DUHS Inpatient General Decompensation Prediction

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1 Introduction

1.1 Background

Patients in hospital sometimes decompensate for complex reasons and the general ward is usually a harder setting than Intensive Care Unit (ICU) to detect deterioration [1]. Also, compared with patients admitted directly to ICU [2], patients who suffer unanticipated or delayed transfers to ICU have higher mortality rate [3, 4]. Delayed recognition of deterioration rise from monitoring failures [5] to a great extent. Nurses can fail to detect decompensation due to various reasons such as too much workload [6] and limitation of an individual's capability. Machine learning techniques will be a helpful tool for reducing the rate of preventable adverse events. Before the emergence of machine learning techniques, risk scores had been widely used for identifying and predicting patient deterioration. Most early warning scores are not individual-based, which means they cannot fit specific patients. Therefore, research efforts should lay emphasis on model quality rather than quantity. A comprehensive literature review for this project is available at `https://github.com/ziyuan-shen/DIHI_adult_decomp/raw/master/Docs/Project/literature_review.pdf`.

1.2 Purpose of Study

This project aims to initialize machine learning models for predicting adult inpatients' decompensation (ICU admission, mortality, RRT events, etc). Most preliminary work before building models includes data cleaning, data visualization, data quality assurance and data manipulation etc. The ultimate goal is to reduce patients' deterioration and standardize hospital response protocols. Source code for analysis and methods in this paper is available at `https://github.com/ziyuan-shen/DIHI_adult_decomp`.

1.3 Preliminary Knowledge

1.3.1 Hospital Department Category

As the primary goal of this project is to predict patients' ICU admission, the labelling process includes identifying which units send transfers to ICUs. This process is very dependent on how we categorize hospital departments. Generally, all hospital units are split into three different levels of care: regular, stepdown and intensive care. A regular unit is more commonly known as a general ward, which is also called a floor unit. A stepdown unit provides level of care between a regular unit and an intensive care unit [7]. To our knowledge, level of care of a hospital unit is mostly decided by nurse-patient ratio in Duke Hospital. In this project, there are two specific types of units that are worse additional attention: Emergency Department (ED) and Operation Room (OR). An ED is a special type of regular unit and an OR is a special type of stepdown unit.

1.3.2 Raw Data Element Grouper

A large portion of work this project requires is raw data cleaning and manipulation before building features. For instance, if we want to employ patients' pulse values as a feature, the corresponding raw data is not recorded directly as named pulse. Format and structure of raw data depends on the hospital system as well as data system a hospital employs, such as Epic system. In Duke University Health System (DUHS), vital data contains thousands of different names (flo_measurement_name), in which a list of names could point to the same type of vital sign. For example, pulse values are composed of *"R AN PULSE"*, *"PULSE"*, *"R DUHS AN SPO2 PULSE"*, *"R DUHS PULSE RATE"*, etc. This list of names form what we call data element grouper. The same is true of laboratory data, medication data, etc. Groupers are mostly defined by prior medical knowledge and familiarity with the hospital system. Initially, this project makes use of predefined groupers from previous projects when building features. However, as we proceed to iterate and elaborate the modeling process, the goal is to build updated groupers tailored for this project. One important task done for building new groupers is gap analysis, which will be specified in Section 2.1.4.

2 Methods

To clarify the project workflow, a pipeline is depicted in Figure 1 for reference. Although the flowchart is step by step in general, the process is actually iterative. Findings in the modeling process may possibly affect how we implement feature engineering and label outcomes.

