DUHS Inpatient General Decompensation Prediction

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Content

- Background & Significance
- Purpose of Study
- Exploratory Data Analysis
- Data Preparation
- Modeling
- Conclusion

Content

Backgroud

- Patients in hospital may suffer decompensation
- Fail to detect:
  - Nurses have too much workload[3]
  - Constantly observable information is insufficient for decision making[4]
  - General ward is usually harder setting than ICU[5]
- Consequences:
  - Unplanned transfers, delayed transfers[6] to ICU increase mortality and length of stay[7]

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[3] Patricia R DeLucia, Tammy E Ott, and Patrick A Palmieri. "Performance in nursing". In: *Reviews of human factors and ergonomics* 5.1 (2009), pp. 1–40.

[4] Molly McNett et al. "Judgments of critical care nurses about risk for secondary brain injury". In: *American Journal of critical care* 19.3 (2010), pp. 250–260.

[5] Clemence Petit, Rick Bezemer, and Louis Atallah. "A review of recent advances in data analytics for post-operative patient deterioration detection". In: *Journal of clinical monitoring and computing* 32.3 (2018), pp. 391–402.

[6] Vincent Liu et al. "Adverse outcomes associated with delayed intensive care unit transfers in an integrated healthcare system". In: *Journal of hospital medicine* 7.3 (2012), pp. 224–230.

[7] Matthew M Churpek et al. "Association between intensive care unit transfer delay and hospital mortality: a multicenter investigation". In: *Journal of hospital medicine* 11.11 (2016), pp. 757–762.

Backgroud

Patients show physiologic derangement 6-24 hours prior to deterioration[8].

Current Strategies:

- Risk Scores
  - National Early Warning Score (NEWS)
  - Rothman Index (RI), etc
- Machine Learning (ML) algorithms
  - Logistic Regression
  - Random Forest
  - Artificial Neural Network (ANN), etc

[8] Michael J Rothman, Steven I Rothman, and Joseph Beals IV. "Development and validation of a continuous measure of patient condition using the Electronic Medical Record". In: *Journal of biomedical informatics* 46.5 (2013), pp. 837–848.

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Purpose of Study

1. Define decompensation
2. Create a state-of-the-art of the machine learning model applied for decompensation detection
3. Reduce deterioration and standardize response protocols

Content

Gap Analysis

Goal: identify and build predictive features for this project.

