

# Probability and Random Processes

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Q) Let  $\{X_n\}_{n \geq 1}$  be a sequence of independent and identically distributed random variables each having probability density function

$$f(x) = \begin{cases} e^{-x} & \text{if } x > 0 \\ 0 & \text{otherwise.} \end{cases}$$

For  $n \geq 1$ , let  $Y_n = |X_{2n} - X_{2n-1}|$ . If  $\bar{Y}_n = \frac{1}{n} \sum_{i=1}^n Y_i$  for  $n \geq 1$  and  $\{\sqrt{n}(e^{-\bar{Y}_n} - e^{-1})\}_{n \geq 1}$  converges in distribution to a normal random variable with mean 0 and variance  $\sigma^2$ , then  $\sigma^2$  (rounded off to two decimal places) equals (GATE ST 2023)

**Solution:**

1) Let  $X, Y \sim \exp(1)$  and  $Z = X - Y$

$$p_X(x) = e^{-x}u(x) \quad (1)$$

$$M_X(s) = E(e^{-sX}) \quad (2)$$

$$= \int_0^{\infty} e^{-sx} e^{-x} dx \quad (3)$$

$$= \frac{1}{s+1} \quad (4)$$

ROC for  $M_X(s) : \text{Re}(s) > -1$

Similarly,

$$M_Y(s) = \frac{1}{s+1} \quad (5)$$

$$M_Y(-s) = \frac{1}{-s+1} \quad (6)$$

ROC for  $M_Y(-s) : \text{Re}(s) < 1$

$$M_Z(s) = E(e^{-sZ}) \quad (7)$$

Using,

$$Z = X - Y \quad (8)$$

$$\Rightarrow M_Z(s) = E(e^{-s(X-Y)}) \quad (9)$$

$$= E(e^{-sX}) E(e^{sY}) \quad (10)$$

$$= M_X(s) M_Y(-s) \quad (11)$$

$$= \frac{1}{s+1} \times \frac{1}{-s+1} \quad (12)$$

$$M_Z(s) = \frac{1}{1-s^2} \quad (13)$$

The ROC for the laplace transform :  $|\text{Re}(s)| < 1$

$$M_Z(s) = \frac{1}{2} \left( \frac{1}{1-s} + \frac{1}{1+s} \right) \quad (14)$$

Using Inverse Laplace transform,

$$P_Z(x) = \frac{1}{2} (e^x u(-x) + e^{-x} u(x)) \quad (15)$$

$$p_Z(x) = \frac{1}{2} e^{-|x|} \quad (16)$$

$$\Rightarrow Z \sim \text{Lap}(0, 1) \quad (17)$$

2) Let  $T = |Z|$

$$p_Z(x) = \frac{1}{2} e^{-|x|} \quad (18)$$

$$F_Z(x) = \int_{-\infty}^x \frac{1}{2} e^{-|t|} dt \quad (19)$$

$$= \frac{1}{2} + \frac{1}{2} e^{-x} \quad (20)$$

$$F_T(x) = \Pr(T \leq x) \quad (21)$$

$$= \Pr(|Z| \leq x) \quad (22)$$

$$= \Pr(-x \leq Z \leq x) \quad (23)$$

$$F_T(x) = \frac{1}{2} - \frac{1}{2} e^{-x} - \left( -\frac{1}{2} + \frac{1}{2} e^{-x} \right) \quad (24)$$

$$F_T(x) = 1 - e^{-x} \text{ for } x > 0 \quad (25)$$

$$T \sim \exp(1) \quad (26)$$

$$\Rightarrow |Z| \sim \exp(1) \quad (27)$$

Using equations (8) and (27), we get:

