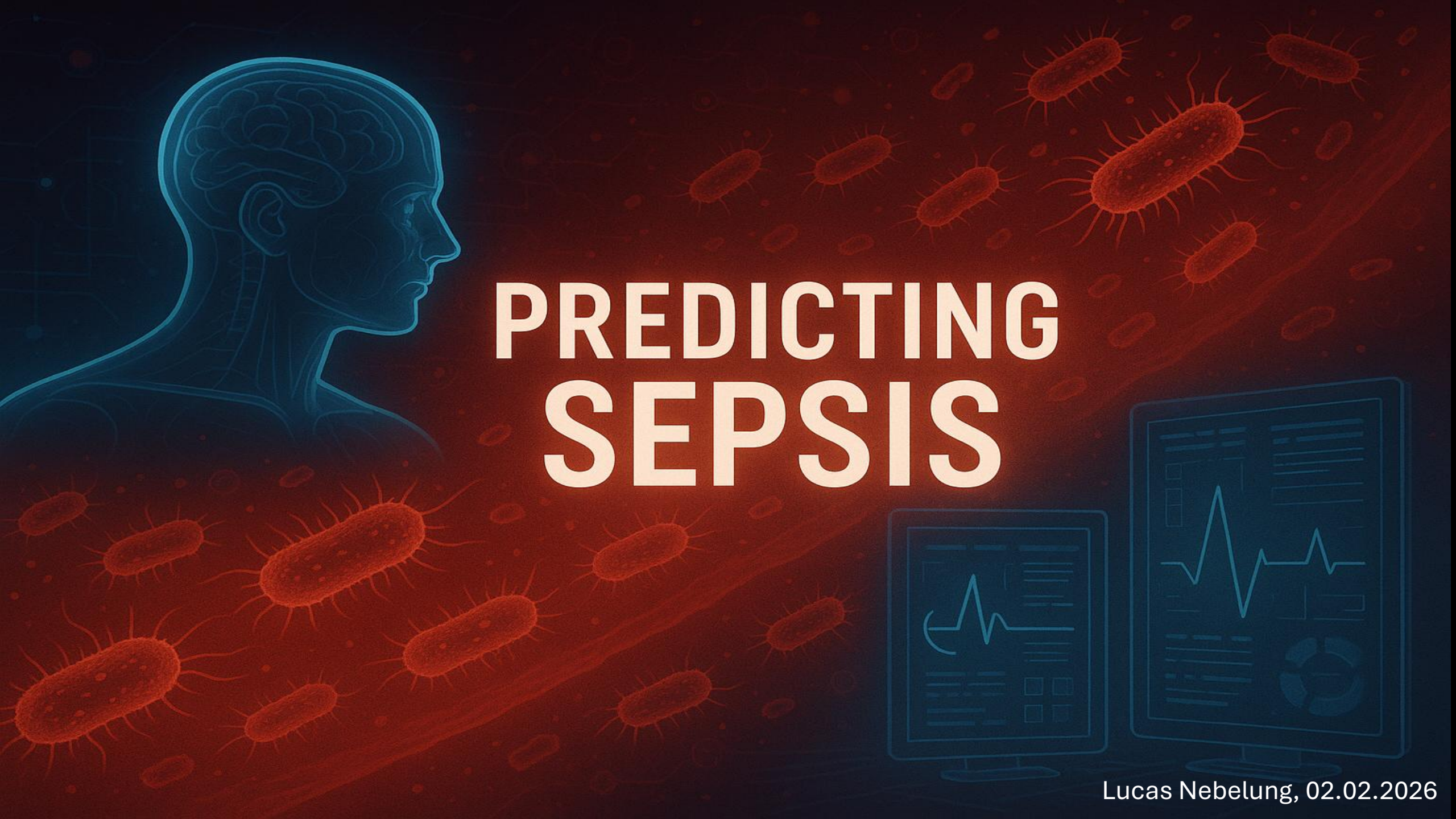
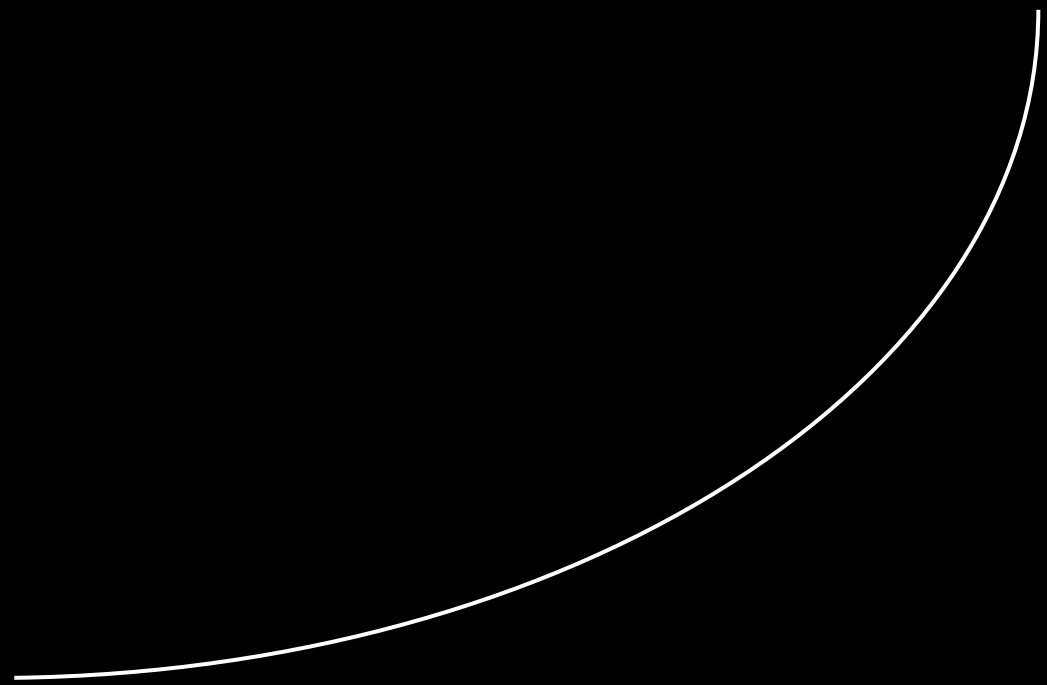
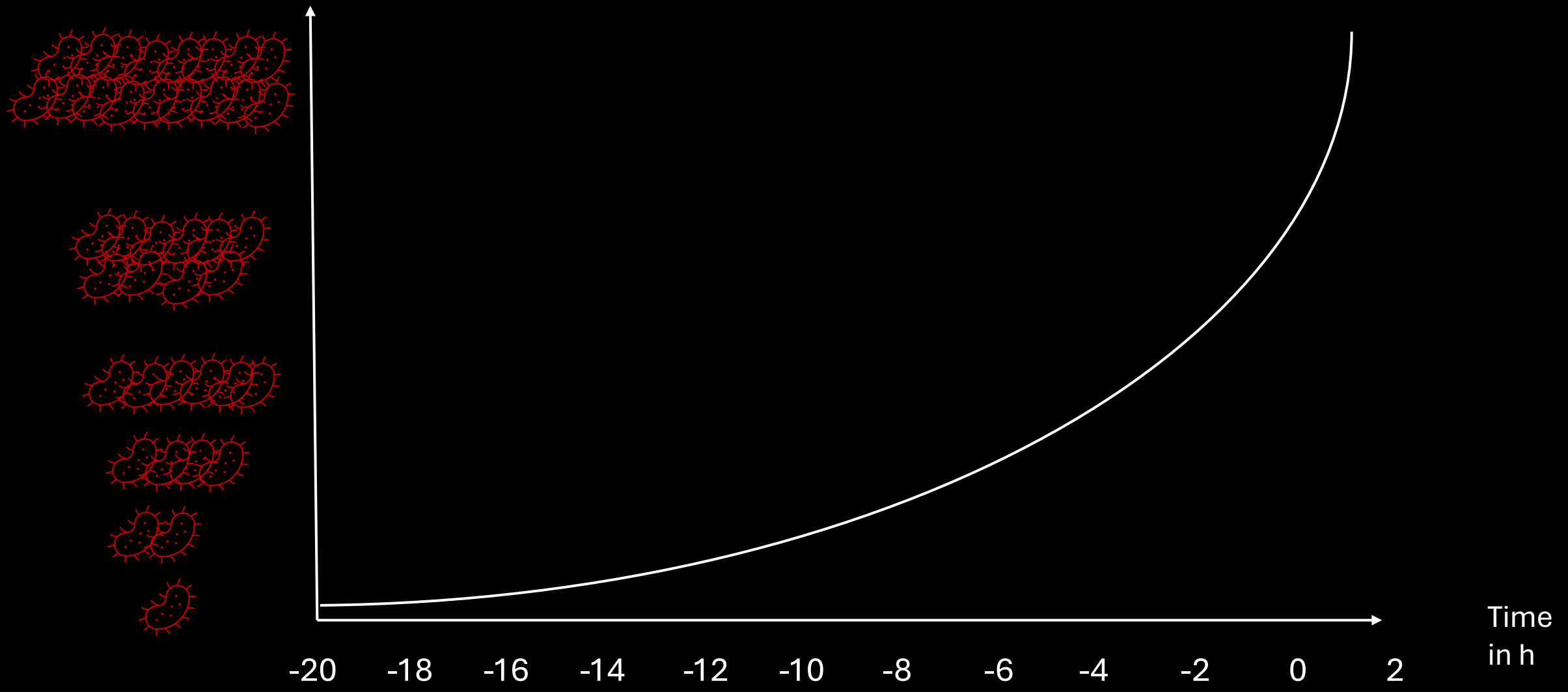
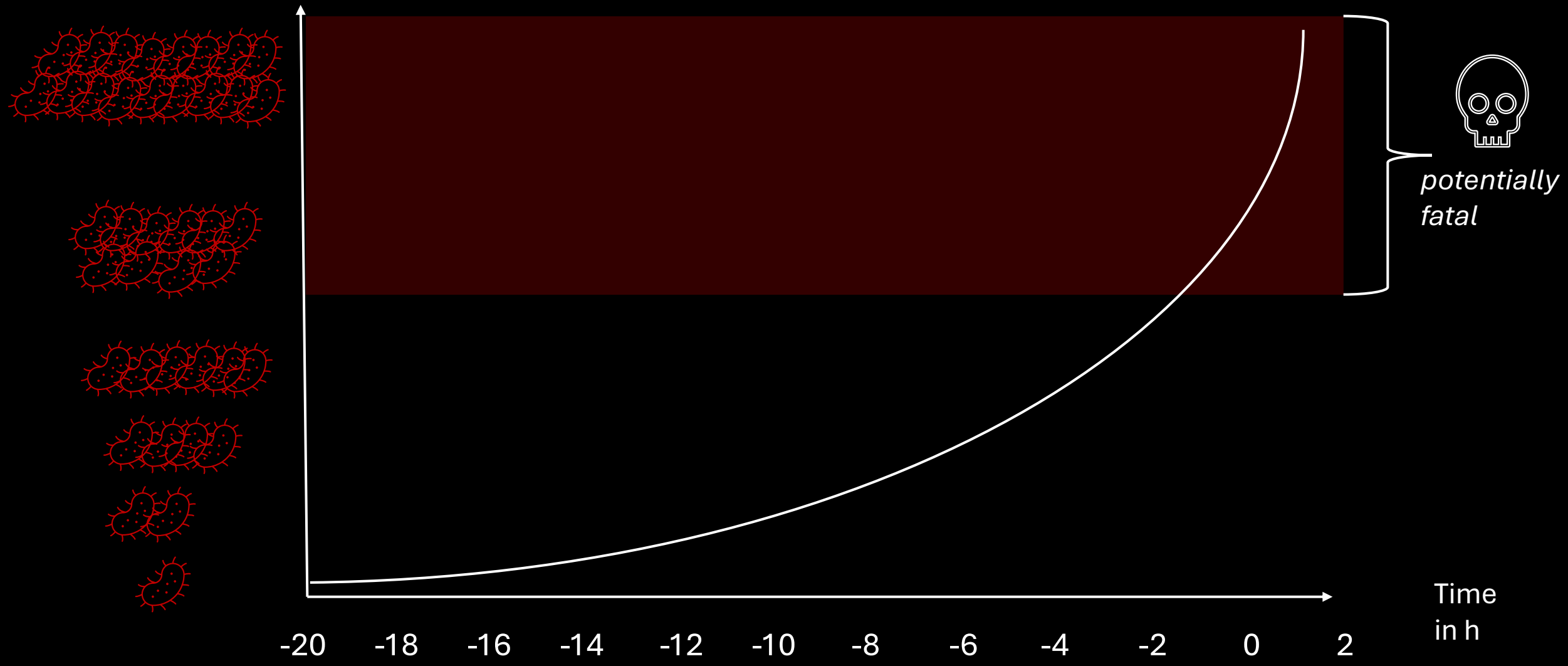
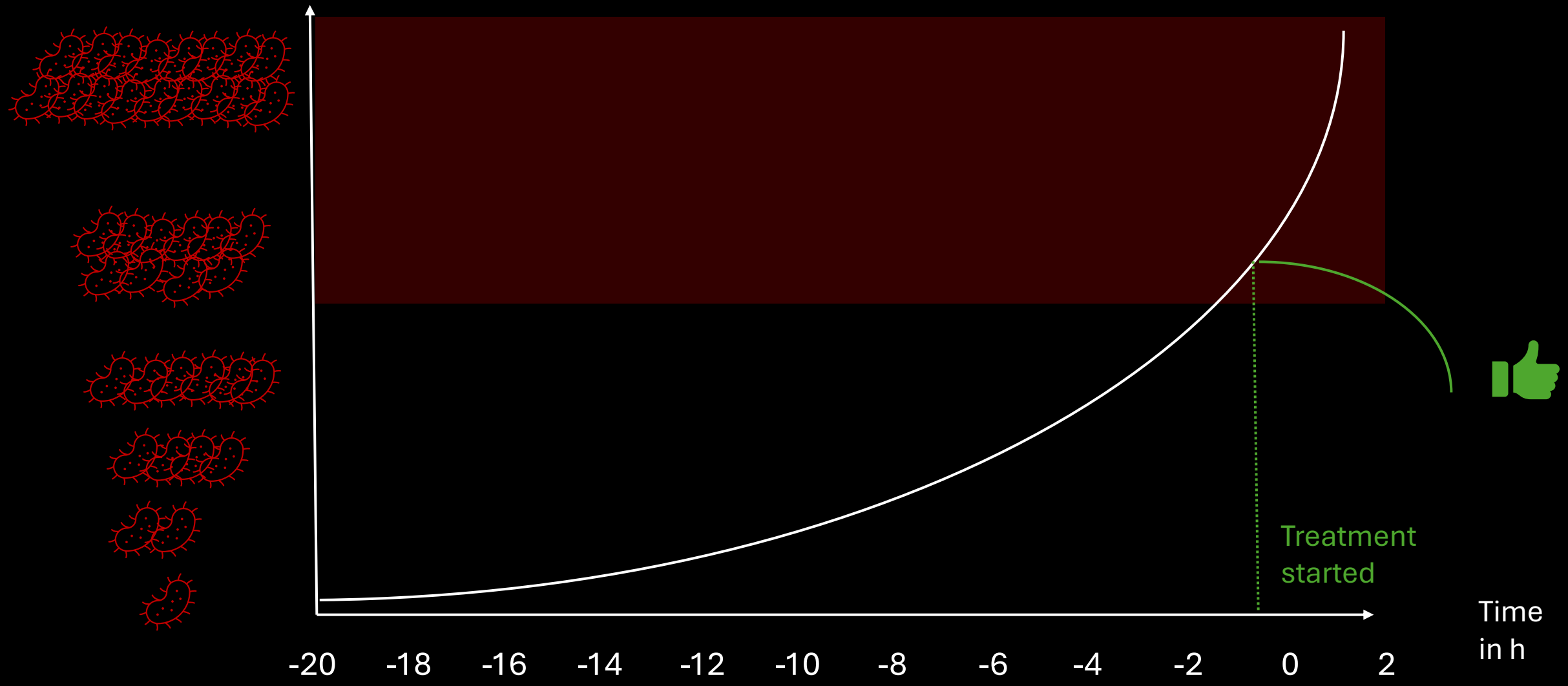


