# Probability & Statistics for EECS: Homework #11

Due on Jan 1, 2024 at  $23\!:\!59$ 

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1. (a)

If  $X \sim \text{Geom}(p)$ , then  $P(X = k) = q^k p$  where q = 1 - p. which means that  $p_k = P(X = x_k) = pq^k$ 

$$\begin{split} H(X) &= \sum_{k} P(X=k) \log_{2}(\frac{1}{P(X=k)}) \\ &= \sum_{k} p_{k} \log_{2}(p_{k}^{-1}) \\ &= -\sum_{k} q^{k} p \log_{2}(q^{k} p) \\ &= -\log_{2} p \sum_{k} q^{k} p - \log_{2}(q) \sum_{k} k q^{k} p \\ &= -\log_{2} p \cdot 1 - \log_{2}(q) \cdot E(X) \\ &= -\log_{2} p - \frac{1-p}{p} \log_{2}(1-p) \end{split}$$

(b)

Let Z be an r.v. whose PMF is  $P(Z = p_k) = p_k$ .

$$E(\log_2 Z) = \sum_k p_k \log_2(p_k)$$
$$= -\sum_k p_k \log_2(\frac{1}{p_k})$$
$$= -H(X)$$

$$\begin{split} \log_2 E(Z) &= \log_2 \left( \sum_k p_k^2 \right) \\ &= \log_2 \left( \sum_k P(X=k) \cdot P(Y=k) \right) \\ &= \log_2 P(X=Y) \end{split}$$

Using Jensen's inequality,

$$E(\log_2 Z) \le \log_2 E(Z)$$

Then we get that  $-H(X) \ge \log_2 P(X = Y)$  which is

$$P(X = Y) \ge 2^{-H(X)}$$

1. (a)

$$X \sim Pois(\lambda)$$
 gives  $P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!}$ 

$$P(X = k | X \ge 1) = \frac{P(X = k)}{1 - P(X = 0)}$$
$$= \frac{\frac{e^{-\lambda} \lambda^k}{k!}}{1 - e^{-\lambda}}$$
$$= \frac{e^{-\lambda} \lambda^k}{(1 - e^{-\lambda})k!}, \quad k \ge 1$$

$$E[X|X \ge 1] = \sum_{k=1}^{\infty} k \cdot P(X = k|X \ge 1)$$

$$= \frac{e^{-\lambda}}{1 - e^{-\lambda}} \sum_{k=1}^{\infty} \frac{k\lambda^k}{k!}$$

$$= \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} \sum_{k=1}^{\infty} \frac{\lambda^{k-1}}{(k-1)!}$$

$$= \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} \cdot e^{\lambda}$$

$$= \frac{\lambda}{1 - e^{-\lambda}}$$

(b)

$$E[X^{2}|X \ge 1] = \sum_{k=1}^{\infty} k^{2} \cdot P(X = k|X \ge 1)$$

$$= \frac{e^{-\lambda}}{1 - e^{-\lambda}} \sum_{k=1}^{\infty} \frac{k^{2} \lambda^{k}}{k!}$$

$$= \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} \sum_{k=1}^{\infty} \frac{k \lambda^{k-1}}{(k-1)!}$$

$$= \frac{\lambda e^{-\lambda}}{1 - e^{-\lambda}} (e^{\lambda} + \lambda e^{\lambda})$$

$$= \frac{\lambda(\lambda + 1)}{1 - e^{-\lambda}}$$

$$\operatorname{Var}(X|X \ge 1) = E[X^2|X \ge 1] - (E[X|X \ge 1])^2$$

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

$$= \frac{\lambda(\lambda+1)(1-e^{-\lambda}) - \lambda^2}{(1-e^{-\lambda})^2}$$

$$= \frac{\lambda-\lambda e^{-\lambda} - \lambda^2 e^{-\lambda}}{(1-e^{-\lambda})^2}$$

$$= \frac{\lambda(1-e^{-\lambda}(1+\lambda))}{(1-e^{-\lambda})^2}$$

1. (a)

The memoryless property of an exponential distribution means

$$P(X_1 > s + t | X_1 > s) = P(X_1 > t)$$

Therefore, the conditional expectation  $E[X_1|X_1>2023]$  is:

$$E[X_1|X_1 > 2023] = E[X_1 - 2023 + 2023|X_1 > 2023]$$

$$= E[X_1 - 2023|X_1 > 2023] + 2023$$

$$= E[X_1] + 2023$$

$$= 2023 + \frac{1}{\lambda_1}$$

(b)

Using the memoryless property of the exponential distribution for each  $X_i$ , we have:

$$\begin{split} E[X_1 + X_2 + X_3 | X_1 > 2023, X_2 > 2024, X_3 > 2025] &= E[X_1 | X_1 > 2023] + E[X_2 | X_2 > 2024] + E[X_3 | X_3 > 2025] \\ &= (2023 + \frac{1}{\lambda_1}) + (2024 + \frac{1}{\lambda_2}) + (2025 + \frac{1}{\lambda_3}) \\ &= 6072 + \frac{1}{\lambda_1} + \frac{1}{\lambda_2} + \frac{1}{\lambda_3} \end{split}$$

1. (a)

Integrating the joint PDF over x:

$$f_Y(y) = \int_{y^2}^1 6xy \, dx = 3y[x^2]_0^1 = 3y(1-y^4)$$

For  $y \in [0, 1]$  and 0 otherwise.

