Blind Signal Classification via Sparse Coding

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Outline

• Motivation
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Motivation

- Competing Cognitive Radio Network (CCRN) models tactical radio networks under competition
  - Blue Force (friend) vs. Red Force (adversary)
  - Dynamic, open spectrum resource for opportunistic data access
  - Nodes are cognitive radios
    - Comm nodes and jammers
  - Strategic jamming attacks

This paper is about signal classification at spectrum sensing level using semi-supervised machine learning approach.
Background: Taxonomy of Spectrum Sensing

- Non-learning based spectrum sensing
  - Energy detection
  - Cyclostationary detection

- Learning-based spectrum sensing
  - Supervised learning (requires labeled examples of all signals you want to classify)
    - Support vector machine (SVM), logistic/softmax regression, neural network
  - Unsupervised learning (no labeled examples required)
    - Clustering techniques (e.g., K-means, GMM): partition data mixed of unknown identities into clusters
  - Semi-supervised (unsupervised feature learning followed by supervised phase)
    - Sparse coding + SVM (you need some labeled examples)
Background: Sparse Coding and Dictionary Learning

- Sparse coding is an unsupervised learning method
  - Transforms raw data into their sparse feature representations given set of basis vectors (dictionary)

- Dictionary learning
  - Learns basis vectors $d_k$ (dictionary atoms) required for sparse coding
Technical Approach: Semi-Supervised Learning with Sparse Coding

- **Classification pipeline**
  1. Extract feature vectors via sparse coding: \( x_i \rightarrow y_i \)
  2. Summarize multiple feature vectors via pooling: \( y_i \rightarrow z \)
  3. Train SVM classifiers that takes pooled sparse-coded input \( z \)

Trained SVM predicts label of unknown input data
Technical Approach (cont’d): Modification of Sparse Coder with Convolution

- Classical inner-product sparse coders are not appropriate for our applications resulting in redundant dictionary atoms
  - Received signals are time series with unknown phases
- Our enhancement: simple convolution sparse coder
  - For S-sparse \( y \), take \( S \) steps of greedily choosing max convolution value and removing its contribution from \( x \) for next

\[
y_i = \max |x \ast d_k|
\]

\[
k \in \{1, \ldots, K\}
\]
Evaluation

• Simulation environment
  – Used MATLAB communications toolbox to generate modulated RF signals
  – Used LIBSVM to train SVM classifiers
  – Used K-SVD algorithm to learn dictionary for sparse coding

• Assumptions
  – There are four signal classes in our experiments
    ➢ Friendly signals: S1 (single-carrier QPSK with rectangular pulse) and S2 (OFDM with raised cosine pulse)
    ➢ Adversary signals: S3 (QPSK with custom pulse) and S4 (OFDM with custom pulse)

• Scenarios
  – Case 1 (Blind clustering) – apply K-means clustering on sparse-coded signals using four classes of signals
  – Case 2 (One-class SVM) – train SVM classifiers using only friendly signals
  – Case 3 (1-vs-all SVM) – train SVM classifiers using mostly friendly signals and some adversary signals
Results: Confusion Matrices

- Confusion matrix is good for visualizing multiclass classification performance

- Confusion matrices for:
  - Case 1 (Blind clustering) – apply K-means clustering on sparse-coded signals using four classes of signals
  - Case 2 (One-class SVM) – train SVM classifiers using only friendly signals
  - Case 3 (1-vs-all SVM) – train SVM classifiers using mostly friendly signals and some adversary signals

Darkest box: 0.89
Lightest box: 0.06
Results: Recall & False Alarm Performance

- Recall & false alarm performances for:
  - Blind clustering – apply K-means clustering on sparse-coded signals using four classes of signals
  - One-class SVM – train SVM classifiers using only friendly signals
  - 1-vs-all SVM – train SVM classifiers using mostly friendly signals and some adversary signals

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Recall 20 dB (0 dB)</th>
<th>False Alarm 20 dB (0 dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1 (Blind clustering)</td>
<td>0.703 (0.582)</td>
<td>0.246 (0.367)</td>
</tr>
<tr>
<td>Case 2 (One-class SVM)</td>
<td>0.768 (0.634)</td>
<td>0.213 (0.307)</td>
</tr>
<tr>
<td>Case 3 (1-vs-all SVM)</td>
<td>0.878 (0.726)</td>
<td>0.141 (0.262)</td>
</tr>
</tbody>
</table>
Summary

• Presented semi-supervised framework for RF signal classification at spectrum-sensing level based on sparse coding
  – Proposed sparse coding + SVM requires no prior knowledge about signals
  – Sparse coding dictionary can be pre-generated or learned

• Developed simulation to assess performance for:
  – Blind clustering – apply K-means clustering on sparse-coded signals using four classes of signals
  – One-class SVM – train SVM classifiers using only friendly signals
  – 1-vs-all SVM – train SVM classifiers using mostly friendly signals and some adversary signals

• Explore more practical applications with cognitive radios

• Improve computational complexity
  – Develop efficient sparse coding and dictionary learning algorithms for mobile handsets