Improving length of stay prediction using a hidden Markov model

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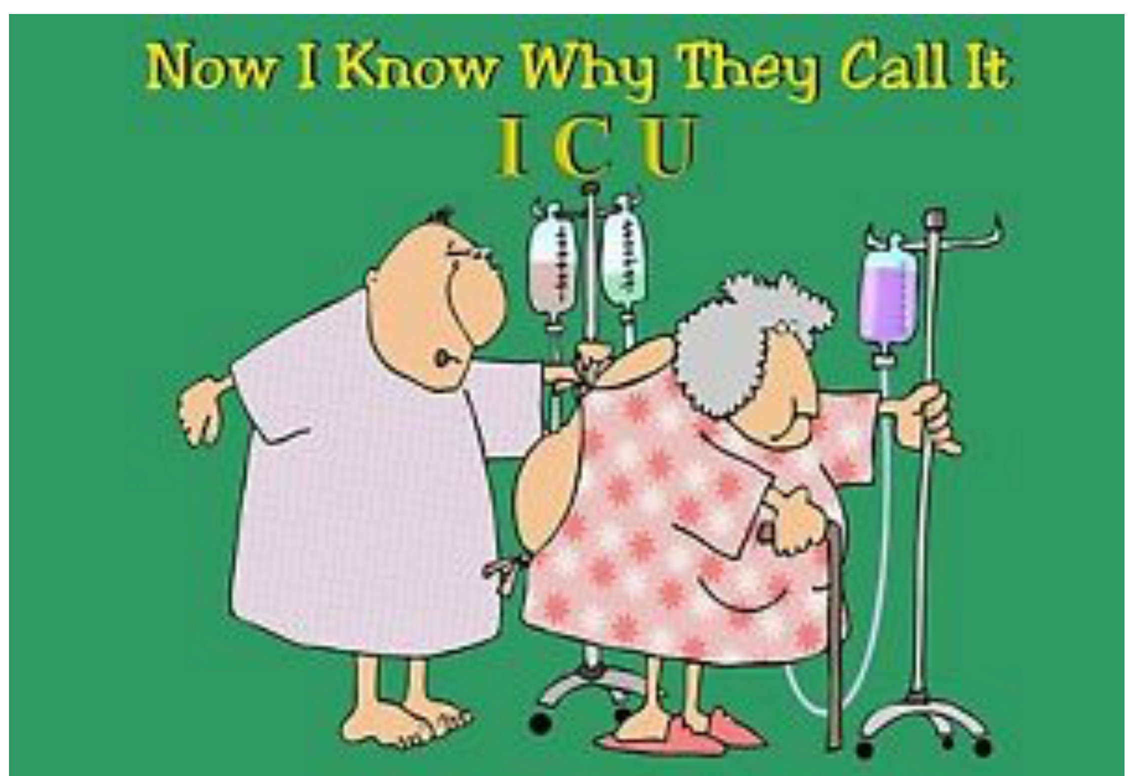


Motivation

- Length of stay significance
  - Intervention to prevent adverse outcomes in patients
  - Optimization of resource allocation (equipments and beds)
  - Allocation of staff and care to high risk patients
  - Improving patients satisfaction and hospitals reputation
- Most of the previous work is on classification rather than regression
- Track multiple physiologic measurements and their interactions over time
- States may be later be interpretable by physicians
- Physician can predict short or long staying patients only half of the time

Problem Statement

- **Input** : physiological measurements throughout time for 48 hours
  - Blood pressure, temperature, heart rate, Glasgow Coma Score, serum glucose, white blood cell count urine output.
- **Output** : Length of stay in ICU in days (Regression)

Properties of dataset

- 4000 patients
- General descriptors including age and gender as well as 37 different physiological measurements

Feature	Avg. update frequency (minutes)	Average # of observations	% of missing values
Glasgow Coma Scale	1039.85	13.26	1.6
Temperature	223.30	16.13	1.6
Heart Rate	63.29	46.48	1.6
White Blood Cell Count	1023.42	2.63	1.8
Serum Glucose	968.04	2.72	2.8
Urine output	113.54	28.65	2.9
NIDiasABP	112.21	21.73	12.7

Baseline models

- Min, Max, Mean, First and Last for each of the 7 variables
  - 35 in total
- five common regression models: LASSO regression, ridge regression, Poisson regression, binomial regression, and support vector regression (SVR)

