ETH zürich

Prediction of Postoperative Complications in Cardiac Surgery

Master Thesis

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Outline

Problem Definition

Motivation

- **Huge amounts** of data collected at the intensive care unit (ICU)
- **High workload** for the ICU staff
- Harder to recognize postsurgical complications
- **Early recognition** can lower the risk of late complications
- No clinical **real-time decision support system**

Postoperative Bleeding

Coagulation Problems:

Bleeding due to non-clotting

Treatment: **transfusion** (blood products)

Surgical Bleeding:

Unstaunched bleeding

Treatment: transfusion at first, if no improvement, **surgical re-exploration**

Early recognition can be crucial

Hard to distinguish at the beginning!

Problem Statement

Predicting the need for surgical re-exploration due to postoperative bleeding in real-time.

Related Work

Electronic Health Records (EHRs) for prediction

Mortality prediction in real-time at the ICU

Methods: e.g. logistic regression, deep learning

Risk factor analysis of surgical bleeding

Data Set

Patients

Bleeding patient: surgical re-exploration within 25 hours after initial surgery

Control group: no surgical re-exploration after initial surgery

All initial surgeries are open heart surgeries

Adult patients only (18+)

3650 patients in total (50% bleeding patients)

Features

Continuous or categorical

Static features: e.g. age, gender, initial surgery type, …

Dynamic features: e.g. bleeding rate, blood pressure, laboratory results, …

72 features in total

Time Slices

Time window: end of initial surgery until start of surgical re-exploration

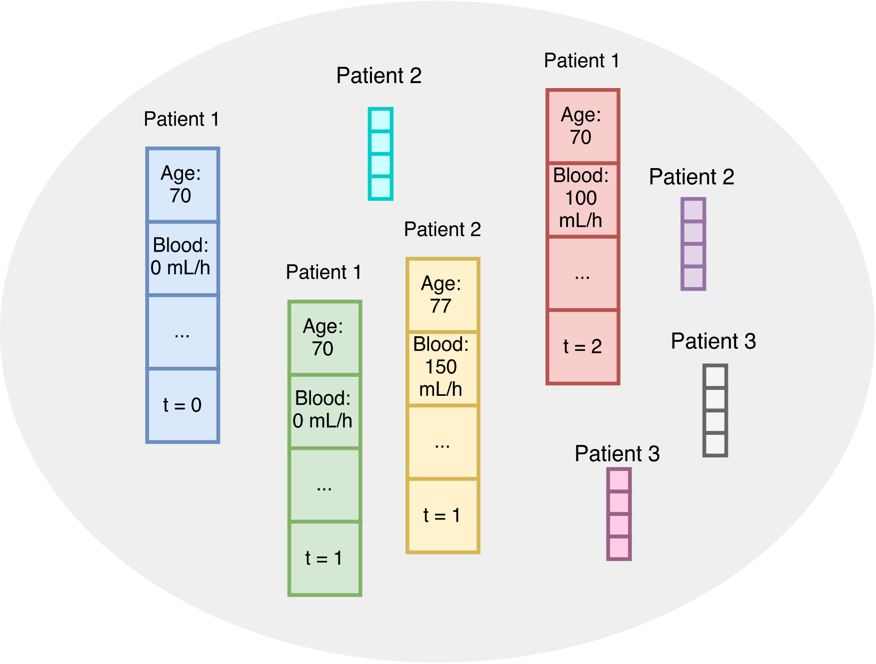
Time slice: feature vector (one per half an hour) labelled with its patient’s class

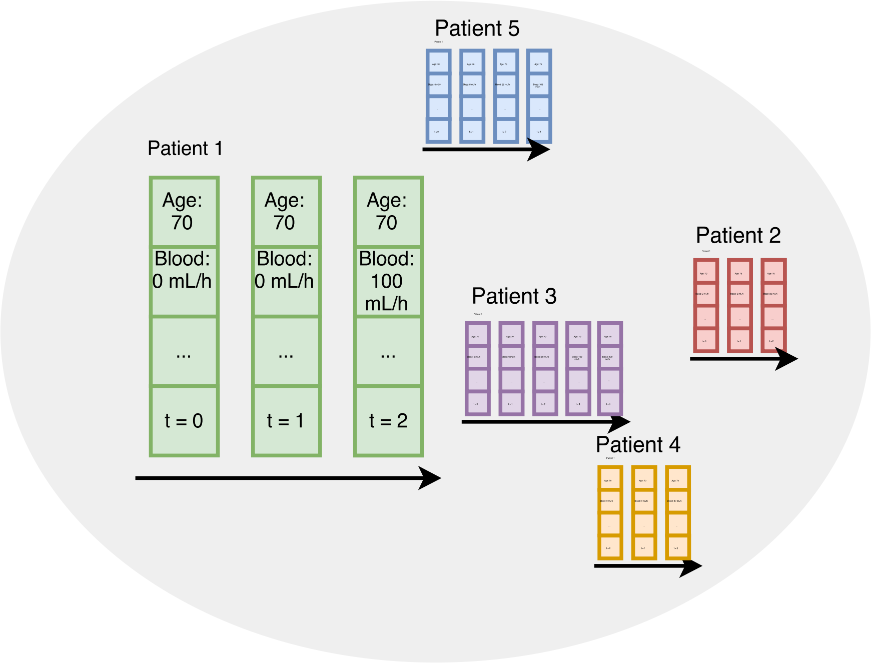
69996 time slices in total

Missing values imputed with:

- last measured value
- default value

Representation





Methods

Clinical Baseline

Decision **in favor** of a surgical re-exploration, if the **bleeding rate** is

> 400 mL/h for 1 hour

> 300 mL/h for 3 hours

> 200 mL/h for 4 hours

Otherwise, no surgical re-exploration needed

from: Robert M. Bojar. Manual of Perioperative Care in Adult Cardiac Surgery. John Wiley & Sons, 2005.

