UiO : Faculty of Medicine
University of Oslo

Machine Learning in Intensive Care Units

Trial Lecture

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2022.10.13

About this talk

Intensive Care Unit (ICU)

The first ICUs

Intensive care medicine

Quality metrics of ICU

Machine Learning in ICU

ICU monitoring and data

Machine Learning

ML in ICU

Case studies

In-hospital mortality

Beyond mortality predictions

The future of ML x ICU

Where we are now

Directions forward

Intensive Care Unit

in a nutshell 

Intensive Care Units (ICU)

Early Intensive Care

1952 Copenhagen Polio epidemic

30–50 new admission per day, 10% require **artificial ventilation**

250 medical students per day, work shifts with 35–40 doctors – 6 staff per patient

Hand ventilate via **tracheostomy**

Mortality from polio in Copenhagen reduced from over 80% to 40%

Put patients in a dedicated ward — ICU

Early neuroscience intensive care unit,
Saint Marys Hospital, Rochester, MN

Mary Hitchcock intensive care unit, c.a. 1950s
Dartmouth-Hitckcock Medical Center, NH

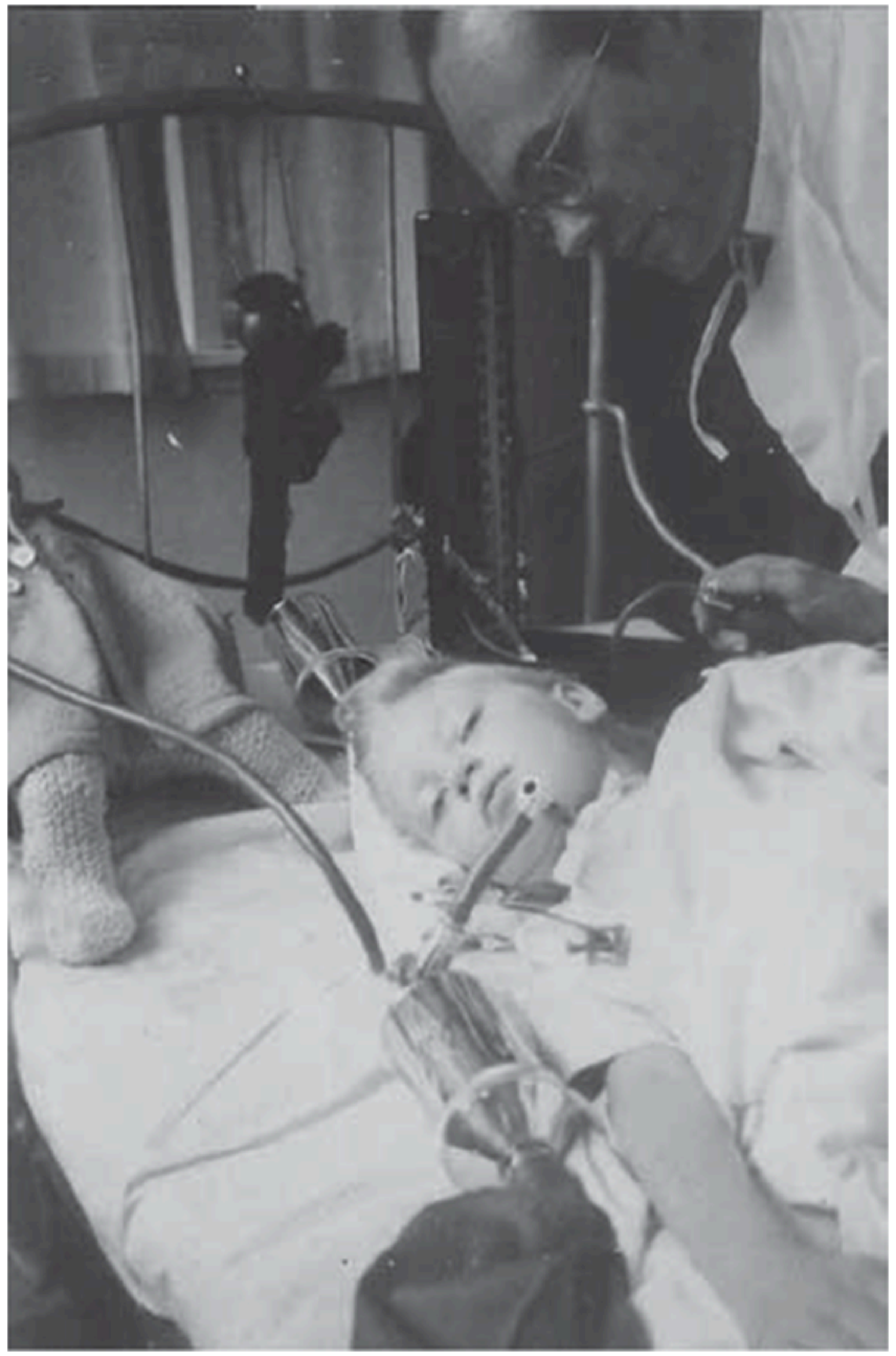


Fig 3. An 8-year-old girl being hand ventilated via a tracheostomy.

Figure sources see Resources section at the end of this talk.

Intensive Care Units (ICU)

Intensive care medicine

Functionalities
Life support, monitoring, resuscitations

General ICU, cardiac, post-operative, neonatal, ···

Healthcare Staff
Multidisciplinary. High staff patient ratio recommended (e.g. 1 patient has 1 doctor, 2 nurses)

Intensive Care
Numerous and invasive monitoring and intervention
- ventilation
- cardiac monitors
- web of intravenous lines, feeding tubes, drains, syringe pumps, ···

Expensive: USA $2902 per day per bed during covid

Intensive Care Units (ICU)

What makes a good ICU

Based on reviews on critical care medicine:

Medical outcomes
Lower mortality rate
Less infections
Lower complication rate, shorter stays ⋯

Patients
Satisfied patient and family
Respect end-of-life decisions
Proper medical intervention

Institution and cost effectiveness
Satisfied staff
Efficiency: bed utilization, processes involved in ICU care
Resource consumption

https://www.nytimes.com/2020/03/31/us/coronavirus-covid-triage-rationing-ventilators.html
https://www.reuters.com/business/healthcare-pharmaceuticals/majority-brazil-covid-19-icu-patients-aged-40-years-or-younger-report-2021-04-13/

Machine Learning in ICU

Machine learning in ICU

ICU monitoring and data

Non invasive
Heart rate, blood pressure, respiratory rate, temperature

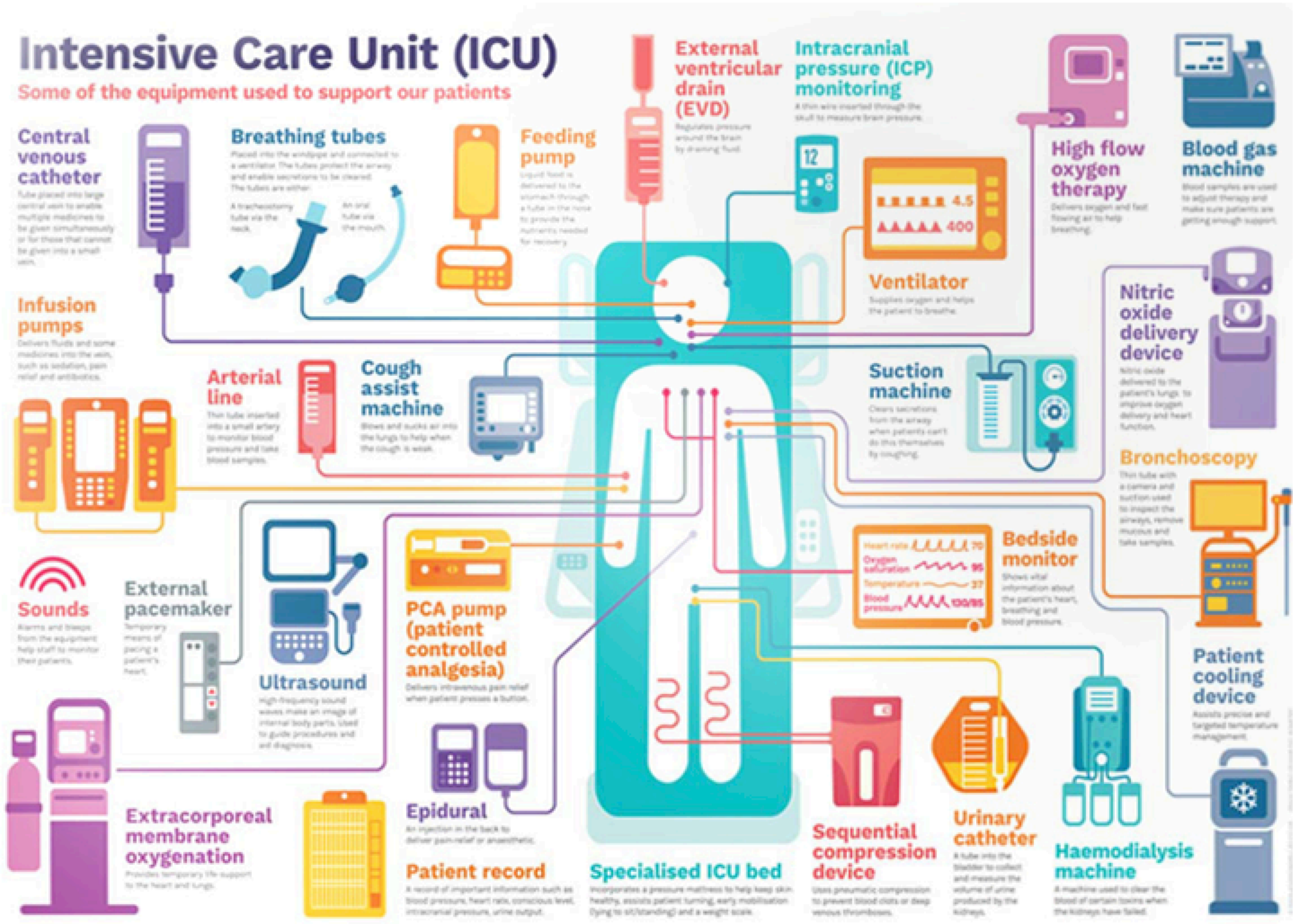
Electrocardiogram (ECG), echocardiogram
Electroencephalogram (EEG), ultrasound ···

Invasive
Blood draws
Arterial line (blood gas measurements)
..

The measurement frequency differ greatly for different monitoring data

Other data
demographics, conditions, diagnosis, notes by nurses ···

MIMIC database is a frequently used data source



MIMIC: Medical Information Mart for Intensive Care
https://www.hospitalgraphics.co.uk/projects/intensive-care-unit-equipment-diagrams/

Machine learning in ICU

Why do Machine Learning in ICU

Need: **Early detection and prediction of high–risk events** is highly relevant in ICU. ML can potentially help clinicians by reducing their workload, and improving the efficiency for clinical decisions

Possibility: Huge amount of **data** of different types are being generated (e.g. MIMIC data)

Note: ML developed with ICU data are <u>not ready</u> yet to be deployed in routine clinical practice.

