Amsterdam UMC
Universitair Medische Centra

Doctors and Technology: Machine Learning at the Bedside

Paul WG Elbers, MD, PhD, EDIC
Intensivist, Department of Intensive Care Medicine
Amsterdam UMC, location VUmc
p.elbers@amsterdamumc.nl

Amsterdam Medical Data Science

Amsterdam Cardiovascular Sciences

Amsterdam Infection & Immunity Institute

Data Science
Section_

pacmed

The future is now

The NEW ENGLAND JOURNAL of MEDICINE

REVIEW ARTICLE

FRONTIERS IN MEDICINE

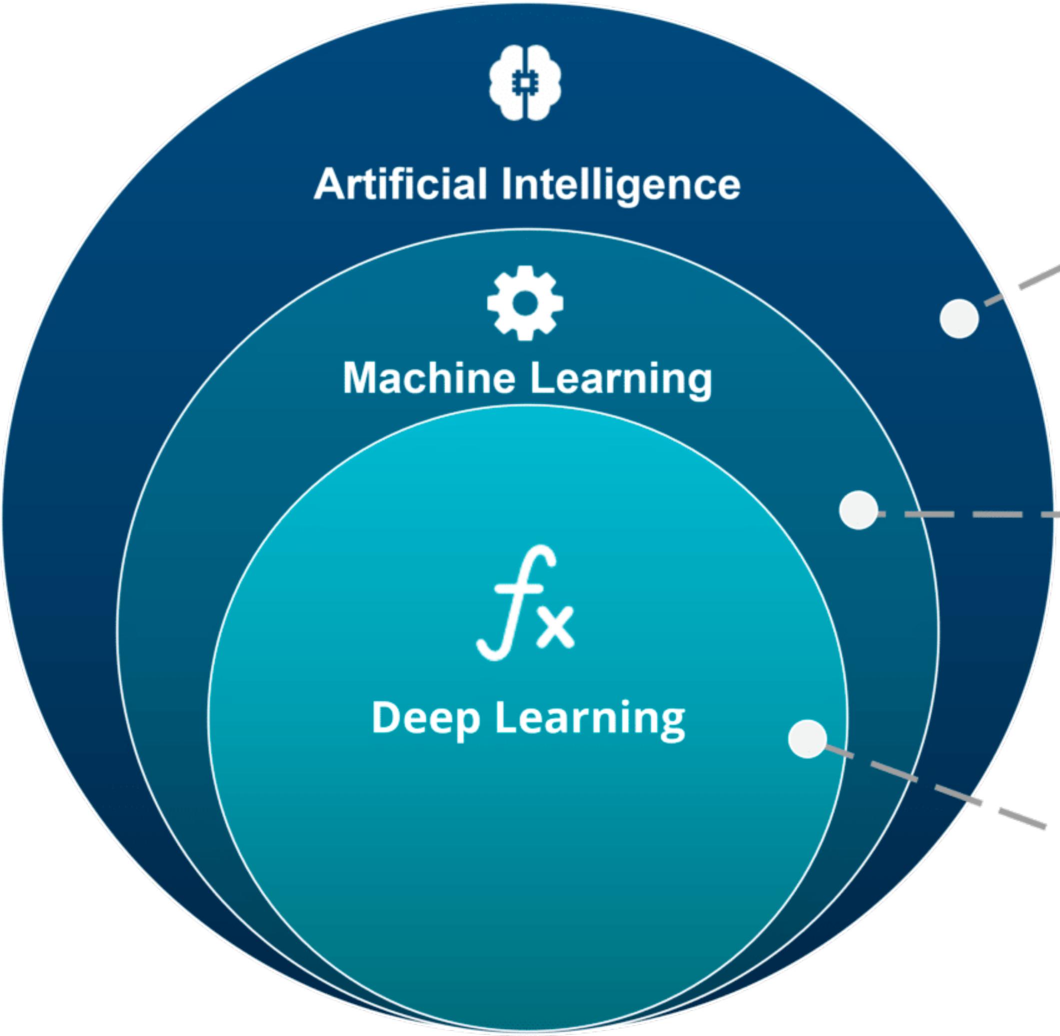
Machine Learning in Medicine

Alvin Rajkomar, M.D., Jeffrey Dean, Ph.D., and Isaac Kohane, M.D., Ph.D.

The promise of machine learning in medicine

The wisdom contained
in the **decisions made by nearly all clinicians**
and the **outcomes of billions of patients**
should inform the care of each patient

Rajkomar NEJM 2019



ARTIFICIAL INTELLIGENCE

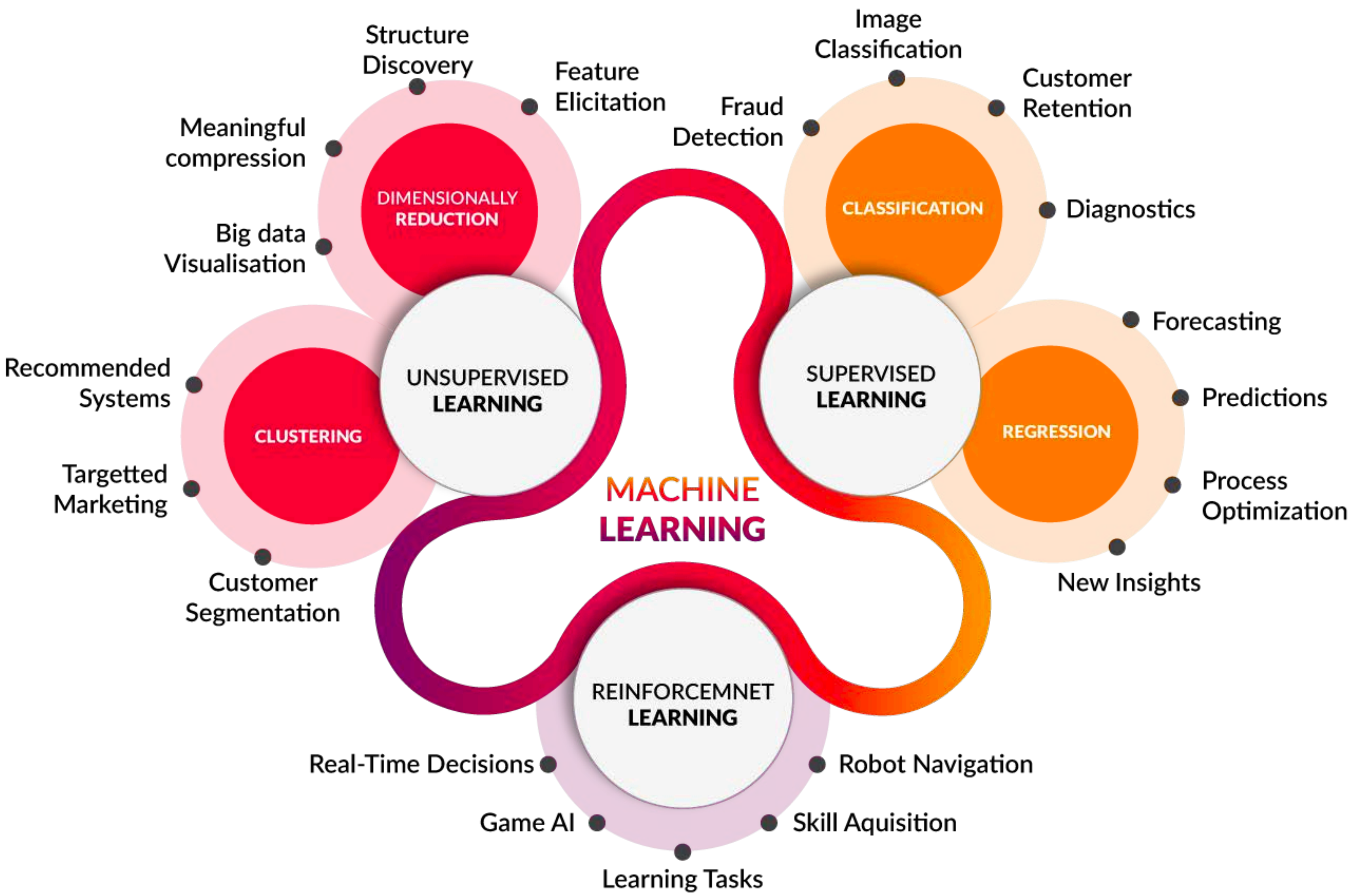
A technique which enables machines to mimic human behaviour

