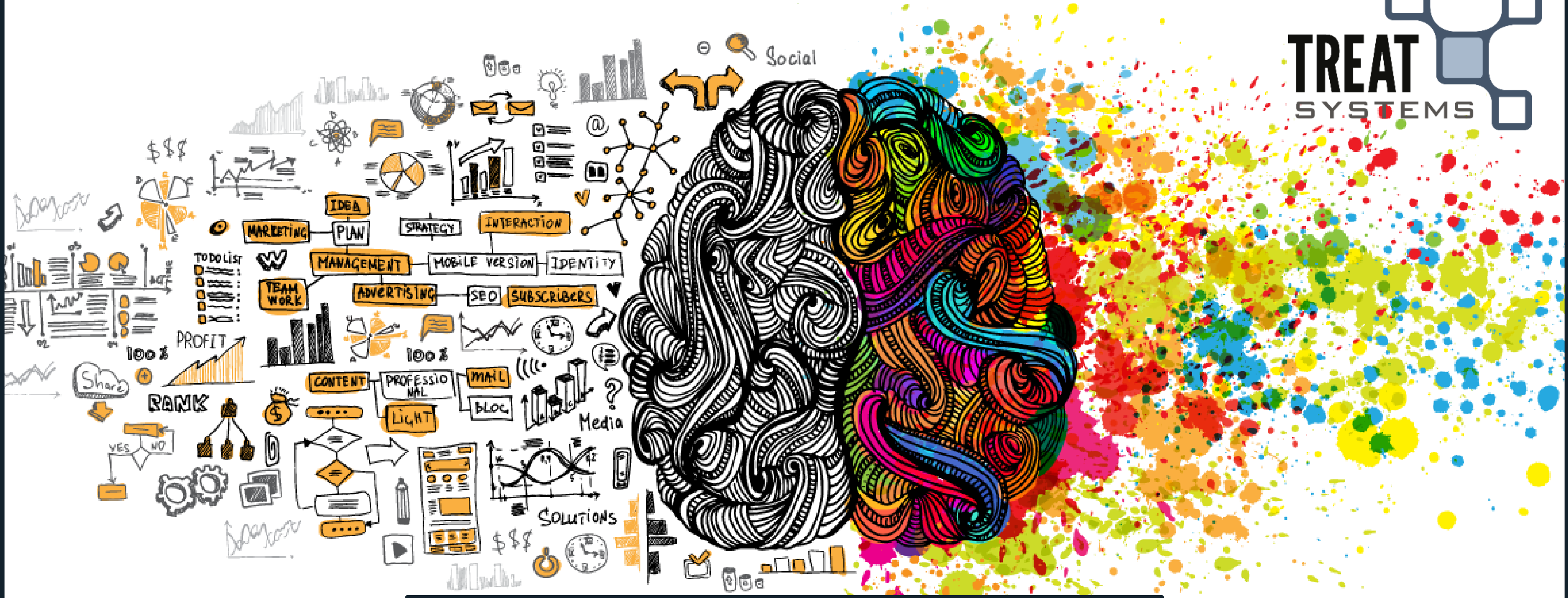

Amphi-TIPS

Kan AI algoritmer og beslutningsstøtte identificere kritisk sygdom allerede i ambulancen?

Who are we?

- Our dynamic team is focused on development and implementation of specialized healthcare IT solutions

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Treat Systems is part of the Judex/Amphi family

Treat Systems services and qualifications

- High performance team

Treat Systems is a dynamic and innovative Danish SMV focused on developing certified healthcare software solutions including decision support, machine learning (ML) and artificial intelligence (AI). Our key clinical focus areas are within infectious diseases, microbiology, antibiotic therapy and antibiotic resistance.

Modelling

- Decision support
- Physiological models
- Machine learning
- Scientific connections to Universities
- Cost-benefit analysis
- Artificial intelligence
- Causal probabilistic (Bayesian) networks

Clinical understanding

- Infectious diseases
- Workflow analysis
- Microbiological and pathological understanding
- Clinical Trails
- Antimicrobial Stewardship
- Sepsis
- Infection control and surveillance

Regulatory compliance

- ISO 13485 – Quality Management System
- ISO 62304 – Software life-cycle processes
- ISO 14971 – Risk Management
- ISO 27001 – Information security
- ISO 27701 – Privacy
- ISO 62366 – Usability
- ISO 14155 – Clinical Investigation

Technologies

- Multi language programming (C#, Angular, C++, JAVA, VBA)
- Web based technologies
- SQL or InterSystems Caché database structure
- Integration to hospital systems e.g. HL7 or FHIR
- Statistical analysis (SPSS, R, Excel, Matlab)

Key Technologies

We have fallen in love with Bayesian networks and cost-benefit

Artificial intelligence (AI)

- Reasoning
- Knowledge representation
- Planning
- Learning
- Natural language processing
- Perception
- **Cost-benefit**

Machine Learning

- Artificial neural networks
- Decision trees
- Support vector machines
- **Bayesian networks**
- Genetic algorithms

Deep Learning

- Deep Neural Network (DNN)
- Convolutional Neural Network (CNN)

Avoid black box modelling

- Tradeoff between performance and transparency

- The disadvantage of advanced AI models is that it can be difficult for humans to see how the model has arrived at a given outcome.

Clinical data

Black box

Input is converted into output

Decision support e.g. risk assessment

You should use visual graphic that supports interpretation of the algorithm's results

Background

- *Prehospital medical records give an opportunity for early identification before arrival at the Emergency dempartment*

- **Rapid identification and appropriate antibiotic treatment is the single most important intervention in treating sepsis**
  - Subtle signs and symptoms
  - Don't wait until the patient is hypotensive!

- **Scores are a common feature in sepsis assessment**
  - qSOFA/SOFA are part of the latest definitions
  - Many publications of ML scores for early identification/severity assessment

AIM: With electronic prehospital medical records, can risk-stratification start prior to ED arrival?
Can existing scores be used and can we do better with ML?

*this presentation contains minor deviations from numbers presented in the abstract due to additional data made available on hospital admissions after submission

Collecting clinical data

- Use what is already available

- All ambulances in Denmark are equipped with devices to collect data in an electronic prehospital medical record (amPHI) which is automatically shared with the emergency department at the arrival hospital
  - Many clinical patient parameters are collected and documented automatically e.g. Blood pressure, pulse, blood saturation and ECG – very different from hospital environment
  - For some critical patients <10% end tidal CO2 (ETCO2) and respiratory frequency (RF) are measured automatically
  - Electronic prehospital records present an opportunity to use this data for decision support – potential to guide diagnostic testing (e.g. POCT), early treatment or interventions

Our Study

-Methods

- **Patients**

  PMR data collected from Danish Regions for all prehospital journeys between 1 July 2016 and 31 December 2020.
- **Data collected**

  All physiological variables (temperature, HR, systolic/diastolic BP, respiratory rate, O2 saturation, GCS and blood glucose).
- **Outcomes**