$$|X_{2n} - X_{2n-1}| \sim \exp(1) \quad (28)$$

$$\Rightarrow Y_n \sim \exp(1) \quad (29)$$

$$M_{Y_n}(s) = \frac{1}{1+s} \quad (30)$$

$$E(Y_n) = \mu_1 \quad (31)$$

$$\mu_1 = -\frac{dM_{Y_n}(s)}{ds} \quad (32)$$

$$= -\frac{d}{ds} \left( \frac{1}{s+1} \right) \Bigg|_{s=0} \quad (33)$$

$$= \frac{1}{(s+1)^2} \Big|_{s=0} \quad (34)$$

$$E(Y_n) = 1 \quad (35)$$

$$E(Y_n^2) = \mu_2 \quad (36)$$

$$\mu_2 = \frac{d^2 Y_n(s)}{ds^2} \quad (37)$$

$$= \frac{d^2}{ds^2} \left( \frac{-1}{(s+1)^2} \right) \Big|_{s=0} \quad (38)$$

$$= \frac{2}{(s+1)^3} \Big|_{s=0} \quad (39)$$

$$E(Y_n^2) = 2 \quad (40)$$

$$\text{Var}(Y_n) = E((Y_n - E(Y_n))^2) \quad (41)$$

$$= E((Y_n - 1)^2) \quad (42)$$

$$= E(Y_n^2) - 2E(Y_n) + 1 = 1 \quad (43)$$

3) We know,

$$\bar{Y}_n = \frac{1}{n} \sum_{i=1}^n Y_i \quad (44)$$

$$E(\bar{Y}_n) = \frac{1}{n} \sum_{i=1}^n E(Y_i) \quad (45)$$

$$= \frac{1}{n} \cdot (n) = 1 \quad (46)$$

$$E(\bar{Y}_n) = 1 \quad (47)$$

$$\text{var}(\bar{Y}_n) = E \left[ \left( \frac{1}{n} \sum_{i=1}^n Y_i \right)^2 \right] - \left( E \left[ \frac{1}{n} \sum_{i=1}^n Y_i \right] \right)^2 \quad (48)$$

$$= \frac{1}{n^2} \left\{ E \left[ \left( \sum_{i=1}^n Y_i \right)^2 \right] - \left( E \left[ \sum_{i=1}^n Y_i \right] \right)^2 \right\} \quad (49)$$

But

$$E \left[ \left( \sum_{i=1}^n Y_i \right)^2 \right] = E \left[ \sum_{i=1}^n \sum_{j=1}^n Y_i Y_j \right] \quad (50)$$

$$= \sum_{i=1}^n \sum_{j=1}^n E[Y_i Y_j] \quad (51)$$

and

$$\left( E \left[ \sum_{i=1}^n Y_i \right] \right)^2 = \left( \sum_{i=1}^n E[Y_i] \right)^2 \quad (52)$$

$$= \sum_{i=1}^n \sum_{j=1}^n E[Y_i] E[Y_j] \quad (53)$$

Putting (51) and (53) in (49), and using the definition of covariance,

$$\text{var}(\bar{Y}_n) = \frac{1}{n^2} \left\{ \sum_{i=1}^n \sum_{j=1}^n (E[Y_i Y_j] - E[Y_i] E[Y_j]) \right\} \quad (54)$$

$$= \frac{1}{n^2} \left\{ \sum_{i=1}^n \sum_{j=1}^n \text{cov}(Y_i, Y_j) \right\} \quad (55)$$

As all the variables are i.i.d's and are thus uncorrelated,

$$\text{cov}(Y_i, Y_j) = \begin{cases} 0 & \text{if } i \neq j \\ \text{var}(Y_i) & \text{if } i = j \end{cases} \quad (56)$$

Putting (56) in (55),

$$\text{var}(\bar{Y}_n) = \frac{1}{n^2} \left( \sum_{i=1}^n \text{cov}(Y_i, Y_i) \right) \quad (57)$$

$$= \frac{1}{n^2} \left( \sum_{i=1}^n \text{var}(Y_i) \right) \quad (58)$$

$$= \frac{1}{n^2} \cdot n = \frac{1}{n} \quad (59)$$

$$\text{var}(\bar{Y}_n) = \frac{1}{n} \quad (60)$$

$$\Rightarrow E(\bar{Y}_n) = 1 \text{ and } \text{Var}(\bar{Y}_n) = \frac{1}{n} \quad (61)$$

By the Central Limit Theorem,  $n \rightarrow \infty \Rightarrow \sqrt{n}(\bar{Y}_n - \mu) \rightarrow \mathcal{N}(0, 1)$

$$\frac{\bar{Y}_n - 1}{\frac{1}{\sqrt{n}}} \sim \mathcal{N}(0, 1) \quad (62)$$

$$\sqrt{n}(\bar{Y}_n - 1) \sim \mathcal{N}(0, 1) \quad (63)$$

We know,

$$\sqrt{n}(Y_n - k) \sim \mathcal{N}(0, \sigma^2) \quad (64)$$

Let us write the taylor expansion of  $g(Y_n)$

around  $k$

$$g(Y_n) = g(k) + g'(k)(Y_n - k) + \frac{1}{2}g''(k)(Y_n - k)^2 + \dots \quad (65)$$

