Using Machine Learning to Predict Respiratory Decompensation

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Artificial Intelligence in the Perioperative Setting: Development, Implementation, and Value

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Conflict of Interest/Funding

- Past: Grant funding from Medtronic to study inpatient respiratory monitoring
- Current: NIH-NCATS 1KL2TR002245, AHRQ R18-HS026616

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Learning Objectives

- At the conclusion of this activity, participants will be able to demonstrate an improved understanding of the **state of the science** in applying machine learning techniques to the clinical problem of respiratory decompensation

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Overview

- Prevention
- Detection (with better monitors– passive and active surveillance)
- Treatment/Early Intervention
- Better Documentation

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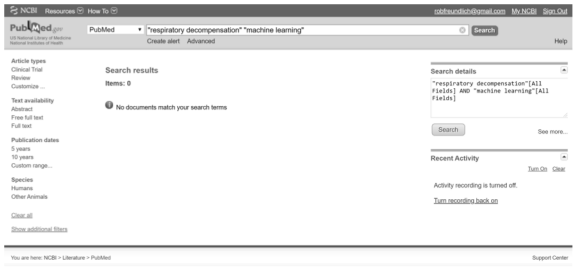
Overview



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Respiratory Decompensation

- Definition:

- "I know it when I see it" – Justice Potter Stewart

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Temporality

- Sudden/abrupt
- Gradual
- Unclear if changed at all (baseline)

Often difficult to determine *when*

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Evidence of Pathology

- Pneumonia
- "Atelectasis"
- Tachypnea/bradypnea
  - Capnography?
- Desaturation
- P:F ratio, S:F ratio

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Evidence of Treatment

- Breathing treatment
- Increased oxygen requirement
- Change in means of oxygen delivery
- Positive pressure ventilation
- Intubation
  - Gabel A+A 2017
- ICU stay
- RRT activation

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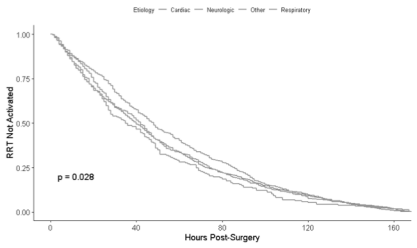
RRTs

- 2,399 RRTs 2010-16; 566 were respiratory (24%), median time to event 48 hours (late)



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Classical regression

- Derivation
- Validation
- Calibration/discrimination
- Publication

- Need an algorithmically-definable *outcome*

- Machine learning?

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Supervised Machine Learning

- Classification: "The problem of identifying to which of a set of categories a new observation belongs" –Wikipedia
- Assumes that category membership is known in the **training** dataset
- Need an algorithmically-definable *outcome*
- Adjustment for noise/human error

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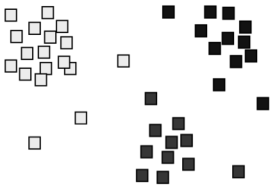
Unsupervised Machine Learning

- Clustering– grouping similar objects



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An Unsupervised Approach to Bananas

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Clusters of Decompensation

- Heterogeneity of population
- Varying severity
- Unclear definitions

- Much more complicated than bananas
- Need better **phenotyping** first

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Predicting Decompensation in Cancer Patients

- 1.6 million new cases in US annually
- Largely outpatient treatment; radio/chemotherapy
- Unplanned hospitalization rates 14-37%
- 50% of chemo patients have severe treatment toxicity
- 80% of patients have non-routine adverse events

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Multimodal Surveillance and Response System

- Passive and active surveillance
  - Smartphone application to report problems
  - EHR-derived data collection based in Epic
  - FitBit sensors
    - Overall activity
    - Heart rate variability
    - Geolocation
  - Routine structured interviews with patients, families

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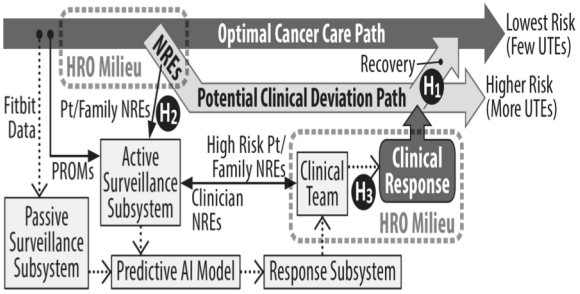

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How to Provide Value

- Critical need to generate algorithm(s) that accurately categorize respiratory decompensation

Future steps:

- Prevention
- Detection (with better monitors– passive and active surveillance)
- Treatment/Early Intervention
- Better Documentation

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