Digital Health and Informatics Innovations for Sustainable Health Care Systems
J. Mantas et al. (Eds.)

doi:10.3233/SHTI240505

Exploring Hospital Overcrowding with an Explainable Time-to-Event Machine Learning Approach

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Abstract. Emergency department (ED) overcrowding is a complex problem that is intricately linked with the operations of other hospital departments. Leveraging ED real-world production data provides a unique opportunity to comprehend this multifaceted problem holistically. This paper introduces a novel approach to analyse healthcare production data, treating the length of stay of patients, and the follow up decision regarding discharge or admission to the hospital as a time-to-event analysis problem. Our methodology employs traditional survival estimators and machine learning models, and Shapley additive explanations values to interpret the model outcomes. The most relevant features influencing length of stay were whether the patient received a scan at the ED, emergency room urgent visit, age, triage level, and the medical alarm unit category. The clinical insights derived from the explanation of the models holds promise for increase understanding of the overcrowding from the data. Our work demonstrates that a time-to-event approach to the over- crowding serves as a valuable initial to uncover crucial insights for further investigation and policy design.

Keywords. Emergency Department, real-world data, Survival analysis, Machine Learning, Healthcare Systems, Explainable Artificial Intelligence (XAI).

1. Introduction

The complexity of ED flows is characterized by high volume and high clinical variability, thus making challenging not only the analysis of the patients flows, but also the organization of the system to provide high quality of care [1,2]. The high pressure is also related to the overcrowding of the hospital [3,4], and high length of stay in the ED is correlated to this "saturation" and the clinical complexity of the patients [1,5].

Therefore, the high length of stay and the key decision regarding discharge or admission to the hospital are highly influenced by both clinical and logistics aspects [3,4]. However, despite the large amount of published research, the overcrowding of EDs is still stands unsolved [6–8]. Moreover, the focus of previous data-driven methods (such as traditional approaches such as multivariate linear models and simulations, or novel techniques based on machine learning and process mining) has been on the volume of

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flows rather than clinical variability, missing considerations on how the complexity of medical evaluation can impact prompt decisions [1,2].

In this work we propose a novel approach to study the overcrowding from the emergency medicine production data abstracting the problem as a time-to-event analysis. The intuition behind this work is to approach the problem like a survival analysis of the hospital flows from which we investigate how much time is needed to process them (length of stay) and make the final decision (admission or discharge).

This novel analytical abstraction of healthcare production data constitutes an opportunity to comprehensively analyse healthcare system operations and increase our understanding of the overcrowding phenomena [9–11].

2. Methods

2.1. Emergency medicine department production data

The data set used for analysis in this work were collected and approved for being analysed by the Academic Hospital of Uppsala (Sweden) and covers all the patients that sought care in the ED during 2019. The data set consisted in 49938 number of visits from 33881 unique patients. The following features were included: hour of arrival 0-24h (T_IN_ED), weekday of arrival (DAY_IN_ED), age, sex, municipality, triage code, arrival with ambulance y/n, reason of visit (chief_complaint), performed imaging assessment in the ED y/n (scan), need of care from the emergency room y/n, specialisation of the clinical team handling the patient (team_care contact), type of speciality that would be needed in case of hospital admission (MA_unit), main ICD10 diagnostic group (ICD_ED_cat2), eventual re-visit y/n, final decision between discharge from the ED or admission to a hospital ward, and length of stay from arrival until the final decision.

2.2. Time-to-event analysis of healthcare logistics

In time-to-event problems the goal is to analyse data where the outcome is the time until an event of interest occurs [12]. A given instance i can be represented by a triplet (X_i , y_i , E_i), where X_i is the feature vector, E_i is the binary event indicator ($E_i = 1$ if the event of interest happened, and $E_i = 0$ for a censored instance), and y_i the observed time for the event happening (T_i), or censoring (C_i).
In this work, we abstracted the problem of studying the healthcare logistic flows of an ED by representing the instances of the healthcare production data with X_i features collected during the visit i, and y_i the length of stay in the ED before discharge T_i or C_i admission to the hospital. Associating the censoring of E_i with the hospital admission allowed to account the major impact on the system resources when patients are not discharged from the healthcare system because the need of further care and monitoring.

In Figure 1 we reported a summary of the analytical pipeline. The analysis was carried out by the following steps:

- **Pre-processing.** The raw data were cleaned and harmonised in a tabular format. A prior feature selection was carried out using RSF using the same approach of Engleber et al. [13].
- **Time-to-event analysis.** five different survival models were used: Cox regression (CPH), Random Forrest (RSF), Gradient boosting (GB), XGB and

DeepSurv. The model performances were evaluated using 5-fold cross validation. The performance was evaluated with the Harrell's concordance index (C-index) [14]. A search-grid approach was used for tuning GB, XGB and RSF.