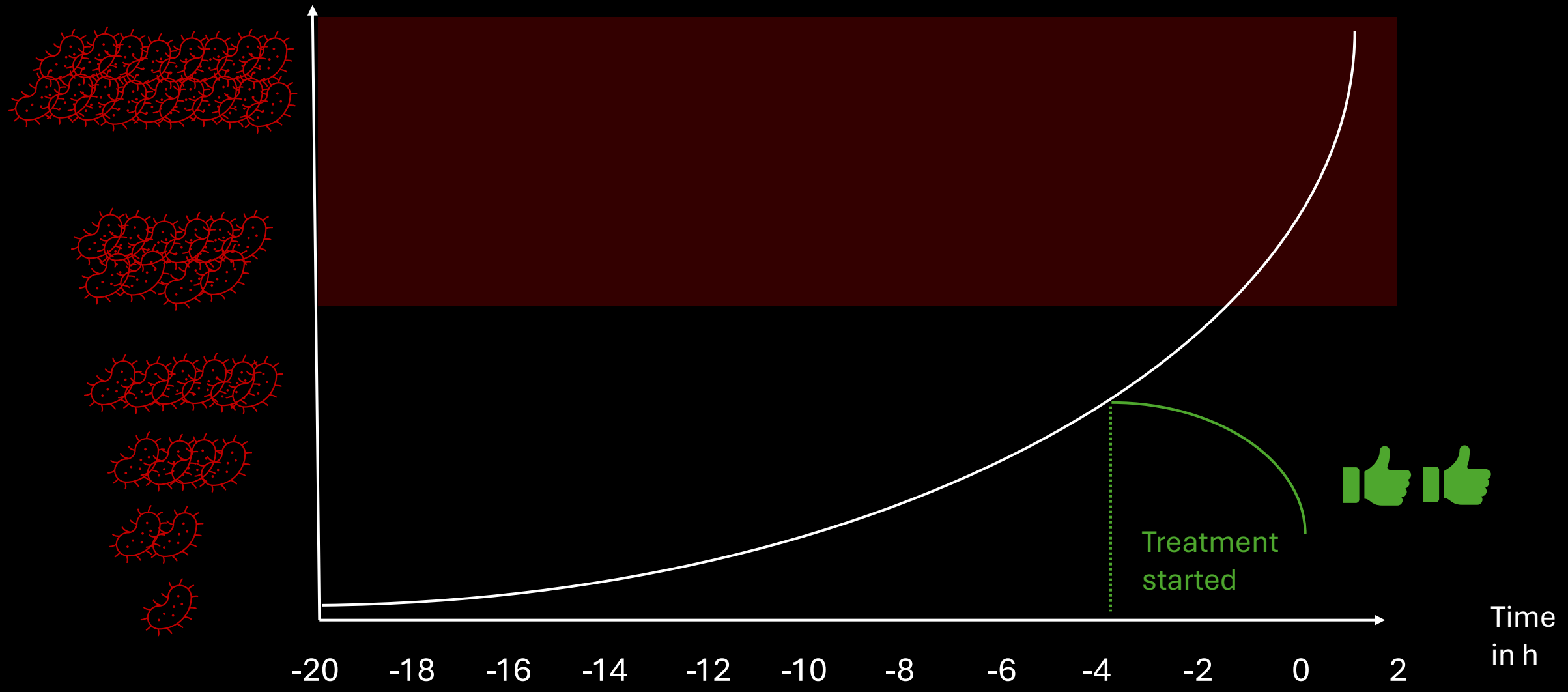
Lucas Nebelung, 02.02.2026

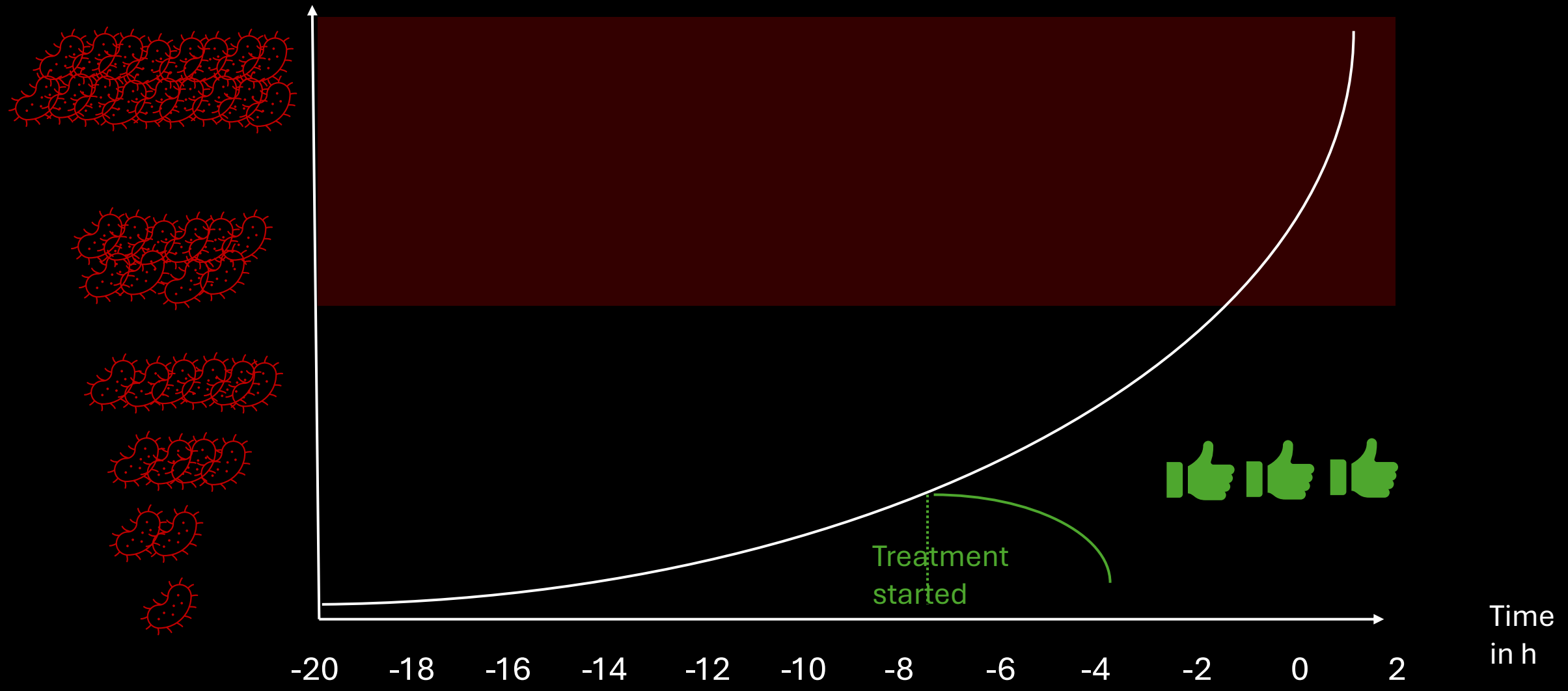



-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
2
Time
in h


potentially
fatal
-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
2
Time
in h


Treatment
started
Time
in h
-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
2


Treatment
started
-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
2
Time
in h


Treatment
started
-20
-18
-16
-14
-12
-10
-8
-6
-4
-2
0
2
Time
in h

“Detecting sepsis early and starting immediate treatment is often the difference between *life and death*.”

https://archive.cdc.gov/www_cdc_gov/media/releases/2017/p0831-sepsis-recognition-treatment.html

Problem Definition

Will the patient develop sepsis within the next 6 hours based on currently available data?

