CS221: AF Classification from modified ECG Lead II recordings using Domain Adaptation

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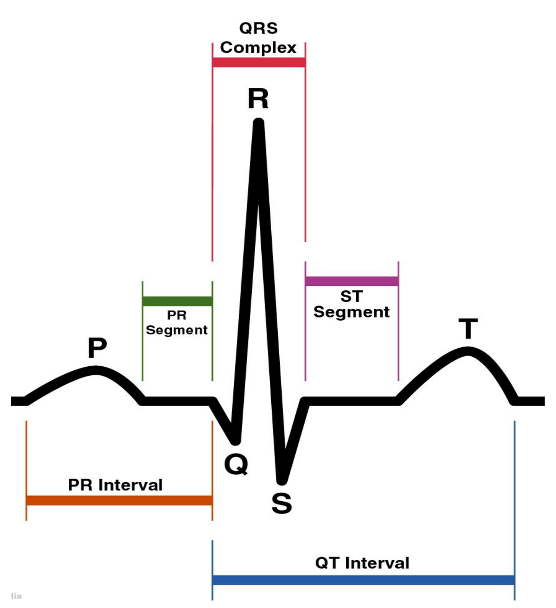
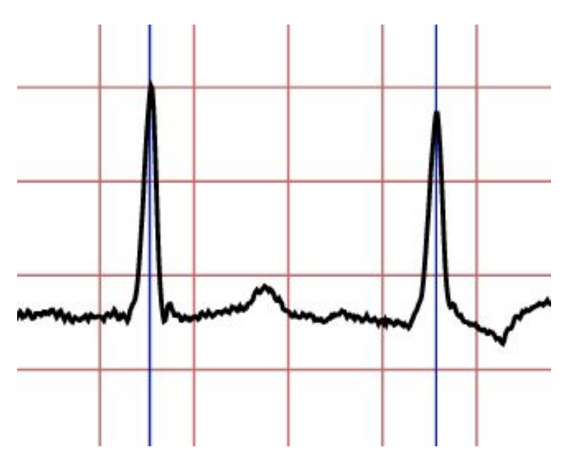
Motivation

Atrial Fibrillation (fast and irregular atria beats) causes 200,000 deaths in US yearly. P waves are not observed in the ECG recordings of AF patients. 1D CNN models have been applied successfully to AF classification, but data labelling is costly.

Domain Adaptation task: We adapt a high-performing model learned on the MIT-BIH Arrhythmia Dataset to an unannotated ECG dataset with related distribution.





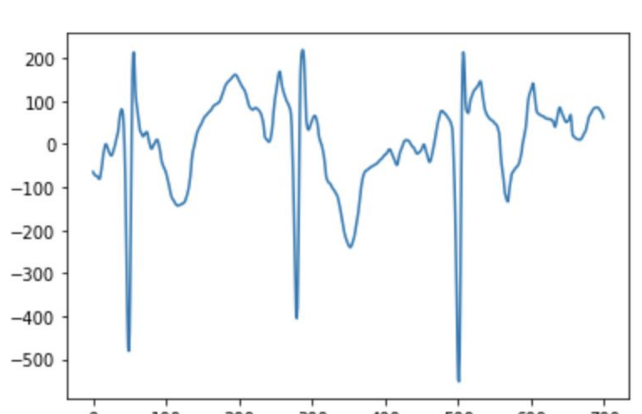
Dataset

MIT-BIH Arrhythmia Dataset

- 48 half-hour Lead II recordings
- Sampled at 360Hz
- Labels: Normal, Noisy, AF, or 10 other classes of heart arrhythmia.
- 110000 labels are available.

