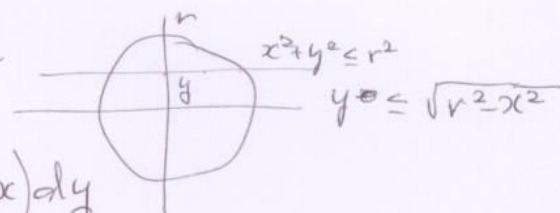


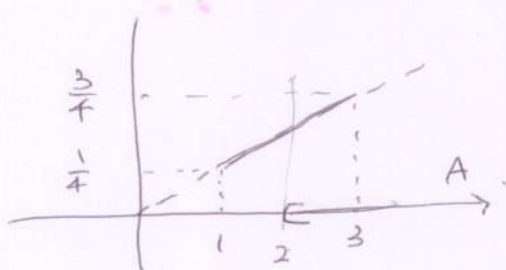
1) a) $f_{X,Y}(x,y) = \frac{1}{\pi r^2}, \quad x^2 + y^2 \leq r^2$

b) $\int_{-r}^r \frac{1}{\pi r^2} dx = \int_{-\sqrt{r^2-y^2}}^{\sqrt{r^2-y^2}} \frac{1}{\pi r^2} dx$



c) $E[Y] = \int_{-r}^r y \cdot \left(\int_{-\sqrt{r^2-y^2}}^{\sqrt{r^2-y^2}} \frac{1}{\pi r^2} dx \right) dy$

c) $E[Y] = \int_{-r}^r \int_{-\sqrt{r^2-y^2}}^{\sqrt{r^2-y^2}} y \cdot \frac{1}{\pi r^2} dx dy$



a) $E[X] = \int_1^3 \frac{x}{4} x dx, \quad P(A) = \int_2^3 \frac{x}{4} dx = \frac{5}{8}$

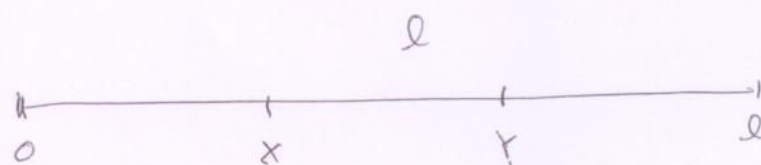
$f_{X|A}(x) = \frac{f_{X,Y}(x)}{P(A)} = \frac{\frac{24}{5}x}{\frac{5}{8}} = \frac{24}{20}x, \quad 2 \leq x \leq 3$

$E[X|A] = \int_2^3 x \cdot \frac{24}{20} x dx$

b) $E[Y] = E[X^2] = \int x^2 \frac{x}{4} dx$

3

a)



$Y \sim U[0, l], \quad f_Y(y) = \frac{1}{l}$

$X \sim U[0, Y], \quad f_{X|Y}(x|y) = \frac{1}{y}$

$f_{X,Y} = f_{X|Y} \cdot f_Y = \frac{1}{ly}$

b) $f_X = \int_0^l f_{X,Y} dy$

c)

d) Note Y and $\frac{X}{Y}$ are independent

$E[X] = E[Y] \cdot E\left[\frac{X}{Y}\right] \quad E[Y] = \frac{l}{2}, \quad E\left[\frac{X}{Y}\right] = \frac{1}{2}$

[4] Refer to the class note.

[5] Definition of conditional density function

$$f_{X|Y} = \frac{f_{X,Y}}{f_Y}$$

Substitute $Y \leftarrow Y, Z$.

$$\Rightarrow f_{X|Y,Z} = \frac{f_{X,Y,Z}}{f_{Y,Z}}$$

[6] a) ~~$Pr(H) = \int_0^1 p \cdot p e^p dp =$~~

b) ~~Instead of p use θ .~~

a) Instead of p use θ .

$$Pr(H) = \int_0^1 \theta \cdot \theta e^\theta d\theta = \int_0^1 \theta^2 e^\theta d\theta.$$

b) $f_{\theta|H}(\theta|H) = \frac{\theta \cdot \theta e^\theta}{Pr(H)} = \frac{\theta^2 e^\theta}{Pr(H)}$

c) $Pr(H_2|H_1) = \frac{Pr(H_2 \cap H_1)}{Pr(H_1)}$

$$Pr(H_1) = Pr(H)$$

$$Pr(H_2 \cap H_1) = \int_0^1 \theta^2 \theta e^\theta d\theta = \int_0^1 \theta^3 e^\theta d\theta.$$

[7]

a) ~~Hint~~

Tips: Think CDF when you deal with continuous R.V.

$$\begin{aligned} Pr(Z \leq z | X=x) &= Pr(X+Y \leq z | X=x) \\ &= Pr(Y \leq z-x | X=x) \\ &= Pr F_{Y|X}(z-x | x) \end{aligned}$$

$$= F_Y(z-x) \quad \swarrow X, Y \text{ are independent}$$

b) $X, Y \sim \text{Exp}(\lambda)$
 $Z = X+Y \sim \text{Exp}(2\lambda)$

$$f_{X|Z} = \frac{f_{X,Z}}{f_Z} = \frac{f_{Z|X} \cdot f_X}{f_Z}$$

c) Same approach.

