

DeepPatient: Leveraging EHR data to predict patient outcomes

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DOCNET

Digitized Patient

Google



UCSF
University of California
San Francisco



DOCTOR IS IN

Google is using 46 billion data points to predict the medical outcomes of hospital patients

Digitized Patient - DOCNET

291 million datapoints

Predicting Patient Deterioration

- Early Detection of patient deterioration
 - Improve clinical outcomes:
 - For each hour sepsis treatment is delayed, the patient's risk of death increases by 4 percent. (New England Journal of Medicine).
 - Reduce hospital costs:
 - A patient at the ICU costs 1000 euros a day to the hospital.

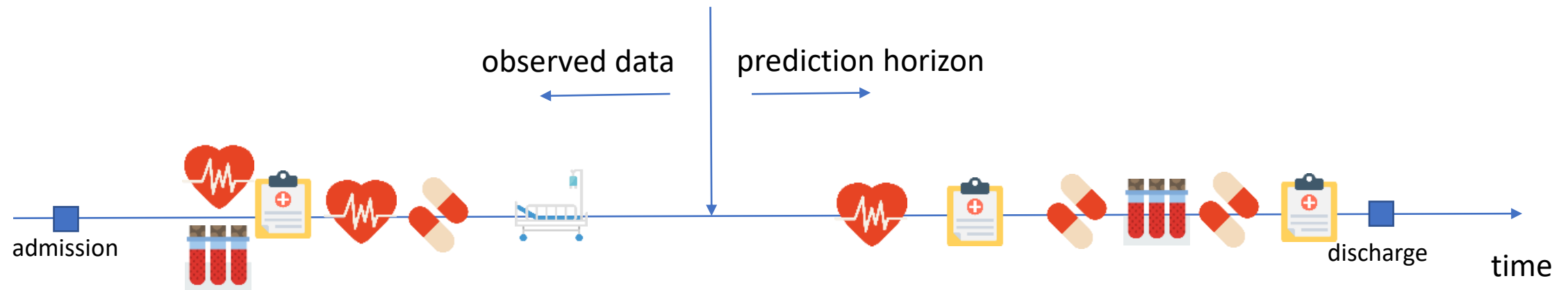
Predicting Patient Deterioration

- Example: NEWS2 (National Early Warning Score – UK – only vital signs)

Physiological parameter	Score						
	3	2	1	0	1	2	3
Respiration rate (per minute)	≤8		9–11	12–20		21–24	≥25
SpO ₂ Scale 1 (%)	≤91	92–93	94–95	≥96			
SpO ₂ Scale 2 (%)	≤83	84–85	86–87	88–92 ≥93 on air	93–94 on oxygen	95–96 on oxygen	≥97 on oxygen
Air or oxygen?		Oxygen		Air			
Systolic blood pressure (mmHg)	≤90	91–100	101–110	111–219			≥220
Pulse (per minute)	≤40		41–50	51–90	91–110	111–130	≥131
Consciousness				Alert			CVPU
Temperature (°C)	≤35.0		35.1–36.0	36.1–38.0	38.1–39.0	≥39.1	

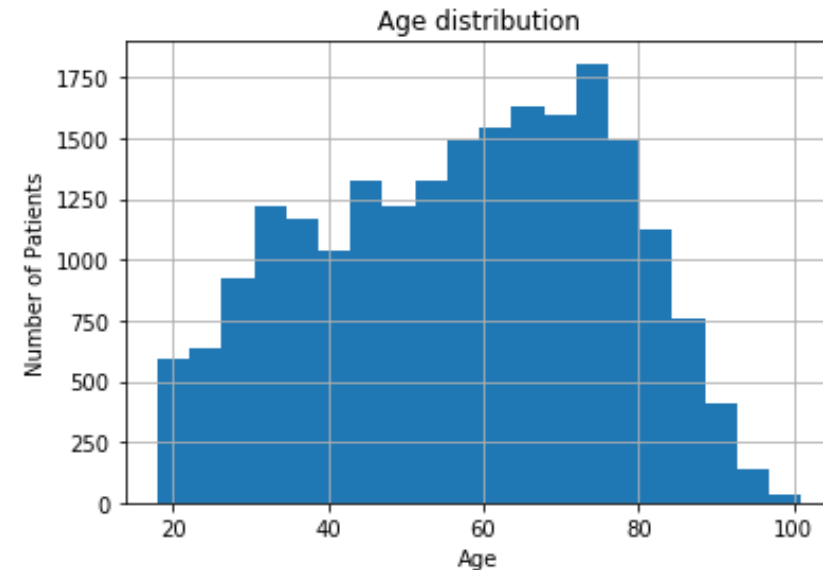
Some definitions before looking at the data

- An **episode** is a sequence of events that describe the stay of a patient in the hospital.
- A **snapshot** is a picture taken from an episode at a given point in time.



Exploratory Data Analysis: Demographics

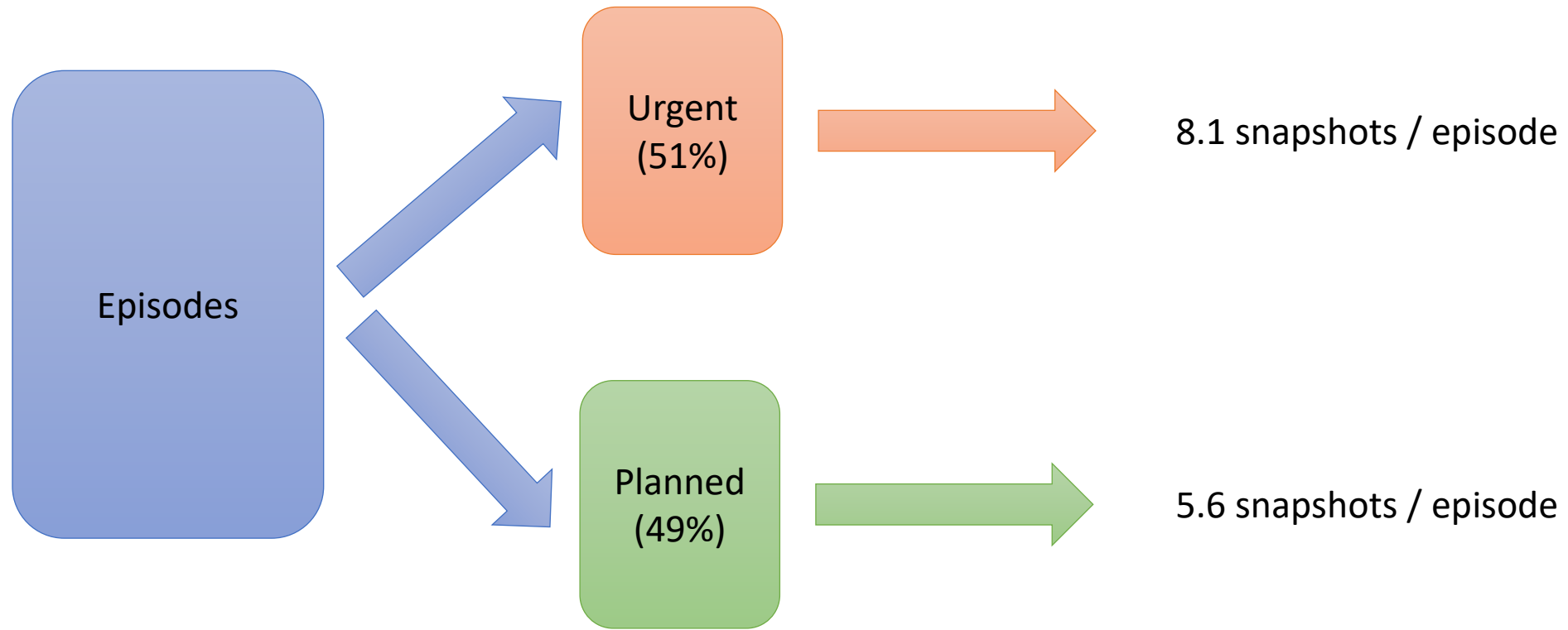
- Training set: 21470 episodes (1 snapshot / day) from 1-year period.
 - Excluded cases: pediatric patients (<18), patients under paliative care.
- Average Age: 57 years old
- Sex: 44% men, 56% women



