Possibilistic, Robust, Ambiguity-preserving (PRAM) Classification & Regression

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Major Point

For Large Scale Processing
Algorithms Need to

(1) Know when they don’t know
(2) Represent all Possibilities

SVM, MLPs
too confident and binary
Overview

• Problem
  – Large Scale Processing
  – Definitions
  – Historical Examples

• Approach
  – Possibilistic Classifiers
  – Self-Organizing Map + Gaussian Process Classifiers

• Experimental Results
Large Scale Processing

• Not just real-time

• More automated processing
  – Accuracy
  – System level development
  – Integration of knowledge sources
  – Management of uncertainty
Definitions

- **Robustness** – Accurately estimating the likelihood that a pattern is not from any class of interest
- **Ambiguity-preserving** – Accurately estimating the likelihood that a pattern represents each class
  – particularly if a pattern could be from multiple classes (e.g. Oaks)
- **Possibility Distribution** – like Probability Distribution but not constrained to sum to 1
  – Mathematically rigorous
NEEDS

• Many Unseen Patterns (Need Robustness)

• Many Ambiguous Patterns (Need Representation)
Self-Organizing Map

Improves Robustness and Ambiguity Preservation 1990s

• Suitable for High Speed Processing
• Handwritten Word Recognition (Optical)
  – Blind Tests of end-to-end systems
• Landmine and IED Detection (Multiple Sensors)
  – Fielded systems (Radar), Many km per day
  – Featured in
    • National Geographic TV: Bomb Hunters Afghanistan
• Spectral Analysis – Classification and Regression
Handwritten Word Recognition

What are these characters?
Are they even characters?

Ha  Q  H
9  J  U
Historical Examples
Handwritten Word Recognition --------- Buried Explosive Object Detection
Historical Examples
Handwritten Word Recognition ----------- Buried Explosive Object Detection
Robustness – Outlier Rejection

Rejection of Outliers as Function of Probability of Detection of Class 1

Rejection of Outliers as Function of Probability of Detection of Class 2
Ambiguity

- Pictures of Oaks
MUFLAG Data – University of Southern Mississippi Gulfport
MUFLAG - Classes
Classes

- RED ROOF
- SHADOW
- LIVE OAK
- GREY ROOF

- ASPHALT
- DEAD GRASS
- SOIL
- LIVE GRASS
Classes as Distributions

- RED ROOF
- SHADOW
- LIVE OAK
- GREY ROOF
- ASPHALT
- DEAD GRASS
- SOIL
- LIVE GRASS
SOM Trained on ... ADGRAT

ASPHALT

GRAASS

SOIL

TREES
8 x 8 Self Organizing Map
SOM Similarity to Grass
Grass “Hot” Regions
Need for Variance in Similarity i.e. Mahalanobis or PCA
CAPO on Spectral Data
Spectral Data from UF – NEON Site
Possibilistic
Gaussian Processes

Math Description Later
Possibilistic Gaussian Process
Ordway Swisher Biological Station
NEON – University of Florida
2010 - AVIRIS Data

Oaks vs Pines vs Outlier Vegetation
OSBS Results
100s of runs
Average Area Under Curve (AAUC)

<table>
<thead>
<tr>
<th>OSBS</th>
<th>SVM AAUC</th>
<th>Gaussian Proc AAUC</th>
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<tbody>
<tr>
<td>With Outliers</td>
<td>78</td>
<td>88</td>
</tr>
<tr>
<td>No Outliers</td>
<td>96</td>
<td>100</td>
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Panama Ground Measurement Results
Made by Stephanie Bohlman et al.
ASD Field Spec 4 (UF CISE Instrument)

<table>
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<th>SVM AAUC</th>
<th>Gaussian Proc AAUC</th>
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<tbody>
<tr>
<td>With Outliers</td>
<td>93.8</td>
<td>96.0</td>
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<tr>
<td>No Outliers</td>
<td>99.6</td>
<td>99.9</td>
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Recommended Future Work

- **Algorithm Development Environment (ADE)**
  - Well Defined Problems, Standardized Evaluation
  - HyspIRI, NEON
  - Vegetation
    - PRAM Classification & Regression (Chemistry)
  - System Level Processing
    - Principle of Least Commitment (David Marr, 1982)
  - Time Series
  - Multiple Information Sources
Hosted Widely Available ADE

- Alg Dev Tools
- Fast Computing
- More Data
  - NEON (NSF)
  - HyspIRI (NASA)