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Data mining using clinical physiology at discharge to predict ICU readmissions

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ABSTRACT

Patient readmissions to intensive care units (ICUs) are associated with increased mortality, morbidity and costs. Current models for predicting ICU readmissions have moderate predictive value, and can utilize up to twelve variables that may be assessed at various points of the ICU inpatient stay. We postulate that greater predictive value can be achieved with fewer physiological variables, some of which can be assessed in the 24 h before discharge. A data mining approach combining fuzzy modeling with tree search feature selection was applied to a large retrospectively collected ICU database (MIMIC II), representing data from four different ICUs at Beth Israel Deaconess Medical Center, Boston. The goal was to predict ICU readmission between 24 and 72 h after ICU discharge. Fuzzy modeling combined with sequential forward selection was able to predict readmissions with an area under the receiver-operating curve (AUC) of 0.72 ± 0.04, a sensitivity of 0.68 ± 0.02 and a specificity of 0.73 ± 0.03. Variables selected as having the highest predictive power include mean heart rate, mean temperature, mean platelets, mean non-invasive arterial blood pressure (mean), mean spO2, and mean lactic acid, during the last 24 h before discharge. Collection of the six predictive variables selected is not complex in modern ICUs, and their assessment may help support the development of clinical management plans that potentially mitigate the risk of readmission.

1. Introduction

Patients readmitted to an intensive care unit during the same hospitalization have an increased risk of death, length of stay, and higher costs (Boudesteijn, Arbous, & van den Berg, 2007; Durbin & Kopel, 1993; Rubins & Moskowitz, 1988). Previous studies have demonstrated overall readmission rates of 4–14% (Baigelman, Katz, & Geary, 1983; Rosenberg & Watts, 2000), of which nearly a third can be attributed to premature discharge from the critical care setting (Baigelman et al., 1983; Durbin & Kopel, 1993). Increasing pressures on managing care and resources in ICUs is one explanation for strategies seeking to rapidly free expensive ICU beds. Faced with this scenario, a clinician may elect to discharge a patient currently in the ICU who has already had the benefits of stabilization and intensive monitoring, to make room for more acute patients allocated in the emergency department, exposing the outwardly transferring patients to the risk of readmission in the short term (Chalfin, Trzeciak, Likourezos, Baumann, & Dellinger, 2007). Moreover, besides the existence of morbidity and mortality issues around readmission, the Centers for Medicare & Medicaid Services already reduced funding for specified avoidable conditions, and it is quite possible avoidable readmission to an ICU will also receive attention.

Previous studies have examined different variables that are assessed at discharge, and that are considered to be predictive of readmission. They include fever, hypoxia, elevated respiratory rate, elevated heart rate, increasing age, ICU length of stay, proximity of extubation to time of discharge, need for organ support on the day of discharge, night discharges and discharge to a high-dependency unit (Baigelman et al., 1983; Chen, Martin, Keenan, & Sibbaldi, 1998; Cooper, Sirio, Rotondi, Shepardson, & Rosenthal, 1999; Durbin & Kopel, 1993; Franklin & Jackson, 1983; Goldfrad & Rowan, 2000; Metnitz et al., 2003; Rosenberg, Hofer, Hayward, Strachan, & Watts, 2001; Rubins & Moskowitz, 1988; Snow, Bergin, & Horrigan, 1985). However, prediction models based on these risk factors have moderate discrimination ability (AUC $\in [0.66 - 0.75]$), and only performed slightly better than models based only upon APACHE II score (AUC = 0.63) at ICU admission (Campbell, Cook, & Adey, 2008). To the best of the authors' knowledge, no useful predictive models based exclusively on physiological variables at ICU discharge have yet been developed.

Our hypothesis is that a small set of commonly available physiological variables at ICU discharge will improve prediction results as well as shed some light on the physiology of patients at risk of

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readmission. The main goal of this work is to identify which of these physiological variables assessable at discharge from an ICU are most predictive of readmission within 24–72 h. We used a data mining approach combining fuzzy modeling with tree search feature selection to a large ICU database (Mendonça, Vieira, & Sousa, 2007). Results are compared to two of the best-known and most widely used medical scores-APACHE II and APACHE III (Knaus, Draper, Wagner, & Zimmerman, 1985; Knaus et al., 1991).

The outline of the work is as follows. In Section 2, we describe the basics of fuzzy modeling and overview the principles of the tree-based feature selection. The setup of the models is presented in Section 3 followed by a description of the used database in Section 4. In Section 5 we present the results from the empirical study described. The discussion is presented in Section 6 and conclusions are drawn in Section 7.

2. Methods

2.1. Fuzzy modeling

Fuzzy modeling is a tool that allows approximation of nonlinear systems when there is little or no previous knowledge of the problem to be modeled (Engelbrecht, 2003; Sousa & Kaymak, 2002). This tool supports the development of models around human reasoning (also referred to as approximate reasoning), and allow an element to belong to a set to a degree, indicating the certainty (or uncertainty) of its membership.

