Conditional Outlier Approach for Detection of Unusual Patient Care Actions

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Abstract

Developing methods that can identify important patterns in complex large-scale temporal datasets is one of the key challenges in machine learning and data mining research. Our work focuses on the development of methods that can, based on past data, identify unusual patient-management actions in the Electronic Medical Record (EMR) of the current patient and raise alerts if such actions are encountered. We developed and evaluated a conditional-outlier detection approach for identifying clinical actions such as omissions of medication orders or laboratory orders in the intensive care unit (ICU) that are unusual with respect to past patient care. We used data from 24,658 ICU patient admissions to first learn the outlier models and then to generate 240 medication and laboratory omission alerts. The alerts were evaluated by a group of 18 intensive care physicians. The results show the true positive alert rate for all study alerts ranged from 0.42 to 0.53, which is promising and compares favorably to the positive alert rates of existing clinical alerting systems.

Introduction

Our objective is to identify patient management actions for a given patient that are highly unusual with respect to past patients and the condition(s) that such a patient suffers from. We conjecture that unusual actions (or outliers) may frequently correspond to medical errors; hence it is worthwhile to raise an alert if they are prospectively encountered. Reduction of medical errors remains a significant healthcare problem (Kohn, Corrigan & Donaldson 2000).

We have developed an outlier-based monitoring and alerting approach that relies on past patient data and on outlier detection methods for the identification of unusual clinical actions. Typically, outlier detection methods (Markou & Singh 2003; Chandola, Banerjee & Kumar 2009) identify unusual data instances that deviate from the majority of examples in the dataset. In our problem and approach the objective is different: we want to identify outliers in a given patient's care, where individual patient management actions depend strongly on the condition of the patient. In this case, outliers correspond to *conditional outliers* (Hauskrecht et al 2007, 2010, 2012).

We evaluated our approach on EMR data for ICU patients. Our conjecture is that unusual clinical actions (e.g., medication orders and lab orders) when they are detected lead to clinically useful alerts. We believe outlier-based monitoring and alerting approach can complement the use of knowledge-based alerting systems that are currently deployed in the hospitals, thereby improving overall clinical coverage of current alerting systems.

Methodology

Preprocessing. Our approach first segments each patient case into multiple patient state instances using fixed 24-hour time segmentation. It then uses a temporal feature construction approach proposed in (Valko & Hauskrecht 2010) to create a wide assortment of features representing a patient instance at a segment of time *t*. Examples are features representing the last value of a patient's platelet count, the slope derived from its two most recent values, and features representing whether a certain medication (e.g., heparin) is currently given to the patient and the duration of the treatment. Finally, every patient state is associated with clinical care actions (medication and lab orders) that were observed in the following 24 hours.

Model building. We use a Support Vector Machine (SVM) (Vapnik 1995) to learn a model that predicts future clinical care actions from the patient-state features. The model is learned in two stages. First, the importance of the different clinical variables and their temporal features is assessed (on the validation set) in terms of the area under the ROC curve (AUROC) of the models defined upon these features. Second, the top k=15 clinical variables for each action and their features were combined and the final linear model was relearned. We note that this approach

performed better than approaches that would regularize out features from the full feature vector. The models were built using the liblinear package (Chang & Ling 2011) with the hinge loss and the L2 regularization options. To remedy some of the biases due to the choice of the linear kernel we use a non-parametric recalibration of the linear projection to estimate $p(\text{action}=1|\ \boldsymbol{x})$ and $p(\text{action}=0|\ \boldsymbol{x})$ reflecting the probability of a future clinical action given observed patient features $\boldsymbol{x}$.

Alert score. We used calibrated SVM model predictions to develop an *alert score* which measures how unusual the actions for the patients are. Briefly, an alert for a binary action *A* (e.g., heparin order) is derived from the probability of the counterfactual action, that is, the action that was not taken. For example, suppose a heparin was not ordered, and *P*(heparin is ordered | patient evidence) = 0.98, then the alert score on ordering a heparin would be 0.98. The alert score allows rank-ordering of alert candidates that are generated for each action and also allows the control of the rate at which alerts are raised for each clinical action by selecting an alert score threshold.