Machine Learning Approaches

Naive Bayes

AdaBoost (Decision Trees)

Logistic Regression

Support Vector Machines (SVM)

K-Nearest Neighbors (KNN)

Feedforward Neural Network (FNN)

Recurrent Neural Network (RNN)

x: input

s: hidden state

o: output

U, ***V***, ***W***: weight matrices

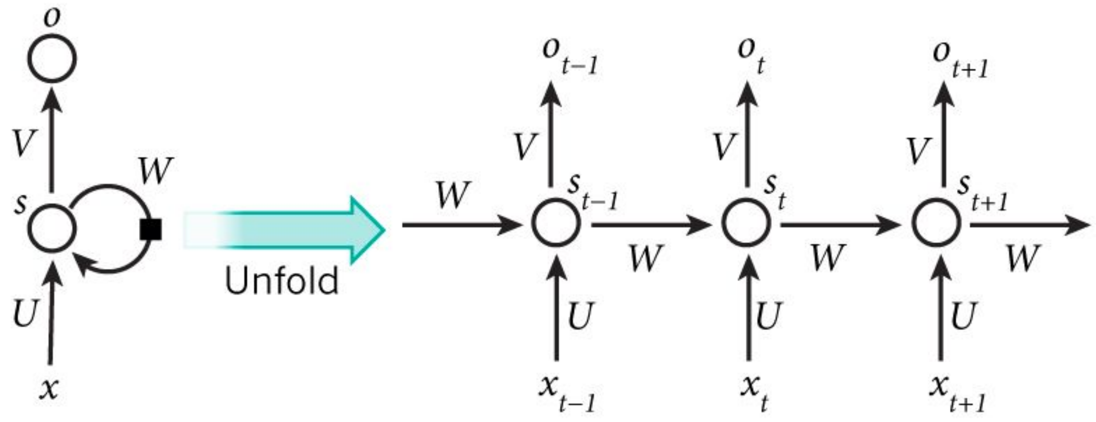


Figure from Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553):436–444, 2015.

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Results & Discussion

Evaluation Metrics

P: number of positive time slices

N: number of negative time slices

TP: number of true positive time slices

TN: number of true negative time slices

FP: number of false positive time slices

FN: number of false negative time slices

Accuracy: $\frac{TP + TN}{P + N}$

ROC AUC: area under the true positive vs. false positive rate curve

Precision:

$$\frac{TP}{TP + FN}$$

Recall:

$$\frac{TP}{P}$$

F1 score:

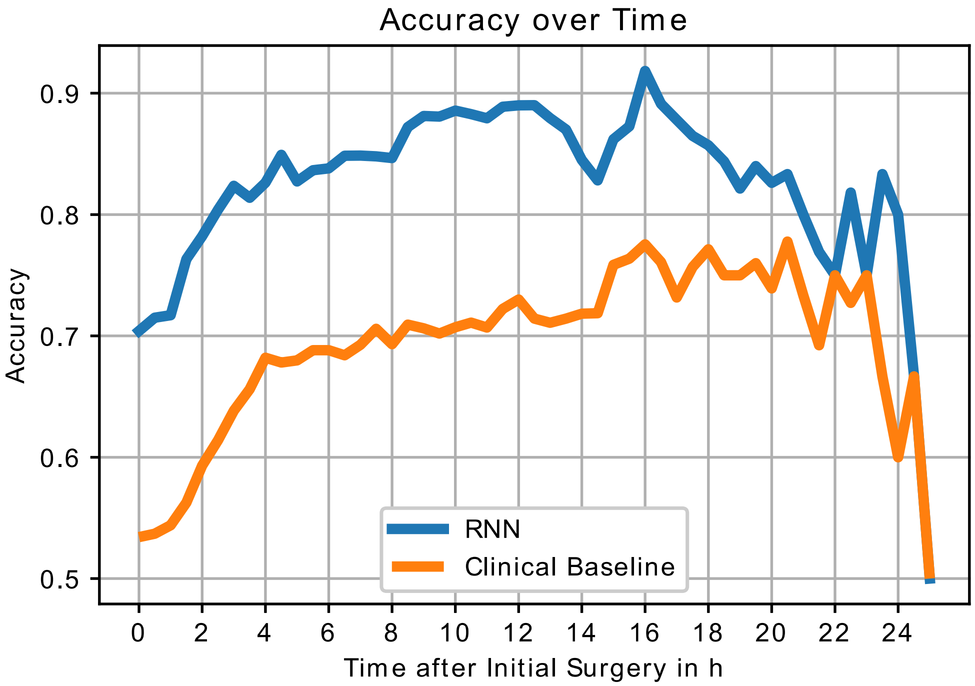
$$2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