Apply the Central Limit Theorem (CLT) to the standardized variable  $Z_n$

$$Z_n = \frac{\sqrt{n}g'(k)(Y_n - k)}{\sigma \sqrt{n}} \quad (66)$$

$$n \rightarrow \infty \implies Z_n \rightarrow \mathcal{N}(0, 1) \quad (67)$$

Compare with standardised variable we get,

$$\implies \sqrt{n}(g(Y_n) - g(k)) \sim \mathcal{N}(0, \sigma^2[g'(k)]^2) \quad (68)$$

$$g(x) = e^{-x} \implies g'(x) = -e^{-x} \quad (69)$$

Using equation (68), we get:

$$\sqrt{n}(e^{-\bar{Y}_n} - e^{-1}) \sim \mathcal{N}(0, e^{-2}) \quad (70)$$

$$\implies \sigma^2 = e^{-2} = 0.14 \quad (71)$$

### Steps for Simulation:

- 1) rand() / (double)RAND MAX:  
This generates a random variable between 0 and RAND MAX and divides it by RAND MAX to obtain a uniform distribution between 0 and 1
- 2) -log(rand() / (double)RAND MAX) :  
This transforms the uniform distribution between 0 and 1 into an exponential distribution by making the values vary from 0 to  $\infty$ .
- 3) Generate '2n' samples of Random Variable  $X$  from the given probability density function.
- 4) Now generate 'n' samples of  $Y = |X_{2n} - X_{2n-1}|$ .
- 5) Now find  $\bar{Y}$  which is mean of 'n' samples of  $Y$ .
- 6) Now calculate  $\sqrt{n}(e^{-\bar{Y}_n} - e^{-1})$  as result.
- 7) Now repeat the process for 'm' simulations so that we get m results.
- 8) Calculate the mean and the variance of the 'm' results obtained earlier using basic mean and variance formula.

