Duke University Health System Inpatient General Deterioration Prediction

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Content

- Background & Significance
- Data Preparation
- Feature Engineering & Modeling
- Experimental Results
- Conclusion

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- Background & Significance
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Backgroud

- Patients in hospital may suffer deterioration
- Fail to detect:
  - Nurses have too much workload[4]
  - Constantly observable information is insufficient for decision making[5]
  - General ward is usually harder setting than ICU[6]
- Consequences:
  - Unplanned transfers, delayed transfers[7] to ICU increase mortality and length of stay[8]

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[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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[9].

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

[9] 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.

Purpose of Study

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

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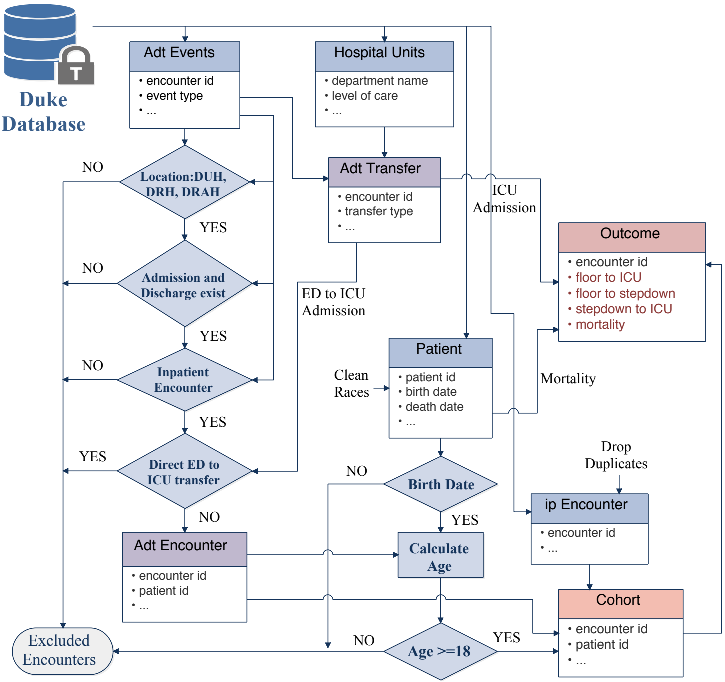
Data Preparation

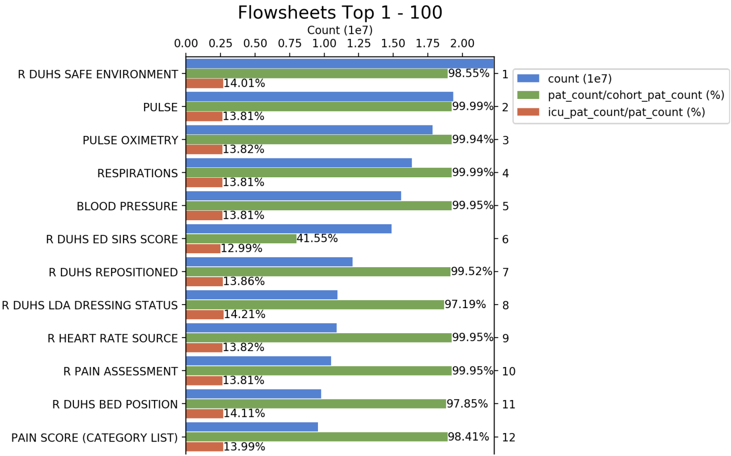
- Cohort Generation


Duke Database
Adt Events
• encounter id
• event type
• ...
Hospital Units
• department name
• level of care
• ...
Adt Transfer
• encounter id
• transfer type
• ...
ICU Admission
Location:DUH, DRH, DRAH
NO
YES
Admission and Discharge exist
NO
YES
Inpatient Encounter
NO
YES
Direct ED to ICU transfer
YES
NO
ED to ICU Admission
Outcome
• encounter id
• floor to ICU
• floor to stepdown
• stepdown to ICU
• mortality
Patient
• patient id
• birth date
• death date
• ...
Clean Races
Mortality
Birth Date
NO
YES
Drop Duplicates
ip Encounter
• encounter id
• ...
Adt Encounter
• encounter id
• patient id
• ...
Calculate Age
Cohort
• encounter id
• patient id
• ...
Excluded Encounters
NO
Age >=18
YES