MACHINE LEARNING

Subset of AI technique which use statistical methods to enable machines to improve with experience

DEEP LEARNING

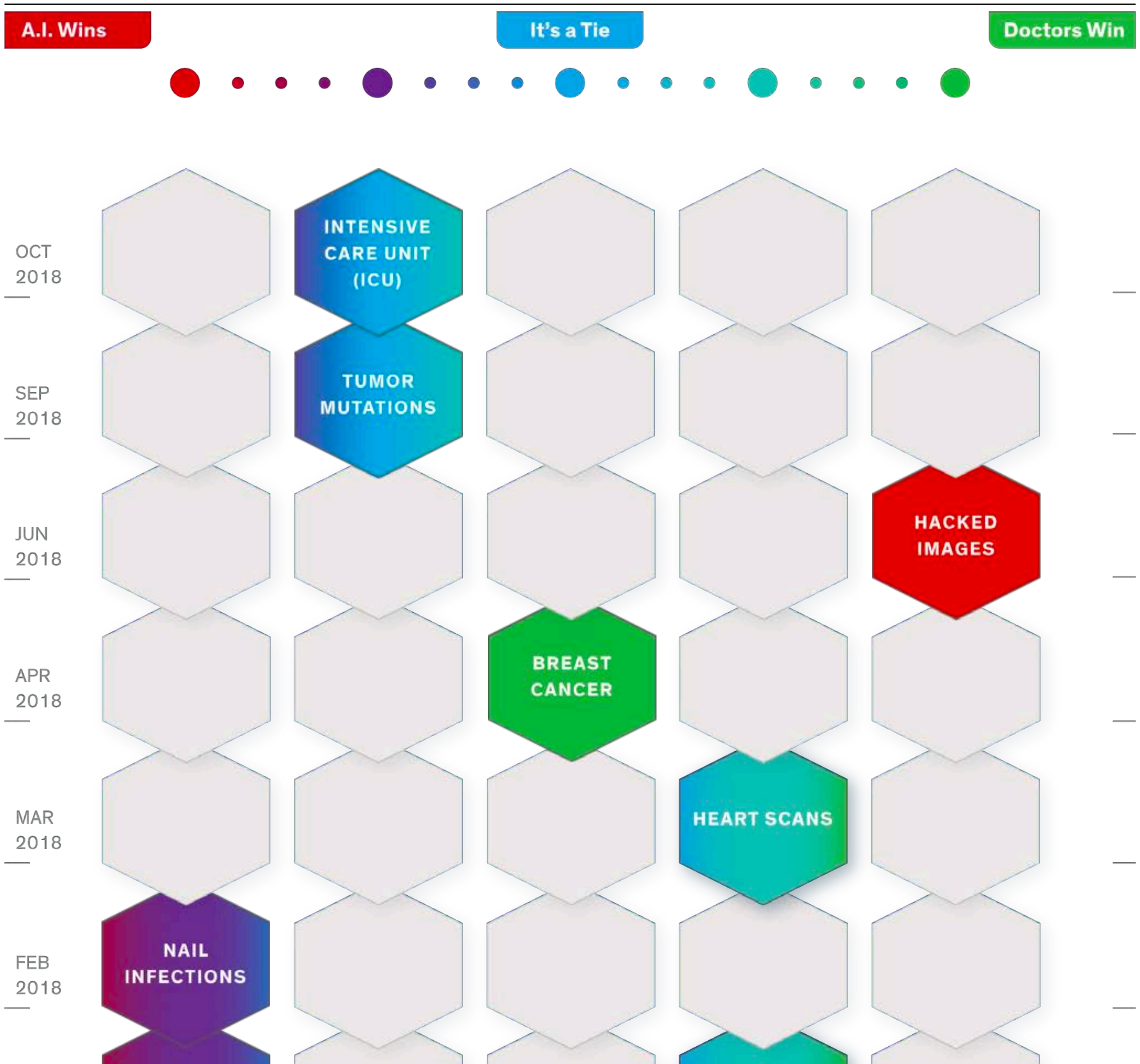
Subset of ML which make the computation of multi-layer neural network feasible


MACHINE LEARNING
UNSUPERVISED LEARNING
DIMENSIONALLY REDUCTION
Structure Discovery
Feature Elicitation
Meaningful compression
Big data Visualisation
CLUSTERING
Recommended Systems
Targetted Marketing
Customer Segmentation
SUPERVISED LEARNING
CLASSIFICATION
Image Classification
Customer Retention
Fraud Detection
Diagnostics
REGRESSION
Forecasting
Predictions
Process Optimization
New Insights
REINFORCEMNET LEARNING
Real-Time Decisions
Robot Navigation
Game AI
Skill Aquisition
Learning Tasks

The ICU is a natural habitat for AI

- Lots of data
- High mortality
- Uncertainty on diagnosis and prognosis
- Decisions with consequences

https://spectrum.ieee.org/static/ai-vs-doctors



Contents lists available at ScienceDirect

Artificial Intelligence In Medicine

journal homepage: www.elsevier.com/locate/artmed

Accurate prediction of blood culture outcome in the intensive care unit using long short-term memory neural networks

