



Convolutional Sparse Coding for Arrhythmia Classification

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Stanford

Problem

- Heartbeats are recording using electrocardiogram (ECG) signals
- Some heartbeats, called *arrhythmias*, deviate from a normal sinus rhythm
- ECG recordings are noisy, high-dimensional
- **Problem**
 - (1) Can we reduce high-dimensional ECG signal to a low-rank or sparse signal?
 - (2) Can we use this low-rank signal to accurately classify the type of arrhythmia exhibited?

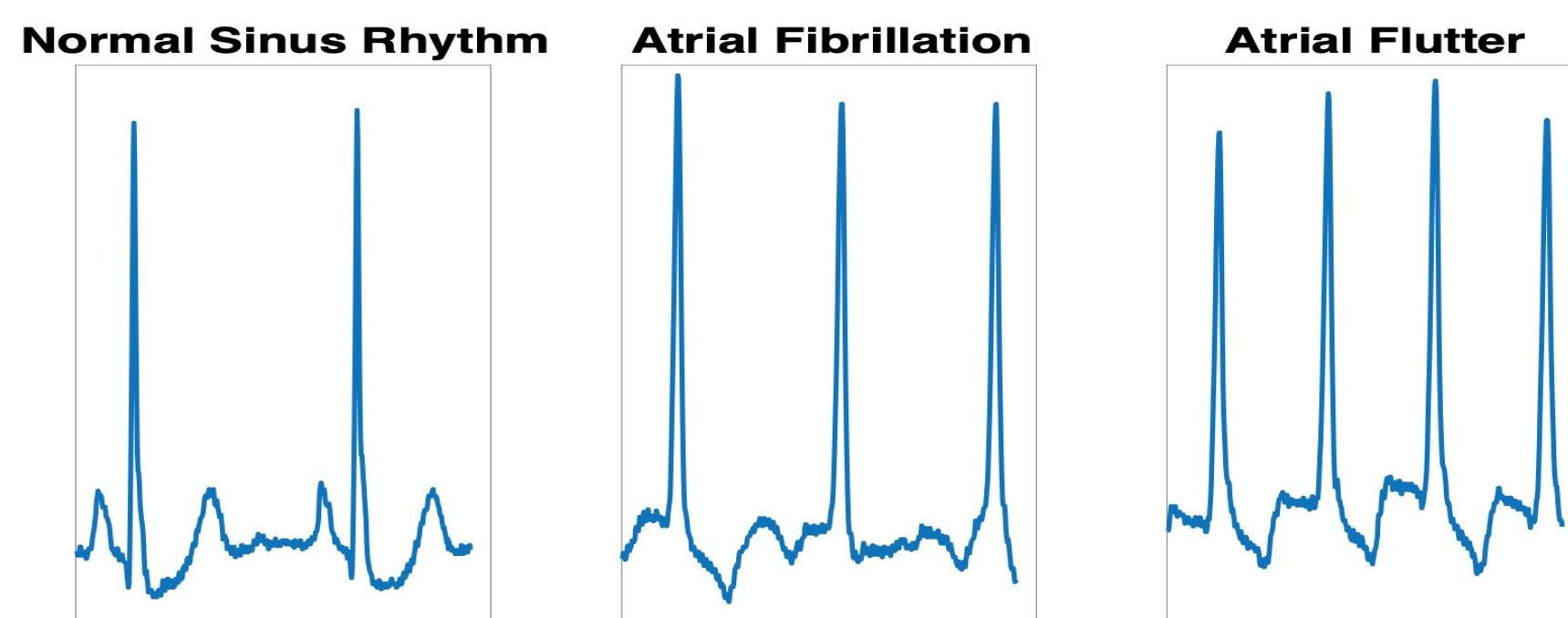


Figure 1: Heart arrhythmias can show distinct patterns differing from normal sinus rhythm. However, misclassification is common because it's often difficult for physicians to pick out the subtle distinguishing features that help differentiate them by eye.

