## TEL502E - Homework 1

## Due 01.03.2016

1. Suppose $X_{1}, X_{2}$ are independent variables uniformly distributed over $[0, \theta]$, where $\theta>0$ is an unknown constant. In order to estimate $\theta$, two estimators are proposed.

$$
\theta_{1}=X_{1}+X_{2}, \quad \theta_{2}=\max \left(X_{1}, X_{2}\right)
$$

(a) Determine whether $\theta_{1}$ is unbiased or not. If it is biased, modify it to obtain an unbiased estimator.
(b) Determine whether $\theta_{2}$ is unbiased or not. If it is biased, modify it to obtain an unbiased estimator.
(c) Compare the variances of the estimators you found in parts (a) and (b). Which would you prefer to use?

Solution. (a) Notice that $\mathbb{E}\left(X_{1}\right)=\mathbb{E}\left(X_{2}\right)=\theta / 2$. Therefore, $\mathbb{E}\left(\theta_{1}\right)=\theta$ and $\theta_{1}$ is unbiased.
(b) Let us find the pdf of $\theta_{2}$ first. We will use the pdf for part (c) also. Note that the $\operatorname{cdf}$ of $\theta_{2}$ is given as,

$$
\begin{aligned}
F_{\theta_{2}}(t) & =P\left(\theta_{2} \leq t\right) \\
& =P\left(\left(X_{1} \leq t\right) \cap\left(X_{2} \leq t\right)\right) \\
& =P\left(\left(X_{1} \leq t\right)\right) P\left(\left(X_{2} \leq t\right)\right) \\
& = \begin{cases}0, & \text { if } t<0 \\
t^{2} / \theta^{2}, & \text { if } 0 \leq t \leq \theta, \\
1, & \text { if } \theta<t .\end{cases}
\end{aligned}
$$

Differentiating, we find $f_{\theta_{2}}$ as,

$$
f_{\theta_{2}}(t)= \begin{cases}2 t / \theta^{2}, & \text { if } 0 \leq t \leq \theta \\ 0, & \text { otherwise }\end{cases}
$$

We now compute $\mathbb{E}\left(\theta_{2}\right)$ as,

$$
\mathbb{E}\left(\theta_{2}\right)=\int_{0}^{\theta} t \frac{2 t}{\theta^{2}} d t=\frac{2}{3} \theta
$$

Therefore $\theta_{2}$ is biased, but $\tilde{\theta}_{2}=\frac{3}{2} \theta_{2}$ is unbiased.
(c) First, note that by independence of $X_{1}, X_{2}$, we have,

$$
\mathbb{E}\left(\theta_{1}^{2}\right)=\mathbb{E}\left(X_{1}\right)^{2}+\mathbb{E}\left(X_{1}\right)^{2}+2 \mathbb{E}\left(X_{1}\right) \mathbb{E}\left(X_{2}\right)=\frac{\theta^{2}}{3}+\frac{\theta^{2}}{3}+\frac{\theta^{2}}{2}=\frac{7}{6} \theta^{2}
$$

Therefore, $\operatorname{var}\left(\theta_{1}\right)=\frac{1}{6} \theta^{2}$.
Notice now that,

$$
\mathbb{E}\left(\tilde{\theta}_{2}^{2}\right)=\frac{9}{4} \mathbb{E}\left(\theta_{2}^{2}\right)=\frac{9}{4} \int_{0}^{\theta} t^{2} \frac{2 t}{\theta^{2}} d t=\frac{9}{8} \theta^{2}
$$

Therefore $\operatorname{var}\left(\tilde{\theta}_{2}\right)=\frac{1}{8} \theta^{2}$.
Since

$$
\operatorname{var}\left(\tilde{\theta}_{2}\right)<\operatorname{var}\left(\theta_{1}\right), \quad \text { for all } \theta,
$$

I would prefer $\tilde{\theta}_{2}$.
2. Show that if $\operatorname{var}(X)=0$ for a random variable, then $X=\mathbb{E}(X)$ (i.e., $X$ is a constant).

