

# Comprehensive Guidelines and Templates for Thesis Writing

Master's Thesis

of  
Author

Date of issue:  
Date of submission:  
Examiner:  
Supervisor:



# Statutory Declaration

I, Author, hereby affirm that the following Master's thesis has been elaborated solely by myself. No other means and sources except those stated, referenced and acknowledged have been used.

(Author)



# Abstract



# Contents

Statutory Declaration .....	iii
Abstract .....	v
1 List of Notes .....	1
2 Notes .....	3
2.0.1 Kuramoto Parameter .....	3
3 Introduction .....	5
4 Medical Background (Sepsis) .....	7
4.1 Sepsis-3 definition .....	7
4.1.1 Sepsis Classification .....	8
4.2 Biology of Sepsis and Cytokine Storms .....	9
4.3 The need for sepsis prediction .....	10
4.4 Maybe Treatment .....	10
5 Problem definition .....	11
6 The Data and Task problems .....	13
7 State of the Art .....	15
7.1 Model Based Methods .....	15
7.2 Data Based Methods .....	15
7.2.1 Selected Works .....	15
8 Dynamic Network Model (DNM) .....	17
8.1 Description .....	17
8.1.1 Functional Models .....	18
8.1.2 Parenchymal .....	18
8.1.3 Immune System .....	18
8.1.4 Kuramoto .....	18
8.2 Implementation .....	18
8.2.1 Standard .....	19
8.2.2 Lie .....	19
9 Latent Dynamics Model .....	21
9.1 Task - Definition of Ins and Outs .....	21
9.2 Data .....	21
9.2.1 MIMIC-III/IV .....	21
9.2.2 YAIB + (Further) Preprocessing .....	21
9.2.2.1 ricu-Concepts .....	21
9.3 Latent Dynamics Model (LDM) .....	21
9.3.1 The high level ideas .....	21
9.3.1.1 Representation Learning and Latent Spaces .....	21

9.3.1.2	Semantics .....	21
9.3.1.3	Autoregressive Prediction .....	21
9.3.2	The Lookup (FSQ) .....	21
9.3.3	Encoder .....	22
9.3.4	Decoder .....	22
9.3.5	Introducing time .....	22
9.3.6	Combining the building blocks .....	22
10	Metrics (How to validate performance?) .....	25
11	Experimental Results .....	27
11.1	Metrics .....	27
11.2	Further Experiments .....	27
11.2.1	Custom Latent Space .....	27
11.2.2	SOFA vs Infection .....	27
12	Conclusion .....	29
13	Appendix .....	31
	Bibliography .....	32



# Acronyms Index

<b>TUHH:</b>	Hamburg University of Technology
<b>SOFA:</b>	Sequential Organ Failure Assessment
<b>qSOFA:</b>	Quick Sequential Organ Failure Assessment
<b>ICU:</b>	Intensive Care Unit
<b>EHR:</b>	Electronic Health Record
<b>YAIB:</b>	Yet Another ICU Benchmark
<b>FSQ:</b>	Finite Scalar Quantization
<b>SI:</b>	Suspected Infection
<b>ABX:</b>	Antibiotics
<b>DNM:</b>	Dynamic Network Model
<b>LDM:</b>	Latent Dynamics Model
<b>ML:</b>	Machine Learning
<b>DL:</b>	Deep Learning



# 1 List of Notes

<input type="checkbox"/> actual functional model   what is learned   connecting parts .....	13
◦	
<input type="checkbox"/> cite .....	13
◦	
<input type="checkbox"/> Entropy, Splay Ratio, MPV Std, Cluster Ratio .....	13
◦	
<input type="checkbox"/> can we fix please? .....	18
◦	
<input type="checkbox"/> center .....	19
◦	
<input type="checkbox"/> wichtig aber wie verknüpfen? .....	20
◦	
<input type="checkbox"/> Important to finish .....	20
◦	
<input type="checkbox"/> cite .....	21
◦	
<input type="checkbox"/> eher project??? .....	21
◦	
<input type="checkbox"/> End this .....	21
◦	
<input type="checkbox"/> Sepsis ModelingComplex SystemsNetwork Physiology .....	27
◦	
<input type="checkbox"/> table for parameters .....	28
◦	
<input type="checkbox"/> SavingsEqx + diffraxLie .....	28
◦	
<input type="checkbox"/> table .....	32
◦	

- How to structure the latent space? Binary classification (sepsis, no sepsis) may not provide enough information to accurately structure the latent space. The options : Add more classes like resilient/vulnerable... maybe even the full spectrum? need to be modeled by R ..... 32
  -
- mapping not really clear, which metrics correspond to sofa/infection ..... 33
  -
- YAIB and other resources care about the onset of infection and sepsis . For sepsis this isn't really problematic since we could use the state transitions as indicators. But for the suspected infection it is problematic, maybe use si\_upr and si\_lwr provided by ( [https://eth-mds.github.io/ricu/reference/label\\_si.html](https://eth-mds.github.io/ricu/reference/label_si.html) ). These would be 48h - SI - 24h adapted from , maybe a bit too much. .... 33
  -
- caption ..... 41
  -