Machine learning in ICU

What is Machine Learning

A family of modeling techniques that automatically **learn from data** and improve the performance on tasks, such as classification (alive/death).

Input → **Model** → Output

Traditional decision rules
based on clinical knowledge

if ECG data {looks like ·········},
then return heart attack

Machine learning

Learn the rules from data

Machine learning in ICU

Terminology

Supervised learning
One category of ML.
Outcome of interest (patient died within 72h) is known

Classification
A task where the label is categorical
(72h mortality, alive/death, 0/1)

Model
A relationship that links input and output

Evaluation
Accuracy, sensitivity and specificity,
area under the curves ···

Learning
Train, validate, test

Input → Model → Output

Features | Class labels

	ID	HR	Temp	BP	…	72h mortality
Train	1	120	39	130		1
	2	100	38	120		0
	…					
	…					
	299	80	37.5	119		0
	300	90	41	123		1
Validate	301	85	38	120		0
	…					
	350	115	36	180		1
Test	351	122	40	140		?
	…					?
	500	100	29	125		?

Machine learning in ICU

Logistic regression

Linear Regression

Outcome = **weight 1** * feature 1 +
weight 2 * feature 2 + ⋯

Logistic regression (LR)

Models binary outcome (1/0, alive or death)

One of the Generalized Linear Models (GLM)
Commonly used in ML for classification tasks

Predicts a probability, normally threshold is 0.5
(Prob > 0.5 is outcome 1)

	Features				Class labels
	W1	W2	W3		
ID	HR	Temp	BP	…	72h mortality
1	120	39	130		1
2	100	38	120		0
…					
…					
299	80	37.5	119		0
300	90	41	123		1
301	85	38	120		0
…					
350	115	36	180		1
351	122	40	140		?
…					?
500	100	29	125		?

Machine learning in ICU

Tree−based methods

Decision tree

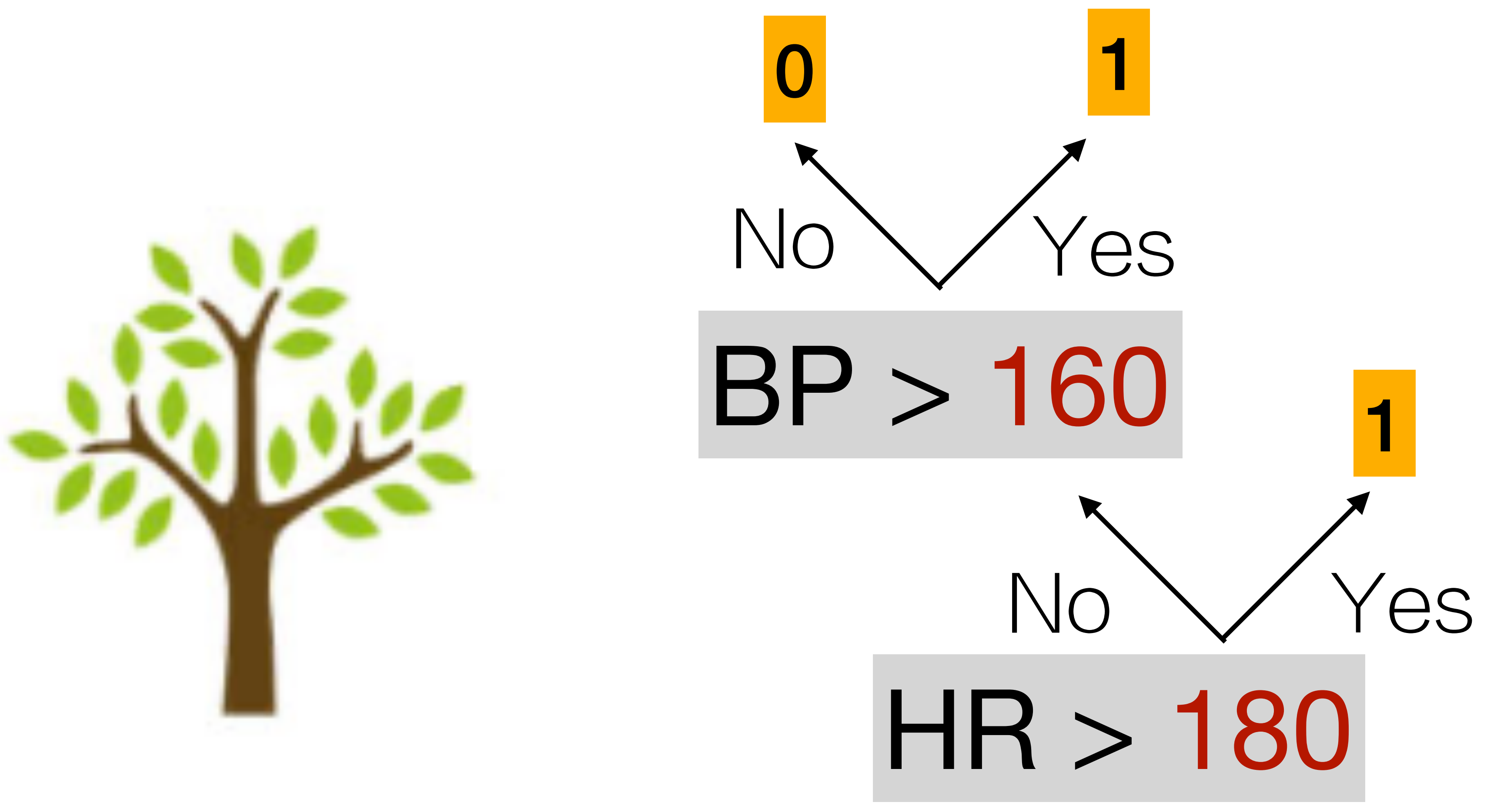
Leaves: class labels
Branches: rules that lead to classifications