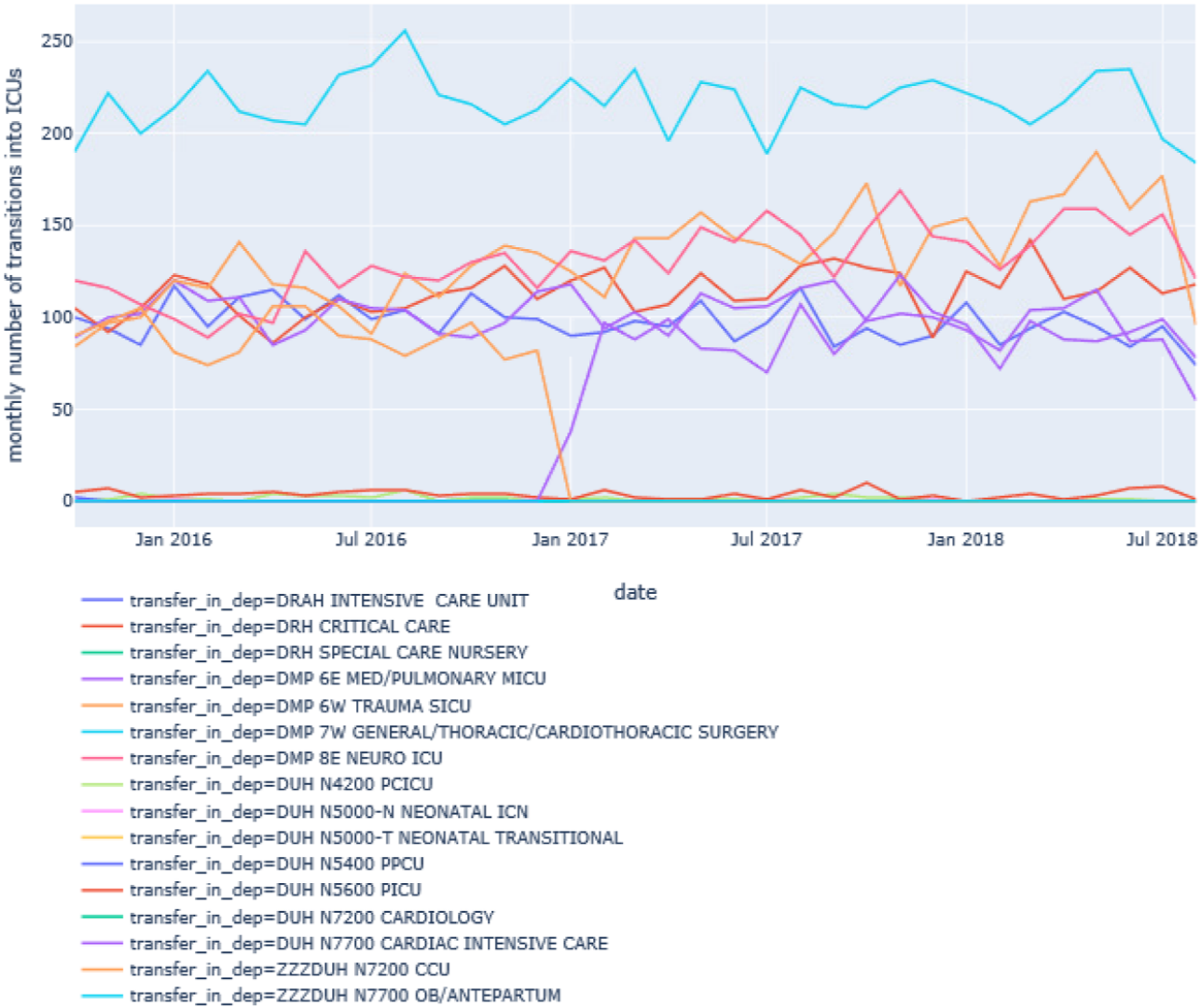
- Two sub-cohorts:
  - encounter with outcome
  - encounter without outcome
- Data element frequency
  - number of times a data element is collected
- Data element prevalence
  - percentage of patients who have a data element collected
- Ratio computation
  - sort from largest to smallest
- medical knowledge input required

