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Artifact adjudication for vital sign step-down unit data can be improved using active learning with low-dimensional models

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Objectives

- Noninvasive vital sign (VS) data collected in a 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

Approach

- Regression-based Informative Projection Recovery (RIPR) facilitates expert annotation
- Requires fewer annotations to obtain an accurate classifier
- Results presented in a human-understandable form, low-dimensional projections

Outcome: Performing active learning reduces the number of alerts that need to be annotated by experts to train the artifact adjudication model.

Active Learning for Artifact Identification

Fiterau, Dubrawski, Chen, Guillame-Bert,
Bose, Hravnak, Clermont, Pinsky

Data Description

- Prospective longitudinal study recruited admissions over 8 weeks in a 24 bed trauma stepdown unit all with noninvasive VS monitoring:
  - Heart Rate (HR) from 5-lead ECG
  - Respiratory Rate (RR) from ECG bioimpedance
  - Systolic (SBP) and Diastolic (DBP) Blood Pressure (oscillometric)
  - Peripheral arterial oxygen saturation (SpO_2) 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, SpO_2<85%
  - Each alert associated with a category indicating the leading abnormal VS
  - 812 alerts of 3 types: RR, SpO_2, BP
  - 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

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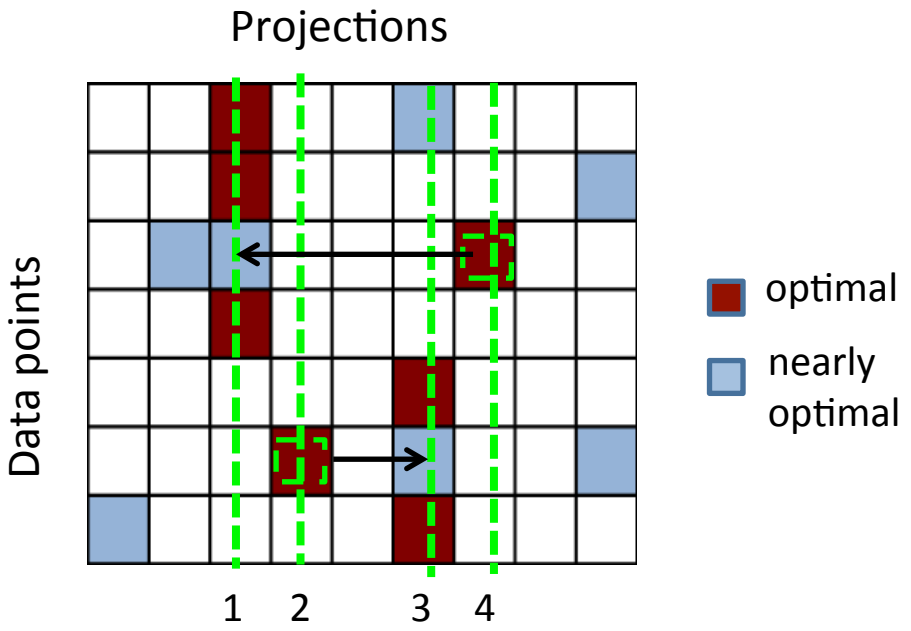
Approach: Finding Informative Projections of Data

- **Aim:** Find a few simple projections of data in which alerts appear as either convincingly correct or easily dismissible
- **Challenge:** Very few existing labels, difficult to tell which projections are useful
- **Solution:** Machine Learning algorithm called Active RIPR: Active Learning for Regression-based Informative Projection Recovery [*]
  - RIPR selects a small number of projections which classify jointly
  - Each alert requires only one projection to be explained
  - The next samples to be labeled are selected based on these projections
  - Sampling criteria: uncertainty, query by committee, information gain, conditional entropy



[*] M. Fiterau, A. Dubrawski, A Unified View of Informative Projection Retrieval, ICMLA 2013