  Positive blood culture, 30-day mortality and ICU admission
- **Comparators**

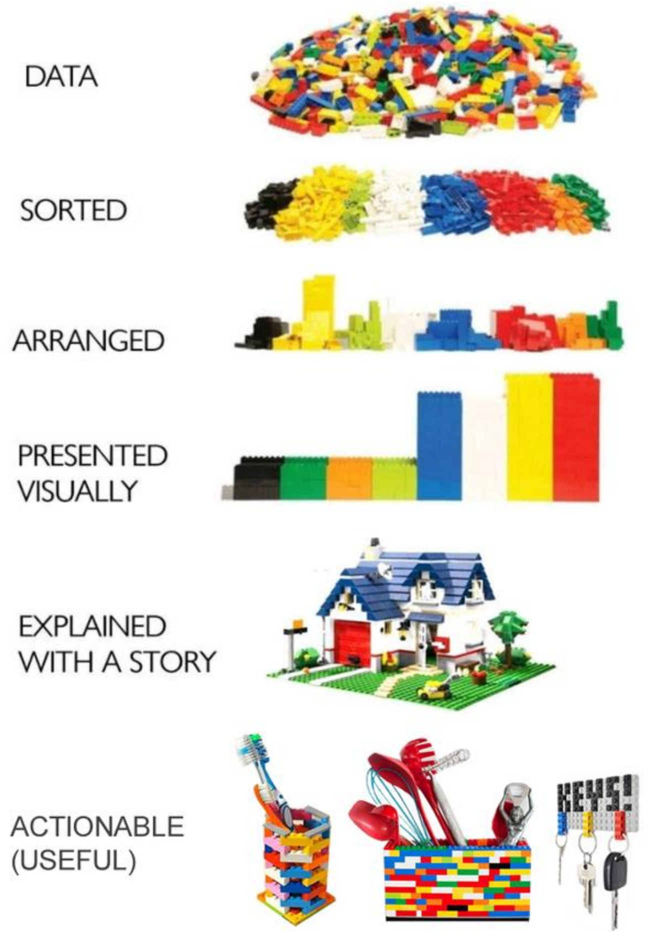
  Standard vital-sign-based clinical triage scores – qSOFA, DEPT (Danish Emergency Process Triage), NEWS2, RETTS
- **Data preparation**

  After cleaning and arranging the data (combining variables, converting to timeslices), data were split into training (2017-2019) and test (2020) sets

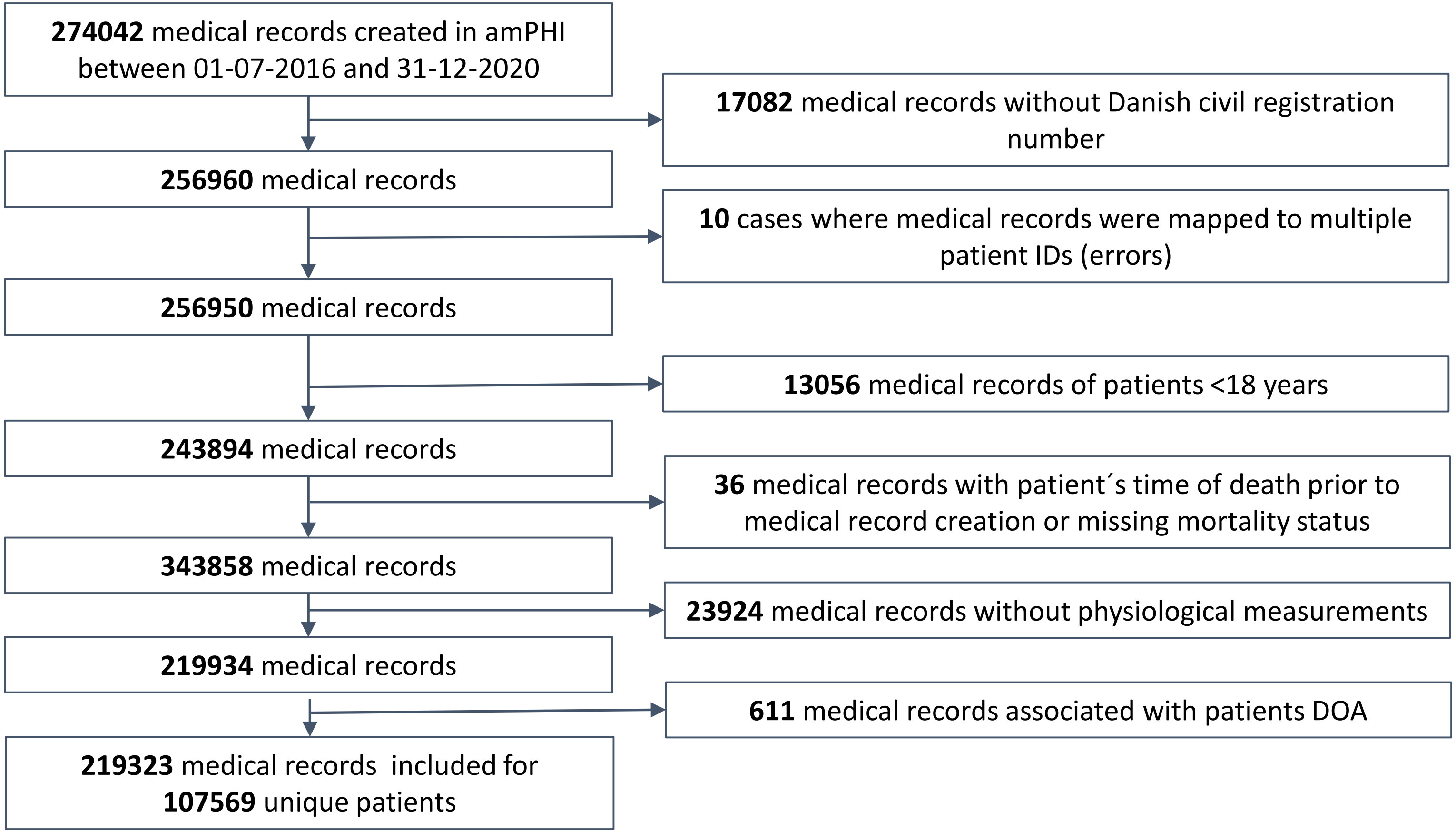
MACHINE LEARNING (ML) MODEL DEVELOPMENT

-BASIC MODEL DEVELOPMENT STEPS

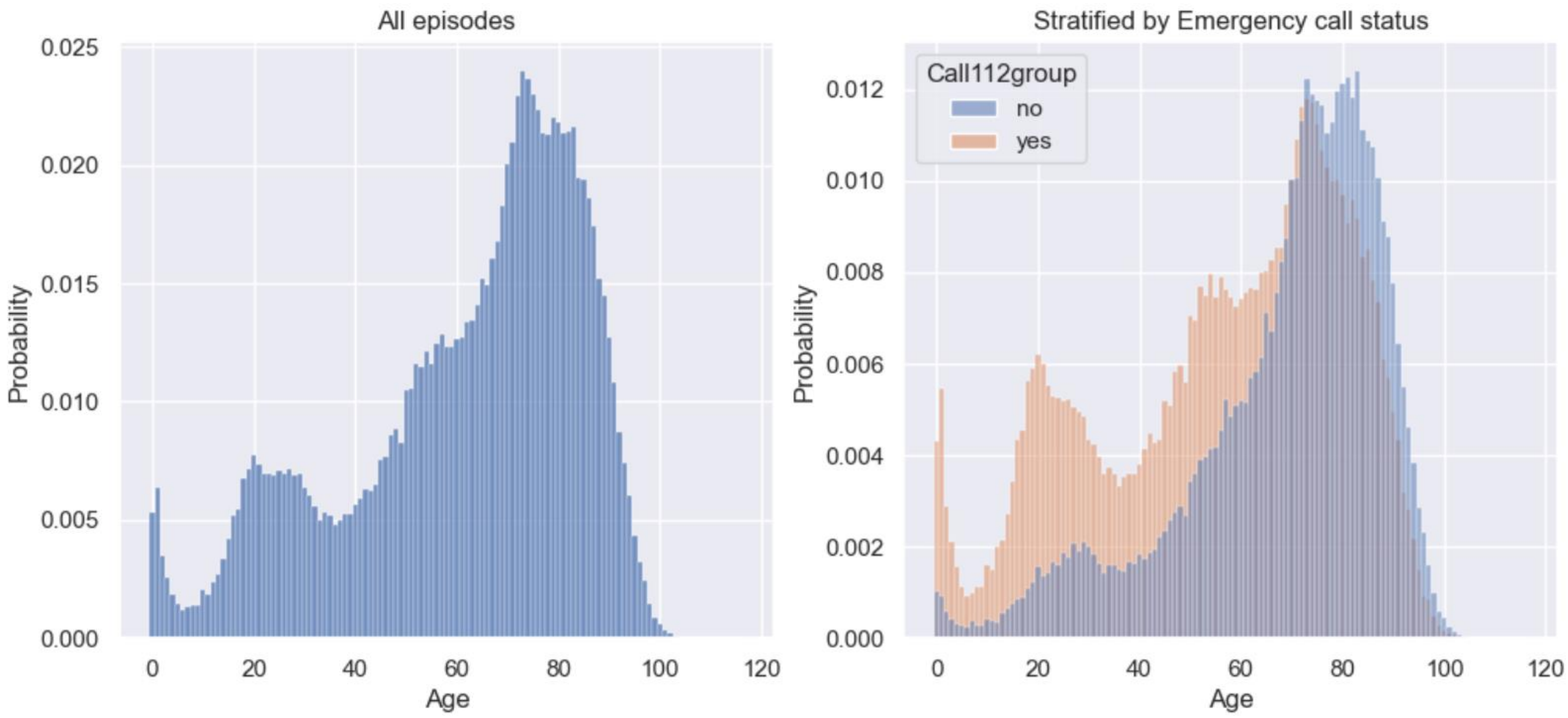
- Using training data
  - Exploratory data analysis – investigate links between variables and to outcomes
  - Feature engineering - identify new features (combinations/transformations)
  - Feature selection
  - Model selection – tuning/optimization of model parameters
- Using test data
  - Model assessment – visualization and interpretation of the results



