Patient Condition Modeling in Remote Patient Management: Hospitalization Prediction

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Abstract. In order to maintain and improve the quality of care without exploding costs, healthcare systems are undergoing a paradigm shift from patient care in the hospital to patient care at home. Remote patient management (RPM) systems offer a great potential in reducing hospitalization costs and worsening of symptoms for patients with chronic diseases, e.g., heart failure and diabetes. Different types of data collected by RPM systems provide an opportunity for personalizing information services, and alerting medical personnel about the changing conditions of the patient. In this work we focus on a particular problem of patient modeling that is the hospitalization prediction. We consider the problem definition, our approach to this problem, highlight the results of the experimental study and reflect on their use in decision making.

1 Introduction

Chronic diseases are the leading cause of death and healthcare costs in the developed countries. Healthcare systems are undergoing a paradigm shift from patient care in the hospital to the patient care at home [3]. It is believed that RPM systems, by providing adequate patient monitoring, instruction, education and motivation (all of which can be done outside of the hospital) facilitate normalization of the patients conditions and prevent re-hospitalization.

Recently, a possible architecture of the next generation of personalized RPM systems was introduced, and a general process of knowledge discovery from RPM data, leading to identification of potentially useful features and patterns for patient modeling and construction of adaptation rules, was considered [2].

In this paper we focus on the problem of timely patient hospitalization prediction, particularly Heart Failure Hospitalization (HFH). Currently, domain experts are using manually designed triggers that should trigger an alarm in the case of possible HFH. Our study shows that with the intelligent data analysis approach for patient modeling, which utilizes information spread across different data sources, it is possible to learn predictive models that are more accurate than the expert-authored triggering rules (with statistical significance).

2 Hospitalization prediction

The problem of HFH prediction can be defined in the following way: based on the available data about a patient at moment t_i cast a prediction (and raise an alarm if deemed necessary) on a daily basis whether the hospitalization for this patient is likely to occur within the next 14 day period, $t_i \dots t_{i+14}$. Figure 1 illustrates the timeline of data availability used by a domain expert or an automated classifier for facilitating this decision making.

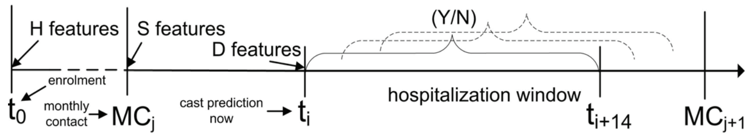

Fig. 1. Hospitalization prediction for the following 14 day window.

At the time of enrolment (t_0) of a patient, complete medical history data (corresponds to H features) is recorded. A record may contain dozens of fields providing different information such as information related to previous hospital admissions, existence of valve diseases, evidence of coronary diseases, arrhythmias, devices implanted, etc. During a monthly phone contact (MC_j) patients are asked to assess quality of life (QoL) symptoms (S features), and report additional data such as disease and non-disease medication (or medication change), number of visits/contacts (at home, by phone, at the office, at the clinic) in the last month. The patients are monitored on a daily basis regarding their vital signs such as weight or blood pressure (source for constructing D features).

Figure 2 shows our approach of constructing positive training instances, i.e. the case when HFH took place. We find a day on which HFH has occurred (t_h), then take the 14 days window $[t_{h-14}, t_h)$ to compute features related to daily measurements. It should be noticed that data for computing these features may include days outside this two week window.

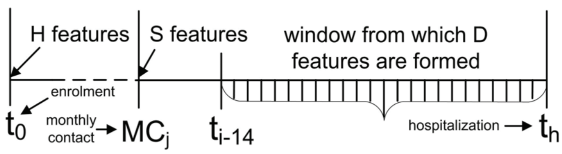

Fig. 2. Forming of a positive (hospitalization tool place) training instance.

3 Experimental study

We performed a quantitative evaluation of our approach on an extract from the TEN-HMS dataset [1] containing information about 426 patients with cardiovascular diseases, 43 of which had at least one HFH.

Our experiment setup consisted of two major steps. In the fist place we applied different classification techniques, including e.g. support vector machines (SVM), decision trees (J48), and rule-based learners (JRip)[3]. By means of cross-validation on the training data, we searched for and fixed the best parameters for each classification technique and best feature set from S, H and D groups of features. Then, the selected classifiers were compared against individual triggering rules on the testing data. All the learnt classifiers were statistically significantly more accurate (about 10% on average) than any of the individual triggering rules according to paired t-test with respect to Youden index (YI) that regards true positive rate (TPR) and false positive rate (FPR) as equally important. J48 showed the lowest FPR, yet having slightly lower YI than SVM and JRip.

4 Conclusions and further work

In this paper[4] we presented a general approach for modeling patient state from historical data of different kinds, including vital signs, system usage, medical history and regular interviews and questionaires. We illustrated the potential of our approach on the example of the HFH prediction problem by providing the results of an experimental study with the data from a real clinical trial.

Our work laid the foundation for facilitating better personalization and alerting services in RPM systems, and we plan to continue working in this direction, particularly improving HFH prediction. We plan to make use of the educational data, motivational messages and other feedback provided to the patient by an RPM system or medical personnel, to obtain reliable and up-to-date information about the symptoms, and to make our prediction approach context-aware.

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[3] We used WEKA 3.6 data mining toolkit, `www.cs.waikato.ac.nz/ml/weka/`

[4] The extended version is accessible at `www.win.tue.nl/~mpechen/projects/rpm/`