## 2 Notes

actual functional model what is learned connecting parts

### 2.0.1 Kuramoto Parameter

Kuramoto Order Parameter

$$R_2^\mu = \frac{1}{N} \left| \sum_j^N e^{i \cdot \varphi_j(t)} \right| \quad \text{with } 0 \leq R_2^\mu \leq 1 \quad (1)$$

cite

$R_2^\mu = 0$  splay-state and  $R_2^\mu = 1$  is fully synchronized.

En-  
tropy,  
Splay  
Ratio,  
MPV  
Std,  
Clus-  
ter  
Ratio



## **3 Introduction**





## 4 Medical Background (Sepsis)

As the most extreme course of an infectious disease, sepsis poses a serious health threat, with a high mortality rate and frequent long-term consequences for survivors. In 2017, an estimated 48.9 million people worldwide suffered from sepsis and the same year, 11.0 million deaths were associated with sepsis [1], which makes up 19.7% of yearly deaths. Sepsis is also the most common cause of in-hospital deaths. Untreated, the disease is always fatal and even with successful treatment, around 40% of those affected suffer long-term consequences, such as cognitive, physical or physiological problems, the so called *post-sepsis syndrome* [2]. Overall, treated and untreated septic diseases in particular represent an enormous burden on the global healthcare system.

The triggers for sepsis are varied, but almost half of all sepsis-related deaths occur as a secondary complication of an underlying injury or a non-communicable, also known as chronic disease [3]. A recent study [4] highlights the importance of early recognition and subsequent treatment of infections in patients, reducing the mortality risk caused from sepsis. Each hour of earlier detection can significantly increase the chance of survival [4], it urges to develop accurate and robust detection and prediction methods, i.e. reducing the time to receive the appropriate medical attention.

Per definition, sepsis is a “life-threatening organ dysfunction caused by a dysregulated host response to infection” [5]. There are multiple (now historic) more specific definitions available and sometimes blurry terminology used when dealing with the sepsis and septic shocks. The following Section 4.1 gives a more detailed introduction to the most commonly used sepsis definition, which is referred to as Sepsis-3. Additionally, Section 4.2 provides a short introduction of both the pathology and biology of sepsis and Section 4.3 talks about the need for reliable sepsis prediction systems.

### 4.1 Sepsis-3 definition

Out of the need for an update of an outdated and partly misleading sepsis model a task force led by the “Society of Critical Care Medicine and the European Society of Intensive Care Medicine”, was formed in 2016. Their resolution, named “Third International Consensus Definitions for Sepsis and Septic Shock” [5], provides until today the most widely used sepsis definition and guidance on sepsis identification.

In general, sepsis does not classify as a specific illness, rather a multifaceted condition of “physiologic, pathologic, and biochemical abnormalities” [5], and septic patients are largely heterogeneous. Most commonly the underlying cause of sepsis is diarrhoeal disease, road traffic

injury the most common underlying injury and maternal disorders the most common non-communicable disease causing sepsis [1].

According to the Sepsis-3 definition, a patient is in a septic condition if the following two criteria are fulfilled:

- a documented or Suspected Infection (SI) and
- the presence of a dysregulated host response

The combination of the two criteria represents an exaggerated immune reaction that results in organ dysfunction, when infection is first suspected, even modest organ dysfunction is linked to a 10% increase of in-hospital mortality. A more pathobiological explanation of what a “dysregulated host response” means is given in the next Section 4.2.

**Confirmed or Suspected Infection** is suggested to characterize any patient prescribed with Antibiotics (ABX) followed by the cultivation of body fluids, or the other way around, with a suspected infection. The timings of prescription and fluid samplings play a crucial role. If the antibiotics were administered first, then the cultivation has to be done in the first 24h after first prescription, if the cultivation happened first, the ABX have to be prescribed in the following 72h [5]. This can be seen in the lower part of figure Figure 1, with the abbreviated ABX. Regardless which happened first, the earlier of the two times is treated as the time of suspected infection onset time.