Tom Van Steenkiste[a], Joeri Ruyssinck[a,*], Leen De Baets[a], Johan Decruyenaere[b], Filip De Turck[a], Femke Ongenae[a], Tom Dhaene[a]

[a] Ghent University – imec, IDLab, Department of Information Technology, Technologiepark 15, B-9052, Ghent, Belgium
[b] Ghent University Hospital, Department of Internal Medicine, De Pintelaan 185, B-9050 Ghent, Belgium

Outcome Prediction in Postanoxic Coma With Deep Learning*

Marleen C. Tjepkema-Cloostermans, PhD; Catarina da Silva Lourenço, BSc[2,3]; Barry J. Ruijter, MD, PhD[2]; Selma C. Tromp, MD, PhD[4]; Gea Drost, MD, PhD[5]; Francois H. M. Kornips, MD[6]; Albertus Beishuizen, MD, PhD[7]; Frank H. Bosch, MD, PhD[8]; Jeannette Hofmeijer, MD, PhD[2,9]; Michel J. A. M. van Putten, MD, PhD[1,2]

npj | Digital Medicine

www.nature.com/npjdigitalmed

ARTICLE OPEN

Reduction of false alarms in the intensive care unit using an optimized machine learning based approach

Wan-Tai M. Au-Yeung[1], Ashish K. Sahani[1], Eric M. Isselbacher[2] and Antonis A. Armoundas[1,3]

Flechet et al. Critical Care (2019) 23:282
https://doi.org/10.1186/s13054-019-2563-x

Critical Care

RESEARCH Open Access

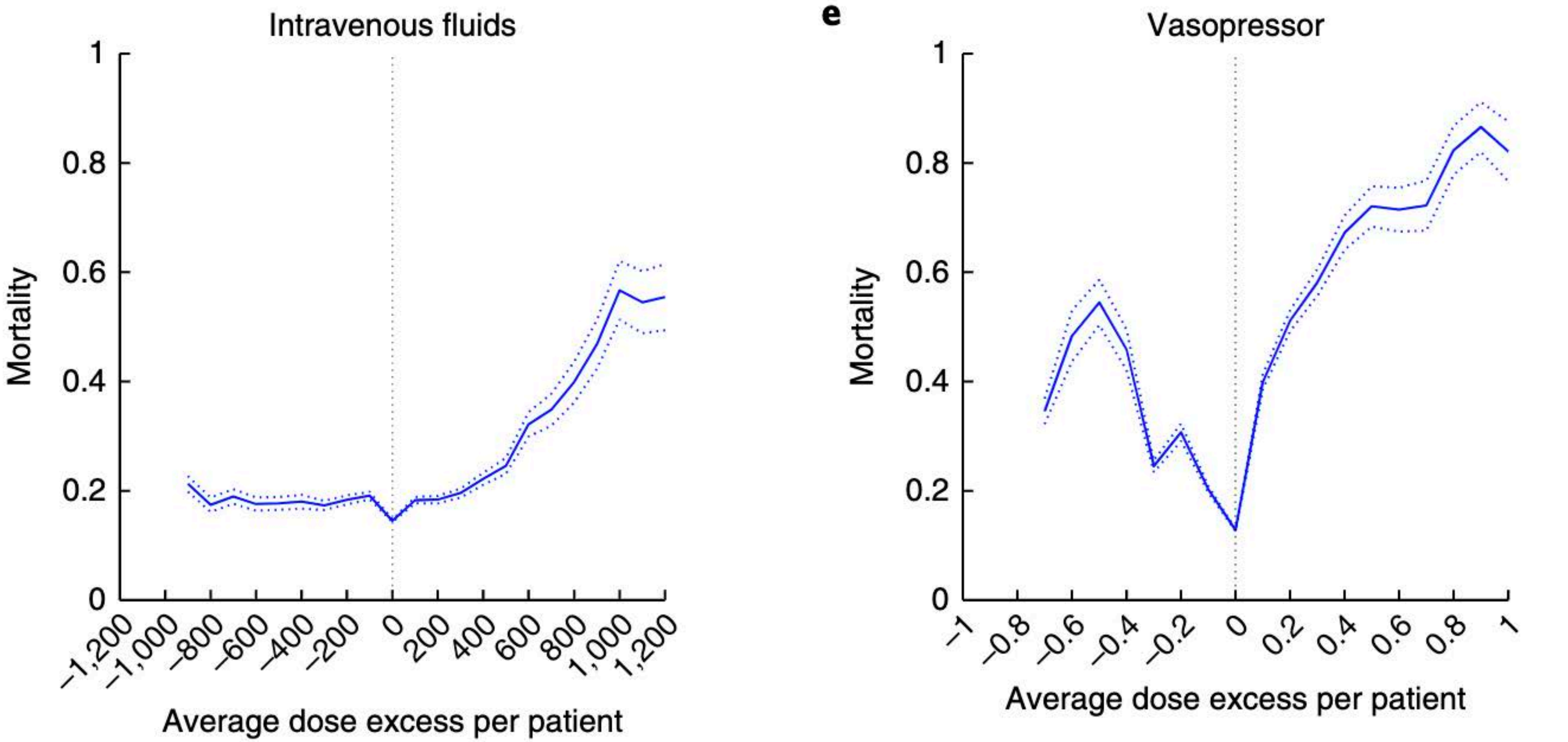
Machine learning versus physicians' prediction of acute kidney injury in critically ill adults: a prospective evaluation of the AKIpredictor

Marine Flechet[3†], Stefano Falini[1†], Claudia Bonetti[2], Fabian Güiza[3], Miet Schetz[3], Greet Van den Berghe[3] and Geert Meyfroidt[3*]

ARTICLES
https://doi.org/10.1038/s41591-018-0213-5
nature medicine

The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care

Matthieu Komorowski[1,2,3], Leo A. Celi[3,4], Omar Badawi[3,5,6], Anthony C. Gordon[1*] and A. Aldo Faisal[2,7,8,9*]



Intravenous fluids
e
Vasopressor
Mortality
0
0.2
0.4
0.6
0.8
1
−1,200
−1,000
−800
−600
−400
−200
0
200
400
600
800
1,000
1,200
−1
−0.8
−0.6
−0.4
−0.2
0.2
0.4
0.6
0.8
Average dose excess per patient

Shillan *et al. Critical Care* (2019) 23:284
https://doi.org/10.1186/s13054-019-2564-9

Critical Care

RESEARCH Open Access

Use of machine learning to analyse routinely collected intensive care unit data: a systematic review

