## LINEAR MODELS AND GLM: ASSIGNMENT 2

Exercise 1. We have defined multivariate Normality as follows: $\boldsymbol{x}=\boldsymbol{\mu}+\mathbf{A} \boldsymbol{z} \sim \mathcal{N}\left(\boldsymbol{\mu}, \mathbf{A A}^{\prime}\right)$ if components of $\boldsymbol{z}$ are i.i.d. standard Normal.
(a) (1 point) Show that if $\boldsymbol{x}$ follows a multivariate Normal distribution by this definition, then $\boldsymbol{\ell}^{\prime} \boldsymbol{x}$ is univariate normal for all $\boldsymbol{\ell}$.
(b) (3 points) Show the converse, that is, if $\boldsymbol{x}$ is a random vector with the property that $\boldsymbol{\ell}^{\prime} \boldsymbol{x}$ is univariate normal for all $\boldsymbol{\ell}$, then $\boldsymbol{x}$ has a multivariate Normal distribution.
You may assume $\boldsymbol{\mu}=\mathbf{0}$.
Exercise 2. (2 points) Prove that for a real symmetric matrix, eigenvectors corresponding to distinct eigenvalues are orthogonal.
Exercise 3. (2 points) For a linear model $\left(\boldsymbol{y}, \mathbf{X} \boldsymbol{\beta}, \sigma^{2} \mathbf{I}\right)$, write $H_{0}: \boldsymbol{\beta} \in \mathcal{C}(\mathbf{B})$ as $H_{0}: \mathbf{H}^{\prime} \boldsymbol{\beta}=\mathbf{0}$ for some $\mathbf{H}^{\prime}$.
Exercise 4. The theory of likelihood ratio tests tells us that under certain regularity conditions, $-2 \log \Lambda(\boldsymbol{y})$ has an asymptotic $\chi_{k}^{2}$ distribution under the null hypothesis, where $\Lambda(\boldsymbol{y})$ is the likelihood ratio and $k$ is the difference in the degrees of freedom of the full and restricted models.
(a) (4 points) Show that this result holds in the linear model case (without invoking the general LRT result).
(b) (1 point) Is the result exact for finite sample size?

Your solution does not have to be mathematically rigorous.
Exercise 5. Let $X_{1}, \ldots, X_{n} \sim \mathcal{N}\left(\mu, \sigma^{2}\right)$. Consider the problem of estimating $\sigma^{2}$.
(a) (1 point) Is the maximum likelihood estimate of $\sigma^{2}$ unbiased? If not, can it be made unbiased by multiplying it with a scalar?
(b) (4 points) What is the MSE of the MLE? How does it compare to the MSE of the unbiased estimate? The mean squared error of an estimator $\hat{\theta}$ of $\theta$ is defined as $\operatorname{MSE}(\hat{\theta}):=E\left((\hat{\theta}-\theta)^{2}\right)$

Exercise 6. Consider the VADeaths dataset available in $R$, which is a two-way classification with one observation per cell (see ?VADeaths for details).

```
> names(dimnames(VADeaths)) <- c("AgeGroup", "PopGroup")
> VADeaths
            PopGroup
AgeGroup Rural Male Rural Female Urban Male Urban Female
    50-54 1.7.7 11.7 8.7 15.4 1.7 
    55-59 1.lllll
    60-64 1.0.9 20.3 1.0
    65-69 [41.0 
    70-74 [rlll
```

Convert it into a data frame as follows:

```
> VADeaths.df <- as.data.frame(as.table(VADeaths), responseName = "DeathRate")
```

Figure 1 gives a plot of the data.
Date: 12 February, 2010.

```
> library(lattice)
> dotplot(DeathRate ~ reorder(PopGroup, DeathRate), data = VADeaths.df,
            groups = AgeGroup, type = c("p", "a"), auto.key = list(columns = 3))
                        50-54 ○ 60-64 \nabla 70-74 \diamond
                    55-59 + 65-69 口
```



Figure 1. A plot of the VADeaths data.
(a) (2 points) Compute the ANOVA table for a two-way classification without interaction (either by hand, or using $R$ ). Which factors are significant?
(b) (3 points) Create a plot corresponding to Figure 1, but replace the observed values with the fitted values. This is roughly what an additive model would have looked like (except for i.i.d. errors).
(c) (3 points) Does the plot suggest the presence of an interaction? How can we test for the interaction? How else can we improve the fit?

Exercise 7. (4 points) Consider the following linear model:

$$
y_{i}=\alpha+\beta f\left(x_{i, n}\right)+\varepsilon_{i}, \quad 1 \leq i \leq n
$$

where $f:[0,1] \rightarrow \mathbb{R}$ is a function, $x_{i, n}:=i / n, 1 \leq i \leq n$ and $\left(\varepsilon_{1}, \varepsilon_{2}, \ldots, \varepsilon_{n}\right)$ are uncorrelated with mean zero and variance $\sigma^{2}$.
(a) Find a sufficient condition for both $\alpha$ and $\beta$ to be estimable for every $n \geq 2$.
(b) Find LSEs of $\alpha$ and $\beta$ when they are estimable.
(c) Find the residual sum of squares for this model.

Exercise 8. (0 points) Verify the following results (assuming all relevant inverses exist):

$$
\begin{aligned}
{\left[\begin{array}{ll}
\mathbf{A} & \mathbf{B} \\
\mathbf{C} & \mathbf{D}
\end{array}\right]^{-1} } & =\left[\begin{array}{cc}
\mathbf{A}^{-1}+\mathbf{A}^{-1} \mathbf{B E}^{-1} \mathbf{C A}^{-1} & -\mathbf{A}^{-1} \mathbf{B E}^{-1} \\
-\mathbf{E}^{-1} \mathbf{C} \mathbf{A}^{-1} & \mathbf{E}^{-1}
\end{array}\right] \\
& =\left[\begin{array}{cc}
\mathbf{F}^{-1} & -\mathbf{F}^{-1} \mathbf{B D}^{-1} \\
-\mathbf{D}^{-1} \mathbf{C F}^{-1} & \mathbf{D}^{-1}+\mathbf{D}^{-1} \mathbf{C F}^{-1} \mathbf{B D}^{-1}
\end{array}\right]
\end{aligned}
$$

where $\mathbf{E}=\mathbf{D}-\mathbf{C A}^{-1} \mathbf{B}$ and $\mathbf{F}=\mathbf{A}-\mathbf{B D}^{-1} \mathbf{C}$.
Exercise 9. Consider the problem of overfitting in a linear model. Suppose that the observations $\boldsymbol{y}$ is correctly modeled by $\left(\boldsymbol{y}, \mathbf{X}_{1} \boldsymbol{\beta}_{1}, \sigma^{2} \mathbf{I}\right)$, but one has fit the model $\left(\boldsymbol{y}, \mathbf{X}_{1} \boldsymbol{\beta}_{1}+\mathbf{X}_{2} \boldsymbol{\beta}_{2}, \sigma^{2} \mathbf{I}\right)$ with some extra terms given by $\mathbf{X}_{2}$. Assume that both $\mathbf{X}_{1}$ and $\mathbf{X}=\left[\mathbf{X}_{1} \mid \mathbf{X}_{2}\right]$ are of full column rank.
(a) (2 points) Show that the least squares estimates of $\boldsymbol{\beta}_{1}$ and $\sigma^{2}$ obtained from the overfitted model are unbiased.
(b) (4 points) Show that the variance-covariance matrix of the least square estimate of $\boldsymbol{\beta}_{1}$ obtained from the overfitted model is larger than that of the estimate obtained from the correct model (larger in the sense that the difference is n.n.d.).

