



Multivariate time series analysis of ICU mortality

Computer Integrated Surgery II

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Introduction

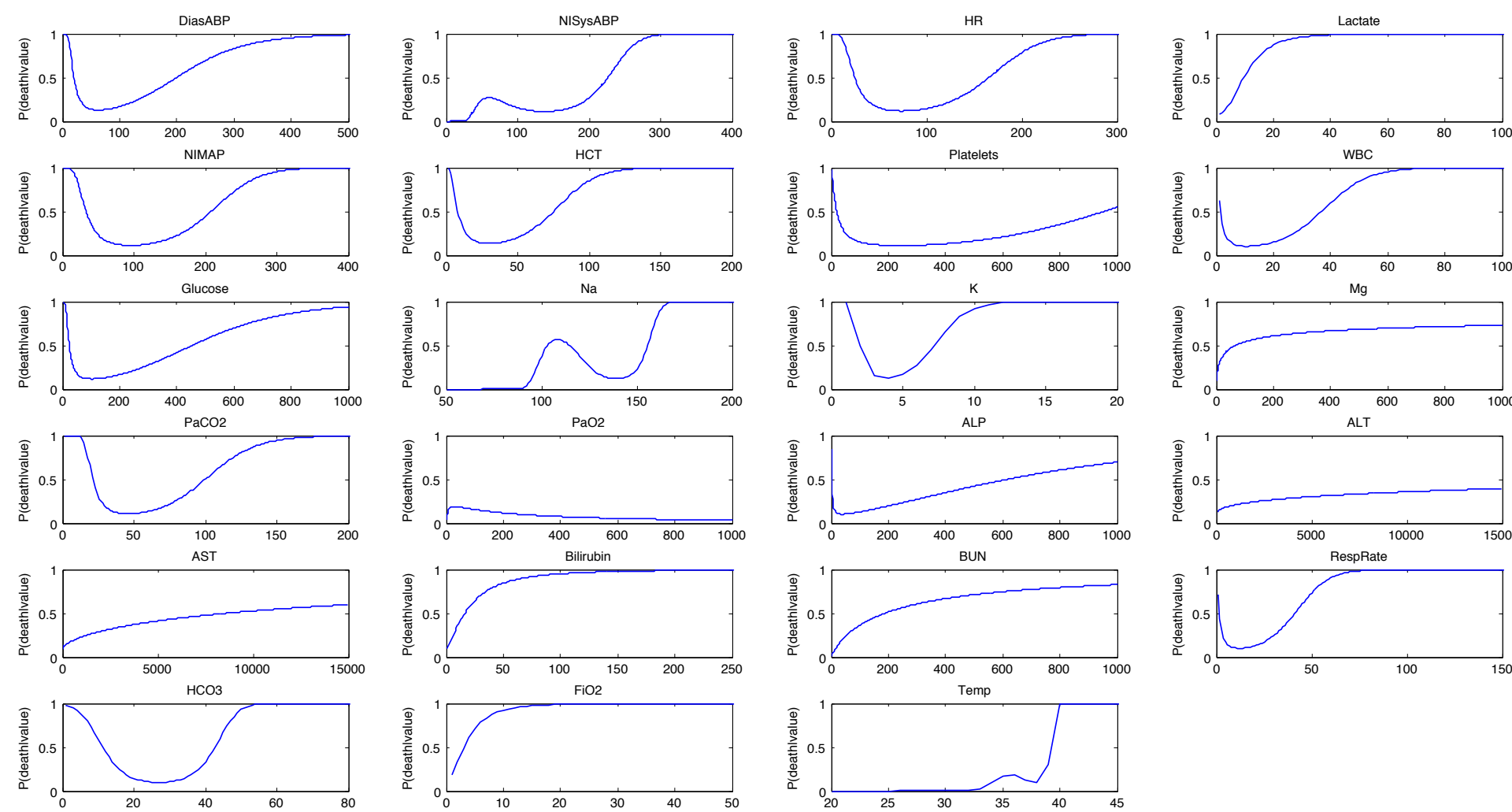
- We developed a patient-specific mortality prediction model based on time-series physiological variables during first 48h of an ICU stay. Under a probabilistic framework, the risk features are defined as log likelihood ratio which associates the observed values with the risk of mortality. Individual features are then aggregated by a logistic function to generate a probability score for mortality risk.
- The modern ICU is a complex, expensive and resource-intensive environment. Tools that quickly and accurately make prediction of a patient's mortality risk are of great significance. It allows for better clinical decision-making and helps control hospital expenses and manages medical resources.