INCLUSION/EXCLUSION



AGE DISTRIBUTION



DESCRIPTIVE STATISTICS - PHYSIOLOGICAL MEASUREMENTS

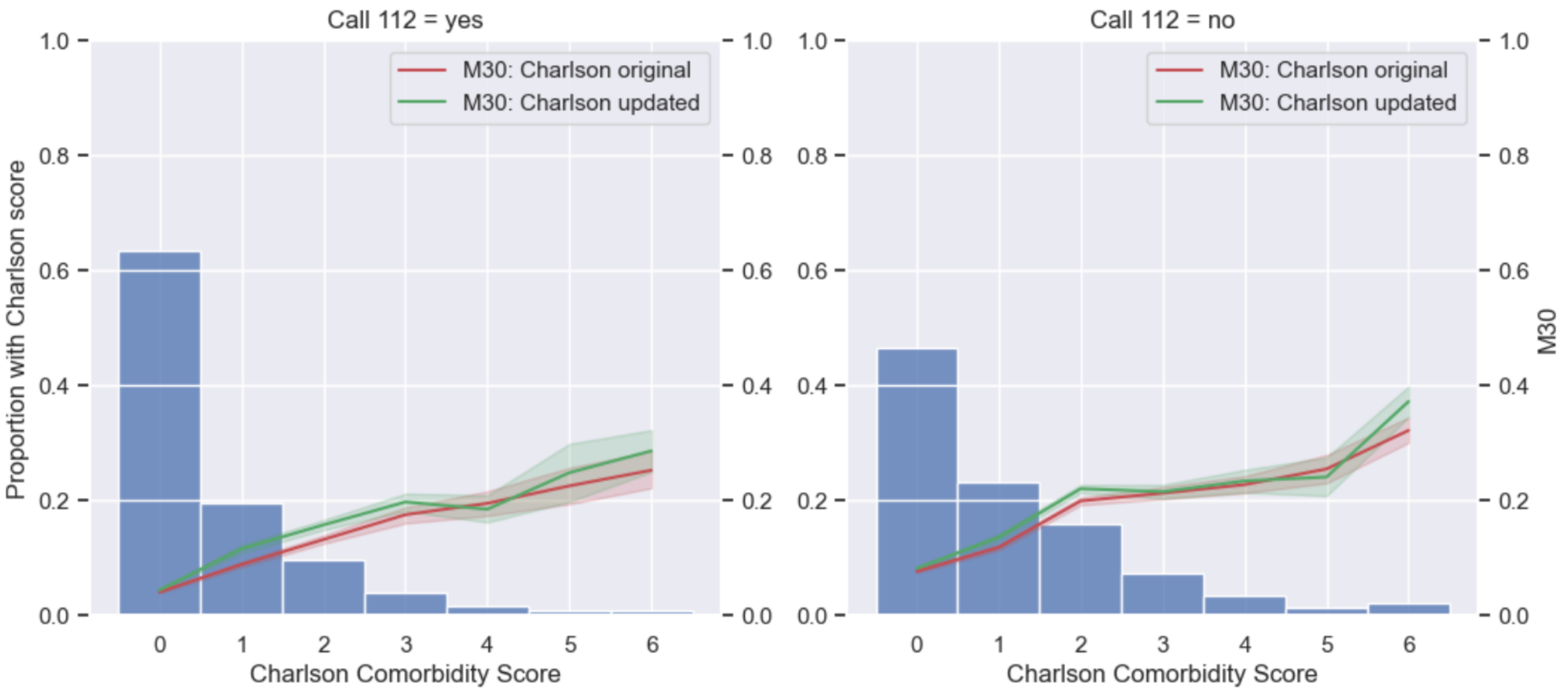
	Journals with measurement, n (%)	Measurements, n	Frequency, median [IQR]	Distribution, median [IQR]
HR	214941 (92.3)	2421800	9.0 [6.0-14.0]	84.0 [71.0-99.0]
SpO2	212723 (91.3)	2181696	8.0 [5.0-12.0]	96.0 [94.0-98.0]
DBP	207563 (89.1)	724691	3.0 [2.0-4.0]	77.0 [66.0-89.0]
SBP	207447 (89.0)	724180	3.0 [2.0-4.0]	136.0 [118.0-156.0]
MAP	203321 (87.3)	630716	3.0 [2.0-4.0]	97.0 [84.3-110.7]
RR	198994 (85.4)	570435	2.0 [1.0-3.0]	18.0 [16.0-22.0]
GCS	205415 (88.2)	450461	2.0 [1.0-3.0]	15.0 [15.0-15.0]
HeartRhythm	80201 (34.4)	117311	1.0 [1.0-2.0]	NaN
etCO2	10365 (4.4)	114977	9.0 [6.0-13.0]	4.3 [3.3-5.2]
Pain (VAS)	60844 (26.1)	114625	1.0 [1.0-2.0]	3.0 [0.0-6.0]
Temperature	96734 (41.5)	108268	1.0 [1.0-1.0]	36.8 [36.6-37.6]
Glucose	57496 (24.7)	66839	1.0 [1.0-1.0]	6.8 [5.6-8.7]
SpCO	319 (0.1)	486	1.0 [1.0-2.0]	96.0 [92.0-98.0]
SpMet	16 (0.0)	20	1.0 [1.0-1.2]	37.0 [36.0-91.5]

	n (%)
Sinus	75294 (64.2)
Sinus tachycardia	20212 (17.2)
Atrial fibrillation	11491 (9.8)
Block configuration	2369 (2.0)
Pacer rhythm	2011 (1.7)
Ischemia/infarction	1853 (1.6)
Bradycardia	1799 (1.5)
Asystole	1140 (1.0)
Unknown/Error	347 (0.3)
Pea	232 (0.2)
Vt	220 (0.2)
Vf	193 (0.2)
Broad tachycardia	150 (0.1)