Results

Classifier	Accuracy	ROC AUC	F1
RNN	**0.818***	**0.889**	**0.802**
FNN	0.797	0.874	0.777
Logistic Regression	0.789	0.855	0.769
AdaBoost	0.788	0.873	0.774
SVM	0.778	0.862	0.772
KNN	0.740	0.813	0.697
RNN-B	0.724	0.799	0.685
Naive Bayes	0.682	0.720	0.633
Clinical Baseline	0.655†	0.642	0.474

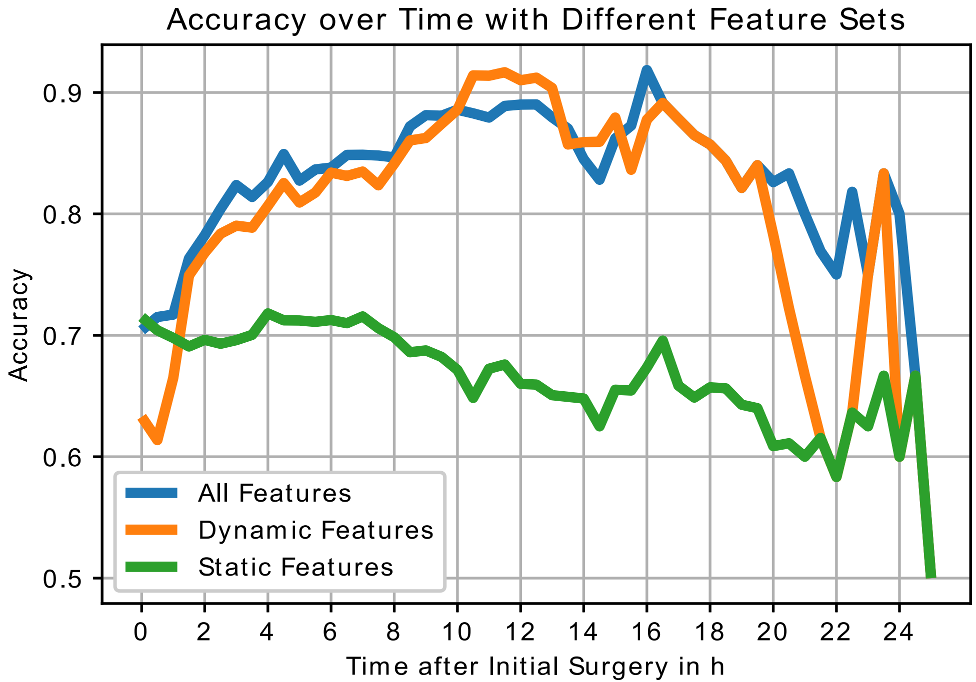
*Significantly better than all other classifiers on a significance level of $\alpha = 0.01$.
†Significantly worse than all other classifiers on a significance level of $\alpha = 0.01$.

Accuracy



Accuracy over Time
Accuracy
0.9
0.8
0.7
0.6
0.5
0 2 4 6 8 10 12 14 16 18 20 22 24
Time after Initial Surgery in h
RNN
Clinical Baseline

Different Feature Sets



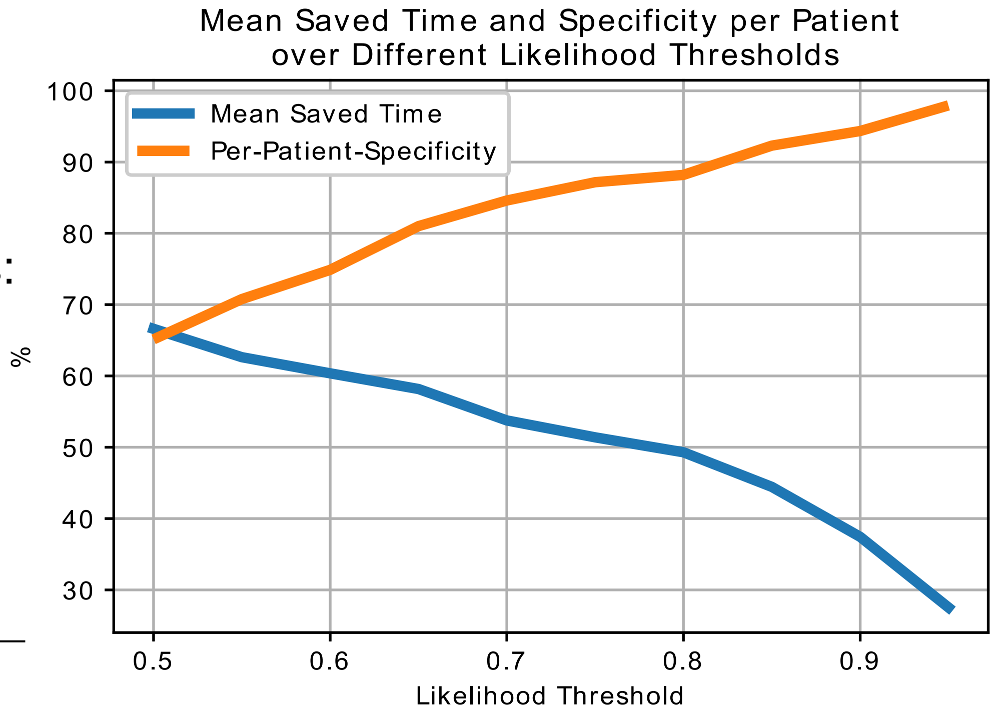
Possible Time Savings

Given **actual time** *s* until re-exploration and the **first time** *f* RNN predicts re-exploration, the relative **saved time** d is defined as:

$$d = \begin{cases} \frac{s-(f+1)}{s} & \text{if } f \text{ exists and } f+1 < s \\ 0 & \text{otherwise} \end{cases}$$