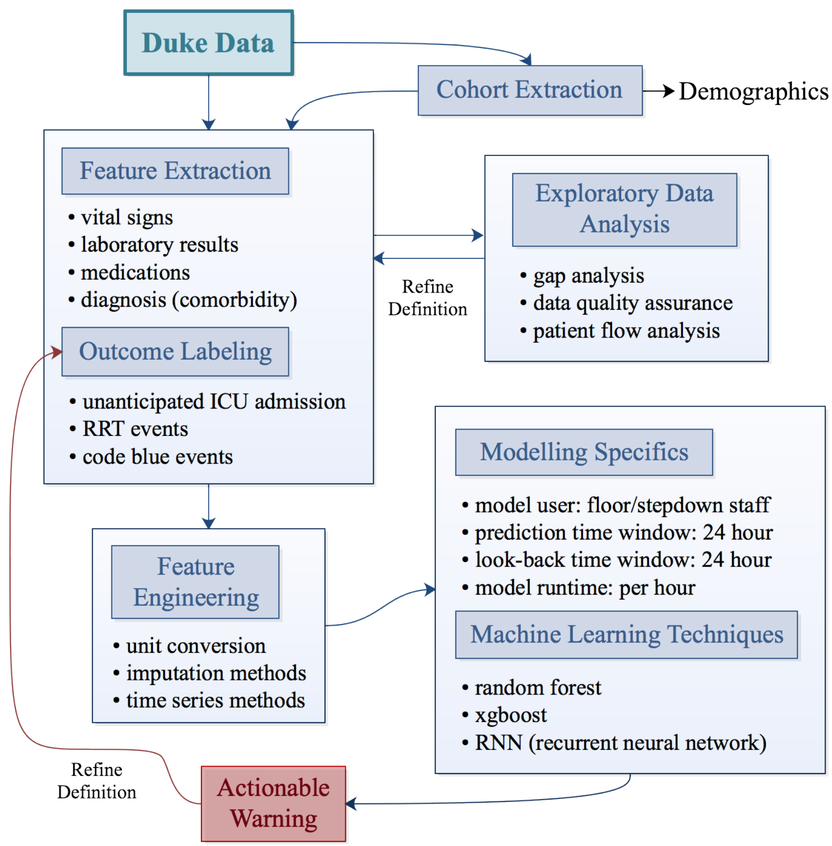

Figure 1: Working pipeline.

2.1 Data Preparation

2.1.1 Cohort Extraction

There is a list of inclusion and exclusion criteria for extracting cohort. In summary, we include all inpatient encounters who are adult patients (age ≥ 18 at hospital admission), and exclude all encounters with ED to ICU transfer and get discharged in ICU. In model v1.0, encounters in cohort span from October, 2014 to

August, 2018. In model v2.0, the cohort is truncated to from October, 2015 to August, 2018 in order to build pre-encounter features. Also, patients' demographics are generated along with the cohort extraction process.

2.1.2 Feature Extraction

Main feature components of this project include vital signs, laboratory results, medications, diagnosis and orders. For pulling vitals, labs and medications, raw data is subset by cohort patient ids and corresponding groupers. For diagnosis, raw data is subset by patient ids.

2.1.3 Outcome Labelling

Although the project goal is to predict patients' deterioration, the primary outcome defined by far is ICU admission. For model v1.0, we label all transfers from non-ICU units to ICU units. In model v2.0, outcome definition is refined by keeping only unanticipated ICU admission. More specifically, we limit transfer-from units to only general floor or stepdown unit. ED or OR to ICU transfers are excluded from outcome, because ICU admission after surgery is usually a planned event, as confirmed by Duke clinicians.

2.1.4 Exploratory Data Analysis

Exploratory data analysis before actually building the model is significant to make sure that model assumption makes sense and preprocessed data is in good quality.

a) Gap Analysis
Gap analysis is defined as raw data element count and distribution comparison between sub-cohort with outcome and sub-cohort without outcome. As explained in Section 1.3.2, grouper is a list of raw data element names that point to the same type of medical measurement we want to build feature upon. Gap analysis is aimed to identify new groupers that would especially contribute to this project. Within each individual sub-cohort, we define data element frequency as the number of times this data element is collected, and data element prevalence as the percentage of patients who have this measurement collected. Then we compute frequency and prevalence ratios by dividing outcome sub-cohort by no-outcome sub-cohort for each raw data element. Simple assumption is that the higher the ratio is, the more predictive a data element will be. Additionally, for outcome sub-cohort, all data are truncated before the patient gets admitted into ICU. A second version of gap analysis is to truncate the data 6 hours before ICU admission to help build a model that is capable of predicting more time ahead.