HMM model Overview

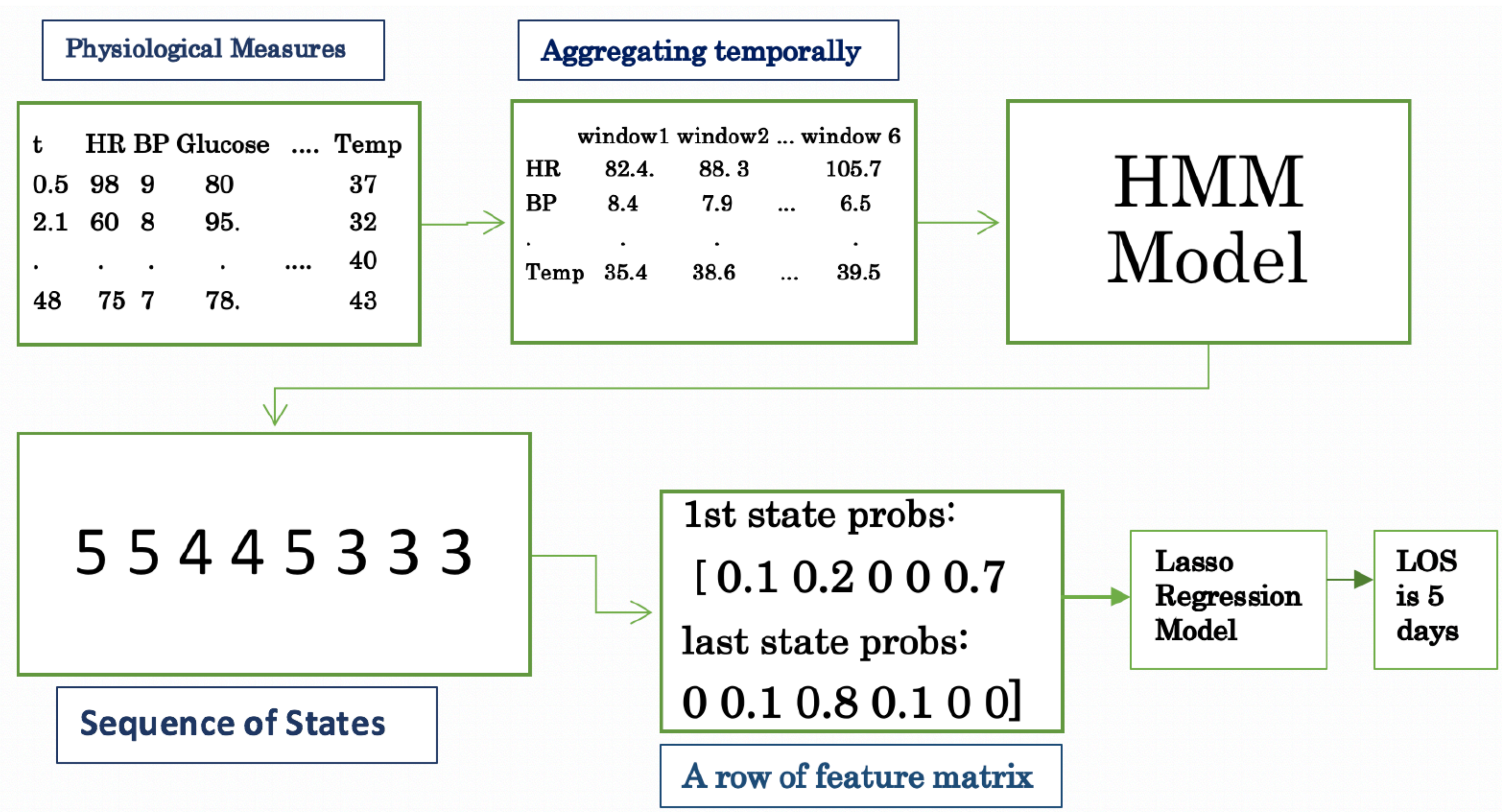
