

Lecture 8

* Gamma Distribution

Gamma Function

$$\Gamma(x) = \int_0^\infty y^{x-1} e^{-y} dy \quad x > 0$$

- Properties
- ① $\Gamma(n) = (n-1)!$ $n \in \mathbb{Z}$
 - ② $\Gamma(x+1) = x \Gamma(x)$

Def: A r.v. X is called a Gamma(α, β) r.v. if it has density

$$f(x) = \frac{1}{\Gamma(\alpha) \beta^\alpha} x^{\alpha-1} e^{-x/\beta} \quad x > 0$$

Here $\alpha > 0$ and $\beta > 0$.

HW: ① Verify that $\int_0^\infty f(x) dx = 1$

② Calculate EX & VX

Proposition: If X_1, \dots, X_n are iid. with exponential(λ) distribution, then $X_1 + X_2 + \dots + X_n \sim \text{Gamma}(n, \lambda)$

Proof: Let $Y_n = X_1 + \dots + X_n$

$$\text{Then } M_{Y_n}(x) = \prod_{i=1}^n M_{X_i}(x)$$

$$\text{Note: } M_X(x) = \frac{1}{(1-\lambda x)^{\alpha}}$$

Now for a $X \sim \text{Gamma}(\alpha, \beta)$

$$\begin{aligned} M_X(x) &= \int_0^\infty \frac{1}{\Gamma(\alpha) \beta^\alpha} y^{\alpha-1} e^{-y/\beta} e^{xy} dy \\ &= \frac{1}{\Gamma(\alpha) \beta^\alpha} \int_0^\infty y^{\alpha-1} e^{-(\frac{1}{\beta} - x)y} dy \end{aligned} \quad \text{⊗}$$

do a change of variables. let $z = (\frac{1}{\beta} - x)y$

$$\text{Then } y = \frac{z}{\frac{1}{\beta} - x} = r z \text{ where } r = \frac{1}{\frac{1}{\beta} - x}$$

$$\text{⊗} = \int_0^\infty (rz)^{\alpha-1} e^{-z} dr (rz)$$

$$= r^\alpha \int_0^\infty z^{\alpha-1} e^{-z} dz$$

$$= r^\alpha \Gamma(\alpha) \quad \text{by defn}$$

$$\text{Then } \frac{1}{\Gamma(\alpha) \beta^\alpha} \cdot r^\alpha \Gamma(\alpha) = \left(\frac{r}{\beta}\right)^\alpha = \left(\frac{1}{1-\beta x}\right)^\alpha$$

Recall that the mgf of $X_1 + \dots + X_n$

$$\left(\frac{1}{1-\lambda x}\right)^n \Rightarrow X_1 + \dots + X_n \sim \text{Gamma}(n, \lambda)$$



Normal distribution / Gaussian distribution

Def: X is called a $N(\mu, \sigma^2)$ r.v. if

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}\right\} \quad -\infty < x < \infty$$

Properties

$$\textcircled{1} \quad E[X] = \mu$$

$$\textcircled{2} \quad V[X] = \sigma^2 \quad \rightarrow \text{standard normal}$$

$$\textcircled{3} \quad \text{If } X \sim N(\mu, \sigma^2) \text{ Then } \frac{X-\mu}{\sigma} \sim N(0, 1) \quad \downarrow \text{standard distribution}$$

$$\textcircled{4} \quad \text{MGF of } N(0, 1) \\ M_{N(0, 1)}(x) = e^{\frac{1}{2}x^2}$$

Properties of MGF

$$\textcircled{1} \quad M_{x+a}(t) = E[e^{t(x+a)}] = e^{ta} M_x(t)$$

$$\textcircled{2} \quad M_{bx}(t) = E[e^{t(bx)}] = E[e^{(tb)x}] = M_x(tb)$$

From $\textcircled{1}$ & $\textcircled{2}$, If $X \sim N(\mu, \sigma^2)$

Then $M_x(t) = M_{\mu+\sigma z}(t)$, where $Z \sim N(0, 1)$

$$M_x(t) = e^{t\mu} M_{\sigma Z}(t) = e^{t\mu} M_z(\sigma t) = e^{t\mu} e^{\frac{1}{2}\sigma^2 t^2 + \mu t}$$

CHAPTER 5 Conditioning

Sps X is a r.v. & A is an event

$$\text{Define } E[X|A] = \frac{E[XI(A)]}{P(A)} = \frac{E[XI(A)]}{P(A)}$$

Suppose $X \sim \text{Unif}[0, 1]$

Calculate $E[X|X > \frac{1}{4}]$

$$= \frac{E[XI(X > \frac{1}{4})]}{P(X > \frac{1}{4})}$$

$$= \frac{\int_{\frac{1}{4}}^1 1 \cdot x dx}{\frac{3}{4}} = \frac{\frac{1}{2}x^2 \Big|_{\frac{1}{4}}^1}{\frac{3}{4}} = \frac{5}{8}$$

Thm: ① If $P(A) > 0$. Then $E(C \cdot | A)$ follows the 5 axioms of probabilities

①a. If $X \geq 0$. $E[X|A] \geq 0$

①b. if c is a constant . then $E[cX|A] = cE[X|A]$

①c.

①d.

①e.