Data Preparation

- Cohort Generation
  - Inpatient encounters
  - Adult patients
  - Emergency department to ICU transfer excluded
- Data Element Count

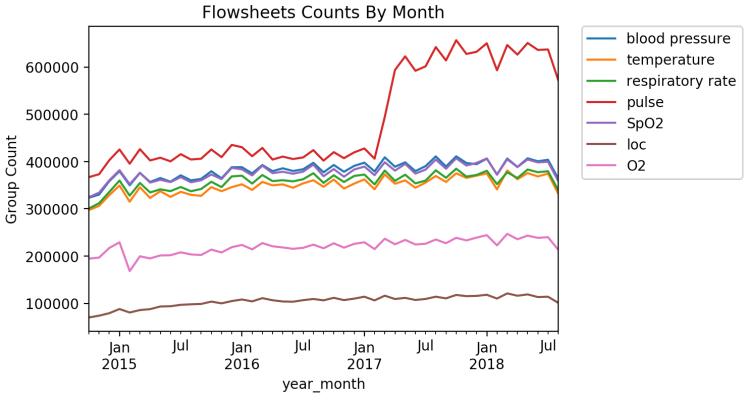
Data Element Count



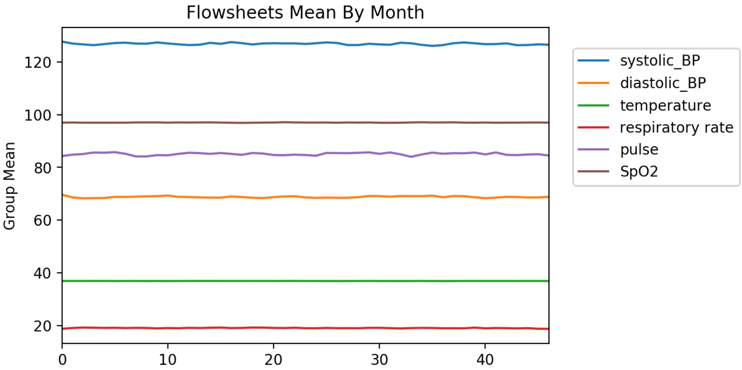
Data Preparation

- Cohort Generation
  - Inpatient encounters
  - Adult patients
  - Emergency department to ICU transfer excluded
- Data Element Count
- Data Pulling
  - Vitals, Labs, Medications, Diagnosis
- Data Quality Assurance

Data Quality Assurance



Data Quality Assurance



Data Preparation

- Cohort Generation
  - Inpatient encounters
  - Adult patients
  - Emergency department to ICU transfer excluded
- Data Element Count
- Data Pulling
  - Vitals, Labs, Medications, Diagnosis
- Data Quality Assurance
- Data Cleaning
  - Remove out of range data
  - Unit conversion, etc

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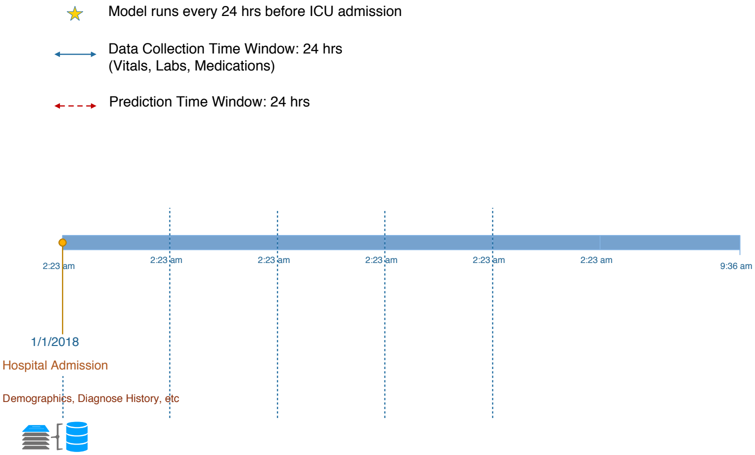
Feature Engineering

Table: Date elements used for prediction.

