# Homework Assignment 4 <br> Due in class, Thursday November 17 

SDS 383C Statistical Modeling I

## 1. Robust statistics

(a) Let $Y$ be a random variable $Y=\mu+\epsilon$ where $\epsilon \sim N(0,1)$ and $\mu$ is a constant. In this question you will compute the elastic net estimator of $\mu$ which minimizes:

$$
\frac{1}{2}(Y-\mu)^{2}+\lambda|\mu|+\frac{\alpha}{2} \mu^{2}
$$

where $\alpha, \lambda>0$. Calculate $\hat{\mu}$.
(b) Calculate the Sensitivity curve for the sample median.
(c) (Extra credit) Assume that the data is generated from iid Uniform $([0, \theta])$. Is the sensitivity curve of the median bounded? Explain your answer.

## 2. Expectation Maximization and k-means

(a) Derive the E and M steps for a Gaussian Mixture Model with two components with means $\mu_{1}, \mu_{2}$ and the same variance $\sigma^{2}$. The mixture proportions are $\pi, 1-\pi$.
(b) Show that if $\sigma$ has a known value and we take $\sigma \rightarrow 0$, the EM algorithm coincides with 2-means clustering.

## 3. Expectation Maximization and multinomials

Let $\mathbf{y}_{\text {obs }}=\left(y_{1}, y_{2}, y_{3}\right)^{T}=(38,34,125)^{T}$ be observed counts from a multinomial population with probabilities $(1 / 2-\theta / 2, \theta / 4,1 / 2+\theta / 4)$.
(a) Derive the MLE of $\theta$.
(b) Now we will solve the same problem using EM. In order to put this in the unobserved data framework, we will pretend that the true data is $\left(y_{1}, y_{2}, y_{3}, y_{4}\right)^{T}$ sampled from a multinomial with probabilities $(1 / 2-\theta / 2, \theta / 4,1 / 2, \theta / 4)$. y is the augmented or complete data. Now define by $\mathbf{y}_{\text {obs }}=\left(y_{1}, y_{2}, y_{3}+y_{4}\right)^{T}$. This is an incomplete data problem because $y_{3}+y_{4}$ is observed, not $y_{3}$ or $y_{4}$.
i. Derive the E and M steps.
ii. Plot the estimated $\theta_{t}$ values vs the number of iterations $t$. Does it converge to the MLE you calculated earlier?

## 4. Linear Discriminant Analysis

(a) Consider Fisher's discriminant analysis which finds $w^{*}:=\arg \max _{w} \frac{\left(w^{T}\left(\mu_{1}-\mu_{2}\right)\right)^{2}}{w^{T}\left(\Sigma_{1}+\Sigma_{2}\right) w}$. Now consider data generated from two Gaussians with parameters $\mu_{i}, \Sigma_{i}, \pi=1 / 2$, for $i \in\{1,2\}$. Show that the direction of the Fisher Discriminant Analysis is exactly the direction found by a Linear Bayes classifier. For this exercise you can assume that $\mu_{i}, \Sigma_{i}, \pi$ are known and $\Sigma=\left(\Sigma_{1}+\Sigma_{2}\right) / 2$.
(b) Using the vowel data available at http://web.stanford.edu/~hastie/ElemStatLearn/ data.html, reproduce the figures 4.8 , and 4.11 in the HTF book. You do not have to generate the linear class boundaries in 4.11 , just the scatter plot.
(c) (Extra credit) Also reproduce Figure 4.10.