Yes or No

-> Binary classification task

Dataset

Early Prediction of Sepsis from Clinical Data: The PhysioNet/Computing in Cardiology Challenge 2019

Matthew Reyna, Chris Josef, Russell Jeter, Supreeth Shashikumar, Benjamin Moody, M. Brandon Westover, Ashish Sharma, Shamim Nemati, Gari D. Clifford

Published: Aug. 5, 2019. Version: 1.0.0

UNIVERSITY OF OXFORD

USC UNIVERSITY OF SOUTHERN CALIFORNIA

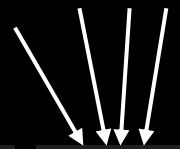
PHILIPS Healthcare

Technische Universität Dresden

and 55 more entries....

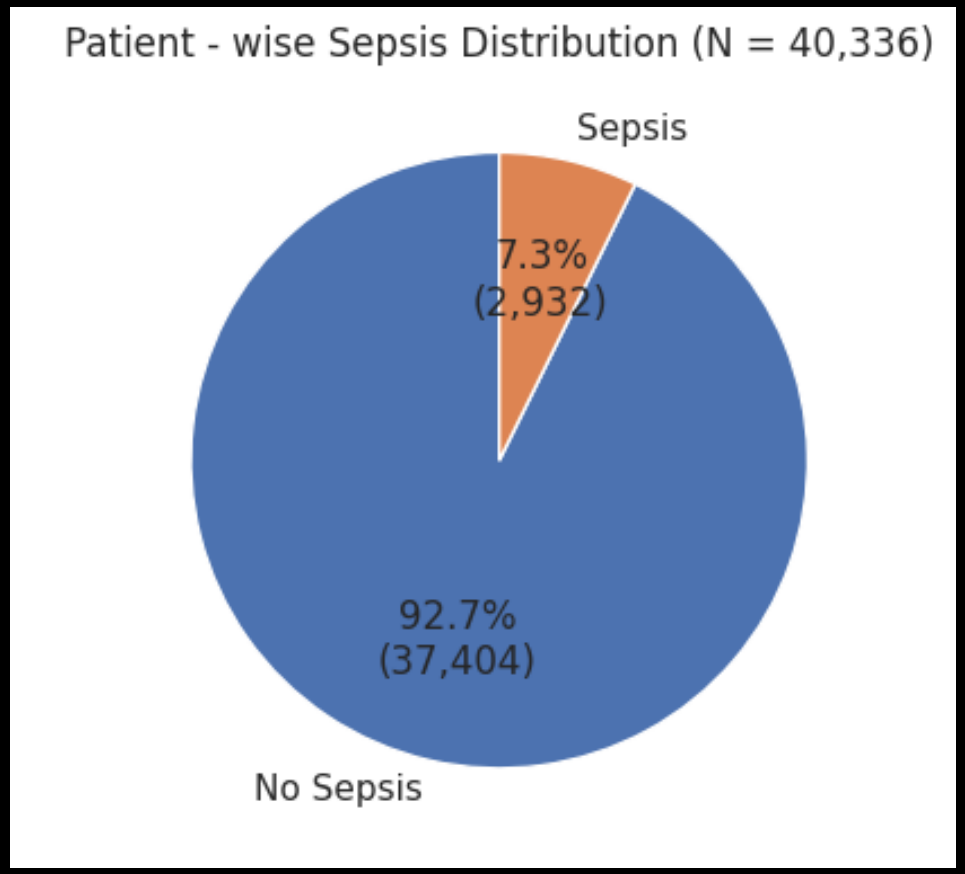
Dataset

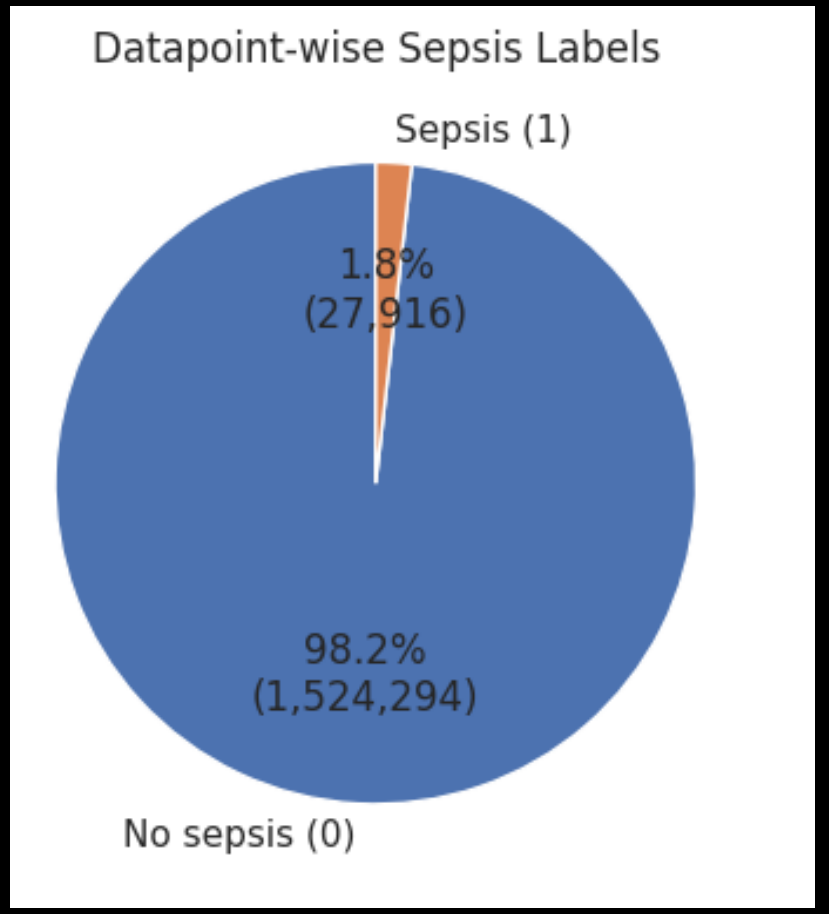
Patient 000001 as an example:



	HR	O2Sat	Temp	SBP	MAP	DBP	Resp	EtCO2	BaseExcess	HCO3	FiO2	pH	PaCO2	SaO2	AST	BUN	Alkalinephos	Calcium	Chloride	Creatinine	Bilirubin_direct	Glucose	Lactate	Magnesium	Phosphate	Potassium	Bilirubin_total	TroponinI	Hct	Hgb	PTT	WBC	Fibrinogen	Platelets	Age	Gender	Unit1	Unit2	HospAdmTime	ICULOS	SepsisLabel
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	1.0	0
3	97.0	95.0	0.0	98.0	75.33	0.0	19.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	2.0	0
4	89.0	99.0	0.0	122.0	86.0	0.0	22.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	3.0	0
5	90.0	95.0	0.0	0.0	0.0	0.0	30.0	0.0	24.0	0.0	0.0	7.36	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	4.0	0
6	103.0	88.5	0.0	122.0	91.33	0.0	24.5	0.0	0.0	0.0	0.28	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	5.0	0
7	110.0	91.0	0.0	0.0	0.0	0.0	22.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	6.0	0
8	108.0	92.0	36.11	123.0	77.0	0.0	29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	7.0	0
9	106.0	90.5	0.0	93.0	76.33	0.0	29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	8.0	0
10	104.0	95.0	0.0	133.0	88.33	0.0	26.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	9.0	0
11	102.0	91.0	0.0	134.0	87.33	0.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	10.0	0
12	104.0	92.0	37.17	138.0	86.67	0.0	19.0	0.0	23.0	0.0	0.0	7.4	86.0	88.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	11.0	0
13	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	12.0	0
14	102.0	93.0	0.0	129.0	77.0	0.0	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	13.0	0
15	108.0	90.0	0.0	122.0	96.67	0.0	27.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	14.0	0
16	106.0	90.0	0.0	0.0	0.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	15.0	0
17	109.0	91.0	36.56	132.0	96.67	0.0	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	16.0	0
18	103.0	90.0	0.0	0.0	0.0	0.0	30.0	0.0	21.0	45.0	0.0	7.37	90.0	91.0	16.0	14.0	98.0	9.3	85.0	0.7	0.0	193.0	0.0	2.0	3.3	3.8	0.3	0.0	37.2	12.5	0.0	5.7	0.0	317.0	83.14	0.0	0.0	0.0	-0.03	17.0	0
19	104.0	92.0	0.0	132.0	81.33	0.0	28.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	18.0	0
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	19.0	0
21	109.0	91.0	37.11	147.0	91.0	0.0	22.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	20.0	0
22	113.0	90.0	0.0	0.0	0.0	0.0	17.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	21.0	0
23	98.0	93.0	0.0	134.0	83.33	0.0	28.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	22.0	0
24	100.0	85.0	0.0	0.0	0.0	0.0	29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	23.0	0
25	102.0	89.0	36.67	132.0	94.0	0.0	32.0	0.0	20.0	0.0	0.0	7.34	96.0	78.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	24.0	0
26	108.0	87.0	0.0	149.0	89.67	0.0	30.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	25.0	0
27	107.0	90.0	0.0	156.0	96.67	0.0	26.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	26.0	0
28	104.0	91.0	0.0	168.0	141.33	0.0	29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	27.0	0
29	102.0	88.0	36.5	146.0	90.67	0.0	27.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	28.0	0
30	106.0	91.0	0.0	137.0	75.67	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	29.0	0
31	112.0	89.0	0.0	157.0	123.67	0.0	20.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	30.0	0
32	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	31.0	0
33	107.0	91.0	37.44	141.0	97.0	0.0	24.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	32.0	0
34	111.0	0.0	0.0	138.0	126.0	0.0	31.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	33.0	0
35	104.0	90.0	0.0	126.0	117.33	0.0	27.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	34.0	0
36	102.0	0.0	0.0	103.0	75.67	0.0	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	35.0	0
37	99.0	89.0	37.11	113.0	96.33	0.0	26.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	36.0	0
38	97.0	89.0	0.0	110.0	72.0	0.0	29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	37.0	0
39	110.0	89.0	0.0	108.0	90.67	0.0	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	38.0	0
40	108.0	89.0	0.0	139.0	102.33	0.0	26.0	0.0	20.0	0.0	0.0	7.33	100.0	89.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	39.0	0
41	117.0	0.0	36.78	126.0	104.67	0.0	22.0	0.0	0.0	48.0	0.0	0.0	0.0	0.0	0.0	22.0	0.0	9.6	85.0	0.7	0.0	133.0	0.0	2.2	3.7	4.6	0.0	0.0	36.2	12.2	0.0	14.7	0.0	338.0	83.14	0.0	0.0	0.0	-0.03	40.0	0
42	107.0	93.0	0.0	0.0	0.0	0.0	21.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	41.0	0
43	117.0	0.0	36.33	126.0	84.0	0.0	25.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	42.0	0
44	0.0	0.0	0.0	0.0	0.0	0.0	29.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	43.0	0
45	114.5	89.5	0.0	157.5	121.17	0.0	26.0	0.0	0.0	18.0	0.0	0.0	7.31	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	44.0	0
46	96.0	95.0	0.0	119.5	87.5	0.0	22.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	45.0	0
47	84.0	95.0	0.0	111.5	67.83	0.0	21.5	0.0	19.0	0.0	0.3	7.32	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	46.0	0
48	86.0	97.0	0.0	127.0	76.33	0.0	18.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	47.0	0
49	99.5	96.0	0.0	143.5	96.17	0.0	21.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	48.0	0
50	100.0	86.5	0.0	181.0	104.0	0.0	30.0	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	49.0	0
51	76.0	0.0	0.0	85.0	53.0	0.0	17.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	50.0	0
52	81.0	99.0	0.0	99.0	51.0	0.0	17.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	51.0	0
53	85.0	100.0	0.0	103.0	48.0	0.0	26.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	52.0	0
54	86.0	93.0	0.0	87.0	44.0	0.0	22.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	53.0	0
55	84.0	85.0	0.0	78.0	44.0	0.0	18.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.14	0.0	0.0	0.0	-0.03	54.0	0
56																																								