Data Type	Data Element Name	# Data Element
Demographics	sex, age, race	3
Vitals	pulse, systolic&diastolic bp, respiration rate, level of consciousness, supplemental oxygen, temperature, etc	8
Labs	white blood cell count, platelets, glucose, sodium, albumin, creatinine, potassium, hematocrit, megnesium, blood urea nitrogen, etc	11
Medications	antibiotics, fluids, insulin, immunosuppresent, vasopressors	5
Diagnose	diabetes, chronic kidney disease, malignancy, myocardial infarction, HIV, chronic obstructive pulmonary disease	6

Model

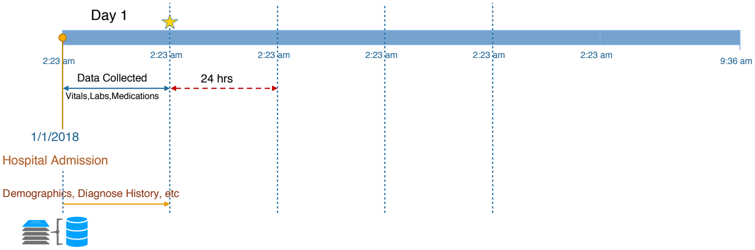

Model runs every 24 hrs before ICU admission
Data Collection Time Window: 24 hrs
(Vitals, Labs, Medications)
Prediction Time Window: 24 hrs
2:23 am
2:23 am
2:23 am
2:23 am
2:23 am
2:23 am
9:36 am
1/1/2018
Hospital Admission
Demographics, Diagnose History, etc

Model

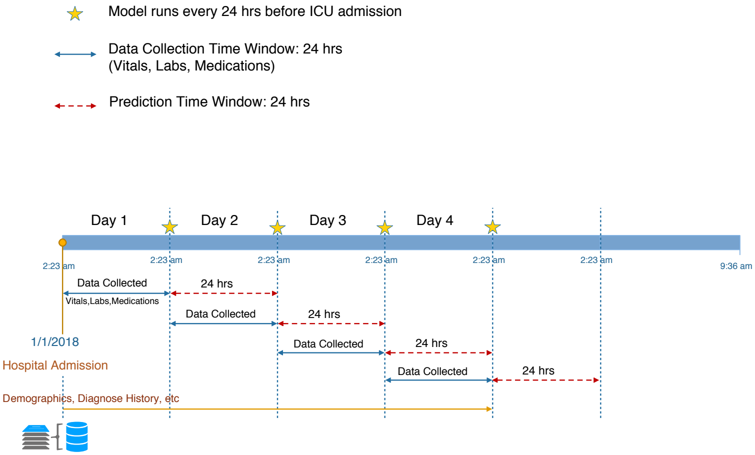
★ Model runs every 24 hrs before ICU admission

⟷ Data Collection Time Window: 24 hrs
(Vitals, Labs, Medications)

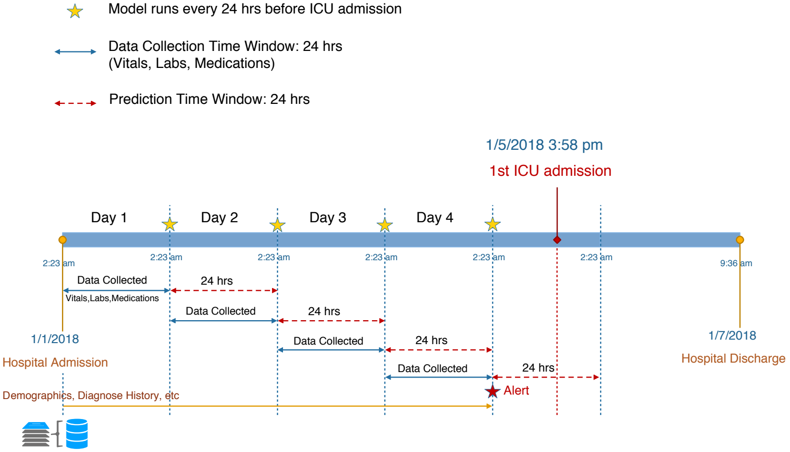
⇠ ⇢ Prediction Time Window: 24 hrs



Model


Model runs every 24 hrs before ICU admission
Data Collection Time Window: 24 hrs
(Vitals, Labs, Medications)
Prediction Time Window: 24 hrs
Day 1
Day 2
Day 3
Day 4
2:23 am
2:23 am
2:23 am
2:23 am
2:23 am
2:23 am
9:36 am
Data Collected
Vitals,Labs,Medications
24 hrs
Data Collected
24 hrs
Data Collected
24 hrs
Data Collected
24 hrs
1/1/2018
Hospital Admission
Demographics, Diagnose History, etc

