## Possible Solutions

## Probability Theory and Statistics <br> (BSc D-ITET)

1. a) The following probabilities are given in the exercise

$$
\begin{aligned}
& \qquad \begin{aligned}
P(<\text { The train departs on time }>) & =P(D o T)=0.7 \\
P(<\text { The train arrives on time }>) & =P(A o T)=0.75 \\
P(<\text { The train departs on time AND arrives on time }>) & =P(D o T \cap A o T)=0.6 .
\end{aligned} \\
& \text { Therefore, we obtain } \\
& P(<\text { The train departs with delay }>)=P(D w D)=1-P(D o T)=0.3 \\
& P(<\text { The train arrives with delay }>)=P(A w D)=1-P(A o T)=0.25
\end{aligned}
$$

We need to compute $P(A o T \mid D w D)$. From the definition of conditional probabilities, one has

$$
P(A o T \mid D w D)=\frac{P(A o T \cap D w D)}{P(D w D)}
$$

Since we already found that $P(D w D)=0.3$, we now focus on the numerator. Since a train can either depart on time or with delay it holds

$$
P(A o T)=P(A o T \cap D w D)+P(A o T \cap D o T)
$$

Therefore, one has

$$
P(A o T \cap D w D)=P(A o T)-P(A o T \cap D o T)=0.75-0.6=0.15
$$

Hence, we calculate

$$
P(A o T \mid D w D)=\frac{0.15}{0.3}=0.5
$$

b) Let $T$ be the event < The member has trained>, and let $F$ be the event < The member finishes the tour>. It is given in the exercise $P\left(T^{c}\right)=0.2$. Moreover, we know from the exercise that

$$
P(F \mid T)=0.85, \quad P\left(F \mid T^{c}\right)=0.6
$$

i) We need to compute $P(F)$. Applying the formula of total probabilities, we get

$$
P(F)=P(F \mid T) P(T)+P\left(F \mid T^{c}\right) P\left(T^{c}\right)=0.85 \cdot 0.8+0.6 \cdot 0.2=0.68+0.12=0.8
$$

ii) We need to compute $P(T \mid F)$. Applying Bayes' formula, we obtain

$$
P(T \mid F)=\frac{P(F \mid T) P(T)}{P(F)}=\frac{0.85 \cdot 0.8}{0.8}=0.85
$$

c) The unconditioned law of $N$ is given by

$$
\begin{aligned}
P(N=n) & =\int_{0}^{\infty} e^{-\lambda} \frac{\lambda^{n}}{n!} \frac{1}{2} e^{-\lambda / 2} d \lambda=\int_{0}^{\infty} e^{-\frac{3 \lambda}{2}} \lambda^{n} \frac{d \lambda}{2 n!} \\
& =\int_{0}^{\infty} e^{-y}\left(\frac{2}{3} y\right)^{n} \frac{2}{3} \frac{1}{2 n!} d y=\frac{1}{2 n!}\left(\frac{2}{3}\right)^{n+1} \underbrace{\int_{0}^{\infty} e^{-y} y^{n} d y}_{=n!} \\
& =\frac{1}{3}\left(\frac{2}{3}\right)^{n} .
\end{aligned}
$$

d) Observe that the distribution obtained in $\mathbf{c )}$ differs from the one in the hint only by the value of the parameter $p$. We solve here the question for a general $p \in(0,1)$.

$$
\begin{aligned}
E[N] & =\sum_{k \geq 0} k p(1-p)^{k}=p \sum_{k \geq 0} k(1-p)^{k} \\
& =p(1-p) \sum_{k \geq 1} k(1-p)^{(k-1)}=p(1-p)\left(-\sum_{k \geq 0}(1-p)^{k}\right)^{\prime} \\
& =p(1-p)\left(-\frac{1}{1-(1-p)}\right)^{\prime}=p(1-p) \frac{1}{p^{2}}=\frac{1-p}{p}
\end{aligned}
$$

Hence for $p=\frac{1}{3}$ as in $\mathbf{c}$ ), we get $E[X]=2$; otherwise, using the hint, $E[X]=3$.
REmark: $N$ has a geometric distribution shifted by -1 , therefore it is consistent to have $\frac{1}{p}-1$ as expected value for $N$.
2. a) $Y$ is a discrete random variable which only takes two values, 0 and 1 . We can compute the probability of each of these by integrating the joint density function. We obtain the following:

$$
P[Y=0]=\int_{0}^{1} 12\left(x^{2}-x^{3}\right)(1-x) \mathrm{d} x=\frac{2}{5}
$$

and

$$
P[Y=1]=1-P[Y=0]=\frac{3}{5}
$$

Therefore, $Y \sim \operatorname{Ber}(p=3 / 5)$.
b) We have $E[X+Y]=E[X]+E[Y]=\int_{0}^{1} 12\left(x^{3}-x^{4}\right) \mathrm{d} x+\frac{3}{5}=\frac{6}{5}$.
c) Since $\operatorname{Cov}(X, Y)=E[X Y]-E[X] E[Y]$, we only need to calculate $E[X Y]$ since we have the other two from the previous exercise. Using the joint density function, we find that

$$
E[X Y]=\sum_{y=0}^{1} \int_{0}^{1} x y f_{X, Y}(x, y) \mathrm{d} x=\int_{0}^{1} 12\left(x^{2}-x^{3}\right) x^{2} \mathrm{~d} x=\frac{2}{5}
$$