8

a) ~~Discrete~~ R.V. $\oplus = \begin{cases} 1 \\ 2 \end{cases}$ Soo knows the answer
Soo does not "

R.V. $P_i = \begin{cases} 1 \\ 2 \end{cases}$, Soo answers correctly
" ~~incorrectly~~

$$Pr(\oplus=1 | P_i=1) = \frac{Pr(P_i=1 | \oplus=1) \cdot Pr(\oplus=1)}{Pr(P_i=1)} \quad \left\{ \begin{array}{l} Pr(P_i=1 | \oplus=1) = 1 \\ Pr(P_i=1 | \oplus=2) = 1/3 \end{array} \right.$$

b) Let \oplus : # of questions that Soo knows
X : # correct answers

$$Pr(\oplus=k | X=6) = \frac{Pr(X=6 | \oplus=k) \cdot Pr(\oplus=k)}{Pr(X=6)} \quad \text{enumerate } k(0 \leq k \leq 6)$$

$$Pr(X=6 | \oplus=k) = \binom{10-k}{6-k} \left(\frac{1}{3}\right)^{6-k} \left(\frac{2}{3}\right)^4$$

↑ If she knows k questions, then there are 10-k questions that she does not know. She successfully guess 6-k questions.

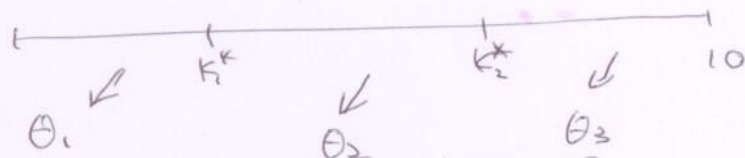
9

a) There will be thresholds k_1^*, k_2^* such that $0 \leq k_1^* \leq k_2^* \leq 10$, and

(Note: Long calculations)

$$Pr(\oplus=\theta_i | k) = \frac{Pr(k | \oplus=\theta_i) \cdot Pr(\oplus=\theta_i)}{Pr(k)}$$

There are j questions among 10 questions that student type θ_i knows



Compare posterior prob. to determine k_2^*

$Pr(\oplus=\theta_1 | k), Pr(\oplus=\theta_2 | k)$ to determine k_1^*

compare post. prob.

$Pr(\oplus=\theta_2 | k) \leq Pr(\oplus=\theta_3 | k)$ to determine k_2^*

$$Pr(k | \oplus=\theta_1) = \sum_{j=0}^k Pr(k, \oplus=j | \oplus=\theta_1) = \binom{10}{0} (0.3)^0 (0.7)^{10} + \binom{10}{1} (0.3)^1 (0.7)^9 + \dots + \binom{10}{k} (0.3)^k (0.7)^{10-k}$$

b) Caution: Very long calculation

$$\Pr(M=m | X=5) = \sum_{i=1}^3 \Pr(M=m | X=5, \oplus=i) \cdot \Pr(\oplus=i)$$

$$\Pr(M=m | X=5, \oplus=1) = \sum_{k=0}^m \binom{10}{k} (0.3)^k (0.7)^{10-k} \cdot \binom{10-k}{5-k} \left(\frac{1}{3}\right)^{5-k} \left(\frac{2}{3}\right)^{10-k}$$

↑
Type 1, k out of 10 questions
are known

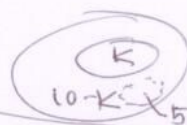
↑
($5-k$) questions are
correctly guessed.

Similarly, compute

$$\Pr(M=m | X=5, \oplus=2) \text{ and } \oplus=3$$

⇒ Compute cases of $m=0, 1, \dots, 5$
and MAP selects one with largest posterior.

$$\text{LMS computes } E[M | X] = \sum_{m=0}^5 m \cdot \Pr(M=m | X=5)$$



CO

a) $\Pr(\oplus=1)=0.3$ & $\Pr(\oplus=2)=0.7$

$$X = 20$$

$$\Pr(\oplus=1 | X=20) = \frac{f_{X|\oplus=1}(20 | \oplus=1) \cdot \Pr(\oplus=1)}{f_X(X=20)}$$