b) Data Quality Assurance
Data quality assurance is defined as checking the stability of data by month over the span of cohort encounters. This could be composed of both features and outcome. This part is mostly completed by Mengxuan.

c) Patient Flow Analysis
Patient flow diagram (Sankey diagram) creation serves as important part of data visualization work. It provides a direct sense of how and what proportion of patients transfer from units to units. It also guides how we define outcomes by communication with clinicians. (Please refer to Section 3.2 for detailed results of patient flow analysis.)

2.2 Feature Engineering

In order to transform pulled data into usable format that can be fed into a model, unit conversion is the very first step. Other preprocessing requirements would include removing out-of-range values, missing value imputation, standardizing numeric values and dealing with class imbalance. Forward fill method and downsampling is employed for model v1.0. How we code each category of features is summarized in Table 1.

Table 1: Feature generation and transformation summary.

Data Type	**Data Element Name**	**Coding**
Demographics	sex, age, race	Indicator, numeric
Vitals	pulse, blood pressure, etc	max, min, average
Vital Miss Flag		Indicator
Labs	platelets, glucose, etc	average
Lab Miss Flag		Indicator
Medications	antibiotics, fluids, etc	Indicator
Diagnose	around 260 icd categories	Indicator
Days to admission		numeric

Remark 1 *Diagnosis features are built out as pre-encounter features. Raw diagnosis are composed of ICD codes. ICD9 and ICD10 codes are combined and categorized as around* 260 *types of comorbidities using CCS mapping* `https://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp#overview`. *Using a similar framework as in Ref [8], we build three variables, one indicating* 1 *year comorbidity before encounter, the other two indicating* $0-3$ *months comorbidity before encounter and* $3-12$ *months before encounter.*

2.3 Modelling

Model v1.0 employs a prediction time window of 24 hours and a look-back (data collection) time window of 24 hours. Model runs every 24 hours after patients' hospital admission and before hospital discharge or ICU admission. Model structure is shown in Figure 2. Floor or stepdown stays less than 24 hours or more than 30 days are excluded from design matrix. In model v2.0 (pending), prediction will be generated every one hour.