Modified ECG Dataset

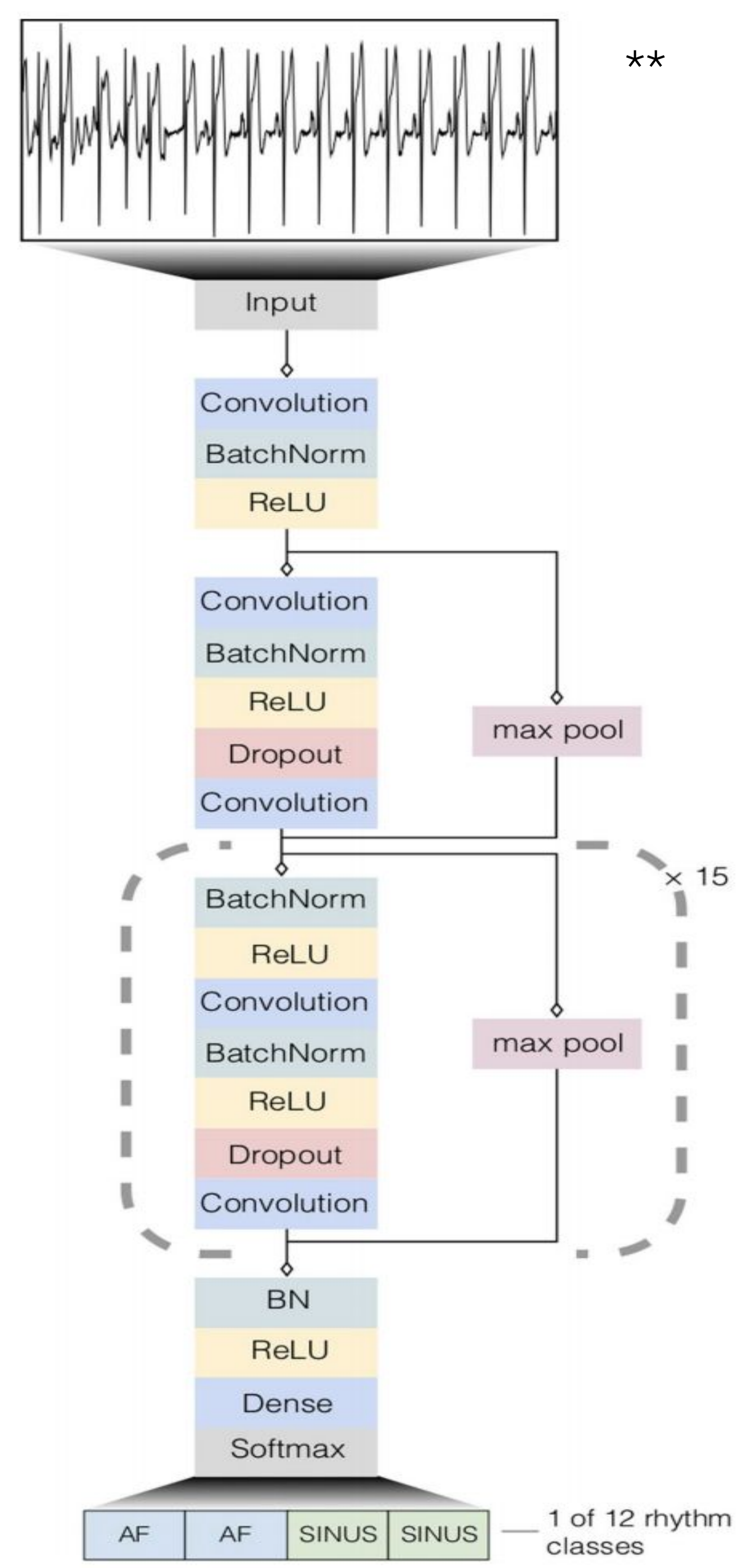
- 8523 ECG recordings (~8-60s) from AliveCor device
- Sampled at 200Hz
- Labels: Normal, AF, Noisy, or Others.
- Dataset treated as unlabelled
- Best classification performance on dataset 0.83



Methods: Classifier

Modified Resnet-34 by Rajpurkar et al.

- Adapted for 1D convolutions.
- In: Segment of sample length 224
- Out: Normal/Noisy/AF/10 other classes



