## THE ROYAL STATISTICAL SOCIETY

## 2003 EXAMINATIONS - SOLUTIONS

## GRADUATE DIPLOMA PAPER I - STATISTICAL THEORY \& METHODS

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(i) $\quad P(X=x)=\sum_{y=0}^{n-x} P(X=x, Y=y)$

$$
\begin{aligned}
& =\sum_{y=0}^{n-x} \frac{n!}{x!y!(n-x-y)!} \theta_{1}^{x} \theta_{2}^{y}\left(1-\theta_{1}-\theta_{2}\right)^{n-x-y} \\
& =\frac{n!}{x!(n-x)!} \theta_{1}^{x} \sum_{y=0}^{n-x}\binom{n-x}{y} \theta_{2}^{y}\left(1-\theta_{1}-\theta_{2}\right)^{n-x-y} \\
& =\binom{n}{x} \theta_{1}^{x}\left\{\theta_{2}+\left(1-\theta_{1}-\theta_{2}\right)\right\}^{n-x}=\binom{n}{x} \theta_{1}^{x}\left(1-\theta_{1}\right)^{n-x}
\end{aligned}
$$

which is $\operatorname{Binomial}\left(n, \theta_{1}\right)$.
It follows by symmetry that $Y$ is $\operatorname{Binomial}\left(n, \theta_{2}\right)$.
(ii) $\operatorname{For} x=0,1, \ldots, n-y$,

$$
\begin{aligned}
P(X=x \mid Y=y) & =\frac{P(X=x, Y=y)}{P(Y=y)} \\
& =\frac{n!\theta_{1}^{x} \theta_{2}^{y}\left(1-\theta_{1}-\theta_{2}\right)^{n-x-y}}{x!y!(n-x-y)!} \frac{y!(n-y)!}{n!\theta_{2}^{y}\left(1-\theta_{2}\right)^{n-y}} \\
& =\binom{n-y}{x}\left(\frac{\theta_{1}}{1-\theta_{2}}\right)^{x}\left(1-\frac{\theta_{1}}{1-\theta_{2}}\right)^{n-y-x},
\end{aligned}
$$

so that, conditional on $Y=y, X$ is $\operatorname{Binomial}\left(n-y, \frac{\theta_{1}}{1-\theta_{2}}\right)$.
(iii) $\quad P($ double six $)=(1 / 6)^{2}=1 / 36 . \quad P($ no six $)=(5 / 6)^{2}=25 / 36$.

The joint distribution of $X$ and $Y$ as defined is given by the multinomial with $\theta_{1}=1 / 36, \theta_{2}=25 / 36$.

Therefore by (i), $E(X)=10 / 36=5 / 18$, since $X$ is $\operatorname{Binomial}(10,1 / 36)$.
By (ii), in the case $Y=0, E(X \mid Y=0)=10 / 11$, since $X$ will be $\operatorname{Binomial}(10,1 / 11)$. (There are 11 ways out of 36 of having at least one six.)
(i) (a) The law of total probability is $P(A)=\sum_{i=1}^{n} P\left(A \mid E_{i}\right) P\left(E_{i}\right)$.

Bayes' Theorem states that $P\left(E_{j} \mid A\right)=\frac{P\left(A \mid E_{j}\right) P\left(E_{j}\right)}{\sum_{i=1}^{n} P\left(A \mid E_{i}\right) P\left(E_{i}\right)}$.
(b) Since $\left\{F_{j}\right\}$ partitions $S, E_{i}$ can be written as the disjoint union of events $\left\{E_{i}\right.$ and $\left.F_{j}\right\} . S$ is the disjoint union of $\left\{E_{i}\right\}$, so $S$ is also the disjoint union of events $\left\{E_{i}\right.$ and $\left.F_{j}\right\}$. Hence $\left\{E_{i}\right.$ and $\left.F_{j}\right\}$ partitions $S$.