**Dysregulated Host Response** is characterized by the worsening of organ functionality over time. Since there is no gold standard for measuring the amount of “dysregulation” the Sepsis-3 consensus relies on the Sequential Organ Failure Assessment (SOFA)-score introduced in ([5], [6]). The score is now regularly used to evaluate the functionality of organ systems and helps to predict the risk of mortality, also outside of a sepsis context. The SOFA score is calculated at least every 24 hours and assess six different organ systems by assigning a score from 0 (normal function) to 4 (high degree of dysfunction) to each. The overall score is calculated as sum of each individual system. It includes the respiratory system, the coagulation/clotting of blood, i.e. changing from liquid to gel, the liver system, the cardiovascular system, the central nervous system and the renal system/kidney function. A more detailed listing of corresponding markers for each organ assessment can be found in table Table 1 in the Section 13. The magnitude of a patients initial SOFA-score captures preexisting organ dysfunction. An increase in SOFA score  $\geq 2$  corresponds to an acute worsening of organ functionalities and a drastic worsening in the patients condition, the indicator for a dysregulated response.

can  
we fix please

#### 4.1.1 Sepsis Classification

The Sepsis-3 definition not only provides the clinical criteria of septic conditions, but also introduces the necessary time windows for sepsis classification. An increase of SOFA  $\geq 2$  in the 48h before or 24h after the SI time, the so called SI-window, is per Sepsis-3 definition the “sepsis onset time”. A schematic of the timings is shown in figure Figure 1.

With respect to which value the increase in SOFA is measured, i.e. the baseline score, is not clearly stated in the consensus and leaves room for interpretation, commonly used approaches include:

- the minimal value inside the SI-window before the SOFA increase,

- the first value of the SI-window,
- or the lowest value of the 24h previous to the increase.

Differences in definitions greatly influence the detection of sepsis, which are used for prevalence estimates for example [7]. Using the lowest SOFA score as baseline, the increase  $\geq 2$  for patients with inspected infection was associated with an 18% higher mortality rate according to [6] a retrospective Intensive Care Unit (ICU)-data analysis.

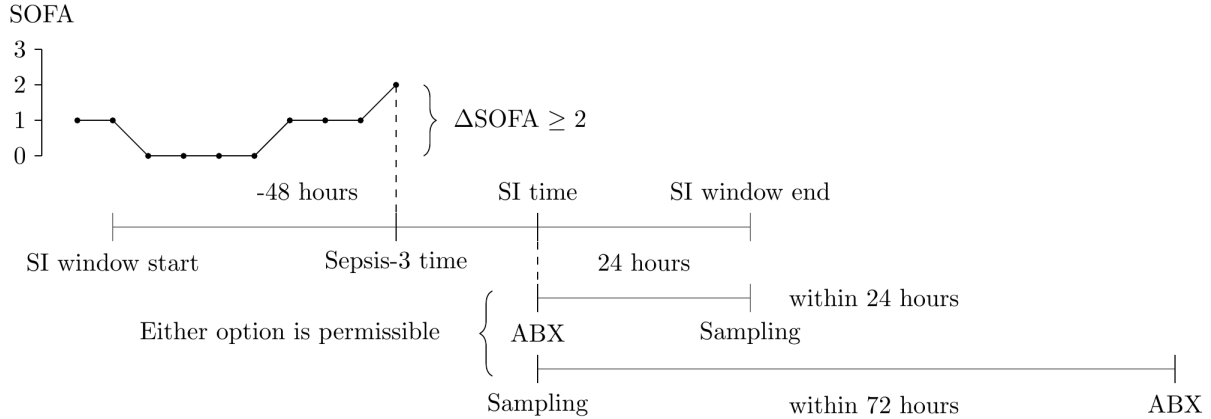


Figure 1: Graphical representation of the timings in the Sepsis-3 definition, taken from [8]

Up until today, even though SOFA was created as a clinical bedside score, some of the markers used in it are not always available to measure or at least not at every 24h [9]. For a faster bedside assessment [6] also introduced a clinical score termed Quick Sequential Organ Failure Assessment (qSOFA), with highly reduced marker number and complexity, it includes:

- Respiratory rate  $\geq 22/\text{min}$
- Altered mentation
- Systolic blood pressure  $\leq 100 \text{ mm Hg}$

Patients fulfilling at least two of these criteria have an increased risk of organ failure. While the qSOFA has a significantly reduced complexity and is faster to assess it is not as accurate as the SOFA score, meaning it has less predictive validity for in-house mortality [6].

center

## 4.2 Biology of Sepsis and Cytokine Storms

The hosts dysregulated response to an infection connected to the septic condition is driven by the release of an unreasonable amount of certain signaling proteins, so called *cytokines* [10]. Cytokines are a broad family of different cells which play a special role in the communication between other, both neighboring and distant, cells [11], this includes immune-cell to immune-cell or immune-cell to other cell types. In the innate immune system, i.e. the body's first line of non-specific defense [12] they regulate the production of anti- and pro-inflammatory immune cells which help with the elimination of pathogens and trigger the healing process right after. They are also involved in the growing process of red and white blood cells.

One specialty of these relatively simple cells is that they can be produced by immune cells or non-immune cells, with different cells being able to produce the same cytokine. Further, cytokines are redundant, meaning targeted cells can show identical responses to different cytokines [13], these features seems to fulfill some kind of safety mechanism to guarantee vital communication flow. After coming to life cytokines have relatively a short half-life (only a

few minutes) but through cascading-effects the cytokines can have substantial impact on their micro-environment.