Within medical-related classification problems, several fuzzy-based models have shown comparable performances to other nonlinear modeling techniques (Fialho et al., 2010b; Ghazavi & Liao, 2008; Horn et al., 2011). Fuzzy modeling is particularly appealing as it provides not only a transparent, non-crisp model, but also a linguistic interpretation in the form of rules and logical connectives. These are used to establish relations between the defined features in order to derive a model. A fuzzy classifier contains a rule base consisting of a set of fuzzy if-then rules together with a fuzzy inference mechanism. These systems ultimately classify each instance of a dataset as pertaining to one of the possible classes defined for the specific problem being modeled (Sousa & Kaymak, 2002). Two classes were considered in the present work: patient will be readmitted or patient will not be readmitted to the ICU after 24–72 h of discharge.

First order Takagi–Sugeno (TS) fuzzy models (Takagi & Sugeno, 1985) were used, which consist of fuzzy rules where each rule describes a local input–output relation. When first order TS fuzzy systems are used, each discriminant function consists of rules of the type:

$$R_j: \ \textbf{If } x_1 \text{ is } A_{j1} \text{ and } \dots \text{ and } x_N \text{ is } A_{jN}$$
$$\textbf{then } y_j = (a_j)^T \mathbf{x} + b_j$$

where, $j = 1,\dots,J$ corresponds to the rule number, $\mathbf{x} = (x_1,\dots,x_N)$ is the input vector, N is the total number of inputs (features), A_{jn} is the fuzzy set for rule R_j and nth feature, and y_j is the consequent function for rule R_j. The degree of activation of the jth rule is given by:

$$\beta_j = \prod_{n=1}^{N} \mu_{A_{jn}}(\mathbf{x}), \tag{1}$$

where $\mu_{A_{jn}}(\mathbf{x}) : \mathbb{R} \to [0,1]$.

The overall output is determined through the weighted average of the individual rule outputs. The number of rules J (defined by the number of clusters), and the antecedent fuzzy sets A_{jn} are determined using fuzzy clustering in the product space of the input and output variables (Sousa & Kaymak, 2002). The consequent parameters for each rule j, are obtained as a weighted ordinary least-square estimate.

Given that this is a classification problem, and that we have a linear consequent, a threshold t is required to turn the continuous output $y \in [0,1]$ into the binary output $y \in \{0,1\}$. In this way, if $y < t$ then $y = 0$, and if $y \geqslant t$ then $y = 1$.

2.2. Feature selection

Feature selection is generally used to identify which of the available variables are closely related to the prediction of the outcome and to discard those unrelated to it, reducing the dimensionality of the dataset (Guyon & Elisseeff, 2003; Hadorn, Keeler, Rogers, & Brook, 1993; Mendonça et al., 2007). From the clinical point of view, this process may bring to light new variables that had not been previously considered as relevant to a given outcome.

In the present work, we compared the performance of a set of variables selected as most predictive after a tree search process, against a established set of variables (medical scores) defined in the literature.

2.2.1. Tree search feature selection

Tree search feature selection is an approach that orders all the possible combinations of features in the form of a tree, in which each branch represents a subset of them (Guyon & Elisseeff, 2003). The main advantages of this method relate to its simplicity, possibility of graphical representation and transparent interpretation of the results which, for clinicians, is particular attractive. The main disadvantage is related to the greedy and thus susceptible approach of finding local optima (Mendonça et al., 2007). In the present work, two variations of this tree search technique were used: sequential forward selection (SFS) and sequential backward elimination (SBE). These techniques were applied by combining them individually with fuzzy modeling in a so-called wrapper method (Hadorn et al., 1993).

A detailed description of the sequential forward selection search approach used here is reported in Mendonça et al. (2007). Briefly, a model is built for each of the features in consideration, and evaluated using a performance criterion upon the test set. The feature that returns the best value of the performance criterion is the one selected. Then, other feature candidates are added to the previous best model, one at a time, and evaluated. Again, the combination of features that maximizes the performance criterion is selected. When this second stage finishes, the model has two features. This procedure is repeated until the value of the performance criterion stops increasing. In the end, all the relevant features for the considered process should be obtained. Discrimination was used as the performance criterion.

The sequential backward elimination algorithm differs from the forward selection approach as it begins with all the features and discards, at each stage, the one with the worst performance. Advantages include the reduction of the number of iterations per stage and, in some cases, of the number of stages, which can ultimately lead to the overall reduction of the computational time. However, when the initial number of features is too large, this approach will use more inputs to build the final model (Mendonça et al., 2007).

2.2.2. Medical scores

Scoring systems for use in ICU patients have been introduced and developed over the last 30 years and allow an assessment of the severity of disease (Bouch & Thompson, 2008).

The Acute Physiology and Chronic Health Evaluation (APACHE) score is probably the best-known and most widely used medical score. This score was designated to measure severity of disease for adult patients admitted to the ICU, by predicting mortalities