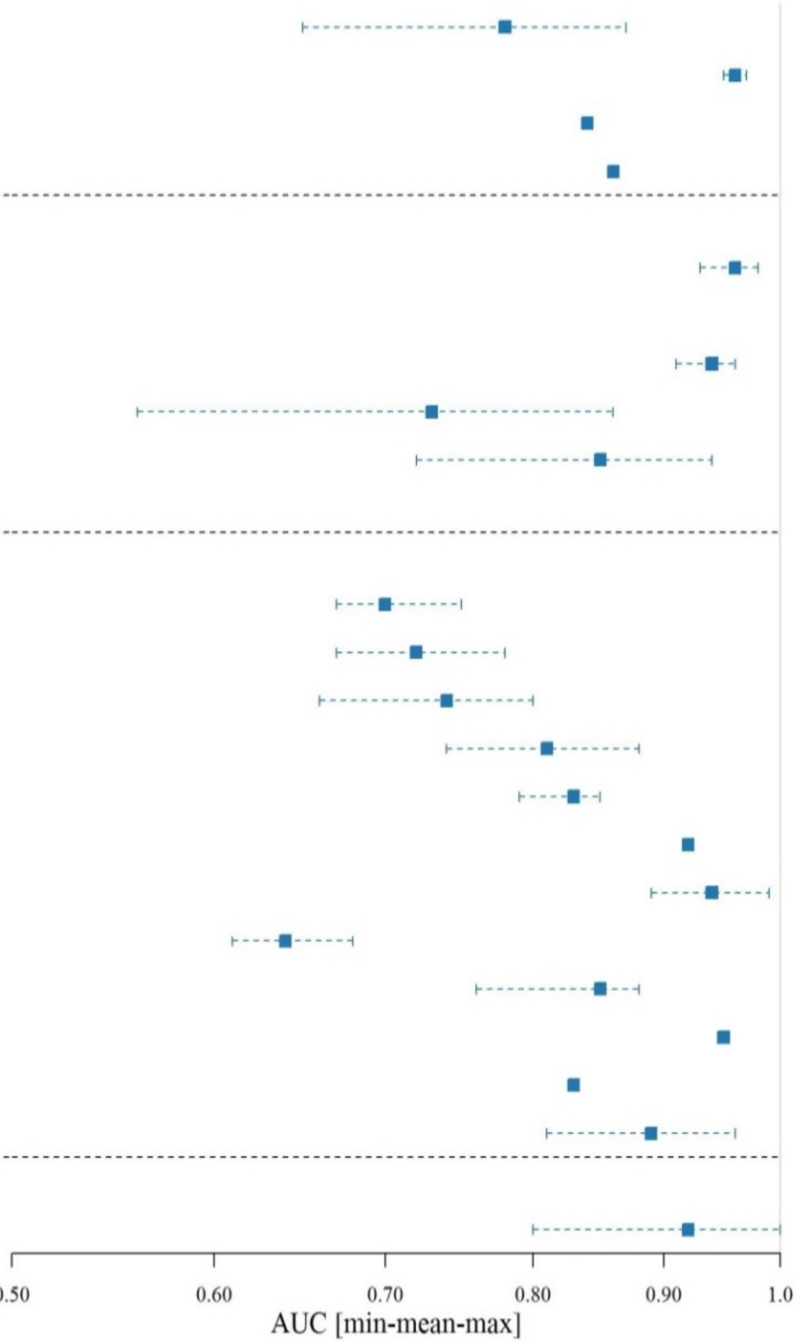
Duncan Shillan[1,2], Jonathan A. C. Sterne[1,2], Alan Champneys[3] and Ben Gibbison[1,4,5*]

Table 1 Number and proportion of papers according to the aim of study and number of patients analysed

Aim of study	Number (%) of papers with this aim[a]	Number of patients analysed					
		< 100	100–1000	1000–10,000	10,000–100,000	100,000–1,000,000	Number not reported
Predicting complications	79 (30.6%)	23 (29.1%)	26 (32.9%)	17 (21.5%)	8 (10.1%)	3 (3.8%)	2 (2.5%)
Predicting mortality	70 (27.1%)	11 (15.7%)	19 (27.1%)	19 (27.1%)	18 (25.7%)	1 (1.4%)	2 (2.9%)
Improving prognostic models/risk scoring system	43 (16.7%)	8 (18.6%)	16 (37.2%)	8 (18.6%)	8 (18.6%)	2 (4.7%)	1 (2.3%)
Classifying sub-populations	29 (11.2%)	11 (37.9%)	8 (27.6%)	6 (20.7%)	2 (6.9%)	0 (0.0%)	2 (6.9%)
Alarm reduction	21 (8.14%)	9 (42.9%)	5 (23.8%)	7 (33.3%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Predicting length of stay	18 (6.98%)	3 (16.7%)	7 (38.9%)	5 (27.8%)	3 (16.7%)	0 (0.0%)	0 (0.0%)
Predicting health improvement	17 (6.59%)	5 (29.4%)	10 (58.8%)	2 (11.8%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Determining physiological thresholds	16 (6.20%)	10 (62.5%)	4 (25.0%)	1 (6.2%)	0 (0.0%)	0 (0.0%)	1 (6.2%)
Improving upon previous methods	5 (1.94%)	2 (40.0%)	1 (20.0%)	1 (20.0%)	1 (20.0%)	0 (0.0%)	0 (0.0%)
Detecting spurious recorded values	3 (1.16%)	1 (33.3%)	2 (66.7%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Total (accounting for duplicates)	258	72 (27.9%)	84 (32.6%)	55 (21.3%)	35 (13.6%)	6 (2.33%)	6 (2.33%)

[a]Where papers had more than one aim, all aims were recorded, so percentages may total more than 100