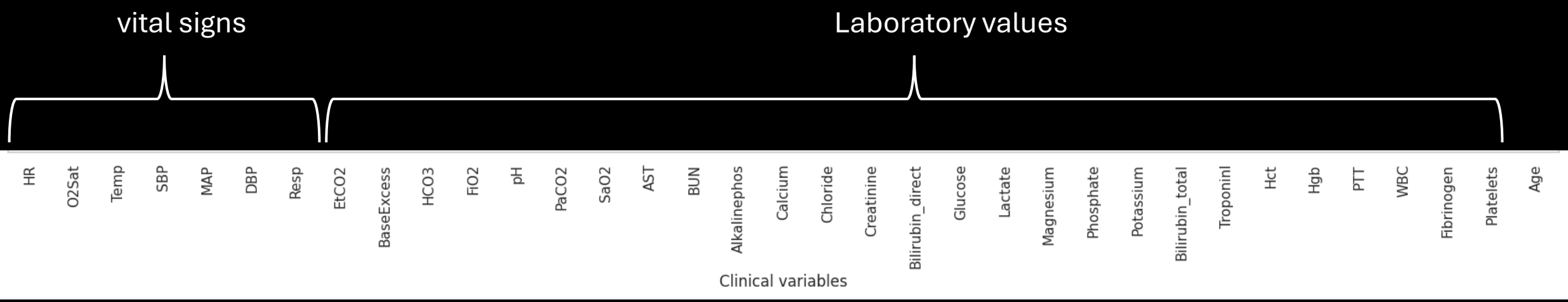
Dataset



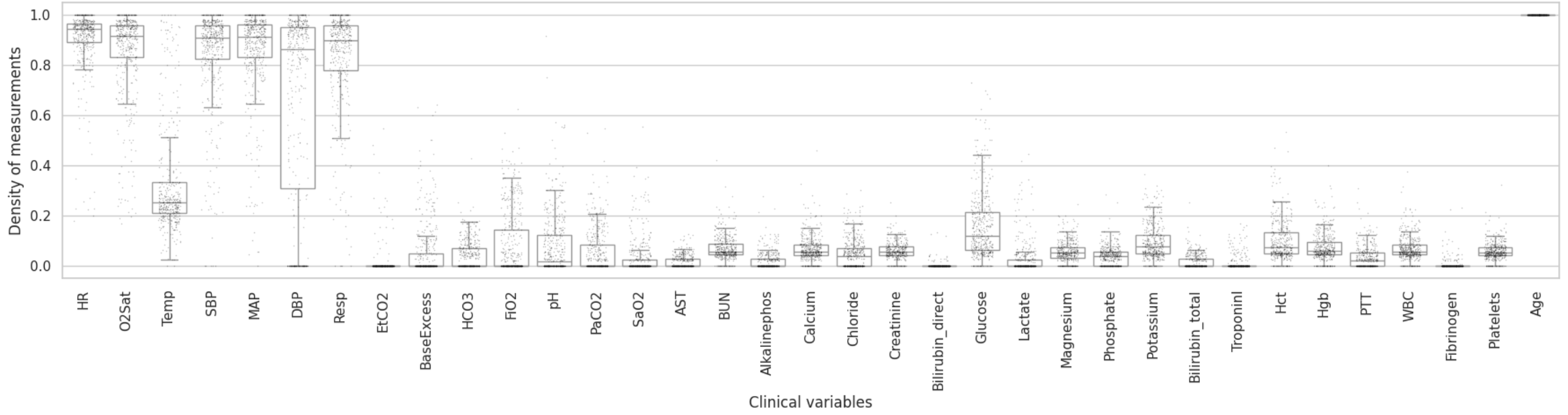


-> 1st challenge: Extreme Imbalance

Dataset


vital signs
Laboratory values
HR
O2Sat
Temp
SBP
MAP
DBP
Resp
EtCO2
BaseExcess
HCO3
FiO2
pH
PaCO2
SaO2
AST
BUN
Alkalinephos
Calcium
Chloride
Creatinine
Bilirubin_direct
Glucose
Lactate
Magnesium
Phosphate
Potassium
Bilirubin_total
TroponinI
Hct
Hgb
PTT
WBC
Fibrinogen
Platelets
Age
Clinical variables

Dataset

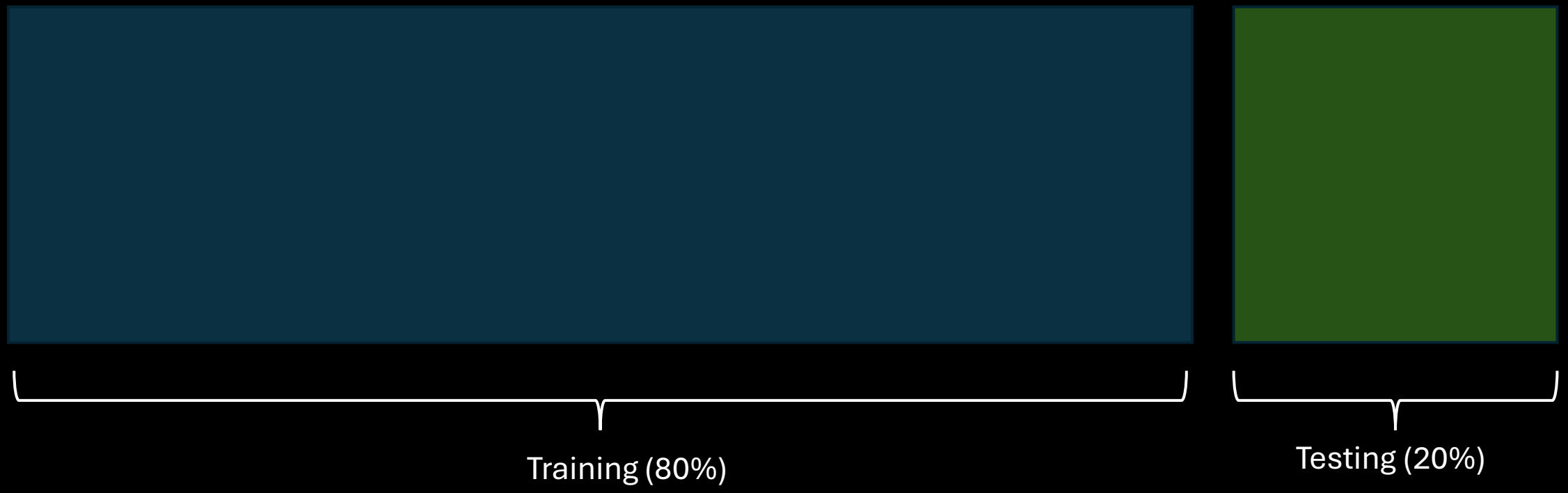


-> 2nd challenge = Many missing values!

