Motivation

Objectives:
- Noninvasive vital sign (VS) data collected in a Step-Down Unit (SDU) with alerts issued when a VS exceeds predefined thresholds.
- Many alerts are artifacts, causing alarm fatigue.
- Need to dismiss these artifacts.
- Training classifiers for automatic artifact adjudication requires expert annotation.
- We aim to reduce annotation effort.

Outcome: Performing active learning reduces the number of alerts that need to be annotated by experts to train the artifact adjudication model. Our framework requires 48% of labels to train an accurate model, while a random forest classifier requires 89%.

Informative Projection Retrieval

- IPR Problem: Find a few simple projections of data in which alerts appear as either convincingly correct or easily dismissible.
- Difficulty: Selecting the best set of projections and determining point assignment.
- Technique: Machine Learning algorithm called RIPR: Regression-based Informative Projection Recovery [*]

RIPR selects a manageable small number of projections
- Each alert requires only one projection to be explained
- Low-dimensional projections allow easy interpretability
- RIPR enables automated classification of alerts

Active Learning Framework

- Challenge: Very few existing labels, difficult to tell which projections are useful.
- Solution: use active learning for existing models using various sample selection criteria:
  - uncertainty sampling, query by committee, information gain, conditional entropy

Active Learning Iterations

The informative projections recovered facilitate labeling

Annotation Examples

- The sample can be confidently classified as a true alert.
- The sample can be somewhat confidently classified as an artifact.
- The sample cannot be confidently classified.

Active Learning for Informative Projection Retrieval

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Data Description

- Prospective longitudinal study recruited admissions over 8 weeks in a 24 bed trauma stepdown unit all with noninvasive VS monitoring:
  - Respiratory Rate (RR) from ECG limb leads
  - Systolic (SBP) and Diastolic (DBP) Blood Pressure (oscimometric)
  - Peripheral arterial oxygen saturation (SpO₂) by finger plethysmography
  - VS data analyzed beyond local instability threshold values:
    - HR<40 or >140; RR<8 or >36; SBP<80 or >200; DBP>110, SpO₂<85%
  - Each alert associated with a category indicating the leading abnormal VS
  - 812 alerts of 3 types: RR, SpO₂, BP
  - 50 features computed, for each VS signal independently, during span of each alert, and a short window (4 minutes) preceding alert onset
  - Features include common statistics of each VS: mean, standard deviation, minimum, maximum, and range of values

Experiments

- Leave-one-out cross-validation was used due to the small amount of data available.
- 10-fold cross-validation: The ActiveRIPR model trained on 90% of the samples. The other samples were used to compute the curve.

Oxygen Saturation Alert Adjudication

- Very good performance in isolating SpO₂ artifact, equivalent to what can be attained with 50% more annotated training data if the Active Learning protocol had not been used.

Active RIPR with the Information Gain Criterion, appears to be the most effective sampling method among tested alternatives. It outperforms other full dimensional classifiers using uncertainty sampling.

This work has been partially funded by the National Science Foundation (awards 0911032, 1320347) and the National Institutes of Health (R01NR013912)