Per-Patient-Specificity:

$$\frac{\text{number of true negative patients}}{\text{number of negative patients}}$$



Problem Complexity and Limitations

Ground truth unknown

Real-time prediction

Missing or incorrect data

Coarse temporal resolution

Conclusion

Conclusion

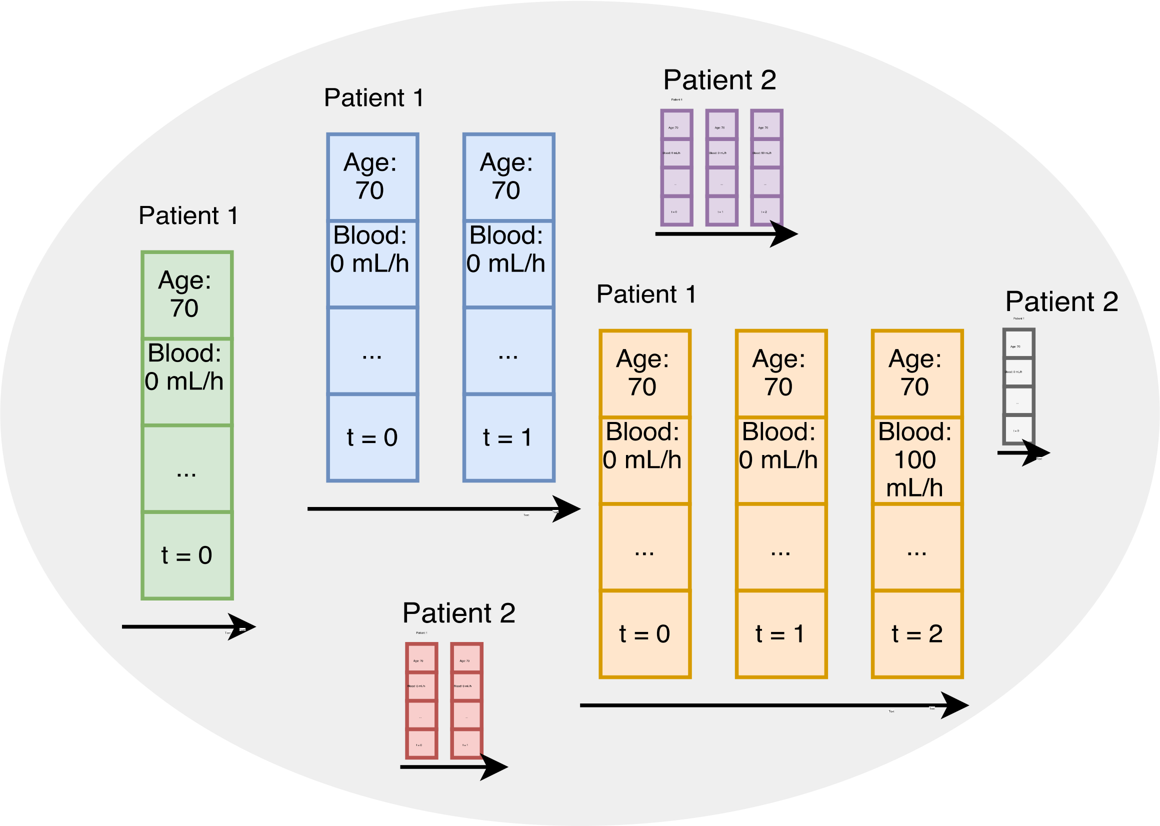
All approaches perform significantly better than the clinical baseline

RNN performs with

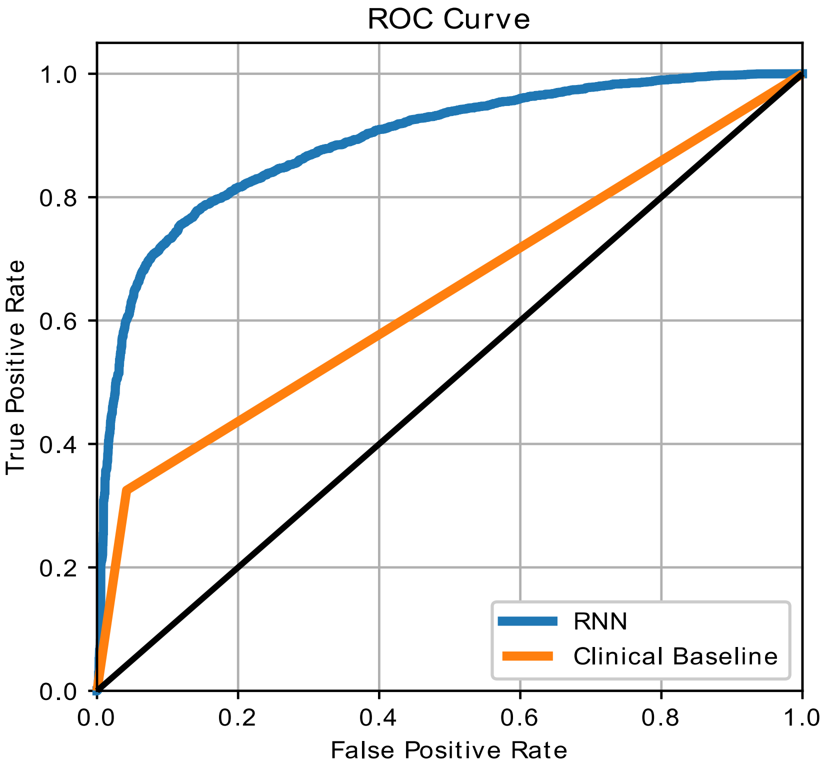
- accuracy of 0.818
- ROC AUC of 0.889
- F1 score of 0.802

