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Auton Lab

Automatic Identification of Alarm Artifacts in Monitoring Critically Ill Patients

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Objectives

- Noninvasive vital sign (VS) data collected in a Step-Down Unit
- Alerts issued when a VS exceeds predefined thresholds
- Many alerts are artifacts, causing alarm fatigue
- Need to dismiss these artifacts

Approach

- Regression-based Informative Projection Recovery (RIPR) enables alert adjudication
- Highly multivariate analysis
- Results presented in a human-understandable form

Outcomes

- Machine Learning improves alert adjudication accuracy, precision, and recall
- Visualizable results
- Models confirm clinicians' insights regarding alerts
- Clinicians can derive new alert adjudication rules from informative low-dimensional projections of complex data

Alert Artifact Identification

Fiterau, Dubrawski, Chen, 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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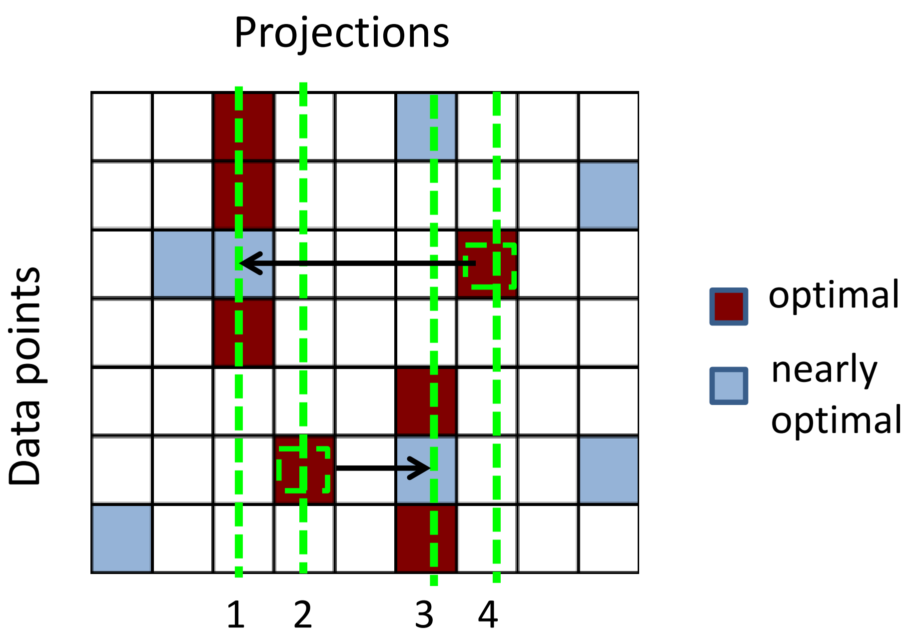
Approach: Finding Informative Projections of Data

- **Aim:** Find a few simple projections of data in which alerts appear as either convincingly correct or easily dismissible
- **Challenge:** There are many candidate projections to choose from
- **Solution:** Machine Learning algorithm called RIPR: Regression-based Informative Projection Recovery [*]
  - RIPR selects a manageably small number of projections that jointly explain multiple alerts
  - Each alert requires only one projection to be explained
  - Low-dimensional projections allow easy interpretability
  - RIPR also enables automated adjudication (classification) of alerts