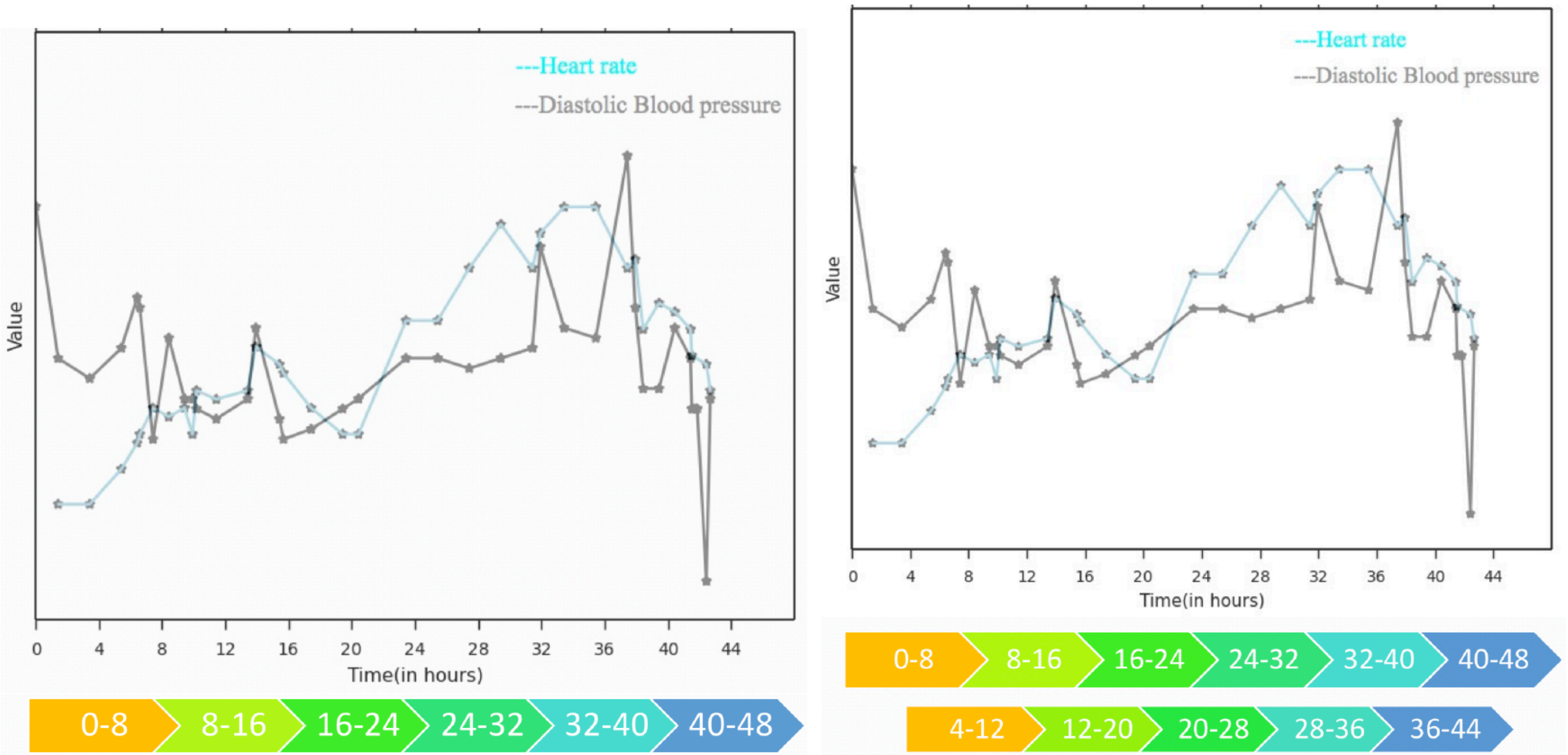