- **Explainable Machine Learning.** The model interpretation of the time-to-event outcomes is made by computing the Shapley values (SHAP) [15].

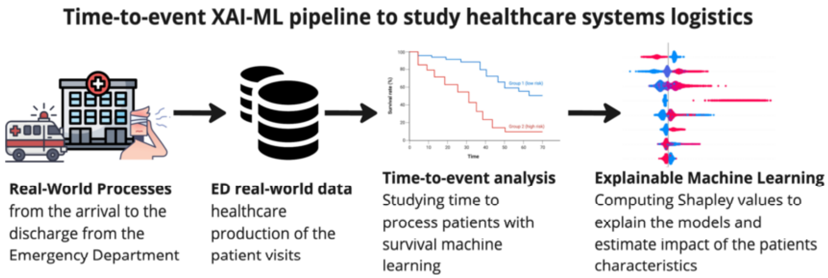
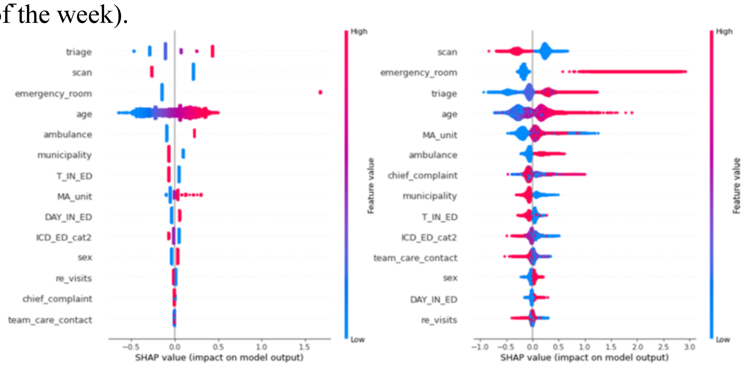


Figure 1. analytical pipeline to study healthcare logistics with a survival analysis approach.

3. Results

All models provided good and similar performances. GB provided the best performance with a C-index of 0.7825 ± 0.0049. SHAP summary plots of the whole data set using CPH as benchmark and best performing GB are shown in Figure 2. Interestingly, CPH provided similar C-index of GB, but less discrimination among the SHAP values, thus providing less insights on the data compared to the other model. The other survival machine learning models showed a similar ranking of the features SHAP values. Looking at the SHAP values generated for the whole data set with the GB model, the five most important features in order were: "scan", "emergency room", "triage", "age" and "MA unit" while the least important were "sex", "DAY IN ED" and "re visits". The "DAY IN ED" lower importance is an interesting finding (the length of stay is not so affected by the day of the week).



(a) SHAP values obtained from CPH (b) SHAP values obtained from GB

Figure 2. SHAP summary plots for CPH and GB for the whole data set

4. Discussion

The aim of this work was to explore a new approach to study overcrowding of healthcare systems by analysing their production using a time-to-event analysis approach.

Formulating the problem of how much time patients spend in the emergency department before a decision is made as a time-to-event analysis allowed us to analyse the follow up pro- cesses behind the data, and how patients' characteristics impact on the entire system.

Moreover, SHAP values allowed to explain the reasoning of the model from the local interpretation of the single patient record to the global effect of the whole flows. This step served as a preliminary sensitivity analysis and provided the occasion to bridge the technical analysis with the clinical aspects that we are interested to discuss regarding the overcrowding problem.

For example, looking at feature "scan" having a lower value which indicates no scan (0 = no) shows that the length of stay was shorter until admission while having a higher value which indicates a scan (1 = yes) gave the patient a longer length of stay until admission. This can be seen as reasonable as the scan is one more process in the ED that will increase waiting time, or that imaging assessment is performed for patients that need more detailed analysis. In contrast, key variables in the decision-making such as chief complaint and ICD10 main diagnosis provided a lower feature importance, thus manifesting the saturation of the system from which regardless your clinical condition, the time you spend in the ED is extremely similar.

5. Conclusions and Future Research

The presented approach provides a valuable combination between data-driven and process analysis. Moreover, this approach allows to concomitantly study the high volume and clinical variability of ED flows and overcome previous limitations [1,2]. However, our approach presents some limitations. The analysed data come with some limitations regarding not reported processes in the hospital that can affect the ED [7]. The granularity of the information in the data is important to consider and should not be underestimated as some major data that does influence on the overcrowding may be missed in the data collection [16,17]. Furthermore, production data do not always reflect the clinical logic in the system. Therefore, despite the results adhere with previous findings validated by the clinical experts [18], the supervision of experts when introducing new variables or adding steps in the pipeline would be required. Furthermore, the approach would benefit from adding further sensitivity analysis steps with the SHAP values to explore robustness of outcomes in function of the data input. Addressing the technical challenges and the active involvement of clinicians would improve the proposed approach and make it more useful for the clinical practice.

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