Now $P(A)=\sum_{i=1}^{n} \sum_{j=1}^{m} P\left(A \mid E_{i}\right.$ and $\left.F_{j}\right) P\left(E_{i}\right.$ and $\left.F_{j}\right)$

$$
=\sum_{i=1}^{n} \sum_{j=1}^{m} P\left(A \mid E_{i} \cap F_{j}\right) P\left(F_{j} \mid E_{i}\right) P\left(E_{i}\right) .
$$

(ii) (a) $\quad P$ (no son haemophiliac)
$=P($ no son haemophiliac $\mid$ woman carrier $) . P($ woman carrier $)$
$+P($ no son haemophiliac $\mid$ woman not carrier).$P($ woman not carrier $)$
$=\left\{\left(\frac{1}{2}\right)^{3} \times\left(\frac{1}{2}\right)\right\}+\left\{1 \times \frac{1}{2}\right\}=\frac{9}{16}$.
$P($ woman carrier $\mid$ no son haemophiliac $)=\frac{1 / 16}{9 / 16}=\frac{1}{9}$.
$P$ (daughter carrier)
$=P($ daughter carrier $\mid$ woman carrier $) . P($ woman carrier $)=\frac{1}{2} \times \frac{1}{9}=\frac{1}{18}$.
(b) $\quad P($ at least one girl carrier)
$=P($ at least one girl carrier $\mid$ daughter carrier) $\cdot P$ (daughter carrier)

$$
\begin{aligned}
& =\left\{1-\left(\frac{1}{2}\right)^{2}\right\} \times \frac{1}{18} \\
& =\frac{1}{24} .
\end{aligned}
$$

(i) The space where $X$ and $Y$ exist jointly is not a rectangular region. It is possible to find points $(x, y)$, e.g. $(1 / 2,3 / 4)$, where both $f(x)$ and $f(y)$ are $>0$ but $f(x, y)=0$; thus $f(x, y) \neq f(x) . f(y)$.
(ii) $\quad E\left(X^{r} Y^{s}\right)=\int_{0}^{1} 6 x^{r+1}\left(\int_{0}^{1-x} y^{s} d y\right) d x$

$$
\begin{aligned}
& =6 \int_{0}^{1} x^{r+1}\left[\frac{(1-x)^{s+1}}{s+1}\right] d x \\
& =\frac{6}{s+1} \frac{(r+1)!(s+1)!}{(r+s+3)!} \quad \text { using the result quoted in the paper } \\
& =\frac{6(r+1)!s!}{(r+s+3)!} \quad \text { for any non-negative integers } r, s
\end{aligned}
$$

Hence

$$
\begin{aligned}
& E(X)=\frac{6 \cdot 2!0!}{4!}=\frac{6 \cdot 2 \cdot 1}{4 \cdot 3 \cdot 2 \cdot 1}=\frac{1}{2}, \\
& E\left(X^{2}\right)=\frac{6 \cdot 3!0!}{5!}=\frac{6 \cdot 3 \cdot 2 \cdot 1 \cdot 1}{5 \cdot 4 \cdot 3 \cdot 2 \cdot 1}=\frac{3}{10}, \quad \text { so } \operatorname{Var}(X)=\frac{3}{10}-\left(\frac{1}{2}\right)^{2}=\frac{1}{20} . \\
& E(Y)=\frac{6 \cdot 1!1!}{4!}=\frac{1}{4}, \\
& E\left(Y^{2}\right)=\frac{6.1!2!}{5!}=\frac{1}{10}, \quad \text { so } \operatorname{Var}(Y)=\frac{1}{10}-\left(\frac{1}{4}\right)^{2}=\frac{3}{80} . \\
& E(X, Y)=\frac{6 \cdot 2!1!}{5!}=\frac{1}{10}, \quad \text { so } \operatorname{Cov}(X, Y)=\frac{1}{10}-\frac{1}{2} \cdot \frac{1}{4}=-\frac{1}{40}, \\
& \text { and so } \rho_{X Y}=\frac{\operatorname{Cov}(X, Y)}{\sqrt{\operatorname{Var}(X) \cdot \operatorname{Var}(Y)}}=-\frac{1}{40} \sqrt{\frac{20 \times 80}{3}}=-\frac{1}{\sqrt{3}} .
\end{aligned}
$$