Paper	Outcome	No. Models	Models	No. Patients	No. Features	Hrs bef. Onset
Emergency Department						
Horng, 2017	Sepsis	13	SVM, GLM, NB, EM	230936	10-12	-
Haug, 2016	Sepsis	6	NB	280143	24	-
Brown, 2012	Severe sepsis and Septic shock	1	NB	132748	5	-
Brown, 2016	Severe sepsis and Septic shock	1	NB	93773	5	-
In-Hospital						
Khojandi, 2018	Sepsis	3	EM	261258	9	0
Futoma, 2017	Sepsis	6	NNM, GLM	49312	32	0-12
McCoy, 2017	Severe sepsis, Sepsis	2	GLM	1665	6	0
Lin, 2018	Septic shock	16	More than 4*	25770	7	3-6
Khoshnevisan, 2018	Septic shock	9	More than 4*	25770	19	4
Thiel, 2010	Septic shock	6	DT	13785	24	Unavailable
Intensive Care Unit						
Wang, 2018	Sepsis	3	GLM, SVM, EM	19358	12	0
Shashikumar II, 2017	Sepsis	3	GLM	1100	4-21	4
Shashikumar I, 2017	Sepsis	7	SVM	682	2-22	4
Desautels, 2016	Sepsis	2	GLM	22853	8	0-4
Nemati, 2018	Sepsis	8	PHM	27527-42411	48	4-12
Calvert II, 2016	Sepsis	1	GLM	1394	9	3
Kam, 2017	Sepsis	7	NNM, LSTM	5789	9	0-3
Moss, 2016	Severe sepsis	2	GLM	3059	7	0
Guillen, 2015	Severe sepsis	9	GLM, SVM, EM	3446	7-19	2
Shimabukuro, 2017	Severe sepsis	1	GLM	142	17	0
Henry, 2015	Septic shock	1	PHM	16234	30	28.2
Calvert I, 2016	Septic shock	2	GLM	Unavailable	9	0-4
ED/In-Hospital/ICU						
Mao, 2017	Sepsis, Severe sepsis, Septic shock	10	EM	1140-239767	3-6	0



we have a problem

Computing science will probably exert its major effects by augmenting and, in some cases, largely replacing the intellectual functions of the physician.

SPECIAL ARTICLE

MEDICINE AND THE COMPUTER

The Promise and Problems of Change

William B. Schwartz, M.D.*

Challenges

- So much data, so little access for data science
- So many models, so little clinical validation
- So many EHRs, so little control for intensivists

although there are thousands of papers
applying machine learning algorithms to medical data
very few have contributed meaningfully to clinical care

Deo Circulation 2015

algorithms that
feature prominently
in research literature are
seldomly executable
at the frontlines of clinical practice

Panch NPDJM 2019

pacmed V1.0.0

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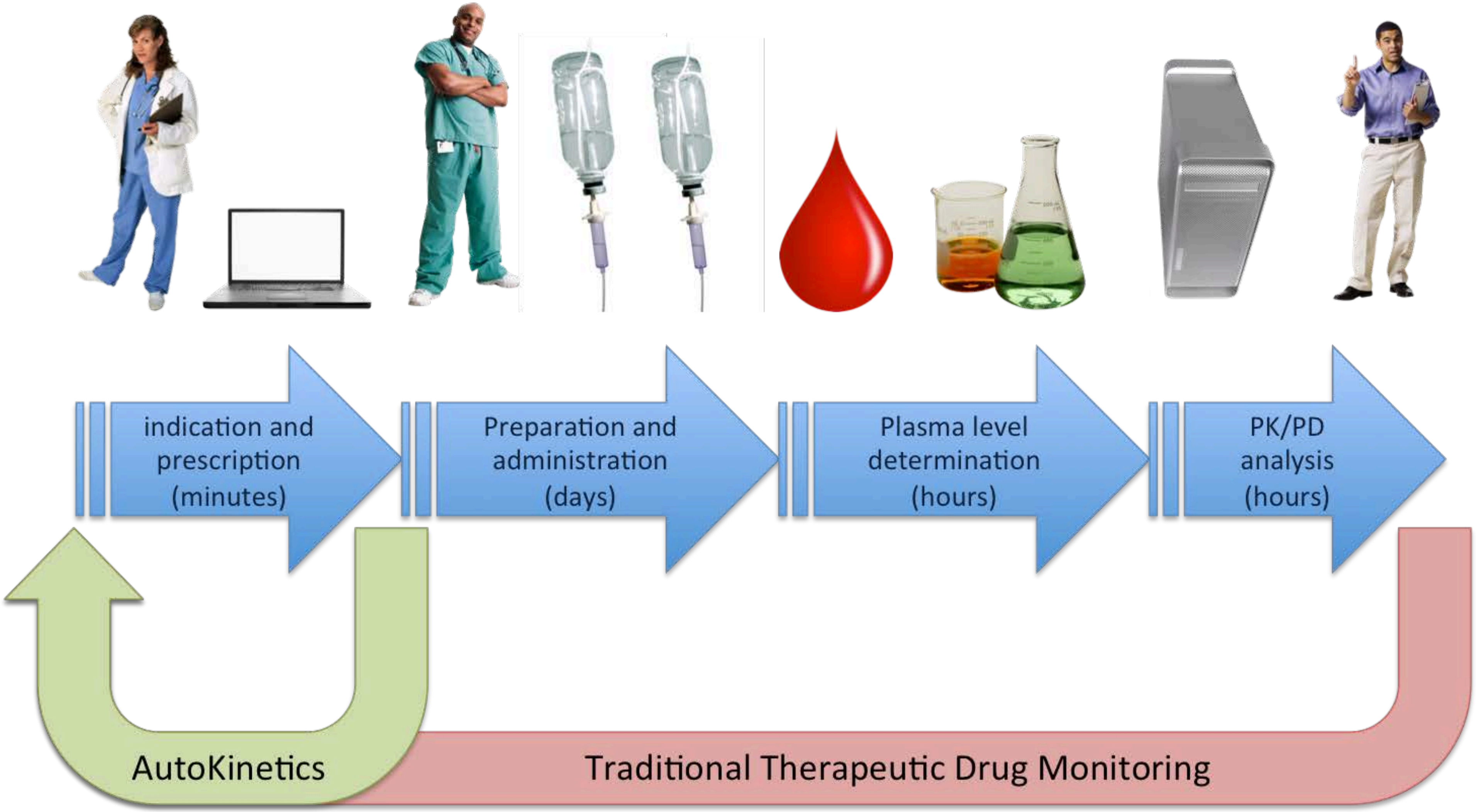
Afdelingsmonitor

Toon zonder ondersteuning

BEDNR.	PATIËNTGEGEVENS	OPNAME DIAGNOSE	HEROPNAME/ MORTALITEIT RISICO	ONDERSTEUNING
01	Janssen, J. Dhr. | 14250 | 1954-11-01	Post-operatief CABG	1.0%	
02	Brandts, M. Mw. | 18282 | 1954-11-11	Coma/verandering bewustzijnsniveau (non-operatief neuro)	1.8%	
03	Estevez, E. Mw. | 15045 | 1940-07-15	Respiratoir - medisch anders	2.5%	
04	Veldhuis, J. Mw. | 14593 | 1962-05-10	Longembolieën	4.7%	
05	Berendse, F. Dhr. | 17359 | 1969-06-12	Cardiovasculair - medisch anders	1.6%	
06	Huygens, S. Dhr. | 15982 | 1968-09-29	Bacteriele pneumonie	6.1%	
07	Tully, T. Dhr. | 15066 | 1939-04-01	Acuut nierfalen	-	
08	Jungens, M. Dhr. | 14290 | 1994-08-15	Bacteriele pneumonie	8.2%	
09	Meester, M. Dhr. | 14688 | 1953-12-16	Congestief hartfalen	-	
10	Waninge, G. Mw. | 15363 | 1932-01-16	Post-operatief	5.4%	

