Predictive Models for Identifying Deterioration in Acutely Admitted Patients

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Introduction

Patients of all sorts and with a wide range of diagnoses are treated in emergency departments around the world every single day. Keeping track of such a diverse group of patients challenges both clinicians and information systems. Research shows that as many as 31 percent of acutely admitted patients who appear normal upon admission deteriorate during their stay – which is associated with high risk outcomes [1]. Many departments utilize expensive patient monitoring equipment. However, most of the automatic measurements made with these monitors are never included in clinical decision making as the stream of information is simply too immense for clinicians to process.

Machine learning techniques can examine and extract knowledge from large databases in an automatic way. Machine learning algorithms have been used in a variety of applications. They have been shown to be of special use in data mining scenarios involving large databases and where the domain is poorly understood and therefore difficult to model by humans [2]. Small improvements in accuracy can have large benefits given the high mortality associated with clinical deterioration and costs of resource utilization for false alarms. Therefore, several machine learning algorithms have been applied in this area and the performance of them evaluated and compared with traditional method.

Deterioration Definition

Jones et al. [3] reviewed publications from 1960 to 2012 and proposed four frameworks to define clinical deterioration and discuss to utility of each. They defined these models as:

- Definitions based on iatrogenesis and medical neglect
- Definitions based on discrete clinical complications
- Definitions based on deranged vital signs
- Future definitions of clinical deterioration

They finally defined deterioration as: *"A deteriorating patient is one who moves from one clinical state to a worse clinical state which increases their individual risk of morbidity, including organ dysfunction, protracted hospital stay, disability, or death"*.

Aim and Objectives

The objectives of this project are to build novel personalized predictive models for deterioration using temporal machine learning techniques, and determine which model is most suitable for seamless integration into clinical decision support systems. Existing prediction models have a high false positive rate, leading to multiple false alarms and alarm fatigue [4]. Although higher sensitivities are desirable and of course that it be clinically practical by generating as few false warnings as possible [5], so we wish to introduce better system for deterioration prediction with respect to both specificity and sensitivity. Therefore, the objectives of this project are:

- To introduce personalized predictive models for clinical deterioration.
- To improve deterioration detection systems in terms of reducing false alarm.
- To build models that can handle messy data.

Methods

In this project, we wish to investigate the potential of automatic deterioration detection using novel machine learning techniques on vital signs collected automatically during regular treatment to further support clinicians in identifying risk patients. The project extends an ongoing effect evaluation study where a new dashboard for monitoring patients admitted to the Emergency Department. In the ongoing project, consenting patients will have their vital values and a subset of admission characteristics registered. This data can potentially be utilized for building better models for identifying patterns of deterioration by coupling them with machine learning algorithms.

Current deterioration detection models cannot handle sparse and diverse clinical data, so alternative machine learning models suitable for this problem could be: Filter-bank with Auto-regressive modelling (AR), Auto-regressive-Moving-Average models (ARMA), Gaussian Mixture Models (GMM) and the Bayesian framework; each of these will be equally assessed and tested.

We wish to introduce personalized predictive system to analyze each patient based on his/her characteristics.

Personalized predictive models are customized for an individual patient and trained using information from similar patients. Compared to global models trained on all patients, they have the potential to produce more accurate risk scores and capture more relevant risk factors for individual patients [6]. It seems Gaussian Processes (GP) are great tools for this problem, because GPs have been successfully used to model and forecast real dynamic systems because of their flexible modeling abilities and their high predictive performances. To make predictions, we apply a certain function to the inputs to obtain an estimate of a certain output.

References

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