

HONG KONG STATISTICAL SOCIETY

2016 EXAMINATIONS – SOLUTIONS

GRADUATE DIPLOMA – MODULE 1

The Society is providing these solutions to assist candidates preparing for the examinations in 2017.

The solutions are intended as learning aids and should not be seen as "model answers".

Users of the solutions should always be aware that in many cases there are valid alternative methods. Also, in the many cases where discussion is called for, there may be other valid points that could be made.

While every care has been taken with the preparation of these solutions, the Society will not be responsible for any errors or omissions.

The Society will not enter into any correspondence in respect of these solutions.

(i)
$$\frac{u}{p(u)} = \frac{1}{k} = \frac{2}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} = \frac{1}{k} \quad [distribution might be implicit]}{p(u)} = \frac{1}{k} \quad [distribution might be implicit]{p(u)} = \frac{1}{k} \quad [distribution might be implicit]{p(u)} = \frac{1}{k} \quad [distribution might be implicit]{p(u)} \quad [distribution might be implicit]{p(u)} = \frac{1}{k} \quad [distribution might be implicit]{p(u)} \quad [distr$$

(i)

$$E(U) = \int_{0}^{a} u \frac{\theta^{n} u^{n-1} e^{-4n}}{(n-1)!} du$$

$$= \frac{\theta^{n}}{(n-1)!} \int_{0}^{b} u^{n} e^{-4n} du$$

$$= \frac{\theta^{n}}{(n-1)!} \frac{1}{\theta^{n+1}} \int_{0}^{a} t^{n} e^{-4n} dt \quad [\text{where } t = \theta u] \quad 1$$

$$= \frac{\theta^{n}}{(n-1)!} \frac{1}{\theta^{n+1}}$$

$$= \frac{n}{\theta} \quad 1$$
Similarly, $E(U^{2}) = \frac{n(n+1)}{\theta^{2}}$. [Give marks also if full working shown.]
2
So, $Var(U) = \frac{n(n+1)}{\theta^{2}} - \frac{n^{2}}{\theta^{2}} = \frac{n}{\theta^{2}}$.
1
(ii)
(a) $f(x) = \int_{x}^{\infty} 4x e^{-(x+y)} dy = 4x e^{-x} \int_{x}^{\infty} e^{-y} dy = 4x e^{-2x}, \quad x > 0$
1, 1, 1
Using part (i), with $n = 2$ and $\theta = 2$, $E(X) = 1$, $Var(X) = \frac{1}{2}$.
1, 1
(b) $f(y|x) = \frac{4x e^{-(x+y)}}{4x e^{-2x}} = e^{-(y-x)}, \quad y > x$
1, 1
(b) $f(y|x) = \frac{4x e^{-(x+y)}}{4x e^{-2x}} = e^{-(y-x)}, \quad y > x$
1, 1
(c) Using the Law of Iterated Expectation,
$$E(Y) = E\{E(Y|X)\}$$
 $= 1 + x$
1
(c) Using the Law of Iterated Expectation,
$$E(Y) = E\{E(Y|X)\}$$
 $= 2$
1
(i)

(i)

$$F(z) = \int_{0}^{z} a \partial^{g^{-1}} \exp(-ad^{\theta}) dt$$

$$= \int_{0}^{\infty} e^{-s} du$$

$$[u = at^{\theta}]$$

$$= 1 - \exp(-az^{\theta})$$
is

$$h(z) = \frac{f(z)}{1 - F(z)} = \frac{a \partial^{g^{\theta^{-1}}} \exp(-az^{\theta})}{\exp(-az^{\theta})} = a \partial^{g^{\theta^{-1}}}$$
(a) $h(z)$ constant for $z \ge 0$ if $\theta = 1$, (b) $h(z)$ decreases with $z \ge 0$ if $(0 \le) \theta < 1$

$$[Don't need to state $\theta > 0$ to get the second of these marks.]$$
(ii)

$$G(y) = P(\text{either component fails in time y)}$$

$$= P(X_1 \le y \text{ or } X_2 \le y)$$

$$= P(X_1 \le y) - P(X_2 \le y) - P(X_1 \le y \text{ and } X_2 \le y)$$

$$= P(X_1 \le y) + P(X_2 \le y) - P(X_1 \le y \text{ and } X_2 \le y)$$

$$= P(X_1 \le y) + P(X_2 \le y) - P(X_1 \le y) \cdot P(X_2 \le y)$$

$$[Give full marks to candidate who realises the survivor function of Y must be the product of the survivor functions of X_1 and X_2 .]

