Machine Learning for Healthcare 2019 – Clinical Abstract Track

Improving Readmissions Modeling with Social Determinants of Health

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Background: Early hospital readmissions are considered to be an adverse outcome, potentially indicating substandard care or inadequate coordination of care after discharge. Up to 17.6% of hospital admissions result in a readmission within 30 days and up to three quarters of readmissions are potentially avoidable.[1] Financial penalties for readmissions incentivize hospitals to prevent readmissions. Therefore, healthcare systems benefit from determining which patients are at high-risk for readmission prior to hospital discharge. Myriad factors contribute to readmission risk; thus, predicting readmission risk is difficult. Accordingly, a variety of patient data, including clinical and social factors,[2] should be considered for this prediction task. Previously developed readmissions models lack these social factors. We developed a 30-day readmissions prediction model using 501patient features from the electronic health record (EHR). We then compared this model to an established readmissions predictive tool, HOSPITAL[3], and demonstrated the impact of social determinants of health in modeling this outcome.

Data: The dataset for this analysis included patient demographics, medical history, vital signs, laboratory values, medication administration and hospital encounter information for patients admitted to three hospitals within our healthcare system between October 2014 and August 2018. Social determinants of health features included race, ethnicity, payor information, zip code, discharge disposition, and social/case manager/therapy notes. Hospital encounters for patients under the age of 18 and those who died during hospital admission were excluded from the cohort. The final cohort included 134,950 patients, with 221,713 inpatient hospital encounters, was used to predict 30-day hospital readmissions.

Methods: Patient data from the EHR was extracted, cleaned and curated for the cohort inpatient encounters. The readmission outcome variable defined as readmission or emergency department visit to the hospital within the 30 days following an index encounter. Four models were trained on 200,003 inpatient encounters and tested on a held-out validation set of 22,171 encounters. Using extreme gradient boosted decision trees, we developed three models with varying input features and compared their accuracy to the HOSPITAL model. All models were cross-validated to find the optimal hyperparameters.

Results: Applying the HOSPITAL model to the same validation set achieved a C-statistic of 0.584 (**Table 1**). By changing the model type to an extreme gradient boosted decision tree, the accuracy measure increased by 8.6%. Adding features to describe social determinants of health increased the accuracy even more, and finally adding health information from the patients encounter (vitals, medication administration, lab values, encounter information) further increased model performance to 0.754.

Table 1: Four readmissions models comparing AUROC when varying input features.

Feature types	Model types	AUROC
HOSPITAL	LR	0.584
HOSPITAL	gradient boosted decision trees	0.670
HOSPITAL + social features	gradient boosted decision trees	0.726
HOSPITAL + social features + EHR encounter features	gradient boosted decision trees	0.754

Implementation: Hospital readmissions are problematic for most hospital systems. Integration of this 30-day readmissions risk calculator, which incorporates social factors, could better help clinical teams identify those at high risk for readmission, and in particular, could identify specific patient needs from a community and social perspective. This work will include workflow optimization to determine which team assets are best positioned to lead discharge planning and marshal additional support for patients at high risk of being readmitted to the hospital shortly after discharge.

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