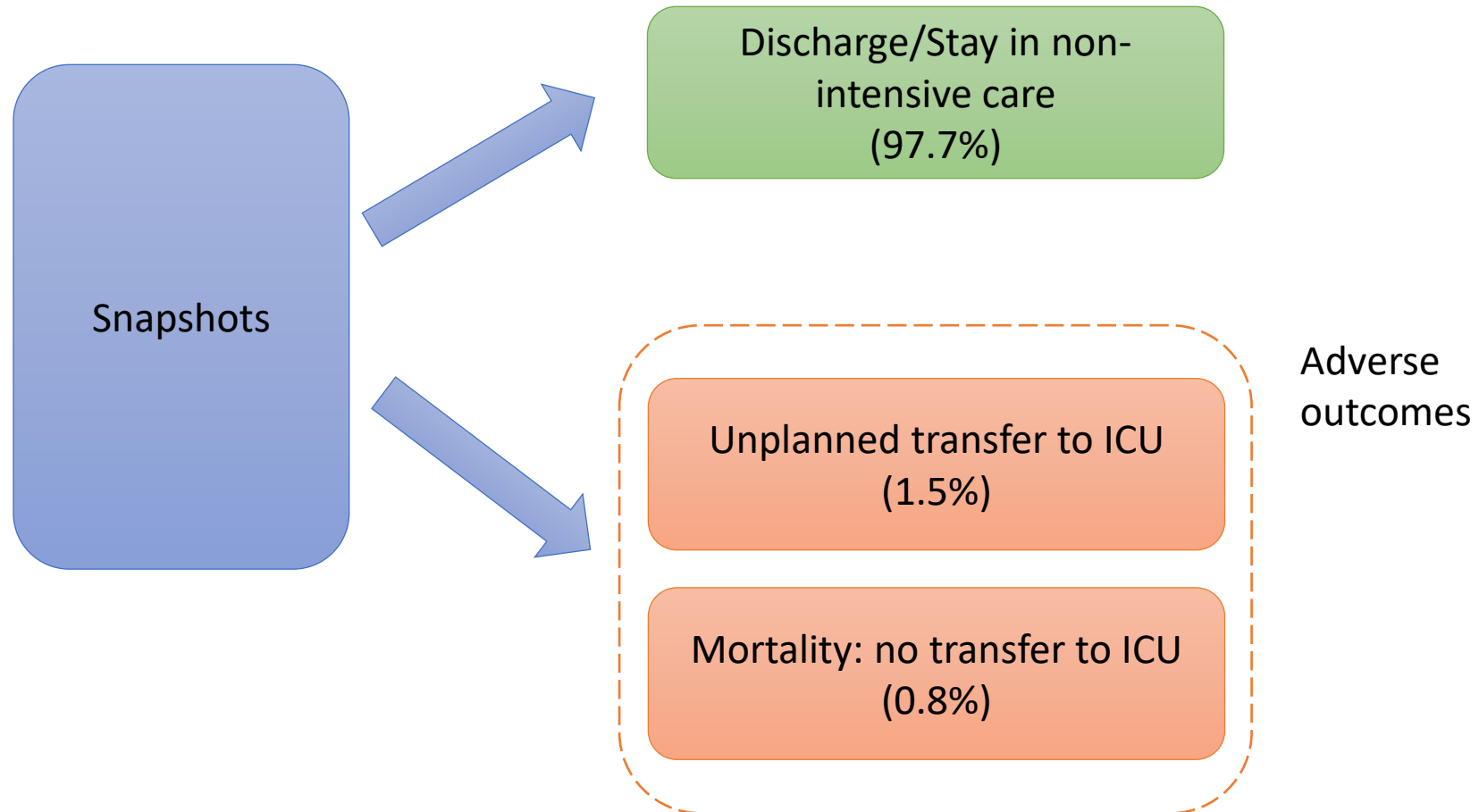
- Total number of snapshots: 147676

6.9 snapshots / episode
(approximate length of stay)