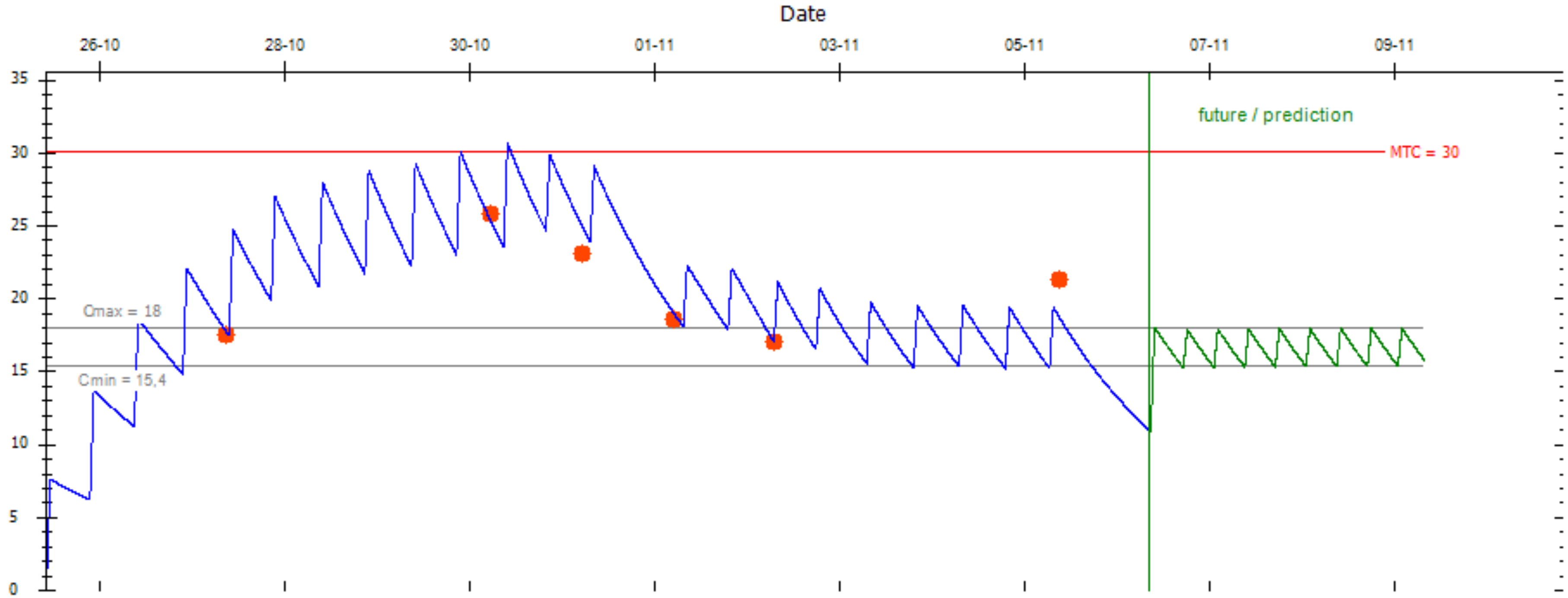
Meer patiënten


indication and prescription (minutes)
Preparation and administration (days)
Plasma level determination (hours)
PK/PD analysis (hours)
AutoKinetics
Traditional Therapeutic Drug Monitoring

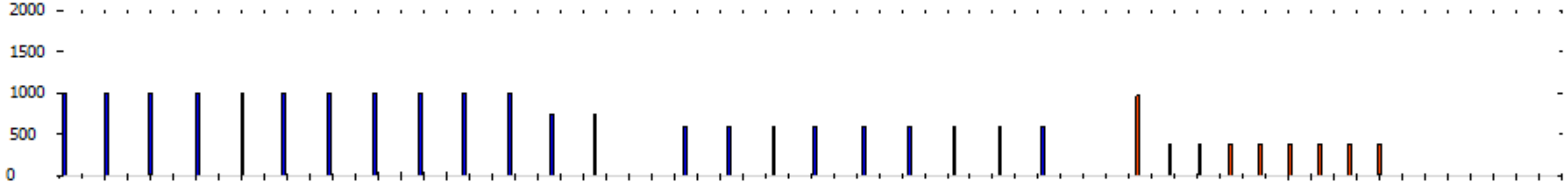
◉ Vancomycine ○ Meropenem ○ Ceftriaxon ○ Cefotaxim ○ Ciprofloxacine

Model = Vancomycine del Mar de Fernández 2007

Vancomycine concentratie (mg/L)



Dosis (mg)



Vancomycine advies

Geef eerst een eenmalige kortlopend infuus vancomycine van 975 mg om 6-11-2017 10:24
Continueer met doseren van 390 mg vancomycine elke 8 uur.
De starttijd is om 6-11-2017 18:24

A Machine Learning Algorithm to Predict Severe Sepsis and Septic Shock: Development, Implementation, and Impact on Clinical Practice

Heather M. Giannini, MD[1]; Jennifer C. Ginestra, MD[1]; Corey Chivers, PhD[2]; Michael Draugelis, BS[2]; Asaf Hanish, MPH[2]; William D. Schweickert, MD[2,3]; Barry D. Fuchs, MD, MS[2,3]; Laurie Meadows, RN, CCRN[4]; Michael Lynch, RN, CEN[1]; Patrick J. Donnelly, RN, MS, CCRN[4]; Kimberly Pavan, MSN, CRNP[5]; Neil O. Fishman, MD[2]; C. William Hanson, MD, III[2]; Craig A. Umscheid, MD, MSCE[2,7,8]

Giannini CCM 2019

TABLE 4. Outcomes in Screen Positive Patients

Outcome Measures	Silent (n = 1,540)	Alert (n = 2,137)	p
Hospital length of stay, median (IQR), d	9 (5–18)	9 (5–18)	0.39
ICU transfer < 6 hr after alert, %	9.2	12.0	0.14
ICU transfer < 24 hr after alert, %	14.4	16.8	0.19
ICU transfer < 48 hr after alert, %	16.4	18.9	0.20
ICU transfer any time after alert, %	25.6	26.1	0.80
Time to ICU transfer after alert, median (IQR), hr	16 (2–108)	8 (2–62)	< 0.01
ICU length of stay, median (IQR), hr	71 (38–163)	85 (43–179)	0.11
Mortality ≤ 30 d after trigger, %	9.8	9.4	0.81
In-hospital mortality, %	10.6	10.3	0.88
Discharged to home, %	59.9	58.4	0.42
Discharged to nursing facility, %	15.3	15.2	0.93
Discharged to inpatient hospice, %	3.4	4.6	0.51
Severe Sepsis or septic shock[a], %	20.5	18.6	0.32

IQR = interquartile range.

