Blind Signal Classification via Sparse Coding

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Outline

- Motivation
- Background
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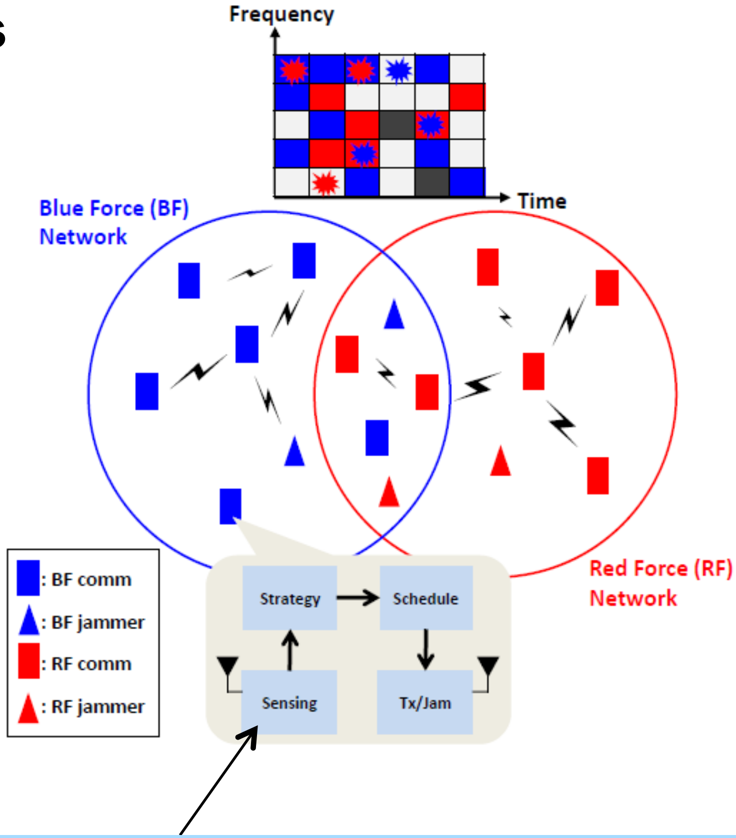
Motivation

- **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**



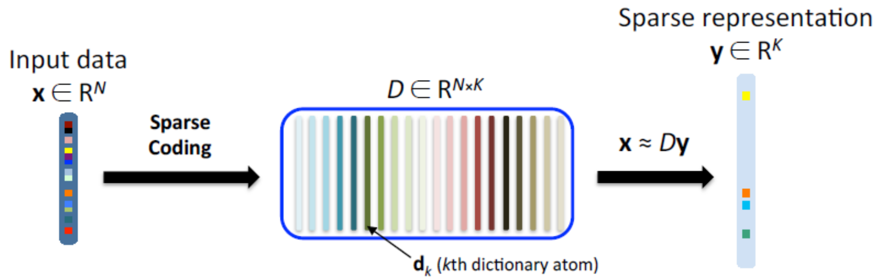
This paper is about signal classification at spectrum sensing level using semi-supervised machine learning approach

Background: Taxonomy of Spectrum Sensing

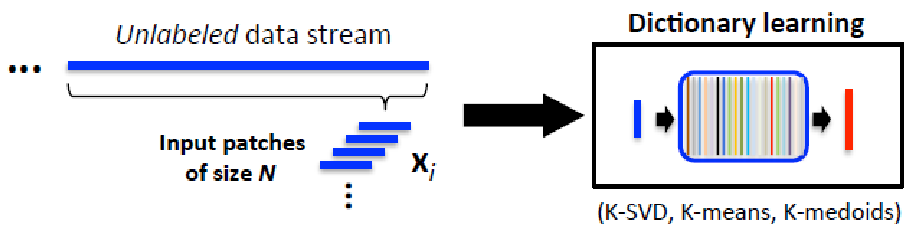
- Non-learning based spectrum sensing
  - Energy detection
  - Cyclostationary detection
- Learning-based spectrum sensing
  - Supervised learning (requires labeled examples of all signals you want to classify)
    - Support vector machine (SVM), logistic/softmax regression, neural network
  - Unsupervised 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)**