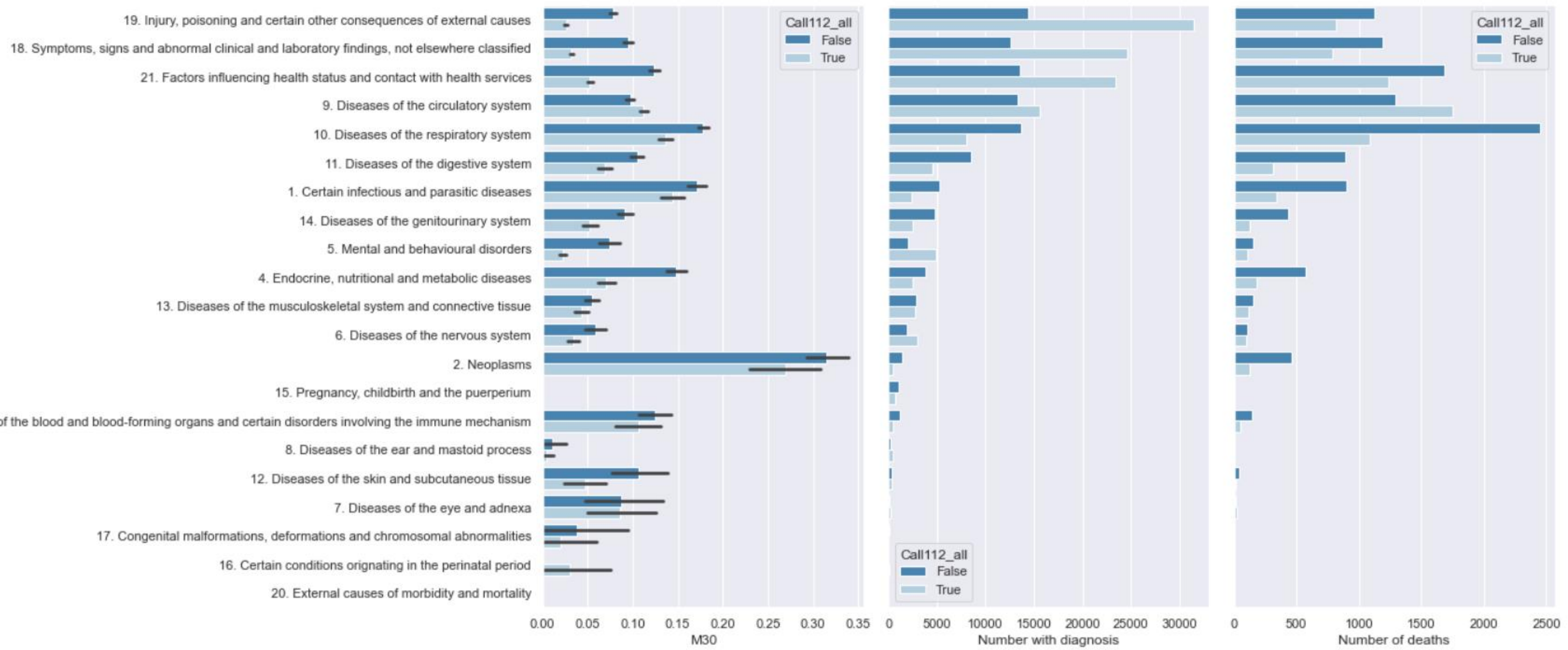
Demographics, outcomes by 112 status

Call112group	no	yes	All
Journals	102462	131706	234168
Mortality			
M30, n (%)	11717 (11.4%)	7733 (5.9%)	19450 (8.3%)
Blood cultures			
BC taken, n (%)	30186 (29.5%)	20086 (15.3%)	50272 (21.5%)
BC+, n (%)	2609.0 (8.6%)	1543.0 (7.7%)	4152.0 (8.3%)
Admission link, n (%)	90642 (88.5%)	117613 (89.3%)	208255 (88.9%)
First department			
Emergency/Acute	67466 (74.4%)	106680 (90.7%)	174146 (83.6%)
Medical	18610 (20.5%)	7324 (6.2%)	25934 (12.5%)
Surgical	2791 (3.1%)	125 (0.1%)	2916 (1.4%)
Pediatrics	771 (0.9%)	3107 (2.6%)	3878 (1.9%)
Other	1004 (1.1%)	377 (0.3%)	1381 (0.7%)
Length of stay			
<1 day, n (%)	30246 (33.4%)	73456 (62.5%)	103702 (49.8%)
1-5 days, n (%)	34608 (38.2%)	28968 (24.6%)	63576 (30.5%)
5-10 days, n (%)	15612 (17.2%)	9087 (7.7%)	24699 (11.9%)
10+ days, n (%)	10177 (11.2%)	6102 (5.2%)	16279 (7.8%)
ICU			
ICU admission, n (%)	2010.0 (2.2%)	3425.0 (2.9%)	5435.0 (2.6%)

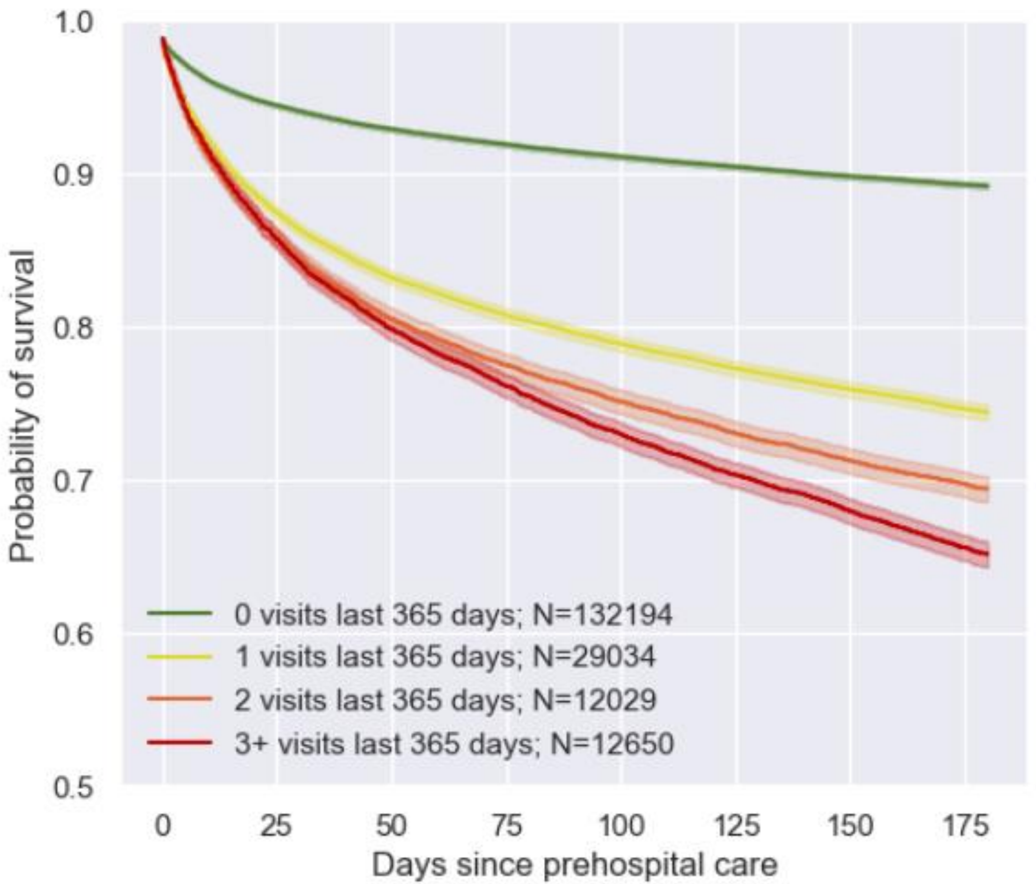
Factors influencing patient outcomes - Charlson