[a]Severe sepsis: > 2 SIRS and positive blood or urine culture and lactate > 2.2; septic shock: severe sepsis and systolic blood pressure < 90 mm Hg.

Critical care

BMJ Open Respiratory Research

Effect of a machine learning-based severe sepsis prediction algorithm on patient survival and hospital length of stay: a randomised clinical trial

David W Shimabukuro,[1] Christopher W Barton,[2] Mitchell D Feldman,[3] Samson J Mataraso,[4,5] Ritankar Das[6]

Shimanukoro et al. BMJ Open Resp Res 2017; Calvert et al. Comp in Biol and Med 2016

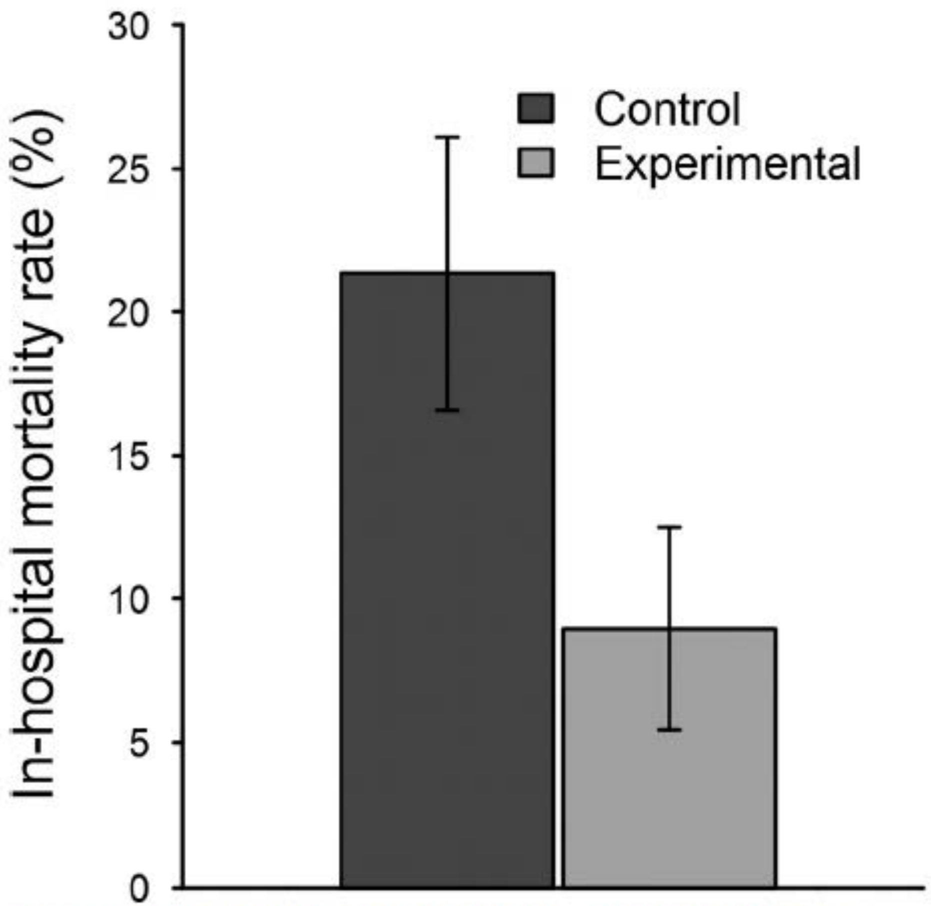


Figure 3 Reduction of in-hospital mortality rate when using the machine learning algorithm. The error bars represent one standard error above and below the average in-hospital mortality rate.