$$g(y) = G'(y) = f_1(y) + f_2(y) - f_1(y) \cdot F_2(y) - F_1(y) \cdot f_2(y)$$

$$1$$

$$\therefore \quad h(y) = \frac{g(y)}{1 - G(y)} = \frac{f_1(y)[1 - F_2(y)]}{[1 - F_1(y)][1 - F_2(y)]} = h_1(y) + h_2(y)$$

$$1$$
In the Weibull case,

$$h(y) = h_1(y) + h_2(y) = \alpha_1 \partial^{y^{\theta^{-1}}} + \alpha_2 \partial^{y^{\theta^{-1}}} = (\alpha_1 + \alpha_2) \partial^{y^{\theta^{-1}}}$$

$$1, 1$$

$$(iii)$$

$$G(y) = P(C_1 \text{ and } C_2 fail in time y) = F_1(y) \cdot F_2(y) \quad [independence]$$

$$1, 1$$

$$(iii)$$

$$G(y) = [F(y)]^2$$

$$1$$
and $g(y) = 2 \cdot F(y) \cdot f(y)$

$$So \quad h(y) = \frac{2F(y)f(y)}{1 - [F(y)]^2} = 2 \cdot \frac{F(y)}{1 + F(y)} \cdot \frac{f(y)}{1 - F(y)} \le \frac{f(y)}{1 - F(y)}$$

$$1$$

$$1$$$$

 $Cov(X_1, X_2) = \rho \sqrt{[Var(X_1).Var(X_2)]} = -20$ **(a)** 1 (i) $E(\underline{X}) = (50 \quad 45)^T$ and $Cov(\underline{X}) = \begin{pmatrix} 64 & -20\\ -20 & 100 \end{pmatrix}$ So 1,1 (ii) The random vector Y has a bivariate normal distribution, with 1 $E(\underline{Y}) = \begin{pmatrix} 0.555 & 0\\ 0 & 0.447 \end{pmatrix} \begin{pmatrix} 50\\ 45 \end{pmatrix} + \begin{pmatrix} -17.76\\ 0 \end{pmatrix} = \begin{pmatrix} 9.99\\ 20.12 \end{pmatrix}$ 1, 1 $\operatorname{Cov}(\underline{Y}) = \begin{pmatrix} 0.555 & 0 \\ 0 & 0.447 \end{pmatrix} \begin{pmatrix} 64 & -20 \\ -20 & 100 \end{pmatrix} \begin{pmatrix} 0.555 & 0 \\ 0 & 0.447 \end{pmatrix}$ 1 $= \begin{pmatrix} 19.71 & -4.96 \\ -4.96 & 19.98 \end{pmatrix}$ 1 [Candidates who use 20.115 instead of 20.12 in these calculations should be awarded full marks.] (iii) The correlation between Y_1 and Y_2 is -0.25, the same as the correlation between X_1 and X_2 . This illustrates the general point that re-scaling 1 random variables (for example, by changing the units of measurement) changes their covariance but not their correlation. 1 **(b)** $\rho_{12} = \rho_{23} = \rho, \ \rho_{13} = \rho^2$ (i) 1,1 (ii) Y is normally distributed with 1 $E(Y) = \frac{1}{2} \left(\mu + \mu + \alpha + \mu + 2\alpha \right) = \mu + \alpha$ 1, 1 $\operatorname{Var}(Y) = (1/3 \ 1/3 \ 1/3)\sigma^{2} \begin{pmatrix} 1 & \rho & \rho^{2} \\ \rho & 1 & \rho \\ \rho^{2} & \rho & 1 \end{pmatrix} \begin{pmatrix} 1/3 \\ 1/3 \\ 1/3 \end{pmatrix}$ 1 $=\frac{\sigma^2}{\rho}(3+4\rho+2\rho^2)$ 1 (iii) $\overline{\mathbf{X}}$ has a multivariate normal distribution with 1 $E(\overline{\mathbf{X}}) = \begin{pmatrix} \mu \\ \mu + \alpha \\ \mu + 2\alpha \end{pmatrix}, \quad \operatorname{Cov}(\overline{\mathbf{X}}) = \frac{1}{n} \begin{pmatrix} \sigma^2 & \sigma^2 \rho & \sigma^2 \rho^2 \\ \sigma^2 \rho & \sigma^2 & \sigma^2 \rho \\ \sigma^2 \rho^2 & \sigma^2 \rho & \sigma^2 \end{pmatrix}$ 1,1