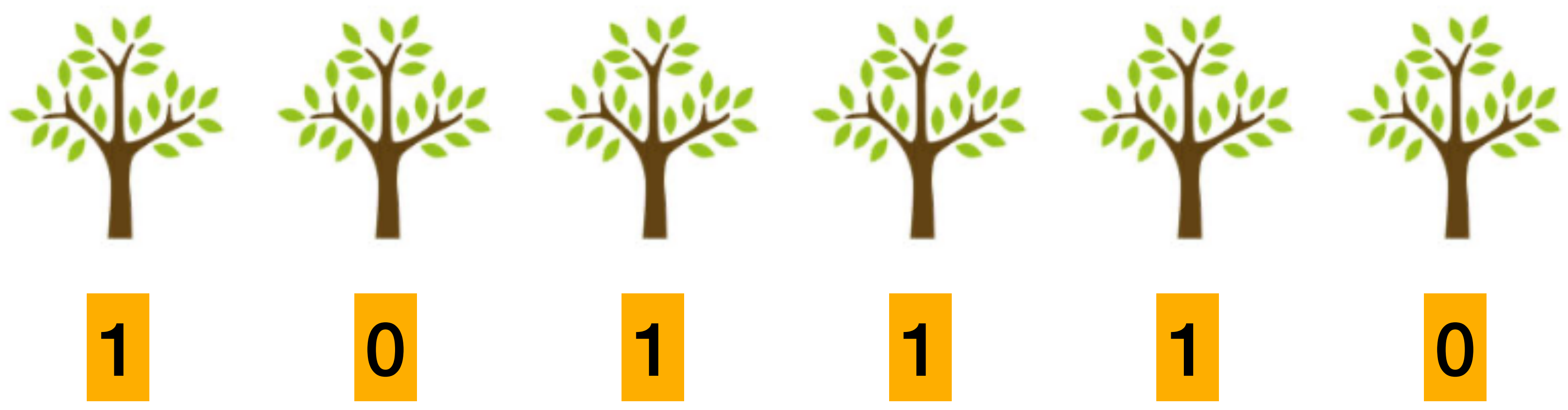
Branching points are learned from data

Random Forest

Different parts of the training data, train multiple trees

Output: the class selected by most trees





Machine learning in ICU

Support Vector Machine

Find a line to separate black and white points

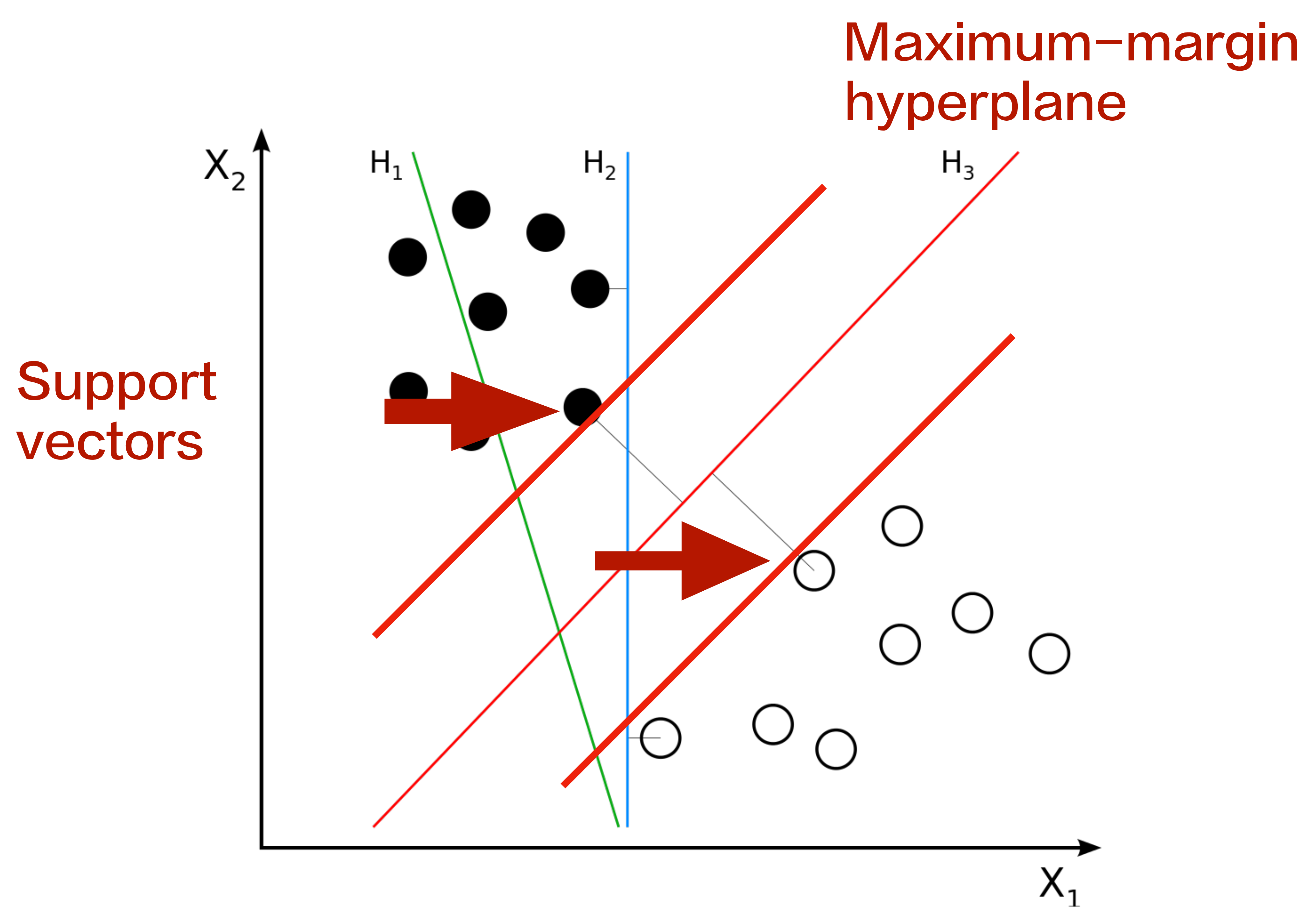
H1: does not separate two classes

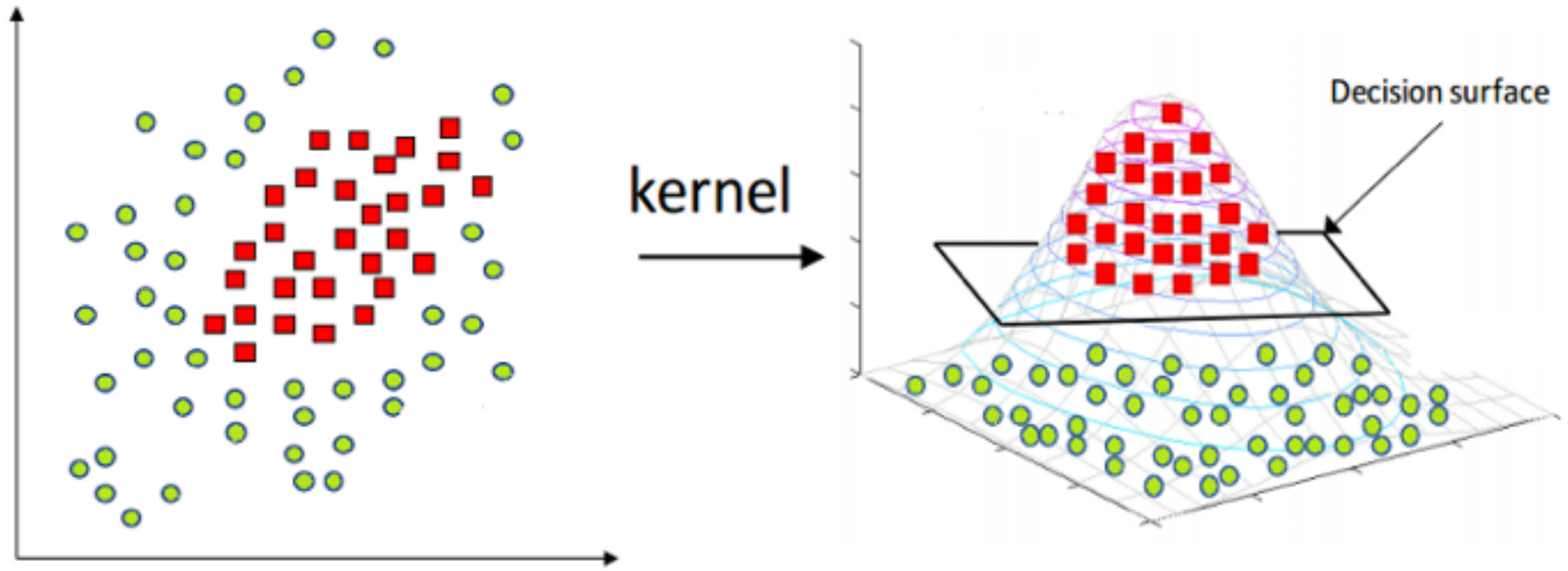
H2: separate two classes, but does not have largest distance

Aims to find a hyperplane to separate classes, where the hyperplane has the largest distance to the nearest training data points of any class.

Kernel trick

When classes are not separable in lower dimension, the kernel function maps the input to a higher dimension





https://medium.com/analytics-vidhya/how-to-classify-non-linear-data-to-linear-data-bb2df1a6b781

Machine learning in ICU

Neural networks

Artificial Neural Networks (ANN)

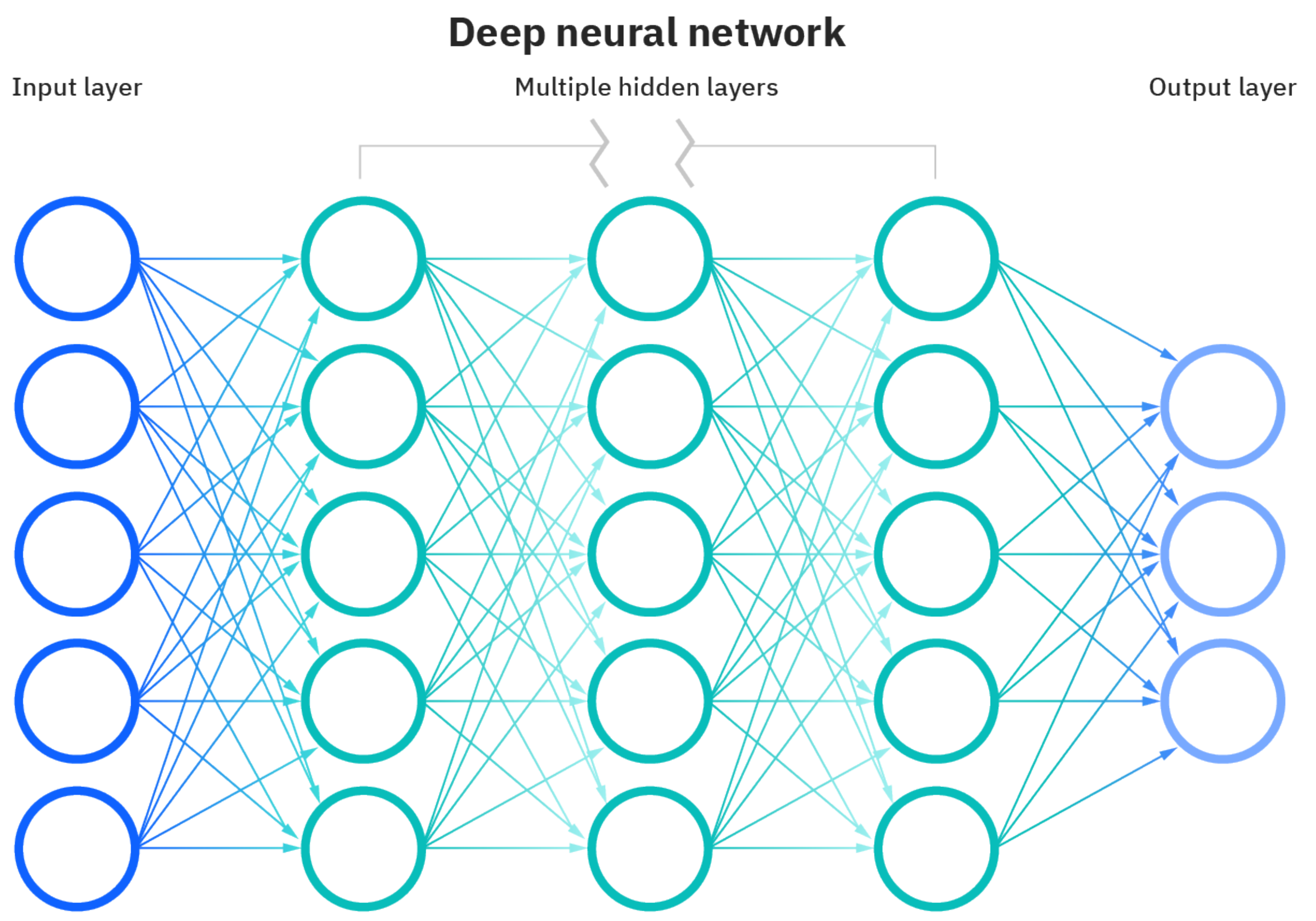
Interconnected group of nodes, inspired by neurons in a brain

A more complex transformation of inputs to produce output

Architectures

‘Deep Learning’: ANN with many layers
Deep neural networks (ANN with multiple layers)
Convolutional neural networks
Recurrent neural networks (e.g. LSTM)
…

Require **lots of data**



Machine learning in ICU

Other techniques

Supervised learning: classification

Logistic regression

Decision trees and random forest

SVM

Neural networks

… …

Other paradigms

Supervised learning: regression

Unsupervised Learning

Semi-supervised learning

Reinforcement learning

… …

In practice, usually combine a few techniques as needed

Machine learning in ICU

Where are we now

In a survey of **494 studies using AI (ML) in ICU**
(2021 review, van de Sande)

Predict complications (22.2%)
Predict mortality (20.6%)
Improve scoring systems (17.4%)
Classify sub-populations (11.7%)

ML in ICU using MIMIC data (61 studies, 2021 review, Syed)

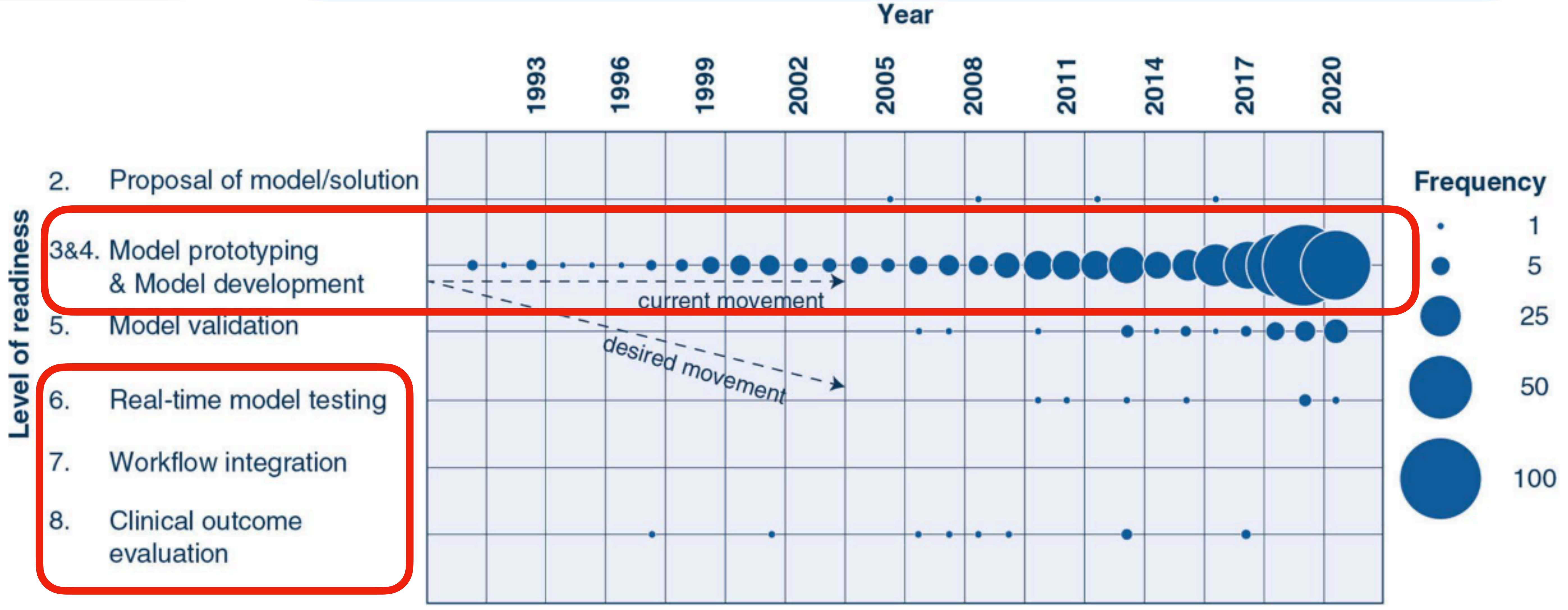
Mortality prediction (30%)
Sepsis, cardiac episodes, acute kidney injury predictions
ICU readmission