(iii) For $0 \leq w \leq 1, P(X+Y \leq w)=\int_{0}^{w} 6 x\left(\int_{0}^{w-x} d y\right) d x$

$$
=6 \int_{0}^{w} x(w-x) d x=6\left[\frac{1}{2} w x^{2}-\frac{1}{3} x^{3}\right]_{0}^{w}=w^{3},
$$

so that the cumulative distribution function is $F_{W}(w)=w^{3}($ for $0 \leq w \leq 1)$ and the probability density function is $f_{W}(w)=3 w^{2}$ (for $\left.0 \leq w \leq 1\right)$.
(i) As $X$ and $Y$ are independent,

$$
\begin{aligned}
& f(x, y)=(\text { pdf of } X)(\operatorname{pdf} \text { of } Y)=\frac{1}{2 \pi \sigma^{2}} \exp \left(-\frac{1}{2 \sigma^{2}}\left(x^{2}+y^{2}\right)\right) \\
& (\text { for }-\infty<x<\infty,-\infty<y<\infty) .
\end{aligned}
$$

For $X=R \cos \phi, Y=R \sin \phi$, the Jacobian is

$$
|J|=\left|\begin{array}{ll}
\frac{\partial X}{\partial R} & \frac{\partial X}{\partial \phi} \\
\frac{\partial Y}{\partial R} & \frac{\partial Y}{\partial \phi}
\end{array}\right|=\left|\begin{array}{cc}
\cos \phi & -R \sin \phi \\
\sin \phi & R \cos \phi
\end{array}\right|=R\left(\cos ^{2} \phi+\sin ^{2} \phi\right)=R
$$

So the joint pdf of $R, \phi$ is $g(r, \phi)=\frac{r}{2 \pi \sigma^{2}} \exp \left(-\frac{r^{2}}{2 \sigma^{2}}\right), \quad$ for $0 \leq r, 0 \leq \phi \leq 2 \pi$.
(ii) The pdf of $R$ is $\int_{\phi=0}^{\phi=2 \pi} g(r, \phi) d \phi=\frac{r}{\sigma^{2}} \exp \left(-\frac{r^{2}}{2 \sigma^{2}}\right), \quad$ for $r \geq 0$.
[This can also be seen because $R, \phi$ exist in a "rectangular" space, and the joint pdf can be written as $\left(\frac{r}{\sigma^{2}} e^{-r^{2} /\left(2 \sigma^{2}\right)}\right)\left(\frac{1}{2 \pi}\right)$ which factorises, so $R, \phi$ are independent.]
(iii) The cumulative distribution function of $R$ is

$$
\begin{aligned}
F(r)=\int_{0}^{r} \frac{u}{\sigma^{2}} \exp \left(-\frac{u^{2}}{2 \sigma^{2}}\right) d u & =\int_{0}^{r^{2} /\left(2 \sigma^{2}\right)} e^{-w} d w \quad\left(\text { putting } w=\frac{u^{2}}{2 \sigma^{2}}\right) \\
& =1-e^{-r^{2} /\left(2 \sigma^{2}\right)} .
\end{aligned}
$$

$\therefore F(k \sigma)=1-e^{-k^{2} / 2}$, which is to be 0.5 . This gives $0.5=e^{-k^{2} / 2}$, or $k=\sqrt{-2 \log 0.5}=1.18$.

$$
\begin{align*}
M_{X}(t)=E\left[e^{t X}\right]=\sum_{x=0}^{\infty} e^{t x} \cdot \frac{e^{-\mu} \mu^{x}}{x!}=e^{-\mu} \sum_{x=0}^{\infty} \frac{\left(\mu e^{t}\right)^{x}}{x!} & =e^{-\mu} \cdot \exp \left(\mu e^{t}\right)  \tag{i}\\
& =\exp \left\{\left(e^{t}-1\right) \mu\right\}
\end{align*}
$$