Metrics

Sequence F1

- Average overlap between prediction sequence and ground truth sequence

4 class vs 13 class

- Trained models on both 4 class and 13 class for comparison

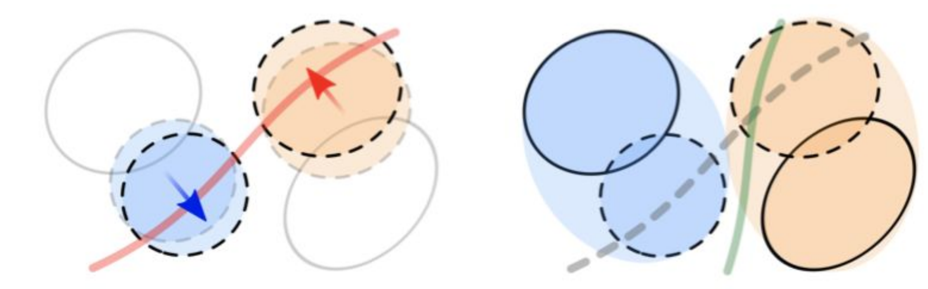
Methods: Drop to Adapt

Problem Statement

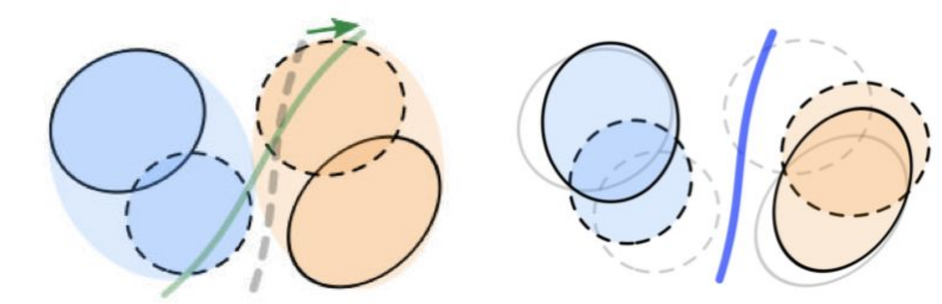
- Labelled source data S={X_S,Y_S}
- Unlabelled target data T={X_T}
- Assume domains share feature space
- Goal: Learn domain-invariant features discriminative with respect to target

Drop to Adapt by Lee et. al

- Uses adversarial dropout to enforce clustering in target data
- Minimizes divergence between distinct target predictions
- Maximizes distance between decision boundaries and target features
- Applies adversarial dropout to (i) feature extractor, (ii) classifier



AdD on feature extractor pushes decision boundary away from feature dense regions



AdD on classifier pushes features away from the decision boundary

Loss functions

Source: *Classification*

$$L_T(\mathcal{S}) = -\mathbb{E}[\mathbf{y}^T \log h(\mathbf{x})]$$

Target: Divergence on adversarial mask

$$L_{DTA}(\mathcal{T}) = \mathbb{E}_{\mathbf{x}_t \sim \mathcal{T}}\left[D_{KL}\left[h(\mathbf{x}_t; \mathbf{m}^s) || h(\mathbf{x}_t; \mathbf{m}^{adv})\right]\right]$$

Target: Distance from decision boundaries

$$L_E(\mathcal{T}) = -\mathbb{E}_{\mathbf{x}_t \sim \mathcal{T}}[h(\mathbf{x}_t)^T \log h(\mathbf{x}_t)]$$

Target: Divergence on perturbed inputs

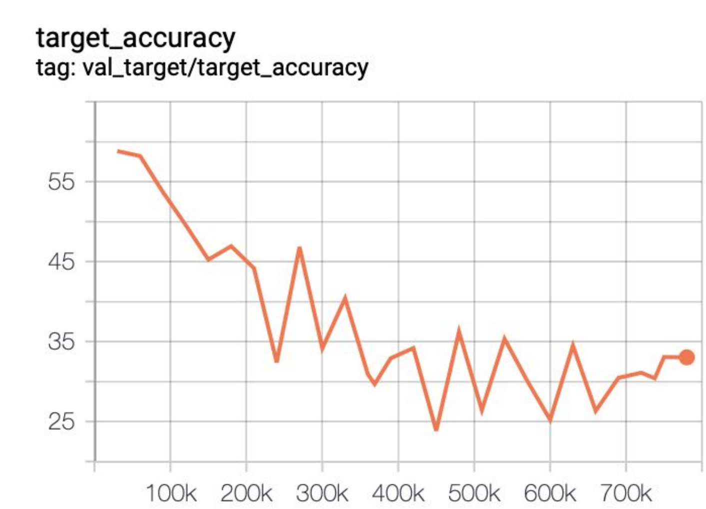
$$L_V(\mathcal{T}) = \mathbb{E}_{\mathbf{x}_t \sim \mathcal{T}}\left[\max_{||r|| \le \epsilon} D_{KL}\left[h(\mathbf{x}_t) || h(\mathbf{x}_t + r)\right]\right]$$