Controlling the alert threshold. We control the alert threshold as follows. Let A be a specific clinical action (e.g., aspirin order) and *PosRate*(A) be the average rate at which that clinical action is observed in the data (e.g., rate at which heparin is prescribed in the ICU population). We limit the clinical action alert rate to *AlertRate*(A) = α * *PosRate*(A), where *PosRate*(A) is estimated from the training set. With this method, the alert rate can be increased or decreased by changing the multiplier α.

Evaluation Study

Data. We used EMR data from 24,658 ICU patient admissions that included time-stamped data on medications, laboratory and physiological measurements. Each patient stay record was segmented into several patient state instances (in 24 hour increments), and each instance was summarized by a vector of over 11,000 different features. The data was split into a training set of 225,894 patient instances and a test set of 104,698 patient instances.

Model building. We built a SVM model for predicting each type of action (medication orders and laboratory orders) from the training set and applied the models to the test set for identifying omissions of medication orders and laboratory orders. In total, we built SVM models for 1075 different medication orders and 222 types of laboratory orders. Out of all the alert models, 99 laboratory and 156 medication omission models were strong predictive models based on their AUROC > 0.75 and positive predictive values. These were used to generate alerts for the study.

Study cases and their assessments. We selected 240 alerts generated by the strong models that included 165 medication-omission alerts (for 64 types of medications) and 75 laboratory-omission alerts (for 22 types of laboratory orders). The study alerts were evaluated by 18 critical care physicians. The reviewers were asked multiple questions related to the alert and its quality. The main study question: Will you take a clinical action based on receiving this alert? was then used to assess the quality of the alerts.

Results. Figure 1 shows the true positive alert rate (TPAR) for the different alert thresholds α that were varied in the interval [0.01 0.1]. The TPARs range from 0.53 for the tightest threshold (0.01) and strongest outliers to TPAR of 0.42 for the 0.1 threshold, which we view as quite promising. In terms of the number of alerts raised, we estimate that our system would generate 0.55 alerts per patient per day for α=0.05.

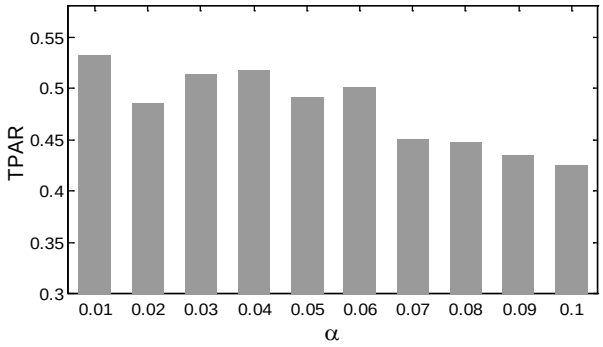

Figure 1. TPARs for the different alert thresholds α.

Discussion

Knowledge-based alerting systems in the literature are usually evaluated in terms of alert override rates (Hsieh et al 2004; Weingart et al 2003; VanDerSisj et al 2006; Baker 2007). The override rates may be influenced by multiple factors, such as the frequency (or the number) of alerts and their quality (Baker 2007, Shah et al 2007). In general, high frequency and low quality alerts can lead to alert fatigue and subsequently to high override rates alerts (Hsieh et al 2004; Weingart et al 2003; Baker 2007, Shah et al 2007, Seidling 2011). In such a case, it is possible that alert overrides may include both unimportant and important alerts. The override alert rates for a variety of drug safety systems reported in the above literature are in the 0.49 to 0.96 range. If override rates approximate false alert rates, then the TPARs for the literature just quoted are in the 0.04 to 0.51 range, and thus, the TPARs in our study compare very favorably to them. Similarly, our results compare favorably to TPARs of 0.01 to 0.14 for clinical monitoring systems reported in (Graham & Cvach 2010).

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