Exploratory Data Analysis: Admission



Exploratory Data Analysis: 7-day Outcome



Major Challenge in Healthcare

Different units emphasize different signals when monitoring the patient

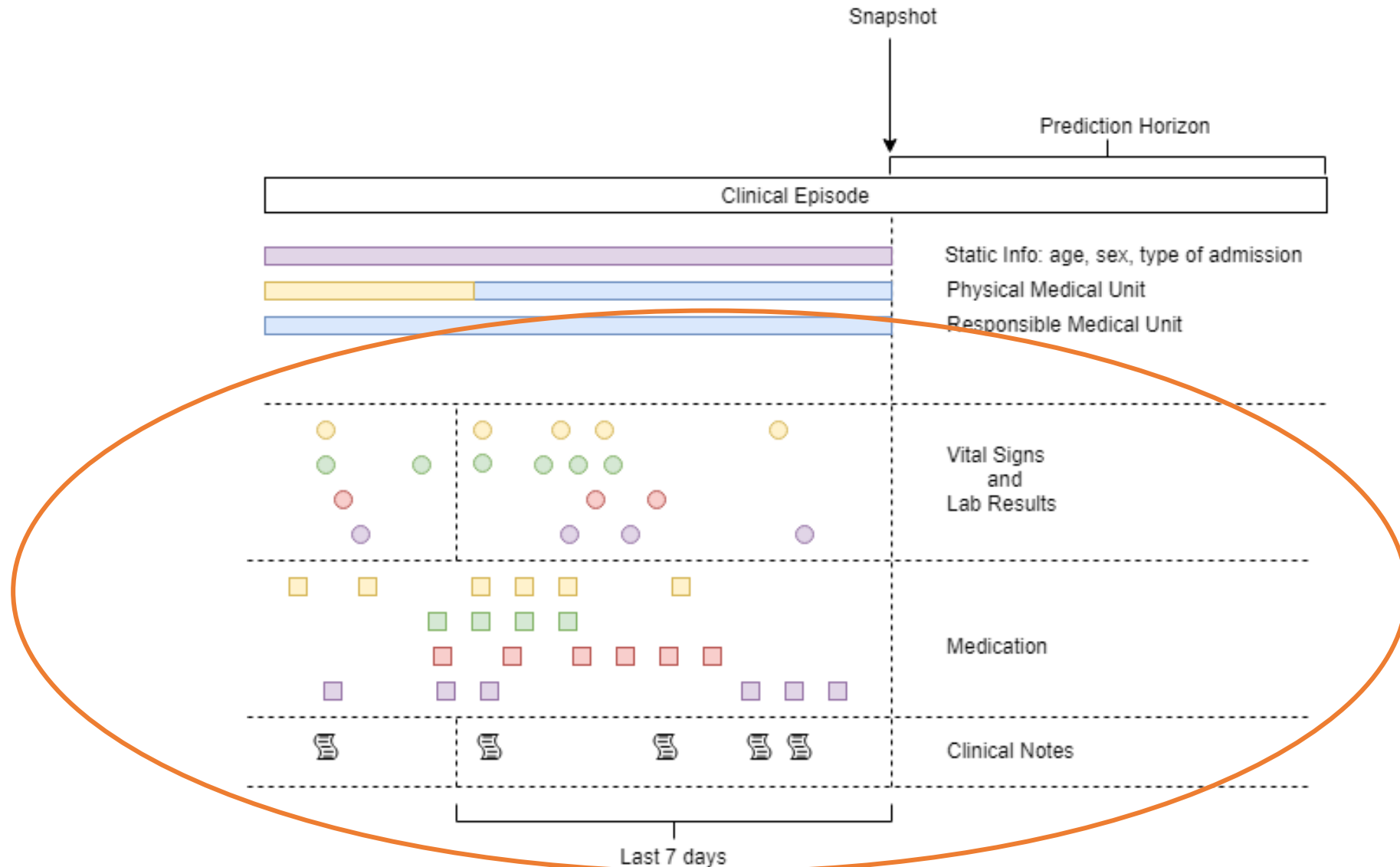
- Heart Rate, Blood Pressure
 - Cardiology: ~4x a day, Plastic Surgery: ~1x day
- Creatinine
 - Renal Transplant: ~1x a day, Internal Medicine: once every 2.5 days

Few measurements means more missing values



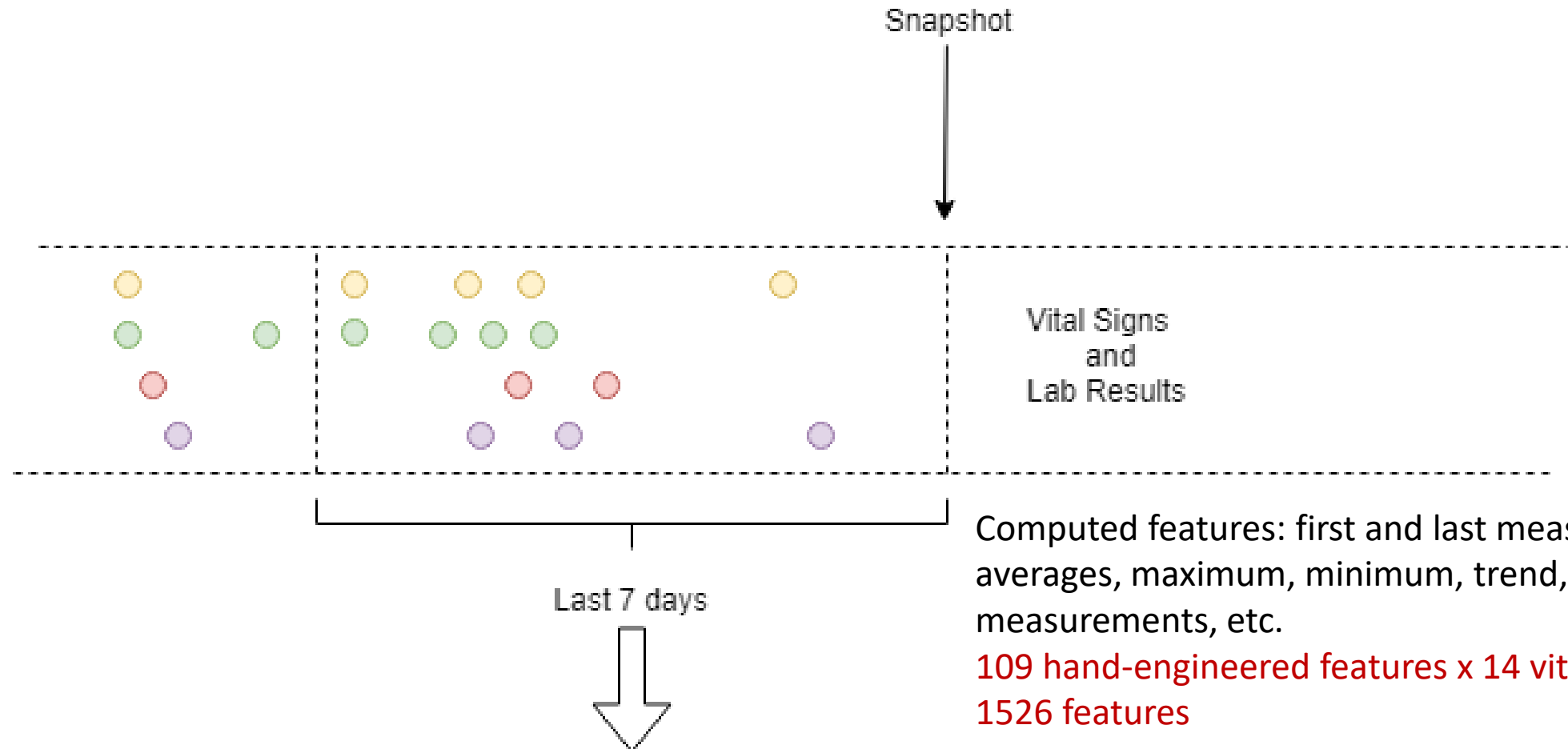
Concept of Informative Missingness

Patient Representation



Non-uniformly spaced
time-series.
How to represent?

