Multi-tier ground truth elicitation framework with application to artifact classification for predicting patient instability

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Context:

- Robust health monitoring systems would **identify artifactual alerts** (due to equipment malfunction or misapplication of sensors) and **distinguish them from true alerts** signifying actual patient's instability
- This capability is important in **reducing alert fatigue** in clinical personnel

Our approach:

- We prototyped a **protocol to collect reliable training data** for development of such robust algorithms
- It uses **Active Machine Learning** (AML) for multi-tier **alert annotation elicitation** at the **minimal effort from a team of expert clinicians**

Methodology

Framework:

- **Machine Learning (ML)** is a powerful methodology which has been successfully applied to handle complexities of bedside data
- It can be used to e.g. discriminate true patient instability from artifact in hemodynamic monitoring data
- ML relies on a **library of expert-annotated examples** to **establish ground truth**
- Collecting expert-annotations can be a **burden on expert clinicians**

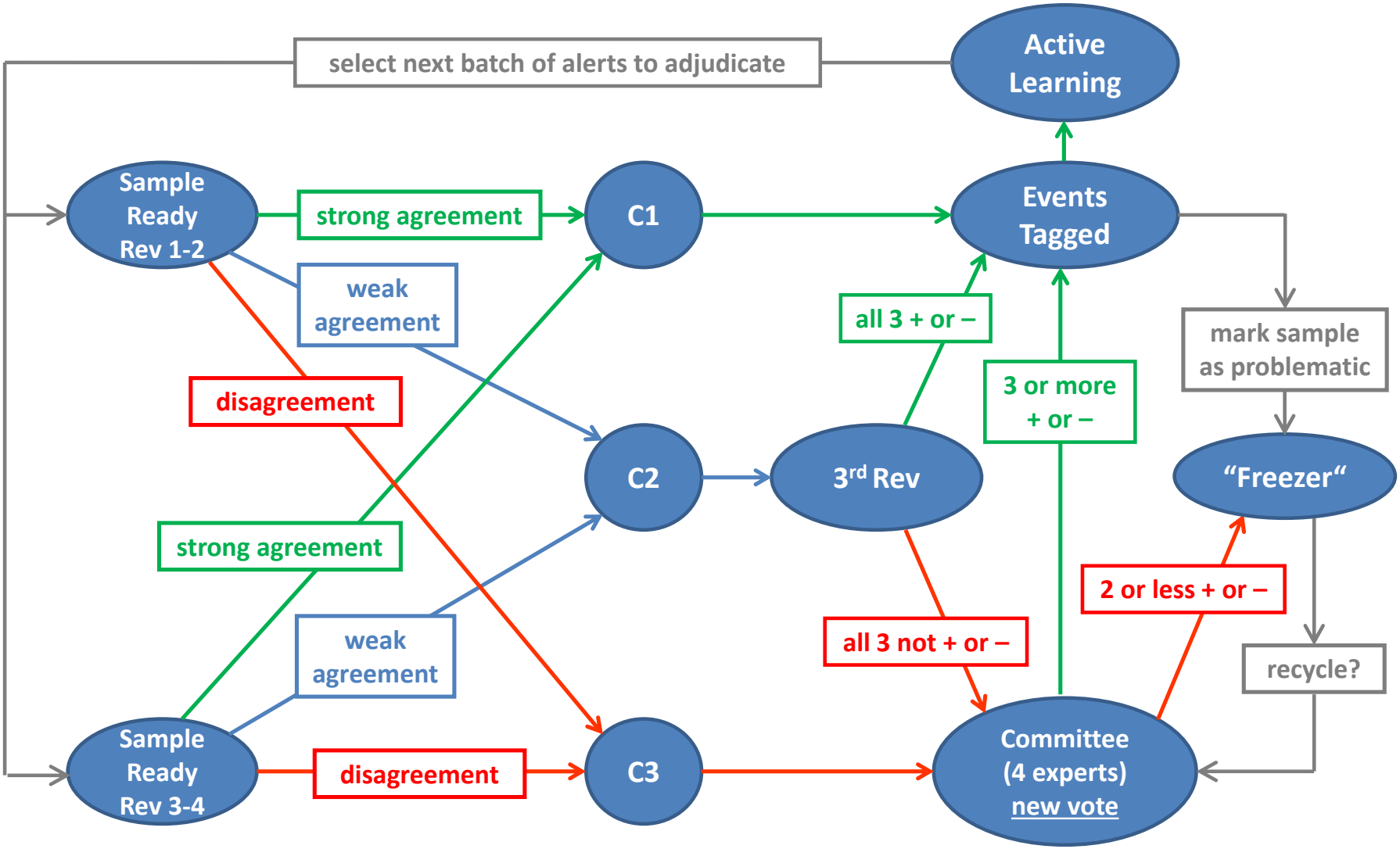
Specific Aim:

- **Develop a protocol for collecting expert annotations that minimizes clinicians' effort while providing informative training data for ML algorithms**
- Methodology: Active Machine Learning (AMR)

Methodology (contniued)

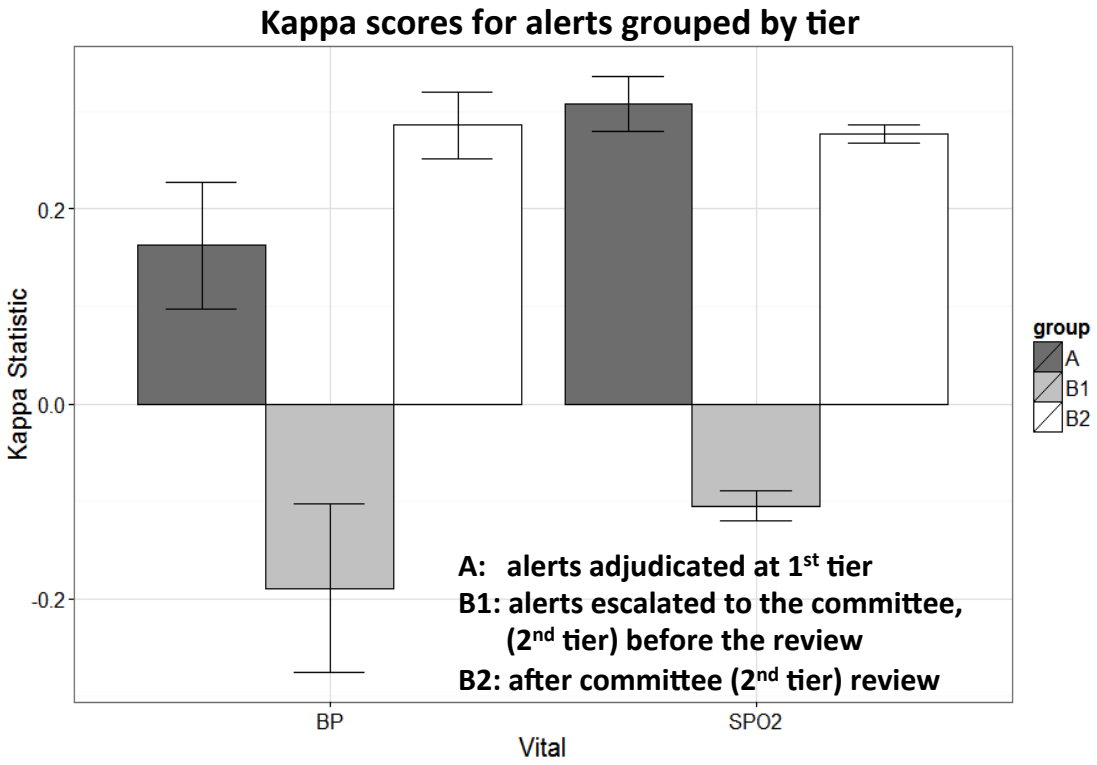
- **The data**, collected from **noninvasive monitoring system** for ECG-derived heart rate (HR) respiratory rate (RR), pulse oximetry (SpO_2), systolic and diastolic blood pressure (BP).
- Data contains **1,582 alert periods** defined as exceedences over pre-set stability thresholds (HR<40 or >140, RR<8 or >36, systolic BP <80 or >200, diastolic BP>110, SpO_2<85%).
- AML **algorithm selects a batch of alerts** which, when adjudicated by experts, would **provide the most useful information** to the alert interpretation algorithm.
- **Reviewers** working individually **score these alerts** on a scale from -3 (artifact) to 3 (true alert) to reflect confidence of assessment.
- Alerts yielding **substantial disagreement or low confidence** are pushed to a **committee review** where consensus can be reached.
- The alerts that cannot be agreed upon are put in a "freezer" and not used in the alert adjudication model building.