The Problem

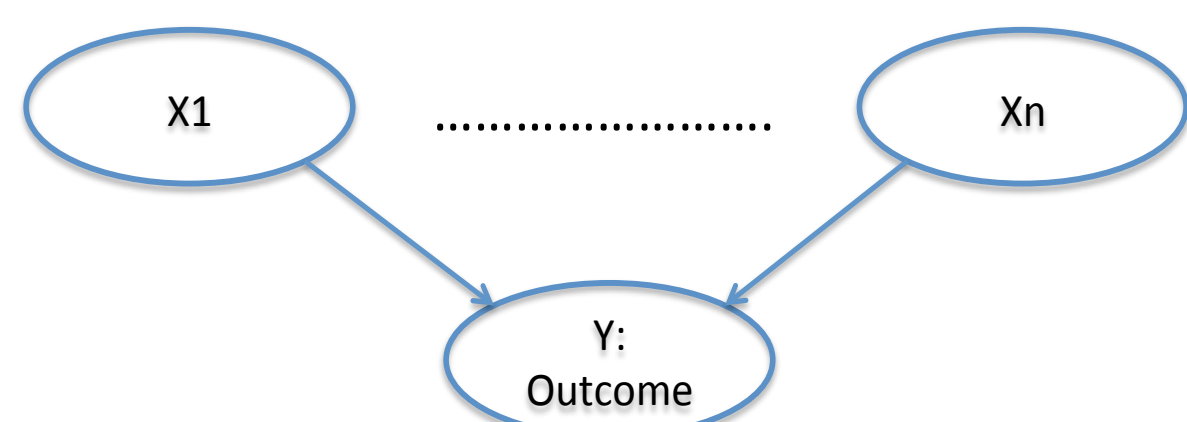
- The cost of care for an ICU patient is estimated to be three times the costs of a general patient. Therefore, the primary focus of ICU is on patients whose extreme conditions can be reversed and who have good chances of surviving after receiving such advanced but expensive medical care.
- Various general acuity-scoring systems are used for patients with critical illness, and can be calibrated from admission status, physiological variables, laboratory tests, organ dysfunction, as well as therapeutic intervention.
- We used the nonlinear model of risk features which allows for richer assumptions about the data generating process.

The Solution

- The nonlinear transformation that associate the observed values of physiological variables (x-axis), to the posterior probability of mortality risk (y-axis).



- Graphical illustration of the logistic function that aggregated independent individual risk features to generate a probability score for mortality risk.