=

$$\frac{f_{X|\oplus=1}(20 | \oplus=1) \cdot \Pr(\oplus=1) + f_{X|\oplus=2}(20 | \oplus=2) \cdot \Pr(\oplus=2)}{0.3 \cdot c_1 e^{-0.04(20)} + 0.7 \cdot c_2 e^{-0.16(20)}}$$

$$= \frac{0.3 \cdot c_1 e^{-0.04(20)}}{0.3 \cdot c_1 e^{-0.04(20)} + 0.7 \cdot c_2 e^{-0.16(20)}}$$

Need to compute c_1 & c_2 also.

$$\Pr(\oplus=2 | X=20) = \dots$$

⇒ MAP selects one with larger posterior.

b) $X = (20, 10, 25, 15, 35)$ $X = (X_1, X_2, \dots, X_5)$

↑
Vector · $f_{X|\oplus} = f_{X_1|\oplus} \cdot f_{X_2|\oplus} \cdots f_{X_5|\oplus}$ (independent)

$$f_{X|\oplus=1} = c_1 e^{-0.04(20)} \cdot c_1 e^{-0.04(10)} \cdots c_1 e^{-0.04(35)}$$

$$= c_1^5 \cdot e^{-0.04(20+10+25+15+35)}$$

b) Cont.

Compute $\Pr(\oplus=1 | X=(20, 10, 25, 15, 35))$ &
 $\Pr(\oplus=2 | X = \dots)$

and pick one with larger posterior

Error computation

Suppose MAP selects $\oplus=1$ (OR $\oplus=2$)

\Rightarrow then compute $\Pr(\oplus=2 | X=(20, 10, \dots, 35))$ OR

$\Pr(\oplus=1 | X=(20, \dots, 35))$

(11)

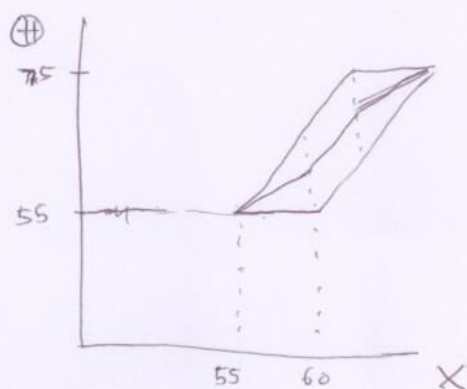
~~Easy~~ Easy & Committed.

(12)

~~Real~~

Real car speed: $\oplus \sim U[55, 75]$

$X = \oplus + W$ where $W \sim U[0, 5]$



~~Similar~~
 Same as the one explained in the class.

(13)

\oplus : $\Pr(\oplus=i) = \frac{1}{100}$, $1 \leq i \leq 100$,

~~X : $\Pr(X=j) =$~~

X : $\Pr(X=j | \oplus=i) = \frac{1}{n}$, $1 \leq j \leq i$.

$\Pr(\oplus=i | X=j) = \frac{\Pr(X=j | \oplus=i) \cdot \Pr(\oplus=i)}{\Pr(X=j)}$

(14)

a) ~~$E[\hat{Y}] = E[Y | Y] = \sum_{i=1}^n E[\frac{Y_i}{Y}] = n \cdot E[\frac{Y_i}{Y}] \Rightarrow E[\frac{Y_i}{Y}] = \frac{1}{n}$~~

b) ~~$\oplus \sim N(0, K)$, $W \sim N(0, m)$~~

~~$\oplus + W \sim N(0, K+m)$~~

a)

$$E[Y_i | Y] = E[Y_j | Y].$$

$$E[(Y_1 + \dots + Y_n) | Y] = n \cdot E[Y_i | Y]$$

$$\stackrel{||}{E[Y | Y]}$$

$$\stackrel{||}{Y}$$

$$\Rightarrow E[Y_i | Y] = \frac{Y}{n}$$

b) $\textcircled{H} \sim N(0, k)$

$$W \sim N(0, m)$$

\textcircled{H} Let S_i be a standard normal $\Rightarrow S_i \sim N(0, 1)$

$$\textcircled{H} = S_1 + S_2 + \dots + S_k$$

$$W = \cancel{S_1} + \cancel{S_2} + \dots + \cancel{S_m}$$

$$S_{k+1} + S_{k+2} + \dots + S_{k+m}$$

From a) $E[S_i | \textcircled{H} + W] = \frac{\textcircled{H} + W}{k+m}$

$$E[\textcircled{H} | \textcircled{H} + W] = E[S_1 + S_2 + \dots + S_k | \textcircled{H} + W]$$

$$= \frac{k(\textcircled{H} + W)}{k+m}$$

c)

$$\textcircled{H} \sim \text{Poi}(\lambda)$$

Let $S_i \sim \text{Poi}(1) \Rightarrow \textcircled{H} = S_1 + \dots + S_\lambda$
 \uparrow integer

Similar approach as b)