MIMIC III data has been cited more than 2000 times since 2016

Level of readiness

Majority (89%) focus on model development with internal validation only

None used in routine clinical practice



Case study:
in–hospital mortality

In–hospital mortality
Overview

Mortality rate can be over 40% for ICU patients (during Covid pandemic), varies for different populations

Illness severity assessment and early warning is crucial for treatment and intervention planning, resource allocation (e.g. triage, who should be prioritised for ICU)

Focus on **in–hospital mortality** among ICU patients. Important measure of ICU quality of care

Mortality prediction as a ML problem
Important outcome, clear definition

Supervised, binary classification

Use structured data: demographics, vital signs, lab variables

Medical scoring systems

↓

Structured ICU data

↓

Feature engineering

ML classification

Discussion

ICU mortality prediction

ICU scoring system

Computed for ICU patients using their first 24h measurement (admission score)

APACHE II (1985)
(Acute Physiology and Chronic Health Evaluation), 0–71 points

Physiological, age, chronic conditions

Higher score -> higher risk

The score itself does not tell the probability of survival

Others: **SAPS II** (Simplified Acute Physiology Score), **SOFA, APACHE III, IV** …

Temperature >41, +4

THE APACHE II SEVERITY OF DISEASE CLASSIFICATION SYSTEM

PHYSIOLOGIC VARIABLE	HIGH ABNORMAL RANGE						LOW ABNORMAL RANGE		
	+4	+3	+2	+1	0	+1	+2	+3	+4
TEMPERATURE — rectal (°C)	≥ 41°	39°-40.9°		38.5°-38.9°	36°-38.4°	34°-35.9°	32°-33.9°	30°-31.9°	≤ 29.9°
MEAN ARTERIAL PRESSURE — mm Hg	≥ 160	130-159	110-129		70-109		50-69		≤ 49
HEART RATE (ventricular response)	≥ 180	140-179	110-139		70-109		55-69	40-54	≤ 39
RESPIRATORY RATE — (non-ventilated or ventilated)	≥ 50	35-49		25-34	12-24	10-11	6-9		≤ 5
OXYGENATION: A-aDO$_2$ or PaO$_2$ (mm Hg) a. FIO$_2$ ≥ 0.5 record A-aDO$_2$	≥ 500	350-499	200-349		< 200				
b. FIO$_2$ < 0.5 record only PaO$_2$					PO$_2$ > 70	PO$_2$ 61-70		PO$_2$ 55-60	PO$_2$ < 55
ARTERIAL pH	≥ 7.7	7.6-7.69		7.5-7.59	7.33-7.49		7.25-7.32	7.15-7.24	< 7.15
SERUM SODIUM (mMol/L)	≥ 180	160-179	155-159	150-154	130-149		120-129	111-119	≤ 110
SERUM POTASSIUM (mMol/L)	≥ 7	6-6.9		5.5-5.9	3.5-5.4	3-3.4	2.5-2.9		< 2.5
SERUM CREATININE (mg/100 ml) (Double point score for **acute** renal failure)	≥ 3.5	2-3.4	1.5-1.9		0.6-1.4		< 0.6		
HEMATOCRIT (%)	≥ 60		50-59.9	46-49.9	30-45.9		20-29.9		< 20
WHITE BLOOD COUNT (total/mm3) (in 1,000s)	≥ 40		20-39.9	15-19.9	3-14.9		1-2.9		< 1
GLASGOW COMA SCORE (GCS): Score = 15 minus actual GCS									
[A] Total ACUTE PHYSIOLOGY SCORE (APS): Sum of the 12 individual variable points									
Serum HCO$_3$ (venous-mMol/L) [Not preferred, use if no ABGs]	≥ 52	41-51.9		32-40.9	22-31.9		18-21.9	15-17.9	< 15

[B] AGE POINTS:
Assign points to age as follows:

AGE(yrs)	Points
≤ 44	0
45-54	2
55-64	3
65-74	5
≥ 75	6

Age >= 75, +6

[C] CHRONIC HEALTH POINTS
If the patient has a history of severe organ system insufficiency or is immuno-compromised assign points as follows:
a. for nonoperative or emergency postoperative patients — 5 points
or
b. for elective postoperative patients — 2 points

DEFINITIONS
Organ Insufficiency or immuno-compromised state must have been evident **prior** to this hospital admission and conform to the following criteria:
LIVER: Biopsy proven cirrhosis and documented portal hypertension; episodes of past upper GI bleeding attributed to portal hypertension; or prior episodes of hepatic failure/encephalopathy/coma.

CARDIOVASCULAR: New York Heart Association Class IV.
RESPIRATORY: Chronic restrictive, obstructive, or vascular disease resulting in severe exercise restriction, i.e., unable to climb stairs or perform household duties; or documented chronic hypoxia, hypercapnia, secondary polycythemia, severe pulmonary hypertension (>40mmHg), or respirator dependency.
RENAL: Receiving chronic dialysis.
IMMUNO-COMPROMISED: The patient has received therapy that suppresses resistance to infection, e.g., immuno-suppression, chemotherapy, radiation, long term or recent high dose steroids, or has a disease that is sufficiently advanced to suppress resistance to infection, e.g., leukemia, lymphoma, AIDS.

APACHE II SCORE
Sum of [A] + [B] + [C]:
[A] APS points ____
[B] Age points ____
[C] Chronic Health points ____
Total APACHE II ____

ICU mortality prediction

Structured ICU data

Demographics (age, sex)
Underlying conditions (diabetes)
Type of admission (emergency)
Procedures and treatment (medication, ventilation) ⋯

Physiological data

Basis for computing disease severity for ICU patients

Time stamped, multiple measurements
Different frequency for each patient and each variable

(Waveforms like ECG, clinical text and images are used less frequently for mortality prediction)

Heart Rate	Blood Pressure
PaO2/FiO2 ratio	Body temperature
Glasgow Coma Score	Serum potassium
Serum sodium	Serum bicarbonate
Serum urea nitrogen	Bilirubin
Urinary output	White Blood Cell
…	…

Physiological variables used in SAPS II (Simplified Acute Physiology Score).
Slight difference across different scoring systems.

ICU mortality prediction

Feature engineering

Raw data is not usable for ML directly, must be processed

Classifiers require a matrix as input

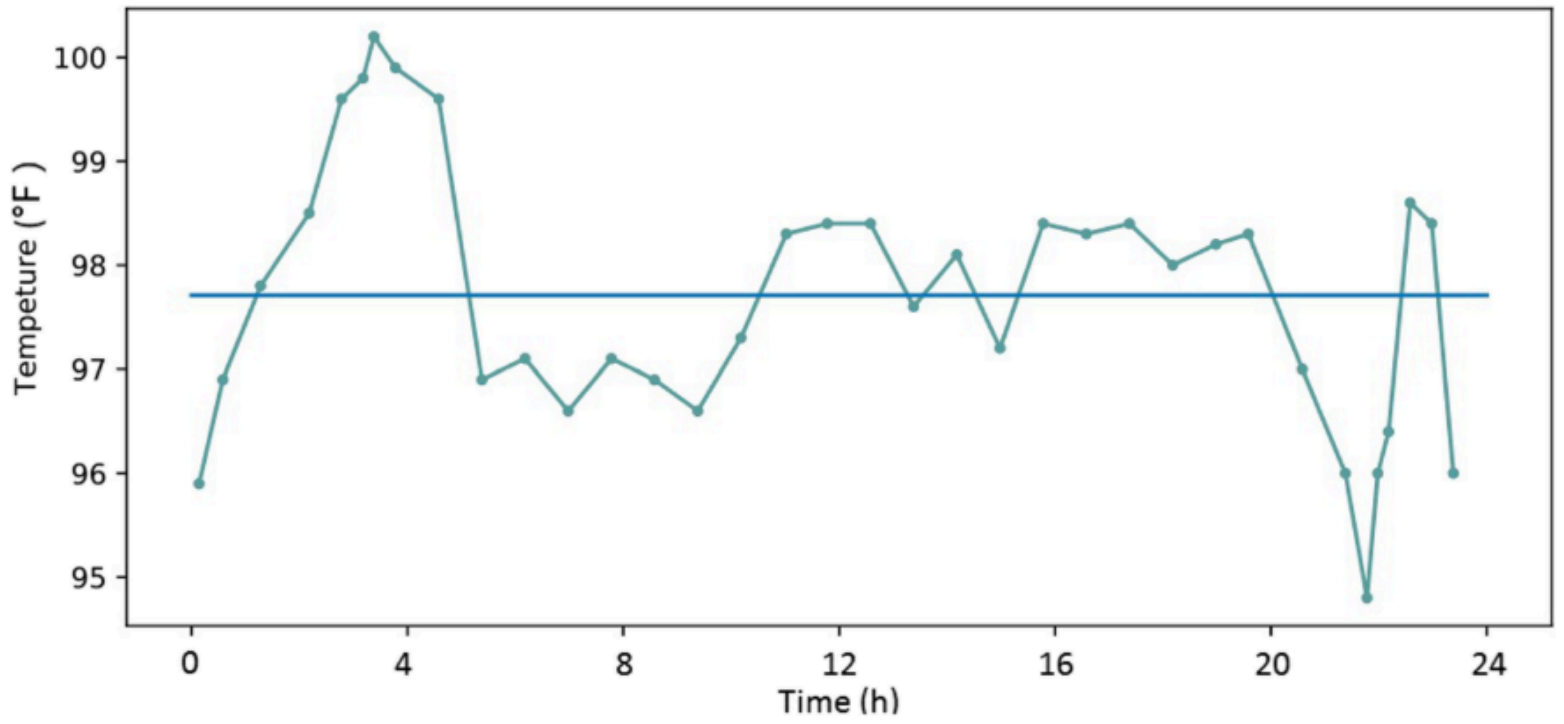
Time stamped multiple measurement need to be summarised

