## STATS 413 PROBLEM SET 3

This problem set is due at noon ET on Sep 30, 2021. Please upload your solutions to Canvas in two files: a PDF file containing the solutions and a ZIP file containing code that reproduces any computer output in the solutions. You are encouraged to collaborate on problem sets with your classmates, but the final write-up (including any code) must be your own.

1. Deviation-from-the-mean regression. Consider a fitting linear model that includes an intercept term. This is equivalent to augmenting the vector of covariates with a constant feature and the vector of regression coefficients with the intercept term:

$$
\mathbb{E}\left[\mathbf{y}_{i} \mid \mathbf{x}_{i}\right]=\beta_{1}^{*}+x_{i}^{T} \beta_{2}^{*}=\left[\begin{array}{c}
1 \\
\mathbf{x}_{i}
\end{array}\right]^{T}\left[\begin{array}{l}
\beta_{1}^{*} \\
\beta_{2}^{*}
\end{array}\right] .
$$

The (augmented) matrix of covariates and vector of OLS coefficients (including the intercept term) has the form

$$
\mathbf{X}=\left[\begin{array}{ll}
1_{n} & \mathbf{X}_{2}
\end{array}\right]=\left[\begin{array}{cccc}
\mid & - & \mathbf{x}_{1}^{T} & - \\
1_{n} & & \vdots & \\
\mid & - & \mathbf{x}_{n}^{T} & -
\end{array}\right], \quad \widehat{\boldsymbol{\beta}}=\left[\begin{array}{c}
\widehat{\boldsymbol{\beta}}_{1} \\
\widehat{\boldsymbol{\beta}}_{2}
\end{array}\right] \underset{\text { scalar }}{\leftarrow} \quad \begin{aligned}
& \text { - } 1 \text {-vector }
\end{aligned}
$$

where $1_{n} \in \mathbf{R}^{n}$ is the vector of length $n$ whose entries are all one and $\mathbf{X}_{2}$ is the matrix whose rows are the $\mathbf{x}_{i}$ 's.
(a) Show that the normal equations $\mathbf{X}^{T}(\mathbf{y}-\mathbf{X} \widehat{\boldsymbol{\beta}})=0$ are equivalent to

$$
\begin{gathered}
\overline{\mathbf{y}}-\widehat{\boldsymbol{\beta}}_{1}-\overline{\mathbf{x}}_{2}^{T} \widehat{\boldsymbol{\beta}}_{2}=0, \\
\frac{1}{n} \mathbf{X}_{2}^{T} \mathbf{y}-\overline{\mathbf{x}}_{2} \widehat{\boldsymbol{\beta}}_{1}-\frac{1}{n} \mathbf{X}_{2}^{T} \mathbf{X}_{2} \widehat{\boldsymbol{\beta}}_{2}=0_{p-1} .
\end{gathered}
$$

where $\overline{\mathbf{y}}=\frac{1}{n} \mathbf{y}^{T} 1_{n}=\frac{1}{n} \sum_{i=1}^{n} \mathbf{y}_{i}$ is the sample mean of the response, $\overline{\mathbf{x}}_{2}=\frac{1}{n} \mathbf{X}_{2}^{T} 1_{n}$ is the (vector of) column means of the covariates (excluding the constant covariate), and $0_{p-1}$ is the vector of length $p-1$ whose entries are all zeros.

Solution: First note the general case:
Given $X^{T} X \beta=X^{T} y, \mathbf{X}=\left[\begin{array}{ll}\mathbf{X}_{1} & \mathbf{X}_{2}\end{array}\right]$ and $\beta=\left[\begin{array}{l}\beta_{1} \\ \beta_{2}\end{array}\right]$.
We can partition into the following:
(1) $X_{1}^{T} X_{1} \beta_{1}+X_{1}^{T} X_{2} \beta_{2}=X_{1}^{T} y$
(2) $X_{2}^{T} X_{1} \beta_{1}+X_{2}^{T} X_{2} \beta_{2}=X_{2}^{T} y$

Now solving for $\hat{\beta_{1}}$ from (1), we get $\hat{\beta_{1}}=\left(X_{1}^{T} X_{1}\right)^{-1} X_{1}^{T}\left(y-X_{2} \hat{\beta_{2}}\right)$
Now we can fill $X_{1}$ with $1_{n}$, and we get the following:
$\hat{\beta_{1}}=\left(1_{n}^{T} 1_{n}\right)^{-1} 1_{n}^{T}\left(y-X_{2} \hat{\beta_{2}}\right) \Rightarrow \hat{\beta_{1}}=\left(\frac{1}{n}\right) 1_{n}^{T}\left(y-X_{2} \hat{\beta_{2}}\right) \Rightarrow 0=\bar{y}-\overline{x_{2}} \hat{\beta_{2}}-\hat{\beta_{1}}$
and from (2)

$$
X_{2}^{T} 1_{n} \hat{\beta_{1}}+X_{2}^{T} X_{2} \hat{\beta_{2}}=X_{2}^{T} y \Rightarrow 0_{p-1}=X_{2}^{T} y-\overline{x_{2}}\left(n \hat{\beta_{1}}\right)-X_{2}^{T} X_{2} \hat{\beta_{2}}
$$

