# Nonparametric Function Estimation Stat $550^{1} \quad$ Chapter 9 Special Topics 

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${ }^{1}$ A course based upon the 2nd edition of Multivariate Density Estimation; Theory, Practice, and Visualization, John Wiley \& Sons, 2015
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## Chapter IX: Other Applications

- An abbreviated sampling of advanced applications
- Classification, Discrimination, and Likelihood Ratios
- The lipid data re-visited
- Risk analysis of plasma lipid dataset.


Figure: (Upper left) Normal fit "-" group. (Upper right) Normal fit " + " group. (Middle left) Overlay of 2 normal fits. (Middle right) Overlap of ASH of $f_{+}$[biweight kernel $\left.h=(21.7,0.33)\right]$ and normal fit to " + " group. (Lower left) Contours of parametric $\log _{10}(L R)$. (Lower right) $\log _{10}(L R)$ nonparametric estimate.

## Likelihood Ratio Views Lipid Data: Parametric vs Nonparametric



Figure: Perspective plots of the $\log _{10}$ likelihood ratio surfaces in previous Figure. The range of the vertical axes is $(-0.91,0.91)$ in both frames, corresponding to a range of odds in favor of disease from 0.15:1 to 8.1:1.

## LANDSAT Classification

Table: Classification Cross-Tabulations Based on Trivariate Gaussian and ASH Fits to the Landsat Data ${ }^{\text {a }}$

|  | PRED | Sunflwr | Wheat | Barley | \% Right | Smoothed |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NORM | Sunflwr | 1,191 | 9 | 0 | 99.3\% | 100.0\% |
|  | Wheat | 10 | 665 | 335 | 65.8\% | 80.3\% |
| TRUTH: | Barley | 10 | 314 | 1,066 | 76.7\% | 93.7\% |
| ASH | Sunflwr | 1,194 | 5 | 0 | 99.5\% | 100.0\% |
|  | Wheat | 7 | 773 | 230 | 76.5\% | 93.7\% |
| TRUTH: | Barley | 3 | 361 | 1,026 | 73.8\% | 89.9\% |

${ }^{a}$ The first 3 columns summarize the predictions of the classifier using the training data. (book)(Classification!majority prediction) (book)(Classification!prediction) The last column summarizes the rates using a classification rule based on a majority rule of a pixel and its 8 neighbors.

## Mixture: MCLUST Library (lipid example)



Figure: Mclust (2005 version) applied to log-lipid dataset ( $n=320$ ).
frametitleClustering: The Mode Tree (Geyser Data)



Figure: A mode tree and dendrogram of the geyser eruption times. The dendrogram is the hierarchical clustering tree based on average linkage.

## Clustering: The 2-D Mode Tree (Lagged Geyser Data)



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## Surprise: Number of Modes Not Monotone With $h$

A simple example where an equal mixture of 3 bivariate normal kernels at the corners of an equilateral triangle can have 1,3 , or 4 modes!


Figure: Contours of a bivariate Gaussian kernel density estimator with $n=3$ points (black dots) on the unit circle forming an equilateral triangle. A highly nonlinear set of contour levels are displayed, so that the contours near the modes are emphasized.

## Clusters in Images



Figure: Gray scale images of the three MRI variables $\left(t_{1}, t_{2}, s d\right)$.

## Hill-Climbing to Local Modes



Figure: (Left) ASH contours of $\left(t_{1}, t_{2}\right)$ of an MRI image with 24,476 pixels. (Center) Hill-climbing of individual pixel values to the nearest mode. (Right) The 70 modes found are superimposed on two contours.

## Tumor Detection



Figure: MRI images and subsets.

## Data With Holes in $\Re^{3}$



Figure: Pairwise scatterplots of 5,000 trivariate simulated points with a hole. The hole is actually a region of lower density rather than a region around the origin with no data.


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## LANDSAT Images and Histogram Equalization






Figure: Histograms of raw data from Landsat scene and transformed data that are more nearly uniform. The increased dynamic range in the gray

## THANK YOU!!

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