Summary statistics on time series

Central tendency (**mean**, median, mode)
Dispersion (sd, **max, min**, range, Q1, Q3, IQR)
First measurement ···

Other techniques
Standardisation, missing data imputation ···

ID	HR	Temp	BP	…	72h mortality
1	120	39	130		1
2	100	38	120		0
…					
…					
299	80	37.5	119		0
300	90	41	123		1
301	85	38	120		0



Example of 24h temperature measurements. (Fig 1 Guo 2020)
Mean temperature is indicated in blue

ICU mortality prediction

Classification performance

Harutyunnyan 2019

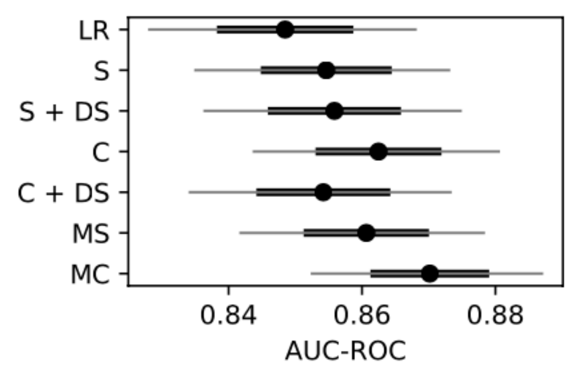
In-hospital mortality is the most common ML carried on MIMIC data

Various benchmarking papers exist
- **traditional scoring systems** (SAPS II)
- **classic ML** (LR, SVM, RF)
- **deep learning** (RNN)
- other **ensemble** methods (boosting)

AUROC is the major metric
(closer to 1 is better)

Scoring systems can reach 0.84
ML is better than scoring in general
LR is among the top classifiers
DL does not have a clear advantage

Model	AUC-ROC	AUC-PR
SAPS	0.7200 (0.7197, 0.7203)	0.3013 (0.3008, 0.3018)
APS-III	0.7500 (0.7497, 0.7503)	0.3568 (0.3563, 0.3573)
OASIS	0.7603 (0.7601, 0.7606)	0.3115 (0.3110, 0.3119)
SAPS-II	0.7768 (0.7765, 0.7770)	0.3762 (0.3757, 0.3767)
LR	0.8485 (0.8279, 0.8682)	0.4744 (0.4188, 0.5293)
S	0.8547 (0.8349, 0.8732)	0.4848 (0.4308, 0.5372)
S + DS	0.8558 (0.8362, 0.8750)	0.4928 (0.4379, 0.5486)
C	0.8623 (0.8436, 0.8807)	0.5153 (0.4640, 0.5680)
C + DS	0.8543 (0.8340, 0.8734)	0.5023 (0.4472, 0.5544)
MS	0.8607 (0.8416, 0.8784)	0.4933 (0.4388, 0.5482)
MC	0.8702 (0.8523, 0.8872)	0.5328 (0.4797, 0.5835)



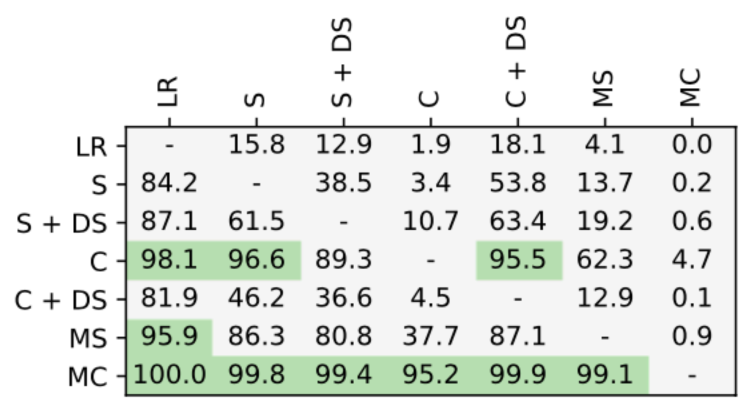


Figure 1. Results for in-hospital mortality prediction task

S. Purushotham et al. *Journal of Biomedical Informatics 83 (2018) 112–134*

Table 9
In-hospital mortality task on MIMIC-III using feature set A.

Method	Algorithm	Feature Set A, 24-h data		Feature Set A, 48-h data	
		AUROC score	AUPRC score	AUROC score	AUPRC score
Score methods	SAPS-II	0.8035 ± 0.0044	0.3586 ± 0.0052	0.8046 ± 0.0083	0.3373 ± 0.0141
	New SAPS-II	0.8235 ± 0.0042	0.3989 ± 0.0120	0.8252 ± 0.0036	0.3823 ± 0.0119
	SOFA	0.7322 ± 0.0038	0.3191 ± 0.0085	0.7347 ± 0.0094	0.2852 ± 0.0167
Super Learner	SL.glm	0.8235 ± 0.0042	0.3987 ± 0.0120	0.8251 ± 0.0037	0.3828 ± 0.0112
	SL.gbm	0.8435 ± 0.0034	0.4320 ± 0.0125	0.8452 ± 0.0052	0.4163 ± 0.0121
	SL.nnet	0.8388 ± 0.0044	0.4200 ± 0.0135	0.8381 ± 0.0055	0.3989 ± 0.0131
	SL.ipredbagg	0.7556 ± 0.0064	0.3104 ± 0.0084	0.7510 ± 0.0078	0.2811 ± 0.0121
	SL.randomforest	0.7576 ± 0.0085	0.3104 ± 0.0084	0.7538 ± 0.0095	0.2830 ± 0.0121
	SuperLearner-I	0.8448 ± 0.0038	0.4351 ± 0.0139	0.8465 ± 0.0057	0.4190 ± 0.0124
	SL.glm	0.8024 ± 0.0043	0.3804 ± 0.0043	0.8013 ± 0.0021	0.3559 ± 0.0238
	SL.gbm	0.8628 ± 0.0037	0.4840 ± 0.0078	0.8518 ± 0.0049	0.4259 ± 0.0209
	SL.nnet	0.8490 ± 0.0079	0.4587 ± 0.0058	0.8383 ± 0.0058	0.4028 ± 0.0180
	SL.ipredbagg	0.8060 ± 0.0069	0.4087 ± 0.0110	0.7816 ± 0.0028	0.3455 ± 0.0159
	SL.randomforest	0.7977 ± 0.0079	0.3958 ± 0.0124	0.7813 ± 0.0059	0.3496 ± 0.0200
	SuperLearner-II	**0.8673 ± 0.0045**	**0.4968 ± 0.0097**	0.8595 ± 0.0035	0.4422 ± 0.0200
Deep learning	FFN	0.8496 ± 0.0047	0.4632 ± 0.0074	0.8375 ± 0.0041	0.4090 ± 0.0169
	RNN	0.8544 ± 0.0053	0.4519 ± 0.0145	0.8618 ± 0.0059	0.4458 ± 0.0144
	MMDL	0.8664 ± 0.0056	0.4776 ± 0.0162	**0.8737 ± 0.0045**	**0.4714 ± 0.0176**

ICU mortality prediction

Discussion

Data

Sample size
(enough data for DL?)

Class distribution
(highly imbalanced?)

Processing
(Mean? Max? First?)

Model

Specification
(feature inclusion)

Parameter tuning
(decision tree depth, number of nodes and layers)

Evaluation

Metric
(Accuracy? AUROC?)

Generalisation
on new data

Interpretation
of model and parameters

What else can ML do in ICU

ML in ICU

Beyond structured ICU data

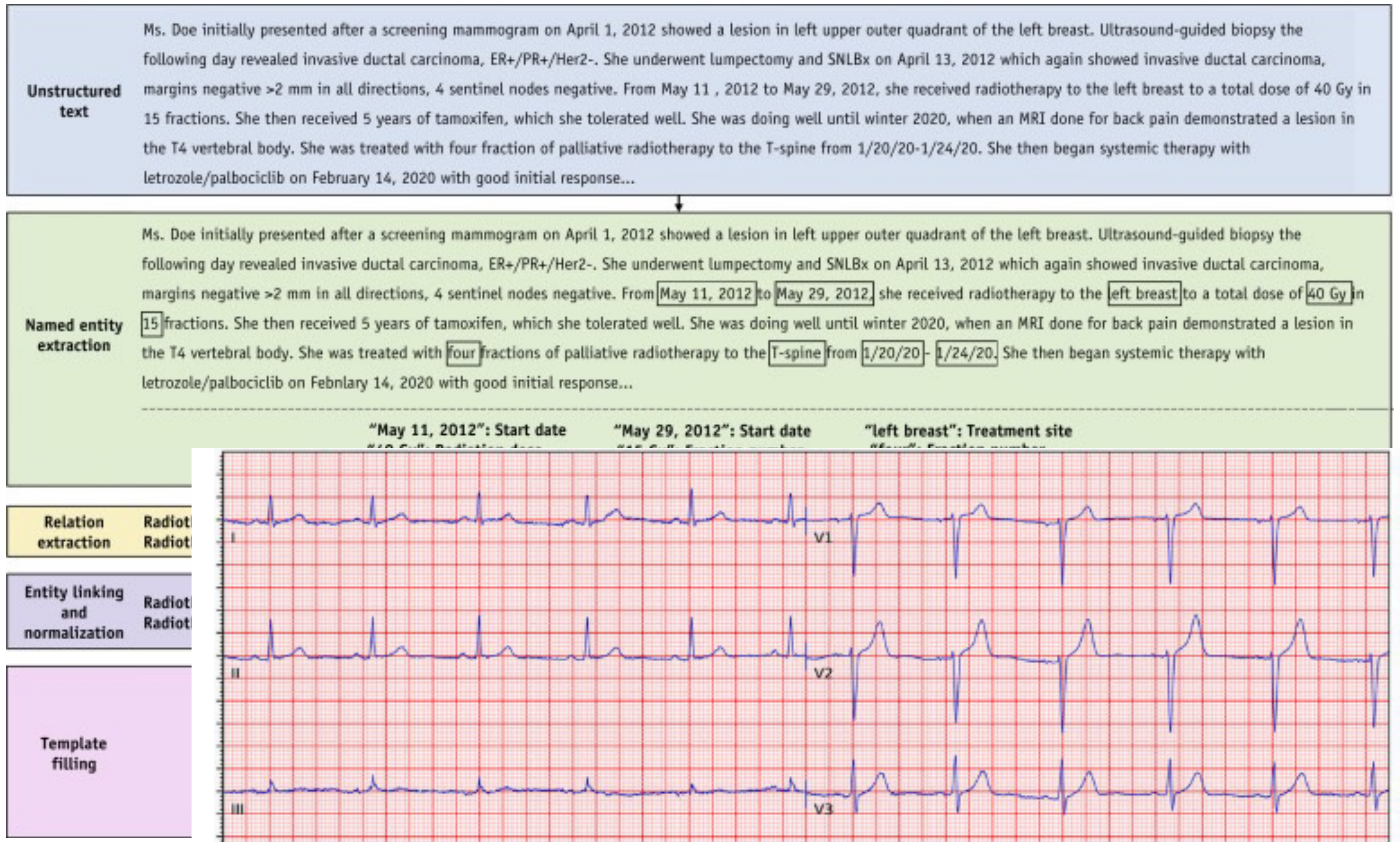
Structured data: demographics, physiology,⋯