Normally, the release of inflammatory cytokines automatically fades out once the initial pathogen is controlled. In certain scenarios a disturbance to the regulatory mechanisms triggers a chain reaction, followed by a massive release of cytokines. It is further coupled with self-reinforcement of other regulatory mechanisms [10], leading to a continuous and uncontrolled release of cytokines that fails to shut down. This overreaction, called *cytokine storm*, is often harmful to the hosts body and can lead to multi organ failure, like in sepsis, and subsequently death. In these cases, the damage done by the immune system's reaction is magnitudes greater than the triggering infection itself.

Even though the quantity of cytokines roughly correlates with disease severity, concentrations of cytokines vary between patients and even different body-parts making a distinction between an appropriate reaction and a harmful one almost impossible [10]. Out of all cytokines, only a very small subset or secondary markers can be measured blood samples to evaluate increased cytokine activity. This makes them hard to study and little useful as direct indicators of pathogenesis or prediction purposes. Since the 90s there has been a lot of research focused on cytokines and their role in the innit immune system and overall activation behavior. But to this day no breakthrough has been done and underlying principles have not been uncovered.

Another branch of research, the study of “omics”, such as cytomics, genomics, epigenomics, transcriptomics, proteomics, and metabolomics, was very recently able to homogenize the pathologies of sepsis but to unfold their full potential larger scale studies are still necessary [14].

TODO[ What happens with the organs in the storm? What about parenchymal cells?]

wichtig  
aber  
wie verknü

### 4.3 The need for sepsis prediction

Important to finish

### 4.4 Maybe Treatment

## 5 Problem definition

This section provides some background on the specific research questions which are investigated in Section 11 using the methods introduced in Section 8 and Section 9 respectively. As discussed in Section 4.3, there is a substantial need for robust methods to identify patients sepsis onset and overall progression. This work provides a proof of concept for such a prediction system.

The increasing availability of high-quality medical data, i.e. multiple physiological markers with high temporal resolution, enables both classical statistical and Machine Learning (ML) (including Deep Learning (DL)) methods (see Section 7). While these purely data-driven approaches often achieve acceptable performance but the explainability of the prediction suffers and limits their adoption in clinical practice .

In parallel, recent advances in the field of network physiology have introduced new ways to model physiological systems as interacting subsystems rather than isolated organs [15]. The Dynamic Network Model (DNM) introduced in [16], allows for a functional description of organ failure in sepsis and shows realistic system behavior in preliminary analysis. An in-depth introduction to the DNM is provided in Section 8. But up until now the dynamic model has not yet been verified on real data, in this work we want to change that. However, this model has not yet been validated against real-world observations, which will be addressed in this work .

To summarize, the specific research questions include:

- **Usability of the DNM:** How and to what extent can the ML-determined trajectories of the DNM be used for detection and prediction, especially of critical infection states and mortality.
- **Comparison with data-based approaches:** How can the model-based predictions be compared with those of purely data-based approaches in terms of predictive power and interpretability.

End this

cite

her  
project???



## 6 The Data and Task problems

In [17], a survey among clinicians regarding AI-assistance in healthcare, one participant emphasizes that specific vitals signs might not be to be of less importance, rather the change/trend of a patients trajectory. Another piece of finding of the same study was the preference of trajectories over plain event predictions.

Figure 2: Sets of [18]

RICU and YAIB use `delta_cummin` function, i.e. the delta SOFA increase is calculated with respect to the lowest observed SOFA to this point.





## **7 State of the Art**

### **7.1 Model Based Methods**

### **7.2 Data Based Methods**

#### **7.2.1 Selected Works**



## 8 Dynamic Network Model (DNM)

- Sepsis Modeling
- Complex Systems
- Network Physiology

As outlined in Section 4, the macroscopic multi-organ failure associated with sepsis is driven by a dysregulated cascade of signaling processes on a microscopic level (see Section 4.2). This involves a massive amount of interconnected components, where the connections mechanics and strenghts can vary over time and space. The interactions can differ substantially between tissues and as sepsis progresses, biochemical thresholds change the behavior of cells [19]. In essence, cell-to-cell and cell-to-organ interaction in septic conditions involve highly dynamic, nonlinear and spatio-temporal relationships [20], which cannot be fully understood by a reduction to single time-point analyzes. While many individual elements of the process are understand in isolation, we still fail to capture the complete picture.

To address these challenges “Network Physiology” provides the necessary tools. It enables the study of human physiology as a complex, integrated system, where emergent dynamics arise from interactions that cannot be explained by their individual parts alone. Rather than focusing on the isolated elements, Network Physiology focuses on the coordination and inter-connection among the diverse organ systems and sub-systems [15]. This approach translates to the mesoscopic level, i.e. the in-between, of the human body, trying to capture the interactions that collectively determine the overall physiological function.

