1. Let $\boldsymbol{x}_{1}, \ldots, \boldsymbol{x}_{n} \in \mathbb{R}^{p}$ be known vectors (all vectors are column vectors in this problem) with $p \leq n$, let $\boldsymbol{\beta} \in \mathbb{R}^{p}$ be an unknown parameter vector, and let $Y_{1}, \ldots, Y_{n}$ be independent Bernoulli random variables such that

$$
\begin{equation*}
P_{\boldsymbol{\beta}}\left(Y_{i}=1\right)=1-P_{\boldsymbol{\beta}}\left(Y_{i}=0\right)=\Phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right), \quad i=1, \ldots, n \tag{1}
\end{equation*}
$$

where $\Phi$ denotes the c.d.f. of the standard normal distribution and "prime" denotes transpose. This problem concerns using the EM algorithm to find the MLE of $\boldsymbol{\beta}$ from the data $\boldsymbol{Y}=\left(Y_{1}, Y_{2}, \ldots, Y_{n}\right)^{\prime}$.
(a) Show that if $\varepsilon_{1}, \ldots, \varepsilon_{n}$ are i.i.d. standard normals and $W_{i}=\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}+\varepsilon_{i}, i=1, \ldots, n$, then

$$
\begin{equation*}
Y_{i}=\mathbf{1}\left\{W_{i}>0\right\}, \quad i=1, \ldots, n \tag{2}
\end{equation*}
$$

have the distribution (1). For the rest of this problem assume the $Y_{i}$ are defined by (2) and observed but that the $W_{i}$ and $\varepsilon_{i}$ are unobserved.
(b) Show that the complete log-likelihood function $\ell_{c}(\boldsymbol{\beta})$ of $W_{1}, \ldots, W_{n}$, if they were observed, is given by

$$
\ell_{c}(\boldsymbol{\beta})=-\frac{1}{2} \sum_{i=1}^{n}\left(W_{i}-\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right)^{2}
$$

up to additive constants.
(c) The E step of the EM algorithm involves computing

$$
Q(\widetilde{\boldsymbol{\beta}}, \boldsymbol{\beta})=E_{\boldsymbol{\beta}}\left[\ell_{c}(\widetilde{\boldsymbol{\beta}}) \mid \boldsymbol{Y}\right] .
$$

Show that

$$
\begin{equation*}
E_{\boldsymbol{\beta}}\left[\left(W_{i}-\boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\right)^{2} \mid \boldsymbol{Y}\right]=E_{\boldsymbol{\beta}}\left[\left(W_{i}-\boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\right)^{2} \mid Y_{i}\right] \tag{3}
\end{equation*}
$$

and, up to additive terms $C, C^{\prime}$ that don't depend on $\widetilde{\boldsymbol{\beta}}$, that

$$
\begin{align*}
& E_{\boldsymbol{\beta}}\left[\left(W_{i}-\boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\right)^{2} \mid Y_{i}=1\right]=\left(\boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\right)^{2}-2 \boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}+\frac{\phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right)}{\Phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right)}\right)+C, \quad \text { and }  \tag{4}\\
& E_{\boldsymbol{\beta}}\left[\left(W_{i}-\boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\right)^{2} \mid Y_{i}=0\right]=\left(\boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\right)^{2}-2 \boldsymbol{x}_{i}^{\prime} \widetilde{\boldsymbol{\beta}}\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}-\frac{\phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right)}{\Phi\left(-\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right)}\right)+C^{\prime}, \tag{5}
\end{align*}
$$

where $\phi$ is the standard normal density function. You don't have to explicitly find $C, C^{\prime}$.
(d) Let $\boldsymbol{X}$ be the $(n \times p)$ matrix with rows $\boldsymbol{x}_{1}^{\prime}, \ldots, \boldsymbol{x}_{n}^{\prime}$, assumed to be of full rank $p$, and let $\boldsymbol{v}=\boldsymbol{v}(\boldsymbol{\beta})$ be the $n$-long vector with entries

$$
v_{i}= \begin{cases}\phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right) / \Phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right), & \text { if } Y_{i}=1 \\ -\phi\left(\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right) / \Phi\left(-\boldsymbol{x}_{i}^{\prime} \boldsymbol{\beta}\right), & \text { if } Y_{i}=0\end{cases}
$$

Show that the recursion for the EM iterates $\left\{\boldsymbol{\beta}^{(k)}\right\}$ given by maximizing $Q(\widetilde{\boldsymbol{\beta}}, \boldsymbol{\beta})$ over $\widetilde{\boldsymbol{\beta}}$ is

$$
\begin{equation*}
\boldsymbol{\beta}^{(k+1)}=\boldsymbol{\beta}^{(k)}+\left(\boldsymbol{X}^{\prime} \boldsymbol{X}\right)^{-1} \boldsymbol{X}^{\prime} \boldsymbol{v}\left(\boldsymbol{\beta}^{(k)}\right) \tag{6}
\end{equation*}
$$

Hint: Write $Q(\widetilde{\boldsymbol{\beta}}, \boldsymbol{\beta})$ in matrix notation using $\boldsymbol{X}$ and $\boldsymbol{v}$ and then maximize over $\widetilde{\boldsymbol{\beta}}$.
2. Let $\theta \sim N(0,1)$ and, conditional on $\theta$, let $Y_{i} \sim N(\theta, 1), i=1,2, \cdots, n$ be i.i.d. Let $\bar{Y}=\sum_{i=1}^{n} Y_{i} / n$.
(a) Compute the density function of $\bar{Y}$.
(b) Compute the posterior distribution of $\theta$ given $\bar{Y}$.
(c) Compute the conditional expectation $E[\theta \mid \bar{Y}]$, and determine the behavior of the posterior distribution of $\theta$ as $n \rightarrow \infty$.

