

Probability theory 1

3/12/21

Recall: Joint conditional distribution:

$$p_A(x, y) = P(X=x, Y=y | A) = \frac{P(X=x, Y=y)}{P(A)}$$

Joint conditional expectation:

$$E(X | A) = \sum_n x_n P(X=x_n | A)$$

Theorem: $E(X) = \sum_n x_n P(X=x_n) = \sum_m E(X|Y=y_m) P(Y=y_m)$

• Tossed two coins until the first coin gives a Tail. $X \sim \#$ Heads for the second coin.

We observe $P(X=i | Y=n) = P(\text{Binomial}(n, p) = i)$

$$E(X | Y=n) = E(\text{Binomial}(n, p)) = np.$$

Applying the theorem above,

$$E(X) = \sum_{n \geq 1} E(X | Y=n) P(Y=n) = \sum_{n \geq 1} np p^{n-1} (1-p) = \dots = \frac{p}{1-p} \quad \square$$

Example: Suppose that the number of people who enter a post office on a given day is a Poisson (λ) random variable. Show that if each person who enters the post office is a male or female with probability p and $1-p$ respectively, then the number of males and females entering the post office are independent Poisson(λp) and Poisson($\lambda(1-p)$) respectively.

Ans: Let $X = \#$ males entering the post office
 $Y = \#$ females entering the post office.

$$X, Y \in \{0, 1, \dots\}$$

Need to show that $X \sim \text{Poi}(\lambda p)$, $Y \sim \text{Poi}(\lambda(1-p))$ and

$$P(X=i, Y=j) = P(X=i)P(Y=j).$$

Now, fix $i, j \in \mathbb{N} \cup \{0\}$.

$$P(X=i, Y=j) = P(X=i, Y=j | X+Y=i+j) P(X+Y=i+j) + P(X=i, Y=j | X+Y \neq i+j) P(X+Y \neq i+j)$$

$$= P(X=i, Y=j | X+Y=i+j) P(X+Y=i+j) \left(\because P(X=i, Y=j, X+Y \neq i+j) = 0 \right)$$

$$= \binom{i+j}{i} p^i (1-p)^j e^{-\lambda} \frac{\lambda^{i+j}}{(i+j)!} = \frac{p^i (1-p)^j e^{-\lambda} \lambda^{i+j}}{i! j!}$$

$$\left. \begin{array}{l} P(A) \\ = P(A \cap B) \\ + P(A \cap B^c) \end{array} \right\}$$

$$= e^{-\lambda} \frac{(\lambda p)^i ((1-p)\lambda)^j}{i! j!}$$

$$\cdot P(X=i) = \sum_{j=0}^{\infty} \frac{e^{-\lambda} (\lambda p)^i ((1-p)\lambda)^j}{i! j!} = e^{-\lambda} \frac{(\lambda p)^i}{i!} \sum_{j=0}^{\infty} \frac{((1-p)\lambda)^j}{j!}$$

$$= e^{-\lambda} \frac{(\lambda p)^i}{i!} e^{(1-p)\lambda} = e^{-p\lambda} \frac{(\lambda p)^i}{i!}$$

Hence $X \sim \text{Poi}(\lambda p)$.

$$\cdot P(Y=j) = \dots = e^{-(1-p)\lambda} \frac{(\lambda(1-p))^j}{j!}$$

Hence $Y \sim \text{Poi}(\lambda(1-p))$

$$P(X=i, Y=j) = \frac{e^{-\lambda} (\lambda p)^i ((1-p)\lambda)^j}{i! j!} = e^{-p\lambda - (1-p)\lambda} \frac{(\lambda p)^i}{i!} \frac{(\lambda(1-p))^j}{j!} = P(X=i) P(Y=j) \quad \square$$

HW: Assume that the # road accidents in Kolkata follows $\text{Poisson}(\lambda)$.
Each accident is reported with probability p , independently of each other. Let
 X and Y be the # accidents that are reported and not reported respectively.
Find the joint distribution of X and Y .