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

Alert Artifact Identification

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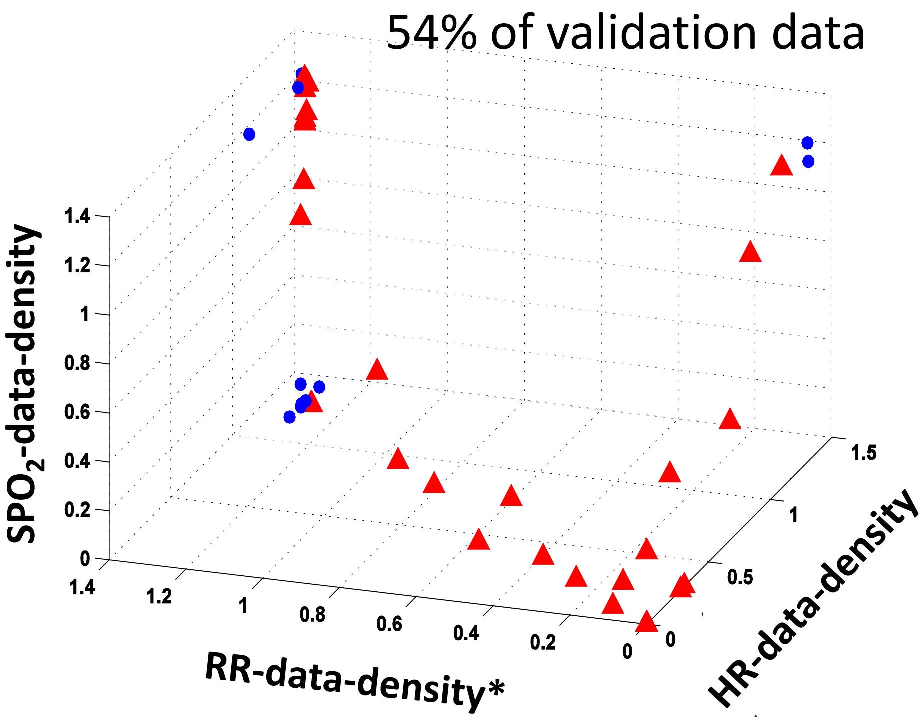
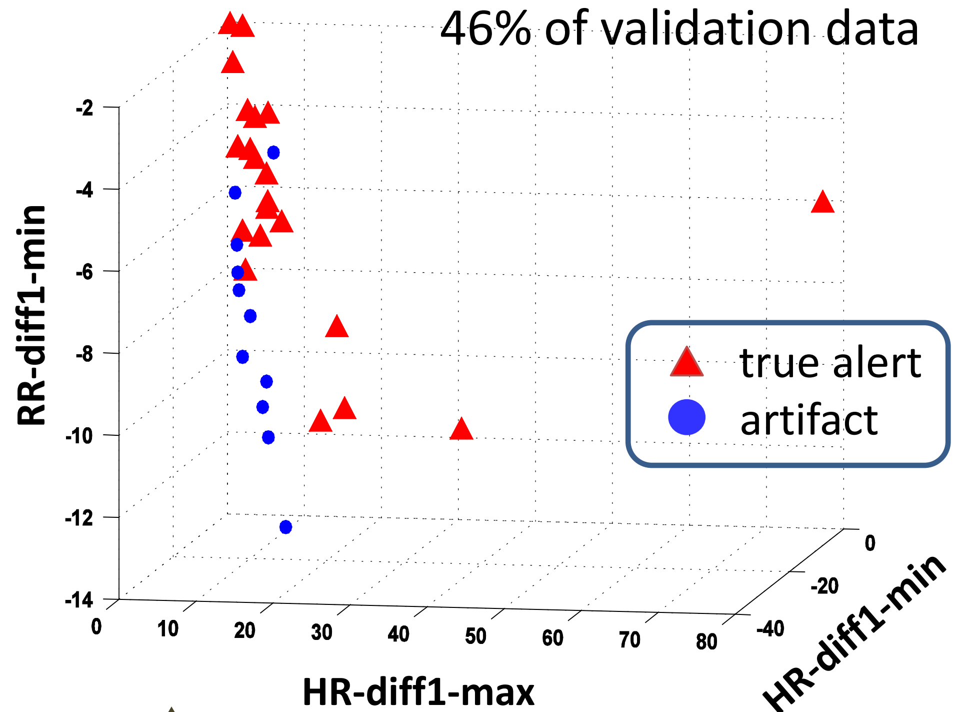
Cross-Validation Results Separate True From False Alerts





Alarm Type	RR	BP		SPO_2	
	2D	2D	3D	2D	3D
Accuracy	0.98	0.833	0.885	0.911	0.9151
Precision	0.979	0.858	0.896	0.929	0.9176
Recall	0.991	0.93	0.958	0.945	0.9957

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

*data density = number of readings over time units: a low value indicates high sparseness

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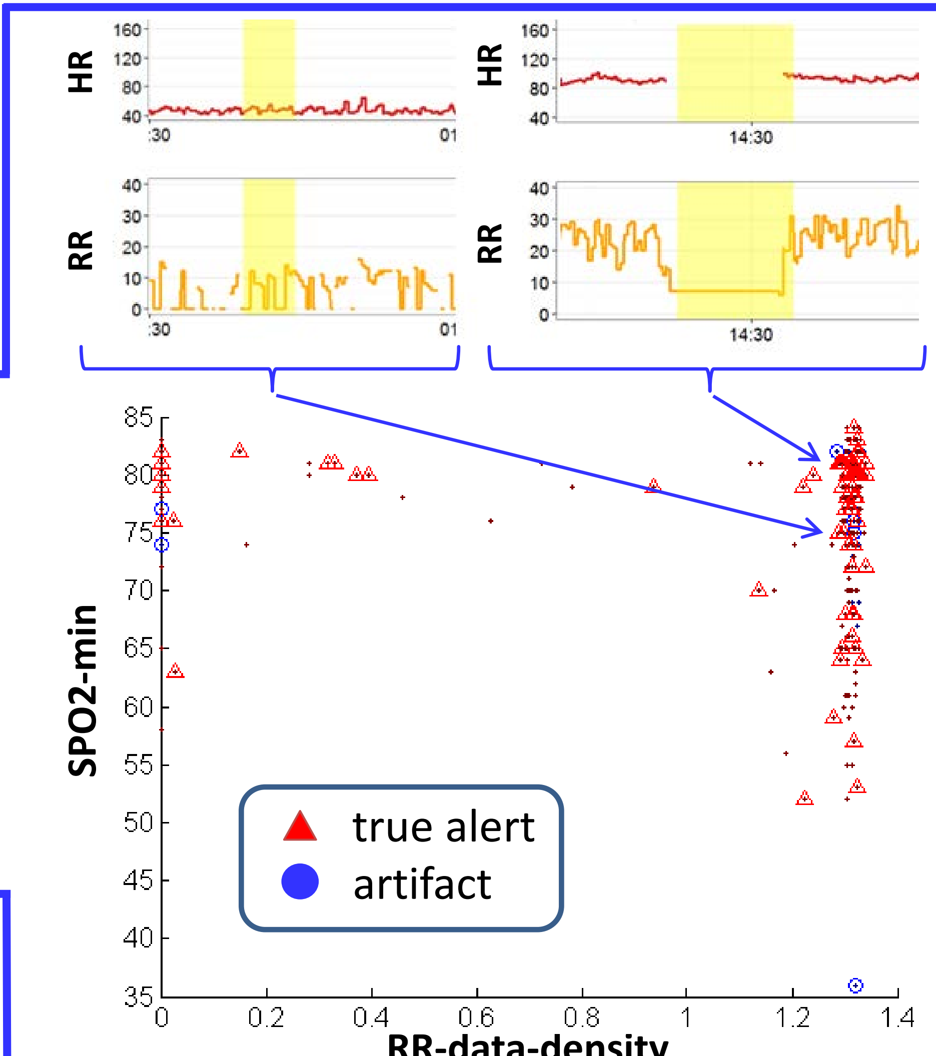
Confirmatory Results and Outlier Detection