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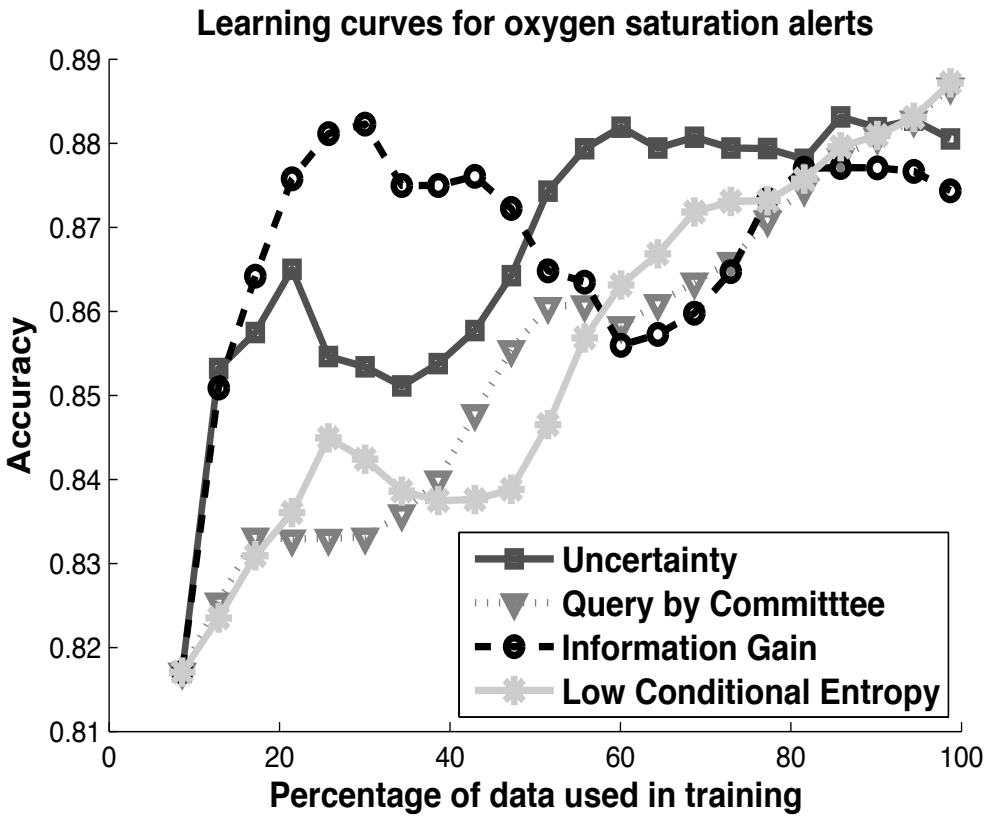
Result: Adjudication of oxygen saturation alerts



We used ActiveRIPR to predict SpO_2 alerts, treating the expert-labeled data as the pool of samples available for active learning.

Percentage of samples needed for classification		Target accuracy 0.85	Target accuracy 0.88
Active Sampling Strategy	Uncertainty	18%	55%
	Query by Committee	46%	48%
	Information Gain	21%	25%
	Conditional Entropy	43%	46%

We performed 10-fold cross-validation, training the ActiveRIPR model on 90% of the samples and using the remainder to calculate the learning curve.

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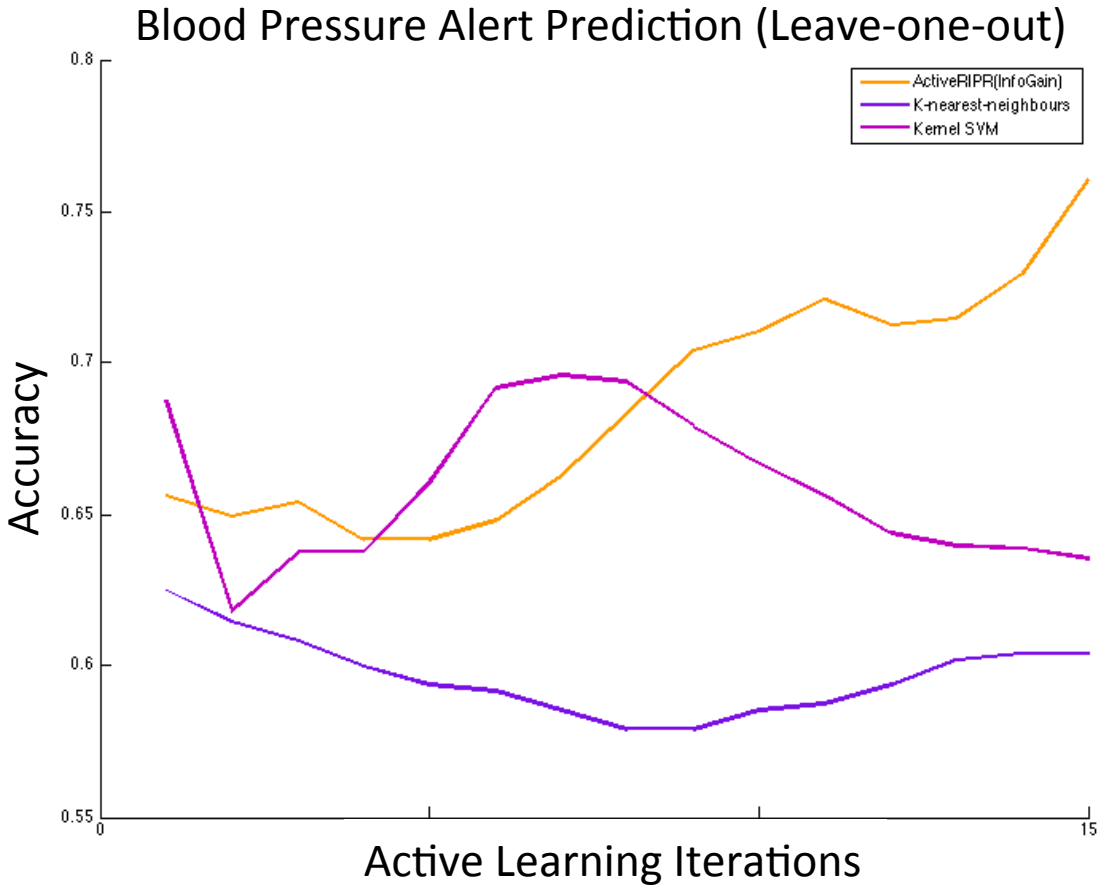
Result: Adjudication of blood pressure alerts



