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Reprint of "Length of stay prediction for clinical treatment process using temporal similarity" ☆

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ABSTRACT

In clinical treatment processes, inpatient length of stay (LOS) is not only a readily available indicator of hospital activity, but also a reasonable proxy of resource consumption. Accurate inpatient LOS prediction has strong implications for health service delivery. Major techniques proposed (statistical approaches or artificial neuronal networks) consider a priori knowledge, such as demographics or patient physical factors, providing accurate methods to estimate LOS at early stages of the patient (admission). However, unexpected scenarios and variations are common places of clinical treatment processes that have a dramatical impact on the LOS. Therefore, these predictors should deal with adaptability, considering the temporal evolution of the patient. In this paper, we propose an inpatient LOS prediction approach across various stages of clinical treatment processes. This proposal relies on a kind of regularity assumption demanding that patient traces of the specific treatment process with similar medical behaviors have similar LOS. Therefore, this approach follows a Case-based Reasoning methodology since it predicts an inpatient LOS of a partial patient trace by referring to the past traces of clinical treatment processes that have similar medical behaviors with the current one. The proposal is evaluated using 284 patient traces from the pulmonary infection CTPs, extracted from Zhejiang Huzhou Central Hospital of China.

1. Introduction

Clinical treatment processes (CTPs) have been widely used in hospitals for clinical and financial purposes. Since there is a strong correlation between patients' cost and length of stay (LOS), standard CTPs, such as clinical pathways (Huang, Lu, Duan, & Fan, 2013, 2012b), are a useful tool to follow up the clinical actions and to calculate the associated cost (Ramos, 1999).

Clinical treatment process management (CTPM) allows the health-care actors to focus on crucial aspects such as evaluating the quality of health services, suggesting the more suitable medical behaviors, and controlling the budget for each medical behavior (Adlassnig, Combi, Das, Keravnou, & Pozzi, 2006). Note that medical behaviors are represented as flexible, transparent, and reusable pieces of functionality that consists of one or several clinical activities required to set up a clinical solution.

Nowadays, CTPM is an open problem for the research community (Lee & Anderson, 2007) since there is myriad of factors that might influence inpatient LOS. For instance, patients may have unexpected complications and medical resources could not be available at this specific time instant in CTPs. In such a case, specific medical measures must be taken. These medical scenarios have an important influence on inpatient LOS. Towards this end, understanding the factors that determine LOS, or a capacity of inpatient LOS prediction, has strong implications for health service delivery, and could promote the development of efficient CTPs (Doering, Esmailian, Imperial-Perez, & Monsein, 2001). For example, the analysis of deviations between actual and predicted inpatient LOS could facilitate health service planning, quality assurance, resource utilization reviews, cost controls, CTPs optimization, etc.

There has been much work done in the area of inpatient LOS prediction over the past decade (Yang, Wei, Yuan, & Schoung, 2010). Most of this work has focused on applying statistical analysis methods (Kelvin, Andy, & Angus, 2003) or artificial intelligence (AI)-based techniques (Tu & Guerriere, 1993; Ng, McLachlan, & Lee, 2006) to predict inpatient LOS in various clinical areas (Yang et al., 2010; Ng et al., 2006). In these works, authors use preoperative/chronic patient-specific information, such as patient demographics, patient conditions or disease characteristics, to provide a general measure of severity of illness, and to make inpatient LOS prediction considering artificial neural networks, or using a logistic

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regression approach. The inclusion of such patient-specific information improves the prediction of LOS, but only at the earlier stage of CTPs, e.g., admission (Yang et al., 2010).

In general, the etiological diagnosis of comorbid patients is not a simple issue, and the therapy administration must be personalized. In such cases, variants happen inevitably in CTPs, and patient therapy and treatment have to be adjusted dynamically, which implicitly changes inpatient LOS. Therefore, the above mentioned prognostic models, which are mainly built on static patients' information, may not provide accurate predictions of inpatient LOS across all stages of CTPs.

As an inpatient CTP trace goes on, i.e., as more and more medical behaviors are performed, the amount of information relating to the inpatient LOS is increasing. The information describing medical behaviors can be used to provide effective inpatient LOS prediction across various stages in CTPs, e.g., admission, pre-operation, operation, recovery after operation, discharge, etc. In fact, LOS prediction, made during later clinical stages, is, in most cases, more accurate than those during the admission stage (Yang et al., 2010; Ng et al., 2006). However, previous studies primarily adopt some AI-based techniques or statistical analysis to predict inpatient LOS, whereas alternative prediction methods that measure medical behaviors in CTPs have received little attention (Yang et al., 2010; Ng et al., 2006).

In this study, we focus on the issue of inpatient LOS prediction based on medical behavior measures for CTPs. This data is regularly recorded by clinical information systems in the form of care-flow logs.