(i)	In this case, $f(x) = 1$ ($0 \le x \le 1$) and $F(x) = x$ ($0 \le x \le 1$).					
	Setting $n = 3$, $i = 2$ and $i = 3$ gives					
	Sound in S, V 2 and J S Bross					
	21					
	$g(w,v) = \frac{5!}{1000} [w]^{1} [v-w]^{0} [1-v]^{0} 1.1 = 6w, 0 \le w \le v \le 1$	1, 1				
		,				
	$r(\mathbf{x}_k,\mathbf{x}_k,\mathbf{x}_m) = c \int_{-\infty}^{1} k^{+1} \int_{-\infty}^{1} m \mathbf{x}_k$					
(11)	$E(W V) = O \int_0^0 W \int_w^0 V a V a W$	1				
	6 1	1				
	$= \frac{0}{1} \int w^{k+1} (1 - w^{m+1}) dw$	1				
	$m+1$ J $_0$					
	$6 \left[w^{k+2} w^{k+m+3} \right]^1$					
	$=\frac{0}{1}\left \frac{n}{1-2}-\frac{n}{1-2}\right $	1				
	$m+1\lfloor k+2 k+m+3 \rfloor_0$					
	6					
	$=\frac{0}{1}$					
	(k+2)(k+m+3)					
	$k = 1, m = 0$: $E(W) = 6/(3 \ge 4) = 0.5$	1				
	$k = 2, m = 0$: $E(W^2) = 6/(4 \ge 5) = 0.3 \implies Var(W) = 0.3 - (0.5)^2 = 0.05$	1.1				
	$k = 0, m = 1$: $E(V) = 6/(2 \ge 4) = 0.75$	1				
	$k = 0, m = 2$: $F(V^2) = 6/(2 \times 5) = 0.6 \implies Var(V) = 0.6 = (0.75)^2 = 0.0375$	11				
	$k = 0, m = 2$. $E(V) = 0/(2 \times 5) = 0.0 \implies Val(V) = 0.0 = 0.0575$ $k = 1, m = 1$: $E(WV) = 6/(3 \times 5) = 0.4$	1, 1				
	$K = 1, m = 1.$ $E(WV) = 0/(3 \times 3) = 0.4$	1				
	$\Rightarrow CoV(W, V) = 0.4 - (0.5) \times (0.75) = 0.025$	1				
(iii)	The median is $W + \theta - \frac{1}{2}$ and the maximum is $V + \theta - \frac{1}{2}$.	1				
	So the difference between the two estimates is $V - W$ (or $W - V$).					
	E(V - W) = E(V) - E(W) = 0.75 - 0.5 = 0.25 (or $E(W - V) = -0.25$)					
	$\operatorname{Var}(V - W) = \operatorname{Var}(V) + \operatorname{Var}(W) - 2 \times \operatorname{Cov}(W, V)$					
	= 0.0375 + 0.05 - 0.05 = 0.0375					
		-				