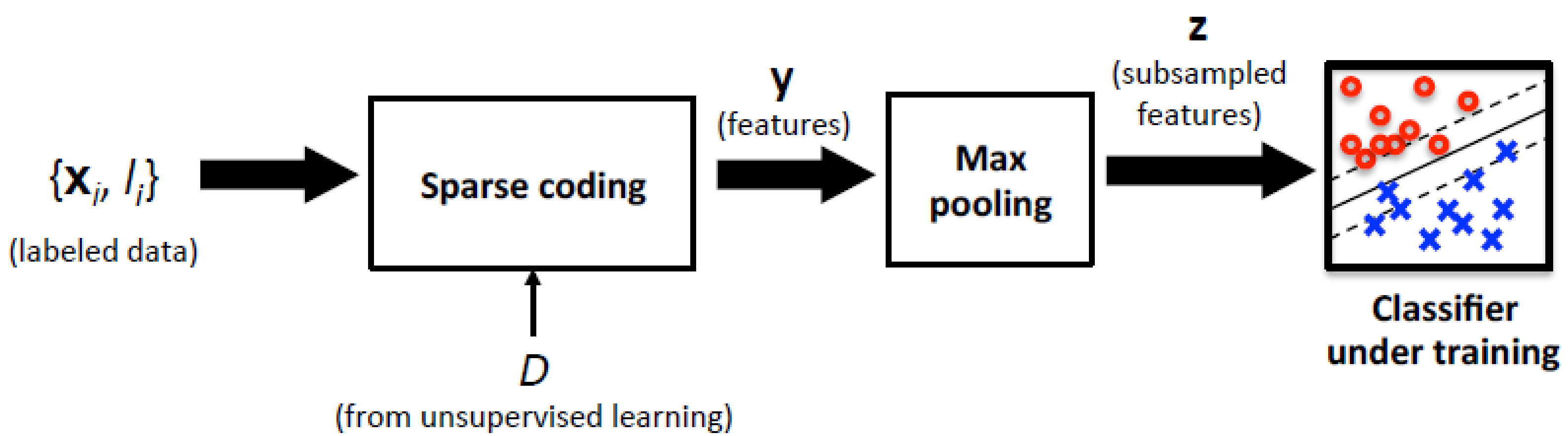


- **Dictionary learning**
  - **Learns basis vectors d_k (dictionary atoms) required for sparse coding**



Technical Approach: Semi-Supervised Learning with Sparse Coding

- **Classification pipeline**
  1. Extract feature vectors via sparse coding: $\mathbf{x}_i \longrightarrow \mathbf{y}_i$
  2. Summarize multiple feature vectors via pooling: $\mathbf{y}_i \longrightarrow \mathbf{z}$
  3. Train SVM classifiers that takes pooled sparse-coded input $\mathbf{z}$



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**

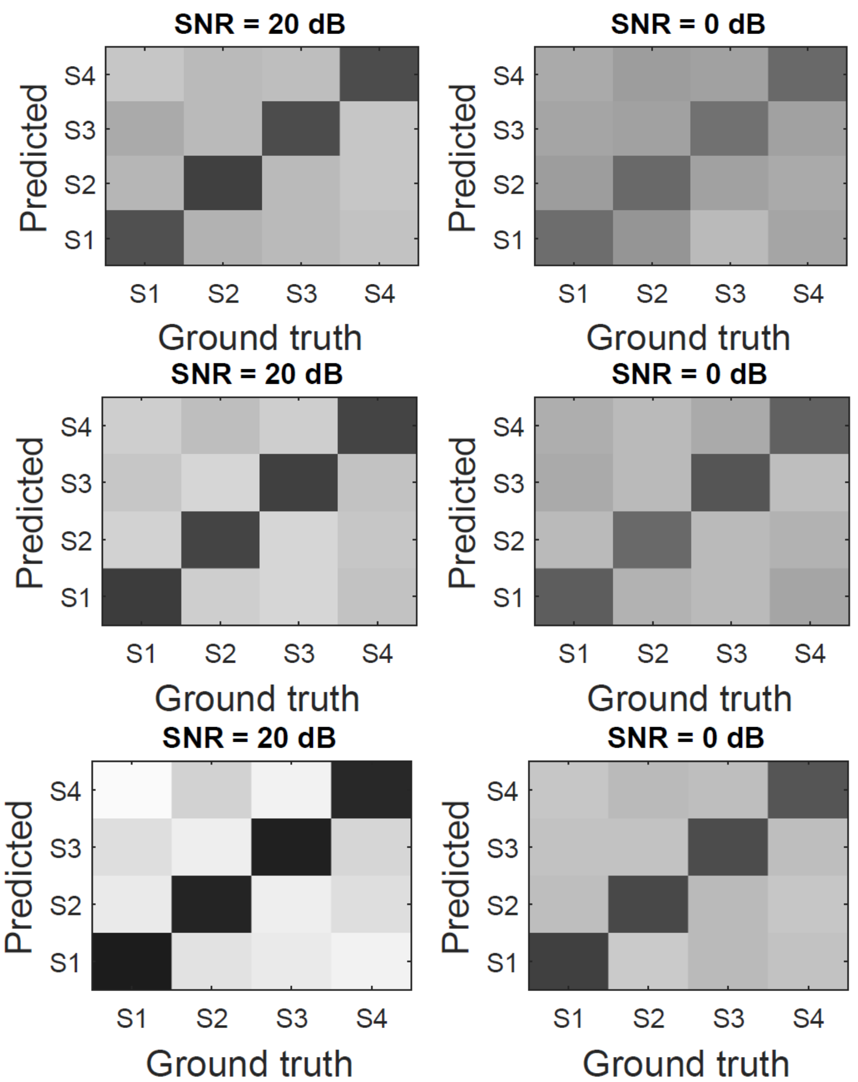
$$y_i = \max_{k \in \{1,\dots,K\}} |\mathbf{x} * \mathbf{d}_k|$$

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

Scenarios	Recall 20 dB (0 dB)	False Alarm 20 dB (0 dB)
Case 1 (Blind clustering)	0.703 (0.582)	0.246 (0.367)
Case 2 (One-class SVM)	0.768 (0.634)	0.213 (0.307)
Case 3 (1-vs-all SVM)	0.878 (0.726)	0.141 (0.262)

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