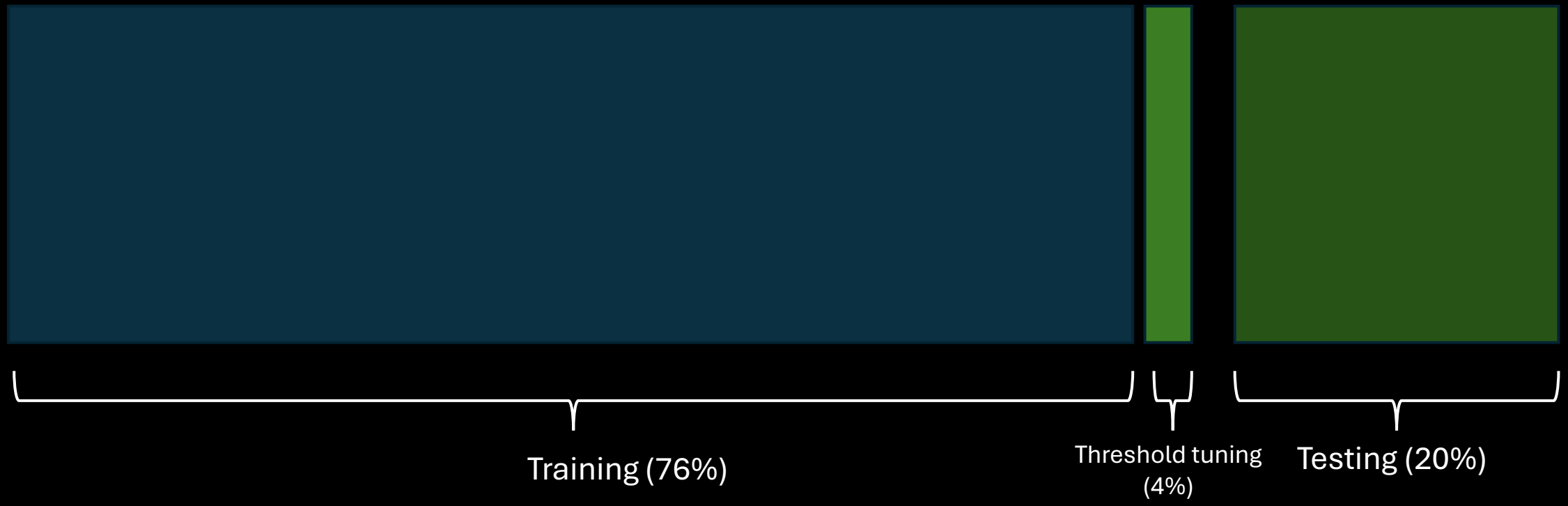
Dataset

Full dataset: 40,336 patients

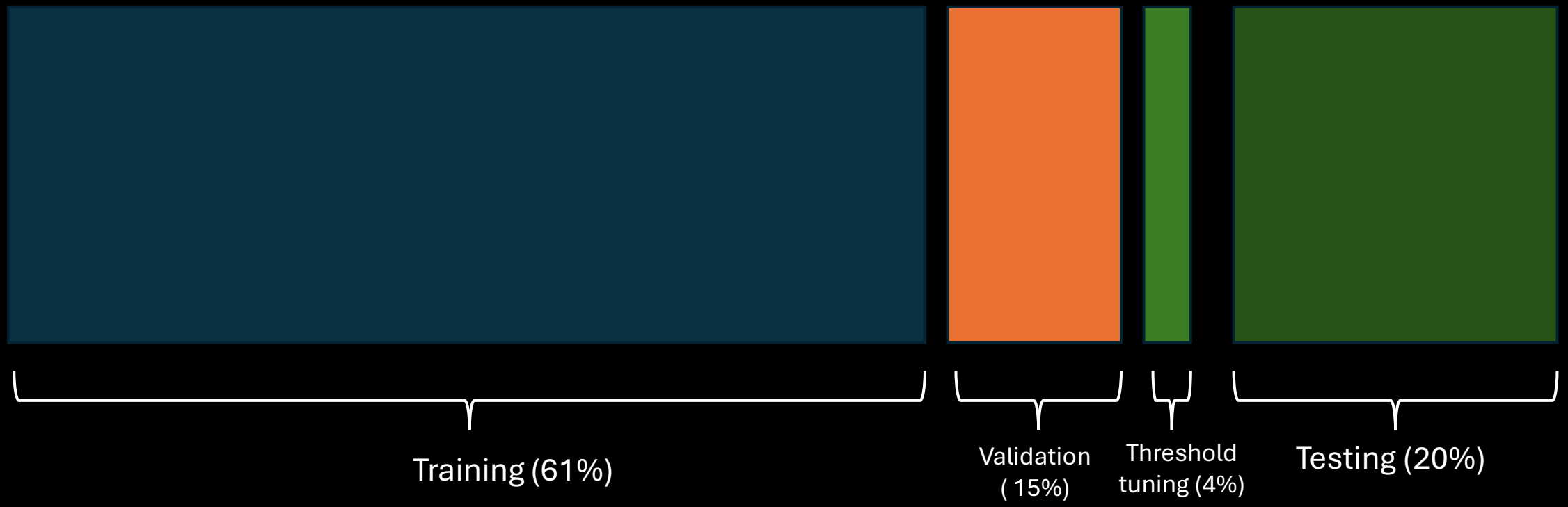
Dataset



Dataset



Dataset



-> All splits were done using a ***stratified*** split based on whether a patient ever gets septic

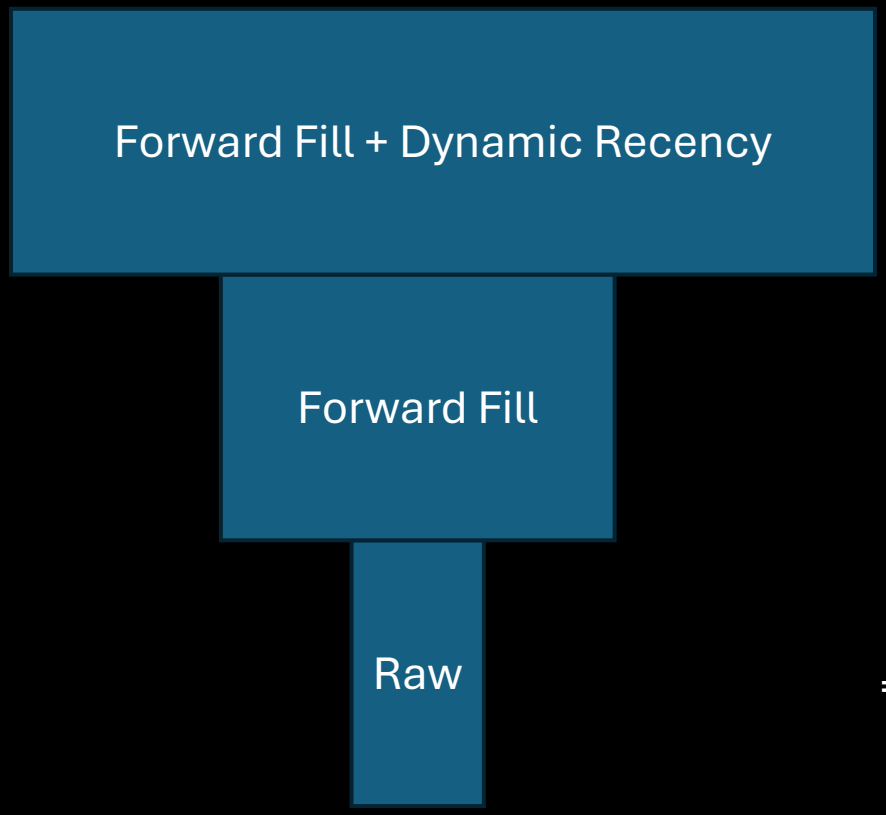
Handling Missing Data

Three preprocessing strategies were attempted:

High

Low

No



Forward-fill missing values and add a recency feature for how old the last measurement is: $r(\mathrm{t}) = 1 * 0.9^{\Delta t}$

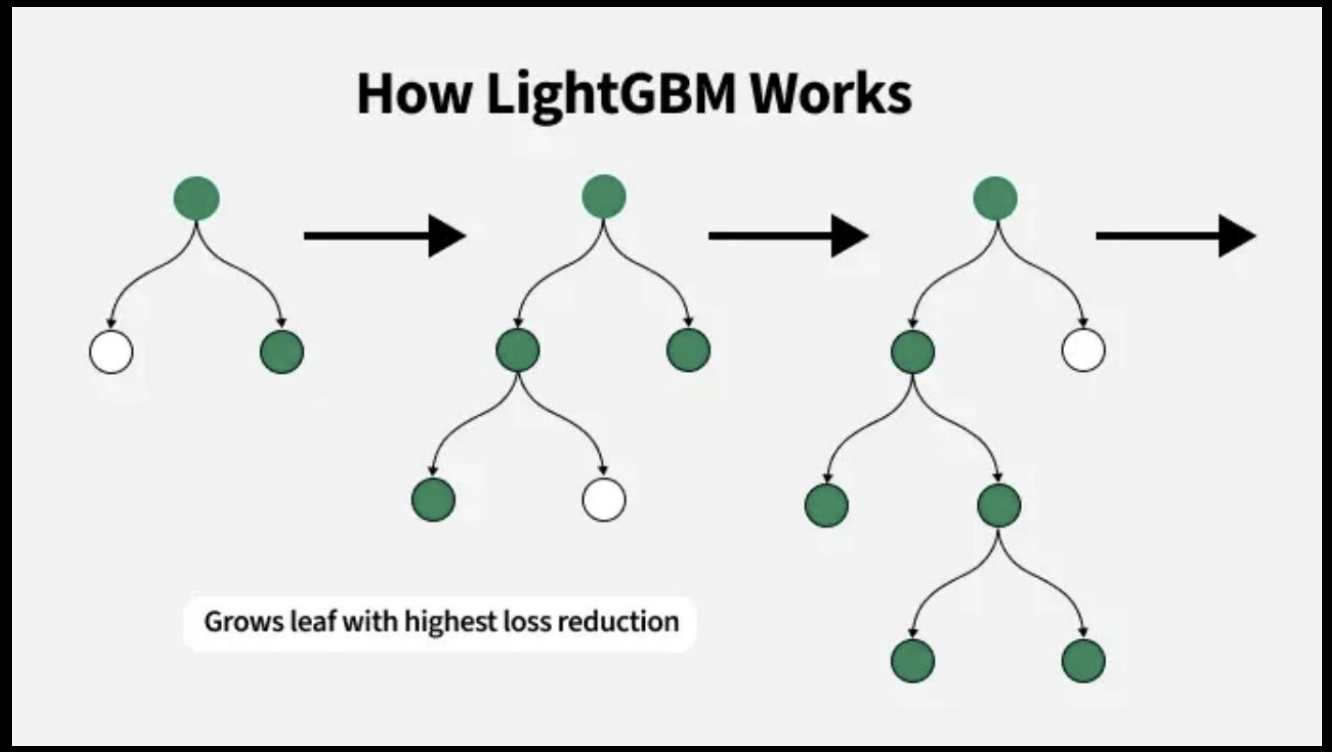
= If a value is missing at time t, replace it with the most recent previous measurement of the same variable.

= No preprocessing: Keep missing values as-is.

Baseline Model

LightGBM

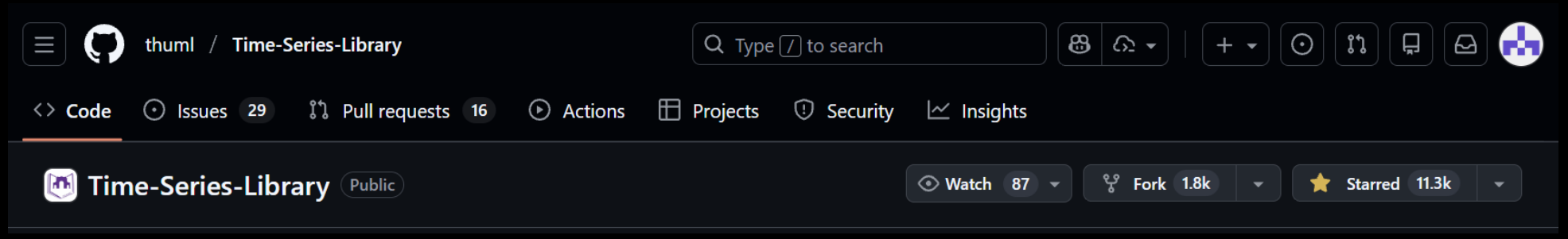
(Light Gradient-Boosting Machine)



- ➔ Efficient and scalable
- ➔ Robust and interpretable
- ➔ Proven to perform well on tabular data (Most popular choice in PhysioNet 2019 Competition)

https://www.geeksforgeeks.org/machine-learning/lightgbm-light-gradient-boosting-machine/

