

1.

(a).

①. Let  $X$  be a set. Let  $\Sigma$  be a  $\sigma$ -algebra over  $X$ .

②. Non-negativity:  $\mu(E) \geq 0, \forall E \in \Sigma$

③. Null empty set:  $\mu(\emptyset) = 0$ .

④. Countable additivity:  $\forall$  countable collections  $\{E_k\}_{k=1}^{\infty}$  of pairwise disjoint sets in  $\Sigma$ :  $\mu(\bigcup_{k=1}^{\infty} E_k) = \sum_{k=1}^{\infty} \mu(E_k)$ .

(b).

$\forall x, y, z \in X$ .  $d(a, b)$  means the distance between  $a, b$ .

①.  $d(x, y) \geq 0$ , "=" holds if and only if  $x = y$ .

②.  $d(x, y) = d(y, x)$ .

③.  $d(x, y) \leq d(x, z) + d(y, z)$

④.  $|d(x, y) - d(x, z)| \leq d(y, z)$ .

2.  $F(x)$  is CDF.  $F(x) = \int_0^x f(u) du = -e^{-u} \Big|_0^x = 1 - e^{-x}, x \geq 0$

(1).  $F_Z(z) = P(Z \leq z) = P(\max(X, Y) \leq z) = P(X \leq z)P(Y \leq z)$   
 $= F_X(z) \cdot F_Y(z)$

$\therefore f_Z(z) = \frac{dF_Z(z)}{dz} = f_X(z)F_Y(z) + F_X(z)f_Y(z) = \begin{cases} 2e^{-z}(1-e^{-z}), & z \geq 0 \\ 0, & \text{o.w.} \end{cases}$

(2).  $F_W(w) = P(W \leq w) = P(\min(X, Y) \leq w) = P(1 - P(\min(X, Y) > w))$

$\therefore f_W(w) = -\frac{d}{dw} (P(X > w)P(Y > w)) = f_X(w)(1 - F_Y(w))$   
 $+ (1 - F_X(w))f_Y(w)$   
 $= \begin{cases} e^{-w}, & w \geq 0 \\ 0, & \text{o.w.} \end{cases}$



3

(1). If  $X$  is Gamma Distribution, then CDF is:

$$F(x) = \int_0^x \frac{u^{\alpha-1} e^{-\frac{u}{\theta}}}{\theta^\alpha \Gamma(\alpha)} du, \text{ now } \alpha=1, \theta=1.$$

$$\therefore F(x) = \int_0^x e^{-u} du = -e^{-u} \Big|_0^x = 1 - e^{-x}$$

$$P(2X \leq x) = P(X \leq \frac{x}{2}) = F(\frac{x}{2}) = 1 - e^{-\frac{x}{2}}$$

$\therefore 2X$ 's distribution is  $\Gamma(\alpha=1, \theta=2)$  \*

(2).

$$\textcircled{1} f(x) = \begin{cases} \frac{1}{\Gamma(1)2^1} x^0 e^{-\frac{x}{2}} = \frac{1}{2} e^{-\frac{x}{2}}, & \text{if } x > 0 \\ 0, & \text{o.w.} \end{cases}$$

$\textcircled{2}$  PDF of  $X$  is  $f(x) = \frac{1}{2} e^{-\frac{x}{2}}$  for  $x > 0$ .

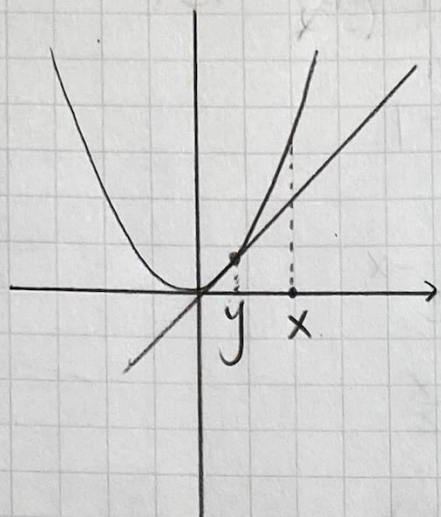
$\Rightarrow X$  follows a  $\chi^2$  distribution with 2 degrees of freedom, denoted  $\chi^2(2)$ .

$$\therefore f(x) = \begin{cases} \frac{x^0 e^{-\frac{x}{2}}}{2^1 \Gamma(1)} = \frac{1}{2} e^{-\frac{x}{2}}, & x > 0. \\ 0, & \text{o.w.} \end{cases}$$



4.