We have $E[X]=M_{X}{ }^{\prime}(0)$ and $E\left[X^{2}\right]=M_{X} "(0)$. Differentiating $M_{X}(t)$ gives

$$
\begin{aligned}
& M^{\prime}(t)=\mu e^{t} \exp \left\{\mu\left(e^{t}-1\right)\right\}, \quad \text { so } M^{\prime}(0)=\mu, \quad \text { and } \\
& M^{\prime \prime}(t)=\mu e^{t} \exp \left\{\mu\left(e^{t}-1\right)\right\}+\mu^{2} e^{2 t} \exp \left\{\mu\left(e^{t}-1\right)\right\}, \quad \text { so } M^{\prime \prime}(0)=\mu+\mu^{2}
\end{aligned}
$$

Hence $\operatorname{Var}(X)=E\left[X^{2}\right]-(E[X])^{2}=\mu+\mu^{2}-(\mu)^{2}=\mu$.
(Note. The results for $E[X]$ and $E\left[X^{2}\right]$ can also be obtained from the power series expansion of $\left.M_{X}(t).\right)$
(ii) $\quad Z=\frac{X-\mu}{\sqrt{\mu}}=\frac{1}{\sqrt{\mu}} X-\sqrt{\mu}$, so (using the "linear transformation" result for moment generating functions) we have

$$
M_{Z}(t)=e^{-t \sqrt{\mu}} \cdot M_{X}\left(\frac{t}{\sqrt{\mu}}\right)=e^{-t \sqrt{\mu}} \exp \left\{\mu\left(e^{t / \sqrt{\mu}}-1\right)\right\} .
$$

Taking logarithms (base $e$ ),

$$
\begin{aligned}
\log \left(M_{Z}(t)\right)=-t \sqrt{\mu}+\mu\left(e^{t / \sqrt{\mu}}-1\right) & =-t \sqrt{\mu}+\mu\left(1+\frac{t}{\sqrt{\mu}}+\frac{t^{2}}{2 \mu}+\frac{t^{3}}{6 \mu^{3 / 2}}+\ldots-1\right) \\
& =\frac{1}{2} t^{2}+\frac{t^{3}}{6 \sqrt{\mu}}+\ldots \rightarrow \frac{1}{2} t^{2} \text { as } \mu \rightarrow \infty
\end{aligned}
$$

Hence $M_{Z}(t) \rightarrow \exp \left(t^{2} / 2\right)$ as $\mu \rightarrow \infty$, and this is the moment generating function of $\mathrm{N}(0,1)$. Hence the limiting distribution of $Z$ is $\mathrm{N}(0,1)$.
(iii) $\quad W=\sum_{i=1}^{n} Y_{i}$ and the m.g.f. of $Y_{i}$ is $M_{i}(t)=\exp \left\{\left(e^{t}-1\right) \mu_{i}\right\}$. By independence, $M_{W}(t)=\prod_{i=1}^{n} \exp \left\{\left(e^{t}-1\right) \mu_{i}\right\}=\exp \left\{\left(e^{t}-1\right) \sum_{i=1}^{n} \mu_{i}\right\}$, i.e. the same form as the original Poisson m.g.f. but with parameter $\sum \mu_{i}$, so the distribution of $W$ is Poisson with parameter $\sum \mu_{i}$.
(i) For the Weibull distribution, $F(w)=\int_{0}^{w} \alpha \theta t^{\theta-1} e^{-\alpha t^{\theta}} d t$; put $u=a t^{\theta}$ to give $F(w)=\int_{0}^{\alpha w^{\theta}} e^{-u} d u=1-\exp \left(-\alpha w^{\theta}\right)$. Thus, from the formula $h(w)=\frac{f(u)}{1-F(u)}$, we have $h(w)=\frac{\alpha \theta w^{\theta-1} \exp \left(-\alpha w^{\theta}\right)}{\exp \left(-\alpha w^{\theta}\right)}=\alpha \theta w^{\theta-1}$. This hazard function is constant if $\theta=1$; it decreases as $w$ increases if $\theta<1$.
(ii) $\quad G(y)=P(Y \leq y)=P\left(X_{1} \leq y\right.$ or $\left.X_{2} \leq y\right)$

$$
\begin{aligned}
& =P\left(X_{1} \leq y\right)+P\left(X_{2} \leq y\right)-P\left(X_{1} \leq y \text { and } X_{2} \leq y\right) \\
& =P\left(X_{1} \leq y\right)+P\left(X_{2} \leq y\right)-P\left(X_{1} \leq y\right) P\left(X_{2} \leq y\right) \quad \text { by independence } \\
& =F_{1}(y)+F_{2}(y)-F_{1}(y) F_{2}(y) .
\end{aligned}
$$