Vitals + Labs

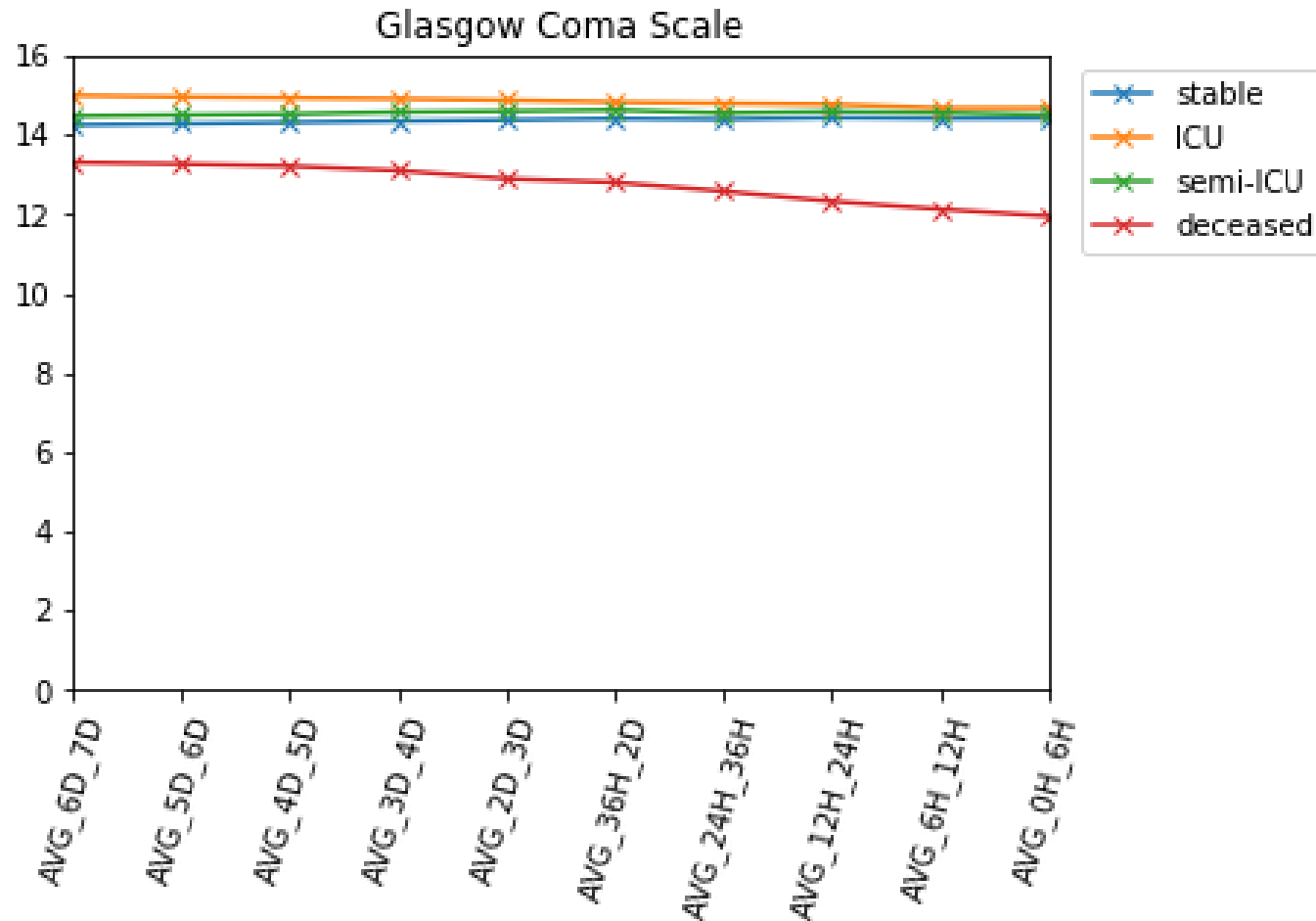


Computed features: first and last measurements, averages, maximum, minimum, trend, number of measurements, etc.

109 hand-engineered features x 14 vitals/labs = 1526 features

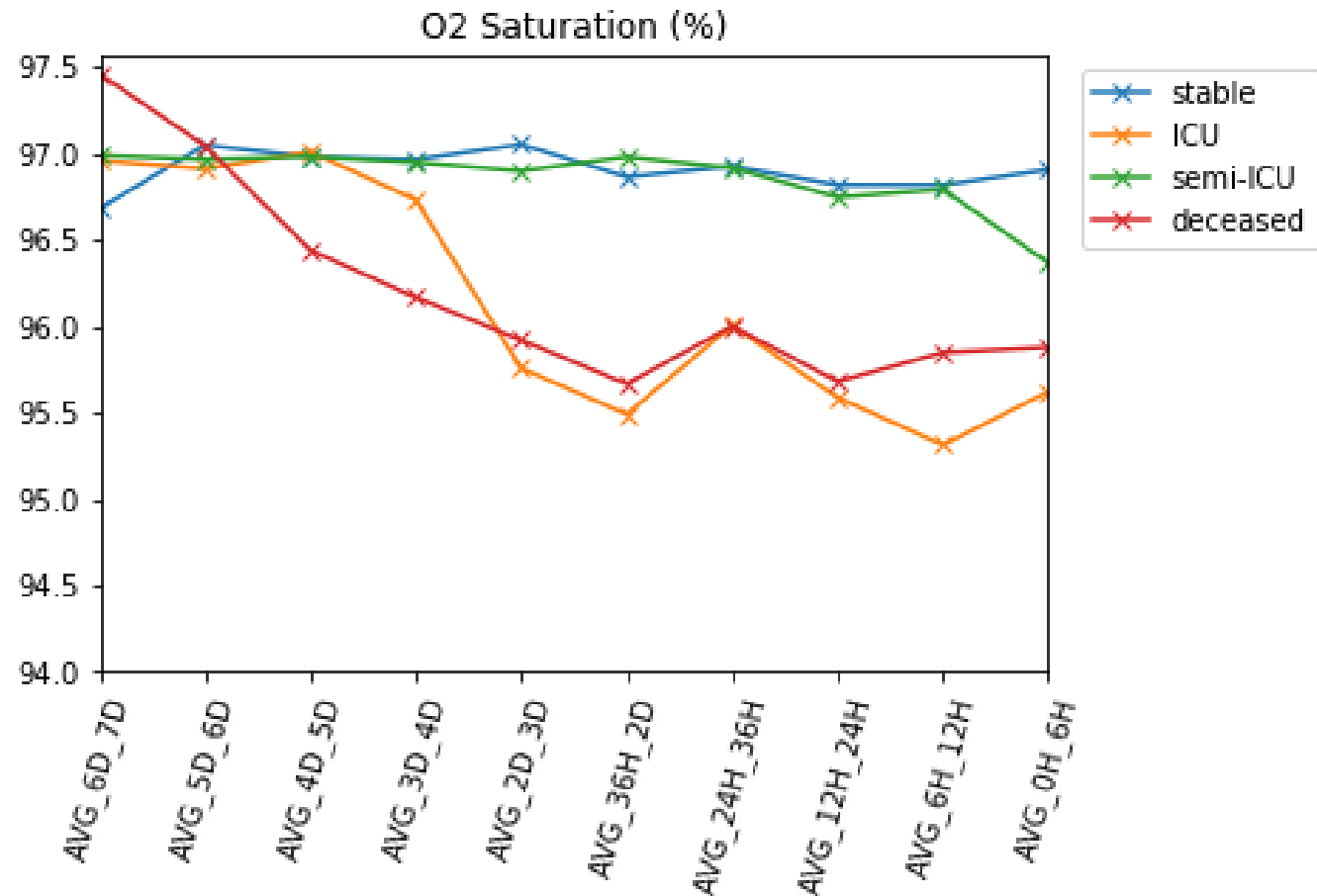
Col 1	Col 2	...	Col 109	Col 1	Col 2	...	Col 109	Col 1	Col 2	...	Col 109	Col 1	Col 2	...	Col 109
37.2	36.9	...	36.6	8.50	NULL	...	1.23	12	NULL	...	13	120	132	...	NULL