Coming Soon

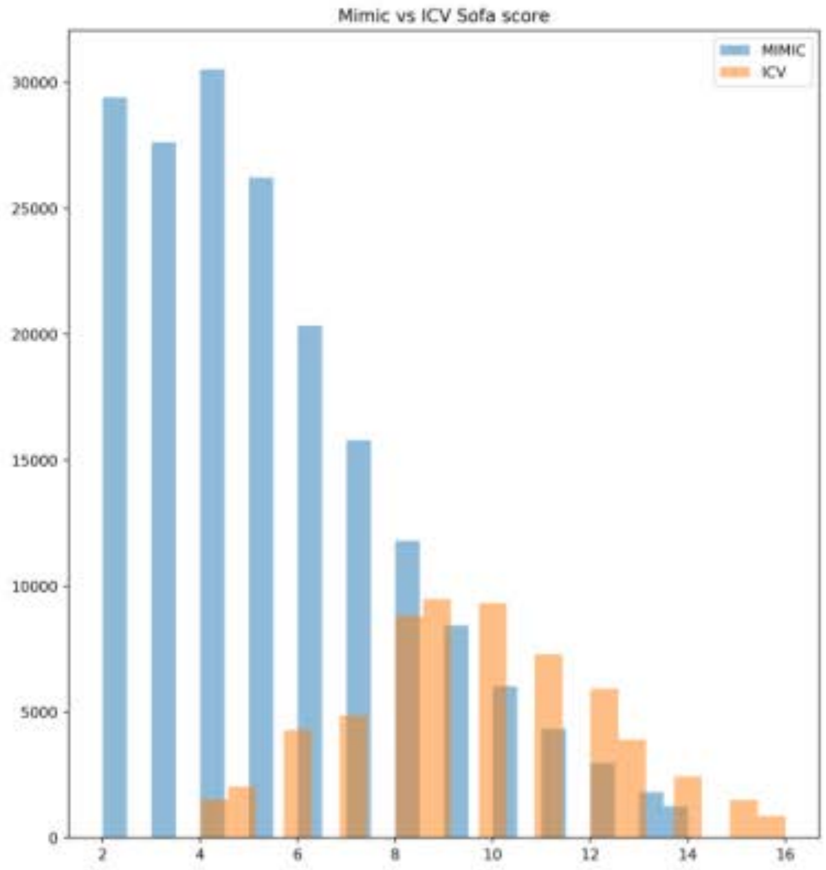
Amsterdam Medical Data Science

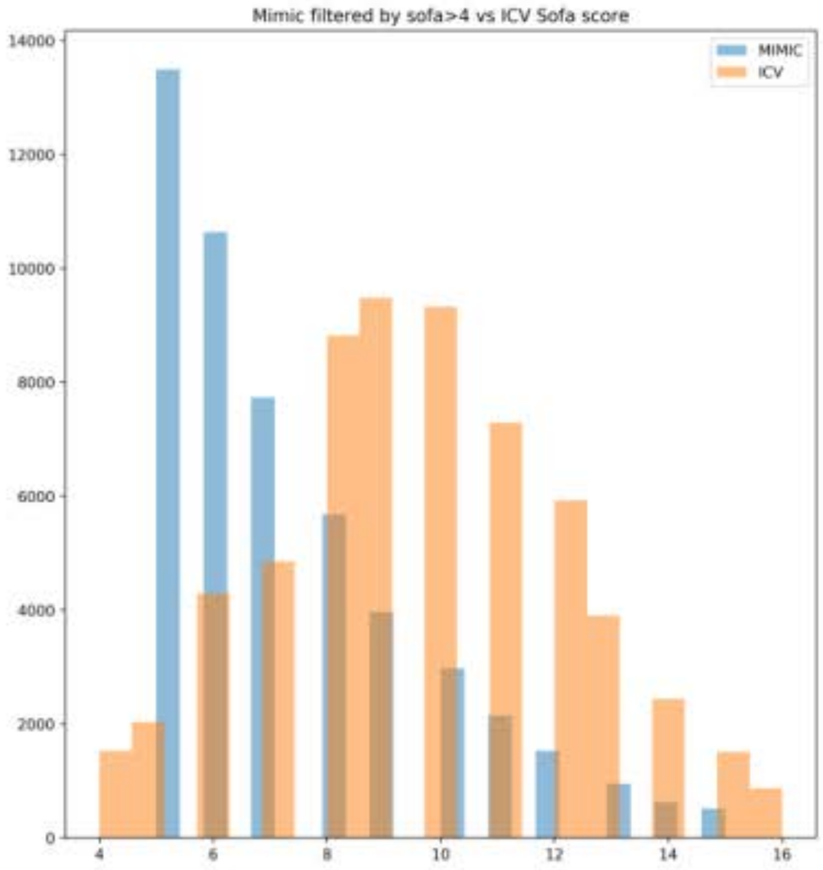
Drop us a line to join the waiting list for AmsterdamUMCdb: info at amsterdammedicaldatascience.nl

Sharing is caring

- MIMIC – 1 center – USA
- eICU – 200 centers – USA

- CCHIC – 5 centers - UK
- M@TRIC – 3 centers - Belgium
- Bristol – 1 center – UK

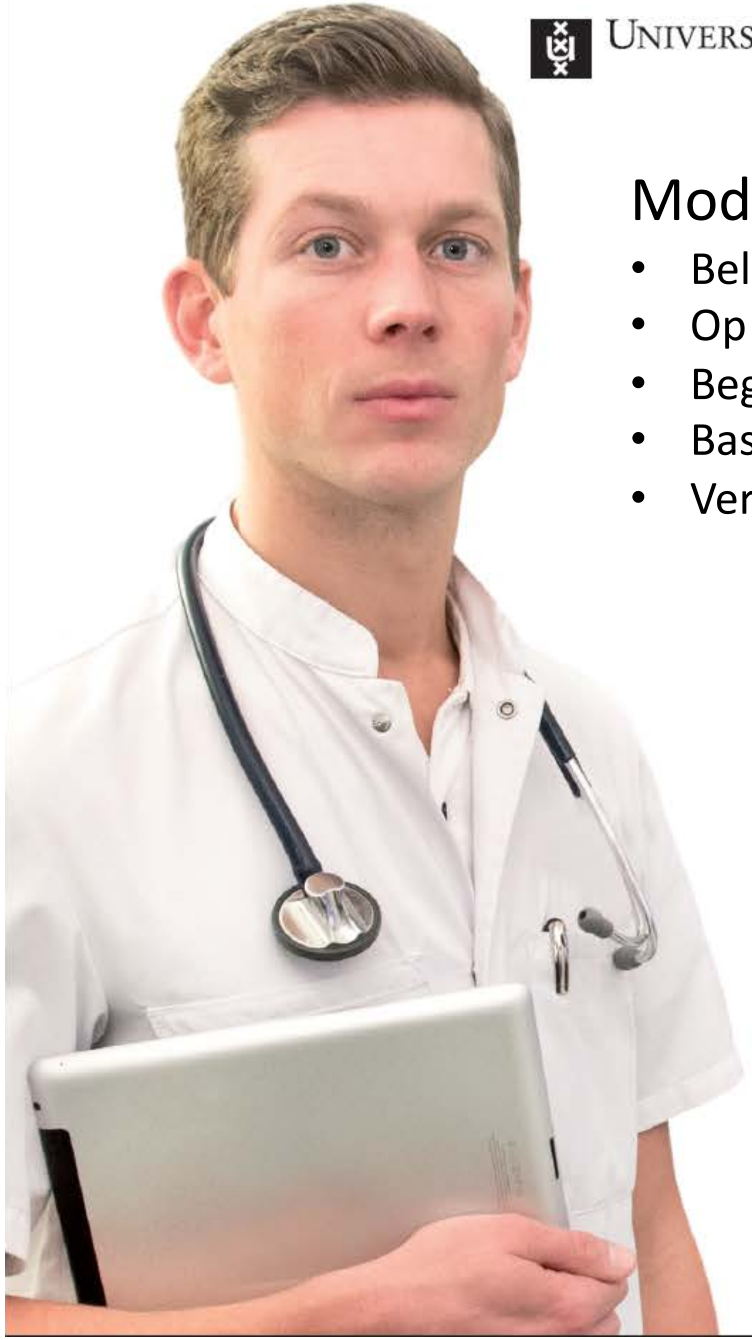

Mimic vs ICV Sofa score
MIMIC
ICV
30000
25000
20000
15000
10000
5000
0
2
4
6
8
10
12
14
16


Mimic filtered by sofa>4 vs ICV Sofa score
MIMIC
ICV
14000
12000
10000
8000
6000
4000
2000
0
4
6
8
10
12
14
16

AmsterdamUMCdb

About

AmsterdamUMCdb is the first freely accesible European intensive care database. It is endorsed by the European Society of Intensive Care Medicine (ESICM) and its Data Sciendce Section. It contains de-identified health data related to tens of thousands of intensive care unit admissions, including demographics, vital signs, laboratory tests and medications.



UNIVERSITEIT VAN AMSTERDAM

Amsterdam UMC
Universitair Medische Centra

Module Health data science/big data (HDS)

- Beloftes en beperkingen van big data
- Op waarde schatten van een HDS studie/artikel/rapport
- Begeleiden en beoordelen van de analyse activiteiten
- Basis machine learning, artificial intelligence en data mining
- Vertrouwelijkheid van data en privacy overwegingen

Health Informatics

Post-initiële master

• deeltijd • modulair • e-learning

www.amc.nl/healthinformatics