## MATH 556 - Assignment 3 Solutions

1 (a) (i) This is not an Exponential Family distribution; the support is parameter dependent.
1 Mark
(ii) This is an EF distribution with $k=1$ :

$$
f(x \mid \theta)=\frac{I_{\{1,2,3, \ldots\}}(x)}{x} \frac{-1}{\log (1-\theta)} \exp \{x \log \theta\}=h(x) c(\theta) \exp \{w(\theta) t(x)\}
$$

where $\quad h(x)=\frac{I_{\{1,2,3, \ldots\}}(x)}{x} \quad c(\theta)=\frac{-1}{\log (1-\theta)} \quad w(\theta)=\log (\theta) \quad t(x)=x$,
so the natural parameter is $\eta=\log (\theta)$.
2 Marks
(iii) This is an EF distribution with $k=2$ :

$$
\begin{aligned}
f(x \mid \phi, \lambda) & =\frac{I_{(0, \infty)}(x)}{\left(2 \pi x^{3}\right)^{1 / 2}} \sqrt{\lambda} e^{\phi} \exp \left\{-\frac{\phi^{2}}{2 \lambda} x-\frac{\lambda}{2} \frac{1}{x}\right\} \\
& =h(x) c(\phi, \lambda) \exp \left\{w_{1}(\phi, \lambda) t_{1}(x)+w_{2}(\phi, \lambda) t_{2}(x)\right\}
\end{aligned}
$$

where

$$
h(x)=\frac{I_{(0, \infty)}(x)}{\left(2 \pi x^{3}\right)^{1 / 2}} \quad c(\phi, \lambda)=\sqrt{\lambda} e^{\phi}
$$

and

$$
w_{1}(\phi, \lambda)=-\frac{\phi^{2}}{2 \lambda} \quad w_{2}(\phi, \lambda)=-\frac{\lambda}{2} \quad t_{1}(x)=x \quad t_{2}(x)=\frac{1}{x},
$$

so the natural parameter is $\underset{\sim}{\eta}=\left(\eta_{1}, \eta_{2}\right)^{\top}$ where

$$
\eta_{1}=-\phi^{2} / 2 \lambda \quad \eta_{2}=-\lambda / 2
$$

2 Marks
In the natural parameterization

$$
c^{\star}\left(\eta_{1}, \eta_{2}\right)=\sqrt{-2 \eta_{2}} \exp \left\{2 \sqrt{\eta_{1} \eta_{2}}\right\}
$$

so, using the results from lectures

$$
E_{f_{X}}[1 / X]=E_{f_{X}}\left[t_{2}(X)\right]=-\frac{\partial}{\partial \eta_{2}} \log c^{\star}\left(\eta_{1}, \eta_{2}\right) .
$$

We have

$$
\log c^{\star}\left(\eta_{1}, \eta_{2}\right)=\frac{1}{2} \log \left(-2 \eta_{2}\right)+2 \sqrt{\eta_{1} \eta_{2}}
$$

and hence

$$
\begin{aligned}
E_{f_{X}}[1 / X] & =-\frac{\partial}{\partial \eta_{2}}\left\{\frac{1}{2} \log \left(-2 \eta_{2}\right)+2 \sqrt{\eta_{1} \eta_{2}}\right\}=-\left\{\frac{1}{2} \frac{1}{-2 \eta_{2}}(-2)+2 \sqrt{\frac{\eta_{1}}{\eta_{2}}} \frac{1}{2}\right\} \\
& =-\frac{1}{2 \eta_{2}}-\sqrt{\frac{\eta_{1}}{\eta_{2}}}=\frac{1}{\lambda}+\frac{\phi}{\lambda}
\end{aligned}
$$