Exploratory Data Analysis



- All non-surgical units
- Steady decline of consciousness level for the deceased patients

Exploratory Data Analysis



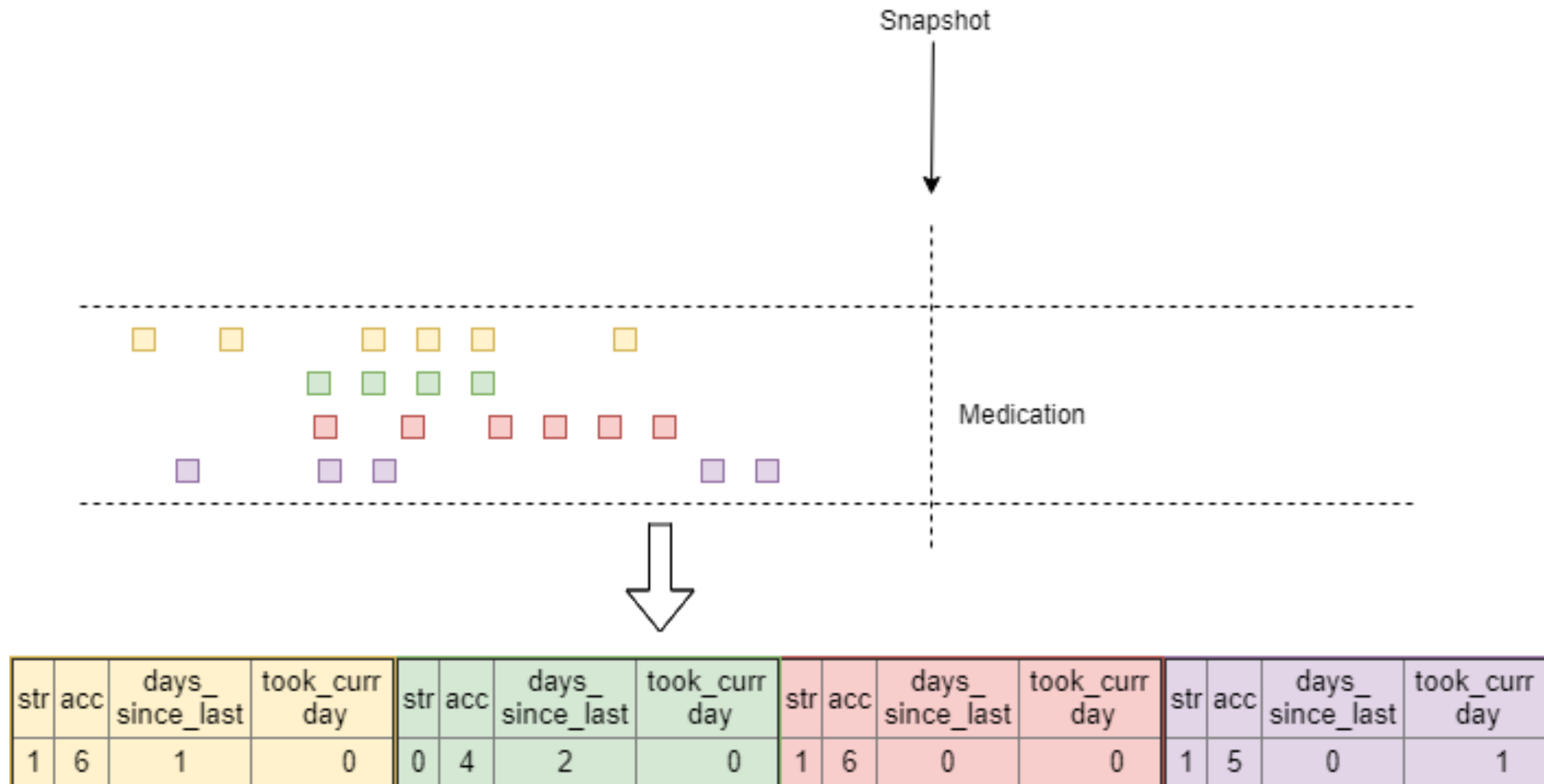
- General Surgery Unit
- 2 percentage point drop for ICU-bound and deceased patients

Medication



- Very large number of medication codes
 - Group by general role:
 - Anti-Infection – Antibacterial
 - Cardiovascular – Anti-Arrithmya
- Feature Engineering
 - For each medication compute 4 features:
 - number of consecutive days taking medication.
 - total number of days taking medication.
 - days since last intake.
 - took medication on current day? (yes/no)
 - 4 computed features x 93 medication groups = 372 features