Figure 1: Steps involved in the prediction of length of stay of a given patient using HMM model with five states, and time resolution = eight hours

Visualization of Data for a single patient



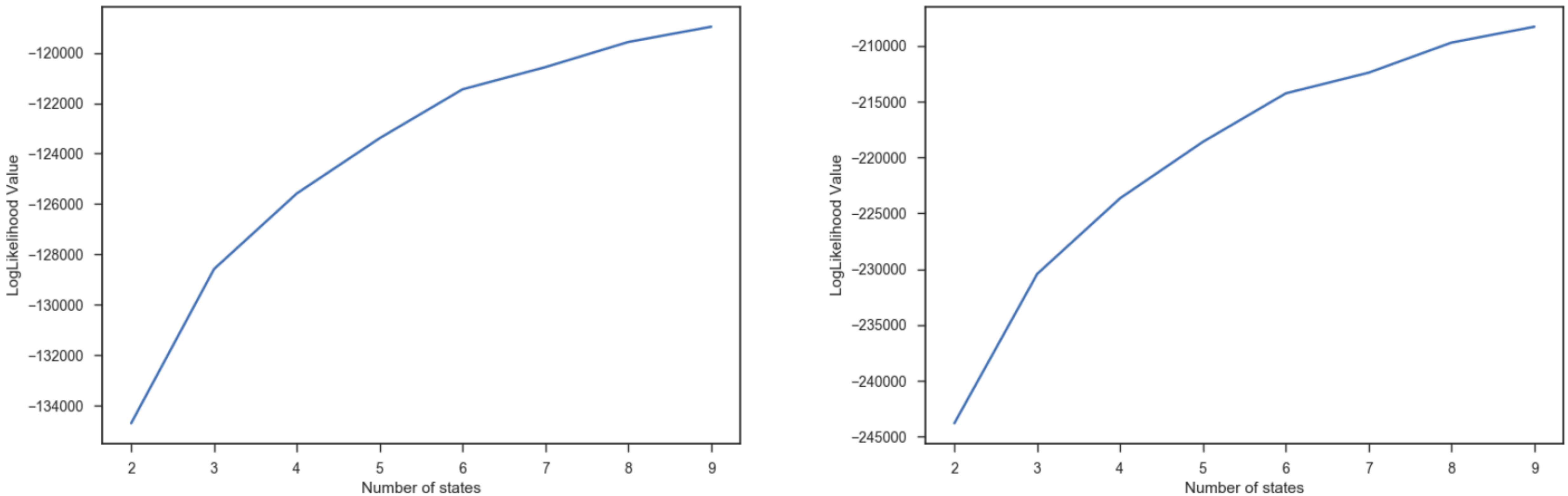
(a) Non-overlapping time windows **(b)** Overlapping time windows

Figure 2: Example of time windows with time resolution = 8 hours for a given patient in the dataset

Design choices

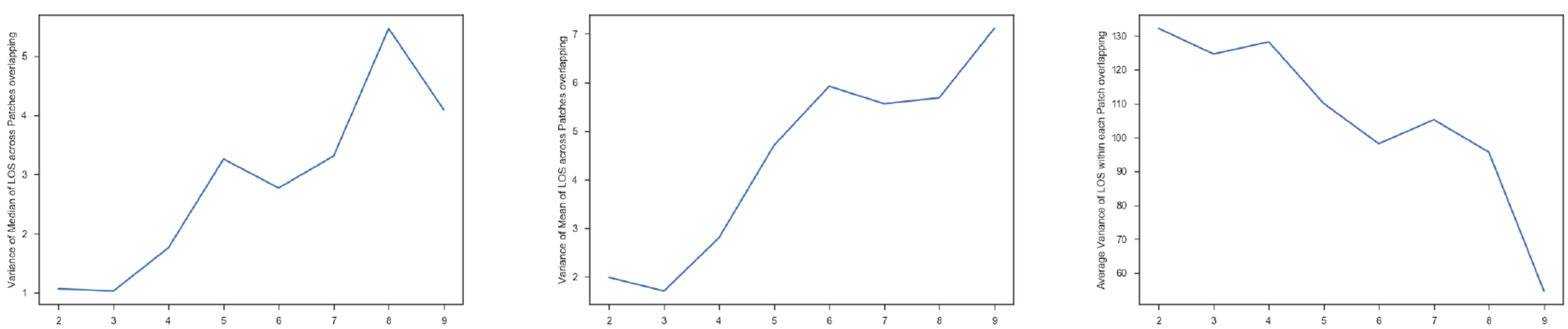
- Number of states
- Overlapping or non-overlapping time windows
- Time Resolution
- Stability of results