The Parenchymal (Equation 2.1<sup>°</sup> and Equation 2.2<sup>°</sup>) and Immune (Equation 2.3<sup>°</sup> and Equation 2.4<sup>°</sup>) layer and their respective states of the dynamical system naturally are consistent with the two cornerstones of the Sepsis-3 definition [5], i.e. SOFA score and suspicion of an infection.

Healthy  $\rightarrow$  sync  $\langle \dot{\varphi}_j^1 \rangle$  and  $\langle \dot{\varphi}_j^1 \rangle$

SOFA  $\rightarrow$  desync  $\langle \dot{\varphi}_j^1 \rangle$

Suspected infection  $\rightarrow$  splay/desync  $\langle \dot{\varphi}_j^2 \rangle$

septic  $\rightarrow$  desync  $\langle \dot{\varphi}_j^1 \rangle$  and  $\langle \dot{\varphi}_j^1 \rangle$

### 8.1 Description

$$\dot{\varphi}_i^1 = \omega^1 - \frac{1}{N} \sum_{j=1}^N \{ (a_{ij}^1 + \kappa_{ij}^1) \sin(\varphi_i^1 - \varphi_j^1 + \alpha^{11}) \} - \sigma \sin(\varphi_i^1 - \varphi_i^2 + \alpha^{12}) \quad (2.1)$$

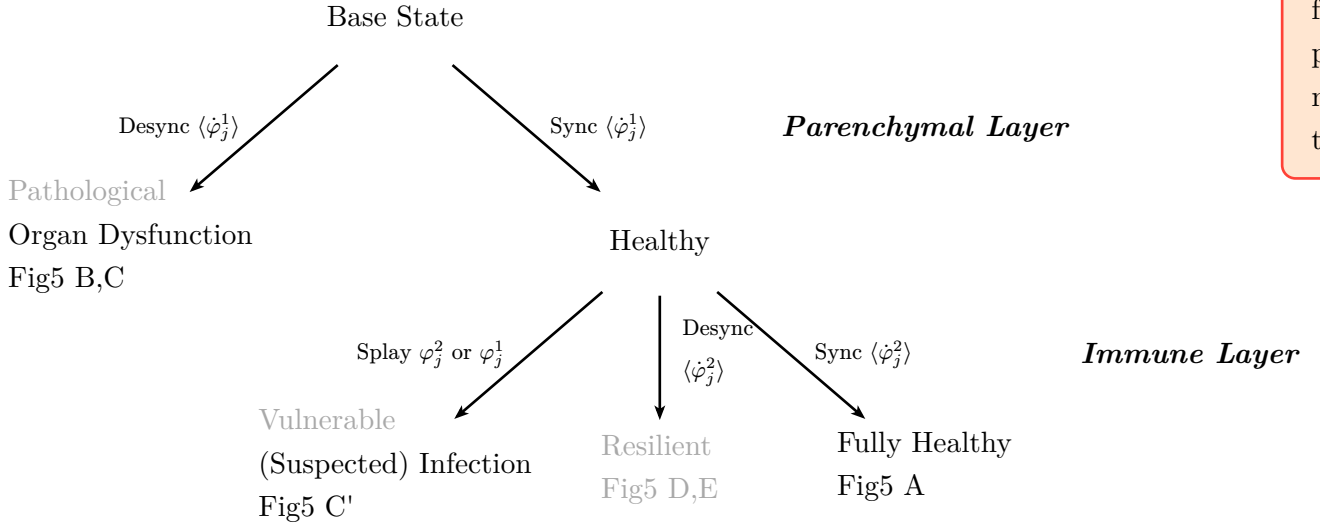
$$\dot{\kappa}_{ij}^1 = -\varepsilon^1(\kappa_{ij}^1 + \sin(\varphi_i^1 - \varphi_j^1 - \beta)) \quad (2.2)$$

$$\dot{\varphi}_i^2 = \omega^2 - \frac{1}{N} \sum_{j=1}^N \kappa_{ij}^2 \sin(\varphi_i^2 - \varphi_j^2 + \alpha^{22}) - \sigma \sin(\varphi_i^2 - \varphi_i^1 + \alpha^{21}) \quad (2.3)$$

$$\dot{\kappa}_{ij}^2 = -\varepsilon^2(\kappa_{ij}^2 + \sin(\varphi_i^2 - \varphi_j^2 - \beta)) \quad (2.4)$$

Introduced in [16] and slightly adapted in [21].