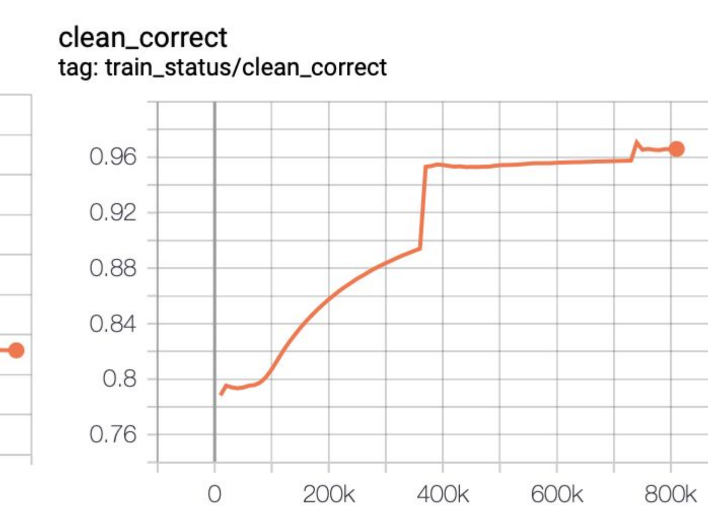
Overall loss:

$$L(\mathcal{S}, \mathcal{T}) = L_T(\mathcal{S}) + \lambda_1 L_{DTA}(\mathcal{T}) + \lambda_2 L_E(\mathcal{T}) + \lambda_3 L_V(\mathcal{T})$$

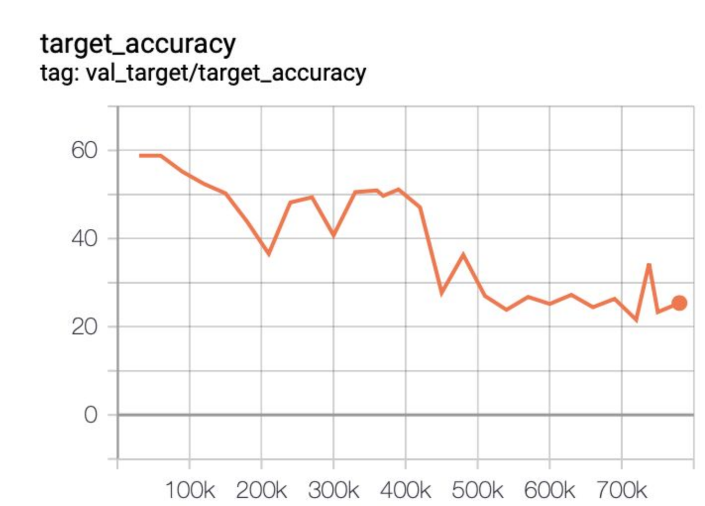
Experiment Results

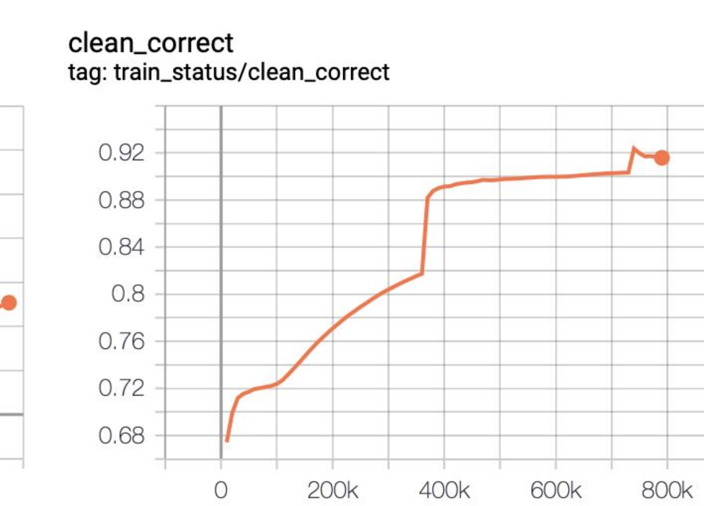
	Sequence F1-4 class	Sequence F1-13 class
Baseline I (Trained on Source, lower bound)		
Source	97.2	90.1
Target	36.1	33.4
Baseline II (Trained on Target, upper bound)		
Target	83.0	-
DTA (Classifier with DTA loss) - Epoch 1		
Source	79.3	71.5
Target	58.8	59.8
DTA (Classifier with DTA loss) - Epoch 3		
Source	97.9	92.3
Target	34.3	34.33





4 class





13 class

Overfitting to Source: As source accuracy increased, target accuracy decreased; more tuning needed

Covariate and Label Shift problem: Source and Target label discrepancy may be a problem. Generalized Domain Adaptation

Assumption of domain-invariant shared feature space may not hold

** Architecture used in final model was different because Dropout function was modified to use Adversarial Dropout

Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks, Pranav Rajpurkar, Awni Y. Hannun, Masoumeh Haghpanahi, Codie Bourn, Andrew Y. Ng

Drop to Adapt: Learning Discriminative Features for Unsupervised Domain Adaptation, Seungmin Lee, Dongwan Kim, Namil Kim, Seong-Gyun Jeong