Deep Learning Models: Framework



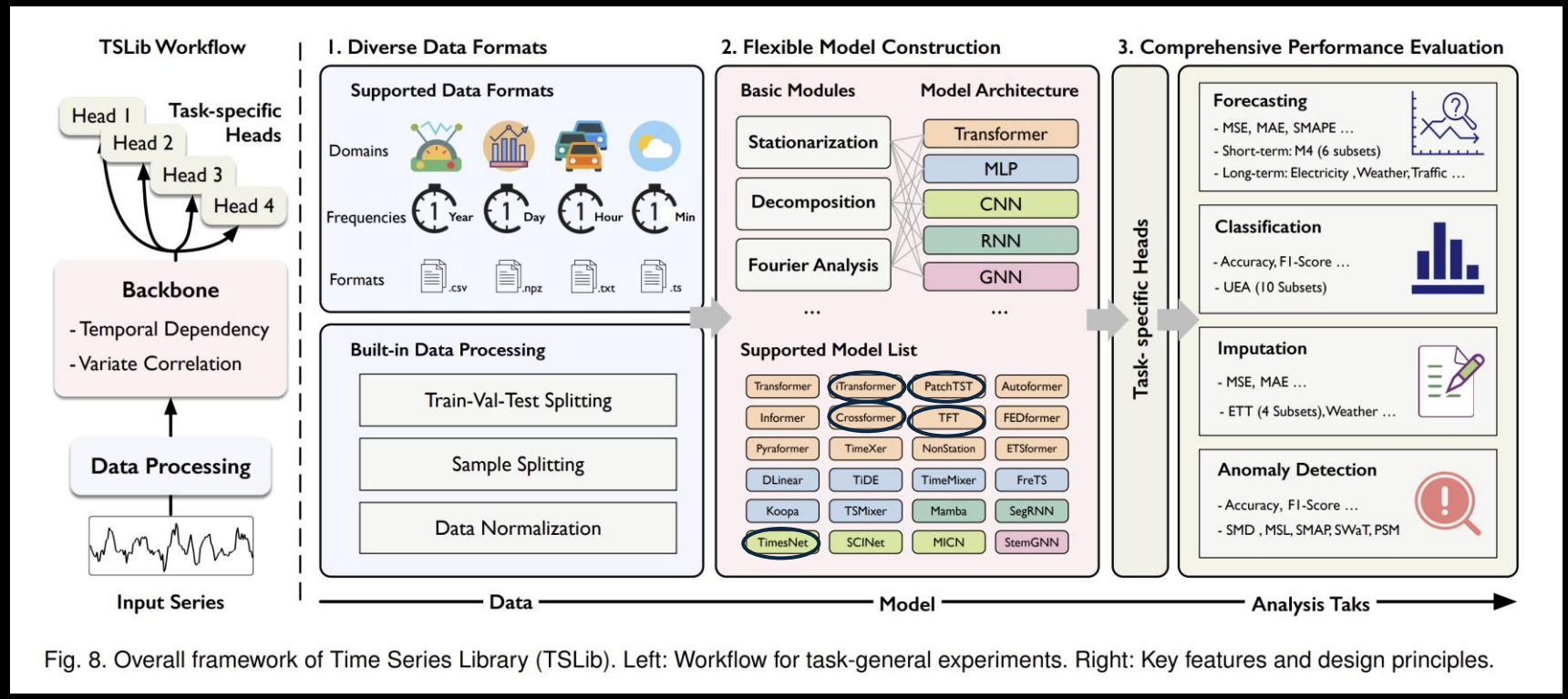


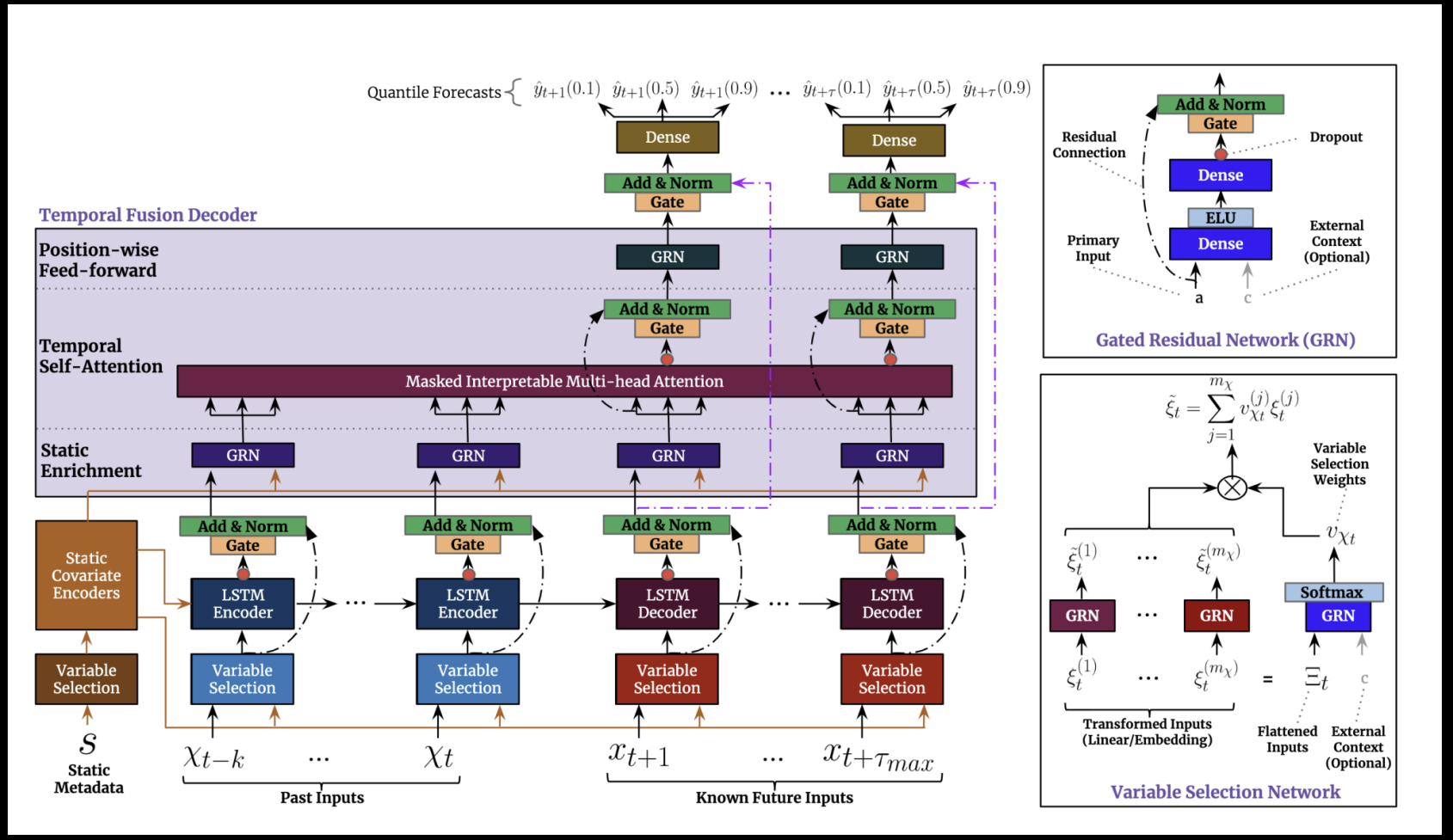
Fig. 8. Overall framework of Time Series Library (TSLib). Left: Workflow for task-general experiments. Right: Key features and design principles.

"A Library for Advanced Deep Time Series Models for General Time Series Analysis."

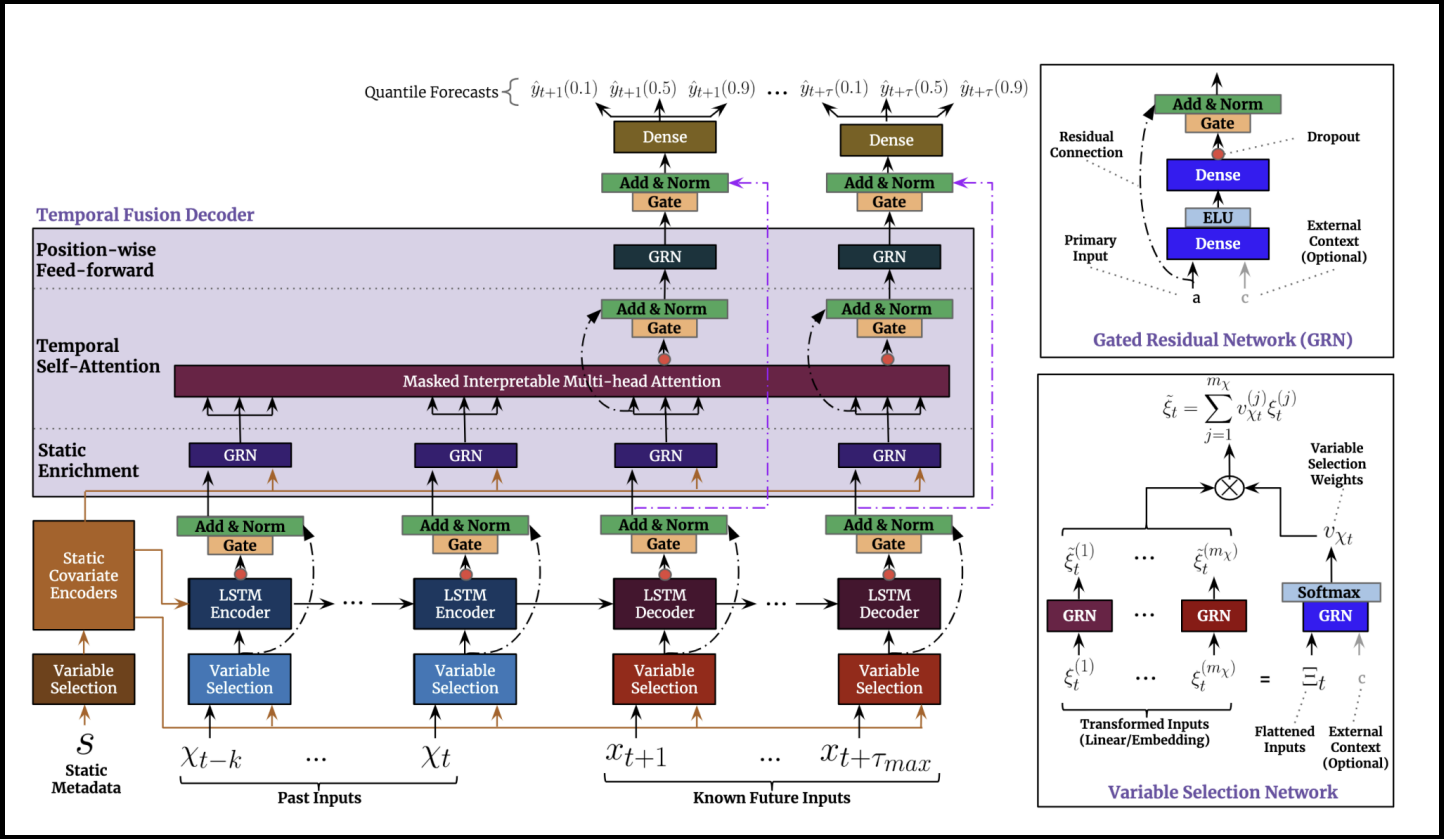
➔ Fully open source 👍
➔ Modular approach 👍