Optimum # of states



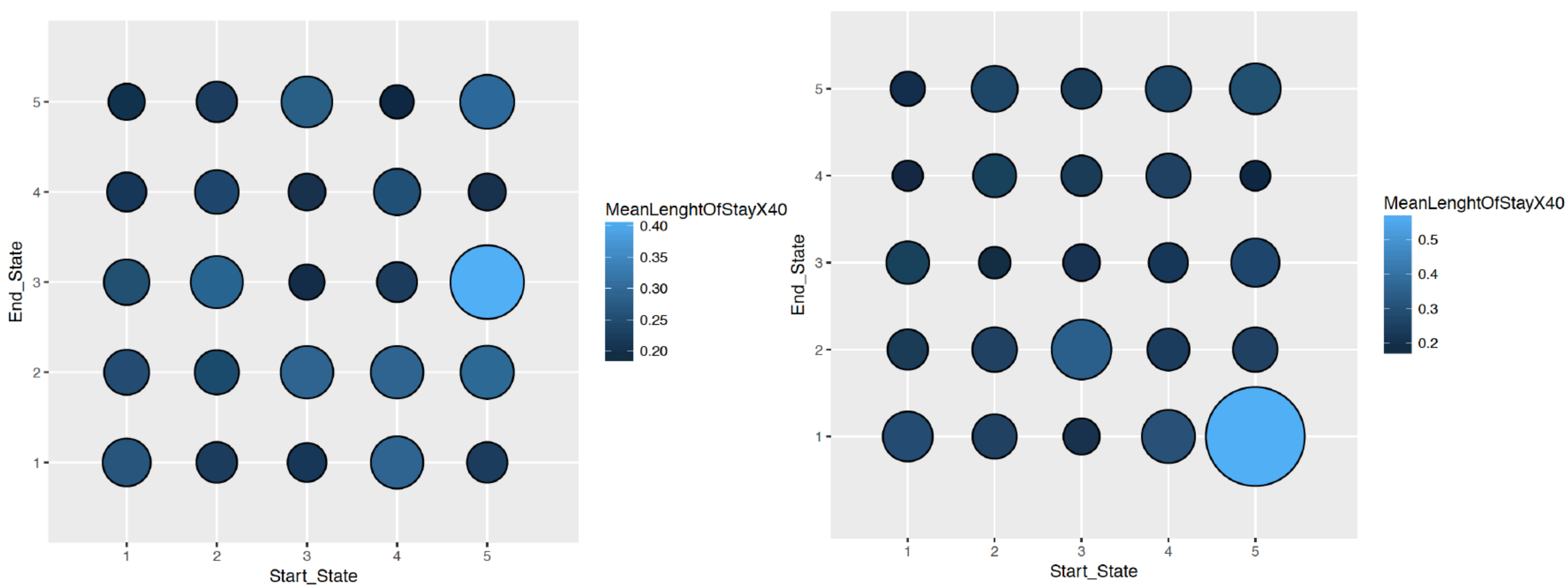
(a) Non-overlapping time windows **(b)** Overlapping time windows

Figure 3: Value of likelihood function vs number of states



(a) Median LOS across start-end pairs **(b)** Mean LOS across start-end pairs **(c)** Avg. variance within start-end pairs