Solution. This is an application of Chebyshev's inequality. But let us show it for a special case, using the Cauchy-Schwarz inequality (CSI).
Suppose var $X=0$ and $X$ is a contiunous random variable with a pdf $f_{X}(t)$ that is non-zero in some interval $I$. Using the decomposition

$$
t f_{X}(t)=\left[t \sqrt{f_{X}(t)}\right]\left[\sqrt{f_{X}(t)}\right]
$$

we have, by CSI,

$$
(\mathbb{E}(X))^{2}=\left[\int t f_{X}(t) d t\right]^{2} \leq\left[\int t^{2} f_{X}(t) d t\right] \underbrace{\left[\int f_{X}(t) d t\right]}_{=1}
$$

Recall that, in order for this to hold with equality, we must have,

$$
t \sqrt{f_{X}(t)}=c \sqrt{f_{X}(t)}, \quad \text { for all } t
$$

where $c$ is a non-zero constant. But since $f_{X}(t)$ is a non-zero function that integrates to 1 , this is not possible (why?). Therefore, $[\mathbb{E}(X)]^{2}<\mathbb{E}\left(X^{2}\right)$. Thus, $\operatorname{var}(X)=\mathbb{E}\left(X^{2}\right)-[\mathbb{E}(X)]^{2}>0$, which contradicts the assumption.
3. Suppose $X$ is distributed as $\mathcal{N}\left(0, \sigma^{2}\right)$. Notice that $X^{2}$ is an unbiased estimator for $\sigma^{2}$. But suppose we are interested in $\sigma$ and not $\sigma^{2}$. Is $|X|$ an unbiased estimator for $\sigma$ ?
(Hint: You do not need to evaluate $\mathbb{E}(|X|)$ to answer this question.)
Solution. Suppose $Z=|X|$ is an unbiased estimator of $\sigma$, that is, $\mathbb{E}(|X|)=\sigma$. Observe that $\mathbb{E}\left(Z^{2}\right)=$ $\mathbb{E}\left(X^{2}\right)=\sigma^{2}$. Thus, $\operatorname{var}(Z)=\mathbb{E}\left(Z^{2}\right)-[\mathbb{E}(Z)]^{2}=0$. But this means, by Q 2 that $Z=|X|=0$, which is clearly not the case. Therefore, $\mathbb{E}(|X|) \neq \sigma$ and $|X|$ is biased as an estimator $\sigma$. In fact, we have $\mathbb{E}(|X|)<\sigma$ (why?).
4. Suppose $X_{1}$ and $X_{2}$ are independent random variables distributed as $\mathcal{N}(\sqrt{\theta}, \theta)$. Two estimators are proposed for $\theta$ :

$$
\theta_{1}=X_{1} X_{2}, \quad \theta_{2}=X_{1}^{2}+X_{2}^{2}
$$

(a) Determine whether $\theta_{1}$ is unbiased or not. If it is biased, modify it to obtain an unbiased estimator.
(b) Determine whether $\theta_{2}$ is unbiased or not. If it is biased, modify it to obtain an unbiased estimator.
(c) Compare the variances of the estimators you found in parts (a) and (b). Which would you prefer?
(Note : You might need the fourth moments of a Gaussian random variable for this part.)
Solution. (a) Observe that

$$
\mathbb{E}\left(\theta_{1}\right)=\mathbb{E}\left(X_{1} X_{2}\right)=\mathbb{E}\left(X_{1}\right) \mathbb{E}\left(X_{2}\right)=\theta
$$

Thus $\theta_{1}$ is unbiased.
(b) First notice that $\operatorname{var}\left(X_{1}\right)=\mathbb{E}\left(X_{1}^{2}\right)-\left(\mathbb{E}\left(X_{1}\right)\right)^{2}=\theta$. Since $\mathbb{E}\left(X_{1}\right)=\sqrt{\theta}$, it follows that $\mathbb{E}\left(X_{1}^{2}\right)=2 \theta$. Similarly, $\mathbb{E}\left(X_{2}^{2}\right)=2 \theta$. Now,

$$
\mathbb{E}\left(\theta_{2}\right)=\mathbb{E}\left(X_{1}^{2}+X_{2}^{2}\right)=\mathbb{E}\left(X_{1}^{2}\right) \mathbb{E}\left(X_{2}^{2}\right)=4 \theta
$$