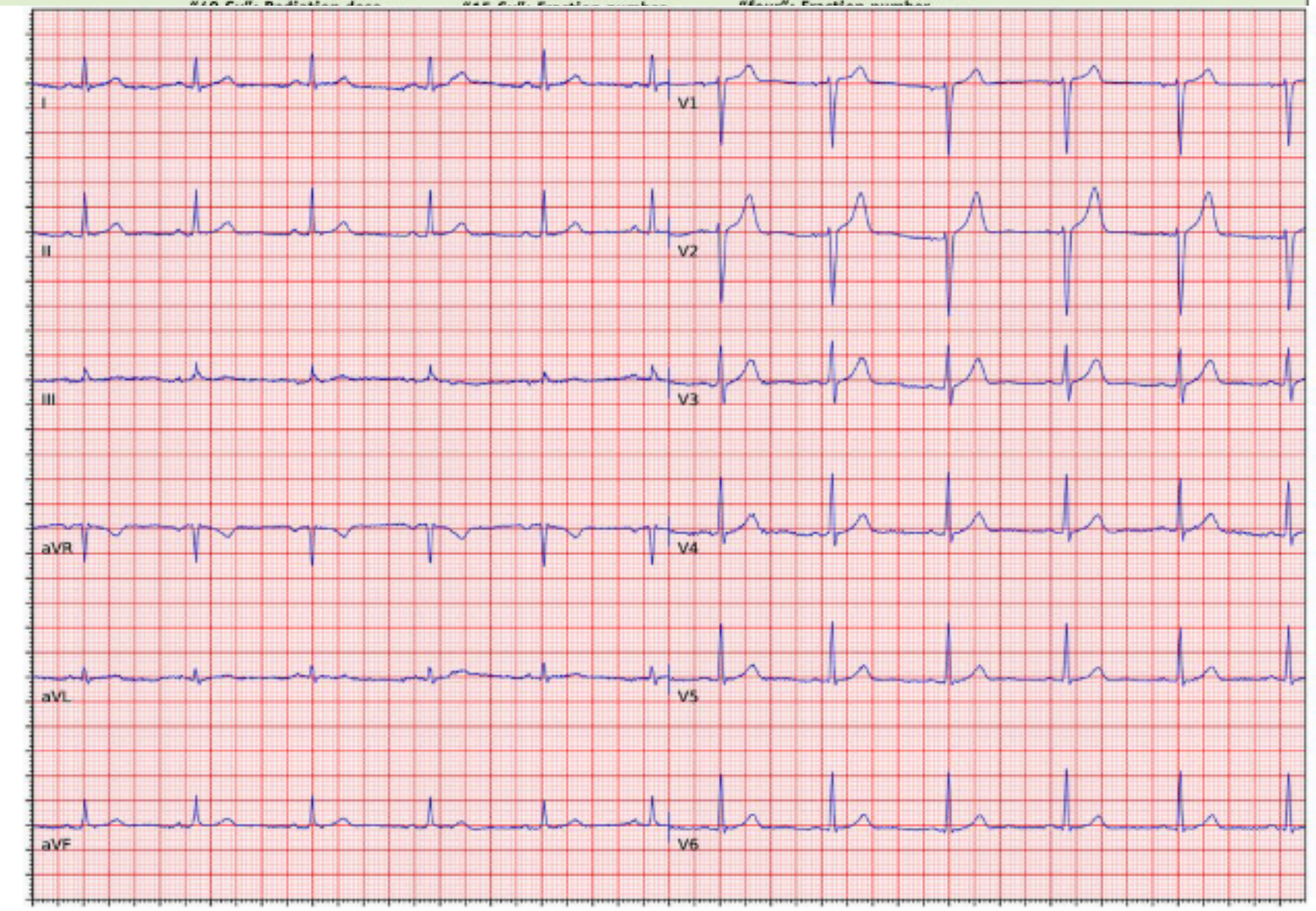
Unstructured text
Clinical notes, require natural language processing (NLP)

Waveforms
ECG, EEG, ⋯

Images and videos
X-ray images
videos taken in ICU wards

Various tasks: understand patient characteristics (phenotyping), detect heart attacks, monitor patient activities⋯





https://www.redjournal.org/article/S0360-3016(21)00118-8/fulltext

ML in ICU
Intervention prediction

Vasopressor administration and weaning
(Wu and Ghassemi 2017)

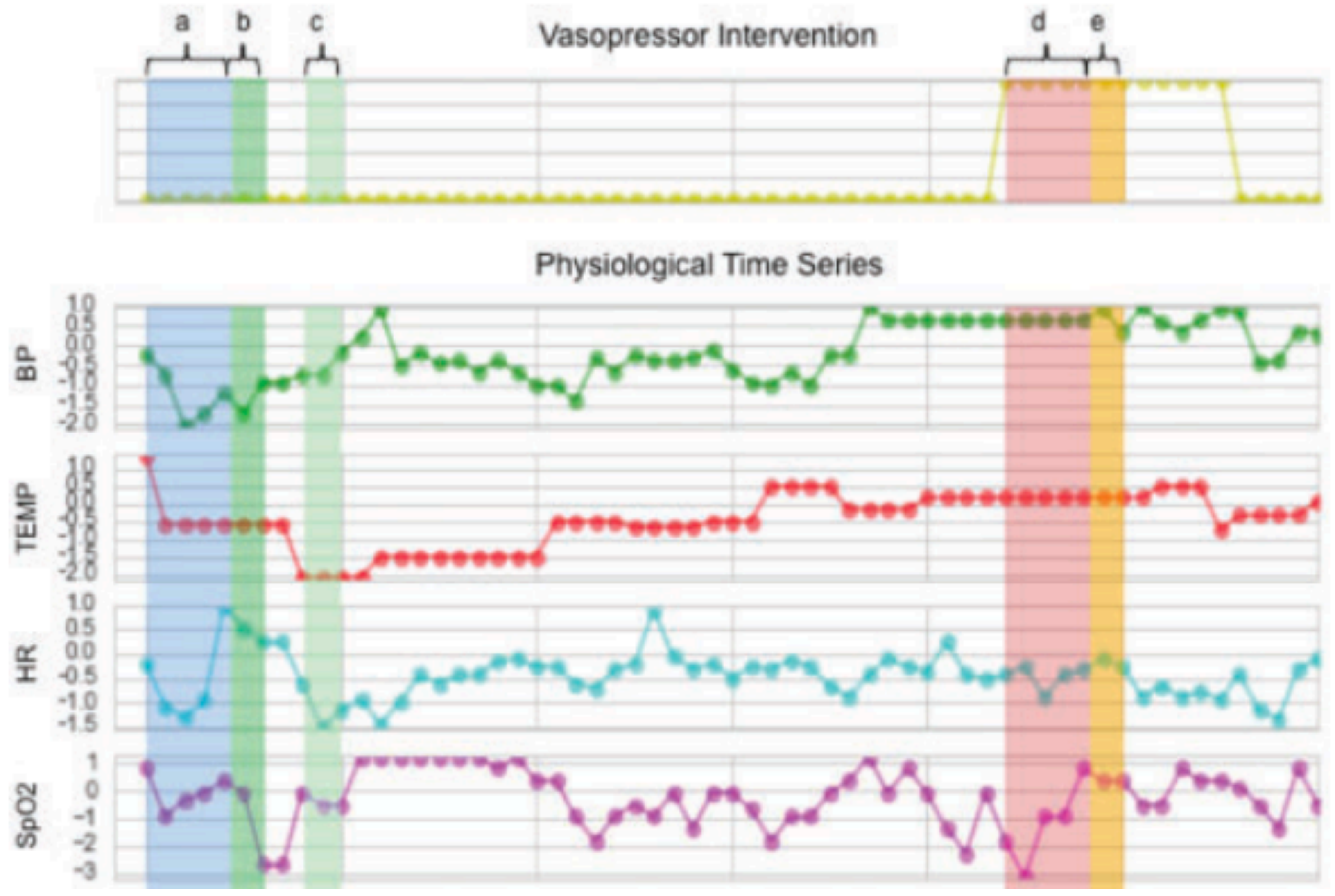
Medication to elevate blood pressure

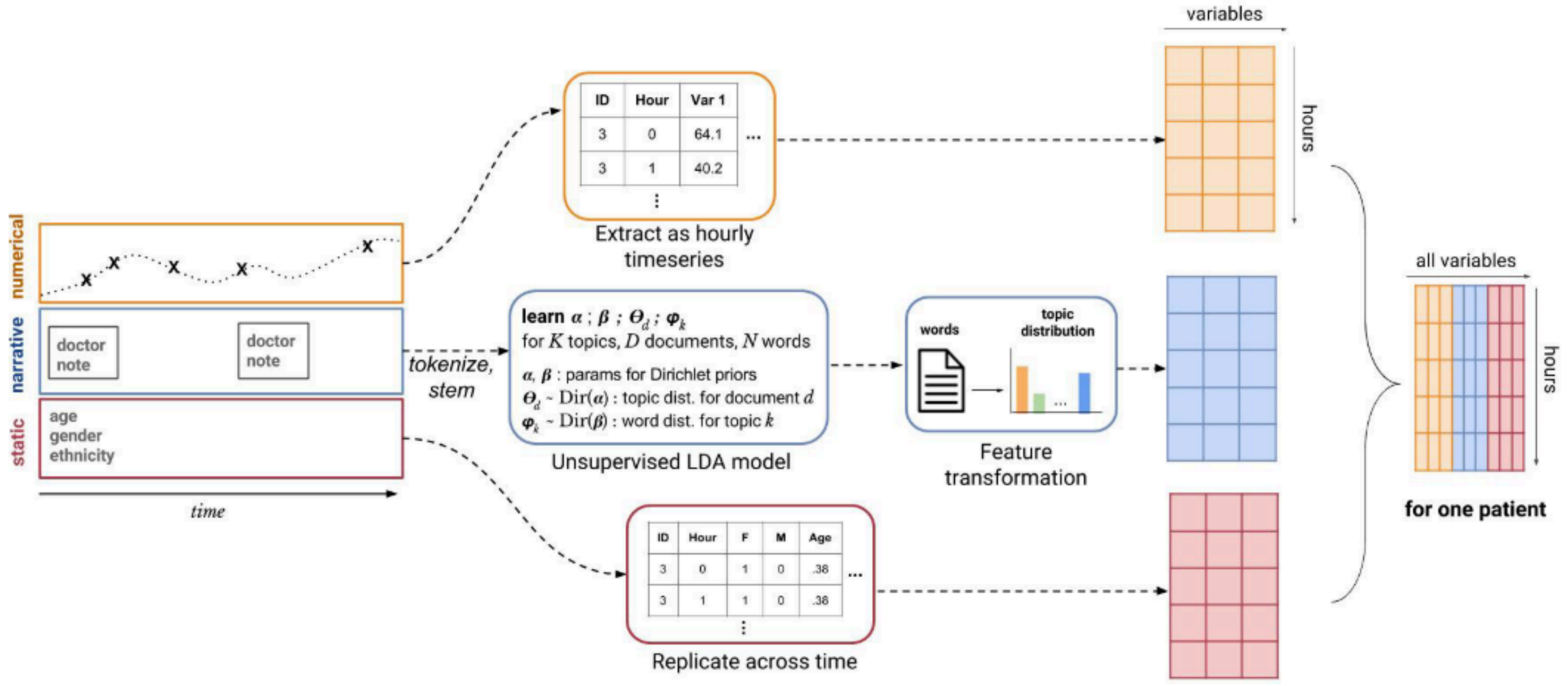
Whether a patient needs vasopressor in 2h;
Whether a patient on vasopressor is ready to be stopped within 2h.