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.

We used ActiveRIPR to predict BP alerts, using the expert-labeled pool of alerts. Leave-one-out cross validation was used due to the small amount of data available.

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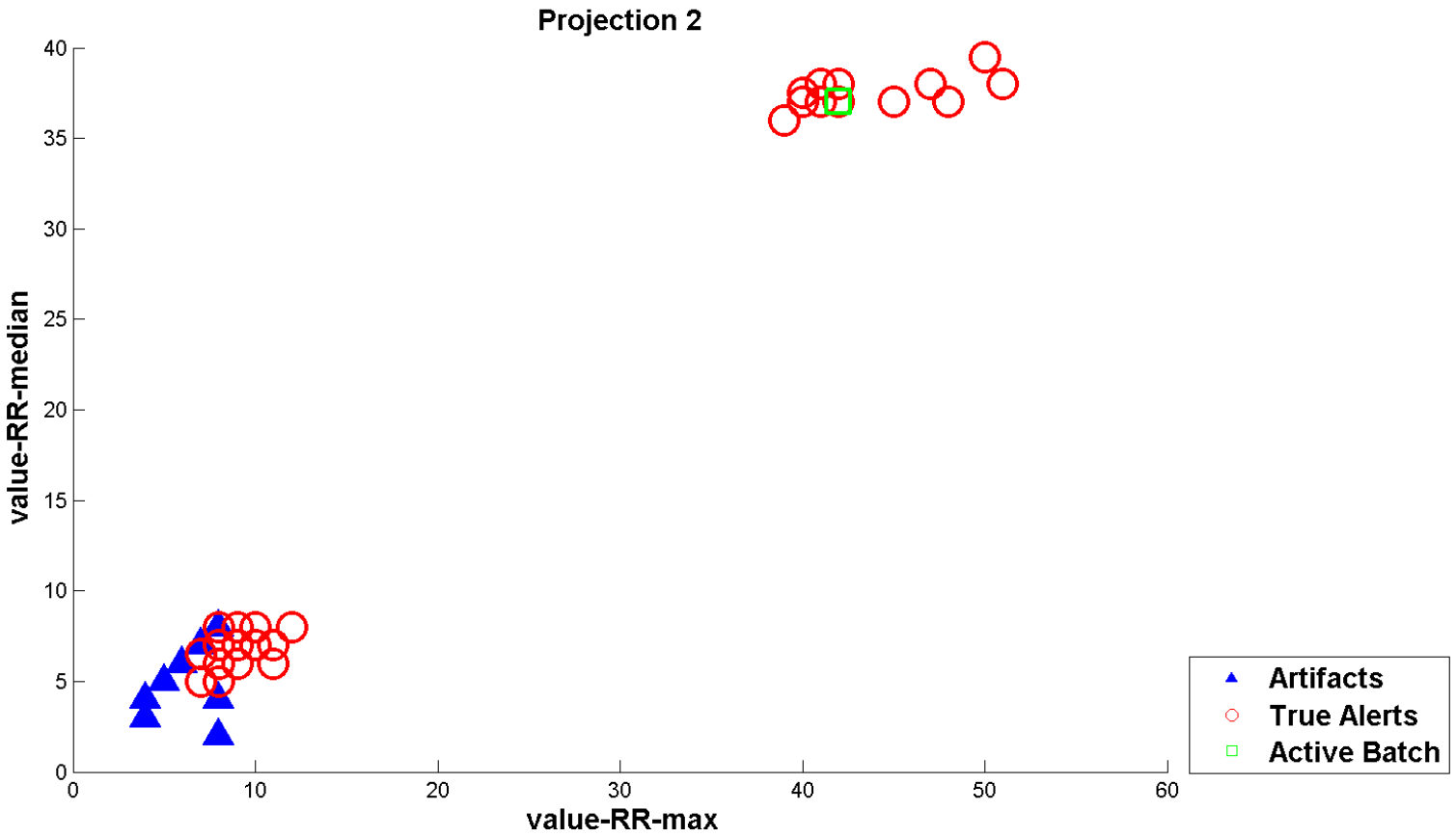
Projection shown to experts during annotation (RR)



The retrieved few low-dimensional projections make it possible for domain experts to quickly adjudicate alert labels.