Mortality by ICD10 code group



Survival Curves, stratified by number of visits in the last 365 days



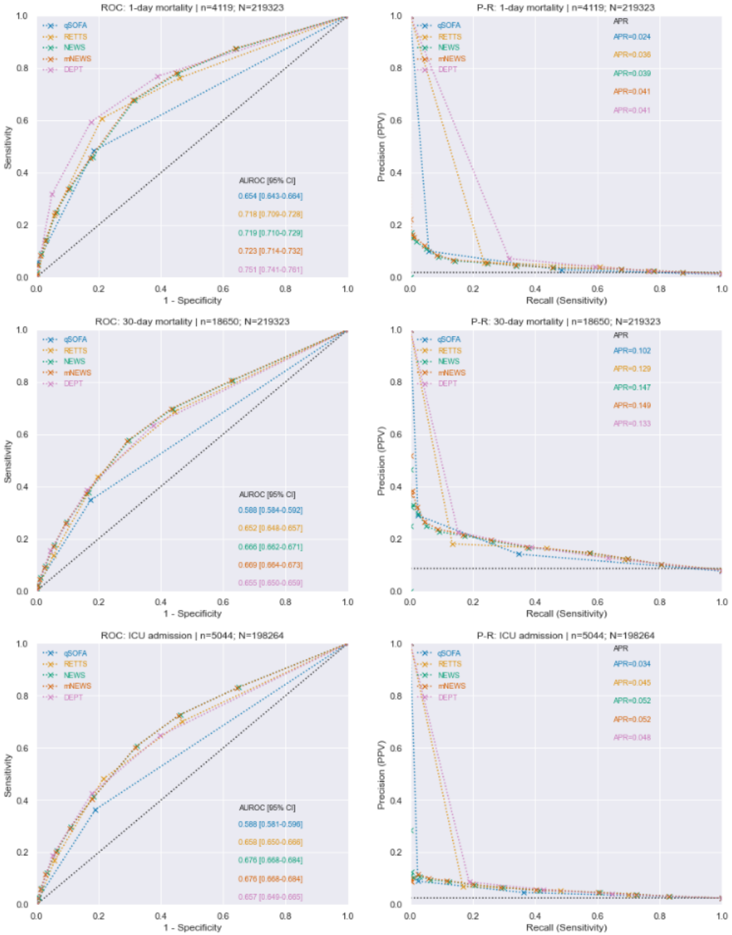
RESULTS AND PERFORMANCE

- A MORE PRECISE ESTIMATE OF THE SEVERITY OF THE PATIENTS CAN BE FOUND VIA ADVANCED DECISION SUPPORT

30-day mortality

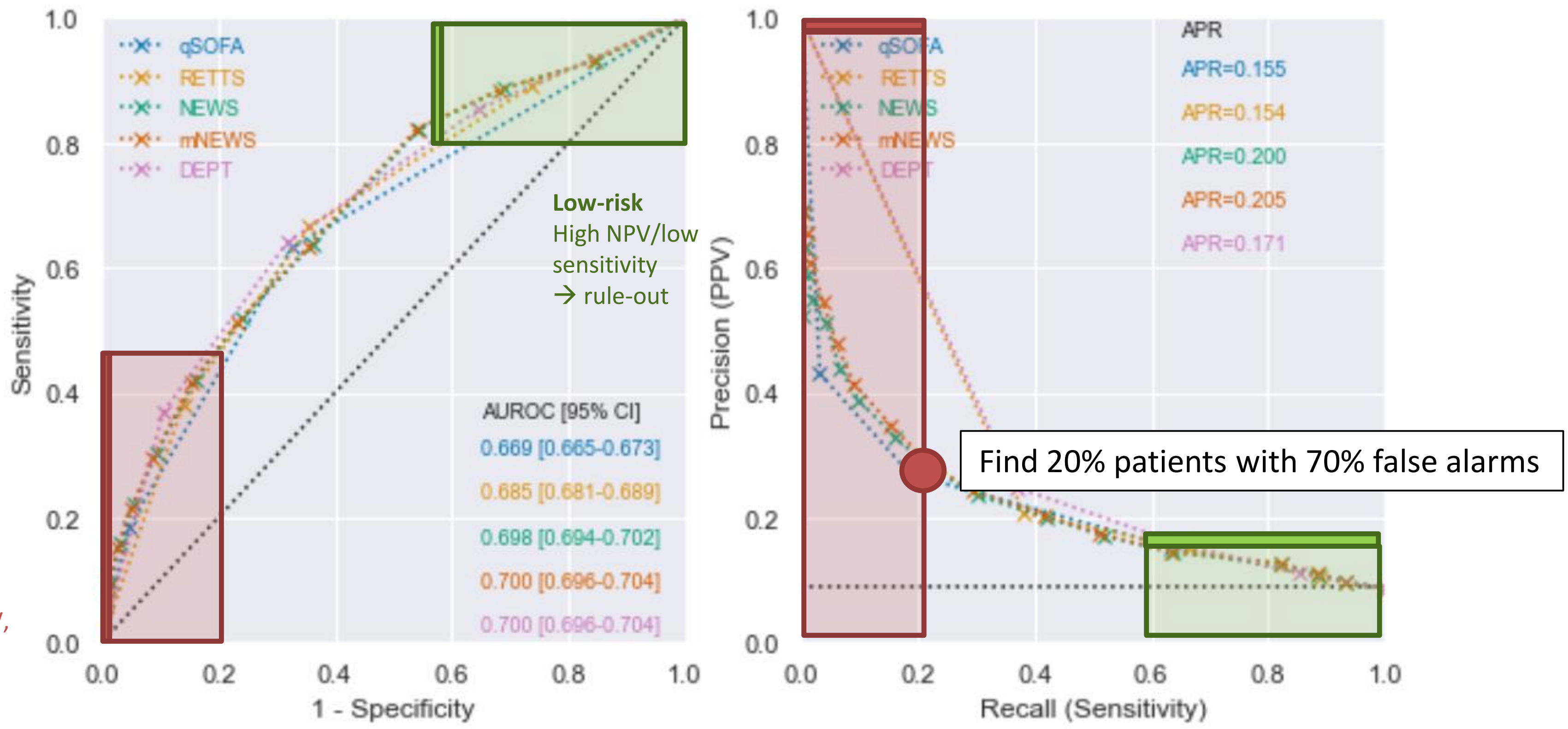
Positive BC

ICU admission



RESULTS AND PERFORMANCE – 30-DAY MORTALITY

- TO UTILIZE THE IMPROVED PREDICTIONS, OPERATING POINTS MUST BE CHOSEN TO GUIDE INTERVENTION VIA ADVANCED DECISION SUPPORT



