] = \Phi(1).$$

B.

Exercise 1.8

Let X be a random variable such that

$$X = \begin{cases} 1 & \text{with probability } p \\ -1 & \text{with probability } 1 - p \end{cases}$$

for some $p \in [0, 1]$. What is $\mathbb{E}[X]$?

Solution: Routine algebra shows that $\mathbb{E}[X] = 1 \cdot p + (-1) \cdot (1-p) = -1 + 2p$. D.

Exercise 1.9

What is Var[X]?

Solution: The variance of X is $\mathbb{E}[X^2] - \mathbb{E}[X]^2 = 1 - (1 - 2p)^2 = 4p - 4p^2 = 4p(1 - p)$.

Exercise 1.10

For what p is Var[X] maximized?

Solution: We know from the previous problem that $Var[X] = 4p - 4p^2$, which has derivative 4 - 8p. The variance is maximized when that derivative is 0, so when $4 - 8p = 0 \Longrightarrow p = \frac{1}{2}$. \boxed{C} .

Exercise 1.11

What is $\mathbb{E}[X^k]$?

Solution: The expected value is $\mathbb{E}[X^k] = 1^k \cdot p + (-1)^k \cdot (1-p) = p + (-1)^k \cdot (1-p)$.

Exercise 1.12

Let X and Y be two independent standard Gaussian random variables. What is $\mathbb{E}[X^2Y]$?

Solution: Since X and Y are independent, $\mathbb{E}[X^2Y] = \mathbb{E}[X^2] \cdot \mathbb{E}[Y] = 0$. A.

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Exercise 1.13

What is Var(X + Y)?

Solution: Since X and Y are independent, Var[X + Y] = Var[X] + Var[Y] = 1 + 1 = 2.

Exercise 1.14

What is Var[XY]?

Solution: The variance is $Var[XY] = \mathbb{E}[(XY)^2] - \mathbb{E}[XY]^2 = \mathbb{E}[X^2]\mathbb{E}[Y^2] = 1$.

Exercise 1.15

What is Cov[X, X + Y]?

Solution: The covariance is Cov[X, X + Y] = Cov[X, X] + Cov[X, Y] = 1 + 0 = 1.

Exercise 1.16

What is Cov[X, XY]?

Solution: The covariance is $Cov[X, XY] = \mathbb{E}[X^2Y] - \mathbb{E}[X]\mathbb{E}[XY] = 0$.

Exercise 1.17

Exercise 1.18

Exercise 1.19

Let $X_1, \ldots X_n$ be i.i.d. with mean μ and variance σ^2 . What is $\mathbb{E}\left[\sum_{i=1}^n X_i\right]$?

Solution: By linearity of expectation,

$$\mathbb{E}\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} \mathbb{E}[X_i] = n\mu.$$

 $oxed{C}$.

Exercise 1.20

What is $Var[\sum_{i=1}^{n} X_i]$?

Solution: Since each of the X_i s are independent,

$$\operatorname{Var}\left[\sum_{i=1}^{n} X_{i}\right] = \sum_{i=1}^{n} \operatorname{Var}[X_{i}] = n\sigma^{2}.$$

B.

Exercise 1.21

What is $\mathbb{E}[(\sum_{i=1}^{n} X_i)^2]$?

Solution: Let $Y = \sum_{i=1}^{n} X_i$. Then,

$$n\sigma^2 = \text{Var}[Y] = \mathbb{E}[Y^2] - \mathbb{E}[Y]^2 = \mathbb{E}[Y^2] - (n\mu)^2,$$

so $\mathbb{E}[Y^2] = n^2 \mu^2 + n\sigma^2$. \boxed{D} .

Exercise 1.22

What is $\operatorname{Var}\left[\frac{1}{n}\sum_{i=1}^{n}X_{i}\right]$?

Solution: Since $Var[aX] = a^2 Var[X]$,

$$\operatorname{Var}\left[\frac{1}{n}\sum_{i=1}^{n}X_{i}\right] = \frac{1}{n^{2}}\operatorname{Var}\left[\sum_{i=1}^{n}X_{i}\right] = \frac{n\sigma^{2}}{n^{2}} = \frac{\sigma^{2}}{n}.$$

B

2 New Concepts

Exercise 2.1

Let $X_n \sim \text{Unif}(-1/n, 1/n)$ and let X be a random variable such that $\mathbb{P}[X=0]=1$.

- 1. Compute and draw the CDF $F_n(x)$ and F(x) of X_n and X respectively.
- 2. Does $X_n \xrightarrow{P} X$? (prove or disprove)
- 3. Does $X_n \rightsquigarrow X$ (prove or disprove)

Solution:

1. The CDF of X is

$$F(x) = \begin{cases} 0 & x < 0 \\ 1 & x \ge 0 \end{cases}$$

and the CDF of X_n is

$$F_n(x) = \begin{cases} 0 & x < -\frac{1}{n} \\ \frac{nt+1}{2} & -\frac{1}{n} \le \frac{1}{n} \\ 1 & x > \frac{1}{n} \end{cases}.$$

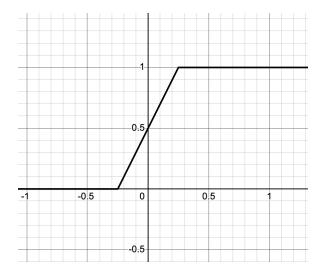


Figure 1: This is the cdf for X_n , when n = 4.

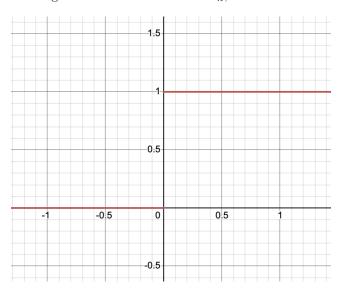


Figure 2: This is the cdf for X.

2. We know that for all ϵ ,

$$\mathbb{P}[|X_n-X|>\epsilon]=\mathbb{P}[|X_n|>\epsilon]=1-\mathbb{P}[|X_n|\leq\epsilon]=1-\min\left(\frac{2\epsilon}{\frac{2}{n}},1\right)=1-\min(n\epsilon,1).$$

Therefore,

$$\lim_{n \to \infty} \mathbb{P}[|X_n - X| > \epsilon] = \lim_{n \to \infty} 1 - \min(n\epsilon, 1) = 0,$$

so X_n does converge to X probabilistically.

3. The CDF of X is

$$F(t) = \begin{cases} 0 & x < 0 \\ 1 & x \ge 0 \end{cases}$$

and the CDF of X_n is

$$F_n(t) = \begin{cases} 0 & x < -\frac{1}{n} \\ \frac{nt+1}{2} & -\frac{1}{n} \le x \le \frac{1}{n} \\ 1 & x > \frac{1}{n} \end{cases}.$$

As n approaches ∞ , $F_n(t)$ approaches

$$F_n(t) = \begin{cases} 0 & x < 0 \\ \frac{1}{2} & x = \frac{1}{2} \\ 1 & x = 1 \end{cases}.$$

Although $F_n(t)$ and F(t) are not the same functions, they have equal values at all points for which F is continous. Thus, X_n converges to X in distribution.

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