Faircare Analytics: Predicting 30-day readmissions

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Github repository

Introduction

The average cost to the patient for unplanned readmissions within 30 days of a prior discharge is estimated to be $16,037. On aggregate, the cost to US hospitals of 30 day readmissions is estimated at $52.4 billion per year. These unplanned readmissions for a variety of reasons including but not limited to gaps in care, or conditions characterized by frequent relapses

We attempted to use predictive models trained on electronic health records to classify patients' readmission risk, allowing for timely intervention hopefully reducing the overall cost of readmission to patients and to the system as a whole.

Stakeholders and Project Objectives

The key stakeholders are inpatient providers and networks. In addition, patients and caregivers would benefit from a readmission risk assessment. The main objective for this modeling project is to achieve high prediction and recall scores on the dataset under consideration. The **UCI Diabetes 130-US Hospitals Dataset (1999–2008)** is a publicly available dataset which was used for this project. A secondary objective was to have comparable accuracy metrics across some demographic categories which we hope will be a preliminary indication that our methods might fare well with a more rigorous bias audit framework.

Methods and Models

Faced with a classification problem with many categorical variables; for example, unique medications with directional values, admission ids and others, the team used logistic regression as a baseline model achieving high AUC scores but low recall scores for successfully predicting a 30-day readmission. In exploratory data analysis we found pairwise weak correlation between most of the encoded variables. Due to the high ratio of records to features, as well as the mix of categorical and numerical variables, XGBoost was settled on as a classification algorithm for the processed data. The target variable was binary: 0 for no/30-or-more day readmission and 1 for a less than 30 day readmission.

Results

Overall, higher AUC scores were observed with the XGBoost algorithm, but without a significant improvement in the recall scores. While the final model had high recall scores for predicting non-readmission, which is to be expected by the high relative frequency of non-readmission, the model performed poorly in correctly predicting readmissions. Across demographics, the recall scores for predicting 30 day readmissions were similarly low, reflecting that the model was consistently underperforming across gender, but there were disparities in the metrics across age and racial categories. We found that the XGBoost classifier to perform a ternary classification (readmitted within 30 days/readmitted after 30 days/not readmitted) always leads to over-fitting. It failed to perform any better than the binary classification. Finally, the binary classification of readmitted vs not readmitted was considerably more successful, with a calibrated XGBoost outperforming other models.

Future Goals

The comparative underperformance across demographics gives hope that a model built along these lines will fare well under a rigorous bias audit framework. We are confident that the XGBoost algorithm is the most suited for this purpose, and that with access to a larger dataset like MIMIC-III or MIMIC-IV characterized by more medical conditions, recall scores will improve. Furthermore, we hope to undertake a different approach to our modeling in the future. Deep reinforcement learning is almost certainly better suited to this purpose.