Integrating the joint PDF over y:

$$f_X(x) = \int_0^{\sqrt{x}} 6xy \, dy = 3x[y^2]_0^{\sqrt{x}} = 3x^2$$

For  $x \in [0,1]$  and 0 otherwise.

And we can find that

$$f_X(x)f_Y(y) = (3y)(3x^2) = 9x^2y \neq 6xy = f_{X,Y}(x,y)$$

Thus, X and Y are not independent.

(b)

$$E[X|Y=y] = \int_{y^2}^{1} x \cdot \frac{f_{X,Y}(x,y)}{f_Y(y)} dx = \int_{0}^{1} x \cdot \frac{6xy}{3y(1-y^4)} dx = \frac{2(1-y^6)}{3(1-y^4)}$$
$$E[X^2|Y=y] = \int_{y^2}^{1} x^2 \cdot \frac{6xy}{3y(1-y^4)} dx = \frac{1+y^4}{2}$$

the variance is:

$$Var[X|Y=y] = E[X^{2}|Y=y] - (E[X|Y=y])^{2} = \frac{1+y^{4}}{2} - \left(\frac{2(1-y^{6})}{3(1-y^{4})}\right)^{2} = \frac{y^{12} - 9y^{8} + 16y^{6} - 9y^{4} + 1}{18(1-y^{4})^{2}}$$

(c)

From (b) we cn find that

$$E[X|Y] = \frac{2(1 - Y^6)}{3(1 - Y^4)}$$
 
$$Var[X|Y] = \frac{Y^{12} - 9Y^8 + 16Y^6 - 9Y^4 + 1}{18(1 - Y^4)^2}$$

#### 1. (a)

the sample mean of the Bernoulli trials:  $\hat{p} = \frac{1}{N} \sum_{i=1}^{N} X_i$ . The variance of a Bernoulli trial is p(1-p), and thus the variance of the sample mean  $\hat{p}$  is  $\frac{p(1-p)}{N}$ . We want to find the value of  $\varepsilon$  such that:

$$P(|\hat{p} - p| \ge \varepsilon) \le \delta$$

Using Chebyshev's inequality, we have:

$$\delta \geq \frac{\sigma^2}{\varepsilon^2}$$

which means that

$$\delta \geq \frac{p(1-p)}{N\varepsilon^2}$$

Solve  $\varepsilon$  to find the confidence interval  $p \pm \varepsilon$ . So we get:  $\varepsilon \ge \sqrt{\frac{p(1-p)}{N\delta}}$ 

Thus the confidence interval is

$$p \in (\hat{p} - \epsilon, \hat{p} + \epsilon)$$

where

$$\epsilon = \sqrt{\frac{\hat{p}(1-\hat{p})}{N\delta}}$$

(b)

The Hoeffding bound for the sum of N i.i.d. random variables  $X_i$  is:

$$P\left(\left|\frac{1}{N}\sum_{i=1}^{N}X_{i}-\mu\right|\geq\varepsilon\right)\leq2\exp\left(-2N\varepsilon^{2}\right)$$

Setting  $2 \exp(-2N\varepsilon^2) = \delta$  and solving for  $\varepsilon$  gives:

$$\varepsilon = \sqrt{\frac{\ln(2/\delta)}{2N}}$$

. The confidence interval is thus:

$$p \in (\hat{p} - \varepsilon, \hat{p} + \varepsilon)$$

where

$$\varepsilon = \sqrt{\frac{\ln(2/\delta)}{2N}}$$

discuss the Impact of  $\delta$  and N

For both methods, as  $\delta$  decreases, the confidence level  $1 - \delta$  increases, leading to a wider interval. As N increases, the interval narrows, indicating a more precise estimate of p.

(d)

The Chebyshev inequality does not require the underlying distribution to be known, but it often provides a looser bound than the Hoeffding bound. The Hoeffding bound gives a tighter interval but assumes that the random variables are bounded and i.i.d.

1. (a)

$$\frac{1}{p} + \frac{1}{1-p}$$

(b)

Suppose that we need X times for HH

$$E(X) = E(X|H)p + E(X|T)(1-p)$$
  
=  $E(X|H)p + (1 + E(X))(1-p)$ 

On the other hand,

$$E(X|H) = E(X|HH)p + E(X|HT)(1-p)$$
  
= 2p + (2 + E(X))(1 - p).

Thus, we can get

$$E(X) = E(X|H)p + (1 + E(X))(1 - p)$$
  
=  $(2p + (2 + E(X))(1 - p))p + (1 + E(X))(1 - p)$ 

Simplify this to get  $E(X) = \frac{1}{p} + \frac{1}{p^2}$ 

(c)