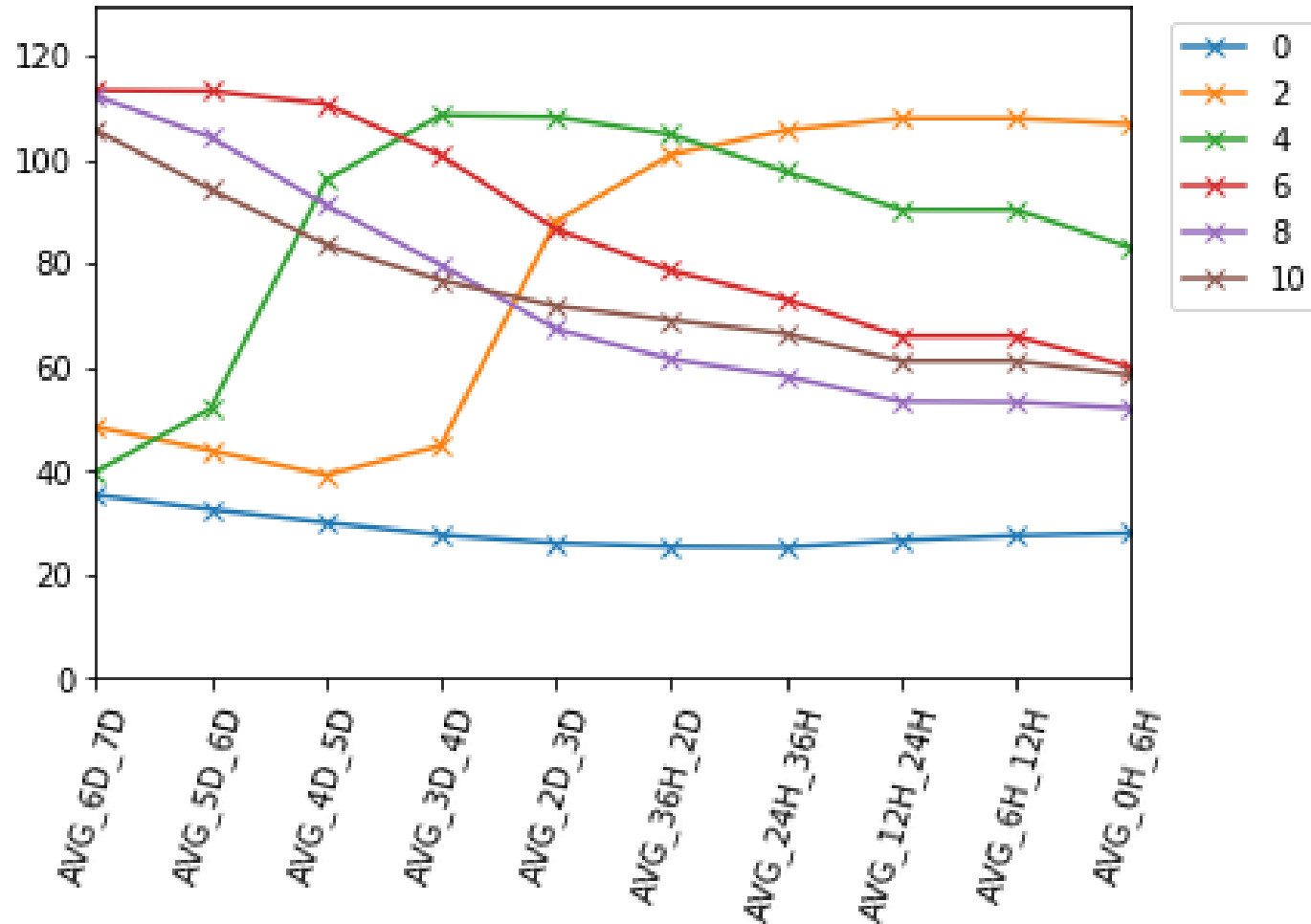
Medication



Exploratory Data Analysis



C-Reactive Protein (mg/L)

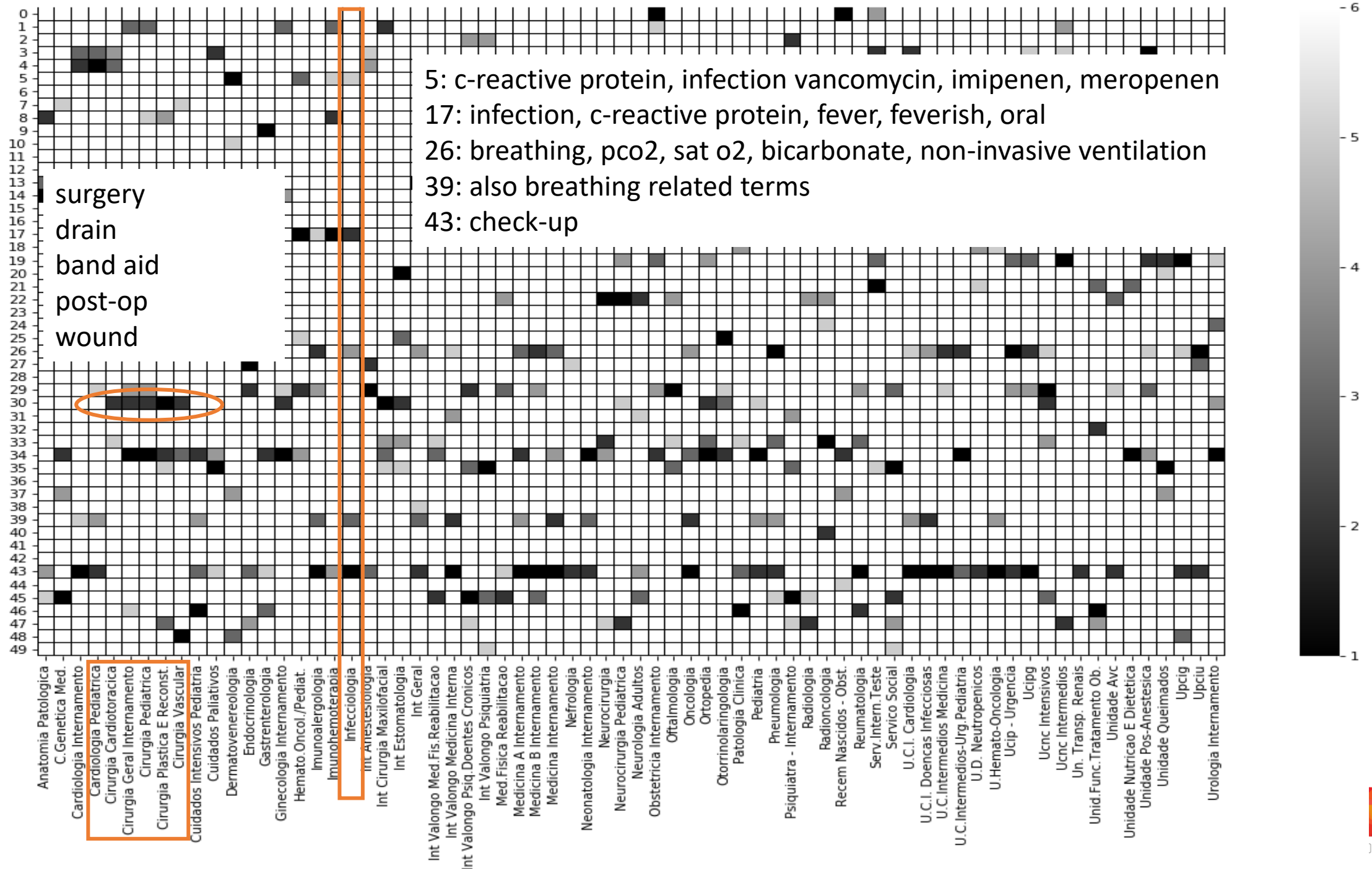


- Internal Medicine Unit
- Consecutive days taking antibacterials
- It takes on average 2 days to reduce C-reactive protein levels (proxy for infection).