Theorem: Let X and Y be random variables having expectation, and
A an event with positive probability. Then,

$$E(X+Y|A) = E(X|A) + E(Y|A)$$

Proof: $X \in \{x_1, x_2, \dots\}$, $Y \in \{y_1, y_2, \dots\}$. Thus $X+Y \in \{x_i + y_j \mid i, j \in \mathbb{N}\}$.

$$E(X+Y|A) = \sum_{i,j} z_{ij} P(X=x_i, Y=y_j|A) \left(\sum_{i,j: \underbrace{z_{ij}}_{x_i+y_j=z_{ij}}} P(Z=z_{ij}|A) \right) \quad x_i+y_j =: z_{ij}$$

$$= \sum_i \sum_j (x_i+y_j) P(X=x_i, Y=y_j|A)$$

$$= \sum_i \sum_j x_i P(X=x_i, Y=y_j|A) + \sum_i \sum_j y_j P(X=x_i, Y=y_j|A)$$

$$= \sum_i x_i \sum_j \frac{P(X=x_i, Y=y_j, A)}{P(A)} + \sum_j y_j \sum_i \frac{P(X=x_i, Y=y_j, A)}{P(A)}$$

$$= \sum_i \frac{x_i}{P(A)} P(X=x_i, A) + \sum_j \frac{y_j}{P(A)} P(Y=y_j, A)$$

$$= \sum_i x_i P(X=x_i|A) + \sum_j y_j P(Y=y_j|A) = E(X|A) + E(Y|A)$$

$$\begin{cases} x_0+y_0=2 \\ x_1+y_2=2 \end{cases}$$

Theorem: If X is a random variable with expectation and A an event with $P(A) > 0$, then

$$E(X|A) = \frac{1}{P(A)} E(X \mathbb{1}_A)$$

Proof:

$$X \mathbb{1}_A(\omega) = x_n$$

$$\text{if } (X^{(\omega)} = x_n, \mathbb{1}_A^{(\omega)} = 1 \Rightarrow X^{(\omega)} = x_n, \omega \in A \Rightarrow \{\omega | X = x_n\} \cap A)$$

$$= 0$$

$$\text{if } (X = x_n, \mathbb{1}_A = 0 \Rightarrow X(\omega) = x_n, \omega \notin A \Rightarrow \{\omega | X = x_n\} \cap A^c)$$

$X \mathbb{1}_A: \Omega \rightarrow \mathbb{R}$

$$E(X \mathbb{1}_A) = \sum_{n=1}^{\infty} x_n P(X \mathbb{1}_A = x_n) + 0 \times P(X \mathbb{1}_A = 0)$$

$$= \sum_{n=1}^{\infty} x_n P(\underbrace{\{\omega: X(\omega) = x_n, \omega \in A\}}_{P(\{\omega_1, \omega_2, \dots\})})$$

$$\left. \begin{array}{l} E(X) \\ = \sum_m y_m P(X = y_m) \end{array} \right|$$

$$= \sum_{n=1}^{\infty} x_n \mathbb{P}(X=x_n, A) = \sum_{n=1}^{\infty} x_n \mathbb{P}(X=x_n | A) \mathbb{P}(A)$$

$$= \mathbb{P}(A) \mathbb{E}(X | A) \quad \square$$

Exercise! Suppose that for random variables X and Y , there exists functions f and g from $\mathbb{R}$ to itself and $c \in \mathbb{R}$ such that

$$\mathbb{P}(X=x, Y=y) = c f(x) g(y) \quad \text{for every } x, y \in \mathbb{R}.$$

Then X and Y are independent.

Ans: Hint: Show that $\mathbb{P}(X=x, Y=y) = \mathbb{P}(X=x) \mathbb{P}(Y=y)$ using

$$1 = \sum_x \sum_y P(X=x, Y=y) = c \sum_x \sum_y f(x)g(y) \Rightarrow c = \frac{1}{\sum_x \sum_y f(x)g(y)} \quad \square$$

Exercise: (HW): IF X is a random variable and $\alpha < \beta$, such that

$P(\alpha \leq X \leq \beta) > 0$, then

$$\alpha \leq E(X | \alpha \leq X \leq \beta) \leq \beta.$$

Theorem: Suppose X and Y are random variables, taking values $x_1, x_2, \dots$ and $y_1, y_2, \dots$ respectively with positive probability. Then $\forall i, j$

$$P(X=x_i | Y=y_j) = \frac{P(Y=y_j | X=x_i) P(X=x_i)}{\sum_{k \geq 1} P(Y=y_j | X=x_k) P(X=x_k)}$$

$\square$ Pf: HW

Exercise! Suppose X follows $\text{Geometric}(p)$. For a fixed $k \in \mathbb{N} \cup \{0\}$, find the conditional distribution of $X-k$ given $X > k$. (HW).