Thus $\theta_{2}$ is biased, but we can derive an unbiased estimator from $\theta_{2}$ as, $\tilde{\theta}_{2}=\theta_{2} / 4$.
(c) Notice that

$$
\mathbb{E}\left(\theta_{1}^{2}\right)=\mathbb{E}\left(X_{1}^{2}\right) \mathbb{E}\left(X_{2}^{2}\right)=4 \theta^{2}
$$

Thus, $\operatorname{var}\left(\theta_{1}\right)=3 \theta^{2}$.
For the second estimator, we have (check this!),

$$
\mathbb{E}\left(\tilde{\theta}_{2}^{2}\right)=\mathbb{E}\left(\frac{1}{16}\left(X_{1}^{4}+X_{2}^{4}+2 X_{1}^{2} X_{2}^{2}\right)=\frac{7}{4} \theta^{2}\right.
$$

Thus, $\operatorname{var}\left(\tilde{\theta}_{2}\right)=\frac{3}{4} \theta^{2}$. Observe that

$$
\operatorname{var}\left(\tilde{\theta}_{2}\right)<\operatorname{var}\left(\theta_{1}\right), \quad \text { for all } \theta
$$

Thus, I would prefer $\tilde{\theta}_{2}$.
5. Suppose $X_{1}$ and $X_{2}$ are independent random variables distributed as $\mathcal{N}(2 \theta, 1)$ and $\mathcal{N}(3 \theta, 1)$ respectively, where $\theta$ is an unknown parameter.
(a) Write down the joint pdf of $X_{1}$ and $X_{2}$.
(b) Compute the Fisher information for $\theta$, that is,

$$
I(\theta)=\mathbb{E}\left(\left[\partial_{\theta}\left(\ln f\left(X_{1}, X_{2} ; \theta\right)\right)\right]^{2}\right)
$$

where $f\left(X_{1}, X_{2} ; \theta\right)$ denotes the joint pdf of $X_{1}$ and $X_{2}$.
(c) Find the UMVUE for $\theta$ in terms of $X_{1}$ and $X_{2}$.

Solution. (a) The joint pdf is,

$$
f\left(x_{1}, x_{2} ; \theta\right)=\frac{1}{2 \pi} \exp \left(-\frac{1}{2}\left(\left(x_{1}-2 \theta\right)^{2}-\left(x_{2}-3 \theta\right)^{2}\right)\right)
$$

(b) Notice that

$$
\partial_{\theta}\left(\ln f\left(x_{1}, x_{2} ; \theta\right)\right)=2\left(x_{1}-2 \theta\right)+3\left(x_{2}-3 \theta\right)=13\left(\frac{2 x_{1}+3 x_{2}}{13}-\theta\right)
$$

Observe now that if $Z=\left(2 X_{1}+3 X_{2}\right) / 13$, then $\mathbb{E}(Z)=\theta$. Thus, $I(\theta)=13^{2} \operatorname{var}(Z)$. But since $X_{1}$ and $X_{2}$ are independent, $\operatorname{var}(Z)=(2 / 13)^{2} \operatorname{var}\left(X_{1}\right)+(3 / 13)^{2} \operatorname{var}\left(X_{2}\right)=1 / 13$. Thus $I(\theta)=13$.
(c) In part (b), we found that,

$$
\partial_{\theta}\left(\ln f\left(x_{1}, x_{2} ; \theta\right)\right)=I(\theta)(z-\theta)
$$

where $z=\frac{2 x_{1}+3 x_{2}}{13}$. Thus, the unbiased estimator $Z=\frac{2 X_{1}+3 X_{2}}{13}$ satisfies the CRLB and must be the UMVUE.