table  
for  
para-  
me-  
ters



Mean Phase Velocities are calculated as followed:

$$\langle \varphi^\mu \rangle = \frac{1}{N} \sum_j^N \varphi_j^\mu \quad (3)$$

### 8.1.1 Functional Models

### 8.1.2 Parenchymal

### 8.1.3 Immune System

### 8.1.4 Kuramoto

## 8.2 Implementation

- Savings
- Eqx + diffrax
- Lie

For parts in the form of  $\sin(\theta_l - \theta_m)$  following [22] one can calculate and cache the terms  $\sin(\theta_l), \sin(\theta_m), \cos(\theta_l), \cos(\theta_m)$  in advance:

$$\sin(\theta_l - \theta_m) = \sin(\theta_l) \cos(\theta_m) - \cos(\theta_l) \sin(\theta_m) \quad \forall l, m \in \{1, \dots, N\} \quad (4)$$

so the computational cost for the left-hand side for  $N$  oscillators can be reduced from  $N(N - 1)$  to  $4N$  trigonometric function evaluations, positively impacting the computational efficiency of the whole ODE-system significantly.

### 8.2.1 Standard

- Actual Mean Phase Velocity instead of averaged difference over time.
- +They Calculate the difference wrong since the phase difference should be  $\text{mod}[2\pi]$
- Different solver accuracy, but very similar
- They are not batching the computation

### 8.2.2 Lie



## 9 Latent Dynamics Model

### 9.1 Task - Definition of Ins and Outs

### 9.2 Data

#### 9.2.1 MIMIC-III/IV

#### 9.2.2 YAIB + (Further) Preprocessing

##### 9.2.2.1 ricu-Concepts

### 9.3 Latent Dynamics Model (LDM)

#### 9.3.1 The high level ideas

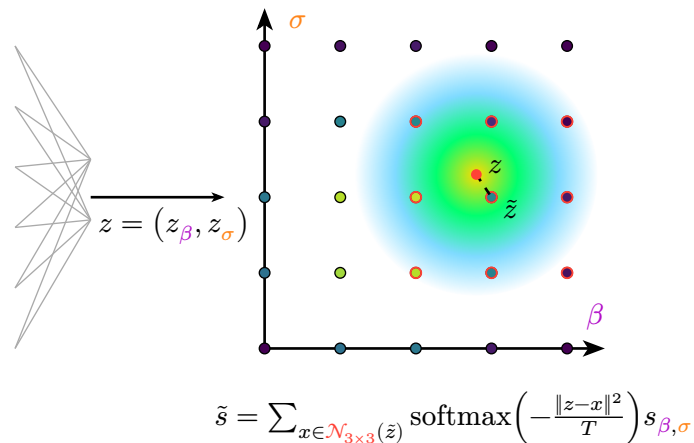
##### 9.3.1.1 Representation Learning and Latent Spaces

##### 9.3.1.2 Semantics

##### 9.3.1.3 Autoregressive Prediction

#### 9.3.2 The Lookup (FSQ)

Quantized Latent-Lookup  
with Gaussian Kernel Smoothing



### 9.3.3 Encoder

### 9.3.4 Decoder

### 9.3.5 Introducing time

### 9.3.6 Combining the building blocks

For a general model setup, the latent space  $z = (a^1, \sigma, \alpha, \beta, \omega^1, \omega^2, \frac{C}{N}, \varepsilon^1, \varepsilon^2)$  represents the parameter of the dynamic network model, so we have

$$z \in \mathbb{R}^d \quad \text{with } d = 9 \quad (5)$$

As shown in the supplemental material of [21], for example, the parameter  $\alpha$  exhibits a  $\pi$ -periodicity, allowing to reduce the effective parameter space by constraining certain parameters with upper and lower bounds. These bounds are omitted here for simplicity but are included in . To further reduce the latent space  $z$ , the we keep  $a^1, \omega^1, \omega^2, \frac{C}{N}, \varepsilon^1$  and  $\varepsilon^2$  fixed. The reduced latent space  $z' = (\sigma, \alpha, \beta)$ :

$$z' \in \mathbb{R}^{d'} \quad \text{with } d' = 3 \quad (6)$$

where both alpha and beta exhibit a periodic behavior Each point in the latent space  $z_j$  can be categorized as either of *healthy*, *vulnerable* or *pathological*.

We relate high-dimensional physiological observations (e.g. samples from the MIMIC-III database) to the latent space via:

$$x_j = f(z_j) + \varepsilon \quad (7)$$

where  $f$  is unknown an unknown function and  $\varepsilon$  the measurement noise. Note that different observations  $x_j$  can be mapped to the same classification, as for the latent space. We define two the two class mappings  $Q$  and  $R$ :

$$Q(x_j) = c_j = R(z_j) \quad \text{where } x_j = f(z_j) + \varepsilon \quad (8)$$

mapping observations and the latent representation to a shared class label  $c$ . To make things more complicated,  $R$  does not directly act on  $z$ , but rather the metrics derived from the solution to a dynamical system (initial value problem) (Equation 2) parameterized by  $z$ . The metrics are detailed in.

In the setting of structured latent variational learning we want to approximate an encoder  $q(z|x)$  to infer the latent variables from observed data  $X$  and the class.