- According to experts, lack of HR signal indicates an RR artifact. The **model validates expert intuition** by correctly selecting HR data density as the most important dimension in RR artifact classification
- Example shown includes two alert episodes that would be classified as non-artifacts. Both have continuous streams of RR data, but the **RR signals are irregular – an uncommon artifact**. Investigation has shown that instances like these can be identified using variance of signal
- RIPR also **highlight potentially mislabeled alerts** allowing clinicians to reconsider their judgments



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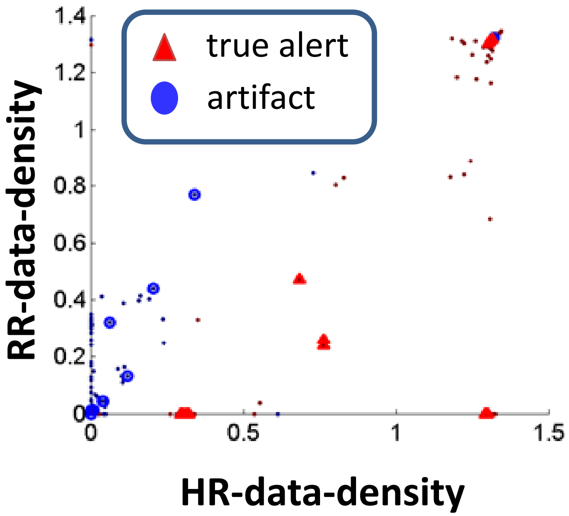
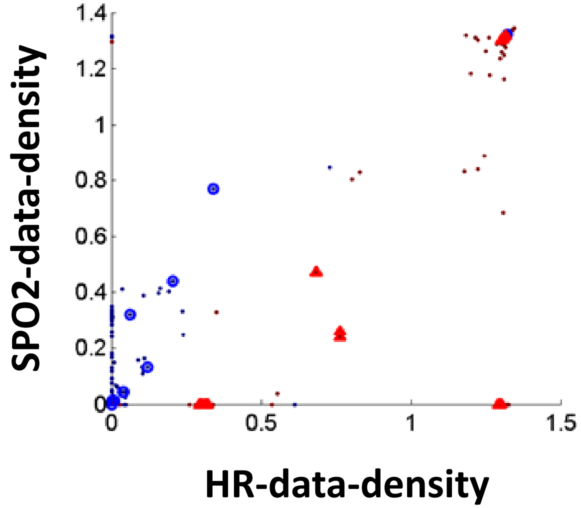
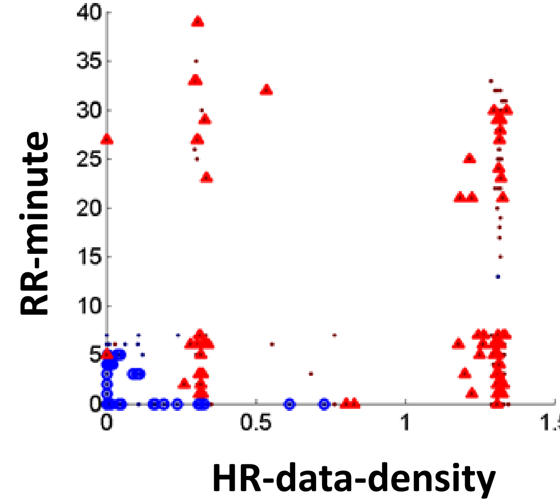
Deriving Artifact Identification Rules (Example: SpO_2)







RR-data-density* <= 0.6
and
HR-data-density <= 0.3

HR-data-density –
SPO_2-data-density <= 0.2

HR-data-density/0.3
+ RR-min/5 <= 1

Conclusion: **(1) RIPR models show high accuracy, precision, and recall or alert adjudication, while presenting results in an easy to understand form; (2) Retrieved projections confirm clinicians' insights and highlight potential mislabelings; (3) Informative low-dimensional projections make it easy for clinicians to derive new alert adjudication rules.**