Outcome Quality Assurance

- Based on cohort of project

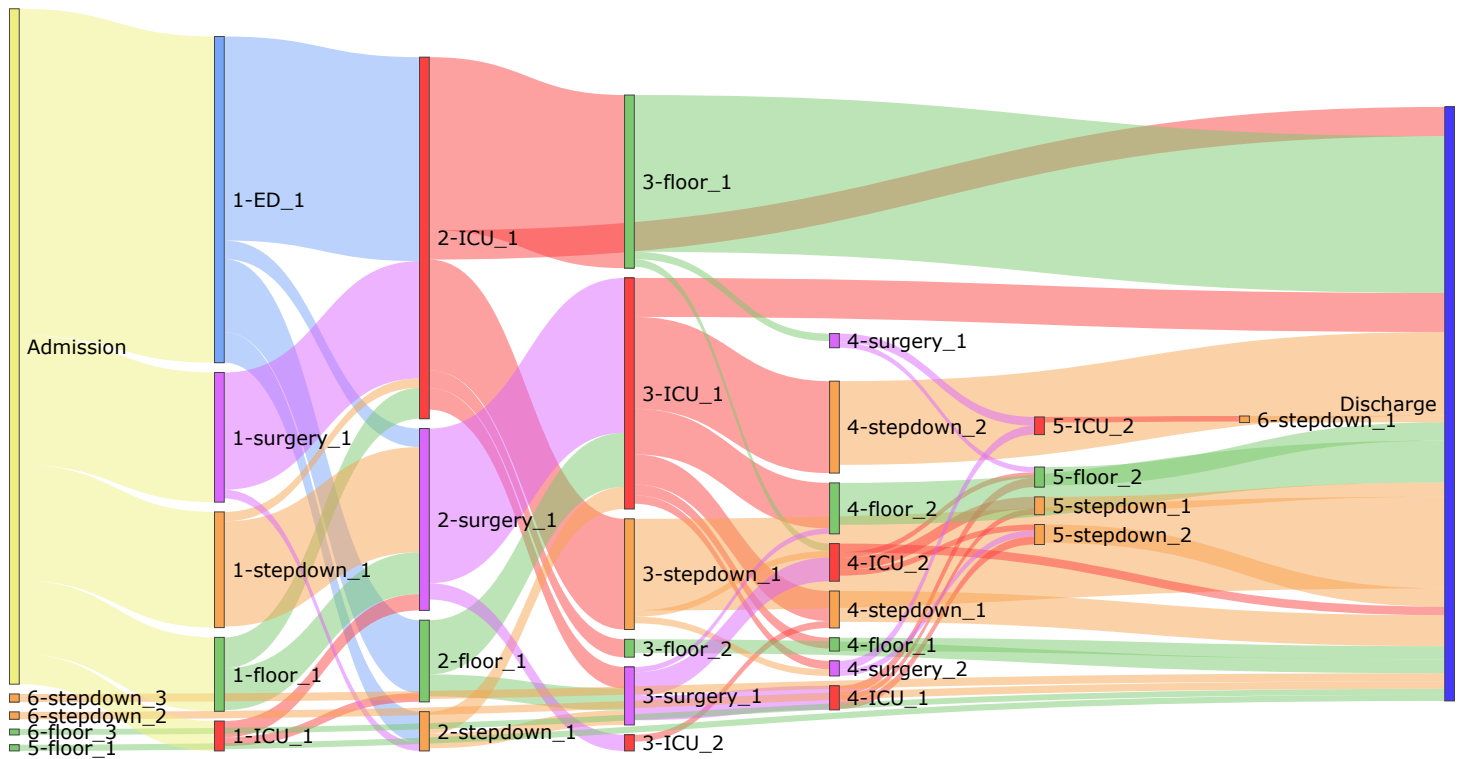
- Update level of care of each unit
- Group by each ICU unit
- Count transfer-in number monthly
- Check abnormal occurrence (neo units)