**How to structure the latent space?** Binary classification (sepsis, no sepsis) may not provide enough information to accurately structure the latent space. The options:

- Add more classes like resilient/vulnerable... maybe even the full spectrum?
  - need to be modeled by  $R$

For the cohort extraction and SOFA calculation I use [23] and [18]. The nice thing is we could interpret larger SOFA scores ( $> 3$ ) as the vulnerable state introduced by [21]. Increases in SOFA score  $\geq 2$  could then be used as definition for sepsis.



mapping not really clear, which metrics correspond to sofa/infection

YAIB [18] and other resources care about the “onset” of infection and sepsis [24]. For sepsis this isn’t really problematic since we could use the “state transitions” as indicators. But for the suspected infection it is problematic, maybe use si\_upr and si\_lwr provided by [23] ([https://eth-mds.github.io/ricu/reference/label\\_si.html](https://eth-mds.github.io/ricu/reference/label_si.html)<sup>o</sup>). These would be 48h - SI - 24h adapted from [25], maybe a bit too much.



## **10 Metrics (How to validate performance?)**



## **11 Experimental Results**<sub>placeholder</sub>

### **11.1 Metrics**

### **11.2 Further Experiments**

#### **11.2.1 Custom Latent Space**

#### **11.2.2 SOFA vs Infection**



## 12 Conclusion





## 13 Appendix

CATEGORY	INDICATOR	1	2	3	4
Respiration	PaO <sub>2</sub> /FiO <sub>2</sub> [mmHg]	< 400	< 300	< 200	< 100
	Mechanical Ventilation			yes	yes
Coagulation	Platelets [ $\times \frac{10^3}{\text{mm}^3}$ ]	< 150	< 100	< 50	< 20
Liver	Bilirubin [ $\frac{\text{mg}}{\text{dl}}$ ]	1.2-1.9	2.0-5.9	6.0-11.9	> 12.0
Cardiovascular <sup>1</sup>	MAP [mmHg]	< 70			
	or Dopamine		$\leq 5$	> 5	> 15
	or Dobutamine		any dose		
	or Epinephrine			$\leq 0.1$	> 0.1
	or Noepinephrine			$\leq 0.1$	> 0.1
Central Nervous System	Glasgow Coma Score	13-14	10-12	6-9	< 6
Renal	Creatinine [ $\frac{\text{mg}}{\text{dl}}$ ]	1.2-1.9	2.0-3.4	3.5-4.9	> 5.0
	or Urine Output [ $\frac{\text{ml}}{\text{day}}$ ]			< 500	< 200

cap-  
tion

<sup>1</sup>Adrenergica agents administered for at least 1h (doses given are in [ $\mu\text{g}/\text{kg} \cdot \text{min}$ ])

# Bibliography

- [1] K. E. Rudd and et al., “Global, regional, and national sepsis incidence and mortality, 1990–2017: analysis for the Global Burden of Disease Study,” *The Lancet*, vol. 395, no. 10219, pp. 200–211, 2020, doi: 10.1016/S0140-6736(19)32989-7<sup>◦</sup>.
- [2] E. C. van der Slikke, A. Y. An, R. E. Hancock, and H. R. Bouma, “Exploring the pathophysiology of post-sepsis syndrome to identify therapeutic opportunities,” *EBioMedicine*, vol. 61, p. 103044, 2020, doi: 10.1016/j.ebiom.2020.103044<sup>◦</sup>.
- [3] C. Fleischmann-Struzek, D. Schwarzkopf, and K. Reinhart, “Inzidenz der Sepsis in Deutschland und weltweit: Aktueller Wissensstand und Limitationen der Erhebung in Abrechnungsdaten,” *Medizinische Klinik - Intensivmedizin und Notfallmedizin*, vol. 117, no. 4, pp. 264–268, May 2022, doi: 10.1007/s00063-021-00777-5<sup>◦</sup>.
- [4] C. W. Seymour *et al.*, “Time to Treatment and Mortality during Mandated Emergency Care for Sepsis,” *The New England Journal of Medicine*, vol. 376, pp. 2235–2244, Jun. 2017, doi: 10.1056/NEJMoA1703058<sup>◦</sup>.
- [5] M. Singer *et al.*, “The Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3),” *JAMA*, vol. 315, no. 8, pp. 801–810, Feb. 2016, doi: 10.1001/jama.2016.0287<sup>◦</sup>.
- [6] J. L. Vincent *et al.*, “The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure. On behalf of the Working Group on Sepsis-Related Problems of the European Society of Intensive Care Medicine,” *Intensive care medicine*, vol. 22, no. 7, pp. 707–710, 1996.
- [7] A. E. W. Johnson *et al.*, “A Comparative Analysis of Sepsis Identification Methods in an Electronic Database,” *Critical Care Medicine*, vol. 46, no. 4, pp. 494–499, Apr. 2018, doi: 10.1097/CCM.0000000000002965<sup>◦</sup>.
- [8] N. Bennett, D. Plöcko, and I.-F. Ukor, “Sepsis 3 label — sep3.” 2025.
- [9] R. Moreno *et al.*, “The Sequential Organ Failure Assessment (SOFA) Score: has the time come for an update?,” *Critical Care*, vol. 27, no. 1, p. 15, Jan. 2023, doi: 10.1186/s13054-022-04290-9<sup>◦</sup>.
- [10] D. Jarczак and A. Nierhaus, “Cytokine Storm—Definition, Causes, and Implications,” *International Journal of Molecular Sciences*, vol. 23, no. 19, 2022, doi: 10.3390/ijms231911740<sup>◦</sup>.
- [11] J. Zhang and J. An, “Cytokines, inflammation, and pain,” *Int Anesthesiol Clin*, vol. 45, no. 2, pp. 27–37, 2007, doi: 10.1097/AIA.0b013e318034194e<sup>◦</sup>.
- [12] “Innate Immune System.” Wikipedia, The Free Encyclopedia.
- [13] R. V. House and J. Descotes, Eds., *Cytokines in Human Health: Immunotoxicology, Pathology, and Therapeutic Applications*, 1st ed. in *Methods in Pharmacology and Toxicology*. Totowa, N.J.: Humana Press, 2007.
- [14] S. Isac *et al.*, “The Omics Complexity in Sepsis: The Limits of the Personalized Medicine Approach,” *J. Pers. Med.*, vol. 14, no. 3, p. 225, 2024, doi: 10.3390/jpm14030225<sup>◦</sup>.
- [15] P. C. Ivanov, “The New Field of Network Physiology: Building the Human Physiome,” *Frontiers in Network Physiology*, 2021, doi: 10.3389/fnetp.2021.711778<sup>◦</sup>.