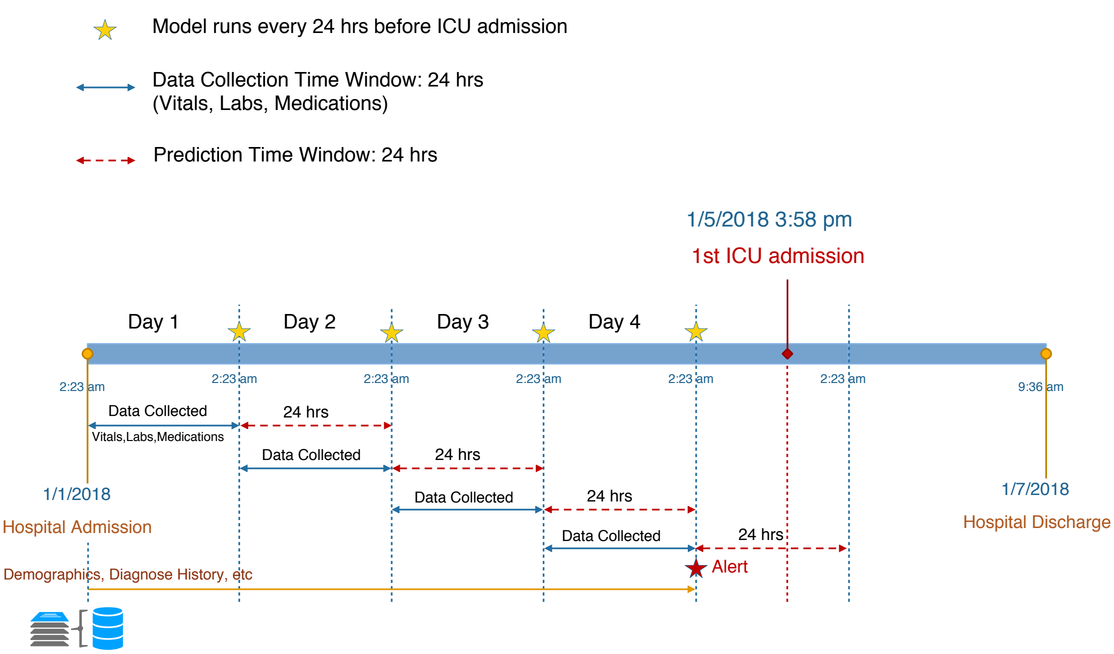

Figure 2: Model v1.0 structure.

3 Results

A large amount of work such as cohort extraction and data preprocessing outputs results as secured data files. However, we are able to show some of summary statistics and visualizations.

3.1 Summary Statistics

Cohort statistics is summarized in Table 2. Here outcome is defined as unanticipated ICU admission.

Table 2: Summary statistics of cohort.

Class	outcome label=1	outcome label=0
#Total Encounters	177213	
#Encounters	6550	170663
Proportion	3.7%	96.3%

3.2 Patient Flow Analysis

Sankey diagrams which visualize patient flow created for the project are shown in Figure 3 and 4. This is where we finally decided how to modify the outcome definition. From Figure 3, most ICU admissions are from surgery and ED. Figure 4 shows raw hospital departments that send transfers from OR to ICU. After confirmation with clinicians, we exclude all OR to ICU transfers from outcomes as they are not unanticipated events.

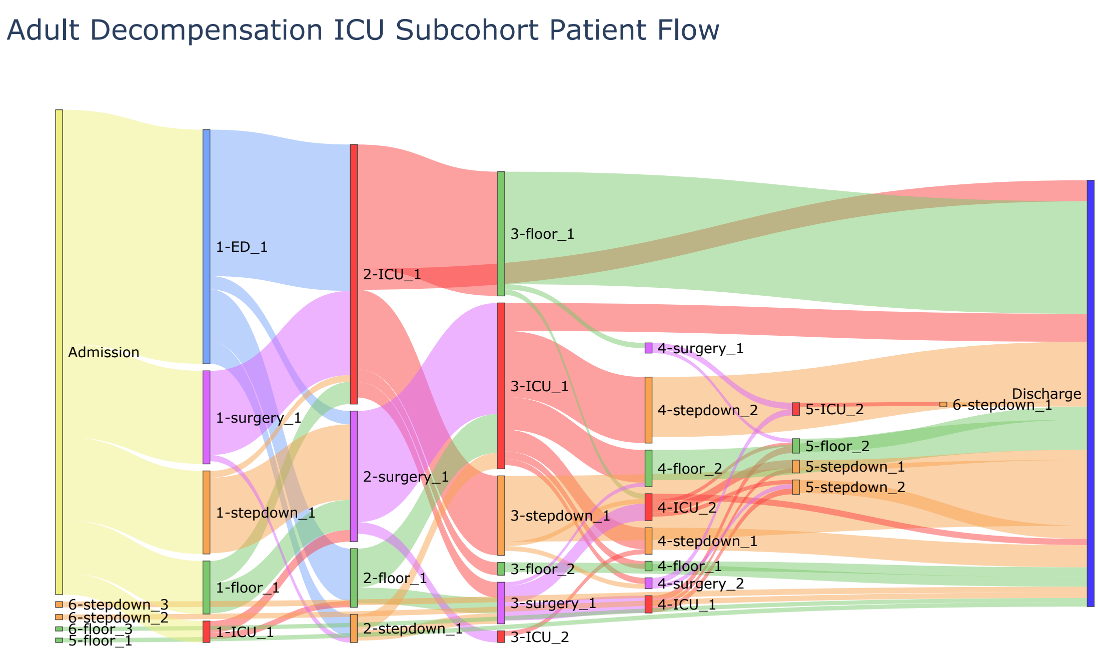

Figure 3: Adult Decompensation ICU Subcohort Patient Flow. Identify from which units patients come before each ICU admission, and to which units patients go after each ICU stay. Sub-cohort: all encounters which touch ICU. Each encounter flow is generated from hospital Admission to Discharge.