Hence $g(y)=G^{\prime}(y)=f_{1}(y)+f_{2}(y)-f_{1}(y) F_{2}(y)-f_{2}(y) F_{1}(y) \quad($ for $y \geq 0)$.

$$
\begin{aligned}
\therefore h(y)=\frac{g(y)}{1-G(y)} & =\frac{g(y)}{1-F_{1}(y)-F_{2}(y)+F_{1}(y) F_{2}(y)}=\frac{g(y)}{\left(1-F_{1}(y)\right)\left(1-F_{2}(y)\right)} \\
& =\frac{f_{1}(y)\left\{1-F_{2}(y)\right\}+f_{2}(y)\left\{1-F_{1}(y)\right\}}{\left\{1-F_{1}(y)\right\}\left\{1-F_{2}(y)\right\}}=h_{1}(y)+h_{2}(y)
\end{aligned}
$$

If $X_{i}$ is Weibull $\left(\alpha_{i}, \theta\right)$, this gives $h(y)=h_{1}(y)+h_{2}(y)=\alpha_{1} \theta y^{\theta-1}+\alpha_{2} \theta y^{\theta-1}$ $=\left(\alpha_{1}+\alpha_{2}\right) \theta y^{\theta-1}$, which is the hazard function of $\operatorname{Weibull}\left(\alpha_{1}+\alpha_{2}, \theta\right)$.
(iii) $\quad G(y)=P($ both components fail in time $y)=F_{1}(y) F_{2}(y)$ by independence. For identical components, $G(y)=\{F(y)\}^{2}$, which gives $g(y)=2 F(y) f(y)$ and so $h(y)=\frac{2 F(y) f(y)}{1-\{F(y)\}^{2}}=\frac{2 F(y) f(y)}{\{1-F(y)\}\{1+F(y)\}}$. Now, $\frac{F(y)}{1+F(y)} \leq \frac{1}{2}($ as $0 \leq F(y) \leq 1)$, and therefore $h(y) \leq \frac{f(y)}{1-F(y)}$, as required.
(i)
(a) $\binom{15}{2}=105$, so $P(0)=\binom{10}{2} / 105=\frac{45}{105}$, and similarly $P(1)=50 / 105$ and $P(2)=10 / 105$. Hence the probability function $(f(x))$ and c.d.f. $(F(x))$ are

| $x$ | 0 | 1 | 2 |
| :--- | :---: | :---: | :---: |
| $f(x)$ | 0.4286 | 0.4762 | 0.0952 |
| $F(x)$ | 0.4286 | 0.9048 | 1.0000 |

The inverse c.d.f. method produces $x=0$ if the random number is $\leq 0.4286$, $x=1$ if the random number is between 0.4287 and 0.9048 , and $x=2$ for 0.9049 upwards. Hence we obtain 1, 0, 2, 1 .
(b) $\quad F(x)=x^{3}$ (for $0 \leq x \leq 1$ ). The inverse c.d.f. method sets $u=F(x)=x^{3}$, so $x=u^{1 / 3}$. So we obtain $0.8142,0.6960,0.9962,0.7894$.
(ii) Generating a $\mathrm{N}\left(9,(1 / 2)^{2}\right)$ random variable requires a $\mathrm{N}(0,1) z$, found as $\Phi^{-1}(u)$, followed by a transformation $x=9+\frac{1}{2} z$.