High-risk

High specificity/PPV, but low sensitivity

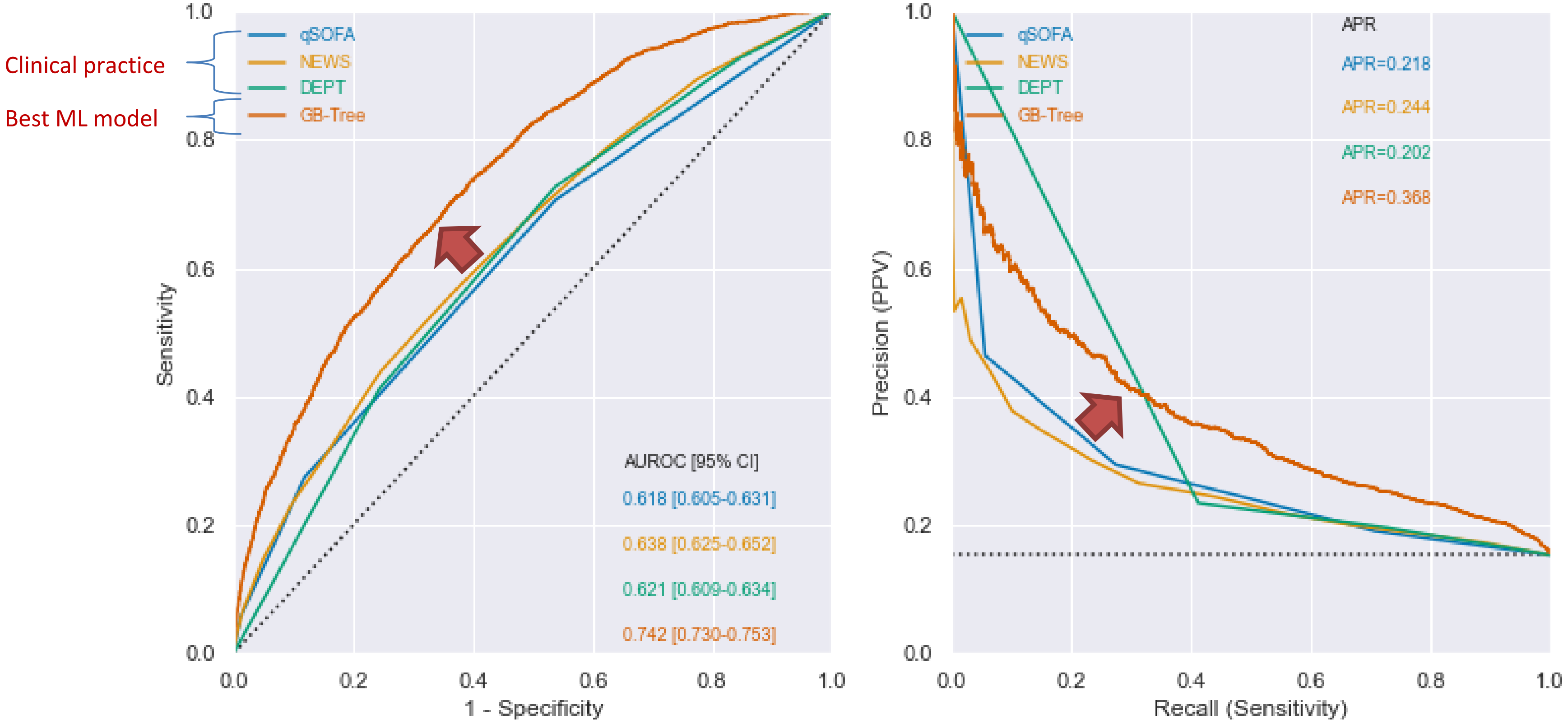
→ rule-in

RESULTS AND PERFORMANCE – 30-DAY MORTALITY

- TO UTILIZE THE IMPROVED PREDICTIONS, OPERATING POINTS MUST BE CHOSEN TO GUIDE INTERVENTION VIA ADVANCED DECISION SUPPORT

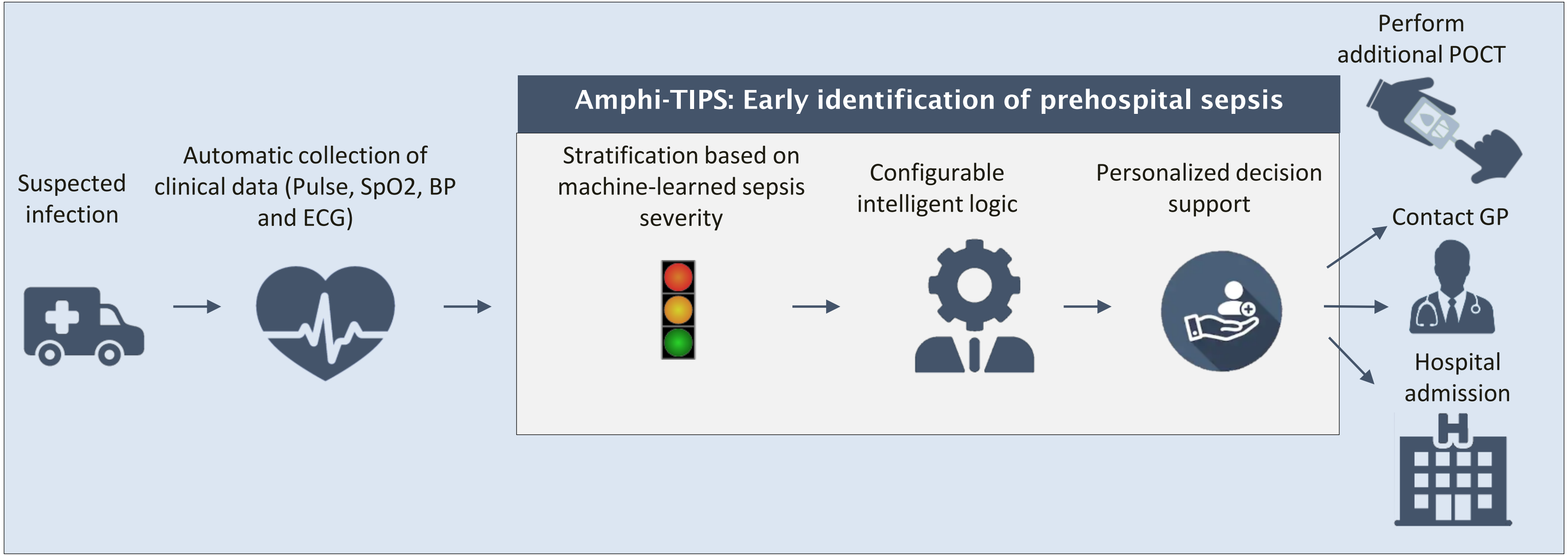
Although ML models perform significantly better than the baseline models there is no magic-bullet cut-off with high sensitivity AND high specificity, PPV.

➔ Choose operating points to stratify patients into risk groups



APPLICATIONS/FUTURE WORK

- Decision support unifies Personalized medicine, Machine learning, Artificial intelligence and clinical practice



SUMMARY

- TAKE HOME MESSAGES

- ☑ **Data is collected and is already collected in the ambulances**
  … why not use this gold mine to automate the clinical workflow using decision support?
- ☑ **The ML models perform significantly better than the baseline models (clinical practice)**
  … However, precision remains low with large numbers of false positives
- ☑ **Potential benefits from use of ML in prehospital risk, but further investigation required**
  … e.g. prospective trial of additional POC test for high risk/safety of low-risk patients