Proposed Approach

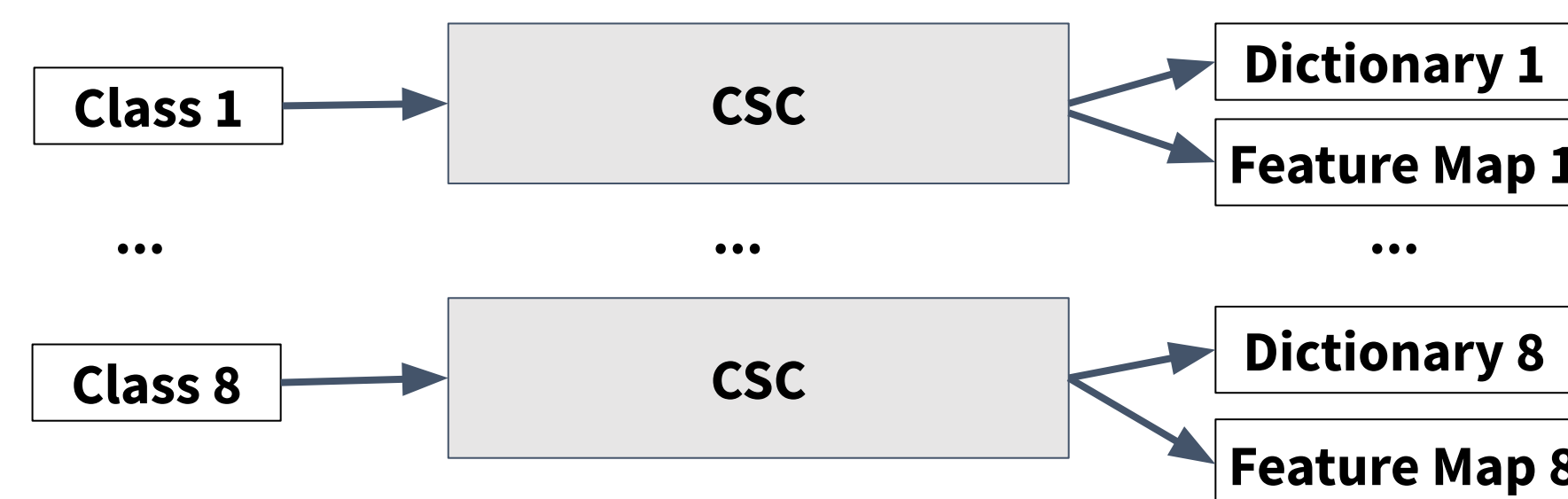
- Learn a dictionary to represent each heartbeat class using **convolutional sparse coding (CSC)**

$$\text{Sparse coding: } x \approx \hat{x}_{SC} = Dz$$

$$\text{Convolutional sparse coding: } x \approx \hat{x}_{CSC} = \sum_{k=1}^K d_k * z_k$$
- Classify heartbeats using feature maps fit to dictionary
 - **Intuition:** Perform feature selection through CSC

Classification Pipeline

Dictionary Learning Pipeline



Classification Pipeline

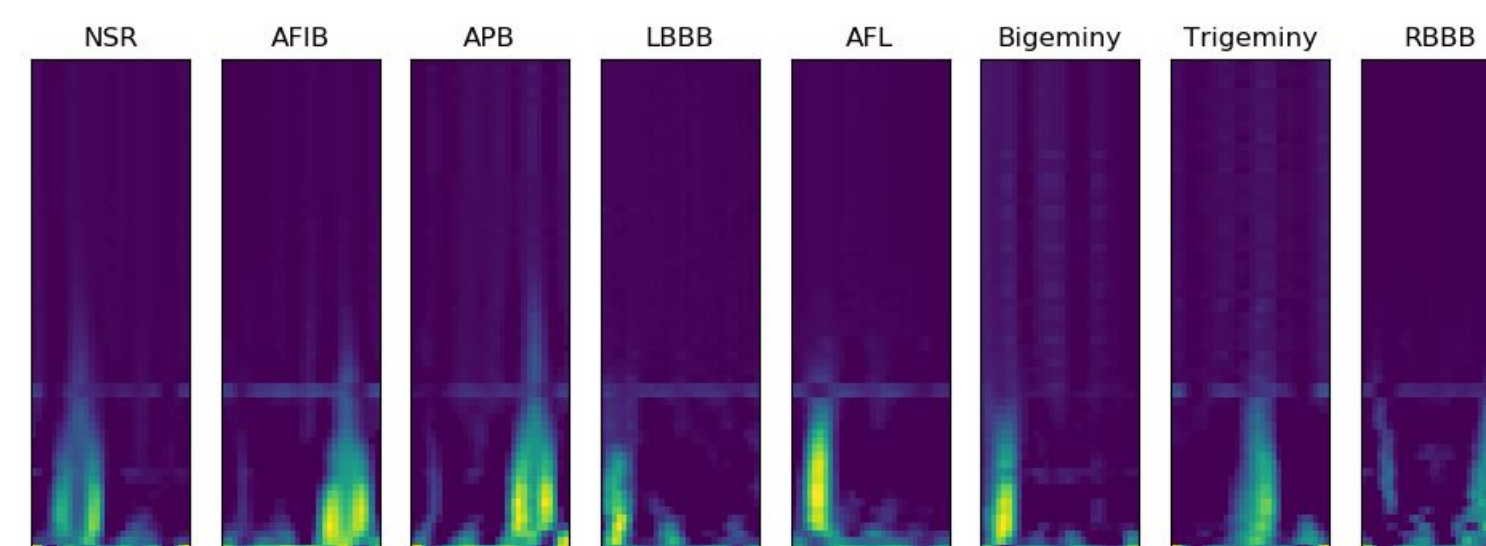
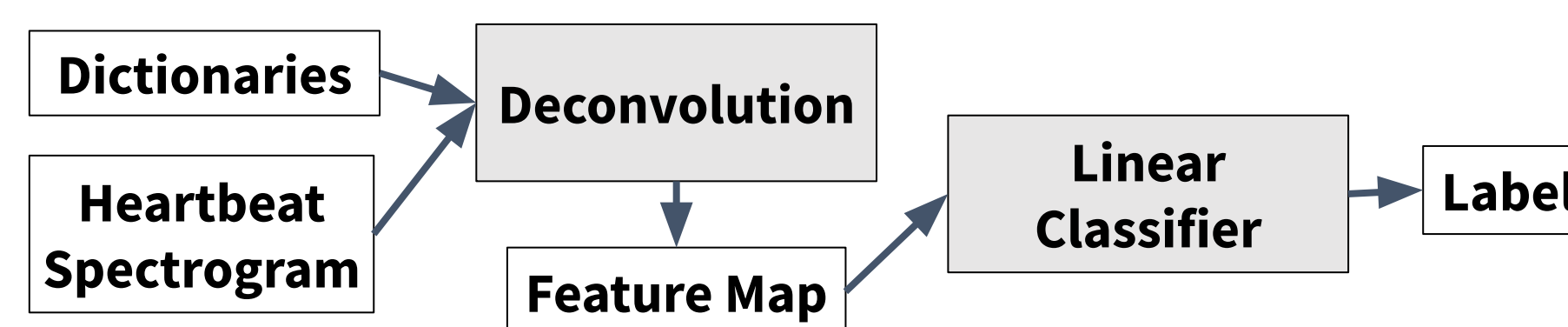