Outcome Quality Assurance



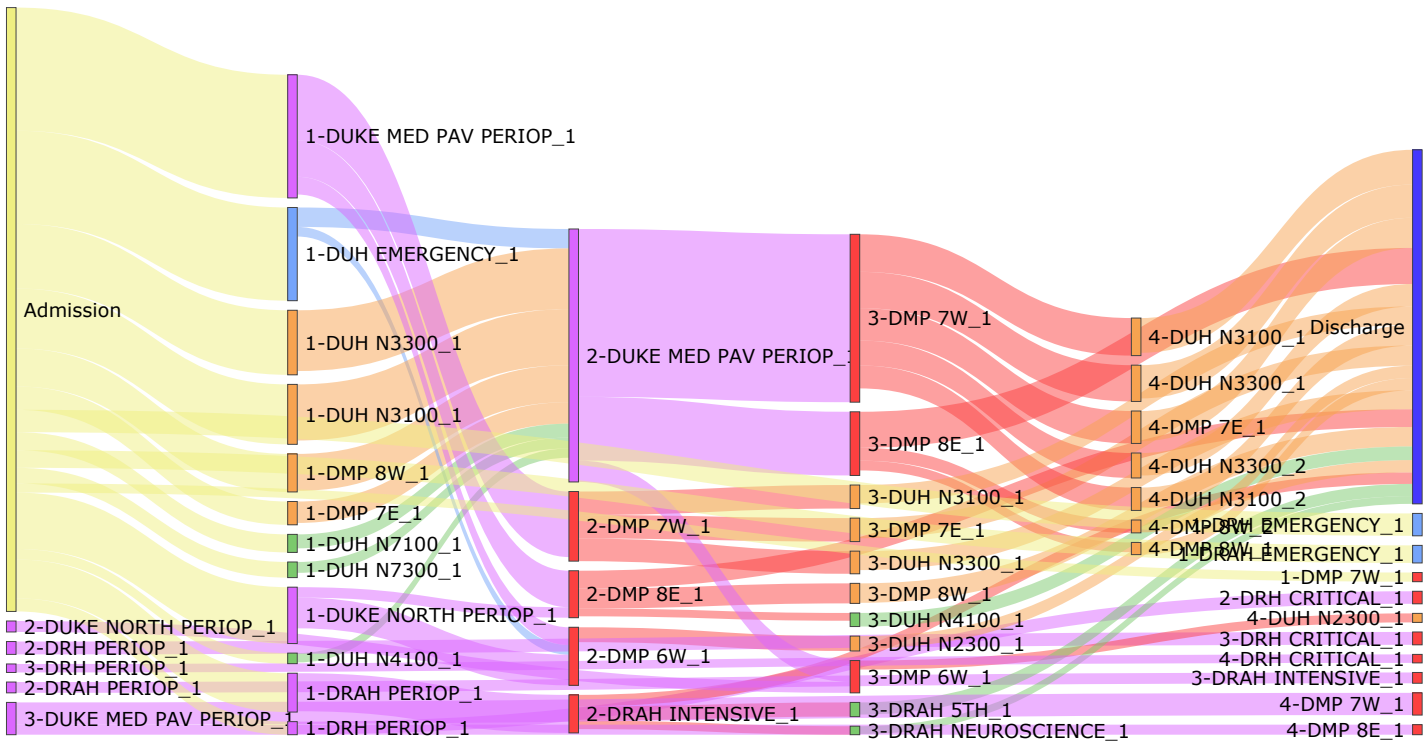
Patient Flow Analysis

Adult Decompensation ICU Subcohort Patient Flow



Patient Flow Analysis

Adult Decompensation OR To ICU Subcohort Patient Flow



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Cohort Extraction

- Cohort Generation
  - Inpatient encounters
  - Adult patients
  - Emergency department to ICU transfer excluded
- Time Span
  - previous model: 2014 - 2018
  - current model: 2015 - 2018
- Pre-encounter features
  - 1-year look-back method

Outcome Labelling

- previous model:
  - non-ICU to ICU transfer
- current model:
  - ED to ICU excluded
  - operation room (OR) to ICU excluded

Feature Engineering

- Vitals
- Laboratory results
- Medications
- Diagnosis
  - keep all 260 categories
  - two variables: one indicating comorbidity 0-3 months before encounter, another indicating comorbidity 3-12 months before encounter

Vital Signs and Lab Results

- Unit Conversion:
  - Convert units and parse number values
- Post Processes:
  - Drop null values
  - Drop duplicates
  - Remove values out of range

Vital Signs and Lab Results

Vital Signs:

- Keep 8 features
  - Blood pressure: split into systolic and diastolic pressure
  - Level of consciousness: 0(alert) and 1(non-alert) labeled
  - Oxygen supply: 0(room air) and 1(anything more) labeled

Lab Results

- Keep 30 features

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Modeling

- Model user:
  - floor or stepdown staff
- Prediction time window:
  - 24 hour
- Look-back time window:
  - 24 hour
- Model runtime:
  - previous model: every 24 hours
  - current model: every 1 hour

