Reducing False Arrhythmia Alarms in the Intensive Care Unit
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INTRODUCTION
- Intensive Care Units have false arrhythmia alarm rates up to 86%, causing slower alarm response times and decreases in patient care
- PhysioNet Challenge provides entrants with time-series data of monitors for 750 patients along with the alarm type (one of five alarms) and accuracy
- We added features and investigated different machine learning techniques to reduce false-alarm rates while maintaining true alarms
- Competition scored by weighted combination of FP, FN, TP, TN

METHODS
- Extracted additional features from time-series traces using MATLAB, using the ECG traces available for every patient and the PPG and ABP traces available for some patients
- Created randomly generated hold-out sets of five different sizes in Python to find which hold-out size was appropriate for the data set due to concerns about the small number of patients with certain alarms.
- Implemented logistic regression, SVM (with CV tuning), and boosted regression trees in R on each group of patients separated by alarm type with the above features; implemented multi-class random forest in R to analyze whether including features from all patients improved sensitivity and specificity.
- Will perform greedy feature selection to see how algorithms perform on a subset of features.

RESULTS
- Traces provided for three sample patients showing difference in data quality
- The below table shows how each of our 22 features were calculated in MATLAB from the traces
- The boosted regression trees and logistic regression classifiers based on each alarm individually were most effective for the alarms. The multiclass random forest including all patients was not as effective as we hoped, possibly because the alarm types are too correlated.

<table>
<thead>
<tr>
<th>Features</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low heart rate</td>
<td>0.87</td>
<td>0.47</td>
<td>0.82</td>
<td>0.49</td>
<td>0.89</td>
<td>0.47</td>
<td>0.91</td>
<td>0.47</td>
</tr>
<tr>
<td>High heart rate averaged over 16 beats</td>
<td>0.87</td>
<td>0.47</td>
<td>0.82</td>
<td>0.49</td>
<td>0.89</td>
<td>0.47</td>
<td>0.91</td>
<td>0.47</td>
</tr>
<tr>
<td>Max heart rate</td>
<td>0.87</td>
<td>0.47</td>
<td>0.82</td>
<td>0.49</td>
<td>0.89</td>
<td>0.47</td>
<td>0.91</td>
<td>0.47</td>
</tr>
<tr>
<td>Highest voltage difference between two heartbeats</td>
<td>0.87</td>
<td>0.47</td>
<td>0.82</td>
<td>0.49</td>
<td>0.89</td>
<td>0.47</td>
<td>0.91</td>
<td>0.47</td>
</tr>
<tr>
<td>Number of heartbeats in 16 seconds</td>
<td>0.87</td>
<td>0.47</td>
<td>0.82</td>
<td>0.49</td>
<td>0.89</td>
<td>0.47</td>
<td>0.91</td>
<td>0.47</td>
</tr>
<tr>
<td>Signal-quality index</td>
<td>0.87</td>
<td>0.47</td>
<td>0.82</td>
<td>0.49</td>
<td>0.89</td>
<td>0.47</td>
<td>0.91</td>
<td>0.47</td>
</tr>
</tbody>
</table>

FUTURE WORK
This project will be continued with the Lucile Packard Children’s Hospital in partnership with David Scheinker and Nicholas Bambos.

FIGURES
- Traces provided for three sample patients showing difference in data quality
- The below figures show the difference in CV performance of logistic regression when we added features using the more reliable ECG trace.
- The below figures show the difference in CV performance of SVM when we added CV tuning based on the score metric provided by the competition.

- Logistic Regression Sensitivity With and Without ECG Features
- SVM Sensitivity With and Without Tuning
- Logistic Regression Sensitivity With and Without ECG Features
- SVM Specificity With and Without Tuning