Therefore, $\operatorname{Cov}(X, Y)=\frac{2}{5}-\frac{9}{25}=\frac{1}{25}$, Hence, $X, Y$ are not independent.
d) Note that $\sin (2 \pi Y) \equiv 0$, therefore it is independent of any other random variable. In particular, it is independent of $X^{2}$.
3. a) We recognize immediately that $X \sim \operatorname{Bin}(N=100, q=(1-p)=0.99)$. We then calculate $\operatorname{Var}(X)=N q(1-q)=0.99$, and we get

$$
P(X \leq \operatorname{Var}(X))=P(X=0)=\binom{100}{0} q^{0}(1-q)^{100}=(0.01)^{100}
$$

b) Since $X$ has a Binomial distribution, we have $E[X]=N(1-p)=100(1-p)$. Using the natural approximation

$$
\frac{\sum_{i=1}^{n} X_{i}}{n} \simeq E[X]=100(1-p)
$$

we obtain the natural estimator $\tilde{p}=1-\frac{\sum_{i=1}^{n} X_{i}}{100 n}$.
c) The likelihood function is defined by $L\left(p ; x_{1}, \ldots, x_{n}\right)=$ the probability to observe the sequence $x_{1}, \ldots, x_{n}$. Since the $X_{i}$, with $1 \leq i \leq n$, are independent, we get

$$
L\left(p ; x_{1}, \ldots, x_{n}\right)=\prod_{i=1}^{n}\binom{100}{x_{i}} q^{x_{i}}(1-q)^{100-x_{i}}=\prod_{i=1}^{n}\binom{100}{x_{i}}(1-p)^{x_{i}} p^{100-x_{i}}
$$

which yields a log-likelihood function given by

$$
\log L\left(p ; x_{1}, \ldots, x_{n}\right)=\sum_{i=1}^{n}\binom{100}{x_{i}}+x_{i} \log (1-p)+\left(100-x_{i}\right) \log (p)
$$

Taking its derivative with respect to $p$ and setting it equal to 0 , gives then the maximum likelihood estimator $\widehat{p}$ :

$$
\begin{aligned}
& \frac{\partial \log L\left(p ; x_{1}, \ldots, x_{n}\right)}{\partial p}=\sum_{i=1}^{n}\left(-\frac{x_{i}}{1-p}+\frac{100-x_{i}}{p}\right)=0 \\
\Longleftrightarrow & \left(100 n-s_{n}\right)(1-p)=s_{n} p \Longleftrightarrow 100 n-s_{n}=100 n p \\
\Longleftrightarrow & p=1-\frac{s_{n}}{100 n}
\end{aligned}
$$

where $s_{n}=\sum_{i=1}^{n} x_{i}$. Consequently, we have $\widehat{p}=1-\frac{\sum_{i=1}^{n} X_{i}}{100 n}$.
REmARK: This yields the same estimator as in part b).
d) We clearly have $n=1+64+20+15=100$, and $s_{n}=100 n-1 \cdot 0-64 \cdot 1-20 \cdot 2-15 \cdot 3=$ $10^{\prime} 000-149=9^{\prime} 851$. Therefore, we get

$$
p^{*}=\frac{100 n-s_{n}}{100 n}=\frac{149}{10000}=0.0149
$$

e) Let us calculate

$$
\begin{aligned}
& E[\widehat{p}]=\frac{100 n-\sum_{i=1}^{n} E\left[X_{i}\right]}{100 n} \stackrel{E\left[X_{i}\right]=100(1-p)}{=} \frac{100 n-100 n(1-p)}{100 n}=p, \\
& \operatorname{Var}(\widehat{p})=\frac{\operatorname{Var}\left(\sum_{i=1}^{n} X_{i}\right)}{(100 n)^{2}} \stackrel{\text { indep. }}{=} \frac{\sum_{i=1}^{n} \operatorname{Var}\left(X_{i}\right)}{(100 n)^{2}} \stackrel{\text { a) }}{=} \frac{100 n(1-p) p}{(100 n)^{2}}=\frac{(1-p) p}{100 n} .
\end{aligned}
$$

Hence, we get

$$
\frac{p^{*}-E[\widehat{p}]}{\sqrt{\operatorname{Var}(\widehat{p})}}=\frac{\sqrt{100 n}\left(p^{*}-p\right)}{\sqrt{(1-p) p}}=\frac{100(0.0049)}{\sqrt{0.99} \sqrt{0.01}} \sim \frac{0.49}{0.1}=4.9
$$

Clearly, under the assumption $p=0.01$, the likelihood of observing $p^{*}$ is very small, since it is roughly 4.9 standard deviations away from its expected value. Therefore, it doesn't support the vendor's claim and indicates that the true value of $p$ is larger than 0.01 .

