# ECE 417 Multimedia Signal Processing Solutions to Homework 3 

UNIVERSITY OF ILLINOIS<br>Department of Electrical and Computer Engineering

Assigned: Tuesday, 9/28/2021; Due: Tuesday, 10/5/2021 Reading: , Sections 1-3

## Problem 3.1

Suppose $\vec{X}=\left[X_{1}, X_{2}\right]^{T}$ is a Gaussian random vector with mean and covariance given by

$$
\vec{\mu}=\left[\begin{array}{l}
1 \\
0
\end{array}\right], \quad \Sigma=\left[\begin{array}{ll}
9 & 0 \\
0 & 4
\end{array}\right]
$$

Sketch the set of points such that $f_{\vec{X}}(\vec{x})=\frac{1}{12 \pi} e^{-\frac{1}{8}}$, where $f_{\vec{X}}(\vec{x})$ is the pdf of $\vec{X}$.
Solution: Your sketch should be an ellipse, centered at the point $\vec{\mu}=[1,0]^{T}$, with a radius of $\frac{\sigma_{1}}{2}=\frac{3}{2}$ in the $x_{1}$ direction, and with a radius of $\frac{\sigma_{2}}{2}=1$ in the $x_{2}$ direction.

## Problem 3.2

Suppose $\vec{X}=\left[X_{1}, X_{2}\right]^{T}$ is a Gaussian random vector with mean and covariance given by

$$
\vec{\mu}=\left[\begin{array}{l}
1 \\
0
\end{array}\right], \quad \Sigma=\left[\begin{array}{ll}
9 & 0 \\
0 & 4
\end{array}\right]
$$

Define $\Phi(z)$ as follows:

$$
\Phi(z)=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} e^{-\frac{1}{2} u^{2}} d u
$$

In terms of $\Phi(z)$, find the probability $\operatorname{Pr}\left\{-1<X_{1}<1,-1<X_{2}<1\right\}$.

## Solution:

$$
\begin{aligned}
\operatorname{Pr}\left\{-1<X_{1}<1,-1<X_{2}<1\right\} & =\operatorname{Pr}\left\{-1<X_{1}<1\right\} \operatorname{Pr}\left\{-1<X_{2}<1\right\} \\
& =\left(\Phi\left(\frac{1-1}{3}\right)-\Phi\left(\frac{-1-1}{3}\right)\right)\left(\Phi\left(\frac{1-0}{2}\right)-\Phi\left(\frac{-1-0}{2}\right)\right)
\end{aligned}
$$

## Problem 3.3

Suppose that, for a particular classification problem, the observations are $\vec{x} \in \Re^{2}$, and the labels are $y \in\{0,1\}$. It just so happens that the correct label of every data point is as follows:

$$
y^{*}(\vec{x})= \begin{cases}1 & \|\vec{x}\|_{2}>1.5  \tag{3.3-1}\\ 0 & \|\vec{x}\|_{2}<1.5\end{cases}
$$

Unfortunately, you aren't allowed to use the correct labeling function. Instead, are required to learn a Gaussian classifier with the following form:

$$
\hat{y}(\vec{x})= \begin{cases}1 & \frac{p_{\vec{X} \mid Y}(\vec{x} \mid 1)}{p_{\vec{X} \mid Y}(\vec{x} \mid 0)}>\eta  \tag{3.3-2}\\ 0 & \frac{p_{\vec{X} \mid Y}(\vec{x} \mid 1)}{p_{\vec{X} \mid Y}(\vec{x} \mid 0)}<\eta\end{cases}
$$

where $\eta$ is a parameter called the likelihood ratio threshold, and where the probability models for for both classes are zero-mean Gaussians, with different covariance matrices $\Sigma_{0}$ and $\Sigma_{1}$ :

$$
p_{\vec{X} \mid Y}(\vec{x} \mid y)=\mathcal{N}\left(\vec{x} \left\lvert\, \vec{\mu}=\left[\begin{array}{l}
0  \tag{3.3-3}\\
0
\end{array}\right]\right., \Sigma_{y}\right)
$$

Suppose that $\Sigma_{0}$ and $\Sigma_{1}$ are known to be the identity matrix, and the scaled identity matrix, respectively:

$$
\Sigma_{0}=\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right], \quad \Sigma_{1}=\left[\begin{array}{ll}
2 & 0 \\
0 & 2
\end{array}\right]
$$

Find a value of $\eta$ so that the Gaussian classifier (Eq. 3.3-2) gives exactly the same decision boundary as the correct decision rule (Eq. (3.3-1)).

Solution: The Gaussian classifier chooses $\hat{y}=1$ under any of the following conditions, all of which are equivalent:

$$
\begin{aligned}
p_{\vec{X} \mid Y}(\vec{x} \mid 1) & >\eta p_{\vec{X} \mid Y}(\vec{x} \mid 0) \\
\ln p_{\vec{X} \mid Y}(\vec{x} \mid 1) & >\ln p_{\vec{X} \mid Y}(\vec{x} \mid 0)+\ln \eta \\
-\frac{1}{2} \ln \left|\Sigma_{1}\right|-\frac{1}{2} d_{\Sigma_{1}}(\vec{x}, \overrightarrow{0}) & >-\frac{1}{2} \ln \left|\Sigma_{0}\right|-\frac{1}{2} d_{\Sigma_{0}}(\vec{x}, \overrightarrow{0})+\ln \eta \\
-\frac{1}{2} \ln (4)-\frac{1}{2}\left(\frac{x_{1}^{2}+x_{2}^{2}}{2}\right) & >-\frac{1}{2}\left(x_{1}^{2}+x_{2}^{2}\right)+\ln \eta \\
\|\vec{x}\|^{2}\left(\frac{1}{2}-\frac{1}{4}\right) & >\ln \eta+\frac{1}{2} \ln (4) \\
\|\vec{x}\| & >\sqrt{4 \ln \eta+2 \ln (4)}
\end{aligned}
$$