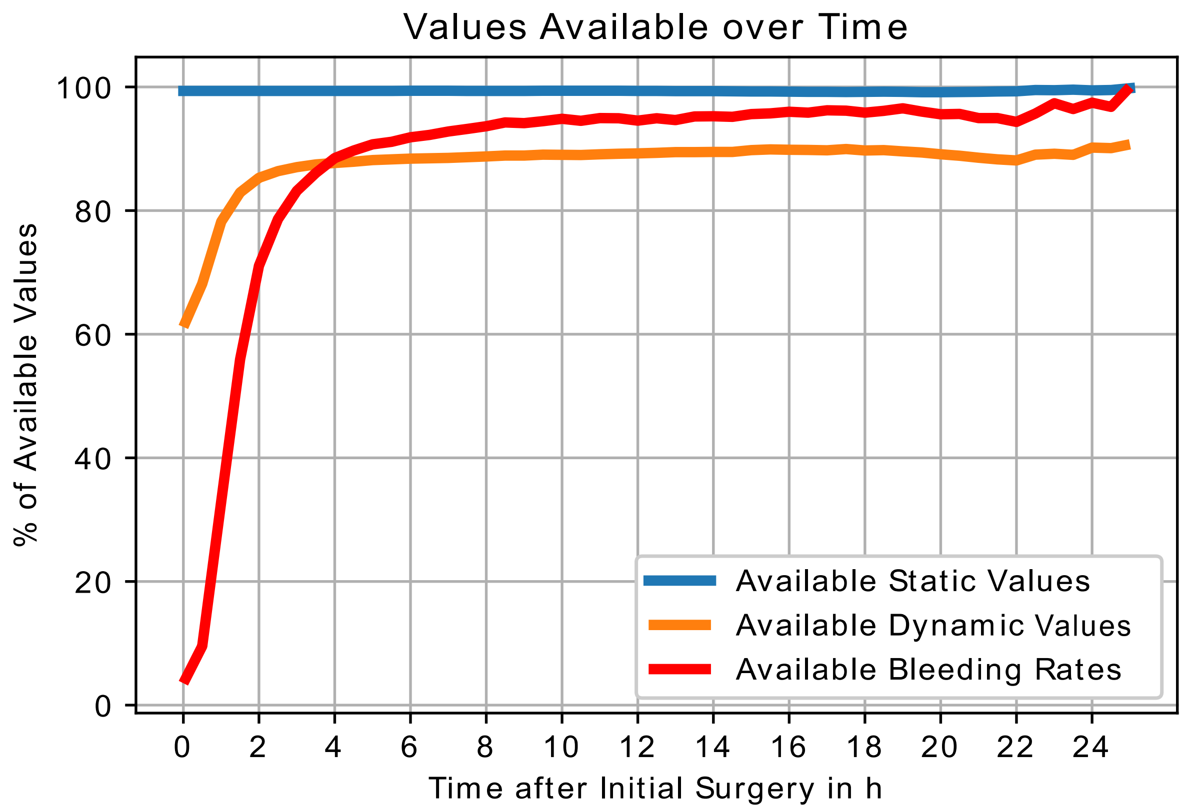
RNN could help decrease the time until re-exploration by up to 65%

Thank you!

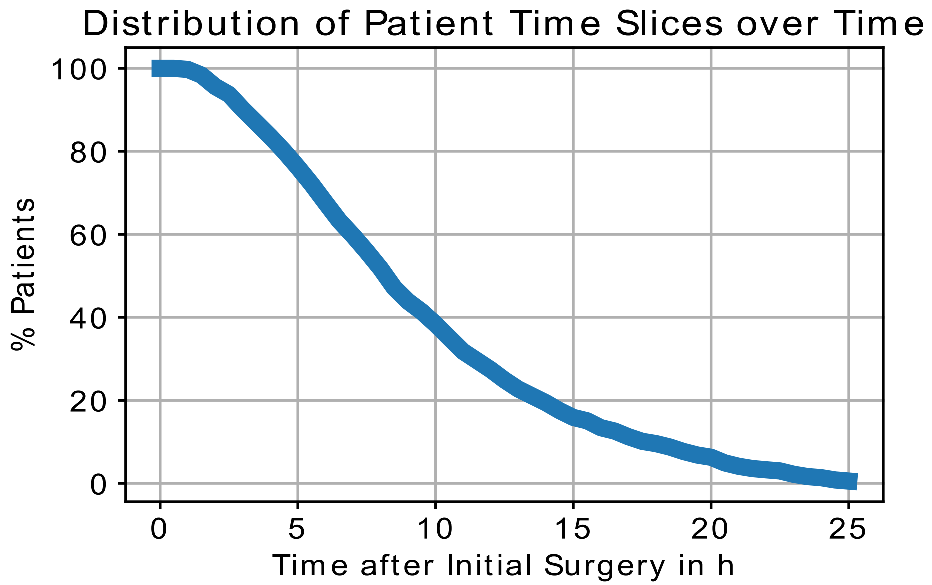

Patient 1
Age: 70
Blood: 0 mL/h
...
t = 0
Patient 1
Age: 70
Blood: 0 mL/h
...
t = 0
Age: 70
Blood: 0 mL/h
...
t = 1
Patient 2
Patient 1
Age: 70
Blood: 0 mL/h
...
t = 0
Age: 70
Blood: 0 mL/h
...
t = 1
Age: 70
Blood: 100 mL/h
...
t = 2
Patient 2
Patient 2