(b) Let $\mathbf{H}_{1}=\frac{1}{n} 1_{n} 1_{n}^{T}$ be the hat matrix of the constant covariate. Show that the OLS estimator excluding the intercept term is $\widehat{\boldsymbol{\beta}}_{2}=\left(\widetilde{\mathbf{X}}_{2}^{T} \widetilde{\mathbf{X}}_{2}\right)^{-1} \widetilde{\mathbf{X}}_{2}^{T} \widetilde{\mathbf{y}}$, where

$$
\widetilde{\mathbf{y}}=\left(I_{n}-H_{1}\right) \mathbf{y}=\mathbf{y}-1_{n} \overline{\mathbf{y}} \quad \widetilde{\mathbf{X}}_{2}=\left(I_{n}-H_{1}\right) \mathbf{X}_{2}
$$

are the deviations from the sample mean of the response and non-constant features. Thus including an intercept in the linear model is equivalent to centering the features and outcomes. Hint: $H_{1}$ is the projector onto $\operatorname{span}\left\{1_{n}\right\}$ (so $I_{n}-H_{1}$ is the projector onto the orthocomplement of $\operatorname{span}\left\{1_{n}\right\}$ ).
Solution: We can use $\hat{\beta}_{1}$ from (1) in (2) (from the solutions above) to solve this:

$$
\begin{aligned}
& X_{2}^{T} 1_{n}\left(1_{n}^{T} 1_{n}\right)^{-1} 1_{n}^{T}\left(y-X_{2} \hat{\beta}_{2}\right)+X_{2}^{T} X_{2} \beta_{2}=X_{2}^{T} y \Rightarrow X_{2}^{T} H_{1} y-X_{2}^{T} H_{1} X_{2} \hat{\beta_{2}}+X_{2}^{T} X_{2} \hat{\beta_{2}}=X_{2}^{T} y \Rightarrow \\
& X_{2}^{T}\left(I_{n}-H_{1}\right) X_{2} \hat{\beta}_{2}=X_{2}^{T}\left(I_{n}-H_{1}\right) y \Rightarrow \hat{\beta}_{2}=\left(\tilde{X}_{2}^{T} \tilde{X}_{2}\right)^{-} 1 \tilde{X}_{2}^{T} \tilde{y}
\end{aligned}
$$

NOTE: $\left(I_{n}-H_{1}\right)$ is symmetric and idempotent.
2. Problem 10 in ISLR §3.7. Don’t do part (h).

## Solution:

## Setup

```
library("ISLR")
## Warning: package 'ISLR' was built under R version 3.6.3
head(Carseats[, c("Sales", "Price", "Urban", "US")])
\begin{tabular}{lrrrr} 
\#\# & Sales & Price & Urban US \\
\#\# & 1 & 9.50 & 120 & Yes Yes \\
\#\# & 2 & 11.22 & 83 & Yes Yes \\
\#\# & 3 & 10.06 & 80 & Yes Yes \\
\#\# & 4 & 7.40 & 97 & Yes Yes \\
\#\# & 5 & 4.15 & 128 & Yes No \\
\#\# & 6 & 10.81 & 72 & No Yes
\end{tabular}
```


## Part a

```
linMod = lm(Sales ~ Price + Urban + US, data= Carseats)
summary(linMod)
##
## Call:
## lm(formula = Sales ~ Price + Urban + US, data = Carseats)
##
## Residuals:
## Min 1Q Median 3Q Max
## -6.9206 -1.6220 -0.0564 1.5786 7.0581
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.043469 0.651012 20.036 < 2e-16 ***
## Price -0.054459 0.005242 -10.389 < 2e-16 ***
## UrbanYes -0.021916 0.271650 -0.081 0.936
## USYes 1.200573 0.259042 4.635 4.86e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ', 1
##
## Residual standard error: 2.472 on 396 degrees of freedom
## Multiple R-squared: 0.2393, Adjusted R-squared: 0.2335
## F-statistic: 41.52 on 3 and 396 DF, p-value: < 2.2e-16
```


## Part b

If price increases by $\$ 100$ and other predictors are held constant, sales decrease by 5.4459 unit sales. Alternatively, when price increases by $\$ 100$, the number of carseats sold decrease by $5,445.9$.

Whether or not it is in a Urban area, it doesn't affect the sales.
A store in the US sales $\sim 1201$ more carseats (in average) than a store that is abroad.

## Part c

$Y_{\text {Sales }}=13.04-0.05 X_{\text {Price }}-0.02 X_{\text {UrbanYes }}+1.20 X_{U S Y e s}$

## Part d

Price and USYes

## Part e

```
linMod2 = lm(Sales ~ Price + US, data= Carseats)
summary(linMod2)
##
## Call:
## lm(formula = Sales ~ Price + US, data = Carseats)
##
## Residuals:
## Min 1Q Median 3Q Max
## -6.9269 -1.6286 -0.0574 1.5766 7.0515
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.03079 0.63098 20.652 < 2e-16 ***
## Price -0.05448 0.00523 -10.416 < 2e-16 ***
## USYes 1.19964 0.25846 4.641 4.71e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ', 1
##
## Residual standard error: 2.469 on 397 degrees of freedom
## Multiple R-squared: 0.2393, Adjusted R-squared: 0.2354
## F-statistic: 62.43 on 2 and 397 DF, p-value: < 2.2e-16
```


## Part f

Based on their R-square values, these two models are not very good. Though, the model from (e) fitting the data slightly better. For both, only $24 \%$ change in response explained.

## Part g

```
confint(linMod2)
```

| \#\# | $2.5 \%$ | $97.5 \%$ |
| :--- | ---: | ---: |
| \#\# (Intercept) | 11.79032020 | 14.27126531 |
| \#\# Price | -0.06475984 | -0.04419543 |
| \#\# USYes | 0.69151957 | 1.70776632 |

