Predicting Patient's Consultation Length in Emergency Departments with Machine Learning

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1 Introduction

Predicting consultation length in Emergency Departments (EDs) is an important step to anticipate upcoming operational bottlenecks that may lead to alterations in the provided service. Faced with numerous challenges, such as increased patient volumes, limited inpatient bed availability, and nurse and physician shortages, EDs encounter frequent capacity limitations, which lead to recurrent ED alteration episodes. The consultation length in ED patients might depend on many factors within and outside the ED. For instance, the patient's demographics, vital signs, arrival time to the ED, triage (severity) level, among others. If consultation length estimates were available early in a patient's ED encounter, capacity limitations could be identified earlier [2]. Hence, we propose two machine learning models to predict consultation length in EDs and thereby create a decision support tool for resource allocation to improve patient care and to reduce patient's waiting time and ED overcrowding.

Our study is motivated by the case of an ED from a university hospital in Montreal. At present, estimates for the length of a consultation as well as the allocation of patients to the doctors are done on the basis of the severity level (triage level). This triage level takes values from one to five. The lower the triage level is, the more urgent the case is and the longer the consultation time is estimaded to be. One of the objectives of this study is to investigate whether the incorporation of other factors such as the patients' arrival mode to the ED, symptoms, age, among others could improve the estimation of the consultation length or not.

2 Method

2.1 Data set description and feature selection

An anonymous dataset with 350,393 entries was collected from March 2008 to September 2017. The consultation length was categorized into three different groups depending on the duration of consultation: short (0-30 min), average(30-60 min) and long (61 min and above). An initial number of 46 features were extracted and created from the input data. After using two different feature selection methods (correlation matrix and feature importances), only the 20 most relevant features were selected. These features include the triage level, the doctor's id, the doctor's shift, the number of patients waiting in the emergency room, the patient's age, gender, number of symptoms, registration hour, registration day, among others.

2.2 Machine learning algorithms

We used two classification algorithms: random forests and neural networks. Both algorithms were tested under two scenarios. In the first scenario (S1) we included the 20 most relevant features, while in the second scenario (S2) we only considered one feature corresponding to the triage level of each patient. Table 1 presents the accuracy of both algorithms for each of these two scenarios.

Algorithm	Iterations/Epochs	Features - Scenario	Testing accuracy
Random forests	100 Iterations	20 features (S1)	59.78%
Random forests	100 Iterations	Triage level (S2)	36.57%
Neural networks	100 Epochs	20 features (S1)	47.52%
Neural networks	100 Epochs	Triage level (S2)	36.67%

TAB. 1: Comparison of the accuracy of two machine learning algorithms using different features.

From Table 1 we can observe that the accuracy of the two classification algorithms significantly increases when additional features are included in the models. Specifically, an increase of 63.4% and a 29.6% in the prediction accuracy can be observed for the random forest and neural network models, respectively. Therefore, we can conclude that the consultation time depends on other factors such as the patients' arrival mode to the ED, symptoms, age, doctor's id, number patients waiting in the ED, among others.

The use of a random forests is suggested over the use of neural networks since this model has a higher testing accuracy, it is easier to understand and it presents a simple way to derive a policy for consultation time classification.

3 Conclusions

We presented two machine learning models to predict patient's consultation length in EDs. Numerical results show that the incorporation of additional features such as the number of symptoms in a patient, the registration day and hour, the doctor's id and the number patients waiting in the ED, can significantly improve the accuracy of the prediction when compared to a model that only incorporates the triage level. Future research perspectives include the incorporation of these predictions in a scheduling model as suggested by [1].

References

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