The remainder of paper is organized as follows. An introduction to CTPs and related work done are introduced in Section 2. Section 3 presents the inpatient LOS prediction proposal, based on retrieving similar traces. In Section 4, we present the experiments from care-flow logs of the CTPs associated with two kinds of diseases: bronchial lung cancer and tuberculosis. These logs are extracted from Zhejiang Huzhou Central Hospital of China. Discussions and conclusions are then outlined in Sections 5 and 6 respectively.

2. Background

In this section, we review the related works on LOS predictions and temporal similarity measures of medical CBR.

2.1. Length of stay prediction

A number of inpatient LOS prediction models have been proposed and implemented in a clinical environment. With respect to the prediction technique employed, most of the prior studies adopt regression-based methods or artificial neural network (ANN)-based methods (Kelvin et al., 2003; Tu & Guerriere, 1993; Ng et al., 2006; Yang et al., 2010). For instance, Kelvin et al. (2003) develop a finite mixture regression model with random effects that allows simultaneously for heterogeneity and dependency. Tu and Guerriere (1993) develop an artificial neural network as a predictive instrument for LOS in the intensive care unit following cardiac surgery. Ng et al. (2006) present an increment expectationCmaximization (EM)-based learning approach in ANN, which enables the neural network to be updated when an input–output datum becomes known to provide an early prediction of patients who will require longer hospital care.

Some alternative inpatient LOS prediction techniques are also reported. Jain (1989) develops a semi-Markov model based methodology that can be used to study the LOS distribution of the patient in various states of the disease. The treatment data on cancer of cervix patients are used to illustrate Jain's approach. Kapadia, Chan, Sachdeva, Moye, and Jefferson (2000) model inpatient care-flow as a discrete time Markov process, which allows estimation of the time spent by patients in different severity of illness states during the intensive care unit. Natwata et al. present a discrete-type proportional hazard model to analyze the LOS of 279 hip fracture patients. Stangl and Huerta demonstrated the suitability of a fully-Bayesian approach to assessing the impact of a managed-care policy on inpatient LOS (Stangl & Huerta, 2000).

Despite prior works are widely used in inpatient LOS predication, they consider preoperative/chronic patient related information to build a prognosis model for particular pathologies at the earliest stages of CTPs. Since there are many factors and uncertainties affecting to illness evolution, LOS could dramatically change, and new LOS predictions could be required at different stages of the patients' stay. In these cases, adaptive LOS predictions, adjusted dynamically, are required.

Therefore, new prediction methods must be proposed to deal with dynamic adjustment, paying attention to the temporal dimension. Moreover, unlike the LOS prediction methods reviewed, CBR techniques could be a suitable approach to estimate LOS, solving part the aforementioned problems. In particular, past patient care-flow traces and a current inpatient trace can be interpreted as a sequence of time events. Therefore, LOS could be estimated by finding the most similar past patient traces for a given inpatient trace. In the next subsection, we review some of these techniques.

2.2. Temporal similarity measures in CBR

Several studies on the temporal similarity problem have been proposed, most of which mainly obtained temporal similarity measures based on the direct comparison between pairs of elements (Juarez, Guil, Palma, & Marin, 2009). In Thompson, Plewniak, and Poch (1999), the similarity between a pair of temporal sequences is measured based on a direct matching between sequences applying commonly the classical distance concepts (e.g. Euclidean or Minkowsky distances). This approach, however, ignores the implicit temporal constraints between all elements of the sequences. In Gusfield (1997), an edit distance method is proposed, which is based on the assumption that the distance between two temporal sequences could reflect the amount of work needed to transform one sequence into another. This approach has been widely used to measure distance in the analysis of textual strings and biological sequences, and has already been introduced into temporal sequence similarity measure (Kum, Chang, & Wang, 2006). Extensions of the approach edit distance, such as the inclusion of operation costs (Moen, 2001; Hay, Wets, & Vanhoof, 2001; Kum et al., 2006), have been also proposed. Note that edit distance is limited to measure the similarity between two sequences, and it does not fulfill symmetry. In Mannila and Moen (1999), the similarity evaluates the relative position of an event type within a window context, which is based on the assumption that event types are similar if they occur in a similar context. In Dojat, Ramaux, and Fontaine (1998), a temporal constraint network is used to describe medical scenarios, proposing a similarity function to quantify the degree of matching between two temporal networks. This similarity measure between scenarios is calculated by the fusion of both networks, and the outcome is a linguistic label (incompatible, compatible, and satisfiable) depending on the consistency of this fusion. However, in Dojat et al. (1998), the similarity measure requires a recognition process to match the current medical session (case) and predetermined temporal scenarios (temporal constraint networks). In Juarez et al. (2009), temporal cases are compared directly to obtain a possible temporal constraint network to perform similarity, avoiding potential matching problems between networks. In Folino, Greco, Guzzo, and Pontieri (2011), proposed an approach to measure similarity between a particular