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Paper Review: Real-time prediction of inpatient length of stay for discharge prioritization

The title of the reviewed paper is "Real-time prediction of inpatient length of stay for discharge prioritization", and it was written by Sean Barnes, Eric Hamrock, Matthew Toerper, Sauleh Siddiqui, and Scott Levin. This paper was chosen because our mentor, Dr. Siddiqui, is a co-author and it provides useful information for constructing a patient census simulation. The goal of our project is to develop a simulation that uses historical data to output an hourly census for a medical-surgical unit. We will then develop a program that uses this census to create a nurse schedule that adequately staffs the unit while minimizing extraneous costs. This paper describes a method of predicting patients' length of stay using various patient attributes and external factors. This gave us background on how to use patient flow data from a hospital unit and how to determine a patient's length of stay, one of the key components of our simulation. We referenced the process in the paper to find factors to use for segmenting our data and predicting length of stay in our own simulation.

The main objective of this study was to use supervised machine learning methods to automate and improve discharge predictions for a medical unit. The authors gave a few reasons why improving discharge predictions would be beneficial. First and foremost, they cited evidence that patient flow is linked to patient safety and satisfaction and indicated that patient flow is a main determinant of hospital resource management. According to former studies, poor patient flow leads to worse patient outcomes because prolonged lengths of stay increase the risk of hospital complications. Additionally, the authors cite increasing pressure on hospitals to deliver cost-efficient care, which heightens the importance of efficient resource management by hospitals. Thus, being able to predict and improve patient flow would also help hospital management, reduce costs, and boost patient satisfaction. The authors go on to discuss real-time demand capacity management (RTDC), a new process for discharge prediction that involves a daily morning huddle of clinicians. Together, the clinicians coordinate patient flow and determine which patients are most likely to be discharged. These patients are prioritized so that they are discharged in an efficient manner, and so more beds will be available for new admissions. The authors indicate some shortcomings of this process: RTDC is highly subjective and variable because it is based on clinicians' opinions, and clinicians must devote time from their morning to take part in this process. To rectify these shortcomings, the study was performed to determine how to automate this process and to develop a model that can predict discharges more accurately than the clinicians in their daily huddle. Ultimately, the authors were able to apply supervised machine learning algorithms to historical data to make daily discharge predictions. In comparison with the clinicians' predictions, the model performed comparably well and outperformed the clinicians on one of the performance metrics. Despite some limitations of this study, the results show that there is potential to apply historical health information to make patient discharge predictions and use these predictions to improve patient flow and staff scheduling.

In terms of the methods, the study was conducted in one medical unit. Patient flow data in this unit over 34 months, from January of 2011 to November of 2013, was used. The data included demographics, admission diagnoses data, patient census, day of the week, elapsed length of stay, and observation status. Age, patient census, and length of stay were numerical variables. The rest of the variables were modeled using binary variables – 0 or 1 to indicate the absence or presence of a category. The patient's reason for visiting the hospital was also recorded in the data and used as an indicator. For RTDC, the clinicians normally make predictions for discharges at 2 p.m. and midnight everyday. To match this process, the machine learning models were designed to produce discharge predictions for these two times and to base these predictions on data that would have been available at 7 a.m., which is when the clinician huddles occurred. The authors trained a few machine learning algorithms using the historical patient flow data and used the algorithms on test data to estimate their performance. Primarily, they applied tree-based methods that iteratively partitioned the data into groups of patients with similar attributes and outcomes. By using these classification trees, they could determine how the predictor variables interact and which variables were most critical for predicting discharges at either 2 p.m. or at midnight. They cited an example that they found – patients who are on observation status are more likely to be discharged, but only when they report chest pain as their chief complaint or when their elapsed length of stay exceeds 12 hours. In their algorithm, they used these trees to classify new patients with novel attributes and determine their likelihood of being discharged.

For the study, they trained the models on patient flow data from January 2011 to March 2013 and used the models to make predictions for 8 months after that. They also collected clinician predictions from the same 8 months for comparison to their model. Out of all the algorithms they used, they found that the regression random forest (RRF) was most accurate in its predictions. They used this model to determine which variables were more important predictors than others, and the two variables that emerged as most important were elapsed length of stay and observation status. Compared to the clinicians' predictions, the RRF model was more aggressive in predicting discharges, but not to a statistically significant amount. The two methods performed comparably well almost across the board for individual discharge predictions. The RRF model outperformed the clinicians in estimating the average number of patients to be discharged each day, and it also performed significantly well when predicting the order in which patients would be discharged.

After providing these results, the authors provide some implications of this study and discuss three ways in which this approach could be utilized in the hospital. Their model can be used to identify individual patients who are most likely to be discharged, and these patients can be prioritized to discharge them as early as possible and free up bed space. Another way would be to prioritize a second tier of patients who are moderately likely to be discharged, which they theorize can have a more significant impact on the number of patients discharged over a period of time. Finally, the daily discharge predictions can be aggregated and used to support bed capacity planning. The authors note that this study opens up the potential for automating and improving the RTDC prediction process. They emphasize that this would eliminate the need for daily clinician huddles and benefit patient flow.

While the study provides convincing results that the prediction process can be automated at a comparable level with current clinician predictions, there are limitations to mention. This study was done in only one medical unit, and its results are likely not generalizable to other units that operate differently or are located in other regions with different populations. The authors' intention was for other units to train the model on their own data to use, but there is not sufficient data to guarantee that the results will still be as accurate for these other units. The authors also recognize that they compared probability-based predictions from the models to binary (stay or discharge) predictions from the clinicians, which is not ideal. Within the actual paper, the authors fail to explain their methods in depth and do not mention what specific machine learning algorithms they used – RRF is mentioned for the first time as one of their models when discussing results. Nevertheless, the study provides adequate insight into the process of discharge predictions and can advise future projects in the same field of improving patient flow. For our own project, we broaden the scale of this study with hospital resource management in mind. We expand upon its work by attempting to improve staff scheduling as well. Instead of predicting patient discharges, we aim to predict patient length of stay to generate an hourly census for a medical unit. To do this, we have referenced this study for factors that affect length of stay, which is directly related to discharge time, as well as for information on how to use the historical patient data that we have obtained. This paper also informed us of how clinicians currently predict the census of their unit, which helped us design our simulation. Overall, the paper provided valuable background and brought up points that we have taken into consideration for our project.

Works Cited

Barnes S, Hamrock E, Toerper M, Siddiqui S, Levin S. Real-time prediction of inpatient length of stay for discharge prioritization. *Journal of the American Medical Informatics Association: JAMIA*. 2016;23(e1):e2-e10. doi:10.1093/jamia/ocv106.