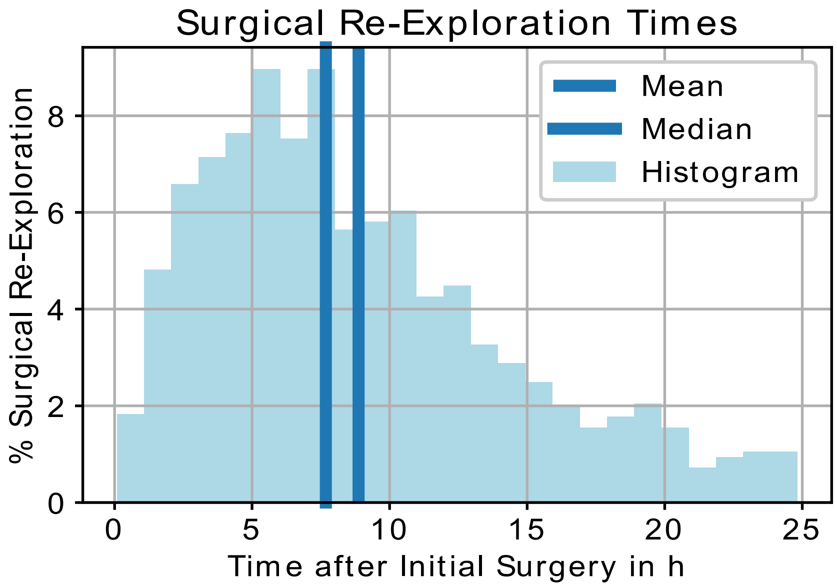
ROC Curve


ROC Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
RNN
Clinical Baseline

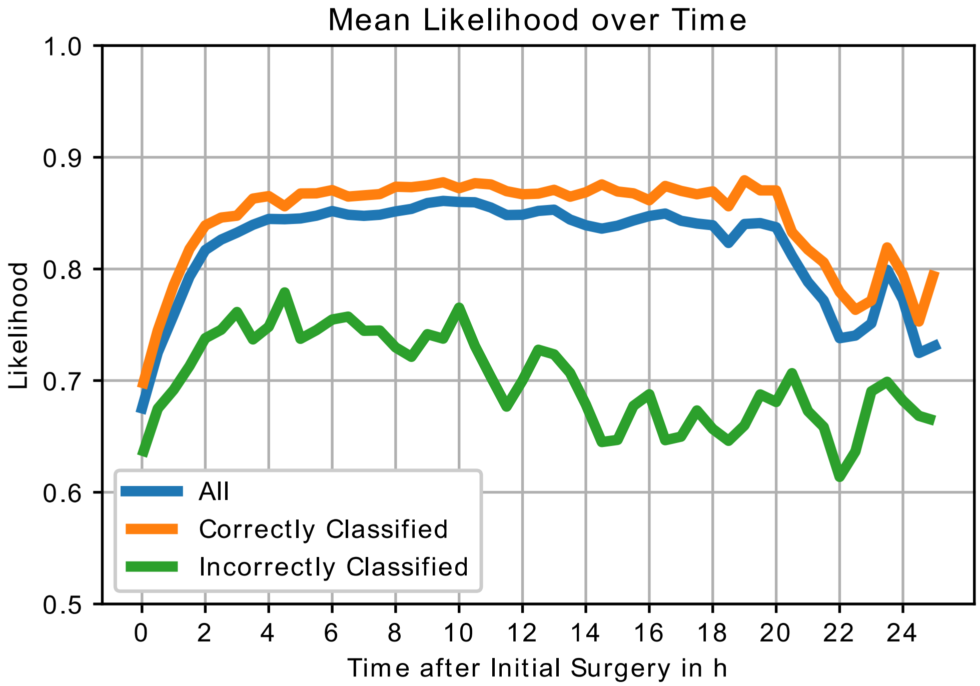

Values Available over Time
% of Available Values
100
80
60
40
20
0
0
2
4
6
8
10
12
14
16
18
20
22
24
Time after Initial Surgery in h
Available Static Values
Available Dynamic Values
Available Bleeding Rates