Model


Model runs every 24 hrs before ICU admission
Data Collection Time Window: 24 hrs
(Vitals, Labs, Medications)
Prediction Time Window: 24 hrs
1/5/2018 3:58 pm
1st ICU admission
Day 1
Day 2
Day 3
Day 4
2:23 am
2:23 am
2:23 am
2:23 am
2:23 am
2:23 am
9:36 am
Data Collected
Vitals,Labs,Medications
24 hrs
Data Collected
24 hrs
Data Collected
24 hrs
Data Collected
24 hrs
Alert
1/1/2018
Hospital Admission
1/7/2018
Hospital Discharge
Demographics, Diagnose History, etc

Feature Engineering

Table: Feature generation and transformation summary.

Data Type	Data Element Name	Coding	# Features
Demographics	sex, age, race	Indicator, numeric	5
Vitals	pulse, blood pressure, etc	max, min, average	20
Vital Miss Flag		Indicator	8
Labs	platelets, glucose, etc	average	11
Lab Miss Flag		Indicator	11
Medications	antibiotics, fluids, etc	Indicator	5
Diagnose	diabetes, chronic kidney disease, etc	Indicator	6
Days to admission		numeric	1
Total			67

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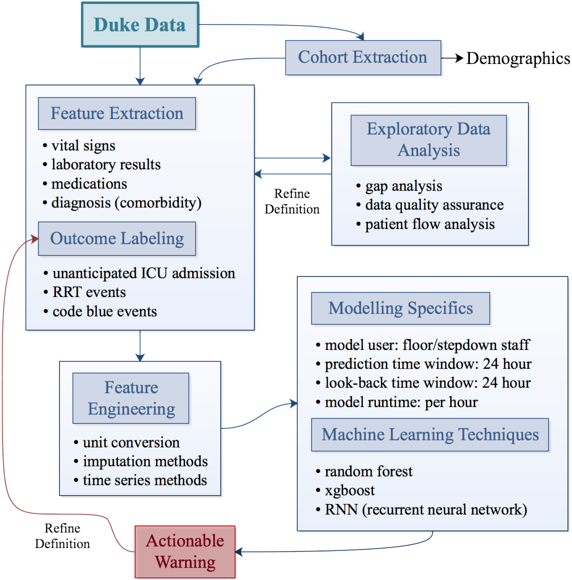
Pipeline


Duke Data
Cohort Extraction
Demographics
Feature Extraction
• vital signs
• laboratory results
• medications
• diagnosis (comorbidity)
Outcome Labeling
• unanticipated ICU admission
• RRT events
• code blue events
Exploratory Data Analysis
• gap analysis
• data quality assurance
• patient flow analysis
Refine Definition
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

Experimental Setting

- **Data Source:** Duke data
- **Outcome:** 24 hour ICU admission
- **Exclusion:**
  - floor/stepdown stay less than 24 hours
  - floor/stepdown stay more than 30 days

Table: Summary statistics of design matirx.

Class	ICU admission flag=1	ICU admission flag=0
#Features	67	
#Total Samples	870107	
#Samples	11300	858807
Proportion	1.3%	98.7%

Model Training

- Preprocessing
    - z-Scoring
- Imbalance Data
    - downsampling
- Algorithm
    - Logistic Regression
    - Random Forest
    - XGBoost
    - Artificial Neural Network
- Optimization
    - parameter search

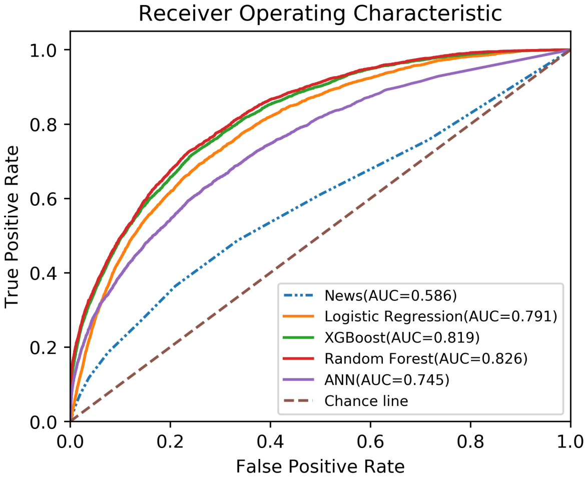
Baseline Model: National Early Warning Score

Table: NEWS scoring criteria as a aggregate weighted system[10].