Several random variables!

For random variables $X_1, X_2, \dots, X_n$ defined on the same sample space, their joint probability mass function is a function

$p: \mathbb{R}^n \rightarrow [0, 1]$, defined by

$$p(x_1, x_2, \dots, x_n) = P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n),$$

$$(x_1, x_2, \dots, x_n) \in \mathbb{R}^n.$$

$$\begin{aligned} & \overline{P(A \cap B | D)} \\ &= P(A | B \cap D) \\ & \quad \underbrace{\quad \quad \quad}_{X \dots X} \end{aligned}$$

$$\mathbb{R}^n = \{(x_1, \dots, x_n) : x_i \in \mathbb{R}, i=1, 2, \dots, n\}$$

The marginal PMF of X_i is

$$P(X_i = x) = \sum_{\substack{(x_1, \dots, x_{i-1}, \\ x_{i+1}, \dots, x_n) \in \mathbb{R}^{n-1}}} p(x_1, \dots, x_{i-1}, x, x_{i+1}, \dots, x_n)$$

If $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is such that $f(x_1, \dots, x_n)$ has an expectation then

$$E(f(x_1, \dots, x_n)) = \sum_{\substack{(x_1, \dots, x_n) \\ = x \in \mathbb{R}^n \mid p(x) > 0}} f(x) p(x)$$

Definition: For $n \geq 2$, $X_1, \dots, X_n$ are independent if

$$P(X_1 = x_1, \dots, X_n = x_n) = P(X_1 = x_1) \cdots P(X_n = x_n)$$

Random variable $X_1, \dots, X_n$ are pairwise independent if $\forall 1 \leq i < j \leq n$,

X_i and X_j are independent.

• Definition: $(\underline{X=Y \text{ a.s.}} \quad \mathbb{P}(X=Y)=1 \Rightarrow \mathbb{P}(\omega: X(\omega)=Y(\omega))=1)$

• Definition: Two random variables X and Y taking the same values ^{$\{x_1, x_2, \dots\}$} are equal in distribution if $\mathbb{P}(X=x_n) = \mathbb{P}(Y=x_n) \quad \forall x_n \in \mathbb{R}$. (write $X \stackrel{d}{=} Y$)

Definition: $\{X_n\}_{n \geq 1}$ is called i.i.d. sequence of random variables if

$X_m \stackrel{d}{=} X_n \quad \forall m, n \in \mathbb{N}$ and $X_1, X_2, \dots, X_m$ are independent for any $m \geq 2$.

Theorem! Suppose $\{X_n\}_{n \geq 1}$ is an i.i.d sequence of random variables^v such that defined on Ω

$E(e^{X_1 + \dots + X_n})$, $E(e^{X_1})$ exists. Then

$$E(e^{X_1 + \dots + X_n}) = (E(e^{X_1}))^n$$

Pf: $E(e^{X_1 + X_2}) = E(e^{X_1} e^{X_2}) = E(e^{X_1}) E(e^{X_2})$ $\left(\because X_1 \text{ \& } X_2 \text{ are independent} \right)$

————— $\textcircled{\star}$

$$E(e^{X_1}) = \sum_n e^{x_n} P(X_1 = x_n) = \sum_n e^{x_n} P(X_2 = x_n) \quad \left(\because X_1 \stackrel{d}{=} X_2 \right)$$
$$= E(e^{X_2}) \quad \text{————— } \textcircled{\star}$$

Combining $\textcircled{\star}$ & $\textcircled{\star}$ we get $E(e^{X_1 + X_2}) = (E(e^{X_1}))^2$.

Q: $E(e^{X_1+X_2+X_3}) = E(e^{X_1+X_2} e^{X_3}) = E(e^{X_1+X_2}) E(e^{X_3})$