Mechanical ventilation (Suresh 2017)

Predict 4h ahead <u>intervention change</u> (onset, wean, stay on, stay off) using neural networks

Can be considered as <u>classification tasks</u>





ML in ICU

ICU capacity prediction

Predict ICU resource use during COVID

Random forest (Lorenzen2021, Denmark)

Predict whether ICU admission, mechanical ventilation needed after n days (n=1, ⋯ 15)

Regression with time lags (Ritter 2021)

Predict number of ICU patient based on number of reported infections

The line between ML and statistics is often blurred

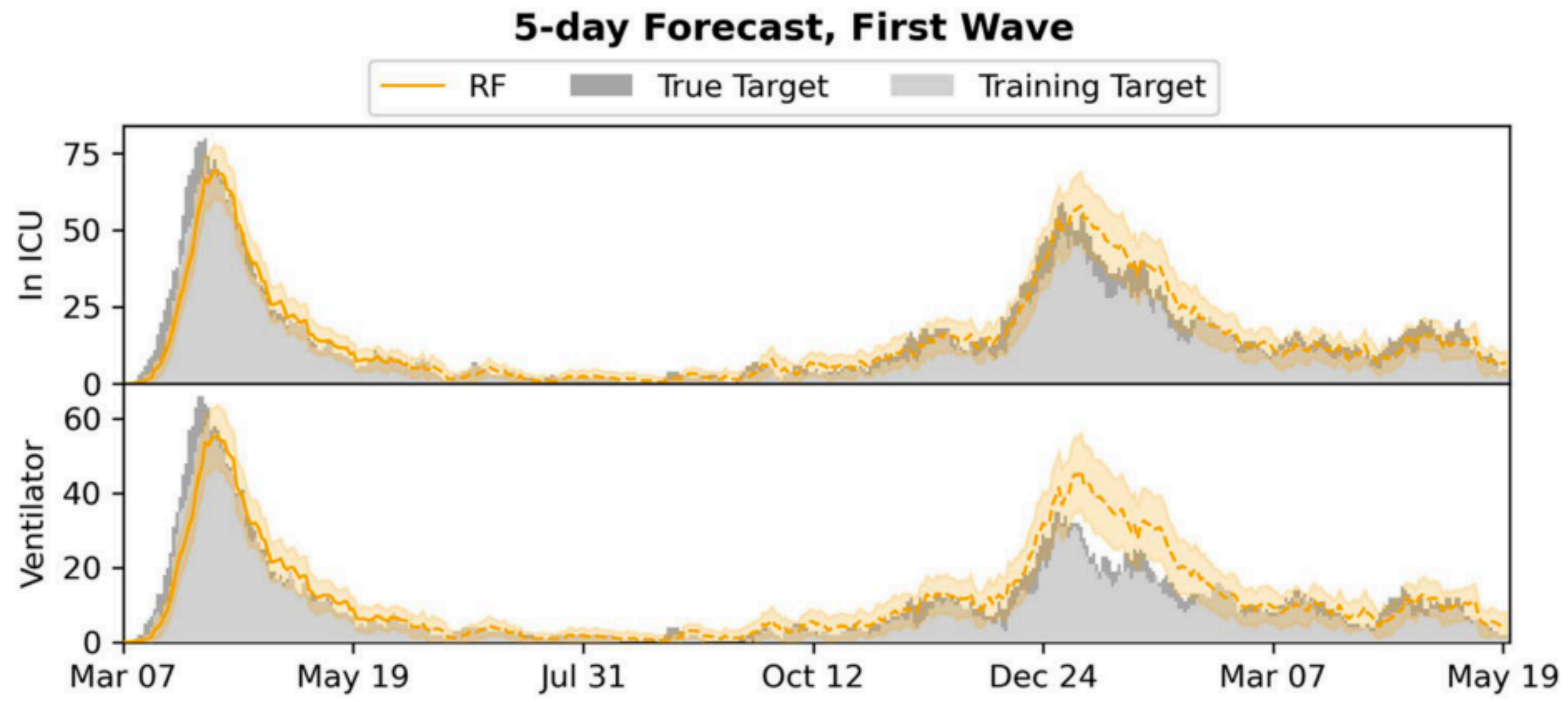


Figure 6. 5-day forecasts of admission to ICU and use of mechanical ventilation, compared to the training and true targets in the first wave setting. Predictions and targets for both the first wave (training data) and the subsequent waves (test data, dashed) are shown, as well as the 95% confidence intervals.

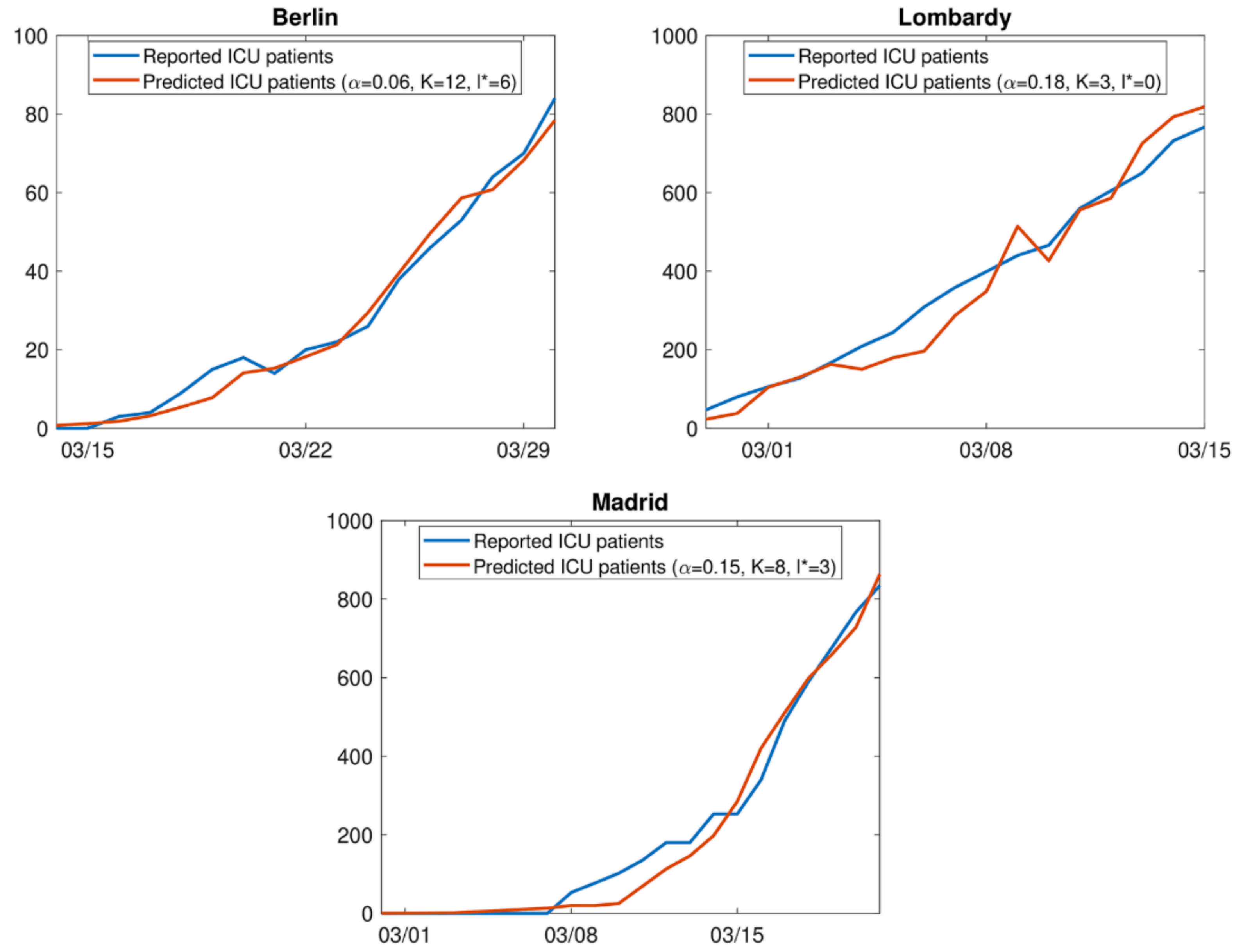


Figure 2. Best model fit for the number of ICU patients with ICU rate α, stay in ICU K and time lag l^* between positive testing and entering ICU, separately for Berlin, Lombardy, and Madrid.