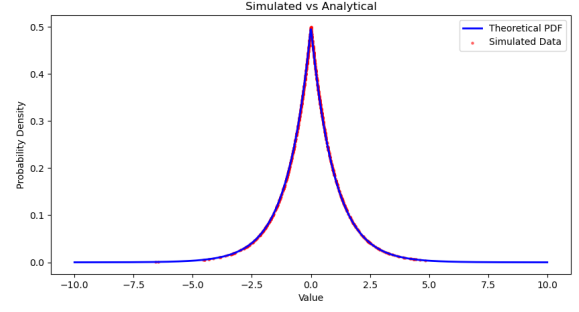


Fig. 1: pdf of the laplacian

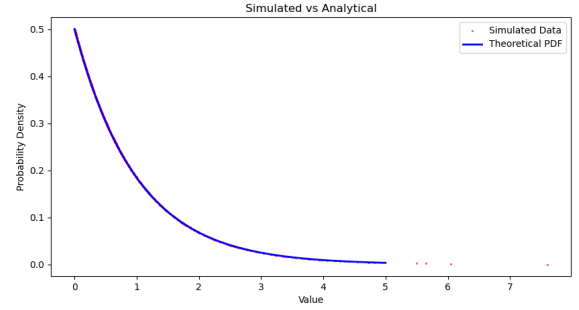


Fig. 2: pdf of absolute of the laplacian

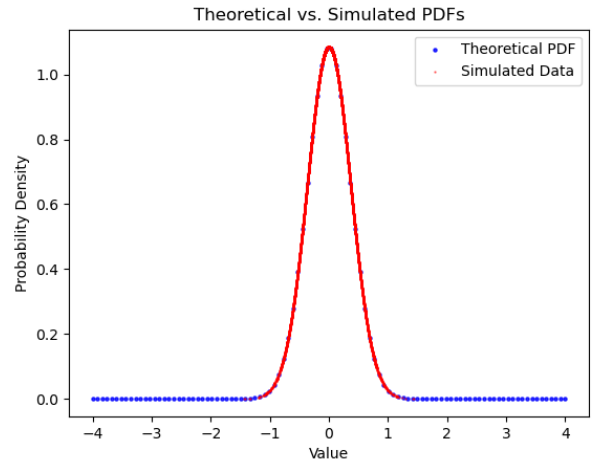
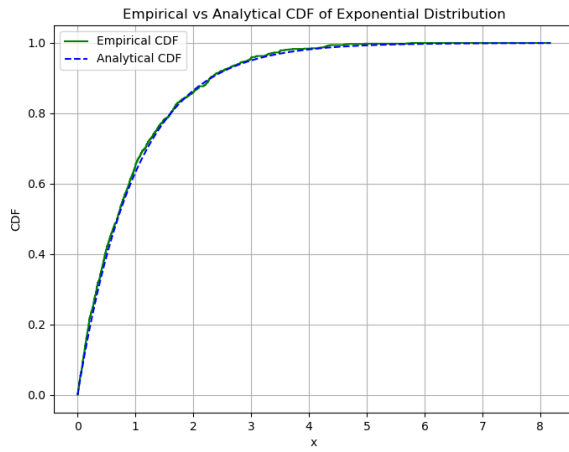
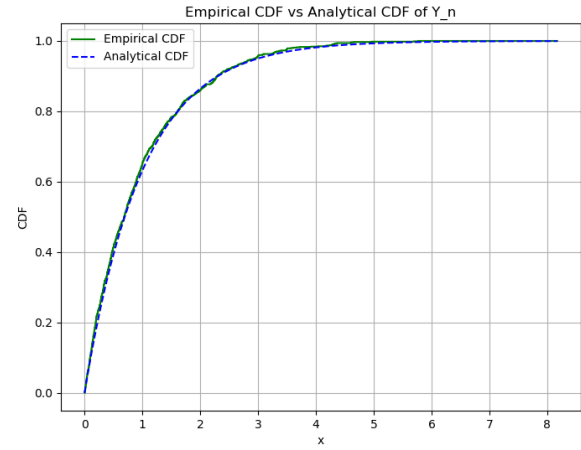
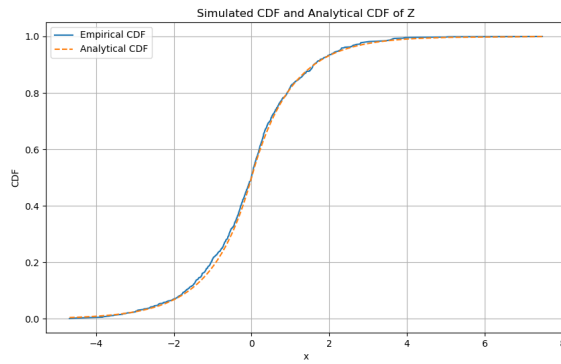
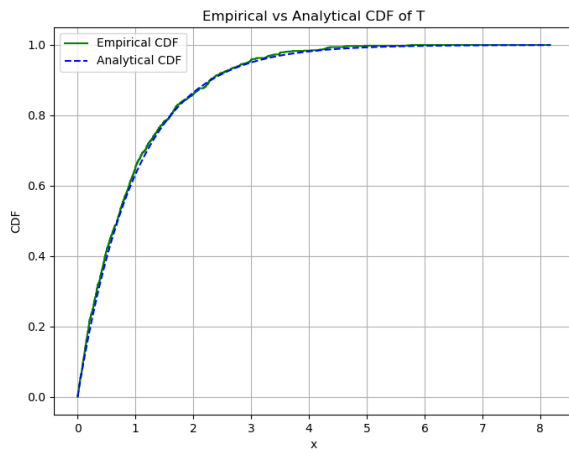
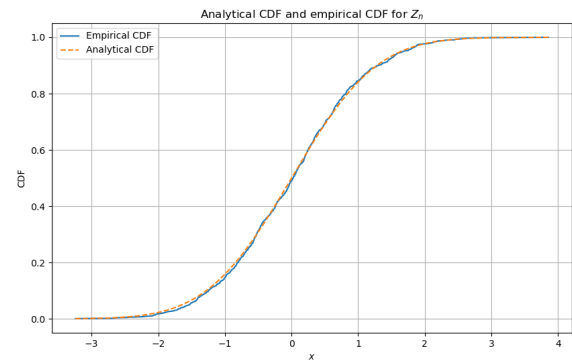


Fig. 3: Gaussian pdf

Fig. 4: Cdf of  $X$ Fig. 7: Cdf of  $Y_n$ Fig. 5: Cdf of  $Z$ Fig. 6: Cdf of  $T$ Fig. 8: Cdf of  $Z_n$