(b) (i) We can re-write $f_{X}$ as

$$
f_{X}(x \mid \eta)=h(x) \exp \{\eta t(x)-\kappa(\eta)\}
$$

where $\kappa(\eta)=-\log c^{\star}(\eta)$, and by integrating with respect to $x$, we note that

$$
\int h(x) \exp \{\eta t(x)\} d x=\exp \{\kappa(\eta)\}
$$

for $\eta \in \mathcal{H}$ as given in lectures. Thus, for $s$ in a suitable neighbourhood of zero, we have

$$
\begin{aligned}
M_{T}(s) & =E_{f_{X}}\left[e^{s t(X)}\right]=\int e^{s t(x)} h(x) \exp \{\eta t(x)-\kappa(\eta)\} d x \\
& =\exp \{-\kappa(\eta)\} \int h(x) \exp \{t(x)(\eta+s)\} d x=\exp \{-\kappa(\eta)\} \exp \{\kappa(\eta+s)\}
\end{aligned}
$$

as $\eta \in \mathcal{H} \Longrightarrow \eta+s \in \mathcal{H}$ for $s$ small enough, as $\mathcal{H}$ is open. Hence, as $K_{T}(s)=\log M_{T}(s)$,

$$
K_{T}(s)=\kappa(\eta+s)-\kappa(\eta)
$$

for $s \in(-h, h)$, some $h>0$ as required.
4 Marks
(ii) By inspection

$$
\ell\left(x ; \eta_{1}, \eta_{2}\right)=\left(\eta_{1}-\eta_{2}\right) t(x)-\left(\kappa\left(\eta_{1}\right)-\kappa\left(\eta_{2}\right)\right)
$$

2 MARKS
2 By iterated expectation

$$
E_{f_{X_{1}}}\left[X_{1}\right]=E_{f_{M}}\left[E_{f_{X_{1} \mid M}}\left[X_{1} \mid M=m\right]\right]=E_{f_{M}}[M]=\mu
$$

and

$$
E_{f_{X_{1}}}\left[X_{1}^{2}\right]=E_{f_{M}}\left[E_{f_{X_{1} \mid M}}\left[X_{1}^{2} \mid M=m\right]\right]=E_{f_{M}}\left[M^{2}+\sigma^{2}\right]=\mu^{2}+\tau^{2}+\sigma^{2}
$$

so that

$$
\operatorname{Var}_{f_{X_{1}}}\left[X_{1}\right]=E_{f_{X_{1}}}\left[X_{1}^{2}\right]-\left\{E_{f_{X_{1}}}\left[X_{1}\right]\right\}^{2}=\tau^{2}+\sigma^{2}
$$

By symmetry

$$
E_{f_{X_{2}}}\left[X_{2}\right]=\mu \quad \operatorname{Var}_{f_{X_{2}}}\left[X_{2}\right]=\tau^{2}+\sigma^{2}
$$

Now,
$E_{f_{X_{1}, X_{2}}}\left[X_{1} X_{2}\right]=E_{f_{M}}\left[E_{f_{X_{1}, X_{2} \mid M}}\left[X_{1} X_{2} \mid M=m\right]\right]=E_{f_{M}}\left[E_{f_{X_{1} \mid M}}\left[X_{1} \mid M=m\right] \times E_{f_{X_{2} \mid M}}\left[X_{2} \mid M=m\right]\right]$ by conditional independence. Therefore

$$
E_{f_{X_{1}, X_{2}}}\left[X_{1} X_{2}\right]=E_{f_{M}}[M \times M]=E_{f_{M}}\left[M^{2}\right]=\mu^{2}+\tau^{2}
$$

Hence

$$
\operatorname{Cov}_{f_{X_{1}, X_{2}}}\left[X_{1}, X_{2}\right]=E_{f_{X_{1}, X_{2}}}\left[X_{1} X_{2}\right]-E_{f_{X_{1}}}\left[X_{1}\right] E_{f_{X_{2}}}\left[X_{2}\right]=\mu^{2}+\tau^{2}-\mu^{2}=\tau^{2}
$$

and

$$
\operatorname{Corr}_{f_{X_{1}, X_{2}}}\left[X_{1}, X_{2}\right]=\frac{\operatorname{Cov}_{f_{X_{1}, X_{2}}}\left[X_{1}, X_{2}\right]}{\sqrt{\operatorname{Var}_{f_{X_{1}}}\left[X_{1}\right] \operatorname{Var}_{f_{X_{2}}}\left[X_{2}\right]}}=\frac{\tau^{2}}{\tau^{2}+\sigma^{2}}
$$

5 Marks
$X_{1}$ and $X_{2}$ are not independent; their covariance is non zero.
1 MARK