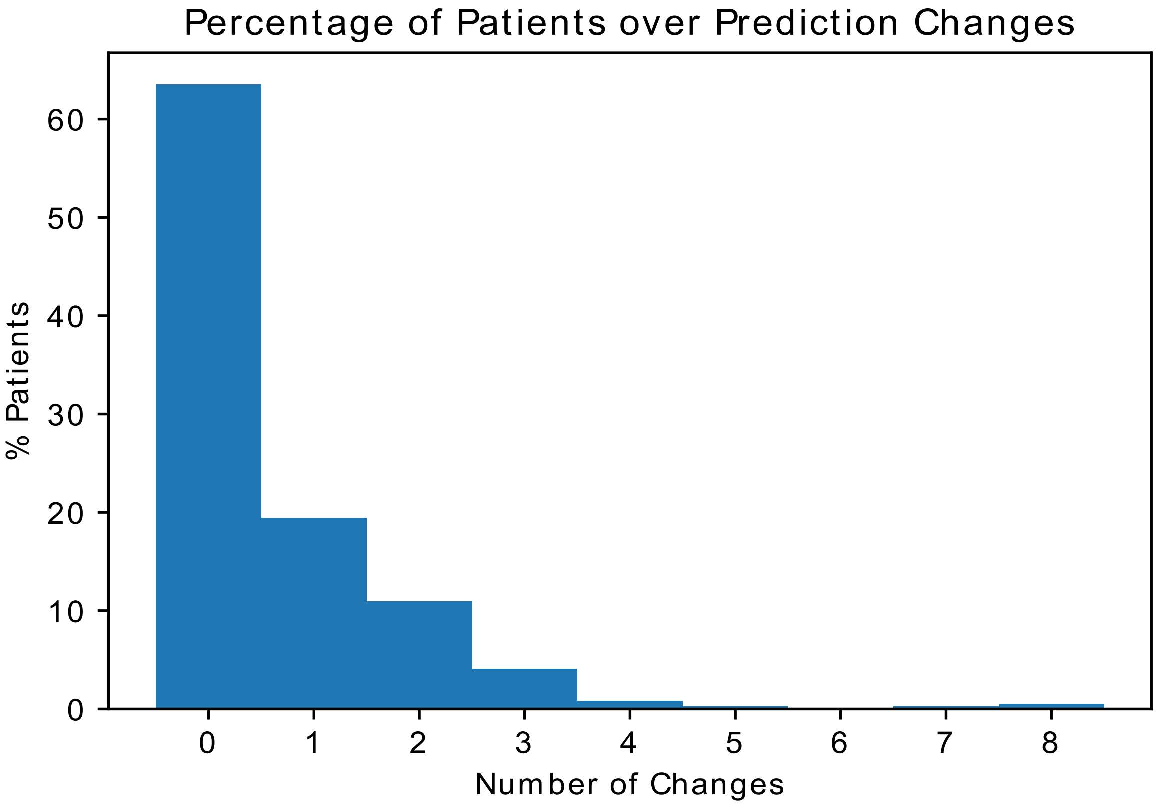
Distribution of Patients



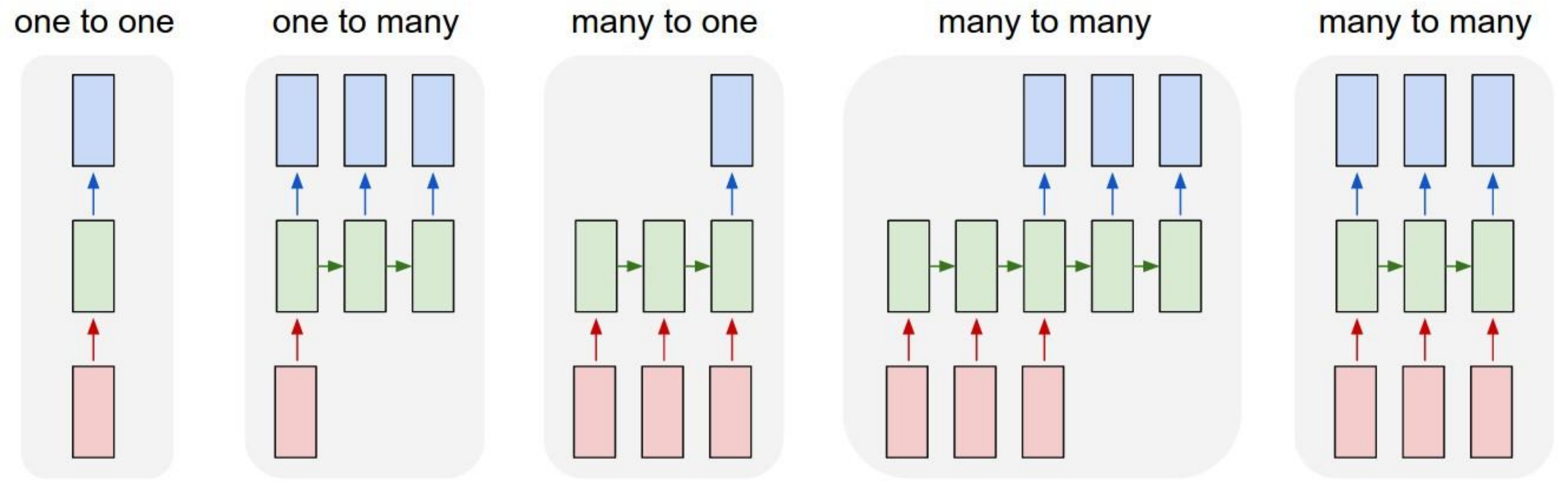


Likelihood

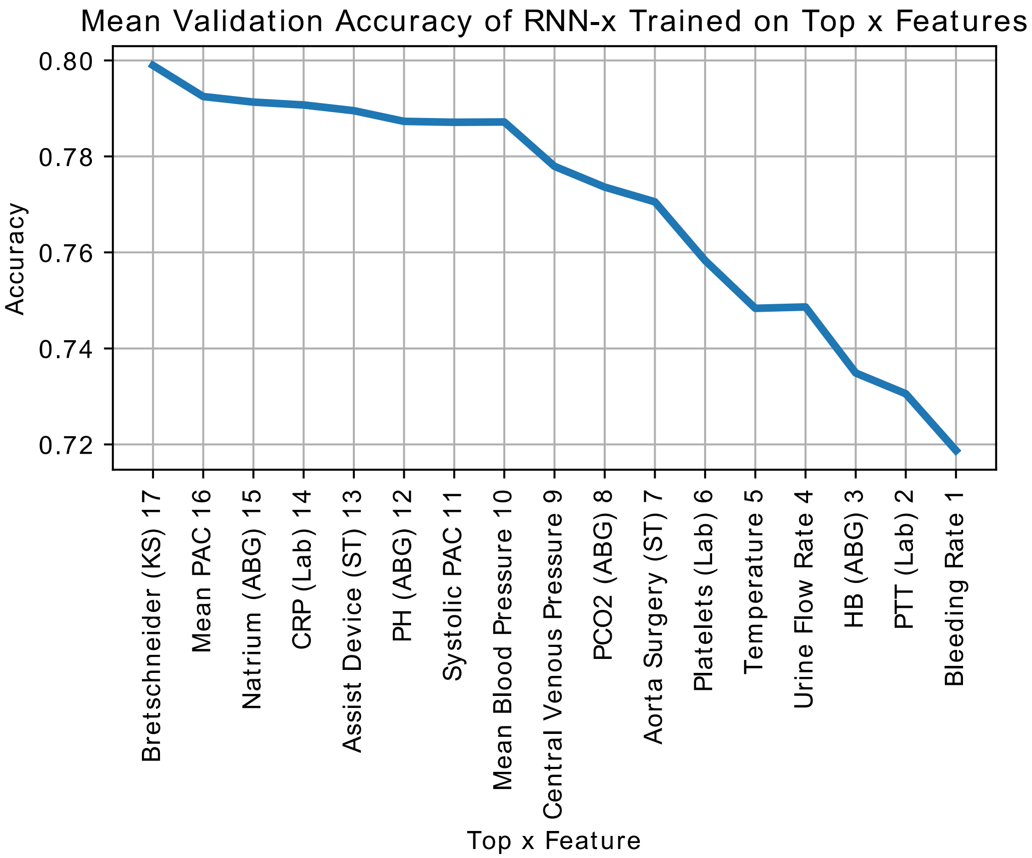

Mean Likelihood over Time
1.0
0.9
0.8
0.7
0.6
0.5
Likelihood
0
2
4
6
8
10
12
14
16
18
20
22
24
Time after Initial Surgery in h
All
Correctly Classified
Incorrectly Classified


Percentage of Patients over Prediction Changes
% Patients
0
10
20
30
40
50
60
0
1
2
3
4
5
6
7
8
Number of Changes

RNN Classification Options



Likelihood

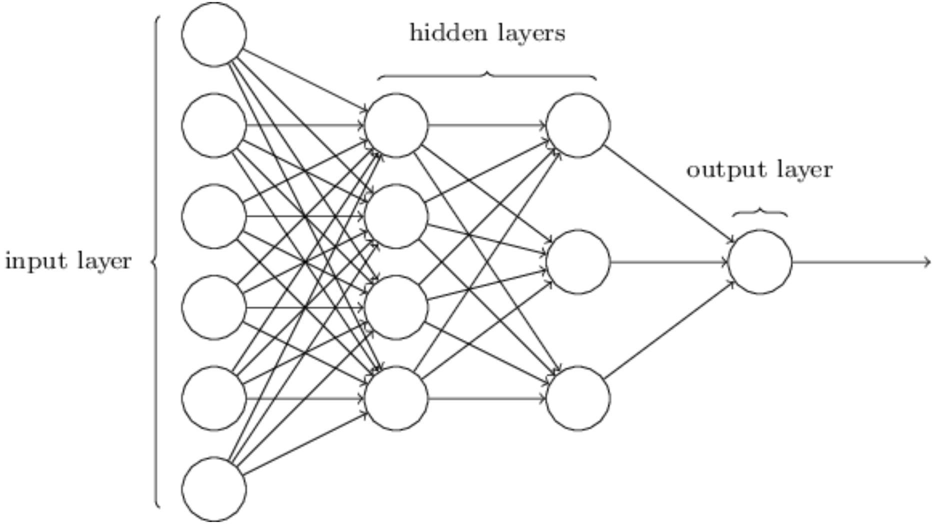


Mean Validation Accuracy of RNN-x Trained on Top x Features
Accuracy
0.80
0.78
0.76
0.74
0.72
Bretschneider (KS) 17
Mean PAC 16
Natrium (ABG) 15
CRP (Lab) 14
Assist Device (ST) 13
PH (ABG) 12
Systolic PAC 11
Mean Blood Pressure 10
Central Venous Pressure 9
PCO2 (ABG) 8
Aorta Surgery (ST) 7
Platelets (Lab) 6
Temperature 5
Urine Flow Rate 4
HB (ABG) 3
PTT (Lab) 2
Bleeding Rate 1
Top x Feature

Feedforward Neural Network (FNN)

Final model:

- Hidden layers: 1
- Hidden nodes: 20
- Activation function: sigmoid
- Regularization: L_2-norm



Recurrent Neural Network (RNN)

Final model:

Hidden layers: 1 (GRU)

Hidden nodes: 40

Activation function: sigmoid