		r					
(i)	$M_{X}(t) = E\left(e^{Xt}\right) = \sum_{x=0}^{m} e^{xt} \binom{m}{x} \theta^{x} (1-\theta)^{m-x}$						
	$=\sum_{x=0}^{m} \binom{m}{x} (\theta e^{t})^{x} (1-\theta)^{m-x}$	1					
	$= (1 - \theta + \theta e^{t})^{m}$ [Binomial Theorem]	1					
	$M'_X(t) = m(1 - \theta + \theta e^t)^{m-1} \theta e^t$	1					
	$\Rightarrow \qquad E(X) = M'_X(0) = m\theta$	1					
	$M_{X}''(t) = [m(1 - \theta + \theta e^{t})^{m-1}]\theta e^{t} + [m(m-1)(1 - \theta + \theta e^{t})^{m-2}\theta e^{t}]\theta e^{t}$	1, 1 1					
	$\Rightarrow \qquad E(X^2) = M''_X(0) = m\theta + m(m-1)\theta^2$						
	$Var(X) = m\theta + m(m-1)\theta^2 - m^2\theta^2 = m\theta(1-\theta)$	1					
(ii)	Each X_i has moment-generating function $M_i(t) = (1 - \theta + \theta e^t)$.	1					
	Let $S = X_1 + + X_n$. Since $X_1,, X_n$ are <u>independent</u> [1 mark], then						
	$M_{s}(t) = M_{1}(t) \cdots M_{n}(t) = (1 - \theta + \theta e^{t})^{n}$	1, 1					
	This is the moment-generating function of the Bi (n, θ) distribution. Using the Uniqueness Property of moment-generating functions, $[1 mark] S \sim Bi(n, \theta)$.						
(iii)	The Central Limit Theorem: Suppose that X_1 ,, X_n is a sequence of <u>independent and identically-distributed</u> random variables, each with (finite) expected value μ and (finite) variance σ^2 . For sufficiently large values of n ,						
	$\frac{\sum_{i=1}^{n} X_{i} - n\mu}{\sqrt{n\sigma^{2}}} \sim N(0,1) \text{ approximat ely}$ [Give mark for correct statement in terms of \overline{X}]						
	In the context of part (ii), $\mu = \theta$ and $\sigma^2 = \theta(1 - \theta)$ using the results proved in (i). So approximately, for large enough <i>n</i> ,						
	$\frac{S - n\theta}{\sqrt{n\theta(1 - \theta)}} \sim N(0, 1) \text{ approximately}$	1					
	or $S \sim N(n\theta, n\theta(1-\theta))$ approximately.	1					
	It was proved in (ii) that $S \sim Bi(n, \theta)$. Therefore, the $Bi(n, \theta)$ distribution can be approximated by the $N(n\theta, n\theta(1-\theta))$ distribution for large enough <i>n</i> .						

(a)	(i) The Tables provided give the following cumulative probabilities [also give this mark if candidate works out point probabilities and uses them to calculate the correct cumulative probabilities]:							
	$\frac{x 0 1 2 3 4 5 \dots}{F_X(x) 0.0821 0.2873 0.5438 0.7576 0.8912 0.9580 \dots}$	1						
	$u_1 = 0.0885$, so $x_1 = 1$ $u_3 = 0.7370$, so $x_3 = 3$ $u_2 = 0.4096$, so $x_2 = 2$ $u_4 = 0.9384$, so $x_4 = 5$	1, 1 1, 1						
	The pseudo-random variates are 1, 2, 3 and 5.							
	(ii) $F(x) = \int_{3}^{x} 10e^{-10(t-3)} dt = \left[-e^{-10(t-3)}\right]_{3}^{x} = 1 - e^{-10(x-3)}, x > 3$	1						
	So $u = F(x) \Leftrightarrow u = 1 - e^{-10(x-3)} \Leftrightarrow x = 3 - \frac{1}{10} \log_e(1-u)$	1, 1						
	$u_1 = 0.0885$, so $x_1 = 3.009$ $u_2 = 0.4096$, so $x_2 = 3.053$ $u_3 = 0.7370$, so $x_3 = 3.134$ $u_4 = 0.9384$, so $x_4 = 3.279$	$\frac{1}{2}, \frac{1}{2}$ $\frac{1}{2}, \frac{1}{2}$						
	The pseudo-random variates are 3.009, 3.053, 3.134, 3.279.							
(b)	 (b) For full table of results, see next page. [Give 1 mark for mapping still different digits to the possible outcomes on the die, 1 mark for discardinal occurrences of the other four digits, 1 mark for not starting till the first "6", 1 mark for applying the other conditions. If a candidate carrying of the correct general procedure makes minor errors, deduct 1 mark.] This simulation required 58 random digits, giving 33 valid rolls of a die. 							
	Repeat the simulation many times (possibly 1000 or 10000). Count to number of rolls of the die required each time. Obtain an appropria interval based on the distribution of the number of rolls required (a example, mean \pm - 1.96s.d., or 2.5 th to 97.5 th percentile of the samp distribution).							