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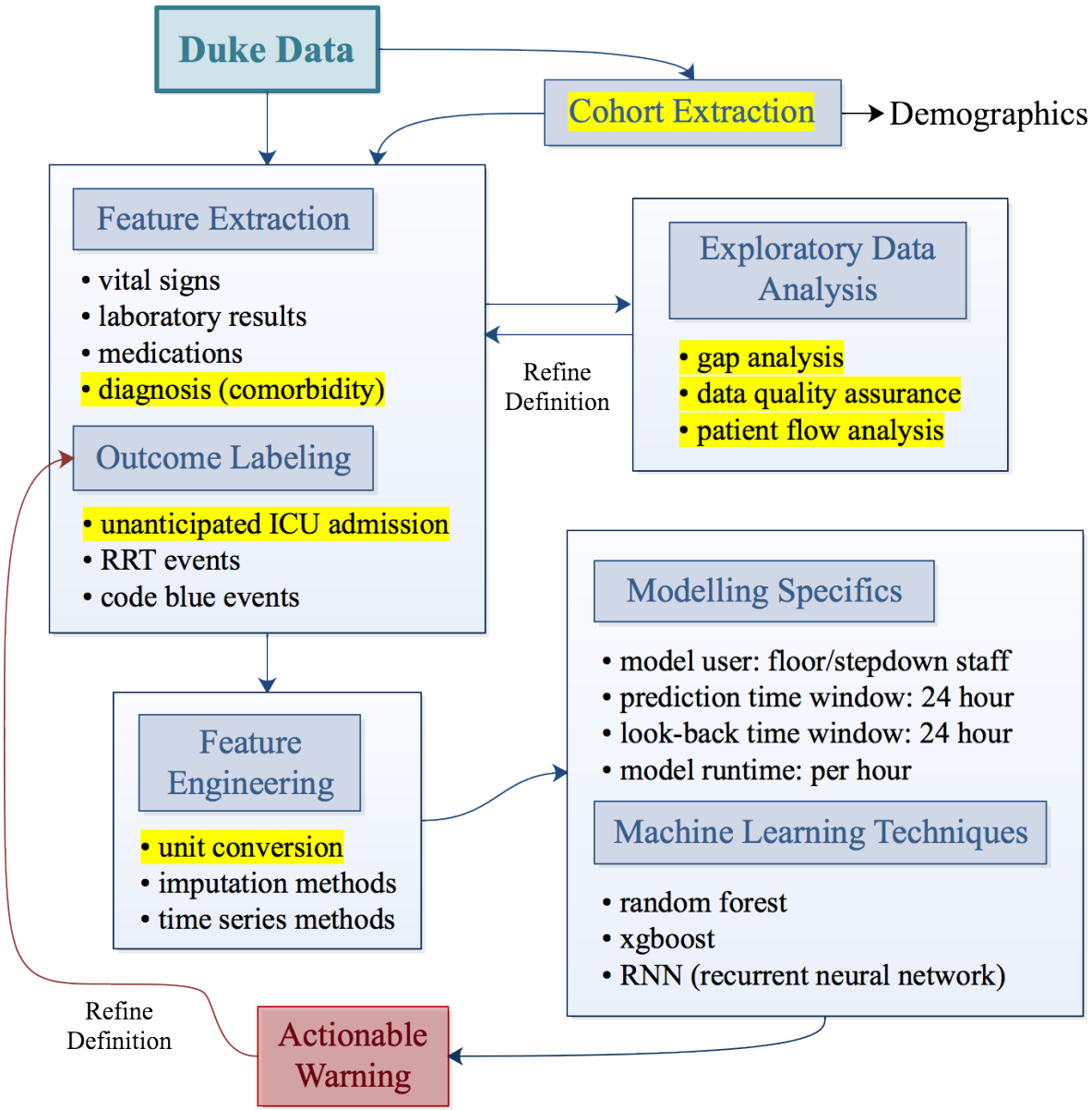
Conclusion


Duke Data
Cohort Extraction
Demographics
Feature Extraction
• vital signs
• laboratory results
• medications
• diagnosis (comorbidity)
Outcome Labeling
• unanticipated ICU admission
• RRT events
• code blue events
Refine Definition
Exploratory Data Analysis
• gap analysis
• data quality assurance
• patient flow analysis
Feature Engineering
• unit conversion
• imputation methods
• time series methods
Modelling Specifics
• model user: floor/stepdown staff
• prediction time window: 24 hour
• look-back time window: 24 hour
• model runtime: per hour
Machine Learning Techniques
• random forest
• xgboost
• RNN (recurrent neural network)
Refine Definition
Actionable Warning

Thank you for listening!

Q&A