For $u=0.5398$, we get $z=0.10$ and hence $x=9.05$.
For $u=0.3372$, we get $z=-0.42$ and hence $x=8.79$.
For $u=0.9887$, we get $z=2.28$ and hence $x=10.14$.
For $u=0.4920$, we get $z=-0.02$ and hence $x=8.99$.
Beginning at $11.00 \mathrm{a} . \mathrm{m}$. and working in decimals of a minute, the times taken to reach B, C, D, E will be $9.05,8.79,10.14,8.99$ minutes. Notice that this means that the bus will need to "wait time" at B and C. The bus leaves B at 11.10 and C at 11.20 . It then leaves $D$ at 30.14 minutes past 11.00 , to arrive at $E$ at 39.13 minutes past 11.00 . It will have waited 0.95 minutes at $\mathrm{B}, 1.21$ minutes at C , and 0 minutes at D .

A sample of arrival times at E could be generated in this way using a larger simulation, and the sample mean used to estimate the expected arrival time. The number of times in the sample, $n$ say, that E is not reached until after 11.40 a.m. could be used in estimating the probability of a late arrival: $\hat{p}=\frac{n}{\text { number of simulations }}$.
(i) The states of the Markov Chain are 0 (not obese) and 1 (obese). If $X_{i}$ is the state reached at age $i(i=0,1,2, \ldots$ years $)$ and $p_{r s}=P\left(X_{i+1}=s \mid X_{i}=r\right)$ for $r=0,1$ and $s=0,1$, the transition matrix is $\mathbf{P}=\left[p_{r s}\right]=\left[\begin{array}{ll}1-\phi & \phi \\ 1-\theta & \theta\end{array}\right]$.
(ii) The two-step transition matrix is

$$
\mathbf{P}^{2}=\left[\begin{array}{ll}
1-\phi & \phi \\
1-\theta & \theta
\end{array}\right]\left[\begin{array}{ll}
1-\phi & \phi \\
1-\theta & \theta
\end{array}\right]=\left[\begin{array}{cc}
(1-\phi)^{2}+\phi(1-\theta) & \phi(1-\phi+\theta) \\
(1-\theta)(1-\phi+\theta) & \theta^{2}+\phi(1-\theta)
\end{array}\right] .
$$

All children are non-obese (state 0 ) at 0 years. So the probability that a child is obese (state 1) at 2 years is given by the "top right" element of $\mathbf{P}^{2}$, i.e. it is $\phi(1-\phi+\theta)$.
(iii) The proportion of children who have never been obese at any stage up to and including 3 years is $\left(p_{00}\right)^{3}=(1-\phi)^{3}$.
(iv) $p_{i+1}=\theta p_{i}+\phi\left(1-p_{i}\right)=\phi+(\theta-\phi) p_{i}$.

Inserting $i=0$ in the expression given in the question gives $\frac{1-(\theta-\phi)^{0}}{1-(\theta-\phi)}$ which equals
0 as required (all children are non-obese at age 0 ). Now supposing the result holds for $p_{i}(i \geq 0)$, we have

$$
\begin{aligned}
p_{i+1}= & \phi+(\theta-\phi) \cdot \frac{1-(\theta-\phi)^{i}}{1-(\theta-\phi)} \phi=\phi\left\{1+\frac{\theta-\phi}{1-(\theta-\phi)}\left[1-(\theta-\phi)^{i}\right]\right\} \\
& =\phi \frac{1-(\theta-\phi)+(\theta-\phi)-(\theta-\phi)^{i+1}}{1-(\theta-\phi)}=\frac{1-(\theta-\phi)^{i+1}}{1-(\theta-\phi)} \phi .
\end{aligned}
$$

Hence by induction the result is true for all $i \geq 0$.
(v) As $i$ increases, $p_{i} \rightarrow \frac{1-0}{1-(\theta-\phi)} \phi$ since $\theta-\phi<1$, i.e. $p_{i} \rightarrow \frac{\phi}{1-(\theta-\phi)}$.

For $\theta=0.8$ and $\phi=0.1, p_{i} \rightarrow \frac{0.1}{1-0.7}=\frac{1}{3}$, so we expect approximately one-third of this adult population to be obese.