#	Digit	Outcome	#	Digit	Outcome	
1	5	-	31	0	Not Roll	
2	2	-	32	0	Not Roll	
3	1	-	33	6	-	
4	0	Not Roll	34	2	Antenna 1	
5	9	Not Roll	35	6	-	
6	0	Not Roll	36	6	-	
7	0	Not Roll	37	2	Antenna 2	
8	9	Not Roll	38	0	Not Roll	
9	6	Body	39	6	-	
10	8	Not Roll	40	8	Not Roll	
11	6	-	41	7	Not Roll	
12	8	Not Roll	42	0	Not Roll	
13	0	Not Roll	43	5	-	
14	8	Not Roll	44	4	-	
15	9	Not Roll	45	9	Not Roll	
16	8	Not Roll	46	9	Not Roll	
17	6	-	47	6	-	
18	3	Leg 1	48	7	Not Roll	
19	6	-	49	5	-	
20	4	Tail	50	6	-	
21	2	-	51	5	-	
22	8	Not Roll	52	3	Leg 3	
23	8	Not Roll	53	9	Not Roll	
24	4	-	54	4	-	
25	5	Head	55	4	-	
26	4	-	56	3	Leg 4	
27	1	Eye 1	57	5	-	
28	9	Not Roll	58	1	Eye 2	
29	3	Leg 2				
30	9	Not Roll				

 $U = 1 - X, V = \frac{Y}{1 - X}$ (i) 1, 1 means X = 1 - U, Y = UV $J = \begin{vmatrix} \frac{\partial X}{\partial U} & \frac{\partial X}{\partial V} \\ \frac{\partial Y}{\partial Y} & \frac{\partial Y}{\partial Y} \end{vmatrix} = \begin{vmatrix} -1 & 0 \\ V & U \end{vmatrix} = -U$ 4@1/2,1 Hence, on the range space $\{(u, v): 0 \le u \le 1; 0 \le v \le 1\}$, 1 g(u,v) = u f(1-u, uv)1 $= u \frac{\Gamma(\alpha + \beta + \gamma)}{\Gamma(\alpha)\Gamma(\beta)\Gamma(\gamma)} (1 - u)^{\alpha - 1} (uv)^{\beta - 1} (u - uv)^{\gamma - 1}$ 1 $=\frac{\Gamma(\alpha+\beta+\gamma)}{\Gamma(\alpha)\Gamma(\beta)\Gamma(\gamma)}u^{\beta+\gamma-1}(1-u)^{\alpha-1}v^{\beta-1}(1-v)^{\gamma-1}$ 1 The joint p.d.f. factorises as the product of a function of u alone and a (ii) 1 function of v alone. Their joint range space is a Cartesian product (or 'rectangular space'). Using the Factorisation Theorem, therefore, U and V1 are independent. The marginal p.d.f.'s are $g(u) \propto u^{\beta+\gamma-1}(1-u)^{\alpha-1}, 0 \leq u \leq 1$ 1 $g(u) = \frac{\Gamma(\alpha + \beta + \gamma)}{\Gamma(\beta + \gamma)\Gamma(\alpha)} u^{\beta + \gamma - 1} (1 - u)^{\alpha - 1}, \ 0 \le u \le 1,$ so 1 1 $U \sim \text{Be}(\beta + \gamma, \alpha)$ i.e. [Give full marks to a candidate who carries out these last two steps in the *reverse order.*] $g(v) \propto v^{\beta-1} (1-v)^{\gamma-1}, 0 \leq v \leq 1$ and 1 $g(v) = \frac{\Gamma(\beta + \gamma)}{\Gamma(\beta)\Gamma(\gamma)} v^{\beta - 1} (1 - v)^{\gamma - 1}, \ 0 \le v \le 1,$ so 1 1 i.e. $V \sim \text{Be}(\beta, \gamma)$ [Give full marks to a candidate who carries out these last two steps in the *reverse order.*] (iii) 1 X = 1 - U, so $X \sim \text{Be}(\alpha, \beta + \gamma)$ 1, 1 *.*.. $Y \sim \text{Be}(\beta, \alpha + \gamma)$ and $Z \sim \text{Be}(\gamma, \alpha + \beta)$, by symmetry