Figure 2: Dictionary elements recovered from training dataset. Note the strong motif similarities between NSR, AFIB, and APB, since normal sinus rhythm is the dominant underlying factor. Similarly, note LBBB and RBBB motifs are significantly different because both conditions block normal sinus rhythm.

Results

	Train Accuracy	Test Accuracy
Raw Signal	49.07%	23.02%
Spect	96.73%	39.19%
Spect + CSC	78.55%	35.76%

Table 1: Least squares multi-class classification results run on the raw ECG signal and on the spectrogram both with and without convolutional sparse coding. Sparse coding does not significantly hinder performance.

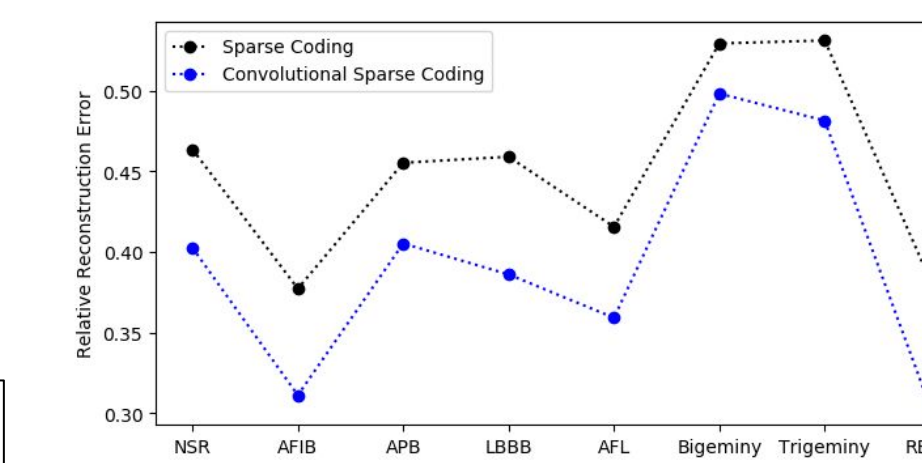


Figure 3: Reconstruction error using standard sparse coding and convolutional sparse coding. Convolutional sparse coding significantly outperforms “patch-based” sparse coding in reconstructing the original data.

Discussion

Dimensionality Reduction

- Convolutional sparse coding outperforms “patch-based” low rank models
- Reconstruction difficulty varies with arrhythmia classes

Classification

- Spectrogram encodes more useful features for classification compared to the baseline raw ECG signal
- Convolutional sparse coding classifies less accurately, but with fewer features (8x compression rate).

Future Work

- Optimize sparsity hyperparameter
- Deep convolutional sparse coding

References

1. Hannun, Awni Y., et al. "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network." *Nature medicine* 25.1 (2019): 65.
2. Moody, George B., and Roger G. Mark. "The impact of the MIT-BIH arrhythmia database." *IEEE Engineering in Medicine and Biology Magazine* 20.3 (2001): 45-50.
3. Anwar, Syed, et al. "Arrhythmia Classification of ECG Signals Using Hybrid Features." *Computational and Mathematical Methods in Medicine*, Hindawi, 12 Nov. 2018

Prior Work

Dimensionality Reduction

- Low rank models (sparse coding, nonneg factorization, etc)
 - Lack translation invariance, require many “patches”

Classification

- Simple linear classifiers leverage expert features
 - Lack flexibility
- Highly accurate CNNs
 - Lack interpretability
 - Require massive datasets (~50,000 patients)