## Problem Set 3

1. Let $p(x, \theta), \theta \in \mathbb{R}$ be a parametric family of densities, and consider the two parameter family

$$
\begin{equation*}
g\left(x ; \theta_{1}, \theta_{2}\right)=p\left(x, \theta_{1}+\theta_{2}\right),\left(\theta_{1}, \theta_{2}\right) \in \mathbb{R}^{2} \tag{1}
\end{equation*}
$$

In the following, we assume the usual regularity of the density that, for instance, allows differentiation under the integeral.
(a) Compute the score functions $U_{1}\left(\theta_{1}, X\right)$ and $U_{2}\left(\theta_{2}, X\right)$ for model (1) and show that they have correlation one, and hence that the information matrix will be singular.
(b) Show that the parameters $\theta_{1}$ and $\theta_{2}$ in model (1) are not identifiable.
2. Compute the variance lower bound provided by the information inequality for the unbiased estimation of the 'signal to noise' parameter

$$
q\left(\mu, \sigma^{2}\right)=\mu / \sigma
$$

when data is sampled independently from the normal $\mathcal{N}\left(\mu, \sigma^{2}\right)$ distribution with both parameters unknown.
3. (a) Let $\mathbf{u}_{1}$ and $\mathbf{u}_{2}$ be non-zero vectors in $\mathbf{R}^{n}$, and define the projection of $\mathbf{u}_{1}$ along $\mathbf{u}_{2}$ to be

$$
P_{\mathbf{u}_{2}} \mathbf{u}_{1}=\frac{\mathbf{u}_{2}}{\left\|\mathbf{u}_{2}\right\|}\left(\mathbf{u}_{1} \cdot \frac{\mathbf{u}_{2}}{\left\|\mathbf{u}_{2}\right\|}\right)
$$

Show that $\mathbf{u}_{2} \perp \mathbf{u}_{1}-P_{\mathbf{u}_{2}} \mathbf{u}_{1}$ and interpret this fact geometrically with a diagram.
(b) Show that

$$
\left\|\mathbf{u}_{1}-P_{\mathbf{u}_{2}} \mathbf{u}_{1}\right\|^{2}=\left\|\mathbf{u}_{1}\right\|^{2}-\frac{\left(\mathbf{u}_{1} \cdot \mathbf{u}_{2}\right)^{2}}{\left\|\mathbf{u}_{2}\right\|^{2}}
$$

(c) Consider a smooth density $p(\mathbf{x}, \theta), \theta \in \Theta \subset \mathbf{R}^{2}$. By inverting the information matrix $I=\left(I_{i j}\right)_{1 \leq i, j \leq 2}$, show that the Cramer Rao bound lower bound for estimating $\theta_{1}$ in the presence of $\theta_{2}$ is the reciprocal of

$$
I_{11}-\frac{I_{12}^{2}}{I_{22}}
$$

(d) For random variables $V, W$ define a dot product

$$
V \cdot W=E V W \quad \text { so that } \quad\|V\|^{2}=E V^{2}
$$

and orthogonality and projections can be defined as usual. Let $U_{1}=U\left(\mathbf{X}, \theta_{1}\right), U_{2}=U\left(\mathbf{X}, \theta_{2}\right)$ be score functions associated with $\theta_{1}, \theta_{2}$ respectively. Show that the lower bound for estimating $\theta_{1}$ in the presence of $\theta_{2}$ is the reciprocal of

$$
\left\|U_{1}-P_{U_{2}} U_{1}\right\|^{2}
$$

4. Consider $n$ independent observations of the linear regression model

$$
Y=\beta_{1} x_{1}+\beta_{2} x_{2}+\epsilon,
$$

where $\epsilon \sim \mathcal{N}\left(0, \sigma^{2}\right)$, and the vectors $\mathbf{x}_{1}, \mathbf{x}_{2}$ are not colinear. Determine the Information matrix for the unknown vector parameter $\left(\beta_{1}, \beta_{2}\right)$, and the effective information for the estimation of $\beta_{1}$ in the presence of $\beta_{2}$.
5. Let $X_{1}, \ldots, X_{m}$ be independent samples from the $\mathcal{U}[0, \theta]$ distribution with $\theta>0$ unknown. Here we consider the asymptotic behavior of $X_{(n)}$, the maximum likelihood estimator. Prove that there exists a sequence of positive constants $a_{n}$ and a non-trivial distribution on a random variable $X$ such that

$$
a_{n}\left(X_{(n)}-\theta\right) \rightarrow_{d} X,
$$

and determine $a_{n}$ and the distribution of $X$.

