# UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN <br> Department of Electrical and Computer Engineering 

## ECE 544NA Pattern Recognition

## Homework 3

Fall 2013
Assigned: Thursday, September 12, 2013
Due: Tuesday, September 24, 2013
Reading: NNPR Chapters $2 \& 3$

## Problem 3.1

We discussed how $k$-nearest neighbors is a very powerful tool for classification, but (in its most general form) is difficult to analyze. Consequently, there is a common misconception that the larger the $k$, the better. $k$-nearest neighbor classification works as follows:
(a) Given some new point $x$, find $k$ nearest neighbors $\left\{X_{(1)}, X_{(2)}, \ldots, X_{(k)}\right\}$ s.t. $d\left(x, X_{(1)}\right) \leq d\left(x, X_{(2)}\right) \ldots \leq$ $d\left(x, X_{(k)}\right)$, where $d(x, y)$ denotes distance between two points $x$ and $y$. The distances are computed over all points in the training set: $\left\{\left(X_{1}, Y_{1}\right),\left(X_{2}, Y_{2}\right), \ldots,\left(X_{N}, Y_{N}\right)\right\}$.
(b) $f_{k n n}(x)=Y_{k n n}=\operatorname{Majority}\left\{Y_{(1)}, Y_{(2)}, \ldots, Y_{(k)}\right\}$, where Majority selects the label $Y$ that occurs most frequently.

In words, we first first find the $k$ closest points to $x$ within the training set, and from their corresponding labels, pick the one that occurs the most (majority). Ties are broken arbitrarily. In the case of 1-nearest neighbor classification, we simply take the label of the closest point in the training set.

Let us take the simple example of binary classification in which we know that $p(X \mid Y=1)$ and $p(X \mid Y=$ $-1)$ are uniform distributions over the unit disks centered at $(2,0)$ and $(-2,0)$, respectively. Prove that in this specific scenario, the risk (assume 0-1 loss) of the 1-nearest neighbor classifier is lower than the risk of the 3 -nearest neighbor classifier.

## Problem 3.2

A Voronoi tessellation is a division of the space $\mathbb{R}^{D}$ into $K$ classes, $C_{1}, C_{2}, \ldots, C_{K}$ such that

$$
C_{k}=\left\{x:\left\|x-\mu_{k}\right\| \leq\left\|x-\mu_{i}\right\| \forall i \neq k\right\}
$$

Notice that by this definition, the boundary $B_{i j}$ is a subset of both $C_{i}$ and $C_{j}$; the decision is arbitrary on the boundary.
(a) Discrimination between classes $\mu_{i}$ and $\mu_{j}$ for any $i$ and $j$, can be performed by evaluating the sign of the linear discriminant $y_{i j}(x)=w_{i j}^{T}\left(x-b_{i j}\right)$. Find the vectors $w_{i j}$ and $b_{i j}$ in terms of $\mu_{i}$ and $\mu_{j}$.
(b) Suppose that each class is Gaussian with a covariance matrix $\Sigma$ common to all classes, and with prior probabilities $\pi_{1}, \pi_{2}, \ldots, \pi_{K}$. The posterior probability $p\left(C_{1} \mid x\right)$ can be written as an extended sigmoid function,

$$
p\left(C_{1} \mid x\right)=\left(1+e^{-f_{12}(x)}+e^{-f_{13}(x)}+\ldots+e^{-f_{1 K}(x)}\right)^{-1}
$$

Write $f_{1 k}(x)$ without using $\mu_{1}$ or $\mu_{k}$ in your answer. You may include $w_{1 k}, b_{1 k}, \Sigma$, and $\ln \frac{\pi_{k}}{\pi_{1}}$ in your answer.

## Matlab Exercises

## Problem 3.3

The smoothing parameter (aka bandwidth), $h$, plays an important role in kernel density estimation. A good criterion for selecting $h$ is one that minimizes the mean-squared error. For a univariate Gaussian kernel, $h^{*} \approx 1.06 \hat{\sigma} N^{\frac{-1}{5}}$ is the optimal choice, where $\hat{\sigma}$ is the estimate of the standard deviation of the samples and $N$ is the number of samples.
(a) Write a function, randgen $(f, N)$ that generates $N$ i.i.d samples from a given probability density function $f$. You may find the built-in matlab function rand to be useful.
(b) For $N=\{10,100,1000\}$, generate $N$ independent samples from an exponential distribution with $\lambda=1$ ( $f(x)=e^{-x}[x \geq 0]$, where [.] is the indicator function).
(c) Compute the sample standard deviation, $\hat{\sigma}$, without making any prior assumptions on the distribution (i.e., DO NOT assume that the data are drawn from an exponential distribution). For each $N$, estimate the optimal bandwidth, $h^{*}(N)$.
(d) Estimate the pdf using kernel density estimation with a Gaussian kernel for each $N$, under three different bandwidth settings: $\left\{h^{*}(N) / 3, h^{*}(N), 3 * h^{*}(N)\right\}$.
(e) Summarize your results by plotting the pdf estimates. You need to have 9 plots overall ( 3 values of N x 3 values of h). Overlay each plot with the true density, $f(x)$ for $x \epsilon[-1,4]$ (to save space, consider using the matlab function subplot( $3,3,$.$) ). Comment on the influence of h, N$, and the kernel itself on the pdf estimates.