Clinical Notes

“The gold is in the clinical notes” - Edward Choi, co-author of the study titled Doctor AI: Predicting Clinical Events via Recurrent Neural Networks

- Topic Modeling using Latent Dirichlet Allocation:
 - Noisy data (typos, names, overhead).
 - Different ways to write notes in different hospital units.



Preliminary Results

- Baseline Models:



Emmanuel Ameisen
AI Lead at Insight AI @EmmanuelAmeisen
Mar 6 · 9 min read

Always start with a stupid model, no exceptions.

- LSTM:



Eric Topol ✓
@EricTopol

Following

We still use dumb algorithms (rules-based, heuristic, univariate) in medicine, developed decades ago. Eagerly await validated smart ones w/ deep neural networks [#AI](#)

Preliminary Results (Dataiku)

- Baseline Models on Dataiku
 - Random Forests
 - Gradient Tree Boosting
 - XGBoost
- Different Feature Sets
 - Vitals/Labs
 - Vitals/Labs + Medication



Preliminary Results (Dataiku)

Target

Train / Test Set

Python environment

FEATURES

- Features handling
- Feature generation
- Feature reduction

MODELING

- Algorithms
- Hyperparameters

EVALUATION

- Metric

Features Handling

Role: AVG_6H

<input type="checkbox"/> # AVG_6H_12H_CAT1 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT10 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT11 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT12 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT14 Reject	OFF
<input checked="" type="checkbox"/> # AVG_6H_12H_CAT15 Min-max rescaling	ON
<input type="checkbox"/> # AVG_6H_12H_CAT16 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT17 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT18 Reject	OFF
<input type="checkbox"/> # AVG_6H_12H_CAT3 Reject	OFF

Handling of "AVG_6H_12H_CAT15"

Role: Reject, Input

Numerical handling: Keep as a regular numerical feature

Rescaling: Min-max rescaling

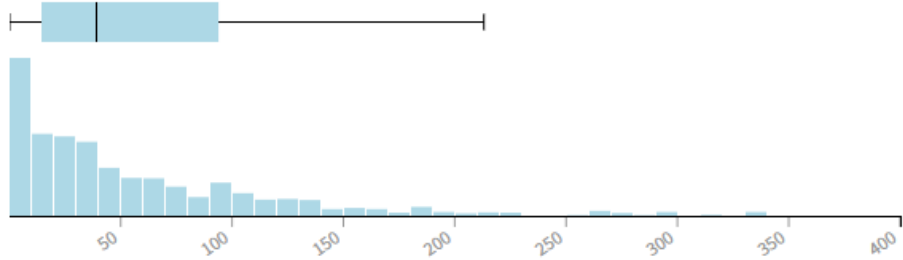
Make derived feats. Generate sqrt(x), x^2, ... features

Variable type: Categorical, Numerical, Text, Vector

Missing values: Impute ...

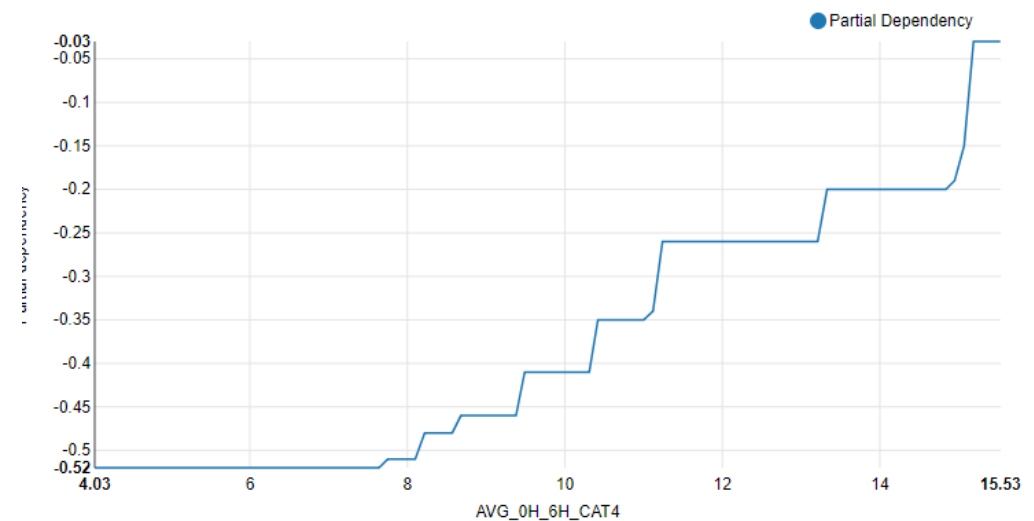
Impute with: Average of values

Min 0.10000, Max 400.80, Mean 65.465, Median 39.100, StdDev 71.886, Mode 4.5000, Distinct values 714, Empty cells 38.6%, Invalid cells 0.0%



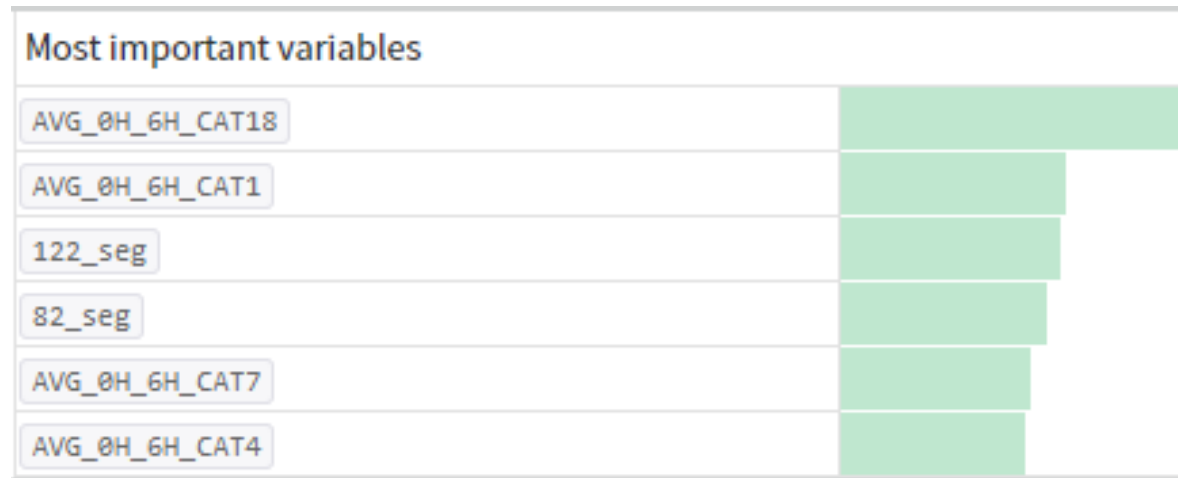
Preliminary Results (Dataiku)