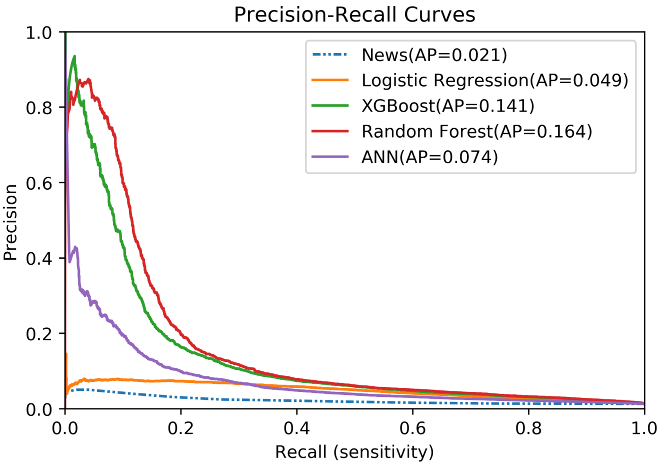
Score	3	2	1	0	1	2	3
Respiration Rate	≤ 8		9-11	12-20		21-24	≥ 35
Oxygen Saturations	≤ 91	92-93	94-95	≥ 96			
Supplemental Oxygen		Yes		No			
Systolic BP	≤ 90	91-100	101-110	111-219			≥ 220
Heart Rate	≤ 40		41-45	51-90	91-110	111-130	≥ 131
Temperature	≤ 35		35-36	36-38	38-39	≥ 39	
Level of Consciousness				A			V,P,U

[10] Ariel L Shiloh et al. "Early warning/track-and-trigger systems to detect deterioration and improve outcomes in hospitalized patients". In: *Seminars in respiratory and critical care medicine*. Vol. 37. 01. Thieme Medical Publishers. 2016, pp. 088–095.

ROC


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
News(AUC=0.586)
Logistic Regression(AUC=0.791)
XGBoost(AUC=0.819)
Random Forest(AUC=0.826)
ANN(AUC=0.745)
Chance line

Precision-Recall



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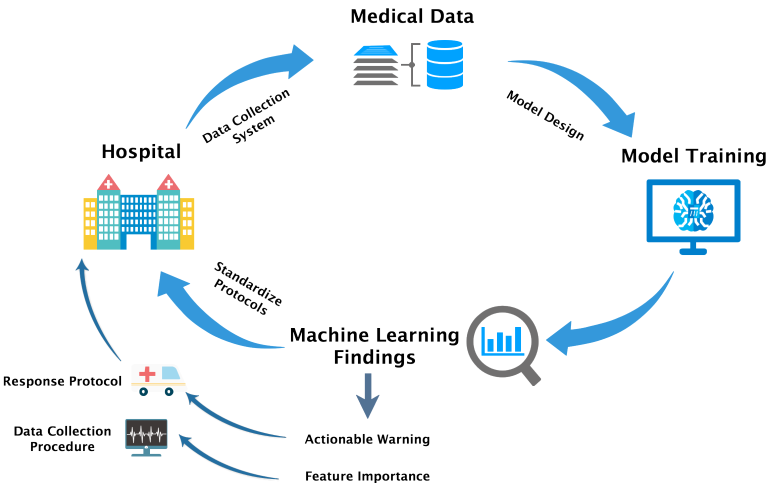
Conclusion


Medical Data
Data Collection System
Model Design
Hospital
Model Training
Standardize Protocols
Machine Learning Findings
Response Protocol
Data Collection Procedure
Actionable Warning
Feature Importance

Achievements

- Github repository

  `https://github.com/ziyuan-shen/DIHI_adult_decomp`

- Publication

  S. Skove, H. Shi, **Z. Shen**, M. Gao, M. Cui, M. Nichols, S. Balu, A. Bedoya, D. Tart, B. Goldstein, W. Ratliff, M. Sendak and C. O'Brien, "Development of Machine Learning Model to Predict Risk of Inpatient Deterioration," *Machine Learning for Healthcare*, Apr 2020. [Abstract Submitted]

Thank you for listening!

Q&A