# STAT 391 

Homework 8
Out Wednesdy May 28, 2020
Due Wednesday June 3, 2020
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## Problem 1 - Least Squares

Let $x_{1}, x_{2}, \ldots x_{n}$ be real numbers, and define by $g(z)$ the function

$$
g(z)=\sum_{i=1}^{n}\left(x_{i}-z\right)^{2}
$$

Show that the minimum of $g$ is attained for

$$
z^{*}=\frac{1}{n} \sum_{i=1}^{n} x_{i}
$$

What is the value $g\left(z^{*}\right)$ ?
[Hint: Take the derivative of $g$ w.r.t. $z$ and solve the equation $g^{\prime}(z)=0$.]
Problem 2 - Logistic regression
Notations follow the textbook.
a. Prove that $\sigma(u)+\sigma(-u)=1$ for all $u$, where $\sigma$ is the logistic $\mathrm{CDF} /$ sigmoid function.
b. Prove that if $u \rightarrow \pm \infty$, the derivative $\sigma^{\prime}(u) \rightarrow 0$. Hence, correctly classified data points away from the boundary have little influence on the log-likelihood. In other words, the parameters $b, \gamma$ will change little, when points far away from the the decision boundary move (or appear/disappear).
Problem 3 - Penalized regression
For this problem, assume $x, \beta \in \mathbb{R}$. Assume that $p\left(y_{1: n} \mid x_{1: n}, \beta\right)$ is the usual Normal model for Least Squares linear regression.
a. Ridge regression optimizes the cost function

$$
\begin{equation*}
J_{\lambda}(\beta)=\sum_{i=1}^{n}\left(y_{i}-\beta x_{i}\right)^{2}+\lambda \beta^{2}, \tag{1}
\end{equation*}
$$

where $\lambda>0$ is a regularization parameter. This parameter is like a smoothing parameter in kernel density estimation, in the sense that it is fixed before we see the data and estimate $\beta$.
Find the analytic solution $\beta^{\text {ridge }}$ of (1) as a function of $\beta^{M L}$ the Least Squares ML estimate of $\beta$.
b. Show that that $\beta^{\text {ridge }}<\beta^{M L}$ for all $\lambda>0$.
[c. - Extra credit] Show that one can augment the data $\left(y_{i}, x_{i}\right)_{1: n}$ so that $\beta^{\text {ridge }}$ is the ML estimate for the new data. Write the corresponding statisical model $P\left(y^{\text {new }} \mid x^{\text {new }}\right)$.
[d. - Extra credit] Now consider Bayesian estimation. Find a prior $p_{0}(\beta)$ so that

$$
\begin{equation*}
J_{\lambda}(\beta)=A \ln p\left(\beta \mid y_{1: n}, x_{1: n}\right)+B, \tag{2}
\end{equation*}
$$

where $A, B$ are constants independent on $\beta$. You need not determine the value of $B$.