HW: PROOF

② If $\{A_k\}_{k=1}^K$ is a decomposition of Ω then

$$E(X) = \sum_{k=1}^K P(A_k)E[X|A_k] \quad \text{⊗}$$

$$\begin{aligned} \text{Proof: RHS of } \text{⊗} &= \sum_{k=1}^K P(A_k) \frac{E[X|A_k]}{P(A_k)} = \sum_{k=1}^K E[X|A_k] = E[X \sum I(A_k)] \\ &= E[X] \end{aligned}$$

Def: Conditional Prob. of events

If A, B are events & $P(A) > 0$. Then $P(B|A) \stackrel{\text{Def}}{=} E(I(B)|A)$

Corollary:

$$P(B|A) = \frac{P(AB)}{P(A)}$$

$$\text{Proof: } P(B|A) = E(I(B)|A) = \frac{E(I(B) \cdot I(A))}{P(A)} = \frac{E[I(AB)]}{P(A)} = \frac{P(AB)}{P(A)}$$

$$\text{We see that if } A, B \text{ are independent. } P(B|A) = \frac{P(A)P(B)}{P(A)} = P(B)$$

Proposition: If $\{A_k\}$ is a decomposition of Ω . Then $P(B) = \sum P(A_k)P(B|A_k)$ LAW OF TOTAL PROBABILITY

Baye's Formula statistical model

$$P(A_j|B) = \frac{P(B|A_j)P(A_j)}{\sum_{k=1}^K P(B|A_k)P(A_k)}$$

prior
parameter data

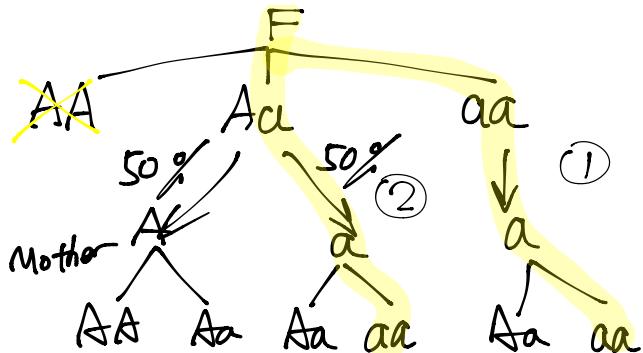
Ex: In genetics , hair color is decided by a pair of genes A & a . A person will have blond hair iff he/she has aa genes.

Sps in the population A appears 80%

$a \dots 20\%$

and we know that a child has blond hair. What's the prob that his/her father has blond hair.

Prob. of interest = $P(X|Y=aa)$
 $X = \text{father's geno type}$, $Y = \text{child's gene type}$.



$$P[\text{path } ①] = 20\% \times 20\% \times 100\% \times 20\%$$

$$P[\text{path } ②] = 80\% \times 20\% \times 2 \times 50\% \times 20\%$$

Remember father blond \Leftrightarrow Genes follow by Bayes rule desired prob
 $\frac{P(\text{path } ①)}{P(\text{path } ①) + P(\text{path } ②)} = 20\%$

Conditional distribution as a r.v.

Ex: Sp's one's blood pressure (X) is related to age Y . Then we know that for each given y we can calculate $E[X|Y=y]$

Note: When y changes, $E[X|Y=y]$ also changes

Therefore, guesses of one's blood pressure is changing with this person's age, in other words, it's a function of age.

Now Sp's: $E[X|Y=y] = f(y)$

Then we define $E[X|Y] = f(Y)$ which says that the conditional Exp. of X given Y is a function of Y . in particular it is a random variable.

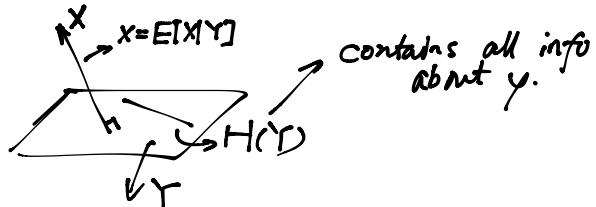
Once Y is discrete. $E[X|Y=y] = \frac{E[X|Y=y]}{P[Y=y]} \stackrel{\text{Def}}{=} f(y) \quad \otimes$

$E[X|Y] \stackrel{\text{def}}{=} f(Y)$

DEF: X, Y are two r.v. $E[X|Y]$ is defined as a function of Y s.t.

$E[(X-E[X|Y])H(Y)] = 0$ for any function H .

projection of X onto Y plane is $E[X|Y]$



*Consistency in the discrete case. Let $f(Y)$ be defined in \oplus and Sps Y is discrete. Then I only need to show that $f(Y)$ satisfies \checkmark .

Need to show $E[(X-f(Y))H(Y)] = 0$. for any H

Now let us consider each case $Y=y$. for instance y can take y_1, \dots, y_K

$$\begin{aligned} (***) &= \sum_{i=1}^K \left\{ E[X|Y=y_i] - f(y_i) \right\} H(y_i) \cdot P(Y=y_i) \\ &= \sum_{i=1}^K \underbrace{\left[\frac{E[X|Y=y_i]}{P(Y=y_i)} - f(y_i) \right]}_{=0 \text{ by def}} \times H(y_i) \times P(Y=y_i) \end{aligned}$$

So $(***) = 0$