This is exactly the same as Eq. 3.3 if $\sqrt{4 \ln \eta+2 \ln (4)}=1.5$, i.e.,

$$
\eta=e^{\frac{(1.5)^{2}-2 \ln (4)}{4}}
$$

## Problem 3.4

Suppose you have a scalar random variable $X$, with training examples $\left[x_{1}, x_{2}, x_{3}, x_{4}\right]=[-1,0,1,2]$. You want to try to model these data using a Gaussian mixture model, with the form

$$
\begin{equation*}
p_{X}(x)=\sum_{k=0}^{1} c_{k} \mathcal{N}\left(x \mid \mu_{k}, \sigma_{k}^{2}\right) \tag{3.4-1}
\end{equation*}
$$

You have initial parameter estimates $\mu_{0}=0, \mu_{1}=1, \sigma_{0}^{2}=\sigma_{1}^{2}=1$, and $c_{0}=c_{1}=0.5$. Perform one iteration of EM training. What are the new values of $\mu_{0}, \mu_{1}, \Sigma_{0}$ and $\Sigma_{1}$, after one round of EM training? Write your answer in terms of the normal probability density functions $\mathcal{N}\left(x \mid \mu, \sigma^{2}\right)$, for numerical values of $x, \mu$ and $\sigma^{2}$.

Solution: The gamma probabilities are

$$
\begin{aligned}
\gamma_{1}(1) & =\frac{0.5 \mathcal{N}(-1 \mid 1,1)}{0.5 \mathcal{N}(-1 \mid 0,1)+0.5 \mathcal{N}(-1 \mid 1,1)} \\
\gamma_{2}(1) & =\frac{0.5 \mathcal{N}(0 \mid 1,1)}{0.5 \mathcal{N}(0 \mid 0,1)+0.5 \mathcal{N}(0 \mid 1,1)} \\
\gamma_{3}(1) & =\frac{0.5 \mathcal{N}(1 \mid 1,1)}{0.5 \mathcal{N}(1 \mid 0,1)+0.5 \mathcal{N}(1 \mid 1,1)} \\
\gamma_{4}(1) & =\frac{0.5 \mathcal{N}(2 \mid 1,1)}{0.5 \mathcal{N}(2 \mid 0,1)+0.5 \mathcal{N}(2 \mid 1,1)}
\end{aligned}
$$

and similarly for $\gamma_{0}$. The re-estimated parameters are written in terms of the gamma probabilities, so they will be

$$
\begin{aligned}
& \mu_{0}=-\left(\frac{\mathcal{N}(-1 \mid 0,1)}{\mathcal{N}(-1 \mid 0,1)+\mathcal{N}(-1 \mid 1,1)}\right)+\left(\frac{\mathcal{N}(1 \mid 0,1)}{\mathcal{N}(1 \mid 0,1)+\mathcal{N}(1 \mid 1,1)}\right)+2\left(\frac{\mathcal{N}(2 \mid 0,1)}{\mathcal{N}(2 \mid 0,1)+\mathcal{N}(2 \mid 1,1)}\right) \\
& \mu_{1}=-\left(\frac{\mathcal{N}(-1 \mid 1,1)}{\mathcal{N}(-1 \mid 0,1)+\mathcal{N}(-1 \mid 1,1)}\right)+\left(\frac{\mathcal{N}(1 \mid 1,1)}{\mathcal{N}(1 \mid 0,1)+\mathcal{N}(1 \mid 1,1)}\right)+2\left(\frac{\mathcal{N}(2 \mid 1,1)}{\mathcal{N}(2 \mid 0,1)+\mathcal{N}(2 \mid 1,1)}\right) \\
& \sigma_{0}^{2}=\left(\frac{\mathcal{N}(-1 \mid 0,1)}{\mathcal{N}(-1 \mid 0,1)+\mathcal{N}(-1 \mid 1,1)}\right)+\left(\frac{\mathcal{N}(1 \mid 0,1)}{\mathcal{N}(1 \mid 0,1)+\mathcal{N}(1 \mid 1,1)}\right)+4\left(\frac{\mathcal{N}(2 \mid 0,1)}{\mathcal{N}(2 \mid 0,1)+\mathcal{N}(2 \mid 1,1)}\right) \\
& \sigma_{1}^{2}=4\left(\frac{\mathcal{N}(-1 \mid 1,1)}{\mathcal{N}(-1 \mid 0,1)+\mathcal{N}(-1 \mid 1,1)}\right)+\left(\frac{\mathcal{N}(0 \mid 1,1)}{\mathcal{N}(0 \mid 0,1)+\mathcal{N}(0 \mid 1,1)}\right)+\left(\frac{\mathcal{N}(2 \mid 1,1)}{\mathcal{N}(2 \mid 0,1)+\mathcal{N}(2 \mid 1,1)}\right)
\end{aligned}
$$