Open For Discussion

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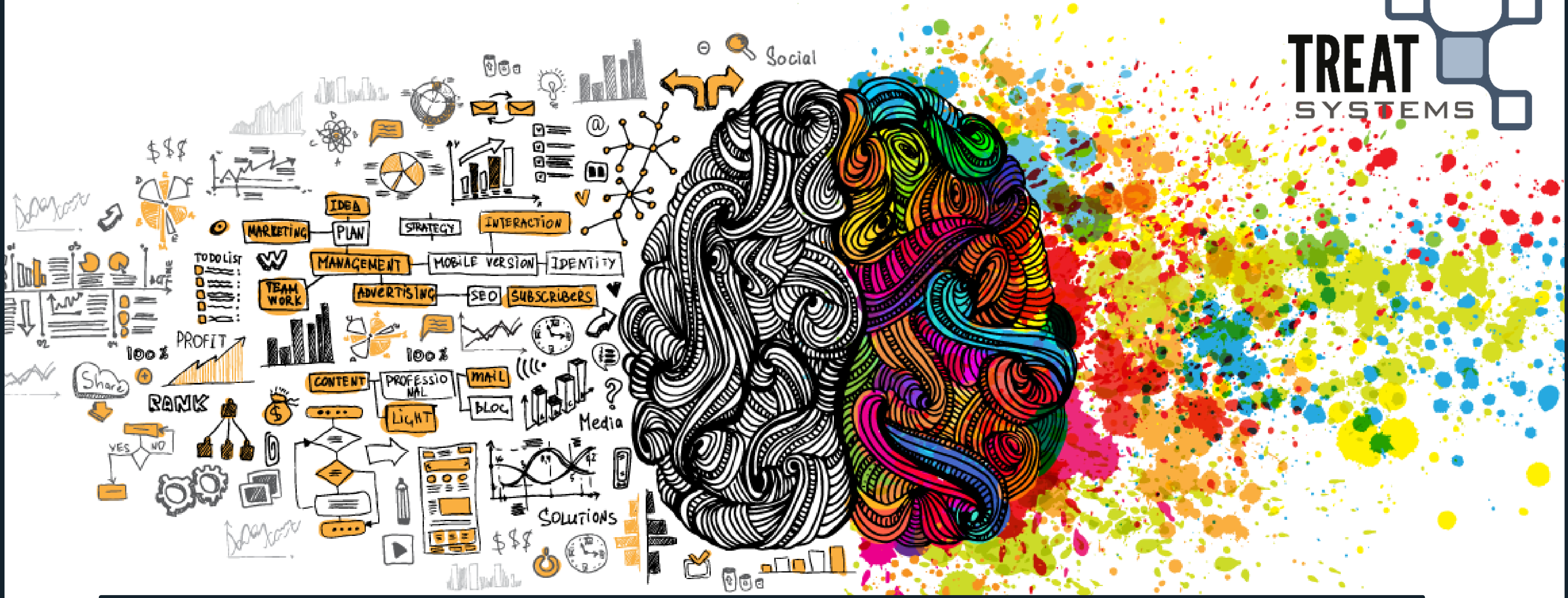
TREAT SYSTEMS

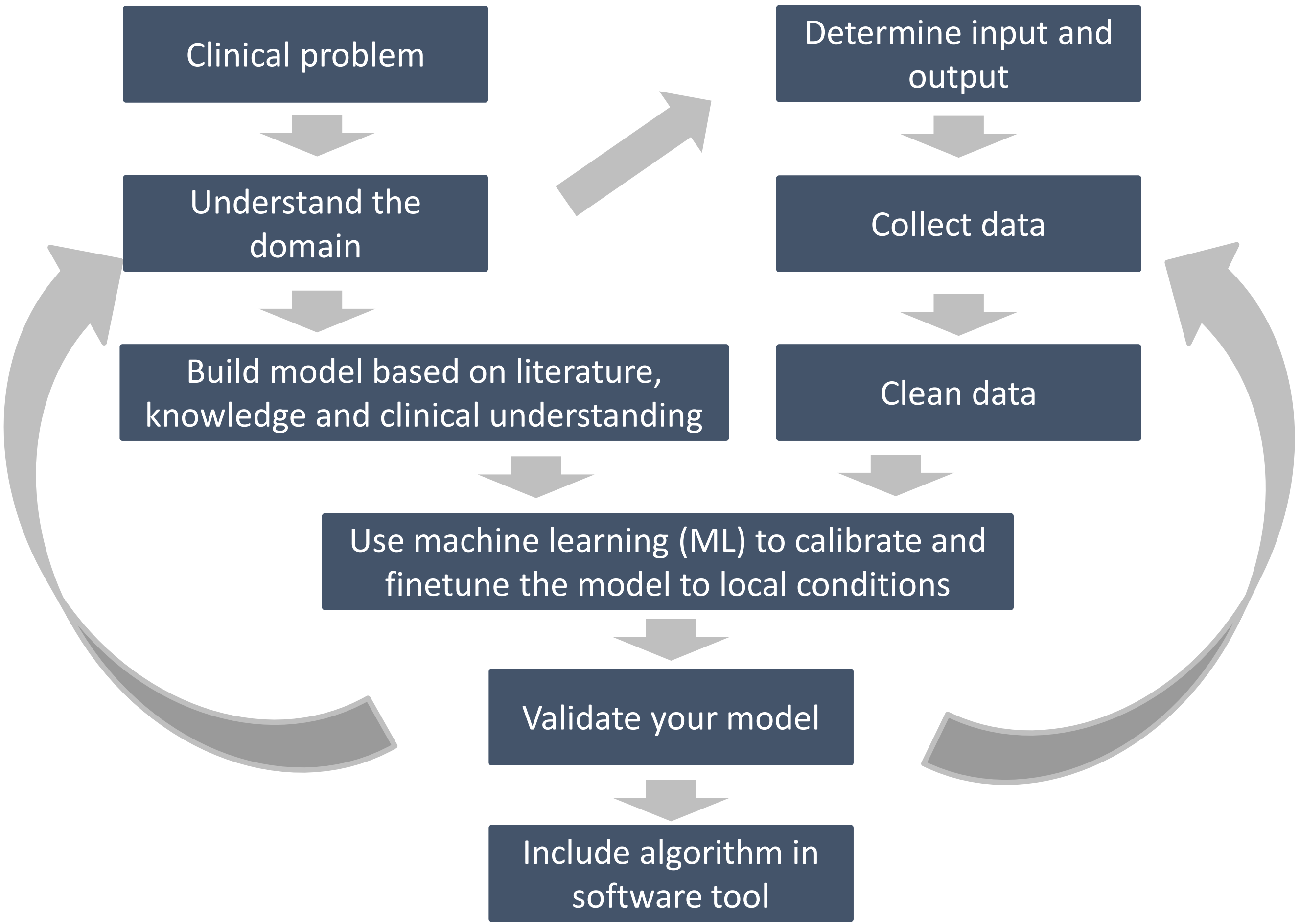


How to take the artificial out of <u>AI</u>

White box and explanatory decision support

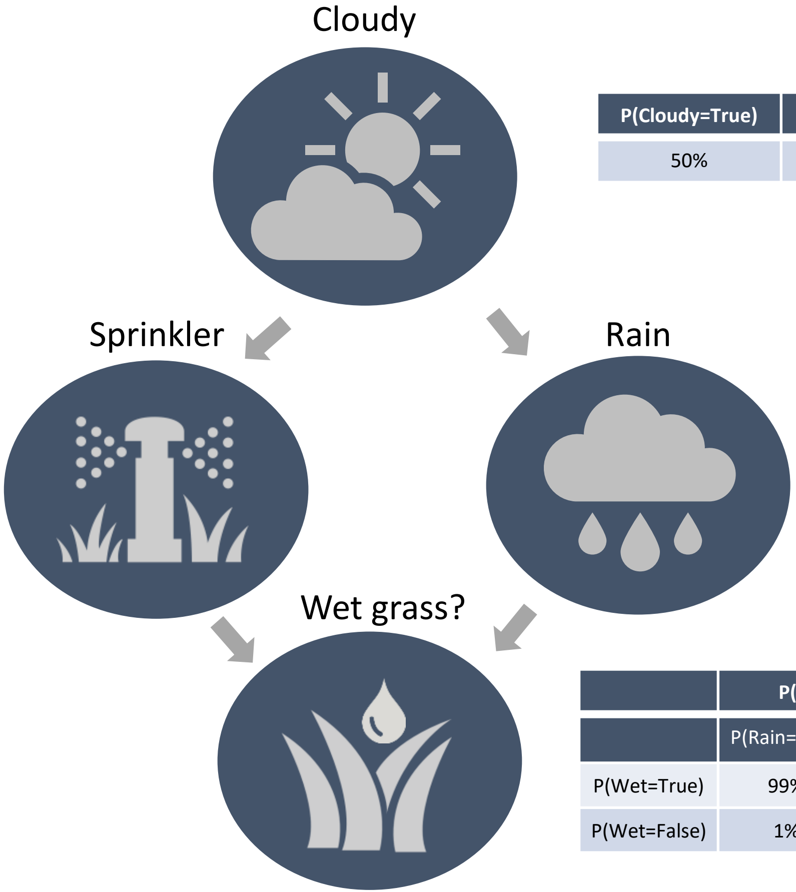
THE APPROACH

HOW DO WE GET THINGS DONE



Causal probabilistic network (Baysian networks)