Schematic diagram of the multi-tier protocol



Results

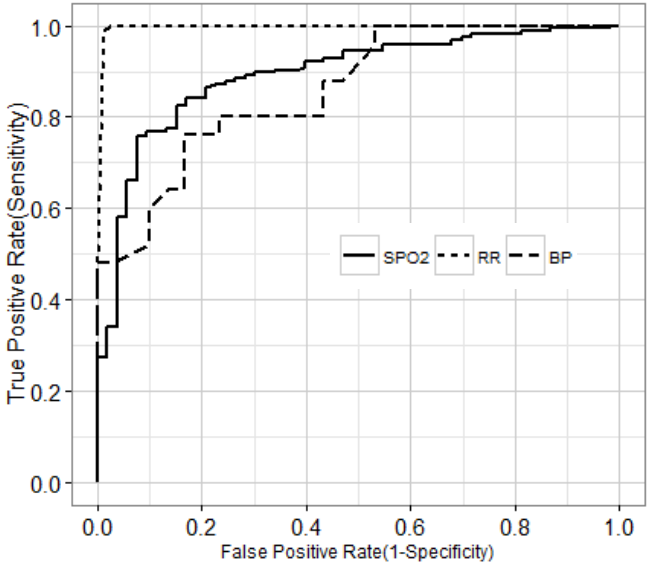
- We **collected 1,941 annotations from 7 expert clinician reviewers on 450 unique alerts** (HR: 60, BP: 80, RR: 80, SpO_2: 230).
- Of those, 26 (32.5%) BP, 115 (50%) SpO_2, and almost none of HR and RR alerts, were **escalated to the 2nd tier review**.
- The results show that the **consensus for alerts initially conflicted improved significantly** as a result of the 2nd tier committee review.
- Weighted pairwise Kappa statistic increases from -0.19 to 0.29 for BP, and from -0.10 to 0.28 for SpO_2 alerts.

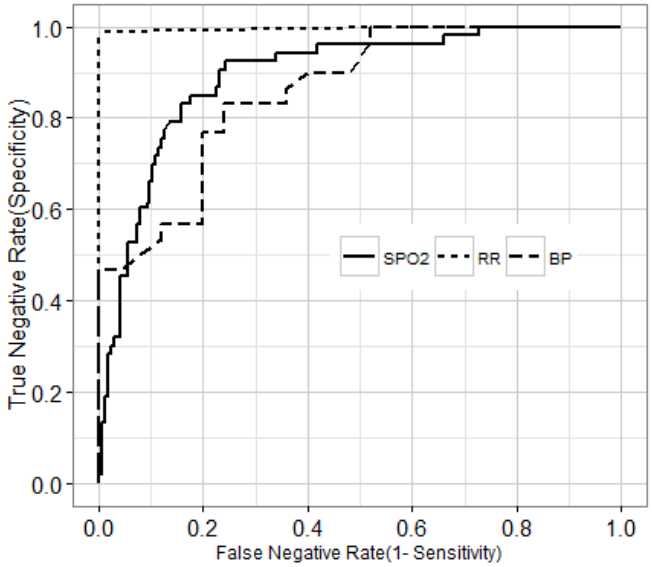


Results (continued)

Preliminary **artifact adjudication model** built using these annotations shown:

- **Very strong ability to identify RR alerts and artifacts** (dense dash line in the ROC diagrams)
- **Ability to very confidently isolate** more than 47% of **true BP alerts** and more than 45% of **BP artifacts**
- **Very good performance in isolating SpO_2** artifact, equivalent to **what can be attained with 50% more annotated training data** if the Active Machine Learning protocol has not been used.





Conclusion

- We implemented a **multi-tier framework** to **elicit ground truth from multiple reviewers** to support development of a prototype of the automated artifact adjudication system.
- The initial results show that **precious human expertize can be utilized efficiently and without loss of performance** of the resulting models of instability.
- The proposed annotation framework can **yield accurate alert adjudication systems while minimizing effort of human experts** required to produce ground truth evidence, **even if very large libraries of reference data are available**.

This work has been partially supported by the NSF Awards 0911032 and 1320347, and by the NIH Grant R01NR013912.