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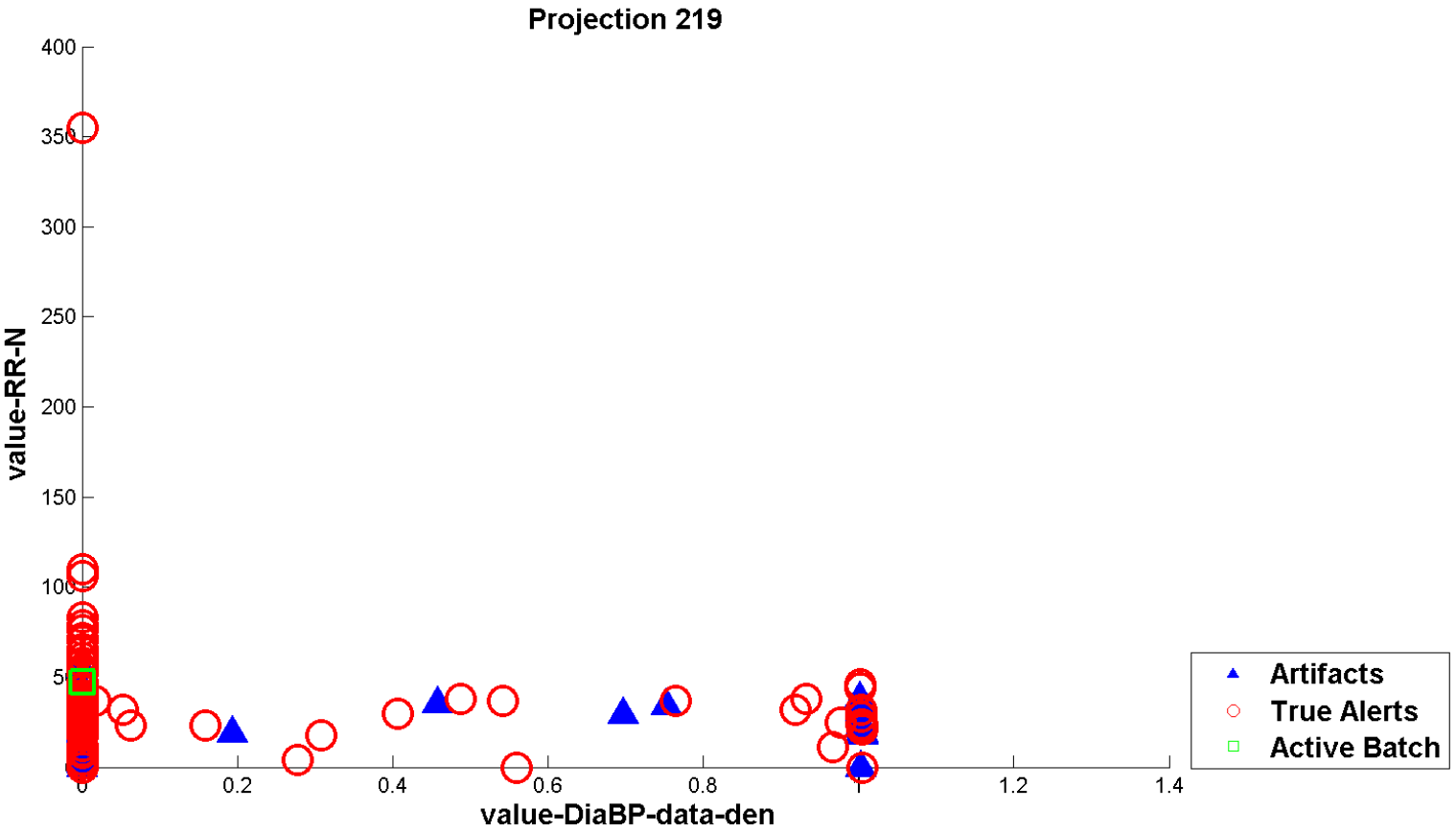
Projection shown to experts during annotation (SPO_2)



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