ICU Readmission

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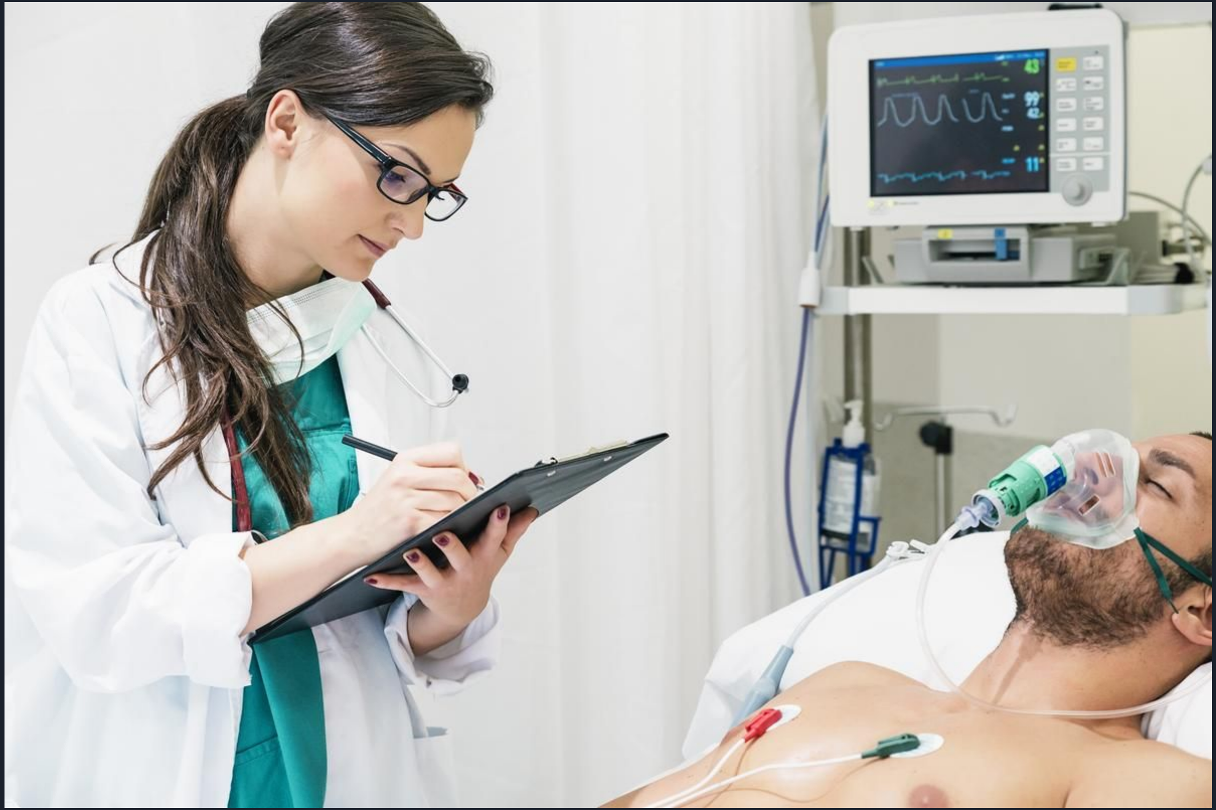
Problem Statement

- ICU readmission is a large problem in the healthcare system as preemptive or late discharge from the ICU can be financially costly and risky for the patient’s well-being. The current techniques and metrics being used to evaluate patient recovery are insufficient to effectively capture chance of readmission, nor do they implement all of the available data.

Example of a Problem



Aims

- Aim 1: Process the complex data available in EHR into a form more suitable for analysis
  - Parse data to find out number of visits, which ICUs those visits were to, and which visits led to readmission
  - Collect data from separate files into single data structure
- Aim 2: Determine features useful for identifying which patients are at risk of readmission.
  - Features clinician's value
  - Features found to be statistically important
  - Derived features
- Aim 3: Develop a predictive model to quantify the likelihood of ICU readmission.
  - Linear regression
  - Machine learning/Neural Networks

Significance

- From the patients' perspective:
  - 2-10 fold increase in the mortality of patients who are discharged before sufficient treatment of illness and readmitted compared to those who require no readmission
  - Financial burden
  - Limited beds and resource for other critically ill patients
- From the clinicians' perspective:
  - Difficult to determine whether the patients should be discharged
  - Further monitoring level of the discharged patients?
- From the hospital's perspective:
  - Resource distribution (e.g. # of beds and doctors per ICU)
  - Hospital care quality improvement

Innovation

- The primary aim is to predict the likelihood of ICU readmission instead of the mortality of patients
- Separate all the data according to different ICU types
- Involve the time varying parameters
- The hypothesis is that the stress response is related to readmission

Approach

- Understand the Data (Aim 1)
  - Compute Relevant Statistics
  - Verify Statistics with clinicians and published values
- Develop List of Features (Aim 2)
  - Incorporate features from SOFA and APACHE that we deem to be significant
  - Utilize input from Dr. Faraday and Dr. Sapirstein to determine features that are significant
  - Propose list of derived features that account for changes over time
- Develop Model (Aim 3)
  - Perform LASSO feature selection to identify features that are statistically significant to predicting a patient’s likelihood of readmission to the ICU
  - Compare models with different combinations of features using ROC curves

Milestones & Timeline

- Understand the Data (Aim 1) Nov. 30
  - Stratify data by different ICUs
  - Compute Relevant Statistics and verify it with the clinicians and published values
- Develop List of Features (Aim 2) Feb. 28
  - Incorporate features from SOFA and APACHE that we deem to be significant
  - Utilize input from Dr. Faraday and Dr. Sapirstein to determine features that are significant
  - Propose list of derived features that account for changes over time
- Develop Model (Aim 3) May. 15
  - Perform LASSO feature selection to identify features that are statistically significant to predicting a patient's likelihood of readmission to the ICU
  - Compare models with different combinations of features using ROC curves

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