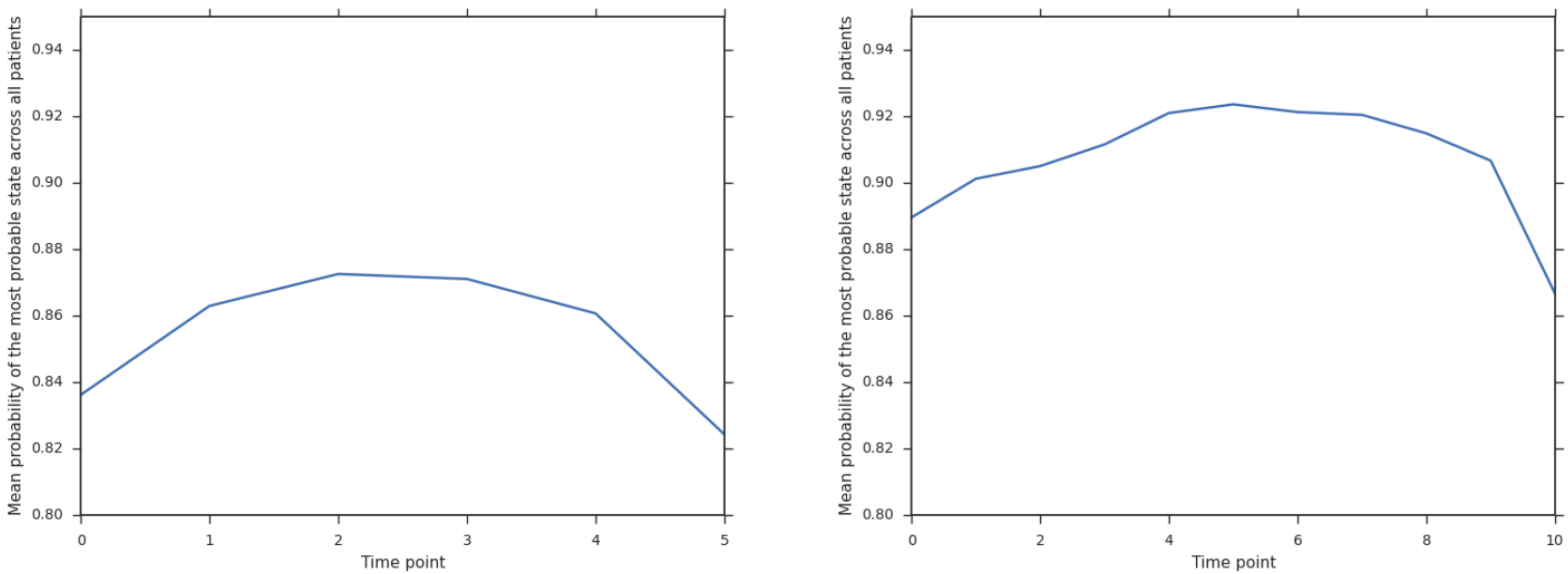
Overlapping or exclusive time windows



(a) Non-overlapping time windows (b) Overlapping time windows

Figure 5: Distribution of patients into possible start-end state pairs with time resolution = 8 and $S = 5$ in overlapping and non overlapping cases.

Overlapping edge - continued

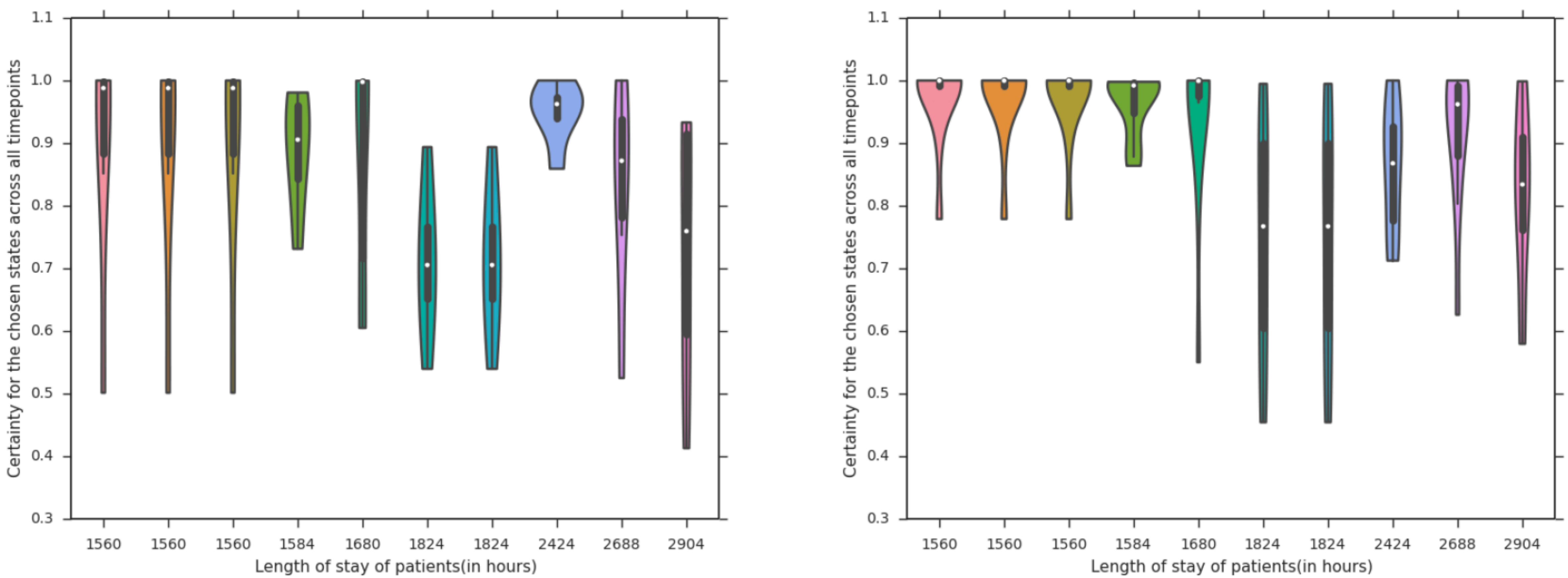


(a) Non-overlapping time windows

(b) Overlapping time windows

Figure 6: Certainty of chosen state over time windows with time resolution = 8 and $S = 8$ overlapping and non overlapping schemes

Overlapping edge-continued



(a) Non-overlapping time windows

(b) Overlapping time windows

Figure 7: Certainty of chosen state over time windows for long staying patients with time resolution = 8 and $S = 8$ in overlapping and non overlapping schemes.