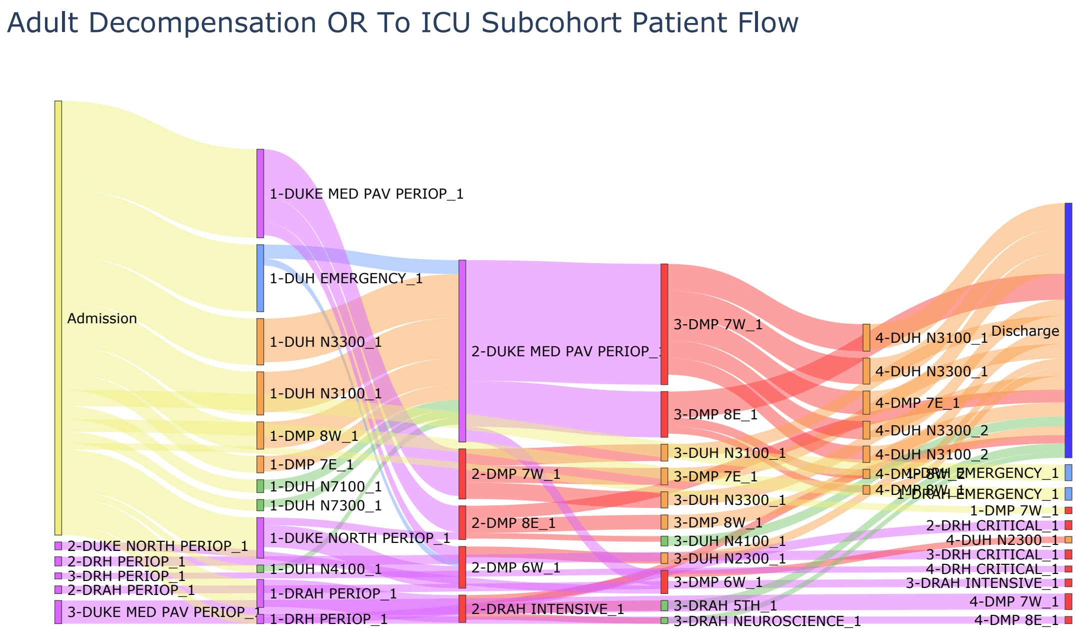

Figure 4: Adult Decompensation OR To ICU Sub-cohort Patient Flow. Identify which units send transfers to the ORs and which ICUs receive transfers out of the ORs. Sub-cohort: all encounters which have OR to ICU transfers.

3.3 Modeling Results

3.3.1 Model v1.0

In summary, model v1.0 is run on cohort from October, 2014 to August, 2018. All ICU admission events are counted as outcome. Model runs every 24 hours with a 24-hour prediction time window and a 24-hour look-back window. Model scores for model v1.0 are given in Figure 5 and 6. National Early Warning Score (NEWS) is used as a baseline model. Results for model v2.0 are still pending.

4 Conclusion

In conclusion, the main idea of this project is that we use Electrical Health Record (EHR) data collected from hospitals to design and train predictive models. The machine learning findings should be used to standardize hospital protocols. As we predict ICU admission, when the model is put into clinical use, it should generate actionable warnings for deteriorating patients, and the potential user can be a floor or stepdown unit nurse or any hospital staff who is in charge of ICU admission. In the long term, the model should help standardize response protocols. Additionally, feature importance can also be generated from the model, which can potentially perform feature selection for us. Another way we expect this might be meaningful is that, if the medical data system requires standardizing data collection procedures, feature importance may function to provide guidance of what specific data to prioritize.