The beauty of causality



P(Cloudy=True)	P(Cloudy=False)
50%	50%

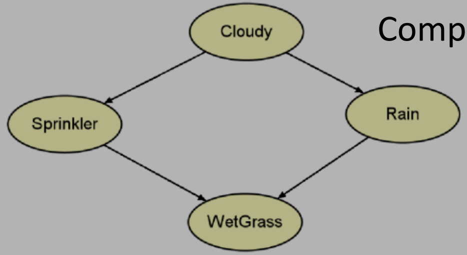
	P(Cloudy=True)	P(Cloudy=False)
P(Sprinkler=True)	10%	50%
P(Sprinkler=False)	90%	50%

	P(Cloudy=True)	P(Cloudy=False)
P(Rain=True)	80%	20%
P(Rain=False)	20%	80%

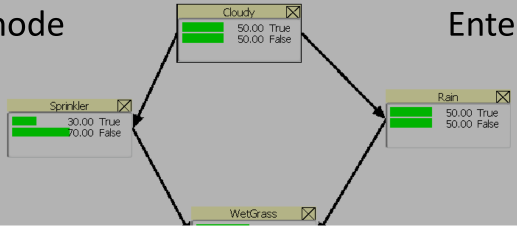
	P(Sprinkler=True)		P(Sprinkler=False)	
	P(Rain=True)	P(Rain=False)	P(Rain=True)	P(Rain=False)
P(Wet=True)	99%	90%	90%	0%
P(Wet=False)	1%	10%	10%	100%

Causal probabilistic network (Baysian networks)

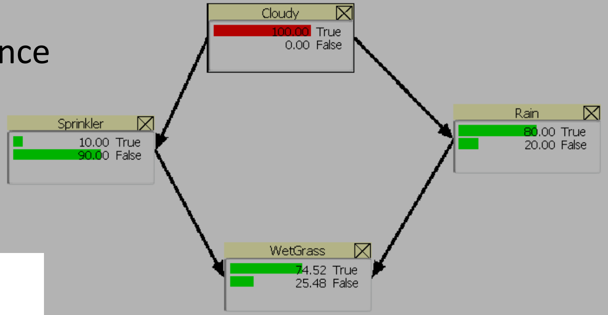
The beauty of causality



Compile/Run mode



Enter evidence



Bayes Formula

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

A, B = events

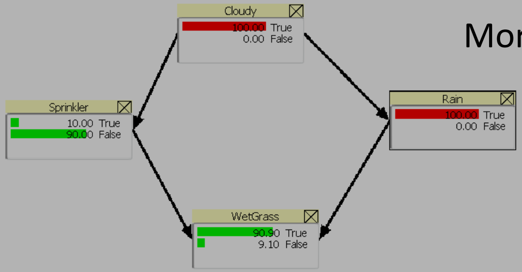
$P(A|B)$ = probability of A given B is true

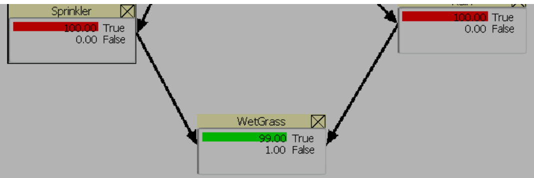
$P(B|A)$ = probability of B given A is true

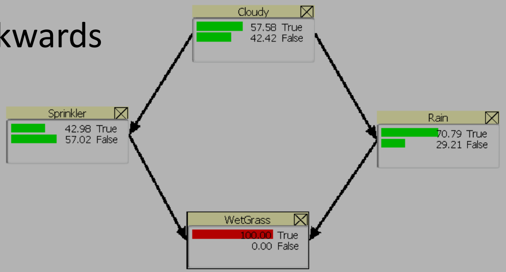
$P(A), P(B)$ = the independent probabilities of A and B

More e

te backwards



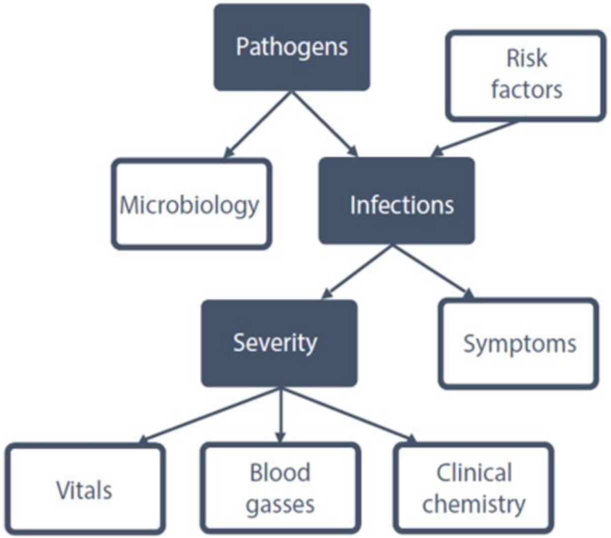




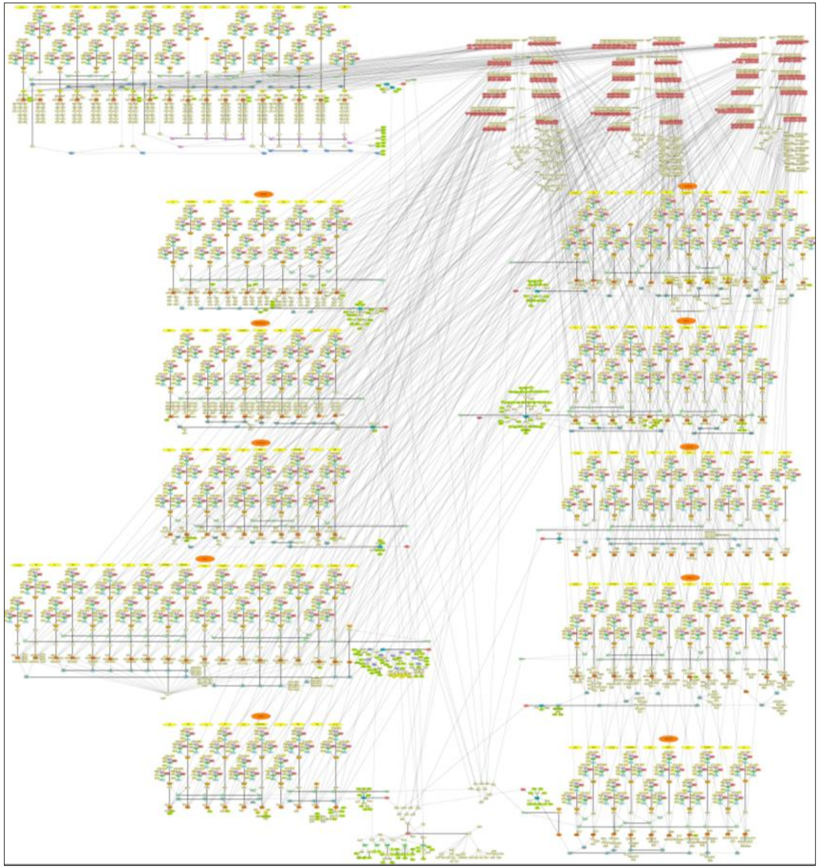
CAUSAL PROBABILISTIC NETWORK (BAYSIAN NETWORKS)

THE BEAUTY OF CAUSALITY

Simple example



Advanced example



TREAT
SYSTEMS