- 
- [16] J. Sawicki, R. Berner, T. Löser, and E. Schöll, “Modeling Tumor Disease and Sepsis by Networks of Adaptively Coupled Phase Oscillators,” *Frontiers in Network Physiology*, vol. 1, 2022, doi: 10.3389/fnetp.2021.730385<sup>◦</sup>.
  - [17] B. Eini-Porat, O. Amir, D. Eytan, and U. Shalit, “Tell me something interesting: Clinical utility of machine learning prediction models in the ICU,” *Journal of Biomedical Informatics*, vol. 132, p. 104107, 2022, doi: 10.1016/j.jbi.2022.104107<sup>◦</sup>.
  - [18] R. van de Water, H. N. A. Schmidt, P. Elbers, P. Thorat, B. Arnrich, and P. Rockenschaub, “Yet Another ICU Benchmark: A Flexible Multi-Center Framework for Clinical ML,” in *The Twelfth International Conference on Learning Representations*, Oct. 2024.
  - [19] R. E. Callard, A. J. T. George, and J. Stark, “Cytokines, chaos, and complexity,” *Immunity*, vol. 11, no. 5, pp. 507–513, Nov. 1999, doi: 10.1016/s1074-7613(00)80125-9<sup>◦</sup>.
  - [20] A. Schuurman, P. Sloot, W. Wiersinga, and et al., “Embracing complexity in sepsis,” *Crit Care*, vol. 27, no. 1, p. 102, 2023, doi: 10.1186/s13054-023-04374-0<sup>◦</sup>.
  - [21] R. Berner, J. Sawicki, M. Thiele, T. Löser, and E. Schöll, “Critical Parameters in Dynamic Network Modeling of Sepsis,” *Frontiers in Network Physiology*, vol. 2, 2022, doi: 10.3389/fnetp.2022.904480<sup>◦</sup>.
  - [22] T. Böhle, C. Kuehn, and M. Thälhammer, “On the reliable and efficient numerical integration of the Kuramoto model and related dynamical systems on graphs,” *International Journal of Computer Mathematics*, vol. 99, no. 1, pp. 31–57, 2022, doi: 10.1080/00207160.2021.1952997<sup>◦</sup>.
  - [23] N. Bennett, D. Plečko, I.-F. Ukor, N. Meinshausen, and P. Bühlmann, “ricu: R’s interface to intensive care data,” *GigaScience*, vol. 12, p. giad41, 2023.
  - [24] M. Moor, B. Rieck, M. Horn, C. R. Jutzeler, and K. Borgwardt, “Early Prediction of Sepsis in the ICU Using Machine Learning: A Systematic Review,” *Frontiers in Medicine*, 2021, doi: 10.3389/fmed.2021.607952<sup>◦</sup>.
  - [25] C. W. Seymour *et al.*, “Assessment of Clinical Criteria for Sepsis: For the Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3),” *JAMA*, vol. 315, no. 8, pp. 762–774, 2016, doi: 10.1001/jama.2016.0288<sup>◦</sup>.