ML in ICU and healthcare

Other applications

Disease trajectory and intervention
Involves causal inference and counterfactual predictions

Phenotyping
Unsupervised learning, no class labels;
Combine data from different sources and types to reveal patient clusters on specific diagnoses and medications

Computer vision on ICU video
Patient activity monitoring

…

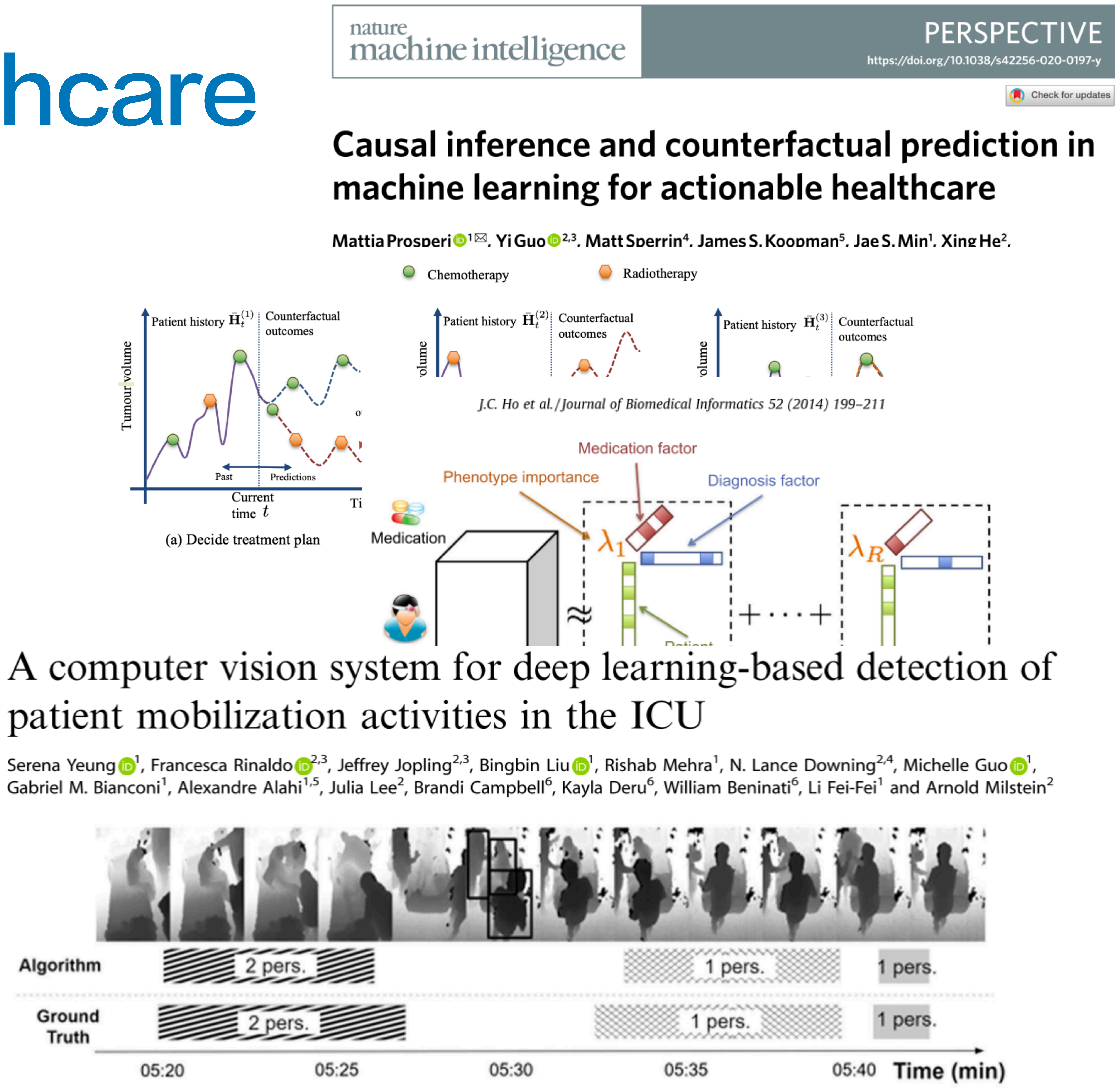


Figure sources see Resources section at the end of this talk.

The future of ML in ICU

The future of ML in ICU

Where are we now (revisited)

1960s
Development of IT systems in hospitals

...

2009
Wide adoption of modern EHR system begins

2016
Over 96% US hospitals have modern EHR.
MIMIC-III data available

50 years history of Electronic Health Records (EHR) systems adoption in USA

2021 (5 years since 2016)
Around 90% of ML research in ICU are in development stage
None in routine clinical practice yet

2000–3000 publications using MIMIC-III data
(MIMIC-IV is available now)

→ Data
Development
Deployment

The future of ML in ICU

Data

Data source and availability

Overuse of MIMIC data
Cited for 2179 times since 2016 – the one and only public data of this type? (eICU is another database in US, but less used)

58k admission, single center in Boston, US – generalisability?

Need more diverse EHR data for research!

Quality and processing

Data is not generated for research purpose, require tremendous processing

Insights from healthcare experts is crucial, need deep understanding of data generation process

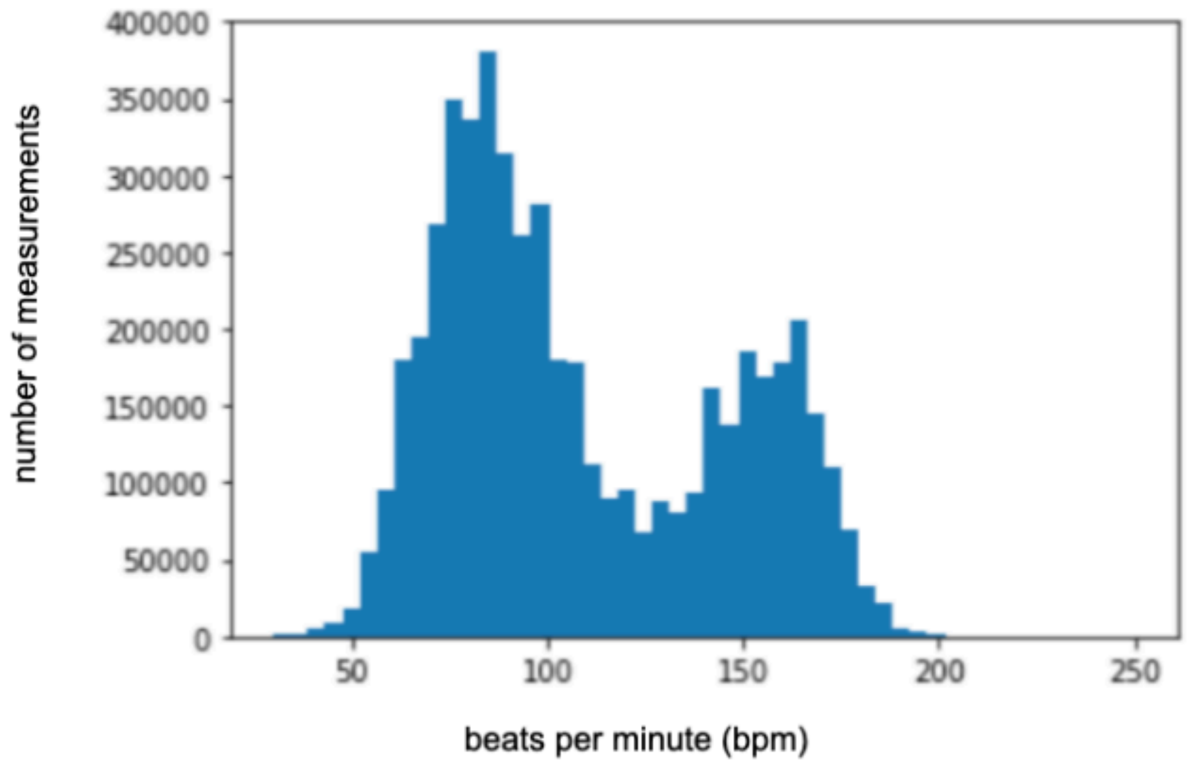
Open Access | Published: 24 May 2016

MIMIC-III, a freely accessible critical care database

Alistair E.W. Johnson, Tom J. Pollard, Lu Shen, Li-wei H. Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi & Roger G. Mark

Scientific Data **3**, Article number: 160035 (2016) | Cite this article

168k Accesses | **2179** Citations | **100** Altmetric | Metrics



Boag 2022

HR distribution indicate mixing of two ICU databases, neonatal and adult

The future of ML in ICU

Development

Ask good questions

e.g. Will the patient die in hospital

->

What can we do

Challenges

Real-time, real-world data

Interpretable models

Causality and intervention

Scalability

Generalisation, bias, fairness

...

The future of ML in ICU

Deployment

Knowledge experts

Clinical experts

ML researchers

IT experts, engineers

Decision makers

Hospital administrators

Regulatory agencies

Local and state government

Choose the right problems

Data, development, evaluation

Ethical concerns

Legal and regulations
(e.g. ML algorithms as a drug?)
…

Users (provider)

Physicians

Nurses

Lab technicians

Users (receiver)

Patients

Family and friends

Summary

Summary

Machine Learning in ICU

What is ICU, what makes a good ICU, what data ICU generates

What is Machine Learning, a few algorithms

How ICU data can be used (mortality risk and other applications)

Future of ML in ICU: data, development and deployment

Resources

Intensive Care Units

Kelly 2014. The history and future of the intensive care unit. Clinical Medicine 2014 Vol 14 No 4:376–9
Dartmouth ICU: https://dartmed.dartmouth.edu/spring04/html/vs_mosenthal.shtml
Garland 2005. Improving the ICU. CHEST 2005, 127:2151–2164
Gallesio 2006. Improving Quality in the Intensive Care Unit Setting. Critical Care Clinics. DOI: 10.1016/j.ccc.2006.04.002

ML in ICU

Johnson 2016. MIMIC-III, a freely accessible critical care database. Scientific Data. DOI: 10.1038/sdata.2016.35.
Van de Sande 2021. Moving from bytes to bedside: a systematic review on the use of artificial intelligence in the intensive care unit. DOI: 10.1007/s00134-021-06446-7
Syed 2021. Applications of machine learning in intensive care unit (ICU) settings using MIMIC dataset: systematic review. Informatics 2021, 8, 16. DOI: 10.3390/informatics8010016.

Future of ML x ICU

Wiens 2019. Do no harm: a roadmap for responsible machine learning for health care. Nature Medicine. DOI: 10.1038/s41591-019-0548-6
Boag 2022. EHR safari: data is contextual. Proceedings of Machine Learning Research 182:1–18, 2022.

Resources

Case studies

Johnson 2017. Reproducibility in critical care: a mortality prediction case study. Proceedings of Machine Learning for Healthcare 2017.
Guo 2020. An evaluation of time series summary statistics as features for clinical prediction tasks. BMC Medical Informatics and Decision Making. DOI: 10.1186/s12911-020-1063-x.
Choi 2022. Mortality prediction of patients in intensive care units using machine learning algorithms based on electronic health records. DOI: 10.1038/s414598-022-11226-4
Harutyunyan 2019. Multitask learning and benchmarking with clinical time series data. DOI: 10.1038/s41957-019-0103-9
Purushotham 2018. Benchmarking deep learning models on large healthcare datasets. Journal of Biomedical Informatics. DOI: 10.1016/j.jbi.2018.04.007
Wu and Ghassemi 2017. Understanding vasopressor intervention and weaning: risk prediction in a public heterogeneous clinical time series database. Journal of the American Medical Informatics Association, 24(3), 2017. DOI: 10.1093/jamia/ocw138
Suresh 2017. Clinical intervention prediction and understanding using deep networks. Proceedings of Machine Learning for Healthcare 2017.
Thambawita 2021. DeepFake electrocardiograms using generative adversarial networks are the beginning of the end for privacy issues in medicine. Scientific Reports. DOI: 10.1038/s41598-021-01295-2
Yeung 2019. A computer vision system for deep learning-based detection of patient mobilisation activities in the ICU. Npc Digital Medicine 2019 2:11. DOI: 10.1038/s41746-019-0087-z
Bica 2020. Estimating counterfactual treatment outcomes over time through adversarially balanced representations. ICLR 2020.
Ho 2014. Limestone: High-throughput candidate phenotype generation via tensor factorisation. Journal of Biomedical Informatics. DOI: 10.1016/j.jbi.2014.07.001.