Combining ICU type

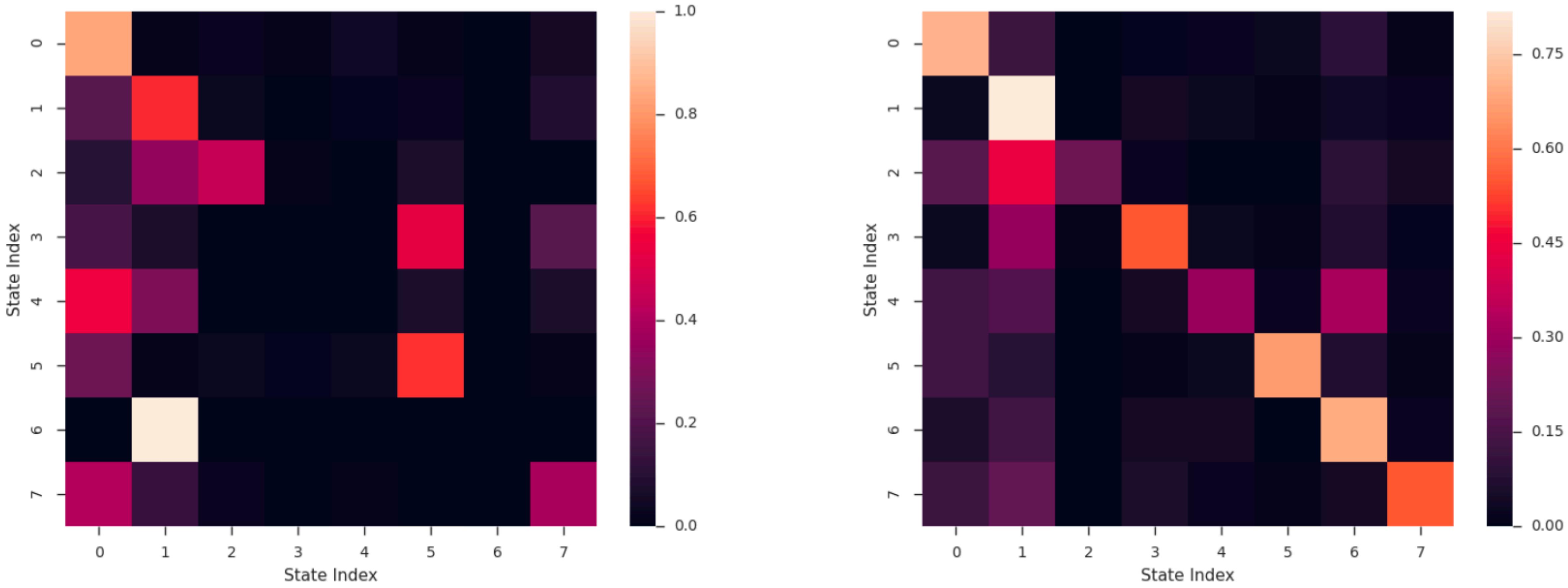
ICU types Combined	% of times model beats baseline (RMSE)
Only 1	33%
Only 2	91%
Only 3	100%
Only 4	75%
All ICUs	97%
(1,2) (3,4)	**93% (100%)**
(1,2,3) (4)	94% (97%)
(1,2,4) (3)	89%(100%)

Table 3: RMSE of baseline models and HMM model

RMSE Comparison

Model	RMSE
Lasso Regression	202.61
Ridge Regression	205.33
Poisson Regression	203.68
Negative Binomial Regresssion	203.43
Linear SVR	206.42
RBF SVR	205.39
HMM Method	**201.31**

Interpretability



(a) ICUs (1,2)

(b) ICUs (3,4)

Figure 8: Heatmap of transition probabilities matrix T for the best-performing HMM.

Future work

- Checking patterns observed on the larger dataset MIMIC III.
- Restraining the states to signify certain characteristics.
- Comparison to Deep learning models.
- Using multitasking with each task being a different ICU type