(1).



Let  $F: \Omega \rightarrow \mathbb{R}$ , which is a differentiable, strictly convex function on a closed convex set  $\Omega$ . ( $\Omega \subseteq \mathbb{R}^d$ ), and  $x, y$  are two points in  $\Omega$

Take  $F(x) = \|x\|^2$   $D_F(x, y) = F(y) - F(x) - \langle \nabla F(x), y - x \rangle$   
 $= \|y\|^2 + \|x\|^2 - 2xy = \|y - x\|^2$

$\therefore$  Squared Euclidean distance is Bregman divergence. #

(2). Entropy denotes as  $H$ .

$$H(x, y) = H(x|y) + H(y) = H(x) + H(F(x)|x) \xrightarrow{0} \because \text{Knowing } x, \text{ automatically knowing } f(x).$$

$$= H(F(x)) + H(x|F(x))$$

$\therefore H(x) = H(F(x)) + H(x|F(x)) \Rightarrow H(F(x)) \leq H(x)$ . #



5.

$$(1). f(x) = \frac{1}{\theta} \quad M_1 = \frac{1}{n} \sum_{i=1}^n X_i = \mu = E(X) = \frac{\theta}{2} \Rightarrow \hat{\theta} = 2\bar{X}$$

$$M_2 = \mu^2 + \sigma^2 = \frac{\theta^2}{3} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$$

$$\Rightarrow \hat{\theta} = \sqrt{\frac{3}{n} \sum_{i=1}^n (X_i - \bar{X})^2} \quad \#$$

$$(2). \ell(\theta) = \prod_{i=1}^n f(x_i | \theta), \quad \hat{\theta} = \arg \max_{\theta \in \Omega} \ell(\theta). \quad \text{又 } f(x|\theta) = \frac{1}{\theta}$$

$$\Rightarrow \ln(\ell(\theta)) = \ln\left(\prod_{i=1}^n \frac{1}{\theta}\right) = -n \ln \theta.$$

$$\frac{d}{d\theta} \ln(\ell(\theta)) = -\frac{n}{\theta}, \quad \forall x > 0.$$

Thus, max. of  $\ell(\theta)$  is at  $\theta = X_n \Rightarrow \hat{\theta} = X_n \quad \#$

$$(3). \text{MAP estimator is: } \arg \max_{\theta} f(x|\theta) f(\theta) = \arg \max_{\theta} \frac{1}{\theta}$$

$$\Rightarrow \hat{\theta}_{\text{MAP}} = \arg \max_{\theta} f(x|\theta) = \hat{\theta}_{\text{MLE}} = X_n \quad \#$$

$$(4). \ell^2(\hat{\theta}, \theta) = (\hat{\theta} - \theta)^2 \int f(x|\theta) = \frac{1}{\theta}, \text{ when } 0 < x < \theta.$$

$$\begin{cases} h(\theta) = 1, \text{ when } 0 < \theta < 1 \end{cases}$$

$$\Rightarrow u(x, \theta) = h(\theta) f(x|\theta) = \frac{1}{\theta}, \quad 0 < x < \theta < 1.$$

$$g(x) = \int_x^1 u(x, \theta) d\theta = \int_x^1 \frac{1}{\theta} d\theta = -\ln x, \quad 0 < x < 1$$

$$k(\theta|x) = \frac{u(x, \theta)}{g(x)} = \frac{1}{-\theta \ln x}, \quad 0 < x < \theta < 1.$$

$$\therefore \hat{\theta} = E(\theta|x) = \int_x^1 \theta k(\theta|x) d\theta = -\frac{1}{\ln x} \int_x^1 d\theta = \frac{x-1}{\ln x} \quad \#$$