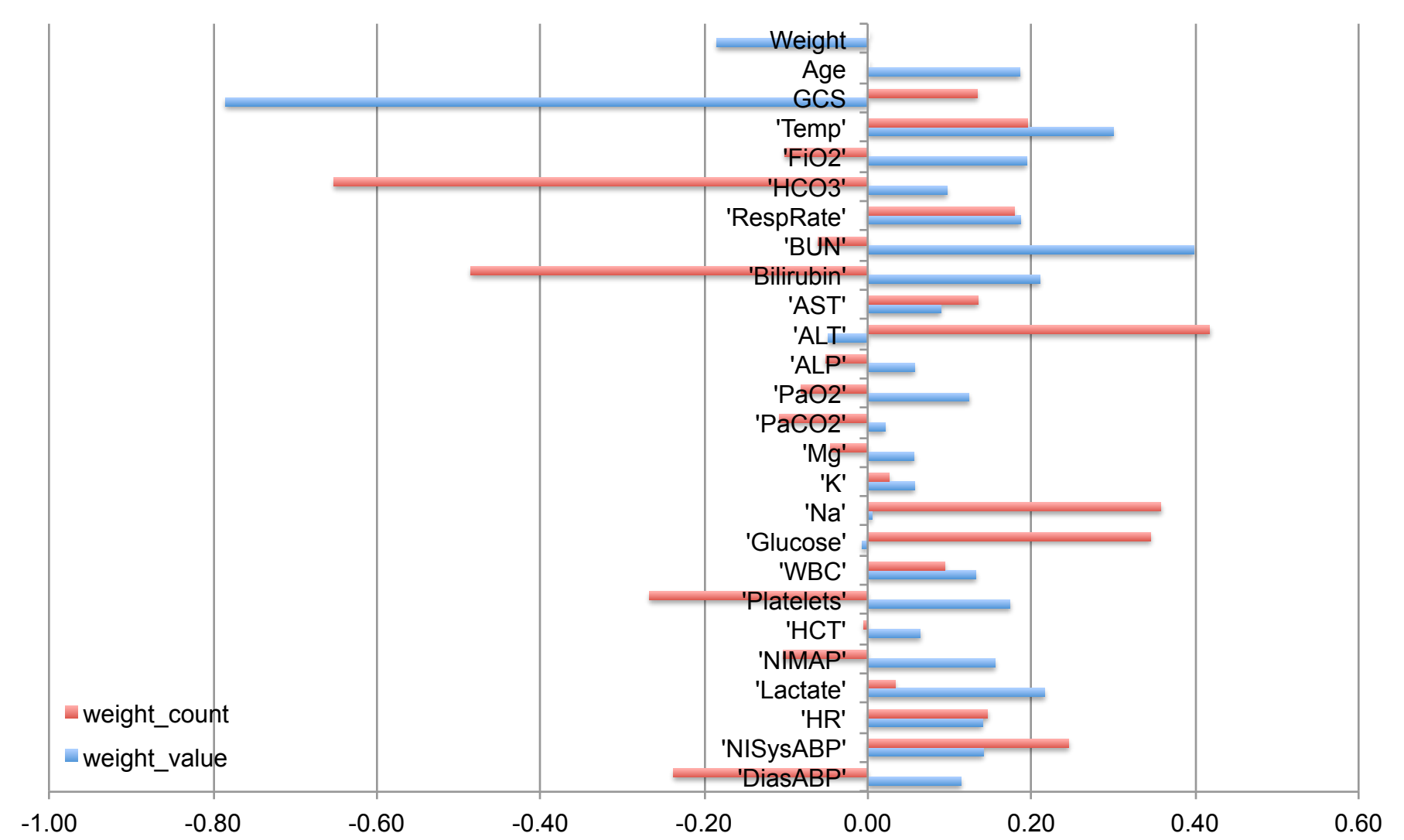


$$P(\text{death} | \{\mathbf{x}_1, \dots, \mathbf{x}_M\}) = \sigma(-\mathbf{w}^T \boldsymbol{\phi}) = \frac{1}{1 + \exp(-\mathbf{w}^T \boldsymbol{\phi})}$$