https://github.com/thuml/Time-Series-Library

Deep Learning Models: Temporal Fusion Transformers

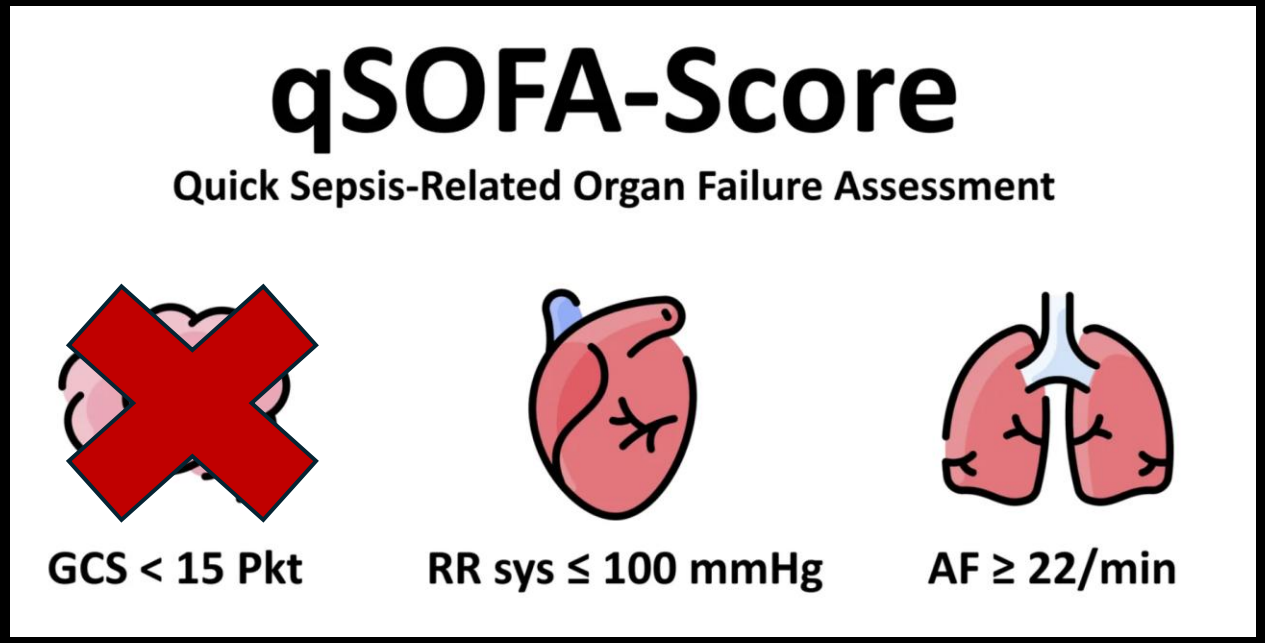


Deep Learning Models: Temporal Fusion Transformers



- Designed for complex time series with heterogeneous inputs
- Captures both short- and long-term temporal dependencies
- High performance with built-in interpretability

Clinical Screening Method: partial qSOFA

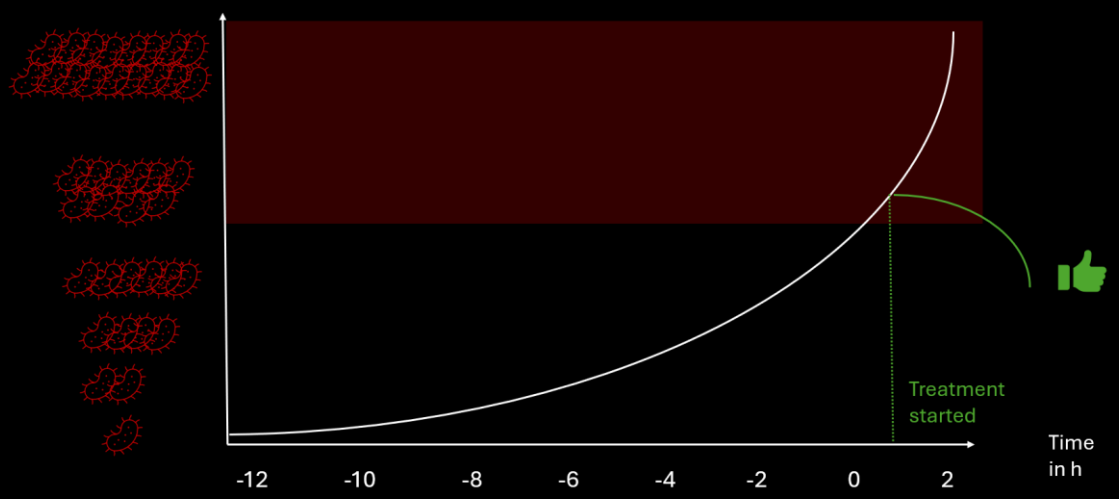


qSOFA is the most commonly used screening tool for sepsis

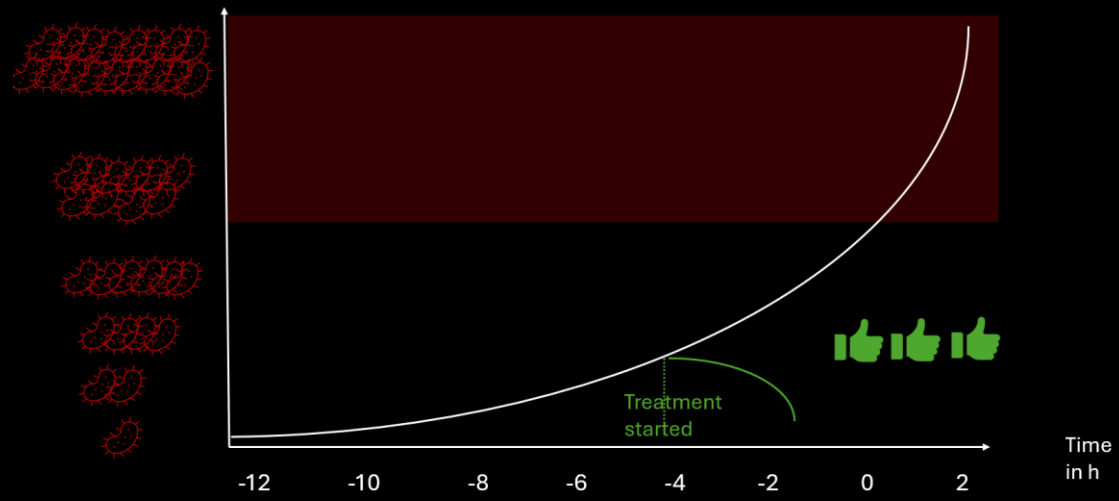
-> But: only based on clinical (i.e. non-laboratory) information.

Problem: GCS not in dataset, therefore only *partial* qSOFA

Evaluation

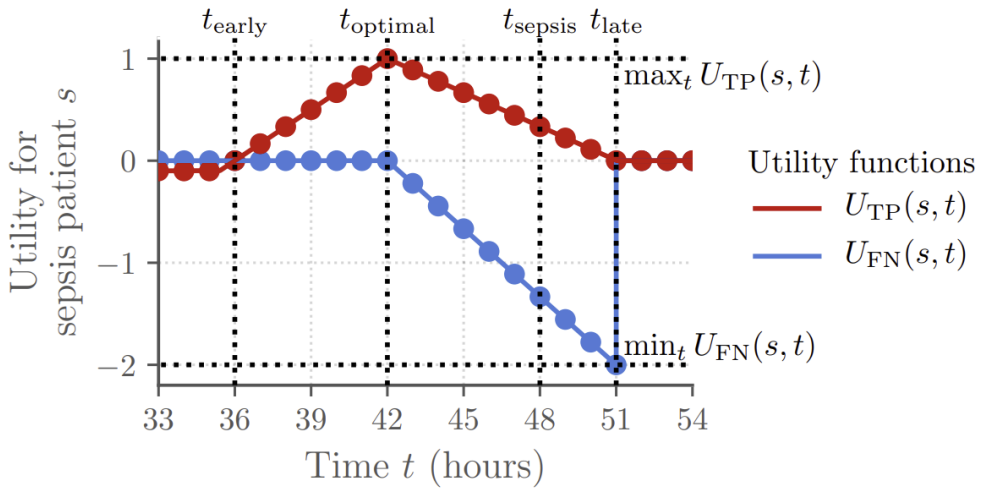


vs

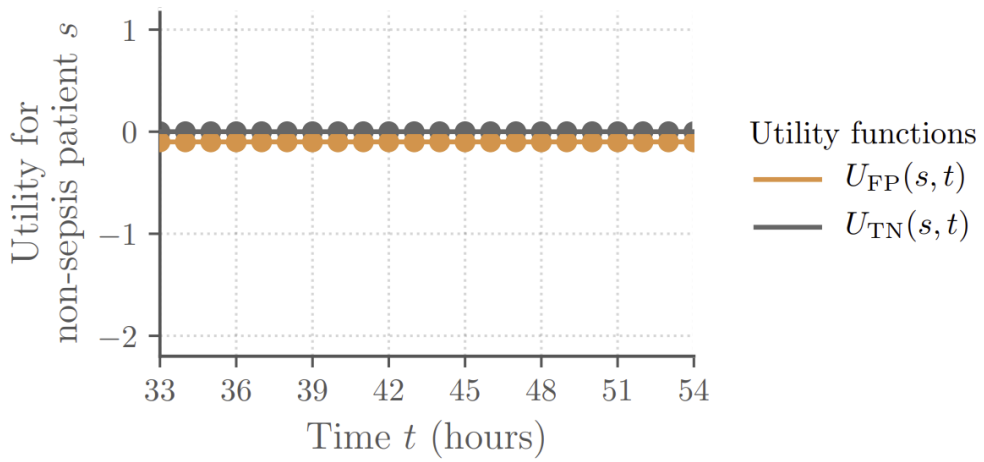


➔ How do we *reward* early sepsis predictions more than late ones and how do we *penalize* missed ones adequately?

Evaluation: Utility Score



(a) Clinical utility for septic patients.



(b) Clinical utility for non-septic patients.