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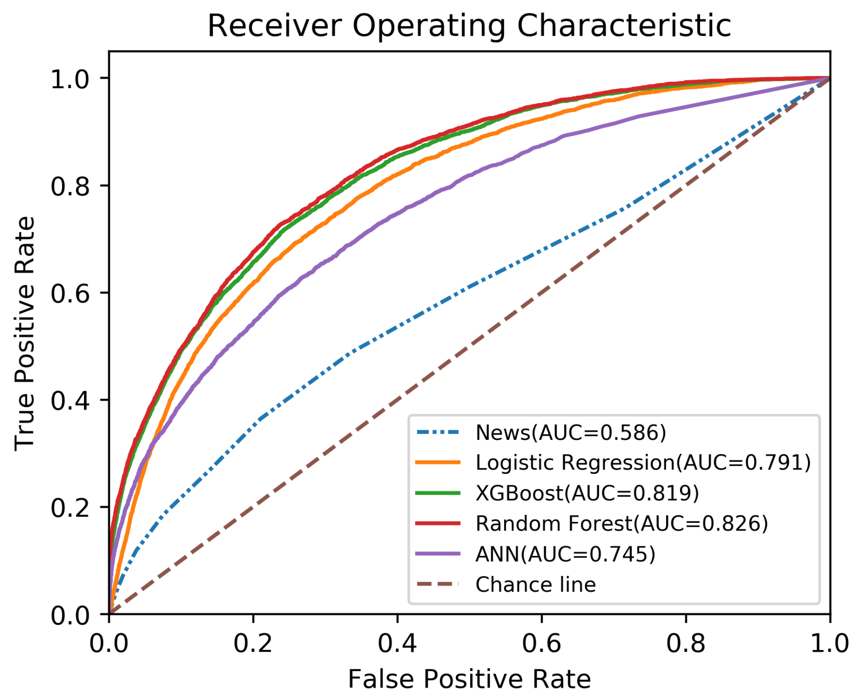

Figure 5: ROC curve for model v1.0.

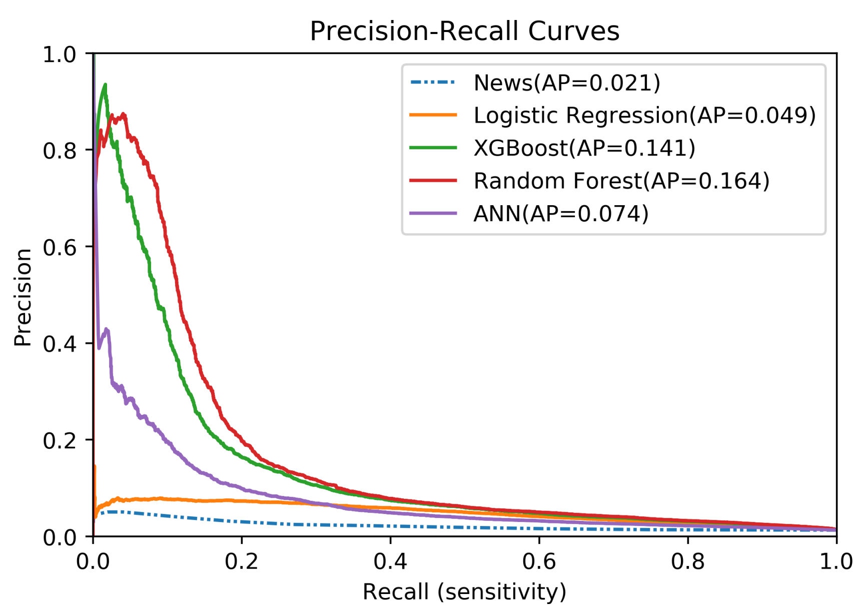

Figure 6: Precision-recall for model v1.0.

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