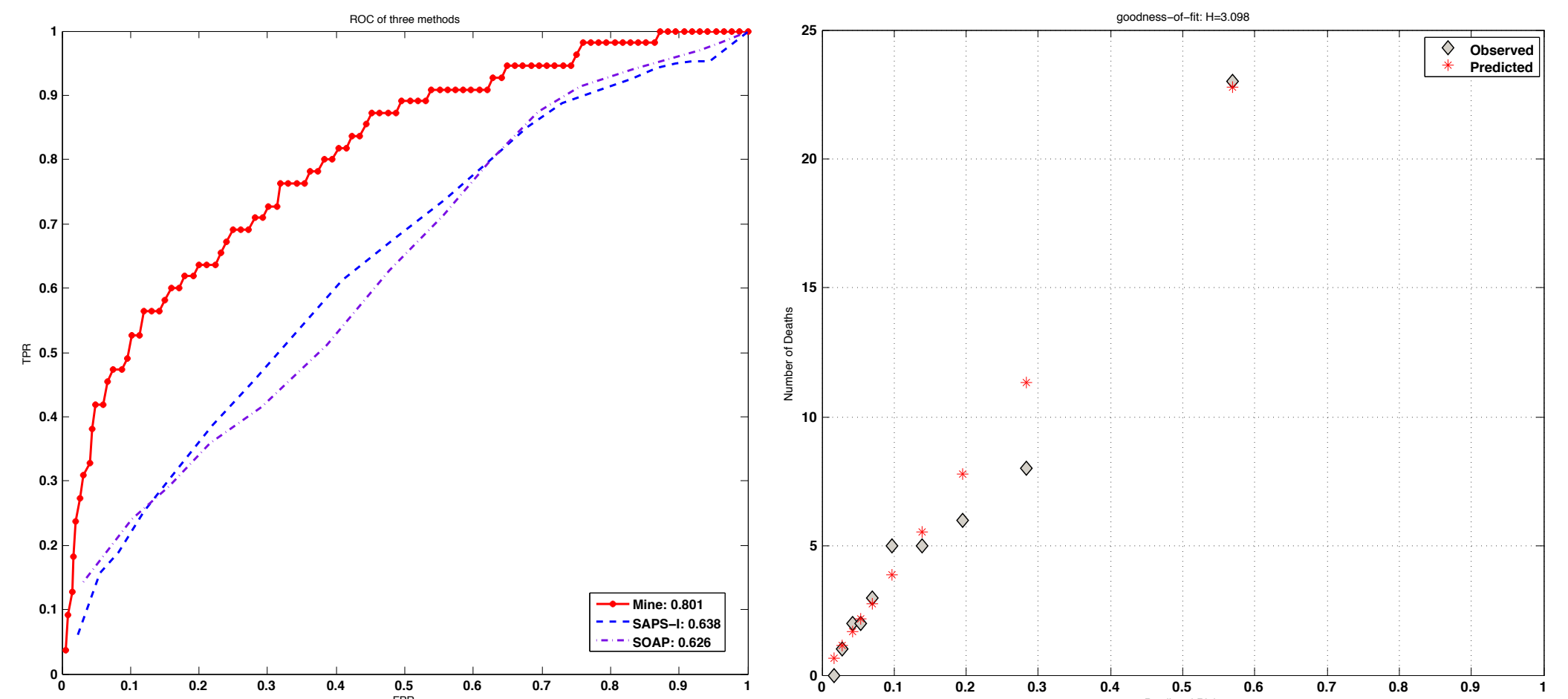
- Definition of risk features that incorporate both the observed values, \mathbf{x}_i , and counts of observations, T_i , within 48h. Values are approximated by one of five long-tail parametric distributions, and counts are approximated by Poisson distribution:

$$\boldsymbol{\phi}(\mathbf{x}_i) = \begin{cases} \log \frac{P(\mathbf{x}_i | \text{death})}{P(\mathbf{x}_i | \text{survive})}, \log \frac{P(T_i | \text{death})}{P(T_i | \text{survive})} \\ \log \frac{P(T_i = 0 | \text{death})}{P(T_i = 0 | \text{survive})} \end{cases}$$

Outcomes and Results



- The learned weight (Blue: values, Red: counts) for each physiological variables in the logistic classifier.



- ROC and associated AUC (Left) for classification performance evaluation, and Hosmer–Lemeshow statistics. For goodness-of-fit.

Future Work

- At individual level, the observed physiological signals and their dynamics over time are affected by many factors, from the intrinsic state of disease, the setup of the monitoring instruments, to the medical interventions received by the patients.
- At population level, outcome-predicting model is also strongly affected by population characteristics and healthcare delivery systems, which is constantly changing.
- Future work can be based on these levels.

Lessons Learned

- The question we address is much more important than the method we use.

Support by and Acknowledgements

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