- Vitals – Gradient Tree Boosting AUC: 0.735
 - Precision 10%, Recall 26% (max F1-score – 5.6% rate of alarm)
 - Precision 20%, Recall 9% (about 1% rate of alarm)
 - Recent measurement were the most important

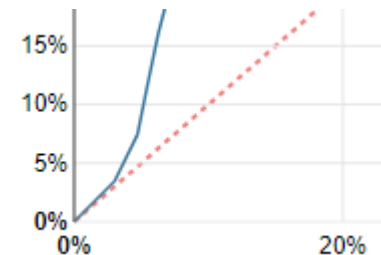


Preliminary Results (Dataiku)

- Vitals+Medication – XG Boost AUC: 0.781
 - Precision 23%, Recall 11% (about 1.1% rate of alarm)



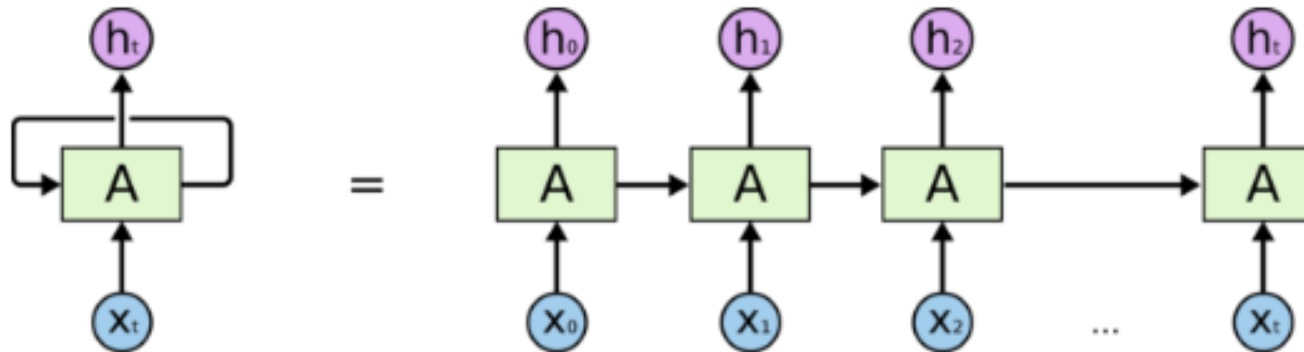
- Random Forest: AUC 0.73 (bad ROC shape)



Deep Patient approach

Preliminary Results (LSTM)

- Powerful to learn from sequence data.
- Capture long term dependencies and non-linear dynamics.



Preliminary Results (LSTM)

- Features
 - Responsible unit (one-hot encoded).
 - Vitals/Labs: taking AVG_24H features (make compatible with timesteps).
- Missing values
 - Forward filling + imputation with average.
- Normalization: [0,1] interval.
- Network starts deciding with 3 days of data.

Preliminary Results (LSTM)

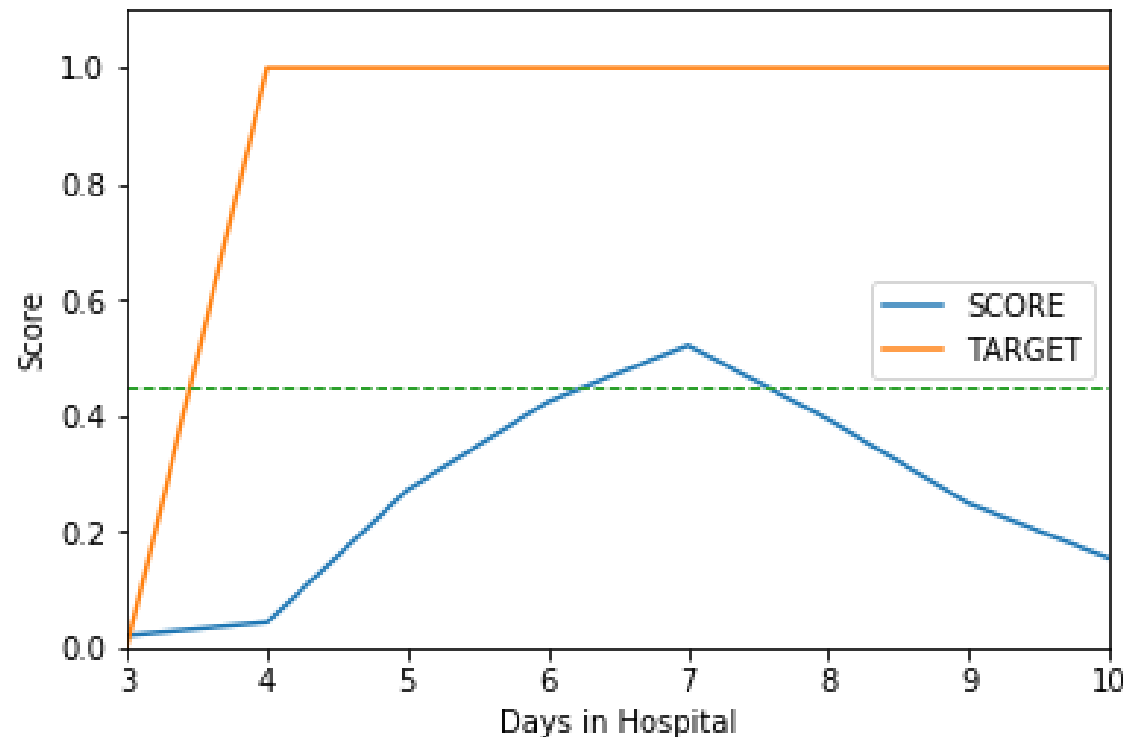
- Two LSTM layers (64 cells) + dense layer (sigmoid).
- 7 time-steps (use last week of data as input).
- 15% of training data used for validation.
- Trained for 40 epochs – used best epoch based on validation error.



Preliminary Results (LSTM)

- AUC: 0.745
 - Precision: 20%, Recall: 28% (rate of alarm – 3.5%)
 - Precision: 24%, Recall: 10% (rate of alarm – 1%)

- Scoring an episode:
(patient goes to ICU on day 11,
alarm sounds on day 7)



But how to find the best
model using
291 million datapoints?

Machine Learning?

26.000 Models
tested/day

Credits:



Conclusions

- Electronic Health Records: rich source of data, first step towards personalized medicine.
- Challenges:
 - Inclusion/Exclusion criteria.
 - Dealing with missing values – treat missingness as features.
 - Best way to incorporate clinical notes.
 - Hyperparameter tuning.
 - LSTM Model Interpretation – attention mechanism.