Evaluation

Model(s) create hourly predictions

Patient 0000007 as Example

	PredictedProbability
2	0.5340326920919986
3	0.7573166166875013
4	0.7970109585800176
5	0.7217623506906001
6	0.680362839730447
7	0.7370480555111093
8	0.7654662167703292
9	0.7606485477998423
10	0.7597913835227376
11	0.6931276372372849
12	0.7263450231403222
13	0.7163432308875632
14	0.7129223634757045
15	0.699253567759149
16	0.7015488057939573
17	0.7120288374607344

Standardized Threshold sweep was conducted to find the best threshold

Goal: Optimise for Clinical utility Score

Utility Score

Model which ALWAYS predicts Sepsis
-> Reaches Utility of -**0.60**

Utility Score

Model which NEVER predicts Sepsis
-> Reaches Utility of **0**

Utility Score

Model which NEVER predicts Sepsis
-> Reaches Utility of **0**

Utility Score

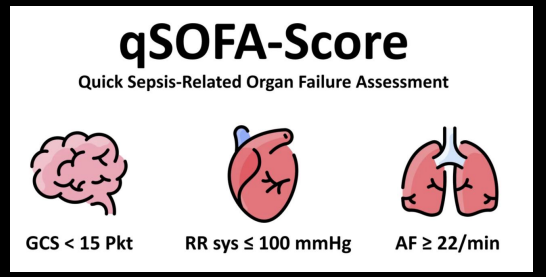
Utility Score

0.6

0.09 — “clinical” qSOFA Model

0 — NEVER Sepsis

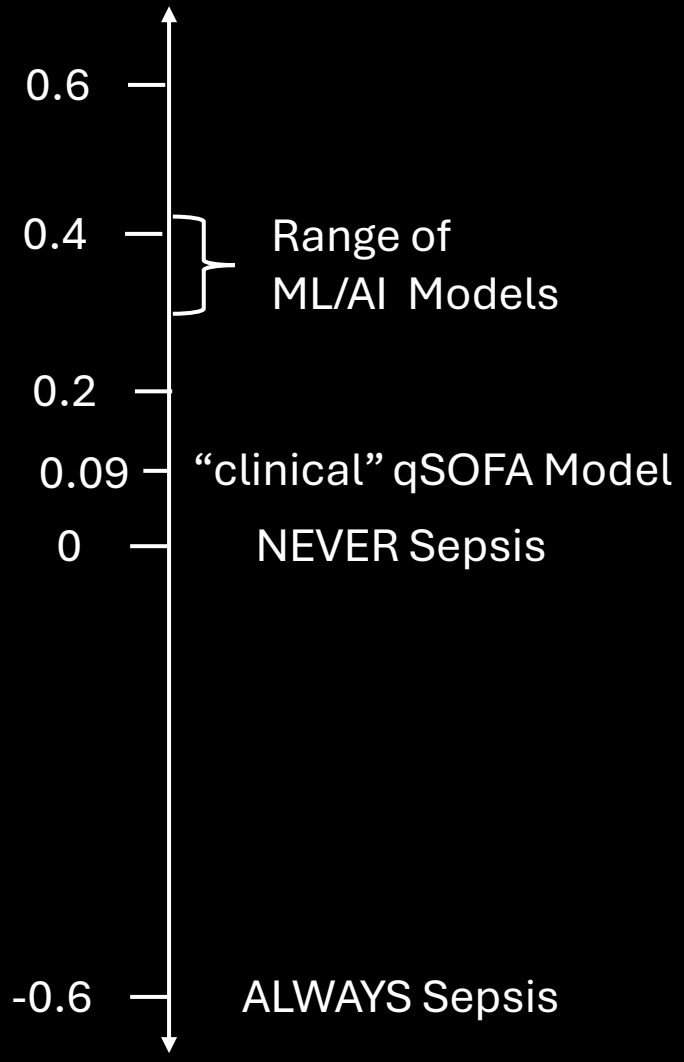
-0.6 — ALWAYS Sepsis



Model based on partial **qSOFA**
-> Reaches Utility of **0.09**

Utility Score

Utility Score



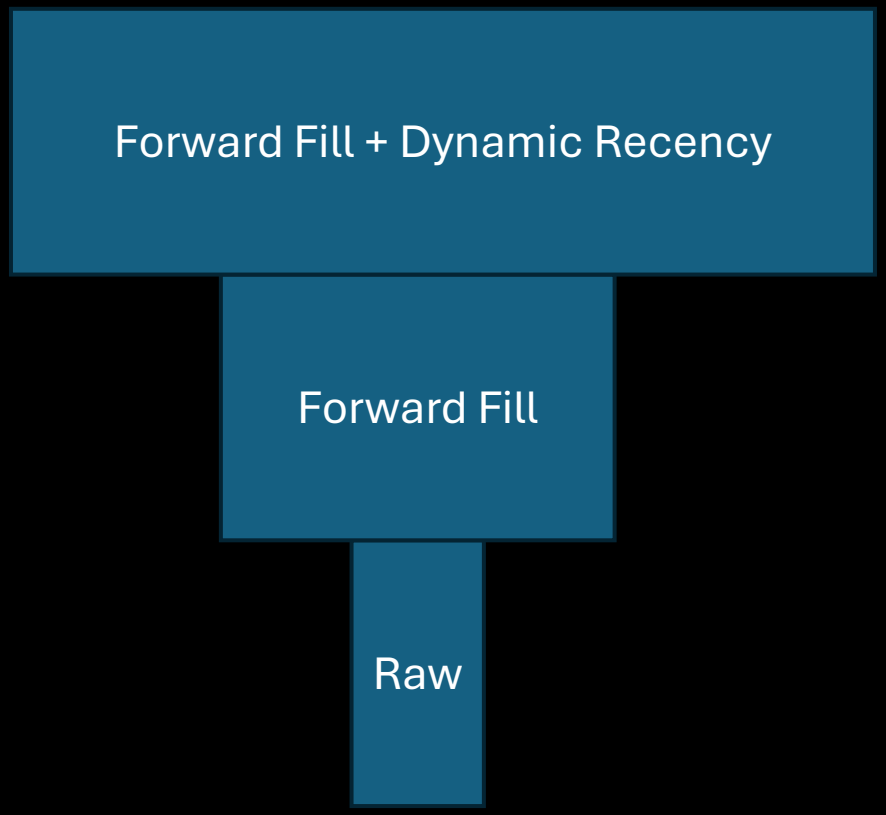
How do ML/AI models perform?

Results

Other evaluated models included:

PatchTST	0.375
Crossformer	0.358
TimesNET	0.333

Results: Data Preprocessing Strategies



	On LightGBM:	On TFT:
High	0.416	0.399
	+0.019	+0.025
Low	0.397	0.374
No	0.384	No loss computable ->No Training possible

Limitations

- **Limited hyperparameter optimization & only single fold:** Deep models were trained with minimal tuning (time/compute constraints) and on a single train/validation split (only LightGBM used 5-fold CV)

- **Regularization trade-offs:** Overfitting was controlled using very strong dropout, gradient clipping and small learning rates. More data would likely improve generalization.

Discussion

LightGBM perfoms better when

- Data is limited
- Data is highly sparse (many missing values) and strongly imbalanced
- Fast training and robustness are prioritized

Temporal Fusion Transformer may perform better when

- Substantially more data is available
- Multimodal inputs are used (e.g., structured data combined with text or image embeddings)
- The task is more complex, (predicting multiple labels instead of a single label)
- Sufficient GPU compute is available

Future Work: Key Question

What are the **most important** improvements to make AI/ML models clinically useful?

Future Work

1

Explainable AI

Make TFT interpretable using built-in attention/feature-importance visualisations to better guide clinicians

2

Add clinical context

Incorporate clinical textual information (e.g. reason of hospital stay) and/or imaging (e.g. chest X-rays) via e.g. the TFT static metadata pathway.

3

Optimise for clinical utility

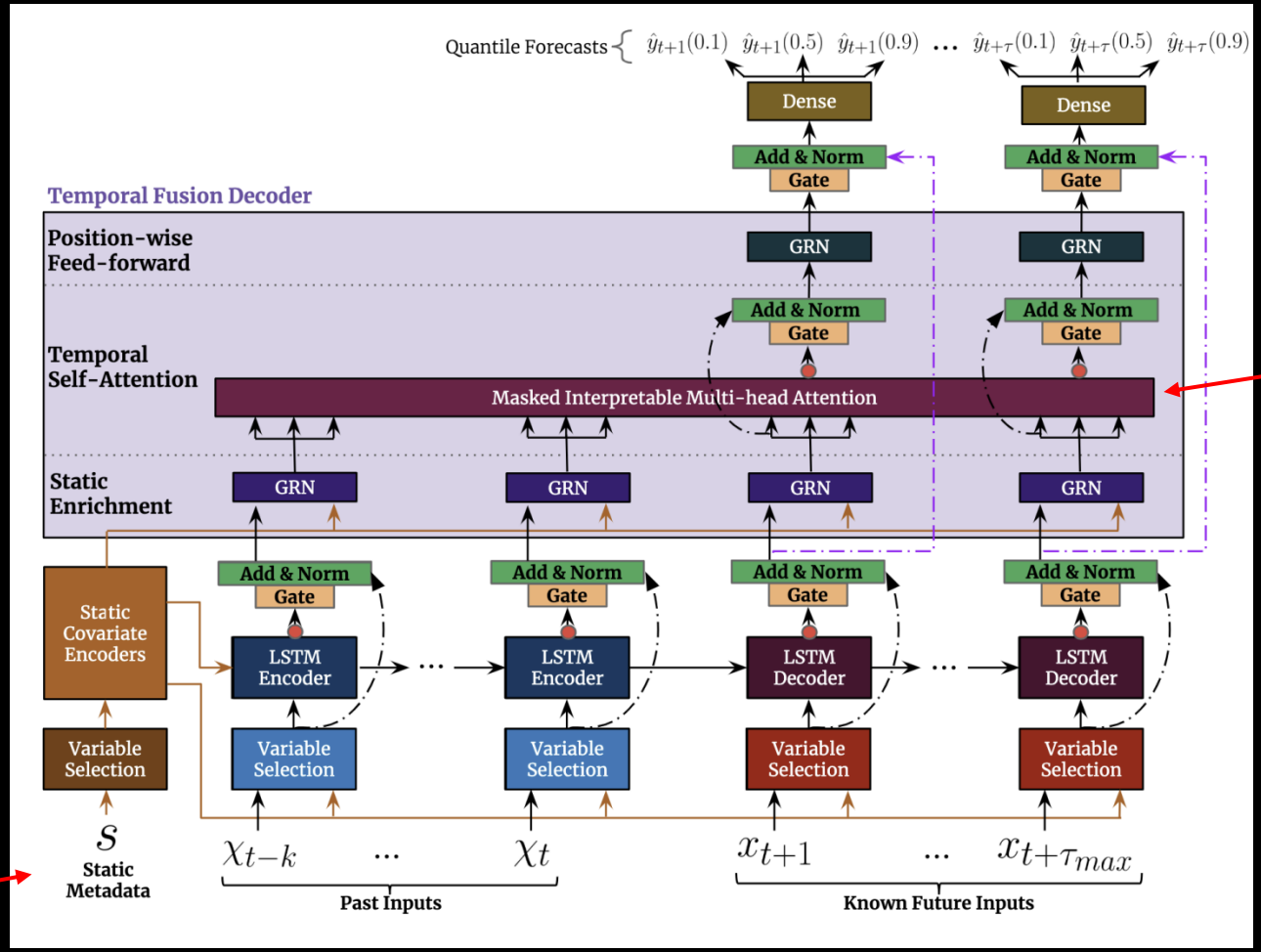
Train end-to-end on the utility score using Reinforcement Learning Approach (instead of probabilities + threshold tuning)

4

Scale data & tasks

Train on **larger datasets** like MIMIC-IV and/or eICU to reduce overfitting and help generalization and **add labels** (e.g., heart failure, ARDS) to improve accuracy.

Model Architecture: Temporal Fusion Transformers



Make attention weights interpretable

Add clinical context (image or text embeddings)

To conclude...

Using AI Prediction Models have the potential to save lives!

Thank you for your attention!

GitHub Link to this project:
https://github.com/LucasNebelung/predicting_sepsis